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

Abdimalik Ali Warsame¹,4 · Ibrahim Abdukadir Sheik-Ali²,4 · Galad Mohamed Barre³,4 · Abdulnasir Ahmed⁵

Received: 14 July 2021 / Accepted: 21 July 2022 / Published online: 9 August 2022
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract
Agricultural production is sensitive to climate variability, so climate change-agriculture sector nexus is topical in developing countries. To this end, this study examines the impact of climate change variables—rainfall and temperature—and non-climatic factors on maize production in Somalia for the period between 1980 and 2018 using the autoregressive distributed lag (ARDL) bound test, dynamic ordinary least square (DOLS), variance decomposition (VD), and impulse response function (IRF). The empirical results of the ARDL bound test confirmed the presence of long-run cointegration between the dependent variable and the explanatory variables. Furthermore, the long-run results revealed that average temperature, average rainfall, and political instability significantly inhibit maize production in the long and short runs, but rainfall has a favorable effect on maize production in the short run. Furthermore, rural population and land area under maize cultivation have negative and positive effects on maize production in the long run, respectively—albeit they are statistically insignificant. The empirical results of the study are robust to different econometric methods. 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 Climate change · Maize production · Cointegration approach · Somalia

Introduction
There is consensus among scholars and researchers that climate change plays a significant role in agricultural productivity. Since the world is experiencing massive population growth, fast urbanization, changes to dietary patterns, and increasing incomes (Thornton et al. 2009; Mihiretu et al. 2019; Ayanlade and Ojebisi 2020; Warsame et al. 2022a), it is expected that the demand for food, including cereal crops, will rise significantly in the near future. Thus, to satisfy human nutrition needs, cereal crops, especially maize, must increase since it is one of the most important food sources for human consumption. However, the negative effect of climate change—variability in rain patterns, rising temperatures, and floods—on crop production is a great challenge for the agriculture sector to meet the ever-increasing demand for its products.

Several empirical studies (Abbas and Mayo 2021; Pickson et al. 2020; Shayanmehr et al. 2020; Warsame et al. 2021) reported the negative impact of climate change on crop production in both developed and developing countries. However, these studies noted that the adverse effect of climate change is more felt in developing countries, especially agriculture-based countries (Shayanmehr et al. 2020; Warsame et al. 2022b). Using Ricardian analysis and quantile regression, Migliore et al. (2019) pointed out that climate variations have an enormous impact on the yields of major crops grown in the Sicilian region, Southern Italy. Pickson et al. (2020), in their study in China, found 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. (2020a, 2020b, 2020c) who found a similar result in the case of China. Similarly, Porter and Semenov (2005) and Zhao et al. (2017) discovered that maximum temperature and water variability have detrimental effects on crop yields. Wheeler and Von Braun (2013) argued that rising temperature and changes in rainfall patterns are still the main factors that determine the agricultural productivity of countries even though there is continuous technological progress.

Furthermore, Amin et al. (2015) found that temperature and rainfall have a significant negative impact on major crops in Bangladesh, particularly the rice and wheat yields. A follow-up study by Xu et al. (2016) estimated a decrease in maize yield in Iowa, the USA from the twentieth century to the twenty-first century by employing simulation and linear regression models. The results from all simulation models indicated a maize yield decline of 15-50% from the late twentieth century to the middle and late twenty-first century, while the results of linear regression revealed that a 1°C rise in temperature leads to a 6% state-averaged maize yield decline. Similarly, using simulation models, Chandio et al. (2020a, 2020b, 2020c) reported 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 impacts on all these crops except wheat. It was observed that rainfall has a positive and significant effect on wheat, thus confirming our argument that different crops react differently to climate variations.

In sub-Saharan Africa, climate change potentially threatens agricultural productivity and maize production specifically. Godwin et al. (2021) observed that rainfall enhances maize production and temperature impedes it in Ghana. In the same vein, recent estimations have shown that maize production will decrease in the distant future due to climate change (Zhang et al. 2021). This is also emphasized by the study of Mccarthy et al. (2021) in Malawi. They found that crop production is severely hit by both floods and droughts, with average losses ranging between 32 and 48%. Moreover, Luhunga (2017) reported similar results in Tanzania. Specifically, the simulations predicted a maize yield decrease of 3.1% and 5.3% under two representative concentration pathways. Sarkodie and Owusu (2017) concluded that there is bidirectional causality between carbon dioxide emissions and agriculture production in Ghana.

In the context of Somalia’s economy, the agriculture sector is still the main source of income for the country. It contributes around 75% to the nation’s gross domestic product and 93% to its total export earnings (Warsame et al. 2022b). Meanwhile, Somalia is one of the countries that is extremely vulnerable to climate variations (Warsame et al. 2021). More precisely, temperature changes 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 harm maize yields which is one of the most important crops in Somalia. Somali farmers heavily depend on rainfall for growing crops; the availability of other means such as drilling is limited. Consequently, maize production decreases sharply in times of rainfall failures (Warsame et al. 2021).

In addition to climatic variations, political instability poses another imminent threat to Somalia’s agriculture sector, especially in 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 the Al-Shabab terrorist group—a terrorist group that operates mainly in Somalia and has an affiliation with Al-Qaeda. Thus, these excessive taxes make the farming business unprofitable, risky, and costly. Also, the political instability in these regions has made interventions by aid agencies extremely challenging and impossible. Thus, this situation has forced many farmers to stop farming activities and increased the displacement (World Bank and FAO 2018).

As evidenced by Figure 1, maize production in Somalia exhibits trending volatility from 1960 to 2019. Maize production was quietly stable during the 1960-1970 periods, but from 1972 to 1974, it dramatically plummeted due to the droughts that occurred in Somalia in the earlier 1970s. However, it immediately recovered in the following years and maize output reached 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 that broke out in Somalia in 1991. Maize output soared to a record level of 287,500 tons in 2001 and 2002 since the collapse of the central government in 1991, but it declined to a low level of 100,000 tons in 2006. This reduction is attributed to the beginning of the war between the Islamic Courts Union (ICU) and the Transitional Federal Government of Somalia backed by the Ethiopian military. Moreover, a destructive drought in 2011—which later turned into famine—reduced maize production from 132,627 in 2010 to 65,126 tons in 2011. From 2011 onwards, maize production has been declining. Hence, it is notable that maize production in Somalia is inhibited by political instability, recurrent droughts, and floods induced by climate change.
Despite the adverse effect of climate change and political instability on maize production, Somalia still 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 aid agencies and the federal government of Somalia from devising adaptation and intervention policies that are aimed at improving water availability, irrigation facilities, and implementing effective 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 it difficult to design a coherent agricultural policy since the scientific evidence that would guide the formulation of specific-context agricultural 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 that investigated the issue empirically and systematically in several ways. First, Warsame et al. (2021) used the crop production index, which in aggregate measures agriculture production. However, by doing so, it introduces a bias resulting from the aggregation since climate change affects different crops in different ways. Therefore, this study tries to solve this aggregation bias by using individual crops to measure agriculture production properly and draw suitable policy implications. Specifically, this study focused on maize production since it is the third most consumed crop in Somalia after staple food crops and sorghum which amounted to 23% between 2016 and 2017 (World Bank and FAO 2018). Besides, Warsame et al. (2021) failed to account for the adverse effect of political instability on agricultural production. This study, therefore, assessed the impact of political instability along with climate variables on maize production amidst the changing climatic conditions in Somalia.

Methodology and data sources

Data

We used annual time series data covering the period 1980-2018. The study used maize production as the dependent variable, while rainfall, temperature, rural population, political instability, and maize area under cereal are used as the regressors. Subsequently, all the variables were converted into a natural logarithm to mitigate heteroskedasticity. The descriptions and sources of the data utilized in this study are illustrated in Table 1.

Econometric modeling

To empirically investigate the long-run and short-run effects of climatic and non-climatic factors on maize production in Somalia, the study utilized the ARDL bound test. We have selected this approach because it has many advantages over the other competing cointegration methods. Specifically, this approach can estimate the long-run and short-run relationship between variables even if the variables of interest are integrated both at the level I (0), the first difference I (1), or the combination of both. It is also useful to be utilized when the sample size of the observations is small. Additionally, it can regress long-run and short-run cointegration using a single equation. Moreover, it takes into consideration the asymmetric function of the coefficients of the conditional error correction and bias-corrected bootstrap methods which can be estimated to draw reliable statistical inferences of the
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 |            |
| Rural population                      | RP     | Percentage of rural population to the total population | World Bank |
| Maize area under cultivation          | MUC    | Square kilometer area | FAO        |

long-run cointegration between sampled variables. Besides, we specified our model by following the works of Adelaja and George (2019), Chandio et al. (2020a, 2020b, 2020c), Warsame et al. (2021), and Chandio et al. (2021) as follows:

\[
\ln MP_t = \beta_0 + \beta_1 \ln AR_t + \beta_2 \ln AT_t \\
+ \beta_3 \ln RP_t + \beta_4 \ln MUC_t + \beta_5 \ln PIS_t + \epsilon_t
\] (1)

\(\ln MP\) is the log of maize production in year \(t\), \(\ln AR\) is the log of average rain in year \(t\), \(\ln AT\) is the log of average temperature in year \(t\), \(\ln RP\) is the log of the rural population in year \(t\), \(\ln MUC\) 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 \(\epsilon_t\) is the error term in time \(t\).

Since the objective of this study is to analyze the impact of climate change variables and non-climate variables on maize production in both the long run and short run, the study rewrites Eq. (1) as long-run cointegration of the ARDL equation in the following manner:

\[ \Delta \ln MP_t = \alpha_0 + \alpha_1 \Delta \ln MP_{t-1} + \alpha_2 \Delta \ln AR_{t-1} + \alpha_3 \Delta \ln AT_{t-1} \\
+ \alpha_4 \Delta \ln RP_{t-1} + \alpha_5 \Delta \ln MUC_{t-1} + \alpha_6 \Delta \ln PIS_{t-1} \\
+ \sum_{i=1}^{q_1} \beta_i (\Delta \ln MP_{t-1}) + \sum_{i=1}^{q_2} \beta_i (\Delta \ln AR_{t-1}) \\
+ \sum_{i=1}^{q_3} \beta_i (\Delta \ln AT_{t-1}) + \sum_{i=1}^{q_4} \beta_i (\Delta \ln RP_{t-1}) \\
+ \sum_{i=1}^{q_5} \beta_i (\Delta \ln MUC_{t-1}) + \sum_{i=1}^{q_6} \beta_i (\Delta \ln PIS_{t-1}) + \epsilon_t \] (2)

The definition of variables remains the same. \(\alpha_0\) is the intercept, \(\alpha_{1-6}\) is the coefficient of long-run, \(\beta_i\) represents the coefficient of short-run variables, \(q\) represents the number of lags, \(\Delta\) is the operator of the first difference, and \(\epsilon_t\) is the error term.

In addition to this, the ordinary least square (OLS) method was employed to estimate Eq. (2), and Wald F-statistic was utilized to test the null hypothesis of no cointegration between the climatic and non-climatic factors on one hand and maize production in Somalia on the other hand against the alternative hypothesis indicating that there is cointegration among variables of interest. In this regard, the Wald F-statistics decides whether to reject the null hypothesis or not by comparing the calculated lower bound critical values I (0) and upper bound critical values I (1) which assumes that all variables are I (0) and I (1), respectively. If the Wald F-statistics is lower than the lower critical value, we fail to reject the null hypothesis, so we conclude that there is no cointegration in our model. If the Wald F-statistics value is higher than the upper value, we reject the null hypothesis and conclude that the variables have a long-term relationship. Once the long-run cointegration between the variables of consideration is established, the next step would be estimating the short-run relationship between scrutinized variables using the following short-run equation:

\[ \Delta \ln MP_t = \sum_{i=1}^{q_1} \beta_i (\Delta \ln MP_{t-1}) + \sum_{i=1}^{q_2} \beta_i (\Delta \ln AR_{t-1}) \\
+ \sum_{i=1}^{q_3} \beta_i (\Delta \ln AT_{t-1}) + \sum_{i=1}^{q_4} \beta_i (\Delta \ln RP_{t-1}) \\
+ \sum_{i=1}^{q_5} \beta_i (\Delta \ln MUC_{t-1}) + \sum_{i=1}^{q_6} \beta_i (\Delta \ln PIS_{t-1}) + \Theta ECT_{t-1} \] (3)

Empirical analysis and discussion

Descriptive statistics

Table 2 summarizes the summary statistics and correlation of the interesting variables of the study. Maize and land under maize cultivation have the 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 the fact that its dummy variable created—given 0 and 1. The highest standard deviation values are shown by the land under maize cultivation (0.49) and maize production (0.48), and this implies how their average values are scattered from their normal values. Furthermore, the average temperature is positively skewed, whereas rainfall, maize, rural population, and land under maize cultivation are negatively skewed. Jarque-Bera points out that political instability is 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 that maize has a positive correlation with rural population and land under maize production. Contrary to that, average temperature, average rainfall, and political instability are established to have negative correlations with maize production. Regarding climate variables, the average temperature is observed to have a positive correlation with average rainfall and political instability, and a negative relationship with land under maize cultivation and rural population. In addition, average rainfall has a positive relationship with land under maize cultivation, and a negative correlation with the rural population and political instability. Land under maize production is positively correlated with the rural population and negatively associated with political instability. The rural population is negatively correlated with political instability.

### Unit root test

To circumvent biased and incorrect inferences, two-unit root tests—augmented Dickey-Fuller (ADF) and Philips Perron (PP)—were employed to check the unit root issues. Table 3 shows the results of unit root tests. Only average rainfall (lnAR) and land under cereal cultivation (lnMUC) were stationary at the level (i.e., I(0)). However, the other variables (lnMP, lnAVT, lnRP, and PIS) were stationary after their first difference (i.e., I(1)). We then proceeded to apply the ARDL

### Table 2 Descriptive statistics

| Variable | lnMP | lnAVT | lnAVR | lnMUC | lnRP | PIS |
|----------|------|-------|-------|-------|------|-----|
| Mean     | 11.98798 | 3.301822 | 3.109788 | 11.97417 | 4.194593 | 0.702703 |
| Median   | 11.89136 | 3.301953 | 3.103335 | 12.14666 | 4.211965 | 1.000000 |
| Maximum  | 12.77507 | 3.334483 | 3.509205 | 12.80050 | 4.293701 | 1.000000 |
| Minimum  | 11.00210 | 2.76998 | 2.656198 | 10.50183 | 4.028632 | 0.000000 |
| Std. dev. | 0.482871 | 0.012893 | 0.191617 | 0.492642 | 0.078921 | 0.463373 |
| Skewness | −0.027885 | 0.378609 | −0.075417 | −0.815656 | −0.701978 | −0.886969 |
| Kurtosis | 2.038555 | 2.864673 | 2.852930 | 3.290418 | 2.373412 | 1.786713 |
| Jarque-Bera | 1.429875 | 0.912192 | 0.068420 | 4.232767 | 3.644044 | 7.120832 |
| Probability | 0.489223 | 0.633753 | 0.966369 | 0.120472 | 0.161698 | 0.028427 |

### Table 3 Unit root tests

| Variable | ADF | PP |
|----------|-----|----|
|          | Level | Level |
| lnMP     | Interception | Intercept and trend | Intercept | Intercept and trend |
| lnMUC    | −2.894* | −4.1069** | −2.9499** | −4.0874** |
| lnMP     | −2.0394 | −3.1723 | −2.0687 | −3.1723 |
| lnAVT    | −2.7240 | −5.9612*** | −2.5689 | −6.5323*** |
| lnAVR    | −6.6817*** | −7.7283*** | −6.8118*** | −7.7236*** |
| lnMAH    | −1.4913 | −1.1631 | −3.1735 | −0.8832 |
| lnRP     | −1.6299 | −1.5753 | −1.6276 | −1.5753 |
| PIS      | −6.1644*** | −6.2071*** | −6.1644*** | −6.2187*** |
|          | First difference | First difference | First difference | First difference |
| lnMP     | −7.1538*** | −7.2022*** | −7.1801*** | −7.2463*** |
| lnRP     | −5.4607*** | −5.9087*** | −5.4578*** | −7.1669*** |
| PIS      | −6.1644*** | −6.2071*** | −6.1644*** | −6.2187*** |

***, **, and * indicate significance level at 10%, 5%, and 1% respectively
estimation technique since none of the variables is integrated at order two (i.e., I(2)).

Cointegration test results

After verifying that none of the scrutinized variables is integrated at second order I (2), we examined the presence of long-run cointegration among the variables using the bound test. The null hypothesis states that the series are not cointegrated against the alternative hypothesis that the series are cointegrated in the long run. Table 4 indicates that the F-statistics (5.5) is greater than the upper bound critical value (4.56) at a 5% significance level. Hence, this confirms the presence of long-run cointegration between maize production, and climate and non-climate variables. Notably, the study used Narayan critical values since our sample size is small which is appropriate for the Narayan critical values. Hendry’s general-to-specific approach was also used to determine the optimal lag length.

The impacts of climate change and political instability on maize production

After verifying that the variables are cointegrated in the long run, we subsequently estimated the long-run coefficients of the parameters. The long-run coefficient results presented in Table 5 revealed that land under maize production is positively cointegrated with maize production in the long run, but it is insignificant. Conversely, average temperature, average rainfall, rural population, and political instability are adversely related to maize production, even though rural population and political instability are statistically insignificant in the long run. Interpretively, a 1% increase in average rainfall impedes maize production by about 0.50% in the long run. Furthermore, average temperature inhibits maize production by about 11.67% for a 1% increase in average temperature. This finding sheds the light on the fact that temperature has a massive adverse influence on maize production in Somalia.

Table 4 Results of the ARDL bound tests for cointegration

| Model       | F-statistic | Significance | Bound test critical values |
|-------------|-------------|--------------|----------------------------|
| lnAP = f (lnAVR, lnAVT, PIS, lnMUC, lnRP) | 5.5057 | 1% | 4.483 | 6.32 |
|             |             | 5% | 3.12 | 4.56 |
|             |             | 10% | 2.56 | 3.828 |

Table 5 Long-run and short-run coefficient elasticities of the model

| Variable | Coefficient (t-statistics) |
|----------|----------------------------|
| lnAVR    | −0.5084* (−2.0339)         |
| lnAVT    | −11.6778*** (−3.3604)      |
| PIS      | −0.0412 (−0.5247)          |
| lnRP     | −0.9952 (−1.4028)          |
| lnMUC    | 0.0656 (−0.6503)           |
| Constant | 46.3443*** (3.525)         |

| ECT (−1) | −0.3185*** (−3.3323)       |
| Δ(lnMP (−1)) | 0.0722 (0.7400)       |
| Δ(lnMP (−2)) | 0.1754 (1.6901)       |
| Δ(lnMP (−3)) | 0.3653** (2.3499)     |
| Δ(lnAVR (−2)) | 0.4956*** (3.3567)   |
| Δ(lnAVR (−3)) | 0.3066** (2.1033)     |
| Δ(lnAVT (−1)) | −10.9463*** (−3.2525) |
| Δ(lnAVT (−3)) | 7.8287** (2.5345)     |
| Δ(lnRP (−3)) | 11.2806*** (3.3348)   |
| Δ(lnMUC) | 0.4599*** (4.9844)      |
| Δ(lnMUC (−3)) | −0.1453 (−1.2036)     |
| Δ(PIS) | −0.5339** (−2.4678)     |

*** and ** indicate significance at 1% and 5% levels, respectively. T-statistics are reported in parenthesis. Δ = differencing

Our findings regarding the adverse effect of temperature and precipitation on maize production are in line with recent empirical studies. For instance, Chandio et al. (2021) discovered that rising temperature significantly reduces rice production in major Asian countries. This study is also consistent with the study of Warsame et al. (2021)—conducted in Somalia—who concluded that temperature harms crop production. But, the impact of climatic
variables—temperature—on maize output is the same as the aggregate crop production of Warsame et al. (2021) findings. They found that a 1% increase in temperature reduces crop production by 11.5% compared to the maize—11.6%—in the long run. On the contrary, they found that a rise in precipitation improves crop production compared to the negative effect of rainfall on maize production 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 could be attributed to the fact that maize is the major cultivated crop in Southern Somalia which depends on irrigation from the rivers. Hence, an increase in rainfall leads to floods which ultimately lead to the reduction of maize crops. Nevertheless, our finding on the negative effects of temperature on maize crops is corroborated with previous studies (see Luhunga 2017; Xu, Twine, & Girvetz 2016), and the adverse impact of rainfall on maize output agrees with previous findings (see Amin et al. 2015; Chando et al. 2020a, 2020b, 2020c).

In addition, Ali et al. (2017) uncovered that rainfall undermines agricultural production in Bangladesh. Likewise, our results corroborate the study of Cudjoe (2021) in Ghana, and Mccarthy et al. (2021) in Mali, which found that temperature hampers maize production. The results of these studies support our conclusion of the negative effect of temperature on maize. Hence, the majority of the existing literature suggest that temperature impedes agriculture production, and rainfall enhances it. But, some studies have established different results from the aforementioned findings. These inconclusive results could be explained by the differences in methodology used, data discrepancy, and the climate nature of the investigating country.

Furthermore, the short-run dynamic effect and error correction term (ECT) are also reported in Table 5. It is established that rainfall significantly enhances maize production in the short run, whereas temperature hampers it. A 1% increase in average rainfall will result in maize production increasing by about 0.49% in the short run. This indicates that an increment in rainfall results in an upsurge in maize production. This is because Somalia depends on the rainfall immensely. So, missing one of the rainy seasons can cause maize output to decrease significantly while it can lead to maize yield increase during the times of the rainfall. A similar outcome was found by Pickson et al. (2020). Average temperature substantially reduces maize production by about 10.8% in the short run if the average temperature is increased by 1%. This result is supported by previous examinations (Warsame et al. 2021). Maize output is highly sensitive to extreme temperature changes as it affects maize yields. Rural population—measured for agriculture labor—significantly improves maize production by about 11.28% in the short run for a 1% increase in rural population. This is contrary to the long-run negative result of the rural population. Likewise, land under maize production increases maize production by about 0.45% in the short run if it is increased by 1%. This corroborates with the long-run positive result of the land under maize production—even though it is insignificant. Political instability significantly hampers maize production in the short run. A one-unit increase in political instability leads to maize production to decrease by about 0.53% in the short run. More importantly, the ECT—reported in Table 5—should be significant and negative in order for the model to converge. Our ECT met both conditions, and we conclude that any deviation shocks that occur in maize production in the short run are being adjusted 31.8% in the long run annually.

The results of diagnostic and stability tests

The study conducted several diagnostic tests such as serial correlation, heteroskedasticity, normality, and model misspecification to avoid spurious findings and validate the statistical adequacy of the estimated model to make relevant conclusions. We also tested the model stability of the study. The findings of these tests presented in Table 6 revealed that no evidence of diagnostic problems has been detected. As such, the variance of error terms is not correlated. The variance of the error terms is constant. The model is correctly specified, and the data are normally and identically distributed. Moreover, the model of the study is stable as shown by Figures 2 and 3 since the line is in between the two critical lines. Thus, it shows that it is significant and stable.

Robust checks using the dynamic ordinary least squares technique

However, relying on a single estimation method can lead to biased results and policy inferences; thus, we re-estimated the long-run coefficient of the parameters using the dynamic ordinary least square (DOLS) estimation method to find robust results. The DOLS results reported in Table 7 revealed that land under maize production and average temperature have adverse effects on maize.
production in the long run—even though the temperature is insignificant. A 1% increase in land under maize production leads to maize crops increasing by about 1.49% in the long run. In addition, average rainfall, rural population, and political instability significantly hamper maize production in the long run. Regarding the interpretation of coefficient elasticities, a 1% increase in average rainfall and rural population contribute to maize production decrease by about 8.59% and 9.72%, respectively, in the long run. Interestingly, political instability hampers maize production by about 1.07% in the long run, if one unit rises in political instability. In summary, the long-run outcome of the ARDL is in line with the results of the DOLS estimation method.

Furthermore, political instability’s adverse effect on agricultural production, in general, is reflected in food insecurity and poverty situations of the prone-conflict Somalia population. Political instability escalates conflicts and wars which disrupt the supply of inputs and outputs as well as its distribution, lead to price shocks, and cause widespread migration of labor due to insecurities. More importantly, political instability hampers both domestic and foreign agricultural investments, sabotaging the accomplishment of full potential agriculture production. However, maize is largely cultivated in the south and central regions of Somalia, and these regions have been severely affected by conflicts compared to the northern, and eastern regions of the country. Therefore, political instability undermines maize production. Thus, the adverse effect of political instability on agriculture production is supported by several previous studies.

![Fig. 2 Cusum test](image1)

![Fig. 3 Cusum square test](image2)
who came to the same conclusion (Adelaja and George 2019; Arias et al. 2019).

**Impact accounting**

Shocks in climate variables have substantial effects on maize production in the short run, and one of the limitations of ARDL and DOLS is their lack of ability to capture this effect. Therefore, we have performed variance decomposition (VD) and impulse response function (IRF) to account for the shock effects of variables on each other.

The results of VD presented in Table 8 revealed that 52.07% of future fluctuations in maize production are explained by historical dynamics in maize production, whereas 18.40% are responsible for land area under maize production. In the same vein, maize production and land area under maize production cause 27.6% and 32.6%, respectively, of future variations in land area under maize production. Attributively, maize production and land area under maize cultivation are closely related, and a rise in land area under maize cultivation contributes to an increase in maize output. Furthermore, future fluctuations in rural population by 44.65%, 20.35%, and 18.9% are due to historical dynamics in land area under maize cultivation, maize production, and average rainfall, respectively. Hence, this sheds the light on how agriculture cultivation activities—maize production and its the land area—are the main drivers of environmental deforestation in Somalia (Warsame and Sarkodie 2021). Regarding climate variables, 42.9% of variations in average temperature are caused by itself, whereas 24% are responsible for maize production. Additionally, rainfall—itself—causes 38.5% of future fluctuations in average rainfall, while maize production and political instability are responsible for 21% and 14.8%, respectively. It is worth noting that maize production is critical for political instability because 34.3% of variations in political instability are caused by maize production, even though political instability is self-responsible for its highest variations (55%).

Besides, the IRF results reported in Figure 4 indicate that a one standard deviation shock in rainfall leads to a decrease in maize output from period 1 to period 5. From period 5.5 to period 9, the response is positive, whereas in period 10, the response is zero. Moreover, maize production responds negatively in the first 3 periods; from periods 3 to 4, the response turns zero if one standard deviation shock increases in average temperature, whereas from periods 8 to 10, the response turns positive. Hence, this contradicts the findings of several studies that concluded that temperature impedes agriculture production. Furthermore, one standard deviation shock in political instability results in maize production decreases in the first 2 periods. From periods 3.5 to 5.5, maize responds substantially decreasing. From period 6, there is a small positive response of maize for one standard deviation shock in political instability. This is in line with several studies that found that conflicts undermine investment, infrastructure, and agriculture production. Maize output responds positively for one standard deviation shock in the rural population in the first 4 periods, but from periods 4.5 to 5.5, the response turns negative before it becomes positive in the periods 6-7. In the final 3 periods, the response turns negative. Finally, land under maize cultivation exerts a negative effect on maize production in the first 4 periods, but from period 4, the response turns into a positive.

**Conclusion**

Climate change-agriculture sector nexus is topical, where rising temperature and rainfall variabilities have posed a threat to the agriculture sector and food security in developing countries. To this end, this study investigated the impact of climate change variables—rainfall and temperature—on maize production in Somalia. Maize crop is cultivated mainly in south and central Somalia, and it is worth noting that this region has been devastated by a long period of political and
Table 8 Variance decomposition

| Period | S.E. | lnMP  | lnAVR | lnAVT | PIS   | lnRP  | lnMUC |
|--------|------|-------|-------|-------|-------|-------|-------|
| 1      | 0.262553 | 100.0000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 2      | 0.394436 | 68.55240 | 4.485295 | 12.39171 | 1.439316 | 2.351564 | 5.781593 |
| 3      | 0.469262 | 70.98917 | 6.042411 | 13.75811 | 1.948879 | 2.667918 | 8.439118 |
| 4      | 0.495059 | 67.13024 | 10.99558 | 12.39171 | 1.948879 | 2.667918 | 8.439118 |
| 5      | 0.522711 | 60.23340 | 12.29446 | 10.92687 | 3.897701 | 3.002075 | 16.60415 |
| 6      | 0.554668 | 56.11963 | 13.61213 | 10.92687 | 3.897701 | 3.002075 | 16.60415 |
| 7      | 0.570656 | 53.18941 | 13.39332 | 10.42046 | 3.803544 | 3.113734 | 17.95068 |
| 8      | 0.584036 | 52.65821 | 13.23698 | 10.33351 | 4.165082 | 3.002075 | 16.60415 |
| 9      | 0.609135 | 52.72992 | 12.35131 | 10.06757 | 3.876721 | 3.023811 | 17.95068 |
| 10     | 0.622908 | 52.07796 | 11.81258 | 10.77753 | 3.707415 | 3.223392 | 18.40112 |

Variance decomposition of lnMUC:

| Period | S.E. | lnMP  | lnAVR | lnAVT | PIS   | lnRP  | lnMUC |
|--------|------|-------|-------|-------|-------|-------|-------|
| 1      | 0.323511 | 26.32358 | 17.48966 | 1.649137 | 0.057096 | 0.112584 | 54.36795 |
| 2      | 0.395662 | 37.01167 | 11.82094 | 3.861367 | 2.882748 | 3.182744 | 41.24052 |
| 3      | 0.456501 | 47.33463 | 9.859219 | 3.394561 | 2.435532 | 2.572892 | 34.0137 |
| 4      | 0.513149 | 37.46251 | 16.18122 | 2.950630 | 10.14068 | 2.411847 | 30.85311 |
| 5      | 0.564858 | 31.35466 | 14.18920 | 6.474427 | 8.491407 | 3.789734 | 35.70057 |
| 6      | 0.606327 | 27.29762 | 16.21330 | 5.943902 | 11.58293 | 3.418760 | 35.56149 |
| 7      | 0.617558 | 27.58365 | 15.66937 | 5.923106 | 11.65055 | 3.511239 | 35.66208 |
| 8      | 0.626177 | 28.26310 | 15.25542 | 6.780808 | 11.41075 | 3.581686 | 34.70292 |
| 9      | 0.647745 | 28.35224 | 14.40346 | 8.491042 | 11.70075 | 3.697135 | 33.35373 |
| 10     | 0.660001 | 27.66043 | 13.89486 | 9.647798 | 12.49223 | 3.61288 | 32.69340 |

Variance decomposition of lnRP:

| Period | S.E. | lnMP  | lnAVR | lnAVT | PIS   | lnRP  | lnMUC |
|--------|------|-------|-------|-------|-------|-------|-------|
| 1      | 0.011263 | 26.74062 | 28.67810 | 0.167894 | 8.764487 | 35.64900 | 0.00000 |
| 2      | 0.014619 | 20.00303 | 35.23589 | 0.704183 | 6.762760 | 35.01163 | 2.282510 |
| 3      | 0.017711 | 31.91983 | 10.34518 | 3.459939 | 3.182744 | 3.182744 | 35.70057 |
| 4      | 0.022103 | 29.51467 | 14.18920 | 6.474427 | 8.491407 | 3.789734 | 35.70057 |
| 5      | 0.025812 | 29.21837 | 14.90307 | 3.810283 | 4.267575 | 3.12143 | 41.74592 |
| 6      | 0.032596 | 19.38267 | 20.50882 | 1.104531 | 4.094950 | 13.18359 | 41.74592 |
| 7      | 0.034715 | 19.58005 | 19.53925 | 1.203744 | 3.739989 | 12.29383 | 43.63859 |
| 8      | 0.037056 | 20.35566 | 18.98257 | 1.216121 | 3.355206 | 11.43955 | 44.65489 |

Variance decomposition of lnAVT:

| Period | S.E. | lnMP  | lnAVR | lnAVT | PIS   | lnRP  | lnMUC |
|--------|------|-------|-------|-------|-------|-------|-------|
| 1      | 0.162241 | 5.45322 | 84.54678 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 2      | 0.197387 | 22.21494 | 64.35834 | 0.333194 | 10.46266 | 0.017921 | 2.612945 |
civil unrests. We added political instability as a main determinant variable of maize output in the study. Several econometric methods such as ARDL, DOLS, and impact accounting—VD and IRF—were espoused with a time series data spanning from 1980 to 2018. The empirical results of the ARDL bound test have shown that the explanatory variables are cointegrated into maize output in the long run. Regarding the long-run coefficient parameters, average temperature, average rainfall, and political instability significantly inhibit maize production in the long run. But, rainfall has a favorable effect on maize production in the short run, whereas temperature and political instability impede maize production in the short run. Furthermore, rural population and land area under maize cultivation have negative and positive effects on maize production in the long run, respectively—albeit they are statistically insignificant. The long-run coefficient elasticities of the ARDL are robustly confirmed by the DOLS cointegration method.

Based on the empirical findings, the study recommends several policy implications. First, the government of Somalia should design policies and initiatives to de-escalate conflicts. Ensuring a friendly politically stable environment will enhance agricultural production by increasing investment, employment, and production. Second, even though climate change—driven by environmental pollution—is a global issue, Somalia’s policymakers should work with their global partners to the fight against rising temperature by reducing environmental degradation via deforestation and greenhouse gases (GHG). Moreover, ensuring the availability of water can enhance agriculture production; hence, policymakers should implement irrigation system practices such as building dams and storing water facilities that can be used during periods of precipitation shocks. This will not only help farmers during the rainy season, but it will also help mitigate floods. Finally, since the study found that land area under maize cultivation stimulates maize production in the long run, the government of Somalia should offer incentives to the farmers and increase the privatization of government lands to the farmers to double the cultivation in the country. But, this should be done with rules and regulations that are in favor of environmental sustainability.

| Table 8 (continued) | MP | lnAVR | lnAVT | PIS | lnRP | lnMUC |
|----------------------|---------|---------|---------|-----|-------|-------|
| 3                    | 0.242149 | 19.88360 | 56.63783 | 8.161432 | 11.21959 | 0.181629 | 3.915918 |
| 4                    | 0.251142 | 18.85165 | 52.92795 | 7.611499 | 10.43045 | 0.709653 | 9.468799 |
| 5                    | 0.263754 | 21.53177 | 48.09128 | 6.954697 | 12.07073 | 2.120836 | 9.230686 |
| 6                    | 0.273570 | 20.44318 | 45.89169 | 8.863658 | 12.83881 | 2.071396 | 9.891265 |
| 7                    | 0.288517 | 21.67477 | 43.31747 | 8.131976 | 14.73445 | 1.870726 | 10.27061 |
| 8                    | 0.314414 | 21.22377 | 38.83511 | 12.34809 | 14.88481 | 3.872834 | 8.835384 |
| 9                    | 0.316042 | 21.02625 | 39.01295 | 12.36535 | 14.99736 | 3.853020 | 8.745066 |
| 10                   | 0.318187 | 21.34262 | 38.56626 | 12.23766 | 14.80441 | 4.067735 | 8.981319 |

Variance decomposition of PIS:

| Period | S.E. | lnMP | lnAVR | lnAVT | lnPIS | lnRP | lnMUC |
|--------|------|------|-------|-------|-------|------|-------|
| 1      | 0.186846 | 38.26599 | 4.214479 | 0.618402 | 56.90113 | 0.000000 | 0.000000 |
| 2      | 0.259185 | 42.16755 | 2.192655 | 6.080622 | 47.58521 | 0.811931 | 1.162031 |
| 3      | 0.331089 | 44.11042 | 5.928814 | 4.434588 | 44.03696 | 0.701855 | 0.787365 |
| 4      | 0.378263 | 40.85585 | 5.282400 | 3.405083 | 48.81589 | 0.764755 | 0.876031 |
| 5      | 0.413780 | 40.72080 | 4.414884 | 2.847207 | 49.47760 | 1.082180 | 1.457334 |
| 6      | 0.439777 | 40.73344 | 4.018921 | 3.118628 | 49.44185 | 1.238675 | 1.448488 |
| 7      | 0.444132 | 38.95132 | 3.838808 | 3.433300 | 51.20538 | 1.183433 | 1.387766 |
| 8      | 0.452643 | 37.61455 | 3.820832 | 3.306450 | 52.57277 | 1.715616 | 1.513843 |
| 9      | 0.462815 | 36.07115 | 3.656760 | 3.177439 | 54.04637 | 1.149075 | 1.899209 |
| 10     | 0.474908 | 34.32811 | 3.504547 | 3.028196 | 55.00942 | 1.098540 | 3.031191 |
Fig. 4  Impulse response function
Author contribution Abdimalik Ali Warsame performed the design of the study, data collection, and analysis, and improved the overall paper. Ibrahim Abdukadir Sheik-Ali wrote methodology, revised introduction and literature, and reviewed and edited the paper. Galad Mohamed Barre wrote introduction. Abdullah Siraj Ahmed wrote literature.

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

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

Abbas S, Mayo ZA (2021) Impact of temperature and rainfall on rice production in Punjab, Pakistan. Environ Dev Sustain 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 Dev 117:184–195. https://doi.org/10.1016/j.worlddev.2019.01.010

Ali S, Liu Y, Ishaq M, Shah T, Abdullah IA, Din IU (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 7(1):898-915. https://doi.org/10.3390/su7010898

Arias MA, Ibáñez AM, Zambrano A (2019) Agricultural production amid conflict: separating the effects of conflict into shocks and uncertainty. World Dev 119:165–184. https://doi.org/10.1016/j.worlddev.2017.11.011

Ayanlade A, Ojebisi SM (2020) Climate change impacts on cattle production: analysis of cattle herders’ climate variability/change adaptation strategies in Nigeria. Change Adap Socio-Ecol Syst 5(1):12–23. https://doi.org/10.1515/cass-2019-0002

Chandio AA, Jiang Y, Rehman A, Rauf A (2020a) 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 AA, Ozturk I, Akram W, Ahmad F, Mirani AA (2020b) Empirical analysis of climate change factors affecting cereal yield: evidence from Turkey. Environ Sci Pollut Res 27(11):11944–11957

Chandio AA, Maggi H, Ozturk I (2020c) Examining the effects of climate change on rice production: case study of Pakistan. Environ Sci Pollut Res 27(8):7812–7822. https://doi.org/10.1007/s11356-019-07486-9

Chandio AA, Gokmenoglu KK, Ahmad M, Jiang Y (2021) Towards sustainable rice production in Asia: the role of climatic factors. Earth Syst Environ. https://doi.org/10.1007/s41748-021-00210-z

Godwin P, Cudjoe PA-A, B AG (2021) The effect of climate variability on maize production in the Ejura-Sekyedumase municipality, Ghana. Climate 9(145):1–15

Luhunga PM (2017) Assessment of the impacts of climate change on maize production in the southern and western highlands sub-agro ecological Zones of Tanzania. Front Environ Sci 5(51):1–16. https://doi.org/10.3389/fenvs.2017.00051

Mccarthy N, Kilic T, Brubaker J, Murray S (2021) Droughts and floods in Malawi: impacts on crop production and the performance of sustainable land management practices under weather extremes. Environ Dev Econ 26:432–449. https://doi.org/10.1017/S1355770X20000455

Migliore G, Zinnanti C, Schimenti E, Borsellino V, Schifani G, Di Franco CP, Ascuto 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 EN, Lemma T (2019) Determinants of adaptation choices to climate change in agro-pastoral dry lands of Northeastern Amhara, Ethiopia. Cogent Environmental. Science 5(1):1636548.s

Pickson RB, He G, Ntiamoah EB, Li C (2020) Cereal production in the presence of the climate change in China. Environ Sci Pollut Res 27(36):45802–45813

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. Afr J Agric Res 13(19):969–977. https://doi.org/10.5897/ajar2018.13111

Sarkodie SA, Owusu PA (2017) The relationship between carbon dioxide, crop and food production index in Ghana: by estimating the long-run elasticities and variance decomposition. Environ Eng Res 22(2):193–202

Shayanmehr S, Henneberry SR, Sabouni MS (2020) Drought, climate change, and dryland wheat yield response: an econometric approach. Intl J Environ Res Public health 5(17):52–64

Thornton PK, Van De Steeg J, 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. Agric Syst 101(3):113–127. https://doi.org/10.1016/j.agsy.2009.05.002

Warsame AA, Sheik-Ali IA, Jama OM, Hassan AA, Barre GM (2022a) Assessing the effects of climate change and political instability on sorghum. J Clean Prod. https://doi.org/10.1016/j.jclepro.2022.131893

Warsame AA, Sheik-Ali IA, Hassan AA, Sarkodie SA (2022b) Extreme climatic effects hamper livestock production in Somalia. Environ Sci Pollut Res:1–13. https://doi.org/10.1007/s11356-021-18114-w

Warsame AA, Sarkodie SA (2021) Asymmetric impact of energy utilization and economic development on environmental degradation in Somalia. Environ Sci Pollut Res 1–13. https://doi.org/10.1007/s11356-021-17595-z

Warsame AA, Sheik-ali A, Osman A, Sarkodie SA (2021) Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. Environ Sci Pollut Res 5(17). https://doi.org/10.1007/s11356-020-11739-3

Wheeler T, Von Braun J (2013) Climate change impacts on global food security. Clim Chang 112(2):525–533. https://doi.org/10.11007/s11356-019-07486-9
World Bank, FAO (2018) Somalia Country Economic Memorandum: Rebuilding resilient and sustainable agriculture in Somalia. World Bank; FAO

Xu H, Twine TE, Girvetz E (2016) Climate change and maize yield in Iowa. PLoS One 11(5):1–20. https://doi.org/10.1371/journal.pone.0156083

Zhang L, Zhang Z, Tao F, Luo Y, Cao J, Li Z, Xie R (2021) Planning maize hybrids adaptation to future climate change by integrating crop modelling with machine learning. Environ. Res. Lett

Zhao C, Liu B, Piao S, Wang X, Lobell DB, Huang Y et al (2017) Temperature increase reduces global yields of major crops in four independent estimates. Proc Natl Acad Sci 114(35):9326–9331

Publisher’s note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.