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MAIZE OUTPUT SUPPLY RESPONSE TO CLIMATIC AND OTHER INPUT VARIABLES IN ETHIOPIA

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ABSTRACT

Climate change is among the major challenges to sustainable agricultural production in Ethiopia. Production of cereal crops, especially maize, is very responsive to changes in rainfall and temperature, as climatic parameters influencing productivity. This paper analyzes how climatic and other variables affect the supply of maize in Ethiopia. The data were obtained from secondary sources and cover the period 1981–2018. Data were analyzed using the Autoregressive Distributed Lag (ARDL) approach. The Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQ) were used to select the optimum number of lags. In order to detect whether unit root is present in the series, Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests were carried out. The presence of long-run equilibrium was found between maize output and temperature, rainfall, and other included variables. The results show that, in both the long and shortrun, all included climatic variables had a negative relationship with maize output supply, although temperature showed statistical insignificance ($P>0.10$). The result showed that maize crops are highly sensitive to extremes of rainfall – both shortage in the initial growing period and excessin the vegetative and fruiting stages. It was concluded that farmers face climate-related risk due to variations, particularly in rainfall. Therefore, farmers should adapt by using short-duration and climate-tolerant varieties of maize, along with engagement with eco-friendly production systems.

Contribution/Originality: This study analyzed the supply response of maize in Ethiopia using various econometric procedures. The novelty of the study is its integration of climatic and non-climatic variables to generate the long-run equilibrium parameter and evaluate its statistically significant robustness.

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1.INTRODUCTION

In sub-Saharan Africa (SSA), maize (*Zea mays*) remains a vital staple food for promoting food security and nutrition among both adults and children. Maize cultivation has increased over the past few decades, and the crop currently ranks among the most widely extensively cultivated crops with more than 36 million hectares devoted to its production in 2017(FAOSTAT, 2019). This datum implies that of the 200 million hectares estimated cropland areas in SSA, maize production occupies about 17%.

According to Mandefro, Tanner, and Twumasi-Afriyie (2002), Ethiopia is considered the third largest producer and supplier of maize crop in Africa, next to South Africa and Tanzania. It accounts for about 10% of the area cultivated, while its productive output is estimated to be about 12% of the production level of the region. Furthermore, the yield levels of maize crop exceed the regional average yield level, with about 1.7 metric tons/ha compared to 1.5 metric tons/ha for the African region. In Ethiopia, maize is among the primary cereal crops with the highest rank in terms of production volume (CSA, 2018). Climatic parameters are critical inputs in maize production. Therefore, maize is largely grown under rainfed agronomic conditions and it is also one of the most extensively grown crops in Ethiopia, thriving under different agro-climatic zones among people with diverse socioeconomic conditions.

Regionally, maize is mostly grown in the southwestern and western parts of Oromia, western and northwestern parts of Amhara, parts of the Southern Nations, Nationalities, and Peoples' Region (SNNPR), and Benshangul-Gumuz regions. Available data show that Oromia region accounts for about 56% of maize production while about 25% comes from the Amhara region (CSA, 2018). Minor maize-producing regions include SNNP, with a share of 14%, Benshangul-Gumuz (2.4%), and Tigray (2%).

Maize production is now being limited by climate change since the crop is mainly cultivated during the long-rainfall period between May and September (Mosisa, 2012). Specifically, a scrutiny of the past trends of weather situation in Ethiopia signifies that rainfall and temperature are dynamic with significant changes over time. Meteorological data show that Ethiopia has experienced increasing temperatures over the past 38 years (Belay et al., 2021). These changes are compromising production of cereal crops, and maize is among those most affected (Keno et al., 2018).

It had been shown that in Ethiopia, compared to the actual production potentials, maize is still underperforming from the yield and production perspectives (van Dijk et al., 2020). Similarly, the rain-fed nature of Ethiopian agriculture also threatens food security and the livelihoods of farming households (Kariuki, Njaramba, & Ombuki, 2020). It should be noted that changing climate is manifested through increasing temperature, droughts, floods, and changing rainfall patterns. Plant metabolic rates and pest infestation can result from increases in minimum temperature. A warmer environment can also bring about extension of cropping seasons and facilitate plant growth(Rojas-Downing, Pouyan Nejadhashemi, Harrigan, & Woznicki, 2017). Therefore, climate change can promote pest infestations and consequently lead to drastic reduction in staple crop yields.

Studies conducted to assess the impact of climate change on maize production, particularly at the national level in Ethiopia, are limited. Given the existence of aggregated national data on maize output and input, understanding the supply response of maize output to climate change variables can inform certain vital policy implications. It is evident that supply of cereal output, including maize crop output, to climatic and socioeconomic variables is responsive to recent years' lagged variables, which should be examined in detail to provide information for future use by economic planners and policy makers. Therefore, this study seeks to analyze the supply response of maize output to changes in climate and other associated socioeconomic variables.

2. MATERIALS AND METHODS

2.1. Description of the Study Area

Ethiopia is an East African country that shares borders with Sudan, Eritrea, Djibouti, Somalia, Kenya, and South Sudan (World Bank, 2021). Administratively, Ethiopia is structured into ten Regional States and two City Administrative Councils. Based on a United Nations Population Funds (2021) population projection, the current population of Ethiopia is about 117.90 million with an annual growth rate of 2.6 percent. Maize is one of the major crops in Ethiopia, the majority of the production coming from mid-altitude, sub-humid regions (MOA, 2005).

2.2. Data Type and Sources

In this study, nationally aggregated time series secondary data on maize output, area cultivated, irrigated area under maize, inputs used (fertilizer and improved seed), and price of maize output were obtained from CSA Agricultural Sample Survey reports for the period covering 1981–2018. Secondary data on weather conditions (temperature and precipitation) for the periods 1981–2018 were obtained from the National Meteorological Agency (NMA) of Ethiopia based on data available from 13 representative weather stations in that area based in major maize crop-growing belts. Specifically, average monthly values of data for the short-rainfall season (February–May) and long-rainfall season (June–September) were recorded. In addition, nationally aggregated average data for crop-growing seasons were calculated by taking the average of weather stations selected for the crop over the period 1981–2018. Historical prices of maize outputs were compiled from FAOSTAT database, CSA, and EGTE for the period 1981–2018.

2.3. Empirical Model Specification

In this study, we analyzed the effect of climatic and other input variables on maize supply response with an Autoregressive Distributed Lag (ARDL) model originally developed by Pesaran (2001). The ARDL model provides an efficient platform for testing and estimating long-run relationships based on actual time series data (Hassler & Wolters, 2006) while also being perfectly suited for short-time series (Duasa, 2007). According to Pesaran (2001), ARDL provides flexibility in analyzing variables of different orders of integration.

The general form of the ARDL model with p lags for variable Q and q lag for variable X is presented as Equation 1:

$$Q_t = \alpha_0 + \sum_{i=1}^{p} \beta_i Q_{t-i} + \sum_{i=0}^{q} \beta_i X_{t-i} + U_t \quad (1)$$

where Q_t represents the quantity of maize supplied in year t, Q_{t-i}represents the quantity of maize output supplied in year t-i, X_{t-i} represents quantity of explanatory variables in year t-i, and β_0, β_i, … are long-run coefficients of inputs incorporated in the model;$U_t$is an error term. In this study, the relationship between maize production and climate and non-climatic variables is assumed to take the functional form presented as Equation 2:

$$Q_t = f\,(PrMz_t, La_t, IrrigA_t, Fert_t, ImS_t, RF_t, Temp_t, CO_{2t}) \quad (2)$$

where Q_t is observations on maize output measured in tons,$PrMz_t$ is price of maize output in ETB, La_t is land area cultivated under maize, $IrrigA_t$ is irrigated area under maize, $Fert_t$ is fertilizer consumed under maize production, ImS_t is improved maize seed, RF_t is seasonal rainfalls (short- and long-season) measured in millimeters, $Temp_t$ is crop-growing period mean temperatures (MinTemp and MaxTemp) measured in degrees Celsius, and CO_{2t} is carbon dioxide emission in time t measured in teragram.

The above linear combination in Equation 2 can be transformed into logarithmic form in order to obtain a suitably proficient estimated parameter. This gives Equation 3 below:

$$lnQ_t = \beta_0 + \beta_1 lnPrMz_t + \beta_2 lnLa_t + \beta_3 lnIrrigA_t + \beta_4 lnFert_t + \beta_5 lnImS_t + \beta_6 lnSSR_t + \beta_7 lnLSR_t + \beta_8 lnMinTemp_t + \beta_9 lnMaxTemp_t + \beta_{10} lnCO_{2t} + \varepsilon_t \quad (3)$$

where$lnSSR_t$ is log short-season rainfall in mm, $lnLSR_t$ is log long-season rainfall, lnMinTemp is log minimum temperature in ^0C, lnMaxTemp is log maximum temperature in ^0C, and $lnCO_2$ is log of carbon dioxide. In addition, $\varepsilon_t$is the error term. In order to generate some long-run relationships, Equation 3 is hereby modified as:

$$lnQ_t = \alpha_0 + \sum \alpha_1 lnQt\text{-}i + \sum \alpha_2 lnLa_{t-i} + \sum \alpha_3 lnPrMz_{t-i} + \sum \alpha_4 lnIrrigA_{t-i} + \sum \alpha_5 lnFert_{t-i} + \sum \alpha_6 lnImS_{t-i} + \sum \alpha_7 lnSSR_{t-i} + \sum \alpha_8 lnLSR_{t-i} + \sum \alpha_9 lnMinTemp_{t-i} + \sum \alpha_{10} lnMaxTemp_{t-i} + \sum \alpha_{11} lnCO_{2t-i} + \varepsilon_{t-I} \quad (4)$$

If the variables are cointegrated,there exists an error correction representation. The short-run elasticity coefficients were estimated by the following Dynamics ARDL Error Correction Model (ECM) as presented in Equation 5:

$$lnQ_t = \beta_0 + \sum \beta_1 \Delta lnQ_{t-i} + \sum \beta_2 \Delta lnLa_{t-i} + \sum \beta_3 \Delta lnPrW_{t-i} + \sum \beta_4 \Delta lnIrrigA_{t-i} + \sum \beta_5 \Delta lnFert_{t-i} + \sum \beta_6 \Delta lnImS_{t-i} + \sum \beta_7 \Delta lnSSR_{t-i} + \sum \beta_8 \Delta lnLSR_{t-i} + \sum \beta_9 \Delta lnMinTemp_{t-i} + \sum \beta_{10} \Delta lnMaxTemp_{t-i} + \sum \beta_{11} \Delta lnCO_{2t-i} + \psi iECT_{1-i} + ui (5)$$

In Equation 4, $\psi_i$is a measure of the speed of adjustment (ECM term). This is a measure of the deviations of $Q_t$from the long-run equilibrium values. Akaike Information criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HQ) were used to select the optimum number of lags. In order to detect whether unit root is present in the series, Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests were carried out (Dickey & Fuller, 1979; Gujarati, 2004), with variables a mixture of I(0) and I(1). The first differenced I(1) variables always show stationarity. However, the presence of unit root in a time series implies that spurious results would be obtained from analyzing them at their original level (Heij, De Boer, Franses, Kloek, & van Dijk, 2004; Wooldridge, 2013).

A cointegration test was carried out after testing for stationarity in order to detect the presence of any steady equilibrium relationship (Enders, 2010; Hatanaka, 1996). If there is establishment of the presence of cointegration using the model with at least two I(1) series, some I(0) variables can be added in the ARDL model and this will not alter the I(0) characteristics of the error term (Gujarati, 2004). Cointegration analysis was carried out with Akter and Hong (2011) procedures, which first define an unrestricted vector autoregression (VAR). The analyses were conducted using Eviews 9 Econometric Software.

3. RESULTS AND DISCUSSION

3.1. Results of Preliminary Time Series, Specification, and Robustness Tests

Before estimating the ARDL model, appropriate tests were conducted to detect the presence of unit root and cointegration. Table 1 presents the results of stationarity tests with the ADF and PP approaches. The results of the unit root test show that log mean temperature and log short-rainfall in maize-growing areas are stationary at their original levels (I(0)). Conversely, the following variables were found to be integrated of the order 1: log maize output; log price of maize; log area under maize production; log fertilizer used in maize production; and log long-season rainfall in maize-growing belt. Thus, the variables used in the study are a mixture of I(0) and I (1). Some researchers and econometricians recommend that if the time series exhibit a mixture of I(0) and I(1), the ARDL model is optimal. A bounds test of integration should be conducted in this case to determine the stability of the model. The variance error correction model (VECM) can be used in the case where the variables of interest are integrated to the same degree (Sharma & Singh, 2019). However, for application of ARDL, the two conditions that must be satisfied are that the dependent variable cannot be I(0) and none of the variables must be I(2).

Table-1. Maize output data series – unit root test results.

Variable	ADF						PP	Result
	Level			1st Difference			Level	
	Coefficient	*t*-Stat	*P*-value	Coefficient	*t*-Stat	*P*-value	*P*-value	
LnMzO	-0.6809**	-2.01678	0.8542	-0.27845	-1.21931	0.0000	0.0168	(I(1))
LnPrMz	0.09328	0.73005	0.6681	0.04633	0.40836	0.0000	0.1779	(I(1))
LnArMz	0.5691**	2.25185	0.7695	-0.07010	-0.26046	0.0001	0.1544	I(1))
LnFertMz	0.1018	0.73327	0.9438	-0.05975	-0.51388	0.0000	0.1642	(I(1))
LnTemp	-6.149**	-2.01309	0.0126	1.86684	0.79536	0.0126	0.0102	(I(0))
LnSSRain	-0.470***	-3.16500	0.0064	-0.35255*	-1.6978	0.1112	0.0000	(I(0))
LnLSRain	-0.1390	-0.29179	0.1217	1.03806**	2.26824	0.0385	0.0001	(I(1))

Note: ** Statistically significant at the 5% level.

The results of the cointegration test are presented in Table 2. These show that a linear combination of the variables in the regression was stationary. This implies that there exists a long-run relationship among the variables that were included in the estimated model.

Table-2. Estimation of cointegrating equations.

Dependent variable	Type of test	Test statistics	Critical values	Conclusion
Maize output response	Wald	4.4477**	4.145	Long-run cointegration exists

Note: ** Statistically significant at the 5% level.

The error term from the maize output response model was also subjected to certain residual tests in order to detect non-normality, serial correlation, and heteroscedasticity. The results shown in Table 3reveal that the distribution follows normal distribution based on statistical insignificance of the Jarque–Bera statistic. Therefore, t and F tests can be correctly used for hypothesis testing in respect of the series. In addition, the results show no evidence of autocorrelation as revealed by Breush–Godfrey Lagrange Multiplier (LM) test statistics. However, there is the presence of heteroscedasticity as shown by the LM test for no autoregressive conditional heteroscedasticity (ARCH).

Table-3. Residual properties of maize output response equation.

Type of test	Test statistic	Test statistic value	Probability
Normality test-histogram	Jarque–Bera	0.6419	0.7254
LM	Obs*R^2	2.18476	0.3354
ARCH	Obs*R^2	3.72449	0.0536

A Ramsey reset test was carried out to detect whether the model suffers from any misspecification. The results, as shown in Table 4, imply that the model does not suffer from any form of misspecification. Also, robustness of the estimated parameters was evaluated from the response equation using the CUSUM test, CUSUM residual square test, one-step forecast test, and N steep forecast test. The results, as shown in Figure 1, reveal non-significant divergence of the plots from the zero line. This suggests parameter stability in the estimated equation.

Table-4. Ramsey reset test results.

Dependent variable	*F* statistic	Probability	Conclusion
Log of maize output	3.34726	0.0780	No indication of misspecification error

3.2. Impact of Climatic and Non-Climatic Variables on Maize Output Supply Response

This study sought to determine the response of maize output to climatic and non-climatic variables. To this end, the ARDL model was estimated with both climatic variables (growing season mean temperature, short- and long-season rainfall) and non-climatic variables (lagged maize output, producer price of maize, area cultivated under maize, and quantity of fertilizer used in maize covered area). CO_2 concentration from climate and irrigated area variables were initially included into the model, but were dropped due to the existence of high serial correlation and multicollinearity with other variables.

It was found that the ARDL regression model for maize output supply has good fitness to the data series, with high values of adjusted R^2 (0.955). The adjusted R^2 value of 0.955 in maize output model implies that 95.5% of the variation in maize output is explained by the climatic and non-climatic variables included in the model. The Durban–Watson test on the other hand showed no evidence of serial autocorrelation. The model becomes viable and fit at lag length 1 and first-order difference only; lag length 2 and second-order difference were tried but revealed high serial autocorrelation.

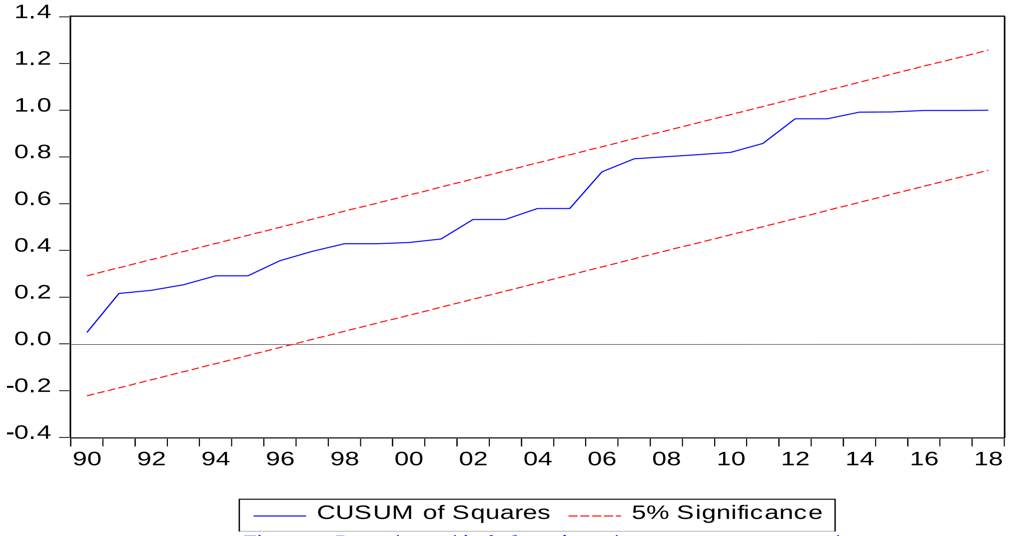

Figure-1. Recursive residuals from the maize output response equation.

The test for cointegration previously revealed existence of long-run cointegration. Hence, long-run elasticity coefficients have been estimated for the maize output model. The long-run elasticity coefficients of ARDL (1, 0, 0, 0, 0, 0, 0) for maize output with respect to climatic and non-climatic variables are presented in Table 5. The climatic and non-climatic variables that were considered in the model after dropping serially autocorrelated variables include log mean temperature during crop-growing period, log short-season rainfall, log long-season rainfall, log producer price of maize, log area cultivated under maize crop, and log quantity of fertilizer used in maize production. The estimated elasticity coefficients show that all climatic variables included in the model have a negative relationship with maize output supply in the longrun. However, the elasticity coefficient for mean temperature is statistically insignificant. The result indicates that a 1% increase in short and longrainfall is responsible for a decrease in maize output supply by 0.77 and 1.0%, respectively.

The result can be justified given that maize is highly sensitive to extremes of rainfall– both shortage in the initial growing period and excessive at the vegetative and grain-filling stages. The findings of this study are consistent with the findings of Siahi, Yego, and Bartilo (2018) who, in their study on the effect of climate change on maize productivity in Kenya, found that the elasticity coefficient of rainfall was negatively related to maize production in the long run, although statistically insignificant. The result indicates that a 1% change in rainfall will decrease maize output supply by 1.64% in the long run.

The elasticity coefficients estimated for socioeconomic variables such as log producer price of maize, log area under maize, and log quantity of fertilizer used showed a positive relationship with maize output. The elasticity coefficients of area cultivated under maize and quantity of fertilizer used have a significant impact on maize output, while that of producer price of maize is statistically insignificant. The result indicate that a 1% increase in area cultivated under maize and quantity of fertilizer used increase maize output by 0.52 and 0.36%, respectively in the longrun. This finding implies that maize output is highly responsive to changes in area cultivated and quantity of fertilizer used in maize production, which is in line with the theory.

The findings of this study arein agreement with those of Chandio, Jiang, and Magsi (2018), who analyzed the effect of support price on wheat production in Pakistan, and found that land area and fertilizer have significantly positive and positive impacts, respectively, on wheat production. Specifically, their results showed that an increase of 1% in the land area cultivated and fertilizer usage will increase wheat production by 0.78 and 0.19%, respectively.

Table-5. Estimated long-run elasticities of maize output with respect to climatic and non-climatic variables.

Variable	Elasticity	Std. error	*T*-ratio	*P*-value
Constant	34.85323	15.35902	2.269235	0.0309
lnPriMz	0.073229	0.090148	0.812315	0.4232
lnArMz	0.517254**	0.213822	2.419084	0.0221
lnFertMz	0.364263***	0.084292	4.321418	0.0002
lnTemp	-4.793830	3.166014	-1.514153	0.1408
lnSSRain	-0.776387**	0.287140	-2.703857	0.0113
lnLSRain	-0.991452*	0.540569	-1.834091	0.0769
R^2	0.9635	Mean dependent var.		3.2211
Adjusted R^2	0.9547	S.D. dependent var.		0.6693
S.E. of regression	0.1424	Akaike info criterion		-0.8709
Sum squared resid.	0.5884	Schwarz criterion		-0.5226
Log likelihood	24.1128	HQ		-0.7482
F-statistic	109.4001	Durbin–Watson stat.		2.3519

Note: *, **, and ***: significant at the 10, 5, and 1% levels.

The short-run dynamic coefficients associated with the long-run cointegration relationships were estimated with an Error Correction Model (ECM) based on the ARDL bounds test approach. The results of the short-run coefficients of ARDL (1, 0, 0, 0, 0, 0, 0) model are presented in Table 6. These show that both temperature and rainfall had negative relationships with maize output in the shortrun. The coefficients of both short- and long-season rainfall have significant impact on maize output, while the coefficient for temperature was statistically insignificant. The results indicate that a 1% increase in short- and long-rainfall seasons led to a reduction in maize output supply by 0.55 and 0.7%, respectively in the shortrun. Inverse relationship that exists between rainfall and maize output could be a result of heavy rainfall that can lead to storms that may destroy maize plants, erosion, and leaching, which would reduce soil productivity.

The statistically significant negative coefficient of ECM (-1) for maize output verifies the long-run relationship among the variables in the maize output model. ECM measures how quickly the endogenous variable adjusts to the changes in the independent variable before the endogenous variable converges to the equilibrium level. This finding is in conformity with the findings of Oparinde and Okogbue (2018), who reported a negative and significant effect of rainfall on maize production in Nigeria. They reported that rainfall had negative and statistically significant impact at the 5% level and had a value of -0.0239. Their findings imply that about 2.39% of disequilibrium in maize output from the previous year's shock converges to the long-run equilibrium in the current year.

On the other hand, the elasticity coefficients of non-climatic variables such as producer price of maize, area under maize, and quantity of fertilizer used on maize production showed positive relationships with maize output in the short run. The coefficient of land area cultivated and quantity of fertilizer used have significant impact on maize output, while the coefficient of producer price is statistically insignificant. The results indicate that a 1% increase in land area cultivated under maize, quantity of fertilizer used, and producer price of maize led to an increase in maize output by 0.36, 0.27, and 0.05%, respectively in the short run. This implies that maize output is highly responsive to changes in land area cultivated and quantity of fertilizer used in the short run.

The findings of this study resonate with those of Kariuki (2016) who, in his study on the effect of climate variability on maize output in Kenya, found that the elasticity coefficients of log price of output and log area under crop showed a positive relationship with maize output in the short run. It was found that a 10% increase in price of output and area under crop led to an increase in maize output by 0.82 and 0.90%, respectively.

Table-6. Short-run elasticities of maize –dynamic ECM model.

Variable	Elasticity	Std. error	*t*-Statistic	Probability
C	24.62264	11.95495	2.05962	0.0485
ECM_{t-1}	-0.70647***	0.12361	-5.71514	0.0000
LNPRIMZ	0.05173	0.06467	0.79999	0.4302
LNARMZ	0.36542**	0.15701	2.32744	0.0271
LNFERTMZ	0.25734***	0.07381	3.48639	0.0016
LNTEMP	-3.38668	2.41366	-1.40313	0.1712
LNSSRAIN	-0.54849***	0.14601	-3.75651	0.0008
LNLSRAIN	-0.70043*	0.39719	-1.76344	0.0884
R^2	0.96351	Mean dependent var.		3.22108
Adjusted R^2	0.95471	S.D. dependent var		0.66929
S.E. of regression	0.14244	Akaike info. criterion		-0.87096
Sum squared resid.	0.58840	Schwarz criterion		-0.52265
Log likelihood	24.1128	HQ ctiterion		-0.74817
F-statistic	109.400	Durbin–Watson stat		2.35188

Note: *, **, and ***: significant at the 10, 5, and 1% level, respectively.

4. CONCLUSION

The study findings indicate that maize output is affected by climate variability as well as by other, non-climatic factors. The elasticity coefficients show that all climatic variables included in the model have a negative relationship with maize output supply in both the long and shortrun. However, the elasticity coefficient for mean temperature is statistically insignificant in both cases. In the longrun, the elasticity coefficients for short- and long-season rainfall showed negative and significant impact on maize output supply. This result can be justified by the fact that maize is highly sensitive to extremes of rainfall – both shortage at the initial growing period and excess at the vegetative and grain-filling stages. In the shortrun, the coefficients of both short- and long-season rainfall have a negative and significant impact on maize output. Inverse relationship existing between rainfall and maize output could be a result of heavy rainfall that caused storms, erosion, and leaching. The highly significant negative elasticity coefficient (-0.71) of ECM (-1) for maize output verifies the long-run relationship among the variables in the maize output model.

The elasticity coefficients of non-climatic variables such as log producer price of maize, log area under maize, and log quantity of fertilizer used showed positive relationship with maize output in both the long and shortrun, although price of maize was insignificant. The results imply that maize output is highly responsive to area under maize and quantity of fertilizer consumed in maize production. In general, it can be concluded that farmers face climate-related risk due to variations in climatic variables, particularly rainfall. Therefore, stakeholders should take adaptation measures such as using short-duration and tolerant varieties of maize and always practice ecofriendly activities and put in place as coping strategies against the menace of climate change.

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