



Impact of Rainfall and Temperature as Aspects of Climate Change on Maize Production in Zimbabwe

Comfort Magwaza¹, Siamarie Lyaro^{2*}

¹Zimbabwe National Statistics Agency, 20th Floor Kaguvi Building, Cnr Fourth St./Central Ave P. O. Box, CY 342 Causeway Harare, Zimbabwe

²Eastern Africa Statistical Training Centre, P. O. Box 35103, Dar es Salaam, Tanzania

*Corresponding Author: siamarie.lyaro@eastc.ac.tz

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Abstract

Zimbabwe experiences variations in maize production such that production fell below 2.2 million tonnes between 2010 and 2021, making maize importation necessary despite implementing resilient agricultural practices for strengthening capacity for adaptation to climate change. This study sought to analyze impact of climate change on maize production in Zimbabwe from 1971 to 2021. The study focused on determination of long-run, short-run, and causality relationships between climate and non-climatic variables and maize production. The study used ADF unit root test to test stationarity of data. Autoregressive distributed lag model was employed to analyse long-run and short-run relationships, while Granger causality test was applied to analyse causal linkages. Results showed that in the long-run mean temperature ($p = 0.001$) and area ($p = 0.017$) were significant factors which affected maize production, while precipitation ($p = 0.05$) and area ($p = 0.05$) were significant factors which affected maize production in the short-run. Also, results from Granger causality test showed that there was a unidirectional causal linkage between precipitation and maize production ($p = 0.004$), and a unidirectional causal linkage between maize production and area under maize production ($p = 0.027$). Generally, findings highlight the need for Government to invest in irrigation system to reduce over reliance on rain-fed maize production.

Keywords: Maize production, Climate change, ARDL, Granger causality test JEL Classification: D24, C12, C32

1 Introduction

Maize is a cereal crop for human consumption or animal feed. Maize belongs to a grass family called Poaceae (Graminae) and originated from Mexico (Buckler and Stevens, 2005). The crop was introduced in Africa in the 17th century by Portuguese, and was quickly adopted due to its short growing season, low labour requirement and high energy yield (Cherniwchan and Moreno-Cruz, 2017). Maize is widely grown throughout the world and has the

highest production of all cereals with around 1.2 billion metric tonnes being produced in 2021 (FAOSTAT, 2021).

There was a noticeable increase in global maize production, such that production increased with more than 104 percent since the year 2000 (FAO, 2022). In 2021, United States of America had the highest production accounting for 31.72 percent, followed by China accounting for 22.54 percent and Brazil accounting for 7.31 percent of the total global maize production. Total production for Africa increased with

2.83 percent between 2020 and 2021 and the total production was around 96.6 million tonnes from 93.9 million of 2020 (FAOSTAT, 2021).

For the case of Africa, highest producers of maize are South Africa with 17.46 percent, followed by Nigeria with 13.19 percent, and Ethiopia with 11.1 percent of the total maize production in the continent. Zimbabwe ranked 18th with a contribution of about 1.52 percent to the total continental production (FAOSTAT, 2021). Zimbabwe experienced variations in maize production since 1970's whereby production fell below the minimum national requirement of 2.2 million tonnes per between 2010 and 2021. This necessitated importation of about 220,000 metric tons of maize annually to supplement for the deficit (FAO, 2022; FAO, 2023; USDA, 2023).

Various studies indicated that production of maize depends on climatic and non-climatic factors. Climatic factors include humidity, temperature, and rainfall (Oparinde and Okogbue, 2018; Shoko et al., 2019; Mapfumo *et al.*, 2020; Musa, 2022). Non-climatic factors include land area under maize, labour, material capital input, fertilizer application, seed varieties, conservation farming system, land reform programme, pests, and diseases (Mvumi, 2013; Tessema et al., 2018; Jian-Zhai et al., 2021; Zhang et al., 2022; Runganga et al., 2022).

The climatic factors in Zimbabwe particularly rainfall and temperature, demonstrated downward and upward trends respectively for more than a decade (WBG, 2021). This implies that there is a need to incorporate Production Theory in Economics to model effects of climatic factors on production of maize in Zimbabwe, a country which also practices conservation agriculture. Therefore, this study was organized specifically to determine the long-run, short-run, and causality relationships between climate variables, the Comprehensive Agricultural Policy (2012-2032) for Zimbabwe, and maize production in Zimbabwe by using annual time series data from 1970 to 2021. Average annual maize production is below the minimum quantity needed to sustain the country both on food and feed and this is causing the country to rely on imports and support from international

organizations to supplement the deficit (Parliament of Zimbabwe, 2017).

2 Material and Methods

2.1 Study Area

The study area is Zimbabwe, a country located in Southern Africa bordering South Africa, Mozambique, Zambia and Botswana; with a population of about 15.1 million (ZIMSTAT, 2023). Zimbabwe lies in between 19° 01' 0.92" South of the equator and 29° 09' 10.09" East of the Prime meridian. The country has a total area of over 39 million hectares, out of which, 33.3 million are used for agricultural purposes. The country experiences a tropical climate with an average rainfall of about 670 mm (WBG, 2021). Zimbabwe was selected because the country's average annual maize production is below the minimum quantity needed to sustain the country both on food and feed and this is causing the country to rely on imports and support from international organizations to supplement the deficit (Parliament of Zimbabwe, 2017).

2.2 Research Design

The study used a quantitative research design. This design seeks to provide a systematic explanation of how research objectives are addressed by the study through statistical procedures. This study sought specifically to determine the long-run, short-run, and causality relationships between climate variables, the conservation agriculture practice and maize production in Zimbabwe by using annual time series data from 1970 to 2021.

2.3 Data Sources

The study used secondary data sources in the analysis. Data for the studied variables were obtained from FAO, FAOSTAT, and World Bank Group. Studied variables included maize produced in tonnes, amount of precipitation in millimetres, mean temperature in Celcius degree, area under maize production in hectares, and a dummy variable for Conservation Agricultural Policy before or after 2012.

2.4 Data Analysis Methods

2.4.1 Stationarity Test

A time series is said to be stationary if its mean, variance and autocorrelations are constant over time. And a time series whose mean, variance and autocorrelation changes overtime is called a non-stationary time series. Stationary time series data is important for effective analysis and estimation (Ghimire et al., 2021). The augmented Dickey-fuller unit root test was used to test for stationarity of variables presented in Table 1. Variables which were not stationary at level were transformed by a method of differencing to make them stationary.

2.4.2 Lag length Selection

Lag length selection is crucial for estimating appropriate number of lags for both dependent and explanatory variables to be used in the ARDL model. Selecting the appropriate lag length helps to ensure that the model captures the underlying patterns and relationships in the data effectively. The study used the Akaike Information Criterion (AIC) to select the optimum lags, AIC balances two important aspects of model performance which are goodness of fit and model complexity, it estimates the lowest lag length in the model. This information criterion is most useful when the sample size is small mostly less than 60 (Liew, 2004).

2.4.3 Autoregressive Distributed Lag (ARDL) Model

The study employed the Autoregressive Distributed Lag (ARDL) Model proposed by Pesaran et al. (2001) to establish the short run and long run relationships between maize production and its determinants. The ARDL model is regarded to be the best econometric approach in comparison to others in a situation where the variables are stationary at I(0) and I(1) (Nasrullah et al., 2021). ARDL technique follows the Ordinary Least Squares approach of modelling once the lag order for the model has been identified. Through ARDL bounds test one can examine the long-run relationship between dependent and independent variables.

Furthermore, presence of the lung-run relationship estimation of the short-run relationship through error correction models (ECMs) (Ghimire et al., 2021). Following

production theory in Economics, relationship between maize production and input factors is expressed as $MProd = f(Prec, MT, A, CA)$ (1)

Equation (1) can be expressed in ARDL form as follows in (2):

$$\Delta \ln MProd_t = \alpha_0 + \sum_{k=1}^n \alpha_1 \Delta \ln MProd_{t-k} + \sum_{k=1}^n \alpha_2 \Delta \ln Prec_{t-k} + \sum_{k=1}^n \alpha_3 \Delta \ln MT_{t-k} + \sum_{k=1}^n \alpha_4 \Delta CA_{t-k} + \sum_{k=1}^n \alpha_5 \Delta \ln A_{t-k} + \lambda_1 \ln MProd_{t-1} + \lambda_2 \ln Prec_{t-1} + \lambda_3 \ln MT_{t-1} + \lambda_4 CA + \lambda_5 \ln A_{t-1} + \epsilon_t \quad \text{..... (2)}$$

Where α_0 stands for the drift component and Δ stands for the first difference, ϵ_t is the white noise term. The ARDL model above was used to establish the long run relationship, however to establish the short run relationship the study used the error correction model (ECM). According to Nasrullah et al. (2021), the general form of the ECM from equation (2) is expressed as follows in (3):

$$\Delta \ln MProd_t = \alpha_0 + \sum_{k=1}^n \alpha_1 \Delta \ln MProd_{t-k} + \sum_{k=1}^n \alpha_2 \Delta \ln Prec_{t-k} + \sum_{k=1}^n \alpha_3 \Delta \ln MT_{t-k} + \sum_{k=1}^n \alpha_4 \Delta CA_{t-k} + \sum_{k=1}^n \alpha_5 \Delta \ln A_{t-k} + \phi ECM_{t-1} + \epsilon_t \quad \text{..... (3)}$$

Where Δ denotes the first difference and ϕ is the ECM coefficient for short run dynamics. ECM denotes the speed of adjustments in long run equilibrium after a shock in the short run.

2.5.4 The Granger Causality

If there exists a co-integration, then it implies there is a causality between the variables in at least one direction (Soufiane and Chamseddine, 2022). Therefore, the Granger causality was used to determine the direction of the short-run and long-run causal relationships between variables. This comprises estimation of the error correction model. The Granger's representation theorem in (Engle and Granger, 1987) shows that cointegrated systems can be estimated and expressed as an error correction

model (Awokuse, 2008). This procedure is highly important as it gives estimates for both the short run and long run relationships as well as the direction of the causation between the variables. The Granger causality model is presented as follows in equation 4:

$$\Delta \begin{pmatrix} MProd_t \\ Prec_t \\ MT_t \\ A_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{pmatrix} + \sum_{i=1}^m \Delta \begin{pmatrix} \gamma_{1i} \vartheta_{1i} \xi_{1i} \omega_{1i} \\ \gamma_{2i} \vartheta_{2i} \xi_{2i} \omega_{2i} \\ \gamma_{3i} \vartheta_{3i} \xi_{3i} \omega_{3i} \\ \gamma_{4i} \vartheta_{4i} \xi_{4i} \omega_{4i} \end{pmatrix} X \begin{pmatrix} MProd_{t-1} \\ Prec_{t-1} \\ MT_{t-1} \\ AP_{t-1} \end{pmatrix} + \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{pmatrix} (ECM_{t-1}) + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \end{pmatrix} \quad (4)$$

Where Δ is the lag operator, ECM_{t-1} is the lagged error term for one period which is derived from the long run cointegration; $\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t}$ and ϵ_{4t} are serially uncorrelated white noise error terms and m is the number of lags (Magoti and Mtui, 2020; Kahyarara, 2020).

3 Results and Discussion

3.1 Descriptive Statistics

Table 1: Descriptive statistics of the variables used

Variables	lnMProd	lnPrec	lnMT	lnA
Median	14.23	6.53	3.073	14.03
Mean	14.11	6.50	3.072	14.02
Std. Dev.	0.46	0.21	0.025	0.22
Max	14.86	6.92	3.126	14.53
Min	12.79	6.10	3.02	13.58
Skew.	-0.71	-0.16	-0.33	0.19
Kurt.	3.16	2.39	2.52	2.69
Jarque-Bera	4.46	1.02	1.41	0.50
Probability	0.11	0.60	0.49	0.78
Obs	52	52	52	52

Source: Authors' compilation (2024).

Results presented in Table 1 shows the distribution of the data and its normality for 52 observations. Results presented by Table 1 show that standard deviations are relatively small implying that the data

are clustered around the mean (Peck et al., 2008). The skewness and kurtosis are relatively close to zero implying the data is normally distributed. The Jarque-Bera values and their corresponding probabilities also show that the data for all the variables is normally distributed at 5% significance level.

3.2 Unit Root Test

Before testing for co-integration, a unit root test was conducted to test for stationarity of the variables, this helps to verify if the requirement for ARDL is met that all the variables should be integrated at order zero and one (I(0) and I(1)), (Oparinde and Okogbue, 2018). Results presented in Table 2 shows that lnMProd, lnPrec and lnMT were all stationary at level I(0), some at 1% level of significance and lnMT at 5% significance level. Hence, the null hypothesis which states that the data contains a unit root ($\rho = 1$) was rejected in favour of stationarity ($|\rho| < 1$) through ADF test. Furthermore, ln A was stationary after the first differencing at 1% level of significance and CA was stationary after the first differencing at 1%

significance level. Hence the study concluded that the data is stationary and has no unit root.

3.3 Bounds Test for Co-integration

Results presented in Table 3 shows the presence of a long run relationship among the variables since their F-statistic (7.710) is greater than the critical values for the lower bound $I(0)$ and upper bound $I(1)$ at all significance levels (10%, 5% and 1%). Therefore, we reject the null hypothesis which says there is no co-integration concluding that there is a co-integration hence there is a long run relationship among the variables. This relates to the findings of Oparinde and Okogbue, (2018) and Shoko et al. (2019).

3.4 Long run Relationship

The presence of co-integration among the variables validates the estimation of the ARDL long run model to find the long run model parameters. The long run

Table 4 also shows that area was statistically significant at 5% significance level with a positive coefficient (0.822); this means a unit increase in area increases maize production by 0.822 units. This result corresponds to Moshi et al. (2023) who found that maize production was affected significantly with area cultivated.

3.5 Short run Relationship

The Error Correction Model was used to find the short run relationship among the variables. The short run relationship model was estimated using ARDL (1, 2, 1, 0, and 0). From Table 5, the results show existence of a short run relationship between precipitation and maize production. The findings reported have a statistically significant error correction ECM (-1)

Table 2: Summary ADF Unit Root Test for stationarity of variables

Variable	At level, $I(0)$		At first differencing, $I(1)$	
	t-statistic	Probability	t-statistic	Probability
lnMProd	-6.032	0.000 ^a		
LnA	-2.521	0.1105	-7.960	0.0000 ^a
LnPrec	-5.923	0.0000 ^a		
LnMT	-3.354	0.0126 ^b		
CA	-0.459	0.8997	-7.071	0.0000 ^a

Note: Z(t) values were -3.579, -3.580 and -3.579 and at 1% level significance level -2.929 at 5% significance level. a and b represent findings at 1% and 5% significance level respectively

relationship model was estimated using ARDL (1, 2, 1, 0, 0) model. The results in Table 4 shows estimated long run coefficients of the climate variable, area and the conservation agriculture on maize production. The coefficient of determination is 0.7902, this means about 79.02% of the factors which affect maize production has been explained in the model. Mean temperature was statistically significant at 1% level with a negative coefficient (-13.173), this means a unit increase in temperature decreases production by 13.173 units. This is supported by the findings of Shoko et al. (2019) who found high temperatures had negative effect on maize production.

coefficient (-0.86) at 1% level, meaning that the speed of convergence towards the long-run equilibrium is 86%.

The coefficient of precipitation is positive and

Table 4: Long run relationship among the variables.

Variable	Coefficient	Standard Error	t-statistic	P>t
lnPrec	-0.014	0.451	-0.03	0.975
lnMT	-13.173	3.543	-3.72	0.001 ^a
lnA	0.822	0.332	2.48	0.017 ^b
CA	0.088	0.172	0.51	0.612
C	37.062	9.865	3.76	0.001 ^a

Note: a shows that the variable was significant at 1% and b shows that the variable was significant at 5% level of significance. $R^2 = 0.7902$

statistically significant at 5% significance level. A unit increase in precipitation increases maize production by 0.685 units; this is in line with the findings of Ammani et al. (2012) and Shakoor et al. (2017). Precipitation had a negative coefficient (-0.624) in the short run at lag 2 and it is statistically significant at 1% level of significance.

Mean temperature is statistically significant in explaining maize production in the short run. It has a negative coefficient (-10.547) implying a unit increase in temperature reduces maize production by 10.547 units, this agrees with the findings of Shakoor et al. (2017) and Oparinde and Okogbue (2018).

Area is statistically significant at 5% level with a coefficient of 0.707 this implies that a unit increase in area planted increases maize production by 0.707 units. This is in line with the findings of Ahsan et al. (2020) who found area cultivated area, and had a positive impact on cereal crop production.

3.6 Granger Causality

Table 3: Bounds testing for cointegration

Equation	Lag	F-statistics	P-value
$\ln MProd = f(\ln Prec, \ln MT, \ln A, CA)$	1, 2, 1, 0, 0	7.710	0.000
Critical value	10%	5%	1%
Lower Bound I(0)	2.45	2.86	3.74
Upper Bound I(1)	3.52	4.01	5.06

Source: Authors' compilation (2024).

Results in Table 5 shows that there is a unidirectional causal link between precipitation and maize production and this is significant (p-

This agrees to the findings by Xiang and Salaymani (2022) who found a unidirectional causality link between rainfall and cereal production.

Table 5: Pairwise Granger causality test

Null hypothesis	Observation	Chi2	P-value
lnPrec does not Granger Cause lnMProd	52	10.87	0.004 ^a
lnMProd does not Granger Cause lnPrec		4.118	0.128
lnA does not Granger Cause lnMProd	52	1.0225	0.600
lnMProd does not Granger Cause lnA		7.1939	0.027 ^b
lnMT does not Granger Cause lnMProd	52	1.9809	0.371
lnMProd does not Granger Cause lnMT		1.6796	0.432

Note: **a** shows significance at 1% and **b** shows significance at 5% level of significance.

Source: Authors' compilation (2024).

value=0.004). This implies that maize production increases due to increase in precipitation. The null hypothesis that says precipitation does not granger maize production is rejected at 1% significance level.

Also, results in Table 6 shows that there is a unidirectional causal link between maize production and the area under maize production and this is significant (p-value= 0.027). This implies that maize

Table 6: Short run relationship among the variables.

Variable	Coefficients	Standard Error	t	P-value
D(lnMProd (-1))	0.14	0.144	0.97	0.337
D(lnPrec)	0.685	0.282	2.43	0.02 ^b
D(lnPrec (-1))	-0.074	0.282	-0.26	0.795
D(lnPrec (-2))	-0.624	0.219	-2.85	0.007 ^a
D(lnMT)	-10.547	2.9	-3.64	0.001 ^a
D(lnMT (-1))	-0.778	3.65	-0.21	0.832
D(lnA)	0.707	0.287	2.46	0.018 ^b
CA	0.075	0.145	0.52	0.606
ECM(-1)	-0.86	0.144	-5.95	0.000 ^a

Note: **a** shows that the variable was significant at 1% and **b** shows that the variable was significant at 5% level of significance.

Source: Authors' compilation (2024).

production leads to increase in the area under maize production of the following years. Therefore, we reject the null hypothesis which states that maize production does not granger cause area under maize production. This result agrees to the findings by Soufiane and Chamseddine, (2022) who found a unidirectional causality between cereal production and land area under cereal production.

3.7 Diagnostic Tests

The diagnostic tests presented in Table 7 tested for heteroscedasticity, serial correlation and normality test. The results for heteroscedasticity in Table 7 shows that the variance of the residuals has no heteroscedasticity since the Breusch-Pagan-Godfrey test p-value (0.1101) is greater than 0.05. Therefore, there is no enough evidence to reject the null hypothesis that the data has no hetero-scedasticity

The Breusch-Godfrey Serial correlation test shows no evidence of serial correlation in the data since the

2021. Specifically, it analysed the long-run, short-run, and causality relationships between climatic and non-climatic variables and maize production. The study employed ADF unit root test, autoregressive distributed lag bounds, and the Granger causality in analysis. Results showed that in the long-run mean temperature ($p=0.001$) and area ($p=0.017$) were significant factors which affected maize production. Furthermore, results showed that precipitation ($p=0.05$) and area ($p=0.05$) were significant factors which affected maize production in the short-run. Also, results from Granger causality test showed that there was a unidirectional causal linkage between precipitation and maize production ($p=0.004$), and a unidirectional causal linkage between maize production and area under maize production ($p=0.027$). The study concluded that climate change has a significant impact on maize production both in the long run and short run. An increase in precipitation increases maize production and an increase in temperature reduces production. These findings imply

Table 7: Diagnostic tests

Dignostic	Statistics	Interpretation
Heteroscedasticity	2.55	No heteroscedasticity
Breusch-Pagan-Godfrey	0.1101	$R^2=0.644$
Breusch-Godfrey Serial	0.59	No evidence of serial correlation
Correlation LM Test	0.4423	
Normality Test	Jarque-Bera Test =4.174 Probability = 0.124	Residuals are normally distributed since the P-value (0.124) is greater than 0.05

Source: Authors' compilation (2024).

p-value (0.4423) is greater than the critical value (0.05). The result for normality test shows that the data has a normal distribution since the p-value for the Jarque-Bera (0.124) is greater than 0.05, this means we do not reject the null hypothesis at 5% level of significance.

4 Conclusions and Policy Implications

The study analysed impact of climate change on maize production in Zimbabwe using time series data for climatic and non-climatic variables from 1971 to

that Zimbabwe has to strengthen capacity for adaptation to temperature and precipitation as aspects of climate change. The study recommends the need to invest in irrigation system to promote production of maize in the short-rainy season, and as well as use seed varieties that are drought resistant.

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