Nexus between Climate Change and Food security in the East Africa Region: An Application of Autoregressive Modelling Approach

Dennis O. Olila*, Vivian Oliver Wasonga

University of Nairobi

College of Agriculture and Veterinary Sciences

P.O.BOX 29053-00625, NAIROBI

Department of Land Resource Management & Agricultural Technology

Corresponding author*: oliladennis@students.uonbi.ac.ke

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Abstract

This study is an attempt to unpack the existing link between climate change variability and food security in the East Africa Community (EAC) region. Specifically, the paper elaborates the main issues in climate change discourse and its implication to the food security equation in the EAC region. A plethora of empirical literature exists in the area of climate change not only at the regional level but also globally. Using secondary time series panel data, the study links cereal production patterns with rainfall and temperature dynamics for from 1961 to 2012. The data was obtained from the Food and Agricultural organization (FAOSTAT) as well as the World Bank knowledge management center. Econometric data analysis was attained using Eviews version 7 and GMDH version 3.8.3 statistical software. The findings of the Autoregressive model indicates that rainfall and temperature are inevitably changing. These findings offer important policy insights on the role played by climate change variability on food security in the EAC region.

Key words: Time series, Autoregressive modelling, rainfall, temperature, Kenya

1. Introduction

1.1 Background information

The phenomenon of climate change and variability has drawn a lot of attention among policy makers and development partners. In their recent publication, the World Bank (2016) opine that climate change and poverty alleviation present a huge challenge to the global community. Climate change and variability is already causing negative impacts in many parts of the world (Jat *et al*., 2012) particularly in Sub-Sahara Africa that is most vulnerable owing to the fact that over 70 percent of the population deriving their livelihoods from agriculture and natural based resource activities (Antwi, 2013).

According to the Intergovernmental Panel on Climate Change (IPCC, 2001), the world has witnessed rising temperatures during the last four decades in the lowest 8 kilometers of the atmosphere. The aforementioned phenomenon is of great concern not only to policy makers but also to development partners and various Non-Governmental Organizations (NGO's) working in the area of climate change and variability. From a global perspective, there is a unanimous agreement that mitigation of negative impacts of climate change calls for cooperation among all countries in the world (UNCCC, 1992).

The African continent is no exception to climate change and variability. As observed by United Nations Framework Convention on Climate Change (UNFCCC, 2006), many African regions perhaps experience variable climates coupled with intra-seasonal to decadal timelines. Empirical evidence shows that climate change curtails sustainable economic and socioeconomic development (Viljoen, 2013). The African continent exhibits high physical sensitivity to climate change (Antwi, 2013). For instance, African Progress Report (APP, 2015) posit that factors such as poverty, dependence on rain-fed agriculture, weak infrastructure; both soft and hard part, as well as limited provision of safety nets are some of the factors that contribute to vulnerability.

Alarmingly, the poor and marginalized, including subsistence farmers in rural Africa are likely to face the worst consequences (CUTS, 2014). It is now clear that both rainfall and temperature variability impacts negatively on food production, water resources, biodiversity, human and livestock populations (Antwi, 2013). In the EAC region, nearly 70 percent of the population live in rural areas where agriculture is the main source of livelihood.

Despite the high dependence on agriculture by rural livelihoods, climate change and variability continues to jeopardize economic development of such communities. This is pegged on the fact that climatic variables such as temperature, radiation, precipitation, humidity among others have a direct impact on the productivity of agriculture, forestry and fishery systems (Antwi, 2013).

It is today common knowledge that climate change and variability is perhaps one of the major challenges facing the world particularly the EAC region where agriculture remains a key economic activity among a majority of the farmers. Antwi (2013) opine that climate change affects agriculture in a number of ways including yield reduction, rising food prices, increased incidence of pests and diseases, water scarcity, enhanced drought periods, soil fertility reduction, high cost of livestock production, as well as creating tensions among the displaced persons.

According to Antwi (2013), the changes on agricultural production will impact on food security. Specifically, reduced yield will affect food supply, and all forms of agricultural production will negatively impinge on livelihoods and capacity to access food. This problem will be exacerbated by the fact a majority of livelihoods are socially excluded from development.

The negative impacts of climate change and variability have been studied widely locally, regionally and globally. For instance, EAC is cognizant of the fact that every major social, economic as well as environmental sector is sensitive to climate change and variability. According to the EAC Food Security Action Plan 2010 – 2015, the EAC region is frequently affected by food shortages and pockets and hunger despite the huge potential and capacity to produce sufficient food for regional consumption and export (East African Community Secretariat, 2010). These challenges emanates from poor market integration which negatively affects trade flow as well as climate change and variability.

In regard to the aforementioned challenges, the EAC food security action plan was formulated with the aim of addressing the challenges of food insecurity in the region (East African Community Secretariat, 2010). This development is in line with the EAC Treaty regarding cooperation in agriculture and rural development in the achievement of food security and rational agricultural production. Agricultural production, processing and preparation sector remain key in various EAC member states. According to East African Community Secretariat (2010), between 70 to 80 percent of the EAC labour force are involved in agriculture; which contributes between 24 and 48 percent of the Gross Domestic Product (GDP).

However, despite the aforementioned attempts geared towards stabilizing food security in the EAC region, the link between climate change and food security has received limited attention. Cognizant of the fact that climate change and variability are expected to compromise agricultural production and food security, it is envisaged that the findings of this study will go along in augmenting various initiatives already put in place to address climate change and food insecurity in the EAC region. Specifically, the study reveals long term patterns of rainfall and temperature and establishes how these key climatic variables influence cereal production in the EAC region. Second, we forecast rainfall, temperature and cereal production in order to offer *ex-ante* policy information on how climate change is likely to compound the regions high poverty levels.

2. **Methodology**

2**.1 Data**

The study uses time series secondary data of rainfall and temperature patterns from Kenya, Uganda, Tanzania and Burundi. The data was obtained from the World Bank Knowledge Management center and from the Food and Agricultural Organization (http://faostat3.fao.org/home/E) of the United Nations. The data ranges from the year 1961 – 2012.

3.1 Model specification

A time series is a collection of observations made sequentially through time (Chatfield, 2000). Generally, these observations are spaced at equal time intervals. The main objective of analysis of time series data is to find a mathematical model capable of explaining data behavior. For instance, Olila and Wasonga (2016) analyzed time series data on carbon dioxide emission by Savanna grasslands in Kenya. A growing interest in comprehending the behavior emanates from the need to predict the future values of the series. Understanding the future values (forecasts) of time series data is vital for *ex-ante* policy making and planning.

According to Chatfield (2000), time series data provides an excellent opportunity to look at *out of sample* behavior (forecasted values) thus providing an opportunity to benchmark with the actual observations. For instance, forecasting of GHG emissions enables formulation of appropriate policies aimed at reducing emissions thus enhancing efficient decision-making. The objective of this study is three fold.

First is to describe the emission data by plotting the actual values and make sense out of the pattern. Having depicted the pattern clearly, the next objective undertaken by this study is to find a suitable model to describe the data generating process. Finally, the study envisages estimating future values (forecasting) of carbon emissions with the assumption that no action is taken to revert the emissions.

From econometric context, we use an autoregressive (AR) model. In an AR (1) model, the variable is regressed on itself by one lag period. Chatfield (2000) stipulates that a process (x_t) is said to be an autoregressive process of order p (abbreviated $AR(p)$) if it is a weighted linear sum of the past p values plus a random shock formulated as:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_p x_{t-p} + z_t \qquad (1)$$

Where z_t denotes a purely random process with zero mean and variance σ_z^2 and t denotes time. Using the backward shift[2] operator B such that $Bx_t = x_{t-1}$, the $AR(p)$ may be written more succinctly in the form:

$$\phi(B)x_t = z_t \qquad (2)$$

Where $\phi B = 1 - \phi_1 - \phi_2 B^2 - \dots - \phi_p B^p$ is polynomial in B of order p. According to Chatfield (2000), the properties of AR processes defined by equation (1) is examined by focusing on the properties of the function ϕ. Since B is an operator, the algebraic properties of ϕ have to be investigated by examining the properties of $\phi(x)$, where x denotes a complex variable rather than by looking at $\phi(B)$. It can be shown that equation (2) has a unique causal stationarity solution if the roots of $\phi(x) = 0$ lie outside the unit circle. This solution may be expressed as follows:

$$x_t = \sum_{j \geq 0}^{\infty} \varphi_j z_{t-j} \qquad (3)$$

Taking into cognizance that for some constants φ_j should conform to $\sum |\varphi_j| < \infty$. Equation (3) above simply postulates that AR process is stationary provided the roots of $\phi(x) = 0$ lie outside the unit circle. The simplest example of an AR process is the first order case formulated as:

$$x_t = \phi x_{t-1} + z_t \qquad (4)$$

The times series literature stipulates that an AR (1) process is stationarity provided that $|\phi| < 1$ is satisfied. It is more accurate to say that there is a unique stationary solution of (4) which is causal, provided that $|\phi| < 1$. The autocorrelation function (*ac.f)* of a stationary AR (1) process is given by $\rho_k = \phi^k$ for $k = 1,2,...n$ (Chatfield, 2000). Note that for a higher order stationary AR processes, the *ac.f* will typically be a mixture of terms which decrease exponentially of damped sine or cosine waves.

According to Nemec (1996), *ac.f* is a convenient way of summarizing the dependence between observations in a stationary time series. In order to obtain ACF, a set of difference equations commonly referred to as Yule-Walker equations are applied. Yule-Walker equation is formulated as:

$$\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} + ... + \phi_k \rho_{k-p} \quad \text{(5)}$$

for $k = 1,2,...n$, $\rho_0 = 0$. One of the important useful property of $AR(\rho)$ process is the ability to show that the partial *ac.f* is zero at all lags greater than ρ; implying that the sample ACF can be used to determine the order of an AR process.

This is done by focusing the lag value at which the sample's partial *ac.f's* "cuts-off" i.e. should be approximately zero or at least not significantly different from zero for higher lags (Chatfield, 2000).

4. Results and discussions

4.1 Kenya's rainfall and temperature patterns

Table 1 shows the results of the autoregressive model. The dependent variable is cereal production while the explanatory variables are rainfall, temperature and the lag of the cereal by four periods. Based on the presented results, the first lag of cereal is statistically significant at one percent.

AR forecasting requires the dependent variable to fulfil some model parameter criteria such as (i) the R-square value should be very high; (ii) there should be no serial correlation; (iii) no heteroskedasticity and (iv) and the residual should follow a normal distribution. It is only after validating the aforementioned that forecasting can be done.

In terms of our results, the lag of cereal is statistically significant at one percent (p-value = 0.000); conforming to one of the most key requirement in time series forecasting. Moreover, our R-square is slightly high (R-Square = 0.573); implying that over 50 percent variation in the dependent variable is attributed to the dependent variables included in the model. Nevertheless, the F-statistic and the corresponding probability is statistically significant at one percent (p-value = 0.000).

Table 1: **Autoregressive model results for Kenya**

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2705444.	3102479.	-0.872027	0.3883
RAINFALL	5378.788	8256.132	0.651490	0.5184
TEMPRATURE	110139.8	134194.3	0.820749	0.4165
CEREAL(-1)	0.628396	0.171716	3.659504	0.0007
CEREAL(-2)	-0.092982	0.203287	-0.457393	0.6498
CEREAL(-3)	0.263049	0.202186	1.301024	0.2005
CEREAL(-4)	0.068436	0.183374	0.373205	0.7109
R-squared	0.573449			
Log likelihood	-689.9540			
F-statistic	9.186633			
Prob(F-statistic)	0.000002			

4.2 Serial correlation test

One of the common problems in time series data is serial correlation. Generally, serial correlation occurs when the error terms from different or adjacent time periods are correlated. Even though serial correlation fails to affect unbiasedness or consistency of the Ordinary Least Squares (OLS) estimators, the efficiency is negatively affected. In regard to this, we postulate a null hypothesis that the model has no serial correlation while the alternative is that the model exhibits serial correlation and apply the Breauch-Godfrey Serial Correlation LM Test.

Table 2 presents the results of serial correlation test. The decision is based on the probability value of the Chi-Square. The results presented show that the Chi-Square probability value is statistically insignificant thereby offering a basis to fail to reject the null. In other words, the model is statistically sound since it does not suffer from serial correlation.

Table 2: Breusch-Godfrey Serial Correlation LM Test

F-statistic	1.524894	Prob. F(2,39)	0.2303
Obs*R-squared	3.481344	Prob. Chi-Square(2)	0.1754

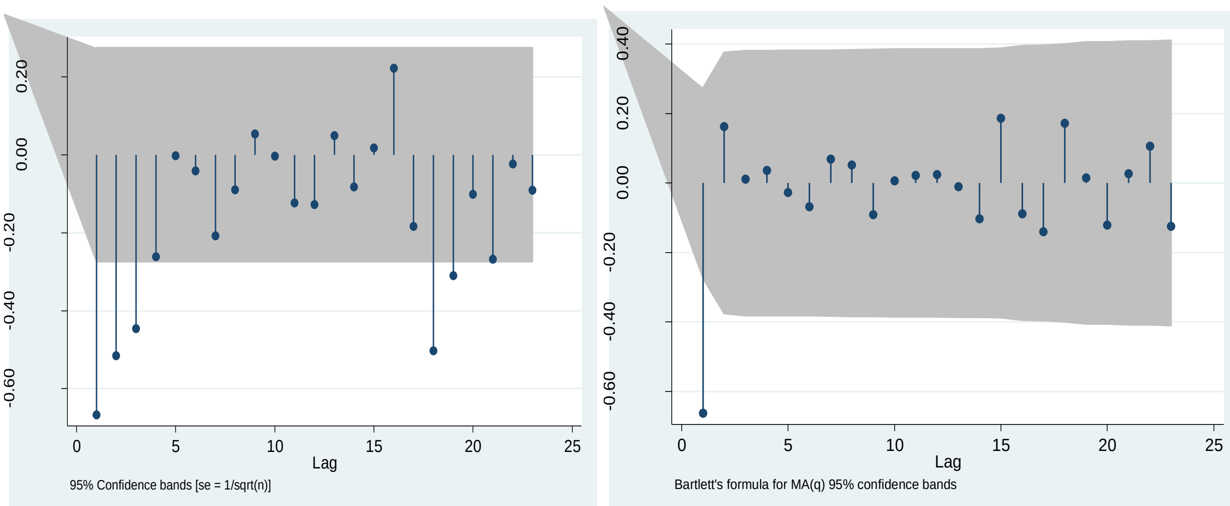


Figure 1: Partial autocorrelation (PAC) and Autocorrelation (AC) for Kenya's temperature

After carrying out serial correlation test, the final step was to identity the AR model. The shaded area is the 95 percent confidence interval. The model for temperature is AR (3) while that for rainfall is AR (2).

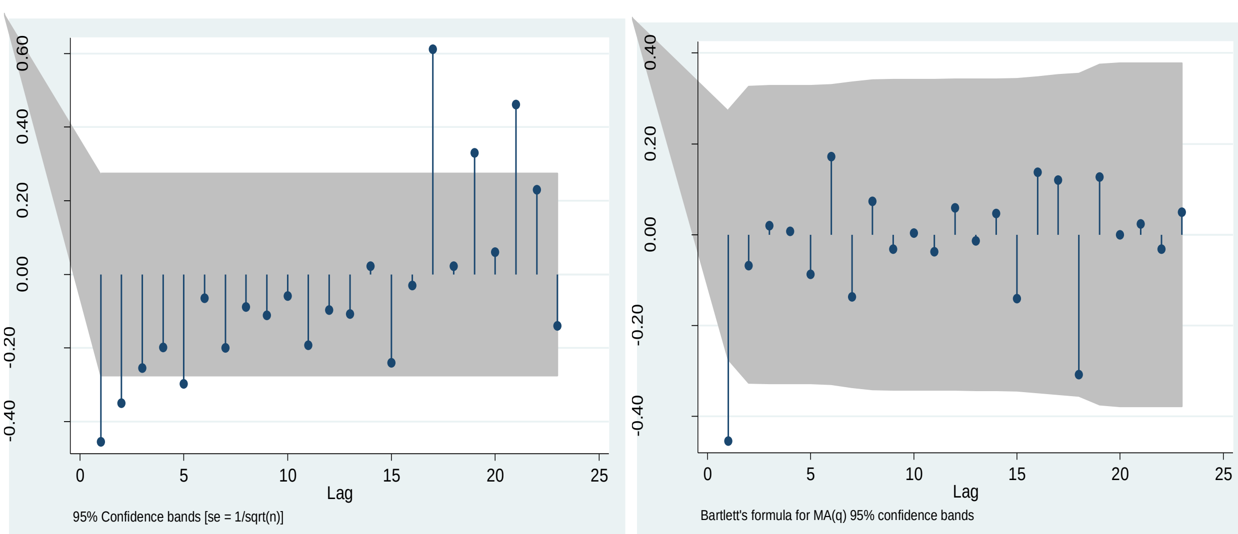


Figure 2: PAC and AC of Kenya's rainfall pattern

4.3 Cereal, rainfall and temperature forecast results for Kenya

Figure 3 presents the results of cereal, rainfall and temperature forecasting. The grey line indicates the actual variability of cereal production, rainfall and temperature patterns from the year 1961 to 2012. It indicates that Kenya has been experiencing rainfall and temperature variability which imposes a negative impact on cereal production. On the other hand, blue line shows the model fit while the while the red line is the predicted cereal, rainfall and temperature patterns. On average, Kenya's cereal production has been on the rise from 1961 to 1912 despite the fluctuations partly attributed to variability of rainfall and temperature patterns.

In terms of prediction, empirical results show that cereal production in Kenya will continue to increase from 4.0 million in 2012 to 6.2 million Tons in 2021; representing a 55 percent increase during this period. This will be attributed to a sharp decline in rainfall and an increase in temperature as shown indicated in the figures below. By 2023, it is envisaged that the drop in cereal production by approximately 65 percent by 2024 is likely to impact negatively on food security in Kenya.

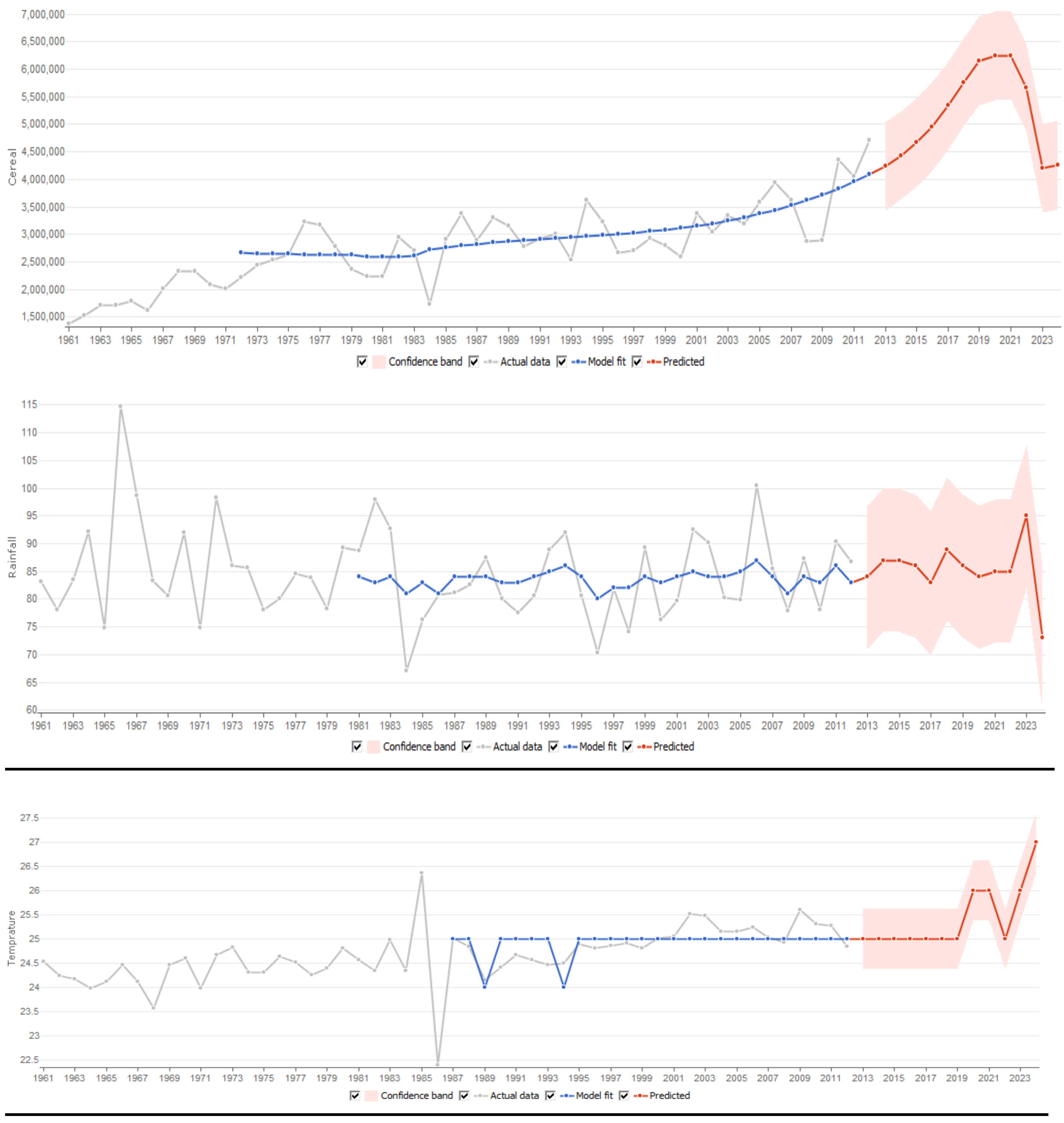


Figure3: Cereal, rainfall and temperature forecast respectively for Kenya

4.2 Uganda’s Cereal, rainfall and temperature patterns

Table 3 shows the model for Uganda’s cereal, rainfall and temperature patterns. Based on these findings, AR (1) is the most suitable model for Uganda time series data. The adjusted R-squared show that the independent variables explain 91 percent variation in the dependent variable.

Table 3: Autoregressive [AR (1)] model results for Uganda

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1205604.	535021.1	-2.253376	0.0296
RAINFALL	6846.091	4009.055	1.707657	0.0953
TEMPRATURE	31756.72	19467.81	1.631242	0.1105
CEREAL(-1)	0.730456	0.154988	4.712992	0.0000
CEREAL(-2)	0.163590	0.192363	0.850421	0.4000
CEREAL(-3)	0.108122	0.191958	0.563261	0.5763
CEREAL(-4)	-0.017391	0.158517	-0.109713	0.9132
R-squared	0.929742			
Adjusted R-squared	0.919461			
F-statistic	90.42763			
Prob(F-statistic)	0.000000			

Further, the study tested for the existence of serial correlation in the data using Breusch-Godfrey Serial Correlation LM test. Since the Chi-Square probability value is statistically insignificant, we conclude fail to reject the null hypothesis of no serial correlation.

Table 4: Breusch-Godfrey Serial Correlation LM test

F-statistic	0.521004	Prob. F(2,39)	0.5980
Obs*R-squared	1.249099	Prob. Chi-Square(2)	0.5355

The results indicating the order of AR is as indicated in the figures (3) and (4) below. Results show that Uganda time the time series temperature data follows and AR (1) model while rainfall data is an AR (2) model.

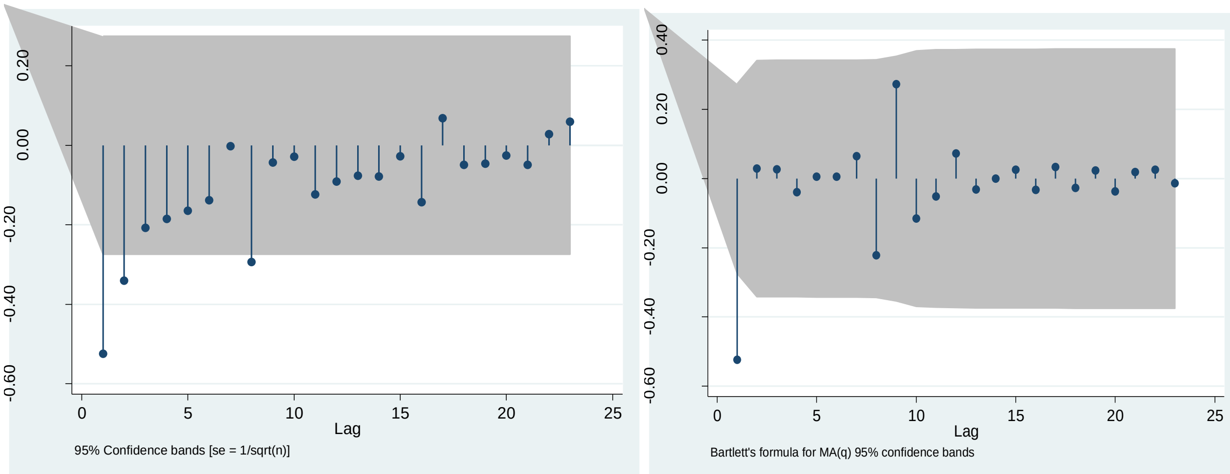


Figure 3: PAC and AC for Uganda respectively for temperature

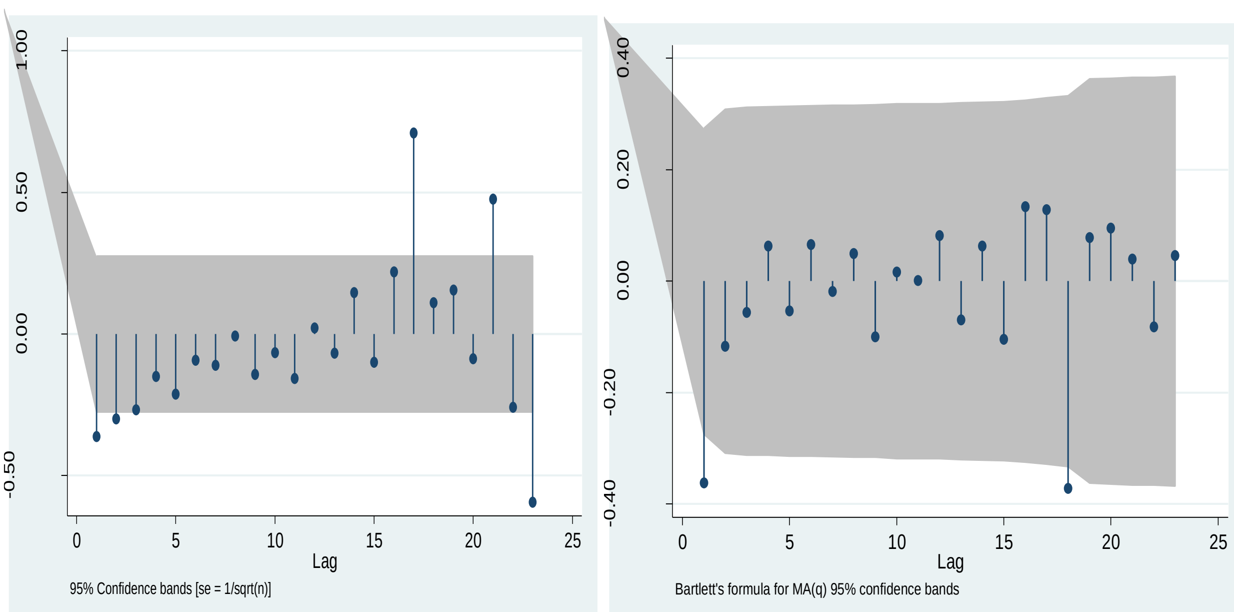
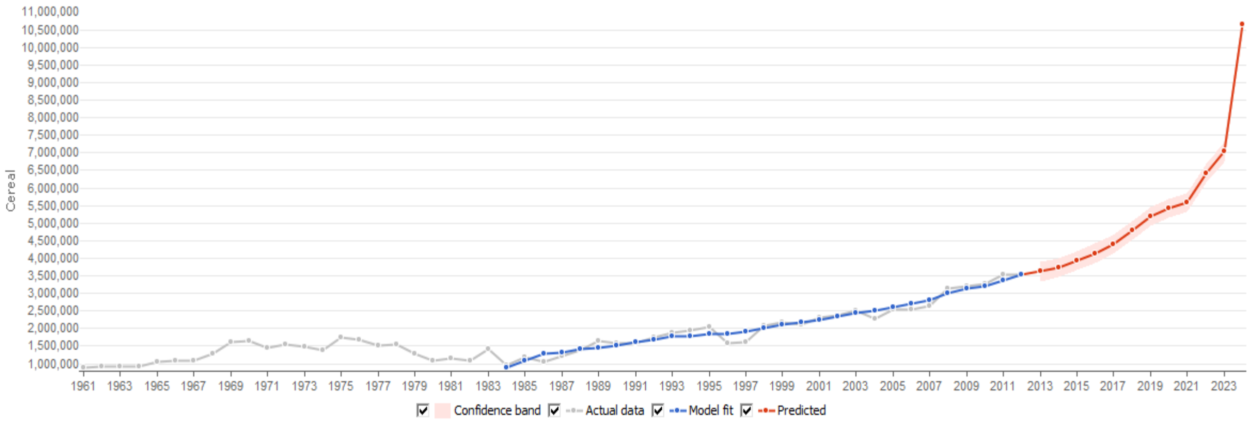
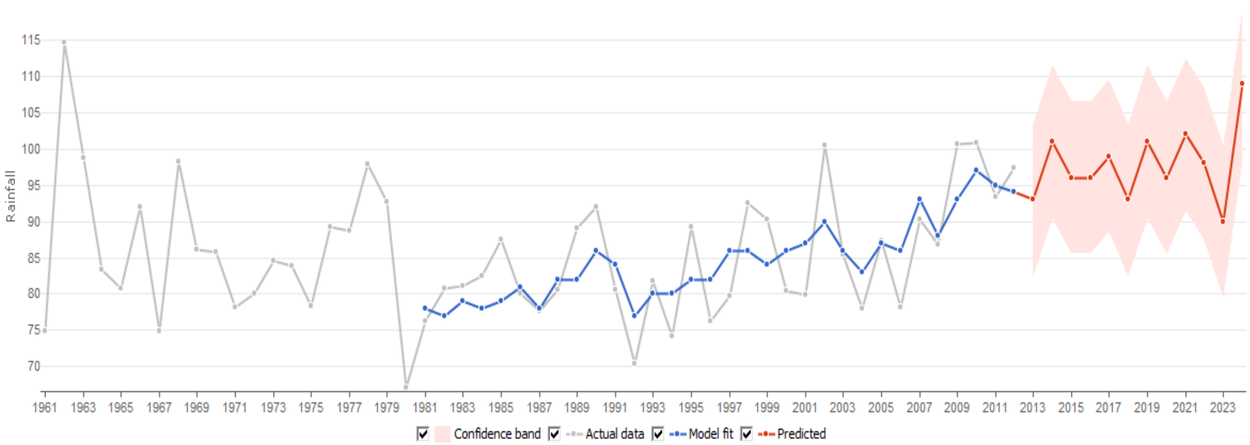


Figure 4: PAC and AC for Uganda respectively for rainfall

Having done the preliminary results in terms of checking for serial correlation and identifying the model, the next step was to forecast the theme series data on the aforementioned parameters and deduce the link between them. Specifically, we forecast cereal, rainfall and temperature patterns and identify if they are correlated with each other. The results are indicated in figure 5 below.

The forecasted results for Uganda indicate that the country has been facing very minimum fluctuations in cereal production between 1961 and 2012 despite the variability in rainfall. This positive progress can be attributed to the increasing demand of cereals from Uganda by countries such as Kenya, South Sudan, and the Democratic Republic of Congo. Second, even though Uganda has witnessed rainfall fluctuations, the fluctuation shave been favorable enough thus leading to higher productivity. The results of projection show that Uganda's maize productivity will continue to increase particularly during 2023 and 2024. The study also indicate that despite the anticipated fluctuation in rainfall patterns, the slight decline in temperature patterns will be good news to farmer particularly during planting season.





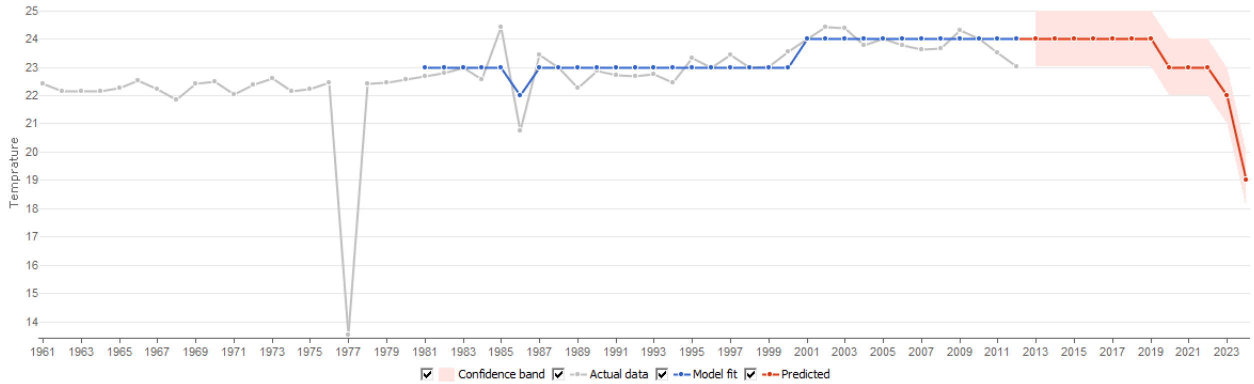


Figure 5: Cereal, rainfall and temperature forecast respectively for Uganda

4.3 Tanzania's rainfall and temperature patterns

Table 5 presents the results of the AR model for Tanzania's cereal production. The data for Tanzania's cereal production follows the second order of Auto regression. This is manifested by the statistically significant lag two variable. Moreover, the overall model fitness as indicated by the F-Statistic value as well as the adjusted Square values are giving a positive indication that the AR (2) model best fits the data.

Table 5: Autoregressive model results for Tanzania

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1405269.	5108230.	-0.275099	0.7846
RAINFALL	10292.53	11810.23	0.871493	0.3886
TEMPRATURE	24064.46	217278.4	0.110754	0.9124
CEREAL(-1)	0.063630	0.154750	0.411178	0.6831
CEREAL(-2)	0.493455	0.143470	3.439420	0.0014
CEREAL(-3)	0.440485	0.156302	2.818161	0.0074
CEREAL(-4)	0.102744	0.177502	0.578836	0.5659
R-squared	0.895342			
Adjusted R-squared	0.880026			
F-statistic	58.45875			
Prob(F-statistic)	0.000000			

Further, the Breusch-Gogfrey cereal correlation test shown non-existence of cereal correlation in the time series data. This is a positive step towards time series forecasting.

Table 6: Breusch-Godfrey Serial Correlation LM test

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F-statistic	2.430012	Prob. F(2,39)	0.1013
Obs*R-squared	5.318764	Prob. Chi-Square(2)	0.0700

Figure 6 and 7 below shows the results of AC and PAC for Tanzania's temperature and rainfall patterns. The temperature data is AR (2) while the rainfall data is AR (3).

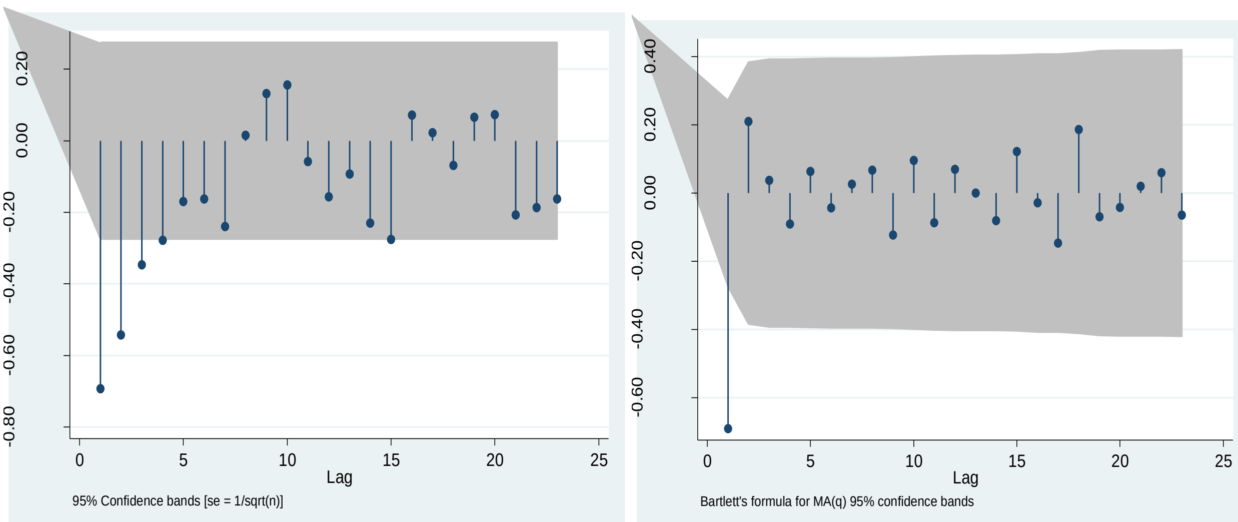

Figure 6: PAC and AC for Tanzania respectively

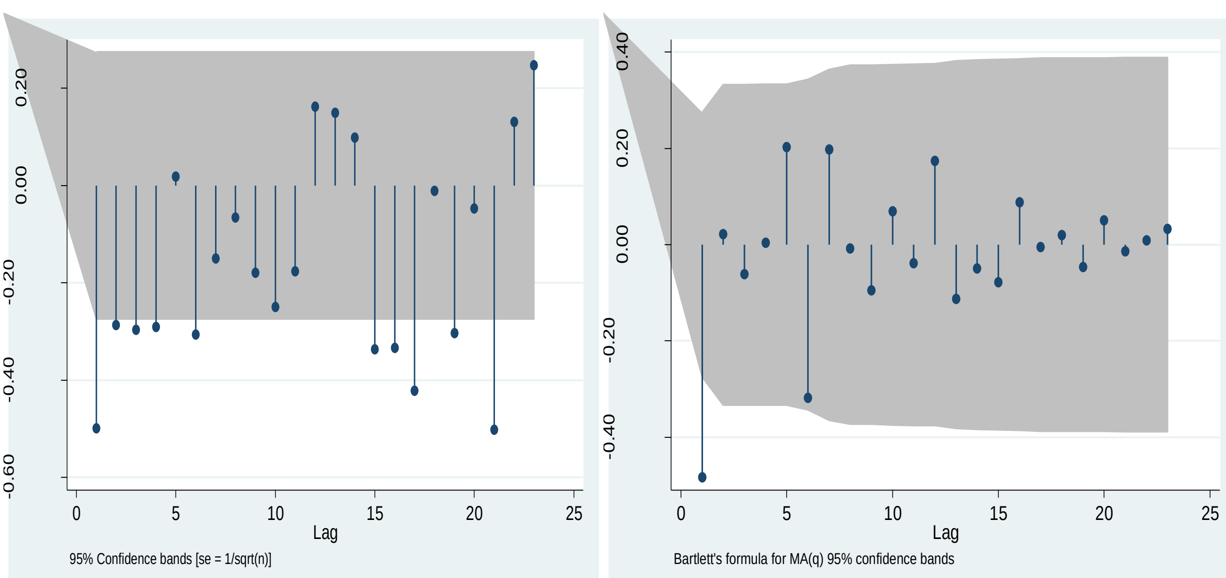

Figure 7: PAC and AC for Tanzania's rainfall respectively

The results of the forecasting model shows that the United Republic of Tanzania has over the years experienced a steady cereal production from 1961 to 2012. The minimal fluctuations are attributed to favorable temperature as well as minimal fluctuations in rainfall. Even though rainfall variability is clearly evident from the graph, there has not been a significant drop capable of warranting a steady reduction in cereal production.

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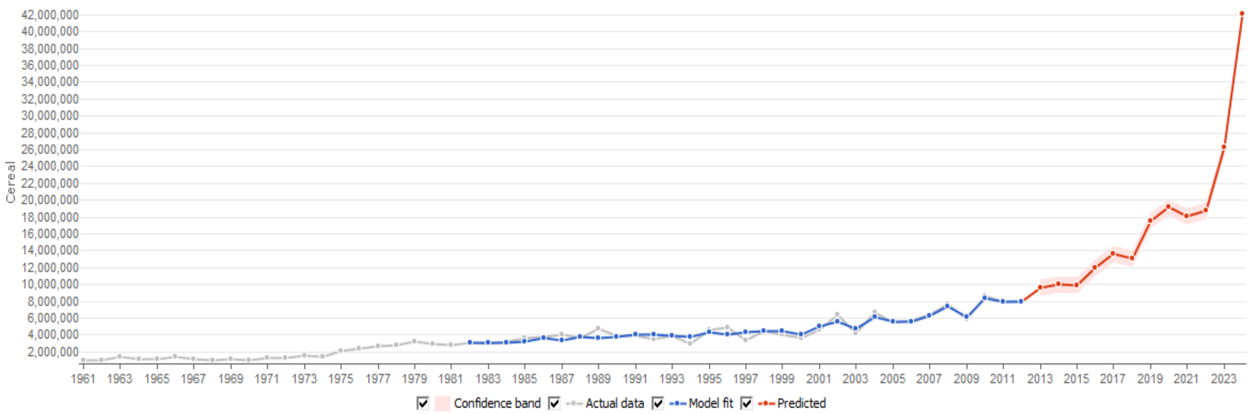

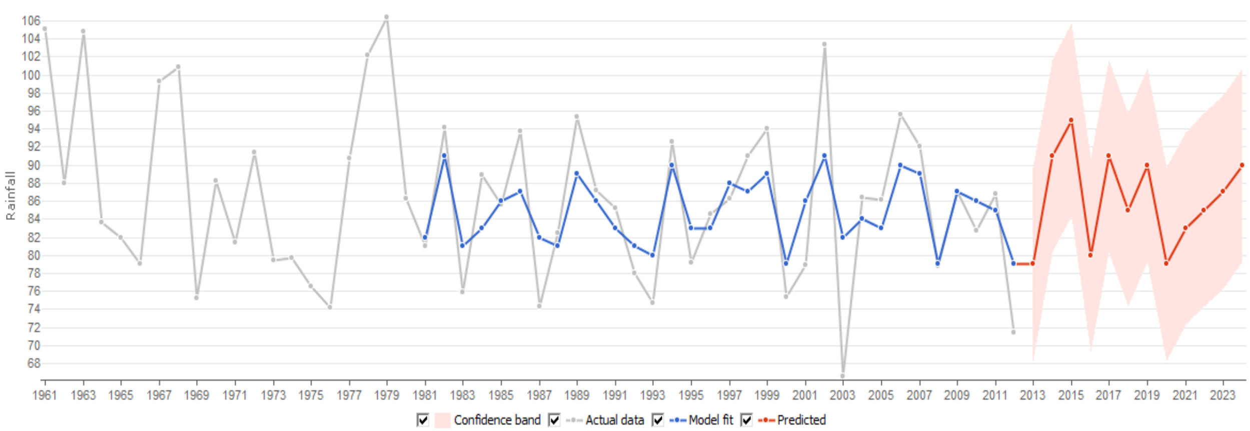

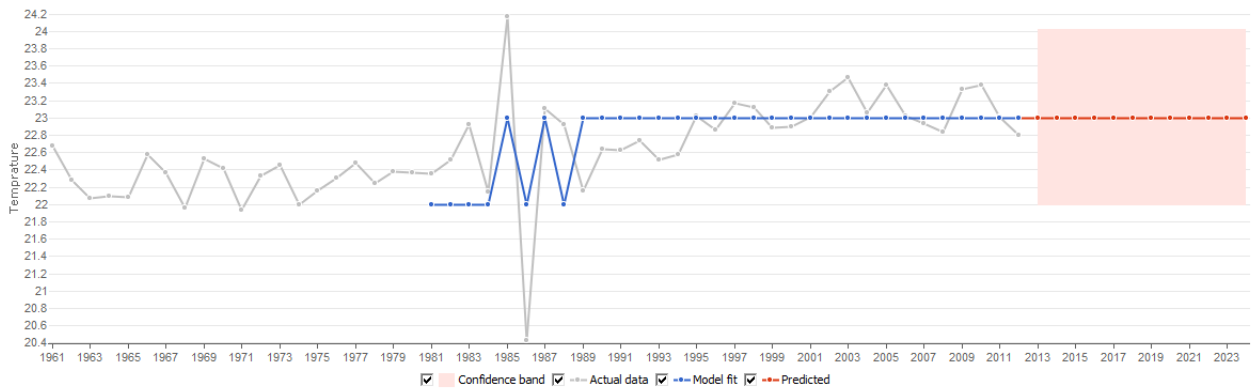

Figure 8: Cereal, rainfall and temperature forecast respectively for Tanzania

4.4 Burundi's rainfall and temperature patterns

Table 8: Autoregressive [AR (2)] model results for Burundi

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.15E-08	8.29E-09	1.393615	0.1715
RAINFALL	-9.38E-11	2.66E-11	-3.524130	0.0011
TEMPRATURE	-1.15E-10	4.45E-10	-0.257691	0.7980
CEREAL(1)	1.15E-14	1.05E-14	1.092990	0.2813
CEREAL	1.000000	1.37E-14	7.31E+13	0.0000
CEREAL(-1)	-1.20E-14	1.47E-14	-0.814979	0.4202
CEREAL(-2)	6.82E-14	1.42E-14	4.792096	0.0000
CEREAL(-3)	-2.22E-14	1.51E-14	-1.474997	0.1485
CEREAL(-4)	-3.95E-14	1.26E-14	-3.124475	0.0034
R-squared	1.000000			
Adjusted R-squared	1.000000			
F-statistic	9.73E+27			
Prob(F-statistic)	0.000000			

Table 9: Breusch-Godfrey Serial Correlation LM test

F-statistic	26682.11	Prob. F(2,36)	0.0000
Obs*R-squared	46.96818	Prob. Chi-Square(2)	0.0000

The model results depict some sort of serial correlation in the, model. The existence of this statistical condition renders the model not appropriate as far as forecasting is concerned.

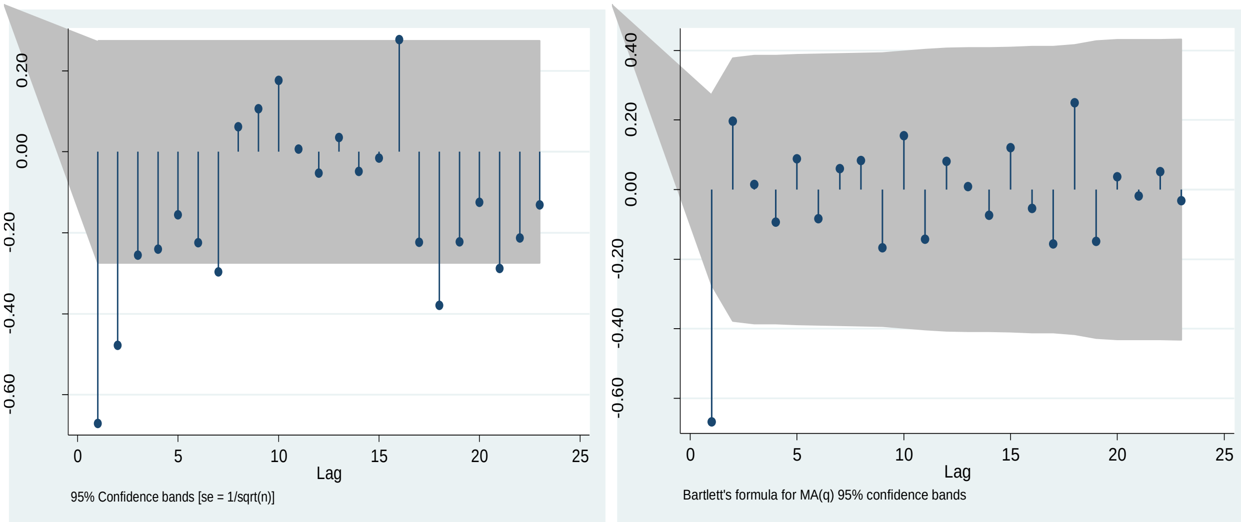

Figure 9: PAC and AC for Burundi respectively

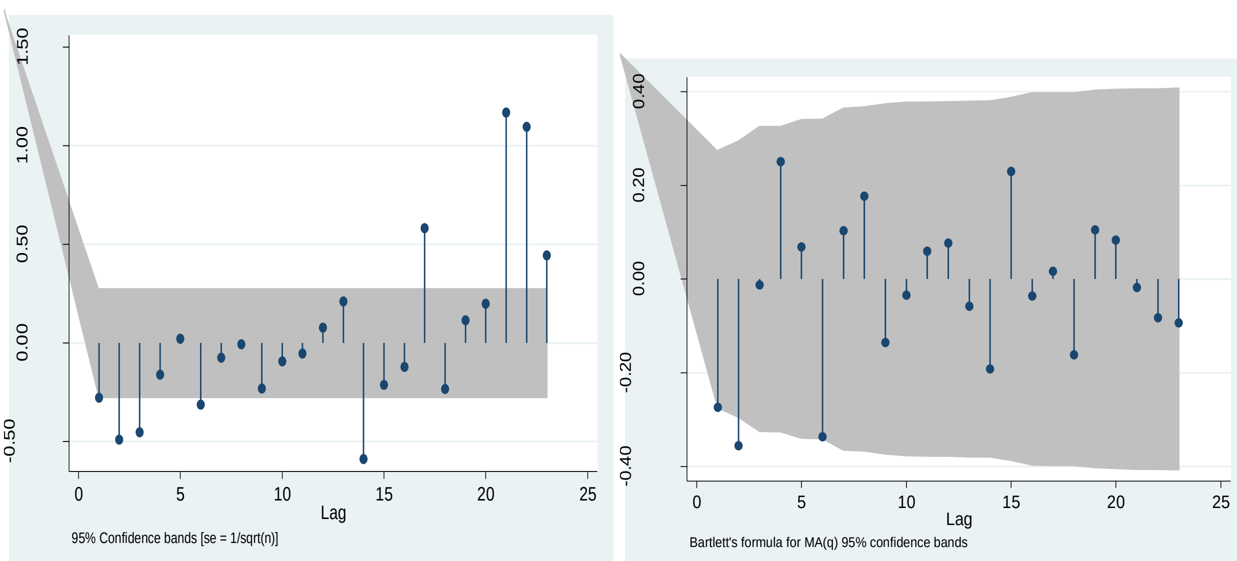

Figure 10: AC and PAC for Burundi's rainfall respectively.

The results of the forecasted model show that despite the fluctuation of rainfall and temperature patterns, Burundi's cereal production has been rising. However, significant are evident during the years 1974, 1984 as well as 2012. Despite these fluctuations, it is worth noting that on average, cereal production has been improving with time.

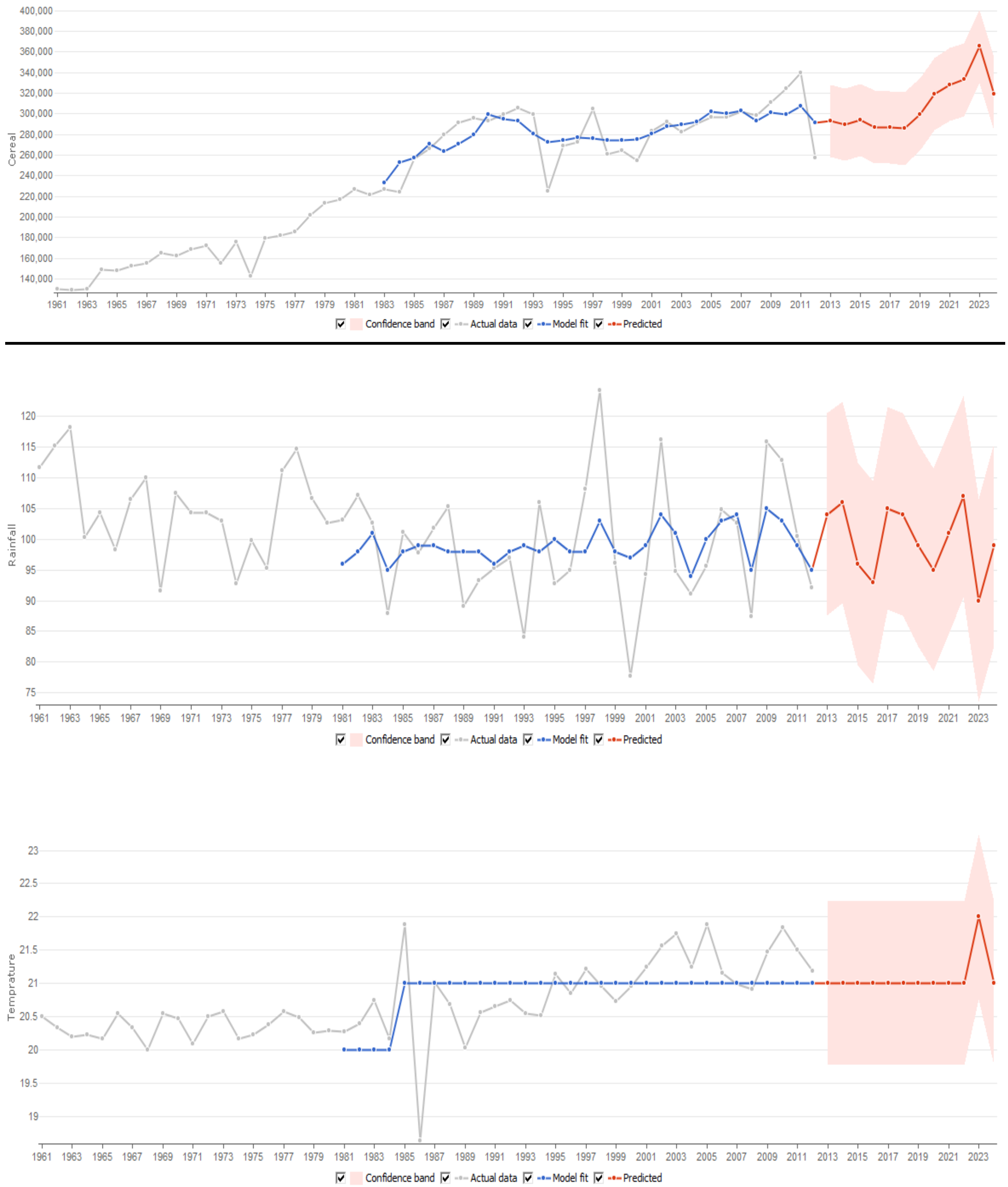

Figure 11: Cereal, rainfall and temperature forecast respectively for Burundi.

Table 11: Summary of model fitness

		Cereal	Rainfall	Temperature
	Mean Absolute Error (MAE)	324212	5.40059	0.2482
	Root Mean Square Error (RMSE)	400031	6.4589	0.3095
	Coefficient of determination (R^2)	0.525742	6.5897	0.2019
KENYA	Correlation	0.7263	0.7121	0.5178
	Mean Absolute Error (MAE)	111816	4.4849	0.3589
	Root Mean Square Error (RMSE)	133803	5.2381	0.4929
	Coefficient of determination (R^2)	0.9648	0.559	0.5724
UGANDA	Correlation	0.9823	0.7528	0.7686
	Mean Absolute Error (MAE)	378650	4.1918	0.36
	Root Mean Square Error (RMSE)	411984	5.2486	0.5095
	Coefficient of determination (R^2)	0.911	0.561	0.2457
TANZANIA	Correlation	0.9551	0.8486	0.5211
	Mean Absolute Error (MAE)	13246.6	6.4622	0.4346
	Root Mean Square Error (RMSE)	1758.6	8.229	0.6187
	Coefficient of determination (R^2)	0.5839	0.2893	0.0504
BURUNDI	Correlation	0.7832	0.6498	0.313

Conclusion and policy implications

This study is an attempt to unpack the existing link between climate change and food security in the East African region. The study uses time series data of rainfall, temperature and cereal production. Using AR model, the study gives past trends and forecasts the patterns of climate change and cereal production. Results indicate that patterns of cereal production resonate well with those of rainfall and temperature over time.

Specifically, forecasted model indicate that Kenya and Burundi are likely to face acute cereal shortage between 2021 and 2023. It is envisaged that a reduction in rainfall accompanied with rising temperature is the likely reason for this impending scenario. This is the same case for Burundi. However, the case for Tanzania and Uganda are different. Cereal production trends in Tanzania have been fairly stable over the years. This is attributed to fairly stable temperature and rainfall patterns.

These finding point out some key policy messages. First, the governments of Kenya and Burundi should enhance their Strategic Grain Reserve (SGR) by 2021 to mitigate any food insecurity challenge that may arise due to impending drought as indicated by the forecasts. Second, Kenya and Burundi could take advantage of the COMESA Free Trade Area (FTA) to import cereals to meet the deficit. Finally, the governments of all the EAC countries should put in place policies geared towards building resilience to climate change and variability. This will go along in complementing the noble interventions already put in place as far as adaptation and mitigation of climate change is concerned.

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