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Research Application Summary

Unpacking the nexus between climate change and cereal production: Implications for food security in the East African region

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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 African Community (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 and rainfall and temperature dynamics from 1961 to 2012. The data were obtained from the Food and Agricultural Organization (FAOSTAT) as well as the World Bank knowledge management center. Econometric data analysis was done using Eviews version 7 and GMDH version 3.8.3 statistical software. The findings of the Autoregressive model showed 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 East African Community region.

Key words: Autoregressive modeling, Kenya, rainfall, temperature, time series

Résumé

Cette étude tente de faire comprendre la relation entre la variabilité climatique et la sécurité alimentaire dans la région de la Communauté de l'Afrique de l'Est. Un bon nombre de données empirique existe dans le domaine du changement climatique non seulement au niveau régional mais aussi mondial. En utilisant des données secondaires de séries temporelles, l'étude vise à établir un lien entre les modèles de production céréalière et les dynamiques pluviométriques et thermiques de 1961 à 2012. Les données ont été obtenues de FAOSTAT et du centre de gestion des connaissances de la Banque mondiale. L'analyse des données économétriques a été faite à l'aide des logiciels statistiques comme Eviews version 7 et GMDH version 3.8.3. Les résultats du modèle autorégressif ont montré que la précipitation et la température ont inévitablement changé. Ces résultats offrent des perspectives politiques importantes sur le rôle que joue la variabilité climatique dans la sécurité alimentaire dans la région de la Communauté de l'Afrique de l'Est.

Mots clés: Modélisation autorégressive, Kenya, précipitations, température, séries chronologiques

Background

Addressing climate change and ending poverty are perhaps the two critical issues facing the world today (World Bank, 2016). Globally, there is a consensus among policy makers as well as scholars that climate change is already causing negative impacts in many parts of the world (Jat *et al.*, 2012). According to the recently adopted Paris agreement, climate change represents an urgent and potentially irreversible threat to livelihoods as well as the planet (UNFCCC, 2015). Taking into cognizance the fact that climate change is a global phenomenon, a joint effort driven by a common objective could perhaps offer the most plausible solution to climate change and variability. 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 the 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 show that climate change curtails sustainable economic and socioeconomic development (Viljoen, 2013). The seasonality has always placed an impediment to climate mitigation. Among the continents of the world, Africa appears to be the most vulnerable to climate change. 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). The overgrowing challenge in terms of predicting rainfall and temperature patterns puts a lot of risk and uncertainty as far as dealing with climate change is concerned. The negative impacts of climate change and variability have been studied locally, regionally and globally. However, there exists an empirical dearth of knowledge on the link between climate change variability and food security in the East African Community (EAC) region. The current study therefore endeavors to fill the aforementioned knowledge gap. The objectives of the study therefore are: (i) to describe the emission data by plotting the actual values and make sense out of the pattern; and ii) 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.

Methodology

The study used time series secondary data of rainfall and temperature patterns from Kenya, Uganda, Tanzania and Burundi obtained from the World Bank Knowledge Management center and ranged from 1961 - 2012. Data on cereal production was obtained from the Food and Agricultural Organization (FAOSTAT) of the United Nations.

A time series is a collection of observations made sequentially through time (Chatfield, 2000). Generally, these observations are spaced at equal time intervals. In this study, the main objective of analysis of time series data is to find a mathematical model capable of explaining data behavior. 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 greenhouse gas (GHG) emissions enables formulation of appropriate policies aimed at reducing emissions thus enhancing efficient decision-making.

The current study uses an autoregressive (AR) model. An AR model is one where a 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:

B

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

Where z_t denotes a purely random process with zero mean and variance σ^2_z with the backward shift operator B such that $Bx_t = x_{t-1}$. It is important to note that the backward shift operator has the effect of changing the period t to a period *t-1*.

The $AR(p)$ model is formulated as follows:

$$\phi(B)\ x_t = Z_t \quad (2)$$

Where $\phi(B)=1-\phi_1-\phi_2(B^2)-\dots-\phi_p B^p$ is polynomial in 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. The solution follows the following formulation:

$$\phi(B)$$

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

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

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

It is imperative to note that the stationarity of *AR* times series is crucial in as far as time series analysis is concerned. This is possible if the following condition if $|\phi| < 1$ is satisfied. One way to test for stationarity is the use of autocorrelation function (ac.f).

According to Chatfield (2000), the ac.f of stationarity $AR(1)$ process is given by $\rho_k = \phi^k$ for k =1,2...n. It is vital to note that when it comes to higher order stationarity *AR* processes, the ac,f is a mixture of terms which cline exponentially. In order to obtain ac.f, a set of difference equations commonly referred to as Yule-Walker equations formulated as:

$$p_k = \phi_1 p_{k-1} + \phi_2 p_{k-2} + \ldots + \phi_k p_{k-p} \quad (5)$$

Where k =1,2...n, $p_0=0$. One of the important useful property of $AR(p)$ process is the ability to show that the partial ac.f is zero at all lags greater than p implying that the sample ac.f 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 "cuts-off" i.e. should be approximately zero or at least not significantly different from zero for higher lags (Chatfield, 2000).

Research application

Kenya's rainfall and temperature patterns. Table 1 shows the results of the autoregressive model for Kenya. The dependent variable is cereal production while the explanatory variables are rainfall, temperature and the lag of the cereal by one period. It is evident that the lag of cereal is statistically significant at one percent. The objective of this study is to forecast the dependent variable from the model.

It is vital to note that before forecasting of the dependent variable, the estimated model should be very good before the forecasting is done. The criteria for determining the fitness of the model is pegged on the following (i) the R-square value should be very high; (ii) there should be no serial correlation; (iii) no heteroskedasticity; and (iv) the residual should follow

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
Temperature	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			

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

a normal distribution. Once all the aforementioned has been reaffirmed, the model is ready for forecasting.

In terms of our results, the lag of cereal is statistically significant at one percent (p-value = 0.000). Generally the rule of the thumb is that at least half of the variables in the model should be significant. The model therefore fulfills this requirement. Moreover, our R-square is slightly high (R-Square = 0.573). In addition, the F-statistic and the corresponding probability is statistically significant at one percent (p-value = 0.000).

The null hypothesis is that the model has no serial correlation while the alternative is that the model exhibits serial correlation. Since, the Chi-Square probability value is statistically insignificant, we have a basis to fail to reject the null. In other words, the model is statistically sound. In terms of heteroskedasticity and normal distribution, we assume that the model meets the necessary requirements. Usually, existence of serial correlation in the model is not good news. In order to do away with serial correlation, one has to remove it. This is done by running the Autoregressive of Order 1 in the model. The Chi-Square value for the above model is statistically insignificant thereby giving a basis to fail to reject the null hypothesis of no serial correlation. The model therefore conforms to the requirements before forecasting is done. Note that the current study carries out both dynamic and static forecasting approaches.

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