# Panel threshold effect of climate variability on agricultural output in Eastern African countries

Mubenga-Tshitaka, Jean-Luc and Gelo, Dambala and Dikgang, Johane and Mwamba, Muteba

University of Johannesburg, University of the Witwatersrand

12 July 2021

Panel threshold effect of climate variability on agricultural output in Eastern African countries

Jean-Luc Mubenga-Tshitaka[1], Dambala Gelo, Johane Dikgang[2] and John W. Muteba Mwamba

**Abstract**

Recent scientific literature shows that in many developing countries, variability in rainfall and temperature in growing season has distortional effects on agricultural output, especially when the variability is high. At what degree or threshold are these variabilities harmful to agricultural output in certain regions of Africa? In this study, we answer this research question using a dynamic panel threshold model on a panel dataset of East African countries for the period 1961 to 2016. We incorporate climate variables disaggregated into growing and non-growing seasons like in Abraha-Kahsay and Hansen (2016). The empirical results indicate that growing rainfall variability has significant effects on agricultural output. More specifically, we found a significant negative effect from rainfall variability in spring and summer, when precipitation exceeds thresholds of -0.533ml and -0.902ml respectively. We found no significant effect in fall. In the case of growing-season temperature variability, we found no significant effects. Policy implications are discussed.

**Keywords**: adaptation policy, climate change, Eastern Africa, Dynamic panel threshold

**JEL Code:** Q10, Q18, Q54

[1] Public and Environmental Economics Research Centre (PEERC), School of Economics, University of Johannesburg, Johannesburg, South Africa. Email: jeanlucmubenga@yahoo.fr.

[2] School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa.

## 1. Introduction

Climate change has emerged as the most important environmental problem facing humankind, at all levels of existence. The impacts of climate change will not be evenly spread across the world. According to the Intergovernmental Panel on Climate Change report (IPCC, 2014), climate change will not only manifest in the gradual changes in average weather conditions, but also in increased frequency and intensity of extreme weather events across regions. According to the World Bank (2010), a 2°C warming above pre-industrial temperatures could induce a permanent reduction in gross domestic product (GDP) of 4 to 5% for Africa and South Asia.

East Africa's economy in particular is highly dependent on agriculture. In Uganda, Ethiopia, Kenya and Tanzania, agriculture represents 30.2%, 47%, 23.8%, and 42.8% respectively of GDP (Salami *et al*, 2010). This leads to these communities being highly vulnerable to any fluctuations in seasonal rainfall amounts. It has been shown that these dependencies could continue for several decades (World Bank, 2007). The threats of climate change are certainly a challenge – especially in developing countries, where poverty is a feature that hinders the development. Noy (2009) reveals that following a natural disaster, a developing country faces a much greater decline in output than a developed economy would. To date there is still much confusion about the effect that climate has on agricultural output, particularly in developing countries. Because of this, the impact of climate change on agriculture is increasingly becoming a major area of scientific concern (Mendelsohn, 2009; 2014; Molua & Lambi, 2007; Lipper *et al.*, 2009; Rui-Li & Geng, 2013; Smit & Yunlog, 1996). For instance, Mendelsohn (2014) investigates the impact of climate change in Asia by employing a Ricardian approach. The findings reveal a small aggregate effect associated with a 1.5°C warming, but damaging effects of about US$84 billion associated with a 3°C warming.

However, there is also an increasing concern about climate change variability per season in the agricultural sector. For instance, early papers such as Mendelsohn *et al.* (1994) found that in the US, on average, higher temperatures in all seasons with the exception of autumn reduced farm values, while more rain outside autumn increased farm values. Victor *et al.* (1996) recognised that the risks associated with rainfall variability include soil erosion, prolonged heavy rains threatening waterlogging, prolonged low-rain periods, early cessation of rains long before the maturity of crops, and too little rainfall for crop water requirements.

East Africa region in particular is characterised by substantial weather variability in the main growing season (Mutai & Ward, 2000; Shreck & Semazzi, 2004). Growing-season climate variability is crucially important – particularly from a policy perspective, as mitigation is feasible even with small-scale technologies (Conway & Schipper, 2011).

In Africa and East Africa, specifically studies show that growing-season variability in precipitation has a negative effect on agricultural output. Barrios *et al.* (2008) found growing-season variation in precipitation to be insignificant, but also that rising annual mean temperature has been detrimental to agricultural output. Rowhani *et al.* (2011) found that growing-season variability in precipitation had a negative effect on agricultural outputs in East Africa, while Ward *et al.* (2014) found that growing-season precipitation variability had a positive impact on agricultural outputs. Recently, Abraha-Kahsay and Hansen (2016) investigated the impact of seasonal precipitation/temperature variability in East Africa by making use of the fixed-effect model and the coefficient of variation as a measure of variability. Their findings were that growing-season precipitation in spring and fall have a negative effect on agricultural output.

The literature also provides sufficient evidence that climate variables are not linearly related to agricultural outputs (Mendelsohn, 2014; Wang *et al.*, 2009; Mishra & Sahu, 2014; Schlenker & Roberts, 2009). For instance, Schlenker and Roberts (2009) investigated the relationship between maize, soybean and cotton yields and temperature in the growing season in the United States, using regression analysis. Their findings revealed that yields increase with temperature up to 29° C for corn, 30° C for soybeans, and 32° C for cotton. But above these thresholds, any further increase in temperature becomes harmful to agricultural output. They added that the non-linear relationship may be observed on isolation of either time-series or cross-sectional variations in temperature and agricultural-product yields. Abraha-kahsay and Hansen (2016) examined the impact of climate change and adaptation policy on agricultural production in East African countries by estimating the production function for agricultural output. These authors incorporated climate variables disaggregated into growing and non-growing seasons, and applied panel fixed-effect techniques. They reported that there is a significant negative effect from growing-season variances in precipitation. Through a simulation technique, they also predicted an output decrease of between 1.2% and 4.5% due to climate change.

In general, the literature finds that climate change and growing-season climate variability have a negative impact on agricultural output (see Abraha-Kahsay & Hansen, 2016). However, there is one important research question that still remains to be answered: is there a threshold at which climate change or growing-season climate variability produces effects on agricultural output? For policy intervention, it would be appropriate to investigate the threshold at which growing-season rainfall and temperature variability affect agricultural output. We believe that the relationship between climate variability and agricultural output is likely to be non-linear. At some (low) level of variability in rainfall and/or temperature, the relationship could be either positive or neutral (non-existent). At a higher level of climate variability the relationship becomes negative. If such a non-linear relationship exists, then in principle it should be possible to estimate the inflexion point, or the threshold at which the sign of the relationship between the two variables would switch. The possibility of such a non-linear relationship is modelled, for instance, by Wang *et al*. (2009), dealing with agriculture in China. When this threshold exists and is ignored, this may significantly bias the relationship between climate variability and agricultural output.

Traditional panel econometric techniques often employed in applied research, such as Polled Ordinary Least Squares (POLS), Fixed and Random Effects, are all limited in their capacity to answer the research question above. On the other hand, although the application of the traditional instrumental variable regression techniques such as Two-Stage Least Squares (TSLS) and the Generalised Method of Moments (GMM) can be efficient in handling the issue of endogeneity, these are not appropriate for non-linear models. Hansen (1999) introduced an econometric framework which allows the investigation of the relationship between two or more variables, if and only if the expected relationship is hypothesised to be non-linear. Nevertheless, the Hansen (1999) model also presents limitations, and one of them is the issue of strict exogeneity of the regressors. In agricultural economics, it has been shown that if there is more capital in the form of livestock (as is the case in Eastern Africa), it is plausible that more output could be produced. The higher the level of output, the higher the investment ratio of capital is likely to be (FAO, 2008; 2013). Hence a causal relationship is possible between capital investment and agricultural output. For this reason, we reinvestigate the econometric effects of climate variability on agricultural output in Eastern Africa, using a dynamic version of the Hansen model. We aim to shed more light on the effects of growing-season variability in rainfall and temperature on agricultural output. We seek to determine whether there is a turning point (a threshold) at which climate variability impacts agricultural output. To the best of our knowledge, this is the first study to answer this specific research question.

The estimation results reveal that the growing season rainfall variability has an impact mainly in the major growing seasons. Lag output is significant across all specifications. In the context of the rural economy that characterises Eastern Africa, the livelihoods of farmers depend on their choice of how to allocate resources to generate the highest income possible, given the constraints they are facing. These decisions depend on the income generated by farmers, making lag output one of the most important features in decision making. After controlling for endogeneity, the results reveal that growing season rainfall variability negatively affects agricultural output; however, there is no significant evidence for the effect of growing season temperature variability in the major season. After using the dynamic panel threshold estimation, we found that the threshold for growing season rainfall in spring is -0.553 in spring , -0.902 in summer, and 1.261 in the fall season. In the case of growing season temperature variability, we found no significant effects.

The rest of the paper is organised as follows. Section 2 is a brief review of the existing literature. Section 3 presents the model specification, and Section 4 describes the data and variables. Section 5 presents the results, and Section 6 concludes.

## 2. Climate variability: a brief literature review

East Africa's economy is highly dependent on agriculture, which generates 40% of the gross domestic product and is the main source of income (up to 80%) (Runge *et al.*, 2004). This makes communities extremely vulnerable to any fluctuations in seasonal rainfall amounts. Because of this dependency, the most important threat to agricultural production is the growing season weather variability documented in the literature in general (Victor, 1996; Rosenzweig *et al.*, 2007; Owusu & Waylen, 2013; Fiwa *et al.*, 2014) and in East Africa in particular (Schreck & Semazzi, 2004; Conway *et al.*, 2005; You *et al.*, 2009; Conway & Schipper, 2011; Bahaga *et al.*, 2014).

Like in some other regions in the developing world, East African livelihoods depend on agriculture rain-fed, and dominated by small-scale agricultural production (World Bank, 2007). The changes observed in the growing season rainfall pattern might potentially lead to food insecurity, lack of jobs and poverty, as the agricultural sector is primarily rain-fed, meaning that agricultural production is sensitive to rainfall fluctuations (Kyei-Mensah *et al.*, 2019).

Numerous studies have estimated the effects of climate change by using production functions in which different proxies are employed for climate change and climatechange variability (Schenker & Lobell, 2010; Rowhani et al., 2011; Blanc, 2012; Ward et al., 2014; Barrios et al., 2008; Molua, 2008; Rosenzweig et al., 1999; Lobell & Burke, 2010). Different climate variables such as annual and seasonal growing temperature and precipitation (Barrios *et al.*, 2009; Ward et al., 2014) have been used as proxies for climate variation in these estimations. Other climate variables have also been considered, such as evapotranspiration, standardised precipitation index, drought and floods (Blanc, 2012); temperature and precipitation variance (Rowhani et al., 2011), and coefficient of variation (Abraha-Kahsay & Hansen, 2016).

The importance of growing season climate variability and its inclusion in the production function has been documented around the world. For instance, Cabas *et al.* (2010) found that increases in both temperature and rainfall variability harm crop production in Nepal and Canada, while temperature variability has been found to have a negative effect on key crops in the US (McCarl *et al.*, 2008). Changes in mean and growing season temperature and rainfall induce heterogeneous impacts, which can be regarded as harmful, beneficial or even negligible, depending on altitude and type of crop (Poudel & Kotani, 2013).

In Africa, and specifically East Africa, studies have shown that growing season climate variability has an effect on agricultural output. For instance, Ward *et al.* (2014) used three estimation techniques (OLS, non-spatial and spacial Heckit models) to assess the impact of growing season variability on aggregate cereal yield in sub-Saharan Africa. They found that in growing season, precipitation variability has a positive impact on agricultural outputs. Abraha-Kahsay and Hansen (2016) employed fixed effect estimation to determine whether growing season variability has an effect on agricultural yield in East Africa. They disaggregated the annual climate variables, to distinguish between two seasons (growing and non-growing), and found a substantial negative impact from growing season variability in rainfall. Rowhani *et al.* (2011) also found that growing season precipitation variability has a negative effect on agricultural outputs in East Africa. On the other hand, Barrios *et al.* (2008) found growing season variation in precipitation to be insignificant.

Most of these studies that have focused on the impact of growing season variability in rainfall have relied on fixed effect models (Barrios et al., 2008; Lobell et al., 2011; Abraha-Kahsay & Hansen, 2016, Ward et al., 2014), which assume that there is a linear relationship between agricultural output and climate variables, or variability in climate variables. Our research sheds light on the non-linear relationship between these, and the threshold below or above which such a relationship becomes harmful to agricultural output.

## 3. Model Specification

### 3.1 Model 1: Standard production function

In the standard production function, the dependent variable (agricultural output) is regressed with inputs expressed as follows:

$$Q = F(L, K, \mathrm{I}) \tag{1}$$

where $Q$ stands for agriculture output, L for labour, K for capital (such as land, machinery and livestock), and I refers to other factors such as fertiliser and irrigation. We assume a Cobb-Douglas production function as in Abraha-Kahsay and Hansen (2016), expressed as follows:

$$Q = L^{\beta_1} K^{\beta_2} \mathrm{I}^{\beta_3} \tag{2}$$

Taking into account the dynamic nature of agriculture, the standard model can be expressed as follows:

$$\begin{aligned} ln(Output_{it}) = \beta_0 + \beta_1 ln(Output_{it-1}) + \beta_2 \ln(Labour_{it}) + \beta_3 \ln(Land_{it}) + \\ \beta_4 \ln(Machinery_{it}) + \beta_5 \ln(Livestock_{it}) + \beta_6 \ln(Fertiliser_{it}) + \\ \beta_7 ln(Irrigation_{it}) + \sum_{n=1}^{3} \alpha_{1s} \ln(Temp_{ist}) + \sum_{n=1}^{3} \alpha_{2s} \ln(Precip_{ist}) + \\ \sum_{n=1}^{3} \lambda_{1s} \ln(Variability_{ist}^{Temp}) + \sum_{n=1}^{3} \lambda_{2s} \ln\left(Variability_{ist}^{Rainfall}\right) + \rho TT_{it} + \mu_i + \\ \varepsilon_{it} \end{aligned} \tag{3}$$

where $Output_{it}$ and $Output_{it-1}$ are the total agricultural production of the country, and the lag of the total agricultural production is *I (i=1,2,*$\cdots n$*)* in year *t(t=1,2,*$\cdots, T$*)*. We include three capital inputs: Land, Machinery and Livestock. We also include Labour, Fertiliser and irrigation; $\mu_i$ is the unobserved time-invariant country-specific effect, $TT_{it}$ is the country-specific time trend, and $\varepsilon_{it}$ is the error term. We follow Barrios *et al.* (2008), Molua (2008) and Abraha-Kahsay and Hansen (2016) in specifying the augmented agriculture production function. $Temp_{ist}$ and $Rainfall_{ist}$ are the mean temperature and rainfall for country *i* in season *s (s=1,2,*$\cdots, S$*)* in year *t*. Likewise, $Variability_{ist}^{Temp}$ and $Variability_{ist}^{Rainfall}$ are growing season temperature and rainfall variability.

The single ordinary least squares (OLS) cross-country regression model is one technique that could be used to perform this estimation. However, this approach has some limitations, and the results may be biased and inconsistent, since it may not take into account the endogeneity of some of the regressors. The regressors might also suffer omitted variables bias, due to unobserved heterogeneity. These difficulties arise firstly due to the assumption that the unobserved heterogeneity or countries' fixed effects are correlated with explanatory variables. Secondly, the lagged dependent variable is also correlated with country-specific fixed effects.

There are two main procedures documented in the panel data literature. The first involves removing the country fixed effects by within transformation method, and the second is first-difference transformation. Tsangarides (2001) suggested that an appropriate panel data estimation should be considered. Fixed and random effect estimators are among the techniques considered in the literature. These pose the problems of endogeneity of regressors, and loss of dynamic information (Nkurunziza & Bates, 2003). Holtz Eaking et al. (1998) and Arellano and Bond (1991) suggests that the two-stages least squared method can use data to find the instruments. Arellano and Bond (1991), Arellano and Bover (1995) and Bundell and Bond (1998) introduced a process that consists of applying the Generalised Method of Moments (GMM).

Equation (3) above introduces the notion of memory or autocorrelation; in other words, today's output is partly explained by last season's output. Due to the dynamic framework, OLS, fixed and random effect processes are not valid. However, Equation (3) above creates the problem of endogeneity, since the lagged variable is endogenous to the error term. To overcome this problem of endogeneity (as OLS is inappropriate), an instrumental variable (IV) must be considered. Anderson and Hsiao (1982) suggested $Output_{it-1}$ and $Output_{it-2}$ as instruments. Arellano and Bond (1991) showed that using $Output_{it-2}$ as an instrument is superior. The list of instruments can be extended: $Output_{it-3}$ ,$Output_{it-4}$ , $\cdots$, $Output_{it-k}$. Arellano and Bond (1991) combined the list of moments condition and formed the GMM. Equation (3) above will be estimated using Arellano and Bon (1991); a first-step GMM estimator will be considered, since it shows results that are more reliable for inferencing (Blundell & Bond, 1998).

**3.2 Model 2: Panel Threshold Model**

We follow Kremer et al. (2013) in establishing a dynamic panel threshold model for the agricultural production function. The Kremer et al. (2013) model is an extension of the static panel threshold model proposed by Hansen (1999) and the cross-section threshold regression of Caner and Hansen (1999). The dynamic panel threshold accounts for non-linearities and endogeneity bias in the model, as it is built on the GMM that solves the endogeneity (Caner &

Hansen, 1999). Indeed, in this study we analyse the role of the growing seasonal variability in temperature and rainfall threshold in the relationship between agricultural output, climate variability and the endogenous regressor (lagged of the output). The expression for the dynamic panel threshold model is written as follows:

$$\ln(Output_{it}) = u_i + \beta_1 \tilde{\pi}_{it} I(\tilde{\pi}_{it} \leq \gamma) + \delta_1 I(\tilde{\pi}_{it} \leq \gamma) + \beta_2 \tilde{\pi}_{it} I(\tilde{\pi}_{it} > \gamma) + \phi Z_{it} + \varepsilon_{it} \tag{4}$$

where the subscripts $i = 1, \cdots, N$ and $t = 1, \cdots, T$ represent the country and time index respectively. $I(\cdot)$ is the indicator function and the threshold $\gamma$. $u_i$ is the country-specific fixed effect while $\varepsilon_{it}$ is the error term, $\varepsilon_{it} \sim iid(0, \sigma^2)$. $\tilde{\pi}_{it}$ (growing season variability) represents the threshold and the regime dependent regressor. $Z_{it}$ represents the vector of endogenous variables where the estimated slope coefficients are regime independent. $ln(Output_{it})$, the log output is the dependent variable. $Z_{it}$ represents the m-dimensional vector of explanatory regressors that might include the lagged output, while $Z_{1it}$ captures the other control variables. The coefficient $\delta_1$ is the regime intercept. $\beta_1$ represents the marginal impact of growing seasonal variability in rainfall and temperature on agricultural output in the long run when the variability is below the threshold, while $\beta_2$ captures the marginal impact of growing seasonal variability in rainfall and temperature above the threshold. The $\beta_i$ coefficients are obtained by GMM estimation. According to Arellano and Bover (1995), the lags of the dependent variables (endogenous variables) $Output_{it-2} \cdots Output_{it-k}$ are used as instruments. Arellano and Bover (1995) confirmed that error terms are not auto-correlated, and the cross-section threshold of Caner and Hansen (2004) applies to the dynamic panel approach. Thus, the individual fixed effects are eliminated by the forward orthogonal deviation transformation.

The forward orthogonal deviation transformation for the error term can be expressed as

$$\varepsilon_{it}^* = \sqrt{\frac{T-t}{T-t+1}} \left[ \varepsilon_{it} - \frac{1}{T-t} (\varepsilon_{i(t+1)} + \cdots + \varepsilon_{iT} \right] \tag{5}$$

The error terms of the forward orthogonal transformation remain homoscedastic; that is,

$$Var(\varepsilon_i) = \sigma^2 I_T \Longrightarrow Var(\varepsilon_i) = \sigma^2 I_{T-1} \tag{6}$$

According to Kremer et al. (2013), firstly the endogenous variable $Z_{2it}$ is estimated as a function of the instrument $X_{it}$ and we obtain the predicted value $\hat{Z}_{2it}$. Secondly, Equation (4) above is estimated by ordinary least squares, after substituting $Z_{2it}$ for the predicted value $\hat{Z}_{2it}$. The residual sum of squares from the equation is noted as $S(\gamma)$, where $\gamma$ denotes the common threshold value to be estimated. The optimal value of the threshold estimated $\hat{\gamma}$ is such that the residual sum of squares is minimised as $\hat{\gamma} = \arg min_{\gamma} S_n(\gamma)$. Thirdly, after obtaining $\hat{\gamma}$, the estimated threshold value, the regression slope coefficients are found by GMM using the instruments and the estimated threshold $\hat{\gamma}$. The 95% critical values for determining the confidence interval of the threshold value are expressed as $\Gamma = \{\gamma: LR(\gamma) \leq C(\alpha)\}$, where $C(\alpha)$ is the 95% percentile of the asymptotic distribution of the likelihood ratio $LR(\gamma)$.

Given the nature of Equation (3) above, and as emphasised in the introduction, one might argue that the relationship between growing season variability and agricultural output may not be linear. It has also been argued that the threshold model can be appropriate for consistently and efficiently capturing the overall effect between the variables.

## 4. Description of data and variables

We constructed a panel of nine countries (Burundi, Djibouti, Ethiopia, Kenya, Rwanda, Somalia, Sudan, Tanzania and Uganda) covering the period from 1961 to 2016. As in Abraha-Kahsay and Hansen (2016), the nine countries were chosen due to their similar crop production season characteristics. Data points were sourced from FAOSTAT (2011).

The FAO' net production index has been used as a dependent variable. It is considered a proxy for total production output and includes both crop and livestock production as well as other agricultural outputs. Land input is a proxy for total area used for agricultural purposes, while machinery input is a proxy for total number of tractors used. For livestock capital input, we use the headcount for cattle, sheep and goats. Labour is proxied by the population fraction active in the agriculture sector. Fertiliser input is the number of metric tonnes of plant nutrients consumed in the agriculture sector, while irrigation input is the agricultural area under irrigation. Our definition and inclusion of these variables follows the example of numerous studies (e.g. Hayami & Ruttan, 1970; Antle, 1983; Barrios et al., 2008; Abraha-Kahsay & Hansen, 2016).

We also follow Barrios et al. (2008), Ward et al. (2014) and Abraha-Kahsay and Hansen (2016) in the treatment of irrigation as indicator of the quality of land capital input. We use the Climate Research Unit (CRU) as the main source of climate data, as did Barrios et al. (2008) and Abraha-Kahsay and Hansen (2016). As in Abraha-Kahsay and Hansen (2016), $Temp_{Springs}$, $Temp_{Summer}$, $Temp_{Fall}$, $Rainfall_{Spring}$, $Rainfall_{Summer}$ and $Rainfall_{Fall}$ represent the mean temperature and rainfall during spring, summer and fall seasons respectively; while $Variability_{Springs}^{Temp}$, $Variability_{Summer}^{Temp}$, $Variability_{Fall}^{Temp}$, $Variability_{Spring}^{Rainfall}$, $Variability_{Summer}^{Rainfall}$ and $Variability_{Fall}^{Rainfall}$ represent growing season temperature and rainfall during spring, summer and fall season respectively. Spring season includes the month of March, April and May; fall comprises the month of September, October and December , while the summer contains the month of June, July and August (Abraha-Kahsay and Hansen, 2016). Seasonal variability in temperature and rainfall follow the definition from Amare et al. (2018). We measure variability as the deviation of the previous year's rainfall and temperature during spring, summer and fall from the 30-year historical average during crop growing seasons (spring, summer and fall). Variability is also referred to as rainfall and temperature anomalies. We also add the growing summer season, as in Abraha-Kahsay and Hansen (2016); apart from spring and fall, the major and minor crop-growing seasons, the summer season can be crucial to the growth and maturity of crops planted in spring. Figure 1 below shows the general trends in rainfall and temperature during the three growing seasons. In general, average growing season variability in rainfall is more significant in all three seasons. There is a trend of gradual decline; spring and fall (the major and minor growing seasons) are more volatile than summer. This has a serious effect on the growth of crops, and is generally characterised by a decreasing trend, while temperature shows an increasing trend, in line with what has been reported in the literature (IPCC, 2007).

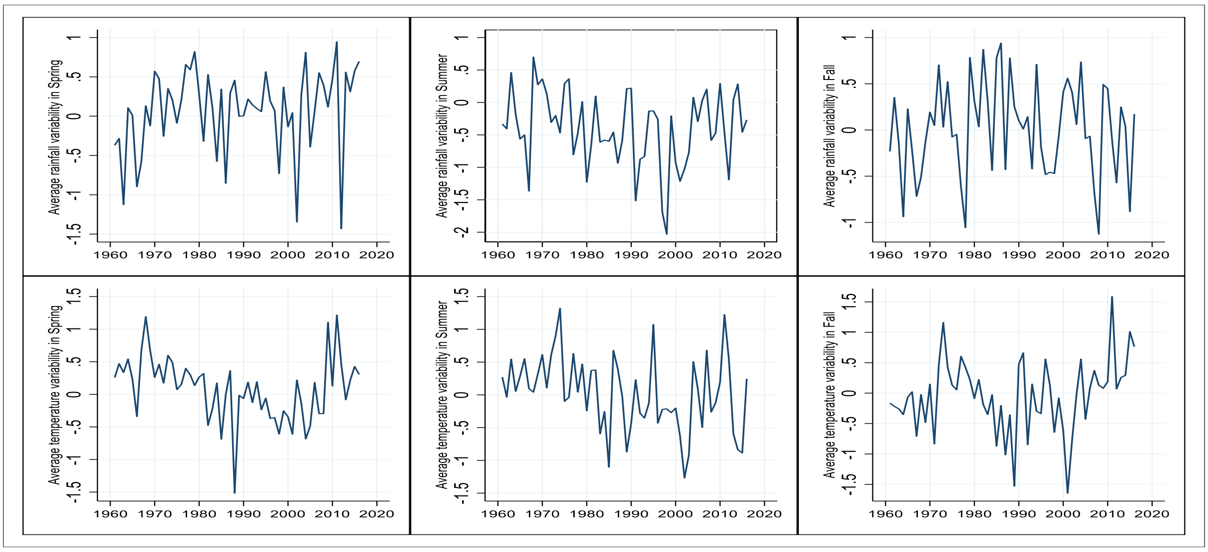


Figure 1: Average seasonal variability in rainfall and temperature

## 5. Estimation Results

We investigate whether the series is stationary. To check the stationarity in our panel, we use the Levin, Lin and Chu (2002) panel unit root test and the Fisher type, based on the augmented Dickey-Fuller tests (Choi, 2001) (See Appendix, Table A1.) Both tests reject the null hypothesis that the panel contains a unit root. We test the presence of serial correlation using the Wald test, following Wooldridge (2002), in which it was rejected.

Table A3 in the Appendix shows the estimation results of the fixed-effect model. The coefficients of the physical inputs vary slightly when one moves across all the specifications, and they do have the expected signs. Livestock and labour parameters are positive and significant across all the specifications, in line with the literature. Machinery and irrigation are insignificant, confirming the lack of such tools in the process of agricultural production. East Africa is dominated by traditional practices, mainly based on human muscle power (FAO, 2008; 2013). Up to 95% of agriculture there is characterised by traditional small scale non-mechanised practices (FAOSTAT, 2011). The land is the most important factor, with coefficients that have the expected sign and significant. An increase of 1% in agricultural land areas is substantially higher compared to coefficients of other regressors. According to Barrios et al. (2008), Sub-Saharan African countries use land much more intensively than other countries. In general, these findings are consistent with the literature (Barrios et al., 2008; Abraha-Kahsay & Hansen, 2016).

Concerning climate variables, the mean effect of rainfall and temperature on the agricultural output during the major growing season (spring) is positive and significant. The major season is characterised by heavy and prolonged rain, but also associated with higher temperature. This favours evaporation, reducing the impact of heavy rain on agricultural output.

During the minor growing season (fall), the coefficients of temperature and rainfall are negative and significant, consistent with expectations. The results for the summer growing season show that the higher temperature affects agricultural output negatively. According to Niang et al. (2014), temperatures in Africa are projected to rise much faster than in the rest of the world; the increase is expected to exceed 2°C by the 21st century, and could reach 4°C by the end of the 21st century.

The growing season rainfall variability of spring has a negative impact on output and the impact tends to persist, even during summer. In line with Conway et al. (2005) who noticed that Eastern Africa has two rainfall regimes that bring rain, from March to May and from October to December, but with great inter-annual variability. Growing season temperature variability had a positive impact during spring (the major growing season), contrary to the results of Abraha-Kahsay and Hansen (2016), who found its effect to be positive and insignificant. It had no effect in summer and fall.

These findings are crucial, given East Africa's rain-fed nature. Growing season rainfall and temperature variability can have a significant impact on output, even if there are no changes observed at the mean temperature and rainfall level. Our results are consistent with the literature on the effect of variability in rainfall and temperature on agricultural crops in East Africa (Abraha-Kahsay & Hansen, 2016; Barrios et al., 2008; Ward et al., 2014; Blanc, 2012; Rowhani et al*.,* 2011; Lobell & Burke, 2008). The majority of these studies found that precipitation variability has a positive effect and temperature variability has a negative impact. For instance, Abraha-Kahsay and Hansen (2016) and Rowhani et al. (2011) both found growing season precipitation variability had a substantial negative effect on output, while Ward et al. (2014) found a positive effect. This is partly in line with our findings, which state that growing season rainfall variability has a negative effect, but growing season temperature variability has a positive significant effect as well.

Table 1 below shows the results of the dynamic GMM using Equation (3) above. The fixed effect estimations and even the random effect estimations are subject to some shortcomings. They have the problem of potential endogeneity of regressors, as well as a loss of dynamic information (Nkurunziza & Bates, 2003). We include in Equation (3), among other things, the lagged variable of agricultural output. The lag of output is significant across all specifications. This implies that the decision to engage in agriculture practices depends heavily on what the last agricultural outcome was. Agriculture in general involves many decisions: what and how much to sell to generate cash, which inputs to use, how and when to use them, how much to store if there is an expectation of more favourable conditions in the market, or in the next agriculture season. Also, small household farmers make these decisions in a market that does not function well. This implies that good agricultural results in the previous season can solve a substantial portion of these questions, and will have significant implications for their choices and livelihoods. Hence, the performance of the last season agricultural output significantly influences the decision of whether or not to continue farming.

Some studies note that experiences farmers are exposed to in the agricultural sector in East Africa, such as drought, constitute a reason to engage in off-farming activities. The proportion of off-farming income generation reveals some important insights (Van den Broeck & Kilic, 2018; FAO, 2015; Kansiime et al., 2018; Wichern et al., 2017). For instance, Van den Broeck and Kilic (2018) report that a significant portion of both rural and urban working-age population participates in off-farming activities. However, in East African countries such as Ethiopia, small household farmers still rely heavily on crop and livestock income, rather than non-farming (FAO, 2015). In the context of the rural economy that characterises East Africa, the livelihood of farmers depends on the choices they make regarding how to allocate resources to generate the highest income possible, given the constraints they face. The current agricultural output depends to a degree on last year's performance; and this holds true for all the models specified. The coefficient of the lag in output is significant, meaning a 1% increase in the lag output coefficient will increase current output by 0.975, 0.979 or 0.988%, depending on the respective specification shown in Table 1 below .

The estimates of the physical parameters do not vary much, except for machinery and irrigation. Land estimates are significant, except for specification (4). The Labour parameter has the expected sign, but is significant only in specification (3). Small-scale farming production in East Africa is done mainly by family members (FAO, 2015). A 1% increase in the size of a farmer's house results in a 0.0394% increase in agricultural output. The marginal effect of each regressor on the dependent variable is lower compared to the estimates under fixed-effect estimation. Not controlling for lag in agricultural output in the estimation of the impact of climate change on agricultural output exaggerates the impact of the effect of growing season variability on agriculture.

GMM offers advantages over the pure cross-country instrumental variable regression, as the unobserved country-specific effect becomes part of the error term, which can bias the estimators. Also, GMM controls for all the potential endogeneity of all explanatory variables, compared to the country fixed specification.

Turning to the effect of climate on agricultural output, the findings are that mean rainfall is positive and significant, while mean temperature is positive and insignificant in the major growing season. The Growing season rainfall variability has a negative sign and is significant, which is in line with the outcome from the fixed-effect estimation. This result is in line with Rowhani et al. (2011), who found that growing season rainfall has a negative effect on yields of sorghum, maize and rice in Tanzania but the growing season temperature increases have the most important impact on yields. We did find negative and statistical evidence of growing-

Table 1: One-step system GMM results for climate variability and agricultural output

| VARIABLES | (1) Ln(output) | (2) Ln(output) | (3) Ln(output) | (4) Ln(output) |
|---|---|---|---|---|
| *L.1 Output* | 0.975*** | 0.979*** | | 0.988*** |
| | (0.00668) | (0.00461) | | (0.00420) |
| *Ln*(Land) | 0.0394*** | 0.0348*** | 0.739* | 0.00716 |
| | (0.0118) | (0.0125) | (0.401) | (0.00897) |
| $Ln(Livestock)$ | 0.0187* | 0.0199** | 0.683 | 0.00556 |
| | (0.0114) | (0.00929) | (0.456) | (0.00823) |
| $Ln(Labour)$ | 0.00573 | 0.00630 | 0.564*** | 0.00393 |
| | (0.00630) | (0.00688) | (0.217) | (0.00442) |
| $Ln(Machinery)$ | 0.0104** | 0.00737* | 0.128 | 0.00191 |
| | (0.00493) | (0.00411) | (0.219) | (0.00382) |
| $Ln(Irrigation)$ | 9.94e-05 | 0.00278 | 0.150 | 0.00197 |
| | (0.00824) | (0.00431) | (0.182) | (0.00436) |
| $Ln(Fertiliser)$ | 0.00341 | 0.00146 | 0.325** | 0.00598** |
| | (0.00247) | (0.00341) | (0.129) | (0.00260) |
| **Mean rainfall variables** | | | | |
| $Ln(Rainfall_{Spring})$ | 0.0200** | 0.0235** | | |
| | (0.00782) | (0.00923) | | |
| $Ln(Rainfall_{Summer})$ | 0.0194* | 0.0150 | | |
| | (0.0108) | (0.0104) | | |
| $Ln(Rainfall_{fall})$ | -0.00591 | | | |
| | (0.0154) | | | |
| **Mean temperature variables** | | | | |
| $Ln(Temp_{Spring})$ | 0.0990 | | | |
| | (0.211) | | | |
| $Ln(Temp_{Summer})$ | 0.0220 | | | |
| | (0.198) | | | |
| $Ln(Temp_{fall})$ | -0.323** | -0.173* | | |
| | (0.164) | (0.105) | | |
| **Growing-season rainfall variables** | | | | |
| $Variability_{Spring}^{Rainfall}$ | 0.00378* | | | |
| | (0.00590) | | | |
| $Variability_{Summer}^{Rainfall}$ | -0.00352 | | | |
| | (0.00442) | | | |
| $Variability_{fall}^{Rainfall}$ | -0.00733 | | | |
| | (0.00603) | | | |
| **Growing-season temperature variables** | | | | |
| $Variability_{Spring}^{Temp}$ | -0.00339 | | | |

| | | | | |
|---|---|---|---|---|
| | (0.00531) | | | |
| $Variability_{Summer}^{Temp}$ | -0.00174 | | | |
| | (0.00512) | | | |
| $Variability_{fall}^{Temp}$ | -0.00721* | -0.00744** | | |
| | (0.00385) | (0.00315) | | |
| Year | 0.000458** | 0.000389* | 0.00427* | 7.42e-05* |
| | (0.000210) | (0.000211) | (0.00252) | (4.03e-05) |
| Observations | 477 | 477 | 504 | 495 |
| Number of id | 9 | 9 | 9 | 9 |
| Time effect | YES | YES | YES | YES |
| Wald $\chi^2$ | 59645.15 | 155233.16 | 2457.73 | 3.18e+08 |
| Prob>$\chi^2$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| AR (1) [p-value] | -2.54 [0.011] | -2.54 [0.011] | -1.14 [0.255] | -2.53 [0.012] |
| AR (2) [p-value] | -1.35 [0.177] | -1.11 [0.268] | -0.27 [0.783] | -0.90 [0.369] |
| Hansen test [p-value] | 0.00 [1.000] | 0.00 [1.000] | 0.21 [1.000] | 0.15 [1.000] |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

season temperature variability in the minor season(fall). Our results are in general partly consistent with the literature on the impact of growing season variability in Eastern Africa (Abraha-Kahsay & Hansen, 2016; Barrios et al., 2008; Blanc, 2012; Rowhani et al., 2011; Lobell & Burke, 2008); but taking into account the lag variable of agricultural output reduces the marginal effect of growing season climate variability. Thus the lag of agricultural output is crucial in explaining the change in agricultural output in East Africa.

The higher value of Wald $\chi^2$ shows that the overall models are jointly significant. The test of autocorrelation in the residual indicates that there is a negative and significant first-order correlation; but the second order is insignificant, suggesting that serial correlation in the error terms is absent. The null hypothesis of the Hansen test is not rejected, suggesting there is no correlation between the over-identified instruments and the error term.

Table 2 below shows the results of the dynamic panel threshold using Equation (3) above to analyse the threshold effect between growing season climate variability and agricultural output, as well as examine fully the possibility an asymmetric non-linear relationship between them. The upper section of Table 2 displays the estimated values of growing season variability in temperature and rainfall threshold and the corresponding 95% confidence interval, while the middle section of Table 2 shows the regime-dependent coefficients of growing season variability in temperature and rainfall. In particular, $\hat{\beta}_1$ and $\hat{\beta}_2$ represent the marginal effect of growing season variability in the low (high) regime, implying that variability is below (above) the estimated threshold value. We apply the dynamic panel threshold to see the long-run impact of growing season rainfall and temperature.

In analysing growing season temperature and rainfall variability on agricultural output, a number of control variables are considered, namely land, labour, livestock, irrigation, machinery, a series of climate variables, and initial income. Each column displays the findings of the dynamic panel threshold for a specific season. The null hypothesis of no threshold effect from growing season variability in temperature and rainfall has been rejected. Consequently, the data used for the study strongly supports the existence of the threshold effect. The regime-dependent coefficients of the effect of rainfall variability in spring, summer and fall are significant, with plausible signs.

The Model (1) results suggest that the threshold for growing season rainfall variability in the spring is -0.553, with a 95% confidence interval widens [-1.222, 1.244]. The coefficient of growing season rainfall variability in spring is negative and significant when threshold is below ($\hat{\beta}_1$= -0.0127), but positive and insignificant relationship above the threshold ($\hat{\beta}_2$= 0.00628). These results are partly in line with Abraha-Kahsay and Hansen (2016), who showed that seasonal rainfall variation in spring reduces agricultural output. In fact, there is a threshold below which such negative impact can be observed: growing season variability in rainfall is negatively correlated with agricultural output below the threshold. There will be a negative marginal effect on agricultural output of 0.0127%, but no marginal effect when the variability is above the threshold.

In summer, shown in Model (2), the threshold is -0.902, with a confidence interval of [-2.348, 0.59]. The coefficient of growing season variability is positive ($\hat{\beta}_2$ = 0.00832) above the threshold, meaning growing season variability in rainfall in summer above the threshold will increase agricultural output by 0.00832%, but no effect is observed below the threshold. In particular, summer is characterised by higher temperatures that favour evaporation. During summer, positive variability in seasonal rainfall coupled with higher temperatures has negligible marginal impact. Crops combine higher temperature and rainfall available to increase germination (Thornton et al., 2010).

The findings also show that growing season variability in rainfall is detrimental when it exceeds the threshold of 1.261 with a 95% confidence interval [-1.270, 1.261] in the fall season. If rainfall variability increases above the threshold, agricultural output will decrease by 0.0147%. In the case of growing season temperature variability, we found no significant effects.

Table 2

| VARIABLES | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) |
|---|---|---|---|---|---|---|
| **Threshold estimates** | | | | | | |
| $\hat{\gamma}$ | **-0.553** | **-0.902** | **1.261** | **-0.336** | **0.488** | **0.970** |
| 95% confidence interval | [-1.222, 1.244] | [ -2.348, 0.549] | [-1.270, 1.261] | [ -0.982, 0.936 ] | [-1.222, 1.049] | [ -1.140, 1.177] |
| $L1.output$ | 0.876*** | 0.867*** | 0.867*** | 0.873*** | 0.871*** | 0.871*** |
| | (0.0227) | (0.0178) | (0.0196) | (0.0142) | (0.0157) | (0.0152) |
| $\hat{\beta}_1$ | -0.0127** | -0.00552 | 0.00322 | -0.00995 | -0.00488 | -0.00266 |
| | (0.00571) | (0.00446) | (0.00377) | (0.00817) | (0.00615) | (0.00486) |
| $\hat{\beta}_2$ | 0.00628 | 0.00832*** | -0.0147* | 0.00429 | 0.00202 | -0.00808 |
| | (0.00813) | (0.00322) | (0.00846) | (0.00869) | (0.00745) | (0.00725) |
| $Ln(Land)$ | 0.0574 | 0.0589 | 0.0616 | 0.0313 | 0.0365 | 0.0439 |
| | (0.0495) | (0.0532) | (0.0441) | (0.0393) | (0.0411) | (0.0438) |
| $Ln(Livestock)$ | 0.0539*** | 0.0578*** | 0.0567*** | 0.0518*** | 0.0533*** | 0.0579*** |
| | (0.0192) | (0.0167) | (0.0185) | (0.0199) | (0.0184) | (0.0204) |
| $Ln(Labour)$ | 0.0276*** | 0.0375*** | 0.0337*** | 0.0363*** | 0.0360*** | 0.0366*** |
| | (0.00859) | (0.0101) | (0.0111) | (0.00775) | (0.00801) | (0.00823) |
| $Ln(Machinery)$ | -0.000144 | -0.00525 | -0.00395 | 0.000282 | 0.000227 | -0.00148 |
| | (0.00499) | (0.00932) | (0.00729) | (0.00465) | (0.00457) | (0.00513) |
| $Ln(Irrigation)$ | 0.00351 | -0.00308 | 3.15e-05 | 0.00147 | 0.000644 | -0.000468 |
| | (0.00914) | (0.00524) | (0.00787) | (0.00933) | (0.00956) | (0.00941) |
| $Ln(Fertiliser)$ | -0.00433 | -0.00328 | -0.00359 | -0.00403 | -0.00413 | -0.00362 |
| | (0.00538) | (0.00464) | (0.00454) | (0.00396) | (0.00420) | (0.00428) |
| **Seasonal climate variables** | | | | | | |
| Precipitation variables | | | | | | |
| $Ln(Rainfall_{Spring})$ | 0.00588 | 0.00585 | 0.00482 | 0.00776 | 0.00804 | 0.00906 |
| | (0.0102) | (0.00919) | (0.00891) | (0.00953) | (0.0101) | (0.00955) |
| $Ln(Rainfall_{Summer})$ | -0.00586 | -0.00206 | -0.00638 | -0.00602 | -0.00659 | -0.00474 |
| | (0.00907) | (0.00762) | (0.00847) | (0.00801) | (0.00801) | (0.00718) |
| $Ln(Rainfall_{Fall})$ | -0.00688 | -0.00671 | -0.0109 | -0.000539 | -0.00151 | 0.00103 |
| | (0.0121) | (0.0140) | (0.0186) | (0.0127) | (0.0111) | (0.0135) |
| Temperature variables | | | | | | |
| $Ln(Temp_{Spring})$ | -0.0630 | -0.0470 | -0.0157 | -0.0874 | -0.0976 | -0.101 |
| | (0.213) | (0.206) | (0.219) | (0.173) | (0.177) | (0.174) |

| | | | | | | |
|---|---|---|---|---|---|---|
| $Ln(Temp_{Summer})$ | 0.118 | 0.218 | 0.217 | 0.227 | 0.241 | 0.207 |
| | (0.124) | (0.159) | (0.149) | (0.181) | (0.167) | (0.165) |
| $Ln(Temp_{Fall})$ | -0.206 | -0.166 | -0.172 | -0.339 | -0.238 | -0.340 |
| | (0.504) | (0.485) | (0.475) | (0.537) | (0.565) | (0.525) |
| Constant | -0.357 | -0.960 | -0.968 | -0.0184 | -0.401 | -0.126 |
| | (1.535) | (1.749) | (1.684) | (1.848) | (1.835) | (1.651) |
| | | | | | | |
| Wald $\chi^2$ | 17995.52 | 19249.34 | 17682.27 | 32482.73 | 39175.23 | 19067.94 |
| p-value (Wald $\chi^2$) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 495 | 495 | 495 | 495 | 495 | 495 |
| Number of id | 9 | 9 | 9 | 9 | 9 | 9 |
| Number of instruments | 433 | 433 | 433 | 433 | 433 | 433 |

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Model (1) represents the effect of rainfall variability in spring, Model (2) represents the effect of rainfall variability in summer, Model (3) represents the effect of rainfall variability in fall, Model (4) represents the effect of temperature variability in spring, Model (5) represents the effect of temperature variability in summer and Model (6) represents the effect of temperature variability in the fall.

Figure 2 below shows the likelihood ratio function computed to estimate the threshold for growing season variability in rainfall and temperature in the three seasons.

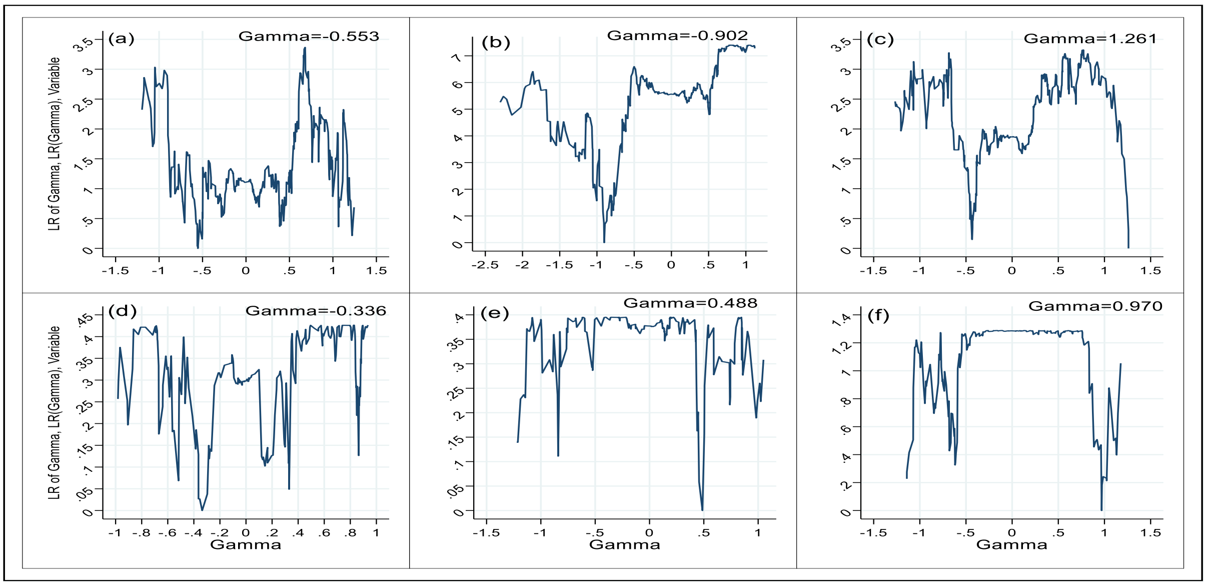


Figure 2: Marginal effects of rainfall and temperature variability on agricultural output in Eastern African countries. (a) Effect of rainfall variability in spring, (b) Effect of rainfall variability in summer, (c) Effect of rainfall variability in fall, (d) Effect of temperature variability in spring, (e) Effect of temperature variability in summer, (f) Effect of temperature variability in fall.

The threshold estimated is the point where the likelihood ratio function is equal to zero, which occurs at points -0.553, -0.902 and 1.261 in spring, summer and fall respectively for rainfall, and -0.336, 0.488 and 0.970 in spring, summer and fall respectively for temperature.

A closer look shows that before the threshold value, the variability in rainfall decreases in spring and summer, confirming the negative sign; while there is an increasing trend for variability in rainfall in fall. There is no clear trend for temperature variability except in summer, when there is a positive trend.

## 6. Conclusion

In this paper, we introduced a GMM estimation to assess the impact of growing season variability in rainfall and temperature in Eastern Africa. We collected data from this part of Africa for the period 1961 to 2016. Contrary to Abraha-Kahsay and Hansen (2016), who incorporated disaggregated growing and non-growing seasons and assessed their impact, our main contribution was to go one step ahead and determine at which threshold levels such growing seasonal variability becomes harmful to agricultural output.

Our results reveal that growing season rainfall variability has an impact mainly in the major growing season. After introducing the GMM estimation, we find that the lag output was significant across all specifications. In the context of the rural economy that characterises Eastern Africa, the livelihoods of farmers depend on how they choose to allocate resources to generate the highest income possible, given the constraints they are facing. These decisions depend on the income that would be generated, making lag output one of the most important features in decision making. After controlling for endogeneity, the results reveal that growing-season rainfall variability affects output negatively, but there is no significant evidence that growing season temperature variability has an effect. However, we realise that the impact of growing season temperature and rainfall depends on the model specification used.

Using the dynamic panel threshold estimation, growing season rainfall threshold was -0.553 in spring with 95% confidence interval of [-1.222, 1,244]; -0.902 in summer, with 95% confidence interval of [-2.348, 0.59]; and 1.261 in fall with a 95% confidence interval of [-1.270, 1.261]. Any change in seasonal rainfall variability below the threshold will decrease agricultural output by 0.0127% in spring; in summer, if it goes beyond threshold then output will increase by 0.00832%. In the fall season, a change in rainfall variability below threshold means agricultural product will decrease by 0.0147%. In the case of growing season temperature, we found no significant effects.

From a policy standpoint, the relevance of growing season precipitation variability for agricultural output is particularly intriguing since its impacts are more easily offset by small-scale technology already utilised by local farmers. To mitigate the effect caused by the growing seasonal variability in precipitation, technologies such as flexible planting and rainwater harvesting. Also, irrigation and other practices to reduce the impact of growing season rainfall variability, such as implementing smart water-management systems that use drop-by-drop or sprinkler irrigation processes to improve agricultural output.

Appendix

Table A1 Test results

| Test | $\chi^2$ | F-Statistic | P-value |
|---|---|---|---|
| Modified Wald test for group | | | |
| Heteroskedasticity | 364.260 | | 0.000 |
| Serial correlation | | 1.785 | 0.266 |
| Hausman | 457.860 | | 0.000 |

Table A 2 Unit root test results

| Variables | LLC | | Fisher | |
|---|---|---|---|---|
| $Ln(Output)$ | -4.4402 | (0.0000) | 1.8221 | (0.0342) |
| $Ln(Land)$ | -1.2621 | (0.0010) | 0.0358 | (0.0049) |
| $\text{Ln}(Machinery)$ | -10.4497 | (0.0000) | 18.0745 | (0.0000) |
| $Ln(Livestock)$ | 0.2371 | (0.0059) | 0.3958 | (0.0000) |
| $Ln(Labour)$ | -1.9130 | (0.0279) | -0.6835 | (0.0075) |
| $\text{Ln}(Irrigation)$ | -3.4407 | (0.0003) | 2.9146 | (0.0018) |
| $\text{Ln}(Fertiliser)$ | -4.1683 | (0.0000) | 8.9815 | (0.0000) |
| $Ln(Rainfall_{Spring})$ | -11.2622 | (0.0000) | 40.3448 | (0.0000) |
| $Ln(Rainfall_{Summer})$ | -12.0324 | (0.0000) | 35.4204 | (0.0000) |
| $Ln(Rainfall_{fall})$ | -10.8219 | (0.0000) | 32.4645 | (0.0000) |
| $Ln(Temp_{Spring})$ | -7.3836 | (0.0000) | 17.3195 | (0.0000) |
| $Ln(Temp_{Summer})$ | -9.8619 | (0.0000) | 26.2175 | (0.0000) |
| $Ln(Temp_{fall})$ | -3.3620 | (0.0000) | 13.2755 | (0.0000) |
| $Variability_{spring}^{Rainfall}$ | -10.8093 | (0.0000) | 35.7789 | (0.0000) |
| $Variability_{Summer}^{Raonfall}$ | -9.5728 | (0.0000) | 33.5396 | (0.0000) |
| $Variability_{Fall}^{Rainfall}$ | -11.9706 | (0.0000) | 34.2576 | (0.0000) |
| $Variability_{Spring}^{Temp}$ | -8.0514 | (0.0000) | 17.3348 | (0.0000) |
| $Variability_{Summer}^{Temp}$ | -10.3162 | (0.0000) | 24.0965 | (0.0000) |
| $Variability_{Fall}^{Temp}$ | -5.6695 | (0.0000) | 13.2755 | (0.0000) |

Table A3: Fixed Effects results of climate variability and agricultural output

| VARIABLES | (a)<br>General<br>Ln(output) | (b)<br>Reduced<br>Ln(output) | (c)<br>Reduced<br>Ln(output) | (d)<br>Physical<br>Ln(output) |
|---|---|---|---|---|
| $Ln(Land)$ | 1.406*** | 1.396*** | 0.984*** | 0.266*** |
| | (0.120) | (0.120) | (0.112) | (0.0798) |
| $Ln(livestock)$ | 0.493*** | 0.486*** | 0.687*** | 0.239*** |
| | (0.111) | (0.110) | (0.127) | (0.0331) |
| $Ln(labor)$ | 0.00142 | 0.00345 | 0.550*** | 0.204*** |
| | (0.0649) | (0.0647) | (0.0413) | (0.0286) |
| $L\mathrm{n}(machinery)$ | 0.318 | 0.290 | 0.275 | 0.121 |
| | (0.0444) | (0.0396) | (0.0436) | (0.0147) |
| $L\mathrm{n}(irrigation)$ | 0.358 | 0.358 | 0.248 | 0.133 |
| | (0.0412) | (0.0407) | (0.0455) | (0.0131) |
| $L\mathrm{n}(fertilizer)$ | 0.239*** | 0.246*** | 0.341*** | 0.0760*** |
| | (0.0280) | (0.0273) | (0.0303) | (0.00869) |
| **Mean Rain fall variables** | | | | |
| $Ln(Rainfall_{Spring})$ | 0.421*** | 0.410*** | | |
| | (0.0923) | (0.0916) | | |
| $Ln(Rainfall_{Summer})$ | -0.0898 | | | |
| | (0.0703) | | | |
| $Ln(Rainfall_{fall})$ | -0.278** | -0.323*** | | |
| | (0.116) | (0.111) | | |
| **Mean Temperature Variables** | | | | |
| $Ln(Temp_{Spring})$ | 2.421* | 1.897 | | |
| | (1.393) | (1.341) | | |
| $Ln(Temp_{Summer})$ | -4.168*** | -4.499*** | | |
| | (1.174) | (1.136) | | |
| $Ln(Temp_{fall})$ | -4.085*** | -3.129*** | | |
| | (1.089) | (0.819) | | |
| **Within growing season rainfall variables** | | | | |
| $Variability_{spring}^{Rainfall}$ | -0.108*** | -0.101*** | -0.0727* | |
| | (0.0370) | (0.0366) | (0.0438) | |
| $Variability_{Summer}^{Raonfall}$ | -0.185*** | -0.177*** | -0.108*** | |
| | (0.0291) | (0.0285) | (0.0311) | |
| $Variability_{Fall}^{Rainfall}$ | 0.0135 | | 0.00191 | |
| | (0.0367) | | (0.0439) | |
| **Within growing season temperature variables** | | | | |

| | | | | |
|---|---|---|---|---|
| $Variability^{Temp}_{Spring}$ | 0.111** | 0.126*** | 0.186*** | |
| | (0.0437) | (0.0414) | (0.0520) | |
| $Variability^{Temp}_{Summer}$ | -0.0556 | | -0.0771 | |
| | (0.0419) | | (0.0504) | |
| $Variability^{Temp}_{Fall}$ | -0.0137 | | 0.0633 | |
| | (0.0419) | | (0.0502) | |
| Year | 0.0336*** | 0.0340*** | 0.0273*** | 0.0123*** |
| | (0.00270) | (0.00262) | (0.00308) | (0.00125) |
| Constant | -44.28*** | -45.67*** | -47.00*** | -26.72*** |
| | (5.807) | (5.628) | (5.934) | (1.739) |
| Observations | 504 | 504 | 504 | 504 |
| Number of id | 9 | 9 | 9 | 9 |

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

**References**

Abraha-Kahsay, G., & Hansen, L. G. (2016). The effect of climate change and adaptation policy on agriculture production in Eastern Africa, *Ecological Economics*, 121, 54-64.

Adhikari, U., Nejadhasheni, P. A., & Woznicki, S. A. (2015). Climate change and Eastern Africa: a review of impact on major crops, *Food and Energy Security*, 4, 2, 110-132.

Amare, M., Jensen, N. D., Shiferaw, B., & Cisse, J. D. (2018). Rainfall shocks and agricultural productivity: implication for rural household consumption, *Agricultural Systems*, 166, 79-89.

Anderson, T. W., & Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data, *Journal of Econometrics*, 18, 47-82.

Angel, J. R., & Huff, F. A. (1997). Change in heavy rainfall in Midwestern United States, *Journal of Water Resources Planning and Management*, 123, 4, 246-249.

Antle, J. M. (1983). Testing the stochastic structure of production: a flexible moment based approach, *Journal of Business and Economic Statistics*, 1, 3, 192-201.

Asfaw, A., Simane, B., Hassen, A., & Bantider, A. (2018). Variability and time series trend analysis of rainfall and temperature in north central Ethiopia: a case study in Woleka sub-basin, *Weather and Climate Extremes*, 19, 29-41.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *The Review of Economic Studies*, 58, 2, 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models, *Journal of Econometrics*, 68, 29-52.

Bahaga, T. K., Mengistu-Tsidu, G., Kucharski, F., & Diro, G. T. (2014). Potential predictability of the sea-surface temperature forced equatorial East African short rains interannual variability in the 20th century, *Quarterly Journal of the Royal Meteorological Society*, 141, 16-26.

Barrios, S., Ouattara, B., & Strobl, E. (2008). The impact of climatic change on agricultural production: is it different for Africa?, *Food Policy*, 33, 287-298.

Blanc, E. (2012).The impact of climate change on crop yields in sub-Saharan Africa, *American Journal of Climate Change*, 1, 1–13.

Bick, A. (2010). Threshold effects of inflation on economic growth in developing countries, *Economics Letters*, 108, 2, 126-129.

Baltagi, B. H., Demetriades, P. O., & Law, S. H. (2009). Financial development and openness: evidence from panel data, *Journal of Development Economics*, 89, 285-296.

Byakatonda, J., Parida, B. P., Kenabotho, P. K., & Moalafhi, D. B. (2018). Analysis of rainfall and temperature time series to detect long-term climatic trends and variability over semi-arid Botswana, Journal of Earth System Science, 127, 25, 1-25. https://link.springer.com/content/pdf/10.1007/s12040-018-0926-3.pdf

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models, *Journal of Econometrics*, 87, 115-43.

Cabas, J., Weersink, A., & Olale, E. (2009). Crop yield response to economic, site and climatic variables, *Climatic Change*, 101, 599-616.

Caner, M. & Hansen, B. E. (2004). Instrumental variable estimation of a threshold model, *Econometric Theory*, *20*, 813-843.

Casimiro, W. S. L., Labat, D., Ronchail, J., Espinoza, J. C., & Guyot, J L. (2012). Trends in rainfall and temperature in the Peruvian Amazon Andes basin over the last 40 years (1965-2007), *Hydrological Processes*, 27, 20, 2944-2957.

Choi, I. (2001). Unit root tests for panel data, *Journal of International Money and Finance*, 20, 2, 249-272.

Conway, D., Allison, E., Felstead, R., & Goulden, M. (2005). Rainfall variability in East Africa: implications for natural resources management and livelihoods, *Philosophical Transactions, Royal Society*, 363, 49-54.

Conway, D., & Schipper, E. L. (2011). Adaptation to climate change in Africa: challenges and opportunities identified from Ethiopia, *Global Environmental Change*, 21, 227-237.

De Longueville, F., Hountondji, Y. C., Kindo, I., Gemenne, F., & Ozer, P. (2016). Long-term analysis of rainfall and temperature data in Burkina Faso (1950–2013), *International Journal of Climatology*, 36, 13, 4393-4405.

Driver, P., & Reason, C. J. C. (2017). Variability in Botswana High and its relationships with rainfall and temperature characteristics over Southern Africa, *International Journal of Climatology*, 32, 1, 570-581.

Elsanabary, M. H., & Gan, T. Y. (2015). Evaluation of climate anomalies impacts on the Upper Blue Nile Basin in Ethiopia using a distributed and a lumped hydrologic model, *Journal of Hydrology*, 530, 225-240.

Eriksen, S., O'Brien, K., & Rosentrater, L. (2008). Climate change in Eastern and Southern Africa: impacts, vulnerability and adaptation, Global Environmental Change and Human Security, Report 2008, *African Journal of Agricultural and Resource Economics*, 2, 45-64.

FAO (2008). Agriculture mechanization in Africa…time for action: planning investment for enhanced agricultural productivity, *Report of an Expert Group Meeting January 2008*, Vienna, Austria, http://www.fao.org/3/k2584e/k2584e.pdf (accessed December 2020).

FAO (2013). Agriculture mechanization in sub-Saharan Africa: guidelines for preparing a strategy, *Integrated Crop Management*, 22, http://www.fao.org/3/a-i3349e.pdf (accessed November 2020).

FAO (2015) .The economic lives of smallholder farmers: analysis based on household data from nine countries, http://www.fao.org/3/a-i5251e.pdf (accessed December 2020).

FAOSTAT (2011). FAO statistical database, http://faostat3.fao.org/home/E (accessed December 2019).

Foster, N. (2006). Exports, growth and threshold effects in Africa, *The Journal of Development Studies*, 42, 6, 1056-1074.

Hayami, Y., & Ruttan, V. W. (1970). Agriculture productivity differences among countries, *American Economic Review*, 60, 5, 895-911.

Gommes, R., & Petrassi, F. (1996). Rainfall variability and drought in sub-Saharan Africa, Environment and Natural Resources Service, *FAO Research, Extension and Training Division*, http://www.fao.org/3/au042e/au042e.pdf (accessed November 2020).

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: estimation, testing, and inference, *Journal of Econometrics*, (2), 345-368.

IPCC (2007). Contribution of Working Group I to the Fourth Assessment Report. *Cambridge University Press*, Cambridge, UK.

IPCC (2014). Climate Change 2014: Working Group II Impacts, Adaptation, and Vulnerability. *Cambridge University Press*, Cambridge, UK.

IPCC (2014a). Climate change 2014 synthesis report. In IPCC The Core Writing Team, R. K. Pachauri, & L. Meyer (Eds.*), Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Geneva,* IPCC, :<http://www.ipcc.ch/pdf/assessment-report/ar5/syr/SYRAR5FINALfull.pdf> (accessed December 2020).

Issahaku, A.R., Campion, B. B., & Edzyle, R. (2016). Rainfall and temperature change and variability in the upper East region of Ghana, *Earth and Space Science*, 3, 284-294.

Kansiime, M. K., Van Asten, P. & Sneyers, K. (2018). Farm diversity and resource use efficiency: targeting agriculture policy interventions in East Africa farming systems, *NJAS Wageningen Journal of Life Sciences*, 85, 32-41.

Khan, M. I., Liu, D., Fu, Q., Dong, S., Liaqat, U. W., Faiz, M. A., Hu, Y., and Saddique, Q. (2016). Recent climate trends and drought behavioral assessment based on precipitation and temperature data series in the Songhua River Basin of China, *Water Resources Management*, 30, 4839-4859.

Kremer, S., Bick, A., & Nautz, D. (2013). Inflation and growth: new evidence from a dynamic panel threshold analysis, *Empirical Economics*, 44, 2, 878, https://www.econstor.eu/bitstream/10419/39331/1/60792313X.pdf (accessed December 2020).

Kyei-Mensah, C., Kyerematen, R., & Adu-Acheampong, S. (2019). Impact of rainfall variability on crop production within the Worobong Ecological Area of Fanteakwa District, Ghana, *Advances in Agriculture,* https://downloads.hindawi.com/journals/aag/2019/7930127.pdf (accessed December 2020).

Levin, A., Chien-Fu, C., & Chia-Shang, J. C. (2002). Unit root tests in panel data: asymptotic and finite-sample properties, *Journal of Econometrics*, 108(1), 1-24.

Lippert, C., Krimly, T., & Aurbacher, J. (2009). A Ricardian analysis of the impact of climate change on agriculture in Germany, *Climatic Change*, 97, 593-610.

Lobell, D.B., & Burke, M.B. (2010). On the use of statistical models to predict crop yield responses to climate change, *Agricultural and Forest Meteorology*, 150, 1443-1452.

Mahendra, M., Fischer, G., & Van Velthuizen, V. (2008). Food security and sustainable agriculture, the challenges of climate change in sub-Saharan Africa, Commission of Sustainable Development, *CSD-16, review session*, United Nations, New-York, https://pdfs.semanticscholar.org/6d40/162006c08e92d367a81629d9d85fc381e028.pdf (accessed November 2020).

McCarl, B. A., Villavicencio, X., & Wu, X. (2008). Climate change and future analysis: is stationary dying? *American Journal of Agriculture Economics*, 90, 1241-1247.

Mendelsohn, R., Hradhaus, W. D., & Shaw D. (1994). The impact of global warming on agriculture: a Ricardian analysis, *The American Economic Review*, 84, 4, 753-771.

Mendelsohn, R. (2009). The impact of climate change on agriculture in developing countries, *Journal of Natural Resources Policy Research*, 1, 1, 5-9.

Mendelsohn, R. (2014). The impact of climate change on agriculture in Asia, *Journal of Integrative Agriculture*, 13, 4, 660-665.

Mishra, D., & Sahu, N. C. (2014). Economic impact of climate change on agriculture sector of Coastal Odisha, *APCBEE Procedia*, 10, 241-245.

Molua, E. L., & Lambi, C. M. (2007). The economic impact of climate change on agriculture in Cameroon, *The World Bank Policy Research Working*, 4364, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1016260 (accessed January 2021).

Mutai, C. C., & Ward, M. N. (2000). East African rainfall and the tropical circulation/ convection on intraseasonal to interannual timescales, *American Meteorological Society*, 13, 3915-3939.

Niang, A., Amarani, F., Salhi, M., Grelu, P., & Sanchez, F (2014). Rains of solitons in a figure of eight passive mode-locked fiber laser, *Applied Physics*, 116, 771-775.

Nicholson, S. E., & Kim, J. (1997). The relationship of the El Nino southern oscillation to African rainfall, *International Journal of Climatology*, 17, 117-135.

Nicholson, S. E. (2017). Climate and climatic variability of rainfall over Eastern Africa, *Reviews of Geophysics*, 55, 3, 590-635.

Nkurunziza, J. D., & Bates, R. H. (2003). Political institutions and economic growth in Africa, CID Working Paper No. 98, *Harvard University*, Harvard.

Noy, I. (2009). The macroeconomic consequences of disasters, *Journal of Development Economics*, 88, 221-231.

Omondi, P., Ogallo, L. A., Anyah, R., Muthama, J. M., & Ininda, J. (2012). Linkages between global sea surface temperature and decadal rainfall variability over Eastern Africa region, *International Journal of Climatology*, 33, 8, 2082-2104.

Owusu, K., & Waylen, P. R. (2013). Identification of historic shifts in daily rainfall regime, Wenchi, Ghana, *Climatic Change*, 117, 2, 133-147.

Perera, H., Sonnadara, D., & Jayewardene, D. (2002). Forecasting the occurrence of rainfall in selected weather stations in the wet and dry zones of Sri Lanka, *Sri Lankan Journal of Physics*, 2, 39-52.

Poudel, S., & Kotani, K. (2013). Climatic impacts on crop yield and its variability in Nepal: do they vary across seasons and altitude?, *Climatic Change*, 116, 327-355.

Rui-Li, L., & Geng, S. (2013). Impact of climate change on agriculture and adaptive strategies in China, *Journal of Integrative Agriculture*, 12, 8, 1402-1408.

Runge, C. F., Senauer, B., Pardey, P. G., & Rosegrant, N. W. (2004). Ending hunger in Africa: prospects for the small farmer, *International Food Policy Research Institute (IFRI)*, https://www.ifpri.org/publication/ending-hunger-africa (accessed January 2021)

Salami, A., Kamara, A. B., & Brixiova, Z. (2010). Smallholder agriculture in East Africa: trends, constraints and opportunities, Working Paper No. 105, *African Development Bank Group*, https://docs.igihe.com/IMG/pdf/working_105_pdf_d.pdf (accessed December 2020).

Schlenker, W., & Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture, *Environmental Research Letter*, 5, 014010, https://iopscience.iop.org/article/10.1088/1748-9326/5/1/014010/meta (accessed October 2020).

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change, *Proceedings of the National Academy of Sciences of the United States of America*, 106 (37), 15594-15598.

Schreck, C. Z., & Semazzi, F. H. (2004). Variability of the climate of Eastern Africa, *International Journal of Climatology*, 24, 681-701.

Slingo, J. M., Challinor, A. J., Hoskins, B. J., and Wheeler, T. R. (2005). Introduction: food crops in a changing climate, *Philosophical Transaction of the Royal Society Publishing*, 360 (1463), 1983-1989.

Slingo, J., Bates, K., Nikiforakis, N., Piggott, M., Roberts, M., Shaffrey, L., Stevens, I., Vidale, P. L., & Weller, H. (2009). Developing the next-generation climate system models: challenges and achievements, *Philosophical Transactions of the Royal Society A: Mathematical Physical and Engineering Sciences*, 367, 815-831.

Smit, B., & Yunlong, C. (1996). Climate change and agriculture in China, *Global Environmental Change*, 6, 3, 205-214.

Udry, C. (2010). The economics of agriculture in Africa: notes toward a research program, *African Journal of Agricultural and Resource Economics*, 5, 1, 284-299.

Rosenzweig, C., Casassa, G., Karoly, D. J., et al. (2007). Assessment of observed changes and responses in natural and managed systems, in Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M. L. Parry, O. F. Canziani, J. P. Palutikof, P. J. van der Linden & C. E.Hanson, Eds., pp. 79-131, Cambridge University Press, Cambridge, UK.

Rowhani, P., Lobell, D. B., Linderman, M., & Ramankutty, N. (2011). Climate variability and crop production in Tanzania, *Agricultural and Forest Meteorology*, 151, 449-460.

Tsangarides, C. G. (2001). On cross-country growth and convergence: evidence from African and OECD countries, *Journal of African Economies*, 10, 355-89.

Umar, D. A., Ramli, M. F., Aris, A. Z., Jamil, N. R., & Aderemi, A. A. (2019). Evidence of climate variability from rainfall and temperature fluctuations in semi-arid region of the tropics, *Atmospheric Research*, 224, 52-64.

Van den Broeck, G., & Kilic, T. (2018). Dynamic of off-farm employment in sub-Saharan Africa: a gender perspective, eLibrary, *World Bank*, https://elibrary.worldbank.org/doi/pdf/10.1596/1813-9450-8540 (accessed January 2021).

Victor, U. S., Srivasta, N. N., Subba-Rao, A. V. M., & Ramana-Roa, B. V. (1996). Managing the impact of seasonal rainfall variability through response farming at a semi-arid tropical location, *Current Science*, 71, 5, 392-397.

Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S., & Zhang, L. (2009). The impact of climate change on China's agriculture, *Agriculture Economics,* 40, 323-337.

Ward, P. S., Florax, R. J., & Flores-Lagunes, A. (2014). Climate change and agriculture productivity in sub-Saharan Africa, a spacial sample selection model, *European Review of Agriculture Economics*, 41, 2, 199-226.

Wichern, J., Van Wijk, M., Descheemaeker, K., Frelat, R., Van Asten, P. J. A., & Giller, K. E. (2017). Food availability and livelihood strategies among rural households across Uganda, *Food Security*, 9, 1385-1403.

World Bank (2007). World Development Report, 2008: Agriculture for Development, *Oxford University Press*, New York.

World Bank (2010). The World Bank Annual Report 2010, *Year Review*, https://openknowledge.worldbank.org/handle/10986/5906 (accessed October 2020).

Wooldridge, J. M. (2002). ECONOMETRIC ANALYSIS of CROSS SECTION and PANEL DATA, MIT Press.

Yang, W., Seager, R., Cane, M. A., & Lyon, B. (2015). The annual cycle of East African precipitation, *Journal of Climate*, 28 (6), 2385-2404.

You, L., Rosegrant, M. W., Wood S., & Sun, D. (2009). Impact of growing season temperature on wheat production in China, *Agriculture and Forest Meteorology*, 149, (7), 1009-1014.