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ABSTRACT

This paper investigates whether the effects of weather variability in temperature and precipitation on agricultural output are short- or long-run. In fact, the study addresses two policy-relevant questions: (1) Does temperature or precipitation variability affect agricultural output, and if so, is the effect short- or long-term? (2) Is the effect of weather variability on agricultural output homogenous across East Africa?

However, there is clear evidence of cross-country dependency. If cross-sectional dependency exists among the cross-sectional countries under investigation, the first generation of panel data techniques is not applicable. We use data from the FAOSTAT for 1961 to 2016 for East African countries, while climate-related variables (temperature and precipitation) are from the Climate Research Unit (CRU). We find that variability in temperature has a long-run impact on agricultural output, while variability in precipitation has a short-run effect. However, after considering the heterogeneity among countries, there is evidence of the long-run effect of precipitation variability in some countries.

Keywords: Climate variability, agricultural output, cross-sectional dependency, heterogeneity

JEL Codes: Q1, Q2, Q54

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1. INTRODUCTION

Climate change projections show that by 2050, East Africa will have higher temperatures and 5-20% more rainfall from December to February, and 5-10% less rainfall from June to August (Hulme et al., 2001; IPCC, 2001; 2007). East African countries are heavily reliant on agriculture. Agriculture accounts for 30.2%, 47%, 23.8% and 42.8% respectively of GDP in Uganda, Ethiopia, Kenya and Tanzania (Salami et al., 2010). As a result, these populations are extremely sensitive to seasonal rainfall changes. It has been demonstrated that these dependencies might last for decades (World Bank, 2007). In addition, agriculture systems in this region are particularly susceptible to disruption due to the lack of resources and technology to deal with changing weather patterns; any change in weather patterns will affect agricultural output.

There has been an increase in the amount of research seeking to quantify the economic effects of climate change (Mendelsohn et al., 1994; Kurukulasuriya and Mendelsohn, 2007; Deschênes and Greenstone, 2007; Dell et al., 2009; Lippert et al., 2009; Dell et al., 2012, Fisher et al., 2012). For instance, the pioneering work of Mendelsohn et al. (1994) strengthened the theoretical underpinning of the Ricardian approach to the economic analysis of the impact of climate change on agriculture. Previously, the traditional production function technique had overlooked farmers' ability to adapt to changing economic and environmental conditions.

In contrast, the Ricardian technique was a cross-sectional analysis that looked at how climate change and other variables influenced agricultural productivity over time (e.g. land values and farm revenues). This had the advantage of taking into account both the consequences of climate change and farmers' ability to adapt to them. Mendelsohn et al. (1994) emphasised the need for adaptation efforts, in which farmers maintain their operations in accordance with climate volatility in order to reap higher benefits from agricultural output. Deschênes and Greenstone (2007) assessed the economic impact of climate change on US agricultural land by estimating the impact of random year-to-year temperature and precipitation fluctuations on agricultural profitability. According to their study, climate change would have increased annual revenues by US$1.3 billion. Large negative or positive impacts are unlikely.

There is also growing concern about the impact of climate change variability on agricultural production per season, particularly in East Africa (Mendelsohn et al., 1994; Schlenker and Lobell, 2010; Lobella and Burkeb, 2010; Rowhani et al., 2011; Blanc, 2012; Ward et al., 2014; Abraha-Kahsay and Hansen, 2016). For instance, Ward et al. (2014) reported that precipitation variability has a beneficial impact on aggregate cereal output in sub-Saharan Africa, whereas Rowhani et al. (2011) and Abraha-Kahsay and Hansen (2016) found that precipitation variability has a negative effect on agricultural output in Tanzania and East Africa.

These studies employed a variety of methods. Early empirical research on climate and agricultural output used cross-sectional regression analysis (Sachs and Warner, 1997), which is subject to omitted variable bias (Hsiang et al., 2017). As a result, cross-sectional regressions might lead to biased estimates of climate change and agricultural output. More recent studies examining the relationship between weather shocks and agricultural output use fixed effects panel regression models (Abraha-Kahsay and Hansen, 2016; Regan et al., 2019). Because fixed effects models account for unobserved time-invariant group heterogeneity, such as variations in institutions, these models are less susceptible to omitted variable bias. They have been used to investigate the link between weather variability and agricultural output (see Barrios et al., 2008; Fisher et al., 2012; Deschênes and Greenstone, 2012; Seo, 2013; Abraha-Kahsay and Hansen, 2016; Burke and Emerick, 2016; Regan et al., 2019).

The inability of fixed effects models to account for long-term climatic variability is their limitation. The distinction between short-term extreme occurrences and long-term consequences is critical, since farmers may be better able to respond to long-term changes than to short-term or catastrophic events, by investing in either adaptation or mitigation. Mitigation and adaptation are two important tools for reducing the risks associated with climate variability.

The studies of Blanc (2012), Kalkuhl and Wenz (2020) and Salahuddin et al. (2020) are among the exception, as they assess the long-run impact of climate change in the agriculture sector and the environment in general. Kalkuhl and Wenz (2020) explicitly assessed the effect of short-term weather shock and long-term climate change on gross regional product, and found that temperature affects productivity. If the global mean surface temperature rises by 3.5°C by 2100, worldwide production will be reduced by 7-14%, with much greater losses in tropical and poor nations.

Our study joins the scant literature that assesses the long-term relationships. We investigate the relationship between climate variability (precipitation and temperature) and agricultural output across East African countries. Our study addresses two policy-relevant issues: (1) Does temperature or precipitation variability affect agricultural output, and if so, is the effect short- or long-term? (2) Is the effect of weather variability on agricultural output homogenous across East Africa?

The assumption that parameters are homogeneous across nations is one of the limitations of panel estimates. Based on the potential for different agricultural systems to expand, and the prevalence of such systems in each of the nations we studied, we expect the impact of temperature and precipitation to be heterogeneous.

Unlike recent studies this study employs a set of second-generation panel data techniques that account for cross-sectional dependence and cross-country heterogeneity – issues that the first generation of panel data estimation techniques fail to address. To the best of our knowledge, Blanc (2012) is the only study that assesses the impact of climate change on agricultural output in the long run by considering cross-country dependency. However, that study assessed the effect of weather-related variables such as temperature and precipitation, but did not include the variability that exists in those variables. Nowadays, the economies of the world have become more integrated, economically and financially, than they were a few decades ago; thus, not accounting for cross-sectional dependency (CD) across countries might lead to misleading results.

The results reveal that variability in temperature has a long-run impact on agricultural output, while variability in precipitation has a short-run effect. The results also show that the long-run temperature variability effect is heterogeneous across East African countries; to some extent, there was also evidence of the long-run effect of precipitation variability. After taking into consideration that countries are different in economic structure and dependent on each other, the findings reveal that precipitation variability effects are noticed in a few countries, such as Djibouti, Ethiopia, Rwanda and Uganda.

The structure of this paper is as follows: the literature is presented in section 2, and methodologies in section 3; section 4 reports findings, and section 5 concludes.

2. Literature review

The effect of climate change on the physical and biological have been documented in the past (for instance McCarthy et al., 2001; Parmesan and Yohe, 2003). However, the importance of weather variability in the growing season has increased (Mutai and Ward, 2000; Conway and Schipper, 2011).

Climate change estimates for southern Africa show that variability and extreme events may become more frequent in the future (Tadross et al., 2005). Due to the increasing interest in the impact of climate variability, several studies have attempted to investigate this issue. But climate variability is expected to increase further in some regions, and have significant consequences on food production.

For instance: in Tanzania, maize, sorghum and rice yields were studied in order to determine the relationship between seasonal climate and crop output (Rowhani et al., 2011). Using a variety of statistical methodologies and climatic data, the influence of seasonal weather averages and variability on yields was assessed at the sub-national scale. The study revealed that Tanzanian cereal yields are affected by both intra and interseason variations in temperature and precipitation. An anticipated seasonal temperature rise in Tanzania of 2°C by 2050 will lower average maize, sorghum and rice yields by 13%, 8.8% and 7.6%, respectively. The same study also showed that a 20% increase in intra-seasonal precipitation variability decreases agricultural production by 4.2%, 7.2 % and 7.6% respectively for maize, sorghum and rice.

Molua (2008) investigated the impact of average climate variation in temperature and precipitation on Cameroon's agricultural production. The results revealed that a decrease of approximately 46.7% in agricultural production could be associated with an increase in temperature of 3.5% in the absence of irrigation facilities. Barrios et al. (2008) used the cross-country panel climatic dataset in an agricultural production framework for developing countries, both sub-Saharan African (SSA) and non-sub-Saharan African (NSSA). The results showed that rainfall and temperature changes have a significant effect on agricultural production in SSA. The effect may be observed for NSSA, but the impact is different.

In addition, three types of statistical model (time series, panel, and cross-sectional) were trained on the simulated historical variability of maize in 200 sites in SSA, and used to forecast future climate change reactions (Lobell and Burke, 2010). The researchers assessed how well statistical models could capture crop responses to warming or precipitation changes. The models performed differently depending on climatic variable and geographical scale, with time-series statistical models replicating site-specific yield responses to precipitation change effectively, but less well for temperature responses. On the other hand, statistical models that used data from several locations, such as panel and cross-sectional models, were better at predicting reactions to temperature change than to precipitation change (Lobell and Burke, 2010). Schlenker and Lobell (2010) combined historical crop production and weather data into a panel framework in order to assess the weather impact on crop yield in Africa. The model showed that estimated crop yield reductions would be 22, 17, 17, 18 and 8% for maize, sorghum, millet, groundnut and cassava, respectively. Ward et al. (2014) added that climate change is predicted to lower grain yields by an average of 36% across SSA by the end of the century, with much of the impact coming from rising temperatures. Ochieng et al. (2016) investigated the impact of climate variability on maize and tea crops in Kenya. They found that climate variability influenced both crops, but the effect differed. Temperature had a negative impact on maize revenues, but a positive effect on tea. Their study also revealed that tea suffers the most if there is too much rain or too much heat; and precipitation had less of an effect on crop yield than temperature did. Alboghdady and El-Hendawy (2016) examined the impact of climate change and variability on agricultural output in the Middle East and North Africa area (MENA). They constructed a panel dataset from 1961-2009 for 20 countries, and used a Fixed Effect regression estimator. The results showed that a 1% rise in winter temperature resulted in a 1.12% drop in agricultural productivity. A 1% increase in temperature change during winter and spring resulted in a drop in agricultural productivity of 0.09 and 0.14% respectively. The results also showed that rising precipitation during the winter and autumn, as well as precipitation variability during the winter and summer, had negative impacts.

However, there is increasing concern about the importance of growing-season weather variability on agricultural output in East Africa (Wheeler et al., 2000; Barrios et al., 2003; Abraha-Kahsay and Hansen, 2016). For instance, Abraha-Kahsay and Hansen (2016) estimated production functions for agricultural output in East Africa, using climatic variables broken down into growing and non-growing seasons. The results reveal that growing-season precipitation variability has a significant detrimental impact on plant growth after using the fixed-effect model.

However, these articles do not consider cross-sectional dependency. They assume that countries are cross-sectional independent. Nonetheless, as the world's economies have become increasingly financially and economically intertwined over the last three decades, cross-sectional dependence (CD) testing is now necessary before panel causality analysis. Blanc (2012) is the only study conducted in Africa that has taken into account cross-sectional dependency in its analysis of the impact of weather-related variables on agricultural output. Our study too did not assume cross-sectional independence. Contrary to most studies on the impact of weather on agricultural output – such as Abraha-Kahsay and Hansen (2016), who assessed the short-run effect – our study considers the long-run impact of weather variability on agricultural output. But contrary to Blanc (2012), who considered the long-run effects of temperature, rainfall and evaporation, but not the long-run effect of the variability of these weather variables. We also attempt to assess whether or not the effects of variability in temperature and precipitation on agricultural output are homogeneous in the long-run.

3. Methodologies

An increasing number of researchers are using panel causality analysis to better understand and predict the relationship between two variables. Studies such as Bersvendsen and Ditzen (2021) and Espoir et al. (2021) propose adopting a proper econometric technique that considers two technical points: slope heterogeneity, and cross-sectional dependency.

First, because the world economies have become more financially and economically connected in the last three decades, testing for cross-sectional dependency (CD) before panel causality analysis is now required. The econometric literature has firmly determined that panel datasets are likely to show substantial CD as a result of this integration (Pesaran, 2004). This dependency may arise as a result of shared shocks, technical cross-country spillovers, market integration, and unobserved components that eventually become part of the error term (Espoir and Ngepah, 2021). If the errors ($\varepsilon_{i,t}$) are not independent across units, failing to account for cross-sectional dependency might lead to erroneous causality results (Herzer and Vollmer, 2012). Second, when it comes to slope heterogeneity, panel data methodologies estimate variations in between cross-sectional units by fixed constants (using fixed, random effects technique and the generalised method of moments). However, individual heterogeneity in slopes among cross-sectional units may be found in some panel datasets. Overlooking this variability may bias the results of causal relationships and lead to erroneous conclusions (Chang et al., 2015; Bersvendsen and Ditzen, 2021). Ignoring slope heterogeneity incorrectly leads to biased findings (Pesaran and Smith, 1995).

For these reasons, this study examines the issue of cross-sectional dependence and slope heterogeneity before assessing the causal relationship between weather variability and agricultural output. Consider a Cobb-Douglass production function of agriculture; our study's functional form is as follows:

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

where Q represents agricultural production, L stands for labour, *K* stands for capital such as land or machinery or animals, and *I* stands for additional elements such as fertiliser and irrigation. For this study, the baseline regression is presented in the following way:

$$ln(Output_{it}) = \beta_0 + \beta_1 ln(Output_{it-1}) + \beta_2 \ln(Labor_{it}) + \beta_3 \ln(Land_{it}) + \beta_4 \ln(Machinery_{it}) + \beta_5 \, ln(Livestock_{it}) + \beta_6 \ln(Fertilizer_{it}) + \beta_7 ln(Irrigation_{it}) + \beta_8 \ln(Temperature) + \beta_9 \ln(Precipitation) + \beta_{10} Variability^{Temperture} + \beta_{11} Variability^{Precipitation} + \mu_i + \varepsilon_{it} \quad (2)$$

where $Output_{it}$ and $Output_{it-1}$ are the total agriculture production of the country and the lag of the total agriculture production $I\ (i=1,2,\cdots n)$ in year $t(t=1,2,\cdots,T)$. We include three capital inputs: Land, Machinery, and Livestock. We also include Labour, Fertiliser and Irrigation; μ_i is the unobserved time-invariant country-specific effect, and ε_{it} is the errors term.

3.1 Econometric techniques

3.1.1 Pesaran (2004) Cross-section dependence (CD)

When working with long-term panel data, it is possible to run into the cross-sectional dependency problem among cross-sectional units. An independent cross-sectional assumption would provide false findings. To counter this, Pesaran's (2004) cross-sectional dependence test is used to determine if cross-sectional units are independent or dependent. The null hypothesis indicates independence, whereas the alternative hypothesis suggests a dependency.

$$CD_{statistics} = \sqrt{\frac{2t}{n(n-1)}} \left(\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \widehat{\rho_{\iota,J}} \right) \quad (3)$$

in which the mean is zero and the variance is one, and ρ denotes the pairwise correlation. For the null hypothesis, cross-sectional dependency does not exist; the alternative hypothesis implies that there is a cross-sectional dependency between cross-sectional units.

3.1.2 Unit root tests

To cope with cross-sectional dependence, it is important to use a consistent unit root econometric method. This study uses a second-generation unit root test. If there is no link between the cross-sections, according to the Pesaran CD test findings, first-generation unit root tests are utilised. If there is a dependence between cross-sections, however, second-generation unit root tests should be used. The second-generation tests that account for cross-sectional dependency are: MADF (Taylor and Sarno, 1998); SURADF (Breuer et al., 2002; Bai and Ng, 2004); PANKPSS (Carrion-i-Silvestre et al., 2005); and CADF (Pesaran, 2007).

Pesaran (2007) introduced the CADF (Cross Sectionally-Augmented Dickey-Fuller Test) panel unit root test to account for cross-sectional dependency. This test, which may be used in both T > N and N > T situations, extends the basic ADF (Augmented Dickey-Fuller Test) regression with initial differences and lagged values of horizontal sections. The CIPS test examines the unit root characteristics of the whole panel; it is based on the CADF test. The estimation equation and hypotheses are as follows:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_t \tag{4}$$

Hypotheses of the CIPS test: H_0 indicates that the series is not stationary; H_1 indicates that the series is stationary. The cointegration technique used by Westerlund and Edgerton (2007) was selected for our investigation.

3.1.3 Westerlund and Edgerton (2007) – Panel LM bootstrap cointegration test

Westerlund and Edgerton (2007) developed a panel cointegration test that allows for dependency both within and between cross-sectional units, as well as correlation both within and between cross-sectional units, based on the Lagrange multiplier test of McCoskey and Kao (1998). In this test, a sieve sampling technique is used as a basis. It has the benefit of lowering the asymptotic test distortions substantially.

To conclude, all units in the panel are cointegrated according to the null hypothesis. In order to estimate long-term and short-term coefficients, the Pooled Mean Group Model (Panel ARDL) approach is employed.

3.1.4 Pooled Mean Group Model (Panel ARDL) and Dynamic Fixed Effect (DFE)

For panel cointegration analysis, Pesaran et al. (1999) proposed the PMG technique (Pooled Mean Group/Panel ARDL). A version of this approach has been developed for the ARDL model. This model allows estimating both short-term and long-term slope coefficients within the scope of the panel cointegration. According to this technique, constant variables, short-term coefficients and error terms can be changed across sections. While this technique does not allow for the change of long-term coefficients between units, it does allow for heterogeneity and the change of error-correction terms across groups in the short-term period. We can rename the explanatory variables in Equation (2) as X for convenience; the Autoregressive distributive lag (ARDL) (p, q) dynamic specification can be written as:

$$ln(Output_{it}) = \sum_{j=1}^{p} \lambda_{ij}\, ln\big(Output_{i,t-j}\big) + \sum_{j=0}^{q} \delta_{ij}\, X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (5)$$

where *Ln (Output)*: is the dependent variable and X: is the k x 10 vector of the explanatory variables. λ_{ij} denotes scalars, and μ_i represents the group-specific fixed effect, while p and q represent lags of dependent and independent variables changing from country to country. The fact that the variables here are cointegrated in the order of I (1) and the error terms I (0) indicates that there is a long-term relationship.

However, deviations from the long-term balance may occur. With a vector error correction model (VECM) to be established, deviations from long-term equilibrium can be expressed as:

$$\Delta ln(Output_{it}) = \phi_i(ln\big(Output_{i,t-j}\big) - \theta_t' X_{it}) + \sum_{j=1}^{p} \lambda_{ij}\, \Delta ln\big(Output_{i,t-j}\big) + \sum_{j=0}^{q} \delta_{ij}\, \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (6)$$

$$\phi_i = -\big(1 - \sum_{j=1}^{p} \lambda_{ij}\big) \quad (7)$$

$$\theta_i = \frac{\sum_{j=0}^{q} \delta_{ij}}{(1 - \sum_k \lambda_{ik})} \quad (8)$$

$$\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im} \qquad (j = 1,2, \ldots, p-1) \quad (9)$$

$$\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im} \qquad (j = 1,2, \ldots, q-1) \quad (10)$$

where ϕ_i stands for the speed of the error correction coefficient. If the error correction coefficient is zero, then there is no short-term connection, according to the definition. This coefficient is anticipated to be negative and smaller than 1. A large amount of time is required for this approach. Because of the correlation between the error term and the estimators whose difference was subtracted from the average.

In our study, the time dimension is large, making this technique suitable. While the constant parameter may be changed in the Pooled Mean Group estimator, the slope parameter cannot be changed. The Dynamic Fixed Effect estimator, on the other hand, assumes that all parameters are constants. Pooled Mean Group Estimators and Dynamic Fixed Effect Estimators are used to estimate short and long-term parameters in our investigation.

3.1.5 Random coefficient regression model

To check whether the slope coefficients are not consistent or homogeneous across panel units, the Swamy (1970) random linear regression model is used. The Swamy (1970) random-coefficients linear regression model does not need to impose the assumption of consistent parameters across panels.

Parameter heterogeneity is addressed as a stochastic variation in a random-coefficients model. Let assume that:

$$Y_i = X_i\beta_i + \epsilon_i \tag{11}$$

where $i = 1, \dots, m$ and β_i is the coefficient vector (K x 1) for the cross-sectional unit, such that

$$\beta_i = \beta + v_i \ , \quad E(v_i) = 0 \ , \quad E(v_i, v_i') = \Sigma$$

To find $\hat{\beta}$ and $\hat{\Sigma}$, the estimator is developed under the assumption that the cross-sectional specific coefficient vector β_i is the result of a random process with a mean vector β and covariance matrix Σ,

$$Y_i = X_i\beta_i + \epsilon_i = X_i(\beta + v_i) + \epsilon_i = X_i\beta + (X_i v_i + \epsilon_i) = X_i\beta + \omega_i \tag{12}$$

where $E(\omega_i) = 0$, and

$$E(\omega_i\omega_i') = E\{(X_i v_i + \epsilon_i)(X_i v_i + \epsilon_i)'\} = E(\epsilon_i\epsilon_i') + X_i E(v_i v_i')X_i' = \sigma_i^2\mathbf{I} + X_i\Sigma X_i' = \mathbf{\Pi}_i$$

where $\Pi \equiv E(\omega\omega')$ represents the block diagonal matrix with Π_i, $i = 1 \dots m,$ along the main diagonal and zeroes elsewhere. The Generalised Least Squares (GLS) estimate of $\hat{\beta}$ is:

$$\hat{\beta} = \left(\sum_i X_i'\Pi_i^{-1}X_i\right)^{-1}\sum_i X_i'\Pi_i^{-1}y_i = \sum_{i=1}^{m} W_i b_i \tag{13}$$

where $W_i = \{\sum_{i=1}^{m}(\Sigma + v_i)^{-1}\}^{-1}(\Sigma + v_i)^{-1}$

$b_i = (X_i'X_i)^{-1}X_i'y_i$ and $V_i = \sigma_i^2(X_i'X_i)^{-1}$, representing the GLS estimator, is a matrix-weighted average of the panel-specific OLS estimators. The variance of $\hat{\beta}$ is:

$$Var(\hat{\beta}) = \sum_{i=1}^{m}(\Sigma + V_i)^{-1} \tag{14}$$

For more information about the slope and heterogeneity see Swamy (1970).

In the presence of cross-sectional dependency and slope heterogeneity, using an econometric approach that imposes homogeneity requirements and ignores spatial interaction effects to assess panel causality between weather variability and agricultural output may provide incorrect results..

4. Data

We compiled a panel of nine nations (Burundi, Djibouti, Ethiopia, Kenya, Rwanda, Somalia, Sudan, Tanzania and Uganda) for our research, 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 gathered from FAOSTAT (2011). As a dependent variable, the FAO's net production index was considered for this study. 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 considered a proxy for total area used for agricultural purposes, while machinery input is measured by total number of tractors used. For livestock capital input, we employed the headcount for cattle, sheep and goats. Labour is measured by the percentage of the population working in agriculture. Agriculture's fertiliser input is taken to be the number of metric tons of plant nutrients used. The consideration of these variables follows numerous studies (see Barrios et al., 2008; Abraha-Kahsay & Hansen, 2016). Mean annual temperature and precipitation data were collected from the Climate Research Unit (CRU), as per Barrios et al. (2008) and Abraha-Kahsay & Hansen (2016).

We measured variability as the deviation of the previous year's rainfall and temperature from the 30-year historical average during crop seasons (Amare et al., 2018). Variability is also referred to as rainfall and temperature anomalies. Figure 1 below reports the general trends in precipitation and temperature during the period under consideration.

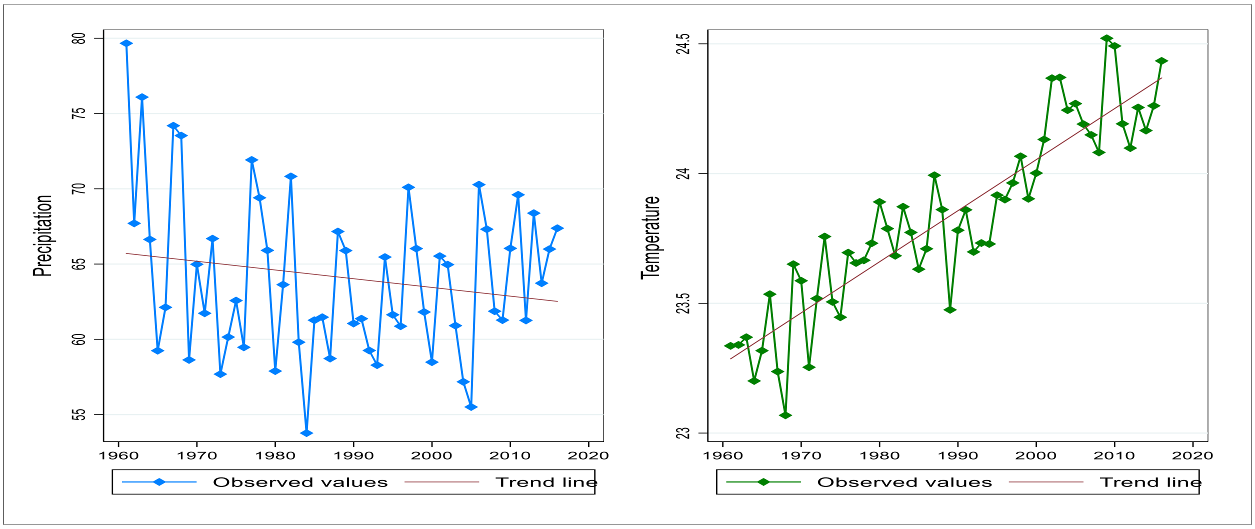

Figure 1 Trends in average precipitation and temperature in East Africa

In general, the average annual temperature is increasing, and the trend becomes more significant as time goes by; while the opposite trend is observed for precipitation. The results are partly in line with studies such as Gebrechorkos et al. (2019), which reported that long-term seasonal rainfall did not show a significant trend (a decreasing trend in the east part of Ethiopia, an increasing trend in Kenya, and a decrease for Tanzania) during the long rainy season. The same study also reported that there is an increasing trend in the maximum and minimum temperatures for virtually the whole eastern region.

5. Empirical analysis

To analyse the time-series characteristics, we took three preliminary steps. First, we looked for cross-sectional dependencies between the variables across panel units. Secondly, we evaluated the panel unit root using specialised tests that accommodate the presence of cross-sectional dependency based on affirmative evidence. Finally, we examined whether or not there is a long-term or cointegration between the agricultural output and the rest of the covariates. If the unobserved dependency in the error terms is overlooked, it might lead to spurious results (Herzer & Vollmer, 2012).

For that, a cross-sectional dependency analysis was performed. The findings of the Pesaran CD test are shown in Table 1 below. Similarly to the results in Table 1, the null hypothesis of no cross-sectional dependence is rejected at the 1% level of significance, and we can conclude that there is cross-sectional dependence in the data. As a result, these data demonstrate that the variables considered had considerable cross-sectional dependence throughout the period 1961-2016. Any study that assesses the impact of weather variability on agricultural output without taking cross-sectional dependence into account might result in misleading findings. Increased economic integration and trade volume might be linked to an increase in dependency, and the results of the cross-sectional analysis confirm this. These nine East African economies have an influence on each other's economic development. Since there is cross-sectional dependency, the first-generation unit root tests are invalidated by these findings. Since cross-sectional units are dependent and heterogeneous, second-panel unit root tests will be used in this research. Pesaran (2007) CIPS unit root test results are considered in this study.

Table 1: Pesaran CD Test (Cross-sectional dependency test)

Variable	CD-test	P-value	Variable	CD-test	P-value
Ln(Output)	29.37	0.00	*Ln(Land)*	29.70	0.00
Ln(Labour)	28.14	0.00	*Ln(Machinery)*	26.29	0.00
Ln(Livestock)	23.53	0.00	*Ln(Irrigation)*	10.60	0.00
Ln(Fertiliser)	6.16	0.00	*Ln(Temperature)*	30.22	0.00
Ln(Precipitation)	18.25	0.00			

The CIPS test, which is one of the second-generation unit root tests that considers cross-sectional dependence, is used in our study. The results are reported in Table 2 below. Based on the results, the order of integration is mixed, i.e. I (0) and I (1). Because some variables are stationary at level and others are stationary at the first difference, the predicted results reveal a mixed integration order. Using the Pesaran (2007) CIPS, the findings were achieved for both intercept and intercept and trend. Our results are consistent with those by Im et al. (2013).

According to Table 2 below, *Ln* (machine), *Ln* (fertiliser), *Ln* (temperature), *Ln* (precipitation), *Ln* (temperature variability) and *Ln* (precipitation variability) are stationary at level. On the other hand, *Ln* (land) is not stationary. The findings of *Ln* (output), *Ln* (livestock), and *Ln* (irrigation) are complex. *Ln* (output) and *Ln* (livestock) are stationary at a 10% level of significance based on the intercept model, but non-stationary based on the intercept and trend model. This leads us to conclude that the two series are not stationary. After computing the first difference, the null hypothesis of panel non-stationary is rejected at a 1% level of significance for all variables. Due to this, we concluded that all our variables were integrated of order one (1). It means there might be at least one long-term equilibrium relationship between the variables. Hence, there is a necessity for panel cointegration testing.

Table 2: Pesaran (2007) CIPS unit root test results

	A level		First difference	
	Intercept	Intercept and trend	Intercept	Intercept and trend
Ln(Output)	-2.472	-2.605	-6.010***	-6.308***
Ln(Machine)	-2.718	-3.178	-5.005***	-5.331***
Ln(Land)	-1.667	-2.080	-5.645***	-5.734***
Ln(Livestock)	-2.326	-2.487	-6.019***	-6.203***
Ln(Labour)	-2.518	-1.049	-0.456***	-0.464***
Ln(Irrigation)	-2.252	-1.970	-5.721***	-5.912***
Ln(Fertiliser)	-3.526	-3.918	-6.190***	-6.420***
Ln(Temperature)	-5.194	-5.207	-6.250***	-6.420***
Ln(Precipitation)	-6.078	-6.309	-5.190***	-6.110***
Temperature variability	-5.103	-5.419	-6.150***	-6.395***
Precipitation Variability	-6.190	-6.420	-6.290***	-6.490***

Note: *** p<0.01, ** p<0.05, * p<0.1, respectively. The critical values of CIPS test at 10%, 5% and 1% levels of significance are -2.21, -2.33 and -2.54 for Intercept, and -2.72, -2.83 and -3.04 for intercept plus trend, respectively.

As cross-sectional units are interdependent, Pedroni (1999; 2004) cointegration metrics are incorrect; an appropriate econometric cointegration method should be considered for efficient results. Ignoring heterogeneous slope coefficients and cross-sectional dependencies in panel data might lead to biased and inconsistent conclusions (Khan et al., 2020).

For these reasons, we employ the Westerlund (2007) cointegration test in order to confirm if the cointegration relationship exists in the long run. This is a panel cointegration test that uses error correction. Westerlund's panel test for cointegration is more robust, according to Hossfeld (2010), because it deals with these issues by detecting structural breakdowns and cross-sectional dependency endogenously. In the presence of heterogeneous and dependent cross-sectional units, this method is appropriate. Using the Westerlund test, one may determine whether there is an error correction for each panel unit or for the complete panel. Statistical categories are broken down into two subcategories, each of which has two statistics in it. The two statistics of the first category are identified as the group mean statistics (G_t, G_a). The two statistics are known as the group mean statistics, while the second two statistics of the category are recognised as panel statistics (P_t, P_a). In both cases, they are pooling information concerning the error correction term along the cross-sectional dimension of the panel. The decision whether or not to reject the null hypothesis is based on the significance of the majority of the four statistics (Miti´c, et al., 2017).

Table 3 below reports the estimated Westerlund (2007) panel cointegration results. They reveal that the null hypothesis of panel no cointegration was ruled out. Except for G_t (which is not significant), the remaining findings, for G_a, P_t, and P_a, respectively, are statistically significant at 1 and 10% level of significance. It appears that the long-term cointegration relationship between variables is well supported by the calculated coefficients. It means the existence of at least one long-run relationship between agricultural output and the regressors. Pooled Mean Group Analysis is employed to assess the short and long-term relationships between the series in order to obtain coefficients.

Table 3: Westerlund (2007) Panel cointegration

	Intercept			Intercept and trend		
Statistics	Values	Z-value	P-value	Values	Z-value	P-value
G_t	-2.0100	-0.7750	0.2190	-2.0380	-0.8700	0.1920
G_a	-11.7***	-2.5340	0.0060	-9.748*	-1.4360	0.0750
P_t	-5.678*	-1.3430	0.0900	-5.856*	-1.5220	0.0640

P_a	-10.8***	-4.4500	0.0000	-8.9***	-3.1960	0.0010

Note: $p < 0.01$***, < 0.05** and 0.1*, respectively

Table 4 below reports the outcomes of the pooled mean group (PMG) estimators. Table 4 has two parts. The coefficients of the long-term relationship are presented in the first part. The short-term relationship coefficients are presented in the second part. We report a reduced version of the model, where the insignificant independent variables are eliminated successively. Model (1) and (2) consider only the impact of the temperature and variability in temperature on agricultural output, while Model (3) and (4) consider precipitation and variability in precipitation. Machinery, livestock, labour, and land have a positive and significant effect on agricultural output in the long run, based on the model (1) specification.

Table 4: Pooled mean group (panel ARDL) model test results.

Coefficients	Model (1)	Model (2)	Model (3)	Model (4)
Long-run coefficient				
Ln(Machinery)	0.087 ***	0.091***	0.073 ***	0.101***
	(0.000)	(0.000)	(0.004)	(0.001)
Ln(livestock)	0.5675***	0.565***	0.655***	0.567***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Labour)	0.349 ***	0.338***	0.321 ***	0.326***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Land)	0.648***	0.607***	0.607***	0.557
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Fertiliser)	0.002	0.006	-0 .013	0.011
	(0.858)	(0.564)	(0.134)	(0.356)
Ln(Temperature)	-5.781***	-5.969***	-	0.579*
	(0.000)	(0.000)		(0.085)
Ln(Precipitation)	-	0.165	-	-5.996
		(0.233)		(0.000)

$Variability^{Temp}$	-0.095**	-0.090*	-	-
	(0.043)	(0.069)		
$Variability^{Precip}$	-	-	0.002	0.003
			(0.311)	(0.520)
Short-run coefficient				
$ECT_{(t-1)}$	-0.208***	-0.199***	-0.197***	-0.181***
	(0.002)	(0.002)	(0.000)	(0.002)
$\Delta Ln(Machinery)$	0.011	-0.001	0.017	0.004
$\Delta Ln(Livestock)$	0.147**	0.175**	0.154**	0.181**
	(0.046)	(0.017)	(0.020)	(0.011)
$\Delta Ln(Labour)$	-1.088	-1.118	-1.064*	-1.403
	(2.475)	(2.492)	(2.075)	(2.310)
$\Delta Ln(Land)$	0.302	0.469	0.389	0.395
	(0.553)	(0.355)	(0.531)	(0.579)
$\Delta Ln(Fertiliser)$	0.001	-0.001	-0.001	0.002
	(0.916)	0.898	(0.930)	(0.888)
$\Delta Ln(Irrigation)$	0.025	-	-	-
Observations	495	495	495	495

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The estimated parameters for the physical inputs considered in this study do not vary across the models specified, and all have the expected signs. The specification in Model (4) confirms the findings except for the land coefficient, which is a positive but not significant coefficient. The irrigation coefficient showed no significance across all specifications, and has been removed. The lack of significance of the irrigation parameter is not a surprise, as 95% of farming in this part of Africa is highly traditional, small-scale, and non-mechanised (Eriksen et al., 2008). However, irrigation facilities are inadequate, since less than 4% of agricultural output in East Africa is generated by irrigation, compared to 33% in Asia (AfDB/IFAD, 2009).

We also find that machinery has significant impact on agricultural output, contrary to the findings of Erikson et al. (2008) and Abraha-Kahsay and Hansen (2016).

Looking at the effect of variable climate on agricultural output, we find that on average, temperature and variability in temperature have a negative and significant effect on agricultural output in the long run. In general, temperature and precipitation variations affect crop yields, as do growing CO2 concentrations in the atmosphere (Wheeler & Von Braun, 2013). Temperature and water quantity are key variables for crop growth; thus, greater temperatures have a detrimental impact on soil quality and soil moisture. However, temperature increases are most likely to have a negative influence on agricultural yields (Ottman et al., 2012). The high temperature observed in the long run is detrimental, as it increases water stress. A reduction in fuel emissions to keep global warming at 1.5 °C is therefore urgently required (IPCC, 2018).

For policy intervention this information is crucial, as it shows that the impact of the increased temperature in the agricultural sector in East Africa is more a long-run phenomenon. Any policy measure intending to reduce the effect of water stress will improve agricultural output, since precipitation and its variability tend to have an effect only in the short run. In East Africa, without irrigation the region's agriculture is subject to rainfall unpredictability and dry periods, even during the rainy season (Mupangwa et al., 2006), putting more stress on the agricultural sector. Policymakers should coordinate efforts to invest in irrigation quickly, in order to ensure food security.

Looking at the short-term relationship, the second part of Table 4 above reveals that the error correction coefficient is negative, as theoretically expected. The error correction coefficient is found to be statistically significant with the expected sign, which supports the cointegration test results. The speed of adjustment tends to increase when one considers Models (1) and (2), where the temperature is considered. The estimated coefficients for physical inputs have the expected sign, but are not significant – except for the labour coefficient, which does have a negative sign but is still not significant. This is because the most driving force in the agriculture sector in the short run are climate related variables than economic variables. The coefficients of temperature are not significant, but have the expected sign. We found that annual precipitation has a positive and significant impact on output in East Africa, while precipitation variability has a negative and significant effect on agricultural output in the short run – in line with Abraha-Kahsay and Hansen (2016), who found that growing variability is having a serious negative effect on East African agricultural output, and that the effect is more pronounced during the main growing season. This is because the East Africa region in particular is characterised by an increase in weather variability; especially in the main growing seasons, spring and autumn (Schreck & Semazzi, 2004; Conway & Schipper, 2011).

Table 5 below reports findings from the dynamic fixed-effect model, and consists of two parts. The first part shows the coefficients of the long-run relationship, and the second reports the short-run relationship. Labour and livestock are significant, with the expected sign, in the long run. Other variables have the expected sign, except for machinery and fertiliser; but not all are significant.

Looking to climate variables, the results reveal that both temperature and precipitation are not significant, but have the expected sign. The variability in both temperature and precipitation is not significant in the long term.

The second part of Table 5 reports the short-run relationship. The error correctional model has the expected sign, and variables are significant across all specifications. Land and livestock are the only parameters that are significant with the expected sign across all specifications in the short run. Climate variables have the sign expected, but are not statistically significant.

Table 5 Dynamic fixed effect (DFE) model test results

Coefficients	Model (1)	Model (2)	Model (3)	Model (4)
Long-run coefficient				
Ln(Machinery)	- 0.042	-0.049	-0.045	-0.047
	(0.067)	(0.066)	(0.065)	(0.066)
Ln(livestock)	0.391***	0.423***	0.396***	0.428***
	(0.128)	(0.127)	(0.115)	(0.128)
Ln(Labour)	0.259**	0.255***	0.284***	0.280***
	(0.111)	(0.109)	(0.104)	(0.104)
Ln(Land)	0.391	0.393	0.408	0.445
	(0.352)	(0.345)	(0.320)	(0.344)
Ln(Fertiliser)	-0.013	-0.008	-0.006	-0.003

	(0.042)	(0.041)	(0.042)	(0.041)
Ln(Temperature)	-1.286	-0.830	-	0.688
	(4.124)	(0.346)		(0.526)
Ln(Precipitation)	-	0.473	-	0.676
		(4.054)		(3.594)
$Ln(Variability^{Temp})$	-0.115	-0.131	-	-
	(0.177)	(0.175)		
$Ln(Variability^{Precip})$	-	-	0.005	0.006
			(0.008)	(0.012)
Short-run coefficient				
$ECT_{(t-1)}$	-0.109***	-0.111***	-0.109***	-0.109
	(0.020)	(0.019)	(0.0192)	(0.0193)
$\Delta Ln(Machinery)$	-0.008	-0.005	-0.006	-0.007
$\Delta Ln(Livestock)$	0.079*	0.077*	0.081**	0.078
	(0.043)	(0.043)	(0.044)	(0.042)
$\Delta Ln(Labour)$	-0.010	-0.017	-0.011	-0.019
	(0.052)	(0.057)	(0.054)	(0.0549)
$\Delta Ln(Land)$	0.377***	0.365***	0.371***	0.370***
	(0.136)	(0.136)	(0.135)	(0.136)
$\Delta Ln(Fertiliser)$	0.0008	-0.0002	-0.0003	-0.0002
	(0.006)	(0.006)	(0.007)	(0.006)
$\Delta \ln(Temperature)$	0.168	0.167	-	0.223
Observations	495	495	495	495

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Given that the PMG gives only the cross-heterogeneous effect in the short term and the weighted-average effect in the long term, it is also possible to obtain the heterogeneous long-run marginal effect of climate variability on output. According the results of PMG for instance, weather related variables affect the agricultural output across the nine countries in the same manner. We carry the analysis one step further, to investigate the heterogeneous effect of climate variables on agricultural output across the nine East African countries. We apply the Swamy (1970) random coefficient linear regression model, which does not impose the assumption of constant parameters across the panel. The results are reported in Table 6 below.

The estimated coefficients for the physical outputs and climate variables do vary across countries. In Burundi, most of the inputs have the expected sign, but are not significant; except livestock input, which is significant, but without the long-run effect of climate variables on output. In Djibouti, labour and livestock are significant, with the expected sign; while other physical inputs have the expected signs, but are not significant, except that machinery does have a negative sign but is not significant. We found evidence of the impact of climate variables in this country. The average temperature and precipitation and their variability have an impact on agricultural output in the long run. In Ethiopia, machinery, labour, land and fertiliser are significant and positive, but the land coefficient is negative and significant. Land in Ethiopia has deteriorated due to climate change, which has had a negative effect on agricultural output. Teshome (2016), for instance, reveals that an increase in temperature, a decrease in rainfall and abnormal precipitation are increasingly making households vulnerable in rural Ethiopia. This is in line with our findings: we found that annual temperature and precipitation have a negative long-term impact on agricultural output. This is opposite to what we reported in Table 4, where the effect was only coming from temperature in the long run.

In Kenya, only the average temperature has a long-run impact on output. Machinery, livestock, labour and fertiliser have an impact on output in the long run in Kenya. Rwanda also shows significant positive impact from the physical input parameters on the agricultural output; except for machinery, which is positive but not significant. Results show that in the long run, temperature and precipitation have an effect, but so does temperature variability. In Somalia, the land variable had a negative effect on agricultural output, confirming the presence of climate change in this region. Labour and fertiliser parameters are positive and significant. We find that only temperature has a negative impact in Somalia. In Tanzania and Uganda, temperature has a long-term impact on the agricultural sector, while no effect is observed in Sudan. In Tanzania there is also the long-run impact of precipitation variability on output.

Table 6: Heterogeneous effect of climate variables on agricultural output

Variable	Burundi	Djibouti	Ethiopia	Kenya	Rwanda	Somalia	Sudan	Tanzania	Uganda
$Ln(Machinery)$	-0.00830	-0.01827	0.10539***	0.06084**	-0.01590	-0.02738	0.07765**	0.05661**	0.14745***
	(0.0240)	(0.02280)	(0.03431)	(0.02604)	(0.03083)	(0.02642)	(0.03517)	(0.02764)	(0.02877)
$Ln(Livestock)$	0.4114 ***	0.49559***	0.23904*	0.30267***	0.51345***	0.91774***	-0.06107	0.70162***	-0.11228
	(0.09125)	(0.05022)	(0.12870)	(0.08720)	(0.06358)	(0.07472)	(0.05831)	(0.18512)	(0.15489)
$Ln(Labour)$	0.08556	1.16237***	1.20105***	0.57441***	0.71111***	0.25175***	0.14081***	0.28452 **	-0.04051
	(0.09067)	(0.10866)	(0.07898)	(0.08869)	(0.06957)	(0.04413)	(0.04603)	(0.14328)	(0.14001)
$Ln(Land)$	-0.08389	0.11931	-0.72601***	-0.04133	0.83716***	-1.70396***	0.56085***	0.57568	2.34100***
	(0.20761)	(0.10253)	(0.18976)	(0.36763)	(0.23458)	(0.38194)	(0.14763)	(0.52084)	(0.59389)
$Ln(Fertiliser)$	0.04143	0.00393	0.09033***	0.07571***	0.02626	0.03488***	-0.05340	0.01965	0.20574***
	(0.02714)	(0.00818)	(0.03356)	(0.01138)	(0.01681)	(0.01164)	(0.03559)	(0.02065)	(0.01958)
$Ln(Precipitation)$	-0.27004	0.72475***	-0.03842	-0.05367	1.10233***	0.00410	0.29691	0.39651*	0.07363
	(0.20389)	(0.19013)	(0.09759)	(0.19777)	(0.23225)	(0.19960)	(0.19919)	(0.23725)	(0.28429)
$Ln(Temperature)$	0.14556	5.03644***	-0.23191	2.02294*	2.76571***	-2.13965**	-1.4054	4.02651***	4.11739***
	(0.40729)	(0.32586)	(0.66974)	(1.07896)	(0.45648)	(1.13533)	(0.80911)	(0.93092)	(1.10957)
$Ln(Variability)^{Precip}$	-0.00234	0.00704**	-0.00897*	-0.00164	0.00989***	0.00078	0.00931	0.00409	0.00707*
	(0.00261)	(0.00324)	(0.00521)	(0.00329)	(0.00324)	(0.00747)	(0.01110)	(0.00301)	(0.00383)
$Ln(Variability)^{Temp}$	-0.02516	0.11009***	-0.09786***	-0.02080	0.04952	0.01055	-0.00474	-0.08516***	0.04907
	(0.03691)	(0.03015)	(0.03286)	(0.03396)	(0.03946)	(0.02934)	(0.03513)	(0.03311)	(0.03954)
Observations	504	504	504	504	504	504	504	504	504
Number of ids	9	9	9	9	9	9	9	9	9

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6. Conclusion

This empirical study aimed to investigate the relationship between weather variability and agricultural output in the long run. In particular, we investigated the relationship between precipitation and temperature and agricultural output across East African countries. The contribution of this paper is twofold. Firstly, the paper attempted to establish whether temperature or precipitation variability affects agricultural output in the short or the long run. Secondly, it examined whether the effects of temperature or precipitation variability on agricultural output are homogenous across East African countries. For that, we considered economic data from the FAOSTAT from 1961 to 2016, and climate data from the Climate Research Unit (CRU). We first tested whether there was cross-sectional dependency in the data; if this had been the case, the first-generation panel econometric techniques would not have been applicable. Variability in temperature and precipitation are measured as the deviation of the previous year's precipitation and temperature from the 30-year historical average. Variability is referred to as rainfall and temperature anomalies observed during the period under consideration. We found that variability in temperature had a long-run impact on agricultural output, while variability in precipitation had a short-run effect. We also found that the long-run temperature variability effect was heterogeneous across East African countries, and to some extent there was also evidence for the long-run effect of precipitation variability.

As per our study findings, it is recommended that studies on the impact of climate change on agricultural output should consider the cross-sectional dependency that exists between countries, as countries do not have the same agricultural system. In addition, the effects of temperature and precipitation variability are different between the short run and the long run. The effect of temperature and precipitation variability on agricultural output is a specific-country reality, due to the different responses that have been put in place. Policies intending to promote irrigation in East Africa can have a significant impact; especially in the short run, as precipitation variability is more serious in the short run. There should also be investment in technology, as agricultural technology provides farmers with several benefits including improved production, and crops that are more adaptable to climate change.

Finally, there are several caveats to this study. First, results from this study are different from those of previous studies, as we attempted to investigate the long-run impact of weather variability on agricultural output. The generality of previous studies should be viewed with caution, as there is evidence of a substantial increase in weather variability in the growing seasons. Future studies should investigate the long-run impact of growing season temperature and precipitation variability on agricultural output under the assumption of cross-dependency in the panel data.

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Appendix

Table A1: Descriptive statistics of economic and climate data

Variables	Mean	St. Dev.
Dependent variable		
Output (in millions of international US dollars)	7444.88	5910.00
Independent variables		
Physical		
Land (1000 persons)	31226.30	34763.56
Labour (1000 of hectares)	19964.49	26190.84
Machinery	3057.55	3835.89
Livestock (Head count of cattle, sheep and goats, in millions)	28.20	31.30
Irrigation (1000 of hectares)	0.48	0.50
Fertiliser (1000 of hectares)	21539.26	36567.19
Climate variables		
Temperature	23.83	2.97
Precipitation	64.11	34.65
$Variability^{Temp}$	0.06	0.35
$Variability^{Precip}$	-0.53	7.30
countries	9	
Sample	504	