Is climate variability subversive for agricultural total factor productivity growth? Long-run evidence from sub-Saharan Africa

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Abstract

It is expected that production in the agricultural sector will be significantly affected by climate change. Therefore, it is projected that countries with extreme climatic conditions will suffer a long-term decline in agricultural productivity beyond the short-term loss of production. Given the gross domestic product (GDP) value of agriculture in many sub-Saharan African (SSA) countries, the effects of climate change on agriculture are likely to permeate their economies. The long- and short-run effects of climate variability on agricultural total factor productivity (TFP) growth in 14 SSA countries are examined using panel data from 1995 to 2016. We employ a twofold approach. First, we use the Data Envelopment Approach (DEA) to calculate the Malmquist Index of Maize Productivity growth. Second, we apply a fully modified ordinary least square estimator and the Granger causality test in heterogeneous mixed panels to evaluate the long- and short-run impacts of climate variability on agricultural TFP development. The empirical results from the long-run analysis show that maize agricultural TFP is negatively associated with climate variability for only five countries. In the short run, our empirical estimation indicates no evidence of causality effect. To mitigate the negative long-run effects – and given that spending on R&D is found to produce negative effects in some of those five countries – policymakers should take immediate action to provide farmers with adequate and expeditious irrigation facilities, including the construction of dams to harvest and store rainfall water for future use.

Key Words: total factor productivity; climate variability; data envelope approach; fully modified ordinary least square; heterogeneous mixed panel.

JEL classification: Q1, Q5, Q24

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1. Introduction

The productivity of weather-dependent sectors, such as agriculture, is anticipated to be greatly impacted by climate change (Antle, 2010; Sachs et al., 1999). It is projected that countries with extreme climatic conditions, such as prolonged droughts, will suffer a long-term decline in agricultural productivity, beyond the short-term loss of production. In light of this, in countries with broad agriculture sectors – especially in the tropics and subtropics, where agricultural production is meteorologically sensitive and adaptation potential is limited – the adverse effects of climate change are likely to be the most extreme. Since rain is a direct input into agricultural production, the agricultural sector is projected to be hit the hardest (Barnwall & Kotani, 2013; Deschenes & Greenstone, 2007). The agriculture sector is therefore considered the most susceptible to climate change, of all the sectors of the global economy (Deressa et al., 2005). Since the agricultural enclave is a sector that generates employment, provides food security, and supplies raw materials to the industrial sector, a decrease in productivity has a significant effect on any country's economy.

Empirical evidence indicates that climate change will continue to have far-reaching effects on agriculture while disproportionately affecting the poor and vulnerable, especially in sub-Saharan Africa (SSA), where agriculture is the primary source of income (Zougmoré et al., 2016). More specifically, climate change would affect food security and food crop farmers' income. Moreover, the four pillars of food security, namely food production, distribution, usage, and stability, could be influenced by climate change. To begin with, extreme weather conditions limit income and ultimately place budget restrictions on farmers' ability to invest in modern methods of farming, leading to a reduction in productivity. Also, because of the nature of agriculture and farming activities, agricultural production is highly affected by the long-term climatic conditions anticipated by farmers. For example, perceptions of potential changes in precipitation will contribute to changes in agricultural practices, and thus affect productivity. In addition, unexpected fluctuations in rainfall and temperature may expose farmers to production risks, resulting in a negative productivity effect (Sivakumar et al., 2005; Kumar et al., 2004). An interesting argument is made that the poor in SSA, especially smallholder farmers, will be more severely impacted by climate change, as their options for diversifying their resources and incomes are limited (Gohar & Cashman, 2016).

Given the importance of agriculture to the GDP, employment, and livelihoods of many SSA countries, the effects of climate change on their agriculture are likely to reverberate across their economies. It is expected that indirect impacts will be felt not only in the related sectors and in the production and selling of agricultural products, but also many other sectors of the economy, because of the effects on income and demand (Bezabih et al., 2011). Campbell et al. (2014) observe that agricultural productivity also relies on the farmer's capacity to take action and develop adaptive techniques, to effectively manage the risks associated with increased variability in climate. However, this cannot be said of smallholder farmers in SSA, as their adaptive capacity is usually low.

Generally speaking, overall improvement in agricultural productivity is determined by the total productivity factor (TFP), which can simultaneously represent both production growth and cost reduction. TFP can be used to identify the causative factors for improvements in the productivity of agriculture for these characteristics (Kunimitsu et al., 2014). An increasing body of evidence from cross-country and panel data studies suggests that extreme climatic shocks may have a major effect on long-term agricultural productivity development (Letta & Tol, 2019; Blanc, 2012; Schlenker & Lobell, 2010). On the other hand, these studies implicitly assume that the effects of climate change on agricultural TFP are uniform for all countries. Therefore, the substantial differences in the climate change-agricultural TFP growth relationship between countries can lead to highly misleading results. In light of this, we took a different approach to examine the long- and short-term effects of climate variability on agricultural TFP development. Climate variability is used instead of climate change since the literature shows that it is a dominant potential source of risk in most parts of SSA for rainfed smallholder agriculture (Zimmerman & Carter, 2003; Dercon, 2002).

We have added to the current literature in the following respects: First, we analyzed the data country by country, to monitor climate variability heterogeneity and the cross-sectional dependence-agricultural TFP growth nexus for 14 SSA countries. Second, using the four-way decomposition method, we applied Data Envelopment Analysis (DEA) to the Malmquist Productivity Index (MPI) to capture changes in maize agricultural TFP growth. Third, we applied a fully modified ordinary least square estimator and the Granger causality test in heterogeneous mixed panels to determine the long- and short-run impact of climate variability on agricultural

TFP growth in SSA. Specifically, employing heterogeneous mixed panels by Emirmahmutoğlu and Kose (2011), we use the idea of a completely adjusted ordinary least square (FMOLS) estimator advanced by Pedroni (2000), and the Granger causality test, by allowing for both long- and short-run relationships between climate variability and agricultural TFP in levels and first differencing. Fourth, we use the cointegration tests of Zivot and Andrews (1992) and Gregory and Hansen (1996) to account for a possible structural split in the cointegration relationship. For those countries where climate variability cointegrates with agricultural TFP, we estimate the coefficients of the long-run relationships using the FMOLS approach, subject to the existence of cointegration. We look at the course of short-run causality in countries where there are no long-run relationships.

The rest of the paper is structured as follows. A literature review is presented in Section 2. The technique used is presented in Section 3. The empirical analysis of the results is discussed in Section 4. Section 5 includes the concluding remarks.

2. Literature Review

In the literature, the economic impacts of climate change have traditionally been shown as estimations of reduction in production due to the effects of changes in average temperature and precipitation. For instance, Dell et al. (2012) showed that temperatures that are one degree Celsius warmer in a given year lead to a decrease in per capita income of about 1.4 percent, but only in poor countries. Letta and Tor (2019) delivered some outstanding discussions on climate changes' acute and immoderate impacts on TFP. They showed that a negative association occurs only in poor countries, where an annual temperature rise of 1°C reduces TFP growth rates by between 1.1 and 1.8%, while the effect in rich countries is negligible. In other fields of research, Blanc (2012) estimated the effect of climate change on SSA crop productivity. Under alternative climate-change scenarios, yield changes by the year 2100 will be close to zero for cassava, but range from -19% to +6% for maize, -38% to -13% for millet, and -47% to -7% for sorghum. Schlenker and Lobell (2010) showed that by the mid-21st century, mean figures for aggregate changes in agriculture productivity in SSA due to climate change would be -22%, -17%, -17%, -18%, and -8% for maize, sorghum, millet, groundnut, and cassava respectively. Except for cassava, there is a 95% likelihood that losses will reach 7% and a 5% chance that they will exceed 27%, in all cases. According to Etwire et al. (2018), extreme climate change will result in a major reduction in average net maize revenue per hectare; maize accounts for more than half of the current food output in Ghana. There is also likely to be widespread substitution of heat-tolerant millet for maize and a decrease in other-crop cultivation, according to a variety of climate-change scenarios used in the analysis. In certain climate-change models, the results also suggest a substantial decrease in the aggregate value of agricultural production.

3. Methodology

3.1 Estimating agriculture total factor productivity (TFP)

The growth accounting methodology has generally been employed to obtain data on TFP. This method is most widely used in the estimation of TFP data at the macro-economic level of research (Hall & Jones, 1999; Kalio et al., 2012; Bilgic-Alpaslan, 2015; Algarini, 2017; Saad 2017; Espoir & Ngepah, 2020). In these studies, TFP was calculated as a basic Solow residual (Solow, 1956), and a traditional Cobb-Douglas framework model was specified, along the lines of the Solow-Swan model. However, a fundamental limitation in the growth accounting methodology is that it does not take into account possible inefficiency which could obstruct farmers from reaching the production frontier. To overcome this limitation, therefore, we employed the four-way Malmquist Productivity Index (MPI) which accounts for efficiency change, technological change, pure efficiency changes, and scale efficiency change. In addition, the MPI technique has the property that it does not require the inclusion of details on input and production costs, or any other relevant assumptions about economic activity (for example, expense or revenue maximization). This aspect makes the index sufficiently versatile and relevant in the context of the developing world, specifically, SSA, where in many cases market price information for commodity products is inaccessible or insufficiently widely published.

MPI requires the measurement of the output-or input-oriented distance of observation (x^{kt}, y^{kt}) in two consecutive cycles (say, base period t = 0 and reference period t = 1) at the boundary of the Constant Return to Scale (CRS) benchmark technology. To follow homogeneous conditions that ensure that the MPI is proportionally characteristic (see Balk & Zofío, 2018), the imposition of CRS is necessary to achieve the distance function. Therefore, in general, there is a disparity between reference technology and real technology. The cone technology of a certain time t, S^{t}, is popularly taken as a benchmark. The function of its output distance is defined by $D_0^t(x^t, y^t) = Inf$ $(\delta/\delta>0, x^t, y^t/\delta) \in S^{t}$.

Operationally, this can be determined within the DEA framework by estimating the program $D_0^t(x^t, y^t)^{-1}$ = $\max_{\phi\lambda}\{\phi|x \geq X^t\lambda, \lambda \geq 0\}$. Then $(x^t, y^t|D_0^t(x^t, y^t)$ is the point on the frontier of the t cone technology duration that is obtained by keeping the vector x input quantity constant while radially extending the vector y output quantity. The distance function of the input is thus specified as $D_0^t(x^t, y^t) = sup\{\delta|\delta>0, (\delta, y) \in S^t\}$ which can be computed by estimating the program $D_1^t(x^t, y^t)^{-1} = \min_{\theta,\lambda}\{\theta \geq X^t\lambda, y \leq Y^t\lambda, \lambda \geq 0\}$. Then $\{x/D_1^t(x^t, y^t), y\}$ is the point on the frontier of the t cone technology duration that is obtained by keeping the vector y output quantity constant while radially contracting the vector x input quantity. For a certain Decision-Making Unit (DMU), the output-oriented MPI – conditional on the t-cone technology – is defined by:

$$M_0^t(x^1, y^1, x^0, y^0) = \frac{D_0^t(x^1, y^1)}{D_0^t(x^0, y^0)} \quad (1)$$

The selection of the base time cone technology then leads to $M_0^0(x^1, y^1, x^0, y^0)$, and the selection of the cone technology reference period leads to $M_0^1(x^1, y^1, x^0, y^0)$. The TFP toolbox measures both reference periods in addition to their geometric mean. The first expanded decomposition of the base-period-output-oriented MPI (called 'Path A') is specified by following Balk and Zofío (2018); thus, we provide meaningful theoretical explanations for the various variables as follows:

$$M_0^0(x^1, y^1, x^0, y^0) = EC_0(x^1, y^1, x^0, y^0) \text{ x } TC_0^{1,0}((x^1, y^1) \text{ x } SEC^0_0(x^1, x^0, y^0) \text{ x } PEC^0(x^1, y^1, y^0) \quad (2)$$

From Equation (2), there are four mutually independent variables with the following interpretation:

$$\text{Efficiency change: } EC_0(x^1, y^1, x^0, y^0) = \frac{D_0^1(x^1, y^1)}{D_0^0(x^0, y^0)} \quad (3)$$

Equation (3) reflects the shift in the DMU's technical efficiency, also known as the catch-up effect.

$$\text{Technological change: } TC_0^{1,0}((x^1, y^1) = \frac{D_0^0(x^0, y^0)}{D_0^1(x^1, y^1)} \quad (4)$$

Equation (4) captures the transition in technological change, often referred to as the frontier-change effect.

Scale efficiency change: $\mathrm{SEC}^0{}_0(x^1, x^0, y^0) = \left[\frac{D_0^0(x^1, y^0)}{D_0^0(x^1, y^0)}\right] \times \left[\frac{D_0^0(x^0, y^0)}{D_0^0(x^0, y^0)}\right]$ (5)

Equation (5) refers to the related gains in scale performance associated with radial increases in input quantities, and the additional impact of changes in the combination of input quantities.

Pure efficiency change: $\mathrm{PEC}^0(x^1, y^1, y^0) = \left[\frac{D_0^0(x^1, y^1)}{D_0^0(x^1, y^1)}\right] \times \left[\frac{D_0^0(x^1, y^0)}{D_0^0(x^1, y^0)}\right]$ (6)

Equation (6) displays the counterparty effects associated with shifts in the combination of output quantities.

An alternate base-period-output-oriented MPI decomposition reverses the order in which inputs and output space shifts occur in the last two expression factors in equation (2). This yields the following:

$$M_0^0\ (x^1, y^1, x^0, y^0) =$$
$$\mathrm{EC}_0(x^1, y^1, x^0, y^0) \times \mathrm{TC}_0^{1,0}((x^1, y^1) \times \mathrm{SEC}^0{}_0(x^1, x^0, y^1) \times \mathrm{PEC}^0(x^0, y^1, y^0) \qquad (7)$$

Equation (7) is referred to as Path B. The variations between equation (2) and the decomposition in equation (7) are slight but notable. The elements that capture technical efficiency and technological change are similar. The radial scale effect factor and input mix effect, however, depend on y^0 in expression (2), but on y^1 in expression (7). The inverse occurs with the effect of the output mix; in expression (2), this impact is conditional on x^1, and in expression (7), on x^0. Following Färe et al. (1994), we estimate each of the distance function terms in equation (7) using a linear programming-based Data Envelopment Analysis (DEA) technique, and combine the four components to form the complete Malmquist Index.

3.2 Standard Model

While estimating a bivariate long-run relationship is typical in panel cointegration studies, it would be irrational to conclude that long-run changes in agricultural TFP are driven primarily by changes in rainfall. However, it is fair to assume that labor, resources, literacy, and R&D spending all play a role in agricultural TFP over time. Thus, we consider a standard type of model:

$$\log(\mathrm{TFP}_{it}) = \alpha_i + \delta_{it} + \beta_{1it}\mathrm{Cvar}_{it} + \beta_{2it}\log(\mathrm{Capital}_{it}) + \beta_{3it}\log(\mathrm{R\&D}_{it}) + \beta_{4it}\log(\mathrm{labor}_{it}) + \beta_{5it}\log(\mathrm{Literacy}_{it}) + \varepsilon_{it} \qquad (8)$$

where α_i and δ_{it} are country-specific fixed effects and time patterns respectively, to account for any excluded country-specificd variables that are either relatively constant over time or change smoothly over time. The vector $\log(TFP)_{it}$ is the log of agricultural TFP overtime periods $t = 1, 2, \dots, T$ and countries $i = 1, 2, \dots, N$, $\log(Capital)_{it}$ is the log of gross capital creation, $\log(R\&D)_{it}$ is the log of research and development investment, $\log(labor)_{it}$ is the log of labor calculated as the total number of agricultural employments, and Cvar_{it} is climate variability proxied by rainfall. Furthermore, for a regression composed of cointegrated variables, there is a stationary error term ε_{it}, which means that no suitable integrated variables are omitted; any omitted non-stationary variable that is part of the cointegrated relationship will enter the error term, resulting in non-stationary residuals and leading to the observed cointegration failure.

In extended vector space, the same stationary relationship also happens if on the other hand there is cointegration between several variables (Johansen, 2000). The absence of missing incorporated variables in the cointegrating vector is a major consequence of estimating cointegration. Cointegration estimators are thus robust (under cointegration) in such a way that variables that do not form part of the relationship with cointegration are omitted. This not only justifies a reduced form (if cointegrated) model but also describes the main variables that should be used in our research to estimate the long-term effect of climate variability on agricultural TFP.

4. Data sources and description

For the period 1995-2016, the FAO database (FAO, 2020) and the ILOSTAT database provide panel data for agricultural production and traditional agricultural inputs (capital and labor) for 14 countries in SSA: Benin, Botswana, Burkina Faso, Ivory Coast, Ethiopia, Ghana, Kenya, Malawi, Mali, Niger, Nigeria, South Africa, Togo, and Zambia. The selection of countries is mainly based on data availability. Maize yield data is measured as thousands of tonnes per hectare; labor is measured by the total number of agricultural jobs; capital is measured by gross agricultural fixed capital formation; the proportion of the adult population who are literate is estimated using data from the World Development Indicators database. Rainfall (climate proxy) is the average monthly rainfall in millimeters and is collected from the Climate Change Information Portal of the World Bank.

Data from agricultural research and development (R&D) valued at millions of US dollars can be found in the IFPRI Agricultural Science and Technology Metrics database hosted by the International Food Policy Research Institute. Our panel data consists of 294 observations, each covering maize production, labor, capital, literacy, rainfall, and R&D expenditure. The average maize yield is about 16 740 tonnes per hectare. The average labor employed in agriculture in agriculture is 6.102689 million. At the same time, the average percentage of the population that is literate is 55%, with an average gross capital formation of about US$466m. The average rainfall for the study period is approximately 68mm, and the average spending on R&D is about US$48m. Maize was selected because of its nutritional value as well as its economic significance. According to Badu-Apraku and Fakorede (2017), maize is the most widely grown food crop in SSA, accounting for more than 40% of total cereal consumption. In SSA, maize provides about 20% of the population's caloric intake. It is also an essential source of protein for the majority of the population and is high in starch. A summary and explanation of the data are presented in Table 1 below.

Table 1. Data description

Variable	Mean	SD	Min	Max
Maize	16 740.22	8 436.57	849	53009
Labour	6 102 689	6 102 689	76914.7	3.30e+07
Capital	465.87	805.02	2.32	4875.11
Rainfall	68.46	30.39	11.36	144.89
Literacy	54.67	21.51	12.85	94.37
R&D	48.46	66.71	0.00	276.9

Table 1 shows that rainfall variability (a proxy for climate variability) is one of our key variables of concern. We follow the previous literature to derive rainfall variability (see Trong-Anh, 2019; Amare et al., 2018) and assess climate variability during the agricultural development season as the deviation of past rainfall from its historical average (21 years). The use of past rainfall is based on the hypothesis that rainfall variability is exogenous to the current decisions of farmers, as seen in the literature (see Amare et al., 2018; Dercon & Christiansen, 2011; Alem et al., 2010), and which is reflected in their choice of inputs for agricultural production. Our climate variability estimate is thus expressed as follows:

$$\text{Climate variability } (\text{Cvar})_{it} = \log\left(\frac{\bar{x}_{it} - x_{it-1}}{x^{SD}}\right) \qquad (9)$$

where $\bar{x}_{it}$ represents the 21-year historical average of rainfall in country ί at a time (t), x_{it-1}indicate past rainfall, and x^{SD} shows the standard deviation from the mean rainfall.

5. Results and Discussion

5.1 Total factor productivity and its decomposition

The improvements in the overall productivity indices and their respective components for the study period are listed in Table 2. Through applying the DEA technique, the EC, TC, SEC, and PEC estimates are derived. Growth in TFP is measured by the overall output of technical efficiency, technological progress, scale efficiency, and pure efficiency change. Considering the TFP indices, where the values are greater than one for either productivity or all of its components, the results suggest an increase in overall productivity and its components. However, the less-than-one values reflect a deterioration in TFP, which means that given the same amount of inputs, the country is not able to generate as much output as before. Estimates for the MPI indicate that overall, between 1996 and 2016, there was a negative increase of around 8.3% in production per year in agriculture. This poor growth shows a deflation in agricultural productivity among the 14 countries over the study span. The results in Table 2 below also show that though TFP is driven by technical efficiency among the 14 countries, the increasing trend could potentially stem from increasing gross capital formation to the agricultural sector by our sample countries. Though many African governments have pledged to raise their annual agricultural spending to 10% of their total national expenditure, as reported in the African Union's declaration in Malabo in 2003, it can be seen from Table 2 below that there are still inefficiencies in the agricultural production of maize during the sample period. Efficiency changes cause negative growth rates in productivity growth; notable among these was 2009 when the rate was -32.3%. On average, efficiency change improves TFP growth by a rate of 0.1% per year. For example, contrary to previous studies, Alene (2010) and Fulginiti et al. (2004) observed that technological progress is the key driver of agricultural productivity in Africa, compared to technical efficiency.

Table 2. Annual productivity growth, efficiency change, technical change, pure efficiency changes and scale efficiency change

Year	EC	TC	PEC	SEC	TFP
1996	0.335	2.286	0.883	0.379	0.765
1997	2.134	0.267	0.907	2.353	0.571
1998	1.322	0.958	1.222	1.082	1.266
1999	1.072	0.534	1.038	1.033	0.572
2000	0.981	1.271	0.978	1.003	1.247
2001	0.925	0.589	0.936	0.988	0.545
2002	0.731	1.211	1.014	0.721	0.885
2003	1.515	0.988	1.070	1.416	1.496
2004	0.971	0.838	0.989	0.982	0.814
2005	0.880	0.832	0.928	0.948	0.732
2006	0.838	3.188	0.805	1.041	2.672
2007	1.373	0.946	1.356	1.012	1.299
2008	0.814	0.890	0.822	0.990	0.724
2009	0.677	1.484	0.767	0.884	1.005
2010	1.251	0.485	1.424	0.878	0.607
2011	1.374	0.224	1.084	1.267	0.308
2012	0.966	1.653	0.976	0.990	1.597
2013	0.998	2.911	0.968	1.031	2.906
2014	1.120	0.754	1.113	1.006	0.845
2015	0.867	1.036	0.918	0.945	0.899
2016	1.152	0.501	1.069	1.079	0.578
Mean	**1.001**	**0.916**	**1.001**	**1.000**	**0.917**

Our findings show further that both technical efficiency and technological progress are significant for the overall growth of maize productivity in the 14 selected SSA countries. The overall technical change was approximately -8.4% per year; however, technical change contributed significantly to TFP growth – notably in 2006, by about 218.8%. Pure efficiency changes (average annual growth rate: 0.1%) also made a significant contribution to TFP growth, though on occasion a negative growth rate was recorded; significant among them was 2009 when it tumbled by approximately 23.3%. On the other hand, no growth was recorded for scale efficiency change in our sample period. Also, TFP growth rates were slightly lower than in studies such as Adetutu and Ajayi (2020). This is because we adopted a non-parametric DEA approach, as opposed to the parametric method used in their study. Heady et al. (2010) confirmed this slight difference in TFP indices, reporting that frontier-based estimates of SSA agriculture productivity yield much higher TFP growth than DEA-based estimates.

5.2 Cointegration Results

We analyze the long-term effects of climate variability on agricultural TFP. In particular, we used heterogeneous panel cointegration techniques that are robust, with omitted variables, slope heterogeneity, and endogenous regressors. We begin by examining the cross-section dependency and unit root test for our panel data. Then we look for a long-term or co-integrating partnership between TFP, climate variability, R&D, capital, labor, and literacy. We measure this relationship among our variables and determine how the robustness of this relationship.

5.3 Cross-section dependency and unit root test

We analyze for cross-dependencies in our panel dataset before running the module unit root test. This is significant because the orthodox literature on cross-sectional and time-series data suggests cross-section-independent errors may occur. There are some explanations for why cross-sectionally-based errors occur in panel data; cross-sectional dependence can occur due to the omission of variables that can affect agricultural TFP. If the dependency on the non-observable variables is ignored, if the errors $\varepsilon_{i,t}$ is still not independent across units, obviously this could lead to spurious estimates (Herzer & Vollmer, 2012). The literature suggests a large range of tests for the analysis of cross-sectional dependence. We applied one of the most widely used, the Pesaran (2004) cross-sectional dependency (CD) test. It is worth noting that the application of the Pesaran CD test, as well as its results, must follow certain key conditions. First, for any variable, the null hypothesis of cross-sectional independence must be tested. Second, for single or multiple breaks in slope coefficients, the researcher must test for robustness; and third, the Pesaran CD test must be performed before the root panel test, because the use of a particular root unit panel test depends on whether or not there is cross-sectional dependency (Alam et al., 2018). Table 3 below summarises the outcomes of the Pesaran CD test. It clearly shows a heavy cross-sectional dependence effect, except for the R&D variable. However, given that our main variables of interest – TFP and climate variability – show evidence of cross-sectional dependency, we perform the unit root test for our model.

Table 3. Cross-section dependence test

Pesaran CD	TFP	Cvar	R&D	Capital	Literacy	Labour
Statistic	21.55***	6.19***	-0.58	35.26***	13.08***	12.77

Note: Null hypothesis: No cross-section dependence. Levels of significance: * p < 0.1, ** p < 0.05, *** p < 0.01.

To evaluate the unit root properties, we use the Pesaran (2007) cross-sectional augmented IPS or CIPS panel unit root test of log(TFP_{it}), log($R\&D_{it}$), log($Capital_{it}$), log($labour_{it}$), log($Literacy_{it}$), and $Cvar_{it}$. This test allows cross-sectional dependency to be accomplished by increasing the normal ADF regression of cross-sectional averages of lagging levels and first-series discrepancies. It requires the measurement of separate cross-sectionally enhanced ADF (CADF) regressions for each region, allowing various autoregressive parameters for each panel member. Formally, the CADF regression model is given by:

$$\Delta y_{it} = y_{it}\gamma_i + p_i\, y_{it-1} + \sum_{j=1}^{ki} \varphi_{ij}\, \Delta y_{it-j} + \alpha_i \overline{y}_{it-1} + \sum_{j=0}^{ki} \eta_{ij}\, \Delta \overline{y}_{t-j} + \nu_{it} \tag{10}$$

where $\overline{y}_t$ is the mean cross-section of y_{it}, $\overline{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$. The null hypothesis is that each series comprises a root unit, H_0: $p_i=0$ for all i, while the alternative hypothesis is that there is trend or stationarity in at least one of the individual series in the panel, H_1:$p_i<0$ for at least one i. The CIPS statistic is determined as the average of the individual CADF statistics to test the null hypothesis against the alternate hypothesis:

$$CIPS = N^{-1}\sum_{i=1}^{Ni} t_i \tag{11}$$

In the above CADF regression, t_i is the OLS t-ratio of ρ_i. Pesaran (2007) tabulates critical values. The test results for the variables in levels and first differences are shown in Table 4 below.

Table 4. Pesaran-2007 CIPS panel unit root test

	At Level		At First Difference	
Variables	Constant	Constant with trend	Constant	Constant with trend
TFP	-5.117***	-5.129***	-5.981***	-6.114***
Cvar	-4.239***	-4.661***	-5.619***	-5.597***
R&D	-2.868***	-3.064***	-4.725***	-4.766***
Capital	-2.070***	-2.241	-4.075***	-4.454***
Literacy	-1.594	-2.101	-2.689***	-3.218***
Labor	1.146	-2.666	-3.743***	-4.232***

Note: ***’ ** Rejection of null hypothesis of non-stationary at the 1% and 5% level of significance, respectively.

The null hypothesis that log(TFP_{it}), log($R\&D_{it}$), log($Capital_{it}$), log($labor_{it}$), log($Literacy_{it}$), and $Cvar_{it}$ have a unit root in levels is not refuted by the CIPS test statistics. Since the unit root hypothesis can be ruled out for the first difference, it is fair to say that the variables are of order 1, I(1). Therefore, the next step in our study was examining whether our panel data have structural breaks.

5.4 Test for Structural Breaks and Robustness

Seasonal rainfall variability is inevitably reflected in highly variable production levels in systems that rely on rainfall as the sole source of moisture for crop development. While seasonal precipitation levels and their variations are important in and of themselves, the nature of 'in-season fluctuations can have major effects on crop productivity (Cooper et al., 2008). Visual observation of rainfall variability and agricultural TFP for the 14 SSA countries (depicted in Figure 1 below) provides some evidence that kinks exist, most notably in 2006 and 2014 for this study. Figure 1 below shows the annual agricultural TFP growth rate and rainfall variability from 1996 to 2016.

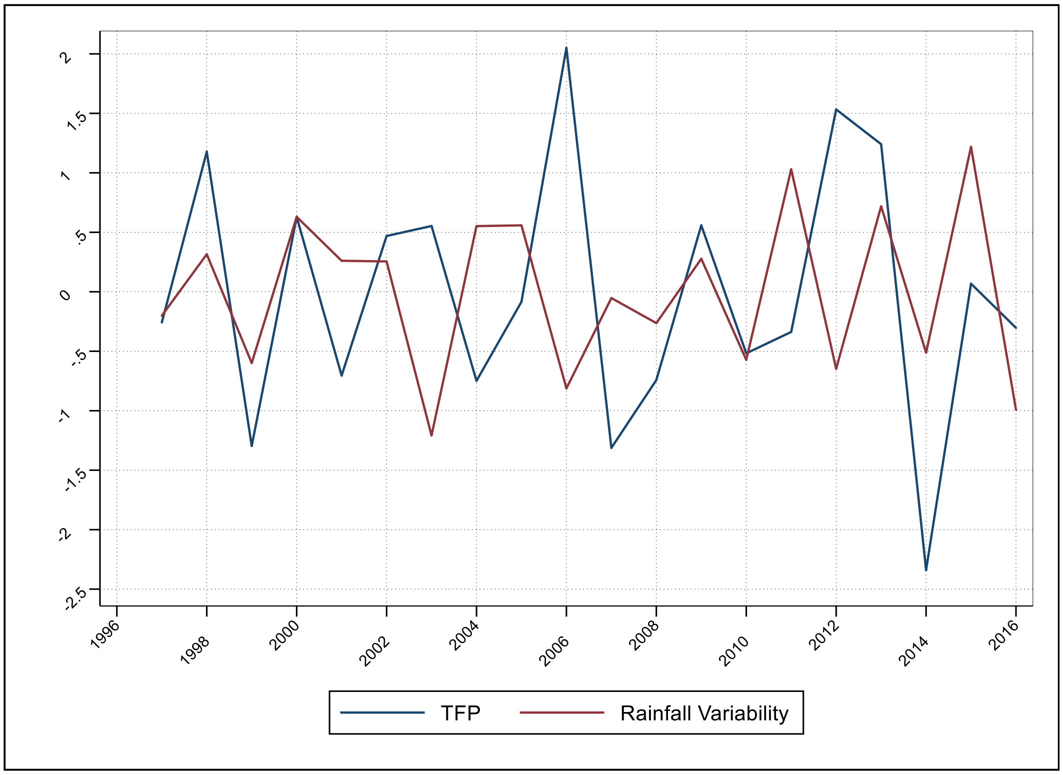

Figure 1. Annual rainfall variability and TFP growth rate in 14 SSA countries, 1996-2016

From Figure 1 above, it is evident that most of the time, when rainfall variability is lower (positive), agricultural TFP growth tends to be positive; but not when rainfall variability increases (e.g. in 1998 and 2014). Agricultural TFP growth tended to decrease in those periods. Therefore, we provide the econometric methodology suggested by Zivot and Andrews (1992) to confirm the structural breaks portrayed in Figure 1 above. The common issue with traditional unit root checks, such as the Pesaran Test in Table 4 above, is that they do not accept the likelihood of a structural break. As an example of an exogenous phenomenon, Perron (1989) revealed that the capacity to reject a unit root decreases when the stationary alternative is valid and a structural split is ignored. Supporting this, Zivot and Andrews (1992) proposed a modification of Perron's (1989) original test in which the exact time of the breakpoint is considered unknown. Instead, to determine the breakpoints, a data-dependent algorithm is used to proxy Perron's (1989) arbitrary method.

Zivot and Andrews began to analyze for a unit root with three models following Perron's understanding of the structural break form: (1) Model A, which allows a one-time shift in the sequence level; (2) Model B, which allows for a one-time shift in the trend function slope; and (3) Model C, which integrates one-time changes in the trend function level and trend function slope.

Zivot and Andrews (1992) used the following regression equations relating to these three models to calculate the root unit against the alternative of a one-time structural split.

$$\Delta y_t = z + \phi y_{t-1} + \beta t + \gamma DU_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t \qquad \text{(Model A)}$$

$$\Delta y_t = z + \phi y_{t-1} + \beta t + \delta DT_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t \qquad \text{(Model B)}$$

$$\Delta y_t = z + \phi y_{t-1} + \beta t + \delta DU_t + \gamma DT_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t \qquad \text{(Model C)}$$

where DU_t is the mean shift predictor variable occurring at each potential break-date (TB), and DT_t is the associated pattern shift variable. Hence, we obtain the following:

$$DU_t = \begin{cases} 1, & if\ t < TB \\ 0, & otherwise \end{cases} \text{ and}$$

$$DT_t = \begin{cases} t - TB, & if\ t < TB \\ 0, & otherwise \end{cases} \text{ and}$$

The null hypothesis in all three models is α=0, which implies that the series y_t contains a unit root with a drift that avoids any structural break; whereas the alternative hypothesis α<0 means that the sequence is a trend-stationary process that occurs with a one-time break at an arbitrary point in time. Each point is seen by the Zivot and Andrews approach as a potential break date (TB) and regresses sequentially with every potential break date. As a break date (TB), the procedure selects from all available breakpoints ($\overline{TB}$). For testing $\hat{\alpha}(= \alpha - 1) = 1$, the date minimizes the one-sided t-statistic. The presence of the endpoints causes the asymptotic distribution of the statistics to diverge into infinity, as noted by Zivot and Andrews (1992). In addition, it is also necessary to select a certain region in such a way that the sample endpoints are not used. Zivot and Andrews (1992) suggest that the 'trimming area' be defined as (0.15T, 0.85 T), which we follow in this study. Table 5 displays the results of the Zivot and Andrew unit root tests for our two main variables of interest: agricultural TFP and climate variability (as determined by rainfall variability). These findings indicate that after first differentiation, we can reject the null unit root for TFP in 12 countries at 1% and 5% significance stages, although we do not reject the unit root hypothesis for the remaining two countries (i.e. Ethiopia and Togo).

Table 5. Zivot-Andrews unit root test

	TFP					Cvar				
	At Level		At First Difference			At level		At First Difference		
Country	Statistic	Level sign 1%(5%)	Statistic	Level sign 1%(5%)	Break year	Statistic	Level sign 1%(5%)	Statistic	Level sign 1%(5%)	Break year
Benin	-4.100	-4.93(-4.42)	-4.918**	-4.93(-4.42)	2004	-3.712	-4.93(-4.42)	-7.045***	-4.93(-4.42)	2009
Botswana	-3.451	-4.93(-4.42)	-6.172***	-4.93(-4.42)	2007	-4.922**	-4.93(-4.42)	-6.704***	-4.93(-4.42)	2012
Burkina Faso	-4.157	-4.93(-4.42)	-6.247***	-4.93(-4.42)	2007	-6.360***	-4.93(-4.42)	-5.763***	-4.93(-4.42)	2010
Ivory Coast	-4.525**	-4.93(-4.42)	-7.034***	-4.93(-4.42)	2007	-6.602***	-4.93(-4.42)	-4.960***	-4.93(-4.42)	2011
Ethiopia	-4.780**	-4.93(-4.42)	-4.053	-4.93(-4.42)	2005	-4.495**	-4.93(-4.42)	-5.742***	-4.93(-4.42)	2003
Ghana	-6.388***	-4.93(-4.42)	-10.411***	-4.93(-4.42)	2007	-5.621***	-4.93(-4.42)	-8.239***	-4.93(-4.42)	2010
Kenya	-9.793***	-4.93(-4.42)	-5.800***	-4.93(-4.42)	2000	-7.164***	-4.93(-4.42)	-6.280***	-4.93(-4.42)	2006
Malawi	-5.698***	-4.93(-4.42)	-6.449***	-4.93(-4.42)	1999	-5.738***	-4.93(-4.42)	-5.824***	-4.93(-4.42)	1999
Mali	-8.828***	-4.93(-4.42)	-7.764***	-4.93(-4.42)	2008	-5.238***	-4.93(-4.42)	-5.320***	-4.93(-4.42)	2003
Niger	-6.232***	-4.93(-4.42)	-11.701***	-4.93(-4.42)	1999	-4.890**	-4.93(-4.42)	-5.395***	-4.93(-4.42)	2003
Nigeria	-5.658***	-4.93(-4.42)	-6.991***	-4.93(-4.42)	2013	-7.218***	-4.93(-4.42)	-4.806**	-4.93(-4.42)	2009
South Africa	-5.903***	-4.93(-4.42)	-5.725***	-4.93(-4.42)	2013	-4.711**	-4.93(-4.42)	-6.861***	-4.93(-4.42)	2013
Togo	-3.942	-4.93(-4.42)	-4.216	-4.93(-4.42)	2011	-4.148	-4.93(-4.42)	-5.620***	-4.93(-4.42)	2011
Zambia	-3.779		-5.454***		2011	-5.867***	-4.93(-4.42)	-6.588***	-4.93(-4.42)	2013

Note: Levels of significance: ** $p < 0.05$, *** $p < 0.01$.

At the same time, for each of the variables employed in this analysis the test endogenously determines the point of the single most important structural break ($\overline{TB}$). Table 5 below shows the break year for each element. Furthermore, in addition to cross-sectional dependence, unit root, and structural break tests, we use the Westerlund (2007) method as a robustness check for cointegration. Four panel-based statistics test the null hypothesis of no cointegration by inferencing the Westerlund (2007) approach if the conditional panel VECM error-correction model is equal to zero (Persyn & Westerlund, 2008). More specifically, the Westerlund test specifies whether error correction occurs for individual panel units or the entire system. It consists of two categories of statistics, with each group having two statistics. In the first category, the two statistics are referred to as panel statistics (Pt, Pa). Both are obtained by pooling information along the panel's cross-sectional dimension corresponding to the error correction term. The two statistics in the second group are also known as the group mean statistics (Gt, Ga). Table 6 below shows the results of the Westerlund test.

Table 6. Westerlund ECM Panel cointegration test

Test Statistic	Value	Probability value
Gt	-4.514***	0.000
Ga	-10.618	0.705
Pt	-15.807***	0.000
Pa	-10.992*	0.082

Note – Alternative: the panel is cointegrated as a whole for G-tests, at least one unit is cointegrated for P-tests. Levels of significance: ** p < 0.05, *** p < 0.01.

Table 6 above shows the findings of the Westerlund Cointegration Test. Three of four measures dismiss the null hypothesis based on bootstrapped critical values of 1% and 10%, thereby supporting the existence of cointegration in our panel.

5.5 Testing for cointegration: the Gregory-Hansen approach

While the existence of cointegration in our panel is confirmed by previous tests, one should also be careful to reject the null hypothesis of no cointegration. We use the Gregory-Hansen (1996) cointegration approach for a further robustness check, which also accommodates potential systemic breaks and thus applies to those countries (i.e. Ethiopia and Togo) for which we were unable to find cointegration using the Zivot and Andrews (1992) process. We adopt the single-equation approach of Gregory and Hansen (1996) following Herzer et al. (2006) and not the system-based approach, since structural breaks can be more clearly modelled using single equations. Furthermore, while system-based approaches usually require prior knowledge of the breaking point, the Gregory-Hansen cointegration technique allows for an unknown structural break. The following models are suggested by Gregory and Hansen (1996):

The level shift model (C):

$$y1_t = \mu_1 + \mu_2\varphi_{t\tau} + \alpha_1^T y2_t + \varepsilon_t \tag{12}$$

The slope change model (C/T) :

$$y1_t = \mu_1 + \mu_2\varphi_{t\tau} + \beta t + \alpha_1^T y2_t + \varepsilon_t \tag{13}$$

And the regime shift model (C/S):

$$y1_t = \mu_1 + \mu_2\varphi_{t\tau} + \beta t + \alpha_2^T y2_t\varphi_{t\tau} + \varepsilon_t \tag{14}$$

where $y1_t$ represents TFP, $y2_t$ indicates climate variability, μ_1 and α_1 are intercepts and slope coefficients before the shift, and μ_2 and α_2 denote changes to the intercept and slope coefficients at the time of the shift. The dummy variable $\varphi_{t\tau}$ is defined by:

$$\varphi_{t\tau} = \begin{cases} 0, & if\ t \leq [\eta\tau] \\ 1, & if\ t > [\eta\tau] \end{cases}$$

where the unknown parameter $\tau \in (0, 1)$ denotes the relative timing of the break, and the integer part is denoted by [ ]. The breakpoint is estimated by calculating the models in the data set for each potential break date, saving the estimated residuals from each iteration, and choosing τ as the value for the estimated residuals that minimizes the unit root test statistics. If the absolute value of ADF is greater than the critical values stated by Gregory and Hansen (1996), we reject the null hypothesis of no cointegration. Table 7 below presents the results of the Gregory-Hansen cointegration test.

Table 7. Gregory-Hansen cointegration test results

	Level shift model		Slope change model		Regime shift model	
Country	ADF	1%(5%)	ADF	1%(5%)	ADF	1%(5%)
Benin	-6.42**[0]	-6.05(-5.56)	-7.77[0]***	-7.31(-6.84)	-4.96[1]	-6.92(-6.41)
Botswana	-4.99[0]	-6.05(-5.56)	-8.57[1]***	-7.31(-6.84)	-5.49[1]	-6.92(-6.41)
Burkina Faso	-4.41[1]	-6.05(-5.56)	-6.34[0]	-7.31(-6.84)	-4.91[1]	-6.92(-6.41)
Ivory Coast	-5.32[0]	-6.05(-5.56)	-5.89[0]	-7.31(-6.84)	-5.86[1]	-6.92(-6.41)
Ethiopia	-5.76[0]**	-6.05(-5.56)	-8.32[0]***	-7.31(-6.84)	-5.77[1]	-6.92(-6.41)
Ghana	-8.35[1]***	-6.05(-5.56)	-12.53[1]***	-7.31(-6.84)	-12.46[1]***	-6.92(-6.41)
Kenya	6.30[1]***	-6.05(-5.56)	-8.95[2]***	-7.31(-6.84)	-6.65[1]**	-6.92(-6.41)
Malawi	-6.16[1]***	-6.05(-5.56)	-6.91[0]	-7.31(-6.84)	-5.66[1]	-6.92(-6.41)
Mali	-9.42[0]***	-6.05(-5.56)	-11.37[0]***	-7.31(-6.84)	-5.43[1]	-6.92(-6.41)
Niger	-7.02[0]***	-6.05(-5.56)	-8.54[0]***	-7.31(-6.84)	-5.55[1]	-6.92(-6.41)
Nigeria	-6.64[0]***	-6.05(-5.56)	-7.95[0]***	-7.31(-6.84)	-5.87[1]	-6.92(-6.41)
South Africa	-6.27[0]***	-6.05(-5.56)	-6.93[0]**	-7.31(-6.84)	-6.26[1]	-6.92(-6.41)
Togo	-5.10[2]	-6.05(-5.56)	-6.84[2]**	-7.31(-6.84)	-4.62[1]	-6.92(-6.41)
Zambia	-6.57[0]***	-6.05(-5.56)	-7.76[0]***	-7.31(-6.84)	-6.73[1]**	-6.92(-6.41)

Numbers in brackets indicate the number of lags. *** (**) indicates a rejection of the null of no cointegration at the 1% (5%) level.

As can be seen, for Benin, Ethiopia, Ghana, Kenya, Malawi, Mali, Niger, South Africa, and Zambia, the Gregory-Hansen test rejects the null hypothesis of no cointegration at 1% and 5% significance levels in the level shift model. When we look at the slope shift model, however, we see that cointegration was found in Benin, Botswana, Ethiopia, Ghana, Kenya, Mali, Niger, Nigeria, South Africa, Togo, and Zambia. In 11 countries, except for Ghana, Kenya, and Zambia, the regime-change model rejected the null hypothesis of no cointegration. What is consistent with the results in Table 6 above is that two countries (i.e. Burkina Faso and Ivory Coast) showed no cointegration in any of the three models. We, therefore, estimated our long-run relationships using all countries except Burkina Faso and Ivory Coast.

5.6 Estimating the long-run relationships

After discovering that TFP and climate variability are cointegrated in Benin, Botswana, Ethiopia, Ghana, Kenya, Malawi, Mali, Niger, Nigeria, South Africa, Togo, and Zambia, the next step in our study was to estimate the long-run relationship between these variables. To do so, we employed Pedroni's (2000) fully modified ordinary least squares (FMOLS) technique. This approach accommodates considerable heterogeneity across each sampling unit and addresses the endogeneity and serial correlation problem of the fitting errors. The methodology is also robust for the exclusion of factors (omitted variables) not used in the relationship of cointegration. We began by defining the standard form of the pooled OLS panel estimator before defining the FMOLS model, to be calculated as follows:

$$Y_{i,t} = \varphi_i + \lambda X_{i,t} + \varepsilon_{i,t} \qquad (15)$$

where $Y_{i,t}$, which represents our dependent variable TFP, is a matrix (1,1), λ represents a coefficient vector of (k,1), $\varphi_{i,t}$ indicates a vector of cross-unit factor heterogeneity, and $\varepsilon_{i,t}$ is a stationary idiosyncratic error term vector. Furthermore, $X_{i,t}$ – a vector of our independent variables – is presumed to be a first-order integrated process for all units (i), with $X_{i,t}$ given as $X_{i,t} = X_{i,t-1} + \mu_{i,t}$. Hence, as Phillip (1995) observed, by correcting the OLS estimator for endogeneity in addition to serial correlation, the FMOLS estimator is constructed. The FMOLS equation is thus defined as:

$$\hat{\vartheta}_{FM} = \sum\nolimits^{N}_{i=1}\sum\nolimits^{T}_{i=1}(X_{i,t} - \bar{X}_{i,t})(X_{i,t} - \bar{X}_{i,t})^{1}]^{-1}[\sum\nolimits^{N}_{i=1}(\sum\nolimits^{T}_{t=1}(X_{i,t} - \bar{X}_{i})Y_{i,t}^{*} + T\bar{\delta}^{*}_{ECT})] \qquad (16)$$

where the transformed vector of $Y_{i,t}$, is $Y_{i,t}^{*}$. This transition is performed to accomplish the correction of endogeneity, and the term $\bar{\delta}^{*}_{ECT}$ helps the predicted errors to be corrected for the serial correlation. The results for the FMOLS estimates for the coefficients for agricultural TFP and other explanatory variables are presented below in Tables 8 and 9. Table 8 demonstrates the existence of a statistically significant long-run cointegrating relationship between TFP and climate variability.

Table 8. Long-run relationships: FMOLS for the 14 countries

logTFP	Coef.	Probability value
Cvar	-0.008(0.003)	0.011
R&D	-1.563(0.026)	0.000
Capital	0.904(0.027)	0.000
Labor	-0.102(0.027)	0.000
Literacy	0.894(0.065)	0.000
Constant	-1.795(0.513)	0.000

Note: Standard errors in parentheses (), *** p<0.01, ** p<0.05, * p<0.1

However, these results implicitly assume that the relationship between TFP growth and climate variability is identical across all 14 countries. That is, a 10% increase in climate variability, all things being equal, reduces agricultural TFP growth across all 14 countries by about 0.08%. As a result, substantial differences between countries in the relationship between agricultural TFP growth and climate variability can lead to highly misleading results, as shown in Table 8 above. To avoid this trend seen in the literature, we estimated the country-specific relationships, and the results are presented in Table 9 below.

Table 9. Long-run relationships: FMOLS based on cointegration test results.

	Dependent Variable: logTFP				
Country	Cvar	R&D	Capital	Labor	Literacy
Benin	0.022(0.000)***	-3.279(0.001)***	0.174(0.000)***	4.773(0.002)***	-1.462(0.001)***
Botswana	0.199(0.000)***	0.969(0.001)***	-0.023(0.000)***	0.302(0.001)***	-2.592(0.007)***
Ethiopia	-0.040(0.000)***	-0.891(0.004)***	-0.375(0.000)***	4.987(0.000)***	-1.529(0.008)***
Ghana	0.039(0.000)***	-0.718(0.000)***	1.139(0.000)***	5.953(0.000)***	-8.723(0.008)***
Kenya	0.165(0.000)***	-0.229(0.000)***	0.116(0.000)***	1.126(0.000)***	-2.408(0.001)***
Malawi	0.322(0.000)***	0.496(0.000)***	-1.826(0.000)***	2.468(0.000)***	-3.605(0.014)***
Mali	-0.226(0.000)***	0.829(0.000)***	-2.209(0.000)***	5.288(0.000)***	-3.143(0.000)***
Niger	-0.207(0.000)***	0.701(0.000)***	0.186(0.000)***	-2.726(0.000)***	1.219(0.000)***
Nigeria	0.042(0.000)***	0.102(0.000)***	0.188(0.000)***	1.453(0.000)***	0.178(0.000)***
South Africa	-0.083(0.000)***	0.920(0.000)***	0.818(0.000)***	1.920(0.000)***	9.016(0.000)***
Togo	0.259(0.000)***	-1.667(0.000)***	-1.202(0.000)***	2.990(0.000)***	-4.541(0.000)***
Zambia	-0.141(0.000)***	-0.478(0.000)***	1.078(0.000)***	-10.004(0.000)***	-5.065(0.000)***

Note: Standard errors in parentheses (), *** $p<0.01$, ** $p<0.05$, * $p<0.1$

These results indicate that the coefficient of climate variability is statistically significant and negatively associated with agricultural TFP in the long run for five countries, namely Ethiopia, Mali, Niger, South Africa, and Zambia. That is, all things being equal, a 10% increase in climate variability will reduce agricultural TFP by 2.26% in Mali, 2.07% in Niger, 1.41% in Zambia, 0.83% in South Africa, and 0.4% in Ethiopia. However, the long-run relationship between climate variability and agricultural TFP was positive and statistically significant in seven countries, namely Benin, Botswana, Ghana, Kenya, Malawi, Nigeria, and Togo. In particular, a 10% increase in climate variability, all things being equal, is expected to increase agricultural TFP by 3.22% in Malawi, 2.59% in Togo, 1.99% in Botswana, 1.65% in Kenya, 0.42% in Nigeria, 0.39% in Ghana, and 0.22% in Burkina Faso. The significant differences between countries, regarding the long-term impact of climate variability and agricultural TFP growth nexus, indicate how misleading our results in Table 7 above can be. Climate variability aside, the results indicate that there also exists a long-run relationship between agricultural TFP and the control variables (i.e. capital, labor, R&D, and literacy) employed in our study. In particular, spending on R&D was found to reduce agricultural TFP by the elasticity of 3.279 in Benin, 0.891 in Ethiopia, 0.718 in Ghana, 0.229 in Kenya, 1.667 in Togo, and 0.478 in Zambia. At the same time, the variable was found to increase agricultural TFP by the elasticity of 0.969 in Botswana, 0.496 in Malawi, 0.892 in Mali, 0.701 in Niger, 0.102 in Nigeria, and 0.920 in South Africa.

From Table A2 in the Appendix, we include the two countries (Burkina Faso and Ivory Coast) that were found to show no long-run relationship in any of our three models in the Gregory-Hansen test; but this still does not change the coefficients of our key variables in Table 9 above. Our findings confirm those of such as Exenberger and Pondorfer (2011), who showed that climate change has harmed agricultural development in SSA. In a fixed-effects model, rainfall has a major positive and necessary impact when traditional (labor, soil, and livestock), as well as modern (capital and fertiliser) inputs, are considered. However, Exenberger and Pondorfer (2011) observed that different relationships between the standard factors can be revealed by dividing countries into low and MedTech zones (in terms of modern inputs). At the same time, Barrios et al. (2008) demonstrated that overall, climate change is a major determinant of SSA agricultural production. However, Barrios et al. (2008) did so using sub-regional aggregation in their study, rather than a comparison between countries. They observed that this could be problematic, as the cross-country aggregation modeling technique has the shortcoming of not capturing within-country variations. Therefore, country-specific characteristics are reduced to regional means. Our findings shed light on this shortcoming in the literature, as countries within the same region were observed to witness the varying impact of climate variability on agricultural productivity in the long run, given that country-specific characteristics are not uniform. Next, we focused on estimating short-run causality (as practiced in the literature) between agricultural TFP and climate variability.

5.7 Short-run causality test

For short-run causality, we use the Emirmahmutoğlu and Kose (2011) Granger causality test in heterogeneous mixed panels to estimate the direction of the short-run causality between agricultural TFP and climate variability. This test is the panel variant for the well-known Toda and Yamamoto (1995) Granger time-series causality test. By taking into account cross-sectional variability, the test makes it possible to determine panel causality between two variables without having to analyze whether the time series of units in the panel is non-stationary or cointegrated (Espoir and Ngepah, 2021). In addition, cross-sectional dependency is taken into account in this system, and Monte Carlo simulations are used to compute the critical values of panel statistics. Thus, a level Vector Autoregressive (VAR) model with $f_i + d\max_i$ is defined to test for Granger causality in heterogeneous mixed and cross-sectional based panels, as follows:

$$X_{i,t} = \gamma_i^x + \sum_{j=1}^{fi+dmax} C_{11,ij} X_{i,t-j} + \sum_{j=1}^{fi+dmax} C_{12,ij} y_{i,t-j} + \varepsilon^x_{i,t} \tag{17}$$

$$Y_{i,t} = \gamma_i^{y} + \sum_{j=1}^{fi+dmax} C_{21,ij} X_{i,t-j} + \sum_{j=1}^{fi+dmax} C_{22,ij} y_{i,t-j} + \varepsilon^{y}_{i,t} \quad (18)$$

where for each i, $d$max is the highest order of integration assumed to occur in the system. In simple terms, we concentrate on checking causality in Equation (14) above from y to x, that is from climate variability to agricultural TFP; and the causality of x to y, that is from agricultural TFP to climate variability in Equation (15) above, by using the same related technique. As shown in Emirmahmutoğlu and Kose (2011), to evaluate the maximum order of integration ($d\text{max}_i$) of the two variables of interest in the VAR method for each country, we used the standard Dickey and Fuller (1981) unit root test. The findings of this test for the panel, as well as the $d\text{max}_i$ values for agricultural TFP and climate variability, are presented in Table 10 below. The Augmented Dickey-Fuller (ADF) p-values are reported for the series levels and first differences. In the VAR system, the cumulative order of integration ($d\text{max}_i$) is determined as 1 for six countries in our panel, and 2 for the remaining countries, depending on whether significance was attained in level or in first differencing for TFP and climate variability.

Table 10. Results of ADF unit root test (model with intercept)[a]

	lnTFP		Cvar		lnR&D		lnCapital		lnLabor		lnLiteracy		
Country	Level	1st Diff	Level	1st Diff	Level	1st Diff	Level	1st Diff	Level	1st Diff	Level	1st Diff	$d\ max_i$
Benin	0.030[C]	-	0.036[C]	-	0.230	0.000[b]	0.061[C]	-	0.627	0.000[b]	0.964	0.483	1
Botswana	0.031[C]	-	0.098	-	0.750	0.000[b]	0.076[C]	-	0.236	0.023[b]	0.001[b]	-	2
Burkina Faso	0.007[b]	-	0.032[C]	-	0.627	0.000[b]	0.859	0.000[b]	0.389	0.333	0.060[C]	-	1
Ivory Coast	0.040[C]	-	0.397	-	0.004[b]	-	0.229	0.000[b]	0.483	0.000[b]	0.059[C]	-	2
Ethiopia	0.007[b]	-	0.136	-	0.350	0.004[b]	0.135	0.028[C]	0.941	0.000[b]	0.771	0.015[b]	2
Ghana	0.000[b]	-	0.366	-	0.038[C]	-	0.536	0.174	0.063[C]	-	0.005[b]	-	2
Kenya	0.000[b]	-	0.001[b]	-	0.170	0.002[b]	0.829	0.000[b]	0.827	0.469	0.596	0.376	1
Malawi	0.000[b]	-	0.008[b]	-	0.897	0.002[b]	0.814	0.028[b]	0.924	0.007[b]	0.145	0.014[b]	1
Mali	0.028[C]	-	0.032[C]	-	0.066[C]	-	0.179	0.000[b]	0.600	0.234	0.425	0.089[C]	1
Niger	0.007[C]	-	0.003[b]	-	0.554	0.000[b]	0.956	0.024[b]	0.029[b]	-	0.985	0.180	1
Nigeria	0.047[C]	-	0.190	0.000[b]	1.000	0.000[b]	0.975	0.045[C]	0.696	0.009[b]	0.714	0.071[C]	2
South Africa	0.052[C]	-	0.135	0.000[b]	0.321	0.030[C]	0.367	0.717	0.927	0.000[b]	0.995	0.950	2
Togo	0.028[C]	-	0.129	0.000[b]	0.089	0.000[b]	0.187	0.003[b]	0.451	0.000[b]	0.526	0.467	2
Zambia	0.014[b]	-	0.224	0.000[b]	0.297	0.001[b]	0.989	0.080[C]	0.619	0.284	0.315	0.212	2

[a] The values in the Table are MacKinnon's (1996) one-sided p-value. [b] Rejects the null hypothesis of unit root at 5%. [c] Rejects the null hypothesis of unit root at 10%

Furthermore, Emirmahmutoğlu and Kose (2011) demonstrated that a slight transformation of equations (14) and (15) is sufficient for a robust test of no causality in the null hypothesis. For example, OLS under the null hypothesis of no causality ($C_{21,ij}=\ldots=C_{22,ij}=0$) in equation (15) can be rewritten, and the estimation of the residuals for each unit can be determined as follows:

$$\hat{\delta}^{y}_{i,t} = y_{i,t} - \hat{\delta}^{y}_{i} - \sum_{fi+1}^{fi+dmax} \hat{\alpha}_{21,ij}X_{i,t-j} - \sum_{j=1}^{fi+dmax} \hat{\alpha}_{22,ij}y_{i,t-j} \quad (19)$$

In addition, following Stine (1987), the residuals in equation (16) are centered as follows:

$$\hat{\delta}_{t} = \hat{\delta}_{t} - (T- q - h - 2)^{-1}\sum_{t=q+h+2}^{T} \hat{\delta}_{t} \quad (20)$$

where $\hat{\delta}_{t} = (\hat{\delta}_{1}, \hat{\delta}_{2} \ldots \hat{\delta}_{NT})^{1}$, $q=\max_{qi}$ and $h=\max d\max_{i}$. Therefore, to test the null hypothesis, a bootstrapping sample of the following is constructed:

$$y_{i,t}^{*} = \hat{\delta}^{y}_{i} - \sum_{j=fi+1}^{fi+dmax} \hat{\alpha}_{21,ij}X_{i,t-j} - \sum_{j=1}^{fi+dmax} \hat{\alpha}_{22,ij}y^{*}_{i,t-j} + \hat{\varepsilon}^{*}_{i,t} \quad (21)$$

where $\hat{\delta}^{y}_{i}$, $\hat{\alpha}_{21,\,ij}$ and $\hat{\alpha}_{22,\,ij}$ are estimates from Equation (16), and $\hat{\varepsilon}^{*}_{i,t}$ are residuals from the bootstrap. Therefore, to test the null hypothesis of Granger no causality against an alternative of Granger causality, cross-country Wald statistics were computed. The findings regarding short-run causalities for the 14 countries are presented in Table 11 below. In this table, for each country, k_i represents the number of acceptable lag orders in level VAR systems.

Table 11. Emirmahmutoğlu and Kose (2011) Granger causality test

Country	k_i	Cvar → TFP W_i	Cvar → TFP p_i	Country	k_i	TFP → Cvar W_i	TFP → Cvar p_i
Benin	1	0.001	0.971	Benin	1	0.001	0.970
Botswana	1	0.143	0.705	Botswana	1	0.135	0.713
Burkina Faso	1	0.104	0.747	Burkina Faso	1	0.007	0.934
Ivory Coast	1	0.003	0.955	Ivory coast	1	0.001	0.978
Ethiopia	1	0.011	0.916	Ethiopia	1	0.016	0.898
Ghana	1	0.033	0.856	Ghana	1	0.042	0.838
Kenya	1	0.010	0.922	Kenya	2	0.000	0.990
Malawi	1	0.343	0.558	Malawi	1	0.319	0.572
Mali	1	2.533	0.772	Mali	1	0.234	0.999
Niger	2	0.150	1.000	Niger	1	7.170	0.208
Nigeria	1	1.313	0.934	Nigeria	1	4.287	0.509
South Africa	1	0.067	0.795	South Africa	1	0.067	0.796
Togo	1	0.009	0.923	Togo	1	0.025	0.874
Zambia	1	0.000	0.997	Zambia	2	0.001	0.981
Fisher test statistic (λ):		4.527		Fisher test statistic (λ):		7.877	

Table 11 above shows that both the null hypothesis of Granger no causality from climate variability to agricultural TFP and Granger no causality from agricultural TFP to climate variability cannot be dismissed for all 14 nations, even at the 10% significance level. In other words, climate variability tends to have no major effect on agricultural TFP in all the 14 countries in the short run; and at the same time, agricultural TFP does not affect climate variability in any of the 14 countries.

6. Conclusions and policy implications

The long- and short-run climate variability-agricultural TFP growth nexus for 14 SSA countries was explored in this report. As opposed to the growth accounting methodology, we used the Malmquist Productivity Index (MPI) to produce agricultural Maize TFP indices, because it accounts for technical performance, technological innovation, changes in pure efficiency, and changes in scale efficiency. As suggested by Pedroni (2000), we then used a completely updated FMOLS estimator and the Granger causality test of Emirmahmutoğlu and Kose (2011) in heterogeneous mixed panels to assess the long- and short-term effects of climate variability on the growth of agricultural TFP. To allow for a possible structural break in the cointegration relationship, we used cointegration tests proposed by Zivot and Andrews (1992) and Gregory and

Hansen (1996). We estimated the coefficients of the long- and short-run relationships in the presence of cointegration.

Our findings show that climate variability for five nations – namely Ethiopia, Mali, Niger, South Africa, and Zambia – is statistically important and negatively correlated with agricultural TFP growth in the long run. That is, a 10% rise in climate variability decreases agricultural TFP by 2.26% in Mali, 2.07% in Niger, 1.41% in Zambia, 0.83% in South Africa, and 0.4% in Ethiopia, all things being equal. However, at the same time, our findings reveal that climate variability has a positive and statistically significant effect on agricultural TFP growth in seven countries, namely Benin, Botswana, Ghana, Kenya, Malawi, Nigeria, and Togo. In particular, a 10% rise in climate variability, all things being equal, is projected to increase agricultural TFP by 3.22% in Malawi, 2.59% in Togo, 1.99% in Botswana, 1.65% in Kenya, 0.42% in Nigeria, 0.39% in Ghana, and 0.22% in Burkina Faso. The significant differences between countries regarding the long-term impact of the climate variability-agricultural TFP growth nexus indicate misleading results from previous studies which implicitly assumed that the relationship between TFP growth and climate variability is identical across countries.

Our empirical findings may serve as a guide for governments and agricultural development policy practitioners in SSA, in the robust design and implementation of resilient climate adaption strategies among farmers. In light of this, urgent and appropriate steps are required to improve the sustainability of food crop cultivation, by taking into account the actual and expected impacts of climate change. Based on the empirical results, this study recommends critical adaptation measures to be considered by public and private partners to resolve the threats that farmers are expected to face because of climate change. In particular, these initiatives should include farming techniques in line with zone-specific climate change conditions, the implementation of crop diversification activities, and the enhancement of agricultural extension services to communicate current climate-resilient adaptation programs to farmers. Furthermore, in those five countries where climate variability exhibits a negative long-run effect on maize TFP, policymakers should take immediate action to provide farmers with adequate and expeditious irrigation facilities, including the construction of dams, to harvest and store rainfall water for future use. In addition, it is important to state that the variables behind the observed climate variability-TFP relationship have not been clarified by this study. To understand the climate variability-TFP nexus, future studies could add new variables such as solar radiation.

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Appendix

Table A1. Average productivity growth and its components by country.

Country		TC	PEC	SEC	TFP
Benin	1.000	0.731	1.000	1.000	0.731
Botswana	1.006	0.741	1.005	1.001	0.746
Burkina Faso	1.000	0.820	1.001	1.000	0.820
Cote D'Ivoire	1.003	0.817	1.001	1.002	0.819
Ethiopia	1.000	0.817	1.000	1.000	0.878
Ghana	1.004	0.933	1.003	1.001	0.937
Kenya	0.999	0.839	0.998	1.002	0.839
Malawi	1.006	0.946	1.004	1.002	0.952
Mali	1.000	0.941	1.000	1.000	0.941
Niger	1.000	0.980	1.000	1.000	0.980
Nigeria	0.999	1.000	1.001	0.998	0.999
South Africa	0.998	0.974	0.998	1.000	0.972
Togo	1.000	1.187	1.000	1.000	1.186
Zambia	0.999	1.169	0.999	1.000	1.168
Mean	**1.001**	**0.916**	**1.001**	**1.000**	**0.917**

Table A2. Long-run relationships: FMOLS for all 14 countries

	Dependent Variable: logTFP				
Country	Cvar	R&D	Capital	Labour	Literacy
Benin	0.022(0.000)***	-3.279(0.001)***	0.174(0.000)***	4.773(0.002)***	-1.462(0.001)***
Botswana	0.199(0.000)***	0.969(0.001)***	-0.023(0.000)***	0.302(0.001)***	-2.592(0.007)***
Burkina Faso	-0.270(0.00)***	0.160(0.0000***	0.118(0.000)***	-0.037(0.00)***	-0.350(0.00)***
Ivory Coast	0.103(0.003)***	0.541(0.028)***	-1.317(0.044)***	4.634(0.182)***	-1.461(0.082)***
Ethiopia	-0.040(0.000)***	-0.891(0.004)***	-0.375(0.000)***	4.987(0.000)***	-1.529(0.008)***
Ghana	0.039(0.000)***	-0.718(0.000)***	1.139(0.000)***	5.953(0.000)***	-8.723(0.008)***
Kenya	0.165(0.000)***	-0.229(0.000)***	0.116(0.000)***	1.126(0.000)***	-2.408(0.001)***
Malawi	0.322(0.000)***	0.496(0.000)***	-1.826(0.000)***	2.468(0.000)***	-3.605(0.014)***
Mali	-0.226(0.000)***	0.829(0.000)***	-2.209(0.000)***	5.288(0.000)***	-3.143(0.000)***
Niger	-0.207(0.000)***	0.701(0.000)***	0.186(0.000)***	-2.726(0.000)***	1.219(0.000)***
Nigeria	0.042(0.000)***	0.102(0.000)***	0.188(0.000)***	1.453(0.000)***	0.178(0.000)***
South Africa	-0.083(0.000)***	0.920(0.000)***	0.818(0.000)***	1.920(0.000)***	9.016(0.000)***
Togo	0.259(0.000)***	-1.667(0.000)***	-1.202(0.000)***	2.990(0.000)***	-4.541(0.000)***
Zambia	-0.141(0.000)***	-0.478(0.000)***	1.078(0.000)***	-10.004(0.000)***	-5.065(0.000)***

Note: Standard errors in parentheses (), *** p<0.01, ** p<0.05, * p<0.1

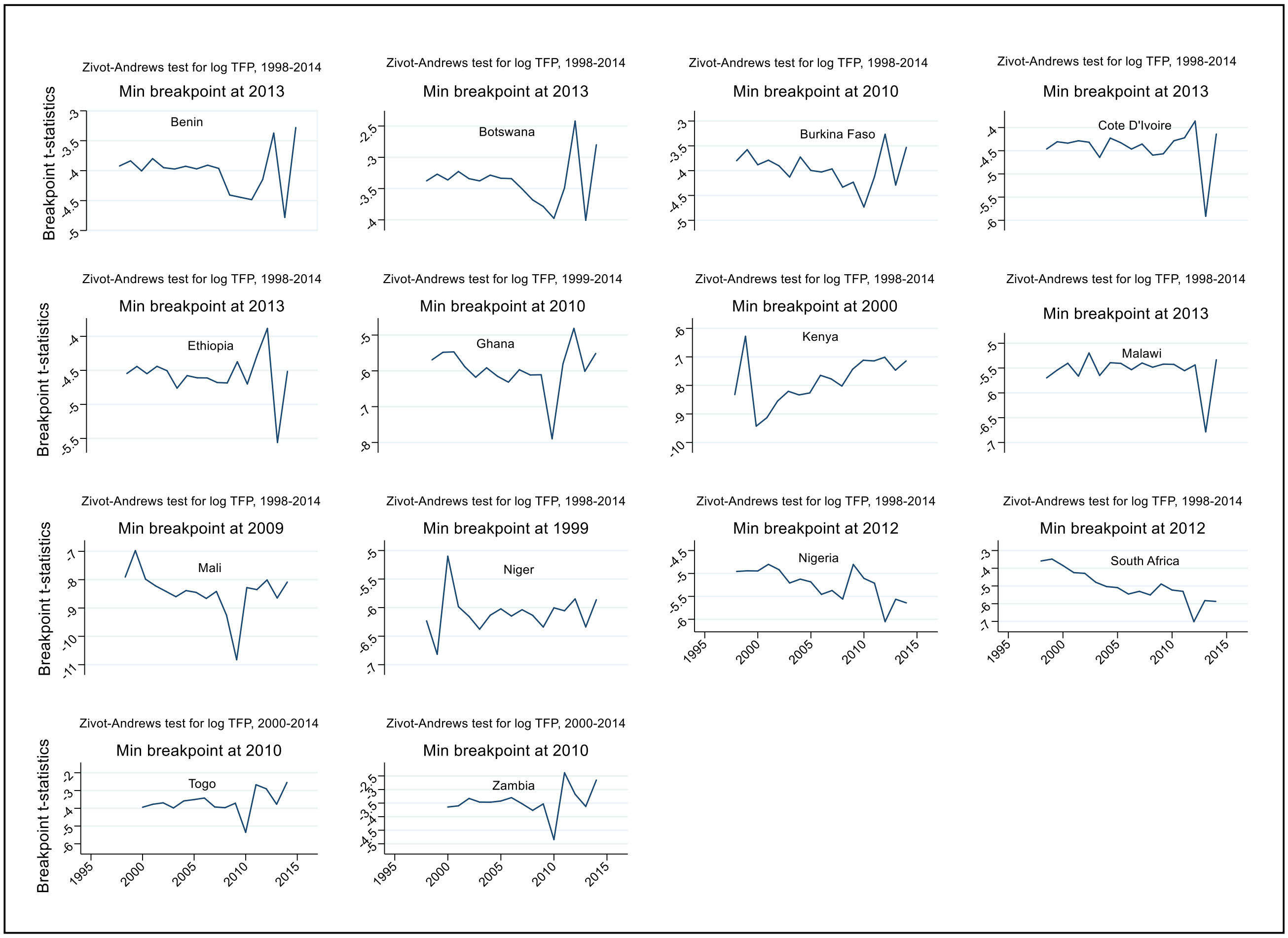

Figure A1. Zivot-Andrews test for structural breaks in TFP, 1996-2016

Figure A2. Zivot-Andrews test for structural breaks in rainfall variability, 1996-2016

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