Environmental Science and Pollution Research (2021) 28:30035–30045
https://doi.org/10.1007/s11356-021-12684-5

RESEARCH ARTICLE

The effects of climate change on African agricultural productivity growth revisited

Kolawole Ogundari[1] · Raphael Onyeaghala[2]

Received: 21 September 2020 / Accepted: 22 January 2021 / Published online: 13 February 2021
© The Author(s), under exclusive licence to Springer-Verlag GmbH, DE part of Springer Nature 2021

Abstract
This paper analyzes the effects of climate change on African agricultural total factor productivity (TFP) growth and test whether agricultural TFP levels are converging in the region. The study uses cross-country balanced panel data covering 35 countries from 1981 to 2010 and a technological catching-up model based on the Ricardian analysis estimated by Feasible Generalized Least Square (FGLS) regression. Historical country-wide rainfall and temperature are climate factors included in the model. Education, capital intensity, and arable land equipped with irrigation are other potential confounding variables in the regression. The empirical results show that levels of African agricultural TFP are converging over time, though the rate of convergence appears relatively slow in the region. We also find that rain significantly increases agricultural TFP growth, but temperature does not affect the study's African agricultural TFP growth. Other results show that education, capital intensity, and arable land equipped with irrigation significantly increased agricultural TFP growth.

Keywords Agriculture · Climate change · Convergence · Total factor productivity · Ricardian model · Africa

Introduction

Agriculture is strategic to achieving food security in Africa, which explains why interventions aimed at improving agricultural productivity are considered important programs to reduce poverty and enhance food security in the region (Ogundari 2014). It is also a significant source of employment and income in Africa (CTA 2012). Unlike other developing regions such as Latin American and South Asia, sustained productivity growth has remained a significant challenge in the African agricultural sector (Fuglie and Wang 2012). The World Bank (2007) revealed that failure to exploit the potential of agriculture in Africa could significantly compromise its role in reducing poverty and enhancing food security.

Responsible Editor: Philippe Garrigues

✉ Kolawole Ogundari
ogundarikolawole@daad-alumni.de

[1] Education Research and Data Center, Olympia, WA 98504, USA

[2] College of Business, Education & Professional Studies, Southwest Minnesota State University, 1501 State Street, Marshall, MN 56258, USA

POSTnote (2006) has stressed the significance of agricultural productivity in reducing poverty and food insecurity worldwide. Fuglie and Wang (2012) argued that improving agricultural productivity has been the world's primary defense against a recurring Malthusian crisis, which postulated that the needs of a growing world population outstrip humankind's ability to supply food. Because of this, agricultural productivity growth has long been considered as the key to overall economic growth worldwide (Alene 2010).

The agricultural total factor productivity (TFP) growth rate in Africa continues to lag behind that of the rest of the world. It fluctuates rapidly. Rosen et al. (2014) reported an annual average TFP change that declined an average of roughly 1% per annum from 1961 to 2010. Using 1970–2004 data for the region, Alene (2010) reported an average growth rate of 1.6%, while Yu and Nin-Pratt (2011) reported an average growth rate of 0.2% using 1960–2006 data. Interestingly, the TFP growth rates in some countries such as Ghana, Nigeria, Benin, Angola, and Malawi have been able to sustain moderate rates of improvement of more than 2% per year for the last two decades (Block 2010). The decline in the technical efficiency level component of the TFP is a significant cause of weak TFP growth in African agriculture (Yu and Nin-Pratt 2011; Alene 2010).

The speed at which agricultural productivity growth keeps pace with food demand growth is vital for global food security. An increase in agricultural productivity is critical to stimulate higher food output and lower food prices (Fuglie and Rada 2013), boost household and national income through increased trade (Awokuse and Xie 2015), and improved access to food (Rada et al. 2013). In addition to the speed, knowledge of the drivers of agricultural productivity growth and whether differences between countries that exist in agricultural productivity growth are prerequisites to meeting global food security challenges. Among the known factors based on the reviewed literature, the effect of climate change on agricultural productivity has gained serious attention among both academicians and government agencies in recent years (Barrios et al. 2008). The surge in global climate change has been linked to this, as it increases the potential for extreme weather events such as extended droughts or flash floods (World Bank 2007).[1]

The importance of temperature and rainfall as auxiliary climate factors on crop yield has been stressed by Cong and Brady (2012). At the same time, there is a slow but steady rise in temperature over the last few decades (Barrios et al. (2008), as a decline in rainfall since the half of the nineteenth century, has been noted in Africa (Nicholson 2001). The implication of this is that climate change has an enormous impact on agricultural productivity in developing countries (Rosenzweig and Parry 1994). Africa depends heavily on rainfed agriculture, making the region vulnerable to climatic shocks (Kotir 2011). About 60% and 30% of African countries are susceptible to drought and extreme weather, respectively (Benson and Clay 1998). IPPC (2007) report concluded that agricultural production and food security are likely to be severely compromised by climate change in many African countries. A literature review shows several studies have contributed to the policy discussion on agricultural productivity in Africa. Many of the studies focus on the estimation and decomposition of agricultural productivity using different methodologies and datasets with different periods (see Alene 2010; Yu and Nin-Pratt 2011; Lusigi and Thirtle 1997; Nkamleu 2004; Fuglie and Rada 2013; Nin-Pratte 2015; Rezek et al. 2011). In addition to decomposing agricultural productivity, other studies identify policy variables that are important in driving agricultural productivity in the region, such as education, research and development, political stability or governance, and capital intensities (Alene 2010; Allen and Qaim 2012; Block 2010; Fulginiti 2010; Rosen et al. 2014; Lusigi and Thirtle 1997).

Except for Barrios et al. (2008) and Exenberger et al. (2014), not much is known about the effects of climate change in African agriculture at cross-country levels.[2] We contribute to the literature on African agricultural development by investigating the impact of climate change in African agricultural total factor productivity (TFP) growth. The two studies focus on the effect of climate change on African agricultural production. Agricultural production refers to the value of total agricultural output or production. However, TFP use in the present study refers to the total agricultural production ratio to all inputs' aggregate contribution, reflecting the production process's overall sophistication (Beugelsdik et al. 2018). Conversely, TFP has always been considered a better and accurate measure of production progress or success to informed better policy decisions (Mozumdar 2012).

The study of convergence frenzy of an economic indicator such as per capita income or gross domestic product (GDP) is often used to show whether the standard of living of poor households improved or increased more rapidly relative to that of the wealthier households following Solow's (1956) seminar paper. The convergence hypothesis in agricultural productivity growth is essential for agricultural policy design at the regional level. Specifically, it provides proof of whether agricultural productivity growth increases faster in some areas than in others. Timmer et al. (2010) noted that convergence is critical to understand whether differences in agricultural productivity levels persist or even increase over time, as differences in TFP play an essential role in explaining income differences across countries (Hall and Jones 1999). Evidence of convergence in agricultural productivity growth could help food policymakers understand agricultural production trends.

There is a proliferation of studies that raises policy discussion on the convergence hypothesis in agricultural production across the globe in recent years (see Gutierrez 1999; Zhan et al. 2017; Rezitis 2005; Liu et al. 2011; Ball et al. 2014; Barath and Ferto 2017). Despite this, not much is known about the convergence hypotheses in Africa agriculture. There is still scarce literature on agricultural productivity convergence in the region except for the work carried out by Lusigi et al. (1998) and Thirstle et al. (2003). In contrast to Lusigi et al. (1998) that focuses on cross-country data in Africa, Thirstle et al. (2003) investigated convergence using cross-state data in Botswana. Therefore, we contribute to the literature on Africa's agricultural productivity by testing the convergence hypothesis using cross-country data in the region.

The remaining part of the paper is organized as follows. The next section presents the data used for the analysis. The

[1] Term climate change in this paper refers to a change in the mean of temperature and rainfall for an extended period.

[2] Although many studies have attempted to explore the effects of climate change on agricultural production or productivity for individual African countries or micro-level analysis (see Amare et al. 2018; Ochieng et al. 2016), the present study focuses on African context as a whole or macro-level analysis.

“Analytical framework” section reviews the analytical framework and empirical models, while the “Results and discussion” section presents the results and discussion. Concluding remarks are provided in the “Concluding remarks” section.

Data description and time-series property of the data

The data availability limits the analysis to 35 countries in Africa.[3] Due to data limitations, the study could only cover from 1981 to 2010. We obtain the country-specific total factor productivity index used in this paper from the United States Department of Agriculture Economic Research Services website (USDA-ERS 2018). The site provides information on how the average agricultural TFP index measured over time to a base-period index value for countries in Africa (for detailed information on how the TFP index was computed, see Fuglie 2012).

The data on the education was obtained from Barro and Lee’s educational attainment dataset in the World 1950–2010 (see Barro and Lee 2013). Agricultural labor, which is measured as an economically active population in agriculture (in thousands) and the value of the agricultural capital stock at 2005 constant price, were used to construct the capital-labor ratio. These were obtained from the FAOSTAT of the FAO database (see FAOSTAT 2018). The capital stock is the value of machinery and equipment and other non-residential structures on the farm (FAOSTAT 2018). We obtained information on the arable land equipped with irrigation as a proxy for irrigation from the FAOSTAT database for the empirical analysis (see FAOSTA, 2018).

Data on climate factors employed in the study include temperature and rainfall obtained from the World Bank Development indicator’s Climate Change Knowledge Portal (WDI 2018). However, we use the average long-run 5-year and 10-year interval to capture climate change in the study. We compute rain variability based on the variance of precipitation (rainfall) by years across the countries in the data. The data used for the empirical analyses are expressed in logarithms.

Table 5 in the appendix presents the variables’ summary statistics, while Table 6 shows the correlation matrix of the explanatory variables used in the regression.[4] Table 7 in the appendix shows the variance inflation factor (IVF) and condition index computed for each explanatory variable in regression as a robustness check to Table 6. The correlation coefficients among the explanatory variables are less than 0 in Table 6, suggesting that the multicollinearity problem is not severe for the estimated model. As a robustness check, the estimated IVF and condition index, which also measures the impact of collinearity among the explanatory variables, are smaller than 10 as a rule of thumb. The implication of this also is that multicollinearity is not exerting an undue influence on the results.

Analytical framework

Convergence hypothesis analysis in African agricultural TFP growth

In the most general sense, the convergence concept describes catching-up or equalizing disparities in an economic variable across regions or countries over time. The idea of convergence hypothesis has been applied to different economic indicators. This includes income or economic growth (see Sala-i-Martin 1996; Bassanini et al. 2001), agriculture (Ball et al. 2014; Barath and Ferto 2017; Rezitis 2005), nutrition (Ogundari and Ito 2015; Angulo et al. 2001), food security (Wan 2005; Borkowski et al. 2009), and poverty (Ravallion 2012; Ouyang et al. 2019). And this has been a very topical subject to investigate among economists over the years. The convergence concept is deep-rooted in two primary competitive theories—neoclassical growth theory (Solow 1956) and endogenous growth theory (Romer 1986).

The tests widely used for estimating the convergence hypothesis are beta-convergence and sigma-convergence analyses. Beta-convergence refers to a catch-up process of economic variables when regions/countries with low initial conditions tend to grow faster than regions/countries with high initial conditions in the long run (Sala-i-Martin 1996). Sigma-convergence measures the reduction in economic variables’ dispersion across countries/regions (Philips and Sul 2007). In other words, the beta-convergence describes the pace of particular economies in reaching the state of long-term equilibrium. Simultaneously, the sigma-convergence reflects more about reducing disproportions in the level of economic variables across economies. Beta-convergence is a necessary but not a sufficient condition for sigma-convergence (Lichtenberg 1994).[5] However, two well-known frameworks for implementing beta-convergence analyses are unconditional (absolute) and conditional convergence.[6] According to Paas

[3] The countries included in the sample are Angola, Benin, Botswana, Burkina-Faso, Burundi, Cameroon, Chad, Cote’d’ Ivoire, Ethiopia, Gabon, Guinea, Gambia, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Swaziland, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.

[4] The data that support the findings of this study are available from the corresponding author upon reasonable request.

[5] Beta-convergence does not necessarily mean sigma-convergence, but they are complementary.

[6] Sigma-convergence has always been estimated using the absolute convergence framework.

et al. (2007), absolute convergence exists when countries or regions converge with one another in the long-term regardless of the initial conditions, while conditional convergence exists when countries or regions converge with one another in the long term provided their structural characteristics are identical.

Another convergence test that allows for a wide range of possible time paths and individual heterogeneity is club convergence (Philips and Sul 2007; Paas et al. 2007). Club convergence exists when regions or countries similar in both their structural characteristics and initial factors converge with one another in the long term (i.e., common steady-state). However, club convergence is analogous to sigma-convergence. Because the catching-up process (i.e., beta-convergence) rather than a reduction on the dispersion (i.e., sigma-convergence) of agricultural TFP across countries in Africa aligned with the study's objective, we estimate this hypothesis described subsequently below.

Consistent with earlier discussion, there are unconditional and conditional beta-convergence analyses. Thus, for the empirical purpose, unconditional (absolute) and conditional beta-convergence is represented by Eqs. 1A and 1B, respectively defined below

$$\Delta\left(\ln\mathrm{TFP}_{\mathrm{i,t}}\right) = \alpha_0 + \beta\left(\ln\mathrm{TFP}_{\mathrm{i,t-1}}\right) + \nu_{\mathrm{i,t}} \quad \text{for } t = 1, \ \ ..T; i = 1, \ldots N \tag{1A}$$

$$\Delta\left(\ln\mathrm{TFP}_{\mathrm{i,t}}\right) = \pi_0 + \eta\left(\ln\mathrm{TFP}_{\mathrm{i,t-1}}\right) + \varphi_{\mathrm{k}}\, \mathrm{X}_{\mathrm{ik,t}} + \upsilon_{\mathrm{i,t}} \quad \text{for } t = 1, \ \ ..T; i = 1, \ldots N \tag{1B}$$

where $\mathrm{TFP}_{i,t}$ represents the total factor productivity for i country at time t; Δ is the differencing operator which define the growth of TFP_t; ln means the logarithm transformation; TFP_{t-1} is the initial value of TFP_t; $X_{ik,t}$ is a vector of kth structural characteristics of the economies/countries/regions such as education, capital stock, population growth rates, and mortality rates, etc.; β, η and, φ_k are the parameters to be estimated, as β and η measure the convergence effect; α_0 and π_0 are the estimated intercept; $\nu_{i,t}$ and $\upsilon_{i,t}$ are the error terms.

With no auxiliary variables representing structural characteristics across the economies included in Eq. 1A, convergence depends on this specification's initial conditions. In contrast, as in absolute convergence, the initial conditions are irrelevant because the structural characteristics are included in Eq. 1B to uncover any evidence of convergence, which suggests that equilibrium differs by the economy, making each particular economy approach its unique equilibrium differently. According to Paas et al. (2007), conditional convergence can occur even if the absolute convergence hypothesis is not valid.

Empirically, convergence exists if the estimated β and η are negative and significant in Eqs. 1A and 1B. A statistically significant $\beta < 0$ or $\eta < 0$ implies that beta-convergence is in line with the neoclassical growth model's proposition in African agricultural productivity in the study.

Thus, consistent with each specification above, convergence speed can be computed using the framework employed in Wan's (2005) work defined below.

$$\text{Convergence speed} = \left(1 - e^{-\beta}\right) \cong \beta\% \ 2\mathrm{A}$$
$$\text{Convergence speed} = \left(1 - e^{-\eta}\right) \cong \eta\% \ 2\mathrm{B}$$

Ricardian model

A Ricardian model is a well-established approach for analyzing climate change's impact on agriculture (Ortiz-Bobea 2020). Within the context of African agriculture, the Ricardian model of climate change impacts on the agricultural TFP growth is consistent with conditional beta-convergence defined below.[7]

$$\Delta\left(\ln\mathrm{TFP}_{i,t}\right) = \tau\left(\ln\mathrm{TFP}_{i,t-1}\right) + \gamma\left(\mathrm{Climate}_{i,t-5 \text{ and } t-10}\right) + \theta_k\left(X_{ik,t}\right) + \zeta_i + = \alpha_{i,t} \tag{3}$$

where TFP is as defined earlier; Δ is differencing operator which define the growth of TFP between t-1 and t; ln means the logarithm transformation; $\mathrm{TFP}_{t\text{-}1}$ represents the initial level of TFP; climate is a vector of climate factors considered in the study defined as the average long-run 5- and 10-year interval to capture climate change;[8] τ is the estimated coefficient of $\mathrm{TFP}_{t\text{-}1}$ which serve as the measure of the convergence effect in the study; X represents a vector of kth other potential drivers of agricultural TFP, which include education/human capital, capital intensities, and irrigation; γ represents the estimated effect of climate factors on TFP growth defined by Δ(TFPt,t); θ_k represents the estimated effect of variables X_k on the TFP growth; ζ_i represents country-specific effect; $\alpha_{i,t}$ is the error term of the regression.

The choice of the structural characteristics/variables included in the X_{ik} is guided by previous studies that account for potential confounding factors in agricultural TFP growth such as irrigation (Schlenker et al. 2005), capital intensities (Ball et al. (2014), and investment in human capital (Reimers and Klasen 2013).

[7] We also estimate the unconditional or absolute beta-convergence in the study presented in model 1 of Table 3.

[8] We follow Barrios et al. (2010) and Chieng et al. (2016) to specify the average long-run temperature and rainfall over 5- and 10-year intervals in time t-5 and t-10 to t, respectively. Abidoye and Abidoye and Odusola (2015) also used 5-year intervals to capture climate change in their study. All of these studies focus on Africa.

Table 1 Panel unit root tests

Variables	Levin-Lin-Chu[1]		Harris-Tzavalis[1]		Im-Pesaran-Shin[1]	
	Level	Differenced	Level	Differenced	Level	Differenced
TFP	−2.9875 [0.9527]	−23.2047 [0.0000]	0.9142 [0.7399]	−0.2449 [0.0000]	2.8926 [0.9981]	−15.2186 [0.0000]
Temperature	−14.7019 [0.0000]	−38.5210 [0.0000]	0.4184 [0.0000]	−0.3668 [0.0000]	−6.9611 [0.0000]	−30.0964 [0.0000]
Rain	−5.9879 [0.0000]	−9.2861 [0.0000]	0.1022 [0.0000]	−0.4705 [0.0000]	−12.7936 [0.0000]	−31.8297 [0.0000]
Capita/labor	−4.4978 [0.3896]	−21.6891 [0.0000]	0.9283 [0.9289]	0.0451 [0.0000]	0.4141 [0.6606]	−13.2634 [0.0000]
Education	−7.2299 [0.6789]	−33.7639 [0.0000]	0.9209 [0.8491]	−0.3116 [0.0000]	2.0903 [0.9817]	−26.3096 [0.0000]
Irrigation	−9.1318 [0.0000]	−15.9160 [0.0000]	0.2780 [0.0000]	−0.1031 [0.0000]	−1.2581 [0.0000]	−5.8621 [0.0000]

[1] H_0: panels contain unit roots; p value in the bracket; differenced is based on first differenced; all variables are expressed in logarithm

Results and discussion

Panel data specific tests: unit root, Hausman tests, and serial correlation

Given that time-varying macroeconomic variables are often not stationary, we present the panel unit root test result in Table 1. Three-panel unit root tests (Levin-Lin-Chu, Harris-Tzavalis, and Im-Pesaran-Shin) were carried out on the variables to provide robust estimates. The results show that the TFP index, capital stock-labor ratio, and education were not stationary at the level judging by the p value >0.5 presented in the table but become stationary with first differences. The results of other variables (temperature, rainfall, and irrigation) were found to be stationary at the level judging by the p value less than 0.01.

We subsequently perform the Hausman (1978) specification test to compare the random and fixed effects models for the data presented in the second row of Table 2. However, with a p value less than 0.01, the result shows that differences between the random effects and fixed effects coefficient are systematic, as the fixed effect is more robust to the data than the random effect specification.

In recognition of the data's cross-section time-series nature, we also followed Baltagi (2005) work that there is a possibility of a serial correlation between the error terms across the period in a time-series cross-sectional panel data, which is likely to bias the efficiency of the results (i.e., standard error). We subsequently perform the test for serial correlation using Wooldridge (2002) test statistics, presented in the second row of Table 2. Given the p value of less than 0.01, we reject the null hypothesis of no serial correlation. Because of this, we employed the Feasible Generalized Least Square Method (FGLS) to estimate parameters of Eq. 3 since the model is robust to time-series cross-sectional (TSCS) contemporaneous correlation problem following the work of Baltagi (2005).[9]

Convergence hypothesis test in African agricultural TFP growth

Presented in Tables 3 and 4 are the results of the estimated catching-up model employed to investigate convergence in levels of African agricultural total factor productivity (TFP) based on Eq. 3. The estimated coefficient of initial TFP denoted by TFP_{t-1} serves to measure the convergence effect in the study. The result of the absolute or unconditional beta-convergence represented by model 1 in Table 3 is negative but insignificant[10]. Simultaneously, the conditional beta-convergence result represented in models 2–7 is negative and significantly different from zero. We equally uncover evidence of conditional beta-convergence in Table 4. Results show that the convergence hypothesis in African agricultural total factor productivity seems to be driven by differences in the structural characteristics such as capital, education, irrigation, and climate factors in the study. In other words, the convergence of African agricultural TFP is conditional on these variables, indicating that they play an important role in the convergence process in the region. Thus, it supports the rejection of the null hypothesis of no-convergence in levels of African agricultural TFP in the study.

Although the number of studies that have examined convergence in African agriculture is limited, nevertheless, a closer look at the literature shows that Lusigi et al. (1998) found no evidence of convergence in African agricultural TFP[11]. Thirstle et al. (2003) find evidence of divergence in

[9] A similar approach has been used by Ball et al. (2014) and Ogundari and Aromolaran (2017) for cross-state and cross-country data analyses, respectively.

[10] The estimated unconditional or absolute beta-convergence in model 1 is similar to Eq. 1A.

[11] Lusigi et al. (1998) is the only known cross-country study that test the convergence hypothesis in African TFP.

Table 2 Panel data tests

Tests	Statistics	*p* value
Hausman test of fixed effect vs. random effect	Chi-square statistic = 48.80	0.0000
Woodridge's test of serial correlation of error component	*F*-statistic = 43.250	0.0000

Woodridge (2002) test statistic of the null hypothesis of no serial correlation

Bostwana agricultural productivity based on annual cross states time-series covering 1981–1996. From a global perspective, our literature search shows that Ball et al. (2014) found evidence of convergence in the US agricultural total factor productivity. Ball et al. (2001) found evidence of convergence in agricultural productivity levels in twelve OECD countries. Cechura et al. (2014) investigated the milk sector's catching-up hypothesis for 24 E.U. member states over 2004–2011. They found no sign that poorly performing farmers are catching up to better performing farms in these regions. Zhan et al. (2017) found evidence of convergence in Chinese agricultural productivity levels, and Barath and Ferto (2017) found evidence of convergence in European agriculture between 2004 and 2013. The evidence of the convergence of agricultural productivity has always been mixed in the literature.

Across all the model specifications, in Tables 3 and 4, the results also show that the estimated speed of convergence, which measures how quickly the growth of African agricultural productivity increase over time to the steady-state path, ranges from about 0.99–1.8%, which appears relatively slow.[12] A higher speed of convergence (let say from 50% and above) is the expected minimum value to successfully reduce malnutrition and food insecurity in the developing economies, as noted by Headey (2013). The evidence of convergence and slow speed of convergence in African agricultural productivity levels has implications on the region's food policy. *First*, it shows that the agricultural productivity gap between countries in the region has lessened. *Second*, it shows that countries further outside the technological frontier will likely have more rapid agricultural productivity growth in the region. *Third*, evidence of convergence might be an indication of sustained technological diffusion among farmers in the region.[13] *Fourth*, the observed low speed of convergence can be attributed to many factors, including institutional constraints such as lack of efficient credit markets, weak extension services, and poor transportation networks in the region. These are known agricultural development problems in Africa.

Effects of climate change on African agricultural productivity growth

Presented in Tables 3 and 4 are the results of climate change factors defined by 5- and 10-year temperature and rain average coupled with a measure of rain variability on agricultural TFP. This is consistent with previous studies by Barrios et al. (2008) and Exenberger et al. (2014). With climate change factors specify only as long-run 5- and 10-year average in Table 3, the result shows that rainfall consistently increases African agricultural productivity (see models 2–7). The results show that the long-run effect of precipitation (rain) is consistently positive and significant across the models. The results are the same for the average long-run temperature and rainfall coefficient over 5- and 10-year intervals in the table. Despite various model specifications reported in the table, the results show that temperature has no significant effect on African agricultural productivity growth.

Since agricultural production is mainly rainfed in Africa, it is vital to understand how rain shocks defined by rainfall variability impact agricultural productivity in the region. Ito and Kurosaki (2009) defined a rainfall shock as the deviation from the rainfall level in a particular year. In recognition of this, we include rain variability in the results presented in Table 4. Despite having the measure of rain variability in the model, the impact of rain and temperature is significantly positive and consistent with the results obtained in Table 3. However, the coefficient of rain variability shows that rain shock induces a significant negative effect on Africa's agricultural productivity in the estimated models 4–6, especially when the average 10-year interval of rain and temperature is considered climate change drivers in the study. The implication of this is that rainfall variability poses agricultural production risk in the region in the long run, which increases the risk of technology adoption. The coefficient of rain variability is insignificant when the average 5-year interval of rain and temperature is considered climate change drivers.

A literature review shows that Barrios et al. (2008) obtained a significant positive and negative effect of rainfall and temperature on agricultural production in sub-Saharan Africa (SSA), respectively. In contrast, Exenberger et al. (2014) found evidence of a significant positive effect of rainfall and an insignificant negative effect of temperature on agricultural production in SSA. Also, Patrick et al. (2011) found evidence that cereal yields across Sub-Saharan Africa decline and

[12] Using model 4 of Table 3 as an example, convergence speed is equivalent to 1.1% (i.e., 0. 0106×100).

[13] Martin and Mitra (2001) found strong evidence of a rapid convergence in levels and growth rates of TFP in agriculture as a result of the international dissemination of innovation.

Table 3 Estimated catching-up model

Explanatory variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
TFP_{t-1}	−0.0015 [0.0022]	−0.0099*** [0.0033]	−0.0104*** [0.0033]	−0.0106*** [0.0034]	−0.0137** [0.0056]	−0.0143*** [0.0046]	−0.0175*** [0.0055]
Climate change ($Rain_{t-5}$)		0.0036*** [0.0009]		0.0034*** [0.0009]			
Climate change ($Temp_{t-5}$)			−0.0070 [0.0043]	−0.0063 [0.0042]			
Climate change ($Rain_{t-10}$)					0.0048*** [0.0027]		0.0049** [0.0020]
Climate change ($Temp_{t-10}$)						−0.0095 [0.0118]	−0.0095 [0.0119]
ΔCapital/labor		0.0691*** [0.0153]	0.0774*** [0.0151]	0.0711*** [0.0155]	0.0644*** [0.0253]	0.0824*** [0.0244]	0.0829*** [0.0246]
ΔEducation		0.0216*** [0.0079]	0.0181** [0.0079]	0.0211*** [0.0079]	0.0235** [0.0111]	0.0221*** [0.0168]	0.0262** [0.0117]
Irrigation		0.0045*** [0.0003]	0.0042*** [0.0003]	0.0045*** [0.0003]	0.0047*** [0.0003]	0.0042*** [0.0008]	0.0046*** [0.0009]
Constant		0.0223** [0.0155]	0.0636*** [0.0218]	0.0463** [0.0235]	0.0335** [0.0105]	0.0876** [0.0374]	0.0797** [0.0373]
Autocorrelation	AR (1)	AR (1)	AR (1)	AR (1)	AR (1)	AR (1)	AR (1)
Number of countries	35	35	35	35	35	35	35
Number of observation	1050	875	875	875	700	700	700
Wald test [p value]	0.000	0.000	0.000	0.000	0.000	0.000	0.000

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; all variables are expressed in logarithm

Table 4 Estimated catching-up model with rain variability included

Explanatory variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
TFP_{t-1}	−0.0093*** [0.0034]	−0.0099*** [0.0033]	−0.0101*** [0.0034]	−0.0158*** [0.0051]	−0.0151*** [0.0046]	−0.0183*** [0.0054]
Climate change ($Rain_{t-5}$)	0.0036*** [0.0009]		0.0035*** [0.0009]			
Climate change ($Temp_{t-5}$)		−0.0069 [0.0042]	−0.0062 [0.0043]			
Climate change ($Rain_{t-10}$)				0.0070*** [0.0032]		0.0050*** [0.0022]
Climate change ($Temp_{t-10}$)					−0.0103 [0.0118]	−0.0103 [0.0117]
Rain variability	0.1121 [0.0101]	0.0121 [0.0108]	0.0104 [0.0105]	−0.0516*** [0.0126]	−0.0578*** [0.0231]	−0.0574*** [0.0236]
ΔCapital/labor	0.0720*** [0.0156]	0.0809*** [0.0154]	0.0739*** [0.0157]	0.0729*** [0.0230]	0.0857*** [0.0242]	0.0857*** [0.0244]
ΔEducation	0.02178*** [0.0079]	0.0183** [0.0078]	0.0213*** [0.0079]	0.0211*** [0.0014]	0.0229*** [0.0016]	0.0269*** [0.0102]
Irrigation	0.0045*** [0.0003]	0.0041*** [0.0003]	0.0045*** [0.0003]	0.0047*** [0.0007]	0.0042*** [0.0008]	0.0046*** [0.0009]
Constant	0.0129 [0.0177]	0.0539** [0.0234]	0.0371 [0.0253]	0.0345 [0.0257]	0.1273** [0.0407]	0.1189*** [0.0407]
Autocorrelation	AR (1)	AR (1)	AR (1)	AR (1)	AR (1)	AR (1)
Number of countries	35	35	35	35	35	35
Number of observation	875	875	875	700	700	700
Wald test [p value]	0.000	0.000	0.000	0.000	0.000	0.000

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; all variables are expressed in logarithm increase with increasing temperatures and precipitation, respectively. Using cross-country data from Eastern Africa, Abraha and Gårn (2014) obtained evidence that rainfall increases agricultural output significantly in the region with no significant effect from temperature. These studies consistently identify precipitation (rain) as a critical driver of agricultural production in the region.

Our findings are consistent with many previous studies that African agricultural productivity growth is much more sensitive to rainfall than the region's temperature. Despite the significant positive long-run effect of precipitation on agricultural productivity in the study, it is also important to note that rainfall has been declining since the half of the nineteenth century in Africa, as revealed by Nicholson (2001). The implication of this is that agricultural policymakers in the region must take action that is likely to minimize the African agricultural sector's exposure to unexpected drought in the future. Of course, this includes adopting climate-smart farming practices to reduce the sector's exposure to unforeseen circumstances associated with a sudden drop in rainfall in Africa's future.

Effect of other control variables on African agricultural productivity growth

Across all the model specifications presented in Tables 3 and 4, the results show that the capital-labor ratio has a significant and positive effect on agricultural productivity growth, suggesting that technology embodied in the capital is an essential driver of agricultural productivity growth study. Ball et al. (2014) found a positive and significant effect of capital intensities on agricultural productivity growth in the USA. The positive and significant impact of education across all the model specifications in Tables 3 and 4 shows education is an essential driver of agricultural productivity growth in Africa. The link between human capital and agricultural productivity results from such instances as the possession of some years of schooling enabling farmers to have the capacity to evaluate new and improved input varieties critically and to be able to read and follow product instructions for chemical inputs and other aspects of modern farm technology (Wouterse 2016).

A review of the literature shows that Reimers and Klasen (2012) found a positive impact of education on agricultural productivity in developing countries. Similarly, in a review of empirical literature using meta-analysis technique on efficiency studies published from Africa, Ogundari (2014) found evidence that over the years, education ranked first among the key drivers of African agricultural efficiency levels, followed by years of experience and extension.

The other results from Tables 3 and 4 show that arable land equipped with irrigation significantly increases African agricultural productivity growth in the region in all the model specifications in Tables 3 and 4. Reimers and Klasen (2012) found a positive effect of land equipped with irrigation on agricultural productivity in developing countries, although the authors defined agricultural productivity using partial productivity. The result shows that access to irrigation technology has an enormous impact on agricultural productivity. Of course, this enables smallholder farmers to produce consumable food grains directly and diversify their cropping and supplement moisture deficiency in agriculture to increase production and food consumption (van der Veen and Tagel 2011).

Concluding remarks

Identifying the drivers of agricultural productivity growth and whether differences exist in agricultural productivity across countries in Africa is a prerequisite to meeting the region's challenges. In this context, the present study tests the convergence hypothesis using the catching-up model in levels of African agricultural total factor productivity (TFP) indices across 35 countries from 1981 to 2010 in the region. We also investigate climate change, capital intensity, human capital, and arable land equipped with irrigation effect on African agricultural total factor productivity (TFP) growth in the study. We use the Feasible Generalized Least Square (FGLS) model to estimate the catching-up model.

The empirical results found evidence of convergence in African agricultural total factor productivity levels over time. The convergence is conditional on climatic factors such as rainfall, capital, irrigation, and education (human capital), indicating that they play an important role in the region's convergence process. The convergence speed ranges from about 1 to 2% per annum, which appears relatively slow in the region. We also found rainfall to be an essential driver of agricultural productivity growth, as the temperature has no significant effect on agricultural productivity growth in the region. The analysis also shows that capital intensities capture by capital-labor ratio, education (human capital), and arable land equipped with irrigation are essential drivers of agricultural productivity growth in Africa.

The existence of convergence and significant positive long-run effect of rainfall have implications on agricultural and food policy in the region. For instance, it is an indication that the agricultural productivity gap between countries in the region has lessened. It also shows that countries further outside the technological frontier will likely have more rapid agricultural productivity growth in the future. The evidence of convergence might be an indication of sustained technological diffusion among farmers in the region. The low speed of convergence can be attributed to many factors, such as lack of efficient credit markets, weak extension services, and poor transportation networks, known as agricultural development problems in the region.

In conclusion, continued elimination of institutional constraints highlighted above to the agricultural development is highly recommended to promote intensification of agricultural innovation diffusion and, thus, higher food production in the region.

Appendix

Table 5 Descriptive statistics of variables used in the regression

Variables	Description	Mean	Std. Dev.
TFP	Total factor productivity index in percentage	103.9789	30.4460
Rain	Annual average rainfall in Millimeter	88.0903	50.1904
Rain variability	Rainfall variability over time	0.6052	0.0761
Temperature	The annual average temperature in Celsius	24.2249	3.6318
Capital/labor	Capital stock per labor capture capital intensities	3.0918	4.0338
Education	Average years of education	5.2982	4.1341
Irrigation	Total arable land equipped with irrigation in hectares (1000)	117.2331	271.7313

Table 6 Correlation matrix of the variables

Variables	TFP_{t-1}	Rain	Rain variability	Temperature	ΔCapital/labor	ΔEducation	Irrigation
TFP_{t-1}	1.0000						
Rain	0.0112	1.0000					
Rain variability	0.0001	−0.0683	1.0000				
Temperature	−0.2998	−0.0617	−0.0265	1.0000			
ΔCapital/labor	0.0009	0.0475	0.0758	0.0760	1.0000		
ΔEducation	0.0171	−0.0451	0.0025	0.0251	−0.0305	1.0000	
Irrigation	0.0180	−0.1288	−0.0869	0.0396	0.0178	−0.0333	1.0000

All variables are expressed in logarithm

Table 7 IVF and condition index for the variables

	TFP_{t-1}	Rain	Rain variability	Temperature	ΔCapital/labor	ΔEducation	Irrigation
IVF	1.16	1.04	1.03	1.06	1.02	1.01	1.12
Condition index	1.00	1.12	1.00	1.16	1.29	1.23	1.49

All variables are expressed in logarithm

Acknowledgements The authors thank the anonymous reviewer for the helpful comments on the earlier version of the manuscript.

Author contribution The first author (K.O) retrieves and analyzes the data and prepares the write up for the manuscript. The second author (R.O) checks the results, proofread the document, and provides policy guidance for the write up.

Data availability The data will be made available upon request from the lead author.

Declarations

Ethics approval and consent to participate This study does not require ethical approval.

Consent for publication We at this moment give the publisher the consent to publish the paper in this journal.

Competing interests The authors declare no competing interests.

References

Abidoye BO, Odusola AF (2015) Climate change and economic growth in Africa: an econometric analysis. J Afr Econ 24(2):277–301

Abraha K. G and H. L. Gårn (2014): The effect of climate change and adaptation policy on agricultural production in Eastern Africa, IFRO Working Paper, No. 2014/08, University of Copenhagen, Department of Food and Resource Economics (IFRO), Copenhagen.

Alene AD (2010) Productivity growth and the effects of R&D in African agriculture. Agric Econ 41:223–238

Allen, S. L, and M. Qaim (2012). Agricultural productivity and public expenditure in sub-Saharan Africa. IFPRI Discussion paper 01173 Washington DC.

Amare M, Jensen ND, Shiferaw B, Cisse JD (2018) Rainfall shocks and agricultural productivity: implication for rural household consumption. Agric Syst 166:79–89

Angulo AM, Gil JM, Gracia A (2001) Calorie intake and income elasticities in E.U. countries: a convergence analysis using cointegration. Pap Reg Sci 80(2):165–187

Awokuse TO, Xie R (2015) Does agriculture matter for economic growth in developing countries? Can J Agric Econ 63:77–99

Ball VE, Bureau J-C, Butault J-P, Nehring R (2001) Levels of farm sector productivity; an international comparison. J Prod Anal 15:5–29

Ball VE, San-Juan-Mesonada C, Ulloa CA (2014) State productivity growth in agriculture: catching-up and the business cycle. J Prod Anal 42:327–338

Baltagi B (2005) *Econometric analyses of panel data*, 3rd edn. IE Wiley, England

Barath L, Ferto I (2017) Productivity and convergence in European Agriculture. J Agric Econ 68(1):228–248

Barrios S, Outtara B, Strobl E (2008) The impact of climate change on agricultural production: is it different for Africa? Food Policy 33: 287–298

Barrios S, Bertinelli L, Strobl E (2010) Trend in rainfall ad economic growth in Africa: a neglected cause of the African growth tragedy. Rev Econ Stat 92(2):287–298

Barro RJ, Lee JW (2013) A new dataset of educational attainment in the Worlds, 1950-2010. J Dev Econ 104:184–198

Bassanini, A., Scarpetta, S. and Hemmings, P. (2001), "Economic growth: the role of policies and institutions: panel data. Evidence from OECD countries", OECD Economics Department Working Paper No. 283, OECD Publishing, Paris, available at doi:https://doi.org/10.1787/722675213381 (accessed February 8, 2015).

Benson C, Clay E (1998) The impact of drought on sub-Sharan Economics, World Bank Technical Paper. No. World Bank, Washington. D.C, p 401

Beugelsdik S, Klasing MJ, Milionis P (2018) Regional economic development in Europe: the role of total factor productivity. Reg Stud 52(4):461–476

Block, S (2010). The decline and rise of agricultural productivity in sub-Saharan Africa since 1961. NBER Working paper series No. 16481. http://www.nber.org/papers/w16481.

Borkowski B, Duke H, Szozesny W (2009) Food consumption convergence within Europe: a panel data analysis. Pol J Environ Stud 18(5B):41–47

Cechura, L., A. Grau, H. Hochmann, I. Levkovych, and Z. Kroupova (2014). Catching up or falling behind in Eastern European Agriculture- the case of milk production. Paper presented at the 142nd EAAE Seminar Growing Success? Agriculture and Rural Development in an Enlarged E.U. Corvinus University of Budapest, Hungary.

Cong R-G, Brady M (2012) The interdependence between rainfall and temperature: copula analyses. Sci World J 2012:405675. https://doi.org/10.1100/2012/405675

CTA (2012). Technical Centre for Agriculture (CTA)'s Policy Brief. Number 4 February 2012. Wageningen, The Netherlands

Exenberger, A., A. Pondorfer, and M. H. Wolters (2014). Estimating the impact of climate change on agricultural production: accounting for technology heterogeneity across countries. Kiel Working Paper No. 1920. Kiel Institute for the World Economy, Kiel Germany.

FAOSTAT (2018). Food and Agriculture Organization Corporate Statistical Database. Available at: www.faostat.fao.org(accessed, September 2018)

Fuglie KO (2012) Productivity growth and technology capital in the global agricultural economy. In: Fuglie K, Wang SL, Ball VE (eds) Productivity growth in agriculture: an international perspective. CAB International, Wallingford, pp 335–368

Fuglie K. O and N. E. Rada (2013). Resources, policies, and agricultural productivity in sub-Saharan Africa. Economic Research Report No. 145, Washington, DC.

Fuglie, K, and S. L. Wang (2012). Productivity growth in global agriculture shifting to developing countries. *Choices*, 4th Quarter 2794): 7 pages.

Fulginiti LE (2010) What comes first, agricultural growth or democracy? Agric Econ 41:15–24

Gutierrez L (1999). Agricultural productivity growth and convergence among countries. *Cahiers d'economie et sociologie rurales*, No. 537-25.

Hall RE, Jones CI (1999) Why countries produce so much more output than others? Q J Econ qq4:83–116

Hausman. J. A (1978). Specification test in econometrics, Vol. 46(6): 1251-1271.

Headey D (2013) Developmental drivers of nutritional change: a cross-country analysis. World Dev 42(2):76–88

IPPC (2007). Intergovernmental Panel on Climate Change reported tiled "climate change 2001: impacts, adaption, and vulnerability-contribution of working group II to the third assessment".

Ito T, Kurosaki T (2009) Weather risk, wages in kind, and the off-farm labor supply of agricultural households in a developing country. Am J Agric Econ 91(3):697–710

Kotir JH (2011) Climate change and variability in sub-Saharan Africa: a review of current and future trends and impacts on agriculture and food security. Environ Dev Sustain 13(3):587–605

Lichtenberg FR (1994) Testing the convergence hypothesis. Rev Econ Stat 76(3):576–782

Liu Y, Shumway CR, Rosenman R, Ball VE (2011) Productivity growth and convergence in U.S. Agriculture: new cointegration panel data result. Appl Econ 43:91–102

Lusigi A, Thirtle C (1997) Total factor productivity and the effects of R&D in African Agriculture. J Int Dev 9(4):529–538

Lusigi A, Piesse J, Thirtle C (1998) Convergence of per capita income and agricultural productivity in Africa. J Int Dev 10(1):105–115

Martin W, Mitra D (2001) Productivity growth and convergence in agriculture versus manufacturing. Econ Dev Cult Chang 49:403–422

Mozumdar L (2012) Agricultural productivity and food security in the developing world. Bangladesh J Agric Econ XXXV(1&2):53–69

Nicholson SE (2001) Climatic and environmental changes in Africa during the last two centuries. Clim Res 17:123–144

Nin-Pratte A (2015). Inputs, productivity, and agricultural productivity in Africa south of Saharan. IFPRI Discussion paper No. 01432, Washington DC.

Nkamleu G (2004) Productivity growth, technical progress, and efficiency change in African agriculture. Afr Dev Rev 16(1): 203–222

Ochieng J, Kirimi L, Mathenge M (2016) Effects of climate variability and change on agricultural production: the case of small-scale farmers in Kenya. NJAS-Wageningen J Life Sci 77:71–78

Ogundari K (2014) The paradigm of agricultural efficiency and its implication on food security in Africa: what does meta-analysis reveal? World Dev 64:690–702

Ogundari K, Aromolaran AB (2017) Nutrition and economic growth in sub-Saharan African: a causality test using panel data. Int J Dev Issues 6(2):174–189

Ogundari K, Ito S (2015) Convergence and determinants of change in nutrient supply: evidence from sub-Saharan African countries. Br Food J 117(12):2880–2898

Ortiz-Bobea A (2020) The role of nonfarm influences in Ricardian estimates of climate change impact on U.S. Agriculture. Am J Agric Econ 102(3):938–959

Ouyang Y, Shimeles A, Thorbecke E (2019) Revisiting cross-country poverty convergence in the developing world with a special focus on sub-Saharan Africa. World Dev 117:13–38

Paas, T., A. Kuusk, F. Schlitte, and A. Vork (2007), Econometric analysis of income convergence in selected E.U. countries and their Nuts 3 level regions, The University of Tartu Faculty of Economics and Business Administration Working Paper, 60.

Patrick S, Ward, Raymond J.G.M. Florax, and Alfonso Flores-Lagunes (2011). Climate change and agricultural productivity in sub-Saharan African: a spatial sample selection model. Working Paper # 11-4. Dept. of Agricultural Economics at Purdue University.

Philips PCB, Sul D (2007) Transition modeling econometric convergence tests. Econometrics 75(6):1771–1885

POSTnote (2006). *Food security in developing countries*. Published by Parliamentary Office of Science and Technology, U.K., Issues No. 274.

Rada, N.E., S. Rosen, and J. Beckman (2013). Evaluating agricultural productivity's impact on food security. Selected paper prepared for presentation at the International Agricultural Trade Research Consortium's (IATRC's) 2013 symposium: productivity and its impacts on global trade, June 2-4, 2013 Seville Spain

Ravallion M (2012) Why don't we see poverty convergence? Am Econ Rev 102(1):504–523

Reimers M, Klasen S (2013) Revisiting the role of education for agricultural productivity. Am J Agric Econ 95(1):131–152

Rezek P, Cambell R, Rogers K (2011) Assessing total factor productivity growth in sub-Saharan African agriculture. J Agric Econ 62:357–374

Rezitis AN (2005) Agricultural productivity convergence across Europe and the United States of America. Appl Econ Lett 12(7):443–446

Romer P (1986) Increasing returns and long-run growth. J Polit Econ 94: 1002–1037

Rosen, S., B. Meade, K. Fuglie, and N. Rada (2014). International food security assessment, 2014-2024, GFA-25, U.S. Department of Agriculture, Economic Research Service, June 2014.

Rosenzweig C, Parry M (1994) Potential impact of climate change on World agriculture. Nature 367:133–138

Sala-i-Martin X (1996) The classical approach to convergence analysis. Econ J 106(437):1019–1036

Schlenker W, Hanemann WM, Fisher AC (2005) Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. Am Econ Rev 95(1):395–406

Solow RM (1956) A contribution to the theory of economic growth. Q J Econ 70(1):65–94

Thirstle C, Piessa J, Lusgi A, Suhariyanto K (2003) Multi-factor agricultural productivity, efficiency, and convergence in Bostwana, 1981-1996. J Dev Econ 71(2):605–624

Timmer MP, Inklaar R, O'Mahony M, Ark v B (2010) *Economic growth in Europe: a comparative industry perspective*. Cambridge University Press, New York

USDA-ERS (2018). International Agricultural Productivity. https://www.ers.usda.gov/data-products/international-agricultural-productivity/

van der Veen A, Tagel G (2011) Effect of policy interventions on food security in Tigray, northern Ethiopia. Ecol Soc 16(1):18. https://doi.org/10.5751/ES-03895-160118

Wan GH (2005) Convergence in food consumption in rural China: evidence from household survey data. China Econ Rev 16(1):90–102

WDI (2018). World Development Indicators' Climate Change Knowledge Portal. https://climateknowledgeportal.worldbank.org/download-data

Wooldridge JM (2002) *Econometric analysis of cross-section and panel data*. MIT Press, Cambridge

World Bank (2007). World Development reports in 2008. Agriculture for development. Washington, DC: World Bank. Available @ DOI: 10.1596/978-0-8213.

Wouterse F (2016) Can human capital variables be technology changing? An empirical test for rural households in Burkina Faso. J Prod Anal 45:157–172

Yu, B, and A. Nin-Pratt (2011). Agricultural productivity and policies in sub-Saharan Africa. IFPRI Discussion paper No. 01150 Washington DC.

Zhan J, Tian X, Zhang Y, Yang X, Qu Z, Tan T (2017) The effects of Agricultural R&D on Chinese agricultural productivity growth: new evidence of convergence and implications for agricultural R& D policy. Can J Agric Econ 65(3):453–475

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.