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A nonparametric analysis of climate change nexus on agricultural productivity in Africa: implications on food security

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Abstract

Earlier research largely ignored the effects of climate change on the growth of agricultural total factor productivity (TFP) in Africa. This study shows how climate inputs impact TFP growth in addition to other productivity growth indicators and metrics, as well as how they can impact overall input efficiency as productivity drivers. We use a panel of 42 African nations from 1999 to 2019 and a nonparametric data envelopment analysis-Malmquist technique. The non-parametric analysis revealed that the average growth rate of the non-climate-induced TFP estimates was 1.9%, while the average growth rate of the climate-induced TFP estimates was 2.4%. Accounting for temperature and precipitation separately, TFP grew by 2.3% on average. This growth rate (2.3%) is slightly less than the combined effect of temperature and precipitation (2.4%) but higher than the typical TFP growth rate (1.9%) that ignores climate variables, indicating that TFP growth in African agriculture risks being underestimated when climate inputs are ignored. We also find the distribution of the climate effects to vary across regions. In northern Africa, for example, the temperature-induced TFP growth rates were negative due to rising temperature in the region. Evidence from the decomposed TFP estimates indicates that climate variables also influence productivity determinants. However, technology improvement is fundamental to mitigating the effects of extreme weather inputs on TFP growth in Africa's agriculture. As a result, a few policy suggestions are provided to help policymakers deal with the effects of climate change on TFP growth in Africa's agriculture and ensure food security. The study advocated for a reevaluation of the climate–agriculture effect in order to fully comprehend the role of climate factors and their contributions to agricultural TFP growth in Africa.

Introduction

The theoretical literature on climate change is extensive and encompasses all sectors. However, agriculture accounts for the majority of our knowledge of climate effects (Blanc, 2011; McCarl and Hertel, 2018; Hertel and de Lima, 2020). The climate effects on crops, livestock, land, labor productivity, factor productivity and environmental quality have all been studied (Edame *et al.*, 2011; Valipour, 2017; Mechiche-Alami and Abdi, 2020; Sridhara *et al.*, 2022). There is evidence regarding weather variables, such as precipitation and temperature, explaining much of the output growth in agriculture (Liang *et al.*, 2017). In general, productivity occurs when the transformed inputs generate the maximum feasible output. A more preferred measure of productivity growth in agriculture is total factor productivity (TFP) (Fuglie, K. 2012; Ding and Zhang, 2021). TFP is defined as a measure of total output expressed over a measure of total input (O'Donnell, 2021). In the context of agricultural output such as crops and livestock, farmers evaluate the overall growth of farms by considering the combination of different inputs, including land, labor, capital, materials and services that are under their control, as well as other natural variable inputs that they do not directly control but are important in the production process (Rahman and Salim, 2013; Food and Agriculture Organization, 2018; O'Donnell, 2021).

Thus, agricultural economists are normally concerned with the potential impacts of nature by studying how natural inputs may affect physical productivity outcomes. Normally, they use either process-based simulation models (biophysical or agronomic) or econometric techniques to estimate these effects. In general, the simulation approaches need less data, but they make a lot of assumptions about how accurate the models are and how climate changes affect crop yields. On the other hand, the econometric approaches consider the past effects of climate over time and space and make inferences for the future by extrapolating information from the past (Suresh *et al.*, 2021). As a result, numerous approaches for mitigating the effects of climate variability on agricultural production have been developed. Despite their benefits, most of these approaches have been applied to partial growth indicators with restricted data and time dimensions. There have been few attempts to investigate the impact of climate change on aggregate growth indicators such as agricultural TFP (Liang *et al*., 2017; Hertel and de Lima, 2020). However, most of these studies employed different parametric methods to control for the effects of climate variability on agricultural TFP. On average, TFP has been found to be highly sensitive to both short-run and long-term climate variability (Chambers and Pieralli, 2020; Chancellor *et al*., 2021). Some researchers have combined climate variables with either aggregate or farm-level inputs or outputs to estimate production functions and stimulate the potential effects of future climate factors on TFP growth (Qi *et al*., 2015; Njuki *et al*., 2018; Chancellor *et al*., 2021). For example, Ogundari and Onyeaghala (2021) studied climate change effects on agricultural TFP growth in 35 African countries using the Ricardian model on historical rainfall and temperature data drawn from 1981 to 2010. Their analysis revealed that rainfall has a significant positive impact on TFP growth in sub-Saharan Africa, but temperature did not show any substantial effect.

Climate variables have also been factored into production frontier analyses such as data envelopment analysis (DEA) and stochastic frontier analysis (SFA) to decompose productivity into measures of technology and various components of efficiency change (Hughes and Lawson 2011; Chancellor *et al*., 2021). Hughes and Lawson (2011) used farm-level data to estimate a nonparametric model linking farm-level TFP indices with a variety of location-specific rainfall and temperature variables to control for climate effects on TFP. Their results showed productivity increases that are linked to long-term climate effects. Recently, Chambers and Pierall (2020) recognized the stochastic nature of climate variables in a nonparametric framework and incorporated them directly into the production function analysis (Chambers and Pieralli, 2020; Chambers *et al*., 2020). The authors found climate-related changes rather than technological innovation to be the primary determinant of the slowdown in productivity growth. Based on the evidence, the authors warned that excluding the effects of weather in productivity estimation could result in a potential bias in TFP estimates (Chambers *et al*., 2020). In the same way, Plastina *et al*. (2021) used agricultural production and weather data from 16 US states to demonstrate how ignoring the effects of climate shocks can alter TFP growth and its decomposed components. The authors found evidence that productivity growth in agriculture is sensitive to climate change.

These studies have primarily focused on the developed world, specifically the USA and Australia, whereas the current study focuses on Africa, which is particularly vulnerable to weather adversity, and there is limited evidence on the analysis of climate factors as drivers of productivity growth. To date, only a few studies have examined the impact of climate change on TFP increases in African agriculture, with the vast majority employing the parametric SFA on old data that has nearly a decade gap. Accordingly, this research argues that most TFP growth studies, particularly those using a nonparametric methodology, have ignored the effects of weather on the aggregate measure of agricultural productivity growth in Africa. In fact, the empirical literature on the climate–agriculture nexus in Africa has mostly relied on methods involving parameter specification (i.e., SFA or Cobb–Douglas production function). These methods can be problematic due to restrictions imposed on the nature of the production technology. Unlike previous studies, the current study is interested in using weather inputs as factors of production to determine their effects on productivity drivers and growth rather than their parameter elasticities. Hence, the nonparametric DEA-Malmquist approach is employed because it allows us to achieve this goal in a relatively straightforward manner. This is the first study to incorporate climate variables into the production technology of African agriculture using the Malmquist productivity index method. The study is justified because crop growth is sensitive to changing weather and Africa's farming system is more dependent on the natural environment. Consequently, climate variables become natural inputs, and including them in the production technology can help control for the effects of weather on TFP growth and its drivers and reduce biases in productivity estimates (O'Donnell, 2012, 2021).

Except for the value-added measure of TFP, which does not require the use of intermediate inputs in agricultural production technology, the nonparametric framework involving gross output value of production does not limit or restrict the types of inputs used in the production technology in agriculture (Schreyer, 2001; Gray *et al*., 2011; Bernard *et al*., 2022). However, due to the differential nature of the climate–agriculture effects, as evident in previous studies, the current study uses a single output, comprising the aggregate production value of 162 crops in a panel of 42 countries, to estimate the nonparametric DEA-Malmquist index and compare the results across the five geopolitical regions of Africa. Our objective is similar to previous studies conducted in the USA (Liang *et al*., 2017; Chambers *et al*., 2020; Plastina *et al*., 2021). As far as we know, this study is one of the very few that used the nonparametric DEA-Malmquist method to control for the direct effect of climate change factors on agricultural TFP growth. In fact, aside from the OECD countries (Chambers and Pieralli, 2020; Plastina *et al*., 2021), we do not know of any such study for Africa's agriculture.

The contribution of this study can be summarized as follows: to begin with, the study shows how controlling for the effect of nature in agricultural growth analysis is critical for identifying biases in productivity outputs in Africa, where farming activities are largely traditional due to the limited use of agricultural technology. Secondly, the nonparametric literature, applying the DEA-Malmquist approach in Africa, is not only limited but has also failed to account for climate effect on productivity growth. A gap which the current study tries to address by testing the sensitivities of agricultural TFP to climate variables in a nonparametric framework and demonstrating how ignoring climate factors could lead to biases in TFP estimates in Africa's agriculture. Finally, given that the nonparametric technique is not subject to parameter assumptions, this flexibility will provide a deeper understanding of the actual stochastic nature of climate change effects on TFP growth in Africa. The study makes suggestions for policy changes that can help Africa's agriculture deal with the effects of climate change in a way that improves productivity growth and ensure food security.

Materials and methods

Study design

Our study is designed in four phases. First, following Chambers and Pieralli (2020) and Plastina *et al*. (2021), we apply a nonparametric technique to estimate TFP using a combination of climate variables and conventional input and output variables from crop production values to estimate an output-oriented DEA-Malmquist index (Fare *et al*., 1994). Secondly, we assess the impact of climate variables on TFP change by directly

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controlling for climate variability in the production frontier technology. Thirdly, we compare the results of steps 1 and 2 to determine possible bias in TFP change as a result of the omission of weather effects from the production technology. Finally, we made two more sets of TFP estimates to test the individual effects of the two climate variables (temperature and precipitation) on TFP growth and its components (TECCH, TECH and SECH). We drew an analogy to show how accounting for these variables together or separately may change TFP estimates across African countries and regions. The main goal of this exercise is to quantify the effects of climate shocks and demonstrate why climate variables should not be disregarded in the measurement and decomposition of agricultural TFP change in Africa.

DEA-Malmquist index specification

The DEA-Malmquist index is a nonparametric analytical technique that calculates the production frontier using a linear programming system. It is common practice to utilize the Malmquist index technique as a traditional TFP measure since it enables the decomposition of TFP change into components with respect to the frontier (i.e., a technical change index, an index of technological change and a scale efficiency change) (Nondo and Jaramillo, 2018; Ding and Zhang, 2021; Bernard *et al.*, 2022). The index takes both the border's movement and the separation between each production entity and the frontier into account. The frontier may be defined as nations (DMUs) that have embraced best-practice technology as a result of advancements. The Malmquist index's usage in growth studies is fairly simple and convenient because it assesses productivity increases over time without imposing prior assumptions (Pathak, 2019).

Empirical specification

Consider agricultural inputs m as a function of both physical market inputs represented by x and climate factors denoted by c, with $m = x + c$, for each country j at time t. This method allows for the calculation of the climate-inclusive TFP index (C_{TFP}), which is based on m inputs and y output, where y represents the country j's total crop production at time t. In other words, the two climate variables (i.e., temperature and precipitation) are jointly accounted for alongside the conventional inputs when the m variable is used in the production technology. As stated in the study's design, we examine both the combined effects of these variables and their individual effects (see Equations 1, 2 and 3). As a result, we derived a typical TFP index (N_{TFP}), a precipitation control index (P_{TFP}) and a temperature control index (H_{TFP}). According to the productivity accounting approach, productivity can be measured in relation to two periods (t and $t+1$). Thus, using the method of Chambers and Pieralli (2020), the productivity index for $t+1$ is then calculated with regard to t, the base period:

$$C_{TFP_{t,t+1}} = \left(\frac{y_{jt}}{m_{jt}}\right) \Big/ \left(\frac{y_{jt+1}}{m_{jt+1}}\right) \tag{1}$$

The C_{TFP} represents the combined effects of the climate-inclusive measure of TFP growth. The other three measures of TFP, as described above, can be shown mathematically as follows:

$$N_{TFP_{t,t+1}} = \left(\frac{y_{jt+1}}{x_{jt+1}}\right) \Big/ \left(\frac{y_{jt}}{x_{jt}}\right) \tag{2}$$

The N_{TFP} is a measure of TFP change that does not take into account climate input variables in production technology. y_{jt}- denotes total crop production output y for the country in year t. While x_{jt} represents the conventional market and material inputs used by country j for crop production in time t, this is the typical TFP estimate that is normally used to explain productivity growth trends and patterns in Africa. In this study, however, it is used as a reference base for our climate control productivity estimates:

$$P_{TFP_{t,t+1}} = \left(\frac{y_{jt+1}}{x_{jt+1} + p_{jt+1}}\right) \Big/ \left(\frac{y_{jt}}{x_{jt} + p_{jt}}\right) \tag{3}$$

P_{TFP} is the TFP estimate that exclusively controlled for the effect of precipitation in the production technology. The below expression captures the effect of temperature, H_{TFP}:

$$H_{TFP_{t,t+1}} = \left(\frac{y_{jt+1}}{x_{jt+1} + h_{jt+1}}\right) \Big/ \left(\frac{y_{jt}}{x_{jt} + h_{jt}}\right) \tag{4}$$

Our goal is to estimate the agricultural productivity of Africa in a nonparametric framework while accounting for natural inputs and to contrast the results with a conventional productivity approximation that ignores climate considerations. Instead of creating a weather productivity index like Chambers *et al.* (2020), we create climate-inclusive indices to demonstrate how the omission of natural weather inputs may impact the measurement and decomposing of agricultural TFP in Africa. Following Fare *et al.* (1994), the Malmquist output-oriented distance function for the production technology is estimated, based on the constant return to scale (CRS) assumption (Bernard *et al.*, 2022):

$$MP_t^{Ocrs} = \{(y_{jt}, m_{jt}): m(c_{jt} x_{jt}) \text{ that produces } y\} \tag{5}$$

Equation (5) accounts for the stochastic nature of climate variability in agricultural production technology (Chambers and Pieralli, 2020). The Malmquist output distance function at period t is given in Equation (6) (Fare, *et al.*, 1994; Henderson and Russell, 2005):

$$\begin{aligned} D_t^0(y_{jt},\ x_{jt}, c_{jt}) &= \min\{\theta: (y_{jt},\ x_{jt}, c_{jt}) \in P_t^{Ocrs}\} \\ &= [\max\{\theta: (y_{jt},\ x_{jt}, c_{jt}) \in P_t^{Ocrs}\}]^{-1} \end{aligned} \tag{6}$$

Under the framework of Equation (6), productivity growth at time t is calculated by dividing the observed output y_{jt}, by the highest output that could be produced from the observed total input, which includes climate, at time t:

$$D_t^0(y_{jt},\ x_{jt}, c_{jt}) = \frac{y_{jt}}{(y_{jt},\ x_{jt}, c_{jt})}$$

or (7)

$$D_t^0(y_{jt},\ m_{jt}) = \frac{y_{jt}}{(y_{jt}\ m_{jt})}$$

where $m_{jt} = x_{jt} + \ c_{jt}$ = climate-inclusive input bundle:

x_{jt} = traditional inputs (land, labor, capital and materials)
c_{jt} = climate variables (temperature and precitation)

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We can now decompose a climate-inclusive productivity index for a given country from period t to period $t+1$ using Equation (7), as described by Fare *et al.* (1994):

$$D_t^0(y_{t+1},\ m_{t+1}, y_t,\ m_t) = \left[\frac{d_t(m_{t+1}, y_{t+1})}{d_t(m_t, y_t)}\frac{d_{t+1}(m_{t+1}, y_{t+1})}{d_{t+1}(m_t, y_t)}\right]^{1/2} \tag{8}$$

The function $d_t^0(y_{t+1},\ m_{t+1}, y_{t,}\ m_t)$ indicates the distance between periods t and $t+1$technology. The expressions (m_{t+1}, y_{t+1}) and (m_t, y_t) are aggregate input and output vectors of two periods, t and $t+1$, respectively. The period t technology is denoted by the first component in the bracket $d_t(m_{t+1}, y_{t+1})/d_t\ (m_t, y_t)$, while the period $t+1$ technology is represented by the second component $d_{t+1}(m_{t+1}, y_{t+1})/d_{t+1}(m_t, y_t)$ (Bernard *et al.*, 2022). Each numerator and denominator $D_t^0(m_t, y_t)$, $D_{t+1}^0(m_t, y_t)$,$D_t^0(m_{t+1}, y_{t+1})$, and $D_{t+1}^0(m_{t+1}, y_{t+1})$ represents a distance function that, when compared, measures the effectiveness of a country's productive technology throughout two different periods, t and $t+1$. To estimate the Malmquist index, these functions must first be linearly estimated through the DEA technique. D^0 is the geometric mean of the distance function. $D^0 > 1$ signifies TFP growth during the specified time frame (t and $t+1$). $D^0 < 1$ denotes a drop in productivity, whereas $D^0 = 1$ denotes stagnation (Caves *et al.*, 1982). For simplicity, m_t is used to represent the aggregate value of the climate-inclusive input bundle $(c_t + x_t)$, where c_t is a measure of two climatic variables (temperature and precipitation), and x_t measures the conventional input (labor, capital, material). Equation (8) can be further decomposed into two separate efficiency components (efficiency change, denoted by EFCH, and technical efficiency change, denoted by TECH):

$$EFCH = \frac{d_t(m_{t+1}, y_{t+1})}{d_t(m_t, y_t)} \tag{9}$$

$$TECH = \left[\frac{d_t(m_{t+1}, y_{t+1})}{d_{t+1}(m_{t+1}, y_{t+1})}\frac{d_t(m_{t+1}, y_{t+1})}{d_{t+1}(m_{t+1}, y_{t+1})}\right]^{1/2} \tag{10}$$

The climate-inclusive TFP index (C_{TFP}) can be expressed as below using Equations (10) and (11) (Fare *et al.*, 1994):

$$C_{TFP} = \frac{d_{t+1}(m_{t+1}, y_{t+1})}{d_t(m_t, y_t)}\left[\frac{d_t(m_{t+1}, y_{t+1})}{d_{t+1}(m_{t+1}, y_{t+1})}\frac{d_t(m_{t+1}, y_{t+1})}{d_{t+1}(m_t, y_t)}\right]^{1/2} \tag{11}$$

The component outside the bracket in (11) is the technology used between periods t and $t+1$. It represents a measure of efficiency change (EFCH). This happens when adjustments to the ratio of actual outputs allow a nation to advance toward a higher productivity frontier. It is frequently referred to as 'technology catch-up' because it indicates a nation's effective utilization of productive technology, such as land, labor and capital, under advantageous agro-climatic circumstances. The second element measures technological advancement (TECCH). It embodies the potential movement of a productive technology toward the frontier (Nondo and Jaramillo, 2018; Ding and Zhang, 2021). Changes in technological know-how, adjustments to the total amount of input used, and adjustments to the observable patterns of the climate may all be responsible for the potential shift in the technological frontier (Chambers and Pieralli, 2020). In Africa, where agriculture is reliant on nature for the production of crops and livestock, the effect of the non-market input (e.g., climate variability) on agricultural productivity is even more profound.

Variable selection and data sources

The gross value of 162 crop commodities, \$1000 at a constant 2015 global average, is our single output variable (crop_output). Our input matrix includes land (crop_land), labor (Agr_labor), capital (Agr_capital), agricultural machines (Agr_machine), fertilizer (Fert_Agr) and irrigation land (tot_IrriArea). Climate controls include the annual mean of precipitation (Prcip_Amean) and temperature (Temp_Amean). All factors were selected based on earlier research (Kumar and Raj Gautam, 2014; Liang *et al.*, 2017; Njuki *et al.*, 2018; Sridhara *et al.*, 2022). The number of economically active adults (males and females) who work mostly in agriculture is used to calculate the labor force. Cropland refers to the area used for crops per 1000 ha. The capital variable represents the value of net capital stocks at constant 2015 prices of \$1.000. The service flows of capital equipment and farm stocks of farm machinery, which are measured in millions of metric tons, serve as representations of agricultural machinery. The fertilizer variable is measured by total N, P_2O_5 and K_2O nutrients from inorganic fertilizers and N from organic substances. Irrigation is the total area currently equipped for irrigation, at 1000 ha. Data for all of the above variables were obtained from the US Department of Agriculture (USDA) Economic Research Service database, updated as of October 2021. We used this database because it was designed to measure global agricultural TFP (Baráth and Fertő, 2020; Plastina *et al.*, 2021). Its primary source is the FAOSTAT database (Food and Agriculture Organization Statistics). The temperature and precipitation variables are the annual means of historical time series data recorded under the Coupled Model Intercomparison Projects (CMIP6_SSP119). The Shared Socio-economics Pathways (SSP1-1.9) is a climate scenario driven by different socio-economic assumptions selected to promote climate models for CMIP6. The CMIP6 is an expansion over CMIP5 which aims to keep warming below 1.5°C above pre-industrial levels by 2100. It was initiated following the Paris Agreement, during which nations committed to continuing their attempts to keep global warming to 1.5°C. Table 1 provides a statistical summary of these variables. A detailed explanation of these variables and their sources is provided in the Appendix (Table A1).

According to the data in Table 1, the average annual mean temperature (2000–2019) was 24.55°C, with a standard deviation of 2.95 and a minimum and highest mean of 17.6 and 29.38, respectively. Precipitation has an annual average mean of 997.17 mm and a standard deviation of 635.69 mm, with the minimum and maximum annual precipitation being 22.5 and 2785.33 mm, respectively. To better understand the trend and distribution of these variables across Africa, we created five regional diagrams, as shown in Figures 1–5.

These regional graphs illustrate the annual variations of countries' temperatures and precipitation in each region, as well as how the distribution changes over time. Most nations in Eastern, Southern and Central Africa, for example, are now seeing increases in temperature and precipitation (see Figs. 1–3). In Northern Africa, many countries saw an irregular pattern of increases in temperature for most of the last two decades (Fig. 4). In Western Africa, on the other hand, the annual average

Table 1. Variable statistics

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
crop_output	840	4,737,480	7,402,201	26,499	5.27×10^7
crop_land	840	5456.422	7871.947	37.813	60,978.72
Agr_labor	840	4381.928	5778.45	11.332	34,604.76
Agr_capital	840	7074.648	18,831.98	18.48099	188,491.2
Agr_machine	840	585.0611	1127.269	0.76	5562.778
Fert_Agr	840	142,100.9	271,231	71.91682	1,703,655
tot_IrriArea	840	305.0485	651.9632	1	3823
Temp_Amean	840	24.55212	2.945231	17.6	29.38
Prcip_Amean	840	997.1672	635.694	22.5	2786.33

temperature is decreasing while precipitation is increasing (Fig. 5). Differences in the distribution of these climate variables are important in explaining the vulnerability of Africa's agricultural industry to climate change.

Results

Table 2 displays variations in TFP change components as a result of ignoring and/or considering climate effects. According to the analysis, temperature and precipitation are critical natural inputs that are sensitive to TFP growth in Africa's agriculture. The climate-induced total factor productivity (C_TFP) increased by 2.4% on average (1.024), which was higher than the 1.9% increase in non-climate-induced TFP (N_TFP = 1.019). However, when temperature 'H_TFP' and precipitation 'P_TFP' are accounted for separately, the growth rate (2.3%) is slightly lower than the climate-induced TFP outputs (C_TFP = 2.4%) but higher than the typical TFP (N_TFP = 1.9%).

The determinants of TFP growth are also impacted by climate change. When climate variables are not taken into account, scale efficiency (SECH) decreases (N_TFP = 0.999). Accounting for precipitation (P_TFP) and temperature (H_TFP) helps recover scale efficiency losses by 0.7 and 0.4%, respectively. Similarly, technical efficiency change (TECH) decreases under the combined effect of temperature and precipitation—climate-induced TFP (C_TFP = 1.002), but technical efficiency is boosted when these climate inputs are factored in separate production models (P_TFP = 1.004 and H_TFP = 1.006). This result is in line with previous findings, and it shows that farmers are more technically efficient when the weather is 'normal'. Changes in temperature and precipitation have an impact on technological advancement in African agriculture as well. In fact, in contrast to the components of productivity determinants attributable to efficiency changes, such as scale efficiency change (SECH) and technical efficiency change (TECH), we find evidence that the effect of climate change on technological progress (TECCH) is consistent under either climate variable (P_TFP = 1.017 and H_TFP = 1.017). It is the only productivity factor that gets better proportionally to the number of weather controls. This means that productivity can be enhanced in areas with limited technology use but with an ideal agro-ecological system, and conversely, advancements in technology will lessen the impact of unfavorable weather variability on productivity growth in Africa. We created Figure 6 to conceptualize the differences between conventional agricultural TFP and climate-induced TFP; it illustrates the variation in productivity estimates between those with and without climate effects over the study period.

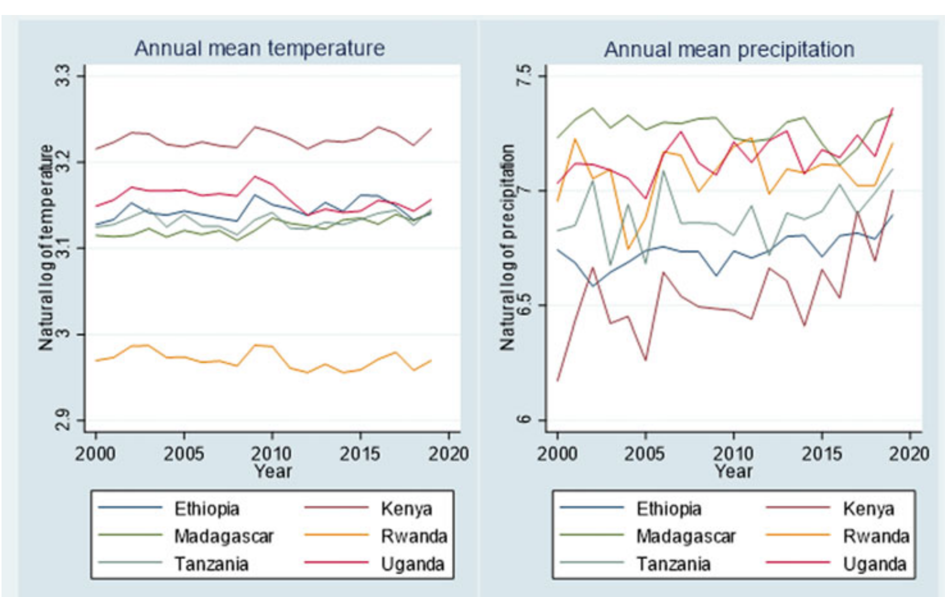

Fig. 1. Distribution of temperature and precipitation in Africa: Eastern Africa, SSA (2000–2019).

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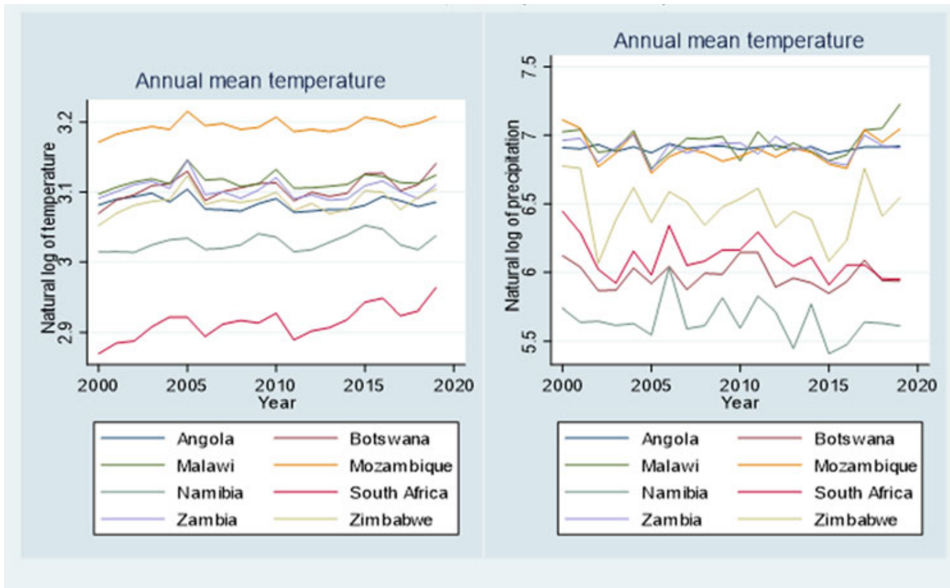

Fig. 2. Distribution of temperature and precipitation in Africa: Southern Africa, SSA (2000–2019). *Source*: Authors' calculation.

Between 2000 and 2005, the upward growth of climate-induced TFP was noticeably different from that of typical TFP. Growth was consistent from 2005 through at least 2007, with little difference between the climate-induced and the traditional TFP estimates. However, growth was erratic from 2008 to 2015, and the climate effect played a significant role in this growth dynamic. From 2017 to 2019, growth stabilized once more. The mitigating effect of the climate controls, which became apparent starting in 2010 and continued upward, can be attributed to enhanced agricultural inputs such as better irrigation systems, improved crop varieties and increased use of agricultural technologies. In general, a 3-yr growth pattern connected to weather effects was seen.

Regional analysis of climate-induced TFP

Africa is divided into five geopolitical zones known as regions and eight primary geographical features (the Sahara, the Sahel, the Ethiopian Highlands, the savanna, the Swahili Coast, the rainforest and the African Great Lakes). The Sahara and Sahel areas encompass a huge chunk of the continent and are home to more than 95% of Africa's countries. Despite their differences in animal and plant species, physical geography, environment and resources and human geography, the continent's ecology is dominated by tropical and subtropical ecosystems and semi-arid plains. This makes Africa particularly vulnerable to climate change because it is home to the world's largest desert, and desertification persists in most fertile

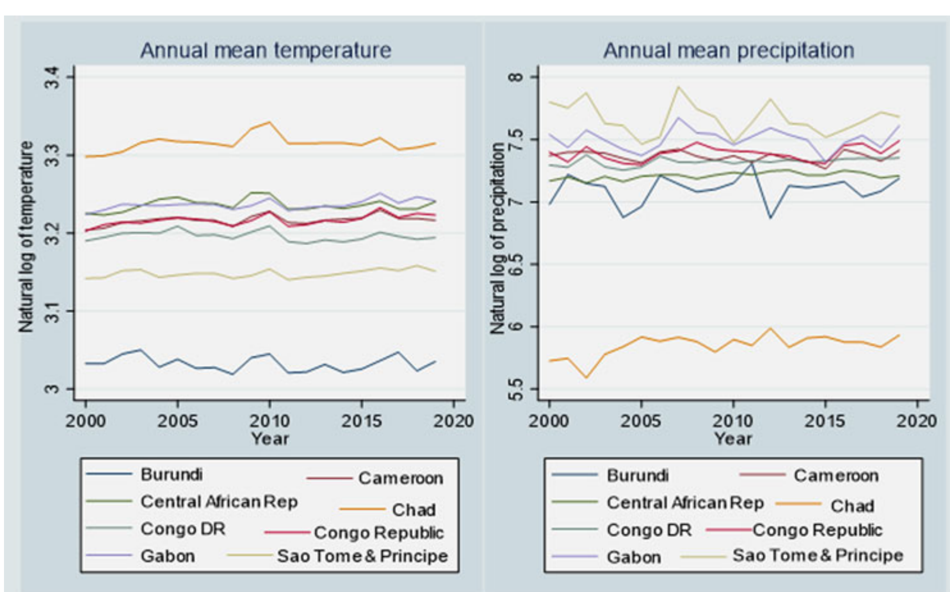

Fig. 3. Distribution of temperature and precipitation in Africa: Central Africa, SSA (2000–2019).

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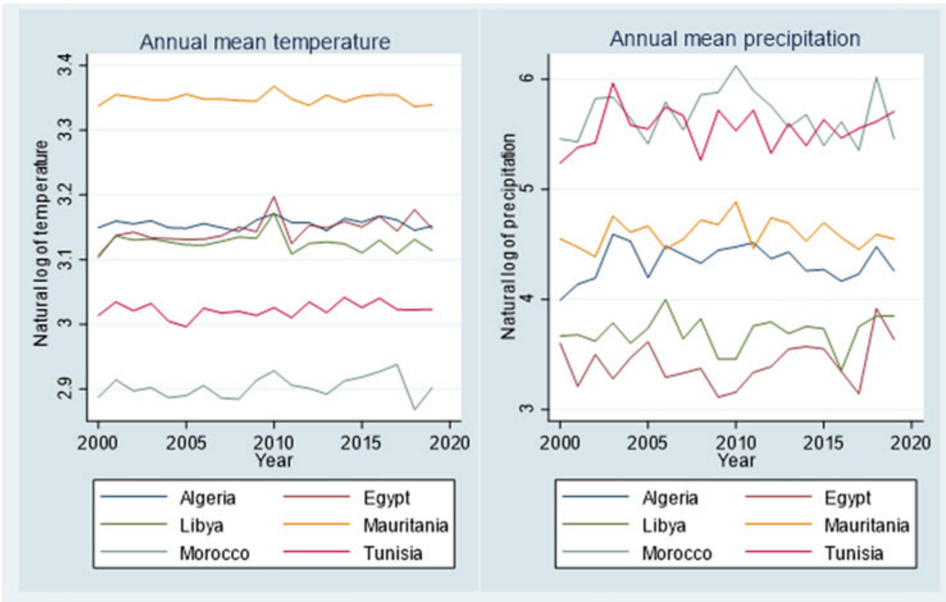

Fig. 4. Distribution of temperature and precipitation in Africa: Northern Africa, SSA (2000–2019).

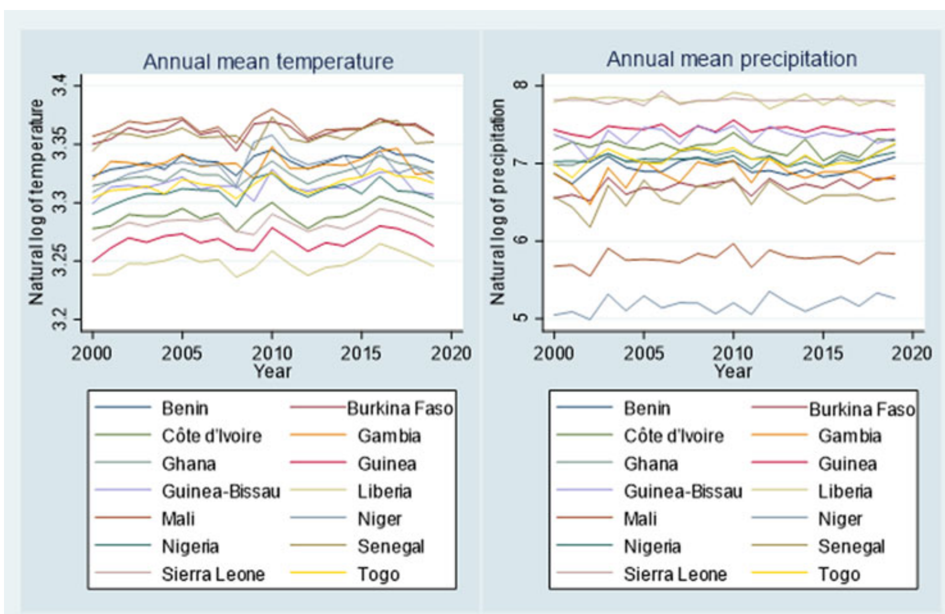

Fig. 5. Distribution of temperature and precipitation in Africa: Western Africa, SSA (2000–2019).

places as a result of global warming, drought, deforestation and intensive farming. We analyze the outcomes of the study across Africa's five geopolitical subdivisions to better understand how these characteristics influence Africa's agricultural productivity development. Table 3 provides a summary of the regional findings. On average, the normal TFP growth rates (N_TFP) are lower than those of the climate-induced TFP (C_TFP) as well as the decomposed climate-induced indices (P_TFP and H_TFP) in all regions. However, the growth rates differ by region, and the effect of climate variables on productivity determinants varies considerably across regions as well, confirming Africa's geo-ecological diversity. Comparatively, Northern Africa (see region 4 in Table 3) experienced the highest growth rates in both climate-induced TFP change (C_TFP = 1.041) and non-climate control TFP change (N_TFP = 1.036), respectively. A 5% increase in TFP growth is realized by the combined effects of temperature and precipitation (C_TFP). For the decomposed component of TFP, the climate variables improve technology change (TECCH) by up to 12%, which was

Table 2. Climate-inclusive TFP

TFP outputs	C_TFP	N_TFP	P_TFP	H_TFP
TFPCH	1.024	1.019	1.023	1.023
TECCH	1.021	1.015	1.017	1.017
TECH	1.002	1.006	1.004	1.006
SECH	1.004	0.999	1.007	1.004

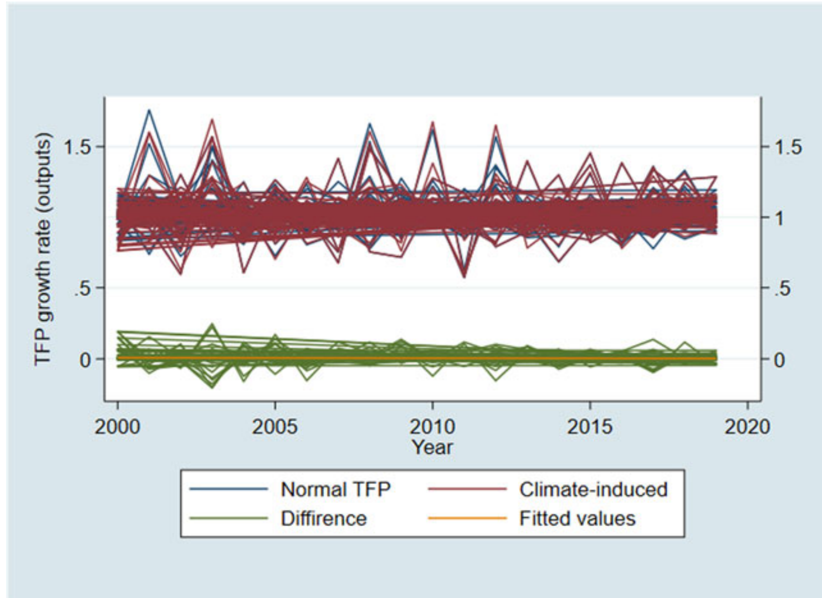

Fig. 6. Difference between climate-induced and normal TFP: Africa, 2000–2019 TFP estimates. *Source*: Authors' calculation. DEA-Malmquist index estimates of crop productivity.

Table 3. Regional analysis of TFP estimates

TFP outputs	C_TFP	N_TFP	P_TFP	T_TFP
Region 1 = Southern Africa, SSA				
TFPCH	1.022	1.018	1.021	1.021
TECCH	1.018	1.014	1.016	1.016
TECH	1.004	1.008	1.007	1.010
SECH	1.013	1.000	1.021	1.021
Region 2 = Central Africa, SSA				
TFPCH	1.014	1.010	1.013	1.013
TECCH	1.014	1.012	1.015	1.015
TECH	0.998	0.999	0.997	1.000
SECH	1.001	1.000	1.001	0.999
Region 3 = Eastern Africa, SSA				
TFPCH	1.015	1.008	1.014	1.015
TECCH	1.013	1.011	1.010	1.011
TECH	1.001	1.005	1.004	1.005
SECH	1.001	0.994	0.999	1.000
Region 4 = Northern Africa				
TFPCH	1.041	1.036	1.037	1.036
TECCH	1.034	1.022	1.026	1.024
TECH	1.003	1.012	1.006	1.009
SECH	1.006	1.002	1.011	1.003
Region 5 = Western Africa, SSA				
TFPCH	1.028	1.021	1.027	1.027
TECCH	1.024	1.015	1.019	1.019
TECH	1.002	1.007	1.004	1.007
SECH	1.002	0.999	1.004	1.000

the major determinant of climate-induced TFP growth (C_TFP = 1.034) in the region. However, when compared with temperature, precipitation played a substantial role in driving productivity growth in the region.

In comparison with North Africa, Western and Southern Africa are the second and third most productive regions. Both collectively and separately, temperature and precipitation significantly drive agricultural productivity in these regions as well. For example, in Western Africa (region 5), the C_TFP grew at an annual rate of 2.8% while the N_TFP grew at 2.1%. Technology progress largely stimulated TFP growth, and the effect of both climate variables was positive on all productivity determinants. For Southern Africa (region 1), the climate-induced TFP grew at 2.2% (C_TFPP = 1.022), while the non-climate control TFP grew at 1.8% (N_TFP = 1.018). The separate estimates of P_TFP and H_TFP also showed an increasing trend with equal magnitudes of growth rates (P_TFP = 1.021, H_TFP = 1.021). Similar positive effects of climate variables on TFP and its determinants (TECCH, TECH and SECH) were observed for Central Africa and Eastern Africa (regions 2 and 3). However, productivity growth rates in these regions were relatively low for both C_TFP and N_TFP estimates. Accounting for the individual effects of temperature and precipitation shows a recovery of productivity and efficiency losses in regions where their combined effects are negative. However, the frequency and intensity of extreme climate variables can offset the positive effects of agronormal weather inputs and cause low productivity growth in the regions where they are most prevalent. For instance, technical efficiency will decline if the average effect of temperature and precipitation is negative (anomalies). Thus, if temperatures continue to rise above the agronomic range suitable for crops growth, the prospects for Africa's food security will be highly threatened because agricultural output will be significantly affected (Nther Fischer *et al.*, 2005; Asfawa *et al.*, 2016; Mundia *et al.*, 2019; Beltran-Pena and D'Odorico, 2022). Evidence from previous studies showed that TFP growth rates have been inconsistent and have, on average, remained low in comparison with other regions of the world (Alene, 2010; Ogundari and Onyeaghala, 2021; Bernard

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et al., 2022). The impact of regional levels of climate variability in Africa and their implications on agriculture have also been reported (Marti and Puertas, 2020; Ogundari and Onyeaghala, 2021; Sridhara et al., 2022). It is hardly surprising, then, that nonparametric analysis can confirm what other methods have already shown.

Discussion

The major goal of this study was to show how weather impacts should be taken into account when analyzing production in African agriculture using nonparametric methods. Studies on productivity and efficiency typically use DEA, a nonparametric methodology. This method has a significant advantage over other productivity measurement techniques such as the SFA method because it can estimate the productivity growth and efficiency levels of a firm (DMU) without specifying a particular functional relationship between inputs and outputs. Despite this, the majority of academics have not considered weather-related aspects under the nonparametric framework. Therefore, we show how the use of natural inputs may change estimates of agricultural productivity in Africa. To achieve this, we decomposed TFP growth into increases in efficiency and technological advancement, using the Malmquist productivity index. Understanding how climate variables interact with production technologies is crucial for mitigating the extreme effects of future weather and sustain productivity increases in agriculture. It also helps us understand how the exclusion of climate factors could lead to a bias in productivity estimates.

The findings of the study highlight Africa's enormous and diverse geography and discuss how this diversity is important in the analysis of the climate–agriculture nexus in Africa. We directly compared the estimated results across the five regions of Africa to understand the influence of climate variables on TFP growth and their regional distributions. The evidence shows that climate factors play a significant role in determining agricultural productivity growth in Africa. By simultaneously accounting for temperature and precipitation and incorporating them into the production technology, productivity increased in comparison with the traditional TFP estimates. This indicates that the average impact of these weather-related inputs—rainfall and temperature—has generally been within the range of agronomic normal and that this has helped boost Africa's TFP outputs. Compared to changes in temperature, precipitation has had a bigger and better effect. The literature has documented farmers' reliance on environmental factors in African agriculture, and this result is consistent with that documentation (Edame et al., 2011; Mundia et al., 2019).

The regional analysis sheds more light on how natural inputs affect productivity growth and how this impact varies over time across regions in Africa. For instance, in Western, Central and Southern Africa, accounting for temperature and precipitation revealed that where rainfall is agronomically ideal, climate-induced TFP increased. However, in most of the northern part, where temperatures are higher than national averages for agricultural use, climate-induced productivity is slowing. This warming climate, driven on by rising temperatures, which would limit agricultural output and drastically affect food availability, threatens the possibility of food-secure Africa. Figure 7 illustrates the distributional effect of temperature and precipitation on regional agricultural productivity.

The findings of this study not only supported previous studies but also corroborated current developments in many African countries. For instance, in this year's human development reports, the United Nations Secretary-General, Antonio Gutierrez, cautioned of a lengthy global food crisis caused by the convergence of war, the COVID-19 pandemic and rising temperatures (Human Development Report, 2022). In addition to causing global warming, the increase in temperature has caused a significant disruption in global food production and supply, with wider socio-economic implications for developing countries. The devastating weather effects on Africa's agriculture are already visible, as food shortages have begun to impact the most vulnerable rural populations, causing starvation and hunger. To avoid a potential food emergency crisis in Africa, urgent steps must be taken to ensure that the necessary adaptation and mitigation measures are in place, making Africa's agriculture more resilient to climate change. This will help African countries enhance productivity growth for food availability and sustain socio-economic stability while protecting the continent's ecosystem.

To conclude, it is important that we emphasize a few key points that can be quite helpful, particularly for policymakers: first, ignoring weather inputs can significantly impact the accuracy of productivity estimates and present unsubstantiated assessments of TFP growth and productivity drivers in Africa's

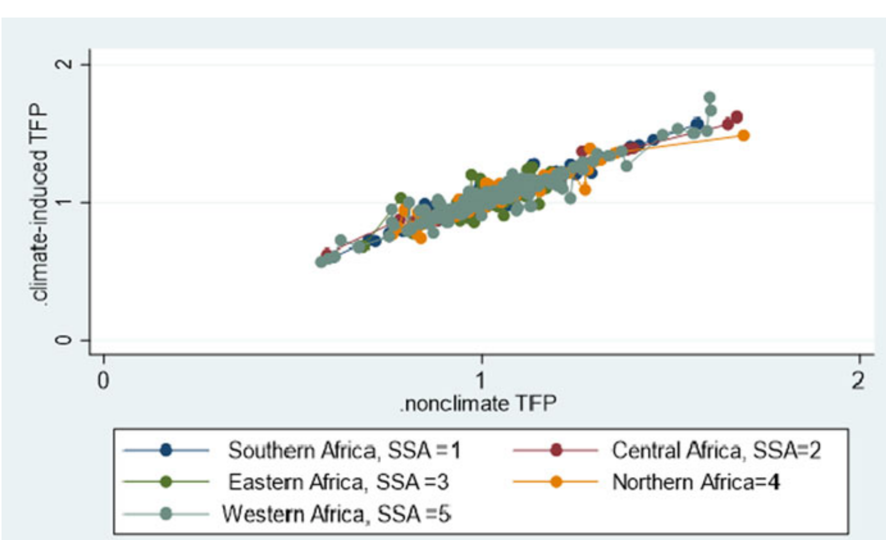

Fig. 7. Regional distribution of TFP growth rate: Africa, 2000–2019 TFP. *Source*: Authors' calculation. DEA-Malmquist index estimates of crop productivity.

agriculture. This could have serious consequences for national agricultural policies across Africa. Secondly, agricultural TFP growth rates can be boosted when weather factors are considered in estimating the production technology of many African countries. While regular climate variability helps enhance productivity growth and makes up for the technology deficit in Africa's agriculture, it should be noted that technological advancement is critical in mitigating the effects of negative weather variables on TFP growth on the continent. Therefore, African governments and policymakers should put a high priority on getting more farmers to use sustainable technology to reduce and smooth out temperature and rainfall extremes now and in the future. Thirdly, the evidence regarding the little use of agricultural technology in Africa and the heavy reliance on traditional farming systems makes it look very likely that some of what has been said about the role of technological progress in African agriculture could be explained by climate factors rather than actual technology use (Reynolds *et al.*, 2015; Bertelli, 2020). Therefore, more research is required to reevaluate national productivity estimates in Africa's agriculture sector.

Finally, some restrictions apply to this study. Although the DEA-Malmquist approach has the benefit of being able to decompose productivity growth without imposing any parameter restraints, the statistical significance of our results could not be verified because the nonparametric approach does not account for the errors that result from other undetectable factors of production (Lee *et al.*, 2011). Moreover, TFP is a measure of the unknown (i.e., growth that cannot be explained solely by the inputs used); as such, it is difficult to identify or capture all facts that explain its growth using the nonparametric approach advocated by this study.

Data

All the generated data are available in the manuscript.

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Author contributions. All authors contributed to the study conception and design. Conceptualization was done by Boima M. Bernard; material preparation, data collection and analysis were performed by Boima M. Bernard, Xin Wang and Mulinga Narcisse. The first draft of the manuscript was written by Boima M. Bernard and all authors commented on previous versions of the manuscript. Formal analysis and data visualization was done by Sehresh Hena. Project administration and supervision was carried out by Yanping Song. All authors read and approved the final manuscript.

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References

Alene AD (2010) Productivity growth and the effects of R&D in African agriculture. *Agricultural Economics* **41**, 223–238.

Asfawa S, Di Battista F and Lipper L (2016) Agricultural technology adoption under climate change in the Sahel: micro-evidence from Niger. *Journal of African Economies* **25**, 637–669.

Baráth L and Fertő I (2020) Accounting for TFP growth in global agriculture —a common-factor-approach-based TFP estimation. *AGRIS On-line Papers in Economics and Informatics* **12**, 3–13.

Beltran-Peña A and Odorico P (2022) Future food security in Africa under climate change. *Earth's Future* **10**, E2022E–F2651.

Bernard BM, Jr Song Y, Hena S, Ahmad F, Wang X (2022) Assessing Africa's agricultural TFP for food security and effects on human development: evidence from 35 countries. *Sustainability* **14**, 6–17. https://doi.org/10.3390/su14116411

Bertelli O (2020) Food security measures in sub-Saharan Africa. A validation of the LSMS-ISA scale. *Journal of African Economies* **29**, 90–120.

Blanc É (2011) The impact of climate change on crop production in Sub-Saharan Africa. Policy 2014–2015.

Cachia Franck (2018) Guidelines for the measurement of productivity and efficiency in agriculture. *Food and Agriculture Organization*, 69. https://doi.org/10.13140/RG.2.2.31566.72006

Caves D W, Christensen L R and Diewert W E (1982) The economic theory of index numbers and the measurement of input, output, and productivity. Econometrica **50**, 1393–1414.

Chambers RG and Pieralli S (2020) The sources of measured US agricultural productivity growth: weather, technological change, and adaptation. *American Journal of Agricultural Economics* **102**, 1198–1226.

Chambers RG, Pieralli S and Sheng Y (2020) The millennium droughts and Australian agricultural productivity performance: a nonparametric analysis. *American Journal of Agricultural Economics* **102**, 1383–1403.

Chancellor W, Hughes N, Zhao S, Soh WY, Valle H and Boult C (2021) Controlling for the effects of climate on total factor productivity: a case study of Australian farms. *Food Policy* **102**, 102091. https://doi.org/10.1016/j.foodpol.2021.102091.

Daniel J, Henderson R Robert (2005) Human Capital and Convergence: A Production-Frontier Approach. International Economic Review **46**, 1167–1205.

Ding C and Zhang R (2021) The measurement and influencing factors of total factor productivity in the Chinese rural distribution industry. *Sustainability* **13**, 4–12. https://doi.org/10.3390/su13158581

Edame GE, Ekpenyong AB, Fonta WM and Ejc D (2011) Climate change, food security and agricultural productivity in Africa: issues and policy directions. *International Journal of Humanities and Social Science* **1**, 205–223.

Fare R, Grosskof S, Norris M and Zhang Z (1994) Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries. American Economic Reviews **1**, 66–83.

Fuglie K (2012 Productivity Growth and Technology Capital in the Global Agricultural Economy. In: Fuglie K., Wang, S.L. and Ball, V.E. (eds.), *Productivity Growth in Agriculture: An International Perspective*. Wallingford, UK: CAB International, pp. 335–368.

Gray E, Jackson T and Zhao S (2011) Agricultural Productivity: Concepts, Measurement and Factors Driving It—A Perspective from the ABARES Productivity Analyses. *Australian Bureau of Agricultural and Resource Economics and Sciences*, pp. 2–14.

Hertel TW and de Lima CZ (2020) Viewpoint: climate impacts on agriculture: searching for keys under the streetlight. *Food Policy* **95**, 3–10. doi: https://doi.org/10.1016/j.foodpol.2020.101954

Hughes N, Lawson K, Davidson A, Jackson T and Sheng Yu (2011) Productivity pathways: climate-adjusted production frontiers for the Australian broadacre cropping industry.

Human Development Report (2022) Report 2021/2022. Uncertain times, unsettled lives: shaping our future in a transforming world. Available at http://hdr.undp.org.

Kumar R and Raj Gautam H (2014) Climate change and its impact on agricultural productivity in India. *Journal of Climatology & Weather Forecasting* **2**, 1–4.

Lee K-R, Leem B-I, Lee CW and Lee C (2011) Malmquist productivity index using DEA frontier in Stata. *The Stata Journal* **vv, Number ii**, 1–9.

Liang XZ, Wu Y, Chambers RG, Schmoldt DL, Gao W, Liu Cs, Liu YA and Sun C (2017) Determining climate effects on US total agricultural productivity. *Proceedings of the National Academy of Sciences of the United States of America* **114**, E2285–E2292.

Marti L and Puertas R (2020) Analysis of the efficiency of African countries through their ecological footprint and biocapacity. *Science of the Total Environment* **722**, 137504.

McCarl BA and Hertel TW (2018) Climate change as an agricultural economics research topic. *Applied Economic Perspectives and Policy* **40**, 60–78.

Mechiche-Alami A and Abdi AM (2020) Agricultural productivity in relation to climate and cropland management in West Africa. *Scientific Reports* **10**, 3393.

Mundia CW, Secchi S, Akamani K and Wang G (2019) A regional comparison of factors affecting global sorghum production: the case of North America, Asia and Africa's Sahel. *Sustainability* **11**, 2135.

Njuki E, Bravo-Ureta BE and O'Donnell CJ (2018) A new look at the decomposition of agricultural productivity growth incorporating weather effects. *PLoS ONE* **13**, 1–21.

Nondo C and Jaramillo JR (2018) Analyzing Africa's total factor productivity trends. *International Journal of Sustainable Economies Management* **7**, 45–61.

Nther Fischer G, Shah M, Tubiello FN, Van and Velhuizen H (2005) Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990-3080, https://doi.org/10.1098/rstb.2005.1744.

O'Donnell CJ (2012) Nonparametric estimates of the components of productivity and profitability change in U.S. agriculture. *American Journal of Agricultural Economics* **94**, 873–890.

O'Donnell CJ (2021) Estimating the effects of weather and climate change on agricultural productivity: Centre for Efficiency and Productivity Analysis. Working Paper Series No. WPO32021, ISSN No. 1932-4398.

Ogundari K and Onyeaghala R (2021) The effects of climate change on African agricultural productivity growth revisited. *Environmental Science and Pollution Research* **28**, 30035–30045. https://doi.org/10.1007/s11356-021-12684-5.

Pathak HP (2019) Malmquist productivity index approach in assessing performance of commercial banks: evidence from Nepal. *NRB Economic Review* **31**, 25–55.

Plastina A, Lence SH and Ortiz-Bobea A (2021) How weather affects the decomposition of total factor productivity in U.S. agriculture. *Agricultural Economics* **52**, 215–234.

Qi L, Bravo-Ureta BE and Cabrera VE (2015) From cold to hot: climatic effects and productivity in Wisconsin dairy farms. *Journal of Dairy Science* **98**, 8664–8677.

Rahman S and Salim R (2013) Six decades of total factor productivity change and sources of growth in Bangladesh agriculture (1948–2008). *Journal of Agricultural Economics* **64**, 275–294.

Reynolds TW, Waddington SR, Anderson CL, Chew A, True Z and Cullen A (2015) Environmental impacts and constraints associated with the production of major food crops in sub-Saharan Africa and south Asia. *Food Security* **7**, 795–822. https://doi.org/10.1007/s12571-015-0478-1.

Schreyer P (2001) The OECD productivity manual: a guide to the measurement of industry-level and aggregate productivity. *Int Product Monit* **2**, 37–51.

Sridhara S, Gopakkali P, Manoj KN, Patil KKR, Paramesh V, Jha PK and Prasad PVV (2022) Identification of sustainable development priorities for agriculture through sustainable livelihood security indicators for Karnataka, India. *Sustainability* **14**, 1831. https://doi.org/10.3390/su14031831

Suresh K, Khanal U, Wilson C, Managi S, Quayle A and Santhirakumar S (2021) An economic analysis of agricultural adaptation to climate change impacts in Sri Lanka: an endogenous switching regression analysis. *Land Use Policy* **109**, 105601. https://doi.org/10.1016/j.landusepol.2021.105601.

Valipour M (2017) Calibration of mass transfer-based models to predict reference crop evapotranspiration. *Applied Water Science* **7**, 625–635.

Appendix

Table A1. Variable description

Variable	Description	Source
Output (crop)	Gross value of 162 crop commodities, \$1000 at constant 2015 global average farm gate-price	FAO FAOSTAT
Cropland	Total cropland (including arable land and land in permanent crops), 1000 ha	FAO Cropland except for sub-Saharan Africa, where cropland = FAO Area Harvested. Adjustments to FAO historical cropland estimates made for China, Indonesia, and Colombia.
Irrig	Total area equipped for irrigation, 1000 ha	FAO FAOSTAT Area Equipped for Irrigation.
Labor	Number of economically active adults (male and female) primarily employed in agriculture, 1000 persons	ILO ILOSTAT labor force survey estimates (if available) or modeled estimates (1991+), supplemented with GDCC estimates and previously published FAO estimates (pre-1991).
Capital	Value of net capital stock, \$1000 at constant 2015 prices	FAO FAOSTAT Net Capital Stock (1995+), which is derived from the sum of past capital investments depreciated for wear and tear estimated using perpetual inventory method (PIM). Pre-1995 estimates derived from inventories of livestock and machinery capital.
Machinery	Farm inventories of farm machinery, measured in thousands of metric horsepower (1000 CV) in tractors, combine-threshers and milking machines	Compiled from multiple sources: Pre-2010 data from FAOSTAT, post-2010 data from National Agricultural Censuses, Private sector data on sales of new tractors and combines, and modeled estimates.
Fertilizer	Total N, P_2O_5, K_2O nutrients from inorganic fertilizers and N from organic fertilizers applied to soils, in 1000 metric tons	International Fertilizer Association (IFA), except for 15 small countries which is from FAO FAOSTAT; FAO FAOSTAT Manure Applied to Soils.
Temp_Amean	Annual mean temperature	The Global Meteorological Forcing Dataset (GMFD) for land surface modeling developed by the Terrestrial Hydrology Research Group at Princeton University.
Prcip_Amean	Annual mean precipitation	The Global Meteorological Forcing Dataset (GMFD) for land surface modeling developed by the Terrestrial Hydrology Research Group at Princeton University.

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