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Agricultural total factor productivity growth, technical efficiency, and climate variability in sub-Saharan Africa

Frank Bannor¹, Johane Dikgang and Dambala Gelo²

Abstract

Despite continuous reforms and increased spending in the agricultural sector, Africa remains a net food importer. Previous research has argued that agricultural productivity is lower in Africa than in all other parts of the world due to challenging ecological conditions – soil fertility challenges and extreme climate. Increasing the region's food supply requires significant increases in agricultural productivity, which in turn depends on investment in research and development (R&D). This study examines how climate variability (proxied by rainfall variability) affects agricultural total factor productivity (TFP) of maize in 14 sub-Saharan African countries (SSA). Maize farming in Africa – due to its significance in regional food production, evident climate variability, and the need to significantly increase efficiency – is an ideal region of investigation for climate impacts on maize production. We apply a Data Envelopment Analysis (DEA) on the Malmquist Productivity Index (MPI) to decompose productivity growth into technical efficiency and technological progress. In addition, a single-stage maximum-likelihood estimation of a true fixed effect was used to investigate how climate variability affects maize productivity through technical efficiency. The results show that climate variability has a negative effect on technical efficiency in the agricultural production of maize. Furthermore, increased spending on R&D is required to enhance technical efficiency and productivity.

Key Words: climate change, data envelopment analysis, maize, technical efficiency, total factor productivity, research and development.

JEL classification: Q1, Q5

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1. Introduction

Sub-Saharan Africa (SSA) has suffered from reduced farming productivity historically. This has actually limited even more socio-economic development by lowering the available agricultural surplus for the supply of other economic activities and sectors (Ronnback & Theodoridis, 2018). In spite of its enormous agricultural capacity and substantial investment in agriculture, Africa has actually ended up being a net importer of food as well as agricultural items. A variety of elements, consisting of fast population growth, plan distortions, weak establishments, bad framework, low and stagnant agricultural productivity, contribute to the current situation in the SSA. (Rakotoarisoa et al. 2011). Our focus in this article is partially on this last: agricultural productivity.

One general consensus in the literature is that agriculture relies heavily on productivity for growth. In comparison to overall economic growth, which is powered by increases in total factor input productivity (Jorgenson et al. 2016), total factor productivity (TFP) in agriculture accounts for around three quarters of global growth (Fuglie, 2015). This dependency on productivity reflects the strong dependence of agriculture on inherently scarce resources such as land and water; and it is these resource constraints that have caused concern, considering our rapidly growing global population and climate change (Fuglie et al., 2017).

Despite these concerns, agricultural productivity worldwide has been able to rise significantly in order to meet increasing demand, primarily due to substantial investments in R&D. (Ruttan, 1982). The secret to achieving productivity growth through new knowledge and innovation is R&D investment (Alston et al. 1999; Hall & Scobie, 2006; Rahman & Salim, 2013). In SSA, this process is also taking place (see Masters, Bedingar & Oehmke, 1998; Maredia, Byerlee & Pee, 2000; Beintema & Stads, 2011; Adetutu & Ajayi, 2020). Although it has been shown that SSA's agricultural productivity growth has been powered by R&D investment over the past decades, which in turn has driven productivity growth, and that returns are fairly high (see Masters et al., 1998; Maredia et al., 2000), these returns tend to be significantly lower than in other parts of the world. Is this attributable to drastic changes in the climate? SSA is one of the regions worst affected by climate change and it is possible that better returns will be generated by the same investment elsewhere. Surprisingly, little work has been done to shed light on the connection between agricultural productivity, technical efficiency, and climate change.

A better understanding of the relationship between R&D spending, TFP growth and climate change is important, not just for the assessment of public investment returns, but also for the creation of realistic scenarios for potential agricultural productivity growth and climate change mitigation strategies to mitigate the impacts involved. The goal of this study is to investigate the transmission channels and the degree to which agricultural TFP is influenced by climate variability. This paper adds to the scant transmission channel literature in which climate variability affects agricultural TFP by assessing the effect of climate variability on agricultural productivity. By building on the efficiency theory, we contribute to the literature to investigate how climate variability (proxied by rainfall variability) determines maize agricultural TFP in 14 SSA countries. As variability in the climate captures adjustments that occur within a much shorter duration, we make use of climate variability as opposed to climate change. In so doing, we contribute important empirical evidence regarding the transmission channel (technical efficiency) through which climate variability affects agricultural TFP in SSA.

This paper investigates how climate variability determines technical efficiency in agricultural TFP using a single-stage maximum-likelihood estimation of a true fixed-effects approach, during the period 1995 to 2016. Our approach is twofold. First, we use the Data Envelopment Analysis (DEA)-based Malmquist Productivity Index (MPI) to measure maize TFP changes over time, by decomposing TFP into technical efficiency and technological progress. Second, based on evidence of inefficiencies in the agricultural production of maize, we apply a single-stage maximum-likelihood estimation of a true fixed-effects approach to investigate how climate variability determines technical efficiency in maize TFP within the sampling period (1995 to 2016).

The remainder of the paper continues as follows. Section 2 offers a literature review. Section 3 sets out the analytical model. Section 4 presents data and sources. Section 5 explains the findings, and Section 6 concludes.

2. Literature review

In the context of country-level and cross-country assessments of the effects of climate change on agricultural production, many studies have examined these effects using various analytical methods, variable choices, and samples. The wider literature generally suggests that climate variability affects agricultural production (see Letta & Tol 2019; Chen et al., 2015; Schlenker &

Roberts, 2009; Fankhauser & Tol, 2005). Hurley (2010) argues that this can be attributed to the fact that climate variability poses a risk to farmers (especially those in developing countries), who are often risk averse. Because variability in the climate induces danger, farmers' expectation of shocks associated with the climate could influence their decisions through multiple, interdependent production choices – such as the hiring of labour, use of resources, and the application of fertiliser to avoid losses – and thus affecting agricultural production. At the same time, Di Falco and Chavas (2009), Brown et al. (2010), Barrios et al. (2010), Dercon and Christensen (2011) and Amare et al. (2018) also provide evidence that climate variability gives rise to crop production risks. This, they observe, increases farmers' risk of technology adoption; especially in a rainfed-agricultural region such as SSA, where insurance and information markets are non-existent and the constraint of capital exists, reducing agricultural production in the process.

Studies focusing on identifying sources of agricultural productivity growth and trends (see Sheng et al., 2019; Letta & Tol, 2018; Alejandro & Sergio, 2018; Gadanakis & Areal, 2018; Pires & Garcia, 2012; Rezek et al., 2011; Alene, 2010) reveal that agricultural TFP has witnessed a decline over the past decade. Sheng et al. (2019) document that China's agricultural TFP grew at a rate of 2.4% per annum before 2009; after 2009, average agricultural production growth slowed down. Alejandro and Sergio (2018) show that while technical efficiency demonstrates a positive overall trend, a negative overall trend is demonstrated by allocative efficiency.; the overall impact is a slowing down of TFP growth in US agriculture. Gadanakis and Areal (2018) observed that agriculture productivity deteriorated over their study period (2007 to 2011) for all farm sizes in East Anglia in the United Kingdom. Letta and Tol (2018), investigating the correlation between weather, climate, and total factor productivity, found that a relationship exists in poor countries such that a degree Celsius change in temperature reduces TFP growth rates between 1.1% and 1.8%. Similarly, Pires and Fernando (2011), investigating the productivity of nations, found that changes in allocative efficiency coupled with technical changes account for a greater number of the variations between developed and developing countries in economic growth. Over the past four decades, Rezek et al. (2011) have observed very little increase or decrease in the growth rate of agricultural productivity in SSA. Overall, agricultural production declined from the late 1960s until the late 1970s, they found. Considering the above research, the relative association between climate change and TFP growth has been a prominent theme in the agricultural productivity literature. However, these studies were reluctant to perform an empirical review of the

transmission channel by which the growth of agricultural TFP may be influenced by climate change.

3. Methodology

3.1 The Malmquist Productivity Index (MPI)

In the non-parametric sense, Malmquist (1953) first introduced the MPI concept and other authors researched and further improved it (see Caves et al. 1982; Färe, Grosskopf et al. 1989; Färe et al. 1992; Färe et al. 1998; Thrall, 2000). The MPI reflects the growth in TFP of a decision-making unit (DMU). That is, under the various inputs and multiple output systems, it reflects enhancement or regression of efficiency along with advancement or regression of frontier technology over time (Tone, 2004).

We use the MPI approach to measure performance changes over time in order to decompose TFP into technical efficiency and technological progress. Estimation of TFP using MPI is common in the literature (see Gadanakis & Areal, 2018; Färe et al., 1992) due to its robustness and ability to separate technological progress (changes in technology that lead to an increase in productivity) and change in technical efficiency (Maximum output from minimal input quantities). Therefore, the MPI approach is premised on calculating distance functions. Alene (2010) noted that the distance function helps to model a behavioural assumptions-free input-output production technology, with the output distance function considering the maximum proportional expansion of the output vector with the cognizance of a given input vector taken. Our study therefore adopts a production technology using a $P(x)$ output package, which demonstrates the set of all output vectors (y) that can effectively be generated using an input vector (x). At the same time, the output possibilities of the input vector boundary can be represented as the output vector, which, without leaving the range, cannot be increased by a uniform element. The function of output distance expressed on the output set can therefore be stated as:

$$D_0^t(x^t, y^t) = \min [\beta^t : \{(x^t, y^t)/\alpha\} \in \mathcal{Y}^t] \quad (1)$$

where the notation D^t is the distance function, y^t shows the vector of output, x^t indicates the vector of inputs and \mathcal{Y}^t represents the technology used at time t . From Equation 1 above, $D_0^t(x^t, y^t)$: the distance function should have a value that is either less than or equal to 1, since the y output vector

is an element that belongs to the possible P output set (x). In addition, because the position of y is on the outer boundary of the possible production set, the distance function would assume a unitary value; and again, y could take on a value greater than 1, since its location is outside the possible production set.

Following Färe et al. (1994), we formulated the distance function to capture the proportional maximum change in output that is needed to satisfy the condition (x^t, y^t) in connection to technology at $t+1$, which can be stated as $D_0^{t+1}(x^t, y^t)$. Hence, we can express the MPI as follows:

$$M_1^t = \left[\left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \right) \right] \quad (2)$$

Given the formulation in Equation 2 above, the reference point for technology is in period t – that is, D_0^t . On the other hand, we could express technology with the reference period ($t+1$), and thus our specified MPI is as follows:

$$M_1^{t+1} = \left[\left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)} \right) \right] \quad (3)$$

As far as the growth rate of the TFP is concerned, the MPI calculates the changes in the TFP between two data points by calculating the distance ratio of each data point to the particular technology defined in the two adjacent periods, provided that the option of period t or $t+1$ as the base year could be arbitrary (i.e., the base year could be either period t or period $t+1$). Färe et al. (1994) argued that the output located MPI could be defined as the geometric mean of the two Malmquist indexes t and $t+1$ to do away with the selection of an arbitrary benchmark. That is, the Malmquist function of the input orientation can be expressed as follows for each process:

$$\begin{aligned} M_1^t &= (y^{t+1}, x^{t+1}, y^t, x^t) \\ &= \left[\left(\frac{D_0^t(y^{t+1}, x^{t+1})}{D_0^t(y^t, x^t)} \right) x \left(\frac{D_0^{t+1}(y^{t+1}, x^{t+1})}{D_0^{t+1}(y^t, x^t)} \right) \right]^{1/2} \end{aligned} \quad (4)$$

where M_1^t refers to MPI from period t , and $D_0^t(y^{t+1}, x^{t+1})$ is the input distance from $t+1$ time observation to the technology period of t . A value of M_1^t greater than 1 indicates a positive growth

of the TFP from period t to period $t+1$, while a value less than 1 indicates a decline in the TFP. It should be observed that Equation 4 above is the geometric mean of two indexes measuring TFP.

The first part is estimated taking cognizance of technology at period t , and the later part is estimated taking cognizance of technology at period $t+1$ (see Alene, 2010). The indices are estimated using the non-parametric DEA approach to construct a piecewise frontier enveloping the data points (see Charnes et al., 1978). According to Balcombe et al., (2008) the main advantage of the DEA approach is that it prevents mis-specification errors and helps to evaluate improvements in quality concurrently in a multi-output, multi-input situation.

The use of the DEA formula in calculating MPI makes it easy to ‘quantify’, because DEA does not require pricing information. Furthermore, TFP's technology assumption for estimating the MPI¹ in our study is Constant Returns to Scale (CRS). Grifell-Tatjé and Lovell (1995) state that non-CRS methods do not accurately measure a change in productivity.

Therefore, our index in Equation 4 above can be decomposed into two components: firstly, the change in efficiency; and secondly, the change in technology. The decomposition is expressed as follows:

$$M_1^t = \left[\left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \right) \right] * \left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \right) \left(\frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right) \right]^{1/2} \quad (5)$$

$\Delta TE \qquad \qquad \qquad \Delta TP$

where ΔTE is the part capturing changes in technical efficiency $\left[\left(\frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \right) \right]$, while

ΔTP is the part capturing changes in technological progress $\left[\left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \right) \left(\frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right) \right]^{1/2}$.

Färe et al. (1992) argued that the first part, which captures technical performance, indicates how much farther or closer an organization gets to the frontier of best practice. Likewise, the later part, which is an index of technological change, measures how far the frontier changes. As is the case with the TFP calculation using the MPI, which means an increase, decrease or stagnation respectively, the two components have values that are more, less or equal to unity.

Therefore, our MPI in Equation 5 above allows us to decompose TFP growth into technical efficiency and technological progress, and then further assess whether there are inefficiencies in TFP. However, our MPI does not allow us to determine the drivers of technical efficiency. Thus, to investigate how climate variability determines technical (in)efficiency, we rely on a single-stage maximum-likelihood estimation of a true fixed-effects approach.

3.2. Theoretical framework

To examine how climate variability influences technical efficiency in the sampling period, we follow Battese and Coelli (1992) and Green (2005a) in expressing a time-varying technical (in)efficiency model. Earlier studies considered technical inefficiency to be time-invariant (Pitt & Lee, 1981; Schmidt & Sickles, 1984), which implied that inefficient producers produced output below the best-practice production frontier without ever learning from experience. Kumbhakar et al. (2015) showed that the tendency to learn is great, as producers operate in a highly competitive market.

In the presence of varying climatic conditions, the possibility of farmers learning more about the use of inputs into agricultural processes as time progresses becomes even more likely (see Sesmero et al., 2017). Therefore, a specification to capture the time-varying technical inefficiency model was given by Battese and Coelli (1995), which is expressed as follows:

$$\log \varphi_{it} = f(\log \Phi_{it}; \psi) + \varepsilon_{it} \quad (6)$$

where φ_{it} represents technical (in)efficiency. Technical inefficiency is expressed in terms of real production, as compared to relatively practical production. Exogenous factors affecting technical inefficiency are denoted by Φ_{it} , ψ is a parameter to be estimated, and ε_{it} shows the error term. Battese and Coelli (1995) observed that the error term ε_{it} , is defined by the truncation of the normal distribution with zero mean and variance σ^2 , such that the point of truncation is $-\Phi_{it}\sigma$. Therefore, our model in Equation 6 above can be expanded as follows:

$$\log (\varphi)_{it} = \psi \log \Phi_{it} + \varepsilon_{it} \quad (7)$$

3.2.1 Climate variability and technical inefficiency

As a large share of its national economies are agriculture dependent, SSA is one of the world's most sensitive regions to change (Slingo et al., 2005). In recent years, temperatures across the SSA have risen by 0.5°C according to the IPCC (2014) and are predicted to increase by another 4°C by the end of the twenty-first century, along with irregular patterns of rainfall.

The literature, however, provides mixed results on the effect on agricultural development due to climate change. Some studies (see Alene, 2010; Salim & Islam, 2010) found that in Africa and Australia, climate change increased agricultural TFP by an elasticity of 0.5 and 0.17, respectively. Others (see Bocchiola et al., 2019; Amare et al., 2018; Niang et al., 2014; Knox et al., 2012; Hansen et al., 2011) found that the low productivity seen in the agricultural sector in most developing nations could be due to climate change, given that agriculture in most developing countries is rain-fed. Amare et al. (2018) argue that the decision of a farmer to implement inputs for agricultural enhancement is influenced not only by capital constraints, but also by variability in pre-year precipitation, which generates uncertainty about the phase of agricultural production. Similarly, Fankhauser and Tol (2005) asserted that climate variability could affect the depreciation of capital, the supply of labour, and productivity growth. They showed that economic growth could be stifled, given that the effects they studied are negative. Therefore, climate variability could adversely affect agricultural production.

We use climatic variability (proxied by rainfall variability) in our model to capture the adverse effects of climate variability on technical efficiency. Our model in Equation 7 above is, therefore, generalized as follows:

$$\log (\varphi)_{it} = \psi_1 \log (Clim_Var_{it}) + \lambda_{it} + \varepsilon_{it} \quad (8)$$

where λ_{it} represents a vector of other explanatory variables, with ψ being a parameter to be estimated.

3.2.2 R&D and technical efficiency

The general consensus in the literature is that R&D boosts agricultural production. The inclusion of R&D in our study is based on both empirical and theoretical evidence supporting this claim. Previous studies on agricultural productivity growth over the past decade show that R&D

investment is one of the main sources of productivity growth, with the returns on agricultural R&D been quite reasonable in the process (see Khan et al., 2018; Andersen, 2015; Alene & Coulibaly, 2009; Alene, 2010; Salim & Islam, 2010; Maredia et al., 2000; Masters et al., 1998). Given this insight, we control for R&D in our model from Equation (8) above. This gives equation 9 below:

$$\varphi_{it} = \psi_1 \log(Clim_Var_{it}) + \theta \log(R_D)_{it} + \lambda_{it} + \varepsilon_{it} \quad (9)$$

where R_D_{it} is R&D, and θ is a parameter to be estimated.

3.2.3 Literacy and technical efficiency

The percentage of the adult population that is literate as a proxy for education was used by Hayami and Ruttan (1986) and thus accounted for disparities in labour quality. High literacy is therefore expected to increase agricultural productivity, given that a farmer is therefore endowed with the knowledge and capacity to use the information provided by agricultural extension officers. Alene (2010) argued that farmers could benefit from a more educated populace, given that they could provide improved agricultural services and thereby increase production of agriculture with the same inputs (and vice versa). Therefore, we add literacy to Equation 9 above and arrive at equation 10 below:

$$\varphi_{it} = \psi_1 \log(Clim_Var)_{it} + \theta \log(R_D)_{it} + \gamma \log(L_R)_{it} + \lambda_{it} + \varepsilon_{it} \quad (10)$$

where L_R represents literacy rate, and γ is a parameter to be estimated.

3.3 The general stochastic frontier analysis (SFA) model

The SFA focuses on seeking an estimator for one of the components of TFP: the degree of technical performance, Pires and Garcia (2012) noted. Therefore, in addition to technological improvements, which are captured by a time trend and the interactions of the regressors² with time, technical performance is also calculated by the SFA. Following Pires and Garcia (2012), our stochastic frontier model of development is expressed as follows for each country (i) in a time (t):

$$\log(y)_{it} = f(\gamma_{it}; \delta) \cdot \exp(v_{it}) \cdot \exp(-u_{it}) \quad u_{it} \geq 0 \quad (11)$$

where y_{it} is the vector for the quantities produced by the different countries, γ_{it} is the vector for the factors used in production, and δ is the vector for the parameters that define the production process. The vectors v_{it} and u_{it} describe various components of the error: while v_{it} refers to the random element of the error, u_{it} refers to a downward deviation from the output frontier – that is, the technical inefficiency component; hence the negative sign and the limit $u_{it} \geq 0$. From Equation 11 above, $f(\gamma_{it}; \delta) \cdot \exp(v_{it})$ represents the stochastic production frontier and v_{it} has a symmetrical distribution to capture the random effects of measuring errors and exogenous shocks. The level of technical efficiency is measured by $\exp(-u_{it})^2$. Also, (v_{it}) is identically and independently distributed (iid), with zero mean and variance $\sigma_v^2 \sim N(0, \sigma_{vii}^2)$. However, to estimate the SFA model, we apply the translog production function.

3.4 The transcendental logarithm (translog) production function

Our study estimates the SFA model according to Christensen et al. (1971)'s transcendental logarithm (translog) production function and the true model of fixed effects developed by Greene (2005a). Biddle (2012) observed that the translog production function assumes no unitary or constant elasticity of substitution between inputs compared to the Cobb-Douglas production function, which has the unrealistic assumptions of constant return to scale (CRS) and decreasing marginal productivity (DMP), so its separability of inputs reduces the problem of multicollinearity (see Lyu et al., 1984).

For the purpose of our empirical research, we use the true fixed-effect SFA model based on its desirable function of distinguishing invariant-country heterogeneity from time-varying technological inefficiency (see Mazorode, 2019). Therefore, assuming a translog production function with four factors of production – that is, area of land (z), labour (L), capital (K) and fertiliser (f) – our translog model can be expressed as:

$$\begin{aligned}
 \log(Y)_{it} = & \delta_i + \beta_1 \log(z)_{it} + \beta_2 \log(L)_{it} + \beta_3 \log(K)_{it} + \beta_4 \log(f)_{it} + \beta_5 \log(0.5(z)^2)_{it} \\
 & + \beta_6 0.5 \log(L)^2_{it} + \beta_7 0.5 \log(K)^2_{it} + \beta_8 0.5 \log(f)^2_{it} + \beta_9 [\log(z) \log(L)]_{it} \\
 & + \beta_{10} [\log(z) \log(K)]_{it} + \beta_{11} [\log(z) \log(f)]_{it} + \beta_{12} [\log(L) \log(K)]_{it} \\
 & + \beta_{13} [\log(L) \log(f)]_{it} + \beta_{14} [\log(K) \log(f)]_{it} + \beta_{15} Year_t + \beta_{16} [\log(z) (Year)]_{it} \\
 & + \beta_{17} [\log(L) (Year)]_{it} + \beta_{18} [\log(K) (Year)]_{it} + \beta_{19} [\log(f) (Year)]_{it} \\
 & + 0.5 \beta_{20} (Year)^2_t + v_{it} - u_{it}
 \end{aligned} \tag{12}$$

From Equation (12) above, subscripts i and t represent country and year respectively, Y shows the real value-added, and Year is a variable indicating a trend to accommodate the possible frontier shifts – that is, it captures technological changes, and its squared term captures ‘non-monotonic’ changes in technology. Furthermore, we interact the trend variable (Year) with the factors of production to accommodate Hicks-neutral technological progress (see Wang & Wong, 2012). v_{it} refers to the random element of the error, and u_{it} refers to the technical inefficiency component of the error. Assuming that the null hypothesis $\beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = 0$ is rejected at 5% significance level, our translog model expressed in Equation (12) above will therefore collapse to a Cobb-Douglas production function, specified as follows:

$$\log(Y)_{it} = \delta_i + \beta_1 \log(z)_{it} + \beta_2 \log(\mathcal{L})_{it} + \beta_3 \log(\mathcal{K})_{it} + \beta_4 \log(\mathcal{F})_{it} + \beta_5 \text{Year}_{it} + v_{it} - u_{it} \quad (13)$$

where it is expected that β_1 , β_2 , β_3 , and β_4 will have a positive impact on agricultural total factor productivity (TFP).

3.5 Estimation technique

3.5.1 Single-stage maximum likelihood estimator (MLE) approach

Rather than a single stage, previous studies used the two-step approach to evaluate drivers of technical inefficiency. This approach follows the idea of predicting the specific observed inefficiency index, and then regressing the predicted index (x_{it}) on a given vector of exogenous variables (z_{it}) (Battese & Coelli, 1995). Battese and Coelli (1995) showed that there is a misspecification error in the two-stage approach. Kumbhakar and Lovell (2000) demonstrated that compared to using two stages, the single-stage estimation approach is premised on the assumption that v_{it} and u_{it} are independent (of each other and the regressors) and identically distributed (*iid*).

On the other hand, the two-stage approach assumes that x_{it} as well as z_{it} affect production output and performance incidentally through efficiency. This would signify that x_{it} and z_{it} are both correlated with u_{it} in our specified model in Equation 13 above. However, Amsler et al. (2016) and Schmidt (2011) revealed that this later claim contradicts the *iid* assumption. Kumbhakar et al. (2018) argued that the two-stage estimation procedure is biased in this respect.

To avoid this limitation, we used the single-stage maximum-likelihood estimator approach, as it addresses the limitation in the two-stage approach (see Battese & Coelli, 1995). This approach captures the regression of inputs on output as well as the prediction of technical inefficiency scores (u_{it}). This is then regressed using technical inefficiency regressors (z_{it}). Kumbhakar et al. (2015) observed that this approach mitigates the biasedness in the two-stage approach. Therefore, our maximum likelihood estimator follows the expression:

$$\text{Log}(y)_{it} = [f(\gamma_{it}; \delta) + v_{it}] - (Z_{it}; \phi + \omega_{it}) \quad (14)$$

where $\text{TE}_{it} = \exp(-u_{it}) = \exp -\{(Z_{it}; \phi + \omega_{it})\}$. We then substitute our technical inefficiency model from Equation (11) above and our translog model from Equation (12) above into Equation (14) above. We thus obtain our true fixed-effects stochastic frontier panel model as follows:

$$\begin{aligned} \log(Y)_{it} = & \delta_i + \beta_1 \log(z)_{it} + \beta_2 \log(\mathcal{L})_{it} + \beta_3 \log(\mathcal{K})_{it} + \beta_4 \log(\mathcal{F})_{it} + \beta_5 \log 0.5(z)^2_{it} \\ & + \beta_6 0.5 \log(\mathcal{L})^2_{it} + \beta_7 0.5 \log(\mathcal{K})^2_{it} + \beta_8 0.5 \log(\mathcal{F})^2_{it} + \beta_9 [\log(z) \log(\mathcal{L})]_{it} \\ & + \beta_{10} [\log(z) \log(\mathcal{K})]_{it} + \beta_{11} [\log(z) \log(\mathcal{F})]_{it} + \beta_{12} [\log(\mathcal{L}) \log(\mathcal{K})]_{it} \\ & + \beta_{13} [\log(\mathcal{L}) \log(\mathcal{F})]_{it} + \beta_{14} [\log(\mathcal{K}) \log(\mathcal{F})]_{it} + \beta_{15} \text{Year}_{it} + \beta_{16} [\log(z) (\text{Year})]_{it} \\ & + \beta_{17} [\log(\mathcal{L}) (\text{Year})]_{it} + \beta_{18} [\log(\mathcal{K}) (\text{Year})]_{it} + \beta_{19} [\log(\mathcal{F}) (\text{Year})]_{it} \\ & + 0.5 \beta_{20} (\text{Year})^2_{it} + v_{it} - [\psi_1 \log(Clim_Var)_{it} + \theta \log(R_D)_{it} + \gamma \log(L_R)_{it} \\ & + \mu \log(V_L)_{it} + \lambda_{it} + \varepsilon_{it}] \end{aligned} \quad (15)$$

Therefore, Equation (15) above becomes our final specification to be estimated using the maximum likelihood estimator. The rationale behind the use of MLE is its capability of maximising the log-likelihood function obtained from the distributional assumptions.

In addition, we perform the likelihood ratio (LR) test to affirm our choice of the translog against the Cobb-Douglas production function. Our LR test statistic is computed as follows:

$$-2[L(H_0) - L(H_1)] \quad (16)$$

where $L(H_0)$ shows the estimated values of the log-likelihood from the Cobb-Douglas model (restricted), and $L(H_1)$ represents the log-likelihood from the SFA model (unrestricted) with an imposed restriction of 5% degrees of freedom (see Mazorodze, 2019). Kodde and Palm (1986) provided critical values for the log-likelihood function.

4. Data sources and description

Table 1 below details the data used in the analysis. The 22-year period from 1995 to 2016 is covered in our research. The Food and Agriculture Organization (FAO), World Development Indicators (WDI), the World Bank's Climate Change Information Platform and the International Labour Organisation (ILO) databases provide the long-run country-level panel data for 14 sub-Saharan African countries. R&D data calculated in millions of US dollars is sourced from the database of Agricultural Science and Technology indicators of the IFPRI (International Food Policy Research Institute). Maize yield is measured at 1000 per hectare; agricultural land area is measured at 1000 per hectare as the amount of arable land and land under permanent crops; labor is measured at 1000 per hectare as the total number of agricultural employees; capital is measured at millions of US dollars as the formation of gross fixed capital in agriculture; fertiliser is measured at tonnes as the fertiliser applied to crops; literacy was measured as the total number of adults (aged 15 and above) who are literate; and rainfall was measured as monthly average rainfall in millimetres. Our panel data consists of 308 observations for maize yield, land, capital, labour, fertiliser, literacy, rainfall, and R&D spending. Our choice of maize as the subject crop was influenced by its nutritional value, as well as by the economic significance of the crop. Maize is the main food crop cultivated in SSA and accounts for more than 40 percent of total cereal consumption, according to Badu-Apraku and Fakorede (2017). In the SSA, maize provides about 20 percent of the population's calorie intake. It is also an important protein source (and is high in starch) for most of the SSA population. Table 1 below presents a description of the data.

Table 1. Data description

Variable	Observation	Mean	SD	Min	Max
Maize	308	16575.51	8292.68	849	53009
Land	308	8904.92	9849.27	184	43400
Labour	308	6057702	7728374	76914.74	3.35e+07
Capital	308	453.37	791.06	2.32	4875.11
Fertiliser	308	77874.24	110329.40	11	570800
Rainfall	308	68.39	30.45	11.36	144.89
R&D	308	48.11	66.32	0	276.90

In addition, with regard to our conventional inputs: land had an average of 8904 hectares, indicating the average use of land size for agriculture in the 14 countries; the overall number of people working in agriculture in the 14 countries shows a labor average of 6057702 people. At the same time, the average literacy rate is 54% for the 14 countries. The 54 percent average literacy follows the premise that some form of formal education has been received by more than half of the population over the age of 15. Also, the mean fertiliser usage by farmers is 77874. Average spending on R&D is about US\$48m between the 14 countries. This is very low, e.g., compared to South Africa's average spending of about US\$212.02m in the same timeframe. Low R&D investment, however, is not surprising given that agricultural R&D is highly dependent on donor and development bank financing in many SSA countries, which in most cases, is short-term and ad hoc by nature (Beintema & Stads, 2014). From Table 1 above, climate variability (proxied by rainfall variability) is one of our key variables of interest. We follow previous literature (see Trong-Anh, 2019; Amare et al., 2018) in calculating climate variability as a deviation of past rainfall from its historical average (22 years) during the season of agricultural production. According to the literature (see Amare et al., 2018; Dercon & Christiansen, 2011; Alem et al., 2010), the use of past rainfall is grounded in the theory that rainfall variability is exogenous to farmers' present decisions, and thus is reflected in their choice of inputs in agricultural production. Our measure of climate variability is thus expressed as follows:

$$\text{Climate Variability (Clim_Var)}_{it} = \log\left(\frac{\bar{x}_{it} - x_{it-1}}{x^{SD}}\right) \quad (17)$$

where \bar{x}_{it} represents the 22-year historical average of rainfall in country i at a time (t) , x_{it-1} indicates past rainfall, and x^{SD} shows the standard deviation from the mean rainfall.

5. Results and discussion

5.1 Malmquist Index (MI) of maize productivity

Table 2 below presents the annual aggregate Malmquist indices for SSA countries regarding agricultural productivity growth and inputs (capital, labour, land and fertiliser), change in technical efficiency, and technological progress. Our estimates show that overall, there was a negative growth of about 8.3% in SSA agriculture productivity per year between 1995 and 2016. The poor growth shows there has been stagnation in agricultural productivity during this period. This is

contrary to the agricultural productivity growth figure of about 1.6% yearly reported by Alene (2010). The estimates further reveal that while mean technical efficiency grew by 0.1% over this period, technological progress declined by about 8.4%. Though SSA countries experienced their highest technical efficiency growth in 1997, this was rendered meaningless by the poor and negative growth rate in technological progress. The negative mean TFP growth rate further highlights the enormous and unrelenting challenges facing agricultural productivity growth in SSA.

Table 2. Annual maize productivity growth rate, efficiency change and technical progress in SSA agriculture.

Year	TFP Growth	Efficiency Change	Technical progress
1996	-23.5	-66.5	126.8
1997	-42.9	113.4	-73.3
1998	26.6	32.2	-4.2
1999	-42.8	7.2	-46.6
2000	24.7	-1.9	27.1
2001	-45.5	-7.5	-41.1
2002	-11.5	-26.9	21.1
2003	49.6	51.5	-1.2
2004	-18.6	-2.9	-16.2
2005	-26.8	-12	-16.8
2006	167.2	-16.2	218.8
2007	29.9	37.3	-5.4
2008	-27.6	-18.6	-11
2009	0.5	-32.3	48.4
2010	-39.3	25.1	-51.5
2011	-69.2	37.4	-77.6
2012	59.7	-3.4	65.3
2013	190.6	-0.2	191.1
2014	-15.5	12	-24.6
2015	-10.1	-13.3	3.6
2016	-42.2	15.2	-49.9
Mean	-8.3	0.1	-8.4

In contrast to previous studies, such as Alene (2010) and Fulginiti and Perrin (1997), which stated that technological advancement was the main driver of agricultural productivity in Africa rather than technical efficiency, our findings show that both technical efficiency and technological advancement are important for SSA's overall productivity factor growth. The negative growth rate in technical efficiency change signifies a high level of inefficiency. Given that technological progress reflects increases in factors of production (capital, land, labour) as well as improvements in their use, the decline in mean technical progress growth rate per year also implies that SSA

agriculture has experienced an average 8.4% decrease in the application of innovation and new knowledge to improve existing resources and factors of production in agricultural processes.

Moreover, the picture that emerges regarding TFP growth rate, technical efficiency changes and technical progress for individual countries was no different from that for the cumulative. As seen in Table 3 below, most countries in SSA have experienced negative TFP growth rates and a decline in both efficiency change and technical progress. In particular, only two countries (Zambia and Togo) recorded positive TFP growth rates, of 16.8% and 18.6% respectively.

Table 3. Malmquist indices of country-level maize total productivity growth, efficiency change and technical progress in agriculture in SSA

Country	TFP Growth	Efficiency Change	Technical Progress
Benin	-26.9	0	-26.9
Botswana	-25.4	0.6	-25.9
Burkina Faso	-18	0	-18
Cote D'Ivoire	-18.1	0.3	-18.3
Ethiopia	-12.2	0	-12.2
Ghana	-6.3	0.4	-6.7
Kenya	-16.1	-0.1	16.1
Malawi	-4.8	0.6	-5.4
Mali	-5.9	0	-5.9
Niger	-2	0	-2
Nigeria	-0.1	-0.1	0
South Africa	-2.8	-0.2	-2.6
Togo	18.6	0	18.6
Zambia	16.8	-0.1	16.9
Mean	-8.3	0.1	-8.4

Regarding efficiency change growth rate, only four countries (Botswana, Ivory Coast, Ghana, and Malawi) recorded positive growth rates, of 0.6%, 0.3%, 0.4% and 0.6% respectively. At the same time, six countries (Benin, Burkina Faso, Ethiopia, Mali, Niger, and Togo) recorded unitary

efficiency, with the four countries remaining (Zambia, South Africa, Nigeria and Kenya) recording a decline in efficiency change growth rate of 0.1%, 0.2%, 0.1% and 0.1% respectively.

Though Botswana (for example) recorded positive technical efficiency growth, it performed poorly in terms of growth of technological progress, recording a decline of 25.9% over the sampling period (1995 to 2016). The same could be said for both Ghana and Malawi, which experienced growth rates of 0.4% and 0.6% respectively in technical efficiency, but a decline in technological progress of 6.7% and 5.4% respectively. Our estimates further reveal that both technical efficiency and technological progress matter to agricultural productivity growth in SSA countries.

5.1.2 Cumulative productivity growth

Extracting cumulative productivity growth demonstrates the significance of relative changes in technical efficiency and technological progress as important drivers of agricultural productivity growth. Figure 1 presents measures of annual cumulative growth rate (technological progress and change in technical efficiency), using maize production as a proxy for agricultural output.

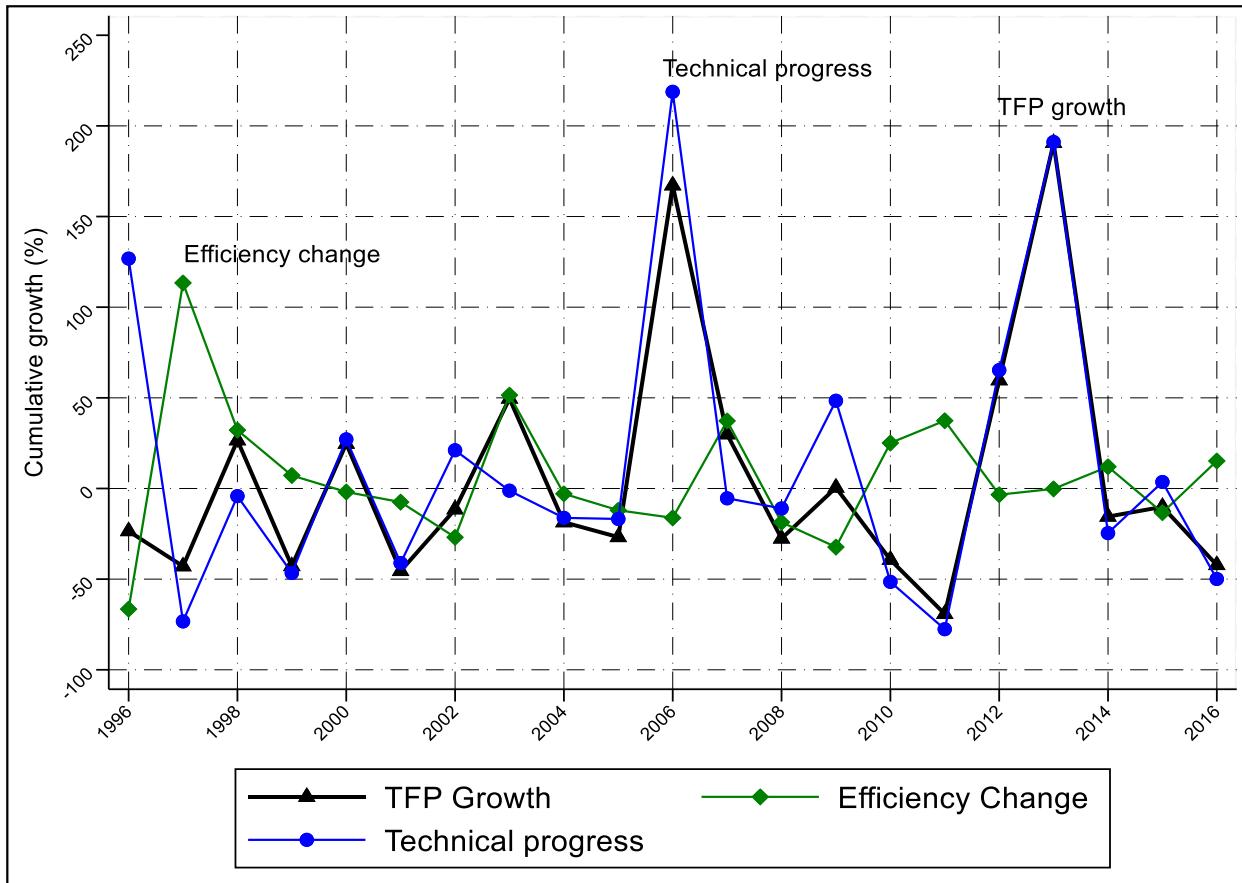


Figure 1: Annual cumulative productivity growth, efficiency change and technical progress in agriculture in SSA.

Though positive cumulative growth rates were seen as signs of efficiency change in the 1990s, they experienced a sharp decline in the early and middle part of the 2000s. Technological progress was characterised by positive cumulative growth rates in the 2000s. Over the period 1995-2016, the cumulative rates of efficiency change and technical progress for maize were 5.89% and 12.85% respectively. In particular, while most SSA countries experienced positive cumulative efficiency growth rates in nine (non-consecutive) years (1997-1999, 2003, 2007, 2010-2011, 2014 and 2016), a positive cumulative technical progress growth rate was experienced in only eight years (1996, 2000, 2002, 2006, 2009, 2012-2013 and 2015). In the same period, the highest cumulative growth rate for technical efficiency (113.4%) was experienced in 1997, and that of technical progress (218.8%) in 2006. The two components witnessed their highest decline, (-66.5% and -77.6% respectively) in 1996 and 2011, respectively.

5.2 Determinants of technical (in)efficiency

5.2.1 SFA Technical efficiency Scores

The true fixed effects of technical inefficiency scores are shown in Figure 2 below. The overall technical efficiency score for maize is 81.2%. This means there is potential to increase the production of maize in the region by about 19%, using existing inputs and resources. In general, there was variation throughout 1995-2016, in terms of maize's efficiency. Although average efficiency was 83.3% and 84% in 1996 and 1997 respectively, there was a significant decline (of approximately 79%) in both 1999 and 2000. This worsened in 2001, to 81.4%, before a rebound of an all-time high of 91.7% in 2006. However, this declined to 73.1% the following year; it stagnated between 2008 and 2013, and then increased for the remainder of the period.

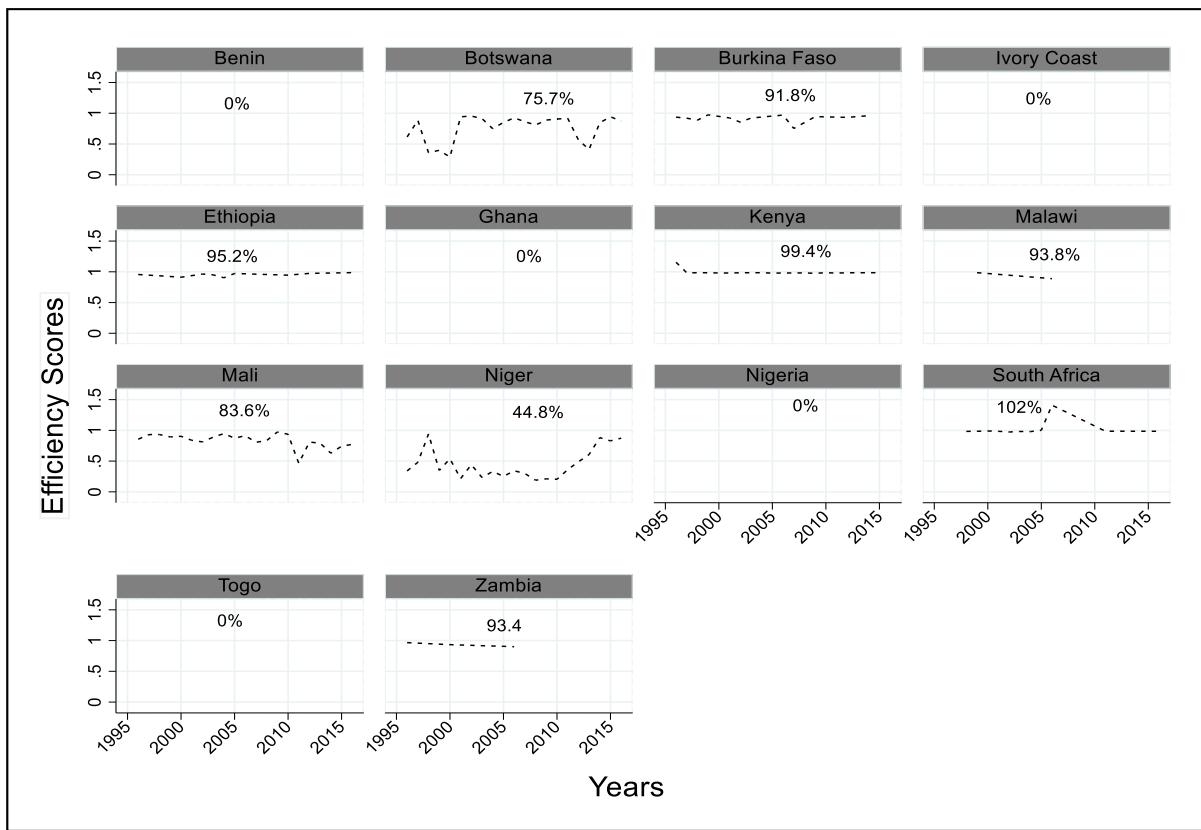


Figure 2: Maize technical efficiency scores in SSA.

The case was no different with the individual (country-level) efficiency scores, where there were also variations in maize efficiency. The most efficient maize-producing countries were South Africa (102%) and Kenya (99.4%), closely followed by Ethiopia (95.2%), Malawi (93.8%),

Zambia (93.4%), Burkina Faso (91.8%) and Botswana (75.7%). The least efficient maize-producing countries were Benin (0%), Ghana (0%), Nigeria (0%), Ivory Coast (0%), Togo (0%) and Mali (44.8%). This implies that these countries have more scope to improve their current maize production levels, given their existing resources. The figures also reveal that South Africa is the best-performing country, and thus the frontier for the remaining 13 countries. South Africa's high efficiency level could be attributed to the fact that the country spends an average of about US\$212m annually on R&D compared with less efficient countries such as Benin and Ivory Coast, which on average spend about US\$10.11m and US\$35.7m respectively on R&D. In addition, one of the biggest challenges facing most farmers in SSA is a lack of farming skills, resources, and sufficient mechanisation. Generally, farming is done on small plots of land with little or no access to irrigation. Because of one or more of these issues, the majority of smallholder farmers in SSA are unable to produce optimally. The case is somewhat different for South Africa, as it is one of the few countries in the SSA region to boast a sophisticated and productive agricultural sector. As agriculture in South Africa is dominated by commercial farming, we are of the view that commercial farming could be a reason for its high efficiency compared to the other 13 countries.

5.2.2 Functional form tests

The findings from the functional diagnostic tests carried out are summarized in Table 4 below. The null hypothesis $\beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = 0$ is rejected, thus providing evidence that the translog production function is preferred to the unrestricted Cobb-Douglas production function. Additionally, the functional test confirms Hicks' non-neutral technical changes, given that the interactions among the time trend variable (t) and the inputs (capital, land, fertilizer and labour) at the 1 percent level of significance are found to vary significantly from zero.

Table 4. Functional Tests

Null Hypothesis	P-Value	Decision
$\beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = 0$	0.0000	Translog
$\beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = 0$	0.0071	Hicks non-neutral TC

$\beta_{15}=\beta_{20}=0$	0.0084	Non-Monotonic TC
LR Statistic=114.945		Technical Inefficiencies

Note: 5% critical value for LR = 2.706

The practical test also confirms, in addition, non-monotonic technical changes over time. This is obvious in the results of the joint test, which shows that the joint effect of the time trend variable (t) and its square (t)² is statistically significant at the level of 1%. The log-likelihood ratio (LR) test simultaneously demonstrates the existence of inefficiencies. The corresponding test statistic is 114.945, which at the 5 percent significance stage is much greater than the crucial value of 2.706. Hence, in our model, we reject the null hypothesis of no technical inefficiency. The functional diagnostic test therefore provides empirical evidence to support our selection, and therefore our SFA estimate using a translog production function as opposed to a specification of Cobb Douglas production function. The Hausman test is also performed to distinguish between SFA models of fixed-effects and random-effects.

Table 5. Hausman Specification Test

Test: H_0 : difference in coefficients not systematic

$$\begin{aligned}
 \text{chi2}(19) &= (b-B)'[(V_b-V_B)^{-1}](b-B) \\
 &= 96.02 \\
 \text{Prob}>\text{chi2} &= 0.0000
 \end{aligned}$$

The Hausman test indicated that the fixed-effects SFA model is the most appropriate, thus signifying that in our model, our conventional inputs (capital, land, labour and fertiliser) are correlated with unobserved heterogeneity.

5.2.3 Maximum Likelihood Estimation (MLE) Results

Empirical findings on the drivers of (in)efficiency are presented in Table 6 below. Even though the preferred model of estimation is the translog production model, for robustness we also estimate

the Cobb Douglas function. Our main discussion therefore centres on the translog model. The Cobb Douglas function is reported in Models 1 and 2, while the translog function is reported in Models 3 and 4. In Model 3, we control for all conventional inputs, including climate variability and R&D. In Model 4, in addition to same controls as in Model 3, we introduce a third variable: literacy. As expected, the procedure for maximum likelihood attained convergence after 100 iterations, for both fixed and random effects estimation.

Table 6. True fixed-effects estimation

Variable	Cobb Douglas		Translog	
	Model (1)	Model (2)	Model (3)	Model (4)
$\log(\mathcal{K})_{it}$	0.087 (0.082)	0.087 (0.089)	-0.911 (0.962)	-0.352 (0.902)
$\log(z)_{it}$	0.523** (0.241)	0.520** (0.260)	6.194*** (1.703)	4.827*** (1.652)
$\log(\mathcal{L})_{it}$	0.118 (0.103)	0.116 (0.109)	-4.322*** (1.536)	-2.221 (1.511)
$\log(\mathcal{F})_{it}$	0.147** (0.065)	0.148 (0.067)	-1.971** (0.857)	-2.580*** (0.818)
$\log 0.5(z)^2_{it}$	--	--	-0.015 (0.344)	-0.491* (0.295)
$0.5\log(\mathcal{L})^2_{it}$	--	--	0.538*** (0.162)	0.319** (0.162)
$0.5\log(\mathcal{K})^2_{it}$	--	--	-0.351** (0.124)	-0.385*** (0.111)
$0.5\log(\mathcal{F})^2_{it}$	--	--	0.059 (0.042)	0.082** (0.039)
$[\log(z)\log(\mathcal{L})]_{it}$	--	--	-0.473*** (0.172)	-0.257 (0.166)
$[\log(z)\log(\mathcal{K})]_{it}$	--	--	0.513*** (0.178)	0.706*** (0.149)
$[\log(z)\log(\mathcal{F})]_{it}$	--	--	-0.094 (0.071)	0.062 (0.076)
$[\log(\mathcal{L})\log(\mathcal{K})]_{it}$	--	--	-0.181*** (0.066)	-0.229*** (0.064)
$[\log(\mathcal{L})\log(\mathcal{F})]_{it}$	--	--	0.133** (0.061)	0.095 (0.060)
$[\log(\mathcal{K})\log(\mathcal{F})]_{it}$	--	--	0.073 (0.071)	-0.044 (0.065)
Year _t	-0.002 (0.009)	-0.002 (0.009)	0.142 (0.108)	0.111 (0.107)
$[\log(z)(Year)]_{it}$	--	--	-0.014 (0.015)	-0.041*** (0.013)
	--	--	0.003	0.006

[log(\mathcal{L})(Year)] _{it}	--	--	(0.006)	(0.006)
	--	--	0.023*	0.033***
[log(\mathcal{K})(Year)] _{it}	--	--	(0.011)	(0.010)
	--	--	-0.017	-0.002
[log(\mathcal{F})(Year)] _{it}	--	--	(0.009)	(0.008)
	--	--	0.001	-0.0005
0.5*Year ² _t	--	--	(0.001)	(0.001)
Technical Inefficiency Model				
Lag1log(Clim_Var) _{it}	0.101 (0.256)	0.085 (0.331)	0.608** (0.238)	0.899*** (0.263)
Lag1log(R_D) _{it}	-1.459*** (0.288)	-1.523 (0.717)	-1.601*** (0.224)	-2.044*** (0.434)
log(L _R) _{it}	-- --	0.048 (0.494)	-- --	0.187 (0.297)
Observation	130	130	130	130
Prob > Chi ²	0.0000	0.0000	0.0000	0.0000
Log-likelihood	-26.9675	-27.0839	38.9116	30.3884

Note: *, **, *** denotes $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively. Standard errors are in parenthesis.

Beginning with the results from the fixed effects estimation, whose coefficients are interpreted as elasticities in the stochastic frontier model; the signs thereof fall under theoretical expectations. The results show that land has a positive effect on agricultural TFP. A percentage increase in land is thus projected to increase agricultural TFP, *ceteris paribus*, by about 4.827 percent. A percentage rise in labor and fertiliser, however, decreases agricultural TFP by a margin of 4.32 percent to 2.58 percent, maintaining constant inputs of land and resources. At 1 percent significance level in our translog specification, the interaction between land and the time trend variable (year) is negative and important, indicating that technical progress was land-saving during our sampling period. On the other hand, at 1 percent significance level, the relationship between capital and the time trend variable is positive and important, suggesting that technical progress was capital-using and land-saving during our sampling period (1995 to 2016).

Moving to the technical inefficiency model, the signs of our key determinants of (in)efficiency are in line with economic theory. It is important to understand that technical inefficiency is the dependent variable here. A positive sign on a specific variable thus means that the variable raises the level of technical inefficiency and thus has a negative impact on the level of technical efficiency. A negative sign, on the other hand, means that the variable decreases technical inefficiency and thus has a positive influence on technical efficiency. Our key variable of interest – climate variability – is positive in both Models 3 and 4 of our fixed-effects estimations and is

significant, at 5% and 1% respectively. This signifies that climate variability strongly increases technical inefficiency. Stated differently, climate variability reduces agricultural technical efficiency. From Models 3 and 4, climate variability increases technical inefficiency by between 0.61% and 0.9%. This also means that a 10-percentage point rise in climate variability would result in a 6.08 percent to 8.99 percent decrease in the performance of technical efficiency in the following year, all other things being equal, which is in line with the proof in the literature (see Amare et al., 2018; Dercon & Christiaensen, 2011; Barrios et al., 2010; Brown et al., 2010; Di Falco & Chavas, 2009).

This supports the claim that climate variability gives rise to crop production risks. This in turn increases farmers' risk of technology adoption, especially in a rain-fed agricultural region such as SSA, where there is an absence of insurance markets, a lack of information, and constraints on capital. Thus, this behavioural decision by farmers impacts on agricultural production. Alternatively, as argued by Hurley (2010), climate variability makes maize farming inherently risky. Therefore, how much a farmer will produce is not known, because of unpredictable weather when the seed is cultivated. Hence, this risk (among others) has a vital effect on the decisions taken by farmers regarding labour hire, fertiliser use and choosing improved seed varieties, which all affect maize yield.

Against this backdrop we use lag1 of the variance, given that farmers' production decisions and their expectations regarding conditions in the upcoming growing season are significantly influenced by their memory of previous weather conditions (see Sesmero et al., 2017). On the other hand, at 1 percent, the R&D coefficient is negative and statistically significant. This illustrates that, with increased spending on R&D, technical inefficiency decreases. That is, spending on R&D increases technical efficiency in the following year by 1.60% to 2.04%. In other words, an increase in R&D spending of 10 percentage points, with all other things being equal, lowers technical inefficiency in the subsequent year by about 16% to 20.4% in agricultural TFP. This result, therefore, provides evidence to support the theoretical claim that R&D spending improves technical efficiency, and thus agricultural TFP. However, the coefficient of literacy as a determinant of technical inefficiency was found to be positive, but not statistically significant.

In an attempt to corroborate our preferred model – fixed effects – we also report on the random-effect estimation, in Table 7 below. Land is positive and statistically significant at 1%, signifying that, land is a major factor of production, and thus improves agricultural total factor productivity, *ceteris paribus*. Labour and fertiliser both have negative coefficients and are statistically significant at 1%, implying that holding all other variables constant, a percentage increase in the use of both labour and fertiliser decreases agricultural total factor productivity. In both Models 3 and 4 the interaction between land and the time trend variable (year) is negative and significant; the interaction between labour and the time trend variable (year) is positive and significant. Hence, from the random-effect estimation, technical progress during the sampling period (1995 to 2016) is seen to be labour-using and land-saving.

Table 7. Random effects estimation

Variable	Cobb Douglas		Translog	
	Model 1	Model 2	Model 3	Model 4
$\log(\mathcal{K})_{it}$	-0.048 (0.060)	-0.043 (0.067)	1.712 (1.113)	1.413 (1.077)
$\log(z)_{it}$	0.612*** (0.058)	0.562*** (0.059)	6.678*** (1.276)	7.322*** (1.243)
$\log(\mathcal{L})_{it}$	-0.222*** (0.048)	-0.222*** (0.046)	-3.141*** (1.146)	-3.362*** (0.674)
$\log(\mathcal{F})_{it}$	-0.050 (0.035)	-0.049 (0.036)	-4.040*** (1.055)	-3.859*** (0.887)
$\log 0.5(z)_{it}^2$	-- --	-- --	-0.288** (0.129)	-0.261 (0.212)
$0.5\log(\mathcal{L})_{it}^2$	-- --	-- --	0.372 (0.269)	0.372*** (0.098)
$0.5\log(\mathcal{K})_{it}^2$	-- --	-- --	-0.147 (0.101)	-0.150 (0.100)
$0.5\log(\mathcal{F})_{it}^2$	-- --	-- --	0.125** (0.052)	0.136*** (0.039)

[log(z)log(\mathcal{L})] _{it}	--	--	-0.370***	-0.427***
	--	--	(0.096)	(0.161)
[log(z)log(\mathcal{K})] _{it}	--	--	0.531***	0.534***
	--	--	(0.082)	(0.094)
[log(z)log(\mathcal{F})] _{it}	--	--	-0.077	-0.095
	--	--	(0.062)	(0.060)
[log(\mathcal{L})log(\mathcal{K})] _{it}	--	--	-0.304***	-0.280***
	--	--	(0.059)	(0.067)
[log(\mathcal{L})log(\mathcal{F})] _{it}	--	--	0.262***	0.254***
	--	--	(0.061)	(0.055)
[log(\mathcal{K})log(\mathcal{F})] _{it}	--	--	-0.109	-0.110
	--	--	(0.074)	(0.068)
Year _t	0.023*** (0.006)	0.023*** (0.006)	-0.139 (0.103)	-0.185 (0.115)
[log(z)(Year)] _{it}	--	--	-0.021*** (0.006)	-0.016** (0.007)
[log(\mathcal{L})(Year)] _{it}	--	--	0.019*** (0.006)	0.020*** (0.005)
[log(\mathcal{K})(Year)] _{it}	--	--	0.007 (0.009)	0.003 (0.009)
[log(\mathcal{F})(Year)] _{it}	--	--	-0.001 (0.008)	-0.0005 (0.008)
0.5*Year ² _t	--	--	0.002** (0.001)	0.003 (0.001)
Technical Inefficiency Model				
Lag1log(Clim_Var) _{it}	0.287** (0.134)	0.300** (0.141)	0.175 (0.147)	0.231 (0.147)
Lag1log(R_D) _{it}	-0.613*** (0.183)	-0.621*** (0.206)	-1.277*** (0.286)	-1.420*** (0.283)
log(L _R) _{it}	--	0.039 (0.306)	-- (0.469)	0.951** (0.469)
Observation	130	130	130	130
Prob > Chi2	0.0000	0.0000	0.0000	0.0000
Log-likelihood	-14.1264	-13.6231	23.6023	26.4348

Note: *, **, *** denotes $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively. Standard errors are in parenthesis.

Using the technical inefficiency model, climate variability is positive but not significant in both Models 3 and 4. Though it is not significant, our main interest here is the sign of the coefficient (+), which is evidence to support the fixed-effects estimation result that climate variability increases technical inefficiency, and thus reduces technical efficiency. R&D is negative and

significant at 1%, supporting the fixed-effects estimation that a percentage increase in R&D spending reduces technical inefficiency and therefore increases technical efficiency.

6. Conclusions and policy implications

This paper studies the impact of climate variability on technical efficiency in Sub-Saharan Africa's total agricultural factor productivity (SSA) using panel data covering the period 1995 to 2016. A two-step approach, that is, parametric and non-parametric approaches, is used in the paper. Using a Malmquist Productivity Index (MPI) calculation of total factor productivity, the non-parametric Data Envelopment Analysis (DEA) method shows that both technical performance and technological advancement matter in SSA's total agricultural factor productivity.

Our MPI estimates show that overall, there was a negative growth rate in SSA agricultural productivity per year during the period under study. Most countries in SSA experienced negative total factor productivity (TFP) growth rates and a decline in both efficiency change and technical progress. Only two countries (Zambia and Togo) recorded positive TFP growth rates, of 16.8% and 18.6% respectively.

Based on our findings that inefficiency was present, we proceeded by applying a single-stage maximum-likelihood estimation of a true fixed-effects approach to determine how climate variability influences technical efficiency. This analysis revealed the presence of technical inefficiencies in agricultural TFP. Climate variability (proxied by rainfall variability) was found to be a critical driver of agricultural technical inefficiency. We further provided evidence that increased spending on R&D decreases technical inefficiency. To mitigate the negative effects of climate variability, increased spending on R&D may be key to improving technical efficiency. From the onset, our study focused on how variability in rainfall determines (in)efficiency in agricultural TFP. Future research can utilise variables such as temperature and solar radiation to dig deeper into the implications for agricultural TFP growth in SSA. Availability of data is the biggest hurdle in doing so at present.

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