African Development Review
Revue africaine de développement

*African Development Review*, Vol. 31, No. 4, 2019, 462–475

# Dynamics of Agricultural Productivity and Technical Efficiency in Togo: The Role of Technological Change

**Mikémina Pilo**

***Abstract*:** In the search for ways to boost agricultural productivity for the take-off of the so-advocated agricultural transformation, we investigate in this paper whether there is room under current technologies to boost agricultural productivity through technical efficiency, focusing on the five administrative regions of Togo. We use a regional stochastic frontier model, which assumes that farmers maximize return to the outlay in order to account for potential endogeneity and regional heterogeneities to a panel data for the period 2000–2014. The findings reveal that technical efficiency in agriculture varies considerably across regions and over time. In addition, our results indicate that the country can rely on irrigation intensification to sustain its move towards higher agricultural technical efficiency, while higher rainfall variability puts additional pressure on the achievement of such objective. The policy message drawn from this study supports policy strategies designed to promote irrigation and increased rainfall variability management tools, such as weather insurance, as sound agricultural technical efficiency driven options.

## 1. Introduction

Economic prospects and poverty reduction in sub-Saharan Africa (SSA) are closely associated to productivity in agriculture, particularly in most developing countries (Bachewe *et al.*, 2018; Willy and Holm-Müller, 2013; De Janvry and Sadoulet, 2010). The large share of the labour force in agriculture in SSA indicates that agricultural sector growth will benefit a larger proportion of the population of the region. Improving agricultural performance is therefore vital to boost food and nutrition security and reduce poverty. Accordingly, given the concentration of the poor and vulnerable populations in the agricultural sector in this region, inclusive growth is difficult to achieve without structural change of the sector. Rising agricultural productivity is the key to making permanent increases in the standard of living.

In SSA, agriculture contributes at least 40 per cent of exports, 30 per cent of GDP, up to 30 per cent of foreign exchange earnings and provides employment for 70 to 90 per cent of the labour force in the region as a whole (AfDB, 2013). However, the region is falling behind and even falling apart in terms of agricultural transformation (Bachewe *et al.*, 2018). As sourced from Willy and Holm-Müller (2013), agricultural productivity in SSA has been rising at only moderate rates since the 1990s and remains far below levels found in other parts of the world. The overall productivity growth of the sector continues to lag behind the rest of the world, growing at roughly half the average rate of developing countries (IFPRI, 2015). According to Gollin *et al.* (2014), labour in developing countries is 4.5 times more productive in the non-agricultural sector compared to the agricultural sector. In the middle-income countries this ratio is 3.4. As for African countries, non-agricultural labour is 6 times more productive than agricultural labour (McCullough, 2017; Gollin *et al.*, 2014). McMillan and Harttgen (2014) confirm also that large cross-sector productivity differentials persist in SSA. As a result, the continent is still at the first stage of a true agricultural transformation. This trend can be partially explained by high rates of land fragmentation, intensive tillage of land, nutrient mining and extraction of crop residues to feed livestock, harsh weather conditions, soil degradation, traditional farm

Mikémina Pilo (corresponding author), University of Kara, PO Box 43, Kara, Togo; e-mail: pilomikemina15@gmail.com

practices, low rate of innovations adoption and use at large scale (Di Falco *et al.*, 2011; Willy and Holm-Müller, 2013). Consequently, food insecurity is a common and frequent challenge for African countries (FAO, 2016).

This situation prevails in almost all countries of the region including Togo. Here, agriculture is still the core sector for economic growth, employing over 65 per cent of the population in mainly subsistence agriculture and contributing to GDP at the level of an average 40 per cent during the last 10 years (QUIBB,[1] 2015). However, the performance of the country in terms of agricultural productivity has been stagnating for a long period, and despite government efforts in recent decades, it has only increased moderately these last years. For instance, an average crop yield in Togo was only 1.1 ton per hectare in 2014 compare to an average of 16.8 in Asian countries (FAO, 2015). Consequently, the average revenue of agricultural farm household is US$66.3 per month (QUIBB, 2015). This revived recently a strong debate among agriculture stakeholders regarding how agricultural productivity can be increased sustainably. In the same vein, many agricultural stakeholders criticize the role of many factors such as fertilizer and labour in driving the productivity of the agricultural sector. It is even argued by some stakeholders that productivity growth in the agricultural sector does not depend on the quantity of inputs used but on farmers' technical knowledge. For Ogunniyi *et al.* (2017), a comprehensive transformation of the agriculture sector in Africa requires investment in technology and innovation. Agricultural innovation has direct and indirect effects on livelihood and productivity improvement of the beneficiaries (Adebayo *et al.*, 2017). To participate in this debate, this study aims to investigate the dynamics of crop productivity growth and technical efficiency. It covers the five regions of the country since efficiency can vary across and within agro-ecological zones (Njkan and Alhadji, 2017).

The remainder of the paper is structured as follows. Section 2 presents a brief literature review on the topic while Section 3 describes agricultural development in Togo. The fourth section deals with the research methodology and Section 5 presents the empirical model. Section 6 discusses the findings. The paper ends with concluding remarks.

## 2. Brief Literature Review

### *2.1 Theoretical Review*

The analysis of this paper falls under the Agricultural Household Model (AHM) framework. The departure idea of the model is that in less developed countries, farmers make joint decisions over food consumption, labour and production (Singh *et al.*, 1986). Indeed, most farm households in developing countries earn at least part of their livelihood through their own farm production. Moreover, they often consume at least a portion of the output of their productive activities, and household labour is often an important input into the production process of the enterprise. Consequently, individuals make simultaneous decisions about production (the level of output, the demand for factors, and the choice of technology) and consumption (labour supply and commodity demand). This mixture of the economics of the firm and of the household is characteristic of most farm households in developing countries and provides an interesting framework for our analysis. However, because data on consumption bundles are not available, we assume the separability hypothesis between production and consummation decisions to hold.

### *2.2 Empirical Review*

Productivity literature established that agricultural productivity growth can arise from many sources but only changes in technological innovations and efficiency with which available technologies are used can drive permanent increases in productivity (Bokusheva *et al.*, 2012; Basu *et al.*, 2001). For instance, Young (1992) found in his study on Singapore that the total factor productivity growth is not different from zero and argued that the country will be able to sustain further growth by only reorienting its policies from factors accumulation to innovation promotion. In the same line, Krugman (1994) established that a nation's sustained growth can only arise from a rise in output per unit of input. As for Schultz (1964), a significant sustainable increase of agricultural productivity becomes available only through technological change.

Technical efficiency is the measure with which a farmer comes closer to the production frontier. This efficiency component is affected by technical progress. Indeed, innovation that leads to adoption of best practices by farmers (technical progress) shifts the production frontier, a shift which may increase technical inefficiency in a shorter period, since the adoption and efficient management of best available practices by farmers usually take some time. The duration of the transition towards best practices is closely linked to the quality of extension services. In well-functioning extension institutions, the time gap between technical progress and increased technical efficiency is highly reduced.

Very few studies have dealt with dynamic analysis of the agricultural sector in Togo (Karmel *et al.*, 2014). However, these studies failed completely to account for endogeneity and regional heterogeneity. This might have led to biased estimates. Indeed, a possible simultaneity in input decisions, technical change development and technical efficiency are potential sources of endogeneity, as pointed out by Bokusheva *et al.* (2012). This study accounts for this paramount drawback and consequently provides more consistent estimates. In addition, regional heterogeneity is taken into consideration.

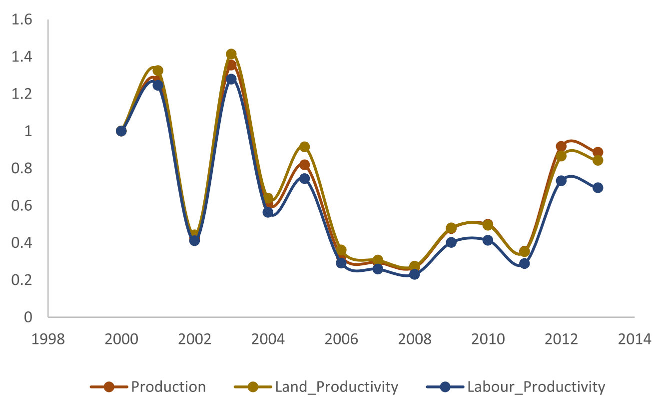
Two types of approaches are commonly applied in efficiency analysis related to productivity: the frontier and the non-frontier approaches (Karmel *et al.*, 2014; Kiendrebeogo, 2012; Nkamleu, 2004). The non-frontier approach mainly employs deterministic techniques which include growth accounting and index numbers. As for the frontier approach, it includes data envelopment analysis (DEA), a deterministic technique, and stochastic frontier analysis (SFA), an econometric technique. The main difference between frontier and non-frontier models is that the former models assume that observed production units do not fully utilize the best practices (Del Gatto *et al.*, 2011).

At micro level, the analysis of efficiency has been based on two competing models: the SFA and DEA techniques. SFA considers economic theory to define the frontier while DEA uses observed data. The comparative advantage of the DEA method is that it requires only data related to inputs and output quantities. However, it has a considerable drawback which potentially renders its estimates inconsistent. This drawback has to do with the fact that this approach's estimates are sensitive to measurement errors or other noise in the data because it attributes all deviations from the frontier to inefficiencies. The parametric SFA method frontier caters for this shortcoming. Indeed, the strength of this latter approach is that it considers stochastic noise in data and allows the statistical testing of hypotheses concerning production structure and degree of inefficiency.

Unfortunately, the standard SFA approach as commonly specified in the efficiency literature does not control heterogeneity and endogeneity (Bokusheva *et al.*, 2012; Kumbhakar, 2011). Bokusheva and Hockmann's (2006) empirical findings reveal the presence of simultaneity in inputs decision, technical development and technical efficiency. Considering these results, most of the estimates of empirical studies are more likely biased. Thus, based on regional data, we apply the return to the outlay model, which provides consistent estimates in the presence of endogeneity (Kumbhakar, 2011), to analyse regional productivity and technical efficiency development in Togo. Indeed, Kumbhakar (2011) shows that one can successfully deal with endogeneity in the return to the outlay model by using a specific specification of the production technology.

In a country like Togo, while the production technologies of cereals are similar, they considerably differ from those used for other agricultural goods production such as yam, cassava and so forth. Thus, assuming that all crops have the same production function may lead to inconsistent estimates. To avoid this, we consider only cereals in our analysis. Crops that are considered include rice, maize, beans, millet and sorghum. These are the five most important cereals in terms of the area coverage.

**Figure 1: Output, partial productivities in Togolese agriculture (2000 = 1) [Color figure can be viewed at wileyonlinelibrary.com]**



## 3. Agriculture Development in Togo

This section provides general information on the development of Togolese agriculture since 2000. Thus, Figure 1 depicts the evolution of agricultural output, labour and land productivities. As can be seen, only two years (2001 and 2003) recorded agriculture output greater than that of 2000. Although the observed agricultural output fluctuates highly along the period of study, two main trends can be noticed in its development. Indeed, it exhibits a decreasing trend up to 2008 and an increasing trend after 2008. The emerging output trend observed after 2008 stands as part of the positive effects of the country emergency program implemented following the 2005 crisis strengthened by the national agricultural and food security investment programme (PNIASA) implemented later in 2009 jointly by the Togolese government and the World Bank. These two programmes promoted massive agricultural investment.

The two partial productivities (land productivity and labour productivity) have trends similar to the output's trend as they have a decreasing trend until 2008 and increasing trend thereafter. However, while the rates of variations of the three variables are quite the same between 2000 and 2008, output and land productivity increased during the second period (2008 to 2014) at a slightly higher rate compared to labour productivity. This seems to indicate that total gross output is mainly drawn by land productivity.

Figure 2 shows the agricultural inputs development during the period of interest. As one can see, the man land ratio (MLR) is relatively constant from 2000 to 2014, the study period. Except Urea intensity, which has a relatively decreasing trend, both NPK (nitrogen, phosphorus and potassium) and capital intensities have overall increasing trends with a sharp increase from 2007.

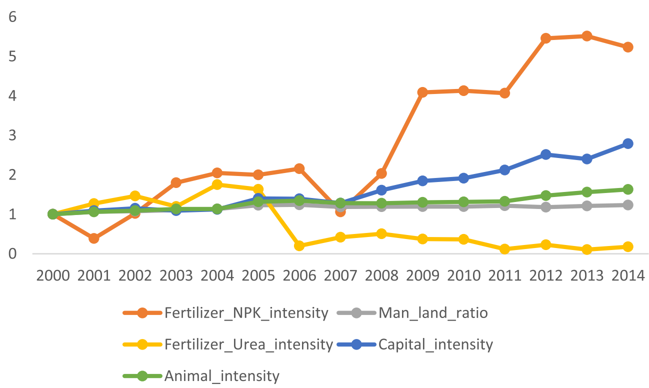
These higher rates are the result of the national agricultural programme on facilitating small producers' access to inputs. Under this programme the Togolese government has taken measures to support smallholder farmers. Thus, under the national maize programme, fertilizer and other inputs such as higher yield varieties (HYV) are allocated to small-scale producers. Similarly, within the framework of this policy prescription, fertilizers are subsidized each year up to 40 per cent for the 2005–2006 season, 42 per cent for the 2007–2008 season, and about 50 per cent for the season 2009–2010, and up to 15 per cent for commercial seeds.

## 4. Research Methodology

### 4.1 Analytical Approach of Technical Efficiency

Technical efficiency can be viewed from two perspectives: output and input. In this study, we adopt the output oriented technical efficiency approach. In his early study, Farrell (1957) suggested a way of measuring technical inefficiency. According to this author, technical inefficiency is measured as one minus the equiproportionate expansion of output for a given level of inputs. The score of one in this formulation stands for technical efficiency. Under this definition, the departure point of the conceptual framework of this study is the production technology. Thus, let $P(x)$ defined by Equation (1) be production technology:

**Figure 2: Factor use in Togolese agriculture (2000 = 1) [Color figure can be viewed at wileyonlinelibrary.com]**



$$P(x) = \{y{:}xcanproducey\} \tag{1}$$

$x$ is a set of inputs while $y$ represents output. For each $x \geq 0$, the output set can be modelled by isoquant defined as:

$$IsoqP(x) = \{y{:}y \in P(x); \theta_y \in P(x), \forall\ \theta \in (1, +\infty)\} \tag{2}$$

Not all producers operate at a point where they utilize the minimum required inputs to achieve their objective (Kumbakhar and Lovell, 2000). Indeed, for many reasons including management inefficiencies, market failure, and other internal and external factors, producers may not be producing the maximum possible output. This raises the challenge of technical efficiency. We then specify the technical efficient component as:

$$EffP(x) = \{y{:}y \in P(x), y' \notin P(x), \forall\ y' \geq y\} \tag{3}$$

The rationale behind this efficiency presentation is that output production can be expanded towards the boundary of the possibility frontier using the same amount of inputs. To assess this measure of efficiency, one has to first identify the frontier a farm is facing and thereafter measure how far the latter is from it. As previously discussed, two main techniques, econometric and non-econometric approaches are commonly used in the literature for this purpose.

We assume here that the farmer maximizes return to the outlay to choose optimal quantities of inputs and output(s) given the technology. That is, inputs and output(s) are decision variables and are therefore endogenous from an economic point of view, leading to an endogeneity problem for econometric estimations (Kumbhakar, 2011). As a result, one cannot use the standard production and distance function formulations unless the econometric endogeneity problem associated with regressors is solved in advance (Guan *et al.*, 2009). Kumbhakar (2011) resolved the endogeneity problem deriving a particular form of the estimating equation in which the regressors are ratios of inputs and outputs. Therefore, using this formulation, the standard ML can be used to estimate efficiency consistently.

## 4.2 Data Sources

The analysis is done at regional level and covers the period 2000–2014. This period is considered because of a data limitation constraint. The regions considered are the five administrative regions of Togo. The data come mainly from the Togolese National Agricultural Statistical Agency (DSID, 2016), and the Centre of Agricultural Input Provision (CAGIA, 2016) for the five administrative regions of the country. Additional data are gathered from FAOSTAT database (FAO, 2016) and the literature on the topic. Eight variables are under consideration: cereal production, defined as cereal gross production; agricultural capital, defined as physical assets used in agricultural production repeatedly over several production periods (it excludes non-durable assets such as fertilizer, pesticide used during a single production season); fertilizer captured through NPK and UREA; land is measured as sown area; agricultural labour is measured as the number of agricultural workers. Other variables considered are irrigated land, rainfall, high yield varieties, and livestock, measured as the number of heads of cattle, sheep and goats.

## 4.3 Data Aggregation

Our study dealt with two challenges when aggregating data. The first challenge is related to cereal production aggregation and the second concerns livestock aggregation. We consider in this study five crops that are rice, maize, beans, millet and sorghum. To sum up their respective production outputs, two ways are available from the literature: using the nutritional value of the crop or using the unit price. The nutritional value approach is not suitable because we are interested in productivity. In addition, unit prices of the considered crops are not available at regional level. We then used a new approach inspired by Njuki *et al.* (2011) in their attempt to compare livestock production. The first step is to compute the ratio of the observed crop production to the respective FAO average yield per hectare. This gives the average number of hectares needed to produce that amount of each crop if the farm were to operate at FAO productivity level. At the second step, we sum up these values across the crops to obtain total production that can be viewed as the total number of hectares that would be needed to produce the

**Table 1: FAO average crops yields for the period**

| Crop | Average yield (kg per ha) |
|---|---|
| Maize | 1187 .81 |
| Millet | 697.79 |
| Sorghum | 968.18 |
| Beans | 347.00 |
| Rice | 2225.05 |

***Source:*** FAO (2016).

observed outputs across the respective crops if farms were operating at the FAO average yield per hectare. Table 1 presents the average FAO yield per hectare used in the exercise.

To aggregate the type of livestock used in this study (cattle, sheep and goats), we followed FAO (2012) to use as weight the tropical livestock conversion factor unit (TLU) of 0.7 for cattle and 0.1 for sheep and goats.

### *4.4 Productivity Variable Definition*

From the previous subsection, it is clear that the definition of the notion of productivity will slightly differ from its common definition in economic literature. We define production as the number of hectares that would have been required to produce the observed level of production if farms were operating at FAO average yield level. Computing the ratio of this production to the cereal sown land, we obtain the ratio of the number of hectares that would have been required under the FAO average yield to the number of hectares really used. This ratio is referred to as *relative land productivity*. If farms operate above FAO yield, the relative land productivity is greater than the unit. By contrast, if they operate below that level, the relative land productivity will be less than the unit.

## 5. Empirical Model

The departure of the empirical model is the following agricultural production function which is drawn from production theory:

$$\ln y_{it} = f(x_{it};\alpha) + \eta_i + v_{it} - u_{it} \tag{4}$$

where $y_{it}$ is the agricultural output by producer (here by region) $i$ in period $t$; $x_{it}$ is a vector of inputs; $\alpha$ is a vector of technological parameters to be estimated; $\eta_i$ is a vector of unobserved producer-specific effect (here region specific effect); $u_{it}$ is a technical inefficiency component assumed to be i.i.d; $v_{it}$ is a stochastic noise component assumed to be i.i.d and $f(x_{it};\alpha)$ stands for the production frontier. Most studies on the topic refer to the Solow growth theory[2] model to estimate Equation (4) specified above by Maximum Likelihood (ML) method. In this type of formulation and in order to have consistent and unbiased estimates, the inputs have to be exogenous, that is, not correlated with either inefficiency or a noise component (Bokusheva *et al*., 2012). However, this is rarely the case as the new growth theories argue that possible simultaneity in input decisions, technical change development and technical efficiency likely lead to endogeneity. To account for this paramount drawback, we use an appropriate modelling approach named ‘return to the outlay model’ (Kumbhakar, 2011).

Thus, following Kumbhakar (2011), the agricultural technology is specified as:

$$A_{it} f(x_{it};y_{it}) = 1 \tag{5}$$

with $\ln y A_{it} = \eta_i + v_{it} - u_{it}$

Contrary to $f(.)$ in Equation (4), Equation (5) specifies a transformation function. The assumption of return to outlay maximization by the producer is made from here. Under this behavioural assumption, one can write the production function as[3]:

$$\ln\left(\frac{y_{1it}}{x_{it}}\right) = g(\ln\hat{x}_{it};\alpha) + \eta_i + v_{it} - u_{it} \tag{6}$$

The dependent variable in Equation (6) is partial productivity in log of input $x_1$, $j$ is the production input subscript, $\hat{x}_{it}$ is the vector of $J - 1$ other inputs normalized by the input $x_1$. The functional form of $g(.)$ is to be derived from the functional form of $f(.)$ (Kumbakhar, 2011). That is, if $f(.)$ is a Cobb Douglas function, $g(.)$ will also be a Cobb Douglas.

To account for determinants of inefficiency and heteroscedasticity in the noise term, we employ the following formulations[4]:

$$\sigma_{u,it} = \exp\left(\sum_{k=1}^{K}\gamma' Z_{it}\right) \tag{7a}$$

$$\sigma_{v,it} = \exp\left(\sum_{k=1}^{K}\delta' w_{it}\right) \tag{7b}$$

$w$ and $z$ are regional variables that explain heteroscedasticity (production risk) and inefficiency respectively.

For the empirical estimation, we rewrite the expression in Equation (6) in the following way:

$$\ln\left(\frac{y_{1it}}{x_{it}}\right) = E\left(u_{it}\right) + g(\ln\hat{x}_{it};\alpha) + \theta_{it} \tag{8}$$

$$\text{With:}\theta_{it} = -\eta_i - v_{it} + (u_{it} - E(u_{it}) \tag{9}$$

When $\eta_i = 0$ this formulation makes $E(\theta_{it})= 0$, which is the standard formulation for the random effect in panel data models. When region-specific effects are assumed to be fixed, they are included in $\alpha$ function and $\theta_{it} = -v_{it} + (u_{it} - E(u_{it})$ become a zero mean random variable. Thus, if $E(u_{it})$ is a constant it will be subsumed by the intercept in $g(\ln\hat{x}_{it};\alpha)$.

Because of the heteroscedasticity assumption stated previously (in Equation (7a)), $E(u_{it})$ depends on $z$ variables. That is, $\sqrt{\frac{2}{\pi}}\sigma_u(z_{it})$, which is not a constant. Hence, the intercept term $E(u_{it}) - \alpha_0$ becomes a function of the $z_{it}$ variables and is region-specific and time-varying. This leads finally the production technology to be specified as:

$$\ln\left(\frac{y_{1it}}{x_{it}}\right) = \sqrt{\frac{2}{\pi}}\sigma_u\left(z_{it}\right) + g(\ln\hat{x}_{it};\alpha) + \theta_{it} \tag{10}$$

That is to say that $z$ variables can be included in the model as regressors as well as input variables. In that case, $z$ variables will be part of the production technology to capture regional heterogeneity. Equation (7a) will then be explicitly specified as $\ln\left(\frac{x_{1it}}{y_{1it}}\right) = m(\ln\hat{x}_{it}; z_{it}\alpha) + \theta_{it}$ where the $m(.)$ function includes both $x$ and $z$ variables, as in the study by Bokusheva *et al.* (2012). However, this formulation does not allow direct identification of the parameters affecting efficiency development. This pushed us, given the recent advances in panel data techniques, to adopt the specification in two steps as presented in Equations (11) and (12) for the empirical estimation considering that $g(.)$ has a Cobb-Douglas empirical specification (Model 1). The choice of Cobb-Douglas empirical specification is supported by the fact that the Cobb-Douglas production function exhibits a flexible functional forms for the production technologies (Allen and Hall, 1997).

$$\ln\left(\frac{y_{1it}}{x_{it}}\right) = \alpha_0 + \sum_{j=2}^{J=4}\alpha_j \ln\hat{x}_{jit} + \theta_{it} \tag{11}$$

$$\ln(u_{it}) = \beta_0 + \sum_{l=1}^{L=4} \beta_l \ln \hat{z}_{lit} + \sum_{m=1}^{M} \beta_m \ln \hat{z}_{mit} + \vartheta_{it} \tag{12}$$

Kumbakhar (2011) argues that independent variables in Equations (11) and (12) are exogenous since they are specified in ratio terms. The estimated equations appear then as: argues that independent variables in Equations (11), (12) are exogenous since they are specified in ratio terms. The estimated equations appear then as:

$$\ln(PROD) = \alpha_0 + \alpha_1 \ln\widehat{LAB}_{1it} + \alpha_2 \ln\widehat{CAP}_{2it} + \alpha_3 \ln\widehat{UREA}_{3it} + \alpha_4 \ln\widehat{NPK}_{4it} + \varnothing_{it} \tag{13}$$

$$\ln U_{it} = \beta_0 + \beta_1 \ln\widehat{IRR}_{it} + \beta_2 \ln\widehat{HYV}_{it} + \beta_3 \ln\widehat{RISK}_{it} + \beta_4 \ln\widehat{LIV}_{it} + \vartheta_{it} \tag{14}$$

We simultaneously estimate the two equations thanks to the recent advances made in the area of efficiency estimates with panel data (Beloti *et al.*, 2012). In order to have an idea on the robustness of our results, we run a second estimates considering that $g(.)$ has log quadratic functional form (Model 2). The variables used in the estimates are presented in Table 2.

# 6. Results and Discussions

## *6.1 Stochastic Frontier Estimates*

Model validation is crucial in empirical studies before results interpretation. Thus, before learning the messages that our estimate conveys, we spent some time on our models validation tests, which are presented in Table 3. Indeed, the stochastic frontier panel model estimated is only valid if the three null hypotheses can be jointly rejected.

Defined as the ratio $\sigma_u^2/(\sigma_u^2 + \sigma_v^2)$, the parameter $\gamma$ indicates whether the inefficiency effects are likely to be significant in the analysis of regional agricultural productivity depending on whether it is statistically significant or not. From the likelihood ratio test, we rejected the null hypothesis that the inefficiency effects are not stochastic. The second null hypothesis that the inefficiency effects are absent from the model is also abandoned. To assess whether the inefficiency effects are not linear we test the third null hypothesis. From this later test we strongly rejected the hypothesis of inefficiency effects being non-linear. Thus, these three hypotheses are rejected at the 5 per cent level of significance and we consequently conclude that the joint effect of the four identified agriculture productivity inefficiency determinants is significant, although some might not be individually statistically significant. The effects of inefficiency in the defined stochastic model can therefore be assumed stochastic and related to irrigation, high yield varieties, climate risk and livestock. We can now move forwards to interpret the model results and infer policy implications with a low risk of being mistaken (less than 5 per cent).

**Table 2: Variables definition**

| Variables | Definition | Measure | Expected effect |
|---|---|---|---|
| $PROD$[a] | Relative land productivity | Ratio | |
| $\hat{LAB}$ | Agricultural worker to land ratio | No. of workers per ha | + |
| $\hat{CAP}$ | Capital to land ratio | CFA per ha | + |
| $\hat{UREA}$ | Urea to land ratio | Kg per ha | + |
| $\hat{NPK}$ | NPK to land ratio | Kg per ha | + |
| $\hat{LIV}$ | Livestock to land ratio | TLU per ha | ± |
| $\hat{IRR}$ | Irrigated land to cereal land ratio | Ratio | + |
| $\hat{HYV}$ | Area under HYV to land ratio | Ha | + |
| $\hat{RISK}$ | Rainfall variability[b] | mm | − |

[a]The computation of this variable is presented in the data section., [b]This variable is computed for the raining season months using the standard formulae of the variance.

*Source:* Author, 2018.

**Table 3: Tests of the model validity**

| Null hypothesis | Log(likelihood) | $\chi^2_{0.95}$ | Test statistic |
|---|---|---|---|
| $H_0$: $\gamma = 0$ | −2.73 | 7.82 | 55.22** |
| $H_0$: $\alpha_{1=\ldots=}\alpha_4=0$ | −26.71 | 9.48 | 103.18** |
| $H_0$: $\delta_1 =\ldots=\delta_6$ | −111.66 | 9.48 | 273.08** |

*Note:* ** indicate that the null hypothesis is rejected.
***Source:*** Author, 2018.

The stochastic frontier specified to represent cereals production is a linearized version of the logarithm of Cobb-Douglas functional form in which the dependent variable is cereal productivity by region. We run this model using Battase and Coelli technique which Stata command has been released recently in 2012. However, to estimate the inefficiency score we follow the Jondrow *et al.* (1982) estimator. Table 4 contains the empirical estimation results but for a robustness check we additionally run a log-quadratic functional form.

From the estimation results, we note that the coefficients in the two regressions have the expected sign and the statistically significant coefficients in the Cobb-Douglas production frontier are also statistically significant in the log-quadratic frontier. Further discussions focus only on the Cobb-Douglas frontier model.

The coefficients of the stochastic frontier have all the expected signs, except labour intensity. Labour intensity has negative elasticity. This seemingly surprising result can be easily explained. Indeed, the negative elasticity of labour may likely be due to the fact that this variable can be seen as an inverse proxy of land size per capita. This is to say that small farms have higher productivity since when the farm is small, the farmer might exhibit more optimizing behaviour. This negative relationship

**Table 4: Panel stochastic frontier inefficiency models estimates**

| *Variables* | *Model 1* | *Model 2* |
|---|---|---|
| *Production technology model* | | |
| ln*UREA* | 0.486 *** (0.064) | 0.328*** (0.188) |
| ln*CAP* | 2.450*** (0.336) | 3.443** (0.104) |
| ln*LAB* | −4.768 (4.716) | −6.800 (25.591) |
| ln*NPK* | 0.446*** (0.054) | 0.285*** (0.046) |
| $\ln^2$*UREA* | | −6.047*** (2.000) |
| $\ln^2$*CAP* | - | 1.069** (0.131) |
| $\ln^2$*LAB* | - | −1.850 (2.612) |
| $\ln^2$*NPK* | - | 0.086* (0.010) |
| ln*UREA**ln*CAP* | - | 6.100** (2.559) |
| ln*UREA**ln*LAB* | - | 18.674 (17.414) |
| ln*UREA**ln*NPK* | - | 0.344*** (0.100) |
| ln*CAP**ln*LAB* | - | 1.257*** (0.538) |
| ln*CAP**ln*NPK* | - | 1.216*** (0.136) |
| ln*LAB**ln*NPK* | - | −0.132 (0.187) |
| *Const.* | −0.653*** (0.074) | −0.700*** (0.091) |
| | *Inefficiency model* | |
| ln*IRR* | −0.274** (0.141) | −0.140*** (0.058) |
| ln*LIV* | 0.250 (0.183) | 0.077 (0.095) |
| ln*HYV* | −2.295 (1.520) | −1.271 (5.853) |
| ln*RISK* | 1.221*** (0.356) | 0.577*** (0.095) |
| *Cont.* | −1.771*** (0.515) | −1.825*** (0.205) |
| *Time-var* | YES | YES |
| *Hetero* | YES | YES |

*Source:* Author, 2018.

between farm size and agricultural productivity has been well established all over the African continent (Barett, 2010; Thapa, 2007; Barbier, 1984).

The positive signs of fertilizer (Urea and NPK) and capital intensities confirm our expectations. The estimated coefficients of Urea, capital and NPK are respectively 0.49, 2.45 and 0.45 and are all highly significant. Increase of capital intensity appears to have the highest impact on agricultural productivity. Indeed, agricultural productivity is elastic to capital intensity since a 1 per cent increase of capital intensity increases agricultural productivity by 2.45 per cent. This higher elasticity is the result of the current low capital intensity of the agricultural sector. Increasing fertilizer intensity can also be seen as a productivity driven strategy. A 1 per cent increase of Urea intensity increases agricultural productivity by 0.49 per cent while an NPK increase of the same percentage leads to a productivity increase by 0.45 per cent.

However, any increase of agricultural productivity based on these strategies is only helpful in the short term. Policy makers who are interested in increasing agricultural growth in the long term, should look for strategies that have the potential to increase technical efficiency. To inform policy makers on such strategies, the particular interest of this paper, we now turn to discuss inefficiency model estimates.

From our estimates, four factors that are livestock, irrigation, high yield varieties and climatic risk appear to jointly drive technical inefficiency. However, only two of them have individually significant effects on inefficiency scores. Firstly, irrigation intensity has a negative and significant effect on technical inefficiency. As the share of irrigated land increases by 1 per cent, technical inefficiency decreases by 0.27 per cent. High yield varieties elasticity is also negative but not significant, meaning that HYV cannot be targeted in the future in the search for higher efficiency under current conditions. Increase of rainfall variability is a factor which does not act in favour of an increasing technical efficiency trend. A 1 per cent increase of climate risk decreases technical inefficiency by 1.22 per cent. Climatic risk perception might trigger adaptation to climate change process when farmers believe that the observed changes are anthropogenic (Mase *et al.*, 2017). However, because the overall aim in adapting to climate change is to reduce downside risk, the adopted strategies might not be the best yield-driven productive technologies. For instance, drought resilient varieties might have lower yield compare to HYV. Similarly, because of the absence of an insurance market, many farmers are reluctant to take up new technologies. This result tells us that adaptation to climate change strategies can highly diverge from best practices and this can be easily understood since the objective functions might differ under the two conditions. In stable and predictable weather conditions, farm households are most concerned with maximizing income from farm activities while when the weather becomes more unpredictable, farm households tend to be more concerned about securing a minimum level of income to the whole family (safety-first hypothesis). They then increase their investment directed to riskless strategies.

Model 2 presented in Table 4 allows us to double check whether the previous discussions are sensitive to model specification. Overall, the results of this second model are in line with the results of the first estimates in terms of signs of the estimated coefficients and their significance except the coefficient of livestock intensification which is significant in Model 2 while it is not significant in Model 1.

## *6.2 Efficiency Considerations*

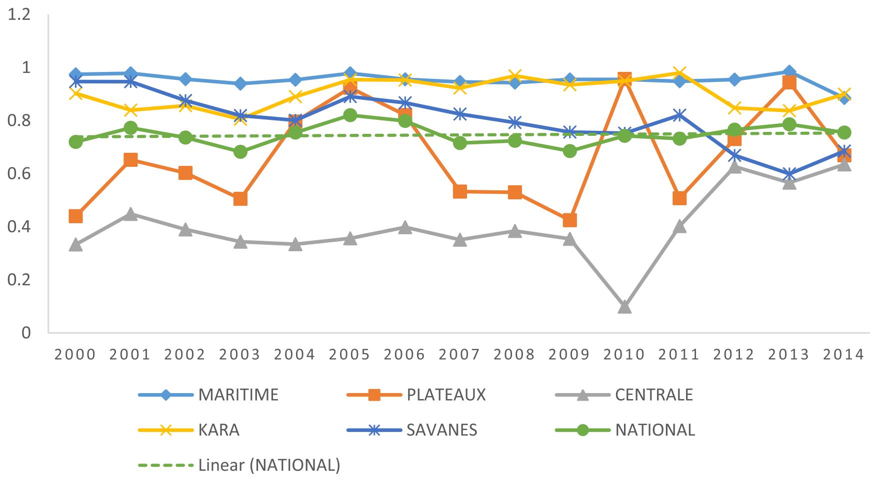
Table 5 presents technical efficiency scores statistics per region of analysis and at national level. At the national level, the estimates reveal that average agricultural productivity technical efficiency is 0.74. This result is similar to the findings of Karmel *et al.* (2014) that indicate that Togolese agricultural technical efficiency is 0.76. The analysis of these scores indicates

**Table 5: Technical efficiency descriptive statistics per region**

| Region | Mean | Std. Err. | Min | Max |
|---|---|---|---|---|
| Maritime | 0.95 | 0.02 | 0.88 | 0.98 |
| Plateaux | 0.67 | 0.19 | 0.42 | 0.95 |
| Centrale | 0.40 | 0.13 | 0.10 | 0.63 |
| Kara | 0.90 | 0.05 | 0.80 | 0.97 |
| Savanes | 0.80 | 0.10 | 0.60 | 0.94 |
| **National** | **0.74** | **0.01** | **0.68** | **0.82** |

*Source:* Author, 2018.

**Figure 3: Evolution of technical inefficiency per region [Color figure can be viewed at wileyonlinelibrary.com]**




that if we consider the threshold of 0.90 as good performance in terms of technical efficiency, three regions — Plateaux, Centrale and Savanes — have the potential to increase their cereal productivity through technical efficiency. As shown above, this can be done by focusing mainly on irrigation infrastructures promotion and climatic risk management.

Figure 3 depicts the dynamics of regional agricultural technical efficiency development across regions and over time. First of all, the technical efficiency of regional agricultural production varies considerably. While Centrale and Plateaux regions were operating most of the time at a lower efficiency compared to the national average, the remaining regions — Kara, Maritime and Savanes — were operating mostly above the national average during the study period. The figure indicates that one should worry more about the Plateaux region, which was operating with high efficiency variability, and the Savanes region, which showed a decreasing trend on the study period while the positive trend observed in the Central region needs to be strengthened. At national level, technical efficiency oscillates between 0.68 and 0.82 but the variation is far lower compared to what is observed in the Plateaux region.

## 7. Concluding Remarks

African countries have been struggling to increase their agricultural productivity, which can be viewed as a precondition to any agricultural transformation of the continent. Throughout the process, the possibility of long- and short-run increases of productivity should be taken into account. To inform policies aiming at sustainably increasing long-term agricultural productivity, this study provided insights on the dynamics of technical efficiency by focusing on the role played by technological change intensification. Because of the differences that exist between the five Togolese regions, we base our analysis on a panel dataset in which the five regions represent the unit of analysis over the period from 2000 to 2014. Contrary to most of the studies on the topic, we followed Kumbhakar (2011) to adopt a regional stochastic frontier model, which assumes that producers maximize return to the outlay to deal with regional heterogeneity and potential endogeneity that might occur.

The empirical results establish that intensification of irrigation has the potential to boost agricultural productivity by increasing technical efficiency. Indeed, as the share of irrigated land increases by 1 per cent, technical inefficiency decreases by 0.27 per cent. By contrast, climatic risk puts additional pressure on the move towards higher agricultural technical efficiency. An increase of climatic risk by 1 per cent decreases technical efficiency by 1.22 per cent.

In line with these findings, two types of policies can be formulated to increase farmers' technical efficiency. The first one is a sustainable irrigation intensification promotion policy. However, an irrigation strategy is by nature highly costly and rarely affordable by smallholder farmers. To cater partly for this constraint, a community-based irrigation scheme development, to take advantage of economies of scale, should be a preferable option. The Sidiki village based irrigation scheme in the Savanes region of Togo could inspire any initiative in this sense.

The second policy package that might increase technical efficiency according to this study is climate risk management. Because when facing higher risk farmers tend to be concerned with 'security first' that limits higher yields technologies adoption that are usually associated with higher risk, reducing the level of risk in terms of productivity loss will undoubtedly enhance the probability of adopting higher yields practices. Thus, weather insurance provision will increase farmers' technical efficiency by reducing production risks to which farmers are exposed. Weather insurance transforms many risky technologies into almost riskless technologies thus creating incentives for farmers to adopt and use them.

However, introducing weather insurance into an agricultural market like Togo's is a complex exercise. Indeed, despite its promising prospects to increase farmers' productivity, a weather insurance index might face considerable challenge since doubts exist over whether poor farmers struggling to feed their families would be willing to buy insurance. This is where learning from experiences of other countries is crucial. Thus, to increase the probability of success of such an initiative, such insurance should be based on insurance systems emerging all over Africa, like the weather insurance market prevailing in East Africa (e.g., Kenya, Malawi).

## Acknowledgement

This research was undertaken under AERC/AfDB Scholars Exchange Program for Research and Mentorship Fellowship. Only the author is responsible for the content of this article.

## Notes

1. Unified Questionnaire of Welfare Indicators.
2. Slow growth theory assumes that perfect competition prevails and technological progress is exogenous.
3. See equation (11) in Kumbhakar (2011) for details.
4. We follow Kumbhakar and Lovell (2000) and Wang (2002) to express these equations.

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