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## Heterogeneity, transient, and persistent technical efficiency: implications for African agrifood systems

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This study departs from conventional estimation of technical efficiency by distinguishing between transient and persistent technical efficiency while accounting for heterogeneity to gain insights for transforming agri-food systems in Africa. A four-error component stochastic frontier model with a translog specification, assuming a half-normal distribution, is applied to panel data comprising 980 observations from 49 countries between 2000 and 2019. Our results show that output is significantly explained by land, labor, and capital. In addition, technological innovation, represented by log (t), consistently emerges as a significant driver of output. The heterogeneity analysis reveals that Cameroon, Ghana, South Africa, Egypt, Cote d'Ivoire, Nigeria, Malawi, and Benin exhibit significantly higher output levels. Persistent technical inefficiency is dominant, with significant heterogeneity in agricultural output. Specific interventions to address persistent technical inefficiency in the agrifood system should include strengthening value chains and farm credit markets, stabilizing land reform policies, promoting the adoption of modern technology, and improving governance. Human capital development through training and education could help mitigate transient technical inefficiency. We conclude that a viable strategy for the transformation of agrifood systems in Africa is to clearly differentiate between short-term (transient) and long-term (persistent) policies, tailored to the unique characteristics (heterogeneity) of each country or region. Therefore, the results are crucial given the ongoing implementation of the Comprehensive Africa Agriculture Development Programme and Agenda 2063.

#### KEYWORDS

technical efficiency, transient inefficiency, persistent efficiency, stochastic frontier analysis, changing the agrifood system, Africa, data panel

#### 1 Introduction

Agrifood systems (AFS) are defined as coordinated actors and activities involved in the food value chain from field to fork (Govaerts et al., 2021). In a broader sense, these include knowledge, institutions, practices, infrastructure, production, transportation, processing, distribution, marketing, disposal, and consumption. Recently, AFS have received growing research interest throughout the world. For example, the theme for the 32<sup>nd</sup> International Conference of Agricultural Economists held in India was "transformation toward sustainable agrifood systems." A year prior to this, the African Association of Agricultural Economists, along with the Agricultural Economics Association of South Africa, held a joint conference in Durban under the theme "Through Crisis: Building Resilient Agrifood

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Systems in Africa." The main reason for the growing attention on AFS is that traditional ways of food production and consumption have produced the climate change crisis, while poverty, hunger, and food and nutrition insecurity continue to grow unabated.

The concept of efficiency was first introduced in the early 1950s by Debreu (1951) and Koopmans (1951). It was further refined by Farrell (1957), who described efficiency as the degree to which the decision-making unit uses input to produce output. Using the non-parametric data envelopment analysis (DEA) approach, which permits multiple inputs and outputs, this researcher also identified two types of efficiency, namely, technical and allocative efficiencies. The former refers to the ability of a firm to obtain maximum output from a given set of inputs, while the latter reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices and the production technology (Coelli et al., 2005). The combination of technical efficiency (TE) and allocative efficiency (AE) yields economic efficiency (EE). After a decade, Aigner et al. (1977) developed a regression-based stochastic frontier analysis (SFA) to estimate efficiency, and these two methods have remained the most commonly used for efficiency analysis. However, the main concern in efficiency analysis within the context of transforming the AFS revolves around a strong emphasis on mix efficiency, short-term (transient) and longterm (persistent) efficiencies (O'Donnell, 2012; Bokusheva et al., 2023). But the study pays attention to transient and persistent technical efficiency.

Extensive literature has been published on the analysis of efficiency in agriculture on a global scale. This includes several reviews (Batiese, 1992; Bravo-Ureta and Pinheiro, 1993; Thiam et al., 2001) and meta-analyses (Bravo-Ureta et al., 2007; Iliyasu et al., 2014; Ogundari and Brümmer, 2011). Within the context of Africa, Thiam et al. (2001) relies on only two studies from the continent, while Bravo-Ureta et al. (2007) considers 14 studies but fails to shed light on agricultural efficiency for the different regions. Ogundari and Brümmer (2011) is restricted to a single African nation. Notwithstanding these drawbacks, the review by Ogundari (2014) remains the most comprehensive examination of agricultural efficiency in Africa and its regions. One of the main findings of this study is that agricultural efficiency estimates derived in different parts of the continent vary according to the methodology applied, type of dataset, geographic location, and study timeframe. Although these reviews have laid a solid foundation for efficiency analysis, they remain silent on transient and persistent technical efficiency and the determinants thereof. However, Berisso and Heshmati (2020) and Adom and Adams (2020) are the few existing studies on transient and persistent technical efficiency. Although both apply SFA on a panel dataset, they are different in terms of study area and remain silent on implications for the transformation of AFS. Our study aims to examine transient and persistent technical efficiency in African agriculture using the four-error component stochastic model, famously known as the Generalized True Random-Effects (GTRE) model, applied to panel data from 49 countries over 19 years. Although we cover the same number of African nations as Adom and Adams (2020), our study extends the time frame by 3 years, providing more recent estimates and allowing the identification of variables that were not previously explored. In addition, this study applies the Bayesian Generalized True Random-Effects (BGTRE) model, incorporating African regional dummy variables as shifters of the production frontier, to draw implications for the transformation of AFS. Classifying technical efficiency into transient and persistent allows for the development of more targeted policies aimed at improving agricultural productivity as part of the broader effort to transform AFS in Africa. The study has one main research question: Is the agriculture sector in Africa transiently or persistently inefficient? The remaining sections are organized as follows. The method, which includes an estimation procedure and data, is discussed in Section 2. The results are presented in Section 3, followed by the conclusion and policy implications in Section 4, and the bibliography in Section 5.

### 2 Methodology

#### 2.1 Data information and model

The study considers panel data of 49 countries in Africa from 2000 to 2019. The minute details of data sources, variable information, individual countries, and regions are discussed in Myeki et al. (2022, 2023). However, the overall summary of variables is presented in Table 1 below. It is clear from the table that the study consisted of a single output, the gross value of agricultural output from crops, livestock, and aquaculture, \$1,000 at constant 2015 prices. Three input variables were considered: land, labor, and capital. Land is the quality of adjusted agricultural area measured per 1,000 hectares of "rainfed equivalent cropland." Labor is the number of economically active adults (male and female) who are employed in agriculture, measured per 1,000 persons. While capital is the net capital stock measured in \$1,000, taking 2015 as the base. Compared to 2000 to 2004, output grew by an average of 19% in 2005 to 2009, followed by 41% and 61% in subsequent periods. Land grew at an average of 9%, 21%, and 34% over the reported periods, respectively. For labor, the average growth was 11%, 17% and 24% while capital had 19%, 47%, and 83%, respectively. Much of the growth in both output and inputs happened during 2015 to 2019. As can be seen in Table 1, the gross output averaged \$5,274,339 (Std. dev = 9,676,909), ranging from 30 024 in Sao Tome and Principe in 2015 to 5,930,633 in Nigeria in 2019. The summary of inputs shows that land averaged 5,808 hectares (8,740) with a range from 37.39 ha in Djibouti in 2006 to 62,459 ha in Nigeria in 2019. On average, 3,241 people were employed in agriculture, ranging from 11.33

TABLE 1 The summary of input-output variables for the study.

Variables	Unit of measurement	Label	Mean	Std. Dev
Output	\$	у	5,274,339	8,676,909
Land	ha	$x_1$	5,804	8,740
Labor	n	<i>x</i> <sub>2</sub>	3,241	4,272
Capital	\$	<i>x</i> <sub>3</sub>	5,971	17,604

in Sao Tome and Principe in 2002 to 21,298 in Nigeria in 2011. On the other hand, capital had an average of 5,971 (17,604) with a range from 4.83 in Djibouti in 2000 to 188,491 in Nigeria in 2019.

It employs the GTRE model by Colombi et al. (2014), Kumbhakar et al. (2014), and Tsionas and Kumbhakar (2014) to estimate transient and persistent inefficiency in the agricultural sector for the continent. The model is expressed as follows:

$$y_{it} = \alpha_0 + f(x_{it}, t; \beta) + \mu_i - \eta_i + v_{it} - u_{it},$$
(1)

where  $y_{it}$  is the dependent variable defined as the logarithm for agricultural output of nation *i* in period *t*,  $\alpha_0$  is the intercept,  $f(x_{it}, t; \beta)$  is the production technology, including a time trend t to account for technological change,  $x_{it}$  is a vector of inputs (in logs), and  $\beta$  is a vector of unknown parameters to be estimated. Additionally, the  $\mu_i$  represents time-invariant firmspecific latent (unobserved) heterogeneity,  $\eta_i$  denotes the persistent (time-invariant) technical inefficiency,  $u_{it}$  captures transient (timevarying) technical inefficiency, and  $v_{it}$  is a random noise term. The composite error term for the model described in Equation (1) is  $\varepsilon_{it} = \mu_i - h_i + v_{it} - u_{it}$  with  $\mu_i \sim N(0, \sigma_{\mu}^2)$ ;  $v_{it} \sim N(0, \sigma_{\nu}^2)$ ;  $\eta_i \sim N^+(0,\sigma_n^2)$ , and;  $u_{it} \sim N^+(0,\sigma_u^2)$ . Numerous stochastic frontier models are embedded in the GTRE model defined in Equation (1). For instance, dropping both  $\mu_i$  and  $\eta_i$  leads to a "pooled" model proposed by Aigner et al. (1977), described as follows:

$$y_{it} = \alpha_0 + f(x_{it}, t; \beta) + v_{it} - u_{it}$$
 (2)

The  $v_{it}$  is a random variable assumed to be identically and independently distributed *iid* with zero mean and variance  $\sigma_v^2 (v_{it} \sim N(0, \sigma_v^2))$ , assumed to capture the effect of random noise; and  $u_{it}$  is the time-varying non-negative half-normal inefficiency random variable, which is assumed to be *iid* with zero mean and variance  $\sigma_u^2 (u_{it} \sim N^+ (0, \sigma_u^2))$ . Discarding  $\eta_i$  and  $u_{it}$  from the same model, described by Equation (1), yields the standard panel stochastic frontier model with random effects (RE) developed by Pitt and Lee (1981), expressed in Equation (3). The error specification of this equation is  $\varepsilon_{it} = v_{it} - h_i$ , distributed as  $v_{it} \sim$  $N (0, \sigma_v^2)$  and  $\mu_i \sim N^+ (0, \sigma_u^2)$ 

$$y_{it} = \alpha_0 + f(x_{it}, t; \beta) + \mu_{it} - v_{it}$$
 (3)

On the other hand, removing  $\eta_i$  alone from Equation (1) leads to Greene (2005a,b)'s true random effect (TRE) model in Equation 4, depending on whether  $\mu_i$  is correlated with the error term  $(\mu_i \sim N^+ (0, \sigma_u^2), v_{it} \sim N (0, \sigma_v^2) \text{ and; } u_{it} \sim N^+ (0, \sigma_u^2)$ 

$$y_{it} = \alpha_0 + f(x_{it}, t; \beta) + \mu_i + v_{it} - u_{it}$$
(4)

The study adopted an approach of Filippini and Hunt (2015) and Alberini and Filippini (2018) where the GTRE model and three traditional models described in Equations (2–4) are estimated separately and compared to each other for robustness. Moreover, we also employed the translog functional form based on loglikelihood ratio test results (see Table 2), leading to rejection of the Cobb-Douglass functional form. Thus, the final model is expressed as follows:

$$\ln y_{it} = \alpha + \sum_{j=1}^{3} \beta_j \ln x_{jt} + \frac{1}{2} \sum_{j=1}^{3} \sum_{k=1}^{3} \beta_{jk} \ln x_{jt} \ln x_{kt} + \mu_i - \eta_i + \nu_{it} - u_{it},$$
(5)

where  $\ln y_{it}$  represents the agricultural output of individual nation *i* in period *t* while  $\alpha_0$  is the intercept.  $x_{jt}$  represents the three key inputs used to derive agricultural output, and they include land, labor, and capital.  $\beta_{jt}$  is a vector of unknown parameters to be estimated. The  $\mu_i$  represents time-invariant firmspecific latent (unobserved) heterogeneity,  $\eta_i$  denotes the persistent (time-invariant) technical inefficiency,  $u_{it}$  captures transient (timevarying) technical inefficiency, and  $v_{it}$  is a random noise term. Models described in Equations (1–5) were implemented using STATA 17 software.

For confirmatory purposes, we also estimated the GTRE model using Bayesian SFA analysis, where the different subregions of Africa were used as shifters of efficiency. Although extended to include panel data analysis by Koop (1994), the Bayesian framework is novel to Van den Broeck et al. (1994). The advantages of the framework include the ability to minimize the loss associated with an estimation error; permit probability statements about unknown parameters, hypotheses, and models; provide exact finite-sample results for most estimation problems; and allow for the ease of incorporating restrictions that allow for a formal treatment of parameters and model uncertainty. Let  $\theta = (\theta_1, \dots, \theta_k)$  denote the unknown parameters of the GTRE model to be estimates  $p(\theta)$ =  $p(\boldsymbol{\beta}, \sigma_w, \sigma_h, \sigma_v, \sigma_u)$  denotes the probability density function (pdf) of prior information for parameters while  $L(y, \mathbf{X} \mid \theta)$  is the likelihood function. The posterior distribution follows from Bayes's theorem as follows:

$$p(\theta \mid y, \mathbf{X}) \propto L(y, \mathbf{X} \mid \theta) p(\theta), \tag{6}$$

where  $p(\theta \mid y, \mathbf{X})$  is the posterior pdf and  $\propto$  denotes "is proportional to." Put simply, the posterior pdf is proportional to the likelihood function multiplied by the prior pdf. Thus, the posterior distribution includes all the information on the parameters contained in the prior and the data. The prior pdf  $p(\theta)$  can be non-informative or informative. The complex models that do not allow inference by analytical methods, implementing the Bayesian approach, require the use of iterative Markov Chain Monte Carlo (MCMC) algorithms such as the Metropolis-Hastings and Gibbs Sampling, which focus on sampling from the conditional distribution for blocks of the parameter vector. The Gibbs Sampler algorithm used by Koop et al. (1992) is particularly useful for problems involving latent variables, such as SFA models, and is commonly used in the literature. The researcher can write their own MCMC algorithms or just specify the model but use the Bayesian inference using Gibbs Sampling (BUGS) software, such as WinBUGS or JAGS, to handle the MCMC sampling. In our study, we used JAGS in R through the "APEAR" package to implement the final BGTRE model, which is expressed below.

$$\ln y_{it} = \alpha + \sum_{j=1}^{3} \beta_j \ln x_{jt} + \frac{1}{2} \sum_{j=1}^{3} \sum_{k=1}^{3} \beta_{jk} \ln x_{jt} \ln x_{kt} + \sum_{i=1}^{4} \beta_l D_l + \mu_i - \eta_i + v_{it} - u_{it},$$
(7)

where i = 1,..., n denotes the *i*-th country, and t = 1.  $x_{it}$  is a vector of *j*-th used inputs normalized by the means. The three inputs used in agricultural output are land, labor, and capital.  $D_l(l = 1, 2, 3)$  are regional dummy variables, denoting East Africa, North Africa, West Africa, and Southern Africa, all of which were included for the comparisons for regional performance in terms of transient and persistent technical inefficiency. The  $\alpha$  and  $\beta$  are unknown parameters to be estimated. Again, the  $\mu_i$  represents time-invariant firm-specific latent (unobserved) heterogeneity,  $\eta_i$  denotes the persistent (timeinvariant) technical inefficiency, uit captures transient (timevarying) technical inefficiency, and  $v_{it}$  is a random noise term. We also computed partial output elasticities with respect to inputs with the purpose of examining the sensitivity of output change when a change in inputs occurs. The equation to derive partial elasticities is as follows:

$$E_{j} = \frac{\partial \ln y_{it}}{\partial \ln x_{jt}} = \hat{\beta}_{j} + \hat{\beta}_{jj} \ln x_{jt} + \sum_{k=1}^{3} \hat{\beta}_{jk} \ln x_{kt},$$
(8)

where  $\hat{\beta}_j$ ,  $\hat{\beta}_{jj}$  and  $\hat{\beta}_{jk}$  are the parameters of the BGTRE model estimated in Equation (7). The returns to scale for this model

TABLE 2 The summary of diagnostic test for the study.

are computed by summing up the partial output elasticities with respect to inputs, as follows:

$$RTS = \sum_{j=1}^{3} E_j \tag{9}$$

#### 3 Empirical findings

#### 3.1 Summary of diagnostic tests

A series of diagnostic tests were performed to ascertain the most appropriate models, and the results are shown in Table 2. Our first null hypothesis was concerned with testing for the presence of multicollinearity. Since the Variance Inflation Factor (VIF) for the three variables is <10, the null hypothesis is rejected, implying that the independent variables are independent of one another. Using the log-likelihood ratio (LR) test, the findings (test statistic = 959.96; critical = 9.50 and df = 1) show that the null hypothesis stating that inefficiency is not present was rejected, thus indicating the presence of inefficiency and the fact that we cannot use the ordinary least squares. Additionally, the panel effect was found to be significant across the dataset, indicating that heterogeneity is significant. This also suggests that we cannot use the pooled model. The assumption of truncated normal distribution for the inefficiency term was rejected using the Breusch-Pagan (BP) test, which suggests that a half-normal distribution is appropriate. This result implies that we could not test if inefficiency varies over time because such a test requires a truncated normal distribution.

Moreover, testing between fixed and random effects models using the Hausman test showed a p-value of zero, indicating that random effects were appropriate. The results in Table 2 further reveal that the translog stochastic frontier model is preferred over

Hypothesis	Variable	Test	Estimates	Conclusion
(1) Null	Variables	VIF	1/VIF	Decision
H0: Multicollinearity is present	Land	5.24	0.19	Reject H0
	Labor	1.93	0.52	Reject H0
	Capital	3.74	0.26	Reject H0
(2) Null		LR test	Critical value	Decision
H0: No technical inefficiency		959.56	9.50	Reject H0
(3) Null		BP-test	<i>P</i> -value	Decision
H0: No panel effect		7696.45	0.00	Reject H0
(4) Null		LR test	<i>P</i> -value	Decision
H0: Truncated normal distribution		17.42	0.00	Reject H0
(5) Null		Hausman test	<i>P</i> -value	Decision
H0: Fixed effect is appropriate		38.60	0.00	Reject H0
(6) Null		Test statistics	Critical value	Decision
H0: Cobb-Douglass is appropriate		214.77	12.59	Reject H0

Variable	Рос	oled	RE		TRE		GTRE	
	Coef	T-stat	Coef	T-stat	Coef	T-stat	Coef	T-stat
Intercept	15.89***	547.10	16.03***	349.06	15.35***	923.34	15.32***	236.31
$lnx_1$	0.61***	20.43	0.81***	25.77	0.84***	55.73	0.83***	26.91
$lnx_2$	0.15***	7.81	0.08***	3.01	0.16***	15.56	0.07**	2.52
lnx <sub>3</sub>	0.24***	10.56	-0.02	-0.74	-0.06***	-4.89	-0.01	-0.36
lnt	0.11***	4.19	0.15***	14.18	0.16***	18.98	0.15***	13.83
$0.5 ln x_1^2$	-0.29***	0.07	0.10***	2.68	0.11***	4.50	0.09**	2.40
$lnx_1lnx_2$	0.42***	5.37	-0.09*	-2.00	-0.19**	-5.78	-0.09	-1.89
$lnx_1lnx_3$	0.24***	3.92	0.06	1.47	0.11***	4.35	0.08**	-1.87
$lnx_1lnt$	-0.11	-0.26	0.05***	3.72	0.06***	4.66	0.05***	3.46
$0.5 ln x_2^2$	-0.00	-0.13	0.05	1.78	0.07***	4.94	0.04	1.56
$lnx_2lnx_3$	0.42***	-10.71	-0.04	-1.52	-0.03	-1.66	0.06**	-2.27
$lnx_2lnt$	0.05*	1.79	-0.01	-0.94	-0.02***	-2.64	-0.01***	-0.74
$0.5 ln x_3^2$	0.08***	3.06	-0.04*	-2.39	-0.06***	-6.00	-0.04**	-2.31
lnx <sub>3</sub> lnt	0.01	0.34	0.01	1.03	0.01	0.87	0.01	1.23
$0.5 lnt^2$	0.04	1.34	0.05***	5.55	0.07***	7.12	0.05***	5.18
Model properties								
λ	2.49***	49.50	9.26***	91.83	1.90***	114.79	1.04***	68.75
$\sigma_{uit}$	0.48***	15.28	-	-	0.12***	11.38	0.07***	7.10
$\sigma_{vit}$	0.19***	9.50	0.09***	21.47	0.07***	10.40	-0.09*	1.86
$\mu_i$	-	-	-	-	0.42***	63.63	-0.11***	19.10
$\eta_i$	-	-	0.89***	8.87	-	-	0.35***	7.28
LR	-338.55		750.07		749.65		924.86	

#### TABLE 3 Summary of translog stochastic production models (N = 980).

\* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001.

the Cobb-Douglas functional form. Although not presented in the table, we also found that variables were stationary while using the Hadri-LM test. Next, we present the results for the translog stochastic frontier models.

## 3.2 Estimates of translog stochastic frontier model

Table 3 presents the parameter estimates for pooled, RE, TRE, and GTRE models. The first three models are nested in the latter. Nonetheless, the coefficient lnt is positive for all estimated models, indicating that agriculture in Africa has experienced technological progress over the study period. The findings suggest that Africa is on the right track in terms of adopting technology to improve agricultural efficiency and productivity. The variables land, labor, and capital are all significant at the 1% level for the pooled and TRE models. This finding was expected because improvement on: (i) land through the application of better fertilizer, (ii) labor through training and education, and (iii) capital through investment in farm machinery and equipment are all highly likely to improve efficiency. Surprisingly, the coefficient for variable capital for RE and GTRE is negative and insignificant, indicating a lack of empirical evidence for the relationship between output and capital for the two models. The coefficient for  $\eta$  is 0.35% and significant in GTRE, suggesting that persistent inefficiency is dominant compared to transient inefficiency (0.07%). This implies that over the study period, agriculture in Africa had an average persistent technical efficiency of 65% and a transient technical efficiency of 93%. The heterogeneity and persistent inefficiency are significant, indicating that the GTRE model is appropriate.

## 3.3 Estimates of Bayesian stochastic frontier model

The estimates for the Bayesian stochastic frontier model with translog specification are shown in Table 4. The Gibbs sampler was run for one chain, with a burn-in of 200,000 iterations, 10,000 retained draws, and a thinning to every 40th draw in order to reduce the level of autocorrelation of the chain. This table clearly shows that a percentage increase in any of the inputs leads to an increase in agricultural productivity in Africa. For instance, with each unit increase in agricultural land allocated in Africa,

output increases by 0.67%, and this increase falls within the 95% posterior probability interval (0.60%, 0.74%). A unit increase in labor leads to a 0.14% increase in output. In addition, this increase falls in a 0.09% to 0.20% interval with 95% posterior probability. On the other hand, the coefficient for t is 0.02 and positive, indicating technological progress over the study period. These findings are significant, as shown by the same sign for the values of the confidence interval. However, the agricultural output has been more responsive to changes in land compared to labor. On the other hand, a unit increase in capital is associated with a 0.04% increase in output, and this falls in the 0.02% to 0.07% interval with 95% posterior probability. These findings correspond to those discussed earlier in Table 2 and suggest that production behaves well and meets the monotonicity assumption. The results also imply that countries can continue to increase their input levels until any increase in input yields no additional output. The results further reveal that the Monte Carlo (MC) error is lower than the corresponding posterior standard deviation, suggesting convergence of the model and accuracy of estimates. However, if evidence of significance was present, the result would suggest that East Africa is 0.47% more productive compared to Central Africa, while North Africa, Southern Africa, and West Africa are more productive by 0.29%, 0.26%, and 0.10%, respectively. The coefficient for gamma  $(\gamma)$  is significant and positive, indicating that 0.81% of the variation in agricultural output among the African nations is attributed to the variations in technical efficiency. The value of lambda ( $\lambda$ ), gives information about the inefficiency level of the agriculture sector. Put in simple terms, it shows by how much an African country has fallen short of the total output. Similarly to Table 2, the persistent technical inefficiency  $(\sigma_{ui})$  is dominant at 0.10%, while transient inefficiency  $(\sigma_{uit})$  was at 0.08%.

With respect to the results of Equation (9), the value of returns to scale for BGTRE is 0.86, indicating that agricultural production in Africa achieved a decreasing return to scale over the study period. This value is slightly higher by 0.07 compared to that of the GTRE model at 0.79. It suggests that the proportion of output is less than the desired increased inputs during the production process. We found that agricultural output is more responsive to land and labor use. More details of elasticity estimates for each country are presented in Appendix Table 6.

#### 3.4 Estimates of inefficiency and heterogeneity

In this section, we present the results for various efficiencies, beginning with those models discussed in Table 3. The pooled model yielded an average efficiency (transient efficiency) score of 0.69%, ranging from 0.22% to 0.93%, while RE had an average (persistent efficiency) score of 0.50% with a range from 0.17% to 0.98%. The TRE model produced an average efficiency score of 0.89, implying room for improving efficiency by 11% without changing the input and current technology. The main model (GTRE) yielded averages of 0.73% and 0.93% for persistent and transient efficiencies, respectively, leading to

TABLE 4 Bayesian estimates of translog stochastic frontier (N = 980).

Variable	Coeff	SD	MCerr	[95% C.I]				
Intercept	-0.47	0.27	0.07	-1.11	0.02			
$lnx_1$	0.67 <sup>s</sup>	0.04	0.00	0.59	0.74			
$lnx_2$	0.14 <sup>s</sup>	0.03	0.00	0.09	0.20			
lnx <sub>3</sub>	0.05 <sup>s</sup>	0.01	0.00	0.02	0.07			
lnxt	0.02 <sup>s</sup>	0.00	0.00	0.01	0.02			
$0.5 ln x_1^2$	0.12 <sup>s</sup>	0.03	0.00	0.07	0.17			
$lnx_1lnx_2$	-0.04	0.02	0.00	-0.06	0.00			
$lnx_1lnx_3$	0.01	0.01	0.00	-0.01	0.03			
$lnx_1lnt$	0.00	0.00	0.00	0.00	0.01			
$0.5 ln x_2^2$	0.03	0.02	0.00	-0.01	0.06			
$lnx_2lnx_3$	-0.01	0.01	0.00	-0.03	0.00			
$lnx_2lnt$	-0.00	0.00	0.00	-0.00	0.00			
$0.5 ln x_3^2$	-0.01	0.01	0.00	-0.02	0.01			
lnx <sub>3</sub> lnt	0.00	0.00	0.00	-0.00	0.00			
$0.5lnt^2$	0.00	0.00	0.00	0.00	0.00			
Inefficiency determinants								
East Africa	0.48	0.39	0.06	-0.31	1.34			
North Africa	0.29	0.39	0.05	-0.55	0.99			
Southern Africa	0.26	0.29	0.04	-0.35	0.83			
West Africa	0.09	0.27	0.04	-0.36	0.76			
Model properties								
λ	2.37 <sup>s</sup>	0.92	0.06	1.12	4.22			
γ	0.81 <sup>s</sup>	0.09	0.01	0.66	0.97			
$\sigma_e$	0.15 <sup>s</sup>	0.05	0.00	0.09	0.24			
$\sigma_v$	0.06 <sup>s</sup>	0.01	0.00	0.05	0.07			
$\sigma_u$	0.13 <sup>s</sup>	0.05	0.00	0.08	0.23			
$\sigma_{ui}$	0.095	0.06	0.01	0.02	0.22			
$\sigma_{uit}$	0.08 <sup>s</sup>	0.01	0.00	0.07	0.09			
$\sigma_{wit}$	0.66 <sup>s</sup>	0.08	0.00	0.51	0.83			

Central Africa is used as a base for regional dummy comparisons. s stands for significant.

an overall average efficiency score of 0.68%. This suggests that persistent efficiency has less contribution to the overall efficiency of the agricultural sector in Africa over the study period (see Figure 1). The efficiency estimates of the Bayesian stochastic frontier reveal an overall average efficiency of 0.84%, ranging from 0.52% to 0.91%. However, there is a slight difference between transient and persistent efficiency, showing that transient efficiency dominates by 1%. Nonetheless, further details of efficiency scores obtained from BGTRE for each sampled African nation over the study period are presented in Appendix Table 5. The results for heterogeneity in Appendix Table 7 show that Cameroon, Ghana, South Africa, Egypt, Cote d'Ivoire, Nigeria, Malawi, and Benin have significantly large agricultural outputs. On the



other hand, Libya, Niger, Cape Verde, Sao Tome, and Principe, Comoros, Equatorial Guinea and Djibouti had significantly low agricultural output.

# 4 Discussion and implications for African agrifood systems

The study aimed to examine heterogeneity and transient and persistent technical inefficiency to draw lessons for the transformation of AFS in Africa. The main finding to emerge from the study is that persistent inefficiency was dominant in agriculture on the continent. This was also evident for most of the sampled countries. These findings correspond to Adom and Adams (2020) reporting that persistent technical inefficiency constrained the overall efficiency of the sector on the continent for 49 nations from 1990 to 2016. It suggests that the remaining inefficiency is driven by short-term (transient) agrifood system inefficiency. Moreover, country or regional characteristics (such as resource endowments, infrastructure, value chains, and institutions) appear to influence the transformation and efficiency of AFS.

Another important finding is that both GTRE and BGTRE have consistently shown progress in resolving transient technical inefficiency for the continent over the study period. These findings corroborate Myeki et al. (2022), who established that short-term (transient) technical efficiency was the main driver of productivity in Africa for the first 16 years of the 21st century while using the DEA method on panel data from 49 countries to derive Fare-Primont TFP estimates. The finding implies that investment in education and training in conjunction with technology innovation could increase the resilience and sustainability of agrifood systems

in the face of shocks such as COVID-19, pest infestations, trade restrictions, changing diets and customer preferences, wars, and extreme weather events.

The results for the coefficient on both land and labor for the same models (GTRE and BGTRE) match those of Singvejsakul et al. (2021), who employ the Bayesian stochastic frontier to analyze agriculture productivity and efficiency in four Asian countries over a period of 29 years. However, this finding suggests that part of the effort to transform AFS should involve a coordinated reform, prioritizing the relationship between land, labor, and food systems. Nonetheless, the returns to scale of 0.79 in Table 2 and 0.86 in Table 3 are contrary to the value obtained by Pisulewski and Marzec (2019) at 1.16, exhibiting increasing returns to scale in Polish farmers. However, they are almost similar to Berisso (2019) who report a value of 0.71 while studying heterogeneity, persistent and transient efficiency for cereal farms in Ethiopia. A possible explanation for this result could be the law of diminishing returns. However, taken together, these have serious implications for the transformation of agrifood systems in the African continent.

#### 5 Conclusion

In view of the ongoing effort to transform AFS in Africa by increasing productive efficiency in agriculture as one possible strategy, the study was designed to estimate both transient and persistent technical efficiency for policy guidance. Balanced panel data from 49 countries were applied using a four-error component stochastic frontier model with a translog specification. The heterogeneity results show that Cameroon, Ghana, South Africa, Egypt, Cote d'Ivoire, Nigeria, Malawi, and Benin have significantly large agricultural outputs. Regarding the nature of technical inefficiency in African agriculture, our findings demonstrate the predominance of long-term (persistent), which appears to stem from country- or region-specific structural challenges. This leads to our first policy recommendation: the continent must develop a long-term strategy for comprehensive agricultural transformation that takes into account country-specific characteristics to improve persistent efficiency. This plan could include, among other things, vertical integration, agro-processing, and infrastructure development. The study also discovered a small room for improvement in transient efficiency, which can be addressed by focusing on managerial issues, extension service programs, and training to enhance the adoption of modern technologies.

Given that land and labor are more responsive to increases in output, a comprehensive and stable land reform policy, along with adherence to decent work standards, is crucial for the transformation of AFS in Africa. These policy measures are likely to enhance productivity, promote economic growth, and strengthen food security across the continent. Future studies should expand the time frame of our study and focus on/(in)efficiency.

#### Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Author contributions

LM: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. NM: Writing – review & editing. YB: Writing – review & editing.

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#### Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025. 1505465/full#supplementary-material

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