RAAE

Review of Agricultural and Applied Economics
Acta Oeconomica et Informatica
***ISSN 1336-9261, Vol. XXIV, Issue 1, 2021*: 76-87**
doi: 10.15414/raae.2021.24.01.76-87

REGULAR ARTICLE
Received: 7.10.2020; Revised: 17.2.2021; Accepted: 26.2.2021; Published online: 28.2.2021

SPATIOTEMPORAL EVALUATION OF DRY BEANS AND GROUNDNUT PRODUCTION TECHNOLOGY AND INEFFICIENCY IN GHANA

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ABSTRACT

Research background: A combination of technology and efficiency gains will drive future intensification programs aimed at fostering food and nutrition security in the developing world. Specifically, the adoption of improved varieties and use of quality seed alongside good agronomic practices will be critical.

Purpose of the article: Given the space-time availability of technology, this study investigates how production efficiency (technical efficiency, technology gap, and meta technical efficiency) has changed over time and assesses the possibility of heterogeneous technology adoption in Ghana.

Methods: The study constructs a rich nationally representative dataset of dry beans and groundnut farmers that constitutes 15 production seasons in Ghana. Using a sample of 10,518 farmers from 10,051 households, a Meta Stochastic Frontier (MSF) approach is used to access changes and determinants efficiency and technology adoption.

Findings & Value added: We find that farms are operating under heterogeneous technologies along ecological lines and that the technology gap has been reducing over time. Improvements in meta technical efficiency could be driven by the gains in the technology gap ratio. Technical efficiency levels across the two legumes averaged about 61% and did not significantly improve between 1987 to 2017. The key determinants for the observed trends were farmer education, mechanization, access to agricultural extension services, and land ownership. Holding ecological technologies constant, legume farmers generally performed poorly because of technical inefficiency, implying that a general improvement in farmer managerial skills could substantially improve farm output. The study recommends policies/programs be formulated on a case-by-case basis; to ensure specificity and wider impacts, if production is to improve.

Key words: efficiency; Ghana; dry bean; groundnut; technology gap
JEL Codes: D13; Q12; O55

INTRODUCTION

Achieving 'close to' potential mean yields of staple crops in Sub-Saharan Africa remains elusive among small-scale farmers. Available evidence shows that adoption rates and national mean yields of several crops have remained low **(Alliance for a Green Revolution in Africa (AGRA), 2016; Binswanger-Mkhize and Savastano, 2017**). These disparities have been attributed to the extreme vulnerability of crops to biotic and abiotic stresses **(Feed the Future, 2013**) and the use of inefficient production practices and technology gaps **(Combary, 2017; Nishimizu and Page, 1982)**. This is against the backdrop that governments and non-governmental organizations have been promoting initiatives such as breeding and supplying yield-enhancing technologies (improved seeds, fertilizers, and pesticides) and extension services. However, the realization of the impacts of Ag investments takes time following adoption. A key policy question thus concerns how efficient farmers have been and how this has been changing overtime, whether technology adoption is heterogeneous, and what factors have influenced production efficiency.

This study examines the temporal and spatial dimensions of production efficiency of dry beans (cowpea (*Vigna unguiculata*) and Bambara beans (*Vigna subterranean*)) and groundnut (*Arachis hypogaea*) farmers in Ghana. The paper investigates how production efficiency has changed over time and assesses the possibility of heterogeneous technology adoption. Using the Meta Stochastic Frontier (MSF) approach, the study; (1) assesses factor contributions to ecology specific, national and meta-frontier efficiencies, (2) quantifies temporal pure Technical Efficiency (TE), Technology Gap Ratio (TGR), and Meta Technical Efficiency (MTE), and (3) evaluates farmer and institutional factors that have influenced technical inefficiency and adoption of superior technologies. The empirical strategy is implemented using a rich nationally representative dataset that covers 15 production seasons between 1987 and 2017 in Ghana. This data presents a unique opportunity to empirically assess the nature of observed legume production patterns in Ghana over time.

LITERATURE REVIEW

Production efficiency can be categorized into technical or allocative efficiency, with the two combining to form economic efficiency (**Farrell, 1957**). Due to the paucity of reliable data on input prices at the farmer level, technical efficiency, which deals with how well farmers manage inputs to reach potential yields is the most commonly used measure. The literature presents two main orientations - i.e., output or input - in measuring technical efficiency. Output orientation compares the observed output to its potential given a set of input and technology while the input orientation measure compares observed input levels to its minimum potential necessary to produce a given output level **(Belotti, Daidone, Ilardi, and Atella, 2013).** These two orientations are empirically implemented either using the non-parametric Data Envelopment Analysis (DEA), or the Stochastic Frontier Analysis (SFA) methods. DEA ignores deviation outside the control of farmers (i.e. white noise) while SFA employs econometrics and as such incorporates randomness into the production process (**Belotti *et al.*, 2013**). Consequently, the SFA approach is used in this study because it incorporates randomness and fits the data best. The existence of a homogeneous production technology and management practices puts all farmers on the production frontier. However, deviations can be observed that can be attributed to technical inefficiency and/or production risk (**Bokusheva and Hockmann, 2005**).

Empirical evidence into smallholder production efficiency has mostly been static in time (single-season analysis) and limited in geographic scope. This kind of analysis, therefore, does not allow for spatial and temporal analysis of production efficiency and its dynamics. It has been noted that failure to account for technological differences could lead to falsely attributing production shortfalls due to technology gaps to inefficient input use **(Battese, Rao, and O'Donnell, 2004)** leading to suboptimal policy prescriptions. A handful of studies on Ghana have shown that low production levels for maize **(Owusu, 2016; Wongnasa and Awunyo-Vitor, 2019)**, rice **(Asravor, Wiredu, Siddig, and Onumah, 2019)**, vegetables **(Tsiboe, Asravor, and Osei, 2019)**, and cocoa could be attributed to ecological and regional technological gaps. Furthermore, some have shown that technology gaps could exist along gender differences of farm owners and managers **(Djokoto *et al.*, 2017)** or methods of production used by farmers, both conventional/organic **(Onumah *et al.*, 2013)**. The only studies also on Ghana and focusing on leguminous crops do not consider technology gaps but they show that production could be improved by reducing technical inefficiency **(Avea *et al.*, 2016; Awunyo-Vitor, Bakang, Gyan, and Cofie, 2013; Etwire, Martey, and Dogbe, 2013).**

This study differs from earlier empirical studies conducted on legumes in Ghana on two fronts: First, the possibility for heterogeneous technology adoption is considered in explaining the nature of observed production. Secondly, production technologies and efficiencies were analysed over an extended period allowing the study to isolate trends and temporal dynamics. By putting the nature, dynamics, and spatial distribution of legume production on a solid empirical footing, the output from this study offers ground truth that informs the policy dialogue and supports crop improvement agendas.

DATA AND METHODS

Data and Sample

The data used comes from three sources; (1) all seven Ghana Living Standards Surveys (GLSSs); (2) the first and second waves of the Ghana Socioeconomic Panel Surveys (GSPS); and (3) the Ghana Africa Research in Sustainable Intensification for the Next Generation Baseline Evaluation Survey (GARBES). Detailed information on the harmonization of these datasets is published elsewhere. Except for GSPS, each round of data collection has a sample of new households. Thus, the study data is a pooled/repeated cross-section dataset of Ghanaian legume farmers. The sample used in this study was limited to farmers originating from the dry bean and groundnut producing households, with yield measured in kg/ha above the 5th and below the 95th percentile by survey, ecology, and legume. The final sample consists of 10,518 farmers originating from 10,051 households.

The data is nationally representative covering all but one ecology: Rain Forest, Semi-Deciduous Forest, Transitional Zone, Guinea Savanna, and Sudan Savanna, of Ghana. The farming systems are highly heterogeneous and supportive of many types of farming. Most of the cultivated lands and production are in Guinea Savanna and Sudan Savanna Zones. Ideally, given their balanced annual rainfall and modest temperatures, these two ecologies have the optimal conditions for growing legumes. Due to data limitations and problems associated with thin data, observations from Semi-Deciduous Forest and Rain Forest are combined and reported as the Forest Zone.

Empirical model specification, model selection and estimation

Suppose environmental, farmer demographics, and factor usage in farms define the Stochastic Frontier Production (SF) function models for distinct groups. Then the SF function representing a group of farmers faced with similar circumstances (j) can be expressed as Eq. 1.

$$y_i = f^j(x_i)e^{\varepsilon_i},\ \varepsilon_i = v_i - u_i \qquad (1)$$

Where: y_i is output and x_i represent production inputs for the i^{th} farmer. Deviations from the frontier are captured by ε_i that is composed of production risk (v_i) and technical inefficiency (u_i). The distributional assumptions of the deviations (v_i and u_i) underpin the estimation of Equation (1). Generally, v_i follows a normal distribution with zero mean and variance $\sigma^2_{v_i}$ $[v_i \sim N(0, \sigma^2_v)]$, but u_i has different distributions based on its negative skewness **(Belotti *et al.*, 2013)**.

Eq. 1 implies that production-output-increasing inputs simultaneously increase production variability **(Just and Pope, 1979)**. However, inputs may have varying effects on production output and its variability. The stochastic components (v_i and u_i) could also be influenced by exogenous variables other than inputs **(Just and Pope, 1978, 1979)**. A better model should allow technical inefficiency increasing and decreasing effects. As such, technical inefficiency is redefined as $\sigma_{u_i}^2 = \exp(\boldsymbol{w}_i\boldsymbol{\alpha})$, where $\boldsymbol{w}_i$ and $\boldsymbol{\alpha}$ are, respectively, vectors of explanatory variables and parameters **(Caudill, Ford and Gropper, 1995).** If the null hypotheses $H_o: \boldsymbol{\alpha} = 0$ is not rejected, then there is no statistical justification for the inefficiency increasing and decreasing effects **(Aigner, Lovell, and Schmidt, 1977).** Furthermore, the group specific TE of the i^{th} farmer is calculated as $TE_i = E[\exp(-u_i)\,|\hat{\varepsilon}_i]$.

Following **Huang, Huang, and Liu (2014)**, under the Meta-Stochastic Frontier (MSF) approach, Eq 1. is first estimated separately for each group (*j*), and then in the second step, the predicted output levels from the group SFs are used as the observation for a pooled SF that captures all ecologies to estimate the MSF. In the second step, the conventional one-sided error term (u_i^M) serves as the estimate for any technology gaps amongst the diverse groups. The MSF which envelops all group-specific frontiers $[f^j(x_i)]$ is represented as Eq. 2.

$$f^j(x_i) = f^M(x_i)e^{-u_i^M},\ u_i^M \sim N^+\big(0, \exp(\boldsymbol{w}_i\boldsymbol{\alpha})\big), \qquad (2)$$

Where: u_i^M is strictly greater than zero, implying that $f^j(x_i) \le f^M(x_i)$. The ratio of group *j*'s frontier to the MSF is the technology gap ratio (TGR) that can be defined as Eq. 3.

$$TGR_i = \frac{f^j(x_i)}{f^M(x_i)} = e^{-u_i^M} \le 1 \qquad (3)$$

The TGR depends on the accessibility and adoption level of the available MSF which in turn depends on farmer-specific circumstances. Each farmer's meta-frontier technical efficiency (MTE) is thus estimated as Eq. 4.

$$MTE_i = f^j(x_i)[f^M(x_i)e^{v_i}]^{-1} = TGR_i \times TE_i \qquad (4)$$

Following **Avea *et al.* (2016) and Etwire *et al.* (2013)**, the empirical model in this study formulates the functional form of the production function as a Translog due to its relative flexibility over the Cobb-Douglas form **(Awunyo-Vitor *et al.*, 2013)**. Moreover, the Cobb-Douglas functional form is nested within the Translog, which allows us to evaluate it. We run a battery of model specification tests including functional form tests, skewness, likelihood ratio, variance, and inefficiency tests, and model significance to select a suitable model (Table 2). The empirical model used in this study is of the form of Eq. 5.

$$\ln y_{ijt} = \beta_{0r} + \textstyle\sum_k \beta_{kj} \ln x_{kijt} +$$
$$\tfrac{1}{2}\textstyle\sum_s \sum_k \beta_{skj} log \ln x_{kijt} \ln x_{sijt} + v_{ijt} - u_{ijt}$$
$$u_{ijt} \sim N^+\big[0, \exp(\boldsymbol{w}_{ijt}\boldsymbol{\alpha})\big],$$
$$v_{ijt} \sim N(0, \sigma_v^2) \qquad (5)$$

Where: y_{jit} is total production (kg) for the i^{th} farmer in ecology j at time *t*. The variable x_{kjit} represent the k^{th} input (total land, seed, family and hired labour, and pesticides) used by the i^{th} farmer for production and a trend variable.

Whilst u_{ijt} can take on varied distributions, the study assumes a half-normal distribution (i.e., $u_{ijt} \sim N^+\big[0, \exp(\boldsymbol{w}_{ijt}\boldsymbol{\alpha})\big]$) due to non-convergence in the case of other distributions. Following **Tsiboe *et al.* (2019)**, the covariates in $\boldsymbol{w}_{ijt}$ control for farmer characteristics (age, education, and gender), institutional factors (land ownership, credit, and extension), and a trend and constant term.

Based on the likelihood-ratio tests, the null hypothesis of the Cobb-Douglas out-performing the Translog functional form for the production function (i.e., H_0: β_{skj} = 0) was rejected for all models. This shows that the Translog is appropriate for our data. Furthermore, the **Coelli (1995)** and **Schmidt and Lin (1984)** skewness test for ordinary least squares residuals are negative for all the models, suggesting that the variation of production in these ecologies are negatively skewed. Similarly, the **Gutierrez *et al.* (2001)** test for the null hypothesis of no one-sided error is rejected across most of the models. This further validates the strength of estimating the model using SFA.

The parameters of the ecology- and Meta-frontiers were estimated via maximum likelihood, using the "*frontier*" command in Stata 16. The elasticity for each input is estimated as the first derivative of the frontiers with respect to that input, evaluated at the inputs means. Thus, production returns to scale (RTS) are estimated as the summation of all the input elasticities. The delta method is used to estimate the standard errors for all parameters. Point estimates of parameters and their standard errors were used to evaluate the null hypothesis that they were not different from zero. The only exception is the RTS, where the relevant null hypothesis was that of unity, indicating constant returns to scale.

RESULT AND DISCUSSION

Descriptive statistics

The average age of a legume farmer was 46 years, and women make up about 22% of legume farmers in the sample (Table 1). The farmers had an average of two years of schooling with the mean years of formal education increasing at a rate of 3% per annum. This is consistent with the improvement in education due to free basic education. The production area for dry beans and groundnut averaged one hectare with yields averaging 535, and 790 kg/ha, respectively. Though mean yields significantly improved over the study period, they are less than half the yield potential of available technologies **(Ministry of Food and Agriculture [MOFA], 2017)**. This signifies room for improvement. About 11% of farmers reported access to credit and the probability of accessing credit declined by 0.1% annually over the study period.

Model specification tests

The likelihood ratio test for the null hypothesis that the production frontiers for a given legume are similar across ecologies is rejected. This supports the fact that dry beans and groundnut farmers are operating under heterogeneous technologies along ecological lines. The total production variance for the model without the inefficiency effects for dry bean and groundnuts (Table 2), show that the empirical model explains the variation in output for the ecology frontiers and the Meta-frontier at varying levels.

Input Elasticity, productivity, and technical change

We found that land with input elasticities ranging from 0.42 to 0.53 for dry beans and 0.53 to 0.62 for groundnut, was the most important and significant factor in their production (Table 3). The highest contribution of land for dry beans was in the Guinea Savanna Zone, and the lowest was in the Transitional Zone. For groundnut, the highest was in the Transitional Zone and the lowest contribution was in the Forest Zone. While the contribution of seed, hired labour, and pesticides are also significant, their spatial heterogeneities are lower than that of land. For both legumes, the lowest contribution for hired labour was in the Sudan Savanna and highest in Transitional Zones, respectively. Finally, family labour is only important in the production of beans making the highest and lowest contribution in the Sudan Savanna and Transitional Zones, respectively. The elasticity estimates are in line with those of earlier studies **(Avea *et al.*, 2016; Awunyo-Vitor *et al.*, 2013)**. Because of the rising demand for land, coupled with declining farm size due to growing populations **(Jayne, Chamberlin, and Muyanga, 2012)**, improving productivity via the enhancements in the responsiveness of output to non-land inputs is inevitable.

Our estimates reveal that the production of both legumes is characterized by decreasing returns to scale (returns to scale values less than one) (Table 3). This implies that the output of both legumes will proportionately decrease if all inputs are increased by the same proportion. Though for a different legume crop, **Avea *et al.* (2016)** showed that soybean production in Northern Ghana is characterized by constant returns to scale.

Considering the productivity parameter (i.e., the constant term), dry beans, and groundnut farmers in the Guinea Savanna had the highest productivities estimated at 1.56 and 2.19, respectively (Table 3). Guinea Savanna's productivity was lower [higher] than the MSF for dry beans [groundnuts] but was closer to that of the MSF than their peers in other ecologies. Residing in these ecologies could partly be exerting a positive influence on observed efficiency levels. Thus, observed factor-specific variations in ecology frontiers could explain the different positive effects on meta-frontier ratios. Comparing the two legumes, ecology-specific frontiers and MSF are higher for dry beans than for groundnuts. Theoretically, this implies that dry bean farmers are performing better than groundnut farmers. The overall technical change parameter for the MSFs for both legumes is negative (- 0.02 for dry beans and -0.03 for ground nuts) and statistically significant implying that production technologies used have declined over the study period (Table 3).

Table 1 Summary Statistics of Dry beans and Groundnut Farmers

Variable	Mean (SD)	Trend (%)
Farmer[a]		
Female (dummy)	0.22†(0.415)	0.39*†[0.047]
Age (years)	45.87†(15.415)	0.19*[0.044]
Education (years)	2.23†‡(4.229)	3.03*†[0.384]
Land owned (dummy)	0.66†‡(0.475)	0.63*†‡[0.043]
Land (ha)[a]		
Dry beans	1.05†(2.972)	7.78†[53.566]
Groundnut	1.08†(2.034)	-7.63*†[3.730]
Yield (kg/ha)[a]		
Dry beans	534.49†(1792.702)	2.71*†[0.635]
Groundnut	789.91†(1816.972)	0.47*†[0.215]
Input use[a]		
Seed (kg/ha)	68.41†‡(631.867)	9.19†‡[227.103]
Family labour (AE)	3.49†(1.924)	0.22*‡[0.066]
Hired labour (man-days/ha)	15.07†‡(63.845)	1.96†[4.972]
Pesticide (Litre/ha)	4.99†‡(23.369)	-2.85†‡[343.158]
Household[b]		
Size (AE)	6.07†(3.469)	0.24*[0.070]
Dependency(ratio)	1.54(1.798)	-0.28[0.161]
Credit(dummy)	0.11(0.313)	-0.09*†[0.032]
Mechanization(dummy)	0.18†(0.382)	1.19*†[0.059]
Extension(dummy)	0.21†(0.407)	0.57*†[0.049]

Note: * Indicates significance at $p<0.05$; *†* and *‡* indicate significant ($p<0.05$) variation across ecology and crop, respectively.

[a] Farmer sample size; Dry beans [5,763], Groundnut [7,774], Pooled [10,518]

[b] Household sample size; Dry beans [5,626], Groundnut [7,497], Pooled [10,051]

Data Sources: GLSS, GSPS, and GARBES data.

Table 2 Hypothesis Tests for Ecology- and Meta- Frontier Models for Dry beans and Groundnut Production

Test/statistic	Ecology production frontier				National frontier	Meta-
	Sudan Savanna	Guinea Savanna	Transitional Zone	Forest Zone		Frontier (MSF)
Dry beans						
Sample size	3,083	1,653	420	334	5,614	5,614
Log likelihood	-3,299	-1,832	-559	-477	-6,538	421
Cobb-Douglas test	545.73***	208.32***	78.76***	65.71***	691.94***	8039.94***
Schmidt & Lin (1984) [a] skewness test	-0.05	-0.21	-0.15	-0.35	-0.26	-0.07
Coelli, (1995) [ab] skewness test	-3.25*	-8.27*	-1.47	-2.22*	-15.94*	-117.39*
Gutierrez (2001) [a] LR test	2.46	16.29***	4.77*	12.96***	65.79***	18.19**
Inefficiency variance $[\sigma_u]$	0.50 (0.106)	0.83 (0.072)	1.07 (0.159)	1.50 (0.150)	0.83 (0.037)	0.19 (0.015)
Total production variance $[\sigma^2 = \sigma_u^2 + \sigma_v^2]$	0.67 (0.071)	1.00 (0.088)	1.64 (0.252)	2.57 (0.366)	1.06 (0.045)	0.09 (0.004)
Gamma $[\gamma = \sigma_u^2/\sigma^2]$	0.38*** (0.120)	0.69*** (0.063)	0.69*** (0.106)	0.87*** (0.057)	0.64*** (0.032)	0.38*** (0.047)
Inefficiency function test	40.02***	23.01**	50.71***	9.11	94.37***	497.69***
Model significance	4241.82***	1829.06***	395.80***	218.77***	6285.71***	82932.27***
Groundnut						
Sample size	3,758	2,659	749	330	7,496	7,496
Log likelihood	-3,627	-2,921	-937	-456	-8,318	178
Cobb-Douglas test	612.86***	298.19***	151.14***	48.84***	1016.62***	7785.75***
Schmidt & Lin (1984) [a] Skewness test	-0.12	-0.33	-0.15	-0.07	-0.37	0.50
Coelli, (1995) [ab] Skewness test	-11.26*	-16.45*	-2.74*	-0.44	-31.44*	1803.53
Gutierrez (2001) [a] LR test	11.83***	79.65***	6.57**	2.70	167.74***	-
Inefficiency variance $[\sigma_u]$	0.57 (0.058)	1.01 (0.040)	0.99 (0.132)	1.46 (0.277)	0.88 (0.025)	0.00 (0.072)
Total production variance $[\sigma^2 = \sigma_u^2 + \sigma_v^2]$	0.63 (0.046)	1.22 (0.064)	1.36 (0.189)	2.52 (0.598)	1.06 (0.035)	0.05 (0.001)
Gamma $[\gamma = \sigma_u^2/\sigma^2]$	0.52*** (0.068)	0.83*** (0.025)	0.72*** (0.096)	0.84*** (0.125)	0.74*** (0.020)	0.00 (0.005)
Inefficiency function test	121.11***	87.39***	8.14	113.22***	119.01***	1016.82***
Model significance	5279.34***	2903.14***	696.75***	335.83***	8171.97***	84244.32***

Significance levels: * p<0.10, ** p<0.05, ***p<0.01

[a] Null hypothesis of no one-sided error (i.e. no inefficiency) was tested

[b] Values less than the critical value of 1.96 confirms the rejection of the null hypothesis.

Data Sources: Author rendering of GLSS, GSPS1, and GARBES data.

Table 3. Elasticities for Ecology- and Meta- Frontier Models for Dry beans and Groundnut Production

	Ecology production frontier					
	Sudan Savanna	Guinea Savanna	Transitional Zone	Forest Zone	National frontier	Meta-Frontier
Beans						
Land elasticity	0.49***(0.017)	0.53***(0.025)	0.42***(0.047)	0.47***(0.075)	0.50***(0.013)	0.50***(0.004)
Seed elasticity	0.18***(0.010)	0.09***(0.012)	0.09***(0.019)	0.03(0.035)	0.12***(0.006)	0.11***(0.002)
Family labour elasticity	0.09***(0.028)	0.02(0.040)	-0.20**(0.098)	-0.06(0.129)	0.04*(0.023)	0.03***(0.009)
Hired Labour elasticity	0.02***(0.005)	0.01(0.007)	0.09***(0.023)	0.11***(0.027)	0.02***(0.003)	0.02***(0.001)
Pesticide elasticity	-0.03**(0.010)	-0.02*(0.011)	0.06***(0.019)	0.00(0.049)	-0.01*(0.007)	0.00(0.002)
Returns to scale	0.75***(0.033)	0.63***(0.046)	0.47***(0.107)	0.54***(0.165)	0.68***(0.027)	0.66***(0.010)
Productivity	0.81***(0.181)	1.56***(0.424)	1.51**(0.768)	1.11**(0.503)	1.66***(0.218)	2.05***(0.124)
Annual trend (%)	-0.01*(0.004)	-0.01*(0.006)	0.03*(0.016)	-0.02(0.019)	-0.02***(0.003)	-0.02***(0.001)
Groundnut						
Land elasticity	0.56***(0.016)	0.62***(0.022)	0.54***(0.037)	0.53***(0.058)	0.58***(0.012)	0.58***(0.004)
Seed elasticity	0.17***(0.008)	0.10***(0.007)	0.06***(0.019)	0.04(0.032)	0.13***(0.005)	0.11***(0.002)
Family labour elasticity	0.02(0.023)	0.01(0.030)	-0.11(0.072)	-0.03(0.140)	0.00(0.018)	0.00(0.007)
Hired Labour elasticity	0.01***(0.003)	0.03***(0.004)	0.06***(0.019)	0.10***(0.030)	0.03***(0.003)	0.03***(0.001)
Pesticide elasticity	-0.03***(0.010)	-0.01*(0.009)	0.02(0.014)	0.06**(0.031)	-0.01(0.006)	0.01***(0.002)
Returns to scale	0.74***(0.027)	0.75***(0.035)	0.57***(0.076)	0.70**(0.138)	0.73***(0.021)	0.73***(0.007)
Productivity	0.65***(0.087)	2.19***(0.332)	0.54*(0.317)	0.96**(0.373)	1.33***(0.131)	1.82***(0.092)
Annual trend (%)	-0.01*(0.003)	-0.01***(0.004)	-0.03**(0.011)	0.03**(0.012)	-0.02***(0.002)	-0.03***(0.001)

Note: Significance levels: * p<0.10, ** p<0.05, ***p<0.01
[a] Null hypothesis of constant returns to scale was tested.
Data Sources: GLSS, GSPS, and GARBES data.

Technology gap, Technical Efficiency, and Meta-frontier Technical Efficiency

The TGR ranged between 0.81 to 0.93 for dry beans and 0.86 and 0.93 for ground nuts (Figure 1, panel a). On average, the TGR was 0.84 and 0.86 indicating a technology gap (required to match the best technology) of 15% and 14% for dry beans and groundnut farmers, respectively. Farmers growing temporal dynamics show that the TGR increased over the study period for both legumes (Figure 2, panel a). The TGR was highest in the Forest Zone for dry beans and the Guinea Savanna for groundnuts (Figure 1, panel a). These values are higher when compared to those of other crops grown in Ghana; 0.56 and 0.75 for okra and tomato, respectively **(Tsiboe *et al.*, 2019)**, 0.73 for rice **(Asravor *et al.*, 2019)**, and 0.79 for cocoa. These findings suggest that legume farmers, on average, perform better than those growing other crops for which TGR has been measured in Ghana. The high TGRs in this study are not surprising given the low range of variance due to the technical inefficiency parameter (γ). Changing the model specification could influence the size of γ (Table 2), however, this was not the case in this study. Also, altering the production function form did not significantly improve the size of γ nor the size of the TGRs. This implies that output variation across ecologies could also be due to idiosyncrasies such as biotic and abiotic shocks.

Overall, the best and worst performing farmers for dry beans were those from the Transition Zone and Forest zone with average TE of 0.72 and 0.45, respectively. For groundnuts, the highest TE (0.72) was in the Sudan Savanna and lowest in the Transitional Zone (0.52) (Figure 1, panel b). These variations can be explained by changes in production environments, available technologies and their usage. According to **Asravor *et al.* (2019),** TE with differentiated production technology varies along ecological lines. For instance, in rice production, TE decreases from northern to southern Ghana. These differences occur because of variations in weather, biotic conditions, and production practices across zones. Rainfall, for example, changes from being unimodal in the north to bimodal in the south of Ghana. Our fitted mean estimates across space and time for the study period reveal that dry bean TE has been stable over time while that of groundnuts have been declining (Figure 2 panel b). These findings are consistent with earlier estimates that show that legume farmers operated between 53-89% efficiency levels **(Avea *et al.*, 2016; Awunyo-Vitor *et al.*, 2013; Etwire *et al.*, 2013)**.

A major caveat about the TE scores we have discussed above is that they do not tell us how farmers perform relative to the broader legume-specific sector production frontier. Our legume-specific MTE compared to the TE of the farmers accounts for these variations. After accounting for the ecology-specific differences in production technologies, the mean MTE is 0.535 and 0.525 for dry bean and groundnut, respectively. The MTE improves from Southern to Northern Ghana. Specifically, the most technically efficient dry bean and groundnut farmers compared to their meta-frontier are those in the Sudan Savanna zone with MTE of 0.614 and 0.624 respectively (Figure 1, panel c).

Determinants of Technical Efficiency and Technology gap

In Table 4, negative coefficients imply that the variable has an increasing [decreasing] effect on technical efficiency [technology gap] and vice versa. Male-headed farms have the best technologies and are also more efficient. Except for the Transition and Forest Zone and MTE for groundnuts, the gender effect is important in all ecologies for both crops. Whilst the coefficient for farmer education does not affect technical inefficiency, the same pushes both dry bean and groundnut farmers away from the best production technology.

Land ownership improves TE and minimizes technology gaps for dry bean farmers. This effect is not only important at the national level but also in Sudan and Guinea Savanna Zones. For groundnuts, land ownership has the same effect as that of dry beans except in the Transitional Zone (with a technical inefficiency measure of 0.4) where it is associated with a decrease in TE. These findings suggest that changes in land tenure towards near ownership rights would enhance the efficiency of dry bean production. For both legumes, mechanization is associated with a reduction in technical inefficiency and technology gaps. The effect is significant at the national level for dry beans and Sudan and Guinea Savanna Zones and the national level for groundnuts.

The effect of credit availability is a reduction in the technological gap for the meta frontier of ground nut farmers. It is also associated with, an ambiguously positive technical inefficiency score which suggests a reduction in TE in the Guinea Savanna Zone for groundnuts (Table 4). While we will normally expect credit to improve TE if farmers invest the credit in TE enhancing techniques, we cannot tell for certain how they spent their credit in this sample. Access to agricultural extension services is associated with a significant improvement in TE in the production of dry beans at the national and Sudan Savanna Zone level. For groundnuts, extension services were positively associated with TE in Sudan and Guinea Savanna Zones and at the national level. For the most part, extension services reduced the technology gap in all zones but fell short in the Transition Zone where it was associated with a negative TE (an inefficiency score of 0.39).

Our study explores the importance of ecological variation in explaining differences in production by classifying farms based on ecologies. The study finds that pesticide, hired labour, mechanization, extension, and credit usage significantly varied across ecologies. As noted by **Antwi-Agyei, *et al.* (2012)** and **Armah *et al.* (2011),** ecological variations are important in explaining farm output, input usage, and crop production. Noting that such variations are caused by differences in climate, farming systems, and levels of social-economic development.

The study found significant variations in yields across ecologies with farmers in the Transitional and Forest Zone ecologies reporting the highest yields. The Transitional Zone is a major commercial food-producing zone in Ghana **(Amanor and Pabi, 2007)** and has the longest growing days and well-balanced annual precipitation **(MOFA, 2017)**. Even with this historical significance and conducive environment, operations in the Transitional Zone are labour-intensive with the highest average labour usage of 20 man-days worked per hectare and the lowest level of mechanization. Generally, the levels of mechanization remain low (18%) across Ghana with Sudan and Guinea Savanna Zones having the highest mechanization rates for groundnuts and the Guinea Savanna Zone for dry beans. Disparities exist in access to extension services across ecologies. About 30% of the farmers reported accessing extension services with the Transitional Zone having the highest levels of access followed by farmers in Guinea Savanna and Forest Zone.

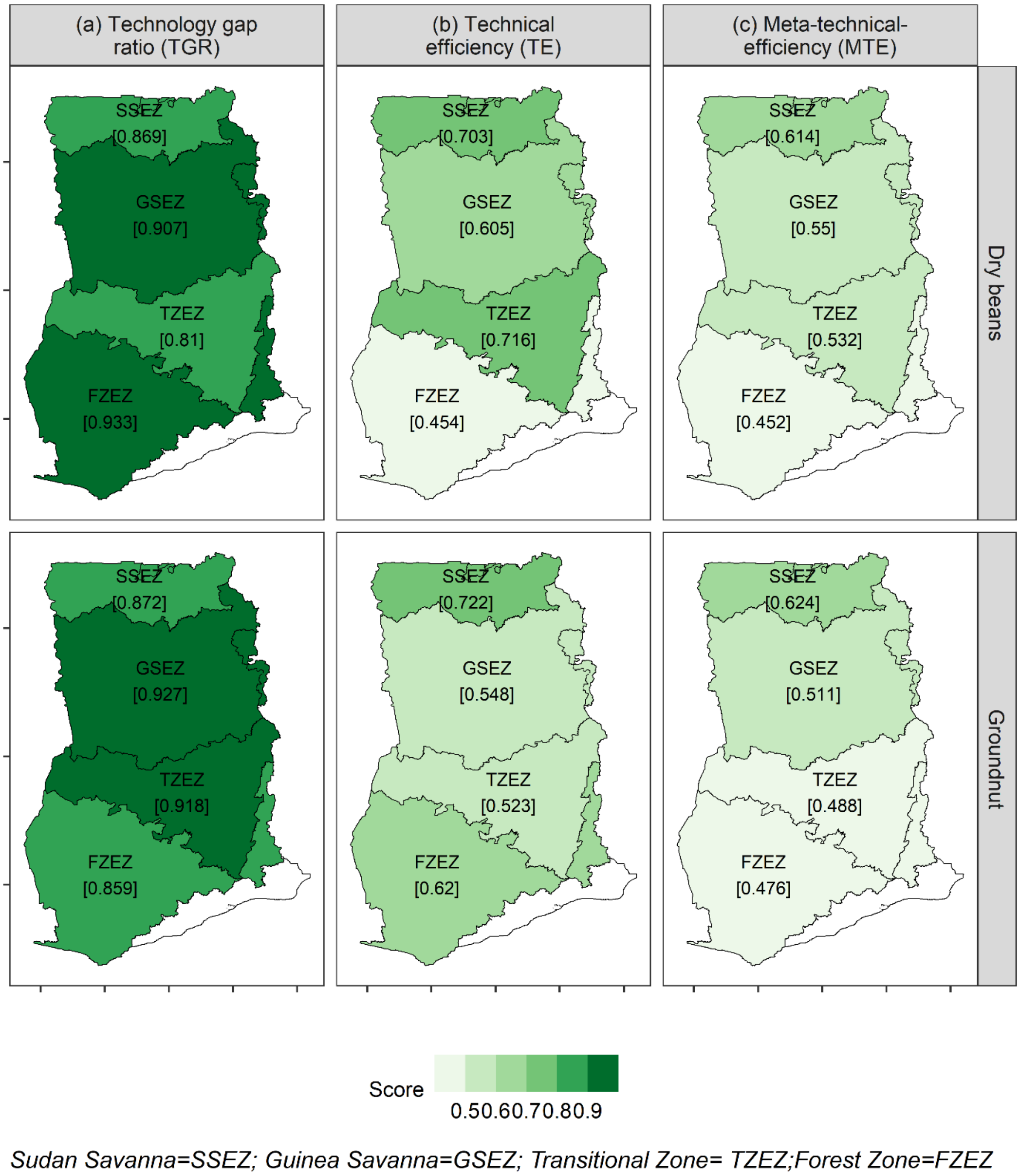

Figure 1. Dry beans and Groundnut Production Technology Level and Technical Efficiency Across Ecologies

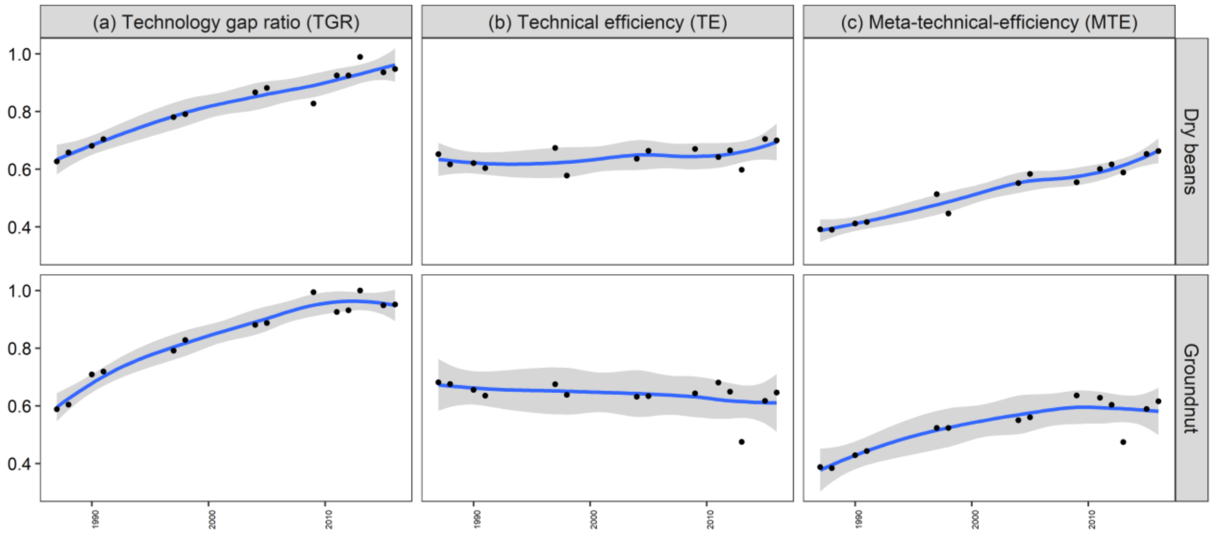

Figure 2. Temporal Dynamics in Dry beans and Groundnut Production Technology Level and Technical Efficiency

DISCUSSION AND POLICY IMPLICATIONS.

The findings from this study have several implications that can be inferred at the national and ecology levels. Policies will thus have to be formulated on a case-by-case basis, for specificity and wider impacts, if production and efficiency are to improve. First, we found that holding ecological technologies constant, legume farmers generally performed poorly because of pure farmer technical inefficiency. Furthermore, mean yields obtained by farmers remain far below the attainable yields of available technologies. This will call for extensive and widespread popularization of available legume varieties whose adoption and use are still extremely low. Most importantly, there is a need to tailor the seed systems of different crops to meet supply gaps while staying responsive to farmer needs. The seed sector should, be bolstered right from the production of Early Generation Seed to the production of Quality Declared Seed. Also, easing access to agricultural inputs would go a long way in improving production.

Secondly, the observed performance heterogeneity across ecologies can be exploited to improve production. This can be through leveraging existing good practices and creating synergies between and across ecologies. For example, farmers could benefit from simple technology transfer. The most efficient but technologically disadvantaged farmers in the transition zone for beans could benefit from technology transfer from their peers in the Forest Zones. They could be targeted with yield-enhancing technologies like improved seed varieties, fertilizers, among others. Farmers who are better off in terms of technology (e.g., Forest Zone farms) but less efficient could benefit from interventions aimed at improving farmer managerial practices and skills via targeted extension, farmer field schools, and village agents peer training programs. The same logic could apply to groundnut farmers to improve their production.

Furthermore, ecological variations in TGR, TE, and MTE capture important stresses that may be associated with environmental and climatic changes. It is thus important that breeding efforts, aimed at producing high-yielding and productivity enhancing legume varieties and management options, take these into account. Specifically, breeding and agronomic research should be focused on ensuring that the ecological needs of regions are fully factored into the development of new and climate-smart technologies. The trade-off here is between developing ‘a one size fits it all’ and agroecological suited varieties and practices for maximum returns.

Finally, since land; both in terms of ownership and farm size, was the greatest contributor to legume production, policy should put more effort into the development of non-land-based interventions that allow legume intensification and yield improvements at the intensive margin. This is critical given that farm size in Ghana, just like in a host of other countries in sub-Saharan Africa is diminishing. Also, programs that hasten land ownership through formal documentation should be of strategic importance in delivering productivity gains.

CONCLUSIONS

Renewed recognition of the historical role research, development, and technology transfer initiatives have had on technical and efficiency transformation has spurred interest in more focused research and outreach to ensure food security and income generation in developing countries. Developing tailored breeding and agronomic management systems to produce climate-smart, efficiency-enhancing, and high productive technologies is one such effort. However, given the heterogeneity in the production environment and farmer behaviour, it is hard to assess gains from such programs.

This paper employed the Meta-stochastic-frontier analysis to a rich nationally representative dataset of dry beans and groundnut farmers that spans over three decades in Ghana to quantify trends in technical efficiency, technology gap, and meta technical efficiency. Factors that have affected technical efficiency and technology gap are also documented.

Table 4. Determinants of Dry beans and Groundnut Technical Inefficiency/ Technology Gap

	Ecology production frontier				National frontier	Meta-frontier
	Sudan Savanna	Guinea Savanna	Transitional Zone	Forest Zone		
Dry beans						
Female(dummy)	0.39**(0.155)	0.48***(0.157)	0.68*(0.405)	0.59**(0.259)	0.47***(0.085)	0.45***(0.113)
Age(ln[years])	-0.12(0.188)	-0.10(0.175)	0.33(0.478)	0.82**(0.387)	0.06(0.101)	-0.02(0.124)
Education(ln[years])	-0.02(0.020)	0.03*(0.017)	0.06(0.047)	0.02(0.028)	0.02**(0.010)	0.06***(0.015)
Land owned(dummy)	-0.83***(0.157)	-0.30**(0.138)	0.33(0.325)	-0.12(0.221)	-0.47***(0.074)	-0.34***(0.109)
Mechanization(dummy)	-0.27(0.220)	-0.21(0.145)	-0.45(0.557)	-0.21(0.239)	-0.21**(0.088)	-0.41***(0.154)
Credit(dummy)	0.19(0.170)	0.29(0.189)	0.41(0.398)	0.04(0.238)	0.20**(0.098)	-0.18(0.172)
Extension(dummy)	-0.75***(0.227)	-0.16(0.164)	-0.04(0.361)	0.17(0.306)	-0.24**(0.099)	0.17(0.176)
Trend	-0.02(0.010)	-0.03***(0.011)	0.35***(0.099)	-0.03(0.025)	-0.03***(0.006)	-0.16***(0.008)
Constant	-0.71**(0.335)	0.40*(0.222)	-8.76***(2.714)	0.96**(0.382)	0.51***(0.131)	-0.28*(0.162)
Groundnut						
Female(dummy)	0.32***(0.112)	0.58***(0.087)	0.11(0.186)	0.04(0.282)	0.42***(0.059)	-0.05(0.077)
Age(ln[years])	0.29**(0.149)	-0.03(0.109)	-0.03(0.235)	1.10***(0.418)	0.13*(0.073)	-0.08(0.088)
Education(ln[years])	-0.02(0.015)	0.01(0.012)	-0.01(0.022)	0.04(0.041)	0.01*(0.007)	0.02***(0.009)
Land owned(dummy)	-0.77***(0.143)	-0.23***(0.083)	0.40**(0.182)	-0.17(0.247)	-0.25***(0.053)	-0.05(0.072)
Mechanization(dummy)	-0.51**(0.231)	-0.20**(0.101)	-0.04(0.228)	-0.05(0.350)	-0.26***(0.078)	-0.38***(0.120)
Credit(dummy)	-0.25(0.206)	0.23**(0.106)	0.11(0.205)	0.20(0.372)	0.01(0.074)	-0.46***(0.120)
Extension(dummy)	-0.40***(0.127)	-0.19**(0.092)	0.39**(0.193)	-0.16(0.314)	-0.15**(0.064)	-0.27**(0.120)
Trend	0.04***(0.010)	-0.04***(0.006)	0.00(0.017)	0.24***(0.067)	-0.01(0.005)	-0.16***(0.009)
Constant	-2.15***(0.294)	0.77***(0.142)	-0.46(0.686)	-4.86***(1.857)	-0.06(0.126)	-0.54***(0.101)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01. Data Sources: GLSS, GSPS, and GARBES data.

Whilst causes of low legume yields have mostly been attributed to biotic and abiotic stresses, this study supplies more knowledge arguing that low legume yields are observed because of farmer inefficiencies in using available technologies and production resources. Earlier studies relying on data limited to single seasons and specific regions in Ghana show that this is likely to be true. Thus, by overcoming the limitation of its predecessors, this paper supplies a holistic insight to facilitate understanding of the spatial and temporal dimensions of legume production technology and technical inefficiency in Ghana.

The results show that across the study period, dry bean TE has been stable over time while that of groundnuts has been declining. MTE for dry beans has been increasing at an increasing rate while that of groundnuts has been increasing at a decreasing rate. Farmers use technology that is about 15% short of the best available technology. However, holding ecological technologies constant, the study finds mean efficiency levels of 62 and 60% for dry beans and groundnut, respectively. The overall trend shows that the improvement in MTE could be driven by the decline in the TGR. Most importantly, bean and groundnut farmers are using heterogeneous technologies along ecological lines.

Taken as a whole, achieving desired yield levels to meet supply shortfalls will require interventions specifically tailored to farm production abilities and production circumstances. Blanket interventions aimed at improving productivity and efficiency will perpetuate the status quo. Thus, a careful assessment of all intended interventions before dissemination will generate more optimal outcomes of policy.

Due to data limitation, this research did not identify the best technologies [managerial practices, inputs, and Varieties] used by farmers but only indicates where such technologies and practices could be located. The study thus recommends this for future research to ensure that specific technologies and managerial practices are fronted. Where modern technologies are limited, the output from this study could provide valuable information on where dry bean and groundnut productivity could be increased by reducing technical inefficiency and/or technological gaps.

Acknowledgments
The authors acknowledge the Ghana Statistical Service, Institute of Statistical Social and Economic Research (ISSER), Economic Growth Center, and International Food Policy Research Institute (IFPRI) for making the dataset publicly available. All errors are the responsibility of the authors.

Data availability
Replication materials are available in GitHub at https://github.com/ftsiboe/Agricultural-Productivity-in-Ghana

REFERENCES

AGRA. ALLIANCE FOR A GREEN REVOLUTION IN AFRICA (2016). Ghana early generation seed study. Retrieved September 5, 2020, from https://www.agrilinks.org/sites/default/files/resource/files/ghana_early_generation_seed_report.pdf

AIGNER, D., LOVELL, C. A. K., & SCHMIDT, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21–37. https://doi.org/10.1016/0304-4076(77)90052-5

AMANOR, K. S., & PABI, O. (2007). Space, time, rhetoric and agricultural change in the transition zone of Ghana. *Human Ecology*, *35*(1), 51–67. https://doi.org/10.1007/s10745-006-9081-6

ANTWI-AGYEI, P., FRASER, E. D. G., DOUGILL, A. J., STRINGER, L. C., & SIMELTON, E. (2012). Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. *Applied Geography*, *32*(2), 324–334. https://doi.org/10.1016/j.apgeog.2011.06.010

ARMAH, F. A., ODOI, J. O., YENGOH, G. T., OBIRI, S., YAWSON, D. O., & AFRIFA, E. K. A. (2011). Food security and climate change in drought-sensitive savanna zones of Ghana. *Mitigation and Adaptation Strategies for Global Change*, *16*(3), 291–306. https://doi.org/10.1007/s11027-010-9263-9

ASRAVOR, J., WIREDU, A., SIDDIG, K., & ONUMAH, E. (2019). Evaluating the environmental-technology gaps of rice farms in distinct agro-ecological zones of Ghana. *Sustainability*, *11*(7), 2072. https://doi.org/10.3390/su11072072

AVEA, A., ZHU, J., TIAN, X., BALEŽENTIS, T., LI, T., RICKAILLE, M., & FUNSANI, W. (2016). Do NGOs and development agencies contribute to sustainability of smallholder soybean farmers in Northern Ghana - *A Stochastic Production Frontier Approach. Sustainability*, *8*(5), 465. https://doi.org/10.3390/su8050465

AWUNYO-VITOR, D., BAKANG, J. A, GYAN, S. K., & COFIE, S. (2013). Estimation of farm level technical efficiency of small-scale cowpea production in Ghana. *American-Eurasian Journal of Agricultural and Environmental Science*, *13*(8), 1080–1087. https://doi.org/10.5829/idosi.aejaes.2013.13.08.11013

BATTESE, G. E., RAO, D. S. P., & O'DONNELL, C. J. (2004). A Metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis*, *21*(1), 91–103. https://doi.org/10.1023/B:PROD.0000012454.06094.29

BELOTTI, F., DAIDONE, S., ILARDI, G., & ATELLA, V. (2013). Stochastic frontier analysis using Stata. *The Stata Journal*, *13*(4), 719–758.

BINSWANGER-MKHIZE, H. P., & SAVASTANO, S. (2017). Agricultural intensification: The status in six African countries. *Food Policy*, *67*, 26–40. https://doi.org/10.1016/j.foodpol.2016.09.021

BOKUSHEVA, R., & HOCKMANN, H. (2005). Production risk and technical inefficiency in Russian agriculture. *European Review of Agricultural Economics*, *33*(1), 93–118. https://doi.org/10.1093/erae/jbi036

CAUDILL, S. B., FORD, J. M., & GROPPER, D. M. (1995). Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity. *Journal of Business and Economic Statistics*, *13*(1), 105. https://doi.org/10.2307/1392525

COELLI, T. (1995). Estimators and hypothesis tests for a stochastic frontier function: A Monte Carlo analysis. *Journal of Productivity Analysis*, *6*(3), 247–268. https://doi.org/10.1007/BF01076978

COMBARY, O. S. (2017). Analysing the efficiency of farms in Burkina Faso. *African Journal of Agricultural and Resource Economics*, *12*(3), 242–256.

DJOKOTO, J. G., OWUSU, V., & AWUNYO-VITOR, D. (2017). Technical efficiency in organic and conventional agriculture - a gender comparison. *Review of Agricultural and Applied Economics*, *20*(2), 3–11. https://doi.org/10.15414/raae/2017.20.02.03-11

ETWIRE, P. M., MARTEY, E., & DOGBE, W. (2013). Technical efficiency of soybean farms and its determinants in Saboba and Chereponi districts of Northern Ghana: A Stochastic Frontier Approach. *Sustainable Agriculture Research*, *2*(4), 106. https://doi.org/10.5539/sar.v2n4p106

FARRELL, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, *120*(3), 253. https://doi.org/10.2307/2343100

FEED THE FUTURE. (2013). Feed the future food security innovation center: research on legume productivity. Retrieved from https://feedthefuture.gov/sites/default/files/resource/files/ftf_factsheet_fsiclegumes_may2015.pdf

GUTIERREZ, R. G., CARTER, S., & DRUKKER, D. M. (2001). On boundary-value likelihood-ratio tests. *Stata Technical Bulletin*, *10*(60), 15-18.

HUANG, C. J., HUANG, T.-H., & LIU, N.-H. (2014). A new approach to estimating the metafrontier production function based on a stochastic frontier framework. *Journal of Productivity Analysis*. https://doi.org/10.1007/s11123-014-0402-2

JAYNE, T., CHAMBERLIN, J., & MUYANGA, M. (2012). Emerging land issues in african agriculture: implications for food security and poverty reduction strategies. In Paper presented as part of Stanford University's Global food policy and food security symposium series, Sponsored by the Center for Food Security and the Environment and the Freeman Spogli Institute for International Studies, Stanford, California. Retrieved from https://www.agrilinks.org/sites/default/files/resource/files/Stanford_Paper_April 2012.pdf

JUST, R. E., & POPE, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics*, *7*(1), 67–86. https://doi.org/10.1016/0304-4076(78)90006-4

JUST, R. E., & POPE, R. D. (1979). Production function estimation and related risk considerations. *American Journal of Agricultural Economics*, *61*(2), 276. https://doi.org/10.2307/1239732

MOFA. MINISTRY OF FOOD AND AGRICULTURE (2017). Agriculture in Ghana: facts and figures (2016). Document Provided by Ministry of Agriculture, Accra, Ghana. Accra, Ghana.

NISHIMIZU, M., & PAGE, J. M. (1982). Total factor productivity growth, technological progress and technical efficiency change: dimensions of productivity change in Yugoslavia, 1965-78. *The Economic Journal*, *92*(368), 920. https://doi.org/10.2307/2232675

ONUMAH, J. A., ONUMAH, E. E., AL-HASSAN, R. M., & BRÜMMER, B. (2013). Meta-frontier analysis of organic and conventional cocoa production in Ghana. *Agric. Econ. Czech*, *59*(6). 271–280. https://doi.org/10.17221/128/2012-AGRICECON

OWUSU, V. (2016). Technical efficiency of technology adoption by maize farmers in three agro-ecological zones of Ghana. *Review of Agricultural and Applied Economics*, *19*(02), 39–50. https://doi.org/10.15414/raae.2016.19.02.39-50

SCHMIDT, P., & LIN, T. F. (1984). Simple tests of alternative specifications in stochastic frontier models. *Journal of Econometrics*, *24*(3), 349–361. https://doi.org/10.1016/0304-4076(84)90058-7

TSIBOE, F., ASRAVOR, J., & OSEI, E. (2019). Vegetable Production technical efficiency and technology gaps in Ghana. *African Journal of Agricultural and Resource Economics*, *14*(4). Retrieved from http://afjare.org/wp-content/uploads/2020/01/3.-Tsiboe-et-al.pdf

WONGNAA, C. A., & AWUNYO-VITOR, D. (2019). Scale efficiency of maize farmers in four agro ecological zones of Ghana: A parametric approach. *Journal of the Saudi Society of Agricultural Sciences*, *18*(3), 275–287. https://doi.org/10.1016/j.jssas.2017.08.003