Vegetable production technical efficiency and technology gaps in Ghana

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Abstract

This study characterises the nature of the vegetable production shortfall throughout Ghana for remedial action to be taken. By applying the meta-stochastic frontier analysis to a sample of okra, pepper and tomato farmers, the results show that the ranking of production inputs in production is in the order land, hired labour, fertiliser, pesticide and family labour. Furthermore, the results also suggest that vegetable production is characterised by diseconomies of scale. Technical efficiency for okra, pepper and tomato farmers in Ghana is estimated at 54%, 74% and 58% respectively, and this has generally increased for okra and pepper but remained stable for tomato. Technology gaps are close to non-existent for pepper cultivation, modest for tomato, and severe for okra. This implies that, whilst there is no potential for production gain from redistributing pepper technology throughout Ghana, there is limited potential for tomato and substantial potential for okra. Pepper farmers could potentially benefit from managerial improvements.

Key words: Ghana; efficiency; okra; pepper; technology gap; tomato

1. Introduction

Vegetable production provides a source of livelihood for about 30% of all crop-producing households in Ghana and represents approximately 32% of the total crop sales for the producing households (Ghana Statistical Service [GSS] 2012). Furthermore, Ghana's favourable agronomic conditions for vegetable cultivation, coupled with its proximity to, and bilateral relations with, the European Union (EU), position the country at an advantage to benefit from vegetable exports. However, this advantage has not been fully exploited over the years, inter alia due to low productivity. Official statistics put annual EU vegetable imports from Ghana at around \$9 million for 2008 to 2013. However, for the same period, whilst the value of pepper (Capsicum sp.) and eggplant (Solanum melongena) exports to the EU declined by 10% and 11% annually respectively, that of all vegetables declined by 10.5%. While most Ghanaian vegetables are not exported (only 2.3% are), statistics also indicate that domestic production was 23% below consumption for 2002 to 2013, and this deficit has grown annually by 22%. Consequently, 4 000 tons of vegetables are imported to make up for the consumption deficit in Ghana (FAO 2019). The divergence in production and consumption can be attributed to low yields, as will be shown in this paper, and to increased food demand due to population growth, urbanisation, and changing consumer preferences (Ministry of Food and Agriculture [MOFA] 2009).

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Ghana's attainable yields for eggplant, pepper and tomato (Solanum lycopersicum) are 15 000, 30 000 and 20 000 kg/ha respectively. However, the respective national mean yields in 2016 were estimated at about 50% of these yields (MOFA 2017). Low yields are observed partly because of the extreme vulnerability of vegetables to biotic and abiotic stresses, and because of deficiencies in public and private investment in productivity-enhancing technologies. Nonetheless, the literature argues that, aside from technological advancements, productivity can also be improved through the efficient use of existing technologies and resources (Combary 2017). In crop production, efficiency is the relationship between attainable and realised yields, coupled with optimum behaviour by the farmer, subject to prevailing production technologies and input prices. Farrell (1957) categorised efficiency into technical and allocative components, with the two combining to form economic efficiency. Technical efficiency pertains to how maximum output can be attained with a given set of factor inputs. Aside from the decline in vegetable exports to the European Union (EU) and domestic consumption deficits, Ghana experienced the prohibition of exports of pepper, eggplant and some gourds (Momordica sp., Lagenaria sp. and Luffa sp.) to the EU in 2015. This prohibition resulted from the interception of Ghanaian exports contaminated with harmful organisms at the EU entry ports. Nonetheless, with support from several development partners, including the EU, the Plant Protection and Regulatory Service Department of MOFA implemented corrective measures at Ghana's exit ports for produce exports. These efforts have led to the development of the Ghana Green Label scheme, which is aimed at promoting safe fruit and vegetable production, postharvest handling and distribution, and the use of good and environmentally sustainable agricultural practices (Ghana Green Label 2017). As a result, Ghana resumed the export of the formerly prohibited vegetables to the EU in 2018. Information on the sources and spatial distribution of vegetable production shortfalls consequently is crucial if Ghana is to maximise its benefits from vegetable production and exports, given these new favourable developments.

Previous studies relevant to Ghanaian agriculture have examined production shortfalls due to technical inefficiency for mango (Mensah & Brümmer 2016), legumes (Avea *et al.* 2016), maize (Owusu 2016), and rice (Asravor *et al.* 2019), for specific regions in Ghana. However, to the best of our knowledge, only three studies – all in the grey literature – have analysed those of tomato and pepper. Furthermore, none of these studies on tomato and pepper analysed the technical inefficiency that encompasses the whole of Ghana. They also make no mention of the nature of the observed production shortfalls throughout Ghana. For instance, Ghanaian vegetable farmers could be using different production technologies that are constrained by the physical environment (e.g. climate and soil type) and/or an enabling environment (e.g. credit and extension); thus, failure to account for these differences could lead to falsely attributing production shortfalls due to technology gaps to technical inefficiency (Battese *et al.* 2004). The aim of this paper was to bridge the knowledge gap by characterising the nature of vegetable production shortfalls throughout Ghana into their technical inefficiency and technology gap components.

The study uses a sample of 4 498 okra (*Abelmoschus esculentus*), pepper and tomato farmers, drawn from seven cross-sectional population-based surveys fielded throughout Ghana from 1987 to 2017, to estimate meta-stochastic-frontier (MSF) models that account for heterogeneity in technology and technical inefficiency.¹ The data used has the widest coverage of Ghanaian vegetable farmers across time and space than any of the previous studies. As such, it presents a unique opportunity to disentangle not just the nature of vegetable production shortfalls throughout Ghana, but also their spatiotemporal dynamics. Reference maps showing the spatial distribution of ecology-level vegetable-specific technical efficiency and technology gaps, holding ecology-level technology

¹ Whilst households reported cultivating several vegetables, this study focuses on only okra, pepper and tomato because they were the only vegetables with enough observations for any meaningful analysis. Okra, pepper and tomato accounted for 22%, 52% and 12% of the value of production of vegetable-cultivating households for 2012 to 2017 respectively [Ghana Living Standards Surveys (GLSS) 6 and 7].

constant, were also created. Consequently, this study puts the nature, spatial distribution and temporal dynamics of vegetable production shortfalls in Ghana on a solid empirical footing, which helps to assess the validity of the subject matter, while informing the policy dialogue on where and how production could be increased amidst limited technologies. Specifically, the output of this study provides valuable information on how the productivity of vegetable farmers could be increased by implementing the correct policies based on the nature of production shortfalls. This, in turn, can help Ghana take advantage of the favourable developments in vegetable export and help meet the existing domestic demand deficits.

2. The meta-stochastic frontier

Two main methods were used to empirically measure technical inefficiency: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The DEA and SFA can both be implemented either from an output or input orientation; however, the difference between the two is how deviations outside the control of farmers (i.e. white noise) are handled. Specifically, DEA ignores white noise, whilst SFA accounts for it in the production process (Belotti *et al.* 2013). Concerning the two main orientations, whilst the output method compares observed output to its potential, given the input sets and the technology, the input orientation compares observed input levels to its minimum potential that is necessary to produce a given output level. Consequently, the output-oriented SFA is preferred for this study due to data restrictions and the need to account for white noise.

Following from the main objective of this paper, the SFA was implemented, using new developments in the MSF literature (Huang *et al.* 2014), to capture farmers' usage of specific technologies based on their ecology. Specifically, the study assumes that a homogeneous ecology-specific production technology, coupled with best horticultural practices that allow maximum potential output for an input set, put all farmers on the optimal point of the production frontier. However, due to technical inefficiency and/or production risks, some farmers may deviate from the potential output attainable in their respective ecology (Bokusheva & Hockmann 2005). The stochastic frontier (SF) production function for the *j*th ecology can be specified as:

$$y_{jit} = f_t^j (x_{jit}) e^{v_{jit} - u_{jit}},\tag{1}$$

where y_{jit} is the total output (kg) of the *i*th farmer at time *t*, and x_{jit} represents the set of factor inputs (land, family and hired labour, fertiliser and pesticide). For the functional form of $f_t^{j}(\cdot)$, this study preferred the translog because of its relative flexibility to other functional forms. The error terms, v_{jit} and u_{jit} , are deviations from the frontier due to random effects (production risk) and technical inefficiency respectively. To prevent loss of observations due to the zero input levels reported by some farmers, a method proposed by Battese (1996) is adopted.

The SF represented by Equation (1) is motivated by the distributional assumptions underlying v_{jit} and u_{jit} . Whilst u_{jit} is usually assumed to follow different distributions and varied specifications, v_{jit} is assumed to follow a normal distribution, with zero mean and variance $\sigma_{v_j}^2 [v_{jit} \sim N(0, \sigma_{v_j}^2)]$. Due to its negative skewedness, u_{jit} is assumed to follow a half-normal, exponential, truncated or gamma distribution (Belotti *et al.* 2013).

Just and Pope (1979) and Caudill *et al.* (1995) have shown that the stochastic components (v_{jit} and u_{jit}) could be influenced by non-input covariates. Thus, a superior model would allow technical inefficiency increasing and decreasing effects. Following Caudill *et al.* (1995), technical inefficiency is modelled as $\sigma_{u_{jit}}^2 = \exp(\mathbf{w}_{jit}\boldsymbol{\alpha})$, where \mathbf{w}_{jit} and $\boldsymbol{\alpha}$ are vectors of explanatory variables and their

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parameters respectively. Covariates included in w_{jit} for this study are farmer characteristics (age, education and gender), institutional factors (land ownership, credit, mechanisation, irrigation and extension), and a trend. Rejecting the null hypothesis $H_0: \alpha = 0$ provides statistical justification for $\sigma_{u_{jit}}^2 = \exp(w_{jit}\alpha)$.

Under the MSF approach, Equation (1) is first estimated separately for each ecology and, in the second step, the predicted output levels from the ecology-specific SFs, $(\hat{y}_{jit} = f_t^j(x_{jit}))$, are used as the observation for a pooled SF that captures all ecologies to estimate the MSF via maximum likelihood.² Furthermore, the ecology-specific technical efficiency (TE) of the *i*th farmer in period *t* is calculated as $TE_{jit} = E[\exp(-u_{jit}) |\hat{\varepsilon}_{jit}]$. In the second step, the conventional one-sided error term (u_{jit}^M) serves as the estimate for any technology gaps amongst the ecologies. The MSF that envelops all ecology-specific frontiers, $[f_t^j(x_{jit})]$, is represented as:

$$\hat{y}_{jit} = f_t^{\,j}(x_{jit}) = f_t^{\,M}(x_{jit})e^{-u_{jit}^{\,M}}, \quad u_{jit}^{\,M} \sim N^+(\boldsymbol{w}_{it}\boldsymbol{\beta}, \sigma_u^2),$$
(2)

where u_{jit}^{M} is strictly greater than zero, implying that $f_t^{j}(x_{jit}) \leq f_t^{M}(x_{jit})$. Consequently, the ratio of ecology *j*'s frontier to the MSF is the technology gap ratio (TGR), represented as:

$$TGR_{jit} = \frac{f_t^{j}(x_{jit})}{f_t^{M}(x_{jit})} = e^{-u_{it}^{M}} \le 1$$
(3)

The TGR depends on the accessibility and adoption level of the available MSF, which in turn depends on farmer characteristics, institutional factors, and the production environment. Consequently, each farmer's meta-frontier technical efficiency (MTE) is:

$$MTE_{jit} = f_t^{\ j}(x_{jit}) \left[f_t^{\ M}(x_{jit}) e^{v_{it}} \right]^{-1} = TGR_{jit} \times TE_{jit}$$

$$\tag{4}$$

The MSF is implemented separately for each vegetable. The TE, TGR and MTE are then summarised in maps to show their spatial heterogeneity. Given their respective parameters, the elasticity of each input is estimated as the first derivative of the respective frontier with respect to that input, evaluated at the input mean. Consequently, the production returns to scale (RTS) are also estimated as the summation of all the input elasticities.

3. Research area and data

3.1 Research area

Ghana, a lower-middle-income country in West Africa, occupies a total area of about 24 million hectares (ha). The country is divided into ten administrative regions, with close to 51% of its 29 million people living in rural areas (MOFA 2017). Furthermore, about 45% of Ghanaian households are classified as agrarian, and agriculture accounted for 18.9% of the country's GDP in 2016 (MOFA 2017). In terms of ecology, Ghana's vegetation is broadly classified as coastal savanna (CSEZ), forest zones (rainforest and semi-deciduous forest) (FZEZ) in the central part, and Sudan/Guinea savanna (SGEZ) in the north (see Figure 1). There is also the transitional zone (TZEZ) between the SGEZ and FZEZ. The SGEZ areas are grasslands with scattered trees, where annual precipitation ranges between 800 and 1 200 mm per year (MOFA 2017). Precipitation ranges from 600 mm in the CSEZ to 2 800 mm in the FZEZ. Rainfall distribution is bimodal in the FZEZ and CSEZ, resulting in major and

² All variables are standardised by their sample means by survey, vegetable and ecology before estimation.

minor growing seasons, but the SGEZ has a unimodal distribution, which gives rise to one growing season (MOFA 2017). Despite the differences in weather and soil conditions, vegetables could do well under different agroecological zones. Specifically, pepper and okra are relatively easy to grow, as both are tolerant to Ghana's agroclimatic conditions and may be grown as rainfed crops, in contrast to tomato. In 2016, the annual area planted to tomato, pepper and okra was 48 920, 14 970 and 3 290 ha respectively (MOFA 2017). Table A1 and Figures A1 and A2 in the Appendix show the breakdown of key ecological statistics.



Source: Rhebergen et al. (2016)

3.2 Data

The data is drawn from the seven most recent Ghana Living Standards Surveys (GLSSs), fielded between 1987 and 2017, and is available from the GSS National Data Archive (2019). All GLSSs are nationally representative, focusing on the household as the main socio-economic unit to provide insights into living conditions in the country. The GLSSs follow a two-stage stratified sampling design, where enumeration areas are first selected using a probability that is proportional to population size to form the primary sampling units allocated to the ten regions. Households are then selected systematically from a list in the primary sampling unit. It is worth noting that, for each GLSS, new households are sampled, and thus the pooled data is not panel. Consequently, the data used in this study is a cross-sectional sample of the population of Ghanaian vegetable farmers at roughly five-year intervals. The study eliminates farmers with yield (kg/ha) above the 2.5th and below the 97.5th percentiles by survey, ecology and vegetable. Hence, the final sample is composed of 4 498 farmers, consisting of 1 720, 3 026 and 1 569 farmers cultivating okra, pepper and tomato respectively. The total number of farmers is less than the sum across vegetables because a farmer could cultivate a number of different vegetables. Summary statistics of variables used in this study are presented in Table 1.

3.3 Summary statistics

Table 1 shows that vegetable farming in Ghana is dominated by men (69%), and farmers had an average age of about 45 years, with about four years of formal education. The average age of the farmers suggests that they are still productive and economically active.

Variable	Mean	Trend (%)
Farmer ^a		
Female (dummy)	0.31† (0.46)	0.11*†‡ [0.05]
Age (years)	44.84 (15.07)	0.41* [0.05]
Education (years)	4.13† (4.86)	1.93*† [0.22]
Land owned (dummy)	0.71 (0.45)	-0.21*† [0.05]
Land (ha) ^a		
Okra	1.16 (2.68)	-17.40† [46.43]
Pepper	1.10† (3.78)	-40.84 [298.94]
Tomato	1.54 (3.68)	-8.69† [17.03]
Pooled	1.72 (5.46)	-47.73 [205.82]
Yield (kg/ha) ^a		
Okra	6.84† (2,390)	3.17* [1.38]
Pepper	1 219 (16 018)	~
Tomato	1 063† (3 216)	1.45 [1.18]
Input use ^a		
Family labour (adult equivalent [AE])	2.84†‡ (1.62)	0.15 [0.08]
Hired labour (man-days/ha)	24.70 (85.31)	16.69† [70.24]
Fertiliser (kg/ha)	48.58† (142.76)	-7.30‡ [140.44]
Pesticide (litre/ha)	13.42‡ (59.52)	-16.83†‡ [16.69]
Household ^b		
Size (AE)	5.07†‡ (3.08)	-0.01 [0.08]
Female head (dummy)	0.25†‡ (0.43)	0.00†‡ [0.05]
Dependency (ratio)	1.32 (1.59)	-0.20 [0.17]
Crop diversification (index)	0.55†‡ (0.24)	-0.98*†‡ [0.05]
Mechanisation (dummy)	0.06† (0.24)	-0.10* [0.03]
Irrigation (dummy)	0.02† (0.13)	0.06*† [0.02]
Credit (dummy)	0.15† (0.36)	0.18* [0.04]
Extension (dummy)	0.29† (0.45)	-0.82*† [0.05]

* Indicates significance at p < 0.05

~ Trend was not estimable

 \dagger and \ddagger indicate significant (p < 0.05) ecology and vegetable variation respectively. The variations were determined via a linear regression for continuous variables and a probit model for dummies. A trend variable and fixed effects for ecology and vegetables, as well as their interactions, were included in the estimation.

^a Farmer sample size: okra (1 720), pepper (3 026), tomato (1 569), and pooled (4 498)

^b Household sample size: okra (1 714), pepper (3 010), tomato (1 569), and pooled (4 472)

A higher proportion of the farmers (71%) were landowners, with mean farm sizes of 1.16 ha, 1.10 ha and 1.54 ha for okra, pepper and tomato respectively. Given their farm sizes, mean yields of 684, 1 220 and 1 063 kg/ha were recorded for okra, pepper and tomato farmers respectively. These yields were relatively small compared with the national averages as stated for 2016, partly because they were averages over the period 1987 to 2017. In terms of input usage, the rates across all the three vegetables were 25 man-days/ha, 49 kg/ha and 13 litre/ha for hired labour, fertiliser and pesticide respectively. The farmers in the sample originated from households of about five members, with a 1.32 dependency ratio, and the households were rarely headed by females (25%). The mean crop diversification index was 0.55, implying that, generally, vegetable-producing households were relatively diversified rather than specialised. About 30% of these households had access to extension services, and only 15% had access to credit. Furthermore, only a few households had access to mechanisation (6%) and irrigation (2%).

To ascertain the trends and ecological variation in the variables in this study, linear regression for continuous variables and the probit model for dummies were estimated. A trend variable and fixed effects for ecology and vegetables, as well as their interactions, were included in these estimations. Upon estimation, a joint test for significance of the margins on the ecology fixed effect was taken as indicative of ecological variation in the respective variable. The same was used to determine variation across vegetables. Furthermore, the estimated margin on the trend variable was taken as the annual change in that respective variable.

Trend analysis of the variables over the forgoing period (1987 to 2017) shows that, whilst the mean age and education of farmers have been increasing significantly, the dominant representation of men in production and land ownership has declined. In terms of production, whilst there were no significant changes in farm sizes across the three vegetables, the productivity (kg/ha) of okra and tomato has increased. It also follows that there have not been any significant changes in the usage rates of all inputs. With respect to the household characteristics, Table 1 shows that the diversification level of vegetable farming households has declined significantly and their access to credit and irrigation [mechanisation] improved [worsened]. In terms of ecological variation, Table 1 shows significant variations for male domination in production, farmer education, land under cultivation, female household headship, crop diversification, and access to irrigation and extension. Finally, for variation across vegetables, Table 1 shows significance for input usage and household characteristics.

4. Results

The translog maximum likelihood estimates for the output function and output idiosyncratic variance parameters are presented in Tables A2 to A4 in the Appendix. The model diagnostics are in Table 2, and the estimates for the elasticities and inefficiency drivers are presented in Tables 3 and 4 respectively. Finally, the temporal dynamics and spatial distribution of production technology and TE and MTE are shown on Figures 2 and 3 respectively.

4.1 Model diagnostics

The model diagnostics shown in Table 2 indicate that the Cobb-Douglas production function is rejected in favour of the translog, implying that the latter functional form is the most appropriate. All the skewness tests – Coelli (1995) and Schmidt and Lin (1984), the skewness test for ordinary least squares residuals, and the one-sided generalised likelihood-ratio test of Gutierrez *et al.* (2001) – justify the use of the SFA. Furthermore, the null hypothesis, $H_o: \alpha = 0$, is also rejected, providing further justification for the technical inefficiency functions. Using the likelihood ratio test, the null hypothesis that the production frontiers for a given vegetable are similar across ecologies is soundly rejected.

The magnitude of the total production variance $[\sigma^2 = \sigma_u^2 + \sigma_v^2]$ for the models without the inefficiency effects indicates that the models explain a considerable amount of the variation in vegetable output. Furthermore, the proportion of vegetable production variance due to technical inefficiency $[\gamma = \sigma_u^2/\sigma^2]$ ranges from 0% to 90% for this study. However, previous studies of other crops estimated this value to be 67% (Mensah & Brümmer 2016), 19% (Avea *et al.* 2016), about 45% (Owusu 2016), and 71% (Asravor *et al.* 2019). The parameter γ suggests that a considerable amount of the observed variation in output for the ecology frontiers [meta-frontier] could be attributed to the inefficient use of inputs [technological gaps]. Finally, the chi-squared statistics also indicate that all models are significant.

	Sudan/ Guinea Savanna (SGEZ)	Transitional Zone (TZEZ)	Forest Zone (FZEZ)	Coastal Savanna (CSEZ)	National frontier	Meta- frontier
Okra						
Observations	652	326	496	246	1,720	1,720
Log-likelihood	-1 137	-489	-790	-404	-2 975	-1 335
Cobb-Douglas test	100.68***	48.53***	30.17*	78.70***	83.56***	275.81***
Schmidt & Lin (1984) ^a	-0.41***	-0.26*	-0.29***	0.06	-0.43***	-0.97***
Coelli (1995) ^{ab}	-4.32	-1.95	-2.60	0.38	-7.28	-16.34
Gutierrez et al. (2001) ^a						
LR test	23.49***	5.11**	8.03***	-	48.96***	371.97***
Inefficiency variance						
$[\sigma_u]$	1.86	1.36	1.39	0.06	1.68	1.08
Total variance[$\sigma^2 =$						
$\sigma_u^2 + \sigma_v^2$]	4.34	2.53	2.73	1.66	3.77	1.19
Gamma $[\gamma = \sigma_u^2 / \sigma^2]$	0.80***	0.73***	0.71***	0.00	0.75***	0.98***
Inefficiency function test	28.45***	51.82***	14.83	28.60***	26.86***	25.65***
Model significance	276.52***	222.03***	412.49***	173.65**	698.47***	5 056.75***
Pepper						
Observations	532	590	1,401	503	3,026	3,026
Log-likelihood	-856	-938	-2,457	-777	-5,294	-2,807
Cobb-Douglas test	88.54***	122.98***	197.90***	75.51***	178.72***	992.58***
Schmidt & Lin (1984) ^a	0.36***	-0.15	-0.11*	0.32***	-0.01	-0.17***
Coelli (1995) ^{ab}	3.37	-1.45	-1.71	2.89	-0.16	-3.81
Gutierrez et al. (2001) ^a						
LR test	-	5.11*	3.80**	-	0.20	28.33***
Inefficiency variance						
$[\sigma_u]$	0.01	1.34	1.24	0.02	0.67	0.75
Total variance $[\sigma^2 =$						
$\sigma_u^2 + \sigma_v^2]$	1.53	2.65	3.11	1.36	2.26	0.75
$Gamma[\gamma = \sigma_u^2 / \sigma^2]$	0.00	0.68***	0.49***	0.00	0.20	0.75***
Inefficiency function test	86.81***	20.06**	136.75***	10.12	38.03***	102.46***
Model significance	336.01***	384.71***	1 002.15**	566.22**	1 544.48**	9 221.62***
<u>Tomato</u>						
Observations	297	280	682	309	1 568	1 568
Log-likelihood	-492	-386	-1 080	-464	-2 604	-1 296
Cobb-Douglas test	64.28***	47.68***	37.31**	73.23***	35.92**	183.58***
Schmidt & Lin (1984) ^a	-0.45***	-0.15	0.15	-0.43***	-0.25***	0.22***
Coelli (1995) ^{ab}	-3.19	-1.00	1.56	-3.05	-4.02	3.58
Gutierrez <i>et al</i> . (2001) ^a						
LR test	13.89***	2.27	-	17.48***	24.81***	-
Inefficiency variance[σ_u]	1.98	1.08	0.01	1.67	1.54	0.01
Total variance $\sigma^2 =$						
$\left[\sigma_u^2 + \sigma_v^2 \right]$	4.39	1.80	1.49	3.10	3.22	0.79
Gamma $[\gamma = \sigma_u^2 / \sigma^2]$	0.89***	0.65***	0.00	0.90***	0.73***	0.00
Inefficiency function test	14.79	18.45**	36.60***	171.64**	37.18***	609.96***
Model significance	310.45***	294.34***	855.84***	288.71**	1 014.71**	5 517.59***

Table 2: Hypothesis tests for ecology and meta-frontier models for selected vegetables in Ghana (1987 to 2017)

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

^a The null hypothesis of no one-sided error was tested

^b Values less than 1.96 confirm the rejection of the null hypothesis

4.2 Okra

Table 3 reveals land to be the most significant (p < 0.05) input for okra production, with the highest and lowest contributions estimated for farmers in FZEZ and TZEZ respectively. Land is followed by hired labour, pesticide, fertiliser and family labour. For their spatial distribution, the highest and lowest are TZEZ and SGEZ for hired labour; SGEZ and FZEZ for pesticide; FZEZ and SGEZ for fertiliser; and FZEZ and TZEZ for family labour. The RTS at the ecological level are not statistically (p < 0.05) different from constant returns to scale (CRS). However, the RTS for the MSF is statistically (p < 0.05) characterised by decreasing returns to scale (DRS), indicating that, per the industrial production frontier, output will increase less than proportionately if all inputs are increased by the same proportion. This further implies that long-run average costs are increasing, which his an indication of diseconomies of scale (Truett & Truett 1990). Furthermore, the productivity parameter indicates that okra farmers in the FZEZ [SGEZ] have technology that is likely closest to [furthest from] the MSF. The technical change parameter also suggests that, on average, there has not been any significant (p < 0.05) technological change in okra production since the 1980s.

The mean TE for okra-producing farmers was estimated at 0.54. Figure 2(a) demonstrates that, for okra generally, TE has declined for okra farms in the country since the 1980s. In terms of its distribution, Figure 3(ai) reveals the spatial heterogeneity in the mean TE levels of okra farms in the country, with mean scores ranging from 0.40 in SGEZ to 0.78 in TZEZ. From highest to lowest, the TGR, which measures the degree of tangency to the MSF and indicates the room available for technological improvements, was estimated at means of 0.70, 0.61, 0.50 and 0.45 for okra farms in the SGEZ, FZEZ, CSEZ and TZEZ respectively. The low magnitude of these estimates indicates the existence of substantial room for farmers to increase okra productivity by adopting the best technologies currently in Ghana. The actual technology gaps in production technology range from 30% to 55% for farmers in the SGEZ and TZEZ respectively.

Corroborating the technical-change parameter, Figure 2(b) for okra indicates that the TGR has not changed since the 1980s. After accounting for ecology-specific differences in production technologies, the long-run mean (1987 to 2017) MTE – in descending order – is 0.35, 0.29, 0.28 and 0.27 for okra farms in the TZEZ, FZEZ, SGEZ and CSEZ respectively. The temporal dynamics shown in Figure 2(c) for okra paint a peculiar picture that suggests that the overall production shortfall for okra production in Ghana can reasonably be attributed to technological gaps.

The findings reveal that the shortfalls in okra production could be curtailed by redistributing technology throughout Ghana so that all farmers use the best available technology. However, for specificity, Figure 3(aii) shows that, whilst okra production technology increases as one moves from the south toward the north, the closeness of farmers to the best available technology is concentrated in central Ghana. Okra farmers in the SGEZ and TZEZ could benefit from improvements in farmer managerial practices and technology transfer respectively. In contrast, okra farmers in FZEZ and CSEZ will benefit from both technology transfer and improvements in farmer managerial practices.

Table 3: Production parameters for vegetable production in Ghana (1987 to 2017)

		¢				
	Sudan/Guinea savanna	Transitional zone	Forest zone	Coastal savanna	National frontier	Meta-frontier
	(SGEZ)	(TZEZ)	(FZEZ)	(CSEZ)		
Okra						
Land	0.19*** (0.03)	0.12*** (0.04)	0.31*** (0.04)	0.21*** (0.06)	0.22*** (0.02)	0.22*** (0.01)
Family labour	0.19 (0.13)	0.13 (0.13)	0.21* (0.12)	0.19 (0.22)	0.14** (0.07)	0.15*** (0.03)
Hired labour	0.07 (0.05)	0.30*** (0.06)	0.25*** (0.05)	0.13 (0.08)	0.15*** (0.03)	0.16*** (0.01)
Fertiliser	0.06 (0.05)	0.07 (0.09)	0.20*** (0.07)	0.07 (0.14)	0.11*** (0.04)	0.08*** (0.02)
Pesticide	0.34*** (0.07)	0.12** (0.06)	-0.01 (0.06)	0.14* (0.09)	0.18*** (0.04)	0.23*** (0.02)
Returns to scale ^a	0.84 (0.16)	0.74* (0.15)	0.96 (0.14)	0.74 (0.23)	0.80** (0.08)	0.83*** (0.04)
Productivity	0.60*** (0.19)	1.02*** (0.22)	3.25*** (1.05)	1.83*** (0.53)	2.08*** (0.32)	2.47*** (0.15)
Annual trend (%)	0.01 (0.01)	0.02 (0.02)	0.01 (0.01)	0.00 (0.03)	0.01*** (0.01)	0.01*** (0.00)
Pepper						
Land	0.16*** (0.04)	0.21*** (0.03)	0.23*** (0.03)	0.25*** (0.03)	0.22*** (0.01)	0.22*** (0.01)
Family labour	-0.03 (0.12)	0.04 (0.11)	0.03 (0.08)	0.21* (0.11)	0.05 (0.05)	0.07*** (0.02)
Hired labour	0.21*** (0.05)	0.30*** (0.04)	0.29*** (0.04)	0.32*** (0.05)	0.28*** (0.02)	0.28*** (0.01)
Fertiliser	0.37*** (0.06)	0.12* (0.06)	0.26*** (0.05)	0.21*** (0.07)	0.23*** (0.03)	0.24*** (0.01)
Pesticide	0.04 (0.06)	0.10** (0.05)	-0.12*** (0.04)	0.01 (0.10)	0.01 (0.03)	0.02 (0.02)
Returns to scale ^a	0.76* (0.14)	0.76** (0.11)	0.70*** (0.09)	1.00 (0.16)	0.79*** (0.06)	0.83*** (0.03)
Productivity	0.94*** (0.28)	1.69*** (0.42)	0.93*** (0.24)	0.91*** (0.27)	1.13*** (0.18)	1.02*** (0.05)
Annual trend (%)	-0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.03** (0.01)	0.01 (0.01)	0.01*** (0.00)
Tomato						
Land	0.19 (0.28)	0.07* (0.04)	0.17*** (0.03)	0.09 (0.06)	0.15*** (0.02)	0.14*** (0.01)
Family labour	0.02 (0.21)	0.08 (0.12)	0.05 (0.09)	0.40*** (0.14)	0.10 (0.06)	0.12*** (0.04)
Hired labour	0.25* (0.13)	0.27*** (0.06)	0.16*** (0.04)	0.30*** (0.06)	0.22*** (0.03)	0.22*** (0.01)
Fertiliser	0.22 (0.39)	0.25*** (0.08)	0.17*** (0.06)	0.28*** (0.10)	0.23*** (0.04)	0.21*** (0.02)
Pesticide	0.14 (0.09)	0.18** (0.07)	0.23*** (0.05)	0.03 (0.09)	0.19*** (0.03)	0.21*** (0.02)
Returns to scale ^a	0.81 (0.25)	0.85 (0.14)	0.78** (0.11)	1.10 (0.19)	0.88 (0.07)	0.90** (0.04)
Productivity	2.83* (1.58)	1.84*** (0.54)	3.26*** (0.74)	5.51*** (1.69)	2.89*** (0.39)	3.35*** (0.14)
Annual trend (%)	-0.01 (0.05)	0.00 (0.01)	-0.09*** (0.01)	-0.08*** (0.02)	-0.02*** (0.01)	-0.03*** (0.00)

Significance: * p < 0.10, ** p < 0.05, *** p < 0.01^a Null hypothesis of constant returns to scale was tested



Figure 2: Temporal dynamics in vegetable production technology and efficiency in Ghana (1987 to 2017)

In terms of their spatial distribution, the highest and lowest are SGEZ and TZEZ for fertiliser, and TZEZ and FZEZ for pesticide. Like okra, pepper cultivation is also characterised by DRS, indicating that output will increase less than proportionately if all inputs are increased by the same proportion, and production is characterised by diseconomies of scale. However, unlike okra, the productivity parameter indicates that pepper farmers in TZEZ [FZEZ] have technology that is likely closest to [furthest from] the MSF. The technical change parameter also suggests that, like okra, there has not been any significant (p < 0.05) technological change in pepper production since the 1980s.



gure 3: Spatial distribution of mean [standard deviation] of vegetable production techno and efficiency in Ghana (1987 to 2017)

4.3 Pepper

Unlike the case for okra production, Table 3 shows that hired labour is the most important factor input for pepper. Hired labour is followed by land, fertiliser, family labour and pesticide, in that order. The highest and lowest estimates for land, family labour and hired labour elasticities are all obtained for

farmers in the CSEZ and SGEZ. The mean TE for pepper farmers is estimated at 0.74, and Figure 2(a) shows that this has increased since the 1980s. From highest to lowest, Figure 3(bi) reveals that pepper farmers in the CSEZ, FZEZ, SGEZ and TZEZ are operating at 0.84, 0.83, 0.80 and 0.50 levels of TE respectively. The TGR for pepper farmers is highest in the FZEZ (0.99), followed by the TZEZ (0.96), CSEZ (0.95) and then SGEZ (0.93). These high TGRs indicate that there are no substantial disparities in the level of pepper technology endowment across ecologies. The results imply that, on average, farmers are only operating at about 5% below the potential industrial output defined by the MSF. As shown in Figure 2(b), the TGR for pepper vas stable between 1987 and 2006, but has since declined. Furthermore, these findings suggest that pepper farmers are equipped with advanced pepper-cultivation technologies, and thus any deviation of actual from potential output could be attributed to managerial inefficiencies, as indicated by the MTE. From highest to lowest, the MTE are 0.82, 0.81, 0.74 and 0.49 for the CSEZ, FZEZ, SGEZ and TZEZ respectively. In terms of policy, a blanket treatment of improvements in farmer managerial practices could benefit all farmers. However, appropriate measures should be taken to curtail the increasing technology gap, as indicated by Figure 2(b).

4.4 Tomato

Unlike the case with okra but like pepper, hired labour is the most important factor input for tomato production, as shown in Table 3. Hired labour is followed by land, fertiliser, pesticide and then family labour. In terms of their spatial distribution, the highest and lowest are the CSEZ and FZEZ for hired labour, SGEZ and TZEZ for land, CSEZ and FZEZ for fertiliser, FZEZ and CSEZ for pesticide, and CSEZ and SGEZ for family labour. The RTS for tomato production is similar to that of okra and pepper. The mean TE for pepper farmers was estimated at 0.58, and Figure 2(a) shows that this has fluctuated between 1986 and 2017. In descending order, the mean TE of tomato farmers is estimated at 0.74, 0.63, 0.55 and 0.43 for the FZEZ, CSEZ, TZEZ and SGEZ respectively. Also, in descending order, an average TGR score of 0.80, 0.79, 0.75 and 0.64 is obtained for tomato farms in the TZEZ, SGEZ, CSEZ and FZEZ respectively. These estimates reveal the potential productivity gaps that must be bridged by tomato farmers in the TZEZ (20%), SGEZ (21%), CSEZ (25%) and FZEZ (36%) to attain the maximum level of output defined by the MSF. These results demonstrate the substantial opportunities that exist for tomato farmers to significantly improve farm productivity by bridging these gaps. It is evident from the findings that farmers in the TZEZ are the closest to the best-practice industrial meta-technology, with MTE estimated at 0.46, followed by farmers in the CSEZ (0.44), FZEZ (0.40) and SGEZ (0.33). The spatial distribution and temporal dynamics of the TGR for tomato do not corroborate each other in terms of the main source of production shortfall. Whilst the spatial distribution indicates TE, the temporal dynamics indicate TGR. These differences suggest that, in the long [short] run, interventions such as the transfer of befitting technologies [managerial practices] from leading ecologies to lagging ones should be pursued. Particularly, in the long run, farmers in the FZEZ and CSEZ could benefit from technology updating to that used by their peers in the TZEZ and SGEZ. In contrast, in the short run, farmers in the SGEZ have relatively higher TGR but low TE, thus they could benefit from improvements in farmer managerial practices to those used by their counterparts in the FZEZ.

4.5 Inefficiency/technology gap drivers

The drivers of technical inefficiency shown in Table 4 indicate a positive association between female farmers and technical inefficiency, suggesting a gender gap that resonates with the literature (Avea *et al.* 2016).

Table 4: Drivers of inefficiency/technology gap in Ghanaian vegetable production (1987 to 2017)

		National				
	Sudan/Guinea savanna	Transitional zone	Forest zone	Coastal savanna	frontier	Meta-frontier
	(SGEZ)	(TZEZ)	(FZEZ)	(CSEZ)	nontier	
Okra						
Female (dummy)	0.31 (0.20)	-0.56 (0.54)	0.27 (0.24)	0.79* (0.41)	0.24* (0.12)	0.28*** (0.10)
Age (ln[years])	-0.11 (0.22)	-1.14 (0.71)	0.45 (0.34)	-0.30 (0.46)	-0.06 (0.15)	0.20 (0.13)
Education (ln[years])	-0.03 (0.12)	-1.97** (0.87)	-0.08 (0.19)	0.02 (0.37)	-0.11 (0.09)	0.21*** (0.08)
Crop diversification (index)	-0.02 (0.42)	-3.62*** (0.87)	-0.90* (0.48)	2.30** (1.13)	-0.26 (0.22)	-
Land owned (dummy)	0.70*** (0.24)	0.53 (0.47)	0.05 (0.23)	-0.05 (0.49)	0.34*** (0.13)	-0.14 (0.10)
Irrigation (dummy)	-0.48 (0.54)	-3.80* (1.96)	0.63 (0.58)	-1.56 (1.60)	-0.30 (0.41)	0.08 (0.32)
Mechanisation (dummy)	-0.32 (0.27)	1.40 (1.83)	-0.90 (0.92)	-2.69*** (0.87)	-0.16 (0.25)	-0.07 (0.25)
Credit (dummy)	-0.97*** (0.34)	1.37* (0.78)	0.38 (0.27)	0.11 (0.53)	-0.05 (0.15)	0.18 (0.13)
Extension (dummy)	-0.17 (0.22)	-0.67 (1.01)	-0.55** (0.27)	-0.99** (0.47)	-0.35** (0.14)	-0.03 (0.09)
<u>Pepper</u>						
Female (dummy)	1.82 (1.17)	-0.09 (0.19)	-0.06 (0.85)	-0.20 (0.56)	0.15 (0.13)	-0.01 (0.45)
Age (ln[years])	-0.18 (0.97)	-0.11 (0.26)	0.22 (0.64)	-0.59 (1.21)	0.10 (0.19)	-0.94 (0.59)
Education (ln[years])	0.13 (0.29)	-0.24 (0.17)	0.45 (1.47)	0.38 (0.50)	0.12 (0.13)	-1.68*** (0.43)
Crop diversification (index)	0.08 (1.54)	0.06 (0.38)	0.08 (2.94)	0.44 (1.24)	-0.18 (0.27)	-
Land owned (dummy)	0.02 (0.54)	0.31* (0.18)	-0.79 (1.40)	0.97* (0.56)	-0.16 (0.13)	0.86 (0.52)
Irrigation (dummy)	1.54 (1.26)	-0.89 (0.82)	0.33 (0.91)	-6793.99 (0.00)	-0.64 (0.47)	0.55 (0.50)
Mechanisation (dummy)	-0.93 (1.06)	0.30 (0.43)	15.30** (7.60)	8.40** (3.40)	0.99*** (0.29)	1.95*** (0.41)
Credit (dummy)	-82.42*** (13.91)	-0.05 (0.24)	0.56 (1.15)	-0.94 (1.17)	0.03 (0.22)	0.94** (0.47)
Extension (dummy)	-141.56 (0.00)	-0.21 (0.23)	-0.25 (0.31)	1.65 (0.00)	-0.32** (0.14)	-12.04 (139.27)
Tomato						
Female (dummy)	-0.13 (0.88)	-0.35 (0.39)	0.40 (0.26)	0.39 (0.41)	0.03 (0.12)	0.25** (0.11)
Age (ln[years])	0.16 (1.27)	-0.06 (0.47)	0.39 (0.37)	-0.15 (0.42)	0.07 (0.17)	0.16 (0.15)
Education (ln[years])	0.07 (0.49)	0.22 (0.36)	0.07 (0.22)	0.12 (0.27)	0.03 (0.10)	0.27*** (0.10)
Crop diversification (index)	-1.00** (0.42)	-0.99 (0.70)	-1.75*** (0.51)	0.46 (1.13)	-0.55** (0.23)	-
Land owned (dummy)	0.16 (0.73)	0.54 (0.47)	0.23 (0.29)	-0.24 (0.42)	0.38*** (0.14)	0.37*** (0.12)
Irrigation (dummy)	-4.15 (51.87)	-977.15 (0.00)	8.53** (3.66)	-0.72 (1.13)	-8.51 (52.90)	-1.44 (1.21)
Mechanisation (dummy)	-1.00 (1.43)	-1.08 (0.87)	-1098.76 (0.00)	-3.49 (4.15)	-1.58*** (0.47)	-75.07 (0.00)
Credit (dummy)	-0.70 (0.93)	-0.09 (0.39)	0.81 (0.56)	-63.65*** (5.82)	-0.26 (0.17)	0.13 (0.12)
Extension (dummy)	0.01 (0.50)	-0.71** (0.32)	0.10 (0.26)	0.37 (0.43)	-0.03 (0.12)	0.07 (0.11)

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

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Farmers' education decreases okra production inefficiency in the TZEZ, minimises pepper technological gaps, and maximises okra and tomato technological gaps. Crop diversification minimises okra and tomato technical inefficiency, but has no significant effect on that of pepper. Mechanisation improves okra technical efficiency in the CSEZ and minimises that of pepper in the FZEZ and CSEZ. Credit access significantly reduces technical inefficiency, but only for pepper and okra in the SGEZ and for tomato in the CSEZ. Finally, extension access was negative for most of the models, implying that it is technical inefficiency minimising. Farmers with extension access are knowledgeable in good managerial practices and are also more likely to use the optimum input application rates, and thus are relatively more technically efficient than their peers with no access. Except for tomato, extension minimises technology gaps, albeit not significantly.

5. Conclusion

The study has characterised the nature of vegetable production shortfalls throughout Ghana, with the aim of informing policy on the remedial actions to be taken to attenuate farm-level inefficiency and technology gaps. This could help boost vegetable production to enable Ghana to take advantage of existing export market opportunities and to minimise domestic deficits. This objective was achieved by applying meta-stochastic-frontier analysis to a sample of 4 498 okra, pepper and tomato farmers, drawn from seven cross-sectional population-based surveys. The findings reveal land and hired labour as the most significant contributors to vegetable production in Ghana, followed by fertiliser, pesticide and family labour. In addition, vegetable production in Ghana is characterised by decreasing returns to scale (DRS), implying that total farm output for all crops increases less proportionately with a proportionate increase in all inputs. The returns to scale (RTS) also indicates that vegetable production is characterised by diseconomies of scale. Furthermore, the technical change parameter estimate for all crops depicts a general decline or no change in the output level of all three vegetables since the 1980s.

In terms of meta-frontier technical efficiency (MTE), okra, tomato and pepper farmers in Ghana are currently operating at 54%, 74% and 58% levels of efficiency, indicating that the cultivation of these crops in the country is associated with varying degrees of production inefficiency. Technical inefficiency has generally increased for okra and pepper and been stable for tomato since the 1980s. Estimates of technological gap ratios suggests that the gaps are close to non-existent for pepper production (5%), relatively modest for tomato production (26%), and relatively severe for okra production (44%). This implies that, whilst there is no potential for production gains from redistributing pepper technology throughout Ghana, there is limited potential for tomato, and substantial for okra.

Overall, in terms of policy recommendations, the results of this study suggest that, generally, okra and pepper production can be enhanced through the redistribution of technology to minimise technological gaps, and that tomato production can be improved through improvements in farmer managerial practices (e.g. training in good agricultural practices). For specific policies, whilst okra [pepper] {tomato} farmers in the SGEZ and TZEZ [all ecologies] {SGEZ} will benefit from improvements in farmer managerial practices, their peers in the FZEZ and CSEZ {FZEZ and CSEZ} region will benefit from technology transfer. These policy measures will contribute significantly to efforts by stakeholders to boost vegetable cultivation in the various ecologies of the country and enable the smallholder farmers not only to meet domestic demand, but also to take advantage of the existing export market opportunities available to Ghana.

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Appendix

Table A1: Population, climatic and soil characteristics across ecologies in Ghana

Variable	Sudan	Guinea	Transitional	Semi-deciduous	Dainforest	Coastal
variable	savanna	savanna	zone	forest	Kaimorest	savanna
Population						
Area (1 000 km ²)	50.12	25.92	14.21	16.66	18.48	10.81
Population density (N/km ²)	59.09	162.76	140.14	89.61	37.99	115.97
Agric. population (%)	55.41	38.73	55.00	45.59	77.09	31.63
Rural population (%)	48.50	38.39	56.68	48.42	79.46	30.48
10-year average rain						
Mean [mm/year]	943.29	1 128.52	1 244.52	1 310.65	1 443.30	1 064.89
CV [%]	17.55	10.54	9.85	9.57	13.36	10.93
Soil						
pH	4.28-7.40	4.13-7.44	4.10-7.66	4.21-7.34	4.40-6.70	4.29-8.28
Organic matter (%)	0.52-6.74	0.06-7.63	0.00-11.18	0.05-11.31	0.19-13.83	0.00-4.84
N (%)	0.00-0.11	0.00-0.18	0.00-0.39	0.00-0.39	0.00-0.37	0.00-0.25
P (mg/kg soil)	0.00-4.54	0.00-6.35	0.00-3.41	0.00-3.92	0.00-0.26	0.00-7.51
CEC	0.00-6.41	0.00-7.86	0.00-9.55	0.00-6.54	0.00-1.21	0.00-6.96

All values are calculated as weighted averages (by area) using data retrieved from published reports (Ministry of Food and Agriculture [MOFA], 2017)

	E	cology produc	National	Mata		
	Sudan/Guinea	Transitional	Forest	Coastal	National	Meta-
	(SGEZ)	(TZEZ)	(FZEZ)	(CSEZ)	Irontier	irontier
Production function	, , , , , , , , , , , , , , , , , , ,					
Land(ln[ha]) {ln[1}	-0.04 (0.06)	0.05 (0.08)	$0.32^{***}(0.07)$	0.11 (0.10)	$0.12^{***}(0.04)$	0.11*** (0.02)
Hired labour(ln[days]) {lnI2}	0.31* (0.17)	0.06 (0.23)	0.06 (0.18)	0.23 (0.29)	0.24** (0.10)	0.24*** (0.04)
Family labour(ln[days])	0.07 (0.07)	0.33*** (0.11)	0.35*** (0.08)	0.03 (0.11)	0.20*** (0.04)	0.21*** (0.02)
Fertiliser (ln[kg]) {lnI4}	0.00 (0.09)	-0.16 (0.14)	-0.03 (0.12)	0.19 (0.16)	0.04 (0.06)	0.00 (0.04)
Pesticide(ln[litre]) {lnI5}	0.34* (0.19)	-0.02 (0.09)	0.03 (0.10)	0.18 (0.14)	0.16*** (0.05)	0.24*** (0.03)
Trend {lnI6}	0.08*** (0.03)	0.00 (0.04)	0.02 (0.03)	0.03 (0.05)	0.04*** (0.01)	0.03*** (0.01)
0.5·lnI1·lnI1	-0.04* (0.02)	-0.11*** (0.04)	-0.03 (0.02)	-0.07* (0.04)	-0.07*** (0.01)	-0.05*** (0.01)
0.5·lnI2·lnI2	0.38 (0.26)	0.22 (0.39)	-0.42 (0.37)	-0.62 (0.65)	-0.07 (0.18)	0.11 (0.08)
0.5·lnI3·lnI3	-0.11** (0.04)	-0.12* (0.07)	0.05 (0.04)	0.08 (0.08)	-0.03 (0.03)	-0.01 (0.01)
0.5·lnI4·lnI4	0.07 (0.04)	0.15* (0.08)	0.09 (0.07)	0.00 (0.11)	0.00 (0.03)	0.05** (0.02)
0.5·lnI5·lnI5	0.16* (0.08)	-0.01 (0.04)	-0.09** (0.05)	0.03 (0.09)	0.02 (0.03)	0.04* (0.02)
0.5·lnI6·lnI6	0.00** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00** (0.00)	0.00** (0.00)
lnI1.lnI2	-0.04 (0.06)	-0.08 (0.08)	0.01 (0.07)	-0.01 (0.13)	0.03 (0.04)	0.01 (0.02)
lnI1.lnI3	-0.04 (0.03)	0.03 (0.03)	0.02 (0.02)	-0.08* (0.05)	-0.01 (0.01)	-0.01* (0.01)
lnI1.lnI4	0.04 (0.03)	-0.02 (0.04)	-0.01 (0.02)	0.09* (0.05)	0.01 (0.02)	0.02 (0.01)
lnI1.lnI5	0.00 (0.03)	-0.01 (0.03)	0.02 (0.02)	0.05 (0.04)	0.03** (0.01)	0.02*** (0.01)
lnI1.lnI6	0.01*** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	0.00*** (0.00)
lnI2.lnI3	-0.05 (0.10)	-0.02 (0.12)	-0.01 (0.08)	0.30* (0.16)	0.04 (0.05)	0.03 (0.02)
lnI2.lnI4	0.04 (0.10)	-0.19 (0.15)	-0.24** (0.12)	0.67*** (0.26)	0.04 (0.07)	0.03 (0.04)
lnI2.lnI5	0.09 (0.08)	-0.12 (0.09)	0.07 (0.09)	-0.30 (0.18)	-0.04 (0.05)	-0.05* (0.03)
lnI2.lnI6	-0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)	0.00 (0.02)	0.00 (0.01)	0.00** (0.00)
lnI3.lnI4	0.02 (0.04)	0.09* (0.05)	-0.05 (0.03)	-0.14* (0.08)	0.00 (0.02)	-0.01 (0.01)
lnI3.lnI5	0.10*** (0.04)	0.06 (0.04)	-0.01 (0.03)	0.13*** (0.05)	0.03 (0.02)	0.03** (0.01)
lnI3.lnI6	-0.01 (0.00)	0.00 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00* (0.00)	0.00*** (0.00)
lnI4.lnI5	-0.11*** (0.04)	-0.04 (0.05)	0.03 (0.05)	-0.07 (0.06)	-0.02 (0.03)	-0.04** (0.02)
lnI4.lnI6	0.01* (0.00)	0.02** (0.01)	0.01** (0.01)	0.00 (0.01)	0.01** (0.00)	0.01*** (0.00)
lnI5.lnI6	0.00 (0.01)	0.01** (0.00)	-0.01 (0.01)	0.00 (0.01)	0.01** (0.00)	0.00** (0.00)
Constant	-0.51 (0.32)	0.02 (0.22)	1.18*** (0.32)	0.60** (0.29)	0.73*** (0.15)	0.91*** (0.06)
Dummies of zero input		· · · · · · · · · · · · · · · · · · ·	· · · · · ·			
lnI3	0.38 (0.29)	-0.84* (0.51)	-0.52 (0.40)	-0.37 (0.31)	-0.33* (0.17)	-0.22*** (0.07)
lnI4	0.54 (0.33)	-0.03 (0.23)	-0.52** (0.22)	-0.61* (0.33)	-0.13 (0.13)	-0.22*** (0.06)
lnI5	0.64** (0.27)	-0.50* (0.27)	-0.65 (0.48)	-0.15 (0.28)	-0.22 (0.15)	-0.04 (0.07)
lnI3.lnI4	-0.38 (0.45)	0.44 (0.57)	-0.58 (0.51)	0.64 (0.62)	-0.01 (0.24)	0.09 (0.11)
lnI3.lnI5	-0.79** (0.33)	0.27 (0.76)	0.61 (0.69)	0.34 (0.53)	0.14 (0.24)	-0.04 (0.08)
lnI4.lnI5	-0.38 (0.35)	0.26 (0.33)	0.48 (0.50)	0.15 (0.43)	0.02 (0.18)	0.04 (0.08)
lnI3.lnI4.lnI5	0.90* (0.50)	-0.26 (0.83)	0.12 (0.76)	-1.17 (0.81)	0.13 (0.30)	0.26** (0.11)
Uncertainty function				. ((. ()
Mean	-0.11 (0.21)	0.00 (0.14)	-0.14 (0.21)	0.18 (0.15)	0.00 (0.11)	-2.52*** (0.26)
Variance	0.95 (0.10)	1.00 (0.07)	0.93 (0.10)	1.09 (0.08)	1.00 (0.05)	0.28 (0.04)

Table A2: Meta-stochastic frontier results for okra p	production in Ghana ((1987 to 2017)
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Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01Data sources: Ghana Living Standards Surveys [1987/88, 1988/89, 1990/91, 1997/98, 2005/06, 2012/13, 2016/17]

	Ecology production frontier				National	Moto
	Sudan/Guinea	Transitional	Forest	Coastal	function	function
	(SGEZ)	(TZEZ)	(FZEZ)	(CSEZ)	Ironuer	ironuer
Production function						
Land $(\ln[ha]) \{\ln[1]\}$	0.09 (0.07)	-0.04 (0.05)	0.00 (0.04)	0.15*** (0.05)	0.05* (0.02)	0.05*** (0.01)
Hired labour(ln[days])	0.17 (0.21)	0.07 (0.16)	0.23 (0.15)	0.27 (0.19)	0.17* (0.09)	0.19*** (0.03)
Family labour(ln[days])	0.47*** (0.08)	0.32*** (0.06)	0.52*** (0.07)	0.39*** (0.07)	0.42*** (0.04)	0.42*** (0.01)
Fertiliser (ln[kg]) {ln]4}	0 24** (0 11)	0.00(0.11)	0.24* (0.14)	0.02 (0.15)	0 19*** (0 06)	0 19*** (0 03)
Pesticide(ln[litre]) {ln[5}	0.01 (0.13)	0 27*** (0 08)	-0.16* (0.09)	-0.19(0.19)	-0.01 (0.05)	0.00(0.02)
Trend {lnI6}	-0.04 (0.03)	0.27 (0.00) 0.11***(0.02)	-0.12*(0.07)	0.10*** (0.03)	0.02*(0.01)	-0.03 *** (0.01)
$0.5 \cdot \ln 11 \cdot \ln 11$	0.01(0.03)	0.00(0.02)	-0.04***(0.02)	-0.01 (0.01)	-0.01 (0.01)	-0.01 *** (0.00)
$0.5 \ln 12 \ln 12$	0.00 (0.02)	-0.25 (0.32)	0.04 (0.02)	-0.56 (0.36)	0.01 (0.16)	-0.01 (0.06)
0.5·lnI3·lnI3	0.04 (0.01)	-0.23 (0.32)	-0.03 (0.03)	0.00(0.06)	-0.03*(0.02)	-0.03 * * * (0.01)
0.5 lnI4 lnI4	0.00(0.03)	0.07 (0.12)	-0.03 (0.03)	0.15 (0.10)	-0.03(0.02)	-0.03 (0.01)
$0.5 \ln 15 \ln 15$	-0.05 (0.07)	-0.01 (0.04)	-0.04 (0.04)	0.07 (0.07)		0.02*(0.01)
0.5·lnI6·lnI6		-0.01 (0.04)	0.01** (0.00)	-0.01*** (0.00)	0.01(0.02)	0.02 (0.01) 0.00*** (0.00)
lnI1 lnI2	0.00 (0.00)	-0.01 (0.00)	0.01 (0.00)	-0.01 (0.00)	0.00(0.00)	0.00 (0.00)
lnI1 lnI3	0.02(0.02)	-0.01 (0.01)	0.02 (0.03)	-0.02 (0.02)	0.02(0.02)	0.02 (0.01)
InI1 InI4	0.02(0.02)	0.00 (0.03)	0.00(0.01)	0.02(0.02)	0.02 (0.01)	0.00(0.00) 0.02***(0.01)
InI1 InI5	-0.07**(0.03)	-0.02 (0.02)	0.03*(0.02)	-0.03 (0.02)	-0.01 (0.01)	-0.01 (0.01)
lnI1.lnI6	0.00 (0.00)	$0.01^{***}(0.00)$	$0.01^{***}(0.00)$	0.00 (0.00)	0.01*** (0.00)	$0.01^{***}(0.00)$
InI2.InI3	0.03 (0.10)	-0.06 (0.05)	-0.05 (0.06)	0.34*** (0.08)	-0.03 (0.04)	-0.01 (0.02)
InI2.InI4	-0.01 (0.11)	-0.30** (0.13)	-0.10 (0.10)	-0.02 (0.14)	-0.10* (0.05)	-0.10*** (0.03)
InI2.InI5	-0.05 (0.11)	-0.08 (0.07)	0.04 (0.11)	-0.28** (0.11)	-0.02 (0.04)	-0.04* (0.02)
InI2.InI6	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01** (0.00)	-0.01*** (0.00)
lnI3.lnI4	-0.07 (0.05)	0.04 (0.04)	0.03 (0.05)	-0.11* (0.06)	0.01 (0.02)	0.00 (0.01)
lnI3.lnI5	0.06 (0.04)	-0.03 (0.02)	0.06* (0.04)	0.00 (0.04)	0.04** (0.02)	0.03*** (0.01)
lnI3.lnI6	-0.01*** (0.00)	0.00 (0.00)	-0.01*** (0.00)	-0.01 (0.01)	-0.01*** (0.00)	-0.01*** (0.00)
lnI4.lnI5	0.13** (0.06)	-0.02 (0.07)	-0.01 (0.04)	0.09 (0.06)	0.04* (0.02)	0.03*** (0.01)
lnI4.lnI6	0.01** (0.01)	0.01 (0.01)	0.00 (0.01)	0.01* (0.01)	0.01* (0.00)	0.01*** (0.00)
lnI5.lnI6	0.00 (0.01)	-0.02*** (0.00)	0.01** (0.00)	0.01 (0.01)	0.00 (0.00)	0.00*** (0.00)
Constant	-0.06 (0.30)	0.52** (0.25)	-0.08 (0.26)	-0.09 (0.30)	0.12 (0.16)	0.02 (0.05)
Dummies of zero input						
lnI3	0.01 (0.26)	-1.34*** (0.38)	0.14 (0.24)	-1.05*** (0.27)	-0.35** (0.15)	-0.40*** (0.06)
lnI4	-1.07*** (0.26)	-0.15 (0.19)	-0.58*** (0.19)	-0.03 (0.30)	-0.45*** (0.12)	-0.45*** (0.06)
lnI5	0.29 (0.26)	-0.27 (0.28)	0.43** (0.21)	0.13 (0.36)	0.22* (0.13)	0.26*** (0.06)
lnI3.lnI4	-0.11 (0.39)	0.68 (0.45)	-0.04 (0.34)	-0.13 (0.54)	0.03 (0.19)	0.15* (0.08)
lnI3.lnI5	-0.35 (0.34)	0.80 (0.53)	-0.47 (0.42)	0.14 (0.42)	-0.16 (0.22)	-0.25*** (0.08)
lnI4.lnI5	0.39 (0.32)	0.03 (0.32)	-0.03 (0.24)	-0.53 (0.39)	-0.04 (0.15)	-0.04 (0.07)
lnI3.lnI4.lnI5	0.00 (0.46)	-0.90 (0.61)	0.01 (0.56)	0.26 (0.63)	-0.11 (0.26)	-0.15 (0.10)
Uncertainty function						
Mean	0.33*** (0.09)	-0.29 (0.21)	0.56*** (0.08)	0.20*** (0.07)	0.46*** (0.06)	-1.00*** (0.03)
Variance	1.18 (0.05)	0.87 (0.09)	1.32 (0.05)	1.10 (0.04)	1.26 (0.04)	0.61 (0.01)
C' 'C' 1 1 *	- 0 10 ** 0 04	*** < 0.01				

Table A3: Meta-stochastic-frontier results for pepper production in Ghana (1987 to 2017)

Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01 Data sources: Ghana Living Standards Surveys [1987/88, 1988/89, 1990/91, 1997/98, 2005/06, 2012/13, 2016/17]

	Ecology production frontier				National	Mata
	Sudan/Guine	Transitional	Forest	Coastal		Meta-
	a (SGEZ)	(TZEZ)	(FZEZ)	(CSEZ)	ironuer	ironuer
Production function						
Land(ln[ha]) {lnI1}	0.00 (0.64)	0.05 (0.07)	0.20*** (0.06)	0.07 (0.10)	0.14*** (0.04)	0.12*** (0.01)
Hired labour(ln[days])	0.30 (0.25)	0.04 (0.19)	0.16 (0.14)	0.66*** (0.22)	0.23** (0.09)	0.20*** (0.04)
Family labour(ln[days]) {lnI3}	0.35*** (0.13)	0.26*** (0.10)	0.13** (0.06)	0.47*** (0.09)	0.29*** (0.04)	0.29*** (0.02)
Fertiliser (ln[kg]) {lnI4}	0.40 (0.39)	0.19* (0.10)	0.11 (0.10)	0.25* (0.13)	0.18*** (0.06)	0.18*** (0.03)
Pesticide(ln[liter]) {lnI5}	-0.04 (0.20)	0.10 (0.10)	0.29*** (0.08)	-0.16 (0.15)	0.17*** (0.04)	0.19*** (0.02)
Trend {lnI6}	0.04 (0.09)	0.07** (0.03)	-0.07*** (0.03)	-0.18*** (0.04)	-0.01 (0.01)	-0.08*** (0.01)
0.5·lnI1·lnI1	0.03 (0.14)	-0.06** (0.03)	-0.04** (0.02)	-0.04 (0.03)	-0.02 (0.02)	-0.02** (0.01)
0.5·lnI2·lnI2	0.30 (1.10)	0.73** (0.33)	0.19 (0.28)	-0.11 (0.44)	0.36* (0.19)	0.21*** (0.08)
0.5·lnI3·lnI3	0.04 (0.05)	-0.01 (0.06)	0.02 (0.04)	-0.05 (0.07)	0.01 (0.02)	0.03** (0.01)
0.5·lnI4·lnI4	-0.04 (0.25)	-0.09 (0.10)	0.03 (0.05)	0.22*** (0.09)	0.05* (0.03)	0.04** (0.02)
0.5·lnI5·lnI5	0.08 (0.16)	0.00 (0.07)	0.01 (0.03)	0.14 (0.09)	0.00 (0.02)	0.01 (0.01)
0.5·lnI6·lnI6	0.00 (0.00)	-0.01*** (0.00)	0.00 (0.00)	0.01*** (0.00)	0.00 (0.00)	0.00*** (0.00)
lnI1.lnI2	-0.02 (0.28)	0.02 (0.07)	-0.02 (0.05)	-0.02 (0.09)	-0.02 (0.04)	-0.01 (0.02)
lnI1.lnI3	0.00 (0.13)	0.02 (0.03)	0.02 (0.02)	0.01 (0.03)	0.02 (0.01)	0.02*** (0.01)
lnI1.lnI4	0.01 (0.07)	-0.07 (0.05)	0.03** (0.02)	-0.03 (0.04)	0.01 (0.01)	-0.01 (0.01)
lnI1.lnI5	0.06 (0.04)	0.00 (0.03)	-0.01 (0.02)	-0.01 (0.04)	0.01 (0.01)	0.01 (0.01)
lnI1.lnI6	0.02 (0.02)	0.00 (0.01)	-0.01* (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
lnI2.lnI3	0.22* (0.12)	-0.15 (0.11)	-0.07 (0.06)	0.27** (0.11)	0.01 (0.05)	0.01 (0.02)
lnI2.lnI4	-0.05 (0.34)	-0.09 (0.16)	-0.20** (0.09)	-0.09 (0.13)	-0.11* (0.06)	-0.09** (0.04)
lnI2.lnI5	-0.04 (0.42)	0.11 (0.11)	0.12** (0.06)	-0.05 (0.12)	0.04 (0.05)	0.07** (0.03)
lnI2.lnI6	-0.01 (0.02)	0.01 (0.01)	-0.01 (0.01)	-0.02 (0.01)	-0.01 (0.01)	0.00 (0.00)
lnI3.lnI4	0.02 (0.07)	0.07 (0.07)	-0.01 (0.03)	0.03 (0.04)	0.00 (0.02)	0.00 (0.01)
lnI3.lnI5	-0.05 (0.15)	-0.05 (0.05)	0.00 (0.02)	0.00 (0.04)	-0.01 (0.01)	-0.03*** (0.01)
lnI3.lnI6	-0.01 (0.02)	0.00 (0.01)	0.01 (0.00)	-0.01*** (0.01)	0.00* (0.00)	$0.00^{**}(0.00)$
lnI4.lnI5	-0.07 (0.14)	0.13*** (0.05)	0.01 (0.03)	-0.17*** (0.05)	0.01 (0.02)	0.00 (0.01)
lnI4.lnI6	-0.02 (0.02)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.00)	0.00 (0.00)
lnI5.lnI6	0.02 (0.02)	0.00 (0.01)	-0.01 (0.00)	0.02** (0.01)	0.00 (0.00)	0.00 (0.00)
Constant	1.04* (0.56)	0.61** (0.29)	1.18*** (0.23)	1.71*** (0.31)	1.06*** (0.13)	1.21*** (0.04)
Dummies of zero input						
lnI3	-1.08 (2.00)	-0.94* (0.56)	-0.45* (0.26)	-1.18*** (0.34)	-0.74*** (0.19)	-0.74*** (0.08)
lnI4	0.76 (0.80)	-0.26 (0.21)	-0.83*** (0.19)	-0.65** (0.32)	-0.40*** (0.13)	-0.56*** (0.07)
lnI5	-0.59 (0.37)	-0.06 (0.25)	-0.22 (0.24)	-1.19*** (0.35)	-0.41*** (0.14)	-0.38*** (0.06)
lnI3.lnI4	0.16 (1.20)	0.80 (0.67)	0.34 (0.38)	1.07** (0.54)	0.44 (0.27)	0.55*** (0.15)
lnI3.lnI5	1.53 (2.44)	-0.38 (0.49)	-0.39 (0.46)	1.14** (0.46)	0.63** (0.28)	0.74*** (0.12)
lnI4.lnI5	-0.87 (1.71)	-0.61* (0.33)	-0.09 (0.30)	0.95** (0.41)	-0.04 (0.18)	0.03 (0.08)
lnI3.lnI4.lnI5	-0.98 (1.56)	#N/A	0.22 (0.54)	-1.77*** (0.68)	-0.72** (0.34)	-0.93*** (0.18)
Uncertainty function						
Mean	-0.54 (2.63)	-0.62*(0.35)	0.15 (0.09)	-0.20 (0.17)	-0.11 (0.13)	-1.75*** (0.06)
Variance	0.76 (1.00)	0.73 (0.13)	1.08 (0.05)	0.90 (0.08)	0.94 (0.06)	0.42 (0.01)

Table A4: Meta-Stochastic-Frontier Results for Tomato Production in Ghana (1987-2017)

Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01 Data sources: Ghana Living Standards Surveys [1987/88, 1988/89, 1990/91, 1997/98, 2005/06, 2012/13, 2016/17]



Figure A1: Vegetable farmers' demographics by ecology in Ghana (1987 to 2017)



Figure A2: Vegetable production input use rate by ecology in Ghana (1987 to 2017)



Figure A3: Vegetable production parameters in Ghana (1987 to 2017)