Do data envelopment and stochastic frontier analyses produce similar efficiency estimates? The case of Ghanaian maize production

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Abstract

This study applied stochastic frontier analysis (SFA) and data envelopment analysis (DEA) to examine the technical efficiency of maize production in northern Ghana using cross-sectional data from 360 maize farmers for the 2011/2012 cropping season. Farm size, seed, fertiliser and herbicides had a positive effect on maize output. Agricultural mechanisation, extension services, experience and gender influenced technical efficiency. The study recommends that access to tractors be expanded to increase farmers' production efficiency. Maize production could improve if less-experienced farmers learn from the accumulated knowledge of experienced farmers, including through extension. Agricultural extension services should be strengthened to disseminate improved farming practices to farmers for increased efficiency. Female farmers should be supported by removing socio-cultural barriers by raising awareness in order to correct the wrong traditions and perceptions inimical to women's full participation in farming so as to bring improvements in technical efficiency.

Key words: data envelopment; stochastic frontier; efficiency

1. Introduction

The consumption of maize, an important staple, has been increasing over the years in Ghana, from 42.5 kg per capita in 2000 to 43.8 kg per capita in 2005 (Ministry of Food and Agriculture [MoFA] 2011). However, even though average yield of maize has also been improving, it is still less than a third of the achievable yield of 6.0 mt/ha. Moreover, the increase in maize production over the years can be attributed to the expansion of the area cultivated, rather than improvements in crop productivity, as shown in Figure 1. The low productivity has been associated with total reliance on rainfall, and low utilisation of improved seed varieties, fertilisers, herbicides, pesticides and mechanisation (MoFA 2010).

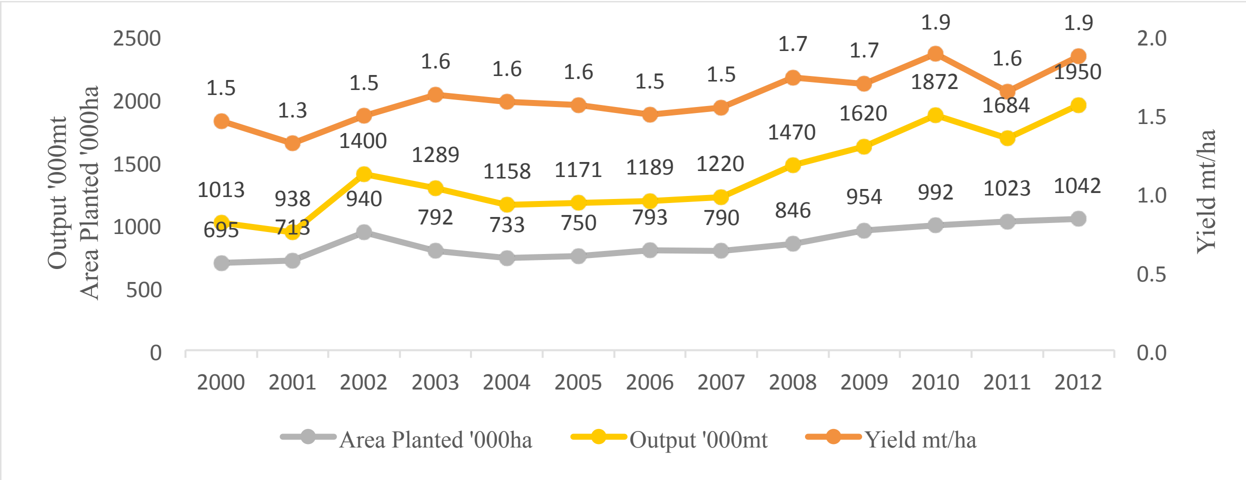

Figure 1: Area, output and yield of maize in Ghana from 2000 to 2012
Source: FAOSTAT country data

Agricultural productivity can be improved through the development and adoption of new technologies and the efficient use of the existing technologies without damaging the natural resource base in Ghana (Bhasin 2002). The ability of maize farmers in Ghana to improve yield levels and achieve sustainable production depends on efficient farm practices, thus technical efficiency. Technical efficiency is affected by both farm and farmer characteristics, such as age, level of education and total number of years of schooling, land area used for maize production, soil fertility and quantity of fertiliser used, quality and quantity of seed used, labour quantity and cost, farmer's managerial ability or experience, access to credit facility, extension visits and off-farm work (Alhassan, 2008).

Studies carried out on technical efficiency in Ghana have focused mostly on the stochastic frontier analysis (SFA) (Bhasin 2002; Al-hassan 2008), with very few using data envelopment analysis (DEA) (Abatania *et al*. 2012). This comparative study tests whether there are significant differences between the SFA, which requires the specification of the functional form of the production frontier and the distributional assumptions of the inefficiency component, and the DEA, which does not require these statistical assumptions in efficiency estimation.

2. Methods

2.1 Data, sampling approach and study area

The data were collected between January and February 2013 in the Northern, Upper East and Upper West regions of northern Ghana for the 2011/2012 cropping season. A semi-structured questionnaire was used for the personal interviews with the maize farmers. Six communities were randomly selected from the regions in each of the six districts. Ten maize households were also randomly sampled from each community – 60 per district and 120 per region – and a total sample size of 360 was realised. The districts were West Mamprusi, Savelugu/Nanton, Kassena/Nanakana, Builsa South, Lawra and Nadowli. The languages spoken in the study area are Mamprulli and Dagbani, in which interviews were done without interpreters, and Kasem, Buli and Dagaare, for which the services of interpreters were used in the interviews. The average duration per interview was two hours. Data collected included the socioeconomic and demographic characteristics of maize farmers, as well as those directly related to maize production and output, such as farm size in hectares, seed quantity used in sowing (kg), quantity of fertiliser applied (kg) and input prices, among others. Permission to access the 36 communities was obtained from community leaders. Northern Ghana makes up about 41% of the country's total land area (MoFA 2011). Rainfall distribution is unimodal, with an annual mean of 1 100 mm.

2.2 Empirical model of the stochastic frontier analysis

Stochastic frontier analysis (SFA), developed by Aigner *et al.* (1977) and Meeusen and Van den Broeck (1977), based on Farrell (1957) and Aigner and Chu (1968), was applied in this study. It decomposes the error term into exogenous random effects and the one-sided inefficiency component (Coelli 1995).

The translog functional form was found appropriate following a generalised likelihood ratio test, and is given by:

$$lnY_i = \beta_0 + \sum_{k=1}^{5} \beta_k \, lnX_{ik} + {}^{1}\!/_{2} \sum_{k=1}^{5} \sum_{j=1}^{5} \beta_{kj} \, lnX_{ik} \, lnX_{ij} + V_i + U_i \quad (1)$$

where ln represents logarithm to base $\boldsymbol{e}$; Y is the output of maize (in kg); X_1 is farm size in hectares; X_2 is seed quantity (kg) used for planting; X_3 is fertiliser quantity (kg); X_4 is labour (number of persons), X_5 is quantity of herbicides (litres), and X_i are the five inputs for the translog model. The inefficiency model is given as follows:

$$U_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6 + \varepsilon_i \quad (2)$$

where Z_1 is access to agricultural mechanisation; Z_2 is years of farmer in maize cultivation; Z_3 is years in school; Z_4 is agricultural extension visits; and Z_5 is gender of the farmer (1 = male, 0 = female); Z_6 is credit received (GH¢); ε_i is a two-sided error term; and δ_i is a vector of parameters to be estimated. Equations (1) and (2) are estimated by the maximum likelihood, which yields consistent estimators for β, δ, γ and σ_z^2, where $\gamma = \sigma^2/\sigma_z^2$ and $\sigma_z^2 = \sigma_v^2/\sigma^2$.

2.3 Empirical model of the input-oriented DEA and tobit

The DEA was developed by Charnes *et al.* (1978), building on Dantzig (1951), Farrell (1957), Boles (1966), Shephard (1970) and Afriat (1972). It is a non-parametric method for assessing the efficiency of decision-making units (DMUs). The analysis of production efficiency using the DEA helps inefficient farms to determine the extent to which they could improve their input use relative to 'best practice' firms (Shafiq & Rehman 2000). The input-oriented model is preferable because input quantities are usually the primary decision variables of firms, and are also under the control of firm managers (Coelli *et al.* 2005). Nonetheless, the choice of orientation has a minor effect, and the input- and output-oriented models estimate exactly the same frontier and also identify the same set of efficient firms (Coelli & Perelman 1996).

Following Shafiq and Rehman (2000), the input-oriented DEA is given as

$$Min \, Z_g \quad (3)$$

subject to

$$\sum Y_j \, \lambda_j \leq Y_g \quad (4)$$

$$\sum_{i=1}^{s} X_{ij} \, \lambda_j - X_g \, Z_g \leq 0 \quad (5)$$

$$X_i, Y_j \leq 0 \quad (6)$$

$$\sum \lambda_j = 1 \quad (7)$$

where $j = 1, \ldots, 360$ is the number of DMUs in the sample, and $i = 1, \ldots, 5$ is the number of inputs (farm size, seed, fertiliser, labour and herbicides). Z_g is the relative efficiency score of the DMU, $'g'$, under study, λ_j are multipliers for input levels of a referent farm that an inefficient farm should aim at to achieve efficiency, X_{ij} is the level of use for the ith input on the jth farm, Y_j is the level of output on the jth farm, Y_g is the level of the output on unit $'g'$, and X_g is the vector of the levels of inputs being used by the DMU $'g'$.

The tobit model that is used in analysing the determinants of technical efficiency is given as:

$$y_i^* = x_i'\beta + u_i \tag{8}$$

$$y_i^* = \begin{cases} y_i^* = x_i'\beta + \varepsilon_i & if\ y_i^* > 0 \\ 0 & if\ y_i^* \leq 0 \end{cases} \tag{9}$$

$$u_i \sim IIND(0, \sigma^2) \tag{10}$$

The subscript, $i, = 1, \ldots., n$; y_i^*, is a latent variable; x_i is a vector of explanatory variables; β is a vector of unknown parameters; and u_i is a disturbance term. The empirical model is expressed as:

$$Y_i^* = \beta_0 + \beta_1 M_1 + \beta_2 M_2 + \beta_3 M_3 + \beta_4 M_4 + \beta_5 M_5 + \beta_6 M_6 + U_i \tag{11}$$

where Y_i^* is the TE estimate of the respondent; $M_1 \ldots . M_6$ are the same socioeconomic variables as in Equation (2); U_i is the error term; and β_i is a vector of parameters to be estimated. Stata version 13 was used for estimating both the SFA and DEA. The distributional assumption for the inefficiency was the normal half normal for the SFA. The variable returns to scale were assumed for the DEA, because it allows the division of efficiency into technical and scale efficiencies (Banker *et al*. 1984).

3. Results

3.1 Demographic characteristics of respondents

Agriculture in Ghana accounts for more than 30% of GDP and three-quarters of export earnings, and employs 60% of the labour force (MoFA 2011). Maize is a very important staple food in Ghana, accounting for more than 50% of total cereal production in the country, and it is grown in all agro-ecological zones (Akramov & Malek 2012). The bulk of maize produced goes into food consumption and it is arguably the most important food security crop. Many households cultivate maize for home consumption, since farmers in the study area are mainly subsistence farmers. Maize cultivation from sowing to harvesting takes three to four months in a single growing season, which starts in May and lasts until the end of October, when the rains stop and give way to the dry harmattan season in the study area.

The main method of land preparation for maize cultivation in northern Ghana is the use of farm tractors, followed by bullocks. The use of herbicides is also very common, as the respondents sprayed their plots to get rid of weeds before ploughing. Maize was cultivated in northern Ghana as a mono-crop by 66.5% of respondents. Mono-cropping has a better output chance, as it does not have to compete with other crops on the same plot for water, nutrients and space, among others. Nonetheless, some farmers undertook mixed cropping to reduce the risk of total crop failure.

From the results in Table 1, it can be seen that the mean age of maize farmers was about 41 years, which falls within the economically active age (15 to 60). The mean household size and household labour were 8.66 and 5.75 respectively. The gap between household size and household labour (above 15 years) has implications for farm labour, especially in northern Ghana, where household heads rely on their households to provide labour for farming activities.

Table 1: Descriptive statistics of variables

Variable	Description	Minimum	Maximum	Mean	Std dev.
Age	Number of years	18	79	40.89	11.42
Sex of household head	Dummy; 0 = female, 1 = male	0	1	1.15	0.36
Educational status	Number of years of formal education	0	16	4.69	5.74
Farm size (ha)	Number of hectares cultivated	0.2	12.1	1.76	5.10
Experience	Number of years in maize cultivation	1	40	10.33	6.93
Household size	Number of members in household	2	35	8.66	6.92
Household labour	Household members who work on farm	1	21	5.75	5.28
Maize seed	Quantity of seed (kg) sowed	3.3	198	30.53	3.49
Herbicides	Quantity of herbicides (in litres) used	0	36	6.41	5.14
NPK fertiliser	Quantity of NPK fertiliser (kg) used	0	2 250	265.5	273.38
Ammonia fertiliser	Quantity of ammonia fertiliser (kg) used	0	1 500	181.5	182.52
Maize output	Quantity of maize (kg) harvested	50	18 000	2 091	2 375.79
Credit	Amount received (in GH¢)	0	2 000	12.82	117.70

Sample size = 360
Source: Authors' computation

The average farm size of 1.76 hectares corroborates the findings of the studies by Nyanteng and Seini (2000) and the Ghana Statistical Services (2007), which found that farm households operate with smaller landholdings. A household used 30.53 kg of maize to sow 1.76 hectares. Similarly, a household on average used 6.4 litres of herbicides, 265.5 kg of NPK and 181.5 kg of ammonia fertiliser on 1.76 hectares. In Ghana, one litre of herbicides is diluted to spray an acre. Given the mean farm size of 1.76 ha (4.3 acres), this means that farmers in the study area over-apply it, or they spray more than once within the cultivation period, as herbicides are increasingly being used to complement manual weeding, if not substituting it completely. The average credit amount of GH¢ 12.8 was inadequate to support maize production.

3.2 Tests of hypotheses for the stochastic frontier model

The stochastic frontier model, which decomposes the error term into random effects and inefficiency components, is a better representation of maize production than the average response model. Therefore, a variation in technical efficiency could be attributed to the inefficiency term. This is corroborated by the results in Table 2, and the value of gamma (γ) in Table 3. The generalised likelihood ratio test also found the translog to be the appropriate functional form.

Table 2: Tests of hypotheses for choice of functional form and inefficiency

Null hypothesis	Log likelihood function (H_0)	Test statistic λ	Critical value	Decision
$H_0: \beta_{ij} = 0$	-301.598	25.262	24.996 (15)	Reject H_0: Translog appropriate
$H_0: \delta_1 = \cdots = \delta_6 = 0$	-307.748	37.562	12.592 (6)	Reject H_0: Inefficiency present

Critical values are at 5% significance level and obtained from the χ^2 distribution table. Figures in brackets are the number of restrictions.

3.3 Determinants of maize output in northern Ghana

The input variables used in the translog had each been deflated against their mean values preceding estimation, and therefore the first-order coefficients could be interpreted as partial production elasticities. The first-term variables, with the exception of labour, were all statistically significant at 1%, as shown in Table 3. The coefficients of these variables were also positive and thus had a significant effect on productivity in the initial stage. For example, the coefficient of farm size, which was 0.324, means that, when farm size increased by 100%, output would also increase by about 32%, all other inputs being held constant.

Table 3: Maximum likelihood estimates of stochastic frontier model

Variable	Parameter	Coefficients	Standard error
Constant	β_0	0.136	0.093
Farm size	β_1	0.324***	0.087
Seed	β_2	0.365***	0.084
Fertiliser	β_3	0.206***	0.052
Labour	β_4	0.101	0.073
Herbicides	β_5	0.387***	0.069
Farm size squared	β_6	-0.143	0.209
Seed squared	β_7	-0.177	0.164
Fertiliser squared	β_8	-0.246***	0.105
Labour squared	β_9	0.005	0.303
Herbicides squared	β_{10}	0.137	0.104
*Farm size*seed*	β_{11}	-0.005	0.303
*Farm size*fertiliser*	β_{12}	0.224**	0.101
*Farm size*labour*	β_{13}	0.033	0.033
*Farm size*herbicides*	β_{14}	-0.119	0.110
Seed fertiliser*	β_{15}	-0.027	0.093
Seed labour*	β_{16}	0.158	0.133
Seed herbicides*	β_{17}	0.158	0.133
*Fertiliser*labour*	β_{18}	-0.085	0.092
*Fertiliser*herbicides*	β_{19}	0.174**	0.069
*Labour*herbicides*	β_{20}	-0.102	0.109
Sigma squared	σ_v^2	-1.522***	0.142
Gamma	γ	0.786***	0.382
Mean efficiency		0.740	
Returns to scale		1.383	
Log-likelihood function		-288.967	

***, ** and * indicate values statistically significant at 1%, 5% and 10% respectively.

Some of the interaction terms for the pooled data were statistically significant and had both positive and negative signs. "Fertiliser squared", farm size and fertiliser, and fertiliser and herbicides, were all statistically significant at 5%. For example, the squared of the variables for farm size, seed, fertiliser and labour had negative signs of -0.143, -0.177, -0.246 and -0.005 respectively, in line with the *a priori* expectation.

The value of gamma (0.786) was statistically significant, which means that 78.6% of the total variation in output resulted from factors within the control of the farmer, thereby suggesting that technical inefficiency had a significant effect on output (Hjalmarsson *et al*. 1996; Sharma *et al*. 1997; Wadud & White 2000). The remaining 21.4% was due to factors outside the control of the farmers. The sigma squared value of 1.522 was significantly different from zero at 1%, indicating the correctness of the specified distributional assumption for the inefficiency term, U_i. The returns to scale value of 1.383 revealed increasing returns to scale. This means that maize production in northern Ghana was in stage one of the production function, and therefore inputs were being under-used.

3.4 Results of the input-oriented data envelopment analysis

The input-oriented model was estimated because input uses are under the control of farmers, and thus so are the decision variables in production (Coelli *et al.* 2005). The results in Table 4 show that the inputs could be reduced without affecting output – farm size by 0.33 hectares, seed quantity by 6.18 kg, fertiliser by 97.09 kg, labour by 0.68 units, and herbicides by 1.1 litres.

Table 4: Input-oriented DEA results for northern Ghana

Slack input variables				
Farm size (ha)	Seed (kg)	Fertiliser (kg)	Labour	Herbicides (litres)
0.33	6.18	97.09	0.68	1.11

Source: Authors' computation

Furthermore, the technically efficient farmers had farm sizes that were relatively larger and used smaller quantities of inputs. For instance, the efficient farmers used an average of 395.80 kg of inorganic fertiliser, 27.04 kg of seed and 4.04 litres of herbicides, and employed three people on a 3.37 hectare plot to produce a yield of 2.34 tons/ha of maize. For the inefficient farmers to move up to the production level of the efficient farmers, they would have to increase plot size by 0.16 hectares, and reduce chemical fertiliser use by 55.53 kg, seed by 4.72 kg, herbicides by 1.07 litres and labour by 0.61 in order to boost yield by 0.58 tons/ha. Meanwhile, the maize agronomic recommendations of the Savannah Agricultural Research Institute of Ghana suggest a chemical fertiliser application rate of 180 kg/ha of NPK applied within two weeks after planting, and 120 kg/ha of sulphate of ammonia applied after four to six weeks by drilling to a depth of five to seven centimetres (Adu *et al.* 2014). A reduction in chemical fertiliser use may be substituted by the application of animal manure and compost, and crop rotation with leguminous crops.

3.5 Determinants of technical efficiency

The stochastic frontier analysis (SFA) was estimated using the one-step procedure in Stata. The tobit model was used to estimate the determinants of technical efficiency for the DEA. The technical efficiency estimates for the DEA were obtained using a Stata user-written code by Yong-bae and Choonjoo (2010).

This section compares the determinants of technical efficiency between the SFA and DEA. Unlike the SFA, where both the determinants of output and technical inefficiency are computed simultaneously, this is not the case for the DEA model. With respect to the latter, the prevalent method in the literature to find the determinants of technical efficiency gaps among DMUs is tobit regression analysis, because the efficiency scores are censored at the maximum value (Bravo-Ureta & Pinheiro 1993; Coelli *et al.* 2002; Wouterse 2008; Yong-bae & Choonjoo 2010). The technical efficiency of each DMU was regressed on a set of socioeconomic variables to explain the determinants of technical efficiency. Thus, to make a meaningful comparison, as is done in the literature, the authors explain the determinants of 'technical efficiency' by negating the signs of the inefficiency component as produced by the SFA model, instead of 'technical inefficiency' as is normally done using SFA alone.

For instance, Table 5 shows that agricultural mechanisation had a positive effect on farmer efficiency relative to the SFA, meaning farmers who had access to agricultural mechanisation were more technically efficient. The use of hoes or cutlasses places limitations on the amount of land that can be brought under cultivation (Fonteh 2010; Benin *et al.* 2011). The use of tractors in land preparation reduces production inefficiency through timely land preparation and planting. A study by Houssou *et al.* (2014) in Ghana shows that tractor owners ploughed an average of 20 hectares of their own farmlands and provided ploughing services of nearly 160 hectares per year. The authors also found about 25% of tractor owners provided complementary services, such as maize shelling. The agricultural mechanisation variable is the only variable that is significant in both the SFA and DEA. However, while the coefficient in the former is positive, it is negative in the latter. In the light of the above explanation, we would conclude that the SFA result is preferable, because it appeals to reasoning and is consistent with the theory.

Experience had a positive and significant effect on technical efficiency only for the SFA. Lapple (2010) and Okike *et al*. (2004) emphasise the importance of experience for technical efficiency because of the expected acquisition of dexterity in crop cultivation over a period of time.

Table 5: Comparison of the determinants of technical efficiency

Variable	Parameter	Coefficients	
		SFA	DEA
Constant	δ_0	2.542 (0.813)	0.799 (0.039)
Agricultural mechanisation	δ_1	0.435** (0.194)	-0.029** (0.012)
Experience	δ_2	0.106** (0.047)	0.001 (0.002)
Education	δ_3	0.177 (0.130)	-0.006*** (0.002)
Extension	δ_4	0.236 (0.215)	0.027* (0.015)
Gender	δ_5	1.023* (0.388)	0.019 (0.035)
Credit	δ_6	0.002 (0.003)	8.484E-05 (0.000)
Mean efficiency		0.74	0.77

***, ** and * indicate values statistically significant at 1%, 5% and 10% respectively
Figures in brackets are the standard errors. Sample size = 360.

The educational status of the respondents had a negative but significant effect on technical efficiency for only the DEA. Thus, farmers with no formal education were more technically efficient than those with formal education. Likewise, access to agricultural extension service had a positive effect on technical efficiency only under the DEA. In relation to northern Ghana, Al-hassan (2008) found agricultural extension services to be significant in determining the technical efficiency of both irrigated and non-irrigated rice farmers. Ghana's Agriculture Ministry (MoFA 2007) recognised the importance of education in improving farmers' efficiency and suggested that the high illiteracy rate among farmers could be reduced by constantly facilitating their access to information on new production approaches, opportunities and policies in the agricultural sector. According to Bhasin (2002), farmers learned from agricultural extension agents and, if they followed the advice of the extension officers, it would certainly enhance their efficiency levels. The gender of the household head had a positive and significant effect on technical efficiency only for the SFA. Male farmers were more technically efficient than female farmers. We interviewed household heads and collected data on household production of maize. Again, maize is a household food security crop in the study area, and given that most respondents are small-scale subsistence farmers, the farming objectives of the households regarding maize were similar, hence the comparison of female maize producers' efficiency to their male counterparts in the study area. More so, even if women have different farming objectives, the collective household objective of food security is given priority. In the study area, among the tasks of the women within the household were sowing, fertiliser application and food preparation on their husbands' farms, even when they had to be working on their own maize plots, which affected their technical efficiency. However, in both models, credit was not statistically significant, although it was positive.

The statistical SFA performed better in estimating the determinants of efficiency with three positive significant variables (mechanisation, experience and gender), whereas mechanisation and education had a negative effect and with only extension having a positive effect on efficiency for the DEA. The results differ because the DEA does not distinguish stochastic noise from inefficiency, hence its estimates have inbuilt statistical noise. Nonetheless, both the SFA and DEA measure how closely the production unit operates to the frontier of the production possibility set.

The mean estimate for the DEA (77%) was slightly higher than the SFA (74%), which is in consonance with the theory. Wadud and White (2000) reported mean technical efficiency estimates of 79.1% and 85.8% for the SFA and DEA respectively for farm households in Bangladesh. Alene *et al*. (2006) also reported lower mean technical efficiency for the SFA than for the DEA in a study of the production efficiency of intercropping annual and perennial crops in southern Ethiopia. The DEA is unable to separate statistical noise from technical inefficiency, hence its higher values (Sharma *et al*. 1997; Chakraborty *et al*. 1998; Johnes 2006). In other studies, such as that by Madau (2012), who estimated efficiency levels of citrus farming in Italy, the mean technical efficiency estimates were almost the same (71% for SFA and 71.1% for DEA). This study used the paired t-test (in Table 6) to determine whether the mean technical efficiency estimates of the SFA and DEA were statistically different. The null hypothesis, Ho: mean (diff) = 0 was not rejected in favour of the alternative hypothesis, Ha: mean (diff) ≠ 0. Therefore, the mean technical efficiency scores of the two models were not statistically different.

Table 6: Paired t-test of the mean technical efficiency estimates

Model	Null hypothesis	T statistic	Critical value	Decision
Mean diff = mean (DEA-SFA)	H_0: mean(diff) = 0	1.559	1.960	Do not reject H_0

Ho: mean (diff) = 0, Ha: mean (diff) ≠ 0. Critical value is at the 5% significance level and obtained from the T distribution table.
Source: Authors' computation

Goddard (2001) argues that the efficiency scores obtained from both the parametric and non-parametric approaches can be similar. Furthermore, Greene (1997) suggests that the robustness and appropriateness of these two approaches also depend on the value of "λ" corresponding to σ_u/σ_v for the SFA. For example, if λ gets closer to +∞, it means that all variations from the frontier are as a result of inefficiency, which is the chief argument of the deterministic frontier. In addition, if λ is close to 0, SFA is worth opting for. The value of λ in this study was 78.6%, thus 78.6% of the total variation in maize output was due to inefficiency, whilst the rest resulted from statistical noise. The fact that about 21% of the total variation in output could be attributed to random error or weather conditions means that the mean technical efficiency estimates of both the SFA (74%) and the DEA (77%) were similar.

Even though the results of the paired t-test of mean efficiency scores in Table 6 reveal no significant differences, the scatter plot in Figure 2 shows variation in efficiency estimates between the SFA and DEA for the individual maize farmers, with higher scores obtained from the DEA because of its inability to separate statistical noise from technical inefficiency. That notwithstanding, technical inefficiency was present in both models.

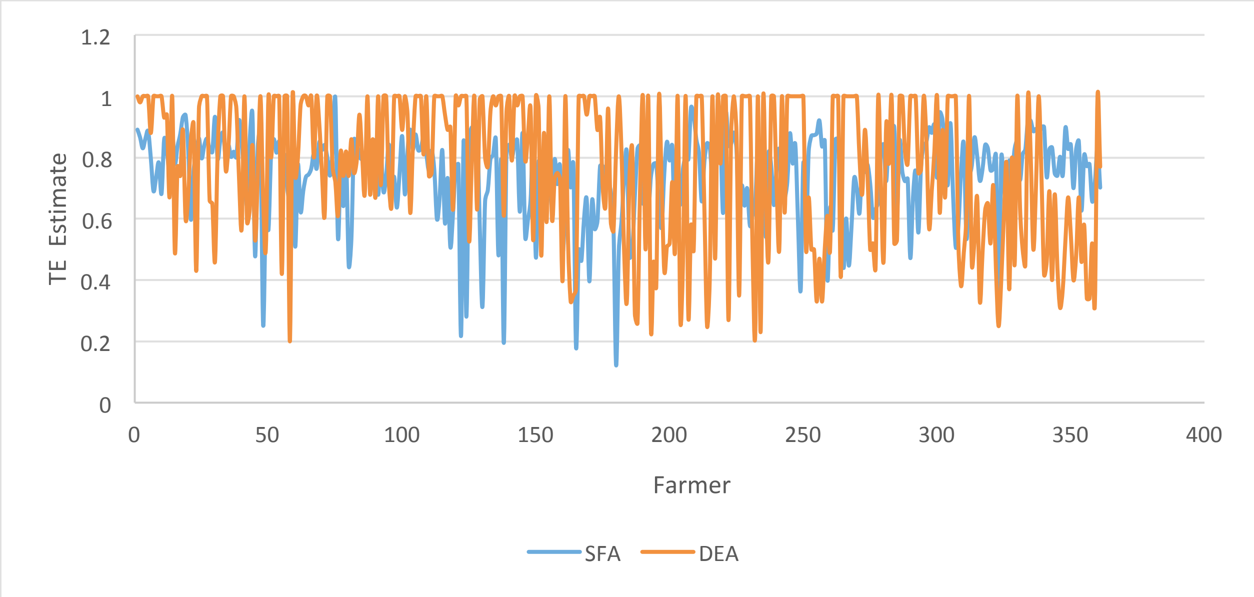

Figure 2: Comparison of TE estimates, SFA vs DEA.
Source: Authors' computation

4. Conclusions and recommendations

The mean estimates (SFA 74% and DEA 77%) showed the existence of technical inefficiency in maize production in northern Ghana. This implies that a farmer attains a mean level of output equal to 74% of what could be achieved under full efficiency, and therefore 26% of potential maize output is lost to inefficiency. Relative to the determinants of efficiency, the SFA produced many more positive and significant variables than the DEA because it separates statistical noise from inefficiency, and thus is preferred. The findings of this study are plausible in the sense that agriculture in the study area, as in many developing countries, is subject to a lot of risks beyond the control of farmers, such as drought, fall army worm invasion and bushfires. Given that the DEA does not take this into consideration, it is not surprising that it gives a mean efficiency slightly higher than that of the SFA. The implication is that, but for the fact that the former does not recognise statistical noise, the two mean efficiency estimates would have been the same. The superiority of the SFA to the DEA, per our study, lies in the fact that the findings are consistent with the theory and, for that matter, with our *a priori* expectations. Also, as already known, the SFA gives us the coefficients of the conventional inputs with respect to the output, which is also important for policy formulation. Based on our findings, access to and use of agricultural mechanisation services should be promoted, since they increase the technical efficiency of maize production. There should also be development of appropriate and affordable agricultural machinery to increase the range of farm operations that require mechanisation. Furthermore, male-headed households were more technically efficient than female-headed households. Female farmers should be supported by removing the socio-cultural barriers through awareness raising and lobbying by gender activists. Farmers with many years of experience in maize production were more technically efficient, and opportunities such as nucleus farms and farmer field schools, which bring less-experienced farmers together with more experienced ones to tap into the accumulated knowledge of the latter would improve maize production. Lastly, the agricultural extension system should be well resourced by government to provide effective extension service to farmers to enable them to improve maize output and reduce technical inefficiency in northern Ghana.

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