Research Article

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Technical efficiency of resource-poor maize farmers in northern Ghana

Abstract: Farm productivity in most developing countries remains low, hence the need to enhance technical efficiency (TE) of producers. This study evaluates the TE of maize production in rural Ghana, using primary data from a survey of smallholder producers. A two-stage double bootstrap data envelopment analysis (DEA) approach was used to assess TE and its determinants. The results revealed a bias-corrected mean TE of 68% (as opposed to 81% using the traditional DEA approach). Hence, with the prevailing technology and current input levels, farmers can increase their TE of maize production by 32%. TE increased with adoption of improved varieties, weeding frequency, and herd size but decreased with producer's age, household size, educational status, and group membership. Subsequently, these factors need to be carefully considered in targeting policies for increasing maize productivity. The study observed increased adoption of improved varieties and training in efficient methods of weed control as important measures to enhance TE of maize farmers.

Keywords: data envelopment analysis, double bootstrap, technical efficiency, truncated regression, northern Ghana

1 Introduction

The agricultural sector in Ghana is pivotal to national development because of its huge role in creating employment especially in rural areas, food and income security, and provision of raw materials for industry. The sector makes about 20.3% contribution to gross domestic product through the export of agricultural commodities including cocoa and nontraditional export crops especially fresh fruits [1]. Agriculture supports employment and income generation, providing a source of livelihood for over 60% of Ghanaians [2]. The crop subsector in Ghana is dominated by cereal, root, and tuber crop production, and contributes significantly to household income of rural dwellers in particular and ancillary workers along the agricultural value chain.

Maize is the most important cereal crop cultivated by most Ghanaian farm households for food and income and has a high domestic demand to feed both humans and livestock. Due to inefficiency in production and other factors that confront farmers [3], the average yield is below the achievable level. The low yield of maize can also be attributed to dependence on rainfall for production, use of rudimentary tools and low uptake of modern technologies such as inorganic fertilizers and improved seeds [4,5]. As a result, most smallholders produce below the optimum output level, given their resource endowment and the production environment in which they operate.

In order to raise the productive ability of peasant maize producers in Ghana, there is the need to improve resource use efficiency. Awunyo-Vitor et al. [6] noted that to increase productivity of maize in Ghana, farmers should emphasize not only on adoption of improved technologies, but also on utilizing available resources efficiently. According to Danso-Abbeam et al. [7], output growth in maize has been the result of land expansion rather than increase in productivity. Farmers therefore require skills to allocate scarce production resources in a manner that maximizes output or minimizes input level during production. Hence, assessment of technical efficiency (TE) is imperative to aid smallholders to improve upon their production efficiency and increase their income from farming.

Abdulai et al. [8] investigated the TE of maize cultivation in Ghana. The authors measured the mean technical efficiency of Ghanaian maize cultivators to be 77% using data

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envelopment analysis (DEA). In a comparative TE analysis of maize farmers in Ghana, Abdulai et al. [9] estimated a mean TE of 74% using stochastic frontier analysis (SFA) and 77% using DEA. Wongnaa and Awunyo-Vitor [10] investigated the role of efficiency of maize cultivation in Ghana in the light of sustainable development goals and obtained an average TE of 58.1%. Awunyo-Vitor et al. [6] also observed that maize producers in Ghana were generally technically inefficient. In other studies that used SFA, Bempomaa and Acquah [11] evaluated the TE of maize producers as 67%, whereas Addai and Owusu [12] obtained a value of 64.1% for producers across different ecological areas of the country. More recently, Martey et al. [13] found that maize producers who used credit in farming had TE of 68% compared to 62% for nonusers of credit. However, Oppong et al. [14] obtained a relatively high TE score of 83% for maize producers in the middle belt of the country. The foregoing studies show that maize cultivation in Ghana is characterized by technical inefficiency in production, hence, examining ways to increase the productive efficiency of maize producers is very essential.

This study is important in two ways. First, most of the previous studies that used the nonparametric procedure to estimate TE of maize cultivation in Ghana applied the traditional DEA approach without bias-correction. This study, thus, extends the literature further by using the two-stage double bootstrap DEA model to assess the TE of smallholder maize growers in Ghana. Second, the study examined the relative performance of maize farmers in order to identify slacks (excess inputs) from maize production for each individual farmer and how farmers with slacks can attain optimality relative to farmers with zero slack values. This was achieved by using the input-oriented DEA which has the capability to identify slacks (excess inputs) after calculating TE of each farmer relative to the production frontier [8].

The rest of the study is presented as follows. Section 2 provides a review of the DEA methodology while Section 3 describes the methodology which highlights the data collection, estimation procedure as well as the analytical models. Section 4 presents the key findings, which are discussed in the light of previous studies in Section 5. The conclusion and policy recommendations emanating from the study are provided in Section 6.

2 Review of the DEA methodology

Traditionally, the common approaches for estimating productive efficiency are SFA and DEA. Where the SFA approach is parametric and requires a specific functional form, DEA is non-parametric and does not require a specific functional form. The SFA approach estimates TE by estimating how far a producer is from the most efficiency production frontier and reckons deviations from this efficient frontier as inefficiency. As an efficiency estimation approach, DEA provides a way to assess relative efficiency of firms or individuals (the decision-making unit, DMU) by comparing them to the best performer. The main advantage of the SFA approach over the DEA is its ability to distinguish between inefficiency from statistical noise and measurement error. The SFA has seen much application in agriculture compared to the DEA because agricultural production is typically associated with several factors beyond the control of producers hence, introducing variability in output. However, it has been observed that given the same data set, there is no significant difference between the results produced by the SFA translog model and the variable returns to scale (VRS) DEA frontier [15].

According to Simar and Wilson [16], a common problem with DEA application is the presence of unknown serious correlations between the estimated efficiencies for the DMUs. Consequently, DEA estimate from the first-stage analysis cannot be regressed on factors hypothesized to affect efficiency without violating the basic estimation assumptions. They argued that the process for generating the efficiency scores lack a well-defined data generation process (DGP) hence a second-stage regression with the estimated DEA scores is problematic.

Førsund and Sarafoglou [17] observed that the traditional DEA is sensitive to outliers, hence easily flattens the DEA scores to maximum, which according to De Stefanis and Storti [18], can give rise to results without meaningful economic interpretation. Also, traditional DEA uses the whole sample to generate the DEA score for each firm (making the DEA scores serially correlated). Simar and Wilson [16] therefore proposed the double bootstrap DEA approach that uses bootstrapping procedures to generate bias-corrected efficiency estimates that seek to improve efficiency of estimation. The extant literature shows that considerable attention has been given to the double bootstrap DEA approach proposed by Simar and Wilson [16] as an alternative to the traditional DEA on the premise that it addresses the aforementioned weaknesses of the traditional DEA approach.

This study therefore uses the double bootstrap DEA approach to estimate TE of maize producers in northern Ghana. Very few TE studies in Ghana have used this approach, therefore this study differs from other previous studies. Methodologically, studies on the application of

DEA in estimating TE in Ghana are very limited [8]; most studies have relied only on the applications of SFA [12,19–21] with just a few relying on DEA [22]. Among the few studies that have used the DEA approach, only Abatania et al. (2012) and Nkegbe (2018) have used the bootstrap DEA to assess TE of Ghanaian farmers, implying that efficiency estimates from the previous studies have not accounted for biases associated with the tradition DEA method.

3 Materials and methods

3.1 Study area

The research was carried out in the Tolon District of northern Ghana, which is 90% rural, with about 94% of households being agrarian. The district forms a part of the country's northern savannah and is characterized by grassland interspersed with drought-resistant trees. The rainfall pattern in the area is unimodal and lasts between May and October. Annual rainfall is approximately 110 mm with daytime temperatures rising to a maximum of 40 degrees Celsius in the dry season. Crops cultivated in the study area include rice, maize, cowpea, yam, among others. Most households in the area grow maize as a staple crop with only a few producing mainly for the market. Depending on the level of production at the end of the season, some households may decide to sell a part of their produce for cash.

3.2 Sampling and data collection

A sample of 180 maize farmers were selected at random from seven communities in the Tolon district for the study. The selection of communities was guided by extension agents who had jurisdiction over these areas. Farmers were interviewed face-to-face with the aid of carefully drafted questionnaires that solicited information on individual, farm, and institutional factors, as well as production data. The data covered maize production activities for the 2018 farming season.

For decision-making, the factors affecting TE may be of great importance to policy-makers. Therefore, the study identified the factors influencing efficiency. Variables for the second-stage analysis were chosen based on previous studies and *a priori* expectations. TE was assumed to increase with the following variables: age of the respondent [23], educational status [24], access to credit [25], household size [24], weeding frequency [24], herd size [19], farmer group membership [19,26], improved variety adoption [27], and soil fertility status [24]. As farmers grow old, they become more experienced in farming, which is anticipated to increase their efficiency of production. Formal education enhances access to information, which is expected to improve efficiency of smallholders. Similarly, access to credit facilitates acquisition of inputs to perform farm activities in time to promote efficiency, while larger households are expected to be able to overcome labour shortages during critical periods of crop production that may impact negatively on output and efficiency. Farmers who carry out regular weeding are expected to be more efficient, while members of farmer associations are expected to benefit from the services provided by the groups to enhance their TE.

3.3 Estimation procedure

The nonparametric DEA method was used to estimate producers' TE. Two alternative approaches which can be used in the estimation are Farrell's [28] efficiency measure and Shephard's [29] output distance function. Shephard's [29] procedure is the reciprocal of Farrell's [28] approach. The study used Farrell's [28] approach with an input-orientation; hence, a positive coefficient of any of the independent variables in the second-stage analysis implies that the variable improves TE, and vice versa.

The choice of an input-oriented VRS DEA was informed by a priori expectation that smallholder's maize production is typically subject to VRS. With constant returns to scale (CRS) assumption, average productivity does not depend on the scale of production, which is not usually feasible. Also, the approach adopted for the study is justified as producers have greater control over the factors of production than the output.

DEA allows measurement of efficiency of DMUs by comparing efficiency to a frontier generated by linear programming. The approach was proposed by Charnes et al. [30], with CRS assumption. This supposition is valid when all production units operate at optimum scale [31]. A VRS DEA model was generalized by Banker et al. [32] such that the weight for each DMU sums up to unity. DEA analysis is based on either an input- or output-orientation. This study used the former approach. Assuming N farms, turning out M output(s) and deploying K factors of production, the model is stated as follows:

minimize θ
subject to

$$
\begin{aligned}
-y_i + \lambda\,Y &\geq 0, \\
\theta x_i - \lambda X &\geq 0, \\
N1'\lambda &= 1, \\
\lambda &\geq 0,
\end{aligned}
\tag{1}
$$

where Y signifies an output matrix; X indicates an input matrix; y_i signifies an output vector of the ith DMU; x_i implies an input vector of each DMU; λ denotes an $n \times 1$ vector which serves as a weight system that forms an optimal combination of inputs and output for each DMU; θ is a scalar for each DMU (where a value of 1 means a technically efficient DMU or point on the frontier; $N1$ is an $n \times 1$ vector of unities (where $N1'$ is its transpose) ensuring that the weights allotted to the benchmarking DMUs add up to unity.

The DEA model minimizes the inputs in comparison with the empirically generated frontier. θ in equation (1) signifies pure TE. The CRS DEA model can be obtained by excluding the constraint $N1'\lambda = 1$ in equation (1). The corresponding θ in the CRS DEA model represents total (production) efficiency. Scale efficiency is derived as the ratio of the efficiency score under CRS to the score under VRS assumption. Therefore, scale efficiency exists if the θ derived from CRS DEA does not equate to θ derived from VRS DEA [31].

The traditional approach of estimating DEA in two steps, whereby the initial efficiency estimates are regressed on a number of factors hypothesized to influence efficiency using Tobit or truncated regression, has been criticized by some authors [16]. The criticism is based on the assertion that the DEA scores from the first-stage regression are subject to serious correlations. Also, it has been argued that the approach is not supported by a well-defined DGP. McDonald [33] argues that using Tobit model in the second-stage analysis is defective as the DEA estimates are not obtained using a censoring procedure. Simar and Wilson [16] thus suggested a bootstrapping procedure that provides "bias-corrected" efficiency estimates. This procedure is based on constructing and simulating a DGP that generates artificial bootstrap samples from which "reliable" standard errors and confidence intervals are derived. Simar and Wilson [16] presents the technical description of the double bootstrap approach. This study used 2000 bootstrap iterations.

Following Simar and Wilson [16], the determination of the factors influencing TE was carried out by regressing the first-stage bias-corrected DEA estimates of the ith DMU under VRS assumption on a set of environmental factors using truncated regression analysis. The regression model is presented as follows:

$$
\theta_i^\star = \beta_0 + \sum_{i=1}^{6} \beta_i W_i + \varepsilon_i,
\tag{2}
$$

where $\theta_i^\star$ is the bias-corrected DEA score from the first-stage estimation, W_i signifies a vector of factors affecting $\theta_i^\star$, and β_i implies a vector of coefficients. The independent variables in equation (2) include producer's age, educational status, number of household members, choice of crop variety, frequency of weeding, herd size, credit access, and association membership. The age of the farmer is expected to influence TE, but the direction of influence is indeterminate. This is because older farmers may be more experienced in farming and thus likely to be more efficiency. However, younger farmers may be more adventurous and enterprizing, thus enhancing their efficiency. Formal education, access to credit, and farmer group membership are hypothesized to increase TE, in the same way as herd ownership, more frequent weeding and adoption of improved crop varieties.

4 Results

4.1 Description of the sample

The description of the variables included in the study are shown in Table 1.

Farmers produced 1,509 kg of maize using 90 person-days of labour and 5.1 acres of land. Also, farmers used 26.5 and 566 kg of seed and fertilizer, respectively. Pesticide use amounted to 4.63 L while capital used in production amounted to GH¢ 172. The descriptive statistics indicate that farmers use relatively low amount of capital, pesticide, and fertilizer in the study area. Contextual variables explaining efficiency were selected based on the extant literature and *a priori* expectation. Close to 36% of the respondents cultivated improved maize varieties, while 31% have received formal education. The mean age of the respondents is 34 years, implying that they are in their youthful and productive years. On average, a typical maize-producing household comprised 10 members and owned 4 cattle (herd size). In most farming communities, the herd size is a proxy for wealth status as poor households do not normally

Table 1: Descriptive statistics of the variables

Variables	Mean	Std. dev.	Min.	Max.
Output variable				
Maize output in kilogramme	1,509	1,014	175	5,450
Input variables				
Farm size in acres	5.13	3.14	1	20
Total labour in man-days	90.4	49.3	23	326
Seed (kg)	26.5	15.9	5	100
Fertilizer (kg)	566	363	100	2,250
Pesticides (L)	4.63	3.27	0	24
Capital in Ghana cedis (GH¢)[†]	172	99.2	25	498
Contextual variables explaining efficiency				
Variety (1 = if improved)	0.36	0.48	0	1
Age in years	34.4	9.50	18	75
Household size	10.5	5.28	3	37
Frequency of weeding	2.12	0.32	2	3
Herd size (number of cattle)	3.79	5.78	0	23
Educational status (1 = if educated)	0.31	0.46	0	1
Credit (1 = if farmer used credit)	0.65	0.48	0	1
Farmer group (1 = if member)	0.46	0.50	0	1

[†]1.0 US$ is equivalent to 5.4 GH¢. Source: Authors computation based on survey data, 2018.

own cattle. Cattle are also used in farm operations to reduce drudgery, thus improving efficiency. Sixty-five percent of the respondents had access to credit, whereas 46% belonged to a farmers' group. Also, on average, farmers carried out two weeding activities during the cropping season (weeding frequency). Farmers who carry out regular weeding of their farms are expected to have higher output and efficiency as weeds compete with food crops for nutrients. Maize farmers require two weeding activities per cropping season but performing an extra weeding helps to control noxious weeds that negatively impact on crop yields.

4.2 Estimation of TE

Table 2 presents the TE scores from the two-stage double bootstrap DEA model. The initial and bias-corrected DEA scores are presented and discussed.

The results reveal that the respondents had a bias-corrected mean TE of 68%. Hence, producers can increase TE by 32% using the same level of inputs and technology. Meanwhile, the TE estimates without bias-correction indicated a mean value of 81%. Nearly 47% of the respondents had TEs above 70% while 9.5% had TE not exceeding 50%.

Table 2: Distribution of TE estimates

Efficiency range	Traditional DEA score		Bias-corrected DEA score	
	Frequency	%	Frequency	%
≤0.40	1	0.56	6	3.33
0.41–0.50	5	2.78	11	6.11
0.51–0.60	18	10	32	17.8
0.61–0.70	27	15	47	26.1
0.71–0.80	37	20.6	50	27.8
0.81–0.90	28	15.6	32	17.8
0.91–1.00	64	35.6	2	1.11
Total	180	100	180	100
Mean	0.81		0.68	
Minimum	0.29		0.25	
Maximum	1.00		0.92	

Source: Authors computation based on survey data, 2018.

Table 3 depicts the slacks of the inputs used in production. The slacks indicate a radial reduction in the input variable to obtain the same level of output. Hence, farmers could potentially reduce farm size by 0.603 acres without reducing the level of output. Similarly, labour could be reduced by 5.8 man-days, seed by 0.50 kg, pesticides by 0.28 litres, and capital by 9.78 GH¢ to achieve the same level of output.

Table 4 shows the classification of the returns to scale. As shown by the results, maize production in Tolon district exhibits increasing returns to scale (IRS). The result suggests that maize cultivators operate at an inefficient portion of the production function. A proportionate increase in the level of production inputs will therefore result in a more than proportionate increase in the level of output. From the findings, 80% of the sampled farmers experienced IRS.

4.3 Determinants of TE

The study also investigated and reported the factors explaining TE of the respondents (Table 5). The adoption variable is significant and positive, suggesting that adoption of improved maize varieties improves TE. To simplify the estimation, we assumed that the adoption of improved variety is exogenous. The results further show that younger farmers have higher efficiency in production than older farmers. Younger farmers are more energetic and likely to be more innovative, which can enhance their efficiency of production.

Furthermore, TE of maize production decreased with household size. This implies that larger households do

Table 3: Slacks of the input variables

Input	Farm size	Labour	Seed	Fertilizer	Pesticide	Capital
Slack	0.603	5.807	0.501	27.188	0.283	9.783

Source: Authors computation based on survey data, 2018.

Table 4: Returns to scale

Classification	Frequency	%
IRS	144	80
CRS	10	5.6
Decreasing returns to scale	26	14.4

Source: Authors computation based on survey data, 2018.

Table 5: Determinants of TE

Variables	Observed coefficient	Bootstrap std. error	*P* > |z|
Adoption of improved variety	0.037*	0.019	0.055
Age	−0.002**	0.001	0.029
Household size	−0.006***	0.002	0.001
Frequency of weeding	0.148***	0.030	0.000
Herd size	0.007***	0.002	0.000
Educational status	−0.044**	0.019	0.024
Access to credit	0.024	0.019	0.209
Farmer group membership	−0.035*	0.020	0.076
Constant	0.666***	0.056	0.000

***, ** and * indicate statistical significance at 1, 5 and 10% levels, respectively. Source: Authors computation based on survey data, 2018.

not allocate labour resources judiciously in production. Furthermore, it was found that farmers who carried out more frequent weeding activities on their farms were more efficient than those who carried out less frequent weeding. The result agrees with *a priori* expectation and consistent with good agronomic practice. Regular weed control reduces weediness and competition between crops and weeds for soil nutrients.

The study also revealed that herd size and TE are positively correlated. In other words, farmers with larger herd size tend to be more technically efficient. The study also found that educated farmers recorded lower TE, a result which is contrary to *a priori* expectation. Furthermore, TE decreased with farmer group membership, suggesting that farmer-based organizations (FBOs) in the study area are ineffective in promoting efficiency of production of their members.

5 Discussion

5.1 Description of the sample

The data show that the respondents are peasants who cultivate small acreages and use limited amount of production inputs such as chemical fertilizer, pesticides, and capital. Smallholder farmers are typically resource-poor and tend to rely more on family labour for production. With regard to technology adoption, only 36% of the respondents adopted improved maize varieties, which is expected to impact on the level of TE. As indicated by Anang [34] and Anang et al. [35], adoption of improved maize varieties enhances TE of farmers and maize productivity. Another important characteristic of the respondents is the low level of education which has the propensity to reduce their productive efficiency. As shown by previous studies, education enhances technology adoption and access to information thereby promoting the productive efficiency of smallholders. This is in consonance with Anang [34] and Anang et al. [35] in their studies involving small-scale farmers in northern Ghana.

5.2 Estimation of TE

The two-stage double bootstrap DEA model estimates revealed that the TE scores were overestimated without bias-correction. In other words, using the traditional DEA approach resulted in higher efficiency scores relative to the double bootstrap approach. The result further revealed that maize producers in the study area are not optimizing their input utilization, hence there is scope for efficiency gain through improvement in resource allocation. Efficiency gain of 32% is possible with the same level of resources and technology. The DEA estimate of 77% in the study of Abdulai et al. [9] is quite similar to the DEA

score obtained in this study (without bias correction, i.e., 81%). As indicated earlier, the double bootstrap procedure permits valid inference and ensures statistical efficiency.

The TE scores under the traditional and bias-corrected approaches revealed some interesting patterns. The traditional DEA approach reported more farms with very high TE scores (91–100%). Meanwhile, for the same efficiency range, the bias-corrected approach reported fewer farms. On the other hand, the bias-corrected approach reported more farms with TE scores between 41 and 90% relative to the conventional approach. Hence, the conventional approach predicts many farms with very high efficiency scores which the bias-corrected approach downsizes or "corrects" by applying the double bootstrap technique to improve the estimation efficiency.

Smallholder maize farmers in the study area were found to use more inputs in production than necessary as indicated by the slacks of the input variables. All the six input variables were over-utilized in production despite being scarce resources. For instance, farmers could potentially downsize their acreage by 0.6 acres to produce at the same level of output. Thus, judicious allocation of scarce production resources is one way to enhance the efficiency of smallholder farmers to increase farm-level productivity. Studies by Abdulai et al. [8] and Shafiq and Rehman [36] have indicated that farmers in Ghana and Pakistan, respectively, use far greater amounts of inputs in production than required.

The production function of the sampled farmers depicted IRS suggesting that the farmers were not operating at the efficient portion of the production function. This point is buttressed by the over-utilization of production inputs by the respondents. The finding of this study compares with the result of Abdulai et al. [8] which indicated that 84% of maize farmers in northern Ghana were operating at IRS.

5.3 Determinants of TE

Adoption of improved varieties has been shown to improve TE and productivity of smallholder farmers [34,35]. The positive effect of improved maize variety adoption on TE is therefore in line with *a priori* expectation. The result shows that farmers must be encouraged to adopt improved seeds by increasing access to modern varieties and subsidized farm inputs. The result agrees with Tefaye [37] in a study of smallholder maize producers in Ethiopia.

Younger farmers were more technically efficiency in production, which agrees with Onumah et al. [38] as well as Shaheen et al. [39], who considered young farmers to be progressive and therefore more likely to adopt more efficient production techniques. Similarly, Martey et al. [40] in a study of Ghanaian maize producers observed that younger farmers were more technically efficient because of their dynamism with regards to technology adoption.

The inverse relationship between household size and TE of maize production implies that larger households do not allocate labour resources judiciously in production. Agrarian households in developing countries depend largely on household labour for farm activities. The extant literature shows that agriculture in developing countries is labour-intensive. One consequence of this is that larger households are likely to deplore more labour in production than is required, which may reduce their TE level. However, this is not always the case but depends on the proportion of economically active members in the household. Households with very high number of dependants may face labour challenges in production which can negatively impact on efficiency. This might also account for the finding of this study. The result is opposed to that of Rahman et al. [41] in their study of rice cultivation in Bangladesh.

The study further highlighted the importance of regular weed control to reduce competition for soil nutrients and ensure proper crop growth. In northern Ghana, soils are generally low in fertility, therefore competition with weeds has the tendency to reduce crop yield, hence efficiency of production.

Another key finding of the study is the positive relationship between herd size and TE, which is in line with Anang et al. [21] in their assessment of TE of rice cultivation in northern Ghana. Owners of cattle are likely to be wealthier farmers and thus able to overcome liquidity constraints that affect acquisition and allocation of inputs in production. Owners of cattle are also likely to use animal traction to carry out some aspects of production which can help to reduce drudgery and enhance TE.

Contrary to expectation, obtaining a formal education was associated with lower TE. The result, although contrary to expectation, has been reported by other researchers in Ghana. Donkoh et al. [22] observed that educated smallholders in northern Ghana were less technically efficient. Similarly, Asante et al. [42] observed that educated yam producers in Ghana were less technically efficiency compared to noneducated farmers. Abdulai et al. [8] observed that farmers with formal education tend to be more of part-time farmers while their counterparts

with no formal education are normally full-time. While the former groups are engaged in formal employments such as teaching and clerical works, the latter tend to be unskilled labour and are mostly full-time farmers with little livelihood diversification. Being full-time, the latter groups are likely to be more efficient than the former who may have divided attention.

The study also showed that TE reduced with farmer group membership, contrary to the important roles that farmer groups play especially in rural areas. This result is opposed to that of Asante et al. [43], Kuwornu et al. [23], and Donkoh et al. [22], which showed that group membership decreased inefficiency in production. Excessive politicization of farmer associations and absence of effective support mechanisms from both public and private organizations are some of the factors that contribute to the ineffectiveness of farmer organizations, thus reducing the impact they have on their members. Mwangi and Kariuki [44] noted that as a result of free-riding behaviour of some group members, farmer associations may negatively affect technology adoption, thus adversely impacting on the level of efficiency. Other reasons for inefficiency on the part of some FBOs are members attending unproductive meetings and also not applying the improved farming practices and information about very good technologies efficiently in their maize production.

6 Conclusions and policy recommendations

The study adopted a double bootstrap DEA methodology to measure the TE of maize producers in the Tolon district of Ghana. This procedure improves efficiency estimation and thus provides more realistic TE estimates relative to the conventional DEA approach. The results provide evidence of inefficiencies in maize production among the producers. This suggests that the producers are not optimizing their input utilization, hence there is a scope for efficiency gain through improvement in resource allocation. Specifically, maize farmers were producing at 68% efficiency level. TE increased with adoption of improved varieties and herd size but decreased with farmer's age, household size, educational status, and group membership. Furthermore, respondents who carried out more frequent weeding of their farms were more technically efficient than those who carried out less frequent weeding.

Policies to boost the TE of peasant maize cultivators in Ghana must focus on dissemination of improved

technologies, especially improved varieties to farmers. Improved varieties are high-yielding and make efficient use of inputs such as chemical fertilizer to optimize output. Furthermore, farmers should be trained in efficient methods of weed control to ensure higher efficiency of maize production. As shown by the results, regular weeding enhanced TE. Training in integrated pest management techniques, and crop rotation may help to reduce the impacts of weeds, and hence, raise the TE of the producers. Farmers should also be encouraged and supported in livestock rearing because of the positive relationship between the number of cattle owned and TE.

As indicated earlier, younger farmers are more innovative and energetic hence their higher efficiency levels. In supporting the farmers, affirmative actions may be taken in their favour. Other farmers who may benefit from such affirmative actions are farmers with small family size, farmers with little-or-no formal education, and farmers who do not belong to FBOs. However, there are other categories of farmers who also need support. For instance, as older farmers may not be as strong as their younger counterparts, they may be supported with output-enhancing inputs such as tractor or bullock services and improved seed varieties. Also, they may be supported with extension services (from mature and experienced staff), sensitization, and training to appreciate improved agricultural practices.

While farmers with formal education may not devote adequate time to their farms, as a result of their other engagements, they may, however, benefit from soft loans to enable them hire farm workers to assist them on their farms. Technical inefficiency of farmers with large families may be as a result of disproportionate amounts of labour on their farm plots. In a typical Ghanaian farm household, every member of the household is a farm worker, irrespective of the age, resulting in duplication of work and disguised unemployment. This means that sometimes, the marginal productivity is zero or even negative. In this case, training and sensitization of the farmers on gender roles and division of labour as well as support to expand farm lands may help improve the TE of such farmers. The land tenure system, and in most cases, lack of land titles, are what inhibits farmers from assessing and expanding their lands. Other constraints to farm expansion are lack of complementary inputs such as cash, tractor services, fertilizer, and irrigation facilities. The current "Planting for Food and Jobs" and "Planting for Exports" are good examples of support programmes to combat these challenges. Lastly, there is a need for government to streamline and monitor the activities of FBOs for their effective functioning. FBOs must also be

supported with training and sensitization devoid of unnecessary politicization.

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