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Assessing the technical efficiency of maize production in northern Ghana: The data envelopment analysis approach

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Abstract: Maize is a major source of food and cash for smallholder farmers. However, average yield in Ghana is less than a third of the achievable yield and thus the need to close this gap by improving the technical efficiency of farming households through employing the right combination of productive resources to achieve food sustainability. This study used the input-oriented data envelopment analysis to examine the technical efficiency of maize production in northern Ghana[1] using cross-sectional data for the 2011/2012 cropping season. The mean technical efficiency was 77%, giving credence to the existence of production inefficiency. Technically, efficient farmers used an average of 395.80 kg of chemical fertilizer, 27.04 kg of seed, 4.04 l of weedicides and hired labour of three persons to produce a yield of 2.34 tons/ha of maize. Largely, maize production exhibited increasing returns to scale. Agricultural mechanization and level of formal education did not have positive effects on technical efficiency, whereas agricultural extension had a positive effect on technical efficiency. Technical efficiency in maize production could

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PUBLIC INTEREST STATEMENT

Maize is the most consumed staple in Ghana. However, over the years, even though yield has been increasing, there is still a significant gap between actual yield and potential yield. This calls for measures to increase the efficiency of farmers. This study sought to assess production inefficiencies by examining input use relative to maize output and what factors accounted for that in northern Ghana. The study involved 360 farming households selected from the Northern, Upper East and Upper West Regions. The results show that maize farmers obtained 77% of potential output, and could still obtain 23% more through efficient maize cultivation practices under the current production technology. On the whole, as expected, efficient farmers used less amounts of inputs than inefficient farmers. Also, extension services played an important role in boosting the efficiency of farmers. The agricultural extension department should be strengthened to provide effective extension services to farmers to improve cultivation practices.

be improved through informal and non-formal educational platforms where farmers without formal education learn improved cultivation practices. The agricultural extension department should be strengthened to provide effective extension services to farmers to improve on their technical efficiency. Animal and other non-mechanized power sources are complementary technologies and as such should be allowed to co-exist in Ghanaian agriculture.

Subjects: Agriculture & Environmental Sciences; Agriculture; Development Economics

Keywords: data envelopment analysis; technical efficiency; maize; northern Ghana

1. Introduction

The aim of Ghana's Medium Term Agriculture Sector Investment Plan [METASIP] (Ministry of Food and Agriculture [MoFA], 2010) is to modernize agriculture, which will culminate in a structurally transformed economy evident in food security, employment opportunities and poverty reduction. To this end, the country's investment plan is to achieve an agricultural GDP growth of at least 6% annually and which also requires at least 10% of government's total expenditure allocation to achieve growth rates necessary to meet the goal of poverty and hunger eradication. Agriculture in Ghana is dominated by small scale producers. Yields of most crops are generally low (20–60% below their achievable level) with, for example, cassava at 12.4 mt/ha against a potential yield of 28.0 mt/ha (MoFA, 2011).

Maize is a very important staple food in Ghana accounting for more than 50% of total cereal production in the country and 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 with a per capita consumption of 43.8 kg/head in 2005 (MoFA, 2011). Even though, average yield has been rising; from 1.5 mt/ha in 2005/07 to 1.7 mt/ha in 2008/10, this yield is less than a third of the achievable yield of 6.0 mt/ha. This therefore requires an increase in productivity to close the yield gap in order to spur up agricultural growth. Agricultural growth can be further achieved by improving the technical efficiency of farming households in maize cultivation. Maize production is largely dependent on farmers' technical efficiency, which is also a function of their socio-economic indicators and farm characteristics. This raises the research questions: what is the technical efficiency of maize production in northern Ghana? What factors influence efficiency and what input quantities are required to produce at the technically efficient point? Thus, the objective of this study is to assess how maize farmers can produce very close to or on the production possibility frontier through the efficient use of variable inputs. The study of technical efficiency, therefore, gives direction to farmers to employ the right combination of productive resources to achieve food sustainability given the strong linkage between food insecurity and poverty. Indeed, the Demographic and Health Survey (DHS) report further explained that 18.2% of Ghanaians who fell below the extreme poverty line were chronically food insecure (GSS, 2008). In terms of extreme poverty, northern Ghana accounts for 52.7% of the extremely poor in Ghana (Ghana Statistical Service [GSS], 2014). This calls for sustained growth in agriculture to tackle hunger, food insecurity and poverty. This is particularly important because majority of Ghanaians grow and consume maize, and for that matter, any technology that would lead to an increase in productivity of inputs for maize cultivation would bring about real income gains for the rural population.

2. Methodology

2.1. Data, sampling approach and study area

The data were collected between January and February, 2013 in the three regions (Northern, Upper East and Upper West) of northern Ghana for the 2011/2012 cropping season. The three regions of northern Ghana together make up about 41% of the country's total land area (MoFA, 2011). In terms of population, the three regions constitute only about 17% of the country's population (GSS, 2012). Amongst the three regions, Northern Region has the largest population while the Upper West Region has the least population (GSS, 2012). Rainfall distribution is unimodal giving a single growing season of 180–200 days with an annual mean of 1,100 mm. The dry season starts in November and ends in March/April with maximum temperatures of about 42°C occurring towards the end of the dry season. The data collection were carried out in six districts, two districts in each of the three regions. Multi-stage sampling methods were used in identifying a district where six communities were randomly selected in each district and from which 10 maize households were also randomly sampled to get a total of 60 respondents for each district. Each region had a sample size of 120 respondents, thus a total of 360 maize households was reached for the three regions.

2.2. Data envelopment analysis

The efficiency of production firms is usually measured either by parametric (such as the stochastic frontier analysis [SFA]) or by non-parametric methods, such as the data envelopment analysis (DEA), which does not place a priori functional relationship for the production function, as well as the distributional form of the inefficiency component. The disadvantage of the DEA is its inability to separate inefficiency from statistical noise and/or measurement error. Nonetheless, Madau (2012) argues that, under the same set of data, the SFA translog model and the variable returns to scale DEA frontier would produce similar results. Therefore, the SFA model holds no real advantage over DEA in estimating technical efficiency scores and efficiency variability. In spite of the numerous studies carried out on technical efficiency in Ghana, most have focused mainly on the SFA (Addai & Owusu, 2014; Alhassan, 2008; Bempomaa & Acquah de-Graft, 2014; Bhasin, 2002; Donkoh, Ayambila and Abdulai, 2013; Kuwornu, Amoah, & Seini, 2013) with very few using the DEA (Abatania, Hailu, & Mugera, 2012). However, the additional advantage of the input-oriented DEA over the SFA is its ability to identify slacks (excess inputs) after estimating efficiency relative to the production frontier. Koopmans (1951) defined a firm as fully technically efficient when the DEA score is 1 with no slack values for the production inputs. Thus, aside providing the efficiency estimates for the individual maize farmers in this study, the DEA also gives the individual slack inputs for each inefficient farm and how they can become technically efficient relative to the best practice farms that have zero slack values.

The DEA measures the efficiency of farm firms using linear programming techniques to envelop observed input–output vectors as tightly as possible (Boussofiane, Dyson, & Thanassoulis, 1991). It makes a comparison of inefficient firms relative to the “best practice” ones within a sample group (Shafiq & Rehman, 2000). The decision-making unit (DMU) is described as efficient when the DEA score is equal to one and all slacks are equal to zero (Cooper, Seiford, & Tone, 2006; Koopmans, 1951). Charnes, Cooper, and Rhodes (1978), originally used the constant returns to scale to measure efficiency under the assumption that all the DMUs were operating at their optimal scale. Subsequently, Banker, Charnes, and Cooper (1984) used the variable returns to scale (VRS) to measure efficiency thereby allowing the division of efficiency into technical and scale efficiencies.

The input-oriented DEA identifies technical inefficiency as proportional reduction in input use, with output levels held constant (Coelli, Rao, & Battese, 2005) and it is also in line with Farrell’s (1957) input-based estimation of technical inefficiency. More importantly, 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). This approach is widely applied in the literature (e.g. Charnes et al., 1978; Isik & Hassan, 2002, 2003; Hauner, 2005; Havrylchyk, 2006; Pasiouras, 2006, 2007; Rezitis, 2006). On the other hand, Chakraborty, Biswas, and Lewis (1998); Chavas, Petrie, and Roth (2005); Wouterse (2008); and Mansor, Nurjihan, and Hassanpour (2013) used the output-oriented DEA. Coelli and Perelman (1996), however, argue that the choice of orientation has minor effect on the scores obtained and that both the input- and output-oriented models estimate exactly the same frontier and also identify the same set of firms as being efficient. Cooper et al. (2006) estimated input-oriented efficiency under the assumption of convexity, strong disposability and CRS of the economic production activities. Following Shafiq and Rehman (2000), the input-oriented model is empirically given as:

$$Min\ Z_g \tag{1}$$

s.t

$$\sum Y_j\ \lambda_j \leq Y_g \tag{2}$$

$$\sum_{i=1}^{s} X_{ij}\lambda_j - X_g\ Z_g \leq 0 \tag{3}$$

$$X_i,\ Y_j \leq 0 \tag{4}$$

$$\sum \lambda_j = 1 \tag{5}$$

where $j = 1, \ldots,\ 360$ is the number of farms or DMUs in the sample, $i = \ 1,\ \ldots,\ 5$ is the number of inputs included in the analysis and they include farm size (in ha), quantity of seed planted (kg), quantity of fertilizer applied (kg), labour quantity and quantity of weedicides used (litres). Z_g is the relative efficiency score of the DMU, *"g"*, under study, λ_j are lambda values that are used as multipliers for the input levels of a referent farm to indicate the input levels that an inefficient farm should aim at to achieve efficiency, X_{ij} is the level of use for the *i*th input on the *j*th farm, Y_j is the level of output on the *j*th 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 minimum value of Z_g (≤ 1) for the unit *"g"* is calculated by "combining" the performance of all units being analyzed. This is done in such a way that, for each input, the combination of inputs does not exceed the inputs of unit *"g"* and for each output the combination of outputs is at least as great as that of unit *"g"*. On solving the model separately for each DMU in the sample, the efficiency scores (≤1 for the inefficient units and 1 for the efficient ones) and the slack variables are established.

2.3. The Tobit model

The widely used methodology for estimating the determinants of efficiency gaps among DMUs is the Tobit model (Featherstone, Langemeier, & Ismet, 1997; Yong-Bae & Choonjoo, 2010), because all the efficiency indices have 1 as an upper bound and 0 as a lower bound. The Tobit model (Tobin, 1956) describes a non-negative dependent variable, y_i and an independent variable (vector) x_i. Theoretically, the model is expressed as:

$$y_i^* = x_i\beta + u_i \tag{6}$$

$$y_i^* = \begin{cases} y_i^* = x_i\beta + \varepsilon_i & if\ y_i^* > 0 \\ 0 & if\ y_i^* \leq 0 \end{cases} \tag{7}$$

$$u_i \sim IIND(0, \sigma^2) \tag{8}$$

Here the subscript $i = 1, \ldots., n$; y_i^* is an unobserved dependent (latent) variable, x_i is a vector of explanatory variables, β is a vector of unknown parameters, and u_i is a disturbance term.

Empirically, the technical efficiency estimate of each DMU is regressed on a set of socioeconomic variables to explain the determinants of technical efficiency (Bravo-Ureta & Pinheiro, 1993; Coelli, Rahman, & Thirtle, 2002) as:

$$Y_i^* = \beta_0 + \beta_1 M_1 + \beta_2 M_2 + \beta_3 M_3 + \beta_4 M_4 + \beta_5 M_5 + \beta_6 M_6 + U_i \tag{9}$$

where Y_i^* is the technical efficiency estimate of the respondent; M_1 is access to tractor for agricultural mechanization services; M_2 is the years of experience in maize cultivation; M_3 is the educational status of respondents; M_4 is number of agricultural extension visits; and M_5 is sex of the farmer (a dummy variable, 1 for males and 0 for females); M_6 is the amount of credit received during the cropping season (in GH¢[1]); U_i is the error term; and β_i is a vector of parameters to be estimated.

Access to and use of agricultural mechanization services is expected to have a positive effect on technical efficiency. Males are also expected to be more technically efficient in maize production than females in the study area. Similarly, experience, level of formal education, number of agricultural extension visits, amount of credit to support maize production are all also expected to have positive effect on farmers' efficiency. Other variables that could affect efficiency of maize production are training in maize production, distance from home to farm, occurrence of droughts or floods. However, the data set did not contain such information to be used in the analysis.

3. Results and discussion

3.1. Demographic characteristics of respondents

The mean age of about 41 years (see Table 1) in the study area revealed that a typical farmer was within the economically active age bracket as the national description includes people from 15 to 60 years of age. The study found a higher mean household size of 8.66 compared with 6.56 obtained in the 2010 census by the Ghana Statistical Service for northern Ghana. This is also twice the national average of 4.4 (GSS, 2012). Meanwhile, the mean household labour of 5.75 is also less than the average household size. This means that the number of household members that could offer farm labour was far less than the total household members. The discrepancy between household size and household labour has implications for farm labour especially in northern Ghana where household heads rely on their household members to provide labour for almost all of their crop production activities. This also implies that households had more dependants, at least three dependants per household in the study area. Nonetheless, this dependency ratio of 1:3 is lower than the national mean value of 1:4 recorded in the 2010 census (GSS, 2012). The average farm size of 1.76 ha (4.3 acres) is similar to the less than 2 ha reported by the GSS in 2007 further reinforcing the fact that the majority of rural farm households were indeed operating with quite smaller land holdings. Similarly, Nyanteng and Seini (2000) stated that over 90% of the country's food production came from farm holdings of 3 ha or less.

Table 1. Descriptive statistics of variables

Variables	Minimum	Maximum	Mean
Age of respondent (years)	18	79	40.89
Maize plot size (in hectares)	0.2	12.1	1.76
Number of years in maize cultivation	1	40	10.33
Household size	2	35	8.66
Household labour	1	21	5.75
Quantity of maize seed (kg/ha) used in sowing	1.88	55.68	17.35
Quantity of weedicides (litres/ha) used	0	20.45	3.64
Quantity of NPK fertilizer (kg/ha) used	0	1278.40	150.85
Quantity of Ammonia fertilizer (kg/ha) used	0	852.27	103.12
Quantity of maize (kg) harvested	50	18,000	2091
Price in GH¢ per bag (100 kg) of maize	40	80	58.81
Number of visits by agricultural extension agents	1	4	3.07
Amount of credit received in GH¢	0	2000	12.82

Source: Authors' Computation, 2017.

The mean quantity of maize seed used in cultivation was 17.35 kg/ha. This implies a household would need 17.35 kg (about five bowls) to sow a hectare of land.

Similarly, a household on average required 3.64 l (3.6 bottles) of weedicides to apply on a hectare of farm land to control weeds. The mean values of NPK and Ammonia fertilizers were 150.85 kg (about three bags) and 103.12 kg (two bags), respectively. A household therefore used about three bags of NPK and two bags of Ammonia fertilizer to apply on a hectare plot in order to obtain an average yield of 2,091 kg (about 21 bags) of maize. Meanwhile, a household on average, received a credit amount of GH¢ 12.8, which was woefully inadequate to support maize production.

3.2. Empirical findings

The DEA results for Northern Region showed a mean efficiency of 85%. The results further explained that the inputs could be reduced in the following way without affecting current output; farm size by 0.16 ha, quantity of seed by 4.96 kg, fertilizer by 86.51 kg, labour by 0.63 units and weedicides by almost one litre even after an initial reduction of all inputs by 15% as shown in Table 2. Similar interpretation applies to the Upper East and Upper West Regions.

On the whole, the mean efficiency for the pooled sample was 77% and for instance, land area or farm size could be slashed by 0.33 ha without reducing output, despite an initial minimization of all the farm inputs by 23%. A similar study by Shafiq and Rehman (2000) who applied the input-oriented DEA to examine input use inefficiency in cotton production in Pakistan's Punjab region explained that the quantities of inputs used were higher than would be required to achieve present levels of crop output and recommended minimization of input use. Nonetheless, this mean efficiency estimate (77%) is higher than that reported (69.4%) by Coelli et al. (2002) who applied the DEA to examine the technical, allocative and scale efficiency of rice cultivation in Bangladesh, but lower than (89%) reported by Rios and Shively (2005) in a study on farm size and efficiency in Vietnam coffee production.

According to Adu et al. (2014), the maize agronomic practices recommended by the Savannah Agricultural Research Institute of Ghana indicate fertilizer application rate of 180 kg/ha of NPK applied 7–10 days after planting and 120 kg/ha of Sulphate of Ammonia applied 4–6 weeks by drilling 5–7 cm away from the maize plant would produce 4.5-7.5tons/ha depending on the maize variety. Soil management and nutrients conservation efforts can also be complemented by application of organic fertilizer, crop rotation or intercropping with leguminous crops. More so, planting improved maize seeds with good germination rates reduces the number of seeds per hole thereby reducing the quantity of seeds used. Weedicides application could also be reduced by thorough land preparation before ploughing to further suppress weed growth. A look at Table 3 also shows that the technically efficient farmers had farm sizes that were slightly larger than the average for the sampled farmers.

Table 2. Results of input-oriented DEA model for the three regions of northern Ghana

Region	Efficiency Score	Slack input variables					Output
		Farm size (ha)	Seed (kg)	Fertilizer (kg)	Labour	Weedicides (litres)	
Northern	0.85	0.16	4.96	86.51	0.63	0.97	807.26
Upper East	0.76	0.75	8.76	122.62	0.82	1.06	411.51
Upper West	0.69	0.30	4.59	79.92	0.54	1.22	492.34
Pooled	0.77	0.33	6.18	97.09	0.68	1.11	574.23

Source: Authors' Computation, 2017.

Table 3. Comparison of average input use between inefficient and efficient farmers in northern Ghana

Input use	Farm size (Ha)	Fertilizer use (kg)	Seed use (kg)	Weedicides (litres)	Labour quantity	Yield (tons/ha)
Average Inefficient Farmers	3.21	451.32	31.76	5.11	3.63	1.76
Average Efficient Farmers	3.37	395.80	27.04	4.04	3.02	2.34

Source: Authors' Computation, 2017.

More importantly, the efficient farmers used an average of 395.80 kg of fertilizer, 27.04 kg of seed, 4.04 l of weedicides and employed three persons on a 3.37 ha 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 (referent) farmers, they would have to increase plot size by 0.16 ha, reduce chemical fertilizer use by 55.53 kg, seed use by 4.72 kg, weedicides use by 1.07 l and labour by 0.61 in order to boost yield by 0.58 tons/ha.

As regards the technical efficiency scores across the various returns to scale types, the Northern Region had the highest efficiency scores with the VRS specification having a score of 85%. This was followed by the Upper East Region while the Upper West Region recorded the lowest scores amongst the regions. The VRS had the highest technical efficiency estimate of 77% whereas the CRS had the lowest efficiency estimate of 55% for the pooled data as shown in Table 4. On the average, all the three regions including the pooled data exhibited increasing returns to scale. This means that an increase in the use of inputs would lead to a more than proportionate increase in output.

Overall, there was increasing returns to scale (IRS) in maize production. The Northern Region had the highest percentage (95%) of respondents with IRS, followed by the Upper East and the Upper

Table 4. VRS frontier technical efficiency estimates for the three regions

Region	CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS	RTS Meaning
Northern	0.64	0.85	0.76	0.74	0.93	IRS
Upper East	0.55	0.76	0.75	0.71	0.67	IRS
Upper West	0.47	0.69	0.68	0.67	0.75	IRS
Pooled	0.55	0.77	0.73	0.71	0.78	IRS

Source: Authors' Computation, 2017.

Table 5. Distribution of returns to scale (RTS) across the three regions

RTS	Northern		Upper East		Upper West		Pooled	
	Freq	%	Freq	%	Freq	%	Freq	%
DRS	3	2.5	9	7.5	8	6.7	20	5.6
CRS	3	2.5	20	16.7	13	10.8	36	10.0
IRS	114	95	91	75.8	99	82.5	304	84.4
Total	120	100	120	100.0	120	100.0	360	100.0

Source: Authors' Computation, 2017.

West. On the whole, 84.4% of respondents for the pooled data had IRS while 5.6% experienced DRS as presented in Table 5.

3.3. Tobit regression analysis of the determinants of technical efficiency

The determinants of technical efficiency[2] are presented in Table 6. The analysis shows mixed results. For example, farmers who had access to agricultural mechanization services were rather less technically efficient compared with those who did not have access (see Figure 1).

A baseline survey conducted across the country by MoFA in 2005 revealed that about 40% of farmers used some form of agricultural mechanization. The mechanization of farm operations is a very important step toward increasing production efficiency (Kibaara, 2005).

The possible reasons for this result that was also contrary to a priori expectation could be the following. The average farm size for farmers who used agricultural mechanization services was 3.5 ha compared with 0.97 ha for those who did not use any form of agricultural mechanization. Agricultural mechanization services in northern Ghana for maize were mainly ploughing, threshing and carrying farm produce to farmers' homes and market centres. However, many of the conventional production and output enhancing practices, such as sowing, fertilizer application, weeding and weedicides application and even harvesting were mainly manual and a relatively large farm size could be affected if these practices were not carried out in a timely manner.

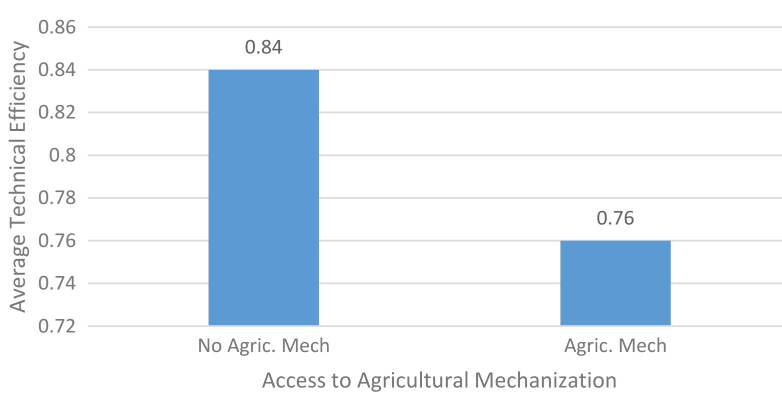
Given that 321 out of 360 respondents had access to agricultural mechanization services, they would still be technically inefficient if access is hampered by significant delays to get the tractors to their plots because of the tractor to farmer ratio of 1:1800 in Ghana (Benin et al., 2011), which is further exacerbated by even fewer tractors in the study area. Timely ploughing is particularly crucial as a survey by Nakamura (2013) in the Northern Region revealed that majority of farmers

Table 6. Tobit analysis of technical efficiency

Variable	Parameter	Coefficients	Standard error
Constant	δ_0	0.799	0.039
Agric. mech.	δ_1	−0.029**	0.012
Experience	δ_2	0.001	0.002
Education	δ_3	−0.006***	0.002
Extension	δ_4	0.027*	0.015
Gender	δ_5	0.019	0.035
Credit	δ_6	8.484E-05	0.000

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

Figure 1. Average efficiency and agricultural mechanization.



experienced about 2–3 weeks delay after the first rains to access tractor ploughing services because tractor owners could not attend to all farmers at the same time. In this case, a smallholder farmer would have a higher chance of ploughing on time compared with a large holder farmer should both farmers succeed in accessing a tractor only late in the ploughing period, because the latter would take more time to complete ploughing. A smallholder farmer could also employ animal ploughing services to stay within the ploughing time, which was also the case in northern Ghana. Bullock ploughing serves as an intermediate and transitional technology between the hoe and cutlass-based agriculture and tractor-based mechanized agriculture. Animal ploughing helps to ease ploughing bottlenecks and complement the use of tractors and as such should be allowed to co-exist in Ghanaian agriculture. Timely access to tractor services could be enhanced more by personal ownership of a tractor than hiring services (Houssou, Diao, & Kolavalli, 2014).

A major consideration for farmers wishing to hire tractor services is timeliness and its effect on farming operations particularly ploughing, sowing, harvesting and more importantly output during the cropping season which is wholly rainfall dependent. In situations where tractor ownership and hiring are not perfect substitutes, there are likely to be delays for farmers in accessing tractor hiring services even though hiring saves the farmer of operating and maintenance cost of the tractor (Edwards, 2009).

Similarly, farmers with no formal education were more technically efficient (79%) than those with formal education (75%) as indicated in Figure 2. Those with no formal education had enough time to attend to their farms compared with those who were either in school or engaged in formal employment after completion of their studies who could only devote Saturday or Sunday for farm activities. This is corroborated by the fact that the average farm size for maize farmers with no formal education was 3.9 ha as against 2.5 ha for those with formal education. More so, many of the farmers in the study area had no formal education because farming is considered as a "profession of the uneducated".

Most strikingly, farmers with no formal education who were 203 out of 360 respondents could also combine the right input mix and produce at higher technical efficiency levels. For example, a farmer does not necessarily need formal education to know and apply the right quantity of weedicides, fertilizer or sowing at optimal plant density as these can easily be learnt by observation or demonstration by a colleague farmer or agricultural extension agent. The lack of formal education by farmers could be mitigated relative to the application of output enhancing inputs with support from agricultural extension agents, agro-inputs dealers, farmer-to-farmer knowledge sharing and learning by doing, which was the case in this study.

The effect of formal education on technical efficiency has been mixed. Wouterse (2008) using the DEA methodology found the education level of the household head significant in determining the technical efficiency of migrant cereal farmers in Burkina Faso.

Figure 2. Average efficiency and educational status.

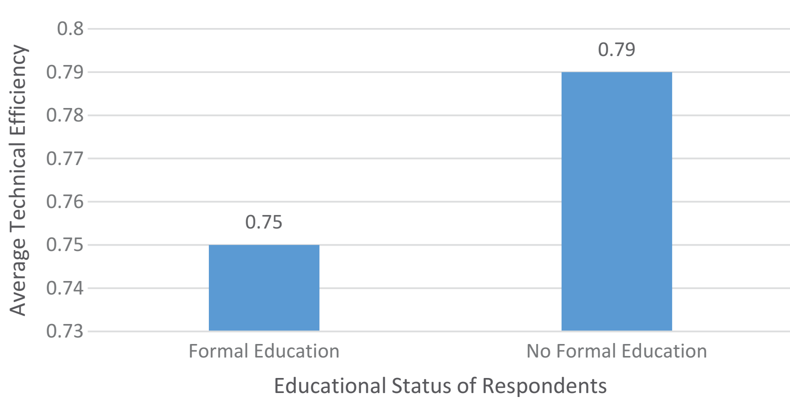
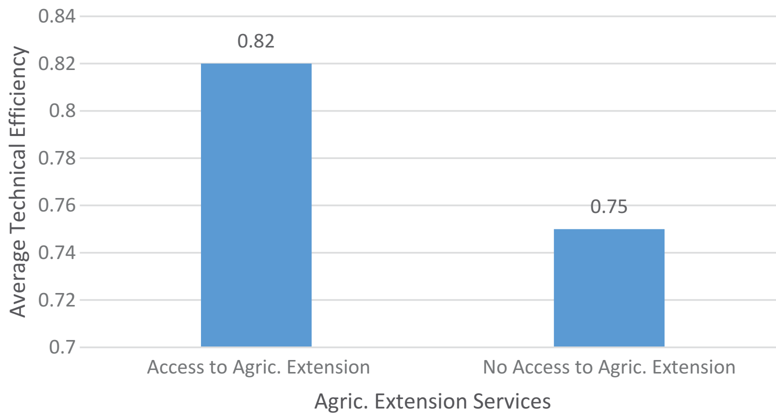


Figure 3. Average efficiency and agricultural extension service.



In line with a priori expectation, farmers who had access to agricultural extension services were more technically efficient (82%) than those without access to agricultural extension (75%) as shown in Figure 3. Agricultural extension agents focus on imparting key messages to farmers with the aim of improving production techniques including land preparation, use of improved seed varieties, crop spacing, as well as the timeliness of operations, such as weeding, pest control and fertilizer application.

According to Evenson (2001) and Gautam (2000), a well-functioning agricultural extension system is pivotal to increasing the productivity of staple food crops and thus presents a credible avenue for moving millions of people out of poverty. The World Development Report (World Bank, 2008) further emphasized the importance of agricultural extension service in the dissemination of technologies adapted to African conditions so as to spur an African green revolution if it is given the necessary institutional support. It can contribute to the reduction of the maize productivity differential by increasing the speed of technology transfer to farmers to improve their cultivation practices. This is because agricultural extension provides the means by which information on new technologies, better farming practices and management skills can be transmitted to farmers. Agricultural research findings would be meaningless, unless they are accepted and adopted by farmers who are the end users of the research output and this adoption is facilitated by agricultural extension workers.

The sex of the household head, number of years of experience in maize cultivation and credit amount were not statistically significant in this study.

4. Conclusions

This study employed the input-oriented DEA to examine the technical efficiency of maize production in northern Ghana using cross-sectional data for the 2011/2012 cropping season. Maize production exhibited increasing returns to scale with a mean technical efficiency of 77%. More so, the quantities of inputs used were higher than would be required to achieve present levels of maize output, and thus accounted for the inefficiency. Access to agricultural mechanization and number of years of formal education had negative effect on efficiency, whereas access to extension service had positive effect. Technical efficiency in maize production could be further boosted through informal and non-formal educational platforms where farmers learn improved cultivation practices due to the low formal education of farmers. Similarly, the agricultural extension department of MoFA should be strengthened to provide effective extension services to farmers to improve their technical efficiency. Last but not least, animal ploughing and other non-mechanized methods help to ease ploughing bottlenecks and complement the use of tractors and as such should be allowed to co-exist in Ghanaian agriculture.

Abbreviations

CRS – Constant Returns to Scale; **DEA** – Data Envelopment Analysis; **DHS** – Demographic and Health Survey; **DMU** – Decision Making Unit; **DRS** – Decreasing Returns to Scale; **GDP** – Gross Domestic Product; **GSS** – Ghana Statistical Service; **IRS** – Increasing Returns to Scale; **METASSIP** – Medium Term Agriculture Sub-Sector Investment Plan; **MoFA** – Ministry of Food and Agriculture; **NIRS** – Non-Increasing Returns to Scale; **SSA** – Sub-Saharan Africa; **TE** – Technical Efficiency; **VRS** – Variable Returns to Scale.

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Competing Interest

The authors declare no competing interests.

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Declarations

A related study entitled "*Do Data Envelopment and Stochastic Frontier Analyses produce similar efficiency estimates? The case of Ghanaian maize production*" has been accepted by the African Journal of Agricultural and Resource Economics to be published in September, 2018. We wish to state that both papers were written concurrently and so proper referencing could not be made of each other.

Authors' contributions

SA designed the study, structured the concepts, reviewed literature and much of the data analysis under the guidance of PKN and SAD. All authors read and approved the final manuscript.

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Notes

1. Northern Ghana comprises the Northern, Upper East and Upper West Regions which are all located in the north of the country.
2. 1 USD = 4.5GH¢ as at July, 25, 2018.
3. We performed the estimations for the determinants of technical efficiency using the fractional response and compared with the Tobit. The Akaike information criterion (AIC) was used to inform the choice between these two models. The Tobit model was chosen because it had the lowest AIC value. See appendix tables (A1 and A2) for the results.

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Appendix

Table A1. DEA Analysis of the Determinants of Technical Efficiency

Variable	Parameter	Tobit model	Fractional response model
		Coefficient	**Coefficient**
Constant	δ_0	0.799	1. 758
		(0.039)	(0.328)
Agric. mech.	δ_1	−0.029**	−0.702**
		(0.012)	(0.276)
Experience	δ_2	0.000	0.002
		(0.002)	(0.011)
Education	δ_3	−0.006**	−0.034**
		(0.002)	(0.012)
Extension	δ_4	0.027*	0.199
		(0.015)	(0.082)
Gender	δ_5	0.019	0.105
		(0.035)	(0.161)
Credit	δ_6	8.484E-05	1.162E-04
		(0.000)	(1.470E-04)

Figures in brackets () are robust standard errors. ***, ** and **indicate values statistically significant at 1%, 5% and 10%, respectively.

The authors performed the estimations for the determinants of technical efficiency using the fractional response and compared with the Tobit. The Akaike information criterion (AIC) was used to inform the choice of selection of the between these two models. The Tobit model was chosen because it had the lowest AIC value. It is expressed as:

$$\frac{-2logL}{n} + \frac{2k}{n}$$

Where L is the log likelihood function, n is the sample size and k is the number of parameters in the model.

Table A2. Results of Akaike information criterion model selection test

Model	log likelihood function	Number of parameters	AIC	Decision
Tobit	18.458	6	−0.069	Accept
Fractional response	−192.937	6	1.038	Reject

Sample size is 360 for each model.