

## Technical Efficiency of Maize Farmers in Ghana: A Stochastic Frontier Approach

*Abdul-Hanan Abdallah and Awal Abdul-Rahaman*

Department of Agribusiness Management and Finance, Faculty of Agribusiness and Communication Sciences, University for Development Studies, Ghana

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**ABSTRACT:** The purpose of this study is to examine the technical efficiency of Ghanaian maize farmers from the parametric perspective. In this study, the stochastic frontier approach (SFA) assumed the Cobb-Douglas functional form and technical efficiency of Ghanaian maize farmers is then estimated using first phase data from the database of sub-Saharan Africa's intensification of food crops agriculture (*Afrint I*). Using household characteristics, human capital, farmer's resource situation, social capital and experience variables, the study found that farmers are producing below the frontier with average technical efficiency of 53 percent. Policy variables such as *credit access; education and extension access* and *farm size* played a stronger role in technical efficiency levels.

**KEYWORDS:** Technical Efficiency, Stochastic Frontier Approach, Maize farmers, Ghana.

### 1 INTRODUCTION

The role of agriculture in the Ghanaian economy cannot be overemphasized. Until recently, agricultural sector was central to economic activities in Ghana accounting for 40.4 percent of GDP with an expected annual growth rate of 4.3 percent (MoFA, 2013). Currently, the agriculture sector is persistently reported to account for the greatest proportion of Ghana's export earnings with principal agricultural exports being cocoa, timber, horticultural products, fish/sea foods, game and wildlife (Kuwornu et al, 2013). For example, in 2006, 41.1% of foreign exchange was derived from traditional and non-traditional crops (MoFA, 2013). It is solely responsible for providing food security for both the rural and urban population and supplying raw materials to feed industries. Components of the sector include crops, cocoa, livestock, forestry and fisheries with the crops sub-sector leading in annual GDP contribution (MoFA, 2013). The major staple crops produced in Ghana include cereals (mainly rice and maize) and starchy staples such as yams, cassava and plantain.

Among the cereals, maize is the largest staple crop in Ghana and contributes significantly to consumer diets. For instance, per the study of Morris et al (2001), a nationwide survey carried out in 1990 revealed 94% of households relying on maize for their daily meals. Per that same study (Morris et al., 2001), maize and maize-based foods were reported to account for 10.8% and 10.3% of household food expenditures by the poor and all income groups respectively. It is the number one crop in terms of area planted and accounts for 50-60% of total cereal production.

Additionally, maize represents the second largest commodity crop in the country after cocoa. It is one of the most important crops for Ghana's agricultural sector and for food security (MiDA, 2012). The production of maize in Ghana is for three main reasons: food production for consumption, raw materials for industry and production for export (Djokoto, 2012). Unfortunately, the maize sector is unable to meet the targets as producers are repeatedly reported to produce yields below attainable levels and thus, causing a deficit amounting to \$45.886 million plus supplement from food aids, amounting to 9346.0 Mt between 2000 and 2010 alone (MoFA, 2013). Also, projected figures for household consumption depicts that there is considerable unfulfilled demand for processed maize for human uses and for the growing animal feed sector within Ghana (MoFA, 2013). Also in the last four years, the annual domestic deficit has been estimated to fall between 84,000 and 145,000 metric tons. As a result, a shortfall in domestic production ranges between 9 and 15 percent of total human

consumption in these years (MiDA, 2012) and thus, causing a variation in average rural wholesale price from 2001 to 2010 (see Figure 1 below).

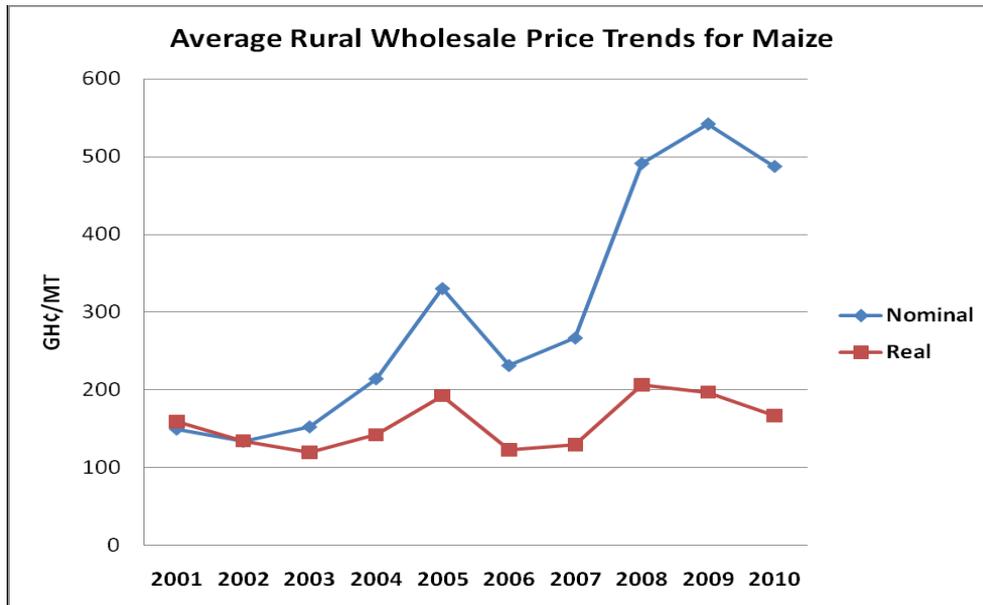


Figure 1: Average rural wholesale price trends for maize

Source: MoFA, 2013.

The Ghana government's policy objective for the grain sub-sector is to encourage increased production so that self-sufficiency and food security for the country can be achieved. It is as a result of this objective that government partnered with the International Institute of Tropical Agriculture (IITA), which has a mandate for maize research in West and Central Africa, to develop and disseminate improved maize technologies to meet the requirements of their major clients and small-scale farmers (Manyong et al., 2000). However, despite this effort, the performance of maize sector has been dwindling per the report of MiDA (2012). This raises questions about the efficiency with which resources are used in Ghana especially in periods when aids are supplied to farmers under favorable weather conditions. One way of answering these questions is to unravel the current levels of technical efficiency of producers. In this manner, production losses due to inappropriate combination of inputs and technologies will be appreciated. This will provide basis for the formulation of specific policies for boosting the efficiency of maize production in the study area and thus lift farmers to a commercial level and out of poverty.

The rest of the study is structured as follows. Section 2 outlines the methodology employed; section 3 presents the empirical results; and section 4 provides the conclusions.

## 2 METHODOLOGICAL FRAMEWORK

The concept of technical efficiency can be traced back to productive efficiency as first introduced by Farrell (1957) who argued that there were two components of efficiency: technical efficiency and allocative efficiency. In accordance with Farrell's methodology, productive efficiency is equal to the product of technical efficiency and allocative efficiency where, technical efficiency is associated with the ability to produce on the frontier isoquant. In other words, technical inefficiency reflects deviations from the frontier isoquant. Since then, there has been growing literature on the alternative techniques used in measuring technical efficiency of smallholder farmers. Dominant among these techniques are the econometric (or parametric) approach and the mathematical (or non-parametric) approach. The two techniques use different methods to envelop data, and in doing so they make different accommodation for random noise and for flexibility in the structure of production technology.

In the case of the former, a functional form is imposed on the production function and assumptions are made about the data used while there is no such approach in the latter. Popular among nonparametric approaches is the Data Envelopment

Analysis (DEA) while that of the parametric include the Cobb-Douglas, constant elasticity of substitution and translog production functions (see Forsund et al., 1980; Battese, 1992; Coelli et al., 1998).

Also, the non-parametric approach assumes that all the deviations from the frontier are as a result of firms' inefficiency. The parametric approach which is stochastic on the other hand, assume that part of the deviations from the frontier are due to random events and part is due to firm specific inefficiency and therefore decomposes the error term into a two-sided random error that captures the random effects outside the control of the firm and the one-sided efficiency component as argued by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

The stochastic production frontier is therefore defined as:

$$Y_i = f(X_i; \alpha_i) + \varepsilon \tag{1}$$

Where  $Y_i$  is the output of farmer  $i$ ,  $X_i$  are the input variables,  $\alpha_i$  are production coefficients and  $\varepsilon$  is the "error term that is composed of two elements, that is:

$$\varepsilon = v_i - u_i \tag{2}$$

Where  $v_i$  is the stochastic error which is assumed to be identically, independently and normally distributed with zero mean and a constant variance ( $\sigma_v^2$ ). The other second component ( $u_i$ ) is a one-sided error term which is independent of  $v_i$  and is normally distributed with zero mean and a constant variance ( $\sigma_u^2$ ), allowing the actual production to fall below the frontier but without attributing all short falls in output from the frontier as inefficiency.

The maximum likelihood estimation of equation (1) yields consistent estimators for  $\beta$ ,  $\lambda$  and  $\sigma^2$  where  $\beta$  is a vector of the unknown parameters,  $\lambda = \sigma_u/\sigma_v$  and  $\sigma^2 = \sigma_u^2 + \sigma_v^2$ . Given the fitted values of  $\varepsilon$  and the respective parameters, Jondrow et al (1982) argued that conclusions can be drawn about the technical inefficiency ( $u_i$ ) of individual farmers. This is given by the mean of the conditional distribution of inefficiency term  $u_i$  defined as:

$$E(u|\varepsilon_i) = \frac{\sigma_u - \sigma_v}{\sigma} - \left[ \frac{f(\varepsilon_i\lambda|\sigma)}{1 - F(\varepsilon_i\lambda|\sigma)} - \frac{\varepsilon_i\lambda}{\sigma} \right] \tag{3}$$

Where  $\lambda = \sigma_u/\sigma_v$ , while  $f$  and  $F$  stand for the standard normal density and cumulative distribution function, respectively evaluated at  $\varepsilon_i\lambda/\sigma$ . We define the farm-specific technical efficiency in terms of observed output ( $Y_i$ ) to the corresponding frontier output ( $Y_i^*$ ) using the existing technology derived from the equation above as:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{E(Y_i|u_i, X_i)}{E(Y_i|u_i = 0, X_i)} = e^{-[E(u_i|\varepsilon_i)]} \tag{4}$$

The values of TE range between 0 and 1 where the latter shows that the farm is fully efficient.

**2.1 STOCHASTIC FRONTIER PRODUCTION FUNCTION**

This study uses the stochastic frontier approach (SFA) to estimate the technical efficiency of maize farmers. The stochastic frontier production function independently proposed by Aigner et al., (1977) and Meeusen and Broeck (1977) decomposes the error term into a two-sided random error that captures the random effects outside the control of the farmer and the one-sided inefficiency component. Thus, the stochastic approach allows for statistical noise (Thiam et al., 2001). The general stochastic model is given as:

$$Y_i = f(X_i; \alpha_i)\varepsilon \tag{5}$$

Where,  $i=1, 2, \dots, n$

In this study, a Cobb-Douglas production function was used as the functional form of the stochastic frontier production function to define the relationship between output and inputs. The reason for choosing this type of production function is that it is linear in its logarithmic form, and allows for the usage of Ordinary Least Squares (OLS). The Cobb-Douglas functional form is not only simple but it is also self-dual. At the same time, this function type has been widely used for production function analysis by many researchers (Battese et al., 1993; Bravo-Ureta and Pinheiro, 1993; Djokoto, 2012).

However, the Cobb-Douglas production function model has a number of limitations. The major criticism is that it cannot represent all the three stages of neoclassical production function,. Secondly, the elasticities of this type of a function are constant irrespective of the amount of input used. However, regardless of these limitations the Cobb-Douglas production function was used for its mathematical simplicity. It is also not exclusive to labour and capital but to other variables.

Theoretically Cobb-Douglas production function in this study is expressed as follows:

$$\ln Y = \ln \beta_0 + \sum_{j=1}^3 \beta_j \ln X_{ji} + v_i - u_i \quad (6)$$

Where  $\ln$  represents logarithm to base  $e$ ,  $Y$  is the value of output of maize (in GH¢);  $X_1$  is farm size measured in hectares;  $X_2$  is the labour cost (in GH¢);  $X_3$  is cost of fertilizer used (in GH¢);  $X_4$  is the value of seeds used,  $X_5$  the value of agrochemicals used (in GH¢);  $v_i$  is a random error that is assumed to be independently and identically distributed as  $N(0, \sigma_v^2)$  random variables and  $u_i$  is the non-negative technical inefficiency effects that are assumed to be independently distributed among themselves and between the  $v_i$ s, such that  $u_i$  is defined by the truncation (at zero) of the  $N(\mu_u, \sigma_u^2)$  distribution, where  $u_i$  is defined by:

$$u_i = \theta_0 + \sum_{j=1}^8 \theta_j Z_{ji} \quad (7)$$

Where  $Z_1$  is the dummy variable that has a value of 1 if the farmer is a male, and 0 if the farmer is a female (*gender dummy*),  $Z_2$  represents the age of the household head measured in years and included to account for human capital,  $Z_3$  represents the years of formal education of the farmer,  $Z_4$  represents the farm size (in acres),  $Z_5$  is the dummy variable that has a value of 1 if the farmer used irrigation and 0 if otherwise (*irrigation dummy*),  $Z_6$  is the dummy variable that has a value of 1 if the farmer received extension services, and 0 if otherwise (*extension dummy*),  $Z_7$  is the dummy variable that has a value of 1 if the farmer is a member of a farmer-based group and 0 otherwise (*group dummy*) and  $Z_8$  is the dummy variable that has a value of 1 if the farmer access credit, and 0 if otherwise (*credit dummy*)

For constant returns to scale, the sum of the parameter coefficients,  $\beta_s$  must be equal to one (1). For increasing returns to scale, they must be greater than one, and for decreasing returns to scale they must be less than one. In mathematical form the returns can be expressed as follows:

$$\beta_i = \frac{\delta Y / Y}{\delta X_i / X_i} \quad (8)$$

Where  $\beta_i$  is the elasticity of production with respect to input used and considered the most important property of the Cobb-Douglas production function.

## 2.2 DATA AND DESCRIPTIVE STATISTICS

The data used for this study are drawn from the database of sub-Saharan Africa's intensification of food crops agriculture (*Afrint*). The data consisted of two phases, *Afrint I*, which lasted from 2001 to 2004, and *Afrint II* between 2007 and 2010. The first phase of data (*Afrint I*) used for this study contains primarily information of four important staple food crops in sub-Saharan Africa (including Ghana, Kenya, Malawi, Nigeria, Tanzania, Ethiopia, Mozambique, Uganda and Zambia) namely maize, sorghum, rice and cassava. The countries were selected based on their suitability to the charting progress in intensification, induced from below by farmers themselves, or state induced, as in the Asian Green Revolution. According to the *Afrint*, the sample was drawn in four stages, of which the country selection described above was the first one. The next stage was regions within countries, followed by selection of villages within regions, and with selection of farm households as the last stage. All stages except the final one (where households were sampled after having made up household lists) have been based on purposive sampling. To ensure credibility of data, point estimates from the sample were compared with those from other sources, for examples yields for the various crops with FAO statistics, but no apparent sample bias was detected. This paper uses data from 434 farmers in Ghana and concentrate primarily on variables affecting maize production. Readers interested in performance of the other crops are referred to the more comprehensive CABI publication (Aryeetey et al. 2011). Thus, the summary of the descriptive statistics of the explanatory variables used in this study is presented in Table 1.

Previous studies of peasant agriculture have shown that household outputs can be captured using value of output of the farmer (Coelli and Fleming, 2004; Chavas et al., 2005; Gonzalez and Lopez, 2007). For this reason, output is therefore represented by its value (GH¢) and the result indicate that on average the *total value of output* was found to be GH¢ 254.13. This was achieved by utilizing on average, less than 1 hectare of *land*, GH¢ 13.23 of *labour*, GH¢ 20.56 of *fertilizer*, GH¢ 52.09 of *seeds* and GH¢ 53.02 of *agro-chemicals* for production.

As indicated, the stochastic frontier methodology used in this study makes it possible to evaluate factors related with inefficiency. To do so, several socioeconomic and technical variables were incorporated into the model based on the

literature and on data availability. For example, *education* and *extension* variables were incorporated to capture human capital for maize cultivation while *age* represents farmer's experience. For these variables, as the statistics indicate, the population of Ghanaian maize farmers is dominated by the middle-aged whose educational level is at the minimal. The statistics also indicate that about 71 percent of the farmers received extension services. To account for household characteristics, *gender* and *credit* dummies were included and the results show that more than half (57 percent) of the population are males while close to 25 percent access credit. In addition, *membership to association*, a dummy variable that is equal to 1 if the household head is a member of a social group, is included as a proxy for social capital. Meanwhile, 22 percent of the respondents were members of social groups existing in their various communities. Finally, *irrigation* and *farm size* variables were incorporated to capture the farmer's resource situation since abundant resource stocks can improve efficiency. However, less than 30 percent had access to irrigation water supply.

Table 1: Summary Statistics of Variables

Variable	Mean	Std. Dev.
Revenue (GH¢)	254.129	416.211
Farm size (ha)	0.780	3.006
Labour cost (GH¢)	13.229	70.032
Fertilizer cost (GH¢)	20.556	56.819
Seed (GH¢)	52.088	101.500
Agro-chemicals (GH¢)	53.015	321.120
Gender (dummy)	0.57	0.455
Age of farm manager (in years)	49.168	14.954
Education (in years)	5.747	5.274
Irrigation (dummy)	0.295	0.457
Extension services (dummy)	0.712	0.453
Membership to association (dummy)	0.221	0.416
Credit access (dummy)	0.247	0.431

Source: Authors' computation based on survey, 2002

### 3 RESULTS AND DISCUSSIONS

The maximum likelihood estimates are presented in Table 2. The function coefficient which measures the proportional change in output when all inputs included in the model are changed in the same proportion is approximately 0.78, which indicates that returns to size are decreasing. Out of the five variables in the Cobb-Douglas stochastic frontier model, the parameter estimates of three variables are found to be statistically significant. These are *farm size*, *labour cost* and *agro-chemicals*. Additionally, all the parameter estimates of these variables are significant at 1%. This means that a 1% increase in each of these variables used in the production of maize will lead to an increase in output value by 0.32%, 0.17% and 0.28% respectively. The result exhibited by agro-chemicals is in line with the *a priori* expectation of this study and that of Kwarteng and Towler (1995) who contend that weeds and fungi attacks on maize plant reduce its ability to photosynthesize leading to drastic yield reduction. Application of chemicals protect the maize from the destruction of pests, insects and fungi among others as the activities of these organisms on maize lead to lower levels of output. A farmer who uses agro-chemicals therefore stands the chance of increasing maize output. For labour, the result is also consistent with Amaza et al., (2001) who reveal that farmers who had the main objective of income maximization in food crop production will tend to allocate hired labour more efficiently. Food crop production such as maize is labour intensive and therefore will require more labour especially for weeding and harvesting operations.

Turning to the technical efficiency model, the parameter  $\gamma = \sigma_u^2 / \sigma^2$  is statistically significant at the 5% level, with an estimated value of 0.94. These results indicate that inefficiency is highly significant among the studied households. This might also be interpreted to mean that the differences between actual (observed) and frontier output is dominated by technical inefficiency (that is, factors within the control of the farmers). This thus, confirms that technical inefficiency is stochastic in the area.

All coefficients for the human capital variables (*education* and *extension*) present positive and significant effects on household technical efficiency. These results support the premise that increases in human capital enable rural households to improve resource utilisation and thus achieve higher productivity (Solís et al., 2008). As found in some studies (e.g. Oyewo, 2011), education enable farmers update their emerging technologies and hence become more efficient than their illiterates counterparts. As a matter of fact, positive relationship between *extension* and efficiency appears to be the most robust

finding in much efficiency literature as argued Bravo-Ureta and Pinheiro (1993). The result is consistent with the notion that public investment geared to improving provision of managerial support and the dissemination of information to farmers via extension programs or other forms of nonformal education are likely to lead to a higher levels of efficiency.

Also, the variables that constitute household characteristics (*gender and credit access*) present positive and statistically significant effects on TE. For *gender*, the results suggest the efficiency of male-headed households over their female counterparts. Women performed crucial roles in the domestic and economic life of society which affected their technical efficiency. This included the unmeasured non-economic activities (such as child care, cooking, cleaning, etc.) performed by females in the household. Moreover, some customs, traditions, religious beliefs, and social norms placed restrictions on women's activities both on- and off-farm and hence their ability to access new information and use technologies. This finding is in line with that of Solís *et al.* (2008) on technical efficiency and soil conservation in El Salvador and Honduras where female-headed households exhibited lower technical efficiency than male-headed households.

The significant and positive effect of *credit* on TE suggest that farmers with more access to credit are technically efficient than their inaccessible counterparts. The result is not surprising since credit enable farmers to pay for the new technology and undertake long-term investments that improve efficiency.

Also, *age* variable which is used to capture "experience" also had a negative effect on technical inefficiency and was statistically significant at 1%. This suggests that farmers with many years of experience are more technically efficient than those with few years. It is often argued that increase in farming experience provides better knowledge about the production environment in which decisions are made (Oyewol, 2009; Abdulai and Huffman, 2000; Lapple, 2010).

With respect to the variables used to capture the farmer's resource situation, only *farm size* exhibit a positive and significant relation with efficiency. The link between *farm size* and efficiency has been a major discussion in literature but some have found no statistically significant correlation between *farm size* and technical efficiency (Bravo-Ureta and Evenson, 1994). In contrast, the result in this study as in other studies (Bravo-Ureta and Pinheiro, 1997; Aboki *et al.*, 2013 etc.) supports the notion that large farms have efficiency advantage over the other farms in the sample. Already, most of the increases in output over recent years have been associated to increases in the area under maize cultivation. Land plays a vital role in farming with an impact on productivity and as one of the most available resources one can use efficiently.

*Membership to association* which is a proxy for social capital is positive and significant at 10% level. This implies that a farmers' social capital decreases efficiency in maize production. The result of the social capital variable contradicts the finding of Seligson (1982).

Table 2: MLE estimates for stochastic production function for Ghana and Nigeria

Variable	Coefficient	Standard Error
<b>Stochastic frontier</b>		
Lnfarm size	0.319	0.050***
Lnlabor cost	0.174	0.030***
Lnfertilizer	0.028	0.033
Lnseeds	0.048	0.052
Lnchemicals	0.282	0.058***
Constant	2.740	0.060***
<b>Inefficiency model</b>		
Gender	-0.428	0.161***
Age of farm manager	-0.009	0.003**
Education	-0.071	0.013***
Farm size	-0.290	0.033***
Irrigation	0.107	0.215
Extension services	-0.297	0.123**
Membership group	0.326	0.128**
Credit access	-0.211	0.159
Constant	1.625	0.236***
<b>Variance parameter</b>		
$\sigma^2 = \sigma_v^2 + \sigma_u^2$	0.659	0.086*
$\gamma = \sigma_u^2 / \sigma^2$	0.937	0.018**
$\sigma_u^2$	0.618	0.088*
$\sigma_v^2$	0.041	0.010**
Mean technical efficiency	0.527	
Function coefficient	0.775	
Log likelihood	373.003	

Note: \*, \*\* and \*\*\* denote  $p < 0.001$ ;  $p < 0.005$  and  $p < 0.10$ , respectively.

Source: Authors' computation based on survey, 2002

### 3.1 LEVELS OF TECHNICAL EFFICIENCY OF MAIZE FARMERS

The results obtained from the econometric estimation indicate that technical efficiency indices range from less than 50 percent to 100 percent for the farms in the sample with an average of 53 percent (Table 3). This is less than 68 percent found by Rao *et al.* (2003) in their study where they compared African agricultural sector with world agricultural sector using 1986-1990 panel data. Though comparisons cannot be made due to differences in geographical location of farmers and use of different technologies in production, the mean technical efficiency of Ghana is far below that of the averages for Central (95 percent), Eastern (85 percent), Northern (95 percent), Western (92 percent), Southern Africa (96 percent) and Europe (90 percent) as revealed by Nkamleu *et al.* (2006) and Andrew and Cesare (2008). This indicates that the maize farmers in the study area produced 53 percent of the potential stochastic frontier output based on the present state of technologies as well as the level of input. These results imply that if the average farmer in the sample was to achieve the technical efficiency level of his or her most efficient counterpart in Ghana, he or she would realize 47 percent more productivity. Possibly, the adoption of the practice of technologies will increase maize production in the region by an average of 47 percent to enable these maize farmers to attain the potential stochastic frontier output level. Also, the wide range of technical efficiency values indicates large variations in performance across farms. For example, the results show that 43 percent of the farmers have technical efficiency below 50 percent followed by 17 percent of the population whose efficiency ranges from 71 percent to 80 percent. This closely followed by farmers with efficiency values ranging from 61 percent to 70 percent. Further, the results show that few of the farmers (less than 2 percent) are producing maize with technical efficiency ranging from 91 to 100 percent.

**Table 3: Technical efficiency distribution of maize farmers in Ghana**

Efficiency range	Frequency	Percent
≤ 0.5	187	43.1
0.51-0.60	58	13.4
0.61-0.70	68	15.7
0.71-0.80	74	17.0
0.81-0.90	42	9.7
0.91-1.00	5	1.2
Total	434	100.0

Source: Authors' computation based on survey, 2002

#### 4 CONCLUDING REMARKS

In this study, as in most empirical works, the stochastic frontier production function to assume the Cobb-Douglas functional form and the technical efficiency of Ghanaian maize farmers is estimated using data from the database of sub-Saharan Africa's intensification of food crops agriculture (*Afrint I*). Also, the effects of policy variables and farmer characteristics on technical efficiency are also estimated. The study obtained two important results. First, the study found that that returns to size are decreasing and that substantial gains in output can be realized by increasing the levels of inputs used in production. In particular, factors such as *farm size, labour and access to agro-chemicals* are the significant determinant of maize output. Second, the study indicates large variations in performance across farms in 2002 with an average technical efficiency of 53 percent in Ghana. Significant factors that contribute to technical efficiency include household characteristics (*sex and credit access*), human capital (*education and extension*), farmer's resource situation (*farm size*) and years of experience (*age of the farm manager*).

From policy point of view, household characteristics such as *credit access*; human capital such as *education and extension access* and farmer's resource situation such as *farm size* are the variables found to be most promising for action. For farmer's resource situation, reducing market imperfections in the pricing of natural resources such as land will improve farmers' access for farming to increase both efficiency and output. Concerning credit access, there is the need for stakeholders to streamline loan application procedures, intensify education of farmers on loan procedures and promote flexibility in types of collateral demanded by financial institutions in order to enhance access. With regard to the human capital variables, the use of mass extension methods should be emphasized to facilitate the education of farmers on emerging technologies in farming since there is limited number of extension officers in the country. For instance, mass communication through radio, TV, communication vans and dissemination through farmer groups can be used to facilitate the education of these farmers to improve in technical efficiency.

It must be indicated clearly that these results should not be extended to economic efficiency since the allocative efficiency component is not considered in this study. Also, caution should be taken in the interpretation of these results because the data could not permit the incorporation of all variables that might affect technical efficiency.

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