Estimating Economic Efficiency of Mango Production in Ghana

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Abstract

In Ghana, Mango production is the major cash crop activity in the Yilo Krobo Municipality. However, the productivity of the crop has been persistently low over the past years. Studies have suggested that one key factor of productivity growth is efficiency in resource and technology use. This study estimated the economic efficiency of mango production to determine the scope for an increase in mango production using the existing technology. A multistage sampling technique was used to randomly select and collect primary data from sixty two registered mango farmers. Stochastic production frontier analysis was used to estimate the economic efficiencies and their determinants among mango farmers. The results of the analysis indicated that mango farmers were technically, allocatively and economically inefficient, and that the presence of technical allocative and economic inefficiencies had effects on mango production. In addition, the results revealed that farm-specific and farmer-specific characteristics were significant predictors of the technical, allocative and economic inefficiency levels exhibited by mango farmers. Furthermore, farmers exhibited increasing returns to scale. Based on these findings, policy makers should focus on promoting efficient use of existing technology and resources in mango production. The Ministry of Food and Agriculture should develop an integrated and holistic extension strategy to provide training for farmers on resource use efficiency, information, and access to inputs and services.

Keywords: Mango production, economic efficiency, stochastic frontier analysis, Ghana
INTRODUCTION

Ghana has comparative advantage in mango production due to its bimodal rainfall system, and this is accredited to the Yilo Krobo Municipality (Ministry of Food and Agriculture [MoFA], 2013; Micah & Inkoom, 2016). The Adventist Development Relief Agency [ADRA] (2006) reported that mango production is one area if well developed and harnessed can easily become a major economic boost after cocoa. In taking advantage of this great economic potential presented by mango production, there has been an intensive private and public investment as well as introduction of improved technologies and innovations to farmers. Despite all these interventions, empirical evidence shows a continuous decline in mango output. In addition, inefficiency in production has been identified as a major factor in the low productivity that has characterized mango production in the Municipality (MoFA, 2013). In dealing with decline in agricultural productivity, most Sub-Saharan African countries often resort to the use of new technologies and innovations as strategies to increase agricultural productivity. However, it has been proven that productivity growth is not only achieved through the introduction of new technologies to farmers but by the efficient use of the technologies (Wambui, 2005; Sentumbwe, 2007; Farrell (1957). As noted by Farrell (1957) the measurement of efficiency (that is, technical efficiency, allocative efficiency or economic efficiency), is an important factor for productivity growth and that output growth is not only achieved through technical innovation but also through the efficiency with which such technologies are used. Furthermore, it is conceived that farm firms could increase their productivity or output growth even when there is no technical change. This is achieved by making a more efficient use of inputs and by operating closer to the technology frontier (Coelli, Rao, O’Donnell, & Battese, 2005). It is believed that, the reduction of inefficiencies is usually within the control of the farm firm. Thus, the objective of this efficiency analysis is to isolate the efficiency component in order to measure its contribution to productivity. In addition, the estimation of efficiency is very functional as it indicates the performance measure of production units. Furthermore, the measurement of determinants of inefficiency enhances the identification of the sources of efficiency differentials among production units (Wambui, 2005; Sentumbwe, 2007; Farrell 1957; Coelli et al., 2005). From the aforementioned, the empirical analysis of economic efficiency is important to determine the benefit that can be obtained by improving the performance in mango production with a given input set and the existing technology.

The general objective of the study was to examine the economic efficiency in mango production in the Yilo Krobo Municipality in the Eastern Region of Ghana. Specifically, the study sought to:

- estimate the technical, allocative and economic efficiencies in mango production
Examine the determinants of technical, allocative and economic efficiencies in mango production.

Research Questions

- Are mango farmers economically, technically and allocatively efficient in production?
- What are the determinants of economic, technical and allocative efficiencies in mango production?

Conceptual and Theoretical Underpinning

In economic literature, production is defined as the process of transforming inputs into economically useful output (Greene, 2007). With the problem of resource scarcity, both economic theorist and policy maker deem it necessary that production units are able to increase output at existing technology without absorbing additional resource. This opened the door to discussion on efficiency in production. Farrell in 1957, building on the work of Koopmans (1951) and Debreu (1951), provided a sound theoretical and empirical measure of productive efficiency (Kumbhakar & Lovell, 2000; Ouattara, 2012; Coelli et al., 2005). Farrell’s effort provided a more satisfactory approach to estimating farm level efficiency—one which accounts for all inputs and yet avoid the index number problem (Farrell, 1957). Since then, efficiency estimation in agricultural production has remained an area of important research. This is because it is a factor for productivity growth as it shows the extent to which it is possible to raise productivity with the existing resource base and available technology. Efficiency therefore, defines the ability of a firm using the existing technology to produce as large as possible an optimal output given a set of inputs, at the minimum cost (Farrell, 1957; Lovell, 1993; Greene, 2007). The identification of an efficient (best-practicing) production unit is known by the point on the production frontier or the distance from the frontier (Daraio & Simar, 2007; Coelli et al., 2005). Farrell (1957) posited that efficiency has two main components: technical efficiency which measures the success of a firm to obtain maximal output from a given set of inputs, and allocative efficiency which measures the success of a firm to use the inputs in an optimal proportion, given their respective prices and the production technology. The combination of these two measures provides an overall measure for economic efficiency. As components of economic efficiency, technical and allocative efficiency can be derived from production and cost functions respectively. Economic efficiency (EE) measurement requires the input and/or output quantity data, together with input and/or output price data as well as producer’s behavioral assumption. Behavioral assumption of producers can be cost minimization, profit maximization, or revenue maximization (Farrell, 1957; Battese, 1992; Coelli, Rao, O’Donnell, & Battese, 2005). As indicated by Chukwuji, et al., (2006) economic efficiency is realized when the producer combines resources in the least combination to obtain maximum output (technical) as
well as ensuring least cost to generate maximum revenue (allocative). This suggests that to have an economically efficient production set, technical efficiency alone is not sufficient. This implies that the input combination should be selected appropriately based on their respective prices (Erkoc, 2012). Farmers’ direct benefit from economic efficiency improvement therefore, relates to cost saving or increase in gross margin (Kiatpathomchai, 2008). In measuring efficiency levels of farm firms, two separate methods have being developed by researchers under the rubric of mathematical programming approach (Data Envelopment Analysis [DEA]) and econometric approach (Stochastic frontier Analysis [SFA]). In DEA, multiple outputs and inputs are reduced to a single input-output form after which efficiency scores are computed using linear programming. Here all deviation from the frontier is attributed to farm inefficiencies. However, because of the non-stochastic nature of DEA, it prevents researchers to attain comprehensive and sustainable results in many cases (Erkoc, 2012; Coelli et al., 2005; Greene, 2007). As a result, an econometric approach or Stochastic Frontier Analysis (SFA) is often preferred owing to its ability to distinguish the impact of variation in efficiency from external stochastic error on firm’s output (Coelli et al., 2005). Stochastic Frontier Analysis as noted by Kumbhakar et al., (2000) is credited to two simultaneous scholarly papers. One by Meesuen and Van der Brock (1977) and other by Aiger, Lovell, and Schmidt (1977). Later a third using the SFA model was produced by Battese and Corra (1977). This three SFA models took into consideration the composed error term (noise effect and inefficiency effect). Also due to the possibility of obtaining producer-specific efficiency estimates, the choice for SFA was greatly enhanced (Jondrow, Lovell, Materov & Schmidt, 1982; Kumbhakar et al., 2000).

Empirically, several studies have used the concept of efficiency to evaluate the performance and productivity potential of tree crop farmers in Ghana. For instance, a study conducted by Nkamleu, Nyemeck, and Gockowski, (2010) on technology gap and efficiency in cocoa productionn, showed that cocoa farmers exhibited a low level of efficiency in production. The study reported that, farmers were about forty-four percent efficient in production. This implies that farmers were operating about fifty-six percent below the frontier. In a similar study on productivity and technical efficiency in cocoa production, Onumah, Al-Hassan, and Onumah, (2013), reported that cocoa farmers in the Eastern Region of farmers were not efficient as there were found operating below the frontier. The study reported a mean efficiency level of eight-five percent, which means farmers were operating fifteen percent below the frontier. The study further reported that factors such as access to credit, technical support and extension service were significant predictors of efficiency level. Furthermore, a study by Aneani, Anchirinah, Asamoah, and Owusu-Ansah, (2011) on economic efficiency in cocoa produciton reported that cocoa farmers in Ghana were not efficient in production as there were found operating below
the frontier. Additionally an empirical report by Adzawla, Fuseini, and Donkoh, (2013) on the technical efficiency of cotton production in the Yendi Municipality revealed that, farmers were not fully efficient in production. The study noted that, the mean efficiency as exhibited by the farmers was about eighty-eight percent, hence twelve percent below the frontier output.

METHODOLOGY

Data Types, Sources and Collection Method
A multistage sampling technique was used to randomly select and collect primary data from registered mango farmers. At the first stage, the Yilo Krobo Municipality in the Eastern Region of Ghana was purposively selected for the study due to its comparative advantage a bimodal mango production system. At the second stage, to minimize the effect of yield differential due to plant age, a stratified sampling technique was used to select eighty-five mango farmers with farm establishment of seven years and above. Finally simple random technique was used to select sixty-two mango farmers from whom data were collected for the analysis. The R Environment software was used to process the data. The stochastic frontier models were estimated using the frontier package in R.

Analytical Frameworks and Techniques
This study adapted the stochastic frontier model originally and independently proposed by Meeusen and van der Brock (1977) and Aigner, Lovell, and Schmidt, (1977). To get technical, economic and allocative efficiency estimates, the maximum likelihood estimation method was employed. The Cobb-Douglas functional form was fitted to the SFA models.

Specification of Analytical Models:
Stochastic Production Frontier Function for Technical Efficiency
The standard stochastic production frontier for estimating technical efficiency in mango production was specifies as:

$$q_i = f(x_i, \beta) + \epsilon_i$$

$$\{ \epsilon_i = v_i + u_i; i = 1, 2, 3..., n \}$$

(1)

Where $q_i$ denote output level for the $i^{th}$ farmer; $X_i$ denote vector of inputs; $\beta$ denote unknown parameters to be estimated; $\epsilon_i$ denote the composed error term consisting of two independent factors $v_i$ and $u_i$. $\nu_i$ Denote the stochastic noise and other factors outside the control of the farmer; $u_i$ denote the non-negative inefficiency term (Coelli et al., 2005). Basically, estimation of the production frontier assumes that the boundary of the production function is defined by the “best practice” firm. Thus the stochastic frontier production function specified in model (1) distinguishes the observed output ($q_i$) from the frontier output ($q^*_i$). The measure of technical efficiency of the $i^{th}$ firm relative to the production frontier was specified as:
Technical efficiency depends on the value of the unobservable $u_i$ being predicted. TE picks a value between 0 and 1. When $u = 0$ (i.e. $\text{TE}=1$) the firm is said to be producing on the frontier, hence technically efficient. On the other hand if $u > 0$, production will lie below the frontier and the firm is inefficient. The measure of the level of technical inefficiency of any mango farmer is described by the margin by which a mango farmer lies below its production frontier.

**Stochastic Cost Frontier Function for Economic and Allocative Efficiency**

To estimate allocative and economic efficiencies, the cost frontier dual to the production frontier function was adopted, with the behavioral assumption of cost minimization. The cost frontier dual of the production function with linear homogeneity condition in input prices imposed was therefore specified as:

$$
C_i / W_i = f(\alpha W_i / W_n) + f(q_i^o) + v_i + u_i
$$

(3)

Where $C_i$ denotes the minimum cost to produce output $q_i$. $W_i$ denote vector of input prices, and $\alpha$ denote unknown parameters to be estimated. $q_i^o$ Denote observed output adjusted for statistical noise. In the cost function the $u_i$ now defines how far the firm operates above the cost frontier. The measure of cost efficiency relative to the frontier is expressed as the ratio of the minimum predicted cost ($C_i$) to the actual observed cost ($C_i^*$). This is mathematically expressed as:

$$
CE_i = \frac{C_i}{C_i^*} = \exp(-u_i)
$$

(4)

If allocative efficiency is assumed, $u_i$ is closely related to the cost of technical inefficiency. This assumption makes the interpretation of the $u_i$ in a cost function comprehensible, with both technical and allocative inefficiencies possibly involved. Farrell (1957) noted that the overall cost efficiency (economic efficiency) is a product of technical efficiency and allocative efficiency. From this, the measure of input Allocative efficiency (AE) of individual farmers is given by the ratio of cost efficiency to input-oriented technical efficiency. This is mathematically expressed as:

$$
AE_i = \frac{CE_i}{TE_i}
$$

(5)

As such, allocative efficiency is bounded by zero and one. A value of one means the firm is allocatively efficient and a firm of zero means otherwise. To get the allocative efficiency as specified by equation 5, we used the frontier package in R as proposed by Henningsen, (2014)
to decompose the cost efficiency into (cost) technical efficiency and (cost) allocative efficiency as done by Coelli et al., (2005, p.273, Table 10.2).

Parameterization of efficiency estimator

In SFA estimation, the composed error terms are assumed to have certain distributional assumptions. That is, $v_i \sim iid \, N(0, \sigma_v^2)$ and $u_i \sim iid \, N^+ (0, \sigma_u^2)$. Also $v_i$ and $u_i$ are distributed independently of each other and of regressors (Kumbhakar et al., 2000; Battese, Malik, and Gill, 1996). In measuring firm-specific efficiency, the correct estimator should be based on the conditional expectation of the exponential of $u_i$ (Battese & Coelli, 1992). Following Battese et al., (1977), the firm-specific technical or cost efficiencies are expressed in terms of the parameterization below:

$$
\gamma = \frac{\delta^2 u}{\delta^2} = \frac{\delta^2 u}{(\delta^2 v + \delta^2 u)}
$$

(6)

Where the gamma parameter ($\gamma$) is bounded between zero and one. A value of $\gamma = 1$ means that the deviations from the frontier are entirely due to technical or cost inefficiency. On the other hand, if $\gamma = 0$, it indicates that the deviation from the frontier are entirely due to noise effects. Hence, for $0 < \gamma < 1$, variability in output is characterized by the presence of both inefficiency and statistical noise.

Specification of the Empirical Efficiency Models:

Stochastic Production Frontier

The Cobb-Douglas functional form for estimating technical efficiency was specified as:

$$
\ln q_i = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + v_i - u
$$

(7)

Where $q_i$ denote output of mango (kilogram) produced. $X$s denote five input mix: $X_1$ - land size (hectares); $X_2$ - labor (man-days); $X_3$ - Equipment (GHS); $X_4$ - agrochemicals (litres) and $X_5$ - fertilizer (kilograms). $\beta$s Denote unknown parameters to be estimated. $v_i$ Denote random noise; $u$, denote technical inefficiency.

Stochastic Cost Frontier

The Cobb-Douglas functional form for estimating cost efficiency with linear homogeneity in input prices imposed was specified as:

$$
\ln C_i/W_i = \alpha_0 + \alpha_1 \ln W_1 + \alpha_2 \ln W_2 + \alpha_3 \ln W_3 + \alpha_4 \ln W_4 + \alpha_5 \ln W_5 + \theta_i \ln q_i + v_i + u
$$

(8)
Where $C_i$ denotes minimum cost (GHS); $W_i$ denote price for the input mix: $W_1$ - cost of land (GHS); $W_2$ - cost of labour (GHS); $W_3$ - cost of equipment (GHS); $W_4$ - cost of agrochemical (GHS); $W_5$ - cost of fertilizer (GHS); $W_6$ - cost of transportation (GHS) and $q_i^a$ denote observed output of mango adjusted for any statistical noise. $\alpha$s Denote unknown parameters to be estimated.

**Estimation of Determinants of Technical, Allocative and Economic inefficiencies**

As indicated by Battese and Coelli (1995) the mean inefficiency ($u$) is correlated to the farmer-specific and farm-specific characteristics of producers. To find out the determinants of efficiency differentials among mango farmers, the inefficiency scores were regressed on selected farmer-specific and farm-specific variables. Thus the analytical and empirical OLS multiple linear regression models for examining the determinants of technical, allocative and economic inefficiencies are specified as:

$$u_{i,t,a,e} = \delta_0 + \sum_{n=1}^{r} \delta_n Z_n$$

(9)

$$u_{i,t,a,e} = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \ldots + \delta_{11} Z_{11}$$

(10)

Where $u_{i,t,a,e}$ denote the inefficiency scores; the subscripts $t$, $a$ and $e$ denote the technical, allocative and economic inefficiency effects respectively; $\delta$s denote unknown parameters to be estimated; $Z$s denote variables that influence efficiency: $Z_1$ denote Age (years); $Z_2$ denote Sex(dummy); $Z_3$ denote household Size(Count); $Z_4$ denote education level (years); $Z_5$ denote farming experience(years); $Z_6$ denote number of extension visits received (Count); $Z_7$ denote access to credit (dummy); $Z_8$ denote Global GAP certification status(dummy); $Z_9$ denote number of times pruning is done in the year (Count); $Z_{10}$ denote access to technical support (dummy); and $Z_{11}$ denote perceived effect on non-availability of processing factory (dummy).

**RESULTS AND DISCUSSIONS**

**Presentation of the Major Analyses and Findings**

Parameter Estimates of the Stochastic Production and Cost Frontier Models

Table 1 presents results of the estimated coefficients for the Cobb-Douglas stochastic production and cost frontiers. The estimated stochastic production frontier shows that the production function is monotonically increasing in all inputs. In addition, the estimated sigma square ($\sigma^2$) of 0.0062 for the production frontier and 0.122 for the cost frontier which were found to be significantly different from zero, suggest a good fit of the models and the correctness of the specified distributional assumptions respectively. In addition, for the production frontier, the gamma parameter of 0.9182 indicates the presence of inefficiency and that technical inefficiency effects are significant in determining the level and variability of mango yield in the Yilo Krobo Municipality. From theory, the gamma picks values between zero and one and this indicates the
importance of the inefficiency term. When gamma equals zero, it means that inefficiency term \( \mu \) is irrelevant or absent and when it is equal to one it means noise term \( v \) is irrelevant and that technical inefficiency accounts for all deviations from the production frontier (Henningsen, 2013). The estimated gamma parameter of 0.9182 implies that both inefficiency and statistical noise are important for explaining the deviations from the production frontier. However, inefficiency is more important than noise. To estimate the proportion of total variance due to inefficiency the R programming software was used and a value of 0.9162 was obtained. This implies that 91.62% of the variance is totally due to technical inefficiency effects whiles only 8.38% was due to statistical noise effects. For the cost frontier model Table 1 reveals that the coefficients of the input prices were all non-negative. This suggests that the estimated cost function is monotonically non-decreasing in input prices. Furthermore, the coefficient of the output quantity was non-negative, implying that this cost function is monotonically non-decreasing in output quantities. The high gamma value of 0.9546 obtained implies that cost inefficiency was present. This value being close to one suggests that both inefficiency and statistical noise explain the variance in the cost frontier function. To know the total variance due to cost inefficiency, the R programming language was use to extract the proportion of variance due to cost inefficiency and a value of 1.00 was obtained. This indicates that the variance found was fully due to cost inefficiency.

### Table 1: Parameter Estimates from the Maximum Likelihood Stochastic Frontier Models

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>Variables</th>
<th>Coefficient</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>8.233***</td>
<td>0.688</td>
<td>Constant</td>
<td>1.418*</td>
<td>0.996</td>
</tr>
<tr>
<td>In(X1)</td>
<td>0.839***</td>
<td>0.158</td>
<td>In(W1/W6)</td>
<td>0.004***</td>
<td>0.941</td>
</tr>
<tr>
<td>In(X2)</td>
<td>0.113*</td>
<td>0.063</td>
<td>In(W2/W6)</td>
<td>0.408***</td>
<td>0.674</td>
</tr>
<tr>
<td>In(X3)</td>
<td>0.065*</td>
<td>0.039</td>
<td>In(W3/W6)</td>
<td>0.017</td>
<td>0.817</td>
</tr>
<tr>
<td>In(X4)</td>
<td>0.058*</td>
<td>0.042</td>
<td>In(W4/W6)</td>
<td>0.212***</td>
<td>0.538</td>
</tr>
<tr>
<td>In(X5)</td>
<td>0.044*</td>
<td>0.143</td>
<td>In(W5/W6)</td>
<td>0.055***</td>
<td>0.996</td>
</tr>
<tr>
<td>In(Q)</td>
<td>0.068***</td>
<td>0.144</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Variance Parameters:

<table>
<thead>
<tr>
<th>( \sigma^2 )</th>
<th>0.006***</th>
<th>0.002</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma )</td>
<td>0.918***</td>
<td>0.076</td>
</tr>
</tbody>
</table>

Log likelihood 100.315

<table>
<thead>
<tr>
<th>Variance Parameters:</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma^2 )</td>
</tr>
<tr>
<td>( \gamma )</td>
</tr>
<tr>
<td>Log Likelihood</td>
</tr>
<tr>
<td>0.122***</td>
</tr>
<tr>
<td>0.955***</td>
</tr>
<tr>
<td>38.233</td>
</tr>
</tbody>
</table>

Note:*; **; ***: Statistically significant at alpha levels of 10 %, 5 % & 1 % respectively

Source: Field Data, 2014
From the production frontier, the results also revealed that the coefficients of the explanatory variables labour($X_2$), equipment($X_3$), agrochemical($X_4$) and fertilizer($X_5$) in the stochastic production frontier function were significant at ten percent alpha level whiles land was significant at one percent alpha level. These coefficients also define the output elasticities of production. The output elasticity’s imply that, output level is positively and significantly influenced by the share of land, labor, equipment, agrochemicals and fertilizer allocations to mango production. It also implies that increasing the inputs levels by one percent would lead to a significant percentage increase in the output level of mango. For instance, a percentage increase in land, labor, equipment, and agrochemical and fertilizer allocation to mango production would result in about 0.839, 0.113, 0.065, 0.058 and 0.044 percentage increase in output respectively. In addition, summing up the output elasticity’s of the variable inputs from the production frontier model shows that, farmers are operating at an increasing return to scale with a return to scale index of 1.11. This suggests that output increases by a larger proportion in response to proportionate increase in variable inputs. From this result it can be concluded that an efficient and optimal use of land, labor, equipment, fertilizer and agrochemical at the given technology would ultimately lead to a significant productivity increase in mango production.

Now with respect to the cost frontier model, apart from cost of equipment ($W_3$), all the other explanatory variables: cost of land ($W_1$), cost labor ($W_2$), cost of agrochemical ($W_4$) and cost of fertilizer ($W_5$) in the cost frontier were significant at 1%, 5% and 10% alpha levels respectively. The coefficient estimates of the cost function mean that when the cost of land, labor, equipment, agrochemical and fertilizer increase by one percent, the total cost share for these respective inputs would increase by 0.004, 0.408, 0.017, 0.212 and 0.055 percent respectively. Furthermore, the coefficient of output implies that when output increases by one percent, total cost share would increase by 0.068 percent. Using the homogeneity condition, the coefficient of transport cost ($W_6$) can be estimated as $[1-(W_1+W_2+W_3+W_4+W_5)]$ and this gave a value of 0.303. This value also suggests that a percentage increase in transportation cost will result in about 0.303 percentage increase in the total cost share.

**Distribution of Technical, Allocative and Economic Efficiencies among Mango Farmers**

Table 2 gives summary statistics of the farm level efficiency distribution among mango farmers interviewed. The frontier package in R as proposed by Henningsen , (2014) was used to generate the economic, technical and allocative efficiency scores. The approach decomposed the cost efficiency into (cost) technical efficiency and (cost) allocative efficiency as done by Coelli et al., (2005, p.273, Table 10.2). In general, farmers were not fully efficient: technically, allocatively and economically. This finding agrees with the reports by Aneani et al., (2011), Daadi, Gazali,
and Amikuzuno (2014), and Nkamleu *et al.*, (2010) who found out that cocoa farmers in Ghana on the average were not efficient in production.

The technical efficiency scores obtained range from 0.5102 to 0.9859 with a mean of 0.8479. On the average, mango farmers were about 85% technically efficient in production. This further suggests that mango farmers were operating 15% below the efficient frontier. Given this, for an average mango farmer to obtain the technical efficiency level of its most efficient colleague farmer, the farmer could achieve about 14% cost saving [i.e., \(1 - (85/99)\)]. Likewise, estimation for the less technically efficient mango farmer suggests a cost saving of 47% [i.e., \(1 - (52/99)\)]. The results also revealed that, 64.5% of the mango farmers obtained a technical efficiency scores of 80 percent and above.

On the issue of allocative efficiency, results indicate that, the average allocative efficiency score was 0.2981 with a range of 0.3943 to 0.1866 as shown in Table 2. The allocative efficiency score of 0.2981 obtained for this study implies that resource allocation and efficiency use by farmers, given the prevailing inputs prices faced by farmers, is around 30%. Thus, the average farmer was about 0.7 distance point away from the efficient frontier. In addition, the results indicated that none of the mango farmers interviewed had an allocative efficiency score above 40%. It can thus be concluded from this result that resources could be allocated to their best alternative uses and prices could as well be allowed to perform their allocative functions in the use of inputs.

The average economic efficiency score according to the empirical results was found to be 0.2528 with a range of 0.3887 to 0.0952. This result implies that on the average, mango farmers’ economic performance was 75% below the economically efficient frontier.

### Table 2: Summary Statistics of Technical, Allocative, and Economic Efficiencies

<table>
<thead>
<tr>
<th>Efficiency</th>
<th>Mean</th>
<th>Max</th>
<th>Min</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical (TE)</td>
<td>0.8479</td>
<td>0.9859</td>
<td>0.5102</td>
<td>0.1033</td>
</tr>
<tr>
<td>Allocative (AE)</td>
<td>0.2981</td>
<td>0.3943</td>
<td>0.1866</td>
<td>0.0513</td>
</tr>
<tr>
<td>Economic (EE)</td>
<td>0.2528</td>
<td>0.3887</td>
<td>0.0952</td>
<td>0.0579</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Frequency Distribution of TE, AE and EE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency levels (%)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>------------------------</td>
</tr>
<tr>
<td>81-100</td>
</tr>
<tr>
<td>61-80</td>
</tr>
<tr>
<td>41-60</td>
</tr>
<tr>
<td>21-40</td>
</tr>
<tr>
<td>20 and below</td>
</tr>
</tbody>
</table>
A further look at the mean scores for technical and allocative efficiencies seems to suggest that the productive performance of farmers on the average is somewhat good. However, comparing these to economic efficiency score suggests otherwise; consequently a farmer may be technically and/or allocatively efficient but not economically efficient. With this we can conclude that for a better assessment of farm level performance, economic efficiency gives a better representation of the state of affairs than both technical and allocative efficiency. Furthermore, the level of economic efficiency recorded from this study suggests that farmers are performing below their optimum potential, hence the need to improve on their overall efficiency. The situation of inefficiency in production is costly as it causes a reduction in profit below the maximum value attainable under full efficiency (Bifarin et al., 2010), hence the need to have appropriate measures to enhance farmers productive efficiency in mango production. The economic efficiency mean score of 0.2528 also indicates the average potential in mango production in the Yilo Krobo Municipality. From this empirical result, it can be concluded that economic inefficiency exists in mango production in the Yilo Krobo Municipality. The result revealed that none of the mango farmers interviewed had an efficiency scores above 40%. The average economic efficiency score of 0.2528 further suggests that on average, mango farmers in the study area could reduce cost of production of mango by 75% at the current level of mango outputs, if they produce efficiently.

**Determinants of Technical, Allocative and Economic Inefficiencies**

Table 3 present results on the sources of technical, allocative and economic inefficiencies among mango farmers in the Yilo Krobo Municipality in the Eastern Region of Ghana. From theory knowledge on sources of inefficiencies gives indications as to which factors to tackle if improving farmers’ economic performance is the goal of any policy intervention. In literature, several socio-economic characteristics have been identified to influence the efficiency level in mango production (Daadi et al., 2014; Buyinza, Bukenya, Nabalegwa, & Byakagaba, 2010; MohdIdris, Siwar, & Talib, 2014; Mensah & Brümmer, 2016). The explanatory variables included in the model are: Age (Z₁); Sex (Z₂); Household size (Z₃); Education level (Z₄); farming experience (Z₅); extension visit received (Z₆); access to credit (Z₇); GlobalGAP certification status (Z₈); frequency of pruning (Z₉); access to technical support (Z₁₀) and perceived effect of non-availability of processing facility in the municipality (Z₁₁). In general, determinants with negative coefficients are said to reduce inefficiency in production, whiles determinants with positive coefficients contribute to increasing inefficiency in production. The result revealed that
with the exception of number of extension visits received, all the explanatory variables were significant determinants of technical efficiency at 1%, 5% and 10% respectively. On allocative efficiency the findings showed educational level, farming experience and perceived effect of non-availability of processing facility were the only significant determinants at 1%, 5% and 10% respectively. Additionally, the result indicated that, with the exception of access to technical supports, all the other determinants of economic efficiency were significant at 1%, 5% and 10% respectively.

From theory the age of the farmer is expected to have either a positive or negative effect on inefficiency. Results from this study showed that age had a negative effect on technical and economic inefficiencies, but positive effect on allocative inefficiency. This implies that whiles technical and economic efficiencies increase with age, the allocative efficiency declines with the age of farmers. This observation on technical and economic efficiencies could be attributed to the fact that older farmers through experiential learning are able to acquire more technical knowledge making them more efficient. On the other hand with respect to allocative efficiency, most often than not, older farmers tend to be traditional and conservative and as such often show less willingness to adopt new farming technologies and innovations, hence could be less efficient. A further look at Table 3 shows that the variable sex had a negative effect on all three inefficiency components. This intuitively implies that, female farmers were less efficient than their male counterparts. This could properly be attributed to the fact that most female farmers are most often less empowered in their access to productive resources. This, coupled with social roles assigned to women, often render female farmers in most Ghanaian societies less productive and efficient. Additionally, household size had a negative effect on technical and economic inefficiencies but a positive effect on allocative inefficiencies. Intuitively, this suggests that farmers with higher household size were more technically and economically efficient but less allocatively efficient. As labor theory suggests, when farm family labor is beyond the optimal threshold, it tend to affect productivity and efficiency of farm firms. This implies that beyond the optimal threshold any addition to farm labor supply does not significantly add to productivity improvement. Furthermore, years of farming experience showed a negative effect on all three inefficiency components. This as expected therefore suggests that as farmers stay in production, they tend to acquire more technical know-how through experiential learning and this resultantly makes them more efficient in carrying out their production activities in subsequent years. Evidence from the study also revealed that years of education had a positive effect on technical inefficiency, but a negative effect on economic and allocative inefficiencies. The implication of this is that, more educated farmers were less allocatively and economically inefficient than their counterparts. However, in some situations, highly educated farmers are
often engaged in off-farm economic activities reducing their time allocation to their farm business. This properly accounts for the observed situation where highly educated farmers were technically inefficient.

In addition, the study also revealed that the number of extension visits received in the production year showed a positive effect on technical inefficiency but negative effect on allocative and economic inefficiencies respectively. From this result, it can be inferred that farmers with higher level of extension visits were more allocatively and economically efficient, but less technically efficient than their counterparts with low level of extension visits. One reason that can account for this situation would be the timeliness of information delivery and its appropriate usage by recipient farmers.

Table 3: Parameter Estimates for the Determinants of Inefficiencies in mango production

<table>
<thead>
<tr>
<th>Variable</th>
<th>Technical Inefficiency</th>
<th>Allocative Inefficiency</th>
<th>Economic Inefficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Constant</td>
<td>0.323***</td>
<td>0.134</td>
<td>0.881***</td>
</tr>
<tr>
<td>Z1</td>
<td>-0.002 **</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Z2</td>
<td>-0.039 ***</td>
<td>0.043</td>
<td>-0.029</td>
</tr>
<tr>
<td>Z3</td>
<td>-0.006***</td>
<td>0.009</td>
<td>0.005</td>
</tr>
<tr>
<td>Z4</td>
<td>0.004**</td>
<td>0.007</td>
<td>-0.004*</td>
</tr>
<tr>
<td>Z5</td>
<td>-0.020 **</td>
<td>0.029</td>
<td>-0.007**</td>
</tr>
<tr>
<td>Z6</td>
<td>0.004</td>
<td>0.047</td>
<td>-0.002</td>
</tr>
<tr>
<td>Z7</td>
<td>-0.003***</td>
<td>0.005</td>
<td>-0.004</td>
</tr>
<tr>
<td>Z8</td>
<td>-0.014 ***</td>
<td>0.047</td>
<td>-0.017</td>
</tr>
<tr>
<td>Z9</td>
<td>-0.002 *</td>
<td>0.007</td>
<td>0.003</td>
</tr>
<tr>
<td>Z10</td>
<td>-0.035***</td>
<td>0.056</td>
<td>-0.005</td>
</tr>
<tr>
<td>Z11</td>
<td>-0.059***</td>
<td>0.052</td>
<td>-0.065**</td>
</tr>
</tbody>
</table>

Note:*, **,***; statistically significant at alpha levels of 10 %, 5 % & 1 % respectively
Source: Field Data, 2014

Credit is an important factor which is expected to improve farmers’ liquidity in facilitating timely acquisition of inputs. It also facilitates farmers’ willingness to adopt modern production technologies as this often comes at a cost. In this study it is assumed that access to credit enhances farmers’ efficiency level. As such it was therefore expected to have a negative effect on inefficiency, to which the result as shown in Table 3 exactly confirms. The result indicate that access to credit had a negative effect on all three inefficiency components. This finding implies
that receiving credit tends to increase farmers’ overall efficiency in production. It was also discovered that frequency of pruning had a negative effect on technical and economic inefficiencies, but a positive effect on allocative inefficiency. It can therefore, be concluded that, the higher the frequency of standard pruning activity in mango production, the higher the efficiency level in production. This however, if not allocatively utilized well, tends to reduce efficiency. Interview with technical experts indicated that, if pruning is done to the required specification and standard, it helps to increase the output level per tree, hence productivity improvement. This brings the farmer closer to the frontier output level, hence improvement in efficiency level in production. Finally, Global GAP certification status, access to other technical support and perceived impact of non-availability of processing facilities within the municipality all had negative effect on all three inefficiency components. This suggests that increasing farmers’ access to these facilities will tend to reduce technical, allocative and economic inefficiencies in mango production.

CONCLUSIONS
From the results of this study, the following conclusions are drawn:
Mango farmers in the Yilo Krobo Municipality were producing below the frontier and the optimum economic potential as they were found to be technically, allocatively and economically inefficient in production.

With the exception of number of extension visits received, all the explanatory variables included in the technical inefficiency model were significant determinants of technical efficiency. Additionally, educational level, farming experience and perceived effect of non-availability of processing facilities were the only significant determinants of allocative efficiency among mango farmers.

Finally, it was realized that with the exception of access to other technical supports, all the other determinants of economic efficiency were significant.

RECOMMENDATIONS
To address the issue of economic inefficiency in mango production it is recommended that extension strategies should be focused on providing farmers with training, information, and access to inputs and services. In this regard, the Ministry of Food and Agriculture through the District Department of Agriculture should organize regular capacity building workshops and field demonstrations on resource use efficiency for mango farmers in the Yilo Krobo Municipality.

The Government of Ghana should use its public-private partnership policy on agro-industrial development framework to promote and encourage direct investment in agro-processing factories within the municipality.
REFERENCES


