

## Estimation of Technical Efficiency and Its Determinants of White Maize Production in Vinh Long Province: A Stochastic Production Frontier Approach

Nguyen Huu Dang  
College of Economics, Can Tho University, Vietnam.

— *Review of* —  
**Integrative  
Business &  
Economics**  
— *Research* —

### ABSTRACT

The aim of this study is to estimate technical efficiency and its determinants in white maize production in Vinh Long province, Vietnam, based on a cross-sectional data collected in 2014 from 176 white maize farmers by using the stochastic frontier approach. The Cobb-Douglas stochastic frontier production function, incorporating inefficiency effects was employed to analyze the data. The results revealed that the technical efficiency ranged from 63.46 to 99.54%, with an average of 82.58%. Significant factors found to positively affect white maize yield were seed quantity, potash fertilizer, labor, and maize variety while nitrogen fertilizer and pesticide were negatively related to the white maize yield. Significant determinants of technical efficiency that were positively related to technical efficiency include education attainment, training, credit access and household labor.

Keywords: Technical efficiency, maize farms, determinants of technical efficiency, stochastic frontier production function.

### 1. INTRODUCTION

Technical efficiency, which reflects the ability of the firm to obtain maximum output from a given set of inputs (Farrell, 1957). It indicates that technical efficiency is the ratio of the actual output over the maximum output. Previous studies around the world so far found that the mean technical efficiency of maize farmers range 40.00-96.90 percent, implying that the output per farm or the yield of maize can be increased by 3.10-60.00 percent, given the existing technology and level of inputs. The lower level of mean technical efficiency was found in study of Geta *et al* (2013) while the highest one was found in study of Rahman *et al* (2013). Among of this range of technical efficiency, Addai *et al* (2014) found that technical efficiency of maize producers in the forest, transitional and savannah zones of Ghana were 79.9%, 60.5% and 52.3% respectively; Etim *et al* (2013) revealed that the mean efficiency of maize producers in Uyo, Nigeria was 71%; Abawiera *et al* (2016) found the mean technical efficiency of maize farmers in Ghana is 58.1%; while Viengpasith *et al* (2012) disclosed that mean technical efficiency of smallholder maize farmers in Laos was 85%.

In addition, Addai *et al* (2014), reveal that extension; mono cropping, gender, age, land ownership and access to credit positively influence technical efficiency of maize farmers; while Abawiera *et al* (2016) indicated that an increase in educational level, maize farming experience, extension contact seeds would increase the technical efficiency of maize producers. Likewise, Etim *et al* (2013) found that age of farmers, technical assistance, credit and market affect technical efficiency of maize farmers;

Viengpasith *et al* (2012) found that major contributing factors to technical efficiency were educational levels, experience of farmers, farm size, agricultural group membership, and credit access; Rahman *et al* (2013) also found that the farmers' age, education and training had significant positive effect on maize production; Essilfie *et al* (2011) found that education, age of the farmer, household size impacted on technical efficiency; and Geta *et al* (2013) found factors that significantly affected the technical efficiency were farm size and use of high yielding maize varieties.

Vinh Long province located in the south of the Mekong River Delta, Vietnam. Its economy is agriculture based economy as the share of agricultural sector is 30.78 percent while those of industrial and service sectors are 23.37 percent and 45.85 percent, respectively. White maize cultivation is the important subsector of Vinh Long province since it plays a crucial role in employment creation, income generation, poverty reduction, and food security. It has around 12,000 ha of mono white maize production area and thousands hectare of white maize –rice rotation cultivation. However, maize production in Vinh Long has recently been confronted with problems such as the rapid increase in labor cost and other material input costs, which in turn, caused the decrease in the farmers' levels of input use. A reduction in input use may have negative impacts on maize yield and the productive efficiency of maize farmers as well. These lead to question that how is the level of technical efficiency of maize farmers and what factors affect the farm's technical efficiency. Thus, this study is aim to estimate technical efficiency and identify determinants of technical efficiency of the white maize farmers in Vinh Long province.

## 2. THEORETICAL FRAMEWORK

Among the various approaches developed to estimate productive efficiency, the stochastic frontier production function approach (Aigner *et al.*, 1977; Meeusen *et al.*, 1977) and the data envelopment analysis (DEA; Charnes *et al.*, 1978) are the most popular. In agricultural production where data are likely to be greatly influenced by systematic errors due to the effects of weather conditions, climate change, diseases, etc., the stochastic frontier approach is considered more appropriate than the DEA approach.

The stochastic frontier production function was independently proposed by Aigner *et al* (1977) and Meeusen *et al* (1977). The original specification involved a production function specified for cross-sectional data which had an error term with two components, one to account for random effects and another to account for technical inefficiency. Following Battese (1992), the stochastic frontier production function can be expressed in the following equation:

$$Y_i = f(x_i; \beta) \exp(V_i - U_i) \quad (1)$$

where  $i = 1, 2, \dots, N$  and  $Y_i$  represents the possible production level for the  $i^{\text{th}}$  sample unit;  $f(x_i; \beta)$  is a suitable function (e.g., Cobb-Douglas or Translog) of the vector,  $x_i$  of inputs for the  $i^{\text{th}}$  unit and a vector;  $\beta$  is a vector of parameters to be estimated; and  $N$  represents the number of the units involved in a cross-sectional survey. This model is such that the possible production  $Y_i$  is bounded above by the stochastic quantity,  $f(x_i); \exp(v_i)$ , hence, the term stochastic frontier. Besides,  $V$  is the symmetric error term accounting for random variations in output due to factors outside the control

of the farmer such as weather, disease, bad luck, and measurement error whereas  $U$  represents the technical inefficiency relative to the stochastic frontier, which assumes only positive values. The distribution of the symmetric error component  $V$  is assumed to be independently and identically distributed as  $N(0, \delta_v^2)$ .

However, the distribution of the one sided component  $u$  is assumed to be half normally ( $u > 0$ ) distributed as  $N(0, \delta_u^2)$  and, thus, measures shortfalls in production from its notional maximum level. If  $u = 0$ , then the farm lies on the frontier obtaining maximum output given variable and fixed inputs; but, if  $u > 0$ , then the farm is inefficient and makes losses or the production lies below the frontier function and the distance of  $Y_i$  and  $Y_i^*$  measures the extent of the farmers' technical inefficiency (Coelli *et al*, 2005). Therefore, the larger the one sided error is, the more inefficient the farm becomes.

*Technical efficiency.* The technical efficiency of an individual producing unit is defined in terms of the ratio of the observed output of the corresponding frontier output, given the available technology (Coelli *et al*, 2005). Thus the technical efficiency of unit  $i$  in the context of the stochastic frontier production function is the following expression.

$$TE_i = \exp(-U_i) \quad (2)$$

$$TE_i = Y_i / Y_i^* = f(x_i; \beta) \exp(V_i - U_i) / f(x_i; \beta) \exp(V_i) = \exp(-U_i) \quad (3)$$

$Y_i$  is an observed output and  $Y_i^*$  is the frontier output.  $X_i$ ,  $\beta$ s, and  $V_i$  are as defined earlier. In this case,  $Y_i$  achieves its maximum value of  $f(x_i; \beta) \exp(V_i)$  if and only if  $TE_i = 1$ . Otherwise,  $TE_i < 1$  provides a measure of the shortfall of observed output from maximum feasible output in an environment characterized by stochastic elements that varies across producers.

### 3. METHODOLOGY

#### 3.1 Sampling and data collection

The data in this study is cross – sectional data collected by directly interviewing 176 white maize farmers in three districts of Vinh Long province, namely Binh Tan, Tam Binh and Tra On. About 60 white maize farmers per each district were selected by random sampling. The data collection includes quantity of input use, while maize yield in the first crop of 2014 and other data related to the farm's specific characteristics.

#### 3.2 Empirical model

This study employed the stochastic frontier analysis following the single-stage estimation procedure developed by Battese and Coelli (1995, 2005). The stochastic frontier production function would be estimated by the Cobb-Douglas or the translog functional forms as follows:

- *The Cobb-Douglas stochastic frontier production form:*

$$\ln Y_i = \beta_0 + \sum_{j=1}^7 \beta_j \ln X_{ji} + \beta_8 D_i + V_i - U_i \quad (4)$$

- *Translog stochastic frontier production form:*

$$\ln Y_i = \beta_0 + \sum_{j=1}^7 \beta_j \ln X_{ji} + \beta_8 D_i + \frac{1}{2} \sum_{j=1}^7 \sum_{k=1}^7 \beta_{jk} \ln X_{ji} \ln X_{ki} + \sum_{j=1}^7 \beta_{j8} \ln X_{ji} * D_i + V_i - U_i \quad (5)$$

where,  $\beta_j$ : regression coefficients of the explanatory variables in the estimated stochastic production function, where  $j = 1, 2, \dots, 7$ ;  $Y_i$ : white maize yield (kg/ha).  $X_{ji}$  are factors contributing to white maize yield, consisting of:  $X_{1i}$ : land area (ha/farm);  $X_{2i}$ : amount of seed used (kg/ha);  $X_{3i}$ : amount of nitrogen used (kg/ha);  $X_{4i}$ : amount of phosphate used (kg/ha);  $X_{5i}$ : amount of potash used (kg/ha);  $X_{6i}$ : amount pesticide used (g/ha);  $X_{7i}$ : human labor used (man-days/ha);  $D_i$ : white maize variety dummy (1 = hybrid variety (MX 10 variety); 0 = conventional variety).  $V_{it}$ : random variable assumed to be independently and identically distributed (iid)  $N(0, \sigma_v^2)$  and independent of  $U_i$ ;  $U_i$ : non-negative random variable that is assumed to account for technical inefficiency in production. The subscripts  $j, i$  refer to the  $j^{th}$  input used of  $i^{th}$  farm.

Simultaneously estimated with the frontier model was the white maize farmer level technical inefficiency (TIE) model. The TIE model for the white maize farm is expressed mathematically as follows:

$$TIE_i = U_i = \delta_0 + \sum_{j=1}^8 \delta_j Z_{ji} + \xi_i \quad (6)$$

where,  $\delta_j$ : regression coefficients of the explanatory variables in the estimated technical inefficiency model, where  $j = 1, 2, \dots, 8$ ;  $Z_{ji}$ : factors contributing to technical inefficiency such as,  $Z_{1i}$ : gender of farmer dummy (male = 1; female = 0);  $Z_{2i}$ : age of the farmer (years);  $Z_{3i}$ : education attainment of farmer (years of schooling);  $Z_{4i}$ : experience of the farmer in white maize farming (years);  $Z_{5i}$ : membership in farmers' association (member = 1; not member = 0).  $Z_{6i}$ : credit access dummy (with credit = 1; no credit = 0);  $Z_{7i}$ : attendance in training on white maize production dummy (with training = 1; no training = 0);  $Z_{8i}$ : household labor (person);  $\xi_i$ : error terms, assumed to be independently and identically distributed with mean = 0 and variance =  $\sigma_\xi^2$ ; and the subscripts  $j, i$  refer to the  $j^{th}$  characteristic of  $i^{th}$  farm.

- *Test for the appropriate functional form (i.e., Cobb-Douglas vs. Translog):* the appropriate functional form was determined using the following selection criterion: (i) overall significance of the estimated equation based on the generalized Likelihood Ratio (LR) test, (ii) the number of significant variables based on the t-test, (iii) consistency of signs of the MLE coefficients with economic theory, and (iv) absence of multicollinearity. The likelihood ratio statistic ( $\lambda$ ) used for the generalized Likelihood Ratio (LLR) test is given as follows:

$$\lambda = -2[L(H_0) - L(H_1)] \quad (7)$$

where,  $L(H_0)$ : value of the log-likelihood function of a restricted frontier model (or the Cobb-Douglas) as specified by a null hypothesis,  $H_0$ ;  $L(H_1)$ : value of the log-likelihood function of an unrestricted frontier model (or translog model) as specified by the alternative hypothesis,  $H_1$ . The LR test statistic ( $\lambda$ ) has approximately a chi-square ( $\chi^2$ ) distribution with the number of degrees of freedom equal to the difference between

the parameters involved in  $H_0$  (Cobb-Douglas) and  $H_1$  (translog). The critical value was obtained from the normal  $\chi^2$  table. The decision for this test was to reject the null hypothesis ( $H_0$ ) if  $\lambda$  is greater than the critical  $\chi^2$  value and vice versa.

- *Test for the appropriate frontier estimators (OLS vs. MLE)*: Using the same statistical testing procedure (generalized LR test) as testing for appropriate functional form mentioned above. However,  $L(H_0)$  in the formula refers to the value of the log-likelihood function of the OLS frontier model as specified by the null hypothesis,  $H_0$ , while  $L(H_1)$  is the value of the log-likelihood function under the alternative hypothesis,  $H_1$  (i.e., MLE model). Similarly, the test statistic  $\lambda$  has approximately a chi-square distribution. The degree of freedom is equal to the number of parameters involved in the inefficiency model plus one ( $k + 1$ ), where  $k$  is the number of parameters or restrictions or explanatory variables except the intercept. The critical  $\chi^2$  value was obtained from the Kodde and Palm (1986). The decision rule for this test is to reject the null hypothesis ( $H_0$ ) if  $\lambda$  is greater than the critical  $\chi^2$  value and vice versa.

Anyway, another test would be able to employ. The value of gamma parameter may lie between zero and one. A value of  $\gamma = 0$  indicates that technical inefficiency is absent and the OLS is a more adequate estimation procedure to describe the parameters in the model. A value of  $\gamma$  close to one means that there exists technical inefficiency in the model, or if  $\gamma = 1$ , all the deviations from the frontier are entirely due to technical inefficiency and the MLE adequately characterizes the data. LR results for the functional and frontier estimation method tests were automatically derived by using the Frontier 4.1.

## 4. RESULTS AND DISCUSSION

### 4.1 Socio-economic characteristics of interviewed farming households

On average, the interviewed white maize farmers have 8.45 years of schooling, 7.26 years of white maize farming experience, 0.58 ha of white maize farming area and 2.53 household labors. The average distance from the main white maize field to the farmer's house is 1.64 km, which implies that most of the farmers are living near their white maize fields. There is 24 percent of interviewed white maize farmers accessed the formal credit while another 76 percent were self-financing for their white maize farming; 32 percent of interviewed white maize farmers participated in the short white maize production training organized by local extension workers while another 68 percent did not join any training related to white maize farming over last three years; and 53 percent of interviewed white maize farmers are member of local farmer's association (Table 1).

**Table 1. Socio-economic characteristics of 176 interviewed white maize farmers in Vinh Long province, Vietnam**

Farm 's characteristics	Unit	Average	Std. Dev.
Gender dummy	1: male; 0: female	0.87	0.34
Educational attainment	Year	8.45	2.08
White maize farming experience	Year	7.26	2.63
Farm size	Ha	0.58	0.26
Credit access dummy	1: borrowed; 0: not	0.24	0.43
Training dummy	1: Participated; 0: not	0.32	0.46
Farmer's association membership dummy	1: member; 0: not	0.53	0.50
Household labor	No. of person	2.53	1.22
Distance (largest field – house)	Km	1.64	1.05

Source: Author's survey in 2014.

#### 4.2 Input use and yield of the interviewed white maize farmers

The average amount of seeds used by the interviewed white maize farmers was 9.56 kg/ha. The interviewed white maize farmers applied several types of fertilizers. The most commonly used fertilizers were urea, single superphosphate, ammo-phos (or Di-Ammonium Phosphate), complete fertilizer (contains nitrogen, phosphorous, and potassium) and muriate of potash, among others. In terms of active fertilizer ingredient form, on average, the interviewed white maize farmers applied 132.27 kg/ha of nitrogen fertilizer, 134.25 kg/ha of phosphate fertilizer and 62.78 kg of potash fertilizer.

In addition, the interviewed white maize farmers applied several types of pesticides in both liquid and powder pesticides. In terms of active pesticide ingredient and by converting the liquid pesticides into powder pesticide, on average, the interviewed white maize farmers applied 1,008.48 g/ha (~1,008.48 ml/ha); the lowest level of pesticide application was 290.94 g/ha while highest one was 2,520.72 g/ha. The labor use was ranged 90.51-176.32 man-day/ha, an average of 153.05 man-day/ha. White maize yield of the interviewed farmers was, on average, 13,676.92 kg/ha; the lowest level of yield was 10,684.62 kg/ha while highest one was 16,923.08 kg/ha (Table 2).

**Table 2. Mean levels of input use per hectare and white maize yield of 176 interviewed white maize farmers in Vinh Long provinces, Vietnam**

ITEM	Maximum	Minimum	Mean	Std. Div.
Seed (kg/ha)	15.50	7.94	9.56	3.65
Fertilizers by ingredients:				
Nitrogen (kg/ha)	225.70	78.70	132.27	59.55
Phosphate (kg/ha)	244.51	81.04	134.25	64.37
Potash (kg/ha)	91.33	50.86	62.78	21.32
Pesticide by active ingredients (g/ha)	2,520.72	290.94	1,008.48	436.70
Labor (man-days/ha)	176.32	90,51	153.05	52.49
White maize yield (kg/ha)	16,923.08	10,684.62	13,676.92	1,868.51

Source: Author's survey in 2014.

### 4.3 Results of the stochastic frontier production analysis

#### 4.3.1 Testing results for appropriate functional form and estimator

The result of LR test indicated that the translog functional form was more appropriate than the Cobb Douglas since the value of likelihood ratio statistic ( $\lambda$ ) was 113.417, which was greater than that of critical value (60.097). Therefore, the  $H_0$  was rejected. However, except the interaction and square variables in the translog model, the Cobb Douglas resulted in more significant variables than the translog model based on T-test. Moreover, the signs of coefficients of variables in the Cobb Douglas were more consistent than those of the translog model. In addition, based on the result of testing for multicollinearity, the translog model contained serious multicollinearity problem. Hence, the Cobb Douglas functional form was chosen to analyze the data. Besides, gamma parameter  $\gamma$  was close to 1 (0.924), which indicated the existing of technical inefficiency in the model. Thus, the MLE was adequately characterizes the data.

#### 4.3.2 Results of the stochastic frontier production analysis

The results of the frontier production function revealed that the seed, nitrogen and potash fertilizers, pesticide, labor, and maize variety are found significantly to affect white maize yield at one or five or ten percent probability level, while the area and phosphate fertilizer was found to have no significant effects on maize yield at 10 percent probability level.

In a Cobb-Douglas frontier production function, the regression coefficients are already the output elasticity. For instance, the regression coefficient of seed of 0.22 indicates that a one percent increase in seed usage would result in a 0.22 percent increase in white maize yield, *ceteris paribus*. With regard to nitrogen fertilizer and pesticide usages, the study found that the farmers might be overuse of nitrogen fertilizer and pesticide as their coefficients are exhibited negative signs with white maize yield. Potash fertilizer, on the other hand, positively influenced white maize yield. The regression coefficient of potash of 0.12 indicates that a one percent increase in potash fertilizer would increase white maize yield by 0.12 percent, other factors held constant. Similarly, the regression coefficient of variety is positive (0.117), implying that the farmers planted to hybrid varieties have a higher yield than those planted to conventional varieties, other factors held constant. This is in line with finding of Abawiera *et al* (2016) and Dlamini *et al* (2012). Likewise, labor was found positively affected white maize yield. This implies that maize farming is labor intensive and use traditional technology that rely heavily on labor usage. This is in line with findings of Etim *et al* (2013), Dlamini *et al* (2012) and Olowa *et al* (2010).

**Table 3. MLE of the Cobb-Douglas stochastic production and technical inefficiency functions, white maize farming in Vinh Long province, Vietnam.**

Variable symbol	Variable name	Parameter	Coefficient	Std. Error	T-ratio
<i>Frontier Production Function</i>					
	Constant	$\beta_0$	7.611***	0.502	15.176
ln A	Area (kg)	$\beta_1$	0.068 <sup>ns</sup>	0.093	0.732
ln S	Seed (kg)	$\beta_2$	0.220**	0.083	2.651
ln N	Nitrogen (kg)	$\beta_3$	-0.295**	0.138	-2.137
ln P	Phosphate (kg)	$\beta_4$	0.031 <sup>ns</sup>	0.094	0.336
ln K	Potash (kg)	$\beta_5$	0.123*	0.073	1.694
ln LP	Pesticide (g)	$\beta_6$	-0.052***	0.019	-2.745
ln L	Labor (man-day)	$\beta_7$	0.106**	0.051	2.085
DV	Variety dummy (1=MX10; 0=others)	$\beta_8$	0.117***	0.043	2.721
<i>Technical Inefficiency Function</i>					
	Constant	$\delta_0$	2.192***	0.529	4.143
Z <sub>1</sub>	Gender dummy	$\delta_1$	-0.037 <sup>ns</sup>	0.027	-1.388
Z <sub>2</sub>	Age of farmer (years)	$\delta_2$	0.092 <sup>ns</sup>	0.151	0.607
Z <sub>3</sub>	Education attainment (years)	$\delta_3$	-0.074**	0.037	-2.015
Z <sub>4</sub>	Farming experience (years)	$\delta_4$	-0.040 <sup>ns</sup>	0.034	-1.181
Z <sub>5</sub>	Membership dummy	$\delta_5$	-0.003 <sup>ns</sup>	0.285	-0.012
Z <sub>6</sub>	Credit access dummy	$\delta_6$	-0.048*	0.026	-1.855
Z <sub>7</sub>	Training dummy	$\delta_7$	-0.076***	0.024	-3.167
Z <sub>8</sub>	Household labor	$\delta_8$	-0.160***	0.067	-2.377
<i>Variance Parameter</i>					
$\sigma^2$			0.036***	0.013	2.792
$\gamma$			0.967***	0.017	56.864
Log-likelihood function			144.816		
LR test of the one-sided error			119.152		
Mean technical efficiency (%)			82.58		

Note: \*\*\*, \*\*, and \* indicate statistically significant at 1%, 5%, and 10% probability level, respectively; and ns denotes insignificant.

Source: Author estimates.

*Determinants of technical efficiency:* The average technical efficiency was 82.58 percent, which implies that with the recent input level, the white maize sample farmer-respondents could be able to increase their white maize output by 17.42 percent by improving technical efficiency factors. This is to examine the effects of socio-economic and farm-specific factors on technical efficiency of the interviewed white maize farmers.

A negative sign of the regression coefficient of an explanatory variable in the technical inefficiency function indicates that the variable improves technical efficiency. A positive sign means the opposite. The factors which were found positively affect technical efficiency of the interviewed white maize farmers were education attainment



of the farm operator, participation in white maize production training programs, credit access and household labor.

The positive relationship between education attainment and technical efficiency might also be attributed to that the higher educated farmers adopted new production technology better than the lesser educated farmers. Likewise, the regression coefficient of participation in training dummy has a negative sign, which indicates that the interviewed white maize farmers who participated in training programs on white maize farming which were conducted by local extension workers or the staff of the Department of Agriculture and Rural Development and some NGOs were more technically efficient than those who did not attend the afore-mentioned training programs. The explanation is that the interviewed white maize farmers who attended training programs on white maize farming learned more about new technological developments and therefore were able to adopt better farm management practices in white maize farming. Thus, they tended to have more efficient use of resources than those who were not able to attend any training at all. This finding confirms the results of Abawiera *et al* (2016), Ayinde *et al* (2015), Addai *et al* (2014), Binam *et al.* (2004) and Seyoum *et al.* (1998) reported that farmers who sought technical information and had adequate extension contact were associated with higher levels of technical efficiency.

In addition, the regression coefficient of credit access dummy exhibited a negative sign and is statistically significant at ten percent probability level. This suggests that the farmers who accessed to the formal credit would be more technically efficient than others. This is in line with findings of Addai *et al* (2014), Etim *et al* (2013) and Salau *et al* (2012). Likewise, the regression coefficient of household labor shown a negative sign and is statistically significant at one percent probability level. This indicates that the larger number of family labors engage in maize farming have more technical efficient than smaller one. This finding is consistent with the result of Ayinde *et al* (2015) and Olowa *et al* (2010).

On the other hand, gender, age and farming experience of the farm operator, and member of local farmer's association dummy had no significant effects on technical efficiency at ten percent probability level.

*Distribution of technical efficiencies:* The predicted technical efficiencies of the interviewed white maize farmers differed substantially ranging from 63.46 percent to 99.54 percent. About 6.25 percent of the total the interviewed white maize farmers belonged to the most efficient category (95 - 100%). Only few (10.23%) of the interviewed white maize farmers had technical efficiencies below 70 percent. Majority (29.55%) of the interviewed white maize farmers belonged to the category (85 -<90%), indicating that most of the interviewed white maize farmers were very technically efficient (Table 4).

**Table 4. Distribution of technical efficiency of 176 white maize farmers in Vinh Long province, Vietnam**

Technical efficiency (TE, %)	No. of Farmers	Percent
< 70	18	10.23
70-<75	12	6.82
75-<80	20	11.36
80-<85	29	16.48
85-<90	52	29.55
90-<95	34	19.32
95-100	11	6.25
Total	176	100.00
Average		82.58
Minimum		63.46
Maximum		99.54
Std. Dev.		10.17

Source: Author estimates

#### 4. CONCLUSIONS AND RECOMMENDATIONS

The study is to estimate the technical efficiency and determinants of technical efficiency in white maize production in Vinh Long province, Vietnam, based on a cross-sectional data collected in 2014 from 176 white maize farmers. The Cobb-Douglas stochastic frontier production function, incorporating inefficiency effects was employed to analyze the data, using the Frontier 4.1. The results revealed that the average technical efficiency was 82.58%. With the recent input level, the white maize farmers could be able to increase their white maize yield by 17.42 percent by improving technical efficiency factors. Significant factors that were found to positively affect white maize yield were amount of seed, potash fertilizers, labor, and maize variety while nitrogen fertilizer and pesticide were negatively related to the white maize yield. Significant determinants of technical efficiency were positively related to technical efficiency were education attainment, training, credit access and household labor.

In order to further improve the while maize yield and technical efficiency of the white maize farming households, the study recommends to the while maize farmers to increase amount of seed and labor usage; using hybrid maize variety; improving fertilizer management focusing on efficient use of fertilizer; reducing pesticide usage. In addition, the study recommends to the local government to intensify extension services particularly the conduct of training programs; providing continuous support for massive propagation and dispersal hybrid or high-yielding varieties in cooperation with the private sector; facilitating credit accessibility of the farmers; and improving the level of education of farmers through short technical training.

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