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Efficiency of Rice Farms and its Determinants: Application of Stochastic Frontier Analysis

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ABSTRACT
In the context to achieve the self sufficiency in rice production at 75% of local consumption, Malaysian authority consistently encourages the increase of rice production by the improvement of the yield through the utilization of the optimal input used, new technology and farm management. However, these efforts is hampered by the low productivity which is caused mainly by the inefficient used of input and subsequently affects the production inefficiency as well. Hence, in order to address those problems, this study aims to measure the production and subtitution elasticity, the existing level of rice farm efficiency and determinants of the efficiency using the stochastic frontier analysis. Out of five inputs, land, seed and chemical significantly influence the rice farms in MADA, Malaysia. Further, since the rice farms operated at the increasing return to scale, there was a possibility to increase the production by improving the input use. On average, the sampled farms in this study had the tecnical efficiency at 0.854 and implied those rice farms still could increase its output about 14.6% at a given inputs. The farmer's access to credit and their education level were the important determinant upon the rice farms technical efficiency.

Key words: Technical efficiency, elasticity, inefficiency model, rice farms

INTRODUCTION
Rice remains the strategic crop in Malaysia as it is the main staple food of 28 billion Malaysian peoples. On 2012, the local consumption was about 2.1 million tons and production was only able to meet 68.5% of it (DoS, 2013). Hence, Malaysia's stance on food security is largely translated in terms of achieving self-sufficiency in rice production at about 75% of local consumption.

Despite the strategic function of rice, the increase of paddy production triggered by the land expansion is quite difficult currently due to the decreasing of land used for the food crop since the country's rapid economic development occupies more agricultural area mainly for housing, business and industrial purposes. Further, for two last decades, total number of paddy area is not more than 0.7 million hectares with the average growth only about 0.27% per year. Malaysian authority, therefore, attemp to consistently increase the paddy production by the improvement of yield through the utilization of the optimal input used, new technology, farm management and provides the insentive for farmers such as the price support and the yield increase insentive.

Up to now, government provides input subsidy schemes which are 240 kg ha^{-1} mixed fertilizer and 80 kg ha^{-1} for organic fertilizer as well as RM 200/ha/season subsidy for pesticide control. The price support is currently at RM 248.1 t^{-1} with the guaranteed minimum price of RM 750 t^{-1}. In addition, government provides the yield increase incentive of RM 650 for increasing in yield at farm level compare to previous year and production increase incentive in form of ploughing expenses at a maximum of RM 100 ha^{-1} and additional fertilizer of RM 140/ha/season (Vengedasalam *et al.*, 2011). Although, there have been many countinous efforts on rice farms, however, there was no significant improvement in the yield. The average yield at 3.9 t ha^{-1} (DoS, 2013) the actual paddy farm yields in Malaysia vary from 3-5 t ha^{-1} and it was below than the neighboring countries such as Indonesia and Vietnam at 4.9 and 5.5 t ha^{-1}, respectively (FAOSTAT, 2012).

Those conditions conceive that the difficulties on improving the yield is potentially caused by the unintensive use of inputs due to the unefficient management on paddy farms. Thus, the improvement on the efficiency of input used and farm efficiency will be fundamental and the measurement of the existing farms efficiency including the relationship betwen input and output, therefore, much more useful since it could provide the information about the gap of input used and efficiency performance among the farms and the potential to be improved (Kumbhakar and Lovell, 2000).

Several studies on the efficiency aspect have been conducted in Malaysia such as Radam and Nasir (2001) applied the production frontier in measuring the rice technical efficiency, Ghee-Thean *et al.* (2012) measured technical efficiency of Malaysian paddy farming yet, the substitution elasticity of inputs that provide the information on which group of inputs could be increased or decreased to gain more output did not receive the special attention on those studies. Therefore, this study aims (1) To measure the production and substitution elasticities, (2) To evaluate the existing condition of rice farm by estimating the technical efficiency and (3) To identify determinants of the efficiency.

THEORETICAL FRAMEWORK

Stochastic frontier production function and inefficiency effect model

Stochastic frontier production function: Stochastic frontier production function have been widely used to estimate technical efficiency of agricultural products due to many criticisms on DEA approach or deterministic frontier production function. Those criticisms related to the assumption of deterministic/DEA approach that all deviation from the frontier are associated with inefficiency, whereas in agricultural production, those assumptions were difficult to be accepted because of the inherent variability of the production due to weather, pest, diseases, etc. (Coelli and Battese, 1996). Stochastic frontier production function was proposed firstly by Aigner *et al.* (1977) to account the presence of measurement error in production in the specification and estimation of frontier production function. Therefore, stochastic frontier production function has two error terms which are error component v_i and error component u_i. Stochastic frontier production function was presented as the following model:

$$y_i = f(x_i, \boldsymbol{\beta})+v_i-u_i \tag{1}$$

where, y_i is the output obtained by the farm i, x_i is the vector of used input, $\boldsymbol{\beta}_i$ is a vector of parameters to be estimated and ϵ_i is a composed error including v_i and u_i. The error component v_i account the measurement error in the output variable due to the weather, the combined effect of the unobserved input on production, errors in the observation and measuring of data. Then, the error component u_i account the existence of technical inefficiency on the production and is assumed to be distributed independently of v_i.

According to Omondi and Kelvin (2013), the composed error causes the deviation from the frontier. The systematic error component, v_i, captures random deviation from frontier that caused by factors beyond farmers control such as temperature and natural hazard which is assumed to be independently and identically distributed with a mean of zero and constant varance. Further, u_i is a non negative error component that depicts deviation from the frontier caused by controllable factors and represent the inefficiencies in production. It is asssumed to be half normal, identically and independently distributed with a mean of zero and constant variance.

With given the input vector, x_i, the potential output is defined as the maximal output obtained when there is no inefficiency effect on the production and formulated as follows:

$$Y^* = \exp(X_i\boldsymbol{\beta}+v_i) \tag{2}$$

The estimated technical efficiency of the ith farms can be defined as the ratio of the observed output for the ith farms relative to the potential or the frontier output, given the available technology and can be formulated as follows:

$$TE_i = \frac{Y}{Y^*} = \frac{\exp(X_i\beta + v_i - u_i)}{\exp(X_i\beta + v_i)} = \exp(-u_i) \tag{3}$$

Based on the Eq. 3, the technical efficiency score is between zero and one and is inversely to the inefficiency effect (Coelli and Battese, 1996).

Principally, Aigner *et al.* (1977) suggested to use a likelihood function to allow two variance parameters which are:

$$\delta^2 = \delta_u^2 + \delta_v^2 \text{ and } \lambda = {}^{\sigma_u}\!/_{\sigma_v} \tag{4}$$

In this model, when λ is greater than 1 means that the variance of the inefficiency effect (u_i) is greater than the stochastic error (v_i) and vice versa when the λ is less than 1. The parameter value of gamma must lie between zero and one, whereas the value 0 indicate that all deviations from the frontier are due to entirely to noise and value 1 indicate that all deviations are due to the inefficiency effect.

According to Radam *et al.* (2010), stochastic frontier analysis from simple regression analysis. It requires seperate assumption to be made to the distributions of the inefficiency and error components and therefore potentially leading to more accurate measures of relative efficiency. Then, SFA differs from simple regression analysis in term of estimated method used, whereas simple regression uses ordinary least squares to estimate the frontier function, SFA utilize the maximum likelihood estimation.

The log likelihood function that is to be maximised is:

$$\ln L(y \mid \beta, \sigma_v, \varnothing) = N\left[\ln\frac{1}{\varnothing} + \frac{1}{2}\left(\frac{\sigma_v}{\varnothing}\right)^2\right] + \sum_{i=1}^{N}\left[\ln F^*\left(\frac{-\varepsilon}{\sigma_v} - \frac{\sigma_v}{\varnothing}\right) + \frac{\varepsilon_i}{\varnothing}\right] \tag{5}$$

where, $\phi = \sigma_u$ and F^* is the cumulative distribution function of the standard normal distribution.

Maximum Likelihood Estimation (MLE) fit a surface over data where it measure the best practice, compare to OLS that fit a line through the centre of data using regression method where it measure the average practice. Furthermore, maximum likelihood estimation could gives better estimation which statistically shows the significance of lamda (λ) which is able to show the existence of technical inefficiency in data.

Determinants of inefficiency effect model: As mentioned at previous section that the stochastic frontier production function involves estimation of a function with a composite error term, including a symmetric and a one-sided component. The one-sided component is associated with technical inefficiency of production and measures the extent to which observed output deviates from potential output given a certain level of inputs and technology. Thus, technical inefficiency effects model is an extension of the more usual stochastic error component frontier function which allows for identification of factors which may explain differences in efficiency levels between observed farm units (Wilson *et al.*, 2001). From that model, we can identify determinants of the inefficiency in the input use of production process.

Variables that are most often used to explain the inefficiency effect model which are the managerial aspect and farmer characteristics such as age, education or schooling and experience. For example, Bravo-Ureta and Pinheiro (1993) analyzed the inefficiency effects model as the function of age, level of education, farms size, access to credit and utilisation of extension services; Rahman and Rahman (2009) included the land fragmentation and resources ownership as factors on inefficiency model and Wadud and White (2000) take into account the land fragmentation, environmental degradation, irrigation infrastructure, age and schooling on the inefficiency effect model.

The technical inefficiency effect, for the i-th farm, u_i, is defined by the truncation (at zero) of the $N(\mu_i, \sigma_u^2)$ distribution where the farm specific mean is specified as:

$$\mu_{it} = z_{it}\,\delta \tag{6}$$

where, z_i is a vector of the explanatory variables which has a constant value and δ is a vector of unknown scalar parameter to be estimated (Isyanto *et al.*, 2013).

Production and substitution elasticity: Production elasticity shows the percentage change of ith rice output due to 1% changes in jth inputs. According to Sharma *et al.* (1999), the production and substitution elasticity cannot be obtained directly from the translog production frontier. Further, recent study conducted by Chiang *et al.* (2004) mentioned that production elasticity is evaluated at sample means for each input factor Xj (j = 1, 2,..., 5) with the equation as follows:

$$\eta X_{ij} = \frac{d\ln Y_i}{d\ln X_{ij}} = \frac{dY_i}{dX_{ij}} \times \frac{X_{ij}}{Y_i} = \beta_j + \sum_{k=1}^{5} \beta_{jk} \ln X_{ik} \tag{7}$$

Hicks Elasticity of Subtitution (HES) (Ferguson, 1969) in the translog frontier production function can be written as follows:

$$\eta_{ij} = \frac{\beta_{jj} + EX_j(EX_j - 1)}{EX_j^2} \tag{8}$$

Then, the cross elasticity of substitution for input j and k is presented as:

$$\eta_{jk} = \frac{\beta_{jk}}{EX_j \times EX_k} + 1 \quad (9)$$

where, EX_j and EX_k are sample mean of input j and k. The positive η_{jk} implies that inputs j and k are joinly complementary and the negative η_{jk} means that both input has the competitive relationship.

METHODOLOGY

This study uses the Stochastic Frontier Analysis (SFA) to obtain the technical efficiency scores, the production and subtitution elasticity that reflect the respon of output respect to the change on inputs and the relationship among inputs. The Cobb Douglas and transcendental logaritm (translog) functional forms were included in the analysis due to Thiam *et al.* (2001) and Ahmad and Bravo-Ureta (1996) who stated the contrary result on technical efficiency from those functions. Thiam *et al.* (2001) mentioned that the average TE from Cobb Douglas function was significantly lower that those on the Translog function since it more restricted functional form. In contrast, Ahmad and Bravo-Ureta (1996) concluded that the functional form has a discernible but rather small impact on estimated efficiency and further, those authors suggested that the comparison between two functional form in efficiency studies was warranted.

In measuring the technical efficiency level of individual farms, one output and five inputs were used whereas the output was defined as the paddy production for one season (t). Five production inputs were land (ha), seed (kg), fertilizer (kg), pesticide (L), labor (man h). The empirical model of Cobb Douglas and Translog frontier production function could be written as follows:

Cobb douglas frontier production function:

$$\ln y_i = \beta_0 + \sum_{i=1}^{5} \beta_i \ln x_i + \varepsilon_i \quad (10)$$

Translog frontier production function:

$$\ln y_i = \beta_0 + \sum_{i=1}^{5} \beta_i \ln x_i + \frac{1}{2}\sum_{i=1}^{5} \beta_{ii} \ln x_i^2 + \sum_{i=1}^{5}\sum_{j=1}^{5} \beta_{ij} \ln x_i \ln x_j + \varepsilon_i \quad (11)$$

where, β_0 is the constant, β_i, β_{ii}, β_{ij} are the production function parameters to be estimated for each input, yi and xi represent the quantity of output paddy in t ha^{-1}, land in hectare, seed in kg ha^{-1}, fertilizer in kg ha^{-1}, pesticide in L ha^{-1}, labour in man-day during the production period.

The inefficiency effect model to the production is independently distributed and truncated at zero of the normal distribution. This inefficiency effect model is defined to estimate the effect of farmer's socio economic factors upon the technical efficiency and enrich by variable of credit. The following ineffficiency model was:

$$\mu_i = \delta_0 + \delta_1 age + \delta_2 HHsize + \delta_3 Job + \delta_4 Ext + \delta_5 Landown + \delta_6 Credit + \delta_7 Education$$

where, μ_i is technical inefficiency and δ is regression coefficient. Seven factors were included in the ineffiency effect model which were farmer's age, household size, job, involvement on extension service, land ownership, access to credit and education.

On one side, the older farmers may have more experience in rice farms and hence they likely more efficient than younger one. Conversely, they also may be more conservative and less willing to adopt new technology and thereby having greater inefficiencies in the production. In this study, the farmer's age is expected to have a positive sign upon the inefficiency model due the less willing to adopt new technology. The household size (persons) is expected to have a negative sign. It means farms with more household member perhaps having less inefficiency or having greater efficiency in the rice farms.

The main job is the dummy variable which 1 is rice farmers as the main job and 0 for otherwise. This factor is expected to have the negative sign since the main job of rice farmer reflects more attention to manage the farm and thereby could lead to less inefficiency or greater efficiency. The coefficient of the involvement on extension service is expected to be negative upon the inefficiency effect due to more knowledge on production could guide farmers to be a good producer and hence provide the less inefficiency. This factor is expressed in dummy whereas 1 for farmers who involve actively and 0 for otherwise. The land ownership is a dummy variable (1 if has the own land and 0 otherwise) and access to credit is a dummy as well whereas 1 if had an access to credit and 0 otherwise. Those factors are expected to have the negative sign to the inefficiency effect model. Lastly, education level of farmers (years) is expected to have a negative sign to the inefficiency effect model since more educated farmers will tend to be more efficiently manage of rice farms.

The survey was conducted at Muda Agricultural Development Authority (MADA), Malaysia and data collection was guided by the structures questionnaire. Research sample of 150 farmers were drawn using simple random sampling. The parameters of the stochastic frontier production function and inefficient model coefficient were estimated simultaneously by the method of maximum likelihood using the computer program, FRONTIER version 4.1.

RESULT AND DISCUSSION

The summary of statistics for variables gathered from the survey is reported in Table 1. The average paddy production of the sampled farms was 2.37 t with the minimum production at 1.05 t and maximum production at 5.42 t. Standard deviation of the production was quite high (77.38) which indicated the large variability on paddy production among the sampled farms.

On average, the seed used on paddy farms was about 68 kg and there were some farms used it until 113 kg. Yet, the variability of used seed among the sampled farms was not large since the

Table 1: Summary statistics of variables in the stochastic frontier production functions

Variable	Average	Minimum	Maximum	Standard deviation
Production (kg)	2373.790	1054.850	5421.680	77.382
Land (ha)	4.250	1.028	9.530	2.137
Seed (kg)	68.045	15.060	113.680	18.054
Fertilizer (kg)	351.975	237.590	659.920	83.795
Pesticide (L)	1.896	1.000	8.180	1.387
Labor (man h)	25.653	5.260	51.969	17.725
Age (years)	53.540	22.000	84.000	11.180
Household size (person)	5.150	1.000	11.000	1.980
Education (years)	9.000	0.000	16.000	2.630

standard deviation for seed was lower than for other inputs. The large variability on input used among farms was found on the utilization of fertilizer which was 83.79 and indicated that many farms did not comply with a good farm practice especially in the utilization of the fertilizer.

The farmer's sociodemographic characteristics as mentioned on Table 1 were the farmer's age, household size and farmer's education. Farmers on MADA were mostly the old farmers since on average the farmers age was about 53 years and even there were some farmers at 84 years old. The average size of their household was roughly 5 persons and mostly they had education at 9 years or level of 'Sekolah Menengah".

Production and substitution elasticity: Table 2 presents the result of stochastic frontier including the production elasticity and inefficiency effect model for Cobb Douglas and Translog Production function estimated by the maximum likelihood method. Before proceeding to the production elasticity for both model, we discuss about the variance paramaters which are the sigma square and the value of gamma (γ). The sigma square for both model was 0.1404 and 0.0889 and statistically significant at 1% level indicated a good fit whereas the specified distribution assumption of the composite error term was correct. Further, the estimated value of gamma (γ) in the Cobb Douglas and Translog model at 0.9304 and 0.9099 respectively and statistically different from zero at 1% level. It reflected that 93.04 and 90.99% variation in the output of rice farms attributed to the presence of technical inefficiency in the resource use during the production. These result therefore confirmed the relevance of stochastic parametric production function and maximum likelihood estimation in this study.

Comparing the production elasticity between the Cobb Douglas and Translog production model, there was a significant differences among both models. Using a Cobb Douglas, all input significantly influenced the production at the positive sign except for labor. Yet, the magnitude of elasticities for those inputs which were less than 1, indicated that the production was inelastic to the changes of those inputs.

Out of five inputs, the highest elasticity was for the fertilizer i.e., 0.20 and implied that 1% increase of fertilizer could increase the production at 0.20%. The same finding was obtained by Omondi and Kelvin (2013), however, was not consistent with the value found by Ghee-Thean *et al.* (2012) and Wadud and White (2000). Further, the sum of all production

Table 2: Estimation result and production elasticities

	Cobb-douglas production frontier			Translog production frontier		
Variable	Parameter	Coefficient	t-value	Parameter	Coefficient	t-value
Production elasticity						
Constant	b0	0.77350	1.6473	b0	-0.79010	-0.1455
land	b1	0.09660	3.4638***	b1	1.50680	2.4482***
seed	b2	0.11960	2.9058***	b2	1.49490	1.3263**
fertilizer	b3	0.20040	2.3456**	b3	0.23800	0.1872
chemical	b4	0.08510	2.5846**	b4	1.16840	1.1917**
labor	b5	0.00680	0.3412	b5	0.01350	0.4519
Variance parameter						
	σs^2	0.14040	2.4311***	σs^2	0.08890	3.8106***
	γ	0.93040	32.8021***	γ	0.90990	33.5127***
Log-likelihood function		172.10278			180.73314	

*,**,***Significant at 10, 5 and 1% level, respectively

elasticities was 1.28, indicating that on average the rice farms has the increasing return to scale. This means if the rice farm increased all inputs by 1%, production would increased by 1.28%. This result suggested that there is a possibility to increase the production by improving the use of input.

The result of Translog production model showed the significant influence of land to the rice production at 1% level. Then, seed and chemical significantly influenced the rice production at 5% level and even the elasticity of those inputs were higher than elasticities on Cobb Douglas due to the effect of relationship among inputs on the Translog production function. Meanwhile, fertilizer and labor did not have the significant effect to the production.

The land had the highest elasticity and implied that this input had the major function on the rice farms. Moreover, according to its elasticity magnitude which was 1.5039, indicated the output in rice farms was elastic to the changes of land. These result was not strictly comparable with studies by Wadud and White (2000) that obtained the lower coefficient for land (0.5274).

Other inputs that had the high elasticity were seed and chemical which were 1.49 and 1.16. This indicated 1% increase on these inputs would be responded by the output increase at 1.49 and 1.16%, respectively. Conversely, the production elasticity respect to fertilizer and labor were lower than other inputs which were 0.238 and 0.292. These magnitudes suggested that output in rice farms was inelastic to the changes of fertilizer and labor due to the inefficiency use on those inputs.

Substitution elasticity for input in rice farm is depicted on Table 3. The negative substitution elasticity for pair inputs of seed-pesticide (-0.7539) indicated the competitive relationship among these pair inputs. This happened since the increase of seed use had compensated by the reduce of the pesticide because most of sampled farmers utilized the new varieties with the good durability so that it didnot require much pesticide during the production season. Conversely, the positive elasticity for other pair inputs indicated the complementary relationship among them and implied these pair input should be increased together to obtain the higher production. For example, the positive estimated HSE for pair input land-seed (0.9698), land-fertilizer (1.0185) and land-labor (0.7577) implied the complementary relationship and therefore, these inputs need to be increased together to increase the production.

In order to ensure that inefficiency effect are absent from the model, the following hypothesis were tested with generalized likelihood-ratio test and the result are presented on Table 4. The first hypothesis was for checking that each farms was fully technically efficient due to no inefficiency effect on the model. The null hypothesis was $\gamma = \delta_0 = \delta_1 = ... = \delta_8 = 0$ and the likelihood ratio test with 8 degrees of freedom indicated that the null hypothesis could be rejected. It implied the existence of inefficiency effect on rice farms.

Table 3: Hicks substitution elasticity for inputs used in rice farms

Inputs	Subtitution elasticity
land-seed (β_{11})	0.969823331
land-fertilizer (β_{12})	1.018462889
land-pesticide (β_{13})	3.107081569
land-labor (β_{14})	0.757679978
Seed-fertilizer (β_{15})	1.008919299
Seed-pesticide (β_{16})	-0.753953549
Seed-labor (β_{17})	0.953193806
Fertilizer-pesticide (β_{18})	0.972126865
Fertilizer-labor (β_{19})	0.968834264
Pesticide-labor (β_{20})	0.493429092

Table 4: Hypothesis test for model specification and inefficiency effect model

Test	Null hypothesis	Likelihood value of the reduced model	Likelihood value of the full model	Likelihood ratio test (LR)	$\chi^2_{0.05}$ critical value	Degrees of freedom	Decision
1	$\gamma = \delta_0 = \delta_1 = ... = \delta_n = 0$	173.76	183.12	18.72	14.85*	8	Reject H_o
2	$\gamma = 0$	148.06	183.12	70.12	2.7*	1	Reject H_o
3	Translog SFPF can be reduced to C-D SFPF	172.10	183.12	22.04	7.26	15	Reject H_o

*$\chi^2_{0.05}$ obtained from Kodde and Palm (1986)

Table 5: Distribution of farms technical efficiency score

Efficiency score	No. of farms	Percentage
0.00-0.09	0	0
0.10-0.19	0	0
0.20-0.29	0	0
0.30-0.39	0	0
0.40-0.49	0	0
0.50-0.59	6	4.00
0.60-0.69	10	6.67
0.70-0.79	15	10.00
0.80-0.89	54	36.00
0.90-1.00	65	43.33

Further, the second hypothesis was conducted to test the presence of stochastic inefficiency. The null hypothesis is $\gamma = 0$ that specifies the inefficiency are not stochastic. However, the likelihood ratio test confirmed that the null hypothesis was rejected. Therefore, this result implied the stochastic inefficiency was exist and the traditional average response function wasnot an adequate representation of data.

The third hypothesis conformed that Cobb Douglas production function was not suitable for analysis. Based on the likelihood ratio which was 22.04 and was higher than the critical value, the hypothesis on Cobb Douglas model was rejected. It suggested that the Translog production model was more suitable for rice farms data.

Technical efficiency and its determinants: Since, the hypothesis result mentioned that translog production model was more suitable for data, further measure of technical efficiency and its determinant used that model. The estimated technical efficiency of the ith farms was defined as the ratio of the observed output for the *i*th farms relative to the potential or the frontier output.

Result indicated that, on average, the sampled farms in the study had the technical efficiency at 0.854 with a standard deviation of 0.106. This implied that rice farms still could increase its output about 14.6% at a given amount of existing inputs when the inefficiency effect could be reduced. The small value of standard deviation reflected the variability of technical efficiency scores among the sampled farms was not large. The best-practice farms had the technical efficiency at 0.977 and mean this farms were very closed to the optimum production frontier since they just need to increase the output by 12.3% on a given set of inputs.

Table 5 shows the distribution of farm specific technical efficiency. More than 40% of sampled farms were the best-practice farm since they had the efficiency scores about 0.9 or greater. These farms haved used the input optimally and were likely could decrease the inefficient effect on the production.

Table 6: Determinant of inefficiency model on rice farms

	Cobb-Douglas production frontier			Translog production frontier		
Variable	Parameter	Coefficient	t-value	Parameter	Coefficient	t-value
Inefficiency model						
Age	d1	0.0036	1.4966	d1	0.0011	0.5052
Household size	d2	-0.0115	-0.8479	d2	-0.0123	-1.1643
Job	d3	-0.0769	-0.8264	d3	-0.0352	-0.4962
Extension	d4	0.0109	0.1921	d4	-0.0107	-0.2334
Experience	d5	0.0007	0.2423	d5	0.0004	0.1645
Land ownership	d6	-0.0548	-0.7487	d6	-0.0294	-0.5565
Access to credit	d7	-0.2385	-1.6157**	d7	-0.1728	-2.0748**
Education	d8	-0.1643	-1.6556**	d8	-0.1686	-2.1091**

*,**,***Significant at 10, 5 and 1% level, respectively

Further, there were 36% of rice farms that closed to the average score of efficiency (with a range of efficiency score from 0.8-0.89). The group of sampled farm that need to be improved were those that had the efficiency score below the average level and there were 20.67% rice farm that fall into that condition. These farms were trapped on the inefficient use of input and thereby they could not achieved the maximum output as achieved by the best practice farms.

Determinant of technical efficiency could be explained by estimation of the inefficiency effect model and its result is shown on Table 6. Farmer who has an access to credit and education level of farmer had the significant effect on the inefficiency. While age, job, household size, involvement on extension service and land ownership had no significant effect to the inefficiency model.

Those significant determinants on the technical inefficiency model had the negative sign and it conform to a priori expectation. For example, the estimated of coefficient for farmer's access to credit was negative and significant at 5% level. It implied that the use of credit could decrease the inefficiency effect to production. On other words, farmers who had used the credit were having the greater efficiency since farmers with less liquidity constraints may obligate the farms to use the optimal input and thereby closed to the optimum output. This result was consistent with study by Bravo-Ureta and Pinheiro (1993).

Further, the estimated coefficient of farmer's education was negative as well and statistically significant at 5%. This result implied that the higher level of education decrease the inefficiency effect or increase technical efficiency on rice farms. On other word, more educated farmers were more likely to be efficient farmers due to their better skills, access to information and good farm management. The same result was obtained by Coelli and Battese (1996), Dhungana *et al*. (2004), Linh (2012) and Isyanto *et al*. (2013).

CONCLUSION

The findings of this study showed that all estimated parameters in the Cobb Douglas and Stochastic Frontier production model had positive signs and conformed to the priori expectation. Out of five inputs, land, seed and chemical significantly influence the rice farms in MADA, Malaysia and even the rice output was elastic to the changes of those inputs due to their elasticity at more than one. Therefore, these result reflected the high productivity of those inputs to the rice farms production. Further, since the rice farms operated at the increasing return to scale, there was a possibility to increase the production by improving the input use. The use of seed should be improved by new varieties with the good durability to the pest because this study indicated that farmers could reduced the use of chemical pesticide during the production season.

On average, the sampled farms in this study had the tecnical efficiency at 0.854 and implied that those rice farms still could increase its output about 14.6% at a given inputs. Still, more than 40% of sampled farms were the best-practice farm with the efficiency scores about 0.9. These farms haved used the input optimally and were likely could decrease the inefficient effect on the production. Significant determinant upon the rice farms efficiency were farmer's access to credit and education while, age, job, household size, involvement on extension service and land ownership had no significant effect. Farmers who had used the credit were having the greater efficiency due to their less liquidity constraints may obligate the farms to use the optimal input and thereby closed to the optimum output. Further, more educated farmer were more likely to efficient due to their better skills, access to information and good farm management. Thus, the improvement of rice farms efficiency level could take into account both factors.

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