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Evaluation of Technical, Allocative, and Economic Efficiency in Rice Production; A Case Study on Rice Farmers in Brunei Darussalam

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Many studies have shown that increasing efficiency is the best option in increasing output compared to introducing new technology, in the short run. This paper attempts to investigate the efficiency level of individual rice farmers and determinant of inefficiencies among rice farmers in Brunei. The empirical result shows that the means of technical, allocative and economic efficiencies were at 76.3%, 65.7% and 53.1% respectively. This suggests that there is a considerable room for improvements in increasing rice productivity through better use of available resources given the state of technology. This study shows that improvements in irrigation and soil fertility may reduce overall inefficiencies among rice farmers in Brunei. Factors like farm size, age, gender, experience and training have a significant impact in increasing/decreasing farmer's efficiency. Another noteworthy variable is that, farmers who joined cooperatives or associations are more efficient than farmers who do not.

Key words: Productive efficiency, self–sufficiency, rice farmers, rural development, Brunei Darussalam

INTRODUCTION

Food self–sufficiency is an important agenda because Brunei Darussalam (hereafter Brunei) imports large bulks of overall food requirements from foreign countries. Natural disasters and political uncertainties in the producing countries where Brunei imports its food might affect food supply to the nation. For this reason, the government perceives that reaching self–sufficiency in food production is crucial. Consequently, the government has aggressively carried out various programs and plans in order to increase rice production. Although rice is the main staple food or traditional diet for Bruneians, domestic or local rice production is still at an unsatisfactory level. About 97 percent of domestic rice consumption is imported with about 3 percent of self–sufficiency level (DAA, 2009a). This poor production output in the Bruneian rice sector could be associated with poor infrastructures, farmers who still practice traditional methods, low rice yields where the average rice yield is about 1 metric ton per hectare, and so on. Steps have been taken by the Department of Agriculture and Agribusiness (DAA) to raise domestic rice production from the present meager 3 percent self–sufficiency to a more acceptable figure (DAA, 2009b). The DAA is targeting a 20 percent, equivalent to a 6,000 metric ton increase of local rice production by 2010, and a 60 percent (equivalent to 18,000 metric tons) increase by 2015 in a bid to achieve self–sufficiency in rice production (DAA, 2008).

Therefore, it is important to note that in order to increase rice productivity, rice farmers must adopt modern rice farming methods such as new technologies, good agricultural practice, and so on. However, introducing new technologies like machinery is very costly, and sometimes farmers are not making efficient use of existing technologies (Herdt and Mandac, 1981). For this reason, increasing productivity through more efficient utilization of available scarce resources is more reasonable and cost effective than introducing new technologies (Bravo–Ureta and Pinheiro, 1997). The analysis of efficiency is generally associated with the possibility of farms producing certain optimum level of output from a given bundle of resources or certain level of output at least cost. This study was therefore designed to investigate the rice production efficiency of rice farmers in Brunei as well as to identify factors that influence their efficiency.

MATERIALS AND METHODS

Analytical Framework[1]

Production efficiency relates to the degree which a farmer produces the maximum feasible output from a given bundle of inputs (an output oriented measure), or uses the minimum feasible level of inputs to produce a given level of output (an input oriented measure). The most popular approach to measure efficiency is the use of stochastic frontier production function (Rahman, 2003; Coelli *et al*, 2005). Therefore, in order to identify the factors affecting rice yield and assess the efficiency of rice farmers in Brunei, the stochastic frontier production function is applied. The Cobb–Douglas stochastic frontier production model is assumed to be an appropriate model for this analysis because the methodology employed requires that the production function be self –dual. The model specified for a farmer in given season is defined as;

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[1] The model presented in this section is based on stochastic frontier approach presented by Bravo–Ureta and Rieger (1991), Bravo–Ureta and Evenson (1994), Bravo–Ureta and Pinheiro (1997) which is an extension of the model introduced by Kopp and Diewart (1982).

$$Y_i = f(X_{ij}; \beta) \quad (1)$$

where Y_i is the output of the ith farmer, X_{ij} is the jth input used by farmer i, and β is a vector of unknown parameters. We can possibly derive technically efficient input quantities (X_{it}) for any given level of output $\overline{Y}$, by solving simultaneously equation (1) and the observe input ratios $X_1/X_i = X_i$ where k_i is the ratio of the observed level of inputs k_i and X_i (i>1)at output $\overline{Y}$.

We assume that the production function in equation (1) is self dual (*e.g.* Cobb Douglas), therefore, the dual cost frontier can be derived and written in general form as;

$$C_i = h(P, Y; \alpha) \quad (2)$$

where C is the minimum cost to produce output Y, P is the vector of input prices for the ith farmer and α is a vector of parameters to be estimated. The economically efficient input vector for the ith farmer, X_{ie}, can be derived by applying Shephard's Lemma, the system related to the cost minimizing input demand functions through its partial derivatives with respect to input prices. From this demand equation for the jth input, we obtain,

$$\frac{\partial C}{\partial P_i} = f(P, Q; \theta) \quad (3)$$

where θ is a vector of parameters. The observed technically efficient input vector, X_{it}, and economically efficient input vector, X_{ie}, cost production of the ith farm are used to compute allocative efficient input vector, X_{ia}, the actual cost operating input. The basis of calculating *TE* and *EE* are as follows;

$$TE = (X_t \cdot P)(X_a \cdot P) \quad (4)$$

$$EE = (X_e \cdot P)(X_a \cdot P) \quad (5)$$

Finally, in Farrel (1957) methodology, *AE* can be explained as a product of *TE* and *AE*. Therefore we can calculate *AE* from equations (4) and (5) as;

$$AE = (X_t \cdot P)(X_e \cdot P) = (EE)/(TE) \quad (6)$$

However, Farrel (1957) deterministic frontier approach is extremely sensitive to outliers which according to Schmidt and Lovell (1978), the parameters are not estimated in any statistical sense, but are merely computed via mathematical programming techniques. In addition, efficiency measures obtained from deterministic models are affected by statistical noise as noted by Schmidt (1985–1986).

Therefore, Stochastic Frontier Production Function is applied in this study and specified from equation (1) as follow;

$$\ln(Y_i) = \beta_0 + \sum\nolimits_i \beta_i \ln X_{ij} + \varepsilon_{ij} \quad (7)$$

where

$$\varepsilon_{ij} = v_{ij} - u_{ij} \quad (8)$$

The essential idea behind the stochastic frontier model is that ε_i is a "composed" error term (Aigner *et al.*, 1977; Meeusen and Van de Broeck, 1977). The two components v_{ij} and u_{ij} are assumed to be independent of each other. The v_{ij} represent random error or variations in output that are assumed to be independent and identically distributed as $N(0, \sigma_v^2)$ due to factor outside the control of farmers(*e.g* weathers, natural disasters, *etc.*) as well as the effects of measurement error in the output variable, left out explanatory variables from the model and stochastic noise.

The u_{ij} is a non–negative random variable, associated with technical inefficiencies of production, which are assumed to be independently distributed such that u_{ij} is obtained by truncation (at zero) of the half normal distribution ($u \sim |N(0, \sigma_u^2|$) (Battese and Coelli, 1995). The maximum likelihood estimation of equation (7) yields consistent estimators for β, γ and σ_v^2, where β is a vector of unknown parameters, $\gamma = \sigma_u^2/\sigma^2$ and $\sigma^2 = \sigma_v^2 + \sigma_u^2$. Jondrow *et al.* (1982) have further shown that the assumptions made on the statistical distributions of v and u, making it possible to calculate the conditional mean of u_i given ε_i as ;

$$E(u_i | \varepsilon_i) = \sigma * \left[\frac{f^*(\varepsilon_i \lambda / \sigma)}{1 - F^*(\varepsilon_i \lambda / \sigma)} - \frac{\varepsilon_i \lambda}{\sigma} \right] \quad (9)$$

where F^* and f^* are the standard normal density and distribution functions respectively, evaluated at $\varepsilon_i \lambda / \sigma$, and $\sigma_*^2 = \sigma_v^2 + \sigma_u^2 / \sigma^2$. Subtracting v from equation (7) yields the result in

$$\ln(Y_i^*) = \beta_0 + \sum_{i=0}^{n} \beta_i \ln X_{ij} - u_i = \ln(Y_i) - v_i \quad (10)$$

where $\ln(Y_i^*)$ is defined as the farm's observed output adjusted for the statistical noise contained in v_i. From this equation, we can compute the TE input vector, X_{it}, and derive the cost frontier which is the basis for calculating minimum cost factor demand equations which in turn, used to estimate economic efficiency, X_{ie}. Since the cost frontier is based on duality function like Cobb–Douglas production function, the model can be written as:

$$\ln(Y_i^*) = \beta_0 + \sum_{i=0}^{n} \beta_i \ln P_{ij} + \gamma \ln(Y_i^*) \quad (11)$$

where P_{ij} is the jth input prices for rice production for ith farm and $\ln(Y_i^*)$ is total rice production output that is adjusted for any statistical noise. The efficiency indices in this study are predicted using the FRONTIER 4.1 software (Coelli, 1996), which is based on its conditional expectation, given the model assumptions.

Source of Data

The primary data for this study was collected in a field survey by direct interview with rice farmers in Brunei/Muara District and Temburong District in June 2010. Farmers in Brunei plant and harvest rice once a year. In Brunei/District, three groups of farmer associations namely KOSEKA (Cooperatives), Kg Bebuloh (Village), and Mukim Pengkalan Batu (Village) were interviewed. On the other hand, farmers in Temburong were randomly selected because there were no farmer's associations or cooperatives available. Appointments for interviewing were made prior to the interview so that farmers have ample time to answer the questionnaire and to avoid disturbing farmers working in the farm. A total of 82 farmers were interviewed – 62 farmers from the Brunei/Muara district and 20 farmers from Temburong.

The questionnaire in this study was structured to elicit responses from the selected farmers on their households farming activities. These include information on farm size, material inputs and cost, labor supply and wages, and so on, as well as quantities of rice output and prices. Socio–economic data of the farmers such as age, level of education, farming experience, and so on were also collected.

EMPIRICAL RESULTS AND DISCUSSION

Empirical Model

The production of each farm was assumed to be characterized by a Cobb–Douglas function. It is one of the most popular ways of functional form to estimate the relationship between inputs and outputs. In addition, the Cobb–Douglas functional form is fit to separate stochastic frontier production for rice using maximum likelihood procedures (Bravo–Ureta and Evenson, 1994). From equation (7), the stochastic frontier production function to be estimated is;

$$\ln(Y_i) = \beta_0 + \beta_1 \ln Fertilizer + \beta_2 \ln Herbicide + \beta_3 \ln Pesticide + \beta_4 \ln Labor + \beta_5 \ln Machinery + \varepsilon_{ij} \quad (12)$$

where Y_i = rice yield of ith farmer in metric ton per hectare, *Fertilizer* is defined as the quantity of fertilize usedr in kilogram per hectare, *Herbicide* is the quantity of herbicide used in milliliter per hectare, *Pesticide* indicates the amount of pesticide used in milliliter per hectare, *Labor* represents the number of hired labors per hectare, *Machinery* is defined as the amount of machinery operating cost per hectare and ε_{ij} is the composed error term defined in equation (8). Table 1 presents the summary statistics for some of the important variables used in the stochastic frontier production function.

Empirical Results and Discussion

The Maximum Likelihood Estimates (MLE) of parameters in the stochastic frontier defined by equation (1) is presented in Table 2. For comparison, Ordinary Least Squares (OLS) estimates of average production func-

Table 1. Summary Statistics of the Variables Used in the Technical Efficiency Model

Variable	Unit	Mean	Std. Dev.	Min	Max
Yield	Tonne/ha	1.74	0.75	0.51	3.75
Fertilizer	Kg/ha	182.04	100.92	18.00	450.14
Herbicide	ml/ha	12.30	7.44	2.00	30.21
Pesticide	ml/ha	2.60	2.06	0.00	8.00
Labor	person/ha	1.68	1.59	0.00	5.00
Machinery	B$/ha	116.53	152.08	0.00	750.09

Note; B$1=US$0.80 as of March, 2011 currency exchange rate

Table 2. The OLS and ML Estimates for Parameters of the Stochastic Frontier Production Function for the Rice Farmers in Brunei uring the 2010 Cropping Season

Variables	Parameters	Coefficients	t–ratio	Coefficients	t–ratio
		OLS		MLE	
Constant	β_0	0.5026**	1.90	0.5152*	1.60
Fertilizer	β_1	0.0224***	2.86	0.0244***	2.97
Herbicide	β_2	0.0198**	1.87	0.0198**	1.94
Pesticide	β_3	0.0417	1.01	0.0418	1.05
Labor	β_4	0.2281***	2.02	0.2481***	2.10
Machinery	β_5	0.2550***	3.99	0.2640***	4.15
R^2		0.57			
Model Variance	σ_5			0.3800*	1.72
Gamma	γ			0.6400***	3.89
Log–Likelihood				54.5900	

Note; ***, ** and * are statistically significant at 1%, 5% and 10% respectively.

tions are also shown. The coefficient R^2 shows that 57 percent of the proportion of the total sample variation in the dependent variable is explained by the independent variable.

From the results, all of the estimated coefficients except pesticide had the expected positive signs and were statistically significant at 1, 5, and 10 percent levels respectively, in both the OLS and ML estimates. This indicates that additional increase in the use of these variables, *ceteris paribus*, may increase the rice yield. For example, the estimated coefficient of labor is statistically significant at the 1 percent level. Therefore, the rice yield or output can be increased by 0.25 percent with a percent increase in labor.

Another variable worth to mention is machinery. The result also shows that a percent increase in machinery use will also increase rice yield by 0.26 percent. Additional input in both labor (0.25) and machinery variables (0.26), if combined, can boost the rice output up to 0.50 percent. This indicates that both machinery and labor are very important in raising rice yield. The coefficient of pesticide is found to be insignificant in both OLS and ML estimate. However, our result shows that, rice yield does not increase so much with additional application in herbicide and fertilizer.

As explained before, the maximum likelihood estimation can derive gamma (γ), which is associated with the variance of technical in efficiency effects in the stochastic frontier, and is estimated to be 0.64, suggesting that systematic influences that are unexplained by the production function were the dominant sources of random errors. This indicated that 64 percent of the total variability of rice yield for the farmers was due to differences in technical inefficiency among farmers and is statistically significant at the 1 percent level. In other words, rice output can be optimized if the technical inefficiencies among farmers are minimized. The dual cost frontier calculation derived from equation (11) is given as;

$$\ln C_i = 1.1861 + (0.1419)\ln P_F + (0.0845)\ln P_H + (0.0705)\ln P_P + (0.3044)\ln P_L + (0.2726)\ln Y^* \quad (13)$$

where C_i is the minimum cost of rice production per ith farm; P_F is the price of fertilizer in B\$/kg, P_H price of herbicide in B\$/ml, P_P price of pesticide in B\$/ml, P_L wage rate of labor per day in B\$ and Y^*, is the farm output adjusted for any statistical noise.

Table 3 shows the result of the frequency and percentage distribution of Technical, Allocative, and Economics Efficiencies of rice farmers in Brunei. From equation (7) and (12), this study revealed that *TE* indices of rice farmers range from 23.3 percent to 99.7 percent and the mean of *TE* is 76.3 percent. This indicates that the 'best' practice farmer operated at 99.7 percent efficiency, while the 'least' practice farmers we found operated at about 23.2 percent level. Also, from the result obtained, more than 48 percent of the farmers interviewed were more than 80 percent technically efficient. This result also help to reveal that average farmer in the sample could save average of 23.5 percent (*i.e.*, 1–[76.3/99.7]) of cost–saving if a farmer was to achieve the *TE* level of his most efficient counterpart. Similarly, for the most technically inefficient farmer, he could realize cost–saving of 76.7 percent (*i.e.*, 1–[23.3/99.7]). Although farmers in Brunei are relatively efficient, there are clear opportunities that exist to increase their efficiencies by 24 percent given the prevailing current set of inputs, prices and technology at that time. The *AE* indices of rice farmers range from the lowest of 1.8 percent to the highest of 85.3 percent with a mean *AE* of 65.7 percent. From the combination effect of technical and

Table 3. Frequency and Percentage Distribution of Technical (TE), Allocative (AE) and Economic (EE) Efficiency Estimates of Rice Farmers in Brunei during the 2010 Cropping Season

Efficiency Level (%)	Technical Efficiency		Allocative Efficiency		Economic Efficiency	
	No[a]	%[b]	No[a]	%[b]	No[a]	%[b]
<10	0	0	2	2.4	7	8.5
11–20	0	0	4	4.9	0	0.0
21–30	4	4.9	1	1.2	0	0.0
31–40	4	4.9	0	0.0	13	15.9
41–50	0	0.0	0	0.0	13	15.9
51–60	8	9.8	13	15.9	17	20.7
61–70	13	15.9	18	22.0	16	19.5
71–80	14	17.1	41	50.0	16	19.5
81–90	15	18.3	3	3.7	0	0.0
>90	24	29.3	0	0.0	0	0.0
Mean (%)	76.3		65.7		53.1	
Minimum (%)	23.3		1.8		0.4	
Maximum (%)	99.7		85.3		77.5	

Note: [a] indicates the number of farmers, [b] indicates the percentage of total farmers.

allocative efficiency factors, we can get the economic efficiency level among the farmers in the study. The mean *EE* in this study is 53.1 percent, with indices ranging from 0.4 percent to 77.5 percent. From these figures, we can suggest that if the average farmer in the study were to reach *EE* level of its counterpart, then the average farmer could realize cost–savings of 31.5 percent (*i.e.*, 1–[53.1/77.5]). Using the same calculation, we can assume that an economically inefficient farmer can gain an economic efficieny of 99.5 percent (*i.e.*, 1–[0.4/77.5]). From the figures in Table 3 we can conclude that although *TE* index of farmers in Brunei is considered high, allocative inefficiency among farmers need serious attention in order to improve the *EE*. As already explained, *EE* is composed of *AE* and *TE*. Therefore, economic inefficiency arises from a combination of the technical and allocative components.

Socio–Economic Factors Affecting Farmer's Efficiency

In order to understand factors that are affecting efficiency, investigating farm/farmer characteristics with the computed *TE*, *AE* and *EE* indices separately is necessary. One approach is to compute correlation coefficients or to conduct other simple non–parametric analysis called 'two–step' method (Bravo–Ureta and Evenson, 1994). This method received many criticisms from several authors[2], who argued that the socioeconomic variables should be incorporated directly in the production frontier model because such variables may have a direct impact on efficiency. However, Kalirajan, (1991) defended this approach by contending that the socioeconomic attributes have a roundabout effect on production, hence, should be incorporated into analysis indirectly (Bravo–Ureta and Evenson, 1994; Bravo–Ureta and Pinheiro, 1997; Sharma *et al.*, 1999). Ray (1988) has argued that the two–step procedure is justifiable if one assumes that the production function is multiplicatively separable in what he calls discretionary and nondiscretionary inputs. The former inputs are those typically included in production function models while latter are those commonly used to explain variations in efficiency (Bravo–Ureta and Evenson, 1994). The model used is a two–limit tobit model procedure, given that the efficiency indices are bounded between 0 and 1 (Greene, 1980). The model can be written as;

$$\begin{aligned} EFFICIENCY = {} & \delta_0 + \delta_1 FARM\ SIZE + \delta_2 AGE \\ & + \delta_3 GENDER + \delta_4 EDU + \delta_5 EXP \\ & + \delta_6 COOP + \delta_7 SOIL + \delta_8 IRRI \\ & + \delta_9 TRAINING + \delta_{10} EXT \\ & + \delta_{11} VARIETY \end{aligned} \tag{14}$$

where *EFFICIENCY* is the technical efficiency, allocative efficiency, or economic efficiency of farmers calculated in the previous frontier functions. The variables used in this study are usually adopted in many studies in other stochastic frontier literatures. All variables are dummy variables and are defined as follows: *FARM SIZE* is defined as the acreage of farmer's rice field in hectare where 1=<2.5, 0=otherwise. *AGE* is defined as the age in years of the primary decision maker in the farming operation where 1=>40years, 0=otherwise. *GENDER* is the gender of the farmers, where 1=male,0=female. *EDUCATION* is defined as whether or not farmers have ever attended formal school where 1=yes,0=otherwise. *EXPERIENCE* indicates the number of year that the farmers have been involved in rice faming. *COOP* represents that if the farmer is a member of any cooperatives where 1=yes, 0=otherwise. *SOIL* indicates the level of soil fertility according to the farmer's perspective where 1=fertile, 0=otherwise. *IRRI* is the source of water used to supply water into the rice farm, where 1= irrigation, 0=otherwise. *TRAINING* indicates that if farmers have ever attended any training related to rice farming where 1=yes, 0=otherwise. *EXT* indicates if any extension workers went to visit rice farmer's farm, where 1=yes, 0=no. *VARIETY* is defined as the type of rice variety used, where 1= *HYV* (high–yielding varieties), 0=conventional (local) variety.

There are some points worth discussing from Table 4. First, Bruneian farmers are considered small–scale farmers by looking at the average size of farm of 1.96 hectares, where the largest scaled farmer operates 5 hectares and the smallest 0.8 hectares. The average age of farmers is between 40–50 years where most of them are retirees. The average level of experience of farmers is less than 10 years, probably one of the least in Asia, where the average duration of growing modern rice varieties is more than 10 years (Rahman, 2003). This is because farmers in Brunei only start to be involved in rice farming after they retire from the public or private sector, and the number of Bruneians who starts rice farming only increased few years back when the government emphasized on increasing local rice production by providing incentives to encourage Bruneians to plant

Table 4. Summary Statistics of the Variables Used to Estimate Source of Inefficiencies

Variable	Mean	Std. Dev	Min	Max
FARM SIZE	1.96	1.56	0.8	5
AGE	4.65	0.54	3	5
GENDER	0.67	0.47	0	1
EDU	1.36	1.01	0	4
EXP	2.85	1.63	1	5
COOP	0.31	0.47	0	1
SOIL	0.24	0.43	0	1
IRRI	0.35	0.48	0	1
TRAINING	0.79	0.41	0	1
EXT	0.89	0.31	0	1
VARIETY	0.70	0.47	0	1

[2] Battese *et al.*, (1989), Kumbhakar, (1994), Lin and Ma, (2006)

rice. Soil fertility in Brunei is not considered as one of the best for rice planting, where only 24 percent of the farmers perceived the soil of their land as fertile. Only 31 percent of the farmers interviewed are members of a cooperative, and lack of water supply in the rice field is one of the major constraints to achieve good yield. Only an average of 35 percent of farmers has access to irrigation.

Table 5 presents the results of the Two Limit Tobit Equations to estimate socio–economic factors that affect efficiency. According to the results, the estimated coefficient of *FARM SIZE* shows a robust and positive relationship with *TE* and *EE* but negative with *AE*. This indicates that farmers with small farm (less than 2.5ha) tend to have *TE* and *EE* advantage compared to big farms (more than 2.5 ha). This is perhaps not surprising. The finding is in conformity with the findings of Berry and Cline (1979) which stated that small farms's higher efficiency of resource utilization is primarily attribute to 'labor–market dualism'. They assume that these market concepts are applicable to a small–farm situation, where labor is largely drawn from the family, land is inherited, seed and manure are produced on the farm, and much of the output is consumed by the household. Negative relationship of *AE* and farm size could be due to ineffective cost of wage labor compared to family labor since large farms rely mainly on hired labor while small farms rely mainly on family labor. In contrast, Hien *et al.* (2003) stated that farmers with larger farms may encounter fewer problems than those with small farm in applying inputs at the right time and in the appropriate quantities. In addition, they have advantages over small farm in investment of hiring machinery and labor or other appliances or tools. Findings by Kalirajan (1981), Bravo–Ureta and Pinheiro (1997) and Idiong (2007) support the notion that farmers with larger farms tend to be more efficient than farmers with small farms which is in contrast to findings by Herdt and Mandac (1981), Lingard *et al.* (1983) and Zyl *et al.* (1995). Nevertheless, with these findings we can conclude that farm size significantly determines levels of efficiency in rice production.

AGE was found to have a negative and statistically significant connection with *TE* only. This finding could suggest that an increase in age leads to technical inefficiency of farmers. One of the possible explanations to this situation was reasoned by Shehu *et al.* (2007) who stated that the general ability to supervise farming activities decreases as farmers advance in age. These results are consistent with the findings of Kalirajan and Flinn (1983) and Bravo–Ureta and Evenson (1994). Younger farmers are likely to have formal education, and therefore might be more successful in gathering information and understanding new practices, which in turn will improve their efficiencies. As far as technical efficiency is concerned, the effect of farming experience, usually measured in number of years the farmer has been involved in rice farming, is one of the socio–economic factors that has been given great attention in many stochastic production function literature.

The results concerning *GENDER* suggest that farmer who is female has a positive association with *AE* but negatively associated with *EE*. Therefore, we can assume that female farmer exhibit higher levels of *AE*, but lower levels to *EE* equation. The roles of women in agriculture are well documented in Norton and Alwang (1993). Women have dual roles where they not only manage the affairs of the household but also the farm. Women are more efficient in making decision in selecting inputs in relation with market price compared to men. However, overall, men are more economically efficient in more labor intensive work like felling trees, ploughing, and so on.

The estimated coefficient *EXP* indicates that farmers with more farming experience tend to be more efficient in rice production. One of the reasons for the posi-

Table 5. Two Limit Tobit Equations to Estimate Technical (TE), Allocative (AE), and Economic (EE) Efficiency of Rice Farmers in Brunei during the 2010 Cropping Season

Variable	Parameters	TE		AE		EE	
		Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Constant	δ_0	0.6732***	0.0639	0.9582***	0.0413	0.6432	0.0552
FARM SIZE	δ_1	0.0920***	0.0339	–0.1531***	0.0219	0.1953***	0.0293
AGE	δ_2	–0.0607**	0.0316	–0.0219	0.0204	0.0372	0.0279
GENDER	δ_3	–0.0260	0.0322	–0.0515**	0.0208	0.0703**	0.0270
EDU	δ_4	0.0670	0.0313	0.0106	0.0203	0.0493	0.0317
EXP	δ_5	0.0473**	0.0367	–0.0085	0.0236	0.0507**	0.0321
COOP	δ_6	0.1900**	0.0371	0.0317	0.0239	0.2070***	0.0259
SOIL	δ_7	0.3320***	0.0335	–0.2580	0.0216	0.2834***	0.0289
IRRI	δ_8	0.2177***	0.0387	0.0935***	0.0249	0.2718***	0.0334
TRAINING	δ_9	0.1172***	0.0430	0.0164	0.0217	–0.1097	0.0371
EXT	δ_{10}	–0.0214	0.0463	0.0572**	0.0298	0.0175	0.0400
VARIETY	δ_{11}	0.1334*	0.0397	0.0081	0.0256	0.1521*	0.0343
Log–Likelihood		56.69		94.34		68.44	

Note; ***, ** and * are statistically significant at 1%, 5% and 10% respectively.

tive contribution of the variable to *TE* and *EE* could be that farmers with more years of experience tend to become more efficient through 'learning by doing' (Shehu *et al*, 2007). Furthermore, increased farming experience may lead to better assessment of importance and complexities of good farming decision, including efficient use of inputs.

Of all variables, the most worth mentioning variable in relation to efficiency is *COOP*. A positive relationship between *TE* and *EE* implies that farmers who joined cooperatives or associations, or formed an organization, tend to be more efficient than farmers who do not. Membership in farmers organizations/cooperatives allow the farmers to have the opportunities of sharing information with other farmers especially on 'how to use' knowledge on modern rice production practices by interacting with other farmers. Furthermore, farmers who joined or formed organization/cooperatives in Brunei are given priority to attend the so called 'Farmer's School Course' which was introduced and funded solely by the government through the Department of Agriculture. In this course, farmers were taught on rice field management, modern rice planting technique, use of pesticide and other chemicals and so on. Therefore, inefficiencies among farmers can be reduced if farmers joined or formed any organization or cooperatives.

The statistically strong significant effect of *SOIL* dummy variable with *TE* and *EE* indicates that this variable has significant influence upon the observed efficiency differentials. The positive coefficient is expected and supports the notion that farmers with farms of high soil fertility are more efficient than farmers with farms of low soil fertility. This can be explained by the facts that farmers with farms of low fertility tend to overuse inputs like fertilizer in order to increase inputs. Most literature omitted soil variable in their study, where there is a danger that physical differences in factors such as soil could play important factors in affecting efficiency among farmers as observed by Coelli *et al*. (2002). Of all the dummy variables, the IRRI variable is the only one that has uniformly the same sign and is statistically significant in all three efficiency equations. Poor infrastructure like in irrigation has proven to have positive effects on a farmer's inefficiency. In fact that most of the farmers have limited or no availability of proper water supply because no irrigation system is available. Most of the farmers interviewed lamented the unavailability of proper irrigation system, as they believed it can help to improve rice yield and efficiency.

TRAINING was found to be only significant in *TE*, which indicates that training is directly related to productivity. Therefore, we can conclude that, farmer who went to or attended farm–related training are more technically efficient than farmers who do not.

The *EXT* variable has a strong association with *AE*, which indicates that farmers who receive and follow the advice from extension workers regarding use of inputs according to prices are more allocatively efficient than farmers who do not.

The last variable included in the tobit equations is *VARIETY*. Although the impact of rice variety on *TE* and *EE* are not high, adoption of new varieties should be encouraged in rice production. Not only can this brings higher yields but also creates a sustainable, safe environment, and stable yield for the long run (Hien *et al*., 2003) Therefore, the role of Brunei Agricultural Department in introducing new technology to farmers should be emphasized here.

CONCLUSION

This paper uses a stochastic frontier production model to analyze the technical, allocative and economic efficiency among 82 rice farmers in Brunei during 2010 single cropping season. In the stochastic frontier production, the explanatory variables, particularly the labor and machinery, have significant effects on rice productivity. Therefore, considerable amounts of investment in these two variables could be important in improving rice yield. Moreover, the recommendation of use of appropriate and proper dosage of fertilizer and herbicide could also bring greater benefit for rice growers such as increasing rice output per hectare.

Rice yield per hectare in Brunei shows a very unsatisfied level of averagely 1 ton per hectare. However, positive rice productivity growth can be achieved if farmers are making efficient use of available resources and the existing technologies, and if the institutional factors that affect efficiency are resolved. Therefore, an examination of the relationship between efficiency and various institutional variables is important to reveal a clear strategy that could be recommended to improve performance. This analysis shows an average technical efficiency of 76 percent for rice farmers, which reveals that there is room for improvement in the productivity of rice among farmers in the sample in order to achieve maximum efficiency.

This study also reveals average levels of technical, allocative, and economic efficiencies are equal to 76.3 percent, 65.7 percent, and 53.1 percent, respectively. These results suggest that substantial gains in output and/or decrease in cost can be attained given existing technology. The results also point to the importance of examining not only *TE*, but also *AE* and *EE* when measuring productivity. Productivity gains stemming from technological innovation remain of critical importance in agriculture despite the role that higher efficiency levels can have on output. Therefore, research efforts directed towards the generation of new technology should not be neglected.

From a policy point of view, farm size has significant impact on overall efficiency whether the farmer has a big farm or vice versa. Although there are many arguments in the literature, whether large–farm farmers is more technically efficient than farmers with small farms, as far as rice farmers in Brunei are concern, it is recommended that land accumulation should be considered and future land granting policy should be considered and reviewed. It is also suggested that farmer should operate on medium–size farm to compensate on loss of cost on operating in big farms.

It is revealed that farmers who have farms of low soil fertility are more inefficient than farmers who have farms of high soil fertility. Consequently, they tend to overuse inputs like fertilizer, pesticide, labor and so on in order to achieve maximum output. This is true from the authors' observation during the survey. The unbalanced application of these inputs is one of the important factors that contribute to inefficiency. Therefore, proper training or adoption of integrated pest management (IPM) method is recommended not only to improve the soil fertility and efficiency but also for the development of sustainable agriculture. Individual farmers who used irrigation are more efficient in all three equations than those who did not. Water shortages cause the farmers to be inefficient especially rain–fed farmers. Therefore, it is suggested that the Bruneian government would seriously consider investing or upgrading rice farming infrastructure such as the construction of irrigation systems to increase cropping intensity, as well as a drainage system which will be useful not only for efficient water management but also to help to wash out the nutrient toxicity in the soil.

One of the most significant finding is that farmers who join organizations or cooperatives are more efficient because of the benefits they are receiving like technical assistance, priority to attend training, and so on. This is proven by looking at the training variable where efficiency improved in farmers who joined who joined organizations/cooperatives and participated in farm management training, compared to those who did not. Therefore, farmers who are not members of any organization or cooperatives are encouraged to join or form one. Hence, the authors suggest that specific government agencies like the agricultural department should organize farmer–training courses and encourage farmers to join it as this can improve their overall efficiencies.

The extension variable indicates that farmers who receive and follow the advice from extension workers regarding use of inputs according to prices are more allocatively efficient than farmers who do not. This enable the farmers to follow effective resource–use patterns and practices to improve the efficiency of paddy farms. It was found that farmers who have more than 5 years experience are more efficient. Therefore, it is recommended that farmers who have less than 5 years experience to attend rice–farming training or courses.

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REFERENCES

Aigner, D. J., C. A. K., Lovell and P. J. Schmidt 1977 Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* **6**: 21–37

Battese, G. E., and T. J. Coelli 1995 A Model for Technical Efficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics* **20**: 325–332

Battese, G. E., T. J. Coelli and T. C. Colby 1989 Estimation of Frontier Production Funtions and The Efficiencies of Indian Farms Using Panel Data from Icrisat's Village Level Studies. *Journal of Quantitative Economics* **5**: 327–348

Berry, R. A., and W. R. Cline 1979 *Agrarian Structure and Productivity in Developing Countries*. John Hopkins University Press

Bravo–Ureta, B. E., and R. E. Evenson 1994 Efficiency in Agricultural Production: The Case of Peasant Farmers in Eastern Paraguay. *Agricultural Economics*, **10**: 27–37

Bravo–Ureta, B. E., and A. E. Pinheiro 1997 Technical, Economic and Allocative Efficiency in Peasant Farming; Evidence from Dominican Republic. *The Developing Economics* **35**(1): 48–67

Bravo–Ureta, B. E., and L. Rieger, 1991 Dairy Farm Efficiency Measurement Using Stochastic Frontiers and NeoClassicial Duality. *American Journal of Agriculture Economics* **41**(2): 421–428

Coelli, T. J., S. Rahman and C. Thirtle 2002 Technical, Allocative, Cost and Scale Efficiencies in Bangladesh Rice Cultivation: A Non–Parametric Approach. *Journal of Agricultural Economics* **53**(3): 607–626

Coelli, T. J., D. S. P. Rao, and G. E. Battese, 2005 *An Introduction to Efficiency and Productivity Analysis*. Second Edition. Springer Publication

Coelli, T. J., 1996 *A Guide to Frontier 4.1: A Computer Programme for Stochastic Frontier Production Function and Cost Function Estimation*. Centre for Efficiency and Productivity Analysis (CEPA) Working Papers. Department of Econometrics, University of New England, Armidale, Australia

Department of Agriculture and Agrifood (DAA) 2008 *Towards Self Sufficiency in Rice Production*. Ministry of Industry and Primary Resources, Brunei. Government Printing

Department of Agriculture and Agrifood (DAA) 2009a *Brunei Darussalam Agriculture Statistics in Brief, 2008*. Ministry of Industry and Primary Resources, Brunei. Government Printing

Department of Agriculture and Agrifood (DAA) 2009b *Strategic Plan for Mid–Term Program, 2008–2013*. Ministry of Industry and Primary Resouces

Farrell, M., 1957. The measurement of Productivity Efficiency. *Journal of The Royal Statistics Society*, Series A, **120**(3): 253–290

Greene, W. 1980 Maximum Likelihood Estimation of Econometric Frontier Functions. *Journal of Econometrics* **13**: 5–25.

Herdt, R. W., and A.C. Mandac 1981 Modern Technology and Economic Efficiency of Philippine Rice Farmers. Economic Development and Cultural Change. *Journal of the Economic Development and Development Change*, University of Chicago **29**(2) 375–399

Hien, T. M., T. Kawaguchi and N, Suzuki 2003 A Study on Technical Efficiency of Rice Production in The Mekong Delta–Vietnam by Stochastice Frontier Analysis. *Journal of Faculty of Agriculture,* Kyushu University **48**(1.2): 325–357

Idiong, I. C., 2007 Estimation of Farm Level Technical Efficiency in Smallscale Swamp Rice Production in Cross River State of Nigeria; A Stochastic Frontier Approach. *World Journal of Agricultural Sciences* **3**(5): 653–658

Jondrow, J., C. A. K. Lovell, I. Materov and P. Schmidt 1982 On the Estimation of Technical Efficiency in the Stochastic Frontier Production Function Model. *Journal of Econometrics* **19**(2/3): 233–238

Kalirajan, K., 1981. An Econometric Analysis of Yield Variability in Paddy Production. Canadian. *Journal of Agricultural*

Economics **29**(3): 283–294

Kalirajan, K. 1991. The Importance of Efficient Use in the Adoption of Technology: A Micro Panel Data Analysis. *Journal of Productivity Analysis* **2**(2): 113–126

Kalirajan, K. and J. C. Flinn 1983 The Measurement of Farm–Specific Technical Efficiency. Pakistan. *Journal of Applied Economics* **2**(2): 167–180

Kopp, R. J., and W. E. Diewart 1982 The Decomposition of Frontier Cost Functions Deviations into Measures of Technical and Allocative Efficiency. *Journal of Econometrics* **19**(2–3): 319–331

Kumbhakar, S. C. 1994 Efficiency Estimation in a Profit Maximizing Model Using Flexible Production Function. *Agricultural Economics* **10**: 143–152

Lingard, J., L. Castillo and S. Jayasuriya 1983 Comparative Efficiency of rice farms in Central Luzon, The Philippines. *Journal of Agricultural Economics* **34**(2): 163–173

Lin, C. C. and Y. C. Ma. 2006 An Estimation of Production Efficiency of Taiwanese Firms in Mainland China; A Comparison of One–Step and Two–Step Estimation of Stochastic Frontier Approach. Research Paper presented at the Asia Pacific Economic Associaton (APEA) Conference, Seattle, USA

Meeusen, W. and J. Van De Broeck 1977 Efficiency Estimation from Cobb–Douglas Production Function with Composed Errors. *International Economic Review* **18**: 435–444

Norton, G. W. and J. Alwang. 1993 Comparative Agriculture Systems and the Role of Women. *In* "Introduction to Economics of Agricultural Development". McGraw–Hill Inc. Ch. 9 pp.149–166

Rahman, S. 2003 Profit Efficiency Among Bangladesh Rice Farmers. *Food Policy, Elsevier* **28**: 487–503

Ray, S. 1988 Data Envelopment Analysis, Nondiscretionary Inputs and Efficiency; An Alternative Interpretation. *Socio–Economic Planning Sciences*. **22**(4): 167–176

Schmidt, P. 1985–1986 Frontier Production Functions. *Econometric Reviews* **4**(2): 289–328

Schmidt, P., and C. A. K. Lovell 1978 Estimating Technical and Allocative Inefficiency Relative to Stochastic Production and Cost Frontiers. *Journal of Econometrics* **9**: 343–366

Sharma, K. R., P. Leung and H. M. Zalleski 1999 Technical, Allocative and Economic Efficiencies in Swine Production in Hawaii; A Comparison of Parametric and Non–Parametric Approaches. *Agricultural Economics*. **20**: 23–35

Shehu, J. F., S. I. Mshelia, and A. K. Tashikalma 2007 Analysis of Technical Efficiency of Small–scale Rain–fed Upland Rice Farmers in North–west Agricultural Zone of Adamawa State, Nigeria. *Journal of Agriculture and Social Sciences* **3**(4): 133–136

Zyl, J. V., H. Binswager. and G. Thirtle 1999 *The Relationship Between Farm Size and Efficiency in South African Agriculture*. Policy Research Working Paper. The World Bank