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GEOGRAPHICAL DISTRIBUTION OF TECHNICAL EFFICIENCY IN INDONESIAN RICE PRODUCTION DURING THE PERIOD OF 1979-1994

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Abstract

Agriculture still plays a key role in Indonesian economic development, but rice production is still less competitive than that in other countries. One possible cause is low productivity, which is to some extent dependent on technical efficiency. This study measures the technical efficiency of rice production in five regions, and examines factors determining its variability. This study uses stochastic frontier of production functions to estimate the technical efficiency. The results indicate that variation in rice production is due largely to variation in technical efficiency. Rice production in Bali is the most technically efficient, whereas in Kalimantan, Sulawesi and Nusa-Tenggara are still inefficient. The efficiency is dependent on facilities available in each region, government programs and the quality of land. Thus there is still a considerable opportunity for improvement in productivity of rice farms outside Java and Bali, given the state of agricultural technology for rice production. Improving agricultural facilities, such as water irrigation and training is capable of enhancing productivity of rice.

Keywords: *technical efficiency, stochastic frontier production function, panel data analysis*

INTRODUCTION

Agriculture still plays a key role in developing economies (Hayami and Rutan, 1985). In Indonesia around 1990s agriculture still absorbs approximately 50 per cent of employment and provides share around 20 per cent of GDP (Hill, 2000). It contributes 20 per cent of the agricultural gross domestic product, which is valued at Indonesian Rupiah (Rp) 112 495 million at current market prices. This is 39 per cent of the total GDP. In particular, rice is important because of its outstanding position in the national political economy, because it generates substantial income, employment and food security. It is, furthermore, the livelihood for the majority of Indonesian farmers, contributing more than 50 per cent of the total food grain production and most of the dietary energy requirement. Rice is grown on almost 11 million hectares, accounting for more than half of the total cultivated area in food production (Badan Pusat Statistik [BPS], 1998).

Despite the fact that Indonesia has an abundance of land, it is still uncompetitive in the global market. The cause is the productivity of rice farms is still low, particularly in some regions where rice has not been intensively cultivated. Therefore the rice productivity of farm needs to be enhanced. Adopting new technology is one the options to do this. However, if farmers in some regions have not used existing technology efficiently, Shapiro (1983) and Belbase and Grabowski (1985) argue that efforts to improve efficiency may be more cost effective than introducing new technologies as a means of increasing agricultural productivity. A study on efficiency is selected as a way of exploring the reasons that suppress productivity in Indonesian rice farming.

This paper attempts to analyse the efficiency of Indonesian rice production. The analysis utilises a stochastic frontier production technique, and decomposes the effect of wetland, government programs, and geographical characteristics. This paper gives an overview of stochastic production function theory, including a definition and techniques use. It is followed by explanations of variables and the data set used. The results from the model and their discussion lead us to interpretations and conclusions.

LITERATURE REVIEW

Technical efficiency (TE) can be defined as the ability of a producer to result in maximum output given a set of inputs and technology (Kumbhakar and Lovell, 2000; Sadoulet and de Janvry, 1995). Methodologically, there are two main types of estimating technical efficiency: parametric and non-parametric. The parametric approach relies on a specific functional form and can be sub-divided into deterministic and stochastic models. The deterministic model holds the assumption that any deviation from the frontier is due solely to inefficiency, while the stochastic model allows for statistical error. The non-parametric a pproach is independent of functional forms, and there no a specific functional form required in estimating TE. Econometric techniques for the estimation of efficiency can be separated into primal and dual approaches that depend on the underlying behavioural assumptions made. Greene (1993) argues that the technical inefficiency (TI) measures derived from the dual models are not straightforwardly interpreted. According to the type of data, the econometric estimation of frontier functions can also be sorted into cross-section or panel data analyses. The ability of observing each unit more than once is capable of resulting in more accurate estimates of efficiency than single cross-section observations (Greene,1993; Lovell, 1993).

Related to stochastic frontier production, there two approaches. The first approach is error component model that incorporate a composed error structure with a two-sided symmetric term and a one-sided component (Aigner *et al*., 1977); Meeusen and van den Broeck, 1977). The one-sided component reflects inefficiency, while the two-sided error captures the random effects outside the control of the production unit including measurement errors and other statistical noise typical of empirical relationships. The second approach recently proposed by Kalirajan *et al.* (1996) is called varying coefficients model that allows different coefficient among firms. This approach has been used to estimate technical efficiency and productivity growth of Indian agriculture (Kalirajan *et al*., 2001) and Chinese economy (Kalirajan, 2004).

The main difference between error component and varying coefficients models is that coefficient of production technology. In the error component model, all firms are assumed to have the same coefficient technology but have different productivity (intercept), which represents inefficiency. The frontier production technology is representation of which a firm with the smallest inefficiency. In contrast, in the varying coefficients model, all firms are assumed to have both different productivity and coefficients of technology. The frontier production technology is the representation of the combination of best productivity and coefficients of technology in each firm. One of the drawbacks of this model is highly increasing return to scale of frontier production technology, which is slightly unrealistic in the long run economies.

From an econometric perspective, the estimation of stochastic frontiers with panel data analysis has some advantages, compared with cross-sectional estimation. A major feature of panel data is the ability to decompose productivity growth into technological change and TE. Another key element is that consistent estimates of TI are provided when adding more observations on the same subject, whereas adding more units to a given cross-sectional data set still has a problem of consistency. The panel data analysis also has an advantage in that it opens up an opportunity for computing efficiency by estimating the fixed effects model. This eliminates the need for imposing distributional assumptions on the one-sided error term and also avoids the assumption that the inefficiency term is uncorrelated with the independent variables (Schmidt and Sickles, 1984). Moreover, TE can be modelled as time-varying or time-invariant and suitable statistical tests can be applied to determine which alternative is consistent with the data at hand (Ahmad and Bravo Ureta, 1996).

The frontier methodology has become a widely used analytical tool in applied production economics since the original work of Farrell (1957). This is due largely to its consistency with the definition of production, profit or cost function theories. Its reputation is shown by the large number of methodological and empirical frontier analyses over the last two decades. Battese (1992) and Bravo-Ureta and Pinheiro (1993) review the applications of frontier methodology to examine TE in agriculture. These reviews highlight the efforts that have been devoted to measuring efficiency in developing countries where agriculture plays a key role in economies, using the broad collection of available frontier models. Some studies that focus on agricultural production efficiency using various approaches have been done by Widodo (1989); Battese and Tessema (1993); Kumbhakar (1994); Bravo Ureta and Evenson (1994); Llewelyn and William (1996); Coelli (1996a); Tadesse and Krishnamoorthy (1997); Amaza and Olayemi (2002) Umetsu *et al.* (2003); and Dhungana *et al.* (2004);

This study is different from the previous ones in some aspects. First, this study employs data sets on output and input per hectare to estimate production functions. This is based upon the assumption that the production functions are restricted to be exhibiting constant returns to scale. In this case, TE measures how efficient, on average, farmers in each region operate a hectare of farmland. The advantages of using data on output and inputs per hectare, compared with farm level and aggregate data, are the capacities to measure TE of farms at regional level, and eliminating intensification effects (rice being grown more than once a year). This happens in some regions where there is no constraint in water supply. However, one limitation of using data per hectare is being unable to measure individual TE of each farm operation.

Second, this study uses stochastic frontier production functions, that is, the production representing the best practice that has two components, one to account for random effects and another to account for technical inefficiency (Coelli, 1996). Previous studies on TE in Indonesian agriculture were conducted using non-parametric and parametric deterministic methods. The non-parametric TE models, which are referred to as data envelopment analysis (DEA), are based on mathematical programming techniques. The methods have a major disadvantage, i.e. they are deterministic and consequently influenced by an extreme observation. The parametric deterministic model assumes that any deviation from the frontier is due solely to inefficiency while the stochastic approach allows for statistical noise that represents uncontrollable factors. In agriculture, the uncontrollable factors include pest outbreak, weather and climate. Therefore, a basic problem with deterministic frontiers is that any measurement error, and any other source of stochastic variation in the dependent variable, is set in the one-sided component making the resulting TE estimates sensitive to outliers. The stochastic frontier production model is capable of addressing this sensitivity problem by incorporating a composed error structure (Greene, 1993). Furthermore, the stochastic frontiers also make it possible to estimate standard errors and to generate test hypotheses.

In terms of data used, this study used a balanced panel model. According to Greene (1993), models that rely on panel data are likely to yield more accurate efficiency levels given that there are repetitive observations on the same object. Another significant feature of this paper is to investigate the effect of geographical characteristics on TI. In most cases, TI is influenced by characteristics of farms, as reported by Munroe (2001).

THEORETICAL FRAMEWORK

Efficiency of a production unit is defined as how effectively it uses variable resources for the purpose of profit maximization, given the best production technology available, the level of fixed factor, and product and factor prices (Sadoulet and Janvry 1995). Consider a firm with production technology $f(X)$ that shows the maximum output Y attainable from various input vectors X, and suppose that the firm produces Y^0 level of output using inputs X^0. According to Kumbhakar (1988), the firm is then said to be technically efficient if $Y^0 = f\left(X^0\right)$, and technically inefficient if $Y^0 < f\left(X^0\right)$. The presence of technical inefficiency implies that productivity of one or more inputs are lower than what it would be with technical efficiency, which is dependent on function form of the technology.

To measure technical efficiency, it is appropriate to use the stochastic production frontier because agricultural output is typically treated as a stochastic variable due to natural shocks such as weather conditions, pests and diseases outbreak. By following Aigner *et al.* (1977) and Meeusen and van den Broeck (1977), a method of estimating a stochastic frontier production function allows the disturbance term (ε) to be composed of two parts, a systematic component (v) and a one-sided component (u). In relation to panel data, a functional form of a stochastic production function is specified as:

$Y_{it} = f(\mathbf{X}_{it}, \beta, t) \exp\{\varepsilon_{it}\}$ .... (1)
$i = 1, 2 \ldots . n$, and $t = 1, 2, \ldots T$.

where Y is output, $\mathbf{X}_{it}$ is a vector of inputs and β is a vector of parameters to be estimated. The error term (ε_i) is, then defined as:

$\varepsilon_{it} = v_{it} - u_{it}$ .... (2)

The systematic component v_{it}, which captures random variation in output due to factors outside the control of the farmer, is assumed to be independently and identically distributed (*iid*) as N (0, $^{2}_{v}$), independent of u_{it}, which measures the TI relative to the stochastic frontier. Most of the empirical literature suggests that, u_i is assumed to have a non-negative (one-sided) half-normal distribution with N (0, σ_u^2).

Consider $^{2}_{u}$ and $^{2}_{v}$ are the variances of the parameters one-sided (u) and systematic (v) respectively, and define:

$\sigma^2 = \sigma_v^2 + \sigma_u^2$ .... (3)

According to the study of Jondrow *et al.* (1982), the ratio of the two standard errors:

$\gamma = \sigma_u^2 / \sigma^2$ .... (4)

represents a total variation of actual output deviating from the frontier. It can be attributed to TE (Battese and Corra, 1977). Thus, based on the assumption that u_i and v_i are independent, the parameters of the production frontier can be estimated using a maximum likelihood method. Furthermore, given a multiplicative production frontier for which the production function is specified, the farm-specific TE_{it} of the ith farm in the time tth period is estimated using the expectation of conditional random variable ε_i as shown by Battese and Coelli (1988). That is:

$$TE_{it} = \frac{E(Yit \mid uit, Xkit)}{E(Yit \mid uit = 0, Xkit)} = \exp\{-u_{it}\} \ ..... \ (5)$$

It is shown that the TE_{it} lies between 0 and 1. When TE is equal to 1, the actual output lies on the stochastic frontier production.

METHODOLOGY

This study uses primal approaches, or the direct estimation of the production functions. Work of Thiam *et al.* (2001) concludes that the primal approaches result in more accurate estimates of TE. Furthermore, this study employs Cobb-Douglas (CD) yield function. This model is used because of drawbacks of estimating a production function involving aggregate time-series data in agriculture, which is exact multicollinearity among inputs. This is because the input uses increase proportionately with the increase in area under cultivation. To overcome the problem, the production function is estimated using data per hectare. This is based on an assumption that the production function exhibits constant returns to scale (CRS). Kompas (2002) uses the assumption of a “technical’ CRS production function, which is consistent with the empirical literature on agricultural production functions. Thus, dividing both right and left hand sides by land, results in a production function where land is constant and can disappear in the model. The yield function is specified as:

$$\ln y_{it} = \ln \beta_0 + \Sigma\, \beta_k \ln \mathbf{x}_{kit} + \psi_1 T + \varepsilon_{it} \ .... \ (6)$$

where y_{it} = paddy output in kg/ha, x_{1i} = seed in kg/ha, x_{2i} = labour used in monetary terms/ha, x_{3i} = fertilisers used in kg/ha, x_{4i} = compost used in monetary terms/ha, x_{5i} = pesticides used in kg/ha, ln = natural logarithm. Time (T) is included in the model to account for smooth technological progress (O'Neill *et al.*, 1999). In this case, estimating TE using per hectare data can be interpreted as indicating how an efficient farm in each region operates a hectare of paddy field.

Using STATA ver.8 permits two different parameterisations of the inefficiency terms u_{it}: a time-invariant model and the Battese and Coelli (1992) parameterisation of time-effects. In the time-invariant model, the inefficiency term is assumed to have a truncated-normal random distribution, which is constant over time within panel, that is $u_{it} = u_i$. However, a recent study by Druska and Horrace (2004: 196) argue that ‘if T [time] is somewhat large, the usually time-invariant unobserved heterogeneity models (e.g., FE) may not be applicable, since it is widely held that heterogeneity may change in long run dynamic economic system (particularly when it is viewed as TE)’. Thus, the Battese and Coelli’s (1992) parameterisation of time effects (time-varying decay model) is also used. The inefficiency term is modelled as a truncated-normal random variable multiplied by a specific function of time, that is $u_{it} = u_i\, e^{\eta(t-T)}$, where T corresponds to the last time period in each panel, η is the decay parameter to be estimated, and u_i are assumed to have a $N(\mu, \sigma_u^2)$ distribution truncated at zero. In both models, the idiosyncratic error term is assumed to have a normal distribution with a zero mean. The only panel-specific effect is the random inefficiency term (Kumbhakar and Lovell, 2000)

To improve the TE, it is necessary to recognize the sources of variation influencing the TE. A model of estimating the factors is expressed as:

$$TE = \delta_0 + \delta_1 AREA + \delta_2 WET + \delta_3 TRN + \delta_4 JAV + \delta_5 BAL \quad (7)$$

where AREA is total rice-planted area in each province (thousand ha), WET is amount of wetland (%), TRN is a dummy for training program (1 if there is a training program), JAV is a dummy for region of Java, and BAL is a dummy for region of Bali.

It is interesting to see the effect of geographical characteristics of a region on TE. If the characteristics have negative impacts on TE, this means that the region is not conducive to operate farms. The total amount of rice-planted area represents scale or a number of farms in each region. It could be the case that it has a significant impact on TE. This is dependent on how farm operators interact with each other. The proportion of wetland in each region is expected to increase TE. This is because rice will grow better in wetland. Training programs are expected to enhance TE, since the training enables the farmers to effectively implement the existing agricultural technology. Java is selected to be source of TE because of political reason, that is, this island is of Indonesian rice bowl and field laboratory of rice at which rice is cultivated intensively and various programs have been conducted. Bali is culturally unique because of well-organised agriculture in terms of irrigation, which is absent in other Indonesian regions. Technically, rice will grow optimally in controllable irrigation system. Therefore, both locations are expected to have positive impact on TE. Other regions: Nusa Tenggara, Kalimantan, Sulawesi and Sumatera are not included in the source of efficiency because there is no speciality hypothesised to increase efficiency.

This study uses a two-step process for estimating the model of efficiency, i.e. the production frontier is first estimated and the TE of each firm is derived. These are subsequently regressed against a set of variables, $\mathbf{Z}_{it}$, which are hypothesised to source of rice farms' efficiency in each region (Bravo-Ureta and Evenson, 1994). One important to note is that since TE lies between zero and one, estimating the model using OLS will result in biased estimators. Greene (1993) suggests that estimating a model with truncated dependent variable can be conducted using tobit regression model with lower and upper limits zero and one respectively.

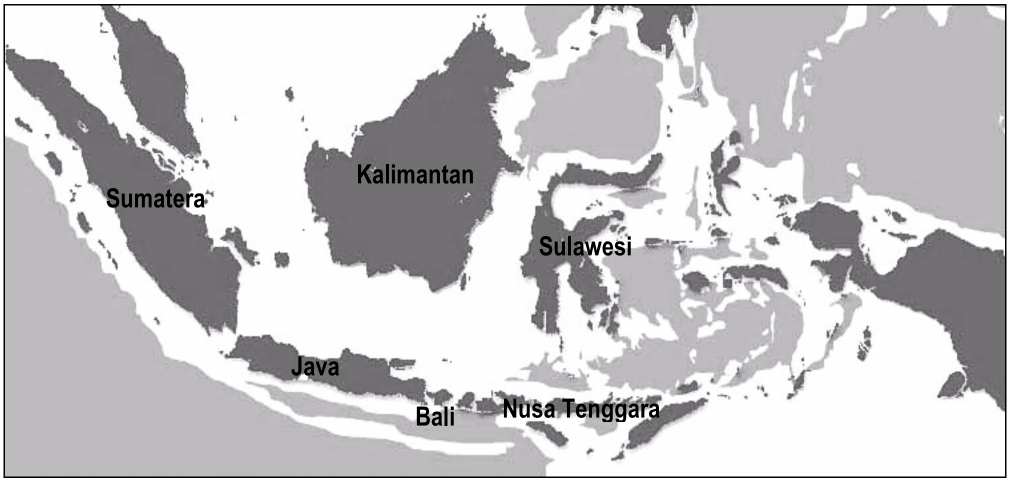
Geographical Distribution of Technical Efficiency

The distribution of TE among regions is modelled as:

$$TE_{it} = \phi_0 + \phi_1 SUM + \phi_2 BAL + \phi_3 KAL + \phi_4 SUL + \phi_5 NTG \quad (8)$$

where SUM, BAL, KAL, SUL, and NTG, are geographical dummy variables of Sumatera, Bali, Kalimantan, Sulawesi and Nusa Tenggara respectively, which are equal to one for the corresponding region, and zero otherwise. The location of the regions is shown in Figure 1. The region of Java (if all dummies are equal to zero) is preferred as a base of comparison because in this region rice is being intensively cultivated, and therefore the TE is hypothesised to be higher than that in other regions. The model is estimated using OLS.

Figure 1: Area of Study



Testing Hypothesis

Some hypotheses are built in this study. The first hypothesis is that identifying technological progress, T. This is important since this analysis employs time-series data relatively large. The formal formulation of test is:

Ho: ψ_1=0 and H_1: ψ_1>0

The second hypothesis is to identify whether TE matters in Indonesian rice produ tion, i.e. variation in actual outputs that deviate from production frontier is due to variation in TE. It can be formally formulated as:

Ho: $\gamma = 0$ and H_1: $\gamma > 0$

The next hypothesis is to identify whether TE is time-invariant or time-varying. The formal formulation of test is:

Ho: $\eta = 0$ and H_1: $\eta \neq 0$

The further hypothesis is that TE is dependent on some geographical characteristics. It can be formally formulated as:

Ho: $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ and H_1: at least one of them $\neq 0$

The last but not least hypothesis is that there is variation in average TE across regions. It can be formally formulated as:

Ho: $\phi_1 = \phi_2 = \phi_3 = \phi_4 = \phi_5 = \phi_6 = 0$, and H_1: at least one of them $\neq 0$

Data and Variables

This paper uses the balanced panel data consisting of 23 provinces in Indonesia during 1979-1994[1]. Unit root tests on variables have been conducted using an augmented Dickey-Fuller test. The tests show that there is no unit root in such variables. The total number of observations used is 368. The database established from various publications of the Indonesian statistical bureau (BPS) and Indonesian agricultural

[1] The balanced panel data at which there is no missing observation in each year and region is only fulfilled by available data during the periods of 1979-1994. After the period, the data is discontinued and the availability is three-yearly interval. Thus, it is impossible analyse balanced panel data if including more recent data. As mentioned in literature review, the balanced panel analysis is the significant feature of this study. The starting point of 1979 is somewhat too old. However, this study is to capture time-varying technical efficiency that needs long period.

reports. Table 1 shows a brief description of these variables and their sources, and Table 2 shows summary statistics for key variables used in this analysis. Descriptively, it can be seen from Table 2 that the level of output of rice per hectare in Java and Bali is much higher that that in other regions, as well as, on average, the level of input use. Related to the area under rice cultivation, Java has the widest area. More than 95 per cent land under rice cultivation in Java and Bali is wetlands. Kalimantan is the only region that has no training at all.

Table 1: Data Used and Source

Variable	Description	Sources
Rice production	Rice yield in each province (kg/hectare)	BPS (1979-1995)
Seed	Seed used in rice production (kg/hectare)	BPS (1979-1995)
Fertilisers	Amount of fertilisers used in rice production (kg/hectare)	BPS (1979-1995)
Compost	Organic fertiliser used in rice production (Rp/hectare)	BPS (1979-1995)
Pesticides	Pesticides used in rice production (kg/hectare)	BPS (1979-1995)
Labour	Labour hired in rice production (Rp/hectare)	BPS (1979-1995)
Area	Total areas under rice cultivation (000 hectare)	BPS (1979-1995)
Wet land	Proportion of wetland relative to the total area (%)	BPS (1979-1995)
Training	Farmer's training program, dummy variable (1 if there is a training)	Untung (2000), Alimoeso *et al.* (2001).

Note: BPS (1979-1995) is "*Statistik Indonesia*" published by BPS Jakarta.
Source: author's collection

Table 2: Summary Statistics for Key Variables

Variable	Region					
	Sumatera	Java	Bali	Kalimantan	Nusa Tenggara	Sulawesi
Rice (kg/ha)	3206.12	4551.69	4685.63	2185.09	3063.25	3125.94
	(600.05)	(526.08)	(495.02)	(338.06)	(904.56)	(749.51)
Seed (kg/ha)	39.90	39.06	40.94	32.22	40.94	38.06
	(2.15)	(3.11)	(2.20)	(6.43)	(2.16)	(6.85)
Pesticides (kg/ha)	1.68	3.49	1.30	0.56	1.30	1.56
	(0.47)	(1.76)	(0.38)	(0.28)	(0.37)	(0.78)
Fertilisers	175.51	341.44	209.86	71.26	209.86	152.86
(kg/ha)	(49.97)	(66.40)	(48.21)	(40.42)	(47.43)	(72.18)
Compost	463.36	2156.25	460.31	289.63	460.31	141.25
(kg/ha)	(218.90)	(1135.83)	(346.13)	(231.02)	(340.51)	(116.26)
Labour (RP/ha)	83,349	188,587	94,044	46,697	94,044	72,898
	(39,992)	(95,639)	(44,788)	(24,366)	(44,060)	(42,186)
Area (ha)	302,475.8	1,287,474	167,765.3	214,535.1	190,178.4	232,829.9
	(170,879.6)	(705,524.9)	(7,888.42)	(106,121.2)	(62,376.5)	(264,331.3)
Wet land (ha)	248,847.9	(1,207,224)	164,056	153,968.5	148823.8	213,457.4
	(154,014.4)	(672,001)	(6,290.44)	(104,866.3)	(86,432.48)	(264,513.5)
Training	0.23	0.38	0.38	0	0.19	0.09
	(0.43)	(0.49)	(0.5)	(0)	(0.40)	(0.29)

Note: Figures in the parentheses represent standard deviations
Source: Author's calculation

RESULTS AND DISCUSSIONS

Table 3 shows CD production functions estimated using fixed effect and random effect panel regression and time-invariant and time-varying frontier panel estimations. All coefficients on explanatory variables indicate that model of CD is suitable because there is no significantly negative marginal product of productive input. Pesticides have significantly negative sign, pesticides are not productive input, but protective input instead (Lichtenberg and Zilberman, 1986).

It can be seen that technological progress has a significant contribution to the productivity of rice. It can also be seen that γ in both time-invariant and time-varying models are significant. These indicate that around 97 per cent of variation in actual output relative to the production frontier is explainable by variation in TE. Furthermore, the stochastic production frontier is time-invariant, which is indicated by insignificancy in η. This implies that TE is time-invariant or constant over time with level of technological progress. However, the technological progress rises over time, meaning that the TE grows proportionately with the increase in technological progress.

Table 4 shows parameters on source of variation in technical efficiency. It can be seen that rice farms operated over wide areas have significant difference in TE. This implies that farmers operating rice farms in wide areas are less technically efficient. Thus large areas are not conducive for operating rice farm. It could be the case that in such areas there is a bad competition on accessing resources, that cause farmers are not able to operate their farm efficiently. As expected, wetland, training, Java and Bali have positive and robustly significant effects on TE. It is obvious that high TE is in wetlands because of the fact that rice technically grows much better in wetlands. It is clear therefore, that rice farms situated in provinces where wetlands dominate areas under rice cultivation have more technically efficient rice farming than those areas lacking wetland.

Training is capable of raising TE. This means that farmers in the places where agricultural training exists are able to operate rice farms more technically efficiently. In other words, the average production function comes closer to the stochastic frontier production. This is logical since the training, in this case, is on management of agro-ecosystems in which farmers are trained on how to analyse their rice farms based on the observed information (Untung, 1996). This finding is in line with most cases summarised by Munroe (2001) that in developing country agriculture, extension programs have a significant impact on increasing TE.

Table 3: Estimated Production Functions

Variables	Average function (Panel Regression)		Stochastic frontier function (MLE)	
	Fixed effect	Random effect	Time-invariant	Time-varying
Intercepts	7.491384[a] (0.2191)	7.3876[a] (0.2268)	7.8221[a] (0.2214)	7.8254[a] (0.2218)
Seed	-0.0638[ns] (0.0407)	-0.0747[b] (0.0415)	-0.0712[c] (0.0393)	-0.0718[c] (0.0394)
Fertilisers	0.0289[a] (0.0081)	0.0284[a] (0.0083)	0.0285[a] (0.0080)	0.0290[a] (0.0083)
Compost	-0.0058[ns] (0.0043)	-0.0037[ns] (0.0044)	-0.0044[ns] (0.0042)	-0.0043[ns] (0.0042)
Pesticides	-0.0128[a] (0.0063)	-0.0141[a] (0.0064)	-0.0138[b] (0.0062)	-0.0137[b] (0.0062)
Labour	0.0495[a] (0.0229)	0.06267[a] (0.0232)	0.0584[a] (0.0218)	0.0578[a] (0.0219)
Time trend	0.0159[a] (0.0024)	0.0143[a] (0.0025)	0.0148[a] (0.0023)	0.0151[a] (0.0026)
	F=197.98[a] R^2= 0.24	χ^2 =1139[a] R^2=0.26	L-L= 453.13 χ^2 (6)=1213[a]	L-L= 453.17 χ^2 (6)=350[a]
σ^2			0.1251[a] (0.0713)	0.1263[a] (0.0721)
σ_u^2			0.1216[a] (0.0713)	0.1228[a] (0.0721)
σ_v^2			0.0035[a] (0.0003)	0.0035[a] (0.0003)
γ			0.9718[a] (0.0162)	0.9721[a] (0.0161)
η				-0.0007[ns] (0.0029)
White's test	NR^2=66.4[a]	NR^2=37.2[ns]		

Note: Figures in the parentheses represent standard errors; a) significant at α= 1%; b) significant at α= 5%; c) significant at α= 10%; ns) insignificant. The White's test is conducted on the regression of idiosyncratic errors, v_i, on independent variables and its interactions. L-L stands for Log likelihood

Source: Author's calculation

Table 4: Source of Variation In Technical Efficiency

Independent variable	Coefficient	Standard error
Constant	0.2848[a]	0.0104
Area	-6.85e-08[a]	6.68e-09
Wetland	0.0031 [a]	0.0002
Training	0.0153[a]	0.0053
Java	0.5470[a]	0.0123
Bali	0.6137[a]	0.0151
Log-likelihood	656.49[a]	
χ^2	7673.23	

Note: dependent variable is TE estimated with time-invariant model; a) significant at α= 1%;
Source: Author's calculation

Table 5: Distributional Technical Efficiency Among Regions

Regions	Coefficient	Standard Error
Intercept	0.9146	0.0126[a]
Sumatera	-0.2340	0.0154[a]
Bali	0.0620	0.0282[b]
Nusa Tenggara	-0.2761	0.0218[a]
Sulawesi (Celebes)	-0.2479	0.0178[a]
Kalimantan (Borneo)	-0.4357	0.0178[a]
R^2	0.6714	
F(5,362)	147.90a	

Note: Figures in the parentheses represent standard errors; a) significant at α= 1%;
b) significant at α= 5%
Source: Author's calculation

Java and Bali have positive and significant impact on TE. This means that rice farms in Java and Bali are more technically efficient than those is other regions. One of the factors is that Java is considered as a rice-bowl area, in which government policy has conducted a lot of intensification programs (Barbier, 1989). In addition, Bali has the best system of irrigation management through a "Subak", an agricultural institution that controls the distribution of irrigation water to its members (Sepe, 2001).

Table 5 shows that the only coefficient on Bali, is significantly positive. This means that, on average, rice farms in Bali are the most technically efficient. Furthermore, the coefficient on Kalimantan is the most negative and significant. This means that rice farms in Kalimantan are the least technically efficient. Related to the geographical characteristics, the variation in TE is probably associated with differences in soil heterogeneity, rainfall pattern, culture and other factors among regions.

Further indication shown in Table 5 is that Balinese are the most technically efficient rice-growers in the Indonesian archipelago, with the average technical efficiency of 0.97; in contrast, Kalimantan has the most technically inefficient farms, with the average technical efficiency of 0.47. It could be the case that Kalimantan is not suitable for rice farming. In Sumatera, Sulawesi and Nusa Tenggara, the TE is about 0.6, and therefore there is considerable opportunity for improvement in the rice productivity of the rice farms. In this case, rice farms in such areas given the existing technology for rice production can still make further improvements in rice productivity. In the case of provinces in Kalimantan, it would be better to replace rice with other commodities, which would grow better in the ecosystem of Kalimantan.

CONCLUSION

Rice production in Indonesia is still not capable of being competitive in the open market. This is probably because the productivity of rice is still low, particularly in areas outside of Java. Because of the fact that most Indonesian people rely on rice for dietary energy requirements, it is important to raise productivity of rice. There are two choices for increasing productivity, adopting new technology and raising level of TE. Adopting new technology will be effective if the process of production with existing technology is technically efficient. However, if the production with the existing technology is technically inefficient, raising TE will be cost effective. Thus, estimating TE of rice production is a proper choice. After the TE is determined, then factors affecting the differential TE can be found, and subsequently TE can be raised using such factors.

Using stochastic frontier production functions indicates that TE has a key role in affecting Indonesian rice production. Furthermore, in some regions outside Java and Bali, rice farm technical efficiency is less than the average. This means that with the existing technology, rice production can still be increased. Regional characteristics that have positive effect on TE are wetland, training, intensification and irrigation management. Rice farms in wetlands which are more technically efficient is sensible since rice grows better in wetlands. This corresponds to the fact that rice farming in Bali, where irrigation is well organized, is technically operated at the highest efficiency. Another important factor that significantly increases TE is training programs. It makes sense because farmers will be more capable of implementing the existing technology after participating in training. This implies that the average production function will approach the stochastic frontier production. This appears in Java and Bali where various extension programs have been implemented, and as a result farmers in both regions operate rice farms more technically efficiently than those in other regions.

One interesting indication to note is that TE grows over time. The growth in TE is proportionately with the increase in technological progress. This means that rice farms in each region are getting more technically efficient. The implication is that the average production function is getting closer to the stochastic frontier production.

Since rice production outside Java and Bali is still technically inefficient, there is enough room for improvement in the productivity of rice farms, given the state of agricultural technology for rice production. This can be done by improving irrigation facilities and converting dry land into wetland. It will be an ideal policy if this is supported by carrying out training programs in corresponding regions.

Limitation

There are two limitations in this study. First, this study uses the balanced panel aggregate regional data, which is slightly less effective than using firm level data. However, the regional data can still be interpreted as the mean efficiency measure of farms within the selected regions (Kalirajan *et al*., 1996). Second, data used is study is somewhat old in terms of time period. This is because of unavailability of yearly continual panel data until recent year that fulfils balanced panel data analysis.

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