Decomposition Measures of Technical Efficiency for Pepper Farming in Sarawak, Malaysia

Alias bin Radam and Ismail bin A. Latiff[*]

Abstract

The paper analysed the components of efficiency in the production of pepper in Sarawak, Malaysia. Results showed that the average farm could have increased its output by as much as 551 per cent. Inefficiency was mainly derived from the excessive utilisation of farm inputs Analysis of farm size and efficiency indicated the improvement in several efficiency measures but the gain was not overall. Thus farmers should increase farm size and utilise farm inputs to optimum levels. This would increase efficiency levels, reduce input costs and directly increase farm income.

[*]The authors are Lectures of the Department Agricultural Economics at the University Pertanian, Malaysia.

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I. Introduction

Pepper is an important commodity in Sarawak. It is listed as the fourth biggest income earner, employs over 52,000 households and covers about 9,500 hectares of the state land area (Ministry of Primary Industries, 1990). As an agricultural crop, it is subjected to the vagaries of price fluctuations of white and black pepper products. The high prices of 1986/87 had induced greater production but this led to an eventual decline in export prices by 1990. During the periods of low prices many farms were faced with losses that they had to stop production. Thus, the inevitable solution is to evaluate the production efficiency of the pepper farms. Does efficiency differences exists between farms and what can be done to increase production efficiency to optimum levels?

In standard micro-economic theory, production technology is represented by the transformation (production) function that defines the maxi-

*The authors are Lectures of the Department Agricultural Economics at the University Pertanian, Malaysia.

mum attainable outputs from different combinations of inputs. Hence, the transformation function describes a boundary or a frontier. If the production frontier is known, the technical inefficiency of any particular farm can be assessed easily by simply comparing the position of the farm relative to the frontier. In practice, however, only observations of output levels achieved and input levels employed are available. From these observations the production frontier are then empirically constructed. Numerous methods have been developed for the empirical measurement of frontier production functions. These methods can be categorised into the parametric and non-parametric approaches.

Measuring efficiency using a non-parametric approach began essentially with Farrell (1957). His estimation was based on linear programming techniques where a convex disposal hull was constructed based on observed input-output combinations. The efficiency measure developed were used to measure the efficiency of individual decision making units an in Charnes, et al. (1978), Byrnes, et al. (1984,1987,1988), Grabowski and Pasurka (1988) ,Weersink, et al. (1990), and among others. Non-parametric procedures for estimating production frontier functions possess a number of attractive properties: (a) they do not impose any ad-hoc functional form on the production frontier such as those dictated by parametric procedures, (b) they do not necessitate any distributional assumptions on efficiency, (c) they allow estimated of frontiers with multiple outputs and multiple inputs without resorting to restrictive aggregation assumptions, and (d) simulation evidence has shown that the production frontier estimated outperformed translog deterministic statistical frontiers even when the true frontier was of the translog variety (Banker, et al., 1988).

The purpose of this paper is to estimate the technical efficiency for a cross section of Sarawak pepper farm. The empirical analysis will be based on the deterministic non-parametric approach of Fare, el al. (1985). The next section discusses the methodology used in measuring the technical efficiency of farm. The paper then proceeds with the data and empirical results and finally ends with the conclusions.

II.Methodology

Fare, et al. (1985) begin by specifying a transformation function, T, which satisfies constant returns to scale and strong input disposability:

$$T=\{(x,y):y\leqq Yz, Xz\leqq x, z\in Rk^{+}\} \qquad (1)$$

where

x= a (n x 1) vector of inputs

y= a (m x 1) vector of output

k= the number of farms

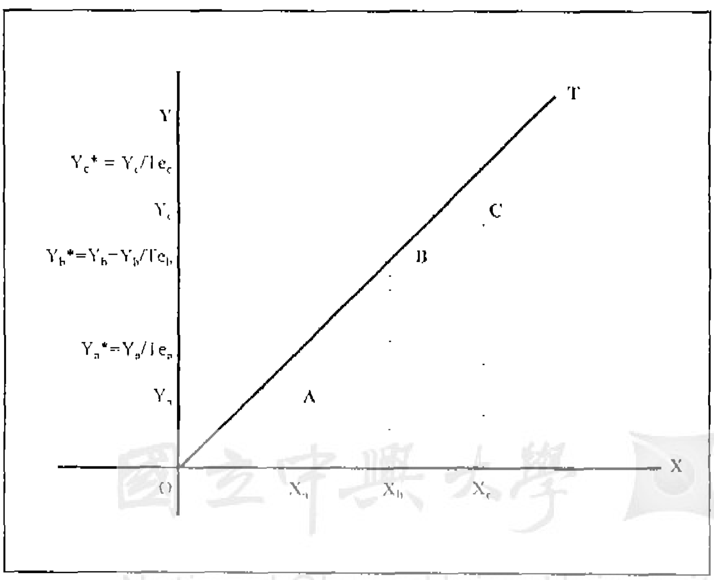
X= the (n x m) matrix of observed inputs

Y= the corresponding (m x k) matrix of outputs, and

z= the intensity with which any activity (x,y) is utilised.

The transformation set is illustrated in Figure 1, with m = n = 1, implying one input and one output, with three farm observation A,B, and C. The transformation set is bounded by the line OT and the X axis and this correspondents to the notation of a total product curve, Individual farm effciency is determined relative to the constructed technology frontier. For farm A, the maximum potential output, given its observed input use Xa, is Ya*. The overall measure of technical efficiency is equal to the ratio of actual to the potential or efficient output. For farm A, this is Ya/Ya* which is equivalent to the measure of inefficiency as defined by Farrell (1957). The overall measure of technical efficiency, TE, for individual observation i, can be expressed

Figure 1 Transformation Set (T) Under Constant Return to Scale



$$TE\ (x_i,y_i)=\max\ \{x_i,\Theta\ y_i)\in T\} \qquad (2)$$

and can be calculated through solution of the following linear programming problem:

$$TE\ (x,y)=\max\Theta \qquad (3)$$

st

$$\sum_{i=1}^{308} x_{ij}\ z_i \leqq x_i \qquad j=1,2,....,5$$

$$\sum_{i=1}^{308} y_i\ z_i - y_i\Theta \leqq 0$$

$$x_i,y_i \leqq 0$$

The first constraint is wiht respect to inputs. In this study five inputs are used namely number of vines cultivated, fertiliser, chemical, herbicide and labour (manday). The left-hand side of the constraint constitutes the theoretical efficient farm against which the i^{th} farm is compared. The constraint states that the theoretically efficient farm uses an amount of inputs that is less than or equal to the amount utilized by the i^{th} farm in producing the output of the i^{th} farm.

The second constraint is with respect to the output. The output constraint consists of two parts. The component $\Sigma\ y_i z_i$, represents the maximum output of the theoretically efficient farm, given the actual level of inputs used by the ith farm. The component $(-y_i\Theta)$ is the actual level of output of the i^{th} farm, which is obtained by multiplying farm output, Y_i, and the level of inefficiency, Θ .If the farm is overall technically efficient, the $\Theta = 1$. As a result, the component $\Sigma\ y_i z_i$ is exactly offset by $(-y_i\Theta)$. Hence, the level of output of the i^{th} farm is the same as the theoretically efficient farm output. If the farm is technically inefficient. then $\Theta > 1$ which indicates that the theoretically efficient output $[\Sigma\ y_i z_i]$ is greater than the actual output of the i-th farm, y^i. Since 308 farms were surveyed, a series of 308 such linear programming exercises must be solved to determine the technical efficiencies of each farm.

Overall technical efficiency can be disaggregated into two components namely scale and pure technical efficiencies. In order to distinguish between these two components the original transformation set T specified in equstion (2) is modified to allow for increasing and decreasing return to scale. Afriat (1972) has shown that by restricting the intensity vector to sum to one, all the three types of increasing, constant and decreasing returns to scale can occur. A new transformation set incorporating this non-constant return to scale technology can be expressed as:

$$T' = \{(x,y): y \leqq Y_z, X_z \leqq x, z \in R_k^+\ \Sigma z_i = 1\} \qquad (4)$$

The new transformation set is shown in Figure 2 along with the original three farms A, B, C and bounded by the curve X_aABCT'. Pure technical efficiency (PE), can now be defined relative to the frontier. For any particular observation (x_i, y_i), pure technical efficiency can be expressed as:

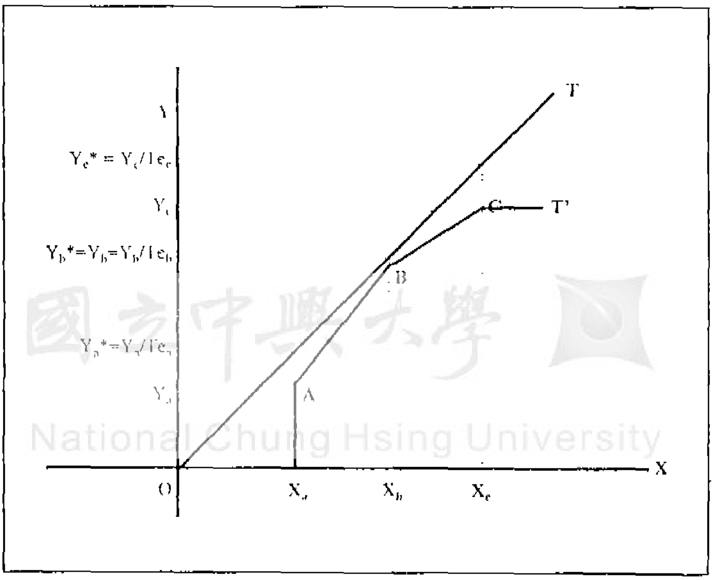
$$PE\ (x_i, y_i) = \max\ (\Theta_i : (x_i, y_i) \in T') \tag{5}$$

Thus, PE equals one for all three observations in Figure 2, since all of them are on the technology frontier. To calculate this value numerically, the linear programming problem given by equation (3) is solved with an additional constraint that sums up the elements of the intensity vector to one:

$$\sum_{i=1}^{308} z_i = 1 \tag{3a}$$

Following Byrnes et al. (1987) and Weersink et al. (1990), one can determine the scale efficiency, SE, that is whether a farm operates under constant or non-constant returns to scale by taking the ratio of TE to PE for an observation. This can be expressed mathematically as

Figure 2 Transformation Set(t) Under Non-Constant Return To Scale



$$SE(x_i,y_i)=TE(x_i,y_i)/PE(x_i,y_i) \quad (6)$$

If the tetchnology exhibits constant returns to scale at the observed input and output combination, the SE $(x_i,y_i)=1$. Non-constant returns to scale occurs when SE $(x_i,y_i)\neq 1$. In Figure 2, $\Theta = 1$ for all the three observations; however, this is not always the case. At B both PE (x_b,y_b) and TE (x_b,y_b) equals to one and thus SE $(x_b,y_b)=1$. Observations A and C represent cases of increasing and decreasing returns to scale respectively. PE (x_a,y_a) and TE (x_c,y_c) are both equal to one, while TE (x_a,y_a) and TE (x_c,y_c) are both greater than one. To determine the direction of non-constant returns to scale, a third transformation set, T^*, which imposes non-increasing returns to scale, is defined. This is done by restricting the intensity variables so that $\Sigma z_i \leqq 1$. The new transformation set is

$$T=\{(x,y):y\leqq Yz,Xz\leqq x,z\in R_k+,\Sigma z_i\leqq 1\} \quad (7)$$

The non-increasing returns to scale technology frontier is illustrated in Figure 2 by the curve OBCT'. Given the above transformation set, another measure of scale efficiency, WE*, relative to this set can be written for observation(x_i,y_i),as

$$WE^*(x_i,y_i)=\max(\Theta_i:(x_i,\Theta y_i)\in T^*\} \quad (8)$$

This eguation differs from the pure technical efficiency measure only in the inequality restriction on the summation constraint for the intensity variable elements. Consequently, it is calculated by solving a third linear programming problem given by eqution (3) and the following constraint replaces equation (3a):

$$\Sigma z_i \leqq 1 \tag{3b}$$

There are two possible cases when SE$\neq$ 1. If TE$=$ WE* , increasing returns to scale exist and if TE$\neq$ WE* then decreasing returns to scale exists.

The next component of overall technical efficiency is congestion, i.e., over-utilisation of some input(s) to the point that output falls. Under strong disposability of inputs, congestion cannot occur. In order to model the possibility that some inpus might have an adverse effect on output (if they are used in too high proportions), we changed the technology and imposed only weak rather than strong disposability of inputs. According to Fare, et al. (1985), this can be accomplished by changing the constaint Xz < X into Xz$=$ λ_v, where $0 < \lambda < 1$. The technology frontier can be represented as follows:

$$T^{**}(x_i,y_i){:}y < Y_z,X_z = \lambda_v, 0 < \lambda \leqq 1, z \in R_k+, \Sigma z_i = 1\} \tag{9}$$

where λ permits the over-utilisations of inputs by relaxing the strong disposability assumption. Another measure of pure technical efficiency, PE*, can now be derived relative to the frontier of this weakly disposable technology:

$$PE^*(x_i,y_i)=\max\{\Theta_i:(x_i,\Theta y_i)\in T^{**}\} \quad (10)$$

This is calculated by solving the following linear programming problem:

$$PE^*(x_i,y_i)=\max\Theta \quad (3c)$$

st

$$\sum_{i=1}^{308} x_i z_i = \lambda x_i \qquad j=1,2,\ldots\ldots,5$$

$$\sum_{i=1}^{308} y_i z_i - y_i\Theta \leqq 0$$

$$\sum_{i=1}^{308} z_i \leqq 1$$

$$0 < \lambda \leqq 1$$

The effects of congestion CE, or over-utilisation of any particular input, can then be determined by the following calculations.

$$CE(x_i,y_i)=PE(x_i,y_i)/PE^*(x_i,y_i) \quad (11)$$

Congestion is evident for an individual farm if CE > 1 (weersink, 1990). Over-utilisation of inputs is not present if the pure technical efficiency measures as defined under weak (PE*) and strong (PE) input disposability assumptions are equal.

With the above conceptual framework and if one assumes that the technology obeys strong disposability of inputs with constant returns to scale, then $TE(x_i,y_i) = PE^*(x_i,y_i)$. Thus $TE(x_i,y_i)$ can be regarded as the Farrell's measure of constant returns to scale under the strong disposable input assumption. Hence we have the following disaggregation:

$$TE(x_i,y_i) = SE(x_i,y_i).CE(x_i,y_i).PE^*(x_i,y_i) \qquad (12)$$

In summany equation (12) is a decomposition of Farrell's measure of technical efficiency into (a) scale efficiency which measures output loss due to deviations from constant return to scale, (b) congestion efficiency which measures output loss due to over-utilisation of inputs and (c) pure technical efficiency which measures output loss due to technical inefficiency. With respect to all the measures, production is efficient in the relevant range if the measures equal to unity. If there is inefficiency due to scale, congestion or pure inefficiency, the corresponding measure will be more than unity. Thus the difference between unity and the observed value yields the percentage of potential output loss due to a particular type of inefficiency.

In order to determine the efficiency measures for the sample farms, individual linear programming exercises were carried out for each of the measures described by equations (3), (3a), (3b) and (3c). Since 308 farms were investigated, the results of the analyses were based on 1232 linear programming solutions. The data and results of the analyses were presented in the following section.

III.Data and empirical results

The data employed in this study consisted of information on production and inputs used by a sample of 308 pepper farms in Sarawak. The

Table 1 Summary of Data Used

	Small Farm	Medium Farm	Large Farm	All Farm
Output(kg)	1598.73 (1123.86)	1744.27 (1513.85)	2302.71 (1646.99)	2003.09 (1577.97)
Fertilizer(kg)	1932.48 (1006.39)	1959.13 (1815.13)	2126.31 (1893.84)	2039.19 (1756.57)
Chemical(lt)	265.99 (181.22)	278.18 (356.26)	436.97 (645.55)	356.23 (513.83)
Herbicide(lt)	473.07 (461.63)	413.11 (574.77)	396.83 (607.95)	414.07 (575.33)
Labor (manday)	381.04 (130.97)	383.09 (153.62)	466.53 (148.75)	424.77 (153.35)
No.of Vines	181.92 (37.95)	343.21 (62.25)	800.81 (359.27)	548.88 (365.45)

Note: Figures in parentheses are standard deviation.

Table 2　Frequency Distribution of Technical Efficiency Measures

	Technical Efficiency			
	Overall (TE)	Pure (PE*)	Scale (SE)	Congestion (CE)
100%	12 (3.90)	43 (13.96)	24 (7.79)	24 (7.79)
90-99.9%	2 (0.65)	2 (0.65)	142 (46.10)	67 (21.75)
80-89.9%	4 (1.30)	10 (3.25)	49 (15.91)	71 (23.05)
70-79.9%	9 (2.92)	4 (1.30)	35 (11.36)	40 (12.99)
60-69.9%	13 (4.22)	17 (5.52)	27 (8.77)	28 (9.09)
50.59.9%	14 (4.55)	17 (5.52)	5 (1.62)	20 (6.49)
40-49.9%	23 (7.47)	24 (7.79)	3 (0.97)	16 (5.19)
30-39.9%	45 (14.61)	41 (13.31)	5 (1.62)	9 (2.92)
20-29.9%	62 (20.13)	59 (19.16)	6 (1.95)	15 (4.87)
10-19.9%	83 (29.95)	59 (19.16)	7 (2.27)	8 (2.60)
Less than 10%	41 (13.31)	32 (10.39)	5 (1.62)	10 (3.25)
Total	308 (100.00)	308 (100.00	308 (100.00)	308 (100.00)

Note: Figure in parentheses are percentages to the total farms were further divided into small, medium and lange farms. The division is based on the number of vines planted by the farms. A small farm is defined as having the minimum number of 200 planted vines. This is because input subsidies and other agricultural services are only provided by the government to the small farms. Outputs produced by the farms in the sample are in physical unit (kg). Inputs of production include the number of vines, fertiliser, herbicide, chemical are in physical unit while labour is in man-day equivalent. A summary of the data statistic is presented in Table 1.

The series of four linear programming models were solved to determine the measure of technical efficiency and the direction of the returns to scale for each of the 308 sarawak pepper farms in the sample. The linear programming models will generate the efficiency levels of each farm by comparing the utilisation of inputs and relative to all other farm. Table 2 summarises the frequencies of estimated measures of overall technical efficiency (TE), pure technical efficiency (PE*), Congestion efficiency (CE), and scale efficiency (SE). The overall technical efficiency for the whole sample of farms ranged from 1.1 to 100.0 per cent, with 3.90 per cent of the farms exhibiting complete overall efficiency. The mean efficiency value was calculated at 23.60 percent, and this meant that the farm in the sample were operating at a lower level of technical efficiency.

Table 3 shows the means and standard deviations of the four measures of efficiency for the sample as a whole as well as by farm size. The overall technical efficiency, TE, of the farms on average is 6.51. Recall that a value of unity represents efficient prodction, i.e. actual output is equal to maximum potential output as defined by the best practice in the sample. Thus the result indicated that farm could have produced 551 per cent more than they actually produced had they all been operating with overall technical efficiency. The decomposition of technical efficiency into scale, pure and congestion efficiency component showed pure inefficiency to be the primary source of technical inefficiency in the farm operations. The average pure technical efficiency is 5.26. Thus, output could have been increased by 426 per cent if the farms were pure technically efficient. The average scale efficiency measure is 1.93. This means that output could have been increased by 93 per cent if farms had been operating at constant returns to scale. The congestion technical efficiency measure is 1.49. This also meant that output could have been increased by 49 Per cent if farm had used inputs optimally. With respect to efficiency, it is apparent that pure efficiency contributed the biggest share of output loss. On average, scale and congestion technical inefficiencies were also important sources of overall technical inefficiency.

As discussed in the previous section, constant, increasing or decreasing returns to scale can be determined by taking the ratios of TE(x,y)and PE(x, y). We*(x,y) is used to determine if scale inefficiencies are due to operating at constant, increasing or decreasing returns to scale. Farms exhibiting constant returns to scale are scale efficient, i.e.,SE(x,y) = 1. Scale inefficiency as a source of technical inefficiency suggests that various farm size

Table 3 Mean and Standard Deviation of Technical Efficiency by Farm Size

	Efficiency Measure			
	Overall	Pure	Scale	Congestion
Small	3.4808 (2.3830)	3.8741 (3.0362)	1.7409 (1.1058)	0.7464 (0.5460)
Medium	7.3286 (10.8490)	7.2401 (13.1590)	2.5297 (8.9772)	1.5390 (3.5490)
Large	6.8591 (9.4025)	4.3287 (6.0214)	1.5790 (3.6739)	1.6823 (1.6910)
All	6.5051 (1.9309)	5.2613 (8.9932)	1.9309 (5.8911)	1.4902 (2.4228)

Note: Figure in parentheses are percentages to the total

do influence their technical efficiencies. In order to provide more direct evidence of this, the farms were grouped according to three different size categories: small (≦ 200 vines), medium (201-400 vines) and large (>400 vines) farms. The results obtained by the size class suggests that the performance does very by farm size. The composition on the inefficiency changes systematically. In general as farm size increases, inefficiency also increases.

Pure and scale inefficiency initially increases as farm size increases from small to medium. But as farm becomes large, the inefficiency decreases slightly. This could be due to gains to technical and scale efficiency as size of operation is being increased. Congestion inefficiency on the other hand, increases as farm size becomes large. This implied that farms kept increasing farm input use even past their optimum levels with respect to outputs acheived.

The most significant efficiency differences appeared in the scale measure in both size classification. A firm is scale inefficient when it operates at non-constant returns to scale. The evidence presented in Table 4 shown that, on average the larger the farm size, the more scale inefficient they became and production was concentrated at the point of decreasing returns to scale. That is, these farms could have increased total factor productivity

Table 4 Returns to Scale Distribution by Farm Size

	Constant	Increasing	Decreasing
Small	42 (89.36)	4 (8.51)	1 (2.13)
Medium	69 (65.09)	4 (3.77)	33 (31.13)
Large	43 (27.74)	2 (1.29)	110 (70.97)
All	154 (50.00)	10 (3.25)	144 (46.75)

Note: Figure in parentheses are percentages to the total had they been operating at a smaller scale. However, in the case of small and medium farms, they are very likely to be producing at the point of constant returns to scale.

The presence of pure inefficiency as the major source of technical inefficiency indicated the inability of farms to solve certain technical problems in the production process thus resulting in losses of output to the farms. In other words, pure technical inefficiency occurs when, given the existing technology and input combinations, a firm could produce more output with the inputs it currently employs (or the same level of output with fewer inputs).

From the standpoint of congestion efficiency, only 7.8 per cent of the farms in the sample performed well i.e were efficient and production oc-

Table 5 Usage of Inputs in Pepper Farm

	Congestion Inefficiency	Congestion Efficiency	Quantum of Excess (%)
Fertilizer(kg)	2068.54	1961.64	22.26
Herbicide(lt)	423.21	305.86	38.37
Chemical(lt)	326.56	234.03	39.54
Labor(manday)	425.07	421.21	0.92

curred on the isoquant. The output of the rest of the farms could have been increased by reducing the application of some inputs. Thus, farms that are faced with congestion inefficiency showed that their usage of inputs in the production of pepper were higher if compared to the efficient farm levels. Table 5 indicated that the quantity of excess utilization of inputs was at the 22.2, 38.4, 39.5 and 0.9 per cent, for fertiliser, herbicide, chemical and labour respectively.

Ⅳ.Conclusion

The purpose of this paper is to estimate the technical efficiency for a cross-section of Sarawak pepper farms and to provide an explanation for inefficiencies that currently exist. By relaxing the assumption of strong disposability and constant returns to scale on production frontier, technical efficiency can be disaggregated into three components namely scale, pure and congestion efficiencies. These components can identify the sources of inefficiency in production and can be easily calculated as solutions to relatively simple linear programming problems.

The results of the study indicate that the production of Sarawak pepper in the sampled farms are technically inefficient. Farms had the potential to increase production by up to 551 per cent more than they were actually producing had they all been operating at overall technical efficiency. Output could have been increase by up to 426 per cent if optimal efficiency is achieved. Another source of inefficiency is due to non-optimal scale of production. About 3.25 per cent of farms are operating at increasing returns to scale while 46.8 per cent are at the decreasing returns to scale. On average, output could have been increased by 93 per cent if farms had been operating at optimal scale efficiency. In the case of congestion inefficiency, all inputs used are at a level higher than the optimal levels suggested by the production models.

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