# Input Use Inefficiencies in the Production of Sugar Cane in Central Negros Area, Philippines An Application of Data Envelopment Analysis

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**Input Use Inefficiencies in the Production of Sugar cane in Central Negros Area, Philippines**

**An Application of Data Envelopment Analysis**



M. Dina Padilla-Fernandez and Peter L. Nuthall*


## Abstract

This research attempts to identify sources of input use inefficiency for sugar cane production in the Central Negros area, The Philippines. Non-parametric Data Envelopment Analysis was used to determine the relative technical, scale, overall technical, allocative and economic efficiencies of individual farms which use the same inputs and produce the same raw material (cane) and output (sugar). Under a specification of variable returns to scale (VRS), the mean pure technical, scale, overall technical, allocative and economic efficiency indices were 0.7580, 0.9884, 0.7298, 0.7941 and 0.6025.

Input use differences between the purely technical efficient and inefficient farms is statistically different for area, seeds and labour inputs. There was no significant variation in the use of fertiliser and power inputs. For the overall technically efficient and inefficient farms, use of seeds and NPK fertiliser were statistically different. Apart from the lower amount of seeds, fertiliser and power used, the larger profit obtained by the economically efficient farms was due to the lower price paid for each input except labour.

The productive efficiency of small, medium and large farms were also determined. Small farms appeared to be economically inefficient compared to the large ones while medium and large farms appeared to be equally economically efficient. Analysis of input use differences among farm size class shows that the higher input usage by the large farms tends to increase the quantity produced and with the low price of inputs, generates a larger profit per hectare. The higher input prices faced by the small farmers tends to reduce the amount of input used thus giving a lower profit. Thus, part of the allocative efficiency differences between the farm size groups may be attributed to the differences in the input price, resulting from market power.


## 1 Introduction

Agricultural production efficiency generally focuses on the possibility of producing the optimal level of output from given resources, or producing a certain level of output at lowest cost. This study investigates whether sugar cane farmers are efficient in their resource utilisation and consequently how efficiency might be improved. If the farmers are operating efficiently, then only by introducing improved methods of production can farm outputs be increased. In contrast, if this is not the case production can be increased through improved management practices and transferring the experiences of the efficient farmers to the less efficient ones (Abate, 1995).

A variety of methods have been used to measure efficiency. Ordinary least squares (OLS) regression is conventionally used for estimating the production function (Battese, 1992). However, it is argued that the OLS method estimates an 'average' response (Seiford and Thrall, 1990; Ali and Chaudhry, 1990 and Pitt and Lee, 1981) and ignores the significance of the resource use efficiency of the individual farmers.

An alternative is the concept of the efficient frontier which involves an envelope encompassing all the input-output combinations of interest. This envelope contains 100 per cent efficiency observation(s) and is termed the best practice technology [Trewin *et al.*, 1995].

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Various models of frontier functions have been formulated to provide useful insights into best-practice technology. The models differ with respect to the assumptions on the frontier, which may be deterministic or stochastic. Currently, the stochastic frontier and the deterministic non-parametric Data Envelopment Analysis (DEA) are the primary approaches (Coelli, 1995). DEA was used in this study, largely as it does not require specifying a production function form.

The paper contains a brief discussion of the theoretical measurement of efficiency (Section 2) and this is followed by a description of the DEA methodology (Section 3). The data collected on the farmers' and farm' characteristics is outlined in Section 4. In Section 5 the measurement and analysis of productive efficiency are presented including an analysis of farm size as it is commonly argued that large farms perform better. This is tested in Section 6. Then follows a discussion of the results and a conclusion containing implications for improving the resource use in sugar cane production.

## 2 Theoretical Measurement of Efficiency

A method for measuring productive efficiency was presented by Farrell (1957) in which he hypothesised that efficiency could be dichotomised into two sub-components reflecting the physical efficiency of the input-output production transformation (the technical component) and the economic efficiency of optimal factor allocation (price efficiency) [Kopp, 1981]. Technical efficiency 'measures a firm's success in producing maximum output from a given set of inputs,' whereas allocative efficiency 'measures a firm's success in choosing an optimal set of inputs' (Farrell, 1957 p.259).

Consider Figure 1 in which the points *A* to *D* represent the actual farms being studied. It is assumed that farms use two inputs of production, $X_1$ and $X_2$, to produce an output, *Y*. The best practice frontier in this case is determined by the farms which use the 'fewest' inputs in producing the given level of output, *i.e.* the lower bound of the input requirement set. Following Farrell, the observed points can be 'enveloped' using piecewise linear segments, in which case the best practice frontier is the lower bound labelled *C, D, E,* which corresponds to the notion of an isoquant in neoclassical production theory.

In this case, points (farms) *C, D,* and *E* are operating on this best practice frontier and are therefore considered to be technically efficient. Farrell suggested measuring the efficiency of any observation relative to the frontier by calculating how many inputs could be reduced and still produce the given output level. For farm *A*, its technical efficiency would be gauged as *OB/OA, i.e.* the ratio of 'minimal' to actual input usage, while holding input proportions constant. As long as the frontier isoquant has a negative slope, an increase in the input per unit output of one factor will, *ceteris paribus*, imply lower technical efficiency (Farrell, 1957).

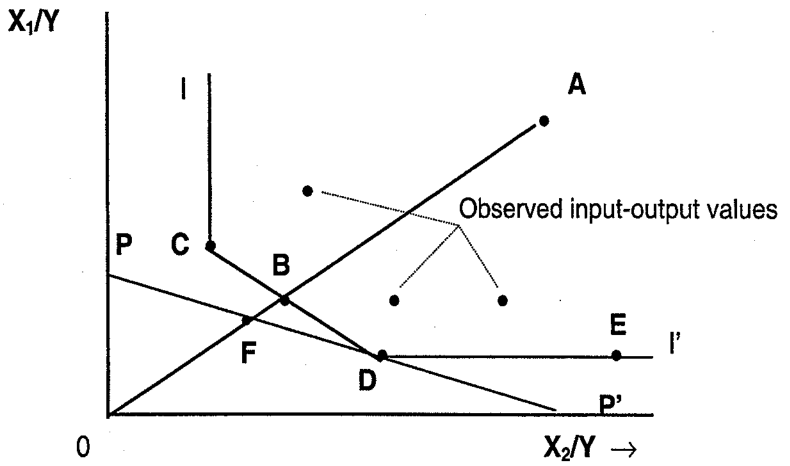


**Figure 1. Technical and Allocative efficiency of farms in relative input-input space. Source: Coelli, (1995)**

Technical efficiency is measured in terms of distance from the frontier. An index of efficiency can be based on a distance along a ray from the origin. That is, the ratio of the distance of the frontier from the origin to the distance of that unit (farm) along a ray from the origin. It immediately follows that any point on the frontier has an efficiency score of unity, where unity denotes efficient (best practice) performance (Desai and Walters, 1991). In general, technical efficiency satisfies the relation $0<TE<1$. Alternatively, $TE<1$ implies that the farm is technically inefficient (Chavas and Aliber, 1993).

Farrell (1957) also defined and provided a measure for allocative efficiency. Allocative efficiency can be calculated if the price ratio is known. In Figure 2 line *PP'* represents the slope equal to the ratio of the two input prices. The corresponding cost minimising point is *D*. Taking, for example, farm *A*, its ray passes through the line *PP'* at point *F*. The cost at point *F* is the same as that of the allocatively efficienct point *D*. Thus *F* can substitute for *D* in terms of cost. The allocative efficiency of the farm operating at *A* therefore can be defined as *OF/OB*. The distance *FB* represents the reduction in production costs that would occur if production were to occur at point *D*, instead of at point *B* (Coelli, 1995).

If AE= 1 the firm is said to be allocatively efficient. Alternatively, AE<1 implies allocative inefficiency. Note that to calculate the index of allocative efficiency it is necessary to solve for the efficient input level from the estimated model. In this case, (1 - AE) measures the maximal proportion of cost the technically efficient farm can save by behaving in a cost minimising way (Chavas and Aliber, 1993). The ratio *OB/OA* is the measure of technical efficiency of a farm with input-per-unit- of output values at point *A* and *OD/OA* measures its overall economic efficiency.

The distinction between technical and allocative efficiency gives rise to possible alternatives for describing the relative success of farms in achieving efficiency, i.e., a farm might display both technical and allocative inefficiency as given by a point such as *A*, where neither of the efficiency conditions are met; a farm might display technical efficiency but allocative inefficiency as shown by a point such as *B*; and a farm may have achieved both technical and allocative efficiency, as shown at point *D*. Economic efficiency is attained at point *D*. The 'achievement of either one of the efficiencies may be seen as a necessary but not sufficient condition to ensure economic efficiency. The simultaneous achievement of both efficiencies provides the sufficient conditions to ensure economic efficiency' (Ellis, 1988 p.66).

The identification of the best practice frontier also allows the determination of increasing, constant and decreasing returns to scale. Information about whether a unit is operating at increasing or decreasing returns to scale can prove useful in indicating a potential redistribution of resources (Boussofianne *et al.*, 1991).

The concept of scale has a pure definition in economics. Changes of scale refer to the simultaneous increase of 'all' productive resources in the same proportion. If this simultaneous increase in all resources results in a constant percentage increase in output, the current production level is referred to as achieving constant returns to scale. If it results in a decreasing percentage increase in output it is diminishing returns to scale; and *vice-versa* for increasing returns to scale (Ellis, 1988).

In practice, equal across-the-board changes in resource use are rarely observed, nor are practical. While the use of fertiliser and labour may be doubled, it would be rare for all items of fixed capital (land, buildings and machinery) to be doubled. For this reason the term 'scale' is often used in an impure way, to refer to a large change in the volume of resources committed to production (*e.g.*, the purchase of a tractor) without adhering to the equal percentage change in all inputs (*ibid.*).

For a single-input single-output case, most productive scale size (mpss) is simply that scale for which the average productivity measured by the ratio of total output to total input is maximised. In the context of multiple inputs and multiple outputs, the 'mpss' for a given input and output mix is the scale size at which the outputs produced 'per unit' of the inputs is maximised. For each input and output mix there is a corresponding 'mpss.' Only by employing knowledge of input and output prices can an optimal scale (where marginal productivity is equal to the ratio of the output price to the input price) and mix for the technology be determined.

In order to maximise the average productivity, one would increase the scale size if increasing returns to scale were prevailing, and decrease the scale size if decreasing returns to scale were prevailing (Banker, 1984). If the price of both inputs and outputs are given, the most profitable scale can be determined through ensuring the marginal physical product equals the inverse ratio of input price to output price at the profit maximising point. Thus the marginal value product of input divided by the input price should equal one if allocative efficiency is being observed. This ratio is often referred to as the allocative efficiency ratio (Ellis, 1988), which is discussed further in the next section.

Figure 2 illustrates these concepts of technical and scale efficiencies. This time, the input-output mix representation is used rather than the two-product approach. The figure depicts the production possibility set for the input-output mix (*X, Y*). The line *BED* is the boundary of the production possibility set for the input output mix *(X, Y)* where *X* and *Y* are scalars. Under the assumption of constant returns to scale (CRS), which is denoted by the straight line-total product curve, *OP*, farm *E* is overall relatively technically efficient, which implies that this farm is also purely technically efficient and scale efficient. It lies on the frontier and has constant returns to scale. Farms *B* and *D* are inefficient as they lie below the CRS frontier.

Allowing for variable returns to scale, this gives the technical efficiency frontier, $x_B BED$. Farms *B* and *D* become technically efficient as well as farm *E*. Farm *E* represents the production possibility that maximises the 'average productivity', measured by the slope of the line *0E* (or the ratio $y_E/x_E$), for the mix of output *Y* and input *X*. Thus, farm *E* also represents the most productive scale size (mpss) for the given mix. It lies on the frontier and has constant returns to scale.

Increasing returns to scale prevail at farm *B* since the average productivity measured by the slope of the line *0B* (or ratio $y_B / x_B$) is less than the slope of the line *0E*. On the other end, decreasing returns to scale prevail at farm *D* since the average productivity measured by the slope of the line *OD* is less than at farm *E*.

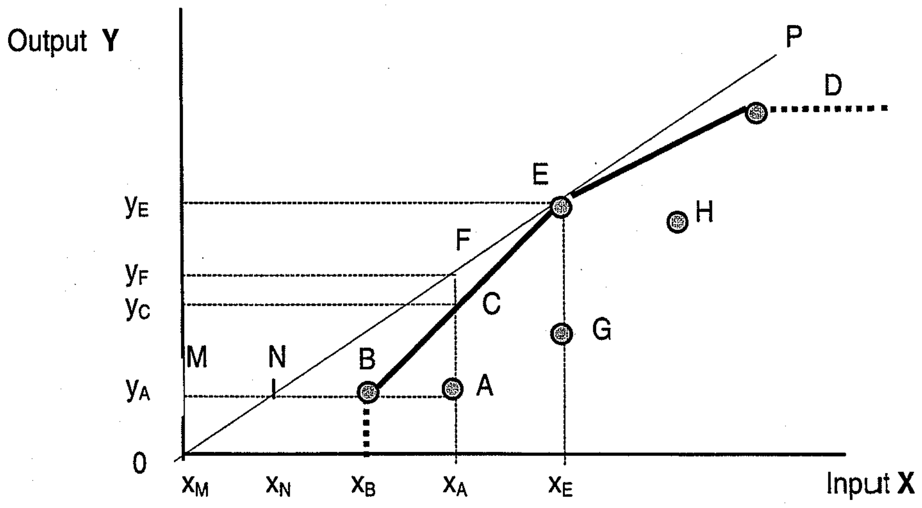


**Figure 2. Technical and scale efficiencies in the space of input-output mix.**
**Source: Boussofianne *et al.*, (1991)**

The inefficiency of farm *A* can be measured if it is compared with farm *E* or with 'unit *N*.' The latter is not within the production possibility set but in numerical terms it has the same average productivity as farm *E*. The overall technical and scale efficiency of farm *A* in comparison to unit *N* is the ratio $x_M x_N \ / x_M \ x_A$. The pure (input) technical efficiency of farm *A* is measured by the $x_M x_B$ / $x_M x_A$ by comparing it with farm *B* on the efficient production frontier with the same scale size as farm *A*. Note that this will not be the same as in the 'output' efficiency measure except for the constant returns to scale technology. Finally, the (input) scale efficiency of farm *A* is measured by the ratio $x_M x_N / x_M x_B$, so that the overall technical and scale efficiency ratio $x_M x_N \ / x_M \ x_A$ is equal to the product of technical efficiency $x_M x_B \ / x_M x_A$ and the scale efficiency $x_M x_N / x_M x_B$. In an analogous manner it can be seen that the factor $y_C \ / y_A$ is a measure of the pure technical (output) efficiency of farm *A*.

It is apparent that the overall technical and scale efficiency measure $x_M x_N \ / x_M \ x_A$ is less than the pure (input) technical efficiency measure efficiency $x_M x_B \ / x_M x_A$. This is inevitable due to the constraint imposed on scale efficiency measurement. This relationship between two efficiency measures holds also for the general case of multiple inputs and outputs (Banker, Charnes and Cooper, 1984).

Although a farm may be technically inefficient in an overall sense, it is possible for it to be purely technically efficient, while experiencing inefficiencies in scale (Llewelyn and Williams, 1996). This is also illustrated in Figure 2. Farms *B* and *D* are purely technically efficient, since they lie on the frontier, but exhibit scale inefficiencies. Farm *H* is both scale inefficient and pure technically inefficient since it lies below the frontier. Theoretically, the same level of input could be used to achieve a higher level of output, which would allow this farm to be on the frontier between farms *E* and *D*. Farm *G* is pure technically inefficient since it is not on the production frontier, but is scale efficient, because it produces at input level $x_E$, the scale-efficient level of input.

## 3 Empirical Approach to Efficiency Measurements using Data Envelopment Analysis

Charnes, Cooper and Rhodes (1978) reformulated Farrell's approach into a mathematical programming problem and coined the term Data Envelopment Analysis (DEA). It builds on the individual firm evaluations of Farrell (1957) and extends the engineering ratio approach to efficiency measures from a single-input, single-output efficiency analysis to multi-input, multi-output situations (Seiford and Thrall, 1990).

$$Efficiency = \frac{output}{input}$$

$$\Downarrow$$

$$Efficiency\ of\ unit\ j = \frac{u_1 y_{1j} + u_2 y_{2j} + \ldots}{v_1 x_{1j} + v_2 x_{2j} + \ldots}$$

*where* $u_1$ = *the weight given to output 1*
$y_{1j}$ = *amount of output 1 from unit j*
$v_1$ = *weight given to input 1*
$x_{1j}$ = *amount of input 1 to unit j*

This measure of efficiency requires a common set of weights to be defined. This causes difficulties as alternative measures can be proposed (Boussofianne *et al.*, 1991). Charnes et al (1978) proposed a measure of efficiency for each decision making unit (DMU) by obtaining the maximum ratio of these weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity.

The Charnes, Cooper and Rhodes model (CCR) assumes constant returns to scale (CRS), and compares DMU's on a strict output to input ratio. In many settings, small units are qualitatively different from large units and a comparison between the two may distort measures of comparative efficiency. Thus, another constraint, $u_0$ was added in the CCR model. The new formation assumes variable returns to scale (VRS) and this is due to Banker, Charnes and Cooper (1984) and is known as the BCC model. The following algebraic model for the BCC (input-oriented)[1] in ratio form is:

$$Max \quad h_0 = \frac{\sum_{r=1}^{t} u_r y_{rjo}}{u_0 + \sum_{i=1}^{m} v_i x_{ij0}} \qquad (1)$$

$$subject \quad to$$

$$\frac{\sum_{r=1}^{t} u_r y_{rj}}{u_0 + \sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1, \ldots, n$$

$$u_r, v_i, \geq \varepsilon > 0, \quad u_0 \, unconstrained \; in \; sign$$

where $y_{rj}$ is the amount of output $r$ from unit $j$; $x_{ij}$ is the amount of input $i$ to unit $j$; $u_r$ is the weight given to output $r$; $v_i$ is the weight given to input $i$; $n$ is the number of units; $t$ is the number of outputs; $m$ is the number of inputs; and $\varepsilon$, a positive small number.[2]

The $y_{rj}$ and $x_{ij}$ (all positive) are the known outputs and inputs of the $j$th farm and the $u_r$ and $v_i$ are the variable weights to be determined by the solution of this problem- *i.e.,* by the data on all of the farm's that are being used as a reference set. The efficiency of one member of this reference set of $j = 1,\ldots,n$ farm's is to be rated relative to the others. It is therefore represented in the functional, for optimisation- as well as in the constraints- and further distinguished by assigning it the subscript '0' in the functional (but preserving its original subscript in the constraints). The indicated maximisation then accords this farm the most favourable weighting that the constraints allow (Farrell, 1957).

The $u_r$ and $v_i$ are constrained to be greater than or equal to some small positive quantity ($\varepsilon$) in order to avoid any input or output being totally ignored in determining the efficiency. The solution to the above model gives a value $h_0$, the efficiency of a farm and the weights leading to the efficiency. If $h_0 = 1$ then that farm is purely technically efficient relative to the others but if $h_0$ turns out to be less than 1 some other farm(s) is more purely technically efficient than that farm, even when the weights are chosen to maximise that farm's efficiency.

[1] Charnes, Cooper and Rhodes (1978) used an input-oriented model. The method sought to identify technical inefficiency as a proportional reduction in input usage. This corresponds to Farrell's input-based measure of technical inefficiency.

[2] To eliminate false technical inefficiency determinations (recognised by Farrell) stemming from optional entries of $u_r$ and $v_i \geq 0$, it was immediately replaced by the non-Archimedean (M).

This non-linear ratio model can be converted to linear programming (LP) model.[3] The linearization process is relatively straightforward by letting the denominator of the objective function be equal to one and be treated as a constraint so that it can be deleted from the objective function, and subsequently multiplying both sides of the ratio constraints by the denominator to result in a linear programme (Kao *et al.*, 1993). The resultant linear programme is:

*Primal model*: *Dual Variables*

$$Max \quad h_0 \sum_{r=1}^{t} u_r y_{rj0} \qquad\qquad Z_0 \qquad\qquad (2)$$

*subject to*

$$\sum_{i=1}^{m} v_i x_{ij0} = 1 \qquad\qquad \lambda_0$$

$$\sum_{r=1}^{t} u_r y_{rj} - u_0 + \sum_{i=1}^{m} v_i x_{ij} \le o \qquad j=1,2,\ldots, n$$

$$-v_i \le -\varepsilon \qquad i=1,2,\ldots, m \qquad s_I^+$$

$$-v_i \le -\varepsilon \qquad i=1,2,\ldots, t \qquad s_I^-$$

By definition, every linear program (LP) has a dual associated with it (Dantzig, 1963 in Kao *et al.*, 1993). The dual model is constructed by assigning a variable (dual variable) to each constraint in the primal model and constructing a new model on these variables. This is shown as:

*Dual Model*:

$$Min \quad Z_0 - \varepsilon \sum_{r=1}^{t} s_r^+ - \varepsilon \sum_{i=1} s_i^- \qquad\qquad (3)$$

*subject to*

$$Z_0\, x_{ij0} - \sum_{j=1}^{m} \lambda_j x_{ij} - s_i^+ = 0 \qquad i = 1,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{ij} - s_r^- = y_{rj0} \qquad r = 1,\ldots,t$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \;,\; s_r^+,\; s_i^- \ge 0$$

[3] In theory, fractional programming problems may be replaced with linear programming equivalents. The transformation developed by Charnes and Cooper (1962 in Seiford and Thrall, 1990 p.11) for linear fractional programming selects a representative solution [ *e.g.*, the solution $(u,v)$ for which $v_T X_0=1$ ] from each equivalence class and yields the equivalent linear programming problem. Charnes *et al.* (1978) used this theory to make their formulation computationally tractable for the large numbers as well as the small number of observations. Also see Charnes *et al.* (1978) for some computation for the transformation.

Although solving the dual model is equivalent to solving the primal model (because all information will be obtained in solving either program), the dual form is the generally preferred form to solve since it involves fewer constraints than the primal[4] (Coelli, 1995). Note that the linear programming problem must be solved *n* times, once for each firm in the sample. The $s_I^+$ and $s_I^-$ in the dual are the reduced costs of the primal variables *v* and *u*, respectively; $\lambda_0$ is the reduced cost of the slack variables of the primal (as shown in M2). The $s_I^+$ represents a vector of non-negative slack associated with the output inequalities and $s_I^-$ represents a vector of non-negative slack associated with the input inequalities. A value of $Z_0$ is then obtained for each firm, which will be the efficiency score for the *j-th* farm. From the objective function, it is clear that the conditions for a farm to be Pareto efficient are $Z_0 = 1$ and the slack variables are all zero (Charnes *et al.*, 1978 p.443). If a farm is not efficient, the constraints in M3 imply that by decreasing $x_{ij}$ by $(1- Z_0)\, x_{ij} + s_i^+$ and increasing $y_{ij}$ by $s_r^-$, the associated farm becomes efficient (Charnes *et al.*, 1978). In short, the solution to this model seeks the values of $\lambda_j$ to construct a composite unit with outputs $\Sigma\lambda_j y_{rj}$, $r=1,...,t$, and inputs $\Sigma\lambda_j x_{ij}$, $i=1,...,m$, outperforming unit $j_0$.

To illustrate this situation, refer to Figure 3 where the farms using input combinations C and D are the two efficient farms which define the frontier, and farms *A* and *B* are inefficient farms. The Farrell (1957) measure of technical efficiency gives the efficiency of farm *A* and *B* as *0A'/0A* and *0B'/0B*, respectively.

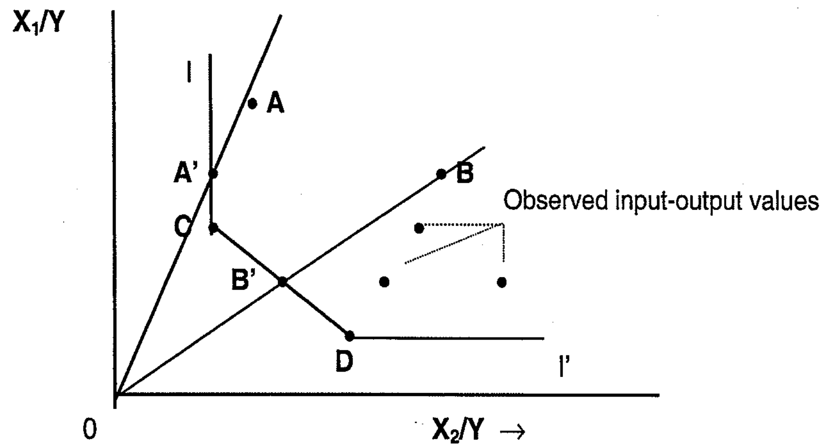


**Figure 3. Efficiency measurement and input slacks.**
**Source: Coelli, (1997.**

Assuming that *CI* and *DI'* are parallel to the axes, it is not clear as to whether the point *A'* is an efficient point since one could reduce the amount of input $x_1$ used (by the amount of *CA'*) and still produce the same output. This is known as input slack. Some authors argue that both the Farrell measure of technical efficiency and any non-zero input or output slacks should be reported to provide an accurate indication of technical efficiency of a unit in a DEA analysis (Coelli *et al.*, 1997). Authors, such as Ali and Seiford (1993), have suggested the use of a second-stage linear programming problem to ensure the identification of an efficient frontier point by maximising the sum of slacks required to move from the first-stage projected point (such as *A'* in Figure 3) to a Koopman's efficient frontier point (such as point *C* in Figure 3). However, there are problems associated with this second-stage LP. The sum of slacks is maximised rather than minimised thus it identifies not the nearest efficient point but the furthest efficient point. Moreover, it is not invariant to

[4] The primal model has *n+t+m+1* constraints whilst the dual model has *m+t* constraints. As *n*, the number of units, is usually considerably larger that t+m, the number of inputs and outputs, it can be seen that the primal model will have many more constraints than the dual model. For linear programs in general the more constraints, the more difficult a problem is to solve. Hence for this reason it is usual to solve the dual DEA model rather than the primal (Boussofianne *et al.*, 1991 p.2).

units of measurement. That is, 'the alteration of the unit measurement, say for a labour input from days to hours (while leaving other units of measurement unchanged), could result in the identification of different efficient boundary points and hence different slack and $\lambda$ values' (*ibid* p.175).

Coelli (1997) suggests using a multi-stage DEA method but it is more computationally demanding. It identifies efficient project points which have input and output mixes as similar as possible to those of the inefficient points, and that it is also invariant to units of measurement. Nevertheless, the importance of slacks can be overstated. Ferrier and Lovell (1990 in Coelli, *et al.*, 1997) emphasised that slacks may be essentially viewed as allocative inefficiency.

Going back to the model (3), the appearance of the additional variable $u_0$ introduces a corresponding constraint $\sum_{j=1}^{n} \lambda_j = 1$ and this has the effect of enveloping the data more closely, allowing variable returns to scale to be exhibited (Piesse *et al.*, 1996). Thus, farm $j_0$ will be operating at decreasing returns to scale if and only if the $\sum_{j=1}^{n} \lambda_j > 1$. If the sum is lower than one, farm $j_0$ will be operating at increasing returns to scale and if the sum is one the unit will be operating at the most productive scale for its input-output mix.

It is noteworthy that without the convexity constraint in (3), the efficient boundary can be extrapolated from the most productive scale size for a given input/output mix (*e.g.,* a composite unit at point *N* in Figure 2 is based on an extrapolation of the average productivity at point *E*.) Such an extrapolated composite unit however may not be attainable for the given scale size of unit $j_0$. The convexity constraint ensures that the composite unit is of similar scale as unit $j_0$, and it is not an extrapolation of another composite unit operating at a different scale size *i.e.,* an inefficient unit is only 'benchmarked' against units of a similar size, or small size. The efficiency measure yielded in respect of unit $j_0$ in model 3 is its pure technical efficiency (Boussofianne *et al.*, 1991). Overall efficiency of a farm is the product of pure technical efficiency and scale efficiency.

The general LP formulation to determine the degree of allocative efficiency for the $j_0$ th farm (assuming constant or increasing returns to scale) is:

$$Min \sum_{i=1}^{m'} P_{ij0} Z_i \qquad (1)$$

*subject to*

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj0} \; (r = 1,2,\dots, t) \qquad (2)$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} - Z_i = 0 \; (i = 1,2,\dots, m') \qquad (3)$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ij0} \; (i = m'+1,\dots, m) \qquad (4)$$

$$\sum_{j=1}^{n} \lambda_j \geq 1 \qquad (5)$$

The variables are defined as earlier with the addition of the $P_{ij}$ $(i=1,2,...,m';j=1,2,...,n)$ as the price per unit for each controllable resource of type *i* at the *j*th farm. The *m-m'* inputs are environmental factors, not controllable by the farm. The LP decision variables are $Z_i \geq 0$ $(i=1,2,...,m')$ and $\lambda_j \geq 1$ $(j=1,2,...,n)$. The equations (1) to (5) are always feasible by taking $\lambda_{jo}=1$, and $Z_i = x_{ij}$. The $j_o th$ farm is said to be allocatively efficient only if $\sum_{i=1}^{m'} P_{ij0}Z_i^* = \sum_{i=1}^{m'} P_{ij0}x_{ij0}$ where the asterisk denotes the optimising values of the LP of (1) to (5). The total cost variance between allocative efficiency and actual cost, for the $j_o th$ farm, is: $\sum_{i=1}^{m'} P_{ij0}(x_{ij0} - Z_i^*)$ and the allocative efficiency score is:

$$\frac{\sum_{i=1}^{m'} P_{ij0}(Z_i^*)}{\sum_{i=1}^{m'} P_{ij0}x_{ij0}},$$ a number between 0 and 1. Note that constraint (2) together with the objective function, determine the most cost effective use of each of the controllable resources so as to meet the specified output vector $(y_{1,jo}, y_{2,jo},...,y_{t,jo})$, at minimum total cost, $\sum_{i=1}^{m'} P_{ij0}Z_i^*$.

It should be noted that the DEA technique has limitations e.g., it does not take account of the possible influence of measurement error and other noise in the data (Coelli, 1995). However, it does not require a specific functional form to specify the frontier. Lewin, Morey and Cook (1982, in Seiford and Thrall, 1990) recognised that since the non-parametric DEA methodology requires only a single observation (for each input and output) per unit, it may be more sensitive to errors in the data (measurement errors, data entry errors, and others).

However there are nice features in the DEA technique. It can provide information such as benchmarks as it identifies the sources and level of inefficiency. The efficiency of a farm (or decision making unit-DMU) is measured relative to similar farms and thus estimates a 'best practice' frontier (benchmark). These units differ in the quantities of inputs which they consume and in the outputs which they produce (Stewart, 1996 p.654). DEA optimises on each farm relative to all other farms in the observed population with an objective of calculating a discrete piecewise frontier determined by the set of Pareto-efficient[5] farms and with the sole requirement that each farm lies on or below the extremal frontier (Charnes, *et al.,* 1995 p.5). Farms that do not lie on or within the frontier are 'inefficient'. Each farm (not on the frontier) is scaled against a convex combination of the farms on the frontier facet closest to it to determine its source and level of inefficiency.

Figure 4 shows a simple example of a data envelope in two product space. The output distance function is suitable to present the idea of Pareto-efficient farms since it measures possible changes in production for given input use. Each farm consumes the same amount of a single resource input to produce different amounts of outputs *y1* and *y2*. Within a given amount of resource input, farms providing greater amounts of the outputs will be the efficient ones. Applying the DEA approach to this set of farms will identify farms *F1, F2, F3* and *F4* as efficient, and so provide an envelope round the entire data set. The data envelope has been notionally extended to the axes by the dashed lines *F1 y'2* and *F4 y'1* to enclose the data set. Farms *F5* and *F6* are within this envelope and therefore are inefficient.

[5] The idea is based on the concept of Pareto optimality, which states that, within the given limitations of resources and technology, there is no way for a farm to produce more of some desired commodity without reducing the output of some other desired commodity (Zeleney, 1982 in Kao, *et al.,* 1993 p.75).

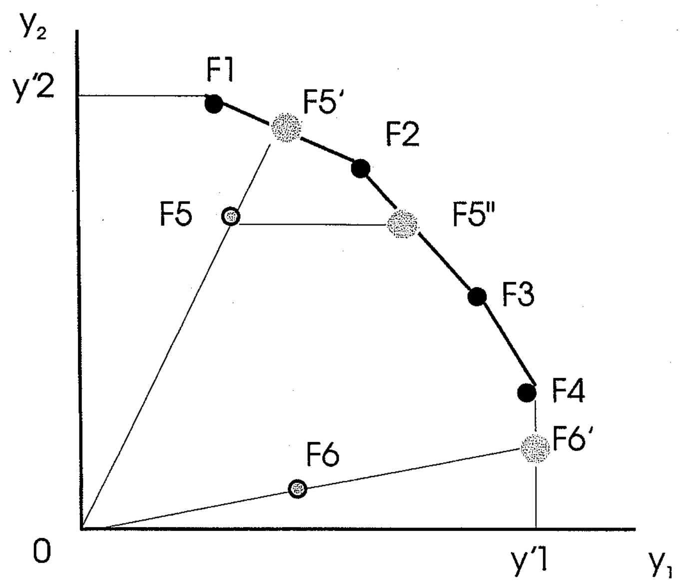


**Figure 4. Output-orientated DEA.**
**Source: Boussofianne *et al.*, (1990)**

Farms *F1, F2, F3* and *F4* are technically efficient since no other farm produces more of at least one product without producing less of the other. Farms *F5* and *F6* are inefficient since more of both products could be produced by a linear combination of farms *F1* and *F2 or F2* and *F3* for *F5* while *F4* and *y'1* for *F6.*

For each inefficient farm, DEA identifies the sources and level of inefficiency for each of the inputs and outputs. The level of inefficiency is determined by comparing the farm to a single referent farm or to a convex combination of other referent farms located on the efficient frontier that utilise the same level of inputs and produce the same or a higher level of outputs. This is achieved by 'requiring solutions to satisfy inequality constraints which in effect can increase some outputs (or decrease some inputs) without worsening the other outputs (or inputs) (Charnes, *et al.,* 1995 p.6).

In Figure 4, for inefficient farms such as *F5*, the technical efficiency measure *0F5/0F5'* reflects the level of production for a specific farm relative to the best (or efficient) farms, given its own use of inputs. An intuitive explanation of the measures is that technical inefficiency indicates production loss relative to the potential maximum, given the output ratio.

The convex combination (or peer group) of inefficient farm *F5* are farms *F1* and *F2.* A set of efficient targets for farm *F5* is provided at *F5'.* These targets are obtained by a pro rata increase in the outputs of farm *F5.* Clearly there are other possible targets for farm *F5.* For example if the output level $y_2$ could not be increased for farm *F5* then a target *F5"* could be set, which would rely entirely on increasing output $y_1$. For farm *F6* the pro rata increase leads to the set of targets *F6'.* However *F6'* is clearly dominated by farm *F4* that produces the same amount of output $y_1$ but more output $y_2$. In this case the pro rata increase needs to be supplemented by a further increase in the output of $y_2$ to provide an efficient target. Returning to farm *F5*, the set of targets *F5'* can be obtained from a weighted average of the peer farms *F1* and *F2.* Thus farm *F5* can be thought of as a composite unit made up of a weighted average of the peer units and this composite unit provides a target for the inefficient unit. Fortunately, these calculated improvements (in each of the inputs and outputs) for inefficient farms can be an *indicative* for potential improvements for inefficient farms. As the projections are based on the *revealed* best-practice performance of "comparable" farms that are located on the efficient frontier.

Besides identifying the sources and level of inefficiency, DEA also provides a summary measure of the relative efficiency of the observed farms. Since each farm is characterised by a single summary relative efficiency score, some form of rank ordering can be done. Looking at the distribution of DEA efficiency scores by output levels in Figure 5, 'a ranking on the farms on the basis of the output measure alone has ranked farms 28 and 29 in the top four and farm 16 as fourth from the bottom. The DEA analyses, however, indicate that farms 28 and 29 have the potential to improve output by 12% and 6%, respectively, whereas farm 16 is performing as well as can be expected. Farms 28 and 29, which are performing at a high level but not at their DEA potential, ought to be given goals toward improving their performance.'

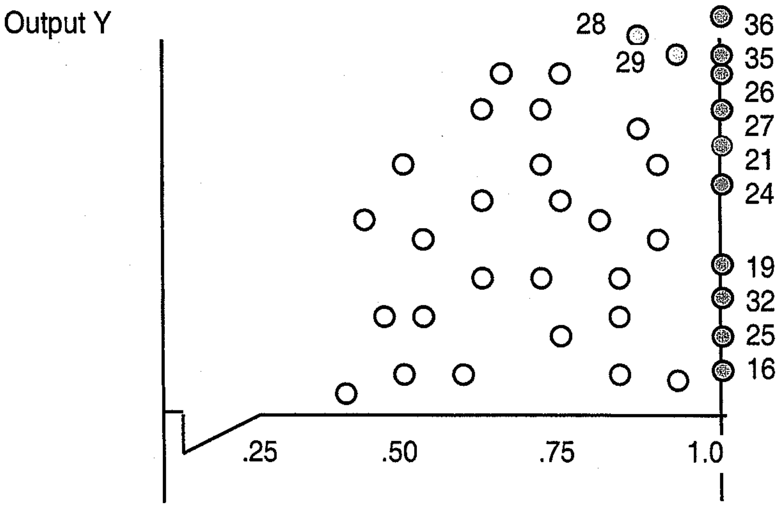


**Figure 5. Distribution of DEA efficiency scores by output.**
**Source: Charnes *et al.*, (1995), adapted from Lewin and Morey, (1981).**

This study used the non-parametric DEA approach mainly for the following reasons:
(1) the major interest of the study is to measure the efficiency of individual farmers. DEA is applicable since it focuses on individual observations in contrast to population averages;
(2) DEA can provide some detailed information *e.g.,* input use of an individual farm and its peers, or best practice farms, which can be used for benchmarking performance. Benchmarking is a procedure for improving performance by identifying best practice, measuring performance against best practice and then forming benchmarking partnerships between best-practice (peer) and non-best-practice farms so that the latter can identify and then eliminate their less efficient practices. Typically, the best-practice benchmark represents an amalgam of the best practices on one or more farms (Jaforullah and Whiteman, 1999); and
(3) DEA has not been regularly applied in agriculture and this study demonstrates its applicability in agriculture by using this technique in sugar cane production.

## 4 Data

The data were collected from a stratified randomly drawn sample consisting of 127 farmers from the Central Negros area in the Philippines during the Crop Year 1997-98. For the purpose of the study, farms with less than 10 hectares are considered small; less than 50 hectares, medium; and above 50 hectares, large.

The Philippine's sugar industry has been experiencing a continuous decline in production for almost a decade. In Crop Year (CY) 1995-96 alone, the country imported around 605,460 metric tons (MT) of raw sugar and 211,208 MT of refined sugar (Basic Sugar Statistics, SRA, 1996). The decline, which is attributed to high production costs, especially fertiliser costs, price competition with artificial sweeteners, imported sugar (and the proliferation of smuggled sugar), limited land availability, and rapid urbanisation, has posed serious challenges for the long-term survival of the industry.

The present sugar world price of 29.04 US-cents per kilogram, and the 19.8 to 22 US-cents per kilogram production costs of Australia, Brazil and Thailand (Sugar Letter, Sugar Y Azucar, 1996) suggest that the Philippine's sugar production cost of 28.60 cents per kilogram is unprofitable. This raises the role of productive efficiency in profitability. It is believe that the future of the sugar industry in the Philippines will depend on its ability to enhance economic performance through improved productive efficiency.

**4.1 Characteristics of Sugar cane Farmers and Farms (Table 1).** Around 44 per cent of the respondents graduated from college and this is reflected in the extent of the educational levels of the respondents, which is very high (12 years of schooling = second year in college) (Table 1). Around 27 per cent of the respondents had no exposure to any extension service. Although the maximum number of exposures to extension was high, the majority reported to have no more than 20 contacts (over two years) despite the average of 9.44. There were few younger sugar cane farmers, and, equally, few older ones. On average, the respondents were middle aged with a household size of around 4. Half of them have part-time jobs.

In terms of land topography and soil types, 49 per cent of the respondents' total area is flat, 19 per cent is slightly rolling while 32 per cent is rolling. The majority (46.3 per cent) of the total area is clay loam; around 20 per cent is sandy loam while 33.45 per cent is sandy clay loam.

Only 48.37 per cent of the total area was planted to new varieties of sugar cane, 41 per cent to the old varieties, while 10.63 per cent was in a mixed variety. Fertiliser application varied from as high as 729 kilograms per hectare to no application at all, except for N fertiliser. It is clear that there is a wide variation in input use. Such a variation in the levels of inputs being used suggests that possibly these levels represent a mismanagement of resource use.

**Table 1. Selected farm and farmer characteristics, including technology adoption.**

| Item | Mean | Std Dev | Minimum | Maximum |
|---|---|---|---|---|
| Farmer's human capital | | | | |
| Years of education (EDUC) | 12.54 | 3.3 | 3 | 21 |
| Years of farming experience (EXP) | 17.18 | 12.16 | 1 | 51 |
| No. of exposures to extension (EXTN) in 2 years | 9.44 | 21.85 | 0 | 200 |
| Socio-economic | | | | |
| Age (AGE) (years) | 51.42 | 11.01 | 25 | 78 |
| Household size (HH) (people) | 3.94 | 1.92 | 1 | 8 |
| No. of hrs. in off-farm work/year (OFFWORK) | 615.68 | 840.24 | 0 | 3120 |
| Farm environment | | Hectares | | |
| Topography: Flat topography (FLAT) | 18.31 | 31.09 | 0 | 156 |
| Slightly rolling (SROL) | 6.70 | 19.81 | 0 | 132 |
| Rolling (ROL) | 11.95 | 41.88 | 0 | 310 |
| Soil types: Clay loam (CLAY) | 17.11 | 45.91 | 0 | 310 |
| Sandy clay loam (SCLAY) | 7.49 | 20.25 | 0 | 120 |
| Sandy loam (SANDY) | 12.37 | 24.85 | 0 | 109 |
| Adoption of technology | | Hectares | | |
| New varieties | 17.86 | 34.58 | - | 270 |
| Old varieties | 15.12 | 28.97 | - | 227 |
| Mixed varieties | 3.99 | 10.14 | - | 59 |
| | | Kilograms per hectare | | |
| Nitrogen (N) | 377.52 | 111.65 | 36 | 729 |
| Phosphorus (P) | 139.41 | 82.37 | 0 | 368 |
| Potassium (K) | 179.28 | 153.37 | 0 | 480 |

## 5 Measuring and Analysing Productive Efficiency

**5.1 Measuring Pure Technical Efficiency.** Individual technical efficiency levels were derived and analysed using output-based DEA frontiers through the Warwick[6] Windows DEA program. In contrast to the parametric approach, in DEA it is not necessary to use statistical techniques to estimate the production frontier. However there are various steps to consider in carrying out efficiency measurements using DEA.

**5.1.1 Definition and Selection of Farm Units.** According to Golany and Roll (1989), the definition and selection of farm units is the first step to consider. Of particular importance is the homogeneity of the units. This implies a basic assumption that differences in performance among 'like' units exist and are measurable, but they are not due to differences in the quality of the basic resources. However, it is not always possible to have complete homogeneity so variables like topography are used in the explanatory models.

The next step is to determine the size of the sample. The larger the sample, the larger the probability of capturing high performance units which determine the efficiency frontier. Also, a large set enables a sharper identification of typical relations between inputs and outputs. Furthermore, it is possible to incorporate more factors into the analysis (Golany and Roll, 1989)

The determination of DMUs to enter the DEA evaluation process is affected by two kinds of boundaries. One comprises the organisational, physical or regional boundaries that define the individual units. The other relates to the time periods used in measuring the DMU's activities. Preferably, the time periods to be considered should be 'natural ones', corresponding to seasonal cycles and budgeting or auditing periods. Long periods may obscure important changes occurring within them, while short periods may give an incomplete picture of the DMU's activities (*ibid.*).

Golany and Roll defined a homogenous group of units as one where: (1) the units under consideration perform the same tasks and with similar objectives; (2) all the units perform under the same set of market conditions; and (3) the factors (both inputs and outputs) characterising the performance of all units in the group, are identical, except for differences in intensity or magnitude.

In view of these definitions, only those farmers producing regulated sugar are included, *i.e.,* those producing *muscovado* sugar are not included. To obtain a more statistically valid result, several years production data is needed. Since the study depended on farmers' memory, only one-year of data was possible as the farmers could not even recall their last year's production data. Generally, the cropping year for sugar cane begins in September and ends in August of the next year, therefore, and due to the availability of data, Crop Year 1997-98 was considered.

This crop year could be atypical due to the occurrence of drought caused by the El Niño phenomena.[7] Generally the annual totals for all the sugar milling Districts in the Philippines show more than enough rainfall (Sugar cane Farm Management Training Manual, 1997). Therefore, the farm efficiencies may be related to this phenomenon and the results may apply for this crop year only. Future research must collect more data to verify the results. However, it must also be remembered that DEA gives the relative efficiencies; and these may not be different given a different season.

**5.1.2 Selection of Factors.** All factors that have a bearing on the performance of the units to be analysed should be listed. If an input is omitted, the relative efficiencies determined will not reflect

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[6] Warwick Windows DEA User's Guide, 1996.

[7] In CY 1997-98, the annual rainfall measured by the Agromet station in La Granja Agricultural Research and Extension Centre was only 1,171.4 mm. Annually, the cane plants need about 1,346.2 mm (about 53 inches) of rainfall for good growth and maximum yield (Sugar cane Farm Management Training Manual, 1997). Therefore, the amount of annual rainfall for this crop year was not sufficient for complete cane plant growth.

the performance of units in terms of their effective (or otherwise) use of that resource. Similarly, if some outputs are omitted, the assessment ignores the performance of the units on that output (Thanassoulis *et. al.*, 1987).

Factors can be either fully or partially controllable, or they may be 'environmental' factors outside the control of the managers. Some of the factors will be quantitative, while other factors may be qualitative in nature, in which case numerical values[8] need to be assigned in order to include them in the mathematical evaluation of efficiency (Golany and Roll, 1989).

The selection of inputs and outputs can affect the discriminating powers of DEA (Boussofianne *et al.*, 1991). However, the more input and output variables are included in the model, the higher will be the number of DMUs with an efficiency score at unity (Nunamaker 1985 in Johnes and Johnes, 1993). Boussofianne *et al.* (1991) gave a clear explanation on this and connected it with the determination of the size of the comparison group:

> 'This arises due to the flexibility in the choice of weights in determining the efficiency of each individual unit. In seeking to be seen to be efficient a unit can allocate almost all its weight to a single input and output. The unit for which one particular ratio of an output to an input is highest can allocate all its weights to that ratio and appear efficient. The total number of ratios will be the product of the number of inputs and outputs and this product is a reasonable indicator of the minimum number of efficient units. Hence with six inputs and six outputs at least 36 or so units will appear efficient, so that the total number of units in the set needs to be much greater than 36 for the method to be of any discriminatory value' (p.4).

Thus, the initial list was reduced to include only the most relevant factors. Golany and Roll listed three stages to be carried out in refining the initial list. The first stage is the critical examination by expert decision-makers in the field where the DMUs operate. This stage is called judgmental screening. Some factors may be repeating virtually the same information; some may not be regarded as crucial, while others may appear to be conflicting or confusing. Judgement may be exercised, *inter alia*, along the following lines: (1) Is the factor related to, or contributing to, one or more of the objective set for the application?; (2) Is the factor conveying pertinent information not included in other factors?; (3) Does the factor contain elements (*e.g.,* price) which interfere with the notion of technical efficiency?; and (4) Are data on the factor readily available and generally reliable?

Another stage is the DEA quantitative screening involving possible aggregation of factors into a summing factor. Aggregation depends strongly on the objectives of the analysis. One issue concerning quantitative factors is the handling of cases where zero values are encountered for some factors. In principle, DEA models can handle cases with zero values as long as there exists at least one input and one output for each DMU which is non-zero. However, such cases should be handled with care, as the computational algorithms may be sensitive to zero values (Charnes *et. al.*, 1986).

The last stage is the DEA-based analyses. This is the running of alternative DEA models to examine and fine-tune the list of factors to be included. The factors that remain in the list are entered into the model. This can be started with the most 'strict' model- the Charnes, Cooper and Rhodes model (assumes constant returns to scale). The Banker, Charnes and Cooper (BCC) model, on the other hand, is less strict as it incorporates some of the explanations of efficiency differences into the models themselves (*e.g.*, variable returns to scale). In the procedure proposed in this study, the analysis is started with the BCC model.

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[8] The usual practice is to locate some measurable surrogate variable which is assumed to bear a known relation to varying levels of the qualitative factor. Typically, several possible surrogates may be tried out for each qualitative factor until a suitable one is located. Criteria for the choice of surrogate factors are: the degree of correspondence between variations in the surrogate data and the examined factors; the ability to express this correspondence in a functional form and the general compliance of the results to the objectives (Golany and Roll, 1989).

**5.1.3 The Output.** Besides sugar, molasses and bagasse are produced. The cane is crushed by mill companies for an agreed share of the sugar, molasses and bagasse, as calculated on the weight of cane and the analysis of the first expressed juice. Each local farmers' association maintains a chemist and other personnel to oversee the weighing of the cane and sugar analyses. The average sugar production sharing ratio is close to 65 per cent for the planter and 35 per cent for the mill company, but covers a range of 60:40 to 70:30.

The extracted juice is first weighed and then treated with lime and finally evaporated to form the raw sugar crystals. This is the output factor that is considered in this study. The raw sugar may then be processed to form brown sugars *e.g.*, *muscovado* or refined and sifted to produce white sugars *e.g.*, granulated, caster and icing sugar. The syrup that is drained away from the raw sugar is molasses; it may be processed to form golden syrup or fermented to form rum. The fibrous residue of sugar cane, bagasse, is used in the manufacture of paper, cattle feed, and fuel.

The farmers' share of raw sugar, measured in 50 kilo bags, was the only output considered in this study. Data on molasses was not collected because it was assumed that its inclusion would have minimal bearing on the efficiency measurement, as generally the molasses and sugar production are highly correlated. The farmers' share of bagasse, on the other hand, has no value. If the farmers want to consume their bagasse they can reclaim their share anytime.

**5.1.4 The Inputs.** Only land planted to sugar cane, *i.e.*, cropped land, is included in the analysis. Thus land devoted to other crops, *e.g.*, rice and corn and livestock, were excluded as only small areas are used for subsistence purposes. Although data on land topography and soil types were collected, they were not treated as discriminating input factors in the first instance, but were used to formally classify homogenous groups.

Sugar cane can either be an annual or semi-perennial crop. Its output depends on the daily and monthly maintenance operations on the farm, starting from land preparation up to harvesting and ratooning (second and subsequent years production). The cultivation of sugar cane involves around 21 farm operations and approximately 6 farm inputs. In the initial list, all of these inputs and output were classified according to the types of crop- plant and ratoon (Figure 6). The classification resulted in 49 inputs and 2 outputs. Using 127 units, the number of farm units with an efficiency score of 1.0 was found to be 110 (87 per cent). The minimum efficiency score obtained was 0.70.

The input factors were reduced by grouping the variables into major farm practices *e.g.*, person-days for plowing, harrowing and furrowing were grouped into one variable- land preparation practice, and so on. This resulted in 24 inputs and 2 outputs. The number of efficient farms was reduced from 110 to 106 while the minimum efficiency score obtained increased from 0.70 to 0.73. Further reductions were made in the inputs. All operations that used animal power (expressed as person-animal days) were combined as well as the operations that used machines (expressed as person-tractor days). Likewise, all of the operations that used hand power *i.e.*, the preparation of seedpieces, planting, replanting, liming, fertilising, weeding, irrigation and land clearing were combined into one factor and expressed in person-days. In addition, the output as well as the inputs of the two types of crop culture (ratoon and plant crops) was aggregated. This resulted in 1 output and 7 inputs that gave a reduction in the number of efficient farm units from 106 to 41. Meanwhile the minimum efficiency score obtained decreased from 0.73 to 0.37.

Further reduction of inputs was considered. Since land preparation and cultivation are carried out by person-animal power and/or by person-machine combinations, they were combined into the number of hours of power used. Based from the survey data on person-animal days and person-machine days, the conversion factor derived for sugar cane cultivation is: 1 hour of animal work = 0.13587 hours of machine work. This resulted in 1 output and 6 inputs. The number of efficient units was reduced to 26 although the reduction in the minimum efficiency score was minimal, from 0.37 to 0.36.

Another farm input that was thought to affect the efficiency levels was the aggregation of organic and chemical fertilisers (expressed in 50-kilo bags). In sugar cane production, chemical fertiliser is most commonly used with only 4 respondents using organic fertiliser (0.12, 4 and 20 bags per hectare). Of the two farmers who applied 20 bags of organic fertiliser, one applied 14 bags and the other 20 bags of chemical fertiliser per hectare. Summing these bags gives non-sensical figures so these two kinds of fertiliser were disaggregated. In theory, determining the amount of NPK nutrients applied enabled a direct comparison. However, since the organic fertiliser has no nutrient analysis (and because only a few applied it), this input factor was later dropped. According to Kao *et al.*, (1993), selecting inputs and outputs that are not representative will result in evaluated efficiencies that are misleading. Using only the chemical fertiliser input provides consistency across all farms. In any case, chemical fertiliser is by far the most important to sugar production. However, the effect of this factor increased the number of efficient units from 25 to 28 while the efficiency scores for some of the inefficient farm units remained more or less the same.

Canepoints and stools, used in planting and replanting, were also combined (both were expressed in *lacsa* = 10,000 canepoints or stools). Ratoon crops do not have seed inputs but are grown from stubble. Most of the respondents (there are 22 farm units with ratoon crop only) reported their previous rate of planting canepoints and these were tested as a replacement for zero values in relation to seed inputs. However, farmers 6, 10, 19, 36, 63, 75 and 112 did not report on this aspect. Planter 6 was already in the 6th ratoon and planter 12 in the 4th ratoon. The rest were in 2nd to 3rd ratoon. Since these seven farm units did not have data on their previous rate of planting and did not replant, their zero values could not be replaced. Nonetheless, the DEA was run with, and without, the replacement seed input to ensure that the results were not particularly dependent on the substitution. Twenty-four (24) efficient farms were obtained after the assessment and most of them were relatively inefficient farms based from the previous assessment. Therefore, the use of historical canepoint data blurred the efficiency score of the farm units. In view of this, it was decided that the seed replacement input be excluded.

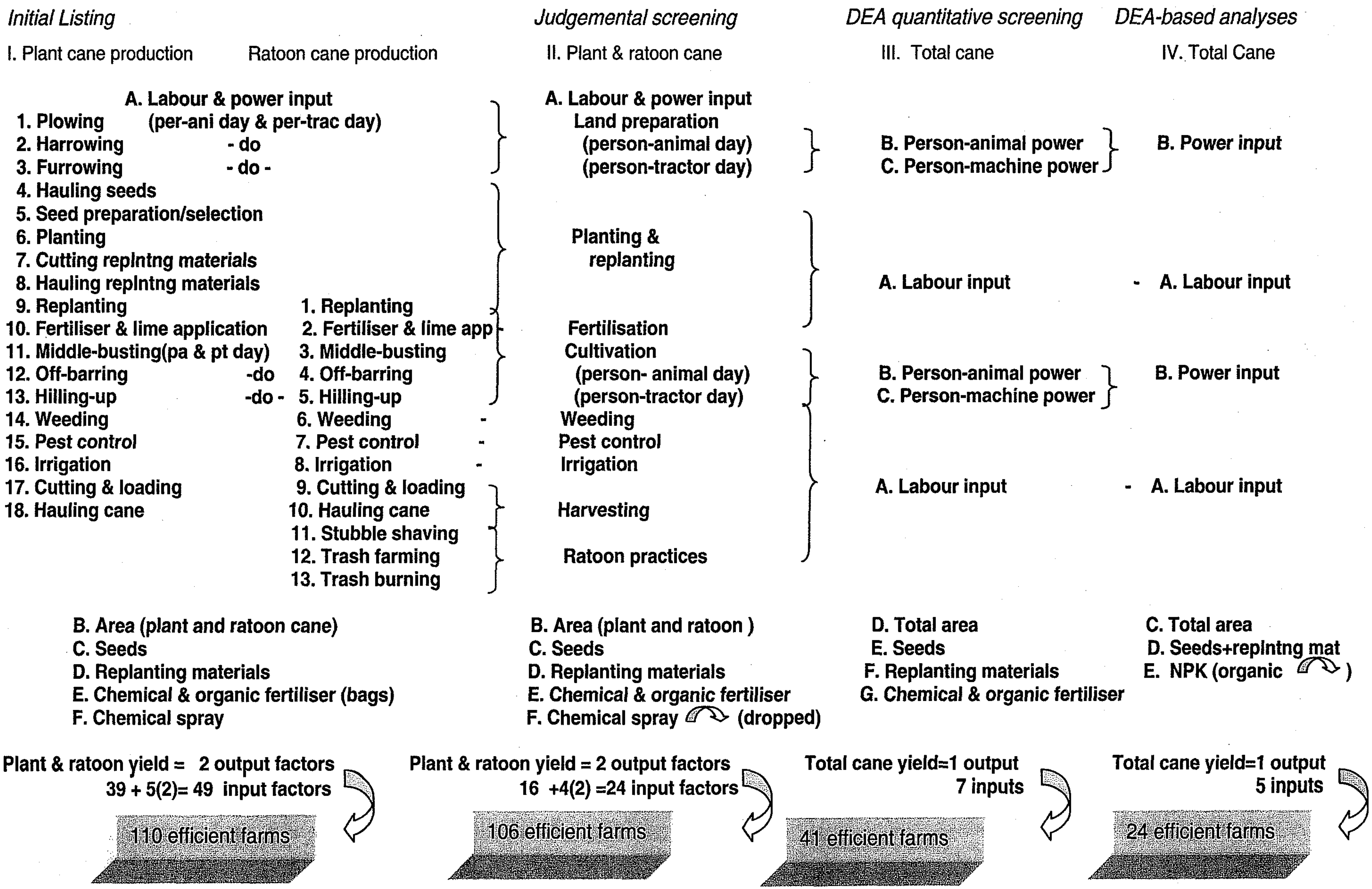


Figure 6 The initial and final listing of the input-output factors used in DEA technique.

Moreover, using the previous rate of planting as an input and, similarly with other inputs, *e.g.*, fertiliser which has a carry over effect (and can be felt in the next cropping year), requires simulation over years, but this was beyond the scope of this study. The combination of seed and replanting materials resulted in 1 output and 5 inputs.[9]

Therefore, the inputs used in the analyses include cropped area (measured in hectares); seeds and planting materials (measured in number of *lacsa*); an aggregated NPK fertiliser input (measured in kilograms); power (measured in number of hours) and an aggregated labour input (measured in person-days). The decision to use these factors was made on the grounds that these inputs represent the significant resources under the planter's control that enable the DMUs efficiency levels to be discriminated between. This does not mean that all other inputs are irrelevant, but that with the data available they did not help discriminate.

Table 2 shows the summary statistics and displays the wide variation in production and input combinations contained in the sample.

**Table 2. Summary statistics of the physical input and output per farm.**

| Input-Output per farm | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Output | | | | |
| Tonnes cane | 2170.11 | 3198.86 | 19.20 | 17730.35 |
| Input | | | | |
| Area (ha) | 36.96 | 50.55 | .50 | 310.00 |
| Seeds (*lacsa*) | 217.73 | 306.38 | .00 | 1772.50 |
| NPK (kgs) | 29963.68 | 44881.37 | 64.00 | 240020.00 |
| Power (hours) | 884.12 | 1228.50 | 8.15 | 8038.35 |
| Labour (person-day) | 4291.50 | 6097.65 | 41.00 | 34584.50 |

**5.1.5 Results of the Assessment.** The most efficient farm units with respect to the five inputs are given an efficiency value of 1.00 in the DEA procedure. Others have an efficiency rating (on a scale of <1.00 to zero) that is established relative to the units with maximum efficiency. It is noteworthy that DEA assessment yields the relative efficiency of each farm unit, not the absolute efficiency level relative to what is technically possible with perfect management.

[9] This 1 output and 5 input combination was subsequently modified 4 to 5 times by replacing the number of bags and NPK nutrients for the fertiliser input. This was to test the sensitivity of the results to changes in input-output specifications. Using the number of bags of fertiliser (organic and chemical) as an input reduced the number of efficient farm units from 25 to 24. Consequently, the efficiency scores increased (by 0.0011 to 0.0918). among the farms who used organic fertiliser, all but 1 maintained their efficiency scores. The efficiency score of this farm unit (planter 32) decreased from 0.81 to 0.79. Planter 32 used 0.12 kg/ha of organic fertiliser and this small amount seems to have no bearing on the sugar production. A further fine-tuning used NPK applied instead of the number of bags (chemical fertiliser), and this time, the number of efficient farm units went back to 25. A chemical fertiliser user such as Planter 17, who used to be inefficient in the previous assessment, became efficient when NPK input was used. Planter 17 applied 8 bags of Ammonium sulphate (21-0-0) and 3 bags of mono-ammonium phosphate (16-20-0); these two types of fertiliser have different amounts of available nutrients. Therefore the magnitude of the NPK nutrients applied explained further the efficiency differences among farm units.

**5.1.6 Technical Efficiency Levels of the Individual Farms.** Table 3 presents the frequency distribution of the efficiency levels of the sample farms. Almost 81 per cent of the sample farmers are inefficient.

**Table 3 Distribution of technical efficiency scores.**

| | ALL FARMS | | | |
|---|---|---|---|---|
| EFFICIENCY SCORE | Frequency | Per cent | Minimum | Maximum |
| 1.00 | 24 | 18.9 | 1.00 | 1.00 |
| 0.90-0.99 | 15 | 11.8 | 0.9005 | 0.9933 |
| 0.80-0.89 | 20 | 15.7 | 0.8067 | 0.8964 |
| 0.70-0.79 | 22 | 17.3 | 0.7005 | 0.7966 |
| 0.60-0.69 | 23 | 18.1 | 0.6084 | 0.6982 |
| 0.50-0.59 | 15 | 11.8 | 0.5106 | 0.5989 |
| 0.40-0.49 | 7 | 5.5 | 0.4407 | 0.4997 |
| 0.30-0.39 | 1 | 0.8 | 0.3945 | - |
| Total | 127 | 100 | | |
| Mean | 0.777 | | (0.168) | |
| Median | 0.758 | | | |
| Coefficient of Skewness | -0.190 | | (0.215) | |
| Coefficient of Kurtosis | -1.037 | | (0.427) | |

Numbers in parentheses are standard errors.

The technical efficiency levels of the inefficient farms range from 0.3945 to 0.9933 so there is a potential to increase farm output of approximately 60 per cent from the existing level of inputs. These estimates provide important information for policy-makers on the nature of the production technologies used by the farmers, and facilitate identification of the factors causing such variations in technical efficiency. The mean efficiency level of 0.777 implies that on average the respondents are able to obtain around 78 per cent of potential output from a given mix of inputs. This also implies that around 22 per cent of production, on average, is foregone due to technical inefficiency.

The efficiency distribution of the sample has a slight skewness to the left as proved from the measures of skewness in Table 3. That is, the efficiency distributions tend to cluster to the right and there is a long 'tail' to the left. This skewness is due to the distribution of less efficient farms within the efficiency range of 0.50 to 0.99 *i.e.*, more farmers lie higher-up along the efficiency spectrum.

The technical efficiency distribution has two modes (peaks), for inefficient and efficient farms.

**5.1.7 Analysis of Input Use and Output Differences between Technically Efficient and Inefficient Farms.** This section considers the variation between the efficiency groups and their statistical difference in terms of input and output.

As shown in Table 4, the average output varies between the relatively efficient and inefficient farms. The efficient farms achieved higher sugar cane yield per hectare than the inefficient ones. The t-test for equality of means show that output differences are significant at $p$ =0.05 level. This is due to their input usage in terms of seeds, which is high and significantly different, while less significant in the use of power and land. The difference in NPK and labour use is not significant.

**Table 4. Input-output data: Purely technically efficient and inefficient farms.**

| Farms | Yield** (TC/HA) | Area* (Has.) | Seeds*** (10,000/ha) | NPK (kilogram/ha) | Power** (hours/ha) | Labour (person-day/ha) |
|---|---|---|---|---|---|---|
| **Efficient farms** | 55.93 | 54.55 | 4.34 | 632.45 | 18.99 | 101.57 |
| **Inefficient farms** | 48.10 | 32.86 | 5.79 | 698.11 | 23.50 | 106.84 |

Note: Independent sample test was applied to test for equality of means. This test is not dependent on the assumption of normality as for most tests.

*** Significant at 1 per cent
** Significant at 5 per cent
* Significant at 10 per cent

DEA determines 'slack' variables which provide an indication of the inputs that are in excess supply and those that are effectively constraining production. To be fully efficient, a farm should have no slacks. For the farms that are not technically efficient, all have one or more excess inputs (slack variables).

In Table 5 the total number of farms for which each variable was slack is shown. Labour is the main constraint, effectively limiting output for approximately 80 per cent of the total sample. Labour shortage, especially during the time of harvesting, is a serious problem as it can delay the operation which leads to high sugar-yield losses. Land and power inputs are the next most binding constraints. On the other hand, the NPK fertiliser input appears to be in surplus for many farms, as well as the seeds. This is sensible as the seeds (cane tops) can be taken from the other farms and are sometimes free of charge. These cane tops are not included in the processing of sugar cane as they contain less sugar.

**Table 5 Analysis of slack inputs and adjustment to inputs and output: All technically inefficient farms (TIE).**

| Input & output | TIE farms *n*= 103* | Per cent of total | Per cent of Input and output adjustments to give 100% efficiency | | | |
|---|---|---|---|---|---|---|
| | | | Mean | Std Dev | Minimum | Maximum |
| Output | | | 44.45 | 32.31 | 0.70 | 153.50 |
| Inputs | | | | | | |
| Land | | | | | | |
| Seed | 45 | 44 | 17.52 | 14.14 | 1.10 | 66.00 |
| NPK fertiliser | 65 | 63 | 24.91 | 16.66 | 1.10 | 78.20 |
| Power | 59 | 57 | 30.98 | 15.73 | 2.60 | 72.30 |
| Labour | 40 | 39 | 21.03 | 12.54 | 3.30 | 55.30 |
| | 19 | 18 | 17.67 | 10.28 | 2.10 | 35.80 |

* Number of TIE farms with the stated input as slack.

An average of 44.45 per cent increase in production would be realised if the technically inefficient farms reduced their input use by around 17, 25, 31, 21 and 18 per cent of land, seeds, NPK fertiliser, power and labour, respectively. Take for example farm 118, with an efficiency score of .61. The production practices of farm 118 and its referents (farms 91, 25, 47 and 124 that are efficient and, through a linear combination (*lambda* values), form the boundary point on the ray created by the example farm) are compared in Table 6. The use of some inputs (*e.g.*, NPK fertiliser) by farm 118 is 'excessive.' This comparison would suggest strategies for farm 118 to rationalise the use of its inputs. As noted the *lambda* [10] (in Table 6) values provide a composite farm which would produce the equivalent level of output, but by using lower levels of some of the inputs.

[10] *Lambdas* are the weights in the linear combination (composite farm) of farms 91, 25, 47 and 1 24.

**Table 6. Input use levels of farm 118 and its referent farms.**

| Variables included in the DEA model | Input Use of Farm 118 | Input Use Levels of the Referent Farms | | | | Composite Farm |
|---|---|---|---|---|---|---|
| | | Farm 91 | Farm 25 | Farm 47 | Farm 124 | |
| *Lambda* values | | 0.003 | 0.684 | 0.300 | 0.013 | |
| Output | | | | | | |
| Tonnes sugar per Hectare | 49.09 | 91.60 | 79.56 | 93.73 | 80.98 | 83.86 |
| Inputs | | | | | | |
| Area | 44.10 | 83.20 | 58.30 | 10.00 | 78.00 | 44.14 |
| Seed/ha | 5.33 | 6.50 | 5.24 | 6.50 | 5.00 | 5.62 |
| NPK fertiliser/ha | 1022.06 | 1039.00 | 515.82 | 692.50 | 1048.00 | 577.31 |
| Power/ha | 30.12 | 51.95 | 24.29 | 16.10 | 41.91 | 22.14 |
| Person day/ha | 115.19 | 147.52 | 112.01 | 151.10 | 121.98 | 123.97 |

In general, there was no significant difference in the quantity use of fertiliser and power inputs between the efficient and inefficient farms. The variations may most likely reflect differences in management decisions *e.g.,* on the way farmers combine various inputs that show up in differences in technical efficiency, as distinct from the issue of allocative efficiency, as defined by Farrell (1957), which is studied in the following section.

### 5.2 Measuring Scale Efficiency

A scale element was included to determine the extent to which any (in)efficiency is the consequence of the farms' scale of operations. Information as to whether a farm is operating at increasing or decreasing returns to scale can prove useful in indicating a potential redistribution of farm resources.

The efficiency calculated from the BCC model is pure technical efficiency (or technical efficiency in this study). Banker, Charnes and Cooper (1984) extended the original DEA model (the Charnes, Cooper and Rhodes- CCR) to disentangle the effect of scale efficiency. In the CCR model all DMUs are assumed to be efficient at their current scale so that the efficiency measured is independent of scale considerations. Banker *et. al.,* showed that the CCR overall technical efficiency measure can be regarded as the product of technical and scale efficiency measures (Banker and Thrall, 1992).

The CCR model allows for the decomposition of technical inefficiency between scale inefficiency (inappropriate scale) and pure technical efficiency (operating on an efficient isoquant) [Llewelyn and Williams (1996)]. Thus scale efficiency is calculated from the ratio of overall efficiency to (pure) technical efficiency.

In order to maximise the average productivity, one would increase the scale size if increasing returns to scale were prevailing, and decrease the scale size if decreasing returns to scale were prevailing (Banker, 1984).

Of the 24 purely technically efficient farms (from the comprehensive sample), 12 farms were found to be scale efficient. This means, half of the purely technically efficient farms are overall technically efficient. Two purely technically inefficient farms (farm nos.14 & 57) were found to be scale efficient too. This means, although they are technically inefficient, they are operating at the optimum scale. Table 7 shows that only 9 per cent of the sample farms are on the overall technical efficiency frontier (or combined frontier).

**Table 7. Overall, technical and scale efficiency levels of the sample farms.**

| EFFICIENCY | Overall | Technical | Scale |
|---|---|---|---|
| Number of efficient farms | 12 | 24 | 14 |
| % efficient | 9 | 19 | 11 |
| Maximum score | 1.0 | 1.0 | 1.0 |
| Minimum score | 0.3933 | 0.3945 | 0.6977 |
| Mean score | 0.7431 | 0.7771 | 0.9582 |
| Median score | 0.7298 | 0.7580 | 0.9884 |
| Standard deviation | 0.1637 | 0.1684 | 0.0633 |

Fewer farms are on the combined frontier than on the separate efficiency frontiers. This is inevitable due to the constraint imposed on scale efficiency measurement. The variation in technical efficiency is far less than for overall efficiency, with less than 20 per cent of the farms on the technical efficiency frontier. The major source of overall inefficiency appears to be technical efficiency, as against scale efficiency. This suggests that by eliminating scale inefficiency and pure technical inefficiency, farmers could increase output by 26 per cent by operating at the optimal scale and by eliminating pure technical inefficiency through the adoption of the best practices of efficient farms. As shown in figure 7, pure technical inefficiency accounts for 22 per cent while scale inefficiency only around 4 per cent.

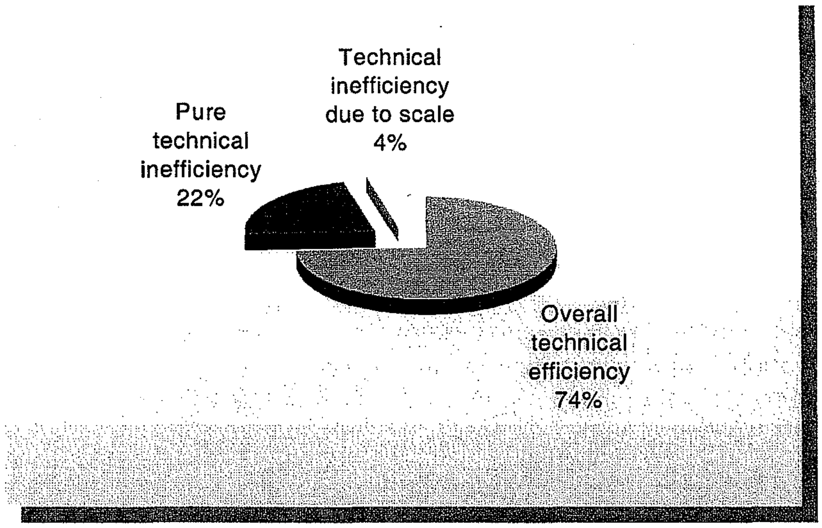


**Figure 7. Efficiency of use of inputs: A sample of Philippine sugar cane farms.**

The scale efficiency results are summarised in Figure 8. Of the 127 sugar cane farms, 9 per cent (12) are operating at constant returns to scale, 42 per cent (51) are operating at increasing returns to scale, while 49 per cent (64) are operating at decreasing returns to scale. Twelve of the farms that were not on the overall efficiency frontier are 100 per cent technically efficient. The remaining 12 technically efficient farms are scale inefficient farms and 9 exhibit decreasing returns while 3 exhibit increasing returns to scale.

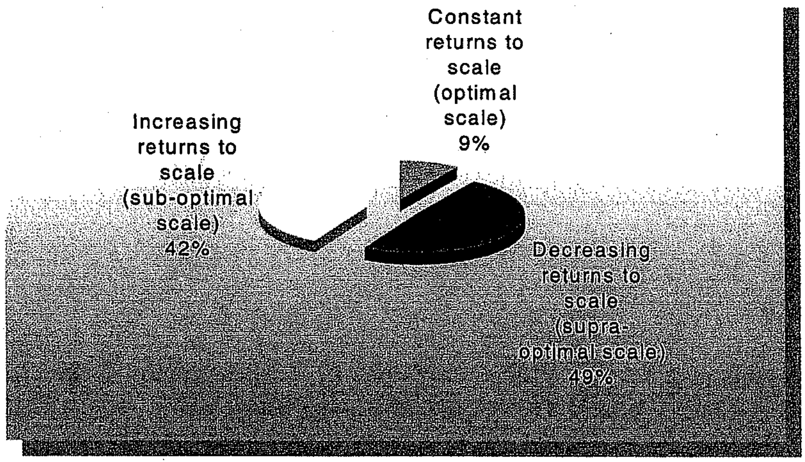


**Figure 8. The scale efficiency of a sample of Philippine sugar cane farms.**

The characteristics of these groups are summarised in Table 8. It would appear that the large increase in technical efficiency could be achieved by addressing the problem of IRS farms. To remove the sub-optimal scale would increase the overall technical efficiency of 51 farms by around 5 per cent from .7198 to .6723. To remove the DRS farms, on the other hand, would increase the overall technical efficiency of 64 farms by an average of 3.1 per cent.

**Table 8. Technical efficiency and scale of sugar cane farmers in the Central Negros area.**

| | CRS farms | IRS farms | DRS farms |
|---|---|---|---|
| Number | 12 | 51 | 64 |
| Average measure of technical efficiency (%) | | | |
| Overall technical efficiency | 1.00 | .6723 | .7502 |
| Pure technical efficiency | 1.00 | .7198 | .7809 |

Table 9 gives the input levels for the farms grouped according to scale efficiency. This data suggests the need to decrease most inputs with, no doubt, more efficient management of the resources. This is the difficult part.

**Table 9. Average input use of technically efficient farms (by various returns to scale).**

| Various returns to scale | Yield (tonnes cane/ha) | Average area (Ha./ farm) | Seeds (1 lacsa=10,000) | NPK (kilograms) | Power (hours) | Labour (person-days) |
|---|---|---|---|---|---|---|
| | | | Per hectare | | | |
| CRS farms (12) | 54.63 | 41.01 | 3.34 | 515.13 | 19.50 | 98.90 |
| IRS farms (51) | 43.26 | 8.87 | 5.82 | 652.65 | 21.34 | 97.05 |
| DRS farms (64) | 53.67 | 58.59 | 5.62 | 744.02 | 24.29 | 114.15 |

**5.2.1 Analysis of Input and Output Differences between Overall Efficient and Inefficient Farms.** As shown in Table 10, the average input and output per hectare of the farms varied between the efficiency classes. As expected, Class 1 farms obtained the lowest yield because they were technically and scale inefficient. Class 3 obtained a higher yield (than Class 1) because they are technically efficient. They are scale inefficient because they are not operating at optimal size. In comparison to the technically and scale efficient farms (Class 4), Class 2 farms obtained a lower yield because they were technically inefficient (although they produced at a scale-efficient level of input). However, the outputs of the overall technically efficient and the inefficient farms were not statistically different although their input use in terms of seeds and NPK fertiliser were statistically different.

**Table 10. Average input-output data: Purely technical and scale efficient (TE & SE) and inefficient (TIE & SIE) farms.**

| Farm class | Yield (tonnes per ha) | Ave. Area (ha) | Seeds (10,000 Per ha) | NPK (kg./ha) | Power (hours/ha) | Labour (person-day per ha) |
|---|---|---|---|---|---|---|
| (1) TIE & SIE | 48.06 | 32.86 | 5.80 | 699.50 | 23.48 | 106.75 |
| (2) TIE & SE | 50.60 | 33.00 | 5.56 | 627.91 | 24.60 | 111.34 |
| (3) TE & SIE | 57.22 | 68.09 | 5.34 | 749.76 | 18.48 | 104.23 |
| Mean (Overall inefficient) | 49.06 | 36.54 | 5.74 | 703.50 | 22.97 | 106.57 |
| (4) TE & SE Overall efficient | 54.64 | 41.01 | 3.34 | 515.13 | 19.51 | 98.90 |

t-tests for equality of means between the overall efficient and inefficient farms show that except seeds and NPK fertiliser, there are no significant variations.

### 5.3 Measuring Allocative Efficiency

Given the technology, farms might be expected to make adjustments in their input levels to achieve allocative efficiency (Kalirajan, 1990), with inputs being allocated according to their relative prices (Torkamani and Hardaker, 1996) so that the marginal product of each input equates to its cost and product price ratio.

Economic efficiency is a term applied to the concept of overall efficiency with allocative and technical efficiency forming its component parts. However, even when resources are allocated optimally, actual realised output may be below potential due to the use of some inferior technique. In some cases, the decision-maker may prefer this technically inferior approach. Apparent inefficiency may also occur because methods used to measure efficiency are inadequate (Kelly, 1977).

It is noteworthy that data on sugar cane cost of production was reported as being very confidential by some farmers. Thus, information, particularly on their farm's debt and asset value, profit or loss statements were not obtained. Net profit figures were calculated from a knowledge of the input and output and the related prices. In this study, all prices are measured in Philippine peso (PhP1.00= NZ$0.05).

**5.3.1 The Output.** The sugar prices varied depending on the classification of sugar. However, due to the many classification changes it was not possible to obtain the actual price of sugar received by the farmers. Generally, the domestic and export sugar is sold in the local farmers' associations thus farmers face similar transaction costs and/or market imperfections. Farmers received similar prices between and among the mill districts on Negros Island so the average composite price of sugar (PhP 595.50/ per fifty-kilo bag) in the Negros mill districts for CY 1997-98 was used.

**5.3.2 The Inputs.** The input costs were obtained from the farmers. Four variable inputs were considered. Seed, replanting materials and fertiliser expenses were aggregated into one variable. In estimating the total cost of fertiliser, the physical quantities of chemical fertilisers were recorded and the 50kg bag price used. The labour expense variable was calculated as the sum of hired-labour and management cost used in sugar cane production (*viz.,* planning, land preparation, including machine hired and custom work, planting, replanting and fertilisation, irrigation, cultivation as well as harvesting). Operating and maintenance (OM) expenses included the cost of fuels and oils, supplies, interest on operating expenses, the machines, land and buildings maintenance and depreciation costs. Depreciation was calculated by the straight-line method. Part of the depreciation costs should have been considered as a fixed cost, however it was combined with the variable cost (Operating & Maintenance – O & M) on the grounds that the consequent increase in the number of variables would reduced the discriminatory power of the DEA method. Moreover, the land rental was disaggregated to form one factor cost.

The inaccuracy of data on the land tax could have been moderated by combining it with the operating and maintenance costs. This, however, would have ignored inefficiencies due to the payment of land tax by some farmers. In the end, for comparability, it was assumed all land was leased. The average land rental gathered for the year was P5,573.28 per hectare.

Table 11 shows the summary statistics of the input and output values.

**Table 11. Summary statistics of the input and output values (Pesos) per farm.**

| Input-output value per **farm** | Mean | Std Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Output - Sugar | P1,292,302.80 | P1,904,922.12 | P11,433.60 | P10,558,423.00 |
| Input | | | | |
| Seeds & NPK | 229,525.53 | 327,268.33 | 1,160.00 | 1,661,740.00 |
| Labour & power | 548,795.34 | 786,875.16 | 5,920.00 | 4,219,320.00 |
| O & M | 173,796.75 | 385,526.06 | 0. | 3,571,203.30 |
| Land rental | 206,004.67 | 281,724.23 | 2,786.64 | 1,727,717.00 |

**5.3.3 Results of the Assessment.** The allocatively efficient farms with respect to the four input expenses are given an efficiency value of 1.00 while the allocatively inefficient farms have < 1.00. Table 12 presents the frequency distribution of the efficiency levels of the sample farms. Only 18 per cent of the sample farmers are allocatively efficient. The mean efficiency level of 0.7941 suggests that, on average, farmers could reduce their factor costs by about 21 per cent without reducing their current output. This also implies that a considerable amount of profit, on average, is foregone due to allocative inefficiency.

**Table 12. Distribution of allocative efficiency scores.**

| | ALL FARMS | | | |
|---|---|---|---|---|
| EFFICIENCY SCORE | Frequency | Per cent | Minimum | Maximum |
| 1.00 | 23 | 18.1 | 1.00 | 1.00 |
| 0.90-0.99 | 16 | 12.6 | 0.9127 | 0.9927 |
| 0.80-0.89 | 25 | 19.7 | 0.8037 | 0.8967 |
| 0.70-0.79 | 23 | 18.1 | 0.7043 | 0.7977 |
| 0.60-0.69 | 26 | 20.5 | 0.6054 | 0.6882 |
| 0.50-0.59 | 14 | 11.0 | 0.5018 | 0.5943 |
| Total | 127 | 100 | | |

| | | |
|---|---|---|
| Mean | 0.7941 | (0.151) |
| Median | 0.8037 | |
| Coefficient of Skewness | -0.108 | (0.215) |
| Coefficient of Kurtosis | -1.212 | (0.427) |

Number in parentheses are standard errors.

The efficiency distribution of the sample has a very slight skewness to the left as shown by the measures of skewness which is due to the distribution of less efficient farms within the range of 0.50 to 0.99 *i.e.*, more farms lie higher-up along the efficiency spectrum. In terms of steepness, the coefficient of kurtosis indicates a platykurtic (flat) shape indicating that the efficiency scores are not concentrated around the mean value and at the lower tail (as in a normal curve), but has more efficiency scores in the intermediate regions.

Of the 12 overall technically efficient farms, half of them are found to be allocatively efficient *i.e.,* they are the economically efficient farms (Table 13). Only a few of the sample farms are on the economic efficiency frontier (or combined frontier). This is inevitable since economic efficiency is the product of technical and allocative efficiency. The mean economic efficiency level of .6025 implies that there exists a potential for increasing the profitability of the farms by 40 per cent simply by adopting the technology of the 'best-practice' farms and through optimal resource-allocation.

**Table 13. Economic, purely technical and allocative efficiency levels of the sample farms.**

| EFFICIENCY | Economic | Overall Technical | Allocative |
|---|---|---|---|
| Number of efficient farms | 6 | 12 | 23 |
| % efficient | 5 | 9 | 18 |
| Maximum score | 1.0 | 1.0 | 1.0 |
| Minimum score | 0.2487 | 0.3933 | 0.5018 |
| Mean score | 0.6025 | 0.7431 | 0.7941 |
| Median score | 0.5839 | 0.7298 | 0.8037 |
| Standard deviation | 0.2117 | 0.1637 | 0.1512 |

**5.3.4 Analysis of Input Use and Output Differences between Economically Efficient and Inefficient Farms.** As shown in Table 14, average output and inputs vary between the efficiency classes. A statistical test was not calculated on the variation due to the insufficient number of economically efficient farms. The economically efficient farms realised a larger profit than the inefficient ones due to the lower amount of inputs applied (seeds, fertiliser and power), and the lower cost of each input except labour, and the relatively high amount of output.

**Table 14. Average yield, physical input and cost, profit and cost per hectare: Allocatively (in)efficient and Overall Technically (in)efficient farms.**

| Input-output | Farm class AIE& OTIE *n*=98 (1) | Farm class AE & OTIE *n*=17 (2) | Farm class AIE & OTE *n*=6 (3) | Economically Inefficient *n*=115 Ave (1+2+3) | Economically Efficient *n=6* TE & AE |
|---|---|---|---|---|---|
| Average area | 34.71 | 47.09 | 30.92 | 36.26 | 51.10 |
| Profit/ha | P117.49 | P8,650.08 | P1305.46 | P1375.19 | P6973.29 |
| Tonnes sugar/ha | 47.03 | 60.73 | 42.72 | 48.74 | 66.55 |
| Physical inputs/ha | | | | | |
| Seeds (*lacsa*) | 5.57 | 6.71 | 2.67 | 5.59 | 4.02 |
| NPK (kgs.) | 695.11 | 751.87 | 474.85 | 692.16 | 555.42 |
| Power (hours) | 22.72 | 24.47 | 19.39 | 22.80 | 19.62 |
| Labour (person-day) | 105.84 | 110.74 | 88.48 | 105.67 | 109.32 |
| Total cost/ha * | P27,749.52 | P27,516.80 | P24,137.55 | P27,537.71 | P32,657.31 |
| **Input cost/ha** | | | | | |
| Seeds (*lacsa*) | P1,206.82 | P1,071.88 | P 389.78 | P1,147.35 | P 788.95 |
| NPK (kgs) | 4,606.83 | 5,051.35 | 3,639.67 | 4,621.32 | 3,531.67 |
| Power (hours) | 2,308.26 | 2,522.41 | 1,910.81 | 2,318.64 | 1,999.58 |
| Labour (person-day) | 8,947.46 | 10,405.23 | 8,154.92 | 9,112.97 | 13,899.28 |
| Overheads | 1,807.64 | 715.01 | 949.21 | 1,611.57 | 1,069.02 |
| Fuel and repairs | 1,002.35 | 335.45 | 1,629.78 | 939.77 | 1,769.24 |
| Depreciation | 945.93 | 591.19 | 1,308.71 | 914.08 | 2,067.96 |
| Interest on loans | 490.94 | 1,187.05 | 581.40 | 1,403.14 | 1,958.33 |
| **Input cost/unit** | | | | | |
| Seeds (1 lacsa) | P 226.70 | P 156.43 | P 150.96 | P 213.89 | P 214.46 |
| NPK (per kgs.) | 6.76 | 6.79 | 8.47 | 6.89 | 6.34 |
| Power (per hour) | 106.15 | 107.77 | 101.96 | 106.17 | 116.65 |
| Labour (per person-day= 8 hours) | 88.45 | 95.26 | 98.97 | 90.25 | 132.88 |

* This includes land rentals.

Among the different farm classes, the high profit realised by Class 2 was remarkable. The high production (tonnes sugar per hectare) is similar to the technically efficient farms, and they have a low input cost on labour, overheads, fuels and repairs, depreciation and interest on loans. The low profit in Class 1 and Class 3 was due to the high cost on seeds and fertiliser, respectively, and also due to their low yield.

As with purely technical efficiency, it is also possible to work out what is required by allocatively inefficient farms to become efficient. For example, take the case of farm 114, which revealed the lowest allocative efficiency score of .5018 (Table 15).

**Table 15 Input cost levels of Farm 114 and its referent farms.**

| Variables included in the DEA model | Farm 114 | Referent farms | | | | Target for farm 114 |
|---|---|---|---|---|---|---|
| | | Farm 45 | Farm 99 | Farm 30 | Farm 91 | |
| *Lambda* values | | 0.230 | 0.748 | 0.017 | 0.004 | |
| Output | | | | | | |
| Gross income per hectare | P240,379.5 | P432,771.3 | P191,755.0 | P276,979.1 | P277,597.9 | P248,789.18 |
| Input cost | | | | | | |
| Seeds& NPKfertiliser | 49,198.3 | 36,066.6 | 15,794.0 | 29,455.9 | 49,198.3 | 20,806.77 |
| Power & labour | 163,845.5 | 130,862.4 | 163,845.5 | 88,714.2 | 94,030.6 | 154,539.04 |
| Operating cost | 35,313.3 | 0.0 | 10,620.1 | 35,313.3 | 24,644.6 | 8,642.74 |
| Land rental | 57,126.1 | 57,126.1 | 37,941.0 | 29,302.3 | 28,372.6 | 42,130.87 |

For most of the inputs, the referent farms were spending considerably less than farm 114. Using the *lambda* values of the referent farms, the target which farm 114 can aim to become allocatively efficient is presented in the last column of Table 15. This farm needs to decrease its expenditure in all inputs, and most importantly on seeds, fertiliser and farm operating costs. This will need an increase in managerial skill to simultaneously maintain output.

## 6 Farm Size and Productive Efficiency.

Historically, the notion of efficiency in large sugar cane farms has been used as an argument against land reform in the Philippines. It is argued that small-scale farms produce relatively less due to uneconomic size. The use of technology such as tractors and harvesters is considered to be more appropriate and economically efficient on large farms.

Contrary to normal production economics wisdom, some evidence indicates that small farms are more profitable than large farms (Lau and Yotopoulos, 1971). In this study, it was assumed that there is a difference in the economic efficiency levels between small, medium and large sugar cane farms for testing purposes.

The comprehensive samples were grouped into the same farm size[11] categories. To ensure comparability of the group efficiency scores, an hypothetical farm was created and included in all groups. The output of the farm was valued at P 55,815.02 per hectare, while the cost of production was calculated at P7,544.64 for seeds and NPK fertiliser, P20,662.50 for power, labour and overheads cost, and P17,505.70 for operating and maintenance expenses. This made the comparison farm 'efficient'.

[11] The value of farm assets may be a more relevant measure of the size of a farm than hectareage and value of farm sales. However, it was impossible to obtain this data Observed gross revenue also gives a measure of size which reflects quantity of production. However, the measure may be biased by crop failure or inventory sales.

In Table 16 the distributions of allocative, overall technical and economic efficiency levels by farm size groups are shown. Fifteen, 12 and 7 per cent of medium, large and small farms are economically efficient. Recall that with the inclusion of the hypothetical farm, group comparability and comparisons are possible..

**Table 16. Distribution of the allocative efficiency scores by farm sizes (Sub-sample with an hypothetical farm).**

| EFFICIENCY SCORE | Small farms $n = 54$ | | | Medium farms $n = 40$ | | | Large farms $n = 33$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | AE | PTE | EE | AE | PTE | EE | AE | PTE | EE |
| 1.00 | 12 | 11 | 4 | 13 | 9 | 6 | 9 | 9 | 4 |
| 0.90-0.99 | 6 | 5 | 1 | 7 | 6 | 5 | 7 | 7 | 6 |
| 0.80-0.89 | 9 | 10 | 10 | 5 | 7 | 4 | 6 | 1 | 5 |
| 0.70-0.79 | 11 | 5 | 7 | 6 | 8 | 6 | 5 | 7 | 1 |
| 0.60-0.69 | 11 | 9 | 6 | 5 | 5 | 8 | 6 | 7 | 7 |
| 0.50-0.59 | 5 | 9 | 5 | 4 | 5 | 2 | - | 2 | 5 |
| 0.40-0.49 | - | 4 | 6 | - | - | 5 | - | - | 3 |
| 0.30-0.39 | - | 1 | 15 | - | - | 4 | - | - | 2 |
| Mean | 0.804 | 0.757 | 0.620 | 0.845 | 0.823 | 0.711 | 0.859 | 0.834 | 0.727 |
| Median | 0.803 | 0.761 | 0.616 | 0.900 | 0.854 | 0.727 | 0.878 | 0.855 | 0.694 |
| SD | 0.152 | 0.190 | 0.224 | 0.158 | 0.151 | 0.225 | 0.133 | 0.146 | 0.206 |
| Minimum | 0.513 | 0.392 | 0.306 | 0.547 | 0.539 | 0.307 | 0.616 | 0.566 | 0.352 |
| Maximum | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |

The mean economic efficiency ranges from 0.62 to .727 for small, medium and large groups. This implies that there exists a potential for increasing the profitability of the farms by 38, 29 and 27 per cent, respectively. The results also suggest that technical rather than allocative efficiency is the more important cause of economic inefficiency. Only around 14 to 20 per cent of mean inefficiency is due to allocative efficiency.

Looking at the median allocative and economic efficiency levels, the small farms obtained the lowest while the medium farms the highest (although in terms of mean efficiency, the large farms obtained the highest). The Kruskal-Wallis method was used to test the efficiency differences among the different sub-groups. At a probability of greater than 0.05, the null hypothesis of no difference for allocative and overall technical efficiency assessment was accepted. However, Kruskal-Wallis analysis shows that the economic differences are significant (Table 17).

**Table17. Kruskal –Wallis test: Allocative, overall technical and economic efficiency measurements by farm size.**

| Type of efficiency assessment | No. of farm size group | Value of K-W statistics | Level of probability |
|---|---|---|---|
| Allocative | 3 | 2.8868 | 0.2361 |
| Overall Technical | 3 | 4.1778 | 0.1238 |
| Economic | 3 | 6.7602 | 0.0340 |

The Mann-Whitney U test was used to compare the efficiency differences between the two sub-group combinations within a group. Between the farm sizes, the overall technical efficiency differences between small and large farms revealed a significant result (Table 18). The economic efficiency differences between small and medium, and between small and large farm groups also revealed significant results. This implies that the small farms appear to be not as economically efficient as the larger ones, while medium and large farms appear to be equally economically efficient.

**Table 18. The Mann-Whitney statistical test: Efficiency measurement by farm size.**

| Type of efficiency measurement | A standard Z-value | Significance level 2-Tailed p |
|---|---|---|
| Allocative | | |
| 1. Small and Medium | -1.2932 | 0.1960 |
| 2. Small and Large | -1.5460 | 0.1221 |
| 3. Medium and Large | -0.1134 | 0.9097 |
| Overall technical | | |
| 1. Small and Medium | -1.8279 | 0.0676 |
| 2. Small and Large | -2.2886 | 0.0221 |
| 3. Medium and Large | -0.6703 | 0.5027 |
| Economic | | |
| 1. Small and Medium | -2.0673 | 0.0387 |
| 2. Small and Large | -2.2892 | 0.0221 |
| 3. Medium and Large | -0.1400 | 0.8887 |

These results may be linked to the level of physical input and its cost. Generally the relative use of inputs (per hectare) is much greater on large farms relative to small farms (Table 19). Per hectare, the high amount of input used by the large farms tends to increase their relative output and with the low price of inputs thus generating a larger profit.

The t-test for equality of means shows that between small and large farms the difference in input use is highly significant ($p$ = 0.01 level) in terms of land area, NPK fertiliser application and labour while less significant ($p$ = 0.05 level) in the use of seeds and power. The difference in output is also highly significant ($p$ = 0.01 level), while between small and medium farms, the difference in NPK fertiliser is highly significant ($p$ = 0.01 level), while less significant in the use of seeds ($p$ = 0.05 level) and labour ($p$ = 0.10 level). The difference in the use of the power input is insignificant. The difference in output is significant ($p$ = 0.10 level).

**Table 19. Comparison of average input-output data.**

| Input-output | Farm sizes | | | All |
|---|---|---|---|---|
| | Small | Medium | Large | Farms |
| Average area | 4.08 | 26.04 | 104.01 | 36.96 |
| Profit/ha | - P227.47 | P2,031.82 | P4,216.39 | P1,639.67 |
| Tonnes sugar/ha | 40.91 | 51.47 | 61.47 | 49.58 |
| Physical inputs/ha | | | | |
| Seeds (lacsa) | 5.01 | 5.89 | 5.89 | 5.52 |
| NPK (kgs.) | 557.25 | 735.62 | 835.39 | 685.70 |
| Power (hours) | 20.08 | 22.62 | 26.88 | 22.65 |
| Labour (person-day) | 93.53 | 111.73 | 118.85 | 105.84 |
| Total cost/ha | P24,571.17 | P28,621.00 | P32,392.65 | P27,879.06 |
| **Input cost/unit** | | | | |
| Seeds (lacsa) | P273.93 | P191.31 | P155.62 | P213.92 |
| NPK (kgs) | 7.05 | 6.77 | 6.53 | 6.82 |
| Power (hours) | 106.77 | 110.46 | 101.91 | 106.67 |
| Labour (person-day) | 97.98 | 86.86 | 89.46 | 92.26 |

Note: Independent samples were applied to test mean differences.

Between medium and large farms, the difference in the use of NPK fertiliser and power is less significant at $p$ = 0.10. The more inputs employed by the large farms may be reflected by the very high percentage of large farms operating at decreasing returns to scale as shown in Table 9. The majority of the small farms are operating at increasing returns to scale.

The difference in all of the input prices (per unit) is highly significant ($p = 0.01$ level). Between small and medium farms, the difference in labour input price (per unit) is highly significant at $p = 0.01$ level. Between medium and large farms, the differences in all of the input prices are significant at 5 per cent. This suggests that large farms have comparative advantage in obtaining a lower price for their inputs thus the use of more inputs. For example, for labour, the large farmers can bargain for a lower wage because of the longer contract they can offer to the workers.

The low cost of seeds incurred by the large farmers is reasonable since a large hectareage can produce sufficient cane tops and planting material thus minimising the cost of seeds. The small farmers have to buy seeds from neighbouring farms. In the case of power, small farmers usually hire tractors and since the scope of work is on a per hectare basis, the cost is high, whereas those large farms with tractors can maximise their use although they pay more overheads, fuels, repair and depreciation costs.

The inaccessibility of rural financial institutions to small farmers may be reflected in the large amount of interest paid by the farmers to the moneylenders. It should be emphasised that there were no agricultural loans provided to sugar cane farmers, although the farmers' associations extended loans to the farmers in the form of fertilisers, the cost of which is deducted from their sugar proceeds. The rest of their operating expenses were borrowed from the moneylenders. It is clear that part of allocative efficiency differences between the small and large farms can be attributed to the differences in the input prices.

## 7 Conclusions and Implications

This study has empirically measured the technical, scale, overall technical, allocative and economic efficiency of sugar cane farmers, using the DEA method. The first factor encountered in this technique is its sensitivity to changes in the input-output specification. Thus, a large number of DEA runs were carried out and various grouping techniques were employed to assess sensitivity.

DEA provides relative efficiency scores, that is, the assessment of whether a farm is efficient in comparison with the other units in the set, thus, direct comparison of efficiency scores from different groups is not appropriate. Units with a relative efficiency of 1 may or may not be efficient in absolute terms and with respect to other groups. This was recognised through including an hypothetical farm which was included in ALL groups to act as a common benchmark.

With DEA the construction of the 'efficient frontier' is achieved without having to make any assumptions regarding the underlying functional form and the statistical errors associated with the specification of such a function are also avoided. Moreover, the technique is advanced in accommodating multiple inputs and/or outputs.

The most interesting feature of DEA is the data obtained for individual farms. It is possible to identify the adjustments that can be made in the use of inputs on inefficient farms by comparing them with their 'peer' farms. The factors that can be manipulated to minimise the excessive use of inputs and hence reduce the costs of production can be established, and vice versa. In addition, the slack variables provide an indication of the inputs that are in excess supply. In this study, labour was the main constraint, effectively limiting output for approximately 80 per cent of the total sample. Land and power inputs were the next most binding constraints, whereas NPK fertiliser appears to be in surplus for many farms, as well as the seed input. Other important information is the most productive scale size (or optimum scale size). In this study, the average optimum land size obtained was around 41 hectares.

It was found that the mean efficiency level was 0.78 implying that, on average, the Philippine sugar industry could increase its output by 22 per cent from a given mix of inputs through the adoption of the best practices of the efficient farms.

The mean scale efficiency level of 0.96 and the mean overall technical efficiency level of 0.74 implies that the major source of overall the technical inefficiency appears to be pure technical, as against scale efficiency. This suggests that by eliminating scale inefficiency and pure technical inefficiency, the Philippine sugar industry could increase overall technical efficiency by 26 per cent by operating at the optimal scale and by eliminating pure technical inefficiency through the adoption of the best practices.

The mean allocative efficiency of 0.8 implies that on average the respondents could reduce their factor costs by about 20 per cent without reducing their current output. The reduction in costs from improvements in efficiency is very important to enhance profitability, especially on small farmers who earn a negative net return from sugar cane production.

The mean economic efficiency level of 0.6 implies that there exists a potential for increasing the profitability of the farmers by 40 per cent simply by adopting the technology of the 'best practice' farms and through optimal resource-allocation. It must also be remembered that these results relate to the position of the 'efficient' farms. It might also be possible for these farms to in fact improve their efficiency through 'perfect' management.

Analysis of input use differences between the purely technical efficient and inefficient farms is statistically different but only in the use of area, seeds and labour inputs. There was no significant variation in the use of fertiliser and power inputs. For the overall technically efficient and inefficient farms, however, their input use in terms of seeds and NPK fertiliser were statistically different from each other.

No statistical test was applied to confirm the hypothesis that the input used by the economically efficient and inefficient farms are statistically different because of the small number of the economically efficient farms. Apart from the lower amount of seeds, fertiliser and power inputs applied, this larger amount of profit obtained by the economically efficient farms was due to the lower price paid for each input except labour.

The productive efficiency of small, medium and large farms were also determined. Small farms appeared to be not as economically efficient as the large ones while medium and large farms appeared to be equally economically efficient. Therefore, from an agricultural policy point of view, the trend towards larger farm sizes could have a beneficial impact on the efficiency of the Philippine sugar industry as a whole.

Analysis of input use differences among farm size groups shows that the higher input usage by the large farms tends to increase the quantity produced and, with the low price of inputs, generates a larger profit per hectare. The higher input prices faced by the small farmers tends to reduce the amount of input used thus giving a lower profit. Part of the allocative efficiency differences between the farm size groups may be attributed to the differences in the input price. Thus, government co-operative programs that provide farmers access to cheaper farm inputs through bulk purchasing may actually lead to increased productive efficiency.

**References:**

Abate, G. (1995) *Production Efficiency Analysis: The Case of Smallholder Farming in the Coffee Sector of Ethiopia and Kenya, Farming Systems and Resource Economics in the Tropic,* Wissenschaftsverlag Vauk Kiel KG.

Banker, R.D. (1992) Estimation of Returns to Scale using Data Envelopment Analysis, *European Journal of Operational Research*, **62**:74-84.

__________ (1984) Estimating Most Productive Scale Size Using Data Envelopment Analysis, *European Journal of Operational Research*, **17**:35-44.

Banker, R.D. and Thrall, R.M. (1992) Estimation of Returns to Scale Using Data Envelopment Analysis, *European Journal of Operational Research*, **62**: 74-84.

Basic Sugar Statistics (1996) Sugar Statistics Division, Planning and International Sugar Affairs Office, Sugar Regulatory Administration, Philippines (Unpublished).

Battese, G.E. (1992) Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications in Agricultural Economics, *Agricultural Economics*, **7**:185-208.

Boussofiane, A., Dyson, R.G. and Thanassoulis, E. (1991) Applied Data Envelopment Analysis (Invited Review), *European Journal of Operational Research*, **52**:1-15.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978) Measuring the Efficiency of Decision Making Units, *European Journal of Operational Research*, **2:** 429-444.

Coelli, T.J. (1995) Recent Developments in Frontier Modelling and Efficiency Measurement, *Australian Journal of Agricultural Economics*, **39**: 219-245.

Ellis, F. (1988) *Peasant Economics: Farm Households and Agrarian Development*, Cambridge University Press, Cambridge.

Farrell, M.J. (1957) The Measurement of Productive Efficiency, *The Journal of the Royal Statistical Society*, **120**:253-90.

Golany, B. and Roll, Y. (1989) An Application Procedure for DEA, *OMEGA International Journal of Management Science*, **17** (3):237-250.

Jaforullah, M. and Whiteman, J. (1999) Scale Efficiency in the New Zealand Dairy Industry: A Non-Parametric Approach, *The Australian Journal of Agricultural and Resource Economics*, **43** (4): 523-541.

Johnes, G. and Johnes, J. (1993) Measuring the Research Performance of UK Economics Departments: An Application of Data Envelopment Analysis, *Oxford Economic Papers*, **45**:332-347.

Kalirajan, K.P. (1990) On Measuring Economic Efficiency, *Journal of Applied Econometrics*, **5**:75-85.

Kao, C., Chang, P., and Hwang, S.N. (1993) Data Envelopment Analysis in Measuring the Efficiency of Forest Management, *Journal of Environmental Management*, 38:73-83.

Kelly, P.D. (1977) A Frontier Production Function Approach to Measuring Technical Efficiency in the New South Wales Egg Industry, *Quarterly Review of Agricultural Economics*, **30** (3):254-272.

Kopp, R.J. (1981) The Measurement of Productive Efficiency: A Reconsideration, *The Quarterly Journal of Economics*, **96** (3):476-503.

Llewelyn, R.V. and Williams, J.R. (1996) Nonparametric Analysis of Technical, Pure Technical and Scale Efficiencies for Food Crop Production in East Java, Indonesia, *Agricultural Economics*, **15**:113-126.

Seiford, L. M. and R. M. Thrall (1990) Recent Developments in DEA, *Journal of Econometrics*, **46**:7-38.

*Sugar cane Farm Management Training Manual, Outreach Program of the Sugar Industry* 1997 Ed. Sugar Regulatory Administration: Philippines.

Thanassoulis, R.G. and Dyson, R.G. (1992) Estimating Preferred Target Input-Output Levels Using Data Envelopment Analysis, *European Journal of Operational Research*, **56:** 80-97.

*The Warwick Windows DEA Software User's Guide* (1996) c/o Thanassoulis, E., Warwick Business School, Warwick University, Conventry, U.K.

Torkamani, J. and Hardaker, J.B. (1996) A Study of Economic Efficiency of Iranian Farmers in Ramjerd District: An Application of Stochastic Programming, *Agricultural Economics* **14:**73-83.