J. ISSAAS Vol. 15 No. 1: 77-90 (2009)

TECHNICAL EFFICIENCY IN THE PRODUCTION OF SUGAR CANE IN CENTRAL NEGROS AREA, PHILIPPINES: AN APPLICATION OF DATA ENVELOPMENT ANALYSIS

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(Received: February 5, 2009; Accepted: May 16, 2009)

ABSTRACT

This paper attempts to identify the sources of input use inefficiency in sugar cane production in the Central Negros area, Philippines. Non-parametric Data Envelopment Analysis was used to determine the relative technical, scale and overall technical efficiencies of individual farms which use the same type of inputs and produce the same output (cane). Under a specification of variable returns to scale, the mean technical, scale and overall technical efficiency indices were estimated to be 0.7580, 0.9884 and 0.7298, respectively. The major source of overall inefficiencies appears to be technical inefficiency rather than scale effect. Input use differences between the technically efficient and inefficient farms are highly significant in terms of area, seeds and labor inputs. There was no significant difference in the use of fertilizer and power inputs. For many farms, labor is the most binding constraint, followed by land and power inputs while seeds and NPK fertilizer are not binding.

This paper also provides evidence that the overall technical efficiency of sugar cane farmers in Central Negros is positively related to farmers' age and experience, access to credit, nitrogen fertilizer application, soil type and farm size.

Key words: scale efficiency, frontier efficiency, input use, sugar cane production

INTRODUCTION

Sugar has always been a major contributor to the Philippine economy. In 2006, it accounted for 1.03% of gross national product. In terms of total agricultural export revenue, it accounted for 3.37%. As an industrial crop, it provides a significant source of livelihood through farming, processing and trading activities. Currently, there are approximately 58,996 sugar cane farmers in the Philippines, cultivating around 398,720 hectares of sugar cane land. Around 5 million people are employed in the industry and other sugar-related activities. From a net importer of sugar in 1995, the country achieved self-sufficiency in 2003 this being earlier than the 2005 target year under the Sugar Master Plan. The growth rate of sugar production has been achieved mainly through the expansion of cultivated areas. Sugar cane was planted in 382,956 hectares for crop year 2007, up from the 372,339 hectares in crop year 1995-96. However, this pattern of growth can no longer continue due to the on-going land conversion, competition from other crops and the declining land frontier.

Although the government has identified some 60,250 hectares as potential sugar cane plantation sites, this available resource could only supply the market with 222 to 225 million liters of bioethanol for the 5% mandate for next year (10% blend for 2011). Therefore, a strategy for developing the Philippine sugar cane industry should focus on increasing farm productivity. The country's national average yield of 60 tons cane per hectare is still one of the lowest among sugar producing countries in Southeast Asia. At the farm level, productivity varies enormously.

The high costs of fuel and fertilizer as well as the unstable world and domestic sugar prices over the last year now have discouraged farmers to invest in their farms. Moreover, sugar producers lament that the impending cut in the tariffs of sugar under the Asean Free Trade Area (AFTA)-Common Effective Preferential Tariff (CEPT) scheme could further erode their competitiveness. By 2010, existing tariffs on sugar products, ranging from 28- 38%, will go down to between zero and 5% under the AFTA-CEPT. By 2010, the sugar cane industry will experience some imbalance when the country begins implementing the Biofuels Act and when sugar tariffs reduce to zero. In view of the vital contribution and role of the industry to the Philippine economy, the production of sugar cane must be given proper support by the government if it is to be made competitive. This can be attained by improving the technical efficiency of the sugar cane farmers, that is, their ability to achieve maximum output within their resources and current technology.

This paper investigates sugar cane farms' efficiency in use of inputs and attempts to determine the factors influencing such efficiencies. An understanding of how productive efficiency arises will help craft interventions to make sugar cane farmers become more efficient and competitive.

METHODOLOGY

Study Area and Sampling Procedure

The study area was Negros, a small island in the Philippines. Negros accounts for around 55 per cent of the total area planted to sugar cane nationwide, thus accounting for the province's largely mono-crop character. The province has two pronounced seasons, wet and dry. The dry season is from late December to May for the northern part, and from November to May for the southern portion. The rainy season starts in June, reaches its peak in September and ends in October for the northern part. For the southern portion, the wet season begins in June, attains its peak in August and tapers off towards November. The northern part of the province, largely influenced by the proximity of the seacoast, is of coraline origin. The southern part, especially the interior, strategically influenced by the presence of the volcano Kanla-on, is of volcanic origin.

The central portion of Negros Island was chosen as it has relatively homogeneous farm samples in terms of geographic characteristics, market conditions and farming practices. The random samples were selected from stratified sub samples based on farm size. In the Philippines, farms with less than 10 hectares are considered small; less than 50 hectares, medium; and above 50 hectares, large for sugar cane production. This farm size classification was followed in the study. A total of 140 respondents equally distributed over the study area were interviewed using a structured questionnaire. Out of 140 respondents, 127 were deemed of reliable information. The survey was conducted for crop year 1997-98, beginning in September 1997 and ending in August 1998.

Analytical Procedure

Frontier efficiency measurement using DEA. The measurements of efficiency and the estimation of production frontiers were researched extensively after Farrell's (1957) seminal work. The efficiency of a firm has two components: technical (or physical) efficiency and allocative (or price) efficiency. Technical efficiency (TE) measures the ability of a farm to produce maximal potential output from a given input. Allocative efficiency (AE) measures the ability of a farm to utilize the cost-minimizing input ratios or revenue-maximizing output ratios. One needs to be technically efficient before one can be allocatively efficient and attainment of both is required for economic efficiency (Coelli, 1996).

Further studies on efficiency measurement decomposed technical efficiency into purely technical and scale efficiency. Scale efficiency measures the optimality of the firm's size, or when it operates where average and marginal products are equal (Forsund *et al.*, 1980). Scale inefficiency takes two forms- either increasing or decreasing returns to scale. A farm displaying increasing returns to scale (IRS) [economies of scale] is too small for its scale of operation. Unit costs decrease as output increase. In contrast, a farm with decreasing returns to scale (DRS) is too large for the volume of activities that it conducts. Unit costs increase as output increases.

Estimation of a production frontier differs depending on the assumptions made about the outer bound of the frontier, which may be deterministic or stochastic, while the technique for estimation may be parametric, or non-parametric. Currently, the stochastic frontier and the deterministic non-parametric methods are the primary approaches and these involve econometric methods and mathematical programming respectively (Coelli, 1995). The choice between these techniques depends on the underlying reasons for estimating productive efficiency. This paper uses the deterministic, non-parametric approach using Data Envelopment Analysis (DEA) because it can identify the sources and the level of inefficiency for each farm unit.

This method measures the relative efficiency of the Decision Making Units-DMUs (farms in this study) by estimating an empirical production frontier from the actual input and output data from each farm. The efficiency score of a farm is then measured by the distance between the actual observation and the frontier obtained from all the farms under evaluation. This frontier is constructed by the solution of a sequence of linear programming (LP) problems – one for each farm in the sample.

DEA can be either input- or output-orientated. The input-orientated DEA method defines the frontier by seeking the maximum possible proportional reduction in input usage, with output levels held constant, for each farm. The output-orientated DEA method seeks the maximum proportional increase in output production with input levels held fixed. The two measures provide the same technical efficiency scores when constant returns to scale (CRS) technology applies, but are unequal when variable returns to scale (VRS) is assumed (Färe *et al.,* 1994). This paper assumes a VRS technology and selected an output orientation because the concern is to maximize output from a given set of inputs, rather than the converse.

An output-oriented LP model, developed by Charnes *et al*. (1978) is defined as:

$$\max_{\theta,\lambda,s_i^-,s_i^+} \quad z_k = \theta_k + \varepsilon \cdot \bar{1}s^+ + \varepsilon \cdot \bar{1}s^-$$

$$\begin{aligned} \textit{subject to}: \quad & \theta_k Y_k - Y\lambda + s^+ = 0 \\ & X\lambda + s^- = X_k \\ & \lambda_{ji},\ s_{ki}^-,\ s_{mi}^+ \geq 0 \end{aligned}$$

where Y denotes an $s \times n$ matrix of output measures; X denotes an $m \times n$ matrix of input measures; $Xk = \{xik\}$ denotes inputs $(i = 1, 2, \ldots, m)$ employed by farm k $(k = 1, 2,\ldots, n)$; $Yk = \{yrk\}$ denotes outputs $(r = 1, 2, \ldots, s)$ produced by farm k; $s+$ and $s-$ are slack variables; λ is an intensity (weight) vector; ε is a non-Archimedean (infinitesimal) constant; $\bar{1}$ are row unit vectors of dimension $1 \times s$ (outputs) and $1 \times m$ inputs; and θ is a scalar defining the proportional augmentation applied to all outputs of farm k.

Non-zero elements of the optimal λ- identify the set of dominating farms on the production frontier, against which farm k is evaluated. Dominating farms are on the frontier and define the reference point (peers) for the DMU k. The presence of the non- Archimedean (infinitesimal) constant in the objective function allows the maximization over θ to preempt the minimization involving slack variables, *e.g.*, regardless of the values of *s+* and *s-*, their multiplication by ε will not allow them to have any impact on θ. The optimization is computed in a two-stage process. First, maximum augmentation of outputs is achieved by obtaining the optimal value of θ^*. In a second stage, the DMU is moved onto the efficient frontier via slack variables s^{+*} and s^{-*} (Charnes *et al.*, 1997).

The above LP is solved N times – once for each farm in the sample. Each LP produces a θ - parameter and a λ- vector. The θ - parameter provides information on the technical efficiency score for the *k-th* farm and the λ− vector provides information on the *peers* of the (inefficient) *k-th* farm. The peers of the *k-th* farm are those efficient farms that define the facet of the frontier against which the (inefficient) *k-th* farm is projected. The optimal solution to each problem, θ^*, which satisfies $1 \leq \theta^* \leq \infty$, measures the maximal proportional increase in output levels for the *k-th* farm with inputs held constant. Hence, $1/\theta^*$ measures technical efficiency of the *k-th* farm, where the technical efficiency score will lie between zero (inefficient) and one (efficient). If $\theta = 1$, no increase in outputs is possible, which means the farm lies on the frontier and is thus technically efficient under Farrell's definition.

The output-oriented VRS model is obtained from the CRS model by adding a convexity constraint $\bar{1}\lambda=1$ to the CCR model. The model was developed by Banker *et al.* (1984) and is called the output-oriented BCC model. The measure of technical efficiency obtained in this model is also named 'pure technical efficiency' as it is free of scale effects. Therefore, the scale efficiency values for each analyzed farm can be obtained by the ratio between the scores for technical efficiency with constant and variable returns. Thus: $SE = TE_{CRS} / TE_{VRS}$. Production is scale efficient if SE=1.0, or if the $TE_{CRS} = TE_{VRS}$.

A critical issue in non-parametric programming technique is its sensitivity to the selection and number of inputs and outputs to be used as they can affect the discriminating powers of DEA (Boussofianne *et al.*, 1991*)*. Thus, the list of variables must be reduced to include only the most relevant factors (judgmental screening). This could be done through aggregation of variables into summing factors. In terms of the number of observations, it should exceed the total number of inputs and outputs several times. The larger the sample, the larger is the probability of capturing high performance units which determine the efficiency frontier (Golany and Roll, 1989).

In this paper, the input-output data used was treated as follows:

1. The Output. The farmers' share of raw sugar, measured in 50 kilo per bag (LKg), was the output considered. 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.

2. The Inputs. The cultivation of sugar cane involves around 21 farm operations. 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. 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 seed pieces, planting, replanting, liming, fertilizing, weeding, irrigation and land clearing were combined into one factor and expressed in person-days. In addition, the output and the inputs of the two types of crop culture (i.e., ratoon and plant crops) were aggregated.

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 was 1 hour of animal work = 0.13587 hour of machine work. Only land planted to sugar cane, *i.e.*, cropped land, is included in the analysis.

For fertilizer input, determining the amount of NPK nutrients applied enabled a direct comparison. While cane points and stools used in planting and replanting were combined (both were expressed in *lacsa* = 10,000 cane points or stools). Hence, the inputs used include cropped area (hectares); seeds and planting materials (*lacsa*); an aggregated NPK fertilizer input (kilograms); power (hours) and an aggregated labor input (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. The summary statistics for variables used in the efficiency analysis are shown in Table 1.

Table 1. Summary statistics of the physical inputs and output (per farm).

Items	Mean	Std Deviation	Minimum	Maximum
Output- LKg sugar	2,170.11	3,198.88	19.20	17,730.35
Input				
Area (ha)	36.96	50.55	.50	310.00
Seeds (lacsa)	217.73	306.38	.00	1772.50
NPK (kgs)	29,963.68	44,881.37	64.00	240,020.00
Power (hrs)	884.12	1,228.50	8.15	8,038.35
Labor (person-days)	4,291.50	6,097.65	41.00	34,584.50

After the input-output variables were organized, the models were solved using DEA linear programming models with the aid of the Warwick DEA computer software package developed by Thanassoulis and Emrouznejad (1996).

Regression analysis using the Tobit model

In the context of policy implications, it is more important to determine what influences inefficiency (or to which variables it is related) than simply to measure it. Hence, the DEA scores were regressed on farm specific characteristics using the Tobit model in Limdep Version 7 software. Limited dependent variables (scores of DEA are bounded by 0 and 1) were used instead of the usual regression system. Since the parameter estimation of the Tobit model is usually done by maximum likelihood, it provides consistent and asymptotically efficient estimators for parameters and variance (Greene, 1997). This implies validity of standard inference procedures, such as t statistics and F tests.

The general model formulation with a limited dependent variable, as proposed by Greene, is given by $y_i^* = X_i \beta + \varepsilon_i$, where y_i^* is a latent variable; X_i represents a vector of explanatory variables; and β are the parameters to be estimated. It is assumed that the errors are normally distributed, with mean zero and ε^2, $\varepsilon \sim N(0, \sigma^2)$. Considering that in this paper the efficiency scores were defined by DEA, where the limit for a unit to be efficient is 1 ($y^c = 1$), the observed variables (y_i) were defined as follows:

If, $y_i^* < y^c$, *then* $y_i = y_i^*$

If, $y_i^* < y^c$, *then* $y_i = y_i^c$

For the dependent variable, the DEA scores obtained in the CRS model was chosen for its high accuracy in discriminating efficiency *i.e.*, every efficient farm in the CRS model is mandatorily efficient in the VRS model. Thus, overall technical efficiency scores were regressed on different combinations of explanatory variables. The explanatory variables used were: (1) the actual age (AGE) of the farmer; (2) farmer's years of formal schooling (EDUC); (3) the years in sugar cane farming (EXPER); (4) the number of extension exposures (EXTN) for the past two years. This latter variable was the number of visits the farmer made to demonstration trials and research centers, group discussions, training on farm practices, and extension advice on various farm practices; and (5) a simple dummy variable for credit access was also included (D_{crdt} = 1 if the farmer had access to credit, otherwise zero).

The variables for topography and soil type were measured as fractions of the area with flat (FLAT), slightly rolling (SROL) and rolling (ROL) topography, and the fraction of the area with clay loam (CLAY), sandy clay loam (SCLAY) and sandy loam (SANDY) soil. However, after initial testing, it was evident that only one variable for topography and soil type was necessary (TOPO =1- FLAT, 2= SROL and 3= ROL and STYPE= 1 CLAY LOAM, 2= SANDY CLAY and 3= SANDY LOAM.

The total NPK of fertilizer was also included as an explanatory variable (it should be noted that this was also used as an input in the technical efficiency measurement). However, it was disaggregated into nitrogen (N), phosphorus (P) and potassium (K) variables to determine, as far as possible, which nutrients contribute to farm efficiency. The level of significance in hypothesis testing for the farm and farmer's characteristics and adoption of technology was set at 5 per cent.

RESULTS AND DISCUSSION

Efficiency Analysis

Almost 81% of the sample farms are inefficient (Table 2). The mean efficiency level of 0.777 implies that, on average, the respondents are able to obtain around 78% of potential output from a given mix of inputs. This also implies that around 22% of production, on average, is foregone due to technical inefficiency. In other words, the shortfall of the observed output from the frontier output primarily reflects the inefficient use of the factors that are within the control of the farmers. The technical efficiency levels of the inefficient farms range from 0.3945 to 0.9933 so there is a potential to increase farm output from between 0.7 and 60% from the existing level of inputs.

Of the 127 farms, 24 were identified as DEA-efficient. These 24 farms defined the efficient frontier and represent the best practice farms for combining land, seed, NPK fertilizer, power and labor to produce maximum sugar output. As expected, the efficient farms achieved a higher yield in terms of tons cane per hectare (tc/ha) than the inefficient ones.

T-test for equality of means shows that the output differences are significant at the $p=0.05$ level (Table 3). In terms of input use, on average, technically efficient farms used lesser inputs (except land) than inefficient ones. The difference in the use of seeds is highly significant, while less significant in the use of power and land. There was no significant variation in the use of NPK and labor inputs.

Table 2. Distribution of technical efficiency scores.

Efficiency Score	All farms 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.

Table 3. Average input-output data: Purely technically efficient and inefficient farms.

Farm Class	Yield** (tc/ha)	Area* (ha/farm)	Seeds ** (10,000/ha)	NPK (kg/ha)	Power** (hrs/ha)	Labor (person days/ha)
Efficient	55.93	54.55	4.34	632.45	18.99	101.57
Inefficient	48.10	32.86	5.79	698.11	23.50	106.84

Note: Independent sample test was applied for equality of means. This test is not dependent on the assumption of normality as for most tests. The level of significance in hypothesis testing was set at 10 per cent.
***Significant at 1 per cent level
** Significant at 5 per cent level
* Significant at 10 per cent level

To determine if inefficiency is the consequence of the farms' scale of operation, the technical efficiency (CRS) was decomposed into pure technical efficiency (VRS) and scale efficiency. Table 4 shows the overall technical efficiency (OTE), pure technical efficiency (PTE) and scale efficiency (SE) indexes of the respondents. The data reveals that the major source of overall technical inefficiency appears to be technical, as against scale efficiency. Mean scale efficiency of the sample farms is relatively high (.95) as inefficiency only accounts for around 4 per cent. This further confirms that sugar cane farms' inefficiencies were mainly due to improper input use.

Table 4. Overall, technical and scale efficiency index for sugar cane farmers in Central Negros, CY 1997-98.

Efficiency	**Overall technical efficiency (OTE)**	**Pure technical efficiency (PTE)**	**Scale efficiency (SE)**
Number of efficient farms	12	24	14
% efficient	9	19	11
Maximum score	1	1	1
Minimum score	.3933	.3945	.6977
Mean score	.7431	.7771	.9582
Median score	.7298	.7580	.9884
Standard deviation	.1637	.1684	.0633

In order to substantiate the nature of scale inefficiencies, the analysis further disaggregated into those farms that exhibit IRS and DRS. 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 *i.e.*, increase the input size if IRS and decrease the input size if DRS were prevailing to maximize average productivity. In brief, the most productive scale size is the output scale that maximizes "average product". In the Warwick version of DEA, the range of the omega (Ω) values for DMUs under variable returns to scale (BCC model) is interpreted as follows: (1) if the range is positive, IRS hold at the part of the efficient boundary where the DMU is located; (2) if the range is negative, DRS hold; and (3) if the range includes 0, CRS hold.

Of the 127 sugar cane farms, 9 per cent are operating at CRS, 42 per cent are operating at IRS, while 49 per cent are operating at DRS (Table 5). It would appear that larger increase (5%) in technical efficiency could be achieved by addressing the problem of IRS rather than DRS farms.

Table 5. Technical efficiency and various returns to scale for sugar cane farms.

	Constant Returns to Scale	**Increasing Returns to Scale**	**Decreasing returns to scale**
Number and (%)	12 (9)	51 (42)	64 (49)
Ave. measure of TE (%)			
OTE	1.00	.6723	.7502
PTE	1.00	.7198	.7809
diff		.05	.03

Table 6 gives the input levels for the farms grouped according to scale efficiency. The presence of DRS on larger farms may be attributed to lack of managerial ability to utilize the available land effectively. By and large, except for land input under IRS farms, the data suggests the need to decrease most inputs with, no doubt, more efficient management of the resources. This is the difficult part.

Table 6. Average input use of sugar cane farms (by various returns to scale).

VRS	Yield (tc/ha)	Ave. Area (ha/farm)	Per Hectare			
			Seeds (10,000/ha)	NPK (kg/ha)	Power (hrs/ha)	Labor (person day/ha)
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

As expected, the overall technically efficient farms achieved a higher sugar cane yield per hectare than the inefficient ones. However, the t-test for equality of means shows that the output differences are not significant (Table 7). In terms of input use, on average, overall technically efficient farms used less input (except land) than inefficient ones. It should be noted that for this particular sample, the most productive farm size is around 41 hectares. However, differences in the use of inputs except seeds and NPK are not significant.

Table 7. Average input-output data: Overall technically efficient and inefficient farms.

Farm Class	Yield (TC/HA)	Area (ha/farm)	Seeds (10,000/ha)	NPK (kg/ha)	Power (hrs/ha)	Labor (person day/ha)
Mean (Overall technically inefficient- OTIE)	49.06	36.54	5.74	703.50	22.97	106.57
TE & SE (Overall technically efficient – OTE)	54.64	41.01	3.34	515.13	19.51	98.90

T-test for equality of means between OIE and OE farms show that except seed and NPK fertilizer, there are no significant variations.

This paper shows that there are important input use inefficiencies in sugar cane production in Central Negros. This can be interpreted by the `slack' variables in the DEA estimation. A slack value indicates the amount by which a DEA model constraint is not satisfied, and therefore represents the amount by which an input is overused relative to how the most efficient farms use the input. Thus, technically efficient farms do not have excess inputs while technically inefficient farms have one or more excess inputs.

Table 8 shows that NPK fertilizer input appears to be in surplus for many farms (63%), as well as the seeds, followed by power, labor and land. 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. While excesses in NPK fertilizer usage can be attributed to improper fertilization and non soil test based application. Testing is very important in determining actual fertilizer requirements of soils. Similar results in the analysis of input use were obtained by Gül (2006) in apple farming and Alemdar and Őren (2006) for wheat farming in Southern

Anatolia, Turkey. Thus, from these results, technically inefficient farms can reduce their input use by around 17, 25, 31, 21 and 18 percent of land, seeds, NPK fertilizer, power and labor, respectively and still achieve, on average, around 44 per cent increase in production.

Table 8. Analysis of slack inputs and adjustment to inputs and output: All technically inefficient farms.

Input & Output	TIE Farms N=103	Percent of Total	Percent of Input and Output Adjustments to Attain 100% Efficiency			
			Mean	Std Dev	Minimum	Maximum
Output LKg sugar/ha			44.45	32.31	0.70	153.50
Inputs						
Land	45	44	17.52	14.14	1.10	66.00
Seed	65	63	24.91	16.66	1.10	78.20
NPK	59	57	30.98	15.73	2.60	72.30
Power	40	39	21.03	12.54	3.30	55.30
Labor	19	18	17.67	10.28	2.10	35.30

DEA also determines those variables that effectively constrain production, and hence efficiency. Thus, next to land, labor is the main constraint, effectively limiting output for approximately 80 per cent of the sampled farms. Labor shortage, especially during the time of harvesting, is a serious problem as it can delay the operation which leads to high sugar-yield losses. To demonstrate how DEA is used to evaluate the input decisions of technically inefficient farms, and to estimate potential yield gains from reallocating inputs, consider farm 118 with an efficiency score of .6084. The production practices 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 9. The use of some inputs (*e.g.*, NPK fertilizer) by farm 118 is `excessive.' This comparison would suggest strategies for farm 118 to rationalize the use of its inputs. As noted *lambda* (these are the weights in the linear combination (composite farm) of farms 91, 25, 47 and 124) values provide a composite farm which would produce the equivalent level of output, but by using lower levels of some of the inputs.

Table 9. 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				Compo site Farm
		Farm 91	Farm 25	Farm 47	Farm 124	
Lambda values		0.003	0.684	0.300	0.013	
Output LKg sugar/ha	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/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

Sources of Inefficiency

Tobit regression analysis on the relationships between technical efficiency scores and farmer's experience, age, access to credit, soil type, N fertilizer and farm size show that all coefficients except age, N-fertilizer and soil type (sandy loam soil) are positive (Table 10).

Table 10. Results of Tobit regression analysis.

	Overall Technical Efficiency			
Variable	**Coefficient**	**Standard Error**	**P[l Z l > z]**	**Mean of X**
Experience	.0317	.0177	.0734	17.18
Age	-.0147	.0108	.1747	51.42
Dummy variable proxied for CREDIT	.7884	.3592	.0282	.5862
Soil Type	-.2997	.1682	.0749	2.039
N fertilizer	-.0054	.0018	.0032	238.42
Farm area	.0100	.0033	.0022	38.04
Log likelihood function	-71.8019			
Sigma	1.2646	.2170		

The age variable does not have a significant relationship with farmers' efficiency. However, its inclusion in the equation improved the explanatory power of the model. Age and experience are generally related, though the impact on efficiency is not necessarily the same. In this analysis, the age coefficient is negative while experience is positive. This finding is in parallel with Msuya and Ashimogo (2005) whose study found experience to be a better predictor of technical efficiency than age for Mtibwa Sugar Estate outgrowers in Tanzania. They argued that sugar cane cultivation is very strenuous giving the younger farmer an advantage. Farmers' experience was found to be a good predictor of efficiency, better than education and exposure to extension services. Sugar cane farmers' expertise probably assists in ensuring the optimal timing and use on inputs. This confirmed the findings of Kalirajan and Shand (1985), who used a sample of South Indian farmers and found experience to be a better predictor of production efficiency than education. They argued that in cases where new technology is well adapted to local conditions, technical knowledge (or expertise) might be more important than education (Antle and Crissman, 1990).

The dummy credit variable shows a positive relationship with farmers' technical efficiency. Access to credit may be an instrumental motivation to produce efficiently apart from being able to purchase the inputs necessary for production efficiency. This proved the findings of Nchare (2007) who found access to credit to be significantly correlated with technical efficiency of coffee producers in Cameroon. However, for coffee producers in Vietnam, although access to credit is positively correlated with efficiency, the pattern is statistically weak (Rios and Shively, 2005).

The sign of sandy loam soil is negative which is unexpected. Around 46% of the flat area is sandy loam which is ideal for sugar cane growing. Low lying land floods easily so that coarse-textured soils are desirable especially in areas with heavy rainfall. This means a flat area with sandy loam may yield more production in good weather conditions, but the drought in Crop Year 1997-98 may have interfered. Sandy loam soil can hold less moisture than clay loam and sandy clay loam soil. Even the new varieties planted to 49% of the sandy loam soil did not help in increasing productivity as D_{HYV} did not show any significant effect on efficiency. The N-fertilizer variable shows a negative and significant impact on efficiency. This may be due to the improper application of N-fertilizer in that the farmers may have applied too much N, which can be detrimental to the plant as it produces toxic substance. The positive sign of farm size suggests that bigger farms are more efficient. This is in contrast to rice farming (in the Philippines) as analyzed by Herdt and Mandac (1981) and Lingard, Castillo and Jayasuriya (1983). However, these findings confirm the conclusions reached by Msuya and Ashimogo (2005) that farm size significantly determines levels of technical efficiency in sugar cane production. However, Zyl *et al.* (1995) took note of the findings for sugar cane production in Eastern Transvaal that showed small-scale farms (on average of 7 hectares) were as efficient as the large-scale (on average of 68 hectares) ones.

CONCLUSIONS AND RECOMMENDATIONS

The most interesting feature resulting from the use of DEA is the data obtained for individual farms. This can be used by any extension workers as an instrument in giving advice to farmers on a one-on-one basis on how to improve their production efficiency. DEA results enable examining the adjustments that can be made in the use of inputs on inefficient farms by comparing them with their `peer' or “referent” farms. Furthermore, the DEA slack variables provide an indication of the inputs that are in excess supply. In this study, NPK fertilizer appears to be in surplus for many farms, as well as the seed input. The labor input was the main constraint, effectively limiting output for approximately 80 per cent of the total sample. The most productive scale size (or optimum scale size) of each input could also be determined.

This study showed that there are important resource-use inefficiencies in sugar cane production in Central Negros. Central Negros sugar cane farmers could increase their output by 22% through better use of available inputs by rationalizing the use of NPK, especially N- fertilizer, and seed inputs. A soil test should be conducted to determine fertilizer requirements of the soil in Central Negros. The proper selection of seed pieces should be adopted to realize potential benefits.

However, it should be noted that inefficiency is not just a result of the amount of inputs used. Factors such as the timing of fertilization, other cultural practices, and exogenous factors such as age and experience, also affect efficiency. The strong positive effect of experience on efficiency implies that learning-by-doing would likely be important as newer, more productive technology becomes available. Extension education could be effective by targeting farmers with longer farming experience as the traditional concept among the older farmers that ‘experience is the best teacher’ may mean they may well be more receptive. But this also means the younger farmer’s lack of experience needs replacing with good extension. The negative effect of age, although not significant, suggests that policies to induce youth to return, or go into sugar cane farming, could be important.

Capital should be made easily available, and in sufficient amounts, to service the capital needs of the farmers and other borrowers. The mills could also promote agricultural partnerships on this. Millers could give credit and technical guidance to small producers in return for the delivery of a specific quantity and quality of cane at a stipulated time. The collective efforts of farmers and millers can mean production efficiency and economic prosperity.

Soil management practices should also be given priority and practices that prevent erosion and help water retention and thus increase efficacy of fertilizer should be encouraged. In terms of NPK fertilizer application, the DEA analysis indicated that this input appears to be in surplus for many farms. In the estimated regression model, the negative effect of N fertilizer on efficiency is alarming. Information regarding the time and proper application of fertilizers should be disseminated to realize the benefits from fertilizer use. This could be done through soil analysis and management program. Further development of the extension service responsible for the dissemination of the importance of soil analysis and soil management should be considered as a serious instrument for increasing sugar cane production and thus profit.

The positive effect of farm size on efficiency implies that larger farm sizes could have a beneficial impact on the efficiency of the Philippine sugar industry as a whole. This, however, runs against the trend set by the land reform law (CARL) which pursues social equity.

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