Measuring the economic inefficiency of Nepalese rice farms using data envelopment analysis

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A data envelopment analysis of a sample of 76 Nepalese rice farmers reveals average relative economic, allocative, technical, pure technical and scale inefficiencies as 34, 13, 24, 18 and 7 per cent, respectively. The significant variations in the level of inefficiency across sample farms are attributed to the variations in the 'use intensities' of resources such as seed, labour, fertilisers and mechanical power. In addition, a second stage Tobit regression shows the variation is also related to farm-specific attributes such as the farmers' level of risk attitude, the farm manager's gender, age, education and family labour endowment. Based on the empirical findings, policy implications and development strategies for improving efficiency of Nepalese rice farms are briefly discussed.

1. Introduction

Farrell's (1957) seminal paper has led to many applications of efficiency measures to evaluate the performance of decision making units. Several of them have focused on the estimation and explanation of agricultural efficiency in developing countries. For example; Pakistan (Ali and Chaudhary 1990; Parikh *et al*. 1995; Battese *et al*. 1996; Shafiq and Rehman 2000), India (Battese and Coelli 1992; Battese and Tessema 1993; Kumbhakar 1994; Battese and Coelli 1995; Coelli and Battese 1996; Tadesse and Krishnamoorthy 1997), Bangladesh (Wadud and White 2000), China (Wang *et al*. 1996; Xu and Jeffrey 1998; Yao and Liu 1998), Indonesia (Squires and Taber 1991; Llewelyn and Williams 1996), Philippines (Dawson *et al*. 1991; Kalirajan 1991), Iran (Torkamani and Hardaker 1996), Vietnam (Tran *et al*. 1993), Paraguay (Bravo-Ureta and Evenson 1994), Ethiopia (Seyoum *et al*. 1998) and Nigeria (Ajibefun *et al*. 1996). These studies

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show substantial inefficiency and identify the potential to improve the productivity of agricultural production in developing agriculture. However, Nepalese agriculture has not received attention in the published literature.

Despite the continuous efforts that have been made in Nepal to improve agricultural productivity since the inception of the first 5-year development plan in 1956, food production has not kept pace with population growth. Nepal's population is projected to increase by more than 2 per cent per annum until the year 2020. Food demand is projected to increase from 4 079 000 metric tons in 1997 to 6 909 000 metric tons in 2020 (Thapa and Rosegrant 1995; Central Bureau of Statistics (CBS) 1998). In the absence of productivity growth, because growth from area expansion has already reached its limit, it is expected that by 2020 Nepal will have to use its limited foreign currency reserves to import approximately three million tons of food every year to meet domestic food demand.

To achieve productivity growth, either technological innovation or the more efficient use of production technologies, or some combination of both, are required. In developing countries most new agricultural technologies have only been partially successful in improving productivity (Xu and Jeffrey 1998). This is often attributed to a lack of ability and/or an unwillingness to adjust input levels on the part of producers resulting from the familiarity with traditional agricultural systems (i.e., Schultz's 'poor but efficient' hypothesis) and/or the presence of institutional and cultural constraints (Ghatak and Ingerset 1984). These considerations suggest that, in some cases, there might exist a negative relationship between technical progress in 'conventional production technology' and realised efficiency.[1] If farmers are not efficiently using existing technology then efforts designed to improve efficiency may be more cost effective than introducing new technologies as a means of increasing agricultural productivity (Shapiro 1983; Belbase and Grabowski 1985). Therefore, an efficiency study was selected as a means of exploring the reasons that hinder productivity growth in Nepalese rice farming.

Rice was selected because of its prominent position in the national economy. Rice generates substantial income, employment and food security, and is the livelihood for the majority of the Nepalese people. It contributes 20 per cent of the agricultural gross domestic product (AGDP) which is valued at 112 495 million Nepalese Rupees at current market prices. This is 39 per

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[1] Conventional rice technology, as assumed throughout the present paper, is not traditional in the Schultz sense (Schultz 1964) but is, instead, the currently available post green revolution technologies represented in the varieties, chemical fertilisers, insecticides, pesticides, irrigation, and the like.

cent of the total GDP. Rice alone contributes more than 50 per cent of the total food grain production and more than 50 per cent of the dietary energy requirement of the country's 22 million population (Ministry of Finance 1998). Rice is grown on almost 1.5 million hectares, accounting for more than half of the total cultivated area (2.6 million hectares) in food production (CBS 1998).

The present study uses a two-step methodology. In the first step, data envelopment analysis (DEA) is used to model efficiencies as an explicit function of discretionary variables. In the second step, farm specific variables such as a farmer's risk attitude, age, education, gender and family labour endowment are used in a Tobit regression framework to explain variations in measured inefficiencies. Besides its contribution to Nepalese agriculture, this research also makes a contribution to the agricultural application of DEA by incorporating the producer's risk attitude as a farm specific attribute to explain inefficiency. Previous researchers have considered the producer's risk preference in joint analyses of input allocation and output supply decisions (e.g., Love and Buccola 1991, 1999; Saha *et al*. 1994; Chavas and Holt 1996). A recent article by Kumbhakar (2002) extends the standard production risk model to accommodate technical inefficiency and the producer's attitude toward risk. Unlike these previous researchers, we tested whether a farmer's risk attitude explains farm inefficiency in a Tobit regression framework. This can provide some insight for future research that might incorporate farmers' risk preferences directly in the DEA efficiency measures.[2] Furthermore, unlike many previous efficiency studies, this study evaluates whether women as farm managers are efficient compared to their male counterparts. The results reinforce the need to fully consider the role of women in developing agricultural research and development strategies. As in other efficiency studies, this research utilises survey data, which is enterprise-specific and avoids the potential interpretation difficulties that can arise when variables are constructed as aggregates.

The rest of the paper continues with Section 2 containing the analytical framework, while Section 3 contains the definition and sources of the data used. In Section 4, the empirical results from the analysis are presented and discussed. Finally, the policy conclusions are given, as are the limitations of the findings, and future research areas suggested.

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[2] Recent work by Preckel *et al*. (2000), which is currently in progress (P.V. Preckel, pers. comm., 2003) presents an adaptation of a non-parametric efficiency test to the evaluation of the behaviour of risk averse producers. The test also produces an estimate of producer's level of risk aversion.

2. Analytical framework

2.1 Measurement of efficiency

The absolute efficiency position of farmers is usually not known. Therefore the problem is to measure the efficiency of one farm relative to others. There are two main competing paradigms for estimating the relative efficiency of farms: parametric and non-parametric. The parametric approach assumes a functional relationship between output and inputs and uses statistical techniques to estimate the parameters of the function. The sampling theory estimators that are typically used have statistical properties that are known in large samples. The non-parametric approach, in contrast, constructs a linear piecewise function from empirical observations on inputs and outputs without assuming any *a priori* functional relationship between them. Simar and Wilson (2000) show how a simple statistical model of the data generating process can be used to determine the statistical properties of a non-parametric (DEA) estimator, which is analogous to the parametric method. However, DEA is also not without criticism – it is deterministic rather than stochastic, so it is sensitive to outliers and data measurement errors. Comprehensive reviews of the two approaches are provided by Kalirajan and Shand (1999); Charnes *et al.* (1994); Coelli (1995); Lovell (1993); Green (1993); Ali and Seiford (1993); Fried *et al.* (1993); Bravo-Ureta and Pinheiro (1993); Bjurek *et al.* (1990) and Bauer (1990).

Given the alternative empirical tools available, the choice as to the 'best' method is unclear (Olesen *et al.* 1996). Few rigorous empirical analyses have been carried out in assessing the sensitivity of efficiency measures to the choice of DEA and parametric methodology in agriculture (e.g., Sharma *et al.* 1999; Wadud and White 2000). The limited findings show that efficiency score estimates from each approach differ quantitatively, although the ordinal efficiency ranking of farms obtained from the two approaches appear to be quite similar. The evidence would suggest that the choice is somewhat arbitrary, though to a certain degree the choice between alternative modelling approaches depends upon the objectives of the research, the type of farms and assumptions regarding the data generating process. We used the non-parametric DEA technique developed by Charnes *et al.* (1978) (CCR) and Banker *et al.* (1984) (BCC). We could have used a stochastic frontier approach instead, but we expect qualitatively the results would be similar under both approaches.

2.2 Data envelopment analysis

The evaluation of farm (the decision-making unit) performance is usually based on economic efficiency, which is generally composed of two major components: technical efficiency and price or allocative efficiency. Technical

efficiency is defined as the ability of a farm to either produce the maximum possible output from a given bundle of inputs and a given technology, or to produce the given level of output from the minimum amount of inputs for a given technology. Technical efficiency can be decomposed into two components: pure technical efficiency and scale efficiency. When one separates the scale effect from the technical efficiency, the pure technical efficiency is obtained. Scale efficiency relates to the most efficient scale of operation in the sense of maximising average productivity. A scale efficient farm has the same level of technical and pure technical efficiency. Allocative efficiency is defined as the ability of a farm to equate marginal value product and marginal cost.

These five relative measures of efficiency, as mentioned in preceding text, are derived using the input-orientated DEA approach (Charnes *et al.* 1978; Banker *et al.* 1984; Fare *et al.* 1985, 1994).[3] They are estimated by solving a separate linear programming problem for each decision making unit in the sample. The estimation methods used in this research are explained below.

Assume that farm j ($j = 1, 2, \ldots, 76$) produces a single output (y_j) using a combination of inputs x_{ij} ($i =$ land, seed, fertiliser, human labour, mechanical labour, other) as defined in section 3. In what follows, we let c_{ij} represent the unit price for input i used by farm j, x_{ij}^* represents the cost minimising vector of inputs i for the jth farm given the input prices c_{ij}; λ_j is an $n \times 1$ vector of constants, and $\forall_j$ denotes 'for all j'.

2.2.1 Economic efficiency

In order to derive overall economic efficiency (EE), we first solve the following cost minimising DEA model under the constant returns to scale (CRS) assumption (Fare *et al.* 1985, 1994).

$$MC_j(y_j, x_{ij}^*, c_{ij}) = \min_{x_{ij}^*, \lambda_j} c_{ij} \cdot x_{ij}^* \quad \text{s.t.} \quad \sum_{j=1}^{n} y_j \lambda_j - y_j \geq 0;$$

$$x_{ij}^* - \sum_{j=1}^{n} x_{ij} \lambda_j \geq 0; \lambda_j \geq 0 \quad \text{for } \forall_j \tag{1}$$

where $MC_j(y_j, x_{ij}, c_{ij})$ is the minimum total cost under the CRS assumption, λ_j values are the weights to be used as multipliers for the input levels of the jth farm to indicate the input levels that the farm should aim at

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[3] Note that the efficiency measurement will be different under the input-orientated model relative to the output-orientated DEA model as the former minimises the input to obtain the given level of output, whereas the latter maximises output from the given level of input.

to achieve efficiency. After denoting the actual cost for observation j as $c_{ij} \times x_{ij}$, EE is defined as the ratio of minimum to actual observed costs, $EE_j(y_j, x_{ij}, c_{ij}) = [MC_j(y_j, x_{ij}^*, c_{ij})]/(c_{ij} \times x_{ij})$. If $EE_j = 1$, then farm j is considered economically efficient.

2.2.2 Technical efficiency

The overall technical efficiency (TE) ($TE_j(y_j, x_j) = \theta_1$) is independent of input prices and computed by solving the following input orientated CCR DEA model (2) under a CRS assumption (Charnes *et al*. 1978; Fare *et al*. 1985, 1994).

$$\min_{\theta_1, \lambda} \theta_1 \quad \text{s.t.} \quad x_{ij}\theta_1 - \sum_{i=1}^{m} x_{ij}\lambda_j \geq 0; \; \sum_{j=1}^{n} y_j\lambda_j - y_j \geq 0; \; \lambda_j \geq 0 \tag{2}$$

$$\text{for } \forall_j, \theta_1 \text{ unconstrained}$$

If $\theta_1 = 1$, the farm is on the frontier and is technically efficient under CRS. If $\theta_1 < 1$, then the farm lies below the frontier and is technically inefficient.

2.2.3 Allocative efficiency

Allocative efficiency (AE) is computed by using Farrell (1957) decomposition relationship: $AE_j(y_j, x_{ij}, c_{ij}) = [EE_j(y_j, x_{ij}, c_{ij})]/[TE_j(y_j, x_{ij})]$ based on the constant returns to scale assumption.

2.2.4 Pure technical efficiency

Adding the restriction $\sum_j \lambda_j = 1$ in model (2) relaxes the CRS restriction and envelops the data more closely than the CRS technology. Thus, we compute pure technical efficiency (PTE = θ_2) as a relative measure of efficiency under a less restrictive variable returns to scale (VRS) technology. This model is known as the BCC model (Banker *et al*. 1984). Note that θ_1 and θ_2 represent the proportional decrease in input that can be obtained by the farm to produce the given output under CRS and VRS assumptions, respectively.

2.2.5 Scale efficiency and its sources

Because the VRS technology is more flexible and envelops the data in a tighter way than the CRS technology, the VRS measure (PTE) is equal to, or greater than, the CRS measure (TE). Using the relationship between PTE and TE computed above, the scale-efficiency (SE) measure for a farm is computed (Favero and Papi 1995; Johnes 1995; Bjurek *et al*. 1990) as:

$$SE_j(y_j, x_{ij}) = \frac{TE_j(y_j, x_{ij})}{PTE_j(y_j, x_{ij})} \tag{3}$$

where $SE_j = 1$ indicates a scale efficient farm that is operating at a point of CRS. A value $SE_j < 1$, indicates the two technologies (CRS and VRS) do not coincide, and the farm is not operating at a point of CRS.

Different scale properties for inefficient units are determined following Forsund and Hjalmarsson (1979) and Forsund and Hernaes (1994). Specifically, we estimate the output maximising technical efficiency measure (θ_4) by solving model (4) (also known as the output-orientated BCC model) (Banker $et\ al$. 1984).

$$\max_{\theta_4, \lambda} \theta_4 \quad \text{s.t.} \quad \sum_{j=1}^{n} y_j \lambda_j - y_j \theta_4 \geq 0; \ x_{ij} - \sum_{i=1}^{m} x_{ij} \lambda_j \geq 0; \ \sum_j \lambda_j = 1; \ \lambda_j \geq 0 \tag{4}$$

$$\text{for } \forall_j, \theta_4 \text{ unconstrained}$$

where θ_4 represents the proportional increase in output that can be obtained by the farm given input vector x_{ij}. The properties of average returns to scale are then determined as: (i) increasing returns to scale (IRS) if $\theta_2 > \theta_4$, and decreasing returns to scale (DRS) if $\theta_2 < \theta_4$.[4]

2.3 Determining factors explaining inefficiency

Use of a second stage regression model to determine the farm specific attributes in explaining inefficiency is suggested in a number of studies (e.g., Kalirajan 1991; Parikh and Shah 1995; Hallam and Machado 1996; Llewelyn and Williams 1996; Sharma $et\ al$. 1999; Shafiq and Rehman 2000; Wadud and White 2000). An alternative to this approach is to incorporate farm specific attributes in the efficiency model directly (e.g., Battese $et\ al$. 1989; Kumbhakar $et\ al$. 1991; Battese and Coelli 1995). The merits and demerits of both approaches are provided in Ferrier and Lovell (1990), Kalirajan (1991), Kumbhakar $et\ al$. (1991) and Battese and Coelli (1995). The present study employs the former approach and uses a model to analyse the role of farm specific attributes in explaining inefficiency in Nepalese rice farms. To motivate our empirical model we assume

$$y^* = \beta_0 + \beta_1 z_1 + \beta_{11} z_1^2 + \beta_2 z_2 + \beta_3 z_3 + \beta_4 z_4 + \beta_5 z_5 + e$$
$$= Z\beta + e \tag{5}$$

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[4] Alternatively, scale efficiency can be characterised by estimating the input orientated non-increasing returns to scale DEA model using relation (2) with the additional constraint $\sum_j \lambda_j \leq 1$ as suggested in Seiford and Thrall (1990).

$$y = \begin{cases} y^* & \text{if } y^* < 100 \\ 100 & \text{otherwise} \end{cases} \tag{6}$$

where y is a DEA efficiency index (after rescaling between 0 and 100) used as a dependent variable, z_1 = age; z_2 = education; z_3 = risk aversion; z_4 = family labour endowment, z_5 = gender of household (a binary variable). Z is the vector of independent variables related to farm specific attributes, β is the unknown parameter vector associated with the farm specific attributes, and e is an independently distributed error term assumed to be normally distributed with zero mean and constant variance, σ^2. Therefore, the model assumes that there is an underlying, stochastic index equal to $(Z\beta + e)$, which is observed only when it is less than 100 and, henceforth, qualifies as an unobserved, latent variable. The dependent variable in the regression equation (5) cannot have a normal distribution. Rather, it has a censored distribution, because its value lies between 0 and 100. Ordinary Least Squares estimation using a censored sample yields inconsistent estimates. Instead we estimate the Tobit regression model (5) using the maximum likelihood approach (Tobin 1958). It is possible to show that the expected value is:

$$E(y \mid Z) = 1 - \Phi(b) \times 100 + \Phi(b)Z\beta - \sigma\phi(b), \tag{7}$$

where $b = (100 - Z\beta)/\sigma$. Moreover, the marginal effect for $i = 2, 3$ and 4 (i.e., all variables other than age and gender) can be computed as:

$$\frac{\partial E(y|Z)}{\partial z_k} = \Phi(b)\beta_k \tag{8}$$

However, the marginal effect for $i = 1$ (age variable) is

$$\frac{\partial E(y|Z)}{\partial z_1} = \Phi(b)(\beta_1 + 2\beta_{11}) \tag{9}$$

Finally, for $i = 5$ (gender), the effect of a discrete change in gender from 0 to 1 is evaluated as

$$E(y \mid z_5 = 100) - E(y \mid z_5 = 0) \tag{10}$$

The explanatory variable 'risk aversion' in the Tobit regression is measured as Arrow Pratt's average absolute risk aversion (R_A), obtained from non-linear least squares estimation of a negative exponential utility function, $U_t = 1 - \exp(-R_A Z_t)$, $R_A > 0$, for each of the 76 DMU. The subscript t ($t = 1, \dots, 5$) refers to the number of observations for each farm, U_t is the scale of utility ranging from 0 to 1 with respect to a corresponding

certainty equivalent monetary gain, R_A is an unknown parameter to be estimated, Z_t is the certainty equivalent monetary gain equivalent to the expected income of a risky prospect, and *exp* is the exponential operator. Both variables U_t and Z_t were generated by interviewing the sampled farm households and finding the equally likely certainty equivalent (ELCE) using the methodology discussed in Anderson *et al.* (1977). As estimation of risk aversion using a utility function requires prior assumption of functional form, the risk coefficient we have estimated may be different with the change in the functional form assumption. The justification for choosing an exponential utility function is because it often provides the fairest estimates of the risk aversion attitude across sample farms compared to polynomial specifications (Dillon and Scandizzo 1978). Young (1979) argued that farmers in less-developed countries are more uniformly risk averse than their wealthier counterparts, so the exponential function will be more appropriate than a polynomial function.

3. Study area, sampling and data collection

The data was obtained in 1999 from interviews with 76 randomly selected rice farming households selected from the 380 households in four adjoining villages of the Agyauli Village Development Committee (VDC) in the Nawalparasi district.[5] The selected villages were Tribhuvani, Tribhuvantar, Danda and Gondhar. These are predominantly rice producing and have a similar topography, soil type and irrigation environment. The data was for the 1998 normal rice-growing season (June–December). The area represented the subtropical monsoon-based irrigated flat and lowland rice production environment that lies at 300 m above sea level. The farms selected were owner-operated, had similar food security objectives, and faced a similar economic and marketing environment for inputs and outputs.

Rice production in the area is used to meet the family's food requirement, with the surplus sold. All the farms used a similar technology of rice production (both inputs and outputs) except for differences in intensity and management. The selected sample households were interviewed with a three-section structured questionnaire. The first section recorded the socio-economic profiles of the households and the second recorded inputs and the output together with their prices. The third section recorded the choice of 50:50 gamble amounts and the corresponding certainty equivalents (to obtain the ELCE discussed).[6] The variables selected for use in this research are defined in table 1.

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[5] The VDC is a grass roots level geopolitical administrative organisation in Nepal.

[6] The interviews were conducted by the first author and so reduced the chance of interviewer bias.
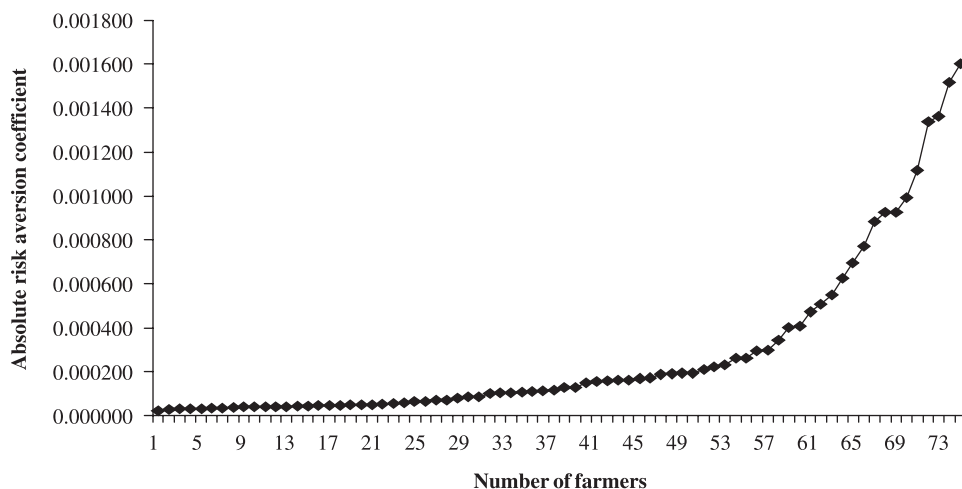
Figure 1 Cumulative distribution of farmers according to their absolute risk aversion.

Table 2 gives the descriptive statistics of the inputs, output and prices. Farms in the sample differ in operating size, intensity of input use and rice output. Most farms show little variation in unit prices indicating a competitive market for factor inputs in the sampled area.

Table 3 shows that land had the highest cost share among the six inputs. This was followed by the human and mechanical labour inputs. Both shared approximately 48 per cent of total cost. Seed and other inputs contributed only 4 per cent of the total costs.

The socio-economic variables are summarised in table 4. Approximately 60 per cent of the operators had primary level education and 20 per cent had no education at all. A reasonable degree of observed variation in the level of risk aversion is shown in figure 1.

4. Results and discussions

4.1 Data envelopment analysis efficiency measures

The summary statistics of the relative efficiency ratings are given in table 5,[7] and distributions provided in figure 2. The average level of Farrell's overall economic efficiency is 66 per cent. This means, in principle, that the sample

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[7] All five measures of relative efficiency were computed using Warwick DEA software (Thanassoulis and Emrouznejad 1996).

Table 1 Variable definitions and measurement

Variables	Unit	Definitions
Age (z_{1j})	Year	Age of household head for farm j[†]
Age^2 (z_{2j})	Year^2	Square of age variable for farm j
Education (z_{3j})	Year	Household head's years of schooling for farm j[‡]
Gender (z_{4j})	1, 0	1 if the household is managed by male, 0 otherwise for farm j
Family labour (z_{5j})	per cent	Percentage share of labour from family source consumed in rice production for farm j
Risk attitude (z_{6j})	Fraction	Estimated Arrow Pratt's average absolute risk aversion coefficients for farm j
Rice output (y_{1j})	kg/farm	Quantity of rice grain yield produced per farm for farm j
Land (x_{1j})	Kattha/farm	Area of the rice plot wherein input-output data was collected for farm j 1 kattha = 338.40675 square meters
Seed (x_{2j})	kg/farm	Amount of seed used for farm j
Labour (x_{3j})	Person-days/farm	Total amount of family and hired labour used in rice production for farm j
Mechanical labour (x_{4j})	Rs/farm	Cost incurred for using animal power and machine labour (tractor) for rice production for farm j
Fertiliser (x_{5j})	Rs/farm	Cost incurred for inorganic and organic fertilisers for rice production for farm j
Other (x_{6j})	Rs/farm	Cost incurred for using shallow tube-well irrigation, pesticides and herbicides for farm j
Land rent (c_{1j})	Rs/kattha	Cost for renting 1 kattha of land for rice production for farm j
Seed price (c_{2j})	Rs/kg	Cost for purchasing 1 kg of seed for rice production for farm j
Wage (c_{3j})	Rs/person-day	Cost for hiring 1-person day labour for rice production for farm j
Mechanical labour rent (c_{4j})[§]	Rs	Assumed Rs1 per unit of costs incurred for mechanical labour for farm j
Fertiliser (c_{5j})[§]	Rs	Assumed Rs1 per unit of cost incurred for fertiliser for farm j
Other inputs (c_{6j})[§]	Rs	Assumed Rs1 per unit of costs incurred for shallow-tube well irrigation, pesticide and herbicides for farm j

[†]The person who is responsible for managing the household business is called the household head. [‡]Those who had no history of formal enrolment in school are considered equivalent to 3 years primary schooling if they are able to read and write. People who cannot read and write were considered as illiterate, and were assigned the value of zero for years of schooling. [§]As variables x_4, x_5 and x_6 are expressed in value terms, the calculation of the unit price for these inputs was far from satisfactory. Therefore the unit price of these inputs is expressed in Rs1 as in Ferrier and Lovell (1990). 'Household' refers to the family unit consisting of the close members of families living together sharing the income commonly on private properties. Rs, Rupees, a Nepalese currency and Rs1 = $US(1/76) in December 2002. 'Kattha' is a local unit for measuring area.

Table 2 Descriptive statistics of the input, output and prices for the sample farms

Description	Unit	Mean	Standard deviation	Minimum	Maximum
Input and output variables (including missing values, zeros)					
Land	Hectare	0.63	0.58	0.08	3.78
Seed	kg/farm	37.13	33.70	7.50	225.00
Labour	Person-days/farm	88.88	74.84	19.50	500.00
Mechanical labour	Rs/farm	2195.00	1797.00	140.00	9500.00
Fertilisers	Rs/farm	1499.00	1652.00	0.00	9670.00
Other inputs	Rs/farm	207.00	309.00	0.00	1320.00
Rice yield	kg/farm	2194.00	1897.73	300.00	11 500.00
Price of input					
Land rent	Rs/ha	11 820.00	0.00	11 820.00	11 820.00
Seed price	Rs/kg	15.00	0.00	15.00	15.00
Labour wage	Rs/person-day	65.52	1.36	65.00	70.00

Zero represents the non-use of the corresponding input.

Table 3 Percentage share of total cost contributed by each input

Description	Mean	Standard deviation	Minimum	Maximum
Land rent	40.57	5.54	20.35	54.13
Seed	3.22	0.88	1.68	5.88
Labour	34.96	6.11	24.96	56.27
Mechanical labour	12.58	3.39	5.05	20.90
Fertilisers	7.61	4.61	0.00	21.63
Other costs	1.08	1.45	0.00	7.51

Sum of all input shares may not be equal to 100 because of rounding errors. All types of costs other than farm land tax incurred for rice production are included in the above list. Land tax on agriculture is negligible.

Table 4 Socioeconomic variables for the sample farms: descriptive statistics ($n = 76$)

Description	Unit	Mean	Standard deviation	Min	Max	No. farms
Farm characteristics						
Age	Years	47.15	11.38	26	78	–
Education	Schooling years	4.22	3.46	0	12	–
Male headed household	No. farms	–	–	–	–	68
Female headed household	No. farms	–	–	–	–	8
Family size	No. people	7.83	3.75	3	27	–
Risk attitude	Absolute risk aversion coefficient	2.844E-04	3.789E-04	2.0E-05	1.6E-03	–

Table 5 Descriptive statistics of the per cent efficiency indices

Efficiency measures	Mean scores	Standard deviation	Minimum	Maximum
Economic (EE)	66	16	37	100
Allocative (AE)	87	10	60	100
Technical (TE)	76	15	41	100
Pure technical (PTE)	82	16	43	100
Scale (SE)	93	10	52	100

All EE, AE, and TE measures are the CCR DEA solutions, whereas PTE measure is the BCC DEA solution. The former model characterises the constant returns to scale whereas the latter assumes variable returns to scale.
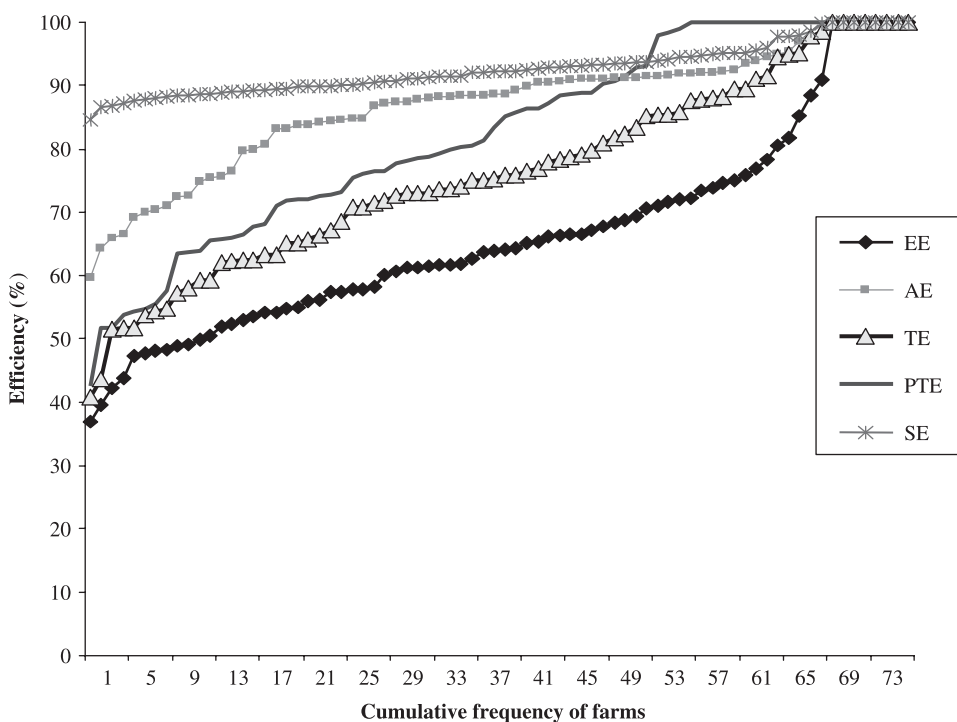

Figure 2 Distribution of various measures of efficiency. EE, economic efficiency; AE, allocative efficiency; TE, technical efficiency; PTE, pure technical efficiency; SE, scale efficiency.

farms can potentially reduce their overall cost of rice production, on average, by 34 per cent and still achieve the existing level of output.[8]

Figure 2 shows the different frequency distributions for the different efficiency measures. Approximately 67 per cent of the farms have achieved less

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[8] However, farmers' objective, risk attitude, and skill might impact their potential and desire to achieve overall economic efficiency.

Table 6 Summary of returns to scale results (*n* = 76)

Characteristics	No. farms	Rice output (kg/ha)		
		Mean	Min	Max
CRS	8	5126	4255	5910
DRS	32	3292	2304	5817
IRS	36	3518	2305	5122

CRS, constant returns to scale; DRS, decreasing returns to scale; IRS, increasing returns to scale.

Table 7 Spearman's rank correlation

Efficiency measures	EE	AE	TE	PTE	SE
Economic (EE)	1.0	0.45	0.86	0.64	0.38
Allocative (AE)		1.0	0.07	0.01	0.47
Technical (TE)			1.0	0.80	0.26
Pure technical (PTE)				1.0	−0.16
Scale (SE)					1.0

than 70 per cent EE. In contrast, 92, 68, 78 and 96 per cent of the farmers achieved more than 70 per cent AE, TE, PTE and SE, respectively. This shows the potential for increasing the productivity on the farms.

The measures of relative allocative and technical efficiency provide evidence as to the source of deviations from overall cost-minimising behaviour. Many sampled rice farms employed the 'wrong' input mix, given input prices, so that, on average, costs were 13 per cent higher than the cost minimising level. However, farms have the potential to reduce their physical input, on average, by 24 per cent, and still produce the same level of rice output. The decomposition of the technical efficiency measure produced estimates of 18 per cent pure technical inefficiency and 7 per cent scale inefficiency (table 5). The sources of scale inefficiency and their corresponding output levels were also determined and are reported in table 6. By eliminating scale inefficiency the farms can increase their average technical efficiency level from 76 to 82 per cent.

The Spearman rank correlations between different measures of efficiency are presented in table 7. These estimates provide evidence that there is a weak positive correlation between technical efficiency and allocative efficiency, which supports the hypothesis that the technically efficient sample farms might not necessarily be allocatively efficient. The reason was unknown, though it might be a result of variation in the farmers' goals, socioeconomic attributes, or possibly a random effect.

4.2 Farm specific factors related to farm inefficiency

Five separate Tobit regressions explaining efficiency as defined in equation (5) to (10) were estimated using Shazam Version 9.0 (Northwest Econometrics 2001). Both *Tobit regression coefficients* β_k, and *marginal effects* using the relations defined in equations (8), (9) and (10) are presented in table 8. The Tobit regression coefficients are interpreted to analyse the directional relationship between efficiency and covariates.

   The results in table 8 showed that the farmer's age has a negative, but a positive quadratic, effect on all efficiency measures. However the parameters are only significant for EE and TE at the 5 per cent significance level. This suggests that younger farmers are more likely to be inefficient than their older counterparts. This is consistent with the findings of Llewelyn and Williams (1996), Ajibefun *et al*. (1996), Seyoum *et al*. (1998) and Coelli and Battese (1996). The quadratic age variable has a positive coefficient indicating that inefficiency drops with age, perhaps because of experience. This result endorses the observations of Kalirajan and Shand (1985) and Stefanou and Saxena (1988), who found a positive effect of experience on farm productivity. This might suggest some policy implications such that the dissemination of the best farming practices should be strategically focused to young farmers to reduce the average inefficiency of the population.

   As expected, the results also revealed a consistent pattern of positive and significant relationships between operators' years of schooling, and EE, TE and PTE. The more educated farmers are more likely to be efficient as compared to their less educated counterparts, perhaps as a result of their better skills, access to information and good farm planning. Similar results were also reported by Moock (1976), Stefanou and Saxena (1988), Ali and Flinn (1989), Parikh *et al*. (1995), Battese *et al*. (1996), Wang *et al*. (1996) and Llewelyn and Williams (1996). In the long run, increasing private and public investment in education might lead to better performance in the agricultural sector. However, in the short run, inefficient farmers may be better off by learning from the benchmarking practices of the relatively efficient farms in their locality. Organisations should, of course, give attention to educating the inefficient farmers using the best practices of their efficient counterparts, perhaps using extension tools such as field days on the efficient farms (the lists of peers for each farm that can be used to create benchmarks are available in Dhungana (2000)).

   Of significant interest is that mixed results were obtained for the relationships between absolute risk aversion and the various measures of efficiency. The risk aversion coefficient is significant only in the AE and PTE equations at the 15 per cent level. However, it is positively related to TE and PTE, and negatively related to EE, AE and SE. It indicates that the higher

Table 8 Tobit regression coefficients ($n = 76$)

Independent variables (X_i)	Tobit normalized coefficients ($\alpha = \beta/\sigma$)					Regression coefficients (β)					Marginal Effects ($\partial E/\partial x_k$)*				
	EE	AE	TE	PTE	SE	EE	AE	TE	PTE	SE	EE	AE	TE	PTE	SE
Constant	6.96 (2.25)[a]	11.88 (2.38)[a]	7.55 (2.31)[a]	5.83 (2.35)[a]	12.81 (0.01)[a]	111.67 (35.39)[a]	112.90 (20.90)[a]	113.83 (33.98)[a]	108.89 (43.30)[a]	127.74 (22.79)[a]					
Age	−0.16 (0.08)[b]	−0.09 (0.08)	−0.17 (0.09)[b]	−0.11 (0.09)	−0.14 (0.09)	−2.60 (1.36)[b]	−0.87 (0.80)	−2.52 (1.31)[b]	−2.01 (1.67)	−1.42 (0.88)[c]	−0.05 (0.03)[b]	−0.08 (0.07)	−0.16 (0.08)[b]	−0.43 (0.36)	−0.38 (0.24)[c]
Age²	0.002 (0.001)[b]	0.001 (0.001)	0.002 (0.001)[b]	0.001 (0.001)	0.002 (0.001)	0.03 (0.01)[b]	0.01 (0.008)	0.03 (0.01)[b]	0.025 (0.02)	0.016 (0.009)[c]	−				
Education	0.09 (0.04)[b]	0.02 (0.04)	0.094 (0.045)[b]	0.08 (0.05)[c]	0.02 (0.04)	1.41 (0.71)[b]	0.21 (0.42)	1.42 (0.67)[b]	1.50 (0.86)[c]	0.21 (0.45)	0.03 (0.01)[b]	0.13 (0.07)	0.09 (0.04)[b]	0.33 (0.19)[c]	0.06 (0.12)
Risk attitude	−147.19 (328.6)	−790.80 (335.92)[b]	312.31 (329.6)	516.32 (343.9)	−305.57 (330.3)	−2362.9 (5269.3)	−7512.0 (3191)[b]	4709.9 (4956.3)	9649.49 (6405.8)	−3045.9 (3281.1)	−47.71 (106.4)	−220.77 (492.32)[b]	306.53 (322.5)	2109.8 (1400)	−832.19 (896.4)
Share of labour from family sources	0.005 (0.005)	0.002 (0.004)	0.005 (0.004)	0.0007 (0.005)	0.003 (0.005)	0.08 (0.07)	0.02 (0.04)	0.08 (0.07)	0.01 (0.09)	0.03 (0.05)	0.002 (0.007)	+0.008 (0.007)	0.005 (0.004)	0.003 (0.02)	0.002 (0.01)
*Gender (1 if male, 0 otherwise)	−0.61 (0.43)	−0.88 (0.43)[b]	−0.28 (0.42)	0.11 (0.43)	−0.69 (0.43)	−9.82 (6.81)	−8.36 (4.07)[b]	−4.25 (6.40)	2.07 (7.99)	−6.90 (4.31)[c]	−9.82 (6.81)	−8.36 (4.07)[b]	−4.25 (6.41)	2.07 (7.99)	−6.90 (4.31)[c]
Standard error of the estimate (σ)	16.05	9.49	15.08	18.68	9.96										
F($(100-X\beta)/\sigma$)	0.97	0.90	0.93	0.78	0.72										
Log likelihood function	−295.09	−258.19	−289.37	−261.82	−256.42										
Sq corr. Between obs and expected	0.14	0.15	0.15	0.12	0.06										

EE, economic efficiency; AE, allocative efficiency; TE, technical efficiency; PTE, pure technical efficiency; SE, scale efficiency. Five Tobit regression equations with dependent variables EE, AE, TE, PTE and SE are estimated separately. Values in parentheses are asymptotic standard errors. Superscripts a, b, and c represent the significance level at 1, 5 and 10 per cent, respectively. Ho: $\beta = 0$ against Ha: β?0. Marginal effect is for the effect of discrete change of dummy variable (gender) from 0 to 1.

risk aversion, the greater the likelihood of being cost, price and scale inefficient, and the greater the likelihood of being technically efficient. Further examination of the correlation between farmers' level of risk aversion and input levels shows mixed results. For example, risk aversion is positively correlated with inputs such as land, seed and human labour, and negatively correlated with other inputs (mechanical labour, fertiliser, chemicals and irrigation). The interesting observation is that the more risk averse the farmers are, the more they tend to allocate greater levels of inputs from household resources and less of purchased inputs. Inputs such as land, seed and human labour are mostly contributed from household resources. Chemical fertilisers, mechanical labour and pesticides are purchased without direct control over availability and prices. The more risk averse the farmers are, the more likely they are to be technically efficient, which probably is attributed to their tendency to allocate resources under their discretion more optimally. They also tend to underutilise purchased resources such as fertiliser and chemicals, maybe because of production uncertainty. The latter observation is consistent with Williams *et al.* (1992) and SriRamaratnam *et al.* (1987), who found that producers with higher levels of risk aversion are less likely to prefer high levels of nitrogen. Contrary to this, Llewelyn and Williams (1996) reported higher fertiliser use, particularly of urea, associated with the least efficient farms, arguing that it may be because of the 'risk evasive action' of the inefficient farms. The more risk averse the farmers are, the more likely they are to be scale inefficient, probably because they operate farms beyond an efficient size. In addition, the more risk averse the farmers are, the more likely they are to be more cost and price inefficient. It is interesting to note that technically efficient farmers having the same level of risk attitude may not necessarily be equally price and cost efficient. Technical efficiency may be related to farmers' perceptions of production uncertainty, whereas price efficiency may be more closely related to farmers' perception of price uncertainty. Therefore, different perceptions of production and output price uncertainty might have resulted in the different relationships between risk attitudes and technical and price inefficiency.[9] Our empirical observations might not be sufficient to precisely answer the question on what causes farmers with high levels of risk aversion to be more cost and price inefficient compared to their counterparts with low risk aversion. This warrants further research.

The results reveal statistically insignificant but consistently positive relationships between the share of family labour and all efficiency measures (at

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[9] Output price uncertainty is difficult to distinguish from production uncertainty in agriculture.

conventional significance levels). This tends to negate the widely held belief that farmers in developing economies are likely to use excessive family labour, and hence operate inefficiently. The value of using family labour might be a result of the scarcity of employed seasonal labour. Farmers with a large pool of family labour might benefit from being able to use these labour resources at the right time, particularly at peak cultivation times. If so, public policy should support the introduction of labour-saving technology required at, for example, the cultivation peak time.

The gender dummy showed a negative effect on all efficiency measures except PTE. This indicates that women managers are likely to be relatively less cost, price and scale inefficient compared to their male counterparts. This finding reinforces the importance of women farmers in the agriculture of developing countries and is consistent with the findings of Gladwin (1991) and Lele (1991) for African agriculture. It is also consistent with the finding reported by Moock (1976) that women, as farm managers, play major roles in farm-level decision making. The argument that women farmers are less efficient than male farmers (FAO 1985) is rejected in this case. Considering the extensive involvement of women in Nepalese rice farming, it would be economically rational to involve them in rice development strategies.

5. Conclusions

Four conclusions arise from our analysis of inefficiency. First, farmers and agencies that are involved in agricultural development programs need to appreciate there is an inefficiency problem. Operating at best practice, farm families would be able to release inputs for use in alternative economic activities to generate extra income for the family's welfare, or use cost savings to purchase new technologies such as improved seeds, fertilisers and land improvement. Surplus resources such as fertiliser could be reallocated to increase the productivity of other crops such as wheat, maize, potato etc., where lack of fertiliser is a problem. Similarly, surplus labour could be re-deployed to other economic activities such as livestock enterprises, vegetable farming or off-farm employment if an opportunity exists. Optimal reallocation of surplus labour in cash-generating activities can increase the welfare of the household. Surplus seed can be used to supplement food for the family.

Second, benchmarking using the efficient farms would be helpful for setting targets and finding the weakness of the current practices. The relatively efficient farms can also improve their efficiency further through learning the best allocation decisions from other efficient farms, and continually striving to interpret and use research station results. The usefulness of DEA for promoting the best agricultural management practices through benchmarking

has been well documented in the published literature (e.g., Fraser and Cordina 1999).

Third, the factors which significantly impact farmers' resource allocation decisions differ widely among farmers. Program effectiveness may depend largely on the extent to which such differences are recognised. To be successful, efficiency improvement programs should be flexible enough to accommodate the diversity of both farmers and their need for improvements. For example, creating separate groups of younger and older, educated and uneducated, high, medium and less risk averse farmers, might be required for educational purposes. Similarly, developing and implementing separate programs for farmers who are inefficient in fertiliser, seed, labour and chemical use would probably be useful.

Fourth, it is important to recognise the impact of the inherent risk aversion factor on efficiency, and similarly gender. It is interesting to speculate whether managerially important attributes of one gender can be isolated and passed to the other gender through training. Similarly, it would be interesting to study what gives rise to a particular risk aversion level and whether training would alter the level.

Finally, it is worth noting that the present study has some limitations. Because of the need to rely on farmers memories, the efficiency analysis is based on a single season (June–December 1998). Extrapolating the results to other areas, years and seasons needs to be done with care. Furthermore, factors such as the timing of fertiliser application, irrigation, transplanting and weeding can have an impact on efficiency. Therefore, inefficiency is not just a result of the differences in the quantities of land, seed, fertilisers, human labour, mechanical labour, irrigation and chemicals revealed in this research. Also institutional factors such as extension, systems research and general policies need to be examined. Future research needs to concentrate on developing the appropriate frontier model that encompasses all components of the whole farming system including quality and time variation components. Explicitly incorporating these other factors in the analysis can only give rise to improvements in measured efficiency levels. In addition, recent developments on testing the restrictions of the behavioural assumptions in non-parametric efficiency models like DEA, as suggested in Simar and Wilson (2001), could be promising directions for further research.

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