



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

EXPLAINING ECONOMIC INEFFICIENCY OF NEPALESE RICE FARMS: AN EMPIRICAL INVESTIGATION

Basanta R. Dhungana^a, Peter L. Nuthall^b and Gilbert V. Nartea^c
(Applied Management and Computing Division, Lincoln University)

Abstract

Efficiency has been proven to be an important managerial tool in improving total factor productivity in agriculture. The four sources of economic inefficiency: allocative, technical, pure technical and scale inefficiency of a sample of seventy-six Nepalese rice farmers were examined using the data envelopment analysis (DEA) decomposition method. The inefficiency indices computed by the DEA were then used as the dependent variable in a Tobit (censored) regression model using decision-makers' attributes as the explanatory variables.

The results revealed relatively large inefficiencies among the farms sampled. The average economic, allocative, technical, pure technical and scale inefficiencies were 34%, 13%, 24%, 18%, and 7% respectively. There is also a significant variation in the level of inefficiency across farms. The inefficiencies are attributed to the variations in use intensities of resources such as farm land, seed, human labour, fertilisers and mechanical power. The inefficiencies were explained by farmers' level of age, education, gender, family labour endowment and risk aversion. Therefore, to be successful the efficiency improvement program must be flexible enough to accommodate the diversity of farmers and their improvement needs. The results also suggest that increasing effort towards educating farmers on best practices can enhance efficiency in Nepalese rice farming. Other policy implications and development strategies are also drawn from the findings.

(Key words: efficiency, frontier, DEA, rice farming, Tobit regression, socioeconomic attributes, risk attitude)

^a Mr Dhungana is Postgraduate student.

^b Dr Nuthall is Associate Professor in Farm Management

^c Dr Nartea is Senior Lecturer in Agribusiness Management

Corresponding addresses:

P.O. Box 84, Applied Management and Computing Division
Lincoln University, Canterbury, New Zealand

E-mail: Basantard@hotmail.com / Dhunganb@tui.lincoln.ac.nz^a
Nuthallp@tui.lincoln.ac.nz^b, Narteag@tui.lincoln.ac.nz^c

1. Introduction

The purpose of this research is to measure and explain the economic inefficiency of Nepalese rice farms. Recent research has focused on the estimation and explanation of various components of production inefficiency in agriculture (for e.g., Sharma et al., 1999; Torkamani and Hardaker, 1996; Bravo-Ureta and Evenson, 1994; Ali and Chaudry, 1990). Many have focused either on technical efficiency (Bravo-Ureta and Evenson, 1994) or allocative efficiency (for e. g., Wang et al., 1996; Ali and Flinn, 1989). The commonly observed variation in a firm's performance can not solely be ascribed to variation in either technical or allocative efficiency, though attaining the technical or allocative efficiency is the necessary condition for evaluating a firm's performance. Clearly sufficient conditions for optimum performance requires attainment of both allocative and technical efficiencies (Yotopoulos and Nuggent, 1976). Attaining both pure technical and scale efficiencies is the sufficient condition for attaining technical efficiency, though the necessary condition can be achieved through attaining either. Thus, decomposition of the economic efficiency into its sources allows a careful analysis of where to direct efficiency improvement.

This study differs from previous work on the efficiency of agricultural producers in that it identifies the allocative, pure technical and scale inefficiencies, including constant, increasing and decreasing returns to scale, as the sources of economic under performance. It uses the Charnes, Cooper and Rhodes (1978) (CCR) and Banker, Charnes and Cooper (1984) (BCC)'s Data Envelopment Analysis models in which the sources of efficiencies are modelled as an explicit function of discretionary variables in the first step. In the second step, farm specific variables such as a farmer's risk attitude, age, education, gender and family labour endowment are modelled in a Tobit regression to explain the likelihood of changes in inefficiencies by these factors.

As in other studies (such as Sharma et al., 1999; Wilson et al., 1998, Xu and Jeffrey, 1998; Tadesse and Krishnamoorthy, 1997; Battese et al., 1996) this research also utilises survey data which is enterprise specific and hence allows the model to be formulated in a way that avoids the potential interpretation difficulties that can arise when variables are constructed as aggregates when in fact there are more than one output and inputs in a farming system.

The rest of the paper continues with section 2 which analyses the rationale of this research and this is followed by a review of the methods. In sections 4 and 5 the conceptual model, hypothesis statement and analytic techniques are provided, while section 6 contains the definition and sources of the data used. In section 7, 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.

2. Performance of the Agricultural sector in Nepal

Despite the continuous and considerable efforts that have been made to improve the agricultural productivity since the inception of the first-five-year-development plan in 1956, food production in Nepal has not kept pace with the population growth. For example, since 1990 Nepal has gradually become a modest net importer from a position of being a net exporter of food grains prior to the 1980s (APPROSC/JMA, 1995). The production of total food grains (rice, maize, wheat, millet and barley) in the country has increased only 1.18% per annum over the last 20 years (from 1977/78 to 1996/97) (CBS, 1998; Thapa and Rosegrant, 1995). This rate was lower than the population growth (2.3%) during that period (CBS, 1998). More importantly, the increase was mainly a result of an area expansion rather than productivity growth. This evidence indicates the poor performance of the agriculture sector in the past years.

Five major problem areas are identified that have adversely affected the performance of the agricultural sector in Nepal (Thapa and Rosegrant, 1995). First, agency managed irrigation systems which have received the major share of investment in agriculture in the last two decades have been unable to deliver reliable and adequate water supplies to farmers, thus limiting gains from new agricultural technology. Second, the public sector, which until recently had a monopoly on the importation and distribution of fertiliser, failed to meet the demand of farmers to substantially improve crop productivity. Third, the lack of responsiveness of the research and extension system to address the farmer's problems appropriately. Fourth, the neglect of marketing in government agricultural programs has severely limited growth even in those

areas where farmers have demonstrated their ability to generate surplus production. Macroeconomic policy environments such as the exchange rate, pricing policies for major inputs and outputs, preferential treatments for public sector enterprises and unnecessary restrictions to the private sector were not conducive for agricultural growth.

The poor performance of agriculture in the past means the majority of the rural population earned low incomes, hence low savings and limited investment opportunities. As a result, growth in non-agricultural sectors remained low, which in turn limited the employment growth and aggravated rural poverty¹. It is also reported that the low productivity of agriculture promotes environmental degradation, such as deforestation, particularly in the hills (Bajracharya, 1983; Kumar and Hotchkiss, 1988).

Nepal's population is projected to increase by more than 2 per cent per annum until the year 2020. The food demand is projected to increase from 4,079,000 metric tons in 1997 to 6,909,000 metric tons in 2020 (CBS, 1998; Thapa and Rosegrant, 1995). In the absence of productivity growth, because growth from area expansion has already reached its saturation, by 2020 Nepal should import about 3 million tons of food every year to meet the domestic food demand by spending its limited foreign currency reserves.

Productivity growth can be achieved by either technological innovation or the efficient use of production technologies, or some combination of both. Schultz (1964) argued that the continuous creation / introduction of a new technology has been regarded as a standard for distinguishing a modern agricultural system from a traditional system. However, in developing countries most new agricultural technologies have been only partially successful in improving productivity (Xu and Jeffrey, 1998). This is often attributed to a lack of ability and / or a willingness 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 may exist a negative relationship between technical progress in 'conventional production technology'² and realised efficiency. 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 (Belbase and Grabowski, 1985; Shapiro, 1983). Russel and Young (1983) concluded that the efficiency study can show the scope for improved performance and can be very useful in the formulation and analysis of agricultural policy. Thus the subject of efficiency was selected as a means of exploring the reasons for production inefficiency that hinders the productivity growth in Nepalese agriculture with reference to rice farming.

Rice was selected due to its prominent position in the national economy. Rice generates substantial income, employment, food security and livelihood of the majority of the Nepalese people. It contributes 20% of the agricultural gross domestic product (AGDP)³ and more than 50% of the total food grain production of the country (MOF, 1998). Rice alone contributes more than 50% of the dietary total calorie requirement, and is grown on almost 1.5 million hectares which accounts for more than half of the total cultivated area (2.6 million hectares) in food production (CBS, 1998). In addition, rice is a political commodity and food riots may erupt if citizens perceive changes in prices to be too great or abrupt.

In the last decade rice production has increased by an average of 3% per annum. This increment is partly due to the expansion of the rice area and partly due to improvement of technology

¹ World Development Report (1997) shows 53.1% of the population under absolute poverty living on less than \$1 a day.

² Conventional rice technology as assumed throughout this paper is not traditional in the Schultz sense but is, instead, currently available post green revolution technologies represented in the varieties, chemical fertilisers, insecticides, pesticides, irrigation, and the like.

³ The contribution of the AGDP to the total GDP, of US\$ 4316 million at producers' prices, constituted 39.13 percent in the Fiscal Year (FY) 1997/98 (CBS, 1998).

Note: The Nepalese Fiscal Year (FY) starts on July 16 and ends on July 15 of the following year. The exchange rate used to convert the local currency into United States Dollar is 1 US\$= Rs 68.00.

(Thapa & Rosegrant, 1995). There has been a substantial rise in the cost of production of rice in recent years due to the effects of reduced government fertiliser subsidy, and an increase in rural labour wages. For example, between 1990 and 1993 the price of Complexal (contains 20% N₂O plus 20%P₂O₅) and Murate of Potash (MOP) fertilisers were increased by 122% and 267% respectively (Thapa & Rosegrant, 1995). The price subsidy on Urea fertiliser has also substantially declined in recent years. Subsidies on other fertilisers like Complexal, Sulphate, Diamonium Phosphate (DAP) and Triple Super Phosphate (TSP) have already been eliminated (Thapa & Rosegrant, 1995) so the price of fertiliser has increased. Since rice is the crop that uses the major share of the fertiliser imports (CBS, 1996), efficient use of fertiliser in producing rice is a significant factor for cost efficient production.

There is also a possibility to achieve sufficient growth in rice production by developing hybrid rice in the short run, and a 'super' high-yielding new variety in the longer-run. However, conventional breeding practices used by the National Research System (NARS) may take a very long time to get progress in this direction. In the absence of future technological breakthroughs, Nepalese farmers will face increasing costs of production due to the increasing cost of labour, land, water, and fertilisers, and consequently consumers will face a shortage of rice. Furthermore, some other externalities, such as economic growth and commercialisation of agriculture, may reduce the profitability of rice farming relative to the cultivation of crops with a higher income elasticity and this may further reduce rice supply. Considering the slow growth in the rice productivity in recent years, and the declining investments in productivity enhancing technologies and infrastructure (Thapa and Rosegrant, 1995), it is important to determine whether it is possible to increase rice productivity in economically efficient ways. Removing inefficiency would allow exhausting the potential gain that could be attained by the efficient use of the current level of rice technology available at the farm.

3. Production Frontier and efficiency measurement

The absolute efficiency is not known for a population. Therefore the problem is to measure the efficiency of one farm relative to others within a population sample. The production frontier approach has been popular in recent years relative to the traditional method of measuring relative efficiency following more than four decades of development after the groundbreaking work of Farrell (1957). The production frontier approach constructs either the production frontier representing the maximum level of output attainable from a given set of inputs, or the input isoquant representing the minimum level of input in producing a given level of output, all for a given technological constraint. Traditionally, the average production function (i.e., best-fit method using the regression model) was employed for estimating the efficiency index. Coelli (1995) argued that estimating the frontier function has two major advantages over estimating an average production function. Firstly, estimation of an average function only provides the technology function of an average firm, whereas the estimation of a frontier function will be influenced by the best performing firms and hence reflects the technology and systems they are using. Secondly, the frontier function represents an estimate of best practice technology against which the efficiency of firms within the industry can be measured.

Bauer (1990) gives a further three reasons for using frontier modelling. First, the notion of a frontier is consistent with the underlying economic theory of optimising behaviour. Second, deviations from a frontier have a natural interpretation as a measure of the efficiency with which decision-making units (DMUs) pursue their technical or behavioural objectives. Finally, information regarding the structure of the frontier and the level of efficiency of DMUs has many policy implications.

There are two main competing paradigms for estimating the frontiers: parametric and non-parametric. Coelli (1995) presents a recent review of both techniques indicating the main difference is that the non-parametric approach does not have any prior assumptions regarding the statistical properties of the data, whereas the parametric frontier approach yields standard errors for its estimates. Non-parametric frontiers are estimated using the mathematical programming approach commonly known as Data Envelopment Analysis (DEA)(Charnes et al., 1978) whereas the parametric frontiers are estimated using econometric techniques. DEA does not impose unwarranted structure on the technology that might create a distortion in the efficiency measures (Fare et al., 1985). Llewelyn and Williams (1996), however, pointed out that it can't separate deviations from the frontier into their systematic and random components and thus attributes all deviations to inefficiency of the observed firm and thus may overstate inefficiencies. In contrast, the parametric approach provides a consistent framework for analysing efficiency (Chavas and

Aliber, 1993) but it does have an important weakness in that the hypothesis on the parametric form can never be detected (Varian, 1984; Banker and Maindiratta, 1988). Thus the assumption may not hold so the distribution and measurement of the efficiency term may reduce the relevance of the results (Chavas and Aliber, 1993).

Given the alternative empirical tools available, the choice as to the 'best' method is unclear. With the recent notable exceptions, no rigorous analysis has been done in assessing the sensitivity of efficiency measures to the choice of methodology. Bravo-Ureta and Rieger (1990) compare the results of deterministic (both programming and econometric analyses) and stochastic parametric efficiency models for a sample of US dairy farms while the estimates from each approach differ quantitatively, the ordinal efficiency ranking of farms obtained from the different models appear to be quite similar. Similarly, a recent study conducted by Sharma et al. (1999) on Hawaiian swine farms also showed different efficiency ratings from stochastic and DEA frontier methods but they concluded that relatively DEA produced the more robust results compared to the stochastic frontier method. Very recently, Jaforullah (1999) has also evaluated the technical efficiency of Bangladeshi handloom firms using parametric - stochastic and deterministic methods as well as a nonparametric - data envelopment analysis. He concluded that the three methods produced different individual and mean technical efficiencies. He, however, found that the three methods were consistent in ranking individual production units. This evidence would suggest that, to a certain degree, the choice between alternative modelling approaches may be somewhat arbitrary.

This research uses the non-parametric DEA technique. The reasons for this selection include the following: (i) it places no restriction on the functional form of the production relationship, (ii) it provides the level of efficiency for individual farms and indicates whether improvement is possible. This is consistent with the main objective of this research as it is aimed at investigating sources and amounts of relative inefficiency and so create a quantitative basis for reallocating resources for individual farmers, (iii) it has a relative advantage where there are limited data as statistical requirements demand a large number of observations for stochastic production frontier analyses.

There are two alternative approaches for examining the effect of farm specific characteristics on farm efficiency. One is to incorporate both efficiency determining and efficiency explaining variables in the efficiency measurement model such as DEA. The other is usually referred to as a two-step procedure where the efficiency is measured first for the individual units (using DEA), and then a regression model is estimated where the level of inefficiency is expressed as a function of the socioeconomic variables such as age, education, risk attitude, etc..

A two-step procedure has been used to explore the inefficiency explaining factors by a number of studies (for example, Kalirajan 1991; Parikh and Shah 1995; Hallam and Machado 1996, Llewelyn and Williams 1996, Sharma et.al, 1999). This procedure has been criticised by some who argue that socio-economic variables should be incorporated directly in the production frontier model because such variables may have a direct impact on efficiency (Battese, Coelli and Colby 1989, Battese and Coelli, 1995). Despite such criticisms, the two step procedure is still popular. Kalirajan (1991) has defended the two step procedure by contending that the socio-economic attributes have a roundabout effect on production and, hence, should be incorporated into the analyses indirectly. Ray (1988) has argued that the two step procedure is justifiable if one assumes that the production function is multiplicatively separable in what he calls discretionary and non-discretionary inputs. The former inputs are those typically included in production function models while the latter are those commonly used to explain variations in efficiency. On the other hand, the second - stage regression can be useful to correct the efficiency scores for other factors (excluding the discretionary factors encompassed by DEA) such as the risk attitude and socio-economic attributes of the farmers. The estimated regression coefficients can be used for adjusting all efficiency scores corresponding to a common level of socio-economic environment (e.g. the sample means). It also has the advantage of being easy to estimate.

Existing studies aimed at directly incorporating firm specific characteristics such as education, experience, size etc. are limited to the parametric approach (Kumbhakar et al. 1991, Battese and Coelli, 1995). Without prior assumptions on whether the firm specific factors have a positive or negative impact on economic performance (see, for example, Ferrier and Lovell, 1990), the non-parametric DEA technique can not easily incorporate them.

It should be noted, however, the inefficiency scores from DEA are limited to values between 0% and 100%. For example, farmers who achieved Pareto efficiency always have inefficiency index 0%. In

such a situation, the dependent variable in the regression equation can't be expected to have a normal distribution and instead demonstrates a censored distribution⁴. Ordinary Least Squares estimation based on a censored sample with a limited dependent variable would yield inconsistent estimates. An alternative would be to include in the analysis only those observations for which inefficiencies are greater than zero. However, this alternative would result in sample selection bias in the estimated coefficient of the OLS model. Tobit analysis estimates the likelihood of change in inefficiency. This suggests that ordinary least squares regression is not appropriate and that Tobit estimation should be used (Tobin, 1958) because Tobit estimation allows for the inclusion of observations which have zero inefficiency. Tobit coefficients are estimated by the method of maximum likelihood.

4. Conceptual model and research hypothesis

Based on the review, the following conceptual model has been designed to address the inefficiency problems prevailing in Nepalese agriculture. Farmers' normative resource allocation decisions are based on either the maximisation of the farm output at given input, or the minimisation of the input to produce the targeted output. Despite this goal, farm inefficiency may vary among the farmers due to differences in application and quantity of the input used and output produced; inappropriate combinations of farm inputs and output with respect to their prices, and a non-optimal scale of operations. Such differences can be attributed to farm specific characteristics. Therefore the model of farm inefficiency should consider all inputs, outputs, farm specific factors and risk attitude of the decision maker (Figure 1) assuming that the farmers are operating under the same technological, economic, marketing, and physical production environment. Thus this research is organised with the conceptual model displayed in the Figure 1.

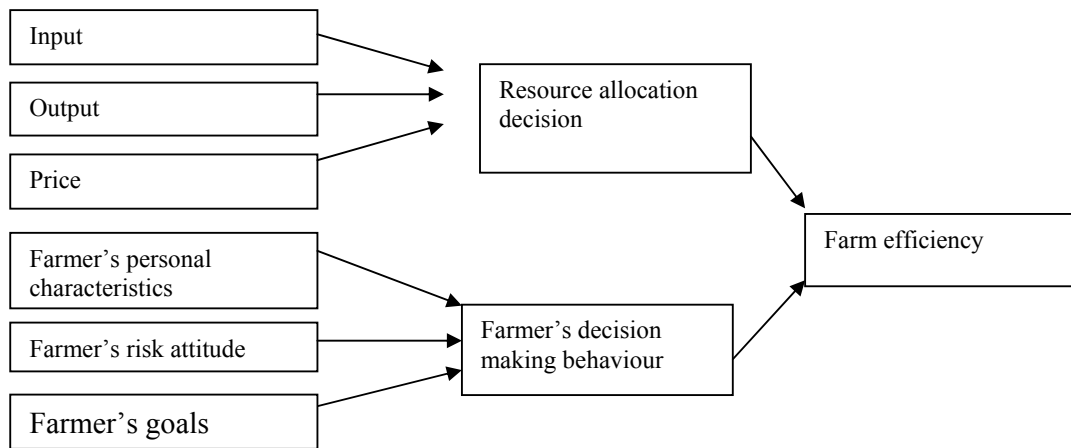


Figure 1. Conceptual model: Factors affecting farm efficiency.

4.1 Resource allocation decision versus farm efficiency

A number of hypotheses were formulated for testing in an attempt to explore whether there were any differences in the level of efficiency. These were:

Hypothesis 1: There is a variation in technical efficiencies among the rice farms in a given technology setting. This may arise due to a variation in intensity of physical input use.

Hypothesis 2: There is a difference in the allocative efficiencies among the rice farms. Compared to each other, some spent less and the others spent more to achieve the same level of output.

⁴ In statistical literature, the term censored applies to a sample in which some observations are recorded only as above (or below) some threshold. For a detailed discussion of censored response models and limited dependent variables, see Maddala (1985) or, Long (1997).

Hypothesis 3: There is a variation in scale efficiencies among the farmers. Comparing each, all farms may not be operating at an optimal scale due to the resource constraint at the farm level.

Hypothesis 4: It is not mandatory that technically efficient farmers are also price efficient. It may be dictated by an individual's goal whether to maximise physical output or profit; or some other objectives.

4.2 Farmers' decision making behaviour versus farm efficiency

Farmers' decision making behaviour may be influenced by the farm specific characteristics. This may include variables such as risk attitude, age, education, family labour endowment and gender. Thus, further hypotheses were formed for testing. These were:

Hypothesis 5: Younger farmers are skilled with access to information and, hence, less inefficient as compared to their older counterparts.

Hypothesis 6: Education provides understanding and hence the ability to analyse and access new information. The more education an individual gets, the higher will be the level of efficiency.

Hypothesis 7: It is hypothesised that both male and female operators are equally efficient given an equal access to technologies and information.

Hypothesis 8: The larger the family labour supply used in the production, the lower the technical efficiency of the farm. A large pool of family labour may induce the farmer to use excessive labour resources given the alternative employment opportunities do not exist. Thus a higher percentage share of labour from family sources is hypothesised to have a negative effect on technical efficiency.

Hypothesis 9: Risk attitude of the farmers plays an important role in a farmer's resource allocation decision. Producers with higher levels of risk aversion would be less likely to prefer high levels of nitrogen fertiliser (Williams et al., 1992; SriRamaratnam et al., 1987). This may imply that the higher the level of risk aversion, the less likely the farmers would achieve Pareto efficiency in the sense that these farmers tend to fear using the optimal level of resources.

5. Analytical techniques

5.1 Efficiency measurement in Data Envelopment Analysis

Five relative measures of efficiency using constant and variable returns to scale assumptions for the frontier are depicted in Figure 2. Let x_1 and x_2 denote the two inputs used in production. The data is initially enveloped with the restrictive technology exhibiting constant returns to scale (CRS) and strong disposability of inputs (SDI)⁵ which is denoted by L^{sk} and represents the isoquant or lower bound of the set of all input combinations for the given output level. Given input prices, as represented by isocost line CD, the cost minimising input combination for the given output level is at point E.

Following Farrell (1957), the overall efficiency for the inputs is defined as the ratio of minimum to actual observed costs and measured as OF/OR for a Decision Making Unit, R (DMU_R) (Figure 2).

Mathematically, to compute the overall *economic efficiency*, EE_j for DMU_j , the following linear programming problem for minimum cost, $MC_j (y_{tj}, x_{ij}, c_{ij})$, for the technology must be solved (Fare et al., 1985, 1994):

⁵ SDI allows for the backward bending of the isoquant.

$$MC_j(y_{rj}, x_{ij}, c_{ij}) = \min_{x_{ij}^*, \lambda_j} c_{ij} \cdot x_{ij}^* \quad \text{-----(1)}$$

subject to :

$$\sum_{j=1}^n y_{rj} \lambda_j - y_{rj} \geq 0$$

$$x_{ij}^* - \sum_{j=1}^n x_{ij} \lambda_j \geq 0$$

$$\lambda_j \geq 0 \quad \text{for } \forall j$$

where,

y_{rj} = represents the known quantity of output r (all positive) from DMU_j,

x_{ij} = represents the known quantity of input i (all positive) from DMU_j,

c_{ij} = the unit price each of the m inputs for DMU_j,

x_{ij}^* = represents the cost minimising vector of input i for the jth DMU, given the input prices c_{ij} ;

u_r = is the weight for output r,

v_i = is the weight for input i,

n = the number of DMUs,

k = the number of outputs,

m = the number of inputs,

λ_j = the N×1 vector of constants and

\forall_j = denotes for 'all' j units

The solution to problem (1) is the estimated minimum cost, $MC_j(y_{rj}, x_{ij}, c_{ij})$, for the farm. Denote the actual cost for observation j as $c_{ij} \times x_{ij}$. Then the cost minimising economic efficiency is defined as the ratio of minimum to actual observed costs:

$$OE_j(y_{rj}, x_{ij}, c_{ij}) = \frac{MC_j(y_{rj}, x_{ij}, c_{ij})}{c_{ij} \times x_{ij}} \quad \text{-----(2)}$$

The overall technical efficiency (TE), the minimising input combination for the given output level is at point S in Figure 2. Farrell proposed to measure this input minimising efficiency as the ratio of efficient input usage to actual input usage which is represented as OS/OR for a rice farm operating at point R. Note that this technical efficiency ($TE = \theta_1$) is independent of input prices and computed by solving the following CCR DEA model (Charnes et. Al.; Fare et al., 1985, 1994).

$$\text{Min}_{\theta_1, \lambda} \theta_1 \quad \text{-----(3)}$$

Subject to :

$$x_{ij} \theta_1 - \sum_{i=1}^m x_{ij} \lambda_j \geq 0; \quad i = 1, \dots, m$$

$$\sum_{j=1}^n y_{rj} \lambda_j - y_{rj} \geq 0; \quad r = 1, \dots, k$$

$$\lambda_j \geq 0 \quad \text{for } \forall_j, \theta_1 \text{ unconstrained}$$

The price dependent component, i.e., the allocative efficiency, AE_R , is measured as OF/OS. This allocative measure captures inefficiency due to the fact that a farmer R, even if on the isoquant with its factor proportions, does not pick the 'right' input combination given relative input prices. The allocative efficiency, AE, is computed as

$$AE_j(y_{rj}, x_{ij}, c_{ij}) = \frac{OE_j(y_{rj}, x_{ij}, c_{ij})}{TE_j(y_{rj}, x_{ij})} \quad \text{-----(4)}$$

where, relative unit price of each of the s outputs that DMU_j receives as p_{rj} .

A summary of the Farrell (1957) decomposition of relative cost minimising efficiency based on the constant returns to scale assumption for the frontier technology is given by

The source of scale inefficiency can be due to either increasing or decreasing returns to scale. There is no prior assumption about the technologies of the observation, therefore the scale properties of the observations are only limited to observations on the frontier (see Banker and Thrall 1992). Scale properties of the inefficient farm are confounded with the overall technical inefficiency.

Following Fare et al. (1985) the sources of scale inefficiency (increasing or decreasing) can be determined by solving an additional DEA problem with non-increasing returns to scale (NIRS) imposed.

This can be done by altering the DEA model in equation (2-10) by substituting the $\sum_{j=1}^n \lambda_j = 1$ restriction

with $\sum_{j=1}^n \lambda_j \leq 1$, to provide

the NIRS TE scores (θ_3).

The nature of the scale inefficiencies (i.e., due to increasing or decreasing returns to scale) for a particular DMU can be determined by examining whether the NIRS TE (θ_3) score is equal to the VRS TE score. If they are unequal then increasing returns to scale exists for that DMU. If they are equal then decreasing returns to scale apply.

$$\begin{aligned} & \text{Max}_{\theta_4, \lambda} \theta_4 && \text{-----(8)} \\ & \text{Subject to} \\ & \sum_{i=1}^m x_{ij} \lambda_j - x_{ij} \theta_4 \geq 0; \quad i=1, \dots, m, \\ & y_{rj} - \sum_{j=1}^n y_{rj} \lambda_j \geq 0; \quad r=1, \dots, s, \\ & \lambda_j \geq 0 \quad \text{for } \forall_j \text{ and } \theta_4 \text{ unconstrained.} \end{aligned}$$

Alternatively, by solving the an additional output oriented BCC DEA model (8) for efficiency measure (θ_4) different scale properties at the corresponding reference points can be determined. One way of getting only one expression for the scale properties for inefficient farms is to determine the average scale property over that part of the envelopment surface between the reference points for inefficient units, and using the relationship established in Forsund and Hjalmarsson (1979) and applied in Forsund and Hernaes (1994). That is:

$$\varepsilon = \frac{\ln(\theta_4)}{\ln(\theta_2)} \text{-----(9)}$$

where θ_4 is the output maximising pure technical efficiency, θ_2 is the input minimising efficiency, and ε is the average scale elasticity. The nature of the average returns to scale is then determined by

$$\begin{aligned} & \text{If } \theta_2 > \theta_4 = \text{increasing average returns to scale} \\ & \text{If } \theta_2 < \theta_4 = \text{decreasing average returns to scale} \end{aligned} \quad \left| \text{-----(10)} \right.$$

5.2 Farm specific characteristics and Tobit regression model

The structural equation of the Tobit model is presented as follows (Long, 1997),

$$Y = \begin{cases} Z\beta + \varepsilon & \text{if } Z\beta + \varepsilon > 0 \text{ and} \\ 0 & \text{if } Z\beta + \varepsilon \leq 0 \end{cases} \text{-----(11)}$$

where:

Z = a vector of regressor variables,

β = a vector of unknown coefficients (Tobit coefficients),

ε = a vector of independent and identically distributed normal random variables assumed to have mean zero, and constant variance, σ^2 .

Unlike the OLS case, the value of a Tobit coefficient does not represent the expected change in the dependent variable given a one unit change in an explanatory variable. Rather, the Tobit model estimates a vector of normalised coefficients which can be transformed into the vector of first derivatives by multiplying the standard error of the estimates. These give the probability of changes in dependent variable due to one unit change in an explanatory variable keeping the other variable constant in the model.

5.3 Measurement of risk attitude

The negative exponential function (Anderson et al, 1977, Chap.4) used to compute the Arrow Pratt's average absolute risk aversion coefficient is represented as:

$$U = 1 - e^{-R_A X} \text{ and } R_A > 0 \text{ -----(12)}$$

where:

U = Scale of utility ranging from 0 to 1 with respect to a corresponding certainty equivalent monetary gain.

R_A = Arrow Pratt's absolute risk aversion coefficient

X = Certainty equivalent monetary gain equivalent to the expected income of a risky prospect

e = natural log

Both variables U and X were generated by interviewing the farm household following the ELCE (equally likely certainty equivalent) method of DEU (direct elicitation of utility function) approach as discussed in Anderson et al. (1977). The parameter ' R_A ' of the above function is estimated using the non-linear least squares technique.

6. Data and methods

6.1 Data Sources

The data used in this study is based on a direct interview survey of 76 randomly selected rice farming households from the 380 households of four adjoining villages of Agyauli-VDC⁶ of Nawalparasi district of Nepal conducted over early 1999. 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 meters altitude above sea level. The farms selected were owner operated, had similar food security objectives, faced a similar economic and marketing environment for inputs and outputs. All the farms used a similar technology of rice production (both inputs and outputs) except for differences in intensity and management.

6.2 Data recording

The questionnaire consisted of three major sections. The first section recorded the socio-economic profiles of the households, the second section recorded rice input, output and their prices, and the third section recorded the choice of 50:50 hypothetical gamble amounts and the corresponding certainty equivalents to obtain the risk attitudes following the Anderson et al. (1997) procedure of ELCE (Equally

⁶ VDC stands for Village Development Committee, a grass root level geopolitical administrative organisation in Nepal.

Likely Certainty Equivalent). The interviews were conducted by the first author and so reduced the chance of interviewer bias that might have arisen with more than one enumerator.

Farmers were introduced to the purpose of the study and made aware of the importance of the information. They were given sufficient time to think, recall, and consult with their family members before answering any question. All active family members took part in the interview. Each interview took, on average, 1.5 hours for collecting section one and two, and 1.5 hours for the elicitation of risk attitude (section III). An attempt was made to create a natural decision environment during the interview similar to what the farmers experience in their day to day business. Immediately after completion of the interview, the data was entered, edited and compiled in a spread sheet. Any inconsistencies and suspicions were corrected by revisiting the interviewee.

6.3 Definitions of the variables

The variables selected for use in this research are defined as follows:

Table 1. Socio-economic variables, their definition and measurement

Variables	Unit	Definitions
Age (z_{1j})	Year	Age of household head ⁷ for DMU j
Age ² (z_{2j})	Year ²	Square of age variable for DMU j
Education (z_{3j})	Year	Household head's years of schooling for DMU j ⁸
Gender (z_{4j})	1, 0	1 if the household is managed by female, 0 otherwise for DMU j.
Family labour (z_{5j})	%	Percentage share of labour from family source consumed in rice production for DMU j.
Risk attitude (z_{6j})	Fraction	Estimated Arrow Patt's average absolute risk aversion coefficients for DMU j.
Rice output (y_{1j})	Kg/farm	Quantity of rice grain yield produced per farm for DMU j
Land (x_{1j})	Kattha/farm	Area of the rice plot wherein input-output data was collected for DMU j. 1kattha = 338.40675 square meters.
Seed (x_{2j})	Kg/farm	Amount of seed used for DMU j
Labour (x_{3j})	Person-days/farm	Total amount of family and hired labour used in rice production for DMU j.
Mechanical labour (x_{4j})	Rs/farm	Cost incurred for using animal power and machine labour (tractor) for rice production for DMU j
Fertiliser (x_{5j})	Rs/farm	Cost incurred for amount of inorganic and organic fertilisers for rice production for DMU j.
Other(x_{6j})	Rs/farm	Cost incurred for using shallow tube-well irrigation, pesticides and herbicides for DMU j.
Land rent (c_{1j})	Rs/kattha	Cost for renting 1 kattha of land for rice production for DMU j.
Seed price (c_{2j})	Rs/kg	Cost for purchasing 1 kg of seed for rice production for DMU j
Wage (c_{3j})	Rs/person-day	Cost for hiring 1-person day labour for rice production for DMU j
Mechanical labour rent (c_{4j})*	Rs	Assumed Rs1 per unit of costs incurred for mechanical labour for DMU j
Fertiliser (c_{5j})*	Rs	Assumed Rs1 per unit of cost incurred for fertilisers for DMU j.
Other inputs (c_{6j})*	Rs	Assumed Rs1 per unit of costs incurred for shallow-tube well irrigation, pesticide and herbicides for DMU j.

* Since variable x_4 , x_5 and x_6 are expressed in value terms, the calculation of the unit price for these inputs are far from satisfactory. Therefore the unit price if these inputs is expressed in Rs 1 as in Ferrier and Lovell (1990).

Note: **Household** refers to the family unit consisting of the close member of families living together

⁷ The person who is responsible for managing the household business is called the household head.

⁸ Those who had no history of formal enrolment in school are considered equivalent to three years primary schooling if they able to read and write. People who can not read and write were considered as illiterate, meaning they have been assigned the value of zero for years of schooling.

sharing the income on private properties commonly.
Rs stands for Ruppes, a Nepalese currency and Rs1 = US\$(1/68). 'Kattha' is a local unit for measuring area of the farm.

6.4 Data Analysis

The five measures of relative efficiencies were computed for each of the seventy-six farms using Data Envelopment Analysis (Charnes et al., 1978; Banker et al., 1984). The inefficiency indices computed by the DEA were then used as the dependent variable in a Tobit (Censored) regression model (Tobin, 1958) using decision makers' attributes as explanatory variables. The explanatory variables included socio-economic variables as well as attitude towards risk represented by the Arrow-Pratt absolute risk aversion coefficient. The Arrow-Pratt risk aversion coefficient was computed using a negative exponential representation of the elicited utility function (Anderson et. al., 1977).

7. Results and discussion

7.1 Descriptive statistics of the data

Table 2 shows the descriptive statistics of the prices, input and output related to rice production of the sample farms. It reveals that farms in sample are small in operating size with differences in intensity of input used and output produced. Most farms have shown little variation in the wage for labour and price for the output.

Table 2. Descriptive statistics of input, output and prices paid / received for the sample farms for 1998 (n=76).

Description	Unit	Mean	Std. Dev.	Minimum	Maximum
Input and output variables (included missing values, zeros)					
Land	Hectare	0.63	0.58	0.08	3.78
Seed	Kg / farm	37.13	33.70	7.5	225
Labour	Person-days/farm	88.88	74.84	19.50	500
Mechanical labour	US\$/farm	32.28	26.42	2.06	139.71
Fertilisers	US\$/farm	22.04	24.30	0.00	142.21
Other inputs	US\$/farm	3.04	4.54	0.00	19.41
Rice yield	Kg/farm	2194	1897.73	300	11500
Price of input and output					
Land rent	US\$/ha	124.41	0.00	124.41	124.41
Seed price	US\$/kg	0.22	0.00	0.22	0.22
Labour wage	US\$/person-day	0.96	0.02	0.96	1.03
Rice grain price	US\$/kg	0.16	0.02	0.10	0.02

Zero represents the no use of the corresponding input.

Table 3. Percentage share of total cost contributed by each input (n =76) for 1998

Description	Mean	Std. 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

Note: 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 very negligible and nearly does not exist.

Table 3 shows that the opportunity costs for using land capital had the highest cost share among the six

inputs. This was followed by the human and mechanical labour inputs. Both shared about 48% of the total cost. The seed and other inputs contributed only 4% of the total costs. All inputs have shown variation in their percentage share of total cost across the farms.

The socio-economic variables are summarised in Table 4. About 60% of the operators had primary level education and 20% had no education at all. A reasonable degree of variation in the level of risk aversion was observed among the farms.

Table 4. Socioeconomic variables for sample farms: Descriptive statistics (n=76)

Description	Unit	Mean	Stand. Dev.	Min	Max	Number of farms
Farm characteristics						
Age	Years	47.15	11.38	26	78	-
Education	Schooling years	4.22	3.46	0	12	-
Male headed household	Number of farms	-	-	-	-	68
Female headed household	Number of farms	-	-	-	-	8
Family size	Number of 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	-

7.2 Average efficiency measures of the Nepalese rice farms

The summary statistics of the relative efficiency⁹ ratings are given in a Table 5. The average level of Farrell's overall economic efficiency is 66%. This means that the sample farms can potentially reduce their overall cost of rice production, on average, by 34% and still achieve the existing level of output.

Table 5: Descriptive statistics of the % efficiency indices of the rice farms (n = 76)

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

Note: 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 (CRS) whereas the latter assumes variable returns to scale (VRS).

The relative level of the allocative and the technical measures provide evidence as to the source of deviation from overall cost-minimising efficiency. The sample of rice farms employed the 'wrong' input mix, given input prices, so that their costs were 13.07% higher than the cost minimising level. On the other hand, the farms have the potential to reduce their physical input, on average, by 24%, and still produce the same level of rice output.

The decomposition of the technical efficiency measure produced the sources of technical inefficiency as 18% pure technical inefficiency and 7% scale inefficiency (Table 5). By eliminating the scale inefficiency the farms can increase their average technical efficiency level from 76% to 82%. The sources of scale inefficiency were also determined and reported in the Table 6. About 47% and 42% of the rice farms exhibited increasing returns to scale (IRS) and decreasing returns to scale (DRS) respectively. Only 11% of the farms exhibited constant returns to scale (CRS) meaning they were operating at the optimal scale. Since scale refers to size, the descriptive statistics of variables indicating the farm size is reported in Table 6.

Table 6. Summary of returns to scale results (sample size = 76)

⁹ The relative efficiency was computed using Warwick DEA software (Thanassoulis and Emrouznejad, 1996).

Characteristics	Unit	Increasing	Constant	Decreasing
Average farm area	Ha	0.35	0.45	0.99
Average output / farm	Kilograms	1219	2291	3267
Average output / ha	Kilograms	3518	5126	3292
Average cost / farm	US\$	156	192	395
Average cost / kg of output	US cents	9.94	8.38	12.09
Average cost / ha	US\$	277	260	398
Average revenue / farm	US\$	191	356	520
Average revenue / ha	US\$	552	797	524
Number of farms	Number	36	8	32

The eight scale efficient farms show medium size but less than the average farm size, lowest average cost per unit of rice output and highest rice yield per unit of land. On the other hand decreasing returns to scale occurs on relatively large farms and they had the lowest yield per unit of area and highest average cost per unit of output. Increasing returns to scale occurs on relatively small size farms that have the moderate output level per hectare of land and average cost per unit of output. The results revealed the U-shaped average cost curve for farm area and output.

In summary, the different efficiency rankings of individual farms provide the evidence in support of the hypothesis that the sample farmers are different in terms of allocative, technical, pure technical and scale efficiencies (Hypotheses 1, 2, 3 and 4). The paired comparison t-test statistic between technical and allocative efficiencies also revealed a significant statistic meaning that technically efficient farms may not be allocatively efficient (in support of hypothesis 4). However, the reason was unknown. It may be guided by farmers' goal or it was just random. (section 4.1 for hypotheses statements).

7.3 Efficiency distribution across the rice farms

The purpose of analysing the efficiency distribution (Table 7) is to gain insight and understanding of the potential productivity improvement on the farms. Only 11% of the rice farms based on the sample were efficient in terms of economic, allocative, technical and scale measures. However, 26 % of farmers demonstrated pure technical efficiency. This reveals that about 15% of the sample farms are technically inefficient due only to inefficient scale of operation.

Table 7 further indicates the different frequency distributions for the different efficiency measures. For example, the proportion of the inefficient farmers having less than 70% EE were 67% which indicates a left skewed frequency distribution curve for economic efficiency measure. On the other hand, 92%, 68%, 78% and 96% of the farmers achieved more than 70% allocative, technical, pure technical and scale efficiency respectively, suggesting a right skewed frequency distribution curve for these measures. The more left skewed the distribution curve is, the higher will be the potential for increasing the productivity on the farms. The overall impression indicates asymmetric efficiency distribution and a substantial potential to improve the economic efficiency of Nepalese rice farms.

Table 7. Distribution of the farms over the relative efficiency spectrum (n=76)

Efficiency (%)	EE	AE	TE	PTE	SE
E<40	2	0	0	0	0
40 ≤ E<50	9	0	2	1	0
50 ≤ E<60	17	1	10	7	1
60 ≤ E<70	23	5	12	9	2
70 ≤ E<80	12	10	23	16	4
80 ≤ E<90	4	25	14	14	9
90 ≤ E<100	1	27	7	9	52
E=100	8	8	8	20	8

E = efficiency, EE= economic efficiency, AE = allocative efficiency, TE = technical efficiency, PTE = pure technical efficiency, SE = scale efficiency

7.4 Farm specific factors related to farm inefficiency

Tobit regression models were estimated to assess the socio-economic factors associated with various measures of inefficiency reported in section 7.2. The Tobit regressions defined in Equation 11 were estimated using the Tobit procedure in Shazam Version 7.0, an econometric computer program. Inefficiency measures were first obtained by subtracting the level of efficiency computed in section 7.2 from 100. Then, each inefficiency measure was regressed on the farmer's age, education, risk aversion, family labour endowment and gender of the household head. All five regression results are summarised in Table 8.

The β is the transformed Tobit normalised coefficient which indicates the effect of a unit change in one of the explanatory variables on the probability of change in the dependent variable, assuming that the other variables are held constant. For example, increasing one year of schooling of the operator would result in 1.43%, 1.40% and 1.41% reduction in the probability of economic, technical and pure technical inefficiencies respectively. All the significant β coefficients presented (Table 8) are interpreted analogously.

The probabilities of explaining the economic, allocative, technical, pure technical and scale inefficiencies by the set of given explanatory variables are 0.98, 0.91, 0.94, 0.78 and 0.63 respectively (see Table 8). The probability value closer to 1 may indicate the robustness of the model and vice versa. This suggests robustness of the four inefficiency models.

Table 8. Tobit regression coefficients and their asymptotic normal statistics testing variation in various measures of inefficiency of the sample farms (n=76)

Independent variables (X_i)	β coefficients corresponding to dependent variable (Y_i)				
	EI	AI	TI	PTI	SI
Constant	-1.3073 (-0.04)	-4.8457 (-0.23)	-9.0747 (-0.27)	-15.107 (-0.34)	-17.872 (-0.64)
Age	2.5863 ^b (1.91)	0.8825 ^d (1.11)	2.50 ^b (1.91)	2.1208 ^c (1.25)	1.2071 ^d (1.13)
Age ²	-0.03175 ^a (-2.34)	-0.010 ^c (-1.26)	-0.0309 ^a (-2.35)	-0.0260 ^c (-1.53)	-0.0134 ^d (-1.25)
Education	-1.4287 ^b (-2.01)	-0.2027 (-0.48)	-1.4014 ^b (-2.09)	-1.4099 ^b (-1.62)	-0.1038 (-0.19)
Risk attitude	2361.0 (0.45)	7636.6 ^c (2.46)	-4536 (-0.92)	-9315.6 ^c (-1.43)	5233.8 ^c (1.30)
Share of labour from family sources (%)	-0.0872 ^d (-1.20)	-0.015 (-0.35)	-0.0773 ^d (-1.12)	-0.0133 (-0.15)	-0.0465 (-0.82)
Gender (1 if household head is female, 0 otherwise)	-9.9015 ^c (-1.46)	-8.1758 ^b (-2.02)	-4.0869 (-0.64)	2.7080 (0.33)	-9.0953 ^b (-1.60)
Standard error of the estimate	16.038	9.4424	15.060	18.944	12.038
The predicted probability of (Y) > limit given average X(I)	0.9799	0.9085	0.9353	0.7755	0.6313
Log likelihood function	-295.03	-257.81	-289.30	-259.26	-221.73
Squared correlation between observed and expected values	0.1492	0.1578	0.1494	0.1232	0.0719

Note: $Y = (n \times 1)$ column vector of dependent variable, $X = (k \times n)$ matrix of independent variables; $n =$ number of DMUs in the sample and $k =$ number of independent variables.

EI, AI, TE, PTI and SI refer to the economic, allocative, TI = technical, PTI = pure technical and SI = scale inefficiency respectively and were entered as a dependent variable (Y_i) separately in five regression equations. Values in parentheses are asymptotic normal statistics for β coefficients for the respective explanatory variables. ^a, ^b, ^c and ^d denote asymptotic normal statistics significant at 1%, 5%, 10% and 15% level respectively.

Further, collinearity diagnostics and heteroskedasticity tests were conducted for all five inefficiency models to evaluate these assumptions in a Tobit framework. OLS regressions were used to perform the

tests.¹⁰ The tests show no evidence of collinearity and heteroskedasticity except for the scale inefficiency model. This indicates the usefulness of the data for drawing policy implications based on economic, allocative, technical and pure technical inefficiency models for improving the total factor productivity.

The results showed that the farmer's age has significant and positive, but quadratic, effect on economic, allocative, technical, pure technical and scale inefficiencies at below 15% significance level. This negates the hypothesis that younger farmers are less inefficient than their older counterparts. The results indicate younger farmers are less likely to be technically as well as allocatively more inefficient compared to their older counterparts, probably due to the fact that younger farmers are less experienced, and hence less knowledgeable in rice farming practices as compared to their older counterparts. The effect of experience on firm decisions have been long been recognised by economists (e.g. Rausser, 1978). Kalirajan and Shand (1985) and Stefanou and Saxena (1988) also found a positive effect of experience on farm productivity. On the contrary, Llewelyn and Williams (1996) found that younger farmers are more technically efficient than their older counterparts. This may suggest some policy implications such that the dissemination of the best farming practices should be strategically focused to younger operators to reduce the average inefficiency of the population.

The results also revealed a consistent pattern of a negative but significant relationship between operators' years of schooling, and economic, technical and pure technical inefficiencies, consistent with what is expected. The more educated farmers are less likely to be inefficient as compared to their less educated counterparts, perhaps due to their better skills, access to information and good farm planning. Similar results also reported by Mock (1981), 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). This finding may have the following policy implications - in the long run, increasing private and public investment in education may lend to better performance of the agricultural sector. However, in the immediate short run individual inefficient farmers may be better off by learning from the benchmarking practices of the relatively efficient farms in their locality. Government and non-government organisations as well as individuals should give attention to educating the inefficient farms about the best practices of their efficient counterparts. This can be done by farmer's field days at the efficient farms.

A mixed result was found between risk aversion and various measures of inefficiency. Risk aversion is significantly and positively related with allocative and scale inefficiencies at 10% level and negatively related with pure technical inefficiency. The technical inefficiency coefficient, though appeared insignificant, shows a negative relation. Further the correlation between farmers' level of risk aversion and level of input use shows mixed results. For example, risk aversion is positively correlated with inputs such as land, seed and human labour, and negatively correlated with the factors such as mechanical labour, fertiliser, chemicals and irrigation. The interesting result is that the more risk averse the farmers are, the greater the chance of allocating higher levels of their own inputs and less levels of purchased inputs. Inputs such as land, seed and human labour are the inputs that the sample farmers mostly contributed from their household resources. On the contrary, inputs such as chemical fertilisers, mechanical labour and chemicals should be purchased in the market for which they would have no direct control over their timely availability and prices.

Based on the arguments above, the overall impression is that farmers who have high levels of risk aversion are likely to be more cost inefficient but less technically inefficient. This is probably because of their tendency to maximise the use of household resources while minimising the use of outside resources over which they would have little or no control. Contrary to this, Llewelyn and Williams (1996) reported higher fertilizer use, particularly of urea associated with the least efficient farms, arguing that it may be due to the 'risk evasive action' of the inefficient farms. On the other hand, consistent with the finding of this research, other studies (such as Williams et al., 1992; SriRamaratnam et al., 1987) found that producers with higher levels of risk aversion would be less likely to prefer high levels of nitrogen.

The following policy conclusion can be drawn from the finding. Often it would not be possible for highly risk averse farmers to reduce their inefficiency by using their traditional resources such as own land,

¹⁰There is no formal procedure available for carrying out diagnostic tests in the Tobit model itself (Long, 1997).

seed and family labour. When technological advancement continues to occur more fertilisers, chemicals and mechanical labour may be necessary to attain the economic threshold level of production. In such a situation, highly risk averse farmers are likely to be more economically inefficient than their less risk averse counterparts. On the other hand, the least risk averse farmers perhaps may tend to use excessive resources so that they would be operating at decreasing returns to scale and hence reducing their efficiency further. Both high, as well as low (at the extremes), levels of risk aversion relative to input allocation could possibly be due to a lack of knowledge on best practices. This can be remedied by educating the farmers about the efficient practices through bench marking exercises.

The results also showed consistent negative coefficients for all inefficiency measures but only significant relationships between the percentage share of labour from family sources and economic and technical inefficiency at 15% level. This negates the evidence against the widely held belief that farmers in developing economies are excessively using their family labour resources, and hence operating inefficiently. Instead it indicates that farmers were using their family labour more efficiently. This may be due to the scarcity of seasonal labour available. Farmers with a large pool of family labour are able to use them at the right time. On the other hand, farmers who depend on hiring labour for cultivation may not be able to use them at the right time because of the scarcity of labour at peak cultivation times. Public policy should also support the introduction of the labour saving technology in rice farming considering that it would not jeopardise the employment opportunities. However, the findings should be validated through future research before adopting any new policy.

The gender dummy showed a negative effect on all inefficiency measures except technical inefficiency but significant effect on economic, allocative and scale inefficiencies at 10% level. This indicates that women managers are relatively price efficient in the use of the inputs at their disposal, although this did not translate into having higher economic efficiency. In addition, four Tobit regressions out of the five suggest a consistent pattern of these negative relationships between gender and farm inefficiencies indicating that female household heads (operators) tend to be less inefficient compared to their male counterparts. This finding indicates 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 Mook (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. Considering the extensive involvement of women in Nepalese rice farming, it would be economically rational to involve them in rice development strategies.

8. Conclusions

Four main findings arise from the analysis of inefficiency. First, realisation of an inefficiency problem at the farm level is necessary on the part of farmers and agencies that are involved, or interested, in agricultural development programs. The findings revealed that more than 90% of the farmers are producing above minimum cost. On average, 34% of the total costs of the sample farms could be saved. The cost savings can be achieved by using inputs up to the level at which their marginal contribution to productive value is equal to the factor costs. This would help to reduce the existing level of factor costs, on average, by 13%. The second involves using less inputs to achieve a similar level of output. This would save, on average, 24% of the currently used quantity of factor inputs. About 90% of the farms are scale inefficient. Operating at the optimal scale, these farms can save 7% of their currently used resources. Operating at the best practices, farm families would be able to use the surplus savings (otherwise wasted) in alternative economic activities to generate extra income for the family's welfare or, they can invest in rice farming to purchase new technologies such as improved seeds, fertilisers and land improvement. The surplus resources, such as fertiliser, can be reallocated to increase the productivity of other crops such as wheat, maize, potato, etc where lack of fertiliser is a problem. Similarly, the surplus labour can be re-deployed to other economic activities such as livestock enterprises, vegetable farming or, off-farm employment if an opportunity exists. Alternatively, surplus family labour can be spent for leisure and household welfare activities such as taking care of children. Surplus seed can be used to supplement food for the family.

Second, the inefficient farms can emulate the best practices of efficient farms. Benchmarking could be helpful for setting the targets and finding out the weakness of the current practices. The efficient farms can also improve their efficiency further through exchanging and learning the best allocation decisions from

other efficient farms.

Third, according to the results of this study and other research, the factors which significantly impact farmers' resource allocation decisions differ widely among farmers. Program effectiveness will depend largely on the extent to which such differences are recognised. To be successful, efficiency improvement programs must be flexible enough to accommodate the diversity of both farmers and their need for improvements. For example, separate groups of younger and older, educated and uneducated, high, medium and less risk averse farmers are required. Similarly, developing and implementing suitable programs for farmers who are inefficient in fertiliser, seed, labour and chemical use separately would increase the chances of achieving success.

Finally, the results suggest that implementing education programs on best practices already adopted by the farms can boost the current productivity level. Therefore, individuals, government and non-government organisations involved, or interested, in agricultural development programs should make an effort to increase their investment in education.

9. Research limitation:

One of the limitations of this research arises from the limited sample size. The findings and the conclusions are specific to the rice farms of the research villages. In order to extrapolate them to the whole population of rice producers in the district, or in Nepal, it would be necessary to obtain further samples.

Farm input - output results might vary from season to season because they mostly depend upon the climatic factors such as rainfall, humidity, sun light, temperature (soil and air) and wind. The efficiency analysis carried out in this research is based on a single season (June-December, 1998). Variation may occur because of several reasons. There may be changes in individual's decision making behaviour due to the impact of learning and experience, biophysical environments such as soil and climate may change over time and they may have a consequent impact on farms' input-output decisions. Thus, the results should not be taken as fixed rather they should be used as indicators of areas of weakness of the farms.

Variations in the quality of inputs and output are common among agricultural producers. The quality variations may have substantial effect on determining the level of farm efficiency. For example, the quality of the farmland such as natural soil fertility, soil texture and structure, seed quality and labour skill, the quality of output may all affect efficiency. Similarly, other factors such as the timing of fertiliser application, irrigation, transplanting and weeding can have an impact on efficiency. These factors were not taken into account in this research. Therefore, the misallocation may not be limited to only factors such as land, seed, fertilisers, human labour, mechanical labour, irrigation and chemicals which were accounted for in this research.

A final important limitation is the deterministic feature of the DEA technique and the fact that only one year data was available. This means that the computed efficiency indices may reflect random factors such as weather and prices. This might have produced biased results. To mitigate this problem, as an alternative a stochastic model could be used for this research but it also suffers from criticism such as the arbitrary assumption of the functional form for the technology which must be used to construct the frontier and may also result in inaccurate efficiency indices.

10. Future research

It was concluded that there was a substantial variation in the allocative and technical efficiency among the rice farms of the sample. The magnitude and the specific sources of inefficiency, such as physical input and factor costs, varied among the sample farmers. It would be interesting to develop the appropriate frontier model that encompasses all components of the whole farming system and captures the quality and time variation in the input and output. Focusing on other factors that are not incorporated in the model through revisiting the farms of the sample in the research area would also be interesting. Comparing the efficiency analysis using both the DEA and stochastic frontier method would also be fascinating.

References

- Ali, M., and Flinn, J.C. (1989). Profit efficiency among Basmati rice producers in Pakistan Punjab. *American Journal of Agricultural Economics*, 71, 303 - 310.
- Ali, M., and Chaudhry, M. A. (1990). Inter-regional farm efficiency in Pakistan's Punjab: a frontier production function study. *Journal of Agricultural Economics*, 41, 62-74
- Anderson, J., Dillion, J. and Hardakar, J. (1977). *Agricultural Decision analysis*. Ames: Iowa State University Press.
- APPROSC/ JMA (1995). *Agricultural Perspective Plan, Nepal*. Prepared for: National Planning Commission, His Majesty's Government of Nepal and Asian Development Bank. Agriculture Project Service Centre (APROSC) and John Mellor Associates, Inc. Washington.
- Bajrachrya, D. (1983). *Fuel, food, or forest? Dilemmas in a Nepali village*. *World Development* 11, No. 12.
- Banker, R. D., and Maindiratta, A. (1988). Non-parametric analysis of technical and allocative efficiency in Production. *Econometrica*, 56, 1315-1332.
- 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.
- Banker, R.D., Charnes, A., and Cooper, W.W.(1984). Models for the estimation of technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30, 1078-1092.
- Battese, G.E., Coelli, T.J. (1995). A model for technical efficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*.
- Battese, G.E., Malik, S.J., Gill, M.A. (1996). An investigation of technical inefficiencies of production of wheat farmers in four districts of Pakistan. *Journal of Agricultural Economics*, 47, 37-49.
- Battese, G.E., T.J. Coelli and T. C. Colby (1989). Estimation of frontier production function and the efficiency of Indian farms using panel data from ICRISAT's village level studies. *Journal of Quantitative Economics*, 5, 327-348.
- Bauer, Paul W. (1990). Recent development in the econometric estimation of frontiers. *Journal of Econometrics*, 46,39-56.
- Belbase, K. and R. Grabowski (1985). Technical efficiency in Nepalese agriculture. *Journal of Developing Areas*, 19, 515-525.

- Bravo-Ureta, B.E. and Evenson, R.E. (1994). efficiency in agricultural production: The Case of peasant farmers in Eastern Paraguay. *Agricultural Economics*, 10, 27-37.
- Bravo-Ureta, B.E., Rieger, L. (1990). Alternative production frontier methodologies and dairy farm efficiency. *Journal of Agricultural Economics*, 41, 215-226.
- Byrnes, Patricia and Valdmanis, Vivian (1994). Analysing technical efficiency of hospitals. In Charnes, Abraham; Cooper, Williams; Lewin, Arie Y.; and Seiford, Lawrence M. (ed.), *Data Envelopment Analysis: Theory, Methodology and Application*. Kluwer Academic Publishers, Boston/Dordrecht/London.
- CBS (1998). *Statistical Year Book of Nepal*. His majesty's Government of Nepal, National Planning Commission Secretariat, Central Bureau of Statistics, Kathmandu.
- Charnes, A.; Cooper, W.W.; and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2, 429-444.
- Chavas, J. P. and Aliber, M; (1993). An analysis of economic efficiency in agriculture: a non-parametric approach. *Journal of Agriculture and Resource Economics*, 18, 1-16.
- Coelli, T.J. (1995). Recent developments in frontier modelling and efficiency measurement. *Australian Journal of Agricultural Economics*, 39, 219-245
- Thanassoulis, Emmanuel and Emrouznejad, Ali (1996). *Warwick Windows DEA User's Guide*. Warwick Business School, UK.
- FAO (1985). Women in developing agriculture. Food and Agricultural Organisation of the United Nations, Rome.
- Fare, R., Grosskopf, S., and Lovell, C. A. K. (1985). *The measurement of efficiency of production*. Kluwer-Nijhoff Publishing, Boston, MA.
- Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of Royal Statistical Society*, 120, 11-37
- Ferrier, G.D. and Lovell, C.A.K. (1990). Measuring cost efficiency in banking: econometric and linear programming evidence. *Journal of Econometrics*, 46, 229-245.
- Forsund, F. R. and Hjalmarsson, L. (1979). Generalised Farrell measures of efficiency: an application to milk processing in Swedish Dairies. *Economic Journal*, 89, 294-315.

Forsund, Finn R. and Hernaes, Erik (1994). A comparative analysis of ferry transport in Norway. In Charnes, A., Cooper, Williams W., Lewin, Arie Y. and Seiford, Lawrence M. (ed.), *Data Envelopment Analysis: Theory, methodology and applications*. Kulwer Academic Publisher, Boston/Dordrecht/London.

Ghatak, S., Ingerset, K. (1984). *Agriculture and economic development*. John Hopkins Univ. Press, Baltimore.

Gladwin, C.H. (editor) (1991). *Structural adjustment and African women farmers*. University of Florida Press, Gainesville, FL.

Hallam, D. and Machado, F. (1996). Efficiency analysis with panel data: A study of Portuguese dairy farms. *European Review of Agricultural Economics*, 12, 79-93.

Jaforullah, M. (1999). A comparison of production frontier methods using Bangladesh Handloom textile industry data. *Economic Discussion Papers No. 9911*, University of Otago, New Zealand.

Kalirajan, K.P. (1991). The importance of efficient use in the adoption of technology: a macro panel data analysis. *Journal of Production Analysis*, 2, 113-126.

Kalirajan, K.P., and Shand, R.T. (1985). Types of education and agricultural productivity: a quantitative analysis of Tamil Nadu rice farming. *Journal of Development Studies*, 21, 232-243.

Kumar, S. K. and Hotchkiss, D. (1988). *Consequences of deforestation for women's time allocation, agricultural production, and nutrition in hill areas of Nepal*. Research Report No. 69. International Food Policy Research Institute, Washington D.C.

Kumbhakar, S. C., Ghosh, S. C. and McGuckin, J. T. (1991). A generalised production frontier approach for estimating determinants of inefficiency in U. S. dairy farms. *Journal of Business and Economic Statistics*, 9, 279-286.

Lele, U. (1991). Women, structural adjustment, and transformaton: Some lessons and questions from the African experience. In: C.H. Gladwin (ed.), *Structural adjustment and African women farmers*. University of Florida Press, Ginsville, FL, pp. 46-80.

Llewelyn, Richard V., and Williams, Jeffery R (1996). Non-parametric analysis of technical, pure technical and scale efficiencies for food crop production in East Java, Indonesia. *Journal of Agricultural Economics*, 15, 113-126.

- Long, J. Scott (1997). *Regression models for categorical and limited dependent variables*. SAGE Publications, Thousand/ Oaks/ London/ New Delhi.
- Maddala, G. S. (1985). *Limited-dependent and qualitative variables in econometrics*. Econometric Society Monograph No. 3. Cambridge University Press, Cambridge, U.K
- Moock, P. (1976). The efficiency of women as farm managers: Kenya. *American Journal of Agricultural Economics*, 58, 831-835.
- MOF (1998). *Economic Survey Report*. Ministry of Finance, His Majesty's Government, Kathmandu, Nepal.
- Parikh, A., Ali, F., Shah, M.K. (1995). Measurement of economic efficiency in Pakistani agriculture. *American Journal of Agricultural Economics*, 77, 675-685.
- Rausser, G.C. (1978). Active learning, control theory and agricultural policy. *American Journal of Agricultural Economics*, 60, 476-90.
- Ray, S. (1988). Data envelopment analysis, nondiscretionary inputs and efficiency: an alternative interpretation. *Socio-Economic Planning Science*, 22, 167-176.
- Russel, N.P. and Young, T. (1983). Frontier production functions and the measurement of technical efficiency. *Journal of Agricultural Economics*, 34, 139-150.
- Schultz, T.W. (1964). *Transforming traditional agriculture*. Yale University Press, New Haven, CT.
- Shapiro, K. H. (1983). Efficiency differentials in peasant agriculture and their implications for development policies. *Journal of Development Studies*, 19, 179-190.
- Sharma, Khem R., Leung, PingSun, Zaleski, Halina M. (1999). Technical, allocative and economic efficiencies in swine production in hawaii: A comparison of parametric and nonparametric approaches. *Agricultural Economics*, 20: 23-35.
- SHAZAM Econometric Computer Program (1993). *User's Reference manual Version 7.0*. McGraw-Hill Book Company.
- SriRamaratnam, S, Bessler, D.A., Rister, M.E., Matocha, J.E. and Novak, J. (1987). Fertilisation under uncertainty: an analysis based on producer yield expectations. *American Journal of Agricultural Economics*, 69, 349-357.
- Stefanou, S.E. and Saxena, S. (1988). Education, experience and allocative efficiency: a dual approach.

American Journal of Agricultural Economics, 70, 338-345.

Tadesse, Bedassa and Krishnamoorthy, S. (1997). Technical efficiency in paddy farms of Tamil Nadu: an analysis based on farm size and ecological zone. *Agricultural Economics*, 16, 185-192.

Thapa, G.B. and Rosegrant, M.W. (1995). *Projections and policy implications of food supply and demand in Nepal to the year 2020*. Winrock International, Policy Analysis in Agriculture and Related Resource Management, Research Report No. 30.

Tobin, J. (1958). Estimation of relationship for limited dependent variables. *Econometrica*, 26, 26-36

Torkamani, Javad, and Hardaker, J. Brian (1996). A study of economic efficiency of Iranian farmers in Ramjerd district: an application of stochastic programming. *Journal of Agricultural Economics*, 14, 73-83.

Varian, H. (1984). The nonparametric approach to production analysis. *Econometrica*, 52, 579-97.

Wang, J., Cramer, G.L., and Wailes, E.J. (1996). A shadow price frontier measurement of profit efficiency in Chinese agriculture. *American Journal of Agricultural Economics*, 78, 146-156.

Williams, J. R., Maddux, L.D., Barnes, P.L. and Rowell, C. P. (1992). Risk analysis of nitrogen fertilisation rates for corn and soybeans. *Journal of Production Agriculture*, 5, 226-232.

Wilson, P., Hadley, D., Ramsden, S. and Kaltsas, I. (1998). Measuring and explaining technical efficiency in U. K. potato production. *Journal of Agricultural Economics*, 49, 294-305.

World Development Report (1997). Published for the World Bank, Oxford University Press.

Xu, Xiaosong and Jeffrey, Scott R. (1998). Efficiency and technical progress in traditional and modern agriculture: evidence from rice production in China. *Agricultural Economics*, 18, 157-165.

Yotopoulos, P. A. and Nugent, J. B. (1976). *Economic development: Empirical investigations*. Harper and Row, New York.