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Measuring the Extent of Technical Inefficiency in Nepalese Agriculture Using SDF and DEA Models

by

Chandra Bahadur Adhikari
Trond Bjørndal

SNF Project No. 1105
Mat- og ressursøkonomi

INSTITUTE FOR RESEARCH IN ECONOMICS AND BUSINESS ADMINISTRATION
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Chandra Bahadur Adhikari[1]

and

Trond Bjorndal

Abstract

Alleviation of poverty is a central issue in Nepal. Given the limited stock of land, and the infant/unorganised manufacturing sector, increased demand for food has to be satisfied by improving production efficiency. This paper examines how this could be achieved. An SDF model and DEA model identify the existence of a high degree of technical inefficiency in Nepalese agricultural production system, suggesting that there is a substantial prospect of increasing agricultural productivity using the existing level of inputs and resources more efficiently. Among the three farm sizes in the data set, medium size farmers achieve a higher technical efficiency than large and small farm sizes, suggesting that productive efficiency can be increased with the encouragement of creating medium size holdings. The observed decreasing returns to scale also implies that productivity gains could be achieved by breaking up of large farms into small family farms. The technical inefficiency model suggests the potential for shifting production frontier upwards by providing ownership of land, increasing farmers' education, and knowledge and increasing land quality including irrigation facilities.

JEL Classifications: D24; L25; Q12

Key Words: Technical efficiency; Farm size; Distance Function; DEA; Nepal

[1] Corresponding author. Corresponding address: 48 Blenheim Road, Reading, UK, RG1 5NQ.
E-mail addresses: chandra.adhikari@gmail.comk (C. B. Adhikari); Trond.Bjorndal@port.ac.uk (T. Bjorndal).

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I. Introduction

In Nepal, much effort, time and money have been employed in different sectors of the economy to reduce poverty and inequality. During the last decade, aggregate poverty declined, however, the decline was uneven across geographical regions. This resulted in a sharp increase in regional inequality (WB, 2006). Recently, all political parties have agreed to alleviate poverty through land. However, as Nepal is a mountainous country, only a small part of the land could be brought under cultivation. Population pressure on the limited supply of useful land has been mounting over the years. Against this background, the aim of this article is to extract the principal findings from the empirical analyses of technical efficiency and relate them to the research questions.

In this article two methods of analysis, namely the parametric stochastic distance function (SDF) and the non-parametric data envelopment analysis (DEA), will be applied using the farm household survey data to measure technical efficiency in Nepalese agriculture. The primary analysis is based on the parametric SDF approach to measuring levels of technical efficiency. Using the same dataset, technical efficiency is also measured by applying the non-parametric DEA methodology to check the consistency and robustness of the specified model and to compare results between parametric and non-parametric techniques. The estimated technical efficiencies are also related across farm-size groups to address the age-old debate in the international literature on farm size and efficiency. The efficiencies will also be related to the specific geographic and ecological zones distinct to Nepalese agriculture.

The article is organized as follows. Section 2 briefly explains the basic characteristics of the farming system and the data, including the source and method of collection. Section 3 discusses the construction of variables used to estimate the empirical models. Section 4 presents the estimated results from the SDF frontier model. Results on returns to scale and technical efficiency are discussed further in different subsections. Technical efficiency scores are also connected to farm size and ecological zone. Section 5 estimates the non-parametric DEA model and compares the technical efficiency results with those derived from the parametric methodology. This section also compares results on the determinants of farm efficiency between the direct estimates (first stage) obtained from the SDF model and the second stage results from the DEA model. The article ends with conclusions and a discussion of policy implications in Section 6.

II. Basic Characteristics of Farming and Data

Nepal is a landlocked mountainous country. Steep slopes and permanent snow cover large areas; hence, only 20% of Nepal's total land is cultivated. Nepalese society is very hierarchical in nature in terms of production relations. Land appears to be one of the basic assets and the main source of income for the majority of Nepalese people. However, the scarce farmland is unequally distributed and typically misallocated among potential users (NPC, 1998; WB, 2006). Much of the agricultural land is occupied by a small number of upper income households, whereas a large number of lower income households are obliged to survive with less. Landowners, who have more agricultural land, have fewer farming skills, and those with more skills have less adequate land for cultivation. Cultivation methods are still non-mechanised. The landholding class that extracts the major share of the agricultural surplus largely invests in sectors other than agriculture. Agricultural productivity is much lower than in other countries in the region. Consequently, the relationship between land and poverty is embedded in Nepalese agrarian society.[2]

A major portion of the income for poor people still comes from cultivation. Due to the specific nature of the subsistence type of rural economy, and the relationship existing among the different modes of peasantry (landowning and landless) and the patron-client relationship, people attach a unique value to land. Land has not only been the source of survival, family wealth and income generation, it has also provided a way of life and maintaining dignity. Lack of access to land can push people to social exclusion, reduce human capabilities and lead to political uprisings, violence and conflict

The prospect of expanding agricultural land in Nepal is virtually non-existent. Increased food production to meet the needs of the growing population in the long term will have to come mainly through improvements in production efficiency and appropriate reorganisation of existing agricultural land. Hence, it is crucial to examine whether land reform can be a viable strategy in a subsistence agricultural country like Nepal. The answer to that question requires a comprehensive empirical study on productive efficiency in agriculture with respect to a redistributive land reform programme and its ability to ameliorate poverty.

The data for this study are taken from the Nepal Living Standards Survey (NLSS) conducted in 2003 by Central Bureau of Statistics (CBS) Nepal. A final adjusted total sample of 2,585 households is used for the empirical analyses in this article. The NLSS 2003/04 (CBS, 2004) details sampling and

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[2] However, the scarce farmland is unequally distributed and typically misallocated among potential users (NPC, 1998; WB, 2006). Much of the agricultural land is occupied by a small number of upper income households, whereas a large number of lower income households are obliged to survive with less. Landowners, who have more agricultural land, have fewer farming skills, and those with more skills have less adequate land for cultivation. Cultivation methods are still non-mechanised. The landholding class that extracts the major share of the agricultural surplus largely invests in sectors other than agriculture. Agricultural productivity is much lower than in other countries in the region. Consequently, the relationship between land and poverty is embedded in Nepalese agrarian society.

data collection procedures as well as the instruments employed in the survey. The NLSS was with assistance from the World Bank and the UK Department for International Development (DFID), strictly following the World Bank's Living Standard Measurement Survey (LSMS) method. The survey provides a large database including detailed input and output data on agricultural production and wide range of household-specific social and economic information. The sample was taken from six geographical strata. A two-stage stratified sampling method was used to select the sample households. The sampling population consisted of 36,067 Primary Sampling Units (PSU) spread over all 75 districts of Nepal. The PSU are wards that represent the smallest administrative units of the country. In the first stage, 334 PSU were randomly selected. In the second stage, 12 households were chosen for the interview with equal probability from each selected PSU, totalling 4,008 households. The survey was unable to reach eight PSU even after repeated attempts due to a Maoist insurgency. Accordingly, these were dropped. The actual sample was 3,912 households covering 326 PSU representing all ecological zones in Nepal. It was problematic to include the sharecropping household data in the analysis for two reasons: first, there was no market value for sharecropped land and second, there was no location information for those lands. Therefore, sharecropping observations were excluded due to incomplete or missing data. Some observations with implausibly low or high values were dropped as outliers. Recording or entry errors might have been responsible for the extreme values in these observations. It was problematic to include the sharecropping household data in the analysis for two reasons: first, there was no market value for sharecropped land and second, there was no location information for those lands.

The dataset provides the information necessary to estimate the proposed empirical models discussed in this study.

III. Construction of Variables and Farm Size

Construction of Output Variables

A production technology is characterised as the transformation of a set of inputs into a set of outputs. In the context of efficiency and productivity measurement, the choice of output variable(s) is very important. Many previous studies used physical yields of specific crops or the value of products per unit of farmland as the output variable.[3] However, these are not relevant measures of overall efficiency since they are partial indices (Binswanger, Deininger and Feder, 1995).

Moreover, agriculture is characterised by a joint production system where a specific set of inputs is used to produce a specific set of outputs. Specifically, small farm households in Nepal engage in subsistence mixed farming.

[3] Examples include Kimhi, 2006; Dorward, 1999; Haq, Khan and Ahmad, 2002; Alvarez and Arias, 2004.

Cereal crops dominate the peasant households, who sell some surplus or purchase some deficit amount of food items. Some recent studies attempted to aggregate total output into a single index, assuming all crops are equally important. Obviously, this may not be true. In this study four output variables are defined, incorporating 67 different crops, 7 livestock products, and some other farm related production output contained in the survey data.[4]

Each output variable is measured in terms of Nepalese rupees (NR) and is obtained by multiplying the physical quantity by its respective average price.[5] The average price for each product was calculated from the per-unit selling prices of households.

The four output variables are as follows: q_1= Cereal crop: This group includes paddy, maize, wheat, and other cereal crops and accounts for 49.05% of total agricultural produce in the dataset. q_2= Pulses: This output includes 11 different types of pulses and legumes and 5 tuber and bulb crops and represents 9.84% of total production. q_3= Cash crops consists of cash crops such as sugarcane, jute, tobacco, cotton, 5 oil seed crops, 8 spices and different winter and summer vegetables which comprise 31.09% of total output. q_4= Other outputs: This includes 5 citrus and 12 non-citrus fruits and other minor outputs.

Construction of Production Inputs

Six production variables are defined so as to encompass the inputs used in agricultural production:x_1=Human labour (hours): In Nepal human labour is intensively used in farming practices as mechanical inputs like tractors and power tillers are not common.[6] The hired labour and family labour were added in order to construct the labour variable. The unit of labour employed is taken in standard hours.

Farmed Land (hectares): Total land was divided into irrigated and rain-fed and treated as two separate production inputs as follows:X_2= Irrigated land (hectares): area of farmed land with irrigation facilities. X_3= Rain-fed land (hectares): area of farmed land without irrigation facilities.

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[4]Other household incomes derived from a variety of sources such as labour wages, non-agricultural enterprises/activities, remittances and transfer incomes, interests earned from bank accounts, shares, stocks, and treasury bills, internal and external pensions were excluded. The obvious reason for the non-inclusion of such incomes is that they have no direct connection to farm outputs.

[5] In the NLSS 12 different units were used to measure agricultural product. It was therefore a little cumbersome to construct the average price.

[6] Collecting accurate data on labour inputs in smallholder agriculture is difficult. However, in this study this variable is constructed as follows. As there was no standard wage rate for the hired labour in the data, a common daily wage rate was calculated from the prevailing rate that each household paid for hiring labour. The total number of hired labour hours for each household was then calculated by dividing the total expenditure for hired labour by the average wage rate. The family labour employed was calculated indirectly from the amount of time each family member engaged in agricultural activity during the year.

X_4= Capital service[7] (Rs): The capital share is included in the model as a proxy of risk aversion. First, farm assets and domestic animals are aggregated based on their respective prices. The capital service variable is then constructed, calculated as 10 percent[8] of the total amount of farm assets.

X_5 = Purchased inputs (Rs): Expenses for purchased inputs, in particular fertilizers and seeds.

X_6= Other Costs (Rs): This variable includes the costs of irrigation, transportation, storage, improvements on land, repair and maintenance of equipment, veterinary services, animal fodder, and rent for draught animals, tractors, threshers and other machinery (expressed in Rs).

A number of households contained zero observations for either output or input variables. This problem has been addressed by constructing additional dummy variables that indicate for every observation whether each of the (four output and six input) variables has a zero value. This procedure means that efficient estimates are obtained using the full dataset.

Construction of Farm-Specific Variables

In addition to the variables described above, eight relevant farm-specific variables are included in the inefficiency effect model:

Z_1 = Owned land (hectares): To capture the effect of access to agricultural credit the amount of owned land is included in the model as a proxy of the ability of the owner to obtain credit by offering the land as collateral.

Z_2 = Value of land per hectare (Rs) is measured as the market value of land owned.

Z_3 = Extension Service (dummy): This takes on the value of 1 if agriculture extension service is received and 0 otherwise.

Z_4 = Age of the head of the household (years): This is intended to represent the experience of the farm manager.

Z_5 = Family head's education (years): This is the level of formal education (in terms of years) by the household head and is a proxy for the farm manager's skill.

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[7] Farm assets and domestic animals are the major forms of household wealth or stock of capital in rural Nepal. Farmers rely on domestic cattle for draught power including tillage and transport, manure, milk, meat and as a stock of wealth. Farm equipment includes ploughs, carts, threshers, water pumps, tractors and power tillers, while livestock comprises buffaloes, bullocks, cows, donkeys, horses, mules, yaks and others.

[8] In Nepal the official nominal interest rate is 10%. The capital share is taken as the equivalent of the interest rate.

Z_6 = Access to road (hours) is the distance from the farm to a vehicle passable road.

In Nepal, there are three main different agro-climatic zones: the Terai, Mountain and Hill regions. Each region is significantly diversified in terms of elevation and mode of agricultural production. For this reason, regional dummies are included in the model with the Terai region is reference:

Z_7 = Mountain dummy, i.e., the value is 1 if the farm is located in the Mountain region and 0 otherwise.

Z_8 = Hill dummy, i.e., the value is 1 if the farm is located in the Hill region and 0 otherwise.

In order to provide an insight into the age-old debate on small vs. large farm efficiency differences, this analysis aggregates groups of farms into small, medium and large based on the size of the operational holding. Following the World Bank (2006), farm size is categorised as follows: small farms are less than 1.00 hectares, medium farms are 1.00 to 2.00 hectares, and large farms are 2.00 hectares or more.

Descriptive statistics for the farm data are presented in the Table 1. After discussing background and data the next section employs the empirical model of parametric SDF frontier to examine technical efficiency in Nepalese agriculture.

IV. Parametric Stochastic Distance Function (SDF) Analysis

The principal methodology employed in this article to measure technical efficiency is the stochastic distance function (SDF) approach. The main reason for this specification is that agriculture in developing countries shows substantial variability in production due to random factors, including resource availability, missing variables, environmental influences, weather, and measurement errors. Consequently, the frontier and technical efficiency results derived from deterministic methodologies, as well as DEA methods, could lead to biased estimates because those methods do not address stochasticity in the empirical model. Agriculture is also a joint production system where multiple outputs are produced by using multiple inputs. Previous stochastic frontier analyses are based on a single output or aggregated single index output, implicitly assuming that the weight of all products is equal. To overcome this problem, the distance function technique is applied to estimate the stochastic frontier that can accommodate the multi-output multi-input problem.

Depending on the nature of the production system, a distance function can be specified with either an input or an output orientation. If the application of inputs is more flexible than the outputs produced, the best choice is an output-oriented specification (Coelli *et al.*, 2005, Paul and Nehring, 2005). On the other hand, if inputs are essentially fixed, then output composition is the primary economic performance determinant and an input-oriented specification is preferable. In Nepalese agriculture the balance of inputs used is more flexible than outputs and therefore an output distance function is specified and the results are compared and contrasted with the results obtained from the non-parametric DEA model.

The translog SDF methodology employed largely follows Pascoe, Koundouri and Bjørndal (2007), O'Donnell and Coelli (2005), Paul and Nehring (2005), and Coelli and Perelman (1996, 2000). Those authors extended their methodology from that of Shephard (1970).

Given a production possibility frontier, the distance between the frontier and a specific farm is a function of the vector of inputs used, '**x'**, and the level of outputs produced, '**y'**. Consider a case of a multiple output multiple input production function, where a farm uses the p×1 input vector $\boldsymbol{x} = (x_1, \ldots\ x_p)'$ to produce the M×1 output vector $\boldsymbol{q} = (q_1, \ldots, q_M)'$, the production relation can then be explained by the technology set as follows.

$$S = \{(x, q): x \text{ can produce } q\} \quad (1$$

This set consists of all input output sets (x, q), such that 'x' can produce 'q'. This production function can also be represented using a technical transformation function. The functional relationship defined by the set, S, may be correspondingly defined in terms of the output set, P(x), which represents the set of all output vectors. The vector q can be produced by using the input vector, x. In notational expression, the output set is defined by

$$P(x) = \{q: x \text{ can produce } q\} = \{q : (x, q) \in S\} \quad (2)$$

The output sets are sometimes identified as production possibility sets associated with various input vectors x. Following O'Donnell and Coelli (2005) and Fare and Primont (1995), the production technology can be assumed to satisfy a standard set of axioms including convexity, strong disposability, closedness and boundedness.

This production relation can also be explained in terms of the output distance function:

$$D(x, q) = \min \{\delta : \delta > 0, (q/\delta) \in S\} \quad (3)$$

Some simple properties of D(x, q), derived from the axioms on the technology set as listed in Fare, Grosskopf and Lovell (1985) and Coelli *et al*. (2005), can be specified: i. D(x, 0) = 0 for all non-negative x; ii. D(x, q) is non-decreasing in q and non-increasing in x; iii. D(x, q) is linearly homogeneous in q; iv. D(x, q) is quasi-convex in x and convex in q; v. If q belongs to the production possibility set of x (i.e., $q \in P(x)$), then $D(x, q) \leq 1$; and vi. Distance is equal to unity (i.e., D(x, q) = 1) if q belongs to the frontier of the production possibility set.

The distance measure D(x, q) is “the inverse of the factor by which the production of all output quantities could be increased while still remaining within the feasible production set, for the given input level” (O’Donnell and Coelli, 2005, p 497). The distance function measure is therefore equivalent to a Farrell-type output-oriented measure of technical efficiency.

The Stochastic Distance Function Model

Most recent studies applying the distance function approach have made use of the translog form because imposing linear homogeneity in output is impossible for the other flexible functional forms (Pascoe *et al,* 2007; Irz and Thirtle, 2005; Paul and Nehring, 2005; O’Donnell and Coelli, 2005). Following these studies, the distance function model in this study is specified by using a translog functional form.

The translog output distance function for M outputs and P inputs can be specified as:

$$\ln D = a_0 + \sum_{m=1}^{M} a_m \ln q_m + 0.5\sum_{m=1}^{M}\sum_{n=1}^{M} a_{mn} \ln q_m \ln q_n + \sum_{p=1}^{P} b_p \ln x_p + 0.5 \sum_{p=1}^{P}\sum_{j=1}^{P} b_{pj} \ln x_p \ln x_j + \sum_{p=1}^{P}\sum_{m=1}^{M} g_{pm} \ln x_p \ln q_m \tag{4}$$

where the a_o, a_m, a_{mn}, b_p, b_{pj}, and g_{pm} are unknown parameters and ln represents the natural logarithm. From Euler’s theorem the homogeneity of degree one in outputs implies:

$$\sum_{m=1}^{M} a_m + \sum_{m=1}^{M}\sum_{n=1}^{M} a_{mn} \ln q_n + \sum_{p=1}^{P}\sum_{m=1}^{M} g_{pm} \ln x_p = 1, \tag{5}$$

that will be satisfied if

$$\sum_{m=1}^{M} a_m = 1, \sum_{m=1}^{M} a_{mn} = 0 \text{ for all n, and } \sum_{m=1}^{M} g_{pm} = 0 \text{ for all p} \tag{6}$$

The symmetry restrictions require $a_{mn} = a_{nm}$ and $b_{pj} = b_{jp}$ for all m, n, j and p.

Following Lovell *et al.* (1994), we impose the homogeneity constraint in the model.[9] “Substituting these constraints into the distance function is equivalent to normalising by one of the outputs” **(**O’Donnell and Coelli, 2005; 499). If output M is chosen to normalise, Equation (4) becomes:

[9] Most of the stochastic distance function models have imposed conditions of homogeneity and monotonicity (i.e., the non-increasing/decreasing properties).

$$\ln D/q_M = a_0 + \sum_{m=1}^{M-1} a_m \ln q_m^* + 0.5 \sum_{m=1}^{M-1}\sum_{n=1}^{M-1} a_{mn} \ln q_m^* \ln q_n^* + \sum_{p=1}^{P} b_p \ln x_p +$$
$$0.5 \sum_{p=1}^{P}\sum_{j=1}^{P} b_{pj} \ln x_p \ln x_j + \sum_{p=1}^{P}\sum_{m=1}^{M-1} g_{pm} \ln x_p \ln q_m^*, \tag{7}$$

where q_m^* =q_m/q_M. Equation (7) can be written in more compact form as

$$ln(D/q_M) = TL\ (x,\ q/q_M, \beta), \tag{8}$$

or

$$ln(D)-ln(q_M) = TL(x,\ q/q_M, \beta) \tag{9}$$

where TL (.) represents to the translog function and β is the vectors of a, b and g parameters.

Rewriting the equation by substituting –ln(D) = –u as a one sided error term, captures the effects of inefficiency

$$-lnq_M = TL(x,\ q/q_M, \beta) - u \tag{10}$$

A symmetric error term, v, can be added in this model to address the effects of data noise. Then the translog model is

$$-ln\ q_M = TL(x,\ q/q_M, \beta)-u+ v \tag{11}$$

The parameters of this model can be estimated using maximum likelihood assuming that '*u'* is a non-positive random variable independently distributed as truncations at zero of $N(0,\sigma_u^2)$ and 'v' is an independently and identically distributed random variable which is $N(0,\sigma_v^2)$. Equation (11) can equivalently be specified as

$$ln\ q_M = TL(x,\ q/q_M,\ \beta) - u+ v \tag{12}$$

This translog stochastic distance function model is in a normal stochastic frontier form with a two-part error term. As in the ordinary stochastic frontier model, the '*u*' in this model is the deviation from the frontier and '*v*' is a random error.

The translog distance can be written as:

$$ln(q_M^*) = TL(x,\ q/q_M,\ \beta)+ v \tag{13}$$

Equation (5.12) may be rewritten using equation (13)

$$ln\ q_M = ln\, q_M^* -u \tag{14}$$

or

$$\ln\left(\frac{q_M}{q_M^*}\right) = (-u) \tag{15}$$

This illustrates that the technical efficiency (TE) of a farm is the ratio of its mean production to the corresponding mean production if the farm utilised its levels of inputs most efficiently (Battese and Coelli, 1988), i.e.:

$$TE = \frac{q_M}{q_M^*} = \exp(-u) \tag{16}$$

This takes values between 0 and 1, with TE = 1 indicating that the farm is fully efficient. To sum up, the difference between q_M and q_M^* is embedded in u. If u = 0, then q_M equals to q_M^* implying that the production unit lies on the frontier. In this condition, the farm is technically efficient. If u > 0, the level of the farm's production lies somewhere below the frontier, implying that the farm is technically inefficient.

The technical inefficiency distribution parameter, '*u*' can be a function of various operational and farm-specific variables hypothesised as follows

$$u_i = \delta_0 + \sum_{p=1}^{8} \delta_p z_{pi} + w_i \tag{17}$$

where z_i is a 1×p vector of various farm specific variables which may influence efficiency of a farm, δ is a set of parameters to be estimated and w_i*'s* are the random variables defined by the truncation of the normal distribution with mean 0 and variance σ_u^2, such that the point of truncation is $-z_i\delta$ i.e., $w_i \geq -z_i\delta$. These assumptions are consistent with u_i being a non-negative truncation of the N $(z_i\delta, \sigma_u^2)$ distribution (Battese and Coelli, 1995).

Equations 13 and 17 are simultaneously estimated by maximum likelihood approach running Frontier 4.1 (Coelli, 1996).

Results and Discussion

Test of the Model Specification

Two hypotheses have been tested with regard to the model specification. The first is a technical inefficiency test, with null hypothesis $H_o: \gamma = 0$ and the alternative hypothesis $H_1: \gamma > 0$. When the null hypothesis is not rejected, the result implies that the SDF frontier is rejected in favour of a standard linear model with normal error, implying that the '*u*' term should be removed from the model. If the null hypothesis is rejected, it implies that inefficiency exists.

As discussed earlier, if the model has been estimated using maximum likelihood, the hypothesis for inefficiency effects can be tested using Wald, LM and LR tests. However, because of the one-sided nature of the alternative hypothesis, these tests are difficult to interpret. Moreover, they do not always have the asymptotic chi-square distributions. Coelli (1995) shows that the LR test statistic is asymptotically distributed as a mixture of chi-square distributions. The test statistic in this model is:

$$LR = -2[-1913.44+1823.80] = 179.27 \tag{18}$$

This test statistic exceeds the 5% critical value $\chi^2_{0..95}(2)$ = 5.138. As the test has an asymptotic distribution, the critical value is taken from Table (1) in Kodde and Palm (1986). This value is smaller than the 5% critical value $\chi^2_{0.95}(2) = 5.99$ that has been used by several authors including Battese and Coelli (1988). On this basis we reject the null hypothesis of no inefficiency effects. The test implies that inefficiency exists in the production system and that specification of the SDF model is justified.

The second hypothesis tested is the choice of the functional form, Cobb-Douglas vs. translog. The null hypothesis that the model is Cobb-Douglas is imposed as $a_{mn=}b_{pj=}g_{pm} = 0$ in equation 7. Testing the Cobb-Douglas model versus the translog, the generalised likelihood-ratio test statistic (λ) is found as follows:

$$\lambda = -2[-1965.56 + 1823.59] = 283.94 \tag{19}$$

This value is greater than 38.93, the 99% critical value for χ^2 distribution with 23 degrees of freedom. The null hypothesis is rejected, implying that the translog frontier is preferred and captures the production behaviour in Nepalese agriculture.

In the stochastic regression results the parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$ represent the variances of the random variables v_i and u_i. The γ parameter is estimated to be 0.96 with standard error 0.014, and is statistically significant. It indicates that 96% of the variation in the composite error term is due to the inefficiency component. This implies that the random component of the inefficiency effects contributes significantly to agricultural production analysis.

Production Elasticity

In the output distance function model, each of the first order output elasticities with respect to input provide the specific productive contribution to total output. Such elasticities represent the returns to or output contributions from X_k changes, similar to output elasticities from production function estimation. The first-order elasticities of the translog distance-function model can also be decomposed into second-order effects to reflect input or output composition changes as scale expands (Paul and Nehring, 2005). These measures present further insights into the production systems. The second-order elasticities provide production complementarities or substitutions among the variables. A negative sign on the elasticity implies a substitute, whereas a positive sign reflects a complement.

In the output translog distance function, the partial derivative of the output with respect to the m^{th} output provides the ratio of the shadow prices of q_M and q_m. It reflects the slope of the production possibility curve or the marginal rate of transformation between q_M and q_m.

The one sided error term, u, which is the deviation of a particular observation from the estimated frontier, provides the level of technical inefficiency. The inefficiency measures provide the percentages by which production could be increased, or input use reduced, to reach the production frontier.

An output oriented translog distance function can be said to be well behaved if the function is monotonically increasing and concave in input quantities (Kumbhakar, 1994). Monotonicity implies positive elasticities of inputs within the data range. The complete regression results of the output oriented distance function model across the entire sample are reported in Appendix 1. All input elasticities with respect to output are positive and highly significant; thus, the model demonstrates a well behaved production technology.

The signs of the first order output coefficients are negative and statistically significant. The second order output elasticities have correct (negative) signs, indicating that the transformation curve has a concave shape. The cross (with the exception of $q_3 \times q_4$) and squared output terms are significant across specifications, and many cross-input terms are also significant. The result thus indicates the possibility of substitution among output variables.

As expected, the estimated first order output elasticities for all conventional (Xs) inputs have correct (positive) signs and all elasticities are statistically significant at the 1% level. The positive signs of these elasticities indicate that farms can increase output by using more of these inputs. In output oriented translog distance function the production elasticities indicate how overall output changes with the variation in an individual input, keeping other input and output ratios constant, which is similar to output elasticities in production function estimation (Paul and Nehring, 2005). The elasticity of irrigated land (0.2) indicates that a 1% rise in irrigated land would increase overall output by 0.2%. In other words, it seems possible to increase output by increasing irrigated land and maintaining the existing levels of other inputs. Similarly, other production elasticities imply that increases in these inputs will also increase output.

Irrigated land is found to have the highest elasticity (0.20) followed by labour (0.18), rain-fed land (0.16), capital share (0.15), and seeds and fertilisers (0.07). The high elasticity of the irrigated land indicates that irrigation is the most important input determining yields in Nepalese agriculture followed by human labour. The elasticity of uplands or rain-fed lands (0.16) suggests that they are no less important if they are utilised properly. In the same way, increases in the amount of capital, high quality seeds, fertilisers and other expenses can increase total output. The estimated elasticity for other expenditures (0.03) is relatively small but is highly significant, implying that an increase in other expenses also contributes somewhat to total output. The distance function results also show four squared-input terms to be significant and two to be insignificant.

Most of the cross q–X terms (17 out of 24) are found to be insignificant.The positive sign of the cross product effect indicates that these variables are complementary. This means that if the value of one variable is increased, it also increases the impact of another variable on total output. The results of the model show that the cross products between variables x_1 and x_3 and also x_2 and x_6 are positive and statistically significant. The cross products between x_1 and x_4; x_3 and x_4; and, x_3 and x_6 are also positive but not statistically significant. The rest of the cross products are negative and none of them are statistically different from zero. This indicates that none of these variables are substitutes.

Returns to Scale

The sum of first-order input elasticities measures distance function-based scale economy. The sum measures the percentage change in output if all inputs were changed proportionally. If this estimate is equal to 1, it implies constant returns to scale.[10] This means doubling the inputs would double the output. The sum of the first order input elasticities in this model is equal to 0.78, i. e., less than 1.[11] This illustrates the existence of decreasing returns to scale at the mean. Imposing the restriction that the sum of output elasticities of all inputs be equal to 1, we can test the hypothesis of constant returns to scale:

$$t = \frac{(\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6) - 1}{Se(\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6)} = \frac{0.784044 - 1}{0.08739} = -2.47119 \qquad (20)$$

As the absolute value of the computed t-statistic 2.47 is greater than the critical t-value at the 5% level of significance, we reject the null hypothesis of constant returns to scale. The rejection of the null hypothesis is the indication of decreasing returns to scale prevailing in Nepalese agriculture. This suggests that productivity gains could be achieved by reducing the size of the farm (Gilligan, 1998). Thus, reducing farm size by breaking up large farms could lead to increased aggregate productivity.

[10] The constant returns to scale assumption in the translog stochastic production frontier impose a number of linear restrictions in the parameters as follows: $\beta_1+ \beta_2 + \beta_3+ \beta_4+ \beta_5+ \beta_6 =1$, $2\beta_{11}+ \beta_{12}+ \beta_{13}+ \beta_{14}+\beta_{15}+\beta_{16}=0$, $\beta_{12}+2\beta_{22}+\beta_{23}+\beta_{24}+\beta_{25}+\beta_{26}=0$, $\beta_{13}+2\beta_{23}+2\beta_{33}+\beta_{34}+\beta_{35}+\beta_{36}=0$, $\beta_{14}+2\beta_{24}+2\beta_{34}+2\beta_{44}+\beta_{45}+\beta_{46}=0$, $\beta_{15}+2\beta_{25}+2\beta_{35}+\beta_{45}+2\beta_{55}+ \beta_{56}=0$, $\beta_{16}+2\beta_{26}+2 \beta_{36}+\beta_{46}+\beta_{56}+ 2\beta_{66}=0$ (for mathematical details, see Boisvert, 1982).
Note however that to simplify the examination of the results, the input data (and farm specific variable as well as output data) was normalised by dividing throughout by the mean of each variable such that the sum of each variable was equal to zero.

Technical Efficiency

As discussed earlier, the technical efficiency of the farm is the ratio of its mean production to the corresponding mean production if the farm utilised its levels of inputs efficiently. The technical efficiency for each farm can be defined as $TE = exp(u_i)$, where exp denotes the exponential operator. The estimated technical efficiency scores range widely from 0.07 to 0.93, with a mean efficiency score of 0.73. This indicates that a high degree of technical inefficiency is present relative to the best performing farms. It follows that a large proportion of farms operate far from the efficient frontier, implying a substantial scope for improving productivity using the existing level of inputs and resources efficiently.

The estimated average efficiency score 0.73 indicates that typical Nepalese farms can increase agricultural production by 27% adopting the technology and the techniques used by the “best practice” farms. Alternatively, on average, there is the potential to achieve the existing level of output by reducing 27% of their inputs. The frequency distribution of the estimated technical efficiency scores is reported in Table 2 by farm size classification.

The last two columns of Table 2 show the overall (national) frequency distribution. Only 1.32% of farms had an efficiency index of more than 90%, and 16.49% of farms were operating in the less than 60% technical efficiency range. The highest relative frequency of the technical efficiency index is found in the 81-90% range, followed by 71-80% and 61-70% range.

Technical Efficiency and Farm Size

Relative land pressure may be the most important factor in explaining differences in technical efficiency between farm sizes. The average technical efficiency is highest in medium size farms (77%), followed by large (75%) and small (72%). This implies that on average, medium size farms are more efficient than large and small ones. This result cannot be far away from the general expectation. Presumably the observed high efficiency of medium farms is due to farmers having agriculture as their main occupation and allocating their resources more effectively, leading to higher farming intensity.

Table 2 shows that 4.95% of large farms were operating at a technical efficiency of more than 90%, followed by medium 1.52% and small 0.82%. The frequency of farms operating in the less than 50% range of technical efficiency was 10.41%, 10.26%, and 15.32% in small, medium, and large size farm respectively. This latter result further confirms the high percentage of less efficient farm in the large farm size group. The estimated frequency distributions of the efficiencies are plotted in Figure 1.

The mean technical efficiency of 73% is consistent with other studies using cross section data.[12] It is also similar to the average efficiency score calculated by Bravo-Ureta and Pinheiro (1993). They found the average efficiency score to be 70%, derived from 30 studies conducted by various authors in developing countries using the stochastic frontier and cross section data. Similar results have been found for Nepal.[13]

The difference in the average technical efficiencies in different farm sizes was tested using ANOVA with a one-way classification. The calculated *F*-ratio 25.597 is greater than the critical value of 4.61, at a 1% level of significance. This shows strong evidence rejecting the null hypothesis of no difference in the average technical efficiency in different farm size groups. So that the average technical efficiency in different farm size groups is significantly different. The average medium size farm is 6.96% more efficient than an average small farm and 2.13% more efficient than an average large farm.

It is worthwhile to briefly reconcile the result on returns to scale and the relationship between the mean technical efficiency and farm size. Theoretically, if farms are profit maximizers, the production function is concave and one should observe decreasing returns to scale (RTS). Farm size is often viewed as a determinant of inefficiency, and farm size is also related to RTS but inefficiency and RTS are not directly related to the econometric model specified in this study. In this study, RTS is measured at the mean, while technical efficiency and farm size are related counting how many farms fall in a specific TE range. To look at the exact relationship between RTS and TE one would need to examine this for each farm, not at the mean.

If the technology is concave the bigger size farms will have a smaller RTS, but they may not necessarily be more (or less) efficient. So, the mean RTS is not comparable with the mean efficiency of technical efficiency of any farm size group. Interpreted another way, if we think of mean RTS as the RTS for a farm that has its input levels the same as the mean, its inefficiency is unlikely to be the same as mean inefficiency.

Technical Efficiency and Ecological Zone

Nepalese agriculture is characterised by extreme heterogeneity because of its geographical diversity. Therefore, agro-climatic potential may be one of

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[12] For example, Squires and Tabor (1991) found 68% technical efficiency in Indonesian peanuts, 70% off-Java rice and 69% in Java rice. Rawlins (1985) found 73% in Jamaican crops; Taylor and Shonkwiler (1986) found 71% in Brazilian farms; Kalirajan (1981) found 67% in Indian rice farms and Huang and Bagi (1984) found 89% in Indian farms.

[13] Belbase and Grabowski (1985) using a deterministic method found mean technical efficiency (TE) to be 80% in the Nuwakot district in Nepal (84% for rice and 67% for maize). Ali (1996), found average TE to be 75% for wheat farming in the Rupandehi district and Sharma, Pradhan, and Leung (2001) found 79% for rice farmers in the Chitwan district. Both of these studies used SFA model. Dhungana *et al*. (2004) using a DEA model found mean TE to be 76% for rice farmers in four villages of Agauli village development committee (VDC) of the Nawalparasi district.

the important factors explaining differences in agricultural output. Table 3 reports the distribution of efficiency scores by ecological zones.

The table shows that the average technical efficiency is similar between the Hill and the Mountain regions, but it is higher in Terai. The higher average efficiency in Terai is as expected. The Mountain and Hill regions are considered to be relatively unproductive because of geographical conditions.

While testing the hypothesis of no difference in the technical efficiency in these three ecological regions, using the one-way ANOVA, the calculated F-ratio is found to be 5.56. The critical value of F-ratio at 1% level of significant is 4.61, which is less than the calculated value. Hence, the hypothesis of equal technical efficiency is rejected, implying that the Terai region is more efficient than the Hill and Mountain regions.

Sources of Inefficiency

The empirical results clearly reveal that the inefficiency scores vary across farm size and ecological zone over time. Next we discuss some specific variables that affect such variations.

The z_1 to z_8 variables as defined in Equation (17) are included as potential determinants of technical efficiency. The algebraic sign, value of estimated coefficients and level of significance are the elements that determine the level of inefficiency.

The expected sign of the coefficient of owned land (z_1) is negative on the inefficiency effects. Owned land is the proxy of access to credit. Larger parcels of owned land would lead to a greater ability to access credit, and subsequently to less inefficiency effects. The expected sign of the coefficient of value of land per hectare (z_2) is negative. A higher value of land may reflect a higher quality of land that would be expected to be more efficient from the production point of view.

The coefficient of extension service (z_3) in the model is expected to be negative. Access to extension services in agriculture is likely to promote efficiency.

The coefficient of the age of the family head (z_4) could be positive or negative. Older farmers are likely to have more farming experience than the younger entrants and hence less inefficiency. However, it is also likely that they might be more conservative and thus less receptive to modern and newly introduced agricultural technology.

The coefficient of the family head's education (z_5) is expected to have a negative sign. This implies that farmers with more education respond more rapidly when new technology becomes available.

The sign of the coefficient for the access to road (z_6) (the distance the farmer must travel from the residence to a vehicle passable road) is expected to have a positive impact on inefficiency.

The dummy variables z_7 (Mountain dummy) and z_8 (Hill dummy) are expected to have positive effects because these regions are considered to be less conducive to high value agricultural production, as discussed above. These regions mainly rely on conventional farming practices that emphasise producing staple food crops.

Table 4 reports the estimates of the technical inefficiency function (equation 17). The dependent variable is technical inefficiency, not technical efficiency. Thus, a negative sign of the coefficient of an explanatory variable implies a reduction in technical inefficiency or a rise in technical efficiency. The results show that, with the exception of access to road, the signs of all variables are as expected. Results will be further discussed below.

If farms operate using different technologies depending on their size and ecological zone, the production frontier estimated using the stochastic frontier method would become farm-specific. In this context, the assumption of an equal slope coefficient across farms will no longer be valid and consequently, efficiency measurements might not be reliable. Therefore, it is desirable to compare the stochastic distance-function frontier results with the results derived from DEA to check the consistency and robustness of the model. In the following section, the DEA model is employed.

V. Nonparametric Data Envelopment Analysis (DEA)

The purpose of this section is to introduce the data envelopment analysis (DEA) model and compare the results with those derived from the stochastic distance function (SDF) model. Though the methodologies to estimate efficiency differ significantly, both methods define technical efficiency as the observed production relative to the corresponding potential, given the quantity of inputs used. The technical efficiency scores estimated from the output-oriented DEA frontiers are therefore comparable with the scores obtained from the SDF.

In this section output oriented Constant Returns to Scale (CRS), as well as Variable Returns to Scale (VRS), and DEA frontiers are estimated using the same output and input variables and the same data set as in the SDF model.

Consider the situation of 2,585 farms, each producing 4 different types of crops using 6 different inputs. The *i*th farm uses x_{ki} units of the k_{th} input in the production of y_{ri} units of the *r*th crop. A separate linear programming problem is solved for each of the 2,585 farms in the sample. The output-based technical efficiency for the *i*th farm can be obtained by solving the following LP problem:

$$\underset{\phi_i,\lambda_j}{Maximize}\,\phi_i \qquad (21)$$

subject to

$$\phi_i y_{ri} - \sum_{j=1}^{2585} \lambda_j y_{rj} \leq 0 \qquad \text{r = 1, … , 4 outputs,}$$

$$x_{ki} - \sum_{j=1}^{2585} \lambda_j x_{kj} \geq 0 \qquad \text{k = 1, … , 6 inputs}$$

$$\sum_{j=1}^{2585} \lambda_j = 1 \text{ (variable returns to scale)}$$

$\lambda_j \geq 0$ j = 1, …, 2585 farms,

where ϕ_i is the proportional increase in outputs possible and λ_j the weight or intensity variable used to derive all possible linear combinations of sample observations. When the value of ϕ_i in Equation (21) is 1, $\lambda_i = 1$, and $\lambda_j = 0$ for $j \neq i$, the *i*th farm lies on the frontier and is technically efficient. For the inefficient units, $\phi_i > 1$, $\lambda_i = 0$, and $\lambda_j \neq 0$ for $j \neq i$. The output based technical efficiency index of the *i*th farm (TE_i) can be computed as follows:

$$TE_i = \frac{1}{\phi_i} \tag{22}$$

Table 5 presents the results of the empirical estimates of the DEA model. The table shows frequency distribution and summary statistics for the technical efficiency scores in terms of variable returns to scale (VRS), constant returns to scale (CRS) and scale efficiency (SE).The estimated mean technical efficiencies for the sample households for the VRS and CRS DEA frontier are 0.48 and 0.47 respectively, whereas it was 0.73 for the SDF. The DEA results also verify that there is substantial productive inefficiency in Nepalese agriculture. Out of 2,585 households, 329 households are fully efficient under the VRS model. However, in terms of the CRS model, only 244 households are fully efficient.

The individual efficiency measures derived under the VRS DEA model are equal to or greater than those obtained from the CRS DEA model. To compute a measure of scale efficiency (SE) under DEA the following equation is used:

$$SE = \frac{TE_{CRS}}{TE_{VRS}} \tag{23}$$

The mean scale efficiency for the sample households is 0.98. Out of the 2,585 households, 2,003 show constant returns to scale, 439 increasing returns to scale, and the remaining 143 show decreasing returns to scale. However, in terms of the SFA there are decreasing returns to scale prevailing in Nepalese agriculture in general.

VI. Comparison of TE Scores Derived from SDF and DEA

A majority of studies have compared the technical efficiency results derived from SFA and DEA methods in agriculture[14] These findings generally show that while the efficiency scores produced from each approach differ quantitatively, the ordinal efficiency ranking of farms obtained from the two approaches appear similar. Table 6 compares the technical efficiencies derived from SDF and DEA.

Table 6 shows that technical efficiency scores estimated using the two methods vary greatly. The mean technical efficiencies estimated from the DEA models are lower than those estimated from the stochastic frontier. As can be seen, a majority of farm households have efficiency of more than 70% in terms of SDF but the corresponding figure is very low in the DEA results. These results are not surprising because the DEA approach attributes any deviation of the data points from the frontier to inefficiency, whereas the SDF also accounts for a random error component.

As compared to SDF measures, the DEA efficiency measures have a considerably higher variability. The variability of the DEA efficiency measure ranges from a minimum of 0.02 to a maximum of 1 whereas in SFA it ranges from 0.07 to 0.93. To examine the efficiency rankings between the two approaches, correlation coefficients between the technical efficiency rankings from the SDF and both CRS and VRS scale models of the DEA are computed and reported in Table 7. The statistical significance test confirms that all the correlation coefficients are positive and significant.

As discussed above, the majority of studies found evidence that, using the same data set, estimated technical efficiency scores derived from the SFA approach are generally higher than those obtained from the DEA (Drake and Weyman-Jones, 1996; Ferrier and Lovell, 1990). However, analysing a sample of Guatemalan farmers, Kalaitzandonakes and Dunn (1995) reported a significantly higher level of mean technical efficiency under DEA than under the SFA. That contrasts sharply with this study and most other studies.

VII. Factors Determining Inefficiency

There are essentially two ways for estimating the farm specific attributes in explaining inefficiencies. The first is to include farm specific attributes in the efficiency model directly as has been done in the SDF model above. The other approach is to use a second stage regression model as applied in a number of studies including Kalirajan (1991), Sharma, Leung and Zaleski (1999), and Shafiq and Rehman (2000).

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[14] Examples include, Ferrier and Lovell (1990); Kalaitzandonakes and Dunn (1995); Drake and Weyman-Jones (1996); Hjalmarsson *et al.* (1996), Sharma *et al*. (1997; 1999).

The second stage regression model is now used to determine the farm specific attributes in explaining efficiency in Nepalese agriculture. The empirical model assumed is as follows:

$$y^{*} = Z\beta + e \tag{24}$$

where y^{*} is a DEA efficiency index used as a dependent 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 and normally distributed error term with zero mean and constant variance, σ^2.

As defined earlier in the case of the stochastic model, all z_1 - z_8 variables are potential determinants of technical efficiency. The expected signs of all variables were discussed earlier in section 4. Estimated parameters of equation (24), which are estimated by Tobit regression procedures available in LIMDEP 8.0 (Green, 2002), are reported in Table 8. The response variable in this model is technical efficiency (as opposed to technical inefficiency in the case of SDF model). The signs of the parameters are therefore opposite of the technical inefficiency model above**.** Thus, the signs are simply changed to make the results of both models consistent.

Table 8 shows that the Tobit regression results are consistent with the SFA model. By and large, the same signs and relative values are found in both model estimations and hence have the same effects on technical efficiency (or inefficiency) of all regressors. With the exception of distance to road, the signs related to all other inefficiency (or efficiency) determinants are as expected. In both cases, owned land has a significantly positive effect on efficiency (or negative effect on inefficiency). The largest absolute value of owned land among the Tobit regression coefficients suggests that ownership of land might be the most important determinant of efficiency. As owned land is the proxy of access to agricultural credit, the positive effect on efficiency indicates that farmers with more owned land have more access to agricultural credit so that they are more efficient.

In both models, the value of land, a proxy for land quality, has a significantly negative effect on inefficiency, as expected. This implies that households with a higher quality of land are more efficient than those having low quality land.

The household head's age has a positive effect on efficiency in both models. However, the estimated coefficients are not significant in both models.

The variable for extension service reflects the influence of the government extension programme. Both the SDF and the Tobit regressions give the same result, namely that the extension dummy variable has positive effects on efficiency but it is not statistically significant in both cases.[15]

Surprisingly, the result indicates that the farther from a road, the more efficient the farm. This effect is not expected but it is significantly different from zero. The underlying reason behind this could be that higher quality (irrigated) farmlands are relatively far away from residential areas and town centres so that access to roads is not available. However, the small value of the coefficient in both models suggests that the impact of this variable is quite limited.

As expected, the results of both regression models reveal positive relationships between the level of education of the household head and technical efficiency. This is also statistically significant in the DEA model (although not in the SDF model). It suggests that increasing investment in education may lead to better performance in the agricultural sector.

As expected, the dummy variables for the Mountain and Hill regions have a negative effect on efficiency. This implies that the Terai (plain) region, taken as the base case, has a positive effect on efficiency.

To sum up, farmers with owned land, more education, higher quality of land, and who live in the Terai region have a higher level of technical efficiency than the farmers not possessing those attributes.

These results suggest that policy makers in Nepal need to understand that there is a high degree of inefficiency in the agricultural production systems. Where inefficient households are able to surplus some resources, they could be used to make additional income to enhance household welfare. For instance, surplus labour could be diverted to off-farm employment where an opportunity exists. Households could use the additional income to acquire new technologies including improved seeds, fertilizers, and new agricultural implements. Further, they could invest in land improvement. All this would lead to improved technical efficiency and thereby household welfare. Increasing household welfare is an effective way of alleviating poverty.

The factors that significantly influence farmers' resource allocation decisions differ widely among individual farmers. The effectiveness of new policies designed to increase efficiency and productivity may depend largely on the extent to which such differences are recognised. In a broad sense, inefficiency should not be viewed as just a result of the differences in the use of input quantities. Institutional factors including extension systems,

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[15] The evidence shows that in Nepal relatively few farmers receive extension services (WB, 2006). However, it is not clear whether this is a problem of lack of availability or whether the services do not meet the needs of farmers. Our regression results also reach the conclusion that extension services have no significant effect on efficiency.

education, research and general policies are also important. Efficiency enhancing policies must be flexible enough to accommodate these realities.

VIII. Conclusions and Policy Implications

The results show that the variation in output among agricultural farms in Nepal is due to differences in technical efficiency. Variations in amounts of production inputs have a significant influence on the level of production and efficiency across farm households. Results confirm that the level of inefficiency is also related to farm specific attributes. Owned land is the major determinant of inefficiency followed by land quality (value of land) and education.

The results demonstrate that the level of technical efficiency among agricultural households differs significantly across size groups and across agro-ecological zones. Medium size farms achieve the highest technical efficiency in the Nepalese context. Decreasing returns to scale also suggest that productivity gains can be achieved by reducing the size of larger farms.

Based on the findings, the following policy implications can be derived with regard to increasing efficiency so as to reduce poverty and promote equity.

In view of the limited arable land and other resources, satisfying the increased demand for food through domestic production must come through improvements in productivity, from technological progress or increases in technical efficiency at the farm level. Technical progress relates to the development and adoption of modern technologies, whereas TE refers to the farmer’s ability to achieve maximum output from a given set of inputs by using available productive technology efficiently. Given the existing production technology in Nepal, there is limited prospect of technical progress. In this context, the policy makers need to understand that an increase in technical efficiency is relatively cost effective and therefore government policies should be directed towards this.

This study shows that given the present state of agricultural technology, farms have a potential for enhancing productivity by increased use of inputs. Irrigation is identified as the main factor for determining yields in agriculture. Therefore, government policy should give a high priority to increasing irrigation facilities. In the same way, government policy should facilitate the supply of and access to required capital, high quality seeds, fertilisers and other inputs for farmers.

Access to agricultural credits, the quality of land and education are recognised as the most influential determinants of efficiency. These are also the shifting factors of the production frontier. Government policies should target increased access to credit for farmers through ownership of land along with enhancement of land quality and increases in the level of education, training and knowledge of farmers. These types of policies and practices could contribute to increased technical efficiency.

The findings reveal that the medium sized farm (i.e., between one and two hectares) is more efficient than large and small sized farms. This suggests maintaining medium farm size would be beneficial. Policies targeted at creating medium sized farms by breaking up large farms and the merger of small farms might have beneficial effects on efficiency, although this issue may need to be studied further. Access to land by the poor through redistributive land reform can increase productivity and promote efficiency.

The existence of a high degree of technical inefficiency also suggests that farmers' resource allocation decisions differ widely among individual farmers. Farmers' interactions with each other should have some beneficial effect towards catching up on new technology. Producers' organisations can also improve efficiency in the delivery of government support services and empower them to get involved in many activities.

The analysis clearly demonstrates that technical efficiency varies significantly across farm-size groups and ecological zones. The effectiveness of new policies designed to increase efficiency and productivity may depend largely on the extent to which such differences are recognised. Efficiency improvement policies should be flexible enough to accommodate these realities**.** For instance, younger and older household managers, educated and uneducated, with and without capital, with irrigated land and rain-fed land, might comprise sub groups with small, medium and large farms located in the Terai, Hill and Mountain ecological zones. Therefore, policies targeting separate groups, rather than 'one size fits all', will be an effective approach to improve efficiency and productivity. In the same way, recognising farmers who are inefficient in using some resources (such as fertiliser, seeds and labour) would be useful in treating them separately for intervention purposes.

The findings suggest that government efforts through agriculture extension programmes have failed to have a significant effect on technical efficiency. Government policies should facilitate the private sector to come forward and assist in diffusing modern technologies through extension and training, so that farmers can apply available agricultural technology more efficiently.

Among the three geographical regions, the observed average inefficiency is higher in the Hill and Mountain regions. Government policies should be targeted to increasing TE in these areas by taking into account the varying circumstances that can be observed.

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APPENDIX 1: STOCHASTIC DISTANCE FUNCTION RESULTS (FRONTIER 4.1)

Variables	Coefficient	St. Err.	t-ratio	Variables	Coefficient	St. Err.	t-ratio
Constant	1.001	0.031	32.131	x11	0.063	0.057	1.114
Cereal Crops (q12)	-0.561	0.011	-51.471	x22	0.036	0.015	2.465
Pulses (q21)	-0.121	0.009	-13.465	x33	0.055	0.013	4.223
Cash Crops (q31)	-0.182	0.009	-19.396	x44	0.035	0.008	4.493
Other Crops (q41)	-0.136	0.008	-17.644	x55	0.06	0.009	6.985
DO1	-4.403	0.162	-27.112	x66	0.005	0.007	0.658
DO2	-0.788	0.093	-8.431				
DO3	-1.437	0.104	-13.857	x1q1	-0.029	0.009	-3.235
DO4	-1.244	0.082	-15.217	x2q1	0.016	0.004	3.739
Cereal×Pulses (nm12)	0.009	0.002	3.701	x3q1	0.001	0.004	0.217
Cereal×Cash (nm13)	-0.005	0.002	-1.986	x4q1	-0.007	0.003	-2.842
Cereal×Other (nm14)	-0.002	0.002	-1.324	x5q1	<.001	0.002	0.242
Pulses×Cash (mn23)	0.003	0.001	2.715	x6q1	-0.001	0.002	-0.662
Pulses×Other (mn24)	-0.004	0.001	-3.894				
Cash×Other (mn34)	<.001	0.001	0.059	x1q2	0.012	0.009	1.325
Cereal×Cereal (nm11)	-0.002	0.003	-0.656	x2q2	-0.012	0.004	-2.903
Pulses×Pulses (mn22)	-0.008	0.003	-2.89	x3q2	-0.003	0.004	-0.699
Cash×Cash (mn33)	0.001	0.002	0.538	x4q2	-0.001	0.002	-0.576
Other×Other (mn44)	0.006	0.002	3.407	x5q2	-0.001	0.001	-0.684
Labour (x1)	0.177	0.023	7.745	x6q2	0.002	0.002	1.41
Irrigated Land (x2)	0.202	0.015	13.572	x1q3	0.007	0.007	0.898
Rainfed Land (x3)	0.156	0.013	12.004	x2q3	0.002	0.003	0.542
Capital Service (x4)	0.148	0.011	13.682	x3q3	0.002	0.003	0.543
Purchased Inputs (x5)	0.072	0.014	5.229	x4q3	0.004	0.002	2.06
Other Costs (x6)	0.029	0.012	2.405	x5q3	0.001	0.001	1.09
D_i1	-0.591	0.032	-18.302	x6q3	-0.003	0.001	-1.892
D_i2	-0.274	0.033	-8.263	x1q4	0.01	0.005	1.892
D_i3	-0.082	0.201	-0.408	x2q4	-0.006	0.003	-2.167
D_i4	-0.401	0.173	-2.325	x3q4	<.001	0.002	0.014
D_i5	-0.002	0.162	-0.012	x4q4	0.004	0.002	2.502
x1x2	-0.008	0.021	-0.357	x5q4	-0.001	0.001	-0.811
x1x3	-0.035	0.02	-1.744	x6q4	0.002	0.001	1.623
x1x4	0.02	0.012	1.715				
x1x5	-0.014	0.008	-1.749	Constant (Z0)	-1.07	0.71	-1.51
x1x6	-0.015	0.008	-1.928	Owned Land (Z1)	-0.6	0.21	-2.92
x2x3	0.028	0.009	3.072	Value of Land (Z2)	-0.28	0.09	-3.19
x2x4	-0.008	0.006	-1.339	Extension Service (Z3.)	-0.98	0.6	-1.63
x2x5	-0.002	0.004	-0.694	Age of HH (Z4)	-0.09	0.11	-0.81
x2x6	0.008	0.004	2.073	Education of HH (Z5)	-0.04	0.05	-0.68
x3x4	<.001	0.005	0	Access to Road (Z6)	-0.09	0.04	-2.45
x3x5	-0.006	0.003	-1.81	Mountain Dummy (Z7)	0.16	0.12	1.36
x3x6	<.001	0.003	0	Hill Dummy (Z8)	0.15	0.08	2.04
x4x5	-0.004	0.002	-1.809	sigma-squared	3.276	1.073	3.052
x4x6	-0.002	0.002	-0.842	Gamma	0.962	0.014	67.99

Table 1: Descriptive Statistics of Variables

Variables	Unit	Mean	Std. Dev.	Minimum	Maximum
Value of Cereal Crops	NR	17,532.2	20,520.3	0	499,728
Value of Pulses	NR	3,503.08	8,116.14	0	199,026.3
Value of Cash Crops	NR	5,071.42	14,373.4	0	350,429.8
Value of Others Crops	NR	12,642.6	47,084.6	0	1312,800
Labour (X_1)	Hours	7,399.22	3,769.42	614	50,053.01
Irrigated Land (X_2)	Hectares	0.44	0.81	0	13
Rain-fed Land (X_3)	Hectares	0.44	0.64	0	8.8
Value of Capital Share (X_4)	NR	5,077.1	8,242.52	0	148,040
Cost of Seeds Plus Fer. (X_5)	NR	1,662.45	3,558.66	0	92,800
Other Costs (X_6)	NR	1,920.44	4,951.34	0	109,200
Owned Land (Z_1)	Hectares	0.76	0.96	0.01	18.62
Value of Land Per Hec. (Z_2)	NR	1,041,025	2,864,097	10,811.5	44,941,927
Age of Family Head (Z_4)	Years	46.02	13.97	16	91
H.H. Education Level (Z_5)	Years	3.46	3.72	1	17
Access to Road (Z_6)	Hours	7.42	14.33	0	120

Source: NLSS dataset.

Table 2: Distribution of Technical Efficiency (TE) by Farm Size

TE %	Small	%	Medium	%	Large	%	All	%
< 10	4	0.22	0	0	2	0.45	6	0.19
11-20	22	1.2	1	0.19	1	0.45	24	0.93
21-30	26	1.42	6	1.14	2	0.9	34	1.32
31-40	51	2.78	2	0.38	3	1.35	56	2.17
41-50	88	4.79	16	3.04	13	5.86	117	4.53
51-60	147	8	29	5.51	14	6.31	190	7.35
61-70	280	15.24	63	11.98	31	13.96	374	14.51
71-80	586	31.9	152	28.9	50	22.52	788	30.48
81-90	617	33.64	249	47.34	96	43.24	962	37.21
>90	15	0.82	8	1.52	11	4.95	34	1.32
Total Farm	1836	100	526	100	223	100	2585	100
Ave. TE	0.72		0.77		0.75		0.73	

Table 3: Distribution of Technical Efficiency by Ecological Zone

TE (%)	Mountain	%	Hill	%	Terai	%	All	%
< 10	0	0.00	3	0.24	2	0.21	5	0.19
10-20	3	0.82	9	0.71	12	1.25	24	0.93
21-30	7	1.91	17	1.35	10	1.04	34	1.32
31-40	9	2.45	24	1.90	23	2.40	56	2.17
41-50	19	5.18	68	5.39	30	3.13	117	4.53
51-60	28	7.63	104	8.25	58	6.06	190	7.35
61-70	56	15.26	179	14.20	140	14.63	375	14.51
71-80	108	29.43	425	33.70	255	26.65	788	30.48
81-90	137	37.33	418	33.15	407	42.53	962	37.21
>91	0	0.00	14	1.11	20	2.09	34	1.32
Total	367	100	1261	100	957	100	2585	100
Ave. TE	0.7214		0.7216		0.7419		0.7291	

Table 4: Factors Affecting Technical Inefficiencies

Variables	Coefficient	Std-error	t-ratio
Constant (Z0)	-1.07	0.71	-1.51
Owned Land (Z1)	-0.6	0.21	-2.92
Value of Land (Z2)	-0.28	0.09	-3.19
Extension Service (Z3.)	-0.98	0.6	-1.63
Age of HH (Z4)	-0.09	0.11	-0.81
Education of HH (Z5)	-0.04	0.05	-0.68
Access to Road (Z6)	-0.09	0.04	-2.45
Mountain Dummy (Z7)	0.16	0.12	1.36
Hill Dummy (Z8)	0.15	0.08	2.04
sigma-squared	3.276	1.073	3.052
Gamma	0.962	0.014	67.991

Table 5: Technical Efficiency Scores from DEA

TE Percent	CRS	%	VRS	%	SE
0- 10	64	2.48	64	2.48	0
10-20	262	10.14	261	10.1	0
20-30	542	20.97	462	17.87	0
30-40	423	16.36	488	18.88	0
40-50	371	14.35	351	13.58	3
50-60	265	10.25	250	9.67	8
60-70	176	6.81	158	6.11	14
70-80	101	3.91	101	3.91	45
80-90	77	2.98	72	2.79	116
90-99	61	2.36	50	1.93	396
1	243	9.4	328	12.69	2003
Total	2585	100	2585	100	2585
Mean TE	0.47		0.48		0.98
Minimum	0.02		0.02		0.45
Maximum	1		1		1
Standard Deviation	0.26		0.27		0.06

Table 6: Comparing SDF and DEA Results

TE (%)	SDF	%	CRS	%	VRS	%
0- 10	5	0.19	64	2.48	64	2.48
10-20	24	0.93	262	10.14	261	10.10
20-30	34	1.32	542	20.97	462	17.87
30-40	56	2.17	423	16.36	488	18.88
40-50	117	4.53	371	14.35	351	13.58
50-60	190	7.35	265	10.25	250	9.67
60-70	375	14.51	176	6.81	158	6.11
70-80	788	30.48	101	3.91	101	3.91
80-90	962	37.21	77	2.98	72	2.79
90-99	34	1.32	61	2.36	50	1.93
1	0	0.00	243	9.40	328	12.69
Total	2585	100	2585	100	2585	100
Mean TE	0.73		0.47		0.48	
Minimum	0.07		0.02		0.02	
Maximum	0.93		1.00		1.00	
Standard Deviation	0.15		0.26		0.27	

Table 7: Correlation Matrix for TE Rankings

	SDF	CRS	VRS
SDF	1		
CRS	0.39347	1	
VRS	0.40048	0.98386	1

Table 8: Estimates of Determinants of Technical Inefficiency (First Stage and Second Stage) Models

Variable	SDF Model			Tobit Model				Mean X
	Coef.	St. Er.	t-Ratio	Coef.	St. Er.	t_Ratio	P	
Z0	-1.07	0.71	-1.51	0.449	0.022	-20.457	<0.001	
Z1 (Owned Land)	-0.6	0.21	-2.92	0.014	0.006	-2.395	0.017	0.753
Z2 (Value of Land)	-0.28	0.09	-3.19	0.001	<0.001	-5.295	<0.001	10.740
Z3 (Extension)	-0.98	0.60	-1.63	0.009	0.020	-0.462	0.644	0.079
Z4 (Age)	-0.09	0.11	-0.81	<0.001	<0.001	-1.097	0.272	46.094
Z5 (Education)	-0.04	0.05	-0.68	0.005	0.002	-2.920	0.004	3.456
Z6 (Road)	-0.09	0.04	-2.45	0.002	<0.001	-5.792	<0.001	7.499
Z7 (Mountain)	0.16	0.12	1.36	-0.064	0.019	3.41	0.001	0.142
Z8 (Hill)	0.15	0.08	2.04	-0.064	0.012	5.354	<0.001	0.488
sigma-squared	3.276	1.073	3.052					
Gamma	0.962	0.014	67.991					
Sigma				0.268	0.004	71.903	<0.001	

Graph 1: Frequency Distribution of Efficiency