Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: a non-parametric approach

Technical, Allocative, Cost and Scale Efficiencies in Bangladesh Rice Cultivation: A Non-Parametric Approach

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Abstract: *Applying programming techniques to detailed data for 406 rice farms in 21 villages, for 1997, produces inefficiency measures, which differ substantially from the results of simple yield and unit cost measures. For the Boro (dry) season, mean technical efficiency was 69.4%, allocative efficiency was 81.3%, cost efficiency was 56.2% and scale efficiency 94.9%. The Aman (wet) season results are similar, but a few points lower. Allocative inefficiency is due to overuse of labour, suggesting population pressure, and of fertilizer, where recommended rates may warrant revision. Second-stage regressions show that large families are more inefficient, whereas farmers with better access to input markets, and those who do less off-farm work, tend to be more efficient. The information on the sources of inter-farm performance differentials could be used by the extension agents to help inefficient farmers. There is little excuse for such sub-optimal use of survey data, which is often collected at substantial costs.*

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1. Introduction

In Bangladesh, agriculture employs sixty per cent of the population, but produces only thirty per cent of national income (McIntire, 1998). Rice is the major staple crop, occupying about 70 percent of gross cropped area and accounting for 93 percent of total cereal production (Bangladesh Bureau of Statistics, 1996).

Being a food deficit country, owing to a fast growing population in an already densely populated country, Bangladesh has pursued a policy of rapid technological progress in agriculture, leading to diffusion of a rice-based 'Green Revolution' technology package. This led to a substantial increase in rice production from 11,504 thousand metric tonnes in 1968-70 to 18,211 thousand metric tonnes in 1992-94, with a corresponding increase in cropping intensity from 146.5 percent to 176 percent (Rahman and Thapa, 1999).

However, the current production scenario is not that encouraging on two accounts. First, there has been an apparent decline in the average yields of modern rice varieties. Second, the level of adoption of the new methods has stagnated. The yield levels of modern rice varieties have declined from 3.8 tonnes/ha in 1968-1970 (during the inception stage) to 2.4 tonnes/ha in 1992-1994 (the mature adoption stage), thereby, raising doubts about the sustainability of food-grain production (Rahman and Thapa, 1999). Furthermore, even though modern rice varieties currently account for only about 49 percent of total rice area, Bera and Kelly (1990) claim that the ceiling adoption level in Bangladesh has nearly been reached. Therefore, it appears that new varieties must be developed and ways must be sought to improve the efficiency of the existing technology. Thus, the measurement of farm-level efficiency in rice production in Bangladesh is the first aim of this paper. Then, the efficiency differentials across farms are explained, which may assist policy makers in identifying ways to improve efficiencies.

Past studies which seek to measure efficiency differentials among farms are dominated by the use of simple measures, such as yield per hectare and cost per unit of output, which are easy to calculate and understand, but tell one very little about the reasons for any observed differences among farms. Yield-per-hectare figures are of little use when the amounts of non-land inputs used (such as labour and fertiliser) differ among farms. Cost per unit of output figures go some way towards addressing the problems with yield comparisons, but they can also be quite misleading measures of performance when input prices differ across geographical regions, as is the case in Bangladesh. Furthermore, simple cost comparisons do not tell us what portion of the cost difference is due to inefficient use of the given input bundle (technical inefficiency) and what part is due to the incorrect choice of input ratios, given the input prices faced by the farmer (allocative inefficiency). In addition, neither yield nor unit cost measures tell us anything about the existence, or otherwise, of scale economies.

In this study, we attempt to avoid the problems inherent in these simple measures by constructing non-parametric production frontiers using data envelopment analysis (DEA) and then use them to produce a range of efficiency measures. We calculate four different measures: technical efficiency, allocative efficiency, cost efficiency and scale efficiency.

The DEA approach has been applied to allocative efficiency in developed country agriculture by Chavas and Aliber (1993), who consider economies of scope for Wisconsin farms and by Sharma, Leung and Zaleski (1999), whose application is to swine production in Hawaii. The developing country literature is reviewed by Bravo-Ureta and Pinheiro (1993).

The few previous studies of the efficiency of Bangladeshi rice producers have been narrow in their focus. Hossain (1989) conducts a Cobb Douglas profit function analysis of relative economic and price efficiency between modern technology adopters and non-adopters. The results indicated that modern technology adopters were fully price efficient in the allocation of fertiliser compared to the non-adopters. However, both groups were found to be price inefficient in the use of labour, which was attributed to the low opportunity cost of family labour.

Banik (1994) estimated technical efficiency of 99 modern Boro rice farmers in the central region of Bangladesh at 82 percent and found that farm size and tenure status had no influence on efficiency. Deb (1995) estimated technical efficiency of rice farmers in the south-western region of Bangladesh using a Cobb-Douglas production frontier. He reports estimated mean technical efficiency at 74 percent, but his input set was confined to material inputs only. He also investigated the relationship between efficiency and education, age, a technology index (measured by the area under modern rice varieties and/or modern irrigation), natural disaster, tenure status, farm size, and family size. Technology, natural disasters and tenure status were found to have a significant influence upon efficiency. Finally, Sharif and Dar (1996) estimated the technical efficiency of traditional and HYV (high yielding varieties / modern) rice farmers in a single village utilising a Cobb-Douglas production frontier. They observed that Boro season cultivation was technically inefficient relative to that in the Aman and Aus seasons.

This study differs from previous work in several ways. First, this uses a non-parametric programming technique known as data envelopment analysis (DEA). Hence, it is not necessary to assume a simplistic functional form, such as the Cobb-Douglas, which imposes constraints on the production technology, such as constant production elasticities and unitary elasticities of substitution. Second, the sample covers a much wider range of villages than previous studies. Third, except for Hossain (1989), who covers allocative efficiency, all of these studies simply look at technical efficiency, whereas this investigation estimates technical, allocative, cost and scale efficiencies for each farm in the sample.

The narrow focus on technical efficiency measurement is not confined to analyses of Bangladeshi rice farmers. In fact, even among frontier analyses of other agricultural industries, the vast majority of studies confine their attention to the issue of technical efficiency, and tend to ignore these other equally important aspects of agricultural performance.[1] This study will also provide useful information for policy formulation in Bangladesh and serve as an illustration of the output that may be derived from survey data using these methods.

The next section describes the methodology; section three the data and section four the results, before the concluding comments in the final section.

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[1] Comprehensive reviews of the literature on efficiency measurement in agriculture using frontier methods are given by Battese (1992) and Coelli (1995).

2. Methodology

The efficiency measurement methods used in this paper are derived from those presented in Fare, Grosskopf and Lovell (1985, 1994), which are based upon the work of Farrell (1957); Afriat (1972); Charnes, Cooper and Rhodes (1978) and others. A comprehensive introduction to DEA methods is provided in Coelli, Rao and Battese (1998). The four efficiency measures used here (technical, allocative, cost and scale) are briefly described next.

Technical Efficiency

Technical efficiency relates to the degree to which a farmer produces the maximum feasible output from a given bundle of inputs, or uses the minimum feasible amount of inputs to produce a given level of output. These two definitions of technical efficiency lead to what are known as output-oriented and input-oriented efficiency measures, respectively. These two measures of technical efficiency will coincide when the technology exhibits constant returns to scale, but are likely to differ otherwise. In this study, we use input-oriented efficiency measures because they lead to a natural decomposition of cost efficiency into its technical and allocative components. We do not expect this choice to have a large bearing on our results, given that the farmers in our sample have very small areas of land and hence the technology is unlikely to be significantly affected by non-constant returns to scale.[2]

[2] This is bourn out in the scale efficiency results, which are listed later in this paper.

The DEA production frontier is constructed using linear programming techniques, which give a piece-wise linear frontier that "envelopes" the observed input and output data. Technologies produced in this way possess the standard properties of convexity and strong disposability, which are discussed in Fare, Grosskopf and Lovell (1994).

The DEA model is used to simultaneously construct the production frontier and obtain the technical efficiency measures. The model is presented for the case where there are data on K inputs and M outputs for each of N farms.[3] For the i-th farm, input and output data are represented by the column vectors x_i and y_i, respectively. The K×N input matrix, X, and the M×N output matrix, Y, represent the data for all N farms in the sample.

The DEA model used for calculation of technical efficiency is:

$$
\begin{aligned}
&\mathrm{Min}_{\theta,\lambda}\ \theta, \\
&\text{Subject to} \quad -y_i + Y\lambda \geq 0, \\
&\qquad\qquad\quad \theta x_i - X\lambda \geq 0, \\
&\qquad\qquad\quad N1'\lambda = 1 \\
&\qquad\qquad\quad \lambda \geq 0,
\end{aligned}
\tag{1}
$$

where θ is a scalar, N1 is an N×1 vector of ones, and λ is an N×1 vector of constants. The value of θ obtained is the technical efficiency score for the i-th farm. It will satisfy: $\theta \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient

[3] The general case of M outputs is presented in the linear programs in this section to illustrate that analyses need not be confined to single output case as it is in this study.

farm, according to the Farrell (1957) definition. Note that the linear programming problem must be solved N times, to obtain a value of θ for each farm in the sample.

The DEA problem in equation (1) has an intuitive interpretation. The problem takes the i-th farm and then seeks to radially contract the input vector, x_i, as much as possible, while remaining within the feasible input set. The inner-boundary of this set is a piece-wise linear isoquant (SACDS′ in Figure 1), determined by the frontier data points (the efficient farms) in the sample. The radial contraction of the input vector, x_i, produces a projected point, $(X\lambda,Y\lambda)$, on the surface of this technology. This projected point is a linear combination of these observed data points. The constraints in equation (1) ensure that this projected point cannot lie outside the feasible set.

Figure 1 here

In Figure 1, the four farms (A, B, C and D) are producing the same level of output, using various amounts of two inputs, denoted by x_1 and x_2. Farms A, C and D form the production frontier (or isoquant) because it is not possible for any of these farms to radially reduce their input usage, and still remain within the production possibility set. Farm B, however, is inefficient because it can reduce its input usage to the projected point B′, so its technical efficiency (TE) is 0B′/0B.

Allocative Efficiency and Cost Efficiency

If input price information is available, allocative efficiencies can also be measured using the isocost line, HH′, which is tangential to the isoquant at the point C. If all farms face the same relative prices reflected by this line, farm C is producing at minimum cost, while the other farms are not.[4] Thus, even though farms A and D are technically efficient, they are not cost efficient because they are allocatively inefficient. That is, they do not utilise the inputs in optimal proportions, given the observed input prices, and hence do not produce at minimum possible cost. Farm B is both technically inefficient and allocatively inefficient. Its allocative efficiency can be measured by the ratio 0B″/0B′, and its cost efficiency by the ratio 0B″/0B. Then, cost efficiency is equal to the product of the technical and allocative efficiency scores (0B″/0B = 0B′/0B×0B″/0B′).

The cost and allocative efficiencies are obtained by solving the following additional cost minimisation DEA problem:

$$
\begin{aligned}
&\min_{\lambda, x_i^*} \; w_i' x_i^*, \\
&\text{st} \quad -y_i + Y\lambda \geq 0, \\
&\qquad x_i^* - X\lambda \geq 0, \\
&\qquad N1'\lambda = 1 \\
&\qquad \lambda \geq 0, \qquad\qquad (2)
\end{aligned}
$$

[4] The farms can also face different price vectors, as is the case in the empirical analysis in this study.

where w_i is a vector of input prices for the i-th farm and x_i* (which is calculated by the model) is the cost-minimising vector of input quantities for the i-th farm, given the input prices w_i and the output levels y_i. The total cost efficiency (CE) of the i-th farm is calculated as

$$CE = w_i'x_i^* / w_i'x_i.$$

That is, CE is the ratio of minimum cost to observed cost for the i-th farm. The allocative efficiency (AE) is then calculated residually by

$$AE = CE/TE.$$

Scale Efficiency

The DEA models discussed so far have been variable returns to scale (VRS) DEA models. That is, they permit the constructed production frontier to have (local) increasing, constant or decreasing returns to scale properties. One can easily impose constant returns to scale (CRS) upon the DEA problem in equation (1) by deleting the convexity constraint ($N1'\lambda=1$). This allows calculation of the scale efficiency measure discussed below.

Figure 2 illustrates the calculation of scale efficiency using a one-input (x), one-output (y) example. The CRS and VRS frontiers are indicated in the figure. Under CRS, the input-oriented technical inefficiency of the point P is the distance PP_C. However, under VRS, the technical inefficiency would only be PP_V. The difference between these two TE measures, P_CP_V, is due to scale inefficiency. These concepts can be expressed in ratio efficiency measures as:

$TE_{CRS} = AP_C/AP$

$TE_{VRS} = AP_V/AP$

$SE = AP_C/AP_V$

where all of these measures are bounded by zero and one. Given this, it is clear that we can easily calculate scale efficiency (SE) as:

$SE = TE_{CRS}/TE_{VRS}$

Figure 2 here

One shortcoming of this measure of scale efficiency is that the value does not indicate whether the farm is operating in an area of increasing or decreasing returns to scale. This latter issue can be resolved by running an additional DEA problem with non-increasing returns to scale (NIRS) imposed. This is done by altering the DEA model in equation (1) by substituting the $N1'\lambda = 1$ restriction with $N1'\lambda \leq 1$.

Having generated efficiency scores for the farms, the variations in efficiency scores were regressed on the farm-level characteristics, in order to explain the differences. Because of the bounded nature of the efficiencies (between zero and unity), a Tobit model was used, with the upper limit was set at one.

The NIRS frontier is also plotted in Figure 2. The nature of the scale inefficiency for a particular farm can be determined by seeing whether the NIRS TE score is equal to the VRS TE score. If they are unequal, as is the case for the point P in Figure 2, then increasing returns to scale exist for that farm. If they are equal, as is the case for point Q in Figure 2, then decreasing returns to scale apply. Finally, if $TE_{CRS} = TE_{VRS}$, then by definition, the farm is operating under CRS.

3. Data and Variables

The data used in this study come from a survey of rice producers, conducted during February to April 1997 in three agro-ecological regions of Bangladesh. Samples were collected from eight villages of the Jamalpur Sadar sub district of Jamalpur, representing wet agro-ecology, six villages of the Manirampur sub district of Jessore, representing dry agro-ecology, and seven villages of the Matlab sub district of Chandpur, representing wet agro-ecology in an agriculturally advanced area. A total of 406 farm households from these 21 villages were selected following a multistage stratified random sampling procedure.

Rice in Bangladesh is grown in all three seasons, Aus, Aman and Boro. Aman is the monsoon season while Boro and Aus fall in the dry season and overlap each other. Moreover, the modern Boro rice competes with modern Aus rice and has similar characteristics. These modern varieties are grown by substituting land from traditional Aus rice, jute, traditional broadcast Aman rice and minor dry season crops, such as pulses and oilseeds (Hossain *et al*., 1990). The data for the present study show that modern

Boro rice is dominant, accounting for 35 percent of gross cropped area, followed by modern Aman rice (32 percent of gross cropped area), so the analysis concentrates on these two crops.

The *output* is measured as kilograms of rice harvested. The inputs, for which both quantities and the corresponding prices are used, are land planted to rice, family and hired labour, fertiliser, seed and draft animals

These five are the main inputs used in rice production in Bangladesh. Additional variables that could be considered are irrigation, chemicals and capital. These were not included for various reasons. Irrigation was not included because it was effectively uniform across the sample. Chemicals were not included because they were used on only a small proportion of farms, and generally in a reactive way. That is, pesticides would tend to be applied in response to a pest infestation. Hence, one tends to observe a negative relationship between chemical use and yields. The capital used on these farms was in the form of wooden ploughs and hand tools. These items were also essentially uniform across the farms.

We also attempt to explain efficiency differences among farms using farm-specific variables that were collected specifically for this purpose. These are infrastructure, experience, family size, working adults in the household, education of the head of household, total land cultivated, tenancy, soil fertility, the share of non-agriculture income, extension contact and the agricultural training of the head of household.

This is one of the most exhaustive lists of farm-specific variables that any analysis has used to attempt to explain efficiency differentials.[5] However, information on some variables of interest was not available. In particular, we wished to assess the effect of credit constraints upon technical and allocative efficiencies, but the survey information collected was inadequate. Data was collected on the amount of outstanding credit, but this information was of limited use because it was not known if those farmers who had not taken out credit had enough money to cover their needs or faced a credit constraint.

4. Results and discussion

Summary statistics for the sample data are reported in Table 1. Information is presented for the Aman and Boro seasons separately because of the substantial differences between wet season and dry season cultivation methods. The table shows that these farms are quite small, with an average size of only one third of a hectare and that the mean production is 30 percent higher in the Boro season. The implied average yields are 3.3 and 4.6 tonnes/ha for Aman and Boro, respectively, which are comparable with yield levels reported in past studies. For example, Hossain (1989) reports 3.5 and 4.0 tonnes/ha, and Hossain *et al.* (1990) report 3.5 and 5.1 tonnes/ha.

The input quantities are similar across the seasons, with the exception of labour, which is a little higher, and fertiliser, which is almost 30 percent higher in the Boro season. Input prices are also similar across the seasons, with the exception of the fertiliser price, which jumps by 20 percent in the Boro season, and land rental, which rises by almost a third.

[5] See Bravo-Ureta and Pinhero (1993) for a detailed survey.

[Table 1 in here]

The farm-specific variables provide a summary of the characteristics of these farms. The average level of education is less than four years; the average age of the farmer is 47; average family size is six; 20 percent of income is derived off-farm; approximately 50 percent of farms are owner-operated; only 10 percent of farmers have had contact with extension officers during the past year; and only 5 percent have had any training in the past seven years.

The results of the DEA methods described in the previous section are reported in Table 2. Summary statistics for the measures of technical, allocative, cost and scale efficiencies are listed in Table 2.[6] The average technical efficiency score is 0.662 for the Aman season and 0.694 for Boro. This suggests that the average farm is producing only about two thirds of the potential output level. Average technical efficiency in the Aman season is a few percentage points below the Boro season, which may be partly due to the monsoon rains causing occasional flood damage.

[Table 2 here]

The mean allocative efficiency scores are 0.780 and 0.813, for Aman and Boro, respectively. These scores indicate that these farmers could reduce costs by about 20 percent, by taking more notice of relative input prices when selecting input quantities. Thus, allocative inefficiency adds to the degree to which costs can be reduced in this industry. When allocative and technical efficiencies are combined to form cost efficiency measures, the average cost efficiency scores are 0.517 and 0.562 for Aman and Boro, respectively.

Allocative efficiency can be further investigated, following equation 3, as the cost minimizing DEA model produces the cost efficient input quantities (x_i*) for each farm in the sample. Thus, for the i-th farm one can specify which inputs are being over- or under-used by comparing the cost efficient input levels (x_i*) with the technically efficient input levels (θx_i). For instance, farm B in Figure 1 is over-using input x_2 and under-using input x_1. Movement from the point B′ to the point C will correct this problem.

Thus, the systematic over-use of inputs is shown in Table 3, which reports the average ratios of technically efficient input levels to cost efficient input levels for each of the five inputs. A ratio greater than unity indicates overuse of that input, so there is considerable overuse of labour and fertiliser. The overuse of labour is not unexpected, as many of these farms are very small (0.33 hectares on average), yet they support an average of two hired workers and six family members. With little opportunity for alternative work, this over-use is evidence of disguised unemployment. The hired labour wage was also applied to family labour in the analysis and if the cost of family labour is reduced to reflect the disguised unemployment, the allocative inefficiency with respect to labour is much reduced.

The overuse of fertiliser is a little surprising, given the credit constraints that many farmers face, but the recommended fertiliser rates were based upon recommendations developed when fertiliser was subsidised. These results suggest that these recommended rates of fertiliser application may need to be revisited.

[Table 3]

[6] All the efficiency measures are calculated for each farm in the sample, but this level of detail cannot be exploited here.

The last results reported in Table 2 are the mean levels of scale efficiency, which were 0.933 and 0.949 for the Aman and Boro rice, respectively. These figures indicate that farm size issue is much less important relative to the amount of technical and allocative efficiency. Finally, Table 2 lists the percentages of farms, which have increasing returns to scale (IRS), constant returns to scale (CRS) and decreasing returns to scale (DRS). Over the two seasons, the results are fairly evenly distributed, suggesting that there is no systematic pattern of farms being too big or too small. Indeed, there is no real reason why scale efficiency should be important in rice production under Bangladesh conditions, but the scale efficiency results only reflect the farms in the sample, which are all small. It is possible that significantly larger farms could realise scale economies.

As was noted earlier, the above efficiency measures provide richer information on efficiency differentials than simple yield and unit cost measures. To illustrate this point yields were calculated for the farms in this data and converted into efficiency measures by expressing *yield efficiency* as the ratio of observed yield to maximum yield in the sample. The sample means for yield efficiency were found to be 0.519 and 0.602 for Aman and Boro, respectively. These values illustrate the point rather well. Compared to the DEA technical efficiency scores of 0.662 and 0.694, the yield efficiency measures significantly overstate the degree of technical inefficiency because they do not account for differences in the usage of non-land inputs across farms.

Similarly, *unit cost efficiency* was calculated as the inverse of the ratio of observed unit cost to the minimum unit cost in the sample. The sample means for unit cost efficiency were found to be equal to 0.559 and 0.619 for Aman and Boro respectively, whereas the DEA cost efficiency scores were 0.517 and 0.562. These unit cost efficiency measures understate the degree of cost inefficiency because they do not account for the substantial variations in input prices across farms. These two comparisons suggest that simple yield and unit cost measures do not provide accurate guidance in the analyses of agricultural performance.

Factors explaining efficiencies

The results thus far indicate that efficiency scores vary substantially across farms and that the average level of inefficiency is significant. To explain some of these variations, the efficiency scores were regressed on the farm-level characteristics, using a Tobit model, since the efficiencies vary from zero to unity. The Tobit results are listed in Table 4 and elasticity estimates derived from these regression results (evaluated at the sample means) are reported in Table 5.

[Tables 4 and 5 here]

The tenancy result indicates that owner-operators are more cost efficient, but the effect is picked up only in the more labour intensive Aman season. As in the previous studies, such as Deb (1995), education was not correlated with efficiency and this result may be explained by the average education level of less than four years, reported in Table 1. Larger families are clearly a cause of lower efficiencies in the less labour intensive Boro season, when surplus labour is more of a problem. This variable captures this effect, with the result that the number of working adults was not a significant indicator of under-employment. The age variable shows only that older farmers were more cost efficient in the Boro season, at the 10% significance level, but the more experienced farmers were less technically and cost efficient in the Boro season. The older, more experienced farmers have more knowledge of their land and traditional practices, but are also less willing to adopt new ideas, and the second effect is dominant.

Poor infrastructure has negative effects on both technical and allocative efficiencies. Both would be adversely affected by not having inputs to use at the correct time, in insufficient quantities, or not at all. The coefficient associated with the amount of land cultivated, offers another chance to investigate returns to scale and the results are both consistent with the DEA outcomes and shed more light. The larger farms are both more allocatively and cost efficient in the Aman season, which accounts for the majority having IRS, as reported in Table 2. However, in the Boro season, the larger farms are allocatively inefficient, which explains the majority having DRS, as reported in Table 2. Thus, the larger farms appear to have advantages in the labour intensive monsoon season, but are disadvantaged in the less labour intensive season.

The insignificant effects of the *soil fertility* variable indicate that this variable has little influence upon the observed efficiency differentials. This lends support to the assertion that much of the efficiency differences across the sample farms can be attributed to management issues rather than physical differences.[7] This is an important result in an efficiency study such as this, where there is always a danger that the efficiency differences will be simply the result of omitted physical differences in factors such as soil.

The percentage of income earned off-farm was included to reflect the relative importance of non-agricultural work in the household. The consistent negative signs on the estimated coefficients point towards a situation where increasing land fragmentation has meant that many households are unable to support themselves through agriculture, and hence must turn to off-farm work, and subsequently do not pay as much attention to their crops relative to other farmers. Finally, the weak results for extension and training are not unexpected, given the limited resources that are devoted to these activities. However, the low efficiency scores suggest that these activities should be supported, since full technical efficiency would mean increasing output by about fifty per cent.

Finally, this paper has reported means, but the individual farm-level information has been passed on to local extension advisers. The efficiencies and vectors of cost-efficient input quantities are useful information and for inefficient farms, there is a set of efficient peers. These can indicate the reasons for technical inefficiency, since the peers get more output using similar mixes of inputs.[8]

5. Conclusions

This study uses data envelopment analysis (DEA) to analyse the efficiency of Bangladeshi rice farmers. Using detailed survey data for 1997, for 406 rice farms spread over 21 villages, measures of efficiency are estimated, which differ substantially from those obtained using simple yield and unit cost measures. The Boro (dry) season results indicate mean technical efficiency of 69.4 percent, mean allocative efficiency of 81.3 percent and mean scale efficiency of 94.9 percent. The Aman (wet) season results are similar, but a few points lower. The majority of allocative inefficiency can be attributed

[7] Addition regressions were also run, where dummy variables for village and region were included. However, these were also observed to be insignificant in explaining efficiency differences.
[8] In many farming systems, especially were animal production is important, the farmers need to optimise in a multi-period framework and cross section results may also be of limited value. However, for Bangladesh, the dominance of one annual crop lessens this problem.

to overuse of labour and fertiliser, pointing towards a disguised unemployment problem, and a set of fertiliser rate recommendations that warrant revision.

Second-stage regressions attempt to explain variations in efficiencies between farms. The results obtained indicate that large families are likely to be more inefficient, further highlighting the hidden unemployment problem. We also find that those farmers who have better access to input markets, and those who do less off-farm work, tend to be more efficient. Age, education, experience, soil fertility, extension and training do not have a large influence on efficiency levels.

Overall, we have clearly demonstrated that analyses of agricultural performance that focus on the use of simple yield per hectare and unit cost figures are inadequate on two fronts. First, they may be providing seriously misleading measures of relative farm performance. Second, there is a wealth of information on the sources of inter-farm performance differentials, which is hidden in such simple measures. There is little excuse for such sub-optimal use of survey data, which is often collected at substantial cost. The DEA methods outlined in this paper are easy to calculate and interpret.[9] These methods can also accommodate multiple-output farms and can also be applied to almost any industry.[10]

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[9] See Coelli *et al*. (1998), which describes the use of free computer software that can be downloaded from the web at http://www.une.edu.au/econometrics/cepa.htm.

[10] An impressive survey of applications of DEA can be found in A.Charnes, W.W. Cooper, A.Y. Lewin and L.M. Seiford (1995).

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Appendix: Variable Definitions

O*utput* is measured as kilograms of rice harvested.

Inputs: The input variables are defined as follows:

Land = Area (ha) planted to rice by the farmer.

Labour = Amount of both own and hired labour (person-days) used.

Fertiliser = Amount of fertiliser (kg) of all three kinds (Urea, Triple Super Phosphate and Muriate of Potash) applied to the crop.

Seed = Amount of seed (kg) used. (In the case where farmers purchase seedlings for transplantation, the cost of purchase is converted to weight of seed by using standard methods).

Draft animals = Amount of animal power services (pair-days) used. (In the case of contract hire, the cost is converted to equivalent pair-days by dividing it by the daily hiring rate of animal power services, which applies in that village).

Land rent = Amount of rent paid (Taka/ha) for the use of land by tenants (imputed for the owner operators).

Wage = Wage (Taka/day) paid to agricultural labour (imputed for family supplied labour).

Seed price = Price of seed (Taka/kg) used for rice cultivation (in case of seedlings purchased, it is converted to equivalent seed quantity to determine the imputed seed price).

Animal price = Charges for hired bullock pair (Taka/day) used for rice production (imputed for family supplied animal power).

Fertiliser price = Weighted average of the prices of the three types of fertiliser (Taka/kg).

Farm-specific Variables:

Infrastructure = A composite index of the degree of underdevelopment of infrastructure. This was constructed using the cost of access approach. A total of 13 elements are considered for its construction. These are, (1) primary market, (2) secondary market, (3) storage facility, (4) rice mill, (5) paved road, (6) bus stop, (7) bank, (8) union office, (9) agricultural extension office, (10) high school, (11) college, (12) thana (sub-district) headquarter, and (13) post office. The variables are coded so that a high index value indicates a highly underdeveloped infrastructure.

Experience = Number of years the farmer has been producing rice.

Family size = Number of people in household.

Working adults = Number of working family members in the farm household. This variable, and the one above, are used to pick up possible disguised unemployment.

Education = Years of schooling completed by the farmer.

Land cultivated = Total area of land cultivated by the farm household.

Tenancy = Dummy variable for tenure status. The value is 1 if the farmer is an owner operator, and 0 otherwise.

Soil fertility= A composite index of soil fertility. This is constructed from test results of soil samples collected from the representative farm plots of the study villages during field survey for crop year 1996. Ten soil-fertility parameters were tested. These are: (1) soil pH, (2) available nitrogen, (3) available potassium, (4) available phosphorus, (5) available sulphur, (6) available zinc, (7) soil texture, (8) caption exchange capacity (CEC) of soil, (9) soil organic matter content, and (10) electrical conductivity of soil. A high value of this index implies better soil fertility.

Non-agriculture income share = Proportion of total household income obtained from non-agricultural sources.

Extension contact = Dummy variable to measure the influence of agricultural extension on efficiency. Value is 1 if the farmer has had contact with an Agricultural Extension Officer in the past year, and 0 otherwise.

Training = Dummy variable to measure the influence of agricultural training on efficiency. Value is 1 if the farmer had any training on agriculture in the past seven years, and 0 otherwise.

Table 1. Summary statistics

Variables	Modern Aman rice				Modern Boro rice			
	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum
Output and Inputs:								
Rice output (kg)	1,204.50	1,285.00	37.00	8211.30	1,516.50	1,505.80	93.00	11,197.00
Land cultivated (ha)	0.36	0.38	0.01	2.31	0.33	0.34	0.02	2.83
Animal power (pair-days)	9.16	9.94	0.35	60.00	9.09	9.71	0.50	75.00
Fertiliser (kg)	72.63	86.41	1.00	780.00	92.63	99.02	1.00	700.00
Seed (kg)	32.10	33.50	1.80	225.00	33.49	35.27	2.00	320.00
Labour (day)	27.95	26.94	2.00	140.00	31.33	27.68	2.00	170.00
Land rent (taka/ha)	7,845.50	3,009.40	1,339.00	19,484.00	10,429.00	3,970.40	1,779.00	26,681.00
Fertiliser price (taka/kg)	5.59	1.62	4.00	10.00	6.82	1.46	4.00	10.00
Seed price (taka/kg)	9.86	1.53	4.00	15.00	9.96	1.16	5.00	15.00
Labour wage (taka/day)	45.92	7.75	25.00	65.00	46.01	9.53	30.00	65.00
Animal wage (taka/pair-days)	84.85	18.46	30.00	110.00	84.58	18.88	30.00	110.00
Farm-specific variables:								
Education of household head (years)	3.84	4.40	0.00	15.00	3.64	4.32	0.00	15.00
Experience (years)	25.37	14.66	0.00	65.00	25.49	14.35	0.00	70.00
Age (years)	47.41	14.88	15.00	80.00	46.89	14.81	17.00	90.00
Family size (persons)	5.89	2.38	1.00	16.00	6.04	2.56	1.00	17.00
Working member (persons)	2.17	1.29	0.00	7.00	2.05	1.30	0.00	7.00
Infrastructure index (number)	37.52	14.84	14.87	73.55	34.98	14.70	14.87	73.55
Soil fertility index (number)	1.69	0.19	1.38	2.00	1.69	0.19	1.38	2.00
Non-agricultural income share (%)	0.18	0.30	0.00	0.96	0.20	0.32	0.00	0.96
Tenancy (%)	0.56	0.50	0.00	1.00	0.49	0.50	0.00	1.00
Extension visit (%)	0.12	0.33	0.00	1.00	0.10	0.30	0.00	1.00
Training receipt (%)	0.05	0.23	0.00	1.00	0.05	0.23	0.00	1.00
Number of observations (n)	351	-	-	-	422	-	-	-

Table 2. Technical, allocative, cost and scale efficiency estimates

	Modern Aman rice				Modern Boro rice			
	TE	**AE**	**CE**	**SE**	**TE**	**AE**	**CE**	**SE**
Mean	0.662	0.780	0.517	0.933	0.694	0.813	0.562	0.949
Std. dev.	0.185	0.117	0.170	0.092	0.161	0.100	0.143	0.079
Minimum	0.301	0.278	0.203	0.458	0.322	0.391	0.258	0.407
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
< 60 %	43.30	5.70	72.36	1.42	33.18	3.79	62.56	0.71
60 – 69 %	17.95	16.52	14.25	1.99	23.93	9.48	21.09	0.95
70 – 79 %	14.81	31.34	6.55	5.13	18.72	23.93	10.19	4.98
80 – 89 %	10.26	31.05	3.70	12.54	9.72	44.55	3.79	8.53
90 – 100 %	13.68	15.38	3.13	78.92	14.45	18.25	2.37	84.83
IRS (%)	-	-	-	53.56	-	-	-	31.04
DRS (%)	-	-	-	38.18	-	-	-	58.06
CRS (%)	-	-	-	8.26	-	-	-	10.90

Table 3. Input use ratios

	Level of input use				
	Land	**Labour**	**Seed**	**Fertiliser**	**Animal power**
Modern Aman rice					
Mean	1.212	1.665	1.056	1.828	1.365
Standard deviation	0.358	0.680	0.449	0.985	0.500
Maximum	5.059	4.253	4.231	8.029	4.013
Overusing farms (%)	45.02	95.73	55.92	78.44	52.84
Modern Boro rice					
Mean	1.060	2.367	1.144	1.306	1.170
Standard deviation	0.221	1.055	0.418	0.426	0.460
Maximum	2.943	6.906	3.345	3.153	4.000
Overusing farms (%)	84.90	84.62	41.60	82.05	76.92

Table 4. Factors explaining efficiency

Variables	Modern Aman rice			Modern Boro rice		
	TE	AE	CE	TE	AE	CE
Constant	4.3448	6.5854	3.6988	5.2068	8.9031	5.0580
	(6.940)*	(10.129)*	(6.010)*	(9.037)*	(14.289)*	(8.887)*
Tenancy	0.2111	0.1974	0.3101	0.0799	-0.0975	0.0243
	(1.771)	(1.666)	(2.610)*	(0.743)	(-0.911)	(0.227)
Education	-0.0054	-0.0266	-0.0184	-0.0218	0.0068	-0.0146
	(-0.359)	(-1.764)	(-1.224)	(-1.551)	(0.483)	(-1.040)
Family size	-0.0177	-0.0322	-0.0329	-0.0558	-0.0393	-0.0685
	(-0.662)	(-1.214)	(-1.240)	(-2.462)*	(-1.748)	(-3.033)*
Working adults	-0.0011	0.0255	0.0244	-0.0827	0.0472	-0.0428
	(-0.023)	(0.534)	(0.512)	(-1.819)	(1.045)	(-0.947)
Age	-0.0093	0.0039	-0.0051	0.0059	0.0064	0.0108
	(-1.340)	(0.558)	(-0.738)	(0.972)	(1.061)	(1.798)
Experience	0.0128	-0.0048	0.0071	-0.0180	-0.0015	-0.0188
	(1.727)	(-0.650)	(0.967)	(-2.724)*	(-0.227)	(-2.849)*
Infrastructure	-0.0182	-0.0060	-0.0159	-0.0135	-0.0122	-0.0164
	(-4.531)*	(-1.513)	(-3.990)*	(-3.760)*	(-3.432)*	(-4.579)*
Land cultivated	0.1775	0.5131	0.3910	0.1613	-0.7093	-0.2515
	(1.063)	(3.078)*	(2.358)*	(0.974)	(-4.303)*	(-1.542)
Soil fertility	-0.0519	0.2793	0.0683	0.1281	0.2197	0.1736
	(-0.175)	(0.947)	(0.232)	(0.460)	(0.794)	(0.628)
Non-farm income	-0.2601	-0.5319	-0.4697	-0.3117	-0.0317	-0.2491
	(-1.375)	(-2.811)*	(-2.486)*	(-1.963)*	(-0.201)	(-1.577)
Extension visit	0.2684	0.1685	0.2846	0.2640	-0.1745	0.1869
	(1.501)	(0.954)	(1.613)	(1.496)	(-1.000)	(1.071)
Training	0.0167	0.1205	0.1451	0.2585	-0.3136	0.0293
	(0.063)	(0.456)	(0.550)	(1.094)	(-1.339)	(0.125)
Log-likelihood	27.457	251.227	128.300	104.471	392.315	237.755

Note: * significant at 5 percent level

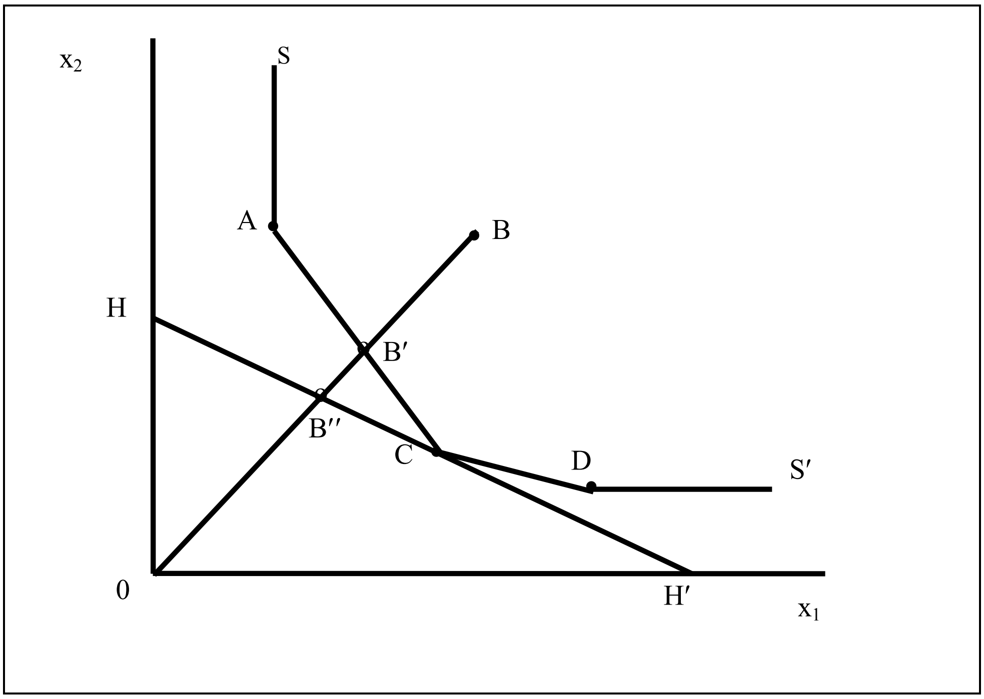
Table 5. Tobit elasticities

Variables	Modern Aman rice			Modern Boro rice		
	TE	AE	CE	TE	AE	CE
Tenancy	0.0326*	0.0157*	0.0541***	0.0089	-0.0054	0.0029
Education	-0.0057	-0.0145*	-0.0220	-0.0180	0.0028	-0.0127
Family size	-0.0286	-0.0269	-0.0602	-0.0767**	-0.0268*	-0.0996***
Age	-0.1216	0.0259	-0.0754	0.0628	0.0338	0.1224*
Experience	0.0894*	-0.0173	0.0563	-0.1044***	-0.0043	-0.1150***
Infrastructure	-0.1876***	-0.0317	-0.1854***	-0.1072***	-0.0482***	-0.1381***
Working adults	-0.0007	0.0078	0.0164	-0.0386*	0.0109	-0.0211
Land cultivated	0.0175	0.0260***	0.0435**	0.0121	-0.0264***	-0.0200
Soil fertility	-0.0241	0.0668	0.0358	0.0493	0.0418	0.0705
Non-farm inc.	-0.0131	-0.0138***	-0.0268**	-0.0143*	-0.0007	-0.0121
Extension visit	0.0088	0.0029	0.0106	0.0058	-0.0019	0.0044
Training	0.0002	0.0009	0.0024	0.0032	-0.0019	0.0004

Notes: The significance of the elasticities is based on standard error of the Tobit regression coefficients.

*** = significant at 1 percent level (p<0.01)
** = significant at 5 percent level (p<0.05)
* = significant at 10 percent level (p<0.10)

Figure 1: Technical and Allocative Efficiencies



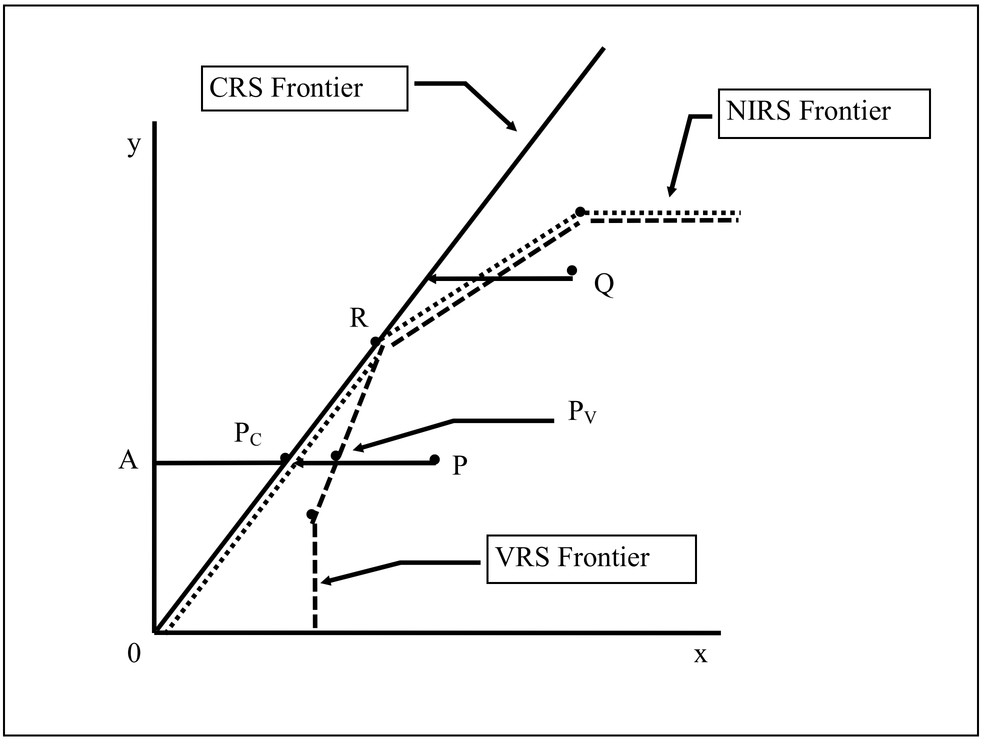


Figure 2: Constant, Increasing and Decreasing Returns to Scale