Measuring Efficiency in Agricultural Research:
Strength and Limitations of Data Envelopment Analysis

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Introduction

Performance measurement of research operations is considered to be a particularly difficult undertaking as the research process is unpredictable and its outputs are manifold while comparing the relevance of outputs is troublesome. In general, research performance assessment distinguishes many different models representing different schools of thought and disciplines. For example, performance can be measured by using a single indicator as well as applying more complex measurement systems using multiple input and output measures to indicate the research process. One of the problems particularly related to performance assessment of research operations is to integrate a set of very distinct indicators into overall performance measures.

In this paper we will set forth Data Envelopment Analysis (DEA) which is an evaluation method particularly adapted to comprise a set of multiple indicators of performance and we discuss its usefulness in research evaluation. DEA enables frontier estimation with the use of non-parametric programming models leading to a ranking of all units of observation on the basis of technical efficiency scores. The focus is not on the estimation of an average technology production function used by all units analyzed but to identify the best practicing units, a best practice production frontier is constructed, and all units of analysis are related to this frontier. DEA also avoids the application of common set of weights when determining relative efficiency of different outputs but uses the principle of Pareto efficiency. This is assumed to lead to a better understanding of the conditions under which the units of analysis operate. These characteristics of DEA lead to the assumption, that it is particularly useful in research performance assessment (da Silva e Souza et al., 1997). Recently, DEA is rapidly becoming an accepted tool in economic analysis of production units practical use in studies increases daily. There is a huge amount of empirical studies applying DEA in analysis of farm efficiency, banking, health care (hospitals, doctors), education (schools, universities), banks, manufacturing, benchmarking, management evaluation, fast food restaurants, retail stores and many others[1].There is simple but suitable software available from the internet (e.g. DEA-P© and EMS©) and commercial software designed particularly for management use like for example Frontier Analyst©.

The paper does not comprise any empirical data from the field. It rather constitutes an in-depth description of the method as a basis for a theoretical discussion on the applicability of the method in assessing research performance. The aim of the paper is to familiarize the reader with the method and to discuss its usefulness in research evaluation. The paper is thought to be used as a reference to future research work related to evaluation of agricultural research. In the first part of the paper we briefly elaborate on the DEA method of measuring economic efficiency. In the second part, we distinguish economic efficiency into allocative and technical

[1] *There is ample information on DEA available on the Internet. For further reading on DEA http://www.emp.pdx.edu/dea/homedea.html can be useful. The page includes discussions on the method and results from empirical analysis. A large set of electronically published papers on methods and empirical results can also be made available from the cite of the Centre for Efficiency and Productivity Analysis from the University of New England http://www.une.edu.au/econometrics/deap.htm.*

efficiency. The latter is the core measure used in DEA. In part three the two basic DEA models, the constant return to scale (CRS) model and the variable return to scale (VRS) model, both used in the literature are presented. They are illustrated with the use of an hypothetical example. In section four we discuss some extensions of the model, related to scale efficiency, the inclusion of prices and weights, and the decomposition of the technical efficiency term. In part five we discuss strength and limitations of the DEA method and its usefulness in research evaluation, by presenting a summary of experiences with DEA generated and published elsewhere.

1. Measuring efficiency

Assume that there is a set of units of observations (for abbreviation we call them units in the following)[2] which are to be analyzed. Analysis of economic efficiency, now, entails the comparison of units with a measure of productivity. A measure of productivity is a relation of real inputs to real outputs.

Usually, the relative efficiency of any unit is calculated by forming an index of the ratio of a weighted sum of outputs to a weighted sum of inputs. Assume there is a sample of n units where each unit utilizes j inputs to produce r different outputs. The ratio of output to input then measures the efficiency of a particular unit in the sample. The efficiency of unit 1, for example, would be computed according to:

$$E_1 = \frac{u_1 y_{11} + u_2 y_{21} + ... + u_s y_{s1}}{v_1 x_{11} + v_2 x_{21} + ... + v_m x_{m1}} = \frac{\sum_{r=1}^{s} u_{r1} y_{r1}}{\sum_{j=1}^{m} v_{j1} x_{j1}} \qquad (1)$$

where E_1 = the efficiency of unit 1
u_r = the weight given to output r
y_{r1} = the amount of output r from unit 1
v_j = the weight given to input j
x_{j1} = the amount of input j to unit 1

Within the DEA approach, multiple inputs and multiple outputs are reduced to a single virtual input and virtual output and finally to a single summary relative efficiency score. The development of the DEA recognizes the difficulty in seeking a common set of weights to determine relative efficiency. It is a distinct characteristic of DEA to recognize the legitimacy, that units might value inputs and outputs differently and therefore adopt different weights. DEA proposes that each unit should be allowed to adopt a set of weights which shows it in the most favorable light in comparison to the other units (Dyson et al. 1990). This means that the values of the u's and v's are not established from empirical data but are estimated from the model with the help of programming techniques.

The weights (multipliers) for both outputs and inputs are to be selected so as to calculate the Pareto-efficiency measure of each unit (Charnes et al. 1995). Pareto efficiency is attained when no input can be reduced without reducing the output or when no output can be increased without increasing the input.

No unit can have a relative efficiency score greater than unity. The DEA calculations are designed to maximize the relative efficiency score of each unit, subject to the condition that the set of weights obtained in this manner for each unit must also be feasible for all the other units included in the calculation. DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface (or frontier) over the data. Efficiency measures are then calculated relative to this surface.

DEA is different from parametric average least square estimations because it reveals an understanding about the individual unit instead of the depiction of an average unit. Further, parametric approaches require the imposition of a specific functional form (e.g. a regression equation, a production function, a cost function) relating the independent variables to the dependent variables. DEA does not require any assumption about the functional form. It rather calculates a maximal performance measure for each unit relative to all other units in the observed population with the sole requirement that each unit lies on or below the outer frontier.

2 In most of the DEA literature they are called Decision Making Units (DMUs)

2. Technical and Allocative Efficiency

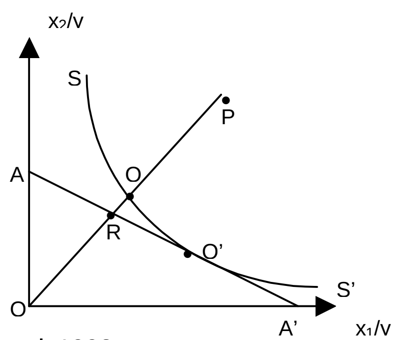
There are different approaches to efficiency. Setting forward the frontier analysis approach, Farell (1957) proposed that the economic efficiency of a unit consists of two components:

(a) Technical efficiency: Reflects the ability of a unit to obtain maximal output from a given set of inputs, and

(b) Allocative efficiency: Reflects the ability of a unit to use the inputs in optimal proportions given their respective prices and the production technology.

The two components are graphically demonstrated in Figure 1. We assume, that a set of economic units use two inputs (x_1 and x_2) to produce a single output (y), under the assumption of constant returns to scale.

Figure 1: Technical and Allocative Efficiencies



P = an inefficient unit

Q = a technically efficient unit

Q' = an allocatively efficient unit

AA' = the isocost line

SS' = the isoquant of efficiency

R' = an hypothetical point on the isocost line indicating equal to Q' costs

After Coelli et al. 1998

Knowledge of the unit isoquant of fully efficient units represented by SS' permits the measurement of technical efficiency. The unit uses quantities of inputs defined by, for example, point P. Technical inefficiency can be represented by the distance QP, which is the amount by which all inputs could be proportionally reduced without a reduction of the output level. Technical efficiency is then usually expressed in percentage terms by the ratio QP/0P, which represents the percentage by which all inputs need to be reduced to achieve technically efficient production. Technical efficiency is commonly measured by the ratio 0Q/0P which is equal to one minus QP/0P.

Technical Efficiency: $TE_i = 0Q/0P = 1 - QP/0P$ (2)

If the input price ratio, represented by the slope of the isocost line, AA' is also known, allocative efficiency may also be calculated. The allocative efficiency (AE) of the unit operating at P is defined to be the ratio 0R/0Q since the distance RQ represents the reduction in production costs that would arise if production were to occur at the allocatively (and technically) efficient point Q', instead of the technically efficient, but allocatively inefficient, point Q.

Allocative Efficiency: $AE_i = 0R/0Q$ (3)

The total economic efficiency is defined to be the ratio 0R/0P where the distance RP can also be interpreted in terms of cost reduction. We can show that the product of technical and allocative efficiency measures provides the measure of overall economic efficiency.

Economic Efficiency: $EE_i = 0R/0P = (0Q/0P)x(0R/0Q) = TE_i \times AE_i$ (4)

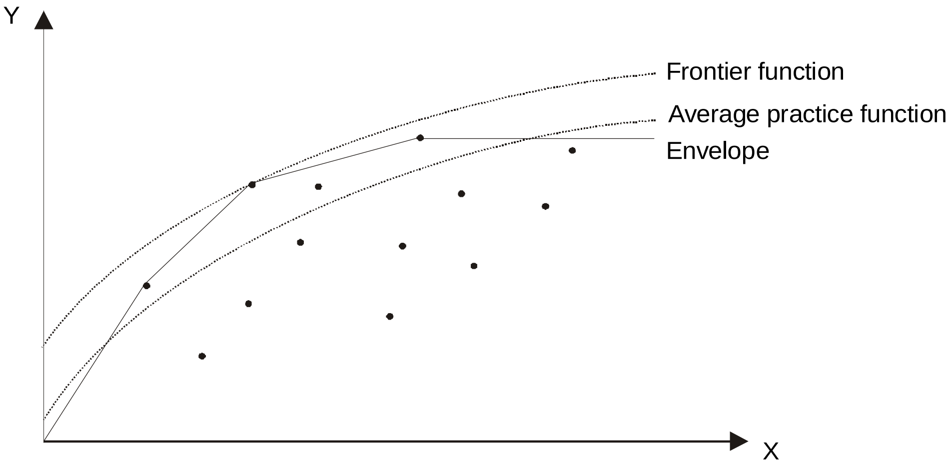
In the above graphical illustration (Figure 1) we used an input orientated model, i.e. an isoquant representing constant output (y) determined through the quantities of two inputs. (x_1 and x_2). Alternatively also output oriented models can be used. In this case a production possibility isoquant has to be determined representing output quantities (y_1 and y_2) achieved with a constant input of (x). In the input-oriented case, the DEA method defines the frontier by seeking the maximum possible proportional reduction in input usage, with output levels held constant, for each unit. In the output-oriented case, the DEA method would seek the maximum proportional increase in output production, with input level held fixed. The two measures provide the same technical efficiency scores when constant returns to scale technology applies, but are unequal when variable returns to scale are assumed. In any case, frontier analysis measures require the knowledge of an efficient isoquant. This must be estimated from the sample data. Farrell (1957) suggested the use of either:

(a) a non-parametric piece-wise linear convex isoquant which is determined by the use of a mathematical programming model, i.e. DEA.

(b) a parametric function (e.g. a Cobb-Douglas form, or others) fitted to the data which is estimated using econometric approaches, i.e. Stochastic Frontier Analysis (SFA).

Figure 2 shows an input-output model of a set of units to be analyzed and the application of three different approaches to the estimation of a production function, (1) an average practice production function using least square estimators, (2) a frontier function using maximum likelihood estimators (SFA approach), and (3) an envelope function generated by linear programming (DEA approach). In the following we will present the methodology of measuring efficiency using an envelope function, i.e. we restrict ourselves to the DEA approach.

Figure 2: Approaches to frontier estimation



After Cantner and Hanusch, 1998

3. The DEA Model

Sequentially two basic DEA models have been developed by theorists:

(a) Charnes, Cooper, and Rhodes (1978) included multiple-output multiple input technologies at **c**onstant **r**eturns to **s**cale and developed the **CRS** model, and

(b) Färe, Grosskopf and Lovell (1985) introduced a model of **v**ariable **r**eturns to **s**cale, the **VRS** model.

3.1 The CRS Model

Under the restriction that each unit's efficiency is judged against its individual criteria (individual weighting system), efficiency of a target unit h_i can be obtained as a solution to the following problem: Maximize the efficiency of unit i, under the restriction that the efficiency of all units is ≤ 0. The algebraic model is as follows:

$$\max_{u,v} \cdot h_1 = \frac{\sum_{r=1}^{s} u_{r1} y_{r1}}{\sum_{j=1}^{m} v_{j1} x_{j1}},$$

$$subject \cdot to: \quad \frac{\sum_{r=1}^{s} u_{r1} y_{ri}}{\sum_{j=1}^{m} v_{j1} x_{ji}} \le 1 \cdot \ for \cdot each \cdot unit \cdot i,$$

$$u_r, v_j \ge 0$$

(5) the fractional model

Where
h_1 = technical efficiency of unit 1 to be estimated
u_r and v_j = variables to be estimated
y_i = outputs of the i_{th} unit
x_i = inputs of the i_{th} unit
i indicates the n different units
r indicates the s different outputs
j indicates the m different inputs

The u's and v's are variables of the problem and are constrained to be greater than or equal to 0. The solution of the above model in relation to unit 1 gives the value h_1, the efficiency of unit 1, and the weights, u and v, leading to that efficiency.

The DEA problem of equation (5), is a fractional linear program in which the numerator has to be maximized and the denominator minimized simultaneously, in other words, it has an infinite number of solutions. To solve the model it is first necessary to convert it into linear form so that the methods of linear programming can be applied. It is important to note that in maximizing a fraction or ratio it is the relative magnitude of the numerator and denominator that are of interest and not their individual values. It is thus possible to achieve the same effect by setting the denominator equal to a constant and maximizing the numerator. A transformation developed by Charnes and Cooper (1962) for fractional programming allows the introduction of a constraint $\Sigma vx_i = 1$, meaning that the sum of all inputs is 1. We can write the so called „multiplier form" of the programming problem as:

$$\max_{u,v} \cdot h_1 = \sum_{r=1}^{s} u_{r1} y_{r1}$$

$$subject \cdot to: \quad \sum_{r=1}^{s} u_{r1} y_{r1} - \sum_{j=1}^{m} v_{j1} x_{ji} \le 0, \cdot for \cdot each \cdot unit \cdot i$$

$$\sum_{j=1}^{m} v_{j1} x_{j1} = 1$$

$$u_r, v_j \ge 0$$

(6) the primal model

Note, that the linear programming problem must be solved n times, once for each unit in the sample. A value of h is then obtained for each unit. Clearly, as the objective function is varying from problem to problem the weights obtained for each target unit may be different.

Formulation of the dual linear program

For linear programs in general it is true that the more constraints the more difficult a problem is to solve. For any linear program it is possible to formulate a partner (dual) linear program using the same data, and the solution to either the original linear program (the primal) or the partner (the dual) provides the same information about the problem being modeled. DEA is no exception to this. In the case of DEA switching to duality reduces the number of constraints in the model. Hence, for this reason, it is usual to solve the dual DEA model rather then the primal.

The dual model is constructed by assigning a variable (dual variable) to each constraint in the primal model and constructing a new model on these variables. After this transformation we come to the following equivalent envelopment model of the programming problem:

$$\min_{\Theta,\lambda} \quad \Theta_1$$

$$subject \cdot to: \quad -y_{r1} + \sum_{i=1}^{n} \lambda_{1i1} y_{r1} \geq 0,$$

$$\Theta_1 x_{i1} - \sum_{i=1}^{n} \lambda_{1i1} x_{j1} \geq 0, \qquad \text{(7) the dual model}$$

$$\lambda_{i1} \geq 0$$

where θ_1 = the technical efficiency score for unit 1 to be estimated
λ_i = a n-dimensional constant to be estimated
y_i = outputs of the i-th unit
x_i = inputs of the i-th unit
i indicates the n different units
r indicates the s different outputs
j indicates the m different inputs

A simple numerical example

We will illustrate input orientated DEA (compare section 2.) using a simple example involving two inputs x_1 and x_2 and one output y of five units. We assume that those units are five agricultural research institutes involved in maize breeding which use two types of inputs, i.e. research infrastructure (measured in depreciated monitory values of land for experimental plots, laboratories, and research equipment) and labor (measured in number of researchers) for producing one type of output, i.e. new maize varieties (a difference between the relevance of different varieties cannot be made within the scope of the example).

Table 1: Data Example 1

Research Institute	Output y (Number of new varieties)	Input x_1 (infrastructure in 1000 USD)	Input x_2 (Number of researchers)	ratio x_1/y	ratio x_2/y
1	1	2	5	2	5
2	2	2	4	1	2
3	3	6	6	2	2
4	1	3	2	3	2
5	2	6	2	3	1

As said above, the DEA frontier is the result of running five linear programming problems – one for each of the five institutes. Using data from example one (see table 1) for institute 3 we could rewrite equation (7) as follows:

$$\begin{aligned} \text{Min}_{\theta,\lambda} \quad & \theta, \\ \text{s.t.} \quad & -y_3 + (y_1\lambda_1 + y_2\lambda_2 + y_3\lambda_3 + y_4\lambda_4 + y_5\lambda_5) \geq 0, \\ & \theta x_{13} - (x_{11}\lambda_1 + x_{12}\lambda_2 + x_{13}\lambda_3 + x_{14}\lambda_4 + x_{15}\lambda_5) \geq 0, \\ & \theta x_{23} - (x_{21}\lambda_1 + x_{22}\lambda_2 + x_{23}\lambda_3 + x_{24}\lambda_4 + x_{25}\lambda_5) \geq 0, \\ & \lambda_i \geq 0 \end{aligned} \qquad (8)$$

In table 2 we put the problem in an linear programming table format:

Table 2: Linear minimization problem of unit 3

	θ	λ_1	λ_2	λ_3	λ_4	λ_5	MIN	MAX
Objective	1							
1.Con		1	2	3	1	2	3	
2.Con	6	-2	-2	-6	-3	-6	0	
3.Con	6	-5	-4	-6	-2	-2	0	

Table 3 exposes the results of the linear programming problems of the 5 institutes. The values of θ and λ which provide a minimum value for θ of institute 3 are listed in row 3: The results of the linear programming problems of institute 1,2,4 and 5 are displayed in row 1, 2, 4 and 5 respectively.

Table 3: CRS DEA Results of example 1

Research Institute	θ	λ_1	λ_2	λ_3	λ_4	λ_5
1	0,5		0,5			
2	1,0		1,0			
3	0,833		1,0			0,5
4	0,714		0,214			0,286
5	1,0					1,0

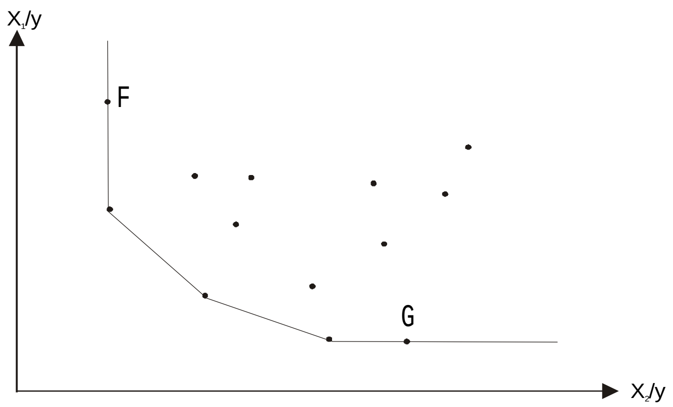
We can see that DEA analysis leads to a list of efficiency parameters (column θ). Those can easily be used to compare different units of analysis (in our case research institutions). The comparison is undertaken without attributing values (weights) to the two inputs. Efficiency is only established on Pareto criteria. We see, that under conditions of constant returns to scale institute 2 and 5 are technical efficient. Institute 3 is only to 83% efficient (institute 1 to 50% and institute 4 to 71%). Institute 3 should be able to reduce the consumption of human resources and research infrastructure by 16,7% without reducing its output.

The λ columns tell us to which extent the technical efficiency of inefficient units is determined through the existence of peer units (best practice units). The peer units, in our case, are institute 2 and 5 each having a technical efficiency score θ of 1,0. The λs define the relation of the unit to its next two relevant peers. For example, institute 4 is influenced by the peer institute 2 (to a degree of 0,214) and by the peer institute 5 (to a degree of 0,286).

The input and output slack problem

In example 1 we can compare inefficient units with efficient units by proportionally reducing the inputs of inefficient units till they hit the frontier. However, there are cases when higher efficiency can be reached but not through a proportional reduction of the two inputs. Rather it is sufficient to reduce only one input. The problem arises because of the sections of the piecewise linear frontier which run parallel to the axes (in Figure 3 this is the case for points F and G). The variable θ as defined by equation (7) cannot reflect this type of unproportional efficiency increase.

Figure 3: Piecewise linear convex isoquant



After Coelli et al. 1998

How can this problem dealt with? In a way, the optimization program has to include the identification of the extreme cases which run parallel to the axes. This can be achieved by replacing the constraint that the u's and v's are ≥ 0 by the constraint that the u's and v's are ≥ to some small positive quantity ε in order to avoid any input or output being totally ignored in determining the efficiency. This would lead us from formula (6) to:

$$
\begin{aligned}
&\max_{u,v} \cdot h_1 = \sum_{r=1}^{s} u_{r1} y_{r1}, \\
&subject \cdot to: \quad \sum_{r=1}^{s} u_{r1} y_{r1} - \sum_{j=1}^{m} v_{j1} x_{ji} \le 0, \cdot for \cdot each \cdot unit \cdot i \\
&\qquad\qquad\qquad \sum_{j=1}^{m} v_{j1} x_{j1} = 1, \\
&\qquad\qquad\qquad u_r, v_j \ge \varepsilon
\end{aligned}
\tag{9}
$$

Formulating the dual problem we would change from formula (7) to :

$$
\begin{aligned}
&\min_{\Theta,\lambda} \quad \Theta_1 - \left(\sum_{j=1}^{m} \varepsilon s_{j1}^{+} + \sum_{r=1}^{s} \varepsilon s_{r1}^{-} \right) \\
&subject \cdot to: \quad -y_{r1} + \sum_{i=1}^{n} \lambda_{i1} y_{ri} - s_{r1}^{-} = 0, \\
&\qquad\qquad\qquad \Theta_1 x_{j1} - \sum_{i=1}^{n} \lambda_{i1} x_{ji} - s_{j1}^{+} = 0, \cdot \\
&\qquad\qquad\qquad \lambda_{i1} \ge 0
\end{aligned}
\tag{10}
$$

where ε = some marginally small, but positive quantity
s^{+}_{r} = the slack variables for s outputs
s^{-}_{j} = the slack variables for m inputs

Table 4 presents the results of the 5 linear problems of example 1 under the inclusion of slack variables. We can see that institute 1 could increase efficiency just to 100% simply by reducing input 1 (i.e. human resources) by 50%.

Table 4: CRS DEA results of example 1

Research Institute	θ	λ_1	λ_2	λ_3	λ_4	λ_5	s^+_1	s^-_1	s^-_2
1	0,5		0,5					0,5	
2	1,0		1,0						
3	0,833		1,0			0,5			
4	0,714		0,214			0,286			
5	1,0					1,0			

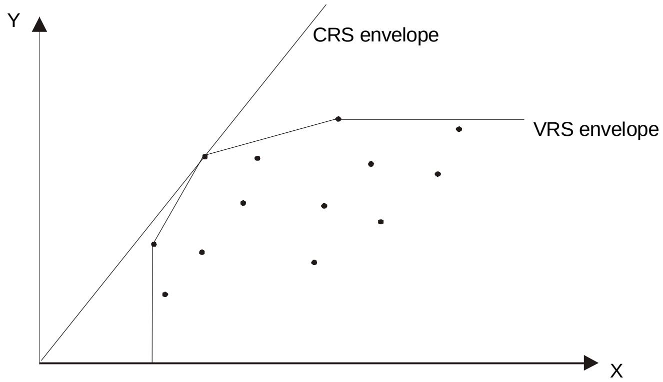
3.2 The VRS model

The constant return to scale assumption is only appropriate when all units are operating at an optimal scale. Imperfect competition, constraints on finance, etc. may cause a unit not to operate at optimal scale. To overcome this problem a DEA model with variable returns to scale has been developed in which variables of technical efficiencies are measured which are confounded to scale efficiencies. This is done by adding the convexity constraint $\Sigma\lambda_{il} = 1$ to equation (10), meaning that under variable returns to scale the λ add to one.

$$
\begin{aligned}
&\min_{\Theta,\lambda} && \Theta_1 - \left(\sum_{j=1}^{m} \varepsilon s^+_{ji} + \sum_{r=1}^{s} \varepsilon s^-_{ri} \right) \\
&subject \cdot to: && -y_{r1} + \sum_{i=1}^{n} \lambda_{i1} y_{ir} - S^-_{r1} = 0, \qquad\qquad (11) \\
& && \Theta_1 x_{j1} - \sum_{j=1}^{n} \lambda_{i1} y_{ji} - s^+_{l1} \geq 0, \\
& && \sum_{i=1}^{n} \lambda_{i1} \geq 1
\end{aligned}
$$

This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS conical hull and thus provides technical efficiency scores which are greater than or equal to those obtained using the CRS model (see Figure 4).

Figure 4: CRS and VRS envelope



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In table 5 we present the results of the calculations of VRS DEA model of example 1. We can see that under conditions of variable returns to scale no statement regarding inefficiencies of the institutes under observation can be made. Each of the institutes is technically efficient.

Table 5: VRS DEA results of example 1

Research Institute	θ	λ_1	λ_2	λ_3	λ_4	λ_5	S^+_1	s^-_1	s^-_2
1	1,0	1,0							
2	1,0		1,0						
3	1,0			1,0					
4	1,0				1,0				
5	1,0					1,0			

However, it is rare that the VRS calculations give us results in which all units are efficient. To demonstrate this we apply a second example. The dataset of this simple one-input one-output problem is shown in table 6:

Table 6: Data example 2

Research Institute	Output y (Number of new varieties)	Input x (Number of researchers)	x/y
1	1	2	2
2	2	4	2
3	3	3	1
4	4	5	1,25
5	5	6	1,2

The computation of the model gets us the results as shown in table 7. We can see that under the conditions of variable returns to scale there are two institutes, institute 2 (Θ = 0,625) and 4 (Θ = 0,9) which could increase their technical efficiency simply through decreasing the inputs or increasing the outputs. If an institute turns out to be inefficient even when the most favorable weights have been incorporated in its efficiency measure, as implied by variable returns to scale condition, then this is a strong statement. In particular, the argument that the weights are incorrect is not tenable to the VRS model (Dyson et al. 1990).

Table 7: VRS DEA Results of example 2

Research Institute	θ	λ_1	λ_2	λ_3	λ_4	λ_5	s^+_1	s^-_1	s^-_2
1	1,0	1,0							
2	0,625	0,5		0,5					
3	1,0			1,0					
4	0,9			0,5		0,5			
5	1,0					1,0			

4. Further application of DEA

4.1 Scale efficiency and pure technical efficiency

Many studies have decomposed the TE scores obtained from a CRS DEA into two components, one due to scale efficiency and one due to pure technical efficiency. This may be done by conducting both a CRS and a VRS DEA upon the same data.

In table 8 results of the CRS and VRS calculations of example 2 are presented. We can see how overall technical efficiency can be decomposed to pure technical efficiency and scale efficiency. Scale efficiency is equal to the ratio of CRS technical efficiency to VRS technical efficiency. Following this column 4 can be computed by devising column 2 by column 3. Unit 2, for example, is both inefficient under CRS and VRS technologies. The CRS technical efficiency is 50% the VRS technical efficiency is 62,5% and the scale efficiency is 80%.

Table 8: Results of CRS, VRS and Scale efficiencies of example 2

Research Institute	CRS -θ	VRS -θ	Scale -θ
1	0,500	1,000	0,500
2	0,500	0,625	0,800
3	1,000	1,000	1,000
4	0,800	0,900	0,889
5	0,833	1,000	0,833
mean	0,727	0,905	0,804

However, a shortcoming of the measure of scale efficiency generated above is that the value does not indicate whether the unit is operating in an area of increasing or decreasing returns to scale. This may be determined by running an additional DEA problem with non-increasing returns to scale (NIRS) imposed. This can be done by altering the equation (8) by substituting the N1'λ = 1 restriction with N1'λ ≤ 1. Doing this in our example 2, we observe that unit 2 is on the increasing returns to scale portion of the VRS frontier (column 5).

4.2 Price information and allocative efficiency

If one has price information (or a weighting system) and is willing to consider a behavioral objective, such as cost minimization or revenue maximization, then one can measure both technical and allocative efficiencies. This involves the application of a price vector w_i of input prices for each unit. Applying the VRS model without slack variables we come to model (12):

$$\begin{aligned} \min_{\Theta,\lambda} \quad & \omega_1 x_1^* \\ subject\cdot to: \quad & -y_{r1} + \sum_{i=1}^{n} \lambda_{i1} y_{ri} \geq 0, \\ & x_1^* - \sum_{i=1}^{n} \lambda_{i1} x_{ij} \geq 0, \\ & \sum_{i=1}^{n} \lambda_{i1} \geq 0 \end{aligned} \qquad (12)$$

x^*_i (which is calculated by the LP) is the cost-minimizing vector of input quantities for the i-th unit, given the input prices w_i and the output levels y_i. The total cost efficiency of the i-th unit would be calculated from the ratio of minimum cost to observed cost:

$$CE = w_i' x_i^* / w_i' x_i \qquad (13)$$

On can then use equation (3) to calculate the allocative efficiency residually as AE = CE/TE.

4.3 Decomposition of the inefficiency term

Many exogenous factors can influence the efficiency scores derived from DEA. Typically those factors fall out of the category of traditional inputs. They are usually out of the control of managers and administrators of the unit under investigation. Examples for exogenous factors are: location characteristics, educational differences, age, and others. There is basically two ways accommodating exogenous variables in DEA (compare Coelli et al. 1998).

(1) The overall set of units to be analyzed is divided into different datasets according to some discriminative

variable, e.g. geographical location. For example, units could be analyzed according to which city or state they belong to. In result, a set of different DEAs is carried out, one for each location. This ensures, that no unit is compared with another unit of a different, possibly more favorable, environment.

(2) The variable(s) describing the exogenous effect is directly included into the LP formulation, either as an input or an output, or as a neutral variable.

(3) A second stage analysis after the DEA is carried out regressing the DEA efficiency scores them upon the exogenous variables. The sign of the coefficients scores from the first stage are regressed upon the exogenous variables. The sign of the coefficients of the environmental variables indicate the direction of the influence, and standard hypothesis tests can be used to assess the strength of the relationship. The second stage regression can also be used to correct the efficiency scores for exogenous factors by using the estimated regression coefficients to adjust all efficiency scores so that they correspond to a common level of environment (Coelli et al., 1998). As DEA efficiency scores range between zero and one, frequently they are equal to one. Traditional OLS regression is based on the assumption of normal distribution of the dependent variable. Therfore, Tobit regression methods which are designed for truncated distibutions (in this case the theshold is one) are appropriate in analysis (Mc Carty and Yaisawarng, 1993; Gillespie et al. 1997)

5. A Critical View on DEA in Agricultural Research Evaluation

The DEA estimator of technical efficiency, as introduced by Charnes, Cooper and Rhodes (1978), has found use in many efficiency measurement studies and has been modified and extended in several ways as presented in the DEA survey by Seiford (1996). DEA, which is fast becoming an alternative and a complement to traditional central-tendency analysis, provides a new approach to traditional cost-benefit analysis, frontier estimation, policy making, and to theories of best practice. DEA is rapidly becoming more and more accepted in the economic analysis of production units. Just to name some examples, DEA has been used in the analysis of the American brewery industry (Day et al., 1995), the American Ratite industry (Gillespie et al, 1997), contracting of behavioral health services in Florida (Byrnes and Freeman, 1997), the Swedish agricultural sector (Jonasson and Apland, 1996), the Missouri grain farming sector (Kalaitzandonakes et al., 1992), global agricultural productivity (Rao and Coelli, 1998) and the Brazilian agricultural research system (da Silva et Souza et al. 1996). Analyzed data sets vary in size. Some analysts work on problems with as few as 15 or 20 UNITs while others are tackling models with up to 25,000 units to be analyzed on a sequent parallel computer with custom software.

DEA is a methodology using both, the frontier approach and the linear programming approach. In the following we will thus involve in (1) a discussion on the frontier approach and (2) a discussion on the linear programming approach before we elaborate on the usefulness of DEA in agricultural research evaluation.

5.1 Frontier approaches versus average practice approaches

A frontier is a bounding function. Many bounding function exist in micro-economics: a production function represents the maximum output attainable form a given set of inputs; a cost function represents minimum cost, given input prices and output; a profit function represents maximal profit, given input and output prices and so on. Yet empirical work in all fields of economics, has been dominated by average ordinary least square estimations (ordinary least squares) and its variants, which fit a curve of average best fit through the sample. However, a curve (frontier) could rather be fitted over the data, as would be appropriate for a production or profit function, or under the data as would be appropriate for a cost function (Coelli, 1995). The main advantages of estimating frontier functions, rather than average functions, are the following:

Strength of the frontier approach:

- Estimation of an average function will provide a picture of the technology of an average unit, while the estimation of a frontier function will be most heavily influenced by the best performing units and hence reflect the technology they are using which is the best practice technology already existing. The frontier is only estimated from the data of the best-practice units and not, as in classical least square estimation procedures, under incorporation of also the inefficient units.

- The frontier function represents a best practice technology against which the efficiency of units can be measured. Best-practice (worst practice) units can then be analyzed and be used as good (or bad) examples. Day et al (1992), for example, have applied DEA in order to identify strategic groups. Following the concept of strategic groups, they argue that with the use of DEA significant insights, new knowledge, and unexpected theories can arise from studying the best or worst of a population.

- Efficiency solutions from frontier estimations characterize each unit by a single summary relative efficiency score (Charnes et al. 1995). This is a measure simple to interpret by operations analysts and managers. In an application of the DEA approach to an agricultural sector model in Sweden Jonasson and Apland (1996) found, that DEA was more appropriate in avoiding the problem of overspecialization (the assumption that all units use a highly efficient technique) than traditional linear programming models and the estimated price response of farms was more realistic.

- In DEA inputs and outputs can have very different units without requiring an a priori tradeoff between the two. For example, x_1 could account for the number of human resources involved and x_2 could be account for investments measured in a currency unit.

Limitations of the frontier approach

The same characteristics that make DEA a powerful tool can also create problems which should be kept in mind using DEA:

- Since frontier estimation is an extreme point technique, noise (even symmetrical noise with zero mean) such as measurement error can cause significant problems.

- In cases where a common production technology exists (as it cannot be assumed among agricultural research units) the application of frontier approaches is not useful. However, in parametric approaches the usefulness of applying a frontier model rather than an average practice model can be tested. Since DEA is a nonparametric technique, statistical hypothesis tests are difficult and are the focus of ongoing research. However, efficiency scores close to one will indicate that it is rather an average production technology which represents the production conditions in the sample of units of analysis.

- Data requirements for DEA as for all frontier estimation are exceeding data requirements for classical best practice evaluation. If entire multiple input multiple output relations are modeled, i.e. Malmquist total factor productivity is concerned, data requirement for the method are quite massive. However, DEA does not require data on prices which in some traditional methods constitutes the bottleneck.

- One distinct characteristic of the technical efficiency scores derived from frontier estimation is that they vary according to sample sizes. In very small samples, efficiency scores seem to be very high. By a judicious choice of weights a high proportion of units in the set will turn out to be efficient and DEA will thus have little discriminatory power. The more units of analysis are included the lower average technical efficiency scores become. DEA is good at estimating "relative" efficiency of a UNIT but it does hardly converge with "absolute" efficiency. In other words, it can tell how well a unit is doing compared to peers but not compared to a "theoretical maximum." An efficiency score from one DEA study (e.g. grain farms in Missouri) cannot be compared with efficiency scores from another study (e.g. grain farms in Mississippi). However, this can be avoided when farms in Missouri and Mississippi are merged in one model. The geographical location would then be an exogenous factor determining technical efficiency. The average efficiency score of both farms from Missouri and Mississippi would be lower than both the average of Mississippi and the Missouri sample respectively.

- Another concern to DEA is that a unit can appear efficient simply because of its pattern of inputs and outputs and not because of any inherent efficiency. An approach to resolving this issue is to constrain the weights in some way (Dyson et al., 1990). Determining a minimum weight for any input and output would ensure that each input and output played some part in the determination of the efficiency measure. Similarly, a maximum limit could be placed on weights to avoid any input or output being over-represented. Clearly these limits should not be heavily constraining as this would tend towards each unit being measured using a common set of weights. Hence a compromise is sought between weights flexibility on the one hand and a common set throughout the system on the other.

5.2 Programming approaches versus econometric approaches to frontier analysis

There are two main approaches to frontier estimation, i.e. DEA and stochastic frontier analysis. In relation to the parametric stochastic frontier analysis DEA has some distinct strength:

Strength of the mathematical programming approach

- It is general in its character. Reference technology levels for each input and output are defined by a linear combination for sample observations of each input and a linear combination of sample observation of each output. Restrictions inherent in assuming specific production functions are avoided (Arnade, 1998).
- It does not necessitate any distributional assumptions on inefficiency
- It allows estimation of frontiers with multiple outputs and multiple inputs without resorting to restrictive aggregation assumptions.
- It does not necessitate data on factors determining inefficiency as in SFA. Inefficiency is purely generated out of the input-output relations.

Limitations of the mathematical programming approach

- Since a standard formulation of DEA creates a separate linear program for each UNIT, large problems can turn out to be computationally intensive.
- The estimated production frontiers have and consequently no statistical properties and tests to be evaluated upon.
- Non-parametric frontiers attribute all deviations from the frontier to inefficiency and do not account for random influences. Hence they are particularly sensitive to outliers and measurement errors.

Problems exist with the robustness of technical efficiency rankings estimated by different methods. Kalaitzandonakes et al. (1992) for example found, that efficiency rankings estimated by frontier estimations vary according to the methodology used. They compared three methods, i.e. deterministic frontier models, stochastic frontier models and DEA models. They concluded, that mixed empirical evidence on the technical efficiency of units of analysis may be a result of variation in the estimation procedures employed. Coelli (1998) used a dataset on the Australian electricity industry in a comparison of SFA and DEA. As a result, he called for an attempt to mathematically ascertain the reasons for the divergence of the results derived from the two methods. He suggested that future research could try to apply a window method which obtains more stable DEA frontiers by pooling the data from 2 or 3 adjacent years to construct the required frontier.

Some simulations have shown that production frontiers estimated with DEA procedures outperform translog deterministic stochastic frontiers in approximating the true production frontier (Seiford, 1990). That could even be proven for the case when the true frontier was of the translog type variety (Banker et al. 1988). However, this has not been evidenced in all cases. Kalaitzandonakes et al (1992), for example found, that latent variable parametric models can reconcile conflicting efficiency series by accounting for measurement error.

5.3 Application of DEA in Agricultural Research Performance Evaluation

Recently, multi input and output evaluation schemes are becoming more important though continuos application of those schemes in monitoring and evaluation systems is hardly achieved. At ISNAR, Peterson (1998) developed a framework of output/outcome evaluation and periodic organizational management assessment. The method involves identification of research objectives, development of output indicators and weighting of the respective outputs. However the method does not involve in overall aggregation of the performance indicators. In order to address the weighting problem, also at ISNAR, an ex-ante evaluation method for priority setting in biotechnology research has been developed (Braunschweig 1997). It is based on the judgements of peers applying the Analytical Hierarchy Process (AHP). This method was particularly successful in accounting for impact with the use of subjective peer knowledge. First attempts to apply DEA in agricultural research evaluation are made in Brazil, where 37 national agricultural research institutes were evaluated (da Silva e Souza et al, 1997). However, problems still exist with regard to the standardization of the outputs, as different research outputs within DEA categories are still difficult to compare (G. Alex, 1999). The application of a standard weighting system or peer judgement on the relevance of research outputs may be useful here.

In a University of Hohenheim / ISNAR project on research performance assessment in Cameroon and Tanzania, agricultural research performance of national research organizations and national universities has been analyzed. First steps involved the development of a cumulative performance indicator (CPI) to describe the performance of research institutions (Hartwich, 1998). This approach combined quantitative data on research outputs with weighted scores based on qualitative assessments of the research using AHP. Analysis of an institution's research performance yield a weighted outputs indicator, which can be divided by the institution's budget or another input measure to give the cumulative performance indicator (Alex, 1998). In a further step, a methodology was developed which combined the above evaluation methods; within categories, the AHP was used to weigh different outputs, then, to avoid further agglomeration of categories which cannot be compared, DEA was applied calculating Pareto efficiencies. This led to an overall weighted technical efficiency indicator with which the research units under investigation could be compared (Hartwich, forthcoming). The indicator proved to be a very informative and easy to interpret measure. Its values corresponded to observations in the field. It clearly identified areas of comparative advantages and weaknesses of research units and it guided to management decisions which could lead to higher performance of the units and the whole research system. It also identified types of research organizations (Universities, NAROs, international Centers) which were particularly technically efficient.

In general, DEA is appropriate where units can properly value inputs or outputs differently, or where there is a high uncertainty or disagreement over the value of some input or outputs. The method is for example conveniently used in the analysis of farm enterprises when it is assumed that the units do not produce with an identical production technology, i.e. on an average practice function. We conclude that DEA is a method with distinct characteristics making it an appropriate tool for research performance evaluation:

1. DEA avoids the assumption that all units of analysis produce (generate research results) under the same condition. As the research process is highly individual different research units may involve research operations under very different conditions. It is likely, that only some research units may have found a particular best practice way of conducting research. This technological know how of conducting research is not attained by the other units. Therefore, the assumption of a frontier of best practicing units is rather valid to the research sector than the assumption that all units use the same technology.

2. DEA enables simultaneous analysis of multiple inputs and multiple outputs. Before, in the aim to come to overall performance indicators, practitioners had to apply weights derived from different rather subjective scoring methods and priority setting exercises. Often the thus derived weights were criticized. The concept of Pareto efficiency used by DEA is an appropriate quantitative tool to avoid the weighting problem.

3. DEA overcomes the problem of relating output measures to market prices, i.e. no weighted average of productivity can be computed. In research evaluation the crucial problem is always how to compare research outputs, e.g. how to compare a researcher who wrote 40 scientific papers on the economics of farming systems with a researcher who developed a knew agronomic technology. In analysis of public

   goods like research outputs marketprices are hardly available. Seiford (1996) in his bibliography on DEA refers to a large amount of studies related to the use of DEA in comparing public sector institutions, where prices for public goods are hardly available.

4. DEA results in an easy to interpret overall efficiency score. Best practice units can now be analyzed and success factors can be identified. The inefficiency residual can be decomposed when additional data on characteristics of the units of analysis are derived. This further analysis can include regression analysis

using OLS or Maximum Likelihood estimators signifying important institutional constraints.

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