Measuring the Efficiency of Managerial and Technical Performances in Forestry Activities by Means of Data Envelopment Analysis (DEA)

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ABSTRACT

The relation between the most productive scale size for particular input and output mixes and returns to scale for multiple-input multiple-output situations is explicitly developed. Data Envelopment Analysis (DEA) has been extensively applied in a range of empirical settings to identify relative inefficiencies, and provide targets for improvements. It accomplishes this by developing peer groups for each unit being operated (Decision Making Unit: DMU).

This paper introduces the technique and focuses on some of the key issues that arise in applying DEA in practice. Some illustrations of the practical applications of these results to the estimation of most productive scale sizes and returns to scale for Forest Owner's Associations (FOAs) at the local level in Japan are also provided to emphasize the advantage of this method in examining specific segments of the efficient production surface.

Keywords: *Data Envelopment Analysis (DEA), efficiency, target setting, performance, Forest Owners' Associations (FOAs)*

INTRODUCTION

In the estimation of production correspondence, determining the optimal scale for the production process is often of considerable interest. For a single-input single-output case, the most productive scale size is simply that scale for which the average productivity measured by the ratio of total output to total input is maximized. On the other hand, at the optimal scale size, the marginal productivity is equal to the ratio of the output price to the input price.

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The concept of average productivity is commonly extended to the case of multiple inputs by the use of input prices to aggregate the multiple inputs, and by the estimation of the correspondence between the total input cost and the output. But input prices are affected by many factors other than the pure technological correspondence between the inputs and the outputs that characterize the production process.

Prices are likely to be more volatile than the pure technological characteristics. Therefore, estimation of the cost function alone is likely to retain its relevance for managerial and policy decisions for a shorter period than estimation of the purely technological relation between the physical quantities of inputs and outputs. For this reason, it is useful to distinguish between the problem of determining the *minimum cost mix* of inputs and outputs on the basis of their relative prices, and the problem of determining *the most productive scale size* for particular input and output mixes. In other words, for each input and output mix there is a most productive scale size, while the overall optimal scale size depends on the prevailing prices. The former is related to the concept of returns to scale, while the latter is associated with economies of scale [16]. The focus of this paper will be on the problem of estimation of a most productive scale size for different input and output mixes.

First, data envelopment analysis (DEA) techniques for estimating efficiency production frontiers are introduced. Then it is shown how these conceptual constructs may be measured by examining a simple diagram representing a two-dimensional section of a possible production set for a mix of inputs and outputs. Finally, there are brief descriptions of practical applications of DEA in the form of a case study that concerns problems of performance assessment experienced by Forest Owners' Associations (hereinafter referred to as FOAs) at the local level in Japan .

SIMPLE MATHEMATICAL DEVELOPMENT

Data Envelopment Analysis (DEA) and Decision Making Units (DMUs)

DEA is an approach comparing the efficiency of organizational units such as firms, departments, schools, hospitals, divisions or administrative branches, and similar instances where there is a relatively homogeneous set of units [2, 4, 6, 8, 10].

The breakthrough came in the research work undertaken by Charnes, Cooper and Rhodes (hereinafter referred to as CCR) [7].

In the simplest case where a process or unit has a single input and a single output, efficiency is defined simply as:

$$Efficiency = \frac{input}{output}$$

More typically, processes and organizational units have multiple incommensurate inputs and outputs, this complexity can be incorporated in an efficiency measure by defining the efficiency as:

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs}$$

This definition requires a set of weights to be defined. This can be difficult, particularly if a common set of weights to be applied across the set of organizational units is sought. This problem can be resolved by arguing that individual units may have their own particular value systems and therefore may legitimately define their own peculiar set of weights. CCR [7] propose that the efficiency of a target unit j_0 can be obtained by solving the following mode:

$$Max\, h_0 = \frac{\sum_{r=1}^{t} u_r y_{rj0}}{\sum_{i=1}^{m} v_i x_{ij0}}$$

subject to

$$\frac{\sum_{r=1}^{t} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \; j = 1, \ldots, n,$$

$U_r, V_i \ge 0$

$i = 1, \ldots, m; \; r = 1, \ldots, t$

where

y_{rj} = amount of output r from unit j,
x_{ij} = amount of input i to unit j,
u_r = the weight given to output r,
v_i = the weight given to input i,
n = the number of units,
t = the number of outputs,
m = the number of inputs.

In the solution to this model the efficiency of unit j_0 is maximized subject to the efficiencies of all units in the set having an upper bound of 1. The key feature of the above model is that the weights u_r and v_i are treated as unknown. They will be chosen so as to maximize the efficiency of the targeted unit j_0. The efficiency of unit j_0 will either equal 1, in which case it is efficient relative to the other units, or will be less than 1, in which case the unit is inefficient. For an inefficient unit, the solution identifies corresponding efficiency units (i.e. efficient with the same weights) which form a peer group for the inefficient unit.

In their original paper [7], CCR introduce the generic term 'Decision Making Units' or 'DMUs' to describe organizational units that have common inputs and outputs to be assessed for efficiency.

Weakness and/or Strength of DEA Approach

Efficiencies of all units relative to the set can be found by solving a similar model targeting each unit in turn. The values of the weights would generally differ from unit to unit and flexibility in the choice of weights is both a weakness and a strength of this approach. It is a weakness because a judicious choice of weights may allow a unit to be efficient, but there may be concern that this has more to do with the choice of weights than any inherent efficiency. The flexibility is also a strength, however, for if a unit turns out to be inefficient even when the most favorable weights have been incorporated in its efficiency measure, then this is a strong statement, and the argument that the weights are inappropriate is not tenable [5].

The DEA model is a fractional linear program but may be converted into linear form in a straightforward way so that the methods of linear programming (LP) can be applied [1, 13].

Frontier Functions of Efficiency

The term 'productive efficiency' is used to describe how well an organizational unit is performing in utilizing resources to generate outputs or outcomes. The empirical approach to the measuring of efficiency based on the production function, favored by most economists, is parametric (either stochastic or deterministic). Here, the form of the production function is either assumed to be known or is estimated statistically. The advantages of this approach are that any hypotheses can be tested with statistical rigour and that relationships between inputs and outputs follow known functional forms.

However, in many cases, there is no known functional form for the production function and, indeed, it may be inappropriate to talk in terms of such a function. This is most clearly the case in public sector organizations. This is the basis for the development of the frontier approach to estimating efficiency [3, 9, 11, 15].

Let us begin by presenting a DEA efficiency measure generated from the graphical development shown in Figure 1.

Consider the case of three management units (*A*, *B* and *C*) producing only a single input-output (*X* and *Y*). From the figure we deduce that unit *B* is most efficient, and we can give *B* a reference efficiency score and compute scores for *A* and *C* relative to that. Thus, we can define a frontier of best achieved performance. For any unit not on the frontier, we can identify a target point on the frontier that represents what that unit could be achieving.

				Improvement	
DMUs	A	B	C	Input model; A1	Output model; A2
Input; X	2	3	4	1	2
Output; y	1	3	2	1	2
Efficiency;Y/X	0.5	1	0.5	1	1

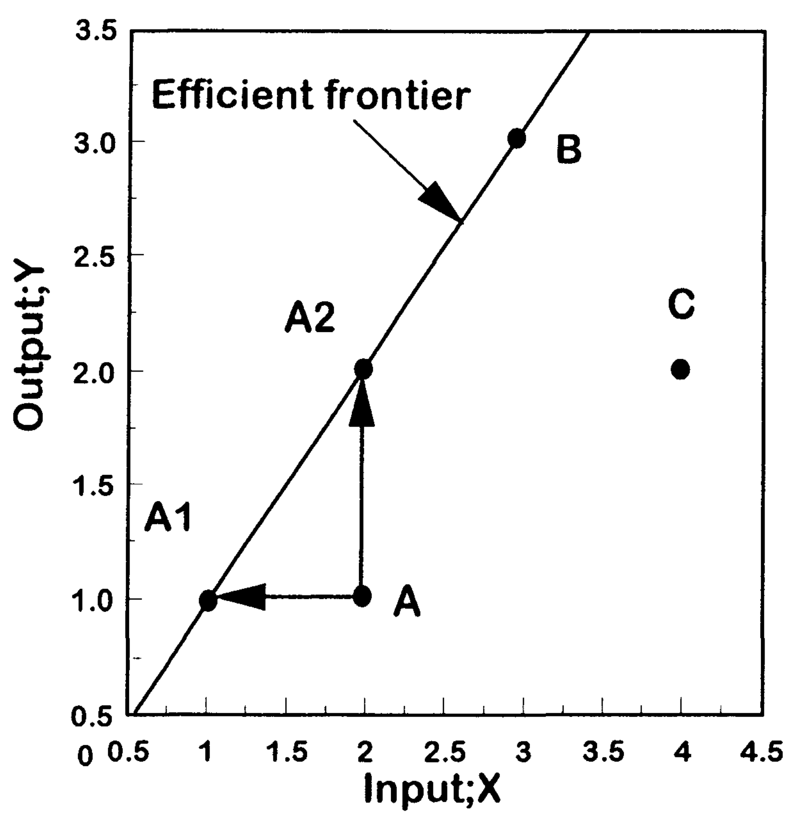

Figure 1. A simple efficiency measure: constant returns to scale.

In the case of unit *A*, the targets to be set for scale efficiency are the points *A1* (*Input model*), *A2* (*Output model*) and some point (*Mixed model*) on the line *A1A2*; the input model moves from *A* to *A1* by contracting input while holding output constant. *A1* achieves the same level of output at *A* but with 50% of the input. Therefore, *A1* is 100% efficient from an input perspective. The output model moves from *A* to *A2* by expanding output while holding input constant. A uses the same level of input as *A2* but has only 50% as much output. Therefore, *A2* is 100% efficient when measured from an output perspective.

Figure 2 shows a single output situation: *Y* and inputs *X1* and *X2*. There are three DMUs, *A*, *B* and C, where the axes represent input consumed per unit output: *Y=1* produced.

The efficiency frontier is designated by the line *C* to *B*; the frontier is assumed to extend parallel to the axes beyond C and *B*. The best performance is now in the direction of the bottom left-hand corner of the graph. DEA efficiencies for point *A* are therefore calculated as:

$$\textit{DEA efficiency} = \frac{OP}{OA}$$

DMUs	A	B	C
Input; X1	4	4	2
Input; X2	3	2	4
Output; Y	1	1	1

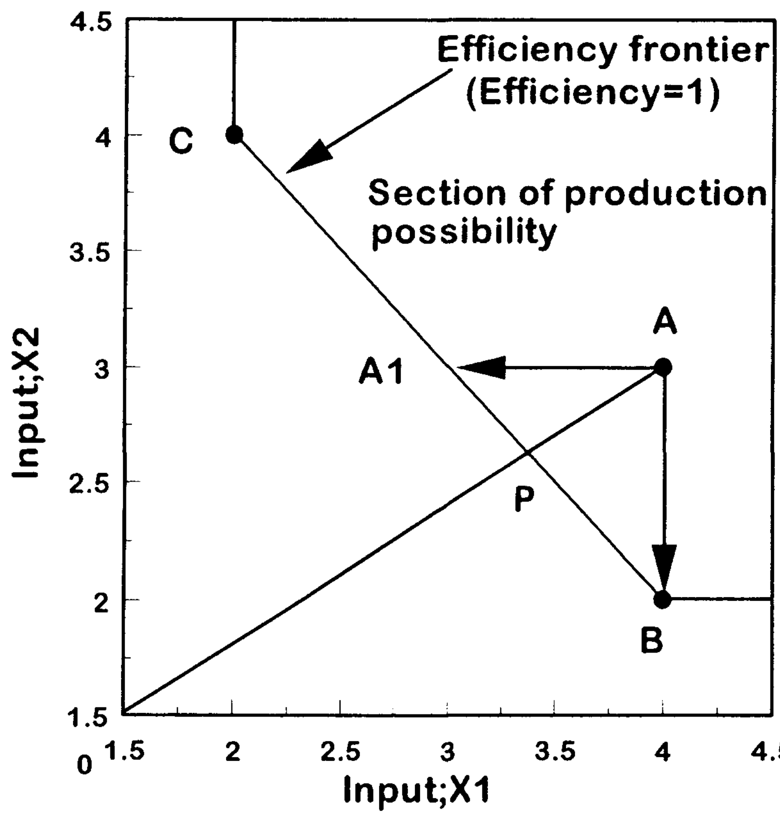

Figure 2. Efficiency and inefficiency characterizations relative to isoquant: efficiency frontier under CCR Models.

SOME PRACTICAL APPLICATIONS OF DEA

Problem Formulation: Performance Assessment in the Public Sector

This section is based on a case study that interprets DEA and shows ways of using it in evaluating and controlling managerial behavior in public sectors of Japanese forestry. The case study concerns Forest Owners' Associations of Mie Prefecture, located in the south-eastern part of central Japan. It deals with problems of managerial performance assessment typical of those that the author has encountered in a consulting practice.

Characteristics of the public sector, such as FOAs, include the lack of a profit motive behind the provision of goods or services, something that the competitive market cannot or will not provide. These goods or services are to benefit the local community or society as a whole, with no direct relationship between the recipient and the provider of the funds. Because net income and return on investment have no meaning, the primary goal has been the protection of assets and the provision of needed goods and services at the lowest feasible cost. The goals and objectives are often not clearly stated or are many-faceted and require trade-offs. Without the factor of profitability, progress toward goals and the relationship of costs to outcomes is difficult to measure. Often the budget is used as a means of acquiring money rather than for planning, managing, and control.

Under these circumstances, it is important that specific aspects of efficiency and the most productive scale size be employed to ensure wise stewardship of forest resources.

Setting Up a Performance Measuring System of DEA

The art of management may be summarized by the words *Decision* and *Control*. Leadership, pastoral care, planning, and the other managerial attributes can all be subsumed by these two overriding demands. For both, information is vital, and a major part of that information relates to judgments of the performance of people and processes. Very rarely are these judgments easy, or they concern the relationships between many, often conflicting, factors.

Few decisions can be made in isolation, since any part of an organization necessarily reacts with many other parts. An organization is an interconnecting system that requires integrated checks and controls. It is a complex system that needs sophisticated tools to manage it, at both the strategic and day-to-day levels. In turn, these tools involve the collection and analysis of data to provide relevant and concise information to aid the decision makers.

Managing complex operations is itself a complex operation that relies on the provision of information for its decision and control processes. In certain situations, where the performance of a group of units needs to be assessed, DEA can play a part. The value of its contribution will depend on how well the analysis is planned and how well the results are integrated with other elements of management information.

Figure 3 shows an outline schematic process structure for introducing DEA into a management information cycle of FOAs. Throughout the exercise it is essential, to make the work relevant and useful, to keep in mind:

- the roles and objectives of the organization,
- the roles and objectives of the units,
- the objectives of the performance assessment exercise.

It is also important to prevent the analysis from becoming a theoretical exercise. To this end, local management should be involved in all stages of the work, from the definition of factors to the interpretation of results. This will also ensure that the results are relevant to the units themselves as well as to central management. Some of the major benefits from introducing performance measures are that management gains:

- a better understanding of the process carried out within the units of the organization,
- a means for better control,
- a knowledge of where and when management action is needed to improve performance.

DEA, together with the actual process of introducing this analytical approach into the organization's management information structure, provides an ideal means of realizing these benefits. It also provides an additional tool to aid the evaluation of the quality of managerial control and decision making at the local level.

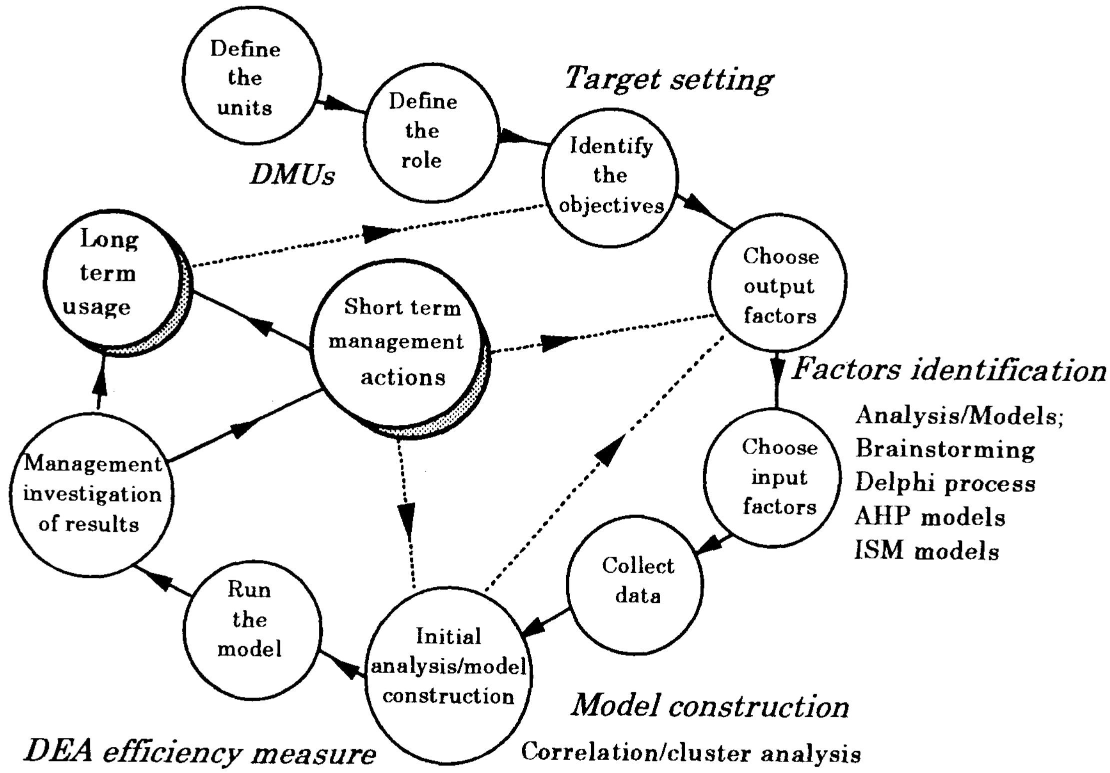

Figure 3. Schematic process structure of introducing DEA into a measurement information cycle of FOAs.

Table 1. Factors for three efficiency measure models used: Data based on average value of 1991-1994 financial years.

	Factors	Model 1	Model 2	Model 3
Outputs	Total revenue (TR)	*	*	*
	Total profit (TP)		*	
	Total forestry employee in FOA (TFE)			*
Inputs	Total FOA members (TFOAM)	*	*	
	Total staff (TS)	*	*	
	Total private forest owner over 50 ha (TPFO)	*		
	Total forestry workers as regular employee (FTW)	*		*
	Total investment fund (TIF)	*	*	
	Jurisdictional forest area of FOA (JFA)	*	*	*
	Total asset (TA)	*	*	
	Total cost (TC)	*		*
	Number of harvest machine holdings (HNMH)	*		*
	Number of sawmills over 50 Kw (NSM)	*		*
	Timber storage capacity area (TSCA)	*		*
	Total timber sale (TTS)			*
	Total lumber product (TLP)			*
	Total reforestation area (TRA)			*
	Total thinning area (TTA)			*
	Total log harvest (TLH)			*

Case Study

Table 1 summarizes the application of this approach in building the efficiency model. The table shows the factors in the model together with the efficiency measurement.

The author will not discuss details of the factors employed that reflect natural relationships with constituent parts of efficiency (e.g. capital, labor, skill, administration, production infrastructure, forest resources) rather than causal relationships. These factors were identified in discussions with administrative officers in local offices. The final input/output factors for each model were determined by using statistical correlation analysis. The measure of efficiency may be biased in relation to that factor. More details related to choosing the factors for a performance measuring model are shown in references [12, 14]. The data came from 28 FOAs of Mie Prefecture, shown in Figure 4, and are based on average values of 1991-1994 financial years.

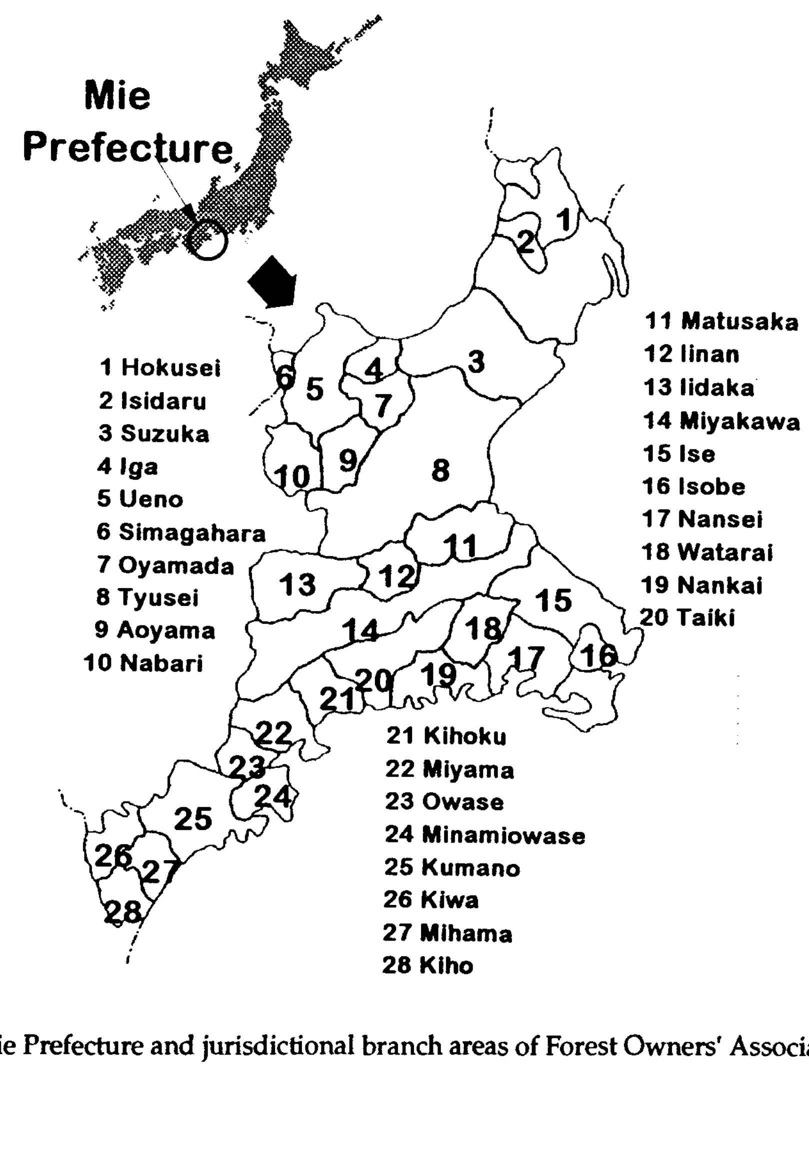

Figure 4. Map of Mie Prefecture and jurisdictional branch areas of Forest Owners' Associations (FOAs).

The initial simple measure of efficiency is *Total revenue* (TR) versus *Total staff* (TS). Figure 5 shows TR plotted against TS for all the FOAs. The straight line through *Iga* and the origin denotes all points equal in efficiency to that of *Iga*. The line can be regarded as an efficiency frontier since all points below the line have a lower TR/TS ratio and hence lower efficiency. In the figure, all other FOAs appear below this line, thus confirming that *Iga* is the most efficient of the FOAs. It should be noted that this development assumes constant returns to scale, which implies that an increase in TS is matched by a proportionate increase in TR regardless of the value of TS from which the increase occurs.

A further point to note is that regression analysis, represented by the dotted line in Figure 5, establishes a target level of TR for a given level of TS based on average performance. *It gives no information about best performance.*

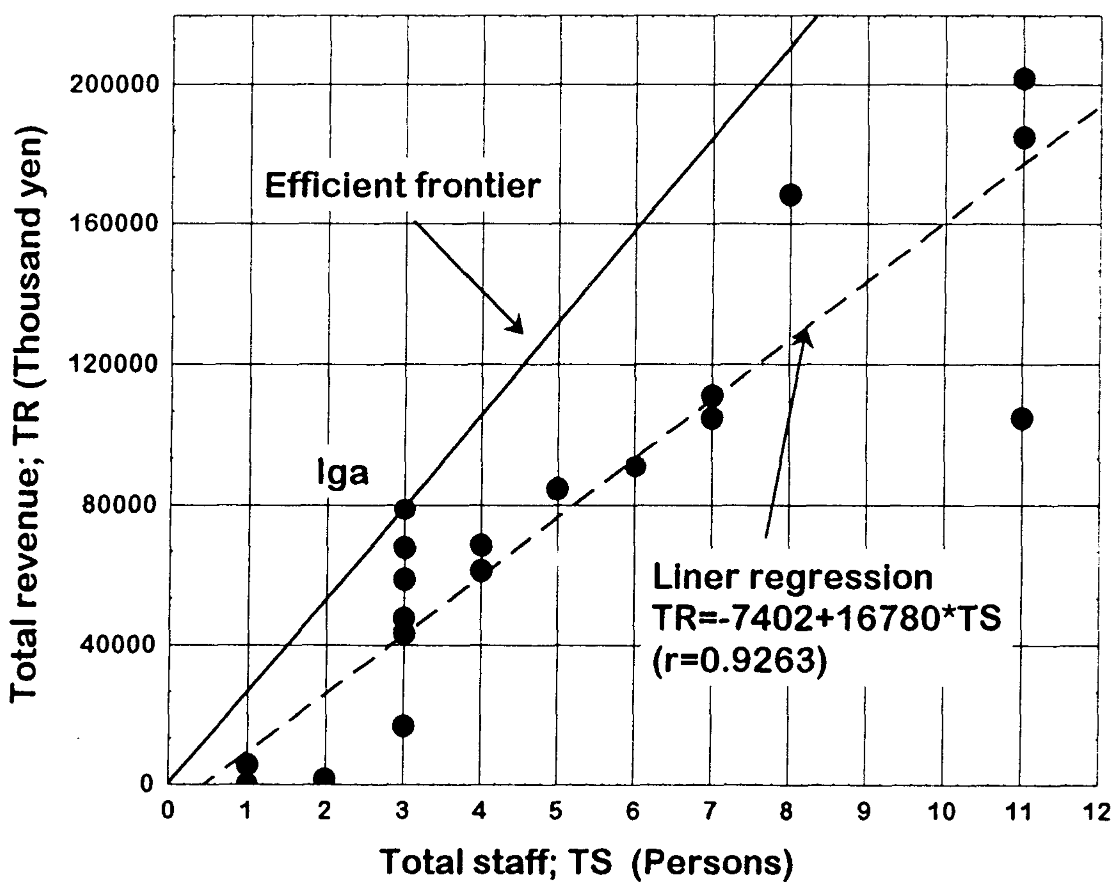

Figure 5. FOAs efficiency calculation: Total revenue versus Total staff.

By again assuming constant returns to scale, the efficiency measure of two distinct outputs produced from a single input can be demonstrated as shown in Figure 6. The boundary formed by the straight line joining the 4 FOAs, *Miyama, Miyakawa, Nabari,* and *Nanto,* together with horizontal and vertical lines to the axis, envelop the remaining FOAs in a manner such that any point on the boundary performs better than any point within the boundary. In this case, the frontier is determined by only four FOAs which represent clearly demonstrable, achieved performance.

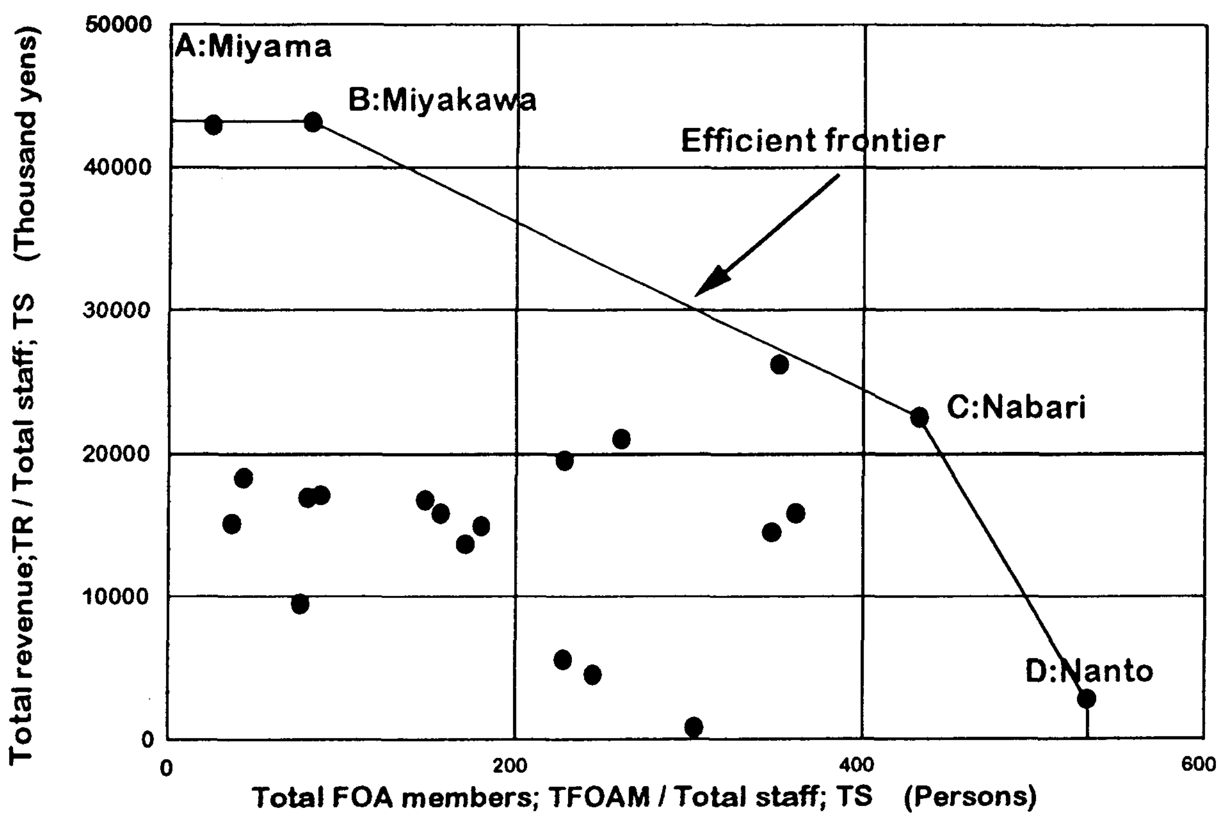

Figure 6. DEA efficiency measure of two distinct outputs (Total revenue and Total FOA members) produced from a single input (Total staff): The axes represent outputs per unit input.

An efficiency measure result that accounts for all the identifiable factors of Table 1 is given in Table 2.

The greater variation-in-efficiency score for FOAs is observed between Model 3 and Models 1 and 2. There is no significant difference between Model 1 and Model 2. This would indicate that if the relationship between efficiency and the component part proportions that reflect the breakdown of *Total profit* (TP) with particularly low values of many FOAs into *Total revenue* (TR) is present, then the existence of TP is obscured by the dominance of the effect of TR. A further question arises as to which constituent parts of the input factors associated with product potentials, such as Number of harvest machine holdings (NHMH), Number of sawmills over 50 Kw (NSM) and Timber storage capacity area (TSCA) should be incorporated in the model.

For these reasons the inclusion of TP as an output in Model 2 would not be justified. Model 1 can therefore be regarded as a model for the FOAs, managerial efficiency measure. The results show that *Matusaka, Simagahara, Aoyama, Kihoku,* and *Miyama* are identified as efficient. It is clear that *Matusaka* FOA is the best performer because it produces more TR than the other four FOAs, as shown

Table 2. Computed managerial efficiency scores (E) and rankings (R).

	Model 1		Model 2		Model 3	
FOA	E	R	E	R	E	R
Suzuka	0.0122	15	0.7408	11	0.6296	18
Isidaru	0.0009	18	0.0096	28	0.9784	11
Hokusei	0.0001	22	0.8352	7	1.0000	1
Tyusei	0.5737	7	0.6338	17	1.0000	8
Matusaka	1.0000	1	1.0000	1	0.2088	28
linan	0.1893	8	0.7252	13	0.9088	12
lidaka	0.1498	10	0.7498	10	0.4004	24
Miyakawa	0.0825	12	0.7119	15	0.2332	27
lse	0.0006	20	0.0096	27	1.0000	1
lsobe	0.0007	19	0.0463	26	0.6618	17
Nansei	0.5767	6	0.9172	6	0.5601	20
Nanto	0.0150	13	0.2036	24	0.9897	9
Watarai	0.0000	27	0.5714	18	0.2569	26
Taiki	0.0000	26	0.7960	9	0.4584	21
lga	0.0001	23	0.6887	16	0.5800	19
Ueno	0.0012	17	0.0802	25	0.7635	15
Simagahara	1.0000	1	1.0000	1	1.0000	1
Oyamada	0.0001	24	0.7376	12	0.4459	22
Aoyama	1.0000	1	1.0000	1	0.7889	13
Nabari	0.0024	16	0.7189	14	0.3737	25
Kihoku	1.0000	1	0.8201	8	1.0000	1
Miyama	1.0000	1	0.9559	5	0.7193	16
Owase	0.0002	21	1.0000	1	1.0000	1
Minamiowase	0.1166	11	0.3128	23	1.0000	1
Mihama	0.0001	25	0.3686	22	0.7837	14
Kiho	0.1790	9	0.4207	21	0.9861	10
Kiwa	0.0138	14	0.4552	20	0.4448	23
Kumano	0.0000	28	0.4581	19	1.0000	1

in Figure 7. Although the above results show that *Matusaka* FOA is best in managerial performance, the whole picture can not be produced because of the variation in efficiency of the four FOAs, with poor performance in Model 3 (*Hokusei, Ise, Owase,* and *Kumano*). It is not possible with the limitation of current data to identify the exact reasons. Nevertheless, the results in Model 3 can lead to important findings in each FOA in terms of the interaction between product potentials and managerial performance.

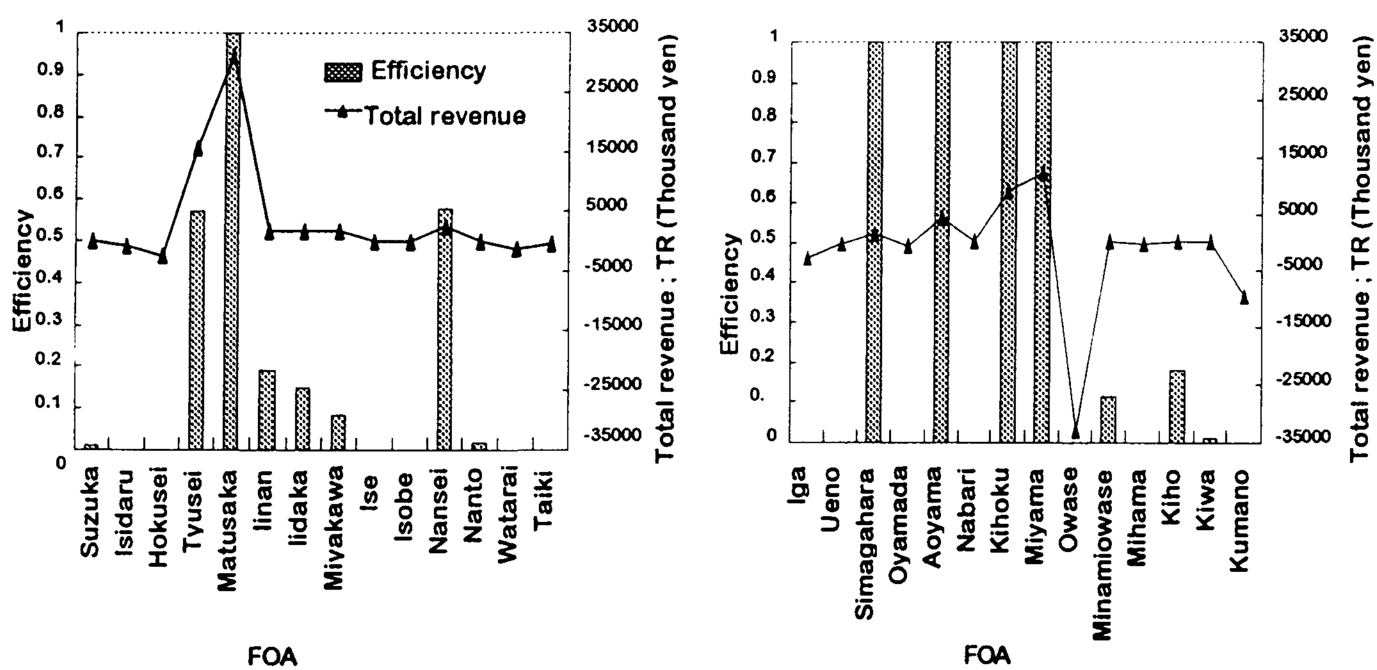

Figure 7. Plot of DEA efficiency scores (bands) and Total revenue (lines).

CONCLUSION

This paper has introduced Data Envelopment Analysis (DEA) and it has highlighted some of the ways in which it can be used.

DEA is a linear programming-based method for measuring the relative efficiency of organizational units. Such units as Forest Owners' Associations (FOAs), typically use a number of resources to secure a number of outputs. A key stage in a DEA assessment is the identification of the input/output variables pertaining to the units being assessed. These must reflect all resources used, outputs secured, and the environment in which each unit operates. They must not be excessive in number in comparison to the number of units being assessed if the method is to keep its discriminatory power.

Apart from the measure of the relative efficiency of each unit, DEA also yields other information that can prove useful in gaining a better insight into the performance of each unit and in guiding units to improve their performance. A DEA assessment identifies efficient peer units for every inefficient unit. Peer units can be used to highlight the weak aspects of the performance of the corresponding inefficient unit. The input/output levels of a peer unit can also prove to be useful target levels for the inefficient unit. DEA yields other target input/output levels as well for each inefficient unit.

The assessment model used can be manipulated to yield targets that are compatible with preferences over changes to individual input/output levels for attaining relative efficiency or to allow for the fact that certain inputs and outputs are exogenously fixed.

There exists a very large volume of literature on DEA, but there are few reports of the practical application of DEA analysis in our field.

By presenting a case study based on real data, this paper provides a comprehensive and practical guide to the use of DEA in (1) solving real problems encountered by the public sectors, such as FOAs, which in recent years have been forced to strive for greater efficiency, and (2) achieving better managerial control and decision making in the face of increased competition and dwindling forest resources.

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