*Journal of Environmental Management* (1993) **38**, 73–83

# Data Envelopment Analysis in Measuring the Efficiency of Forest Management

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*Received* 8 *April 1992*

One major concern in environmental management is how to manage efficiently the scarce natural resources necessary to improve the standards of life. To this end, a tool is required to measure the relative efficiency of the management achievements. In this paper, an approach entitled data envelopment analysis (DEA), which is widely used in management science, is introduced to measure the efficiency of forest management. The detailed steps in application, some technical problems to be noticed and the models available for selection are described. In addition to measuring efficiency, the DEA approach can also be used for generating directions for making improvements. A real case of Taiwan forests is used as an example.

*Keywords*: data envelopment analysis, efficiency, forest management, linear programming.

## 1. Introduction

Forests occupy more than one-third of the Earth's surface area, and forest management plays an essential role in environmental management. The task of forest management requires the application of business methods and technical forestry principles to the operation of a forest property (Society of American Foresters, 1958). Traditionally, timber production is deemed as the sole function of forests by most people. With a wave of concern about environmental deterioration in the last two or three decades, serious questions are being raised about the diminishing availability of wild space, the reduction in aesthetic variety and the need for both mental and physical recreation. The changing system of values has a profound influence on the ways the forests are managed. Today, most forests are managed for a multiplicity of purposes. For instance, in the United



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States, the national forests are managed mainly for outdoor recreation, range, timber, watershed and wildlife and fish purposes as stated in the 1960 Multiple Use-Sustained Yield Act (Gregory, 1972).

From the input side, many factors such as land, budget, work force, etc. have to be suitably allocated and managed in a co-ordinated way to assure high productivity of each resource. To evaluate the efficiency that the resources are used and achievements accomplished, an appropriate method has been pursued by forest managers. One major problem in measuring the efficiency of a forest is posed by the non-market nature of many products and services. This problem makes using the usual economic measures of efficiency such as benefit–cost ratio or net present value difficult. Another problem encountered is the incommensurability of different measurements. Assigning prespecified weights to different factors (inputs and outputs) is one possibility, but has the usual index number problem. One approach which overcomes these deficiencies is the data envelopment analysis (DEA) approach proposed by Charnes *et al.* (1978), which measures the relative efficiency of decision-making units (DMUs) that transform multiple inputs into multiple outputs. The primary merit of this approach is that the weights applied to inputs and outputs are solved from a linear program instead of being prespecified somewhat arbitrarily. Efficiency scores thus calculated are considered under the most favorable condition. This special feature can largely reduce the complaint from the unit which has been evaluated as inefficient.

Recently, Kao and Yang (1991) applied the DEA approach to evaluate the efficiency of forest management. Their emphasis is on the introduction of the idea of DEA. A careful examination discloses that several basic assumptions imposed by the DEA approach are violated and some technical problems are ignored. In this paper, the detailed steps of applying the DEA approach to measuring the efficiency of forest management is discussed, using as an example the Taiwan forests. In the following section we introduce the idea of the DEA methodology to open the discussion.

## 2. Data envelopment analysis

Data envelopment analysis (DEA) is a methodology for measuring the relative efficiency of decision-making units (DMUs) with multiple inputs and multiple outputs. The idea is based on the concept of Pareto optimality, which states that, within the given limitations of resources and technology, there is no way of producing more of some desired commodity without reducing the output of some other desired commodity (Zeleny, 1982). Consider a simple example of five DMUs (districts or working circles in the context of forest management), denoted as $A$, $B$, $C$, $D$ and $E$ in Figure 1, each DMU applies a different amount of a single input $X$ to produce a different amount of a single output $Y$. A piecewise linear production function is constructed from these sampled DMUs. DMUs $A$, $B$, $C$ and $D$ lie on the production function, hence they are efficient with efficiency score 1. DMU $E$, on the other hand, is dominated by $E'$, a convex combination of $C$ and $D$. Consequently, the efficiency score of $E$ is $EI_E/E'I_E$, that is, the ratio of the actual output to the maximum output that could be produced from a fixed input amount. This idea for measuring the efficiency of DMUs with multiple inputs and multiple outputs is elegantly specified as a linear fractional programming model by Charnes *et al.* (1978) and later modified by Banker *et al.* (1984) as:

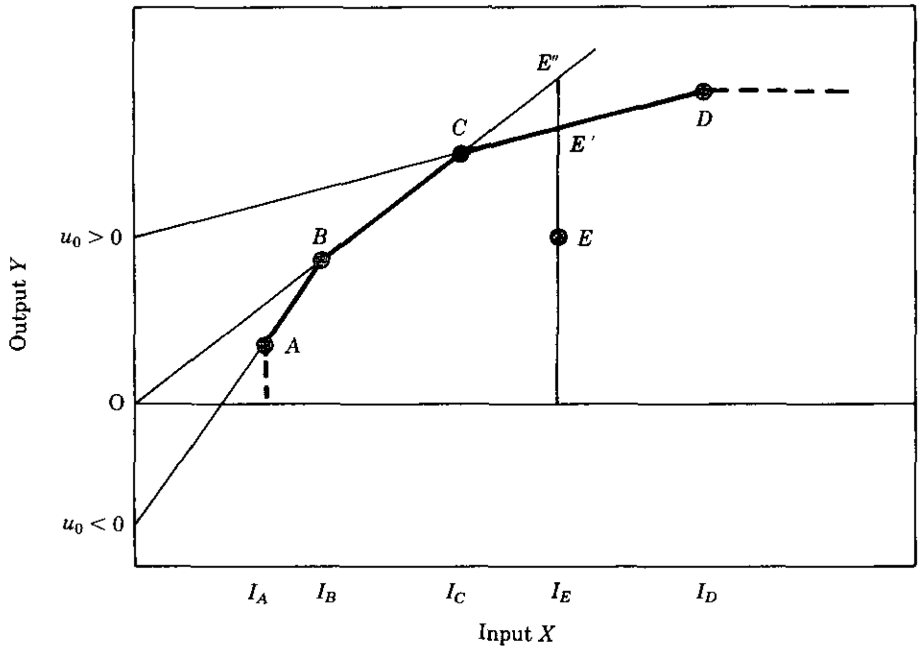


Figure 1. Estimated production function and the efficiencies of the sampled DMUs.

$$E_r = \max \sum_{k=1}^{t} v_k Y_{rk} / (u_0 + \sum_{j=1}^{s} u_j X_{rj})$$

$$\text{s.t. } \sum_{k=1}^{t} v_k Y_{ik} / (u_0 + \sum_{j=1}^{s} u_j X_{ij}) \leqslant 1 \quad i = 1,\ldots,n \tag{1}$$

$$u_1,\ldots,u_s;\ v_1,\ldots,v_t \geqslant \varepsilon > 0,\ u_0 \text{ unconstrained in sign,}$$

where $X_{ij}$ = amount of the $j$th input consumed by the $i$th DMU; $Y_{ik}$ = amount of the $k$th output produced by the $i$th DMU; $u_j$ = weight applied to the $j$th input, there are $s$ inputs; $v_k$ = weight applied to the $k$th output, there are $t$ outputs; $n$ = number of sampled DMUs; $E_r$ = measured efficiency score of the $r$th DMU. Note that $\varepsilon$ is a small non-Archimedean quantity imposed as a lower bound for each weight to restrict assigning zero to unfavorable factors (Charnes *et al.*, 1979). This non-linear model can be linearized by letting the denominator of the objective function be equal to one and be treated as a constraint so that it can be deleted from the objective function. Subsequently, we multiply both sides of the ratio constraints by the denominator to result in a linear program.

In Figure 1, the DMUs with input amount between $I_A$ and $I_B$ are in the region of increasing returns to scale, DMUs with input amount between $I_B$ and $I_C$ are in the region of constant returns to scale and DMUs with input amount between $I_C$ and $I_D$ are in the region of decreasing returns to scale. Graphically, it is very easy to verify that, in measuring the efficiency of a DMU, if $u_0$* solved from model (1) is negative, zero or positive, then this DMU is in the region of increasing, constant or decreasing returns to scale, respectively. Banker *et al.* (1984) provide a rigorous proof. By assigning zero to $u_0$, the production function constructed from the sampled DMUs in Figure 1 is the straight line $OE''$. The efficiency of $E$ become $EI_E/E''I_E$. In this case, the inefficient part $E''E'$ is due to scale. Consequently, $E'I_E/E''I_E$ is considered as the scale efficiency of $E$. The original efficiency measure $EI_E/E'I_E$ is called technical efficiency. The product of scale efficiency $E'I_E/E''I_E$ and technical efficiency $EI_E/E'I_E$ is aggregate efficiency $EI_E/E''I_E$.

The DEA approach has been widely applied to the evaluation of the efficiency of public programs, non-profit organizations and cases where some inputs and outputs do not have market values. Many interesting applications are contained in the bibliographical list of Seiford (1990).

## 3. Selection of inputs and outputs

The DEA technique for measuring efficiency relies on the observed inputs and outputs of the sampled DMUs. Identifying the right inputs and outputs is thus the key to the success of this technique. Selecting inputs and outputs which are not representative will result in evaluated efficiencies which are misleading. The total number of inputs and outputs also has some effect on the measured efficiencies; the more factors considered, the more will be the DMUs which are Pareto-efficient. Basically, selection of inputs and outputs should conform to the purpose of evaluation. In forest management, suppose the American forests are to be evaluated, then the outputs from recreation, range, timber production, watershed and wildlife and fish should be collected under the Multiple Use-Sustained Yield Act. An in-depth consultation with experts in the study area is also recommended. In the example of Kao and Yang (1991), the inputs and outputs selected are obtained through a long discussion with the people at the headquarters and district offices of the Taiwan Forestry Bureau. Thus, they are quite reliable. The factors selected by Kao and Yang (1991) are budget, initial stocking, labor and land as inputs, and timber production, average stocking, recreation and by-products as outputs. In this study the same factors are considered. To be specific:

*Inputs*

1. Budget: money allocated to each district each year in U.S. dollars.
2. Initial stocking: the volume of forest stocking before the period of evaluation in cubic meters.
3. Labor: work force in number of employees.
4. Land: area in hectares.

*Outputs*

1. Timber production: timber harvested per year in cubic meters.
2. Average stocking: the average volume of forest stocking in cubic meters as a measure of soil conservation.
3. Recreation: the number of annual visits of tourists.
4. By-products: the monetary value of by-products obtained each year in U.S. dollars.

The national forests of Taiwan are divided into 13 districts. Kao and Yang (1991) measure the efficiencies of these districts based on the above stated inputs and outputs. According to Thomas *et al.* (1986) and Bowlin (1987), the number of DMUs should be at least twice the total number of inputs and outputs specified in the model to be able to produce meaningful results. Banker *et al.* (1989) even suggest that, whenever possible, there should be three times as many DMUs. In our case, four inputs and four outputs are considered, hence at least 16 forests are required. In Taiwan, in terms of scale, there are four other forests which are similar to the 13 forest districts: the forests of the Forest

Development Office, Forest Research Institute, Taiwan University and Chun Hsin University. Therefore, these four forests are also included to make a total of 17 forests.

Data for each factor may stay relatively stable or change drastically along the time horizon (Taiwan Forestry Bureau, 1988). To be representative, a 10-year average from 1978 to 1987 is calculated. Monetary values are also deflated by the wholesale price indices with 1975 as the base year. Table 1 shows the input and output measurements of the 17 forests.

In addition to the requirement on the number of DMUs, Thomas *et al.* (1986) also suggest that the number of outputs should be less than the number of inputs. Hence, at least one output should be deleted from the study of Kao and Yang (1991) to fulfill this recommendation. How to select the output to be deleted will be discussed later.

There is another consideration in selecting inputs and outputs. In the general study concerning inputs and outputs, it is desired that there exist positive correlations between inputs and outputs, for the cause–effect relationships do not otherwise hold. This concept also prevails in the DEA methodology. Violation of this relationship is readily detected from the correlation coefficients between inputs and outputs. In Table 2, the correlation coefficient between each input and output is calculated. Surprisingly, recreation and by-products have negative correlation coefficients with every input. Hence, these two outputs have to be excluded because they have no relation with the inputs. Deletion of these two outputs accomplishes the requirement that the number of outputs should be less than the number of inputs at the same time.

For general cases, this procedure may not be able to delete unnecessary outputs. One possible way suggested by Lewin *et al.* (1982) is to delete the outputs which are highly correlated with other outputs. The reason is that in this case the outputs to be deleted are redundant in representing the input–output relation. By the same token, if there are too many inputs, then the inputs which are highly correlated with other inputs are considered as redundant, and can thus be deleted.

## 4. Efficiency measurement

In the preceding section, several technical issues of the DEA methodology are discussed. The data set finally determined consists of four inputs: budget, initial stocking, labor and land; and two outputs, timber production and average stocking, from 17 forests. To calculate technical efficiency, model (1) is applied to the data set. By further restricting $u_0$ in model (1) to zero, the aggregate efficiency is solved. Taking the ratio of aggregate efficiency to technical efficiency derives scale efficiency. These efficiency scores of each forest are recorded in Table 3. The sign of $u_0$ being negative, zero or positive indicates that the corresponding forest is in the region of increasing, constant or decreasing returns to scale, respectively, as discussed in an earlier section. As far as aggregate efficiency is concerned, the study of Kao and Yang (1991) concludes that five forests (of the 13 forest districts of the Taiwan Forestry Bureau) are inefficient. In Table 3, in addition to the five forests found in Kao and Yang (1991), there is one more forest, Luan Ta, which is inefficient (the Forest Development Office does not belong to the Taiwan Forestry Bureau). Thus, the effect of including four more forests and deleting two outputs is to reduce the number of efficient forests by one.

The DEA has another interpretation from the economic point of view. By definition, every linear program has a dual associated with it (Dantzig, 1963). When model (1) is transformed to a linear program, a dual can be formulated as:

TABLE 1. Input and output data of the 17 forests in Taiwan

| Forests | Inputs | | | | Outputs | | | |
|---|---|---|---|---|---|---|---|---|
| | Budget ($1000) | Ini. stock (1000 m³) | Labor (persons) | Area (1000 ha) | Timber (m³) | Ave. stock (1000 m³) | Recreation (vists) | By-products ($) |
| Wen Shan | 4110·42 | 5040·21 | 270 | 60·85 | 15 845·34 | 5172·25 | 14 573·58 | 64 373·22 |
| Chu Tung | 9303·70 | 13 446·87 | 598 | 108·46 | 47 190·95 | 18 864·45 | 6995·67 | 34 978·35 |
| Ta Chia | 6350·89 | 8273·63 | 421 | 79·06 | 21 567·57 | 10 474·66 | 33 734·90 | 57 998·42 |
| Tah Sue Shan | 12 285·19 | 10 947·01 | 860 | 59·66 | 8406·09 | 11 710·66 | 9635·09 | 71 043·13 |
| Pu Li | 4333·16 | 9929·60 | 271 | 84·50 | 39 039·00 | 12 251·66 | 0 | 57 392·40 |
| Luan Ta | 10 448·42 | 13 356·76 | 592 | 127·28 | 57 110·54 | 13 813·70 | 0 | 80 988·26 |
| Yu Shan | 12 154·38 | 8145·07 | 863 | 98·80 | 42 810·04 | 12 432·99 | 399 833·72 | 424 928·92 |
| Nan Nung | 8837·76 | 10 856·02 | 852 | 123·14 | 55 203·66 | 9178·86 | 7560·80 | 177 001·44 |
| Heng Chung | 5350·62 | 8617·14 | 285 | 86·37 | 39 237·89 | 6875·05 | 1 081 887·89 | 56 123·23 |
| Kuan Shan | 5868·58 | 24 037·76 | 216 | 227·20 | 44 076·80 | 27 284·45 | 0 | 89 971·20 |
| Yu Li | 4081·00 | 15 755·87 | 205 | 146·43 | 37 295·72 | 19 298·01 | 0 | 33 971·76 |
| Mu Kua | 12 594·65 | 23 026·00 | 775 | 173·48 | 9628·14 | 23 532·56 | 41 860·72 | 17 157·17 |
| Lan Yang | 14 515·26 | 17 843·35 | 2723 | 171·11 | 19 728·98 | 18 859·74 | 83 997·90 | 50 374·78 |
| Forest Devel. Office | 18 936·97 | 17 581·85 | 1399 | 93·65 | 42 114·40 | 17 303·71 | 0 | 0 |
| Forest Research Inst. | 909·77 | 1422·06 | 351 | 13·65 | 19 074·51 | 1582·85 | 0 | 0 |
| Taiwan University | 1730·30 | 376·43 | 165 | 33·52 | 13 572·25 | 499·11 | 1 061 481·19 | 475 846·57 |
| Chun Hsin Univ. | 296·69 | 1591·02 | 49 | 8·23 | 3858·22 | 1570·04 | 67 726·32 | 310 380·46 |

TABLE 2. Correlation coefficients between inputs and outputs

| Inputs | Outputs | | | |
|---|---|---|---|---|
| | Timber production | Average stocking | Recreation | By-products |
| Budget | 0·264 | 0·578 | −0·239 | −0·254 |
| Initial stocking | 0·336 | 0·969 | −0·383 | −0·501 |
| Labor | 0·024 | 0·356 | −0·185 | −0·196 |
| Area | 0·439 | 0·909 | −0·253 | −0·323 |

TABLE 3. Efficiency scores estimated under piecewise linear model

| Forests | $u_0$ | Technical efficiency | Scale efficiency | Aggregate efficiency |
|---|---|---|---|---|
| Wen Shan | − | 0·7762 | 0·9451 | 0·7336 |
| Chu Tung | 0 | 1 | 1 | 1 |
| Ta Chia | − | 0·9102 | 0·9833 | 0·8950 |
| Tah Sue Shan | 0 | 1 | 1 | 1 |
| Pu Li | 0 | 1 | 1 | 1 |
| Luan Ta | + | 1 | 0·8815 | 0·8815 |
| Yu Shan | 0 | 1 | 1 | 1 |
| Nan Nung | + | 1 | 0·7658 | 0·7658 |
| Heng Chung | 0 | 1 | 1 | 1 |
| Kuan Shan | 0 | 1 | 1 | 1 |
| Yu Li | 0 | 1 | 1 | 1 |
| Mu Kua | + | 1 | 0·8193 | 0·8193 |
| Lang Yang | + | 0·7534 | 0·9868 | 0·7435 |
| Forest Devel. Office | + | 1 | 0·9749 | 0·9749 |
| Forest Research Inst. | 0 | 1 | 1 | 1 |
| Taiwan University | 0 | 1 | 1 | 1 |
| Chun Hsin Univ. | 0 | 1 | 1 | 1 |

$$\begin{aligned}
&\min\ z-\varepsilon\left[\textstyle\sum_{j=1}^{s} s_j^{+}+\sum_{k=1}^{t} s_k^{-}\right]\\
&\text{s.t. } \textstyle\sum_{i=1}^{n} w_i Y_{ik}-s_k^{-}=Y_{rk},\ k=1,\ldots,t\\
&\quad z-\textstyle\sum_{i=1}^{n} w_i=0 \qquad (2)\\
&\quad zX_{rj}-\textstyle\sum_{i=1}^{n} w_i X_{ij}-s_j^{+}=0,\ j=1,\ldots,s\\
&w_i,\ s_j^{+},\ s_k^{-}\geqslant 0.
\end{aligned}$$

The original linear program (usually termed primal) and the dual have the same value of the objective function at optimum (Dantzig, 1963). In addition, $s^+$ and $s^-$ in dual are the reduced costs of the primal variables $u$ and $v$, respectively; $w$ is the reduced cost of the slack variable of the primal [not shown in model (1)]. Hence, solving the dual is equivalent to solving the primal because all information will be obtained in solving

TABLE 4. Slack values of each forest

| Forests | Aggregate efficiency | Budget | Initial stocking | Labor | Area | Timber production | Average stocking |
|---|---|---|---|---|---|---|---|
| Wen Shan | 0·7336 | 127·79 | 0 | 0 | 7·71 | 0 | 0 |
| Chu Tung | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Ta Chia | 0·8950 | 0 | 0 | 4·42 | 8·18 | 5642·64 | 0 |
| Tah Sue Shan | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Pu Li | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Luan Ta | 0·8815 | 3197·51 | 0 | 0 | 0 | 0 | 0 |
| Yu Shan | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Nan Nung | 0·7658 | 1484·76 | 0 | 0 | 0 | 0 | 0 |
| Heng Chung | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Kuan Shan | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Yu Li | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mu Kua | 0·8193 | 1739·08 | 0 | 0 | 0 | 46 083·15 | 0 |
| Lang Yang | 0·7435 | 0 | 0 | 1310·60 | 12·02 | 30 347·32 | 0 |
| Forest Devel. Office | 0·9749 | 14 583·82 | 0 | 811·96 | 0 | 0 | 0 |
| Forest Research Inst. | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Taiwan University | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Chun Hsin Univ. | 1 | 0 | 0 | 0 | 0 | 0 | 0 |

either program. Nevertheless, model (2) provides extra information pertaining to efficiency improvement. From the objective function, it is clear that the conditions for a DMU to be Pareto efficient are $z^*=1$, and $s^{+*}=s^{-*}=0$, where "*" indicates an optimal solution. If a DMU is not efficient, the constraints in model (2) imply that by increasing $Y_{rk}$ by $s_k^{-*}$ and decreasing $X_{rj}$ by $(1-z^*)x_{rj}+S_j^{+*}$, the associated DMU becomes efficient (Charnes *et al.*, 1978). As a reference, the set of ($z^*$, $s^{+*}$, $s^{-*}$) values for each forest is listed in Table 4, from which how to eliminate inefficiencies is straightforward. Evidently, every efficient forest must have zero value for all slack variables, and this is true as indicated in Table 4.

## 5. A variational model

The production function constructed from model (1) is piecewise linear in its shape (refer to Figure 1), and the region under the production function composes a convex set. In economic terms, this model requires that marginal products be non-increasing. This assumption restricts the estimation of the classical S-shaped production function. The problem occurs at the region of increasing marginal products. To overcome this drawback, Banker and Maindiratta (1986) and Kao (1986) propose a piecewise log-linear model which is very similar to the piecewise linear model, with arithmetic linear combinations being replaced by geometric combinations. In symbols, the model is:

$$\begin{aligned} E_r &= \max\ \textstyle\prod_{k=1}^{t} Y_{rk}^{v_k} / u_0 \prod_{j=1}^{s} X_{rj}^{u_j} \\ \text{s.t.}\quad & \textstyle\prod_{k=1}^{t} Y_{ik}^{v_k} / u_0 \prod_{j=1}^{s} X_{ij}^{u_j} \leqslant 1,\ i=1,\dots,n \\ & \textstyle\sum_{k=1}^{t} v_k = 1 \\ & u_0,\ u_j,\ v_k \geqslant \varepsilon > 0. \end{aligned} \tag{3}$$

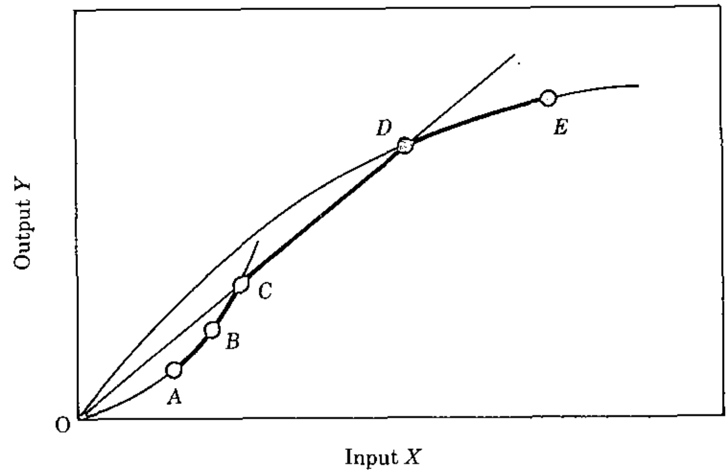


Figure 2. Piecewise log-linear production function.

This model is easily linearized by taking logarithms. The denominator of the ratio expression is generally interpreted as the production function. In this model the production function is of the Cobb–Douglas form. A DMU is in the region of increasing, constant or decreasing returns to scale depending on its associated $\Sigma_{j=1}^{s} u_j$ being greater than, equal to or less than 1, respectively. The efficiency calculated from model (3) is technical efficiency. By restricting the sum of $u_j$, $j=1,\ldots,s$ to 1, the score calculated is aggregate efficiency. As in the linear model, the ratio of aggregate efficiency to technical efficiency is scale efficiency. A diagram of this model is depicted in Figure 2 for cases of single-input and single-output.

Although the log-linear model permits the identification of increasing marginal products, it is not without its flaws. The numerator of the ratio expression in model (3) can be considered as the production transformation curve, which is generally expected to be strictly concave (Henderson and Quandt, 1980). For each additional units of one product that is given up, the increases in the output of other products become smaller. In the log-linear model, this is not true because $\Pi_{k=1}^{t} Y_{rk}^{v_k} = c$ is a convex curve (Kao, 1988). Both of the linear and loglinear models have their pros and cons, there is no general consensus as which one to adopt. Essentially, the adoption depends on the assumption imposed on the form, or shape to be more specific, of the production function.

Table 5 shows the results from evaluating the efficiencies of the 17 forests by applying model (3). Comparing this table with Table 3, one finds that both models have a consistent conclusion on economic scales of the 17 forests. As far as the efficiency scores are concerned, the log-linear model in general results in a higher measurement. Finally, as in the linear model, when model (3) is linearized to a linear program and its dual is formulated, the slack variables of the dual provide a direction for making improvement.

## 6. Conclusion

The main objective of measuring efficiency is to gain an insight of how far a DMU being evaluated can be expected to increase its outputs by merely increasing its efficiency with its current resource base. This is especially important in the management of scarce

TABLE 5. Efficiency scores estimated under piecewise log-linear model

| Forests | $\Sigma u_j$ | Technical efficiency | Scale efficiency | Aggregate efficiency |
|---|---|---|---|---|
| Wen Shan | $>1$ | 0·8149 | 0·9015 | 0·7347 |
| Chu Tung | $=1$ | 1 | 1 | 1 |
| Ta Chia | $>1$ | 0·9380 | 0·9518 | 0·8927 |
| Tah Sue Shan | $=1$ | 1 | 1 | 1 |
| Pu Li | $=1$ | 1 | 1 | 1 |
| Luan Ta | $<1$ | 1 | 0·8370 | 0·8370 |
| Yu Shan | $=1$ | 1 | 1 | 1 |
| Nan Nung | $<1$ | 1 | 0·6942 | 0·6942 |
| Heng Chung | $<1$ | 1 | 0·9934 | 0·9934 |
| Kuan Shan | $=1$ | 1 | 1 | 1 |
| Yu Li | $=1$ | 1 | 1 | 1 |
| Mu Kua | $<1$ | 0·9736 | 0·8227 | 0·8010 |
| Lang Yang | $<1$ | 0·7543 | 0·9821 | 0·7408 |
| Forest Devel. Office | $<1$ | 1 | 0·9740 | 0·9740 |
| Forest Research Inst. | $=1$ | 1 | 1 | 1 |
| Taiwan University | $=1$ | 1 | 1 | 1 |
| Chun Hsin Univ. | $=1$ | 1 | 1 | 1 |

natural resources. In the past years, much effort has been put on searching for a proper method for measuring relative efficiency [see, for example, the literature review of Førsund *et al.* (1980) and Kopp (1981)]. The major problem in measuring efficiency lies on the incommensurability of different output measurements as well as input measurements. This problem is solved in the pathbreaking work of Charnes *et al.* (1978) by the DEA approach stemmed from the concept of Pareto optimality. Since then, the DEA approach has received considerable attention from both researchers and practitioners (Seiford, 1990). One reason is that this approach has an advantage of evaluating DMUs under the most favorable condition (Lewin and Morey, 1985).

In this paper, the procedure and technical problems to be noted in applying the DEA methodology are illustrated by an example in forest management. Basically, this approach is most suitable for organizations where pursuing profit is not the major objective. Several points to bring the attention of the potential users of this approach which are not considered in Kao and Yang (1991), including: (1) inputs and outputs should possess positive correlations to be representative; (2) the number of inputs is recommended to exceed the number of outputs in order to aid in the interpretation of the results; and (3) the number of DMUs in the data set should be at least twice the total number of inputs and outputs to result in more meaningful measures of efficiency. As far as the models are concerned, there are in general two types of models, i.e. piecewise linear and piecewise log-linear, available for adoption. Selection of the models depends on the assumption imposed on the shape of the production function. Different models result in somewhat different efficiency scores; however, the difference is not much, as is exposed in Table 3 and Table 5.

To conclude, the efficiency scores evaluated by the DEA approach provide a relative measure. A DMU with unity efficiency by no means implies that there is no room for making improvement. The performance of an efficient DMU can still be improved, only its efficiency score stays the same at unity. The effect is revealed in the decreased efficiency scores of some other DMUs.

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