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Measuring the performance and returns to scale of forest management plans using data envelopment analysis approach (Case study; Iranian Caspian forests)

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ABSTRACT

The aim of this study was to assess the relative efficiency of the Iranian forest management plans using the non-parametric method – Data Envelopment Analysis (DEA) as a well-known and robust technique for measuring the relative efficiency of organizations. The relative efficiency of forest management plans was calculated using the most frequency DEA models such as global technical efficiency (CCR), local pure technical efficiency (BCC) and Scale Efficiency (SE) on 12 units in Guilan Province, Iran. According to the results of CCR and BCC models, the efficiency averaged 0.83 and 0.93, respectively. The results of SE discussed a worrying aspect of these units efficiency; namely, there were only 3 efficient forest management plans (Shafaroud, Nav and Fiyab). However, the Scale Efficiency Index (SEI) brings out some interesting points; there were approximately 58% (7 units out of 12) under Increasing Returns to Scale (IRS). Therefore, the managers of forest management plans should focus more on the plans under IRS, so that they will have the opportunity to become more efficient through growth, otherwise managers will not be able to promote their overall productivity.

Key words: Data envelopment analysis; Measuring the performance; Returns to scale; Forest management plans.

INTRODUCTION

Efficiency and productivity measurement in organizations has received a great deal of attention both in research and in practice. It means that determining the efficiency has become increasingly important in many areas of human activity. In forestry, the determination of efficiency of forest management plans is very complicated because of multiple goals of forest management, i.e. in the last few decades, forest management has been focused on multifunction usage (economic, ecological and social functions) and general benefits of forests. Owing to the multiple benefits and advantages offered by the forest as well as the non-market nature of part of these outputs, measuring the efficiency in forestry is highly demanding (Sporcic *et al.* 2009). Approach to this problem is particularly interesting when there are no clear success parameters, and when the efficiency of using several different resources/inputs is measured for achieving several different outputs. A well-documented method in the operations research is Data Envelopment Analysis (DEA) that was originally introduced by Charnes *et al.* (1978) in the form of mathematical programming, based on an earlier work of Farrell (1957). Afterwards, In the DEA literature, many authors have extended techniques to measure the relative performances of operational units in different conditions. DEA utilizes linear programming (LP) to evaluate the relative performance of a set of homogeneous decision making units (DMUs) with multiple incommensurate inputs and outputs without requiring a specified functional form.

The LP can be formulated in many ways and is a transformation of the original fractional programming problem, see section 2.1.2: Output Maximization and Input Minimization DEA Programs on page 42 of Ramanathan (2003) as well as section 2.5: Data Envelopment Analysis on page 29 of Subhash (2004). Indeed, attempts to understand the relationship between the technology of a DMU, its efficiency and environment, and the measurement of Returns to Scale (RTS) are not new to DEA. But one of the key properties of the production structure is the scale of operations.

It receives particular interest because the existence of economies or diseconomies of scale may have different implications for the market structure and conduct. Hence, the economic concept of RTS has also been widely studied within the framework of DEA to answer a critical quest in any study of productive efficiency; whether the underlying technology exhibits increasing, constant, or decreasing returns to scale. The economic concept of RTS is extremely important in forestry as well, because forests are rare recourses and also have multifunction (marketable and non-marketable) uses in which monitored by forest management plans. So, in a rational insight, assessing the performance of these plans to propose appropriate solutions for improving their performance and scale efficiency state is really vital.

In general, two main categories have been followed for treating RTS in DEA: first, RTS measurement using BCC-DEA models; this type of research efforts includes Banker & Thrall (1992), Tone (1996), Golany & Yu (1997), Sueyoshi (1999), Cooper *et al.* (2000), Tone & Sahoo (2003); the second, RTS measurement developed by Färe, Grosskopf & Lovell (FGL-DEA model) who used a quantitative measurement of scale elasticity. In fact, this type of research can be traced to the efforts of Färe *et al.* (1983, 1985, and 1994). Noteworthy, the alternative measurements provided by the FGL-DEA approach is an important one because this approach identifies RTS through the ratios of a series of relative efficiencies obtained from different DEA models with radial measure, which has different constraints (Färe *et al.* (1983). These ratios are developed from the model pairs that differ only in conditions of the convexity and sub-convexity that are satisfied (Banker *et al.* 2004). Despite that DEA has been applied in a wide range of applications, there are few studies in forestry by this non-parametric approach. For instance, Kao & Yang (1992) used the DEA efficiency results to appraise three alternatives proposed by the Taiwan Forestry Bureau for reorganizing the 13 forest districts considered in their earlier study (Kao & Yang 1991). The efficiency of 19 public Forestry Boards in Finland was evaluated using DEA (Viitala & Hanninen 1998).

The efficiency of the Croatian forestry organization was evaluated by non-parametric models (Sporcic *et al.* 2009), their research revealed DEA as a powerful multi criteria decision making tool for support in forest management. The DEA model was used to measure the productive efficiency of forest enterprises in the Mediterranean Region of Turkey (Korkmaz 2011).

DEA was first used to assess the efficiency of Iranian forest industries by Mohammadi Limaei (2013). He investigated the efficiency of 14 Iranian forest companies and forest management in 2010. Efficiency of the companies was estimated using a traditional DEA model and a two-stage DEA model.

Therefore, due to the important role of forests to include multiple usage (economic, ecological and social functions) this study is conducted to estimate the relative efficiency and returns to scale of some forest management plans in the north of Iran to disseminate the necessary information for manager of forest management plans until they will be able to adjust the units operating scale and become more efficient through growth. The DEA method is, therefore, well suited to be used in this case study.

MATERIALS AND METHODS

DEA models

Conventionality DEA is defined as a linear programming methodology (Lin & Wang 2014) which allows to assess the performance of multiple DMUs when the production process presents a structure of multiple inputs and outputs (Tone & Tsutsui 2014; Oral *et al.* 2014). In this matter, there are many DEA models with their pros and cons, thus, with respect to this paper goals, the most frequently applied DEA model is used as follows.

CCR model

Charnes *et al.* (1987) formulated a DEA model, referred to as CCR [Charnes, Cooper & Rhodes], with Constant Returns to Scale (CRS) assumption (Model 1). A CRS assumption implies that all DMUs would be able to increase their output by a similar proportion, given an increase in the rate of their inputs, no matter what their scales are. The efficiency score resulting from a CCR model is called the global technical efficiency.

$$[CCR] \quad \min y_0 = \theta - \varepsilon\left(\sum_{r=1}^{s} \overset{+}{\underset{r}{s}} + \sum_{i=1}^{m} \overset{-}{\underset{i}{s}}\right)$$

$$st:$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - \overset{+}{\underset{r}{s}} = y_{r0} \qquad (r = 1,2,\ldots,s)$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j + \overset{-}{\underset{i}{s}} = \theta\, x_{i0} \qquad (i = 1,2,..,m)$$

$$\lambda_j, \overset{+}{\underset{r}{s}}, \overset{-}{\underset{i}{s}} \geq 0 \quad \forall i,j,r \qquad (j = 1,2,\ldots,n) \tag{1}$$

where: x_{ij} = amount of input i used by unit j,

y_{rj} = amount of output r is produced by unit j,

ε = a small non-Archimedean quantity which prohibits any inputs/outputs factor to be ignored.

Due to the input-oriented nature of this model, the objective function tries to reduce input amounts (θ) by fixing output levels. In fact, θ is a real decision variable and λ is a non-negative vector of decision variable that in this sample to choose each allowable vector (λj) for making an upper limit for outputs and a lower limit for inputs of DMU0. Hence the optimal θ, denoted by θ*, is not greater than 1 (Cooper *et al.* 2007).

Definition 1.A decision maker is fully efficient if and only if both $\theta^* = 1$ (optimal solution problem) and $\overset{+}{\underset{r}{s}}{}^{*} = \overset{-}{\underset{i}{s}}{}^{*} = 0$ (slack input and output variables).

BCC model

The CCR model (Model 1) can be modified to accommodate Variable Returns to Scale (VRS). This model was introduced by (Banker *et al.* 1984), referred to as BCC, and requires a convexity constraint (2) added to the CCR model (1). Noteworthy, the convexity of the production possibility set is a maintained hypothesis in DEA because the convexity ensures that when two or more input–output combinations are known to be feasible, any weighted average of the input bundles can produce a similarly weighted average of the corresponding output bundles (Subhash 2004). Therefore, in this model, each DMU against other DMUs in the same scale range as well as the efficiency score provided by a BCC model is called local pure technical efficiency.

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (j = 1,2,\ldots,n) \tag{2}$$

Definition 2. The definition of efficient decision maker is the same as definition 1.

SE model

The scale efficiency (SE) of a DMU can be calculated based on its global technical efficiency and local pure technical efficiency resulting from CCR and BCC models, respectively (3). SE represents the inefficiency of a DMU which is merely due to its scale of operations. This model can be formulated in the following form (Cooper *et al.* 2007).

Definition 3. A decision maker is fully efficient if and only if both $\theta^* = 1$ (optimal solution problem).

$$SE = \frac{\theta^*_{CCR}}{\theta^*_{BCC}} \quad (3)$$

SEI/ FGL model

Färe et al. (1985) introduced the following "scale efficiency index" (SEI) method or FGL model, which is based on Non-Increasing Returns to Scale (NIRS), to determine the nature of local RTS for DMU_o (Tone & Sahoo, 2005):

$$[SEI/FGL] \quad \min y_0 = \theta - \varepsilon\left(\sum_{r=1}^{s} s_r^+ + \sum_{i=1}^{m} s_i^-\right)$$

$$st:$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0} \qquad (r = 1, 2, ..., s)$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{i0} \qquad (i = 1, 2, .., m)$$

$$\sum \lambda_j \le 1 \qquad (j = 1, 2, ..., n)$$

$$\lambda_j, s_r^+, s_i^- \ge 0 \quad \forall i, j, r$$

(4)

In fact, they proposed a method by changing $\sum_{j=1}^{n}\lambda_j = 1$ from (Model 2) to $\sum_{j=1}^{n}\lambda_j \le 1$ (Model 4) and these following steps:

If $\theta^*_{CCR} = \theta^*_{BCC}$, then DMU_o exhibits CRS and also is fully efficient by SE; otherwise if $\theta^*_{CCR} < \theta^*_{BCC}$, then DMU_o exhibits IRS if $\theta^*_{SEI} < \theta^*_{BCC}$, and DMU_o exhibits NIRS if $\theta^*_{SEI} = \theta^*_{BCC}$.

Case study

The area of natural forest in Iran is approximately 12.4 million hectares, equal to 7.5% of the total area of Iran. Of this, approximately 1.9 million hectares are commercial forests called Iranian Caspian, Hyrcanian or Northern forests which is controlled by forest management plans.

In this research, according to forestry experts' idea, two inputs (plantation cost and stock before executing the forest management plan, called stock 1) and two outputs (harvesting revenue and stock after executing the plan, called stock 2) were considered. At least 12 forest management plans had to select using rule of thumb in DEA approach. Hence, the number of DMU should follow:

$$n \ge \max\{m \times s, 3(m+s)\}$$

where n = number of DMUs, m = number of inputs, and s = number of outputs. Afterwards, we assume that this (or other) degrees of freedom conditions are satisfied and that there is no trouble from this quarter (Cooper *et al.* 2011). It should be noted that the length of the planning horizon includes 10 years. Hence, in this case, the average data of a ten-year period were considered. Moreover, the monetary data were adjusted by the Consumer Price Index (CPI) of Iran in the base year 2011 (Table 1).

RESULTS

The results of global technical efficiency (CCR) and local pure technical efficiency (BCC) are meaningfully different; the number of efficient units by CCR is 3 and by BCC is 6 and also the efficiency averages for CCR and BCC are 0.83 and 0.93, respectively (Table 2). The results of BCC and FGL models indicate that most of forest management plans 58% (7 out of 12) are under IRS.

Also, this comparative approach shows that two forest management plans are under NIRS and the rest of them are under CRS as well as they are fully efficient (score 1) by SE model (Table 3).

The results of the scale efficiency (SE) model show the distance between the boundary fixed and variable returns to scale (CCR and BCC) in which based on this model there is a considerable distance between them, i.e. there are only 3 (Shafaroud, Nav and Fiyab) efficient forest management plans (Fig. 1).

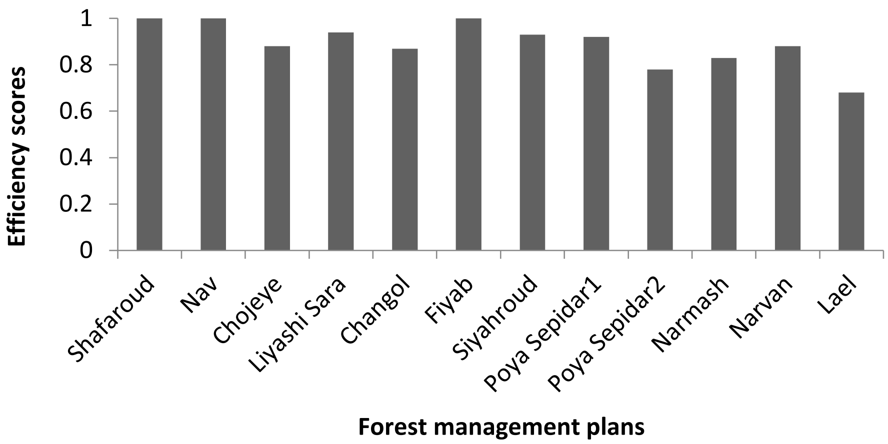

Fig. l. The result of SE model.

Table 1. Mean values of input and output data of forest management plans used in DEA models.

Forest management plans	Input		Output	
	Plantation cost (Iranian million Rials)	Stock 1 ($m^3.ha^{-1}$)	Harvesting revenue (Iranian million Rials)	Stock 2 ($m^3.ha^{-1}$)
Shafaroud	53.07177	210.52	14173.86	226.46
Nav	254.2138	219.62	104653.89	254.12
Chojeye	236.1694	231.77	22571.13	226.59
Liyashi Sara	387.4239	241.558	50075.23	250.06
Changol	514.7962	197.516	33551.23	214.75
Fiyab	95.52919	236.904	49391.76	319.84
Siyahroud	249.4373	255.86	39079.87	254.06
Poya Sepidar1	135.333	289.45	53353.27	358.97
Poya Sepidar2	318.9613	208.93	34815.33	174.21
Narmash	148.601	193.77	22207.49	218.42
Narvan	189.1934	180.5	37928.82	210.3
Lael	361.6372	159.67	32885.47	138.71

In this study, GAMS software was used for model analyses.

Table 2. Results of CCR and BCC models.

Forest management plans	CCR	BCC
Shafaroud	1	1
Nav	1	1
Chojeye	0.72	0.81
Liyashi Sara	0.79	0.84
Changol	0.81	0.93
Fiyab	1	1
Siyahroud	0.74	0.79
Poya Sepidar1	0.92	1
Poya Sepidar2	0.64	0.82
Narmash	0.83	0.99
Narvan	0.88	1
Lael	0.68	1

Table 3. Results of RTS.

Forest management plans	BCC	SEI/FGL	RTS
Shafaroud	1	1	Consistent*
Nav	1	1	Consistent*
Chojeye	0.81	0.72	Increasing
Liyashi Sara	0.84	0.79	Increasing
Changol	0.93	0.81	Increasing
Fiyab	1	1	Consistent*
Siyahroud	0.79	0.79	Non-increasing
Poya Sepidar1	1	1	Non-increasing
Poya Sepidar2	0.82	0.64	Increasing
Narmash	0.99	0.83	Increasing
Narvan	1	0.88	Increasing
Lael	1	0.68	Increasing

* Under CRS and also fully efficient by SE model.

DISCUSSION

To provide a preliminary picture of Iranian forest management plans performance and returns to scale, fundamental analyses were performed using different DEA models. In this study the input- oriented DEA models are used for efficiency evaluation because the DMUs can be optimized using their proper inputs. The CCR and BCC input-oriented models with fixed and variable returns to scale were used for measuring the global technical efficiency and local pure technical efficiency respectively. The results are summarized in Table 2. As shown in the Table, the efficiency averaged 0.83 and the number of efficient units was 3 by CCR model, while the efficiency averaged 0.93 and the number of efficient units was 6 by BCC model. These differences may be due to the features of returns to scale in these two models. In constant returns to scale method or CCR, a small unit, regardless to its optimum scale, is compared to the other units which could be higher than it. Consequently, the small units get a lower efficiency score than the other units. In variable returns to scale method or BCC, each unit is compared with the same optimum scale units. Consequently, the number of efficient units by CCR is less than BCC approach. These results are in line with those obtained by Kao (2000); Nvrud & Baardsen (2003); Diaz-Balteiro *et al.* (2006); Sporcic *et al.* (2009), who obtained similar logical consequences. The SE is calculated from the results of the CCR and BCC; based on model 3. The results of this approach are shown in Fig. 1 exhibiting that the SE of forest management plans is quite low, i.e. there are only 3 (out of 12) efficient forest management plans in which the distance between CCR and BCC is found to be considerable. In addition, SE less than 1 for the other plans indicates that the overall efficiency may be improved by changing the practical scale. These noticeable remarks pointed out in similar previous studies (Vahid & Sowlati 2007; Zadmirzaei *et al.* 2015) on forest industries.On the contrary, the SE cannot determine the elasticity of scale efficiency or RTS; when VRS are considered, the technical efficiency indices are greater than, or equal to, the efficiencies under constant returns to scale (CRS). A technically efficient DMU may be operating at increasing (IRS) or non-increasing (NIRS) returns to scale. Thus, to closer this gap, SEI/FGL-DEA model is used (model 4). The results of RTS are shown in Table 3 where there is a comparison between BCC and SEI model. As it can be observed, based on this comparative approach, most of the forest management plans 58% (7 out of 12) are under IRS. Also two plans are under NIRS and the rest of them are under CRS as well as they are fully efficient (score 1) by SE model. In like manner Salehirad & Sowlati (2007) and also Gaspar *et al.* (2009) using RTS models figured out that the adjustment of firms to their optimal size is slow due to their particular. Inputs, introducing a new complication, as firms cannot choose the optimal level of any inputs instantaneously. Consequently, scale measures must account for this fact. So, obviously, the interpretation of the RTS brings out some interesting points to determine the elasticity of scale efficiency to apply whole capacities of production units.

CONCLUSION

Measuring the relative efficiency of forest management plans has allowed us to determine their average levels of technical efficiency, and to identify the RTS that could permit them to denote the elasticity of scale efficiency for improving their current level of efficiency or reduce their inefficiencies. To sum up, with respect to obtained efficiency scores from CCR and BCC models it can be proclaimed that the investigated forest management plans generally give us fine performances. It means that these fully efficient plans reduce their inputs consumption, while keep a constant output level and consequently increase their efficiency and profitability. However, the results of the SE model discuss a worrying aspect of plans efficiency in which there was a considerable distance between these plans optimum operating scales (only 3 efficient plans out of 12). But the quest for economies of scale is more interesting to determine whether the scale inefficiencies are because the plans are producing at below or above the optimal level. With this intention, the SEI/FGL-DEA model brings out some interesting points; forest management plans under CRS are completely efficient in operating scales, i.e. these plans use all capacities of their optimum operational scale to generate more revenues and make sound business sense. The forest management plans under IRS would be attractive acquisition targets because they have the opportunity to become more efficient through growth. On the other hand, forest management plans under NIRS are unattractive merger/acquisition targets since they are already "too large". In conclusion, the managers of forest management plans should more focus on plans under IRS (approximately 58% of the investigated forest management plans) until they will be attained the optimum operational scale. Otherwise managers will not be able to promote their overall productivity. Therefore, the main contribution of this study is accepted by results of this work: to disseminate the necessary information for manager of forest management plans until they will be able to adjust the units operating scale and become more efficient through growth.

Limitation and future research directions

It should be noted that the limitations of the study can be defined with respect to the dataset and DEA models. In relation to the dataset, depending on data accessibility, we may also consider some other variables such as plantation costs, harvesting costs, road construction costs, forest tending costs, economic values of the stock 2, etc. Finally, although some factors that could have affected the performance were discussed here, more comprehensive research is required to fully explain performance variations of the forest management plans. For instance, if there are large price variations, it is rational to adapt harvesting to prices. In such cases, it is important to have flexible systems with some extra harvesting capacity which can be employed when prices are very good. In contrast, when prices are not very good, it does not prefer to harvest at full capacity utilization (see also Lohmander *et al.* 2008; Mohammadi Limaei *et al.* 2010).

Therefore, as future research avenues, it is recommended that the other researchers consider the multidimensional economic database as input and output variables on application of DEA in forest management contexts because of multifunction usage (economic, ecological and social functions) of forests.

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چکیده

هدف از تحقیق مذکور ارزیابی کارایی نسبی طرح‌های جنگلداری ایران با استفاه از روش ناپارامتریک تحلیل پوششی داده‌ها (DEA) است. برای این منظور، از DEA بعنوان روش شناخته‌شده و قدرتمند جهت اندازه‌گیری کارایی نسبی سازمان ها استفاده گردید. کارایی نسبی ۱۲ طرح جنگلداری در استان گیلان با استفاده از مدل‌های رایج DEA از قبیل کاریی فنی جهانی (CCR)، کارایی فنی خالص محلی(BCC) و کارایی مقیاس (SE) محاسبه گردید. مطابق نتایج مدل های CCR وBCC، میانگین کارایی بترتیب ۰/۸۳ و ۰/۹۳ بوده است. نتایج SE تصویر نگران کننده‌ای را در خصوص کارایی واحدهای تحت ارزیابی بیان داشت، بدین معنی که تنها ۳ طرح جنگلداری (شفارود، ناو و فیاب) کارا اعلام گردیدند. اما بکارگیری شاخص کارایی مقیاس (SEI) نکات قابل توجه‌ای را در این خصوص بیان داشت، بطوریکه تقریبا ۵۸٪ (۷ از ۱۲واحد تحت ارزیابی) در ناحیه بازه به مقیاس افزایشی تولید (IRS) قرار داشتند. بنابراین، مدیران طرح‌های جنگلداری می‌بایست برای افزایش کارایی بیشترین تمرکز خود را بر روی طرح‌ها در ناحیه IRS قرار دهند، در غیر این صورت قادر به افزایش بهره‌وری کلی خود نخواهند بود.

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