Chapter 20

Nonparametric Model for Business Performance Evaluation in Forestry

Mario Šporčić and Matija Landekić

Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/57042

1. Introduction

Determination of efficiency has become increasingly important in many areas of human activity. 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. In such measurements, we are always interested in determining the degree of efficiency of individual organisations, institutions, associations, etc. in relation to others acting under similar conditions. In doing so, the compared objects are presented through data on used resources/inputs and data on achieved outputs.

In forestry, the determination of efficiency of forestry companies is extremely complex because of multiple goals of forest management. The principle of sustainable development represents the management and use of forests and forest land in the way to preserve their biological diversity, productivity, regeneration capability, vitality and potential in order to enable forests to fulfil now and in future their key economic, ecological and social functions. The above stated makes the conditions of forest management increasingly demanding and imposes the necessity of continuous analyses of all relevant business performance indicators.

In the last few decades, forest management has been focused on multifunctional use and general benefits of forests. Due to multiple benefits and advantages offered by forests, as well as the non-market nature of a part of these outputs, the measurement of performance in forestry is highly demanding. In such conditions, it is pretty difficult to apply conventional economic methods, such as cost-benefit analysis, internal rate of return and others for determining business success. The right evaluation method must be selected in order to determine whether the resources are used efficiently.

Taking into consideration multiple inputs and multiple outputs of forest management, in this paper Data Envelopment Analysis (DEA) was applied for determining the performance level of forest management units. DEA represents a methodology suitable for the efficiency analysis of numerous production units, but is not traditionally used in forestry. Although it was first applied in the forestry sector in 1986 [1], the number of papers based on measuring the performance by non-parametric techniques, such as DEA, is still very limited in forestry literature. The basic idea is to determine the performance through the efficiency level of individual DMUs[1] based on the relationship between a complex input and a complex output.

Data Envelopment Analysis, as the technique for measuring productivity and efficiency, is widely applied in many areas. It was used, for example, for making comparisons between organisations [2], companies [3], regions and countries [4]. For determining business performance it was applied in banking [5], agriculture [6], wood industry [7], schooling [8], etc. In DEA bibliography [9] there are approximately 3,200 published DEA papers. However, in the area of management of renewable natural resources, it is still not sufficiently present. In forestry literature there is only a limited number of DEA papers [10 - 13], and it yet has to be introduced and accepted in forestry as a management tool at a strategic and operating level of decision making.

So, this paper assesses the efficiency of basic organizational units in the Croatian forestry, forest offices, by applying Data Envelopment Analysis (DEA), a nonparametric methodology for measuring relative efficiency of comparable decision making units with more inputs and outputs. The relative efficiency of compared forest offices is calculated in the paper with the most frequently used DEA models - CCR and BCC model. According to the aquired data, conducted calculations and analysis, the results of global technical efficiency (obtained by CCR model), local pure technical efficiency (obtained by BCC model) and scale efficiency were determined. The results also included the calculation of efficiency frontier, frequency of efficient units in reference set of inefficient units, determination of sources and values of inefficiencies, influence of the forest offices' structural characteristics on their efficiency and the average efficiency of forest offices grouped with respect to the forest administrations and regions they belong to. The research reveals DEA as a powerful multi criteria decision making tool and a possible, very valuable support in forest management.

1.1. Efficiency and the possibility to measure relative efficiency

In the business analysis some indicators are calculated which represent the basis for evaluation and comparison of business performance (indicators of liquidity, profitability, cost-effectiveness, etc.). However, these indicators in the calculations take into account only some of the accounting issues, and so represent partial performance indicators. At the same time, multi-criteria analysis of these partial indicators can't identify the best-performing unit, because it is unlikely that one of the units has all the observed simple indicators the best i.e. better than the other compared units.

1 DMU (Decision Making Unit) is any production or non-production unit that uses certain inputs so as to achieve certain outputs.

If we want to calculate an indicator of business performance which will reflect efficiency of the organizational unit we take into consideration the ratio of output and input. If we want to calculate a measure of efficiency that will consider more inputs and more outputs, it is necessary to make a selection of inputs and outputs that will be taken into the calculation, and it is necessary to join a certain weight to inputs and outputs in order to define a single measure of efficiency for each organizational unit.

Absolute measure of efficiency can be determined when we have explicitly defined relationship between inputs and outputs, or when we know the association that for every combination of inputs joins a specific set of possible outputs. If this relationship is known then, from the relation between really achieved and theoretically achievable outputs of each individual unit, it is possible to determine their absolute efficiency.

The concept of relative efficiency is used when it is not possible to define theoretically possible level of efficiency, and so the certain units are compared with those units whose business performance, given the state of manufacturing technology, is the best.

DEA methodology does not require the pre-determined weight of inputs and outputs, and does not require any knowledge of the explicit links between inputs and outputs. Based on the known empirical data about the level of inputs and outputs for each unit DEA calculates its relative efficiency compared to other units. Observed unit reaches 100% relative efficiency (rating 1) if and only if compared with the other units it doesn't show inefficiency in the use of any inputs or outputs. Specifically, for a unit is said to be relatively efficient if:

1. it can not increase any of its outputs without -
   - **a.** an increase of its inputs, or,
   - **b.** reducing some of its remaining outputs
2. it can not reduce any of its inputs without -
   - **a.** reducing some of its outputs, or,
   - **b.** increasing some of its remaining inputs.

2. Material and methods

2.1. Generally about Data Envelopment Analysis

The story about DEA begins with the doctoral dissertation of Edward Rhodes, who has tried to evaluate the curriculum of public schools in Texas in the United States. At that time, it was a challenge to assess the relative efficiency of schools with multiple inputs and outputs, and without the usual information on prices and costs. As a result, the formulation of CCR model[2] was developed and the first DEA paper was published in the European Journal of Operational Research in year 1978 [14].

DEA was originally developed as a tool to measure the effectiveness of organizations working on non-profit basis (public schools and hospitals, military establishments), where it is not possible to determine efficacy based on the value of their inputs and outputs. Later, the DEA has found application in profit organizations (companies, banks), and its development has resulted in over 3,000 papers published by the year 2001 [9].

Today, we find the application of DEA in many areas, such as education (public schools and universities), health care (hospitals, clinics, health centers), banking, sports, market research, agriculture, retail, transportation, hospitality, construction, etc. Bibliography of DEA which was published in 1994 [15] recorded 472 papers which were published in the period 1978. - 1992. References from 2002 [9] state the number of 3203 papers in the period of 1978. - 2001. Such a number of articles shows the great importance and interest for the DEA methodology and its applications.

The reasons for the rapid growth probably lie in the fact that DEA is an interdisciplinary applicable methodology, which is also suitable in cases where other approaches do not provide satisfactory results because of complex or unfamiliar nature of relationship between multiple inputs and outputs. So, in recent years, data envelopment analysis has become a central technique in the analysis of productivity and efficiency.

2.2. Mathematical and statistical basics of DEA

Data envelopment analysisis is a deterministic, non-parametric methodology for determining the relative efficiency of comparable decision making units considering their similar work technology and performance of similar tasks. Decision making units (DMUs) represent any production or non-production units that have the same types of inputs and outputs, and they differentiate one from another according to the level of available resources and the level of activity within the transformation process (inputs to outputs). DEA determines the relative efficiency of analysed units by constructing the empirical efficiency frontier i.e. frontier or margin of production possibilities (this term is used although the analysis may consider unproductive sectors) based on the information about used inputs and achieved outputs of all units included in the analysis. The most successful units (best practice units), the ones that determine the efficiency frontier, gain the grade '1', and the degree of technical inefficiency of all other units is calculated based on the distance of their input-output ratio in relation to the efficiency frontier (Figure 1).

For each unit included in the analysis a particular problem of linear programming is solved and its maximum efficiency, regarding other units in the reference set, is determined. The relative efficiency of the unit is calculated as the ratio of weighted sum of outputs and weighted sum of inputs. Weight of outputs and inputs for each unit is determined so to make its measure of efficiency maximum possible, with the limitation that the result of the relative efficiency can not be over one ('1'). A model defined in such a way maximizes the result of the relative efficiency of each unit provided that the gained set of weights must be feasible and attainable for any other unit in the observed group. This means that DEA defines the best possible

2 Today, there are many DEA models that differ regarding returns to scale (models which assume constant and models aimed at increasing outputs - output oriented). CCR model (by Charnes, Cooper and Rhodes) is one of the basic and most frequently used models.

http://dx.doi.org/10.5772/57042

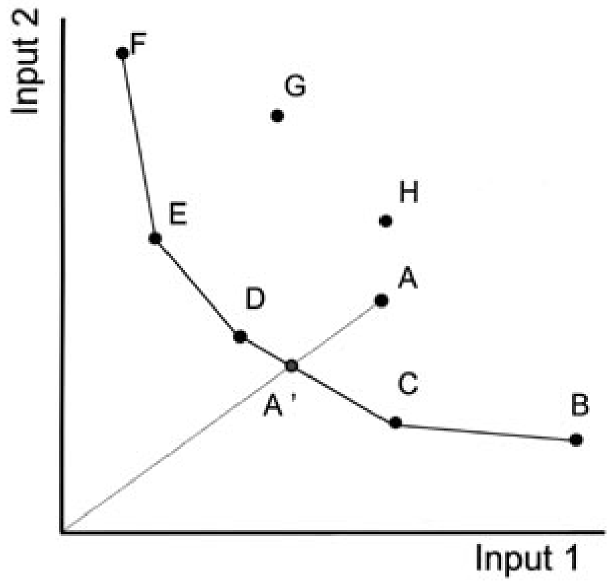

Figure 1. Graphical description of efficiency frontier in DEA model (two-input example)

achievable efficiency frontier i.e. production possibilities, and sets the maximum output for each unit at a given level of its inputs.

DEA is based on the extreme values and each DMU is compared only with the best units. The basic assumption is that if a particular unit with X inputs (resources) can produce Y outputs (products), the other units should be able to do the same if they are working efficiently. The center of the analysis lies in finding the 'best' virtual production unit for each actual/real unit. If the virtual unit is better than the original, whether it achieves more outputs with the same inputs or it achieves the same outputs with fewer inputs, then the real unit is inefficient.

In the next section a simple example will be given to explain the theoretical basis on which the Data envelopment analysis stands. First, numerical example of mathematical assumptions and procedures necessary in different DEA models will be presented. And then the graphical representation of the same example will describe the concept of Data envelopment analysis.

2.2.1. Simple numerical example

A simple numerical example might help show what is going on. Assume that there are three baseball players (DMUs), A, B, and C, with the following batting statistics. Player A is a good contact hitter, player C is a long ball hitter and player B is somewhere in between.

- Player A: 100 at-bats, 40 singles, 0 home runs
- Player B: 100 at-bats, 20 singles, 5 home runs
- Player C: 100 at-bats, 10 singles, 20 home runs

Now, as a DEA analyst, we combine parts of different players. First let us analyze player A. Clearly no combination of players B and C can produce 40 singles with the constraint of only 100 at-bats. Therefore player A is efficient at hitting singles and receives an efficiency of 1.0.

Now we move on to analyze player B. Suppose we try a 50-50 mixture of players A and C. This means that lambda=(0.5, 0.5). The virtual output vector is now,

lambda Y = (0.5 * 40 + 0.5 * 10, 0.5 * 0 + 0.5 * 20) = (25, 10)

Note that X = 100 = X(0) where X(0) is the input(s) for the DMU being analyzed. Since lambdaY > Y(0) = (20, 5), then there is room to scale down the inputs, X and produce a virtual output vector at least equal to or greater than the original output. This scaling down factor would allow us to put an upper bound on the efficiency of that player's efficiency. The 50-50 ratio of A and C may not necessarily be the optimal virtual producer. The efficiency, theta, can then be found by solving the corresponding linear program.

It can be seen by inspection that player C is efficient because no combination of players A and B can produce his total of 20 home runs in only 100 at bats. Player C is fulfilling the role of hitting home runs more efficiently than any other player just as player A is hitting singles more efficiently than anyone else. Player C is probably taking a big swing while player A is slapping out singles. Player B would have been more productive if he had spent half his time swinging for the fences like player C and half his time slapping out singles like player A. Since player B was not that productive, he must not be as skilled as either player A or player C and his efficiency score would be below 1.0 to reflect this.

This example can be made more complicated by looking at unequal values of inputs instead of the constant 100 at-bats, by making it a multiple input problem, or by adding more data points but the basic principles still hold. (*Source:* [16]).

2.2.2. Graphical example

If it is assumed that convex combinations of players are allowed, then the line segment connecting players A and C shows the possibilities of virtual outputs that can be formed from these two players. Similar segments can be drawn between A and B along with B and C. Since the segment AC lies beyond the segments AB and BC, this means that a convex combination of A and C will create the most outputs for a given set of inputs.

This line is called the efficiency frontier. The efficiency frontier defines the maximum combinations of outputs that can be produced for a given set of inputs. The segment connecting point C to the HR axis is drawn because of disposability of output. It is assumed that if player C can hit 20 home runs and 10 singles, he could also hit 20 home runs without any singles. We have no knowledge though of whether avoiding singles altogether would allow him to raise his home run total so we must assume that it remains constant.

Since player B lies below the efficiency frontier, he is inefficient. His efficiency can be determined by comparing him to a virtual player formed from player A and player C. The virtual player, called V, is approximately 64% of player C and 36% of player A. (This can be determined

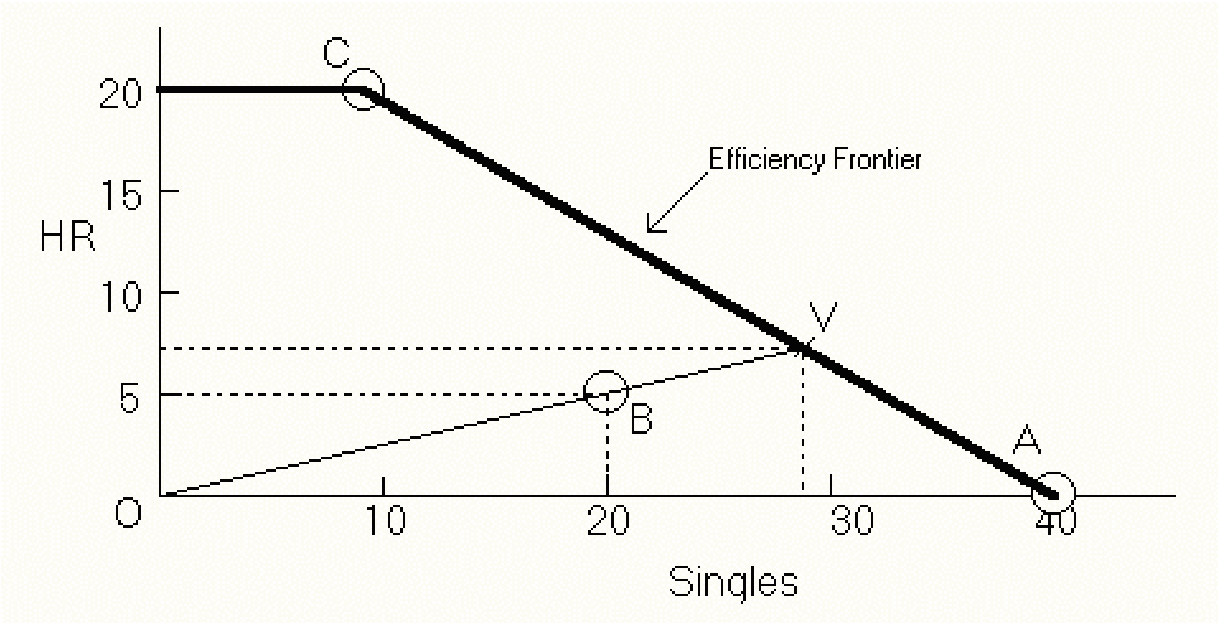

Figure 2. Graphical example of DEA for player B

by an application of the lever law. Pull out a ruler and measure the lengths of AV, CV, and AC. The percentage of player C is then AV/AC and the percentage of player A is CV/AC.)

The efficiency of player B is then calculated by finding the fraction of inputs that player V would need to produce as many outputs as player B. This is easily calculated by looking at the line from the origin, O, to V. The efficiency of player B is OB/OV which is approximately 68%. This figure also shows that players A and C are efficient since they lie on the efficiency frontier. In other words, any virtual player formed for analyzing players A and C will lie on players A and C respectively. Therefore since the efficiency is calculated as the ratio of OA/OV or OC/OV, players A and C will have efficiency scores equal to 1.0.

The graphical method is useful in this simple two dimensional example but gets much harder in higher dimensions. The normal method of evaluating the efficiency of player B is by using an LP formulation of DEA (*Source:* [16]).

To conclude this section, DEA models are linear programming methods that calculate the efficiency frontier of a set of DMUs and evaluate the relative efficiency of each unit, therby allowing a distinction to be made between efficient and inefficient DMUs. Those identified as "best practice units" (i.e., those determining the frontier) are given a rating of one, whereas the degree of inefficiency of the rest is calculated on the basis of the Euclidian distance of their input-output ratio from the frontier [17].

Compared to regression or stochastic frontier analysis methods, DEA shows several advantages. First, DEA allows handling multiple inputs and outputs (with different units) in a noncomplex way. Second, DEA does not require any initial assumption about a specific functional form linking inputs and outputs. While a typical statistical approach (regression analysis) is based on average values, DEA is an extreme point method and compares each producer with only the «best» producers. Efficiency is determined relatively with respect to other production units in the observed group.

2.3. DEA approach in evaluation of forestry units' performance

Since DEA was introduced by Charnes, Cooper and Rhodes [14] several analytical models have been developed depending on the assumptions underlying the approach. For instance, the orientation of the analysis toward inputs or outputs, the existance of constant or variable (increasing or decreasing) returns to scale and the possibility of controlling inputs. According to Farrell [18], technical efficiency represents the ability of a DMU to produce maximum output given a set of inputs and technology (output oriented) or, alternatively, to achieve maximum feasible reductions in input quantities while maintaining its current levels of outputs (input oriented). In this study, output oriented DEA seems more appropriate, given it is more reasonable to argue that forest area, growing stock and other inputs should not be decresed. Instead, the goal of forest sector should be increased outputs of forest management, and improved general state of forests.

Given the selected orientation and the diversity of units characterizing our example, we first applied *CCR model* proposed by Charnes et al. [14]. This model assumes constant returns to scale. Following Cooper et al. [19], we begin by the commonly used measure of efficiency (output/input ratio) and we try to find out the correponding weights by using linear programming in order to maximize the ratio. To determine the efficiency of n units (forest offices) n linear programming problems must be solved to obtain the value of weights (v_i) associated with inputs (x_i), as well as the value of weights (u_r) associated with the outputs (y_r). Assuming m inputs and s outputs and transforming the fractional programming model into a linear programming model, the CCR (Charnes–Cooper–Rhodes) model can be formulated as Cooper et al. [19]:

$$\begin{aligned} &Max\ \ \theta = u_1 y_{10} + \ldots + u_s y_{s0} \\ &\text{Subject to}: v_1 x_{10} + \ldots + v_m x_{m0} = 1 \\ &\qquad u_1 y_{1j} + \ldots + u_s y_{sj} - v_1 x_{1j} - \ldots - v_m x_{mj} \leq 0 \quad (j = 1, 2, \ldots, n) \\ &\qquad v_1, v_2, \ldots, v_m \leq 0 \\ &\qquad u_1, u_2, \ldots, m_s \leq 0 \end{aligned} \tag{1}$$

Due to lack of information concerning the form of the production frontier, an extension of CCR model, Banker–Charnes–Cooper (BCC) model was also used. This model incorporates the property of variable returns to scale. The basic formulation of the model, best known as the BCC model is as follows:

$$
\begin{aligned}
&Max \;\; \theta = u_1 y_{10} + \ldots + u_s y_{s0} - u_0 \\
&\text{Subject to}: v_1 x_{10} + \ldots + v_m x_{m0} = 1 \\
&\qquad u_1 y_{1j} + \ldots + u_s y_{sj} - v_1 x_{1j} - \ldots - v_m x_{mj} - u_0 \le 0 \quad (j = 1, 2, \ldots, n) \\
&\qquad v_1, v_2, \ldots, v_m \ge 0 \\
&\qquad u_1, \mu_2, \ldots, u_s \ge 0
\end{aligned}
\tag{2}
$$

Where u_0 is the variable allowing identification of the nature of the returns to scale. This model does not predetermine if the value of this variable is positive (increasing returns) or is negative (decreasing returns). The formulation of the output oriented models can be derived directly from models described in (1) and (2), see [19].

In this study, two measures of efficiency are applied – technical and scale efficiency (SE). Measurement of allocative efficiency requires data on production costs which were not available in our data set. For computing the applied models, DEA Excel Solver software was used.

2.3.1. Sample selection and data description

State forests in the Republic of Croatia (RC) are mostly managed by the company Croatian forests Ltd – they account for approximately 80% of the total forest-covered area or 1,991,537 ha. The company Croatian forests consists of: headquarters in Zagreb, 16 regional forest administrations (FA) and a total of 169 forest offices (FO). In the current three-layer organisation of the Croatian forestry, forest office is the organisational unit in which the basic tasks of forestry activities are carried out and most income and direct costs of forest management are incurred in.

The efficiency analysis of selected forest offices is carried out based on the information adopted from the Croatian forests' ltd yearly reports. Additional applications and more robust data may provide additional insights for the evaluation of forest management.

The research includes 48 forest offices. The selected forest offices are the representatives of four main regions in the Croatian forestry: lowland flood-prone forests (I), hilly forests of the central part (II), mountainous forests (III) and karst/Mediterranean forests (IV). Each region is represented by two forest administrations i.e. by six forest offices from each forest administration. The sample of organisational units (Figure 3) and data involved in this research (yearly values of selected inputs and outputs) are shown in Table 1.

Inputs and outputs were selected so as to reflect business activities of the investigated decision making units – forest offices as the basic organisational units of the Croatian forestry, which perform the basic professional and technical operations in forest management (regeneration and silviculture of forests, wood harvesting) in a certain part of the forest economic area of RC, and where most income is achieved and direct costs incurred from the core business activity of forest management.

According to the *Forest Act*, along with conventional production of wood, forest management must also provide additional outputs. They are related to silviculture, protection and use of forests and forest land for construction and maintenance of forest infrastructure, all in accordance with general European criteria for ensuring sustainable forest management. Also, the goal of Croatian forests ltd. and its administrations and offices is business profitability. Most income comes from sold wood and hence the segment related to maintaining and enhancing the production function of forests (increment of growing stock) becomes increasingly important. Accordingly, the inputs and outputs considered in this example are:

Inputs

1. Land, I1 – forest area in thousand hectares
2. Growing stock, I2 – volume of forest stock in cubic meters per hectare
3. Expenditures, I3 – money spent in hundred-thousand croatian kunas (7,5 kn ≈ 1 EUR)
4. Labour, I4 – number of employees in persons

Outputs

1. Revenues, O1 –yearly income in hundred-thousand croatian kunas (7,5 kn ≈ 1 EUR)
2. Timber production, O2 – timber harvested in cubic meters per hectare
3. Investments in infrastructure, O3 – forest roads built in kilometres
4. Biological renewal of forests, O4 – area of conducted silvicultural and protection works in hectares

DMU	Inputs				Outputs			
	Area I1, 10^3 ha	G. stock I2, m^3/ha	Costs I3, 10^5 kn	Employees I4, N	Income O1, 10^5kn	Harvest O2, m^3/ha	Investments O3, km	B. renewal O4, ha
Lowland flood-prone forests (I) Forest administration Vinkovci (A)								
1. Gunja	5.84	234.00	300.10	68	315.51	4.30	1.80	547.34
2. Otok	10.72	418.00	470.31	100	538.41	7.13	0.00	3846.34
3. Strizivojna	4.31	294.00	149.90	40	160.61	4.42	0.00	510.00
4. Strošinci	4.84	394.00	141.83	40	141.04	4.28	1.21	493.87
5. Vinkovci	5.70	234.11	219.23	77	226.77	4.98	0.00	1748.59
6. Županja	6.54	364.00	177.64	61	393.10	8.78	0.00	583.70
Forest Administration Nova Gradiška (B)								
7. N. Gradiška	12.39	242.95	320.47	85	288.71	5.12	3.10	1221.10
8. N. Kapela	8.40	218.75	151.21	71	130.73	3.61	0.00	229.98

http://dx.doi.org/10.5772/57042

DMU	Inputs				Outputs			
	Area I1, 10^3 ha	G. stock I2, m^3/ha	Costs I3, 10^5 kn	Employees I4, N	Income O1, 10^5kn	Harvest O2, m^3/ha	Investments O3, km	B. renewal O4, ha
9. Novska	11.73	263.02	289.54	64	320.66	4.04	0.70	649.10
10. Okučani	6.56	276.00	124.73	26	144.76	3.91	0.98	91.69
11. S. Brod	6.23	210.00	217.88	61	229.30	5.21	0.00	461.13
12. Trnjani	5.77	265.00	145.37	55	128.97	3.40	1.00	237.00
Hilly forests of the central part (II) Forest Administration Zagreb (C)								
13. D. Stubica	2.60	239.04	23.24	12	21.12	2.47	0.00	51.00
14. Krapina	4.47	248.00	115.63	37	100.67	5.01	2.27	457.00
15. Novoselec	10.50	211.03	243.74	63	289.85	4.89	2.00	991.28
16. Popovača	7.64	201.00	158.69	52	168.71	3.24	3.00	829.00
17. Samobor	6.46	232.00	85.62	21	75.59	3.61	1.72	179.55
18. Zagreb	6.59	270.00	166.56	35	140.90	4.09	0.00	269.12
Forest Administration Koprivnica (D)								
19. Čakovec	3.36	139.00	59.97	23	45.62	2.41	0.00	679.60
20. Ivanec	2.86	235.00	79.96	22	61.49	4.54	0.00	41.93
21. Koprivnica	6.53	331.00	219.34	65	215.91	5.05	0.00	556.06
22. Križevci	9.78	298.68	235.18	67	255.43	5.24	5.50	679.87
23. Ludbreg	5.00	271.00	129.40	35	123.20	4.30	0.50	380.00
24. Varaždin	5.12	187.00	108.90	37	85.73	1.71	0.00	119.82
Mountainous forests (III) Forest Administration Delnice (E)								
25. Gerovo	7.04	316.13	181.84	53	202.73	6.21	0.00	118.17
26. Gomirje	5.43	297.30	119.95	39	118.33	4.58	0.00	55.92
27. Klana	6.81	251.12	96.88	38	79.79	2.82	3.50	59.08
28. Mrkopalj	9.25	314.00	179.28	50	190.23	4.92	0.00	894.00
29. Prezid	5.57	336.45	127.39	44	128.10	5.10	0.00	91.00
30. R. Gora	6.20	361.00	167.88	44	177.89	5.34	0.26	48.00
Forest Administration Gospić (F)								
31. Brinje	17.25	208.00	215.07	43	212.38	2.55	7.10	390.85
32. D. Lapac	20.07	193.57	172.41	41	213.71	1.89	9.24	40.35

DMU	Inputs				Outputs			
	Area I1, 10^3 ha	G. stock I2, m^3/ha	Costs I3, 10^5 kn	Employees I4, N	Income O1, 10^5kn	Harvest O2, m^3/ha	Investments O3, km	B. renewal O4, ha
33. Gospić	34.95	142.00	268.40	59	225.58	0.99	6.00	389.00
34. Gračac	49.87	140.66	204.33	45	167.67	0.77	4.15	329.64
35. Korenica	25.05	171.92	299.38	50	289.70	1.60	15.73	190.59
36. Udbina	20.99	144.62	268.05	61	246.95	1.67	22.59	139.23
Karst/Mediterranean forests (IV) Forest Administration Buzet (G)								
37. Buje	7.55	75.34	58.56	33	61.52	0.12	0.00	307.81
38. Buzet	2.63	129.98	49.26	15	47.09	1.02	0.00	97.70
39. C-Lošinj	9.36	82.91	40.04	13	39.74	0.21	0.00	205.00
40. Opatija	9.04	154.00	76.53	24	77.33	1.23	0.00	99.00
41. Poreč	7.05	77.17	42.50	19	45.32	0.10	0.00	118.59
42. Rovinj	6.55	76.53	39.70	16	44.00	0.03	0.00	120.00
Forest Administration Split (H)								
43. Brač	9.61	81.54	27.67	8	27.72	0.00	0.00	30.21
44. Dubrovnik	19.51	108.16	44.09	9	45.45	0.00	0.00	115.94
45. Makarska	7.24	115.00	40.81	13	50.85	0.00	1.35	198.15
46. Sinj	44.14	51.85	67.19	27	71.95	0.01	7.30	113.86
47. Šibenik	28.14	91.57	53.01	19	60.69	0.00	0.00	105.00
48. Zadar	28.72	121.63	138.33	27	118.17	0.02	6.48	157.31

Table 1. Input and output data of DMUs selected for efficiency measurement

There are 48 forest offices evaluated in this model. For the basic DEA models, the number of offices (units under consideration) should be a minimum of between 3 to 5 times the total number of input and output factors. Thus, we have limited the total number of inputs and outputs to eight factors.

Table 2 presents the descriptive statistics of the variables used in the analysis. A wide variation in both inputs and outputs is noticable. The input use is in some cases twenty times larger than that used by other offices, while variation in output variables is even higher. Such variation in the level of input and output implies that there are big differences between conditions under which individual forest offices operate. These differences are not unexpected, since the sample involves all representative areas managed by Croatian forests. However, it may also be a sign of poor management of resources in individual forest offices.

http://dx.doi.org/10.5772/57042

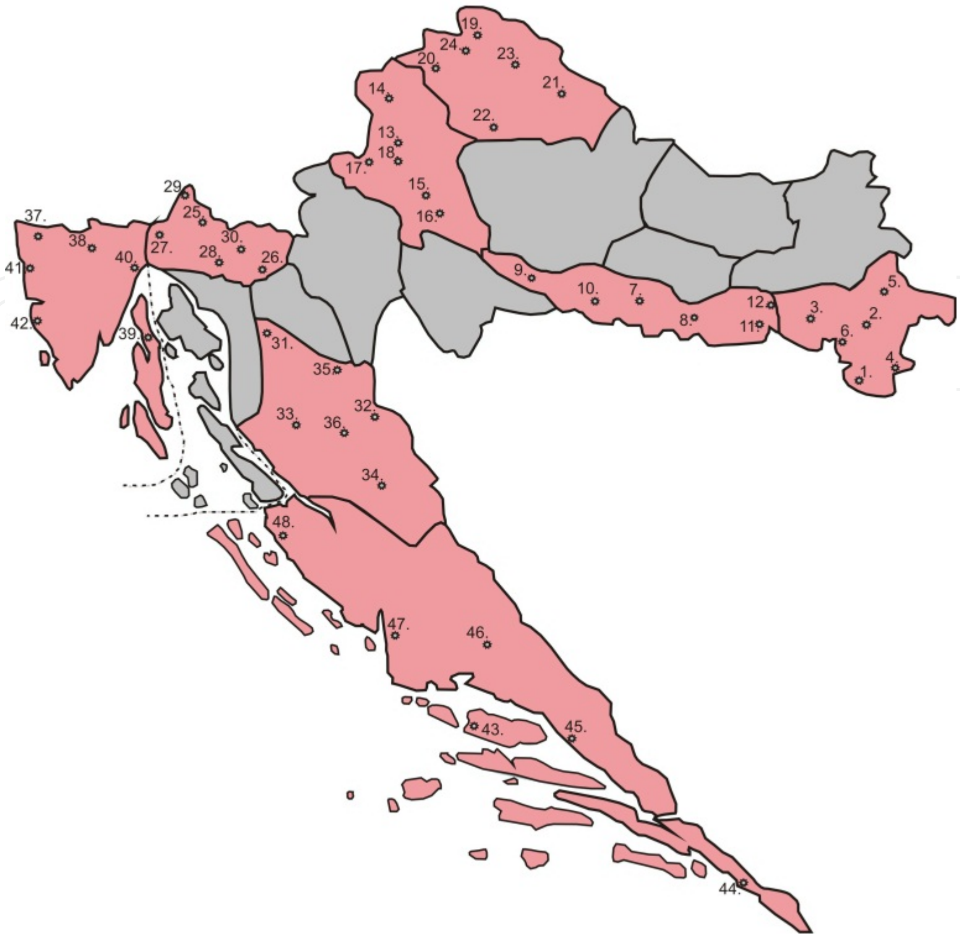

Figure 3. Sample of the organisational units (Forest offices) included in the research

Variable	Mean	St. deviation	Min	Max	Total
Inputs					
Area, 10^3 ha	11.42	10.36	2.60	49.87	547.96
G. stock, m^3/ha	214.98	91.94	51.85	418.00	-
Costs, 10^5 kn	152.35	93.61	23.24	470.31	7312.99
Employees, N	42	21	8	100	2007
Outputs					
Income, 10^5 kn	157.20	106.40	21.12	538.41	7545.68
Harvest, m^3/ha	3.06	2.19	0.00	8.78	-
Investments, km	2.24	4.29	0.00	22.59	107.48
B. renewal, ha	422.26	606.34	30.21	3846.34	20268.47

Table 2. Descriptive statistics of the variables used in the DEA model

3. Results

3.1. Technical and scale efficiency

Technical and scale efficiency were determined individually for each forest office. Results obtained by the application of the output-oriented DEA are given in table 3.

DMU	Efficiency			DMU	Efficiency		
	CCR	BCC	SE		CCR	BCC	SE
1. Gunja	1.000	1.000	1.000	25. Gerovo	0.814	0.836	0.974
2. Otok	1.000	1.000	1.000	26. Gomirje	0.721	0.726	0.993
3. Strizivojna	0.831	0.926	0.897	27. Klana	0.807	0.820	0.984
4. Strošinci	0.826	0.865	0.955	28. Mrkopalj	0.810	0.827	0.979
5. Vinkovci	1.000	1.000	1.000	29. Prezid	0.738	0.762	0.969
6. Županja	1.000	1.000	1.000	30. R. Gora	0.755	0.782	0.965
7. N. Gradiška	0.952	0.981	0.970	31. Brinje	0.866	0.883	0.981
8. N. Kapela	0.677	0.723	0.936	32. D. Lapac	0.990	1.000	0.990
9. Novska	0.924	0.929	0.995	33. Gospić	0.984	0.996	0.988
10. Okučani	1.000	1.000	1.000	34. Gračac	0.779	0.786	0.992
11. S. Brod	1.000	1.000	1.000	35. Korenica	1.000	1.000	1.000
12. Trnjani	0.561	0.590	0.951	36. Udbina	1.000	1.000	1.000
13. D. Stubica	1.000	1.000	1.000	37. Buje	0.745	1.000	0.745
14. Krapina	1.000	1.000	1.000	38. Buzet	0.501	1.000	0.501
15. Novoselec	1.000	1.000	1.000	39. C-Lošinj	0.695	1.000	0.695
16. Popovača	0.879	0.897	0.981	40. Opatija	0.500	0.593	0.844
17. Samobor	1.000	1.000	1.000	41. Poreč	0.568	1.000	0.568
18. Zagreb	0.756	0.769	0.984	42. Rovinj	0.595	1.000	0.595
19. Čakovec	1.000	1.000	1.000	43. Brač	0.538	1.000	0.538
20. Ivanec	1.000	1.000	1.000	44. Dubrovnik	0.813	1.000	0.813
21. Koprivnica	0.645	0.645	1.000	45. Makarska	0.956	1.000	0.956
22. Križevci	0.898	0.904	0.994	46. Sinj	1.000	1.000	1.000
23. Ludbreg	0.816	0.819	0.996	47. Šibenik	0.591	0.867	0.682
24. Varaždin	0.407	0.524	0.777	48. Zadar	0.843	0.924	0.913

Table 3. Relative efficiency of Forest offices

http://dx.doi.org/10.5772/57042

The average CCR efficiency of the investigated forest offices is 0.829, which means that an average (assumed) forest office should only use 82.9% of the currently used quantity of inputs and produce the same quantity of the currently produced outputs, if it wishes to do business at the efficiency frontier. In other words, this average organisational unit, if it wishes to do business efficiently, should produce 20.6%[3] more output with the same input level.

According to the BCC model, the average efficiency is 0.904. This means that an average forest office should only use 90.4% of the current input and produce the same quantity of output, if it wishes to be efficient. In other words, to be BCC efficient it should produce 10.6%[4] more outputs with the same inputs.

In spite of a relatively high mean efficiency (83 or 90%) and regardless of the used model (CCR or BCC), the lowest level of relative efficiency ranges between 0.407 (CCR) and 0.524 (BCC). This implies firstly that individual units can reduce the level of used input up to 59.3% or 47.6%, without affecting the output level, and secondly that there are significant differences in production and business activities between the analysed units.

According to the CCR model, 15 forest offices are relatively efficient (31%), while a total of 24 units (50%) are rated '1' according to the BCC model. Incompatibility between CCR and BCC efficiency is most conspicuous with forest offices with extremely low values of one or more input variables. According to the model with variable returns (BCC), the efficiency of such units is much higher than according to the model with constant returns (CCR). This may indicate the influence of size or volume of activities of the observed units on the level of their efficiency, but it can also mean that the BCC model with the selected input and output variables cannot make proper distinction between efficient and inefficient units. Such results may, however, also be useful if additional models of decision making are applied. The results of DEA analysis may then be used as the first filter of inefficient units. The survey of DEA results is given in Table 4.

	CCR model	**BCC model**	**Scale eff. (SE)**
Number of forest offices (DMU)	48	48	48
Relatively efficient DMUs	15	24	16
Relatively efficient DMUs (in %)	31 %	50 %	33 %
Average relative efficiency, E	0.829	0.904	0.919
Maximum	1	1	1
Minimum	0.407	0.524	0.501
Standard deviation	1.170	0.129	0.138
DMUs with efficiency lower than E	23	18	12

Table 4. Results obtained with the base case DEA models

3 It can be easily obtained that 20.6 % = (1 – 0.829)/0.829

4 It can be easily obtained that 10.6 % = (1 – 0.904)/0.904

The interpretation of scale efficiency scores allows for some interesting remarks. Scale efficiency shows how close or far the size of the observed unit is from its optimal size. The efficiency of 100% indicates that the size and volume of activities are well balanced. The values lower than 100% mean that the level of technical efficiency is at least partly under influence of size or volume of activities of the observed unit.

The scale efficiency of 0.919 means that the analysed forest offices would increase their relative efficiency on average by 8% if they adapted their size or volume of activities to the optimal value. Relatively efficient are 16 (33%) units. Almost all of them (15) are also efficient according to the CCR model (Table 3). Forest offices that are efficient only according to the BCC model (Table 3) do not show the same efficiency level in case of determination of scale efficiency. This indicates their inadequate size or inadequate volume of activities expressed by the main parameters of their production and business performance. These are mostly the units with low values of one or more input and output variables – Karst/Mediterranean forest offices with low growing stock, number of employees, annual cut, etc.

3.2. Sources and values of inefficiency

By selecting output-oriented models projection course of inefficient units against the efficiency frontier was determined. By comparing empirical and projected data, it is possible to identify the sources of inefficiency as well as their value. The lower the percentage of projected input values in empirical input values, the higher is on average the source of inefficiency caused by this input. The higher the percentage of projected output values in empirical output values, the higher is the source of inefficiency caused by this output. Table 5 shows percentage shares of average projected values in total empirical input and output values of CCR and BCC model.

	Inputs/Outputs	CCR	BCC
Inputs	Area. I1	85.48	93.85
	G. stock. I2	93.47	98.06
	Costs. I3	96.60	96.64
	Employees. I4	96.94	97.37
Outputs	Income. O1	125.64	118.68
	Harvest. O2	268.04	158.94
	Investments. O3	219.45	207.23
	B. renewal. O4	167.61	156.03

Table 5. Sources and average amounts of inefficiency, CCR and BCC model

It can be concluded from the above Table that the second and third output – annual cut and investments - affect the inefficiency of forest offices most seriously. Then follow the activities of forest regeneration and achieved income with a somewhat lower impact on inefficiency of forest offices.

In the period concerned the observed units should have produced on average 25.64% more than the produced quantity of output O1, 168.04% more than the produced quantity of the second output O2, 119.45% more than output O3 and 67.61% more than the produced quantity of output O4. Similarly, they should have used 85.48% of the used quantity of the first input I1, 93.47% of the quantity of output I2, 96.60% of the third input I3 and 96.94% of the used quantity of input I4. Then they would be CCR-efficient.

For achieving BCC efficiency, it was necessary to produce on average 18.68% more than the produced quantity of the first output I1, 58.94% more than the second output O2, 107.23% more than output O3 and 56.03% more than output O4. With such an average increase of output, the observed forest offices would do business efficiently according to the BCC model.

It should be noted that the projected values are achievable because some forest offices involved in the analysis achieved them successfully.

3.3. Structural characteristics and efficiency of forest offices

Forest offices differ among themselves in a series of structural characteristics and hence professional and technical operations are carried out in different conditions with respect to the surface area, number of employees, means of work, growing stock, etc. Differences between the basic structural characteristics of the analysed forest offices are shown in Table 1 and 2. Based on the efficiency results of forest offices grouped according to the values of their basic structural characteristics – surface area, growing stock and number of employees, it has been determined to what extent the given environment affects the efficiency of specific units.

The average efficiency with respect to surface area was determined as the arithmetic mean of the efficiency of forest offices that belong to a certain surface area class (Figure 4). The highest levels of efficiency according to all three models were recorded for forest offices that manage a surface area ranging between 10 and 15,000 hectares (the average efficiency is 0.969 according to the CCR model, 0.977 according to the BCC model and 0.991 according to the SE model). The lowest levels of efficiency were determined for the group of forest offices with a surface area from 5 to 10,000 hectares.

The volume of the managed growing stock was taken as the second criteria for grouping the analysed units. Forest offices are divided into classes with respect to the growing stock expressed in m^3 per hectare, and the average efficiency of individual classes is presented in Figure 5.

Forest offices that manage the lowest growing stock volume (less than 100 m^3/ha) also have the lowest average relative efficiency, according to the CCR and SE model (0.676 and 0.689, respectively). According to these models the highest level of efficiency is recorded for forest offices with growing stock ranging between 200 and 300 m^3/ha i.e. over 300 m^3/ha – 0.890 (CCR) and 0.984 (SE) for the group III (200-300 m^3/ha) and 0.824 (CCR) and 0.980 (SE) for the group IV of forest offices (> 300 m^3/ha). Only one forest office manages the growing stock exceeding 400 m^3/ha and it was not separated in a special class but was included in the group IV.

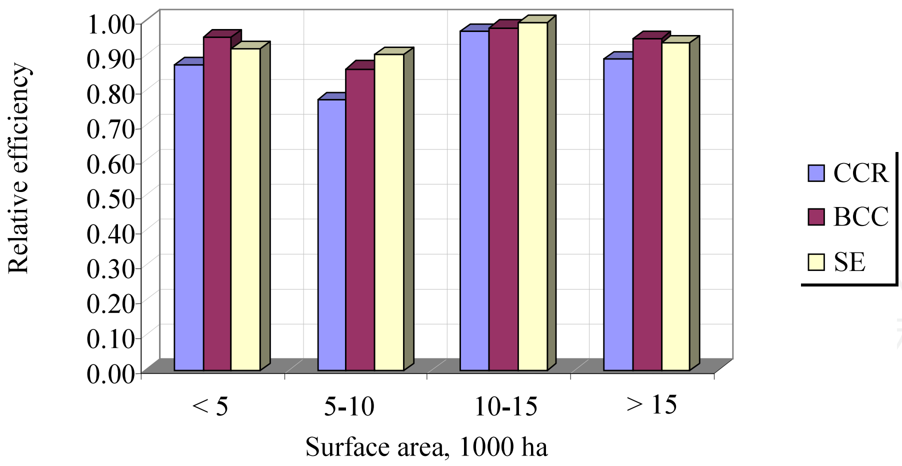

Figure 4. Average relative efficiency of forest offices grouped with respect to surface area

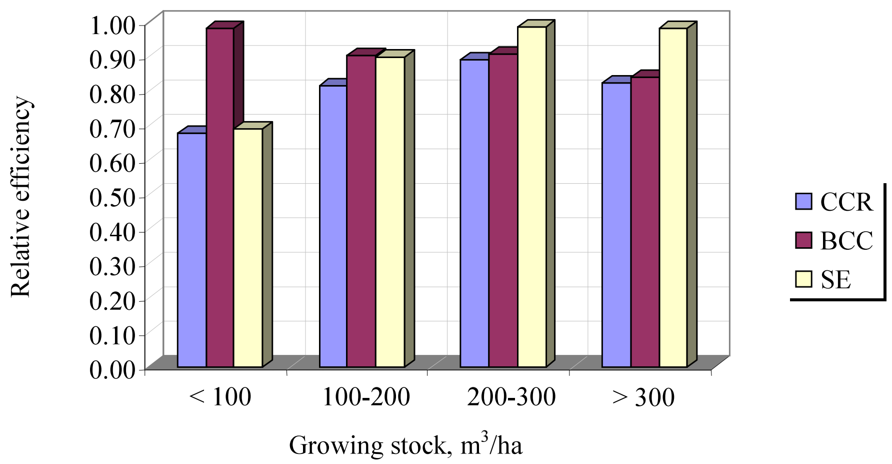

Figure 5. Average relative efficiency of forest offices grouped with respect to growing stock

According to the BCC model, the average efficiency of all groups is assessed as relatively high. The highest average efficiency of forest offices with low growing stocks in the Karst and Mediterranean areas is the effect of increasing returns to scale, where it is considered that little increase of input (growing stock, etc.) would result in more than proportional increase of output (income, allowable cut, etc.). This assumption may be considered wrong for the said forest offices, if bad structure and poor quality of growing stock in the Karst and Mediterranean area are taken into account.

The observed forest offices employ 2,007 workers. Their number ranges from a minimum of 8 workers to a maximum of 100 workers per forest office. The number of workers in individual forest offices is mainly connected with the quantity and volume of production tasks. The average efficiency of forest offices with respect to the number of employees is presented in Figure 6.

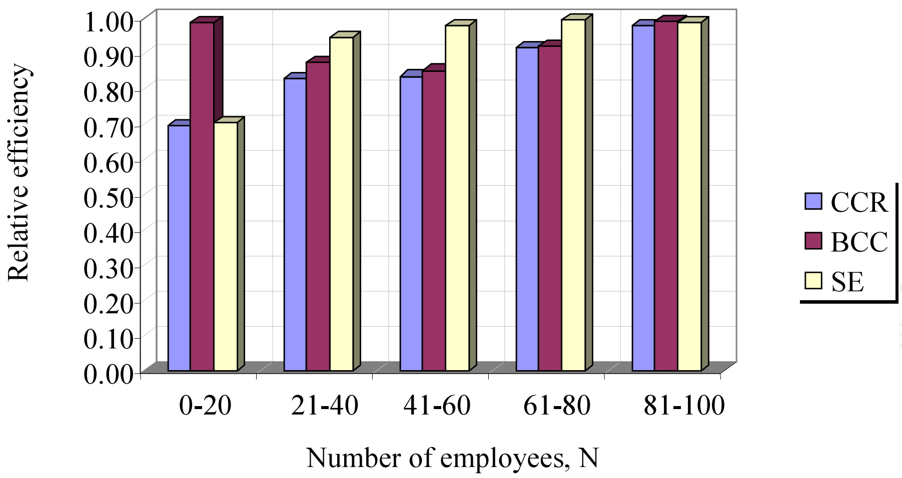

Figure 6. Average relative efficiency of forest offices according to the number of employees

It can be seen that the highest level of CCR and SE efficiency is achieved by Forest offices with the highest number of employees (group IV and V). For forest offices with 61 to 80 employees, the determined BCC, CCR and scale efficiency is 0.914, 0.920 and 0.992, respectively. In the group with more than 80 employees there are only two forest offices and their efficiency is approximately 0.985 regardless of the applied model.

3.4. Relative efficiency of forest administrations and regions

The sample of forest offices included in the analysis comes from eight Forest administrations. Six Forest offices from each selected Forest administration account for 35% (FA Split) to 67% (FA Nova Gradiška and Buzet) of the total number of offices that make individual Forest administrations. The efficiency level of individual Forest administrations is calculated as the weighted arithmetic mean of the pertaining Forest offices' relative efficiency (Figure 7). Surface areas of Forest offices are taken as weights.

On average Forest administrations A (0.959), C (0.934) and F (0.916) have the highest relative efficiency according to the CCR model. FA G has the lowest average efficiency (0.613), while the Forest Administrations D, E and H are assessed better with average values between 0.778, and 0.822. FA B (0.868) gets closer to the average efficiency of 90%.

According to the scale efficiency, the Forest administrations A, B, C, D, E and F are assessed similarly, and the level of their average efficiency ranges between 0.963 and 0.993. Like in CCR model, FA G and FA H represent the 'worst' units with average scale efficiency 0.687 and 0.855, respectively.

The average efficiency of the most successful forest administration according to the BCC model is 0.974 (A). Then follow Forest administrations H (0.957), C (0.939), F (0.924) and G (0.913). Forest administrations B, D and E have the lowest BCC efficiency.

For success assessment of Forest administrations, besides their average efficiency, it is also important to take into account the number of Forest offices that define the efficiency frontier.

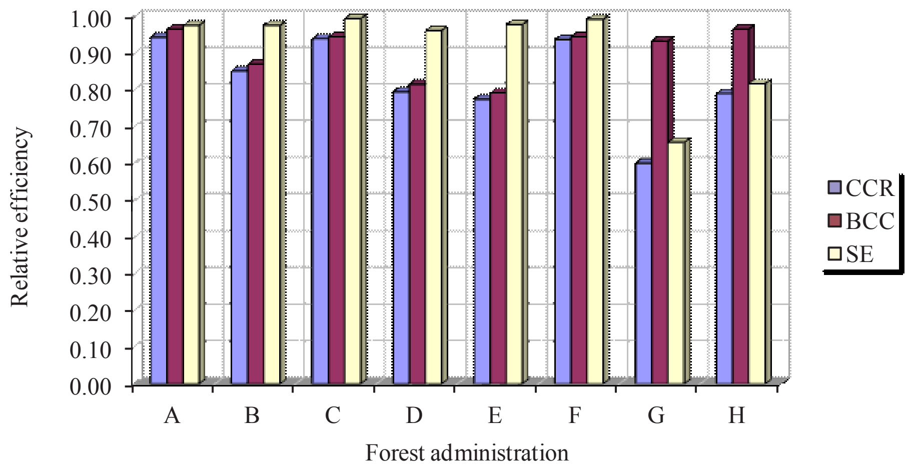

Figure 7. Average relative efficiency of Forest administrations

In this way it was determined that the efficiency frontier was on average most frequently determined by Forest offices of Forest administrations A and C (CCR and SE model) i.e. Forest administrations G and H according to the BCC model (table 3).

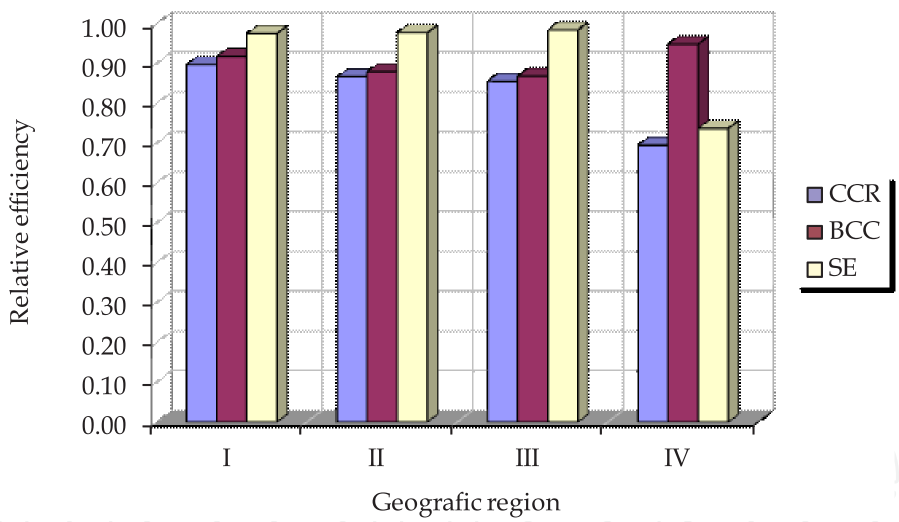

Figure 8. Average relative efficiency by geographic regions

The average relative efficiency of forest management in different geographical regions is also calculated as the weighted (by areas) mean efficiency of Forest offices situated in individual regions. The highest average efficiency was achieved in the area (I) lowland flood-prone forests – 0.907, somewhat lower in the area (II) hilly forests of the central part and area (III) mountainous forest – 0.862 and 0.890, and the lowest in the area (IV) Karst/Mediterranean area – 0.773, according to the CCR model. According to the BCC model, the average efficiency of lowland, hilly and mountainous forest offices is 0.924, 0.874 and 0.899, respectively, while the average efficiency of Karst/Mediterranean forest offices is somewhat higher and namely 0.946. The average scale efficiency of continental regions is relatively uniform and it ranges around 0.980, while in the Karst/Mediterranean area it is much lower and namely 0.816. The average relative efficiency of organisational units grouped by regions is shown in Figure 8.

4. Discussion and conclusions

In this very dynamic period of management of natural resources, when forest experts face the challenges of professional and responsible management of forests and forest land, having to observe at the same time the protection requirements of their ecological, social and economic functions, as well as challenges of profitable management of forestry companies, managers need different models for converting the accounting and financial data into useful information. In this paper the models of Data Envelopment Analysis were applied for the assessment and comparison of organisational units in croatian forestry. In applying these models, a number of variables can be taken into consideration, so as to obtain a more comprehensive indicator for evaluating business activities of organisational units in forestry.

Organizational units in forestry, besides final 'products' (volume of the harvested wood, length of the constructed forest roads, renewed forest areas etc.), provide through forest management a range of services and beneficial functions that forests offer to users. Because of that the efficiency of forestry units is more difficult to assess than the efficiency of the ordinary production units which are dealing with simple commodity production. Specifically, it is difficult to quantify the amount of resources (inputs) that are needed to 'produce' a certain amount of such services and the general goods. It is also difficult to quantify the amount of these outputs. Thus, a common feature of the organizational units in forestry is that a part of their output consists of services and general benefits, most of which are difficult to express materially. The business analysis in forestry requires that such 'intangible' outputs are in the best way possible replaced by other more easily accessible and measurable substitute variables. Comprehensive business analysis also imposes the need to use multiple methodologies and models which together can give more integral description of production and business results and provide better performance indicators.

In this paper, Data envelopment analysis is presented and used for the evaluation and comparison of forestry organizational units' performance i.e. efficiency of Forest offices. DEA represents methodology which at the same time considers multiple variables, so that it can provide a more comprehensive measure of business conduct in forestry. As a technique for measuring productivity and efficiency DEA experienced wide usage in many areas. However, in the field of natural resource management it is still not represented enough. In the forestry literature there is only a limited number of papers based on the determination of the efficiency by nonparametric techniques such as DEA. This as well as other non-traditional methods should yet to be introduced and accepted in forestry as a management tool on both strategic and operational level of planning and decision-making.

Through comparisons by DEA methods it is possible to determine the greatest achievements which are objectively feasible for the most important natural and financial business segments and the total business results, but also to identify the resources whose use, taking into account the objective circumstances, isn't efficient enough. In addition, this approach allows detection of possible improvements in the business, but also the sources of the failure in business management. Based on the presented research of business performance evaluation in the paper it is considered that the application of DEA in forestry could be, as well as in many other business systems, a very strong support to planning and decision-making.

As for the disadvantages and limitations of DEA, one of the major drawbacks of DEA method is low discrimination of in/efficient units in the upper range of efficiency. Specifically, the number of single-efficient units increases with the number of input and output variables. The number of decision making units considerably larger than the number of variables (n >> m + t) is not always sufficient enough for a 'harsher' i.e. more severe distinction of efficiency. The reason for that partly lies in the flexibility of the method and the described way of determining the weights of inputs and outputs. In order to overcome this problem, several different models have been developed like "Cone-Ratio Method", "Assurance Region Method" and "Proportion-based Weights" [19].

Another limitation is the overall complexity of the method. Since the standard formulation of DEA model calculates separate linear program for each compared unit, extensive comparisons can be computationally intensive. Therefore, the model can seem quite complex and less attractive. Furthermore, DEA method is good in estimating "relative" efficiency, but it stretches very slowly the absolute efficiency. In other words, the analysis shows how efficient a particular decision making unit is in comparison to other units, but not how successful the DMU is compared to the "theoretical maximum". One of the main disadvantages of DEA method is its sensibility to extreme observations and random errors. The basic assumption is that there are no random errors and that all deviations from efficiency frontier represent inefficiency.

The advantage of DEA methodology over traditional techniques (i.e. multiple regression, stochastic frontier) is in the comparison of units with multiple inputs and outputs, whereby they can be expressed in different units of measure. Furthermore, the selected inputs and outputs are assumed to have a correlation, however it is not necessary to know the explicit form of this correlation. DEA enables a direct comparison of the DMU with other units or a combination of units with similar work/production technologies and similar tasks. Using the best units as the reference values (benchmarks), DEA indicates to inefficient units what changes in their resources are needed in order to improve their business performance.

In this paper the relative efficiency of organisational units of 'Croatian Forests' ltd is calculated based on CCR and BCC output-oriented DEA models. Shares have been determined of projected values of inputs and outputs in empirical values, as well as sources and amounts of inefficiency. Scale efficiency of Forest offices has also been determined. The effect of structural characteristics on relative efficiency of forest offices is determined, and so is the average efficiency of Forest administrations and geographic regions.

On the average, global technical efficiency obtained by CCR model amounts to 0.829. Local pure technical efficiency, obtained by BCC model is 0.904, and scale efficiency is 0.919. A higher level of efficiency is averagely achieved by forest offices with an area from 10 to 15,000 hectares and with the growing stock from 200 to 300 m^3/ha. A relatively higher efficiency is achieved by units in continental regions. The analysis of amounts and causes of inefficiencies shows that inefficiency is more significantly affected by outputs O2 and O3 (allowable cut and investments).

DEA solutions and the results of relative efficiency like the ones in the presented research can be interesting to forestry experts, managers and researchers due to three properties of this method:

- Characterisation of each organisational unit by a single result of relative efficiency,
- Improvements proposed by the model to inefficient units are based on achieved results of units that manage their business efficiently,
- Considering the problems with DEA is an alternative and indirect approach to specifying abstract statistical models and decision making based on residual analysis or analysis with coefficients – parameters.

In this way, DEA with its characteristics can become a new management tool in forestry which can be used for the analysis of business efficiency that enables a new approach to organization and data analysis, cost-benefit analysis, estimation of the frontier and the theory of learning from the most successful ones.

Undoubtly, additional research is required to generalise the evidence provided in this study, in particular regarding the explanation of the underlying differences in the use of particular inputs and the production of certain outputs that could improve efficiency of forest management units. Nevertheless, some interesting insights regarding the performance of the forest management units in Croatia may have been provided. It is also considered that by the development and application of Data envelopment analysis and other models of multi-criteria decision making, it is possible to enrich the forestry science and practice by an approach that should provide easier analysing, planning and predicting in forest management.

Author details

Mario Šporčić* and Matija Landekić

*Address all correspondence to: sporcic@sumfak.hr

University of Zagreb, Faculty of Forestry, Department of Forest Engineering, Zagreb, Croatia

References

[1] Rhodes, E., 1986: An explanatory analysis of variations in performance among U.S. national parks. In: SILKMAN R. (Ed.), Measuring Efficiency: An Assessment of DEA, pp. 47–71.

[2] Sheldon, G.M., 2003: The efficiency of public employment services. A nonparametric matching function analysis for Switzerland. Journal of Productivity Analysis 20, 49-70.

[3] Galanopoulos, K., Aggelopoulos, S., Kamenidou, I., Mattas, K., 2005: Assesing the effects of managerial and production practices on the efficiency of commercial pig farming. Agricultural Systems – article in press, available online at www.sciencedirect.com

[4] Vennesland, B., 2005: Measuring rural economic development in Norway using data envelopment analysis. Forest Policy and Economics 7 (2005): 109-119

[5] Davosir Pongrac, D., 2006: Efikasnost osiguravajućih društava u Republici Hrvatskoj. Magistarski rad, Ekonomski fakultet, Zagreb, str. 1–139 + III.

[6] Bahovec, V., Neralić, L., 2001: Relative efficiency of agricultural production in county districts of Croatia. Mathematical Communications - Supplement 1 (2001), 1: 111–119.

[7] Diaz-Balteiro, L., Herruzo, A.C., Martinez, M., Gonzalez-Pachon, J., 2006: An analysis of productive efficiency and innovation activity using DEA: An application to Spain's wood-based industry. Forest Policy and Economics, vol. 8 (7): 762-773.

[8] Glass, J.C., McKillop, D.G., O'Rourke, G., 1999: A cost indirect evaluation of productivity change in UK universities. J Prod Anal 10 (2): 153–75.

[9] Tavares, R., 2002: A bibliography of Data envelopment analysis (1978-2001). Ructor Research Report.

[10] LeBel, L.G., 1998: Technical efficiency evaluation od logging contractors using nonparametric model. Journal of Forest Engineering, 9 (2): 15-24.

[11] Kao, C., 2000: Measuring the performance improvement of Taiwan forests after reorganization. Forest Science, 46 (4): 577-584.

[12] Lee, J.Y., 2005: Using DEA to measure efficiency in forest and paper companies. Forest Products Journal, 55 (1): 58-66.

[13] Šporčić, M., 2007: Ocjena uspješnosti poslovanja organizacijskih cjelina u šumarstvu neparametarskim modelom. Disertacija, Šumarski fakultet Sveučilišta u Zagrebu, str. 1-112.

[14] Charnes, A., Cooper, W.W., Rhodes, E., 1978: Measuring the efficiency of decision making units. European Juornal of Operational Research 2: 429-444.

[15] Charnes, A., Cooper, W., Lewin, A., Seiford, L., 1994: Data envelopment analysis, theory, methodology and applications. Kluwer Academic Publishers, Boston.

[16] A Data Envelopment Analysis (DEA) Home Page. http://www.emp.pdx.edu/dea/homedea.html (accessed 15 Juny 2013)

[17] Coelli, T.J., Prasada Rao, D.S., Battese, G.E., 1998: An introduction to efficiency and productivity analysis. Kluwer Academic Publishers, Boston.

[18] Farrell, M.J., 1957: The measurement of productive efficiency. Journal of the Royal Statistical Society, Series A 120 (3): 253-281.

[19] Cooper, W.W., Seiford, L.M., Tone, K., 2003: Data Envelopment Analysis – A Comprehensive Text with Models, Applications, References and DEA-Solver Software, Kluwer Academic Publishers, p. 1–318.

IntechOpen