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Efficiency analysis of forestry journals: Suggestions for improving journals' quality

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ABSTRACT

In this paper we attempt to assess the impact of journals in the field of forestry, in terms of bibliometric data, by providing an evaluation of forestry journals based on data envelopment analysis (DEA). In addition, based on the results of the conducted analysis, we provide suggestions for improving the impact of the journals in terms of widely accepted measures of journal citation impact, such as the journal impact factor (IF) and the journal *h*-index. More specifically, by modifying certain inputs associated with the productivity of forestry journals, we have illustrated how this method could be utilized to raise their efficiency, which in terms of research impact can then be translated into an increase of their bibliometric indices, such as the *h*-index, IF or eigenfactor score.

1. Introduction

The process of journal evaluation goes back many years in time, and various tools for ranking and comparing journals have been proposed. Nowadays, it is common practice to use the well-established impact factors (IF) as the standard measure of journal quality (Garfield, 1955, 2006). The IF – which has been devised by the Thomson Reuters' (formerly Institute of Scientific Information (ISI)) Web of Science – of a journal, in a given year, is essentially the average number of citations the articles published in that journal have received over a specific period of time.

IFs are widely accepted as the standard measure of journal quality, and hence of researcher quality too. However, there are several studies nowadays that highlight the disadvantages and inefficiencies of the IF (see, e.g., Block & Walter, 2001; Seglen, 1997; Whitehouse, 2002). Specific disadvantages of the IF have led to the introduction of other measures of journal impact. Modifications of the IF have been proposed to cover both longer (see, e.g., Garfield, 1998; Vinkler, 1999) and shorter (Citation Immediacy Index) periods of time. The interested reader can also refer to Moed and van Leeuwen (1996) and MacRoberts and MacRoberts (1989) for a thorough discussion on the criticism of impact factors, and citation metrics in general. For a more recent critique on the IF and its alternatives, we refer to Leydesdorff (2012).

Recently, it has been suggested (Braun, Glänzel, & Schubert, 2005, 2006; Chapron & Husté, 2006; Rousseau, 2007, among others) that the *h*-index (Hirsch, 2005) could be used as an alternative for the ranking of journals. Almost immediately, a number of publications concerning the application of the *h*-index to journal rankings, or proposing modifications of the

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h-index to account for differences in a journal's size (Rousseau, 2007; Vanclay, 2006) or differences in the lifespan of journals (Sidiropoulos, Katsaros, & Manolopoulos, 2007) appeared in the literature (see Malesios & Arabatzis, 2012 for more on this subject).

More specifically, Braun et al. (2005, 2006) suggest that the use of h-type indices in journal ranking could be employed as a supplementary indicator to impact factors because of two important properties of the h-index: its robustness to accidental citations and the fact that it combines quantity (articles published) with impact (citations received). In addition to the work of Braun et al. (2006), Schubert and Glänzel (2007) apply the Paretian theoretical model of Glänzel (2006) to the journal citation data of Braun et al.

Other contributions to the subject have been made by Vanclay (2007), Rousseau (2007), Saad (2006), Miller (2006), Barendse (2007), Molinari and Molinari (2008) and Moussa and Touzani (2010), among others.

The h-index is based on the distribution of citations received by a given researcher's publications. By definition:

"*A scientist has index h if h of his N_p papers have at least h citations each, and the other ($N_p - h$) papers have at most h citations each*".

Despite its widespread popularity, the h-index has also raised a lot of criticism. There is a vast literature of articles that stress the disadvantages of the index (see, e.g. Adler, Ewing, & Taylor, 2008; Vinkler, 2007), while a large number of relevant modifications and generalizations of the index have appeared in the literature, intended to correct its deficiencies.

The criticism by Adler et al. is not solely targeted towards the h-index, but includes all relevant metrics that use citation data in their calculation. Nevertheless, despite the latter criticism, the h-index is increasingly utilized as a standard tool for research evaluation, including journal evaluation, standing thus as a competitor to IF (Pratelli, Baccini, Barabesi, & Marcheselli 2011). For a comprehensive and critical review of the h-index and similar indices, see Panaretos and Malesios (2009), Alonso, Cabrerizo, Herrera-Viedma, and Herrera (2009) and Schreiber (2010).

In this paper, by utilizing data envelopment analysis (DEA) methodology (Boussofiane, Dyson, & Thanassoulis, 1991), we attempt to provide an evaluation of forestry journals. In addition, based on the results of the conducted analysis, we offer suggestions on how to improve the impact of journals, in terms of widely-accepted measures of journal citation impact, such as the journal IF and the journal h-index. More specifically, a categorization of the ISI forestry journals into four major categories is presented—according to their efficiency levels derived from the DEA analysis. The obtained categorization is then compared to other existing rankings of the selected journals and the relevant findings are thoroughly discussed. By examining optimum combinations of the input variables of the DEA model, we provide valid suggestions for the improvement of a journal's citation performance, as expressed by its output variables, in our case the journal h-index, the 5-year IF and the eigenfactor score.

2. Evaluations of forestry journals

There are only a few studies in the literature which assess the scientific impact of forestry journals. Among them, we single out Vanclay (2008a, 2008b), who collected data from 180 forestry journals and compared their rankings based on the journal impact factor, the h-index and an expert ranking. Other contributions to the subject were made by Vanclay (2007), who also supports the use of h-indices instead of IFs in journal ratings, given the considerable "favourable" properties of the former, such as robustness against possible errors attributed to publications and citations in the tails of the associated distributions, "grey literature" or accidentally counted "highly-cited" articles.

In another study, after analyzing bibliometric data between 1990 and 2002 involving the faculty members of selected southern US Universities that offered a doctoral program, Kelsey and Diamond (2003) tried to establish a current core list of the most highly-cited forestry journals. By using three faculty ranks, the authors concluded that assistant professors and associate professors mainly use journals with an ecological, environmental, and plant-science emphasis, compared to full professors.

Vanclay (2012) also examines the publication patterns of 79 forest scientists, who have been awarded major international forestry prizes (between 1990 and 2010), to find significant correlations between their publication patterns and other established journal metrics. Among other interesting findings of the study, we find that prize winners exhibit their elite performance a decade before and two decades after their award.

Malesios and Arabatzis (2012) attempt a comparative ranking of the most prestigious forestry journals, which in addition to the previous analyses, proposes a supplementary indicator to the journal h-index, in an effort to account for the different dimensions of forestry journals. They also try to verify the empirical findings of previous studies, such as, for example, the correlations between the journal h-index and expert rankings.

3. Data

To assess the impact of scientific journals in the field of forestry, a total number of 54 journals were selected from the forestry journal category included in the ISI Web of Science (WoS) list (http://thomsonreuters.com/products_services/scientific/Web_of_Science), accessed in November 2011. We have chosen the ISI list of forestry journals mainly for two reasons: firstly, due to the fact that the WoS is a comprehensive database widely accepted by the scientific community for providing valid citation data, and secondly, because the non-ISI journal calculation of bibliometric indices has been frequently reported to be imperfect (Jacsó, 2008). Most of the studies agree that the Web of Science is a valid database which at least contains journal publications mainly, as opposed to Google Scholar which contains different types of sources, including journal papers, conference papers, books, theses and reports (Meho & Yang, 2007). For instance, Falagas, Pitsouni, Malietzis, and Pappas (2007) quote that: "Google Scholar offers results of inconsistent accuracy". In another bibliometric study, Franceschet (2010) states that: "The databases of the Institute for Scientific Information have been the most generally accepted data sources for bibliometric analysis". Therefore, the journals associated with forestry research and practice included in the Thomson Scientific ISI clearly constitute the bulk of the most eminent and recognizable forestry journals, as shown in relative studies (Vanclay, 2008a).

4. Efficiency analysis of forestry journals

4.1. Inputs and outputs of the study

The bibliometric data on the forestry journals included the total number of articles published by each journal from the inclusion of the journal in the ISI list up to the year 2010, the frequency of publication within a year of each journal, the eigenfactor score of each journal up to 2010, the journals' *h*-index, and finally the IF and 5-year IF of the journals up to 2010 (a description of the aforementioned indices can be found in the Appendix).

Techniques for measuring the performance of firms, units, employees are gaining the interest of the scientific community. The optimal allocation of available resources is another concern of businesses and industries in order to achieve economies of scale. In this study, the efficiency of 54 forestry journals is examined through Data Envelopment Analysis (Halkos & Tzeremes, 2011). The examined issue can be viewed as a production procedure, which takes into account the produced and consumed units in order to determine the optimum pair (Debreu, 1951; Koopmans, 1951).

DEA is an extreme point technique used to measure the efficiency of Decision Making Units (DMUs) using given inputs and outputs. Then, based on the efficiency produced, the optimal input and output pairs can be selected.

The inputs of this study are defined to be the following:

$X1$:	Frequency of publication of a journal within a year (**FRQ**)
$X2$:	Articles published per year (**ApY**)

The selection of inputs for our analyses is valid both from a theoretical and empirical perspective, since the number of articles (N) and frequency of publication have been shown in various studies to be associated with the impact of researchers/journals, as expressed by the (journal) *h*-index and the IF. For instance, in the theoretical study by Egghe (2005) (see also Egghe & Rousseau, 2006), the author shows that in the theoretical context of an information production process, if a system has N sources (where N stands for articles) and a Lotka function exponent α, the system's unique *h*-index is given by the expression: $h = \sqrt[\alpha]{N}$. More specifically, in the context of journals, Molinari and Molinari (2008) reported through an empirical investigation that the *h*-index is associated with the number of published papers, since it can be expressed as: $h = h_m N^{\beta}$, where N denotes the number of papers published by the journal and β is approximately 0.4 in all of the cases examined. All of the above-mentioned theoretical results are simply another way of stating the overall impression created, that a journal that publishes many articles is more likely to get a higher IF/*h*-index.

The frequency of publication of a journal has also been shown to be associated with the journal *h*-index. Frequently published journals may have an advantage, since an article published earlier in the year has a better chance of being cited than one published later. For instance, Malesios and Arabatzis (2012) have shown, through an empirical investigation of a list of 39 journals in the field of forestry included in the ISI WoS, that their *h*-index is positively correlated with their frequency of publication within a year; they applied a generalized linear model (GLM) analysis, using the journal *h*-index as a dependent variable and various factors assumed to affect the *h*-index as independent variables, including the frequency of publication covariate.

The outputs are selected on the basis of the journals' performance. In a production procedure, one of the outputs would be the sales of a store. When examining the efficiency of journals, the output chosen to measure efficiency will be based on three indices which measure the quality of a journal, namely the 5-year impact factor, the *h*-index of a journal and its eigenfactor score.

$Y1$:	Eigenfactor score (**EGSC**)
$Y2$:	*h*-index (**H**)
$Y3$:	5-year impact factor (**IF5**)[1]

The outputs used in our study have been extensively investigated in the literature, as to which are the potential factors that may increase their values. For instance, see Egghe (2005), Molinari and Molinari (2008), Malesios and Arabatzis (2012) regarding the *h*-index, or Metze (2010) for the IF. Specifically for the IF, which is a measure that includes both the number of papers (source items) and the citations (C) received in its calculation, one could think of many straightforward and/or more indirect methods to achieve such an increase. For example, the IF may be improved by increasing the number of citations, which means including items that are more citable (such as review papers, etc.) or by reducing/removing specific source

[1] For journals with a lifespan of less than 5 years, the latest IF found is taken into account as the most suitable proxy (Halkos & Tzeremes, 2011).

items, for instance case reports. On the other hand, abstracts, which are not defined as source items, but whose received citations are counted when calculating the IF, can provide some sort of benefit. The same holds for editorials or letters (which are not counted as source items either). In the case of the *h*-index, although an increase in N or C does not necessarily imply a direct increase in its value, it has been shown to be positively associated with both the number of articles and the number of citations.

4.2. Methodology

4.2.1. Implementing DEA analysis

In the following, each journal is regarded as a DMU. In order to propose certain actions for the policy of each journal, first a ranking is obtained through DEA analysis. The efficiency of a DMU is defined as the ratio of outputs to inputs. Certain DEA models were developed for the maximization of this ratio, taking into account the inputs (input-oriented efficiency) or the outputs (output-oriented efficiency). After measuring the journals' efficiency through DEA analysis, a ranking is proposed for the examined journals and several suggestions are made to the inefficient journals in order for them to increase their efficiency. The previous action can consequently increase the outputs of each journal and therefore lead to the improvement of a journal's quality.

Let $x \in R_n^+$ be the vector of inputs and $y \in R_m^+$, and F the set of all feasible pairs of inputs and outputs, so that $F = \{(x, y) \in R_{n+m}^+ / x \to y\}$.

The previous procedure can be formulated via linear programming (LP) models (Cooper, Seiford, & Zhu, 2011; Førsund & Sarafoglou, 2002). Many DEA formulations have been developed in the literature globally (Banker, Cooper, Seiford, Thrall, & Zhu, 2004).

The two basic models developed for returns to scale are the CCR model of Charnes, Cooper, and Rhodes (1978) and the BCC model of Banker, Charnes, and Cooper (1984). The first model for measuring the efficiency of DMUs and thus evaluating their performance though a linear programming model was initially designed by Charnes et al. (1978), and extended by Banker et al. (1984),

As is the case with all techniques, DEA has limitations concerning the minimum number of inputs and outputs. A generally empirical rule of thumb is that the provided observations of the DMUs examined (inputs and outputs) should be more than or equal to 2^{x+y}, where x and y are the vectors of inputs and outputs, so that $x \in R^n$, $y \in R^m$ and $x, y > 0$. Let us assume that $x = (X1, X2)$ and $y = (Y1, Y2, Y3)$ are the vectors of inputs and outputs, respectively. Then, if there are $n = 54$ DMUs, the following holds: $54 > 2^{inputs+outputs} = 2^5 = 32$. There are therefore enough DMUs to compute the efficiency through DEA analysis.

4.2.2. The Bootstrap algorithm

In order to compute a true estimate of DEA efficiency, the Bootstrap methodology was introduced (Efron, 1979; Efron & Tibshirani, 1986). The Bootstrap algorithm is a computer simulation procedure, where random "replica" samples are drawn with replacement from the original population. Let $X = \{x_1, x_2, \ldots, x_n\}$ be a random sample drawn from the original population and d the unknown distribution of the parent data. The statistic $\hat{u} = u(X)$ derived from the sample is approximately the same as the corresponding statistic $u = u(d)$ derived from the parent population. As bootstrap is a computer-based procedure, some samples are expected to appear more than once, while others not even once. Let $X^* = \{x_1^*, x_2^*, \ldots x_n^*\}$ be a randomly drawn sample from the original population and $x_j^*, j = 1, \ldots, n$ the sample's items. The probability of each item drawn within the sample X^* being equal to the corresponding item of the observed X is equal to $1/n$, and $\hat{d}$ is the empirical density function of X^* drawn from the observed X. As described above, $\hat{d}$ is an empirical function expressed as:

$$\hat{d}(r) = \begin{cases} \frac{1}{n}, & r = x_i^*, \quad i = 1, \ldots, n \\ 0, & \text{otherwise} \end{cases}$$

Let $\hat{d}$ be a consistent estimator of d and $\hat{u}^* = u(X^*)$ be the estimated parameter of drawn sample X^*. The previous leads us to the conclusion that the distribution of $\hat{u}^*$ around $\hat{u}$ is approximately the same as $\hat{u}$ around u or $(\hat{u}^* = \hat{u})|\hat{d} \sim (\hat{u} - u)|d$ (Desli & Ray, 2004).

DEA estimators are considered to be biased by construction of the technique (Simar & Wilson, 1998, 2000). The proposed bootstrapped procedure for the computation of the real DEA efficiency and bias estimation is the following:

I. Compute $u = u\ (X)$ where X is an observed sample.
II. Draw with replacement a bootstrapped sample X_b^*, $b = 1, \ldots, B\}$ from the observed sample X.
III. Estimate the statistic $\hat{u}^* = u(X_b^*)$, where X_b^* is the b-th drawn sample from the observed X.
IV. Repeat II–III, B times (B must be large).
V. Calculate the bootstrap estimates of u as an average $\hat{u}^*(\bullet) = \frac{1}{B}\sum_{b=1}^{B}\hat{u}_b^*$.

The estimated bias is computed by the difference of the expected $\widehat{u}$ and the actual u or $bias^d = E_d(\widehat{u}) - u$, where $E_d\,(\bullet)$ is the expected value of the unknown distribution, d. The standard error of $\widehat{u}^*(\bullet)$ can be computed as being $se_B(\widehat{u}^*(\bullet)) = \sqrt{\frac{1}{B-1}\sum_{b=1}^{B}(\widehat{u}_b^* - \widehat{u}^*(\bullet))^2}$. After removing the bias from the estimates, the bias-corrected estimates from each bootstrap sample can be calculated by ${}^c\widehat{u}_b^* = \widehat{u}_b^* - 2 \cdot bias_B$. Finally, after computing the bias-free estimates, the (1–2a)% confidence interval for u is the following: $({}^c\widehat{u}_{b,a}^*, {}^c\widehat{u}_{b,(1-a)}^*)$.

4.2.3. CRS vs VRS

As mentioned already, there are two models of DEA, BCC and CCR. In order to choose between these two models, a hypothesis test developed by Simar and Wilson (2002) is adopted. The statistical test is given below:

$$T(X_n) = \frac{1}{n}\sum_{i=1}^{n}\frac{\widehat{V}^{CRS}, n(X_i, Y_i)}{\widehat{V}^{CRS}, n(X_i, Y_i)} \tag{1}$$

In Eq. (1), the nominator represents the efficiency obtained by the constant returns to scale model (CRS) (Charnes et al., 1978), while the denominator represents the efficiency obtained by the variable returns to scale model (VRS) (Banker et al., 1984). The hypothesis testing of whether the CRS or VRS model will be used is expressed by the following hypotheses:

H_0: Choose CRS.
H_1: Choose VRS.

The point (*p-value*) where the null hypothesis (H_0) or the alternative (H_1) is accepted is given below:

$$p = \frac{1}{B}\sum_{b=1}^{B}\frac{1(T^{*,b} \le T^{obs})}{B} \tag{2}$$

In Eq. (2), $1(\bullet)$ represents the indicator function, $T^{*,b}$ the value of the statistical test of the b-th bootstrapped sample, B the bootstrapped replications and T^{obs} the value of the statistical test on the originally observed population.

As far as the orientation of the model is concerned, the input orientation is essentially chosen because the inputs of the model represent measures that can be changed, like the frequency of publication in a given year or the articles per year of life of the examined journals. The main goal of the study is to find the optimum levels for increasing efficiency by increasing the outputs. After performing the DEA analysis, several suggestions can be made concerning the frequency of publication and the published articles per year, so as to increase the journals' efficiency. For this reason, input-oriented VRS or CRS models are examined. The efficiencies obtained by input-oriented CRS and VRS models are presented by the following linear programming (LP) formulations:

$$V^{CRS} = \begin{cases} (x, y) \in R_{n+m}^{+} \\ y \le \sum_{i=1}^{n}\lambda_i y_i \\ \sum_{i=1}^{n}\lambda_i x_i \le x, \\ \lambda_i \ge 0, \quad i = 0, 1, \ldots, n \end{cases} \qquad V^{VRS} = \begin{cases} (x, y) \in R_{n+m}^{+} \\ \sum_{i=1}^{n}\lambda_i y_i \ge \lambda_i y_i \\ \sum_{i=1}^{n}\lambda_i x_i \le x, \\ \sum_{i=1}^{n}\lambda_i = 1 \\ \lambda_i \ge 0, \quad i = 0, 1, \ldots, n \end{cases}.$$

4.3. Results

4.3.1. Descriptive statistics of inputs and outputs

In this section, the descriptive results of the inputs and outputs of the study are presented. The implementation of the DEA analysis was carried out via R language using the FEAR package (Wilson, 2008) on a Pentium Dual-Core 2.6 GHz. As shown in Fig. 1, the median of the journals' years in the ISI derived from the boxplot is 11 years, while most of the journals' years in the ISI range from 1 to 15, as indicated in the histogram. The number of journals with a publication period that is less than or equal to 10 years is 26, which means that 28 have more than 10 years of publication time, since their inclusion in the ISI. The median is a more suitable figure to use compared to the average, due to the fact that the range of observed values is quite extensive.

Descriptive statistics of the inputs and outputs are presented in Table 1. The average frequency of publication of the examined journals is 6 times/year. This means that the average publication frequency of the examined journals is about 1

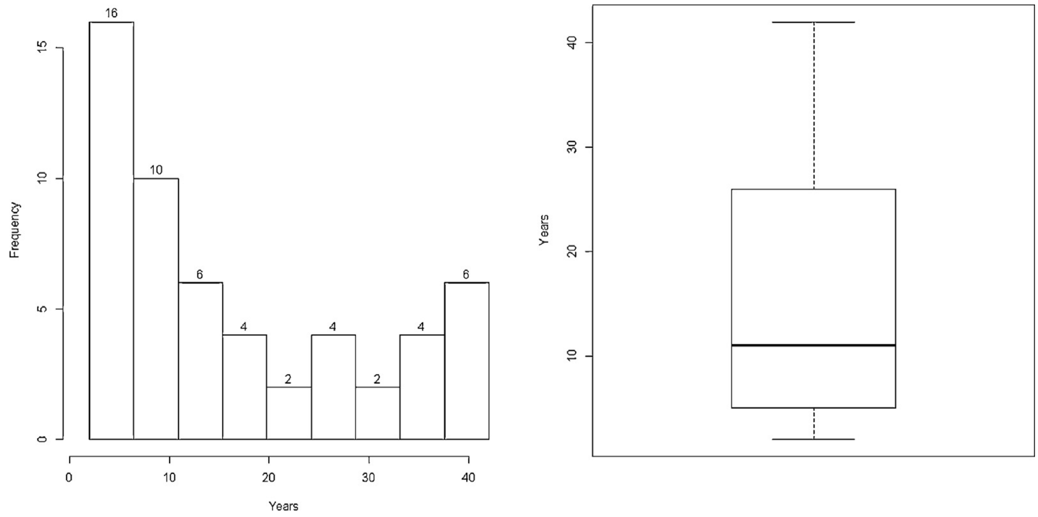

Fig. 1. Combined Histogram–Boxplot of Journals' inclusion time in the ISI WOS (in years).

Table 1
Descriptive statistics of the study's inputs and outputs.

Statistical measures	Inputs		Outputs		
	Frequency (FRQ)	Articles published per year (ApY)	Eigenfactor Score (EGSC)	h-index (H)	5-year impact factor (IF5)
Mean	6	56	0.00331	27.59	1.19
Standard deviation	2	7	0.05757	5.25	1.09
Range	23	223	0.03835	100	4.02

publication every 2 months. The mean value of the second input, articles published per year, is 56. As concerns the outputs, the mean eigenfactor score is 0.00331, the mean h-index is 27.59 and the mean 5-year IF is 1.19.

4.3.2. 1st stage analysis

The results of the statistical test presented in Section 4.2.3, which was carried out in order to accept the H_0 or H_1 hypothesis, are the following: $T^{obs} = 0.570$ $T^{*,b} = 0.794$, p-value = 0.571.

From the results shown above, it can be seen that the p-value of the statistical test, is 0.571, and greater than its significance level, which is 0.05 in this case. Therefore the null hypothesis (H_0) is accepted, and the CRS model is the most suitable model for measuring the efficiency of forestry journals. Journal efficiencies are presented in Table 2. A rank analysis based on

Table 2
Input efficiencies derived from the CRS DEA model.

Journal	DMU	Input efficiency	Journal	DMU	Input efficiency	Journal	DMU	Input efficiency
Agr Forest Meteorol	DMU1	100%	Forest Policy Econ	DMU19	49%	North J Appl For	DMU37	37%
Agroforest Syst	DMU2	72%	Forest Prod J	DMU20	27%	Plant Ecol	DMU38	57%
Allg Forst Jagdztg	DMU3	31%	Forest Sci	DMU21	100%	Rev Arvore	DMU39	13%
Ann Forest Sci	DMU4	54%	Forest Syst	DMU22	57%	Rev Chapingo Ser Cie	DMU40	6%
Appl Veg Sci	DMU5	100%	Forestry	DMU23	100%	Scand J Forest Res	DMU41	46%
Aust Forestry	DMU6	85%	Holzforschung	DMU24	77%	Silva Fenn	DMU42	67%
Austrian J for Sci	DMU7	35%	Iawa J	DMU25	73%	Silvae Genet	DMU43	68%
Balt For	DMU8	18%	Int Forest Rev	DMU26	38%	South Forests	DMU44	30%
Can J Forest Res	DMU9	94%	Int J Wildland Fire	DMU27	100%	South J Appl For	DMU45	42%
Cerne	DMU10	10%	Invest Agrar-Sist R	DMU28	82%	Sumar List	DMU46	4%
Cienc Florest	DMU11	25%	J Forest	DMU29	41%	Sylwan	DMU47	3%
Croat J for Eng	DMU12	35%	J Forest Econ	DMU30	92%	Tree Genet Genomes	DMU48	89%
Dendrobiology	DMU13	43%	J Forest Res-Jpn	DMU31	31%	Tree Physiol	DMU49	80%
Dendrochronologia	DMU14	97%	J Trop for Sci	DMU32	17%	Tree-Ring Res	DMU50	100%
Eur J Forest Res	DMU15	73%	J Veg Sci	DMU33	100%	Trees-Struct Funct	DMU51	81%
Forest Chron	DMU16	43%	Madera Bosques	DMU34	15%	West J Appl For	DMU52	36%
Forest Ecol Manag	DMU17	100%	Nat Area J	DMU35	69%	Wood Fiber Sci	DMU53	67%
Forest Pathol	DMU18	50%	New Forest	DMU36	51%	Wood Sci Technol	DMU54	100%

input efficiency is also presented (Allen, Athanassopoulos, Dyson, & Thanassoulis, 1997). Each journal is ranked based on pre-determined intervals of input efficiency, which are presented below:

- D, if $\%\varphi^{CRS} \in (0, 33.3]$
- C, if $\%\varphi^{CRS} \in (33.3, 66.6]$
- B, if $\%\varphi^{CRS} \in (66.6, 99.9]$
- A, if $\%\varphi^{CRS} = 100$.

From Table 2 we observe that 13 journals have efficiencies belonging to the first efficiency interval (0, 33.3] and are ranked with D. The journals that belong to this category are:

Allgemeine Forst und Jagdzeitung, Baltic Forestry, Cerne, Ciencia Florestal, Forest Products Journal, Journal of Forest Research, Journal of Tropical Forest Science, Madera Y Bosques, Revista Arvore, Revista Chapingo Serie Ciencias Forestales Y Del Ambiente, Southern Forests, Sumarski List, Silwan. The percentage of journals belonging to this category is 24.07%.

The next category concerns journals with efficiencies belonging to the interval (33.3, 66.6]. In this category, journals are ranked based on their input efficiency with C. It concerns 17 journals or 31.48% of the total journals examined, which are the following: *Annals of Forest Science, Austrian Journal of Forest Science, Croatian Journal of Forest Engineering, Dendrobiology, Forest Chronicle, Forest Pathology, Forest Policy and Economics, Forest Systems, International Forestry Review, Journal of Forestry, New Forests, Northern Journal of Applied Forestry, Plant Ecology, Scandinavian Journal of Forest Research, Silva Fennica, Southern Journal of Applied Forestry, Western Journal of Applied Forestry*.

Fifteen or 27.78% of the examined journals belong to the third ranking category, their input efficiency belonging to the interval (66.6, 99.9]; they are thus ranked with B. These journals are the following: *Agroforestry Systems, Australian Forestry, Canadian Journal of Forest Research-Revue Canadienne De Recherche, Dendrochronologia, European Journal of Forest Research, Holzforschung, IAWA Journal, Investigation Agraria-Sistemas Y Recursos Forestales, Journal of Forest Economics, Natural Areas Journal, Silvae Genetica, Tree Genetics and Genomes, Tree Physiology, Trees-Structure and Function, Wood and Fiber Science.*

Finally, there are only 9 journals or 16.67% of the total number of journals examined in the last category, with an input efficiency equal to 100%. In this category the journals are ranked with A. Having an input efficiency of 100% means that their input and output combinations are optimal and form the benchmark; therefore, no further suggestions for the improvement of their inputs are required. The abbreviated titles of the journals that fall into this category are: *Agricultural and Forest Meteorology, Applied Vegetation Science, Forest Ecology and Management, Forest Science, Forestry, International Journal of Wildland Fire, Journal of Vegetation Science, Tree-Ring Research, Wood Science and Technology*.

The ranked efficiencies are presented in Fig. 2 with an overall analysis for each journal expressed in DMUs for each rank.

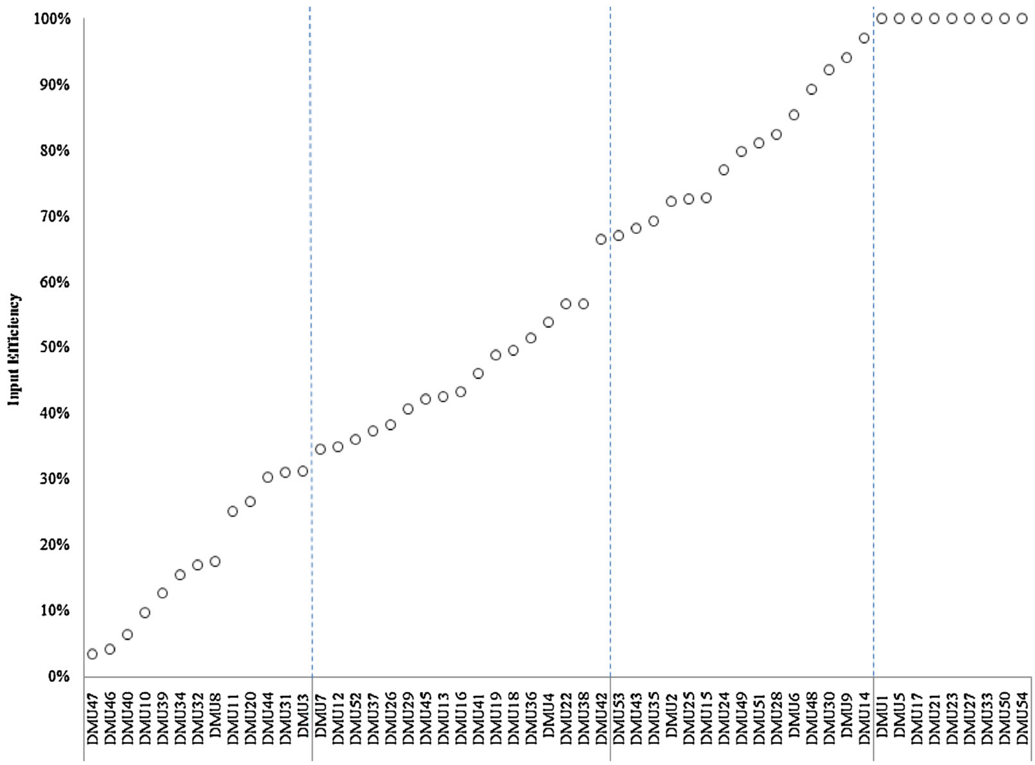

Fig. 2. Ranked input efficiencies.

Table 3
Input efficiency, bias-corrected efficiency, confidence intervals and variance estimates obtained by bootstrapping (2000 samples).

Journal	Input efficiency	Bias corrected Input efficiency	σ^2	10%	90%
Agr Forest Meteorol	1.00000	0.750744	0.015194	0.652776	0.961314
Agroforest Syst	0.72289	0.620154	0.007251	0.539337	0.712404
Allg forst jagdztg	0.31212	0.262008	0.007967	0.23036	0.304939
Ann Forest Sci	0.53968	0.434157	0.009186	0.380485	0.52226
Appl Veg Sci	1.00000	0.73124	0.019866	0.647637	0.962281
Aust Forestry	0.85354	0.732112	0.006354	0.645481	0.830366
Austrian J for Sci	0.34598	0.289513	0.008657	0.252014	0.338647
Balt For	0.17513	0.153769	0.003595	0.138755	0.169375
Can J Forest Res	0.94015	0.76902	0.010207	0.657188	0.905439
Cerne	0.09753	0.084865	0.004727	0.075413	0.09455
Cienc Florest	0.25244	0.202129	0.012453	0.174733	0.243791
Croat J For Eng	0.35037	0.300152	0.005879	0.266834	0.342423
Dendrobiology	0.42521	0.365903	0.006318	0.323962	0.418175
Dendrochronologia	0.97146	0.818451	0.004724	0.740531	0.941953
Eur J Forest Res	0.72703	0.60709	0.006474	0.538925	0.700222
Forest Chron	0.43373	0.380012	0.007559	0.326865	0.430406
Forest Ecol Manag	1.00000	0.757891	0.014646	0.660064	0.961939
Forest Pathol	0.49553	0.422674	0.004302	0.382655	0.477735
Forest Policy Econ	0.48863	0.391023	0.008684	0.346315	0.466817
Forest Prod J	0.26685	0.229504	0.004599	0.205315	0.258895
Forest Sci	1.00000	0.83828	0.005489	0.74684	0.966676
Forest Syst	0.56579	0.443627	0.018455	0.372283	0.552184
Forestry	1.00000	0.818693	0.006116	0.734397	0.96311
Holzforschung	0.77036	0.652368	0.005485	0.577942	0.741681
Iawa J	0.72578	0.640857	0.003196	0.577836	0.702922
Int Forest Rev	0.38300	0.325188	0.004548	0.291257	0.369167
Int J Wildland Fire	1.00000	0.781206	0.008646	0.698594	0.949154
Invest Agrar-Sist R	0.82396	0.690389	0.008226	0.60506	0.804051
J Forest	0.40663	0.35006	0.007112	0.302751	0.398662
J Forest Econ	0.92264	0.775139	0.007227	0.683471	0.893203
J Forest Res-Jpn	0.31127	0.258431	0.006694	0.23013	0.301554
J Trop for Sci	0.17001	0.147277	0.005146	0.130744	0.165464
J Veg Sci	1.00000	0.779128	0.01066	0.689628	0.960417
Madera Bosques	0.15499	0.129215	0.007047	0.114979	0.1507
Nat Area J	0.69242	0.598833	0.003662	0.541286	0.667674
New Forest	0.51391	0.44326	0.004293	0.397134	0.49599
North J Appl For	0.37425	0.318383	0.004287	0.28865	0.363628
Plant Ecol	0.56613	0.449815	0.010259	0.390692	0.542365
Rev Arvore	0.12697	0.104436	0.010291	0.088862	0.121073
Rev Chapingo Ser Cie	0.06454	0.056263	0.003757	0.050835	0.062552
Scand J Forest Res	0.46152	0.393115	0.005568	0.348377	0.447093
Silva Fenn	0.66578	0.57303	0.004164	0.515686	0.642804
Silvae Genet	0.68097	0.578116	0.004899	0.518272	0.659893
South Forests	0.30367	0.259023	0.00514	0.23055	0.294234
South J Appl For	0.42119	0.36318	0.004214	0.327197	0.407567
Sumar List	0.04146	0.03519	0.004592	0.031763	0.039957
Sylwan	0.03384	0.029139	0.004791	0.026047	0.032828
Tree Genet Genomes	0.89244	0.741036	0.007239	0.652419	0.857772
Tree Physiol	0.79908	0.649154	0.008382	0.56484	0.76838
Tree-Ring Res	1.00000	0.794944	0.007597	0.715948	0.96106
Trees-Struct Funct	0.81054	0.680122	0.004922	0.611186	0.783178
West J Appl For	0.36063	0.315686	0.003615	0.284131	0.349053
Wood Fiber Sci	0.66964	0.566481	0.006908	0.496437	0.654176
Wood Sci Technol	1.00000	0.815935	0.006937	0.731906	0.968389

In Table 3 the input efficiency is presented, as derived from the CRS input-oriented model. Furthermore, after performing the bootstrap algorithm for 2000 replications, the bias-corrected input efficiency is also presented for each journal, along with the corresponding variance estimate. Finally, the derived 90% bootstrap confidence interval is also calculated.

4.3.3. 2nd Stage analysis

In this section, an analysis to determine any exogenous factors that may affect input efficiency is conducted (Bogetoft & Otto, 2010). Such exogenous factors may involve other parameters that were not included in the DEA process or dummy variables. As reported in the descriptive statistics of the inputs of the study, according to Table 1, the mean value of the FRQ input is 6 times/year. Setting the mean FRQ as a threshold for this analysis, two groups of input efficiencies are created from the initial population. Let K be the initial population of input efficiencies, K_1 the input efficiencies of the journals that have a frequency of publication $\leq$6 times/year (1st group) and K_2 of journals with a frequency of publication higher than 6

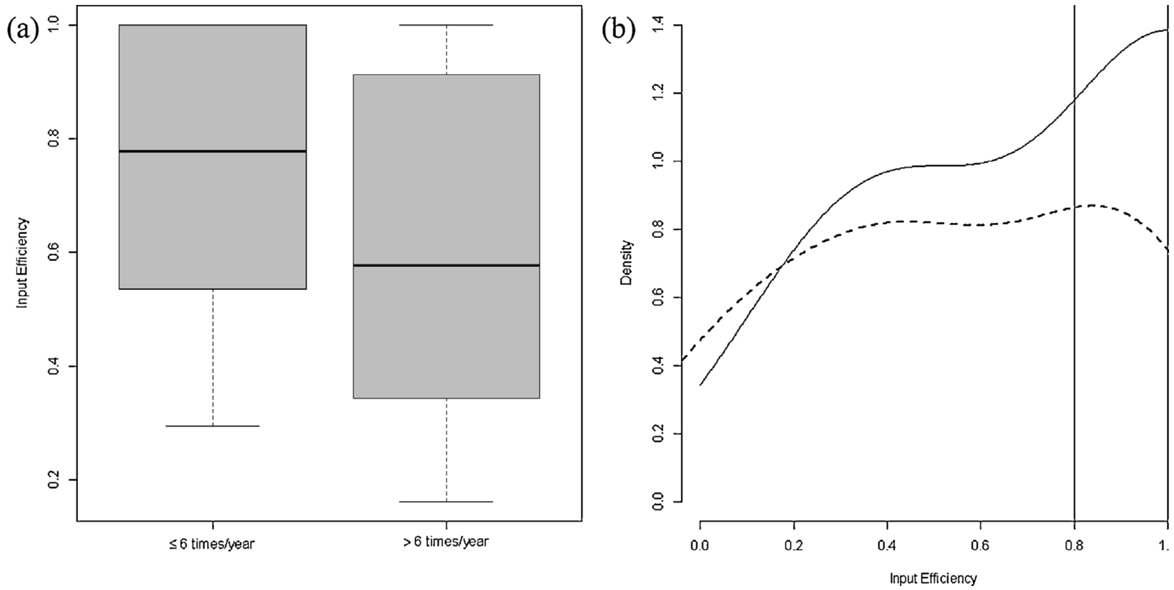

Fig. 3. (a) Boxplot of the groups examined, (b) Density plot for the two groups (solid line ≤6 times/year, dashed line >6 times/year, vertical lines at 0.8 (80%) and at 1 (100%) input efficiency.

times/year (2nd group). If the corresponding densities of the input efficiency of groups K_1 and K_2 are g_1 and g_2, respectively, then the following hypothesis is considered:

$$H_0 : g_1 = g_2$$

$$H_1 : g_1 \neq g_2$$

In order to determine whether to choose the null hypothesis or the alternative, the non-parametric Kruskal–Wallis (KW) rank sum test is used. This test allows hypothesis testing without the restriction of normality of distributions. An intuitive thought would be that as the frequency of publication increases, more articles would accordingly be published, so that a journal's eigenfactor score, *h*-index and 5-year IF would increase as well. The latter fact would lead to higher input efficiency. After conducting the KW rank sum test, the *p*-value of the KW rank sum test is found to be equal to 0.14 and higher than 0.05. Thus the null hypothesis reinforces the previous thought.

Based on the boxplot in Fig. 3(a), we observe that 75% of the observations of the first group have an input efficiency of 1 or 100%, while, for the second group, an input efficiency of 1 or 100% is simply the largest non-outlier value. The latter fact means that the first group contains higher input efficiencies than the second. This conclusion is verified through the density plot of Fig. 3(b) of the examined groups. As can be seen, the input efficiency (solid line) of group 1 seems to have a steeper density mass, that is closer to 1 (100%). In the input efficiency interval [0.8, 1] shown by the vertical lines in Fig. 3(b), the density of group 1 is higher than the density of group 2.

A valid conclusion that emerges from the above analysis is that the average input efficiency of group 1 (K_1) is higher than that of group 2 (K_2). Thus a journal with a frequency of publication ≤6 is expected to be more efficient than a journal with a frequency of publication that exceeds 6 times a year. The same result can be derived through the density of efficiency, in accordance with the groups of frequency of publication and the corresponding input efficiency. In Fig. 4(a), the density plot of the input FRQ and the input efficiency is shown, while in Fig. 4(b) and (c), the density plots of the frequency groups of ≤6 times/year and >6 times/year are presented. From Fig. 4(b), it can be concluded that the highest density region (dark grey area) is concentrated at frequencies between 3 and 5 times/year, which yield a high-input efficiency. The circle in the high-density region represents the mode of frequency, which is 4 in this case, and the approximate input efficiency, which is 0.8 (80%). On the contrary, for the second group of frequencies, it can be concluded that as the frequency of publication increases, thus the input efficiency decreases. The mode is approximately 13, yielding an input efficiency of more than 0.2 (20%), which is relatively low.

4.3.4. Suggestions for increasing the eigenfactor score, the h-index and the IF

In this section, valid proposals are made regarding the inputs of journals with rankings D, C and B, and how they can achieve higher outputs and therefore an improvement in the journals' quality. In addition, the slack values will be estimated for the inefficient journals, i.e. journals with efficiency lower than 100% (Thanassoulis & Dyson, 1992).

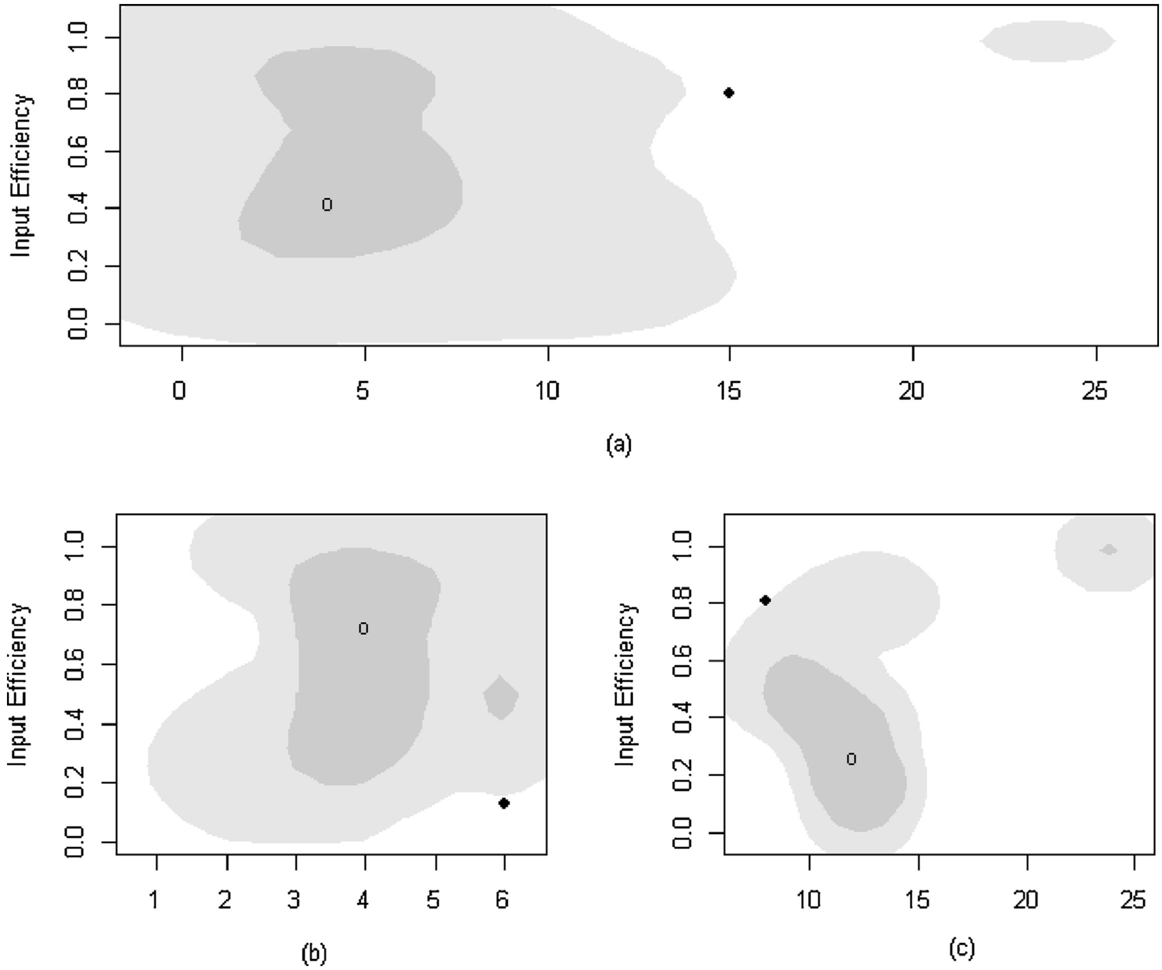

Fig. 4. Density plot of: (a) FRQ with input efficiency, (b) subgroups of frequency of publication ≤ 6 times/year, (c) subgroups of frequency of publication > 6 times/year.

In order to interpret the second stage analysis of the CRS input-oriented model, the following linear programming model is considered (Cook & Seiford, 2009):

$$\begin{aligned}
&\min \varphi - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{i=1}^{s} s_i^+\right)\\
&s.t.\\
&\sum_{i=1}^{m}\lambda_j x_{ij} + s_i^- = \varphi x_{io}, \quad i = 1, \ldots, m\\
&\sum_{i=1}^{m}\lambda_j x_{rj} - s_i^+ = \varphi y_{io}, \quad r = 1, \ldots, n\\
&\lambda_j \geq 0, \quad j = 1, \ldots, n
\end{aligned} \tag{3}$$

In the above-formulated LP model, φ^* is the efficiency score of each DMU obtained by the initial run of the DEA model, ε is defined as a very small positive number and s_i^- and s_i^+ represent slack values. When dealing with inefficient DMUs (DMUs with an efficiency lower than 1 or 100%), the inputs of the study should be reduced in order to reach the benchmark. Thus the new reduced inputs and the target outputs are computed using Eqs. (4) and (5).

$$\hat{x}_{io} = \varphi * x_{io} - s_i^-, \quad i = 1, \ldots, m \tag{4}$$

$$\hat{y}_{ro} = y_{ro} + s_i^+, \quad r = 1, \ldots, s \tag{5}$$

Based on Eq. (4), the new input of an inefficient DMU is the product of the corresponding efficiency minus the slack value. The target output values for inefficient DMUs are computed as the target output values plus the slack value. When reducing inputs and increasing outputs, the efficiency scores of inefficient DMUs increase in order to reach the benchmark.

For this reason, several suggestions are made so that the inputs and the outputs can reach the benchmark and eventually all journals can become 100% efficient. The aforementioned suggestions will be made in terms of reducing operating costs rather than increasing the examined outputs (EGSC, H, IF5). As the examined DEA model is an input-oriented model, a constant returns to scale (CRS), a reduction to the number of articles published per year (ApY) in a journal and a reduction in the frequency of publication (FRQ) below a certain level are not permitted. In order to attain the lowest rationally acceptable level regarding the suggestions on the two examined inputs, a confidence interval analysis is conducted. Suggestions are made only if an input whose lower bound is higher than or equal to the lower value of the confidence interval.

First a single sample Kolmogorov–Smirnov (KS) non-parametric normality test is applied to each of the above inputs individually. As each of the examined inputs are tested on whether they are normally distributed or not, the empirical density function is defined as follows:

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} 1_{X_i \le x},$$

where $1_{X_i \le x}$ is the indicator function, so that:

$$1_{X_i \le x} = \begin{cases} 1, & X_i \le x \\ 0, & \text{otherwise} \end{cases}$$

Moreover, the KS statistic is the following: $D_n = \sup_x |F_n(x) - F(x)|$.

Thus, if the empirical distribution comes from $F(x)$, which in this case is assumed to be the normal distribution, then $D_n \to 0$. We therefore examine the following hypotheses:

H_0: The examined input comes from a normal distribution.
H_1: The examined input does not come from a normal distribution.

The results derived from the above hypothesis using articles per year (ApY) and frequency of publication (FRQ) as inputs are presented below:

KS test for articles per year (ApY)

- $D = 1$.
- *p-value* = 2.2×10^{-16}.

KS test for articles per year (FRQ)

- $D = 0.9587$.
- *p-value* = 2.2×10^{-16}.

The null hypothesis is rejected, as the *p-value* is in both cases equal to $2.2 \times 10^{-16} < 0.05$. According to the non-parametric KS test described above, the inputs ApY and FRQ do not come from the normal distribution. The previous conclusion is reinforced, as the value of *D* differs greatly from 0, as stated in the results shown above.

Based on the above result of the KS test, the examined confidence interval cannot be computed from a normal distribution. Therefore, the 2.5% and 97.5% empirical confidence bands for the above inputs are considered. Regarding the articles per year (ApY) input, the empirical confidence interval is: (2.5%, 97.5%) = (10, 200). For the frequency of publication (FRQ) input, the corresponding empirical confidence interval is the following: (2.5%, 97.5%) = (2, 21).

Based upon the aforementioned confidence intervals, the inputs for which proposals will be made are presented in Tables 4–6; they are calculated using the proposed LP model (3) and Eqs. (4) and (5) for the calculation of the target inputs and outputs.

By way of illustration, column FRQ* of Table 4 represents the reduced levels of frequency of publication, while the ApY* column represents the reduced levels of article publication per year of the examined journals. The next two columns represent the current eigenfactor score value (EGSC) of each journal and the target value of the eigenfactor score, if the journal adopts the proposed reductions. As can be seen from the above table, the largest margin of increase is that of *Silvae Genetica* journal with 116%. This journal can achieve an eigenfactor score of 0.0018 compared to 0.00083, which is its current value. In order to do this, the journal must reduce the frequency of publication to 4 times a year and reduce the articles per year to 31. Similar proposals hold for the rest of the journals in Table 4 in order for them to achieve higher eigenfactor score values.

In Table 5, the largest margin of increase in the *h*-index (H) is observed in relation to *Dendrochronologia* journal with 130%. In accordance with the previous analysis, the best level of reduction in the frequency of publication is 3 times/year,

Table 4
Target inputs and percentage increase of eigenfactor score (EGSC).

Journals	FRQ*	ApY*	EGSC initial value	EGSC target value	Increase
Silva Fenn	3	28	0.00227	0.00286	26.11%
New Forest	3	21	0.0014	0.00195	39.21%
Nat Area J	3	27	0.00103	0.00166	61.20%
Wood Fiber Sci	3	41	0.00233	0.00380	63.10%
J Forest	3	50	0.00272	0.00473	74.01%
Agroforest Syst	3	45	0.00207	0.00421	103.25%
Iawa J	3	24	0.00119	0.00248	108.26%
Forest Chron	3	40	0.0018	0.00379	110.36%
Silvae Genet	4	31	0.00083	0.00180	116.55%

Table 5
Target inputs and percentage increase of *h*-index (*H*).

Journals	FRQ*	ApY*	*H* initial value	*H* target value	Increase
Ann Forest Sci	4	32	24	30.04	25%
Eur J Forest Res	3	30	17	25.33	49%
J Forest Econ	3	15	8	13.88	74%
Tree Genet Genomes	4	38	18	31.46	75%
Dendrochronologia	3	17	7	16.12	130%

while the articles published per year should be 17. This optimal pair can lead to an increase in the journal's *h*-index from 7 to 16.12.

According to Table 6, the largest margin of increase is that of *Forest Products Journal* with 84%. This involves an increase in its 5-year impact factor (IF5) from the current value of 0.608–1.12. In order for the journal to achieve the best publishing practice and reach the benchmark of highest efficiency, the frequency of publication input should be decreased to 3 times per year. Moreover, the number of articles published per year should be decreased to 36.

4.3.5. Comparing the proposed and current rankings of journals

A correlation coefficient test is performed in order to examine the association between the rankings of journals obtained using the DEA method with other rankings published, such as the Scimago Journal Ranking (SJR) for 2010, and the ranking of forestry journals presented by Vanclay (2008a). The measure used for this purpose is Pearson's correlation.

In the next table (Table 7), the rankings obtained by SJR and DEA are presented. As can be seen, only the journals with both rankings (49 out of 54 journals) were examined in the correlation analysis. The rankings of the SJR were obtained for the year 2010.

The numerical rankings for SJR and input efficiency (DEA) were assigned, based on Table 8.

The correlation of the two rankings presented in Table 8 is 0.745 and statistically significant (p-value < 0.001). This result shows there is quite a strong positive relationship between the two examined rankings.

In the next table (Table 9), the rankings of forestry journals are presented based on each journal's impact factor and *h*-index, as presented by Vanclay (2008a). This ranking list concerns forestry journals covering a time period from 2000 to 2007.

The numerical rankings for Vanclay (2008a) and input efficiency (DEA) were assigned, based on the following table.

The two rankings presented in Table 10 have a correlation of 0.496, which is statistically significant (p-value < 0.001), and can be considered adequate, given the fact that Valclay's (2008a) ranking of forestry journals is examined for the time period 2000–2007, while the data in the current study have been examined according to WoS data up to the year 2010.

Table 6
Target input and percentage increase of 5-year impact factor (IF5).

Journals	FRQ*	ApY*	IF5 initial value	IF5 target value	Increase
Plant Ecol	7	73	2.184	2.36	8%
J Forest	3	50	1.465	1.63	11%
Agroforest Syst	3	45	1.245	1.45	16%
Wood Fiber Sci	3	41	1.123	1.31	17%
Trees-Struct Funct	6	45	1.9	2.23	18%
Holzforschung	5	59	1.402	1.72	23%
Silvae Genet	4	31	0.798	1.03	29%
Forest Chron	3	40	0.845	1.3	54%
Can J Forest Res	11	142	2	3.43	72%
Tree Physiol	12	87	2.686	4.73	76%
Forest Prod J	3	36	0.608	1.12	84%

Table 7
Comparison of the ranking of forestry journals proposed by input efficiency (DEA) and SJR (2010).

Journal	Input efficiency (DEA)	SJR	Ranking SJR	Ranking DEA
Agricultural and Forest Meteorology	100%	Q1	1	1
Agroforestry Systems	72%	Q2	2	2
Allgemeine Forst und Jagdzeitung	31%	Q3	3	4
Annals of Forest Science	54%	Q4	4	3
Applied Vegetation Science	100%	Q1	1	1
Austrian Journal of Forest Science	35%	Q3	3	3
Baltic Forestry	18%	Q3	3	4
Canadian Journal of Forest Research-Revue Canadienne de Recherche Forestiere	94%	Q1	1	2
Cerne	10%	Q3	3	4
Ciencia Florestal	25%	Q3	3	4
Croatian Journal of Forest Engineering	35%	Q3	3	3
Dendrobiology	43%	Q3	3	3
Dendrochronologia	97%	Q1	1	2
European Journal of Forest Research	73%	Q1	1	2
Forest Ecology and Management	100%	Q1	1	1
Forest Pathology	50%	Q1	1	3
Forest Policy and Economics	49%	Q2	2	3
Forest Products Journal	27%	Q2	2	4
Forest Science	100%	Q1	1	1
Forestry	100%	Q1	1	1
Holzforschung	77%	Q1	1	2
Iawa Journal	73%	Q1	1	2
International Forestry Review	38%	Q2	2	3
International Journal of Wildland Fire	100%	Q1	1	1
Journal of Forestry	41%	Q2	2	3
Journal of Forest Economics	92%	Q2	2	2
Journal of Forest Research	31%	Q2	2	4
Journal of Tropical Forest Science	17%	Q2	2	4
Journal of Vegetation Science	100%	Q1	1	1
Madera y Bosques	15%	Q4	4	4
Natural Areas Journal	69%	Q2	2	2
New Forests	51%	Q2	2	3
Northern Journal of Applied Forestry	37%	Q2	2	3
Plant Ecology	57%	Q1	1	3
Revista Arvore	13%	Q3	3	4
Revista Chapingo Serie Ciencias Forestales y Del Ambiente	6%	Q4	4	4
Scandinavian Journal of Forest Research	46%	Q2	2	3
Silva Fennica	67%	Q2	2	2
Silvae Genetica	68%	Q2	2	2
Southern Forests	30%	Q2	2	4
Southern Journal of Applied Forestry	42%	Q2	2	3
Sumarski List	4%	Q4	4	4
Tree Genetics & Genomes	89%	Q1	1	2
Tree Physiology	80%	Q1	1	2
Tree-Ring Research	100%	Q1	1	1
Trees-Structure and Function	81%	Q1	1	2
Western Journal of Applied Forestry	36%	Q2	2	3
Wood and Fiber Science	67%	Q2	2	2
Wood Science and Technology	100%	Q1	1	1

Nevertheless, the ranking proposed by Vanclay (2008a) and SJR (2010) differs from that proposed by the DEA method, as all the data provided to the DEA method (inputs and outputs) are taken into consideration in order to arrive at an efficiency, based on which the ranking is proposed. Consequently the ranking proposed by the DEA method integrates all the available data making the ranking more complete, instead of ranking each journal individually based on a single measure, such as the *h*-index or the IF.

Table 8
Numerical rankings of SJR and input efficiency (DEA).

SJR	Input efficiency (φ) DEA	Rank
Q1	100%	1
Q2	(66.6, 99.9]%	2
Q3	(33.3, 66.6]%	3
Q4	(0, 33.3]%	4

Table 9
Comparison of the ranking of forestry journals proposed by input efficiency (DEA) and the ranking proposed by Valclay (2008a).

Journal	Input efficiency (DEA)	Valclay (2008a)	Ranking Valclay (2008a)	Ranking DEA
Agricultural and Forest Meteorolgy	100%	A1	1	1
Forest Ecology and Management	100%	A1	1	1
Tree Physiology	80%	A1	1	2
Plant Ecology	57%	A1	1	3
Canadian Journal of Forest Research	94%	A1	1	2
Forest Science	100%	A1	1	1
Journal of Forestry	41%	A1	1	3
Journal of Vegetation Science	100%	A1	1	1
Trees Structure and Function	81%	A1	1	2
International Journal of Wildland Fire	100%	A1	1	1
Annals of Forest Science	54%	A	2	3
Agroforestry Systems	72%	A	2	2
Scandinavian Journal of Forest Research	46%	A	2	3
Holzforschung	77%	A	2	2
Forest Policy and Economics	49%	A	2	3
Forestry	100%	A	2	1
Applied Vegetation Science	100%	A	2	1
Silva Fennica	67%	A	2	2
Forest Products Journal	27%	A	2	3
Forestry Chronicle	43%	A	2	3
Wood Science and Technology	100%	A	2	1
International Forestry Review	38%	A	2	3
Forest Pathology	50%	A	2	3
New Forests	51%	A	2	3
Dendrochronologia	97%	A	2	2
Wood and Fiber Science	67%	A	2	2
Revista Arvore	13%	A	2	3
Southern Journal of Applied Forestry	42%	B	3	3
Tree-ring Research	100%	B	3	1
Silvae Genetica	68%	B	3	2
Allgemeine Forst - und Jagdzeitung	72%	B	3	2
Journal of Forest Economics	92%	B	3	2
Iawa Journal	73%	B	3	2
Western Journal of Applied Forestry	36%	B	3	3
Australian Forestry	85%	B	3	2
Jounal of Tropical Forest Science	17%	B	3	3
Invest Agraria Sistemas y Recursos Forestales	82%	B	3	2
Nothern Journal of Applied Research	37%	B	3	4
European Journal of Forest Research	73%	B	3	2
Ciencia Florestal	25%	B	3	3
Journal of Forest Research	31%	B	3	3
Cerne	10%	B	3	4
Dendrobiology	43%	B	3	4
Baltic Forestry	18%	C	4	4
Madera y Boscued	15%	C	4	3
Sylwan	3%	C	4	4

Table 10
Numerical rankings of Valclay (2008a) and input efficiency (DEA).

Valclay (2008)	Input efficiency (φ) DEA	Rank
A1	100%	1
A	(66.6, 99.9]%	2
B	(33.3, 66.6]%	3
C	(0, 33.3]%	4

5. Conclusions and further suggestions

An examination of the efficiency of journals can lead to a large number of proposals and suggestions and even to corrections of some "inadequate practices" in terms of publishing policies on behalf of journals, in order to achieve the optimal efficiency and therefore the optimal inputs and outputs. The present study has shown that only a small fraction of the 54 forestry journals included in the ISI bibliometric database, which numbers some of the most prestigious journals in the field of forestry, achieved maximum efficiency, indicating that there is still space for improving quality even at the highest levels. Furthermore, within the framework of the study, the examined forestry journals were ranked on efficiency, and several suggestions were made concerning the target outputs of the study, which were defined as being the eigenfactor score (EGSC), h-index (H) and 5-year impact factor (IF5). These suggestions are analytically presented in Tables 4, 5 and 6. Also in the 2nd stage analysis of the current study, an exogenous factor that affects efficiency was examined. In the latter analysis, journals with a current frequency of publication of 6 or fewer times a year appear to be more efficient than those with a higher frequency of publication.

Table 11
Mean values of inputs and outputs of fully efficient journals.

$\overline{FRQ}$	$\overline{ApY}$	$\overline{EGSC}$	$\bar{H}$	$\overline{IF5}$
9	73	0.00925	57.77	2.197

According to Table 2, only 9 journals among a total of 54 are fully efficient. The mean values of all inputs ($\overline{FRQ}$, $\overline{ApY}$) and outputs ($\overline{EGSC}$, $\bar{H}$, $\overline{IF5}$) of fully efficient journals are presented in Table 11. The analysis indicates the mean inputs of efficient journals, and proposes that the optimal pairs of mean frequency of publication ($\overline{FRQ}$) and mean articles per year published ($\overline{ApY}$) are 9 times a year and 73 articles, respectively. A journal adopting the previous mean input values could reach a level of 0.00925 as an average eigenfactor score ($\overline{EGSC}$), 57.77 as an average h-index ($\bar{H}$) and, finally, 2.197 as an average 5-year IF ($\overline{IF5}$). The latter suggestions which involve the examined journals are regarded as requiring a long-term period of implementation. This derives from the fact that, for most of the journals, all the inputs and outputs concern data that are taken from the date of inclusion of the journal until the present time. Thus, any suggestion concerning changes to the inputs and outputs is expected to increase the indices examined (EGSC, H, IF5), but only after a considerable period of time has passed since the implementation of the specific changes.

Nevertheless, we must note that our analysis has been based purely on quantitative measurements, concerning both the DEA inputs and outputs. This was done mainly due to the fact that to incorporate more complex measurements in the analysis, such as the quality of a publication, is an extremely complicated task and prone to subjectivity. Despite the latter limitations, the quantitative suggestions deriving from the current study indirectly also imply changes in qualitative characteristics. For instance, the suggestion to reduce the source items of a journal (published citable papers) involves changes in qualitative characteristics. A reduction in the number of source items primarily means – apart from reducing "non-citable items" – selecting more high-quality articles for publication, and rejecting articles of a lower quality, that do not contribute to an increase in the journal's performance over time. We have shown though a modeling approach that a reduction in the number of publications of "lesser impact" (not at all or merely citable), on the one hand, will increase the IF, as a natural outcome by definition, while at the same time achieving an increase in the journal's h-index too (contrary to the intuitive belief that more articles should lead to higher h-indices), which may be attributed to the fact that less citable items are far from the h-core papers that essentially contribute towards increasing h-index values.

Based on the existing data from WoS (2010), the analysis proposes certain actions (exact numbers for reducing the frequency of publication and articles per year) to the examined journals, so as to improve their quality by increasing certain indices. Each journal can then adapt the recommended actions, according to its internal procedures used for the selection of papers.

Appendix A. Definition of the indices

The *journal h*-index is the highest number h of articles in a journal that have each received h or more citations (Braun et al., 2005, 2006).

The *impact factor* of a journal for a given year is the average number of citations received per paper published in that journal during the two preceding years; for instance, the 2011 IF is given by: $\text{IF} = C_{2011}^{2009-2010}/N_{2009-2010}$, where $N_{2009-2010}$ is the number of articles published in the specific journal for the years 2009 and 2010, while $C_{2011}^{2009-2010}$ is the number of citations received by these publications in 2011 (Garfield, 1955).

The *5-year impact factor* of a journal is the IF calculated by dividing the number of citations in the given year by the total number of articles published in the five previous years (Garfield, 1998).

The *eigenfactor score* is based on the number of times articles from the journal published in the past five years have been cited in a given year, but it also considers which journals have contributed these citations, so that highly-cited journals will influence the network more than lesser-cited journals. As a measure of importance, the eigenfactor score increases in accordance with the total impact of a journal (Bergstrom, 2007; West, Bergstrom, & Bergstrom, 2010).

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