142. Jahrgang (2025), Heft 4, S. 297–320

Austrian Journal of Forest Science
Centralblatt für das gesamte Forstwesen

A Data-driven Two-Stage Bootstrap Approach for Analyzing Forestry Technical Efficiency in Sweden

Ein daten-basierter zwei-stufiger Bootstrap-Ansatz zur Analyse der forsttechnischen Effizienz in Schweden

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Keywords: Double Bootstrap, contextual variables, data envelopment analysis, technical efficiency, Swedish forest sector

Schlüsselbegriffe: Double Bootstrap, Kontextvariablen, Data Envelopment Analysis, technische Effizienz, schwedischer Forstsektor

Abstract

The purpose of this research is to conduct a performance assessment of forestry operations across counties in Sweden. We employed a two-stage double bootstrap data envelopment analysis (DEA) approach to evaluate the efficiency of production units. The first stage examines the technical efficiency scores by a variable returns-to-scale slack-based DEA model. In the second stage, we applied the double bootstrap DEA model to determine the impact of explanatory variables that affect the efficiency of forested counties. To the best of our knowledge, this is the first attempt to forestry technical efficiency assessment in Sweden by using double Bootstrap two-stage data envelopment analysis model. Overall, this study highlights the superiority of the bootstrap DEA approach in identifying inefficiencies and evaluating efficiency under uncertainty, providing valuable insights for forestry practices. Our results indicated that approximately 43% of the counties studied are fully efficient, reflecting the high overall efficiency score of 0.8512 in the Swedish forest sector. We show that the two

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contextual variables, regional density and deadwood, have a negative influence. In contrast, precipitation and gross domestic product have positive coefficients, indicating a positive relationship with efficiency. To address uncertain measurement bias, a double bootstrap DEA model is employed, resulting in an adjusted overall efficiency score of 0.7480. The estimation results have varying degrees of uncertainty for contextual variables, emphasizing the robustness of the influences on the true efficiency of forested counties in Sweden.

Zusammenfassung

Ziel dieser Studie ist die Leistungsbewertung forstwirtschaftlicher Betriebe in Landkreisen in Schweden. Wir verwendeten einen zweistufigen Double-Bootstrap-Ansatz der Data Envelopment Analysis (DEA), um die Effizienz der Produktionseinheiten zu bewerten. In der ersten Stufe untersuchten wir die technischen Effizienzwerte mithilfe eines DEA-Modells mit variablen Skalenerträgen. In der zweiten Stufe wendeten wir das Double-Bootstrap-DEA-Modell an, um den Einfluss von erklärenden Variablen auf die Effizienz bewaldeter Landkreise zu bestimmen. Unseres Wissens ist dies der erste Versuch, die technische Effizienz der Forstwirtschaft in Schweden mithilfe eines zweistufigen Double-Bootstrap-DEA-Modells zu bewerten. Insgesamt unterstreicht diese Studie die Überlegenheit des Bootstrap-DEA-Ansatzes bei der Identifizierung von Ineffizienzen und der Bewertung der Effizienz unter Unsicherheit und liefert wertvolle Erkenntnisse für die forstwirtschaftliche Praxis. Die Ergebnisse zeigen, dass etwa 43% der untersuchten Landkreise voll effizient arbeiten, was den hohen Gesamteffizienzwert von 0.8512 im schwedischen Forstsektor widerspiegelt. Wir zeigen, dass die beiden Kontextvariablen regionale Dichte und Totholz einen negativen Einfluss haben. Im Gegensatz dazu weisen Niederschlag und Bruttoinlandsprodukt positive Koeffizienten auf, was auf einen positiven Zusammenhang mit der Effizienz hindeutet. Um Messfehler zu berücksichtigen, wird ein doppeltes Bootstrap-DEA-Modell verwendet, das zu einem angepassten Gesamteffizienzwert von 0.7480 führt. Die Schätzergebnisse weisen unterschiedliche Unsicherheitsgrade für die Kontextvariablen auf, was die Robustheit der Einflüsse auf die tatsächliche Effizienz bewaldeter Landkreise in Schweden unterstreicht.

1 Introduction

Approximately 70% of Sweden's total land area is covered by forests and this proportion has remained consistently stable over an extended period. Swedish forestry is deemed to be sustainably managed in the long term. The legislative framework in Sweden ensures a harmonious equilibrium between production objectives and environmental considerations within the realm of multifunctional forestry practices. The primary objective of the forestry standard established by the Swedish Endorsement of Forest Certification is to promote economically viable and valuable forest production, while simultaneously safeguarding biodiversity, cultural heritage, and social and aesthetic values (Lundmark *et al.* 2014). Considering the need to maintain equilibrium between the aforementioned multifunctional forestry values—i.e., inputs of forest resources and their associated outputs, the forest sector assumes a critical role in Sweden. This involves the pursuit of strategies aimed at achieving an optimal balance in the utilization of forest resources (Eurostat 2019). To do this, technical efficiency is a good indicator. Technical efficiency assesses DMU's success in producing more outputs by using fewer inputs. A DMU is said to be technically efficient if and only if it produces the maximum output from the minimum quantity of inputs.

In so doing, a well-documented managerial tool, known as data envelopment analysis (DEA), was initially developed by Charnes *et al.* (1978). DEA is a nonparametric methodology used to analyze the relative efficiency of a set of comparable and homogeneous decision-making units (DMUs). These DMUs are homogeneous in the sense that they consume multiple incommensurate inputs to produce multiple incommensurate outputs. DEA estimates the production technology set using an axiomatic foundation. It empirically constructs the smallest production set containing data and satisfying a minimum of production economic regularities. DEA can be easily extended to cases to determine the most efficient region, provides information about sources of inefficiency, it enables us to make decisions on funding, planning, or management. Stochastic frontier analysis (SFA) on the other hand is a parametric approach. it makes a priori assumptions about the structure of the production possibility set. It allows us to assume a stochastic relationship between the inputs and outputs. In particular, it allows us to assume that deviations from the frontier may reflect not only inefficiencies but also noise in the data. In terms of methods, DEA is an approach based on mathematical programming, while the SFA approach has a much more connection to econometric theory. In the choice between DEA and SFA, a key question is whether one wants flexibility in the mean structure or precision in the noise separation.

In applied studies utilizing DEA, it is common to observe point estimates of inefficiency without any consideration or discussion of the uncertainty surrounding these estimates. Many research papers describe efficiency as being computed or calculated, rather than estimated, and the results are frequently referred to as efficiencies rather than efficiency estimates. To tackle this, the DEA literature suggests the utilization of bootstrap methods as well-documented approaches. These methods aim to estimate true efficiency by considering the increased uncertainty arising from potential measurement errors (Simar & Wilsons 2004; Tziogkidis 2012). Another limitation of the DEA application is its inherent challenges related to homogeneity. These challenges emerge when there are contextual factors that influence the environmental efficiency of DMUs, leading to unfair comparisons among forest managers. According to Banker and Natarajan (2008), contextual variables include both exogenously fixed factors and those that are within the control of DMUs' managers. To address these issues and ensure a comprehensive evaluation process, managers should incorporate two-stage efficiency measurements. In the first stage, they calculate relative efficiency to assess the performance of DMUs. In the second stage, they employ various regression models to independently account for the effects of contextual factors and obtain reliable results (Djordjević *et al.* 2023). This approach enables a more accurate assessment of DMUs' performance by accounting for the influence of contextual variables.

To the best of our knowledge, there has been no prior research conducted to evaluate the technical efficiency of the forest sector in Sweden using the DEA and simultaneous double bootstrap approaches, despite the significant importance of this sector in the Europe. This creates a remarkable opportunity to delve into the sector's performance and uncover novel insights. Therefore, considering this research gap, the primary contribution of this study is to fill this void by:

- Computing the technical efficiency of forest sectors in different counties of Sweden (our studied DMUs) by incorporating a Slack-based DEA (SBM-DEA) model

- Estimating the bias-corrected efficiency of the studied DMUs and subsequently ranking them based on the obtained results using the bootstrap DEA approach.

- Justifying the impact of contextual factors on the DMUs' true efficiency scores by developing a double bootstrap regression model

The remaining sections of this practical research are structured as follows: Section 2 reviews related studies in various practical cases and forest management. Section 3 provides a detailed description of the applied DEA, bootstrap, and double bootstrap regression analyses. Section 4 applies the proposed procedure to a real dataset in the Sweden forest sector. Sections 5, 6 and 7 present the obtained results, discussion, and concluding remarks, respectively.

2 Literature review

In the realm of forestry and its related industries, numerous conventional DEA models have been employed over the past few decades to evaluate technical efficiency (TE). Researchers have endeavored to adapt these widely used DEA models to align with the specific requirements of their case studies. The extended novel DEA models are essentially derived from the fundamental DEA models—CCR (Charnes et al. 1978) and BCC (Banker et al. 1984). These models enable the measurement of TE under constant returns to scale (CRS) and variable returns to scale (VRS) production frontiers, respectively.

DEA is known as a data-oriented approach, which may encounter sensitivity issues pertaining to data orientation. The pioneering models in this field adopt a radial approach, focusing on proportional changes in inputs or outputs. However, in the context of real-world businesses, not all inputs or outputs exhibit proportional behavior. To address this limitation, non-radial variations of the SBM-DEA models have been developed, capable of accommodating non-proportional relationships. Despite significant advancements made over the last five decades, a definitive superior DEA method has yet to emerge. The basic models (CCR and BCC) continue to dominate various applications. For instance, Kao and Yang (1991) were the first to attempt TE assessment of the Taiwan Forestry Bureau within the DEA framework. Since then, numerous further research studies have been conducted in diverse scenarios involving forestry and forest-based sectors, utilizing different traditional DEA models (Kao 2010, Zadmirzaei *et al.* 2016; Obi & Visser 2017; Strange *et al.* 2021; Jingxin *et al.* 2021; Amirteimoori *et al.* 2023a, Jin *et al.* 2025; Wang *et al.* 2025). More recently, there has been a wave of research focused on developing enhanced fuzzy SBM-DEA models to address the challenges posed by uncertain environments. These studies have also integrated novel artificial intelligence (AI) algorithms to quantify both technical efficiency and environmental efficiency, specifically targeting the reduction of CO_2 emissions in forest harvesting systems. Noteworthy contributions in this field include the works of Amirteimoori *et al.* (2023b), Zadmirzaei *et al.* (2024) and Amirteimoori *et al.* (2024).

Moreover, the DEA model relies on the assumption that decision-makers operate in homogeneous environments. However, this assumption proves inadequate in the context of environmental systems, where the generation of environmental benefits or negative impacts is influenced by variables that are beyond the control of managers. These variables are referred to as „external exogenous, non-discretionary and/or environmental/contextual factors“. Generally, two approaches can be used to consider these influencing factors on performance results: the modified DEA models eliminate non-discretionary factors, while multi-stage DEA and regression models adjust the environmental/contextual effects. Banker and Morey (1986) were the pioneering researchers who introduced the DEA model for managing exogenous factors. Subsequently, several researchers explored this intriguing approach, including Syrjanen (2004), Camanho *et al.* (2009), Amirteimoori *et al.* (2014), and Taleb *et al.* (2018). Moreover, a limited number of studies addressed the impact of exogenous environmental factors on forest resources. For example, Hof *et al.* (2004) employed a four-stage methodology to mitigate the influence and bias introduced by exogenous factors. Macpherson *et al.* (2013) criticized previous work for solely presenting adjusted results without comparing them to the unadjusted ones. Consequently, they conducted a comprehensive analysis in their recent study, comparing adjusted and unadjusted results to emphasize the significance of considering exogenous factors in environmental assessments, using the basic DEA model and regression analyses. Zadmirzaei *et al.* (2017) recommended specific DEA models to effectively control exogenously fixed factors and ensure accurate evaluations. They argued that traditional DEA approaches tend to overestimate the efficiency of DMUs. In an uncertain environment, Zadmirzaei *et al.* (2019) developed a novel marginal chance-constrained DEA model, which accounted for external exogenous inputs and hybrid outputs. A recent study introduced a fuzzy nondiscretionary DEA model, integrated with an artificial immune system, for measuring technical efficiency and identifying optimal values of DMUs (Amirteimoori et al. 2021). More recently, Tan *et al.* (2023) firstly applied a super-efficient DEA model to evaluate forestry eco-efficiency (FECO) in 30 Chinese provinces and cities from 2008 to 2021. In the second stage, they also used the Tobit regression model to explore contextual factors affecting FECO and gain insights into multifunctional forestry development.

To improve the methodological robustness and precision of DEA studies, it is imperative to integrate uncertainty measures and acknowledge the inherent estimation aspect of efficiency values. By embracing a comprehensive approach that diligently considers and quantifies uncertainty, researchers can deliver a more refined and dependable assessment of the technical efficiency exhibited by DMUs. This elevated approach holds the potential to facilitate well-informed decision-making processes and foster a deeper comprehension of the merits and constraints associated with DEA as an effective management tool. One well-established method for addressing this issue is the bootstrap technique, which has been widely employed in DEA literature to estimate the true efficiency value by considering the increased uncertainty associated with potential measurement errors. Bootstrap DEA models have emerged as a crucial tool in the realm of diverse banking systems and manufacturing industries, showcasing their wide-ranging development and application (Aggelopoulos & Georgopoulos 2017; Gardijan Kedžo & Tuškan Sjauš 2021; Samad & Armstrong 2022; Wu & Wang 2022; Yue & Yin 2023). These models have been meticulously crafted and deployed to address intricate challenges and optimize decision-making processes within the dynamic landscape of these sectors. However, there has been limited research on the implementation of the Bootstrap DEA approach specifically in industries related to natural resources. For instance, Long *et al.* (2020) employed double bootstrap procedures in their study to conduct DEA and examine the technical efficiency within the context of intensive white-leg shrimp farming in Vietnam. Moreover, Shahi *et al.* (2022) utilized DEA models' measurement capabilities to optimize the performance modeling of sawmills in Ontario. The robustness and benchmarking abilities of the bootstrap DEA models are employed to obtain reliable technical efficiency scores. On the other hand, the artificial neural network (ANN) models utilize abstract learning from a restricted data set to enhance predictive power in the analysis of sawmill performance.

3 Materials and methods

Data envelopment analysis is a powerful benchmarking tool for examining the relative technical efficiency of homogeneous decision-making units (DMUs) with multiple incommensurate inputs and outputs. In efficiency estimation using DEA approach, an empirical production possibility set is constructed using the observed DMUs in the sample and the boundary points of this production set are considered as efficient frontier. DEA is frequently used to assess the relative efficiency in the forest sector. In efficiency estimation in the industrial sector, choosing the underlying model is an important issue. In performance evaluation in the forest sector, we found that most of the DMUs do not operate on an optimal scale. Therefore, we think the variable returns to scale models are more appropriate than the constant returns to scale models. In our real case, to evaluate the relative efficiencies of the DMUs in the forest sector, we have used the slack-based measure (SBM) model of Tone (2001) in variable returns to scale environment. The reason for using SBM model of Tone (2001) is that this model is a non-radial model that deals directly with inputs excess and outputs shortfall. In this sense, input-output inefficiencies are considered. Moreover, in our real application in the forest sector in Sweden, we found that most of the sectors do not perform at an optimal scale. In this sense, as Pai *et al.* (2020) suggested, the variable returns to scale models are more appropriate to evaluate the performances of the DMUs than the constant returns to scale models.

Suppose we have *J* DMUs to be evaluated. Each *DMU* uses *M* inputs to generate *S* outputs. Specifically, DMU_j uses the input vector $x_j = (x_{1j}, x_{2j}. \dots, x_{Mj}) \in \mathbb{R}_+^M$ to produce the output vector $y_j = (y_{1j}, y_{2j}. \dots, y_{Sj}) \in \mathbb{R}_+^S$. The mathematical formulation of the SBM model of Tone (2001) in variable returns to scale environment is as follows:

$$
\begin{aligned}
&\beta_o^* = Min\ \beta - \frac{1}{M}\sum_{i=1}^{M}\frac{s_i}{x_{io}} \\
&s.t. \\
&\beta + \frac{1}{S}\sum_{r=1}^{S}\frac{d_r}{y_{ro}} = 1, \\
&\sum_{j=1}^{J}\lambda_j x_{ij} + s_i = \beta x_{io}, \qquad i = 1, \dots, M, \\
&\sum_{j=1}^{J}\lambda_j y_{rj} - d_r = \beta y_{ro}, \qquad r = 1, \dots, S, \\
&\sum_{j=1}^{J}\lambda_j = \beta, \\
&s_i, d_r, \lambda_j \geq 0, \qquad for\ all\ i, j, r.
\end{aligned} \tag{1}
$$

In this model, suppose $(\beta^*, \lambda^*, s^*, d^*)$ is an optimal solution. DMU_p is said to be full-efficient if and only if $\beta_o^* = 1$. If DMU_p is not efficient, its efficient projection is (x_p^*, y_p^*) in which

$$x_p^* = \sum_{j=1}^{J} \lambda_j^* x_j \qquad (2)$$
$$y_p^* = \sum_{j=1}^{J} \lambda_j^* y_j$$

As all we know, in classic DEA models, we construct an empirical production possibility set and the boundary points of this set is considered as our underlying efficient frontier. The relative technical efficiencies of the DMUs are usually overestimated by DEA. In other words, the DEA efficiency scores might be biased. In this sense, the use of bootstrapping techniques is useful to derive bias-corrected efficiency scores. Bootstrap DEA improves the estimation because it uses sampling variations to analyse the sensitivity of the estimated efficiency scores.

In the first stage of the double bootstrap DEA procedure, the following bootstrap is used to obtain a bias-corrected efficiency score $\tilde{\beta}_{jk}^*$ as an estimate for β_o^*. Toward this end, we use the following modified four-step procedure proposed by Simar and Wilson (2007):

Step 1: Solve the SBM model (1) to calculate β_j^*, the SBM efficiency score of

$DMU_j: (x_j, y_j)$ for $j = 1, 2, \dots, J$.

Step 2: For $k = 1$ to 2000, repeat the following steps:

Step 3: Select at random with replacement $\tilde{\beta}_{jk}^*: j = 1, \dots, J$ from $\{\beta_1^*, \beta_2^*, \dots, \beta_J^*\}$.

Step 4: Set $x_j^{*k} = \frac{\beta_j^*}{\tilde{\beta}_{jk}^*} x_j$, and calculate the $\tilde{\beta}_{jk}^*$, the SBM efficiency score of

$D\widetilde{M}U_{jk}: (x_j^{*k}, y_j)$ for $j = 1, 2, \dots, J$ by solving the following LP models:

$$
\begin{aligned}
&\tilde{\beta}^{*}_{jk} = Min\,\beta - \frac{1}{M}\sum_{i=1}^{M}\frac{s_i}{x_{io}} \\
&s.t. \\
&\beta + \frac{1}{S}\sum_{r=1}^{S}\frac{d_r}{y_{ro}} = 1, \\
&\sum_{j=1}^{J}\lambda_j x^{*k}_{ij} + s_i = \beta x_{io}, \qquad i = 1, \dots, M, \\
&\sum_{j=1}^{J}\lambda_j y_{rj} - d_r = \beta y_{ro}, \qquad r = 1, \dots, S, \\
&\sum_{j=1}^{J}\lambda_j = \beta, \\
&s_i, d_r, \lambda_j \geq 0, \qquad for\ all\ i, j, r.
\end{aligned}
\tag{3}
$$

$\tilde{\beta}^{*}_{jk}$ is considered as an estimate for β^{*}_{j}. By repeating the bootstrap procedure, we analyze the sensitivity of the DMU_j: (x_j, y_j) to the estimated frontier made by $D\widetilde{M}U_{jk}$: (x^{*k}_{j}, y_j) .

Now, in the second stage, 2000 bootstrap estimates are performed to evaluate the impact of non-discretionary (or explanatory) variables on bias-corrected efficiency by using the following truncated regression model:

$$
Log(\beta^{*}_{j}) = \sum_{d=1}^{D}\mu_d z_{dj} + \varepsilon_j \tag{4}
$$

in which β^{*}_{j} is the SBM efficiency of DMU_j obtained from Model 2 and z_{dj}: $d = 1, \dots, D$, are contextual variables and ε_j is an error term. Moreover, μ_d: $d = 1, \dots, D$ are the weights corresponding to the contextual variables.

4 Case study and observed data

This application utilizes a comprehensive panel dataset encompassing the years 2018 to 2022, focusing on 21 forested counties located in Sweden. The specific regions and their corresponding counties can be found in Table 1. Thus, the total number of observations we have, which is 21 forested counties studied (or DMUs), meets the rule of thumb in DEA terminology for selecting the appropriate number of DMUs, as well as their respective inputs and outputs (Cooper *et al.* 2011) ($n \geq Max\{MS, 3 * (M + S)\}$ in which J, M and S are respectively the number of DMUs, inputs and outputs). Given the limitations of our dataset and the existing body of research in the forest sector (Gutiérrez & Lozano 2013; Hoogstra & Burger 2013; Zadmirzaei *et al.* 2017 and 2019; Mohammadi Limaei 2020; Amirteimoori *et al.* 2021; Susaeta *et al.* 2024), two inputs (x_j) — „forest area" and „forest employees", and three corresponding outputs (y_j) — „biomass" (the total mass of living components of a tree above the stump level), „growing stock" (the volume of timber available for harvest or currently growing in a specific region), and „gross volume of felled trees" (the total volume of trees that have been cut down within a forest stand) were collected from Swedish Forest Agency (http://pxweb.skogsstyrelsen.se/pxweb/en/Skogsstyrelsens%20statistikdatabas/?rxid=03eb67a3-87d7-486d-acce-92fc8082735d) and from Swedish forest statistic (Skogsdata 2023). It is worth highlighting that the county-level dataset utilized in this study encompasses the above variables, which collectively encapsulate the primary dimensions of land, labor, and output related to regional wood supply. Consequently, this data set constitutes a coherent set for comparative efficiency analysis, as the previously mentioned research has employed these variables with analogous measurement units. We selected these parameters because they represent the core operational resources and measurable outputs available consistently across all counties for the study period and because DEA is designed to work with such comparable input–output bundles without imposing a parametric production function (Charnes *et al.* 1978; Cooper *et al.* 2007). To ensure that differences in county size do not mechanically drive the results, the analysis uses a slacks-based SBM under a Variable Returns to Scale (VRS) assumption, which permits decomposition of overall inefficiency into pure technical and scale efficiency and thus distinguishes managerial performance from scale effects (Banker *et al.* 1984; Tone, 2001). Finally, bias-corrected bootstrap inference is applied in the second stage to test for any remaining association between size and efficiency (Simar & Wilson, 1998). Taken together, these standard methodological choices ensure that the selected variables are appropriate for the county-level wood-supply interpretation and guard against the frontier being an artefact of mixed-scale measurements or simple size premia.

Table 2 provides an overview of the statistics related to the inputs and outputs utilized in various DEA analyses.

Table 1: Different regions and counties in Sweden.

Tabelle 1: Verschiedene Regionen und Landkreise in Schweden.

Region	Counties
I-Norrland (DMU01-05)	Norrbotten, Västerbotten, Jämtland, Västernorrland, Gävleborg
II-Svealand (DMU06-12)	Dalarna, Värmland, Örebro, Västmanland, Uppsala, Stockholm, Södermanland
III-Götaland (DMU13-21)	Östergötland, Västra Götaland, Jönköping, Kronoberg, Kalmar, Gotland, Halland, Blekinge, Skåne

Table 2: Mean of the input and output variables.

Tabelle 2: Mittelwert der Eingabe- und Ausgabevariablen.

Counties	Input		Output		
	Forest area (10^3 ha)	Forest Employees (No.)	Biomass (million tons)	Growing stock (m³sk/ha)	Gross volume of felled trees (10^3 m^3)
Min	139	61	7.76	93	304
Max	5709	3766	177.1	205	8745
Mean	1330.19	1540.95	73.99	160.81	4447.05
Std	1442.11	957.78	53.14	29.72	2604.48
Median	700.00	1600.00	53.48	167.00	4141.00
Q1	383.00	714.00	28.51	142.00	2206.00
Q3	1625.00	2038.00	115.03	181.00	6693.00

Table 3 presents an overview of the utilization of contextual factors in regression analysis, aiming to identify the effects of exogenous elements on the competitiveness and efficiency of the forestry sector in Sweden. Hence, to enhance the strategic understanding of a country, certain macro-level managerial factors have been carefully examined based on the available data. These factors, sourced from (World Bank 2019a and 2019b), include: „GDP“ (serves as an economic performance indicator), „regional density—RD“ (calculates the ratio of forest area to land area, highlighting the spatial distribution of forests), „deadwood volume“ (regarded as both ecologically valuable and economically undesirable in terms of forest management challenges in the short term), „Mean Annual Temperature—TEMP“ and „Mean Annual Precipitation —PRECIP“ (representing climatic conditions).

Table 3: Descriptive statistics of the contextual variables for Sweden counties.

Tabelle 3: Deskriptive Statistiken der Kontextvariablen für schwedische Landkreise.

Variables	Description and unit of measures	Mean	STD	Maximum	Minimum
RD	The proportion of forest area within a specific county in Sweden (10^3 ha)	578.44	265.11	3387.1	27.02
GDP	Gross domestic product (mil SEK)	199947.66	78942.54	1340350.0	18810
TEMP	Mean annual temperature (°C)	6.66	1.85	8.7	2.2
PRECIP	Mean annual precipitation (mm)	713.83	69.26	835.4	571.8
Deadwood	The total volume of Standing deadwood (including veteran trees, stumps, and snags) (m^3/ha)	10.58	2.42	15	6.8

5 Results

5.1 SBM-DEA efficiency

We first applied the conventional SBM-DEA model to this data set. Toward this end, we pooled all data in a sample and each county–year observation is treated as a separate DMU. In this case, we considered 105 observations. The estimated efficiency scores, along with their improvement values, are listed in Table 4.

Table 4: SBM efficiency scores and improvement values (projection changes) of the studied DMUs.

Tabelle 4: SBM-Effizienzwerte und Verbesserungswerte (Projektionsänderungen) der untersuchten DMUs.

DMUs	Counties	SBM – DEA Efficiency	Forest area	Forest Employees	Biomass	Growing Stock	Gross volume of felled trees
01	Norrbotten	0.3345	2252.0686	481.5429	231.7284	113.6159	5832.4170
02	Västerbotten	1.0000	3958.0000	1616.0000	177.1000	113.0000	8745.0000
03	Jämtland	1.0000	3433.0000	714.0000	174.6700	128.0000	7953.0000
04	Västernorrland	1.0000	1848.0000	2579.0000	124.2700	147.0000	7609.0000
05	Gävleborg	0.9600	1542.4632	2408.0665	112.8868	154.5031	7800.5711
06	Dalarna	0.6172	2016.7785	659.4884	119.1371	148.2786	6157.6016
07	Värmland	0.8662	1274.2579	2157.3782	101.5080	186.4407	6695.5623
08	Örebro	0.6575	574.4646	462.7716	49.4031	172.0462	3790.4575
09	Västmanland	0.7212	297.7519	178.5692	27.4241	168.6023	2219.6768
10	Uppsala	1.0000	537.0000	486.0000	40.1900	173.0000	3725.0000
11	Stockholm	0.5261	261.4449	384.4077	24.4718	166.4506	1855.5457
12	Södermanland	1.0000	383.0000	238.0000	28.5100	175.0000	2860.0000
13	Östergötland	0.7273	629.5431	859.0103	59.8181	184.7353	4362.2701
14	Västra Götaland	1.0000	1419.0000	3766.0000	115.0300	191.0000	8174.0000
15	Jönköping	1.0000	746.0000	2695.0000	64.7900	181.0000	4723.0000
16	Kronoberg	0.9567	648.2741	988.6117	56.6483	153.2607	2931.9634
17	Kalmar	0.7833	687.4985	1281.1808	61.3029	179.5376	4738.2018
18	Gotland	1.0000	139.0000	61.0000	7.7600	134.0000	304.0000
19	Halland	0.9516	296.5451	1496.4054	35.8882	203.2572	2048.4279
20	Blekinge	1.0000	208.0000	625.0000	17.9800	205.0000	969.0000
21	Skåne	0.7744	379.0081	1096.6179	43.9919	189.6836	2392.3884
Mean		**0.8512**	**1127.4674**	**1214.9984**	**78.9098**	**163.9234**	**4553.7201**

It can be observed that most of the DMUs studied (*i.e.*, 9 out of 21) are fully efficient (score = 1), with an average efficiency score of approximately 0.851. Due to the non-radial variation of the applied SBM-DEA model, these fully efficient units enhance efficiency and productivity by increasing their outputs while reducing input levels. Conversely, the remaining units with efficiency scores less than 1 should improve their efficiency by implementing adjustments to their input and output datasets through projection changes. For instance, DMU05 (Gävleborg), which exhibits inefficient (score = 0.9600), should increase its first, second, and third outputs (*i.e.*, biomass, growing stock, and gross volume of felled trees) by 112.8868 million tons, 154.5031 m^3sk/ha, and 7800.5711 m^3, respectively, compared to the observed output values listed in Table 2. At the same time, there is a capacity to reduce the first and second inputs by 1542.4632 and 2408.0665, respectively. This adjustment would bring it closer to the production or efficiency boundary point. Similarly, the other inefficient forested counties should also apply the same procedure to increase their performance.

An important point to be noted is that forest area is considered as input and hence, inefficient DMUs must reduce inputs to become efficient. At first sight, it is not rational to reduce forest areas. However, the forest area we considered as input is a mix of productive and nonproductive areas and hence to become efficient, we suggest reducing nonproductive forest areas.

5.2 The results of first-stage bootstrap DEA

The bias-corrected efficiency of all the studied DMUs is computed using the first bootstrap DEA approach to rank them comprehensively. The results are described in Tables 5 and 6.

Table 5: Bootstrap-DEA efficiency and full ranking scores.

Tabelle 5: Bootstrap-DEA-Effizienz und vollständige Ranglistenergebnisse.

DMUs	Counties	Bias	Bias-corrected score	Rank
01	Norrbotten	0.1059	0.2414	21
02	Västerbotten	0.1148	0.8852	5
03	Jämtland	0.1054	0.8946	4
04	Västernorrland	0.1302	0.8698	8
05	Gävleborg	0.1419	0.8581	10
06	Dalarna	0.1107	0.5387	18
07	Värmland	0.1371	0.7741	13
08	Örebro	0.1708	0.5193	19
09	Västmanland	0.0933	0.6653	15
10	Uppsala	0.1052	0.8948	3
11	Stockholm	0.1620	0.3884	20
12	Södermanland	0.1309	0.8691	9
13	Östergötland	0.1107	0.6483	16
14	Västra Götaland	0.1202	0.8798	7
15	Jönköping	0.1179	0.8821	6
16	Kronoberg	0.1482	0.8518	11
17	Kalmar	0.0668	0.7575	14
18	Gotland	0.0739	0.9261	1
19	Halland	0.1617	0.8383	12
20	Blekinge	0.0961	0.9039	2
21	Skåne	0.1869	0.6204	17
Mean		**0.1234**	**0.7480**	

In Table 5, the bias-corrected efficiency of each DMU is determined by subtracting the bias from the initial efficiency scores, which are already calculated using the SBM-DEA model (Table 5). This adjustment is made by employing the Bootstrap DEA model, which ultimately enables an acceptable ranking of the DMUs. As a result, by quantifying the bias to be approximately 0.1234, the overall efficiency of all DMUs experienced a decrease from 0.8512 to 0.7480. In this case, DMU18 (Gotland) secured the top rank with an efficiency rating of 0.9261, while DMU01 (Norrbotten) attained the lowest position with an efficiency rating of 0.2414. The bias-corrected improved inputs and outputs are listed in Table 6.

Table 6: Bias-corrected improvement values of the studied DMUs.

Tabelle 6: Bias-korrigierte Verbesserungswerte der untersuchten DMUs.

Counties	Forest area	Forest Employees	Biomass	Growing Stock	Gross volume of felled trees
Norrbotten	1864.241	355.9413	223.1353	106.6892	5748.128
Västerbotten	2628.791	837.6189	178.7973	114.1054	8827.928
Jämtland	3003.469	500.5617	175.2736	128.4559	7979.089
Västernorrland	1258.042	1463.439	125.3731	148.2561	7672.997
Gävleborg	1415.924	2035.99	107.7211	142.6036	7669.812
Dalarna	1943.561	528.9152	115.0305	141.4617	6042.841
Värmland	928.2739	1359.442	96.6115	175.2905	6609.56
Örebro	566.508	394.6887	43.12009	163.535	3715.64
Västmanland	212.736	101.5069	22.96668	161.3741	2181.324
Uppsala	433.5987	349.4362	40.31598	173.5594	3736.241
Stockholm	247.9004	354.5135	22.14914	160.4094	1817.702
Södermanland	300.7178	173.3778	28.65033	175.5017	2867.038
Östergötland	487.9714	532.8766	50.75413	173.3956	4306.77
Västra Götaland	1351.319	3656.349	115.1058	191.0763	8176.979
Jönköping	549.6065	1848.188	65.27804	182.1781	4752.403
Kronoberg	433.7742	579.6347	54.04809	149.3546	2898.72
Kalmar	691.403	1243.565	57.34373	167.7674	4647.419
Gotland	129.2639	-30.4163	7.778551	134.1834	304.375
Halland	227.5103	1140.056	27.49768	197.081	2017.93
Blekinge	163.264	472.5651	18.03449	205.5299	971.2746
Skåne	276.3841	750.3685	34.24207	184.3217	2360.385
Mean	**910.2028**	**888.0294**	**76.62987**	**160.7681**	**4538.312**

5.3 The results of second-stage double bootstrap DEA

Lastly, the results of the double bootstrap regression analysis for the contextual variables and their impact on the bias-corrected efficiency score by double bootstrap DEA model are shown in Table 7.

Table 7: Results of double bootstrap regression for the contextual variables.

Tabelle 7: Ergebnisse der doppelten Bootstrap-Regression für die Kontextvariablen.

Variables	Coefficients	Standard Error	p-value	95% bootstrap confidence interval	
				Lower	Upper
RD	-9.9E-04	5.56E-05	0.0432	-1.4E-04	-8.7E-06
GDP	1.4E-07	8.78E-08	0.0401	1.7E-08	3.2E-06
TEMP	0.0291	0.02721	0.1611	2.1E-03	0.2321
PRECIP	0.0018	0.0004	0.0093	1.2E-04	0.0235
Deadwood	-0.0044	0.0114	0.0337	-0.0812	-0.0009

The coefficient values in Table 7 indicate the direction and significance of the relationship between each contextual variable and the bias-corrected efficiency score by double bootstrap DEA regression model. For instance, for the RD variable, an increase in the RD variable is associated with a negligible decrease in the efficiency score. Similarly, the Deadwood variable has a negative coefficient, indicating that an increase in deadwood results in a negligible decrease in the efficiency score. The coefficient –0.0044 for this variable shows that the percentage change in technical efficiency associated with a one-unit increase in deadwood is $100(e^{-0.0044} - 1) = -0.44$. The standard error of 0.0114 indicates a moderate amount of uncertainty in this estimate. In contrast, The PRECIP variable has a positive coefficient of 0.0018, indicating that an increase in precipitation is positively related to the efficiency scores. Likewise, a positive coefficient for GDP suggests that an increase in GDP leads to an increase in efficiency score. The standard error of 8.78E-08 suggests a relatively small amount of uncertainty in the estimation.

The p-values in the fourth column of Table 7 indicated that the variables RD, GDP, PRECIP and Deadwood are statistically significant. However, the TEMP variable has a p-value of 0.1611, indicating that it is not statistically significant.

6 Discussion

In this analysis, some extended DEA approaches have been employed to assess the relative efficiency of different forested counties in Sweden by considering the contextual variables. Toward this end, a modified SBM-DEA model was first applied to estimate the relative efficiency and improvement values of the studied DMUs. The results showed that almost 43% of the DMUs studied were fully efficient, with a relatively high average overall efficiency score of 0.8512 (Table 4). The observed outcomes can be attributed to the non-radial characteristics of our SBM-DEA model. This model enables simultaneous reduction of inputs and enhancement of outputs, effectively improving the overall efficiency of DMUs (Djordjević & Krmac 2019; Tone *et al.* 2020). For managerial translation, practitioners must prioritize the SBM component-wise improvement vectors, as these specify precise adjustments required for studied inputs (forest Employees and forest area) and outputs (biomass, growing stock, gross volume of felled trees). While the bias-corrected efficiency score β serves as a screening index (input shortfall $\approx 1 - \beta$; output multiplier $\approx 1 / \beta - 1$), the non-radial nature of SBM necessitates component-specific vectors to guide actionable interventions—such as organizational and process improvements (*e.g.,* reassignment, retraining, contractor optimization) rather than abrupt workforce reductions, or site-appropriate silviculture and harvest planning to enhance productivity per unit of forest area without rapid expansion.

In the second stage, a bootstrap DEA model, as a modified benchmarking technique, was used to compute the bias-corrected efficiency scores and hence fully rank all studied DMUs (Table 5). The finding indicated that the utilization of the bootstrap DEA approach allowed for the adjustment of measurement bias and efficiency scores, resulting in a decrease in overall efficiency from 0.8512 to 0.7480. The results showed that the bootstrap DEA approach exhibited superior discriminative ability compared to traditional DEA models in estimating true efficiencies when data uncertainties existed, enabling accurate identification of inefficiencies, a crucial aspect of DEA analysis. These findings highlight the benefits of using the bootstrap DEA method for evaluating efficiency in the presence of uncertainty (Trakakis *et al.* 2022; Vaseei *et al.* 2023). Lastly, a double bootstrap DEA is developed to adjust the impact of contextual variables on the bias-corrected efficiency of our studied DMUs (Table 7). The results indicate that RD and Deadwood variables have negative coefficients, implying they decrease the efficiency score. In contrast, the precipitation variable has a positive coefficient, indicating a positive relationship with the score. The variable TEMP is not statistically significant. Similarly, an increase in GDP leads to an increase in efficiency. Overall, the estimation has a moderate amount of uncertainty for contextual variables and a relatively small uncertainty for GDP. These findings are completely consistent with the recent research conducted in diverse management domains, supporting the notion that macroeconomic indicators, as well as climatic factors, exert a positive influence on bootstrap performance outcomes (López-Penabad *et al.* 2020; Wu & Wang 2022; Arhin *et al.* 2023). As the main consequence, practical constraints—such as limited usable forest area, accessibility challenges, budgetary limits, and regulatory biodiversity constraints—must be explicitly addressed. In sum, the extended SBM–DEA framework with bootstrap corrections yields robust benchmarking, and when integrated with component-wise diagnostics, local accounting, and staged pilots, it enables realistic management interventions that respect ecological and regulatory boundaries.

Policy implications

The empirical results of this study underline the importance of linking efficiency outcomes in Swedish forested counties to broader policy frameworks that address both economic and environmental dimensions. The observed positive relationship between regional GDP and forestry efficiency, together with the nuanced influence of precipitation and deadwood, demonstrates that forest policy cannot be conceived solely in terms of resource productivity, but must be embedded in integrated strategies that align with contemporary EU initiatives. Anchoring regional actions within instruments such as the New EU Forest Strategy, the Deforestation Regulation, the Nature Restoration Regulation, Fit-for-55, and the LULUCF framework provides a coherent basis for fostering multifunctional forest management while simultaneously supporting climate, biodiversity, and economic objectives.

Advancing the forest-based value chain requires coordinated measures that enhance local processing capacity, improve supply-chain efficiency, and create stable demand for sustainable wood products in construction and related sectors. By mobilizing sawlogs, pulpwood, and fuelwood into higher-value applications, counties can capture a larger share of forest-related GDP growth and reinforce the link between economic development and efficiency gains. Public procurement policies and green building standards are especially valuable for stimulating uptake, while innovation programs and cohesion funds can accelerate the transition towards engineered wood and circular uses of biomass. At the same time, compliance mechanisms such as the deforestation regulation should be reframed as market-enabling opportunities to strengthen transparency and traceability, thereby improving the competitiveness of Swedish forest products. Similarly, LULUCF accounting rules and the Fit-for-55 package can incentivize carbon-positive management practices and material substitution benefits if carefully structured to avoid discouraging higher-value uses of timber. Parallel attention to biodiversity is essential: integrating deadwood retention and restoration objectives through spatially targeted planning and payments for ecosystem services ensures that ecological commitments are met without undermining the economic viability of forest owners.

Taken together, these considerations suggest that the most effective policy pathway is one that interweaves economic development with ecological stewardship, situating local forestry practices within a broader European policy context. Such an approach has the potential not only to enhance the competitiveness of the Swedish forest-based value chain, but also to contribute to long-term resilience and sustainability in the face of climate change and evolving market demands.

7 Concluding remarks

In this paper, we applied the two-stage double bootstrap DEA procedure to evaluate the forest efficiency and its associated factors in 21 counties in Sweden for 2018–2022. In the first stage, we evaluated the efficiency scores by a SBM DEA model in VRS environment using two outputs and three inputs. Then, in the second stage, we utilized the double bootstrap DEA analysis to identify the factors affecting the efficiency scores obtained in the first stage.

The main findings from the first stage analysis showed that the overall average efficiency for Sweden forest sector from the proposed SBM-DEA model was 0.8512, while after recognizing the bias, the bias-corrected efficiency score was estimated at 0.7480. This means that there is potential to improve Sweden forest efficiency by up to 25%.

Contextual variables, such as RD and Deadwood, exhibited a negative impact on efficiency, while GDP showed a moderate positive correlation. In the second stage, the bootstrap DEA model was used to compute bias-corrected efficiency scores and rank the counties studied. Moreover, a double bootstrap DEA was developed to adjust the impact of contextual variables on efficiency. The results showed that RD and Deadwood variables had negative coefficients, indicating a decrease in efficiency, while precipitation, and GDP had positive coefficients, indicating a positive relationship with efficiency.

While this study aimed to incorporate a comprehensive set of variables to reflect real efficiency estimation, data availability limitations necessitated methodological trade-offs. A consistent and comprehensive dataset across all Decision-Making Units (DMUs) from national forestry databases and statistical sources was not accessible for all proposed variables. Specifically, variables including merchantable forest area (as opposed to total forested area), machine hours (both own and contracted), harvesting service costs, administrative staff salaries, fuel consumption, net investment (capex–depreciation), output distinctions (e.g., calamity versus normal fellings, sawlogs versus industrial wood), and site quality indicators (e.g., site index) were inconsistently reported or missing for a substantial portion of the sample. These gaps precluded their inclusion without introducing speculative assumptions or bias, which would compromise the validity of the results. To ensure methodological integrity, the analysis was restricted to variables with reliable and consistently documented availability across the sample. Further studies with access to harmonized, institutionally standardized datasets would enable richer variable specifications and enhance the robustness of efficiency estimates. As the future research directions, it is strongly recommended that other well-known uncertain DEA approaches (Fuzzy or stochastic DEA) be developed to deal with impreciseness and ambiguity in Swedish forest management systems.

The use of DEA and robust optimization can also help us derive reliable efficiency estimates. These problems should be addressed in future research when more comprehensive data sets are available.

Declarations

Financial Interest: The authors have no relevant financial or non-financial interests to disclose.

Conflict of Interest: We declare that we have no known competing financial interests.

Data Availability: Data is provided within the manuscript.

Funding: The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

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