Research paper

Assessing the efficiency of the forestry sector in EU countries

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Abstract. This paper deals with a quantitative assessment of the production efficiency of the forestry sector in EU countries, which is largely neglected in the literature. Only a few studies have been conducted so far, processing data mainly in the first half of the last decade. In contrast to these studies, in this article we focus on the period between 2016 and 2020. Therefore, the main objective of this paper is to compare the efficiency of the forest sector to fill the gap. The empirical results of this study show that the leaders in this sector are Germany, Finland, and the Czech Republic. These countries are fully efficient throughout the period under review. In contrast, Bulgaria lags far behind, with an efficiency score typically around 35%. The results of the cluster analysis show that although countries have similar characteristics, their efficiency scores are not necessarily at the same level.

Key words: efficiency evaluation, EU countries, data envelopment analysis, forestry.

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Introduction

The forest ecosystem is one of the most important renewable resources on our planet. Forests provide multiple benefits to society through their ability to capture and store carbon, thereby reducing the carbon footprint and also mitigating climate change on the ground. Not only do forests have a positive impact on climate and water quality, they are also home to many species of animals and important organisms. Forests also have important abilities to limit soil erosion, protect homes and the infrastructure from negative impacts, such as landslides, and protect rivers and lakes from sediment pollution (European Commission, 2020).

Forestry not only has a positive impact on nature and living organisms, but also leads to socio-economic benefits as it creates a needed resource (wood). Unfortunately, there are no legal, economic, or environmental constraints on the logging process (Villanueva *et al.*, 2023). The European Environment Agency (2023) reports that a major problem in the forestry sector is the poor health of forests and their declining acreage. According to the analyses of Janová *et al.* (2022), at least in the con-

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ditions of the Czech Republic this problem can be minimized through sustainable forest management.

Forestry is one of the sectors where governments are actively involved through state-owned enterprises. According to the European Parliament (2022), around 60% of Europe's forests are privately owned and 40% are nationally owned. Surprisingly, studies aimed at quantitatively assessing the efficiency of state-owned enterprises in the EU are not common for this sector. The results of this research could serve individual governments not only when preparing, for example, subsidy programmes for individual enterprises, but also when deciding on the functioning of state enterprises themselves. In the case of non-European areas (especially in China), it is possible to find many studies where the efficiency of the use of inputs in the production of outputs is analysed in a quantitative way.

However, if we focus on the area of the European Union or Europe, we will find that this is a relatively little-explored area. In 2022, a study by Gutiérrez & Lozano (2022) was published, in which the authors dealt with a quantitative evaluation of efficiency at the level of individual EU/EFTA countries. In this study, the authors also mention, among other things, that by 2018 they had identified only 25 forest-related DEA studies. While more than half of these studies use data (one year or years) falling only in the last millennium. From their list of studies, for example, Šporčić & Landekić (2014), which uses an advanced mathematical apparatus to quantitatively assess efficiency, can be mentioned for the European region.

Kovalčík (2018) and Kovalčík (2020) are examples of more recent studies that quantitatively evaluate the efficiency of the areas in the EU. Kovalčík (2018) compared the efficiency of Slovak forestry with other European countries. To evaluate efficiency, he used the non-parametric method of data envelopment analysis (DEA). He analysed sector results from 2005 to 2008 on a sample of 22 European countries. He assembled two models for the evaluation. In the first model, Austria, Bulgaria, Finland, Greece, Hungary, Poland, Sweden, and Spain proved to be efficient. A larger number of efficient countries were identified in the second model. In addition to the aforementioned countries, Switzerland, Germany, Italy, the Netherlands, and the Czech Republic were identified. Kovalčík (2020) subsequently focused on detailed analyses of the efficiency of Slovak forestry contractors in the period between 2012 and 2016. This analysis showed that most companies in Slovakia do not work efficiently, in particular due to outdated technology. In addition to investing in innovation, Kovalčík (2020) also recommends a reduction in turnover.

A similar period was used by the above-mentioned Gutiérrez & Lozano (2022), who analysed 28 EU/EFTA countries between 2010 and 2015. They also used the DEA method to calculate efficiency. The main causes of inefficiency were identified as being outages of production. Greece, Bulgaria, and Italy were among the countries with the lowest evaluation of relative efficiency. On the other hand, the countries that have adopted a public-sector timber-green policy, such as Belgium, Denmark, Germany, and the Netherlands, have an effectively functioning forestry sector.

Lundmark *et al.* (2021), using the DEA method, tried to analyse achievable and sustainable improvements in timber harvesting in forests in Sweden for the period between 2008 and 2014. In their study, they draw attention to the negative price effect that may arise if the timber harvesting process is made more efficient, whereby obtaining a greater volume of production.

Based on the analysis of four Central European countries (Czech Republic, Germany, Hungary, Slovakia) in the period between 2009 and 2016, Staňková *et al.* (2022), using DEA and the stochastic frontier analysis method, found that there are

differences in efficiency depending on the size of enterprises. State-owned enterprises, which are among larger enterprises, have lower efficiency because they try to promote other (government) objectives, such as employment.

From the point of view of the data used, the most up-to-date study was conducted by Neykov *et al.* (2021). Neykov *et al.* (2021) focused on a comparative analysis (using the DEA method) of the Bulgarian and Slovak forestry sectors in the period between 2014 and 2018. Like Kovalčík (2018), Neykov *et al.* (2021) emphasise the necessity of the availability of high-quality technologies to ensure the efficiency of the forestry sector. Furthermore, they found that companies that rely on external service providers achieve lower efficiency values than other companies in the given sector.

The main aim of this article is, similarly to the aforementioned studies, to evaluate the efficiency of the forestry sector in EU countries. However, unlike the above studies, we focus on a completely different time period. Aggregated data from the EUROSTAT database were used for the analysis for six of the most recent years. Our analysis therefore focused on the time period between 2015 and 2020. This article will make it possible to follow up on previous research, whereby filling the gap, as there is currently no research for the EU region analysing data from recent years.

Materials and Methods

Efficiency in the forestry sector was calculated for EU countries with data available from the EUROSTAT database. The analysis focuses on the forestry sector, which according to the international classification is designated by the NACE A2 code (forestry and logging).

In our analyses, we focused on the evaluation of production efficiency and therefore on variables that directly affect the production process in the forestry sector. Similarly to, for example, Gutiérrez & Lozano (2022), we used a variable for the number of employed persons in units of thousands as the labour factor. Another input variable is the area of wooded land in units of thousands of hectares, which already falls under the capital factor. This variable was also used by Lundmark *et al.* (2021) for their research. The last input variable (also capturing the capital factor) is the growing volume of timber in forests in units of thousands of cubic meters, which is recommended for research by, for example, Šporčić & Landekić (2014).

We decided to capture the output in the forestry sector using two variables. The first output variable is roundwood production in units of cubic meters. Roundwood production is defined as the total amount of timber removed from forests and other wooded areas over a certain period. The values given are reported as roundwoods under bark, i.e. without bark. Šporčić & Landekić (2014) also worked with this output variable. The second output variable is the gross value added at basic prices. These are gross value added values for sector A according to the NACE code. Gross value added represents the value of output less the value of intermediate consumption, thereby allowing the financial side to be included in the analysis on the output side. This variable is measured in millions of euros in the database. Gutiérrez & Lozano (2022) also worked with this variable in their study. The basic characteristics of the input and output variables used are shown in Table 1.

It is clear from Table 1 that the average value of the number of employees has a decreasing trend. The lowest number of employees in this sector is in Slovenia. The average value of the area of wooded land increased from 2015 to 2020, and had a growing trend, which can be supported by subsidies from the European Union, which help countries in the area of new afforestation. Along with this, the growing volume of wood in forests also increased.

The median value of roundwood production did not differ significantly in the given period. An increase can be seen in the median values of the roundwood production in 2018 and 2019, which can be explained, for example, by the bark beetle calamity in central Europe (Bárta *et al.*, 2021). Because when the bark beetle calamity hit, the countries were forced to harvest the damaged timber from the forests. The gross value added and its calculated average for all the monitored European Union countries had an increasing trend between 2015 and 2018, then a slump occurred in 2019, followed by a decreasing trend.

Table 1. Basic characteristics of the input and output variables used.

Variable	Char.	2015	2016	2017	2018	2019	2020
Employees (thousand)	Min	4	3	4	3	3	2
	Average	26	26	26	25	25	24
	Median	22	233	23	24	21	19
	Max	73	77	86	73	63	72
Area of wooded land (thousand hectares)	Min	1,248	1,246	1,244	1,242	1,240	1,238
	Average	7,874	7,885	7,896	7,905	7,915	8,215
	Median	3,833	3,841	3,854	3,867	3,880	3,896
	Max	27,980	27,980	27,980	27,980	27,980	27,980
Volume of timber (thousand cubic metres)	Min	378,530	381,900	386,000	389,300	393,100	397,030
	Average	1,374,903	1,392,871	1,401,526	1,409,962	1,418,532	1,462,409
	Median	768,150	771,780	775,370	782,250	786,470	937,885
	Max	3,663,000	3,663,000	3,663,000	3,663,000	3,663,000	3,663,000
Roundwood production (thousand cubic metres)	Min	4,357	4,263	4,484	4,975	4,397	3,891
	Average	21,955	22,091	23,083	24,746	24,855	23,613
	Median	12,294	12,794	12,896	14,392	14,822	13,318
	Max	74,300	74,800	74,300	75,233	77,821	78,673
Value added (millions of EUR)	Min	150	182	196	216	198	198
	Average	1,255	1,266	1,277	1,336	1,262	1,180
	Median	876	860	833	919	870	665
	Max	3,446	3,511	3,784	4,111	4,187	4,046

In total, it was possible to include 18 EU countries in the analyses. In the case of the Czech Republic, only one observation in one period was missing, so we retained this country in the analysis and therefore the estimates for 2020 were made without this country. Nine EU countries could not be included in the analysis due to unavailability of data in two or more periods, namely Belgium, Cyprus, Denmark, Greece, Ireland, Luxembourg, Malta, the Netherlands and Portugal.

Given the scope of the analyses, as the first step countries were divided into groups with similar characteristics. A cluster analysis was used for this purpose, similarly to Zámková *et al.* (2021). The graphical result of the cluster analysis – a dendrogram – allows the groups of countries that have the most similar characteristics to be identified according to the variables in Table 1. On the basis of the identified clusters, it was possible to record extensive results (especially when assessing the evolution of efficiency) for a few clusters formed that are in a similar situation. In the case of cluster analysis, it is necessary to focus on setting the distances between clusters and also between objects. Since our selected variables have different units, we used the standardised Euclidean distance to calculate the pairwise distance between pairs of observations. For this procedure, Ward's method for calculating the distance between clusters has proved to be particularly useful in practice, see for example, Kovárník & Staňková (2021). The cluster analysis was performed in the MATLAB computer system (version 2023a). Technical details of these procedures can be found in Everitt *et al.* (2011).

A non-parametric data envelopment analysis (DEA) method was adopted for the quantitative evaluation of efficiency. This method has been successfully applied in the field of forestry, for example in the research of Staňková *et al.* (2022). The DEA method can generally be considered the most widely used method for quantitative assessment regardless of sector. In addition to the previously mentioned studies, such as Gutiérrez & Lozano (2022) and Šporčić & Landekić (2014), the DEA method can be found, for example, across different domains from purely traditional manufacturing areas, such as in Gaebert & Staňková (2020), to the sustainability of individual economy assessments as in Hampel *et al.* (2016). Similarly to the aforementioned studies, we used the radial CCR model originally developed by Charnes *et al.* (1978) for our analysis. Based on input (x) and output (y) variables, the input-oriented efficiency of each country o can be measured by solving n times the following CCR model:

$$\min z = \frac{\sum_i^r u_i y_{io}}{\sum_j^m v_j x_{jo}} \tag{1}$$

$$\text{subject to} \quad \frac{\sum_i^r u_i y_{io}}{\sum_j^m v_j x_{jo}} \leq 1, k = 1,2,\dots,n,$$

$$u_i \geq \varepsilon, i = 1,2,\dots,r,$$

$$v_j \geq \varepsilon, j = 1,2,\dots,m,$$

where z is the efficiency measure of country o and ε is an infinitesimal constant. Thus, the DEA model allows a comparative comparison of the ratio of the so-called virtual output to the virtual input. The efficiency results can then be presented in a normalized state on the interval 0 to 1 (or 0% to 100%). Only those countries that achieve a score of 1 (100%) can be described as fully efficient. The efficient country achieves the ideal ratio in the value of z. Thus, hypothetically, if another inefficient country is given the amount of inputs of an efficient country, it will achieve a lower amount of outputs than the efficient country.

The efficiencies in each year were calculated using the CCR input-oriented model. For technical (mathematical) reasons, it is not important whether we use the input or output orientation of the model for the efficiency calculation itself, as the resulting efficiency score will be the same in both models. For technical details about the DEA method see Charnes *et al.* (1978).

In order to adequately assess changes over time, in addition to the standard models for each year, we also calculated changes in efficiency using the Malmquist production index as in Staňková (2020). It is possible to decompose this index and analyse its two parts – the change in individual efficiency and the change in the pro-

duction possibilities frontier. To calculate MI, it is necessary to solve a total of four optimisation problems (in our case, four CCR models). The Malmquist index (*MI*) can be thought of as the geometric mean of two efficiency ratios (*E*), where one is the efficiency change measured by the period 1 technology and the other is the efficiency change measured by the period 2 technology:

$$MI = \left[\frac{E^1((x_o, y_o)^2)}{E^1((x_o, y_o)^1)} * \frac{E^2((x_o, y_o)^2)}{E^2((x_o, y_o)^1)}\right]^{1/2} \quad (2)$$

For both the index and its components, values greater than one indicate improvement in a given area and values less than one indicate deterioration. When calculating the index from period 1 to 2, data for both periods must be available. Therefore, here the Czech Republic causes a complication in the calculation of the index between 2019 and 2020, as there are no data available for the country in 2020. In terms of calculating changes, it is only possible to work with calculations up to 2019 for the Czech Republic and up to 2020 for the other 18 countries. In addition to the aforementioned decomposition, the Malmquist index has another positive feature, namely that it allows not only to evaluate adjacent time periods, but also to calculate the overall change for the entire period under consideration (i.e. between 2015 and 2020). The technical details of this procedure (as well as the CCR model) can be found in Cooper *et al.* (2007). All CCR models were constructed in DEA SolverPro (version 15f).

Results

The results section is divided into two parts. First, the results of the cluster analysis are presented, followed by the results of the production efficiency calculation.

Created clusters

Based on the cluster analyses performed each year, it was found that the identified clusters were homogeneous throughout the period under study. Since there were no dramatic changes in the groups formed during the period, Figure 1 shows the dendrogram for 2015 and 2020 only. The first group (blue in both periods) is the smallest, as it includes only Poland, Romania, and Italy. The three countries are similar in terms of staffing levels. Italy and Romania have almost identical levels of this variable, especially in 2015. However, all three countries have the highest values in the employee's variable, which puts them in the same group. In addition, all three countries are similar in the ratio of the area of wooded land to the total area of the country – this ratio is around 30%.

The second cluster is made up of four countries: Sweden, Finland, France, and Germany. In 2015 (green cluster), Germany was most similar to France. In 2020 (red cluster), we can see that Germany is moving further away from the other three countries, but still falls in the same cluster as them in terms of similarity. This relationship can be explained mainly through the variable number of employees. Germany is generally one of the countries with a higher number of employees, but there is a jump of 19% in 2020, which sets it apart from the other countries in the cluster. However, the sizes of the area of wooded land are very close to each other. The countries grouped in the second cluster are all large countries with strong economies. They differ from other clusters by having more than three times the production volume and more than twice the value added.

The last (third) cluster contains the remaining countries. However, it contains one less country in 2020 (green cluster) than in 2015 (red cluster) because, as mentioned in the previous chapter, it was not possible to obtain all the necessary data for the Czech Republic in 2020. Given the fact that the Czech Republic was part of this

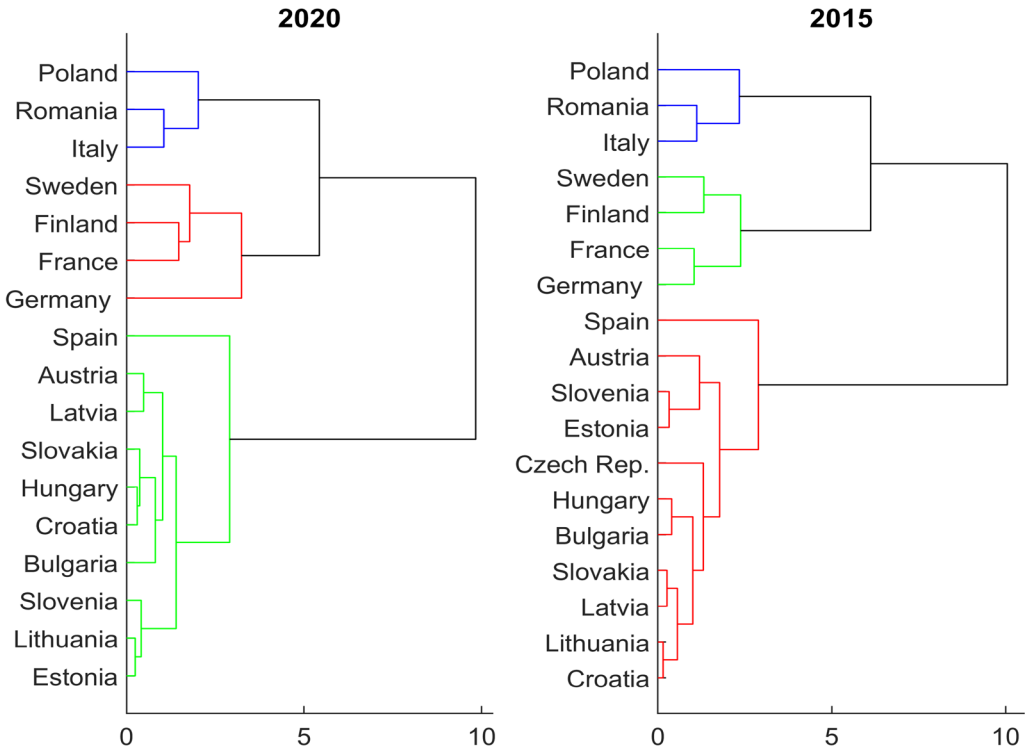


Figure 1. Dendrogram with clusters formed in 2020 and 2015.

cluster of countries from 2015 to 2019, we assume that it would remain in the same cluster in 2020.

Since this third cluster consists of a larger number of countries, it contains the most heterogeneous results. According to the resulting dendrogram, Spain is the most isolated in this cluster, as it is one of the largest producers in this cluster. Although its production is on a par with Romania, in terms of value added it lags far behind other large producers (i.e. countries in the second and especially the first cluster). The countries of the third cluster are generally characterised by their lagging behind in value added. They are also distinguished from other clusters by a lower value in the variable of employees and generally lower production associated with a lower area of wooded land. The average values of the variables for each cluster for 2015 and 2020 can be found in Table 2.

Table 2. Average values of variables for each cluster for 2015 and 2020.

Cluster No.	Year	Employees	Area of wooded land	Volume of timber	Roundwood production	Value added
1	2015	58.27	8,539.35	2,051,903.33	1,593.80	20,580.70
	2020	57.60	8,659.39	2,169,730.00	1,795.50	22,514.91
2	2015	27.78	19,661.00	3,111,322.50	3,375.43	60,083.94
	2020	28.38	19,765.25	3,205,397.50	2,843.32	65,072.36
3	2015	17.80	4,007.80	643,860.91	473.35	10,064.28
	2020	14.74	4,157.04	654,347.00	414.84	9,262.07

Production efficiency results

Table 3 presents a summary of the basic characteristics of the efficiency score calculations. According to the average and median, the forestry sector in EU countries is at a relatively high level. In 2015, 2016, and 2020, more than 25% of the countries are identified as fully efficient. Another positive sign is the finding that 75% of the countries did not drop below 55% efficiency. However, the absolute minimum efficiency gained was found to be only 22% (namely in 2019).

Table 3. Basic efficiency characteristics aggregated for all countries.

Characteristic	2015	2016	2017	2018	2019	2020
Minimum	0.4101	0.3891	0.3552	0.2795	0.2200	0.3207
Lower quartile	0.6797	0.5959	0.6141	0.5612	0.5517	0.6225
Median	0.8467	0.8966	0.7821	0.7751	0.7981	0.9770
Average	0.8119	0.7967	0.7574	0.7404	0.7428	0.8359
Upper quartile	1	1	0.9684	0.9396	0.9913	1
Maximum	1	1	1	1	1	1

A detailed view of country efficiency is provided in Table 4, which, in addition to the resulting efficiency scores, also shows the average scores over the whole period and the derived country ranking. Only three countries can be described as being fully efficient throughout the period under review. These are Finland, Germany, and the Czech Republic. Although the Czech Republic does not have a result for 2020, we expect it to also be among the top countries in 2020.

Table 4. Derived ranking of countries by calculated efficiency rate for the period between 2015 and 2020.

Country	Efficiency in						Average	Rank
	2015	2016	2017	2018	2019	2020		
Finland	1	1	1	1	1	1	1.0000	1–3
Germany	1	1	1	1	1	1	1.0000	1–3
Czech Rep.	1	1	1	1	1	X	1.0000	1–3
Austria	1	1	1	0.9520	0.9610	0.9770	0.9820	4
Estonia	1	1	1	1	0.8060	1	0.9680	5
Sweden	1	1	0.9130	0.8060	1	1	0.9530	6
France	1	0.9450	0.9480	0.8900	0.9140	0.8790	0.9290	7
Italy	0.8930	0.9360	0.8730	0.9020	0.9650	1	0.9280	8
Slovenia	0.8310	0.9910	0.8040	0.8680	1	1	0.9160	9
Latvia	0.8620	0.8570	0.8010	0.7320	0.6310	1	0.8140	10
Slovakia	0.8240	0.7530	0.7010	0.7440	0.7900	1	0.8020	11
Poland	0.8300	0.7540	0.7160	0.6340	0.6200	0.8460	0.7330	12
Spain	0.6780	0.5870	0.5910	0.5590	0.5290	0.5830	0.5880	13
Hungary	0.6850	0.6200	0.5830	0.4680	0.5200	0.6200	0.5820	14
Lithuania	0.6050	0.5880	0.5310	0.4830	0.4150	0.5790	0.5340	15
Romania	0.4100	0.3890	0.3960	0.5680	0.6370	0.7830	0.5310	16

Country	Efficiency in						Average	Rank
	2015	2016	2017	2018	2019	2020		
Croatia	0.5750	0.5300	0.5070	0.4430	0.3630	0.6230	0.5070	17
Bulgaria	0.4210	0.3900	0.3550	0.2800	0.2200	0.3210	0.3310	18

Two of the top countries fall into the second cluster defined by us, but the Czech Republic has been included in the third cluster. However, the Czech Republic (followed by Austria) is one of the largest producers in the third cluster. Moreover, it is also possible to find other common characteristics that have contributed to this high level of efficiency in these countries. In all three countries there is an upward trend in the gross value added for the agriculture, forestry, and fishing sectors. Further, these countries have a different strategy regarding human resource management as they show a downward trend in the average number of employees, but according to the report by Trading Economics (2023), individual worker bonuses are increasing in these countries. The importance of the forestry sector in these countries is also reflected in the fact that there are many secondary and higher education institutions that provide study programmes directly focused on forestry (Study in Germany, 2023; Lesy ČR, 2023).

Countries like Austria and Estonia did not reach 100% in terms of average scores, but were fully efficient in at least the first half of the years. However, as already indicated above, Austria is very similar to the Czech Republic in terms of production results, so it is logical that it also occupied a position of efficiency very close to the Czech Republic.

At the other end of the rankings in Table 4 is Bulgaria, which received an average efficiency score of just 33.1%. Bulgaria is the only country that failed to reach the 50% efficiency level throughout the period under review. The following lowest countries are Lithuania, Romania, and Croatia, which, however, achieved at least 50% efficiency on average. Like the three best countries, the three worst countries do not come from the same cluster. Bulgaria and Croatia were placed in the third cluster, but Romania was placed in the first cluster. A detailed view of the efficiency results according to the identified clusters is given in Table 5.

In terms of the aggregated values in Table 5, it is possible to conclude that the best results were achieved by the countries of the second cluster. The average results for clusters one and three are very close. The first cluster has an average efficiency score of only 0.48 percentage points higher and therefore received the notional second place. However, the average results of the third cluster are positively affected by the full efficiency status of the Czech Republic. Without this country, the average efficiency results of this cluster would be lower. It is remarkable that the Czech Republic manages to operate efficiently in the forestry sector even though according to the input characteristics it was classified in the cluster analysis in the cluster that obtained the lowest average efficiency score.

Table 5. Derived ranking of identified clusters by calculated average efficiency rate for the period between 2015 and 2020.

Cluster	Efficiency in						Average	Rank
	2015	2016	2017	2018	2019	2020		
1	0.7110	0.6930	0.6617	0.7013	0.7407	0.8763	0.7307	2
2	1	0.9863	0.9653	0.9240	0.9785	0.9698	0.9706	1
3	0.7710	0.7560	0.7157	0.6845	0.6577	0.7703	0.7259	3

When evaluating efficiency, changes over time can also be tracked in detail. Table 6 summarises the results of the Malmquist index and its two components – the change in individual efficiency (catch-up effect) and the change in the production possibilities frontier (frontier shift). Table 6 shows both the total and average results. The total results are calculated as the total change between 2015 and 2020 (only the Czech Republic has a change for 2019). The average results are then calculated from individual year-on-year changes over the whole period (in the case of the Czech Republic, again only up to 2019).

In terms of efficiency, based on the overall values, only eight countries show a deterioration in efficiency (i.e. have a total coefficient value below one). However, a positive sign for the sector is that in terms of overall border values, there has been an increase in production possibilities in all but four countries (Romania, France, Austria, and Slovakia).

If we want to assess the situation as a whole (i.e. through the Malmquist index), in terms of the total indicator, 12 countries have improved and only six countries have worsened their situation. The least favourable situation is for Bulgaria, which not only occupies the worst position in terms of the derived efficiency ranking in Table 4, but also shows a negative tendency in the Malmquist index due to repeated significant declines in its efficiency.

Table 6 was arranged according to the results of the cluster analysis. However, as mentioned above for the efficiency assessment, it is not possible to generalise the results according to the identified clusters when considering changes in production possibilities and the Malmquist index.

Table 6. Results of the overall and average Malmquist index, including decomposition into efficiency change (catch-up) and production possibilities change (frontier).

Cluster	Country	Catch-up		Frontier		Malmquist	
		Total	Average	Total	Average	Total	Average
1	Poland	0.8814	0.9523	1.0495	1.0812	0.9250	1.0247
	Romania	1.5298	1.1029	0.9719	0.9987	1.4869	1.0940
	Italy	1	1.0169	1.1369	1.0103	1.1369	1.0250
2	Sweden	1	1.0073	1.0864	1.0183	1.0864	1.0173
	Finland	1	1	1.1212	1.0313	1.1212	1.0313
	France	0.8790	0.9738	0.9705	0.9969	0.8530	0.9695
	Germany	1	1	1.0368	0.9940	1.0368	0.9940
3	Bulgaria	0.6839	0.8606	1.1326	1.1115	0.7745	0.9514
	Estonia	1	0.9653	1.2003	1.0687	1.2003	1.0326
	Spain	0.8603	0.9505	1.0167	1.0407	0.8746	0.9884
	Croatia	0.9325	0.9337	1.1024	1.0831	1.0280	1.0039
	Latvia	1.0460	0.9468	1.1705	1.0952	1.2244	1.0332
	Lithuania	0.8582	0.9357	1.1986	1.0689	1.0286	0.9963
	Hungary	0.8063	0.9405	1.0950	1.0529	0.8828	0.9790
	Austria	0.9782	0.9878	0.8438	0.9362	0.8254	0.9236
	Slovenia	1.2025	1.0471	0.9048	0.9807	1.0880	1.0183
	Slovakia	1	0.9936	1.0625	1.0536	1.0625	1.0444
	Czech Rep.	1	1	1.2934	1.0674	1.2934	1.0674

In terms of these indicators, countries are heterogeneous within clusters.

Discussion

The forestry and logging sector does not currently have a unified forest policy at the level of the European Union, the management of this sector is only a national matter. The outputs from measuring the efficiency rate could serve to evaluate the situation in individual countries in the field of forestry and also as a reference framework for the European Union. The most up-to-date data set that was available was used for the work, with some data missing for countries belonging to the European Union. Kovalčík (2018) perceives the limited validity and traceability of the data set used as a big problem, for the reason that each country has a national methodology for the application of economic accounts for forestry, and from this it follows that the availability of data at the national level may be limited. For the efficiency of the forestry sector, variables can be taken into account so that the range of measurements is as comprehensive as possible in the issue of forestry.

In our cluster analysis, EU countries with available data were divided into three groups. Forest Europe (2020), for example, divides European countries (Russia aside) only by geography into six groups: North Europe, Central-West Europe, Central-East Europe, South-West Europe, South-East Europe. This division has been used by, for example, Nichiforel *et al.* (2018) in their analyses. However, a comparison with our efficiency results shows that, for example, the top three countries are not in the same group of countries according to the Forest Europe (2020) breakdown. The three clusters we created better capture the obtained efficiency scores. Finland and Germany, the top-ranked countries, are together in the same cluster as opposed to the geographical divisions as in Nichiforel *et al.* (2018) and Forest Europe (2020). This fact only demonstrates the importance of quantitative evaluation of efficiency, as efficiency is determined by many factors.

Unfortunately, the quantitative assessment of efficiency in this sector is largely neglected in the EU, as very few studies have been conducted in recent years, and there is no indication that the number of such studies is increasing. Published studies focus more on the assessment of forest companies than on assessments using macro data, i.e. countries.

The closest possible comparison of our results is with the study by Gutiérrez & Lozano (2022), who also compared the efficiency of EU countries in a different time period. According to Gutiérrez & Lozano (2022), Croatia as the last acceding state to the European Union is inefficient. This reflects the results from the research conducted in this study, where Croatia is among the inefficient states with a very low level of efficiency. According to the calculated average level of efficiency, it is in the penultimate place. However, the reliability of our results can be proven even when compared with research using micro economic data. For example, Neykov *et al.* (2021) examined the efficiency of forest enterprises in Bulgaria and Slovakia and concluded that enterprises in these countries are typically highly inefficient. It can be assumed that if the majority of Bulgarian and Slovak companies are inefficient, then even from an aggregate point of view, these two countries will also be inefficient compared to other countries, and this is exactly what was confirmed in our research. Even within the framework of the aggregated analyses, Bulgaria and Slovakia are countries with a very low estimated level of efficiency.

Staňková *et al.* (2022) focused on the efficiency of enterprises in Central European countries, identifying German enterprises as the best, followed by Czech enterprises (they named mainly larger enterprises), which should serve as peer units for inefficient enterprises from Slovakia and Hungary. Even in our study, Germany and the Czech Republic are among the top countries.

Furthermore, our empirical results show that although according to the cluster analysis the conditions are the same for certain countries (i.e. they fall into the same cluster), their efficiency is not always at the same level. This is particularly evident in the case of the Czech Republic, which as an individual is one of the three fully efficient countries throughout the period under review, although it was ranked among the countries with the worst efficiency scores on average according to the cluster analysis. It may therefore be assumed that this is a consequence of the fact that each EU Member State has its own forest policy. In addition, the Czech Republic can benefit from its geographical proximity to Germany and the interconnectedness of trade, as well as the sharing of knowledge and technology.

For the forestry sector as a whole, it can be stated that there has been an overall improvement in the situation in most countries over the six years under review. The systematic increases in production possibilities that we see owing to the growth of the production possibilities frontier can also be seen as a positive. It can be assumed that this is due to investments in new technologies. This idea is also supported by the findings of Neykov *et al.* (2021), who believe that Bulgaria is lagging behind precisely due to the lack of modern technology.

A constant question for future research, however, is whether the COVID-19 pandemic has disrupted the functioning of businesses in individual countries to such an extent that their production, and consequently their efficiency, has been affected. Unfortunately, it has not yet been possible to adequately explore the post-2020 period as the necessary data were not available.

Conclusion

This article focuses on an assessment of the production efficiency of individual EU countries in the forestry sector. Attention was paid to the most up-to-date data available. The results of our research show that the best countries are Finland, Germany, and the Czech Republic, as only these three countries were fully efficient throughout the period under review. On the other hand, the worst performer is Bulgaria, which also lags far behind other inefficient countries.

The empirical results also show that evaluating efficiency is quite complicated. Although it is possible through cluster analysis to identify groups that have similar conditions, their efficiency is not always at the same level. This is most evident in the case of the Czech Republic, which is one of the top countries in terms of efficiency, but according to the cluster analysis was classified as inefficient. The Czech Republic is even in the same cluster as Bulgaria.

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