The Data Envelopment Analysis approach to analyse fisheries efficiency in the Mediterranean and black sea countries

Asma Chaker *
University of Bejaia (Algeria), asma.chaker@gmail.com

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Abstract:
Mediterranean and black sea fisheries face great challenges in the different countries, mainly because of the stock collapse and the increasing burden human activities such as fishing. This study aimed to examine the Mediterranean and black sea countries' efficiency. Data was collected from the 2020 report on the state of Mediterranean and Black Sea fisheries, and a total of 19 countries was analysed. Specifically, this study relies on the comprehensive efficiency analysis of 19 countries through a non-parametric technique, using a two-stage Data Envelopment Analysis (DEA) analysis. First, calculating the efficiency levels under both Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS), before applying the bootstrap technique to derive the bias-corrected efficiency values under the Banker, Charnes and Cooper (BCC) model. The results showed that almost 76% of the countries are efficient, while this percentage drops to 60% when correcting the scores from bias. In a second step, some factors affecting the bias-corrected efficiencies were examined using the boostrapped truncated regression. The important findings were that the natural factors (Jurisdictional waters and Coastline) affect the efficiency, while the local and managerial factors (disparity between the number of artisanal fisheries compared to industrial ones) does not really affect the efficiency levels.

Keywords: Mediterranean and Black Sea countries, efficiency analysis, data envelopment analysis (DEA), bootstrapped truncated regression, efficiency determinants.

1. INTRODUCTION:

According to the last report of the Food and Agriculture Organisation (FAO) on the State of Mediterranean and Black Sea Fisheries (2020), the percentage of the overfished stock decreased by 12% between 2012 and 2018, as well as the exploitation ratio which has decreased by 0.5 times over the same period, it is almost a throwback to the 80s. Even if the fish stock remain overexploited, the trend of overfishing is inversed. Francesc Maynou (2020) tried to shed the light on these over exploitation, and found that the number of vessels in the Mediterranean has fallen by more than 40%, due to an exit rate 4.5 times greater than the entry rate of new vessels. This decrease has and will remain without beneficial consequences for the conservation of stocks and ecosystems if no bold

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* **The sender author.**

measures are taken into account with a view to reforming fisheries management in the Mediterranean.

In this context, focussing on fisheries efficiency is important to understand the actual management process, and what led to such an overcapacity situation. The main objective of measuring fisheries efficiency is to acquire knowledge about their inputs and outputs to understand and improve their management, that can be used to implement corrective measures leading to economic viability and why not sustainability of the sector, including human well-being of fishers and maintaining the viability of natural systems. To that aim, Kirkley and Squires (1999) proposed to apply DEA to fisheries, and the FAO (1998) never stopped recommending the use of DEA to analyse fisheries efficiency and compare fisheries units. That was a result of the seminal work of some authors who applied DEA to fisheries such as Kirkley et al. (1999). Afterward, FAO has consistently recommended the application of DEA to study and compare the performance of fisheries. Since then, DEA has been used increasingly to estimate technical efficiency in fisheries, and a large number of articles emerged (Esmaeili & Omrani, 2007; Felthoven, 2002; Madau et al., 2009; Maravelias et al., 2008; Pratama & Hapsari, 2019; Thanh Pham et al., 2014).

The application of DEA to fisheries is relatively new compared to other empirical analysis of efficiency. Its use to analyse the efficiency of fisheries has been intensified and supplemented by other methods to overcome its weaknesses, such as bootstrapping and regression models. Tingley and Pascoe (2005) used DEA and tobit regression to investigate the effects of some factors on the rate of capacity utilisation for a range of UK fleet segment. The results indicate that all fleet segments could potentially increase their revenue, and suggest that changes in stock abundance are the main factor affecting capacity utilization, with no significant trends observed for the economic variables. Walden (2006) applied the bootstrapped DEA approach to examine the technical efficiency of 201 mid-Atlantic scallop dredge vessels operating in 2003, and the results show that there was an important technical inefficiency in the fleet, and the vessels have the potential to harvest far more than the MSY level of output. Pham et al. (2014) analysed the economic performance and capacity efficiency of 45 gillnetters in Da Nang gillnet fishery. He demonstrated that large-scale vessels has positive profits and better economic performance compared to small-scale vessels. He also points out a situation of overcapacity, and explained it by the optimal use of inputs or by enhancing the current policies. Oliveira et al. (2014) investigate the existence of demand seasonality for bivalves from the artisanal dredge fleet operating along the coast of the Portugal mainland. They used DEA and Tobit regression, and revealed that the demand increases in the summer on the South coast whereas the increase occurs in winter on the western coast. This demand seasonality should be taken into consideration in fisheries management plan in order to increase the profitability of the vessels. Finally, the study of Cao et al. (2021) was based on a double bootstrap DEA technique to compare input oriented capacity utilization based on physical versus economic measures. The results show that economic measures give a lower capacity utilization than the one obtained by physical measures. They conclude that physical variables are capable of capturing the essential economic differences between vessels.

This study aims to examine the fisheries' efficiency levels of 19 Mediterranean and Black Sea countries using two-stage DEA approach. In the first stage, it applies an input-oriented data envelopment analysis (DEA) and performed a bootstrap in order to correct efficiency scores. More than calculating the efficiencies for each country, this study's purpose is to identify the factors influencing these scores. The second stage combined the results obtained in the first one with a truncated regression model to examine the impact of some exogenous variables on the countries efficiency ranges. To that aim, we raised a series of hypothesis that was examined in the second stage. The two first are related to natural assets, while the two last concerns local and/or national choices to develop one métier on the detriment of the others. The whole set of hypothesis is presented below and will be examined in the last section.

Hypothesis 1: Jurisdictional Waters and efficiency. Clearly, any human activity based on natural resources relies on the area where it is practiced. We considered, as a measure of the Jurisdictional waters in the Mediterranean, the Internal waters, Territorial sea, Exclusive economic zone, Ecological protection zone, Fisheries protection zone, and Fisheries/ecological protection zone (De Vivero, 2009). This first hypothesis stipulates that Jurisdictional waters positively influences the efficiency of the countries, i.e. the efficiency achieved is improved by the area of the jurisdictional waters.

Hypothesis 2: Coastline and efficiency. The choice of this hypothesis obeys the same logic that led to choose jurisdictional waters as an environmental variable. The second hypothesis implies a positive relationship between this variable and efficiency, since the coastal zones are used in majority by Small Scale Fisheries (SSF) that constitute 82.79% of the total métiers in the area of study (FAO, 2020).

Hypothesis 3: SSF and efficiency. Another factor that can affect efficiency is the number of SSF. It enables understanding if the efficiency registered results from of the high number of small scale fisheries. The third hypothesis implies a positive relationship between this variable and the efficiency.

Hypothesis 4: Industrial Fisheries (IF) and efficiency. The aim is to understand if the efficiency is the result of the development of industrial fisheries. This hypothesis implies a positive relationship between this variable and efficiency.

2. Methods:

2.1.Data Envelopment Analysis

Based on the efficiency concept and the piecewise-linear presentation, proposed by Farell (1957), Charnes, Cooper and Rhodes (1978) coined the term Data Envelopment Analysis (DEA) proposing a model (CCR) which had an input orientation and assumed constant returns to scale. Since the CCR assumption is only appropriate when all DMUs are operating at an optimal scale, Banker, Charnes and Cooper (1984) suggested an extension of the CRS DEA model to account for variable returns to scale (VRS) situations. It is important to notice that the CCR and the BCC models were the first to apply DEA to multiple input and multiple output processes to assess efficiency, and Banker (1984) was the precursor using the classical economics concept returns to scale into the DEA method.

The popularity of the application of DEA in different fields of science is due to its ease of use as well as its various advantages. Researchers focused on its considerable advantages such as allowing greater flexibility in the frontier estimation, and accommodating multiple outputs into the analysis (Tingley et al., 2005; Tingley et al., 2003).

Regarded to the specifications of fisheries production, and taking into account natural resources, applying DEA to measure efficiency and compare between countries, is more appropriate when adopting an input-oriented approach, particularly since the objective is not to maximize the production.

2.2.Bootstrapping

Being deterministic and ignoring noise in the data, the DEA has not stopped being criticized. To overcome these limitations, bootstrapping allows statistical inference into the deterministic efficiencies. The bootstrapped DEA approach improves the accuracy of the estimates which tend to be overestimated compared to the bias-corrected efficiency scores (Cinaroglu, 2021; Nguyen et al., 2015).

Efron (1979) was the first to introduce the statistical inference with the bootsrapping idea to calculate confidence intervals based on resampling, before Simar and Wilson (1998) proposed and developed later (2000; 2007) a suitable bootsrapping method for the non-parametric DEA efficiency estimates to be corrected from bias.

Bootstrapping was thus a real complement for the DEA, their concomitant application has increased in different fields including fisheries (Cao et al. 2021; Oliveira et al. 2014 ; Walden 2006).

2.3.Bootstrapped Truncated Regression

In the case of the non-parametric analysis of efficiency, recourse to the identification of efficiency determinants proves to be of great relevance, combining the DEA with a regression analysis on the returns of the DEA as a dependent variable (López-Penabad et al. 2020). To better understand the influence of the sample as well as the determinants linked to the countries' efficiency levels, we used the bootstrapped truncated regression model, before calculating the confidence intervals.

Afterwards, we investigate the reach of some factors (jurisdictional waters, coastline, SSF and IF) that could influence efficiency levels achieved by countries. The latter are regressed using the function below and corrected by bootstrapping.

$$\theta_i = \beta_0 + \beta_1\, Jurisdictional\ waters + \beta_2\, Coastline + \beta_3\, SSF + \beta_4\, IF + \varepsilon_i$$

Where i represents the countries, θ_i the value of the countries' corrected efficiencies. β_0 the intercept, $\beta_1, \beta_2, \ldots, \beta_4$, are the parameters to be determined (regression coefficients), and ε_i is the error term.

In practice, this methodology was carried out with the R language (https://cran.r-project.org). Thus we calculated the deterministic efficiency achieved by each country (using the package "deaR" in R (Coll-Serrano et al. 2021). Next, the bootstrapping technique was applied to the model with 2000 repetitions to obtain more accurate efficiency scores, and the "Benchmarking" package in R program was used during bootstrapping procedure (Bogetoft & Otto, 2020). In a second step, we used these bias-corrected efficiency scores to assess countries' performance and understand its determinants through bootstrapped truncated regression, that was performed using the package "truncreg" (Croissant, Zeileis, 2018). To do this, we used bootstrapping and calculated the 95% confidence intervals of regression coefficients with 200 iterations. These main packages were supplemented where necessary (to implement tests or descriptive statistics) by specific other packages.

2.4.The data

Despite the substantial importance of inputs and outputs for a DEA analysis, there is no standards or recommendations for their selection. The choice was made on the basis of studies in the field of fisheries and available data.

Table 1. Inputs and outputs data envelopment analysis (DEA) model.

Categories	Variables	Definition
Inputs (4)	Operating vessel number Capacity in gross tonnage Engine power in kilowatt Employment	Production factor Technical characteristic : the space dedicated to catches inside the vessel Technical characteristic : the power that the engine can put out. Human production factor
Outputs (2)	Revenue *1000 $ Production in tons	Measures the economic importance of the sector Measures the importance of the activity and the pressure on fish stocks (the weight of fishing on the fish stock)
Exogenous variables (4)	Small Scale Fisheries *100 Industrial fisheries *100 Coastline *1000 km Jurisdictional waters *1000 km²	The number of small scale vessels The number of industrial vessels The length of the coast The fishing area allowed to for each country

This study considers the dataset of 19 Mediterranean and Black Sea countries[1]. Data on operating vessel number, capacity in gross tonnage, engine power in kilowatt, employment, production in tons, and revenue was mainly collected from the last report of the FAO "*The State of Mediterranean and Black Sea Fisheries 2020*" (FAO, 2020). The environmental data is collected from official reports and databases (De Vivero, 2009; Commission on the Protection of the Black Sea Against Pollution, 2009).

Because some lacks in the data and the DEA sensitivity to missing data, we omitted 9 countries in the study, 7 from the Mediterranean (Bosnia and Herzegovina, Israel, Libya, Monaco, Montenegro, Palestine, and Syrian Arab Republic), and 2 from the Black Sea (Georgia and Russian Federation), i.e. from the original 37 countries, the final sample includes 114 observations of 19 countries.

Due to the deficiency of standardized values when comparing countries based on environmental and marine indicators, we tried to focus on data that are available and measured the same manner for the whole sample, always within the possibilities of the information provided by national and international organizations.

Table 2. Descriptive statistics of inputs and outputs.

	Production	Revenue	Operating vessel	Capacity	Engine power	Employment
Mean	52254,3684	185072,908	4270,73684	42493,0526	276742,842	11804,4211
S. D.	60732,337	272640,597	4397,7375	42415,0915	279716,695	13127,7704
Min	134	1072,6	72	355	5513	103
Max	199230	1114118,05	13300	132483	863979	40527

Source: elaborated on the basis of R outputs.

Before performing DEA analysis and examining the results, table 2 presents the descriptive statistics and the Spearman rank correlation test between the inputs and outputs of the study. In another step, the isotonicity characteristic between input and output variables was verified through the calculation of correlation coefficients, meaning that an increase in an input cannot lead to a decrease in the output. The correlation coefficients were positive, and displays high ranks either between inputs and outputs, or inside each category, meaning that this DEA model is valid to examine the efficiency score of fishery production between countries.

[1] We considered Turkey two times, since it borders the Mediterranean in the east -Turkey M-and the Black Sea in the north -Turkey BS.

Table 3. Descriptive statistics of efficiency determinants.

Statistics	Efficiency	Jurisdictional waters	Coastline	SSF	If
Mean	60,05	79,14	2,56	35,49	7,22
S. D.	21,00	68,18	3,67	39,70	9,10
Min	25,87	0,28	0,05	0,63	0,08
Max	82,33	246,07	15,02	123,28	33,06

Source: elaborated on the basis of R outputs.

The second stage required another set of variables called the determinants of efficiency (environmental or exogenous variables). To the aim of collecting data, a panoply of databases was consulted, the data on jurisdictional waters was collected from (De Vivero, 2009), the coastline from (Magnan, 2009) and completed for the black sea countries from a report on the marine litter in the Black Sea (Commission on the Protection of the Black Sea Against Pollution, 2009), and all other data were provided by the FAO (2020) report on the situation of Mediterranean and black sea fisheries.

3. **Results:**

3.1.The first stage

The countries with an efficiency less than 1, means that fisheries efficiencies are not as profitable as they could be if they were operating in a revenue efficient manner.

Under the CCR model, only 5 countries were efficient (France, Greece, Italy, Spain, Romania), resulting in 26.3% of the countries identified as being efficient with a relative efficiency score of 1. The average efficiency was about 62.56%, ranging from 26.18% to 83.59% with a highly dispersed results.

Table 4 : Descriptive statistics and efficiency range, both for the BCC and the CCR model.

	BCC		CCR	
Mean	0,7559		0,6256	
S. D.	0,2816		0,2930	
Min	0,3125		0,2618	
Max	1		1	
E* range	Countries	Countries in %	Countries	Countries in %
0.2 ≤ E < 0.3	-	0	Cyprus, Malta	10.5
0.3 ≤ E < 0.4	Cyprus, Egypt, Malta	15.8	Egypt, Morocco, Slovenia, Tunisia, Turkey M, Bulgaria	31.6
0.4 ≤ E < 0.5	Morocco, Turkey M, Bulgaria	15.8	-	0
0.5 ≤ E < 0.6	Tunisia	5.3	Algeria, Croatia	10.5
0.6 ≤ E < 0.7	-	0	Turkey BS	5.3
0.7 ≤ E < 0.8	-	0	Lebanon	5.3
0.8 ≤ E < 0.9	Albania, Algeria, Lebanon, Ukraine	21.1	Albania, Ukraine	10.5
0.9 ≤ E < 1	-	0	-	0
E =1	Croatia, France, Greece, Italy, Slovenia, Spain, Romania, Turkey BS.	42.1	France, Greece, Italy, Spain, Romania	26.3

Source: elaborated on the basis of R outputs. *E: efficiency.

Considering variable returns to scale model, efficiency increased considerably with values close to 75.59% in mean terms, with 3 other countries with an optimal scale (Croatia, Slovenia and Turkey BS). Thus, the percentage of fully efficient countries increased to 42%.

The results of the BCC model are always higher than those of CCR, but they were particularly contrasted for Croatia and Turkey (BS), with a jump in efficiency scores respectively from 58% and 66% to 100%.

In order to avoid the limitation related to the noise existence, we corrected the DEA efficiency estimates from bias by using the bootstrapping technique, and estimating the confidence intervals with 2000 repetitions. The table 5 displays the descriptive statistics, both for the original and the corrected efficiency. Following on, our analysis focusses on BCC model.

Once the corrected efficiency scores were calculated, the range of all corrected efficiencies were moderately lower than the original scores for each country. These potential improvements in efficiency scores take into account the statistical inference derived from the bootstrapping process. In addition, no country, once the bootstrap was applied, got the value of 1. According to the corrected scores, the efficiency stood at 60.08%, meaning that, there is a general overcapacity of about 39.92%, and the countries could potentially decrease their input level by this amount to reach the relative maximum efficiency level.

Table 5. Descriptive statistics of the BCC model, deterministic and corrected efficiency.

	Deterministic E	Corrected E
Mean	0,7559	0,6008
S.D.	0,2816	0,2102
Min	0,3125	0,2593
Max	1	0,8227

Source: elaborated on the basis of R outputs.

The statistics show the average and standard deviation of the efficiency scores exposed by the original and corrected scores of the model under study. As we can see, the BCC with corrected efficiencies has a lowest standard deviation (0.2102 compared to 0.2816 for the deterministic model), which means that the scores' spread is less than in the original model.

Looking at the distribution of efficiency scores and bias corrected scores across countries, it is observed that each country's efficiency score decreased, the decrease varies from 5% for Malta, to 26% for Italy and Turkey BS.

We conducted the Mann–Whitney nonparametric test to inspect any differences in the efficiency scores between the models before and after the bias correction. The results showed that there was a significant difference ($W = 265$, $p = 0.01375$) between the null hypothesis compared to the alternative one. Therefore, the null hypothesis was rejected under the BCC model, and the alternative hypothesis of inequity between the efficiency scores and corrected efficiency score under the BCC model was accepted. Thus, the bias correction helped us to improve our results.

In accordance with the DEA principles, we tested the normality of each model (CCR and BCC, in addition to Model 1, Model 2, Model 3, Model 4 that will be used in the table 6) we used in our study as the requirement to conduct independent sample t-test. Among the three tests for normality designed for detecting all kinds of departure from normality, we used Shapiro-Wilk's test since it is considered to be more accurate in cases of small samples. All the results show that the data does not fit the distribution normally with 95% confidence, and the DEA can be used to assess efficiency.

In another step, we tested the robustness of DEA results. To that aim, we conducted a sensitivity analysis by removing a specific input each time and then studying the results. We removed respectively operating vessel, capacity, engine power and employment in the models from 1 to 4, and conducted a BCC analysis. The model 0 is the original BCC model of our study. The efficiency scores with and without bias, the bias and the confidence interval are presented in the table 6.

Table 6. Original and corrected efficiency, Bias and the Confidence Interval (models 0-4)

	Model 0	Model 1	Model 2	Model 3	Model 4
Original efficiency	0,7559	0,7559	0,6827	0,7558	0,7074
Corrected efficiency	0,6005	0,6008	0,5013	0,6043	0,5516
Bias	0,1554	0,1551	0,1814	0,1515	0,1558
Lower bound	0,4908	0,4910	0,4101	0,4945	0,4560
Upper bound	0,7425	0,7420	0,6608	0,7431	0,6920

Source: elaborated on the basis of R outputs.

Table 6 displays the results of the bootstrapping, namely the bias, and the confidence intervals of the efficiency scores. The biases were very close (between 0.15 and 0.18) and relatively small for all efficiency measures. Bootstrapping showed that the confidence intervals for efficiency measures did not vary considerably over the re-samples. The table reports that capacity, followed by employment are the variables that have the most important influence on the efficiency scores of our study. The less influential is the number of vessels and engine power. Based on the results of bootstrapping, the bounds (the lower and the higher) were lower in the model without capacity (the most influential input), and the higher with the original model.

Even if the model 1 shows slight differences from the original model (table 6), real changes are registered in the detailed countries scores, and the bias corrected efficiency rangs from 7% in Turkey M, to 26% in Slovenia. That's why we consider that the two models are different, and that the operating vessels constitute an important input in addition to be the first one concerned by the management measures in each countries.

The table 7 presents the nonparametric pairwise Spearman's rank correlation test. The correlation coefficient equals to 1 states that the scores are exactly the same, meaning that the efficiency scores remain unchanged, and the variable doesn't have any impact/influence whether it is incorporated in the original model or not. While a correlation coefficient of 0 shows the variable has a great weight and excluding it from the analysis will completely change the results.

Table 7. Spearman rank correlation coefficients: original and bias-corrected efficiency.

	E*	E* 1	E* 2	E* 3	E* 4
E*	1				
E* 1	1	1			
E* 2	0,85630	0,85630	1		
E* 3	1	1	0,85629	1	
E* 4	0,87902	0,87902	0,71345	0,87899	1
	Bc E**	Bc E** 1	Bc E** 2	Bc E** 3	Bc E** 4
Bc E**	1				
Bc E** 1	0,99996	1			
Bc E** 2	0,79916	0,79951	1		
Bc E** 3	0,99972	0,99972	0,79871	1	
Bc E** 4	0,84189	0,84362	0,60941	0,84352	1

Source: elaborated on the basis of R outputs. *E: Efficiency; **Bc E: Bias-corrected Efficiency.

The Spearman's rank correlation scores were positive ad relatively high, varying from 0.71345 (between the model 4 and the model 2) to 1 (between the original model and the model 1) with the bias. For the bias corrected models, the scores varied from 0.60941 (between the model 4 and the model 2) to 0.99996 (between the original model and the model 1).

3.2.The second stage

In this part, we are going to examine our hypothesis scrutinizing some natural and local factors that could affect efficiency. This analysis is performed using truncated regression with bootstrapping. The model uses the bias-corrected efficiency for each country, as the dependent variable, and as regressors (exogenous variables) the variables relative to jurisdictional waters, coastline, SSF, and IF observed in each country. The empirical results from bootstrapped truncated regression model are reported in Table 8.

Table 8. Results of bootstrap truncated regressions.

	Coefficients	CI* (LB**)	CI* (UB***)
(Intercept)	55,16	32,20	69,46
Jurisdictional waters	0,03	-0,28	0,21
Coastline	2,56	-2,57	11,79
SSF	-0,10	-0,97	0,54
IF	-0,02	-2,64	1,43
Sigma	19,13	17,60	22,45

Source: elaborated on the basis of R outputs. *CI: Confidence intervals; **LB: Lower Bound; ***UB: Upper Bound.

Table 8 summarizes the results from bootstrapped truncated regression model and presents the coefficients and confidence intervals at 95% after the bootstrap. Apparently, the number of SSF and IF were statistically insignificant and showed a negative relationship, meaning that a greater number of traditional vessels lead to a decrease of the efficiency, and the efficiency level decreases with their increasing, since the most efficient countries have lower levels of SSF and IF.

In parallel, coastline and jurisdictional waters had a positive coefficients and thus they are directly related to efficiency, showing that a taller linear coast and a larger fishing area means higher levels of efficiency, and the most efficient countries have higher levels of coastline and jurisdictional waters.

Theorically, it is possible to increase the efficiency of a country by decreasing the vessels number, but it is important to note that the decrease of SSF métiers should be five times more than the decrease of total métiers. Also, the increasing of the efficiency can be reached by a longer coastline and a bigger fishing area. Even if it is not possible to increase coastline and jurisdictional waters, the results highlights that these determinants explains the differences of efficiencies between countries.

4. **Discussion:**

In DEA, the relative efficiency of a country is estimated by comparison to the best practices observed in the other countries. The revenue efficiency for each country is assessed by the models CCR and BCC, evaluating the capacity of each country in minimizing the fundamental inputs (operating vessel, capacity, engine power, employment), regarding the total landing and the fishing revenue in each country.

After correcting efficiencies from bias, all countries with optimal scores lost a percentage of their efficiency. Therefore, if we consider the first five places (Croatia, Greece, Lebanon, Ukraine, Spain), three of the fully efficient countries remain well ranked, in addition to two other countries that reach the best practice frontier. The latter (Lebanon and Ukraine) did not lose an important amount of their efficiency, which allows them to ameliorate their ranking.

Taking the original BCC model as a reference, all the countries registered a gap between the different models (table 6) with bias a part from fully efficient countries, the difference reaches a max of 56% for Ukraine in the fourth model. Considering the bias corrected models, the first and third models shows only minimal changes (between 7% and 26% in the model without operating vessels and between 6% and 25% in the model engine power). These results concern all countries of our study, except the optimal ones. In the model without capacity, only the efficiency scores of Turkey M and Ukraine remain the same, all the others were influenced when setting aside capacity as an input of the model. This finding confirms that the capacity is the most influential input of the study. Even after bootstrapping, all the scores changed with a highest rate registered in Algeria (18%). Finally, in the model omitting employment, only the efficiency of Albania, Turkey M and Ukraine changed considerably, all the others were less influenced by the omission of employment as an input of the model. This was not very different from the results of the bias corrected efficiency comparison, where all the scores changed, with a peak registered in Ukraine (48%).

The Spearman's rank correlation test for models without these less influential inputs showed the highest values, compared to the rank correlation of the most influential inputs that presents the lowest rank correlation. However, in general, the different models confirmed the conclusion that the original DEA model is robust.

Since traditional fisheries are predominant in the Mediterranean and Black Sea Fisheries, with a slightly higher prevalence in the Black Sea compared to the Mediterranean (FAO, 2020), it ends up weighing on coastal zones with no ability to use the whole jurisdictional waters of countries by traditional vessels. This justifies that the area of jurisdictional waters is the least argument for improving efficiency, especially for countries that have an Exclusive Economic Zone which is not fully used by traditional métiers, contrary to the length of the coastline which is the favorite area for small scale fisheries, and that constitute a source of pressure on coastal zones.

According to the results, the environmental variables depict insignificant results at the 5% level. In addition, the two local and managerial variables does not come with the expected sign, which means that it is better to decrease the flotilla size in order to increase the efficiency. This result is very important in terms of fisheries sustainability, when all the indicators point out the overfishing in the Mediterranean (Maynou, 2020) and Black Sea (FAO, 2020). Even if jurisdictional waters is a variable with a paramount importance when speaking about ficheries, in this model, the scores were insignificant with a low coefficient compared to coastline. This results can be explained by endogeneity factors such as the development of traditional fisheries that cannot be expanded in a large, but a long area near the coast because of means' lack (Pham et al. 2014). The jurisdictional waters and coastline variables come with the positive sign, meaning that they affect the efficiency of the country positively.

In conclusion, based on the bootstrapped truncated regression model, the DEA VRS efficiency scores of inefficient countries could be explained by the size of the fishing area and the length of the coastline, and not by the size of each métier. Therefore, fleet-increase policies should never be considered in order to bring the harvesting capacity in line with target output levels.

5. **Conclusion**:

This article is intended to explain that countries policymakers in fisheries service must be aware of their efficiencies position in their geographical zone compared to their bordering countries and of the regional imbalances to provide effective measures, particularly for the inefficient countries in the area of study.

Based on the nonparametric DEA Approach, this study aims to analyse the fisheries' efficiency rate of Mediterranean and Black Sea countries under the variable returns to scale assumption and input orientation. In another step, and in order to understand the registered efficiencies, we assessed the potential effect of some determinant variables through regression by applying the principle of bootstrapping.

The main conclusions of our work for the proposed efficiency model indicate that countries achieved a pure efficiency value of 0.62. In terms of the differentiation between CCR and VRS efficiency, the countries got better scores in the latter (0.76), and thus having greater opportunities for improvement in the last one. Subsequently, by applying the bootstrapping method, we corrected the bias in the efficiency estimates. The scores were commonly reduced, with an average of 0.60.

The sensitivity DEA analysis point out that the main inputs of the study are the capacity of the vessel and the employment compared to the engine power and operating vessel, and confirmed the robustness of the model. Thus, the results indicate that country-level efficiency significantly increases when incorporating the four inputs in the model.

The second stage of the analysis showed that jurisdictional waters and coastline variables are positively related to the total efficiency. However, the number of artisanal and industrial fisheries reduces slightly the likelihood of the countries to be fully efficient. Later, the negative sign of SSF and IF regression coefficients comforts the results of the sensitivity analysis in the first stage, where the number of operating vessels was the less important input of the DEA model.

Through efficiency evaluation, the main fisheries inputs and outputs were explored by country, identifying the main causes of inefficiency, and it is no more by increasing the number of operating vessels. The countries themselves also need more information to improve their performance, since increasing the investment in the number of operating vessels is known as the simplest way to improve the production and is no more the most sustainable one.

Therefore, from policy perspective, policy makers should shift from an excessive focus on the investment in physical capital (operating vessels) towards a better management of fisheries. Policy makers need to enhance the way through which each country should focus on the sustainability of its fisheries in the long-term, i. e. better managing scarce resources in harmony with the sustainability of the human activity.

The measurement of fisheries efficiency should be integrated into the management of the sector in each country. As it would serve to compare its achievements to those of bordering countries and identify its strengths and weaknesses, it would also be an instrument to orientate decision-making into more sustainable practices, in order to avoid declining economic benefits for fishermen, fishing industries and entire coastal areas that rely on fishing for their support and survival.

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