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Investigating the competitive factors of container ports in the Mediterranean area: an experimental analysis using DEA and PCA

Gianfranco Fancello[1[0000-0001-5233-5126]], Patrizia Serra[1[0000-0001-9815-5016]], Daniel M. Vitiello[1[0000-0002-3880-7681]] and Valentina Aramu

[1] DICAAR – Department of Civil and Environmental Engineering and Architecture, University of Cagliari, Cagliari 09123, Italy
pserra@unica.it

Abstract. In the maritime world scenario, various challenges are affecting Mediterranean container ports, which are trying to keep high their efficiency and their competitiveness through infrastructural and managerial improvements. The identification of the priority actions requires the analysis of the productivity of each port in relation to the use of its resources. This study applies Data Envelopment Analysis (DEA) and Principal Component Analysis (PCA) in order to investigate the potential factors that can affect the efficiency of Mediterranean container ports. These methods use six input variables (yard area, berth depth, number of quay cranes, equipment, berth length and distance of the port from the Suez-Gibraltar axis) and one output variable (port throughput expressed in TEUs). The results can help to highlight the potential factors of success for Mediterranean container ports and to identify future policies and management strategies aimed towards the strengthening of the analyzed context.

Keywords : Data Envelopment Analysis; Principal Component Analysis; benchmarking; container port; Mediterranean Sea

1 Introduction

Container ports represent the fastest and most immediate access doors to internal markets and constitute crucial nodes of integrated and multimodal supply chains, whose efficiency depends strictly on the efficiency of their ports. To stay competitive, container ports must carry out operations with maximum efficiency to meet the requirements of a continually growing and diversified demand. Not surprisingly, the assessment of port efficiency is among the areas that have attracted much attention in logistics in the last decades [1].

This paper focuses on the specific case of Mediterranean container ports in an attempt to elucidate the most representative factors of their efficiency. The Mediterranean basin has always played a key role in global trading markets due to its key positioning along the main East-West trading routes (known as pendulum routes) and its centrality with respect to both the Atlantic and North European markets, and the Asian and African ones. The unique location of its ports offers network advantages to ocean carriers due to the shortened transit times to major emerging markets, in particular to and from Asia. It is estimated that Mediterranean ports collectively currently handle almost 40% of the world's containerized trade flows [2]. Their future growth trend will depend on several factors, both endogenous and exogenous, which can contribute to determine their success or failure in the market. Some of these factors are mentioned below:

- Mediterranean container ports show different levels of technological advancement [3]. The best Mediterranean container ports are equipped with state-of-the-art handling equipment (for example, super post panamax cranes), often controlled by high performance IT applications. The advent of technology has caused major organizational and technical changes in the port sector. Vertical integration, blockchain and terminal automation are some of the elements that are changing activities in container terminals, and which can constitute distinctive and competitive factors of ports [4]. However, not all Mediterranean ports are able to keep up with these changes in the same way.
- Naval gigantism is another critical factor that affects container trade. In 2013, ships over 10,000 TEU (Twenty equivalent unit) were 14% of the global fleet, 36% at the beginning of 2020 [5]. Naval gigantism directly affects ports, as there are only a few ports properly structured to efficiently manage last generation container ships.
- External commercial strategies can both strengthen or hamper the centrality of the Mediterranean area. From one side, the Belt and Road initiative, for instance, supports the infrastructure of Euro-Asian trade, with particular attention to the port of Piraeus, which aims to become the largest logistics hub in the Mediterranean. On the other side, new alternative routes can pose a threat to Mediterranean ports. For example, the Arctic route has become more plausible given the climate change phenomenon, which has stronger and quicker implications in the Arctic region than elsewhere. The coastal states of the area have begun to take advantage of the sea route that connects the Atlantic and the Pacific Ocean to integrate the conventional trade routes during the summer season. Furthermore, more and more shipping companies decide to use the Cape Route and bypass the Suez Canal, due to slow steaming practice and high fees of the Suez Canal, thus rising interest in African ports [6] at the expense of the ports of the Mediterranean.
- The private sector has been playing an increasing dominant role in the global container market, where few world carriers and global terminal operators control ever-greater market shares. Generally, global enterprises initiate their development plans in the Mediterranean, as they are the decision makers for possible port of calls or the potential buying out of a port's terminal [7].

The effects of the Covid-19 pandemic, which is contributing to transform further the shipping market and the global supply chains, now further complicate this ever-changing market scenario. In such an evolving scenario, Mediterranean ports are required to improve their functionality and productivity to meet new needs and acquire ever-higher market rates [8].

This paper intends to investigate the factors that most affect the efficiency of container ports in the Mediterranean area by applying and combining Data Envelopment Analysis (DEA) and Principal Component Analysis (PCA). The application considers 35 major Mediterranean container ports characterized in terms of supply (berth length, yard area, number of QCs, depth) and demand variables (TEUs moved in 2019).

The framework of the article is as follows: Section 2 presents a brief literature review of the most applied methods used to analyse efficiency of container ports. Section 3 describes the methodology used while Section 4 illustrates the selected input and output variables. The results of the analysis are provided and discussed in Section 5. Finally, Section 6 concludes the paper.

2 Literature review

In the last decades, there has been a growth of interest in the evaluation of container ports efficiency. Most of the available methodologies are based on Multi-Criteria Decision-Making methods. Table 1, created by adapting to the port area the table proposed by Fancello et al. [9] for road transport, summarizes the main strengths and weaknesses of the most used methods applied to container port efficiency.

Among the available methods for evaluating efficiency, DEA has been chosen for this study because of its following features that, in the authors' opinion, make it very attractive for benchmarking port efficiency:

- Differently from Electre III, DEA does not use any subjective parameter.
- Through the identification of the efficiency frontier, DEA allows to identify not only the most efficient units but also their distance from the inefficient ones.
- DEA can handle multiple inputs and outputs with independent production function specification.
- Some methods, like TOPSIS, use indicators for which the input-output relationship may not be immediate, while DEA results are easily understood.
- PROMETHEE requires obtaining and considering a distribution function, while DEA does not.
- SFA is based on an assumption made a priori for the production function, which may be not appropriate for every port, while DEA provides great flexibility.
- PCA-DEA allows considering the correlation between variables and generates non-discrete positive principal components, thus improving the strength of DEA [19].
- DEA helps decision-making units to remove other sources of inefficiency from the observations.
- DEA allows maximizing profits or minimizing resources by using an input- or an output-oriented approach.
- However, DEA can be also subject to some weaknesses, such as:
- DEA can be sensitive to the presence of an outlying observation that could determine an erroneous efficiency frontier used to measure inefficient DMUs.
- DEA results are sensitive to the choice selection of input and output variables: the number of efficient DMUs on the frontier increases with the number of input and output variables.
- DEA does not consider the correlation between the chosen variables.

Table 1. Most common methods applied to container port performance.

Method	Strengths	Weaknesses	First author	Year	Reference
AHP	Easy to use. Scalable.	Possible inconsistencies in the classification criteria. Problems of interdependence between criteria and alternatives.	Ismail	2018	[10]
ELECTRE III	Considers uncertainty and vagueness.	Not useful for classification purposes. The lowest performance based on certain criteria is not identifiable. Results can be difficult to interpret.	Gao	2018	[11]

PROMETHEE	Easy to use. Eliminates scale effects among alternatives.	Requires the assignment of weights but does not provide a clear methodology to assign values.	Kim	2012	[12]
TOPSIS	Easy to use. Number of steps does not depend on the size of the problem.	Does not consider attributes correlation. Difficult to weight attributes.	Celik	2009	[13]
HHI	Easy to use. It is not influenced by arbitrary factors.	Depends on the size of the sample.	Elbayoumi	2016	[14]
SFA	Recognizes the fact that external factors can influence production.	Based on an assumption made a priori for the production function.	López-Bermúdez	2019	[15]
DEA	Quantifies efficiency. Evaluate the efficiency of alternatives against each other. Can manage multiple inputs and outputs.	Assumes that all inputs and outputs are exactly known. Is sensitive to the number of variable measurements. Does not evaluate the correlation between variables.	Iyer	2021	[16]
CLUSTERING	Easy to use. Identifies homogeneous groups.	Not useful for classification purposes. Results can be difficult to interpret.	Fancello Serra	2014 2020	[8] [1]
PCA-DEA	Considers the correlation between variables. Improves the strength of DEA model.	Assumes that all inputs and outputs are exactly known. Is sensitive to the number of variable measurements.	Venkatasubbaiah Perico	2018 2020	[17] [18]

In order to increase the DEA strength and consider the correlation between variables, DEA has been used together with PCA in different fields, but only rarely it has been applied to container port efficiency. Among the others, Venkatasubbaiah et al. [17] evaluated and analyzed the performance of 28 container terminals in south East Asia using a DEA-PCA hybrid method. The hybrid method was performed implementing PCA to the cross-efficiency matrix obtained through DEA and was used to determine the ultimate cross-efficiency of each DMU. Périco and da Silva [18] applied a hybrid method of BCC-DEA with PCA to evaluate performance of the 24 largest ports in Brazil. They used PCA as a validation method among the chosen variables but applied PCA-DEA considering the initial proposal of variables, as the commonalities of the variables did not allow excluding any. Almost all the documents analyzed apply DEA as a benchmarking technique to compare ports in a geographic area. This paper proposes a decision support tool based on DEA and PCA to define which elements may have the greatest influence on the efficiency of ports in the Mediterranean area.

3 Methodology

3.1 Data Envelopment Analysis

DEA is a performance measurement technique, formulated by Farrell in 1957, that can be used for evaluating the relative efficiency of Decision-Making Units (DMUs). In this application, Mediterranean container ports are identified as the DMUs forming the sample. DEA method is based on a non-parametric approach that leads to the definition of a flexible efficient frontier. The efficiency of each DMU is measured comparing the ratio of outputs (production) to inputs (resources), subject to the condition that the same ratio for all DMUs must be less than or equal to one. The two basic DEA models are:

- the **CCR model** [20], which produces an objective evaluation of efficiency assuming constant returns to scale (CRS);
- the **BCC model** [21], which considers variable returns to scale (VRS) and estimates the pure technical efficiency of the DMUs.

In the first phase of the study, DEA is applied using both CCR and BCC models. Their formulation can be input- or output-oriented. The first approach examines if a DMU wastes inputs in the production phase, while the latter if the outputs are maximized.

CCR MODEL. The CCR model requires all inputs and outputs to be positive. It is based on CRS, in which all inputs and outputs are driven back to a single virtual input and a single virtual output. Weights must be non-negative and that make the ratio for DMUs greater than 1.

- *Input-oriented*

The goal of the input-oriented model is to verify the efficiency conditions through the minimization of a real variable θ, as described below:

$$min_{(\theta,\lambda)}\ \theta$$

s.t.

$$\theta x_o - \lambda X \geq 0$$

$$\lambda Y \geq y_o$$

$$\lambda \geq 0$$

where $\lambda = (\lambda_1, \dots, \lambda_n)^T$ is a transposed non-negative vector of variables.

- Output-oriented

The purpose of the output-oriented model, instead, is to verify the efficiency conditions through the maximization of a real variable τ.

$$max_{(\tau,\mu)}\ \tau$$

s.t.

$$x_o - \mu X \geq 0$$

$$\tau y_o - \mu Y \leq 0$$

$$\mu \geq 0$$

where $\mu = \lambda\tau$ and $\tau = 1/\theta$.

The input-oriented approach evaluates efficiency in terms of the best reduction of inputs given an observed level of output, while the output-oriented one assesses competitiveness in terms of commercial potential.

BCC MODEL. The BCC model represents an extension of the CCR model. Its efficient frontier is not a straight line through the origin, as in the case of the CCR model, but a convex function, due to variable returns to scale. The modification is applied, both in CCR and in BCC model, by adding a convexity constraint to the model:

$$e\lambda = 1,$$

where e is a unit row vector.

BCC model estimates the pure technical efficiency of the DMUs. The complexity of the case with multiple inputs or outputs lies in the weighting of the quantitative variables by the calculation of efficiency, as it deals with dimensionally different variables. DEA allows using variable weights obtained from the observations and chosen to maximize the efficiency indices of each DMU relative to any other DMU present in the sample. To be considered optimal, the weights must be non-negative, and the relative efficiency index must be between zero and one.

3.2 Principal Component Analysis

In a second phase of the study, with a view to later applying the DEA by considering several input variables together, PCA is applied to identify the input variables that have the greatest weight in the description of the phenomenon under study. PCA is typically used to reduce the dimensionality of a data set by transforming the set of variables into a smaller one (the so-called principal components - PCs) that still contains most of the information in the original set. The first PC is obtained by projecting the data geometrically on the axis that produces the smallest total projection error, given by the perpendicular distance between the data and their projection, and the greatest variance. The subsequent PCs are selected similarly, but with the additional requirement of no correlation with the previous PCs. The PCs are ranked by their variances in descending order: the first PC is the one that describes the largest share of variance in the sample. Each PC is expressed as an uncorrelated linear combination of input and output variable, which are multiplied by the corresponding eigenvectors. Each eigenvector, associated with a variable, represents the weight of that variable in determining the i-th PC. The i-th PC will be more influenced by the variables with higher eigenvectors in absolute value. In this study, PCA is used to rank the variables from the most influential to the least influential from a statistical point of view.

4 Data description

This study considers the 35 main Mediterranean container ports (Fig. 1) in terms of TEUs handled in the last decade. In 2019, the 35 ports, as a whole, handled nearly 60M TEUs.

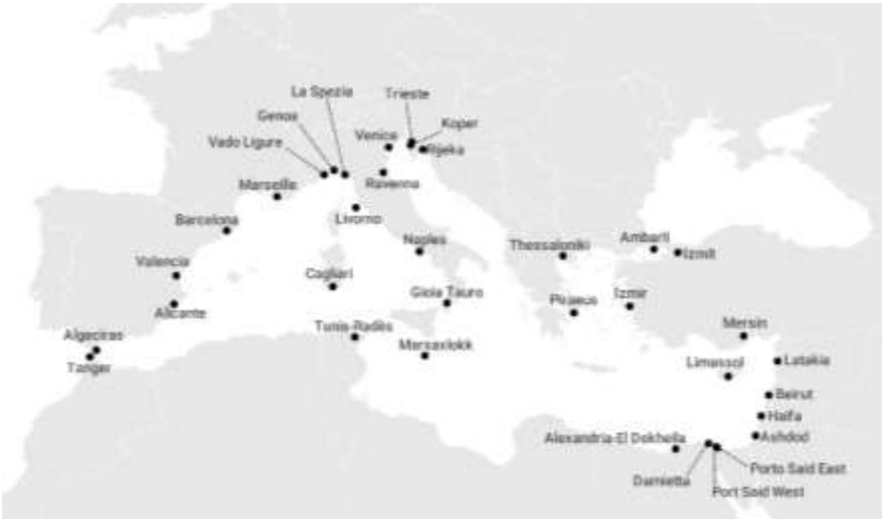

Fig. 1. Geographical location of the 35 container ports (Source: Authors)

The efficiency of a container port may depend on its physical-organizational characteristics and on the correct use of land, infrastructures and equipment. As we have seen previously, DEA requires the definition of input and output variables. Following some literature hints, the input variables can be differentiated in three macro-groups:

- Capital inputs: these variables describe the physical port characteristics, such as yard area, terminal area, storage area, berth length, number of berths, berth depth and others. If well managed, they can represent the effective resources for port activity [4,6,17].
- Non-capital inputs: such as labour, number of cranes, number of pieces of equipment, environment, costs, etc. [22,23].
- Geographic inputs: the port position among global trades is a potential performance factor for container ports as well as their proximity to internal markets and transport networks [24,25].

The output variables should represent the port production. Therefore, the most used indicator is the annual container throughput, measured in TEUs. In this study, the choice of the input variables was based on the literature reviews about DEA studies on port efficiency provided by Schøyen and Odeck [26], Julien et al. [27], Iyer and Nanyam [16] and Fancello et al. [28]. In detail, three capital inputs, Yard Area (Yard) - m^2, Berth Length (Berth) - m, Maximum Depth (Depth) - m, two non-capital inputs, no. of Quay Cranes (QC), no. of Yard Equipment (Equipment), and one geographic input (Distance) measuring the distance (nm) between each port and the ideal Suez-Gibraltar axis, were chosen as input variables. Port data were collected from official websites of the ports and are updated to 2019. Container throughput in 2019, expressed in terms of TEUs, was identified as the only output variable.

Table 2. Input and output variables.

	Inputs						Output
	Yard	QC	Distance	Berth	Depth	Equipment	Throughput

	[m^2]	(no.)	[nm]	[m]	[m]	(no.)	(TEU)
Minimum	111,000	2	1	515	10	17	54,542
Maximum	1,807,739	40	745	4,790	20	346	5,650,000
Mean	673,562	16	299	1,927	15	130	1,698,748
Median	500,000	14	260	1,520	16	98	1,229,081
Std. dev.	452,487.149	10.854	240.047	1236.302	2.218	90.247	1,575,066.848

5 Results

The application was performed using input- and output-oriented approaches and both CCR and BCC methods. 12 combinations were tested, of which 6 applying an input-oriented approach (IO) and 6 an output-oriented one (OO). Each combination was taken out considering one output variable, fixed for all the combinations (Throughput 2019) and one input variable, changed each time, according to Table 3.

Table 3. Combinations of input and output variables.

	Inputs:					
	QC	Berth	Yard	Depth	Equipment	Distance
Output:	Test 1, IO	Test 2, IO	Test 3, IO	Test 4, IO	Test 5, IO	Test 6, IO
Throughput 2019	Test 1, OO	Test 2, OO	Test 3, OO	Test 4, OO	Test 5, OO	Test 6, OO

Table 4 provides the scores for each DMU, calculated by applying both CCR and BCC methods using an input-oriented approach. In the case of the CCR model, for each test, only one DMU reaches efficiency, totalizing a unitary score (Algeciras for test 1 and 2; Valencia for test 3 and 4; Haifa for test 5; Port Said East for test 6). In the case of the BCC model instead, more DMUs totalize a score equal to 1.000 in each combination tested. The ports that achieve efficiency are Piraeus (6 times), Algeciras (5), Valencia (4), Port Said East (3), Alicante (2), Haifa (2), Koper (2), Marsaxlokk (1), Rijeka (1), Tanger (1), Thessaloniki (1) and Tunis (1). Algeciras is the best performing port in the combinations that uses QC (test 1) or Berth (test 2) as the input variable while Valencia is the best one when Yard (test 3) or Depth (test 4) variable is considered. The two ports obtain efficiency using both methods.

Table 4. CCR and BCC results: Input-Oriented approach (IO).

	Test 1		Test 2		Test 3		Test 4		Test 5		Test 6	
DMUs	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC
Alexandria.-El Dekheila	0.684	0.736	0.643	0.675	0.572	0.583	0.436	0.902	0.210	0.246	0.011	0.020
Algeciras	**1.000**	**1.000**	**1.000**	**1.000**	0.946	0.946	0.889	0.919	0.461	0.930	0.400	**1.000**
Alicante	0.450	**1.000**	0.185	**1.000**	0.204	0.740	0.038	0.679	0.080	0.415	0.001	0.010
Ambarli	0.431	0.443	0.381	0.388	0.584	0.589	0.588	0.824	0.195	0.276	0.002	0.002
Ashdod	0.527	0.586	0.440	0.471	0.502	0.516	0.282	0.718	0.391	0.391	0.004	0.008
Barcelona	0.605	0.618	0.534	0.542	0.464	0.467	0.630	0.844	0.240	0.353	0.004	0.005
Beirut	0.405	0.459	0.622	0.675	0.512	0.530	0.233	0.659	0.174	0.185	0.002	0.004
Cagliari	0.114	0.286	0.055	0.339	0.068	0.278	0.030	0.594	0.041	0.239	0.001	0.014
Damietta	0.563	0.653	0.410	0.452	0.241	0.251	0.223	0.709	0.137	0.157	0.026	0.077
Genoa	0.397	0.413	0.306	0.314	0.261	0.264	0.549	0.861	0.188	0.255	0.002	0.002
Gioia Tauro	0.579	0.604	0.414	0.426	0.283	0.286	0.438	0.709	0.371	0.497	0.003	0.004
Haifa	0.410	0.456	0.470	0.503	0.502	0.516	0.282	0.718	**1.000**	**1.000**	0.003	0.006

Izmir	0.639	0.839	0.321	0.533	0.472	0.621	0.111	0.586	0.172	0.274	0.000	0.002
Izmit	0.431	0.467	0.378	0.398	0.427	0.436	0.290	0.626	0.459	0.523	0.001	0.002
Koper	0.562	0.665	0.896	**1.000**	0.955	**1.000**	0.207	0.723	0.109	0.132	0.000	0.001
La Spezia	0.524	0.578	0.597	0.636	0.918	0.943	0.321	0.776	0.338	0.354	0.001	0.003
Latakia	0.286	0.463	0.223	0.655	0.090	0.174	0.076	0.719	0.241	0.654	0.000	0.003
Limassol	0.411	0.621	0.271	0.672	0.206	0.353	0.076	0.603	0.075	0.170	0.001	0.005
Livorno	0.320	0.394	0.230	0.303	0.296	0.339	0.190	0.787	0.224	0.303	0.001	0.003
Marsaxlokk	0.717	0.744	0.698	0.714	0.728	0.735	0.500	0.767	0.222	0.304	0.850	**1.000**
Marseille	0.479	0.530	0.241	0.258	0.156	0.160	0.267	0.659	0.312	0.321	0.001	0.003
Mersin	0.730	0.781	0.727	0.759	0.527	0.536	0.384	0.754	0.145	0.175	0.002	0.003
Naples	0.327	0.417	0.326	0.488	0.611	0.754	0.152	0.720	0.061	0.091	0.001	0.004
Piraeus	0.764	**1.000**	0.817	**1.000**	0.921	**1.000**	0.905	**1.000**	0.438	**1.000**	0.007	**1.000**
Port Said East	0.804	0.824	0.742	0.754	0.478	0.481	0.606	0.833	0.701	**1.000**	**1.000**	**1.000**
Port Said West	0.348	0.447	0.387	0.595	0.207	0.260	0.138	0.670	0.100	0.151	0.052	0.250
Ravenna	0.230	0.448	0.181	0.776	0.156	0.444	0.059	0.826	0.064	0.258	0.000	0.001
Rijeka	0.402	0.670	0.270	0.842	0.493	**1.000**	0.067	0.671	0.218	0.630	0.000	0.001
Tanger	0.817	0.819	0.957	0.959	0.615	0.615	0.833	0.893	0.548	**1.000**	0.150	0.350
Thessaloniki	0.592	0.851	0.454	0.988	0.317	0.497	0.117	0.811	0.509	**1.000**	0.000	0.002
Trieste	0.595	0.732	0.571	0.751	0.354	0.405	0.137	0.569	0.293	0.396	0.000	0.001
Tunis	0.301	0.516	0.141	0.466	0.108	0.234	0.094	**1.000**	0.250	0.773	0.001	0.017
Vado Ligure	0.041	0.286	0.026	0.444	0.027	0.306	0.010	0.559	0.025	0.405	0.000	0.003
Valencia	0.717	0.856	0.639	0.729	**1.000**	**1.000**	**1.000**	**1.000**	0.303	0.662	0.010	0.933
Venice	0.391	0.517	0.173	0.292	0.250	0.332	0.161	0.865	0.117	0.189	0.000	0.001

Similarly to Table 4, Table 5 illustrates the results of both CCR and BCC models when an output-oriented approach is used. Apart from the port of Marsaxlokk, all the other ports that achieve efficiency using the input-oriented approach also achieve efficiency when the output-oriented approach is used.

Table 5. CCR and BCC results: Output-Oriented approach (OO).

	Test 1		Test 2		Test 3		Test 4		Test 5		Test 6	
DMUs	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC
Alexandria.-El Dekheila	0.684	0.713	0.643	0.658	0.572	0.576	0.436	0.675	0.210	0.381	0.011	0.348
Algeciras	**1.000**	**1.000**	**1.000**	**1.000**	0.946	0.946	0.889	0.927	0.461	0.970	0.400	**1.000**
Alicante	0.450	**1.000**	0.185	**1.000**	0.204	0.253	0.038	0.051	0.080	0.094	0.001	0.032
Ambarli	0.431	0.554	0.381	0.550	0.584	0.585	0.588	0.609	0.195	0.550	0.002	0.550
Ashdod	0.527	0.550	0.440	0.447	0.502	0.507	0.282	0.318	0.391	0.530	0.004	0.261
Barcelona	0.605	0.638	0.534	0.611	0.464	0.588	0.630	0.652	0.240	0.588	0.004	0.588
Beirut	0.405	0.418	0.622	0.651	0.512	0.519	0.233	0.241	0.174	0.296	0.002	0.220
Cagliari	0.114	0.130	0.055	0.057	0.068	0.069	0.030	0.032	0.041	0.056	0.001	0.029
Damietta	0.563	0.609	0.410	0.421	0.241	0.241	0.223	0.263	0.137	0.241	0.026	0.208
Genoa	0.397	0.481	0.306	0.466	0.261	0.466	0.549	0.648	0.188	0.466	0.002	0.466
Gioia Tauro	0.579	0.583	0.414	0.467	0.283	0.447	0.438	0.457	0.371	0.623	0.003	0.448
Haifa	0.410	0.419	0.470	0.479	0.502	0.507	0.282	0.318	**1.000**	**1.000**	0.003	0.257
Izmir	0.639	0.792	0.321	0.337	0.472	0.488	0.111	0.111	0.172	0.232	0.000	0.107
Izmit	0.431	0.436	0.378	0.380	0.427	0.429	0.290	0.308	0.459	0.629	0.001	0.304
Koper	0.562	0.616	0.896	**1.000**	0.955	**1.000**	0.207	0.258	0.109	0.199	0.000	0.170
La Spezia	0.524	0.543	0.597	0.615	0.918	0.941	0.321	0.401	0.338	0.479	0.001	0.264
Latakia	0.286	0.338	0.223	0.240	0.090	0.090	0.076	0.112	0.241	0.249	0.000	0.058
Limassol	0.411	0.510	0.271	0.292	0.206	0.210	0.076	0.082	0.075	0.113	0.001	0.071
Livorno	0.320	0.336	0.230	0.233	0.296	0.299	0.190	0.294	0.224	0.303	0.001	0.140
Marsaxlokk	0.717	0.728	0.698	0.704	0.728	0.731	0.500	0.500	0.222	0.493	0.850	0.850

Marseille	0.479	0.494	0.241	0.270	0.156	0.257	0.267	0.267	0.312	0.449	0.001	0.257
Mersin	0.730	0.762	0.727	0.746	0.527	0.529	0.384	0.420	0.145	0.343	0.002	0.343
Naples	0.327	0.349	0.326	0.340	0.611	0.636	0.152	0.202	0.061	0.129	0.001	0.121
Piraeus	0.764	**1.000**	0.817	**1.000**	0.921	**1.000**	0.905	**1.000**	0.438	**1.000**	0.007	**1.000**
Port Said East	0.804	0.814	0.742	0.746	0.478	0.566	0.606	0.628	0.701	**1.000**	**1.000**	**1.000**
Port Said West	0.348	0.376	0.387	0.409	0.207	0.208	0.138	0.162	0.100	0.166	0.052	0.129
Ravenna	0.230	0.285	0.181	0.199	0.156	0.161	0.059	0.131	0.064	0.086	0.000	0.039
Rijeka	0.402	0.538	0.270	0.300	0.493	**1.000**	0.067	0.087	0.218	0.218	0.000	0.054
Tanger	0.817	0.906	0.957	0.958	0.615	0.850	0.833	0.869	0.548	**1.000**	0.150	0.935
Thessaloniki	0.592	0.792	0.454	0.878	0.317	0.326	0.117	0.224	0.509	**1.000**	0.000	0.079
Trieste	0.595	0.680	0.571	0.617	0.354	0.359	0.137	0.143	0.293	0.369	0.000	0.140
Tunis	0.301	0.373	0.141	0.147	0.108	0.109	0.094	**1.000**	0.250	0.309	0.001	0.054
Vado Ligure	0.041	0.047	0.026	0.027	0.027	0.027	0.010	0.010	0.025	0.030	0.000	0.010
Valencia	0.717	0.963	0.639	0.963	**1.000**	**1.000**	**1.000**	**1.000**	0.303	0.963	0.010	0.996
Venice	0.391	0.437	0.173	0.175	0.250	0.253	0.161	0.357	0.117	0.175	0.000	0.105

Table 6 shows mean values of the IO and OO scores, both for CCR and BCC methods. As regard to the CCR method, the highest average scores are obtained in Test 1, Test 2 and Test 3, using both the IO and OO approach, while, in the case of the BCC, the highest average scores are obtained in Test 1, Test 2 and Test 4 (only for the IO approach). In both methods, the Distance variable assumes very low average values, which indicate that the DMUs are not very efficient with respect to this input variable. While the BCC model produces different results when using input- and output- oriented approaches, the CCR model produces more robust results both in the case of an input or output approach, thus resulting more suitable to evaluate the effectiveness of container ports.

Table 6. Mean values of IO and OO scores, both CCR and BCC methods.

	Test 1		Test 2		Test 3		Test 4		Test 5		Test 6	
	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC	CCR	BCC
Mean IO	0.503	0.621	0.449	0.623	0.441	0.531	0.323	0.759	0.269	0.449	0.072	0.164
Mean OO	0.503	0.578	0.449	0.525	0.441	0.491	0.323	0.393	0.269	0.449	0.072	0.332

To validate the CCR results, which identify the QC (Test 1), Berth (Test 2) and Yard (Test 3) variables as those that most influence the evaluation of efficiency, it was decided to apply the PCA to verify that the variables identified are the most representative. The eigenvector components are considered as weights of the variables. To do this, six principal components were identified (Table 7).

Table 7. Eigen analysis of the Correlation Matrix.

PCs	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalue	36.661	0.9611	0.6673	0.5086	0.1516	0.0453
Proportion	0.611	0.160	0.111	0.085	0.025	0.008
Cumulative	0.611	0.771	0.882	0.967	0.992	1.000

The first principal component (PC1) is chosen to minimize the perpendicular distance between the variables and their projection. For this reason, PC1 reaches the greatest eigenvalue and represents 61% of the sample variability. The cumulative value is the cumulative proportion of the sample variability given by consecutive PCs. PC2 cumulative, obtained from the sum of PC1 and PC2 proportion, reaches 0.771, which means having a representativeness of 77% of the sample variability. The eigenvector's components of the PC1 (Table 8) represent the weight of each corresponding variable in determining the

PC1. The variables that are correlated the most with PC1 are QC (0.499), Berth (0.492), Yard (0.444) and Equipment (0.417). By increasing the values of QC, Berth, Yard, Equipment and Depth, PC1 enhances its value. PC1 is negatively correlated with Distance variable (-0.149).

Table 8. Principal component PC1 eigenvector.

Variable	QC	Berth	Yard	Equip.	Depth	Distance
PC1	0.499	0.492	0.444	0.417	0.340	-0.149

The variables with higher eigenvector's components in absolute value are QC, Berth, and Yard, thus confirming that they are the most significant in the problem at hand.

6 Conclusions

This study applied DEA and PCA for evaluating the factors that most affect the efficiency of 35 major Mediterranean container ports. In a first step, port productivity was assessed on the basis of 12 tests, which differ in the method applied (CCR or BCC), in the approach used (input- or output-oriented approach) and in the input variable used (one variable selected among QC, Berth, Yard, Equipment, Depth, or Distance).

Among the sample, some ports are more affected than others by the method or the approach applied. Few ports, such as Piraeus, are fully efficient - or close to efficiency - in a large number of tests, demonstrating that their capital and non-capital input variables are correctly sized in relation to demand. Other ports, such as Haifa, achieve efficiency only respect to one variable, resulting oversized respect to the others. Furthermore, other ports (e.g. Alicante) achieve high efficiency scores only applying the BCC method, thus comparing them with smaller ports.

In the tests performed by entering QC or Berth or Yard as the input variable, the average score settles around 0.5. This means that, with respect to these parameters, the average efficiency of the sample as a whole is about 50%.

The results obtained using Depth or Equipment as input variables are more sensitive to the approach and to the applied method. In the combinations having Distance as the input variable, the mean scores show that ports are very far from the efficient frontier. This could mean either that the ports are very far from the main route or that the Distance variable is not significant for the assessment of port efficiency. To confirm these results, the PCA was applied. The variables QC, Bert and Yard are the ones characterized by the highest eigenvector's components in absolute value: they can be identified as the most representative of the efficiency of Mediterranean container ports.

The proposed analysis can help highlight the potential success factors for Mediterranean container ports, thus providing decision-makers with useful insights for the implementation of future policies and management strategies aimed at strengthening the Mediterranean port context.

Future studies will have to investigate the correlation of QC, Berth and Yard variables, which are resulted to be the most significant in this study, and apply the DEA-CCR to the combination of two or more input variables. Furthermore, the role of the distance variable when assessing port efficiency should be further investigated.

References

1. Serra, P., Fancello, G., 2020. Performance assessment of alternative SSS networks by combining KPIs and factor-cluster analysis. European Transport Research Review, 12(1), 1-24.
2. UNCTAD, 2020. Review of Maritime Transport 2020 (United Nations publication. Sales No. E.20.II.D.31. New York and Geneva).
3. Serra, P., Fancello, G., 2020b. Use of ICT for More Efficient Port Operations: The Experience of the EASYLOG Project. In Lecture Notes on Computer Science - International Conference on Computational Science and Its Applications (pp. 3-14). Springer, Cham.
4. Ghiara, H., Tei, A., 2021. Port activity and technical efficiency: determinants and external factors. Maritime Policy & Management, 1-14.
5. Alphaliner Monthly Monitor January, 2020. Monthly Monitor. Retrieved (www.alphaliner.com).
6. Kalgora, B., 2019. Strategic container ports competitiveness analysis in West Africa using data envelopment analysis (DEA) model. Open Journal of Business and Management, 7(02), 680.
7. Polyzos, S., Niavis, S., 2013. Evaluating port efficiency in the Mediterranean. International Journal of Data Analysis Techniques and Strategies 7, 5(1), 84-100.
8. Fancello, G., Pani, C., Serra, P., Fadda, P., 2014. Port cooperation policies in the Mediterranean Basin: An experimental approach using cluster analysis. Transportation Research Procedia, 3, pp.700-709.
9. Fancello, G., Carta, M., Serra, P., 2020. Data Envelopment Analysis for the assessment of road safety in urban road networks: A comparative study using CCR and BCC models. Case studies on transport policy, 8(3), 736-744.
10. Ismail, A., Elgazzar, S., 2018. Measuring the Egyptian container ports' efficiency: a FUZZY AHP framework. In 23rd Annual Conference of The Chartered Institute of Logistics and Transport, Logistics Research Network (LRN).
11. Gao, T., Na, S., Dang, X., Zhang, Y., 2018. Study of the Competitiveness of Quanzhou Port on the Belt and Road in China Based on a Fuzzy-AHP and ELECTRE III Model. Sustainability, 10(4), 1253.
12. Kim, D.J., 2012. A comparison of efficiency with productivity criteria for European container ports. The Asian Journal of Shipping and Logistics, 28(2), 183-202.
13. Celik, M., Cebi, S., Kahraman, C., Er, I.D., 2009. Application of axiomatic design and TOPSIS methodologies under fuzzy environment for proposing competitive strategies on Turkish container ports in maritime transportation network. Expert Systems with Applications, 36(3), 4541-4557.
14. Elbayoumi, O., Dawood, A., 2016. Analysis of the competition of ports in the Middle East container ports using HHI. Journal of Shipping and Ocean Engineering, 6(6).
15. López-Bermúdez, B., Freire-Seoane, M.J., González-Laxe, F., 2019. Efficiency and productivity of container terminals in Brazilian ports (2008–2017). Utilities Policy, 56, 82-91.
16. Iyer, K. C., Nanyam, V.N., 2021. Technical efficiency analysis of container terminals in India. The Asian Journal of Shipping and Logistics, 37(1), 61-72.
17. Venkatasubbaiah, K., Rao, K.N., Rao, M.M., Challa, S., 2018. Performance evaluation & modelling of container terminals. Journal of The Institution of Engineers (India): Series C, 99(1), 87–96. http://dx.doi.org/10.1007/s40032-017-0410-x. Springer India.
18. Périco, A.E., Ribeiro da Silva, G., 2020. Port performance in Brazil: A case study using data envelopment analysis. Case Studies on Transport Policy, 31-38.
19. Chen, Y., Du, J., David Sherman, H. & Zhu, J., 2010. DEA model with shared resources and efficiency decomposition. European Journal of Operational Research, 207(1): 339–349.
20. Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units, European Journal of Operational Research, Vol. 2, No. 6, pp.429–444.
21. Banker, R.D., Charnes, A., Cooper, W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis, Management Science, Vol. 30, No. 9, pp.1078–1092.

22. Tongzon, J. 2001. Efficiency measurement of selected Australian & other international ports using data envelopment analysis. Transportation Research Part A: Policy & Practice, 35(2), 107-122.
23. Barros, C., and M. Athanassiou. 2004. Efficiency in European Sea Ports with DEA: Evidence from Greece and Portugal. Maritime Economics & Logistics 6: 122–140.
24. Caldeirinha, V. R., Felicio, J. A., & Coelho, J. O. A. N. A. 2009. The influence of characterizing factors on port performance, measured by operational, financial and efficiency indicators. Recent Advances in Environment, Energy Systems and Naval Science, 58-70.
25. Liu, Z., 1995. The Comparative Performance of Public and Private Enterprises: The Case of British Ports, The London School of Economics and Political Science and University of Bath.
26. Schøyen, H., Odeck, J., 2013. The Technical Efficiency of Norwegian Container Ports: A Comparison to Some Nordic & UK Container Ports Using Data Envelopment Analysis (DEA). Maritime Economics & Logistics. 15 (2): 197–221.
27. Julien, S.A., Cowie, J., Monios, J., 2018. Efficiency, productivity and returns to scale in ports: a comparison of data envelopment analysis and econometric estimation with application to Caribbean Small Island Developing States. Maritime Economics & Logistics, 1-26.
28. Fancello, G., Serra, P., Aramu, V., Vitiello, D.M., 2021. Evaluating the efficiency of Mediterranean container ports using data envelopment analysis. Competition and Regulation in Network Industries. https://doi.org/10.1177/17835917211047837.