PERFORMANCE OF THE GREEK FISH FARMING SECTOR: TECHNICAL EFFICIENCY EVALUATION VIA DATA ENVELOPMENT ANALYSIS

MAVROMMATI, Athanasia[1]
TSIOUNI, Maria[2]
KONTOGEORGOS, Achilleas[3]
CHATZITHEODORIDIS, Fotios[4]*

Abstract
The main objective of the current paper is the efficiency analysis of firms in fish sector in Greece using the data envelopment analysis (DEA) under economic instability. For our purpose, DEA models were applied to evaluate the technical efficiency and competitiveness among firms in the sector. The used financial data were regarding to the years 2010–2016, (stress period where the Greek economic crisis was to the peak) with respectively constant and variable returns to scale models, the empirical analysis shows the differences in the efficiency performance of the firms in Greek aquaculture. Research finding indicates that several firms in the sector don't reach technical and scale efficiency and need interventions to restructure their resources usage.
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1. Introduction

Fish farming is an important and promising sector of the Greek economy (Kolokontes et al., 2018) and was established in the early 1980s motivated by the strong European Union (EU) support in establishing pilot-scale farms. Greek aquaculture is dominated by the farming of marine finfish in offshore cages, specifically of gilthead sea bream and European seabass with the combined production capacity of about 116.000 tons in 2016. Modern aquaculture in Greece is dominated by Mediterranean marine species such as European seabass, gilthead seabream and Mediterranean mussels. Marine fish is the top Greek exported animal product and contributes about 11% of the total national agricultural exports (FAO). The sector is oligopolistic, with the eight largest Greek companies to concentrate the approximately 80% of the aggregate sales, benefiting from economies of scale in production, while they hold a stable share, greater than 45% of the EU-27 production. Marine fish farming in Greece provides 12.000 jobs (scientific, technical, workers) mainly in remote and isolated areas. The Greek economy faced between the years 2008 - 2017 a major debt crisis (Kontogeorgos et al., 2016; 2017). In this case, the performance of a crucial sector like the aquaculture sector was challenged. Given the

[1] Assist. Professor, PhD, Department of Business Administration of Food and Agricultural Enterprises, University of Patras, Greece.
[2] Lecturer, PhD, Department of Agriculture, International Hellenic University, Greece.
[3] Assoc. Professor, PhD, Department of Agriculture, International Hellenic University, Greece.
[4] Corresponding Author: Professor, PhD, Department of Regional and Cross-Border Development, University of Western Macedonia, Koila Campus – Kozani, 53100, Greece, E-mail: fxtheodoridis@uowm.gr

importance and the competitive advantages of the sector in Greece, it is important to analyze the technical efficiency and the factors affecting it and how they can help aquaculture industry to achieve a sustainable growth in a such crucial period.

The economic performance and the profitability of the fish sector apart from the natural productivity of the cultivated sea area depend on a combination of structural and economic factors such as production cost, marketing strategies, available re-sources, technical practices, institutional frame, and applied policy (Kontogeorgos et al., 2017). In this study, the non-parametric data envelopment analysis was applied in a sample of 55 aquaculture farms for the estimation of the level of technical efficiency. The existing production technology and the rational allocation of the available re-sources, which are associated with the managerial ability of the producer, are vital for the improvement of the profitability and competitiveness of fish farms.

Many studies have used DEA, developed by Charnes et al. (1978), to estimate technical efficiency in aquaculture in the production frontier literature (Gunaratne, Leung, 1997; Sharma et al., 1999; Coelli et al., 2005; Chang et al., 2010; Nielsen, 2011; Alam, 2011; Arita & Leung, 2014; Theodoridis et al., 2017, Onumah et al., 2018). Technical efficiency refers to the maximum attainable level of output, given a set of inputs and the technology available to the producers. Thus, it is a performance measure by which production units are evaluated. Most of the studies that measure efficiency use the Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis and investigate the extent to which a firm that uses several inputs and produces several outputs, is efficient in the way it allocates its resources (Foussekis & Klonaris, 2003; Cinemre et al., 2006; Shima, 2010; Tan et al., 2011; Tsue et al., 2013). The stochastic frontier approach is considered more appropriate for assessing technical efficiency in a developing-country agriculture, where data are often heavily influenced by measurement errors (Coelli et al., 1998; Chiang et. al., 2004; Dey et al., 2005; Karagiannis et al., 2008; Sandvold, 2016). In recent studies, econometric models have been used to investigate technical efficiency effects because of the computational simplicity and ability to examine the effect of various farm-specific variables (Sharma, Leung, 2000; Dey et al., 2005; Simar, Wilson, 2007, Voulgaris, Lemonakis, 2013).

The paper purpose is to explore the fishery farms competitiveness of Greece in a difficult period of the Greek economy (2010 to 2016). The paper is organized as follows: section two presents the methodology, section three presents the data description, section four the results and discussion, and finally section five the conclusions.

2. Materials and Methods

Data envelopment analysis (DEA) has its origins in the seminal work by Charnes et al. (1978). This non-parametric approach measures technical efficiency estimators as optimal solutions to mathematical programming problems. DEA methodology is based on efficient ration Outputs/Inputs, while the organizations or entities that are responsible for the transformation of inputs to outputs are called Decision Making Units (DMUs). The objective of DEA is to maximize the ration Outputs/Inputs for each DMU under consideration (DMUo). This maximization is achieved by the optimization of the weights for inputs ( ) and outputs ( ), which define the relative magnitude of the corresponding input or output. DEA gives information about three important topics: a) the reference-set of each non-efficient DMU (i.e., the efficient DMUs according to which the DMUo is non-efficient), b) the objectives which the non-efficient units should set up by increasing inputs or decreasing outputs, in order to optimize their operation, and c) the returns-to-scale for each unit (increasing or decreasing).

This study adopted the input oriented CCR and BCC models to evaluate the efficiency of hospitality sector. The CCR model is the fundamental DEA model introduced by Charnes et. al. (1978, pp. 429-444). The model attributes the Global Technical Efficiency and lays on constant returns-to-scale (CRS). The primal non-linear CCR model is presented below:

$$\max_{v_i u_r} h_o = \frac{\sum_{r=1}^{s} u_r y_{r_o}}{\sum_{i=1}^{m} v_i x_{i_o}} \tag{1}$$

$$\text{st.} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \ \forall \ j = 1, \ldots, n$$

$$u_r, v_i \geq \varepsilon$$

$$i = 1, \ldots m \qquad r = 1, \ldots s$$

Where:

h_o : unit's partial productivity

o : the organization under evaluation compare with $j = 1, \ldots, n$ organizations

j : units, $j = 1, \ldots, n$

r : outputs, $r = 1, \ldots, s$

i : inputs, $i = 1, \ldots, m$

y_{rj} : output r of unit j ($r = 1, \ldots, s$)

x_{ij} : input i of unit j ($i = 1, \ldots, m$)

ε : a very small positive number (i.e., $\varepsilon = 10^{-6}$)

v_i, u_r : input and output coefficients, respectively, which maximize the objective function for DMU_o.

The transformation of the above equation to a linear problem (input or output oriented) leads to easiest solution. The dual problems of the input or output oriented models yield to the solution of the primal problems (Boussofiane et. al., 1991, pp. 1-15).

The BCC model proposed by Banker et. al. (1984, pp. 1078–92) yields to Local Pure Technical Efficiency based on variable returns-to-scale (VRS, increasing or decreasing). Supposing that the values of a DMU for CCR and BCC models are and respectively, the scale efficiency for a specific DMU is defined as follows:

$$SE = \frac{\theta^*_{CCR}}{\theta^*_{BCC}} \tag{2}$$

under the condition that $SE \leq 1$.

According to the previous ration the disaggregation of the efficiency is:

[Technical Efficiency (TE)] = [Pure Technical Eff. (PTE)] x [Scale Eff. (SE)]

The above disaggregation is unique and shows the existence of inefficiency and indicates whether the inefficiency is due to the operation of DMU (PTE) or to the non-appropriate returns-to-scale under which the DMU operates, or both.

3. Data Description

The efficiency evaluation of the Greek fish sector was based on data gathering for 55 firms of Greece, while a time span of seven years is considered. The quality of results obtained by using the DEA analysis depends on data's robustness, especially when financial data are used. In this study companies from Greek fishery sector were considered and the financial data used were obtained from the ICAP Hellas (a Greek consultancy firm specializing in the collection and analysis of business data) for the period 2010-2016. The use of the data of the specific period has been based mainly to the fact that the Greek economy in these years was to the peak of a serious economic instability and to checked under economic stress circumstance, so for this reason selected the specific period.

Table 1 shows the input and output variables used in this study. The implementation of DEA involves the identification and measurement of relevant inputs and out-puts, which are common in all production units. In the specification chosen in this study, the relevant inputs used were (1) total human labor measured in individuals (2) farm size measured by infrastructures of the firm, (4) fixed capital cost in value terms, (3) variable capital cost in value terms and (5) working capital a representing of firms' operating liquidity in value terms. Total revenue was selected as the output variable as well the gross profits. Total revenue and profits were used as the output measure in the estimation of efficiency to consider the effect of price variability in the output measure (Theodoridis et. al. 2017).

Table 1: Description of variables in the DEA model

Variables	Description
Total Revenues	Gross output measured in value terms was selected as one of the output variables
Profits	Profits measured in value terms was selected as the second output variable
Labour	Total human labour (including family and hired workers) measured in individuals (input variable)
Size	It is measured by companies' infrastructures in value terms (input variable)
Fixed cost	Fixed capital cost includes mainly the annual expenses of boats and auxiliary equipment and measured in value terms (input variable)
Variable cost	Variable capital cost includes the *costs* of raw materials and packaging and measured in value terms (input variable)
Working capital	Working capital, is the difference between a company's current assets and its current liabilities. Firms in fish industry need a significant level of working capital to generate sales, it is a variable representing operating liquidity and measured in value terms (input variable)

The observations and the variables used ensure the DEA convention that the minimum number of DMUs is greater than three times the number of inputs plus out-put [55≥ 3x (2 + 5)] (Raab, Lichty, 2002). The DEA efficiency scores are obtained by employing an input-oriented model since it is assumed that fishery companies focusing on cost control, having the possibility to adjust input usage. For the estimations the DEAP program (Coelli, 1996) was applied.

4. Results and Discussion

Table 2 presents the frequency distribution technical efficiency scores, with the CRS (constant returns to scale-CCR model) assumptions from 2010 through 2016. It concerns an Input-orientated model that focuses on the amount by which inputs can be proportionally reduced, as outputs remain fixed. The efficiency scores range between 0 and 1. A score of 1 implies that the DMU is on the frontier.

The results in table 2 indicate considerable variation regarding the level of technical efficiency among the fishery farms. For the year 2010, technical efficiency scores ranged from a low of 0.372 to a high of 1.000 (fully efficient farms). Under the DEA model 13 of the 55 farms, i.e., 23.64% of the total sample were fully technical efficient, 22 farms (40%) exhibited technical efficiency less than 60%, 12 farms (21.81%) had technical efficiency between 60 and 79%, and 8 farms (14.55%) operated relatively close to the DEA frontier, exhibiting technical efficiency between 80 and 99%. For the year 2011, technical efficiency scores ranged from a low of 0.462 to a high of 1.000 (fully efficient farms). Under the DEA model 13 of the 55 farms, i.e., 23.64% of the total sample were fully technical efficient, 16 farms (29.10%) exhibited technical efficiency less than 60%, 13 farms (63.63%) had technical efficiency between 60 and 79%, and 13 farms (23.63%) operated relatively close to the DEA frontier, exhibiting technical efficiency between 80 and 99%. For the year 2012, technical efficiency scores ranged from a low of 0.285 to a high of 1.000 (fully efficient farms). Under the DEA model 16 of the 55 farms, i.e., 29.10% of the total sample were fully technical efficient, 22 farms (40%) exhibited technical efficiency less than 60%, 9 farms (16.36%) had technical efficiency between 60 and 79%, and 8 farms (14.54%) operated relatively close to the DEA frontier, exhibiting technical efficiency between 80 and 99%. For the year 2013, technical efficiency scores ranged from a low of 0.495 to a high of 1.000 (fully efficient farms). Under the DEA model 8 of the 55 farms, i.e., 32.73% of the total sample were fully technical efficient, 18 farms (32.73%) exhibited technical efficiency less than 60%, 11 farms (20%) had technical efficiency between 60 and 79%, and 8 farms (14.54%) operated relatively close to the DEA frontier, exhibiting technical efficiency between 80 and 99%. For the year 2014, technical efficiency scores ranged from a low of 0.368 to a high of 1.000 (fully efficient farms). Under the DEA model 12 of the 55 farms, i.e., 21.81% of the total sample were fully technical efficient, 21 farms (38.19%) exhibited technical efficiency less than 60%, 14 farms (25.46%) had technical efficiency between 60 and 79%, and 8 farms (14.54%) operated relatively close to the DEA frontier, exhibiting technical efficiency between 80 and 99%. For the year 2015, technical efficiency scores ranged from a low of 0.455 to a high of 1.000 (fully efficient farms). Under the DEA model 15 of the 55 farms, i.e., 27.27% of the total sample were fully technical efficient, 15 farms (27.27%) exhibited technical efficiency less than 60%, 16 farms (19.10%) had technical efficiency between 60 and 79%, and 9 farms (16.36%) operated relatively close to the DEA frontier, exhibiting technical efficiency between 80 and 99%. For the year 2016, technical efficiency scores ranged from a low of 0.455 to a high of 1.000 (fully efficient farms). Under the DEA model 18 of the 55 farms, i.e., 32.73% of the total sample were fully technical efficient, 16 farms (29%) exhibited technical efficiency less than 60%, 5 farms (9.10%) had technical efficiency between 60 and 79%, and 16 farms (29.10%) operated relatively close to the DEA frontier, exhibiting technical efficiency between 80 and 99%.

Table 2: Frequency distribution of technical efficiency estimate, CRS (2010-2016).

Year	Observations	TE score				total
		<0.60	0.60-0.80	0.80-1.00	=1.00	
2010	Number of farms	22	12	8	13	55
	% of farms	40.00	21.81	14.55	23.64	100.00
2011	Number of farms	16	13	13	13	55
	% of farms	29.10	23.63	23.63	23.63	100.00
2012	Number of farms	22	9	8	16	55
	% of farms	40.00	16.36	14.54	29.10	100.00
2013	Number of farms	18	11	8	18	55
	% of farms	32.73	20.00	14.54	32.73	100.00
2014	Number of farms	21	14	8	12	55
	% of farms	38.19	25.46	14.54	21.81	100.00
2015	Number of farms	15	16	9	15	55
	% of farms	27.27	29.10	16.36	27.27	100.00
2016	Number of farms	16	5	16	18	55
	% of farms	29.00	9.10	29.10	32.73	100.00

The results indicate that a small percentage between 23%-33% of the farms for the years 2010-2016 achieved the highest score of technical efficiency indicating substantial inefficiency in farming operations revealing that few fishery farms utilized the existing technology quite rationally in terms of management. The presence of technical inefficiency indicated that the farmers were insufficient in the utilization of the entrepreneurial factor, which has a great impact on the economic performance of a production unit.

Table 3 presents the average technical efficiency scores, with the CRS (constant returns to scale-CCR model) and VRS (variable returns to scale-BCC model) assumptions from 2010 through 2016. A score of 1 implies that the DMU is on the frontier.

The first column indicates the 55 fishery farms in Greek area and the second column illustrates the technical efficiency (CRS) index results. This efficiency index is equal to 1 for seventeen farms, implying that they operate with relative 100% efficiency, as com-pared to the overall sample.

The third column illustrates the pure technical efficiency (VRS) index results, according to which, a significantly larger number of farms (29) operate with 100% relative efficiency, in transforming their inputs to outputs, as com-pared to the overall sample too. The fourth column indicates the scale efficiency of DMUs.

The evidence on hand indicates that nineteen farms are 100% scale efficient. Thus, the empirical results tend to suggest that the main source of fishery farms' inefficiency is scale economies. The average technical efficiency for the 55 farms and for the period 2010-2016 is equal to 0.772, while the variable technical efficiency is equal to 0.86. This result indicates that when all sources of inefficiency are included, fishery sector could improve on average and given their current output level, their inputs up to 22.8%. This percentage changes to 14% for variable returns-to scale.

Table 3: DEA technical efficiency scores for Greek fish farming companies, 2010-2016.

Firms	Technical Efficiency, CRS	Technical Efficiency, VRS	Scale Efficiency
F1	0.822	0.893	0.920
F2	1.000	1.000	1.000
F3	0.722	0.723	1.000
F4	1.000	1.000	1.000
F5	0.891	1.000	0.891
F6	0.375	0.434	0.864
F7	0.823	0.835	0.986
F8	1.000	1.000	1.000
F9	0.773	0.800	0.966
F10	1.000	1.000	1.000
F11	0.544	1.000	0.544
F12	0.389	1.000	0.389
F13	1.000	1.000	1.000
F14	1.000	1.000	1.000
F15	0.478	0.528	0.905
F16	0.949	1.000	0.949
F17	0.865	0.993	0.871
F18	1.000	1.000	1.000
F19	0.973	1.000	0.943
F20	0.439	0.909	0.483
F21	0.431	0.972	0.443
F22	1.000	1.000	1.000
F23	1.000	1.000	1.000
F24	1.000	1.000	1.000
F25	0.879	1.000	0.879
F26	0.658	0.988	0.666
F27	1.000	1.000	1.000
F28	1.000	1.000	1.000
F29	0.590	0.739	0.798
F30	0.991	0.992	0.917
F31	1.000	1.000	1.000
F32	0.870	1.000	0.870
F33	1.000	1.000	1.000
F34	0.396	0.561	0.706
F35	0.464	0.695	0.668
F36	1.000	1.000	1.000
F37	0.348	0.387	0.900
F38	1.000	1.000	1.000
F39	0.683	0.714	0.957
F40	0.900	0.999	0.901
F41	0.962	1.000	0.962

F42	0.550	0.550	1.000
F43	0.529	0.615	0.861
F44	0.254	0.255	0.996
F45	0.384	0.395	0.972
F46	0.570	1.000	0.570
F47	0.810	0.892	0.908
F48	0.430	0.431	0.998
F49	0.942	1.000	0.942
F50	0.801	0.860	0.932
F51	0.668	0.877	0.762
F52	0.575	1.000	0.575
F53	1.000	1.000	1.000
F54	0.534	0.774	0.721
F55	1.000	1.000	1.000
Mean	0.772	0.860	0.876

The presence of technical inefficiency indicated that the fishery farms was insufficient in the utilization of the entrepreneurial factor, which has a great impact on the economic performance of a production unit. The results in Table 3 indicate that most aquaculture farms in the sample operate below the efficient frontier and may be due to the infant stage (which started its operation in middle of the 1980s) of the industry since more of the farmers are still adjusting themselves into the new cultural practice and techniques. Fishery farmers, who are in many cases characterized by deficient skills on farming practices and accounting techniques and by lack of knowledge on modern strategic planning, cannot allocate rationally the available re-sources; hence, they diverge from the minimum attainable input.

Substantial inefficiencies occurred in the fish farming operation of the sampled farms. Under the prevailing conditions, about 31% and 52% of farms were identified as fully technically efficient under CRS and VRS specification respectively. The observed difference between CRS and VRS measures further indicated that some of the farmer did not operate at an efficient scale and improvement in the overall efficiencies could be achieved if the farms adjusted their scales of operation. In this study the mean technical efficiency score varies between 0.77 and 0.86. These results indicate that technical efficiencies can be increased by at least 18.5% through better use of available resources, given the current state of technology.

According to the VRS model, the fishery farms which seem to be technical inefficient, should invest in organizational factors, concerning management, such as marketing initiatives, improvement in quality, achievement of a better balance between inputs and outputs, and so on. Firm's technical performance constitute firm-level competitiveness which is the ability of the firm to increase in size, expand its market share and its profit. The scale efficiency score indicates whether a firm operates at the most productive scale size (score=1) or not. A score smaller than one indicates that fishery farms are over /under dimensioned.

Table 4: Peers for the year 2016

Firms	Peers. peer1	Peers. peer2	Peers. peer3	Peers. peer4	Peers. peer5	Peers. peer6	Peers. peer7
F1	F52	F22	F16	F24	F13		
F3	F4	F36	F13				
F6	F4	F19	F23	F49			
F7	F8	F13	F22	F14	F4		
F9	F13	F22	F8	F16	F24		
F15	F22	F4	F23				
F17	F14	F22	F38	F13	F24	F27	
F20	F55	F28	F13	F8	F4		
F21	F46	F32	F16	F52			
F26	F23	F4	F22	F49			
F29	F13	F16	F22	F32			
F30	F36	F22	F4	F13	F14	F55	
F34	F4	F22	F49	F23			
F35	F4	F22	F23	F49			
F37	F18	F4	F19				
F39	F53	F22	F8	F4			
F40	F23	F28	F38	F22	F24	F14	
F42	F13	F31	F49	F22			
F43	F4	F22	F8	F55	F28		
F44	F22	F28	F8	F38	F4	F13	F14
F45	F19	F24	F8	F38	F23	F22	F4
F47	F38	F27	F24	F13	F19	F23	
F48	F14	F31	F13	F22			
F50	F8	F22	F18	F16	F13		
F51	F16	F13	F10	F24			
F54	F4	F23	F12				

DEA reveals the slacks for the inefficient farms and gives to each one a reference set (peer group) which allows specific recommendations to improve efficiency (Table 4 and Table 6). According to last year results, seventeen farms were found to be technically efficient (Table 2). These efficient farms together define the best practice or efficient frontier and, thus, form the reference set for inefficient ones. The resource utilization process in these companies is functioning well. It means that the production process of the firms is not characterized of any waste of inputs. In DEA terminology, these farms are called peers and set an example of good operating practices for inefficient ones to emulate. For the year 2016 the efficient farms in Greek fishery sector are eighteen (F2, F4, F8, F10, F13, F14, F18, F22, F23, F24, F27, F28, F31, F33, F36, F38, F53 and F55). The remaining thirty-seven farms have technical efficiency score less than 1 which means that they are technically inefficient. The results, thus, indicate a presence of marked deviations of the firms from the best practice frontier. Indicatively, fishery farm 1 is a peer for fishery farms 52, 22, 16, 24 and 13.

Table 5: Most frequent peers for years 2010-2016

Peer Firms (inefficient / efficient Firm)	Frequency	Years
F1 / F7, F22, F42	6	all years except 2013
F2 / F4, F42, F24, F11	6	all years except 2016
F6 / F4, F22, F19, F24	5	2010-2013, 2016
F9 / F13, F22, F14	6	all years except 2012
F15 / F4, F22, F38, F13	5	2010-2013, 2015
F20 / F55, F13, F4	5	2010-2012, 2014, 2016
F28 / F54, F22, F14	6	2010-2015
F30 / F36, F22, F4, F55	5	2012-2016
F33 / F53, F22, F49	6	all years except 2010
F35 / F4, F22, F42, F24, F4	6	all years except 2011
F37 / F18, F4, F19	7	all years
F39 / F53, F22, F4	7	all years
F40 / F23, F14, F38	6	all years except 2010
F45 / F4, F38, F22, F19, F14	6	all years except 2015

Furthermore, is interesting to present the frequency with which a fishery farm is a peer for other fishery farms over the years 2010-2016 (Table 5). The most inefficient farms during 2010-2016 are Farms 1, 2, 6, 9, 15, 20, 28, 30, 33, 35, 37, 39, 40 and 45. For these inefficient fishery farms the closest efficient fishery farms (are located on the frontier) are the farms 4, 7, 11, 13, 14, 22, 23, 38, 42, 33 among others. If inefficient fishery farms want to improve their performance, they must look at the best practices developed by their respective peers. As we can see in Table 5, farm 1, for example, must look farm 7, 22 and 42 for all years except 2013.

Table 6: Input slacks for the year 2016

Firms	Labour	Size (Infrastructures)	Fixed cost	Variable cost	Working Capital
F1	3.619	0.000	0.000	308634.604	0.000
F2	0.000	0.000	0.000	0.000	0.000
F3	0.000	0.000	0.000	0.000	1524.504
F4	0.000	0.000	0.000	0.000	0.000
F5	0.000	0.000	0.000	0.000	0.000
F6	0.000	269382.904	0.000	110269.062	0.000
F7	0.000	0.000	0.000	0.000	0.000
F8	0.000	0.000	0.000	0.000	0.000
F9	0.000	1548671.067	113958.331	0.000	0.000
F10	0.000	0.000	0.000	0.000	0.000
F11	0.000	0.000	0.000	0.000	0.000
F12	0.000	0.000	0.000	0.000	0.000
F13	0.000	0.000	0.000	0.000	0.000
F14	0.000	0.000	0.000	0.000	0.000
F15	0.177	193513.854	146902.211	0.000	0.000
F16	0.000	0.000	0.000	0.000	283.577
F17	0.000	0.000	0.000	0.000	0.000
F18	0.000	0.000	0.000	0.000	0.000
F19	0.000	0.000	0.000	0.000	0.000

F20	0.000	412286.041	280909.510	0.000	0.000
F21	122.925	0.000	0.000	0.000	40318.163
F22	0.000	0.000	0.000	0.000	0.000
F23	0.000	0.000	0.000	0.000	0.000
F24	0.000	0.000	0.000	0.000	0.000
F25	0.000	0.000	0.000	0.000	0.000
F26	0.000	459844.184	1511720.891	0.000	0.000
F27	0.000	0.000	0.000	0.000	0.000
F28	0.000	0.000	0.000	0.000	0.000
F29	1.395	0.000	0.000	1244774.858	1699.242
F30	0.000	0.000	0.000	0.000	0.000
F31	0.000	0.000	0.000	0.000	0.000
F32	0.000	0.000	0.000	0.000	0.000
F33	0.000	0.000	0.000	0.000	0.000
F34	0.000	112849.795	59979.798	0.000	0.000
F35	0.000	540491.996	747096.725	0.000	0.000
F36	0.000	0.000	0.000	0.000	0.000
F37	11.623	2273873.969	0.000	0.000	1325.820
F38	0.000	0.000	0.000	0.000	0.000
F39	1.846	0.000	387971.166	0.000	0.000
F40	0.000	240932.773	0.000	0.000	0.000
F41	0.000	0.000	0.000	0.000	0.000
F42	0.000	255527.549	2264925.182	303175.223	0.000
F43	0.000	1339498.036	779107.454	0.000	0.000
F44	0.000	0.000	0.000	0.000	0.000
F45	0.000	0.000	0.000	0.000	0.000
F46	0.000	0.000	0.000	0.000	0.000
F47	0.000	0.000	0.000	0.000	0.000
F48	0.000	417294.951	2738831.389	0.000	98.152
F49	0.000	0.000	0.000	0.000	0.000
F50	0.000	1026076.781	0.000	0.000	2229.013
F51	21.193	393154.413	0.000	42026.659	0.000
F52	0.000	0.000	0.000	0.000	0.000
F53	0.000	0.000	0.000	0.000	0.000
F54	0.000	167391.762	0.000	33098.880	0.000
F55	0.000	0.000	0.000	0.000	0.000
Mean	2.960	174923.456	164240.412	37147.017	863.245

For the year 2016, the technical efficient frontier has a slack on input 1 (number of employees), for the fishery farms 1, 15, 21, 29, 37 and 51 , a slack on input 2 (size) for the fishery farms 6, 9, 15, 20, 26, 34, 35, 37, 40, 42, 4, 48, 50, 51 and 54, a slack on input 3 (fixed cost) for fishery farms 9, 15, 20, 26, 34, 35, 39, 42, 43 and 48, a slack on input 4 (variable cost) for fishery farms 1, 6, 29, 42, 51 and 54 and finally a slack on input 5 (working capital) for the fishery farms 3, 16, 21, 29, 37, 48 and 50. Indicatively, in order the fishery farm 6 to be efficient, it should reduce the infrastructures by 269382.904 Euros and the variable cost by 110269.062 Euros (Table 6). Note that the DEA model allows us to determine how a productive unit should change its behavior to become efficient and rise to the efficiency curve. The input-oriented CRS model suggests that for a unit to become efficient it must lower its inputs. In our case, the fishery farms will be efficient if they lower the level of their respectively inputs. All these findings suggest that the performance of many Greek fishery farms can be improved considerably.

5. Conclusion

The aim of this paper is to explore the fishery farms competitiveness of Greece in a difficult period of the Greek economy (2010 to 2016). The performance of these companies has been evaluated through the assessment of their efficiency and analyzed by an input-oriented DEA model. The results indicate that a small percentage between 23%-33% of the farms for the years 2010-2016 achieved the highest score of technical efficiency indicating substantial inefficiency in farming operations revealing that few fishery farms utilized the existing technology quite rationally in terms of management.

On average, the fishery farms in the sample are operating below the production frontier, which indicates room for improvement. All the inputs contain slacks and need to be reduced accordingly. Infrastructures and operational costs are the main in-put in fish production and constituting over half of the production costs is over utilized. Thus, fish farmers need carefully to regulate their production practices to reduce costs and increase turnover. The results suggest that policies at firm level should be focused on the improvement of the firm's efficiency in terms of their investment conditions management, as well as on the improvement of the economies of scale. Managers of fish farming companies in Greece should efficiently use their resources and control of production expenses.

The current study indicates that although Greek aquaculture is mature, there is still much that can be done to improve the efficiency and profitability of Greek fish farms. Efficient management of resources is important. Profitability and productivity can measure and promote to a large extend, the competitiveness of Greek fisheries. Simple messages such as improving feeding practices can have a significant im-pact on farm profitability, transforming aquaculture businesses from just surviving into thriving, profitable enterprises. The fishery farms should be encouraged to give more attention to farm activities such as supervision and management in order to gain the relevant experience and increase their technical efficiency.

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