Technical efficiency of sea bass and sea bream farming in the Mediterranean Sea by European firms: A stochastic production frontier (SPF) approach

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ABSTRACT

In recent years, European producers of cultured sea bass and sea bream have experienced a highly competitive market with low prices that have caused profitability challenges. An important factor of economic competitiveness for firms is to produce efficiently. In this paper, technical efficiency of European producers of cultured sea bass and sea bream is evaluated for the period 2008–2017 using the stochastic production frontier (SPF) approach. In addition, the effect of a set of specific-firm factors on firms’ efficiency is investigated. The majority of firms in the sample were found to have a technical efficiency over 90% with Cypriot and Greek firms being, on average, the most efficient. We also found evidence that the technical efficiency of these firms is positively related to their size. Moreover, the high degree of average efficiency means that further production growth requires innovations that move up the production frontier.

KEYWORDS

Aquaculture; efficiency; production; sea bass; stochastic frontier

Introduction

European sea bass (Dicentrarchus labrax) and gilthead sea bream (Sparus aurata) are the two most economically important farmed fish species in the Mediterranean (Guillen et al., 2019). Traditionally, sea bass and sea bream have been farmed extensively in the coastal lagoons and brackish ponds in northern Italy (vallicultura) and southern Spain (esteros), where fish are allowed to enter inside the lagoons to be trapped and fed naturally until they are harvested (EU, 2012). However, at the end of the 1970s intensive rearing methods to grow-out fingerlings in sea cages were developed and implemented, and this production technology is now dominating the industry. In 2017 the two species represented each one a 10% of the total value of the European aquaculture sector (Eurostat, 2019). Table 1 shows that in 2017 the total European production of cultured sea bass and sea bream was
around 174,038 tons almost evenly divided by the two species (54.5% of sea bream and 45.5% of sea bass). The main producer is Greece with 100,232 tons, which represents 57.6% of the total European production, followed by Spain with 34,661 tons (a 19.9% of the total production).

In the last years, European producers of cultured sea bass and sea bream have had to compete in a very competitive market with low prices, what has caused a significant reduction of profitability in the industry (Globefish, 2015; Llorente et al., 2020). One important factor of economic competitiveness for firms is to produce efficiently. Despite the economic importance of the European sea bass and sea bream aquaculture, there are few studies analyzing its efficiency except for two early Greek studies (Karagiannis & Katranidis, 2007; Karagiannis et al., 2002). The identification of input specific technical inefficiency would help farmers to improve the performance of their farms by providing information to better prioritize their efforts to reduce the use of inputs and expand outputs. Moreover, the identification of factors that determine aquaculture firms’ technical inefficiencies is also an important issue in order to propose managerial decisions in the sector as well as to provide useful information for policymakers to design policies and measures to help farmers (Ngoc et al., 2018).

Most of the literature about efficiency is based on Farrell’s (1957) pioneer paper who developed a conceptual model involving the contraction of inputs to an efficient frontier (Tingley et al., 2005). The frontier production function defines the potential output that can be produced by a firm with the given level of inputs and technology (Kumar et al., 2004), being the ratio of actual to potential production the level of technical efficiency (hereinafter, TE). Thus, if a firm’s actual production point lies on the frontier, it is perfectly efficient while if it lies below the frontier, then it is technically inefficient. Two methodologies are commonly used to describe the efficient production frontier and, therefore, estimate efficiency values (Tingley et al., 2005): the stochastic production frontier (SPF) and the data envelopment analysis (DEA). 1 Both approaches have been widely used to analyze

### Table 1. European production of cultured sea bass and sea bream (2017).

| Country  | Sea bass | %    | Sea bream | %    | Total | %    |
|----------|----------|------|-----------|------|-------|------|
| Croatia  | 5,616    | 53.8 | 4,830     | 46.2 | 10,445 | 6.0  |
| Cyprus   | 2,254    | 31.3 | 4,950     | 68.7 | 7,204  | 4.1  |
| France   | 1,413    | 47.9 | 1,534     | 52.1 | 2,947  | 1.7  |
| Greece   | 44,285   | 44.2 | 55,948    | 55.8 | 100,232 | 57.6 |
| Italy    | 7,039    | 49.5 | 7,173     | 50.5 | 14,212 | 8.2  |
| Malta    | 59       | 2.4  | 2,458     | 97.6 | 2,518  | 1.4  |
| Portugal | 701      | 40.3 | 1,038     | 59.7 | 1,739  | 1.0  |
| Slovenia | 80       | 100.0| 0         | 0.0  | 80     | 0.0  |
| Spain    | 17,656   | 50.9 | 17,005    | 49.1 | 34,661 | 19.9 |
| Total    | 79,102   | 45.5 | 94,936    | 54.5 | 174,038 | 100.0|

Source: EUMOFA using EUROSTAT data.
technical efficiency in the aquaculture sector for different species (e.g., carp, catfish, salmon, tilapia, or trout), production forms (e.g., ponds or cages), and countries (e.g., Bangladesh, China, Malaysia, Norway, Philippines, US, or Vietnam). The SPF approach, which will be used here, is a parametric method that accounts for production uncertainty (stochastic noise) and allows the simultaneous estimation of individual technical efficiency of firms as well as the determinants of technical efficiency. This approach also permits to carry out statistical tests of hypotheses about the production structure and the degree of inefficiency with the same model (Battese & Coelli, 1995). Furthermore, this approach is less sensitive to outliers and sampling variation than the DEA approach (Cesaro et al., 2009).

The purpose of this work is twofold. Firstly, we have evaluated the technical efficiency of European producers of cultured sea bass and sea bream using the SPF approach and, secondly, we have analyzed the effect of some specific-firm factors such as location, production type (organic), years of experience, and size on firms’ inefficiency.

**Data and methodology**

The data used in this research is an unbalanced panel composed of a sample of 73 European firms producing farmed sea bass and sea bream in the Mediterranean during the period 2008 to 2017 with a total of 591 observations. Data were obtained from the ORBIS and EUMOFA databases and all monetary figures are presented in USD.

The data set contains observations on firms from seven different countries: Croatia (7 firms), Cyprus (3 firms), France (3 firms), Greece (27 firms), Italy (15 firms), Slovenia (2 firms), and Spain (16 firms). This sample represents around 70% of the total producers, according to our own estimations. The average production of Greek firms is 6,827 tons, being the country with the largest average production per firm in the sample. The second country with most production in the sample is Spain, which average production per firm is around 3,200 tons. In contrast, France and Slovenia are the countries with the lowest average production per firm with a production of 565 and 223 tons respectively.

Descriptive statistics of the variables are presented in Table 2. The average production (output) of cultured sea bass and sea bream in our sample was 3,776 tons with a range between 2 and 58,931 tons so that we have employed a sample with a wide distribution of the dependent variable in which we have micro, small, medium, as well as large firms. Regarding factor inputs, the average of labor employed by the sampled firms is around 77 employees and the invested capital (total assets) is 34.6 million of USD. As for the variables to explain technical inefficiency, 26% of the sample is
Table 2. Sample descriptive statistics (period 2008–2017).

| Variable                      | N  | Mean | SD  | Min. | Max. |
|-------------------------------|----|------|-----|------|------|
| $Y = \text{Cultured sea bass and sea bream production (tons)}$ | 591 | 3,776 | 8,430 | 2   | 58,931 |
| $LAB = \text{Labor (number of employees)}$ | 591 | 77   | 175 | 1   | 1,150 |
| $CAP = \text{Capital (total assets, mill. \text{USD})}$ | 591 | 34.6 | 82.8 | 0.3 | 692.0 |
| $YEAR = \text{Time trend (year)}$ | 591 | 2,012 | 2.64 | 2,008 | 2,017 |
| $WEST = \text{Firms located in the West Mediterranean Sea (dummy)}$ | 591 | 0.26 | 0.44 | 0   | 1   |
| $EAST = \text{Firms located in the East Mediterranean Sea (dummy)}$ | 591 | 0.42 | 0.49 | 0   | 1   |
| $ORG = \text{Production type (dummy)}$ | 591 | 0.29 | 0.45 | 0   | 1   |
| $AGE = \text{Firm’s experience (years)}$ | 591 | 16.71 | 7.72 | 0   | 41  |
| $SIZE = \text{Firm’s size (inverse of annual revenues, 1/mill. \text{USD})}$ | 591 | 0.78 | 4.16 | 0   | 83.33 |

Source: Authors’ elaboration using EUMOFA and ORBIS databases.

As the data set includes a rather long period of observations ($T=10$ years), a time-varying specification of inefficiency seems to be the most plausible choice. Consequently, we adopted the Battese and Coelli (1995) SPF model for panel data to estimate technical efficiency of European sea bass and sea bream firms. To perform the analysis, translog and Cobb-Douglas production functions in which the inefficiency effect ($u_{it}$) has a truncated normal distribution with mean ($Z_{it} \delta$), where $Z_{it}$ is a set of covariates explaining the mean of inefficiency, are estimated. The empirical model employed in this research to estimate the translog production function is formulated as follows:

$$
\ln(Y_{it}) = \beta_0 + \beta_1 \times YEAR_t + \beta_2 \times \ln(LAB_{it}) + \beta_3 \times \ln(CAP_{it}) + \beta_4 \times \ln(LAB_{it})^2
+ \beta_5 \times \ln(CAP_{it})^2 + \beta_6 \times \ln(LAB_{it}) \times \ln(CAP_{it}) + v_{it} - u_{it}
$$

where $\ln$ denotes the natural logarithm; $Y_{it}$ is the production (tons) of cultured sea bass and sea bream of the $i$-th firm at the $t$-th time period estimated dividing each firm’s annual revenues between the yearly weighted average price of sea bass and sea bream in the national market of the firm; $YEAR_t$ is a variable to account for a technological change and indicates the year of the observation involved (Battese & Coelli, 1995); $LAB_{it}$ is the labor employed by each firm (number of employees); $CAP_{it}$ is the total capital invested by a firm measured by firms’ total assets (millions of USD); $v_{it}$ is a random error term to capture errors beyond the firm’s control which is distributed independently and identically $N(0, \sigma_v^2)$; and $u_{it}$ is the error term used to denote technical inefficiency in the production process, which
is presumed to be non-negative and distributed independently of \( v_{it} \). When \( u_{i,t} = 0 \), the \( i \)-th firm lies on the stochastic frontier and, hence, can be considered technically efficient at time \( t \). If \( u_{i,t} > 0 \), the production lies below the frontier and, hence, the \( i \)-th firm is inefficient. Technical efficiency of the \( i \)-th firm at the \( t \)-th time period (\( TE_{it} \)) can be expressed as the ratio of actual (observed) output relative to the potential (maximum feasible) output (Lachaal et al., 2004):

\[
TE_{it} = \frac{\ln Y_{it}}{E(\ln Y_{it}/u_{it} = 0, x_{it})} = e^{(-u_{it})}
\]

so that this measure takes values between 0 and 1 with smaller ratios reflecting greater inefficiency (inverse relationship). The choice of variables introduced in the production frontier model has been subject to the economic theory of production and data availability.

Simultaneously, the technical inefficiency values estimated using the specified SFP model were regressed using different specific-firm factors as follows (hereinafter it will be referred as the inefficiency effects model):

\[
u_{it} = \delta_0 + \delta_1 YEAR_t + \delta_2 WEST_i + \delta_3 EAST_i + \delta_4 ORG_i + \delta_5 AGE_{it} + \delta_6 SIZE_{it} + w_{it}
\]

where \( YEAR_t \) is included in the inefficiency effects model (3) to allow for a trend in firms’ inefficiency (Battese & Coelli, 1995); \( WEST_i \) and \( EAST_i \) are dummy variables to control firms’ locations,\(^3\) being \( WEST_i = 1 \) when the \( i \)-th firm is located in the West Mediterranean Sea (Spain and France) and 0 otherwise and \( EAST_i = 1 \) when it is located in the East Mediterranean Sea (Cyprus and Greece) and 0 otherwise; \( ORG_i \) is a dummy variable to differentiate the organic and no-organic system of production, being \( ORG_i = 1 \) when the \( i \)-th firm is producing organic fish and 0 otherwise since organic production can be more or less efficient in the use of inputs in the production process (Lakner & Breustedt, 2015); \( AGE_{it} \) is the experience of the \( i \)-th firm at the \( t \)-th time period measured as year \( t \) minus the firm’s year of establishment since the more years of experience operating in the market could have a positive effect on firms’ knowledge to employ the inputs what would increase their technical efficiency (Iliyasu et al., 2016; Misra & Misra, 2014); \( SIZE_{it} \) is the dimension of the \( i \)-th firm at the \( t \)-th time period measured with the inverse of firm’s total annual revenues (millions of USD) so that larger firms can be more efficient because they would obtain increasing production returns related to a higher level of quality in the making decisions or in the organization of the production process (Alvarez & Crespi, 2003; Misra & Misra, 2014; Rezitis & Kalantzis, 2016).\(^4\) Consequently, the intercept of the model, \( \delta_0 \), captures the average efficiency
of those firms located in the Central Mediterranean Sea (Croatia, Italy, and Slovenia) that are not producing organic fish.

Maximum likelihood (ML) estimates of the parameters of the stochastic frontier and the inefficiency effects models were obtained simultaneously using the `sfpanel` command in the STATA statistical software package (version 12.0) developed by Belotti et al. (2013). The statistical properties of these estimates are explicitly discussed in Battese and Coelli (1993).

**Empirical results**

Robust maximum-likelihood (ML) estimates of a time-variant SPF model for the Cobb-Douglas and translog production functions are reported in Table 3. The results show that the two production functions are strongly significant ($p < 0.01$), with a $\chi^2$ value in the Wald test of 1,599.92 for the Cobb-Douglas production function and 4,275.35 for the translog function. A likelihood ratio (LR) test for the null hypothesis that the translog can be reduced to a Cobb-Douglas function was rejected ($\chi^2 = 38.82$, $p < 0.01$). In the following analysis, we will therefore focus on the results from the translog production function.

**Table 3.** Maximum likelihood estimates of the SPF and inefficiency effects models for cultured sea bass and sea bream in the Mediterranean Sea.

| Variable                  | Parameter | Coefficient | t-ratio | Coefficient | t-ratio |
|---------------------------|-----------|-------------|---------|-------------|---------|
| **Stochastic frontier model** |           |             |         |             |         |
| Constant                  | $\beta_0$ | 6.5436      | 0.30    | 22.1466     | 1.08    |
| YEAR                      | $\beta_1$ | -0.0030     | 0.28    | -0.0096     | 0.92    |
| $\ln(LAB)$                | $\beta_2$ | 0.3032***   | 5.94    | 1.4366***   | 5.65    |
| $\ln(CAP)$                | $\beta_3$ | 0.6587***   | 13.94   | -0.2642     | 0.76    |
| $\ln(LAB)^2$              | $\beta_4$ | 0.0542***   | 3.01    |             |         |
| $\ln(CAP)^2$              | $\beta_5$ | 0.0803***   | 3.29    |             |         |
| $\ln(LAB) \times \ln(CAP)$| $\beta_6$ | -0.1612***  | 4.59    |             |         |
| **Inefficiency effects model** |           |             |         |             |         |
| Constant                  | $\delta_0$| -63.1363    | 0.70    | -18.8925    | 0.21    |
| YEAR                      | $\delta_1$| 0.0319      | 0.71    | 0.0099      | 0.23    |
| WEST                      | $\delta_2$| -1.1670***  | 3.28    | -1.0588***  | 0.04    |
| EAST                      | $\delta_3$| -1.4409**   | 2.21    | -1.6055***  | 2.27    |
| ORG                       | $\delta_4$| -0.0702     | 0.26    | -0.1894     | 0.64    |
| AGE                       | $\delta_5$| -0.0292     | 1.40    | -0.0321     | 1.47    |
| SIZE                      | $\delta_6$| 0.1059***   | 5.44    | 0.1046***   | 5.71    |
| **Variance parameters**   |           |             |         |             |         |
| Sigma $u$                 | $\sigma_u^2$| 0.8212***   | 4.47    | 0.8526***   | 4.50    |
| Sigma $v$                 | $\sigma_v^2$| 0.2209***   | 11.27   | 0.1851***   | 10.46   |
| Lambda                    | $\lambda$ | 3.7169***   | 19.83   | 4.6050***   | 24.29   |
| Wald test (chi-square)    |           | 1,599.92*** | 4,275.35*** | 38.82*** |
| Number of observations    | 591       | 591         |         |             |         |
| Number of firms           | 73        | 73          |         |             |         |

Notes: The Battese and Coelli (1995) model has been used to estimate both production functions. $t$-ratios based on cluster-robust standard errors. $\lambda = \sigma_u^2/\sigma_v^2$. LR: Likelihood ratio.

***Significance at the 1% level. **Significance at the 5% level.
To check whether there is significant technical inefficiency, we have tested the null hypothesis \( H_0: \lambda = 0 \). If \( \lambda \) is zero, the differences in the production will be entirely related to statistical noise. On the other hand, if \( \lambda \) is different to zero reveals the presence of technical inefficiency. The estimate of \( \lambda \) in the translog production function was equal to 4.6050 (\( p < 0.01 \)). This result indicates the presence of inefficiency in Mediterranean production of cultured sea bass and sea bream, indicating that the difference between the observed output and frontier output is not due to the statistical variability alone but also due to technical inefficiency.

According to the results presented in Table 3, four parameters of the translog production function were found to be statistically significant at the 1\% significance level. However, the coefficient of the trend variable (\( YEAR \)) was not significantly different to zero, so that we cannot reject the hypothesis of no technical change during the period 2008–2017. In the translog function, the elasticity of production with respect to the factor \( j \) it is given as (Helali & Kalai, 2015):

\[
e_{jt} = \frac{\partial \ln Y_{it}}{\partial \ln X_j} = \beta_j + \beta_{jj} \ln X_{it,j} + \sum_{j \neq k} \beta_{jk} \ln X_{it,k}
\]  

(4)

This elasticity is calculated using the mean values of each input factor. The elasticity of labor is equal to 0.1229, whereas the elasticity of capital is 0.2272. Hence, the capital factor would have more impact than the labor factor to increase sea bass and sea bream production in European firms. Besides, the sum of the labor and capital elasticities in the translog function is equal to 0.3501 < 1, whereby we can reject the null hypothesis of constant RTS (\( \chi^2 = 18.76, p < 0.01 \)), revealing that the firms used in our analysis are operating, on average, at decreasing RTS.

### Determinants of TE

The impact of a set of specific-firm factors on firms’ inefficiency, estimated through the coefficients \( \delta \), are presented in Table 3 as well. The results show that the estimated coefficients of the dummy variables included in the inefficiency effects model to control firms’ locations are both negative and statistically significant. Even though the coefficient of the \( EAST \) variable (\( \delta_3 = -1.6055 \)) is larger than the coefficient of the \( WEST \) variable (\( \delta_2 = -1.0588 \)), the difference between both coefficients is not statistically significant. Therefore, firms located in the East and West Mediterranean appear to be, on average, more efficient than the firms located in the Central Mediterranean. Hence, some biophysical factors related to the locations of firms (e.g., sea temperature) could be impacting positively on firms’ technical efficiency. A similar result to this one was also reported by
Moreover, the positive sign of the coefficient associated with the firm’s size ($\delta_6 = 0.1046$) is highly significant ($p < 0.01$) what implies that large firms are comparatively more efficient than small firms since the size variable has been measured with the inverse of firms’ annual revenues.

As for the rest of the estimated coefficients in the inefficiency model ($\delta_1$, $\delta_4$, and $\delta_5$), they are not statistically significant. Therefore, we cannot reject the null hypothesis of no specific trend in the technical efficiency throughout the ten-year period, neither that the production system and the experience of the firms have had any impact on firms’ technical efficiency.

The annual evolution of firms’ average estimates of TE values in the period 2008–2017 is shown in Figure 1. We can observe that the annual TE mean presents two different patterns during the last decade with a very smooth decreasing linear trend between 2008 and 2014 (the TE mean decreased from 0.936 in 2008 up to 0.891 in 2014), and a small increase after 2014 (the TE mean grew to 0.910 three years later). Hence, the average efficiency of European firms producing cultured sea bass and sea bream in the Mediterranean Sea has been always over the 89% throughout the ten-year period.

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The distributions of firms’ average estimates of TE values in decile range and by country are presented in Tables 4 and 5 respectively. Regarding the distribution of TE values by deciles (Table 4), we observe a concentration of these values in the superior deciles whereas there is only one firm operating below 60% of technical efficiency. The majority of firms have a TE over 0.90 (61.6% of the sampled firms). Therefore, the average level of TE in European firms producing cultured sea bass and sea bream in the Mediterranean Sea was high throughout the 2008–2017 period with a TE mean value of 0.891 (see Table 5).

The analysis of TE values by country (Table 5) shows a wide variation in the average of the estimated technical efficiencies among the European
countries, ranging between 0.820 of Croatia and 0.991 of Cyprus. In addition, some countries have a wide distribution of their firms’ TE values indicating a significant scope for improvement in technical efficiency. In particular, TE values of Italian firms vary from 0.594 to 0.988, with a mean value of 0.843. Likewise, Croatian and Greek firms also present a high variation of their TE values with ranges of 0.276 and 0.254 respectively. On average, Cypriot firms seem to be the most efficient, with a TE mean of 0.991. These firms also present a very short variation in their technical efficiency (TE range = 0.063). Croatian and Slovenian firms seem to be, on average, the least efficient with a TE mean of 0.820 and 0.830 respectively. According to the findings presented in our analysis, the location (East Mediterranean Sea) and the larger size are two factors that are impacting positively on the technical efficiency of Cypriot and Greek firms, whereas these factors are impacting negatively on the technical efficiency of Croatian and Slovenian firms.

**Discussion and conclusions**

The purpose of this article has been twofold. Firstly, we have evaluated the technical efficiency of European producers of cultured sea bass and sea bream in the Mediterranean in the decade from 2008 to 2017, using the stochastic production frontier (SPF) approach. Secondly, we have analyzed the effect of a set of specific-firm factors such as location, production type (organic), years of experience, and size on firms' inefficiency. To conduct
this analysis, we have used an unbalanced panel composed of a sample of 73 firms producing sea bass and sea bream in the Mediterranean Sea from 7 European countries (Croatia, Cyprus, France, Greece, Italy, Slovenia, and Spain). Maximum likelihood (ML) estimates of the parameters of the stochastic frontier and the inefficiency effects model were obtained simultaneously employing the Battese and Coelli (1995) SPF model for panel data.

According to our findings, the firms used in this analysis were operating, on average, at decreasing returns to scale. Furthermore, capital was the input factor with the highest elasticity compared with the labor factor. We found no evidence of a technical change in the production function what can be interpreted as that there were no innovations or adoption of innovations to move the production function of this industry during the period under analysis. This is concerning for the competitiveness of the industry as innovation is key for competitiveness (Asche, 2008; Bergesen & Tveterås, 2019; Kumar et al., 2018), particularly as aquaculture production and thereby competition is growing rapidly in other regions (Garlock et al., 2020).

By the other hand, during the period 2008–2017, the majority of European firms producing cultured sea bass and sea bream in the Mediterranean presented a technical efficiency over 90% with a TE mean value of 89.1%. According to our findings, Cypriot and Greek firms are, on average, the most efficient with a TE mean value of 99.1% and 93.6% respectively. By contrast, the Croatian and Slovenian firms seem to be the least efficient with a TE mean value of 82% and 83% respectively. Our findings show a wide variation in the average of the estimated technical efficiencies among the European countries or even within some countries (e.g., Italy). Hence, there is still some room for TE improvement for some European firms.

Moreover, we found that the technical efficiency of the firms that are farming sea bass and sea bream in the Mediterranean is positively related to their location, probably due to better biophysical and environmental conditions, and their size. Thus, the location (East Mediterranean) and larger size of Cypriot and Greek firms are two factors impacting positively on their technical efficiency, whereas the worse location (Central Mediterranean) and smaller size of Croatian and Slovenian firms are impacting negatively on it. Other former studies have also found a positive relationship between the firm or farm location and size with its technical efficiency (Alam & Murshed-e-Jahan, 2008; Asche & Roll, 2013; Cinemre et al., 2006; Dey et al., 2000; Ngoc et al., 2018; Tveteras & Battese, 2006). For example, Tveteras and Battese (2006) reported that the location and size of salmon farms in Norway are related positively to their technical efficiency. In addition, Ngoc et al. (2018) showed that location was an
important factor for the TE improvement of Vietnamese farms. Finally, we have not observed any trend in technical efficiency throughout the period analyzed.

The improvement in production efficiency is more cost-effective than the introduction of new technologies to increase culture production when producers are not efficient (Dey et al., 2000; Islam et al., 2016). However, European aquaculture firms would have to implement innovative approaches and invest more in modern technologies to produce more efficiently since there is a large proportion of firms producing at a high level of efficiency, but with decreasing returns to scale. In this scenario, an increase of production through a higher employment of input factors (e.g., labor or capital) would be clearly inefficient. Therefore, to move up the production function, firms’ production should be increased primarily through the adoption of improved farming technology (e.g., improvements in feeding or vaccination) or by adopting better management systems (e.g., big-data analysis and artificial intelligence applied to the production process and business management). Obviously, these innovations or improvements should be implemented after a cost-benefit analysis is done to avoid profitability losses for firms. Moreover, improved production processes can also improve competitiveness by allowing more efficient supply chains (Asche et al., 2007, 2018).

Notes

1. Some authors who have applied the SPF approach in the aquaculture industry are Ara et al. (2004), Asche and Roll (2013), Dey et al. (2000), Dey et al. (2005), Iinuma et al. (1999), Islam et al. (2016), or Tveteras and Battese (2006). On the other hand, authors who have employed the DEA approach are Alam (2011), Alam and Murshed-e-Jahan (2008), Bozoglu et al. (2006), Cinemre et al. (2006), Kaliba and Engle (2006), Ngoc et al. (2018), or Sharma et al. (1999).

2. Efficiency studies on aquaculture focus mainly on non-European countries, with the exception of the Norwegian industry of farmed salmon (Asche et al., 2009, 2013; Asche & Roll, 2013; Rocha Aponte & Tveterås, 2019; Roll, 2019; Tveteras & Battese, 2006).

3. This variable can be a proxy for possible differences in general biophysical and environmental conditions (Tzouvelkas et al., 2001). For example, the average temperature of the sea, which is higher in the East Mediterranean Sea, is a recognized factor that influences positively on fish growth (Llorente & Luna, 2013).

4. The inverse of income was used instead of income directly, or other transformations (logarithmic or power), because it has been the only option to obtain the parameter estimates of our model since the estimation method required a convergence of the different solutions (iterative process).

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References
Alam, M. F. (2011). Measuring technical, allocative and cost efficiency of pangas (Pangasius hypophthalmus: Sauvage 1878) fish farmers of Bangladesh. Aquaculture Research, 42(10), 1487–1500. https://doi.org/10.1111/j.1365-2109.2010.02741.x
Alam, M. F., & Murshed-e-Jahan, K. (2008). Resource allocation efficiency of the prawn-carp farmers of Bangladesh. Aquaculture Economics & Management, 12(3), 188–206.
Alvarez, R., & Crespi, G. A. (2003). Determinants of technical efficiency in small firms. Small Business Economics, 20(3), 233–244. https://doi.org/10.1023/A:1022804419183
Ara, L. A., Alam, M. F., Rahman, M. M., & Jabbar, M. A. (2004). Yield gaps, production losses and technical efficiency of selected groups of fish farmers in Bangladesh. Indian Journal of Agricultural Economics, 59(4), 808–818.
Asche, F. (2008). Farming the sea. Marine Resource Economics, 23(4), 527–547. https://doi.org/10.1086/mre.23.4.42629678
Asche, F., Cojocaru, A. L., & Roth, B. (2018). The development of large scale aquaculture production: A Comparison of the supply chains for chicken and salmon. Aquaculture, 493, 446–455. https://doi.org/10.1016/j.aquaculture.2016.10.031
Asche, F., Guttormsen, A. G., & Nielsen, R. (2013). Future challenges for the maturing Norwegian salmon aquaculture industry: An analysis of total factor productivity change from 1996 to 2008. Aquaculture, 396-399, 43–50. https://doi.org/10.1016/j.aquaculture.2013.02.015
Asche, F., & Roll, K. H. (2013). Determinants of inefficiency in Norwegian salmon aquaculture. Aquaculture Economics & Management, 17(3), 300–321.
Asche, F., Roll, K. H., & Tveteras, R. (2007). Productivity growth in the supply chain – another source of competitiveness for aquaculture. Marine Resource Economics, 22(3), 329–334. https://doi.org/10.1086/mre.22.3.42629562
Asche, F., Roll, K. H., & Tveteras, R. (2009). Economic inefficiency and environmental impact: An application to aquaculture production. Journal of Environmental Economics and Management, 58(1), 93–105. https://doi.org/10.1016/j.jeem.2008.10.003
Battese, G. E., & Coelli, T. J. (1993). A stochastic frontier production function incorporating a model for technical inefficiency effects. Working Paper 93/05, Department of Econometrics, University of New England, Armidale, Australia.
Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics, 20(2), 325–332. https://doi.org/10.1007/BF01205442
Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic frontiers using Stata. The Stata Journal: Promoting Communications on Statistics and Stata, 13(4), 719–758. https://doi.org/10.1177/1536867X1301300404
Bergesen, O., & Tveterås, R. (2019). Innovation in seafood value chains: The case of Norway. Aquaculture Economics & Management, 23(3), 292–320.
Bozoglu, M., Ceyhan, V., Cinemre, H. A., Demiryurek, K., & Lilic, O. (2006). Evaluation of different trout farming systems and some policy issues in the Black Sea region. Turkey. Journal of Applied Sciences, 6(14), 2882–2888.
Cesaro, L., Marongiu, S., Arfini, F., Donati, M., & Capelli, M. G. (2009). Methodology for Analysing Competitiveness, Efficiency, and Economy of Scale. Use and applications of DEA. FACEPA Deliverable No. D5.1.3, INEA, Italy.

Cinemre, H. A., Ceyhan, V., Bozoğlu, M., Demiryürek, K., & Kılıç, O. (2006). The cost efficiency of trout farms in the Black Sea region. Aquaculture, 251(2-4), 324–332. https://doi.org/10.1016/j.aquaculture.2005.06.016

Dey, M. M., Paraguas, F. J., Bimbao, G. B., & Regaspi, P. B. (2000). Technical efficiency of tilapia growout pond operations in the Philippines. Aquaculture Economics & Management, 4(1-2), 33–47.

Dey, M. M., Paraguas, F. J., Srichantuk, N., Xinhua, Y., Bhatta, R., & Dung, L. T. C. (2005). Technical efficiency of freshwater pond polyculture production in selected Asian countries: Estimation and implication. Aquaculture Economics & Management, 9(1–2), 39–63.

EU. (2012). Fisheries and Aquaculture in Europe, No. 59, December. European Commission, DG for Maritime Affairs and Fisheries, Belgium.

Eurostat. (2019). Aquaculture in the EU. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/EDN-20191015-2

Farrell, M. J. (1957). The measurement of productive efficiency. Journal of Royal Statistical Society, 120(3), 253–281. https://doi.org/10.2307/2343100

Garlock, T., Asche, F., Anderson, J., Bjørndal, T., Kumar, G., Lorenzen, K., Ropicki, A., Smith, M. D., & Tveterås, R. (2020). A global blue revolution: Aquaculture growth across regions, species, and countries. Reviews in Fisheries Science & Aquaculture, 28(1), 107–116.

Globefish. (2015). Analysis and information on world fish trade. Market reports: European seabass and Gilthead seabream – March 2015. http://www.fao.org/in-action/globefish/market-reports/resource-detail/fr/c/429234/

Guillen, J., Asche, F., Carvalho, N., Fernández Polanco, J. M., Llorente, I., Nielsen, R., Nielsen, M., & Villasante, S. (2019). Aquaculture subsidies in the European Union: Evolution, impact and future potential for growth. Marine Policy, 104, 19–28. https://doi.org/10.1016/j.marpol.2019.02.045

Helali, K., & Kalai, M. (2015). Estimate of the elasticities of substitution of the CES and translog production functions in Tunisia. International Journal of Economics and Business Research, 9(3), 245–253. https://doi.org/10.1504/IJEBR.2015.068544

Iinuma, M., Sharma, R., & Leung, P. (1999). Technical efficiency of carp pond culture in peninsular Malaysia: An application of stochastic production frontier and technical inefficiency model. Aquaculture, 175(3-4), 199–213. https://doi.org/10.1016/S0044-8486(99)00033-2

Iliyasu, A., Mohamed, Z. A., & Terano, R. (2016). Comparative analysis of technical efficiency for different production culture systems and species of freshwater aquaculture in Peninsular Malaysia. Aquaculture Reports, 3, 51–57. https://doi.org/10.1016/j.aqrep.2015.12.001

Islam, G., Md, N., Tai, S. Y., & Kusairi, M. N. (2016). A stochastic frontier analysis of technical efficiency of fish cage culture in Peninsular Malaysia. SpringerPlus, 5(1), 127–137. https://doi.org/10.1186/s40064-016-2775-3

Kaliba, A. R., & Engle, C. R. (2006). Productive efficiency of catfish farms in Chicot County Arkansas. Aquaculture Economics & Management, 10(3), 223–243.

Karagiannis, G., & Katranidis, S. D. (2007). A production function analysis of seabass and seabream production in Greece. Journal of the World Aquaculture Society, 31(3), 297–305. https://doi.org/10.1111/j.1749-7345.2000.tb00881.x

Karagiannis, G., Katranidis, S. D., & Tzouvelekas, V. (2002). Measuring and attributing technical inefficiencies of seabass and seabream production in Greece. Applied Economics Letters, 9(8), 519–522. https://doi.org/10.1080/13504850110099293
Kumar, A., Birthal, P. S., & Badruddin, A. (2004). Technical efficiency in shrimp farming in India: Estimation and implications. *Indian Journal of Agricultural Economics, 59*(3), 413–420.

Kumar, G., Engle, C., & Tucker, C. (2018). Factors driving aquaculture technology adoption. *Journal of the World Aquaculture Society, 49*(3), 447–476. https://doi.org/10.1111/jwas.12514

Lachaal, L., Chebil, A., & Dhehibi, B. (2004). A panel data approach to the measurement of technical efficiency and its determinants: Some evidence from the Tunisian agro-food industry. *Agricultural Economics Review, 5*(1), 15–23.

Lakner, S., & Breustedt, G. (2015). Productivity and technical efficiency of organic farming – A literature survey. *Acta Fytotechnica et Zootechnica, 18*(special issue), 74–77.

Llorente, I., Fernández-Polanco, J., Baraibar-Diez, E., Odriozola, M. D., Bjørndal, T., Asche, F., Guillen, J., Avdelas, L., Nielsen, R., Cozzolino, M., Luna, M., Fernández-Sánchez, J. L., Luna, L., Aguilera, C., & Basurco, B. (2020). Assessment of the economic performance of the seabream and seabass aquaculture industry in the European Union. *Marine Policy, 117*, 103876. https://doi.org/10.1016/j.marpol.2020.103876

Llorente, I., & Luna, L. (2013). The competitive advantages arising from different environmental conditions in seabream, *Sparus aurata*, production in the Mediterranean Sea. *Journal of the World Aquaculture Society, 44*(5), 611–627. https://doi.org/10.1111/jwas.12069

Misra, J., & Misra, S. R. (2014). Technical efficiency of fish farms in West Bengal: Nature, extent and implications. *Agricultural Economics Research Review, 27*(2), 221–232. https://doi.org/10.5958/0974-0279.2014.00026.3

Ngoc, P. T. A., Gaitán-Cremaschi, D., Meuwissen, M. P. M., Le, T. C., Bosma, R. H., Verreth, J., & Lansink, A. O. (2018). Technical inefficiency of Vietnamese pangasius farming: A data envelopment analysis. *Aquaculture Economics & Management, 22*(2), 229–243.

Rezitis, A. N., & Kalantzi, M. A. (2016). Investigating technical efficiency and its determinants by data envelopment analysis: An application in the Greek food and beverages manufacturing industry. *Agribusiness, 32*(2), 254–271. https://doi.org/10.1002/agr.21432

Rocha Aponte, F., & Tveterås, S. (2019). On the drivers of cost changes in the Norwegian salmon aquaculture sector: A decomposition of a flexible cost function from 2001 to 2014. *Aquaculture Economics & Management, 23*(3), 276–291. https://doi.org/10.1080/13657305.2018.1551438

Roll, K. H. (2019). Moral hazard: The effect of insurance on risk and efficiency. *Agricultural Economics, 50*(3), 367–375. https://doi.org/10.1111/agec.12490

Sharma, R., Leung, P., Chen, H., & Peterson, A. (1999). Economic efficiency and optimum stocking densities in fish polyculture: An application of data envelopment analysis (DEA) to Chinese fish farms. *Aquaculture, 180*(3–4), 207–221. https://doi.org/10.1016/S0044-8486(99)00202-1

Tingley, D., Pascoe, S., & Coglan, L. (2005). Factors affecting technical efficiency in fisheries: Stochastic production frontier versus data envelopment analysis approaches. *Fisheries Research, 73*(3), 363–376. https://doi.org/10.1016/j.fishres.2005.01.008

Tveteras, R., & Battese, G. E. (2006). Agglomeration externalities, productivity, and technical inefficiency. *Journal of Regional Science, 46*(4), 605–625. https://doi.org/10.1111/j.1467-9787.2006.00470.x

Tzouvekas, V., Pantzios, C. J., & Fotopoulos, C. (2001). Technical efficiency of alternative farming systems: The case of Greek organic and conventional olive-growing farms. *Food Policy, 26*(6), 549–569.