Efficiency data analysis in EU aquaculture production

Ester Gutiérrez[a§], Sebastián Lozano[a] and Jordi Guillén[b]

[a] Department of Industrial Management, Universidad de Sevilla, Spain

[b] European Commission, Joint Research Centre, Ispra, Italy

ARTÍCULO PUBLICADO EN *AQUACULTURE*

DOI: 10.1016/j.aquaculture.2020.734962

Abstract

This paper analyses the operational efficiency of fish farming across EU Member States using a two-stage Data Envelopment Analysis (DEA) approach. In the first stage, a non-oriented Slacks-Based Measure of efficiency (SBM) DEA model is used to compute efficiency scores in marine and freshwater finfish and shellfish aquaculture subsectors for different EU countries during the period 2014-2016. In a second stage, these scores are processed by standard, censored and fractional regression models to test the effects of some exogenous variables. Between 57% and 74% of the observations, depending on the subsector considered, were efficient. The average technical efficiency was 0.918 for freshwater finfish, 0.885 for marine finfish and 0.802 for shellfish. Extending the best practices to the inefficient countries would involve a reduction of feed costs (2.9% - 4.3%), livestock costs (9.0% - 11.8%), energy costs (2.4% - 25.3%), repairing costs (3.7% - 13.8%) and other operating costs (4.3% - 13.8%)at the same time that an improvement in production value totalling 0.03% for freshwater finfish, 2.13% for marine finfish and 0.37% for shellfish. As regards productivity change in the period under study, there has been a productivity regress in the case of freshwater finfish, productivity increase in the case of marine finfish and an initial productivity increase between 2014 and 2015 followed by a slight decrease between 2015 and 2016 in the case of shellfish. Results also indicate that countries specializing in cultivating freshwater and marine populations are more likely to be on the efficient frontier and that technical efficiency seems to be influenced by the size of the country's gross domestic product and capture fisheries.

[§] Corresponding author: Escuela Superior de Ingenieros
Camino de los Descubrimientos, s/n
41092 Sevilla, Spain
E-mail: egm@us.es
Phone: +34-954486198

Keywords: aquaculture; technical efficiency; productivity change; two-stage DEA; fractional regression

1. Introduction

Aquaculture is the fastest growing animal food producing sector in the world, with an increasing contribution to global food supply and economic growth (FAO, 2014; Lem et al., 2014). According to FAO (2018), global aquaculture production enjoyed an annual growth rate of 9.8% over the period 1980-2000, and 5.8% during the period 2000-2016 (see Figure 1). Aquaculture not only contributes to food security by providing a more reliable source of food than wild-capture fisheries, but it also has a big potential for further growth and development (Kobayashi et al., 2015; Kumar and Engle, 2016). Future prospects for aquaculture are rather optimistic, for example, the World Bank estimates that almost two-thirds of the seafood consumption will be farm-raised in 2030 (Kobayashi et al., 2015).

However, the European Union (EU) seems not to participate in this “Blue revolution”. EU aquaculture production has gone from a moderate annual growth rate of 3.5% over the period 1980-2000, to a negative rate of -0.5% during the period 2000-2016 (see Figure 1). Moreover, EU aquaculture production currently represents less than 1/5 of the EU domestic fish and shellfish supply.

This stagnation of the EU aquaculture production has been explained by a set of inter-linked factors that obstruct its development or expansion. These include the atomized character of the sector, the difficulty of competing with third countries with lower costs and less severe regulatory standards, limited access to space and water, hard administrative procedures concerning to licensing and difficulties in accessing finance and investment (European Commission, 2009; OECD, 2010; STECF, 2014, 2016; Bostock et al., 2016).

========================= Figure 1 ==============================

Nevertheless, the European Commission in its EU's Blue Growth Strategy has identified aquaculture as one of the sectors with higher potential for sustainable jobs and growth (European Commission, 2012).

The European Commission together with the EU countries are trying to boost the EU aquaculture sector. They have invested more than €1.17 billion of public money in the EU aquaculture sector since the year 2000, while €1.2 billion are planned for the period 2014-2020 (Guillen et al., 2019). EU countries developed Multiannual National Strategic Plans for the promotion of sustainable aquaculture between 2014 and 2015. In these plans, EU countries quantify the production growth objectives of their domestic aquaculture sector (European Commission, 2016a)[1]. According to the projections presented in the Member States' Multiannual National Strategic Plans (European Commission, 2016b), countries estimate aquaculture production to increase over 300,000 tonnes (25%) to a total of more than 1.5 million tonnes by 2020. This increase will imply reaching 480,000 tonnes from 330,000 tonnes of marine finfish (60% compared to 2012), 680,000 tonnes from 550,000 tonnes (25%) for shellfish, and a minor increase in freshwater aquaculture. However, there are significant differences in the projections by MS (see table A1 in the annex).

These production targets can look rather optimistic when considering the stagnant growth of the EU aquaculture during the last two decades. However, production increases are already possible with the current levels of resources employed by the EU aquaculture sector, just by using them more efficiently. Efficiency in the aquaculture production is crucial to avoid waste of resources, lead to profitability increases and economic sustainability.

The EU aquaculture sector can be divided into three main sectors: marine finfish, freshwater finfish and shellfish. According to STECF (2018), the marine finfish sector is the most

[1] Available by country at: http://ec.europa.eu/fisheries/cfp/aquaculture/multiannual-national-plans_en.

important economically and generated the largest turnover of €2.73 billion, followed by the shellfish sector with €1.13 billion and the freshwater finfish sector with €1.03 billion.

In the marine sector, the United Kingdom is the main producer of salmon, and only in Ireland salmon is also the main marine finfish species farmed. The production of seabream and seabass is more extended (see Table 1), with Greece being the main producer country in the EU. In the shellfish sector, France is the main producer of oysters, Spain is the main producer of mussels and Italy is the main producer of clams. In many countries, the main species produced in freshwater is trout, where main producer countries are Italy, Denmark and France; while carp is mostly produced in Eastern Europe (Poland, Czech Republic and Hungary).

======================== Table 1 ============================

The objective of this study is to estimate the aquaculture efficiency performance of EU countries in freshwater, marine and shellfish subsectors for the period 2014-2016. To that end, Data Envelopment Analysis (DEA) approach is applied. The remainder of this paper unfolds as follows. In the next section, a literature review on aquaculture efficiency is carried out. Section 3 presents the theoretical framework underlying the proposed approach. In section 4, the dataset and the variables considered are described. The empirical results for the efficiency analysis, as well as the impacts of the contextual factors on the efficiency scores are presented in section 5. Finally, in the last section, we present the conclusions and limitations of this study.

2. Existing efficiency data analysis in aquaculture

Most efficiency analyses on the aquaculture sector apply DEA as the quantitative method to estimate the technological frontier and efficiency of aquaculture operations. This is, mainly, motivated by the existence of multiple inputs and multiple outputs and the lack of a priori knowledge on the functional form of the corresponding production function. Table 2 updates and summarizes the existing DEA research studies in aquaculture (Sharma and Leung, 2003; Illiyase et al., 2014), specifying the location, the number of farms, the time period, the inputs and outputs considered and the main features of the DEA approach used.

=================== Table 2 ========================

Starting with the contribution of Sharma, Leung, Chen and Peterson (1999) that applied a CCR-output oriented model to measure economic efficiency for a sample of Chinese polyculture fish farms, several other DEA efficiency studies were conducted on aquaculture farms in Malaysia (4 papers), US and Bangladesh (3 papers each), China and Vietnam (2 papers each), Denmark, Greece, Iran, Norway, Taiwan and Turkey (1 paper each). The majority of DEA models adopt a conventional CCR and BCC specification with input orientation, i.e., the models aim at minimizing the resources required to achieve the given output level. Iliyasu and Mohamed (2016) use a non-oriented Slacks-Based Measure of efficiency (SBM) DEA model to estimate technical efficiency of fresh pond culture system in Malaysia. Recently, Bayazid et al. (2019) compared the performance of foodplain aquaculture enterprises with different management approaches in Bangladesh using a SBM DEA model. Also, some researchers have used a bootstrapping procedure to correct the potential bias of the technical and cost efficiency measures computed by conventional DEA models (e.g. Chang et al., 2010; Asche et al., 2013a; Iliyasu et al., 2016; Hai et al., 2018).

Other studies (e.g. Kaliba et al., 2007; Hassanpour et al., 2011; Asche et al., 2013a) have investigated the productivity change using a Malmquist index. Thus, for example, Kaliba et al. (2007) used DEA to estimate the total factor productivity growth for U.S. catfish-processing sector during 1986-2005. Another DEA technique, meta-frontier analysis, is used in Nguyen and Fisher (2014), which studied the efficiency of intensive, semi-intensive and extensive shrimp farming practices in Vietnam using a sample of 292 farms. Recently, the studies have also focused on aquaculture cooperatives segment, like Forleo et al. (2018) who studied the Italian cooperatives by measuring budget indexes using CCR-BCC output oriented models.

In recent years, several studies have been published that incorporate a second stage in the DEA analysis to evaluate the impact of specific contextual factors (e.g. non-physical inputs) on technical efficiency of aquaculture production of fish species. The most common second-stage regression method are linear regression models (Iliyasu et al., 2016; Iliyasu and Mohamed, 2016), truncated regression models (Hai et al., 2018) and censored (i.e., Tobit) regression models (Cinemre et al., 2006; Kaliba and Engle, 2006; Alam, 2011; Nielsen, 2011; Hassanpour et al., 2011; Nguyen and Fisher, 2014; Iliyasu et al., 2016; Theodoridis et al., 2017; Zongli et al., 2017). For instance, using data of 89 farms, Nielsen (2011) used a two-stage DEA approach to analyse the impact of water purification systems in farming of freshwater trout in Denmark, using in the first stage input and output-oriented BCC models to compute efficiency and, in the second stage, a Tobit regression model to investigate if farm size had impact on technical efficiency. Other studies, however, adopt a non-linear regression specification in the second-stage, such as logit specification (Hassanpour et al., 2011) and parametric/Bayesian probit specification (Chang et al., 2010).

Almost all the existing efficiency studies in aquaculture refer to farms . Studies that assess the efficiency at the regional or country level are still limited. An exception is Mustapha, Aziz and Hashim (2013), which investigated the freshwater aquaculture efficiency in thirteen states in Malaysia using DEA window analysis over the period 2000-2008. Also, unlike the DEA studies reviewed above, the proposed non-oriented SBM approach considers non-discretionary inputs. Non-discretionary inputs are resources that are beyond managerial control, are not desirable, or it does not make sense to reduce them (e.g. Banker and Morey, 1986). Another contribution of the proposed approach is the use of fractional regressions models in the second stage in order to better capture the data-generating process for DEA scores (Papke and Wooldridge, 1996).

3. Methodology

This study analyses the efficiency performance of the EU aquaculture producers using a two-stage DEA approach covering the period 2014-2016. The first stage uses a non-oriented SBM DEA model to compute the efficiency of the countries. The second stage uses regression analysis to relate these efficiency scores to covariates to test which of them have an influence.

3.1. First-stage DEA model

In this section, the DEA model used is formulated and discussed. DEA is a data-driven methodology to assess the efficiency of a number of decision making units (DMU). It assumes an input-output production system, i.e., each DMU consumes inputs and produces outputs. No assumption is made on the functional form of the corresponding production function. This is done non-parametrically, inferring the Production Possibility Set (PPS) (i.e., the set of feasible operating points) from the observed data using some standard assumptions like that feasibility of the observations, free disposability of inputs and outputs and convexity (see, e.g., Färe et al., 1985; Cooper et al., 2006). The non-dominated subset of the PPS is called the efficient frontier and represents the best practices in the sample. Those observations that do not lie on the efficient frontier can be projected onto it determining both an efficient target operating point and an efficiency score that measures the distance to the efficient frontier. How this projection is done depends on the specific DEA model used. Thus, input-oriented DEA models give priority to the input reduction while output-oriented DEA models give priority to the output increase and non-oriented DEA models aim at both input reduction and output increase simultaneously. Radial DEA models reduce all the inputs equiproportionally and increase all the output equiproportionally while non-radial DEA models can reduce some inputs in a larger proportion than others and increase some outputs more than others.

The DEA model applied in this paper is non-oriented and non-radial. It uses a SBM measure of efficiency, which is an efficiency measure which has several interesting properties (Tone, 2001). In particular, it is units-invariant, i.e., the neither the efficiency score nor the efficient target computed change if the units of measurement of an input or output are changed. SBM has been applied in other sectors (e.g. Lozano et al., 2010; Gutiérrez and Lozano, 2013) and can be extended to handle undesirable outputs (e.g. Lozano and Gutiérrez, 2011) as well as situations in which the production system is modelled as a network of processes (e.g. Lozano, 2015).

In this study, a DMU corresponds to the observation of one country in a specific year during the period 2014-2016) whose relative efficiency is assessed. The inputs and outputs considered are shown in Figure 1. Thus, a single output, namely total production value (PRODUCTION) is considered. The rationale behind selecting the production value as output is that for example, mussels have a low value (0.5 €/kg) while salmon or Bluefin tuna value is much higher (5-10 €/kg) and often they are correlated with their costs, i.e., producing 1 kg of mussels is much cheaper than producing 1 kg of salmon or tuna because mussels do not need to be fed artificially and they can often be caught easily in the wild and hence its raw materials feed and livestock costs are often zero.

On the input side, seven variables are considered: the total number of persons employed (EMPLOYMENT), the balance sheet total (ASSETS), the input costs considered were raw material costs (FEED and LIVESTOCK), purchases of energy products (ENERGY), repair and maintenance costs (REP&MAINT) and OTHER COSTS, including outsourcing costs, equipment rental charges among others. The selection of the inputs was mainly based on their relative weight of total costs. During the last years, the intensification of aquaculture production has increased mainly the use of the fish-based ingredients and the energy consumption (Waite et al., 2014; Shepherd and Jackson, 2013; Tacon and Metian, 2015; Llorente and Luna, 2016; Guillen et al., 2019). However, given the nature of shellfish farming, feed and livestock are not considered as input variables in shellfish production. Mussels, oysters and clams are feed by filtering water, and therefore, there are no feed costs in the shellfish sector. Moreover, most farms obtain the seeds they require directly from the environment, rather than buying them, and so livestock costs are not an adequate measure of the inputs used (STECF, 2018).

Note that the first two inputs are considered non-discretionary and hence the model will not try to reduce them. This is so because we do not want DEA to try to achieve efficiency by reducing the level of employment of the sector or by reducing the assets (closing or downsizing existing facilities). Instead, we employ DEA to try to achieve efficiency by reducing the other three (discretionary inputs) and increasing the output. In other words, the efficient targets computed will maintain the level of employment and the current assets but will detect output shortfalls as well as excess consumption of raw material, energy costs (especially in offshore environments), repair and maintenance costs and other operating costs. The formulation of the proposed model that follows corresponds to finfish sectors. For shellfish sector FEED and LIVESTOCK input variables are discarded from the DEA model as mentioned above.

========================= Figure 2 ============================

Apart from the input and output variables DEA also uses some auxiliary variables. Let

n	number of DMUs
$j = 1, 2, ..., n$	index on DMUs
$EMPLOYMENT_j$, $ASSETS_j$, $FEED_j$, $LIVESTOCK_j$, $ENERGY_j$, $REP\&MAINT_j$, $OTHERCOSTS_j$	inputs consumed by DMU j
$PRODUCTION_j$	output produced by DMU j

0 index of a specific DMU whose efficiency is being assessed

$(\lambda_1, \lambda_2, ..., \lambda_n)$ intensity variables used to compute the target as a linear combination of the observed DMUs

s^{FEED}, $s^{LIVESTOCK}$, s^{ENERGY}, $s^{REP\&MAINT}$, $s^{OTHERCOSTS}$ input slacks (i.e., reduction to be achieved for each discretionary input)

$s^{PRODUCTION}$ output slack (i.e., output increase to be achieved)

$t^{EMPLOYMENT}$, t^{ASSETS}, t^{FEED}, $t^{LIVESTOCK}$, t^{ENERGY}, $t^{REP\&MAINT}$ $t^{OTHERCOSTS}$ target value for each input

$t^{PRODUCTION}$ target value for the output

ξ_0 efficiency score of DMU 0

The proposed non-oriented SBM DEA model is thus

$$\xi_0 = \mathrm{Min}\ \frac{1-\frac{1}{5}\cdot\left(\frac{s^{FEED}}{FEED_0}+\frac{s^{LIVESTOCK}}{LIVESTOCK_0}+\frac{s^{ENERGY}}{ENERGY_0}+\frac{s^{REP\&MAINT}}{REP\,\&\,MAINT_0}+\frac{s^{OTHERCOSTS}}{OTHERCOSTS_0}\right)}{1+\frac{s^{PRODUCTION}}{PRODUCTION_0}}$$

$$\begin{aligned}
&\text{s.t.}\\
&\sum_{j=1}^{n}\lambda_j\cdot EMPLOYMENT_j \le t^{EMPLOYMENT} = EMPLOYMENT_0\\
&\sum_{j=1}^{n}\lambda_j\cdot ASSETS_j \le t^{ASSETS} = ASSETS_0\\
&\sum_{j=1}^{n}\lambda_j\cdot FEED_j = t^{FEED} = FEED_0 - s^{FEED}\\
&\sum_{j=1}^{n}\lambda_j\cdot LIVESTOCK_j = t^{LIVESTOCK} = LIVESTOCK_0 - s^{LIVESTOCK}\\
&\sum_{j=1}^{n}\lambda_j\cdot ENERGY_j = t^{ENERGY} = ENERGY_0 - s^{ENERGY}\\
&\sum_{j=1}^{n}\lambda_j\cdot REP\,\&\,MAINT_j = t^{REP\&MAINT} = REP\,\&\,MAINT_0 - s^{REP\&MAINT}\\
&\sum_{j=1}^{n}\lambda_j\cdot OTHERCOSTS_j = t^{OTHERCOSTS} = OTHERCOSTS_0 - s^{OTHERCOSTS}\\
&\sum_{j=1}^{n}\lambda_j\cdot PRODUCTION_j = t^{PRODUCTION} = PRODUCTION_0 + s^{PRODUCTION}\\
&\sum_{j=1}^{n}\lambda_j = 1\\
&\text{All variables non}-\text{negative}
\end{aligned} \qquad (1)$$

Note that the last constraint imposes convexity on the intensity variables, which corresponds to assuming Variable Returns to Scale (VRS). VRS is considered because the size of the sector in the different countries varies much and a perfect competitive market cannot be assumed to exist. Note also that the constraints corresponding to the non-discretionary variables are different from those of the discretionary ones. Thus, for the two non-discretionary inputs the target corresponds to the observed value for DMU 0 and the constraint only imposes that the PPS contains operating points with a lower value of those inputs. This is the standard way of handling non-discretionary inputs as per Banker and Morey (1986). For the discretionary variables, on the contrary, the target is equal to the convex linear combination of the observed values so that those targets represent a certain reduction (in the case of the input slacks) or a certain increase (in the case of the output slack) with respect to the observed value of DMU 0.

As regards the objective function, it minimizes a ratio whose numerator represents the average percentage input reduction (applicable only to the five discretionary inputs) and whose denominator represents the percentage output increase. Note that, an alternative way of expressing the objective function is

$$\xi_0 = \text{Min} \quad \frac{\frac{1}{3}\cdot\left(\frac{t^{\text{FEED}}}{\text{FEED}_0}+\frac{t^{\text{LIVESTOCK}}}{\text{LIVESTOCK}_0}+\frac{t^{\text{ENERGY}}}{\text{ENERGY}_0}+\frac{t^{\text{REP\&MAINT}}}{\text{REP \& MAINT}_0}+\frac{t^{\text{OTHERCOSTS}}}{\text{OTHERCOSTS}_0}\right)}{\frac{t^{\text{PRODUCTION}}}{\text{PRODUCTION}_0}} \tag{2}$$

Since the computed target must dominate DMU 0, i.e., $t^{\text{FEED}} \le \text{FEED}_0$, $t^{\text{LIVESTOCK}} \le \text{LIVESTOCK}_0$, $t^{\text{ENERGY}} \le \text{ENERGY}_0$, $t^{\text{REP\&MAINT}} \le \text{REP \& MAINT}_0$, $t^{\text{OTHERCOSTS}} \le \text{OTHERCOSTS}_0$ and $t^{\text{PRODUCTION}} \ge \text{PRODUCTION}_0$, it follows that the three ratios in the numerator are less than (or at most equal to) one and the denominator is larger than (or at most equal to) one. Hence $0 \le \xi_0 \le 1$ with a value $\xi_0 = 1$ indicating that DMU 0 is efficient, in which case $s^{\text{FEED}} = s^{\text{LIVESTOCK}} = s^{\text{ENERGY}} = s^{\text{REP\&MAINT}} = s^{\text{OTHERCOSTS}} = s^{\text{PRODUCTION}} = 0$, and $t^{\text{FEED}} = \text{FEED}_0$, $t^{\text{LIVESTOCK}} = \text{LIVESTOCK}_0$, $t^{\text{ENERGY}} = \text{ENERGY}_0$, $t^{\text{REP\&MAINT}} = \text{REP \& MAINT}_0$, $t^{\text{OTHERCOSTS}} = \text{OTHERCOSTS}_0$, and $t^{\text{PRODUCTION}} = \text{PRODUCTION}_0$. It is also easy to see that the computed target is efficient because any additional reduction of the discretionary inputs or any additional increase of the output, if any such additional improvements were feasible, would reduce the ratio and hence the target would not the optimal solution of (1).

The current study involves observations in different time periods. In those cases, different alternatives exist (see Tulkens and VandenEeckaut, 1995). One is to use an intertemporal approach in which the observations of different time periods are pooled to define the DEA technology. Another is to use a contemporaneous approach in which the observations in each time period define the DEA technology corresponding to that time period. A third alternative is to use a sequential approach so that the DEA technology corresponding to each period is inferred from the observations of all previous time periods. When using a contemporaneous or a sequential approach the conventional Malmquist Productivity Index (MPI) and its decomposition into its technical efficiency change and technology change components can be used (Färe et al., 1985). If VRS is assumed, as in this paper, a more complex MPI decomposition is necessary to account for scale efficiency change between periods (see Färe et al., 1994, Ray and Desli, 1997). Instead, when an intertemporal approach is used, the global MPI proposed in Pastor and Lovell (2005) can be used. In this paper, since the time horizon covered by the dataset is relative short (just three time periods) it seems more reasonable not to assume a different DEA technology for each time period and hence use an intertemporal approach. This has the added benefit of using a global MPI, which is simpler than the conventional MPI. In particular, given a certain country c and two different periods t and h, the corresponding global MPI can be computed as $\mathrm{MPI}_c^{t,h} = \frac{\xi_{c,h}}{\xi_{c,t}}$. Thus, if the global efficiency increases from t to h then $\mathrm{MPI}_c^{t,h} > 1$ and productivity increase has occurred while if the global efficiency decreases from t to h then $\mathrm{MPI}_c^{t,h} < 1$ and productivity decrease has occurred.

3.2. Second-stage regression analysis

In order to study the impact of factors that can influence efficiency, the SBM efficiency estimates are regressed on some contextual variables in a second stage analysis. Several statistical regression models are considered. Since they are based on different assumptions their results can also differ. The second-stage regressions models considered include a linear specification (estimated by Ordinary Least Squares, OLS), a censored specification (estimated by maximum likelihood, ML) and fractional specification (estimated by quasi-maximum likelihood, QML).

The standard linear model is not suitable for DEA analyses because it can have boundary problems, i.e., the regression model can estimate efficiency values that fall outside the [0,1] interval. To overcome this drawback, a censored regression with limits efficiency to the [0,1] interval is also considered, with the corresponding validation of normality and homoskedasticity assumptions. However, as Simar and Wilson (2007) pointed out, DEA efficiency estimates from both OLS and ML regression approaches are serially correlated, affecting the results of the conventional inference.

In order to avoid complex prior data transformation and to solve the controversy between competing statistical regression models the Fractional Regression Model (FRM) is considered (Papke and Wooldridge, 1996). The fractional model does not involve any fully parametric assumption about the distributional form of the response variable and DEA efficiency scores are considered descriptive statistics of the relative achievement of DMUs in the sample. The fractional regression model uses a Quasi-Maximum Likelihood Estimator (QMLE) approach and only requires assuming a functional form for conditional mean of the estimated values of the efficiency scores, $E(\xi_i|\mathbf{x}_i)$, that incorporates the desired constraints on it, as it is expressed as follows:

$$E(\xi_i \mid \boldsymbol{x}_i) = G\left(\boldsymbol{x}_i \boldsymbol{\beta}\right) \quad i = 1, 2, \ldots, n \tag{3}$$

where $0 \leq \xi_i \leq 1$, $\boldsymbol{x_i}$ denotes the k-dimensional vector of the variables of the *i-th* DMU observation and $\boldsymbol{\beta}$ a k-dimensional vector of unknown parameters and $G(\bullet)$ is a nonlinear function satisfying $0 \leq G(\bullet) \leq 1$ that can adopt different specifications:

$$G_{\text{logit}}\left(\boldsymbol{x}_i \boldsymbol{\beta}\right) = \frac{\exp(\boldsymbol{x_i} \boldsymbol{\beta})}{\left(1 + \exp(\boldsymbol{x_i} \boldsymbol{\beta})\right)} \tag{4}$$

$$G_{\text{probit}}\left(\boldsymbol{x}_i \boldsymbol{\beta}\right) = \Phi(\boldsymbol{x}_i \boldsymbol{\beta}) \tag{5}$$

$$G_{\text{loglog}}\left(\boldsymbol{x}_i \boldsymbol{\beta}\right) = \exp(-\exp^{(-\boldsymbol{x}_i \boldsymbol{\beta})}) \tag{6}$$

$$G_{\text{cloglog}}\left(\boldsymbol{x}_i \boldsymbol{\beta}\right) = 1 - \exp(-\exp^{(\boldsymbol{x}_i \boldsymbol{\beta})}) \tag{7}$$

Ramalho et al. (2010) proposed other alternative models, labelled two-part fractional models, which can be used in cases where the probability of observing a DEA efficiency score of one is large. The two-part models assume that contextual factors have a different impact on the frontier efficiency and on the inefficiency scores. The first part model is a binary choice model that characterises the probability of observing an efficient Member State using the complete sample. Whereas, the second part of the two-part models only considers the subset of inefficient Member States and uses a different model specification. In order to assess the specification of the one-part fractional and two part fractional models a robust version of RESET test (Ramalho et al., 2011), P test based on Davidson and MacKinnon (1981) and GOFF (Ramalho et al., 2011) can be performed. It should be noted that the efficiency scores are treated as descriptive measures in one-part and two-part fractional regression models.

3.3. Dataset description

The dataset used corresponds to an unbalanced panel database of finfish and shellfish farming across 18-EU Member States and involve labour, physical and monetary inputs used to generate the output of sales volume. The data have been extracted from the biennial reports on economic performance of EU aquaculture sector (STECF, 2016; STECF, 2018) and correspond to the years 2014, 2015 and 2016 (latest year available), covering freshwater finfish, marine finfish and shellfish aquaculture segments.

As indicated in section 3.1, the input variables include EMPLOYMENT, measured as total number of full-time equivalent employees, total ASSETS expressed in million euros, total fish feed costs (FEED), total costs for feed livestock (LIVESTOCK) measured in million euros, energy costs (ENERGY) measured in million euros, repair and maintenance costs (REP&MAINT) measured in million euros, and other operating cost (OTHERCOSTS), measured in million euros. The measure of output is the production/sales value (PRODUCTION) measured in million euros.

In order to identify potential outliers a super-efficiency DEA model (Banker and Chang, 2006; Banker et al., 2017) is applied, using, in our case, an adapted non-oriented VRS SBM formulation (considering EMPLOYMENT and ASSETS as non-discretionary variables). Once an observation is suspicious of being an outlier, a detailed analysis is carried out based on the work of technical experts, in order to understand how the “outlier” contaminates the database. In the present analysis, all the potential outliers were discarded from the final database. This occurs in fresh water sector for three observations, in marine sector for five observations and in shellfish sector for five observations. Thus, some of the arguments for not considering those observations in the final database were the following. Finland in year 2015 and 2016 because of a change in the regulation and segmentation, marine segments are now reported inside freshwater. Italy in 2015 had sometimes wrongly estimated number of employed people. Italy data in 2016 may refer just to the most important species. Hence, some segments could be underestimated by not including minor productions (and it may lead to e.g. overestimated productivity). Bulgaria: marked decrease in raw materials for freshwater in 2015 and 2016.

Summarizing, as mentioned above all in all, thirteen observations were discarded, so the database during the period 2014-2016 contains 39 observations referring to 15 countries in freshwater sector, 28 observations referring to 12 countries in marine sector, and 38 observations referring to 14 countries in shellfish sector. The packages *deaR* (Coll-Serrano et al., 2018) and *frm* (Ramalho, 2018) for the statistical software R were used to calculate the efficiency scores and to fit the fractional regression models. The descriptive statistics of the input and output variables by sector, after outlier analysis, are presented in Table 3. They indicate a great variability of inputs and outputs among EU countries (consider that standard deviations are in most variables as large as the mean). Shellfish sector is the sector that employed more labour during the period, although with a high variability (FTE dispersion increased from 2,220.8 to 2,246.91). In this regard, note that, according to STECF (2016, 2018), the majority of the businesses in the EU aquaculture sector are micro-enterprises with less than 10 employees. On the other hand, it can be observed, on average, large differences in inputs and output over time in the finfish freshwater sector, those difference being less pronounced in the rest of the sectors. In general, the inputs and outputs figures considered fluctuate widely between countries, as a result of the national sector size and on the species and aquaculture farming techniques of each EU country. The expenditures are dominated by raw material (feed costs and livestock costs) over the period 2014-2016. The average value of the FEED variable in freshwater sector decreased from €20.30 million to €17.31 million (15%) and increased in marine sector from €57.55 million to €86.46 million (50%). However, the average value of the LIVESTOCK variable in freshwater sector increased from €14.98 million to €25.32 million (69%) and increased in marine sector from €5.67million to €6.30 million (11%). ENERGY costs have decreased, on average, in freshwater sector (32%) and shellfish (24%), however, in marine sector has increased (42%). In terms of REP&MAINT, total costs kept stable, in freshwater and shellfish sector, while marine sector has increased (40%). Total PRODUCTION value increased by 57% in freshwater finfish and by 3% in shellfish while in marine finfish it decreased by 4%.

============================ Table 3 ============================

4. Results and discussion

4.1. Efficiency scores

Tables 4a, 4b and 4c show the efficiency scores and the slacks computed by the proposed SBM DEA model for each of the three subsectors studied. For freshwater finfish 74% of the observations are efficient and the average efficiency is rather high (0.918). The corresponding figures for marine finfish and shellfish are 57% - 0.885 and 66% - 0.802, respectively. The largest margin for input savings and output increases correspond to marine finfish, followed by shellfish. In accordance with the larger efficiency scores, the potential savings are much more modest for freshwater finfish. Extending the best practices to the inefficient countries would involve a reduction of feed costs (between 2.9% and 4.3%), livestock costs (9.0% - 11.8%), energy costs (2.4% - 25.3%), repairing costs (3.7% - 13.8%) and other operating costs (4.3% - 13.8%). These input reductions can be obtained at the same time that an improvement in production value totalling 0.03% for freshwater finfish, 2.13% for marine finfish and 0.37% for shellfish. In any case, those would be the total improvements for the sector if the different EU countries assessed adopted the best practices represented by the efficient producers. In general, the inefficiencies observed in most EU countries are more related with controlling input costs than with increasing the output level. The exceptions to this are the marine finfish production of Croatia and UK (the former producing seabream and seabass, and the latter salmon).

============================ Table 4 ============================

Tables 5a, 5b and 5c show the efficiency scores grouped by country as well as the corresponding global Malmquist productivity indexes (Pastor and Lovell, 2005). Some countries were efficient in all the periods for which observations are available. In the case of freshwater finfish, those countries are Croatia, Estonia, France, Greece, Italy, Portugal, Sweden and UK (all producing mostly trout, with the exception of Croatia producing mostly carps). For marine finfish, those countries are Cyprus, Italy and Slovenia producing mostly seabream and seabass, Finland producing mostly trout and Ireland producing mostly salmon. Finally, for shellfish, the best performing countries include Bulgaria, Denmark, France, Germany and Greece producing mostly mussels, Italy producing mostly clams and mussels, and Portugal producing mostly clams. As regards productivity change, it seems that in the case of freshwater finfish there has been a productivity reduction in the period under study. The opposite occurred in the case of marine finfish. Finally, in the case of shellfish, productivity increased between 2014 and 2015 and decreased slightly between 2015 and 2016 (but leaving a net overall productivity increase).

============================ Table 5 ============================

4.2. Factors that can influence aquaculture efficiency

In order to identify the factors that can explain the variability of the computed efficiency scores (ξ_i) for the EU countries under study the SBM-DEA efficiency scores obtained in first stage were regressed on four exogenous factors corresponding to geographical, demographic and macroeconomic variables covering 2014-2016.

The explanatory variables selected include the coastline length in kilometres (COASTLINE) obtained from Corine land cover database (EEA, 2006), characteristics related to economic and demographic magnitude of the countries, namely Gross Domestic Product (GDP) in billion PPS

(Worldbank, 2018) and total population (POPULATION) in thousand (Eurostat, 2017), and a characteristic of alternative supply source for fish, i.e., volume of fish caught in the wild (FISHERY) in thousand tonnes (Eurostat, 2015). In addition, two dummy variables FRESHWATER and MARINE are included, which take the value of unity if the country-year is evaluated in the corresponding sector and zero otherwise. It can be noted that, due to the inter country comparison is performed in the present analysis, the variables used are different from those generally used at the firm level and that were shown in Table 1.

The distribution of the efficiency scores computed in the first stage shows that 66% of the European Aquaculture countries were efficient and that the Q1 quartile, the median and the Q3 quartile are 0.7823, 1.000 and 1.000, respectively, indicating a negative skew. The lowest score was 0.117. Hence, in the second stage a suitable lower limit for the efficiency scores is zero and there will not be misspecification considering two-limit censoring regression.

The results of fitting the parametric (OLS, ML) and quasi-parametric fractional regression models described above and two specification tests (Reset test; P-test) are presented in Table 6. A global test procedure of multiple linear model assumptions (Pena &Slate, 2006), based on residual vector, is applied. The global statistic is $\hat{G}_4^2 = 4.02$ with p-value approximately 0.40, thus indicating that at least one of the OLS regressions assumptions are not violated. However, the OLS regression fits 20% of observations outside the range of the unit interval, which suggests that it does not properly gauge the real effect of each factor on the efficiency scores. Moreover, the analysis of the distributional assumptions of Tobit regression model confirms evidence to reject the normality of the residuals at 5% marginal significance level.

As regards the standard one-part fractional regression models, an examination of goodness of fit measures reveals that fractional regression with loglog link function dominates slightly the other specifications in terms of McFadden's Pseudo R^2. The latter can be motivated by the asymmetric character of the distribution of efficiency scores. The specification tests show that the probit, loglog and cloglog specifications could be considered as potential links in the one-part standard regression model specification. For all specifications, the results show that the the coefficients of COASTLINE, POPULATION and FISHERY are not significant and do not help to explain the observed efficiency of the different countries. GDP positively affects efficiency in EU aquaculture production indicating the efficiency level seems to be positively affected by the size of the economy. The coefficients of FRESHWATER and MARINE were also found to be statistically significant (and positive). This suggests that finfish sectors tend to be more efficient than shellfish sector. This can be explained because in finfish aquaculture, the farmer has a higher degree of control of the production cycle (e.g. feeding, medicines, juveniles, broodstock, etc.) than in shellfish aquaculture where the production feeds directly by filtering the water and is more dependent on environmental factors (Guillen et al., 2019).

============================ Table 6 ============================

The results of the two-part fractional models are shown in Table 7. It can be seen that the number of significant variables is smaller (higher) in the first part (second part) of the two-part model than in the one-part fractional regression models. The binary component (first part) tests the impacts of the contextual factors considered on the efficient status of the countries, whereas the fractional component (second part) explains the magnitude of DEA scores of the sub-sample of inefficient countries.

Similar to what occurred in one-part fractional regression models, the results reveal a significant positive relationship between GDP and the probability of the country being efficient. The FISHERY coefficient was statistically significant and negatively explains why countries are associated to be on the frontier, suggesting that the probability of the country being efficient declines with fishing activity. Note that the cloglog specification is the one that seems to show a better fit in this first part and hence the fractional component will assume that cloglog was used for the binary part. The goodness of fit test did not confirm the rejection of all link functions at 10% significance level.

============================ TABLE 7 ============================

The fractional component, which only considers the inefficient countries contributes to explaining why some countries were inefficient, confirms that finfish sector and FISHERY contextual factors affect the inefficient countries at the 1%-10% significance level. RESET and GOFF tests, however, do not reject any specification of the fractional part of the regression model, therefore the link function chosen for the second part barely alter the results. The parameters FRESHWATER and MARINE have positive signs, indicating that finfish farming subsectors are more efficient and competitive in aquaculture production. At a 10% significance level, FISHERY activity coefficient was positive; meaning an increase in the volume of catches of wild species in inefficient countries contributes to an increase in their efficiencies.

4.3. Policies to improve the efficiency of the EU aquaculture sector

This study shows that the largest inefficiencies are found in the marine finfish, followed by shellfish, and less in freshwater finfish farming. In general, these inefficiencies are more related with controlling input costs than with increasing the output level. Thus, significant improvements in efficiency can be obtained by sharing best practices.

However, almost 90% of the estimated 12,500 aquaculture enterprises in the EU are micro-enterprises with less than 10 employees (STECF, 2018). The atomization of the EU aquaculture sector could be a factor that explains these inefficiences. Gasca-Leyva et al. (2002) pointed out that increasing the facility size often leads to an efficiency increase in the production of most commercial species by reducing the average cost of production and increasing productivity.

Similarly, concentration of enterprises (i.e., a reduction in the number of enterprises and an increase in their size, e.g. due to horizontal integration) can also generate economies of scale and efficiency gains (Asche et al., 2013b). Moreover, concentration cannot only lead to increases in production efficiency, but also in other aspects such as the purchases of services, marketing and sales (Asche et al., 2013b; Bergesen and Tveterås, 2019).

One of the factors that explains the higher efficiency of larger companies is their capacity to produce and incorporate innovation (Asche et al., 2013b; Misund and Asche, 2016; Billington and Hydle, 2017). Indeed, innovation and productivity growth have played an important role for the production growth of most successful aquaculture species (Kumar & Engle, 2016; Asche, 2019; Rocha Aponte and Tveterås, 2019).

Despite some concentration in the EU aquaculture sector, most enterprises are micro-enterprises. Most of the enterprises cannot affort having their own R&D staff. Hence, collaboration, between private enterprises and with the public sector, becomes essential to boost efficiency gains in the sector (Bergesen and Tveterås, 2019). Public policies to support R&D and ease general access to its outcomes are essential to boost the efficiency of the sector.

This study also shows that for the inefficient countries, the bigger the wild-capture fisheries sector is, the more efficient aquaculture is. This shows that aquaculture is more efficient in those countries where there is already an established seafood value chain. Therefore, the importance of policies to support different aspects of the value chain, such as transportation, transformation and commercialization, in particular for the most inefficient countries and for micro-enterprises.

Despite some progress, the administrative burden remains an important obstacle to the enlargement and development of the EU aquaculture. Further work on simplifying the administrative procedures is required. Thus, it is required common and harmonised standards for the aquaculture sector to prove that it produces sustainably and that its development should not be blocked.

Likewise, the lack of available space to set or enlarge aquaculture farms is often an obstacle. Maritime spatial planning is a tool to organize the different activities and uses that take place in the sea. Therefore, maritime spatial planning should be able to secure the aquaculture sector some access to the required space. Progress in maritime spatial planning is still reduced in some EU member states.

5. Conclusions

Aquaculture industry in the EU is promoted from a food security perspective, as a driver to provide population with high-quality and healthy seafood. In addition, it is also considered an economic activity that contributes to create employment, to fix population to coastal and rural areas, and that helps to develop environmentally friendly seafood production. However, as an economic activity, efficiency, leading to decreasing resource waste and increasing profitability and economic sustainability must be one of the objectives of any public support program. This will help not only to increase aquaculture production and generate positive social and environmental externalities, but also to make all of this sustainable.

This paper applies a non-oriented SBM DEA model with non-discretionary inputs to the efficiency assessment of different EU Member States during the period 2014-2016. This differs from most DEA studies on aquaculture, which measure efficiency at the farm level. The inputs considered include operational and monetary variables. The output is the value of fish produced. The non-oriented character of the DEA analysis implies that all possible sources of inefficiency are removed, be they in the discretionary inputs or in the output. The DEA analysis indicates that technical efficiency is higher in finfish production (both fresh and marine) than in shellfish, with average efficiency levels in the 0.8-0.9 range. This pattern can be explained by farmers having more control of the production cycle in the finfish aquaculture, than in shellfish aquaculture that is more dependent on environmental factors. Others factors such as consumer' preferences, market concentration and the increase in marine finfish supplies and the decrease in shellfish supplies to a competitive market causing price reductions (in case marine finfish) and price increases (in case shellfish) can also help to explain this pattern. The potential input savings for the whole period are significant, reaching up to 25% in some variables. The potential increase in production is lower, up to 2% in the case of marine finfish. As regards productivity change in the period under study, there has been a productivity reduction in the case of freshwater finfish, productivity increase in the case of marine finfish and an initial productivity increase between 2015 and 2016 followed by a slight decrease between 2015 and 2016 in the case of shellfish. The analysis of the aquaculture efficiency determinants reveals that the efficiency level of EU countries is not completely a consequence of managerial inefficiency. Thus, some contextual factors, particularly the size of the economy and capture fishery affect the efficiency level of aquaculture production. The results indicate that the exogenous variables affect efficient and inefficient EU countries differently, given the extensive number of efficient countries. In particular, countries with a high GDP and poor catches volume are more likely to be on the efficiency frontier. On the other hand, for the inefficient countries larger amounts of wild-caught fish contribute to increase their efficiency score. These factors may be taken into consideration by European institutions, Member States and aquaculture industry stakeholders when assessing performance and evaluating potential technical and operational improvement strategies or policies. Nevertheless, these results should be interpreted with caution as the number of MS considered in the study (18 countries) is relatively small. Some countries (most notably, Germany and Poland) were not included or had disproportionately scarce presence in the study because data on freshwater aquaculture were not available.

Once the performance of European countries in each aquaculture subsector has been assessed, further research can aim at benchmarking the different aquaculture subsectors (freshwater finfish, marine finfish and shellfish). This can be done by using a meta-frontier approach (see, e.g., O'Donnell et al., 2008). Another interesting line of research is to include in the performance assessment, similar as it is done in agriculture (see, e.g., Gutiérrez et al., 2017), the undesirable outputs (e.g. greenhouse gas emissions) generated by aquaculture activities. This would allow computing not only productive efficiency but also environmental efficiency. In addition, this would also allow identifying the best practices among European countries, using them to set improvement targets for the corresponding variables. Finally, a Network DEA approach may be used to model the internal structure of the supply chain of aquaculture production. Although they require more detailed data on the functioning of the system (i.e. at the sub-process level), Network DEA models allow a more fine grained analysis and can also handle undesirable outputs (see, e.g., Lozano, 2016).

Acknowledgements. This research was carried out with the financial support of the Spanish Ministry of Science and the European Regional Development Fund (ERDF) grant DPI2017-85343-P. The authors would like to thank the journal Editor and anonymous reviewers for their constructive comments and valuable suggestions

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List of tables and figure captions

Table 1. Main species farmed by environment in EU countries

	Freshwater	Marine	Shellfish
Bulgaria	trout, carp		mussels
Croatia	carp	seabream & seabass	mussels
Cyprus		seabream & seabass	
Denmark	trout	trout	mussels
Estonia	trout		
Finland	trout	trout	
France	trout		oysters
Germany			mussels
Greece	trout	seabream & seabass	mussels
Ireland	trout	salmon	oysters
Italy	trout	seabream & seabass	clams, mussels
Malta		bluefin tuna	
Netherlands			mussels
Portugal	trout	turbot, seabream & seabass	clams
Romania	carp		
Slovenia		seabream & seabass	mussels
Spain	trout	seabream & seabass	mussels
Sweden	trout		mussels, oysters, crayfish
United Kingdom	trout	salmon	mussels

Table 2. Overview of aquaculture DEA studies

Country/ Region	Aquaculture species/subsector	Dataset (year)	Inputs (unit)	Outputs (unit)	DEA approach	Reference
Bangladesh	Prawn-carp	105 farms (2001-2002)	Labor (man-hours) Fingerling (No) Organic fertilizer (kg) Inorganic fertilizer (kg) Feed (kg)	Prawn production (kg) White fish production (kg)	BCC- Input and output oriented	Alam & Murshed-e-Jahan (2008)
Bangladesh	Pangas fish	60 farms (2006-2007)	Fingerling (No./ha) Bran (rice and wheat) (kg/ha) Wheat flour (kg/ha) Oil cake (kg/ha) Fish meal (kg/ha) Peleted commercial feed (kg/ha) Inorganic fertilizers (kg/ha) Labour (man-day/ha)	Pangas production (kg/ha)	BCC- Input oriented Second stage (Tobit regression: age of the operator; pangas culture experience of the operator; size of pangas ponds; average size of fingerling released; pangas culture period; ratio of peleted commercial feed; location)	Alam (2011)
Bangladesh	Collective Foodplain aquaculture	15 foodplains enterprises (2015-2016)	Area of foodplain(ha) Fingerling (Million BDT) Feed and other (Million BDT) Salaries (Million BDT)	Fish sales (Million BDT)	CCR-BCC-SBM- Input oriented/Output oriented	Bayazid etl al. (2019)
China	Fishpolyculture	115 farms (2007)	Seed (ka/ha) Feed (ton/kg) Labor (Yuan/ha) Other costs (Yuan/ha)	Black carp (kg/ha) Grass carp (kg/ha) Filter-feeder (kg/ha) Other carp (kg/ha) Black carp (Yuan/kg) Grass carp (Yuan/kg) Filter-feeder (Yian/kg) Other carp (Yuan/kg)	CCR-Output oriented	Sharma et al. (1999)
China	Tilapia	48 farms (2012-2013)	Seed (pcs/ha) Feed (Tons/ha) Labor (man/farm) Other costs (Yuan/ha) Price of Tilapia (Yuan/kg) Polyculture species price (Yuan/kg) Price of fry (Yuan/piece) Price of feed (Yuan/ton)	Tilapia (kg/ha) Polyculture species (kg/ha)	CCR-BCC-Input oriented Second stage (Tobit regression: age of operator, education of operator, experience of operator, family members, culture mode, technology support, culture period, fry size, farm size)	Zongli et al. (2017)
Denmark	Trout	89 farms (2007)	Income per kilo ($), Fish and feed ($), Labor ($), Other ($) Capital ($), Sum total cost ($)	Farm production (tons)	BCC- Input and output oriented Second stage (Tobit regression: water purification system; size classes)	Nielsen (2011)

Table 2. Overview of aquaculture DEA studies (cont.)

Greece	Mussels	66 farms (2013-2014)	Farm size (ha) Labor (hours) Variable capital cost (€) Fived capital cost (€)	Gross output (€)	BCC- Output oriented Second stage (Tobit regression: age, experience, farn succession, training, education)	Theodoridis et al. (2017)
Iran	Trout	207 ponds (2003-2007)	Pond area (m^2) Fish larva (piece) Water flow (L/s) Feed (tons) Labor (persons)	Trout production (tons)	BCC- Input oriented Malmquist index Second stage (Logit and Tobit regression: temperature, water discharge imported, education level, number of illiterate labours, number of diploma labours, insurance coverage, governmental tenure)	Hassanpour et al. (2011)
Hawaii	Catfish, Foodfish, Crustacean, Ornamental, Mollusks and Others	82 farms (1997-2002-2007)	Labor expense ($/farm) Number of workers (no/farm) Value of land ($/farm) Size of land (Acre/farm) Value of machinery ($/farm) Other expense($/Farm)	Total sale ($/farm)	CCR-BCC-Output oriented	Arita & Leung (2014)
Malaysia	Shrimp	36 intensive farms 36 semi-intensive farms (1993)	Labor (persondays/ha) Feed (kg/ha) Seed (1,000 PL/ha)	Production value ($/ha)	BCC- Input oriented	Gunaratne & Leung (2001)
Malaysia	Freshwater	13 states (2000-2008)	Area of pond (square meters) Number of culturist	Aquaculture production (tons)	CCR Window analysis	Mustapha et al. (2013)
Malaysia	Freshwater	212 firms (unspecified timeframe)	Stocking density (No) Feed (kg) Labor (Man-day) Other costs (Ringgit)	Total quantity of fish produced (kg)	BCC.Input oriented Second stage (Ordinary Least Squares: age; experience; educational level; farm status; extension services; household size)	Iliyasu et al. (2016)
Malaysia	Freshwater	100 firms (unspecified timeframe)	Stocking density (No) Feed (kg) Labor (Man-day) Other costs (Ringgit)	Total quantity of fish produced (kg)	SBM Second stage (Ordinary Least Squares: age; experience; educational level; farm status; extension services; workshop attended; distance feed supplier; household size; water management)	Iliyasu & Mohamed (2016)

Table 2. Overview of aquaculture DEA studies (cont.)

Norway	Salmon	57 firms (1996-2008)	Feed (1,000 tons) Smolt (1,000 tons) Labor (1,000 h) Area (million cubic meters) Capital cost(10^6 NOK real value)	Production of salmon and trout (1,000 tons)	BCC-Output oriented Malmquist Bootstrap approach	Asche et al. (2013)
Taiwan	Tilapia, Milkfish, Oyster, Clam, Perch, Eel, Grouper	1009 firms (2004-2005)	Operated land area (ha) Seed expenses (NT$) Total used labor (persons·days) Feed expenses (NT$)	Fish production (kg)	BCC-Input oriented Bootstrap approach Second stage (Parametric/Bayesian probit model: oper.characteristics; firm characteristics; environmental characteristics/regions)	Chang et al. (2010)
Turkey	Trout	73 farms (2001)	Labor (1,000 h) Feed (tons)	Trout production (tons)	BCC-Input oriented Second stage (Tobit regression: personal characteristics; characteristics; access to institutions/public goods)	Cinemre et al. (2006)
US	Catfish	32 farms (2001)	Labor (persons) Energy (Btu) Electricity (kWh) Fingerlings (No) Feeds (tons) Other costs ($US)	Live catfish (kg)	BCC-Input oriented Second stage (Tobit regression: size of operation; experience of operator; extension services; land ownership)	Kaliba & Engle (2006)
Vietnam	Shrimp	292 farms (2009)	Seed (1,000 ind/ha) Feed (kg/ha) Labor (h/ha) Fertilizer (kg/ha) Fuel (L/ha)	Yield (kg/ha)	BCC-Input oriented Meta-frontier analysis (Intensive; Semi-Intensive; Extensive) Second stage (Tobit regression: education level, family size, ratio of females to males, shrimp farming experience, training, province, location and technology variables)	Nguyen & Fisher (2014)
Vietnam	Lobster	353 farms (2016)	Fingerlings (no.) Feed (kg) Labor (man hours) Fingerling ($/unit) Feed ($/kg) Labor ($/man hours)	Spiny lobsters (kg) Green lobsters (kg)	BCC-Input oriented (per farm cultivation cycle).Second stage (age, education, household size, cultivation period, location, total cage volume, cage cleaning, distance from the nearest farm, other discharge)	Hai et al. (2018)
Vietnam	Pangasius	80 farmers (2013)	Pond area (ha) Capital (1,000 $US) Feed (1000 $US) Labor (1,000 $US) Others (1,000 $US)	Fish yield (tons)	Russell-type (input-output) Second stage (Bootstrap truncated regression model: age, production experience, education, gender, farm location)	Ngoc et al. (2018)

Notes: BDT: Bangladeshi Taka; NOK: Norwegian Krone. NT$: Taiwan Dollar; PL: Post-Larvae; Ringgit: Malaysian currency.
CCR: Charnes, Cooper and Rhodes (Charnes et al., 1978), BCC: Banker, Charnes and Cooper (Banker et al., 1984)

Table 3. Dataset with summary statistics of the variables (excluding outliers)

	Mean (Standard Deviation)- Fresh Water Finfish			Mean (Standard Deviation)- Salt Water Finfish			Mean (Standard Deviation)- Shellfish		
Inputs	2014	2015	2016	2014	2015	2016	2014	2015	2016
Number of persons employed (expressed as the number of full-time equivalents)	501.50 (523.17)	391.87 (295.22)	387.47 (292.52)	525.46 (630.51)	961.39 (884.86)	820.58 (920.60)	1325.39 (2220.80)	1272.07 (2250.14)	1312.86 (2246.91)
Total value of assets (million EUR)	86.15 (126.08)	85.80 (140.11)	62.75 (57.67)	183.96 (200.72)	374.52 (362.62)	302.91 (360.30)	138.33 (247.25)	114.55 (231.92)	126.03 (253.32)
Feed costs (million EUR)	20.30 (22.67)	19.58 (22.35)	17.31 (16.07)	57.55 (83.87)	99.19 (110.95)	86.46 (103.59)	-	-	-
Livestock costs (million EUR)	5.67 (6.00)	6.72 (8.26)	6.30 (7.91)	14.98 (13.21)	27.95 (16.77)	25.32 (21.57)	-	-	-
Energy costs (million EUR)	4.73 (9.54)	2.57 (3.24)	3.23 (3.99)	3.98 (5.39)	6.65 (7.32)	5.65 (6.64)	5.40 (9.76)	3.15 (5.01)	4.08 (6.29)
Repair and maintenance costs (million EUR)	1.44 (2.58)	1.40 (2.37)	1.42 (1.46)	4.90 (8.21)	7.66 (9.53)	6.87 (9.44)	4.11 (6.33)	3.37 (5.78)	4.43 (6.51)
Other operational costs (million EUR)	7.64 (7.37)	8.46 (10.00)	10.03 (9.74)	43.12 (77.12)	72.82 (97.43)	57.59 (81.89)	11.32 (15.47)	12.86 (25.58)	13.91 (29.96)
Ouputs									
Production value (million EUR)	53.35 (63.93)	47.99 (49.14)	51.33 (44.80)	160.79 (262.94)	267.92 (275.92)	252.74 (291.21)	88.27 (181.81)	90.77 (171.60)	91.26 (174.86)

Table 4a. Efficiency scores and inputs and output slacks in finfish production in freshwater (efficient DMUs in bold)

Country	ξ_0	s^{FEED}	$s^{LIVESTOCK}$	s^{ENERGY}	$s^{REP\&MAINT}$	$s^{OTHERCOSTS}$	$s^{PRODUCTION}$
Bulgaria2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Bulgaria2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Bulgaria2016	0.715	2.74	0.47	0.00	0.27	0.00	0.00
Croatia2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Croatia2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Croatia2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Denmark2014	0.912	1.62	2.65	0.00	0.40	3.98	0.00
Denmark2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Denmark2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Estonia2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Estonia2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Finland2014	0.710	3.38	3.66	0.00	0.73	0.91	0.00
Finland2015	0.759	2.25	5.61	0.31	0.53	1.22	0.00
Finland2016	0.703	1.84	2.61	0.76	0.93	5.14	0.00
France 2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
France 2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
France 2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Greece2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Greece2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Ireland2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Ireland2015	0.817	0.00	0.26	0.07	0.02	0.58	0.00
Ireland2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Italy2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Italy2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Italy2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Latvia2015	0.573	0.00	0.53	0.55	0.07	0.00	0.00
Latvia2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Portugal 2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Portugal 2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Romania2014	0.187	6.94	4.00	1.27	0.67	2.12	0.52
Spain2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Spain2015	0.677	3.14	4.85	0.27	1.40	0.63	0.00
Spain2016	0.761	0.00	4.49	0.00	1.06	0.00	0.00
Sweden2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Sweden2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Sweden2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
UnitedKingdom2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
UnitedKingdom2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
UnitedKingdom2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
	Sum	*21.90*	*29.12*	*3.22*	*6.07*	*14.58*	*0.52*

Table 4b. Efficiency scores and inputs and output slacks in finfish production in marine (efficient DMUs in bold)

Country	ξ_0	s^{FEED}	$s^{LIVESTOCK}$	s^{ENERGY}	$s^{REP\&MAINT}$	$s^{OTHERCOSTS}$	$s^{PRODUCTION}$
Croatia2014	0.393	1.00	3.22	0.90	0.87	7.10	74.17
Croatia2015	0.650	0.00	0.99	0.50	0.75	7.48	15.24
Croatia2016	0.599	0.00	2.33	0.67	0.91	10.86	25.16
Cyprus2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Denmark2014	0.801	2.28	0.37	0.19	0.47	0.03	4.96
Denmark2015	0.924	1.06	5.15	0.02	0.09	0.62	0.00
Denmark2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Finland2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Greece2015	0.803	8.45	1.15	4.28	0.00	6.19	0.00
Greece2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Ireland2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Ireland2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Ireland2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Italy2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Malta2014	0.901	0.00	0.00	0.45	0.26	0.00	0.00
Malta2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Malta2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Portugal2014	0.647	0.23	3.79	1.92	0.00	0.00	0.00
Portugal2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Portugal2016	0.782	0.00	0.20	1.98	0.00	0.00	0.00
Slovenia2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Slovenia2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
Spain2014	0.698	13.54	18.57	10.32	0.00	16.98	0.00
Spain2015	0.832	6.65	2.58	9.07	0.00	25.50	0.00
Spain2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
United Kingdom2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
United Kingdom2015	0.759	63.58	18.23	7.54	3.28	51.96	14.07
United Kingdom2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
	Sum	*96.79*	*56.58*	*37.83*	*6.63*	*126.71*	*133.61*

Table 4c. Efficiency scores and inputs and output slacks in shellfish (efficient DMUs in bold)

Country	ξ_0	s^{ENERGY}	$s^{REP\&MAINT}$	$s^{OTHERCOSTS}$	$s^{PRODUCTION}$
Bulgaria2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Croatia2014	0.160	0.28	0.04	0.30	2.95
Croatia2015	0.155	0.08	0.04	1.86	3.37
Croatia2016	0.117	0.19	0.16	1.99	5.26
Denmark2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Denmark2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Denmark2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
France2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
France2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
France2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Germany2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Germany2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Germany2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Greece2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Ireland2014	0.410	1.33	3.03	12.52	0.00
Ireland2015	0.403	1.70	2.43	11.97	0.00
Ireland2016	0.493	1.55	1.11	7.01	0.00
Italy2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Italy2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Italy2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Netherlands2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Netherlands2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Netherlands2016	0.915	0.03	0.64	1.91	0.00
Portugal2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Portugal2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Portugal2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Slovenia2014	0.427	0.00	0.00	0.03	0.51
Slovenia2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Slovenia2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Spain2014	0.675	0.00	0.18	14.24	0.00
Spain2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
Spain2016	0.537	1.28	1.75	7.52	0.00
Sweden2014	0.387	0.15	0.19	0.11	0.30
Sweden2015	0.304	0.12	0.16	0.10	0.56
Sweden2016	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
UnitedKingdom2014	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
UnitedKingdom2015	**1.000**	**0.00**	**0.00**	**0.00**	**0.00**
UnitedKingdom2016	0.500	0.95	0.71	5.45	0.00
	Sum	*7.67*	*10.45*	*65.00*	*12.94*

Table 5a. Efficiency scores and global Malmquist indexes for freshwater finfish

	Efficiency score			**Global Malmquist index**		
Country	**2014**	**2015**	**2016**	**2014-2015**	**2015-2016**	**2014-2016**
Bulgaria	1.000	1.000	0.715	1.000	0.715	0.715
Croatia	1.000	1.000	1.000	1.000	1.000	1.000
Denmark	0.912	1.000	1.000	1.096	1.000	1.096
Estonia	1.000	1.000	-	1.000	-	-
Finland	0.710	0.759	0.703	1.068	0.927	0.990
France	1.000	1.000	1.000	1.000	1.000	1.000
Greece	-	1.000	1.000	-	1.000	-
Ireland	1.000	0.817	1.000	0.817	1.224	1.000
Italy	1.000	1.000	1.000	1.000	1.000	1.000
Latvia	-	0.573	1.000	-	1.744	-
Portugal	1.000	1.000	-	1.000	-	-
Romania	0.187	-	-	-	-	-
Spain	1.000	0.677	0.761	0.677	1.123	0.761
Sweden	1.000	1.000	1.000	1.000	1.000	1.000
United Kingdom	1.000	1.000	1.000	1.000	1.000	1.000
Average	0.908	0.916	0.932	-	-	-
Geometric mean	-	-	-	0.961	0.992	0.949

Table 5b. Efficiency scores and global Malmquist indexes for marine finfish

	Efficiency score			Global Malmquist index		
Country	**2014**	**2015**	**2016**	**2014-2015**	**2015-2016**	**2014-2016**
Croatia	0.393	0.650	0.599	1.655	0.922	1.526
Crypus	1.000	-	-	-	-	-
Denmark	0.801	0.924	1.000	1.153	1.082	1.248
Finland	1.000	-	-	-	-	-
Greece	-	0.803	1.000	-	1.246	-
Ireland	1.000	1.000	1.000	1.000	1.000	1.000
Italy	-	-	1.000	-	-	-
Malta	0.901	1.000	1.000	1.109	1.000	1.109
Portugal	0.647	1.000	0.782	1.547	0.782	1.210
Slovenia	1.000	-	1.000	-	-	1.000
Spain	0.698	0.832	1.000	1.191	1.203	1.432
United Kingdom	1.000	0.759	1.000	0.759	1.317	1.000
Average	0.844	0.871	0.938	-	-	-
Geometric mean	-	-	-	1.168	1.056	1.176

Table 5c. Efficiency scores and global Malmquist indexes for shellfish

	Efficiency score			**Global Malmquist index**		
Country	**2014**	**2015**	**2016**	**2014-2015**	**2015-2016**	**2014-2016**
Bulgaria	1.000	-	-	-	-	-
Croatia	0.160	0.155	0.117	0.964	0.756	0.729
Crypus	-	-	-	-	-	-
Denmark	1.000	1.000	1.000	1.000	1.000	1.000
France	1.000	1.000	1.000	1.000	1.000	1.000
Germany	1.000	1.000	1.000	1.000	1.000	1.000
Greece	-	1.000	-	-	-	-
Ireland	0.410	0.403	0.493	0.985	1.223	1.204
Italy	1.000	1.000	1.000	1.000	1.000	1.000
Netherlands	1.000	1.000	0.915	1.000	0.915	0.915
Portugal	1.000	1.000	1.000	1.000	1.000	1.000
Slovenia	0.427	1.000	1.000	2.340	1.000	2.340
Spain	0.675	1.000	0.537	1.482	0.537	0.795
Sweden	0.387	0.304	1.000	0.786	3.284	2.582
United Kingdom	1.000	1.000	0.500	1.000	0.500	0.500
Average	0.774	0.836	0.797	-	-	-
Geometric mean	-	-	-	1.082	0.976	1.056

Table 6. OLS, censored and one part fractional regression results

		Linear (OLS)[a]	Censored (ML)[b]	One part (QMLE)			
				Logit	**Probit**	**Loglog**	**Cloglog**
Intercept		-	-	-	-	-	-
COASTLINE		-8.438e-06* (3.81e-06)	0.18e-04 (0.14e-04)	4.100e-05 (2.900e-05)	-2.100e-05 (1.600e-05	-4.100e-05 (2.6e-05)	-1.300e-05 (1.300e-05)
LOG(GDP)		1.390e-01*** (7.06e-04)	0.56e-03 (0.16e-03)	0.285*** (0.08)	0.172*** (0.043)	0.301*** (0.074)	0.105*** (0.034)
POPULATION		-2.167e-09 (3.09e-08)	1.29e-07 (1.38e-07)	0.900e-05 (0.99e-11)	0.900e-05 (0.99e-11)	0.800e-07 (0.900e-08)	0.991e-07 (0.005e-08)
FISHERY		-1.716e-04* (8.912e-05)	-0.26e-04 (3.26e-04)	1.780e-04 (7.570e-04)	1.100e-05 (3.980e-04)	0.137e-03 (0.701e-03)	3.500e-05 (3.110e-04)
FRESH WATER		2.326e-01*** (5.305e-02)	1.12*** (0.22)	1.154* (0.458)	0.596** (0.239)	1.129*** (0.421)	0.421** (0.188)
SALT WATER		2.523e-01*** (5.633e-02)	0.89*** (0.21)	0.828** (0.387)	0.444** (0.205)	0.837** (0.358)	0.297* (0.164)
Log-scale		-	-9.22e-01 (6.90e-02)	-	-	-	-
% of fitted values out of the range [0,1]		20%	0%	-	-	-	-
Pseudo R^2		-	0.42	0.161	0.153	0.170	0.137
Specification tests results (p-values)	RESET test[c]	1.272	9.05***	0.278	0.196	0.271	0.150
	P-test H_1: Logit			-	0.023	0.001	0.372
	P-test H_1: Probit			0.372	-	5.546**	2.937
	P-test H1: Loglog			2.969	0.008***	-	5.431**
	P-test H1: Cloglog			4.455**	1.638	2.838	-

Notes:
Dependent variable: SBM efficiency score. Sample: 105 observations. "*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level, respectively. Corresponding robust standard error are shown in parentheses [a] R^2=0.930. F ratio for overall significance of the linear regression model is equal to $F_{6,99}$ =219.7 and p-value< 2.2e-16. [b] Two Limit Tobit (Shapiro Wilk Normality statistic= 0.814; p-value<0.01). [c] LM statistic

Table 7. Two-part fractional regression results

	Two-part model							
	Binary component				Fractional component (for probit in binary part)			
	Logit	**Probit**	**Loglog**	**Cloglog**	**Logit**	**Probit**	**Loglog**	**Cloglog**
Intercept	-1.91 (1.24)	-1.17 (0.73)	-1.01 (0.96)	-1.66** (0.74)	-0.25 (1.21)	-0.14 (0.72)	0.03 (1.02)	-0.38 (0.66)
COASTLINE	-4.40e-05 (3.60e-05)	-2.50e-05 (2.20e-05)	-3.7e-05 (3.00e-05)	-2.10e-05 (2.10e-05)	0.06e-04 (0.03e-04)	0.04e-04 (0.18)	0.01e-04 (0.23e-04)	0.08e-04 (0.18e-04)
Log(GDP)	0.56** (0.24)	0.34** (0.14)	0.42** (0.20)	0.37*** (0.13)	-0.10 (0.30)	-0.06 (0.18)	-0.04 (0.25)	-0.10 (0.16)
POPULATION	0.03e-08 (0.01e-08)	0.03e-08 (0.01e-08)	0.02e-08 (0.02e-08)	0.03e-08 (0.01e-08)	-0.02e-08 (0.01e-08)	-0.01e-08 (0.02e-08)	0.01e-08 (0.01e-08)	-0.01e-08 (0.01e-08)
FISHERY	-1.67e-03* (9.01e-04)	-1.02e-03* (0.539e-03)	-1.25e-02* (0.69e-03)	-1.08e-03** (1.81e-03)	0.014e-02* (0.08e-02)	0.85e-03* (0.48)	1.10e-03 (0.68e-03)	0.88** (0.44)
FRESH WATER	0.66 (0.53)	0.38 (0.32)	0.53 (0.43)	0.35 (0.31)	1.10*** (0.33)	0.68*** (0.20)	0.84*** (0.25)	0.74*** (0.22)
SALT WATER	0.04 (0.55)	0.01 (0.34)	0.01 (0.43)	0.06e-01 (0.35)	1.25*** (0.29)	0.76*** (0.18)	0.94*** (0.22)	0.80*** (0.21)
Pseudo R^2	0.073	0.074	0.071	0.076	0.529	0.525	0.539	0.513
P-test (Binary part)/ RESET test (fractional part)[a]	1.350	1.281	1.374	1.190	1.974	2.117	2.150	1.239
GOFF-test	1.738	1.200	1.241	1.120	1.949	2.118	2.203	1.310

Notes: Dependent variable: SBM efficiency score. Sample: 105 observations. "*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level, respectively. Corresponding robust standard error are shown in parentheses [a] LM statistic

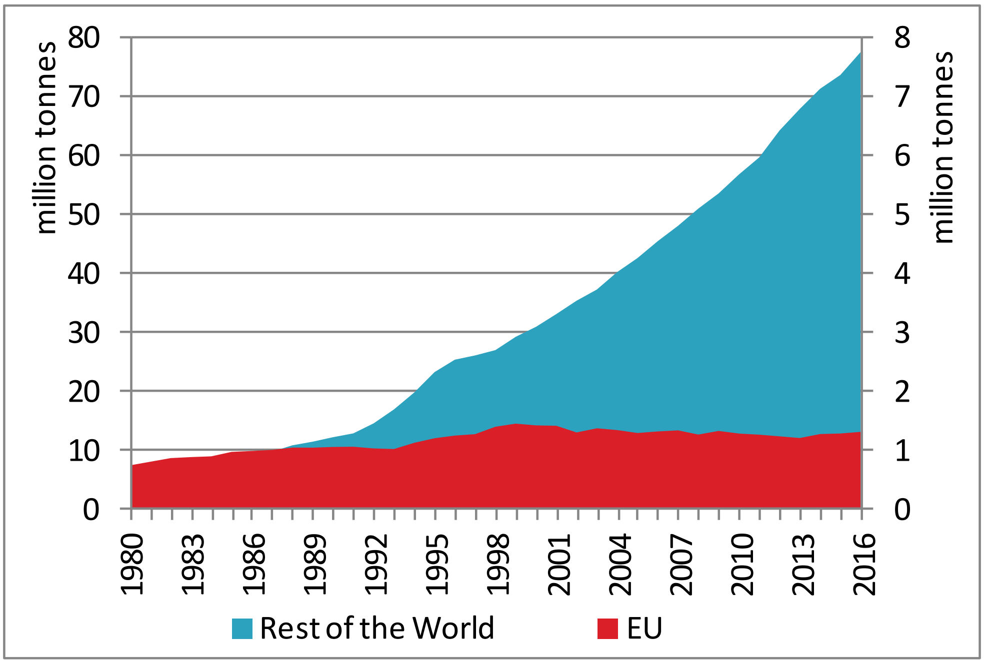

Figure 1. Evolution of the aquaculture production in the EU (right axis) and rest of the world (left axis) for the period 1980-2016. Source: FAO (2018).

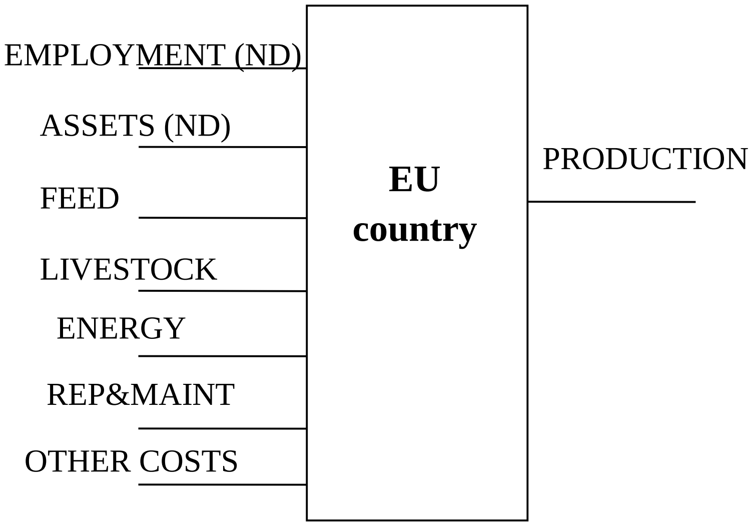

Figure 2. Inputs and outputs considered (ND: Non-discretionary)

Table A1: Aquaculture production and production growth objectives by EU country compared to FAO production.

Country	Reported initial (2014) (t)	FAO production (2014) (t)	Reported goal (2020) (t)	Reported increase (t)	Percentage increase (%)
Austria	3,100	3,483	5,500	2,400	77.4
Belgium	332	44	1,032 [e]	700	210.8
Bulgaria	14,000	15,754	20,000	6,000	42.9
Croatia	13,916 [d]	15,805	24,050	10,134	72.8
Cyprus	53,39~~.~~3 [c]	6,625	6,332 [f]	993	18.6
Czech Republic	20,000	20,952	20,000	0	0.0
Denmark	44,000	36,237	55,000	11,000	25.0
Estonia	[j]	868	[j]		
Finland	13,700	14,412	20,000	6,300	46.0
France	218,000	166,140	265,000	47,000	21.6
Germany	26,500 [d]	41,721	52,000	25,500	96.2
Greece	114,000 [d]	123,314	170,000	56,000	49.1
Hungary	21,500	16,248	27,000 [f]	5,500	25.6
Ireland	36,700	40,190	81,700 [f]	45,000	122.6
Italy	140,879 [c]	157,109	206,854 [g]	65,975	46.8
Latvia	644 [c]	788	2,256 [f]	1,612	250.3
Lithuania	3845	4,393	6,400 [e]	2,555	66.4
Malta	8606	6,073	10,500	1,894	22.0
Netherlands		62,940	[i]	0	0.0
Poland	40,000	38,300	61,000	21,000	52.5
Portugal	10,317	9,785	35,000	24,683	239.2
Romania	10,146 [c]	12,574	36,000	25,854	254.8
Slovakia	1,100 [h]	2,169	2,200 [h]	1,100	100.0
Slovenia	1,155 [d]	1,844	2,420	1,265	109.5
Spain	267,000 [d]	283,828	320,000	53,000	19.9
Sweden	12,500 [c]	15,747	25,000	12,500	100.0
United Kingdom	205,000	194,492	254,000	49,000	23.9
Total EU 28	**1,293,439**	**1,291,834**	**1,770,404**	**476,965**	**36.9**

Source: Multiannual National Strategic Plans for the promotion of sustainable aquaculture by EU member state, FAO, 2018.
[c] Refers to 2013 data.
[d] Refers to 2012 data.
[e] Refers to 2022 data.
[f] Refers to 2023 data.
[g] Refers to 2025 data.
[h] we assume that Slovakian aquaculture production will double from the growth objective: “80% self-sufficiency in volume by 2020, from the current level of 40% self”.
[i] we assume that Dutch aquaculture production levels will be maintained as no growth objective in weight terms is provided, only that production in value will increase by 3%.
[j] no quantitative information is provided in the growth objective: “Estonia’s vision for aquaculture in 2020 is to build up a leading position in their own domestic market and to become a successful exporter of species that suit local farming conditions and have a high demand in foreign markets”.