Fisheries Research 243 (2021) 106087

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

Measuring capacity utilization in fisheries using physical or economic variables: A data envelope analysis of a Vietnamese purse seine fishery

Nga Thi Hong Cao [a,b,*], Arne Eide [b], Claire W. Armstrong [b], Long Kim Le [a]

[a] The Faculty of Economics, Nha Trang University, 02 Nguyen Dinh Chieu, Nha Trang, Khanh Hoa, 57000, Viet Nam
[b] The Norwegian College of Fishery Science, UiT The Arctic University of Norway, Breivika, Tromsø, N-9037, Norway

ARTICLE INFO

Handled by Andre Eric Punt

Keywords:
Capacity utilization
Double bootstrap DEA
Economic variables
Physical variables
Purse seining

ABSTRACT

Data Envelopment Analysis (DEA) studies of fisheries usually apply output oriented capacity utilization based on physical measures. Although physical measures capture important input factors employed in fishing activities (such as boat size, engine power), economic measures directly reflect the cost of inputs employed. This case study investigates whether economic measures are vital or whether capacity efficiency is sufficiently well reflected solely by the use of physical measures. The analysis makes use of a double bootstrap DEA technique and compares input oriented capacity utilization based on physical versus economic measures. The double bootstrap technique was chosen as it allows statistical inference based on the estimated capacity utilization. The results show that economic measures give a lower capacity utilization than that obtained by physical measures. However, no significant difference was found in the capacity utilizations between the two measures. Truncated regression models indicated that factors such as skipper experience and family size did not significantly affect these two measures of capacity utilization at the 5% level. This study concludes that physical variables are capable of capturing the essential economic differences between vessels.

1. Introduction

While fishing is often recorded using physical indicators (e.g. vessel size, fishing time, number of fishers, and fuel consumption), economic indicators, such as revenue, costs, and profit represent normal business indicators. Physical indicators are most frequently used in output oriented capacity utilization studies of fisheries employing Data Envelopment Analysis (DEA) (Kirkley et al., 2001), as such variables are easily available since they often are recorded and used in the management of fisheries (Pascoe et al., 2003a). However, the use of physical versus economic variables may depend on the data available and the aims of the research. Although the latter types of data may be harder to obtain, they are often believed to be more encompassing.

Economic data are generally measured in monetary terms, while physical data are measured along different quantity scales, such as length, volume, weight, etc. (Pascoe et al., 2003a). Physical measures describe some important inputs employed in fishing activity, while economic measures are assumed to capture the full range of inputs employed (Pascoe et al., 2003a; Pascoe and Robinson, 1998). Differences in materials applied for constructing vessels, or on-board technology, are for example, presumably included in the amount of capital measured. While these types of inputs are neither readily available nor easy to include in the production function, the amount of capital can be measured either from the physical input (using engine power or boat size as a proxy for fixed capital) or in terms of value (the value of the vessel and fishing equipment). In addition, the composition of physical inputs are separable and clearly identified. This contrasts with economic measures, where the composition of all the inputs in the aggregate value measure may not be apparent (Pascoe et al., 2003a).

When measuring capacity utilization by economic measures, it reflects the economic optimizing vessel behavior (economic optimization approach), maximizing profit or minimizing costs. Capacity utilization is then identified by the average cost or marginal cost (Berndt and Morrison, 1981; Morrison, 1985; Nelson, 1989). This is based on the dual relationship between cost and production functions. Capacity utilization can be obtained by using the short run average total cost curve, as the ratio between actual output and the output at which the short run average total cost reaches its minimum value (Klein, 1960). Alternatively, capacity utilization can be estimated by use of the total average cost as the ratio between actual output and the optimal output level at

* Corresponding author at: The Faculty of Economics, Nha Trang University, 02 Nguyen Dinh Chieu, Nha Trang, Khanh Hoa, 57000, Viet Nam.
E-mail addresses: ngacth@ntu.edu.vn, tca001@post.uit.no (N.T.H. Cao), arne.eide@uit.no (A. Eide), claire.armstrong@uit.no (C.W. Armstrong), lekimlong@ntu.edu.vn (L.K. Le).

https://doi.org/10.1016/j.fishres.2021.106087
Received 26 March 2021; Received in revised form 13 July 2021; Accepted 14 July 2021
Available online 26 July 2021

which the long and short run average costs are tangents (Berndt and Morrison, 1981; Morrison, 1985). These economic measures of capacity utilizations coincide with the assumptions of long run return to scales. For the former, the production technology is assumed to be constant, whereas this assumption is relaxed in the latter. Another economic measure of capacity utilization is the ratio of actual output and the level of output that maximizes profit in the short run (where marginal cost equals marginal revenue) (Coelli et al., 2002). These are derived from an output oriented approach although it is based on input measures. This approach is also applied for estimating output oriented capacity utilization when using stochastic production frontier functions with the corresponding behavioral objectives (catch maximization, revenue maximization) (Kirkley et al., 2002a). To employ this approach, economic data such as costs and outputs are required.

Data envelopment analysis (DEA) is a non-parametric method based on available economic and/or physical variables that reflects the activity of each unit (fishing vessel in our case). Economic variables measure capacity utilization within a technological–economic framework, providing a production frontier of each unit, representing the optimal (maximum) production at different levels of input combinations. The dual perspective is to look at a given production level, optimizing (minimizing) the combined inputs necessary to obtain this production level.

Physical measures (e.g. vessel size) are used as inputs in DEA in order to estimate capacity utilization, indirectly reflecting the economic decisions of each unit. Output oriented physically based capacity utilization is obtained by the ratio between actual physical output and maximum physical output. Similarly, input oriented physically based capacity utilization is defined by the minimum level of inputs used to sustain the current catch.

The aim of this paper was to analyze and compare capacity efficiency between fishing vessels in the case of using physical versus economic data sets and investigate possible deviations in the estimation of efficiency. There are two approaches to measuring capacity utilization by DEA, either by output or input orientation. Output oriented capacity utilization is measured by the observed outputs at a given level of fixed inputs, while an input oriented capacity utilization assumes a given level of outputs (Pascoe et al., 2003b). A major impetus to analyze the input oriented capacity utilization is that catches (outputs) in fisheries may be regulated at vessel level through non-transferable catch quotas (Asche et al., 2009; Lazkano, 2008). This approach gives exogenous catches (output). In contrast to this, output is endogenous when output oriented capacity utilization is selected (Kirkley and Squires, 2003).

A few empirical studies assume input oriented capacity utilization in fisheries (Castilla-Espino et al., 2006; Nga et al., 2020), while output orientation in general is more common. In this study, input oriented capacity utilization was selected as a measure of technical efficiency since fishers can adjust their inputs, while an increase in outputs is beyond their control due to natural resource constraints. It also seemed more relevant to employ input orientation when analyzing developing countries' fisheries, since the capacity of assessing and controlling outputs, i.e. monitoring harvests, is limited.

Our case study was a Vietnamese purse seine fishery, one of the most important inshore fisheries in Nha Trang, a city in the southern part of Vietnam. As for most Vietnamese fisheries, the purse seine fishery (accounting for 5% of the total fleet) is a multispecies and subsidized open access fishery. The seiners usually operate all year, while the main season is from January to September, mainly targeting anchovy and scads. Bycatches of other fish species (such as sardine, mackerel, and small tuna) account for less than 3% of the total catch landed. Average horsepower (hp) and hull length of the fleet were respectively 303 hp and 16.05 m in 2016, and the average crew number was fourteen per vessel (including the skipper). The educational level was low, with an average of six years in school.

Physical measures such as engine size and vessel hull length are core indicators in Vietnamese fisheries. Since the mid-1990s, purse seiners with engines larger than 90 hp located in Nha Trang have received subsidies aiming to encourage the fishing industry to carry out high sea operations. Hence, the government, in 2016, covered most of the insurance costs, including vessel and crew insurance costs of such vessels. In addition, preferential loans with low interest rates were issued to finance new vessels (Decision, 2014). Both with and without subsidies, most surveyed fishers expressed having recently improved their vessels and invested in new and larger engines to enhance efficiency. Consequently, the fishing effort capacity of the fleet has increased considerably over recent years. In 2016, the Nha Trang purse seine fishing fleet included 130 vessels with a total engine capacity of about forty thousand horsepower. While the number of vessels has been quite stable since 2010 (a decrease of 3.7 %), the engine capacity has increased by almost 170 % (DECAFIREP, 2010, 2016).

2. Data collection

A sample of 52 purse seiners were selected from a population of 130 purse seiners registered in 2016 at Khanh Hoa Department of Capture Fisheries and Resources Protection, Nha Trang. Information about the performance of the 52 vessels was collected from December 2016 to March 2017 at three different sites (Vinh Nguyen, Hon Ro, and Vinh Truong). The vessels were selected in order to reflect the average fleet properties in terms of hull length and horsepower. Table 1 shows the means and standard deviations of hull length and horsepower in the whole fleet and in the sample of the fleet, and the corresponding *t*-test statistics. The *t*-tests confirmed the representativeness of the sample with regard to hull length and horsepower. The *t*-test statistic is defined as $\frac{M_s - M_P}{SD/\sqrt{n-1}}$, where M_s and M_P represent means of the sample and the population, respectively. *SD* is the standard deviation of the sample and *n* is the sample size. Table 1 shows that, in terms of hull length and engine size, our sample of 52 vessels did not significantly differ from the purse seine fleet. The table refers to a two-tail *t*-test at a 5% significance level, and confirms that the tested properties of the sample and the fleet were not found to differ between the two.

Face to face interviews with vessel owners (and/or spouses) were conducted to collect technical and operational information in addition to costs and earnings. Average prices and quantities of each harvested species, and various other economic and social factors of the purse seine fleet, were also collected, in addition to the list of registered fishing vessels in Khanh Hoa in 2016 and other relevant information.

Table 2 shows pairwise correlations between economic and physical variables obtained in the survey. Physical inputs (horsepower, hull length, fuel consumption, and man days at sea) and economic inputs (loans, fixed, variable costs, and the cost of man days at sea), are positively correlated with the respective outputs, catch quantity of anchovy, and the revenue retrieved from this catch. In addition, the pairwise correlation between the physical and economic variables and the different variables are also shown in Table 3.

2.1. Selection of physical and economic variables

Capital and capital utilization are key inputs often used in fishery

Table 1
Sample and population averages and standard deviations of hull length and engine power, and the t-tests of the sample.

Variable	Sample size = 52		Population size = 130		*t* -test statistics	t- Critical value at ($\alpha/2 = 0.025$; 51)
	Mean	SD	Mean	SD		
Hull length	16.05	2.60	15.94	2.86	0.30	2.008
Engine power	303.10	163.27	300.35	173.29	0.12	2.008

Table 2
Pearson correlation between the physical and economic variables. Darker green cell color indicates a significant correlation at the 5% level, light green color indicates 10 % level significance.

	Revenue of anchovy	Revenue of scads	Revenue of others	Anchovy	Scads	Others	Hull length	Horsepower	Fixed cost	Variable cost	Fuel	Loans	Man days at sea
Revenue of scads	0.17	1.00											
Revenue of others	-0.60	-0.24	1.00										
Anchovy	1.00	0.17	-0.60	1.00									
Scads	0.17	1.00	-0.24	0.17	1.00								
Others	-0.60	-0.24	1.00	-0.60	-0.24	1.00							
Hull length	0.55	0.43	-0.26	0.55	0.43	-0.26	1.00						
Horsepower	0.58	0.35	-0.46	0.58	0.35	-0.46	0.80	1.00					
Fixed cost	0.49	0.56	-0.30	0.49	0.46	-0.30	0.67	0.67	1.00				
Variable cost	0.70	0.64	-0.42	0.70	0.65	-0.42	0.56	0.60	0.58	1.00			
Fuel	0.63	0.56	-0.29	0.63	0.56	-0.29	0.57	0.60	0.59	0.90	1.00		
Loans	0.39	0.21	-0.26	0.39	0.21	-0.26	0.32	0.39	0.30	0.44	0.36	1.00	
Man days at sea	0.80	0.57	-0.51	0.80	0.57	-0.51	0.59	0.59	0.62	0.87	0.81	0.36	1.00
Cost of man days at sea	0.80	0.57	-0.51	0.80	0.57	-0.51	0.59	0.59	0.62	0.87	0.81	0.36	1.00

Table 3
Pearson correlation between the physical and economic variables and the different variables.

	Family size	Skipper experience
Revenue of anchovy	0.12	−0.13
Revenue of scads	−0.02	−0.17
Revenue of others	0.02	0.21
Anchovy	0.12	−0.13
Scads	−0.02	−0.17
Others	−0.02	0.21
Hull length	−0.01	−0.19
Horsepower	−0.12	−0.21
Fixed cost	−0.10	−0.21
Variable cost	0.04	−0.04
Fuel	0.08	−0.04
Man days at sea	0.02	−0.20
The cost of man days at sea	0.02	−0.20
Loans	0.13	0.04
Family size	1.00	0.25
Skipper experience	0.25	1.00

efficiency studies (Pascoe et al., 2003a; Pascoe and Tingley, 2016). Capital could be measured in either physical or monetary terms. We measured annual fixed cost of capital invested in monetary units when estimating the capacity utilization of the Nha Trang purse seine fishery. As in several corresponding studies (as by Duy et al., 2015; Guyader et al., 2004; Hoff et al., 2013; Lleonart et al., 2003), repair and maintenance costs of boats and fishing gear were considered fixed costs in this study. Other studies treat such costs as variable costs (Dichmont et al., 2008; Huppert and Squires, 1986), while Pascoe et al. (2015) argue to distribute these costs both into fixed and variable costs, for example depending on fishing gear.

The fleet studied here was rather homogeneous, also in terms of seasonal pattern. This suggests that it is reasonable to assume repair and maintenance costs to be fixed in this particular fishery, while it in other fisheries they have to be treated as variable costs (for example, when seasonal length varies between vessels). In this study, total fixed cost was found by summing up costs of insurance and fees, depreciation of vessel and fishing equipment, and interest payment on loans in addition to costs of maintenance and repair. Horsepower is a simple proxy of the fixed capital stock, involving a single physical measure, used by Pascoe et al. (2003a) when estimating technical efficiency of Norwegian trawlers. In this paper, horsepower and hull length were used as physical measures of the capital employed in fishing. Fuel consumption was measured in both liters and value, providing inputs to the physical and economic models, respectively. The cost of fuel constitutes a major part of the variable costs. Other variable costs are, for example, lubricants, ice, and provisions (Duy et al., 2015; Long et al., 2008). Based on the data availability, loans are represented by a dummy variable in the economic model, which equals one in the case of the vessel owner having borrowed money, and zero if not.

Labor cost was indirectly represented by the number of man days at sea, while other running costs encompassed remaining variable costs. Man days at sea was used in the physical model and the cost of man days at sea was used as a proxy for labor cost in the economic model (shown in the lower part of Table 4). In reality, labor was paid for as a fixed share of net profit, but we assumed a fixed cost of man days at sea provides a reasonable approximation. The cost of man days at sea was defined by man days at sea (number of fishing days multiplied by crew number, including skipper) multiplied by the product of the average daily wage of labor working in the fishing and aquaculture industry in Indonesia (BPS, 2021) and the exchange rate between Indonesian and Vietnamese currencies (FCR, 2021).

Physical outputs included the three catch quantities (anchovy, scads, and others), while the economic outputs were the revenues obtained from the same catches (Table 4).

The selection of the physical and economic variables as described in Table 4 was to purify the two models, i.e. not including economic measures in the physical model and vice versa. To enable comparison of results obtained by the two models, they required the same resolution (the same number of input variables and outputs). However, there were still other common variables in the two models, with an unknown impact on the final result. Additionally, there were available variables that were not utilized.

The lower part of Table 4 displays the common variables used in both models. These were family size and skipper experience. The latter was included in two different variables, motivated from the assumption that

Table 4
Statistics of vessel variables obtained in 2016 in the sample of 52 purse seiners. SD represents the standard deviation of each sample of variables, Min represents the absolute minimum and Max the absolute maximum values within each sample of variables.

Variable	Unit	Mean	SD	Min	Max
Physical					
Input:					
Horsepower	Hp	303.1	163.3	50.0	730.0
Fuel	Liters (dm^3)	32,184.5	12,558.2	9,600.0	72,000.0
Hull length	Meters	16.1	2.6	11.0	22.9
Man days at sea	Days	2,660.0	897.4	600.0	4,500.0
Output (catch):					
Anchovy	Kg	122,139.5	63,063.7	0.0	255,000.0
Scads	Kg	34,922.3	47,416.7	0.0	240,000.0
Others	Kg	3,624.1	11,394.1	0.0	47,600.0
Economic					
Input:					
Total fixed cost	million VND	298.8	139.6	76.0	724.0
Variable cost	million VND	757.6	280.3	228.0	1,438.5
Loans (dummy)	Yes (1)/ No (0)	0.4	0.5	0.0	1.0
The cost of man days at sea	million VND	228.22	76.98	51.47	386.03
Output (revenue):					
Anchovy	million VND	1,421.7	734.1	0.0	2,968.2
Scads	million VND	279.4	379.3	0.0	1,920.0
Others	million VND	54.4	170.9	0.0	714.0
Variables used in both physical and economic DEA calculations					
Skipper experience	Years	26.8	7.2	11.0	39.0
Skipper experience squared	$Years^2$	769.0	364.8	121.0	1,521.0
Family size	Persons	5.0	1.4	3.0	10.0

an expected positive effect of increasing experience at some point will decline. Age was assumed to be a proxy of the skipper's skills. The skills reflected the ability of the skipper to select the best fishing ground, manage and supervise the crew in order to increase the catch quantities (output). The declining rate of increase in skill by age was obtained by a negative term for the squared age.

Family size was defined by number of members in the skipper's household. Livelihood conditions in the community depend on fishing, and an increase in the number of family members in a skipper's household could cause an even greater dependency on fishing activities, in order to sustain the family. Furthermore, when many adult members in a fishing household take part in the family's fishing activities, the labor force working on a fishing vessel tends to be more stable and labor costs can be expected to be lower, implying increasing capacity utilization. In this study, family size was considered a proxy of crew payment.

3. Methodology

A number of different approaches have been used to measure relative capacity utilization in fisheries. DEA (Castilla-Espino et al., 2014; Lindebo et al., 2007; Pascoe and Tingley, 2006; Pham et al., 2014), which is applied here, is often preferred over stochastic production frontier (SPF) approach (Kirkley et al., 2002b, 2004; Pascoe and Tingley, 2016), as it is a relatively simple technique based on a non-parametric approach, not requiring a specification of the production frontier as for the SPF approach. Furthermore, DEA can incorporate multiple outputs in the analysis.

However, there are three main drawbacks that make the deterministic DEA problematic for statistical inference. Firstly, all estimates of technical efficiency are sample specific. Although the DEA method is deterministic, the efficiency is still computed relative to the estimated rather than the true frontier. The efficiency scores obtained from a finite sample are subject to sampling variation of the estimated frontier (Simar and Wilson, 1998).

Secondly, the estimated technical efficiency measures tend to be too optimistic, due to the fact that the DEA estimate of the production set is necessarily a weak subset of the true production set under standard assumptions underlying DEA (Simar and Wilson, 2000). Simar and Wilson (1998, 2000) proposed a procedure based on the smoothed bootstrap method to provide statistical inference regarding technical efficiency measures, including estimation of unbiased confidence intervals of technical efficiency and hypothesis testing, in non-parametric frontier models.

The third drawback is related the problem of the conventional DEA two-step approach to explain the sources of firm level efficiency, where efficiency is estimated in the first stage, and then the estimated efficiencies are regressed on the environmental variables in the second stage. Simar and Wilson (2007) criticized the DEA technical efficiency estimates for being serially correlated. Therefore, standard inference approaches used in the conventional two-step DEA procedure are statistically invalid.

Based on the advantages of the smoothed bootstrap procedure they developed in 1998 and 2000, Simar and Wilson (2007) proposed a double bootstrap procedure (Algorithm 2), which simultaneously provides not only unbiased confidence intervals for technical efficiency estimates but also consistent inference for factors explaining efficiency.

The bootstrap is considered as a way to simulate a true sampling distribution by a Data Generating Process (DGP) from the original data set (Balcombe et al., 2008; Coelli et al., 2005; Olson and Vu, 2009). The DEA model applied here is re-estimated with the new data set or the pseudo replicate data generated by the original data set and this process is repeated many times to yield the empirical distributions of the estimators of the parameter of interest that give a Monte Carlo approximation of the sampling distribution and a feasible inference procedure. The DGP that provides the rationale for Simar and Wilson (2007) double bootstrap is used to estimate capacity utilization and explain the factors affecting capacity utilization.

The double bootstrap DEA procedure is performed by the following seven steps:

The first step is to estimate the capacity utilization (CU) in terms of input orientation for the 52 purse seiners ($j = 1,..,52$) in the sample, based on the DEA framework described by Eq. (1) (see Castilla-Espino et al. (2006) and Nga et al. (2020)).

$$CU_j(u,x) = \min\lambda_j$$

Subject to:

$$\begin{aligned} & u_j \leq \sum_{j=1}^{52} \alpha_j u_j; \\ & \lambda x_j \geq \sum_{j=1}^{52} \alpha_j x_j; \\ & \alpha_j \geq 0; \\ & \sum_{j=1}^{52} \alpha_j = 1 \end{aligned} \quad (1)$$

The capacity utilization (CU_j) is a function of outputs (u) and inputs (x), while λ_j denotes the technical efficiency in terms of input orientation, with a value between zero and one. If the values of CU_j equal one ($\lambda_j = 1$), the vessel capacity is fully utilized, while vessel capacity is not fully utilized if $0 \leq CU_j < 1$. x_j is the amount of the fixed and variable inputs of vessel j employed to produce outputs, while α_j is the intensity variable.

The DEA model above gives us capacity utilization under the assumption of Variable Returns to Scale (VRS). Capacity utilization when assuming Constant Returns to Scale (CRS) can be estimated by relaxing the constraint $\sum_{j=1}^{52}\alpha_j = 1$ in expression (1) (Banker et al., 1984).

The second step uses maximum likelihood theory to estimate $\widehat{\beta}$ of β and $\widehat{\sigma_\varepsilon}$ *of* σ in the truncated regression of $\widehat{Y}_j$ on D_j as described by:

$$\widehat{Y}_j = \beta_0 + \beta_j D_j + \varepsilon_j \geq 1 \tag{2}$$

The left hand side of Eq. (2) is the inverse of the capacity utilization (the capacity utilization score), $\widehat{Y}_j = 1/\widehat{\lambda}_j$, with a value ranging from one to infinity. D_j is the vector of exogenous variables affecting the capacity utilization of the purse seiners. β_0 is an intercept of the model while β_j is the corresponding vector of parameter values to be estimated by the truncated regression model. ε_j is a continuous independent and identically distributed random variable, normally distributed as $N(0, \sigma_\varepsilon^2)$ with left truncation at $(1 - \beta D_j)$ for each vessel j. It is assumed that ε_j and D_j are strictly independent. In this truncated regression model, ε_j represents the other exogenous variables outside the model (the effect of the omitted variables), measurement errors of inputs and outputs, as well as other stochastic noise components affecting capacity utilization. In other words, ε_j reflects that the model partly explains the efficiency levels.

The third step of the bootstrap technique is to perform the procedure 100 times in a first loop to get a set of bootstrap efficiency estimates $E_j = \left\{\widehat{Y^*_{jb}}\right\}_{b=1}^{100}$. This is done by repeating the following four steps (i–iv) for each vessel:

i For each $j = 1,\ldots, 52$, ε_j is normally distributed $N(0, \widehat{\sigma}_\varepsilon^2)$.
ii For each $j = 1,\ldots, 52$, compute $Y_j^* = \widehat{\beta}_0 + D_j\widehat{\beta}_j + \varepsilon_j$.
iii Construct a pseudo data set $\left(X_j^*,\ Y_j^*\right)$, where $X_j^* = \left(\widehat{Y}_j/Y_J^*\right)X_j$ and $Y_j^* = Y$.
iv Using the pseudo data set and expression (1), calculate pseudo efficiency estimates $\widehat{Y_j^*} = 1/\widehat{\lambda_j^*}$ for all $j = 1,\ldots, 52$.

The next step is for each $j = 1,\ldots, 52$, to calculate the bias-corrected estimator $\widehat{\widehat{Y_j}} = \widehat{Y}_j - bias\left(\widehat{Y}_j\right)$ where the bias term is $bias\left(\widehat{Y}_j\right) = \left(1/L_1 \sum_{b=1}^{L1} \widehat{\lambda_{jb}^*}\right) - \widehat{Y}_j$. In this case, L_1 is the first loop repeated 100 times.

The fifth step is to apply truncated maximum likelihood to the data set, regressing $\widehat{\widehat{Y_j}}$ on D_j in order to calculate estimates $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\sigma_\varepsilon}}$.

Then, the bootstrap technique is applied on the truncated regression model by repeating the following three steps (i–iii) 2000 times in the second loop, to generate a set of bootstrap estimates $F = \left\{\left(\widehat{\widehat{\beta^*}},\ \widehat{\widehat{\sigma_\varepsilon^*}}\right)_b\right\}_{b=1}^{2000}$.

i For each $j = 1,\ldots, 52$, ε_j is drawn from a $N(0, \widehat{\widehat{\sigma_\varepsilon}})$ distribution.
ii For each $j = 1,\ldots, 52$, compute $Y_j^{**} = \widehat{\widehat{\beta}}_0 + D_j\,\widehat{\widehat{\beta}}_j + \varepsilon_j$.
iii Adopting truncated maximum likelihood, regress Y_j^{**} on D_j to calculate estimates $\widehat{\widehat{\beta^*}}$ and $\widehat{\widehat{\sigma_\varepsilon^*}}$.

The last step is to use the bootstrap estimates F and the estimates $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\sigma_\varepsilon}}$ generated in the fifth step to construct confidence intervals for β_0, β_j, and σ_ε. The $(1 - \alpha)$ percent confidence interval of β_j is constructed as the probability statement below:

$Pr\left(-b_{\alpha/2} \leq \widehat{\widehat{\beta_j^*}} - \widehat{\widehat{\beta_j}} \leq -a_{\alpha/2}\right) \approx 1 - \alpha$ such that the estimated confidence interval for β_j is $\left[\widehat{\widehat{\beta_j}} + a^*_{\alpha/2}, \widehat{\widehat{\beta_j}} + b^*_{\alpha/2}\right]$. Similarly, the estimated confidence interval for β_0 *is* $\left[\widehat{\widehat{\beta_0}} + a^*_{\alpha/2}, \widehat{\widehat{\beta_0}} + b^*_{\alpha/2}\right]$.

Two main points should be considered when applying the double bootstrap as described above. The first point is that steps three and four employ a parametric bootstrap in the first-stage problem to produce bias-corrected estimates of technical efficiency, $\widehat{\widehat{\delta_j}}$. The parametric structure assumed in Algorithm 2, $\varphi(Z_j, \beta) = Z_j\beta$, shows that the double bootstrap adjusts the estimates, based not only on the input and output information but also on sociological factors. This idea has a link to the parametric approach of technical analysis, the stochastic production function proposed by Battese and Coelli (1995).

The second point referred to above is that in order to explain the sources of vessel efficiency, the truncated regression analysis is conducted in the last steps (referred to above) to explain factors affecting the bias-corrected capacity utilization. Since the dependent variable in Eq. (2) is the reciprocal of capacity utilization, a positive relationship between capacity utilization and the independent variable exists if the sign of the estimated coefficient is negative, and a negative relationship exists if this coefficient obtains a positive value (Balcombe et al., 2008; Long et al., 2020).

Since the estimated input oriented capacity utilization obtains values between zero and one, it creates a censoring problem where these values are removed when estimating the Tobit model or some OLS regression models (Burgess and Wilson, 1998). Therefore, performing a truncated regression with a maximum likelihood method for Eq. (2) avoids this boundary problem. Simar and Wilson (2007) advocated the use of a truncated regression model that explicitly takes into account the bounded domain of the DEA efficiency estimates.

This study used R software with the rDEA package created by Simm and Besstremyannaya (2016). The double bootstrap DEA procedure was employed separately for each of the approaches. This method had two stages. The first stage, in case of the physically based capacity utilization (physical model), estimated capacity utilization by physical inputs (hull length, horsepower, fuel, and man days at sea) and outputs (catch of anchovy, scads, and others), as presented in Table 4. The second stage employed the truncated regression model in which the different variables, such as fishing experience (with the two different variables) and family size (in the lower part in Table 4), were assumed to affect the level of capacity utilization. The variables of the initial physical model were estimated simultaneously along with those included in the bootstrapping. One hundred replications were used for the first loop to compute bias-corrected efficiency estimates and two thousand replications for the second loop, where the truncated regression model for the physical measures was bootstrapped. Similarly, this procedure was also applied for the economic data where the first-stage estimates the economically based capacity utilization (economic model) by using the economic inputs (total fixed cost, variable cost, loans, and the cost of man days at sea) and outputs (revenue of anchovy, revenue of scads, and revenue of others) as reflected in Table 4. The different variables in the lower part of Table 4 show the factors affecting the economically based capacity utilization via the truncated regression model in the second stage.

This study also applied joint models, using economic inputs and physical outputs, and vice versa, as well as combinations of physical and economic inputs and outputs. Results from these joint models are assessed in the discussion section.

4. Results

VRS was selected for both models in the estimation of capacity utilization in this paper. A number of possible factors not included in Eq. (1) could potentially cause fishers not to operate optimally, such as environmental fluctuations, constraints on financing, and different socio-economic characteristics (Coelli et al., 2005). The VRS DEA model might indirectly accommodate some of these factors better than the CRS model.

Fig. 1 shows the estimated capacity utilizations using the physical versus economic model when applying the double bootstrap DEA method (see the black dots). Table 5 shows an average physically based capacity utilization of 0.889, while the average economically based capacity utilization was 0.828. In addition, the lower and upper boundaries of the 95 % confidence interval for the physically based capacity utilization were 0.846 and 0.954, respectively, which suggests that the amount an "average" vessel could reduce its input by increased physically based capacity efficiency ranged from about 5% to more than 15 %. The lower and upper boundaries of the 95 % confidence interval for the economically based capacity utilization were 0.77 and 0.928, respectively, which suggests that the cost of inputs an "average" vessel could reduce by increased economically based capacity efficiency ranged from 7.2%–23%. The median comparison test revealed no significant difference between physical and economic input oriented capacity utilization at the 5% level.

Table 6 shows that the physically based capacity utilization increased with the experience of the skippers, but at a decreasing rate. However, these results were statistically significant at the 10 % level for the physical model only as presented in Table 6. A negative but not significant relationship was found between family size (used as a proxy for payment of crews) and capacity utilization in both models.

We observe from Table 6 that the size of the intercepts of these truncated regression models differ, indicating different random noise impacts on the models. However, only the intercept of the physical model was statistically significant, at the 5% level. Moreover, the finding of the truncated regression model regarding the physically based capacity utilization score indicates that the standard deviation of the error of this model was smaller than that of the economic method (see Table 6).

The differences between the estimates of the two truncated regression models could be explained as a measurement error, and differences in the use of input measures when calculating physically and economically based capacity utilizations. In addition, other factors affecting capacity efficiency include the impact of subsidies, the political arguments for subsidies, variability in weather conditions, stock sizes and distributions, and possible market variations. However, such variables were not addressed in this study.

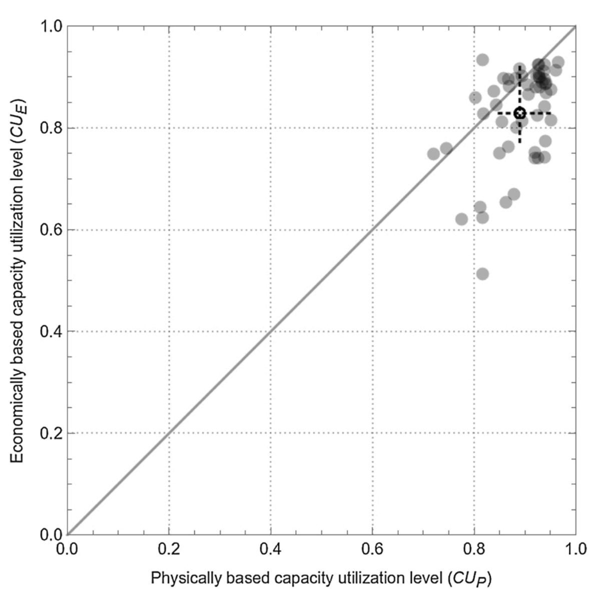

Fig. 1. Physically and economically based capacity utilizations estimated using the double bootstrap DEA method. The diagonal represents the perfect fit between the capacity utilizations of the two measures. The open circle represents the average values of the two methods and the dashed lines, the corresponding 95 % confidence intervals in both directions.

Table 5
Calculated capacity utilization (CU) in the sample of 52 purse seiners, based on the double bootstrap DEA method. CU_P: physically based capacity utilization, CU_E: economically based capacity utilization. SD refers to standard deviation and CI to the 95 % confidence interval.

Criteria	Median	Average	SD	Min	Max	Lower CI	Upper CI
CU_P	0.912	0.889	0.057	0.720	0.965	0.846	0.954
CU_E	0.870	0.828	0.096	0.512	0.934	0.770	0.928

Table 6
Determinants of the capacity utilization scores (the inverse of physically and economically based capacity utilizations) while using double bootstrap estimation. The first column presents the coefficients while using physical measures and the second, the corresponding figures while using economic measures.

Variable	Coefficients while using physical measures	Coefficients while using economic measures
Intercept	1.1293**	0.4899 *
Skipper experience	−0.0275*	−0.0542
Skipper experience^2	0.0007**	0.0019
Family size	0.0194	−0.0201
Standard deviation of errors in the truncated regression	0.1294	0.4072

**,*: Significant at the levels of 5% and 10 %, respectively.

5. Discussion and conclusion

Even though the estimated average capacity utilization found by physical variables was slightly higher than the average of economically based variables, there was no significant difference between the two when doing the median comparison test. Collection of economic data is often dependent on fisher's self-reports regarding their costs, revenues, and profits, which may be less accurate than the physical data. On the other hand, physical data only indirectly reflect the economic realities, but could substitute missing economic measures. Hence, there are issues of uncertainty in the use of both methods, which may also explain why we were unable to differ between the capacity utilizations found by the two methods in this study.

Compared with the technical efficiency of the US mid-Atlantic sea scallop dredge fleet, which had an average bias-corrected technical efficiency of 0.82 using Simar and Wilson's bootstrap (Walden, 2006), the Nha Trang purse seine fishery was more efficient when using the physical measure. In the case of the economic measure, the Nha Trang purse seine fishery was equally as efficient as the US fishery. In general, this shows that the two fisheries were quite close to each other in terms of relative efficiency.

Regarding the factors affecting capacity utilizations, Nga et al. (2020) showed that capacity utilization is an increasing function of skippers' fishing experience, but at a decreasing rate. The estimated parameter values were statistically significant at the 10 % level when assuming a single output (total revenue) in the Nha Trang purse seine fishery. This corresponds to the current study. Family size did not influence capacity utilization in this paper, whereas Nga et al. (2020) found that family size positively affected capacity utilization (significantly at the 10 % level). In contrast to Nga et al. (2020); Ngoc et al. (2009) found that family size negatively affected the technical efficiency of a Nha Trang trawl fishery and skippers' fishing experience positively influenced the technical efficiency when assuming a linear relationship. However, the latter estimate was not found to be statistically significant.

The physical and economic measures of the fixed inputs were highly correlated. Additionally, the variable inputs (fuel, variable cost, and man days at sea) showed high correlation coefficients. The correlation matrix in Table 2 shows a larger variety in the correlations between input variables and output measures. When the coefficients of the variables in the lower part in Table 4 do not significantly differ from zero (at the 5% level) (Table 6), fixed costs, variable costs, loans, the cost of man days at sea, revenue of anchovy, revenue of scads, and revenue of others, are economic variables affecting capacity utilization. Correspondingly, horsepower, hull length, fuel, man days at sea, anchovy, scads, and others are physical variables affecting capacity utilization. The results presented in Table 5 are consistent with the hypothesis that there were significant differences in capacity utilization when using physical and economic measures in the data set, both in average values and ranges. In addition, the average physically based capacity utilization was higher than the average economically based capacity utilization, while about 65 % of all vessels showed quite similar efficiency levels using the two measures (see Fig. 1). Moreover, the width of the 95 % confidence interval for capacity utilization using physical measures was 0.11, and for capacity utilization using economic measures it was 0.16 (see Table 5). This indicates that there was lower statistical uncertainty in the capacity efficiency estimate using physical measures. This may be due to physical data being more robust and more easily identifiable than economic data.

Furthermore, in this study sample, six vessels in particular displayed a large difference in capacity utilization between the two methods. Six of the 52 purse seiners had capacity utilization values between 50–75 % while using economic measures, while the corresponding capacity utilization range was 80–90 % for the physical variables. The difference in capacity utilization ranged between about 30 % to more than 50 % between the uses of physical versus economic variables for these six vessels. These six vessels had relatively high costs in common, which strongly impacted the capacity utilization measured by economic input variables. Some factors may explain this. The six vessels were old vessels with relatively large expenditures for repairs and maintenance. Old engines and time spent maintaining the vessels also affected fishing efficiency. Three of the vessels in question also had large loans, reducing their capacity utilization level when using economic variables. This was not reflected in the physical variables, which may explain some of the large differences in the estimates using the two methods for these vessels.

If the six vessels referred to above are treated as outliers and excluded from the dataset, the average physically based capacity utilization would be 0.897, and the corresponding average economically based capacity utilization 0.866 when using the double bootstrap DEA procedure. A median comparison test (non-parametric test) showed no significant difference between the two at a 5% significance level. Regarding factors affecting the two methods of measuring capacity utilization, only skipper experience (embedded in two different variables) significantly (at the 5% level) influenced physically and economically based capacity utilizations.

Loans were represented by a dummy variable in the economic model since the actual size of each loan was unknown. Hence, there may be substantial differences between the vessels having loans (for example, 10 million VND versus 10 billion VND) that were not reflected in the dummy variable. Such differences may play a role in the different capacity utilization estimates found for the two models.

The findings above show that excess capacity existed in the purse seine fleet in the year studied. This represents an economic loss and may indicate a potential threat of overfishing. If the excess capacity is fully utilized, the overfishing issue could become more critical. However, this study cannot determine whether the purse seine fishery is characterized by overcapacity over time, as the crucial biological factors are unknown, and the data were collected over one year only. However, the results show that five vessels had low relative capacity efficiency using the economic measures. It is not known if these vessels were more efficient in other years, due to factors such as changes in fish distribution patterns or weather conditions. Random noise in production potentially plays a significant role in fisheries, possibly reflected in fleet diversity (Nga et al., 2020).

Fisheries are traditionally characterized by a high degree of stochasticity in catches due to factors such as stock and price fluctuations, weather, and luck, that also may affect efficiency (Fousekis and Klonaris, 2003; Jeon et al., 2006; Ngoc et al., 2009). Although these variables were not part of our survey, the intercept of the truncated regression model may include the impacts of these variables on capacity utilizations, though only statistically significant at the 5% level for the physical model (see Table 6). This study suggests that the double bootstrap DEA method could be used more widely in fishery efficiency studies in which random noise significantly affects the production process. In this study, possible effects of stock changes over time were not included. Hence, a further study should preferably include panel data to measure the change in capacity utilization over several years.

Most fishery managers worldwide apply physical data to manage fisheries while fishers largely consider economic data such as revenues and costs in order to determine the economic status of their fishing operations on an annual basis. The findings here indicate that there is no significant difference in estimated capacity utilization measures when using physical versus economic data in a Vietnamese purse seine fishery. Clearly, physical data for estimating capacity utilization provide useful information for policy makers regarding the situation in a fishery. Such estimations may be expanded in cases where economic data are easily obtained. The additional benefits of considering economic information may, on the margin, be important, particularly if fleet reduction schemes are to be implemented (Pascoe and Tingley, 2006). This study shows the importance of not only collecting physical data but also economic data if that is possible. The combined data give a better understanding of the condition of the fishery and could provide a better background for the development of management policies for sustainable fisheries in the future.

We also applied joint models, using economic inputs and physical outputs, and vice versa, as well as combinations of physical and economic inputs and outputs. Applying the double bootstrap DEA method, we obtained a capacity utilization indicator equal 0.895 when using horsepower, fuel, hull length, and man days at sea as inputs, and revenues of anchovy, scads, and others as outputs. The indicator was 0.822 when using variable costs, loans, fixed costs, and the cost of man days at sea as inputs, and catch quantities of anchovy, scads, and others as outputs. The capacity utilization indicator equaled 0.817 when employing fuel, loans, fixed costs, and man days at sea as inputs, and the catch quantities of anchovy, scads, and others as outputs. The corresponding value was 0.814 when using fuel, loans, fixed costs, man days at sea as inputs and revenue of anchovy, scads, and others as outputs. The indicator equaled 0.897 when applying horsepower, hull length, loans, variable costs, and the cost of man days at sea as inputs and revenue of anchovy, revenue of scads, and revenue of others as outputs. Finally, the capacity utilization indicator equaled 0.891 when applying horsepower, hull length, loans, variable costs, and the cost of man days at sea as inputs and catch quantities of anchovy, scads, and others as outputs. When using a 5% significance level, the first estimated capacity utilization indicator listed here (0.895) was significantly different from the CU_E, but not from the CU_P. The three next cases (indicators of 0.822, 0.817, and 0.814) had the opposite properties, being significantly different from the CU_P but not from the CU_E. The two last cases (indicators of 0.897 and 0.891) were related to the CU_E and CU_P as the first case. In general, the higher indicator values systematically significantly differed from the CU_E, while the relatively lower values differed from the CU_P.

Regarding the factors affecting capacity utilization when mixing physical and economic input and output measures as presented above (the joint models), we found that no factors significantly affected capacity utilization at the level of 5%. However, skipper experience significantly affected the first model at the 10 % level.

The average physically and economically based capacity utilizations of the fleet were 0.889 (estimated to be 0.846 at the lower limit and 0.954 at the upper limit of the 95 % confidence interval) and 0.828 (estimated to be 0.770 at the lower limit and 0.928 at the upper limit of the 95 % confidence interval), respectively when using the double bootstrap DEA. This indicates that to sustain the current catch levels, expected inputs should be reduced by 4.6–15.4 % based on the physical measures and 7.2–23 % based on the economic measures. In the last decade, the development of the Nha Trang purse seine fleet has been enhanced by subsidies. In general, it is acknowledged that subsidies may lead to an economically inefficient industry and an increase in the probability that fish stocks will be exploited beyond their biological limits (Sumaila et al., 2007). Instead of financial support, other types of governmental support (such as training fishermen, providing information on the state of fish stocks, weather forecasts, rescue and life-saving activities in high seas) do not increase fleet capacity and avoid further effort expansion.

Non-parametric DEA is based on the assumption that all the observed units belong to the attainable set. In such deterministic frontier models, statistical inference is now achievable by the use of bootstrap procedures. However, noise was not considered in the DGP of the bootstrap procedures proposed by Simar and Wilson (2008) (see Simar and Zelenyuk, 2011). In the presence of noise, envelopment estimators could behave dramatically since they may be very sensitive to extreme observations that might result only from noise. Due to the stochastic nature of fisheries, future studies could beneficially consider some procedures, for example those proposed by Simar (2007) and Simar and Zelenyuk (2011), who introduced noise in non-parametric frontier models (see also Olesen and Petersen, 2016).

Please indicate the specific contributions made by each author (list the authors' initials followed by their surnames, e.g., Y.L. Cheung). The name of each author must appear at least once in each of the three categories below.

Category 1

Conception and design of study: N.T.H. Cao, Arne Eide, Claire Armstrong; Long Kim Le acquisition of data: N.T.H. Cao; analysis and/or interpretation of data: N.T.H. Cao, Arne Eide;

Category 2

Drafting the manuscript: N.T.H. Cao, Arne Eide; revising the manuscript critically for important intellectual content: N.T.H. Cao, Arne Eide, Claire Armstrong;

Category 3

Approval of the version of the manuscript to be published (the name of all authors must be listed): N.T.H. Cao, Arne Eide, Claire Armstrong and Long Kim Le

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We wish to thank the Norhed project SRV-13/0010for providing financial support for the data collection. We also are grateful for valuable inputs from two anonymous reviewers and the Marine Resource Economics research group at The Arctic University of Norway.

References

Asche, F., Bjorndal, T., Gordon, D.V., 2009. Resource rent in individual quota fisheries. Land Econ. 85 (2), 279–291. https://doi.org/10.3368/le.85.2.279.

Balcombe, K., Fraser, I., Latruffe, L., Rahman, M., Smith, L., 2008. An application of the DEA double bootstrap to examine sources of efficiency in Bangladesh rice farming. Appl. Econ. 40, 1919–1925. https://doi.org/10.1080/00036840600905282.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some model for estimating technical and scale inefficiency in data envelopment analysis. Manage. Sci. 2, 429–444. https://doi.org/10.1287/mnsc.30.9.1078.

Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir. Econ. 20, 325–332. https://doi.org/10.1007/BF01205442.

Berndt, E.R., Morrison, C.J., 1981. Capacity utilization measures: underlying economic theory and an alternative approach. Am. Econ. Rev. 71, 48–52.

BPS, 2021. Average of Net Wage/Salary (Rupiahs) in Indonesia, 2016-2017. Indonesia, S (accessed 03 June 2021). https://www.bps.go.id/indicator/19/1521/3/average-of-net-wage-salary.html.

Burgess, J.F., Wilson, P.W., 1998. Variation in inefficiency among Us hospitals. Infor Inf. Syst. Oper. Res. 36, 84–102. https://doi.org/10.1080/03155986.1998.11732348.

Castilla-Espino, D., Ordaz, F.G., Sharp, B.M.H., 2006. Efficiency and capacity of fully exploited fisheries managed using vessel catch limits combined with effort restrictions. In: IIFET 2006 Portsmouth Proceedings. Corvallis, Oregon, USA. In: https://ir.library.oregonstate.edu/concern/conference_proceedings_or_journals/9w032417v.

Castilla-Espino, D., García-del-Hoyo, J.J., Metreveli, M., Bilashvili, K., 2014. Fishing capacity of the southeastern Black Sea anchovy fishery. J. Mar. Syst. 135, 160–169. https://doi.org/10.1016/j.jmarsys.2013.04.013.

Coelli, T., Grifell-Tatjé, E., Perelman, S., 2002. Capacity utilisation and profitability: A decomposition of short-run profit efficiency. Int. J. Prod. Econ. 79, 261–278. https://doi.org/10.1016/S0925-5273(02)00236-0.

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. An Introduction to Efficiency and Productivity Analysis, second ed. Springer Science and Business Media, New York.

DECAFIREP, 2010. The Anual Report of the Number of Vessels and Engine Power Registered in 2010. Khanh Hoa's Department of Captures Fisheries and Resource Protection (DECAFIREP), Vietnam. http://snnptntkh.gov.vn/news/us/dep/news_detail.aspx?id=20200110170523209975 6.48&idDV=0.5.

DECAFIREP, 2016. The Anual Report of the Number of Vessels and Engine Power Registered in 2016. Khanh Hoa's Department of Captures Fisheries and Resource Protection (DECAFIREP), Vietnam. http://snnptntkh.gov.vn/news/us/dep/news_detail.aspx?id=20200110170523209975 6.48&idDV=0.5.

Decision, 2014. Decision 67/QD-TTg by Vietnam's Prime Minister on July, 7, 2014, on Some Polices Related to Fisheries Development (accessed 07 January 2018). https://thuvienphapluat.vn/van-ban/Bo-may-hanh-chinh/Nghi-dinh-67-2014-ND-CP-chinh-sach-phat-trien-thuy-san-238831.aspx?tab=1.

Dichmont, C.M., Deng, A., Punt, A.E., Ellis, N., Venables, W.N., Kompas, T., Ye, Y., Zhou, S., Bishop, J., 2008. Beyond biological performance measures in management strategy evaluation: bringing in economics and the effects of trawling on the benthos. Fish. Res. 94, 238–250. https://doi.org/10.1016/j.fishres.2008.05.007.

Duy, N.N., Flaaten, O., Long, L.K., 2015. Government support and profitability effects - Vietnamese offshore fisheries. Mar. Policy 61, 77–86. https://doi.org/10.1016/j.marpol.2015.07.013.

FCR, 2021. Indonesian Rupiah (IDR) and Vietnamese Đồng (VND) Year 2016 Exchange Rate. Rate). F.F.C (accessed 03 June 2021). https://freecurrencyrates.com/en/exchange-rate-history/IDR-VND/2016.

Fousekis, P., Klonaris, S., 2003. Technical efficiency determinants for fisheries: a study of trammel netters in Greece. Fish. Res. 63, 85–95. https://doi.org/10.1016/S0165-7836(03)00019-5.

Guyader, O., Daures, F., Fifas, S., 2004. A Bioeconomic Analysis of the Impact of Decommissioning Programs: Application to a Limited-Entry French Scallop Fishery. Mar. Resour. Econ. 19, 225–242. https://doi.org/10.1086/mre.19.2.42629430.

Hoff, A., Andersen, J.L., Christensen, A., Mosegaard, H., 2013. Modelling the economic consequences of Marine Protected Areas using the BEMCOM model. J. Bioeconomics 15, 305–323. https://doi.org/10.1007/s10818-012-9135-3.

Huppert, D.D., Squires, D., 1986. Potential economic benefits and optimum fleet size in the Pacific coast trawl fleet. Mar. Resour. Econ. 3, 297–318. https://doi.org/10.1086/mre.3.4.42628967.

Jeon, Y., Omar, I.H., Kuperan, K., Squires, D., Susilowati, I., 2006. Developing country fisheries and technical efficiency: the Java Sea purse seine fishery. Appl. Econ. 38, 1541–1552. https://doi.org/10.1080/00036840500400525.

Kirkley, J.E., Squires, D., 2003. Capacity and capacity utilization in fishing industries. In: Pascoe, S.G.D. (Ed.), Measuring Capacity in Fisheries FAO Fisheries Technical Paper No 445. Food and agriculture organization of the united nations (FAO), Rome.

Kirkley, J.E., Färe, R., Grosskopf, S., McConnell, K., Squires, D.E., Strand, I., 2001. Assessing capacity and capacity utilization in fisheries when data are limited. N. Am. J. Fish. Manag. 21, 482–497. https://doi.org/10.1577/1548-8675(2001)021<0482:ACACUI>2.0.CO;2.

Kirkley, J., Paul, C.J.M., Squires, D., 2002a. Capacity and capacity utilization in common-pool resource industries. Environ. Resour. Econ. (Dordr) 22, 71–97. https://doi.org/10.1023/A:1015511232039.

Kirkley, J., Paul, C.J.M., Squires, D., 2002b. Capacity and capacity utilization in common-pool resource industries: definition, measurement, and a comparison of approaches. Environ. Resour. Econ. (Dordr) 22, 71–97. https://doi.org/10.1023/A:1015511232039.

Kirkley, J., Paul, C.J.M., Squires, D., 2004. Deterministic and stochastic capacity estimation for fishery capacity reduction. Mar. Resour. Econ. 19, 271–294. https://doi.org/10.1086/mre.19.3.42629435.

Klein, L.R., 1960. Some theoretical issues in the measurement of capacity. Econometrica. 28, 272–286. https://doi.org/10.2307/1907721.

Lazkano, I., 2008. Cost structure and capacity utilisation in multi-product industries: An application to the Basque trawl industry. Environ. Resour. Econ. (Dordr) 41, 189–207. https://doi.org/10.1007/s10640-007-9187-3.

Lindebo, E., Hoff, A., Vestergaard, N., 2007. Revenue-based capacity utilisation measures and decomposition: The case of Danish North Sea trawlers. Eur. J. Oper. Res. 180, 215–227. https://doi.org/10.1016/j.ejor.2006.03.050.

Lleonart, J., Maynou, F., Recasens, L., Franquesa, R., 2003. A bioeconomic model for Mediterranean fisheries, the hake off Catalonia (Western Mediterranean) as a case study. Sci. Mar. 67, 337–351. https://doi.org/10.3989/scimar.2003.67s1337.

Long, L.K., Flaaten, O., Kim Anh, N.T., 2008. Economic performance of open-access offshore fisheries-The case of Vietnamese longliners in the South China Sea. Fish. Res. 93, 296–304. https://doi.org/10.1016/j.fishres.2008.05.013.

Long, L.K., Van Thap, L., Hoai, N.T., Pham, T.T.T., 2020. Data envelopment analysis for analyzing technical efficiency in aquaculture: the bootstrap methods. Aquac. Econ. Manag. 1–25. https://doi.org/10.1080/13657305.2019.1710876.

Morrison, C.J., 1985. Primal and dual capacity utilization: an application to productivity measurement in the US automobile industry. J. Bus. Econ. Stat. 3, 312–324.

Nelson, R.A., 1989. On the measurement of capacity utilization. J. Ind. Econ. 37, 273–286. https://doi.org/10.2307/2098615.

Nga, C.T.H., Eide, A., Armstrong, C.W., Long, L.K., 2020. Economic Performance and Capacity Utilisation in Vietnamese Purse Seine Fishery. Asian Fish. Sci. 33, 58–64. https://doi.org/10.33997/j.afs.2020.33.1.007.

Ngoc, Q.T.K., Flaaten, O., Anh, N.T.K., 2009. Efficiency of fishing vessels affected by a marine protected area – the case of small-scale trawlers and the marine protected area in nha Trang Bay, Vietnam. In: Moksness, E., Dahl, E., Josianne, S. (Eds.), Integrated Coastal Zone Management. Wiley-Blackwell, Norway, pp. 189–206.

Olesen, O.B., Petersen, N.C., 2016. Stochastic data envelopment analysis—a review. Eur. J. Oper. Res. 251, 2–21. https://doi.org/10.1016/j.ejor.2015.07.058.

Olson, K., Vu, L., 2009. Economic efficiency in farm households: trends, explanatory factors, and estimation methods. Agric. Econ. 40, 587–599. https://doi.org/10.1111/j.1574-0862.2009.00400.x.

Pascoe, S., Robinson, C., 1998. Input controls. Input Substitution and Profit Maximisation in the English Channel Beam Trawl Fishery Journal of Agricultural Economics. 49 (1), 16–33.

Pascoe, S., Tingley, D., 2006. Economic capacity estimation in fisheries: a non-parametric ray approach. Resour. Energy Econ. 28, 124–138. https://doi.org/10.1016/j.reseneeco.2005.06.003.

Pascoe, S., Tingley, D., 2016. Capacity and technical efficiency estimation in fisheries: parametric and non-parametric techniques. In: Weintraub, A., Romero, C., Bjørndal, T., Epstein, R. (Eds.), International Series in Operations Research and Management Science. Springer, New York, pp. 273–294.

Pascoe, S., Hassaszahed, P., Anderson, J., Korsbrekke, K., 2003a. Economic versus physical input measures in the analysis of technical efficiency in fisheries. Appl. Econ. 35, 1699–1710. https://doi.org/10.1080/0003684032000134574.

Pascoe, S., Ward, J., Kirkley, J.E., 2003b. Measuring and Assessing Capacity in Fisheries. FAO Fisheries Technical Paper 433/2. Food and Agriculture Organizations of United Nation, Rome.

Pascoe, S., Vieira, S., Thebaud, O., 2015. Allocating repairs and maintenance costs to fixed or variable costs in fisheries bioeconomic models. Appl. Econ. Lett. 22, 127–131. https://doi.org/10.1080/13504851.2014.929619.

Pham, T.D.T., Huang, H.W., Chuang, C.T., 2014. Finding a balance between economic performance and capacity efficiency for sustainable fisheries: case of the Da Nang gillnet fishery. Vietnam. Marine Policy. 44, 287–294. https://doi.org/10.1016/j.marpol.2013.09.021.

Simar, L., 2007. How to improve the performances of DEA/FDH estimators in the presence of noise? J. Product. Anal. 28, 183–201. https://doi.org/10.1007/s11123-007-0057-3.

Simar, L., Wilson, P.W., 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manage. Sci. 44, 49–61. https://doi.org/10.1287/mnsc.44.1.49.

Simar, L., Wilson, P.W., 2000. Statistical inference in nonparametric frontier models: the state of the art. J. Product. Anal. 13, 49–78. https://doi.org/10.1023/a:1007864806704.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. J. Econom. 136, 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009.

Simar, L., Wilson, P.W., 2008. Statistical inference in nonparametric frontier models: recent developments and perspectives. In: Fried, H., Lovell, C., Schmidt, S. (Eds.), The Measurement of Productive Efficiency. Oxford University Press, New York, pp. 423–521.

Simar, L., Zelenyuk, V., 2011. Stochastic FDH/DEA estimators for frontier analysis. J. Product. Anal. 36, 1–20. https://doi.org/10.1007/s11123-010-0170-6.

Simm, J., Besstremyannaya, G., 2016. Package' rDEA' (Accessed 11 December 2017). https://cran.r-project.org/web/packages/rDEA/rDEA.pdf.

Sumaila, U.R., Khan, A., Watson, R., Munro, G., Zeller, D., Baron, N., Pauly, D., 2007. The World Trade Organization and global fisheries sustainability. Fish. Res. 88, 1–4. https://doi.org/10.1016/j.fishres.2007.08.017.

Walden, J.B., 2006. Estimating vessel efficiency using a bootstrapped data envelopment analysis model. Marine Resource Eonomics 21, 181–192. https://doi.org/10.1086/mre.21.2.42629503.