ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

ARCHIVIO ISTITUZIONALE
DELLA RICERCA

Alma Mater Studiorum Università di Bologna
Archivio istituzionale della ricerca

Connecting catch profiles with efficiency: An application to the beam trawl fishery in the Northern Adriatic Sea

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

Published Version:
Ceccacci, A., Russo, E., Mulazzani, L., Malorgio, G. (2024). Connecting catch profiles with efficiency: An application to the beam trawl fishery in the Northern Adriatic Sea. REGIONAL STUDIES IN MARINE SCIENCE, 69, 1-12 [10.1016/j.rsma.2023.103312].

Availability:
This version is available at: https://hdl.handle.net/11585/953165 since: 2024-01-15

Published:
DOI: http://doi.org/10.1016/j.rsma.2023.103312

Terms of use:

Some rights reserved. The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

This item was downloaded from IRIS Università di Bologna (https://cris.unibo.it/).
When citing, please refer to the published version.

(Article begins on next page)

05 December 2025

This is the final peer-reviewed accepted manuscript of:

Alberto Ceccacci, Elisabetta Russo, Luca Mulazzani, Giulio Malorgio, *Connecting catch profiles with efficiency: An application to the beam trawl fishery in the Northern Adriatic Sea*, Regional Studies in Marine Science, Volume 69, 2024, 103312.

The final published version is available online at:

https://doi.org/10.1016/j.rsma.2023.103312
(https://www.sciencedirect.com/science/article/pii/S2352485523005029)

Terms of use:

Some rights reserved. The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

This item was downloaded from IRIS Università di Bologna (https://cris.unibo.it/)

When citing, please refer to the published version.

Abstract

Estimation of technical efficiency in fisheries is most commonly finalized at comparing the conversion from inputs (e.g. time at sea, fuel consumption) to production (i.e. landed fish) among vessels or gears. In this paper we adopt a novel approach focusing on the efficiency of fishing trips characterized by different catch composition within the same fleet. In particular, the case study under analysis is represented by the beam trawl ("*rapido*") fishery of Chioggia (Adriatic Sea, GSA 17), which has been subject to increasing technical and effort limitations in recent years due to its severe impacts on the marine ecosystem. The methodological strategy first involves a cluster analysis of catch profiles to identify homogeneous groups of fishing trips, which are subsequently compared in terms of economic performance based on the efficiency scores from stochastic frontier analysis. By including also an estimation of Greenhouse Gas emissions per trip, the results from our study can be used to inform future management interventions that aim at improving the overall efficiency of the fishery while reducing its carbon footprint and the pressure on the most relevant target species.

Keywords

- Stochastic Frontier Analysis
- K-means clustering
- Fisheries Economics
- Beam trawling
- CO_2 emissions
- Adriatic Sea

Connecting catch profiles with efficiency: an application to the beam trawl fishery in the Northern Adriatic Sea

1. Introduction

One of the most heavily exploited areas in the Mediterranean Sea is the Central-Northern Adriatic Sea (Geographical Sub-Area, GSA 17) (Bastari et al. 2016; Eigaard et al. 2017; Grati et al. 2013; Mazzoldi et al. 2014), a semi-enclosed basin characterized by an extensive continental shelf with sandy seabed and shallow waters (not exceeding 75 meters in the northern sub-basin and 150 meters in the central, with the exception of the 300 meters deep Pomo-Jabuka Pit). Considering the nutrient supply provided by the Po River and other rivers that flow through the Po-Venetian plain, the GSA 17 presents ideal conditions for trawling (Fortibuoni et al. 2017; Pranovi et al. 2015; Russo et al. 2019). The intense fishing pressure implies that, despite a slight decrease in the number of overexploited species in recent years, 73% of stocks are fished outside biologically sustainable levels (FAO 2022).

In this paper we investigate the relationship between technical efficiency[1], catch profiles and Greenhouse Gas (GHGs) emissions in the GSA 17 by focusing on the *rapido* trawl fishery of Chioggia (Venice), which is historically considered as one of the main ports in the Mediterranean Sea (Botter et al. 2006) and represents the first port in the Adriatic Sea both in terms of landings (8,740 tonnes) and operating vessels (189) (FAO 2022). In particular, we focus on 31 vessels from Chioggia, representing respectively 86.1% of the regional *rapido* fleet and 34.1% at the national level (as of 2019) (NISEA 2022b). *Rapido* trawl vessels, introduced in the Veneto region in the mid-1950s, are a type of beam trawl (TBB) characterized by a cone-shaped net with a rigid metallic mouth opening that may reach a width of 4 m and glides across the sea bottom with the help of sleds, allowing fishers to target flatfish and shellfish (Armelloni et al. 2021). Generally, each vessel tows simultaneously 2-4 nets (Pranovi et al. 2000). While *rapido* is not the only trawling gear targeting demersal species in the area (Russo et al. 2020), we choose to focus exclusively on this fleet because its severe impact on the benthic community has been long acknowledged (Giovanardi et al. 1998; Pranovi et al. 2001), hence prompting increasing calls for stricter regulation of the fishery (Bastardie et al. 2017; Armelloni et al. 2021). From an economic perspective, trawling and beam trawling fisheries generate the highest revenues (around 390,000,000 €) and are the major contributors to Gross Value Added (43.3%) in the Adriatic Sea (FAO 2022). Nevertheless, the recent increase in fuel costs has been negatively affecting the profitability of the fishery, especially considering that TBB vessels exhibit the highest incidence of fuel expenses over catch value (more than 40% in 2022) (NISEA 2022a). An additional factor negatively impacting the economic performance of the fleet is the decline in the real price of most fish species

[1] Adopting the frequently applied "output approach" in the fisheries literature (Pascoe and Tingley 2007), technical efficiency is defined as the ability of an economic unit (*rapido* vessel) to maximize the output (catch value) given a set of inputs (time at sea and physical characteristics of the boat).

(nominal prices not keeping up with inflation). Even if this has become more evident in 2022, by looking at the price time series of common sole (*Solea solea*, SOL), which is the most relevant species targeted by TBB in the GSA 17, a historical negative trend can be identified (-3.4% average annual change between 2010 and 2020) (STECF 2022).

Recognising the importance of providing a deep understanding of the specific characteristics (e.g. seasonal, geographical, behavioural) of *rapido* trawlers fishing practices, a combined analysis of catch profiles and technical efficiency has relevant implications for several aspects of fisheries management, namely *i*) the relationship between local regulations and efficiency, *ii*) the impact of diverse efficiency levels on the rent generated by the fishery, *iii*) the influence of multispecificity and catch composition on effective management and *iv*) the identification of the most sustainable fishing practices in terms of CO_2 emissions. First, the relevance of an efficiency analysis of the TBB fishery is related to the regulatory framework applied in the Adriatic Sea. Fisheries management in the GSA 17, as in most Mediterranean basins, is constituted of a variety of instruments such as effort reductions, technical measures (e.g. minimum landing sizes and mesh limitations) and seasonal or permanent area closures (Sabatella et al. 2017). In terms of activity, fishing days of the TBB fishery in the GSA 17 have decreased by 44.2% between 2010 and 2020 (STECF 2022). Taking into account that Mediterranean fisheries are often characterized by low levels of economic efficiency (Colloca et al. 2013; Maynou 2014; Sabatella et al. 2017), capacity reduction programmes that overlook the heterogeneity of a fleet might be ineffective, hence stressing the relevance of individual measures of vessels' efficiency (Gómez and Maynou 2020). Investigation of the relative heterogeneity among vessels also provides crucial information concerning the existence and size of the total producer surplus, which is an important component of the economic welfare generated by a fishery (Jensen et al. 2019). Given the presence of different levels of efficiency, it is advisable to consider in advance the rent distributional effects deriving from effort limitations (i.e. varying levels of reduction in individual producer surplus due to differences in the cost per unit of effort among vessels) and the compensations that might be needed in order to prevent the likelihood of non-compliance by fishers (Flaaten 2011).

Moreover, it is important to remark that regulations based on physical parameters (e.g. the gear used) ignore that vessels within the same fleet may target different species in mixed fisheries, therefore multivariate analysis of catch composition can provide valuable information for management purposes (Lewy and Vinther 1994). Given the growing interest for an ecosystem-based approach to fisheries management (Link 2002; Hilborn 2011; Long et al. 2015), first included in the 2013 reform of the Common Fisheries Policy and still regarded as one of the main instruments for guaranteeing the sustainability of EU fisheries (European Commission 2023a), cluster analysis has the potential to identify patterns of resource usage that can support the definition of appropriate spatial and temporal ecosystem-based management units (Lucey and Fogarty 2013). Additionally, it has been claimed that the results from cluster analysis of catch assemblage have a variety of practical applications, such as

modelling realistic fisher behaviour, supporting scientific advice on previously overlooked species, and understanding potential changes in fishing practices in response to landing obligations (Moore et al. 2019).

In this paper we also include a quantification of the GHGs emissions generated by fishing operations (fishing and navigation) through the estimation of the CO_2 produced by the TBB vessels of Chioggia. The awareness that fishing practices contribute significantly to global GHGs emissions has increased in the last decades (Coello et al. 2015; Driscoll and Tyedmers 2010; Cheilari et al. 2013), and innovative solutions for improved fuel efficiency are widely discussed (Parente et al. 2008; Sala et al. 2011; Fiorentini et al. 2004). This is especially relevant in the case of large-scale fisheries, which tend to be more fuel-intensive than small-scale fisheries (Cavraro et al. 2023; Suuronen et al. 2012). In the Adriatic Sea, previous studies have assessed the energy performance of the TBB fishery relative to other gears and compared the emissions intensity (expressed as CO_2 produced per quantity of landed fish) among the main target species (Russo 2020; Sala et al. 2022). We differentiate our analysis by focusing exclusively on the TBB fleet and confronting the emissions generated by different catch profiles throughout the year 2019 within the same fishery.

To the authors' knowledge, this is the first scientific article connecting the study of technical efficiency with multivariate analysis of catch profiles in fisheries. In addition, while the catch assemblage of TBB in the GSA 17 has been previously investigated through cluster analysis (i.e. main targeted species with respect to other demersal gears operating in the Adriatic Sea) (Armelloni et al. 2021), we are not aware of studies differentiating among the catch profiles of *rapido* vessels at trip level or providing technical efficiency estimates of their fishing operations. Our work attempts to fill this gap and hence to address the concern for increased efficiency of fishing practices in the large-scale sector of the European fleet (Symes 2014; European Commission 2009).

More specifically, the present article addresses the two following research questions: *i*) in the case of the TBB fishery in the GSA 17, how does technical efficiency vary among fishing trips characterized by different catch profiles and *ii*) how do these trips perform in terms of CO_2 emissions? In the next section, we describe the fishing and market data used in the analysis. Section 3 presents the theoretical framework and the empirical approach to address the research questions, while the results are shown in Section 4. We discuss the main findings and the limitations of our approach in Section 5, which also concludes the paper.

2. Data description

2.1. Fishing activity

Raw Automatic Identification System (AIS) data are provided by the Italian Coast Guard (ITC and Traffic Monitoring Department – Rome). The dataset contains several information [Maritime Mobile Service Identity (MMSI), speed, time, and geographical coordinates] on 2,404 fishing trips undertaken by 31 *rapido* trawls (TBB) from the fishery based in Chioggia port in the year 2019. These vessels represent respectively 86.1% of the Veneto

region and 34.1% of the Italian TBB fleet (NISEA 2022b). Concerning the individual characteristics of the vessels, the International Radio Call Sign (IRCS), ship name, and MMSI number are utilized to identify each *rapido*. The vessel IRCS and name, included in the AIS data, are subsequently matched with the EU Fleet Register, which contains data on the physical features of the vessels, such as engine power, length overall (LOA) and year of construction. In some case, such as misspelled IRCS or ship's name, the vessel identification is performed by using the Marine Traffic website. In addition, the speed frequency distribution of each vessel, as well as the catch profiles, are used to detect the principal gear and/or its possible switch.

The analysis of AIS data, relative to the TBB fleet of Chioggia (GSA 17), is performed following the procedure reported in Russo et al. (2020). Briefly, the dataset is processed by using PostgreSQL, an opensource object-relational database. First, all duplicate records and erroneous positions are removed, then the trajectories of each TBB are reconstructed by linearly interpolating the AIS data from the departure to the return port. A trajectory is defined as a sequence of segments with different activity (in port, exiting from port, entering to port, fishing, and navigation) defined on the base of the vessel position and the typical fishing speed range of TBB (4-7 knots) (Russo et al. 2020). Then, the daily quantity of landings, provided by the Chioggia Fish Market, is associated to each fishing trip through the MMSI.

2.2. Market data

With regard to the construction of the output variable, which indicates the value of landings, we make use of the daily prices from Chioggia Fish Wholesale Market. We chose to request the price time series for the five most relevant species caught by the TBB fleet in 2019 in the GSA 17, covering 76.2% of its total landed value according to the Economic and Transversal data by STECF (2022). These are: common sole (*Solea solea*, SOL), common cuttlefish *(Sepia officinalis*, CTC), purple dye murex (*Bolinus brandaris*, BOY), caramote prawn (*Melicertus kerathurus*, TGS) and spottail mantis shrimp (*Squilla mantis*, MTS). In addition, based on previous literature that highlights the importance of these two species for the Chioggia *rapido* fishery (F. Pranovi et al. 2001), we also requested the daily prices of queen scallop (*Aequipecten opercularis*, QSC) and great Mediterranean scallop (*Pecten jacobaeus*, SJA) and included them in the analysis. Taking into account the significance of the seven species under consideration for this fishery[2], the output variable effectively approximates the total revenues generated by fishing trips. Summary statistics of the variables considered in the study are presented in table 1. For a more detailed description, Table A1 reports the summary statistics divided by month.

Table 1
Statistics overview for key fishing trip variables.

Variable	Median	Mean	Std.Dev.

[2] In the year 2019, these species showed the following relevance over the total value landed by TBB in the GSA 17: SOL 42.0%, CTC 11.9%, BOY 10.1%, MTS 7.0%, TGS 5.1% and SJA 4.2%. Data for QSC is aggregated with other scallop species (STECF, 2022).

Engine power (kW)	441.00	433.17	121.00
Fishing time (hours)	17.55	19.48	10.36
Navigation time (hours)	4.91	8.62	28.52
Fuel fishing (liters)	1179.84	1458.38	963.50
Fuel navigation (liters)	281.16	496.85	1933.34
Landings weight (kg)	341.98	423.53	357.97
Landings value (€)	2718.22	3273.53	2721.71
CO_2 (kg)	4493.62	5591.96	6188.08

N= 2404 observations

3. Methodology

With regard to the methodological approach adopted in this paper, we proceed as follows. The first step involves the identification of the most relevant catch profiles in the *rapido* fishery through multivariate analysis of landings composition. We then estimate the technical efficiency of fishing operations by means of Stochastic Frontier Analysis (SFA) and assign an efficiency score to each trip undertaken by the TBB fleet of Chioggia. The previously defined clusters are therefore used to compare the performance of fishing trips characterized by different catch profiles. The latter are lastly evaluated also in terms of environmental footprint through the estimation of the CO_2 emissions per fishing trip. We now describe the methods used in the paper starting from the multivariate analysis of catch profiles.

3.1. Multivariate analysis of catch profiles

Concerning the classification of trips into homogeneous groups, different approaches can be found in the literature. In general, input-based methods rely on either the technical characteristics of fishing operations retrieved from logbooks (e.g. the mesh size used, the trawled area) or direct interviews with fishers. On the other hand, output-based methods assume that catch composition reflects the intentions of fishers and therefore classify fishing trips into métiers through multivariate analysis of landing profiles. Despite their respective benefits and limitations, output-based methods are most commonly used (Marchal 2008).

In this paper we attempt to define groups of homogenous fishing trips by means of cluster analysis, a data-exploratory technique which classifies objects into different clusters based on their internal cohesion and external isolation[3] (Everitt et al. 2011). Cluster analysis is generally divided into partition and hierarchical methods, with both approaches being extensively applied to identify métiers in fisheries. In this paper we apply the k-means partition clustering method (Bastardie et al. 2010; Fall et al. 2006; Lucey and Fogarty 2013; Williams and Ralston

[3] Even if it is not necessary for clustering, a Principal Component Analysis (PCA) can be performed in advance in order to reduce the dimensionality of a dataset by aggregating highly correlated variables into a reduced number of principal components. In the fisheries literature, an initial PCA is commonly conducted in the presence of datasets covering a high number of species (Iriondo et al. 2010; Moore et al. 2019).

2002) to characterize clusters using the species composition of each trip[4]. The method starts by pre-setting a number of *k* clusters to be defined through an iterative process which, depending on the initial seed values, relocates objects to the group whose mean (centroid) is the nearest and the algorithm stops when no objects change group. If the number of clusters is not known *a priori*, it is necessary to calculate and compare alternative solutions with different *k* numbers of groups based on one or more criteria. These typically include *i*) the search for the "kink in the curve" derived from the within sum of squares or *ii*) its logarithm for all cluster solutions, *iii*) the η^2 coefficient (indicating the decrease of the within sum of squares for every solution compared with the total sum of squares) and *iv*) the proportional reduction of error coefficient (indicating the decrease of the within sum of squares for cluster solution *k* compared with the previous solution with one *k-1* clusters) (Makles 2012). We perform the analysis in STATA 16 using the *cluster kmeans* command and determine the appropriate number of clusters by comparing the results of the four criteria for different cluster solutions.

3.2. Technical efficiency and model specification

In a wide range of industries, including the fishing sector, firms can be described in terms of technical efficiency by looking at their generated output given a set of resource inputs. The difference between the observed and the potential production measures the level of technical efficiency of a firm, with inefficient units operating below the frontier. Measurement of technical efficiency will thus depend on the estimation of a production function for a specific industry, which is usually based on either Data Envelopment Analysis (DEA) or SFA. In the former approach the frontier is identified using linear programming techniques, while econometric estimation is performed in the latter. Both DEA (Gómez and Maynou 2020; Guyader and Daurès 2005; Reid et al. 2003; Sangün et al. 2018; Vázquez-Rowe and Tyedmers 2013) and SFA (Dağtekin et al. 2021; Greenville et al. 2006; Pascoe et al. 2001; Solís et al. 2013; Van Nguyen et al. 2019) have been widely applied in the fisheries literature. Even if both approaches have their advantages and disadvantages (Pascoe and Tingley 2007), the present work makes use of SFA due to its ability to take into account statistical noise given the stochastic nature of the production process in the fishery, as opposed to the deterministic nature of DEA (Herrero and Pascoe 2003).

SFA generalizes the classical production function approach, which assumes that there are no differences in the efficient use of inputs among units, by incorporating a non-symmetric two-component error made of a regular idiosyncratic disturbance and a one-sided non-negative component representing technical inefficiency and preventing the achievement of the maximum feasible output (Nguyen et al. 2022). A stochastic frontier production function can be defined as follows:

$$y_{it} = f(x_{it}; \alpha) + v_{it} - u_{it} \tag{1}$$

[4] The variables analyzed are the catch proportions (in terms of weight) of each of the seven species considered (SOL, CTC, BOY, TGS, MTS, QSC, SJA) relative to the total landings. The remaining species are grouped together as the proportion of "other species".

where y_{it} is the (logged) output of producer *i* in the *t*th time period, $f(x_{it};\alpha)$ is the production technology, x_{it} is the vector of (logged) input quantities, α is the vector of associated unknown parameters, v_{it} denotes stochastic noise and u_{it} represents technical inefficiency. The random errors are assumed to be independently and identically distributed following a normal distribution $N(0,\sigma_v^2)$ while technical efficiency is non-negative, independently and identically distributed with variance σ_u^2. If $u_{it}=0$, producer *i* at time *t* lies on the stochastic frontier and is therefore fully efficient. On the contrary, a value greater than zero indicates a production below the frontier. Different distributional assumptions can be made for the inefficiency term u_{it}, with half-normal (Jondrow et al. 1982), exponential (Meeusen and van der Broeck 1977), truncated normal (Aigner et al. 1977) and gamma (Greene 1990) distributions being widely used in the literature. Inefficiency can also be modelled as a function of exogenous variables (Battese and Coelli 1995).

Panel data models for the estimation of technical efficiency can be classified into four groups depending on the assumptions made on the temporal behavior of inefficiency: time-invariant and individual specific, individual specific but time-varying, separated from unobserved individual effects, composed of both a persistent and a time-varying component and separated from unobservable individual effects (Kumbhakar et al. 2015). Given our interest in estimating the efficiency of fishing trips and comparing the scores among catch profiles (rather than vessels), in this paper we apply the model by Kumbhakar and Heshmati (1995), which belongs to the fourth group of models. This allows us to isolate the effect of persistent inefficiency, whose magnitude can be relevant in short panels (only one year in our case) because it reflects the effect of inputs like management (Mundlak 1961)[5]. Technical efficiency is here further decomposed as

$$u_{it} = u_i + \tau_{it} \tag{2}$$

where u_i is the persistent component (vessel-specific and time-invariant) and τ_{it} is the residual component (vessel-specific and time-variant).

The model, which is presented in a random effects framework due to the presence of a fixed input (engine power) and the nature of the data (a rotating panel with some vessels entering and exiting the fishery throughout the year), is estimated following a multistep procedure (Kumbhakar and Heshmati 1995)[6]. In particular, taking a translog function as the production technology, the model is rewritten as:

[5] In the case of a fishery, this could be approximated by skipper skill or experience, which have been indeed included as control variables in previous studies of technical efficiency (Pascoe and Coglan 2002; Del Valle et al. 2003).

[6] A functional form describing the fishing technology (the relationship between inputs and output) has to be chosen for estimation. This can take the form of a Cobb-Douglas, constant elasticity of substitution or translog function (Squires and Kirkley 1999). Here we specify the production function as a translog due of its flexibility and because it does not impose

$$\ln(Y_{it}) = \alpha_0^* + \gamma' X_{it} + u_i^* + \omega_{it}, \tag{3}$$

$$\alpha_0^* = \alpha_0 + E(u_i) + E(\tau_{it}), \tag{4}$$

$$u_i^* = u_i - E(u_i), \tag{5}$$

$$\omega_{it}^* = v_{it} + \tau_{it} - E(\tau_{it}) \tag{6}$$

where the X_{it} vector includes the linear, quadratic and cross-product terms of the (logged) explanatory variables and γ is the corresponding parameter vector. First, the production function parameters γ are estimated using Generalized Least Squares (GLS). The residuals $e_{it} = \ln(Y_{it}) - \hat{\gamma}' X_{it}$ are then used to estimate persistent technical efficiency from:

$$\hat{u}_i = \bar{e}_i - \max_i\{\bar{e}_i\} \tag{7}$$

where $\bar{e}_i$ is the mean of e_i of producer (i.e. vessel) *i* over the time period. Assuming that the residual component of efficiency is truncated at zero as the random errors $N(0, \sigma_\tau^2)$, Maximum Likelihood is used to estimate the intercept α_0, σ_τ^2 and σ_v^2. Lastly, τ_{it} for each observation is estimated based on the JLMS technique (Jondrow et al. 1982):

$$\hat{\tau}_{it} = \frac{\hat{\lambda}\hat{\sigma}}{(1+\hat{\lambda}^2)}\left[\frac{\hat{\lambda}\omega_{it}}{\hat{\sigma}} - \frac{\phi(\frac{\hat{\lambda}\omega_{it}}{\hat{\sigma}})}{\Phi(-\frac{\hat{\lambda}\omega_{it}}{\hat{\sigma}})}\right] \tag{8}$$

where $\lambda = \sigma_\tau/\sigma_v$, $\sigma = \sigma_\tau^2 + \sigma_v^2$, $\Phi(\cdot)$ is the cumulative distribution function of the standard normal variable and $\phi(\cdot)$ is the standard normal density function. The respective scores for persistent (PTE), residual (RTE) and overall (OTE) technical efficiency are finally computed as: $\mathrm{PTE_i} = \exp(\hat{u}_i)$, $\mathrm{RTE_{it}} = \exp(\hat{\tau}_{it})$ and $\mathrm{OTE_{it}} = \exp(\hat{u}_i + \hat{\tau}_{it})$[7]. Regarding the functional specification relating inputs and output, the estimated function is given by:

$$\begin{aligned}\ln V_{it} = \alpha_0 &+ \alpha_{NT}\ln NT_{it} + \alpha_{FT}\ln FT_{it} + \alpha_{KW}\ln kW_i + \alpha_{NTNT}(\ln NT_{it})^2 + \alpha_{FTFT}(\ln FT_{it})^2 \\ &+ \alpha_{KWKW}(\ln kW_i)^2 + \alpha_{NTFT}(\ln NT_{it}\cdot\ln FT_{it}) + \alpha_{NTKW}(\ln NT_{it}\cdot\ln kW_i) \\ &+ \alpha_{FTKW}(\ln FT_{it}\cdot\ln kW_i) + \alpha_4 D_t + v_{it} - u_{it}\end{aligned} \tag{9}$$

constraints on the elasticities of substitution between inputs (García Del Hoyo et al. 2004; Herrero and Pascoe 2003; Squires 1987).

[7] The procedure, and the corresponding STATA code to replicate the analysis, is described in detail by Kumbhakar et al. (2015 p.272).

where V_{it} is the trip output measured as catch value, NT_{it} is the navigation time in hours, FT_{it} is the fishing time in hours, kW_i denotes the engine power measured in kilowatts and D_t is a monthly dummy. Concerning the selection of variables, catch value- instead of landings- is often preferred to denote the output in efficiency studies of fisheries. Even if this implies that the efficiency scores may represent a combination of technical and allocative efficiency given that prices are not fixed, catch value as an output is likely to be more consistent with the behavioral characteristics of the vessel crew (Pascoe and Coglan 2002). As for the input factors, these incorporate fishing effort and fish stock. While the latter is outside the control of the fisher, the former usually comprises a fixed component reflecting fishing power (such as vessel tonnage, length or engine power) and a variable component reflecting the time at sea (Andersen 2002). We therefore use engine power as a fixed input[8] and the hours at sea[9] for each fishing trip as a variable input. Having AIS data that allow us to distinguish between navigation time and fishing time, we attempt to more accurately describe fishing operations by dividing the time at sea in these two parts. Lastly, a dummy approach is adopted to describe monthly stock fluctuations (Coglan et al. 1999; Fousekis and Klonaris 2003; Pascoe and Robinson 1998; Yang et al. 2017).

3.3. CO_2 emissions

With regard to the estimation of CO_2 emissions generated by TBB, these depend on the physical characteristics of the vessel and the time spent at sea during the fishing trip. In particular, based on the engine power of vessels and their respective fishing/navigating time, we are able to compute fuel consumption for fishing FCF_{it} and navigation FCN_{it} of each trip following the equation by Prado (1990):

$$FCF_{it} = a \cdot kW_i \cdot \frac{S_f}{d} \cdot FT_{it} \cdot 0.001, \tag{10}$$

$$FCN_{it} = a \cdot kW_i \cdot \frac{S_n}{d} \cdot FT_{it} \cdot 0.001 \tag{11}$$

where a is the average coefficient set at 0.75 (Prado 1990), S is the specific fuel consumption (set at 188 g/kW*h for fishing and 150.4 g/kW*h for navigation) (Lee et al. 2018) and d denotes fuel density (0.86 kg/l). Finally, fuel

[8] Choosing engine power (rather than length) follows the management measures for demersal fish stocks in Northern Adriatic, which aim to reduce fishing pressure by decreasing the total kilowatts and fishing days in the fishery. Nevertheless, the two inputs highly correlated (*p* 0.65, 1% significance).

[9] The use of navigation and fishing hours can be problematic in the estimation process since the variable may be endogenous- the so-called "simultaneity bias" (i.e. fishers spend more time at sea when the trips are more profitable). However, the selection of inputs based on predicted profits will be subject to mistakes that are uncorrelated with the error components in the production function due to the stochastic nature of the output (i.e. unpredictable weather and environmental conditions, the "luck" component), thus resulting in consistent parameter estimates (Kirkley et al. 1998; Pascoe and Coglan 2002).

consumption is used to calculate the carbon footprint of a fishing trip using the basic method Tier 1 (Park et al. 2015; IPCC 2008) :

$$CO_{2_{it}} = (FCF_{it} + FCN_{it}) \cdot EF \tag{12}$$

where the emission factor EF is set at 2.86 kg CO_2 per liter of fuel consumed (Parker et al. 2018).

4. Results

4.1. Cluster analysis

Table 2
Catch profiles composition and frequency based on cluster analysis. The species under consideration are common sole (SOL), common cuttlefish (CTC), purple dye murex (BOY), caramote prawn (TGS), spottail mantis shrimp (MTS), queen scallop (QSC) and great Mediterranean scallop (SJA).

	Proportion of landings							
	SOL	CTC	BOY	TGS	MTS	QSC	SJA	Other
Cluster 1	0.36	0.35	0.02	0.02	0.03	0.03	0.07	0.13
Cluster 2	0.08	0.04	0.02	0.00	0.01	0.75	0.09	0.01
Cluster 3	0.66	0.07	0.05	0.01	0.06	0.01	0.05	0.10
Cluster 4	0.34	0.05	0.14	0.01	0.06	0.04	0.26	0.10
Cluster 5	0.02	0.10	0.03	0.02	0.07	0.00	0.01	0.75

	Monthly observations										
	J	F	M	A	M	J	J	S	O	N	D
Cluster 1	161	146	89	41	1	1	0	7	44	50	70
Cluster 2	18	31	26	43	39	44	41	29	30	22	20
Cluster 3	33	55	54	87	136	96	83	79	91	104	92
Cluster 4	12	8	47	53	67	68	53	41	33	14	14
Cluster 5	11	14	7	9	10	8	7	18	19	13	15

Since k-means is a stochastic method, the cluster analysis is repeated several times (N=20) with different initial seed values in order to test the robustness of the results. Through graphical inspection of the four criteria described in Makles (2012), we find the most appropriate number to be five clusters. These are reported in Table 2, which shows the average proportion of each of the seven species (SOL, CTC, BOY, TGS, MTS, QSC, SJA) over total landings per catch profile. The remaining species are labelled as "other". The table also provides an indication of the number of observations belonging to the five clusters during each month of the year[10]. Conditional formatting is used to ease the interpretation of the table and to provide a clear indication of both the most relevant species per catch profile and their seasonality. In particular, Cluster 1 is characterized by the prevalence of common

[10] Each year a temporary fishery closure in the Summer season is established. In 2019, the ban (in ital. "*fermo pesca*") took place from July 29th to September 6th in the Veneto region.

sole and common cuttlefish landings and it's the most frequent catch profile over the Winter season (377 observations from December to February). Fishing trips belonging to Cluster 2 almost exclusively target queen scallop and, despite their low frequency (343 observations in 2019), they tend to be quite equally distributed during the year. Cluster 3 is characterized by the highest incidence of sole over total landings and it's the most frequent catch profile of the sample (910 fishing trips), with peaks in May and November. Other than the presence of sole, fishing trips from Cluster 4 also exhibit a proportion of purple dye murex and great Mediterranean scallop higher than the average and they are concentrated between March and October. Lastly, all the observations belonging to Cluster 5 (131 observations) are dropped from the analysis due to the high incidence of the species labelled as "other" (75% of landings), which would compromise the reliability of the efficiency estimates because the revenues from fishing operations would be only partially reflected in the value of landings.

4.2. *Technical efficiency and CO_2 estimation*

Table 3
Monthly variations in efficiency scores and emissions per fishing trip. The results are differentiated by catch profile (Clusters 1-4).

Month			J	F	M	A	M	J	J	S	O	N	D
Cluster 1	**N**		**161**	**146**	**89**	**41**	**1**	**1**	**0**	**7**	**44**	**50**	**70**
	Efficiency	*Mean*	0.67	0.67	0.67	0.62	0.49	0.17	.	0.69	0.66	0.67	0.65
		Std.Dev.	0.1	0.12	0.14	0.12	.	.	.	0.1	0.11	0.11	0.12
	CO_2 Kg	*Mean*	8224	7824	7201	11800	1310	2058	.	6594	6749	6084	7702
		Std.Dev.	7009	4372	3758	13150	.	.	.	1881	2452	2539	3617
Cluster 2	**N**		**18**	**31**	**26**	**43**	**39**	**44**	**41**	**29**	**30**	**22**	**20**
	Efficiency	*Mean*	0.7	0.64	0.68	0.69	0.76	0.75	0.65	0.58	0.62	0.61	0.62
		Std.Dev.	0.13	0.16	0.14	0.13	0.13	0.09	0.17	0.12	0.13	0.13	0.17
	CO_2 Kg	*Mean*	2450	2555	2975	3162	4776	3283	2947	3472	2995	2639	2757
		Std.Dev.	521	586	1868	1869	7909	2112	1814	2141	946	972	729
Cluster 3	**N**		**33**	**55**	**54**	**87**	**136**	**96**	**83**	**79**	**91**	**104**	**92**
	Efficiency	*Mean*	0.62	0.64	0.65	0.66	0.65	0.65	0.68	0.7	0.69	0.69	0.7
		Std.Dev.	0.12	0.11	0.16	0.11	0.13	0.12	0.1	0.11	0.12	0.13	0.12
	CO_2 Kg	*Mean*	4678	4995	3565	5213	6498	4806	4679	3878	5698	4306	5342
		Std.Dev.	3959	3581	1857	2863	19334	2844	3144	2078	3194	2449	2834
Cluster 4	**N**		**12**	**8**	**47**	**53**	**67**	**68**	**53**	**41**	**33**	**14**	**14**
	Efficiency	*Mean*	0.51	0.47	0.61	0.62	0.56	0.59	0.62	0.61	0.58	0.4	0.47
		Std.Dev.	0.15	0.22	0.13	0.12	0.14	0.15	0.13	0.1	0.18	0.16	0.28
	CO_2 Kg	*Mean*	5238	4719	4755	5340	5643	5261	5305	5077	6446	4396	5295
		Std.Dev.	2442	2094	2062	2698	3202	2373	2599	1480	2480	1115	1954

Concerning the analysis of technical efficiency (the estimated production function parameters can be found in Table A2), Table 3 shows the efficiency scores and the CO_2 emissions associated with the four catch profiles (Cluster 1 to 4) during each month of the year. Conditional formatting is used to highlight the relative frequency of observations belonging to one group and to compare the median efficiency scores and emissions among clusters. If read from the top to the bottom, Table 3 allows to confront the four clusters within the same month, while through horizontal reading we can follow the performance of each cluster during the year. First, it emerges that it is important to inspect the efficiency scores and the emissions at the monthly level because both of them tend to vary consistently across the year. For instance, Cluster 2 is characterized by high efficiency between May and June, but it is relatively underperforming in the Autumn months. Similarly, the number of observations denotes whether a catch profile tends to be stable during the year or not. Cluster 1 is indeed the most recurring strategy in the Winter months, while it almost disappears between May and September.

In terms of efficiency, the highest scores are reached by Cluster 2 in May (mean=0.76, median=0.81) and June (mean=0.75, median=0.77). Nevertheless, Cluster 2 is not the most frequent catch profile in these two months (83 observations), but is preceded by Cluster 3 (232 observations) and 4 (135 observations) despite their lower efficiency scores. Vertical reading of Table 3 thus helps us understand if the fishery is operating optimally or, on the contrary, there are vessels that favor one catch profile over the others even if it does not assure the highest value of landings given the set of inputs employed. For instance, in February the vast majority of fishing trips belong to Cluster 1 (146 observations), which is also the catch profile with highest scores (mean=0.67, median=0.70), meaning that vessels targeting together sole and cuttlefish are the most efficient. Likewise, in September Cluster 3 appears to be both the most efficient catch profile (mean=0.70, median=0.70) and the most preferred strategy among fishermen (79 observations). It is interesting to observe that in some periods of the year fishers tend to exhibit mostly one (i.e. in January) or two (i.e. in December) catch profiles, while in others the probability of belonging to one cluster is more equally distributed among the four. This is the case of April, when all the clusters are characterized by at least 40 observations and none of them has an average or median efficiency score lower than 0.62 or greater than 0.69. In other words, *rapido* vessels could either choose to target almost exclusively queen scallop (Cluster 2) or prioritize sole landings (Cluster 3) with no major differences in terms of efficiency. However, the two strategies are definitely not comparable from an environmental point of view, with the median value of CO_2 emissions from Cluster 2 being only 61% of Cluster 3. The result can be explained by the fact that, although in April fishing trips belonging to Cluster 3 are characterized by a higher duration and fuel consumption (Table A3), the value of landings is enough to compensate for the additional input usage. Overall, it can be argued that both Clusters 1, 2 and 3 tend to outperform Cluster 4 in terms of efficiency. In particular, when considering only median values, we estimate the most efficient catch profile to be Cluster 1 in two months (February, March), Cluster 2 in five (January, April, May, June, July) and Cluster 3 in four months (September, October, November, December). TBB targeting together sole, purple dye murex and great Mediterranean scallop

(Cluster 4) are relatively frequent in May (67 observations) and June (68 observations) but they could substantially be more efficient by changing the composition of their landings in favor of sole or queen scallop.

When considering the emissions generated by fishing trips, it is clear that there are significant variations among catch profiles. In addition, we observe that the energy performance of a cluster can also change throughout the year, meaning that a fishing strategy that is sustainable in one period might become excessively polluting in the following months. In general, we see that fishing trips from Cluster 2 are continuously marked by lower levels of CO_2 emissions, so it can be argued that *rapido* vessels targeting mainly queen scallop are the most sustainable during each of the months under consideration (with only two observations, Cluster 1 is not considered a feasible alternative between May and June). The opposite extreme is represented by fishing trips from Cluster 1, which generate severe levels of emissions during most of the year, reaching the highest peaks in April (mean=11800 Kg, median=10080 Kg) and January (mean=8224 Kg, median=8256 Kg). Cluster 3 and 4 show an intermediate energy performance. Specifically, it is worth noting that catch profiles with major sole incidence (Cluster 3) are characterized by great variability both across the year (January median=2885 Kg, October median=5167 Kg) and intramonth, as indicated by the discrepancy between mean and median values and high standard deviations. On the other hand, fishing trips targeting together sole, purple dye murex and great Mediterranean scallop (Cluster 4) tend to be relatively more stable, especially in Spring/Summer, when they are more frequent (May median=4695 Kg, June median=4672 Kg). We also stress the fact that the carbon footprint of each catch profile is a product of both fishing/navigation time and engine power. In this regard, fishing trips from Cluster 2 are not only characterized by a shorter time at sea (19 hours at sea on average) but they are also preferred by TBB with lower engine power (367 kW on average), hence explaining the reduced CO_2 emissions of this catch profile compared to the others[11]. Lastly, the validity of the results is confirmed by examining the ratio of CO_2 emissions to the total value of landings from the seven species being studied. Once more, Cluster 2 fishing trips emerge as the most efficient, displaying a median emission intensity of 0.62 kg of CO_2 per euro earned from catch. This is followed by Cluster 3 (1.67 kg/euro), Cluster 1 (1.82 kg/euro), and Cluster 4 (2.34 kg/euro).

5. Discussion and conclusion

Our analysis shows that linking multivariate analysis of catch profiles to SFA can be an effective tool to understand the dynamics taking place in the fishery at the vessel level, hence providing both managers, fishers and policy-makers practical indications to improve the efficiency of the sector. Including an inventory of GHGs emissions in the analysis also allows to compare the economic performance and the environmental sustainability of the fishery, and therefore to identify the periods of the year or catch profiles where both dimensions coexist.

[11] The highest levels of emissions are associated with Cluster 1, whose catch profile is targeted by powerful *rapido* vessels (478 kW on average) during fishing trips with long time at sea (36 hours). Cluster 3 (416 kW, 26 hours) and 4 (478 kW, 25 hours) lie in between the two.

From a management perspective, our approach highlights that some heterogeneity does exist within the *rapido* fishery of Chioggia. In particular, the differences are related to the fisher's behaviour, probably depending on handed down patterns of fishing performance, the movement of the main target species (e.g. seasonal migrations), regulatory limitations and the characteristics of the fishing grounds (e.g. type of sediment, bathymetry). This aspect could be related to the partial overlapping of fishing grounds with other gears, especially bottom otter trawls, which can compete for the same areas and resources (Russo et al. 2020). Such information should be carefully considered when planning future capacity reduction programmes, because the effectiveness of such measures heavily depends on the efficiency of the units involved (Pascoe and Coglan 2000)[12]. Similarly, further reductions in fishing days as prescribed in the last EU regulations for the GSA 17 (-3% between 2022 and 2023) (Council of the EU 2022; 2023) may not reach the target of reducing the pressure on all fish stocks if fishers are able to switch among catch profiles (i.e. changing the target species). Our analysis shows indeed that TBB- especially the ones with more powerful engines- do not necessarily belong to the same cluster during the whole year and they may even report landings with different composition in the same month. An exception is represented by a few small/medium sized vessels targeting mostly queen scallop (Cluster 2), which show less inter-cluster mobility (Figure A1)[13]. In general, heterogeneity emerges at two levels: firstly, in the differences in technical efficiency among vessels. Secondly, there is heterogeneity in terms of different strategies coexisting throughout the year. Heterogeneity can also be related to differences in physical characteristics of the vessels, with larger TBB being more efficient in specific seasons and smaller TBB in others. For instance, a two-sample t test indicates that vessels with engine power above the average (433.17 kW) have higher scores in February ($Pr(T < t) = 0.0143$), while boats with engine power below the average perform better in July ($Pr(T > t) = 0.0126$).

Depending on the priority weightings placed by management institutions (economic efficiency, carbon neutrality, stock preservation), this type of analysis can support the selection of the most appropriate temporal units for future regulations involving a reduction in fishing days. To ensure that these have no impact on market supply and do not result in the closure of established commercial circuits, it is essential to consider both the distribution of fishing time limitations throughout the year in addition to the fishing time reduction itself (Sánchez Lizaso et al. 2020). On the other hand, even if the introduction of quotas has been traditionally rejected in the Mediterranean Sea due to the multispecific nature of most fisheries (Carpi et al. 2017; Mulazzani et al. 2018), it is reasonable to presume that setting a total allowable catch (TAC) for sole in the Autumn/Winter season would

[12] In the period 2014-2020, 1,877,970 € have been allocated to the TBB segment of the Italian fleet under Article 34 of the European Maritime and Fisheries Fund for permanent cessation of fishing activities (Gambino et al. 2022).

[13] With regard to the influence of the year of construction of the *rapido*, graphical inspection of Figure A1 suggests that older vessels are less able to move among clusters. This is confirmed by the fact that five out of the first six boxes at the top identify TBB with an age above 28 years (median value in the sample). Engine power is indeed negatively correlated with vessel age (p -0.52, 1% significance).

prevent the fall in prices that occurs in November (6.35 €/kg) and December (6.89 €/kg)[14], especially considering that sole represents about 50% of landings in these months.

Two policy options emerge at this juncture. Firstly, the measure of vessel withdrawals, removing from the fleet less efficient boats and/or those disproportionally contributing to GHGs emissions. Although the effectiveness of decommissioning schemes has been historically criticized, especially in Italy (Spagnolo 2010), efficiency analysis could indeed serve as a useful tool to select the most appropriate units to involve (Kirkley and Squires, 2003), in particular in those contexts where fishing effort is above sustainable levels. Secondly, engaging fishers to reorganize and channel production, changing fishing pattern of individual vessels and selecting the more efficient combination of strategy and period. In this regard, an important role could be played by Producer Organizations to engage all relevant stakeholders at the local level (European Commission 2023b), with the Veneto region already having a positive example represented by Territorial Use Rights for clams management (Spagnolo 2007; Lucchetti et al. 2022). Despite the organizational effort required, the latter option appears more feasible, especially considering the socio-economic challenges faced by the industry (Sabatella et al. 2020). Nevertheless, efficiency analysis can also assume a crucial role with regard to the pressing issue of technological modernization of European fleets, which has been recently raised by the Commission (2023a), facilitating the identification of vessels with poor emissions performance.

We stress the fact that our analysis has some limitations. First, we consider data referring to a single year, so our findings do not take into account possible stock fluctuations occurring over the long run, which may imply a change in the behaviour of fishers with regard to the targeted species. In addition, we recognise that the results from efficiency analysis are dependent on the methodology used, meaning that through the application of DEA (instead of SFA) (Pascoe and Tingley, 2007), or the inclusion of different variables describing the fishing technology- for instance through economic (e.g. capital value) rather than physical (e.g. engine power) inputs (Pascoe et al. 2003)-, deviations in the efficiency estimates might occur. Nevertheless, it is important to remark that the use of the model by Kumbhakar and Heshmati (1995) represents an original contribution in the field of fisheries economics, since most of the efficiency studies are rather based on the application of the model by Battese and Coelli (1995) (Pascoe et al. 2003), which does not distinguish between persistent and time-varying inefficiency (Kumbhakar et al. 2015), and therefore is not able to isolate the effectiveness of one catch profile over the others. Lastly, we recognise that this work considers solely the revenues from the most relevant species, therefore the availability of price series for all the landed fish in Chioggia market could possibly alter the results from SFA due to the inclusion of potential additional revenues from non-target and incidentally captured species.

In conclusion, our study shows that there is no catch profile of the TBB fishery in Chioggia that ensures higher efficiency estimates throughout the year. While these depend on the month under consideration, we also

[14] The average 2019 price is 8.98 €/kg, with peaks in August (12.24 €/kg), March (10.64 €/kg) and July (10.31 €/kg).

find that, to maximize the value of the fishery, landings composed mostly of one (i.e. sole or queen scallop) or two (i.e. sole and cuttlefish) species should generally be preferred over more mixed catch profiles (i.e. sole, purple dye murex and great Mediterranean scallop). On the other hand, in terms of CO_2 emissions it emerges that fishing trips targeting queen scallop are constantly more sustainable, due to the lower time at sea and engine power of the vessels, hence resulting in reduced fuel consumption. This is mainly correlated with the distribution of queen scallop, which- compared to other target species- is located closer to the Chioggia port (Russo, 2020). This is extremely relevant when considering the EU objective of reducing GHGs emissions and the environmental footprint from fishing and aquaculture to mitigate the impacts of climate change (European Commission 2023a).

We ultimately stress that this interdisciplinary approach, combining for the first time two methodologies that are normally applied separately in marine science, has the potential to support management and policy-making also in other contexts characterised by multispecies fisheries and heterogeneous fleets. In this regard, the empirical strategy could be further enriched through the inclusion of alternative techniques both in the multivariate analysis of catch profiles (e.g. hierarchical cluster methods) and efficiency estimation (e.g. multi-output stochastic production frontiers and DEA). Incorporating spatial information describing the distribution of the areas swept by vessels during the trip is also a promising possibility for future research, especially in the context of the economic consequences related to the implementation of new protected/ fisheries restricted areas.

6. Acknowledgments

The research leading to these results has been conceived under the International PhD Program "Innovative Technologies and Sustainable Use of Mediterranean Sea Fishery and Biological Resources (www.FishMed-PhD.org). We thank Prof. Fabio Pranovi for the support and the valuable insights during the research process.

7. Appendices

Table A1
Statistics overview for key fishing trip variables.

Variable	January (*235 obs*)			February (*254 obs*)			March (*223 obs*)			April (*233 obs*)		
	m	mdn	sd	m	mdn	sd	m	mdn	sd	m	mdn	sd
Fishing time (hours)	24.0	27.9	11.6	22.6	21.8	11.8	19.3	16.1	10.4	20.6	17.5	11.3
Navigation time (hours)	10.9	7.1	28.0	9.1	6.1	13.8	6.7	4.8	7.1	9.3	4.9	29.1
Fuel fishing (liters)	1838.9	1902.4	1137.9	1690.7	1463.7	1113.7	1475.3	1099.2	979.6	1553.6	1240.9	1029.1
Fuel navigation (liters)	634.2	416.6	1861.0	518.6	362.6	892.5	390.8	267.2	376.3	555.5	260.5	2074.2
Landings weight (kg)	590.7	523.5	374.1	458.2	421.6	310.3	365.4	317.2	263.0	433.9	328.6	589.2
Landings value (€)	4495.3	4034.7	2816.9	3670.2	3396.3	2318.5	3315.3	2796.4	2508.6	3551.7	2671.3	4843.8
CO_2 (kg)	7073.1	6785.6	6339.3	6318.6	5434.4	4230.9	5336.9	4142.2	3331.8	6032.0	4482.8	6630.7
Variable	May (*253 obs*)			June (*217 obs*)			July (*184 obs*)			September (*174 obs*)		
	m	mdn	sd	m	mdn	sd	m	mdn	sd	m	mdn	sd
Fishing time (hours)	15.1	13.4	8.0	17.7	14.4	9.7	16.8	14.5	8.3	15.9	16.6	7.3

Navigation time (hours)	16.0	5.0	74.9	5.8	4.4	7.4	6.6	4.2	9.9	6.9	4.3	7.7
Fuel fishing (liters)	1120.6	949.7	739.7	1302.3	1041.2	843.1	1226.4	1053.0	809.7	1164.4	1119.0	691.7
Fuel navigation (liters)	965.4	294.1	5128.1	313.5	240.5	324.1	354.8	215.4	506.8	386.2	273.7	459.0
Landings weight (kg)	345.5	273.3	310.4	323.8	253.0	270.7	311.1	256.8	253.6	355.9	306.4	227.6
Landings value (€)	2706.4	2170.8	2107.6	2345.5	1928.9	1810.9	2465.3	2182.8	1582.0	2746.6	2465.4	1653.0
CO_2 (kg)	5966.0	3650.9	14666.3	4621.4	3669.9	2673.8	4522.3	3716.3	2831.6	4434.9	4191.9	2326.7

Variable	October (*217 obs*)			November (*203 obs*)			December (*211 obs*)		
	m	mdn	sd	m	mdn	sd	m	mdn	sd
Fishing time (hours)	21.4	19.1	10.3	17.5	17.2	7.6	22.1	19.6	10.9
Navigation time (hours)	8.1	5.5	8.5	5.6	3.9	6.9	7.4	5.4	8.7
Fuel fishing (liters)	1543.0	1405.0	936.3	1309.0	1188.3	773.7	1698.6	1535.5	1031.7
Fuel navigation (liters)	458.3	318.1	494.8	306.1	220.6	310.6	430.2	322.2	486.2
Landings weight (kg)	417.7	351.3	378.4	493.2	454.3	285.1	534.6	492.3	369.3
Landings value (€)	3382.1	2908.7	3024.3	3098.3	2918.2	1742.1	3914.5	3572.1	2632.2
CO_2 (kg)	5723.7	5480.1	2849.1	4619.1	3979.1	2445.4	6088.4	5532.8	3562.1

Table A2
Random effects GLS regression results.

Variable	Coefficient	Std. Err.	p-value
ln *kW*	10.463	4.415	0.018
ln *FT*	0.722	0.532	0.175
ln *NT*	-0.822	0.540	0.128
ln *kW* ln *FT*	-0.238	0.174	0.172
ln *kW* ln *NT*	0.350	0.196	0.073
ln *FT* ln *NT*	0.043	0.064	0.499
ln *kW*^2	-1.775	0.754	0.019
ln *FT*^2	0.172	0.026	0.000
ln *NT*^2	-0.063	0.030	0.034
January	0.108	0.056	0.054
February	-0.074	0.055	0.178
March	-0.114	0.056	0.041
April	-0.143	0.055	0.010
May	-0.172	0.056	0.002
June	-0.402	0.056	0.000
July	-0.274	0.059	0.000
September	-0.083	0.061	0.174
October	-0.160	0.057	0.005
November	-0.016	0.058	0.779
December (ref.)			
Constant	-23.893	12.942	0.065
N		2273	

R squared	0.201
Wald Chi-Square statistic (19)	703.46
Prob>Chi-square	0.000

Table A3
Average hours at sea and liters of fuel consumed per trip.

Catch profile	Mean hours (fishing + navigation)										
	J	F	M	A	M	J	J	S	O	N	D
Cluster 1	39.0	36.8	32.5	53.9	13.4	21.4	.	25.0	28.3	25.6	34.7
Cluster 2	15.9	16.7	17.6	17.9	28.1	17.8	16.6	18.7	20.3	18.3	18.0
Cluster 3	23.7	25.8	19.6	26.4	33.0	24.2	24.3	21.4	31.4	21.9	26.7
Cluster 4	24.9	23.7	22.3	23.8	26.0	24.8	24.3	23.4	29.2	20.4	24.8
Catch profile	Mean liters (fishing + navigation)										
	J	F	M	A	M	J	J	S	O	N	D
Cluster 1	2875.5	2735.7	2517.7	4125.7	457.9	719.5	.	2305.6	2359.9	2127.2	2693.1
Cluster 2	856.5	893.3	1040.1	1105.7	1669.9	1147.9	1030.4	1214.1	1047.1	922.8	963.9
Cluster 3	1635.8	1746.5	1246.6	1822.8	2271.9	1680.4	1636.0	1356.1	1992.3	1505.5	1867.9
Cluster 4	1831.5	1649.8	1662.4	1867.2	1973.0	1839.6	1854.9	1775.2	2253.8	1537.2	1851.6

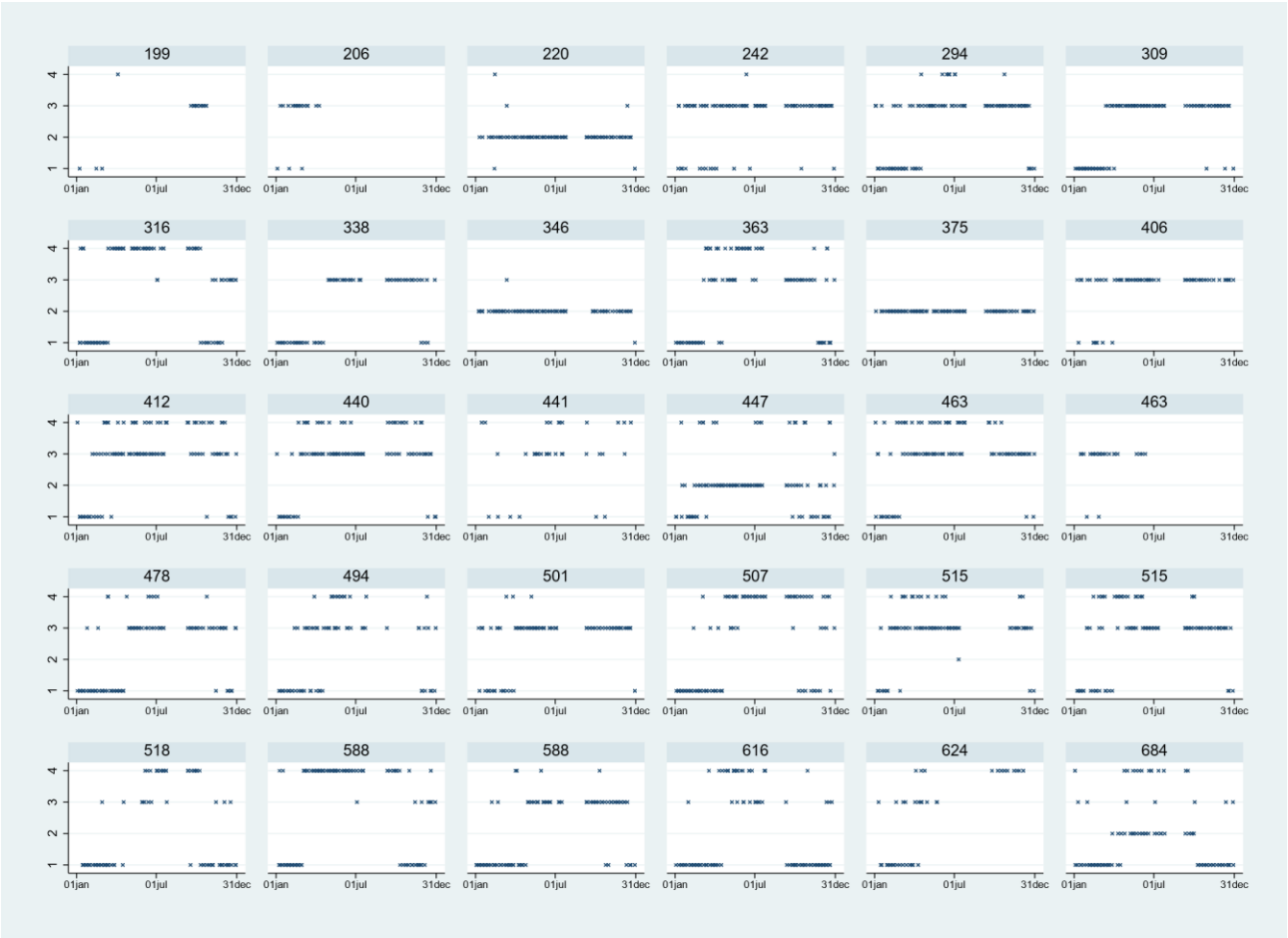

Fig. A1. Catch profile (Clusters 1-4) per trip for each TBB during the year 2019. Boxes are ordered consecutively based on the engine power (kW) of the vessel (reported at the top).

8. Bibliography

Aigner, Dennis, C. A.Knox Lovell, and Peter Schmidt. 1977. "Formulation and Estimation of Stochastic Frontier Production Function Models." *Journal of Econometrics* 6: 21–37. https://doi.org/10.1016/0304-4076(77)90052-5.

Andersen, Jesper Levring. 2002. "Using Different Inputs and Outputs to Estimate Technical Efficiency in Fisheries: An Application to Danish Seiners in the North Sea and Skagerrak." Working Paper N. 10/02. Frederiksberg C, Denmark.

Armelloni, Enrico Nicola, Martina Scanu, Francesco Masnadi, Gianpaolo Coro, Silvia Angelini, and Giuseppe Scarcella. 2021. "Data Poor Approach for the Assessment of the Main Target Species of Rapido Trawl Fishery in Adriatic Sea." *Frontiers in Marine Science* 8 (June): 1–11. https://doi.org/10.3389/fmars.2021.552076.

Bastardie, Francois, Silvia Angelini, Luca Bolognini, Federico Fuga, Chiara Manfredi, Michela Martinelli, J.

Rasmus Nielsen, Alberto Santojanni, Giuseppe Scarcella, and Fabio Grati. 2017. “Spatial Planning for Fisheries in the Northern Adriatic: Working toward Viable and Sustainable Fishing.” *Ecosphere* 8 (2). https://doi.org/10.1002/ecs2.1696.

Bastardie, Francois, J. Rasmus Nielsen, Clara Ulrich, Josefine Egekvist, and Henrik Degel. 2010. “Detailed Mapping of Fishing Effort and Landings by Coupling Fishing Logbooks with Satellite-Recorded Vessel Geo-Location.” *Fisheries Research* 106: 41–53. https://doi.org/10.1016/j.fishres.2010.06.016.

Bastari, Azzurra, Fiorenza Micheli, Francesco Ferretti, Antonio Pusceddu and Carlo Cerrano. 2016. "Large marine protected areas (LMPAs) in the Mediterranean Sea: the opportunity of the Adriatic Sea." *Marine Policy* 68: 165-177. https://doi.org/10.1016/j.marpol.2016.03.010.

Battese, G. E., and T. J. Coelli. 1995. “A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data.” *Empirical Economics* 20: 325–32.

Botter, L., O. Giovanardi, and S. Raicevich. 2006. “The Migration of Chioggia’s Fishing Fleet in the Adriatic from the Mid-Nineteenth to the Early Twentieth Century.” *Journal of Mediterranean Studies* 16 (1/2): 27–44.

Carpi, Piera, Giuseppe Scarcella, and Massimiliano Cardinale. 2017. “The Saga of the Management of Fisheries in the Adriatic Sea: History, Flaws, Difficulties, and Successes toward the Application of the Common Fisheries Policy in the Mediterranean.” *Frontiers in Marine Science* 4: 423. https://doi.org/10.3389/fmars.2017.00423.

Cavraro, Francesco, Marco Anelli Monti, Alberto Caccin, Fabio Fiori, Fabio Grati, Elisabetta Russo, Giuseppe Scarcella, Dario Vrdoljak, Sanja Matić-Skoko, and Fabio Pranovi. 2023. “Is the Small-Scale Fishery More Sustainable in Terms of GHG Emissions? A Case Study Analysis from the Central Mediterranean Sea.” *Marine Policy* 148: 105474. https://doi.org/10.1016/j.marpol.2023.105474.

Cheilari, Anna, Jordi Guillen, Dimitrios Damalas, and Thomas Barbas. 2013. “Effects of the Fuel Price Crisis on the Energy Efficiency and the Economic Performance of the European Union Fishing Fleets.” *Marine Policy* 40: 18–24. https://doi.org/10.1016/j.marpol.2012.12.006.

Coello, Jonathan, Ian Williams, Dominic A. Hudson, and Simon Kemp. 2015. “An AIS-Based Approach to Calculate Atmospheric Emissions from the UK Fishing Fleet.” *Atmospheric Environment* 114: 1–7. https://doi.org/10.1016/j.atmosenv.2015.05.011.

Coglan, Louisa, Sean Pascoe, and Richard Harris. 1999. “Measuring Efficiency in Demersal Trawlers Using a Frontier Production Function Approach.” In *Proceedings of the Xth European Association of Fisheries Economists, The Hague, The Netherlands, 1–4 April 1998*, edited by P. (Pavel) Salz, 236–57. Agricultural

Economics Research Institute (LEI).

Colloca, Francesco, Massimiliano Cardinale, Francesc Maynou, Marianna Giannoulaki, Giuseppe Scarcella, Klavdija Jenko, Josè Maria Bellido, and Fabio Fiorentino. 2013. "Rebuilding Mediterranean Fisheries: A New Paradigm for Ecological Sustainability." *Fish and Fisheries* 14: 89–109. https://doi.org/10.1111/j.1467-2979.2011.00453.x.

Council of the EU. 2022. *COUNCIL REGULATION (EU) 2022/110 of 27 January 2022 Fixing for 2022 the Fishing Opportunities for Certain Fish Stocks and Groups of Fish Stocks Applicable in the Mediterranean and Black Seas*. https://doi.org/10.4324/9780429494512-9.

Council of the EU. 2023. *COUNCIL REGULATION (EU) 2023/195 of 30 January 2023 Fixing for 2023 the Fishing Opportunities for Certain Stocks and Groups of Fish Stocks Applicable in the Mediterranean and Black Seas and Amending Regulation (EU) 2022/110 as Regards the Fishing Opportun*.

Dağtekin, Murat, Osman Uysal, Serhan Candemir, and Yaşar Genç. 2021. "Productive Efficiency of the Pelagic Trawl Fisheries in the Southern Black Sea." *Regional Studies in Marine Science* 45. https://doi.org/10.1016/j.rsma.2021.101853.

Driscoll, John, and Peter Tyedmers. 2010. "Fuel Use and Greenhouse Gas Emission Implications of Fisheries Management: The Case of the New England Atlantic Herring Fishery." *Marine Policy* 34: 353–59. https://doi.org/10.1016/j.marpol.2009.08.005.

Eigaard, Ole, R., Francois Bastardie, Nietls T. Hintzen, Lene Buhl-Mortensen, Paul Buhl-Mortensen, Rui Catarino, ... and Adriaan Rijnsdorp. 2017. "The footprint of bottom trawling in European waters: distribution, intensity, and seabed integrity." *ICES Journal of Marine Science* 74 (3): 847-865. https://doi.org/10.1093/icesjms/fsw194.

European Commission. 2009. *Green Paper. Reform of the Common Fisheries Policy. COM(2009) 163.* http://ec.europa.eu/fisheries/reform/com_2011_417_en.pdf.

European Commission. 2023a. "Common Fisheries Policy - State of Play Accompanying the Document COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT AND THE COUNCIL The Common Fisheries Policy Today and Tomorrow: A Fisheries and Oceans Pact towards Sustainable, Science-Based, Innovative and Inclusive Fisheries Management." Brussels.

European Commission. 2023b. COM 101 Implementation of Regulation (EU) No 1379/2013 on the common organisation of the markets in fishery and aquaculture products

Everitt, Brian S., Sabine Landau, Morven Leese, and Daniel Stahl. 2011. *Cluster Analysis*. 5th ed. John Wiley &

Sons, Ltd. https://doi.org/10.1007/BF00154794.

Fall, Massal, Alassane Samba, and Francis Laloë. 2006. “Aquatic Living Resources Fishing Tactics and Strategies in Coastal Demersal Trawling Fisheries in Senegal.” *Aquat. Living Resour* 19 (4): 307–16. https://doi.org/10.1051/alr:2007001.

FAO. 2022. “The State of Mediterranean and Black Sea Fisheries 2022.” *The State of Mediterranean and Black Sea Fisheries 2020*. Rome. https://doi.org/10.4060/cc3370en.

Fiorentini, Loris, Antonello Sala, Kurt Hansen, Giulio Cosimi, and Vito Palumbo. 2004. “Comparison between Model Testing and Full-Scale Trials of New Trawl Design for Italian Bottom Fisheries.” *Fisheries Science* 70: 349–59. https://doi.org/10.1111/j.1444-2906.2004.00813.x.

Flaaten, Ola. 2011. *Fisheries Economics and Management*. University of Tromsø.

Fortibuoni, Tomaso, Otello Giovanardi, Fabio Pranovi, Saša Raicevich, Cosimo Solidoro, and Simone Libralato. 2017. “Analysis of Long-Term Changes in a Mediterranean Marine Ecosystem Based on Fishery Landings.” *Frontiers in Marine Science* 4 (33). https://doi.org/10.3389/FMARS.2017.00033.

Fousekis, Panos, and Stathis Klonaris. 2003. “Technical Efficiency Determinants for Fisheries: A Study of Trammel Netters in Greece.” *Fisheries Research* 63: 85–95. https://doi.org/10.1016/s0165-7836(03)00019-5.

Gambino, Monica, Paolo Accadia, Marco Costantini, Marina Gomei, Loretta Malvarosa, Evelina Carmen Sabatella, and Rosaria Felicita Sabatella. 2022. “Analysis of the Available Funds Supporting Marine Activities in Some Key European Mediterranean Countries.” *Frontiers in Research Metrics and Analytics* 7: 927383. https://doi.org/10.3389/frma.2022.927383.

García Del Hoyo, Juan José, David Castilla Espino, and Ramón Jiménez Toribio. 2004. “Determination of Technical Efficiency of Fisheries by Stochastic Frontier Models: A Case on the Gulf of Cádiz (Spain).” *ICES Journal of Marine Science* 61: 416–21. https://doi.org/10.1016/j.icesjms.2004.02.003.

Giovanardi, Otello, Fabio Pranovi, and Gianluca Franceschini. 1998. “«Rapido» Trawl Fishing in the Northern Adriatic: Preliminary Observations of the Effects on Macrobenthic Communities.” *Acta Adriatica* 39 (1).

Gómez, Sílvia, and Francesc Maynou. 2020. “Economic, Sociocultural and Ecological Dimensions of Fishing Capacity in NW Mediterranean Fisheries.” *Ocean and Coastal Management* 197 (August). https://doi.org/10.1016/j.ocecoaman.2020.105323.

Grati, Fabio, Giuseppe Scarcella, Piero Polidori, Filippo Domenichetti, Luca Bolognini, Roberto Gramolini, ... and Gianna Fabi. 2013. "Multi-annual investigation of the spatial distributions of juvenile and adult sole

(Solea solea L.) in the Adriatic Sea (northern Mediterranean)." *Journal of Sea Research* 84: 122-132. https://doi.org/10.1016/j.seares.2013.05.001.

Greene, William H. 1990. "A Gamma-Distributed Stochastic Frontier Model." *Journal of Econometrics* 46: 141–63.

Greenville, Jared, Jessica Hartmann, and T. Gordon Macaulay. 2006. "Technical Efficiency in Input-Controlled Fisheries: The NSW Ocean Prawn Trawl Fishery." *Marine Resource Economics* 21 (2): 159–79. https://doi.org/10.1086/mre.21.2.42629502.

Guyader, Olivier, and Fabienne Daurès. 2005. "Capacity and Scale Inefficiency: Application of Data Envelopment Analysis in the Case of the French Seaweed Fleet." *Marine Resource Economics* 20: 347–65.

Herrero, Inés, and Sean Pascoe. 2003. "Value versus Volume in the Catch of the Spanish South-Atlantic Trawl Fishery." *Journal of Agricultural Economics* 54 (2): 325–41. https://doi.org/10.1111/j.1477-9552.2003.tb00066.x.

Hilborn, Ray. 2011. "Future Directions in Ecosystem Based Fisheries Management: A Personal Perspective." *Fisheries Research* 108: 235–39. https://doi.org/10.1016/j.fishres.2010.12.030.

IPCC. 2008. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. Edited by H.S. Eggleston, K. Miwa, N. Srivastava, and K. Tanabe. IGES, Japan.

Iriondo, A., R. Prellezo, M. Santurtún, D. García, I. Quincoces, and E. Mugerza. 2010. "A Multivariate Approach for Metier Definition: A Case Study of Basque Country Trawlers." *Revista de Investigación Marina* 17 (6): 139–48.

Jensen, Frank, Max Nielsen, and Hans Ellefsen. 2019. "Defining Economic Welfare in Fisheries." *Fisheries Research* 218 (May): 138–54. https://doi.org/10.1016/j.fishres.2019.05.011.

Jondrow, James, C. A. Knox Lovell, Ivan S. Materov, and Peter Schmidt. 1982. "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model." *Journal of Econometrics* 19 (2–3): 233–38. https://doi.org/10.1016/0304-4076(82)90004-5.

Kirkley, James, and Dale Squires. 2003. *Capacity and capacity utilization in fishing industries*. FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS.

Kirkley, James, Dale Squires, and Ivar E. Strand. 1998. "Characterizing Managerial Skill and Technical Efficiency in a Fishery." *Journal of Productivity Analysis* 9 (2): 145–60. https://doi.org/10.1023/A:1018308617630.

Kumbhakar, Subal C., Hung-Jen Wang, and Alan Horncastle. 2015. *A Practitioner's Guide to Stochastic*

Frontier Analysis Using Stata. *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*. Cambridge University Press. https://doi.org/10.1017/cbo9781139342070.

Kumbhakar, Subal C, and Almas Heshmati. 1995. "Efficiency Measurement in Swedish Dairy Farms: An Application of Rotating Panel Data, 1976-88." *American Journal of Agricultural Economics*. Vol. 77.

Lee, Jihoon, Chun Woo Lee, Songho Park, Jieun Kim, Subong Park, and Taeho Kim. 2018. "Development of a Low-Energy Midwater Trawl with Different Combinations of Trawl Nets and Trawl Doors through Model Experiments." *Fisheries Science* 84: 323–34. https://doi.org/10.1007/s12562-017-1158-1.

Lewy, Peter, and Morten Vinther. 1994. "Identification of Danish North Sea Trawl Fisheries." *ICES Journal of Marine Science* 51: 263–72.

Link, Jason S. 2002. "What Does Ecosystem-Based Fisheries Management Mean?" *Fisheries* 27: 18–21.

Long, Rachel D., Anthony Charles, and Robert L. Stephenson. 2015. "Key Principles of Marine Ecosystem-Based Management." *Marine Policy* 57: 53–60. https://doi.org/10.1016/j.marpol.2015.01.013.

Lucchetti, A., Giada Bargione, Giulio Barone, and Massimo Virgili. 2022. Italian striped venus clam fisheries management: an ecosystem approach to fisheries-like system for the Mediterranean mollusc sector. *Transition towards an ecosystem approach to fisheries in the Mediterranean Sea*, 17.

Lucey, Sean M., and Michael J. Fogarty. 2013. "Operational Fisheries in New England: Linking Current Fishing Patterns to Proposed Ecological Production Units" 141: 3–12. https://doi.org/10.1016/j.fishres.2012.05.002.

Makles, Anna. 2012. "Stata Tip 110: How to Get the Optimal k-Means Cluster Solution." *The Stata Journal* 12 (2): 347–51. http://www.stata-press.com/data/r12/physed.

Marchal, Paul. 2008. "A Comparative Analysis of Métiers and Catch Profiles for Some French Demersal and Pelagic Fleets." *ICES Journal of Marine Science* 65 (4): 674–86. https://doi.org/10.1093/icesjms/fsn044.

Maynou, Francesc. 2014. "Coviability Analysis of Western Mediterranean Fisheries under MSY Scenarios for 2020." *ICES Journal of Marine Science* 71 (7): 1563–71. https://doi.org/10.1093/icesjms/fsu061.

Mazzoldi, Carlotta, Andrea Sambo, and Emilio Riginella. 2014. "The Clodia database: a long time series of fishery data from the Adriatic Sea." *Scientific data* 1 (1): 1-8. DOI: 10.1038/sdata.2014.18.

Meeusen, Wim, and Julien van der Broeck. 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Errors." *International Economic Review* 18: 435–44.

Moore, Claire, Sarah Davie, Marianne Robert, Lionel Pawlowski, Paul Dolder, and Colm Lordan. 2019.

"Defining Métier for the Celtic Sea Mixed Fisheries: A Multiannual International Study of Typology." *Fisheries Research* 219: 105310. https://doi.org/10.1016/j.fishres.2019.105310.

Mulazzani, Luca, Luca Camanzi, Alfonso Bonezzi, and Giulio Malorgio. 2018. "Individual Transferable Effort Quotas for Italian Fisheries? A Preliminary Analysis." *Marine Policy* 91: 14–21. https://doi.org/10.1016/j.marpol.2018.01.033.

Mundlak, Yair. 1961. "Empirical Production Function Free of Management Bias." *Journal of Farm Economics* 43 (1): 44–56. https://doi.org/https://doi.org/10.2307/1235460.

Nguyen, Bao Hoang, Robin C. Sickles, and Valentin Zelenyuk. 2022. "Efficiency Analysis with Stochastic Frontier Models Using Popular Statistical Softwares." In *Advances in Economic Measurement*, 129–71. Singapore: Palgrave Macmillan. https://doi.org/https://doi.org/10.1007/978-981-19-2023-3_3.

Nguyen, Quang Van, Sean Pascoe, and Louisa Coglan. 2019. "Implications of Regional Economic Conditions on the Distribution of Technical Efficiency: Examples from Coastal Trawl Vessels in Vietnam." *Marine Policy* 102 (February): 51–60. https://doi.org/10.1016/j.marpol.2019.01.016.

NISEA. 2022a. "Impatto Economico Dell ' Incremento Del Costo Del Gasolio Sulla Flotta Peschereccia Italiana."

———. 2022b. "Rapporto Sull'andamento Economico Della Flotta Italiana per Regione."

Parente, Joaquim, Paulo Fonseca, Victor Henriques, and Aida Campos. 2008. "Strategies for Improving Fuel Efficiency in the Portuguese Trawl Fishery." *Fisheries Research* 93: 117–24. https://doi.org/10.1016/j.fishres.2008.03.001.

Park, Jeong A., Caleb Gardner, Myo In Chang, Do Hoon Kim, and Young Soo Jang. 2015. "Fuel Use and Greenhouse Gas Emissions from Offshore Fisheries of the Republic of Korea." *PLoS ONE* 10 (8): 1–12. https://doi.org/10.1371/journal.pone.0133778.

Parker, Robert W.R., Julia L. Blanchard, Caleb Gardner, Bridget S. Green, Klaas Hartmann, Peter H. Tyedmers, and Reg A. Watson. 2018. "Fuel Use and Greenhouse Gas Emissions of World Fisheries." *Nature Climate Change* 8: 333–37. https://doi.org/10.1038/s41558-018-0117-x.

Pascoe, Sean, Jesper Levring Andersen, and Jan Willem De Wilde. 2001. "The Impact of Management Regulation on the Technical Efficiency of Vessels in the Dutch Beam Trawl Fishery." *European Review of Agricultural Economics* 28 (2): 187–206. https://doi.org/10.1093/erae/28.2.187.

Pascoe, Sean, and Louisa Coglan. 2000. "Implications of Differences in Technical Efficiency of Fishing Boats for Capacity Measurement and Reduction." *Marine Policy* 24 (4): 301–7. https://doi.org/10.1016/S0308-

597X(00)00006-3.

———. 2002. “The Contribution of Unmeasurable Inputs to Fisheries Production: An Analysis of Technical Efficiency of Fishing Vessels in the English Channel.” *American Journal of Agricultural Economics* 84 (3): 585–97. https://doi.org/10.1111/1467-8276.00321.

Pascoe, Sean, Parastoo Hassaszahed, Jesper Anderson, and Knud Korsbrekke. 2003. “Economic versus Physical Input Measures in the Analysis of Technical Efficiency in Fisheries.” *Applied Economics* 35 (15): 1699–1710. https://doi.org/10.1080/0003684032000134574.

Pascoe, Sean, and Catherine Robinson. 1998. “Input Controls, Input Substitution and Profit Maximisation in the English Channel Beam Trawl Fishery.” *Journal of Agricultural Economics* 49 (1): 16–33.

Pascoe, Sean, and Diana Tingley. 2007. “Capacity and Technical Efficiency Estimation in Fisheries: Parametric and Non-Parametric Techniques.” In *Handbook of Operations Research in Natural Resources*, 273–94. Springer.

Prado, J. 1990. *Fisherman’s Workbook*. Fao, Fishing News Books.

Pranovi, F., S. Raicevich, G. Franceschini, P. Torricelli, and O. Giovanardi. 2001. “Discard Analysis and Damage to Non-Target Species in the ‘Rapido’ Trawl Fishery.” *Marine Biology* 139: 863–75. https://doi.org/10.1007/s002270100646.

Pranovi, Fabio, Marco Anelli Monti, Alberto Caccin, Daniele Brigolin, and Matteo Zucchetta. 2015. “Permanent Trawl Fishery Closures in the Mediterranean Sea: An Effective Management Strategy?” *Marine Policy* 60: 272–79. https://doi.org/10.1016/j.marpol.2015.07.003.

Reid, Christopher, Dale Squires, Yongil Jeon, Len Rodwell, and Raymond Clarke. 2003. “An Analysis of Fishing Capacity in the Western and Central Pacific Ocean Tuna Fishery and Management Implications.” *Marine Policy* 27 (6): 449–69. https://doi.org/10.1016/S0308-597X(03)00065-4.

Russo, Elisabetta. 2020. “Spatial and Temporal Dynamics of Trawl Fishing Activities in the Northern and Central Adriatic Sea (GSA 17) Analysed by Using Automatic Identification System (AIS) Data.” Università Ca’ Foscari Venezia.

Russo, Elisabetta, Marco Anelli Monti, M Cristina Mangano, Alessandra Raffaetà, Gianluca Sarà, Claudio Silvestri, and Fabio Pranovi. 2020. “Temporal and Spatial Patterns of Trawl Fishing Activities in the Adriatic Sea (Central Mediterranean Sea, GSA17).” *Ocean and Coastal Management* 192: 105231. https://doi.org/10.1016/j.ocecoaman.2020.105231.

Russo, Tommaso, Paolo Carpentieri, Lorenzo D’Andrea, Paola De Angelis, Fabio Fiorentino, Simone

Franceschini, Germana Garofalo, et al. 2019. “Trends in Effort and Yield of Trawl Fisheries: A Case Study from the Mediterranean Sea.” *Frontiers in Marine Science* 6 (APR): 1–19. https://doi.org/10.3389/fmars.2019.00153.

Sabatella, Rosaria Felicita, Paolo Accadia, Maria Cozzolino, Monica Gambino, Loretta Malvarosa, and Evelina Carmen Sabatella. 2020. "Socio-Economic Impacts of the Common Fisheries Policy on South and Central Tyrrhenian Sea (GSA 10) Demersal Trawl Fisheries." In *New Metropolitan Perspectives: Knowledge Dynamics, Innovation-driven Policies Towards the Territories' Attractiveness Volume 1* (pp. 143-154). Springer International Publishing.

Sabatella, Evelina C., Francesco Colloca, Gianluigi Coppola, Fabio Fiorentino, Monica Gambino, Loretta Malvarosa, and Rosaria Sabatella. 2017. “Key Economic Characteristics of Italian Trawl Fisheries and Management Challenges.” *Frontiers in Marine Science* 4 (371). https://doi.org/10.3389/fmars.2017.00371.

Sala, Antonello, Francesco De Carlo, Gabriele Buglioni, and Alessandro Lucchetti. 2011. “Energy Performance Evaluation of Fishing Vessels by Fuel Mass Flow Measuring System.” *Ocean Engineering* 38: 804–9. https://doi.org/10.1016/j.oceaneng.2011.02.004.

Sala, Antonello, Dimitrios Damalas, Lucio Labanchi, Jann Martinsohn, Fabrizio Moro, Rosaria Sabatella, and Emilio Notti. 2022. “Energy Audit and Carbon Footprint in Trawl Fisheries.” *Scientific Data* 9 (428). https://doi.org/10.1038/s41597-022-01478-0.

Sánchez Lizaso, José Luis, Ivan Sola, Elena Guijarro-García, José Maria Bellido, and Ramón Franquesa. 2020. “A New Management Framework for Western Mediterranean Demersal Fisheries.” *Marine Policy* 112 (February): 103772. https://doi.org/10.1016/J.MARPOL.2019.103772.

Sangün, Levent, Osman İnanç Güney, and Ali Berk. 2018. “Economic Efficiency Performance of Small-Scale Fisheries in the East Mediterranean Coast of Turkey.” *New Medit* 17 (4): 71–80. https://doi.org/10.30682/nm1804f.

Solís, Daniel, Larry Perruso, Julio del Corral, Brent Stoffle, and David Letson. 2013. “Measuring the Initial Economic Effects of Hurricanes on Commercial Fish Production: The US Gulf of Mexico Grouper (Serranidae) Fishery.” *Natural Hazards* 66: 271–89. https://doi.org/10.1007/s11069-012-0476-y.

Spagnolo, Massimo. 2007. "The decommissioning scheme for the Italian clam fishery: a case of success." In *Fisheries buybacks*, 133-144.

Spagnolo, Massimo. 2010. "Shared rules for a shared sea: multilevel fisheries governance in Italian fisheries management." In *Handbook of marine fisheries conservation and management*, 415-425.

Squires, Dale. 1987. “Fishing Effort: Its Testing, Specification, and Internal Structure in Fisheries Economics and Management.” *Journal of Environmental Economics and Management* 14: 268–82.

Squires, Dale, and James Kirkley. 1999. “Skipper Skill and Panel Data in Fishing Industries.” *Canadian Journal of Fisheries and Aquatic Sciences* 56: 2011–18. https://doi.org/10.1139/f99-135.

STECF. 2022. *The 2022 Annual Economic Report on the EU Fishing Fleet (STECF 22-06)*. Edited by R. Prellezo, E. Sabatella, J. Virtanen, and J. Guillen. Luxembourg. https://doi.org/10.2760/120462.

Suuronen, Petri, Francis Chopin, Christopher Glass, Svein Løkkeborg, Yoshiki Matsushita, Dante Queirolo, and Dominic Rihan. 2012. “Low Impact and Fuel Efficient Fishing-Looking beyond the Horizon.” *Fisheries Research* 119–120: 135–46. https://doi.org/10.1016/j.fishres.2011.12.009.

Symes, David. 2014. “Finding Solutions: Resilience Theory and Europe’s Small-Scale Fisheries.” In *Social Issues in Sustainable Fisheries Management*, 23–41. Dordrecht: Springer.

Valle, Ikerne Del, Inmaculada Astorkiza, and Kepa Astorkiza. 2003. “Fishing Effort Validation and Substitution Possibilities among Components: The Case Study of the VIII Division European Anchovy Fishery.” *Applied Economics* 35 (1): 63–77. https://doi.org/10.1080/00036840210158949.

Vázquez-Rowe, Ian, and Peter Tyedmers. 2013. “Identifying the Importance of the ‘Skipper Effect’ within Sources of Measured Inefficiency in Fisheries through Data Envelopment Analysis (DEA).” *Marine Policy* 38: 387–96. https://doi.org/10.1016/j.marpol.2012.06.018.

Williams, Erik H., and Stephen Ralston. 2002. “Distribution and Co-Occurrence of Rockfishes (Family: Sebastidae) over Trawlable Shelf and Slope Habitats of California and Southern Oregon.” *Fishery Bulletin* 100 (4): 836–55.

Yang, Chenxing, Xiaobo Lou, Takahiro Matsui, and Junbo Zhang. 2017. “Evaluating the Technical Efficiencies of Fishing Vessels to Achieve Effective Management of Overexploited Fisheries.” *Mitigation and Adaptation Strategies for Global Change* 22: 1149–62. https://doi.org/10.1007/s11027-016-9719-7.

Declaration of interests

☒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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Author statement

Alberto Ceccacci: Conceptualization, Methodology, Formal Analysis, Writing – original draft, Writing – review & editing, Visualization. **Elisabetta Russo**: Methodology, Writing – original draft, Writing – review & editing. **Luca Mulazzani**: Writing – review & editing, Supervision. **Giulio Malorgio**: Writing – review & editing, Supervision.