Overcapacity and dynamics of a tuna fleet facing catch limits and high efficiency: The case of the Indian Ocean tuna fishery

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Overcapacity and dynamics of a tuna fleet facing catch limits and high efficiency: The case of the Indian Ocean tuna fishery

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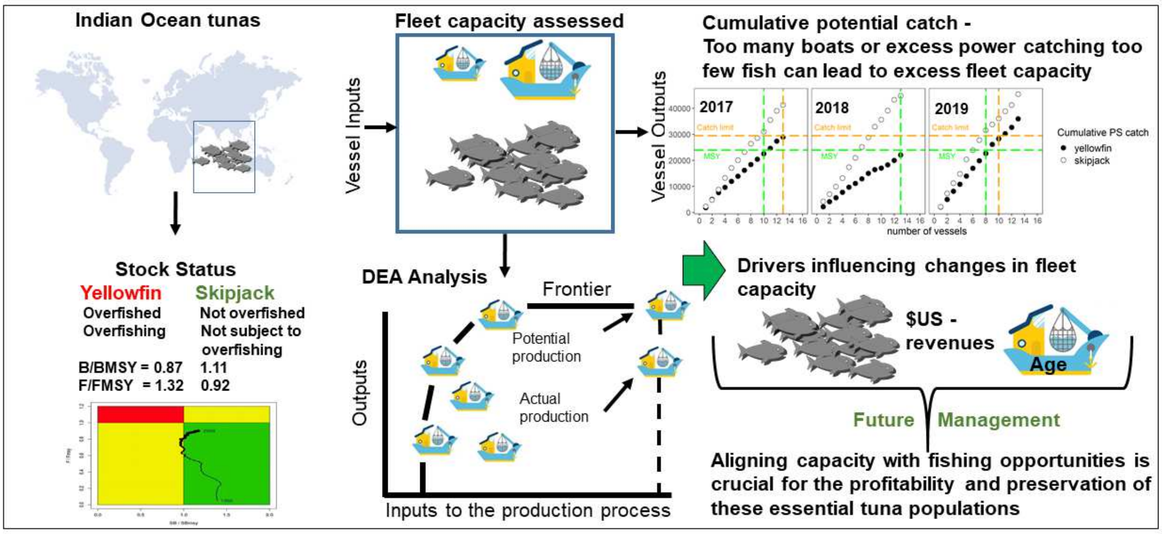
Abstract:

The Indian Ocean Tuna Commission (IOTC) expresses concern over the overfished state and susceptibility to the overfishing of yellowfin tuna (*Thunnus albacares*). Acknowledging the challenges of increased fishing effort in a profitable fishery, our study aims to understand factors influencing French purse seine fishing vessel dynamics. Our primary goal is to assess purse seine vessel utilisation with recent catch limits and compliance with the European Union Common Fisheries Policy (CFP), which mandates measures to align fishing capacity with opportunities to sustain fish stocks at maximum sustainable yield (MSY). Using Data Envelopment Analysis, we evaluate the relationship between vessel fishing capacity to catch limits and the MSY reference point for yellowfin tuna. Random Utility Models identify key drivers influencing the fleets' strategic decisions, rigorously assessed with a machine-learning algorithm. Findings indicate that the French fleet could meet catch limits with approximately 21% fewer vessels if fully utilised and 26% fewer if reduced to meet their equivalent MSY share. Key influencing factors include catch revenue, vessel age, biomass levels, and interest rates. The predictive model achieves a 93% accuracy rate, essential for effectively implementing regional conservation policies that balance economic stakes with sustainable fishing practices. Aligning capacity with fishing opportunities is crucial for the profitability and preservation of these essential tuna populations, resulting in more sustainable and economically viable fisheries.

Graphical abstract:



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Competing interests and ethics

The authors declare that they have no competing financial or non-financial interests that could have influenced the work reported in this paper and that the research does not involve any human participants and/or animals.

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Data availability

The data supporting this study's findings are available from the corresponding authors upon reasonable request and with the permission of IRD.

Author contribution

Conceived and designed the experiments: Alex Tidd. The experiments were performed by Alex Tidd. Analysed the data: Alex Tidd. Contributed reagents/materials/analysis tools: Alex Tidd, Patrice Guillotreau, Laurent Dagorn. Wrote the paper: Alex Tidd, Manuela Capello, Patrice Guillotreau, Laurent Dagorn.

1. Introduction

Since the early 1990s, excessive fishing capacity has surged due to a decade of fleet expansion and technological advancements in the high seas (Newton and Greboval 1999, Watson and Tidd 2018), impacting fisheries globally (Rousseau et al. 2019). This phenomenon is attributed to inadequate management (Ye and Gutierrez 2017), subsidies (Sumaila et al. 2021), and high-seas access to foreign fisheries (Tickler et al. 2018). According to Hilborn et al. (2020), excess fishing pressure results in about a 3-5% loss in potential yields from 50% of the world's potential catch, leading to overfishing in many fish stocks (FAO 2018). A highly efficient fleet facing catch limits (i.e., quotas) may also result in endogenous overcapacity, representing an economic waste of financing resources that could be invested more usefully in other fisheries or other sectors (Rust et al. 2016). Technical efficiency comes from the optimal use of inputs to produce a given quantity of output moving along the production frontier (the maximum level that can be produced using the available inputs), while technical change corresponds to a shift of the production frontier itself (higher output level with the same amount of inputs). The mixture of both, particularly present in high seas fisheries where the digital detection power of fish by larger vessels has increased tremendously, may result in excessive capacity (Tidd et al. 2023a). The excessive capacity can appear even more clearly when a total allowable catch is introduced in the fishery (Felthoven 2002). Conversely, well-managed stocks can show significant improvements, highlighting the potential for recovery and thus solving the overcapacity problem (Hilborn et al. 2020).

Managing tuna fisheries is complex due to the migratory behaviour of tunas which is influenced by environmental conditions, making it accessible to different fishing fleets and countries (Erauskin-Extramiana et al. 2023). This complexity poses political challenges, involving multiple participants with access rights across EEZ frontiers and the high seas, creating intricate interactions among coastal countries and distant water fishing nations (Sinan and Bailey 2020, Sinan et al. 2021). This is particularly true in the Indian Ocean, where a significant proportion of tuna is caught in the high seas by the purse-seine fleet, potentially affecting the available biomass for other fisheries. The Indian Ocean (IO) stands out as a significant tuna fishery, contributing around 20% of global tuna catches and 30% of the world's yellowfin tuna catch (Lecomte et al. 2017), valued at $US16 billion in 2018 (Pew 2020). This fishery primarily targets skipjack (*Katsuwonus pelamis*), yellowfin (*Thunnus albacares*), and bigeye (*Thunnus obesus*) tuna in tropical and subtropical waters near the equator. The IO industrial purse seine (PS) fleet, dominated by around forty-six vessels, mainly from the European Union (EU, Spain and France), Seychelles, Mauritius, and South Korea, plays a pivotal role. These vessels, averaging around 90m in length and over 2,800t in gross tonnage (IOTC 2022) (Figure 1), collectively account for one-third of the IO's tuna catch (Lecomte et al. 2017), 27% of the total yellowfin catch, and 40% of the total skipjack catch in 2020 (IOTC.org, accessed 11/01/24 link). Specifically, the French PS fleet, a significant contributor, focuses on skipjack (53% of its catch) and yellowfin (43% on average over the past decade) using both free-school and drifting fish aggregation devices (DFAD) fishing strategies, with bigeye making up a smaller proportion (4%) (Floch et al. 2021). This underscores the fleet's crucial role in the IO tuna fishery and the global tuna market.

Tuna fisheries management uses Maximum Sustainable Yield (MSY) indicators, SB_{MSY} and F_{MSY}, as policy targets, where F_{MSY} is the fishing mortality that provides MSY and SB_{MSY} the reference point of the spawning biomass to achieve MSY. Within the Indian Ocean (IO) tuna fishery, one particularly pressing issue is the decline in yellowfin tuna stock biomass levels (ISSF 2023). In 2023, yellowfin tuna was considered overfished ($SB < SB_{MSY}$) and subject to overfishing ($F > F_{MSY}$) (*Ibid.*) with a 68% probability. Responding to these concerns and failed attempts to limit effort and maintain stocks at target levels (Aranda et al. 2012, the Indian Ocean Tuna Commission (IOTC) implemented an interim rebuilding plan for yellowfin tuna in 2016. This plan aimed for a twenty per cent reduction in yellowfin catches compared to the 2014 levels (IOTC Resolution 16/01, superseded by Res. 17/01, then by Res. 18/01, 19/01 and 21/01). The overarching objective was to facilitate the recovery of stocks, ensuring they surpass interim target reference points by 2024 with a fifty per cent probability (IOTC 2015). Scientists consider the catch level at MSY to be 349 kilo-tonnes but the current catch level exceeds 430 kilo-tonnes because the same limits do not bind several countries. Those contracting parties harvesting less than 5,000t or having objected to resolution 21/01 (e.g., India, Oman, Somalia, Indonesia, Iran, Madagascar) are no longer bound to it but refer to previous resolutions.

The status of yellowfin tuna stocks remains a cause for significant concern, characterised by both overfishing F / F_{MSY}=1.32 and being overfished SB / SB_{MSY}=0.87 (www.iotc.org, accessed 11/01/24 link). This heightened concern has engaged various stakeholders (Sinan et al. 2021), amplifying the urgency for collective efforts and strategic management. The primary apprehensions stem from DFADs and the high efficiency of purse seine (PS) vessels, particularly in capturing the juvenile segment of the yellowfin population (Fonteneau et al. 2013). Recent studies have highlighted shifts in efficiency within the tuna PS fleet, demonstrating how input controls such as a reduction in the number of DFAD sets and a DFAD seasonal closure can positively impact future spawning stock biomass and catch levels (Tidd et al. 2023a and 2023b, Guillotreau et al. 2024).

The absence of regulatory measures, such as limits on vessel number/power and size adjustments for efficiency, threatens stock sustainability. The distinct status of other tuna species within the same fishery, like skipjack tuna, is not yet subject to overfishing (www.IOTC.org, accessed 11/01/24). This complicates capacity management due to quota limits implemented on yellowfin and bigeye tunas only. Sustaining an efficient management program without constraining capacity is challenging, as the lack of more stringent measures could lead to reduced catch per vessel, economic pressures, and excess fishing capacity. Excess capacity, defined as anything beyond the inputs required to catch a desired quantity of fish, results in economic waste and increases overfishing risks. While excess fishing capacity does not always result in overexploitation, overfishing is more likely to occur when limitations are not well-adjusted or unprofitable. Fishing capacity can become underutilised, making excess capacity more of an economic problem than a resource conservation issue (Pascoe and Gréboval 2003).

This study employs Data Envelopment Analysis (DEA) to evaluate the technical efficiency of the fleet, which is a well-known and robust approach in fisheries economics (Kirkley et al. 2001, Felthoven 2002, Pascoe and Greboval 2003, Vázquez-Rowe and Tyedmers 2013, Tidd et al. 2023a). Our original contribution lies first in estimating the relationship between vessel fishing capacity, the recent catch limit introduced in the Indian Ocean tuna fishery, and the estimated allowable catch if the fleet were to fish at MSY. In line with EU member states' commitment to end overfishing by 2020 (EU 2013), the Common Fisheries Policy (CFP) mandates measures to ensure that fishing capacity corresponds to opportunities, with a legally binding objective to maintain fish stocks at MSY levels. Our analysis explicitly examines the link between the French fleet's fishing capacity and MSY, emphasising the alignment between capacity management and sustainable yield goals applicable to EU and third-country waters. Our approach compares the performance of each vessel against others within a given year based on the catch of yellowfin and skipjack tuna relative to the potential output if all vessels operated optimally. The evaluated ratio represents the average level of capacity utilisation for the fleet and a specified set of inputs. The process above accounts for changes in stock productivity, fishing strategies, innovations and fisheries management policies.

Another original dimension of this study combines technical efficiency and capacity utilisation results with the dynamics (i.e., entry/exit strategic behaviour) of the French PS fleet through a random utility model. We hypothesise that vessels' exit strategies are more likely to occur after phases of declining efficiency and capacity utilisation. Such evidence would provide valuable insights for regional stakeholders to shape long-term policies that balance capacity with fishing opportunities. As various authors emphasised (Hilborn and Walters 1992, Fulton et al. 2011), successful fisheries management necessitates a comprehensive understanding of economic expectations, fish stock size, landing values, license availability, and some external factors. In that regard, predictive models of vessels' strategic behaviour are useful to fisheries managers to anticipate the dynamics of fishing capacity and effort. To ensure the accuracy of such predictions, we cross-validate our strategic behavioural model using a machine-learning approach.

2. Methods

2.1 The dataset

The annual data for the French PS fleet operating in the IO between 1992 and 2019 was obtained from the French Observatory of Exploited Tropical Pelagic Ecosystems (Ob7) fleet registry. This registry provides comprehensive information on various vessel characteristics, including age, gross registered tonnage (t), overall vessel length (m), and engine power (kW). The dataset includes logbook details on catches of yellowfin and skipjack tunas and the total number of sets/days at sea per year for each vessel.

To complement vessel-specific information, ex-vessel price data per metric tonne ($US) for the main target species, skipjack and yellowfin tuna, were obtained from Sovetco, the French trading company selling most of the French-caught frozen tuna and inflation-adjusted to 2015 by the OECD production price index. Additionally, fuel prices as price per barrel ($US) inflation-adjusted to 2015 from the Seypec (Seychelles Petroleum Company) (Dollars per Barrel). Furthermore, information on interest rates from the Organisation for Economic Co-operation and Development (OECD) was obtained (Interest Rates - Long-term Interest Rates - OECD Data." *The OECD*, accessed 17/12/23 link). Total spawning stock biomass for skipjack/yellowfin tuna in tonnes was acquired from the Indian Ocean Tuna Commission (IOTC - www.iotc.org). These diverse datasets were amalgamated by year, creating a comprehensive database for subsequent analysis and exploration.

2.2 Data Envelopment Analysis

Data Envelopment Analysis (DEA) stands as a non-parametric technique (Farrell 1957, Charnes et al. 1978), applicable for gauging the potential output of a Decision-making unit (DMU) for a given set of inputs, DMU being a fishing vessel in this context. The methodology assumes that the production function, delineating how outputs vary with inputs, is unknown. It systematically compares each DMU against all others (Cooper et al. 2000). The fundamental objective is identifying the "frontier" or envelope, which signifies the most efficient combination of inputs to produce the highest output level for the specific DMU (Greene 1993). DMUs with similar characteristics are supposed to achieve an identical output level in a scenario where all else is equal. A DMU positioned on the frontier is assigned a score of one, denoting efficiency. Conversely, a DMU with equivalent characteristics but a lower output is deemed inefficient and gives a score of less than one, indicating inefficiency. The process is deterministic, generating an efficiency score for each DMU.

In the case of fisheries, DMU's inputs are a combination of fixed and variable effort features. Fixed inputs encompass vessel engine power, gross tonnage, and overall length, representing vessel capital stock (only one was selected due to their positive correlation). Variable inputs may include factors like the number of days fished and the number of sets on DFADs and free schools within a year. The two outputs in focus correspond to each vessel's annual catches of yellowfin and skipjack tuna summed separately, measured in tonnes. DEA efficiency scores are computed annually for each vessel within the French purse seine (PS) fleet at that specific time. Therefore, it is unnecessary to include stock biomass or a metric of technological change, as each vessel is essentially fishing on the same biomass using equivalent technology.

2.3 Technical efficiency (TE)

Technical efficiency refers to the relative effectiveness of a fisher or vessel in utilising and combining its inputs to produce an output, considering the production frontier, which represents the most efficient vessels (i.e., benchmarks) in the fleet. We evaluated the technical efficiency score scalar, θ_1, describing the extent to which the catch (production) of each vessel (j) can increase for a given specific quantity of inputs ($x_{j,n}$). These inputs (n) include both fixed factors (such as vessel overall length in meters) and variable factors (number of fishing days). The outputs for each species (m) (yellowfin and skipjack), $y_{j,m}$ for each vessel j, referred to as the decision-making unit - DMU, are measured in terms of the efficient combination leading to a maximum output level (catch by species). Here, J denotes the total number of vessels. The calculation of relative efficiency employs an output-oriented distance function (Färe et al. 1993, Tingley and Pascoe 2005):

$$Max\ \theta_1$$

subject to,

$$\theta_1 y_{j,m} \leq \sum_{j=1}^{J} z_j y_{j,m} \qquad \forall\, m$$

$$\sum_{j=1}^{J} z_j x_{j,n} \leq x_{j,n} \qquad \forall\, n,$$

$$\sum_{j=1}^{J} z_j = 1$$

$$z_j \geq 0 \qquad \forall\, j, \tag{1}$$

The variable z_j is a weighting factor for vessel *j,* the right-hand side of the first line in Eq. (1), representing a weighted sum of all vessel outputs within the year, including the vessel itself. This factor quantifies the optimal linear combination of frontier observations, determining the optimal performance of the specific decision-making unit (DMU) under consideration or the distance to the frontier. Each vessel is individually assessed for the value of θ_1, where the DMU $\theta_1 y_{j,m}$ outputs, and inputs are denoted by $x_{j,n}$.

The technically efficient output is determined by the production (observed catch of each tuna species) multiplied by a scalar, θ_{1m}, signifying the extent to which each output of the DMU can be increased relative to the efficient frontier of a group of DMUs within a year.

When determining technical efficiency in the context of Data Envelopment Analysis (DEA), certain assumptions regarding 'returns to scale' —whether constant (CRS) or variable (VRS)— are crucial, as they directly impact the efficiency score. CRS implies that an increase in input results in a proportional increase in output.

On the other hand, VRS assumes that vessels operate within a framework of variable returns, which is particularly relevant when all DMUs are not functioning at their optimal size. In our analysis, we adopt the assumption of variable returns to scale (VRS) $\sum_{j=1}^{J} z_j = 1$, acknowledging that the change in output may be more significant than, equal to, or less than the change in input—a perspective widely embraced in fisheries economics, denoting non-constant returns to scale (Cooper et al. 2000).

The calculation of technical efficiency (Eq. 1) for each PS vessel during a given year follows this formulation:

$$\mathrm{TE} = \frac{1}{\theta_1} \tag{2}$$

The vessels that exhibit the highest level of technical efficiency operate precisely along the frontier boundary (TE $= 1$). Conversely, less efficient vessels operate within this boundary. As a result, they possess a technical efficiency (TE) score value of less than 1.

2.4 Capacity Utilisation (CU) and Unbiased Capacity utilisation (UCU)

Capacity utilisation (CU) measures how effectively vessels utilise their fixed inputs in terms of actual output compared to the maximum output achievable with those fixed inputs, I.e., capacity. This metric is valuable for understanding vessels' operational efficiency concerning their fixed production factors in the short run. When estimating TE in (Eq.2), the assumption is that the variable inputs (days fished) remain constant at their observed levels. Conversely, when calculating the Capacity utilisation CU (Eq.3), the assumption is that a vessel can adjust its variable inputs, such as the number of days engaged in its activities, to enhance its outputs.

This adjustment allows variable inputs to be fully utilised while keeping outputs constrained by the fixed inputs ($n \in \alpha$) (see Eq.3), such as the vessel length. In this scenario, the fixed input and vessel length remain constant, and the model calculates the capacity utilisation by employing a structure similar to Eq 1. However, in Eq 3, the bounds of the sub-vector of variable inputs $n \in \hat{\alpha}$ are relaxed, allowing these inputs to vary freely. Here, $\lambda_{j,n}$ represents the input utilisation rate by vessel *j* of fixed input *n*. The underlying assumption is that the capacity output (catch level) $\theta_2 y_{j,m}$ remains constant. However, the capacity level can increase through various applications of the variable inputs (Tingley and Pascoe 2005) (see Eq.3):

$$Max\ \theta_2$$

subject to,

$$\theta_2 y_{j,m} \leq \sum_{j=1}^{J} z_j y_{j,m} \qquad \forall\, m$$

$$\sum_{j=1}^{J} z_j x_{j,n} \leq x_{j,n} \quad n \in \alpha,$$

$$\sum_{j=1}^{J} z_j x_{j,n} \leq \lambda_{j,n} x_{j,n} \quad n \in \hat{\alpha},$$

$$\sum_{j=1}^{J} z_j = 1$$

$$z_j \geq 0 \qquad \lambda_{j,n} \geq 0 \qquad n \in \hat{\alpha}$$

(3)

The scalar $\theta_2 \geq 1$ represents the extent to which each Decision-Making Unit's (DMU) output can be augmented concerning the efficient frontier of a group of DMUs within a year. The calculation of Capacity Utilisation (CU) in Eq 4 for each PS vessel during a given year is expressed as follows:

$$\mathrm{CU} = \frac{1}{\theta_2} \tag{4}$$

Similar to TE, CU also ranges between 0 and 1. However, the CU measure may exhibit a negative bias because the observed output might not necessarily be produced in a technically efficient manner, as indicated by TE in Eq 1. Deviations between TE and fishing capacity may occur due to inefficiency or underutilisation. Consequently, it becomes imperative to disentangle these effects and estimate Unbiased Capacity Utilisation (UCU). Correcting this bias involves combining results from the technical efficiency metric (Eq 1 and 2) and the capacity utilisation metric (Eq 3 and 4) to give Eq 5.

$$\mathrm{UCU} = \mathrm{CU}/\mathrm{TE} \tag{5}$$

The DEA linear programming analysis, created and executed using the R software benchmarking tool (Bogetoft 2005), was employed to conduct the analysis above.

The DEA analysis calculates the relative performance of vessels compared to the 'optimally performing' vessel within a given year. Recognising that vessels phased out over time are likely to be the least efficient, and that newer vessels potentially exhibit better performance, the overall fleet should become closer to its optimal level. The UCU outputs of the DEA were then used to estimate the potential output for a fleet comprised entirely of highly effective vessels, i.e., the ones with the highest unbiased capacity utilisation, thereby pinpointing potential capacity levels concerning the yellowfin catch limit. For each year between 2013 and 2019, we utilise UCU to analyse the annual fleet sizes of French purse seiners (PS) and estimate the corresponding species catch that an 'optimally performing' fleet would attain concerning the yellowfin national catch limit set at 29,501 tonnes which was implemented in 2017 and the equivalent French PS catch share of fishing at MSY ~ 23,943. To illustrate, we examine years before 2017 when no catch limit existed and note that before 2013, the stock remained within safe biological limits ($SB > SB_{MSY}$ and $F < F_{MSY}$). Post-2012 marked the onset of overfishing. A vessel's skipjack and yellowfin catch in a given year is arranged in descending order based on its UCU. The potential catch is calculated as the ratio of yellowfin catch to UCU and skipjack catch to UCU. We track the sequential cumulative catch of yellowfin until it reaches the catch limit 2017 to 2019 and 2013 to 2019, the catch at MSY share for the French fleet, summing up the individual vessels identified in the process. This methodology aids in determining the number of optimally performing vessels within the fleet.

2.5 Entry-exit variable choice

The economic literature suggests that fishers base their strategic decisions on various factors, including expectations about changing stock biomass levels (Asche et al. 2008), regulatory frameworks, market fish prices (*Ibid.*), interest rates influencing investment and disinvestment (Anderson 2007, Nøstbakken et al. 2011, Jensen et al. 2012), or fuel costs (Abernethy et al. 2010). While individual vessel cost data would be ideal for a comprehensive investment model, such detailed data is often unavailable. Consequently, several surrogate variables were utilised, with value as a proxy for economic viability and fuel costs representing a proxy for variable costs.

Additionally, the vessel's age was included in the analysis, as older vessels may exit the fleet due to higher maintenance and operational costs, while newer vessels may enter. Interest rates were incorporated into the database to capture the discount rate used for investment and financing decisions. Fishers would not enter or exit the fishery immediately in response to a change in interest rates because of delivery time after a new vessel order but as a strategic decision based on the average annual rate in the previous year, considering that a change in interest rates could affect investment strategies within the fleet (Jensen et al. 2012). For example, if interest rates are low, having capital in the fishery is cheaper, so they stay. Likewise, the stock status for yellowfin and skipjack was lagged. Low spawning stock biomass was assumed to correlate with exit decisions, primarily as the yellowfin catch limit is based on the previous year's catch. Collectively, these variables provide a framework for understanding the complex decision-making process of fishers in response to diverse ecological, economic and market dynamics.

2.6 Entry-exit model description

In the model, the capacity of the fishing fleet is directly influenced by the decisions of individual vessels to enter, stay or exit the fleet. This decision-making process is modelled using the random utility methodology, following the approach outlined in previous studies (e.g., Prellezo et al. 2009, Tidd et al. 2011). Random Utility Models (RUMs), which underlie this methodology, are distinctive in their ability to model discrete decisions without necessitating the assumption of homogeneity among individuals.

RUMs work on the premise that utility, representing the perceived satisfaction or desirability of a choice, drives individual decision-making. This utility comprises deterministic and stochastic components, introducing randomness into the model. The stochastic element acknowledges individual decision processes' inherent variability and unpredictability, hence the term "random" utility model. By incorporating these features, RUMs provide a flexible and nuanced framework for capturing the complex choices made within the fishing fleet. The utility (U) of alternative i is defined as a linear combination of a set of explanatory variables (wi) representing observed individual characteristics, where for a given individual time-event, i, such as vessel exit decisions, a choice j (1 or 0) is made. Where β_j is a vector of parameters for choices j. These characteristics collectively constitute the non-random components of the utility alongside a stochastic error component ε_{ij}. Mathematically expressed as (Eq 6):

$$U_{ij} = \beta_j \, w_i + \varepsilon_{ij} \tag{6}$$

The probability that an individual i makes choice j;

$$Prob_i \, (j) = \frac{exp \, (w_{i\beta_j})}{\sum_{j=1}^{J} exp \, (w_{i\beta_j})} \tag{7}$$

The discrete choice dependent variable j is a polytomous variable parametrised yearly. It takes on unique values of 'entry,' 'exit,' or 'stay' in the PS fishery. Below is an explanation of the choice variables:

i. 'Entry': A French PS vessel is considered to have 'entered' the IO fishery if it joins for the first time during the study period. The vessel can re-enter in another year if it temporarily exits under the French flag for operational reasons. Note that an entry may correspond to a newly built vessel joining the fleet for the first time or an existing vessel from other oceans purchased or moved by a French-flagged company.

ii. 'Exit': A French PS vessel marked with 'exit' is currently part of the fleet but can permanently or temporarily leave during the study period for various reasons (it can be sold, moved to another ocean or decommissioned). However, it may re-enter the fishery in subsequent years. Note that a vessel may have exited from the French flagship but sold or re-flagged and still operate in the IO — these vessels are not further tracked in the analysis.

iii. 'Stay': A French PS vessel designated as 'stay' refers to the period between entering and exiting years. The first year (1992) and the last year (2019) are categorised as 'stay' due to the unavailability of information from the pre- or post-study years.

These categories comprehensively represent the dynamic choices made by individual vessels within the purse seine fishery over the specified study period.

2.7 Entry-exit model selection

Model selection was performed by systematically fitting all possible combinations of available uncorrelated model predictor variables from the full RUM model specification using the R package 'glmulti' to arrive at the five best models (Calcagno et al. 2010). The selection of the candidate model having the lowest ranked Akaike's Information Criterion (AIC) score in this study was guided by the availability of economic data, prior knowledge of the system, and insights from previous investigations, particularly as outlined in Tidd et al. (2011) and

2.8 Entry-exit model performance

We used a machine learning algorithm to evaluate the 'true' error or misclassification of the best-fit model. A Leave One Out Cross-Validation (LOOCV) was employed, following the principles outlined by Kohavi (1995). The data was divided into two subsets: a training set (65%) used to build the model and a test set (35%) used to assess the model's performance by computing the mean square error. This process is iterated *k* times (in our case, 10) by randomly partitioning the data and predicting the test set *k* times. Each model is then evaluated on the various subsets of the data it predicts, comparing the average proportion predicted with the observed data from each test set. A final confusion matrix, comparing observed versus predicted values for all partitioned models, was created to evaluate the overall model performance. Additionally, a weighted *kappa* score for data anomalies, such as class skew in specificity and sensitivity, comprehensively assessed the model's overall performance. The values of *kappa* range from -1 to 1 and provide an index to determine that the results are not due to chance alone (Cohen 1960). A value of less than 0 is equal to no agreement.

3. Results

3.1 DEA efficiency estimates and optimal capacity analysis

The efficiency scores, including UCU, TE, and CU, across all vessels over the study period reveal patterns aligned with the number of vessels exiting the fishery (see Figure 2A/2B). Notably, exit-heavy years like 2001, 2008, 2009, and 2012 exhibit wider dispersions in vessel performance (CU and TE) compared to years with no exit. Despite anomalies like 2018 (no exit with widely dispersed CU) and 1997 (exits with less dispersed CU), TE remains high during exit-heavy years, indicating a consistently high catch per unit effort. In the earlier years (1992-2009), TE scores show wide variations. UCU is highly variable in some exit years (e.g., 2009 and 2012). However, throughout the time series, UCU remains high while overall CU is low and TE is high, suggesting underutilised capacity due to factors other than technical inefficiency. Conversely, in the earlier years (1992-1996), TE was low, CU was low, and UCU was high, suggesting potential inefficiencies and mismatches between actual and potential resource use.

Figure 3 illustrates the cumulative potential catches of yellowfin and skipjack given total UCU, showing a steeper trajectory for skipjack than yellowfin during the catch limit years 2017-2019. This suggests that catch limit regulations influenced changes in fisher targeting behaviour. While only the year 2019 indicates that the catch limit could be achieved with three fewer vessels (about 21% of vessels), years 2017/2018 display low-capacity utilisation (Figure 2A) due to operational challenges hindering full realisation of available capacity. The potential catch share for MSY could have been achieved with about 26% fewer vessels on average if capacity were fully utilised.

3.2 Entry-exit model selection

The results from the Random Utility Model (RUM) model selection are in Table 1. The best model (model 6) demonstrated a McFadden's pseudo-R^2 of 0.51 (model 6), indicating an excellent fit; likewise, the likelihood ratio of 167.6 is highly significant (P<2.22e-16), supporting this result. The Durbin-Watson test statistic (1.81) fell between the critical values of $1.5 < d < 2.5$, suggesting the absence of first-order linear autocorrelation in the data. The Variance Inflation Factor (VIF) to determine multicollinearity resulted in values < 2, indicating minimal collinearity. The estimated parameters and significance are presented in Table 2.

Several variables significantly influence the probability of entry 'versus' stay and exit 'versus' stay choices, as presented in Table 2. These influential variables included yellowfin revenue (rev_yft), skipjack revenue (rev_skj), vessel age (age), past interest rates (int_rates), and the previous year's estimated spawning biomass of yellowfin (ssbyft). Below are some key insights derived from the results:

a. **Vessel Age (age)**: The model intuitively indicates that younger vessels are more likely to enter the fishery. Conversely, meanwhile older vessels tend to exit more over the study period.
b. **Interest Rates (int_rates)**: Interest rates influence the decision to exit versus stay. Increased interest rates suggest that vessels are marginally more likely to exit the fishery than when interest rates are lower. It is intuitive that if interest rates are low, investing in the fishery is cheaper and the opportunity cost of capital is lower, so vessels prefer to stay.
c. **Yellowfin Spawning Biomass (ssbyft)**: The stock status of yellowfin plays an essential role in decision-making, although the difference between the entry/exit coefficients is marginal. However, fishers were more likely to stay when the stock biomass was higher than when choosing to enter or exit.

d. **Skipjack and Yellowfin Revenue (rev_skj, rev_yft)**: Skipjack revenue significantly influences the fleet's decisions. Despite negative coefficients for both entry and exit in skipjack revenue, the prominently significant exit coefficient indicates a preferential tendency to exit when the revenue is low. However, fishers are more inclined to stay in the fishery with increased revenues rather than opt to exit.

These findings provide valuable insights into the complex decision-making process of shipowners, where economic factors, vessel characteristics, and stock biomass collectively contribute to their choices regarding entry, exit, or continuation in the fishery.

3.3 Model performance

The LOOCV results demonstrated high accuracy, with an average accuracy score of 0.93. Additionally, the *kappa* score, a metric considering the agreement between observed and predicted values while accounting for chance, was 0.60, indicating moderate bordering substantial agreement.

4. Discussion

In this investigation, we delved into the fishing capacity of the French Indian Ocean PS fleet. Our first research objective was to understand the evolution of technical efficiency and capacity utilisation of the fleet, particularly after the implementation of catch limits for yellowfin tuna since 2017. A second objective was to analyse the dynamic behaviour of this fleet concerning this evolution and other independent variables to predict the entry-exit behaviours responding to fishing opportunities.

Since the yellowfin catch limit was introduced in 2017 (IOTC Res. 2016/01), our results indicate that the fleet could attain the national catch limit and share associated with fishing at MSY with, on average, three fewer vessels (i.e., between 21% and 26% less capacity), signalling an underutilisation of the existing capacity jeopardising the profitability of the fleet. Additionally, our RUM model, which characterises the fleet's behaviour regarding entry-stay or exit decisions, demonstrated the influence of under-utilised capacity and lower efficiency on the exit behaviour of vessels. Moreover, the model revealed a significant influence of capital ageing, catch revenue from the two main target species, past levels of spawning biomass and interest rates. McFadden's pseudo-R^2 of 0.51 suggests a very good fit (McFadden 1979), along with a high prediction accuracy (93%), which is essential to reliably evaluate the potential consequences of future management policies on fleet dynamics.

The two combined analyses corroborate our observations regarding the behaviour and capacity utilisation of the fleet. For instance, notable changes in PS operations have occurred since implementing the catch limit on yellowfin tuna. To circumvent the catch limit, the fleet has refrained from targeting yellowfin catches (Figure 3) by fishing more intensively on FADs where skipjack prevails (Tidd et al. 2023a, Guillotreau et al. 2024). An analogous behavioural response was observed in the Spanish PS operating in the Indian Ocean (Báez and Ramos 2019). However, in the present study, this avoidance strategy has resulted in highly variable CU levels within the fleet, as depicted in Figure 3. This variability underscores that the same catch could be achieved with fewer vessels operating optimally at full capacity.

A noteworthy year exhibiting substantial CU variation was 2012. During 2011-12, there was a significant increase in yellowfin biomass (Tidd et al. 2023a), accompanied by a more than 2.5-fold rise in the Bangkok price per tonne, exceeding the annual average trend of approximately $US1500. Simultaneously, skipjack prices doubled from approximately $US750 to $US1500 (Williams and Ruaia 2021). Regarding fishing strategies, there were substantial increases in yellowfin catches using relatively more FSC sets and fewer FAD sets in 2012, after the entry of two new vessels targeting high-value tunas for the fresh fish market (Figure 2) ("Sapmer to Target U.S., China with High-end Tuna." *IntraFish.com | Latest Seafood, Aquaculture and Fisheries News*, 21 Dec. 2011, accessed 15/01/24). Nevertheless, there was a decline in catch and biomass for skipjack during this period, as documented by Tidd et al. (2023a). This decline coincided with a significant increase in fuel prices per barrel due to the Arab Spring (Hsiao et al. 2016). Two decades earlier (1992-1996), there were no exit of vessels from the fishery although both CU and TE were low, reflecting inefficiencies in the production process, e.g., outdated technology, poor skipper practices and market-related issues such as demand and competition that affect CU. Improvements in TE and overall CU were made possible through addressing operational issues and aligning resource availability with vessel capacity. In 1997, three vessels exited, and one entered, thus improving both TE and CU efficiencies. This latter sequence demonstrates that the relationship between efficiency and entry/exit strategies is dual: lower fishing opportunities induced by catch limits increase inefficiency and trigger exit strategy for vessels, but the lower capacity resulting from exit decisions upgrades mechanically TE and CU (Felthoven 2002, Rust et al. 2016).

In 2008, high interest rates, fuel costs, and the financial crash likely contributed to several vessels leaving in 2009 amid piracy events (Chassot et al. 2012), falling fish prices, and capital risks. Exiting vessels had a median age of 18 years, contrasting with the 12 years of those that stayed. Newer and larger vessels entered the scene by 2010. Our investigation found a correlation between low interest rates and decisions to remain in the fishery. Elevated interest rates in the preceding year likely influenced financial decisions and contributed to exits. Jensen et al. (2012) observed similar influences on investment decisions for Danish seiners and trawlers and concluded that investments in machinery electronics and vessels are explained using one-year lagged variables. We can also admit that the opportunity cost of capital increases with higher interest rates, shipowners finding then a timely opportunity to sell off their vessels and increase their bank deposits. Additionally, our study identified low skipjack revenue as the primary factor influencing vessels' exits, as shown in Table 2. Yellowfin revenue and biomass had marginal impacts at lower values, with a higher likelihood of vessels remaining when both metrics were elevated.

Given the already enforced reductions in catch limits outlined in Resolution 21/01, affecting sales revenues, current fishing activities are estimated to exceed further the F/F_{MSY} estimate of 1.32 (accessed 11/01/24 link). Considering the French fleet's average age has reached approximately 17 years (Figure 1), any future reduction in the fleet coupled with increasing operating costs and the identified excess capacity in this study is likely to increase efficiency and capacity use. The trend towards exit strategies is evident as two French PS companies, Via Ocean and Sapmer, opted to sell off some of their vessels and permanently exit the Indian Ocean fishery in 2023 (www.seafoodsource.com, accessed 11/11/23). The concern extends to where the capacity is transferred and whether it is replaced in the Indian Ocean by newly registered vessels, re-flagging or involvement in illegal, unreported, and unregulated fishing (IUU) (Aranda et al. 2012). With the apparent larger size and tonnage of the entire PS fleet compared to the French fleet (Figure 1), there is still a possibility of over-capitalisation, particularly when extrapolating our results to the entire fleet. Moreover, it is crucial to extend the examination beyond the PS fleet to encompass all other fleets, especially those artisanal fleets engaged in uncapped catch activities which represent half of the yellowfin tuna catch (IOTC, supporting information collated from reports of the working party tropical tuna meeting, updated July 2021). The convergence of these factors emphasises the critical need for implementing adaptive measures to navigate the ever-changing dynamics of tuna fisheries and ensure the long-term viability of tuna stocks (Heidrich et al. 2023).

These limitations also highlight the need for improved data accessibility and transparency within the fishing industry, particularly concerning the socio-economic aspects of the fishery. In that regard, a socioeconomic working group is planned to collect economic data and support the IOTC management decisions. Addressing these data constraints would contribute to a more comprehensive understanding of the factors influencing fleet behaviour and facilitate more informed policy recommendations for sustainable fisheries management.

Future research will focus on developing a streamlined age-structured biological operating model for skipjack and yellowfin, integrating the discrete choice fleet model from this study with biological models (e.g., Tidd et al. 2023b). This integrated model will provide insights into the fleet's composition, precisely the number of vessels representing fishing effort. The approach considers the interplay between effort, fishing mortality, and endogenous model parameters governing the simulated fleet's capacity. The fleet size dynamically responds to variations in the operational environment, constrained by its carrying capacity, with endogenous model parameters shaping capacity dynamics. This comprehensive approach enhances our understanding of how the fleet adapts to external changes and the implications for fishing effort and capacity.

5. Conclusion

Maintaining the existing fishing capacity while setting catch limits in tuna fisheries not only leads to under-utilisation of the fleet capacity and waste of economic resources, but also jeopardises the conservation of other species (e.g., skipjack and bycatch species caught with DFADs). In the present study, we described the evolution of technical efficiency and capacity utilisation throughout the last three decades and put it in regard to the fleet dynamics.

More specifically, we demonstrated that the fishing capacity of the PS fleet operating in the Indian Ocean was exceeded by 25% the optimal level required to meet the MSY reference point. We also highlight the dual nature of the relationship between efficiency, capacity utilisation and entry/exit strategies. CU may decrease while efficiency remains high during some exit periods, calling for other drivers than the mere efficiency performance to explain investment/disinvestment strategies. In particular, higher interest rates, vessel ageing and poor market conditions tend to favour exit decisions amid other external factors, like the piracy events in 2008-09. Whenever the net balance of registered vessels remains negative for several years (i.e., more exits than entries), TE and CU are more likely to improve again. Having a model able to explain and predict accurately the strategic behaviour of vessels after management decisions represents a useful tool for decision-makers and a potential input for future stock assessment operating models. Aligning capacity with fishing opportunities is crucial for the profitability and preservation of these essential tuna populations, resulting in more sustainable and economically viable fisheries.

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Table 1. In the RUM model, the predictor variables were yellowfin tuna revenue (rev_yft), skipjack revenue (rev_skj), vessel age (age), the past interest rates (int_rates), and the past spawning biomass of yellowfin (ssbyft).

No.	model	AIC	ΔAIC
6	choice~age+rev_yft+ssbyft+rev_skj+int_rates	186.14	0.00
5	choice~age+rev_yft+ssbyft+rev_skj	193.68	-7.54
4	choice~age+rev_yft+ssbyft	221.03	-34.88
3	choice~age+rev_yft	224.71	-38.56
2	choice~age	291.79	-105.64
1	choice~1	335.59	-149.45

Table 2. Multinomial (logged covariates) model estimates resulting from fitting the decisions to 'enter' or 'exit' versus 'stay'.

Variable	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept):enter	90.58	23.06	3.92	8.61E-05	***
(Intercept):exit	143.08	28.35	5.04	4.51E-07	***
log(age):enter	-1.56	0.31	-5.01	5.18E-07	***
log(age):exit	2.058	1.10	1.84	0.064	.
log(ssbyft):enter	-3.55	1.32	-2.68	0.007	**
log(ssbyft):exit	-6.50	1.61	-4.02	5.77E-05	***
log(rev_yft):enter	-2.08	0.45	-4.520	6.16E-06	***
log(rev_yft):exit	-1.66	0.57	-2.89	0.003	**
log(rev_skj):enter	-0.71	0.49	-1.45	0.14	
log(rev_skj):exit	-2.70	0.64	-4.16	3.09E-05	***
log(int_rates):enter	0.79	0.65	1.20	0.22	
log(int_rates):exit	2.60	1.00	2.59	0.009404	**

McFadden's pseudo $R^2 = 0.51$. Statistical significance at '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

Likelihood ratio test: chisq = 167.6 (p = <0.001). Durbin-Watson d = 1.81.

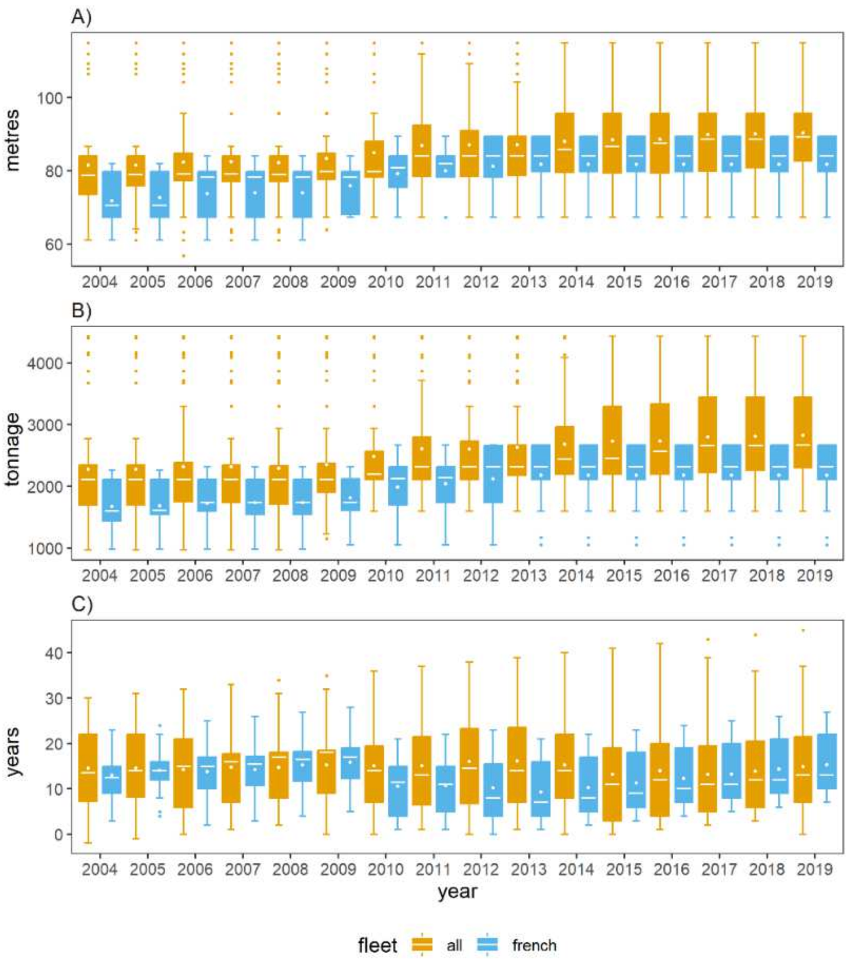

Figure 1 Box and whisker plot of capacity characteristics (**A**) length overall (m), (**B**) gross tonnage (gt), (**C**) age (years) of the IO PS fleet versus the French PS - the horizontal bar at the 50th percentile, the top of the box at the 75th percentile, and the base of the box at the 25th percentile. Whiskers represent the range of data, and the black dots represent the outliers.

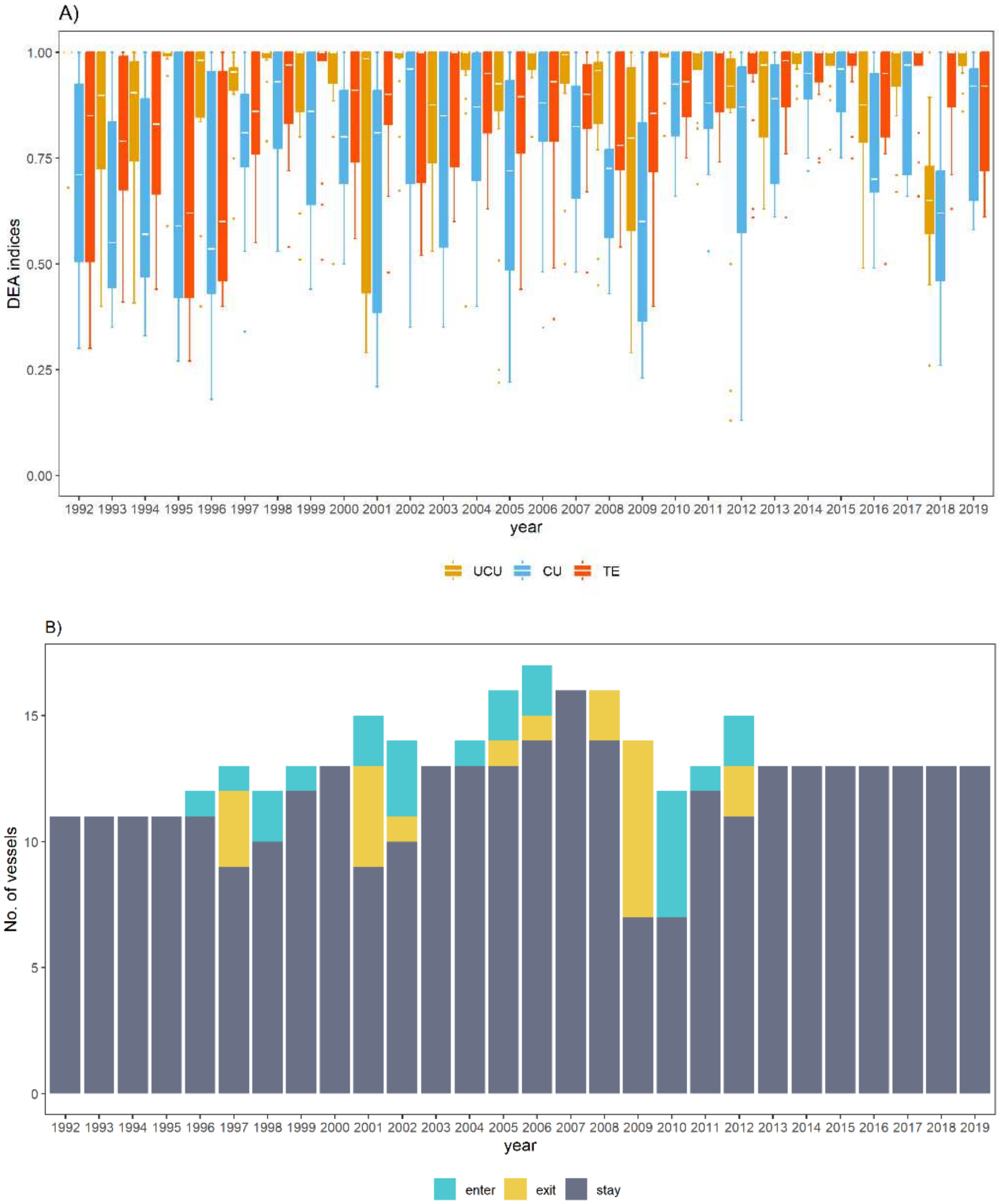

Figure 2 (**A**) Box and whisker plot of the results of the DEA analysis - the horizontal bar at the 50th percentile, the top of the box at the 75th percentile, and the box base at the 25th percentile: UCU = Unbiased capacity utilisation; CU = Capacity utilisation; TE = Technical efficiency. Whiskers represent the range of data, and the black dots represent the outliers. (**B**) Representation of the French-flagged fleet size in the IO and the choices of entry, exit, or stay in the fishery.

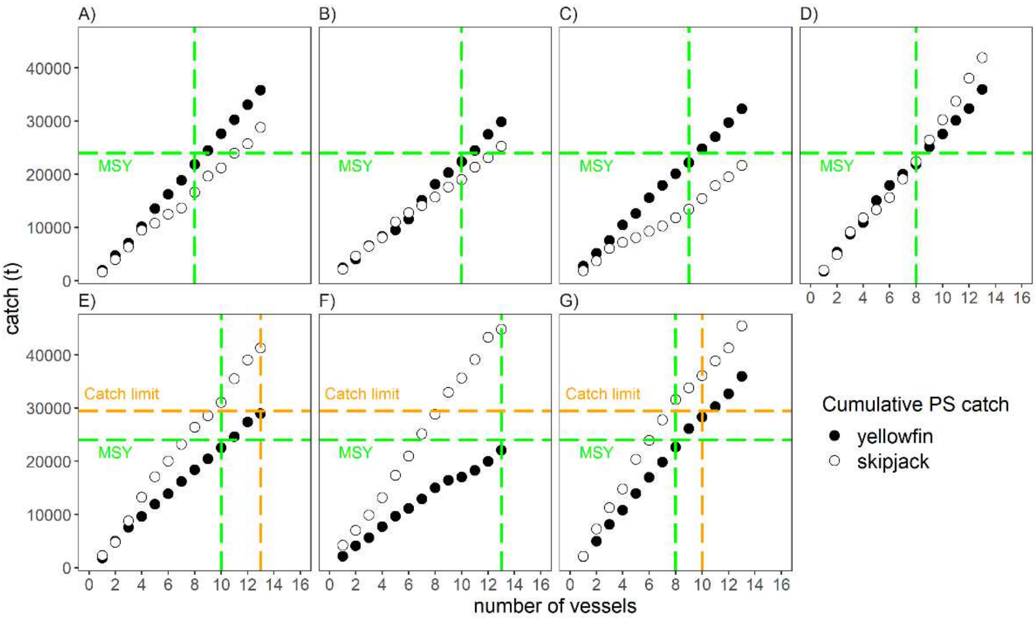

Figure 3 Each facet represents a year from when yellowfin was deemed overfished and subject to overfishing: **A)** 2013, **B)** 2014, **C)** 2015, **D)** 2016, **E)** 2017, **F)** 2018, **G)** 2019. The points represent the cumulative catch of yellowfin (black spheres) and skipjack (white spheres) by vessel (the point) ranked from 1 (most efficient) to the total number of vessels in those years. The orange horizontal line is the yellowfin catch limit of 29,501 tonnes (**E** to **G**) (target, 2017 onwards), and the orange vertical line is the theoretical number of vessels to achieve the catch limit. The green dashed lines would represent the estimated theoretical catch share (23,943 tonnes) and the optimal number of vessels if vessels were to fish at MSY.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- floatimage1.jpeg