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Fleet Behaviour Under Economic Uncertainty: Multi-Species Policy Scenarios for the Purse-Seine Fishery

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ABSTRACT

Managing fishing effort remains a central challenge in achieving sustainability in many fisheries, particularly where high-value species attract intense competition. In the Indian Ocean tropical tuna fishery, understanding how fishers respond to changing bio-economic conditions is essential for developing effective management. This study evaluates the influence of effort-based management measures on the size and investment behaviour of the purse-seine fleet targeting skipjack (*Katsuwonus pelamis*) and yellowfin tuna (*Thunnus albacares*). Using Random Utility Models (RUMs), we identify the key economic drivers of strategic decision-making, validate them through model evaluation, and integrate them with age-structured operating models (OMs). The RUM achieves 93% predictive accuracy, offering a robust basis for exploring policy options that balance conservation and economic objectives. Scenario testing under different cost and price conditions illustrates how economic pressures shape entry and exit decisions within the fleet.

1 | Introduction

As global seafood demand continues to grow (Naylor et al. 2021), understanding the drivers of fleet behaviour is critical for developing fisheries policies that are both biologically and economically sustainable (Hilborn 2007; Thébaud et al. 2023). Although precautionary approaches to fisheries management have gained traction, most efforts still prioritise biological sustainability through single-species assessments, often overlooking the economic and behavioural dynamics that shape how fleets respond to management interventions (Girardin et al. 2016), as well as the complexities of fisheries that target multiple species. An integrated approach that considers the financial viability of fishing operations alongside conservation goals and multi-species management is increasingly necessary.

A complex interplay of market conditions, regulatory constraints, vessel profitability, and broader environmental and economic factors–including fluctuating fuel prices and climate variability – can influence fleet dynamics. Predicting how fleets adapt to changing conditions and management regimes is essential for designing resilient policies. Prior research has shown that restricting access alone is often insufficient, as fishers may shift tactics to maintain profitability (Yew and Heaps 1996). Simulation-based approaches have emerged as valuable tools for exploring fleet responses across different regulatory scenarios (Pelletier and Mahevas 2005; Bastardie et al. 2010; Punt et al. 2016).

This study builds on that work by integrating a biological operating model (OM) with an economic entry-exit model for the Indian Ocean tropical tuna purse-seine fishery (PS). The OM is based on age-structured models of skipjack (*Katsuwonus pelamis*) and yellowfin (*Thunnus albacares*), the two principal species targeted by the fleet. These models simulate stock dynamics over 10 years under varying management regimes. The economic dimension is modelled using a multinomial entry-exit (Random Utility Model–RUM) that predicts fleet size by estimating the probability of vessel entry or exit based on variables such as biomass, costs, and expected revenues (see Tidd, Guillotreau, Mosquiera, et al. 2025). By linking fleet capacity to biological and economic feedbacks, the model aims to explore how regulatory measures influence long-term sustainability and economic resilience.

The Indian Ocean tropical tuna PS fleet is among the most important in the world, comprising 45 active large-scale vessels, primarily flagged to France, Spain, the Seychelles, Mauritius, and Taiwan. The fleet accounts for a significant share of regional skipjack and yellowfin catches, much of which supports the global canned tuna market and some local economies (Guillotreau et al. 2024). Fishing effort is concentrated in equatorial waters (10° N–10° S), mainly using drifting Fish Aggregating Devices (DFADs)–floating objects intentionally deployed to exploit tuna's natural aggregation behaviour and enhance catch rates (Tidd, Guillotreau, Dagorn, and Capello 2025). All DFADs are equipped with echosounder buoys, satellite-linked devices that enable remote tracking of their positions and the tuna biomass in their vicinity (Baidai et al. 2020). Since 2013, the Indian Ocean Tuna Commission (IOTC) has implemented a series of DFAD regulations, progressively reducing the number of operational buoys per vessel, i.e., the number of echosounder buoys that those vessels can monitor daily (Res. 15/08 to 24/02). Yet, empirical evidence suggests these measures have not significantly reduced DFAD-derived catches (Capello et al. 2023).

This study aims to simulate fleet behaviour under multiple projected management scenarios using a coupled bio-economic model. Scenarios include DFAD effort reductions and closures, tested across a 10-year projection period. The model reflects strategic vessel-level decisions: fishing companies respond to declining profitability by exiting the fishery, while favourable conditions (e.g., high stock abundance, lower costs or higher prices) incentivise continued participation or re-entry. These dynamics are governed by endogenous decision rules reflecting economic rationality and access constraints (Gordon 1954; Le Floc'h et al. 2011). The model is cross-validated using leave-one-out (LOOCV) to ensure robust predictive performance.

By capturing the interplay between policy interventions, market forces, fleet behaviour and multi-species stock status, this study offers valuable insights for regional stakeholders and managers (Fulton et al. 2011). It highlights the importance of aligning capacity control measures with realistic behavioural responses and multi-species approaches, ultimately informing more adaptive and effective management of the Indian Ocean tuna fishery.

2 | Methods

2.1 | OM Data

The foundation of this study is aligned with the yellowfin and skipjack tuna stock assessments routinely conducted by the Indian Ocean Tuna Commission (IOTC) [https://iotc.org/], which utilises the Stock Synthesis (SS3) modelling platform. These assessments employ a detailed age-structured framework with quarterly age classes and, for skipjack, spawning seasons spanning multiple geographic regions. They incorporate seasonal dynamics through a quarterly time step and assume combined sexes.

The operating models (OM) developed for this analysis are parameterised using the base SS3 configuration from the 2020 IOTC yellowfin tuna assessment (IOTC–2021–WPTT23–12) and the 2019 IOTC skipjack tuna assessment (IOTC–2020–WPTT22–10). All data were exported from SS3 output files into the R software using the ss3om package (https://github.com/flr/ss3om, accessed January 5, 2025).

2.1.1 | Entry-Exit Data

Annual data for the French purse-seine fleet operating in the Indian Ocean from 1992 to 2019 were sourced from the fleet registry maintained by the French Observatory of Exploited Tropical Pelagic Ecosystems (Ob7). This registry provides detailed information on vessel characteristics, including age, gross registered tonnage (GRT), overall length (in meters), and engine power (in kilowatts). The dataset also includes logbook records, providing annual catch data for yellowfin and skipjack tunas, as well as effort metrics such as the number of sets and days at sea per vessel. As comprehensive operational data are only available for the French purse seine fleet, we assume that the entry, exit, and stay behaviour observed in the French segment is representative of the broader fleet operating in the Indian Ocean. This assumption is necessary because comparable vessel-level data from other flag states are unavailable.

To complement vessel-specific information, ex-vessel price data per metric tonne ($US) for the main target species, skipjack and yellowfin tuna, were obtained from Sovetco. This French trading company sells most of the French-caught frozen tuna, adjusted for inflation to 2015 values using the OECD production price index. Additionally, fuel prices are the price per tonne ($US), inflation-adjusted to 2015 values, collected from Seypec (Seychelles Petroleum Company). 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. The total spawning stock biomass for skipjack and yellowfin tuna in tonnes was obtained 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 | Overview of the Skipjack and Yellowfin Operating Model

The biological operating model (OM) applied in this analysis is an age-structured population dynamics framework tailored to the Indian Ocean yellowfin and skipjack tuna stocks. Natural mortality at age and recruitment are primarily influenced by the OM parameters that set the stock dynamics. As each cohort ages, the population diminishes due to natural and fishing mortality.

The model follows a conventional age-structured formulation for population progression:

$$N_{a,t} = \begin{cases} R_t & \textit{for } a = 1 \\ N_{a-1,t-1} e^{-Z_{a-1,t-1}} & \textit{for } 2 \le a < P \\ N_{a-1,t-1} e^{-Z_{a-1,t-1}} + N_{a,t-1} e^{-Z_{a,t-1}} & \textit{for } a = P \end{cases} \quad (1)$$

where $N_{a,t}$ is the number (in thousands) of fish of age a (where P is the plus-group) at time t (in quarters), $Z_{a,t}$ is the total mortality at age a and time t, with $Z_{a,t} = M_a + F_{a,t}$, where M_a is the natural mortality at age a and $F_{a,t,}$ is the fishing mortality at age a, at time t.

At each timestep, Spawning Stock Biomass (SSB) is computed using:

$$SSB_t = \sum N_{a,t} W_{a,t} O_{\mathrm{a,t}} \tag{2}$$

Here, $W_{a,t}$ is the mean weight (in kilogrammes) of fish at age a and time t and $O_{a,t}$ is the maturity proportion at that age and time.

The recruitment process is governed by a Beverton-Holt stock-recruitment relationship, which includes a saturation point for maximum recruitment:

$$R_t \frac{\left(4hR_0 SSB_{t-1}\right)}{\left(S_0(1-h) + SSB_{t-1}(5h-1)\right)} \tag{3}$$

In this equation, R_0 is the unfished recruitment level, S_0 is the virgin SSB, and h is the steepness parameter.

Catch numbers at age $\mathrm{C_{a,t}}$ are related to the fishing mortality at age through the Baranov catch equation:

$$\mathrm{C_{a,t} N_{a,t} \frac{F_{a,t}}{Z_{a,t}} e^{-Z_{a,t}})} \tag{4}$$

The catch yield in tonnes ($\mathrm{Y_a}$) is calculated as follows:

$$Y_t = \sum C_{a,t} W_{a,t} \tag{5}$$

Projections of stock numbers-at-age from 2019/2020 to 2029 were evaluated under the following management scenarios (see Tidd, Guillotreau, Mosquiera, et al. 2025 for more details on how effort reductions were calculated):

- Scenario 1 (Baseline): Fishing mortality from DFAD-associated sets was constant at average 2020 levels across all quarters.
- Scenario 2a (Reduced DFAD sets by 50%): The number of DFAD sets was halved relative to 2020, with no shift of effort toward free school (FSC) sets.
- Scenario 2b (Reduced number of operational buoys): A 50% cut in operational buoys per vessel modifies DFAD-related fishing mortality-at-age, without reallocating the lost effort to FSC sets.
- Scenario 3 (Q3 DFAD closure): DFAD fishing mortality was set to zero during the third quarter of each year, while maintaining 2020 DFAD effort levels in all other quarters.
- Scenario 4 (Full DFAD ban): This scenario eliminated DFAD-related fishing mortality, simulating a global ban across all quarters.
- Scenario 5 (Quarterly fishery closure for biological recovery): All fishing gears were inactive during the third quarter, simulating a biological rest period. Fishing mortality was zero in Q3, while effort for all gears remained at 2020 levels in the remaining quarters.

Across all scenarios, fishing mortality from other fleets remained fixed at 2020 levels, and no redistribution of PS effort to FSC sets was assumed.

2.3 | 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 information is often unavailable. Consequently, several proxy variables were used: annual ex-vessel revenue as a proxy for economic viability, and annual fuel cost per tonne as a proxy for variable operating 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 both the capital cost and the discount rate (or opportunity cost) 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, the opportunity cost of investing capital in the fishery is lower, so boat owners may decide to stay in the industry rather than invest their money in other industrial or financial assets. Similarly, stock status indicators for yellowfin and skipjack were lagged by one year. A low spawning stock biomass in year t was assumed to influence exit decisions in year $t+1$, reflecting the broader management context of the fishery, where yellowfin catch-limits are linked to previous catch levels. Collectively, these variables provide a framework for understanding the complex decision-making process of fishers in response to diverse ecological, economic and market dynamics. Because the model focuses on annual strategic participation decisions (entry, stay, or exit), catches and revenues were aggregated at the vessel-year level and do not differentiate between fishing set types.

2.4 | Entry-Exit Model Description

In the model, the capacity of the fishing fleet is directly influenced by individual vessels' decisions to enter, remain, 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 drives individual decision-making, representing a choice's perceived satisfaction or desirability. This utility comprises deterministic and stochastic components, introducing randomness into the model (McFadden 1979). The stochastic element acknowledges the inherent variability and unpredictability of individual decision-making processes, 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_{ij}) of individual i is defined as a linear combination of a set of explanatory variables (w_i) representing observed individual characteristics such as vessel age or revenues, where for a given individual time-event, i, such as vessel exit decisions, a choice j (1 or 0) is made. These characteristics collectively constitute the non-random components of the utility alongside a stochastic error component, ε_{ij}. Mathematically expressed as (Equation 6):

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

where β_j as a vector of parameters for choices j.

The probability that an individual i makes choice j can be expressed as:

$$Prob_i\,(j) = \frac{exp\left(w_i\beta_j\right)}{\sum_{j=1}^{J} exp\left(w_i\beta_j\right)} \tag{7}$$

where J represents the total number of possible discrete choices that an individual vessel can make.

The discrete-choice dependent variable j is a polytomous variable parametrised annually. 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 PS vessel is considered to have 'entered' the IO fishery if it joins for the first time during the study period. In line with Mardle et al. (2005), we assume that the performance of a vessel in its first year of entry into the fishery meets the expectations surrounding the entry decision. The vessel can re-enter another year if it temporarily exits under the 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 company.

ii. 'Exit': A PS vessel marked with 'exit' is currently part of the fleet but can be permanently or temporarily removed during the study period for various reasons, such as being sold, relocated to another ocean, or decommissioned. However, it may re-enter the fishery in subsequent years. Note that a vessel may have exited from a national flagship, but sold or re-flagged, and still operate in the IO–these vessels are not further tracked in the analysis. We further assume that the decision to exit or stay is based on the most recent year's performance.

iii. 'Stay': A PS vessel designated as 'stay' refers to the period between the entry and exit 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 capture the dynamic choices made by individual vessels in the PS fishery during the specified study period (10–18 vessels per year).

2.5 | 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 identify the five best models (Calcagno and de Mazancourt 2010). The selection of the candidate model with the lowest 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 by Tidd et al. (2011).

2.6 | Entry-Exit Model Performance

We employed a model evaluation technique to assess 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 entry-exit model data were split 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 squared error. This process is iterated k times (in our case, 10) by randomly partitioning the data and predicting the vessel-choice outcomes for the test set. Each model is then evaluated on the various subsets of the data it predicts, comparing the average proportion predicted with the observed proportions (i.e., the individual vessel choices) in each test set. A final confusion matrix comparing observed and predicted values across all partitioned models was created to evaluate overall model performance. Additionally, a weighted *kappa* score was used to assess the model's overall performance, accounting for data anomalies, such as class skew in specificity and sensitivity. The values of *kappa* range from −1 to 1 and serve as an index of whether the results are not due to chance alone (Cohen, 1960). A value of less than 0 is equal to no agreement.

2.7 | Sensitivity of the Projections With Selected Candidate Independent Model Variables

The capacity of the fishing fleet in the projections is directly determined by individual vessels' decisions to enter or exit the fleet, as described above. This decision is modelled using the scenario projections described in Section 2.2, which links the skipjack and yellowfin OMs directly by stock biomass or catch, provided the variables in the exit-entry model are present. Furthermore, we conduct a sensitivity test by iterating 100 times with a 20% coefficient of variation around the candidate independent variables to characterise the uncertainty in the estimates.

2.8 | Linking OMs

To investigate the interplay between biological conditions and fleet dynamics, we link two species-specific biological operating models (for skipjack and yellowfin tuna) with a multinomial entry-exit model of vessel behaviour. The simulation allows fleet size to adjust endogenously in response to changing conditions. Outputs from the biological models, including projected species-specific catches under different scenarios, are used to derive a range of vessel-level economic indicators, such as estimated total revenues and catches per vessel.

The biological evaluation utilises a numerical simulation model to examine the interplay between the stocks' biological dynamics and the fleet's economic dynamics. Endogenous and exogenous model parameters govern the behaviour of the fleet simulated in this study. Thus, the fleet size in the model responds to changes in the environment it operates in. For example, based on the skipjack catches, we divide the fleet-wide catches from the OM (*OMcatch*) at time t by the total number of active purse seine vessels (*vessno*) in $t-1$ (from the entry exit model) to approximate individual vessel catch inputs i:

$$catch_{i,t}\left(OMcatch_t\right) / \left(vessno_{t-1}\right) \tag{8}$$

This creates a feedback loop: the predicted fleet size (*vessno*) from t-1 affects the expected individual catch in t, which then influences entry and exit in t, as shown in equation (6). This can be calculated from the probabilities in Equation (7) to determine vessel numbers at time t. A sensitivity analysis was conducted for each significant variable identified in Section 2.7 to assess the magnitude of its effect.

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

3 | Results

3.1 | 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, indicating an excellent fit; likewise, the likelihood ratio of 167.6 is highly significant ($p < 2.22\text{e}^{-16}$), supporting this result. The Durbin-Watson test statistic (1.81) fell between the critical values of $1.5 < \text{d} < 2.5$, suggesting the absence of first-order linear autocorrelation in the data. The Variance Inflation Factor (VIF) was used to assess multicollinearity, yielding values below 2, indicating minimal multicollinearity. Descriptive statistics for the variables used in the model are presented in Table 2.

TABLE 2 | Descriptive statistics of variables used in the RUM model.

choice	*n*	variable	mean	sd	min	max
enter	23	age	6.09	6.13	1	17
exit	21	age	17.5	6.02	5	30
stay	329	age	12	6.12	1	27
enter	23	int_rates	4.45	1.13	3.12	7.53
exit	21	int_rates	4.66	0.933	3.32	6.31
stay	329	int_rates	4.09	2.27	0.47	8.54
enter	23	rev_skj	2,315,124	1,318,831	110,209	4,623,104
exit	21	rev_skj	1,190,948	940,722	138,915	3,881,081
stay	329	rev_skj	3,196,261	1,356,216	313,019	8,426,548
enter	23	rev_yft	2,503,576	1,680,899	163,877	6,706,767
exit	21	rev_yft	1,426,420	718,902	605,052	3,229,010
stay	329	rev_yft	4,023,462	1,802,217	688,425	10,423,716
enter	23	ssbyft	1,417,358	386,029	812,610	1,891,028
exit	21	ssbyft	1,323,431	379,331	876,444	1,891,028
stay	329	ssbyft	1,448,605	365,242	812,610	2,244,805

TABLE 3 | Multinomial (logged covariates) model estimates resulting from fitting the decisions to 'enter' or 'exit' versus 'stay'.

Variable	Estimate	Std. Error	z	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	**

Note: 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.

Several variables significantly influence the probability of entry versus stay and of exit versus stay, as presented in Table 3. 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, 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 (entry cost) is cheaper and the opportunity cost of capital is lower, so vessels prefer to stay.

c. **Yellowfin tuna Spawning Biomass (ssbyft)**: The stock status of yellowfin tuna 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 tuna revenue (rev_skj, rev_yft)**: Skipjack revenue significantly influences the fleet's decisions. Despite negative coefficients for entry and exit in skipjack revenue, the significantly prominent exit coefficient indicates a preferential tendency to exit when revenue is low. However, fishers are more inclined to remain in the fishery with increased revenues than to exit. The larger magnitude of the yellowfin revenue coefficient in the entry equation indicates that entry decisions are more sensitive to revenue signals relative to exit decisions, given that "stay" is the reference category. Descriptive statistics (Table 2) show that incumbent vessels generate substantially higher revenues than entrants, consistent with accumulated experience and knowledge of productive fishing grounds.

These findings provide valuable insights into the complex decision-making process of purse seine owners. Economic factors, vessel characteristics, and stock biomass collectively influence their choices regarding entry, exit, or continuation in the fishery.

3.2 | Model Performance

The LOOCV results demonstrated high accuracy, with an average accuracy score of 0.93. Additionally, the *kappa* score, which accounts for chance and measures agreement between observed and predicted values, was 0.60, indicating moderate to substantial agreement.

3.3 | Linking the Two Biological OMs With the Entry-Exit Model

The results demonstrate how changes in key economic drivers influence fleet behaviour under various management scenarios. To isolate the impact of these economic factors, each sensitivity test varied a single economic variable–such as market prices, interest rates, or vessel age–while holding the other variables at their time-series average levels. This approach enables a clearer understanding of how specific economic conditions influence capacity outcomes.

Figure 1 illustrates projected fleet capacity from 2020 onward under various regulatory and economic scenarios. Under the status quo (Scenario 1), the model anticipates a moderate increase of 3–5 vessels, reflecting stable catch revenues and average economic conditions. Scenario 4, which prohibits FAD fishing, results in significantly lower capacity despite high average prices for both skipjack and yellowfin. The restricted fishing strategy limits overall profitability, though the wider spread in the upper quartile suggests that some vessels–likely younger or more efficient–can remain profitable.

Figures 2 and 3 illustrate how adverse economic conditions lead to a reduction in fleet size. In Figure 2, declining average prices for skipjack and yellowfin significantly lower entry incentives, leading to marked fleet contraction. In Figure 3, high interest rates dampen participation by increasing capital costs, reducing the number of vessels by approximately 5–10 compared to baseline levels, despite catch rates improving due to stock recovery (Figures 4 and 5).

Figure 6 illustrates the effect of increasing vessel age: older vessels are more likely to exit, especially when operating margins are tight. This pattern mirrors that of the interest rate scenario, reinforcing how structural and financial factors interact to shape long-term fleet dynamics.

4 | Discussion

In this manuscript, we explored the possibility of combining entry/exit models of purse seine fleet capacity with a series of effort-based scenarios, as depicted in Tidd, Guillotreau, Mosquiera, et al. (2025), for two essential tuna species in the Indian Ocean. Our results suggest that combining these two

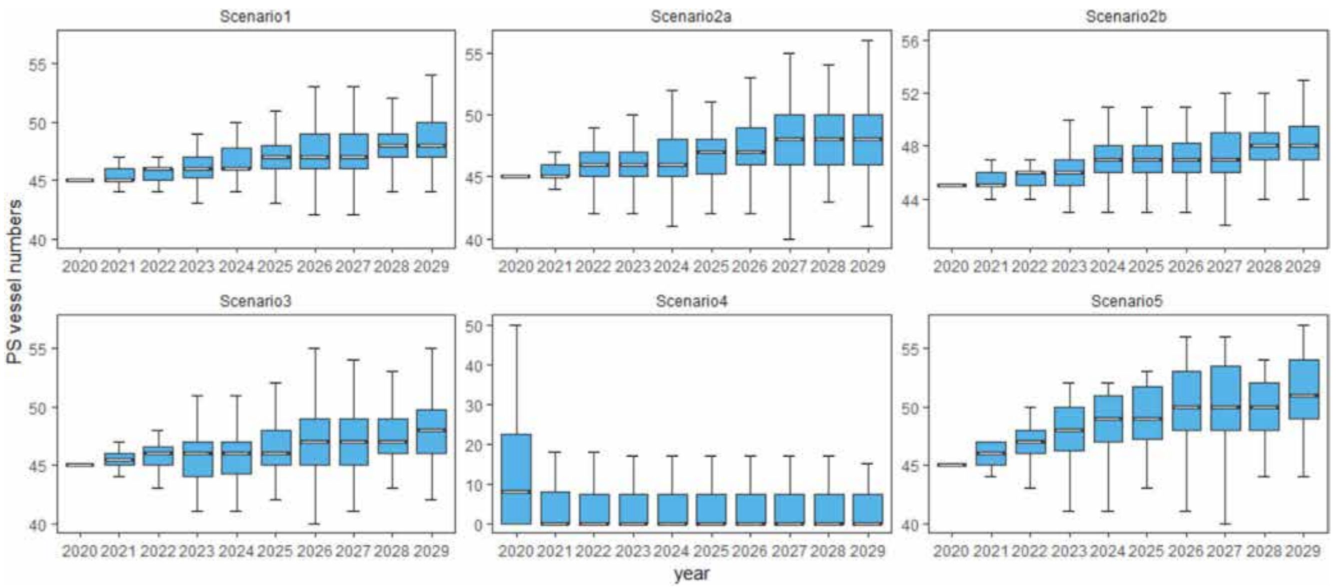

FIGURE 1 | All covariate average time series values (1992–2019) are as follows: Interest rates at 3.94%, yellowfin tuna and skipjack prices at $US1,798 and $US1,188 x catch weight forecasted (revenue), respectively, and the mean age of the vessel at 15, all with a 20% coefficient of variation applied.

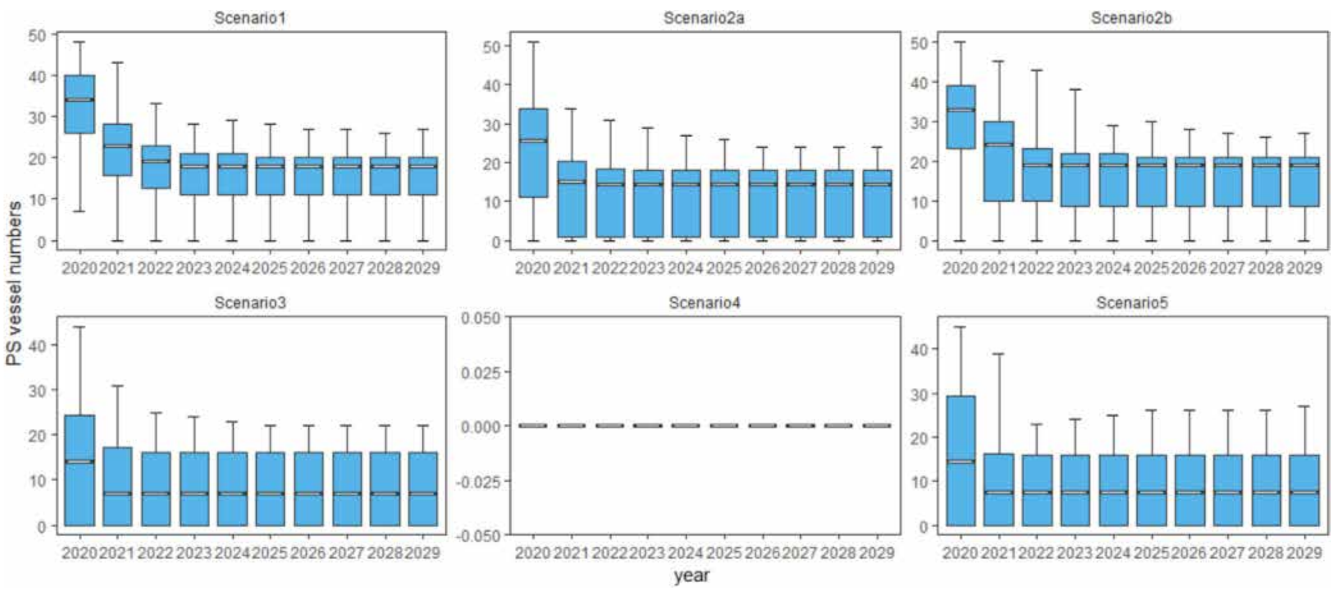

FIGURE 2 | Yellowfin tuna and Skipjack adjusted to the lowest annual time series prices (1992–2019): Interest rates at 3.94%, and yellowfin tuna and skipjack prices at $US853 and $US299 (2000), respectively, with a mean age of 15, all with a 20% coefficient of variation applied.

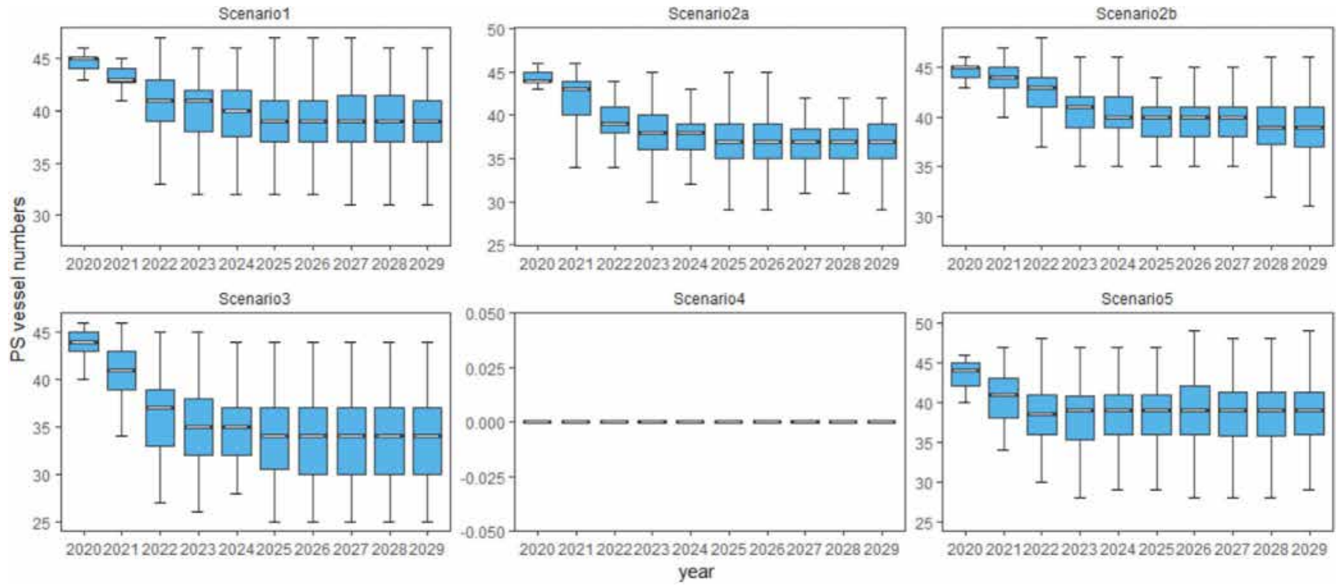

FIGURE 3 | Interest rates based on the highest time series percentage: 8.54% (1993), and yellowfin tuna and skipjack prices at $US 1798 and $US 1188, respectively, with a mean age of 15 all with a 20% coefficient of variation applied.

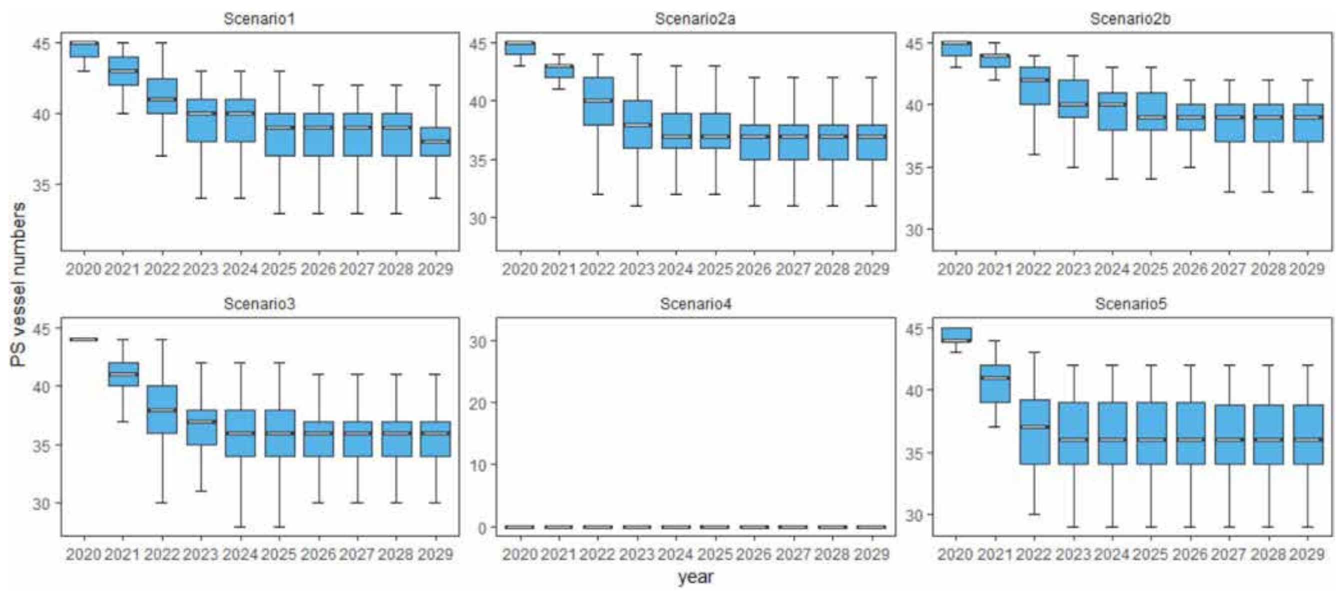

FIGURE 4 | Vessel age adjusted to the highest: Interest rates at 3.94%, yellowfin tuna and skipjack prices at $US1,798 and $US1,188, respectively, and the age of the vessel at 30, all with a 20% coefficient of variation applied.

methodological approaches can yield new insights. However, the dynamics of fishing capacity were not included in the model, thereby ignoring potential feedback mechanisms among biology, fishing effort, and capacity. Instead, we project purse seine fleet size across different bioeconomic scenarios by linking biological operating models for skipjack and yellowfin tuna with a vessel-level entry-exit model. Annual catch projections are converted into revenues, which, along with vessel characteristics and economic conditions, inform the probability of fleet entry or exit in subsequent years. The resulting projections reflect behavioural responses to changes in stock status and economic incentives, but do not explicitly model vessel capacity or efficiency.

The RUM model results revealed significant influences 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 indicates a very good fit (McFadden 1979), accompanied by a high prediction accuracy of 93%, which is essential for reliably evaluating the potential consequences of future management policies on fleet dynamics.

Our investigation revealed a correlation between low interest rates and the decision to remain in the fishery. Elevated interest rates in the preceding year likely influenced financial choices and contributed to exits. Jensen et al. (2012) observed similar influences on investment decisions for Danish seiners and trawlers, concluding that investments in machinery, electronics, and vessels are best explained using one-year lagged variables. However, we also observe that lower interest rates do not significantly support the entry vs stay behaviour.

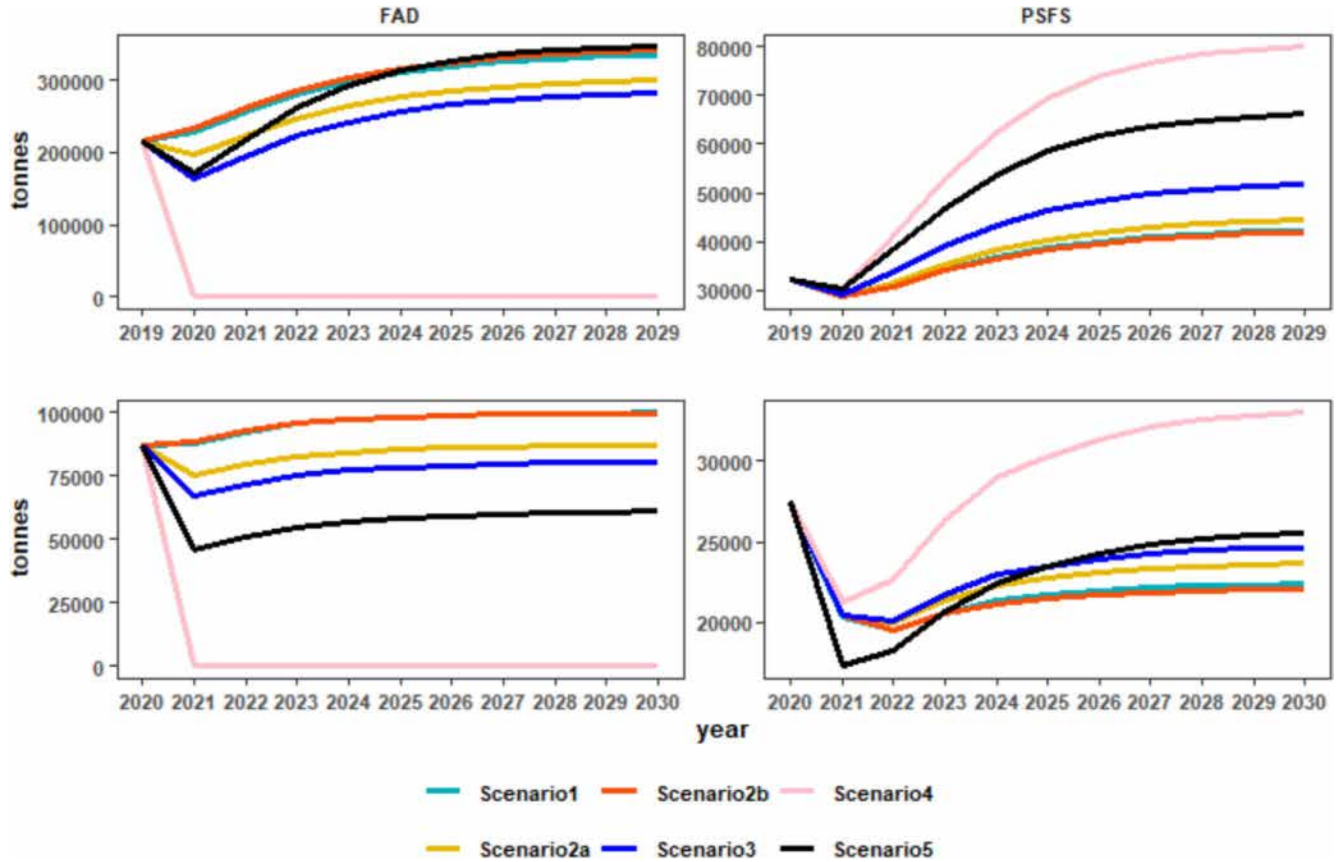

FIGURE 5 | Catch by scenario for skipjack (top) and yellowfin tuna (bottom).

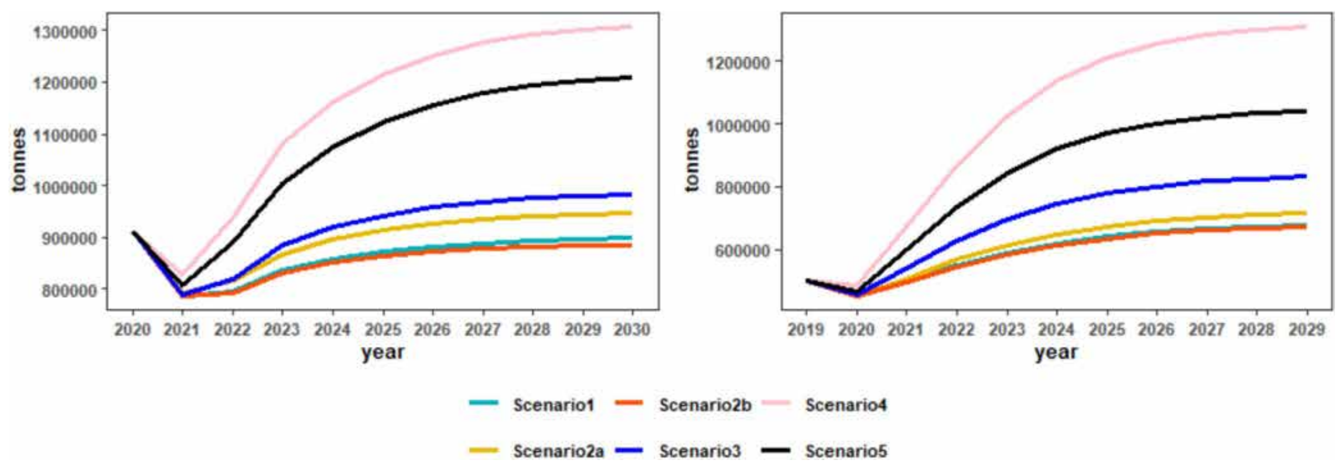

FIGURE 6 | SSB by scenario for yellowfin tuna (left) and skipjack (right).

We must therefore consider the asymmetric effect of interest rates, which has also been observed at the macroeconomic level, particularly in the dynamics between short- and long-term interest rates (Leshoro and Wabiga 2023). A risk-averse attitude can explain why private investors are more reluctant to respond quickly to a decrease in interest rates than to an increase. We can also acknowledge that the opportunity cost of capital increases with higher interest rates, as shipowners find it more profitable to sell off their vessels and invest in financial assets. Additionally, our study identified that lower skipjack revenue emerged as the primary economic factor influencing vessel exit decisions (Table 3), while yellowfin spawning biomass captured broader stock conditions that may affect expectations about future fishing opportunities.

Results from the effort-based reduction scenarios for both OMs, incorporating changes to low prices (revenues) and high costs (vessel age and interest rates), showed how the fleet responded to these changes. The evaluation represents a step forward in assessing the fisheries system, as the model explicitly accounts for fleet dynamics. However, several simplifying assumptions were still made, which must be considered when interpreting the results. First, it was assumed that the IO PS fleet follows the entry/exit dynamics of the French fleet. Because the fleets target the two tuna species, skipjack and yellowfin tuna, this assumption is not entirely unrealistic. However, the French fleet's quota (here, not incorporated) for yellowfin tuna differs from those of the other fleets, so targeting skipjack changes may have altered strategy dynamics (see Tidd, Guillotreau, Dagorn, and Capello 2025). These differences may affect the entry and exit decisions, which are now being disregarded. Finally, the model's outcomes depend on tuna prices (through gross revenue for yellowfin tuna and skipjack). This results in two problems: first, future prices and variable costs for IO tuna are unknown and are assumed constant in the model. Second, the price for yellowfin tuna is considered equal for all sizes. This is a simplification of the observations, in which prices depend on the size of yellowfin tuna, especially for free-school fishing. This simplification is likely to affect our results, especially since the model predicts an increase in *SSB* (a key variable in the entry-exit model) for both stocks in the majority of scenarios (Figure 6), which will result in the average age and size of yellowfin tuna on the catches increasing (Figure 5).

Controlling or influencing fish prices is not a standard instrument in regulating capacity or fishing effort. Most of the literature focuses on taxation or subsidy policies. Clark (1990) discusses how, when prices increase, fishing becomes more profitable; conversely, reducing prices through taxation or subsidies can discourage investment in the fishery. Similarly, Arnason (1990) proposed taxing landings to incentivize capacity reduction. The EU PS fleet is heavily subsidized in the IO via Sustainable Fisheries Partnership Agreements (SFPAs) with coastal nations such as Seychelles and Madagascar. These subsidies encompass direct financial contributions for fishing access, sectoral support, and reduced licensing fees for EU vessel owners (see link accessed April 6, 2025). For instance, the EU fleet under the SFPA benefits from reduced licence fees of $63,000, compared with $110,000–$120,000 for other non-EU fleets (see FAO 2024). Some of these subsidies are considered harmful, such as fuel subsidies, vessel modernisation, and access agreements that can lead to overcapacity and overfishing, impacting regional economies and fish stocks (Andreoli et al. 2023).

As of now, there is no official capacity cap limiting the number of PS operating in the IO under the IOTC. Although several discussions have taken place in the past to address this issue–for example, resolution 15/02, which calls for capacity reporting by vessel type–no such cap has been implemented. Other attempts have been made to manage capacity by limiting the number of active vessels, gross tonnage, and the number of active fishing days. Difficulties arise regarding the definitions of licenced and active vessels, as well as disagreements over allocation among member states. An alternate way to the cap capacity is the 90-day closure (or area-based effort restrictions), which we modelled here (Scenario 3 for PS FAD only and Scenario 5 for all fleets). Both scenarios are beneficial to the stock biomass and to future landings for the PS fleet in general. If variable costs and prices remain at their current levels, the fleet would grow. Even if future management rules prevent the growth of the fleet in terms of the number of vessels, one may expect the fishery to allow capacity to increase unrestrictedly, i.e., through technological creep, which is more difficult to control.

To conclude, we presented a proof-of-concept simulated evaluation using an entry-exit model, coupled with two OMs, based on several simplifying assumptions; therefore, the interpretation of the results should be done with caution. However, LOOCV with the model shows that the resulting model's capacity estimation is at least in the same direction as that observed in the field, as indicated by prediction accuracy. For future predictions, the model predicts an incentive to allow capacity to grow (Figure 1, Scenario 1), owing to the recovery of the two stocks and the resulting increase in landings.

Future work will apply a similar, but more dynamic, model within a Management Strategy Evaluation (MSE) framework (with a complete feedback loop rather than projections as performed here). However, a better understanding of the relationship among capacity, effort, and fishing mortality would need further development. Under the MSE approach, the objective is no longer to come up with a single answer but to evaluate the management consequences of a strategy under alternative assumptions and various sources of uncertainty, and the overall robustness of the approach to these. For example, uncertainty regarding stock dynamics. A key element is to identify the relative impact of particular assumptions about the resource (e.g., the stock-recruitment relationship, natural mortality) or fleet dynamics (e., the implementation of management regulations).

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Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Abernethy, K. E., P. Trebilcock, B. Kebede, E. H. Allison, and N. K. Dulvy. 2010. "Fuelling the Decline in UK Fishing Communities?" *ICES Journal of Marine Science* 67: 1076–1085. https://doi.org/10.1093/icesjms/fsp289.

Anderson, L. G. 2007. "Does Capacity Analysis Help Us Meet Fishery Policy and Management Objectives? Comments." *Marine Resource Economics* 22: 89–93. https://doi.org/10.1086/mre.22.1.42629540.

Andreoli, V., J. J. Meeuwig, D. J. Skerritt, A. Schuhbauer, U. R. Sumaila, and D. Zeller. 2023. "Fisheries Subsidies Exacerbate Inequities in Accessing Seafood Nutrients in the Indian Ocean." *npj Ocean Sustainability* 2: 23. https://doi.org/10.1038/s44183-023-00031-9.

Arnason, R. 1990. "Minimum Information Management in Fisheries." *Canadian Journal of Economics* 23, no. 3: 630–653. https://doi.org/10.2307/135652.

Asche, F., H. Eggert, E. Gudmundsson, A. Hoff, and S. Pascoe. 2008. "Fisher's Behaviour With Individual Vessel Quotas–Over-Capacity and Potential Rent: Five Case Studies." *Marine Policy* 32: 920–927. https://doi.org/10.1016/j.marpol.2008.01.007.

Baidai, Y., L. Dagorn, M. J. Amande, D. Gaertner, and M. Capello. 2020. "Machine Learning for Characterizing Tropical Tuna Aggregations Under Drifting Fish Aggregating Devices (DFADs) From Commercial Echosounder Buoys Data." *Fisheries Research* 229: 105613. https://doi.org/10.1016/j.fishres.2020.105613.

Bastardie, F., M. Vinther, J. R. Nielsen, C. Ulrich, and M. Storr-Paulsen. 2010. "Stock-Based vs. Fleet-Based Evaluation of the Multi-Annual Management Plan for the Cod Stocks in the Baltic Sea." *Fisheries Research* 101: 188–202. https://doi.org/10.1016/j.fishres.2009.10.009.

Calcagno, V., and C. de Mazancourt. 2010. "Glmulti an R Package for Easy Automated Model Selection With (Generalized) Linear Models." *Journal of Statistical Software* 34, no. 12: 1–29. https://doi.org/10.18637/jss.v034.i12.

Capello, M., G. Merino, M. Tolotti, H. Murua, and L. Dagorn. 2023. "Developing a Science-Based Framework for the Management of Drifting Fish Aggregating Devices." *Marine Policy* 153: 105657. https://doi.org/10.1016/j.marpol.2023.105657.

Clark, C. W. 1990. *Mathematical Bioeconomics: The Optimal Management of Renewable Resources*. John Wiley and Sons.

Cohen, J. 1960. "A Coefficient of Agreement for Nominal Scales." *Educational and Psychological Measurement* 20, no. 1: 37–46. https://doi.org/10.1177/001316446002000104.

FAO. 2024. "Institutional and Economic Perspectives on Distant-Water Fisheries Access Arrangements."

Fulton, E. A., A. D. M. Smith, D. C. Smith, and I. E. van Putten. 2011. "Human Behaviour: The Key Source of Uncertainty in Fisheries Management." *Fish and Fisheries* 12, no. 2: 17. https://doi.org/10.1111/j.1467-2979.2010.00371.x.

Girardin, R., K. Hamon, J. Pinnegar, et al. 2016. "Thirty Years of Fleet Dynamics Modelling Using Discrete–Choice Models: What Did We Learn?" *Fish and Fisheries* 18: 638–655. https://doi.org/10.1111/faf.12194.

Gordon, H. S. 1954. "The Economic Theory of a Common Property Resource: The Fishery." *Journal of Political Economy* 62: 124–142.

Guillotreau, P., Y. Dissou, S. Antoine, et al. 2024. "Macroeconomic Impact of an International Fishery Regulation on a Small Island Country." *npj Ocean Sustainability* 3, no. 1: 18. https://doi.org/10.1038/s44183-024-00054-w.

Hilborn, R. 2007. "Managing Fisheries Is Managing People: What Has Been Learned?" *Fish and Fisheries* 8, no. 4: 285–296. https://doi.org/10.1111/j.1467-2979.2007.00263_2.x.

Jensen, F., J. Andersen, and C. L. Jensen. 2012. "Investment Behaviour in Individual Non-Transferable Quota Systems." *Applied Economics* 44, no. 8: 969–978. https://doi.org/10.1080/00036846.2010.528371.

Kohavi, R. 1995. "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection." *In IJCAI* 14, no. 2: 1137–1145.

Le Floc'h, P., F. Daurès, M. Nourry, O. Thébaud, M. Travers, and S. Van Iseghem. 2011. "The Influence of Fiscal Regulations on Investment in Marine Fisheries: A French Case Study." *Fisheries Research* 109, no. 2–3: 257–264. https://doi.org/10.1016/j.fishres.2011.02.012.

Leshoro, T. L. A., and P. Wabiga. 2023. "The Asymmetric Effects of Interest Rates on Private Investment in South Africa." *Acta Universitatis Danubius. Œconomica* 19, no. 3: 161–182. https://dj.univ-danubius.ro/index.php/AUDOE/article/view/2335.

Mardle, S., T. Hutton, P. Wattage, and S. Pascoe. 2005. "Entering and exiting a fishery: A strategic choice?"

McFadden, D. 1979. "Quantitative Methods for Analysing Travel Behaviour of Individuals:Some Recent Developments." In *Behavioural Travel Modelling*, edited by D. Hensher and P. Stopher, 279–318. Croom Helm.

Naylor, R. L., A. Kishore, U. R. Sumaila, et al. 2021. "Blue Food Demand Across Geographic and Temporal Scales." *Nature Communications* 12: 5413. https://doi.org/10.1038/s41467-021-25516-4.

Nøstbakken, L., O. Thébaud, and L. C. Sørensen. 2011. "Investment Behaviour and Capacity Adjustment in Fisheries: A Survey of the Literature." *Marine Resource Economics* 26, no. 2: 95–117. https://doi.org/10.5950/0738-1360-26.2.95.

Pelletier, D., and S. Mahevas. 2005. "Spatially Explicit Fisheries Simulation Models for Policy Evaluation." *Fish and Fisheries* 6: 307–349.

Prellezo, R., I. Lazkano, M. Santurtún, and A. Iriondo. 2009. "A Qualitative and Quantitative Analysis of Selection of Fishing Area by Basque Trawlers." *Fisheries Research* 97: 24–31. https://doi.org/10.1016/j.fishres.2008.12.015.

Punt, A. E., D. S. Butterworth, C. L. de Moor, J. A. A. De Oliveira, and M. Haddon. 2016. "Management Strategy Evaluation: Best Practices." *Fish and Fisheries* 17: 303–334.

Thébaud, O., J. R. Nielsen, A. Motova, et al. 2023. "Integrating Economics Into Fisheries Science and Advice: Progress, Needs, and Future Opportunities." *ICES Journal of Marine Science* 80: 647–663. https://doi.org/10.1093/icesjms/fsad005.

Tidd, A. N., P. Guillotreau, L. Dagorn, and M. Capello. 2025. "Overcapacity and Dynamics of a Tuna Fleet Facing Catch Limits and High Efficiency: The Case of the Indian Ocean Tuna Fishery." *Reviews in Fish Biology and Fisheries* 35: 1–13. https://doi.org/10.1007/s11160-025-09925-y.

Tidd, A. N., P. Guillotreau, I. Mosquiera, D. Fu, L. Dagorn, and M. Capello. 2025. "Equitable Pathways for Sustainable Tuna Fisheries Management in the Indian Ocean." *Marine Policy* 173: 106563. https://doi.org/10.1016/j.marpol.2024.106563.

Tidd, A. N., T. Hutton, L. T. Kell, and G. Padda. 2011. "Exit and Entry of Fishing Vessels: An Evaluation of Factors Affecting Investment Decisions in the North Sea English Beam Trawl Fleet." *ICES Journal of Marine Science* 68: 961–971. https://doi.org/10.1093/icesjms/fsr015.

Yew, T. S., and T. Heaps. 1996. "Effort Dynamics and Alternative Management Policies for the Small Pelagic Fisheries of Northwest Peninsular Malaysia." *Marine Resource Economics* 11: 85–103.