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A DEMONSTRATION MSE FRAMEWORK FOR WESTERN SKIPJACK TUNA INCLUDING OPERATING MODEL CONDITIONING

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SUMMARY

This report documents the demonstration of a management strategy evaluation for Western Atlantic skipjack tuna using the MSEtool R package. The stock is defined using catches from the Brazilian baitboat and handline fleets in the Southwest Atlantic Ocean. The output of a Stock Reduction Analysis (SRA) model, fitted to the catches, CPUE, and length compositions up to 2018, was used to set up and condition OMs. Starting from a base OM, additional OMs were generated to incorporate uncertainty in natural mortality, growth, maturity, selectivity, and steepness to create a reference set of OMs. A suite of example management procedures (MPs), including fixed TACs, index-slope MPs, and harvest control rules (HCRs), was tested in closed-loop simulation. This paper discusses the future work, including additional OM scenarios and consultation with managers and stakeholders, to identify candidate management procedures and performance metrics.

RÉSUMÉ

Ce rapport documente la démonstration d'une évaluation de la stratégie de gestion pour le listao de l'Atlantique occidental à l'aide du paquet MSEtool R. Le stock est défini au moyen des captures des flottilles brésiliennes de canneurs et de ligneurs à main dans l'océan Atlantique Sud-Ouest. Les résultats d'un modèle d'analyse de la réduction des stocks (SRA) ajusté aux captures, à la CPUE et aux compositions par taille jusqu'en 2018 ont été utilisés pour établir et conditionner les OM. À partir d'un OM de base, des OM supplémentaires ont été générés pour intégrer l'incertitude sur la mortalité naturelle, la croissance, la maturité, la sélectivité et la steepness afin de créer un jeu de référence d'OM. Une série d'exemples de procédures de gestion (MP), y compris les TAC fixes, les MP d'indices basés sur la pente et les règles de contrôle de l'exploitation (HCR), a été testée en simulation en boucle fermée. Ce document traite des travaux futurs, y compris des scénarios d'OM supplémentaires et de la consultation avec les gestionnaires et les parties prenantes, afin d'identifier de possibles procédures de gestion et des mesures de performance.

RESUMEN

Este informe documenta la demostración de una evaluación de estrategia de ordenación para el listado del Atlántico occidental utilizando el paquete MSEtool R. El stock se define utilizando las capturas de las flotas brasileñas de cebo vivo y de líneas de mano en el océano Atlántico suroccidental. El resultado de un modelo de Análisis de reducción de stock (SRA) ajustado a las capturas, la CPUE y la composición por tallas hasta 2018 se utilizó para configurar y condicionar los OM. A partir de un OM base, se generaron OM adicionales para incorporar la incertidumbre en la mortalidad natural, el crecimiento, la madurez, la selectividad y la inclinación para crear un conjunto de OM de referencia. Se probó un conjunto de procedimientos de ordenación ejemplo (MP), incluidos TAC fijos, MP índice-slope y normas de control de la

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captura (HCR), en una simulación de circuito cerrado. En el presente documento se examina la labor futura, incluidos escenarios de OM adicionales y la consulta con los gestores y las partes interesadas, para determinar los procedimientos de ordenación candidatos y la medición del desempeño.

KEYWORDS

Stock assessment, potential yield, fishery management

1. Introduction

1.1 Management Strategy Evaluation

Management Strategy Evaluation (MSE) is an approach for establishing rules for managing a fishery by simulation, testing their robustness to various hypothetical scenarios for fishery dynamics (Butterworth and Punt, 1999; Cochrane *et al.*, 1998) (**Figure 1**). These rules, often referred to as Management Procedures (MPs) or Harvest Strategies, typically use streamlined data such as catches and a relative abundance index to generate management advice such as a Total Allowable Catch (TAC).

MSE differs substantially from conventional stock assessment in how models of fisheries dynamics, including stock and exploitation dynamics, are used to derive management advice. In conventional stock assessment, fisheries dynamics models ('stock assessments') are used to directly derive management advice. For example, setting a TAC commensurate with fishing mortality rate at maximum sustainable yield (FMSY levels). MSEs typically use a greater number of fitted fisheries dynamics models ('operating models', abbreviated as 'OMs') that span a wider range of uncertainties to test the robustness of MPs. MSE can allow managers and stakeholders to establish a comparatively simple management rule (the MP), understand its performance, and have confidence that it can perform adequately even when uncertainty in dynamics may be high.

MSE involves closed-loop simulation whereby a candidate MP is successively applied into the simulated future accounting for feedbacks with the operating model (**Figure 1, E**). Closed-loop simulation requires not only an operating model and MPs, but an observation error model that can generate simulated data to be inputted to the MP, and an implementation error model that determines how well the management advice provided by the MP is adhered to in the simulation.

Punt *et al.* (2014) provide a comprehensive summary of the history of MSE implementations that, starting in the 1980s, covers more than 30 stocks including several short-lived pelagic species. In the face of difficulties in establishing defensible stock assessment models (arising from issues such as retrospective bias, data conflicts, numerical convergence problems) and the recognition of uncertainties that cannot be accounted for the provision of advice within the assessment paradigm, MSE has increasingly been adopted as a framework for the selection of management procedures for fisheries in the North Atlantic, including for bluefin tuna (ICCAT, 2020) and swordfish (Hordyk and Carruthers, 2019). Additionally, if an MP is adopted, empirical data can be gathered and compared to those data predicted by the operating model, to indicate whether the operating models should be revised, i.e., exceptional circumstances (Carruthers and Hordyk, 2018a).

1.2 Structure of the skipjack stocks and the Brazilian skipjack fisheries

The Standing Committee on Research and Statistics (SCRS) of the International Commission for the Conservation of Atlantic Tunas (ICCAT) has historically considered the existence of two distinct stocks in the Atlantic Ocean (eastern and western). Although the use of smaller areas has been recommended to monitor the development over time of fishery indicators, the Committee has decided, so far, to maintain the working hypothesis of two different units (SCRS, 2019). The western stock has been mainly caught by Brazil and Venezuela, which together have accounted for 97% of the catches, on average, in the past 10 years (2009-2018). Brazil has caught on average 90% (ranging from 82.6 to 94.4), and Venezuela 7% (4.5-10.5%).

The Brazilian skipjack fishery is mainly done with two different fishing methods: pole-and-line with live bait, in the south and southeast region, and hand line in associated schools, in the northeast coast. The pole and line fishery started in the early 80s and increased very quickly both in terms of number of boats and in landings (Castello and Habiaga, 1989). Notwithstanding, it has become one of the most stable fisheries in Brazil, largely due to its dependency on the live bait the bait-boats need to catch so that they can go fishing for the skipjack. Throughout the past 25 years, the landed weight has ranged from 16,560 tonnes (t) in 1995, to 32,438 t in 2013, with an average catch of 23,238 t. The fluctuation of yearly catches, however, is often attributed to changes in stock availability due to oceanographic conditions (Matsuura and Andrade, 2000) and to live bait availability (Santos and Rodrigues-Ribeiro, 2000) rather than to changes in stock abundance. The fishing ground spans from the southern boundary of the Brazilian EEZ (34ºS), to the coast of Rio de Janeiro (22ºS), with the main fishing season happening from late spring (November-December) to autumn (April-May).

Another fishery that has been catching increasing quantities of skipjack tunas is the hand-line fishery in associated schools (Silva *et al.*, 2018), happening mainly off the northeast coast of Brazil. This fishery started in 2012 and grew rapidly, but its main targets have always been yellowfin tuna and bigeye tuna. In 2019, the SKJ catches by this fishing gear was about 2,000 t, while the baitboat fishery landed about 15,000 t.

1.3 Why MSE for western skipjack tuna?

The reasons for developing an MSE for the western skipjack are multifold. Firstly, since it is a stock largely (90%) caught by a single Contracting Party and mainly by a single fishery, the development of an MSE should be much more straightforward than doing it for multispecies, multi-gear fisheries, such as those for the eastern skipjack tuna. Therefore, the development of an MSE for the western stock may help to advance the application and dissemination of such methodology to other stocks managed by ICCAT. The fact that most of the stock is caught by Brazil greatly enhances its responsibility in leading this process. To Brazil, the development of this MSE will be crucial not only to allow the eco-certification of the Brazilian skipjack fishery, but also to create a learning opportunity for advancing the fisheries management of other fish stocks in the country, using an MSE approach.

1.4 Western skipjack assessment & uncertainties

In 2014, the ICCAT carried out a stock assessment for the western Atlantic skipjack using data up to 2013 (ICCAT, 2014). Several stock assessment methods were applied, including data-limited approaches based solely on catches (Catch-MSY; Martell and Froese, 2012) and a mean length-based mortality estimator (Gedamke and Hoenig, 2006), as well as the more traditional surplus production models, such as ASPIC (Prager, 2002) and the Bayesian Surplus Production model, BSP (McAllister, 2014). The available data included a catch time series from 1952 to 2013 and the standardized catch-per-unit-effort (CPUE) of the Brazilian baitboat, Venezuelan purse seine fleet, the US pelagic longline and a larval index for the Gulf of Mexico. For the length-based model, size data (1980-2011) from the Brazilian baitboat fishery was used.

Overall, all models indicated that Atlantic western skipjack stock was unlikely to be overfished in 2013. Based on multi-model inference, the conclusion of the assessment was that the stock is likely to be well above B^{MSY}. This pattern was observed for all assessment models and MSY estimates were approximately 30,000 t. Nonetheless, there is substantial uncertainty about the absolute level of productivity of the stock, since the magnitude of MSY was largely affected by the prior on the carrying capacity, especially for the BSP model runs, with mean estimates almost doubling when the bound on the prior for carrying capacity is doubled. This uncertainty is due mostly because of insufficient contrast of the catches and the available CPUE time series to estimate the productivity of the stock.

Another issue of uncertainty is the assumption of a single western stock from the US coast to Brazil. In that time, there was no evidence to validate a smaller stock unit (i.e., southwest stock). In fact, the participation of the northwest fleets (i.e., Venezuelan purse-seine and US longline) in the western skipjack landings is much lower than that of the Brazilian baitboat fishery. This might suggest a potential separation between the northwestern and the southwestern stocks. Recent AOTTP results may improve the understanding of skipjack stock structure and movement patterns in the western Atlantic.

Stock assessment results based solely on the southwestern data (i.e. Brazilian catches and CPUE) were much hindered by the evident hyperstability of the baitboat Brazilian CPUE and also by the lack of contrast of fishing effort and landings, which precluded reasonable estimates of reference points for this stock using the surplus production model. Even with all these uncertainties, the western Atlantic skipjack stock is highly likely not overfished, with the recent yields well below the MSY levels. If catches increase sufficiently to have a contrast and a measurable impact on the CPUE associated with negligible changes in other stock indicators (e.g. mean lengths), future estimates of MSY might be higher than previously estimated.

1.5 *Life history of southwestern Atlantic skipjack*

In the southwestern Atlantic Ocean, skipjack reaches up to 87 cm FL (Vilella and Castello, 1991) and over 6 years (Garbin and Castello, 2014). The species grows fast and the von Bertalanffy (VB) growth parameters differ among the available studies: Linf ranges from 87.1 to 92.5 cm, k from 0.16 to 0.24 yr^{-1}, and t_0 from -2.9 to -0.05 years (**Table 1**). The first maturity occurs between the second and the third year of life, with 51 and 52 cm of FL for males and females, respectively (Vilella and Castello, 1991), although Soares *et al.* (2019) reported smaller sizes at maturity: 43.2 for females and 46.2 cm for males. Skipjack spawning is opportunistic with evidence of continuous spawning throughout the year (Matsuura, 1982; Andrade and Santos, 2004; Soares *et al.*, 2019), although there seems to be a higher level of reproductive activity between November and March with peaks in January and February (Goldberg and Au, 1986; Soares *et al.*, 2019). According to the seasonal patterns of the length compositions presented by Andrade and Santos (2004) and Soares *et al.* (2019), there seems be two annual recruitment peaks occurring during fall, which coincides with the end of the fishing season of the pole-and-line fleet in the southwestern Atlantic. The natural mortality, as calculated by several studies using empirical estimators, ranges from 0.41 to 0.77 yr^{-1} (**Table 1**).

2. Methods

2.1 *Data for operating model conditioning*

Catch data

Brazilian catches from 1958-2018 were obtained from the T1-NC database (dated 2020-01-15; **Figure 2**).

CPUE Data and Standardization

The abundance index used in this study was based on an updated CPUE standardization for Brazilian baitboat fishery conducted specifically to condition the operating model and has not yet been presented to the SCRS (**Table 2**). This new updated series has been prepared to be presented at the next skipjack data preparatory meeting in the form of a complete document, describing all datasets and methods used for this purpose. Here, we will provide just a summary of the database and method used in this paper.

For the CPUE standardization, catch and effort data from more than 2,700 industrial bait boat fishing trips between 2000 and 2018 were used. This dataset was compiled by different statistical fisheries monitoring projects conducted by different institutions (e.g. Fundação Universidade do Rio Grande- FURG, Universidade do Vale do Itajaí-UNIVALI, and Universidade Federal Rural de Pernambuco- UFRPE). The data compiled and used in this analysis included: year, season, boat, days at sea, fishing days and skipjack catches in metric tons. The nominal CPUE was defined as metric tons of skipjack caught per fishing day. As the Brazilian bait boat fishery targets only skipjack tuna, the proportion of zero catches was very low (<1%). Thus, the likelihood distribution used to fit the response variable (Yi - CPUE + 1) was the lognormal distribution.

The structures assumed for the models, particularly in terms of temporal and seasonal effects, defines a classical observation of a Gaussian Markov Random Fields (GMRF) (Rue & Held, 2005). Thus, the large size of the random effects vector can make simulation-based inference, such as Monte Carlo Markov Chain (MCMC), computationally inefficient or even unfeasible (Mayer, Sant'Ana & Ribeiro Junior, 2019). For this reason, a method based on numerical approximations was used for Bayesian inference in highly structured latent Gaussian models, as proposed by Rue *et al.* (2009). The methodology called INLA (Integrated Nested Laplace Approximation) makes the use of numerical integration methods to obtain a posterior marginal distribution and bypasses the high computational time and convergence problems in methods such as MCMC. The functions for calculating subsequent distributions are implemented in the statistical environment R (R Core Team, 2020), through the INLA package (Rue *et al.*, 2013), available at www.r-inla.org.

Seven distinct model structures were evaluated, considering fixed and random effects for the covariates or explanatory variables. The choice for the best fit was conducted based on Deviance Information Criteria (DIC), and the Conditional Predictive Ordinate (CPO). As a measure of the diagnostic for the model selected, the Probability Integral Transform (PIT) was used.

Length Data

For the length composition data that was included in the MSE operating models, the information was compiled from distinct sources. For the baitboat fishery between the years 2003 and 2011, the length composition data were obtained from the T2-SZ database (updated 2013-12-10). For both the baitboat and handline fisheries after 2011, the datasets used were combined from specific research projects conducted in Brazil by various institutions (e.g. Fundação Universidade do Rio Grande, Universidade do Vale do Itajaí and Universidade Federal Rural de Pernambuco) and from the ICCAT AOTTP Project. The specimens were measured in the bait and boat and handline Brazilian fishing fleets, operating, respectively, in the south/ southeast coast and off Brazilian northeast coast.

2.2 MSEtool: an open-source MSE framework

Although MSE has many important advantages over conventional stock assessment-based management, historically MSE processes have tended to be relatively expensive, technically complex and time consuming.
However, since 2017, a DFO-UBC partnership agreement (DFO 2017) has supported the development of sophisticated open source R packages for MSE: the Data Limited Methods toolkit, (DLMtool, Carruthers and Hordyk 2018b,c) and the Management Strategy Evaluation toolkit (MSEtool, Huynh *et al.* 2020). These are amongst the fastest, most flexible, and extensible open-source software packages for conducting MSE for fisheries in the full spectrum from data-poor (e.g., prescriptive management such as size limits and time-area closures) to data-rich (e.g., statistical catch-at-age models linked with harvest control rules).

The MSEtool package contains computationally efficient functions for conditioning operating models on a wide range of fishery data types. Also included in MSEtool are a wide range of model-based MPs based on VPA, SRA, statistical catch-at-age, delay-difference and surplus production assessments. These provide a basis for evaluating the cost-benefit of using more complex approaches for provision of management advice. Additionally, MSEtool contains state-of-the-art exceptional circumstances protocols for empirically evaluating the suitability of an MP when it is in use (Carruthers and Hordyk, 2018a).

An advantage of the MSEtool software is that it is computationally efficient and it has a high degree of flexibility in operating model structure. MP development is further aided by more than 100 example MPs that are included in the DLMtool R package, from which tailor-made MPs can be adapted. Additionally, an online library of operating models is available that provides an extensive test-bed for evaluating candidate management procedures.

MSEtool has extensive help documentation and user guides that allow scientists and stakeholders to develop skills in the software and provide reference materials in support of future customization. The software will remain open source and the operating model has been published in the primary literature (MSEtool shares the same operating model as DLMtool). All products developed using this software are made freely available, ensuring that the analyses can be run by other analysts and readily adapted for future data, alternative performance metrics, and revised MPs.

DLMtool and MSEtool are currently used by DFO, the California Department of Fish and Wildlife (Hordyk *et al.*, 2017), the Marine Stewardship Council, the International Commission for the Conservation of Atlantic Tunas, and the US NOAA as MSE frameworks for the testing of management procedures, identifying data collection priorities and quantifying management reference points.

2.3 SRA_scope: a powerful and flexible system for conditioning operating models

A multi-fleet Stock Reduction Analysis (SRA; Walters *et al*., 2006) was developed in Template Model Builder (TMB; Kristensen *et al*., 2016) (see MSEtool vignettes for greater detail on model equations and conditioning on the CRAN website: https://cran.r-project.org/package=MSEtool). The SRA requires complete (all years, all fleets) catch data along with any combination of other data types (that may be temporally patchy) including indices of abundance, catch-at-age, catch-at-length, and mean size (either mean length or mean weight) data. The model can interpret indices in various ways including relative/absolute measures of vulnerable/stock-wide, biomass/numbers/spawning biomass/biomass. Given age and/or length composition data, the model estimates selectivity for fleets and surveys that are either logistic (asymptotic, 'flat-topped') or double-normal ('dome-shaped'), with time blocks to model time-varying fleet selectivity as needed. In MSEtool, the function name is termed 'SRA_scope' to emphasize the fact that these models may not be standalone assessments. Rather, the model is intended to scope the potential range of historical recruitment and biomass estimates that arise from alternative biological and selectivity assumptions and fits to the data.

The SRA model applied here is comparable to statistical catch-at-age (SCA) models, where the model assumes historical catches are known exactly. Commonly applied assessment frameworks such as Stock Synthesis (Methot and Wetzel, 2013) are often cited as SCAs, but in many applications, catches are fitted with such high precision that they function identically to their more computationally efficient counterparts (SRAs). For all operating models conditioned in these analyses, the only substantive difference in fitting in SCA or SRA mode was a substantial improvement in stability and estimation time using the SRA formulation.

For computational flexibility, the SRA used here can be configured to either fit to catches with high precision using a lognormal likelihood function or iteratively solve for the fishing mortality rates such that the predicted catches match the observed catches. Indices are fitted assuming a lognormal likelihood functions while age composition and (optionally length composition) data are assumed to be distributed according to a multinomial distribution.

Given the substantial improvement in computational efficiency of TMB, the SRA model used in this conditioning is at least an order of magnitude faster than previous assessments, typically converging to a positive definite Hessian of model parameters (or not) in a few seconds on a modern laptop. This speed is important for developing operating models since it allows for in-meeting exploration of alternative operating model scenarios. An additional advantage of TMB is that it is native to the R statistical environment and hence the model is linked directly to the MSEtool package and operating models proposed for conducting MSE analyses.

Ultimately, the output from the SRA is used to set up the historical period of the OM. Standardized reports are also available to provide a summary of model estimates, plotted fits to the data, and the accuracy of the conversion of the estimation model to the OM.

2.4 OM conditioning

It is difficult to incorporate all major uncertainties into a single OM. Therefore, a reference set of OMs was used to characterize core uncertainties that could impact MP performance and selection for Western Atlantic skipjack. From a Base OM, five additional OMs were generated for a total of six OMs in the reference set.

Here, the western stock was defined by catches from Brazilian fleets in the Southwest Atlantic Ocean from 1958 to 2018. A two-fleet structure was set up with catches and length compositions for the baitboat and handline fishery in associated schools. The annual multinomial sample size for the length compositions was taken to be the natural logarithm of the nominal sample size. The standardized baitboat CPUE was used as an index of abundance.

For the Base OM, growth and maturity parameters were taken from Soares *et al.* (2019) and natural mortality from the 2014 assessment (ICCAT, 2015). The maturity-at-age and M-at-age schedules was obtained by converting maturity-at-length and M-at-length, respectively, using mean length-at-age (**Table 3**). The Beverton-Holt stock-recruit steepness value of 0.9 was used, indicating relatively high resilience. The fleet selectivity was set to be flat-topped.

The reference set incorporated alternative assumptions about selectivity, growth, natural mortality, and steepness, as follows:

- **(1) Base** – described above.
- **(2) Dome_sel** – the selectivity of the baitboat and handline fleets is dome-shaped.
- **(3) Low_h07** – steepness was set to 0.7 indicating moderate/lower resilience.
- **(4) HighM_age3+** - a higher natural mortality of 0.75 was used for age 3 and higher.
- **(5) Low_t0** – a lower (more negative) von Bertalanffy t0 was used. Previous growth studies estimated a more negative t0 (Garbin and Castello, 2014; see **Table 1**). As a result, young fish are larger than in the Base OM. Here, a value of t_0 = -2 was used. The maturity-at-age schedule remains identical to that in the Base OM.
- **(6) Low_t0_mat** – same as (5) with regards to growth except that the maturity-at-age is re-calculated from maturity-at-length and the lower value of t_0. As a result of the low t_0, the proportion of fish mature is higher at younger ages.

Each OM contained 100 stochastic replicates that incorporated uncertainty in the estimates of recruitment, including the unfished recruitment parameter (R_0) and annual recruitment deviates. From a single SRA fit, the variance-covariance matrix was re-sampled 100 times. Selectivity was constant within OM as estimated in the SRA.

2.5 Management procedures and closed-loop simulation

The projection period for the closed-loop simulation was 40 years, with a two-year data lag, e.g., in 2020, the TAC for 2021 is set with data up to 2018. Future catches were assumed to be known without error and with full compliance to the TAC. The error structure of the index used a lognormal distribution with a coefficient of variation of 0.4 and autocorrelation based on the SRA fit (both in logspace). The selectivity is based on the F-at-age in the terminal year of the historical period from the OM conditioning (**Figure 3**). Non-static MPs were evaluated with both annual and triennial TAC updates, the latter denoted as "3u" in the MP nomenclature.

Several types of management procedures were evaluated over the reference set of OMs. Three constant catch (CC) MPs set a fixed TAC of 15 kilotonnes (kt), 20 kt, or 30 kt, respectively, during the projection period.

Index-slope MPs adjust the TAC up and down as the CPUE increases and decreases, respectively. Three index-slope MPs were evaluated: Iratio, Islope, and GBslope. The Iratio MP (Jardim *et al.*, 2015), incorporating the time lag, sets the TAC as

$$\mathrm{TAC}_{y+1} = \frac{\alpha}{\beta} C_{y-2}$$

where α is the mean of the CPUE in the most recent 2 years, e.g., 2017-2018, β is the mean of the CPUE in the 3 years preceding those for α, e.g., 2014-2016, C is the observed catch, and y indexes year.

The Islope and GBslope MPs (Geromont and Butterworth, 2014), incorporating the time lag, calculate the TAC as

$$\mathrm{TAC}_{y+1} = (1 + b\lambda) C_{y-2}$$

where b is the slope of log(CPUE) in the most recent 3 years, and λ is a tuning parameter (λ = 0.4 for Islope and λ = 1 for GBslope). GBslope has an additional constraint where the TAC cannot exceed 80-120% of the most recent catch.

A 40-10 harvest control rule (HCR) MP was also evaluated in this analysis, using SPiCT, a state-space surplus production model (Pedersen and Berg, 2017), as the assessment model for obtaining the reference points.

Finally, reference MPs can be used to learn about the OMs. For example, an MP that allows no fishing (NFref) can be used to evaluate how quickly a stock can rebuild if it is depleted, while a current effort MP (curE) evaluates a status quo approach (projecting the current fishing mortality).

2.6 Performance metrics

Four preliminary performance metrics (PMs) were used to compare MPs:

(1) **40% B0** – the probability (mean over 100 replicates) that the spawning depletion is greater than 40% during the projection period.
(2) **STC30 (short term catch)** – the probability that the catch exceeds 30 kt in the first decade of the projection period.
(3) **LTC30 (long term catch)** – the probability that the catch exceeds 30 kt in the second decade of the projection period.
(4) **AAVC (average annual variability in catch) –** the probability that the interannual catch variability is less than 20% during the projection period.

Additional short-term catch performance metrics were also calculated with thresholds of 20, 25, 30, 35, and 40 kt (referred to as STC20, STC25, and so on).

3. Results

3.1 OM conditioning

The six OMs estimated the stock to be near unfished conditions until the large increase in catch during the early 1980s (**Figure 4**). Since 2000, the spawning biomass and depletion is informed by the trends in the baitboat CPUE (**Figures 5-6**).

In OMs (1), (3), and (4), the effective selectivity for the projection period is almost knife-edge selection at age 3 (**Figure 3**). The effective selectivity was obtained by using the terminal year F-at-age, which is informed by the estimates of fleet selectivity from fitting to the length data (**Figure 7-10**). In OM (2) with dome selectivity, the age of full selection is estimated to be age 4. While fully maturity is at age 3 in practice in these OMs, a proportion of age 2 individuals is also mature. In OMs (5) and (6), full selectivity is estimated at age 2 due to the lower t0 parameter in relation to the length compositions. While maturity is unchanged in OM (5), full maturity occurs at age 2 in OM (6) with approximately 50% maturity in age 1.

As expected, OM (5) 'Low_t0' has the lowest magnitude of SSB, due to the maturity and growth schedules compared to the other five OMs. A higher proportion of immature catch is estimated in OM (5). As a result, a smaller SSB is needed to explain the observed catches and the spawning depletion is lowest (**Figures 4, 6**).

High apical fishing mortality rates are estimated for the stock (**Figure 12**). This is presumably a combination of high natural mortality rates experienced in younger age classes (using yield-per-recruit considerations) and the high age of full selectivity relative to maturity (using spawning potential ratio considerations). In the model, spawning occurs at the beginning of the year consistent with peak spawning condition occurring during the austral summer months, which will allow for high removal rates in some years without significant harm to the stock.

These same dynamics result in difficulty in estimating MSY reference points in all six OMs. As the apical F increases, the yield curves flatten but do not reach any optima, which could preclude the use of MSY reference points for this stock. Here, we proposed 40% depletion as a proxy for BMSY and subsequent built this proxy into the performance metrics.

3.2 MP evaluation

From the projected catches and arising from closed-loop simulation (**Figures 13-14**), performance metrics can be presented in various ways to filter, rank, and ultimately adopt a management procedure. All performance metrics can be presented in summary tables, which can be color coded (with a gradient) to indicate the metrics for which the MPs perform poorly and well. Trade-off plots can show the range of outcomes for a set of candidate MPs in which those with higher probabilities in the biomass performance metric often also have lower probabilities in the catch performance metric and vice versa (**Figure 15**). For a set of MPs, trade-off plots can characterize the frontier contour along which a reduction in one performance metric is exchanged for a gain in the other. Finally, radar plots can be used to generate polygons whose vertices indicate the range in magnitude of all performance metrics (**Figure 16**). Within the full polygon, a concentric polygon for each MP describes whether the performance metric corresponding to each vertex is high or low. Differently behaving MPs will have polygons that span separate areas of the full polygon. Performance metrics can be reported for individual OMs in the reference set and/or summarized by averaging values across the reference set.

In all OMs, there was a clear trade-off between keeping the SSB above 40% depletion and the achieving high catches (**Table 4**), with the trade-off clearer using STC20 rather than STC30 (**Figures 17-18**). The '40% B0' metric was higher for MPs with lower STC20 and STC30 (**Table 4**). From the radar plots, the CC_30kt and spict_4010 MPs often had the highest STC20 and lower '40% B0' (**Figure 19**). Overall, good short-term catch performance was synonymous with good long-term catch performance. There is high inter-annual variability in catch, denoted by low AAVC, for most MPs, with the exception of the fixed TACs and the index-slope MPs with 3-year updates. Otherwise, the performance of the HCR (spict_4010) and index-slope MPs (Iratio, Islope, GBslope) did not substantially differ between annual and triennial TAC updates.

MPs were less likely to achieve the conservation performance metric with lower '40% B0' in OM (5) compared to the other five OMs. Otherwise, most MPs were likely to have very high '40% B0', except for the CC_30kt and spict_4010 (HCR) MPs. In all OMs, catches of at least 30 kt was not likely to be achieved with any MP, consistent with the yield curve calculations from the OM conditioning. The alternative catch performance metrics STC20 and STC25 show that it is more likely to achieve catches in the range of 20-25 kt for some MPs such as spict_4010 and the 20 or 30 kt fixed TAC (**Table 4**).

4. Discussion

This analysis demonstrated the technical steps associated with the MSE for Western Atlantic SKJ, including OM conditioning, closed-loop evaluation of MPs, and presentation of relevant performance metrics. Alternative assumptions regarding selectivity relative to maturity, arising from alternative growth parameters, generated the most contrast among OMs and subsequent performance of MPs. If catch predominantly consists of mature animals, then the probability of achieving 40% depletion was often high for many MPs. On the other hand, this probability was much lower in the OM where catches consists of an age class (age 2) that is predominantly immature. This finding highlights the need to evaluate robustness of MPs to alternative hypothesis for the maturity and growth parameters. Additional operating models including time-varying behavior for growth and maturity should also be considered for skipjack, for example, as robustness scenarios.

Future catches are not likely to often exceed 30-kt from the MPs evaluated and current set of OMs. The yield curves calculated from the OM conditioning are consistent with this finding. Catches exceeding 25-40 kt, depending on the OM, are not likely to be sustainable over the long term. Historically, annual catches have been as high as 30 kt without notable decrease in the CPUE and truncation in the size structure of the catch. Catches have also decreased following El Nino years. Thus, historical exploitation rates associated with these catches may have been lower than estimated as a result of oceanographic conditions that move fish in and out of waters that cannot be accessed by the fishing fleet. Additional operating models could account for these availability shifts if they are conditioned on indices that incorporate oceanographic conditions as covariates during the standardization process. Such approach will be developed for the Brazilian baitboat CPUE for the next western Atlantic skipjack assessment and might be incorporated in the conditioning of the additional operating models in the future.

Indices of abundance obtained from CPUE of surface fisheries, such as the Brazilian baitboat CPUE, may be hyperstable since these fleets target schools of fish. In initial analyses, assumptions of hyperstable CPUE did not provide any contrast in historical biomass estimates relative to the Base OM due to the relatively flat trend for the entirety of the CPUE series. Nevertheless, the performance of MPs that use CPUE is likely to be dependent on the relationship between the index and stock size. For this reason, these MPs might be not appropriate candidates for management of western skipjack stock.

Considering these factors arising from the demonstration, additional operating models are proposed for future work, including:

(1) A reference set of OMs that include the full range of biological parameters from a comprehensive literature search.
(2) A scenario that models time-varying availability due to periodic oscillations in oceanographic indices. In MSEtool, a spatial OM can be built with time-varying movement of fish in and out of areas not accessible to the fishery.
(3) A robustness scenario for hyperstability in the CPUE.
(4) Robustness scenarios that explore changes in growth or maturity schedules in the future.
(5) Consideration of implementation error of the TAC advice to the true catches and the reporting rate. Currently, there is little insight on the extent of implementation error since the fishery has historically operated without regulations on total allowable catch.

Almost all MPs evaluated here were output control MPs, i.e., TACs, and one MP was effort-based. Effort-based MPs require operationalization of effective fishing effort that can be controlled by management, such as the number of active fishing licenses, number of fishing trips, or number of fishing events. MSEtool can also implement size-based and spatial control rules, along with effort control rule and any combination thereof, in a single MP. However, size-based MPs may not be necessary if growth overfishing is not a concern. MPs that implement spatial closures require operating models with differential productivity assumptions among areas that would potentially be open or closed to fishing. Otherwise, spatial MPs operate as *de facto* effort controls. Further consultation with managers and stakeholders of the Brazilian fishery will be helpful to identify candidate MPs and to refine performance metrics for MP selection.

Exceptional circumstance protocols should be adopted to identify situations when the OMs and/or MP needs re-evaluation once an MP is adopted. For example, future fishing behavior may deviate from the assumptions in the current OMs if fleet selectivity or the current distribution of catches between the baitboat and handline gears significantly changes. Second, new biological life history parameters may be significantly different from historical ones if there are methodological improvements in ageing and maturity classification. Finally, while the current OMs only consider the stock in the Southwest Atlantic off coastal Brazil, increased catches elsewhere in the western Atlantic will warrant future investigation of the stock structure of skipjack in the western Atlantic. If skipjack were to be a single unit stock in the western Atlantic, then spatial expansion of catches impact the productivity of the resource associated with catches in Brazilian waters. Such protocols outline the range of assumptions in the OMs and the situations in which they would break down.

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Table 1. Life history parameters of *Katsuwonus pelamis* from southwestern Atlantic Ocean: VB growth parameters (FL∞, cm), k (yr^{-1}) and t0; Natural mortality (M) and size at first maturity (FL_{50}, cm).

FL∞	*k*	t_0	*M*	FL_{50} *females*	FL_{50} *males*	**References**
87.1	0.22	-2	0.77	52	51	Vilella & Castello (1991)
92.5	0.16	-2.9	0.41; 0.50; 0.63			Garbin & Castello (2014)
90.1	0.24	-0.05	0.47	43.2	46.2	Soares *et al.* (2019)

Table 2. Brazilian baitboat standardized CPUE series.

Year	*Predicted Index*	*SD*
2000	4.007	0.413
2001	3.903	0.406
2002	3.877	0.407
2003	2.987	0.407
2004	3.355	0.407
2005	3.238	0.409
2006	3.830	0.408
2007	4.429	0.405
2008	4.050	0.405
2009	4.085	0.405
2010	3.648	0.406
2011	4.708	0.404
2012	5.815	0.403
2013	4.186	0.405
2014	3.864	0.406
2015	4.044	0.408
2016	4.095	0.411
2017	3.692	0.409
2018	3.397	0.407

Table 3. Biological parameters for the Base OM.

Parameter	**Value**
von Bertalanffy asymptotic length (Linf)	90.1 cm
von Bertalanffy k	0.24 $year^{-1}$
von Bertalanffy t_0	-0.54 years
Length-weight a	0.004
Length-weight b	3.42
Length of 50% maturity	43.2
Length of 95% maturity	50.2
Steepness	0.9
Recruitment standard deviation σ_R	0.4
Natural mortality (age 1 to 6)	1.91, 1.04, 0.74, 0.60, 0.54, 0.51 ($year^{-1}$)

Table 4. Performance metrics for each MP in the six operating models. The color gradient spans red to white to green, corresponding to values of 0, 0.5, and 1, respectively, for each performance metric.

(1) Base_h09

	40% B0	STC20	STC25	STC30	STC35	STC40
NFref	0.99	<0.01	<0.01	<0.01	<0.01	<0.01
CC_15kt	0.95	<0.01	<0.01	<0.01	<0.01	<0.01
Iratio_3u	0.91	0.07	0.02	<0.01	<0.01	<0.01
Iratio_	0.88	0.21	0.05	0.02	<0.01	<0.01
GBslope_3u	0.85	0.27	0.05	0.01	<0.01	<0.01
Islope	0.84	0.52	0.02	<0.01	<0.01	<0.01
CC_20kt	0.84	0.47	<0.01	<0.01	<0.01	<0.01
GBslope	0.84	0.32	0.07	0.03	0.01	<0.01
Islope_3u	0.82	0.60	<0.01	<0.01	<0.01	<0.01
curE	0.78	0.54	0.21	0.07	0.03	0.01
spict_4010_	0.50	0.74	0.49	0.26	0.13	0.06
spict_4010_3u	0.49	0.75	0.50	0.27	0.14	0.07
CC_30kt	0.43	0.85	0.70	0.11	<0.01	<0.01

(2) Dome_sel

	40% B0	STC20	STC25	STC30	STC35	STC40
NFref	0.99	<0.01	<0.01	<0.01	<0.01	<0.01
CC_15kt	0.93	<0.01	<0.01	<0.01	<0.01	<0.01
Iratio_3u	0.95	0.02	<0.01	<0.01	<0.01	<0.01
Iratio_	0.94	0.09	0.01	<0.01	<0.01	<0.01
GBslope_3u	0.95	0.06	<0.01	<0.01	<0.01	<0.01
Islope	0.88	0.14	<0.01	<0.01	<0.01	<0.01
CC_20kt	0.87	0.01	<0.01	<0.01	<0.01	<0.01
GBslope	0.94	0.10	0.01	<0.01	<0.01	<0.01
Islope_3u	0.89	0.18	<0.01	<0.01	<0.01	<0.01
curE	0.63	0.50	0.22	0.09	0.03	0.01
spict_4010_	0.83	0.32	0.13	0.04	0.01	<0.01
spict_4010_3u	0.83	0.33	0.13	0.04	0.02	<0.01
CC_30kt	0.83	0.33	0.14	<0.01	<0.01	<0.01

(3) Low_h07

	40% B0	STC20	STC25	STC30	STC35	STC40
NFref	0.99	<0.01	<0.01	<0.01	<0.01	<0.01
CC_15kt	0.92	<0.01	<0.01	<0.01	<0.01	<0.01
Iratio_3u	0.87	0.06	0.01	<0.01	<0.01	<0.01
Iratio_	0.82	0.20	0.05	0.01	<0.01	<0.01
GBslope_3u	0.78	0.25	0.05	0.01	<0.01	<0.01
Islope	0.74	0.47	0.02	<0.01	<0.01	<0.01
CC_20kt	0.72	0.45	<0.01	<0.01	<0.01	<0.01
GBslope	0.77	0.30	0.07	0.02	0.01	<0.01
Islope_3u	0.71	0.58	<0.01	<0.01	<0.01	<0.01
curE	0.67	0.48	0.17	0.05	0.02	0.01
spict_4010_	0.37	0.66	0.44	0.24	0.13	0.06
spict_4010_3u	0.37	0.68	0.44	0.24	0.12	0.07
CC_30kt	0.24	0.80	0.63	0.10	<0.01	<0.01

(4) HighM_age3+

	40% B0	STC20	STC25	STC30	STC35	STC40
NFref	>0.99	<0.01	<0.01	<0.01	<0.01	<0.01
CC_15kt	0.98	<0.01	<0.01	<0.01	<0.01	<0.01
Iratio_3u	0.96	0.09	0.02	0.01	<0.01	<0.01
Iratio_	0.95	0.24	0.06	0.02	0.01	<0.01
GBslope_3u	0.94	0.28	0.07	0.01	0.01	<0.01
Islope	0.95	0.57	0.03	<0.01	<0.01	<0.01
CC_20kt	0.95	0.53	<0.01	<0.01	<0.01	<0.01
GBslope	0.94	0.32	0.10	0.02	0.01	<0.01
Islope_3u	0.94	0.62	0.02	<0.01	<0.01	<0.01
curE	0.94	0.55	0.23	0.08	0.03	0.01
spict_4010_	0.70	0.81	0.63	0.43	0.26	0.16
spict_4010_3u	0.69	0.83	0.63	0.43	0.26	0.16
CC_30kt	0.77	0.93	0.85	0.20	<0.01	<0.01

(5) Low_t0

	40% B0	STC20	STC25	STC30	STC35	STC40
NFref	0.96	<0.01	<0.01	<0.01	<0.01	<0.01
CC_15kt	0.48	<0.01	<0.01	<0.01	<0.01	<0.01
Iratio_3u	0.60	0.05	0.01	<0.01	<0.01	<0.01
Iratio_	0.51	0.14	0.03	<0.01	<0.01	<0.01
GBslope_3u	0.54	0.16	0.01	<0.01	<0.01	<0.01
Islope	0.25	0.29	0.01	<0.01	<0.01	<0.01
CC_20kt	0.19	0.14	<0.01	<0.01	<0.01	<0.01
GBslope	0.50	0.17	0.03	0.01	<0.01	<0.01
Islope_3u	0.26	0.34	<0.01	<0.01	<0.01	<0.01
curE	0.01	0.66	0.42	0.24	0.13	0.07
spict_4010_	0.04	0.49	0.23	0.10	0.04	0.02
spict_4010_3u	0.04	0.48	0.23	0.10	0.04	0.02
CC_30kt	0.05	0.52	0.28	0.03	<0.01	<0.01

(6) Low_t0_mat

	40% B0	STC20	STC25	STC30	STC35	STC40
NFref	>0.99	<0.01	<0.01	<0.01	<0.01	<0.01
CC_15kt	0.97	<0.01	<0.01	<0.01	<0.01	<0.01
Iratio_3u	0.98	0.03	<0.01	<0.01	<0.01	<0.01
Iratio_	0.98	0.13	0.03	<0.01	<0.01	<0.01
GBslope_3u	0.98	0.13	<0.01	<0.01	<0.01	<0.01
Islope	0.95	0.25	0.01	<0.01	<0.01	<0.01
CC_20kt	0.95	0.12	<0.01	<0.01	<0.01	<0.01
GBslope	0.98	0.17	0.02	<0.01	<0.01	<0.01
Islope_3u	0.95	0.31	<0.01	<0.01	<0.01	<0.01
curE	0.90	0.69	0.47	0.26	0.15	0.09
spict_4010_	0.93	0.48	0.24	0.10	0.04	0.02
spict_4010_3u	0.93	0.48	0.24	0.10	0.04	0.02
CC_30kt	0.93	0.50	0.27	0.03	<0.01	<0.01

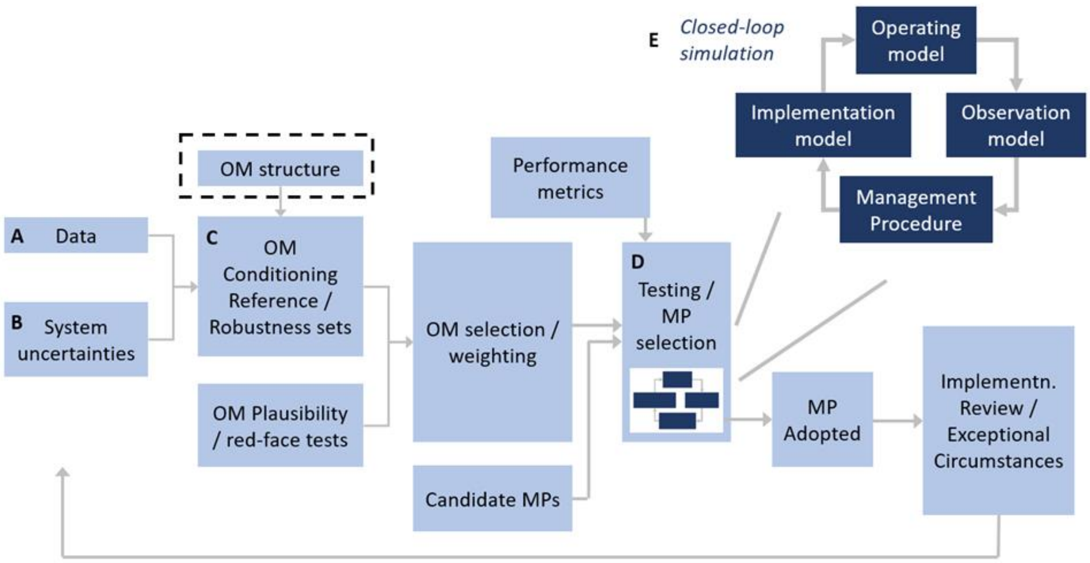

Figure 1. A Management Strategy Evaluation (MSE) process including closed-loop simulation. The technical components behind the MSE includes the structure of the operating model (OM) (highlighted in the dashed box) and its capability to accept the data types currently available for skipjack (A) across a range of system uncertainties (B) in a suitable model conditioning framework (C) that is compatible with existing software (MSEtool) for conducting closed loop simulation testing of management procedures (D, E).

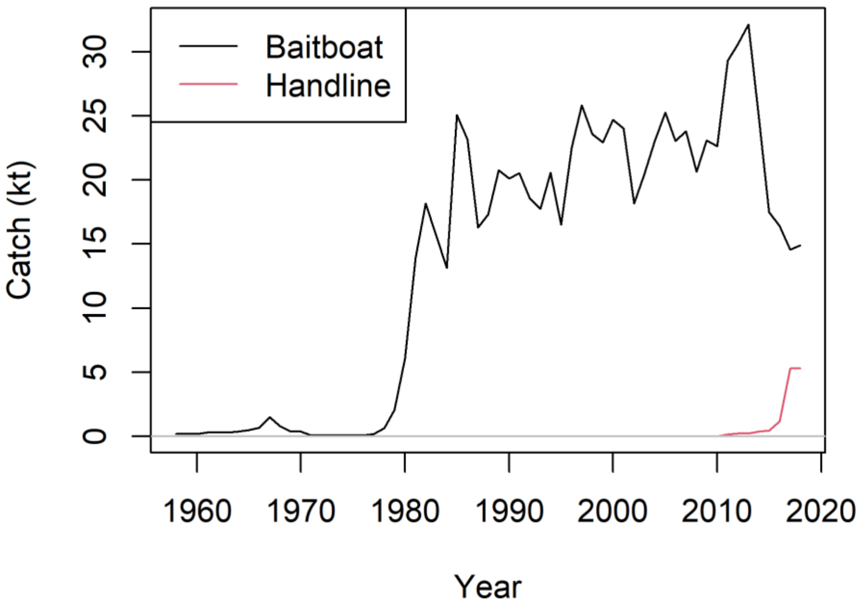

Figure 2. Catches from the Brazil baitboat and handline fisheries.

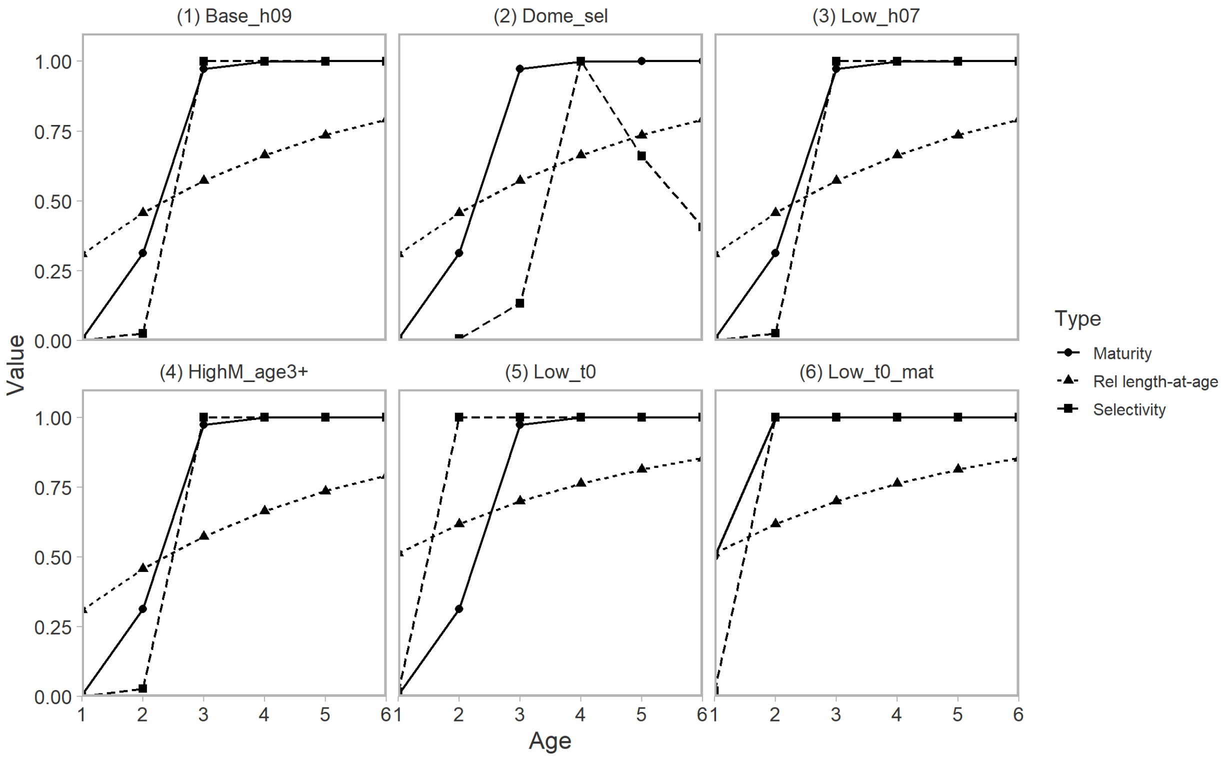

Figure 3. Effective selectivity (from the terminal year F-at-age, dotted lines) in the projection period relative to maturity-at-age (unbroken lines) for the six skipjack operating models. Length-at-age relative to Linf is in dotted lines.

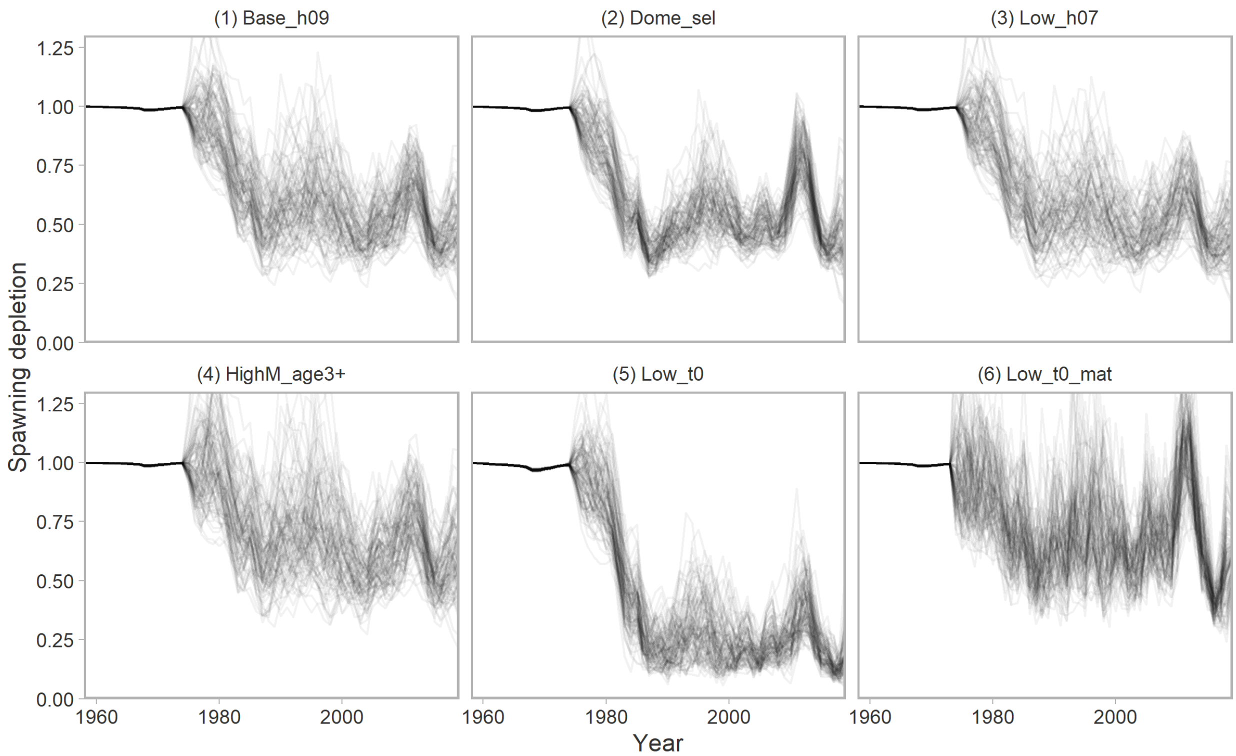

Figure 4. Spawning depletion for the six operating models in the historical period (1958-2018). Recruitment deviates were not estimated prior to 1974. Each line represents one of 100 stochastic replicates obtained from sampling the recruitment estimates using the maximum likelihood estimates from the SRA fit as the means and the variance-covariance matrix from the Hessian matrix.

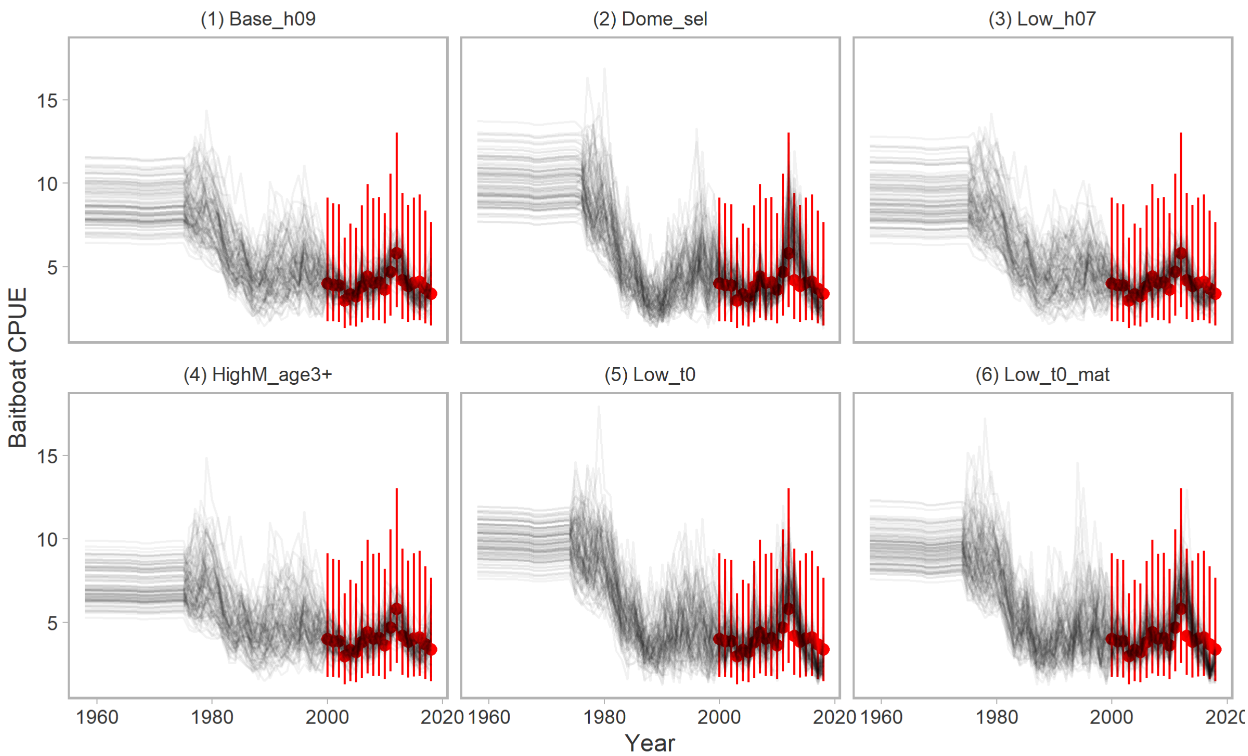

Figure 5. Observed (red dots, with confidence intervals in vertical red lines) and predicted (black lines) baitboat CPUE for the six operating models in the historical period.

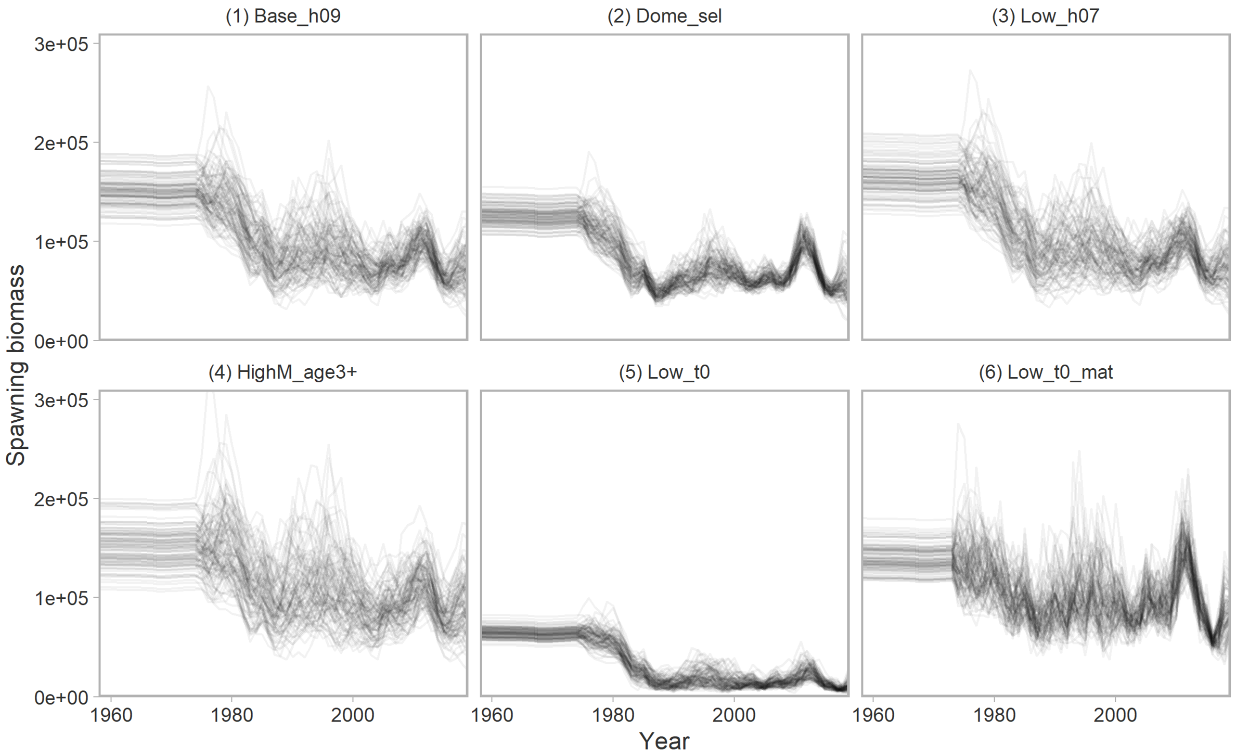

Figure 6. Predicted spawning biomass (tonnes) for the six operating models in the historical period.

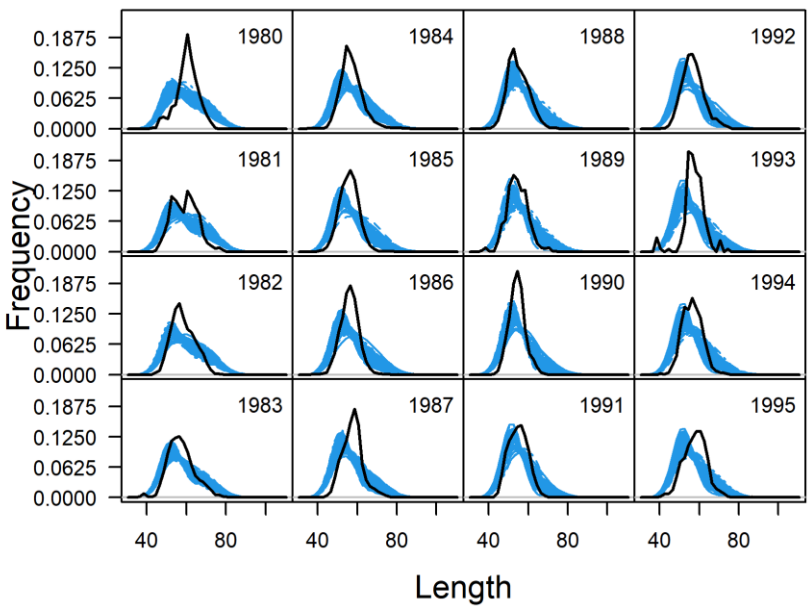

Figure 7. Observed (black lines) and predicted (blue lines) length compositions (1980-1995) from the Base OM (#1) for the baitboat fishery.

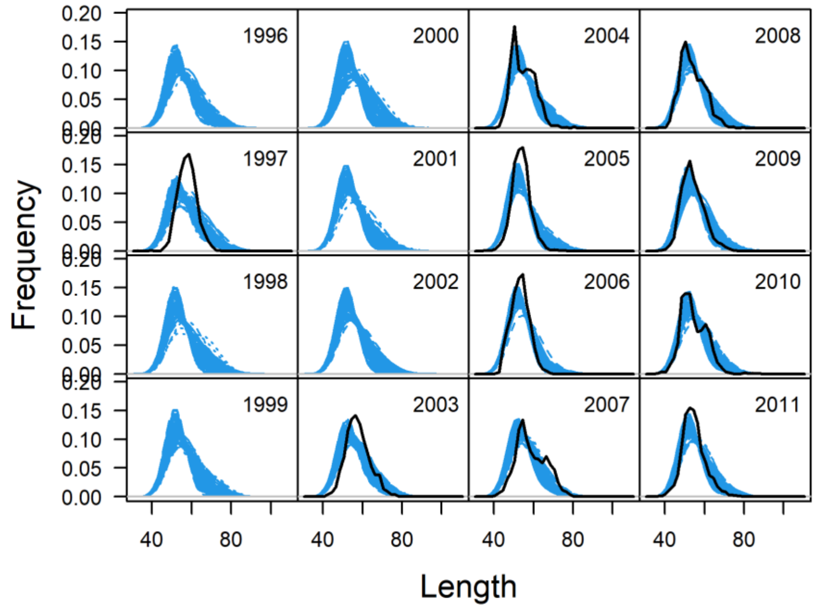

Figure 8. Observed (black lines) and predicted (blue lines) length compositions (1996-2011) from the Base OM (#1) for the baitboat fishery.

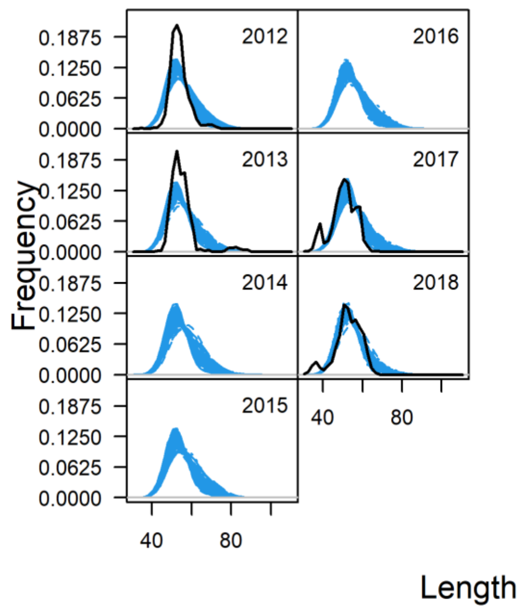

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Figure 9. Observed (black lines) and predicted (blue lines) length compositions (2012-2018) from the Base OM (#1) for the baitboat fishery.

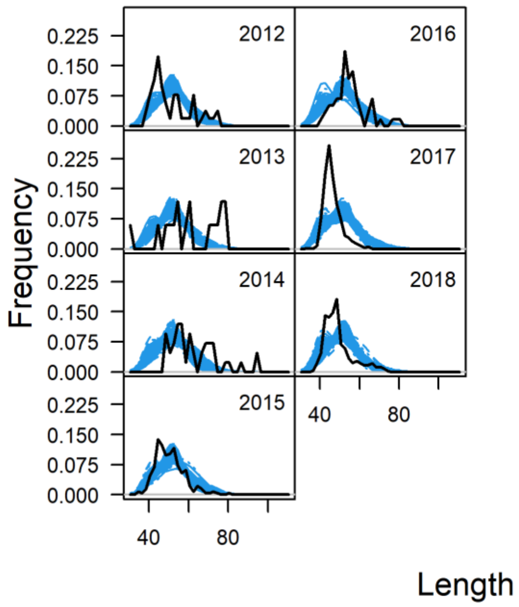

Figure 10. Observed (black lines) and predicted (blue lines) length compositions (2012-2018) from the Base OM (#1) for the handline fishery.

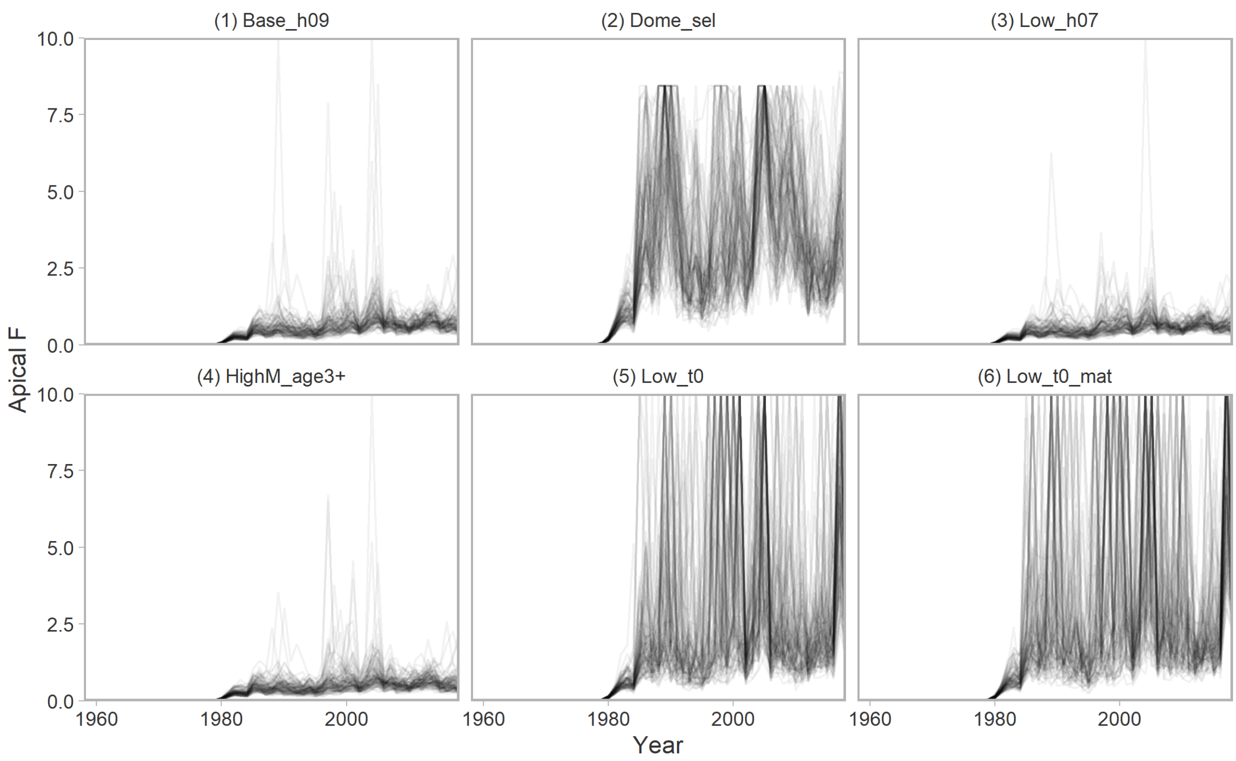

Figure 12. Apical instantaneous fishing mortality rates (per year) for the six operating models in the historical period.

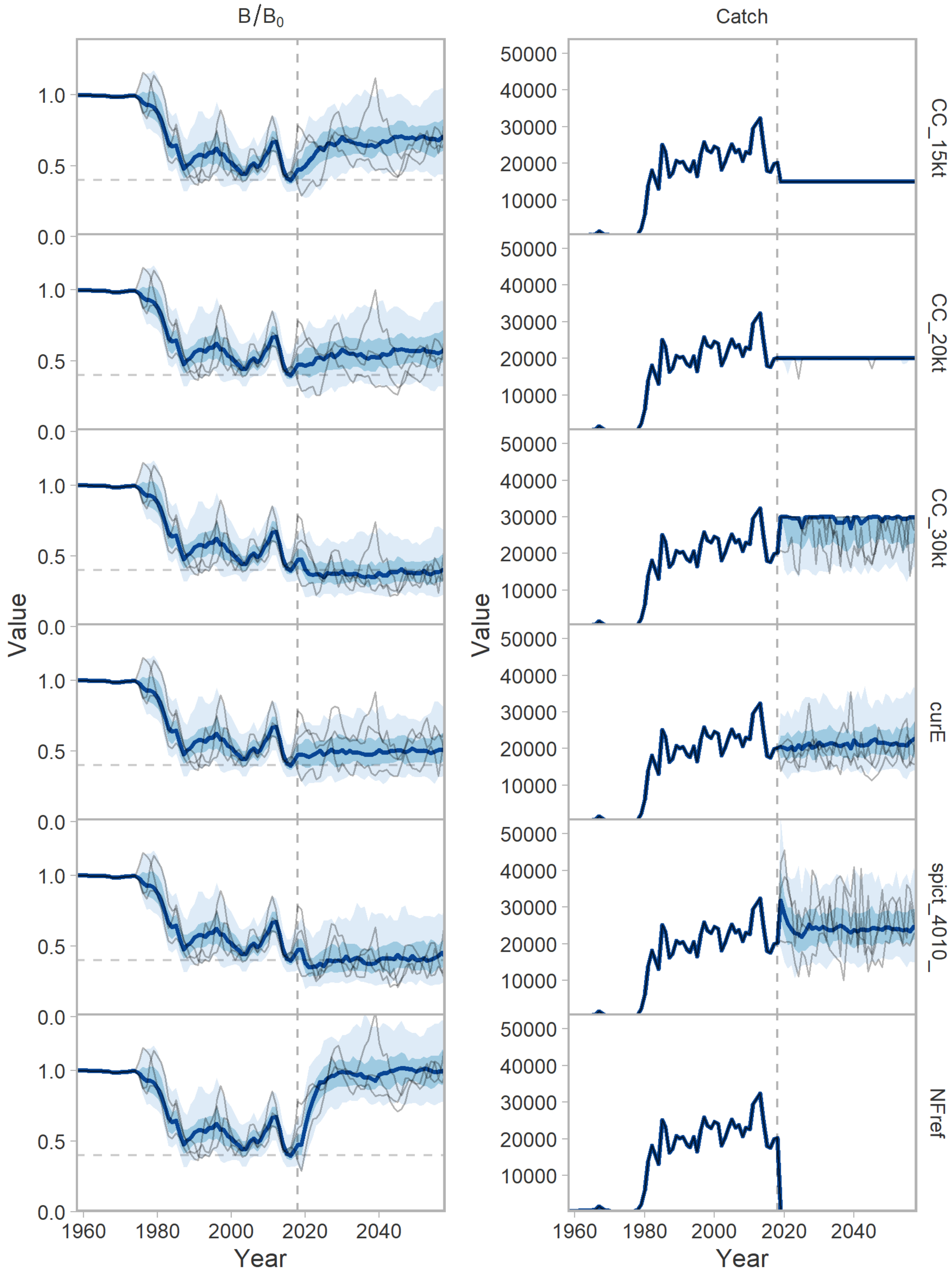

Figure 13. Spawning depletion (left column) and catches (right column) from the closed-loop simulation for a selection of MPs (rows) in the Base OM (#1). Dashed, horizontal lines for spawning depletion indicate a value of 0.4. Dashed, vertical lines separate the historical and projection periods of the operating model. The dark blue line indicates the median from 100 simulation replicates, while lighter blue bands represent the interquartile range and 95% confidence intervals. Solid, grey lines plot 3 individual simulations.

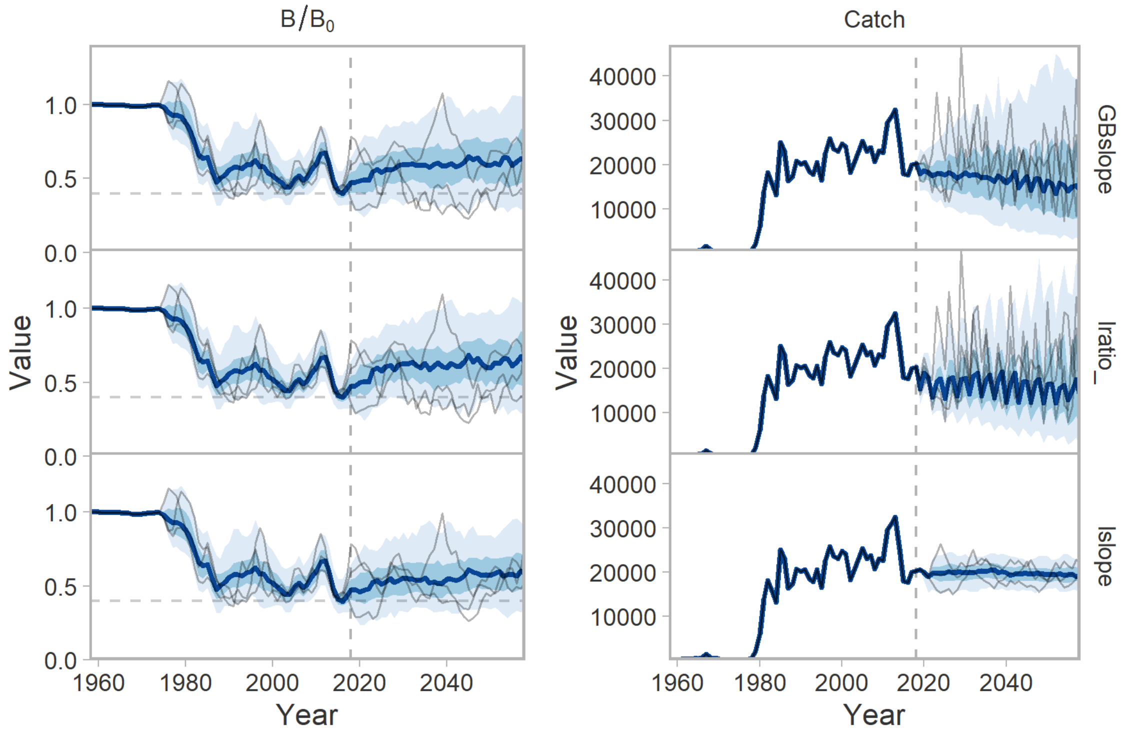

Figure 14. Spawning depletion (left column) and catches (right column) from the closed-loop simulation for three index-slope MPs with annual TAC updates (rows) in the Base OM (#1). See caption of previous figure.

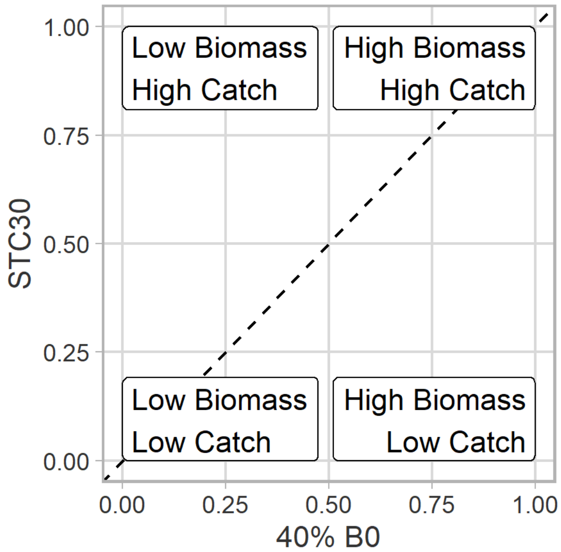

Figure 15. Schematic of a tradeoff plot between a biomass performance metric (x-axis) and catch performance metric (y-axis). The dashed line indicates the one-to-one line.

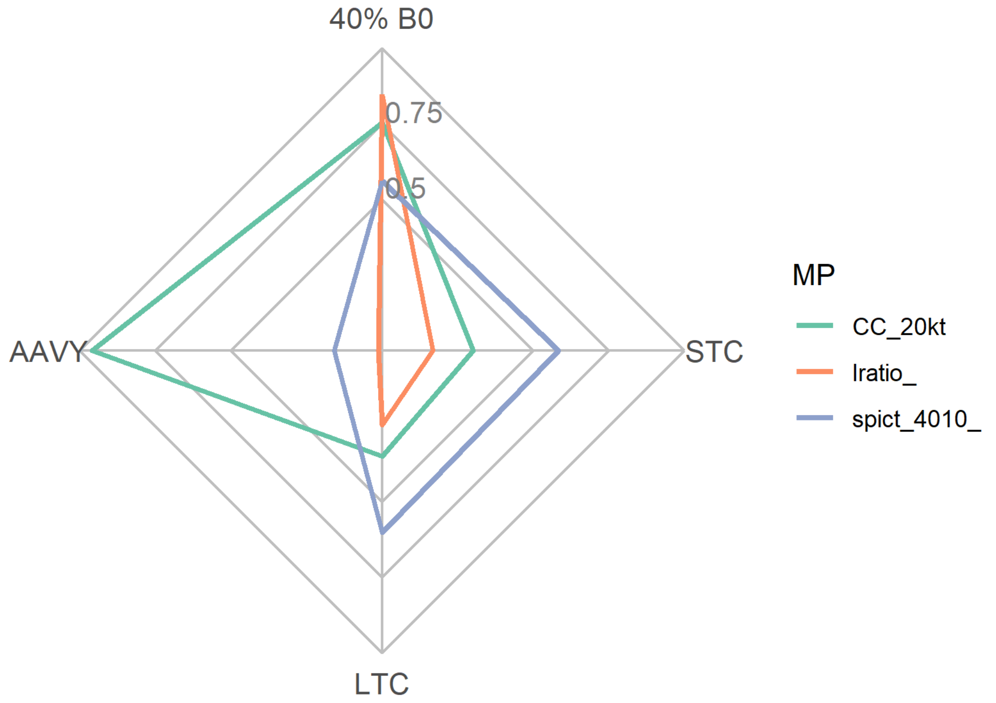

Figure 16. Schematic of a radar plot for four different performance metrics and three management procedures.

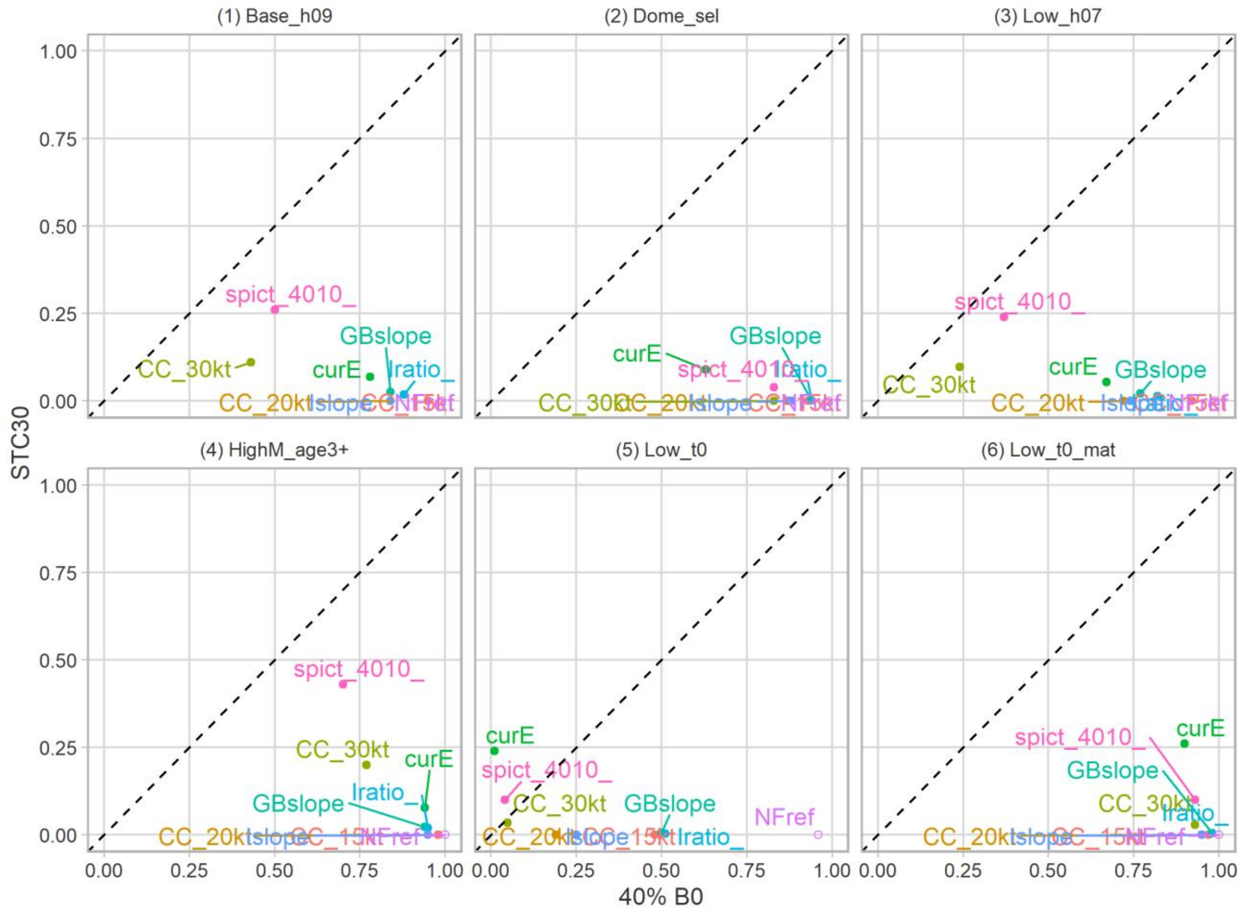

Figure 17. Trade-off plots between '40% B0' and STC30 for the six operating models. Only annually-updated MPs are shown.

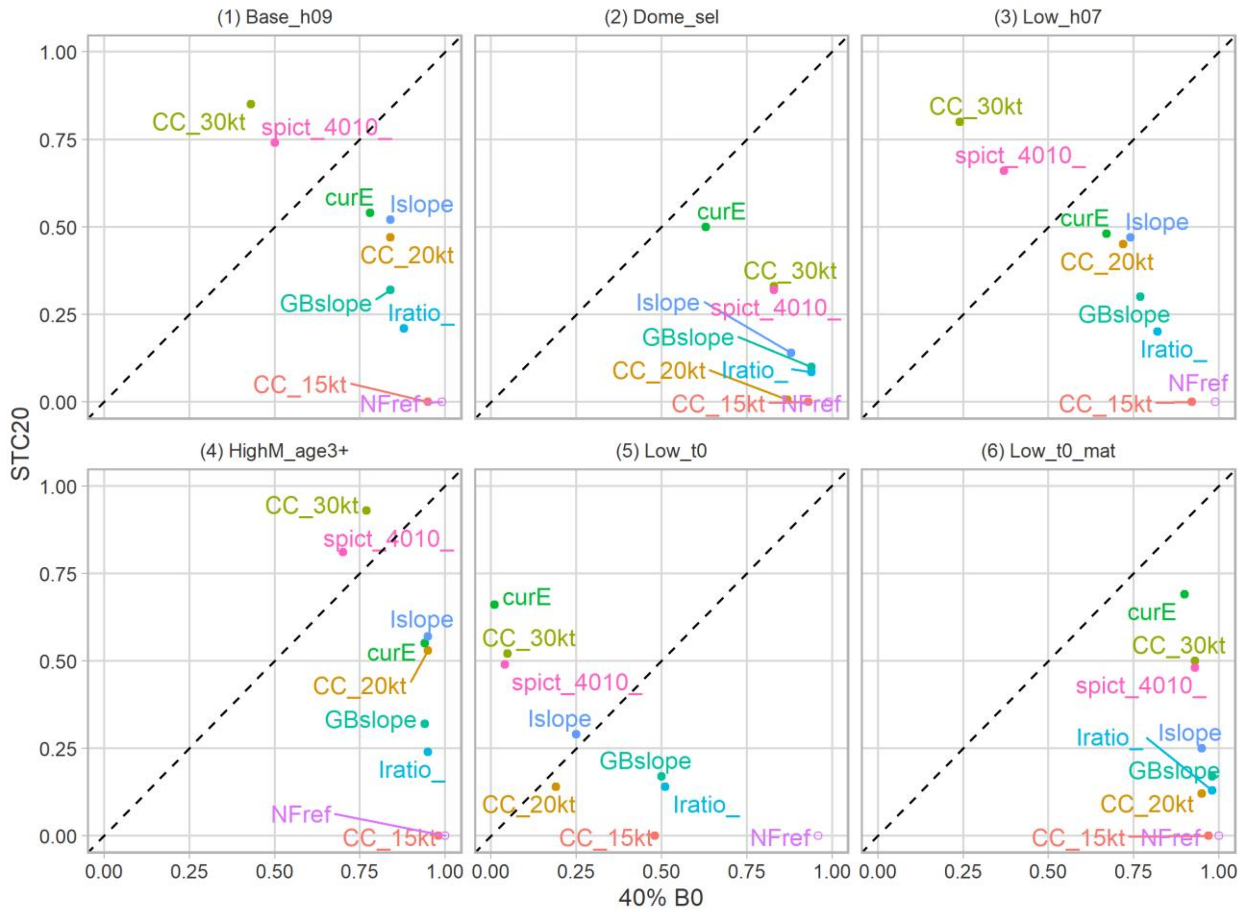

Figure 18. Trade-off plots between '40% B0' and STC20 for the six operating models. Only annually-updated or fixed TAC MPs are shown.

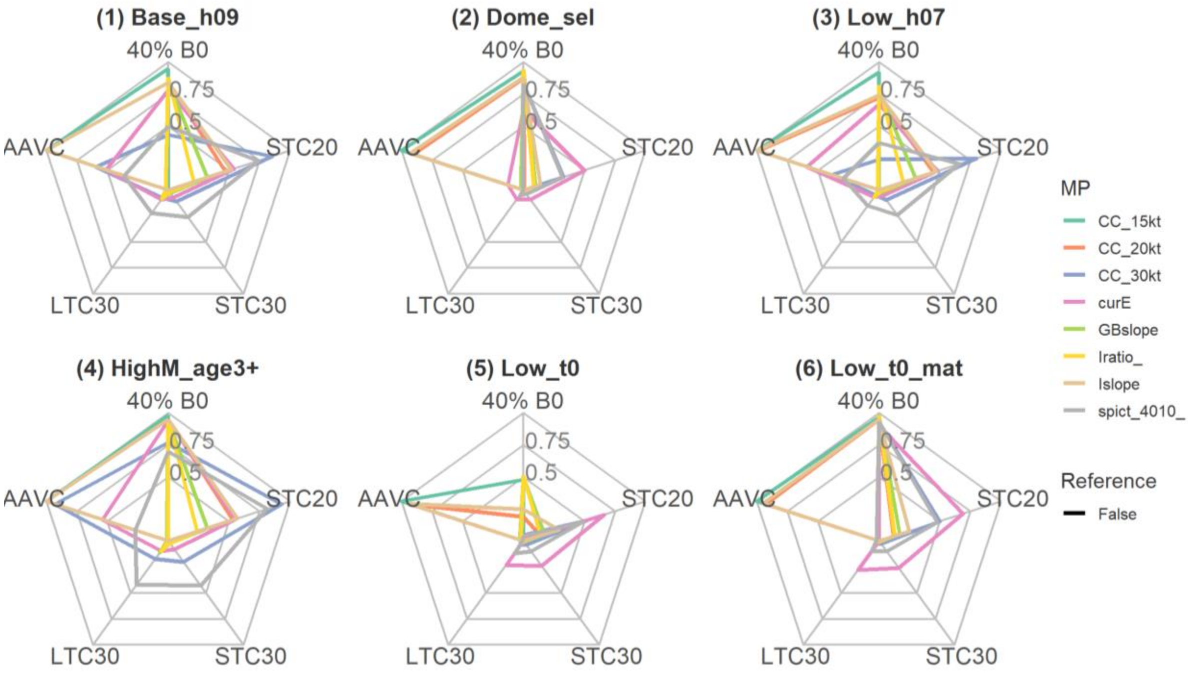

Figure 19. Radar plots showing five performance metrics for annually-updated or fixed TAC MPs in the six operating models.