Collect. Vol. Sci. Pap. ICCAT, 81(9), SCRS/2024/160: 1-13 (2024)

A COMPACT-PROOF-OF-CONCEPT BSH MSE FRAMEWORK USING PRIORS, THE RAPID CONDITIONING MODEL, AND TUNE MANAGEMENT PROCEDURES

Nathan G. Taylor[1]

SUMMARY

This document presents a compact closed-loop simulation framework for blue shark management strategy evaluation (MSE). The approach relies on building operating models using Bayesian prior distributions for key life-history parameters and productivity, considering management procedure (MP) types that ICCAT has already employed, and tuning MPs to minimum performance standards. The document presents an example set of MSE simulations using this approach. The simulations demonstrate a set of MPs, including index-based MPs and model-based MPs where the probability of being above limit reference points of 40% B_{MSY} *is more than 90%. Of the MPs explored, the probability of being in the green quadrant of the Kobe matrix ranged from 60% to 90%. Variability in catch was highest for the model-based MPs. This set of techniques allows for a compact parameterization of a set of simulations that addresses a minimal set of uncertainties for life-history quantities and productivity. The approach therefore economizes on time in illustrating MP performance against typical performance criteria.*

RÉSUMÉ

Ce document présente un cadre de simulation compact en boucle fermée pour l'évaluation de la stratégie de gestion (MSE) pour le requin peau bleue. L'approche repose sur l'élaboration de modèles opérationnels utilisant des distributions bayésiennes a priori pour les paramètres clés du cycle vital et de la productivité, en tenant compte des types de procédures de gestion (MP) déjà utilisés par l'ICCAT et en calibrant les MP à des normes de performance minimales. Le document présente un exemple de simulations de la MSE utilisant cette approche. Les simulations démontrent un ensemble de MP, y compris des PM basées sur des indices et des MP basés sur des modèles-où la probabilité d'être au-dessus des points de référence limites de 40% de B_{PME} *est supérieure à 90%. Sur les MP explorées, la probabilité de se trouver dans le quadrant vert du diagramme de Kobe pourrait être assez faible. La variabilité des captures était la plus élevée pour les MP fondées sur des modèles. Cet ensemble de techniques permet un paramétrage compact d'un jeu de simulations qui tient compte d'un ensemble minimal d'incertitudes pour les quantités du cycle vital et la productivité. Cette approche permet donc de gagner du temps en illustrant les performances des MP par rapport à des critères de performance typiques.*

RESUMEN

Este documento presenta un marco compacto de simulación en bucle cerrado para la evaluación de estrategias de ordenación (MSE) del tiburón azul. El enfoque se basa en la creación de modelos operativos utilizando distribuciones previas bayesianas para los parámetros clave del ciclo biológico y la productividad, teniendo en cuenta los tipos de procedimientos de ordenación (MP) que ICCAT ya ha empleado y calibrando los MP a unas normas mínimas de desempeño. El documento presenta una serie de ejemplos de simulaciones de MSE utilizando este enfoque. Las simulaciones demuestran un conjunto de MP, incluidos los MP basados en índices y los MP basados en modelos, en los que la probabilidad de situarse por encima de los puntos de referencia límite del 40% de BRMS es superior al 90 %. la probabilidad de situarse en el cuadrante verde de la matriz de Kobe podría estar entre el 60 % y el 90 %. La variabilidad de las capturas fue mayor en el caso de los MP basados en modelos. Este conjunto de técnicas permite una parametrización compacta de una serie de simulaciones que aborda un conjunto mínimo de incertidumbres para las cantidades del ciclo vital y la productividad. Por lo tanto, el enfoque ahorra tiempo a la hora de ilustrar el desempeño de los PM en función de criterios de desempeño típicos.

[1] nathan.taylor@iccat.int

KEYWORDS

Bayesian prior probability distribution; management strategy evaluation; operating model; management procedure; harvest strategy; blue shark

1. Introduction

ICCAT Recommendation 23-10, and 23-11 requests that SCRS asses the feasibility of a Management Strategy Evaluation (MSE) for northern and southern blue shark, respectively. MSE at ICCAT has historically relied on an involved process to complete its key components. These key elements are: Operating Model (OM) development, Management Procedure MP development, and defining minimum tuning performance standards for MP. Here I present compact way of parameterizing operating models, a streamlined process for defining and evaluating Management Procedures, and which tuning and/or performance targets might be considered.

2. Operating model development

At ICCAT, OMs have typically been defined using grids to capture parameter uncertainty. Key parameters like steepness (*h*) and natural mortality (*M*) considered in these grids are those that are not estimable (Ludwig and Walters 1985, Magnusson and Hilborn 2007, Hilborn *et al*. 2010) with typical fisheries data using non-linear minimizers like AD model builder (Fournier *et al*. 2012). Making discrete choices about continuous statistical quantities like productivity and mortality parameters is problematic in that: 1. quantities like growth, mortality and steepness are at a minimum correlated (Thorson 2020) and they are even intrinsic to parameters like steepness (Cortes 2016, Mangel *et al*. 2010, Mangel *et al*. 2013) and 2. it is not clear how to give statistical weights to each grid choice.

To avoid the problem of discretising continuous parameters, I use OpenMSE's Rapid Conditioning Model to develop OMs for Blue shark. I follow the basic approach employed for South Atlantic Swordfish (Taylor 2024, Hordyk 2024). This involved:

- Parameterizing an OpenMSE OM object with the parameters from the 2024 blue sharks Stock Synthesis model.
- Build a single-fleet RCM data object using length composition, and commercial catch-per-unit-effort (CPUE) series from the 2023 Blue Shark Data Preparatory Meeting.
- Passing values for M, h, and the von Bertalanffy growth parameters (L_∞, K, and t0) as custom parameters using the multivariate prior of Cortés and Taylor 2023.
- For the total number of MSE simulations (nsim) RCM draws from the priors (the custom parameters) and other parameters (in the original OM object) and fits an age-structured model. This give rise to a distribution of nsim samples of the input parameters, reference points, and time series of biomass, and fishing mortality.
- I explore 3 OMs. One fit to all indices and two others fit to clusters of indices. The clustering technique uses machine learning to group sets of indices together based on the direction and magnitude of their correlation. This computes all pairwise dissimilarities between the correlation coefficients in cluster 1 and the elements in cluster 2. It then considers the largest value of these dissimilarities as the distance between two clusters (see Taylor 2023a).

A schematic of the OM parameterization is presented in **Figure 1**.

Here I use the same approach for including uncertainty in the growth parameters. In the calculation of steepness using the Cortez and Taylor 2023b, the growth parameters were used as input to generate the steepness (the output). But this is not the only reason why it might be a good idea to consider uncertainty in growth: von Bertanffy growth parameters are not well determined in statistical models. While commonly treated as fixed quantities in stock assessments, von Bertanffy growth parameters cannot be estimated very well and especially when individual variability in growth and the cumulative effects of size selective fisheries are considered (Lee, 1912, Ricker 1969, Taylor *et al*. 2005, Goodyear 2019). By capturing the joint uncertainties of all of the vital rates (in this case, growth parameters, mortality, and steepness) , these effects are propagated coherently through OM development to the forward projections and then MP performance (see **Figure 2**.). Trajectories for spawning stock biomass (SSB) and fishing mortality (F) are plotted in **Figure 3**. **Figure 4** shows the different biomass trajectories of OMs configured fitting all indices, the first CPUE cluster, and the second CPUE cluster.

3. Management procedures

The ICCAT Standing Committee on Research and Statistics has chosen MPs that involve simple statistical models (like northern Albacore tuna) or index-based Management Procedures (Rec 22-09). Accordingly, I focussed on a limited number of index-based MPs and a single surplus production model MP. Following Carruthers 2024, the index-based MPs tested were as follows:

- Index target (*It_30*) - reduces TAC when index is below the target level, increases TAC when index is above target level (tuned by adjusting the index target level)
- Index ratio (*Ir_30*) - fishes at a constant multiplier of the recent index level, i.e. a constant F policy (tuned by adjusting the ratio)
- Index slope (*Is_30*) - aims to achieve a constant slope in the index and reduces TAC when slope is below target and increases TAC when slope is above target (tuned by adjusting target slope)

For the model-based MPs, I used SP_MSY which is A surplus production model with a TAC recommendation based on fishing at F_{MSY}, SP_4010, A surplus production model with a 40-10 control rule, SCA_MSY a statistical catch-at-age model with a TAC recommendation based on fishing at F_{MSY}, and SCA_4010, a statistical catch-at-age model with a 40:10 harvest control rule.

3.1 MP tuning

Using the same MP_tune function in Carruthers 2024, index-based MPs were tuned (adjusted index target, index ratio, index slope) to achieve probability of green kobe ($F<F_{MSY}$ & $SSB > SSB_{MSY}$) of 60% (all 50 projection years, all operating models) constrained to achieve 30% variability in catch with a catch cap of 30 kt. The tuned versions of each were labelled with ‘t’ (e.g., Ir_30_t) so that a total of 10 MPs were tested.

4. Simulations

Given that this analysis was for demonstration purposes, the three operating models were run with relatively few MSE simulations (48). For each set of simulations, I compiled performance statistics data for the long-term average TAC for short, medium, and long time frames, the number of limit reference point breaches, the probability of being in the green quadrant of the Kobe matrix, the probability of not overfishing as well as the variability in catch (see **Table 1**).

5. Results and discussion

A Slick app (https://shiny.bluematterscience.com/app/slick) that summarises the results of all these simulations. The file for viewing is available upon request.

The OMs sample the complete range of uncertainty presented (Cortes and Taylor 2023) for growth and productivity parameters. Since Cortes and Taylor 2023 method for determining steepness takes as input the growth and natural mortality parameters, it means that each sample (or row in the matrix of life-history and steepness) maintains coherence between the selection of life-history parameters and the values of steepness that correspond to each.

The historical stock trajectories across all OMs (**Figure 3** and **Figure 4**) indicate a stock that was declining for the first 30 years of the historical period but has since remained constant or that increased slightly.

Tuning the MPs to maximum catch changes of 30% were effective at achieving higher yields as well as the variance and PGK objectives. The tuned version of It_30, It_30_t had significantly higher catches while also maintaining the same conservation and PGK performance.

Time series of projected under different MPs for B_t/B_{MSY}, F_t/F_{MSY} are shown in **Figure 5**. **Figure 6** shows time series of median catch across OMs and simulations, and **Figure 7** shows the Kobe plot in the final projection year. The simulated projected series (**Figure 5** and **Figure 7**) indicate that really any of the MPs tested against the OMs can maintain the stock in the green quadrant of the Kobe matrix. The simulation results indicate that any of the MPs chosen for testing could keep the stock above B_{MSY} levels and below F_{MSY} levels with long-term catch levels ranging from 22, 500-27,000 tons.

Not all model-based MPs worked effectively. Both SP_4010 and SCA_4010 had convergence issues and produced in some years extreme catch values. In addition, I did not attempt to tune the model-based MPs. The untuned SP_MSY and SCA_MSY performance indicated the highest catch (**Table 1**) but also the highest variability in catch and the lowest PGK values of the MPs tested.

The overall message of this paper is not such much about the results themselves but rather that MSE for blue shark could be conducted in a compact, parsimonious manner. Carruthers 2024 illustrated how this approach would work using a grid of OMs based on the base-case Stock Synthesis assessment model. The approach taken here relied on different methods for parameterizing the OM and some different MPs. United the two approaches was a common framework for running the computer code and presenting the analysis. For practical reasons, it was not possible to compare the two approaches, but this could be achieved relatively easily. While there could be many refinements to the approach applied like more challenging OMs for example, but the approach of sampling across the full range of life-history parameters captures a broader range of uncertainty than a typical grid. With respect to the MPs, it would be relatively easy to define a narrow of MPs that achieve a set of putative PGK and LRP targets. The range of targets for key objectives (like the probability of being in the green quadrant of the Kobe Matrix, variability in catch, etc.) the Commission is likely to request exploring is not likely to be that broad. For example, PGK was set to 60% for BFT and ALB; limit reference points of 0.4 BMSY from recs 17-02(6), 13-02(4), and 22-09 were used, and variability in catches for MPs selected ranged from 0.2-0.35 (Taylor *et al*. 2024). Accordingly, one approach to increasing the efficiency of MSE processes could be to tune a limited set of MPs to a range of performance standards that the Commission has previously asked for and allow it to choose from among them.

References

Carruthers T. 2024. Demonstration of technical components of an MSE for North Atlantic Blue Shark. SCRS/2024/141

Cooke J.G. 2011. Outline of a Candidate Management Procedure for Atlantic Bluefin Tuna. Collect. Vol. Sci. Pap. ICCAT, 68(1): 312-318

Cortés E. 2016. Perspectives on the intrinsic rate of population growth. Methods in Ecology and Evolution 7:1136–1145. https://doi.org/10.1111/2041-210X.12592

Cortés E., and Taylor N.G. 2023. Estimates of vital rates and population dynamics parameters of interest for blue sharks in the North and South Atlantic Ocean. Collect. Vol. Sci. Pap. ICCAT, 80(4): 528-545

Fournier D.A., Skaug H.J., Ancheta J., Ianelli J., Magnusson A., Maunder M.N., Nielsen A. & Sibert J. 2012. AD Model Builder: using automatic differentiation for statistical inference of highly parameterized complex nonlinear models - Optimization Methods and Software - Volume 27, Issue 2. Optimization Methods and Software, 27(2), 233–249. https://doi.org/10.1080/10556788.2011.597854

Goodyear C.P. 2019. Modeling Growth: Consequences from Selecting Samples by Size. Transactions of the American Fisheries Society, 148(3), 528–551. https://doi.org/10.1002/tafs.10152

Hilborn R., Conn P.B., Williams E.H., and Shertzer K.W. 2010. When can we reliably estimate the productivity of fish stocks? Can. J. Fish. Aquat. Sci. 67(3): 511–523. doi:10.1139/F09-194

Lee R.M. 1912. An investigation into the methods of growth determination in fishes. Conseil Permanent International Sur L'Exploration Du Mer, 63, 35

Ludwig D., and Walters C.I.J. 1985. Are Age-structured Models Appropriate for catch and Effort Data? Can. J. Fish. Aquat. Sci. 42(6): 1066–1072

Mangel M., Brodziak J. & DiNardo G. 2010. Reproductive ecology and scientific inference of steepness: A fundamental metric of population dynamics and strategic fisheries management. Fish and Fisheries, 11(1), 89–104. https://doi.org/10.1111/j.1467-2979.2009.00345.x

Mangel M., MacCall A. D., Brodziak J., Dick E.J., Forrest R.E., Pourzand R., and Ralston S. 2013. A perspective on steepness, reference points, and stock assessment. Can. J. Fish. Aquat. Sci. 70:930–940. https://doi.org/10.1139/cjfas-2012-0372

Magnusson A. and Hilborn R. 2007. What makes fisheries data informative? Fish Fish. 8(4): 337–358. doi:10.1111/j.1467-2979.2007.00258.x

Hordyk. 2024. Review of Code and Simulation Framework for Southern Swordfish Closed-Loop Simulations. Collect. Vol. Sci. Pap. ICCAT, 81(7): 1-13

Taylor N.G., Walters C.J., and Martell S.J.D. 2005. A new likelihood for simultaneously estimating von Bertalanffy growth parameters, gear selectivity, and natural and fishing mortality. Can. J. Fish. Aquat. Sci 62(1): 215–223. doi:10.1139/f2011-100

Taylor N.G. 2023a. A hierarchical cluster analysis of South Atlantic CPUE data. ICCAT Col. Vol. Sci. Pap. 80(1): 168–175

Taylor N.G. 2023b. An Overview of the Southern Swordfish Closed-Loop Simulation Approach. Collect. Vol. Sci. Pap. ICCAT, 81(7): 1-16

Taylor N.G, Miller S., and Duprey N. 2024. A review of objective, reference points, and performance indicators for Management Strategy Evaluation at tRMFOs. Collect. Vol. Sci. Pap. ICCAT, 81(6), SCRS/2024/028: 1-12

Thorson, J. T. 2020. Predicting recruitment density dependence and intrinsic growth rate for all fishes worldwide using a data-integrated life-history model. *Fish and Fisheries*, *21*(2), 237–251. https://doi.org/10.1111/faf.12427

Table 1. Median performance statistics across three models.

MP	AvTAC_long	AvTAC_med	AvTAC_short	nLRP	PGK	PGK_med	PGK_short	PNOF	VarC	D20
It_30	4,510	5,780	10,700	1.000	0.957	0.981	0.873	0.997	0.1210	1.000
It_30_t	29,400	24,800	19,000	1.000	0.587	0.767	0.779	0.789	0.1200	0.890
Ir_30	21,500	18,300	15,300	1.000	0.878	0.917	0.842	0.952	0.1210	0.991
Ir_30_t	24,200	22,400	18,100	1.000	0.796	0.846	0.800	0.896	0.1190	0.985
Is_30	19,400	19,600	18,600	1.000	0.875	0.906	0.808	0.946	0.0858	0.990
Is_30_t	19,400	19,600	18,600	1.000	0.875	0.906	0.808	0.946	0.0858	0.990
SP_MSY	27,000	26,900	23,200	0.979	0.585	0.517	0.504	0.719	0.4020	0.961
SCA_MSY	24,900	23,200	23,200	0.958	0.606	0.612	0.410	0.760	1.4400	0.940

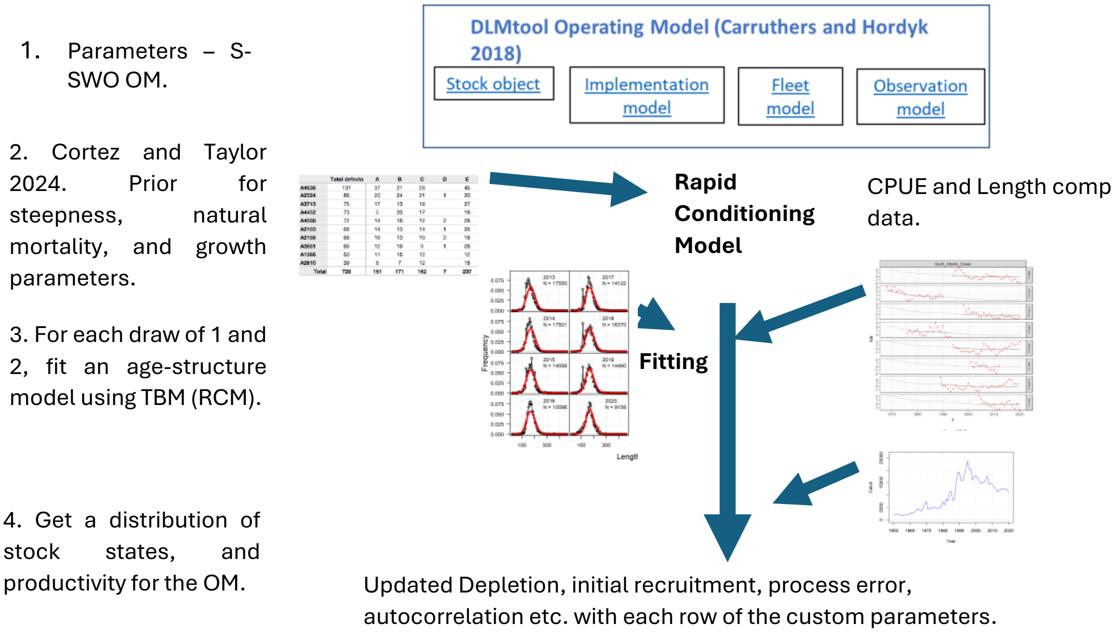

Figure 1. Schematic of the RCM Operating Model design.

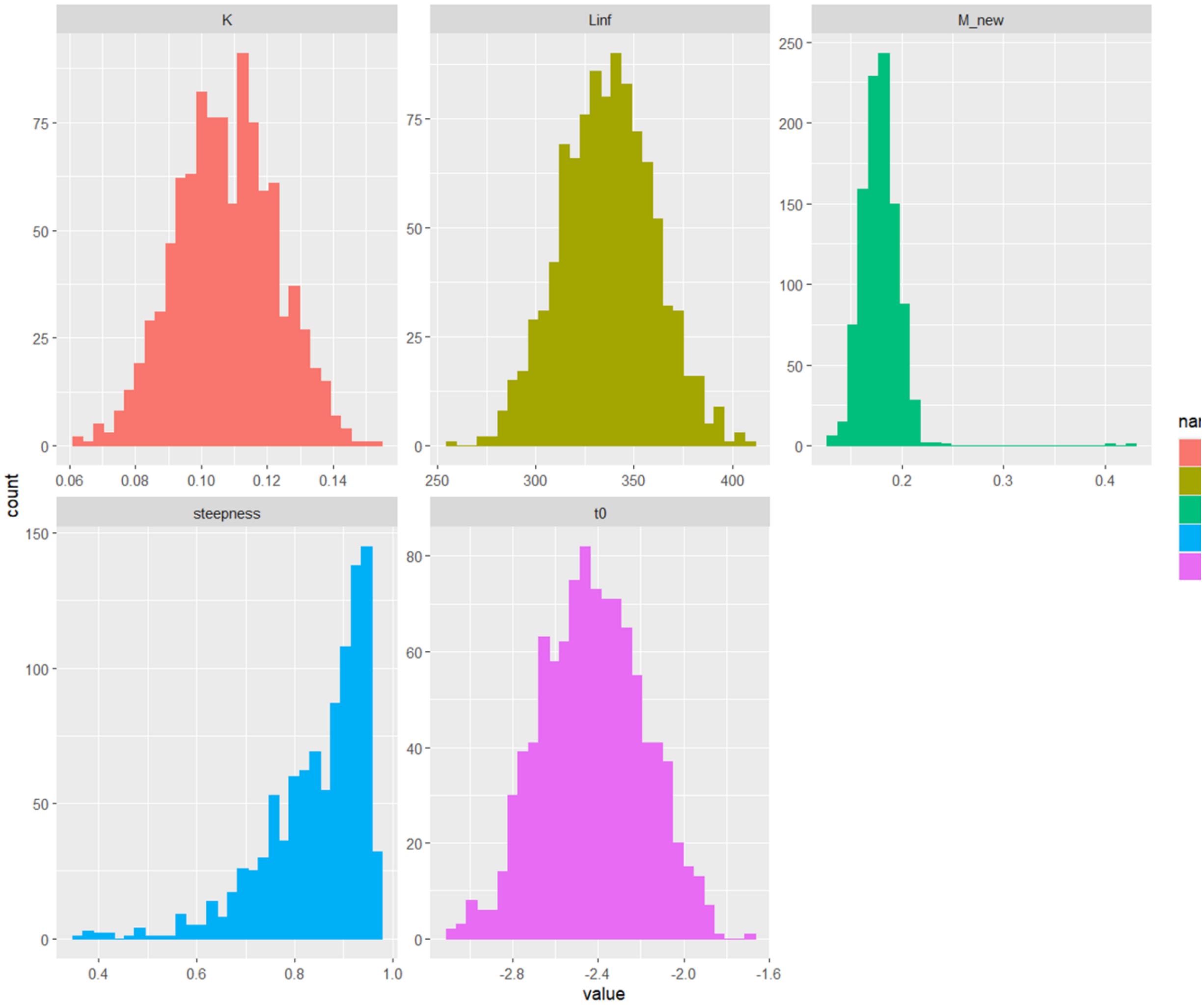

Figure 2. The uncertainty envelope for natural mortality M, asymptotic size Linf, and the von Bertalanffy metabolic growth parameter K.

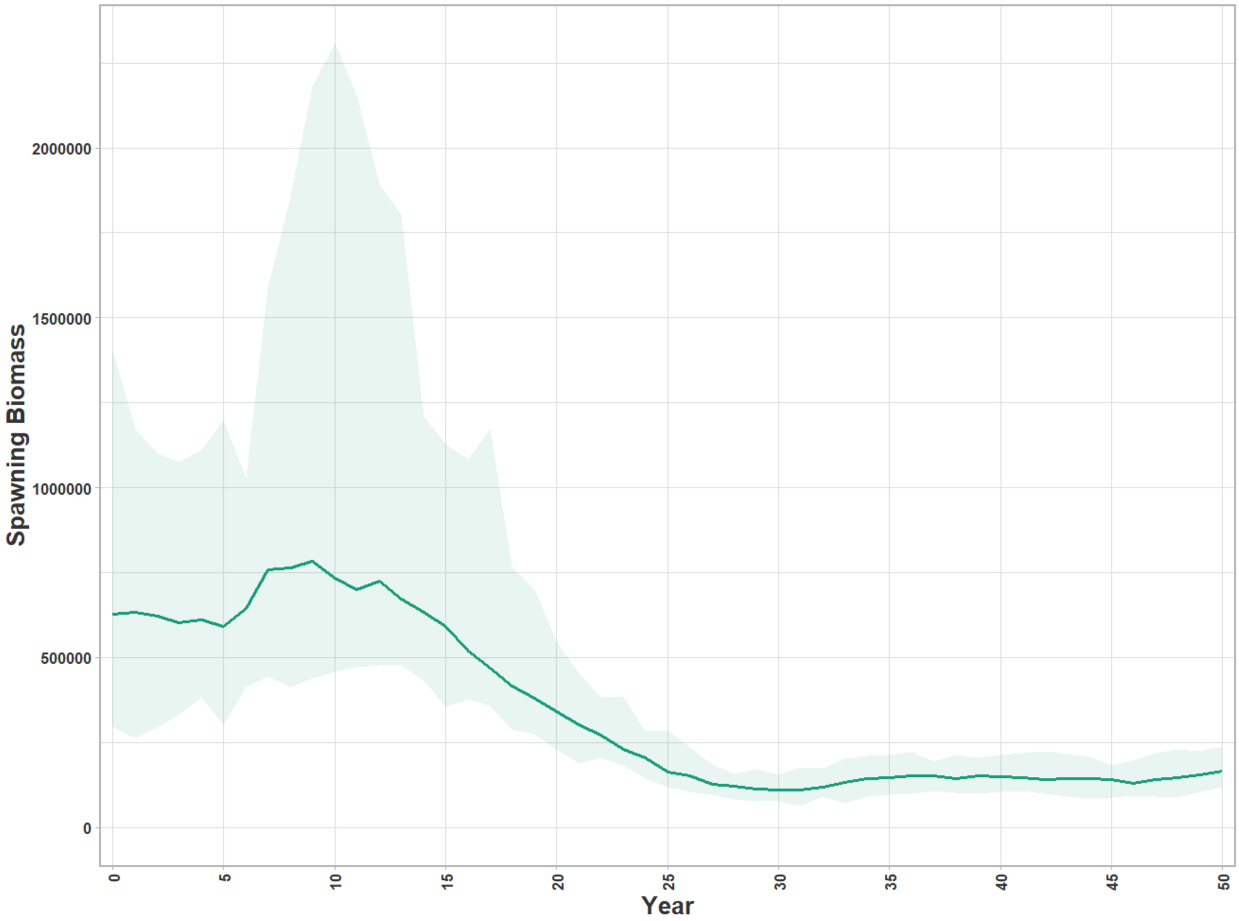

Figure 3. Biomass trajectory for the conditioning period for OM1, fitted to all indices of abundance.

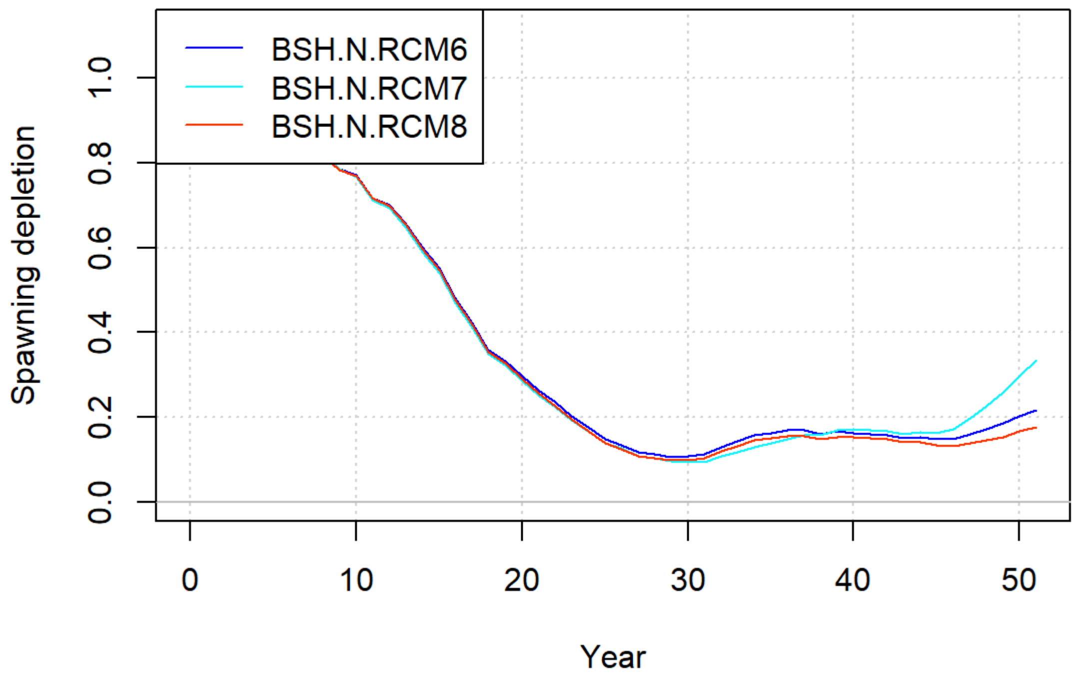

Figure 4. Different median stock trajectories for three OM conditioned in all indices (BSH.N.RCM6), cluster 1 (BSH.N:RCM7), and cluster 2 (BSH.N.RCM8).

Figure 5. Median time series of B/BMSY (top), F/FMSY (bottom), for tuned management procedures to a maximum change of 30% (index slope IS_30_t, index target (It_30_t), index ratio (Ir_30_t), a surplus production model with a target B_MSY level (SP_MSY), a surplus production model with a 40:10 harvest control rule (SP_4010), a statistical catch at age model harvesting at F_{MSY} (SCA), a statistical catch at age model with a 40:10 harvest control rule SCA_4010 and across all OMs.

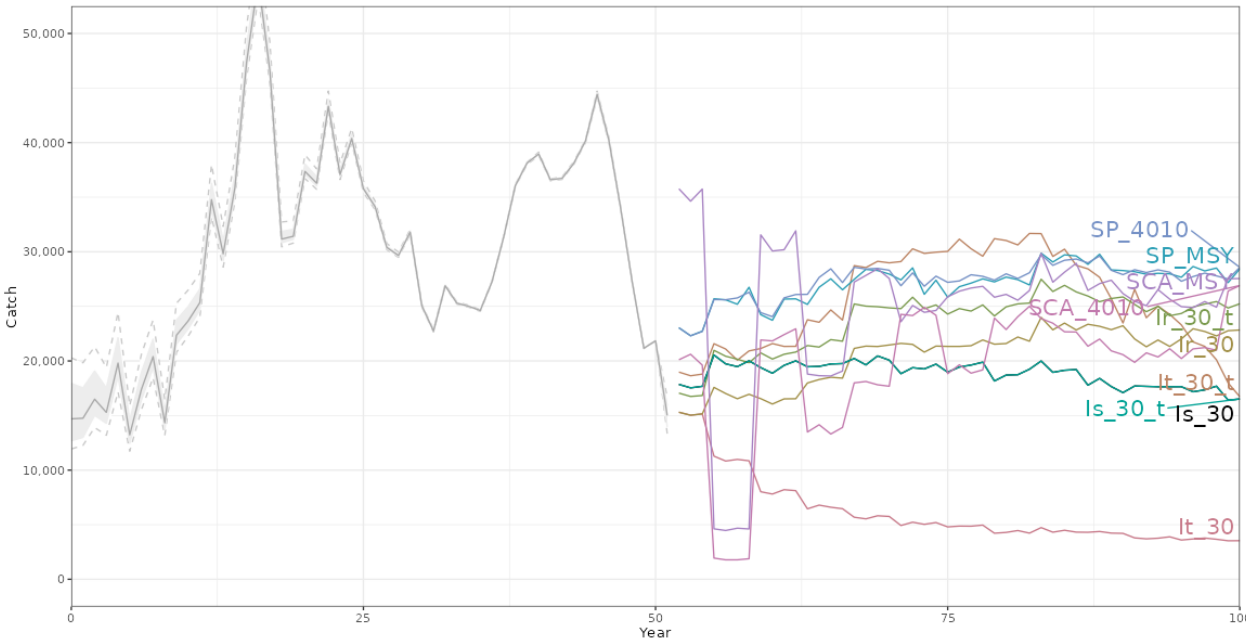

Figure 6. Time series of median trajectories of catch by Management Procedure.

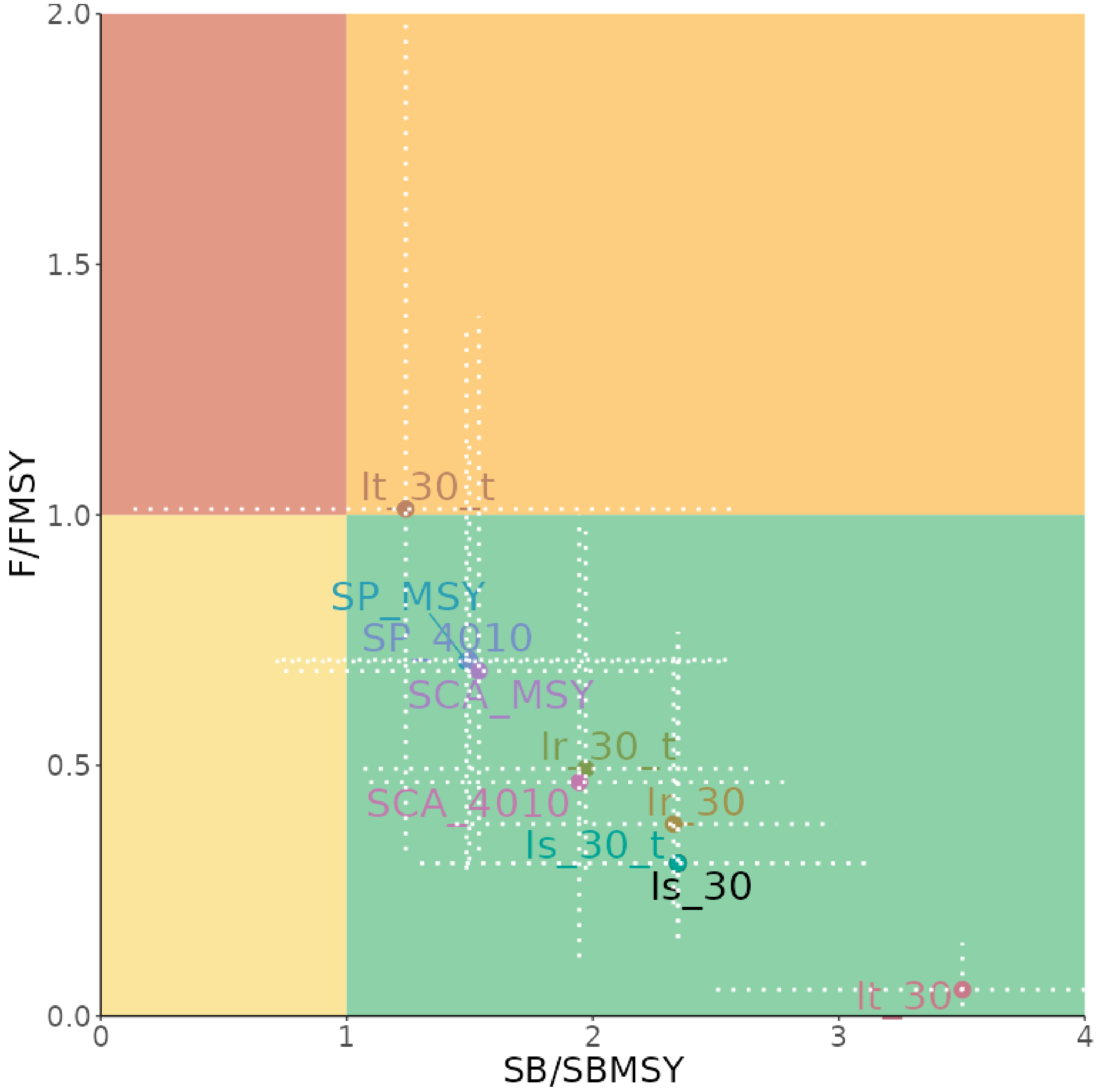

Figure 7. Comparison of trade-offs of 10 management procedures for 3 operating models for S/SMSY and F/FMSY.