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AN OVERVIEW OF THE SOUTHERN SWORDFISH CLOSED-LOOP SIMULATION APPROACH

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SUMMARY

This document summarizes the approach for swordfish close-loop simulations and progress to date. The approach uses two methods to characterize uncertainties in operating models. The first of these is to use multivariate priors to characterize uncertainty in life-history parameters and productivity. The second of these approaches is to capture the uncertainty in the indices by clustering the indices by trend; this allows for sets of different relative abundance series to be treated as separate operating models. For Management Procedures, a large set of candidate Management Procedures were chosen from among those for which there is a history of using data and/or modeling choices for ICCAT swordfish stocks, i.e., those using Catch Per Unit Effort Data and/or simple production models. For selecting among Management Procedures, firstly, minimum satisficing criteria were applied, then future stock trajectories were visually inspected for instability and other long-term undesirable behavior.

RÉSUMÉ

L'approche des simulations en boucle fermée de l'espadon et les progrès réalisés à ce jour sont abordés dans ce document. L'approche utilise deux méthodes pour caractériser les incertitudes dans les modèles opérationnels. La première d'entre elles consiste à utiliser des distributions a priori multivariées pour caractériser l'incertitude des paramètres du cycle vital et de la productivité. La seconde de ces approches consiste à refléter l'incertitude des indices en les regroupant par tendance; cela permet de traiter des ensembles de différentes séries d'abondance relative comme des modèles opérationnels distincts. En ce qui concerne les procédures de gestion, un large ensemble de procédures de gestion potentielles a été retenu parmi celles pour lesquelles il existe un historique d'utilisation de données et/ou de choix de modélisation pour les stocks d'espadon de l'ICCAT, c'est-à-dire celles qui utilisent des données de prise par unité d'effort et/ou des modèles de production simples. Pour sélectionner les procédures de gestion, des critères minimaux de « suffisfaisant » ont été appliqués. Ensuite, les trajectoires futures des stocks ont été inspectées visuellement pour y déceler l'instabilité et d'autres comportements indésirables à long terme.

RESUMEN

Este documento presenta un resumen del enfoque de las simulaciones de circuito cerrado del pez espada y los progresos realizados hasta la fecha. El enfoque utiliza dos métodos para caracterizar las incertidumbres en los modelos operativos. El primero de ellos consiste en utilizar distribuciones previas multivariantes para caracterizar la incertidumbre en los parámetros del ciclo vital y la productividad. El segundo de estos enfoques consiste en captar la incertidumbre de los índices agrupándolos por tendencias; esto permite tratar conjuntos de series de abundancia relativa diferentes como modelos operativos separados. Para los procedimientos de ordenación, se ha elegido un amplio conjunto de procedimientos de ordenación candidatos entre aquellos para los que existe un historial de uso de datos y/u opciones de modelación para los stocks de pez espada de ICCAT, es decir, aquellos que utilizan datos de captura por unidad de esfuerzo y/o modelos de producción simples. Para seleccionar entre los procedimientos de ordenación, primero se aplicaron criterios mínimos de satisfacientes y luego se inspeccionaron visualmente las trayectorias futuras del stock en busca de inestabilidad y otros comportamientos indeseables a largo plazo.

KEYWORDS

Swordfish, Management Strategy Evaluation, simulation, harvest strategy

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1. Overview and Background

This document provides an overview of the simulation methods applied for the closed-loop simulation of southern swordfish. For clarity, I distinguish between close-loop simulations and Management Strategy Evaluation or MSE. For this document, closed-loop simulations are a purely technical exercise i.e., they are the simulations that test Management Procedure performance. This is different from MSE which is a broader process that involves the formulation and refinement of specific objectives with a plan towards adopting a Management Procedure (MP) for implementation in the fishery. There is not currently a process in place for Southern Swordfish to adopt and implement an MP. The use of the term closed-loop simulation lets us separate the technical work conducted so far from a what would potentially be a broader MSE (Punt *et al.* 2016) process involving consultation about objectives that are stock specific.

Closed-loop simulations for southern swordfish began with Taylor *et al*. 2022a.This consisted of a minimalist set of simulations. Here we provide a concise review of the overall approach taken in Taylor *et al.* 2022A and provide some recent updates to the analytical approach.

2. Methods

The approach taken for the southern swordfish closed-loop simulations was minimal. The reasons for this were both methodological and practical. Methodologically, the approach adopted here aims to provide a more parsimonious set of OMs that address key uncertainties (Sharma *et al.* 2020). Practically, there is not a large initiative at ICCAT for MSE on southern swordfish and there are few resources to dedicate to the endeavor. Accordingly closed-loop simulations were organized to maximize analytical returns on a small investment of effort. A schematic of the simulation design's architecture is presented in **Figure 1**.

The first step in defining a more defensible set of OMs was how to parameterize productivity parameters in the OMs. Many MSEs adopt a grid of operating models that consists of selection of fixed life history parameters , typically steepness (Mace and Doonan 1988) and natural morality as well as other parameters. These grids, that can involve well over one hundred OMs (Rosa *et al.* 2018) suffer from the fact that there is often no statistical justification provided for the parameter choices. Plus in most cases, selections of fixed steepness values fail to consider that steepness cannot be considered separately from other vital rates: productivity parameters like steepness and/or the intrinsic rate of growth are to some extent the product of the life-history parameters (Mangel *et al*. 2010, 2013; Cortés 2016). Therefore, sampling from all the vital rates simultaneously is essential to produce a reasonable multivariate distribution of steepness and the input parameters that produce it.

The second step in improving the OM set was to better characterize the effect of data conflicts in parameterizing OMs. Assessments, whether they be used for parameterizing OMs or for catch advice, often simultaneously fit many data sources including different index or survey series. This is not in itself a problem. What is a problem is when there are data series that conflict. These can include conflicts between age or size composition data and index series, tagging data, and catch data. The nature of this problem can be illustrated most easily when one index series increases and another one decreases over the same period: if a statistical model can be made to converge in such situations, then the model will often fit a flat biomass trajectory; the consequences of this fitting are often predictions that is not consistent with either of the indices. To characterize data conflicts in the indices of relative abundance, I adopted a hierarchical clustering approach that uses machine learning to group CPUE series according to their similarity in their correlations (Taylor 2023). Rather that treat the conflicting data series as equally likely each cluster instead forms a different OM or factor in the OM set. In this way, sets of contradictory indices are considered different hypotheses about the state of the stock.

2.1 Operating Model Definition

Rather than choose an arbitrary grid of life history priors and steepness, I first define multivariate priors for steepness and life-history parameters. I rely on two methods. The first of these is to draw prior probability distributions using Thorson *et al.* 2020's Fishlife analysis (Thorson 2020; Thorson *et al.* 2023). This method for generating the prior was applied in the 2022 southern swordfish stock assessment (Anonymous 2022). The second is to apply Mangel *et al*. 2010's method as implemented in Taylor *et al*. 2022b. In the latter case, I modified the original method by generating the growth parameters that were originally samples independently using instead a multivariable normal distribution.

Taylor *et al*. 2022b's original derivation simulated input parameters used to derive steepness from independent distributions. This approach is not correct. Many of the input parameters, and in particular the von Bertalanffy growth parameters and natural mortality are often highly correlated. To address this, I queried the covariance matrix $\sum$ for natural mortality M, asymptotic size L_∞, and the metabolic growth parameter K, from the Genus *Xiphidae* from Fishlife (Thorson 2020). I solved for the correlation matrix ϱ as:

$$\varrho = D^{-1} \sum D^{-1} \qquad \textbf{Eq. 1}$$

where D is given as

$$D = \sqrt{\text{diag}(\Sigma)} \qquad \textbf{Eq. 2}$$

and $\sum$ is the covariance matrix from Fishlife. With ϱ and standard deviations σ from Taylor *et al.* 2022b's simulated priors in hand, we can generate a covariance matrix $\sum'$ for M, L_∞, K, in Taylor *et al.* 2022 as:

$$\Sigma' = \varrho \sigma \sigma^T \qquad \textbf{Eq. 3}$$

where σ is the vector of standard deviations. So that the multivariate normal distribution of M, L_∞, K, $\boldsymbol{X}$, is given by:

$$\boldsymbol{X} \sim N(\mu, \sum') \qquad \textbf{Eq. 4}$$

where μ is the vector of mean parameters.

Lacking any information of the correlations on the other parameters that are inputs for steepness in Taylor *et al.* 2022b, these parameters went unchanged, and X was concatenated to other parameters. To avoid negative values for K and M, we sampled from a truncated multivariate normal distribution. All simulations were done using the truncated multivariable normal distribution package in R tmvtnorm.

With the use of multivariate priors and data clusters, the approach adopted for southern swordfish close-loop simulations can capture a wide range of uncertainties parsimoniously.

2.3 Operating Model Definition and Fitting

The OM grid for southern swordfish consisted of four OMs. This was a 2x2 grid with factors defined by the combination of priors on steepness plus history parameters and by the cluster of indices defined in hierarchical clustering analysis. The naming convention associated with each OM and its corresponding steepness prior formulation and cluster are summarized in **Table 1**.

OMs were defined using OpenMSE's Rapid Conditioning Model (RCM). For each prior type, vectors from the simulated steepness h, L_∞, K were passed to OMs as custom parameters. In this case, the number of simulations used in RCM (n_{sim}) was 96. For each OM, a vector of 96 draws of L_∞, K, and h from the relevant prior (**Table 1**) was passed to OM as custom parameters. All OMs were fitted to the 2013-2020 length composition data. Fitting the length composition information was difficult using multinomial likelihoods. RCM models would not converge using a conventional multinomial likelihood. To allow for errors to introduced in model fitting, I used Schnute and Richard's 1995 multivariate logistic distribution (Schnute and Richards 1995). Using the nomenclature defined above, summaries of each OM are presented in the Output folder as: Operating model (OM) conditioning report for FLC2.html, Operating model (OM) conditioning report for TC2.html, Operating model (OM) conditioning report for FLC1.html, and Operating model (OM) conditioning report for TC1.html. To capture climate change effects or time-varying changes caused by non-stationary in life-history parameters, all OMs allowed for time-varying initial spawning stock biomass (dynamic SSB0).

2.3 Candidate Management Procedures

To streamline the closed-loop simulation for southern swordfish, I tried to avoid some other pitfalls that have made other MSE processes resource intensive. Rather than engaging in competitive CMP design and so-called tuning where MPs are modified to meet certain criteria, the approach here was to test many MPs and simply eliminate non-performing ones from consideration.

So which MPs would be reasonable to consider for southern swordfish? Excluding the reference MPs, there are 118 MPs pre-developed in the R package MSEtool. It is not necessary to consider all of them. For southern swordfish stock assessment and management, there is no tradition of using length-based, area-based, or effort control management measures. These were therefore not considered. No MPs that would have considered using novel datasets or modeling were considered either. Accordingly, I selected 42 either index-based or model-based CMP for testing. These are listed with their links for more detailed descriptions, the input class, the required data and the CMP recommendation output in **Table 2.**

Each MP was tested against each of the four OMs described above. Simulations were parallel processed across OMs.

2.4 Selecting MPs

While there are no defined performance criteria established for southern swordfish, the approach in Taylor *et al.* 2022 (Taylor *et al*. 2022) was define a set of minimal satisficing criteria. These were minimal standards that any OM must meet. While there has been some minor variation in the probability limits used for adopted management procedures at ICCAT, the broad objectives are to avoid Limit Reference Points, to achieve status objectives as measured by the probability of being in the green quadrant of the Kobe matrix, and to limit variability in yield to some reasonable probability. While more exigent satisficing criteria might be considered by ICCAT panels, I start with what could be considered minimal satisfying criteria as eq. 5 below.

$P(B_t > 0.4B_{MSY}) > 80\%$ & $P(B_t > B_{MSY})$ & $P(F_t/F_{MSY}) > 50\%$ & $P(C=0.5Cref > 50\%)$ & $\overline{AAVY} < 1.$ **Eq 5**.

The minimal satisficing criteria makes assumptions about the stock's management objectives. It assumes that: the limit reference point for southern stock is the same as it is for the northern stock i.e., 0.4 B_{MSY} (Rec 17-02(6)); that the probability of being above the limit reference point must be at least 80%; that the desired probability of being in the green quadrant of the Kobe Matrix will be at least 50%; and that the mean catch C relative to the maximum theoretical yield (Cref, a proxy for MSY) is 50%. Given that both the northern albacore and Atlantic bluefin tuna MSEs at ICCAT required a 60% chance of being in the green quadrant of the Kobe plot (Taylor *et al.* 2024), choosing a higher probability might be justified. However, it is not important that these minimum satisficing criteria are what will ultimately be used for decision making; once such criteria have been finalized, then the analysis used to define a final set of MPs can be repeated with the final criteria in minutes.

I divided the selection of MPs into the following steps:

1. Filter all MPs that do not meet the minimum satisficing criteria.
2. Visually inspect time-series plots for catch, F/F_{MSY}, B/B_{MSY} for undesirable trends. Specifically, I looked for MPs that had extreme transient behavior, specifically very large initial catches, very small initial catches, monotonically increasing F/F_{MSY} in the time series. This examination went further in time than the "long" time frame used for calculating performance metrics (21-30 projection years). Instead, I looked at the time series out to 2035 to look for patterns that might be readily visible at shorter time scales.
3. Present the MPs that meet criteria 1 and 2.

3. Results

3.1 Cluster analysis

While 2022 Data Prepeparatory Meeting originally excluded using the Uruguayan Longline Historical index, model fits failed without this historical data historical series. Accordingly, the cluster analysis had to be redone including this index. The cluster analysis broke the CPUE series into two groups (**Figure 2**). Cluster 1 (C1) had JPN.LL1, BRA.LL, CTP.LL2 indices whereas cluster 2 had URU.LL, URU.LL.hist, ZAF.LL, JPN.LL2, CTP.LL1, w.SPN.LL series.

3.2 RCM fits

OM fits are summarized in the OM Conditioning Reports and in the Comparisons of OM conditioning.html document. Different OM had different stock trajectories as absolute magnitudes. In broad terms, OMs using the Taylor prior (TC1 and TC2) tended to have both higher scale than their counterparts that used the Fishlife prior and higher F_{MSY}.

The choice of which cluster of indices to use primarily affected the shape of the historical stock trajectories. OMs fitted to cluster 1 (C1), tended to have a one-way-trip of progressive declines. In contrast, OMS fitted to cluster 2 (C2) had trajectories where there was a decline from the 1960s to the early 1990s followed by gradual increases since. Across all the OMs examined, the current mean spawning depletion ranges from approximately 0.43 to 0.78.

3.3 Selected MPs

Of the 42 MPs tested, 14 MPs passed the minimum satisficing criteria. Three additional MPs were eliminated upon visual inspection: while both MPs that used statistical catch at age (SCA_75MSY and SCA_MSY) had acceptable mean performance, at the upper tail of the distribution of catches the MPs produced unrealistically high numbers (in the order of 10^6 tons) at the upper bounds of the probability distribution and mean catch values in the order of 100 tons. While these might be consistent with some combination of OMs and MPs, MPs predicting catches of that magnitude are unrealistic given the historical removals from the stock.

The third MP that was eliminated was IT5. It is index target MP where the TAC is modified according to current index levels (mean index over last 5 years) relative to a target level, but it is constrained so that the maximum annual changes in catch are limited to 5%. IT5 was eliminate because at the end of the time series, it showed a progressively increasing trend in fishing mortality; while it still met the minimum satisficing criteria it was not considered a desirable property that the MP had progressively increasing F because it meant that the MP did not provide adequate feedback control.

The set of MPs that met the minimum satisficing criteria and that passed the visual inspection are listed in **Table 3.** Example tradeoff plots for the set of MPs that met the minimum satisfying criteria are presented in **Figure 3**.

4. Discussion

The use of multivariate priors allows for continuous variables like natural mortality, steepness, and growth to be treated as continuous quantities in MSE. This is a big improvement over making these same continuous quantities categorical variable; this is in effect what is done in uncertainty grids used in other MSEs when these quantities are fixed. The has to do with the software choice for building operating models. Parameterizing operating models using software that is not able to run the equivalent of stock reduction analysis is effectively a decision to be unable to jointly model the uncertainty in steepness, natural mortality, and growth. This is commonly the case because most stock assessment software packages do not use this statistical technique. Choosing other software, like RCM, is an option that allows for a better statistical treatment of the uncertainty of these key life-history quantities.

A purely statistical approach to selecting MP performance on the basis of minimum satisficing criteria was not entirely sufficient. Examining time series plots of the biomass and fishing mortality was essential. As described above, some MPs might have acceptable mean statistical performance but have properties indicating long term instability or lack of feedback control like progressively increasing F in terminal years. Accordingly, any management procedure selection must consist of a combination of statistical criteria and visual inspection.

A variety of improvements are needed for the MPs. The main one is to control which indices are used in the MPs. Currently the MPs use the default settings. As parameterized, this means that illustrating MP performance according to index choice given one cluster or the other is not possible. A second issue is that when the MSE is run with default settings, data lags in MP implementation are not considered. MPs will need to be modified to account for these changes so that the evaluation of MP performance in theory can be more coherent with the application of MPs in practice.

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Table 1. Operating model nomenclature for each combination of steepness prior (Prior), and the CPUE cluster (Cluster).

Prior/Cluster	**Cluster 1**	**Cluster 2**
Taylor	T.C1	T.C2
FishLife	FL.C1	FL.C2

Table 2. Management procedures tested for southern swordfish including links to additional MP information (Link), a brief description of the MP. It also includes the broad data input class (MPInputClass) i.e., requiring an estimate of abundance (Abundance based, requiring an estimate or assumption of depletion (depletion based), requiring an index of relative abundance (Index-based). The required data column describes the data inputs required to apply the MP and Output describes if total allowable catch or total allowable effort are the output of the MP.

Link	*Description*	*MP Input Class*	*Required Data*	*Output*
DDSS_4010	A state-space delay difference model with a 40-10 control rule.	Abundance-based	Cat, Ind, Mort, L50, vbK, vbLinf, vbt0, wla, wlb, MaxAge	TAC
DDSS_75MSY	A state-space delay difference model with a TAC recommendation based on fishing at 75% of FMSY.	Abundance-based	Cat, Ind, Mort, L50, vbK, vbLinf, vbt0, wla, wlb, MaxAge	TAC
DDSS_MSY	A state-space delay difference model with a TAC recommendation based on fishing at FMSY, and default arguments for configuring DD_SS.	Abundance-based	Cat, Ind, Mort, L50, vbK, vbLinf, vbt0, wla, wlb, MaxAge	TAC
SCA_4010	An statistical catch at age model with a 40-10 control rule.	Abundance-based	Cat, Ind, Mort, L50, L95, CAA, vbK, vbLinf, vbt0, wla, wlb, MaxAge	TAC
SCA_75MSY	An statistical catch at age model with a fixed 75% of Fmsy harvest rate.	Abundance-based	Cat, Ind, Mort, L50, L95, CAA, vbK, vbLinf, vbt0, wla, wlb, MaxAge	TAC
SCA_MSY	An statistical catch at age model with a fixed Fmsy harvest rate.	Abundance-based	Cat, Ind, Mort, L50, L95, CAA, vbK, vbLinf, vbt0, wla, wlb, MaxAge	TAC
SP_4010	A surplus production model with a 40-10 control rule.	Abundance-based	Cat, Ind	TAC
SP_75MSY	A surplus production model with a TAC recommendation based on fishing at 75% of FMSY.	Abundance-based	Cat, Ind	TAC
SP_MSY	A surplus production model with a TAC recommendation based on fishing at FMSY, and default arguments for configuring SP.	Abundance-based	Cat, Ind	TAC
SSS_4010	Simple stock synthesis (terminal depletion fixed to 0.4) with a 40-10 control rule.	Depletion-based	dep, Rec, steep, sigmaR, CV_Ind	TAC
SSS_75MSY	Simple stock synthesis (terminal depletion fixed to 0.4) with with a TAC recommendation based on fishing at 75% FMSY.	Abundance-based	Cat, Ind, Mort, L50, L95, CAA, vbK, vbLinf, vbt0, wla, wlb, MaxAge	TAC

SSS_MSY	A Simple Stock Synthesis model (terminal depletion fixed to 0.4) with a TAC recommendation based on fishing at FMSY, and default arguments for configuringÂ SCA.	Depletion-based	dep, Rec, steep, sigmaR, CV_Ind	TAC
ICI2	The MP adjusts catch based on the value of the index in the current year relative to the time series mean and standard error.	Index based	Cat, Ind	TAC
Iratio	The TAC is adjusted by the ratio alpha, where the numerator being the mean index in the most recent two years of the time series and the denominator being the mean index in the three years prior to those in the numerator. This MP is the stochastic version of Method 3.2 used by ICES for Data-Limited Stocks (ICES 2012).	Index based	Cat, Ind	TAC
Islope1	An index slope tracking MP that incrementally adjusts the TAC to maintain a constant CPUE or relative abundance index, where the reference catch is the average catch	Index based	Cat, Ind, LHYear, Year	TAC
Islope2	An index slope tracking MP that incrementally adjusts the TAC to maintain a constant CPUE or relative abundance index, where the reference catch is 0.7 average catch	Index based	Cat, Ind, LHYear, Year	TAC
Islope3	An index slope tracking MP that incrementally adjusts the TAC to maintain a constant CPUE or relative abundance index, where the reference catch is 0.7 average catch	Index based	Cat, Ind, LHYear, Year	TAC
Islope4	An index slope tracking MP that incrementally adjusts the TAC to maintain a constant CPUE or relative abundance index, where the reference TAC is 0.6 average catch and gain parameter is 0.2	Index based	Cat, Ind, LHYear, Year	TAC
IT10	The Iterative Index Target MP is an index target MP where the TAC is modified according to current index levels (mean index over last 5 years) relative to a target level where the maximum annual changes are 10 per cent.	Index based	Ind, Iref, MPrec	TAC
IT5	The Iterative Index Target MP is an index target MP where the TAC is modified according to current index levels (mean index over last 5 years) relative to a target level where the maximum annual changes are 5 per cent.	Index based	Ind, Iref, Mprec	TAC

Itarget1	Incremental Index Target MP is a management procedure that incrementally adjusts the TAC (starting from reference level that is a fraction of mean recent catches) to reach a target CPUE / relative abundance index	Index based	Cat, Ind, LHYear, Year	TAC
Itarget2	Incremental Index Target MP is a management procedure that incrementally adjusts the TAC (starting from reference level that is a fraction of mean recent catches) to reach a target CPUE / relative abundance index	Index based	Cat, Ind, LHYear, Year	TAC
Itarget3	Incremental Index Target MP is a management procedure that incrementally adjusts the TAC (starting from reference level that is a fraction of mean recent catches) to reach a target CPUE / relative abundance index	Index based	Cat, Ind, LHYear, Year	TAC
Itarget4	Incremental Index Target MP is a management procedure that incrementally adjusts the TAC (starting from reference level that is a fraction of mean recent catches) to reach a target CPUE / relative abundance index	Index based	Cat, Ind, LHYear, Year	TAC
ItargetE1	Incremental Index Target MP - Effort-Based is a management procedure that incrementally adjusts the fishing effort to reach a target CPUE / relative abundance index	Index based	Ind, LHYear, MPeff, Yea	TAE
ItargetE2	Incremental Index Target MP - Effort-Based is a management procedure that incrementally adjusts the fishing effort to reach a target CPUE / relative abundance index	Index based	Ind, LHYear, MPeff, Yea	TAE
ItargetE3	Incremental Index Target MP - Effort-Based is a management procedure that incrementally adjusts the fishing effort to reach a target CPUE / relative abundance index	Index based	Ind, LHYear, MPeff, Yea	TAE
ItargetE4	Incremental Index Target MP - Effort-Based is a management procedure that incrementally adjusts the fishing effort to reach a target CPUE / relative abundance index	Index based	Ind, LHYear, MPeff, Yea	TAE
ITe10	Index Target Effort-Based is an index target MP where the Effort is modified according to current index levels (mean index	Index based	Ind, Iref, MPeff	TAE

	over last 5 years) relative to a target level.			
ITe5	Index Target Effort-Based is an index target MP where the Effort is modified according to current index levels (mean index over last 5 years) relative to a target level.	Index based	Ind, Iref, Mpeff	TAE
ITM	Index Target based on natural mortality rate MP is an index target MP where the TAC is modified according to current index levels (mean index over last number of years determined by natural mortality (M)) relative to a target level	Index based	Ind, Iref, MPrec, Mort	TAC
L95target	A management procedure that incrementally adjusts the TAC to reach a target mean length in catches.	Length based	Cat, L50, LHYear, ML, Year	TAC
SPmod	Surplus production based catch-limit modifier is an MP that makes incremental adjustments to TAC recommendations based on the apparent trend in surplus production.	Abundance-based	Cat, Ind	TAC
SPMSY	Catch trend Surplus Production MSY MP is an MP that uses Martell and Froese (2012) method for estimating MSY to determine the OFL. Since their approach estimates stock trajectories based on catches and a rule for intrinsic rate of increase it also returns depletion. Given their surplus production model predicts K, r and depletion it is straight forward to calculate the OFL based on the Schaefer productivity curve.	Catch based	Cat, L50, MaxAge, vbK, vbLinf, vbt0	TAC
SPslope	A management procedure that makes incremental adjustments to TAC recommendations based on the apparent trend in recent surplus production. Based on the theory of Mark Maunder (IATTC)	Abundance-based	Abun, Cat, Ind, Year	TAC
SPSRA	Surplus Production Stock Reduction Analysis is A surplus production equivalent of DB-SRA that uses a demographically derived prior for intrinsic rate of increase	Depletion-based	Cat, Dt, FMSY_M, L50, MaxAge, Mort, steep, vbK, vbLinf, vbt0, wla, wlb	TAC
SPSRA_ML	Surplus Production Stock Reduction Analysis is A surplus production equivalent of DB-SRA that uses a	Depletion-based	CAL, Cat, Dt, FMSY_M, L50, Lbar, Lc, MaxAge, Mort, steep, vbK, vbLinf,	TAC

	demographically derived prior for intrinsic rate of increase (McAllister method, below)		vbt0, wla, wlb	

Table 3. Selected Management Procedures. Statistics reported at the weighed mean probability of being above BMSY (P100), the weighted mean of being the limit reference point (P40), the weighted mean probabililty of not overfishing (PNOF), the weighted mean probability of being above the reference yield, the weighted mean probability that the average annual variability in effort (AAVE) was greater than 0.2 and the weighted mean probability that the average annual variability in yield (AAVY) was greater than 0.2. Readers can click on hyperlinks for more information on the MPs.

MP	*P100*	*P40*	*PNOF*	*PKOBE*	*Rel Yield*	*Abs.Yield*	*AAVE*	*AAVY*	*AAVY_abs*	*Required Data*	*MPInputClass*
Islope1	0.84	0.92	0.87	0.74	0.68	10.24	0.99	0.97	0.02	Cat, Ind, LHYear, Year	Index based
Islope2	0.84	0.92	0.87	0.74	0.68	10.24	0.99	0.97	0.02	Cat, Ind, LHYear, Year	Index based
Islope3	0.84	0.92	0.87	0.74	0.68	10.24	0.99	0.97	0.02	Cat, Ind, LHYear, Year	Index based
Islope4	0.84	0.92	0.87	0.73	0.67	10.19	0.99	0.97	0.02	Cat, Ind, LHYear, Year	Index based
Itarget1	0.87	0.97	0.91	0.80	0.58	9.71	0.93	0.95	0.06	Cat, Ind, LHYear, Year	Index based
DDSS_MSY	0.87	0.96	0.91	0.79	0.58	26.91	0.82	0.89	0.10	Cat, Ind, Mort, L50, vbK, vbLinf, vbt0, wla, wlb, MaxAge	Abundance-based
Itarget2	0.92	0.98	0.92	0.85	0.56	8.83	0.97	0.97	0.04	Cat, Ind, LHYear, Year	Index based
Itarget3	0.93	0.98	0.93	0.87	0.54	8.24	0.97	0.97	0.03	Cat, Ind, LHYear, Year	Index based
Iratio	0.79	0.91	0.83	0.65	0.51	9.92	0.94	0.98	0.06	Cat, Ind	Index based
DDSS_75MSY	0.90	0.97	0.94	0.85	0.51	15.66	0.89	0.93	0.08	Cat, Ind, Mort, L50, vbK, vbLinf, vbt0, wla, wlb, MaxAge	Abundance-based

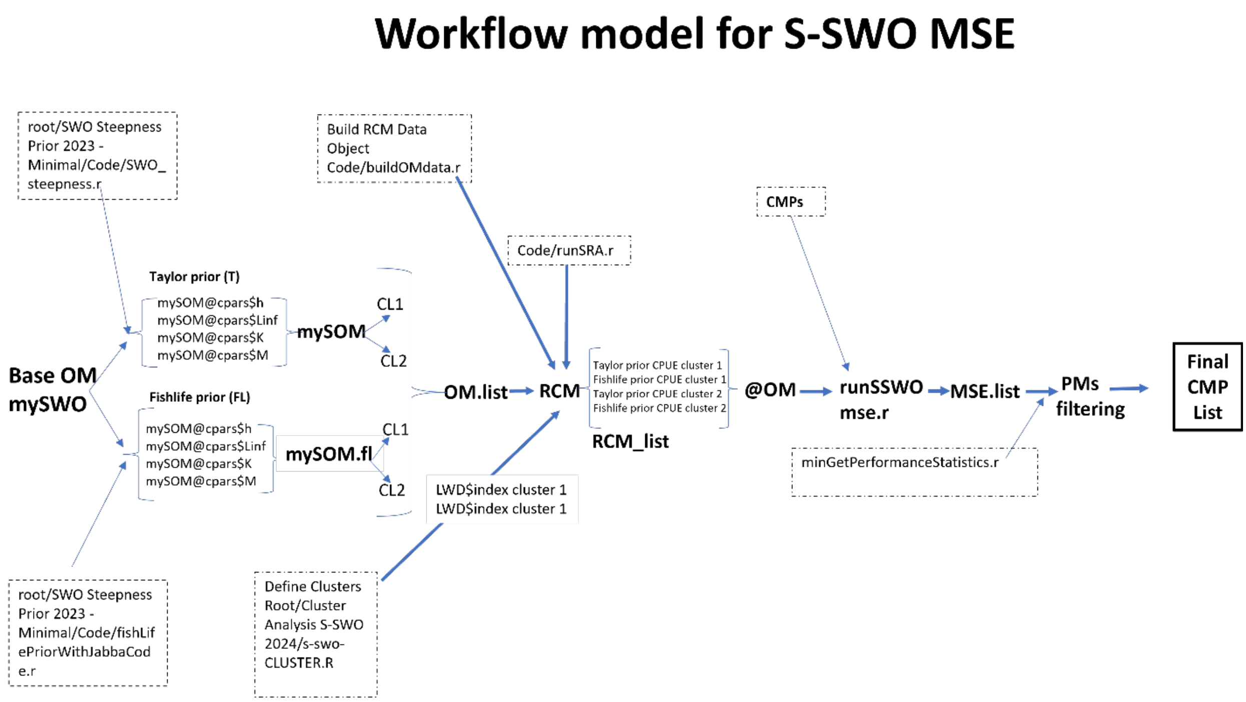

Figure 1. Schematic of S-Swordfish closed-loop simulation.

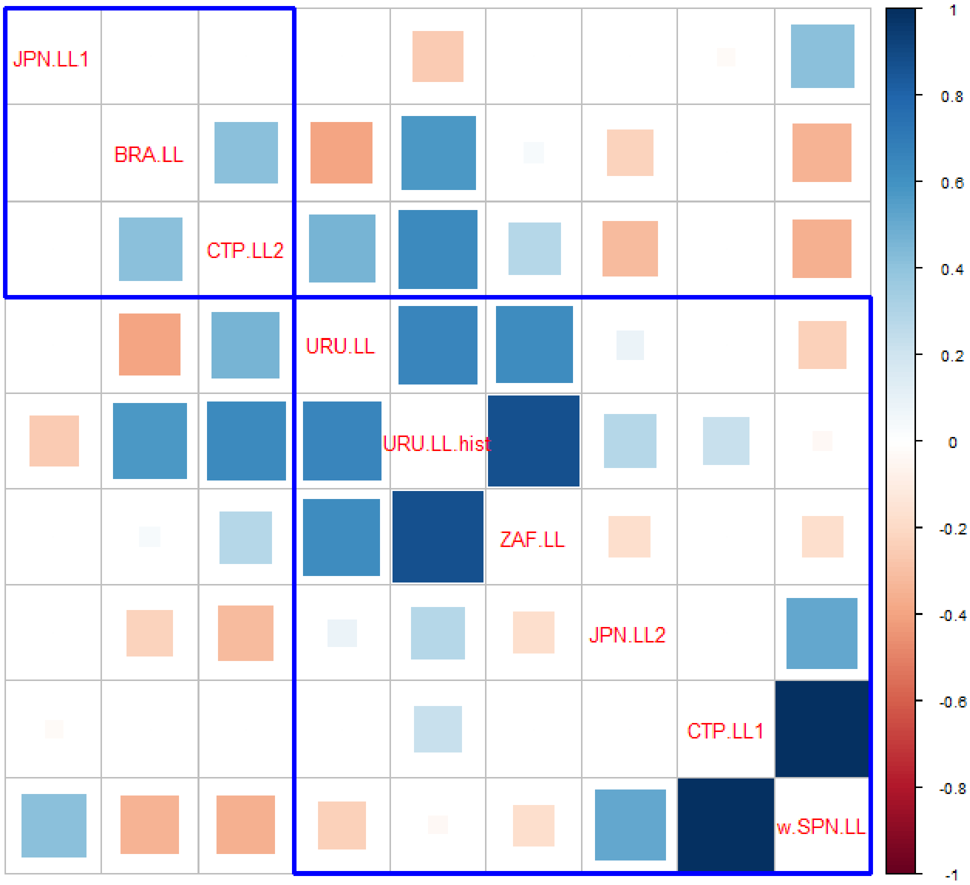

Figure 2. Cluster analysis of southern swordfish CPUEs. The blue boxes denote each cluster.

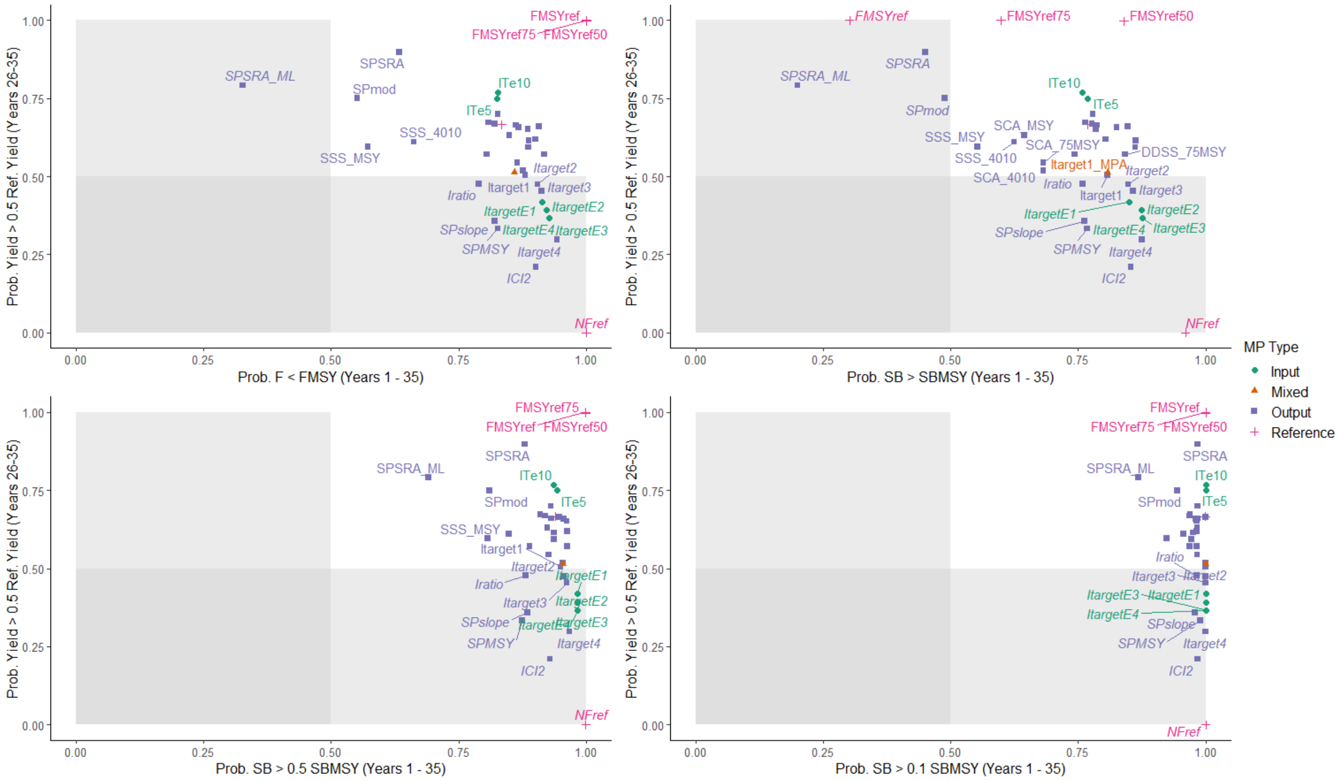

Figure 3. Tradeoff plot of MPs tested against the T.C1 OM.