IOTC Swordfish

Management Strategy Evaluation Update

21ST WORKING PARTY ON BILLFISH– 6–9 September 2023

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Status of the MSE work

- The reference operating model for the Indian Ocean swordfish stock was developed over the last three years and has been endorsed by the IOTC scientific committee. The OM was developed based on the 2020 WPB SS3 assessment, and covered the dynamics of the swordfish until the year 2018. This OM was updated to the current year, 2023, by projecting the stock forward based on the reported catches for 2019, 2020 and 2021 and assuming a 2022 catch at the 2021 level.
- The choices made in 2020 for the construction of the OM by the previous researcher have been revisited. following the feedback received during the 2022 working party on billfish (WBP20). The structural uncertainty grid (different options for the stock assessment model parameters) was simplified by removing those parameters that were found to have little impact on the assessment (e.g. choice of the scaling method for the CPUE indices). This change in the grid resulted in a reduced number of combinations to consider, but in the end in a higher number of valid stock assessment models that can serve as the basis for the OM.
- Further developments to the swordfish MSE included the development and application of two types of candidate MPs, one model-based and one data-based, and the tuning of these MPs (i.e. defining the MP parameters that achieve a certain management goal) for a range of management objectives over the next 11 to 15 years.
- An in-depth analysis of the impact of the choices of the parameters for the CPUE MP was conducted in order to make an informed choice of the value of those parameters that are not obtained by tuning. On the basis of this investigation, a configuration of the CPUE MP with low reactivity to the changes and values in the CPUE index used for management was proposed.

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Operating model development

The status of the current swordfish OM was presented at the 2022 WPB. A document presented a revision of the OM grid that decreased the number of factors considered, by identifying those having little impact on initial stock status and productivity in the OM. Two factors in the grid were eliminated: the choice of selectivity function shape for the CPUE fleets (previously set as double normal or logistic) and the scaling factor applied to the biomass by area estimates (previously based on surface area, biomass or catch). A change in the range of steepness values was also suggested, to 0.6-0.8 from the previous 0.6-0.9 but it was not endorsed by WPB, that noted that values between 0.6 and 0.9 were used for swordfish in other oceans (e.g. at ICCAT). The original structural uncertainty grid and the updated grid after WPB 2022 are given in table 1a and 1b of annex 1 respectively.

The decisions made at WPB were implemented, which resulted in a new grid containing 648 combinations, of which 175 were selected by factorial design optimization (vs 2592 and 108 respectively for the original OM). The SS3 stock assessment was run for these 175 parameter combinations, and 130 runs were ultimately considered acceptable (based on model convergence, biomass index prediction skill, credibility of B0 estimates) and used as a basis for the OM (vs 67 for the original OM).

The SS3 runs based on the latest available stock assessment data for the Indian ocean swordfish cover the development of the stock until the year 2018. In order to conduct simulations starting with a stock status as close as possible to the current status, the OM was projected forward over the years 2019-2022 using the IOTC nominal catch estimates for the years 2019 to 2021, and assuming a status quo fishing mortality for 2022 (F_{2022}=F_{2021}).

The updated OM presents a slightly different distribution of stock status at the end of the assessment period from the previous OM (figure 1), with a broader distribution of values, and, overall, slightly higher values. The updated OM gives the perception of a stock that was unfished at the start of the assessment period, and for which exploitation started in the 1990s, which caused stock size to decrease until the mid-2000s after which it stabilized (figure 2). This is similar to the previous OM.

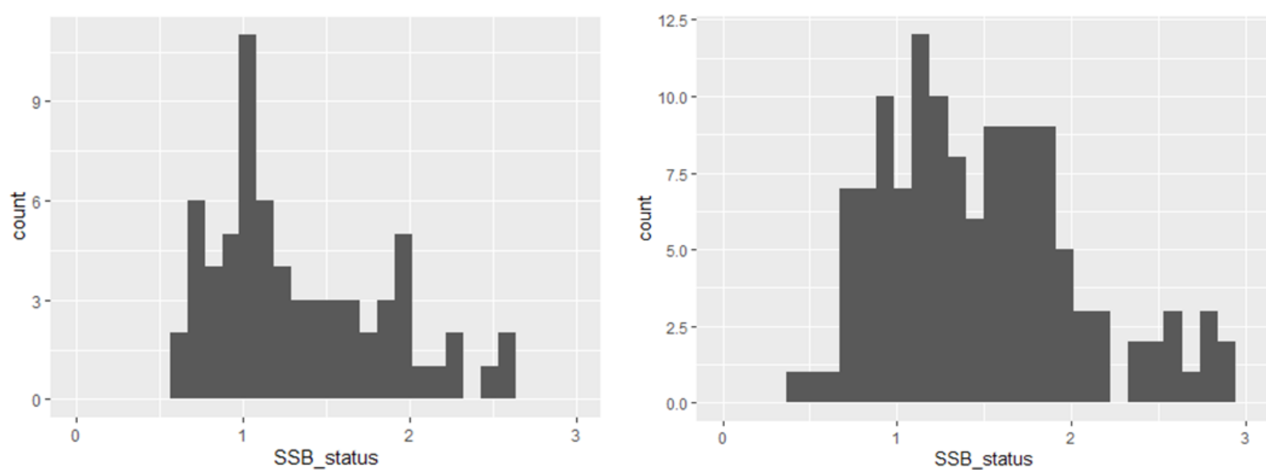

Figure 1 : Distribution of the estimated stock status in 2018 (SB/SB_{MSY}) on the previous OM grid (left) and new one (right).

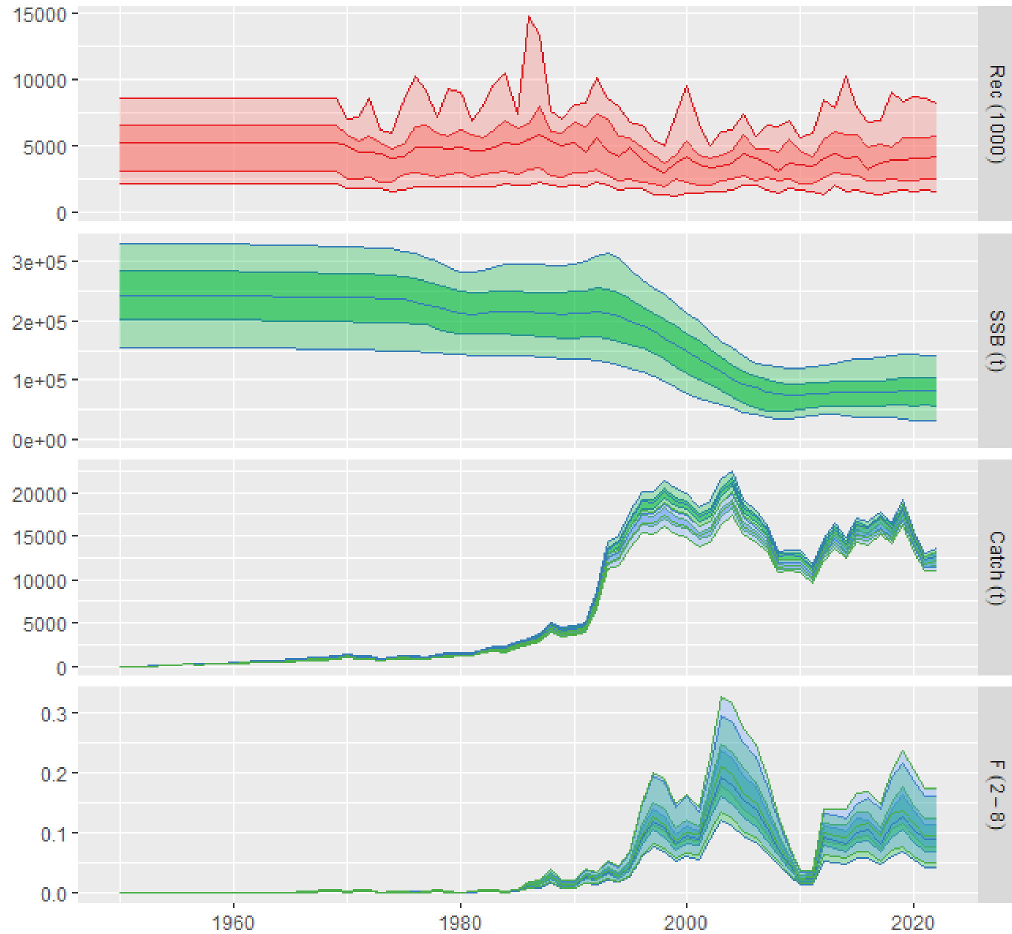

Figure 2: historical stock development in the updated swordfish OM

Candidate Management Procedures

The swordfish MSE analyses focussed on two types of MPs:

- A model-based one, in which the surplus-production model JABBA provides an estimate of current stock status, in terms of current biomass depletion (B/B_0), which is then used in a harvest control rule to determine the advised catch
- A data-based one in which the advised catch changes from the previous level based on both the value and recent trend in a CPUE index.

The two types of MPs are presented below and they were furthermore implemented:

- with a 3 year advice cycle (TAC set for a period of 3 years)

- with an inter-annual TAC variation limit (or TAC stabilizer) of 15 %, whereby when the implementation of the MP leads to a change in TAC larger (in absolute values) that 15%, the TAC applied is that corresponding to the max 15% change (increase or decrease).
- assuming that in a given year, y, when advice has to be given for the 3 following years, y+1 to y+3, data are available until the previous year, y-1 (i.e. 1 year data lag and 1 year management lag)

Model-based MP

Definition

The model-based MPs (figure 3) involve two steps:

- 1) fitting a surplus production model to estimate current depletion rate, and
- 2) applying a Harvest Control Rule (HCR) to the model estimates of current depletion. The shape of the HCR (hockey-stick) is defined by three control parameters :
  - CP1: minimum stock level below which no fishing (or the least possible) should take place,
  - CP2: trigger stock level below which catch advice should be decreased proportionally to current depletion
  - CP3: maximum catch that can be taken when the stock is estimated to be above the trigger level.

Implementation in the swordfish case

The surplus production model JABBA was fitted to the total catches time series and the Japanese longline CPUE index and provided estimates of the depletion rate, as SB/SB0 (SB0 =virgin biomass), in the last year of the assessment period. The limit and trigger depletion rates were set at CP1 = 0.1 (a proxy for $SB=SB_{lim}$) and CP2 = 0.4 (a proxy for $SB=SB_{MSY}$). The maximum catch, CP3, was obtained by tuning the MP to achieve the particular management objectives. In agreement with the decision made by the TCMP-03 (2018), the MP was tuned for three tuning objectives corresponding to a probability of being is in the green quadrant of the Kobe plot (p(Kobe=green)) over the period 2034:2038 of exactly 50%, 60% and 70% (average over all stock replicates and years) respectively.

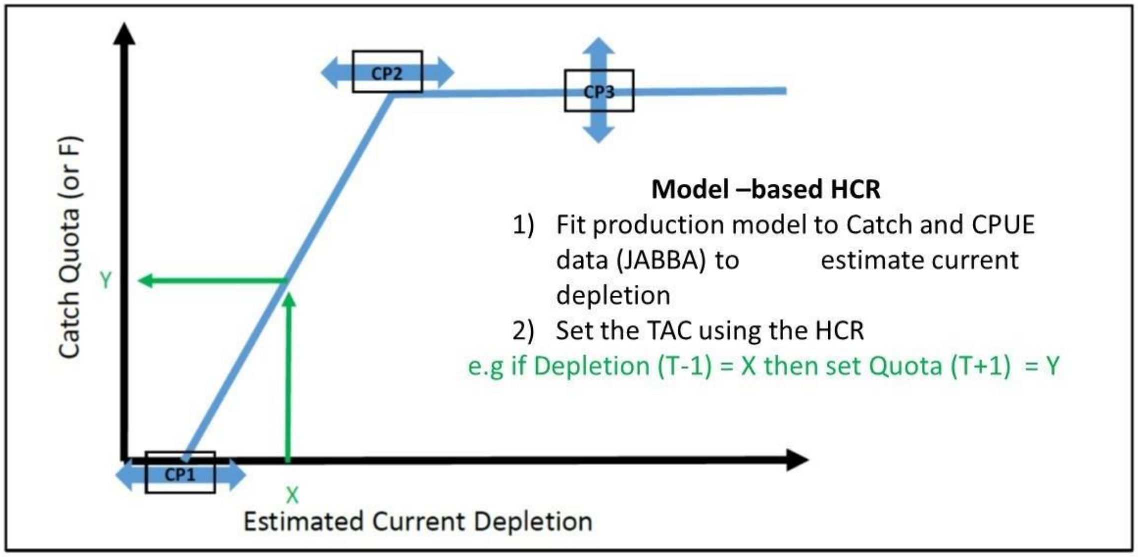

Figure 3. Harvest control rules used in the model-based MP.

Data-based

Definition

The data-based MPs attempt to manage the fishery to achieve a target value of catch rates over a chosen CPUE series. The next TAC is increased relative to the current TAC if current CPUE is above the target CPUE and the CPUE trend is increasing. Conversely, the next TAC is decreased relative to the current TAC if current CPUE is below the target CPUE and the CPUE trend is decreasing. If the CPUE location relative to the target and CPUE slope are in opposite directions, the TAC change could be in either direction, depending on the magnitude of these indicators, and the associated control parameters. Formally, the future TAC is calculated as a proportion, TAC_{mult}, of the current TAC, which is defined as

$$TAC_{mult} = 1 + k_a\, Sl + k_b\, D$$

with

$$k_a = k_1 \; if \; Sl > 0 \; or \; k_a = k_2 \; if \; Sl \leq 0$$

and

$$k_b = k_3 \; if \; D > 0 \; or \; k_b = k_4 \; if \; D \leq 0$$

Where Sl is the slope of the log CPUE over the last 5 years, D is the difference between recent CPUE value (average over the last 3 years) and the target CPUE value, and k_a and k_b are parameters of the relative weight assigned to the previous two quantities (figure 4), controlling the responsiveness of the MP. Control parameters include: CP1) responsiveness to CPUE slope (k1 and k2), CP3) responsiveness to CPUE target deviation (k3 and k4) and CP4) the CPUE target value.

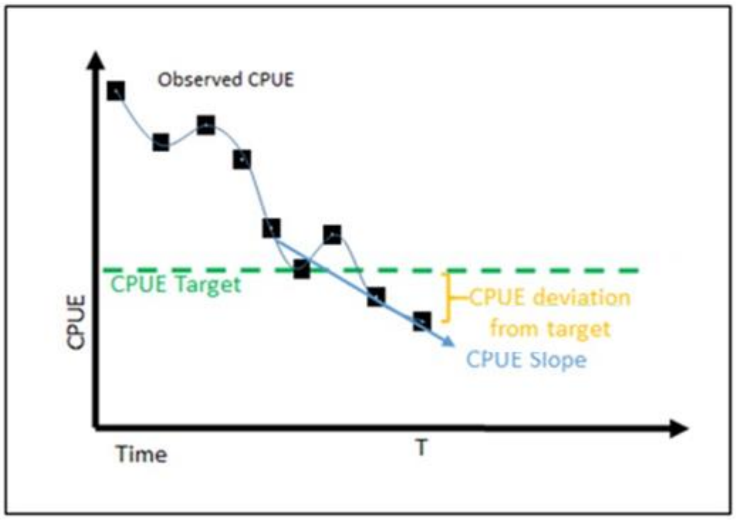

Figure 4 : The CPUE rule is based on the recent slope in the CPUE index and the distance to the target index value.

Implementation in the swordfish case

The CPUE index used for this rule was the Japanese longline CPUE index. The control parameters defining the responsiveness of the MP to both the current distance from the target CPUE and to the slope of the CPUE over the recent years were all set (see section below for a justification of the *k* values chosen). The MP was tuned to estimate the target CPUE value for the same three management objectives as for the model-based MPs.

Performance of the candidate Swordfish MP

MP rankings against key performance indicators are presented in Table 1 and figs. 5-6 illustrate their performance characteristics.

The two types of MP led to similar levels of spawning biomass (for a given tuning objective) expect for P(Kobe = green) = 50% for which spawning biomass was markedly lower with the model-based MP. The model-based MP also led to a wider distribution of values across simulation iterations.

For all tuned MPs, the probability that the stock remains above SB_{lim} for the tuning period was very high (average values above 99%).

The data-based MP (MP1-3) led to larger average catches than the model-based one, but a wider distribution of values across simulation iterations. For the model-based MP, the average catch is consistent across iterations, reflecting the fact that it is most of the time equal to the plateau of the hockey stick harvest control rule. This also results in a low interannual change in the catch although a little less so when the MP is tuned for P(Kobe = green) = 50%, as the stock is more often at SB/SB0 below 40% where catches are decreased from C_{max}. For the data-based MP, interannual change in catches is higher, although it remains at low values (likely due to the implementation of a maximum interannual TAC variation limit of 15%).

Tuning objectives are achieved (mean P(Kobe=green) at 0.5, 0.6 or 0.7) but there is a large variability in this probability between simulation iterations (i.e. the 25th-75th quantile interval ranges from 0 to 1). This specific point was investigated for the 2022 WPB. It was explained by the fact that most of the simulation iterations starting in a given quadrant of the Kobe plot, remain in the same quadrant throughout the simulation period, despite the implementation of a MP. This is due to several factors. First the OM has a large range of initial starting conditions, with numerous iterations far above or far below the SB_{msy}. For these iterations to change quadrant over the tuning period, it would require a MP that imposes a strong change of stock size. This is unlikely to be the case in the present situation, where the initial status for the stock is at p(Kobe=green)=73%, not far from any of the tuning objectives. In addition, due to the high longevity in the stock (31 age-classes), SB is very stable, which reduces the chances of changing quadrant over the tuning period, especially as the tuning period is rather short (5 years).

The main trade-off (figure 6) amongst MPs tested appears to be between MP type, with higher catches but larger interannual variation (and overall uncertainty) for the data-based MP, and lower but very stable catches for the model-based MP.

Table 1: performance of candidate MPs with respect to key performance measures (averaged over the period 2034-2038).

MP	prob(SB>SB_{limit})	Catch Variability	prob(Green)	Mean Catch	SB/SB_{MSY}
MP1	>0.99	6.2	0.5	37149.6 (26571.2-46601)	1.6
MP2	>0.99	5.7	0.62	34421.4 (24348.0-44429)	1.7
MP3	>0.99	5.2	0.7	32498.0 (22853.7-43024)	1.7
MP4	>0.99	5.3	0.49	35031.2 (24245.3-35031)	1.4
MP5	>0.99	3.4	0.6	30652.3 (25633.8-30652)	1.6
MP6	>0.99	2.3	0.71	26820.8 (26249.4-26821)	1.8

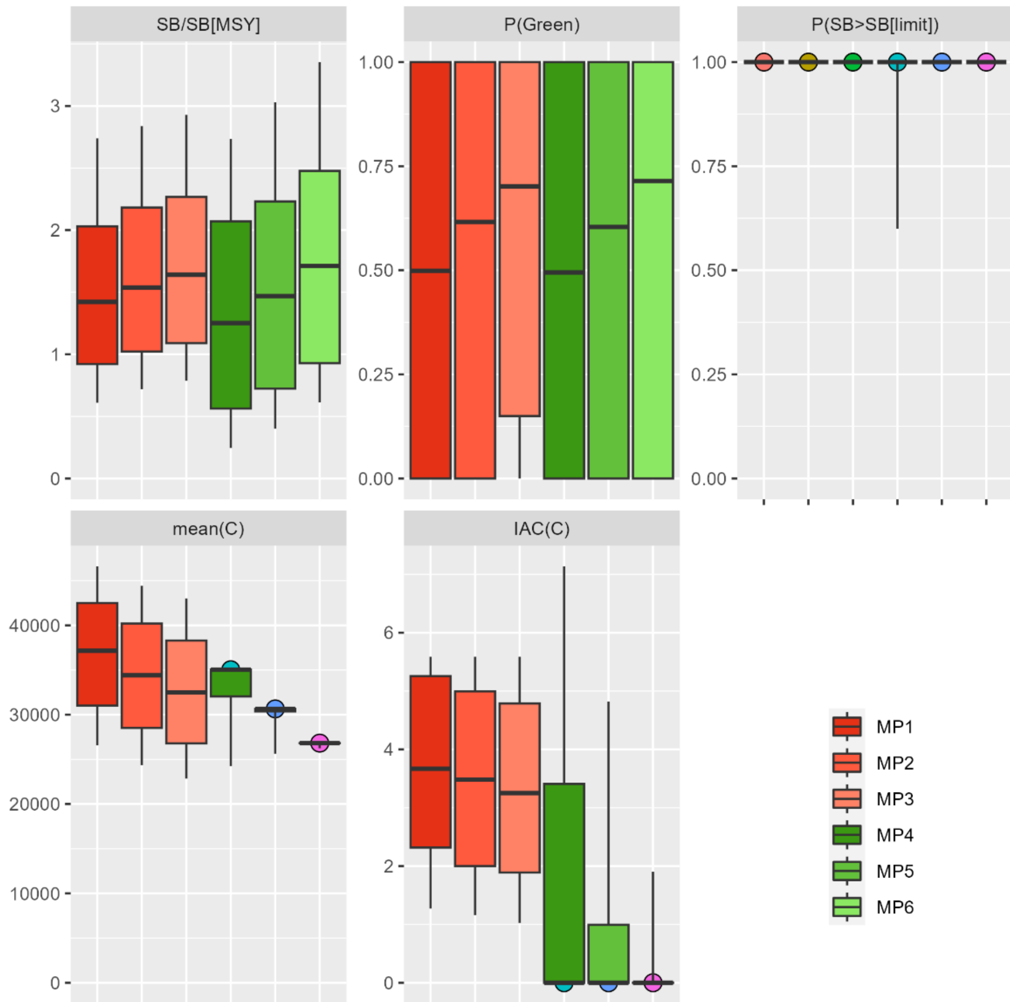

Figure 5. Boxplots comparing candidate MPs with respect to key performance measures averaged over the period 2034-2038. Horizontal line is the median (mean for P(Green)), boxes represent 25th - 75th percentiles, thin lines represent 10th - 90th percentiles. The data-based MPs are depicted in red and model-based MPs are depicted in green

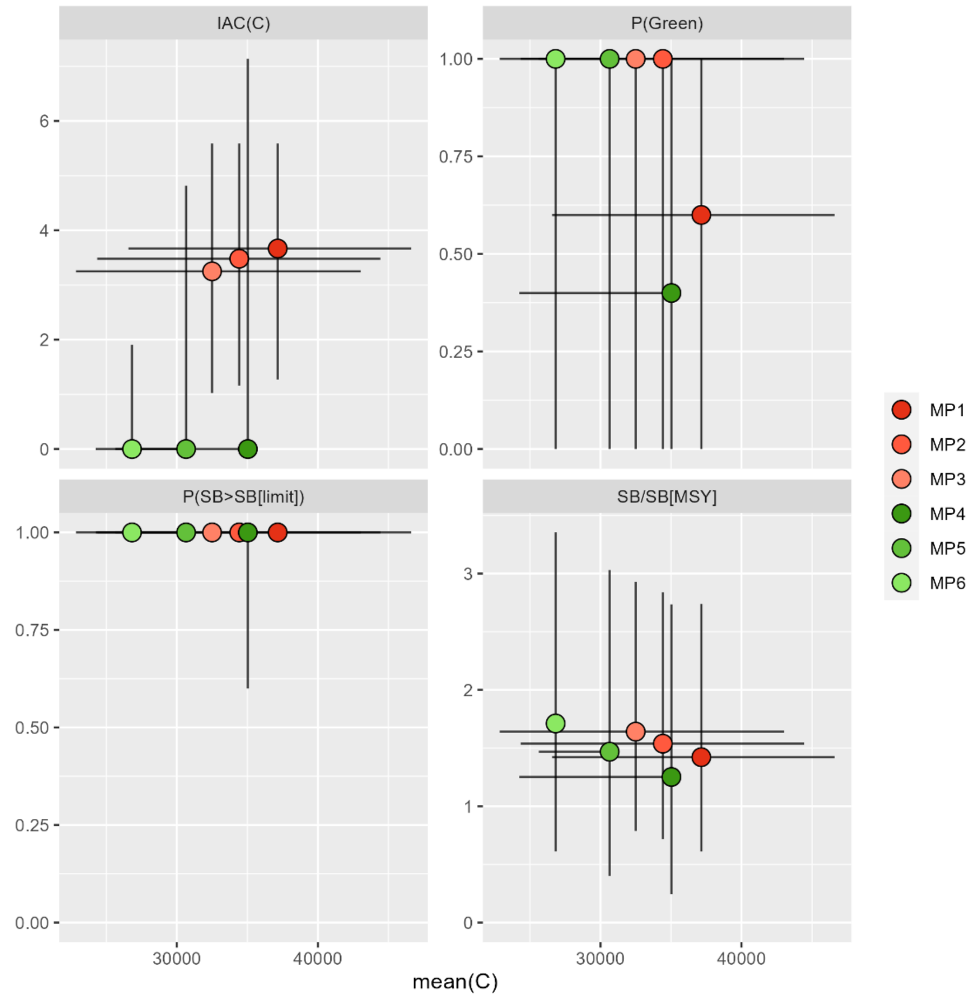

Figure 6. Trade-off plots comparing candidate MPs with respect to catch on the X-axis, and 4 other key performance measures on the Y- axis, each averaged over the period 2034-38. Circle is the median, lines represent 10th-90th percentiles.

Investigation of different parameterization options for the CPUE MP

MP reactiveness to changes in the CPUE index and to the distance to the target value

The CPUE MP has multiple control parameters, and it is not straightforward to decide which parameters should have values chosen a priori and which parameters should have values obtained by tuning. In order to examine the impact of the different parameters on the MP performance, simulations were run for a grid of parameter values and key performance indicators were calculated over the period for which tuning should be done (2034-2038). The grid used was the following :

- k1=k2 varying between 0.1 and 3 and
- k3=k4 varying between 0.1 and 1.2

- target = mean of historical CPUE index values (1.00)

The MP performance indicators were slightly more influenced by the responsiveness to the distance to the target CPUE (k3 and k4, figure 7) rather than to the slope (k1 and k2). The mean catch is rather stable along the isolines for p(Kobe=green), showing that these two performance metrics are linked to a large extent. Along the p(Kobe green) isolines, management strategies that are more reactive to the CPUE index (higher values of k parameters) lead to higher interannual catch variability. For all options on the grid the risk of $SB<SB_{lim}$ was null.

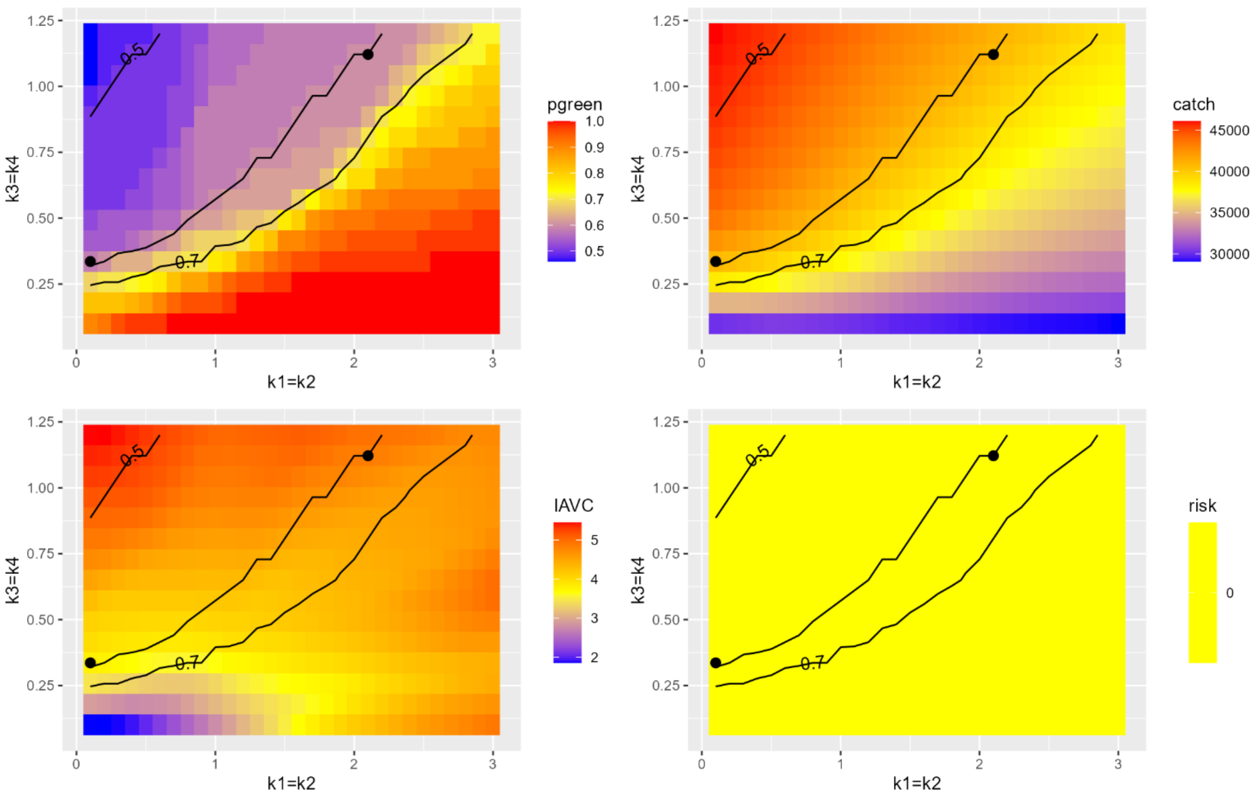

Figure 7 : values of 4 MP performance indicators (pgreen : P(Kobe green), catch : mean catch, IAVC: interannual catch variability and risk3 : p($SB<SB_{lim}$) computed over the period 2034-2038 for a grid of k responsiveness parameters with symmetric response for positive and negative CPUE slope and distance to target (isolines show the 50, 60 and 70% probability of being in the green zone of the Kobe plot).

Impact of the implementation of the TAC variation limit

In order to investigate the impact on the MP performance of the implementation of a 15% TAC interannual variation limit, the CPUE MP was tuned again, with the same *k* parameter values as above, but without the TAC variation limit.

For each tuning objective, the CPUE MP tuned without TAC variation limit consistently had a slightly higher value of the CPUE index target value, meaning that the MP had to be a little more precautionary to achieve the tuning objective than the MPs with the TAC variation limit. Comparison of the performance of the MP with and without TAC variation limit shows that there is overall little difference, the effect of the tuning criteria being overall larger than the effect of implement the TAC variation limit.

Robustness of the different configurations of the CPUE MP to a recruitment failure

The exploration of the performance of the CPUE MP for different types of configuration presented above suggests that configuration with low reactiveness combined to a TAC variation limit led, for the swordfish stock, to slightly better performance than alternative configurations. However, such a MP, with slow reactiveness to changes in stock size and limited possibilities to the change the TAC, might not be capable of protecting the stock in case of unfavourable events.

A robustness test was conducted in which a recruitment failure was simulated at the start of the projection period. A series of poor recruitments were imposed by setting all deviations from the stock-recruitment model to 0.1 for the period 2022-2025. This purely fictive scenario was chosen in order to produce a substantial decrease in stock size, and does not attempt reproduce any event observed in the history of the stock. Simulations were run for the slow CPUE MP with and without the TAC stabilizer (both were tuned beforehand).

Without TAC variation limit and for the base case OM, the risk of falling below Blim increases over the time but remains very low. When a recruitment failure is introduced (left panels, blue curves), the risk increases more quickly and the sMP is not able to prevent the stock from declining. However, even in this case, the risk remains low, below 5%. With TAC variation limit, when a recruitment failure is introduced, p(Kobe green) quickly falls to about 40%, and risk3 increases to around 7%.

This test, based on a purely fictive recruitment scenario, shows that in situations where drastic management measures need to be taken to protect the stock, the TAC stabilizer could potentially lead to an increased risk for the stock, by preventing the MP to be reactive. When deciding on a MP for swordfish, it is therefore important to consider both the benefits (having a more stable TAC, that does not react closely to measurement errors in the CPUE index) and the risks (having a MP not to able react fast enough) of using a TAC variation limit. Potential ways to improve on this situation could be explored, as for instance, defining circumstances where the TAC variation limit should be lifted (e.g. if CPUE slope or difference to target are larger than some limits).

Appendix 1. Changes in the structural uncertainty grid used to generate the swordfish OM

Table 1a : Reference OM structural uncertainty grid

Variable	Values		
Selectivity	Double Normal	Logistic	
Steepness	0.6	0.75	0.9
Growth + Maturity	Slow growth, late maturity (Wang et al.,2010)	Fast growth, early maturity (Farley et al., 2016, otoliths)	
M	Low = 0.2	High = 0.3	Sex-specific Lorenzen M (Farley et al. (2016), otoliths)
Sigma R	0.2	0.6	
ESS	2	20	
CPUE scaling schemes	Area effect x Surface	Catch	Biomass
CPUEs	JPN late + EU.PRT	JPN late	TWN + EU.PRT
Catchability increase	0%	1% / year	

Table 1b : Proposal for a new OM structural uncertainty grid (additions and removals highlighted respectively in bold and with a cross)

Variable	Values		
Selectivity	Double Normal		
Steepness	0.6	0.75	0.90
Growth + Maturity	Slow growth, late maturity (Wang et al.,2010)	Fast growth, early maturity (Farley et al., 2016, otoliths)	
M	Low = 0.2	High = 0.3	Sex-specific Lorenzen M (Farley et al. (2016), otoliths)
Sigma R	0.2	**0.4**	0.6
ESS	2	20	
CPUE scaling schemes			Biomass
CPUEs	JPN late + EU.PRT	JPN late	TWN + EU.PRT
Catchability increase	0%	1% / year	