Management Strategy Evaluation for the Indian Ocean Tuna Albacore Stock

IOTC-2017-WPM08-13 (DRAFT)

Iago Mosqueira*

8th Session of IOTC WPM - 13-15 October 2017, Mahe, Seychelles.

Abstract

This document presents the current status of development of the technical platform, and a set of initial results, for the Management Strategy Evaluation of the Indian Ocean albacore tuna stock. The work includes the development of a reference case Operating Model for the stock, an open source computational platform for the evaluation of alternative Management Procedures, an initial set of simulations for two MPs, and the presentation and output for inspection and analysis of the results. The Operating Model is based around the Stock Synthesis stock assessment conducted by WPTmT in 2016 and incorporates the main sources of uncertainty identified in the estimation of population trajectories and dynamics.

Contents

1	Introduction	2			
2	Operating Model	2			
	2.1 Structure and assumptions	3			
	2.2 Uncertainty grid	4			
	2.3 Model selection	7			
	2.4 Base case Operating Model	8			
3		10			
	3.1 msePT: Pella-Tomlison stock assessment				
	3.2 mseIndex: CPUE trend-based indicator	10			
4	Performance Statistics	11			
5	Tuning	12			
	5.1 MP parameter grids	12			
	5.2 Tuning for $P(B > B_{MSY}) = 0.5$				
	5.3 Tuning for $P(Kobe = GREEN) = 0.75$	13			
6		13			
	6.1 Accessing code and results	17			
7	Discussion				
	7.1 Limitations	17			
	7.2 Next steps	17			
Re	eferences	18			

*European Commission, DG Joint Research Centre (JRC), Directorate D - Sustainable Resources, Unit D.02 Water and Marine Resources, Via E. Fermi 2749, 21027 Ispra VA, Italy. iago.mosqueira@ec.europa.eu

1 Introduction

A simulation model of the albacore tuna (*Thunnus alalunga*) fishery and population in the Indian Ocean has been developed to evaluate the comparative performance of alternative Management Procedures (MP) for this stock under the management of the Indian Ocean Tuna Commission (IOTC). The Operating Model (OM) has been constructed around the current best knowledge of the history and dynamics of the stock, as represented by the stock assessment model reviewed and accepted by the Working Party on Temperate Tuna (WPTmT) of IOTC, and then used by its Scientific Committee (SC) as the basis for providing management advice.

The OM presented here has been constructed using as base case the last stock assessment exercise, carried out in 2016 (IOTC 2016) using the Stock Synthesis 3 modelling platform (SS3, Methot and Wetzel (2013)). Structural uncertainty in this model has been incorporated into the OM contition by means of a grid of alternative formulations for various model parameters that were not being estimated from data.

An initial set of simulation runs for two possible management procedures have been conducted: exploration runs, tentative evaluation runs (for two MPs) and some robustness tests. The runs shown here are presented as proofs of concept and for discussion of the approach taken, including the choice of scenarios. They are expected to be rerun based on feedback and discussion for WPM and SC.

2 Operating Model

The initial deliberations of the strategy to follow for the development of the albacore MSE platform by the WPM (IOTC 2014; IOTC 2015) agreed on using the stock assessment carried out and reviewed by WPTmT, based on SS3 (Methot and Wetzel 2013), as a basis for the population and fishery model to use when building an OM for this stock. Uncertainties concerning structural elements of the model formulation were considered to be the primary factor of concern. Both estimation and observation uncertainty were also relevant but were deemed to be of secondary importance.

The decision was thus made to construct a grid of model runs built around feasible, or at least not too extreme, values for a number of assumptions and fixed parameters in the population model. The impact of some of these elements in the model have already been explored in some detail by the researchers carrying out past stock assessments (Hoyle, Sharma, and Herrera 2014; Langley and Hoyle 2016).

The structure of the uncertainty grid used to build the current operating model has remained stable from previous iterations (Mosqueira and Sharma 2014). It is built around the population dynamics and assumptions in the Stock Synthesis 3 stock assessment framework (Methot and Wetzel 2013) and uses as starting point the stock assessment presented and reviewed at the Sixth Session of the Working Party on Temperate Tunas (Langley and Hoyle 2016).

According to the results of the last stock assessment, shown in Figure 1 the biomass of albacore tuna has been slowly declining as catches increased over the 1950-2000 period, having probably fallen below the B_{MSY} target at some point in the past. The stock then recovered, as a result of a decrease in catches after 2001, and is now considered to be around the target level of $B = B_{MSY}$

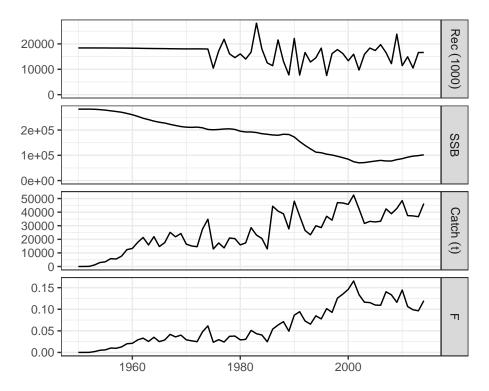


Figure 1: Yearly time series of recruitment, SSB, catch and fishing mortality estimated by the WPTmT SS3 stock assessment for Indian Ocean albcore in 2016.

This latest iteration of the OM has taken into consideration the recommendations made by WPTmT (IOTC 2014, Table 12) with regards to the scenarios for different model parameters, as well as the feedback from the last sessions of WPM (IOTC 2015b IOTC 2016), including the report from the two invited experts. This has had as the main consequence an increase in the size of the full model grid.

2.1 Structure and assumptions

2.1.1 Areas and seasons

The current model partitions the Indian Ocean into four regions, divided latitudinally along the 25°S parallel and longitudinally along the 75°E meridian (Figure 2).

2.1.2 Fisheries

The model includes a total of 11 fisheries, including in this case an aggregaqted Longline fishery for each of the four regions. For a detailed explanation of the data and fleets included in each of these isheries, please refer to Langley and Hoyle (2016).

Table 1: Definition of fisheries used in the albacore operating model, after Langley and Hoyle (2016).

Fishery	Code	Flag	Gear	Area
1	LL1	All	Longline	1 (NW)
2	LL2	All	Longline	2 (NE)
3	LL3	All	Longline	3 (SW)

Fishery	Code	Flag	Gear	Area
4	LL4	All	Longline	4 (SE)
5	DN3	CN-TW	Drift net	3 (SW)
6	DN4	CN-TW	Drift net	4 (SE)
7	PS1	All	Purse seine	1 (NW)
8	Other1	All	Other gears	1 (NW)
9	Other2	All	Other gears	2 (NE)
10	Other3	All	Other gears	3 (SW)
11	Other4	All	Other gears	4 (SE)

2.1.3 CPUE Indices

A new set of standardized CPUE indices has been derived using generalized linear models (GLM) operational from longline catch and effort data provided by Japan, Korea and Taiwan, China. (Hoyle et al. 2016). The operating model conditioning used the same series as the final runs of the stock assessment (Langley and Hoyle 2016), a combined industrial longline series, on each of the four areas, and restricted to the 1979-2014 period (Figure 3).

2.2 Uncertainty grid

Fisheries data is in general less informative that would be ideal when it comes to estimating a large number of model parameters, which are often correlated [@]. In the case of the Indian Ocean albacore stock, a number of reasons are limiting our ability to obtain reliable model fits. Problems exists with the data completeness and quality (Sceretariat 2016), not limited to but including total catch statistics, length distribution in catches, and biological information.

We also depend on our ability to produce sensible indices of changes in abundance in the stock based only on Catch-per-unit-effort data from commercial fleets, where issues of targeting, operating and others are all known to influence the relationship between stock abundance and CPUE [@], despite recent work on standardization of the longline CPUE series for this stock (Hoyle et al. 2016).

The seven factors currently considered in the structural uncertainty grid for the albacore OM are the following

2.2.1 Natural mortality vector (*M*)

A common unknown in most stock assessment models, the base case considered in the stock assessment session was supplemented with alternative values of higher and lower M for either all ages, or different for juveniles (ages 0 to 4) and adults (age 5 or older), for a total of five possibilities,

- Constant M at 0.2 for all ages.
- Constant M at 0.3 for all ages.
- Constant M at 0.4 for all ages.
- M=0.4 at age 0, decreasing to 0.3 at age 5 and older.
- M=0.4 at age 0, decreasing to 0.2 at age 5 and older.

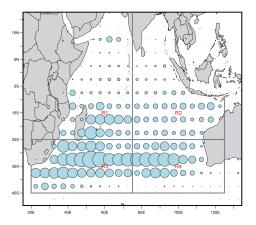


Figure 2: Spatial stratification of the Indian Ocean albacore data and stock assessment model (areas R-1 to R4). Aggregated catches (in numbers of fish) for the Japanese and Taiwanese LL fleets, for the 1950-2014 period, are shown. From (Langley and Hoyle 2016)

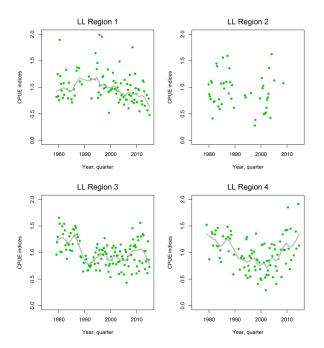


Figure 3: Quarterly standardised CPUE series for the industrial longline fleets from 1979-2014. From Langley and Hoyle (2016).

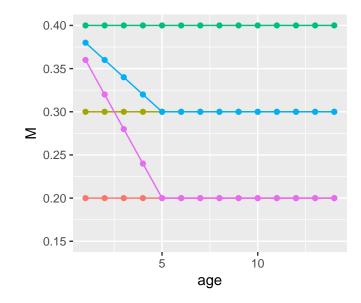


Figure 4: Natural mortality at age vectors used in the OM grid.

2.2.2 Variance of the recruitment deviates (sigmaR)

Two values were considered for the true variability of recruitment in the population (*sigmaR*), 0.4 and 0.6, as set by variable SR_sigmaR in the 3 control file.

2.2.3 Steepness of the stock-recruits relationship (steepness)

Three values for the steepness (h) of the stock-recruitment relationship are being used: 0.7, 0.8, and 0.9. The Beverton and Holt stock-recruit model implemented in SS3 (Methot and Taylor 2011) is as follows,

$$R_y = \frac{4hR_0B_y}{B_0(1-h) + B_y(5h-1)} \tag{1}$$

where R_y is the estimated recruitment for year y, h is steepness, R_0 is the virgin recruitment, B_y is the biomass in year y, and B_0 is virgin biomass, the spawning biomass before fishing started.

2.2.4 Coefficient of variation of the CPUE series (cpuecv)

Four values for the coefficient of variation in the CPUE series were included: 0.2, 0.3, 0.4 and 0.5.

2.2.5 Effective Sampling Size of each length data point (ess)

Three values were used for the relative weight of length sampling data in the total likelihood, through changes in the effective sampling size parameter, of 20, 50 and 100. This alters the relative weighting of length samples and CPUE series in informing the model about stock dynamics and the effects of fishing at length.

2.2.6 Catchability trends in the CPUE Longline fleet (LLq)

Two scenarios were considered for the effective catchability of the CPUE fleet. On the first one it was assumed that the fleet had not improved its ability to fish for albacore over time, or that any increase had been captured by the

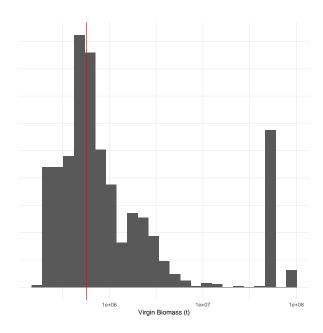


Figure 5: Distribution, in log scale, of the estimates of unfished biomass returned by the complete model grid. The red line show, for reference, the estimate of virgin biomass from the stock assessment run used as basis for the OM.

CPUE standardization process. An alternative scenario considered a 2.5% increase in catchability by correcting the CPUE index to reflect this.

2.2.7 Form of the selectivity curve for the CPUE fleet (*LLsel*)

Two possible functional forms for the selectivity of the CPUE LL fleet were considered: a logistic function (Log), where selectivity stays at the maximum level, or double normal (DoNorm), where selectivity drops at some point in the age range.

2.3 Model selection

The aggregated population model obtained from the complete grid of model runs included a high proportion of unrealistic estimates. The virgin recruitment (LN(R0)) estimates obtained in some of the runs was at the higher limit specified in the model control file ($\ln(R0) < 15$). This probably indicates the model cannot solve the mismatch between the information content of the data and a particular set of fixed parameters. Figure 5 shows the distribution (in log scale) of the estimates of unfished biomass returned by the 1,440 model runs.

In contrast with previous iterations, the model was able to converge in all cases.

2.3.1 Higher limit to estimates of carrying capacity K

The results of an analysis on habitat preferences of tuna stocks (Arrizabalaga et al. 2015) was used to derive a relationship between estimates of carrying capacity (K) and suitable habitat for albacore tuna stocks in all oceans. An upper limit for K for the Indian Ocean stock was derived from the fitted relationship as follows. First, a linear model K 0 + h between estimates of K from the latest stock assessments by RFMO, as in 2016, and those of albacore habitat in Arrizabalaga et al. (2015), h, was fitted to the data in Table 2.

	Habitat size (sq. km)	K (t)
Indian Ocean	6073	474828
Mediterranean	244	
North Atlantic	3752	357600
North Pacific	7547	398200
South Atlantic	3779	350000
South Pacific	7426	307830

Table 2: Estimates of habitat size (h) an carrying capacity (K) used to fit a linear model of the form $K \ 0 + h$ and derive an upper limit for estimates of K from the operating model SS3 runs.

Table 3: Model fit for the relationship between estimates of carrying capacity and suitable habitat area for albacore stocks around the world

	Estimate	Std. Error	t value	$\Pr(> t)$
habitat	61.12	9.695	6.304	0.003236

2.3.2 Lower limit to final vulnerable biomass

Of the remaining model runs, some appeared to estimate recent abundances that appear to be too low, and which could negatively bias the performance of MPs by making it unrealistically hard to manage from such a low stock size. An *ad-hoc* selection step was used in which runs estimating a biomass in 2014 vulnerable to fishing to be lower than twice the reported catches for that year, were not considered any further. A total of 226, out of 1,440 runs, failed this test.

2.4 Base case Operating Model

The application of both selection criteria presented above left a total of 665 model runs as part of the base case OM (Figure 6).

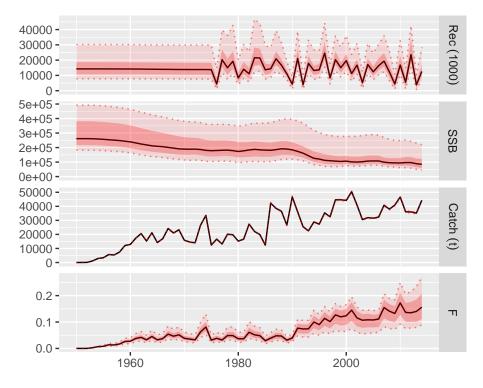


Figure 6: Time series of recruitment, SSB, catch and fishing mortality in the base case OM. Contrours show the 0.90 and 0.75 quantiles, while the black line shows the median trajectory.

A more detailed look at the time series for SSB (Figure 7), shows that most of the support from the model runs is not too distant from the median trajectory, but the tails of the distribution cover a wide range of alternatives views of the history and productivity of the stock.

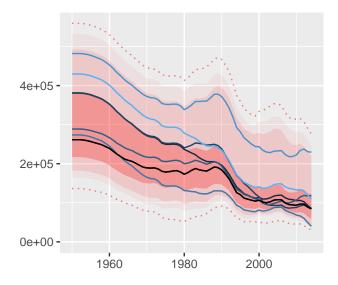


Figure 7: Time series of the estimates of SSB for the 655 model runs included in base case OM. The probability contours depict the 0.99, 0.95, 0.90 and 0.75 quantiles, the black line the median value, while coloured lines show a random choice of six individual iterations.

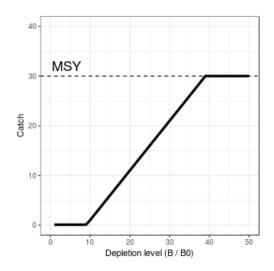


Figure 8: Diagram of the Harvest Control Rule implemented by the msePT MP.

3 Management Procedures

Two types of management procedures have been applied to the base case OM, one based on an stock assessment model, and another that is driven by changes in the CPUE series.

3.1 msePT: Pella-Tomlison stock assessment

The family of management procedures implemented through this function use the results of a biomass dynamics stock assessment to inform the harvest control rule on stock status. A decision is then made on changes to the total allowable catch levels from those set on the previous year of application of the procedure.

Two sources of information are generated to feed the assessment model: total catch in the fishery and an index of abundance. This is being obtained from an observation, with lag, of the biomass available to the CPUE fleet, with different levels of observation error, bias and hyperstability. A Pella-Tomlison biomass dynamics model is then fit to the data. The estimates of both depletion level, as the ratio of the spawning biomass in the last year of data to that in the first year, and of the F-at-MSY reference point, are then passed on to the harvest control rule.

The harvest control rule in Figure 8 returns a suggested value for catch in the next management year based on the depletion level, but can also limit changes in the TAC from previous values, both when increasing and decreasing. The decision is then applied to the stock and fishery, with a given lag, and with or without error.

The MP performance can be thus explored for a number of parameters:

- *Dlimit*, the depletion level at which the fishery is closed, shown at 0.10 in Figure 8.
- *Dtarget*, The target depletion level, shown at 0.40
- *lambda*, multiplier for *Dtarget*, defaults to 1.
- *dlatc*, lower limit to changes in TAC, e.g. 10%
- *dhtac*, upper limit to chnages in TAC, e,g, 10%
- *dlag*, lag in data collection, number of years between last year of data and current.
- *mlag*, lag in management, number of years current and implementation of advice.

3.2 mseIndex: CPUE trend-based indicator

A different set of MPs is implemented by this function. The ony source of information for the harvest control rule is, in this case, the index of abundance provided by the generated CPUE series. As before, the observation refers to

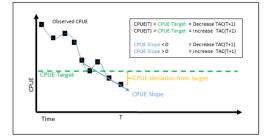


Figure 9: Diagram of the Harvest Control Rule implemented by the mseIndex MP.

chmnages in abundance of the part of the stock available to the choosen fleet. Only a single CPUE series can be used. The same processes related to error, bias and hyperstability covered above are of application in this case.

The harvest control rule takes the form $T_t = T_{t-1} * (1 + \lambda * b)$ where T is the TAC for the previous time step, λ is a response multiplier, and b is the slope of a linear model fit to the last ny years of data (Figure 9).

The parameters controlling the behaviour of this MP are thus:

- lambda, the response multiplier controlling how fast or slow is the rule to respond to changes in CPUE trend.
- *ny*, number of years from last to use to fit the linear trend
- *dlatc*, lower limit to changes in TAC, e.g. 10%
- *dhtac*, upper limit to chnages in TAC, e,g, 10%
- dlag, lag in data collection, number of years between last year of data and current.
- mlag, lag in management, number of years current and implementation of advice.

4 Performance Statistics

All performance indicators in the set adopted by the SC (IOTC 2016b) are computed for every MP run. The performance statistics, and types of management objectives behind them, for the evaluation of management procedures are as follows:

- Status
 - **S1**: Mean spawner biomass relative to unfished, *mean(SB/SB_0)*
 - **S2**: Minimum spawner biomass relative to unfished, *min(SB/SB_0)*
 - **S3**: Mean spawnwer biomass relative to BMSY, *mean(SB/SB_MSY)*
 - **S4**: Mean fishing mortality relative to target, *mean(F/F_target)*
 - **S5**: Mean fishing mortality relative to FMSY, *mean(F/F_MSY)*
 - **S6**: Probability of being in Kobe green quadrant, *P*(*Green*)
 - **S7**: Probability of being in Kobe red quadrant, *P*(*Red*)
 - **S8**: Probability of SB greater than SBMSY, *P*(*SB* > *SBMSY*)
- Fishing mortality
 - **F1**: Probability that spawner biomass is above 20% SB_0, *P*(*SB* > 0.20 *SB*0)
 - **F2**: Probability that spawner biomass is above Blim, *P*(*SB* > *Blim*)
- Yield
 - **Y1**: Mean catch over years, *mean(C)*
 - Y3: Mean proportion of MSY, *mean(C/MSY)*
- Abundance
 - A1: Mean catch rate, *mean(CR)*

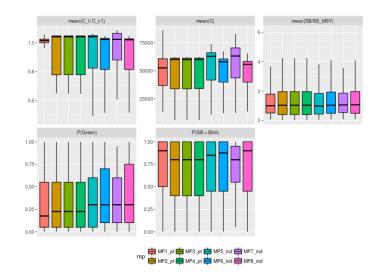


Figure 10: Performance across five indicators for the eight MP parameterizations choosen by tuning for $P(B > B_{MSY})$, four for each of the MP two MPs tested.

- Stability
 - **T1**: Mean absolute proportional change in catch, *mean*(*C*_*t* / *C*_*t*-1)
 - T2: Variance in catch, var(C)
 - **T3**: Variance in fishing mortality, *var*(*F*)
 - **T4**: Probability of fishery shutdown, *P*(*C* < 0.1 *MSY*)

5 Tuning

5.1 MP parameter grids

Given that no precise set of management objectives, and ranking or desired probabilities associated with them, is yet available from IOTC, the procedure employed here for tuning the presented MPs is able to generate a set of results to be used in the dialogue on management objectives taking place in IOTC (IOTC 2016a). A grid of MP parameters was constructed for each MP so as to esnure as wide as possible a range of possible outcomes. Performance indicators were then computed for all MP runs in this grid and a table was generated from which the best performing MPs could be quickly selected according to a given tuning criterion.

Following discussions at the last session of WPM (IOTC 2016c) and the subsequent meeting of the WPM MSE team, two tuning criteria have been initially selected to explore the results of the MSE runs. The first one refers to the objective stated in IOTC Resolution 15/10, On Target and Limit Reference Points and a Decision Framework, Article 6.b.i, to "Maintain the biomass at or above levels required to produce MSY or its proxy and maintain the fishing mortality rate at or below F MSY or its proxy". This is being operationalized as a selection criterion for MPs that are as close as possible to a 0.50 probability of maintaining (spawning) biomass at levels higher than those corresponding to MSY, i.e. $P(B > B_{MSY} = 0.5$. Performance against this objective is computed through statistic S3 above.

5.2 Tuning for $P(B > B_{MSY}) = 0.5$

The four MPs for each of the two types for which the probability of the stock biomass to be greater than the biomass at MSY was closest to 50%. Performance along five indicators (T1, Y1, S3, S6 and F2) appears to be very similar, with the exception of the mean change in catch where one MP appears to be far more stable (Figure 10).

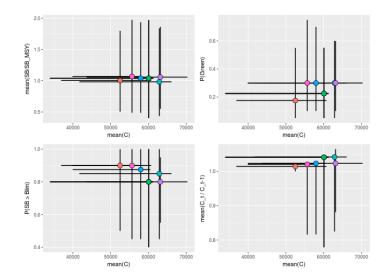


Figure 11: Trade-offs for four performance indicators against mean catch for the eight top MPs tuned for $P(B > B_{MSY})$.

The main trade-off appears to be between mean catches over the long term versus probability of exceeding limits (Figure 11, lower left panel) and being in the green (upper right panel).

The Kobe plot (Figure 12), shows levels of uncertainty in stock status that require further investigation. Given the level of error introduced in the pseudo-stock assessment, it is not completely clear the origin of all this variability.

Finally, figures 13 and 14 present the time series of future SSb and catches expected under the chosen MPs.

5.3 Tuning for P(Kobe = GREEN) = 0.75

A different picture emerges when the MPs selected are those that give a probability of being in the Kobe green as close as possible to 75%. While performance appears to be very homogeneus on certain indicators, for example catch variability (Figure 15, top left), in others the performance is nmarkedly distinct for each MP type ($P(SB > SB_{lim})$, bottom right.)

Similarly, the trade-off plots reflect the same divergence, with almost no differences between the four *msePT* MPs selected (Figure)

6 Software Implementation

The work presented here has been carried out using two main tools: the SS3 stock assessment platform (Methot and Wetzel 2013) for OM conditioning, and the FLR libraries (Kell et al. (2007), http://flr-project.org) for data input of OM model runs, assemblage of the base case OM, implementation and evaluation of the MPs, computational workload, and model output and summaries.

The grid of model runs was constructed by altering for each factor combination the SS3 input files. Manipulation of these files was facilitated by the use of the r4ss R package¹. The setgrid function in the ioalbmse package is responsible for carrying out the alterations for each element in grid as necessary. A generic R package, ss30m, has also been developed to load the results of the SS3 runs into FLR.

¹http://github.com/r4ss/r4ss

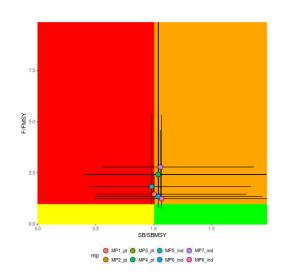


Figure 12: Performance on the Kobe plot of the eight MP parameterizations choosen by tuning for $P(B > B_{MSY})$, four for each of the MP two MPs tested.

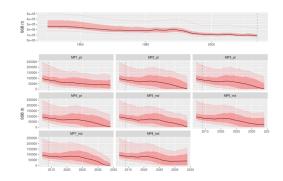


Figure 13: Time series of SSB for the operating model, top, and eight MPS parameterizations, bottom rows, choosen by tuning for $P(B > B_{MSY})$, four for each of the MP two MPs tested.

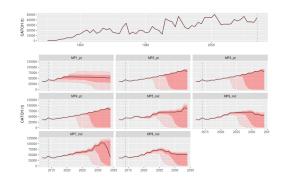


Figure 14: Time series of catch for the operating model, top, and eight MPS parameterizations, bottom rows, choosen by tuning for $P(B > B_{MSY})$, four for each of the MP two MPs tested.

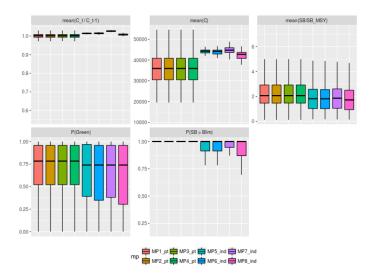


Figure 15: Performance across five indicators for the eight MP parameterizations choosen by tuning for P(Kobe = GREEN) = 0.75, four for each of the MP two MPs tested.

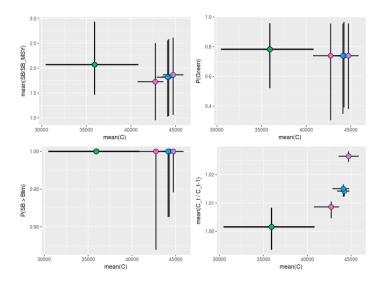


Figure 16: Trade-offs for four performance indicators against mean catch for the eight top MPs tuned for P(Kobe = GREEN) = 0.75.

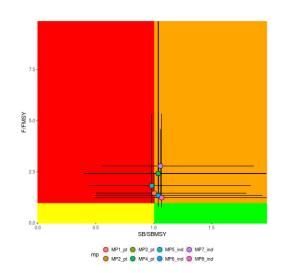


Figure 17: Performance on the Kobe plot of the eight MP parameterizations choosen by tuning for $P(B > B_{MSY})$, four for each of the MP two MPs tested.

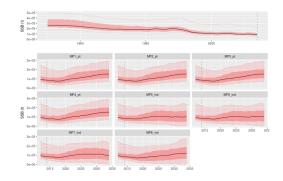


Figure 18: Time series of SSB for the operating model, top, and eight MPS parameterizations, bottom rows, choosen by tuning for P(Kobe = GREEN) = 0.75, four for each of the MP two MPs tested.

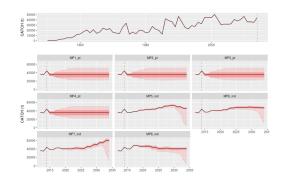


Figure 19: Time series of catch for the operating model, top, and eight MPS parameterizations, bottom rows, choosen by tuning for P(Kobe = GREEN) = 0.75, four for each of the MP two MPs tested.

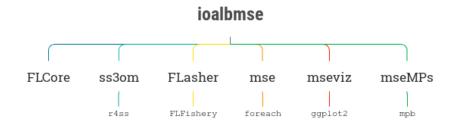


Figure 20: Main R/FLR packages involved in the implementation of the analyses presented.

6.1 Accesing code and results

The source code employed in this work is being kept in an open version control server, namely http://github.com/ iotcwpm/ALB, where current and previous versions of the code can be inspected and downloaded.

7 Discussion

This document presents very briefly most of the work that has been carried out so far to prepare and test a simulation platform for the evaluation of management procedures for Indian Ocean albacore. A base case operating model is now available for this stock, with the ability to be easily applied to the construction of other operating models based on the same computational platform: a combination of SS3 (Methot and Wetzel 2013) and FLR (Kell et al. 2007).

Some extra work is required, as discussed below, to obtain a definite set of MP evaluations. Given the limited manpower available for this work, priorities will need to be identified. some of the development work carried out could be use for other IOTC stocks, specially if an OM is to be developed based on an stock assessment carried out using the SS3 platform.

7.1 Limitations

The set of MP evaluations presented here was carried out as a proof of concept and initial exploration of the performance of the platform and the MPs themselves. No sistematic analysis has yet been done of the effect of different levels of error and bias in the data, most importantly in the CPUE series, on their performance. Identifying those limits and, if possible, relating them to elements of the data collection system (sampling sizes or strategies), would be most valuable to better understand the necessary conditions for MPs to achieve their expected result.

The runs of the model-based MP, *msePT*, presented here were carried out without fitting the actual model, given the limits of computational time available. A direct observation of the abundance, with error, was used instead. A limited comparison between the two procedures was carried out and the results did not differ greatly with the levels of errors and bias in CPUE that have been so far employed. The complete code that incdludes fitting the model on all runs is now ready and can be employed on the next set of runs.

7.2 Next steps

The use of efficient experimental design (Sanchez and Wan 2009) in the evaluation and tuning of MPs should allow for a more detailed exploration of robustness and alternative MPS without an increase in the overall computational workload. Code is already being tested to direct the tuning procedure to 'sample' from areas of the MP parameter space where results are more positive, rather than the 'brute force' approach employed here so far.

A complete set of tuning and robustness runs should be planned, based on the discussion held in WPM, and conducted, in time to offer an updated set of results to the upcoming session of the Scientific Committee. This set would also be presented to the next session of WPTmT in 2018.

The spatial structure of the index of abundance would need to be discussed, or a mechanism for combining the current indices by area could be developed. Simulations have employed a single LL index, that from area 3, to inform both MPs, as this was understood to be more coherent in time.

Simulations have been carried out that consider in effect a single fleet that operates wiuth bthe combined selectivity cuurrently estimated for the whole fishery. The most important fleets currently catch albacore in the Indian Ocean are not very diverse, so differences in selectivity might not be large. Changes in targeting of individual fleets would alter the overall selectivity. The new version of the forecasting software in FLR, a package called FLasher² would allow for simulations to be carried out considering separate fleets. Scenarios on changes of activity for certain fleets, for example, could be analysed. This would, however, require some additional work, and would have to be considered and discussed to optimize the use of the limited available manpower.

References

Arrizabalaga, H., F. Dufour, L., G. Merino, L. Ibaibarriaga, G. Chust, X. Irigoien, et al. 2015. "Global Habitat Preferences of Commercially Valuable Tuna." *Deep Sea Research Part II: Topical Studies in Oceanography* 113: 102–12. doi:http://dx.doi.org/10.1016/j.dsr2.2014.07.001.

Hoyle, S., D.N. Kim, S.I. Lee, T. Matsumoto, K. Satoh, and Y.-M. Yeh. 2016. "Collaborative Study of Tropical Tuna Cpue from Multiple Indian Ocean Longline Fleets in 2016." *IOTC WPTT18, Victoria (SZ) 5-10 November 2016.* IOTC-2016-WPTT18–14.

Hoyle, Simon D, Rishi Sharma, and Miguel Herrera. 2014. "Stock Assessment of Albacore Tuna in the Indian Ocean for 2014 Using Stock Synthesis." *IOTC WPTmT* WPTmT05-24_Rev1.

IOTC. 2014. "Report of the Fifth Session of the Iotc Working Party on Methods." *IOTC WPM07, Victoria (SZ) 5-56 December 2016.* IOTC-2014-WPM05-R[E].

----. 2015. "Report of the Sixth Session of the Iotc Working Party on Methods." *IOTC WPM06, Montpellier (FR) 19–21 October 2015.* IOTC-2015-WPM06-R[E].

----. 2016a. "Chair Report of 1st Iotc Technical Committee on Management Procedures." *IOTC TCMP01, Yogyakarta (IND) 20 May 2017.* IOTC-2017-TCMP01-R[E].

----. 2016b. "Report of the 19 Th Session of the Iotc Scientific Committee." *IOTC SC19, Victoria (SZ) 1-5 December 2016.* IOTC-2016-SC19-R[E].

----. 2016c. "Report of the Seventh Session of the Iotc Working Party on Methods." *IOTC WPM07, Victoria (SZ)* 11-13 *November 2016.* IOTC-2016-WPM07-R[E].

Kell, L. T., I. Mosqueira, P. Grosjean, J-M. Fromentin, D. Garcia, R. Hillary, E. Jardim, et al. 2007. "FLR: An Open-Source Framework for the Evaluation and Development of Management Strategies." *ICES Journal of Marine Science: Journal Du Conseil* 64 (4): 640–46. doi:10.1093/icesjms/fsm012.

Langley, A., and S. Hoyle. 2016. "Stock Assessment of Albacore Tuna in the Indian Ocean Using Stock Synthesis." *IOTC WPTmT* IOTC-2016-WPTmT06-25.

Methot, Richard D, and Ian G Taylor. 2011. "Adjusting for Bias Due to Variability of Estimated Recruitments in Fishery Assessment Models." *Canadian Journal of Fisheries and Aquatic Sciences* 68 (10): 1744–60. doi:10.1139/f2011-092.

Methot, Richard D, and Chantell R Wetzel. 2013. "Stock Synthesis: A Biological and Statistical Framework for Fish Stock Assessment and Fishery Management." *Fisheries Research* 142. Elsevier: 86–99.

Mosqueira, I., and R. Sharma. 2014. "Base Operating Model for Indian Ocean Albacore Tuna, Scenarios Included

²http://flr-project.org/FLasher

and Model Conditioning." *IOTC WPM* IOTC-2014-WPM05-06. http://iotc.org/sites/default/files/documents/2014/12/ IOTC-2014-WPM05-06-ALB-OM.pdf.

Sanchez, Susan M., and Hong Wan. 2009. "Better Than a Petaflop: The Power of Efficient Experimental Design." In *Winter Simulation Conference*, 60–74. WSC '09. Austin, Texas: Winter Simulation Conference. http://dl.acm.org/citation.cfm?id=1995456.1995470.

Sceretariat, IOTC. 2016. "Review of the Statistical Data and Fishery Trends for Albacore." *IOTC WPTmT06, Shanghai (CN) 18-21 July 2016.* IOTC-2016-WPTmT06-07.