Operating model for Indian Ocean albacore tuna.

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IOTC-2015-WPM06-08 – 19-21 October 2015

Abstract

This document presents the results of the work carried out to develop a reference case Operating Model for Indian Ocean albacore. The model is based around the WPTmT stock assessment and incorporates the main sources of uncertainty identified in the estimation of population trajectories and dynamics according to the data available at IOTC.

Contents

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1 Introduction

The reference case Operating Model (OM) constructed for the evaluation of Management Procedures (MP) for the Indian Ocean albacore tuna stock is presented, and its uses and limitations are discussed. The structure and implementation of the population and fishery model used to condition the OM is shown. A number of basic tests are carried out to assess the plausibility of the stock dynamics represented by this model. Example use of the model in evaluating alternative MPs against a range of objectives is included.

2 Model structure and scenarios

The basic structure of the model is equivalent to that presented previously (Mosqueira and Sharma 2014). It is built around the Stock Synthesis 3 stock assessment framework (Methot and Wetzel 2013), and uses as starting point for the analysis of the main sources of uncertainty the stock assessment presented and reviewed at the Fifth Session of the Working Party on Temperate Tunas (Hoyle, Sharma, and Herrera 2014), with one major difference. The separation of the Taiwanese longline (TWN LL) fleet into two periods of operation, early and late, was not considered in the base OM model. The changes in selectivity that the WPTmT runs attempted to capture were not deemed important enough to justify the extra complexity in OM structure.

This 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.

2.1 Dimensions

The model applies a quarterly (three month) time step, and runs over a single region (Figure). Spawning takes place in the fourth quarter, and fish are recruited into the population at the start of the following calendar year, that is they turn into age 1 fish after only three months. The model uses 15 age classes (ages 0 to 14), but age 0 is subsequently dropped from the results and recruitment is assumed to be represented by the abundance of age 1 fish.

The model incorporates catch at length data for a total of seven fleets, as follows

- Japanese longline fleet operating in the North region (`F1_JPN_LL_N`)
- Taiwanese longline fleet operating in the North region (`F2_TWN_LL_N`)
- Purse seine fleet (`F3_PS_N`)
- Other fisheries (`F4_Other_N`)
- Japanese longline fleet operating in the Southern region (`F5_JPN_LL_S`)
- Taiwanese longline fleet operating in the Southern region (`F6_TWN_LL_S`)
- Driftnets (`F7_Drift`)

The separation of longline fleets in Northern and Southern regions (Figure 1) attempts to capture the differences in selectivity due to different main target species for those fleets: tropical tuna in the Northern region and albacore (but also Southern bluefin) in the South.

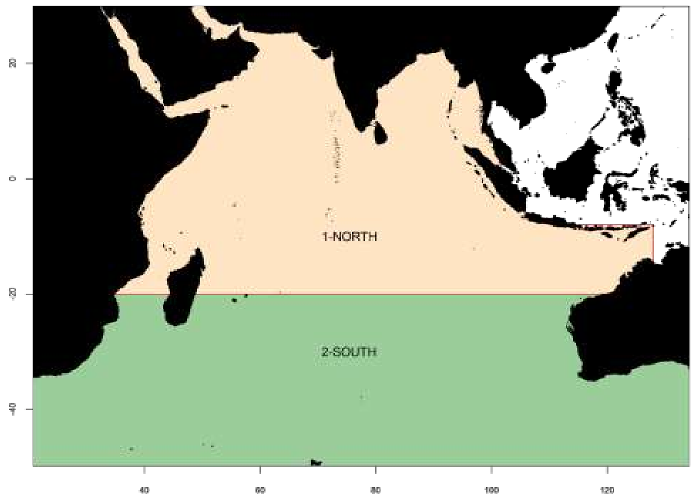

Figure 1: Regions used in albacore OM for separating fleets activity.

2.2 Indices of abundance

Indices of abundance, derived for CPUE series, for four fleets are used for model conditioning.

- Japanese longline fleet operating in the North region (`S1_JPLL_N`)
- Taiwanese longline fleet operating in the North region (`S2_TWLL_N`)
- Japanese longline fleet operating in the Southern region (`S5_JPLL_S`)
- Taiwanese longline fleet operating in the Southern region (`S6_TWLL_S`)

2.3 Natural mortality (M)

Four scenarios for natural mortality at age were considered:

- `0202`: Constant M at 0.2 for all ages.
- `0303`: Constant M at 0.3 for all ages.
- `0402`: M=0.4 at age 0, decreasing to 0.2 at age 5 and older.
- `0403`: M=0.4 at age 0, decreasing to 0.3 at age 5 and older.

2.4 Variability in recruitment deviations (σ_R)

Two values were considered for the true variability of recruitment in the population (`sigmaR`), 0.4 and 0.6.

2.5 Steepness of the stock-recruitment relationship (h)

Three values for the steepness (h) of the stock-recruitment relationship were considered: 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.

There is little or no information in stock assessment data sets to estimate steepness (Pepin), so most tuna stock assessment choose to set it at a fixed value. (Simon 2012) showed that steepness in tuna stocks is likely to be at the high end of the range while (Szuwalski et al. 2014) showed that SSB is more likely to be driven by recruitment than recruitment by SSB.

2.6 Coefficient of variation in the CPUE series (c_v)

Two values for the coefficient of variation in the CPUE series were included: 10% and 20%.

2.7 Weight in final likelihood of trends in length composition (S_{len})

Three values were applied to 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.

2.8 Effective catchability trend over time for CPUE series (q_{LL})

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

2.9 Selectivity function of CPUE fleet (s_{LL})

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.

3 Data

The datasets employed are those used in the WPTmT stock assessment (Hoyle, Sharma, and Herrera 2014, IOTC (2014)). Figure 3 shows the data availability for each type and fleet.

4 Implementation

The source code developed for this model is available at the IOTC WPM public repository, at http:github.com/iotcwpm/ALB. The code necessary to run the OM conditioning, and the resulting outputs, are available as an R package, called 'ioalbmse'. The package can be installed from a session of R 3.2[1], using the following commands

```r
install.packages(c("r4ss", "shiny", "ggplot2", "dplyr",
    "gridExtra", "reshape2"))
install.packages(c("FLCore", "ggplotFL", "ioalbmse"),
    repos="http://iotcwpm.github.io/R/")
```

[1] Available from http://cran.r-project.org

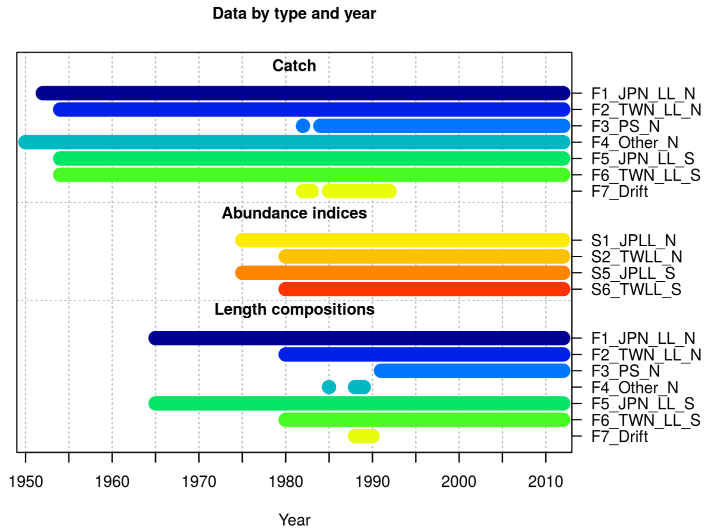

Figure 2: Data coverage by year for each fleet and source: catch, abundance indices and legnth composition.

The model is conditioned using the latest version (3.24f, SS-V3.24f-safe-Lin64) of the Stock Synthesis software (Methot and Wetzel 2013). Preparation of inputs and data, the modification of SS3 control files and out processing has been carried out in the R language (R Core Team 2015), and using the FLR libraries (L. T. Kell et al. 2007). Code and outputs are available as an R package (see Appendix for instructions).

Conditioning of the operating model grid, for a total of 720 runs of the SS3 software, takes approximately 20 hours of computation on a multi-core machine, using 6 CPUs. This gives a total computation time of 180 h.

5 Diagnostics

The aggregated population model obtained from the complete grid of model runs included a high proportion of unrealistic estimates. The virgin recruitment (`LN(R0)`) estimate obtained in some runs was at the higher limit specified in the model control ($ln(R_0) < 15$). This gives indication of a mismatch between the information content of the data and a particular set of fixed parameters, or of conflicts between the various data sources. Figure shows the distribution (in log scale) of the estimates of unfished biomass.

Runs where the final estimate of virgin recruitment was at it maximum, a total of 32, were identified and should be excluded from the operating model set.

For the remaining 688 runs, the relationship between the various parameters in the grid and the values of unfished biomass (B_0) was investigated through a linear model of the form

$$B_0 \sim M + \sigma_R + h + c_v + S_{len} + q_{LL} + s_{LL} \tag{2}$$

where B_0 is the estimated unfished biomass, and all other variable are as above. This simple model, with no interactions, indicated that three of the parameters were responsible for the majority of the variation in B_0 estimates: natural mortality (`M` in Table 1), weight assigned to the length data (`ess`) and the functional form of the selectivity for the CPUE fleet (`llsel`).

Figure **??** shows the estimated values of virgin biomass (B_0) across the various scenarios for those three variables.

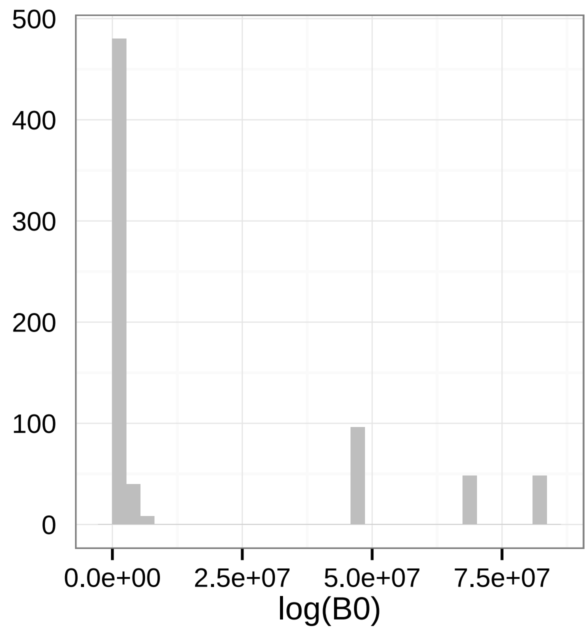

Figure 3: Distribution of estimates of unfished biomass, in log scale, from the full grids of model runs.

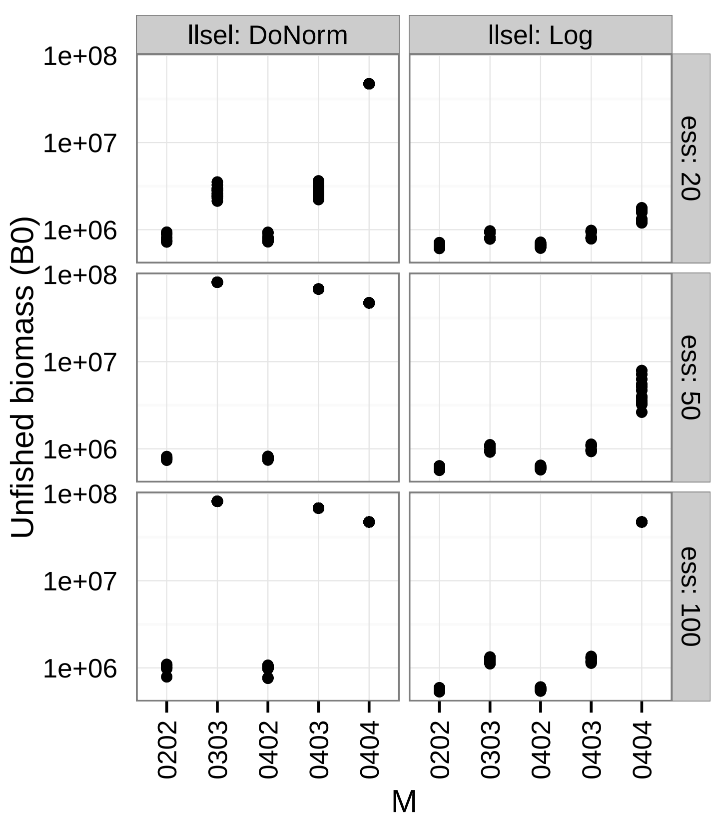

Figure 4: Values of estimated unfished biomass for each scenario of natural mortality (M), selectivity curve (llsel) and weight of length samples (ess).

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
M	4	1.35e+17	3.38e+16	99.18	0.0000
sigmaR	1	6.59e+12	6.59e+12	0.02	0.8894
steepness	2	2.02e+11	1.01e+11	0.00	0.9997
cpuecv	1	2.22e-14	2.22e-14	0.00	1.0000
ess	2	4.79e+16	2.40e+16	70.38	0.0000
llq	1	1.47e+12	1.47e+12	0.00	0.9476
llsel	1	1.20e+17	1.20e+17	353.78	0.0000
Residuals	707	2.41e+17	3.40e+14		

Table 1: Results fo the linear model.

5.1 Plausibility of model hypotheses

- SA runs not all equal
- Prior weighting of hypothesis not carried out
- Likelihood not informative on plausibility, no use for weighted resampling (Hillary) based on it

5.1.1 Profiling of R0

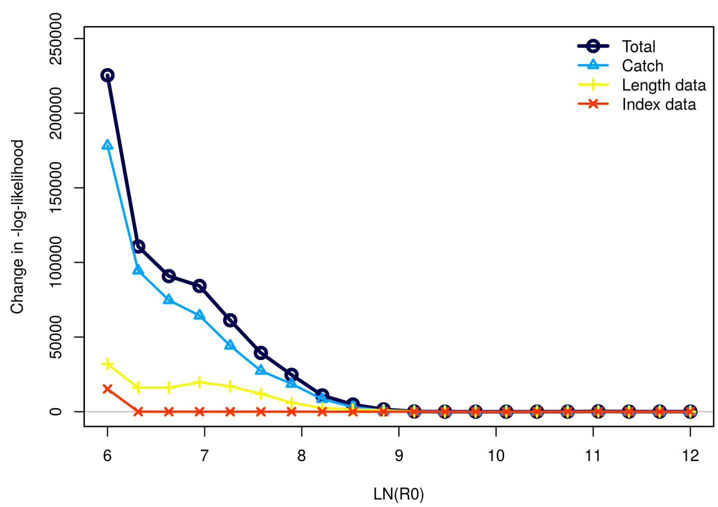

Figure 5: Likelihood profile over the virgin recruitment parameter in log scale, $LN(R_0)$, for values around the best estimate, $ln(R_0) = 9$

5.2 Hessian CN

5.3 MANOVA

6 Post hoc model selection

[...]

The feasibility of the model runs was assesed on our knowledge of the available habitat A for Indian Ocean albacore and the limit this must impose of K, the carrying capacity. Data on estimates of K for albacore stocks across all oceans were obtained from the relevant RFMO-approved stock assessments (IATTC 2014, (**???**)), while estimates of suitable habitat by ocean for albacore were obtained from the authors of (Arrizabalaga et al. 2015) (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 and carrying capacity for most albacore stocks.

A linear model of the form $K \sim 0 + h$, where h is the potential habitat size, and 0 indicates a zero intercept, was fitted using the `lm` function in the R statistical language (R Core Team 2015), and the estimates of the coefficient and its standard error (Table 3) were used to generate an upper plausible limit for K, and by assuming equilibrium conditions prior to the start of industrial fishing, for B_0. This was computed as the upper 99.9% confidence interval around the estimate of the slope coefficient, by using the calculated ratio for the Indian Ocean of $6,073\ t/m^2$.

	Estimate	Std. Error	t value	Pr(>|t|)
habitat	61.1200	9.6948	6.30	0.0032

Table 3: Linear model estimate of the relationship between estimates of K, carrying capacity, and habitat size across stocks and oceans.

The upper limit obtained, $B_0 = 878127$, was then used to select model runs deemed plausible. This brought down the total number of runs included in the operating model to 258, distributed according to the parameters used for setting scenarios as reflected in Figure XX.

6.1 Model tests

The behaviour of the aggregated population model was briefly tested through series of future projections. These tests specifically attempted first to clarify if the reduction in dimensionality of the conditioned model (from seasonal to annual, and the disappearance of birth seasons) had introduced any unexpected quirk in the model population dynamics.

Projections were carried out using the FLash package of the FLR framework (L. T. Kell et al. 2007), by solving for targets on average fishing mortality (F_{bar}), total catch or SSB, for the hindcast exercise, and for F_{bar} only for future projections.

6.1.1 Hindcast projections

The population model was projected forward from the abundances (and other parameters) at age determined by SS3 in 1990, and until 2012. Recruitment was not predicted from the corresponding stock-recruitment relationship but assumed known and extracted from the values estimated by SS3 for that period.

The differences appear small enough ($< 1\%$) to validate the simplification in model structure that the current limitations of the FLR platform impose. An upcoming version of the `FLash` package, used for forecasting and prediction of population and fishery trends, will be able to work at a seasonal time step, as well as for multiple fleets with separate selectivities[2].

[2] See http://github.com/iagomosqueira/FLasher to follow developments.

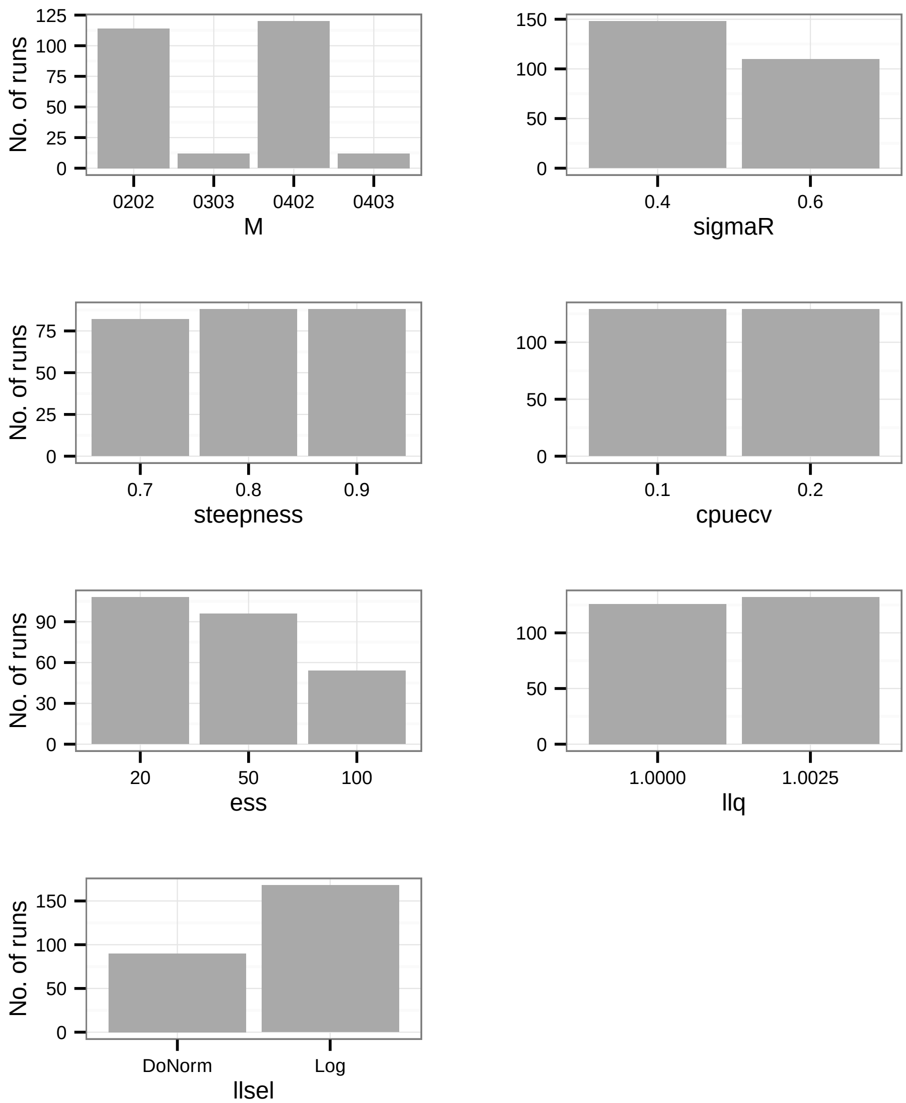

Figure 6: Distribution across scenarios for each parameter of the final selected model runs.

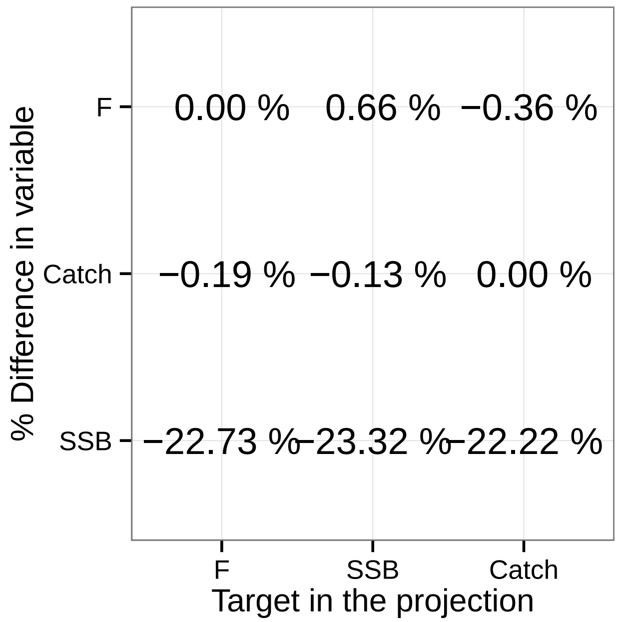

Figure 7: Percent differences in final (2012) average fishing mortality (F), catch and SSB between the conditoned OM and the annual hindcast, when targets were defined to be the F, SSB or Catch vectors in the OM.

6.1.2 Future projections

A series of projections into the future were conducted to evaluate the behaviour of the model under a range of standard conditions. First, the model was projected with constant fishing mortality, equal to the level of 2012 (Figure ??).

The stock was also projected forward under the condition of achieving $F = F_{MSY}$ levels in 2020 (Figure ??).

7 Reference case

7.1 Suitability of the Operating Model

The problems in model fitting highlithed above leave some run for discussion on the suoitability of the model presented for use as reference case OM for Indian Ocean albacore MSE work.

2 issues are stability and reliability

[14:50:30] Laurence Kell: does F/FMSY change due to random fluctions in selection pattern [14:50:54] Laurence Kell: and this ignores the difference between growth and recruitment overfishing

8 Interactive application

A simple interactive application has been developed that allows the exploration of the model runs in the OM. The application is a proof-of-concept of the capabilities of the platform used in this work, and is expected to be extended further to include exploration of MSE runs, including results of the evaluation of alternative MPs. To start the application, please type the following in your R session

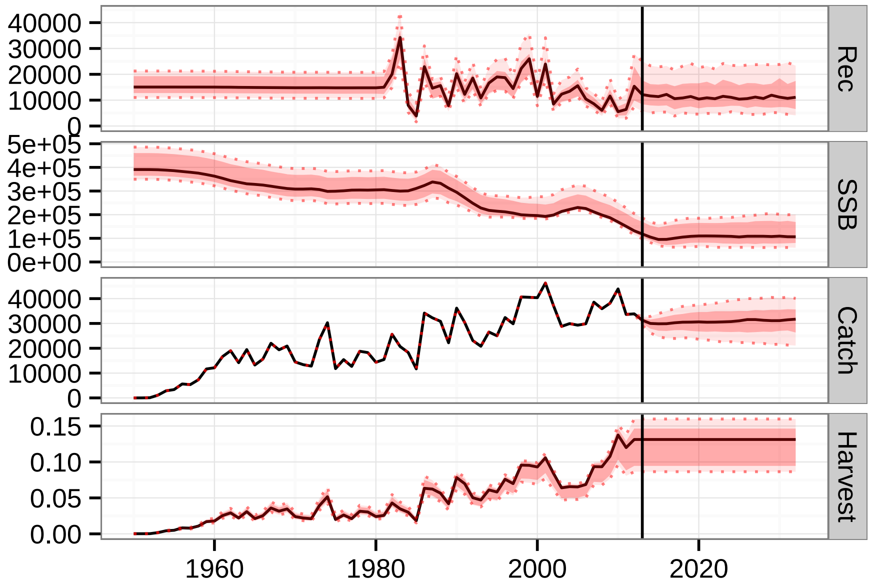

Figure 8: Projection of stock dynamics for 20 years under a fishing intensity equal to that of 2012.

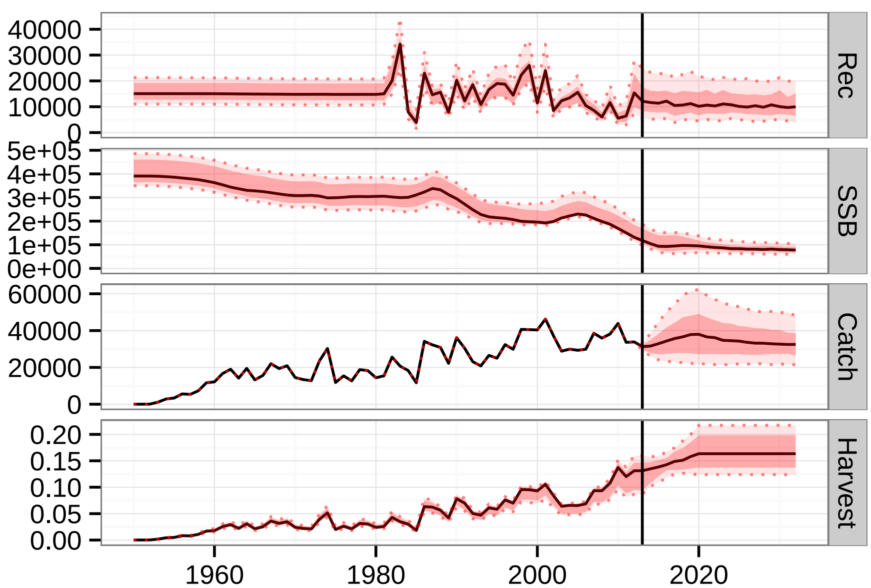

Figure 9: Projection of stock dynamics for 20 years under a fishing intensity to changes linearly to the F_{MSY} levels in 2020.

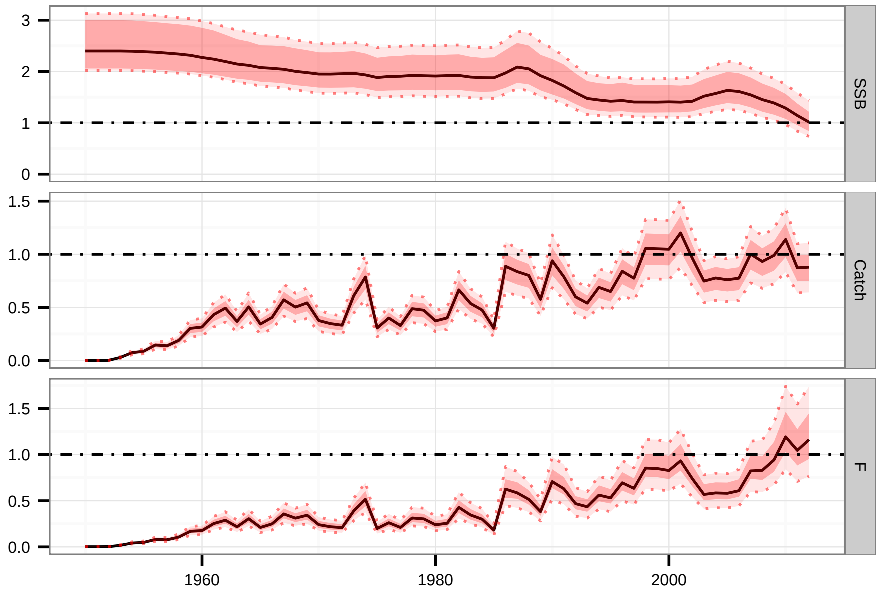

Figure 10: Trajectories over time of the ratios of SSB, Catch and F over their MSY values for the reference case OM.

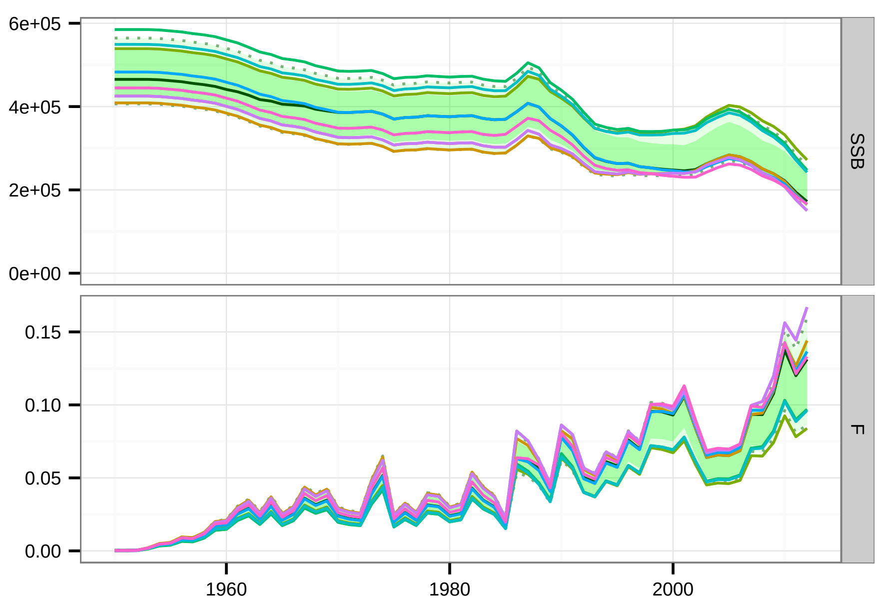

Figure 11: Trends of SSB and average fishing mortality, expressed as 0.50 and 0.90 quantiles, plus individual run trajectories for the reference case OM.

```
library(ioalbmse)
runapp()
```

and proceed to switch to your browser window[3].

9 Example management procedures

[3] A window with the application will be directly visible when running this from the Rstudio development environment.

10 Acknowledgments

Special thanks to Laurie Kell for his most vaulable help and patience. To Rishi Sharma and the members of the WPM MSE team for their support, help and encouragement. This work was funded by the European Commission but it does anticipates the future position of the Commission in this area.

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