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A framework to Management Strategy Evaluation for the South Pacific Jack Mackerel

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I. Background

A commonly used approach to test the performance of fisheries management consists is simulating the mid to long-term developments of the stock under a given management regime, based on the perception from the most recent assessment. Such simulations should represent as precisely as possible the dynamics of the stock and of its fishery and take account of the various sources of uncertainty in the assessment and in the management system. A range of diagnostics can then be calculated from the output of the simulation, which can be used to describe the performance of any given management strategy.

A management strategy evaluation (MSE) tool was developed for jack mackerel, based on the most recent stock assessment available. This document describes the various components of this tool, and the different assumptions made. Some examples of application of this MSE tool are also given.

Though the MSE tool is primarily designed to evaluate the performance of difference harvest control rules, it can be used to simulate the stock's dynamic equilibrium for a range of fishing mortality values, and hence identify fishing mortality and biomass corresponding to MSY. In the simulation, the selectivity of each fleet can be changed to represent the effect of changes in mesh size or in minimum landing size.

The setup of the framework is such that it can easily be updated with the latest assessment results, alternative management plan design and evaluate the performance of the combination on the spot.

II. The management strategy evaluation (MSE) approach

The principle of an MSE is to represent as realistically as possible the true dynamic of the stock and of the fleets exploiting this stock, and to mimic as closely as possible the stock assessment and management procedure which are to be evaluated. The MSE should give a correct perception of the sources of natural variability in the stock and of the uncertainty in the management system. In order to reflect this uncertainty, the simulations are run simultaneously on a large number of replicates of the stock, each representing a likely version of the real stock.

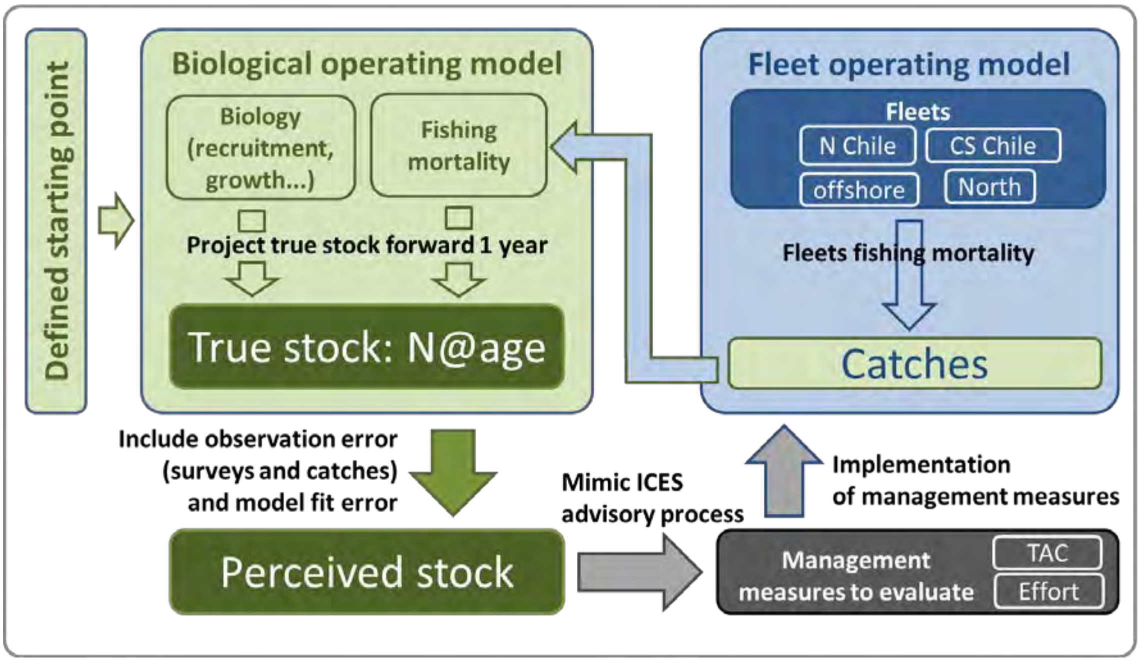


Figure 1 : conceptual representation of the management strategy evaluation

An MSE typically consists in an assemblage of blocks or models, which can be defined as follows (figure 1) :

- The biological operating model which is an age structured population model, representing the real stock. Natural processes such as reproduction, growth, sexual maturation, natural mortality should be represented as realistically as possible, and based on the available knowledge of the biology of the stock.
- The fishery operating model represents the different fleets harvesting the stock. Each has its own selection pattern (age decomposition of the fishing mortality).
- The observation model should give a correct representation of all the sources of uncertainty linked to observation (catch estimation, biological sampling, surveys) and to the assessment model (uncertainty due to model specification and fitting).
- The management module which reproduces the rules according to which a management advice is given based on the most recent output of the stock assessment model.

The initial vectors (numbers at age, fleet selection patterns, biological parameters) for the first year of simulation are taken from the most recent stock assessments.

The following sections give a detailed description of the different building blocks of the MSE for jack mackerel. All the analyses and simulations were done in R (R Core Team ,2013) using the Fisheries Library in R (FLR, Kell et al., 2007).

1. Starting points

The starting point of the simulation was based on the output of the 2012 jack mackerel assessment (SPRFMO, 2012). The assessment output – numbers at age, fishing mortality at age, weights at age etc.. – were available from 1971 until 2012. The simulations start in 2013.

The output of the MSE simulations are influenced by the starting conditions. Furthermore, the output of the assessment are given with confidence intervals, representing the spread of the likely values around the point estimates. In order to have starting conditions reflecting the magnitude of the assessment uncertainty, a range of likely stocks was generated. In practice, for each replicates of the stock in the MSE, the recruitments and the fishing mortality and selectivity at age of each fleet in the historical period were resampled from a multivariate normal distribution of mean and variance-covariances taken from the assessment output. From these newly drawn parameters, the full numbers at age, catch at age, and fishing mortality at age matrices were computed.

2. The biological operating model

The biological operating model is an age structure population model (same age range as the assessment model), in which the real stock is calculated at each time step (usually one year) of the simulation, given the fishing mortality imposed by the fleets. It is crucial that the natural variability of the stock is accurately represented in the biological operating model, in order to be able to evaluate a range of potential reactions to a given management system.

Recruitment

Recruitment is the key component of stock productivity and it is crucial to have a realistic recruitment function in the model. The simulated recruitment should have the same variability as the recruitment observed historically. The stock to recruitment relationship, if existing, should be accurately modelled.

In the simulation tool designed for jack mackerel, two different approaches to model recruitment were implemented : stock to recruit models - where the average recruitment level is linked to the size of the spawning stock – and a recruit to stock approach – where recruitment varies independently from stock size, following another driver e.g. environmental signals.

<u>Recruitment simulation based on Bayesian composite stock - recruitment models</u>
A variety of stock-recruitment models are available to represent the link between SSB and the subsequent recruitment. However for many stocks, the data does not really support one of this model more than the others, and the choice of one stock recruitment model, even if supported by statistical comparison, often remain quite subjective. In addition, simply fitting a stock-recruitment model (e.g. using maximum likelihood) does not really allow to represent the uncertainty in the estimated parameters.

Here, a method combining different stock-recruitment functions, and based on a Bayesian estimation of model parameters was used to give a full representation of the uncertainty in the stock-recruitment model. A complete description of the method can be found in Simmonds et al. (2011). The basic principle are as follow:

- For a range of selected stock-recruitment functional forms (here hockey stick, Ricker and Beverton and Holt were used), a Bayesian estimation of the model parameters is performed.
- For each stock-recruitment function, a set of 1000 models are kept from the MCMC chains.
- Based on the likelihood of each of these models, a probability can be computed for each functional form.
- A subset of stock-recruitment models (one model for each of the replicates of the stock in the MSE) is then randomly sampled from the 3 sets of 1000 models, proportionally to the probability of each functional form.

In the case of jack mackerel, there was no clear indication from the data for a specific functional relationship. Fitting the hockey stick, Ricker and Beverton and Holt models with a Bayesian parameter estimation (assuming normally distributed residuals) shows that there is a large uncertainty in parameter estimates (figure 2). The most likely relationships are Beverton and Holt (50%) and Ricker (40%).

For each of the replicates of the stock in the MSE, the recruitment model is defined by the functional form, the two parameters defining the shape given the functional form, and Sigma, the residuals standard error. Recruitment for a given year y in the simulation is hence modelled by the following formulae :

$$R_{y,k} = rnorm\left(mu_{y,k}, sigma_k\right)$$
$$\text{and} \qquad mu_{y,k} = SRR_k\left(SSB_{y-rec\ age,k}\right)$$

Where SSR_k is the stock recruitment model for the k^{st} replicate of the stock, $sigma_k$ is the corresponding residuals standard error and rec age is the age at recruitment. The function *rnorm()* means sampling one value from a Gaussian distribution with defined mean and variance.

In order to check whether the proposed modelling framework gives an appropriate description of the distribution of recruitment values, 40 000 recruitments where simulated using this method, based on the historical SSB values. The strong similarity in the cumulated distribution of the simulated values and the observed values (figure 3) indicated that the distribution of recruitment values was correctly represented by the Bayesian approach.

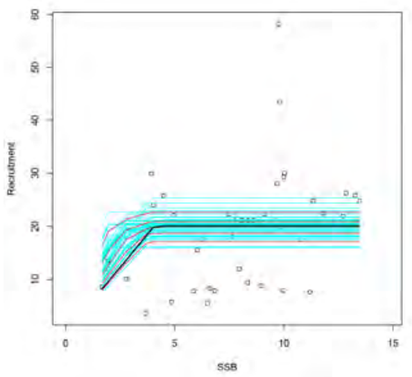
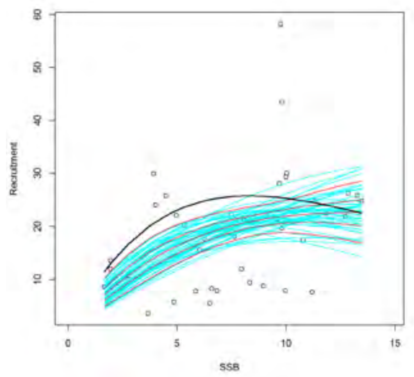
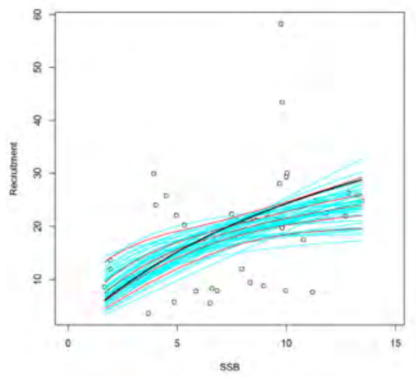
Hockey – stick = 10%	Ricker = 40%	Beverton and Holt = 50%
		

Figure 2: three stock recruitment models fitted to the historical jack mackerel data, using a Bayesian estimation. The blue lines represent a sample from the 1000 models taken on the MCMC chains for each functional relationship (with the 5%, 25%, 50%, 75% and 95% percentiles of the predicted recruitment values in red). The black line is the maximum likelihood estimate. The probability of each functional relationship is also given.

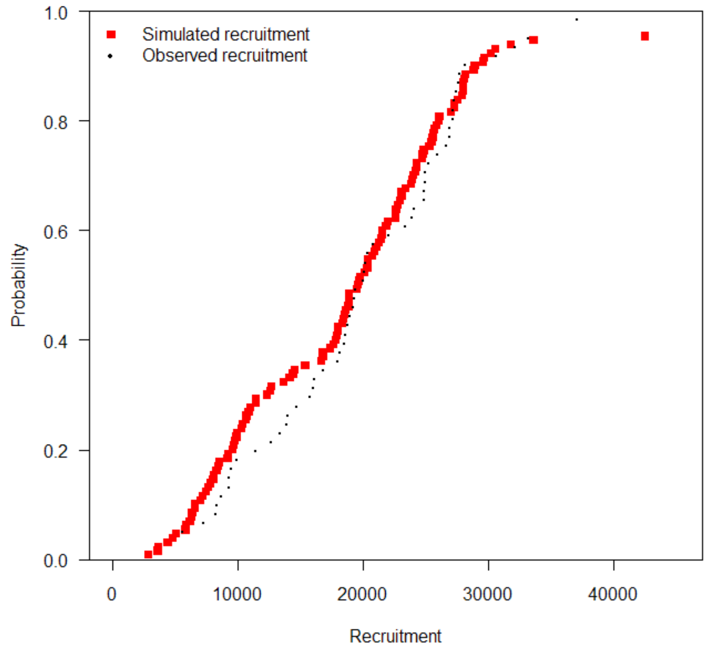


Figure 3 : comparison of the cumulated distribution of simulated recruitment based on the Bayesian approach and of the observed recruitments

<u>Recruitment simulation based on Fourier surrogates</u>

The Fourier surrogates method (see example of application in Planque and Buffaz, 2008) is based on a Fourier decomposition of the original recruitment time series (decomposition of the original time series into a sum of simple periodic functions). The surrogate recruitment time series are constructed by adding random phases in [0,2π] to the Fourier decomposition of the observed recruitment time series, and then computing its inverse Fourier transform. This procedure is known as phase randomization (see e.g. Schreiber & Schmitz 2000). The resulting surrogates recruitment time series are Gaussian and have the same mean, variance and power spectrum as the original data time series. However the general trend can be quite different (figure 4) with some simulated series remaining at low level for the first 20 years and increasing thereafter (e.g. green series) while others first increase and then decrease (e.g. black series).

Using the surrogates recruitment time series in the simulation implies that the strength of a year class is not related to the size of the spawning stock from which it originates. This recruitment scenario represents therefore a situation where recruitment would be driven by an hypothetical environmental signal.

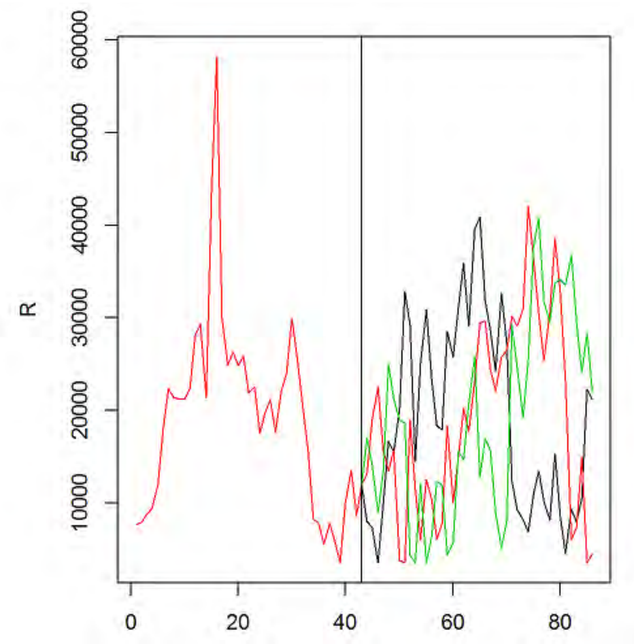


Figure 4 : recruitment simulation using the Fourier surrogates method. The first part of the time series (up to the vertical line) shows the historical recruitment values. In the second part, three Fourier surrogates are shown in red, black and green.

Growth

Preliminary analysis on jack mackerel showed that catch weights at age exhibited a significant degree of temporal autocorrelation. Hence it seemed inappropriate to represent weight at age by purely random variations. Instead an ARMA (auto-regressive moving average) model was fitted to capture the degree of autocorrelation of the variation of the time series. The ARMA models were fitted using the fArma library in R. For each time series, the best model – the optimal set of p and q parameters, being the orders of the autogressive and moving average parts respectively) was obtained by fitting a range of models with varying p and q values and selecting the one with the lowest AIC criteria. Once an ARMA model is fitted to a time series, it can be used to simulate time series with the same characteristics as the original time series.

An ARMA model was first fitted to the time series of weights at age 1, and one weight at age 1 time series was simulated for each replicate of the stock. Then, the growth increment during the second year of the fish (i.e. weight at age 2 minus weight at age 1) was modelled by another ARMA model. Time series of weight increments from age 1 to 2 were generated for each replicate of the stock. The weight increments were added to the weights at age 1 of the corresponding cohort to generate the weights at age 2. Weights at age 3 to 12 were generated in the same way. By doing so, each cohort has a coherent growth history (e.g. no decrease in weight is possible).

This was done for the two different catch weights matrices (one for the Farnorth fleet, and another for the 3 other fleets). As in the assessment, the weights at age in the stock were calculated as an average of the two matrices, weighted by the historical proportion of the catch taken by the FarNorth fleet compared to the sum of the three others.

Natural mortality and maturity

As in the stock assessment model, constant natural mortality and maturity at age were used in the simulations.

3. Fishery operating model

The total fishing mortality, which is used in the biological operating model to compute at each time step the numbers at age at the start of the new year, is the sum of the partial fishing mortalities of the 4 fleets. Each of these fleets has a given selectivity, which is kept constant over time in the simulation, equal to the selectivity at age estimated by the assessment for the terminal year. The proportion of the total fishing mortality represented by each fleet is also constant in time, which means that any change in the total fishing mortality resulting of a given advice affects the 4 fleets in the same way. This also means that the percentage of the catch realised by each fleet in the simulation is constant and equal to the percentage in 2012.

4. The perceived stock

In the simulations – as in reality - management decisions are based on the perception of the real stock provided by a stock assessment. Stock assessment gives a perception of the real stock which can deviate from the real stock for a number of reasons : inaccuracy of the catch data, sampling uncertainty, noise in the survey indices, assessment model mis-specification, assessment model fit uncertainty.

At each new year in the simulation, a new perception of the stock has to be generated, in a way that mimics as closely as possible the uncertainty related to stock assessment. The approach taken for the jack mackerel MSE consisted in adding an error term to the output – abundance and fishing mortality at age - of the biological operating model. This error term was defined as the product of cohort-specific normally distributed deviations and an error amplitude proportional to the assessment uncertainty of the corresponding estimate.

The cohort specific deviations were generated by sampling a random number from a standard normal distribution for each cohort of the projection period, and propagating this value to all the ages for each cohort (figure 5). One matrix of cohort-specific normal deviations was generated for each replicate of the stock.

The amplitude of the error on numbers and fishing mortality at age was calculated from the 200 replicates of the biological stock at the start of the simulation (see section starting points). These replicates were generated by resampling parameters from the stock assessment based on the variance-covariance matrix and therefore the inter-replicate variability of a given estimate represents the uncertainty in the assessment output. A matrix of CV representing the amplitude of the assessment uncertainty was calculated for numbers and fishing mortality at age by computing the standard deviation of a given estimate (N or F at a given age, for a given number of years before the terminal assessment year) across all 200 replicates and dividing by the mean.

The final error was calculated by multiplying the cohort specific deviations by the uncertainty variance, calculated as square of the product between the CV and the estimate from the biological model (figure 5).

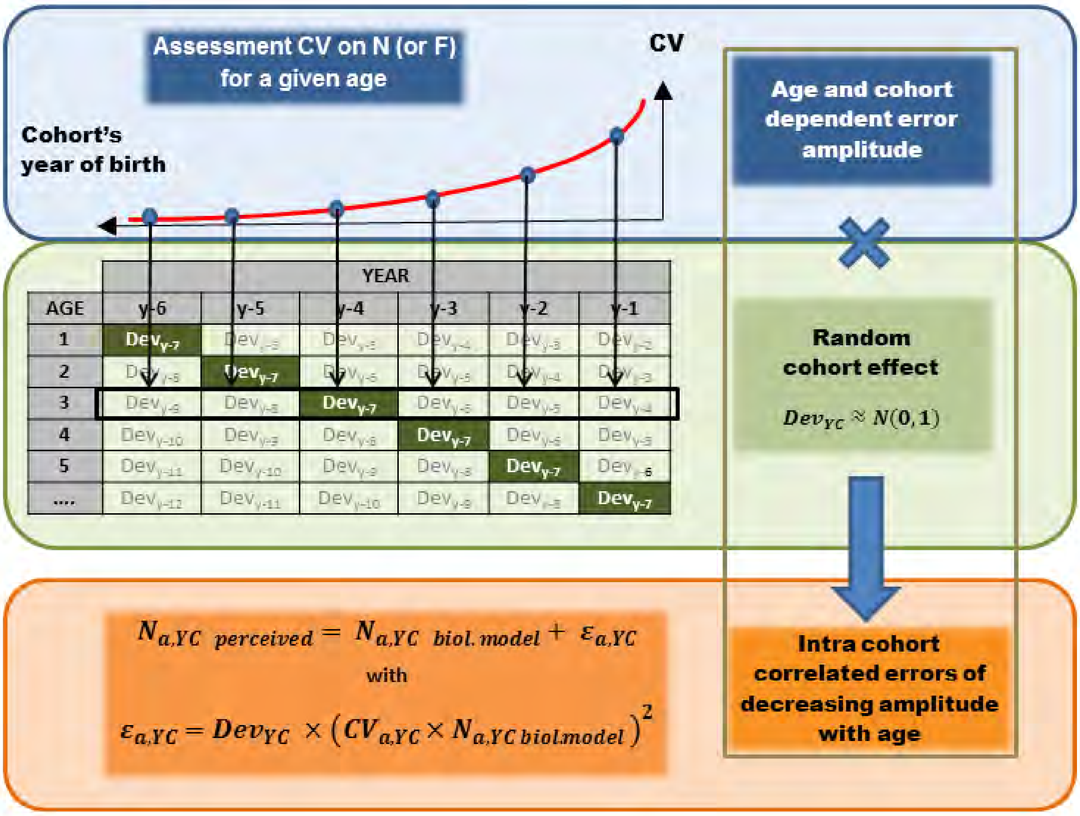


Figure 5 : simulation of assessment errors. Assessment errors are the product of a cohort effect normally distributed and an age and cohort dependent amplitude, representative of the uncertainty in the assessment, derived from on the variance-covariance matrix of the assessment parameters.

5. Implementation of the management rule

At each step of the simulation, a TAC advice is formulated based on the results of the latest assessment. The procedure which is implemented here is similar to the standard ICES procedure, where in a given year *y*, the TAC advice is given for the following year *y+1*, based on a perception of the stock in the previous year *y-1* (figure 6). In order to give a TAC advice, a short term projection of the stock is necessary to get the stock abundance in the advice year *y+1*. The short term forecast is based, as in reality, on the perceived stock.

Here, the survivors at the start of the current year, *y*, are projected forward to the start of the next year, *y+1*, using the assumption that the catch of the current year *y* is equal to the TAC for the same year *y*. Then, based on the numbers at age at the start of the year *y+1*, the harvest control rule is applied : such rule give the value of Fbar which should be applied in the year *y+1* given the value of SSB in *y+1*. The advised TAC in year *y+1* is calculated based on this value of Fbar. In this MSE, it is assumed that the actual catch in a given year is equal to the advised TAC, i.e. that the quotas are fully used and not overshot.

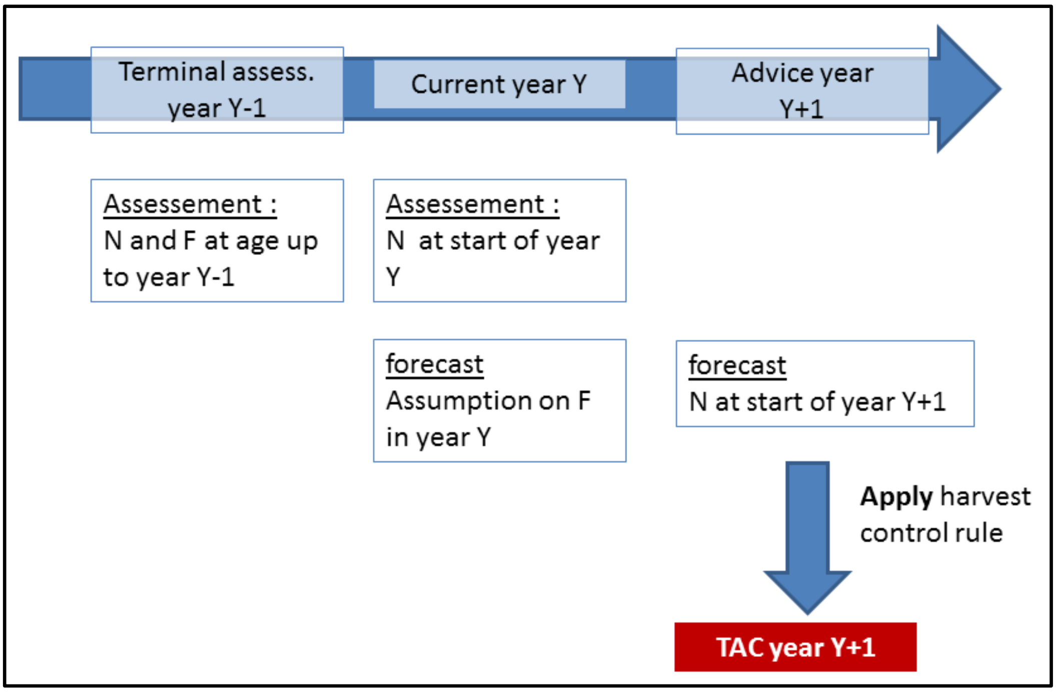


Figure 6 : time line of the advisory process implemented in the MSE. In year y, advice is given for the catch of year y+1 based on a short term forecast of the stock 2 years ahead of the final year estimated in the assessment, y-1.

III. Application of the MSE tool to estimate MSY

A first set of simulations were run to investigate the link between SSB, Yields and fishing mortality at equilibrium. These simulations were run by imposing a constant Fbar value over the simulation period (2013 to 2040) directly in the biological operating model (i.e. not based on the perceived stock, and not implementing any management rule). The aim of these simulation at constant F is to reach a "dynamic" equilibrium, where the stock would be on average at an equilibrium situation corresponding to the level of F imposed, but will still fluctuate around this equilibrium due to the stochastic variability in the model. The equilibrium state is defined by computing the mean of SSB and Yield over the period 2030 to 2040. Inspection of the stock trajectories confirmed that equilibrium was usually reached in 2030. The simulations were run using 200 replicates (generated as explained above) of the stock for each value of Fbar. Hence, for a given Fbar, the variability in mean SSB and mean Yield at equilibrium is the result of the difference in the stock-recruitment models (functional form and parameter values) between replicates.

The results of the simulations using the Bayesian stock recruitment models are show on figure 7 and the results of the simulations using the Fourier surrogate time series are show on figure 8.

For the recruitment scenario based on the Bayesian stock-recruitment models, Fmsy was estimated at F=0.14, corresponding to a yield of around 2 mt, and an SSBmsy of 10.6mt. These estimates are in the line with previous estimates obtained by a range of different methods (Hintzen and Canales, 2012), giving Fmsy in the range of 0.13 to 0.17, MSY between 1.9mt to 2.2mt and Bmsy between 9.3mt and 12.1mt.

The determination of MSY for the recruitment scenario based on the Fourier surrogates was inconclusive. The yield increased with fishing mortality until around F=0.20, and was stable thereafter, with no sign of decrease at high F values. At the same time, the SSB decreased continuously with increasing fishing mortality.

The concept of MSY is based on the principle of density dependent productivity in fish stocks: starting to exploit a virgin fish population relaxes the strength of density dependent mechanisms, and thereby increases the productivity of the stock. Further increasing the exploitation level leads to overexploitation, a situation where the productivity is reduced (starts affecting recruitment, does not let the fish growth to the optimal size). The MSY is the limit between these two states. In the simulations using the Fourier surrogates, there is no link between recruitment and stock size, and hence no density dependence is present in the model. The concept of MSY has no meaning in this case, since the productivity of the stock is governed entirely by extrinsic factors.

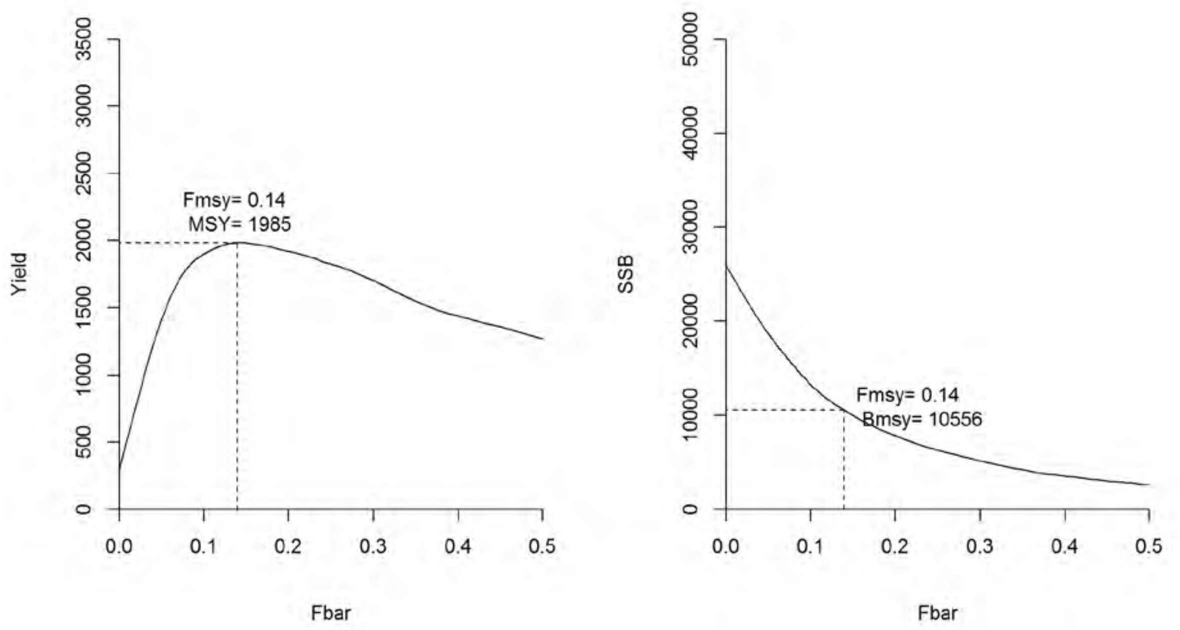
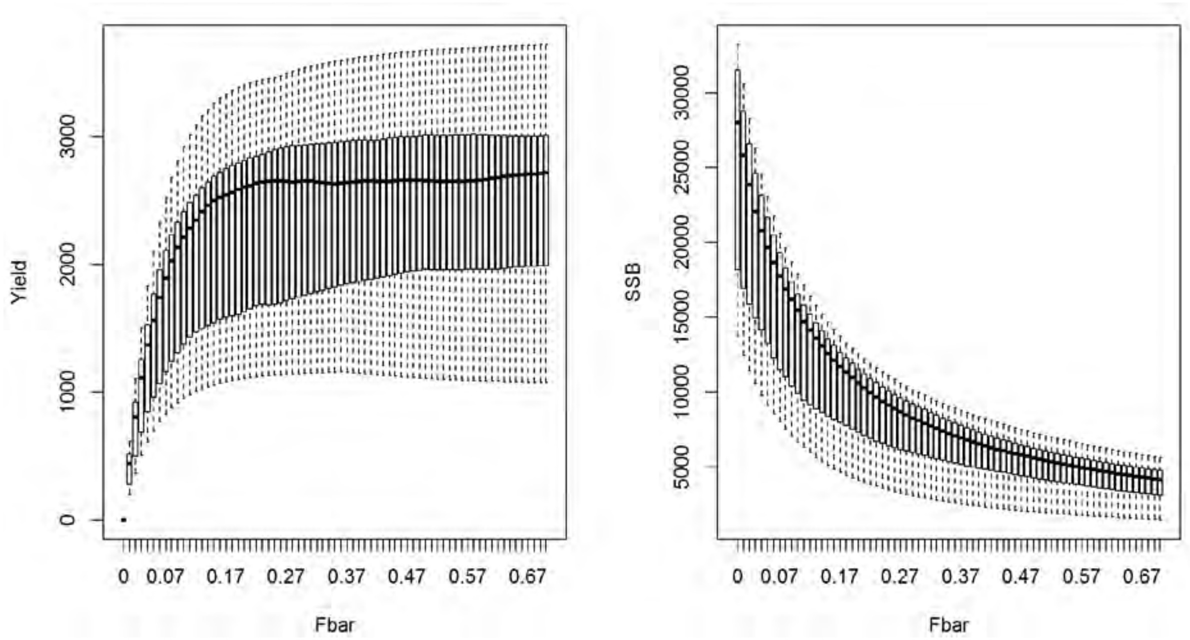


Figure 7 : determination of Jack mackerel MSY based on the Bayesian stock-recruitment models. The plots show the mean yields and SSB over the years 2030-2040 in relation to the Fbar value. Top panel : the boxplot represent the variability of the mean Yield and SSB across the 200 replicates ; bottom panel : relationship between the median value of Yield and SSB and Fbar (smoothed using a lowess smoother), and determination of the MSY.



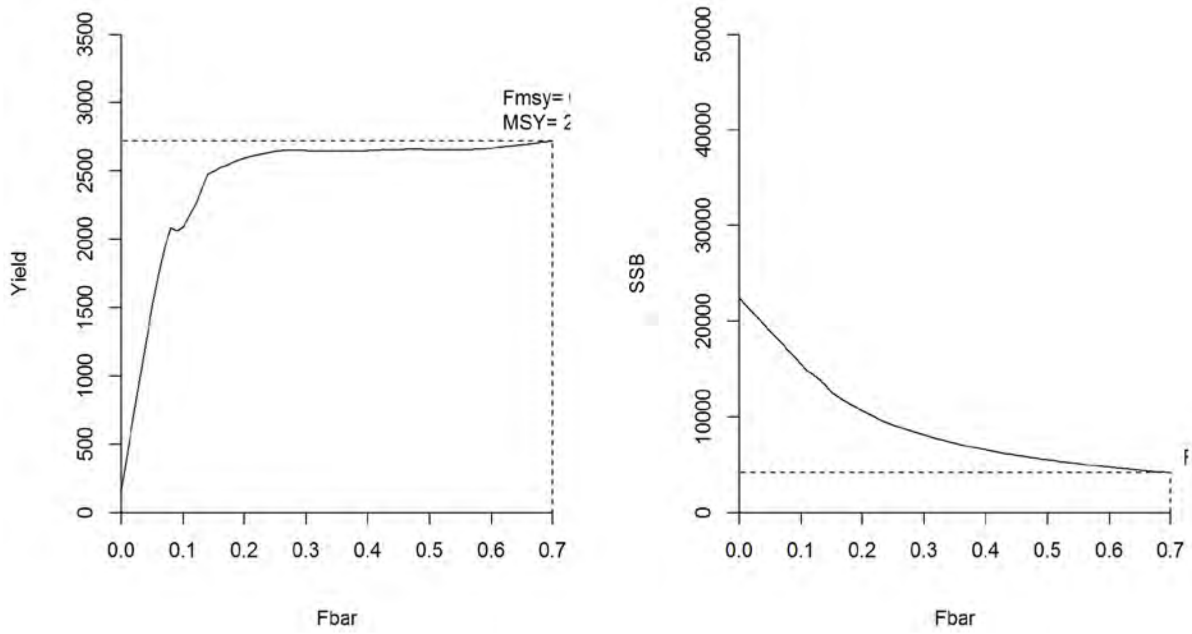


Figure 8 : determination of Jack mackerel MSY based on the Fourier surrogate-recruitment time series. The plots show the mean yields and SSB over the years 2030-2040 in relation to the Fbar value. Top panel : the boxplot represent the variability of the mean Yield and SSB across the 200 replicates ; bottom panel : relationship between the median value of Yield and SSB and Fbar (smoothed using a lowess smoother), and determination of the MSY.

IV. Example of evaluation of the performance of management strategies

In order to illustrate how the simulation tool can be used to evaluate the performance of a management strategy, simulations were run applying different example management scenarios. Diagnostics of the performance of these management scenarios were derived from the output of the simulation.

Since these simulations are only carried out for the purpose of illustration, the Bayesian stock-recruitment scenario was chosen arbitrarily.

1. Management scenarios

Proposed reference points

The table below gives the values of the proposed reference points for the management of the jack mackerel, together with their definition and origin.

	Value	Description	Origin
Biomass reference point			
Bmsy	10.6 mt	Biomass at MSY	Simulations using the Bayesian SR models (see above)
Blim	2.8 mt	Biomass under which recruitment may be impaired	Median of the breakpoint of the 1000 hockey-stick stock recruitment models fitted with the Bayesian approach
Bpa	3.9mt	Biomass below which there is a risk to fall below Blim, given the uncertainty in the assessment	Bpa=Blim * exp(1.645 σ) with σ being the standard error of the SSB estimate, here equal to 0.2 (see ICES, 2007)
Fishing mortality reference point			
Fmsy	0.14		Simulations using the Bayesian SR models (see above)

Scenario 1 : constant fishing mortality “F target” scenario.

The TAC is set so that the fishing mortality in the advice year is equal to a target value. Here the value Ftarget was set at Fmsy=0.14.

Scenario 2 : recovery plan

Given that the stock is currently at a low level, special management measures, aiming at rebuilding the stock to higher levels, could be implemented. Simulations were also run to test the efficiency of a stock recovery management strategy in which :

- F should be annually decreased by 25% until the stock recovers to a level above Blim,
- When Blim is reached, F should be annually decreased by 15% per year until the stock is above Bpa,
- When the stock has recovered at above Bpa, F should be equal to Fmsy.

Scenario 3 : hockey-stick harvest control rule

This harvest control rule aims at maintaining the stock close to MSY. When the stock is at Bmsy or larger, it should be exploited at F=Fmsy. When the SSB falls below Bsmy, F should be reduced from Fmsy proportionally to the decrease of SSB compared to Bsmy (figure 9).

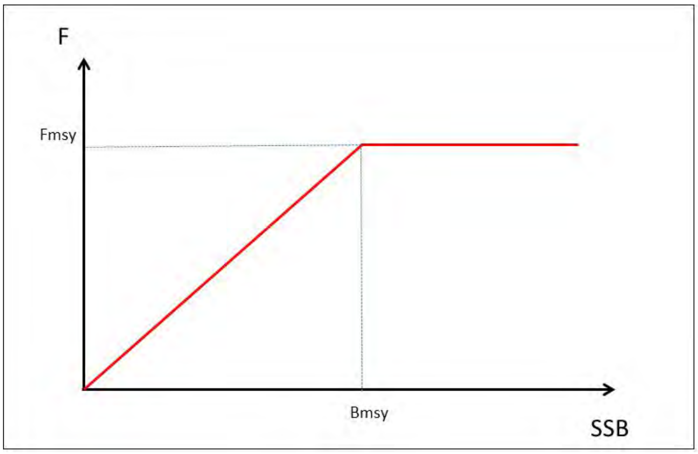


Figure 9 : the hockey-stick harvest control rule

2. Simulation set up and performance diagnostics

The simulations were run with the following set-up :

- simulation first year : 2013
- simulation last year : 2040
- number of replicates : 200
- recruitment : Bayesian models (fitted based on SR pairs from 1970 to 2012)

The performance of the HCR was measures of the risk, recovery speed, yield. The risk corresponds to the probability of SSB falling below Blim, defined as the proportion of the stock replicates for which SSB was below Blim at least one year over the period of years of interest (prob2, as defined by ICES 2013). Given that the stock is at around Blim at the start of the simulation, the probability prob2 was calculated excluding the 5 first years of simulation.

The efficiency of the management in term of recovery was assessed by the rebuilding speed expressed as the number of years after the start of the simulation at which the stock first reached a level above Blim and then, Bpa.

The performance in term of yield was assessed by the mean yield in the short (2013-2017), medium (2018-2027) and long (2027-2040) term. The yield variability was also calculated as the average of the absolute percentage of change between two consecutive years.

3. Simulation results

The figure 10 shows the simulated stock trajectories for the three management strategies implemented. The diagnostics are presented in table 1. SSB trajectories are very similar for the three management scenarios, with an instantaneous increase at levels above Blim, and with Bpa being reached within less than 2 years for the hockey-stick HCR, to 3 years for the F target management. In the long term, SSB reaches Bmsy, and even goes slightly above for the hockey-stick HCR. The risk with respect to Blim is never higher than 1% in the mid and long term. Minor differences are found for fishing mortality, with Fbar going immediately to Fmsy in the F target management, decreasing slightly in 2014 but then going to Fmsy for the recovery strategy, and declining abruptly in 2014 and slowly increasing towards Fmsy for the hockey-stick HCR. In all cases, Fbar is close to Fmsy in the long term. The hockey-stick HCR leads to higher yields in the mid and long term, but at the price of lower yields in the short term and of a slightly higher yield variablity. In all cases, the discrepancies between real and perceived stock are small. Assessment errors are similar in the three cases, with a small imprecision on SSB with no bias, and a small but minor bias on Fbar.

Table 1 : diagnostics of the simulations.

	Management scenario		
Diagnostics	**F target**	**Recovery plan**	**Hockey stick HCR**
Risk	proportion of the stock replicates falling at least once below Blim		
Mid Term	1%	0%	0%
LongTerm	1%	1%	0%
recovery time	Average number of years to go above the specified SSB level		
to Blim	0.33 yr	0.19 yr	0.18 yr
to Bpa	3.02 yr	2.65 yr	1.79 yr
SSB	Average SSB		
Long Term	9.9 mt	10.4 mt	11.0 mt
End	10.7 mt	10.8 mt	11.6 mt
Fishing mortality	Average Fbar		
mean	0.141	0.140	0.126
Long term	0.143	0.142	0.136
End	0.143	0.143	0.138
Yield	Average yield		
Short Term	578 t/yr	555 t/yr	444 t/yr
Mid Term	1269 t/yr	1338 t/yr	1453 t/yr
Long Term	1909 t/yr	1942 t/yr	2071 t/yr
Yield Variability	Mean absolute yield difference between two consecutive years		
	9.6%	10.0%	11.6%
Assessment errors	Difference between real and perceived stock relative to the real stock		
SSB (absolute bias)	4.3%	4.3%	4.0%
SSB (bias)	-0.2%	-0.3%	0.1%
Fbar (absolute bias)	2.1%	2.1%	2.1%
Fbar (bias)	2.0%	2.0%	2.0%

F target Recovery strategy Hockey stick

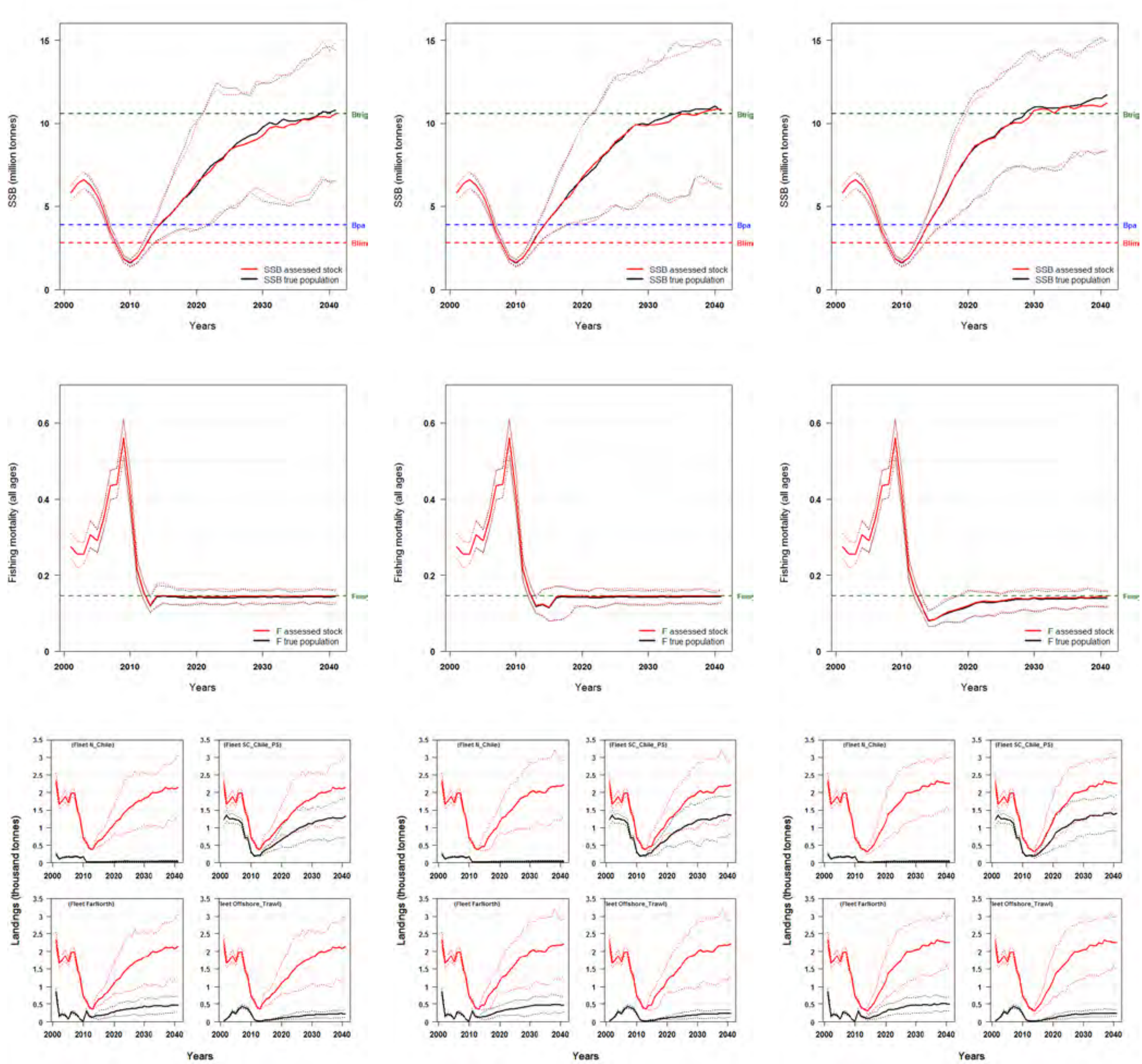


Figure 10 : simulation output for three management scenarios. Jack mackerel SSB (Top panels), fishing mortality (medium panels) and Yield (bottom panels) trajectories (solid lines : median values ; dashed lines : 5% and 95% quantiles of the inter replicates distribution)

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V. Concluding remarks

This document presents a methodological framework to test different management strategies for jack mackerel. Here, only a couple of management strategies were implemented for the purpose of illustration. The next step toward the instauration of a management plan for jack mackerel is the definition of management goals by the stakeholders. Real candidate management strategies should then be defined to fulfil these goals and eventually evaluated using this MSE framework.

The key element in these simulations is the representation of jack mackerel recruitment. All the projections shown here are based on the Bayesian stock recruitment models. It is hence expected that recruitment will increase if SSB starts to rebuilt. However, the decrease in recruitment to low levels in the recent years is quite likely to be associated to environmental drivers, which may have acted in combination with overfishing. The stock recruitment models being fitted based on the historical time series, they do not take account specifically of the recent low productivity of the stock. It is not known whether recruitment can rebuilt to level as high as in these simulations if the SSB start rebuilding.

More research on the environmental determinism of jack mackerel recruitment is needed to build a better knowledge. Until such knowledge is available, MSE simulations based on the Stock-recruitment models should be considered with caution. The reasons for the current low productivity regime are unidentified, and it is impossible to make an assumption on its duration. Therefore, it is uncertain whether the stock can be expected to rebuild as in the simulations shown in this document.

In absence of any knowledge on the drivers of jack mackerel recruitment, the Fourier surrogates time series could be useful to represent a range of potential environmentally-driven recruitment scenarios. Further decisions will have to be made as to whether the surrogates are considered to be an appropriate basis to represent recruitment in jack mackerel MSEs. In any case, simulations should be run using the Fourier surrogates, at least to test the robustness of management strategies to this alternative recruitment scenario.

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Annex

Annex 1 : overview of the jack mackerel MSE

Background		
Motivation	Jack Mackerel is fished both in international waters and in nationals waters from Ecuador to Chile. The stock is assessed annually by SPRFMO, but there is no management plan in place.	
Objectives	Evaluate a set of candidate management strategies for Jack Mackerel in the Southeast Pacific	
Formal framework	Task of WP4 in the EU project "hydrography and Jack Mackerel in the south pacific"	
Authors	Thomas Brunel and Niels Hintzen IMARES / the Netherlands	
Method		
Software	Ad hoc software, written in R/FLR, assessment model in AD model builder. Age structure model, HCR applied on a perceived stock (true stock + noise reproducing the uncertainty in the assessment), different recruitment scenario tested	
Type of stock	Pelagic, widely distributed and migratory, medium lifespan	
Knowledge base	Analytic assessment (age based, 4 fleets, 9 indices)	
Type of regulation	In the simulations, the fishery is managed by annual TACs (and potentially also via measures influencing the selection pattern of each fleet)	
Operating model conditioning		
	Function, source of data	Stochastic? How :
Recruitment scenarios	Bayesian approach[1] fitted on the historical SR pairs (1970-2012). A set of 200 SR models with Bayesian parameters estimation. Proportion of each model (Beverton and Hold, Ricker and Hockey Stick) is based on their respective likelihood.	Stochastic deviations from the SR model normally distributed with a sigma estimated in the SR model fitting
	"Fourier surrogates"[2]: method which generate time series with the same power spectrum as the historical one	Fourier surrogates are by essence stochastic
Growth	Weight at age 1 and annual weights increments from age 1 to 11 modelled by a ARAM (autoregressive moving average) model	Noise (gaussian) on top of the AMRA simulations
Maturity	Same as assessment	Constant in the simulation
Natural mortality	Same as assessment	Constant in the simulation
Selectivity	For the 4 fleets, same as assessment	Constant in the simulations Resampled for each iteration

[1] Simmonds, E. J., Campbell, A., Skagen, D., Roel, B. A., and Kelly, C. 2011. Development of a stock–recruit model for simulating stock dynamics for uncertain situations: the example of Northeast Atlantic mackerel (Scomber scombrus). – ICES Journal of Marine Science, 68: 848–859.

[2] See for instance : Planque B, Buffaz L (2008) Quantile regression models for fish recruitment–environment relationships: four case studies. Mar Ecol Prog Ser 357:213-223.

Initial stock numbers	From assessment	using the varcov matrix Resampled for each stock replicate using the varcov matrix
Decision basis	SSB projected to the advice year	
Number of iterations	200	
Projection time	40 years	
Observation and implementation models		
Assessment in the loop?	No	
Type of noise	Cohort specific deviation * age/year specific effect decreasing with age and time	Cohort effect : N(0,1) Age effect : based on CV on N@age calculated from the varcov matrix of assessment parameters
Comparison with ordinary assessment	Simulated assessment errors have the same CV in the F and N at age in the assessment	
Projection :if yes how ?	Short term forecast 2 years ahead, assuming intermediate year catch is equal to the TAC	
Projection : deviation from WG practice	No catch advice base on short term forecast in the SPRFMO	
Harvest Rules		

Hcr design	<u>Hockey Stick :</u>
	If SSB > Btrigger → F = Ftarget
	If (Blim<SSB<Btrigger) → F = Fmin + (SSB-Blim) * (Ftarget-Fmin)/(Btrigger/Blim)
	If (SSB<=Blim) → F = Fmin
	
	<u>Recovery plan :</u>
	As long as SSB<Blim : reduce F by 25%
	When Blim<SSB<Bpa : reduce F by 15%
	When SSB>=Bpa : apply a Ftarget of 0.15
	
	<u>Target F</u>
	The TAC is set so that F in the advice year is equal to the Target F, set at Fmsy	

Reference points values	Ftarget = Fmsy=0.15 Blim= 2.8mt, Bpa 3.9mt, Bmsy=10.6mt	
Stabilizers	Comparison YES vs. NO stabilizer = max 15% interannual TAC change	
Duration of decision	Annual	
Revision clause	None	
Presentation of results		
Type of diagnostics	Recovery time Risk Fishing mortality Yield Yield variability	
Risk type (and time interval)	Risk : type 2 proportion of the iteration which went below Blim at least once.	
Precautionary risk level	5%	