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AN EXAMPLE OF CONDITIONING AN OPERATING MODEL USING MULTIFAN-CL

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SUMMARY

We use Multifan-CL to develop an Operating Model (OM) for North Atlantic Albacore; conditioning the OM based on three sets of biological parameters. The work is a first step in developing a Management Strategy Evaluation framework for North Atlantic Albacore.

RÉSUMÉ

Nous utilisons Multifan-CL afin de développer un modèle opérationnel (OM) pour le germon de l'Atlantique Nord; en conditionnant l'OM sur la base de trois ensembles de paramètres biologiques. Le travail est une première étape dans l'élaboration d'un cadre d'évaluation de la stratégie de gestion pour le germon de l'Atlantique Nord.

RESUMEN

Utilizamos Multifan-CL para desarrollar un modelo operativo (OM) para el atún blanco del Atlántico norte; condicionando el OM basado en tres conjuntos de parámetros biológicos. El trabajo es un primer paso en el desarrollo de una evaluación de la estrategia de gestión marco para el atún blanco del Atlántico norte.

KEYWORDS

Albacore, Management Strategy Evaluation, Multifan-CL, Operating Model

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1. Introduction

This paper describes the conditioning of an Operating Model (OM) as part of a Management Strategy Evaluation (MSE) for North Atlantic albacore. Where an OM is a mathematical statistical model used to describe resource dynamics in simulation trials and to generate resource monitoring data when projecting forward. MSE describes the process of testing generic MPs or harvest strategies (Rademeyer *et al*., 2007).

Conditioning is undertaken to ensure that the simulations are representative of the actual problem of managing the stock(A'mar *et al*., 2008). There are several ways to condition an OM (Kell *et al*., 2006). The simplest is when the OM is based on a stock assessment model, as in this paper where we use the Multifan-CL (Fournier *et al.*, 1998) North Atlantic albacore assessment to condition the OM. As part of the conditioning process we also consider two hypotheses about biological parameters based on a review of North Atlantic albacore biology (Santiago and Arrizabalaga, 2005) and life history theory (Gislason *et al*., 2010).

2. Material and Methods

2.1 Multifan-CL

Multifan-CL (Fournier *et al.,* 1998) is an ADMB based stock assessment program that implements a statistical, size-based, age-structured and spatial-structured model for use in fisheries stock assessment. It is used routinely for tuna stock assessments by the Oceanic Fisheries Programme (OFP) of the Secretariat of the Pacific Community (SPC) in the western and central Pacific Ocean (WCPO), (Hampton, *et al.*, 2002). Both the Indian Ocean Tuna Commission (IOTC) and ICCAT use Multifan-CL to conduct stock assessments. The model is fitted to time series of catch, effort and size composition data from fishing fleets. Size composition data may be in the form of either length or weight-frequency data, or both. The model may also be fit simultaneously to tagging data, if available. Other information is provided to the model in the form of prior information on estimates of various biological and fisheries parameters and their variability.

2.2 Scenarios

In order to capture the range of uncertainty about the biology of the stock, three alternatives assessment data inputs were created, i.e. OM1) the working group base case; OM2) based on a review of North Atlantic albacore and OM3) based on life life history theory. Although there is also uncertainty about the catch, effort and size data these did not vary between scenarios in this example.

OM1 The model adopted as the base case was an update or continuity run of the previous base case from 2007.

OM2 Biological parameters are based on a review of Northern Albacore biology and fisheries (Santiago and Arrizabalaga, 2005). Parameters were chosen to be consistent, i.e. the natural mortality and maturity-at-age vectors and Von Bertalanffy growth function were chosen so that there were no contradictions between age based parameters and the selected growth curve.

OM3 Life history relationships were used to parameterise an age-structured equilibrium model, where SSB-per-recruit, yield-per-recruit and stock-recruitment analyses are combined, using fishing mortality (F), natural mortality (M), proportion mature (Q) and mass (W) -at-age (Gislason *et al*., 2010).

2.3 Future Projections

Projections for the different management strategies require assumptions about processes such as recruitment. The scenarios were projected from 2000 to 2030 for process error in recruitment, i.e. historic recruit from within a scenario was sampled with replacement to select a recruitment value from 2000 to 2030. The stock was then projected for a fishing mortality equal to FMSY.

2.4 Software

Software used was a biomass production model implemented as a package in R, this allows it to be used with a variety of other packages for plotting, summarising results and to be simulation tested, e.g. as part of the FLR tools for management strategy evaluation (Kell *et al.*, 2007).

3. Results

The parameters are shown in **Figure 1.** Selectivity is estimated while the other parameters are fixed. Assuming that M increases with age results in an increase in selectivity F at older ages, since a higher F is required to explain the catches of larger fish. There is less effect seen for assuming that M is higher at younger ages. In ADMB when fitting a model with multiple parameters it is possible to initially fix some parameters during the frst optimisation (of some other parameters), the fixed parameters are then being estimated in later phases. This helps in fitting since the most influential parameters can be addressed first. The use of phases also allows a range of model formulations to be explored, i.e. from simple to complex. **Figures 2 and 3** show the values of the objective function and number of parameters by scenario and phase.

The biggest change in the likelihood is seen between phase 1 and 2 when selectivity is estimated. In phase 6 when changes in catchability by year are estimated little change in seen in the likelihood. The estimated time series are shown in **Figure 4**, while the corresponding equilibrium values and reference points in **Figure 5** and the kobe phase plots in **Figure 6**. Finally a projection for OM1 is shown in **figure 7**. The biggest difference in the time series is seen for recruitment for OM3 (i.e. when M at younger ages is highest) and F for a U-shaped M (as would have been predicted from **Figure 1**). Changes are seen in the reference points, particularly for OM2 when a U-shaped M is assumed.

4. Discussion and Conclusions

This paper provides an example of conditioning an OM on an assessment model for use as part of an MSE. We only considered 3 OMs based on biology. Estimates of fishing mortality stock status and reference points are highly dependent upon the assumed biology. There is an interaction between the assumed biology (i.e. M) and selectivity, since the lack of older fish in catches can be assumed by either. Previously changes have been made in the biological assumptions in the final phase, i.e. as a sensitivity analyses. This has several potential pitfalls, i.e. i) in ADMB the use of phases is aim to help finding a global maximum, changing important parameters in the final phase may mean that convergence is only to a local minima, ii) it will also be inefficient and iii) the biological assumptions should be part of any formal design used to develop the OM.

Other hypotheses could have been considered, for example some fleets are assumed to have the same selectivity because there was insufficient information in the data to estimate these independently. Selectivity was also assumed not to change over time. Both assumptions are unlikely to be true. The catch and size data are also not true observations but have been generated in a variety of ways. There is therefore considerable uncertainty in the fleet data and assumptions. The indices of abundance also show different trends implying different historic dynamics. Therefore many more scenarios could have been run, reflecting the true uncertainty. Multifan-CL could have been run in a hierarchical design, e.g. if for each set of biological assumptions choices were made about the fleet data and then each phase was run to convergence then a set of scenarios could be developed. These could then be weighted either by applying externally specified weights (e.g. based on the plausibility of the assumptions) or likelihood-based weights based on fits to the data. Choice of scenarios and weightings may require expert judgment, consensus amongst experts may be sought but this may be problematical if some experts may have links with interest groups or tend to be more vocal than others?

An alternative approach is that of the IWC Scientific Committee and CCSBFT which avoided quantification, and instead categories hypotheses as of high, medium and low weight. In cases where there is no agreement, but a plausible case can be made by some for a high weight, a medium weight is assigned. To avoid expert's choices of weights being influenced by the management implications of an associated hypothesis, these weights should ideally be finalised on the basis of informed discussion concerning the hypotheses alone conducted before any computations related to management. However, pragmatically, some flexibility on this point may be entertained in the interests of time for example to identify at an early stage that some hypotheses, although of appreciable plausibility, make little difference in terms of management implications when compared to corresponding default hypotheses, and hence need not be considered further (ACE, 2007). A consideration of robustness could also be made when choosing scenarios, i.e. is a scenario likely to have any effect? if not then ignore it.

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Table 1. Multifan-CL Parameters by phase used to condition the Operating Model under the three scenarios considered.

Phase	**Parameters**
Phase 1	Effort deviation penalties Selectivity shapes Selectivity groupings Catchability groupings Size data weightings Scaling parameter of initial to total population
Phase 2	Seasonal component of catchability Selectivity
Phase 3	Temporal changes in recruitment Length dependant S.D.
Phase 4	Mean length of 1st age class
Phase 5	Individual mean lengths for 1st 2 age classes
Phase 6	Time series change in catchability
Phase 7	Dummy phase. Will be removed in future runs
Phase 8	Dummy phase. Will be removed in future runs
Phase 9	Bevereton Holt SRR Parameters of beta distribution defining prior for steepness

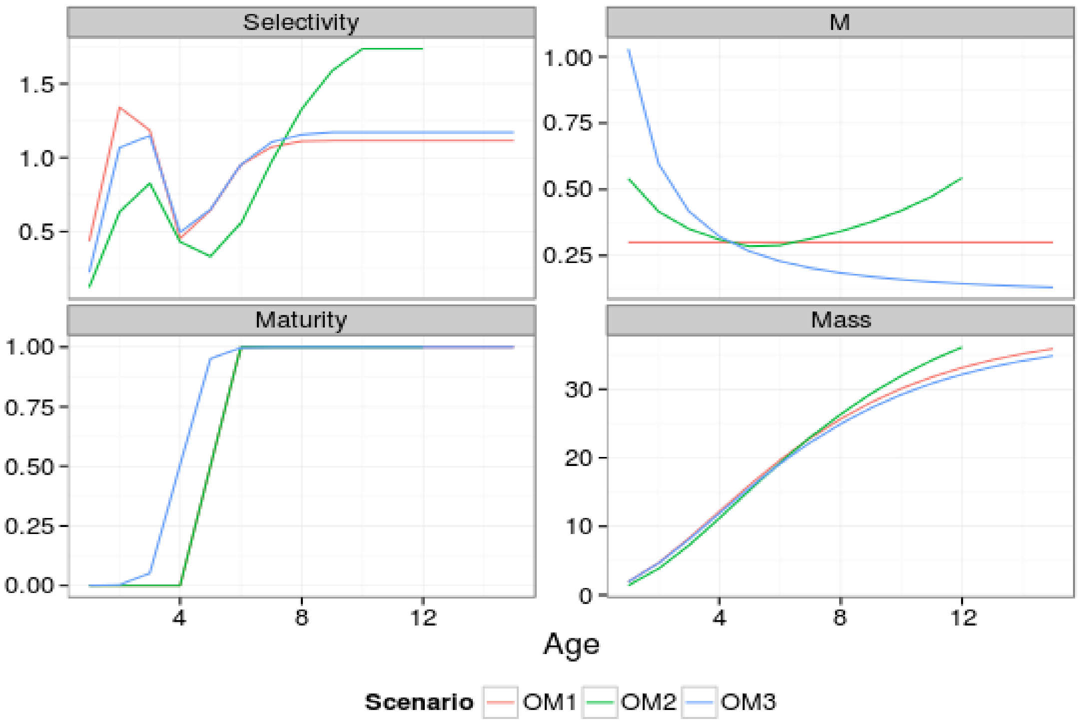

Figure 1. Selectivity, natural mortality (M), maturity (mat) and individual growth (Mass) patterns used to condition the OM under three scenarios.

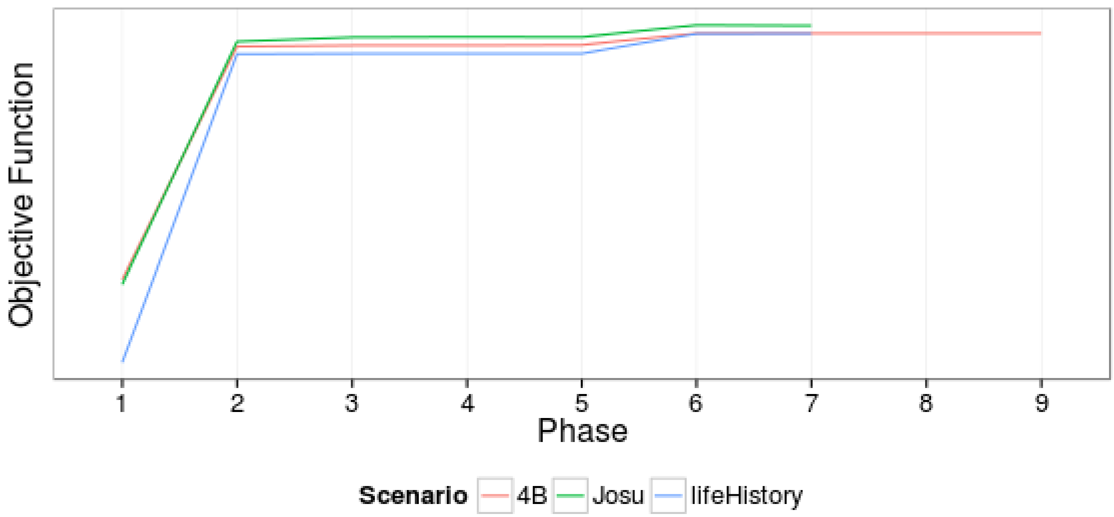

Figure 2. Likelihood by phase and scenario.

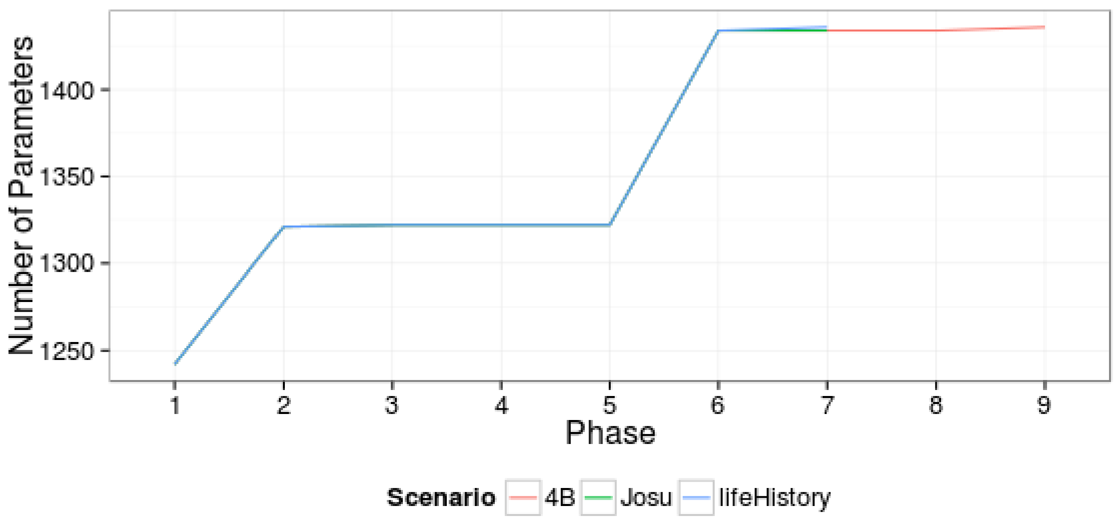

Figure 3. Number of parameters by phase and scenario.

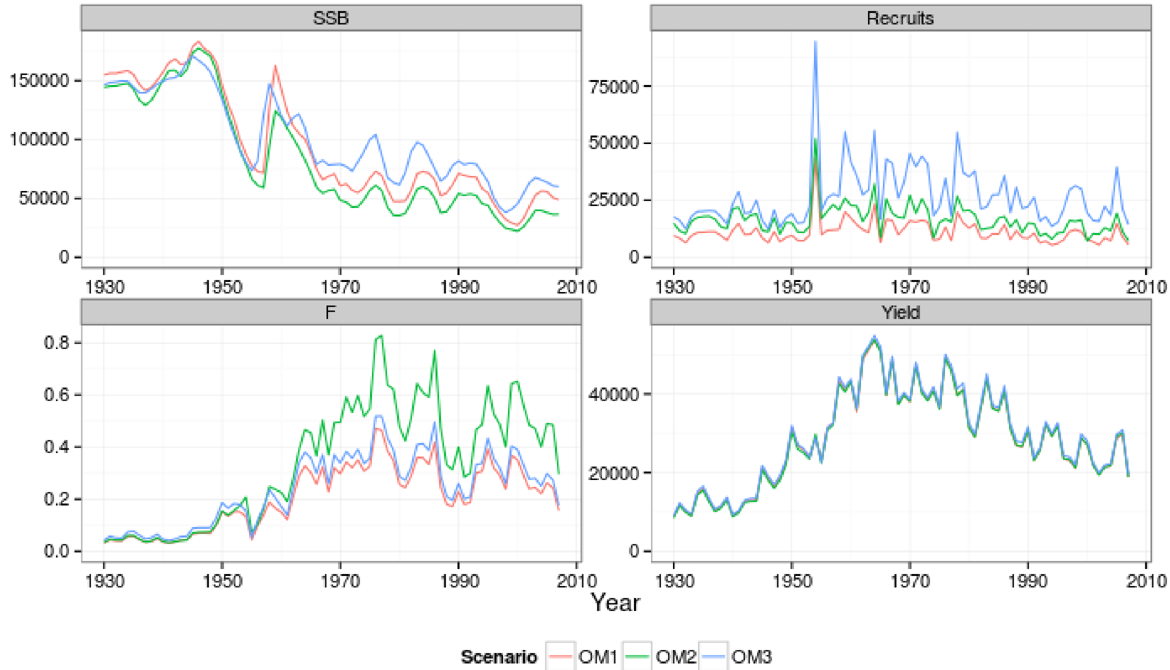

Figure 4. Estimated historic time series of the Operating Models.

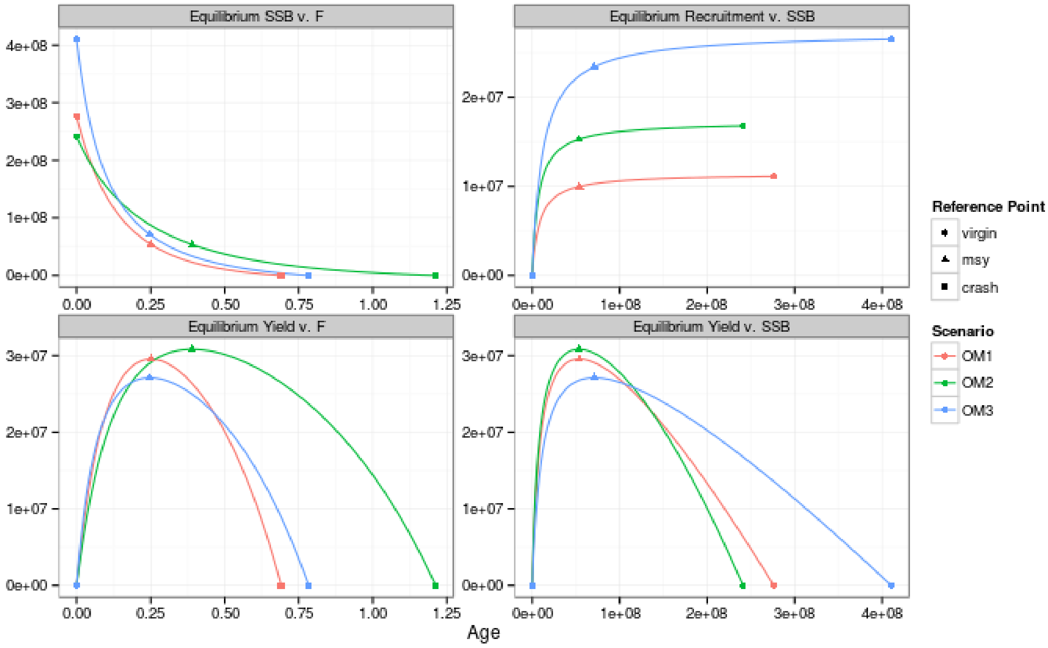

Figure 5. Equilibrium values and reference points estimated by Operating Model scenario.

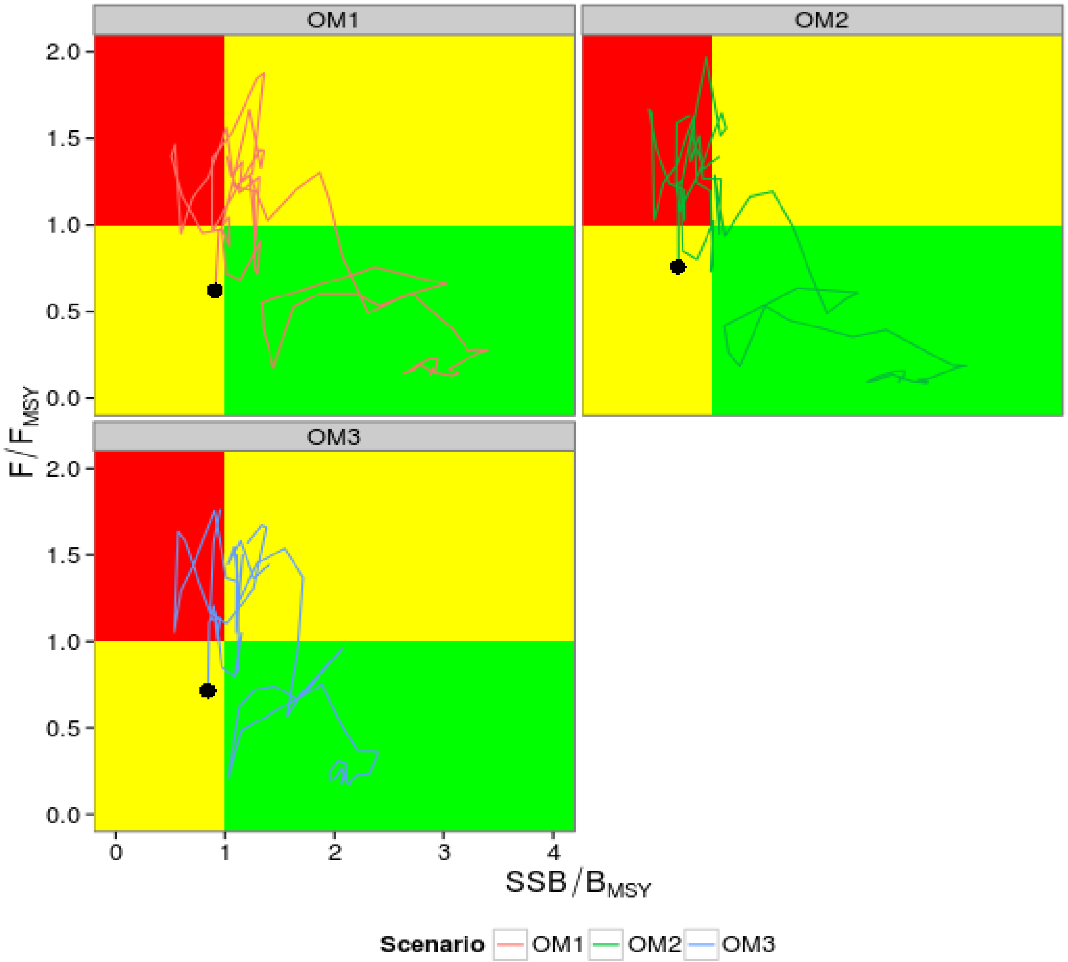

Figure 6. Kobe phase plots for the three Operating Models.

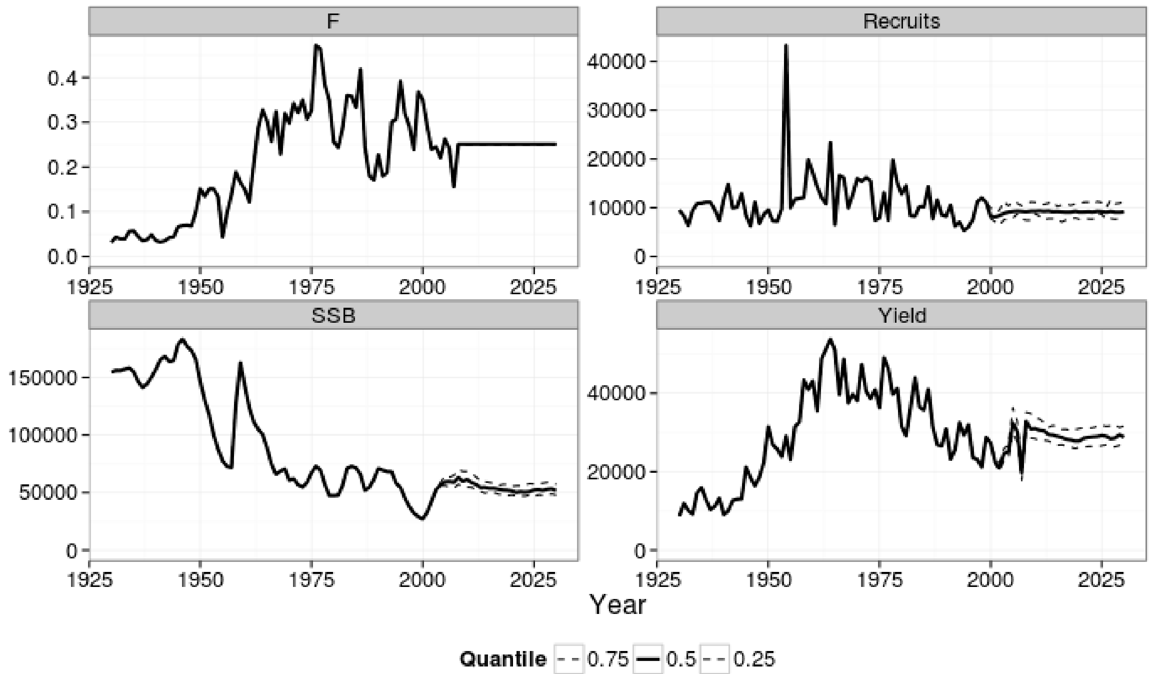

Figure 7. Stochastic projection of OM1 for F = F_{MSY}.