**CONDITIONING AN OPERATING MODEL FOR NORTH ATLANTIC ALBACORE.**

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*SUMMARY*

*When conducting a Management Strategy Evaluation it is required to conditioned an Operating Model, that represent the simulated versions of reality, on data and knowledge for a range of hypotheses about resource dynamics. There are many alternative ways to do this, one way is to use the the currently-used stock assessment model. In this paper we summarise an Operating Model developed for North Atlantic albacore conditioned using Multifan-CL.*

*KEYWORDS*

*Albacore, Conditioning, Management Strategy Evaluation, Operating Model, Stock Assessment, Multifan-CL*

# Introduction

When conducting a Management Strategy Evaluation it is necessary to conditioned a Operating Model (OM), that represent the simulated versions of reality, on data and knowledge for a range of hypotheses about resource dynamics. There are many alternative ways to do this, one way is to use the the currently used stock assessment model. Although use of the assessment model as the OM seems to imply that assessment models describe nature almost perfectly, if a Management Procedure (MP) can not perform well when reality is as simple as implied by an assessment model, it is unlikely to perform adequately for more realistic representations of uncertainty. Basing an OM on the current assessment model also has arguably the lowest demands for knowledge and data.

In this paper we describe the development of an OM for North Atlantic albacore based on the integrated stock assessment Multifan-CL (Fournier et al., 1998). An OM is a mathematical statistical model used to describe the actual resource dynamics in simulation trials and to generate resource monitoring data when projecting forward to simulation test a MP. Where a MP is combination of pre-defined data, together with an algorithm to which such data are input to provide a value for a TAC or effort control measure.

Conducting a Management Strategy Evaluation (MSE) requires six steps (after Punt and Donovan,2007); namely i) identification of management objectives; ii) selection of hypotheses for the OM; iii) conditioning the OM based on data and knowledge, and possible weighting and rejection of hypotheses; iv) identifying candidate management strategies; v) running the Management Procedure (MP) as a feedback control in order to simulate the long-term impact of management; and then vi) identifying the MPs that robustly meet management objectives.

Developing the OM is mainly concerned with steps ii and iii; and there are many alternative ways to condition an OM (see Kell et al., 2006). As pointed out by Kolody et al. (2009) the stock assessment process often appears to involve a haphazard search for a few model specifications which appear to be plausibly, consistent with the data, and a priori expectations. In a stock assessment, the objective is often to find a ‘best‘ model, while when conditioning an OM the objective is to characterise what we don’t know about resource dynamics. Therefore when conditioning an OM generally many scenarios need to be run.

# Material and Methods

***Methods***

*Operating Model*

When fitting assessment models there is often insufficient contrast in the data to estimate parameters for important population processes (e.g. Lee et al., 2012, 2011; Pepin, 2015). While different data sets (e.g. CPUE, catch and length distributions) may show conflicting signals. A variety of scenarios are therefore need to be run to reflect skepticism about the capacity of the model to estimate key parameters. Scenarios are generally developed by evaluating the effect of fixing some parameters, assuming alternative functional form for processes, or by down weighting datasets (e.g. SCRS/2016/014).

In the last North Atlantic Multifan-CL assessment (Anon. 2014), therefore 10 scenarios were considered (**Table 1**). The scenarios investigated the impact of the different dataset (size frequency and CPUEs), changing the start and end dates of the model, incorporating tagging data and alternative natural mortality (M) vectors.

***Analysis***

First the estimated time series and reference points are summarised and then the dynamics summarised.

# Results

***Time Series***

Time series of recruits, SSB, biomass, Fbar , Fapex, harvest rate and catch are shown by scenario in **Figure 1**. In general trends are similar across scenarios and quantities. The main differences is seen between the alternative methods used for calculating exploitation; Fapex (the highest F by age as used by the SCRS) is much more variable than using Fbar (the mean F across reference ages as used by ICES).

***Stock Recruitment Relationship***

A Beverton and Holt stock recruitment relationship (Beverton and Holt, 1993) was fitted to the recruit and SSB time series. The fit to the Base Case and a suite of diagnostics based on the residuals are shown in **Figure 2**; each plot type is then repeated for all scenarios as a separate figure.

The fits are shown in **Figure 3**; there is little evidence for a reduction in recruitment as population size declines. Recruitment quickly saturates as spawning stock biomass (S) increases due to strong density dependence (i.e. compensatory dynamics).

Next the residuals (on the log scale) are plotted to check for systematic patterns that may suggest that assumptions may be violated. The residuals are plotted against SSB in **Figure 4** to check for evidence that the Beverton and Holt stock recruitment relationship may not be appropriate and against year in **Figure 5** to check for stationarity. Recruitment appears to be highest at medium biomass levels, which could suggest over compensation, however, the plots of residuals against year suggest that there may be a year effect as expected recruitment was higher in the 1960s. It is therefore difficult to say whether recruitment is driven by SSB or environment.

The residuals are plotted against the fitted values to check the variance function (**Figure 6**); there is a suggestion that variance may increase with recruitment, i.e. that assuming a log normal error structure may not be appropriate. Therefore quantile-quantile plots are shown in in **Figure 7;** to check the assumed error model. To check for autocorrelation residuals with are plotted with a lag of 1 in **Figure 8**. The residuals appear to be log normally distributed (as they lie along the y=x line) while the regression of residualt+1 against residualt has a slope near to 0 and so there is no significant auto-correlation.

***Production Functions***

The assumed biological parameters and the estimated selection patterns are plotted in **Figure 9**.; these were combined with the stock recruitment relationships to derive age based equilibrium production curves **Figure 10**. The age based production function for the Base Case are compared with the corresponding Pella-Tomlinson production function, and the stock/yield trajectory, in **Figure 11**. The curves of the two production functions are very similar, although population growth rate at small sizes is slightly underestimated by the biomass function. A simulation using the biomass production function is shown for Base Case in **Figure 12**; harvest rate is capped at 0.3. The estimated production is insufficient to explain the catch at small as the population decreases so the stock collapses. This is partly due to the large amount of process error, modelled as recruitment variation in Multifan-CL, in the age based model that is ignored by the biomass production function.

***Stationarity***

Next variability in the time series of recruitment (**Figure 13**) and production (**Figure 14**) is evaluated using a seuential t-test algorithm for regime shifts (the STARS algorithm Rodionov, 2004). The boxes show the means and ±1 standard deviation. For recruitment there appears to be three regimes, with recruitment higher in the middle period. Surplus production is much more variable than recruitment and is driven mainly by strong year classes.

Absolute of estimates quantities, population parameters and reference points are plotted in and relative time series are plotted in **Figures 15** and quantities relative to the corresponding MSY benchmarks in **Figure 16** . Variability between scenarios is greatest for the absolute estimates, and low for the relative values. The biggest variability across time is seen for FMSY, due to mixing exploitation level and selectivity. In contrast the production function parameters (r, k and p) derived from the age based production function do not change much.

The expected value of surplus production as estimated by the age based model are shown in **Figure** **17** (red is the production function with time varying selectivity and recruitment, and black is assuming only time varying recruitment), points are the values by year. The production function is estimated using a moving average (using a 5 year window) for selection pattern and recruitment. Including time varying selection has little effect.

The distributions of the estimates annual surplus production are plotted in **Figures 18** and **19**. The latter figure plots the residuals (i.e. observed-expected) and there appears to be a positive bias.

***Stock Status***

Harvest rate relative to FMSY is plotted in **Figure 20** and stock status in **Figure 21** stock biomass relative to BMSY by scenario. Kobe Phase Plots are shown in **Figure 22** with the 2011 status indicated by the blue point.

***Power Spectra***

For each OM scenario three levels of fishing mortality (FMSY times 0.1, 1 and 2) recruitment, SSB, yield, stock biomass, juvenile biomass and surplus production and their power spectra plotted in **Figures 23,24,25,26,27 and 28**. The spectral analysis shows even though recruitment is a sequence of serially uncorrelated random variables with zero mean and finite variance (white noise) the time series SSB, yield, stock biomass and juvenile biomass are dominated by low frequencies (i.e. long-term variations). This results from the propagation of stochastic recruitment into the age-classes and lead to a smoothing of the SSB (i.e. cohort resonant effects). Productivity in comparison is dominated by medium frequencies, presumably due to the transient effect of a large recruitment.

**Discussion**

The scenarios all showed similar trends, estimates of current stock status, production functions and reference points. The dynamics of the time series are also similar, and are driven by variations in recruitment.

Although there was no auto-correlation in the recruitment deviates, there is evidence for changes in the mean level of recruitment and large recruitments cause an increase in surplus production. Process error in Multifan-CL is modelled as random recruitment this translates into changes in surplus production and long-term fluctuations in biomass and catches. This will have consequences for the MP, e.g. since catches may be driven by process error rather than the expected production.

Using the stock assessment as the OM helps in ensuring estimates of historical and current stock status are consistent with recent advice. Which in turn makes it easier to make the transition from the Kobe Framework (Kell et al., 2015) based on showing alternative management options to the use of a HCR. Choices still have to be made, however, about simulation of uncertainty into the future and around current status.

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