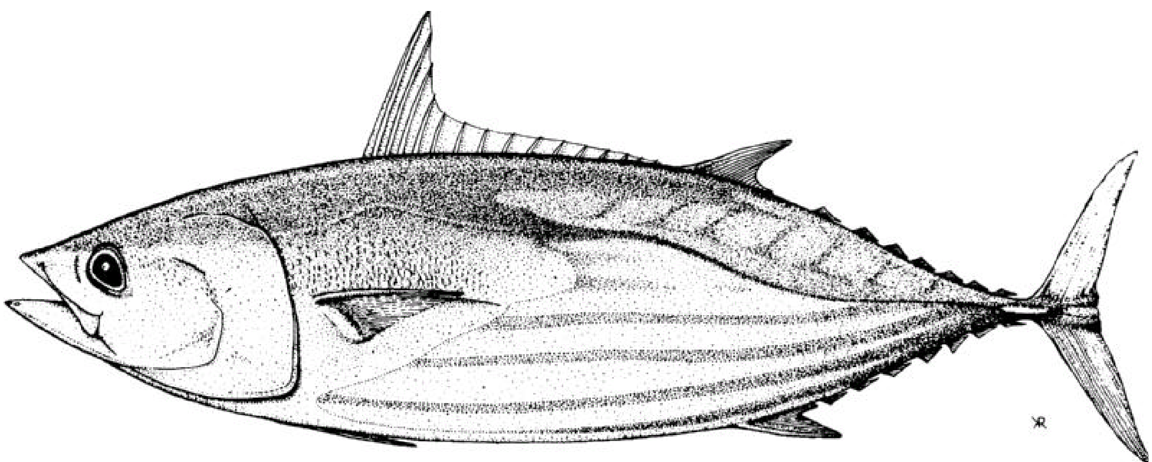
SCTB15 Working Paper

MWG - 8

Application of production models to the assessment of the SCTB-MWG simulated tuna fishery data



Daniel Ricard and Dale Kolody

CSIRO Marine Research
Hobart, Tasmania
Australia

Application of production models to the assessment of the SCTB-MWG simulated tuna fishery data

Daniel Ricard
Dale Kolody
CSIRO Marine Research, Box 1538, Hobart, Tasmania, 7001, Australia
email: Daniel.Ricard@csiro.au, Dale.Kolody@csiro.au

Introduction

The Standing Committee on Tuna and Billfish Methods Working Group (SCTB-MWG) initiated a project to evaluate the performance of MultiFan-CL, and other stock assessment models. Using an operating model that resembles yellowfin tuna fishery dynamics in the Western and Central Pacific Ocean, simulated data sets were generated, with which different assessment approaches could be applied and compared. In this document, we describe the application of age-aggregated (Fox) and age-structured (ASPM) production models to these data (where nominal CPUE is used as a relative abundance index). These models were recently considered for the assessment of Indian Ocean tuna stocks (Ricard and Basson, in prep), hence this evaluation procedure might prove relevant to that fishery as well. This document gives brief details of these models and general comments on the results and perceived suitability of these models to these data.

These simulated assessments were done hastily, and there was little consideration of some of the input assumptions or evaluation of output diagnostics. Specific results from the assessments were summarized in the SCTB-MWG report, and are not described here.

Simulated Data

There were 11 simulated data sets from a single fishery system (MWG1), and 11 simulated data sets (2 of which were essentially identical) from a system with two distinct fisheries operating in separate regions (MWG2). The operating model included complicated stochastic dynamics on relatively fine spatio-temporal scales (LaBelle 2002), but the simulated data sets that were available for analysis were aggregated into relatively coarse spatio-temporal units. The simulated data sets included 148 quarterly observations of total catch in numbers, total effort in hooks, catch length frequency distributions, and tag release and recaptures by length (measurement errors were applied to some or all of these data). Tagging data were ignored for the production models. Additional information on length-at-age, and weight-length relationships and maturity-at-age was provided.

Methods

Data Interpretations

These models require the catch data to be in biomass units, and these were derived directly from the catch length frequency distribution and weight-length relationship provided, with the assumption of no data errors.

Nominal CPUE was used as a relative abundance index for each fishery. However, given the strong seasonality in both catch and effort, only the quarter with the highest overall effort was used for each fishery (eg for the second data set, for fishery 1, we use data from Quarters 1,5,9,… and for fishery 2 we use data from Quarters 4,8,12,…). We attempted to use indices from both fisheries in MWG2, but this led to convergence problems, and in the end, only the index of abundance from the first fishery was used for the parameter estimation.

Age-Aggregated Production Model (Fox)

We chose the Fox model as a representative of one of the simplest possible stock assessment models. In the Fox model, it is assumed that production (growth and recruitment minus total mortality) is a deterministic function of total biomass (details in Appendix). There was information provided about the simulated data that suggested that technological efficiency was increasing over the time series. We attempted to admit this possibility by fitting an extra parameter that describes a linear increase in catchability over time.

The objective function for parameter estimation included terms for the predicted and observed biomass (the latter derived from CPUE and catchability), assuming log-normal observation errors. Four free parameters were estimated in the function minimization: the intrinsic population growth rate r, carrying capacity, k, mean catchability, q, and the *catchability_increase*.

Age-Structured Production Model

The ASPMs that we fit are based on Punt et al. (1995), but have been modified to include auto-correlated stochastic recruitment, and the linear increase in catchability described above. Refer to the Appendix for the details of the ASPM.

Natural mortality was assumed constant by age (0.15 quarterly instantaneous M). Simple and rather arbitrary selectivity functions were adopted, consisting of a linear increase with age from 0.5 (age 1) to 1.0 (ages 12), and constant over all quarters for fishery 1. A casual inspection of the MWG2 catch-length frequency distributions indicates that fishery 2 had lower proportions of small fish than fishery 1, so the selectivity function was adjusted by an arbitrary amount to reflect this (same functional form, but increasing from 0.0 at age 1 to 1.0 at age 12). Recruitment was assumed to be log-normally distributed (CV ~0.6) around the mean with an auto-correlation (lag1) of 0.25 on the deviations (no relationship between stock size and recruitment).

As in the Fox model, the objective function for parameter estimation included terms for the predicted and observed biomass, assuming log-normal observation errors, and the variance was estimated analytically. In addition, the ASPM objective function included priors on the quarterly recruitment deviations (in this case the recruitment CV and auto-correlation were input parameters). The estimated parameters included the unfished equilibrium spawning biomass K^{sp} , the mean recruitment plus 148 quarterly deviations, and the *catchability_increase*.

Parameter Estimation

Model parameters were estimated by minimizing the objective function using AD Model Builder software (Otter Research, Victoria, Canada). There was no consideration of uncertainty around the best fit estimates.

The parameter estimation process generally consisted of fitting all structurally similar data sets (ie 1 vs 2 fisheries) with the same assumptions and minimization procedures. If the minimizer failed to converge in some cases, the assumptions and/or minimization process was altered and repeated for all cases. There were few tests to decide if global minima were reached.

Results and Discussion

Specific results for all of the simulated assessments are submitted to the SCTB-15 Methods Working Group for further consideration. Only general results are discussed below.

Fox

The simple nature of the Fox model prevents it from representing the highly variable stock dynamics that are driven by recruitment variation in the operating model. The function minimization seemed to converge in 21 out of the 22 cases. Absolute biomass was over-estimated by an average of about 300-500 %. Relative biomass depletion estimates were better (average errors of –65% to +35%). The average estimated time series change in catchability (over the whole time series) was double the true value for MWG1 (53% vs 27%), and even worse for MWG2 (106% vs 0%). The estimated r and K parameters were very inconsistent across data sets, presumably indicating that the Fox model is simply not structured to adequately describe the operating model system. Overall, we do not consider the inferences of the Fox model to be very useful in this case.

ASPM

For the 11 data sets of MWG1, the ASPM minimization appeared to converge successfully, and generally produced dynamics that tracked the gross features of the highly variable CPUE to some extent. Catchability was generally estimated to increase (linearly) by a mean of around 66% between the first and last time step (actual increase was 27%). Average absolute and relative biomass estimates were all within a factor of 0.5-2 of the actual operating model values.

It was more difficult for the function minimizer to reach convergence with the data fromMWG2. Only by removing the estimation of the catchability trend, and restricting the variance on the recruitment deviations SD (reduced from 0.6 to 0.3), could seemingly successful minimization be achieved with the majority of data sets. Even with these modifications, convergence could not be attained in one case. The absolute biomass estimates were off by an average factor of 60 or more. This average is a bit deceptive because 1 case was off by 2-3 orders of magnitude, two more were off by a single order of magnitude, and the remainder were mostly within a factor of 2. The relative biomass ratio estimates for MWG2 were about 50% too high.

Conclusions

- We did not find the Fox model to be a very useful tool for describing the simulated stock dynamics. The structure was too simple to describe the considerable recruitment variation that was not related to stock size.

- The ASPM showed some potential for describing the simpler fishery scenario (MWG1), but demonstrated serious problems in the two fishery case.

- The extent to which the Fox and ASPM were successful in describing the relative biomass ratios was probably mostly determined by the strength of the signal in the CPUE time series. In which case, analyses that simply focused on CPUE trends would probably have performed similarly.

- Finally, we emphasize that this exercise was conducted with limited time, and we would hesitate to understate the usefulness of production models (particularly ASPM) based on this experience. The ASPM performance is presumably limited by the quality of natural mortality and selectivity assumptions, and ASPM would presumably be a much better integrative tool if independent estimates of these things were available. Similarly, if catch rate analyses actually improve the quality of the relative abundance indices, this could substantially improve the potential for ASPMs to describe this type of system.

Literature cited

Butterworth D. S., J. N. Ianelli, and R. Hilborn. 2002. A statistical model for stock assessment of southern bluefin tuna with temporal changes in selectivity. CCSBT-MP/0203/4

Fox, William W. 1970. An exponential surplus yield model for optimizing exploited fish populations. *Fish Bulletin* **99**:80–88.

LaBelle, M. 2002. Testing the accuracy of MULTIFAN-CL assessments of the WCPO yellowfin tuna fishery conditions. SCTB 15 MWG-1.

Punt, A., D. Butterworth, and A. Penney. 1995. Stock assessment and risk analysis for the south atlantic population of albacore (*Thunnus alalunga*) using an age-structured production model. *S.Afr.J.mar.Sci.*, **16**:287–310.

Ricard, D and M. Basson. in prep. Application of an age-structured production model (aspm) to the Indian Ocean bigeye tuna (*Thunnus obesus*) resource. Working Party on Tropical Tunas, Indian Ocean Tuna Commission.

Appendix. Equations and Objective Functions for the production models

1.1. Fox Model details

1.1.1. Dynamics

The Fox model (Fox 1970), assumes that the population dynamics can be described adequately with the simple equation:

$$B_{y+1} = B_y + rB_y\left(1 - \frac{\log_e(B_y)}{\log_e(K)}\right) - C_y$$

where,

B_y is the biomass of tuna present at the start of quarter *y*

C_y is the catch for quarter *y*

K is the pre-exploitation biomass (carrying capacity) assumed to exist in the first time-step, and

r is the intrinsic growth rate parameter for the population

In addition to the usual production parameters *r* and *K* we estimate the catchability *q* and a parameter representing the increase in catchability over time (called *catchability_increase*). This additional parameter enables us to admit that catchability might be changing over time. We assume a linear increase in catchability and also assume that the catchability multiplier is 1.0 at the middle of the time-series:

$$q_y = catchability\_multiplier * q$$

$$catchability\_multiplier_y = (1 - catchability\_increase) + (y * (catchability\_increase / 74))$$

where,

q_y is the catchability in quarter y, and
q is the estimated overall catchability.

1.2. Age-Structured Production Model details

The natural mortality rate is set to 0.15 for all age classes and is constant with time. The superscript *l* below indicates the fishery.

1.2.1. Dynamics

The dynamics of the fish population are described by three equations:

$$N_{y+1,0} = R\left(B_{y+1}^{sp}\right)$$

$$N_{y+1,a+1} = \left(N_{y,a} e^{-\frac{M_a}{2}} - C_{y,a}\right) e^{-\frac{M_a}{2}}$$

$$N_{y+1,m} = \left(N_{y,m} e^{-\frac{M_m}{2}} - C_{y,m}\right) e^{-\frac{M_m}{2}} + \left(N_{y,m-1} e^{-\frac{M_{m-1}}{2}} - C_{y,m-1}\right) e^{-\frac{M_{m-1}}{2}}$$

where,

$N_{y,a}$ is the number of tuna age *a* at the start of year *y*

$R\left(B_{y+1}^{sp}\right)$ is the spawners-recruits biomass relationship assumed

$C_{y,a}$ is the total number of tuna age *a* taken by the fishery in year *y*

M_a is the natural mortality rate for fish age *a*

m is the largest age considered (the "plus group")

The fishery is assumed to occur as a pulse catch in the middle of the year. The total number of tuna of age *a* caught each year ($C_{y,a}$) is given by:

$$C_{y,a} = \sum_f C_{y,a}^f$$

where,
f is fishery/fleet concerned (pelagic or ”longline”)

The mass of the fleet-specific annual catch (C_y^f) is given by:

$$C_y^f = \sum_{a=0}^{m} w_{a+\frac{1}{2}} C_{y,a}^f$$
$$= \sum_{a=0}^{m} w_{a+\frac{1}{2}} S_a^f F_y^f N_{y,a} e^{-\frac{M_a}{2}}$$

where,

S_a^f is the fleet-specific (pelagic or ”longline”) selectivity for tuna of age a
F_y^f is the fleet-specific (pelagic or ”longline”) fishing mortality for quarter y
$w_{a+\frac{1}{2}}$ is the weight at mid-quarter

The fleet-specific exploitable biomass is calculated as:

$$B_y^f = \sum_{a=0}^{m} w_{a+\frac{1}{2}} S_a^f N_{y,a} e^{-\frac{M_a}{2}} .$$

The proportion of the resource harvested each year (F_y^f) by fleet l is given by:

$$F_y^f = C_y^f / B_y^f$$

and

$$C_{y,a}^f = S_a^f F_y^f N_{y,a} e^{-\frac{M_a}{2}}$$

1.2.2. Spawning biomass-recruitment relationship

The spawning biomass in year y is:

$$B_y^{sp} = \sum_{a=0}^{m} f_a w_a N_{y,a}$$

where,
f_a is the proportion of sexually mature tuna at age a
(provided with the simulated data)

Ordinarily, the number of recruits is calculated using a Beverton-Holt relationship, but in this case, given prior knowlege about the lack of a relationship, recruitment is described by:

$$R_y = \alpha \exp(\tau_y - \tfrac{1}{2}\sigma_{SR}^2),$$
$$\tau_y = \rho\tau_{y-1} + \nu_y\sqrt{1-\rho^2};\nu \sim Normal(\mu = 0, \sigma_{SR}),$$

where sigma(SR) (the CV around the mean recruitment) and rho (deviation auto-correlation), are externally specified and α is estimated (after Buttterworth et al 2002).

1.2.3. Biomass trajectories

Given a value for the pre-exploitation equilibrium spawning biomass K^{sp} and assuming that the initial age structure is at equilibrium, the initial recruitment R_0 can be calculated as:

$$R_0 = K^{sp} / \left[\sum_{a=1}^{m-1} f_a w_a e^{-\sum_{a=0}^{a-1} M_a} + \left(f_m w_m e^{-\sum_{a=0}^{m-1} M_a} / \left(1 - e^{-M_m}\right) \right) \right]$$

Once the numbers-at-age of the pre-exploitation population have been calculated the population dynamics can be obtained through the previous equations.

1.3. Objective functions

To estimate the Fox and ASPM parameters, the model uses predicted and observed relative abundance indices (*I*) in a likelihood function. The likelihood is calculated assuming that the predicted index of abundance is simply B(t) in both cases. The observed abundance index is the appropriate nominal CPUE series, adjusted for changing catchability (if any):

$$I_y^l = (q_y) CPUE_y.$$

It is assumed that the observed indices are log-normally distributed about the expected value:

$$I_y^l = \hat{I}_y^l e^{\varepsilon_y^l} \text{ or } \varepsilon_y^l = \ln\left(I_y^l\right) - \ln\left(\hat{I}_y^l\right)$$

where,

The simplified negative log-likelihood function is given by:

$$-\ln(L) = \sum_y \left[\ln \sigma_y^l + \left(\frac{\left(\varepsilon_y^l\right)^2}{2\left(\sigma_y^l\right)^2} \right) \right]$$

Independent estimates of $N\left(0, \left(\sigma_y^l\right)^2\right)$ are not available so they are assumed not to be dependent on year (σ_y^l is simplified to σ_l). σ_l is estimated in the likelihood maximization process as:

$$s^{l}=\sqrt{\frac{\sum_{y}\left(e_{y}^{l}\right)^{2}}{n}}$$

where n is the number of data points in the abundance time series. The negative log-likelihood can be further simplified to:

$$-\ln\left(L\right)=n\ln\left(s^{l}\right)+\frac{n}{2}$$

Under this assumption, the maximum likelihood estimate of q^{l} (mean over time) is given by:

$$\hat{q}^{l}=\exp\left[\sum_{y}\left(\ln\left(I_{y}^{l}\right)-\ln\left(B_{y}^{l}\right)\right)\right].$$

Note that in some cases, better function minimization behaviour was achieved by estimating q as a free parameter, rather than using the analytical solution above.

In the ASPM, there is a second likelihood term corresponding to the prior on the quarterly recruitment deviations:

$$-\ln(L)=\sum_{y}(w_{y})^{2}\ .$$