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REDUCING PARAMETER COMPLEXITY IN MULTIFAN-CL STOCK ASSESSMENTS: CATCH CONDITIONING

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Introduction

MULTIFAN-CL is a statistical, age-structured, length-based model routinely used for stock assessments of tuna and other pelagic species. The model is typically fitted to total catch, size-frequency and tagging data stratified by fishery, region and time period. Recent tropical tuna assessments (e.g. Langley et al. 2007) encompass a time period of 1952–2006 in quarterly time steps, and model >20 separate fisheries occurring in 6 spatial regions. The main parameters estimated by the model include initial numbers-at-age in each region (constrained by an equilibrium age-structure assumption), the number in age class 1 for each quarter in each region (the recruitment), growth parameters, natural mortality-at-age (if estimated), selectivity-at-age by fishery (constrained by smoothing penalties or splines), effort deviations (random variations in the effort-fishing mortality relationship) for each fishery and catchability deviations (cummulative changes in catchability with time) for each fishery (if estimated). Parameters are estimated by fitting to a composite likelihood comprised of the fits to the data and prior distributions for various parameters.

The number of parameters estimated by these stock assessment models has grown to >5,000 in recent years, and will continue to grow as additional years are added to the data. While many of these parameters are subject to constraints of various types (bounds, priors, smoothing penalties, etc), such a large number of active parameters in the model is beginning to cause problems in parameter estimation, in particular convergence at local minima. Also, large computational resources are required to compute the Hessian matrix, from which confidence intervals of parameters and dependent quantities are derived. Another outcome of the large numbers of parameters is that techniques such as Monte Carlo Markov Chain (MCMC) cannot be used to obtain an estimate of the posterior density, from which comprehensive and probably more reliable estimates of uncertainty could be derived. It would therefore be desirable to find way to reduce the number of active parameters in MULTIFAN-CL stock assessment models.

A closer inspection of the parameter numbers for the 2007 yellowfin assessment (Table 1) reveals that a large proportion are related to the estimation effort devations (65%) and time series deviations in catchability (5%). Recruitment parameters (25%) also make up a large percentage of the total. Efforts have therefore focused on (1) eliminating effort deviations and catchability deviations as estimated parameters and (2) designing a more efficient recruitment parameterisation. In this paper, we report on part (1), the use of catch conditioning to eliminate effort deviations and catchability deviations as estimated model parameters.

Standard approach – stochastic total catch variation

The approach used to date in MULTIFAN-CL with respect to modeling the total catch observations has been to fit the model predictions of (the log of) the total catches to (the log of) the observations, assuming normally-distributed residuals.

Table 1. Numbers of estimated parameters in the 2007 yellowfin assessment.

Parameter category	Number	%
Tagging over-dispersion parameters	3	0.1
Tag reporting	21	0.4
Recruitment	1,316	25.1
Initial population	1	0.0
Growth	12	0.2
Selectivity	92	1.8
Catchability		
Average	19	0.4
Seasonality	42	0.8
Time-series deviations	272	5.2
Effort deviations	3,417	65.1
Movement	56	1.1
Total	5,251	100

The basic model equations for this framework are as follows (ignoring for simplicity spatial structure):

$$C_{atf} = \frac{F_{atf}}{\sum_f F_{atf} + M_a}\left[1-\exp\left(-\sum_f F_{atf} - M_a\right)\right]N_{at} \tag{1}$$

$$\log(F_{atf}) = \log(s_{af}) + \log(q_{tf}) + \log(E_{tf}) + \varepsilon_{tf} \tag{2}$$

$$\log(q_{t+1,f}) = \log(q_{tf}) + \eta_{tf} \tag{3}$$

where

C_{atf} is the catch in number of age-class *a* during time interval *t* by fishery *f*;

F_{atf} is the instantaneous rate of fishing mortality of age-class *a* during time interval *t* by fishery *f*;

M_a is the instantaneous rate of natural mortality of age-class *a*;

N_{at} is the population number of age-class *a* at the beginning of time interval *t*;

s_{af} is the selectivity coefficient of age-class *a* for fishery *f*;

q_{tf} is the catchability coefficient for fishery *f* during time period *t*;

E_{tf} is the fishing effort for fishery *f* during time period *t*;

ε_{tf} is a robustified, normally-distributed effort deviation for fishery *f* during time period *t*, representing relatively large transient deviations in the effort – fishing mortality relationship; and

η_{tf} Is a normally-distributed catchability deviation for fishery *f* during time period *t*, representing relatively small, cumulative changes in catchability.

The catch likelihood contribution is then:

$$\Theta_c = p_c \sum_t \sum_f \left\{ \log\left(1 + C_{tf}^{obs}\right) - \log\left(1 + C_{tf}^{pred}\right) \right\}^2 \tag{4}$$

where:

$$C_{tf}^{pred} = \sum_a C_{atf} \tag{5a}$$

for fisheries with catches expressed in numbers of fish and

$$C_{tf}^{pred} = \sum_a C_{atf} W_a \tag{5b}$$

for fisheries with catches expressed in weight.

The weighting factor p_c is determined by the prior assumption made about the precision of the observed total catch data.

In this approach, the effort deviations and catchability deviations must be estimated as model parameters, with the following contributions to the objective function:

$$\Theta_\varepsilon = -\sum_f p_{\varepsilon f} \sum_t \varepsilon_{tf}^2 \tag{6}$$

for effort deviations (ignoring for simplicity robustifying terms) and

$$\Theta_\eta = -\sum_f p_{\eta f} \sum_t \eta_{tf}^2 \tag{7}$$

for catchability deviations.

The weighting factors $p_{\varepsilon f}$ and $p_{\eta f}$ are appropriately set to reflect prior assumptions about the variability of effort deviations and catchability deviations, respectively.

Catch-conditioned approach

In the catch-conditioned approach, the observed total catches are assumed to be known without error, i.e. $C_{tf}^{pred} = C_{tf}^{obs}$. Considering all observations of total catch by a fishery in a particular time period *t* leads to the following system of equations:

$$C_{tf}^{obs} = \sum_a C_{atf} \text{, for } f = 1, \ldots, r \text{ fisheries} \tag{8}$$

$$C_{atf} = f\left(\lambda_{tf}, s_{af}, N_{at}, M_a\right) \tag{9}$$

N_{at}, M_a and s_{af} are parameters provided by the function minimizer, leaving *r* unknowns (λ_{tf}) and *r* constraints (equation 8). The λ_{tf} are equivalent to fishing mortality at full selectivity, i.e. $q_{tf}E_{tf}$; therefore $F_{atf} = \lambda_{tf} s_{af}$. The λ_{tf} can then be solved using the Newton-Raphson (NR), which converges trivially in one iteration for simplified catch equations of the form:

$$C_{atf} = F_{atf} \exp(-M_a/2)N_{at} \tag{10}$$

$$N_{a+1,t+1} = N_{at} \exp(-M_a)\left(1 - \sum_f F_{atf}\right). \tag{11}$$

We term this form of catch equations the "SS2 form". A similar approach may be taken with the Baranov form of catch equations; however the NR requires more iterations to converge, resulting in longer computation time. Note that this iterative NR occurs within a single iteration of the overall function minimizer. We have found it useful to initially fit the model from arbitrary starting conditions using the SS2 form of catch equations. Once convergence is obtained the fit can continue using the Baranov form. However, in all trials run to date, we have found that the SS2 form actually fits the WCPO tuna data better than the Baranov form. Given the considerable difference in computation time, this is a pleasing result.

The main technical difficulty that must be dealt with in using the approach described above is that of stability – for any particular iteration of the function minimizer, it is possible to have a set of parameters that will result in the observed catch being larger than the population. This would normally cause the NR algorithm to blow up. However, we deal with this situation by altering the catch equations to allow the system to differentiably transition into a physically impossible, but mathematically tenable state, allowing NR to converge and the overall function minimization to continue. A penalty is added to the objective function in such occurrences, which encourages the function minimizer to converge to a physically meaningful as well as a mathematically tenable solution.

Note that the penalty functions the equivalent of equations (6) and (7) may still be included in the objective function to allow the fishing effort data to impact parameter estimation. For fisheries in which catchability is assumed to be constant, $\varepsilon_{tf} = \log(\lambda_{tf}) - \log(q_{.f} E_{tf})$. For fisheries in which time-series trends in catchability are assumed to occur, a sub-optimization is carried out to estimate q_{tf} by minimizing:

$$\Theta_q = \sum_f \sum_t \left(\lambda_{tf} - q_{tf}\right)^2 + p_{qf}\left(q_{tf} - q_{t-1,f}\right)^2. \tag{12}$$

For the normal case, shown in equation (12), the minimization can be performed very efficiently in one NR iteration. When robustifying terms are added to $\left(q_{tf} - q_{t-1,f}\right)^2$, optimization is more complex requiring higher-precision computation.

Application to yellowfin tuna

Both the standard and the catch-conditioned models were applied to the yellowfin tuna data set, slightly modified from that used in the 2007 assessment (Langley et al. 2007). A modified data set was required because the catch-conditioned model has not yet been formulated to deal with missing catches. Therefore, missing catches, primarily for the various longline fisheries in 2006, were changed to missing effort, which could be accommodated.

Table 2. Likelihood components for the standard and catch-conditioned models, as applied to WCPO yellowfin tuna.

Likelihood component	Standard	Catch conditioned
Number of active parameters	5,513	1,761
Effort deviation penalties	6,370.9	4,679.8
Catchability deviation penalties	224.0	3,910.7
Other penalties	395.2	391.1
Length data	-349,873.3	-349,833.6
Weight data	-760,792.9	-760,715.5
Tagging data	2,626.0	2,638.8
Total catch data	578.3	
TOTAL	-1,100,471.9	-1,098,928.8

Table 2 provides a comparison of the likelihood components obtained using the two models. The number of active parameters has been greatly reduced with the removal of effort deviations and catchability deviations as active parameters in the catch-conditioned model. In the case of the effort and catchability deviation penalties, the effort deviation contribution is considerably reduced, while the catchability deviation contribution is much increased in the catch-conditioned model. The reason for this is that, in the standard model, catchability deviations are computed at two-yearly intervals. At this stage, this feature has not been incorporated into the catch-conditioned model, and the default is that catchability deviations are computed at each time step (quarter). Therefore, many more catchability deviations are being computed attracting a larger overall penalty. Conversely, the effort deviation penalty is smaller in the catch-conditioned version due to more of the variability being allocated to catchability deviations. For the other likelihood components, the values for the catch-conditioned model are generally somewhat greater, although of course there is no total catch contribution to the catch-conditioned likelihood.

A comparison of the main results of the two models is shown in Figures 1–3. Recruitment estimates (Figure 1) are very similar between the two methods, with the catch-conditioned estimates being slightly higher (by 9% overall). Likewise, the biomass estimates (Figure 2) show the same trend, but are slightly higher (by 10% overall) for the catch-conditioned estimates. However, the ratios of biomass to the biomass at maximum sustainable yield (B/B_{MSY}) obtained from the two models are practically identical. The equilibrium yield – fishing mortality relationship (Figure 3) is also consistently estimated by the two models, although there is some divergence in equilibrium yield at levels of fishing mortality greater than the current levels.

Discussion

Based on preliminary tests, it appears that the catch-conditioned model can closely approximate the main results of the standard model. However, some further development of the software is required, e.g., treatment of missing effort or catch or catch observations. Further testing will be conducted over the next year, with the intention of adopting the catch-conditioned approach as the standard for MULTIFAN-CL stock assessments. Further work on reducing the complexity of the recruitment parameterization is also in progress.

References

Langley, A., Hampton, J., Kleiber, P., and Hoyle, S. 2007. Stock assessment of yellowfin tuna in the western and central Pacific Ocean, including an analysis of management options. WCPFC/SC3 SA-WP-1.

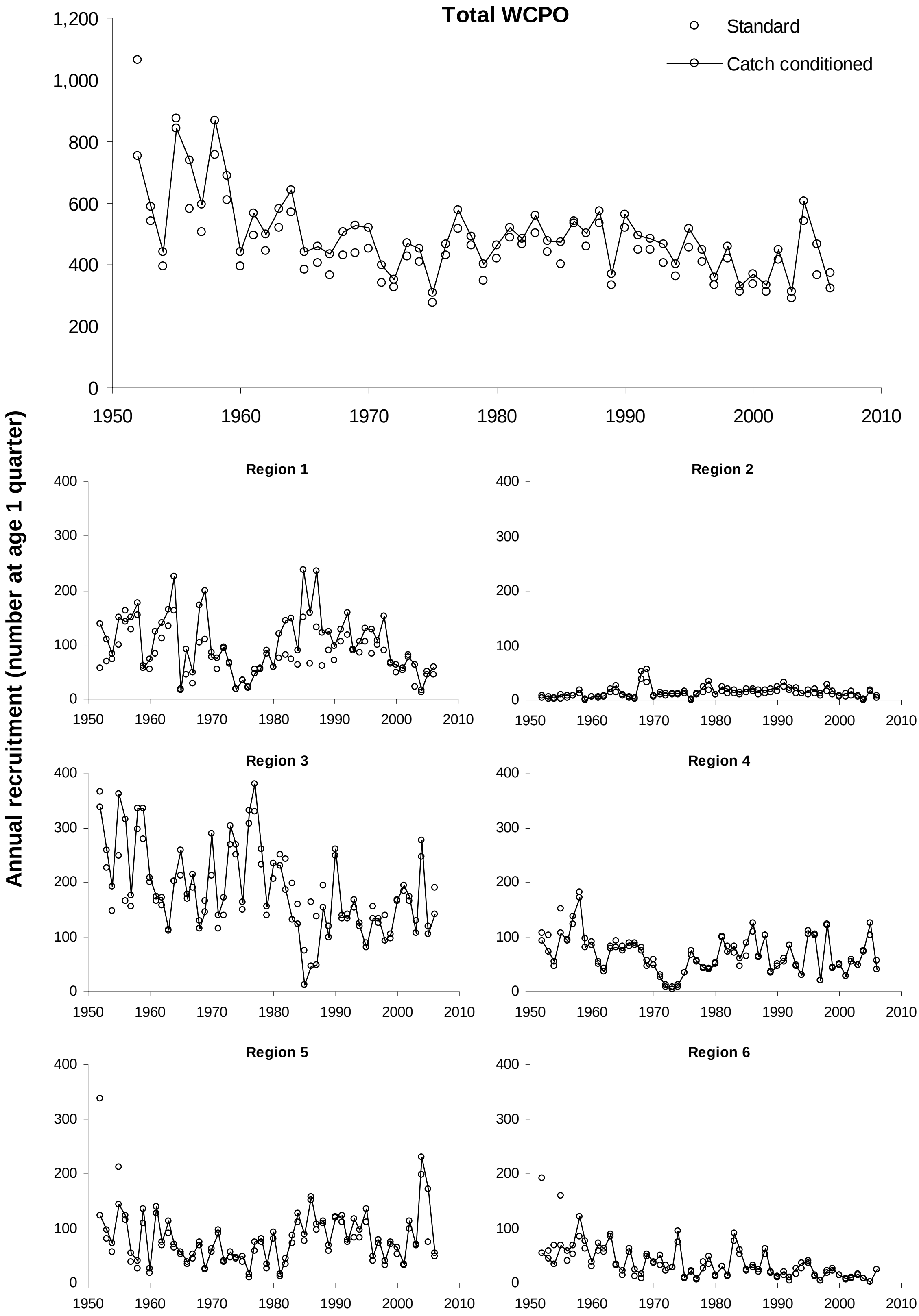

Figure 1. Yellowfin tuna recruitment estimates for the standard and catch-conditioned models.

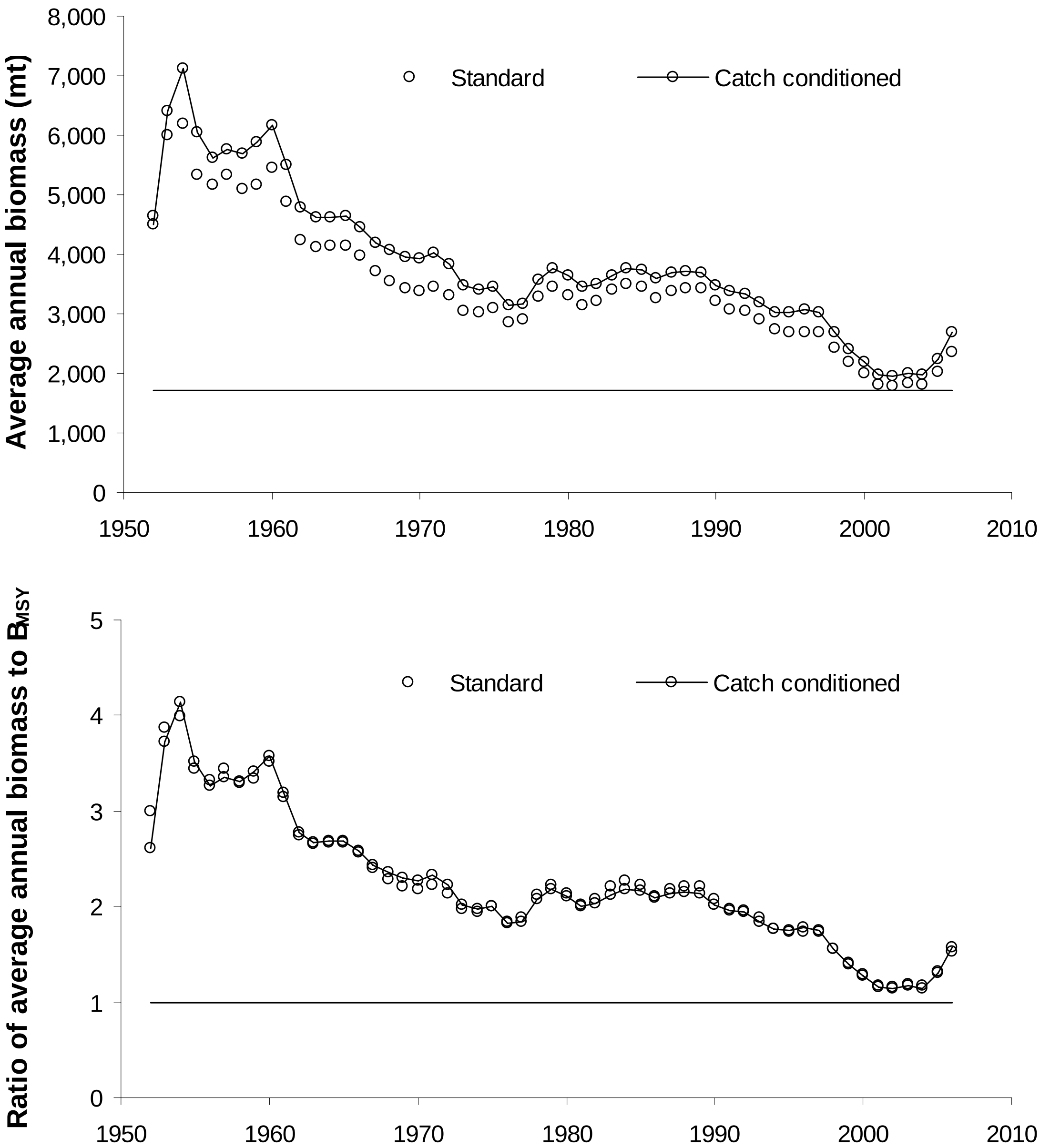

Figure 2. Yellowfin total biomass and B/B_{MSY} estimates for the standard and catch-conditioned models. The horizontal lines in the upper panel are the B_{MSY} estimates for the respoective models.

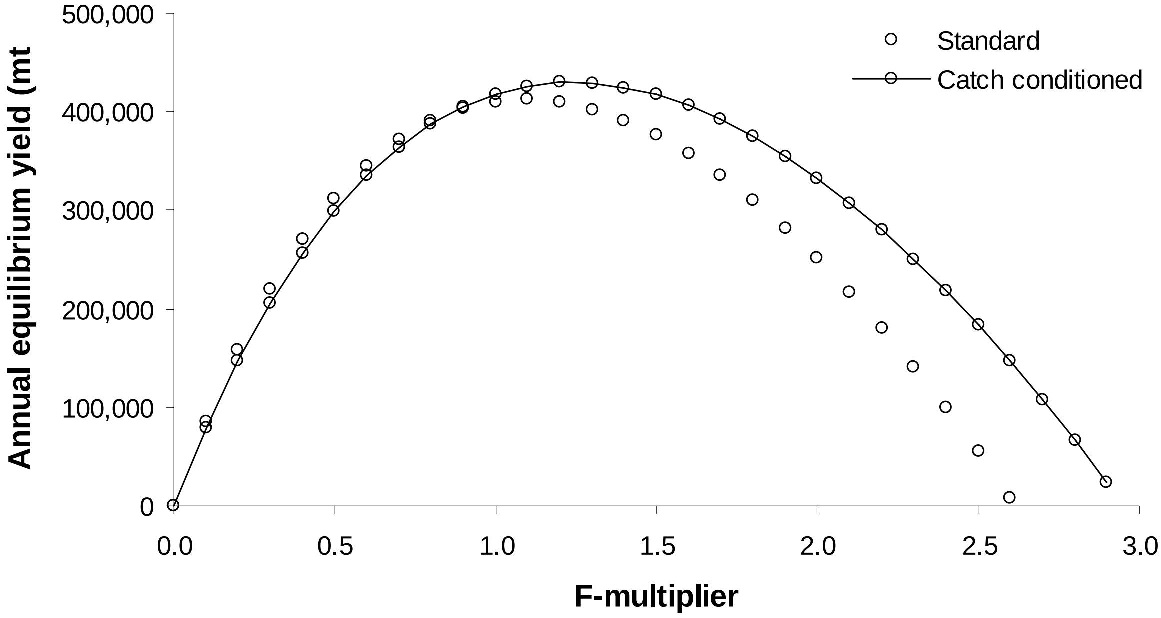

Figure 3. Equilibrium yield curves for yellowfin tuna estimated using the standard and catch-conditioned models.