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Technical specifications and proof of concept analyses for candidate management procedures for southern bluefin tuna

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Contents

Abstract

This report details the development of candidate management procedures (henceforth, CMPs) for application to the Southern bluefin tuna (*Thunnus maccoyii*) stock and fishery. A selection of model-free and model-based approaches are defined and explored. For the model-based approaches an in-depth proof-of-concept analysis is performed to assess the information in the historical data, in relation to the models considered, and the potential utility of the information derived from these models in a management procedure context is discussed.

1 Introduction

The purpose of this document is to give a detailed explanation of the CMPs tested in document CCSBT-OMMP/1006/5, the ideas behind their functional forms and for the model-based CMPs an in-depth look at the information content in the historical data and the potential utility of the information derived using these models in the CMPs themselves. The document is structured as follows:

- An exploration of two model-based approaches: (i) a biomass-dynamic approach utilising the catch biomass, CPUE and the aerial survey data, and (ii) a relative abundance approach using random effects to explain the juvenile and adult biomass dynamics linked to the aerial survey and CPUE data, respectively.
- Possible model-free MPs that utitlise the aerial survey data only
- For all the CMPs the parameters that will be tuned, given the various criteria outlined in the SFMWG meeting report.

2 Model-based CMPs using the CPUE and the aerial survey data

A selection of model-based MPs were explored based on two distinct approaches: biomass dynamic utilising catch biomass, CPUE and the aerial survey data; and relative abundance using only the CPUE and aerial survey in an integrated relative abundance model.

2.1 Biomass dynamic approach

The originally selected MP was based around a Fox biomass-dynamic model while employing the catch composition information to make adjustments to the Fox-predicted TAC given recruitment trends. Our intension was to replace the Fox model with the Pella-Tomlinson model (for reasons outlined later) and to use the aerial survey information rather than the catch composition information to adjust the TAC based on recruitment trends.

The Pella-Tomlinson model [1] is a generalisation of the standard Schaefer model for the aggregated biomass, B_y, of an exploited population:

$$B_{y+1} = B_y + rB_y\left(1 - \left[\frac{B_y}{K}\right]^{m-1}\right) - C_y, \tag{1}$$

where r and K are the intrinsic growth rate and carrying capacity, respectively, and m is a shape parameter controlling the shape of the surplus production curve. The harvest rate expected to produce maximum sustainable yield is $h_{\text{msy}} = r\left(1 - m^{-1}\right)$ with an associated equilibrium yield and biomass of $C_{\text{msy}} = rK\left(1 - m^{-1}\right) / \sqrt[m-1]{m}$ and $B_{\text{msy}} = K/\sqrt[m-1]{m}$, respectively. When fitting such a model to relative abundance data such as CPUE there is usually very strong negative correlation between K and the catchability coefficient q. To reduce this correlation we non-dimensionalise the biomass via K, so $B_y = b_yK$, and obtain

$$b_{y+1} = b_y + rb_y\left(1 - b_y^{m-1}\right) - \frac{C_y}{K}, \tag{2}$$

so that the constant of proportionality relating relative biomass to model-predicted relative abundance: $\widehat{I}_y = Qb_y$ is effectively qK and this can significantly reduce the levels of correlation between Q and K. The reason for doing this is given the "blind" estimation of the key parameters in the MP testing (we either have fixed starting values or a crude algorithm to generate them) then the gradient-based optimiser might perform better with a less-correlated structure to the objective function's surface.

Only the parameters r and K are estimated within the MP - the kind of data informative enough for reliable estimates of both r and K are rare but data with enough information to estimate all three parameters are much rarer still. The value of $m = 1.05$ was assumed because this is the value which is as close as possible to the Fox model used in the previous MP work: the ratio of B_{msy} to K is 0.38 whereas in the Fox model it is 0.37 and the shape and magnitude of the surplus production curves are very similar. A log-normal objective function relating model-predicted to observed CPUE was assumed with the catchability coefficient Q estimated as a nuisance parameter.

2.1.1 Constructing a prior for r

One potential issue with this approach is the estimability of both r and K at the same time. The data exhibit certain "one-way trip" characteristics: the CPUE shows a general decreasing trend with little or no observed recovery with decreased catches over time suggesting that, with the purely historical data, estimating r and K sensibly might be difficult. It is entirely possible and perhaps expected that under the action of an MP where stock recovery begins to occur the information required to estimate both the parameters could develop in the data, but until this happens it might be sensible to constrain the parameters in some fashion. It is hard to imagine how we might sensibly form a prior for K given it is a dimensional parameter, but with r we can perhaps do something.

The Euler-Lotka equation [2] combines the key life-history traits of a given animal (reproductivity, maturity, growth, and natural mortality) and the parameter r into one expression:

$$\sum_{a=0}^{\infty} e^{-ra} m_a w_a \pi_a^s \alpha = 1. \tag{3}$$

In (3) a is the age of the animal, m_a the proportion mature-at-age, w_a the weight-at-age, π_a^s the survival probability to age a from birth:

$$\pi_a^s = \prod_{i=0}^{a-1} \exp\left(-M_i\right), \tag{4}$$

where M_a is the natural mortality-at-age a. Finally, α are the recruits-per-unit-SSB at zero population size - essentially the same parameter from the Beverton-Holt or Ricker models - and is related to the steepness, h, by $\alpha = 4h/(\rho(1-h)$ in the Beverton-Holt model, where ρ is the SSB-per-recruit:

$$\rho = \sum_{a=0}^{\infty} m_a w_a \pi_a^s. \tag{5}$$

In practice ∞ is replaced by the maximum age-class and a plus group is assumed. Both h and M_a are quasi-estimated in the grid runs, conditioned on the catch biomass and CPUE data, so there is a little bit of data recycling going on by using the grid outputs to estimate a prior distribution for r. However, given the historical data do not permit the reliable estimation of r and K and may not until sufficient stock recovery occurs a Bayesian approach to stabilise the MP's parameter estimates, via an informative prior for r, was deemed sensible and such an approach has been advocated before for tunas and elasmobranchs [3]. The Euler-Lotka equation in (3) was solved for each of the 2000 grid cells and the resultant sample for r was bootstrapped with replacement (to robustify the estimates given the "banding" with steepness and M-levels) to obtain a log-scale mean and standard deviation for a log-normal prior for r with mean 0.156 and CV 0.159. In the MP testing maximum posterior density estimates are used but for the proof of concept analyses Bayesian and MCMC methods are used to explore the precision of the estimates of the key parameters and the uncertainty in the process variables derived from them and used in the MPs. For the catchability parameter the natural logarithm of this parameter is actually estimated: an assumed normal prior is conjugate to the likelihood function making the conditional posterior of $\ln(Q)$ normal and, hence, easy to re-sample in the Metropolis-within-Gibbs sampling regime. As mentioned a log-normal prior is assumed for r and K is assigned a uniform prior on $\mathbb{R}^+$.

Figure 1 is a summary of the (marginal) posteriors of the estimated parameters Q, r and K. The estimate of r is somewhat updated from its prior ($p\left[r > r_{\text{prior}}\right] = 0.831$) with a slightly higher CV of 0.18. It should be noted that as one relaxes the constraints of the prior for r the estimates become increasingly unstable and are increasingly strongly negatively correlated with K and a very long tail forms in the joint posterior of both parameters. There is some information on r in the data but still not enough to permit a fully free estimation. The estimate of K is very precise with a CV of 0.022. The resultant biomass dynamics and fits to the CPUE data can be seen in Figure 2. The biomass trend largely mirrors that seen in the OM (albeit with a more optimistic depletion ratio of about 0.14) with biomass currently estimated to be well below B_{msy}. The fits to the CPUE data are noticeably worse than those observed in the OM given the limited nature of the model and its inability to explain in particular the recent CPUE variation using r, K, the model and catches alone.

2.1.2 MPs with aerial survey as an external index

Given the estimates of r and K from the Pella-Tomlinson model fitted to the CPUE and catch biomass data we first considered two CMPs that use r, K and m to construct an essentially $h_{\rm msy}$ core strategy (as with the previously selected MP) with an extra adjustment made based on trends in the aerial survey data. The first set of CMPs are called `PellaT1` and `PellaT2` where the initial TAC in year y when a potential change is scheduled is given by

$$TAC_y = \varphi_{{\rm msy},i}\left(B_y, \delta, \epsilon, C_{\rm msy}, B_{\rm msy}\right) \times \varphi_{AS}\left(\alpha, \epsilon, \mu_{AS}, \rho_{AS}\right), \tag{6}$$

for $i = 1, 2$ relating to the two CMPs where

$$\varphi_{{\rm msy},1}\left(\circ\right) = \begin{cases} \delta C_{\rm msy}\left[\dfrac{B_y}{B_{\rm msy}}\right]^{\epsilon} & \text{for} \quad B_y \geq B_{\rm msy} \\ \delta C_{\rm msy}\dfrac{B_y}{B_{\rm msy}} & \text{for} \quad B_y < B_{\rm msy} \end{cases} \tag{7}$$

and

$$\varphi_{{\rm msy},2}\left(\circ\right) = \begin{cases} TAC_{y-1}\left[1 + \epsilon\delta\left(B_y - B_{\rm msy}\right)\right] & \text{for} \quad B_y \geq B_{\rm msy} \\ TAC_{y-1}\left[1 + \delta\left(B_y - B_{\rm msy}\right)\right] & \text{for} \quad B_y < B_{\rm msy} \\ 0 & \text{for} \quad B_{\rm msy} - B_y > \delta^{-1} \end{cases} \tag{8}$$

where δ is the key tuning parameter and $\epsilon \in [0, 1]$ permits the potential for smaller proportional increases in TAC than decreases. The function $\varphi_{AS}(\circ)$ is defined as

$$\varphi_{AS}\left(\circ\right) = \begin{cases} 1 + \epsilon\alpha\left(\mu_{AS} - \rho_{AS}\right) & \text{for} \quad \left(\mu_{AS} - \rho_{AS}\right) \geq 0 \\ 1 + \alpha\left(\mu_{AS} - \rho_{AS}\right) & \text{for} \quad \left(\mu_{AS} - \rho_{AS}\right) < 0 \\ 0 & \text{for} \quad \rho_{AS} - \mu_{AS} > \alpha^{-1} \end{cases} \tag{9}$$

where μ_{AS} is a 4 year log-scale moving average of the aerial survey (calculated between $y - \beta - 4$ and $y - \beta$) with β a lagging parameter, and ρ_{AS} is a log-scale reference/target level of the aerial survey. The main idea of the two CMPs is to have one (`PellaT1`) that adapts the current catch around MSY relative to the current stock status and dynamics, and the other (`Pellat2`) which adapts the *previous* TAC given the same stock status and dynamic information.

2.1.3 An integrated model and MP using the CPUE and aerial survey data

A second approach looked to integrate the CPUE and aerial survey data together in one estimation scheme. The population model is an augmented version of the Pella-Tomlinson model defined in (2)

$$b_{y+1} = \left[b_y + rb_y\left(1 - b_y^{m-1}\right) - C_y/K\right] e^{\epsilon_y^{RB} - \sigma_{RB}^2/2} \tag{10}$$

The two main questions with this kind of approach are:

1. How much does annual variation in recruitment contribute to annual variation in the exploitable biomass - what is the right value of σ_{RB} given some assumed age 0 recruitment SD σ_r?
2. The aerial survey covers ages 2, 3 and 4 by assumption - what is the correct delay when relating these aggregate recruitment proxy data to variation in the exploitable biomass?

The first question can be solved via simulation. Using the life-history parameters (M and weight-at-age etc.) simulate the stochastic dynamics of SBT for a given level of σ_r and a simple fixed deterministic recruitment level until quasi-equilibrium is achieved. Then for the relevant age classes thought to constitute the exploitable biomass calculate the associated uncertainty in this biomass due to recruitment variation alone. For a given value of $\sigma_r = 0.6$ (assumed in the OM) the resultant uncertainty in the exploitable biomass (ages 4-12/18) ranges from 0.18-0.16: the more cohorts that make up the exploitable stock, the lower the impact the individual variance in these cohorts has on the variance in the exploitable stock.

The second question is really more to do with defining how the signal in the aerial survey relates to information on ϵ_y^{RB} - we are never directly modelling actual age 0 recruitment events only how their appearance in the aerial survey might then relate to a signal in the exploitable stock. In this regard perhaps the easiest solution is to relate the biomass year effects in year y to the aerial survey data in year $y-1$. There is a 1 age-class overlap assumed between the age-classes in the aerial survey and CPUE data anyway and it forms the maximum and minimum age-classes, respectively, assumed present in the two indices.

In terms of likelihood models for the aerial survey data the following is assumed: Let the log-scale aerial survey series, standardised to have mean zero, be denoted by $\tilde{I}_y^{AS}$. The aerial survey recruitment effects ϵ_y^R are then assumed to follow a normal distribution: $\tilde{I}_{y-1}^{AS} \sim N\left(\epsilon_y^R, \sigma_{AS}^2\right)$ and are penalised to have zero mean across the estimated range and variance σ_R^2 (assumed total variation in the aerial survey) in any given year. The biomass recruitment effects are then derived as follows: $\epsilon_y^{RB} = \phi\epsilon_y^R$, where $\phi = \sigma_{RB}/\sigma_R$ is a rescaling parameter to ensure that the recruitment-driven variation in the exploitable biomass is controlled to levels we are expecting (namely σ_{RB}). The biomass recruitment effects before the aerial survey data are available are all assumed to be equal to 1 (i.e. in effect equal to $\sigma_{RB}^2/2$). Values of $\sigma_{AS} = 0.15$ and $\sigma_R = 0.38$ (a CV of 0.4) were assumed given the current levels of precision in the aerial survey standardisation and the assumed CVs of between 0.3 and 0.5 for the aerial survey as generated by the OM.

Figure 4 shows the estimates of the aerial survey year effects, ϵ_y^R, the associated biomass year effects, ϵ_y^{RB}, and the stock biomass. In terms of estimates of r and K the prior for r is now barely updated at all: the posterior mean and CV are 0.165 and 0.16 and ($p\left[r > r_{\text{prior}}\right] = 0.567$) and the estimates of K are a little smaller than before. The interesting kink in the biomass dynamics is caused by the assumption that before the aerial survey all biomass year effects were equal to 1 and that after that they are driven by the trend in the aerial survey but have mean 1 across that year range. Given the substantial decrease in the recruitment signal in the aerial survey post-1996 the model interprets the years 1994-1997 as being better than average recruitments and those that followed significantly lower than average. In terms of fits to the data seen in Figure 5 the aerial survey data are fitted fairly well as are the CPUE apart from the years where the aforementioned kink in the biomass data occurs.

In terms of an MP using the augmented set of estimated parameters and variables the following was considered:

$$TAC_y = \varphi_{\text{msy},i}\left(B_y, \delta, \epsilon, C_{\text{msy}}, B_{\text{msy}}\right) \times \left[\prod_{i=y-\tau+1}^{y} \exp\left(\epsilon_i^R - \epsilon_{i-1}^R\right)\right]^{\frac{\gamma}{\tau}} \tag{11}$$

where δ is as defined before and $i = 1, 2$ denotes which of the MSY target forms to use, τ is the time-frame over which the geometric mean is calculated, and these CMPs are called `PellaT1yreff` and `PellaT2yreff`. The second part of the MP is the (geometric) moving average of the estimated relative recruitment ratio from year to year. The parameter $\gamma \geq 0$ is an influence weighting: for $\gamma = 0$ the term has no effect and for increasing γ this part of the MP gains influence.

2.2 Relative abundance approach

The second model-based approach is a relative abundance one where the dynamics of the adult biomass are decomposed into random recruitment and growth effects. This approach uses a variant on a model advocated in [4] which looked to estimate trends in recruitment and adult biomass as well as adult biomass net growth using random-effect methods. The core population model is itself very simple: recruitment (R_y) and adult (B_y) biomass are related as follows:

$$B_{y+1} = R_y + g_y B_y, \tag{12}$$

where g_y is the adult biomass net growth parameter (encompassing natural mortality, growth and exploitation effects). For the recruitment process the following model is assumed:

$$R_y = \exp\left(\mu_R + \epsilon_y^R\right), \tag{13}$$

with $\epsilon_y^R \sim N\left(-\sigma_R^2/2, \sigma_R^2\right)$. For the g_y a conceptually similar model is assumed and

$$g_y = \exp\left(\mu_g + \epsilon_y^g\right), \tag{14}$$

with $\epsilon_y^g \sim N\left(-\sigma_g^2/2, \sigma_g^2\right)$. For the aerial survey data I_y^{AS} a lognormal relationship to the recruiting biomass is assumed but with a one-year delay: $I_y^R \sim LN\left(q^R R_{y+1}, \sigma_{AS}^2\right)$. The reason for this delay is because we assume that the aerial survey covers ages 2 to 4 and that the CPUE covers ages 4 to 12/18. To make sure that we are more likely to detect the movement of a signal in the aerial survey appearing in the CPUE data this delay is assumed as R_y represents the recruitment biomass contribution to the adult biomass (assumed covered by the CPUE). The situation is simpler for the CPUE likelihood and these data are assumed log-normally distributed about the adult biomass: $I_y^B \sim LN\left(q^B B_y, \sigma_B^2\right)$.

The model as it stands is non-identifiable which was explored at length in [4]. Without at least some information as to the ratio of the recruit and adult catchability parameters q^R/q^B then it will be impossible to identify how much recruitment affects biomass trends and how much the net growth of the biomass affects the biomass trends. To solve this problem we look to the output from the OM runs. From the grid runs we can extract the log catchability parameters for both the aerial surveys and the CPUE data. Given the grid samples over parameters that will clearly alter this ratio (natural mortality, steepness, age range covered by the CPUE) we bootstrapped the mean difference in the log-catchabilities to obtain a best estimate of this ratio. The bootstrapped mean ratio was very precise (around a 3% CV) with an expected value of $q^{AS}/q^{CPUE} = 50280.15$. However, we need to account for the fact that the CPUE in the OM is in *numbers* but here we are trying to relate biomass to biomass. To take account of this in our catchability ratio consider the following ratio:

$$\psi_q = \frac{\sum_{i=a_l}^{a_u} \pi_i^s w_a}{\sum_{i=a_l}^{a_u} \pi_i^s} \tag{15}$$

where π_i^s is the survival probability from age 0 to age i and a_l and a_u are the minimum and maximum ages observed in the CPUE, respectively. This ratio is readily calculable from the grid files outputted from the OM. For each sampled grid cell this ratio was calculated and then a bootstrapped mean and CV were calculated, to robustify the estimates given the banding by M grid option. As with the q ratio estimates the numbers were very precise: a mean and CV of 0.0619 and 0.024, respectively. Assuming $q^B = 1$ this lead to a value of $q^R = q^{AS}/q^{CPUE} \times \psi_q = 3111.136$.

The actual parameters to be estimated are μ_R, μ_g, ϵ_y^R and ϵ_y^g. To avoid identification issues with the recruitment in the first year and net growth year effects in the last year, respectively, they were penalised to have mean zero across years (with $-100 \times |\mathbb{E}[\epsilon_y^\bullet]|$ extracted from the log-likelihood). As with the production models although maximum posterior density estimates were used in the MP testing full MCMC routines were developed to explore the parametric and process variable uncertainty in the underlying models in this phase - the chief reason being we can obtain more detailed information about the variation in the derived trends such as stock growth, recruitment and biomass not retrievable from the ADMB runs. While using the term random effect to be clear this model is more of a Bayesian hierarchical model with a Dirac hyperprior on the variance hyperparameters $\sigma^2_{R,g}$. This contrasts with the strict view of a random effects model which utilises expectation/maxmimisation to estimate all the key parameters: expectation where the joint penalised likelihood of the $\mu_\bullet$ and $\epsilon_y^\bullet$ is integrated over the $\epsilon_y^\bullet$ and maximisation where this marginal likelihood is then maximised for the $\mu_\bullet$.

Figure 6 shows the marginal posterior summary for the parameters μ_R and μ_g and the parameters have posterior mean (and SD) of -1.89 (0.069) and

-0.403 (0.048), respectively, with fairly strong negative correlation between them (-0.59) as one would expect if recruitment makes a significant contribution to the exploitable biomass. The estimated trends in recruit biomass, adult biomass and biomass growth can be seen in Figure 7. For the relative recruitment biomass estimates we observe a sharp decline around 1998 (as seen in 1997 in the aerial survey) hitting the lowest level in 2000. From 2001 to 2004 the estimates are driven by the prior and penalty terms given the absence of data in the aerial survey with the levels of recruitment in 2005 to 2008 staying around the low level. In the years where there are data to estimate the recruitment trend the CVs ranged from 0.128 to 0.146. For the relative adult biomass estimates first to point out that we assume that $B_{1994} = I^B_{1994}/q^B$ and that it is known without error (there are no data to estimate it and we assume a relative abundance model anyway). As one would expect the trend follows that in this particular CPUE series (including the gradual decline from 2002-2007 and the sudden upturn in 2008). The CVs in the estimates (excluding 1994) range from 0.116 to 0.158 with a sustained increase in uncertainty in the middle of the range given the uncertain recruitment dynamics. For the biomass growth estimates they oscillate below 1 until 2002 when they show a marked decline as they alone can explain the biomass decline seen in 2002-2007 as recruitment has already dropped to the lower level by 1998. Clearly the sudden increase in 2008 in the biomass cannot be explained by recruitment and so the biomass growth parameter in 2007 increases to a value just above 1 in this year. The estimate in 2008 is driven by both the prior and the penalties and should not be viewed with close scrutiny. One final general observation would be that the biomass growth parameters are never above 1 with a probability greater than 0.3 and this occurs only once in 2001 given the high CPUE observed in 2002. This suggests that the exploitable biomass is essentially being sustained by the recruitment with total mortality dominating growth for this portion of the stock.

In terms of fits to the data Figure 8 shows a summary of the estimators performance in this regard. For the aerial survey data they are generally fitted quite well but the extremes in these data (the apparently higher variance earlier on) are not fitted so well, presumably given the assumed value of σ_R. For the CPUE data they are also fitted quite well but the model cannot fit the more extreme changes observed in the CPUE - the data never sit outside the 95% credible interval but the median fitted CPUE is much smoother than the observed data. This again is due to the natural constraints placed upon both the recruitment and biomass growth effects via

σ_R and σ_g, respectively.

2.2.1 Relative abundance MPs

As was the case for the production model based CMPs essentially two forms, `brem1` and `brem2`, are explored using the information from the relative abundance model: one where a reference catch level (similar to the idea of adapting C_{msy}) is adjusted given the conditions, and another where the previous year's catch is adjusted given the conditions.

$$TAC_y = \varphi_{\text{brem},i}\left(B_{y-2}, \delta, \epsilon, B^*\right) \times \left[\prod_{i=y-\tau-1}^{y-2} \frac{R_i}{R_{i-1}}\right]^{\frac{\gamma}{\tau}} \times \left[\prod_{i=y-\tau-1}^{y-2} \frac{g_i}{g_{i-1}}\right]^{\frac{\gamma}{\tau}} \tag{16}$$

As before $i = 1, 2$ relates to the two CMPs where

$$\varphi_{\text{brem},1}\left(\circ\right) = \begin{cases} \delta\left[\dfrac{B_{y-2}}{B^*}\right]^{\epsilon} & \text{for} \quad B_{y-2} \geq B^* \\ \delta\dfrac{B_{y-2}}{B^*} & \text{for} \quad B_{y-2} < B^* \end{cases} \tag{17}$$

and

$$\varphi_{\text{brem},2}\left(\circ\right) = \begin{cases} TAC_{y-1}\left[1 + \epsilon\delta\left(B_{y-2} - B^*\right)\right] & \text{for} \quad B_{y-2} \geq B^* \\ TAC_{y-1}\left[1 + \delta\left(B_{y-2} - B^*\right)\right] & \text{for} \quad B_{y-2} < B^* \\ 0 & \text{for} \quad B^* - B_{y-2} > \dfrac{1}{\delta} \end{cases} \tag{18}$$

where δ is the key tuning parameter and as before $\epsilon \in [0, 1]$ permits the potential for smaller proportional increases in TAC than decreases, and $\gamma > 0$ is an influence weighting, driving the relative impact of the trends in recruitment and biomass growth on the TAC. The parameter B^* is a target/reference relative biomass level, in fact given $q^B = 1$ it is a target CPUE level making it very easy to define given the OM-predicted relationship between historical CPUE and SSB.

3 Model-free CMPs using the aerial survey data

To explore the potential utility of an MP that uses only the aerial survey data the following simple index-based MP, `ASMP`, was envisaged:

$$TAC_y = \begin{cases} \delta \left[\exp\left(\mu_{AS} - \rho_{AS}\right)\right]^{\epsilon} & \text{for} \quad \mu_{AS} \geq \rho_{AS} \\ \delta \exp\left(\mu_{AS} - \rho_{AS}\right) & \text{for} \quad \mu_{AS} < \rho_{AS} \end{cases} \tag{19}$$

where

$$\mu_{AS} = \frac{1}{\beta} \sum_{i=y-\beta}^{y-1} \ln\left(I_i^{AS}\right). \tag{20}$$

The parameter δ is the key tuning parameter, as in the relative abundance MPs, with $\epsilon \in [0,1]$ interpretted as it was previously, ρ_{AS} is the target/reference level of the log-scale aerial survey, and β here is the length of moving average of the log-scale aerial survey used as the key index.

4 Tuning and fixed MP parameters

Given the single tuning criteria: $p\left[SSB_{y^*} > 0.2 \times B_0\right] = 0.6, 0.7, 0.9$, it is unlikely to be feasible to sensibly tune more than one parameter per CMP. Given this the following base-case MP parameters were assumed:

- `PellaT1` and `PellaT2`: δ is the key tuning parameter with $\epsilon = 1$, $\beta = 1$, $\alpha = 0.05$, and $\rho_{AS} = 6.91$ (geometric mean in the aerial survey pre-1997)
- `PellaT1yreff` and `PellaT2yreff`: δ is the key tuning parameter with $\epsilon = 1$, $\gamma = 1$, and $\tau = 5$.
- `brem1` and `brem2`: δ is the key tuning parameter with $\epsilon = 1$, $\gamma = 1$, $\tau = 5$, and $B^* = 1.2$ (CPUE levels seen at SSB levels of the 1980s)
- `ASMP`: δ is the key tuning parameter with $\epsilon = 1$, $\beta = 4$, and $\rho_{AS} = 6.91$.

For all CMPs if the maximum change in TAC exceeded the pre-defined level (either 3000 or 5000t) or was smaller than the minimum level (100t) then the MP-predicted TAC was adjusted accordingly.

References

[1] Pella, J.J. and P.K. Tomlinson. 1969. A generalized stock production model. *Bull. Inter-Am. Trop. Tuna. Comm.* **13**: 419–496.

[2] Fisher, R. 1930. The Genetical Theory of Natural Selection. Reprinted by Dover, New York, in 1958.

[3] McAllister, M. K., Pikitch, E. K., and Babcock, E. A. 2001. Using demographic methods to construct Bayesian priors for the intrinsic rate of increase in the Schaefer model and implications for stock rebuilding. *Can. J. Fish. Aquat. Sci.* **58**(1): 1871–1890.

[4] Trenkel, V. 2008. A two-stage biomass random effects model for stock assessment without catches: What can be estimated using only biomass survey indices? *Can. J. Fish. Aquat. Sci.* **65**(6): 1024–1035

5 Figures

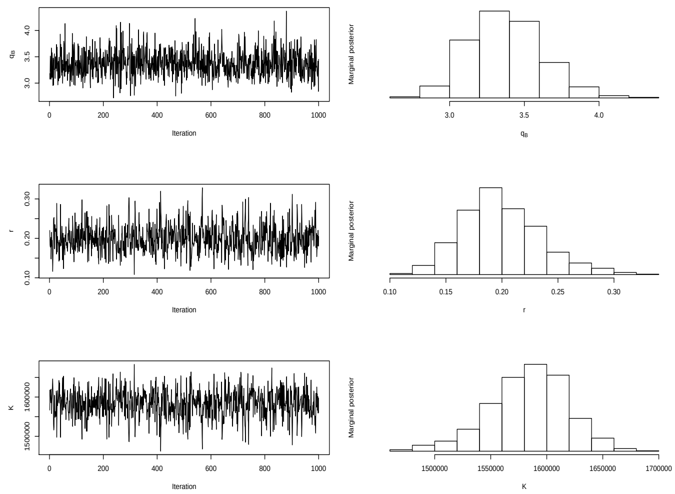

Figure 1: *Trace plots (left) and histograms (right) of the marginal posteriors for the catchability (top), intrinsic rate of increase r (middle) and carrying capacity K (bottom) for the Pella-Tomlinson model fitted to the latest historical (up to 2008) catch biomass and CPUE data.*

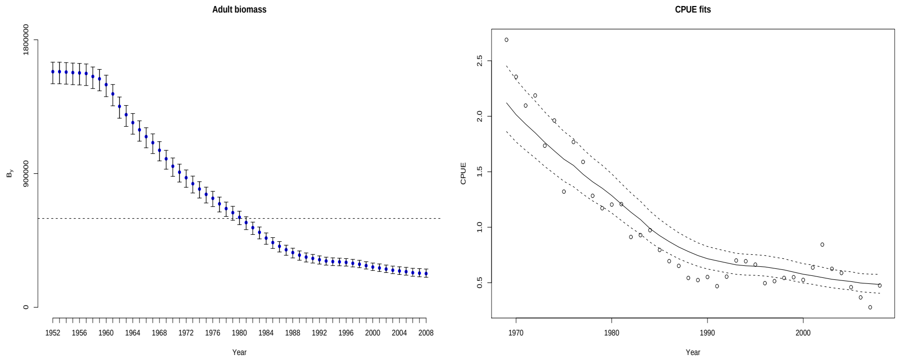

Figure 2: *Historic biomass estimates (left, median dots and whiskers the 95% credible interval) with the dotted line the median estimate of* B_{msy}*, and (right) the fits to the historic CPUE data (dots, data; full and dotted lines the median and 95% credible interval).*

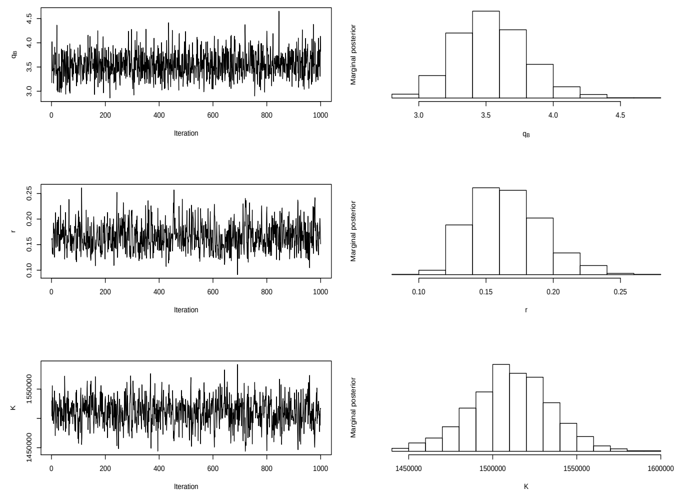

Figure 3: *Trace plots (left) and histograms (right) of the marginal posteriors for the catchability (top), intrinsic rate of increase r (middle) and carrying capacity K (bottom) for the Pella-Tomlinson model fitted to the latest historical (upto 2008) catch biomass, aerial survey and CPUE data.*

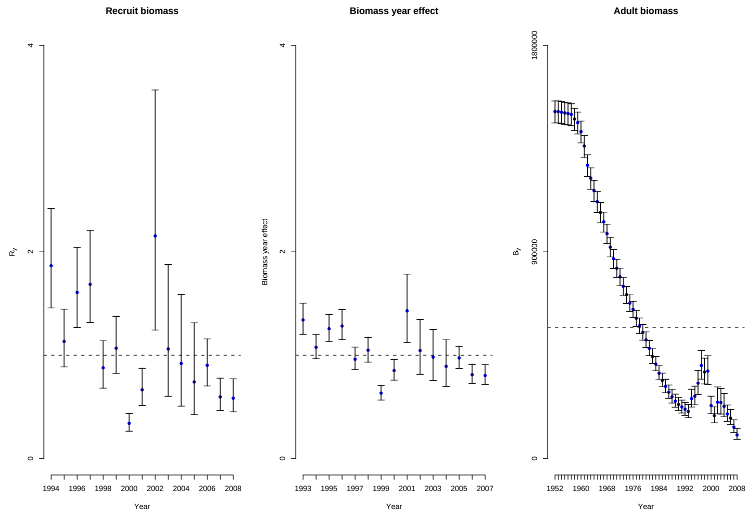

Figure 4: *Relative recruitment biomass (left), biomass year-effect (middle), and total biomass (right) median and 95% credible interval for the Pella-Tomlinson model with the aerial survey data and recruitment effects estimated. For the relative recruitment and biomass figures the dotted line is 1 (expected mean) and for the biomass the dotted line is expected value of* B_{msy}.

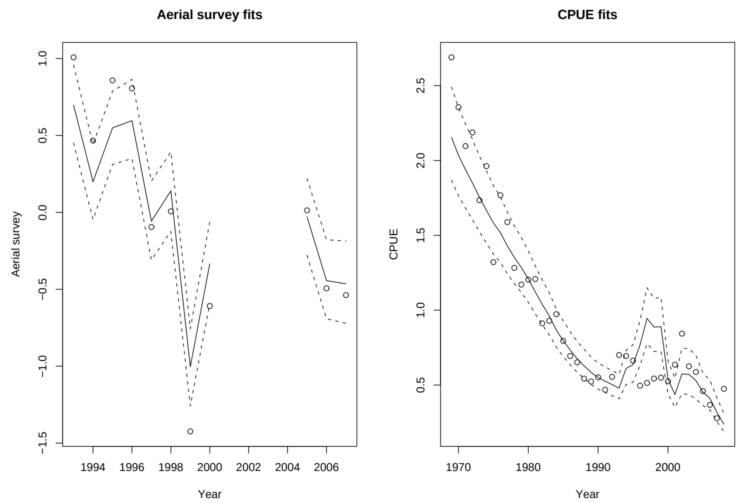

Figure 5: *Fits to the log-scale mean standardised aerial survey data (left) and the base-case CPUE data (right).*

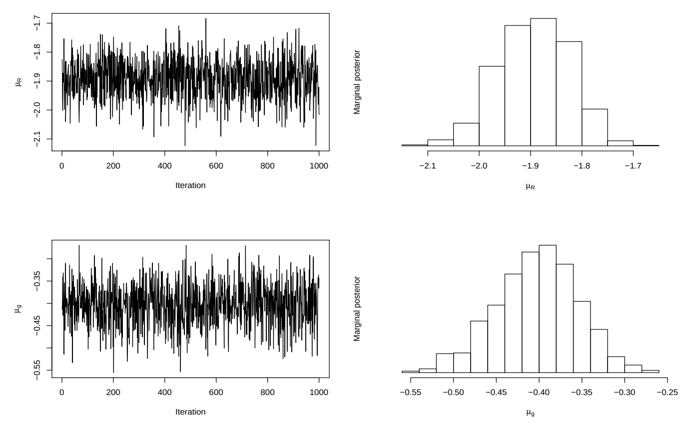

Figure 6: *Trace plots (left) and histograms (right) for the marginal posteriors of μ_R (top) and μ_g (bottom).*

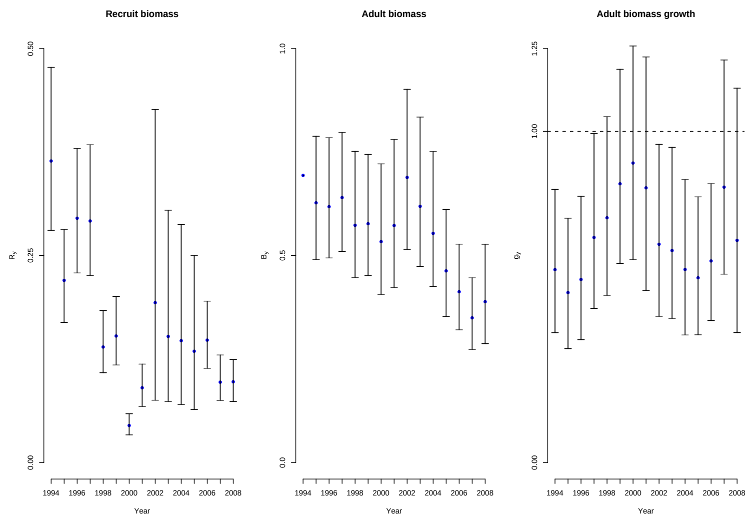

Figure 7: *Summary (median, circle; whiskers, 95% credible interval) of the relative recruitment biomass (left), relative adult biomass (middle) and net biomass growth (right) using the aerial survey and the CPUE data.*

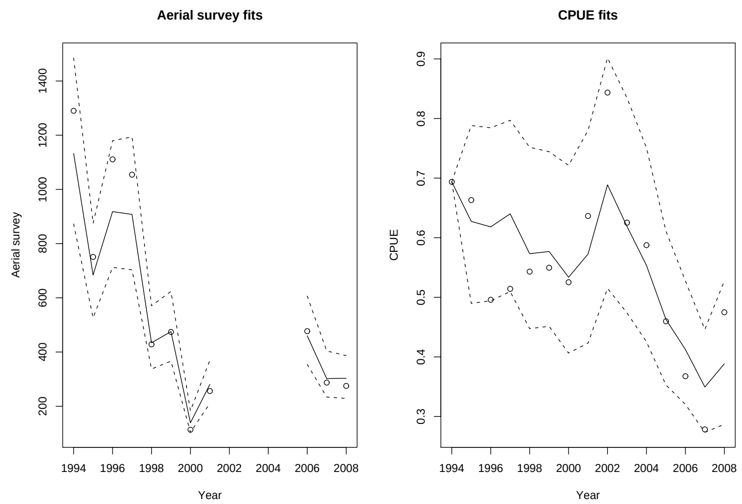

Figure 8: *Fits of the relative abundance biomass dynamic model to the aerial survey data (left) and the commercial CPUE data (right). The points are the data with the full and dashed lines representing the median and 95% credible intervals, respectively.*