

MP estimation performance relative to current input CPUE and aerial survey data

Rich Hillary, Ann Preece, Campbell Davies CCSBT-ESC/1309/19 Prepared for the 18th CCSBT Extended Scientific Committee held in Canberra, Australia 2nd-7th of Septmeber 2013.



CSIRO Marine and Atmospheric Research Wealth From Oceans National Research Flagship Castray Esplanade, Battery Point, Hobart TAS 7000, Australia Telephone : +61 3 6232 5222 Fax : +61 3 6232 5000

Copyright and disclaimer

© 2013 CSIRO To the extent permitted by law, all rights are reserved and no part of this publication covered by copyright may be reproduced or copied in any form or by any means except with the written permission of CSIRO.

Important disclaimer

CSIRO advises that the information contained in this publication comprises general statements based on scientific research. The reader is advised and needs to be aware that such information may be incomplete or unable to be used in any specific situation. No reliance or actions must therefore be made on that information without seeking prior expert professional, scientific and technical advice. To the extent permitted by law, CSIRO (including its employees and consultants) excludes all liability to any person for any consequences, including but not limited to all losses, damages, costs, expenses and any other compensation, arising directly or indirectly from using this publication (in part or in whole) and any information or material contained in it.

Contents

1	Background	1
2	laterial & Methods	
	2.1 Data sets	1
	2.2 MP population & estimation model	1
3	Results	2
	3.1 Parameter estimates	2
	3.2 Data fits and predictive performance	3
4	Discussion	4
5	Acknowledgements	5

CCSBT-ESC/1309/19

Abstract

As in previous years, the performance of the estimation part of the CCSBT MP is explored prior to any TAC calculations. The population model within the MP is fitted to the most recent CPUE (up to 2012) and scientific aerial survey (up to 2013) data to be used in this year's TAC calculation. The model performs more than adequately, with the data well explained and the key parameters well estimated. In summary, given the MP model performs well, and the latest points in the key abundance indices are well within the range tested, there are no impediments to running the MP to set the next TAC schedule.

1 Background

The CCSBT MP is model-based, in that there is a relative abundance population model that is fitted to the scientific aerial survey and standardised Japanese long-line CPUE data and the harvest control rule acts on the model-derived quantities not the raw indices. While not a formal stock assessment, the use of an estimation model means one does have to check that the underlying probability model (population dynamics and likelihood combined) is performing adequately.

This paper assesses the predictive performance of the MP estimation model given the MP input data. The MP model uses the maximum posterior density (MPD) estimate to calculate the TAC but we use Markov chain Monte Carlo (MCMC) methods to fully explore the information content of the data for the MP model, and use the posterior samples to assess the predictive performance of the model itself given the observed data.

2 Material & Methods

2.1 Data sets

Two key abundance data sets are used in the CCSBT MP:

- 1. Standardised Japanese long-line CPUE [1] used in the MP (1994-2012)
- 2. Scientific aerial survey [2] (1993-2000,2005-2013)

2.2 MP population & estimation model

First, it makes sense to revisit the specifics of the MP population model: recruitment (R_y) and adult (B_y) biomass are related as follows:

$$B_{y+1} = R_y + g_y B_y, (2.1)$$

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

$$R_y = \exp\left(\mu_R + \epsilon_y^R\right),\tag{2.2}$$

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

$$g_y = \exp\left(\mu_g + \epsilon_y^g\right),\tag{2.3}$$

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: $I_y^{AS} \sim LN\left(q^R R_{y+1}, \sigma_{AS}^2\right)$. 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: $I_y^B \sim LN(q^B B_y, \sigma_B^2)$. The model is unidentifiable without additional information on the catchability ratio q_R/q_B and the details of how this is dealt with can be found in [3].

Fixed quantities in the MP model are as follows:

- Variance in recruitment biomass random effects: $\sigma_R = 0.38$
- Variance in biomass growth random effects: $\sigma_R = 0.25$
- Observation error for CPUE index: $\sigma_S = 0.2$
- Observation error for aerial survey index: $\sigma_{AS} = 0.15$
- Catchability for CPUE: $q_B = 1$
- Catchability for aerial survey: $q_R = 849.84$
- Initial adult relative biomass: $B_{1994} = q_B^{-1} I_{1994}^B$

In terms of estimated parameters (and priors) we have:

- μ_R and μ_g with uniform priors
- ϵ_y^R and ϵ_y^g with (informative) normal priors and penalties to ensure that over years $\mathbb{E}(\epsilon_y^{\bullet}) = 0$

To efficiently obtain a representative sample from the joint posterior of the parameters a Metropolis-within-Gibbs MCMC routine was written in C++. A burn-in level of 1,000 iterations was used, with 1,000 being retained with a thinning factor of 100 employed to reduce auto-correlation in the Markov chains. Nonconvergence of the chains was explored using regular diagnostic methods [4].

3 Results



Figure 3.1: Median (full) and 95% credible interval (dashed) for the recruitment (left) and adult growth (right) random effects. Posterior estimates are coloured in black with the prior coloured magenta.

3.1 Parameter estimates

Table 3.1 details the posterior estimates of the mean recruitment biomass, μ_R , and adult biomass growth, μ_g , parameters. Given the assumption of uniform priors and the posterior CVs of 0.09 and 0.22 for the recruitment and growth means, respectively, the data are clearly informative.

Parameter	Summary
μ_R	-1.59 (-1.68; -1.48)
μ_q	-0.41 (-0.5; -0.32)

Table 3.1: Summaries of time-independent parameters in terms of posterior median and lower and upper limits of the 95% credible interval.

Figure 3.1 summarises the recruitment biomass and adult biomass growth random effects, in terms of posterior *vs.* prior estimates. In terms of the recruitment random effects, the data are clearly informative across all years - even when the aerial survey data are missing. That is because the three lowest years of CPUE (2006-2008) cannot be explained by low biomass growth alone and are partially attributed to low recruitment from the incoming juveniles. This links with the observed low age 0 recruitments from 1999-2002 in the OM and in other data sources. Adult biomass growth random effects are also well informed by the data, except for the last three years (2012-2014) where they basically line up with the prior. This is because 2012 is the last year of CPUE so 2011 would be the last data-informed estimate of these effects. That is not to say that we have no data on the adult biomass in these years, as the aerial survey in year *y* influences the adult biomass dynamics in year y + 1 - given these data are up to and including 2013 we clearly have information on B_{2014} . The recruitment biomass, adult biomass and adult biomass growth dynamics can be seen in Figure 3.2.





3.2 Data fits and predictive performance

Figure 3.3 details the estimation performance summary of the model, in terms of fits to the data and posterior predictive performance - basically how well does the probability model predict the data postestimation. For posterior predictive analyses the Bayesian *p*-value is the probability with which the predicted discrepancy statistic ("closeness" of the simulated data to the deterministic prediction) is greater than the observed one ("closeness" of the actual data to the deterministic prediction). In this work, as in previous analyses [3], a non-parametric approach is taken with the median absolute deviation used as the discrepancy statistic. Ideally, one would like Bayesian *p*-values as close to 0.5 as possible, with values outside the range of 0.05-0.95 suggesting something systemically wrong with the model.

From Figure 3.3 clearly both data sets are fitted well, with the fits to the CPUE data notably smoother than the raw data without missing the trends. In terms of posterior predictive performance the Bayesian



Figure 3.3: Top row summarises fits to aerial survey (left) and CPUE (right) indices (observed, circles; predicted median (full) and 95% credible interval (dotted lines)). Bottom row summarises the posterior predictive performance of the model (including the *p*-values).

p-values for the scientific aerial survey and CPUE data of 0.42 and 0.57, respectively, also attest to the observation that the data are also being well explained by the model.

4 Discussion

The performance of the estimation part of the CCSBT MP was explored, looking at the information content of the data in relation to the key estimated parameters and the predictive abilities of the MP model. In general, all the parameters are well informed by the data, with the only clear prior forcing coming for the final years (2012-2014) of the adult biomass growth random effects for which there are no CPUE data to inform them. An interesting observation is how the CPUE data inform the recruitment biomass random effects in the missing years of the aerial survey. The CPUE data suggests lower recruitment in those years (as seen in other data and the OM) given the strong dip in the CPUE from 2006 to 2008. This further emphasises the point that by treating the key MP input data in such an integrated manner we can not only reduce the influence of observation error but also extract key (and consistent) information on recruitment and adult biomass dynamics from *both* data sources.

The model fits both data sources well, with no clear residual trends. In terms of predictive performance - i.e. how much like the observed data do model-simulated data look - the model also does well in relation to both abundance indices. The 2012 CPUE and 2013 aerial survey points sit well within the range tested when evaluating the MP so there are no issues relating to exceptional circumstances. In conclusion, there are no issues that would suggest we cannot run the MP for calculating the next TAC schedule.

5 Acknowledgements

This work was funded by AFMA and CSIRO's Wealth from Oceans National Research Flagship.

References

- Itoh, T., Sakai, O., and Takahashi, N. (2013) Description of CPUE calculation from the core vessel data for southern bluefin tuna in 2013 CCSBT-ESC/1309/29.
- [2] Eveson, J. P., Farley, J., and Bravington, M. V. (2013) The aerial survey index of abundance: updated analysis methods and results for the 2012/13 fishing season. *CCSBT-ESC/1309/10*.
- [3] Hillary, R. M., and Preece. A. (2011) Updated technical specifications and performance analyses for MP1. CCSBT-ESC/1107/12.
- [4] Brooks, S. P., and Roberts, G. O. (1997) Assessing Convergence of Markov Chain Monte Carlo Algorithms. *Stat. & Comput.* 8, 319–335.

CCSBT-ESC/1309/19

CONTACT US

- t 1300 363 400 +61 3 9545 2176
- e enquiries@csiro.au
- w www.csiro.au

YOUR CSIRO

Australia is founding its future on science and innovation. Its national science agency, CSIRO, is a powerhouse of ideas, technologies and skills for building prosperity, growth, health and sustainability. It serves governments, industries, business and communities across the nation.

FOR FURTHER INFORMATION

CSIRO Marine and Atmospheric Research Rich Hillary

- t +6<u>1 3 6232 5452</u>
- e Rich.Hillary@csiro.au

w