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

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Abstract

As in previous years, the performance of the estimation part of the CCSBT MP is explored prior to the TAC calculations. We also include the updated MP data inputs and the resultant preliminary TAC recommendation that arises from running the MP, which will be used to set the TAC for 2018–2020. The population model within the MP is fitted to the most recent CPUE (up to 2015) and scientific aerial survey (up to 2016) data. The model performs more than adequately with the majority of the data well explained and the key parameters well estimated. The very high survey estimates of 2014 and, in particular 2016, still fall within the 95% predictive interval. In summary, given the MP estimation procedure performs well, there are no model-specific impediments to running the MP to set the next three-year TAC block. The preliminary TAC recommendation for 2018–2020 is 17,647t (i.e. the maxmimum 3,000t increase permitted).

1 Background

The CCSBT MP is model-based, in that there is a relative abundance population model that is statistically 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 it is necessary 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 updated 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. An additional section we included here, that was not included in previous such papers, are the actual data inputs to the Bali procedure and the preliminary result (in terms of the recommended TAC) of running the MP for the 2018–2020 TAC block.

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 (1994-2015)
2. Scientific aerial survey [2] (1993-2000,2005-2014,2016)

2.2 MP data files

In order to run the standalone version of the MP code in 2016, data files and the code needed to be updated. All changes were uploaded to github. The code used to run the MP (`BaliProc.tpl`) was updated to include code changes developed in 2015 to allow for missing 2015 aerial survey data.

The MP input data file (BaliProc.dat) was updated with new aerial survey and CPUE time series. The CPUE time series used in the MP is the average of 2 base CPUE series multiplied by the over catch correction factors in the historical parts of the timeseries (see Att 10 of 2013 ESC report). The main data file for running the Bali procedure is called BaliProc.dat and can be found in the Appendix.

To account for overall changes in the scale of the aerial survey index, given it is an area-weighted sum, an adjustment is made to the survey-to-CPUE catchability (referred to as the qratio: q_R/q_B) in the MP. A Bayesian bootstrap procedure is used to ensure that the ratio is robust to potential outliers (see the `qratio.tpl` source file for details). Given one can get slightly different answers from different computers, traditionally we have run the procedure on one machine and everyone then uses that value. The data file is qratio.dat (see Appendix). The agreed value of the qratio parameter is 885.593.

2.3 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:

$$B_{y+1} = R_y + g_y B_y, \tag{2.1}$$

where g_y is the adult biomass net growth effect (encompassing natural mortality, growth and exploitation effects). For recruitment to the fully exploited stock 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 and above. 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 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: $\sigma_g = 0.25$
- 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: $q_R = 885.593$
- 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 $\mathbb{E}\left(\epsilon_y^\bullet\right) = 0$

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. Non-convergence of the chains was explored using regular diagnostic methods [4].

3 Results

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 0.04 and 0.1 for the recruitment and growth means, respectively, the data are clearly informative.

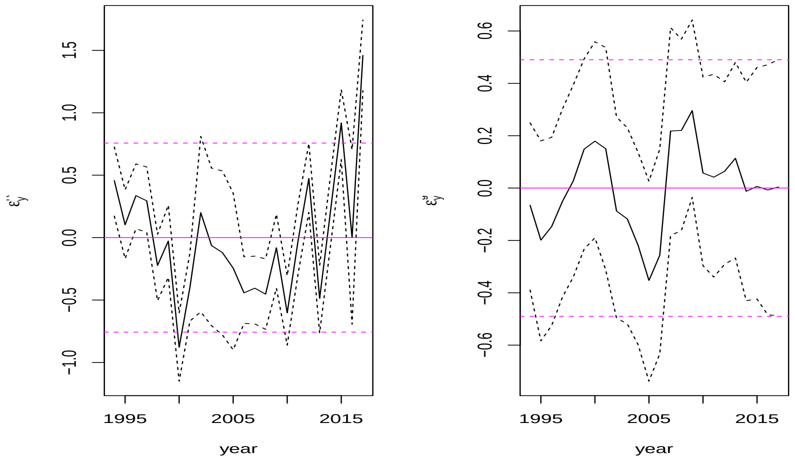

Figure 3.1: **Median (full) and 95% credible interval (dashed) for the recruitment (left) and adult growth (right) random effects. Posterior estimates are coloured in black with the prior coloured magenta.**

Parameter	*Summary*
μ_R	-1.51 (-1.62; -1.41)
μ_g	-0.36 (-0.44; -0.29)

Table 3.1: **Summaries of time-independent parameters in terms of posterior median and, in brackets, the 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. When interpreting how the recruitment terms in the MP model relate to the aerial survey remember always to subtract one year from the model terms to link them to the survey (the model terms represent the biomass *recruiting* into the long-line fleets and are linked to the cohorts seen in the aerial survey the year before). We see that the posterior estimates for the recruitment random effects fall outside the prior 95%ile for both 2015 and 2017 (with the missing year in 2016 shrunk towards the mean as one would expect). Adult biomass growth random effects are also well informed by the data, except for the last three years (2014-2016) where they basically line up with the prior. This is because 2015 is the last year of CPUE so 2014 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 2016 we clearly have information on B_{2017}. 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 summarises the estimation performance summary of the model, in terms of fits to the data and posterior predictive performance. In short, how well does the probability model predict the data post-estimation. 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

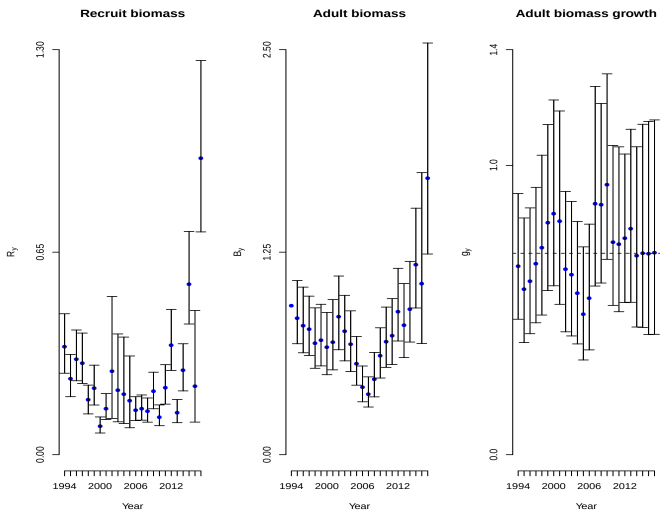

Figure 3.2: **Median (blue circles) and 95% credible interval for the recruitment biomass (left), adult biomass (middle) and biomass net growth (right).**

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.

Figure 3.3 clearly demonstrates that both data sets are fitted well, with the fits to the CPUE data notably smoother than the raw data without missing the trends. The very high survey years in 2014 and 2016 are under-estimated by the model, but are still within the 95% predictive interval. In terms of posterior predictive performance the Bayesian p-values for the scientific aerial survey and CPUE data of 0.37 and 0.64, respectively, also indicate that the data are also being fairly well explained by the model.

3.3 Running the MP

The preliminary TAC calculated for the 2018–2020 block from running the `BaliProc` code in 2016 is 17,647t, a 3000t increase which is the maximum permitted. This recommendation is subject to consideration of exceptional circumstances and meta-rules by the 2016 ESC, with the final TAC decision to be made at the extended Commission.

4 Discussion

The performance of the estimation part of the CCSBT MP was explored, considering 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 (2014-2016) 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 valuable (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 apart from an under-estimation of the high aerial survey points in 2014 and 2016. 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

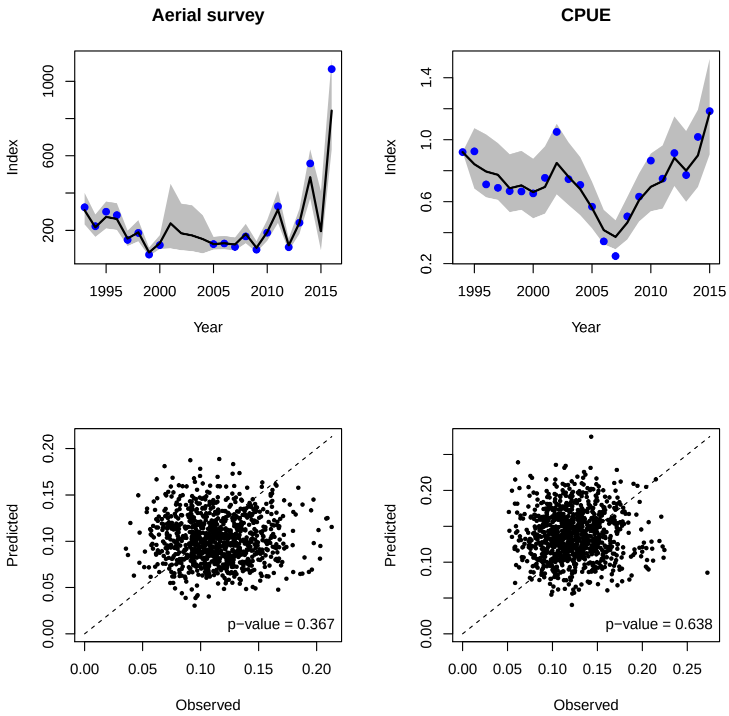

Figure 3.3: **Top row summarises fits to aerial survey (left) and CPUE (right) indices (observed, circles; predicted median (full) and 95% credible interval (dotted lines)). Bottom row summarises the posterior predictive performance of the model (including the p-values).**

indices. The very high 2014 and 2016 survey points, while under-estimated, are still within the 95% predictive interval. In conclusion, there are no issues that would suggest we cannot run the MP for calculating the next TAC block. The preliminary recommended TAC for 2018–2020 arising from running the MP was 17,647t, the maximum (3,000t) increase permitted.

5 Acknowledgements

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References

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[2] Eveson, J. P., Farley, J., and Bravington, M. V. (2016) The aerial survey index of abundance: updated analysis methods and results for the 2015/16 fishing season. *CCSBT-ESC/1609/9*.

[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.

Appendix

The BaliProc.dat file:

```
# Control file for SBT Bali Procedure - updated with data from the 2016
data exchange.
# Last year TAC already set
2017
# TAC in that year
14647
# catchability ratio AS vs CPUE -updated 20/6/2016
#849.843 = 2013 qratio value
885.593
# CPUE series for MP (1969-2015) -ave of BASE w0.8 w0.5 x overcatch multipliers
-updated 15/6/2016
2.3887
2.3219
2.1354
2.1971
1.8767
1.9349
1.4765
1.8997
1.6703
1.4060
1.2015
1.3857
1.3010
1.0253
1.0165
1.0432
0.8720
0.6506
0.6491
0.5405
0.5815
0.6417
0.5278
0.5792
0.8127
0.9203
0.9251
0.7117
0.6897
0.6687
0.6661
0.6538
0.7542
1.0506
0.7460
0.7087
```

```
0.5682
0.3443
0.2496
0.5056
0.6329
0.8652
0.7491
0.9141
0.7722
1.0182
1.1843
#historical aerial survey (1993-2016) (-11.0 = missing data) AS 16/6/2016
323.6244
221.814
299.876
281.26
148.5044
185.9542
69.2512
120.4431
-11.0
-11.0
-11.0
-11.0
125.8429
129.1713
110.7976
167.2365
95.7831
187.0467
328.5074
109.3264
240.4568
558.7715
-11.0
1065.5126
```

The qratio.dat file:

```
# number of bootstrap replicates
1000

#the existing "old" qratio value that needs to be updated
# 838.2094 = 2011 qratio
849.843
# number of data ponts in AS comparison (length of old series effectively)
17

# latest AS (minus missing years AND final years!)- 2016 data
323.6244
221.814
299.876
281.26
148.5044
185.9542
69.2512
120.4431
125.8429
129.1713
110.7976
167.2365
95.7831
187.0467
328.5074
109.3264
240.4568
#558.7715
#-11.0
#1065.5126

# previous AS (minus missing data!)  - 2013 data
348.2291
239.245
315.3104
292.9836
154.1827
184.9522
73.2641
130.8224
128.9778
130.5659
112.7744
174.1606
102.1017
200.3936
352.9442
101.2156
255.694
```

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