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Australian Fisheries Management Authority

Southern Bluefin Tuna Inter-sessional Science 2018-19

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CSIRO Oceans and Atmosphere, Hobart.

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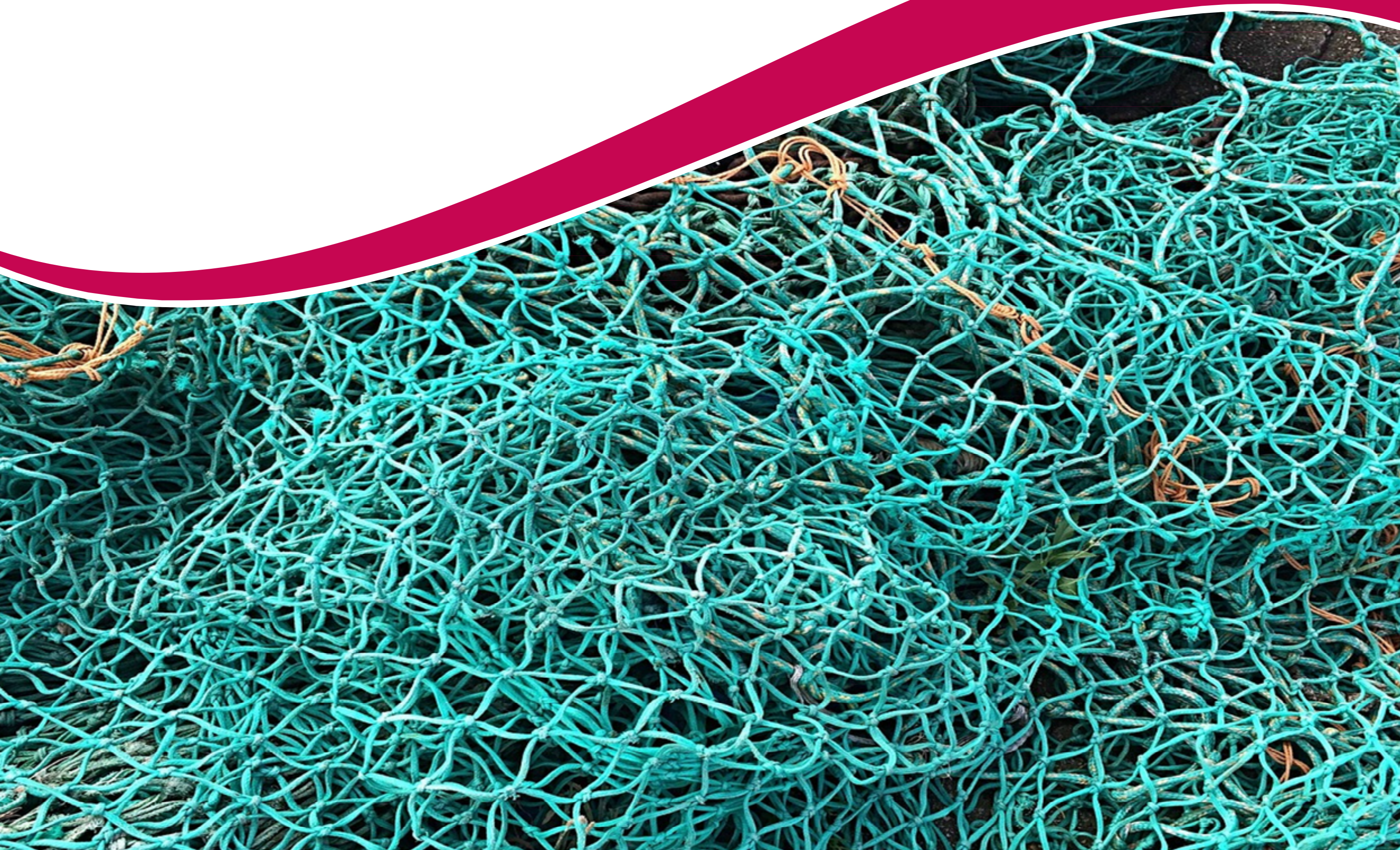

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Version	Updates	Approver

1 Acknowledgements

This work was funded by AFMA and CSIRO. The work was presented to the 2018 CCSBT meetings and reviewed by ABARES, the CCSBT Advisory Panel and CCSBT member scientists.

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2 Non-technical summary

CSIRO provides scientific advice to the Southern Bluefin Tuna MAC and AFMA to support the effective monitoring, implementation and success of management arrangements in the Southern Bluefin Tuna Fishery. Through this project CSIRO participates in the Australian delegation to the Commission for the Conservation of Southern Bluefin Tuna (CCSBT) Extended Scientific Committee (ESC).

The inter-sessional science work plan for 2018/19 included the scientific data exchange, evaluation of exceptional circumstances and fisheries indicators, review of progress in the CCSBT Scientific Research Program, attendance at ESC and Operating Model and Management Procedure (OMMP) technical meetings, consultation and planning discussions.

Results from the project include:

- The SBT operating models have been updated to include new data, including the new gene-tagging data that provides information on juvenile abundance. This is essential for providing updated population dynamics models for testing candidate Management Procedures.
- The current Total Allowable Catch advice was reviewed at the Extended Scientific Committee meeting through the meta-rules process.
- Direct age data and estimates of proportion-at-age of the Australian surface (purse seine) fishery were provided to the CCSBT scientific data exchange.

The direct benefits of this project include: government, industry and community confidence that the SBT rebuilding strategy and MP implementation program is based on the best scientific advice. The work this year on reconditioning of the OMs for MP testing is an incremental step towards the full reconditioning and stock assessment planned for 2020.

3 Background

Through the SBT Inter-sessional Science Project CSIRO provides scientific support and advice to AFMA, SBTMAC, Australian Government and Industry and participates in the Australian delegation to the workings of the Commission for the Conservation of Southern Bluefin Tuna (CCSBT) Extended Scientific Committee (ESC).

The main focus of the technical work program in 2018-19 will be reconditioning of the SBT operating models to incorporate new data from the 2019 CCSBT scientific data exchange. These operating models will be used for testing candidate management procedures, and will integrate the juvenile abundance data from the gene-tagging program.

The next stage of development of candidate MPs is part of the CSIRO project with the Department of Agriculture and Water Resources. That project involves consultation with AFMA, government, Industry and other stakeholders on operational forms of Management Procedure, objectives and trade-offs in performance measures. The AFMA SBT Inter-sessional Science 2018-19 project and the Management Procedure project with the Department are strongly linked.

4 Need

This is essential work that provides ongoing scientific advice to the Southern Bluefin Tuna MAC and AFMA to support the adequate monitoring, implementation and success of management arrangements in the Southern Bluefin Tuna Fishery.

The inter-sessional science work schedule in 2018/19 includes the scientific data exchange, evaluation of exceptional circumstances and fisheries indicators, review of progress in the CCSBT Scientific Research Program, attendance at ESC and Operating Model and Management Procedure (OMMP) technical meetings, consultation and planning discussions.

The reconditioning of operating models to include new data, including the new gene-tagging data, is essential for providing updated population dynamics models for testing candidate Management Procedures. The development of a new MP and the intensive domestic consultation associated with this process is a large piece of work, similar to the work undertaken in the years leading up to the 2011 adoption of the current MP. The development of candidate MPs is covered in a separate project with the Department of Agriculture and Water Resources. Consultation with the Department, AFMA and stakeholders is an essential component of the MP process.

The SBT inter-sessional science project also includes the work on routine otolith archiving, ageing and developing age-length keys for the Australian SBT surface fishery. Provision of these data is a requirement of the Commission for the Conservation of Southern Bluefin Tuna (CCSBT).

5 Objectives

1. Provide scientific advice and support to SBTMAC and AFMA and participate in the relevant domestic and international meetings. Participate in planning, technical consultation, ESC and OMMP meetings, inter-sessional webinars and review of exceptional circumstances.

2. Prepare for the 2019 reconditioning of the SBT operating models, including integrating the new gene-tagging data, for use in management strategy evaluation.

3. Participate in the 2019 CCSBT data exchange.

4. Undertake the routine otolith archiving, ageing and developing age-length keys for the Australian SBT surface fishery and provide data to CCSBT.

6 Results and Discussion

The project results are discussed for each objective below:

6.1 Objective 1: 2018 ESC and OMMP meeting preparation

Provide scientific advice and support to SBTMAC and AFMA and participate in the relevant domestic and international meetings. Participate in planning, technical consultation, ESC and OMMP meetings, inter-sessional webinars and review of exceptional circumstances.

Through the SBT Inter-sessional Science Project CSIRO provides scientific support and advice to AFMA, SBTMAC, Australian Government and Industry and participates in Australian delegation to the Commission for the Conservation of Southern Bluefin Tuna (CCSBT) Extended Scientific Committee (ESC).

CSIRO participated in the CCSBT’s 2018 Operating Model and Management Procedure (OMMP) meeting 18-22 June 2018, and presented two papers on the SBT operating model changes (Hillary et al, 2018a) and preliminary work on tuned candidate Management Procedures (MPs) (Hillary et al, 2018b). These new MPs are designed to use a combination of data: juvenile abundance estimates from gene-tagging, Japanese long line CPUE data and adult abundance estimates from close-kin.

For the 2018 ESC and one day OMMP technical meeting prior to the ESC, CSIRO made additional changes to the SBT operating models (Hillary et al., 2018c) and further refined candidate MPs (Hillary et al, 2018d). The MP development is funded by DAWR through the related MP development project.

Preece, Davies and Hillary participated in the 2018 ESC (2-8th September), presenting a large number of papers and rapportuering technical sections of the ESC report, including the MP related agenda items.

CSIRO provided a review of the meta-rules process for 2018 (Preece et al, 2018a), which considers the potential for exceptional circumstances, their impact and the need for action on the recommended TAC for 2019. Four exceptional circumstances were identified by the ESC. No change to the TAC was recommended.

CSIRO participated in SBTMAC as invited observers, and provided updates on projects and the CCSBT work plan. CSIRO contributed to the ESC summary paper provided to SBTMAC and presented by ABARES. Consultation meetings were held in Port Lincoln on 16th August in preparation for the ESC, and in Canberra on the 18th September in preparation for the Extended Commission meeting. A discussion of outcomes from the 2018 Extended Commission meeting was held in Canberra, 29 Oct, 2018. Hypothetical scenarios for small or limited TAC increases (most likely given current operating model conditions) were played out to discuss implications. Iterative consultation and planning on MP development occurred on 15 Jan 2019 and 16 May, 2019.

Preece, Hillary and Davies also participated in the joint tuna RFMO management strategy evaluation working group (June 2018, Seattle). There are increasing links between tuna RFMOs, with managers, stakeholders, Commissioners and scientists attending meetings in multiple RFMOs and there is an identified need to ensure communication and MSE terminology are consistent. A report of the meeting was presented to the 2018 ESC (Preece et al, 2018b).

6.2 Objective 2: Reconditioning operating models

Prepare for the 2019 reconditioning of the SBT operating models, including integrating the new gene-tagging data, for use in management strategy evaluation.

The SBT OM data files have been updated with new data. The SBT OM software code has been updated to integrate gene-tagging into the SBT OMs. Testing of the software and reconditioning the models is underway. Software for running candidate MPs has also been updated. A paper on the new components added to the SBT OM will be provided at the OMMP meeting (Hillary et al, in prep). The work this year on reconditioning is an incremental step towards the full reconditioning and stock assessment planned for 2020.

6.3 Objective 3: Participate in the 2019 CCSBT data exchange.

The 2019 CCSBT scientific data exchange was completed on the 4th June, 2019. CSIRO has provided to the CCSBT data exchange the raised catch at age for the Australian surface and longline fisheries, direct ageing data for the Australian surface fishery, and the Japanese longline nominal CPUE series. The Japanese longline CPUE series shows an unusually high value for 2018. This is being further investigated by Japan.

Additional data were provided to the data exchange in relation to projects funded by the Commission. These included an update to the first gene-tagging abundance estimate and a second abundance estimate from year 2 of the program, and new close-kin data.

6.4 Objective 4: Australian surface fishery age frequency

Undertake the routine otolith archiving, ageing and developing age-length keys for the Australian SBT surface fishery and provide data to CCSBT.

A report on otolith and ovary collection activities in Australia over the past year, and estimates of proportion-at-age of the Australian surface (purse seine) fishery up to the 2016/17 fishing season, was presented to the 2018 ESC (Farley and Eveson, 2018). Otoliths collected during the gene-tagging program were used to supplement the collection from the surface fishery to develop the age-length keys.

The collection of ovaries from fish during winter and off the spawning ground is part of a collaborative effort across the CCSBT members to develop an independent estimate of the age and length at maturity. A workshop on maturity, held in Indonesia, May 2019, focussed on methods for reading the histology and discussed the data for an analysis of the maturity at age and length.

Direct age and proportions at age data were provided to the CCSBT scientific data exchange in 2019.

7 Benefits / Management Outcomes

Stakeholders in the Southern Bluefin Tuna Fishery benefit from the implementation of a scientifically designed and tested management procedure (Hillary et al, 2016a). The CCSBT MP is used to recommend the global TAC, and encompasses meta-rules that provide a regular schedule and agreed process for review of data, methods, and MP performance. The MP has provided stability, increased certainty and increases in the Australian TAC, over the past 8 years. These benefits have been attested to by Industry, fisheries managers and E-NGOs. An additional benefit has been the time and strategic focus this orderly science and management process has provided to concentrate on planning, prioritising and securing the necessary funding for future inter-sessional science work plans as well as addressing strategic science needs.

In 2018, through this project, CSIRO has provided substantial input to the 2018 OMMP and ESC meetings; presenting papers (Appendix 1) and leading discussions that informed decisions made at the ESC and Extended Commission, providing technical input to meetings, summarising technical model changes and runs, and rapporteured meeting reports.

The 2018 review of meta-rules identified several exceptional circumstances and potential impacts for consideration of actions to modify TAC. No actions to modify the TAC were recommended, although a number of follow up analyses were identified and recommended.

The 2019 reconditioning of the operating models has included code changes for incorporation the data from the juvenile abundance estimation from the gene-tagging program.

The 2018 ESC reviewed monitoring and research priorities. The CCSBT Scientific Research Program has made substantial investment in projects providing monitoring data for recruitment (gene-tagging) and adult abundance (close-kin mark recapture). CSIRO's development of cost-effective methods for monitoring the stock have been incorporated into the CCSBT Scientific Research Program and included in the Commission's budget in 2019. These research programs often have flow on effects for other Australian and International fisheries, potentially leading to improved monitoring, assessment and management of other global stocks.

The direct benefits of this project include: government, industry and community confidence that the SBT rebuilding strategy and MP implementation program is based on the best scientific advice; that previous TAC reductions and current TAC settings have been effective in reducing fishing mortality on the stock and are providing for rebuilding consistent with the Commission's rebuilding plan; and increases in the TAC, with associated economic returns to the Australian Industry and wider community.

8 Conclusion

This SBT Inter-sessional Science 2018-19 project covered the identified priority items of SBTMAC for the 2018 CCSBT work program, and the work up to June 2019 on the CSIRO components of the CCSBT 2019 data exchange. All the objectives of the project have been met.

CSIRO has delivered thorough, rigorous scientific advice on the key agenda items at the 2018 OMMP technical meeting and ESC meeting, and provided briefings, consultation and advice to AFMA, ABARES, Industry and SBTMAC.

The Extended Commission has requested that the ESC transition to a new Management Procedure that will use gene-tagging data as the recruitment index. Development and

MSE testing of new MPs involves a substantial amount of inter-sessional science work, given the ambitious schedule agreed by the CCSBT. The new schedule for MP development aims to adopt a new MP in 2019 and use this to set the TAC in 2020.

Outputs from this inter-sessional science project have been considered in depth by the OMMP and ESC scientist and are reflected in recommendations and advice of the ESC to the Commission, and by the Extended Commission in the 2018 funding decisions and approach to the future work program.

References

Farley J, Eveson P (2018). An update on Australian otolith and ovary collection activities, direct ageing and length at age keys for the Australian surface fishery. CCSBT-ESC/1809/12.

Hillary RM, Preece AL and Davies CR. 2018a. Data generation & changes to SBT OM. CCSBT-OMMP/1806/04.

Hillary RM, Preece AL and Davies CR. 2018b. Initial MP structure and performance. CCSBT-OMMP/1806/05.

Hillary RM, Preece AL and Davies CR. 2018c. Data generation & changes to SBT OM. CCSBT-ESC/1809/19.

Hillary RM, Preece AL and Davies CR. 2018d. Performance of Revised CMPs. CCSBT-ESC/1809/20.

Hillary RM, Preece AL and Davies CR. 2019 (in prep). Changes to SBT OM. CCSBT-OMMP/1906/X

Preece AL, Davies CR, Hillary RM (2018) Meta-rules: consideration of exceptional circumstances in 2018. CCSBT-ESC/1809/18.

Preece AL, Davies CR, Hillary RM (2018). Report on the tuna RFMO MSE working group meeting. CSIRO, Australia. CCSBT-ESC/1809/21.

Appendix 1

Primary papers to the 2018 OMMP and ESC meetings

Farley J, Eveson P (2018). An update on Australian otolith and ovary collection activities, direct ageing and length at age keys for the Australian surface fishery. CCSBT-ESC/1809/12.

Hillary RM, Preece AL and Davies CR. 2018a. Data generation & changes to SBT OM. CCSBT-OMMP/1806/04.

Hillary RM, Preece AL and Davies CR. 2018b. Initial MP structure and performance. CCSBT-OMMP/1806/05.

Hillary RM, Preece AL and Davies CR. 2018c. Data generation & changes to SBT OM. CCSBT-ESC/1809/19.

Hillary RM, Preece AL and Davies CR. 2018d. Performance of Revised CMPs. CCSBT-ESC/1809/20.

Preece AL, Davies CR, Hillary RM (2018a) Meta-rules: consideration of exceptional circumstances in 2018. CCSBT-ESC/1809/18.

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An update on Australian otolith and ovary collection activities, direct ageing and length at age keys for the Australian surface fishery.

Jessica Farley and Paige Eveson

CCSBT-ESC/1809/12

Prepared for the Extended Scientific Committee for the Twenty Third Meeting of the Scientific Committee, San Sebastian, Spain, 3-8 September, 2018

Citation

Farley J, Eveson P (2018). An update on Australian otolith and ovary collection activities, direct ageing and length at age keys for the Australian surface fishery. CCSBT-ESC/11809/12, Twenty Third Meeting of the Scientific Committee, 3-8 September, San Sebastian, Spain.

Acknowledgments

There are many people we would like to acknowledge for their support. Our thanks go to Seatec Pty Ltd for collecting otoliths as part of routine collecting from the South Australian tuna farms in Port Lincoln under AFMA supervision. Our appreciation also goes to Kyne Krusic-Golub (Fish Ageing Services) for sectioning and reading the otoliths, and Scott Cooper for database support. We also thank the boat owners and skippers, and processing factory staff, for allowing us to samples ovaries. This work was funded by AFMA and CSIRO Oceans and Atmosphere.

Contents

1 Abstract

This report provides an update on (i) the southern bluefin tuna (SBT) otolith and ovary collection activities in Australia over the past year and (ii) estimates of proportion-at-age of the Australian surface (purse seine) fishery to include the 2016/17 fishing season.

Otoliths from 211 SBT caught in the Great Australian Bight (GAB) in 2018 were received and archived into the CSIRO hard-parts collection. A further 39 sets of SBT ovaries were collected from SBT caught by commercial longline operations off southeast Australia in July, bringing the total collected by Australia to 247. Histological analysis of the ovaries will be undertaken in preparation for the proposed maturity workshop in March-April 2019.

Age was estimated for 125 SBT from the 2016/17 fishing season and the proportions-at-age were estimated using standard age-length-keys and by applying the method developed by Morton and Bravington (2003) (M&B method) to the combined age-length data and length frequency data obtained from the catch sampling program. Provided that the length frequency data are representative of fish caught in the surface fishery, and given our goal of estimating proportions at age in the catches (not in the population), the M&B estimator with "unknown growth" (see Methods) should be more accurate. For the 2016/17 season, the proportion at age estimates from the M&B method with unknown growth are 63% age 2 and 33% age 3. These estimates suggest a larger proportion of age 2 and smaller proportion of age 3 fish in the catches in 2016/17 than in previous seasons, with the exception of 2013/14 and 2014/15.

2 Introduction

Estimating proportion-at-age

Many stock assessments, including those for southern bluefin tuna (SBT), use age-based parameters within the models to estimate stock abundance, with annual catch in numbers at age (catch-at-age) from some fisheries as input data. For many fisheries, however, the only direct information available is the size distribution of the catch (catch-at-length) and total number caught. Although length provides some information on the age structure of the catch, since age and length are related, there is a need to convert catch-at-length into catch-at-age or infer age from length within the model. Many simulation studies have shown that using direct age data, as opposed to size data, in age-structured assessment models is more likely to give unbiased estimates of stock status. Direct ageing from hard parts (otoliths) identifies different age groups among similarly sized fish and is generally considered a fundamental requirement of fisheries monitoring, particularly for long-lived species such as SBT.

The most common way of using direct age data in assessments has been the construction of age-length-keys from which proportions at age in the catch can be estimated. Morton and Bravington (2003) developed more efficient parametric methods to estimate proportions-at-age for SBT and recommended between 100-200 otoliths from the Australian surface fishery would be sufficient to provide acceptable levels of precision (CVs under 20%). Since 2002, we have been archiving between 100-400 otoliths annually, but only ageing (reading) 100. The additional otoliths provide a reserve which can be aged if we find that the CVs of the proportion-at-age estimates based on 100 samples are too high (i.e., greater than 20%).

Since the 2002 fishing season, Australia has been obliged to provide annual length-at-age estimates for the surface (purse seine) fishery in the Great Australian Bight (GAB) to CCSBT. The current protocol requires that all farm operators provide a sample of 10 fish that have died either in towing operations or within the first weeks after fish have been transferred to stationary farm cages. A company contracted to the Australian Fisheries Management Authority (AFMA) measures the length of each fish and extracts the otoliths from these mortalities. In the past there have been between ~25 and 40 tow cages a year, giving a total of 250-400 otoliths collected from this sector each season. In recent years, however, the number of fish available for otolith sampling has declined primarily because of low mortalities in the cages during the towing operations (Farley et al., 2013).

Maturity

There remains uncertainty about the size and age that SBT mature and the functional form of the maturity schedule. Up until 2013, the SBT operating model (OM) used a “knife-edge” maturity relationship, which specified that 0-9 year olds made no contribution to the spawning biomass or reproductive output of the population and 10+ year olds all contribute in proportion to their weight. In 2013, the method was updated to use the currently available estimates of maturity and additional information provided by the close-kin estimate to give a spawning potential by age (Anon 2013a). It was acknowledged, however, that there was no independent estimate of a maturity schedule for SBT (Anon 2013b). In 2014, a costed proposal for developing one (Farley et al., 2014) was supported by the ESC, and sample collection for maturity was listed as a high priority in the work plan for 2015 and ongoing. A sample size of 220 was proposed to be collected from statistical area 4 by Australia and Japan.

3 Otolith and ovary sampling 2018

A total of 174 sets of otolith were collected from the Australia surface fishery in the 2017/18 fishing season by Protec Marine Pty Ltd (Table 2). The fish were measured to the nearest cm (FL) and the otoliths removed and sent to CSIRO in Hobart. The size range of fish sampled was 75 to 130 cm FL (Fig. 1).

An additional 37 sets of otoliths were received from SBT sampled during CCSBT gene tagging fieldwork in the Great Australian Bight in February 2018 (Table 2; also see CCSBT-ESC/1908/07). As the tagging program was targeting two year-old fish, it provided an opportunity to collect otoliths from fish smaller than those generally sampled from the surface fishery. Otoliths were only collected from mortalities, which were recorded against CSIROs research mortality allowance approved by the CCSBT. The size range of fish sampled was 60-95 cm FL (Fig. 1).

A total of 39 ovaries were collected from SBT caught by a commercial longline operation off southeast Australia in July 2018. The ovaries (or part of one lobe) were removed and brought to the laboratory fresh. A subsample was taken from each ovary and fixed in 10% formalin for future histological analysis. A total of 247 ovaries, collected from fish ranging in size from 89-195 cm FL, have been collected since 2014 (Fig. 2) and should provide an adequate number of samples of the size range over which the transition to maturity occurs. Histological analysis of the ovaries will be undertaken over the next months in preparation for the proposed maturity workshop in Bali in March- April 2019 (see Anon 2017).

Table 2. Number of SBT with otoliths collected from the Australian surface fishery and during gene-tagging operations in the 2018.

SOURCE	NO. OTOLITHS	LENGTH RANGE (CM)	MEAN FL (CM)
Australia surface fishery	174	75-130	99.2
Gene-tagging operations	37	66-99	81.4

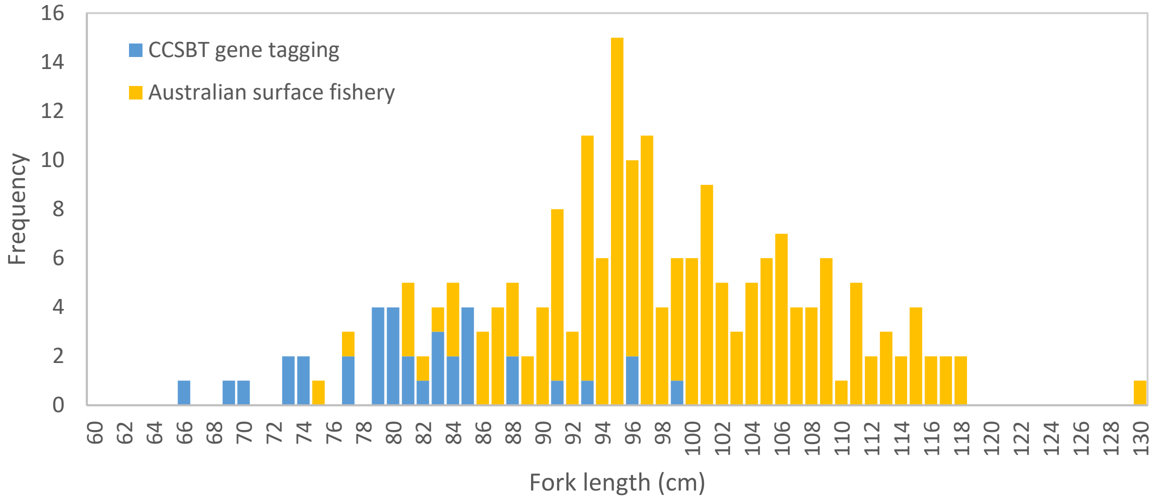

Figure 1. Length frequency of SBT with otoliths sampled from the Australian surface fishery and during gene-tagging operations in the 2018.

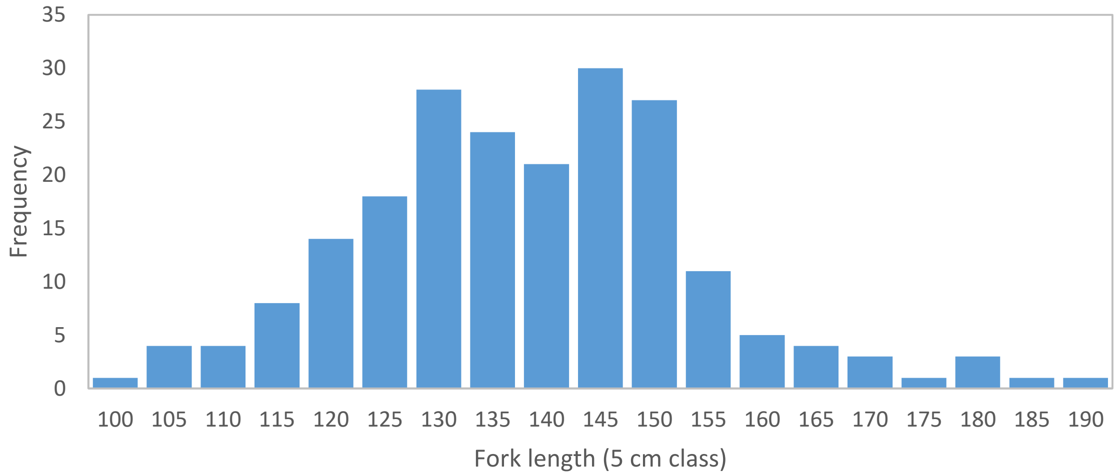

Figure 2. Length frequency of SBT with ovaries sampled in Australia. The lower boundary length value of the bin is shown.

4 Direct ageing

Of the 149 otoliths collected from the Australian surface fishery in the 2016/17 fishing season (see Farley and Eveson, 2017), 100 were selected for age determination. Otoliths were selected based on size of fish (length stratified sampling strategy rather than random sampling) to obtain as many age estimates from length classes where sample sizes were small. The fish selected for age estimation ranged in size from 81-122 cm fork length (FL).

One otolith from each fish was selected, weighed to the nearest 0.01 mg and sent to Fish Ageing Services Pty Ltd (FAS) in Victoria for sectioning and reading. The otoliths were prepared and read following Anon (2002). An ageing reference set (n=50 sectioned otoliths) was read by FAS prior to reading the otoliths for calibration purposes. The selected otoliths were then read at least two times by FAS without reference to the previous reading, size of fish, otolith weight or capture date.

An otolith reading confidence score was assigned to each otolith reading. The precision of readings was calculated using Average Percent Error (Beamish and Fournier, 1981).

A final age estimate was given all 100 SBT selected for ageing. Ages ranged from 2-6 years and the length to age relationship is given in Fig. 3. The average percent error between readings was 2.38% and the percent agreement was 86.0%. When successive readings differed, they were only by ±1 indicating a good level of precision. When readings differed, a final age was obtained by re-examining the otolith with the knowledge of the previous two age estimates as recommended by Anon. (2002).

Age estimates for all otolith collected during CCSBT gene tagging operations in 2017 were also obtained (n=25; see CCSBT-ESC/1908/07).

Table 3 shows the numbers of fish by age in each 5-cm length class from the surface fishery and gene tagging samples (n=125 total). These data are used in both the standard ALK and M&B methods of estimating the proportions of fish at age in the surface fishery (see below), noting that for the M&B method the data are broken down by 1-cm, as opposed to 5-cm, length classes.

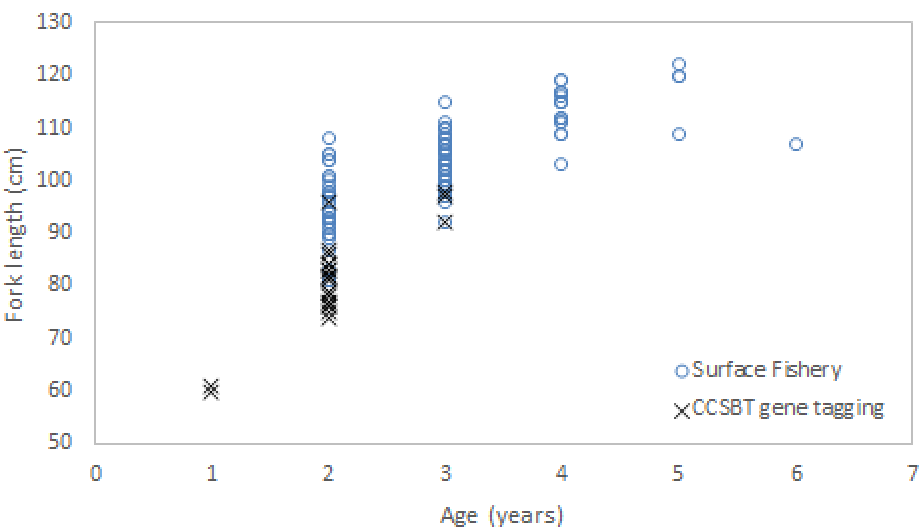

Figure 3. Length at age for SBT caught in the Australian surface fishery and during gene tagging operations in the 2016/17 fishing season (n=125).

Table 3. Age-length-key for the 2016/17 fishing seasons based on length at age from SBT caught in the Australian surface fishery (n=100) and during CCSBT gene tagging operations (n=25). The lower length of each 5cm length bin is given in the first column and ages are shown across the top.

LENGTH (CM)	1	2	3	4	5	6	TOTAL
60	2						2
65							
70		1					1
75		8					8
80		11					11
85		4					4
90		15	2				17
95		10	9				19
100		5	14	1			20
105		3	13	2	1	1	20
110			5	5			10
115			1	9			10
120					3		3
Total	2	57	44	17	4	1	125

5 Age distribution of the surface fishery catch

Methods

The most common way of estimating proportions at age in a given year, using age-at-length samples and a length distribution sample in the same year, is via an age-length key (ALK). The length frequency data are multiplied by the proportion of fish in each age class at a given length to give numbers (or proportions) at age. In mathematical terms, the proportion of fish of age *a*, p_a, is estimated as follows:

$$\hat{p}_a = \sum_l \frac{N_l}{N} \frac{n_{al}}{n_l}$$

where N_l is the number of fish in the length sample of length *l*, n_{al} is the number of fish in the age-length sample of age *a* and length *l*, $N = \sum_l N_l$ and $n_l = \sum_a n_{al}$.

A drawback of the ALK method is that it makes no use of the information about likely age contained in the length frequency data alone—thus it is inefficient, with variance up to 50% higher than necessary (see Morton & Bravington, 2003, Table 2). This is especially true for fisheries that catch young fast-growing fish, such as the Australian SBT surface fishery, where length is quite informative about age. As an alternative to the ALK, Morton and Bravington (2003) developed a parametric method which makes more efficient use of the information in both the length frequency and direct age data. The basis for the method is maximization of the following log-likelihood within each year:

$$\Lambda = \sum_{l} \left\{ N_l \log\left(\sum_{a} p_a p_{l|a} \right) + \sum_{a} n_{al} \log\left(p_a p_{l|a} \right) \right\}$$

where N_l, n_{al} and p_a are defined as above for the ALK, and $p_{l|a}$ is the probability that a fish of age *a* will have length l. Recall that the proportions at age (p_a) are what we are interested in estimating.

Here we assume $p_{l|a}$ follows a normal distribution with mean and variance that are either (a) known *a priori*, or (b) unknown and needing to be estimated together with the proportions at age. The former "known growth" approach is slightly more efficient if accurate estimates are available and if growth is consistent across cohorts; the latter "unknown growth" approach is robust to changes in growth and almost as efficient, so it is generally to be preferred. Variances for the proportion at age estimates can be obtained from the Hessian using standard likelihood theory.

Previously we applied the standard ALK method and the method of Morton and Bravington (hereafter referred to as the M&B method) to the age-length and length-frequency data from the Australian surface fishery in seasons 2001/02 through 2015/16 (see Farley and Eveson, 2017). Here we update the analysis to include data from the 2016/17 season. For the M&B method, we applied both the known and unknown growth approaches for comparison. In the known growth case, mean and standard deviation (SD) in length at age were assumed equal to the values in Table 1. These values were derived using the growth curve for the 2000s reported in Table 3 of Eveson (2011) and assuming the mid-point of the surface catches to be 1 February. The SDs include individual variation in growth, measurement error, and growth within the fishing season, taken as 1 December to 1 April (see Polacheck et al. 2002, p.44-48, for more information on calculating variance in expected length at age). In the unknown growth case, we found it was necessary to set lower and upper bounds on the mean length at age parameters, or else unrealistic estimates could be obtained for data-limited age classes (discussed in greater detail later). We chose fairly generous bounds equal to the mean length at age ±2 standard deviations (SDs), as calculated from the otolith age-length data.

Table 1. Mean and standard deviation (SD) in length at age derived from the growth model for the 2000s.

AGE	MEAN LENGTH (CM)	SD
1	55.0	5.7
2	81.9	6.3
3	102.6	6.8
4	114.7	7.3
5	124.8	7.8
6	133.4	8.2
7	140.7	8.5
8	146.8	8.8

Length samples are taken from the tow cages each year (previously 40 fish were sampled per cage but this was increased to 100 fish per cage in the 2012/13 season and for subsequent seasons), and the data scaled up by the number of fish in each tow cage to estimate the length frequency distribution of the entire catch. For the M&B method, it is important to estimate the "effective sample size"[1] of the length data in order to correctly weight the relative information of direct age data versus length data in the likelihood, and also to estimate variances correctly. This entails a re-scaling of the length frequencies derived from the scaled-up tow cage samples, as described in Basson et al. (2005). Specifically, if T is the number of tow cages in a particular season, c_i is the number of fish in tow cage i, m_i is the total number of fish sampled from tow cage i, and m_{il} is the number of fish of length l in the sample from tow cage i, then we estimate π_l, the frequency of fish of length l over all tow cages, to be

$$\hat{\pi}_l = \sum_i c_i^* \frac{m_{il}}{m_i}$$

where

$$m_i = \sum_l m_{il}$$

and

$$c_i^* = \frac{c_i}{\sum_{j=1}^{T} c_j}.$$

The variance of $\hat{\pi}_l$ is estimated by

$$\mathrm{V}[\hat{\pi}_l] = \sum_i \frac{c_i^{*2}}{m_i}$$

Finally, we estimate the effective sample size of fish of length *l* to be

$$\tilde{N}_l = \frac{\hat{\pi}_l}{\mathrm{V}[\hat{\pi}_l]}.$$

These are the numbers we used as the N_l's for both the ALK and M&B methods.[2]

For the ALK method, the age-at-length and length frequency data were binned into 5-cm length classes. Generally, enough otoliths are available so that there are very few "missing rows" in the ALK for any year when 5-cm length bins are used; i.e., there are very few length bins for which the

[1] The length samples taken from the tow cages do not constitute independent random draws from the entire catch (since the lengths of fish within a tow cage are not representative of the entire catch). The effective sample size refers to the sample size that leads to the equivalent variance as the tow cage samples had in fact been independent random draws.

[2] For the ALK method, which only makes use of the proportion of fish of a given length class and not the absolute numbers, it should not matter whether we use the scaled-up tow cage numbers or the re-scaled effective sample sizes, but for consistency we use the same numbers for all methods.

proportions-at-age cannot be calculated. However, this is not always the case; e.g., for the 2010/11 season there were no fish belonging to length bin 85-90 cm in the age-length data despite ~7% of the observations from the length-frequency data being in this range. The consequences of this were discussed in Farley et al. (2012).

For the M&B method (with known or unknown growth), the age-at-length and length frequency data were binned into 1-cm length classes.

Results

The proportions at age estimated from the standard ALK method, the M&B method with known growth, and the M&B method with unknown growth are compared in Figure 4. The actual values are provided in Appendix A (Tables A1-A3). For many seasons there is reasonably good agreement between the various methods, but for others the estimated proportions at ages 2-4 are considerably different. For example, in the most recent season (2016/17), the standard ALK and M&B method with unknown growth match quite closely, but the M&B method with known growth estimates a much lower proportion of age 2 fish and greater proportion of age 3 fish; a similar result was found in 2013/14 and 2014/15. However, in the previous season (2015/16), the two M&B methods (with known and unknown growth) match closely, but the standard ALK method estimates a considerably greater proportion of age 2 and lower proportion of age 3 fish.

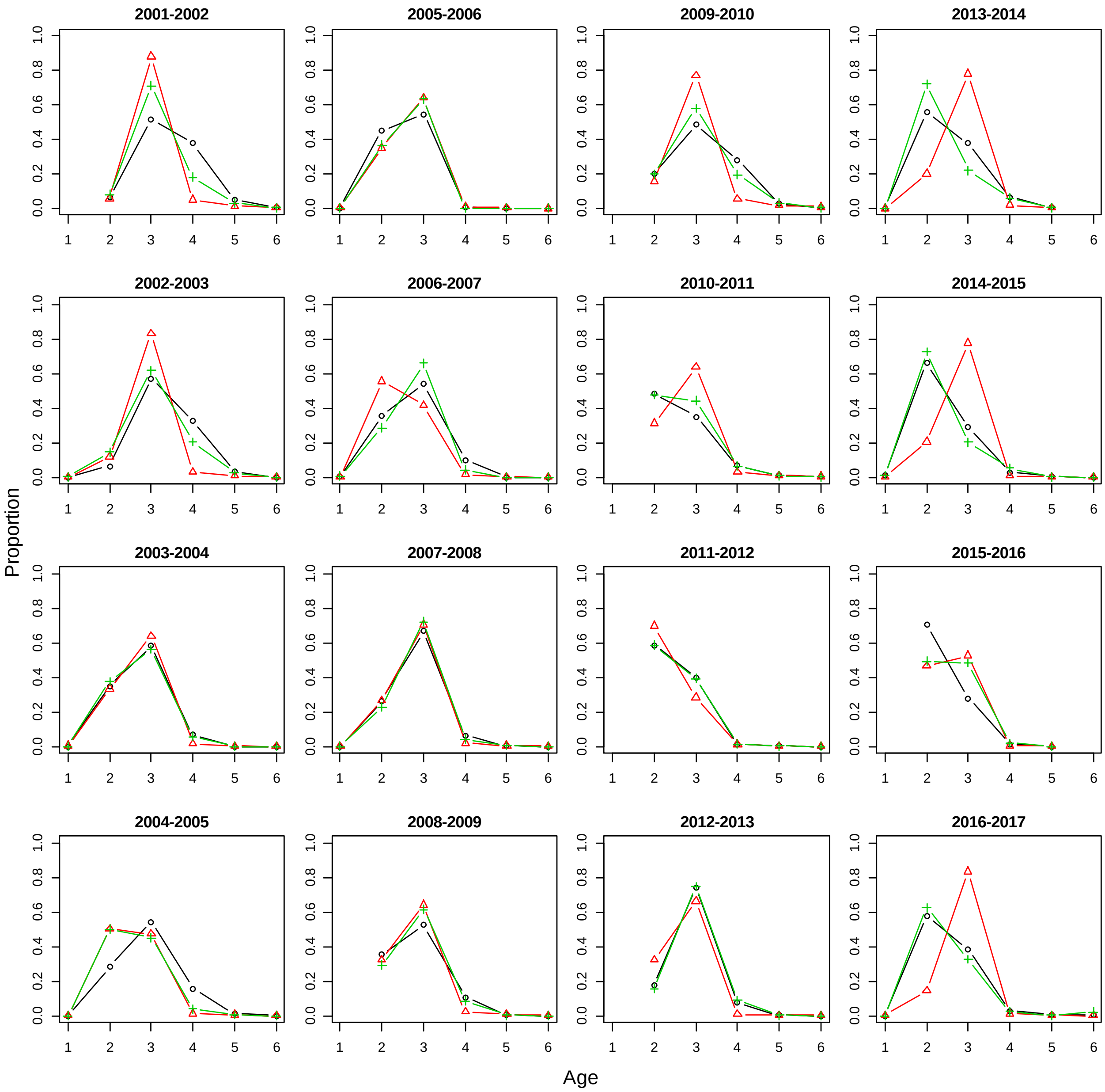

Figure 4. Estimated proportions of fish at age in each fishing season using i) the ALK method (black, open circles); ii) the M&B method with known growth (red, open triangles); iii) the M&B method with unknown growth (green, plus symbols).

The M&B method with unknown growth produces estimates that fit the length data very closely for all seasons (Fig. 5), with the exception of the 2010/11 season (as discussed in Farley et al. 2012). In comparison, the M&B method with known growth does not fit the length data nearly so well (Fig. 6). This is to be expected since the unknown growth method estimates the mean and SD in length at age based on the data (Tables A4 and A5 in Appendix A), and these estimates can be quite different than those derived from the growth model (Table 1). In particular, the mean length estimates from the M&B method for age 2 are larger in all seasons than the estimate from the growth model, and the age 3 and 4 estimates smaller (with one exception for age 3 in 2013/14) (Fig. 7).

The growth model was estimated based on age-length data and tag-recapture data for fish born in the 2000s. It does not include the length-frequency data due to concerns about size-selective fishing (Polacheck et al. 2002, Appendix 3), and is not specific to fish in the GAB nor to seasons. Provided that the length-frequency data are representative of fish caught in the surface fishery, and given our goal of estimating proportions at age in the catches (not in the population), the M&B estimator with unknown growth should be most accurate. Using this method, the proportion at age estimates for the 2016/17 season are 63% age 2 and 33% age 3 (Table A3 in Appendix A). These estimates suggest a larger proportion of age 2 and smaller proportion of age 3 fish in the catches in 2016/17 than in most previous seasons, with the exception of 2013/14 and 2014/15. The mean length at age estimates for the 2015/16 season for ages 2, 3 and 4 are 93.4, 101.1 and 108.8 cm respectively (Table A4 in Appendix A).

The relatively small numbers of otoliths for fish of age 1 and age 5+, as well as the low proportion of fish corresponding to these age classes in the length-frequency data, can lead to difficulties in estimating mean length for these ages. Since the proportion at age estimates are so close to 0 for these age classes, the consequences of incorrectly estimating their mean length should be small. Of some concern, however, are the mean length estimates for age 4 fish, which are sometimes estimated to be very close to the mean length for age 3 (Fig. 5; Fig. 7). It is possible to impose tighter bounds on the mean length at age parameters, but doing so simply results in the age 4 estimates falling on the lower bound, so it is not a very satisfactory solution. A possibility for future consideration is to incorporate *a prior* distributions on the mean length at age parameters—this would provide an intermediate approach to the known and unknown growth methods currently available.

CVs of the estimated proportions at age using the M&B method with unknown growth were calculated by dividing the square root of the Hessian-based variance estimates by the estimates (Table A6 in Appendix A). Where the estimated proportion at age was less than 0.01 (i.e., for age 1 and most of ages 5 and above), we have opted not to show the CV because dividing by such a small number can lead to a very large and misleading CV. For the 2016/17 season, the CV of the estimates for ages 2-4 are 6%, 6% and 42% respectively. In general, the proportion at age estimates are quite precise for ages 2 and 3 (CVs < ~10%), but less so for age 4 and 5 (ranging from 14% to 42%) since these older age classes have less data available. As discussed in Farley et al. (2012), the 2010/11 season was an exception with much higher CVs for the age 2 and 3 estimates than in other seasons due to a contrast between the direct age data and length-frequency data for fish of ages 2 and 3 in this season.

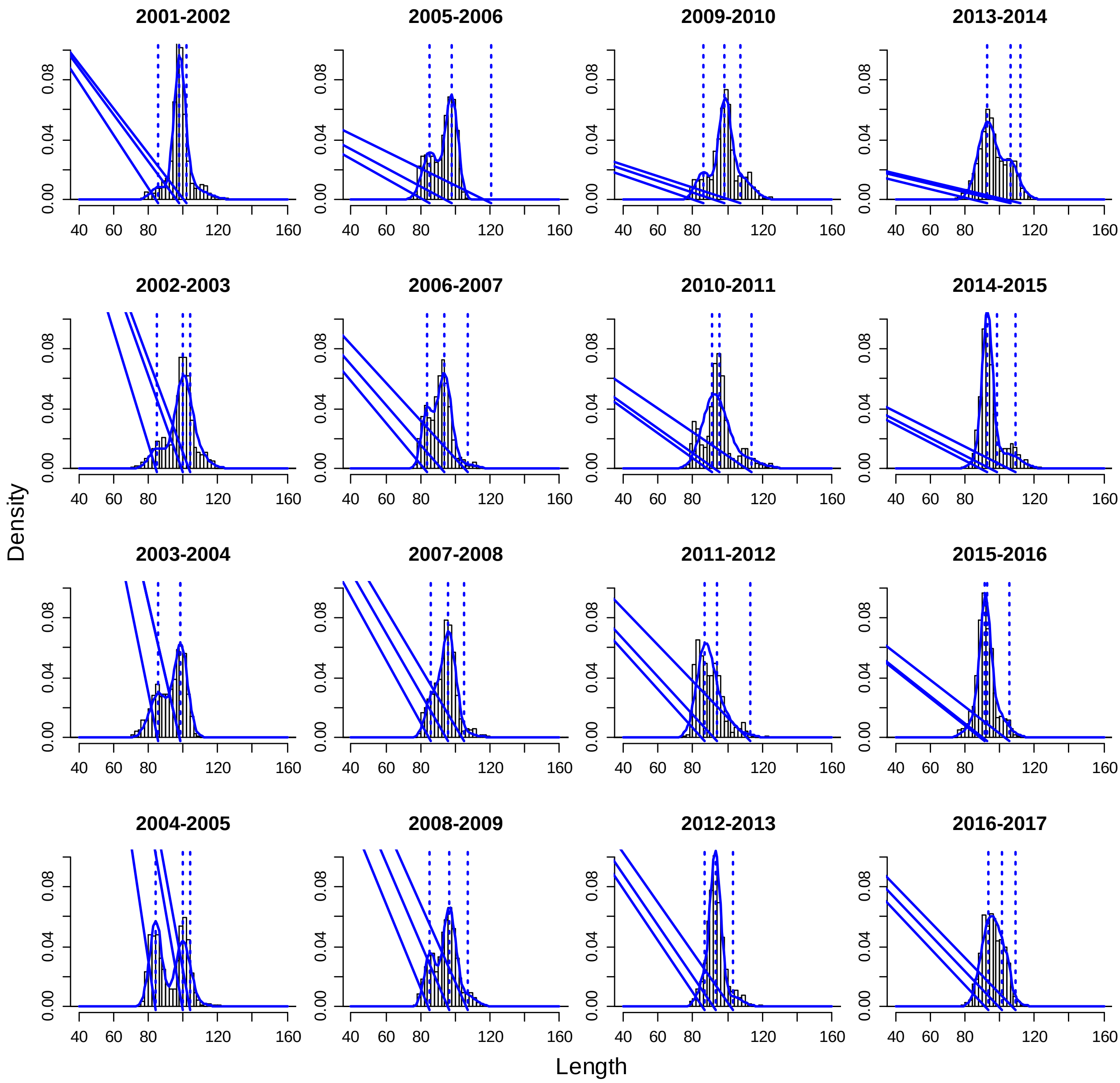

Figure 5. Length distribution of fish caught in the GAB in each fishing season, along with the estimated distribution and estimated mean lengths at age for ages 2-4 from the M&B method with unknown growth (solid blue curve and dashed blu vertical lines).

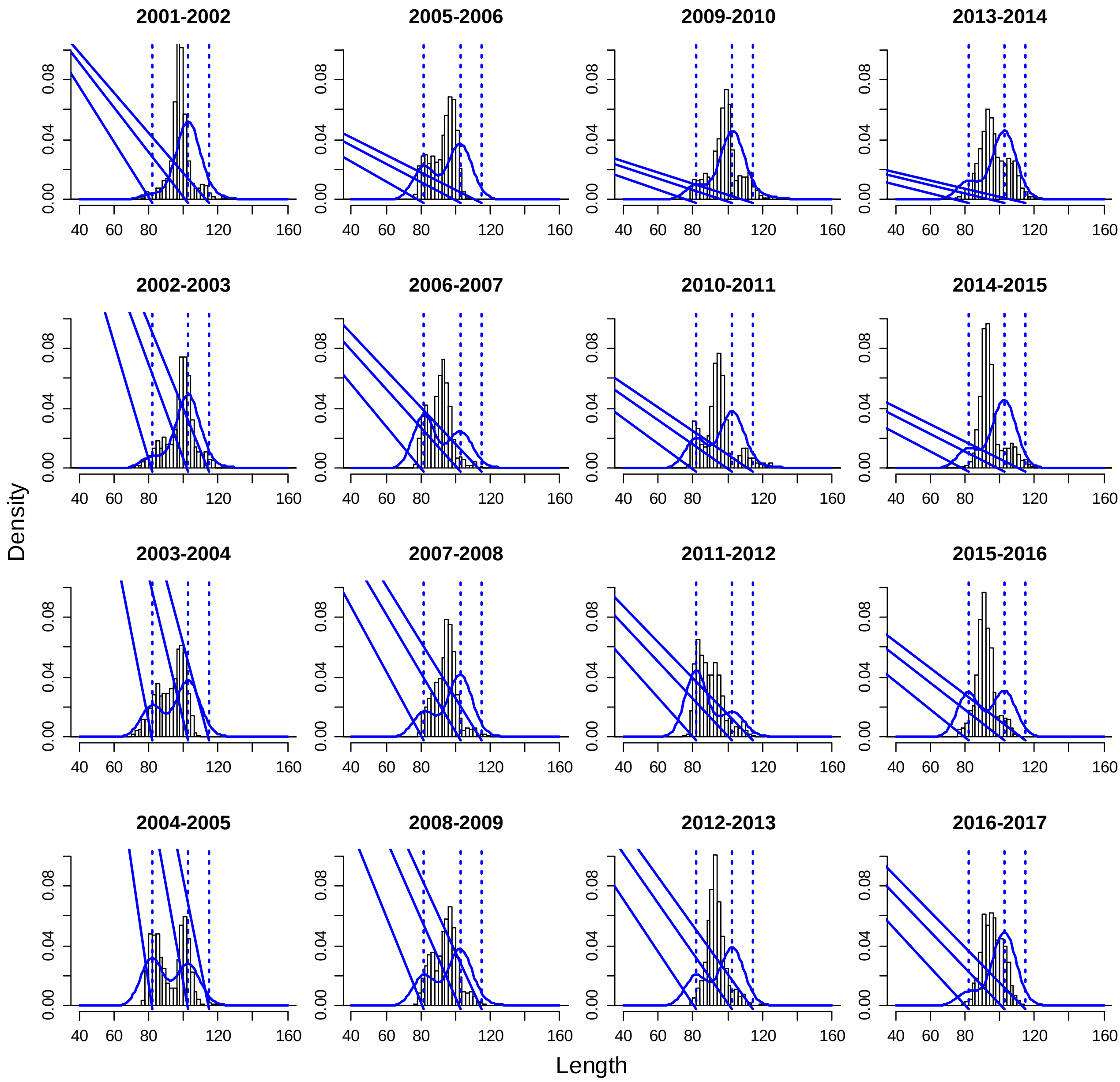

Figure 6. Length distribution of fish caught in the GAB in each fishing season, along with the estimated distribution and "known" mean lengths at age for ages 2-4 from the M&B method with known growth (solid blue curve and dashed blue vertical lines).

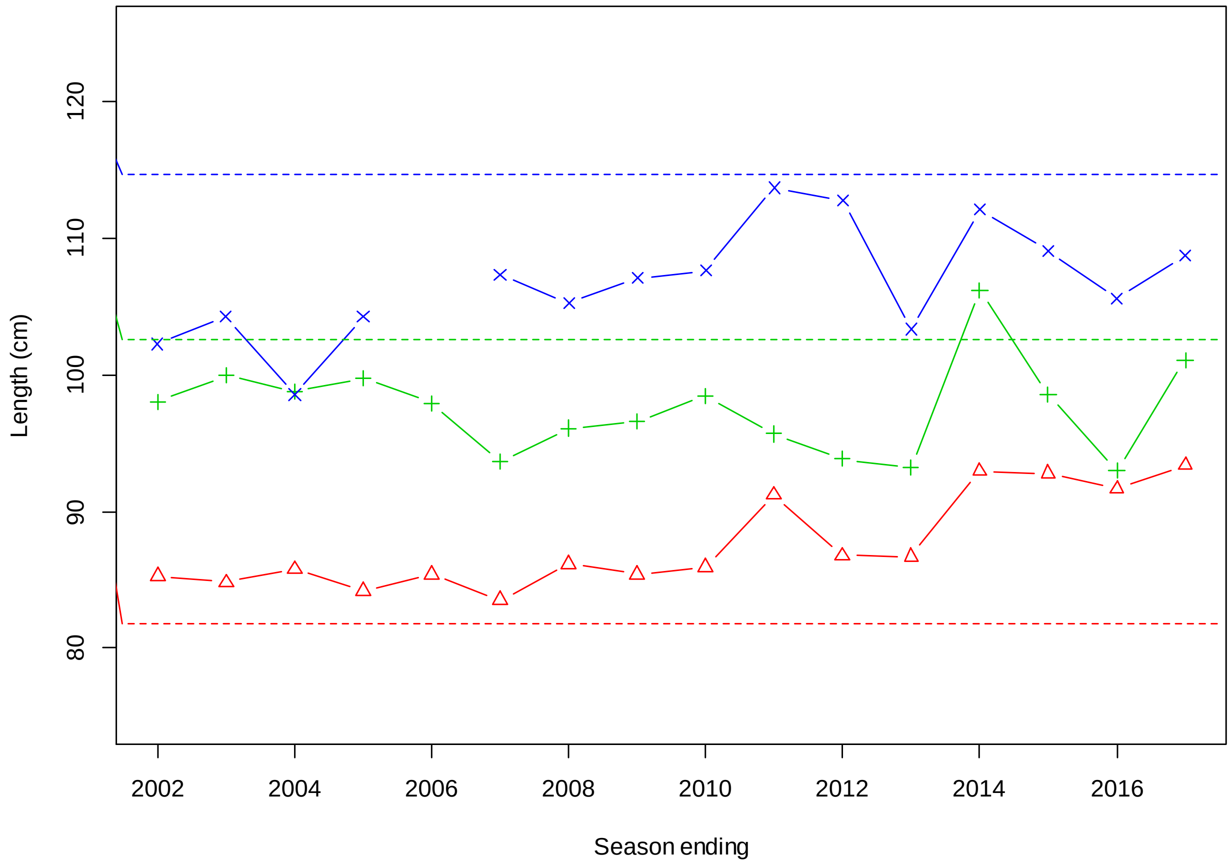

Figure 7. Mean length at age estimates using the M&B method with unknown growth (red triangle = age 2; green plus = age 3; blue cross = age 4). Note the age 4 estimate for 2006 is omitted because there were insufficient data to get a reliable estimate. For comparison, the horizontal dashed lines show the mean length at age estimates for ages 2-4 used in the M&B method with known growth (derived from the 2000s growth model in Eveson 2011).

As in previous reports, we again stress that the proportions at age derived here apply only to fish caught in the GAB surface fishery. They are unlikely to apply to the population of fish found in the GAB due to the size-selective nature of the surface fishery, and they are less likely to apply to the global population since data collected in the GAB are not representative of fish found in other regions (for example, age-1 fish found off Western Australia are smaller on average than age-1 fish found in the GAB at the same time, likely due to a later spawning event; Polacheck et al. 2002).

6 Summary

Direct age estimates were obtained for 125 SBT caught in the GAB in 2016/17, and an additional 211 otoliths were collected in the GAB in 2017/18 for ageing next year. Ovaries were also collected from SBT caught off southeast Australia in July, bringing the total sampled to 247. Histological analysis of the ovaries will be undertaken in preparation for the proposed maturity workshop in March 2019.

For the 2016/17 season, the proportion at age estimates are 63% age 2 and 33% age 3. These estimates suggest a larger proportion of age 2 and smaller proportion of age 3 fish in the catches in 2016/17 than in most previous seasons, with the exception of 2013/14 and 2014/15. The mean length at age estimates for ages 2, 3 and 4 are 93.4, 101.1 and 108.8 cm respectively.

When combined with length-frequency data, the otolith sample sizes for age estimation of the Australian surface fishery (100 otoliths per fishing season; noting that an additional 25 otoliths were obtained this year from the gene tagging project) appear to provide acceptably low CVs for ages 2 and 3. Whether the higher CVs for age classes 4 and 5 are adequate can only be evaluated once the direct age data are used in the SBT operating model. If it is important, then there will be a need to re-evaluate the sampling design for otoliths including (a) number sampled per length class and (b) the number of otoliths that need to be read. The estimated proportions at age will also only be representative of the catch if the size frequency distribution of the fish sampled is representative. This work highlights the need for continued discussion within the CCSBT regarding development of protocols for obtaining representative samples of length at age from all fisheries, and the technical details of how the direct age data will be incorporated into the operating model. The direct ageing data set is a significant resource, which can be improved as more otoliths are collected and read (fish age estimated) from subsequent years.

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Appendix A

Results from fitting the standard ALK method and the Morton & Bravington (M&B) method with known and unknown growth to the Australian surface fishery age-length and length-frequency data.

Table A1: Proportions at age for each fishing season estimated using the standard ALK method. (Four decimal places are shown to retain the small but non-zero proportions for ages 1 and >4). NA = not applicable.

	AGE							
SEASON	1	2	3	4	5	6	7	8
2001-2002	NA	0.0626	0.5130	0.3742	0.0457	0.0039	0.0006	NA
2002-2003	0.0013	0.0652	0.5726	0.3256	0.0350	0.0002	0.0001	0.0000
2003-2004	0.0000	0.3515	0.5817	0.0665	0.0003	0.0000	0.0000	NA
2004-2005	0.0000	0.2853	0.5448	0.1572	0.0122	0.0003	0.0001	0.0000
2005-2006	0.0000	0.4505	0.5448	0.0044	0.0002	0.0001	NA	NA
2006-2007	0.0023	0.3571	0.5405	0.0996	0.0004	0.0001	0.0000	NA
2007-2008	0.0000	0.2637	0.6698	0.0624	0.0036	0.0005	NA	NA
2008-2009	NA	0.3531	0.5273	0.1065	0.0052	0.0000	NA	NA
2009-2010	NA	0.1961	0.4871	0.2798	0.0253	0.0024	NA	NA
2010-2011	NA	0.4864	0.3519	0.0667	0.0124	0.0029	0.0000	NA
2011-2012	NA	0.5886	0.3970	0.0118	0.0022	0.0000	0.0000	NA
2012-2013	NA	0.1749	0.7441	0.0786	0.0020	0.0004	0.0000	0.0000
2013-2014	0.0000	0.5559	0.3748	0.0659	0.0022	NA	NA	NA
2014-2015	0.0156	0.6605	0.2888	0.0297	0.0043	0.0001	NA	NA
2015-2016	NA	0.7070	0.2796	0.0127	0.0002	NA	NA	NA
2016-2017	0.0000	0.5763	0.3838	0.0294	0.0060	0.0045	NA	NA

Table A2: Proportions at age for each fishing seasons estimated using the M&B method with known mean and variance in length at age. NA = not applicable.

	AGE							
SEASON	1	2	3	4	5	6	7	8
2001-2002	NA	0.0575	0.8812	0.0470	0.0108	0.0023	0.0012	NA
2002-2003	0.0013	0.1212	0.8333	0.0318	0.0091	0.0021	0.0005	0.0007
2003-2004	0.0048	0.3336	0.6394	0.0176	0.0036	0.0010	0.0001	NA
2004-2005	0.0016	0.5028	0.4759	0.0129	0.0042	0.0009	0.0012	0.0006
2005-2006	0.0014	0.3502	0.6379	0.0096	0.0008	0.0002	NA	NA
2006-2007	0.0022	0.5585	0.4179	0.0181	0.0026	0.0005	0.0002	NA
2007-2008	0.0006	0.2681	0.7065	0.0197	0.0040	0.0011	NA	NA
2008-2009	NA	0.3247	0.6413	0.0235	0.0086	0.0018	NA	NA
2009-2010	NA	0.1556	0.7692	0.0513	0.0165	0.0074	NA	NA
2010-2011	NA	0.3148	0.6384	0.0313	0.0094	0.0059	0.0003	NA
2011-2012	NA	0.6988	0.2857	0.0114	0.0029	0.0009	0.0003	NA
2012-2013	NA	0.3241	0.6632	0.0088	0.0018	0.0018	0.0002	0.0002
2013-2014	0.0003	0.1984	0.7799	0.0184	0.0030	NA	NA	NA
2014-2015	0.0012	0.2067	0.7792	0.0091	0.0032	0.0006	NA	NA
2015-2016	NA	0.4671	0.5266	0.0055	0.0008	NA	NA	NA
2016-2017	0.0007	0.1465	0.8365	0.0130	0.0027	0.0007	NA	NA

Table A3: Proportions at age for each fishing seasons estimated using the M&B method with unknown mean and variance in length at age. NA = not applicable.

	AGE							
SEASON	1	2	3	4	5	6	7	8
2001-2002	NA	0.0803	0.7093	0.1780	0.0279	0.0040	0.0006	NA
2002-2003	0.0016	0.1465	0.6200	0.2061	0.0256	0.0002	0.0001	0.0000
2003-2004	0.0004	0.3783	0.5647	0.0565	0.0001	0.0000	0.0000	NA
2004-2005	0.0000	0.5025	0.4526	0.0393	0.0053	0.0003	0.0000	0.0000
2005-2006	0.0000	0.3664	0.6322	0.0010	0.0002	0.0001	NA	NA
2006-2007	0.0078	0.2876	0.6621	0.0422	0.0003	0.0001	0.0000	NA
2007-2008	0.0000	0.2287	0.7228	0.0438	0.0042	0.0005	NA	NA
2008-2009	NA	0.2930	0.6170	0.0864	0.0035	0.0000	NA	NA
2009-2010	NA	0.1969	0.5783	0.1939	0.0290	0.0019	NA	NA
2010-2011	NA	0.4775	0.4438	0.0659	0.0100	0.0028	0.0000	NA
2011-2012	NA	0.5885	0.3943	0.0151	0.0022	0.0000	0.0000	NA
2012-2013	NA	0.1568	0.7500	0.0902	0.0022	0.0008	0.0000	0.0000
2013-2014	0.0004	0.7200	0.2187	0.0580	0.0029	NA	NA	NA
2014-2015	0.0120	0.7292	0.2024	0.0525	0.0035	0.0004	NA	NA
2015-2016	NA	0.4941	0.4846	0.0203	0.0010	NA	NA	NA
2016-2017	0.0000	0.6258	0.3270	0.0231	0.0029	0.0211	NA	NA

Table A4: The estimated mean length at age (in cm) for each fishing season using the M&B method with unknown mean and variance in length at age. NA = not applicable.

	AGE							
SEASON	1	2	3	4	5	6	7	8
2001-2002	NA	85.3	98.0	102.3	113.8	119.7	136.3	NA
2002-2003	72.2	84.8	100.0	104.3	113.1	129.7	132.6	141.6
2003-2004	66.2	85.8	98.8	98.6	113.1#	128.3	122.7	NA
2004-2005	44.5#	84.2	99.8	104.3	111.5	120.0#	137.7	137.5
2005-2006	69.2*	85.4	97.9	120.4	130.7	132.8	NA	NA
2006-2007	82.2	83.5	93.7	107.4	129.2	129.8	141.7	NA
2007-2008	57.3	86.2	96.1	105.3	111.4	133.0	NA	NA
2008-2009	NA	85.4	96.6	107.1	117.2	125.4	NA	NA
2009-2010	NA	86.0	98.5	107.6	116.9	126.1	NA	NA
2010-2011	NA	91.2	95.7	113.7	124.6	125.7	143.5	NA
2011-2012	NA	86.8	93.8	112.8	115.3	137.8	126.2	NA
2012-2013	NA	86.7	93.2	103.4	118.0	119.4	140.8	143.4
2013-2014	68.3	93.0	106.2	112.1	125.5	NA	NA	NA
2014-2015	83.8*	92.8	98.6	109.1	121.1	127.5	NA	NA
2015-2016	NA	91.7	93.0	105.6	118.9	0.7NA	NA	NA
2016-2017	60.5	93.4	101.1	108.8	112.1	104.8	NA	NA

Estimate hit lower bound.

* Estimate hit upper bound.

Table A5: The estimated standard deviation in length at age (in cm) for each fishing season using the M&B method with unknown mean and variance in length at age. NA = not applicable.

	AGE							
SEASON	1	2	3	4	5	6	7	8
2001-2002	NA	4.2	3.2	7.3	7.4	7.6	0.2	NA
2002-2003	2.9	4.4	4.8	6.9	6.6	4.6	2.2	2.1
2003-2004	3.5	5.2	3.9	6.4	5.1	4.4	5.6	NA
2004-2005	4.0	3.5	4.3	6.8	7.9	8.8	6.4	7.9
2005-2006	3.1	4.6	3.6	7.6	4.1	2.8	NA	NA
2006-2007	3.2	3.1	4.2	5.9	2.7	3.0	0.0	NA
2007-2008	0.6	3.6	4.2	7.1	8.9	1.7	NA	NA
2008-2009	NA	3.3	3.8	4.9	3.6	2.3	NA	NA
2009-2010	NA	4.3	3.6	5.3	4.3	3.6	NA	NA
2010-2011	NA	6.4	8.0	5.3	3.5	4.7	0.0	NA
2011-2012	NA	4.8	7.5	4.7	6.3	1.9	6.8	NA
2012-2013	NA	3.8	3.0	5.4	3.5	3.9	0.1	0.0
2013-2014	1.8	5.5	4.1	4.9	10.0	NA	NA	NA
2014-2015	2.2	3.0	8.6	5.6	5.3	0.2	NA	NA
2015-2016	NA	2.8	7.4	5.8	0.9	NA	NA	NA
2016-2017	0.7	4.8	4.2	4.7	8.2	1.2	NA	NA

Table A6: Coefficients of variation (CVs) of the estimated proportions at age for each fishing season using the M&B method with unknown mean and variance in length at age. A dash (--) indicates where the estimated proportion at age was less than 0.01. NA = not applicable.

	AGE							
SEASON	1	2	3	4	5	6	7	8
2001-2002	NA	0.13	0.03	0.14	0.25	--	--	NA
2002-2003	--	0.10	0.06	0.18	0.39	--	--	--
2003-2004	--	0.05	0.04	0.31	--	--	--	NA
2004-2005	--	0.03	0.04	0.36	--	--	--	--
2005-2006	--	0.06	0.03	--	--	--	NA	NA
2006-2007	--	0.07	0.03	0.18	--	--	--	NA
2007-2008	--	0.10	0.04	0.31	--	--	NA	NA
2008-2009	NA	0.07	0.04	0.19	--	--	NA	NA
2009-2010	NA	0.09	0.05	0.14	0.37	--	NA	NA
2010-2011	NA	0.22	0.23	0.18	0.32	--	--	NA
2011-2012	NA	0.12	0.17	0.34	--	--	--	NA
2012-2013	NA	0.19	0.04	0.08	--	--	--	--
2013-2014	--	0.02	0.09	0.23	--	NA	NA	NA
2014-2015	0.61	0.03	0.13	0.24	--	--	NA	NA
2015-2016	NA	0.06	0.06	0.42	--	NA	NA	NA
2016-2017	--	0.06	0.12	0.39	--	0.68	NA	NA

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Data generation & changes to SBT OM

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12 June 2018

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Contents

Abstract

This paper details the structural changes made to the SBT Operating Model required to simulate the new data sources: gene tagging, and close-kin mark-recapture (parent-offspring and half-sibling pairs).

1 Background

Initial methods for generating these new data sources, as well as potentially informative indices that could be derived from them, were explored in [1]. Additionally, the stuctural changes required to the SBT OM to accommodate these new data sources in the conditioning phase were outlined in [2]. This paper details the actual technical details of the changes made to the SBT OM projection code (`sbtproj.tpl`), and how the new data generation control parameters are defined in the `mycontrol.dat` files.

2 Gene tagging

Details of how we simulate the gene tagging data in the OM (‘sbtproj‘). Major items covered are:

- The observation error model employed
- Including the ”reality” of the gene tagging process
- Defining the estimates of abundance (and CVs thereof)
- Suggestions about what can be used in a candidate MP setting
- What changes are needed in the control and `sbtOMdata` files

The primary goal of the gene tagging (GT) program is to provide an estimate of the absolute abundance of age 2 fish (and some measure of the uncertainty thereof). Moving back to base principles, if you tag a single 2-year old fish in year y, release it ”randomly” into the population and attempt to recapture it again (via a random sampling method) in year $y+1$ then the chance of finding it is $1/N_{y,2}$. If you tag T fish this probability increases to $T/N_{y,2}$. If you genotyped S fish in year $y+1$ to check for ”recaptures” then you would expect to find the following average number of recaptures:

$$\mathbb{E}(R) = \frac{TS}{N_{y,2}}$$

The default appropriate distribution for these kind of data is the binomial distribution. As per previous discussions about how to model these data, and given the distributional features of the 1990s tagging data, we agreed to a more generalised distribution called the beta-binomial distribution. This is an extension of the binomial model that permits additional variability in the probability of recapture. The tagging data currently in the OM clearly show higher variance than the base multinomial distribution would predict. Some of those sources of additional variance (heterogeneity in assumed static parameters) will not be a feature of the GT program - specifically variation in tag loss and reporting rates. As such, the so-called *over-dispersion* coefficient (degree to which variance is inflated) of the tagging data (*ca.* 1.8) would be an upper bound to the GT over-dispersion coefficient, with a value of 1 (no over-dispersion) being an obvious lower bound. We also propose a simple bias factor to be included into the GT observation error model that is there specifically to deal with recruitment dynamics that result in us systematically sampling a subset of the true age 2 abundance. We would propose the following modification to the expected recapture probability:

$$\tilde{p} = \frac{T}{q^{\mathrm{gt}} N_{y,2}},$$

If we define the over-dispersion coefficient as ϕ. For a given sample size $n = S$, we define the crucial over-dispersion parameter, ω, as follows:

$$\omega = \frac{\phi - 1}{n - \phi},$$

then the parameters of the beta distribution, $p^{\mathrm{gt}} \sim B(\alpha, \beta)$, that underlies the true sampling probability are defined as follows:

$$\alpha = \frac{(n-\phi)\tilde{p}}{(1-\tilde{p})(\tilde{p} + (1-\tilde{p})(\phi - 1))}$$

and

$$\beta = \frac{n - \phi}{\tilde{p} + (1-\tilde{p})(\phi - 1)}.$$

In the practical simulation sense, given the relevant GT control parameters (T, S and ϕ), we first simulate p^{gt} from the underlying beta distribution, and then simulate the number of recaptures, R, from the binomial distribution parameterised by p^{gt} and $n = S$.

The estimate of abundance, given R, T and S is basiscally the classical Petersen estimator:

$$\widehat{N}_{y,2} = \frac{TS}{R},$$

with the approximate CV of this estimate given by $1/\sqrt{R}$.

There are certain adaptive features of the GT program - particularly the post-release resampling program in the farms - that are worth both considering and actively including in the simulation process. The main point of the observation error model is to represent, to the best of our abilities, the actual process of data collection. In the GT program, if we had processed the S samples to find matches and found less than we would prefer (e.g. we have some minimum value, $R_{\min}$), it is the case (as it was this year) that we do have the option of processing an additional number of samples, S_{+}, to hopefully obtain additional matches and, as a result, a more accurate estimate of the age 2 abundance. To be clear, this is no way introduces bias to the estimation process: the proportional increase in sample size would be the same as the proportional increase in the expected number of matches. The expected abundance estimate would be the same, but the accuracy would be increased.

The settings for the GT sampling settings are contained in an augmented `mycontrol.dat` file used for the projections on previous occasions. An example file (`mycontrolGTMP.dat`) is now included in the git repository in the develop branch. The GT control variables are:

1. *Trel*: number of intial "releases", T, from which sample is taken
2. *Srec*: main number of samples, S, taken from harvested fish the following year

3. *Sadd*: ”back-up” samples, S_+ that can be processed if needed
4. *Rmin*: minimum number of matches, R_{min}, if adaptive sampling required
5. *gtadsw*: adaptive sampling switch (0 off; 1 on) - if number of matches less than minimum amount, process the additional back-up samples to get more
6. *qgt*: value of the bias, q_{gt}, in the GT estimator (1, no bias; alternatives will be less than 1 probably...)
7. *phigt*: value of the over-dispersion, ϕ, for the GT simulations (1 means no OD basically)

The text in the augmented `mycontrol.dat` where the GT variables are set is found immediately below where the CPUE and aerial survey control variables are found:

```
# switches for robustness tests highCPUECV, highaerCV and updownq
# if highCPUECV=1 (set sigmaq=0.30 and sigmaaerial=0.30)
# if highAerialCV=1 (set sigmaq=0.20 and sigmaaerial=0.50)
# if updownq = 1 (increase q by 50% for fisrt 5 years)
0 0 0
# control parameters for GT program
# Trel (releases)
# Srec (recapture samples scanned)
# Sadd (additional samples if needed)
# Rmin (minimum number of recaptures)
# gtadsw (switch for adaptive sampling given Rmin; 0 off,1 on)
# qgt (bias level for GAB N2)
# phigt (over-dispersion level)
5000 10000 5000 5 0 1.0 1.0
```

These settings are probably about right (in terms of sampling specifics) given the previous two GT field programs but can and probably will be adjusted as we get more into the work. In terms of files it is the `.s-` named files that contain the summaries of various quantities from the projections. For the future GT data a new file has been created (`.s11`) which contains the key variables of interest:

- Grid element relating to that sample
- Estimated abundance of age 2 fish from GT
- True value of age 2 fish in that projection sample
- The approximate CV of the GT estimate of of age 2 fish
- The observed number of matches given the GT program settings

3 Close-kin mark-recapture

Alongside the gene-tagging (GT) data, the OM will now also simulate close-kin mark-recapture (CKMR) data - both parent offspring (POP) and half-sibling (HSP) pairs. This document covers both the simulation of the data using the SBT OM, as well as some empirical and model-based options for using these data in an MP context.

Cohort	Adult year	Adult age	nK	nC
c	y	a	$\mathrm{Bin}(p, nC)$	$\mathrm{MN}(p_a, M_j)$

3.1 Parent-Offspring pairs

The key covariates of importance in the SBT OM in relation to POPs are:

- The year of sampling, y, of the adult
- The age at sampling, a, of the adult
- The birth year/cohort, c, of the juvenile

while the key parameters and derived variables of importance are:

- Abundance-at-age, $N_{y,a}$
- Relative reproductive output-at-age, φ_a

so that for an juvenile-adult pair $\{i, j\}$, so $z_i = \{c\}$ and $z_j = \{y, a\}$, then the probability of that pair being a POP is given by

$$\mathbb{P}\left(K_{ij} = POP|z_i, z_j\right) = \mathbb{I}\left(c < y < c + a\right) \frac{2\varphi_{a-(y-c)}}{\sum_i N_{c,i}\varphi_i} \tag{3.1}$$

where $\mathbb{I}()$ is the indicator function. The assumed distribution of the POPs is binomial, given the sampling probability in (1), and all juveniles are assumed to be sampled at 3 years old, and that each year there are M_i samples taken. For the adults, a random draw from the multinomial distribution of likely adults is taken (for a given adult sample size, M_j). Both the sample size control parameters are defined in the `mycontrol.dat` file as with the GT control parameters. The data are organised in the same way as the historical POP data are: a 5-d data frame:

where p_a is the distribution of adults in a given year and Bin() and MN() are the binomial and multinomial distributions, respectively.

A quirk of the CKMR data is that future simulated data collection (i.e. from projections) actually alters the data in the past - future adult samples are compared to pre-projection juvenile samples to look for POPs. To be clear, this does not invalidate the use of the actual historical CKMR data in the OM, it just outlines the complex nature of the temporal accumulation of comparisons and matches in the CKMR data.

3.2 Half-Sibling pairs

For the HSP data we compare to juvenile samples and ask: what is the probability that they share a mother or a father? For juvenile samples i and i', the key covariate is their year of birth, or cohort c. The additional derived variables needed for constructing the HSP probabilities are natural mortality and fleet-summed harvest rates:

$$\mathbb{P}\left(K_{ii'} = HSP|z_i, z_{i'}\right) = \frac{4\pi^{\eta} q_{\text{hsp}}}{S_{c_{\max}}} \left(\sum_a \gamma_{c_{\min},a} \left(\prod_{k=0}^{\delta-1} \phi_{c_{\min}+k,a+k}\right) \varphi_{a+\delta}\right) \tag{3.2}$$

where

$$\phi_{y,a} = \exp\left(-M_a\right) \prod_{s=1}^{2} \left(1 - \sum_f h_{s,f,y,a}\right) \tag{3.3}$$

is the annual survival probability, and:

- $\{z_i, z_{i'}\} = \{c_i, c_{i'}\}$
- $c_{\min} = \min\{c_i, c_{i'}\}$
- $c_{\max} = \max\{c_i, c_{i'}\}$
- $\delta = c_{\max} - c_{\min}$
- q_{hsp} is a parameter to cover potentially length-driven or recruitment dynamic differences between POP and HSP absolute abundance information
- π^{η} is the false-negative retention probability (1 minus the false negative exclusion rate defined by the false-positve cut-off)
- $\gamma_{y,a}$ is the true age distribution of adults in year y

Both the sampling distributions of the POP and HSP data are assumed to be binomial. Indeed, extensive work has been done over the years to assess whether more complex distrbutions (such as the beta-binomial) were needed, and found that the predictive properties of the binomial likelihood assumed in the OM were satisfactory as they are (Hillary *et al.*, 2017).

There are only three additional entries required in the `mycontrol.dat` file to accommodate the variables needed to switch on and control the CKMR sampling part of the projection code. Just below the GT settings is the following text:

```
# control parameters for CK program
# Mjuv (juvenile samples)
# Madu (adult samples)
# cksw (0/1 off/on switch to simulate data)
1500 3000 1
```

The first parameter controls the number of juvenile age 3 samples (M_i), the second controls the total number of adult samples (M_j), and the third is a switch to turn the CKMR simulation on (value of 1) or off (value of 0). The simulated future POP data are stored in the `.s12` file (for each grid sample), and the future HSP data are stored in in the `.s13` file.

3.3 Generating indices from CKMR data

A detailed exploration of options were explored in [1]. The key information content in both the POP and HSP data is in the **ratio** of comparisons to matches. The general idea is this: if, over time, the average ratio of comparisons to matches is increasing/decreasing it is highly likely that the total adult abundance (TRO really) is decreasing/increasing. Another complication with using the CKMR data in the MP setting is that the projection and historical data need to be merged together.

Empirical indices can be derived from both the POP and HSP data, and can obviously be combined in a weighted average index that correlates well with the true trend in TRO. As an example, with the default sample size controls in the supplied `mycontrol.dat` file ($M_i = M_j = 3,000$) and a constant catch projection at the current TAC (17,647t) - where the true TRO increases steadily to a median of around 34% by 2035 - we see that:

- The base POP index (no moving average just as defined in [1]) correlates with true TRO at around 60%
- The base HSP index (no moving average as with the POP index) correlates with true TRO around the 65% level
- A combined index of POP and HSP indices (weighted evenly) correlated at just above 60%
- By using say a simple 3 or 4 year moving average of the indices this correlation can be increase to the 70% and above range

The satisfactory level of correlation (better or at least as good as say an actual survey of the TRO with a 25% CV) suggests these indices could indeed be used empirically and in a target-type HCR. As there is a reasonably strong linear relationship between the indices and the true TRO it stands to reason that there is some target value of the index (relative to the current value) that would match reasonably well with the tuning target of future TRO depletion. These indices can be used in much the same form (trend, target or even limit) as were the CPUE and aerial survey indices in the Bali Procedure [3].

4 Acknowledgements

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Initial MP structure and performance

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Contents

Abstract

We document initial MP structures and their performance on the currently defined revised tuning objectives. At this stage, performance is only shown for the MPs tuned to the objectives for the reference set of OMs. We employ the use of: long-line CPUE, the gene tagging data, as well as the close-kin mark-recapture data (both empirically and in a model-based setting). The four candidate tuning objectives (median TRO of 25%, 30%, 35% and 40% of the unfished state by 2035) were obtained for all but one CMP and showed clear differences in likely performance across objectives and across CMPs. MPs which employed target-limit style rules performed better than those which used only trend information. MPs that used CKMR data (empirically or model-based) resulted in generally higher average TACs and lower variability and incosistency for the 30% and 35% tuning objectives. For the 25% tuning objective all MPs act to rapidly increase the TAC and cause TRO decreases post-2035; for the 40% objective all MPs act to rapidly decrcease the TAC causing a a clear disparity between the TAC and the effective replacement yield at the target objective by 2035.

1 Background

The changes required to the SBT OM projection code (`sbtproj.tpl`) were outlined in [1], which built upon ideas for data generation and MP index construction first explored in [2]. In this paper we first detail the types of data and forms of MP we explored, then their performance when tuned to the four tuning objectives using the reference set of OMs.

2 Data and forms of the CMPs

We use three data sources, thought not all three at the same time, in the various CMPs:

1. Japanese long-line CPUE
2. The gene tagging (GT) data (matches and number of comparisons)
3. The close-kin mark-recapture (CKMR) data (matches and number of comparisons)

2.1 MPs using the CPUE & GT data

The usual trend term has been employed previously [3]:

$$TAC_{y+1} = TAC_y\left(1 + k\lambda_y\right)$$

where λ is the log-linear trend in the index under consideration could be modified as follows:

$$\begin{aligned}
\Delta_y^{\text{cpue}} &= 1 + k(1+\nu)\lambda_y \quad \text{if} \quad \lambda_y \leq -\tilde{\lambda}, \\
\Delta_y^{\text{cpue}} &= 1 \quad \text{if} \quad \lambda_y \in (-\tilde{\lambda}, \tilde{\lambda}), \\
\Delta_y^{\text{cpue}} &= 1 + k(1-\nu)\lambda_y \quad \text{if} \quad \lambda_y \geq \tilde{\lambda},
\end{aligned}$$

where:

- k is the usual "gain" parameter
- $\nu \in (-1, 1)$ is an asymmetry parameter that can act more/less strongly on positive/negative trends depending on its relative sign
- $\tilde{\lambda}$ is a "threshold" trend level: given the time-frame employed to estimate the trend, τ years say, and the CV in the index it would be the lower bound at which the estimates of trend will basically

be driven by the noise. The crucial point being we can construct some simple conditions to set this value given τ and the index CV and auto-correlation

As a simple motivating example for how to estimate $\tilde{\lambda}$ consider $\tau = 7$ years and a CV of 0.2 and autocorrelation of around 0.25 (basically, the settings/values in the Bali Procedure and current OM). If our criterion of performance is the probability that we can estimate the correct **sign** in the trend (i.e. positive or negative) then to reduce the proportion of false negatives to 0.05 we would choose $\tilde{\lambda} = 0.07$ i.e. don't bother with anything less than a trend of $\pm 6\%$ as it has a good chance of being spurious and noise driven. Obviously, a critical false positive rate of 0.05 is fairly stringent - the main point being we can define a critical value of this false positive rate and, given the settings of the OM and the MP, calculate a subsequent value of $\tilde{\lambda}$. Say we wanted to get the right trend 3 times out of 4: the minimum "retained" trend estimate would then be $\tilde{\lambda} = 0.03$.

We already included a simple GT-driven log-linear trend style MP in the `testGTinMP` example uploaded it `github`, so we explore some other options here. The main advantage that the GT data have over the aerial survey is that they are absolute, or should be if everything we think we know about spatial stock structure and recruitment dynamics is about right. The lowest estimated cohorts were (age 0 fish from 2000 to 2002), and by age 2 fish the mean abundance was around 700,000 animals. These recruits very likely caused a rapid decrease in the CPUE in the mid 2000s as they entered the long-line fishery, and left a clear hole in the length frequency data as well as signals in both the tagging and SAPUE data. They represent reasonably well-estimated levels of age 2 fish below which we know bad things can happen, suggesting themselves as a potentially useful limit level - now we have in principle estimates of absolute age 2 fish from the GT program.

If we are to use the absolute nature of the GT data then the general principles would be something like:

- Below the limit level the HCR should act strongly to reduce the TAC
- Above the limit level and up to some pre-specified upper level the GT part of the HCR maintains the TAC where it is
- If recent mean recruitment has been suitably elevated (i.e. above a pre-specified level) then the HCR should act to increase the TAC

To calculate the recent mean age 2 abundance from the GT data consider a weighted moving average approach:

$$\bar{N}_{y,2} = \sum_{i=y-1-\tau}^{y-2} \omega_i \widehat{N}_{i,2}$$

where ω_i is a weighting proportional to the number of matches used to produce the GT estimate $\widehat{N}_{i,2}$ (basically inverse variance weighting). The 2 year delay between having the estimate and what year it actually refers to is factored into the calculation. The multiplier for the GT part of the HCR would then be:

$$\begin{aligned}
\Delta_y^{\text{gt}} &= \left(\frac{\bar{N}_{y,2}}{N_{\text{low}}}\right)^{\alpha} \quad \text{if} \quad \bar{N}_{y,2} \leq N_{\text{low}}, \\
\Delta_y^{\text{gt}} &= 1 \qquad\qquad\quad \text{if} \quad \bar{N}_{y,2} \in (N_{\text{low}}, N_{\text{high}}), \\
\Delta_y^{\text{gt}} &= \left(\frac{\bar{N}_{y,2}}{N_{\text{low}}}\right)^{\beta} \quad \text{if} \quad \bar{N}_{y,2} \geq N_{\text{high}}
\end{aligned}$$

with N_{low} the limit level and N_{high} the upper level at where TAC inrceases are permitted. The exponents α and β are to allow for differential responses depending on the situation: we might expect $\alpha > 1$ as we would want to act strongly on poor recruitment levels; alternatively we might have $\beta < 1$ so that

TAC inreases based on increased recruitment are more modest, given increased recruitment does not guarantee the TRO will increase (especically if we increase the Fs they experience as they mature).

2.2 MPs using the CKMR data

From the CKMR data we can derive an empirical index (be it POP, HSP or combined), I_y^{ck} [2], or an actual estimate of the TRO and mean adult Z from the model-based framework. The empirical CKMR indices can clearly capture trends in the true TRO: as it goes up/down, then the number of kin matches (conditional on the sampling regime) should generally go down/up. What complicates this simple interpretation of the trend in the overall number of matches (and what it is telling us) are the following:

1. **Changes in adult "recruitment"**: increases or decreases in the number of sub-adults who survive to become reproductively active due to variations in actual age-0 recruitment and changes in juvenile and sub-adult mortality
2. **Changes in adult mortality** changes in either the TAC or trends in the adult recruitment will clearly alter the harvest rates and, even for an assumed time-invariant M, by extension total mortality/survival

The short-to-medium term effect of these changes can be seen in the empirical indices, driven by the large 2013 recruitment beginning to move its way into and through the adult population. Strong changes in age structure and mortality *have* to have a strong effect on the POP and HSP probabilities . If we could somehow use a model to tease these effects out of the data, there is the *potential* to estimate trends in TRO that correlate far better with the true TRO than the empirical indices can. We could also estimate additional variables of use (like adult recruitment and total mortality).

This is similar to the approach taken when developing the population model behind the Bali Procedure. The specifics would be quite different given the radical difference in the input data (CPUE and aerial survey *vs.* POP and HSP data), but the idea is the same: reduce the variability and bias in the indices by accounting for the underlying population dynamic drivers of the fluctuations causing those biases. We explored a simple age-structured population model:

$$
\begin{aligned}
N_{y,a_{\min}} &= \bar{R}\exp\left(\epsilon_y - \sigma_R^2/2\right), \\
\epsilon_y &\sim N(0,\sigma_R^2), \\
N_{y+1,a+1} &= N_{y,a}\exp\left(-Z_{y,a}\right) \qquad a \in (a_{\min}, a_{\max}), \\
N_{y+1,a_{\max}} &= N_{y,a_{\max}-1}\exp\left(-Z_{y,a_{\max}-1}\right) + N_{y,a_{\max}}\exp\left(-Z_{y,a_{\max}}\right), \\
Z_{y,a} &= Z_y \qquad a \le 25, \\
Z_{y,a} &= Z_y + \frac{a-25}{a_{\max}-25}\left(Z_{a_{\max}} - Z_y\right) \qquad a \in [26, a_{\max}], \\
Z_y &= \frac{Z_{\max}e^{\chi_y} + Z_{\min}}{1+e^{\chi_y}}, \\
\chi_{y+1} &= \chi_y + \zeta_y, \\
\zeta_y &\sim N(0,\sigma_\chi^2), \\
TRO_y &= \sum_a N_{y,a}\varphi_a
\end{aligned}
$$

The main ideas behind the population model are:

- It is only for adults, with a minimum age ($a_{\min}$) defining where fish being to be considered possible reproductively active adults
- Recruitment to the adult stock is assumed to vary randomly around a mean value

Parameter	Value
$a_{\min}$	6
$a_{\max}$	30
σ_R	0.2
σ_χ	0.1
$Z_{\min}$	0.05
$Z_{\max}$	0.4
$Z_{a_{\max}}$	0.5
$\mu_{\chi_{\rm init}}$	-1.38
$\sigma_{\chi_{\rm init}}$	0.2
$q_{\rm hsp}$	0.9

Table 2.1: Settings for CKMR MP population model

- Total mortality, $Z_{y,a}$, has a well-defined age and time structure: between $a_{\min}$ and 25 it is fixed by age, but has a random walk time component
- Between 25 and $a_{\max}$ total mortality rises linearly to a pre-specified maximum $Z_{a_{\max}}$
- The time-varying Z_y variable is constrained to be between $Z_{\min}$ and $Z_{\max}$
- Equilibrium conditions are assumed for the first year age-structure
- A plus group is used for ages above the final true age class, $a_{\max} - 1$
- The total reproductive output (TRO) is defined using a time-invariant ogive, φ_a

The estimate parameters of this model are:

1. The mean adult recruitment, $\bar{R}$
2. The adult recruitment deviations, ϵ_y
3. The initial value, $\chi_{\rm init}$, that "starts" the random walk for Z_y (with an associated normal prior mean and SD)
4. The random walk deviations ζ_y

This is basically the same number of parameters estimated in the Bali Procedure population model [3], so we are not talking about a large number of model parameters, and many of them are going to be constrained deviation parameters. The likelihood model for the POP and HSP data are basically the same as those used in the SBT OM, but where M_a and the harvest rates are replaced by $Z_{y,a}$ to estimate cumulative survival in the HSP likelihood.

Using the same fixed TAC (17,647t) projection we used to explore the utility of the empirical CKMR indices we undertook a full simualtion evaluation of the simplified CKMR estimation model with the settings as laid out in Table 2.1.

Figure 2.1 outlined the estimation performance of the CKMR MP population model, given the settings in Table 2.1 and assumed a future fixed TAC of 17,647t. Clearly, while under-estimating the much later TRO and mean adult Z, it captures the true trends very well. The median correlation between the estimated and true TRO and mean adult Z was 0.97 and 0.86, respectively.

The values for the fixed and prior parameters in the CKMR model are clearly informed by the current OM. The value of the mimimum age, 6, is chosen given the youngest age of a detected parent in the POPs. The maximum age is the maximum age assumed in the OM, and the total mortality at the maximum age is basically the estimated level (around 0.5). Average adult Z at the start of the CKMR data (around the early 2000s) is somewhere around the 0.15 level and the prior mean and SD of $\chi_{\rm init}$ are chosen to reflect this, albeit fairly weakly given the prior variance. The minimum value of Z for the ages less than 25 is fixed at 0.05 which is the lowest level of M_{10} assumed in the OM and the maximum Z is assumed to be lower than the Z at the maximum age. The way that Z increases to the maximum level is also driven by the OM: permitted to increase linearly from age 25 to the maximum age. The value of $q_{\rm hsp}$ is also informed

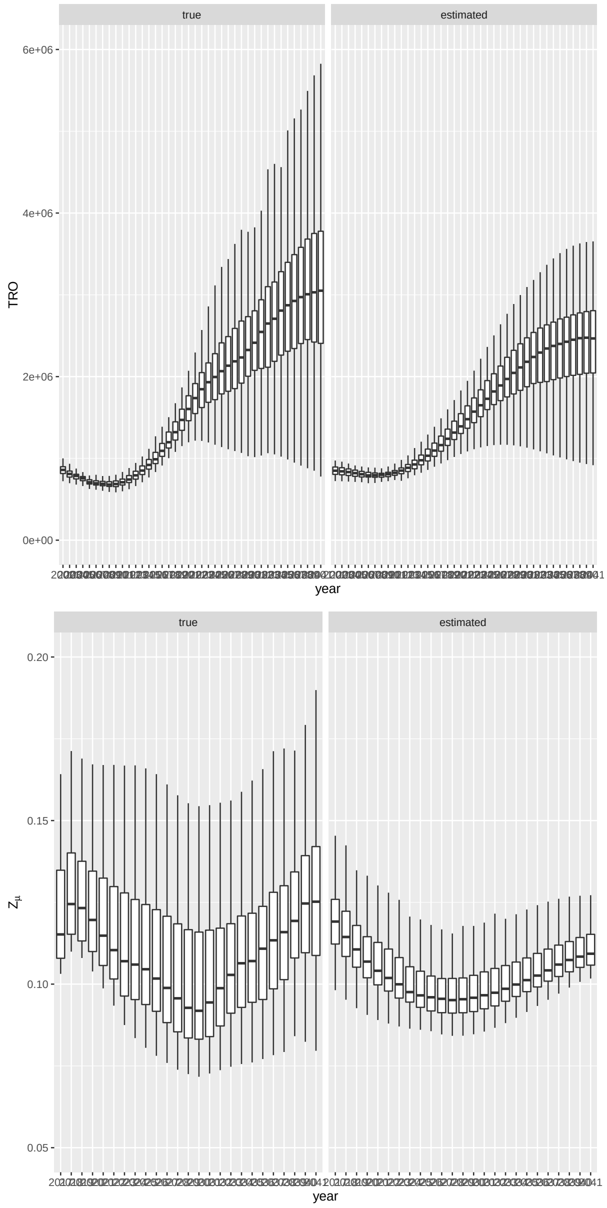

Figure 2.1: *True (left) and estimated (right) TRO (top) and mean adult Z (bottom) for the CKMR MP population model outlined in Table 2.1*

heavily by the OM estimates at around 0.9. So the model rests heavily on things we think we now know about some of these key variables given the inclusion of the historical CKMR data (which is valid in an MP context), but does not assume to know things it simply could not about future parameters and data (which is arguably the most important part of using models in an MP context).

The main thing we do know about where we want the future TRO to go, relative to the present, is that we want it to go up. So, given a reference level of the empirical index centered around the present, $\tilde{I}$, the target level of the TRO we wish to rebuild the stock to will be some multiple of this, $\gamma > 1$. This formulation lends itself to the construction of a target-type HCR element for the CKMR data:

$$
\begin{aligned}
\Delta_y^{\mathrm{ck}} &= (1 - w^{\mathrm{ck}}) + w^{\mathrm{ck}} \frac{I_{y-4}^{\mathrm{ck}}}{\gamma \tilde{I}(1-\delta)} & \text{if} \quad & I_{y-4}^{\mathrm{ck}} \leq \gamma \tilde{I}(1-\delta), \\
\Delta_y^{\mathrm{ck}} &= 1 & \text{if} \quad & I_{y-4}^{\mathrm{ck}} \in (\gamma \tilde{I}(1-\delta), \gamma \tilde{I}(1-\delta)) \\
\Delta_y^{\mathrm{ck}} &= (1 - w^{\mathrm{ck}}) + w^{\mathrm{ck}} \frac{I_{y-4}^{\mathrm{ck}}}{\gamma \tilde{I}(1+\delta)} & \text{if} \quad & I_{y-4}^{\mathrm{ck}} \geq \gamma \tilde{I}(1+\delta),
\end{aligned}
$$

Summarising the key control parameters:

1. The term $w^{\mathrm{ck}} \in (0, 1)$ is a weighting term: closer to zero and there is a lot of "inertia" in this part of the HCR and TACs will move little, regardless of trends; closer to 1 and the HCR moves to being almost a pure target style HCR driven only by the distance of the current CK index relative to the target, $\gamma \tilde{I}$
2. The term $\delta \in (0, 1)$ is a "buffer" term, so that the HCR is instructed to do nothing if the current index above or below the target by a factor of $(1 + \delta)$ or $(1 - \delta)$, respectively
3. The term $\tilde{I}$ is a suitably defined estimate of the "recent" index -best calculated for the period for which we have actual CKMR data
4. The term γ is the index "inflation" value: the amount by which we want to increase the CKMR index from the $\tilde{I}$ level. For example, if we have a reasonably well correlated 1:1 relationship between the CKMR index and TRO, then γ would be the tuning target TRO depletion level divided by the current TRO depletion level. In practice this terms seems well suited to being a tuning parameter, given an array of possible future TRO tuning targets

With the model-based option we will also obtain a potentially usable estimate of mean adult Z, and obviously using the trend in this data may also prove fruitful. Initial runs using the initial CKMR part of the HCR in the model-based context actually showed strange (at first) but after consideration (given how well the model tracks the trends) obvious behaviour. The model accurately estimates when the true TRO is above or below the target level $\gamma \tilde{I}$, and cuts the TAC even if the trend in TRO is going up. This causes it to have to then increase the TAC rapidly once the TRO approaches the target level, and some oscillatory behaviour can emerge.

A modification to the HCR for the model-based CKMR MP was required so that it was able to track the trend in the TRO when *below* the target level (and reduce it if it is not going up fast enough). The minimum expected (log-scale) rate of increase is actually fairly simple to define. Given a time-frame, T, and the inflation factor γ, then $\tilde{\lambda}^{\mathrm{ck}} = \gamma^{T^{-1}} - 1$, and we chose the time-frame as 2007 to 2035.

The modified HCR was defined as follows:

$$
\begin{aligned}
&\Delta_y^{\rm ck} = 1 + k^{\rm ck}\left(\lambda_y^{\rm ck} - \tilde{\lambda}^{\rm ck}\right) \quad \text{if} \quad I_{y-4}^{\rm ck} \leq \gamma\tilde{I}(1-\delta) \quad \text{and} \quad \lambda_y^{\rm ck} < \tilde{\lambda}^{\rm ck},\\
&\Delta_y^{\rm ck} = 1 \quad \text{if} \quad I_{y-4}^{\rm ck} \leq \gamma\tilde{I}(1-\delta) \quad \text{and} \quad \lambda_y^{\rm ck} \geq \tilde{\lambda}^{\rm ck},\\
&\Delta_y^{\rm ck} = 1 \qquad\qquad\qquad\qquad\qquad \text{if} \quad I_{y-4}^{\rm ck} \in (\gamma\tilde{I}(1-\delta), \gamma\tilde{I}(1-\delta))\\
&\Delta_y^{\rm ck} = \left((1-w^{\rm ck}) + w^{\rm ck}\frac{I_{y-4}^{\rm ck}}{\gamma\tilde{I}(1+\delta)}\right)^{\beta^{\rm ck}} \quad \text{if} \quad I_{y-4}^{\rm ck} \geq \gamma\tilde{I}(1+\delta) \quad \text{and} \quad \lambda_y^{\rm ck} < 0,\\
&\Delta_y^{\rm ck} = \left((1+k^{\rm ck}\lambda_y^{\rm ck})(1-w^{\rm ck}) + w^{\rm ck}\frac{I_{y-4}^{\rm ck}}{\gamma\tilde{I}(1+\delta)}\right)^{\beta^{\rm ck}} \quad \text{if} \quad I_{y-4}^{\rm ck} \geq \gamma\tilde{I}(1+\delta) \quad \text{and} \quad \lambda_y^{\rm ck} \geq 0.
\end{aligned}
$$

In terms of naming conventions of MPs (descriptive ones at least) for CPUE we have:

1. **C1**: trend-type CPUE HCR
2. **C2**: target-type CPUE HCR

For GT data we have:

1. **GT1**: limit-type GT HCR
2. **GT2**: trend-type GT HCR

For CKMR data we have:

1. **CK1a**: empircal POP-based target HCR
2. **CK1b**: empircal HSP-based target HCR
3. **CK1c**: empircal POP+HSP combined target HCR
4. **CK2**: model-based (inc. POP and HSP) based
5. **CK2z**: as with **CK2** but including mean adult Z trend

So an MP file called `C1GT2CK1a.tpl` would include CPUE (trend), gene-tagging (limit) and a CKMR empirical POP index (target) HCR. For this initial phase of the work we explored seven CMPs:

1. C1GT1 (CPUE trend, GT limit): **rh1**
2. C1GT2 (CPUE trend, GT trend): **rh2**
3. C2GT2 (CPUE target, GT limit): **rh3**
4. C2GT2 (CPUE target, GT trend): **rh4**
5. C1GTCK1a (CPUE trend, GT trend, CKMR POP index): **rh5**
6. C1GTCK1c (CPUE trend, GT trend, CKMR POP+HSP index): **rh7**
7. C1GTCK2 (CPUE trend, GT trend, CKMR TRO estimate): **rh8**

with their short names used in graphical and other summaries in bold.

3 MP performance on the reference set

Each of the CMPs was tuned to the four tuning objectives, with a tolerance of 1% (i.e. the MP parameters were altered until the probability of meeting the objective was 0.5 ± 0.005). In terms of summary statistics we use the following initial set relating to TRO:

- $\mathbb{P}\left(TRO_{2035} > 0.2TRO_0\right)$: the previous MP tuning objective

- $\mathbb{P}\left(TRO_{2035} > TRO_{2017}\right)$: probability that the TRO in the tuning year is greater than the current level
- $\mathbb{P}\left(TRO_{2040} > TRO_{2035}\right)$: probability that the TRO five years after the tuning year is above that in the tuning year, to catch MPs which increase the TAC too high/fast when attaining the tuning objective and cause a future "undershoot"
- Log-linear trend in TRO from 2021 to 2035: to see if there are trajectories which actually on average go down from when the first TAC change occurs to when the tuning year is reached

and the following set for TACs:

- Mean TAC (across years) from 2021 to 2035
- AAV (from 2021 to 2035)
- Maximum TAC decrease (from 2021 to 2035)
- $\mathbb{P}\left(TAC_{r+3} < TAC_{r+2}\right)$ *if* $TAC_{r+2} > TAC_{r+1}$ *and* $TAC_{r+1} > TAC_r$, for the $r^{\rm th}$ TAC decision (default is currently $r = 1$)
- Mean (averaged over years and from 2021 to 2035) of the lower 10%ile in the TAC

The one perhaps unfamiliar tweak to these is for the TAC up/down statistic. The *expected* probability that this happens is merely the number of times the TAC goes up twice *and then goes down*, divided by the number of times it went up twice. For some tuning objectives and MPs, the TAC going up twice might be a very common occurrence, but where the TAC going down again is not quite as common. For others, the TAC going up twice might be *very* rare, but it coming down again is comparably quite common. For the first case we would have a low and accurate estimate of the up/down statistic; for the second case we would have a very high but very uncertain estimate that doesn't really tell is much at all. If we simply plot the expected probability of going up then down, without some measure of the uncertainty thereof, we are likely to make misguided inferences about MP performance on this statistic. To address this we used a simple Bayesian approach to plotting the likely distribution of this statistic, not just its expectation. For a given MP run, if n_1 is the number of runs where the TAC goes up twice, and n_2 is the number of runs where it subsequently goes down again, assuming an uninformative prior for the probability this happens, $p^{\uparrow\downarrow}$, then the posterior distribution would be a beta distribution: $p^{\uparrow\downarrow} \sim \mathrm{B}(0.5 + n_2, 0.5 + n_1)$. We draw a sample from this distribution when graphically displaying this statistic.

Figure 3.1 shows the performance of the 7 CMPs, for each of the 4 tuning objectives, for the TRO statistics relating to probabilities. Figure 3.2 shows the log-linear TRO growth summary. Figure 3.3 shows the CMP performance for the TAC summary relating to actual catch amount (mean, maximum decrease, and lower 10%ile). Figure 3.4 shows the AAV and up/down catch probability statistics.

3.1 General performance across tuning objectives

At the extremes of the tuning objectives (25% and 40%) all MPs basically have to act to either rapidly increase the TAC (25% objective), or rapidly decrease the TAC (40% objective). This is not surprising given that the constant TAC levels for these two cases are 23,850t (25%) and 11,803t (40%) - both of which are basically 2 maximum TAC changes (for 3,000t max. change) away from the last fixed TAC of 17,647t. In the 25% case all the MPs result in catch levels that causes the TRO in 2040 to have a 65-75% chance of being below the 2035 level. For the 40% objective the rapid and sustained reductions in TAC required result in TRO levels in 2040 that are greater than those in the target year (2035) almost with probability 1, and TAC levels that are on average around 30–35% of MSY levels, even with a TRO in 2040 that is well above the MSY level. So, for the 25% objective all MPs increase the catch above the level at which we would expect the tuning objective to be maintained (it goes down in the future); there is also a significant chance of stock trajectories that go down on average over the rebuilding period. For the 40% objective all MPs rapidly decrease TACs, where the TRO continues rising rapidly after the target year, and

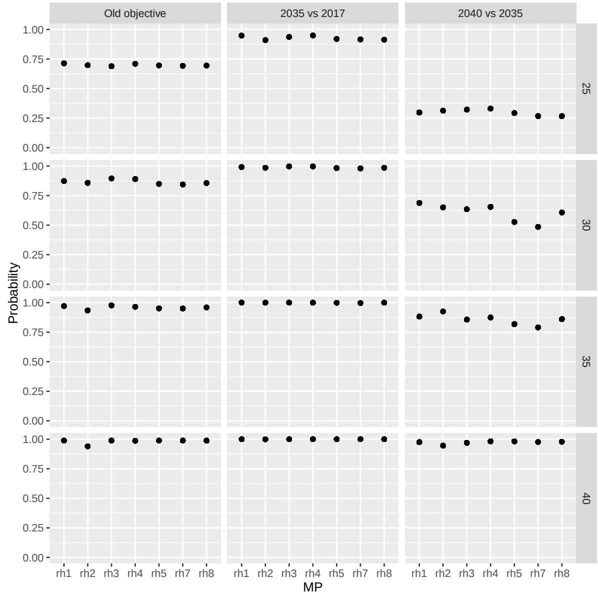

Figure 3.1: *TRO probability summary for each of the CMPs and for each tuning objective.*

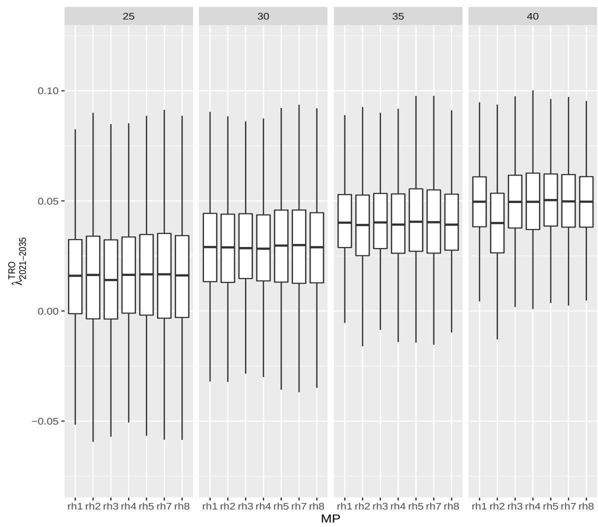

Figure 3.2: *TRO log-linear growth summary for each of the CMPs and for each tuning objective.*

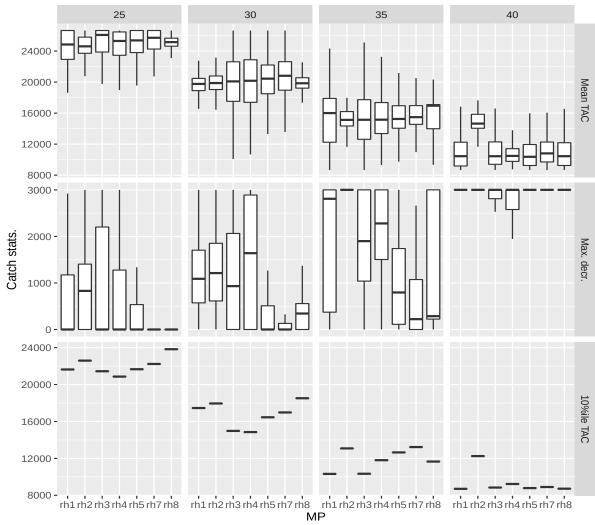

Figure 3.3: *TAC summary for the statistics relating to actual catch amounts: mean TAC (top), maximum decrease (middle), and lower 10%ile (bottom).*

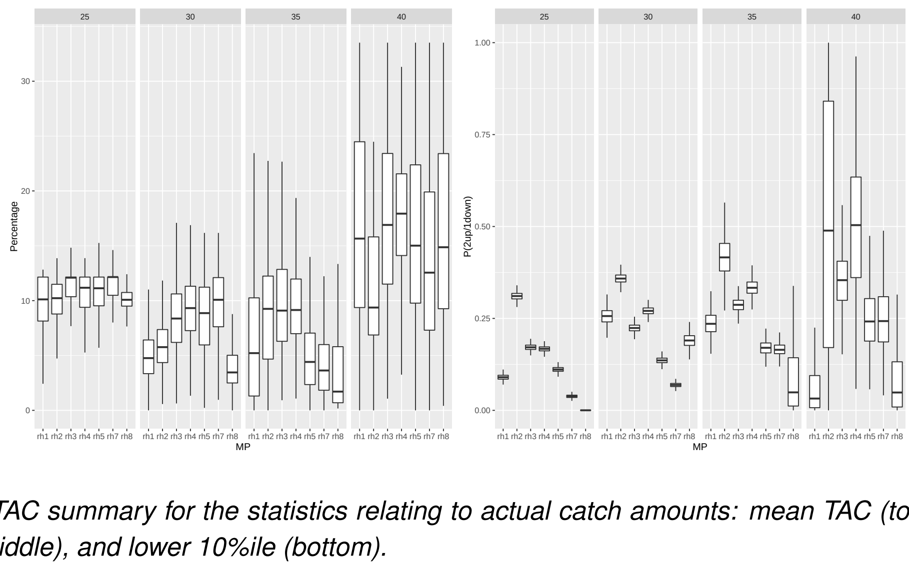

Figure 3.4: *TAC summary for the statistics relating to actual catch amounts: mean TAC (top), maximum decrease (middle), and lower 10%ile (bottom).*

there is a large distance between the average TAC and MSY, even with a TRO level significantly above the level assumed to produce MSY. Henceforth, we only outline the more specific performance of the MPs for the 30% and 35% tuning objectives, given there is more apparent behavioural contrast for these two cases, relative to the extrema.

3.2 MP performance on the TRO statistics for 30% and 35% tuning targets

All the MPs clearly exceed the original tuning objective for the Bali Procedure, so there are no issues there. For the 30% objective, the TRO in 2040 is greater than that in the tuning year (2035) with a probability of around 50% or above for all MPs - though it is basically at 50% for **rh5** and **rh7** (the CKMR empirical MPs). For the 35% objective these probabilities are all at 75% or more - all MPs have a better than average chance of further increasing the TRO post tuning year. For the 30% tuning objective there is a small chance of trajectories that go down on average between 2021 and 2035 with no trend across MPs; for the 35% objective this probability is very low and basically the same across MPs. On average, the CKMR driven MPs seem to result in a more stable TRO trajectory post tuning year (but also with a small chance of it coming down again by 2045), but other than this there is little to clearly separate the MPs looking at TRO summary statistics alone.

3.3 MP performance on the TAC statistics for 30% and 35% tuning targets

Contrasting the MPs with trend vs. target forms for CPUE first: the trend driven MPs (**rh1**, **rh2**) show lower variability in both mean TAC and AAV relative to the target-driven ones (**rh3**, **rh4**). Conversely they have a higher propensity to increase the TAC twice and then decrease it. For the 30% tuning objective the trend-based MPs show lower maximum decreases, relative to their target-based counterparts, but this behaviour reverses for the 35% objective. The MPs including CKMR (**rh5**, **rh6**, and **rh7**) tend to have higher mean TACs (relative to CPUE/GT only MPs), with a significantly and consistently lower chance of decreasing the TAC after 2 increases. For the empirical CKMR MPs (**rh5**, **rh7**) the AAV is comparable to the CPUE/GT MPs for the 30% objective, but lower for the 35% objective. Across all tuning objectives the CKMR including MPs have clearly lower maximum TAC decrease statistics, relative to CPUE/GT MPs. The model-based CKMR MP (**rh8**) consistently has both the lowest AAV and chance of a TAC decrease after two increases, with better than average levels of the lower 10%ile TAC. Mean TAC levels, while more variable for target CPUE-drive MPs and empirical CKMR MPs, relative to the CPUE trend or model-based CKMR MP, were very similar in terms of medians across tuning objectives.

4 Overall summary of initial MP performance

Figures 3.5 and 3.6 show the TAC and TRO worm plot summaries for MPs **rh1**, **rh3**, **rh7**, and **rh8** for the 30% objective to outline the general differences between MPs with different HCRs. The CPUE trend, GT limit MP (**rh1**) shows low TAC variability, but more prominet up/down TAC dynamics (given the 2013 recruitment-driven trend in future CPUE) with TRO still increasing post-tuning objective year. The CPUE target, GT limit MP (**rh3**) shows more TAC variability (both mean and AAV) than **rh1**, but higher TACs later in time and a more stabilising TRO trend post tuning year. The empirical CPUE trend/CKMR target/GT limit MP **rh7** shows higher average catches, little up/down TAC behaviour but with TAC still increasing post-tuning year and the TRO just beginning to come down again by 2045. The model-based CKMR/CPUE/GT MP **rh8** shows a gradual increase in mean TAC early with later slight faster increases. It has the best up/down TAC and AAV performance across all MPs as well as the lowest level of maximum TAC decreases. After the tuning year the TRO begins to stabilise at the target level.

These initial MP explorations have yielded some informative inital results:

- The 25% and 40% tuning objectives (by 2035 with a 3,000t max change in TAC) show the least contrast across MPs as they all have to either rapidly increase (25%) or decrease (40%) the TAC

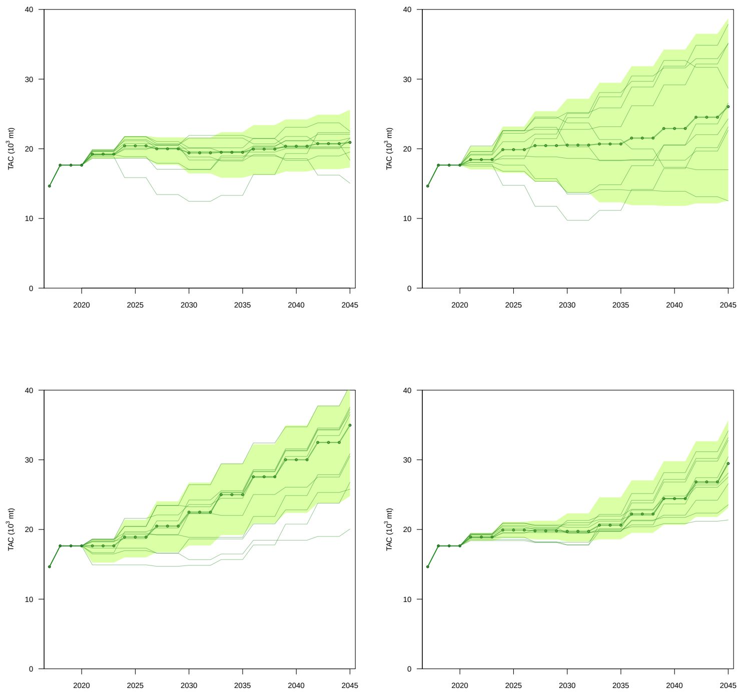

Figure 3.5: *Worm and quantile summary for TAC and MPs **rh1** (top right), **rh3** (top right), **rh7** (bottom left), and **rh8** (bottom right).*

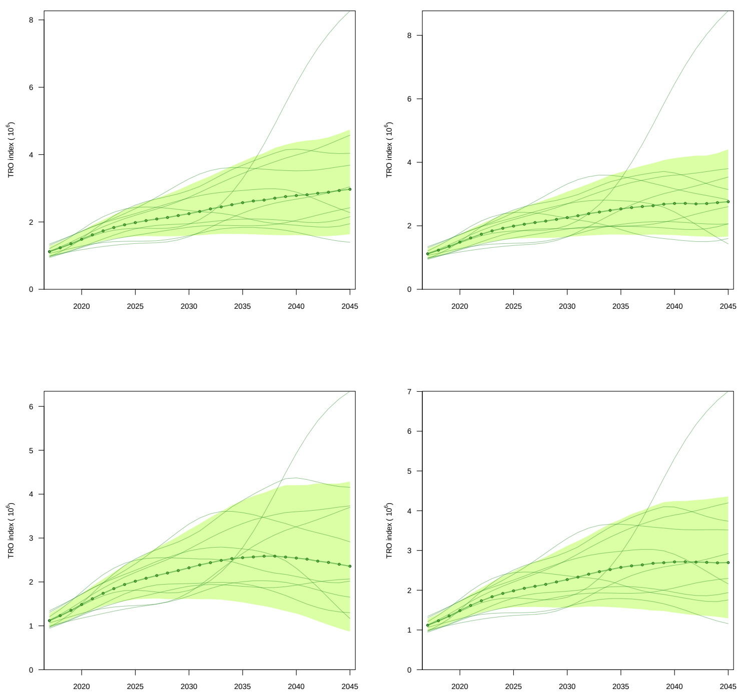

Figure 3.6: *Worm and quantile summary for TRO and MPs **rh1** (top right), **rh3** (top right), **rh7** (bottom left), and **rh8** (bottom right)..*

- The 30% and 35% tuning objectives allow for more behavioural contrast across the CMPs
- Both trend and target features explored for CPUE: the former show low TAC variability but higher up/down TAC behaviour; the latter show more overall TAC varability but comparable up/down behaviour - overall they seem a bit *overreactive* but this can be fixed
- The use of the GT data in the limit form (GT1) versus the trend form (GT2) - even at this stage - looks more promising
- The use of CKMR data is clearly potentially very useful. In the empirical form the tuning to the 30% objective looks a tough aggressive (in terms of TAC increases later in time) but this can be tempered. It is the model-based use of CKMR that seems to show very promising results, with the best AAV stats, the lowest maximum TAC decreases, and the least propensity for decreasing TAC after two increases, as well as mean TAC levels at or above the other CMPs.

For the 30% and 35% objectives, it is clear that when tuning to the reference set (and for the 3-year TAC maximum 3,000t change settings) that a wide array of potential CMPs can be tuned to the objectives, and that they can and do have differing performance characteristics. Choices around how best to use the CPUE (trend, target, less reactive) and the GT data will be best explored via the low recruitment and CPUE-related robustness trials. The CKMR data clearly show promise also in both their empirical and model-based forms.

5 Acknowledgements

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Data generation & changes to SBT OM

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Contents

Abstract

This paper details the structural changes made to the SBT Operating Model required to simulate the new data sources: gene tagging, and close-kin mark-recapture (parent-offspring and half-sibling pairs). It also details a number of changes required to implement a number of new robustness tests related to gene tagging and future selectivity

1 Background

Initial methods for generating these new data sources, as well as potentially informative indices that could be derived from them, were explored in [1]. Additionally, the stuctural changes required to the SBT OM to accommodate these new data sources in the conditioning phase were outlined in [2]. This paper details the actual technical details of the changes made to the SBT OM projection code (`sbtproj.tpl`), and how the new data generation control parameters are defined in the `mycontrol.dat` files.

2 Gene tagging

Details of how we simulate the gene tagging data in the OM ('sbtproj'). Major items covered are:

- The observation error model employed
- Including the "reality" of the gene tagging process
- Defining the estimates of abundance (and CVs thereof)
- Suggestions about what can be used in a candidate MP setting
- What changes are needed in the control and `sbtOMdata` files

The primary goal of the gene tagging (GT) program is to provide an estimate of the absolute abundance of age 2 fish (and some measure of the uncertainty thereof). Moving back to base principles, if you tag a single 2-year old fish in year y, release it "randomly" into the population and attempt to recapture it again (via a random sampling method) in year $y+1$ then the chance of finding it is $1/N_{y,2}$. If you tag T fish this probability increases to $T/N_{y,2}$. If you genotyped S fish in year $y+1$ to check for "recaptures" then you would expect to find the following average number of recaptures:

$$\mathbb{E}(R) = \frac{TS}{N_{y,2}}$$

The default appropriate distribution for these kind of data is the binomial distribution. As per previous discussions about how to model these data, and given the distributional features of the 1990s tagging data, we agreed to a more generalised distribution called the beta-binomial distribution. This is an extension of the binomial model that permits additional variability in the probability of recapture. The tagging data currently in the OM clearly show higher variance than the base multinomial distribution would predict. Some of those sources of additional variance (heterogeneity in assumed static parameters) will not be a feature of the GT program - specifically variation in tag loss and reporting rates. As such, the so-called *over-dispersion* coefficient (degree to which variance is inflated) of the tagging data (*ca.* 1.8) would be an upper bound to the GT over-dispersion coefficient, with a value of 1 (no over-dispersion) being an obvious lower bound. We also propose a simple bias factor to be included into the GT observation error model that is there specifically to deal with recruitment dynamics that result in us systematically sampling a subset of the true age 2 abundance. We would propose the following modification to the expected recapture probability:

$$\tilde{p} = \frac{T}{q^{\mathrm{gt}} N_{y,2}},$$

If we define the over-dispersion coefficient as ϕ. For a given sample size $n = S$, we define the crucial over-dispersion parameter, ω, as follows:

$$\omega = \frac{\phi - 1}{n - \phi},$$

then the parameters of the beta distribution, $p^{\mathrm{gt}} \sim B(\alpha, \beta)$, that underlies the true sampling probability are defined as follows:

$$\alpha = \frac{(n-\phi)\tilde{p}}{(1-\tilde{p})(\tilde{p} + (1-\tilde{p})(\phi - 1))}$$

and

$$\beta = \frac{n - \phi}{\tilde{p} + (1-\tilde{p})(\phi - 1)}.$$

In the practical simulation sense, given the relevant GT control parameters (T, S and ϕ), we first simulate p^{gt} from the underlying beta distribution, and then simulate the number of recaptures, R, from the binomial distribution parameterised by p^{gt} and $n = S$.

The estimate of abundance, given R, T and S is basiscally the classical Petersen estimator:

$$\widehat{N}_{y,2} = \frac{TS}{R},$$

with the approximate CV of this estimate given by $1/\sqrt{R}$.

There are certain adaptive features of the GT program - particularly the post-release resampling program in the farms - that are worth both considering and actively including in the simulation process. The main point of the observation error model is to represent, to the best of our abilities, the actual process of data collection. In the GT program, if we had processed the S samples to find matches and found less than we would prefer (e.g. we have some minimum value, $R_{\min}$), it is the case (as it was this year) that we do have the option of processing an additional number of samples, S_+, to hopefully obtain additional matches and, as a result, a more accurate estimate of the age 2 abundance. To be clear, this is no way introduces bias to the estimation process: the proportional increase in sample size would be the same as the proportional increase in the expected number of matches. The expected abundance estimate would be the same, but the accuracy would be increased.

The settings for the GT sampling settings are contained in an augmented `mycontrol.dat` file used for the projections on previous occasions. An example file (`mycontrolGTMP.dat`) is now included in the git repository in the develop branch. The GT control variables are:

1. *Trel*: number of intial ”releases”, T, from which sample is taken

2. *Srec*: main number of samples, S, taken from harvested fish the following year
3. *Sadd*: ”back-up” samples, S_+ that can be processed if needed
4. *Rmin*: minimum number of matches, $R_{\min}$, if adaptive sampling required
5. *gtadsw*: adaptive sampling switch (0 off; 1 on) - if number of matches less than minimum amount, process the additional back-up samples to get more
6. *qgt*: value of the bias, q_{gt}, in the GT estimator (1, no bias; alternatives will be less than 1 probably...)
7. *phigt*: value of the over-dispersion, ϕ, for the GT simulations (1 means no OD basically)

The text in the augmented `mycontrol.dat` where the GT variables are set is found immediately below where the CPUE and aerial survey control variables are found:

```
# switches for robustness tests highCPUECV, highaerCV and updownq
# if highCPUECV=1 (set sigmaq=0.30 and sigmaaerial=0.30)
# if highAerialCV=1 (set sigmaq=0.20 and sigmaaerial=0.50)
# if updownq = 1 (increase q by 50% for fisrt 5 years)
0 0 0
# control parameters for GT program
# Trel (releases)
# Srec (recapture samples scanned)
# Sadd (additional samples if needed)
# Rmin (minimum number of recaptures)
# gtadsw (switch for adaptive sampling given Rmin; 0 off,1 on)
# qgt (bias level for GAB N2)
# phigt (over-dispersion level)
5000 10000 5000 5 0 1.0 1.0
```

These settings are probably about right (in terms of sampling specifics) given the previous two GT field programs but can and probably will be adjusted as we get more into the work. In terms of files it is the `.s-` named files that contain the summaries of various quantities from the projections. For the future GT data a new file has been created (`.s11`) which contains the key variables of interest:

- Grid element relating to that sample
- Estimated abundance of age 2 fish from GT
- True value of age 2 fish in that projection sample
- The approximate CV of the GT estimate of of age 2 fish
- The observed number of matches given the GT program settings

3 Close-kin mark-recapture

Alongside the gene-tagging (GT) data, the OM will now also simulate close-kin mark-recapture (CKMR) data - both parent offspring (POP) and half-sibling (HSP) pairs. This document covers both the simulation of the data using the SBT OM, as well as some empirical and model-based options for using these data in an MP context.

Cohort	Adult year	Adult age	nK	nC
c	y	a	$\mathrm{Bin}(p, nC)$	$\mathrm{MN}(p_a, M_j)$

3.1 Parent-Offspring pairs

The key covariates of importance in the SBT OM in relation to POPs are:

- The year of sampling, y, of the adult
- The age at sampling, a, of the adult
- The birth year/cohort, c, of the juvenile

while the key parameters and derived variables of importance are:

- Abundance-at-age, $N_{y,a}$
- Relative reproductive output-at-age, φ_a

so that for an juvenile-adult pair $\{i, j\}$, so $z_i = \{c\}$ and $z_j = \{y, a\}$, then the probability of that pair being a POP is given by

$$\mathbb{P}\left(K_{ij} = POP|z_i, z_j\right) = \mathbb{I}\left(c < y < c + a\right) \frac{2\varphi_{a-(y-c)}}{\sum_i N_{c,i}\varphi_i} \tag{3.1}$$

where $\mathbb{I}()$ is the indicator function. The assumed distribution of the POPs is binomial, given the sampling probability in (1), and all juveniles are assumed to be sampled at 3 years old, and that each year there are M_i samples taken. For the adults, a random draw from the multinomial distribution of likely adults is taken (for a given adult sample size, M_j). Both the sample size control parameters are defined in the `mycontrol.dat` file as with the GT control parameters. The data are organised in the same way as the historical POP data are: a 5-d data frame:

where p_a is the distribution of adults in a given year and Bin() and MN() are the binomial and multinomial distributions, respectively.

A quirk of the CKMR data is that future simulated data collection (i.e. from projections) actually alters the data in the past - future adult samples are compared to pre-projection juvenile samples to look for POPs. To be clear, this does not invalidate the use of the actual historical CKMR data in the OM, it just outlines the complex nature of the temporal accumulation of comparisons and matches in the CKMR data.

3.2 Half-Sibling pairs

For the HSP data we compare to juvenile samples and ask: what is the probability that they share a mother or a father? For juvenile samples i and i', the key covariate is their year of birth, or cohort c. The additional derived variables needed for constructing the HSP probabilities are natural mortality and fleet-summed harvest rates:

$$\mathbb{P}\left(K_{ii'} = HSP|z_i, z_{i'}\right) = \frac{4\pi^{\eta} q_{\text{hsp}}}{S_{c_{\max}}} \left(\sum_a \gamma_{c_{\min},a} \left(\prod_{k=0}^{\delta-1} \phi_{c_{\min}+k,a+k} \right) \varphi_{a+\delta} \right) \tag{3.2}$$

where

$$\phi_{y,a} = \exp\left(-M_a\right) \prod_{s=1}^{2} \left(1 - \sum_f h_{s,f,y,a}\right) \tag{3.3}$$

is the annual survival probability, and:

- $\{z_i, z_{i'}\} = \{c_i, c_{i'}\}$
- $c_{\min} = \min\{c_i, c_{i'}\}$
- $c_{\max} = \max\{c_i, c_{i'}\}$
- $\delta = c_{\max} - c_{\min}$
- q_{hsp} is a parameter to cover potentially length-driven or recruitment dynamic differences between POP and HSP absolute abundance information
- π^η is the false-negative retention probability (1 minus the false negative exclusion rate defined by the false-positve cut-off)
- $\gamma_{y,a}$ is the true age distribution of adults in year y

Both the sampling distributions of the POP and HSP data are assumed to be binomial. Indeed, extensive work has been done over the years to assess whether more complex distrbutions (such as the beta-binomial) were needed, and found that the predictive properties of the binomial likelihood assumed in the OM were satisfactory as they are (Hillary *et al.*, 2017).

There are only three additional entries required in the `mycontrol.dat` file to accommodate the variables needed to switch on and control the CKMR sampling part of the projection code. Just below the GT settings is the following text:

```
# control parameters for CK program
# Mjuv (juvenile samples)
# Madu (adult samples)
# cksw (0/1 off/on switch to simulate data)
1500 3000 1
```

The first parameter controls the number of juvenile age 3 samples (M_i), the second controls the total number of adult samples (M_j), and the third is a switch to turn the CKMR simulation on (value of 1) or off (value of 0). The simulated future POP data are stored in the `.s12` file (for each grid sample), and the future HSP data are stored in in the `.s13` file.

3.3 Generating indices from CKMR data

A detailed exploration of options were explored in [1]. The key information content in both the POP and HSP data is in the **ratio** of comparisons to matches. The general idea is this: if, over time, the average ratio of comparisons to matches is increasing/decreasing it is highly likely that the total adult abundance (TRO really) is decreasing/increasing. Another complication with using the CKMR data in the MP setting is that the projection and historical data need to be merged together.

Empirical indices can be derived from both the POP and HSP data, and can obviously be combined in a weighted average index that correlates well with the true trend in TRO. As an example, with the default sample size controls in the supplied `mycontrol.dat` file ($M_i = M_j = 3,000$) and a constant catch projection at the current TAC (17,647t) - where the true TRO increases steadily to a median of around 34% by 2035 - we see that:

- The base POP index (no moving average just as defined in [1]) correlates with true TRO at around 60%
- The base HSP index (no moving average as with the POP index) correlates with true TRO around the 65% level
- A combined index of POP and HSP indices (weighted evenly) correlated at just above 60%
- By using say a simple 3 or 4 year moving average of the indices this correlation can be increase to the 70% and above range

The satisfactory level of correlation (better or at least as good as say an actual survey of the TRO with a 25% CV) suggests these indices could indeed be used empirically and in a target-type HCR. As there is a reasonably strong linear relationship between the indices and the true TRO it stands to reason that there is some target value of the index (relative to the current value) that would match reasonably well with the tuning target of future TRO depletion. These indices can be used in much the same form (trend, target or even limit) as were the CPUE and aerial survey indices in the Bali Procedure [3].

4 New robustness tests

There are a number of new robustness tests that will require changes to the SVT OM:

- **rechigh**: counterpart to **reclow** in that mean recruitment is higher by 50% for n years
- **gtqtr**: $x\%$ increase in q^{gt} per year
- **cpuenocrp**: remove the 0.5% effort creep (increase in q) in projections, but not historically
- **selrev**: reversing the order of estimates at decadal scale.
- **selalt**: 5 year blocks of bimodal and ”recent” selectivity

4.1 Low/high recruitment scenarios

This is now included and is controlled via two parameters in the `mycontrol.dat` file, not one was before. The first parameter is the number of years for which the adjustment to mean recruitment applies (as before); the second is the factor by which mean recruitment is adjusted (1 means no change; < 1 means a reduction: > 1 an increase).

4.2 Trend in gene-tagging bias

A log-linear annual trend in the gene tagging bias parameter q^{gt} is now included in the projections. In terms of settings :

- The value used to set q^{gt} in the `mycontrol.dat` file sets the initial value when the trend is different from zero
- For a given trend, δ, then $q^{\mathrm{gt}}_{y+1} = q^{\mathrm{gt}}_{y}(1+\delta)$

4.3 Effort creep in q for LL_1

This was automatically set at a log-scale positive trend of 0.005 (0.5%) per year. This has now been replaced with a manually set parameter in the `mycontrol.dat` file on the line where the various CPUE scenarios are switched on or off (high CPUE CV, updownq etc.). Just set the parameter to zero to turn off the effort creep; default value is still 0.005.

4.4 Future selectivity scenarios for LL_1

There are two different suggestions currently: one where the selectivity reverses the trend of the last 10-15 years from older to younger animals; the other where we switch between a unimodal and a bimodal structure.

4.4.1 Trend in mean selectivity with age

There are probably a number of ways to do this, but the one i've tried is fairly simple to understand and achieves the general wishes (if i've understood the intent of the robustness test correctly). The selectivity parameters are $\eta_{f,y,a}$ and the selectivity ogive, $s_{f,y,a}$ is defined as:

$$s_{f,y,a} = \frac{\eta_{f,y,a}}{\max_a \left(\eta_{f,y,a}\right)}.$$

For LL_1 a lognormal error term (ζ_a age correlation of 0.7 and SD 0.05) is applied to each class from one year to the next and for ages 3 to 17 (selectivity fixed above age 17). We modify this process to include a selectivity "drift" term gradually moving the distribution towards older animals as follows:

$$\eta_{1,y,a} = (\nu\eta_{1,y-1,a-1} + (1-\nu)\eta_{1,y-1,a}) \times \exp\left(\zeta_a\right)$$

The drift parameter, $\nu > 0$, has an intuitive interpretation. Given selectivity is defined in 4 year blocks, between 2017 and 2045 there will be 8 shifts in selectivity (random without or trend or with drift if defined to be so). A value of $\nu = 0.25$ would be expected to, on average, move the mode of the selectivity $8 \times \nu = 2$ age classes.

Figure 4.1 shows a single realisation from the projections with a drift coefficient of $\nu = 0.25$ (in this case the mean maximum in the selectivity moves about 1 age-class not 2; this varies from realisation to realisation). What is hopefully clear is that we can seemingly achieve the desired effect of gradually moving the selectivity towards older ages using only one fairly easy to interpret parameter. Simply set this parameter to zero in the projection `mycontrol.dat` file to remove the effect and revert to the reference case (it is located next to the q creep parameter).

4.4.2 Modal "flipping"

At the OMMP meeting in June there was some apparent confusion as to what this robustness test is supposed to cover in terms of observed phenomena. Figure 4.2 shows the median estimates of LL_1 selectivity from 2005 to 2016. The bimodality is reasonably clear from 2006 to 2010. However, it actually looks more like a cohort effect, and one almost certainly linked to the very week 1999 to 2002 cohorts. If this is this case then there are two possible interpretations:

1. The fleet actively avoided these cohorts (given their catch rates would have been probably very low, comparatively speaking)

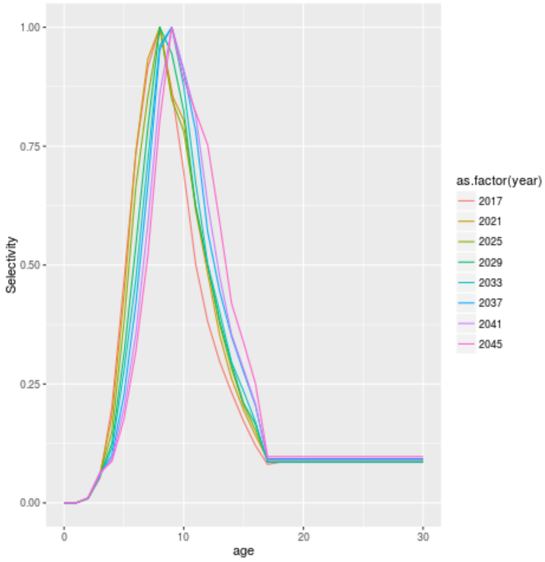

Figure 4.1: *Single realisation of long-line selectivity with drift coefficient of 0.25*

2. The model does not have the flexibility in the recruitment deviates to adequately fit to the hole in the length frequency data caused by the very weak year-classes and modifies the selectivity to achieve this

Whatever the explanation, neither of them suggest that a ”flipping” behaviour in the selection pattern (one block unimodal, the next block bimodal) is something that we've actually seen in the past. This is a test that can be implemented (easy version: include a fixed bimodal pattern in fixed quantities file; harder version: expand the grid to include a year when selection was bimodal) but the question is do we actually think we need it?

5 Acknowledgements

This work was funded by CSIRO and the Department of Agriculture and Water Resources.

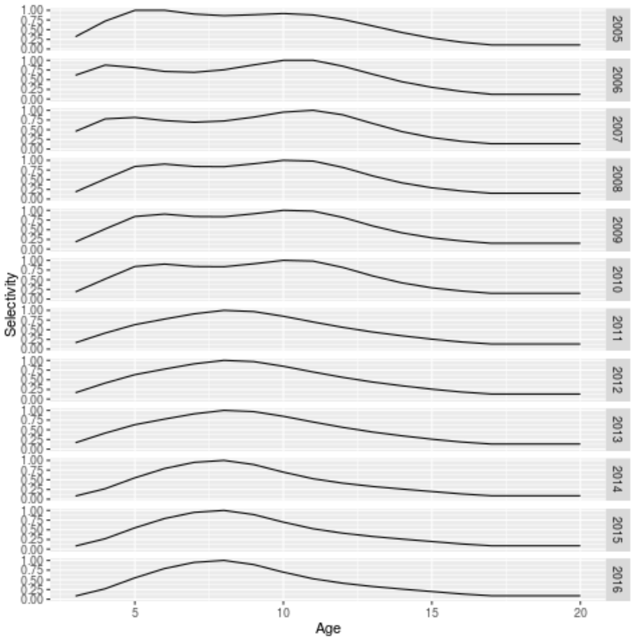

Figure 4.2: *Median estimates of long-line selectivity from 2005 to 2016*

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[1] R. M Hillary, A. Preece, and C. R. Davies (2016) Methods for data generation in projections. *CCSBT–OMMP/1609/07*

[2] R. M Hillary, A. Preece, and C. R. Davies (2017) Updates required for new data sources and reconditioning of the CCSBT OM. *CCSBT–OMMP/1706/04*.

[3] R M. Hillary *et al.* (2016) A scientific alternative to moratoria for rebuilding depleted international tuna stocks. *Fish and Fisheries*. **17**:469–482.

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Contents

Abstract

The performance of three revised forms of Candidate Management Procedures (CMPs) for SBT were explored. The Gene-Tagging+CPUE(rh11) and Gene+tagging+CPUE+Close-kin (rh12) CMPs are modified forms of the examples considered at the June 2018, OMMP9 meeting in Seattle. The third CMP (D25)uses only the Gene-tagging and Close-kin data. Performance of CMPs was compared across the 0.3SSB by 2035 and 0.35SSB0 by 2040 tuning criterion. For the 0.3SSB0 by 2035, there was a general requirement for CMPs to increase the TAC for both the first two TAC decisions (i.e. 2021-2023 and 2024-2026 TAC blocks) in order to meet the tuning criterion. In the case of rh11 and rh12, as a maxTAC constraint was added. This prevented these CMPs from raising TAC (and total catches) to levels that were unsustainable in the longer-term and would, as a result, require substantial TAC decreases in the future. The D25 CMP was not able to be tuned to the 0.3 by 2035 level, so alternative formulations of this CMP will need to be explored further to this tuning combination. All three CMPs could be tuned to the 0.35SSB by 2040 tuning criterion and achieved the 0.2SSB by 2035 with 70% probability. Preliminary results suggest that similar average catch performance can be achieved by rh11 and rh112 for the 0.3SSB by 2035 (20,000 t/yr) ands for 0.35 by 2040 tuning level(17,000-18,000 t/yr), with D25 having similar performance for average catch(18,500 t/yr) for the 0.35 by 2040 level. Both of the CMPs that include the CKMR data have a very low annual average catch variation and a very low to zero probability for both TAC up/down performance statistics, with no loss of robustness against the four trials with the largest impact (as2016, reclow5, cpueupq and cpuehcv).

1 Background

The CCSBT has agreed to develop a new management procedure for recommending the global TAC for SBT as a central component of the rebuilding plan for the stock and fishery. The current management procedure cannot be used to recommend TACs beyond 2018-2020 TAC block because the aerial survey will not be conducted from 2018 onwards. The aerial survey is used as the recruitment monitoring series in the harvest control rule of the current management procedure. The CCSBT has funded a gene-tagging recruitment monitoring program that will provide an index of juvenile abundance to be used in the new management procedure as a replacement for the aerial survey. The new management procedure is required by 2020 for recommending the TAC for the 2021-2023 TAC block. The process of development through to selection of a management procedure requires substantial consultation between scientists, managers, industry and other stakeholders. The process involves iterations of development and revision of management procedures (coding of computer models), presentation of results, discussion of performance and risks and their potential implications, revision of objectives and performance measures, and clarification of relative importance and trade-offs between conflicting objectives. This paper provides updated evaluation and exploration of candidate management procedures following review of initial candidates MPs at the OMMP technical working group meeting in June 2018.

2 Data and forms of Candidate MPs

The ESC has agreed to consider three data sources for use in development and evaluation of candidate MPs. The candidate MPs explored below use different combinations of these data and alternative forms of MP (i.e. analyses, form of HCR). The agreed data sources are:

1. Japanese long-line CPUE
2. The gene tagging (GT) data (matches and number of comparisons)
3. The close-kin mark-recapture (CKMR) data (matches and number of comparisons)

We present initial results of testing 3 alternative CMPs: revised versions of **rh3** (GT+CPUE) and **rh8** (GT+CPUE+CKMR) [2], which were considered at OMMP9 and have been renamed **rh11** and **rh12**, respectively; and an additional CMP, **D25**, which uses only GT and CKMR.

2.1 Candidate MPs using the CPUE & GT data

The original target/limit form of **rh3** descibed in [2] has been slightly modified for this candidate MP **rh11**. The target/limit formulation is retained for years prior to y_{targ}, albeit with a slight modification to include a reactivity parameter β^{cpue} (interpretation is that values of this parameter greater/less than equal to 1 are more/less reactive). For years after the target year, the MP reverts to a trend-driven structure (with gain parameter k^{cpue}).

$$
\begin{aligned}
\Delta_y^{\text{cpue}} &= \left(0.5 \times \left(1 + \frac{\bar{I} - I_{\text{lim}}}{I_{\text{targ}} - I_{\text{lim}}}\right)\right)^{\beta^{\text{cpue}}} \quad \text{if} \quad \bar{I} \geq I_{\text{lim}} \quad \& \quad y < y_{\text{targ}} \\
\Delta_y^{\text{cpue}} &= 2^{-\beta^{\text{cpue}}} \left(\frac{\bar{I}}{I_{\text{lim}}}\right)^2 \quad \text{if} \quad \bar{I} < I_{\text{lim}} \quad \& \quad y < y_{\text{targ}} \\
\Delta_y^{\text{cpue}} &= 1 + k^{\text{cpue}} \lambda^{\text{cpue}} \quad \text{if} \quad y \geq y_{\text{targ}}
\end{aligned}
$$

The target/limit formulation is retained for years prior to y_{targ}, albeit with a slight modification to include a reactivity parameter β^{cpue} (interpretation is that values of this parameter greater/less than equal to 1 are more/less reactive). For years after the target year, the MP reverts to a trend-driven structure (with gain parameter k^{cpue}). The actual HCR works as follows:

$$
TAC_{y+1} = TAC_y \left(\omega^{\text{cpue}} \left(\Delta_y^{\text{cpue}} - 1\right)\right) \times \Delta_y^{\text{gt}},
$$

where ω^{cpue} is the CPUE intertia term and Δ_y^{gt} is the same limit-style GT functional form as used previously. It is referred to as **rh11**. In both this MP and the one using CKMR data the limit form of the gene tagging part of the HCR is unchanged from that explored in the OMMP work and presented at the meeting in Seattle.

2.2 Candidate MPs using the CKMR data

We explored a modified version of the original adult-focused age-structured population model, now with auto-correlated “recruitment” deviations:

$$
\begin{aligned}
N_{y_{\min},a_{\min}} &= \bar{R} \exp\left(\xi_{y_{\min}} - \sigma_R^2/2\right), \\
N_{y,a_{\min}} &= \bar{R} \exp\left(\epsilon_y - \sigma_R^2/2\right), \\
\epsilon_y &= \rho \epsilon_{y-1} + \sqrt{1-\rho^2}\xi_y, \\
\xi_y &\sim N(0, \sigma_R^2), \\
N_{y+1,a+1} &= N_{y,a} \exp\left(-Z_{y,a}\right) \qquad a \in (a_{\min}, a_{\max}), \\
N_{y+1,a_{\max}} &= N_{y,a_{\max}-1} \exp\left(-Z_{y,a_{\max}-1}\right) + N_{y,a_{\max}} \exp\left(-Z_{y,a_{\max}}\right), \\
Z_{y,a} &= Z_y \qquad a \leq 25, \\
Z_{y,a} &= Z_y + \frac{a - 25}{a_{\max} - 25}\left(Z_{a_{\max}} - Z_y\right) \qquad a \in [26, a_{\max}], \\
Z_y &= \frac{Z_{\max} e^{\chi_y} + Z_{\min}}{1 + e^{\chi_y}}, \\
\chi_{y+1} &= \chi_y + \zeta_y, \\
\zeta_y &\sim N(0, \sigma_\chi^2), \\
TRO_y &= \sum_a N_{y,a} \varphi_a
\end{aligned}
$$

Parameter	Value
$a_{\min}$	6
$a_{\max}$	30
σ_R	0.25
ρ	0.5
σ_χ	0.1
$Z_{\min}$	0.05
$Z_{\max}$	0.4
$Z_{a_{\max}}$	0.5
$\mu_{\chi_{\text{init}}}$	-1.38
$\sigma_{\chi_{\text{init}}}$	0.15
q_{hsp}	0.9

Table 2.1: Settings for CKMR MP population model

The estimate parameters of this model are:

1. The mean adult recruitment, $\bar{R}$
2. The adult recruitment deviations, ϵ_y
3. The initial value, χ_{init}, that "starts" the random walk for Z_y (with an associated normal prior mean and SD)
4. The random walk deviations ζ_y

This is similar to the number of parameters estimated in the Bali Procedure population model [4]. There are not a large number of model parameters, and many of them are going to be constrained deviation parameters. The likelihood model for the POP and HSP data are basically the same as those used in the SBT OM, but where M_a and the harvest rates are replaced by $Z_{y,a}$ to estimate cumulative survival in the HSP likelihood. The assumed settings for the CKMR MP population model are detailed in Table 2.1.

The general structure of the revised MP is as follows:

$$TAC_{y+1} = TAC_y \left(\omega^{\text{cpue}} \left(\Delta_y^{\text{cpue}} - 1 \right) + \omega^{\text{ck}} \left(\Delta_y^{\text{ck}} - 1 \right) \right) \times \Delta_y^{\text{gt}},$$

where the inertial terms for the CPUE and CKMR parts of the HCR are now additive, not multiplicative as previously explored. This avoids the quadratic term in the multiplicative case where both trends are consistently positive subtley but consistently making the TAC increases larger than for the additive case, despite the trends being the same in both cases.

Before detailing the changed form of the HCR we recap some useful variables:

- I_y^{ck}: moving average of the estimated TRO from the MP population model (now pushed forward to the current year using the model to project forward for 4 years to avoid too much intertia in the signal when you need it)
- $\tilde{I}$: average estimated TRO from 2003 to 2012 (reference period w.r.t. relative rebuilding criterion)
- γ: proportional amount of TRO rebuilding we wish to achieve

We are interested in the following ratio: $\delta = I_y^{\text{ck}}/(\gamma\tilde{I})$. To get from the current average level of TRO to the 30% level we would consider $\gamma \approx 2$; for the 35% level $\gamma \approx 2.5$. As the ratio δ approaches 1 (i.e. we *think* we are at or close to the target TRO), we would like to have the potential to morph (continuously and possibly smoothly) the behaviour of the MP. It seems that MPs need to be fairly reactive in the first 10–15 years (3–4 TAC decisions) of the projections to be able to tune to the 30% target by 2035, but afterwards that embedded reactivity might be giving rise to continued TAC increases to levels likely to cause the TRO to come back down again post-target year. For the CPUE trend part of the HCR we explore a density-dependent gain parameter:

$$k^{\text{cpue}}(\eta) = k_1^{\text{cpue}}\left(1 - \left(1 + e^{-2\kappa\eta}\right)^{-1}\right) + k_2^{\text{cpue}}\left(1 + e^{-2\kappa\eta}\right)^{-1}$$

where $\eta = \delta - 1$. This is using the logistic function approximation to the Heaviside step function $H[\eta]$ ($H[\eta < 0] = 0$, $H[\eta \geq 0] = 1$). We set $\kappa = 20$ so the transition between the two gain parameters, given η, happens within $\pm 5\%$ of $\delta = 1$. The CPUE multiplier is then just defined as follows:

$$\begin{aligned}
\Delta_y^{\text{cpue}} &= k^{\text{cpue}}(\eta)(1+\nu)\lambda^{\text{cpue}} \quad \text{if} \quad \lambda^{\text{cpue}} \leq 0, \\
\Delta_y^{\text{cpue}} &= k^{\text{cpue}}(\eta)(1-\nu)\lambda^{\text{cpue}} \quad \text{if} \quad \lambda^{\text{cpue}} > 0
\end{aligned}$$

For the CKMR part of the HCR we try to preserve the main elements of the previous candidate MP (**rh8**): ensure a minimum rate of increase in the TRO *beneath* the target level, and once it is achieved we would like to maintain the TRO at that level. To include this kind of behaviour in the HCR we also include some density-dependence in the log-linear growth rate at which the HCR moves from a TAC increase to a TAC decrease:

$$\begin{aligned}
\Delta_y^{\text{ck}} &= 1 + k^{\text{ck}}(\eta)\left(\tilde{\lambda}(\eta) - \lambda^{\text{ck}}\right), \\
k^{\text{ck}}(\eta) &= k_1^{\text{ck}}\left(1 - \left(1 + e^{-2\kappa\eta}\right)^{-1}\right) + k_2^{\text{ck}}\left(1 + e^{-2\kappa\eta}\right)^{-1}, \\
\tilde{\lambda}(\eta) &= \lambda_{\text{min}}\left(1 - \left(1 + e^{-2\kappa\eta}\right)^{-1}\right)
\end{aligned}$$

The threshold level at which a trend goes from a TAC decrease to an increase essentially begins at $\lambda_{\text{min}} > 0$ and, as the estimated TRO approaches the target level, this rapidly dercreases to zero (in a similar way to the CPUE trend term). This is to ensure that a minimum level of rebuilding is encouraged for **all** trajectories below the target, and where above the target the *status quo* is preferred.

2.3 Introduction of a maximum TAC

Along with embedding a kind of switching mechanism in both **rh11** and **rh12**, in terms of behaviour once the target is met, we also introduce a maximum TAC value. This is again to avoid short-term increases to levels of TAC (and, hence, total catch including UAM) that are not sustainable in the long-term, even for the most optimistic grid combinations and future trajectories, and will definitely require large TAC decreases in the future. The value chosen for the maximum TAC was 32,000t. Including UAM (which is approximately and consistently 20% of the TAC) this value would be a total catch of around 36,000t.

2.4 GT and CK Candidate MPs

Candidate MPs that use only the gene-tagging and close-kin data were also explored, using code described earlier [2], for GT and section 2.1 above for CKMR). Various changes to parameters were made to turn off the CPUE component and for tuning the new CMP. This form of CMP is of interest because it is fishery independent and avoids known issues with CPUE and uncertainty in the relationship between CPUE and abundance. This CMP is different because it does not use the recent positive trend in CPUE that drives some of the behaviour seen in other forms of CMP.

3 Candidate MP performance on the reference set

3.1 CMPs tuned to median of 30% of unfished level by 2035

Regardless of the CMP examined, there appears to be a general requirement for *any* CMP to be able to increase the TAC in the first two decisions by around 1,000t each time to be able to tune to this level. In

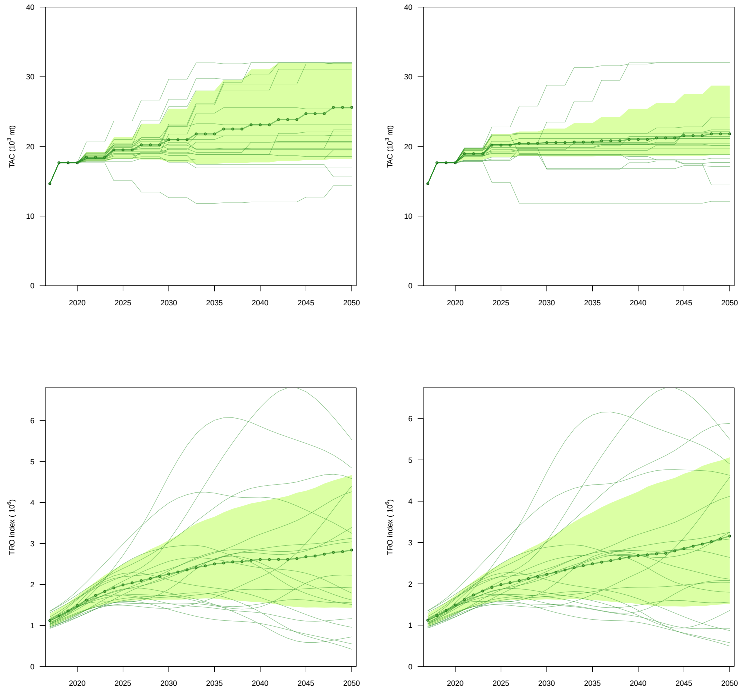

Figure 3.1: *TAC (top) and TRO (bottom) median, 80%CI and 20 random worms for **rh11** (left) and **rh12** (right).*

the case of (**rh11** and **rh12**) this could only really be achieved by making the CMP reasonably responsive to the strong positive signal in the CPUE of the very large 2013 year-class moving through the long-line fishery. In the first 5–7 years of the projections the signals in both the GT and the CKMR data do not make it possible to sensibly construct an HCR that would achieve the required increases in the first two TAC changes and, hence, meet this tuning level.

Figure 3.1 details the TAC and TRO projection summaries (median, 80% CI and 20 worms) for the two MPs (**rh11** and **rh12**). The differences between the two MPs are fairly clear:

- TAC performance: **rh11** shows more variability and a steadily increasing median TAC; **rh12** is far less variable and a slower but still generally increasing median TAC trend after the first two TAC changes
- SSB (TRO) performance: very similar for both, with a slower rate of increase post-2035 for **rh11** than for **rh12** and more variance in SSB (TRO) above the median (given lower levels of catch)

3.2 tuned to median of 35% of unfished level by 2040

Figure 3.2 summarises the TAC and SSB (TRO index) projections for the 35% of unfished level by 2040 tuning level (median, 80% CI and 20 worms) for **rh11** and **rh12**. For this tuning level:

- TAC performance: **rh11** shows more variability and a steadily increasing TAC after 2040 but fairly constant until then; **rh12** is far less variable with minimal chance of consistent TAC increases or decreases before 2040
- SSB (TRO) performance: very similar for both, with a slower rate of increase post-2040 for **rh11** than for **rh12** and more variance in SSB (TRO) above and below the median (given lower levels of catch variability).

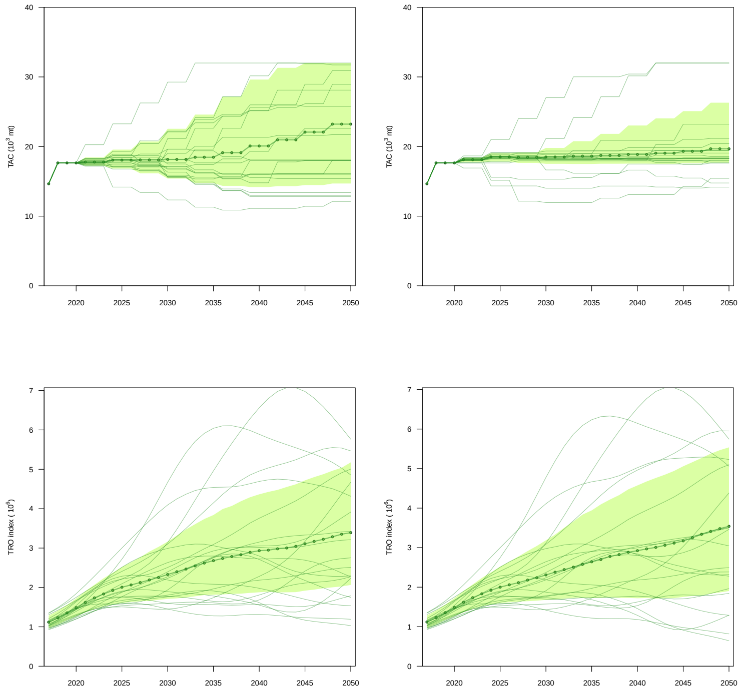

Figure 3.2: *TAC (top) and TRO (bottom) median, 80%CI and 20 random worms for **rh11** (left) and **rh12** (right).*

- TAC performance: **rh11** shows more variability and a steadily increasing TAC after 2040 but fairly constant until then; **rh12** is far less variable with minimal chance of consistent TAC increases or decreases before 2040
- TRO performance: very similar for both, with a slower rate of increase post-2040 for **rh11** than for **rh12** and more variance in TRO above and below the median (given lower levels of catch variability).

3.2.1 GT and CKMR Candidate MP

The Candidate MP that uses only the gene-tagging and close-kin data has only been tuned to reach 35% SSB0 by 2040, and it has a greater than 70% probability of being at least 20% SSB0 by 2035 (the interim rebuilding target). Under this MP, median recruitment trends are positive, median SSB increases through to 2050, there is a low probability of falling below 20% SSB after 2035, and there are TAC increases on average throughout the period of the projections, with low probability of TACs below current levels.

It was difficult to find parameters that would allow this CMP to be tuned to the 30% SSB0 by 2035 target, as higher initial catches are needed to reach this target. When tuned to 35% by 2040, the 30% target is over-shot with more than 58% of the trajectories above this target. We plan to keep investigating alternative parameterisation of this CMP to reach this or other targets that are preferred or requested by the Commission.

4 Candidate MP performance across key robustness tests

For both tuning scenarios the key robustness tests that seemed to make the most difference (specifcially more pessimistic than the reference case) were:

1. **as2016**: remove the 2016 aerial survey point

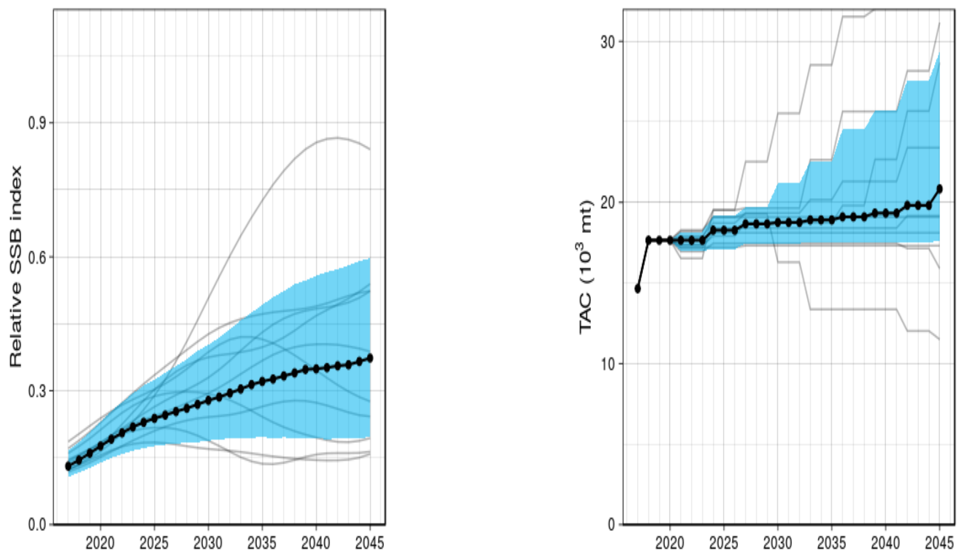

Figure 3.3: *TRO status (left) and TAC (right) for D25 tuned to 35% by 2040.*

2. **reclow5**: mean recruitment reduced by 50% for the first 5 years of the projections
3. **cpueupq**: from 2008 onwards LL catchability is permanently increased by 25%
4. **cpuehcv**: minimum CPUE CV (past and future) is 0.3 instead of the reference case of 0.2

4.1 tuned to median of 30% of unfished level by 2035

Figure 4.1 Summarises stock status (SSB (TRO)) and mean TAC statistics across the important robustness tests for CMPs tuned to median of 30% of unfished level by 2035. Notable results include:

- For the previous rebuilding objective *all* MPs across *all* the displayed robustness trials attained at least the 70% probability of being above 20% of the unfished level by 2035
- Average reference case catches between 2021 and 2035 were around 20,000t for both MPs
- For the maximum TAC decrease, outside of the **reclow5** robustness trial it is less than 1,000t for **rh11** and very close to zero for **rh12**. For the **reclow5** test it is higher and for **rh12** the median is 3,000t so this MP reacts strongly to this test even with the same GT limit term in both MPs
- In terms of AAV, median levels for **rh11** were between 5 and 10%; for **rh12** between 3 and 5%
- In terms of the 2-up-then-down probability for the first 3 TAC changes for **rh11** it was 0.18 for the **reclow5** trial and at or less than 0.12 for the rest. For **rh12** the probability is effectively zero for all trials

4.2 CMPs tuned to median of 35% of unfished level by 2040

Figure 4.2 summarises the SSB (TRO) stock status and mean TAC statistics across the important robustness tests for CMPs tuned to median of 35% of unfished level by 2040.

- For the previous rebuilding objective *all* CMPs across *all* the robustness trials were clearly above the 70% probability of being above 20% of the unfished level by 2035
- Average reference case catches between 2021 and 2035 were around 17,000–18,000t for both CMPs
- For the maximum TAC decrease, outside of the **reclow5** robustness trial it is less than 1,000t for

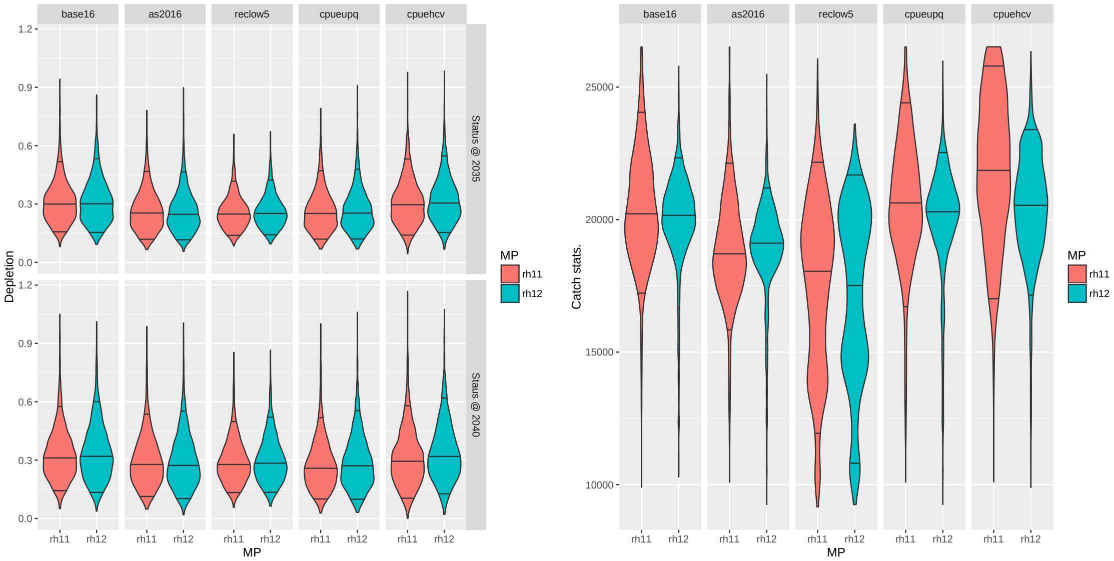

Figure 4.1: *TRO status (left) and mean TAC statistics (right) across the key robustness trials.*

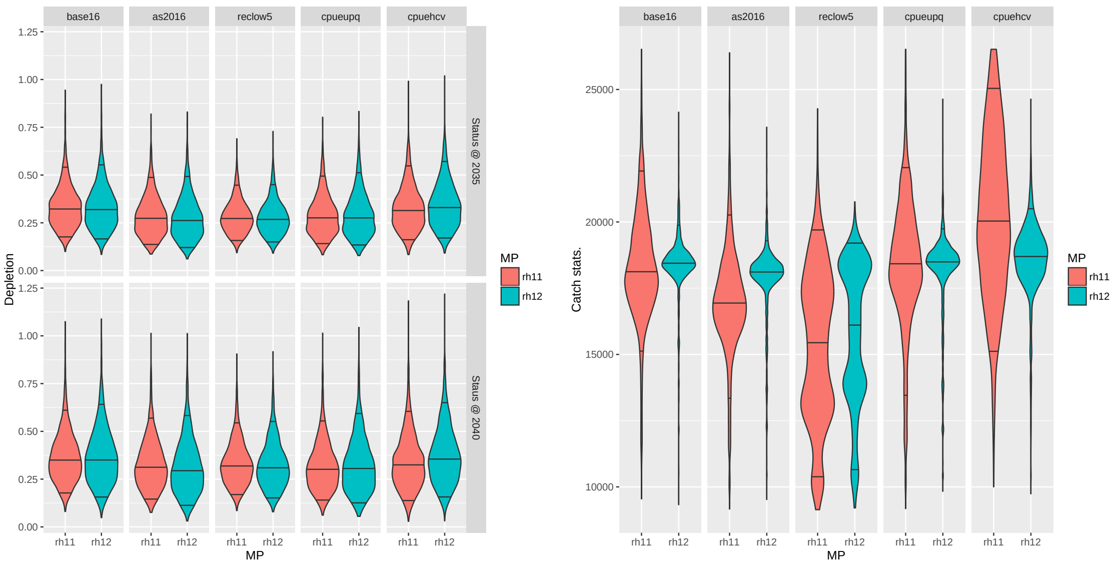

Figure 4.2: *TRO status (left) and mean TAC statistics (right) across the key robustness trials.*

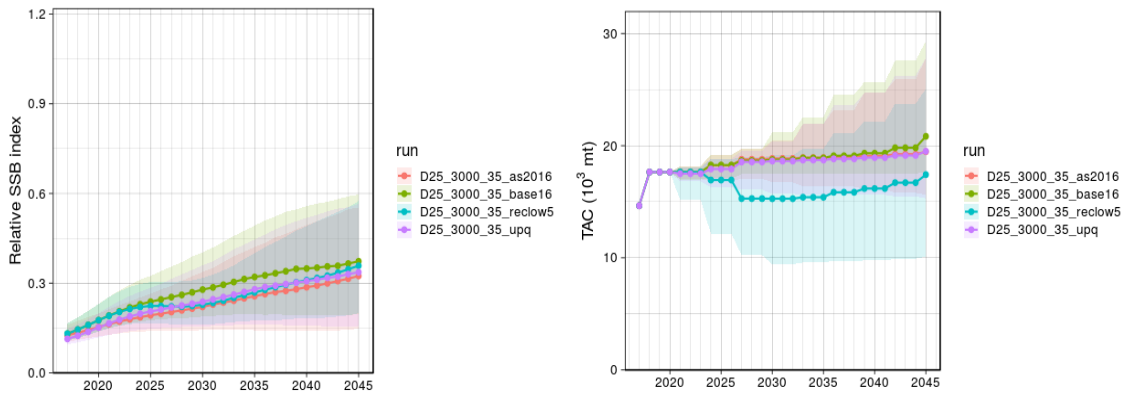

Figure 4.3: *Comparison of SSB and TAC for the base set and 3 robustness tests (noAS, reclow5 and upq)*

Run	base2016	as2016	reclow5	upq
Mean $TAC_{2021\text{-}2035}$	18,533	18,528	16,092	19,407
Mean $TAC_{2036\text{-}2050}$	20,223	19,448	16,829	19,407
AAV (%)	1.9	2.1	5.6	2.1
Status (2035)	0.32	0.26	0.27	0.28
Status (2050)	0.41	0.37	0.44	0.38
Status (2035/2018)	2.17	1.83	1.82	2.15
Status (2050/2018)	2.75	2.62	2.96	2.91
Min. status (2019-2035)	0.16	0.14	0.16	0.14
70% above 20% SSB0	2022	2026	2022	2024
SSB (MSY) year	2027	2031	2033	2030
$\mathbb{P}(SSB_{2041-2050} > SSB_{msy})$	0.74	0.62	0.74	0.66
Max. TAC decr.	0	0	3,000	0
P(2up/1down)	0.003	0.01	0.002	0.01
P(2up/1down) beta	0.007	0.02	0.01	0.015
10%ile TAC	17,303	16,803	11,315	16,114
$\mathbb{P}(SSB_{2035} < 0.2SSB_0$	0.12	0.28	0.19	0.21
$\mathbb{E}(CPUE_{2021-2030}/CPUE_{2019})$	0.9	1.02	0.67	0.9

Table 4.1: *TRO summary for D25.*

rh11 and mostly less than 500t for **rh12**. For the **reclow5** test the median is 3,000t for both MPs so both react strongly for this robustness trial

- In terms of AAV, median levels for **rh11** were between 3 and 8%; for **rh12** between 2 and 5%
- In terms of the 2-up-then-down probability for the first 3 TAC changes for **rh11** it was mostly below 0.12 for all tests. For **rh12** the probability is less than 0.05 except for the **hcpuecv** case where it was 0.1

4.2.1 GT and CKMR CMP

The GT & CK MP was also tested against the key robustness tests **as2016**, **reclow5** and **upq**. The interim rebuilding objective (70% probability of reaching 20% SSB0 by 2035) is still met under these robustness tests, however, and as with the other CMPs,the probability of reaching the new target is reduced. The CMP continues to work effectively under conditions it was not tuned to and median trends in SSB, recruitment and TAC are similar to the base set. The **upq** and **as2016** robustness tests showed similar median trajecories in SSB and TAC. The D25 MP acted strongly in the low recruitment robustness test to cut TAC and maintain rebuilding of the SSB. Performance statistics are provided in Figures 4.3 and 4.4 and Table 4.1.

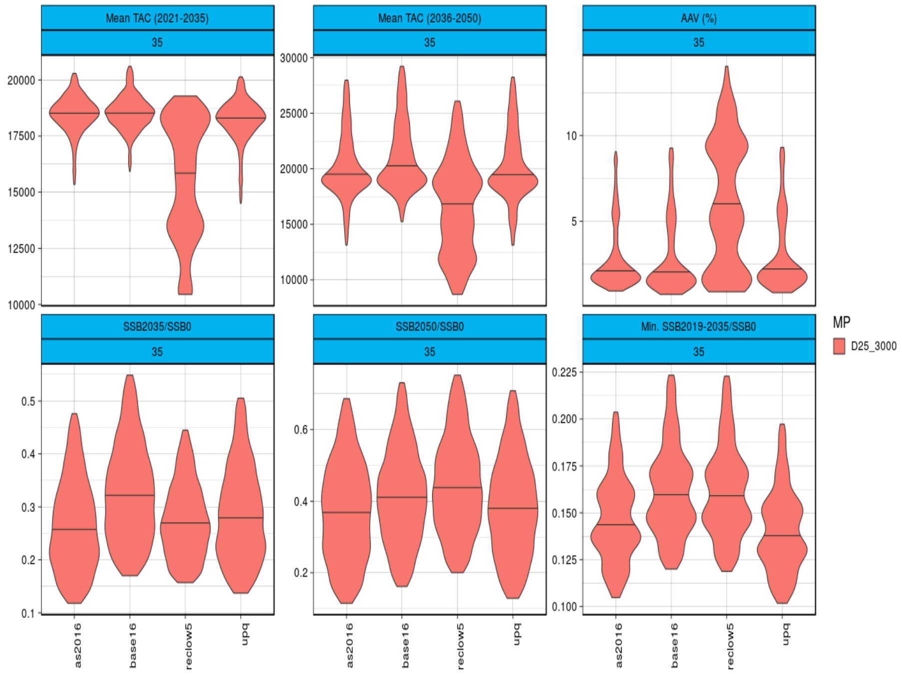

Figure 4.4: *Comparison figures of the main performance meaures for the D25 MP for the base set and three robustness tests.*

5 Conclusions

General conclusions:

- For the 30% by 2035 tuning level, average catches are around 20,000t. A consistent result was that any MP needs to nudge up the TAC by around 1,000t for the first and second decisions to be able to tune to the 30% level. The GT & CKMR CMP was unable to tune to this level as these input data series do not reflect the strong 2013 year class early in the simulation period. This sort-of-necessitates the use of the CPUE data as it "sees" the big 2013 year-class at the right time to give the MPs the signal they need to be able to tune to the 35% by 2035 combination.
- For the 35% by 2035 tuning average catches are around the 17,000–18,000t.
- For same level of relative TRO risk we can reduce the reactivity of the MP using all three data sets (**rh12**) versus the one using only CPUE and GT data (**rh11**). This achieves better performance in terms of AAV and catch variability without any loss of performance in terms of the pessimistic robustness trials. It also makes the chance of a TAC decrease after two initial increases very low across all trials.
- The two clear robustness trials that produce quite different dynamics are the removal of the 2016 aerial survey and the 5-year low recruitment trials. These both result in clearly lower average TACs, but all CMPs appear to still attain the original tuning target of the Bali Procedure even for these robustness trials.

6 Acknowledgements

This work was funded by CSIRO and the Department of Agriculture and Water Resources.

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Meta-rules: consideration of exceptional circumstances in 2018

Preece, Davies, Hillary
CCSBT-ESC/1809/18

Citation

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Contents

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Abstract

The annual review of the CCSBT Management Procedure (MP) input data series, and stock and fishery indicators is intended to identify conditions and/or circumstances that may represent a substantial departure from conditions against which the MP was tested, termed "exceptional circumstances", and where appropriate recommend the required action. In 2018, the ESC will review MP implementation in the context of the TAC set for 2019 which was recommended at the 2016 meeting of the ESC.

Issues identified in 2018 include: 1) changes in estimates of the population dynamics and productivity of the stock identified in 2017 through the updated stock assessment; 2) the unresolved shift in size distribution towards small fish in the Indonesian spawning ground fishery since 2013; 3) the potential for total catches (members and non-members) to be greater than the TAC (either annually or over the 3 year quota block), and 4) the planned absence of the index of recruitment from the scientific aerial survey in 2018. These issues, and their cumulative impacts, will need to be considered by the ESC and principles and process for action agreed, if required.

The meta-rules provide a safety-net around the MP TAC recommendations for circumstances or events not included in the MSE testing phase and will continue to be an essential component of MP development and implementation.

1 Introduction

The meta-rules for the CCSBT Management Procedure (MP) include: an annual review of the input monitoring series for the MP, and fishery and stock indicators; periodic assessments of the status of the stock via reconditioned operating models (3 year intervals); and an in-depth review of the MP performance (6 years intervals). The meta-rules are used to determine whether there is evidence for exceptional circumstances at each of these stages and decide what, if any, action should be taken to deviate from the TAC recommended by the MP (Attachment 10 of the 2013 ESC report (Anon, 2013)). 'Exceptional circumstances' are, conditions and/or circumstances that may represent a substantial departure from which the MP was tested.

In 2018, the ESC will review MP implementation in the context of the TAC set for 2019 which was recommended at the 2016 meeting of the ESC.

Issues of identified in 2018 include: 1) changes in estimates of the population dynamics and productivity of the stock identified in 2017 through the updated stock assessment; 2) the unresolved shift in size distribution towards small fish in the Indonesian spawning ground fishery since 2013; 3) the potential for total catches (members and non-members) to be greater than the TAC (either annually or over the 3 year quota block), and 4) the planned absence of the index of recruitment from the scientific aerial survey in 2018. These issues will need to be considered by the ESC and principles and process for action agreed, if required.

These issues also have potential impacts on re-conditioning operating models and associated work on the development of a new MP. Additional exceptional circumstances may be identified at the ESC following review of stock and fisheries indicators.

2 Meta-rules and exceptional circumstances

The SBT meta-rules include a process for identifying exceptional circumstances. Exceptional circumstances are events, or observations, that are outside the range for which the CCSBT MP was tested and, therefore, indicate that application of the total allowable catch (TAC) generated by the management procedure (MP) may be highly risky, or highly inappropriate.

The exceptional circumstances process under the meta-rules involves the following three steps:

1. Determining whether exceptional circumstances exist;
2. A "process for action" that examines the severity (and implications) of the exceptional circumstances for the operation of the MP, and the types of actions that may be considered;
3. "Principles for action" that determine how recommendations from the MP might be altered, if at all, based on the most recent reconditioning of the Operating Model (OM).

The meta-rules process as adopted by CCSBT can be found at Attachment 10 of the 2013 ESC report (Anon, 2013).

The meta-rules process for review of implementation of the MP TAC decisions is a central component of the implementation and review of the MP. The consideration of exceptional circumstances has identified issues that the Commission or ESC have subsequently responded to, where required, e.g. action on accounting for all sources of mortality and dealing with missing data. The meta-rules provide a safety-net around the MP TAC recommendations and will continue to be an essential component of the new MP being developed.

3 Exceptional circumstances in 2018 and potential severity for MP implementation

The following items may represent exceptional circumstances:

1) changes in estimates of the population dynamics and productivity of the stock, identified in 2017;
2) the unresolved shift in size distribution towards small fish in the Indonesian spawning ground fishery since 2013;
3) potential for fishing mortality (from members and non-members) to be greater than the TAC recommended by the MP;
4) the pre-arranged absence of aerial survey data for 2018.

The first three were reviewed at the 2017 ESC (Preece et al., 2017; Anon, 2017), and are only briefly addressed again here. The fourth item is new in 2018.

In considering the potential for exceptional circumstances arising from these issues, we examine whether: 1) the inputs to the MP are affected, 2) the population dynamics are potentially significantly different from those for which the MP was tested (as defined by the 2011 Reference and Robustness sets of OMs), 3) the fishery or fishing operations have changed substantially, 4) total removals are greater than the MP's recommended TACs, and 5) if there are likely to be impacts on the performance of the SBT rebuilding plan as a result.

The events are considered individually, however, the implications of the combination of events for the performance of the MP and the ability of the ESC to provide robust advice on the status and trends of the stock should also be considered. Further exceptional circumstances may also be identified at the ESC's annual review of stock and fishery indicators.

3.1 Changes in population dynamics and productivity of the stock

The 2017 stock assessment (Hillary et al., 2017) indicated that there were substantial differences in the rebuilding timeframe and estimates of stock productivity from the 2011 operating model results used to test and tune the current MP. The most recent years showed an improvement in stock status (relative depletion) and potential for much earlier rebuilding to the interim target (70% probability of rebuilding to 20%B_0 by 2035) than previously anticipated. Sensitivity tests identified that recent high aerial survey results (2014 and 2016) were the most influential factors in the change in population dynamics.

The 2017 ESC reviewed this potential exceptional circumstance through the meta-rules process, and noted that:

1. Changes to the operating model do not affect the operation of the MP;
2. The operating model changes are positive and lead to earlier rebuilding, even when the 2016 Aerial Survey data are excluded in sensitivity tests (Hillary et al., 2017);

3. The TAC increase recommended by the MP for the 2018-20 quota block was driven by the sustained positive trend in CPUE, with the aerial survey index having a relatively minor influence (Anon, 2016).

The 2017 ESC concluded there was no reason to modify the 2018 TAC recommendation. We suggest that this reasoning also applies to the 2019 TAC. These changes in population dynamics and productivity will affect management strategy evaluation of candidate MPs. The operating models will be reconditioned in 2019 for further testing of candidate management procedures.

3.2 Potential changes in the Indonesian fishery selectivity

Since 2013, unusually large numbers of small fish have been recorded in the Indonesian catch monitoring data from Benoa, Bali (see Sulistyaningsih et al., 2018). It has not been possible to determine whether these fish were caught on or off the spawning ground, and/or whether these data indicate a substantial shift in the selectivity of the Indonesian fishery. Although this is a priority issue for the ESC, it remains unresolved.

The potential shift in selectivity does not affect the data inputs to the MP, but may indicate changes in the operation of the Indonesian fishery that were not included in the OMs used at the time of testing the MP. We recommend that the advice from the 2015-17 ESCs regarding this issue remain the same: the potential change in selectivity is of concern but the immediate implications for the operation of the MP are insufficient on their own to constitute a basis for recommending modification to the MP TAC. The previously recommended need for action to resolve this uncertainty should be urgently pursued by the CCSBT and Indonesia so that the shift may be addressed in the next reconditioning of the operating models in 2019 for management strategy evaluation of candidate MPs.

3.3 Total fishing mortalities exceeding the TAC

The design and simulation testing of the current MP assumed that all removals from the stock were accounted for, i.e. the implementation of the TAC was exact. Additional unaccounted mortality by members and non-members has the potential to undermine the MP-based rebuilding strategy of the Commission. Sensitivity tests, using the reconditioned models for the 2017 stock assessment and an additional catch scenario (UAM1) developed in 2014 (Anon, 2014), indicated that additional catches would impact rebuilding of the stock but the target would still likely be met (given the optimistic population dynamics in the 2017 reconditioning). The agreements at previous ESC meetings were that if these unaccounted catches are occurring they would trigger exceptional circumstances. The 2017 ESC agreed that the scenario was still considered plausible (Anon, 2017).

Accounting for sources of additional mortalities by members has progressed, with the Extended Commission defining a common definition for member’s “attributable catch”. Members will account for all sources of mortality, as defined by the Commission, within their TAC from 2018 onwards and report on their attributable catches to the ESC and Compliance Committee. If the catch quantities to be attributed to total catch by members do not account for their total fishing mortality, then the potential for impact on the rebuilding plan for SBT will remain.

Non-member catches are difficult to quantify (Anon, 2017; Edwards et al., 2016). The Commission has deducted 306t from the annual TAC available for allocation to members for the 2018-2020 TAC block. This 'direct approach' aims to mitigate impact of unaccounted fishing mortality on performance of the MP while a new MP is being developed that is designed to be more robust to these uncertainties. The ESC has agreed that unaccounted mortality estimates will be included in the base set of operating models used for testing and tuning candidate MPs. This mechanism is intended to improve the robustness of the new MP to uncertainty in total mortality and, ideally, avoid the triggering of exceptional circumstances from this uncertainty in the future.

Absence of aerial survey data

The aerial survey was discontinued after completion of the 2017 survey. This was a planned cessation, agreed by the Commission in 2016. Members recognised the risks involved in foregoing future aerial survey results (Anon, 2016), and that this cessation would mean that a new recruitment monitoring program and management procedure would need to be developed.

The gene-tagging program was adopted as the replacement recruitment monitoring program, starting with the pilot study in 2016. The first abundance estimate (age 2 cohort in 2016) from the pilot gene-tagging program was provided in 2018. The gene-tagging and aerial survey abundance estimates are not directly comparable but do in-part overlap. The absolute abundance of the age 2 cohort in 2016 directly estimated by the pilot gene-tagging program would have been included in the 2016 and 2017 aerial survey relative abundance estimates of age 2, 3 and 4 year old fish (i.e., the 2-year old component in 2016 and 3-year old component in 2017).

In the context of the 2019 recommended TAC and exceptional circumstance advice, the absence of the aerial survey index in 2018 means that there is no information on whether the aerial survey index would have been inside or outside the bounds of the trajectories from the operating models used when testing and tuning the MP adopted in 2011. To examine the potential impact of this exceptional circumstance, we can look at recent information on recruitment to examine whether there is currently an increased risk of low recruitments and impact on the rebuilding plan, and whether there will be replacement recruitment data in the near future from the gene-tagging recruitment monitoring program. The key points on recent recruitment are: 1) the recent 3 points in the aerial survey index (2014, 2016-17) are substantially higher than the long term average of the series; 2) there in an increasing trend in stock assessment recruitment estimates since 2002; 3) the gene-tagging program has been established and the pilot project has delivered an estimate of abundance; and 4) the first abundance estimate from the pilot gene-tagging program is similar to recent recruitment estimates in the 2017 stock assessment. These 4 positive outcomes suggest that no action is needed on the TAC recommended for 2019 in light of the absence of the 2018 aerial survey data.

4 Conclusions

Through the meta-rules process we have examined changes in the (most likely) population dynamics since the MP was adopted in 2011, the potential shift in selectivity in the Indonesian fishery, the potential for fishing mortality to be greater than the TAC, and impact on MP implementation from the absence of the aerial survey data. The impacts of these issues have been considered in the context of the 2019 TAC (recommended in 2016).

The change in the estimates of the population dynamics in the reconditioned operating models does not affect running of the MP or the 2019 TAC recommendation.

The Indonesian selectivity change remains unresolved. Similarly, this does not directly impact on the running of the MP or TAC advice, but this issue will need to be addressed for reconditioning operating models in 2018 for management strategy evaluation of candidate MPs. As such it should remain a priority for CCSBT and Indonesia to resolve, particularly as this issue potentially impacts on the close-kin data collection into the future.

The potential for total catches to be greater than the TAC remains a concern. Action has been taken by the Commission so that members will need to account for their attributable catches from 2018 onwards, and an allowance for non-cooperating non-member catches has been made in the 2018-2020 TAC block.

The absence of aerial survey data in 2018 technically triggers exceptional circumstances, however, it is mitigated by the recent levels of higher recruitment and development of a replacement recruitment monitoring program which has provided a first abundance estimate for use in candidate MPs (Preece et al., 2018).

No change is recommended for the 2019 TAC. However, these potential exceptional circumstances have been considered in isolation from one another, and the ESC may wish to consider the risk that cumulative impacts could impose on performance of the MP and the ability of the ESC to provide robust advice on stock status.

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(ESC Agenda item 11, 16)

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Report on the Joint tuna RFMOs MSE working group meeting

Seattle 13-15 June, 2018

Preece, Davies, Hillary

CCSBT-ESC/1809/21

Citation

Preece AL, Davies CR, Hillary RM (2018). Report on the tuna RFMO MSE working group meeting. CSIRO, Australia.

Contents

Abstract

The ICCAT secretariat facilitated the preparation of a meeting of the Joint Tuna Regional Fisheries Management Organisations (RFMOs) Management Strategy Evaluation (MSE) Working Group, in June 2018. This was the second meeting of the group. Several CCSBT Scientific Committee members were present. The SBT Management Procedure (MP) is well established relative to other tuna RFMOs who may have only recently adopted a Harvest Control Rule (HCR), or Harvest Strategy (HS), or are in the process of developing MPs and testing these through Management Strategy Evaluation (MSE). There are increasing links between tuna RFMOs, with managers, stakeholders, Commissioners and scientists attending meetings in multiple RFMOs and there is an identified need to ensure communication and terminology are consistent. The report of the joint tuna RFMOS MSE working group meeting has not yet been finalised, but the recommendations from the working group are now available. The recommendations from the meeting are briefly discussed here, and a link to the report and recommendations will be provided to the scientific Committee members when it becomes available.

1 Introduction

The ICCAT secretariat facilitated the preparation of a meeting of the Joint Tuna Regional Fisheries Management Organisations (RFMOs) Management Strategy Evaluation (MSE) Working Group, held just prior to the CCSBT OMMP meeting, from the 13-15 June 2018, at the University of Washington in Seattle, USA. This was the second meeting of the joint Tuna RFMO MSE group. The first meeting of this working group was held in Madrid, November 1-3, 2016 (see http://www.tuna-org.org/mse.htm). Attendance of some participants was supported by the GEF-FAO-WWF sustainable tuna in the Areas Beyond National Jurisdiction project.

The objectives of the 2016 meeting were to:

• Review current MSE practice, successes, failures and potential areas for collaboration.

• Discuss progress on MSE.

• Identify future actions focusing on areas for collaboration.

The 2018 meeting agenda (http://www.tuna-org.org/Documents/2018/MSE_Working_Group.pdf) followed the 2016 format with an additional agenda item for discussion of 'Provisions for exceptional circumstances', and aimed to include outcomes from other relevant meetings.

The 2018 meeting agenda was organised around six themes:

1. The MSE process and stakeholder dialogue
2. Conditioning operating models
3. Albacore case study currently underway across tuna RFMO's
4. Provision for exceptional circumstances
5. Computational aspects
6. Dissemination of results.

This paper summarises discussions and items of interest to the CCSBT ESC. The report of the 2018 Joint tuna-RFMO MSE working group is not yet available but the recommendations from the meeting have been finalised (we will provide links when they become available). Several SBT scientists were present: Ann Preece, Campbell Davies and Rich Hillary attended from CSIRO; Hilario Murua, Ana Parma, Jim Ianelli and Doug Butterworth also participated. Scientists from most tuna RFMOs and some non-tuna RFMOs (International Whaling Commission, Halibut Commission, and South Pacific RFMO) were participants in the meeting.

2 Discussion

There are increasing links between tuna RFMOs, with managers, stakeholders, Commissioners and scientists attending meetings in multiple RFMOs and an identified need to ensure Management Strategy Evaluation (MSE) related communication and terminology are consistent. The SBT Management Procedure (MP) is one of only a few Harvest Strategies (HS) that are operational in the tuna RFMOs but there is substantial progress and work underway on MSE, and MP, HS, and Harvest Control Rule (HCR) development and stakeholder dialogue. Clarification of MSE and MP related terminology was the starting point for discussions and is a recurring theme in MSE meetings. Succinct summaries of the differences between MPs, HCR and HS were made during the meeting that assisted in general agreement of terms across the tuna RFMOs. Several participants were involved in a meeting held in San Diego (January, 2018) on MSE communication, from which the organising committee has developed a brief non-technical glossary of key MSE terms, specifically targeted at stakeholders (Miller et al, in press). Comments on this were received at the tuna RFMO MSE working group meeting. Further work to specify these in more detail and clarify a broader range of technical terms is still needed.

The structure of tuna RFMO committees and communication between them was of interest for facilitating technical and non-technical review of MSE, MPs and HCRs. Dedicated meetings on MSE, similar to both the technical OMMP working groups and the non-technical Strategy and Fisheries Management Working group at CCSBT, do not occur across all tuna RFMOs but it was recommended that these be established to facilitate dialogue between scientists and between scientists managers and other stakeholders.

Key questions were raised that require further explanation across tuna RFMOs at technical and no-technical levels, in order to facilitate adoption of MPs:

1. The role of stock assessments and separation from management advice. The separation of the roles of: 1) regularly updated stock assessments for current stock status advice, from 2) fully pre-specified MPs for management advice, as conducted by CCSBT, is not widely recognised or adopted across the tuna RFMOs. Management advice (TAC or TAE) in some tuna RFMOs is based on a best assessment approach, and projections using harvest control rules, rather than MSE tested fully specified feedback management procedures.
2. The role of reference points in stock assessment, in contrast to performance statistics for MSE testing. There may not be a common understanding that reference points (target or limit) do not necessarily need to be included explicitly in the HCR of an MP.

The Marine Stewardship Council (MSC) criteria for certification was discussed. A workshop to clarify MSC requirements in relation to forms of harvest strategies has been proposed.

It was noted that stock structure is a key uncertainty in the conditioning of operating models and the development of robust MP, but there is often limited data available for conditioning operating models. Spatial issues in operating models and multi-stock/species structures were recognised as important research areas need to be addressed. Some work is underway on multispecies MSEs.

3 Summary of Recommendations

The recommendations from the meeting have recently been finalised. The following is a brief summary of the recommendations.

MSE process and stakeholder dialogue

1. Avoid assigning the technical MSE development process to a single individual – it is an iterative process that should involve a consistent, core group of experts that regularly reports on progress to other scientists, managers and other stakeholders and implements their feedback.
2. Clarify the role and input of all stakeholders within their MSE process.
3. Include use of other experts (e.g. managers, industry and/or conservation representatives) with experience of the MSE implementation process, to provide capacity building workshops for managers.
4. Set up small technical task groups to discuss and advance key aspects of the MSE process that are of common interest to the Tuna RFMOs
5. Set up the review process for MSE early in the process. To review: 1) the overall MSE process (i.e. the rationale, framework and work plan); 2) specific MSE components e.g. operating models (OMs) and conditioning; and 3) validation of the final technical code for operating models and selected MP.
6. Set up dialogue with the MSC to discuss their criteria for certification in an MSE context.

Conditioning operating models

7. Consider a range of plausible scenarios for OMs which is sufficiently broad so that tested MPs or HCRs do not require amendment or retesting too often.
8. Ensure all OMs are adequately conditioned i.e. ensure that they are sufficiently consistent with the historical data to be considered plausible.
9. Consider stock structure as a potential major source of uncertainty with strong conservation and management implications. Focus on the research needed to provide the necessary data to develop and parametrize the OMs.
10. Consider at a future meeting how to weight the scenarios in OMs relative to plausibility.
11. In multispecies MSE, focus initial OM developments on technical interactions.

Computational aspects

12. Document and validate code. Ensure the mathematical specifications for all code developed for MSE purposes is fully documented, code is validated and made publicly available.

Dissemination of results

13. Trial visualization approaches for presenting MSE results on focus groups to check their suitability for each forum/stakeholder group.
14. Use ‘GitHub’ or similar site for code and graphical presentations of results to facilitate sharing of code across RFMOs.

Further Work

15. Refine a broader glossary of terms.
16. Continue to discuss the topic of ‘Exceptional Circumstances’; to be coordinated by Ann Preece and David Die.
17. Further consider the relative merits of model-based vs empirical MPs.
18. Develop a comprehensive joint TRFMO MSE WG website and link to each RFMO’s MSE webpages.
19. Develop an agenda for the next meeting and work plan and priorities for further activities.

The items of specific interest to the CCSBT scientific committee members potentially include: the joint tuna RFMO initiatives to discuss commonalities and differences in approaches; validation of code, documentation and transparency; spatial stock structure as a potential source of uncertainty in OMs and MPs; trials of visualisation of MSE results; sharing of methods and code across tuna RFMOs; further work on a broader glossary of terms; and contributions to work plans and future activities of the joint tuna RFMO MSE working group.

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