INTER-AMERICAN TROPICAL TUNA COMMISSION

SCIENTIFIC ADVISORY COMMITTEE

FIFTH MEETING

La Jolla, California (USA)
12-16 May 2014

DOCUMENT SAC-05-10b

MANAGEMENT STRATEGY EVALUATION (MSE) IMPLEMENTATION IN STOCK SYNTHESIS: APPLICATION TO PACIFIC BLUEFIN TUNA.

Mark N. Maunder

ABSTRACT

A procedure is described to conduct a management strategy evaluation (MSE) using the Stock Synthesis (SS) general stock assessment program as the operating model. Samples from the posterior distribution of a Bayesian application of SS using Markov Chain Monte Carlo (MCMC) are used to represent the possible states of nature, allowing for uncertainty in parameters used in typical stock assessment models. The bootstrap procedure built into SS for generating random observations is used to include observation uncertainty in the future data used in the harvest control rule. Process error is included by extending the "estimation" period of the stock assessment used to create the operating model to include the period over which the MSE will be conducted. Priors can be put on model parameters that are usually fixed (*e.g.* natural mortality), and the parameters estimated to more accurately represent uncertainty. R code is developed to communicate between the SS-based operating model and the management procedure that is being evaluated. The advantage of using SS is that assessments using SS are already available for many stocks, and these can easily be converted into SS-based operating models to conduct an MSE. The procedure is applied to Pacific bluefin tuna based on the stock assessment carried out by the International Scientific Committee for Tuna and Tuna-like Species in the North Pacific Ocean (ISC), which was conducted in SS. The management procedure, comprised of simple harvest rates applied to two CPUE-based indices of abundance, one for spawners and one for recruits, is compared to a simple catch-based management procedure similar to that evaluated by the ISC's working group on Pacific bluefin tuna.

1. INTRODUCTION

Contemporary fisheries management for major fish stocks generally follows one of two divergent paths. The first, which is more traditional, is to conduct a stock assessment (Hilborn and Walters 1992; Quinn and Deriso 1999; Maunder and Punt 2013) to provide the best estimates of the stock abundance and productivity, and use these to provide management advice (*e.g.* compare estimates of current biomass and fishing mortality (*F*) with MSY-based reference points). The second is to conduct a management strategy evaluation (MSE) to identify an appropriate management procedure to apply to the stock (de la Mare 1986; Butterworth *et al*. 1997; De Oliveira *et al.* 1998; Butterworth and Punt 1999; Smith *et al*. 1999). These approaches have some aspects in common, but their philosophies differ substantially. A main difference is that MSE explicitly takes uncertainty into consideration and attempts to identify management procedures that are robust to the uncertainty. Stock assessments generally present uncertainty (*e.g.* confidence intervals on parameters and quantities of interest, and sensitivity analyses to uncertain fixed parameter values or model structure), but leave it to decision-makers to take uncertainty into consideration when determining annual catch levels. MSE requires the definition of a complete management procedure, including the data collected, the method used to analyze the data, and the harvest control rule (Schnute *et al*. 2007). Multiple management procedures are then evaluated based on predefined performance criteria under different states of nature representing the uncertainty in the understanding of the system.

The states of nature are typically represented by an operating model (OM), which is essentially a stock assessment model (SAM) (*i.e.* a population dynamics model representing the dynamics of the stock and the fishery). Different parameter values and, perhaps, different model structures represent the different possible states of nature. The states of nature used will partly determine which management strategies perform best. Therefore, it is important that the states of nature are chosen carefully and that unrealistic states of nature are avoided. One reasonable approach is to condition the states of nature on the available data. This essentially means fitting the OM to the data as done for a SAM. One complication is that an OM is typically more complex than a SAM (*i.e.* models more processes and/or estimates more parameters), and if fitted to data will frequently encounter convergence problems and the parameters cannot be estimated. These estimation problems can often be overcome by putting priors on the parameters or running separate model fits with different values of the parameters. Two model parameters that are difficult to estimate with typical fisheries data are natural mortality (M) (Lee *et al*. 2011; Maunder and Wong 2011) and the steepness (h) of the stock-recruitment relationship (Lee *et al*. 2012; Maunder 2012; Magnusson and Hilborn 2007; Conn *et al*. 2010). Growth estimation is also problematic for tuna models because of the lack of aging data and the influence of the interaction between growth and length-composition data on estimates of absolute abundance (Maunder and Piner 2014; Aires da Silva *et al*. in press). It may be possible to put priors on natural mortality and growth from external data for the stock in question, related stocks or species, or correlates with life history parameters (Pauly 1980; Jensen 1996; Gunderson 1997; Hoenig 1983). However, the steepness of the stock-recruitment relationship is more problematic. There have been several meta-analyses that can be used to create priors for steepness, but their validity is questionable (Gilbert 1997; Maunder 2012; Maunder and Piner 2014). Even if a reasonable prior for steepness could be constructed, the inherent bias in estimating steepness (Lee *et al*. 2012; Maunder 2012; Conn *et al*. 2010) could still produce biased results. Therefore, it may be appropriate to run several models with alternative steepness values and the weights applied to each value based solely on the prior (*i.e.* do not let the data influence the weighting of steepness).

The similarity of a data-conditioned OM to represent the states of nature in a MSE with a SAM makes the initial development of a MSE for a traditionally-assessed stock relatively simple, and is facilitated by the use of a general stock-assessment program like Stock Synthesis (Methot and Wetzel 2013). These general stock assessment programs include many options for model structure and parameterization, and often allow the inclusion of priors. These features can be used to more fully represent uncertainty in the states of nature.

Developing the states of nature requires estimating the parameter and model uncertainty. There are several ways of estimating uncertainty in stock assessment models (normal approximation, profile likelihood, bootstrap, Bayesian MCMC) and they differ in their computational demands (Maunder *et al*. 2009). Normal approximation is usually the least demanding approach computationally, but produces symmetrical estimates that may not adequately describe the uncertainty. Profile likelihood requires the objective function to be optimized on the order of tens of times, but needs to be repeated for each quantity for which the uncertainty is being estimated. Bootstrap requires the objective function to the optimized on the order of hundreds of times, but estimates the uncertainty for all quantities simultaneously. MCMC requires the objective function to be calculated (not optimized) on the order of millions of times and is usually the most computationally demanding, but also estimates the uncertainty for all quantities simultaneously. Bayesian methods are the only methods that provide estimates of uncertainty as true probability statements. However, Bayesian methods (see Punt and Hilborn (1997) for a review) require priors for all model parameters, including those for which there is no data-based prior information. The priors, including those that represent lack of information, may influence the results. The Bayesian approach, despite the issues related to priors and integration across parameters (Maunder 2003), computational demands, and convergence issues, is probably the most convenient approach to develop the states of nature because it directly estimates probability, allows the inclusion of priors, and estimates uncertainty for all parameters and their correlation simultaneously.

Model uncertainty may also be an important component of developing the states of nature. For example, it may not be clear whether the Ricker (1954) or the Beverton-Holt (1957) stock-recruitment model is more appropriate. If possible, it is convenient to translate the model uncertainty into parameter uncertainty by reparameterizing the model. For example, the Deriso-Schnute (Deriso 1980; Schnute 1985) stock-recruitment model can be used to represent both the Ricker and Beverton-Holt models (and intermediate models) with an additional parameter. Otherwise, additional methods will be required to include the model uncertainty. For example, reversible-jump MCMC can be used in a Bayesian context, but it is complex and has not yet been implemented in general models or in AD Model Builder (ADMB). Different MCMC analyses could be conducted and combined based on the prior probability for each model structure in combination with the data-based evidence. These may need to be modified to deal with estimation bias, as mentioned previously for the steepness of the stock-recruitment relationship.

Pacific bluefin tuna (PBF) is a stock that is of considerable concern. The current ISC stock assessment estimates that any reasonable biomass and fishing mortality limit reference points have been exceeded. The biomass is estimated to have been at very low levels for decades. Unfortunately, the SAM does not adequately fit the data. Nevertheless, a large number of model configurations were tested, and all produced similar results, indicating that urgent management action is needed. Future projections under different management scenarios suggest that juvenile catch may need to be reduced by up to 50% to produce reasonable rebuilding rates. Pacific bluefin is an ideal candidate for MSE, but work is still needed to improve the SAM before it can be used as a reliable OM for MSE. Southern bluefin tuna (SBT), has already undergone MSE (Polacheck *et al*. 1999; Kolody *et al*. 2008) and experience gained with that stock can be used to guide MSE for Pacific bluefin.

Here we develop an initial MSE for Pacific bluefin, using the ISC SS-based SAM as an OM. The analysis is by no means a final MSE to be used for managing this stock. It is only the first step in the process, and will hopefully prompt a collaborative effort among all the interested parties to develop a full MSE that, if found to be appropriate, can be used to provide management advice.

2. METHODS

Stock Synthesis (Methot and Wetzel 2013) is used as the operating model to develop the possible states of nature for testing the management procedure. A Bayesian stock assessment model is developed in Stock Synthesis to allow the conditioning of the operating model on the available data. External code written in R is developed to communicate among the operating model, the assessment model, and the harvest rule, and to loop over the alternative states of nature. This allows maximum flexibility in the assessment model and harvest rule. The Bayesian framework is used for the operating model because it allows the inclusion of multiple sources of uncertainty (*i.e*. parameters that are usually fixed can be estimated with the addition of priors to ensure convergence, while still allowing for uncertainty in the parameter). The model “estimation” timeframe is extended to include the projection period over which the management procedures are evaluated to facilitate the inclusion of process and observation error.

The algorithm used to conduct the MSE using SS is:

1. Determine states of nature. Run the SS stock assessment in MCMC mode to generate the states of nature:
    a. Extend the modelling time frame to include the period over which the MSE will be conducted in .dat file and .ctl files.
    b. Add zero catches for all fisheries for the period of *N* years over which MSE will be conducted. Turn the forecast off and set forecast years to zero.
    c. Modify the control file so that bias correction is 1 for all years. Five lines: endNoBias,startFullBias,endFullBias,startNoBias,maxBiasAdj (this may already be automatic when SS is run in MCMC mode).
    d. Make the abundance index catchabilities as estimable parameters (not estimated analytically) so

that the MCMC takes samples of the catchability parameters.

   e. Make recruitment deviates not a dev_var_vector (i.e. not sum to zero).

   f. Run the model using the MCMC mcsave option. *e.g.* SS –mcmc 1000000 –mcsave 1000 (you can also use the –noest option if the model has already been run with the hessian estimated).

   g. Run the model using the MCMC mceval option. *e.g.* SS –mceval.

   h. The draws from the posterior of the estimated parameters will be in the file posteriors.sso.

2. Evaluate the harvest rule under different states of nature:

   a. Take a sample of the parameters from the posterior and insert them in the par file. This will require matching up the parameters in each file since the posteriors.sso only has the estimated parameters and the par file has all the parameters.

   b. Change the starter file to initiate the model parameters from the par file and do not estimate parameters:

      i. 1 # 0=use init values in control file; 1=use ss3.par.

      ii. 0 # Turn off estimation for parameters entering after this phase.

   c. Put in dummy data where you would like the model to simulate data (including future years). Do not do this in the MCMC stage above, as it will influence the parameter estimates when creating the posterior.

   d. Add one data bootstrap in the starter file:

      i. 3 # Number of datafiles to produce: 1st is input, 2nd is estimates with no error, 3rd and higher are bootstrap.

   e. Run the model using the –nohess command line option.

   f. Take the historical observed data (or the simulated data for this period) and add the simulated data for the future years, if appropriate (from data.ss_new), conduct the assessment, and apply the control rule to determine the quota. Take only the newly-created data point each year from the data.ss_new file because all data points, including the ones that have already been used in the decision rule for previous years, are randomly generated. Make sure you take the value for the third data set, which is the one that is randomly generated. If you are using the previous year's catches in the decision rule (*e.g.* if the assessment model for your decision rule is based on a surplus production model) make sure you use the catch from SS and not from the previous assigned quota because, if the quota is too high, the setting for maximum *F* in SS may cause the catch used in SS to be lower than the quota.

   g. Put the quota calculated by the decision rule in the SS data file as the catch for the appropriate year.

   h. Repeat e-g for each year of the MSE.

   i. Store the appropriate information from the SS output files (*e.g.* ending biomass, average catch).

   j. Repeat a-i for each sample from the posterior.

3. APPLICATION TO PACIFIC BLUEFIN TUNA

We develop an initial MSE for Pacific bluefin, using the ISC SS-based SAM as an OM. The harvest control rule is based on the results of future projections carried out by the ISC, which predict that the population will not increase under the low recruitment scenario (which is consistent with recent recruitment estimates), unless catches of juveniles are reduced by 25-50%. Similar cuts are needed to ensure a high probability of reaching 10% of the unexploited biomass in 10 years, assuming average recruitment. The first scenario is based on constant catch, while the second scenario is based on constant fishing mortality rate. Both are based on 50% reductions in catch or fishing mortality, respectively. The second uses CPUE to index abundance when applying the constant fishing mortality.

The first harvest control rule is based on constant catch similar to that implemented in ISC scenario 6, which reduces juvenile catch by 50%. All fisheries that catch juvenile bluefin have their catch set at 50% of the average catch from 2002-2004, by quarter. Other fisheries have their catch set at the average catch from 2010-2012.

The second harvest control rule is based on two CPUE-based indices of abundance: an index of spawning biomass based on Japanese longline CPUE, and an index of recruitment (one-year-olds) based on Japanese troll CPUE. The catch for each fishery is a harvest rate times the current index of abundance averaged and lagged appropriately (see Table 1). The index used differs by fishery, and is related to the ages selected by the fishery. An average of the index over one or more years is used to correspond to the ages caught by the fishery. The indices and years used are given in Table 1. The harvest rate is calculated as the average catch in the past three years (2010-2012) divided by the average index in the past three years, averaged and lagged appropriately. This "current" harvest rate is then multiplied by 0.5 to approximate the first harvest control rule and allow for rebuilding.

RESULTS

The results from these analyses are preliminary. Under the first management procedure, in which the catch of juveniles is decreased by 50%, the population rebuilds rapidly (Figure 1). There is a large amount of uncertainty in the projections, which comes from both parameter estimation uncertainty and future recruitment uncertainty. Under the second management procedure, in which the catch quota is based on a harvest rate applied to CPUE data, the population initially rebuilds as rapidly as under the first management procedure, but equilibrates at a lower biomass level (Figure 1). The uncertainty in the projections is less than for the first management procedure.

The catch for the harvest rate management procedure is initially lower than for the constant-catch management procedure, but overtakes it by 2021 (Figure 2).

4. DISCUSSION

This research is only the beginning of the development of a management procedure for north Pacific bluefin tuna. We have shown that it is feasible to use the Stock Synthesis program as an OM for MSE, and have developed R code to communicate between the OM and the management procedure. The management procedure includes the data to be collected, the method for analyzing the data, and the harvest control rule. There is a large variety of options available for these three components and they need to be identified and tested in a full MSE. The testing will require agreement from interested parties on the performance criteria (*e.g.* total yield, variability in yield, biomass levels).

The candidate management strategies were simple obvious choices, and a more thorough evaluation of other candidates should be conducted. They could include simple empirically-based rules, like those presented here based on CPUE indices of abundance, or could be more complex model-based rules. Most, if not all, simple empirical decision rules are unable to optimize benefits from the stock: they either attempt to maintain stability, avoid adverse effects, or rebuild to pre-defined targets. The objective for management of tunas in the EPO established by the IATTC Convention is to maximize yield; therefore, decision rules that maximize yield are desirable. Below we outline a "MSY-seeking decision rule" based on the concept of surplus production.

$$
if \begin{cases} \dfrac{I_{t+1}}{I_t} \leq \alpha_{LB} & C_t = \beta_{LB} C_{t-1} \\ \alpha_{LB} < \dfrac{I_{t+1}}{I_t} < \alpha_{UB} & C_t = C_{t-1} \\ \dfrac{I_{t+1}}{I_t} \geq \alpha_{UB} & C_t = \beta_{UB} P_{t-1} \end{cases}
$$

where

$P_t = B_{t+1} - B_t + C_t$

B_t is biomass at the start of year *t* and is equal to the index (*I*) times catchability (*q*).

C_t is the catch in year *t*

$\alpha_{LB} < 1$, $\alpha_{UB} > 1$, $\beta_{LB} \leq 1$, $\beta_{UB} \leq 1$ are the control parameters

Some advantages of this approach are that you do not need to know the production function (*i.e.* you do not need to know natural mortality or the stock-recruitment relationship, which are both typically highly uncertain), it adjusts for changes in productivity, and basing the reduction (when the index decreases) on the catch rather than the productivity reduces the risk of stock collapse if catchability is misspecified. A non-linear relationship between the index and abundance, high variability in the index due to observation or process error, and uncertainty in the estimate of catchability would likely degrade the performance of the harvest strategy. This strategy might be good for fisheries where data are starting to be collected: for example, a tagging program could be used to estimate catchability, and a new survey used as the index. A continuing tagging program might be the basis for the index in absolute or relative terms. An estimate of catchability (*q*) is required for the harvest control rule. Estimates of catchability are available from the recent ISC stock assessments of bluefin and external analyses (Maunder *et al*. 2014). The application of the harvest control rule might be complicated when there are multiple fisheries with different age-structured selectivities and when these selectivities differ from the selectivity of the index of abundance and/or the measure of surplus production. Ideally, the selectivity of the index used for both the control rule and calculating the surplus production is the same or similar to the selectivity of the fishery.

The above MSY-seeking harvest control rule has the flaw that small trends in the index will not trigger changes in catch, but may result in large changes in abundance over extended periods of time. Therefore, the change in the index might be better based on the difference from the index value associated with the last change in catch. The index may have substantial (random, since systematic error is a different issue) observation error, and using the predicted index value from a regression over several years might be more robust. The requirement to have at least three data points in the regression to avoid extreme sensitivity might be appropriate, and would have the possibly desirable attribute that catch cannot be changed two years in a row (a smoother such as a moving average might also be appropriate, and could include years before the last change to create the smoothed estimates). It might also be useful to make the change in catch when the index drops to be proportional to, but greater than, the decrease in the index.

$$
if \begin{cases} \dfrac{\hat{I}_t}{\hat{I}_{last}} \leq \alpha_{LB} & C_t = \left[1 - \dfrac{\hat{I}_{last} - \hat{I}_t}{\hat{I}_{last}} \beta_{LB}\right] C_{t-1} \\ \alpha_{LB} < \dfrac{\hat{I}_t}{\hat{I}_{last}} < \alpha_{UB} & C_t = C_{t-1} \\ \dfrac{\hat{I}_t}{\hat{I}_{last}} \geq \alpha_{UB} & C_t = \beta_{UB} P_{t-1} \end{cases}
$$

Where $\hat{I}_t$ is the index value predicted from a linear regression on the index values, including the year of the last change (I_{last}) to the current year (*t*), with a minimum of three years (or a smoother such as a moving average).

Some suggested values for the control parameters are

$$\alpha_{LB} = 0.9$$
$$\beta_{LB} = 1.5$$
$$\alpha_{UB} = 1.1$$
$$\beta_{UB} = 0.9$$

The ISC SAM for Pacific bluefin does not adequately fit the data, suggesting that it is not correctly structured. The OM has to be a reasonable representation of the system to be useful in MSE. Therefore, before MSE can be used for management of Pacific bluefin the SAM has to be improved. This should be the priority for Pacific bluefin. The MSE OM only represents the parameter uncertainty from the stock assessment. Additional uncertainty in parameters that are fixed in the assessment model (*e.g.* natural mortality, the stock-recruitment relationship, and growth) should also be modelled.

To fully implement the MSE, performance criteria are needed. The development of performance criteria requires input from all interested parties. A substantial amount of work is needed to fully implement a MSE for north Pacific bluefin tuna.

ACKNOWLEDGEMENTS

John Walter and Allan Hicks contributed to the method for using Stock Synthesis as an operating model. The north Pacific bluefin stock assessment was developed by the bluefin tuna working group of the International Scientific Committee for Tuna and Tuna-like Species in the North Pacific Ocean. Discussions with Kevin Piner improved the manuscripts, and he provided the samples from the posterior distribution.

REFERENCES

Aires-da-Silva, A., Maunder, M.N., Schaefer, K.M., Fuller, D.W. In press. Improved growth estimates from integrated analysis of direct aging and tag-recapture data: an illustration with bigeye tuna (*Thunnus obesus*) of the eastern Pacific Ocean with implications for management. Fisheries Research.

Beverton, R.J.H., Holt, S.J. 1957. On the dynamics of exploited fish populations. Fish. Invest., II. Sea Fish 19, 533.

Butterworth D.S., Punt A.E. 1999. Experiences in the evaluation and implementation of management procedures. ICES Journal of Marine Science 56:985–998

Butterworth D.S., Cochrane K.L., De Oliveira J.A.A. 1997. Management procedures: a better way to manage fisheries? The South African experience. In: Pikitch EL, Huppert DD, Sissenwine MP (eds) Global Trends: Fisheries Management. American Fisheries Society Symposium 20, Bethesda, pp 83–90

Conn, P.B., Williams, E.H., Shertzer, K.W. 2010. When can we reliably estimate the productivity of fish stocks? Can. J. Fish. Aquat. Sci. 67, 511–523.

de la Mare WK (1986) Simulation studies on management procedures. Reports of the International Whaling Commission 36: 429–450

De Oliveira, J.A.A., Butterworth D.S., Johnston S.J. 1998. Progress and problems in the application of management procedures to South Africa's major fisheries. In: Funk F, Quinn II TJ, Heifetz J, Ianelli JN, Powers JE, Schweigert JJ, Sullivan PJ, Zhang CI (eds) Fishery Stock Assessment Models. Alaska Sea Grant College Program Report No. AK-SG-98-01, University of Alaska Fairbanks, pp 513–530

Deriso, R.B. 1980. Harvesting strategies and parameter estimation for an age-structured model. Can. J. Fish. Aquat. Sci. 37(2): 268–282.

Gilbert, D. J. 1997. Towards a new recruitment paradigm for fish stocks. Canadian Journal of Fisheries and Aquatic Sciences, 54: 969–977.

Gunderson, D.R. 1997. Trade-off between reproductive effort and adult survival in oviparous and viviparous fishes. Can. J. Aquat. Sci. 54, 990–998.

Hilborn, R., Walters, C.J. 1992. Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Chapman and Hall, New York, 570 pp.

Hoenig, J.M. 1983. Empirical use of longevity data to estimate total mortality rates. Fish. Bull. 82, 898–903.

Jensen, A.L. 1996. Beverton and Holt life history invariants result from optimal tradeoff of reproduction and survival. Can. J. Fish. Aquat. Sci. 53, 820–822.

Kolody, D., Polacheck, T., Basson, M., and Davies, C. 2008. Salvaged pearls: lessons learned from a floundering attempt to develop a management procedure for Southern Bluefin Tuna. Fisheries Research 94 (2008) 339–350.

Lee, H-H, Maunder, M.N., Piner, K.R., and Methot, R.D. 2011. Estimating natural mortality within a fisheries stock assessment model: an evaluation using simulation analysis based on twelve stock assessments. Fisheries Research, 109: 89–94.

Lee, H-H., Maunder, M.N., Piner, K.R., and Methot, R.D. 2012. Can steepness of the stock-recruitment relationship be estimated in fishery stock assessment models? Fisheries Research 125-126: 254-261.

Magnusson, A., Hilborn, R. 2007. What makes fisheries data informative? Fish and Fisheries. 8, 337–358.

Maunder, M.N. 2003. Paradigm shifts in fisheries stock assessment: from integrated analysis to Bayesian analysis and back again. Natural Resource Modeling, 16(4): 465-475.

Maunder M.N. 2012. Evaluating the stock-recruitment relationship and management reference points: Application to summer flounder (*Paralichthys dentatus*) in the U.S. mid-Atlantic. Fisheries Research, 125–126: 20–26.

Maunder, M.N. and Piner, K.R. 2014. Contemporary fisheries stock assessment: many issues still remain. ICES Journal of marine Science doi: 10.1093/icesjms/fsu015

Maunder, M.N. and Punt A.E. 2013. A review of integrated analysis in fisheries stock assessment. Fisheries Research 142: 61– 74.

Maunder, M.N. and Wong, R.A. 2011. Approaches for estimating natural mortality: Application to summer flounder (*Paralichthys dentatus*) in the U.S. mid-Atlantic. Fisheries Research 111, 92– 99.

Maunder, M.N., Schnute, J.T., Ianelli, J. 2009. Computers in fisheries population dynamics. In: Megrey, B.A., Moksness, E. (Eds.), Computers in Fisheries Research. Springer, pp. 337–372.

Methot, R. D., and Wetzel, C. 2013. Stock Synthesis: a biological and statistical framework for fish stock assessment 557 and fishery management. Fisheries Research, 142: 86–99.

Pauly, D. 1980. On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 stocks. J. Cons. Int. Explor. Mer. 39, 175–192.

Polacheck, T. Klaer, N. L., Millar, C., and Preece, A. L. 1999. An initial evaluation of management strategies for the southern bluefin tuna fishery. ICES Journal of Marine Science, 56: 811–826.

Quinn II, T.J., Deriso, R.B. 1999. Quantitative Fish Dynamics. Oxford University Press, New York, 560 pp.

Ricker, W.E. 1954. Stock and recuitment. J. Fish. Res. Board Can. 11, 559–623.

Schnute, J. 1985. A general theory for the analysis of catch and effort data. Can. J. Fish. Aquat. Sci. 42(3): 414–429.

Schnute, J.T., Maunder, M.N., and Ianelli, J.N. 2007. Designing tools to evaluate fishery management strategies: can the scientific community deliver? ICES Journal of Marine Science, 64: 1077–1084.

Smith A.D.M., Sainsbury K.J., Stevens RA. 1999. Implementing effective fisheries-management systems: management strategy evaluation and the Australian partnership approach. ICES Journal of Marine Science 56:967–979

TABLE 1. Indices and lags use in the management procedure (LL = longline)

Fishery	Main ages selected	Index used	Lags used
1	Spawners	LL	-1
2		Troll	-1
3	3 to 6	LL	-2 to -5
4	2 to 6	LL	-1 to -5
5	1	Troll	-1
6	1	Troll	-1
7	1 to 3	Troll	-1 to -2
8	1 to 3	Troll	-1 to -2
9	1 to 2	Troll	-1
10	1 to 4	Troll	-1 to -3
11	Spawners	LL	-1
12	2 to 3	Troll	-1 to -2
13	2 to 3	Troll	-1 to -2
14	1+	LL	-1

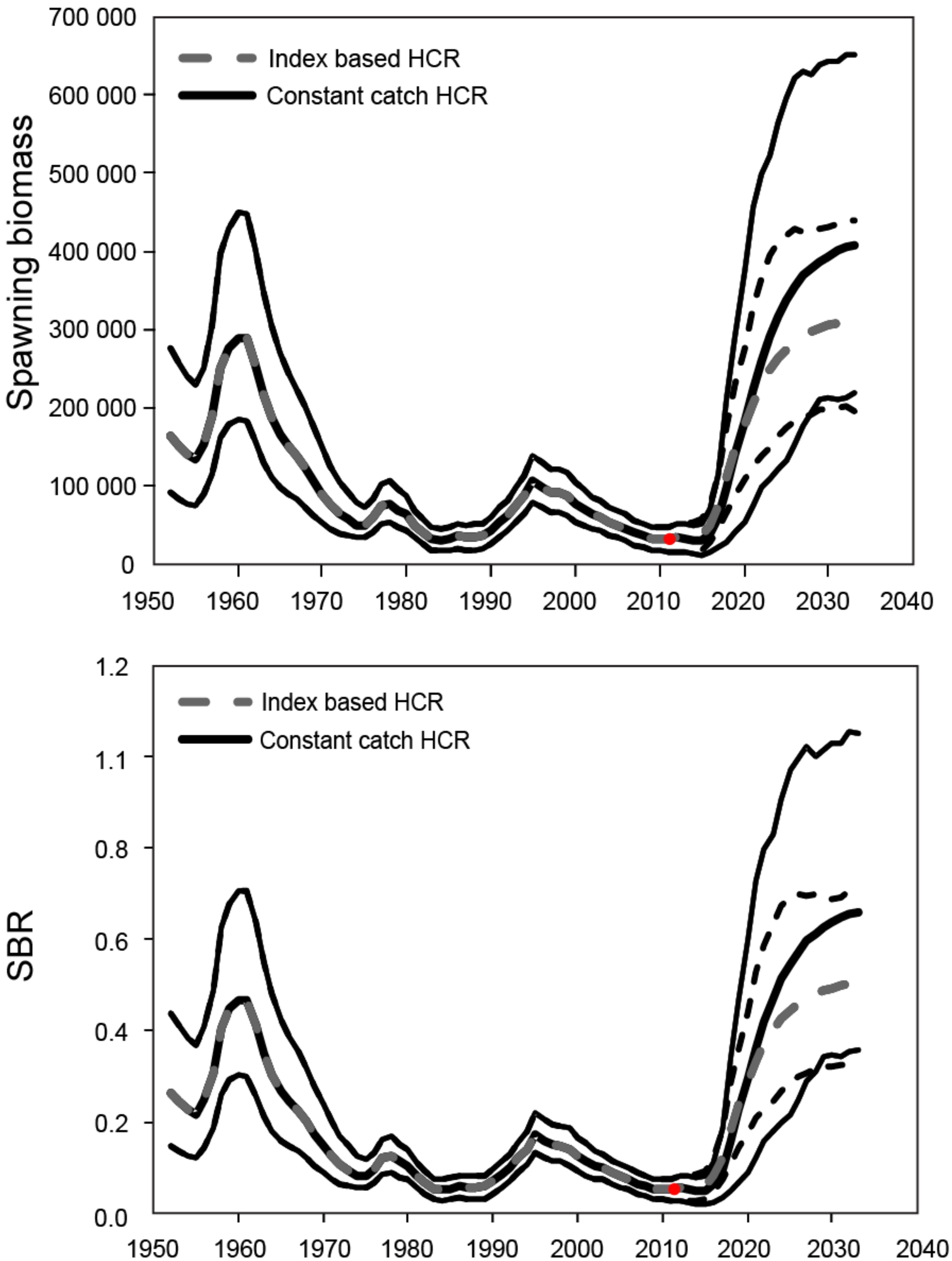

FIGURE 1. Spawning biomass (top panel) and spawning biomass ratio (spawning biomass divided by virgin spawning biomass) (bottom panel) of Pacific bluefin tuna from the MSE, using two harvest control rules: 50% reduction in juvenile catch (Constant-catch HCR), and CPUE index-based constant harvest rate (Index-based HCR). The thin lines represent the 95% credibility intervals.

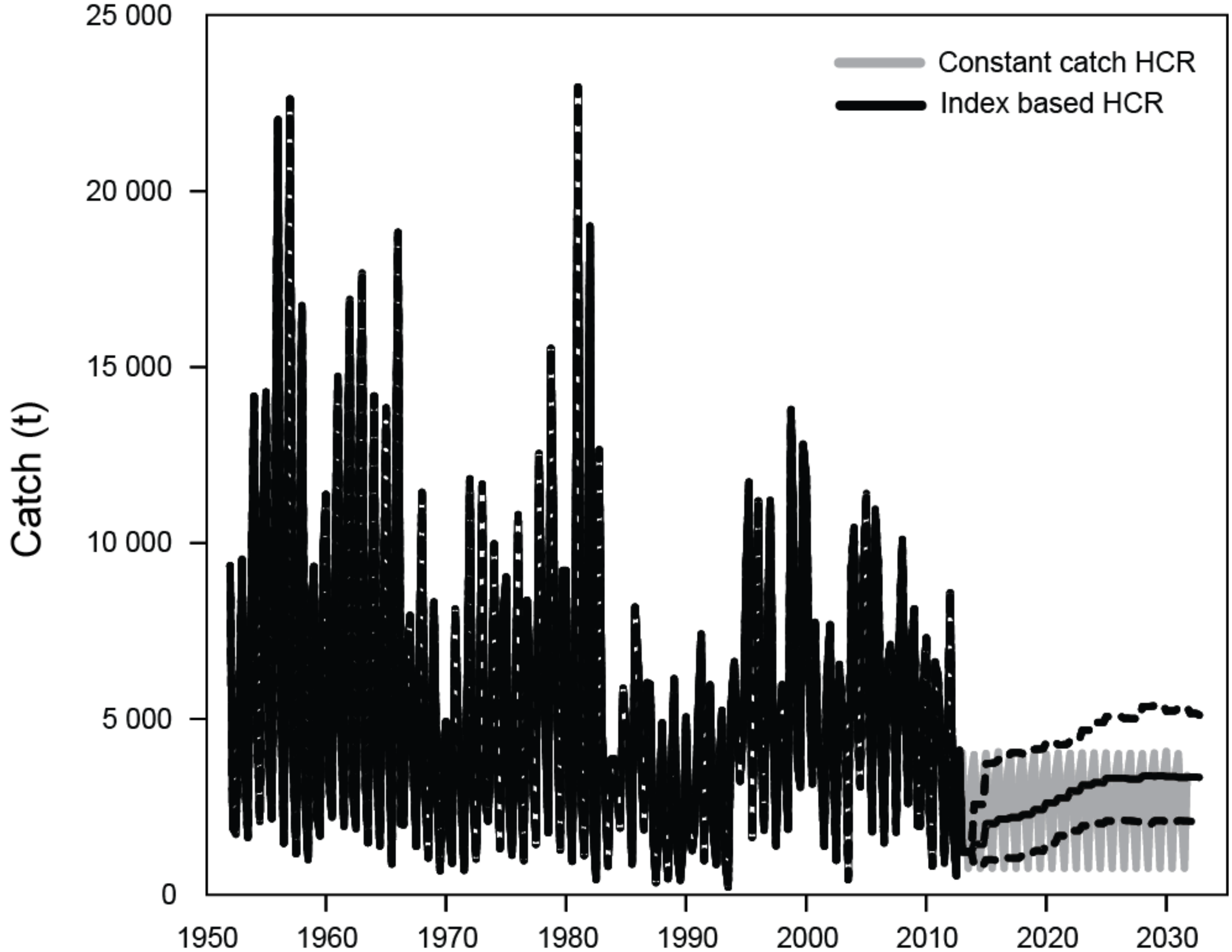

FIGURE 2. Catch of Pacific bluefin tuna from the MSE, using two harvest control rules: 50% reduction in juvenile catch (Constant-catch HCR), and CPUE index-based constant harvest rate (Index-based HCR). The dashed lines represent the 95% credibility intervals for the Index-based HCR.