**INTER-AMERICAN TROPICAL TUNA COMMISSION**

**SCIENTIFIC ADVISORY COMMITTEE**

**2ND MEETING**

**La Jolla, California (USA)**
**9-12 May 2011**

# DOCUMENT SAC-02-11

# EVALUATION OF THE KOBE PLOT AND STRATEGY MATRIX AND THEIR APPLICATION TO TUNA IN THE EPO

Mark N. Maunder and Alexandre Aires-da-Silva



## 1. INTRODUCTION

The first joint meeting of the tuna regional fisheries management organizations (RFMOs), held in Kobe, Japan, in January 2007, produced recommendations to standardize the presentation of stock assessment results and management advice. It was agreed that stock assessment results should be presented using the "four quadrant, red-yellow-green" format now referred to as the Kobe plot. The next step is a strategy matrix that provides alternative options for meeting management targets. Unfortunately, the construction of the Kobe plot and Kobe strategy matrix are not straightforward, and many decisions need to be made about how to calculate the different components and the associated uncertainty. Here we provide a critical evaluation of the construction of the Kobe plot and the Kobe strategy matrix, and their application to the assessment and management of tuna in the EPO.

## 2. KOBE PLOT

The Kobe plot (Report of the first joint meeting of the tuna RFMOs; also called the phase plot) is used to evaluate the status of a stock based on the fishing mortality ($F$) and biomass ($B$) associated with maximum sustainable yield (MSY; *i.e.* $F_{\mathrm{MSY}}$ and $B_{\mathrm{MSY}}$). If the current fishing mortality ($F$) is above $F_{\mathrm{MSY}}$, overfishing is judged to be occurring; if the current biomass ($B$; or some measure of spawning output) is below $B_{\mathrm{MSY}}$, the stock is judged to be overfished. The Kobe plot plots $B/B_{\mathrm{MSY}}$ on the x-axis and $F/F_{\mathrm{MSY}}$ on the y-axis (Figure 1) such that vertical and horizontal lines at 1.0 split the plot into four sections with the upper left representing a phase which is not desirable: overfishing occurring and an overfished stock; and the lower right representing a healthy stock: overfishing not occurring and an underfished stock. The trajectory of the stock over time is plotted so that the historical status of the stock can be seen. Typically a stock starts in the lower right as the fishery develops, then moves into the upper left as the population becomes overexploited, and finally, as appropriate management is applied, it cycles around the center of the plot. There is substantial uncertainty in the quantities used to generate the Kobe plot, and therefore the uncertainty in the current status is often included in the plot (see crosshairs in Figure 1).

## 3. KOBE MATRIX

The Kobe Strategy Matrix (Report of the second joint meeting of the tuna RFMOs, San Sebastian, Spain, June-July 2009), presents the specific management measures that would achieve the intended management target with a certain probability by a certain time. In the case of fisheries managed under a system of Total Allowable Catches (TACs), the outputs would be the various TACs that would achieve a given result. In the case of fisheries managed by effort limitations, the outputs would be expressed as, for example, fishing effort levels or time/area closures. It would also indicate where there are additional levels of uncertainty associated with data gaps. Managers would then be able to base management decisions upon the level of risk and the timeframe they determine are appropriate for that fishery. Table 1 provides examples when the management target is to end overfishing, rebuild a depleted stock, or maintain a sustainable fishery.

## 4. ISSUES

The Kobe Strategy Matrix requires the following considerations (based on Adam Langley pers. com.):

1. Selecting the appropriate models to undertake projections
2. Sampling from the uncertainty envelope of accepted models
3. Assumptions regarding future recruitments
4. What level of catches or effort for the various fisheries
5. Re-evaluation of the reference point definition with temporal changes in the *F*-at-age matrix

The considerations listed above can be grouped into two main issues in constructing the Kobe plot and Kobe strategy matrix: a) temporal changes in the target reference points (4 and 5) and b) calculation of uncertainty (1, 2, and 3). We provide a critical evaluation and exploratory discussion of these issues and how they relate to the construction of the Kobe plot and Kobe strategy matrix and their application to tuna in the EPO.

### 4.1. Reference points

The MSY related quantities $F_{MSY}$ and $B_{MSY}$ are a function of both biological and fishery characteristics (Maunder 2008). MSY is basically the yield per recruit (YPR) tradeoff between natural mortality and growth adjusted by the stock-recruitment relationship. Traditionally YPR is evaluated as a function of the size at entry into the fishery. This is essentially determined by the selectivity curve of the fishery and therefore the MSY quantities will differ depending on what type of gear is used or on the mix of effort among the gears (Sinclair 1993; Maunder 2002); this is denominated conditional MSY (cMSY). As the fishery evolves over time, the mix of effort among gears changes and therefore the corresponding $cMSY_y$ quantities also change over time (as indexed by *y*). Two approaches can be used to account for this change: 1) calculate the $cMSY_y$ quantities each year based on the effort mix (age-specific *F*) in that year or 2) develop the MSY quantities based on a single selectivity that has some desirable characteristic. In the latter case, the selectivity curve could, for example, be based on the current mix of effort or on a hypothetical selectivity curve that gives reasonable MSY levels (*e.g.* the knife-edge selectivity that maximizes MSY). If a single selectivity curve is used for calculating the reference points (such as in method 2 above), then calculation of the value of *F* relative to $F_{MSY}$ becomes complicated, since the *F* at age under different effort mixes are not proportional to the selectivity used for the reference point. Therefore, an alternative method is needed to represent *F*. For example, the spawning potential ratio (SPR) can be used as a common metric (Goodyear 1993). SPR is basically the equilibrium spawning biomass realized from a single recruit under the current mortality levels divided by the spawning biomass realized from a single recruit under no fishing. One of the various SPR proxies for $B_{MSY}$ can be used (*e.g.* $SPR_{35\%}$). An alternative could be $C_{eq}/MSY_{ref}$, where $C_{eq}$ is the equilibrium catch based on the fishing mortality at age in that year and $MSY_{ref}$ is the MSY calculated using the knife-edge selectivity that maximizes MSY. The $C_{eq}$ method addresses both the changing nature of the fishing mortality at age due to changes in the effort mix and the YPR implications of different gears. However, the calculations become more complicated if the recruitment variation is taken into consideration.

The calculations for $F/F_{MSY}$ currently used in the EPO tuna assessments are based on calculating the scaling factor ($F$ multiplier) that would maximize yield given the age-specific $F$ in that year (Aires-da-Silva and Maunder 2011; Maunder and Aires-da-Silva 2011). This is equivalent to calculating $F_{MSY}$ and presenting the ratio $F_y/F_{MSY\ y}$. Recent $F$ estimates are imprecise, so it is considered more robust to take an average over several years. The current EPO tuna assessments base most MSY calculations and comparisons on fishing mortality rate at age averaged over the most recent three years.

The MSY quantities are dependent on the stock-recruitment relationship. Unfortunately, the form and parameters of the stock-recruitment relationship are often highly uncertain (Hilborn and Walters 1992; Quinn and Deriso 1999). In these cases proxies are often used to represent the MSY quantities (Clark 1991). These proxies are often conservative and are chosen so that management measures are either conservative or robust to the uncertainty in the stock-recruitment relationship. For example, biomass levels that are 35 or 40% of the unexploited biomass are often used as proxies for groundfish (Clark 1991). Alternatively, the stock-recruitment relationship could be fixed based on external information (Williams and Shertzer 2003). This external information could be taken from estimates for related species, perhaps from a meta-analysis (Myers *et al.* 1999). The steepness of the Beverton-Holt stock-recruitment relationship could be set at a conservative level (*e.g.* 0.75), which is supported by the small loss in yield when under-specifying the steepness of the stock-recruitment relationship when the actual steepness is high (Jiangfeng *et al.* in review).

Tuna recruitment is highly variable and several regime changes are apparent in the estimates of recruitment. It is possible that a lightly exploited stock could become overfished due solely to annual fluctuations in recruitment or a regime shift in recruitment. Therefore, it might be useful to take the recruitment variation into account when calculating $B_{MSY}$. This could be achieved by projecting the population over the historic period under $F_{MSY}$ using the estimated annual recruitment deviates (so the recruitments are adjusted by the stock-recruitment relationship). The initial population at the start of the modeling time period would need to be based on equilibrium conditions fishing at $F_{MSY}$. The calculations would also have to be repeated for each year's age-specific $F_{MSY}$ to create the Kobe plot taking into consideration both recruitment variability and changes in the allocation of effort among gears. To account for regime shifts, $B_{MSY}$ could be based on average recruitment for the appropriate regime.

There are several ways to calculate $B_{MSY}$. The obvious choice is the spawning biomass, because maintaining reproductive potential might be an important management goal. An alternative choice is the fish that are vulnerable to the fishery. In either case, the biomass used to compare to $B_{MSY}$ should be calculated using the same method. The management implications might differ depending on the method used to calculate the biomass.

### 4.2. Uncertainty

Uncertainty can be separated into several components (Patterson *et al.* 2001):

1. Parameter uncertainty
2. Model or structural uncertainty
3. Statistical assumptions
4. Process variation
5. Implementation error (for management strategies).

There are several methods that can be used for calculating uncertainty (normal approximation, profile likelihood, bootstrap, Bayesian MCMC (see Punt and Hilborn 1997 for a review of Bayesian methods)) and they differ in their computational demands and interpretation (Maunder *et al.* 2009). Normal approximation is usually the least demanding approach, but produce symmetrical estimates of uncertainty that may not adequately describe the uncertainty. Profile likelihood requires the objective function to be optimized on the order of tens of times, but this 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 require priors for all model parameters including those for which there is no prior information. The priors, including those that represent lack of information, may influence the results.

### 4.3. Parameter uncertainty

Parameter uncertainty is calculated conditional on the model being correct and arises because of sampling error in the data. Parameter uncertainty is a typical output of stock assessment models and is easy to incorporate into the Kobe plot and Kobe Strategy Matrix. Confidence intervals can be calculated for parameters, derived quantities (*e.g.* biomass), and projections. The confidence intervals are often calculated and presented as symmetrical quantities, but the uncertainty can be substantially asymmetric for some quantities. Asymmetric confidence intervals can be calculated using bootstrap, profile likelihood, or Bayesian methods (*e.g.* MCMC).

### 4.4. Model or structural uncertainty

Stock assessments are typically conducted under the assumption that the model and its sub-processes (*e.g.* natural mortality, growth, recruitment, movement, selectivity) are a reasonable representation of the population dynamics and of how the observations relate to the population (*e.g.* is CPUE proportional to abundance). However, there may be several alternative models that might represent the sub-processes and it may be uncertain which process should be used (*e.g.* does recruitment follow the Beverton-Holt or Ricker model?).

The line between parameter uncertainty and model uncertainty is blurry. Typically, parameter uncertainty is evaluated based on the precision of parameter estimates from the stock assessment model (*e.g.*, standard errors, confidence intervals), while model structure uncertainty is evaluated by running several models with different structural assumptions (*e.g.*, different stock-recruitment, natural mortality and selectivity curves). In some cases model structure uncertainty is defined as uncertainty due to assumptions about model parameters that are fixed in the model (*e.g.* natural mortality, steepness parameter of the Beverton-Holt stock-recruitment relationship) for which sensitivity analyses are conducted. Both model uncertainty and parameter uncertainty should be included in any estimates of uncertainty. However, it is more complicated to combine the two and therefore they are usually represented separately. In general, model uncertainty is usually larger than parameter uncertainty. Therefore, to better reflect uncertainty on the Kobe plot and Kobe strategy matrix, it might be appropriate to include results from different model structure assumptions (Figure 2). However, this would imply that all scenarios have equal probability and would require only including scenarios that are realistic. Associating probabilities among scenarios for the probability calculations in the Kobe strategy matrix is problematic.

If the model structures can be represented by formulating the structures into a single model so that they are represented by different values of model parameters, then model structure uncertainty can be estimated as parameter uncertainty (*e.g.* the two-parameter Ricker and Beverton-Holt models can be represented by three-parameter stock-recruitment models). Otherwise sensitivity analysis or Bayesian estimation methods (*e.g.*, using reversible jump MCMC) have to be used to investigate or estimate the model structure uncertainty.

### 4.5. Statistical assumptions

The parameters of the stock assessment model are estimated by fitting the model to data. Assumptions have to be made about how the data relates to the quantities estimated by the model. Typically, the sampling distribution assumed for the data is used to generate a likelihood function that is used to measure how well the model fits the data. However, the assumed sampling distribution may be incorrect. For example, age and length composition data are often assumed to follow the multinomial distribution under random sampling, but the data collection methods are not completely random and cause the data to be correlated (Crone and Sampson 1998). In such cases the effective sample size is smaller than the actual sample size and the multinomial likelihood function using the actual sample size is incorrect. There are methods available that can be used to adjust the sample size (Deriso *et al.* 2007; Maunder in press) or select among alternative likelihood functions (Dick *et al.* 2004), but using these methods increases the uncertainty in the estimates (Maunder in press).

### 4.6. Process variation

Most processes in stock assessment models are assumed to be invariant over time. The exception is recruitment, which is often modeled as annual deviates around a stock-recruitment relationship (Fournier and Archibald 1982; Needle 2002). Other processes, such as natural mortality, growth, and selectivity, can also change over time either as a function of stock size or environmental forcing. Unmodeled process variation can lead to bias in the parameter estimates, particularly if there is a trend over time. Process variation could lead to additional uncertainty in parameter estimates. Statistically rigorous approaches are available to model process variation, but they are computationally intensive (Maunder and Deriso 2003). Adequate shortcuts are used instead (Fournier and Archibald 1982) including methods for combining parameter and process variation in projections (Maunder *et al.* 2006). It has also been argued that process variability can be accommodated by estimating the sample sizes and standard deviations of likelihood functions, but we are unaware of any studies that show this.

Process variation is also very important when using forward projections to evaluate management strategies. Since there is often no information about the processes in the future, the stochastic nature of the process variability needs to be included. For tropical tunas, whose recruitment is often highly variable and can comprise a substantial portion of the biomass, this results in substantial uncertainty. Future recruitment can be sampled from a parametric distribution based on assumptions or the historic data, or it can be sampled from the historic data directly. The recruitments themselves can be sampled or the deviates around the stock-recruitment relationship sampled and applied to that relationship. Regime shifts in recruitment and other processes cause additional uncertainty in the projections. A decision needs to be made about what regime will persist in the future or whether each regime should be sampled with a given probability.

There can be a major difference between short-term projections and long-term projections. Short-term projections may have information on recruitment from pre-recruit surveys or relationships with an environmental index. Long-term projections do not have the luxury of this type of data and have to rely on the stock-recruitment relationship and recruitment variability.

### 4.7. Implementation error

Evaluation of management strategies using forward projections generally assume that the management actions are implemented exactly as intended. Unfortunately, the real world with its practical constraints means that the management actions may not act as intended. For example, changes in the environment may cause an effort-based management action to result in a fishing mortality rate higher or lower than intended due to changes in catchability. Different fishing methods often capture different-size fish, and the size of the fish caught can influence reference points and the impact of the fishery on the stock. Management actions may change the allocation of effort among gears and therefore distort the effectiveness of the management action. In addition, stock assessments are imprecise and may contain bias so that management advice used to implement the management actions will contain error. Management strategy evaluation (Butterworth *et al.* 1997; De Oliveira *et al.* 1998; Butterworth DS, Punt AE 1999) could be used as an alternative to the Kobe strategy matrix.

## 5. EPO FISHERIES

The main sources of uncertainty that have substantial impact on management quantities in the tuna assessments are natural mortality, steepness of the stock-recruitment relationship, and the mean size of the old individuals. Other sources of uncertainty include the relationship between CPUE and abundance.

To represent the full range of uncertainty in the assessment all the model parameters should be estimated, but it is typically not possible to do this. Applying informative priors and conducting a Bayesian analysis may enable estimation of model uncertainty, but constructing informative priors is problematic.

The EPO assessments are currently conducted using Stock Synthesis (Methot 2009), so any analyses are restricted to the functionality of Stock Synthesis. Several modifications to Stock Synthesis are needed to implement certain aspects of the calculations.

### 5.1. Steepness of the Beverton-Holt stock-recruitment relationship.

Several recent analyses have shown that in general it is not possible to estimate the steepness of the stock-recruitment relationship because the estimate is either imprecise or estimated on the upper bound (no relationship between recruitment and stock size; Conn *et al.* 2010; Lee *et al.* in prep). A recent meta-analysis of the steepness of the Beverton-Holt stock-recruitment relationship (Report of the 2011 ISSF Stock Assessment Workshop, Rome, Italy, March 14-17, 2011) can be used to guide the development of a prior for steepness. The estimate for southern bluefin tuna (0.6) might be considered a lower bound for steepness, since it is a temperate tuna and only spawns once a year, while tropical tunas spawn continuously throughout the year. Most tropical tunas had a steepness at 0.75 or higher. A reasonable prior for steepness of tropical tunas might have zero probability at 0.6, a linear increase to a relative probability of one at 0.75 and then a relative probability of one for all higher values of steepness (Figure 3). Stock Synthesis allows inclusion of a prior on steepness, but not in the form depicted in Figure 3.

### 5.2. Natural mortality

Natural mortality has been estimated for bigeye tuna using a cohort analysis on tagging data with auxiliary information (Maunder *et al.* 2010). The estimates could be used as a prior. However, they are very uncertain (Figure 4). The implementation of natural mortality in Stock Synthesis is not conducive to applying priors to age- and sex-specific natural mortality.

### 5.3. Average length of old fish

The average length at age is calculated based on age-length data from reading otoliths. Unfortunately, ages can only be accurately obtained from fish up to about age four years for bigeye and yellowfin tuna. Mean length at age can also be obtained from tag-recapture data on length at release, length at recover, and time at liberty. The tagging data can be used to supplement the aging data to provide information on mean length at age for old individuals, using recently-developed statistically rigorous methods (Eveson *et al.* 2004). Unfortunately, few large bigeye and yellowfin tuna are recaptured and, in addition, the growth curves used in the assessment of these species (the von Bertalanffy and the more flexible Richards curve) are not flexible enough to represent their growth, resulting in maximum lengths that are unreasonably high. Therefore, the current growth curves need to be modified before the data can be used to develop a prior for the length of old individuals. If a prior is created, it should be a joint prior for all the parameters of the growth model. Stock Synthesis is not set up to include the two- stanza growth model or multivariate priors.

### 5.4. Bayesian MCMC analysis

Initial runs of a Bayesian MCMC analysis of the bigeye tuna assessment took several days, but showed promise. With current computing equipment it is not possible to quickly get these results for multiple scenarios, but it may be possible to provide estimates of uncertainty for key components of the Kobe plot and Kobe strategy matrix to include in stock assessment or management reports.

The Bayesian analysis is reliant on the estimator being unbiased. However, bias commonly occurs because the model is misspecified, there are quirks in the data, or simply because the estimator is inherently biased. For example, the inability of Stock Synthesis to model a composite growth curve creates a model misspecification that causes the mean length of old fish to be unrealistically high, which influences estimates of management quantities. There is inherent bias in the estimates of steepness that frequently pushes the parameter estimates to the upper bound of the prior. Even if steepness is not estimated at the bound, it may be quirks in the data that are influencing the estimates rather than true signals in the data. Therefore, even if the Bayesian analysis appears to be performing adequately, it is not clear whether the resulting probability statements are appropriate for use in the Kobe plot or Kobe strategy matrix.

## 6. CONCLUSION

The main sources of uncertainty in evaluating management actions using forward projections are 1) parameters for which there is little information in the data and are fixed in the model (*e.g.* natural mortality), 2) model structural uncertainty, and 3) future process variability (*e.g.* recruitment). The current models incorporate future process variability in recruitment and sensitivity analysis can be used to evaluate model structure uncertainty and fixed parameters. There are approaches to include model structure uncertainty into the analysis (*e.g.* Bayesian analyses using reversible jump MCMC), but they are computationally intensive, particularly for the complex age-structured catch-at-length models used to assess tunas in the EPO. Much of the uncertainty in the current EPO bigeye and yellowfin tuna stock assessments can be represented by model parameters, and initial analyses indicate that a full Bayesian MCMC analysis might be a practical method for estimating the uncertainty required for the creation of the Kobe plot and the Kobe strategy matrix. However, inherent biases in the estimators, and biases due to model misspecification or quirks in the data, will flow through into the construction of the Kobe plot and Kobe strategy matrix. Sensitivity analysis may be a more appropriate method to evaluate these biases and model misspecifications, but it is not straightforward to create the probability statements needed for the Kobe strategy matrix from sensitivity analysis. The complexities of the Kobe plot related to time-varying selectivity and recruitment may need to be ignored, but it is the current values that are most important, and estimates of uncertainty should focus on those quantities. Stock Synthesis, the current software used for conducting stock assessments of tuna in the EPO, requires several changes to implement the type of Bayesian analysis that would be used for producing the Kobe plot and Kobe strategy matrix.

## REFERENCES


Aires-da-Silva, A. and Maunder, M.N. 2011. Status of bigeye tuna in the eastern Pacific Ocean in 2009 and outlook for the future. Inter-Amer. Trop. Tuna Comm., Stock Assessment Report, 11: 17-156.

Butterworth, D.S., Cochrane, K.L., De Oliveira, J.A.A. 1997. Management procedures: a better way to management 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.

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

Clark, W.G. 1991. Groundfish exploitation rates based on life history parameters. Can. J. Fish. Aquat. Sci. 48: 734-750.

Conn, P.B., Williams, E.H., and Shertzer, K.W. (2010) When can we reliably estimate the productivity of fish stocks? Canadian Journal of Fisheries and Aquatic Sciences 67: 511-523.

Crone, P. R., Sampson, D. B., 1998. Evaluation of assumed error structure in stock assessment models that use sample estimates of age composition, in: Funk, *F*., Quinn II, T. J., Heifetz, J., Ianelli, J. N., Powers, J. E., Schweigert, J. J., Sullivan, P. J., *C*. I. Zhang, (Eds.), Fishery Stock Assessment Models: Proceedings of the International Symposium on Fishery Stock Assessment Models for the 21st Century held in Anchorage, Alaska, 8-11 October 1998, Alaska Sea Grant College Program Report No. AK-SG-98-01, University of Alaska Fairbanks, pp. 355-370.

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., Maunder, M.N., and Skalski, J.R. 2007. Variance estimation in integrated assessment models and its importance for hypothesis testing. Can. J. Fish. Aquat. Sci. 64: 187-197.

Dick, E.J. 2004. Beyond "lognormal versus gamma": discrimination among error distributions for generalized linear models. Fisheries Research 70 351–366.

Eveson, J.P., Laslett, G.M., and Polacheck, T. 2004. An integrated model for growth incorporating tag recapture, length-frequency, and direct aging data. Can. J. Fish. Aqua. Sci., 61 (2): 292-306.

Fournier, D. and Archibald, *C*.P. 1982. A general theory for analyzing catch at age data. Canadian Journal of Fisheries and Aquatic Science 39, 1195-1207.

Goodyear, *C*. P. 1993. Spawning stock biomass per recruit in fisheries management: foundation and current use. p. 67-81. In S. J. Smith, J. J. Hunt and D. Rivard (ed.] Risk evaluation and biological reference points for fisheries management. Can. Spec. Pub!. Fish. Aquat. Sci. 120.

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

Z., Jiangfeng Zhu, Chen, Y., Dai, X., Harley, S.J., Hoyle, S.D., Maunder, M.N., Aires-da-Silva, A. (in review). Implications of uncertainty in the spawner-recruitment relationship for fisheries management: an illustration using bigeye tuna (Thunnus obesus) in the eastern Pacific Ocean. ICES Journal of Marine Science

Lee, H-H., Maunder, M.N., Piner, K.R., and Methot, R.D. (in review) Can steepness of the stock-recruitment relationship be estimated in fishery stock assessment models?

Maunder, M.N. (in press) Review and evaluation of likelihood functions for composition data in stock-assessment models: estimating the effective sample size. Fisheries Research.

Maunder, M.N. 2002. The relationship between fishing methods, fisheries management and the estimation of MSY. Fish and Fisheries, 3: 251-260.

Maunder, M.N. 2008. Maximum Sustainable Yield. In Sven Erik Jørgensen and Brian D. Fath (Editor-in-Chief), General Ecology. Vol. [3] of Encyclopedia of Ecology, 5 vols. pp. [2292-2296] Oxford: Elsevier.

Maunder, M.N. and Aires-da-Silver, A. 2011. Status of yellowfin tuna in the eastern Pacific Ocean in 2009 and outlook for the future. Inter-Amer. Trop. Tuna Comm., Stock Assessment Report, 11: 3-16.

Maunder, M.N. and Deriso, R.B. 2003. Estimation of recruitment in catch-at-age models. Can. J. Fish. Aquat. Sci. 60: 1204-1216.

Maunder M.N., Harley, S.J., and Hampton, J. 2006. Including parameter uncertainty in forward projections of computationally intensive statistical population dynamic models. ICES Journal of Marine Science 63: 969-979.

Maunder M.N., Schnute, J.T., and Ianelli, J. 2009. Computers in Fisheries Population Dynamics. In Megrey, B.A. and Moksness, E. [eds.]. Computers in Fisheries Research. Springer, pp: 337-372.

Maunder, M.N., Aires-da-Silva, A., Deriso, R., Schaefer, K., and Fuller, D. 2010. Preliminary estimation of age and sex specific natural mortality of Bigeye tuna in the eastern Pacific Ocean by applying cohort analysis with auxiliary information to tagging data. Inter-Amer. Trop. Tuna Comm., Stock Assessment Report, 10: 253-278.

Methot, R.D.Jr., 2009. Stock Assessment: Operational Models in Support of Fisheries Management, in Beamish, R.J., Rothschild, B.J. (Eds.), The future of fisheries science in North America, Fish Fish. Ser., 137-165.

Myers, R.A., Bowen, K.G., and Barrowman, N.J. 1999. Maximum reproductive rate of fish at low population sizes. Canadian Journal of Fisheries and Aquatic Sciences 56, 2404-2419.

Needle, *C*.L. 2002. Recruitment models: diagnosis and prognosis. Reviews in Fish Biology and Fisheries 11: 95-111.

Patterson, K., Cook, R., Darby, *C*., Gavaris, S., Kell, L., Lewy, P., Mesnil, B., Punt, A., Restrepo, V., Skagen, D.W., Stefánsson, G., 2001. Estimating uncertainty in fish stock assessment and forecasting. Fish Fisher. 2, 125-157.

Punt, A.E. and Hilborn. R. 1997. Fisheries stock assessment and decision analysis: the Bayesian approach. Reviews in Fish Biology and Fisheries 7, 35-63.

Quinn, T.J. II, and Deriso, R.B. 1999. Quantitative Fish Dynamics. Oxford University Press, New York, N.Y.

Sinclair, A.*F*., 1993. Partial recruitment considerations in setting catch quotas. Can. J. Fish. Aquat. Sci. 50, 734-742.

Williams, E.H. and Shertzer K.W. 2003. Implications of life-history invariants for biological reference points used in fishery management. Can. J. Fish. Aquat. Sci. 60: 710-720.

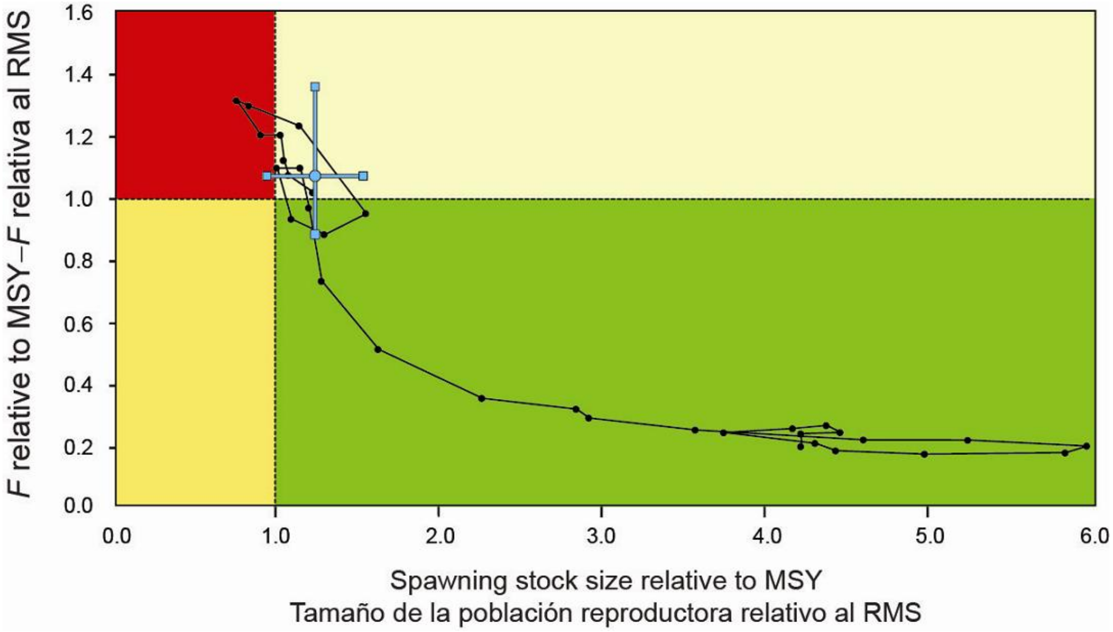


**FIGURE 1.** Kobe (phase) plot of the time series of estimates of stock size and fishing mortality relative to their MSY reference points. Each dot is based on the average fishing mortality rate over three years; the large dot indicates the most recent estimate. The squares around the most recent estimate represent its approximate 95% confidence interval. From Aires-da-Silva and Maunder (this meeting).

**FIGURA 1.** Gráfica de Kobe (fase) de la serie de tiempo de las estimaciones del tamaño de la población y la mortalidad por pesca en relación con sus puntos de referencia de RMS. Cada punto se basa en la tasa de explotación media de un trienio; el punto grande indica la estimación más reciente. Los cuadrados alrededor de la estimación más reciente representan su intervalo de confianza de aproximadamente 95%. De Aires-da-Silva y Maunder (esta reunión).

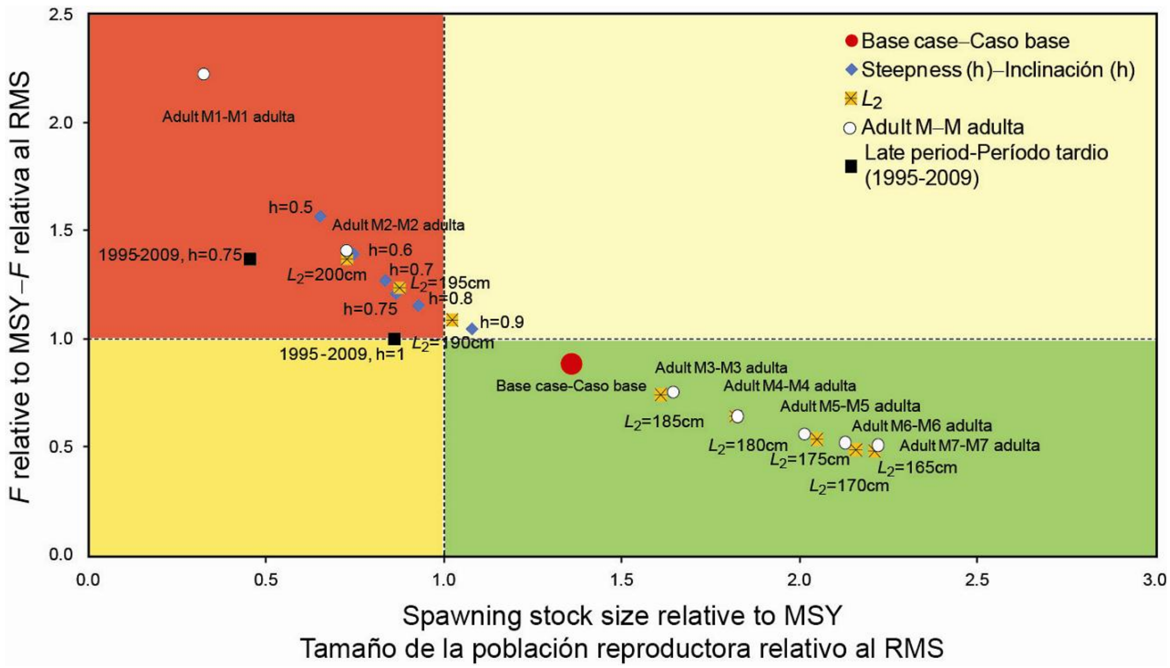


**FIGURE 2.** Phase plot of the most recent estimate of spawning biomass and fishing mortality relative to their MSY reference points for a range of sensitivity analyses. Each point is based on the average fishing mortality rate over the most recent three years. From Aires-da-Silva and Maunder 2011.

**FIGURA 2.** Gráfica fase de la estimación más reciente de la biomasa reproductora y la mortalidad por pesca en relación con sus puntos de referencia de RMS para una gama de análisis de sensibilidad. Cada punto se basa en la tasa de explotación media del trienio más reciente. De Aires-da-Silva y Maunder 2011.

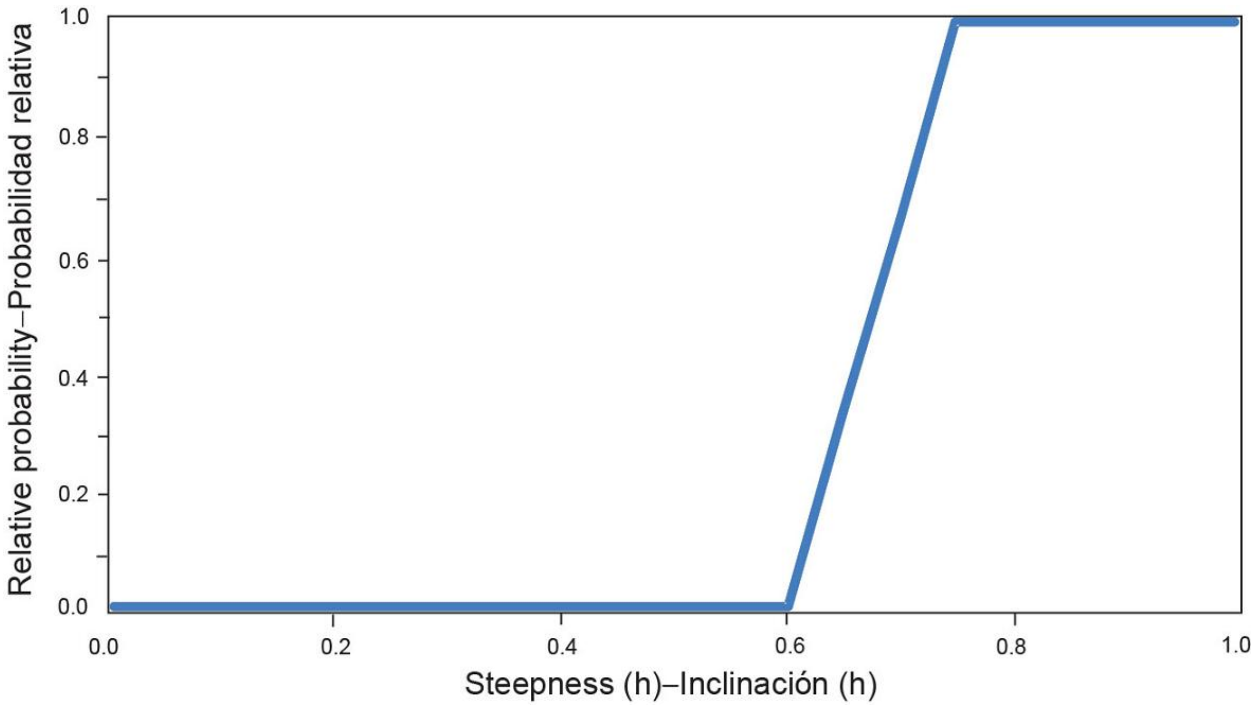


**FIGURE 3**. Proposed prior for the steepness of the Beverton-Holt stock-recruitment relationship for tropical tuna.
**FIGURA 3**. Probabilidad a priori propuesta para la inclinación de la relación población-reclutamiento de Beverton-Holt para el atún tropical.

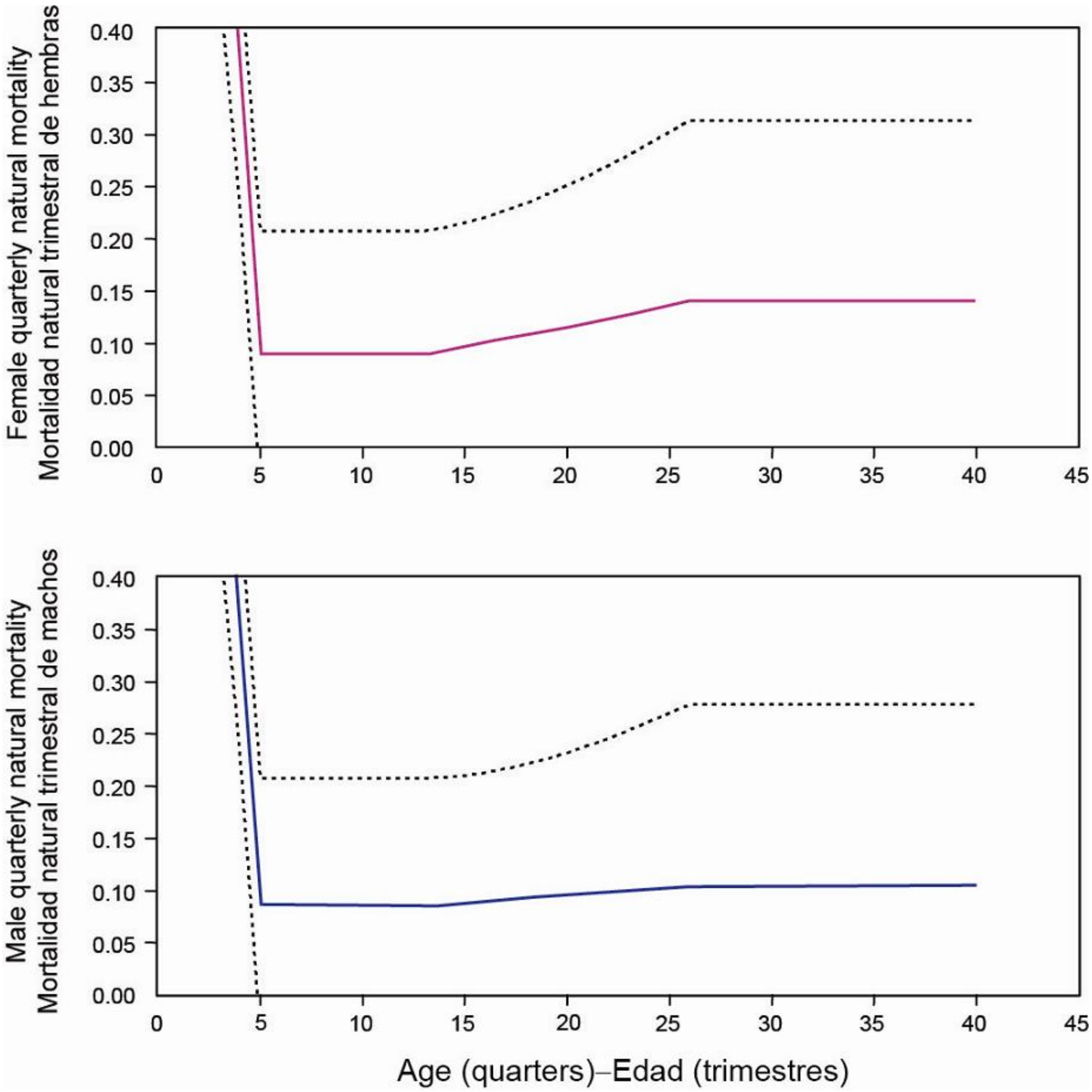


**FIGURE 4.** Estimates of female (top) and male (bottom) quarterly natural mortality by age in quarters, with 95% confidence intervals. The range of the y-axis has been restricted to show the contrast in the natural mortality for old bigeye. From Maunder *et al.* 2010.

**FIGURA 4.** Estimaciones de la mortalidad natural trimestral de hembras (arriba) y machos (abajo), por edad en trimestres, con intervalos de confianza de 95%. Se ha limitado el alcance del eje y para ilustrar el contraste en la mortalidad natural de patudo viejo. De Maunder *et al.* 2010.

**TABLE 1.** Example outlines of Kobe strategy matrices when the management target is to end overfishing (upper), rebuild a depleted stock (middle), or maintain a sustainable fishery (lower). Taken from the Report of the second joint meeting of the tuna RFMOs, June-July 2009.

| Management target | Time frame | Probability of meeting target | | | Data rich/Data poor |
|---|---|---|---|---|---|
| | | A% | B% | C% | |
| Fishing mortality target | In x years | | | | |
| | In x years | | | | |
| | In x years | | | | |

| Management target | Time frame | Probability of meeting target | | | Data rich/Data poor |
|---|---|---|---|---|---|
| | | A% | B% | C% | |
| Biomass target | In x years | | | | |
| | In x years | | | | |
| | In x years | | | | |

| Management target | Time frame | Probability of meeting target | | | Data rich/Data poor |
|---|---|---|---|---|---|
| | | A% | B% | C% | |
| Status quo | | | | | |

**TABLA 1.** Ejemplos de matrices de estrategia de Kobe cuando la meta de la ordenación es poner fin a la sobrepesca (arriba), reconstruir una población mermada (centro), o mantener una pesquería sostenible (abajo). Tomado del Informe de la segunda reunión conjunta de las OROP atuneras, junio-julio de 2009).

| Objetivo de ordenación | Plazo | Probabilidad de cumplir el objetivo | | | Rico en datos/Pobre en datos |
|---|---|---|---|---|---|
| | | A% | B% | C% | |
| Mortalidad por pesca objetivo | En x años | | | | |
| | En x años | | | | |
| | En x años | | | | |

| Objetivo de ordenación | Plazo | Probabilidad de cumplir el objetivo | | | Rico en datos/Pobre en datos |
|---|---|---|---|---|---|
| | | A% | B% | C% | |
| Biomasa objetivo | En x años | | | | |
| | En x años | | | | |
| | En x años | | | | |

| Objetivo de ordenación | Plazo | Probabilidad de cumplir el objetivo | | | Rico en datos/Pobre en datos |
|---|---|---|---|---|---|
| | | A% | B% | C% | |
| Statu quo | | | | | |