Best practices for modeling time-varying selectivity

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Abstract

Changes in the observed size- or age-composition of commercial catch can occur for a variety of reasons including: market demand, availability, temporal changes in growth, time-area closures, regulations, or change in fishing practice, to name but a few. Two common approaches for dealing with time-varying selectivity in assessment models are the use of discrete time-blocks associated with an epoch in the history of the fishery, or the use of penalized random walk models for parametric or non-parametric selectivity curves. Time block periods, or penalty weights associated with time-varying selectivity parameters, are subjective and often developed on an ad hoc basis. A factorial simulation-estimation experiment, with discrete or continuous changes in selectivity, is conducted to determine the best practices for modeling time-varying selectivity in fisheries stock assessments. Both the statistical properties of the assessment model and the policy implications of choosing the wrong model are taken into consideration.

Introduction

There are many reasons why fisheries selectivity may vary over time and the impact of ignoring changes in selectivity in age- or size-structured stock assessment models leads to biased estimates of abundance and mortality rates. Moreover, not accounting for changes in selectivity can lead to extremly optimistic projections in stock abundance (e.g., 2J3KL cod stocks, Walters and Maguire, 1996).

Currently there are two general approaches for incorporating time-varying selectivity in stock assessment models; 1) the use of discrete time-blocks, and 2) continuous penalized random walk approach. The use of discrete time-blocks should be done *a priori*, where the specified time blocks represent periods consistent fishing practice, and a new block is specified when siginificant changes in fishing practice occur that may result in changes in selectivity. In practice, however, the time-blocks are also implemented *post hoc* to justify residual patterns in age- or size-composition data. To some, this practice seems rather subjective, and it is. Another discrete appraoch is to decompose the fisheries catch statistics into specific time periods that correspond to major transitions in fishing practice. For example, the BC herring fishery prior to 1970 was largely a reduction fishery where herring were harvested during the winter months using purse seines. After the collapse of the fishery in 1969, the fishery reopend as a gill-net fishery targeting older sexually mature female herring for valuable roe. This change in fishing practice led to a significant change in the selectivity of the fishing gear.

The alternative approach is to allow for continous changes in selectivity and model estimated selectivity parameters as a penalized random walk. In this case, specification of the variance parameter in how quickly selectivity is allowed to change is also somewhat subjective. It should also be noted that the choice of a time-invariant selectivity is also a subjective structural assumption of the assessment model, and this choice can also greatly influence model results, estimates of reference points, and result in bias forecasts.

Changes in fisheries selectivity also has implications for reference points based on maximum sustainable yield (MSY). Trends towards catching smaller fish result in reductions in the harvest rate that would achieve MSY; therefore, it is important to account for changes in selectivity (and the associated uncertainty) when developing harvest policy for any given stock.

In this paper, we conduct a series of simulation experiments using a factorial design with fixed selectivity, discrete changes in selectivity, and continuous changes in selectivity and compare this statistical fit and estimated policy parameters using simulated data . Simulations are based on population parameters and growth information from the Pacific hake assessment conducted in 2010. Model details, and data can be obtained from Martell et al. (2008). We envoke model selection criterion (Deviance Information Cirterion) to determine the effective number of estimated parameters in each case, as well as, to determine the probability of choosing the correct model.

Methods

Model description

The same statistical catch-age model was used to both generate simulated data sets and estimate model parameter based on simulated data. The simulation-estimation experiments were based on the Pacific hake fishery from 1977 to 2009, using the historical catch time series from US and Canada combined and the empirical weight-at-age data from this fishery (Martell, 2009).

Input data for the model consist of historical removals from all commercial fisheries along with age-composition information based on commercial samples and empircal weight-at-age data from the commercial fishery. Fisheries independent survey information includes an index of abundance based on a systematic coastwide acoustic survey and age-composition information.

Simulation-estimation experiments were based on the maximum likelihood estimates of the initial numbers-at-age and annual recruitment deviations based on fitting the model to the true Pacific hake data. In simulating data, a unique random number seed was used to ensure observation errors in the survey and catch-at-age sampling under alternative hypotheses about the commercial selectivity were repeatable. The annual relative abundance data was assumed to be porportional to the available biomass and to have log-normal measurement errors:

$$I_t = qe^{\sigma_1 \epsilon_t} \sum_a \nu_a N_{a,t} W_a \tag{1}$$

where the random deviate is $\epsilon \sim N(0,1)$, σ is the standard error, ν_a is the age-specific proportion that this selected by the acoustic sampling gear, $N_{a,t}$ is the numbers-at-age, and W_a is the average weight-at-age during the survey.

Age-composition data for both commercial and acoustic surveys were based on random samples from a multivariate distribution with a propability of $p_{a,t}$ of sampling a fish of a given age in a given year. The age-proportion samples must sum to 1 in each year, and random samples were based on the the following:

$$\begin{aligned} x_{a,t} &= \ln(\hat{p}_{a,t}) + \sigma_2 \epsilon_{a,t} - \frac{1}{A}\left[\sum_a \ln(\hat{p}_{a,t}) + \sigma_2 \epsilon_{a,t}\right], \\ p_{a,t} &= \frac{e^{x_{a,t}}}{\sum_a e^{x_{a,t}}} \end{aligned} \tag{2}$$

where $\epsilon_{a,t}$ is a standard random nomral deviate, σ_2 is the standard error, $\hat{p}$ is the expectatation of the proportion-at-age in year t in the sampled catch.

Reference points

Scenarios

Three alternative scenarios for time-varying selectivity are considered: 1) fixed size-based selectivity where changes in size-at-age leads to changes in age-based selectivity, 2) discrete time blocks corresponding to significant changes in fishing practices, and 3) continous changes in selectivity associated with targeting strong cohorts to maximize landed value. These three scenarios result in nine model permutations summarized in Table

References

Martell, S. (2009). Assessment and management advice for pacific hake in u.s. and canadian waters in 2009. *DFO Can. Sci. Advis. Sec. Res. Doc.*, 2009/021:iv+54p.

Martell, S. J. D., Pine, W. E., and Walters, C. J. (2008). Parameterizing age-structured models from a fisheries management perspective. *Can. J. Fish. Aquat. Sci.*, 65:1586–1600.

Table 1: List of model scenarios and labels associated with each scenario explored. For example, scenario 2a is based on simulated data with a fixed selectivity curve, but assumes 3 discrete time blocks in the assessment model.

True states	**Assumed selectivity states**		
	Fixed (a)	**Discrete (b)**	**Continuous (c)**
Fixed (1)	1a	1b	1c
Discrete (2)	2a	2b	2c
Continuous (3)	3a	3b	3c

Walters, C. and Maguire, J. (1996). Lessons for stock assessment from the northern cod collapse. *Reviews in Fish Biology and Fisheries*, 6(2):125–137.