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Towards defining good practices for modeling time-varying selectivity

S. Martell*, I. Stewart

International Pacific Halibut Commission, 2320 West Commodore Way, Suite 300, Seattle, WA 98199-1287, United States

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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.

1. 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 (e.g., Gudmundsson et al., 2012). Moreover, not accounting for changes in selectivity can lead to extremely optimistic projections in stock abundance (e.g., 2J3KL cod stocks, Walters and Maguire, 1996).

Many statistical catch-age models assume age-based selectivity when in fact the underlying harvesting process is size-based. This is a reasonable assumption if fish of a given size maps to a corresponding age; however, when this approach is taken changes in size-at-age associated with changes in growth rates can have serious implications for the interpretation of age-based selectivity. Changing to length-based selectivity and using empirical length-at-age data can resolve some of the model misspecification; however, ontogentic movement of fish can also lead to changes in age-based selectivity when the distribution of fishing effort, or fish distribution relative to effort, changes over time. Recently, the International Pacific Halibut Commission (IPHC) changed from using time-invariant size-based selectivity to time-varying size-based selectivity to account for both ontogeny and the changes in the relative stock distribution (Stewart et al., 2012). The change led to marked improvements in retrospective performance and a trend in estimated spawning biomass that was consistent with trends in survey data. The previous assessment model was unable to consistently match the age-composition information and survey trends due to this model misspecification.

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 of consistent fishing practice, and a new block is specified when significant changes in fishing practice occur that may result in changes in selectivity. This approach is difficult to implement. Scientists are not necessarily qualified to identify breaks associated with changes in fishing behavior, and breaks in the terminal year are not identifiable in the model due to confounding with other model parameters. In practice, however, the time-blocks are also implemented *post hoc* to rectify residual patterns in age- or size-composition data. This practice is often highly subjective. Another discrete approach 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 re-opened using a higher proportion of gill-nets 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. In some cases this can be reconciled by separating fishing fleets in the model as well.

The alternative approach is to allow for continuous 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 subjective. It should also be noted that the choice of a

* Corresponding author. Tel.: +1 206 552 8634.
E-mail addresses: stevem@iphc.int (S. Martell), ian@iphc.int (I. Stewart).

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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. Other altneratives include using random effects (see Mäntyniemi et al., 2013) and cross validation model selection (see Maunder and Harley, 2011). The random effect and cross validation methods allow for the estimation of the variance parameter from the data, thus reducing the subjective nature of specifying penalty weights for selectivity curve parameters.

Changes in fisheries selectivity also has implications for reference points based on maximum sustainable yield (MSY, Beverton and Holt, 1993). 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.

The over-arching objective is to evaluate the relative performance of assuming more or less structural complexity in selectivity when the data are in fact simple and when the data come from a fishery with dynamic changes in selectivity. 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 statistical fit, retrospective bias, and estimated policy parameters using simulated data. We also explore the use of two-dimensional interpolation methods to reduce the number of estimated latent variables when selectivity is assumed to vary over time.

2. Methods

Simulated data were generated from an age-structured simulation model largely based on the 2010 Pacific hake assessment. Simulated data were based on three alternative selectivity scenarios: (1) constant over time, (2) selectivity changes at four specific time-periods (blocks), and (3) selectivity changes continuously over time where the commercial fishery targets the most abundant cohort in each year. Four alternative estimation models were used to estimate the underlying parameters from data generated by each of the simulation models. In each of the assesment, initial parameter values differed from the values used in the simulation models to reduce potential biases associated with starting at values near the MLE estimates. First, we describe the model structure used to simulate data and estimate model parameters, followed by a description of the MSY-based reference points, and lastly the detailed description of the various scenario combinations explored.

2.1. Model description

A statistical catch-age model was used to both generate simulated data sets and estimate model parameters based on simulated data. These simulation–estimation experiments were based on data from 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 available at the time (Martell, 2010). The model was written in AD Model Builder (Fournier et al., 2011) and all model code and data are available from a code repository (see CAPAM branch at https://github.com/smartell/iSCAM).

Input data for the model consist of fishery removals along with age-composition information and empirical weight-at-age data from the commercial fishery. In addition to the commercial data, a fisheries independent survey also exists and includes a relative index of abundance and age-composition information. The actual acoustic survey for Pacific hake historically occurred every three years prior to 2001, then every two years, and since 2011 has occurred every year. For the simulation–estimation experiments we assume that fishery-independent abundance and age-composition information exist for all years.

Table 1
Parameters used for simulation model in the integrated statistical catch-age model.

Description	Symbol	Value
Log unfished age-1 recruits	R_o	3.353
Steepness (Beverton–Holt)	h	0.727
Natural mortality rate	M	0.230
Log average age-1 recruitment	$\bar{R}$	1.300
Log initial recruitment	$\dot{R}$	0.428
Survey standard deviation	σ_1	0.300
Standard deviation in recruitment	σ_R	1.120
Age at 50% selectivity in survey	$\hat{a}$	2.500
Std dev. in 50% selectivity in survey	$\hat{g}$	0.500
Std dev. in age-sampling error	σ_2	0.300

Parameters for the simulation–estimation experiments were based on the maximum likelihood estimates of the initial numbers-at-age and annual recruitment deviations from the 2010 assessment (Martell, 2010). The annual relative abundance data was assumed to be proportional to the available biomass and to have log-normal measurement errors:

$$I_t = qe^{\sigma_1\epsilon_t - 0.5\sigma_1^2}\sum_a \nu_a N_{a,t} W_a \tag{1}$$

where the random deviate is $\epsilon \sim N(0, 1)$, σ_1 is the standard deviation, 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. For simplicity, the scaling parameter was fixed at $q = 1$.

Age-composition data for both commercial and survey samples were randomly drawn from a multivariate distribution with a probability of $p_{a,t}$ of sampling an age-a fish in a given year t. 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 normal deviate, σ_2 is the standard deviation, $\hat{p}_{a,t}$ is the expectation of the proportion-at-age in year t in the sampled catch.

True parameter values used in the simulation model are listed in Table 1. Annual fishing mortality rates were conditioned on the observed catch from the Pacific hake fishery and it was assumed that both natural mortality and fishing mortality occur simultaneously. Simulated age-specific fishing mortality rates were based on the annual age-specific selectivity which differs among three alternative simulation scenarios (see description in Section "Scenarios").

2.2. Parameter estimation

Model parameters were estimated using maximum likelihood methods where the objective function includes additional penalties to constrain the shape of the selectivity curve and how much it is allowed to vary over time (Table 2). There are 6 major components to the objective function that is being minimized: (1) the likelihood of the observed catch (T2.5), (2) the likelihood of the relative abundance index (T2.6), (3) the likelihood of the age-composition information (T2.7), (4) the likelihood of the stock–recruitment estimates given the values of steepness and unfished age-1 recruits (T2.8), (5) prior densities in negative log space for estimated model parameters (T2.9), and (6) penalties and constraints for selectivity coefficients (T2.10).