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. In all scenarios expored, a minum of seven age-specific selectivity coefficients were estimated in fixed selectivity scenarios, and upto 231 selectivity coefficients were estiamted in the time-varying selectivity scenarios. 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.

Methods

Data were generated from an age-structured assessment model based on the Pacific hake assessment conducted at the end of the 2009 fishing season. Simulate data were based on 3 alternativae scenarios that assumes selectivity is (1) constant over time, (2) selectivity changes at 3 specific blocked time-periods, and (3) that selectivity changes continously over time where the commercial fishery targets abundant cohorts over time. 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.

Model description

The same statistical catch-age model was used to both generate simulated data sets and estimate model parameters. 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). 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 historical removals along with age-composition information 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. The acutal acoustic survey for Pacific hake historically occurred every 3 years prior to 1995, then every two years, and since 2011 has occured every year. For our purposes we assumed an annual abundance index is available for each and every year between 1977 and 2009.

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. Initial and annual recruitment deviates were fixed at the maximum likelihood estimates from the real Pacific hake data for all simulations. The annual relative abundance data was assumed to be porportional to the available biomass and to have log-normal measurement errors:

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

where the random deviate is $\epsilon \sim N(0,1)$, σ 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.

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

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

Description	**Symbol**	**Value**
Unfished age-1 recruits	R_o	3.353
Steepness (Beverton-Holt)	h	0.727
Natural mortality rate	M	0.230
Average age-1 recruitment	$\bar{R}$	1.300
Initial recruitment	$\dot{R}$	0.428
Survey standard deviation	σ_1	0.200
Standard deviation in recruitment	σ_R	1.120
Age at 50% selectivity in survey	$\hat{a}$	2.500
Std in 50% selectivity in survey	$\hat{g}$	0.500

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 the Scenarios subsection).

Parameter estimation

Reference points

Reference points based on long-term maximum sustainable yield (MSY-based reference points) were calculated assuming steady-state conditions. It was assumed that removals from the fishery independent survey were negligable. The fishing mortality rate that produced the maximum sustainable yield was determined by setting the derivative of the catch equation to 0 and solving for F_{MSY}. MSY was was subsequently determined by calculating the steady-state catch using F_{MSY}. Similarly B_{MSY} was determined by calculating the steady-state spawning biomass under a fishing mortality rate of F_{MSY}. Detailed descriptions of the steady state calculations for MSY-based reference points can be found in Martell et al. (2008).

All MSY-based reference points were based on the estimated selectivity value in the terminal year of the assessment. In cases where selectivity is assumed to remain constant over time, the estimated MSY-based reference points vary with minor updates to population parameters as the time series increases in length. However in cases where selectity is assumed to vary over time, MSY-based refernce points become highly uncertain as the uncertainty in selectivity in the terminal year is a function of how much selectivity is allowed to vary.

Table 2: 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)**	**2d cubic spline (d)**
Fixed (1)	1a	1b	1c	1d
Discrete (2)	2a	2b	2c	2d
Continuous (3)	3a	3b	3c	3d

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. In addition to a random walk model with annual changes in selectivity, a 2-dimensional cubic spline was also fit to the simulated data (Scenario d).These three scenarios result in nine model permutations summarized in Table 2.

1 Results

References

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Table 3: Statistical performance based on negative log likelihoods, DIC, estimated standard deviations (STD) and Root Mean Square Error in the age-composition data for models fit to fixed, discrete time blocks and continous changes in commercial selectivity.

	Fixed	**Blocks**	**Random walk**	**2d spline**
True selectivity is fixed				
No. estimated parameters	94	108	318	171
Negative log likelihood	-1894.64	-1914.28	-1807.13	-1700.67
Effective No. parameters	89.10	100.93	298.38	154.78
DIC	-3609.29	-3624.48	-2991.07	-3075.36
STD in recruitment devs	1.20	1.20	1.21	1.20
STD in survey devs	0.21	0.21	0.22	0.21
Commercial age comp RMSE	0.19	0.19	0.12	0.16
Survey age comp RMSE	0.18	0.18	0.18	0.18
True selectivity has 3 time blocks				
No. estimated parameters	94	108	318	171
Negative log likelihood	-1736.05	-1862.78	-2065.24	-1972.42
Effective No. parameters	91.08	100.60	311.26	167.13
DIC	-3288.19	-3521.84	-3488.43	-3604.91
STD in recruitment devs	1.21	1.21	1.21	1.21
STD in survey devs	0.22	0.22	0.22	0.22
Commercial age comp RMSE	0.23	0.20	0.15	0.18
Survey age comp RMSE	0.18	0.18	0.18	0.18
True selectivity changes annually				
No. estimated parameters	94	108	318	171
Negative log likelihood	-589.41	-598.70	-641.23	-680.75
Effective No. parameters	93.56	101.35	3.04	164.63
DIC	-989.88	-992.32	-1329.56	-1025.71
STD in recruitment devs	1.70	1.69	1.74	1.81
STD in survey devs	0.30	0.30	0.31	0.32
Commercial age comp RMSE	0.46	0.45	0.37	0.40
Survey age comp RMSE	0.80	0.80	0.92	0.79