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How catch underreporting can bias stock assessment of and advice for northwest Atlantic mackerel and a possible resolution using censored catch

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ABSTRACT

Fish stock assessments routinely integrate catch data. Misreported catches, however, can lead to biased estimates of stock size, production, reference points and poor advice on stock exploitation. Canadian Atlantic mackerel (*Scomber scombrus*) landings are thought to be significantly underestimated because this stock is subject to large bait and recreational fisheries that are not required to report catches. As this might lead to stock size underestimation, we developed a state-space age-structured model that accounts for catch data uncertainties using a censored catch method, which involves data on lower and upper catch limits. We explored how censoring influences parameter estimates and six common reference points, and their sensitivity to the choice of an upper catch limit. Modelling catch as a censored random variable led to more realistic estimation of state variables such as a higher estimate of SSB. The relationship between reference points and the range of possible catches was not straightforward, but $F_{0.1}$, F_{max} and $F_{40\%}$ were more stable than SSB_{msy}, F_{msy} and F_{med}. Applying the censored catch approach to Canadian Atlantic mackerel highlighted the importance of informing the upper catch limit when faced with other sources of uncertainty and showed that it was crucial to provide realistic management advice.

1. Introduction

Fish stock assessments rely generally on several data sources, such as an index of stock abundance and total catches. However, reported catches can be seriously underestimated because of Illegal, Unreported or Unregulated (IUU) activities. Poor quality catch data is a global problem (e.g., Pauly and Zeller, 2016) that could have important consequences, as it might affect the estimation of stock abundance and reference points (RPs), potentially resulting in inadequate management recommendations (e.g., Griffiths, 2015). As a result, several stock assessments based on unreliable catch information have been rejected (ICES, 2013). Given that underreported catch is fairly common, the issue demands the development and examination of new stock assessment methods that can account for biased catches.

A case in which catches are thought to be substantially underestimated is the Atlantic mackerel (*Scomber scombrus*) fishery off the Canadian east coast. This stock is of great economic importance with about 8000 fishing licenses (DFO, 2016) and annual landings averaging 40,000 t between 2000 and 2010 (DFO, 2014). The 2013 assessment showed the stock was at its lowest biomass in the assessment time-series (Grégoire and Beaudin, 2014), but catch underreporting was noted as an important concern that may have led to an under-estimate of actual biomass. The commercial fishery (primarily seine) is obliged to declare landings, but bait and recreational fisheries do not always need to report catches. The bait fishery is mainly to bait American lobster and snow crab pots, and mackerel angling is a common summer activity on the wharves, rocky points and recreational boats in Atlantic Canada. Despite the presumably large proportion of underreported mackerel catch in Canada (MSC, 2014, 2012; Van Beveren et al., 2017), all previous assessments worked only from declared commercial landings (Grégoire and Beaudin, 2014). Although the trend in abundance may be inferred correctly (i.e., the stock may still be at the lowest biomass in the time-series), these assessments are likely underestimating stock size. This idea is underpinned by inconsistencies in the last assessment, as reported catches in recent years were of almost the same magnitude as the estimated mature stock biomass.

Several approaches have been used to correct for unreported catch, as an alternative to methods that avoid the use of fishery dependent data (e.g., Mesnil et al., 2009). For instance, assessments have been made on a relative scale (Cook, 1997), by excluding catch data entirely

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(Cook, 2013), by assuming observation error (Kimura, 1990; Nielsen and Lewy, 2001; Patterson, 1998) or by enriching the data, generally for a rough reconstruction of the actual catch (e.g., Zeller et al., 2007) or less commonly for catch estimation within the assessment model (Plagányi et al., 2011). Yet another – and relatively new – approach is censored catch models, in which reported catches are explicitly considered to be biased. Catch is censored when the exact value is unknown but some information is available, such as the lower and/or upper bound. Censored models have the advantage that adding (often unavailable) data is optional, but not mandatory. The method was first demonstrated by Hammond and Trenkel (2005), using a surplus production model. Later, Bousquet et al. (2010) extended this approach for use in age-structured models and Cadigan (2016a) integrated it in a data-rich state-space model. As all three studies showed the censored catch approach to be promising, we developed a censored catch at age model for Canadian Atlantic mackerel.

By turning catch bias into uncertainty ranges, true catches need to be delimited by minimal and maximal values. Although only a relatively rough guess of the catch limits appears to be required (Bousquet et al., 2010), these bounds might not always be straightforward to determine. Thus far, the lower and upper bounds have usually been set as respectively the reported landings and one or more multiples of these, the latter defined somewhat intuitively because models appeared robust to this choice. For example, Bousquet et al. (2010) even obtained realistic results when setting the upper limit at infinity. However, it is conceivable that for other stocks assessed with different data types (e.g., a spawning stock biomass (SSB) index that is not age structured), setting the limits too wide for certain years might lead to erroneous inferences about stock status during those periods.

Censored catch approaches have been little used and not much is known about the effect of the underreporting rate on age-structured stock assessment models. However, because biomass estimates of the stock usually scale with catch levels, increased total catches can be expected to result in increased biomass estimates. Three questions are explored here:

- How do parameter estimates and RPs compare between an uncensored and a censored model?
- How well do models perform when the upper censoring limit is data-informed (e.g., by a survey of industry participants) or set via intuitive means (e.g., as a constant multiple of the lower limit). The former can require considerably more work to estimate; is it worth it?
- How are parameter estimates and RPs influenced by uncertainty in the upper catch limit and thus the potential magnitude of unreported catch in general?

This analysis can provide important information for the future use of the censored approach, but also increase general knowledge on the use and choice of RPs when catch is highly uncertain. Data inputs consisted only of standard inputs for an age-structured model and therefore results may be applicable to a wide range of stock assessments in which catch data may be biased.

2. Material and methods

2.1. Model framework

The model was developed with Template Model Builder (TMB, Kristensen et al., 2016), an R package that uses automatic differentiation and the Laplace approximation to fit complex nonlinear models that may include random effects. All observation equations are on a log scale and the process and observation error terms are assumed normally distributed unless mentioned otherwise. Annual fishing mortality (F_y) and abundance ($N_{a,y}$) were considered random variables.

We used an age-structured model spanning the years y = 1, …, Y and including A age classes denoted by a = 1, … A. All model parameters are given in Table 1. The model assumes an exponential decrease in cohort abundance ($N_{a,y}$) with total mortality rate ($Z_{a-1,y-1}$) (see Eq. (1.2)). Abundance at age 1 (here considered as recruitment) was calculated as a function of SSB and an environmental factor (Eq. (1.1), see further) and age A was implemented as a plus-group (Eq. (1.3)), so that:

Table 1
List of all model parameters with their notations and definitions.

$N_{a,y}$	Total stock abundance
F_a	Fishing mortality rate at age
F_y	Fishing mortality rate at year
σ_s^2	Survey measurement error variance
σ_{Fy}^2	Annual fishing mortality variance
σ_R^2	Recruitment variance
σ_{crl}^2	Catch-at-age measurement error variance
q	Survey index catchability coefficient
α	Beverton-Holt coefficient
β	Beverton-Holt coefficient
γ	Environmental coefficient
σ_δ^2	Process error measurement error variance
φ_a	Age correlation in process error
φ_y	Year correlation in process error

$$N_{1,y} = f(SSB_{y-1}, E_{y-1}) \tag{1.1}$$

$$N_{2\ldots A-1,y} = N_{a-1,y-1}\exp(-Z_{a-1,y-1} + \delta_{a,y}) \tag{1.2}$$

$$N_{A,y} = N_{a-1,y-1}\exp(-Z_{a-1,y-1} + \delta_{a,y}) + N_{a,y-1}\exp(-Z_{a,y-1} + \delta_{a,y}) \tag{1.3}$$

where δ is the process error (see further). Abundance-at-age for the first year was estimated freely. SSB was calculated as the product of abundance, weight ($W_{a,y}$) and the proportion of mature individuals ($P_{a,y}$, for the start of year) summed over all ages ($SSB_y = \sum_{y=1}^{Y} N_{a,y}W_{a,y}P_{a,y}$).

Total mortality (Z) is the sum of an always positive natural (M) and fishing (F) mortality ($Z_{a,y} = F_{a,y} + M_{a,y}$). We assumed a separable F model, i.e. $F_{a,y} = F_aF_y$. The vector of annual fishing mortality ($\log(F_y)$) was modelled as a random walk with variance σ_{Fy}^2. We assumed that fishing mortality was constant for ages 8 and higher, reducing the number of $F_a$parameters to estimate. Values for F_a were otherwise unconstrained.

Process error is commonly included in contemporary stock assessment models (Maunder and Piner, 2014). We included process errors in the model for N to account for stochastic and unexplained variations caused by migration, natural mortality deviations, etc. (e.g., Gundmundsson and Gunnlaugsson, 2012). Time-independent normal process errors on N have been used before but were considered suboptimal (e.g., Berg and Nielsen, 2016). Therefore, we used a similar process error structure on N as Cadigan (2016a) used for M, with the same assumption that fish cohorts adjacent in years and ages (> 1, recruitment process error is modelled separately) are likely influenced by the same processes, so that all δ have a stationary normal distribution derived from a lag 1 autoregressive process operating over year and age:

$$\mathrm{Cov}(\delta_{a,y}, \delta_{a-1,y-1}) = \frac{\sigma_\delta^2\varphi_{\delta,age}\varphi_{\delta,year}}{\left(1-\varphi_{\delta,age}^2\right)\left(1-\varphi_{\delta,year}^2\right)},\ \mathrm{Corr}(\delta_{a,y}, \delta_{a-1,y-1}) = \varphi_{\delta,age}\varphi_{\delta,year} \tag{2}$$

The subscripts *age* and *year* indicate the respective directions of autocorrelation. Note in Eqs. (1.2) and (1.3) that, for modelling convenience, the process error on $N_{a,y}$ is $\delta_{a,y}$ and not $\delta_{a-1,y-1}$, as might be