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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

Elisabeth Van Beveren[a,*], Daniel Duplisea[a], Martin Castonguay[a], Thomas Doniol-Valcroze[a], Stéphane Plourde[a], Noel Cadigan[b]

[a] Fisheries and Oceans Canada, Institut Maurice-Lamontagne, 850 Route de la Mer, Mont-Joli, G5H 3Z4, QC, Canada
[b] Centre for Fisheries Ecosystems Research, Marine Institute of Memorial University of Newfoundland, St. John's, Canada

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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

* Corresponding author.
E-mail addresses: elisvb@hotmail.com, elisabeth.vanbeveren@dfo-mpo.gc.ca (E. Van Beveren).

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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 expected. Process errors in the first year are set to zero because abundance during this year is freely estimated and there is no information to distinguish process from observation error. More detailed information on the implementation of this error structure is provided by Cadigan (2016a).

We tried several methods (random walk, blocks, stock-recruitment (SR) relationships and deviations from a mean or linear model) and error distributions (normal, lognormal, t-distribution and mixtures) to model age-1 recruitment (described by e.g., Methot and Wetzel, 2013), but for this paper we retained the Beverton-Holt SR relationship with environmental effects. Indeed, previous research on SR relationships for this stock showed that occasional strong recruitment (likely caused by optimal environmental conditions) masked the SR relationship (Duplisea and Grégoire, 2014). Also, for north-west Atlantic mackerel, a recent study by Plourde et al. (2015) demonstrated the influence of several environmental variables on the recruitment rate. Plourde et al. (2015) showed that the second (but not the first) axis of a PCA integrating multiple environmental factors had a significant positive effect on recruitment success, so we selected it as the most appropriate variable for our model, although the environmental coefficient was re-estimated within the model. High values in this time series signify low St. Lawrence River freshwater runoff, a cold surface layer and a high sea-ice index. The series was selected because of its availability over a long period and because it can be considered as a proxy for zooplankton variability (Plourde et al., 2015).

The following SR equation was used, assuming a bias corrected lognormal error (see Maunder and Deriso, 2003) and a controlling environmental effect:

$$f(SSB_{y-1}) = \frac{\alpha SSB_{y-1}}{1 + \beta SSB_{y-1}} exp(\gamma E_{y-1}(\varepsilon_{R,y} - 0.5\sigma_R^2)) \tag{3}$$

where α and β are two parameters of the BH relationship, γ is a coefficient scaling the environmental effect (E_y), $\varepsilon_{R,y}$ is the annual recruitment deviate for year y and $-0.5\sigma_R^2$ is the lognormal bias correction factor. $\varepsilon_{R,y}$ is assumed to be independent as for this case little indication of autocorrelation was present.

We used information from an egg survey (see Grégoire et al., 2013) to help estimate model parameters. Egg surveys provide estimates of annual SSB, with no partitioning by age. To link predicted stock abundance to survey SSB (I_y), the following observation equation was used:

$$I_y = \sum_{y=1}^{Y} qN_{a,y} exp(-Z_{a,y} t_s) W_{a,y} P_{a,y} \tag{4}$$

where q is the survey catchability coefficient and t_s the timing of the survey, expressed as a proportion of the year. The weight matrix provides weights-at-age at time-of-spawning.

The total model predicted catch in numbers ($C_{a,y}$) is assumed to follow the Baranov catch equation:

$$C_{a,y} = N_{a,y}\frac{F_{a,y}}{Z_{a,y}}[1 - \exp(-Z_{a,y})] \tag{5}$$

The available catch data are considered to be largely underestimated. Therefore, we linked estimated total catch and catch-at-age composition to the observed data independently (as did Cadigan, 2016a).

Censored total catch was modelled using the same statistical approach described by Cadigan (2016a) but with total annual predicted catch in mass instead of numbers ($C_y = \sum_{a=1}^{A} C_{a,y}W_{a,y}$), following Cadigan (2016b). Essentially, the likelihood of model catch estimates that fall between the established catch bounds is or approaches one, whereas outside of the bounds, values are given a likelihood of (or going to) zero (Fig. A.1 in Supplementary material). There is a smooth transition between both, which occurs faster as parameter σ_C becomes smaller. Here, $\sigma_C = 0.01$ (as in Cadigan 2016a) to ensure that bounds are sharp and $C_y \in (C_{oy}, U_y)$. Specifically, the censored log-likelihood for the total catches (summed over all ages) with a lognormal measurement error is given by

$$l(L_1, ..., L_Y; \theta) = \sum_{y=1}^{Y} log\left\{\phi_N\left[\frac{log(U_y/C_y)}{\sigma_C}\right] - \phi_N\left[\frac{log(L_y/C_y)}{\sigma_C}\right]\right\} \tag{6}$$

where L_y is the annually observed catch in mass (i.e., the lower limit), U_y the annual upper catch limit in mass and ϕ_N the cumulative distribution function for a N(0,1) random variable. There are thus no extra parameters needed to estimate catches. To improve model convergence we first ran the model by fitting total predicted catches to an intermediate catch level $(L_y + U_y)/2$ with measurement error σ_C, and used the resulting parameter estimates as starting values for the censored catch model run. Additional justification for this procedure is provided in (Cadigan, 2016a).

Catch-at-age composition is an ordinal ordered response, so we selected the continuation-ratio logit approach. Cadigan (2016a) recently extended the use of this transformation to catch-at-age models, and provided an in-depth description of the methodology. Following Cadigan (2016a), we replaced zero's in the data by 0.5, rescaled catches so that original total catches are the same, and adjusted the continuation-ratio logit measurement error variance (σ_{crl}^2) for different ages. The latter was required because when only one general σ_{crl}^2 was estimated, residuals were larger for the ages at the extremes, the model fit was significantly lower and for instance SSB values were believed to be less realistic. We estimated different σ_{crl}^2 for different ages (σ_{crl-A}^2 for a = 1, σ_{crl-B}^2 for a = 2, 8 and 9, σ_{crl-C}^2 for $2 < a < 8$), which is an improvement compared to the ad hoc adjustments used by Cadigan (2016a).

We calculated some common limit RP's: F_{msy}, SSB_{msy}, $F_{0.1}$, F_{max}, $F_{40\%}$ and F_{med} (e.g., Collie and Gislason, 2001; Gibson and Myers, 2004). We first calculated the spawning-numbers-per-recruit based on fishery selectivity (constant over time), M and process error for the last year (based on Eq. (1.2) and (1.3)). This was transformed to spawning-biomass-per-recruit (SPR) and yield-per-recruit (YPR) by taking the weight and proportion of mature fish by age of the final year. F_{msy} and SSB_{msy} are the fishing mortality rate and SSB that produce the maximum sustainable yield (MSY), and are the only two metrics that are based on the SR relationship (Sissenwine and Shepherd, 1987). Note that because an environmental effect was integrated in the SR relationship, it is included in the equilibrium SSB and recruitment equations used for MSY calculations (see Appendix B in Supplementary material). Based on a YPR analysis, F_{max} is the fishing mortality rate that maximises YPR and $F_{0.1}$ is the fishing mortality rate corresponding to 10% of the slope of the YPR curve at the origin (the gain in YPR when the stock is unfished, Gulland and Boerema, 1973). The $F_{40\%}$ RP (consistent with previous mackerel assessments; Duplisea and Grégoire, 2014) is the fishing mortality rate that reduces the SPR to 40% of its unfished level (Goodyear, 1977; Shepherd, 1982). Lastly, F_{med} (Sissenwine and Shepherd, 1987) is based on the ratio of SSB/R (R being recruitment) and corresponds to the fishing mortality rate associated with the median line of the SSB/R relation (i.e., there is 50% chance for recruitment to be greater/lesser than the value of the 50% line). These RPs were estimated internally within the model so that we can evaluate their uncertainty. The SPR and YPR curves were based on the fishing selectivity

The reliability of the model was verified by performing 400 simulations on randomly generated pseudo-data (see Deroba et al., 2015). These were computed by randomly simulating the survey index and catch-at-age matrix, based on the base model's predicted values and standard deviations, using the associated error distributions. The first year values for logN and F_y were fixed because these variables are random variables. This procedure was also used by Nielsen and Berg (2014) and Cadigan (2016a). Censored models could be compared in terms of negative log-likelihood (*nll*) and AIC ($AIC = 2*(nll*n_p)$, with n_p being the number of estimated fixed effect parameters).

2.2. Data

The period 1968–2013 was analysed with the typical data for age-structured models (age-disaggregated catch, weight and proportion mature, total reported landings, an annual SSB index), available for Canadian mackerel from DFO (Department of Fisheries and Oceans). M was fixed at $0.2 \mathrm{yr}^{-1}$, as in previous assessments (DFO, 2012).

Three catch scenarios were explored; 1) no censoring, where true catch is assumed to be close to reported numbers, 2) intuitive censoring, were the upper catch limit (U_y) is arbitrarily set as 1.75 times the reported catch, and 3) data-informed censoring, were the upper catch limit is time-varying and calculated as the total of estimated maximal bait use, recreational fishing and discarding per region. The reported catch was used as the lower catch limit for scenarios 2 and 3.

For scenario 3, estimates were made for the maximal mackerel catch weight that might have been used as bait in the crab and lobster fisheries over the last years (see Appendix A in Supplementary material). This was done for each eastern Canadian management region. Landings of other fisheries, such as tuna, were more than five times smaller than for crab and lobster during the last two decades, and were therefore not considered. We based our estimates of recreational fishing on the only information available, i.e., the quinquennial survey (1990–2010) of recreational fishing in Canada (DFO, 2015). Missing estimates for some survey years were filled with the highest value in the series, and for years in-between we made linear extrapolations. This survey only questions recreational fishers with a fishing license; however, most recreational fishers do not have a license, so we multiplied all estimates by an assumed ratio of 6 between licensed and unlicensed recreational fishers. Finally, we assumed that the discarded mackerel biomass was at most 2% of the reported landings, as a report from the Magdalen Islands calculated this to be less than 1% (J. Aucoin, pers. Comm.).

To investigate the effect of lower or higher catch underreporting, a sensitivity analysis was performed on both censoring scenarios (scenarios 2 and 3) by multiplying the possible catch range ($\Delta C_y = U_y - L_y$) by a sequence from 0.5 to 1.5, with steps of 0.05 (denoted by ΔC_{rel}, the relative catch range).

The model code is available online (https://github.com/elisvb/Statistical-catch-at-age-model).

3. Results

All model runs converged, gradients were < 0.001 and there were no important retrospective patterns (Fig. A.2 in Supplementary material). Residual plots showed that the models fitted the data adequately (Fig. A.3 in Supplementary material). Three outliers (age-1 for 1972, 1978 and 1980) were present in the catch-at-age residuals (Fig. A.3 in Supplementary material), which are believed to be a sampling artefact rather than a modelling problem. Catch-at-age residuals also showed some degree of autocorrelation, resulting in an underestimation of the standard error (but no biased estimates) and potentially a change in the weight of the age composition component of the objective function. Self-test simulations of the data-informed censored model, 93% of which converged, were not troubling, but underestimated SSB before 1995, when the highest levels were reached (Fig. A.4 in Supplementary material). This might in part be caused by the relatively high observation and process error (Table 2), which should be kept in mind when interpreting results. Most general patterns in the state variables were similar to previous stock assessments based on approximately the same data and will thus not be discussed in detail here.

As expected, predicted catch was higher for the censored models, as the model was given more flexibility and increased catch estimates helped the model fit. Moreover, there was a visible difference in predicted catch between the two censoring scenarios (Fig. 1). The intuitive case – which on average had the highest upper limit – resulted in generally higher estimates of catch, and because of the extra flexibility a lower AIC value (1162 versus 1174). During certain years (e.g. 2002–2003), catch estimated by the intuitive scenario was even significantly higher than the data-informed upper limit determined for the alternative scenario. The data-informed case had an upper limit ranging between 1.26 and 2 times the reported catches and ΔC_y (the range of possible catch values) was not related to the reported landings (L_y) (i.e., higher catches did not necessarily result in higher catch underreporting). The general pattern of catch underestimation was the same for both scenarios, with some distinguishable periods. For example, between 1977 and 1995 estimated catch was always closer to the upper catch limit, indicating that the proportion of unreported catch might have been relatively high in this period (Fig. 1).

Table 2
Estimates (Est.) and standard deviations (sd) of parameters for three model formulations; I) a censored model with a data informed upper catch limit (AIC = 1174, nll = 566), II) a censored model with an intuitively determined upper catch limit (AIC = 1162, nll = 560) and III) an uncensored model assuming reported catch to be the true catch (AIC = 1104, nll = 530). The AIC and nll of the uncensored and censored model cannot be compared.

	Data informed		Intuitive		Uncensored	
Para.	Est.	sd	Est.	sd	Est.	sd
σ_s^2	0.57	0.09	0.68	0.1	0.58	0.11
$\sigma_{F_y}^2$	0.36	0.05	0.31	0.05	0.21	0.04
σ_R^2	0.84	0.16	0.83	0.11	0.78	0.12
q	0.57	0.13	0.73	0.13	1.16	0.21
$\log(\alpha)$	0.74	0.96	0.07	0.68	0.93	1.28
$\log(\beta)$	−17.91	1.28	−18.77	1.01	−17.15	1.61
γ	0.27	0.12	0.21	0.11	0.23	0.11
σ_δ^2	0.31	0.05	0.3	0.04	0.33	0.04
φ_a	0.66	0.3	0.54	0.3	0.2	0.4
φ_y	0.08	0.43	0.07	0.29	−0.26	0.43

Although all three scenarios resulted in different catch estimates, the patterns of average fishing mortality (as well as F_y and F_a) and process error were generally very similar (Fig. 2). There were greater differences between the uncensored and censored models, however, in estimates of recruitment and SSB. Censoring the catch leads to a pronounced increase in estimated SSB, in particular before 2000, when SSB was significantly higher. In contrast, the difference between both censoring scenarios was generally small. Despite that the intuitive model resulted on average in higher catch estimates than the data-informed model, SSB was not consequently greater because both models differed in the age dependent processes. For example, selectivity towards the oldest fish was greater in the intuitive model, so that SSB was relatively lower when these fish were more prevalent (i.e., before 1995). Because of differences in SSB and catch estimates between censored and uncensored scenarios, the uncensored model also had a somewhat higher estimate of peak exploitation rate (maximum value of the ratio catch/SSB, 72% for the uncensored case and 68% for both censored scenarios). Other parameter estimates for the three scenarios can be found in Table 2.

Because U_y was based on a rough approximation for both the data-informed and intuitive censoring scenarios, we also performed a sensitivity analysis. For the two choices of censoring, the objective function decreased in a smooth exponential manner over the possible catch range ($0.5 < \Delta C_{rel} < 1.5$). Estimated catch, averaged over all years, increased linearly with increasing catch underreporting, but more steeply for the intuitive scenario because the initial unobserved catch was larger (Fig. 3). Process error fluctuated significantly with increasing ΔC_{rel}, i.e., the average value (over years and ages) could change from about −0.10 to −0.01. The sensitivity pattern of fishing mortality showed a similar trend, with averaged values spanning a wider range (0.53–0.68). Although F and process error in the

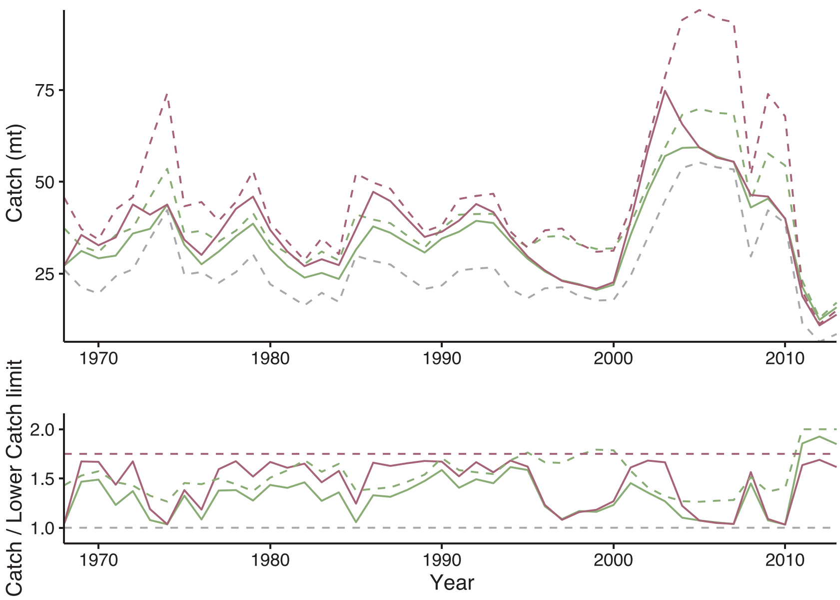

Fig. 1. Catch estimations (solid lines) and censoring limits (dashed lines) of the two censoring scenarios (green: data-informed, red: intuitive). The lower catch limit (or reported catch) is coloured grey as it is the same for both scenarios. The upper panel shows the absolute values and the lower panel shows values standardised by the lower limit. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

interannual transitions of abundance at age appeared to some degree confounded, they were not entirely correlated and process error was well determined (small variance, see Table 2), included differently from F (in Eq. (1) but not in Eq. (4)) and essential to obtain a proper model fit (based on residuals and model output). There was no clear relationship between ΔC_{rel} and most other model parameters, and these relationships differed between censoring scenarios (Fig. 3). Parameter estimates of both censoring scenarios were similar in terms of their sensitivity to the upper catch limit.

Different upper catch limits resulted in different RP values (RPs, Fig. 4). The two censoring scenarios yielded different, sometimes opposite, relationships with ΔC_{rel}. Some RPs were more sensitive to the catch reporting rate than others, i.e., F_{med} and especially the MSY-based RPs were more affected by changes in the upper catch limit, in contrast to $F_{0.1}$, $F_{40\%}$ and F_{max}. Note that the inclusion of an environmental factor in the SR relationship and the calculation of F_{msy} and SSB_{msy} influenced only their scale but not the relationship between the two RPs and ΔC_{rel} (i.e., only values on the left y-axis of Fig. 4 change) as for all ΔC_{rel} the reference point is multiplied by a nearly identical factor (based on the environmental value of the last year and the estimated coefficient). The uncensored scenario did not provide estimates consistently higher or lower than both censoring scenarios (except for $F_{0.1}$). However, the data-informed censoring scenario (theoretically the best model) always produced lower RPs than the uncensored one, except for SSB_{msy} and F_{med}. F_{med} is in part based on the inverse SPR, in contrast to the other fishing mortality RPs. Standard deviations around RPs did not differ significantly between censoring and or upper limit scenarios and were either extremely small or high (for $F_{0.1}$ and SSB_{msy}). When uncertainty was extremely high, it generally exceeding the discussed dissimilarities. Based on time series of F/F_{msy} and SSB/SSB_{msy} (Kobe plot, Fig. 5) depicting stock status over time (for $\Delta C_{rel} = 1$), all three scenarios would result in the same conclusion about stock status and trajectory. The error associated with the estimates is relatively small.

4. Discussion

The censored catch approach can be a useful tool when catch is known to be highly biased. In this application for Canadian Atlantic mackerel, we demonstrated how censoring the catch and the choice of an upper catch limit and hence catch underreporting influenced parameter estimates and reference points (RPs). Censoring the catch led to

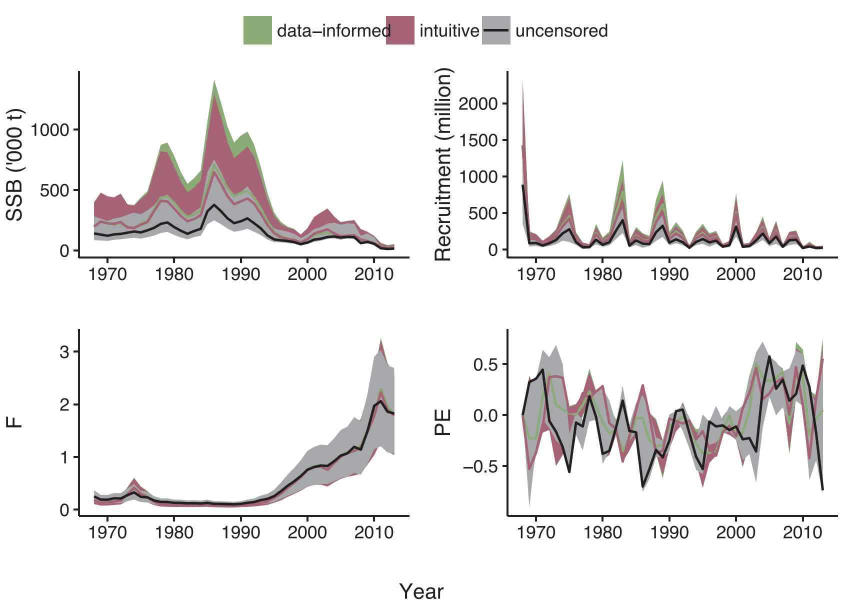

Fig. 2. Comparison of parameter estimates (SSB, recruitment, fishing mortality (F, averaged over ages 1–10) and process error (PE)) between the uncensored and censored models (data informed and intuitive). For the upper plots (SSB and recruitment) the shaded areas indicate the standard deviation of the estimates. Shaded areas in the lower plots (F and PE) indicate inter-age variability, or the 50% central region of functional boxplots.

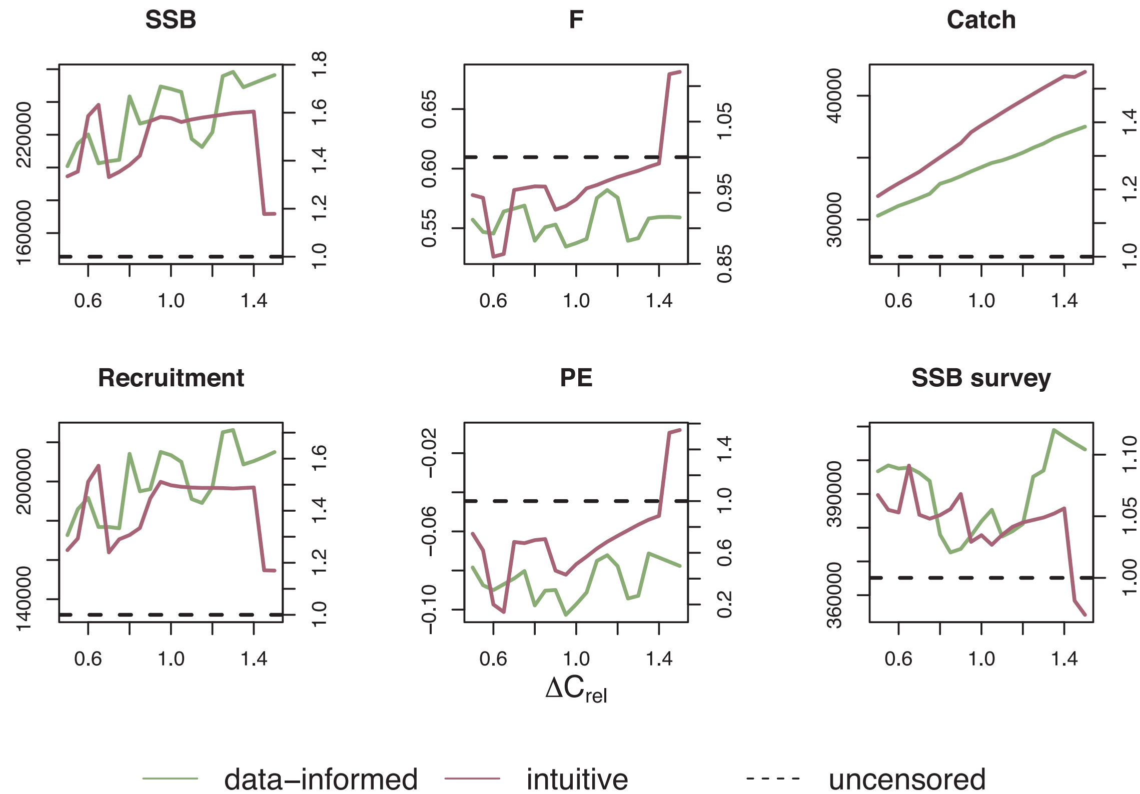

Fig. 3. Values of six parameters (SSB, F averaged over ages 1–10, catch, recruitment, PE = Process Error and SSB survey = the estimated survey index) averaged over all years and if applicable all ages in function of relative underreported catch (ΔC_{rel}). The dashed line indicates the value for the uncensored model. The left y-axis denotes absolute values (masses in tonnes and recruitment in thousands) and the right y-axis is on a relative scale, 1 being the value from the uncensored model.

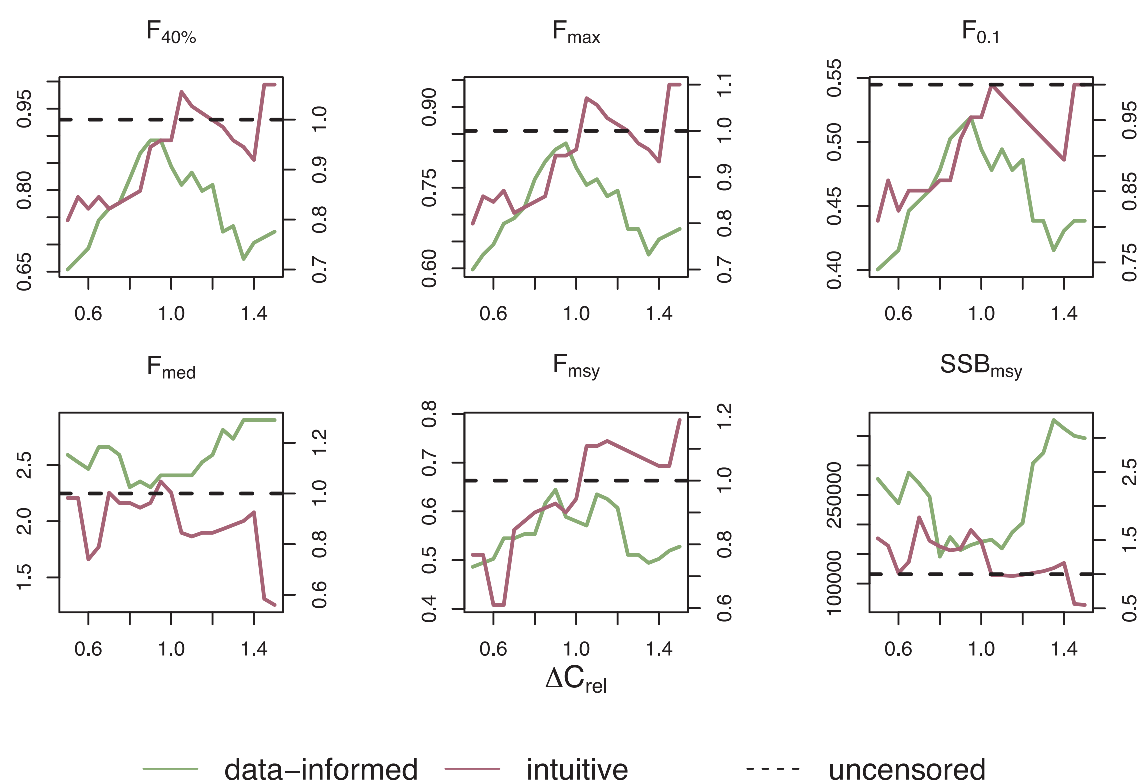

Fig. 4. Reference points in function of relative underreported catch (ΔC_{rel}). The dashed line indicates the value for the uncensored model. The left y-axis denotes absolute values (SSB_{msy} in tonnes) and the right y-axis is on a relative scale, 1 being the value from the uncensored model.

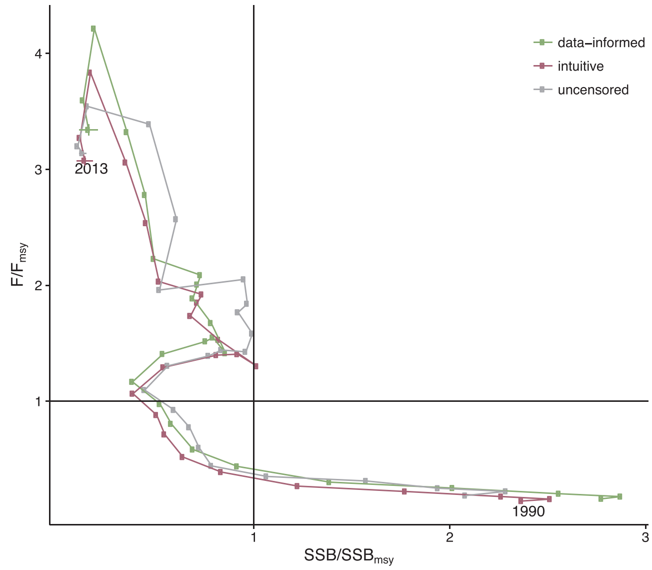

Fig. 5. Trajectories of SSB/SSB_{msy} and F/F_{msy} over time (1990–2013, previous years are more or less static) of Canadian Atlantic mackerel as estimated by the presented model framework, whereby catch is uncensored or censored (data informed or intuitive). For the last year, standard deviations are indicated.

more realistic estimates of SSB and other parameters, but once censored, the relationship between catch underreporting (ΔC) and RPs and parameters was not straightforward. Nevertheless, some RPs were more sensitive to catch underreporting than others. Also, when the model's statistical error (i.e., observed and process error) is relatively high, its sensitivity to the upper catch limit can be significant, and there is a benefit to informing the upper catch limit based on actual data.

4.1. Uncensored vs censored catch and impact on biomass and reference point estimates

The newly created model framework that includes censored catch was an improvement over the previous approach (Grégoire and Beaudin, 2014). The censored approach overcame the most notable issue of the last assessment which showed that estimated SSB in recent years was only slightly larger than reported catch. As reported catch was greatly underestimated, the assessment unrealistically predicted SSB to be around or even lower than the total annual catches. This somewhat undermined the credibility of subsequent advice. The censored catch approach developed solved this inconsistency.

The censored catch model led to an increase in estimated catch, SSB and SSB_{msy}. The increase in biomass and biomass RPs with higher estimates of catch is a generally observed phenomenon of fisheries models (e.g., Groeneveld, 2003; Zeller et al., 2008). When compared to the uncensored model, the data-informed censored scenario produced lower fishing mortality RPs (except for F_{med}) and would thus result in more restrictive management advice. However, the sensitivity analyses on the upper catch limit indicated that when this upper bound is set intuitively very high, some fishing mortality RPs ($F_{40\%}$ F_{max} and F_{msy}) might be larger than in the uncensored case. Nonetheless, a censored catch approach for Canadian Atlantic mackerel should lead to improved catch advice that is more risk averse to overexploitation because of generally lower F RPs as well as greater estimates for biomass RPs and past and current biomass. This is not without reservation however, as arbitrarily setting upper limits for catch censoring can actually increase risk.

4.2. Setting the upper catch limit

Previous work set the upper catch bound intuitively as a constant multiplier of reported catch (possibly differing across distinctive time periods; Hammond and Trenkel 2005; Bousquet et al., 2010; Cadigan 2016a). Bousquet et al. (2010) found that for the southern Gulf of St. Lawrence cod stock, results were nearly insensitive to subjective boundaries. Here our exploration of upper catch limit types (intuitive vs. data-informed) and sensitivity showed the importance of correctly identifying these bounds, especially with large uncertainties in data (observation error) or variability in biological processes (process error). A state-space model with both observation and process errors needs to estimate how to partition these uncertainties within the model. The censored catch approach adds an extra source of flexibility and if the upper limit is only defined intuitively, it can possibly give the model too much leeway for partitioning the uncertainty. This is important because not all uncertainties have an equal effect when it comes to estimating RPs, projections and stock advice. Some authors showed that process error in surplus production models tends to decrease biomass RPs (Bordet and Rivest, 2014; Bousquet et al., 2008), while catch censoring tended to increase them in this study. For stocks such as Canadian mackerel where there are important knowledge gaps in biological understanding (process), relatively short and few survey inputs (observation) and time varying under-reporting in catch (censoring), it is best to provide as much information as possible on censoring levels even if that information is sparse and semi-quantitative.

4.3. Model sensitivity to unreported catch

Little is known about the effect of unobserved catch on integrated catch-at-age models and the resulting RPs, and the censored catch method is well-suited for this. This approach has the advantage that it truly investigates the effect of uncertainty in catch reporting rates (the range of possible catches) and not just catch bias (or wrongfully reported catch). Catch bias can be investigated relatively easily using sensitivity runs exploring alternative catch scenarios. For instance, Rudd and Branch (2016) investigated how different scenarios of misreporting impacted RPs and SSB, based on a Pella-Thomlinson surplus production model (age-aggregated). Like us, they found that underreporting resulted in an underestimation of the stock size and a change in MSY RPs. Their sensitivity analysis on uncensored catch indicated that changes in the reporting rate over time caused parameter estimates to vary in an unstraightforward manner. Our study with an age-disaggregated state-space model showed less clear relationships than the catch scenarios investigated by Rudd and Branch (2016); nevertheless, generic conclusions were still possible and should be applicable to the presently prevailing age-based assessment approaches. For instance, we found that some RPs are more stable ($F_{0.1}$, F_{max} and $F_{40\%}$) than others (F_{med}, SSB_{msy} and F_{msy}), for which our findings agree with previous studies that suggested the use of F_{msy} to be safer than SSB_{msy} (Cadigan, 2013; ICES, 2011). F_{max} was particularly stable in this study because the yield per recruit curve had a clear maximum, in contrast to other studies in which the top of the curve is almost horizontal, so that minor input changes have a large effect on the position of peak yield (e.g., Cadigan and Wang, 2016).

4.4. Underlying mechanisms

The relationship between underreported catch and the model output (parameters and RPs) was difficult to separate from the large observation and process errors associated with the model. Process error is known to influence model performance (see e.g., Punt, 2003) and relatively large statistical errors make the model more sensitive to input changes. Process error has already been shown to be the main source of variability for certain RPs (Cadigan, 2012). Specifically, RPs were estimated based on spawner- and yield-per-recruit curves, which were mostly influenced by process error rather than mortality (M was fixed and F was less sensitive to ΔC_{rel} than process error). Thus, the relatively large process error estimated by our mackerel model may explain why parameter estimates and RPs were so sensitive to the upper limit, contrasting with results obtained by Bousquet et al. (2010) and Cadigan (2016a), who obtained more comparable parameter outputs when selecting different upper limits on catch censoring.

The relatively high process error was likely caused by the data input (survey index and natural mortality values) and unmodelled processes. The main stock index input here was an annual SSB index from an egg survey that fluctuates considerably from year to year and was unavailable for about 40% of the period (19 out of 46 years). Specifically, before 1996 reported landings were less than 6% of the SSB index, whereas in 2010 the index value was of the same magnitude as reported catch. During one of the previous assessments, which also had high parameter variance (Grégoire and Beaudin, 2014), index data prior to 1996 were removed because of lack of fit. Both the quantity and quality of this data might contribute to the statistical error. Moreover, fishing selectivity was modelled as a single parameter vector that is constant over time, whereas reality is much more complex as there are important interannual, fleet and spatial differences. Selectivity of bait and recreational fishing is unlikely to be identical, but catch-at-age data reflected only the catch structure of reported and thus mostly commercial catch. Similarly, process error and its variance might be high as a result of the assumed natural mortality rate (*M*), which was kept fixed at 0.2 because better data was not available, despite evidence based on ecosystem modelling (Savenkoff et al., 2005) and time-varying mortality indices (Grégoire and McQuinn, 2014) that fluctuations occurred over time and age classes. As patterns in process error do not clearly correspond to the variations in M previously reported (Grégoire and McQuinn, 2014; Savenkoff et al., 2005), additional unaccounted for processes are likely responsible. Indeed, western-Atlantic mackerel is a transboundary stock, which during winter migrates as far south as North Carolina (USA). Both components should possibly be considered together, as has been done in past USA stock assessments (TRAC, 2010). This suggests that Canadian and USA data should be combined and that the model should be adapted to acknowledge the seasonal/spatial components (e.g., Methot and Wetzel, 2013), which would further reduce the risk of providing poor management advice by accounting for such population structure (Ying et al., 2011).

The catch censoring approach for Canadian Atlantic mackerel was advantageous as it eliminated some of the concerns with the previous model and likely resulted in more trustworthy estimates of SSB and consequently most RPs. The approach showed that some RPs are preferable to others in terms of sensitivity to catch reporting issues. We highlighted that in a data and biological knowledge situation like Canadian Atlantic mackerel, it is important to inform the upper catch limit as much as possible, even with semi-quantitative or qualitative data. This does require more work and deviates outside the standard software available for age-structured assessment; however, for a stock where previous models had important issues and where catch was thought to be importantly underestimated, a custom-built and flexible censored catch model is crucial for sound and realistic management advice.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fishres.2017.05.015.

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