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ARTICLE

A state-space stock assessment model for northern cod, including under-reported catches and variable natural mortality rates[1]

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Abstract: A state-space assessment model for the northern cod (*Gadus morhua*) stock off southern Labrador and eastern Newfoundland is developed here. The model utilizes information from offshore trawl surveys, inshore acoustic surveys, fishery catch age compositions, partial fishery landings, and tagging. This is done using an approach that avoids the use of subjective data-weighting. Estimates of fishing mortality rates (*F*) are usually conditional on assumptions about natural mortality rates (*M*) in stock assessment models. However, by integrating much of the information on northern cod, it is possible to estimate *F* and *M* separately. It is also possible to estimate a change in the offshore survey catchability by including inshore acoustic biomass estimates. The proposed model also accounts for biased total catch statistics, which is a common problem in stock assessments. The main goal of the model is to provide realistic projections of the impacts of various levels of future fishery catches on the recovery of this stock. The projections incorporate uncertainty about *M* and catch. This is vital information for successful future fisheries. The model has been developed for the specific data sources available for northern cod, but it could be adapted to other stocks with similar data sources.

Résumé : Un modèle d'espaces d'états pour l'évaluation du stock de morues (*Gadus morhua*) au large du Labrador méridional et de l'est de Terre-Neuve est développé. Ce modèle utilise de l'information provenant de levés au chalut hauturier, de levés acoustiques côtiers, des compositions par âge des prises, des débarquements partiels et du marquage. Pour ce faire, une approche qui évite l'utilisation de pondération subjective des données est utilisée. Les estimations des taux de mortalité par pêche (*F*) sont généralement conditionnées par des hypothèses concernant les taux de mortalité naturelle (*M*) dans les modèles d'évaluation des stocks. En intégrant une bonne partie des données sur la morue, il est toutefois possible d'estimer *F* et *M* séparément. Il est également possible d'estimer les variations de la capturabilité obtenue des levés hauturiers en incluant des estimations de la biomasse basées sur les données des levés acoustiques côtiers. Le modèle proposé tient également compte du biais des statistiques sur les prises totales, un problème répandu dans les évaluations des stocks. Le principal objectif du modèle est de produire des projections réalistes des impacts de différents degrés de prises futures sur le rétablissement de ce stock. Les projections intègrent l'incertitude associée à *M* et aux prises. Cette information est d'importance vitale pour les succès des pêches futures. Bien que le modèle ait été développé pour les sources de données disponibles sur la morue, il peut être adapté à d'autres stocks pour lesquels des sources de données semblables sont également disponibles. [Traduit par la Rédaction]

Introduction

A challenge for fisheries management of the Atlantic cod (*Gadus morhua*) stock off southern Labrador and eastern Newfoundland in Northwest Atlantic Fisheries Organization (NAFO) Divisions 2J and 3KL (i.e., northern cod) is the lack of a stock assessment model that can be used to evaluate the impacts of future fishing. There are several reasons for this. The size and spatial distribution of the stock has varied greatly over the past few decades (e.g., Lilly 2008). A moratorium on commercial fishing was declared in 1992, and the stock is presently still at a low level relative to the 1980s. Fisheries were reopened in the inshore in 2006 and continued during 2007–2014. These fisheries are difficult to monitor because there are many participants and many landings sites. For example, 4306 commercial groundfish licenses were issued by Fisheries and Oceans Canada (DFO) for Newfoundland and Labrador in 2010. An estimated 60 352 people participated in the recreational fishery in 2007 (DFO 2007). However, there are no direct estimates of recreational landings for 2009–2012, and estimates in other years are considered to be uncertain (DFO 2013). In addition, commercial fishers often report that recent landings for northern cod are underestimated (DFO 2011). This was also considered to be a problem historically for this stock (e.g., Hutchings and Myers 1995; Halliday and Pinhorn 1996; Rose 2007), although the magnitude of the bias has not been quantified. Information on these fishery catches have been considered too unreliable to include in stock assessment models. Another problem is the level of natural mortality rate (*M*). This may have increased substantially around the time of the moratorium in 1992, although the level and duration is uncertain (Lilly 2008).

Standard assessment models for northern cod fit survey data very poorly (e.g., Shelton and Lilly 2000). A survey-based model was used during 2011–2013 (Cadigan 2013*a*). However, this model cannot be used directly to provide projections for catch advice without additional assumptions about natural mortality rates. It also does not utilize age-sampling information from commercial

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and recreational fisheries, which may be reliable even if reported landings are not. In this paper, the "censored-catch" approach of Hammond and Trenkel (2005) and Bousquet et al (2010) is extended to account for under-reported catches. A censored observation is one for which the exact value is unknown but about which there is partial information, such as a lower bound (right censoring) or an interval known to cover the exact value (interval censoring). Age-composition estimates from commercial and recreational fisheries are considered to be uncertain but not biased. The model is extended into a state-space framework by including process errors in the population dynamics model. State-space models have become the favored approach in modeling time-varying ecological phenomena such as population dynamics (e.g., Schnute 1994; Gudmundsson 1994; Aanes et al. 2007; Maunder and Deriso 2011; Nielsen and Berg 2014), animal movement (Patterson et al. 2008), and animal behavior (Morales et al. 2004). I include uncertainty about M in the process error component of the model. Extensive northern cod tagging information (see Brattey and Healey 2003, 2007; Brattey and Cadigan 2003; Myers et al. 1996) is included in the model to provide information about both fishing mortality rates (F) and M. The model I propose has been developed for the specific data sources available for northern cod, but it could be adapted to other stocks with similar data sources.

Materials and methods

Model notation and parameters are described in the text and also Table 1.

The state-space model for northern cod is based on a common cohort model in which the abundance at age a in year y (i.e., $N_{a,y}$) is equal to that cohort abundance in the previous year times the survival rate, which is expressed in terms of the total mortality rate (Z):

$$N_{a,y} = N_{a-1,y-1} \exp(-Z_{a-1,y-1}) \quad (1)$$

The numbers-at-age in the first year are treated as unknown and free parameters to estimate. The recruitments and Z values are estimated as random effects, which is described later. In the northern cod application, a = 2, …, 12, and y = 1983, …, 2012; however, for convenience I will usually refer to model ages a = 1, …, A and years y = 1, …, Y. For example, model age 1 corresponds to stock age 2, etc. The rationale for the selection of ages and years to model is described at the end of this section. The total mortality rate is $Z_{a,y} = F_{a,y} + M_{a,y}$, where $F_{a,y} > 0$ and $M_{a,y} > 0$ and are unknown quantities to estimate. The Baranov catch equation is used to model catch as a function of N, F, and Z:

$$C_{a,y} = N_{a,y}[1 - \exp(-Z_{a,y})]F_{a,y}/Z_{a,y} \quad (2)$$

State-space models usually involve observations equations and errors for data used to estimate model parameters. They also have process error components to account for the approximations that most models involve. Including process error is typical of contemporary stock assessment models (Maunder and Piner 2014). Both Gudmundsson and Gunnlaugsson (2012) and Nielsen and Berg (2014) assumed multiplicative lognormal process errors (δ) in the state eq. 1; that is, $\log(N_{a,y}) = \log(N_{a-1,y-1}) - F_{a-1,y-1} - M_{a-1,y-1} + \delta_{a,y}$. In this equation, full knowledge of F and M does not provide full knowledge of cohort survival from one year to the next, which is consistent with interpreting Z as an individual death rate rather than a demographic factor. Brinch et al. (2011) used somewhat different models than eqs. 1 and 2 but also included process error in their cohort model equation. Gudmundsson and Gunnlaugsson (2012) suggested that δ be interpreted as "irregular natural mortality", which I interpret as deviations from assumed values for M. They also suggested that δ could represent migrations. In my state-space model, I include only process error in M, and additional considerations are given in the Discussion. I model M as autocorrelated random variables:

$$\log(M_{a,y}) = \log(m_a) + \delta_{a,y} \quad (3)$$

A similar approach has been used for cod in the southern Gulf of St. Lawrence (Swain 2011*a*, 2011*b*) and discussed in Millar and Meyer (2000). The m_a values are fixed at 0.5 for a = 1 (i.e., stock age 2), m_a = 0.3 for a = 2, and m_a = 0.2 for a > 2. These values were chosen to be broadly consistent with previous information about age patterns in M for northern cod. I did not include annual changes in M in m_a; I prefer to model annual variations via δ so that this source of variability can also be included in stock projections. This is considered further in the Discussion. The M process errors ($\delta_{a,y}$) are assumed to have a normal distribution with zero mean but autocorrelated over ages and years because M should be more similar for fish that are close together in age and time. These errors are assumed to have a stationary distribution derived from a lag 1 autoregressive process in both age and year so that

Table 1. Definitions, model notation, and parameters.

Z, F, M	Total, fishing, and natural mortality rates
$\tilde{Z}$, $\tilde{F}$, $\tilde{M}$	Stock size weighted mean Z, F, and M
N, N_S	Total and Smith Sound stock abundance
$N_{+,a}$	Total stock abundance at ages a, $a+1$, …, A
D	Proportion of stock in Smith Sound: $D = N_S/N$
N_x	Number of tagged fish from experiment x
Z_x, F_x	Total and fishing mortality rates for experiment x
C, C_o, U	Model and observed fishery catch and upper bound on catch
C_x, R_x	Model tag catch and reported catch from experiment x
I	Survey index
P	Compositional data proportion
X	Inverse logistic transformation of P
$\boldsymbol{\theta}$, $\boldsymbol{\Psi}$	Vectors of all fixed- and random-effects parameters
δ	Cohort model process error
σ_δ^2	Process error variance parameter
$\varphi_{\delta,\text{age}}$, $\varphi_{\delta,\text{year}}$	Age and year correlation in process errors
σ_F^2	F variance parameter
$\varphi_{F,\text{age}}$, $\varphi_{F,\text{year}}$	Age and year correlation in F
σ_D^2	Variance parameter D
$\varphi_{D,\text{age}}$, $\varphi_{D,\text{year}}$	Age and year correlation in D
r_1, r_2	Mean log-recruitment during (1) 1983–1992 and (2) 1993–2012
σ_r^2	Variance of log-recruitment
σ_C^2	Catch measurement error
σ_P^2	Catch age composition measurement error
σ_I^2	Survey measurement error
σ_{fx}^2	Variance of tagging F deviation from stock F
Φ_N	Cumulative distribution function for a standard normal random variable
φ_N	Probability distribution function for a standard normal random variable
π_b	$= P_b/(P_b + \ldots + P_B)$
γ_y	Annual tag loss rate
λ_{oy}	Externally estimated tag reporting rates for year y = 1996, …, 2006
λ_x	Reporting rate parameter for early tagging experiments
q	Survey index catchability parameter
ρ_a	Age pattern in q: $q_a = q_{\text{full}}\rho_a$

$$(4)\qquad \mathrm{Cov}(\delta_{a,y}, \delta_{a-j,y-k}) = \frac{\sigma_\delta^2 \varphi_{\delta,\mathrm{age}}^j \varphi_{\delta,\mathrm{year}}^k}{\left(1 - \varphi_{\delta,\mathrm{age}}^2\right)\left(1 - \varphi_{\delta,\mathrm{year}}^2\right)},$$
$$\mathrm{Corr}(\delta_{a,y}, \delta_{a-j,y-k}) = \varphi_{\delta,\mathrm{age}}^j \varphi_{\delta,\mathrm{year}}^k$$

This is a simple choice for a covariance model that can account for the types of dependencies in processes errors that one might expect. Note that "age" and "year" in eq. 4 distinguish autocorrelation in the age and year dimension. They do not index age and year; I use a and y for this purpose. Additional details on this age × year time-series process are provided in Appendix A. There is likely high correlation in the M process errors at older ages. To simplify the model, $\delta_{a,y}$ were coupled at stock ages 8+; that is, each year $\delta_{8,y} = \ldots = \delta_{12,y}$. This assumption also helps identify the σ_δ^2 parameter from other variance parameters for F and data sources because it removes a source of variation (i.e., change in M) at these older ages. The process errors in the first year are also partially confounded with the initial abundance parameters, which are freely estimated. I constrained these errors to all equal zero. Swain (2011*a*, 2011*b*) did the same thing in his M random walk model.

Fishing mortalities are modelled similar to the M process errors, with

$$(5)\qquad \mathrm{Cov}[\log(F_{a,y}), \log(F_{a-j,y-k})] = \frac{\sigma_F^2 \varphi_{F,\mathrm{age}}^j \varphi_{F,\mathrm{year}}^k}{\left(1 - \varphi_{F,\mathrm{age}}^2\right)\left(1 - \varphi_{F,\mathrm{year}}^2\right)}$$

I fixed $\varphi_{F,\mathrm{year}} = 0.9$ to make the process more similar to a random walk, consistent with the recommendation of Maunder and Piner (2014). Gudmundsson and Gunnlaugsson (2012) and Nielsen and Berg (2014) also included correlated random walk processes for F. The within-year correlation of F ($\varphi_{\delta,\mathrm{age}}$) was estimated for stock ages 5–12, but it was fixed at zero for ages 2–4. Northern cod at these ages are small, generally weighing much less than 0.5 kg (see table 2 in Cadigan 2013*b*), and these fish are not targeted by commercial fisheries, while age 5 (~1 kg) is often considered to be a targeted size. Hence, I do not expect the same correlation between F at ages 2–4 compared with age 5+. No likelihood function was used for $F_{1-3,1}$ (model ages) similar to Nielsen and Berg (2014), although I did specify a likelihood function for $F_{4-11,1}$ to account for autocorrelation at these ages, which is different from Nielsen and Berg (2014). The F model component explicitly involves just two parameters, σ_F^2 and $\varphi_{\delta,\mathrm{age}}$, but $F_{1-3,1}$ are also like free parameters.

The recruitments, $N_{1,1}, \ldots N_{1,Y}$, are also treated as uncorrelated lognormal random variables:

$$(6)\qquad \log(N_{1,y}) \sim \mathrm{N}\left(r_p, \sigma_r^2\right), \quad r_p = \begin{cases} r_1, & y \le 1992 \\ r_2, & y > 1992 \end{cases}$$

The two mean recruitment parameters (r_1, r_2) were chosen to reflect the large differences in stock size before and after 1992 (e.g., Lilly 2008). The variance (σ_r^2) was fixed at 1.0, which is a large value; hence, $N_{1,y}$ are almost freely predicted except for the very recent recruitments that have little data to inform estimation. However, I assess the impact of alternative choices for σ_r^2.

Model likelihood equations

Catch

Little information has been published by DFO on the methodologies they use to estimate catch, and the precision of their estimates has not been quantified. However, as noted in the Introduction, there are reasons to suspect that there has been underreporting of commercial landings and that recreational catches are difficult to estimate reliably. DFO nominally assumes these statistics are census values with some error. I assume the catch measurement process involves some error (i.e., not a perfect census) and that not all catches are included so that the DFO catch statistics provide a stochastic lower bound on true catches, depending on the magnitude of measurement error (σ_C^2). Similar to Bousquet et al. (2010), I also assume there is an upper bound on true catches that is some multiple of reported catches. I set the upper bound to 2× reported catch at ages 2–12 (e.g., Hammond and Trenkel 2005) for 1993–2012 but 1.5× during 1983–1992 when reported catches were much higher and the fraction of unreported catch may be lower. This is based on the assumption that the amount of cod that could be marketed and sold illegally is roughly fixed over time and probably a much lower fraction of reported catches prior to 1992 compared with since then. However, discarding of fish at sea and on land may have been higher before 1992. The choice of upper bounds is subjective, and I examine the sensitivity of the model to a different choice for the upper bounds.

Let C_y denote the total model predicted catch obtained by summing eq. 2 over stock ages 2–12. Let C_{oy} denote the observed catch and let U_y denote the upper bound on catches. The measurement error is assumed to be lognormal, and the censored log-likelihood for the observed catch time series is

$$(7)\qquad l(C_{o1}, \ldots, C_{oY}|\boldsymbol{\theta}) = \sum\nolimits_{y=1}^{Y} \log\left\{ \Phi_N\left[\frac{\log(U_Y/C_Y)}{\sigma_C}\right] - \Phi_N\left[\frac{\log(C_{oY}/C_Y)}{\sigma_C}\right]\right\}$$

where Φ_N is the cumulative distribution function (CDF) for a N(0,1) random variable. There is no information to estimate σ_C. I simply fix it at a small value, $\sigma_C = 0.01$, to make sure that $C_y \in (C_{oy}, U_y)$ for most years and can otherwise exceed the bounds only by a small amount. In this case the likelihood has a value of one inside the bounds, and zero outside, with a smooth transition between one and zero near the bounds. The log-likelihood can be very small even for values of C_Y that are slightly outside of the bounds, and this can lead to problems when optimizing the likelihood. The solution I use is the replace $\Phi_N(\cdot/\sigma_C)$ in eq. 7 with a mixture of normals, $\Phi_N^*(\cdot/\sigma_C) = p\Phi_N(\cdot/\sigma_C) + (1-p)\Phi_N(\cdot/\sigma_C^*)$, with $p = 0.9$ and $\sigma_C^* = 0.075$.

Optimizing the total likelihood including eq. 7 is sensitive to starting values for parameters even when the normal mixture distribution is used. If model-predicted catches are significantly low (i.e., $C_y < 0.7 \times C_{oy}$) or high (i.e., $C_y > 1.3 \times U_y$), then eq. 7 becomes the log of a very small number and creates a flat ridge on the likelihood surface. This seems to cause the parameter estimation procedure to diverge. The procedure I used to get better starting values is to first fit the model assuming total catches were $(C_{oy} + U_y)/2$ with measurement error σ_C. This ensures that model-predicted catches at starting values are in the interval (C_{oy}, U_y). Then I fit the model using eq. 7, and convergence is usually not a problem (see Simulation testing).

The age distribution of the catches provides important information on mortality rates. Annual sampling of the commercial catch for ages, lengths, and body masses has been used by DFO to estimate the commercial catch-at-age. The sampling protocols are complex and have changed over time. Periodic publications by DFO describe some of this, but from the most recent publication (DFO 2011), it is practically impossible to evaluate from first principles the statistical properties of the catch age-composition information (i.e., catch proportions at age) for northern cod, although this is an active area of research in general (e.g., Thorson 2014). There have been numerous publications focusing on how to model age and length composition information. Recently, Francis (2014) reviewed much of this literature and also studied some of the common approaches using many data sets and simulation analyses. He also studied the logistic normal multinomial distribution, which is commonly advocated for analyses of compositional data (Aitchison 2003), but not commonly used in stock assessment (except Schnute and Haigh 2006; Martell 2011; Martell et al. 2011).

I use a related approach (see Appendix A) based on the continuation-ratio logit, which has been used for modelling length and age distributions (e.g., Kvist et al. 2000; Rindorf and Lewy 2001; Berg and Kristensen 2012). Let $X_{a,y}$ be the continuation-ratio logit (eq. A4 in Appendix A) of $P_{a,y} = C_{a,y}/C_y$ derived from eq. 2. Let $X_{oa,y}$ denote the observed continuation-ratio logit based on the data with zeros replaced (see Appendix A). The catch age composition log-likelihood is

$$(8) \qquad l(\{X_{oa,y}\}|\boldsymbol{\theta}) = \sum_{a=1}^{A-1}\sum_{y=1}^{Y}\log\left[\varphi_N\left(\frac{X_{oa,y} - X_{a,y}}{\sigma_{Pa}}\right)\right]$$

where φ_N is the probability distribution function (pdf) for a N(0,1) random variable

$$\sigma_{Pa} = \begin{cases} 3\sigma_P, & a \le 2 \\ \sigma_P, & 3 \le a \le 7 \\ 2\sigma_P, & a \ge 8 \end{cases}$$

and σ_P is an estimated parameter. The ad hoc age adjustments to σ_P were chosen with a few iterations to account for additional residual variability at these ages. I recommend that standardized residuals be carefully inspected for appropriate residual variation. The errors in $P_{a,y}$ are assumed to be independent, but including correlation, particularly across ages, is possible.

Surveys

Surveys provide important information for estimating model parameters. Let $I_{s,a,y}$ denote the age-based abundance index for survey s. The main index used for assessing northern cod comes from the DFO offshore research vessel (RV) survey. The inshore gillnet catch-rate index provided by the sentinel fishery program is also used. Let t be the midpoint of the survey dates, which is expressed in a fraction of the year. The model-predicted catch for survey s is

$$(9) \qquad E(I_{s,a,y}) = q_{s,a}N_{a,y}\exp(-t_{s,y}Z_{a,y})$$

The $\exp(-t_{s,y}Z_{a,y})$ term projects beginning-of-year stock abundance ($N_{a,y}$) to the time of the survey. The values for $q_{s,a}$ are catchability parameters that adjust stock abundance to the scale of the surveys. If the survey indices are estimated totals for the entire survey area, as is the case in this application for the DFO RV survey, then q may be close to one. DFO survey indices for ages 2–12 and years 1983–2012 are used for model estimation. Indices for age 1 are not used because at this age a substantial amount of cod may be outside of the survey area, and the catchability at this age will be highly variable. Very few cod are caught at ages older than 12 throughout the RV survey time series. Ages 3–10 for 1995–2012 are used for the sentinel gillnet series, which started in 1995. The gear used in this program catches very few fish outside of this range of ages.

The indices are assumed to have a lognormal distribution with mean $E[\log(I_{s,a,y})] = \log(q_{s,a}) + \log(N_{a,y}) - t_{s,y}Z_{a,y}$ and standard deviation $\sigma_{s,I}$, which is also an estimated parameter. The DFO survey indices at all ages in 1986 were anomalously high although the reasons for this are poorly understood (e.g., Baird et al 1991). This was also evident for other groundfish species caught in that year. To accommodate the apparent extra survey error in 1986, σ_I was fixed to be 0.5 for that year and survey. The likelihood term for survey indices is

$$(10) \qquad l(\{I_{s,a,y}\}|\boldsymbol{\theta}) = \sum_a\sum_y\log\left(\varphi_N\left\{\frac{\log(I_{s,a,y}) - E[\log(I_{s,a,y})]}{\sigma_{s,I}}\right\}\right)$$

The lognormal distribution requires survey indices to be positive (i.e., no zeros). However, 19% of the DFO RV indices had values of 0, mostly at older ages. In many stock assessment models, these zeroes are treated as missing values, but this does not seem appropriate for northern cod. I assume these indices were zero because of low stock abundance in the survey area and not because the fish were missed by mistake. I assume that these zeros represent stock densities that are below a detection limit, which I set at 0.005 and which is half of the minimum positive value in the data series. The log-likelihood for a zero index is $l(I_{s,a,y} = 0|\boldsymbol{\theta}) = \log\{\Phi_N[\log[0.005/E(I_{s,a,y})]/4\sigma_{s,I}\}$, where Φ_N is the normal CDF and the standard deviation is increased by four to account for additional variability. The log-likelihood for a zero will be close to zero if $E(I_{s,a,y}) \ll 0.005$, which is very different from substituting 0.005 for a zero index and using eq. 10 for its distribution.

The model is highly parameterized and includes a modelling component for M. The age patterns in q are usually confounded with the level of $Z = F + M$, and it is helpful to fix the age patterns at reasonable values if possible. Most of the northern cod stock overwintered in the offshore in the 1980s (e.g., Lilly 2008), and much of it would have been available to the DFO autumn RV survey. During this period, I have no data or good reasons to expect that q at older ages deviated from a constant value. Therefore, I constrained DFO RV q values to be the same for stock ages 5–12 and lower at ages 2–4. In most preliminary analyses, the values did not differ for ages 3–12 (i.e., models ages 2–11), and so I further simplified the RV q values:

$$(11) \qquad q_a = \begin{cases} \rho_a q_{\text{full}}, & a = 1 \\ q_{\text{full}}, & a > 1 \end{cases}$$

where $\rho_a < 1$. However, I explore the sensitivity of this assumption using a model formulation in which q are estimated freely for most ages. The sentinel gillnet index has a dome-shaped age pattern in q, so I simply estimated these parameters freely for each age.

Spatial model for DFO RV *q*

A fundamental assumption in eq. 9 is that q is constant over time for each age class in the population. However, after the stock collapsed in the early 1990s, it is very plausible that q changed for the DFO RV survey. Not all northern cod are in the area surveyed each fall. This may be more so for younger cod that have grown in inshore areas and become more migratory as they get older. A relatively large inshore aggregation of cod was first observed in the spring of 1995 in Smith Sound, Trinity Bay, on the northeast coast of Newfoundland (e.g., Rose et al. 2011). Their acoustic biomass estimates of this overwintering stock component ranged from about 10 000 to 25 000 tonnes (t) but declined substantially in 2008 and 2009 to a much lower level of less than 1000 t and has been about this level since then (G. Rose, Marine Institute of Memorial University of Newfoundland, St. John's, Newfoundland, personal communication, 2014). Rose et al. (2011) concluded that these fish were immigrants from an offshore stock component, but it is not clear if their rapid disappearance from Smith Sound starting around 2008 was a reverse migration back to the offshore overwintering area or movement to other inshore overwintering areas. However, the DFO RV survey index of spawning stock biomass (SSB) in the offshore increased by 83% during 2004 to 2008 (Brattey et al. 2011), while there have been no observations of large overwintering inshore components since 2009. Rose et al. (2011) concluded that F and M were unlikely to explain the full decline of the Smith Sound component during 2008–2009. Hence, I conclude that reverse migration is a highly plausible scenario to include in the stock assessment model. This potential change in the spatial distribution of the stock could explain some of the high levels of total mortality rates inferred from the DFO RV survey during this time period.

Offshore stock components in this scenario are assumed to migrate inshore and mix with inshore components to feed in the summer. All components are assumed to be equally exploited by the inshore fishery, including the sentinel fishery program. I also assume that both M and Z are the same for the inshore and offshore components. I assume that a portion of the offshore stock was not available to the DFO survey during 1995–2009, in addition to those inshore components that are never available to this survey and are accounted for in the stock assessment model by the q_a parameters in eq. 9; that is

$$E(I_{\mathrm{RV},a,y}) = \begin{cases} q_a N_{a,y}\exp(-tZ_{a,y}), & y \neq 1995,\ldots,2009 \\ q_a(N_{a,y} - N_{S,a,y})\exp(-tZ_{a,y}), & y = 1995,\ldots,2009 \end{cases} \tag{12}$$

where $N_{S,a,y}$ is the abundance of offshore fish that migrated and overwintered in Smith Sound. The estimation procedure I use for $N_{S,a,y}$ is described at the end of this section. Equation 9 is used for the sentinel indices but with different q values and $t = 0.5$.

The size of the Smith Sound component is estimated using acoustic biomass estimates ($\hat{B}_{S,y}$) in Rose et al. (2011), with the observation equation

$$\log(\hat{B}_{S,y}) \sim N\left\{\log\left[\sum_{a=1}^{A} q_{S,a}N_{S,a,y}\exp(-t_y Z_{a,y})w_{a,y}\right], \hat{\sigma}^2_{Sy}\right\} \tag{13}$$

where $q_{S,a}$ are catchability parameters for the acoustic survey with $\max_a q_{S,a} = 1$, $w_{a,y}$ are stock body mass at age, and $\hat{\sigma}_{S,y}$ is the estimated CV of the biomass estimate provided for each survey. Beginning of year stock size is projected to the time of the acoustic surveys, which have usually been in January but in a few years were April–June. Age-composition information was also provided in Rose et al. (2011), and I use this to estimate the age composition of cod in Smith Sound; however, to do this I fix the $q_{S,a}$ parameters because they cannot be reliably estimated with the data I use. During the surveys there seemed to be very few small cod (or any other fish species) in Smith Sound, possibly due to predation by the larger cod. Therefore, I assume that $q_{S,1} = 0.7$, $q_{S,2} = 0.9$, and $q_{S,3+} = 1$ (i.e., stock ages 4+).

The Smith Sound age information was based on simple trawl samples in which the age was determined for all cod caught. The negative binomial (NB) distribution is often considered to be appropriate for modelling the variability in trawl catches (e.g., Cadigan 2011). I assumed the age sample catches ($J_{S,a,y}$) were

$$J_{S,a,y} \sim \mathrm{NB}\{q_{S,y}q_{S,a}N_{S,a,y}, k\} \tag{14}$$

where $q_{S,y}$ is the fully selected exploitation rate for the age samples collected in year y. This extremely small exploitation rate is estimated each year. If the mean of $J_{S,a,y}$ is denoted as $\mu_{S,a,y} = q_{S,y}q_{S,a}N_{S,a,y}$, then for the NB distribution $\mathrm{Var}(J_{S,a,y}) = \mu_{S,a,y} + \mu^2_{S,a,y}/k$ and k is an overdispersion parameter to estimate.

I prefer to model the Smith Sound inshore stock distribution during 1995–2009 using $D_{a,y} = N_{S,a,y}/N_{a,y}$ so that $N_{S,a,y} = D_{a,y}N_{a,y}$ and $N_{a,y} - N_{S,a,y} = (1 - D_{a,y})N_{a,y}$ in eqs. 12–14. I expect these D proportions to vary smoothly over time and with age. I model this behavior using an age and year AR(1) process for the logit of D, with parameters σ^2_D, $\varphi_{D,\mathrm{age}}$, and $\varphi_{D,\mathrm{year}}$ (see Table 1). Hence, D is an age- and year-dependent modification of the DFO RV q model (eq. 12)

$$E(I_{\mathrm{RV},a,y}) = \begin{cases} q_a N_{a,y}\exp(-tZ_{a,y}), & y \neq 1995,\ldots,2009 \\ q_a(1 - D_{a,y})N_{a,y}\exp(-tZ_{a,y}), & y = 1995,\ldots,2009 \end{cases} \tag{15}$$

Tagging data

I used two published sources of tag recaptures. The first was Brattey and Healey (2007), who presented release and recapture information from 84 tagging experiments conducted in Divisions 3KL during 1997–2006. A total of 32 544 fish were tagged in these experiments and 4894 were recaptured. The second source was Myers et al. (1996), who presented information for 16 experiments conducted during 1983–1987 in Division 3K. A total of 10 484 fish were tagged and 2083 were recaptured. Brattey and Healey (2007) presented the mean fish length at the time of release. I obtained this information for the experiments in Myers et al. (1996) from Taggart et al. (1995). These data were age-aggregated, which causes some difficulties with using this information in an age-structured model. A simple approach is to assume all fish in each experiment are the same age. I estimated the mean age of the fish when they were tagged using the mean length of the releases and the fall survey mean age-at-length information for 3K cod in Brattey et al. (2011, their figure 39a). I can then use the F for that age to model recaptures. In preliminary analyses I found the model to be unstable and difficult to estimate. Treating the tagging data this way limits the number of cohorts that the data provide F and M information about, and this may be the reason I had problems.

The tagging data provide F and M information for an aggregation of ages. Let $N_{x,a,y}$ denote the unknown number of fish tagged at age a in year y for some experiment x. I only know the total number of tagged fish, $N_{x,y} = \sum_{a=1}^{A} N_{x,a,y}$. For exposition I assume fish are tagged at the beginning of the year, although in application I adjust for the seasonal time of tagging. Using eq. 1

$$N_{x,y+1} = N_{x,y}\exp(-\tilde{Z}_{x,y}),\ \tilde{Z}_{x,y} = -\log\left[\frac{\sum_{a=1}^{A} N_{x,a,y}\exp(-Z_{a,y})}{N_{x,y}}\right]$$

I can decompose $\tilde{Z}_{x,y}$ into components due to fishing and natural mortality:

$$\tilde{F}_{x,y} = -\log\left[\frac{\sum_{a=1}^{A} N_{x,a,y}\exp(-F_{a,y})}{N_{x,y}}\right], \quad \tilde{M}_{x,y} = \tilde{Z}_{x,y} - \tilde{F}_{x,y}$$

However, I do not know the age composition of $N_{x,y}$ so I cannot compute $\tilde{Z}_{x,y}$ directly in the model. Only cod ≥45 cm fork length were tagged (Brattey and Healey 2007), so I expect that $\tilde{Z}_{x,y}$ is virtually a weighted mean of Z for ages 4–12, but not equally weighted because the mean age at release could be as high as 8 years old in some experiments.

The procedure I used is based on the stock size-weighted versions of $\tilde{F}_{x,y}$ and $\tilde{M}_{x,y}$. Let $N_{+,a,y}$ denote the total number of fish at ages a, $a + 1$, …, A for any age $a > 1$. Using eq. 1

$$N_{+,a+1,y+1} = N_{+,a,y}\exp(-\tilde{Z}_{+,a,y}), \tilde{Z}_{+,a,y} = -\log\left[\frac{\sum_{i=a}^{A} N_{i,y}\exp(-Z_{i,y})}{\sum_{i=a}^{A} N_{i,y}}\right] \tag{16}$$

and

$$\tilde{F}_{+,a,y} = -\log\left[\frac{\sum_{i=a}^{A} N_{i,y}\exp(-F_{i,y})}{\sum_{i=a}^{A} N_{i,y}}\right], \quad \tilde{M}_{+,a,y} = \tilde{Z}_{+,a,y} - \tilde{F}_{+,a,y} \tag{17}$$

Let $\tilde{F}_{x,\bar{a},y}$ denote F for tagged fish that are mean age $\bar{a}$ in year y. I do not use $\tilde{F}_{+,\bar{a},y}$ to approximate $\tilde{F}_{x,\bar{a},y}$ because $\tilde{F}_{+,\bar{a},y}$ is for fish age $\bar{a}$ and older and could be biased for $\tilde{F}_{x,\bar{a},y}$, which includes mortality rates for some ages less than $\bar{a}$. As a solution I computed the mean age of the catch each year for fish older than plus group ages 4, 5, …, 12 and computed $\bar{a}_{yc}$ as the minimum plus group age where the corresponding mean age of the catch was greater than or equal to $\bar{a}$. Note that $\bar{a}_{yc} \leq \bar{a}$. I approximated $\tilde{F}_{x,\bar{a},y}$ as $\tilde{F}_{+,\bar{a}_{yc},y}$, although stochastically as described below. Usually $\bar{a}_{yc} = \bar{a} - 1$ but sometimes the difference could be two or three ages. A better solution is to estimate the age composition of the tagged fish and then model the tag returns by experiment and age at capture; however, this information was not available for this paper.

The size of the tagged population after release is also affected by the tag loss rate each year (γ_y; see Appendix A). If $N_{x,\bar{a},y}$ tagged fish from experiment x survive to year y and are mean age $\bar{a}$, then the size of the tagged population in year $y + 1$ is modelled as

$$N_{x,\bar{a}+1,y+1} = N_{x,\bar{a},y} \exp(-\tilde{F}_{x,\bar{a},y} - \tilde{M}_{+,\bar{a},y} - \gamma_y) \tag{18}$$

For each experiment, fish were tagged in specific geographic locations, and the F they experienced was likely different from the stock as a whole. I assumed these differences were random such that

$$\log(\tilde{F}_{x,\bar{a},y}) \sim N\Big[\log(\tilde{F}_{+,\bar{a}_{yc},y}), \sigma^2_{fx}\Big] \tag{19}$$

The tag catch ($C_{x,\bar{a},y}$) was modelled similar to eq. 2:

$$C_{x,\bar{a},y} = N_{x,\bar{a},y}[1 - \exp(-\tilde{Z}_{x,\bar{a},y} - \gamma_y)]\frac{\tilde{F}_{x,\bar{a},y}}{\tilde{Z}_{x,\bar{a},y} + \gamma_y} \tag{20}$$

In the year of release only a fraction of F and Z were applied, depending on the fraction of a year that the tagged fish were at liberty. Initial tagging mortality was also applied, as described below.

For various reasons, fishermen do not report all tagged fish they catch. For the recent tagging experiments, the reporting rates can be estimated using information from high-reward tagging. This has received considerable attention (Brattey and Cadigan 2003 and Cadigan and Brattey 2006), and recently Konrad et al. (C. Konrad, J. Brattey, and N.C. Cadigan, unpublished data) proposed a time-series approach to estimate annual reporting rates (i.e., λ_y) for these experiments. For simplicity I use their estimates as fixed constants (denoted as λ_{oy} in eq. 21 below), although it is possible to add a likelihood component for these parameters. I also use the estimates of short-term tagging mortality from Brattey and Cadigan (2003). Myers et al. (1996) did not have information to estimate reporting rates externally. They adjusted for this within their tagging model (i.e., their θ parameter) but could not estimate annual reporting rates. In fact they adjusted for the combined effects of initial tag loss, initial tagging mortality, and reporting rates as a single parameter that they estimated separately for each experiment. I follow the same approach and denote this parameter as λ_x. I estimated a total of 16 of these fixed-effect parameters for each of the 16 tagging experiments in Myers et al. (1996) that I use. Hence, I use the notation $\lambda_{x,y}$ for reporting rates, and the model-predicted reported tag catch is

$$R_{x,\bar{a},y} = \lambda_{x,y} \times C_{x,\bar{a},y}, \quad \lambda_{x,y} = \begin{cases} \lambda_{oy}, & y = 1997, \ldots, 2006 \\ \lambda_x, & y = 1983, \ldots, 1989 \end{cases} \tag{21}$$

The observed tag catches from experiment x conducted in year y_x and caught in subsequent years ($R_{ox,\bar{a},y}$) are modelled as Poisson random variables. I only used tag recaptures up to 5 years at liberty for the Myers et al. (1996) experiments because that was all they tabulated. Recaptures for up to 9 years at liberty were provided by Brattey and Healey (2007). Let T_x denote the set of years that recaptures are available for experiment x. The likelihood term for tagging data is

$$l(\{R_{ox,\bar{a},y}\}|\boldsymbol{\theta}) = \sum_x \sum_{y \in T_x} R_{ox,\bar{a},y} \log(R_{x,\bar{a},y}) - R_{x,\bar{a},y} - \log[\Gamma(R_{ox,\bar{a},y} + 1)] \tag{22}$$

Random effects

In addition to likelihoods for data, likelihoods for random effects like the process errors must also be specified. The stochastic processes for log(F), log(M), and logit(D) are autocorrelated over ages and years, and an efficient method for specifying these log-likelihoods is outlined in Appendix A. Recall that the M process errors were coupled at stock ages 8+ and that these errors were fixed at zero for the first year, and a likelihood equation is not required for these fixed values. The first-order age autocorrelation parameter for log(F) ($\varphi_{\delta,\text{age}}$) was constrained to be zero for stock ages 2–4 but estimated as common values for other ages. No likelihood function was used for F at ages 1–3 in the first year. The likelihoods for both log recruitments (eq. 7) and log F for tagging experiments (eq. 19) were based on the normal distribution likelihood with variance parameters estimated as part of the model.

Estimation

Fixed effects parameters, denoted collectively as the parameter vector $\boldsymbol{\theta}$, are estimated via maximum likelihood (MLE) based on the marginal likelihood ($L(\boldsymbol{\theta})$), in which random effects are "integrated out". Let $\boldsymbol{\Psi}$ denote a vector of all random effects. Let S denote the set of all data used in the model, including surveys, catches, etc. The marginal likelihood is

$$L(\boldsymbol{\theta}) = \iiint_{\boldsymbol{\Psi}} f_{\boldsymbol{\theta}}(S|\boldsymbol{\Psi})g_{\boldsymbol{\theta}}(\boldsymbol{\Psi})\partial\boldsymbol{\Psi} \tag{23}$$

where $f_{\boldsymbol{\theta}}(S|\boldsymbol{\Psi})$ is the joint pdf of the data, and $g_{\boldsymbol{\theta}}(\boldsymbol{\Psi})$ is the joint pdf for the $\boldsymbol{\Psi}$ random effects. The template model builder (TMB; Kristensen 2013) package within R (R Core Team 2014) was used to implement the model. The MLEs of $\boldsymbol{\theta}$ maximize $L(\boldsymbol{\theta})$. The user has to provide C++ computer code to calculate $f_{\boldsymbol{\theta}}(S|\boldsymbol{\Psi})$ and $g_{\boldsymbol{\theta}}(\boldsymbol{\Psi})$, but the integration in eq. 23 is then provided by TMB. The high-dimensional integral is numerically evaluated in TMB using the Laplace approximation. The random effects $\boldsymbol{\Psi}$ can be predicted by maximizing the joint likelihood, $f_{\boldsymbol{\theta}}(S|\boldsymbol{\Psi})g_{\boldsymbol{\theta}}(\boldsymbol{\Psi})$; however, these effects are not freely estimated like $\boldsymbol{\theta}$. If no distribution is provided for a random effect, then this effect is still integrated out of the likelihood when estimating $\boldsymbol{\theta}$, but the prediction of the random effect is otherwise the same as if this effect was considered to be fixed (i.e., a regular parameter). Additional information on these procedures is provided by Skaug and Fournier (2006). TMB used automatic differentiation to evaluate the gradient function of eq. 23 and in the Laplace approximation. The gradient function is produced automatically from $f_{\boldsymbol{\theta}}(S|\boldsymbol{\Psi})$ and $g_{\boldsymbol{\theta}}(\boldsymbol{\Psi})$. This greatly improves parameter estimation using a derivative-based optimizer. I use the nlminb function within R (R Core Team 2014) to find the MLE for $\boldsymbol{\theta}$.

The reliability of model estimates was assessed through detailed examination of model estimates and residuals and also retrospective analyses in which the model was fit to less data and results compared with estimates based on the full data time series. Models were fit to subsets of data with recent years left out. This was done for retrospective years 2005 to 2011.

Simulation testing

Simulation testing is important especially for models with random walks (Deroba et al. 2015). A full testing of the accuracy and robustness of the northern cod model, including stock size estimates and other statistical inferences, is beyond the scope of this paper. However, a simple simulation self-test (i.e., Deroba et al. 2015) was conducted in which the model was fit to simulated data generated by the model. This does not really address the reliability of the assumptions of the model, but rather it simply addresses how reliable are model estimates assuming the model is correct and can be viewed as a minimum test of model suitability. I conducted conditional self-test simulations by conditioning on the process errors when generating simulation data. However, these process errors were not fixed when estimating the model with the simulated data. This is the same simulation procedure used by Nielsen and Berg (2014).

The self-test simulations involved computing model predictions of the surveys (acoustic, trawl, gillnet), catch age composition, and tagging data and then randomly simulating these data using the model predictions and assumed statistical distributions in the various likelihood components. Data were simulated using estimated variance parameters. Simulated continuation-ratio logits of the age compositions were generated using model estimates of $X_{a,y}$ and σ_P (i.e., $\hat{X}_{a,y}$ and $\hat{\sigma}_P$). The model was then fit to the simulated data, and the procedure was repeated 1200 times.

Catch projections

An important way fishery science can assist fishery management is by providing reliable projections of the implications of future catch levels. There is uncertainty about the exact values of catches for northern cod, but I can do catch projections based on the model estimates of catch. I evaluate the impact of a range of catch options (±50%) for 2013–2017. I assume that the age pattern in F values will be the same as for 2012. Normally this is based on the mean F pattern in recent years; however, in the northern cod state-space model, F are already smoothed so this does not seem necessary. For each catch option, the fully selected F is found by solving eq. 2. I use the state-space model to project values for M. Projected recruitment, stock weights, and proportions mature are assumed to be equal to the mean of their 2010–2012 values. No projection errors are included in these values, although the recruitment values are unknown and estimated by the model, and this estimation uncertainty is included in the stochastic projections. These are done internally when fitting the model, and I compute standard errors for projection results using the delta method. This allows the M-process errors to accumulate as the number of projection years increases, and this should give more realistic quantification of uncertainty about these projections. This approach also incorporates uncertainty about the initial stock size and catches in the projections.

Results

Four model formulations are presented:

1. Base formulation. The upper bound on catch was set at 1.5× the reported catch (i.e., the lower bound) prior to 1993 and 2× the report catch during 1993–2012.
2. Scenario 2 (or S2 for short). The upper bound on catch is 1.25× the lower bound for all years. This represents the situation where reported catch is more accurate than assumed in the base model.
3. Scenario 3 (S3). The DFO RV q is estimated separately for stock ages 2–6 and 7+. This formulation may allow for some domed age pattern in q.

Table 2. Estimates (Est.) of variance parameters (see Table 1) and some population parameters, with percent coefficients of variation (CV × 100), for four model formulations.

	Base		S2		S3		S4*	
	nll = 2629; AIC = 5356		nll = 2670; AIC = 5438		nll = 2627; AIC = 5361		nll = 2291; AIC = 4659	
Quantity	Est.	CV	Est.	CV	Est.	CV	Est.	CV
σ_{RV}	0.414	10	0.429	9	0.437	9	0.529	7
σ_P	0.318	9	0.343	9	0.322	9	0.351	9
σ_δ	0.536	16	0.547	16	0.540	16	0.424	18
σ_F	0.585	6	0.612	6	0.583	6	0.578	6
σ_{fx}	0.991	7	1.008	6	0.974	6	0.925	6
σ_D	0.502	32	0.493	33	0.484	35	—	—
$\varphi_{\delta,\mathrm{age}}$	0.776	10	0.755	11	0.775	10	0.836	8
$\varphi_{\delta,\mathrm{year}}$	0.704	15	0.707	14	0.688	15	0.888	6
$\varphi_{D,\mathrm{year}}$	0.925	5	0.928	5	0.929	5	—	—
$\varphi_{D,\mathrm{age}}$	0.915	6	0.918	6	0.918	6	—	—
$\varphi_{F,\mathrm{age}}$	0.800	7	0.822	6	0.807	7	0.784	8
Blim (kt)	621	9	589	9	669	10	825	9
SSB_{2012} (kt)	72	16	68	16	82	18	106	17
SSB_{2012}/Blim	0.117	13	0.116	14	0.122	14	0.128	16
q_{full}	1.288	10	1.361	10	1.087	14	0.892	9
$\bar{Z}_{2012}$	0.308	47	0.308	49	0.282	48	0.358	49
$\bar{F}_{2012}$	0.061	27	0.041	21	0.058	25	0.044	22

Note: Base: upper bound on total catch is 2× reported catch for 1993–2012 and 1.5× for 1983–1992. S2: upper bound on total catch is 1.25× reported catch for all years. S3: Base + survey catchabilities (q values) estimated separately for ages 2–6 and 7+. S4*: Base + no change in spatial distribution; this represents a reduced data set. nll denotes the negative log-likelihood, and AIC is the Akaike information criterion. Total (Z) and fishing (F) mortality rates are averaged for ages 5–12, and these averages are population size-weighted.

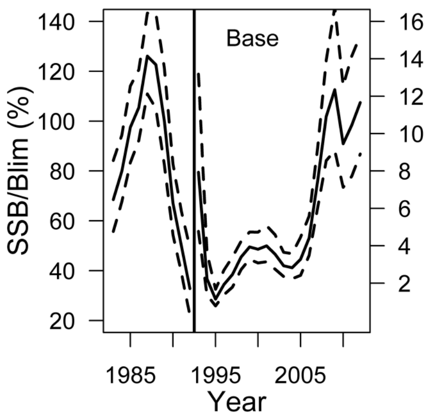
4. Scenario 4 (S4) did not include a change in the spatial distribution of the stock and did not include the inshore data (acoustics or sentinel surveys).

In all scenarios, there was a major conflict in the sentinel gillnet and DFO RV surveys and tagging data. The sentinel indices (see DFO 2013) were at about the same level in 2010–2012 as in 1997–1999, whereas the DFO RV surveys increased substantially. The model could not reconcile these differences. I decided to omit the sentinel gillnet survey indices from the model estimation because of uncertainty about how these fixed gear catch rates relate to the stock as a whole.

The base model estimate of SSB in 2012 (Table 2) was similar to the estimate from model S2, but both were considerably lower than the S3 estimate. The 2012 SSB estimate from S4 was the highest. However, stock status in 2012 (SSB/Blim) was very similar for all models and similar to the survey model used by DFO (i.e., Cadigan 2013*a*) in the 2013 assessment of this stock. The DFO precautionary approach biomass limit reference point (Blim) for this stock was set as the mean SSB during 1983–1989 (DFO 2011). The status evaluation is based on beginning-of-year SSB to conform to the usual practice of DFO. All formulations give very similar stock status results (Fig. 1; also see online Supplemental Figs. S1–S4[2]). Estimates of total and fishing mortality in 2012 (Table 2) have relatively high CVs but, in light of this, are similar. Mean Z estimates for the base and S2–S3 models are similar to the 0.27 value in DFO (2013). The relatively high CVs for the mortality rate estimates may partially be related to no tagging data in the model since 2006. Estimates of the various variance parameters were all similar. The base model results differed most with the S4 model formulation (Fig. 2) compared with the other formulations (see also Supplemental Figs. S5–S7[2]). The S4 model indicated

[2]Supplementary data are available with the article through the journal Web site at http://nrcresearchpress.com/doi/suppl/10.1139/cjfas-2015-0047.

Fig. 1. Stock status relative to the biomass limit reference point (Blim, solid lines) and 95% confidence intervals (dashed lines) for the northern cod (*Gadus morhua*) base model formulation. Two *y*-axis scales are used, and the solid vertical line indicates where the change occurs.



a greater decline in SSB until 1995 and then a greater increase during 2005–2012. This model indicated much higher recruitment productivity and *M* during 1995–2005. The base model estimates of *M* were particularly high at stock ages 5–7 in 1992–1994 (Fig. 3), similar to models S2 and S3 (Supplemental Figs. S8–S9[2]), whereas the S4 model also estimated high *M* at age 5 in 2002–2003 (Supplemental Fig. S10[2]). All models indicated that *M* is age-dependent and can vary substantially over a few years.

The base model fit the data well (Supplemental Figs. S11–S20[2]). There were no major patterns in residuals indicating conflicting signals in the data. Hence, there were no major retrospective patterns either (Fig. 4). One concern is that eight of ten residuals for the last four cohorts in the model had positive DFO RV residuals (Supplemental Fig. S13[2]) but did not appear as strong in the catch age compositions (Supplemental Fig. S11[2]). This is considered further in the Discussion. The model-predicted catch was close to reported catch around 1990 and 2000 (Fig. 5). There was fairly large between-year change in the ratio of reported to predicted catch, which may not be reasonable. The age patterns in *F* (Fig. 6) broadly make sense, with higher selection at older ages prior to 1992 when a substantial fraction of landings were taken by otter trawls that have a sigmoidal selection function (Myers and Hoenig 1997), whereas after 1992 most reported commercial landings are by fixed gear and predominately gillnets. Note that the selectivity changed substantially in 2003 when there was a large-scale inshore fish kill due to freezing, and some of the carcasses, evidently the larger ones, were collected by fishermen and sampled by DFO like a regular fishery. The model indicates an increase in selectivity towards older ages starting in 2009, which may not be realistic (see Discussion).

A large fraction of the stock was estimated to be outside of the DFO RV survey area during 1995–2005 (Figs. 7 and 8). This is in addition to the part of the stock that was regularly outside of the survey area in the autumn.

I conducted 5-year projections till 2017 to evaluate the implications of future catch levels. Some of the projection inputs are given in Table 3. The projections were based on a range of catch multipliers, from 0.5 to 1.5. Results indicate the stock should continue to increase (Fig. 9), although even if catch were reduced by 50% there is less than 5% probability that the stock will exceed Blim in 5 years; that is, the upper 95% confidence limit is 89% of Blim in 2017. The projections are highly uncertain, particularly after 2014. Projection results were reasonably robust to the four model formulation I investigated (Figs. S21–S24[2]).

I assessed the impact of two alternative choices for σ_r^2 compared with the base value, $\sigma_r^2 = 1$. I increased σ_r to 2.0 and this choice had little impact on results. For example, SSB in 2012 decreased from 72.4 to 72.1 kt, and SSB in 2012 relative to Blim decreased from 11.7% to 11.6%. I decreased σ_r to 0.1 and this had a little more impact. SSB in 2012 increased to 77.1 kt and SSB in 2012 relative to Blim increased to 12.3%. These changes were all well within the range of uncertainty for the estimates.

The self-test simulations for the base model did not indicate serious bias in the estimation of SSB or mean *F* at ages 3–8 (Supplemental Fig. S25[2]). The latter was not weighted by population size. The number of simulations that converged was 95%. Most of the standard deviations of the random effects were underestimated (Supplemental Fig. S26[2]), particularly for tagging *F* values (σ_{fx}).

Discussion

The state-space model developed here addresses difficult problems in fish stock assessment, notably biased catches, uncertain *M*, and changes in survey catchability. This was possible for northern cod because of the rich data (tagging and surveys) available for this stock. I demonstrated in a highly plausible scenario that there were large changes in the DFO RV *q* during 1995–2007, and this survey on its own may not always have provided a reliable indicator of trends in the stock. The catchability of this autumn survey will be sensitive to when fish, that are inshore in the summer to feed, return in the autumn to overwintering grounds. Nonetheless, my inferences about stock status are broadly consistent with the survey-based model recently used to assess this stock. SSB in 2012 was estimated to be 12% of Blim in the base model and also in Cadigan (2013*a*), although in the latter model SSB was estimated to be about 1% of Blim during 1995–2005, whereas in the base model it was near 3% on average. The main difference in the two models is how much the stock has increased. The base model suggests SSB in 2012 was 3.6× the average during 1995–2005, whereas the model in Cadigan (2013*a*) suggests it was 14× bigger, which is more similar to the S4 result of an 11.2-fold increase. The S4 model assumed a year invariant *q* for the DFO RV survey, similar to Cadigan (2013*a*), so it is not surprising that these models give similar SSB trend information.

In the base model, I assumed that the RV catchability since 2009 was the same as during 1983–1994 (Fig. 8), but if this is not the case then estimates of stock size could be biased. Recent tagging results that are not included in the model indicate that fishery exploitation rates were 2%–6% on average for 2010–2012 (DFO 2013), while the base model estimates were 5%–7% for ages 5–12 combined. If the estimates of stock size during 2010–2012 were 50% higher, then the exploitation rates would be around 4% and more consistent with the recent tagging results. The change in fishery selectivity towards older ages since 2009 may also be a consequence of an overestimation of *F* at older ages, and consequently *Z*, during this period when *M* was estimated to be close to 0.2 (Table 3), in which case the model could not account for the increase in the catch age composition using constant selectivity. All of this suggests a possibility that the estimates of recent stock size may be biased low.

I estimated large increases in natural mortality rates, particularly at ages 5–7, during 1992–1994. These estimates have fairly high CVs, but others have also concluded that there is evidence that *M* increased for Northwest Atlantic cod stocks (e.g., Shelton et al. 2006; Swain 2011*a*, 2011*b*). The causes remain uncertain, but predation and poor condition immediately prior to spawning have been suggested for some of these stocks. The lack of understanding of the causes and magnitude of the spike in *M* affects the precision of short-term forecasts because these forecasts have to include the possibility that such an event will occur again. This is an important reason why the CVs of projections get large so quickly. It also affects the precision of estimates of the *M* process errors. If I knew that this spike was due to exceptional circumstances that were unlikely to occur again, then it would be better to model this as a one-time

Fig. 2. Comparisons of the four northern cod (*Gadus morhua*) model formulations: base, S2 (better catch), S3 (dome *q*), and S4 (no change in inshore–offshore distribution) for (*a*) spawning stock biomass (SSB), (*b*) recruits per spawner, (*c*) fishing mortality (*F*), and (*d*) natural mortality (*M*). Mortality rates are stock size-weighted means for ages 5–12. Two *y*-axis scales are used in panel (*a*), and the solid vertical line indicates where the change occurs. For the coloured version of this figure, refer to the Web site at http://www.nrcresearchpress.com/doi/full/10.1139/cjfas-2015-0047.

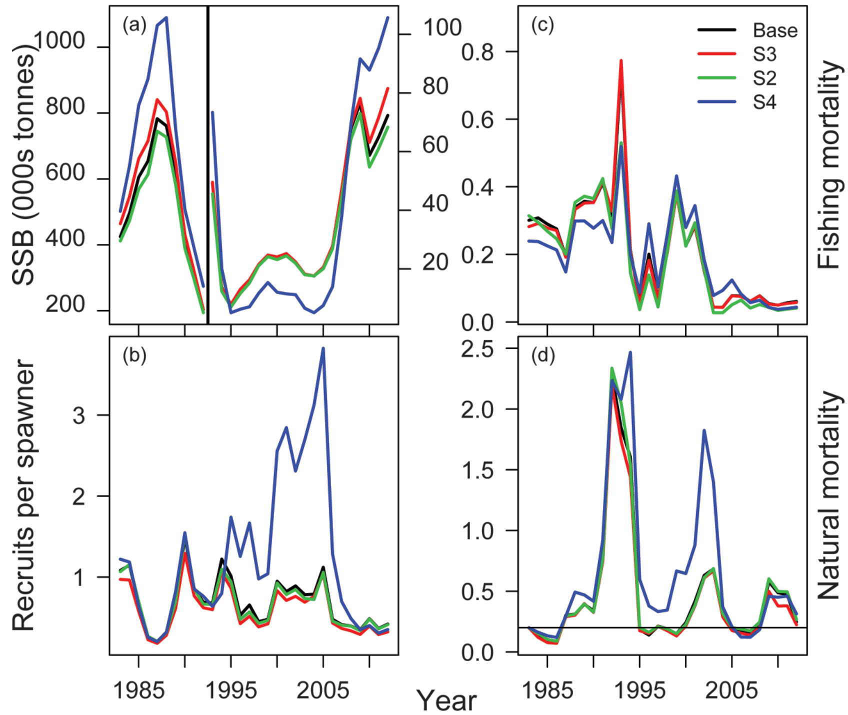


Fig. 3. Illustration of the base model estimates of *M*.

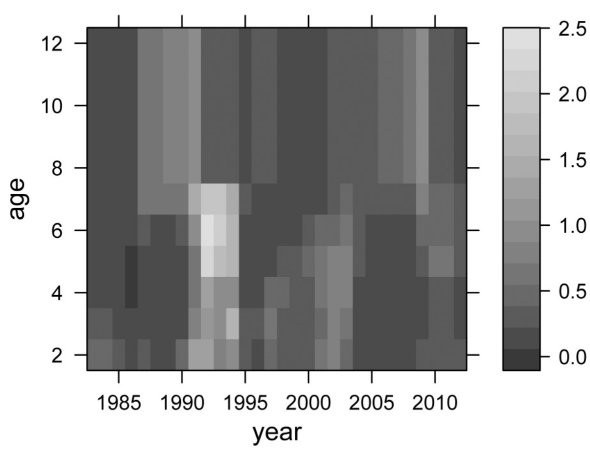
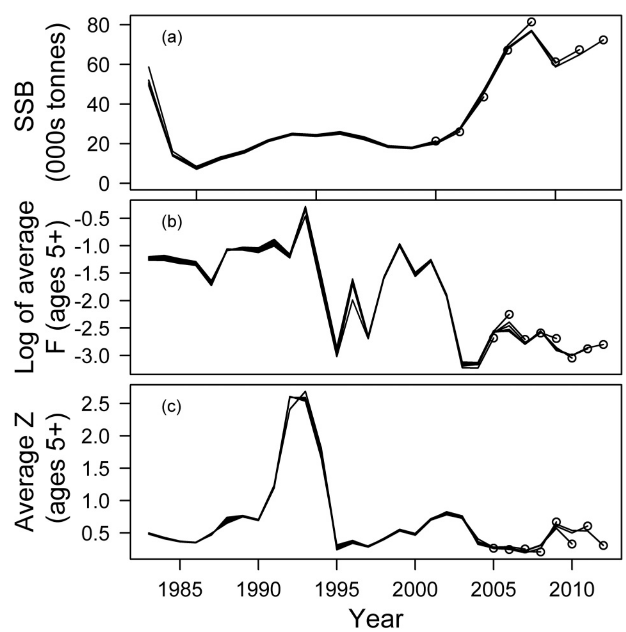


Fig. 4. Base model retrospective estimates of (*a*) SSB, (*b*) log of mean *F*, and (*c*) mean *Z*. Circles indicate the most recent estimate for each retrospective year.



change in *M* in addition to an age and year autocorrelated stochastic process. In an unreported exploratory run, I did this and the CV on the 2017 projection of SSB/Blim deceased from 70% to 50%. The accuracy of the *M* estimates can be improved by utilizing more tagging information that exists but were not available to us. The rich tagging information for this stock also can be used to estimate fishery selectivity, and this is a useful area to improve the model.

Most residuals for the DFO RV survey were positive for the last four cohorts in the base model but negative in the commercial age compositions. It is possible that the selectivity at these young ages is more complex and variable than the model suggests. Another possible improvement is to model the temporal autocorrelation for ages 2–4, which are mostly not targeted sizes, separately from ages 5 and older. This also highlights another major source of uncertainty affecting the precision of short-term forecasts and that is the precision of recent recruitment that will become mature and contribute to SSB in the next few years. Better estimates of the abundance of 0-group and 1-year-old cod and their mortality rates until they reach exploitable sizes will improve short-term forecasts for fisheries management.

In the base (i.e., highly plausible) model scenario, I estimated a large change in DFO RV survey *q* because of a shift in the overwin-

Fig. 5. Base model estimated total catch numbers at ages 2–12 (black lines) and assumed catch bounds (grey lines). The left-hand y axis is in log scale. Superimposed is the observed relative to predicted catch in percent (circles) with y-axis scale on the right-hand side.

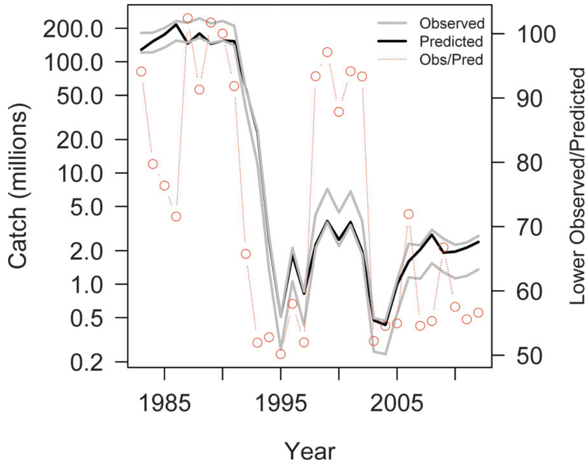


Fig. 6. Illustration of the base model age pattern in F.

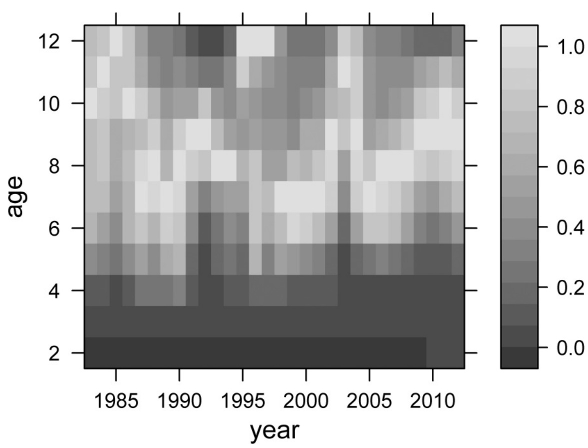
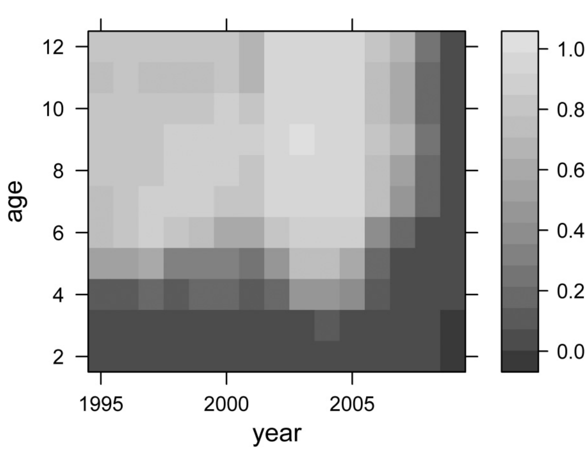


Fig. 7. Illustration of the base model estimates of the proportion of the stock in Smith Sound (D).



tering distribution of some cod from the offshore to the inshore. The change in q was derived based on acoustic biomass estimates in Smith Sound; however, some of this biomass may include a portion of typical inshore overwintering bay stocks that would be accounted for by the DFO RV survey q parameters. For example,

Fig. 8. Multiplicative change in catchability (q) for the DFO RV survey, averaged for ages 5+.

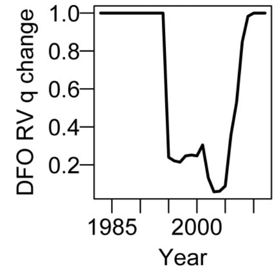
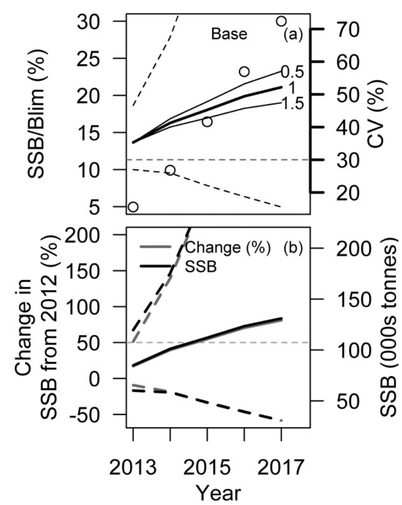


Table 3. Projection inputs.

Age	Mass	Maturity	F	Selectivity	M_{2013}	M_{2014}	M_{2015}	M_{2016}	M_{2017}
2	0.10	0.00	0.001	0.005	0.302	0.350	0.389	0.419	0.442
3	0.28	0.00	0.004	0.033	0.196	0.222	0.243	0.259	0.270
4	0.60	0.05	0.007	0.060	0.178	0.184	0.189	0.192	0.194
5	1.03	0.35	0.020	0.165	0.245	0.231	0.221	0.215	0.210
6	1.57	0.79	0.058	0.464	0.252	0.235	0.224	0.217	0.212
7	2.29	0.97	0.095	0.767	0.229	0.220	0.214	0.210	0.207
8	3.16	1.00	0.121	0.977	0.187	0.191	0.194	0.195	0.197
9	4.14	1.00	0.124	1.000	0.187	0.191	0.194	0.195	0.197
10	5.14	1.00	0.112	0.905	0.187	0.191	0.194	0.195	0.197
11	6.31	1.00	0.076	0.612	0.187	0.191	0.194	0.195	0.197

Note: Mass indicates both stock and catch masses (kg). Maturity indicates the proportion mature. M is natural mortality and F is fishing mortality in 2012. Selectivity denotes the age pattern in average F; that is, $F/\max_a(F_a)$.

Fig. 9. Five-year base model projections of stock status. Dashed lines indicate 95% confidence intervals for projections based on status quo model-predicted catch. (a) Projections for status quo catch (thick solid line) and a 50% increase or decrease in catch (thin solid lines). Circles indicate status quo CVs. The grey horizontal dashed line indicates a CV = 30%, and projections with CVs > 30% should be interpreted with more caution. (b) Projections of SSB (thick solid line) and the percent change in SSB from 2012 (grey line) for status quo catch. The grey horizontal dashed line indicates a 50% increase.



since 2009 less than 1000 t of cod have overwintered in Smith Sound (G. Rose, Marine Institute of Memorial University of Newfoundland, St. John's, Newfoundland, personal communication, 2014) and would be accounted for by q. I can only speculate on the amount of overwintering cod in Smith Sound before 1995, but Rose et al. (2011) concluded that the weight of the historical evidence suggested that there was no exceptional overwintering or spawning concentration in Smith Sound prior to 1995 and especially not in the early 1990s. Hence, I make no adjustments to account for this.

I feel that including process errors in M provides a potential advantage compared with the way Gudmundsson and Gunnlaugsson (2012) and Nielsen and Berg (2014) included process errors in eq. 1, particularly if the process errors are viewed as deviations in M from assumptions. My process errors directly and consistently affect both eqs. 1 and 2, whereas their process errors directly affected only eq. 1. One should be able to derive eq. 2 from eq. 1 if I assume that the fraction $F_{a,y}/Z_{a,y}$ of the deaths in a cohort in year y (i.e., $N_{a,y} - N_{a+1,y+1}$) is due to fishing; however, this is not the case for their equations. Their $Z_{a,y}$ may be different than $-\log(N_{a,y}/N_{a+1,y+1})$. On the other hand, my model does not explicitly allow for immigration, whereas the models proposed by Gudmundsson and Gunnlaugsson (2012) and Nielsen and Berg (2014) do. However, eq. 3 can partially account for immigration, although a cohort cannot increase in size as it gets older, unlike the models in Gudmundsson and Gunnlaugsson (2012) and Nielsen and Berg (2014). Equation 3 may also reflect misreported catch, although I prefer to model this directly using catch bounds.

In a preliminary version of the northern cod model in which tagging information was not used and DFO RV survey catchability was assumed to be constant for all years, I found that the process error variance parameter was highly confounded with the measurement error variance. The total likelihood was fairly flat for different choices of these parameters. This is often the case with age-aggregated production models where Bayesian approaches are commonly used and informative priors for process and (or) measurement error variance have to be used (e.g., Meyer and Millar 1999). This problem has also been recognized in some age-disaggregated stock assessment models (i.e., Linton and Bence 2008). However, this does not seem to be a problem in the approaches of Gudmundsson and Gunnlaugsson (2012) and Nielsen and Berg (2014). This suggests the possibility that their assumption of process errors in eq. 1 but not in eq. 2 may be the reason they can separate this source of variation from measurement error. However, if the main source of process error is in M, which will affect both eqs. 1 and 2, then it is not clear how reliable their approaches may be. This requires further research.

Self-test simulations did not indicate large biases in SSB or F; however, many of the variance parameters were slightly underestimated and some substantially so (i.e., σ_{fx} and σ_D), which could mean that standard errors of model estimates (e.g., stock status, projections) are too low. There is a well-known bias problem with maximum likelihood estimates of variance parameters for models with many mean parameters (e.g., Barndorff-Nielsen and Cox 1994). The bias is negative. The northern cod state-space model is not highly parameterized, with only 49 parameters in the base model formulation and 12 of these were covariance parameters. The sample size was 1371. However, for the 37 mean parameters there were 16 $\boldsymbol{\theta}$ tag reporting rate parameters for the data from the 16 tagging experiments I used from Myers et al. (1996), and seven $q_{S,y}$ parameters for the 7 years of age-composition information from Smith Sound (Rose et al. 2011) that I used. Hence, the likelihood components for these two data sources are highly parameterized, and their variance parameters (σ_{fx} and σ_D) had the largest biases. Many adjustments have been proposed to address this problem (e.g., Barndorff-Nielsen and Cox 1994). One approach that is often successful is restricted maximum likelihood estimation. This can be implemented by simply integrating mean parameters out of the likelihood (e.g., Laird and Ware 1982). Model estimation involves two stages, one for variance parameters and one for mean parameters. This may be a useful improvement to the estimation procedure for the model.

There are several other ways that the state-space model can be improved, and I have already alluded to some of these. Most importantly, offshore acoustic surveys have been conducted for several years since 2005, and this information, once published, should be included in the model. Additional historic and contemporary tagging information also exists that should improve the precision of F and M estimates. Including size and age-composition information for tagged fish is also useful. Commercial catch and age-composition information since 1959 were used in previous assessments of northern cod. It may be difficult to include this information in the state-space model and at the same time estimate both F and M; however, it can be done with additional assumptions about M and by including more of the historic tagging data. Including more of the historic data should improve the understanding of temporal variability in stock productivity, which is critical information for estimating fisheries management (e.g., maximum sustainable yield) reference points. Information on fleet compositions may improve modelling the age patterns in F.

Fisheries managers and stakeholders deserve to know if model-based stock assessment advice is reliable and robust to model assumptions and uncertainties in data. This can be complicated to demonstrate, and there is a trade-off between the usefulness of a model and robustness. A model that is completely insensitive to all changes in data inputs and assumptions will not be useful. Further simulation testing of the proposed model using a spatio-temporal fishery simulation framework and including reasonable deviations in model assumptions is required to demonstrate the robustness and reliability of the approach. However, a challenge (e.g., Deroba et al. 2015) is to decide what the simulation framework should be in an integrative modeling context involving acoustic and trawl surveys and tagging information.

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Appendix A

Vector AR(1) log-likelihood

Let $\boldsymbol{z}_t$ be an $A \times 1$ process error vector that is generated from a vector AR(1) process, $\boldsymbol{z}_t = \varphi_{\text{year}}\boldsymbol{z}_{t-1} + \boldsymbol{\varepsilon}_t$, where $\boldsymbol{\varepsilon}_t$ is multivariate normal with mean 0 and covariance $\boldsymbol{\Sigma}$, and φ_{year} is a scalar autocorrelation parameter that is common to all elements of $\boldsymbol{z}$. I assume that $E(\boldsymbol{z}_1) = 0$ and that $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{\varepsilon}_{t-i}$ are independent for all $i > 0$. It can be shown that the mean of the stationary distribution of $\boldsymbol{z}$ is 0 and the covariance is $\text{Var}(\boldsymbol{z}) = \lim_{t\to\infty}\text{Var}(\boldsymbol{z}_t) = \boldsymbol{\Sigma}/(1 - \varphi_{\text{year}}^2)$. The log-likelihood for $\boldsymbol{\Sigma}$ and φ_{year} given a set of process errors $(\boldsymbol{z}_1, \ldots, \boldsymbol{z}_n)$ can be written

$$l(\boldsymbol{\Sigma},\ \varphi_{\text{year}};\ \boldsymbol{z}_1, \ldots, \boldsymbol{z}_n) = l(\boldsymbol{\Sigma}, \varphi_{\text{year}};\ \boldsymbol{z}_1) + \sum_{t=2}^{n} l(\boldsymbol{\Sigma}, \varphi_{\text{year}};\ \boldsymbol{z}_t|\boldsymbol{z}_{t-1})$$

where $l(\boldsymbol{\Sigma}, \varphi_{\text{year}}; \boldsymbol{z}_1)$ is the log-likelihood based on a multivariate normal (MVN) distribution with mean $\boldsymbol{0}$ and covariance $\boldsymbol{\Sigma}/(1 - \varphi_{\text{year}}^2)$, and $l(\boldsymbol{\Sigma}, \varphi_{\text{year}}; \boldsymbol{z}_t|\boldsymbol{z}_{t-1})$ is based on the MVN distribution with mean $\varphi_{\text{year}}\boldsymbol{z}_{t-1}$ and covariance $\boldsymbol{\Sigma}$, for $t = 2, \ldots, n$.

I also assume that $\boldsymbol{\Sigma}$ has a stationary AR(1) structure with diagonal elements all equal to $\sigma^2/(1 - \varphi_{\text{age}}^2)$ and off diagonal elements proportional to $\varphi_{\text{age}}^{|i-j|}$. Hence, the process errors are autocorrelated across ages and years. The log-likelihood for $\boldsymbol{\theta} = \{\sigma^2, \varphi_{\text{year}}, \varphi_{\text{age}}\}$ can be further simplified. First,

$$l(\boldsymbol{\theta}; \boldsymbol{z}_1) = l(\boldsymbol{\theta}; z_{1,1}) + \sum_{a=2}^{A} l(\boldsymbol{\theta}; z_{a,1}|z_{a-1,1})$$

where $l(\boldsymbol{\theta}; z_{1,1})$ is the log-likelihood based on the univariate $\mathrm{N}\left[0, \dfrac{\sigma^2}{(1 - \varphi_{\text{year}}^2)(1 - \varphi_{\text{age}}^2)}\right]$ distribution, and $l(\boldsymbol{\theta}; z_{a,1}|z_{a-1,1})$ is based on the $\mathrm{N}\left(\varphi_{\text{age}} z_{a-1,1}, \dfrac{\sigma^2}{1 - \varphi_{\text{year}}^2}\right)$ distribution. Second,

$$l(\boldsymbol{\theta}; \boldsymbol{z}_t|\boldsymbol{z}_{t-1}) = l(\boldsymbol{\theta}; z_{1,t}|\boldsymbol{z}_{t-1}) + \sum_{a=2}^{A} l(\boldsymbol{\theta}; z_{a,t}|z_{a-1,1}, \boldsymbol{z}_{t-1})$$

where $l(\boldsymbol{\theta}; z_{1,t}|\boldsymbol{z}_{t-1})$ is based on $\mathrm{N}\left(\varphi_{\text{year}} z_{1,t-1}, \dfrac{\sigma^2}{1 - \varphi_{\text{age}}^2}\right)$ and $l(\boldsymbol{\theta}; z_{a,t}|z_{a-1,t}, \boldsymbol{z}_{t-1})$ is based on $\mathrm{N}[\varphi_{\text{year}} z_{a,t-1} + \varphi_{\text{age}}(z_{a-1,t} - \varphi_{\text{year}} z_{a-1,t-1}), \sigma^2]$.

Continuation-ratio logit

Consider the compositional data $P_1, \ldots, P_B$ for states $1, \ldots, B$ with the basic property that $P_1 + \ldots + P_B = 1$. Let $X_b = \log[P_b/(1 - \sum_{i=1}^{B-1} P_i)]$, $b = 1, \ldots, B - 1$. The logistic normal multinomial distribution is based on assuming $X_1, \ldots, X_{B-1}$ has a multivariate normal distribution with some correlation structure. Francis (2014) concluded that the logistic normal multinomial distribution showed great promise for modelling length and age compositional data in stock assessment. The distribution of $P_1, \ldots, P_B$ is generated from the logistic transformation

$$\text{(A1)} \qquad P_b = \begin{cases} \dfrac{\exp(X_b)}{1 + \sum_{i=1}^{B-1} \exp(X_i)}, & b = 1, \ldots, B - 1 \\ \dfrac{1}{1 + \sum_{i=1}^{B-1} \exp(X_i)}, & b = B \end{cases}$$

To be more precise, Aitchison (2003) referred to eq. A1 as the additive logistic transformation. He argued that for ordered compositional data, such as for ages and lengths, the multiplicative logistic transformation is more appropriate:

$$\text{(A2)} \qquad P_b = \begin{cases} \dfrac{\exp(X_b)}{\prod_{i=1}^{b} [1 + \exp(X_i)]}, & b = 1, \ldots, B - 1 \\ \dfrac{1}{\prod_{i=1}^{B-1} [1 + \exp(X_i)]}, & b = B \end{cases}$$

The inverse of this transformation is

$$\text{(A3)} \qquad X_b = \log\left(\frac{P_b}{1 - P_1 - , \ldots, -P_b}\right) = \log\left(\frac{P_b}{P_{b+1} + , \ldots, +P_B}\right), \quad b = 1, \ldots, B - 1$$

This was the approach used by Stewart and Field (2011) in diet composition analyses of seabirds and seals. If I define $\pi_b = P_b/(P_b + \ldots + P_B) = \mathrm{Prob}(\text{State} = b|\text{State} \geq b)$, then

$$\text{(A4)} \qquad X_b = \log\left(\frac{\pi_b}{1 - \pi_b}\right), \quad b = 1, \ldots, B - 1$$

Equation A4 is also the continuation-ratio logit as defined by Agresti (1996) and has been used for modelling length and age distributions by Kvist et al. (2000), Rindorf and Lewy (2001), Berg and Kristensen (2012), and possibly others.

This compositional data theory has been developed for strictly positive compositions in which all $P_b > 0$. In practice there may be zeros that can be real (i.e., essential) or due to rounding. Issues related to zeros are discussed by Martín-Fernández et al. (2003) and Stewart and Field (2011). For age and length composition data, it may be difficult to decide whether zeros are essential or rounded. Cohort abundance never goes extinct in the northern cod state-space model, so I consider zeros to be due to rounding. I used a simple replacement strategy in which zeros were replaced with a value of 0.5, and then the catches were rescaled so that the total annual catch with replacement values for zeros is the same as the original total catch.

Tag loss rates

Cadigan and Brattey (2003, 2006) estimated tag loss rates from information on double-tagged fish. They showed that Kirkwood's (1981) tag loss model provided a good fit to the data. Let $\Gamma(y - y_x)$ denote the cumulative probability that a tag is retained on a fish in year y when it was initially tagged in year y_x. Kirkwood's model is $\log[\Gamma(t)] = \beta_1\log[\beta_1/(\beta_1 + \beta_2 t)]$, with mean tag loss rate

$$\text{(A5)} \qquad \gamma(t) = \Gamma^{-1}(t)\frac{d}{dt}[1 - \Gamma(t)] = -\frac{d}{dt}\log[\Gamma(t)] = \frac{\beta_1\beta_2}{\beta_1 + \beta_2 t}$$

This is a decreasing function from β_2 when $t = 0$ to zero as $t \to \infty$, and the rate of decrease depends on β_2/β_1. The γ_t in eqs. 18 and 20 are evaluated at midyear using eq. A5 and including the fraction of year at liberty in the release year. I use the same parameter values as in Brattey and Healey (2007).