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Examining non-stationarity in the recruitment dynamics of fishes using Bayesian change point analysis

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Abstract

Marine ecosystems can undergo regime shifts, which result in non-stationarity in the dynamics of the fish populations inhabiting them. The assumption of time-invariant parameters in stock-recruitment models can lead to severe errors when forecasting renewal ability of stocks that experience shifts in their recruitment dynamics. We present a novel method for fitting stock-recruitment models using the Bayesian online change point detection algorithm, which is able to cope with sudden changes in the model parameters. We validate our method using simulations, and apply it to empirical data of four demersal fishes in the southern Gulf of St. Lawrence. We show that all of the stocks have experienced shifts in their recruitment dynamics that cannot be captured by a model which assumes time-invariant parameters. The detected shifts in the recruitment dynamics result in clearly different parameter distributions and recruitment predictions between the regimes. The present study illustrates how stock-recruitment relationships can experience shifts which, if not accounted for, can lead to false predictions about a stock's recovery ability and resilience to fishing.

Keywords: Change point, Productivity, Regime shift, Reproduction, Ricker model, Beverton-Holt model, Spawning stock, Sequential Monte Carlo

1. Introduction

Reproduction forms a vital link between current and future generations. The sustainability of fishing is largely attributable to the ability of a fish stock to renew itself such that it maintains its abundance at a target level despite biomass removal by fishing (Hilborn 2005). The study of fish stock reproduction has largely focused on the relationship between the reproducing component of the stock (i.e. the spawning stock) and the recruitment (Hilborn and Walters 1992). Recruitment of a fish stock is typically predicted using a curve that links spawning-stock biomass with recruit abundance, that is, the stock-recruitment (S-R) relationship. Traditional formulations of this relationship are provided by Ricker (Ricker 1954) and Beverton-Holt (Beverton and Holt 1957) S-R models (but for a comprehensive list of models, see, e.g., Needle 2001). A characteristic of both these models is that at low spawning stock levels recruitment grows steeply as a function of spawning stock biomass, but the rate of increase reduces as spawning stock biomass increases (Hilborn and Walters 1992).

Although S-R relationships form one of the cornerstones for fisheries stock assessments and are widely used for projecting stock development under alternative fishing scenarios, their applicability remains widely debated. Unexplained variations in recruitment have long been known to be present in population dynamics (Hjort 1914). A recent meta-study illustrates this by showing that recruitment and spawning stock biomass show no correlation for 61% of 224 stocks recorded in the RAM legacy database (Szuwalski et al. 2014). In general, fish populations show great variability around the mean recruitment predicted by S-R models, and the resulting large uncertainty in the estimates limits the utility of these predictions. Variations in temperature, food availability, and predation

pressure have been identified as key drivers of such environment-driven recruitment variability (e.g. Brunel and Boucher 2007; Fauchald 2010; Olsen et al. 2011; Okamoto et al. 2012), and it has been suggested that for some species environmental drivers might be a more important source of recruitment variability than the spawning stock biomass (Szuwalski et al. 2014). For example, in the North Sea about 45% of Atlantic cod (*Gadus morhua*) recruitment variability was found to be associated with temperature and food availability, whereas only 10% of variability was attributable to spawning stock biomass (Olsen et al. 2011). In principle, as long as environmental correlates can be identified, S-R models can be modified to account for the additional sources of variation (for examples to this end, see Hilborn and Walters 1992, Chen and Irvine 2001, Begg and Marteinsdottir 2002, Ciannelli et al. 2004, Stige et al. 2013). However, such approaches make the implicit assumption that future recruitment can be predicted by observations made in the past, i.e. that correlations established in the past are indicative of correlations in the future. If fish population dynamics or the entire ecosystem shifts from one state into another such that key productivity parameters and their covariates change, S-R models fitted to observations before such a shift may not describe recruitment after the shift even if the correct environmental correlates have been identified.

It has been increasingly recognized that marine ecosystems can undergo very rapid shifts from one relatively stable state to another due to internal or external forcing (deYoung et al. 2008, Vasilakopoulos and Marshall 2015). The time periods where the ecosystem stays in a certain relatively stable state are often denoted as ‘regimes’, and the change from one stable state to another is called a ‘regime shift’. In fish stocks, the regime shifts may result in changes in their population dynamics. For example, in the 1980s, regime shifts in the

79 North Sea and the Baltic Sea were followed by a decline in the recruitment of Atlantic cod
80 (*Gadus morhua*) (Beaugrand 2004, Alheit et al. 2005). It has also been shown using
81 surplus production models that shifts in marine fish stock productivity are very common.
82 Of the 230 fish stocks studied by Vert-pre et al. (2013), 69% were best explained by a
83 model that took shifts in productivity into account.
84
85 In light of the observed regime shifts in fish stocks and their ecosystems, it seems likely
86 that the parameters of the S-R relationships can also experience shifts. The times when the
87 parameters change are often called change points. Such shifts may partially explain the
88 lack of correlation between spawning stock biomass and recruitment. Indeed, using
89 Bayesian inference, Munch and Kottas (2009) showed that the recruitment dynamics of
90 Japanese sardine (*Sardinops melanostictus*) is characterized by shifts between two
91 alternative regimes in Ricker model parameters. If a fish stock experiences notable shifts
92 in its recruitment dynamics, fitting S-R models using all available data may result in biases
93 in the mean recruitment and unnecessarily large estimates of uncertainty. In 27 of 38 North
94 Atlantic fish stocks studied using maximum-likelihood methods, the relationship between
95 recruitment and spawning stock biomass was not constant but instead was better explained
96 by a model allowing for a stepwise change in the S-R relationship (Ottersen et al. 2013).
97 While showing that S-R relationships can indeed show shifts, the currently applied
98 modelling approaches are limited in the sense of either considering only two alternative
99 regimes or by omitting uncertainty about the inferred timings of the shifts.
100
101 The objective of the present study is to challenge the commonly made assumption that the
102 parameters in S-R models are time-invariant and to investigate whether S-R dynamics

show signals of regime shifts. To this end, we utilize the Bayesian online change point detection algorithm (BOCPD; Adams and MacKay 2007, Perälä and Kuparinen 2015) and expand the methodology to study shifts in the parameters of the Ricker and Beverton-Holt S-R models. Previously, BOCPD has been used to infer change points in linear models with conjugate priors. Here we show how to implement non-linear models with arbitrary prior distributions within a BOCPD framework using Sequential Monte Carlo (SMC) methods. To our knowledge, this has not been done before. We validate our method using simulations, and explore the S-R dynamics of Atlantic cod (*Gadus morhua*), white hake (*Urophycis tenuis*), American plaice (*Hippoglossoides platessoides*) and thorny skate (*Amblyraja radiata*) in the southern Gulf of St. Lawrence marine ecosystem in Canada. This study system is exceptionally well studied and data-rich, thus providing long time series of the S-R dynamics of the four study species. Historically, Atlantic cod, American plaice and white hake supported the largest fisheries for groundfish in the southern Gulf of St. Lawrence, and thorny skate was the most abundant and widely distributed skate in this ecosystem. Here, we investigate whether the S-R relationships of these species experience non-stationarities by detecting shifts in the parameters of the S-R relationships, infer timings of the parameter shifts (change points), and quantify the typical lengths and magnitudes of the resulting ‘recruitment regimes’ as well as the associated changes in the S-R model parameters. In addition to exploring shifts in the S-R model parameters, we account for the uncertainties associated with the change points and regime specific parameters, and propagate the uncertainties into predictions using the posterior predictive distribution.

127 2. Material and methods

128 2.1. Implementation of shifts in the parameters of the stock-recruitment models

129 Our model consists of a model for the length of the current regime and a model for the data
 130 generating process. The regime length is modelled as a Markov process such that, during
 131 the transition from a time step to the next, the regime length can only grow by one (the
 132 current regime continues) or go to zero (a new regime is starting). The data generating
 133 process is the S-R model. We explored the Ricker S-R model (Ricker 1954) and the
 134 Beverton-Holt S-R model (Beverton and Holt 1957). In our analysis, we are interested in
 135 sequentially inferring the posterior and smoothed probabilities of the length of the current
 136 regime and the posterior probability distributions of the model parameters.

137
 138 The Bayesian online change point detection algorithm (BOCPD; Adams and McKay 2007,
 139 Perälä and Kuparinen 2015) detects sudden changes in the parameters of a data generating
 140 process. The algorithm processes the data sequentially one time step at a time ('online'),
 141 and at each time step a new sequential estimation run is started which ignores the data
 142 from previous time steps. Assuming that there is a change point at some time step, one of
 143 the runs will start at the correct time step and the idea is that it will obtain high posterior
 144 probability because of its better predictive performance. The runs are identified in the
 145 algorithm by the number of data points that have been used to update the run-specific
 146 posterior distribution of the parameters. The auxiliary variable used to distinguish the runs
 147 is called 'run length' and it is denoted by $r_t \in \{0, \dots, t\}$. The algorithm infers the posterior
 148 probability distribution of the parameters for all possible regime starting times (or
 149 equivalently for all possible run lengths), and the run length posterior probabilities. This
 150 means that at time step t there are t run-specific posterior probability distributions for

the parameters together with the posterior probabilities of the t run lengths. The full posterior probability distribution of the parameters is a mixture distribution consisting of the run-specific posterior distributions and the mixture weights, i.e. the run length posterior probabilities. Similarly, the full posterior predictive distribution is a mixture of run-specific posterior predictive distributions where the weights are the run length posterior probabilities. In the following we will present the integral quantities constituting the algorithm.

Run length posterior

We assume that the data generating process depends on covariates (i.e. the spawning stock biomass) and write them explicitly as conditioning factors in the probability density functions. The conditional distribution of the run length r_t at time t given the response variables $y_{1:t} = (y_1, \dots, y_t)$ and covariates $S_{1:t} = (S_1, \dots, S_t)$, i.e. the run length posterior distribution, can be formulated recursively (see supplementary material for derivation)

$$p(r_t | y_{1:t}, S_{1:t}) = \sum_{r_{t-1}=0}^{t-1} \frac{p(r_t | r_{t-1}) p(y_t | y_{t-1}^{(r_{t-1})}, S_{t-1}^{(r_{t-1})}, S_t) p(r_{t-1} | y_{1:t-1}, S_{1:t-1})}{p(y_t | y_{1:t-1}, S_{1:t-1}, S_t)}, \quad (3)$$

where $p(r_t | r_{t-1})$ is the change point prior distribution that contains our prior belief of the probability of a shift. The underlying predictive model (UPM) $p(y_t | y_{t-1}^{(r_{t-1})}, S_{t-1}^{(r_{t-1})}, S_t)$ is the predictive density conditional on run length r_{t-1} , i.e. the predictive density using the latest r_{t-1} observed response variables $y_{t-1}^{(r_{t-1})}$ and the corresponding covariates $S_{t-1}^{(r_{t-1})}$. For better readability, the following notation is adopted here and used throughout this paper: $y_s^{(r)} = y_{(s-r+1):s}$ and $S_s^{(r)} = S_{(s-r+1):s}$. The UPM is defined by the data-generating model, and it weights the probabilities of different run lengths by how well

the predictive density associated with the given run predicts the new response variable y_t given the new covariate value S_t . If the new response variable is ‘far away’ from any of the predictive densities of the previous runs, the prior predictive density $p(y_t | y_{t-1}^{(0)}, S_{t-1}^{(0)}, S_t)$ will dominate, which serves as an indicator for a start of a new regime. The last term $p(r_{t-1} | y_{1:t-1}, S_{1:t-1})$ is the run length posterior of the previous time step $t - 1$. The term in the denominator $p(y_t | y_{1:t-1}, S_{1:t-1}, S_t)$ is the normalization factor. The summation is carried out for all possible run lengths from 0 (new regime) to $t - 1$ (the longest possible regime so far).

Change point prior

We define the change point prior probability or the prior probability of a shift using a constant model

$$p(r_t | r_{t-1}) = \begin{cases} \frac{1}{\lambda}, & \text{if } r_t = 0 \\ 1 - \frac{1}{\lambda}, & \text{if } r_t = r_{t-1} + 1 \\ 0, & \text{otherwise} \end{cases}, \quad (4)$$

where the probability of a change point is thus $\frac{1}{\lambda}$. The change point prior has non-zero probability only for two cases: the run length grows by one, i.e., the previous regime continues, or the run length goes to zero, i.e., a new regime starts. The change point prior contains our a priori belief about the frequency of the regime shifts. We set $\lambda = 10$, which means that a priori we expect the shifts to happen on average every 10 years. We examine the sensitivity of the results to the change point prior probability in the supplementary material.

192 Underlying predictive model

193 In this study, we detect change points in the parameters of the Ricker and Beverton-Holt
 194 S-R models, which relate the number of recruits (R_t) in a given year t to the spawning
 195 stock biomass (S_t) that produced the recruits (Ricker 1954, Beverton and Holt 1957). We
 196 model the logarithm of the ratio of the number of recruits and the spawning stock biomass
 197 $y_t = \log\left(\frac{R_t}{S_t}\right)$ as a normally distributed random variable

$$y_t \sim N(f(S_t), \delta_t), \quad (5)$$

198 where the mean is given by the function $f(S_t)$, which depends on the S-R model choice,
 199 and the standard deviation is the unknown parameter $\delta_t = \sigma/\sqrt{c_t}$, where c_t is a known
 200 constant proportional to the sampling intensity in year t . For example, in our application
 201 to the southern Gulf of St. Lawrence (see section 2.3), the R and S data are based on catch
 202 rates in an annual bottom-trawl survey. Sampling intensity in this survey since 1985 was
 203 approximately 2.5 times the sampling intensity in earlier years; accordingly, we set $c_t = 1$
 204 when $t < 1985$ and $c_t = 2.5$ when $t \geq 1985$. Thus, σ corresponds to the standard
 205 deviation of the error before 1985 (when there was a change in vessel and survey
 206 protocols).

207

208 The likelihood function of the parameters (α, β, σ) given a single response variable and
 209 covariate pair (y_t, S_t) can be thus written as

$$L(\alpha, \beta, \sigma | y_t, S_t) = p(y_t | S_t, \alpha, \beta, \sigma) = \frac{1}{\sqrt{2\pi}\delta_t} e^{-\frac{1}{2\delta_t^2}(y_t - f(S_t))^2}. \quad (6)$$

210

211 *Ricker stock-recruitment model*

212 The Ricker S-R model is usually presented as

$$R_t = \alpha^R S_t e^{-\beta^R S_t}, \quad (7)$$

213 where the parameter α^R is the slope of the function at the origin and it corresponds to the
214 maximum recruit production per unit of S_t in the absence of density-dependent factors.

215 The parameter β^R describes the magnitude of the density dependency. The number of
216 recruits first grows as a function of the spawning stock biomass until the maximum
217 number of recruits or ‘carrying capacity for the recruits’ is reached at $S_t = \frac{1}{\beta^R}$ after which
218 the number of recruits starts declining. The carrying capacity for the number of recruits is
219 then $k = \frac{\alpha^R}{e\beta^R}$. For the Ricker S-R model the mean in (5) is

$$f(S_t) = \log(\alpha^R) - \beta^R S_t. \quad (8)$$

220

221 *Beverton-Holt stock-recruitment model*

222 The Beverton-Holt S-R model can be formulated as

$$R_t = \frac{\alpha^{BH} S_t}{1 + \beta^{BH} S_t}, \quad (9)$$

223 where α^{BH} is the slope of the function at origin and β^{BH} controls the
224 density-dependence. Recruitment in the Beverton-Holt model approaches an asymptotic
225 value of $R_\infty = \frac{\alpha^{BH}}{\beta^{BH}}$ as the spawning stock biomass grows. When $S_t = \frac{1}{\beta^{BH}}$ the
226 recruitment is $\frac{1}{2} R_\infty$. For the Beverton-Holt S-R model the mean in (5) is

$$f(S_t) = \log(\alpha^{BH}) - \log(1 + \beta^{BH} S_t). \quad (10)$$

227

228 In the framework of BOCPD and the S-R models presented above, we want to make
229 inference about the S-R model parameters α and β , and the standard deviation of the

error distribution σ using the latest r_t observed response variables $y_t^{(r_t)}$ and covariates $S_t^{(r_t)}$. Bayesian inference is based on calculating the joint distribution of the S-R model parameters and the standard deviation of the error distribution conditioned on the observed response variables and covariates, $p(\alpha, \beta, \sigma | y_t^{(r_t)}, S_t^{(r_t)})$, i.e. the posterior distribution of the parameters given run length r_t at time step t . The posterior distribution for each run length $r_t \in \{1, \dots, t\}$ is calculated recursively by sequential application of the Bayes' rule. The recursion starts from a fixed prior distribution $p(\alpha, \beta, \sigma | y_{t-1}^{(0)}, S_{t-1}^{(0)}) = p(\alpha, \beta, \sigma) = p(\alpha)p(\beta)p(\sigma)$, where the parameters are assumed a priori independent. The prior distributions are provided as an input for the algorithm. The calculation of the posterior distributions of the parameters is analytically intractable, and thus requires approximate numerical methods. Due to the sequential nature of the BOCPD algorithm, we use sequential Monte Carlo (SMC) or particle filter methods for inferring the posterior parameter distributions. However, particle filters suffer from particle degeneracy issues when estimating static parameters. Thus, we use artificial evolution of the parameters to overcome this issue (Liu and West, 2001). Furthermore, to calculate the run length posterior, the posterior predictive density (i.e. the probability density of a new response variable y_{t+1} conditional on a new covariate S_{t+1} and the r_t latest response variables and covariates) $p(y_{t+1} | y_t^{(r_t)}, S_t^{(r_t)}, S_{t+1})$ needs to be evaluated. The evaluation of the posterior predictive density involves 3-dimensional integrals, which can be solved approximately within the SMC framework.

Sequential Monte Carlo algorithm

252 The run-specific posterior distributions are analytically intractable and need to be
 253 calculated using approximate numerical methods. We inferred the posterior distributions
 254 using a sequential Monte Carlo algorithm. The number of particles was set to $N =$
 255 100000. To avoid particle degeneracy, the particle locations were resampled at each time
 256 step using the idea of artificial evolution of parameters (Liu and West, 2001), so that the
 257 number of effective particles after each time step was at least 50000. The artificial
 258 evolution of the parameters was accomplished by moving the particles around in the
 259 parameter space by drawing new particle locations from multivariate normal kernels
 260 whose means are shifted from the particle locations towards the sample mean of the
 261 particle locations. The magnitude of the shift is governed by a smoothing parameter
 262 $0 < h < 1$. The smoothing parameter was chosen arbitrarily, and since the results seemed
 263 reasonable, its role was not examined further nor was it tuned in any way. The resampling
 264 was quite efficient, and it was usually needed to be done only once per time step. The
 265 SMC algorithm works as follows. We only present the update for a single time step. The
 266 update is carried out similarly at each time step (excluding step 0, which is carried out only
 267 before a sequential estimation run starts).

- 268 0) Set the smoothing parameter $h = 0.1$ and calculate $a = \sqrt{1 - h^2}$. Draw N
 269 parameter vectors (particle locations) $\theta_0^{(j)} = (\alpha^{(j)}, \beta^{(j)}, \sigma^{(j)})$, $j = 1, \dots, N$ from
 270 the prior and set the corresponding particle weights to $w_0^{(j)} = \frac{1}{N}$.
 271 Repeat 1-10 until the number of effective particles (N_t^{eff}) is at least 5000:

272 1) Take the natural logarithm of the parameter vectors from the previous time step

273 $\vartheta_{t-1}^{(j)} = \log(\theta_{t-1}^{(j)})$ to avoid negative values for the non-negative parameters

274 later on.

275 2) Calculate the sample mean and covariance matrix from the log-transformed particle

276 locations $\mu_t = E(\vartheta_{t-1})$ and $\Sigma_t = \text{Cov}(\vartheta_{t-1})$.

277 3) Calculate the means of the kernel locations in log-space as

$$m_t^{(j)} = a\vartheta_{t-1}^{(j)} + (1 - a)\mu_t, \quad j = 1, \dots, N.$$

278 4) Transform back to normal space: $\xi_t^{(j)} = \exp(m_t^{(j)})$.

279 5) Calculate weights proportional to the product of the likelihood function evaluated

280 at the kernel means and the weights at the previous time step

$$\omega_t^{(j)} \propto w_{t-1}^{(j)} L(\xi_t^{(j)} | y_t, S_t), \quad j = 1, \dots, N.$$

281 6) Sample N indices from a multinomial distribution according to the weights

$$I_t^{(i)} \sim \text{Multinomial}(\{1, \dots, N\}, \{\omega_t^{(1)}, \dots, \omega_t^{(N)}\}), \quad i = 1, \dots, N.$$

282 7) Draw new particle locations in the log-space from a multivariate normal

283 distribution (and check that they belong to the support of the prior distributions,

284 otherwise draw again)

$$\vartheta_t^{(i)} \sim \text{MVN}\left(m_t^{(I_t^{(i)})}, h^2 \Sigma_t\right), \quad i = 1, \dots, N.$$

285 8) Transform back to original space to get the new particle locations $\theta_t^{(i)} =$

286 $\exp(\vartheta_t^{(i)})$

287 9) Calculate the new particle weights proportional to the ratio of the likelihoods

288 evaluated at the kernel means and at the new particle locations

$$w_t^{(i)} \propto \frac{L\left(\xi_t^{(i)} | y_t, S_t\right)}{L\left(\theta_t^{(i)} | y_t, S_t\right)}.$$

289 10) Calculate the number of effective particles

$$N_t^{\text{eff}} = \frac{1}{\sum_{i=1}^N \left(w_t^{(i)}\right)^2}.$$

290

291 **Algorithm outputs**

292 The output of the algorithm consists of the posterior run length probabilities and the
293 posterior distributions of the parameters for each run. The full posterior distribution of the
294 parameters is a weighted sum of the run-specific posterior distributions of the parameters
295 where the weights are the posterior probabilities of the run lengths r_t (3) (see
296 supplementary material for derivation). Similarly, the posterior predictive density of a new
297 response variable y_{t+1} given a new covariate value S_{t+1} is a weighted sum of the regime
298 specific posterior predictive densities. The posterior predictive density is an integral
299 quantity when predicting the recruitment in the future.

300

301 **Identifying recruitment regimes**

302 The algorithm provides the run length posterior probabilities which can be used as an early
303 indicator of a change point. If the posterior probability that the run length is one is high, it
304 means that the older runs do not explain the new data point well, which suggests that a
305 shift in the parameters has happened. However, high posterior probability can also result if
306 the most recent data point is an outlier caused for example by a gross error in the survey

process. In retrospect, it is also possible to calculate the smoothed run length probabilities $p(r_\tau|y_{1:t}, S_{1:t})$ for any $\tau < t$ recursively using the following equations (Särkkä 2013):

$$p(r_{\tau+1}|y_{1:t}, S_{1:t}) = \sum_{r_\tau=0}^{\tau} p(r_{\tau+1}|r_\tau)p(r_\tau|y_{1:t}, S_{1:t}), \quad (11)$$

$$p(r_\tau|y_{1:t}, S_{1:t}) = p(r_\tau|y_{1:t}, S_{1:t}) \sum_{r_{\tau+1}=0}^{\tau+1} \frac{p(r_{\tau+1}|r_\tau)p(r_{\tau+1}|y_{1:t}, S_{1:t})}{p(r_{\tau+1}|y_{1:t}, S_{1:t})}. \quad (12)$$

The smoothed run length probabilities are not affected by single outliers. After observing the entire data $(y_{1:T}, S_{1:T})$ we can update our belief about the change points by examining the smoothed run length probabilities. The algorithm is probabilistic, and we could choose any number of criteria to divide the data into regimes. We use the smoothed run length probabilities to find the most likely segmentation of the data, which is described next.

The most likely segmentation of data

We divide the data into regimes by calculating the most likely segmentation of data based on the smoothed run length probabilities. The segmentation is an ordered set of run lengths. An example for a dataset of length 10 could be $(1,2,3,4,5,6,1,2,3,4)$. Here, the first 6 data points belong to the first regime, and the last 4 data points belong to the second regime. We go through all possible such segmentations so that the maximum number of regimes is 5. We look only at the cases where the minimum length of a regime is 3 years, except for the first and the last regime, since the data cannot determine when the first regime started or the last regime ended. The most likely segmentation is found by maximizing the product of the smoothed run length probabilities of a segmentation. In the above example the product would be $\prod_{i=1}^6 p(r_i = i) \prod_{i=1}^4 p(r_{6+i} = i)$.

327 **Choosing prior distributions**

328 For the algorithm to perform optimally, there are some considerations related to the
 329 parameter prior distributions. Firstly, since the posterior probability of the start of a new
 330 run depends on the value of the prior predictive density evaluated at the new observation,
 331 the prior should be a proper probability distribution. Secondly, the value of the prior
 332 predictive density should be high enough for all the observations compared to the posterior
 333 predictive densities in order for the algorithm to yield enough probability for the new runs.
 334 Thirdly, we want to assume that all observations are about as likely based on the prior
 335 predictive density, since a priori we do not have any reason to assume otherwise. We also
 336 want the observations to be about equally likely for both S-R models. Finally, since the
 337 S-R models can be parameterized in several different ways, we do not want the inference
 338 to depend on the particular parameterization. To accomplish the above-mentioned goals,
 339 we build our prior distributions using the Jeffreys' method (Jeffreys, 1964). The Jeffreys'
 340 priors depend on the likelihood function for the parameters, and are thus different for each
 341 model. They are invariant to the choice of model parameterization, and produce flat prior
 342 predictive distributions. Such priors have been formulated for the Ricker and
 343 Beverton-Holt S-R models (Millar, 2002). However, these priors are improper, and thus do
 344 not suit our needs. Our solution to this problem is to constrain the priors to a predefined
 345 range of the parameters. The priors we use for the Ricker model are

$$p(\alpha^R) \propto \frac{1}{\alpha^R}, \quad \alpha^R \in [\alpha_{\text{up}}^R, \alpha_{\text{low}}^R],$$

$$p(\beta^R) \propto 1, \quad \beta^R \in [\beta_{\text{low}}^R, \beta_{\text{up}}^R],$$

$$p(\sigma^R) \propto \frac{1}{\sigma^R}, \quad \sigma^R \in [\sigma_{\text{low}}^R, \sigma_{\text{up}}^R].$$

346 For the Beverton-Holt model the priors are

$$p(\alpha^{\text{BH}}) \propto \frac{1}{\alpha^{\text{BH}}}, \quad \alpha^{\text{BH}} \in [\alpha_{\text{low}}^{\text{BH}}, \alpha_{\text{up}}^{\text{BH}}],$$

$$p(\beta^{\text{BH}}) \propto V(g(\beta^{\text{BH}}))^{\frac{1}{2}}, \quad \beta^{\text{BH}} \in [\beta_{\text{low}}^{\text{BH}}, \beta_{\text{up}}^{\text{BH}}],$$

$$p(\sigma^{\text{BH}}) \propto \frac{1}{\sigma^{\text{BH}}}, \quad \sigma^{\text{BH}} \in [\sigma_{\text{low}}^{\text{BH}}, \sigma_{\text{up}}^{\text{BH}}],$$

347 where $V(g(\beta^{\text{BH}})) = \frac{1}{T-1} \sum_t (g_t(\beta^{\text{BH}}) - \frac{1}{T} \sum_t g_t(\beta^{\text{BH}}))^2$ is the sample variance operator,

348 and $g_t(\beta^{\text{BH}}) = \frac{S_t}{1 + \beta^{\text{BH}} S_t}$, $t = 1, \dots, T$. The upper and lower limits were chosen so that the

349 ranges would contain all the plausible values for the parameters. The α parameter, which

350 represents the slope of the S-R curve at the origin was restricted so that the minimum and

351 the maximum of R/S in the data fell into the interval. For the β parameter, we chose the

352 limits so that the resulting carrying capacity k in the Ricker model and the asymptotic

353 value R_∞ in the Beverton-Holt model would fall into an interval where we believe these

354 quantities could be. In addition, the ranges were still widened so that on average each

355 observation for every species and for both S-R models was about equally likely based on

356 the prior predictive density. The upper and lower limits for the parameter priors are listed

357 in Table 1. Since the choice for the support of the parameters is subjective, we examine the

358 robustness of the results to different choices for the supports. The description of the

359 sensitivity analyses is presented in the supplementary material.

360

361 **Missing data**

In case there is missing data for some years, we predict the run length posterior distribution for those years using the one-step prediction equation (11). The run-specific posterior distributions of parameters are assumed not to change during the years of missing data. However, a new estimation run is also started during these years, to account for the possibility of a regime shift during the missing year.

367

2.2. Simulation setup

To validate our method we generated simulated data using the Beverton-Holt and Ricker stock-recruit models. We set the length of the simulation time series $T = 40$, which roughly corresponds to the length of our empirical time series. We drew randomly the number of regimes n^r from the set $\{2,3,4\}$. Next, we divided the time interval $\{1, \dots, T\}$ into n^r regimes with regime lengths $l_i^r, i = 1, \dots, n^r$ randomly chosen from $\{5, 6, \dots, 20\}$ so that the sum of the regime lengths $\sum_{i=1}^{n^r} l_i^r = T$. Next, we generated the regime specific parameters such that every other change in α was positive and every other was negative. The magnitudes of the relative changes were drawn from $U(0.5, 4)$ for the positive changes and from $U(-0.8, -0.2)$ for the negative changes with the constraint that the new $\alpha \in [0.1, 5]$. For simplicity for the first regime $\alpha^R = \alpha^{BH} = 1$ in each simulated data set and the density dependence parameters $\beta^R = 7.4 \cdot 10^{-9}$ and $\beta^{RH} = 14 \cdot 10^{-9}$ were constant during the whole simulation data set. The SSB values were drawn from $U(0, 3 \cdot 10^8)$, and the corresponding $\log\left(\frac{R}{S}\right)$ values were drawn from $N(f(S), \sigma)$. We tested four different noise levels $\sigma \in \{0.3, 0.4, 0.5, 0.6\}$. For each level of noise, we generated 100 data sets. Overall, we had thus 400 simulated time series of (S,R) pairs for both S-R models.

385 We fitted the S-R models to the simulated data using BOCPD, and for comparison using
386 models with time-invariant parameters. The models with time-invariant parameters were
387 fitted using Markov Chain Monte Carlo methods. For each simulated data set, we
388 calculated the proportion of time steps when the true parameter values were inside the
389 estimated 68% and 95% posterior central probability intervals (CPI) and the root mean
390 squared error (RMSE) of the posterior median estimate. We calculated similar scores for
391 the prediction ability of the models at each time step by comparing the true recruitment to
392 the posterior predictive distribution of the previous year given the true spawning stock
393 biomass. We also calculated how many of the change points were found correctly, how
394 many times they were found within two time steps of their actual occurrence, and how
395 many times the change point was completely missed by our method. We also calculated
396 the number of false alarms, i.e., number of change points reported by our method when
397 there actually was none.

399 **2.3. Empirical S-R data**

400 To explore non-stationarities in S-R dynamics of Atlantic cod, thorny skate, American
401 plaice, and white hake (hereafter denoted as cod, skate, plaice, and hake, respectively), we
402 use indices of recruit abundance and spawning stock biomass of these fishes in the
403 southern Gulf of St. Lawrence (sGSL). Data on population abundance and age and size
404 composition were obtained for these species by a bottom-trawl survey conducted by the
405 Canadian Department of Fisheries and Oceans (DFO) each September since 1971. This
406 survey follows a stratified-random design, with stratification based on depth and

geographic area (Fig. S1). Sampling stations are allocated to strata in rough proportion to stratum area. The standard fishing procedure was a 30-min tow at 3.5 knots in all years.

A change in survey gear occurred in 1985 and the survey vessel changed in 1985, 1992 and 2004. Comparative fishing experiments were conducted to calibrate the old and new vessels and gear. When a change in fishing efficiency was detected for a particular species, catches by the earlier vessel/gear were adjusted to be equivalent to those by the new vessel/gear (Benoît and Swain 2003a; Benoît 2006). An uncalibrated vessel conducted the survey in 2003, and some strata were not sampled. Thus, we omitted the data for this year. Consequently, two years have missing data for each stock. One is 2003 and the other one is the year in which the recruits are assumed to be produced by the spawning stock of 2003. For white hake, the estimated change in fishing efficiency in 1985 was not significant, though statistical power was low due to its restricted distribution. Recent population modelling indicated a change in fishing efficiency for this species similar to the non-significant effect estimated by comparative fishing (Swain et al. 2015). Catch rates of this species prior to 1985 were adjusted to account for this change in fishing efficiency.

Fishing during the survey was conducted during daylight hours only (07:00 – 19:00) prior to 1985 and 24-h per day since then. Diel differences in catchability were assessed based on paired day and night survey tows conducted at the same locations and on analysis of the 1985-2001 survey data controlling statistically for annual and spatial variation in catch rates. Estimated species-specific diel effects were similar between approaches, time periods and vessels, and were comparable to results from studies in other areas (Benoît and Swain 2003b). When diel differences in catchability occurred, night catches were adjusted

431 to be equivalent to day catches in order to maintain a consistent time series (Benoît and
 432 Swain 2003a; Benoît 2006). The sampling intensity of the surveys also changed in 1985.
 433 Before 1985, 64-108 tows were conducted annually (mean = 70.6) and since 1985 the
 434 number of tows has increased to 132-244 (mean = 180.8). The survey provides data on the
 435 mean weight of individuals in each age class $w_{a,t}$, the proportion of mature individuals in
 436 each age class $m_{a,t}$, and the mean number of individuals per tow in each age class $n_{a,t}$.

437

438 The estimate of the number of recruits in year t (R_t) is calculated as the mean number of
 439 individuals of age $a = a^R$ per tow, multiplied by the number of trawlable units in the
 440 survey area ($U = 1729346$), where a^R is the assumed age of recruitment. The ages of
 441 recruitment used for the study species are given in Table 1.

$$R_t = N_{a^R} = n_{a^R}U, \quad (1)$$

442 where n_{a^R} is the stratified mean number of recruits per standard tow in year t and N_{a^R}
 443 is the survey estimate of recruit abundance (“trawlable” abundance) in year t . The
 444 estimate of the spawning stock biomass, which produced the recruits, is calculated as

$$S_t = \sum_{a=0}^{a_{\max}} w_{a,t-a^R} m_{a,t-a^R} N_{a,t-a^R}, \quad (2)$$

445 where $w_{a,t}$ is the estimate of the mean weight of individuals in age class a in the
 446 beginning of year t , $m_{a,t}$ is the estimated proportion of mature individuals in age class a
 447 in year t , and $N_{a,t}$ is the estimate of the number of individuals in age class a in year t .
 448 The mean weight at age in the beginning of the year t is calculated as the geometric mean
 449 of the September mean weight at age of the same cohort in years $t - 1$ and t . Survey

450 indices of recruit abundance and spawner biomass are given in Table S1 along with
451 measures of their uncertainty.

452

453 **3. Results**

454 The methods ability to detect the change points in the simulated data depended on the
455 magnitude of the change in α and the level of noise. The smaller the change in α and the
456 higher the noise level the more difficult it was to detect the change points. (Figs. 1, S5).

457 The number of false alarms was positively correlated with the noise level. In the
458 Beverton-Holt model simulations, the number of false alarms were 10, 35, 59 and 71,
459 when the noise levels were 0.3, 0.4, 0.5 and 0.6, respectively. For the Ricker model
460 simulations, the number of false alarms were 15, 29, 44 and 50. To put these numbers in
461 perspective, the total number of change points in the Beverton-Holt and Ricker simulations
462 were 774 and 821, respectively.

463 The estimated posterior distributions for the parameters were much closer to the true
464 parameter values for the BOCPD model than for the model with time-invariant parameters
465 based on the frequency with which the true parameter value was inside the 68% and 95%
466 posterior CPIs (Fig. 2 & S6). The performance of the methods got worse as the level of
467 noise got higher.

468 In addition, the medians of the parameter posterior marginal distributions produced by
469 BOCPD were consistently closer to the true parameter values than those produced by the
470 time-invariant model (Table 2.).

471 The BOCPD model predictions were also better than the predictions of the constant
472 parameter model, both based on the frequency with which the next year's recruitment was
473 inside the CPIs of the posterior predictive distribution, and the RMSE of the median
474 estimates (Fig. 2 & S6, Table 2).

475 In our empirical data, we found shifts in the parameters of both of the S-R models in all
476 four study species. The number of detected regimes based on the most likely segmentation
477 of the data ranged from two to four, and the lengths of the regimes for which both the start
478 and end years were identified ranged from 4 to 21 years (Fig. 3). The shifts radically
479 changed the marginal posterior distributions of the parameters (Figs. 4, S2, and S3). The
480 shifts were mainly driven by changes in α , while β remained relatively constant.

481 Because of this, the changes in carrying capacity, k , and the asymptotic maximum, R_∞
482 reflect the changes in the maximum recruitment per unit of SSB, α (Fig. 5). The
483 parameter estimates for α^R and α^{BH} are almost identical, which shows that the method
484 is not very sensitive to the choice of the S-R model in the studied stocks. This is also seen
485 in the timings of the change points based on the most likely segmentation of the data (Fig.
486 3). Uncertainty related to the regime-specific parameters in the beginning of a new regime
487 was also reflected as an increase in the standard deviation parameter, δ_t , immediately
488 after the shifts (Fig. S3). The changes in the parameters also resulted in clearly different
489 medians of the posterior predictive distributions of R_t at the end of the detected regimes
490 (Fig. 6). The medians of the posterior predictive distributions of $\log\left(\frac{R_t}{S_t}\right)$ are shown in
491 Figure S4.

492

493 For cod, we found shifts in 1976, 1991 and 2013 using the Ricker model (Fig. 3a). The
494 posterior median estimates of α^R at the end of the four resulting regimes were 0.42,
495 1.31, 0.31, and 2.89, respectively. In terms of relative change in α^R the magnitude of
496 the shifts were 212%, -76.6%, and 839%. Using the Beverton-Holt model, the shifts
497 occurred in 1991 and 2013 (Fig. 3b), and the posterior median estimates of α^{BH} at the
498 end of the three resulting regimes were 1.30, 0.35, and 3.01, respectively. In terms of
499 relative change in α^{BH} the magnitude of the shifts were -72.7%, and 749%.
500
501 The shifts found for hake occurred in 1979 and 1997 for both S-R models (Fig. 3c-d). The
502 shifts were driven by changes in α (Fig. 4), although the density dependence parameter β
503 also tended to be higher for the third regime than for the earlier regimes based on the
504 Ricker model (Fig. S2). The posterior median estimates of α^R at the end of the three
505 resulting regimes were 2.37, 0.71 and 1.92, respectively. This resulted in relative
506 change in α^R of -69.8% and 169%. The corresponding posterior median estimates of
507 α^{BH} were 2.95, 0.84, and 2.05, which amount to relative changes of -71.4% and
508 143%.
509
510 Plaice experienced a shift in 1982 when analyzed using the Ricker model (Fig. 3e). The
511 posterior median estimates of α^R at the end of the two resulting regimes were 4.73 and
512 2.36, respectively. In terms of relative change, the magnitude of this shift was -50%.
513 Using the Beverton-Holt model, we found shifts in 1982 and 1986 (Fig. 3f). The posterior
514 median estimates of α^{BH} at the end of the three resulting regimes were 4.46, 1.27, and

515 2.70. The magnitude of the shifts in terms of relative change were thus -71.4% and
516 110% .

517

518 The data point of 1984 in the skate time series seemed to be an outlier, and we removed it
519 from the data set before running the analysis. The shifts for skate as identified by our
520 change point detection scheme occurred in 1988, 1999 and 2006 using both S-R models
521 (Fig. 3g-h). The posterior median estimates of α^R at the end of the four regimes were
522 0.27, 0.72, 0.47, and 1.98, respectively. Translated into relative changes the magnitude
523 of the shifts were 169% , -34.8% , and 324% . The posterior median estimates of α^{BH}
524 were 0.26, 0.83, 0.50, and 2.13. The relative changes between regimes were thus
525 222% , -40% , and 329% .

526

527 The sensitivity analyses showed that increasing the change point prior probability to 0.2
528 resulted in more change points for each stock. On the other hand, when using smaller
529 change point prior probability some of the change points were not detected (Table S2).
530 However, change points were found for each stock using both S-R models with $\lambda = 20$.
531 Most notably, even with $\lambda = 10000$ the two change points in 1991 and 2013 were found
532 for cod with both S-R models (Fig. S10). This indicates that there is ample evidence of at
533 least two change points in the data. Moreover, as λ increased, the parameter posterior
534 marginal distributions showed less year to year variation (Fig. S11), however the
535 distributions at the end of the regimes did not differ much, which is also seen as almost
536 identical medians of the posterior predictive distributions of R_t at the end of the detected
537 regimes (Fig. S12). The results were even more robust to widening the support of the
538 parameters. In some cases, one less change point was found, whereas in some cases one

539 more change point was found (Table S2). Only in the case of plaice, the change of the
540 support affected the timing of the shifts, when the width of the support of α^{BH} was
541 doubled. In general, the widening of the supports did not affect the parameter posterior
542 marginal distributions notably (Fig. S14), with the exception that in cases where the data
543 carried little information about the density dependence parameter β , the uncertainty about
544 β was increased as the support of β was increased (Fig. S15). The resulting medians of
545 the posterior predictive distributions, however, differed very little (Fig. S16).

546

547 **4. Discussion**

548 All four of the studied stocks showed shifts in their S-R parameters during the years
549 1973-2014 (Fig. 3). In comparison with the constant model, which assumes time-invariant
550 parameters, it is clear that the BOCPD predictive distributions at the end of the regimes fit
551 the data much better than the constant model (Fig. 6). This is because the constant
552 parameter model gives equal weight to all observations, whereas the BOCPD model tends
553 to give more weight to the most recent observations when there is evidence of a recent
554 change point. Furthermore, the constant parameter model consistently produces smaller
555 uncertainty in the parameter estimates (Fig. 4), such that as more data accumulates the
556 uncertainty in the constant parameter model estimates is reduced. This prevents the
557 estimate from changing much when a shift in the parameter value happens, and is most
558 apparent in the posterior marginal density of α parameters at the beginning of new
559 regimes. When a shift occurs, the BOCPD posterior median estimate rapidly shifts to a
560 new level. The posterior median estimate of the constant parameter model also tends to
561 shift toward the new level, but this shift occurs much more slowly and the new level may

562 not be reached even 20 years after the shift (e.g. the third regime for the Ricker cod
563 model).

564

565 In the light of the findings of the present study, the commonly assumed stationarity in S-R
566 relationships may often not be valid. Our study showed that shifts in S-R dynamics were
567 common among the four fish species examined, and in the Gulf of St. Lawrence, they can
568 change the level of maximum recruit production per unit of SSB by a factor of eight.

569 While the present study was limited to one marine ecosystem, indications of
570 non-stationarities in the parameters of S-R models have been previously documented in the
571 North Sea (Olsen et al. 2011) and the Pacific Ocean (Munch and Kottas 2009). The present
572 study goes deeper by exploring the nature of temporally shifting dynamics and by
573 presenting novel and flexible methodology. In the following, we discuss our findings with
574 respect to changes seen in the cod, hake, skate and plaice stock dynamics in the Gulf of St.
575 Lawrence, in order to explore potential causes and pathways of shifts. Secondly, we
576 compare our modelling approach to previous attempts to account for temporal changes in
577 S-R dynamics and sketch future directions towards accounting for parameter shifts in
578 fisheries stock assessments.

579

580 Regime shifts are often defined as relatively sudden changes between alternate and
581 persistent (commonly 10-30 years) ecosystem states, involving multiple variables and wide
582 spatial scales (de Young et al. 2008, Jiao 2009, Möllmann et al. 2015). These shifts are
583 often attributed to decadal climate-ocean oscillations which move the ecosystem between
584 two alternate stable states (Jiao 2009). In fact, some scientists reserve the term “marine
585 ecosystem regime shift” to cases linked to climatic forcing (Beamish et al. 2004).

586 However, fishing is now also recognised as an important driver of marine ecosystem
587 regime shifts (Möller et al. 2008, Jiao 2009). For example, direct and indirect effects of
588 harvesting appear to be important drivers of a “regime shift” in the composition of the
589 marine fish community in the southern Gulf of St. Lawrence, from a community
590 dominated by large-bodied fishes to one dominated by small-bodied fishes (Benoît and
591 Swain 2008).

592

593 This study focusses on “regime shifts” in the recruitment dynamics of single species within
594 an ecosystem. In most cases, the identified regimes are “persistent”, lasting for an average
595 of 16-17 years (omitting regimes ending within 10 years of the start of the time series and
596 those starting within 10 years of the end of the time series). They are also consistent with
597 the timing of fishing-induced changes in this ecosystem. A high productivity regime was
598 identified for cod beginning in the mid-1970s and lasting throughout the 1980s (Fig. 4).
599 This coincides with a collapse in the biomass of pelagic fishes in this ecosystem due to
600 overfishing in the 1960s and early 1970s. These fishes appear to have a negative impact on
601 cod recruitment success through predation on the early-life stages of cod (Swain and
602 Sinclair 2000). Pelagic fish biomass recovered in the 1980s, and cod recruitment rates
603 returned to more normal levels in the 1990s. The recruitment rate of White hake has been
604 exceptionally high since the mid-1990s (Swain et al. 2015). This is interpreted as very high
605 survival of small hake since the mid-1990s. A similar pattern of improved survival of
606 small fish is seen throughout the marine fish community of the southern Gulf during this
607 period, and may reflect a release from predation following the collapse of large demersal
608 fish in this ecosystem (Benoît and Swain 2008). The recent period of exceptionally high

609 recruitment rates of hake corresponds with the positive shift in α in 1997 (Fig. 4). Based
610 on population modelling results, Morin et al. (2013) suggested that the S-R relationship of
611 plaice has been stationary since 1976. However, they also noted that the established S-R
612 relationship might not describe the dynamics of the stock adequately in a more productive
613 period prior to 1976. Our study is in line with these conclusions, providing no evidence for
614 a shift in the R-S relationship of this stock since 1982 or 1986 depending on the S-R model
615 used. Consistent with the suggestions of Morin et al. (2013), our results indicate a shift
616 from a more productive to a less productive regime in 1982 (Fig. 4). It has been reported
617 that the productivity of Thorny skate at early life history stages increased from the 1970s
618 to the 1990s and remained high since then (Swain et al. 2013). Swain et al. (2013) could
619 not distinguish between effects due to increased recruitment rate versus increased survival
620 of post-recruit juveniles. Based on our study (Fig. 4), high productivity at early life stages
621 appears to have been mainly due to high survival of post-recruit juveniles in the 1990s and
622 early 2000s (when our estimated S-R parameters changed little), whereas high recruitment
623 success may have been the main contributing factor since the mid-2000s (when a shift to a
624 higher productivity regime is estimated by our model).

625

626 Regimes are often modelled as alternating between two stable states (e.g. Steele 1996,
627 Munch and Kottas 2009). This is not necessarily the case for “real” systems (Steele 1996),
628 particularly when there is an interplay between fishery and climate impacts (Jiao 2009).
629 Our method places no restriction on the number of distinct regimes. It can be used when
630 the system oscillates between two alternate states but is not restricted to this case. In our
631 hake example, estimated recruitment productivity shifted from a high level in the 1970s to

632 a low level, and then back to a high level since the mid-1990s. However, the recent state of
633 high recruitment success for hake is not a return to the earlier state; both the ecosystem and
634 the hake population differed greatly between these two periods (Benoît and Swain 2008,
635 Swain et al. 2016).

636

637 The smoothed probabilities of the start of new regimes (Fig. 3) and the parameter posterior
638 marginal densities (Fig. 4) reveal an interesting synchronicity in the timings of the shifts
639 between species. Atlantic cod is the dominant predatory fish in this ecosystem. Cod
640 biomass declined from the mid-1950s to the mid-1970s due to overfishing (Swain and
641 Benoît, 2015). Recruitment productivity of cod then increased dramatically following the
642 collapse of pelagic fish, potential predators of their early life history stages. This resulted
643 in the rapid recovery of the cod stock due to the production of a series of strong year
644 classes from the mid-1970s to the early 1980s. Cod recovery coincided with declines in the
645 recruitment productivity of hake and plaice, marked by regime shifts in 1979 and 1982,
646 respectively. These shifts in recruitment productivity may result from increased predation
647 by large cod on pre-recruit juveniles of hake and plaice and/or increased competition
648 between these early juveniles and small cod.

649

650 In our study, we have used bottom trawl survey indices of the spawning stock biomass and
651 number of recruits to avoid any pitfalls related to using stock assessment outputs as data in
652 our analysis (Brooks and Deroba, 2015). However, we did not include any uncertainty
653 estimates of the indices in our analysis but simply assumed that the standard deviation of
654 the log-transformed R/S ratios was proportional to the sampling intensity and inferred the
655 noise parameters from the data. Moreover, the changes in survey gear and protocol in 1985

656 and vessel in 1985, 1992 and 2004 might have been misinterpreted as regime changes by
657 our method. In general, the identified S-R shifts did not coincide with the timing of survey
658 changes. However, for cod there is a change point (1991) near 1992 in both the Ricker and
659 Beverton-Holt model analyses, for plaice there is a change point (1986) near 1985 in the
660 Beverton-Holt analysis, and for skate there are change points (1988 and 2006) that are
661 close to the survey changes in 1985 and 2005 in both the Ricker and Beverton-Holt
662 analyses. We examined this further, comparing results for thorny skate with and without
663 adjustment for the changes in the survey. (Effects of survey changes were greatest for
664 thorny skate.) The estimated timing of change points was the same using both adjusted and
665 unadjusted survey data (Fig. S7), though the scale of predicted recruit abundance differed,
666 matching the difference in scale between the two data sets (Fig. S8 and S9). In this case at
667 least, change point detection was robust to changes in fishing efficiency in the survey,
668 whether adjusted for or not.

669
670 Earlier studies modelling recruitment regimes have been limited to two regimes (Munch
671 and Kottas 2009, Ottersen et al. 2013), whereas in the BOCPD model the maximum
672 number of regimes does not have an upper bound other than what is imposed by the length
673 of the observation time series. Thus, direct comparison to the previous methods was not
674 possible. It would be interesting, however, to expand the other methods to handle multiple
675 change points, and to explore other methods for modelling time-varying parameters in S-R
676 models for comparison. Here, we assumed that the parameters change suddenly but in
677 some cases, it could be more realistic to assume that the parameters change gradually.

678

679 Unlike maximum likelihood methods (Ottersen et al. 2013), BOCPD explicitly takes into
680 account uncertainty in both the parameter estimates and the timings of the shifts, and these
681 uncertainties are further propagated into predictions about future recruitment via the
682 posterior predictive distribution. Our method also takes into account the change in the
683 level of noise in the data due to change in sampling intensity, and the method is able to
684 handle years of missing data. Moreover, the earlier studies focused only on the Ricker
685 model, whereas we also applied our method to the Beverton-Holt model. We chose the
686 Ricker and Beverton-Holt S-R models for this study because of their popularity. However,
687 the presented framework easily accommodates any S-R model that can be fitted using
688 sequential Bayesian estimation. Furthermore, we explicitly state our prior assumptions
689 about the residuals in the S-R models, and calculate the posterior distributions of the
690 standard deviation parameters (Fig. S3). Moreover, our model can be also extended to take
691 into account environmental correlates by directly modifying the S-R model to incorporate
692 environmental effects as has been done earlier (e.g. Chen and Irvine 2001). Furthermore,
693 the parameters describing the strengths of the environmental effects can also be assumed
694 piecewise constant as we have done with α and β in this study to allow shifts in these
695 parameters.

696

697 For most of the stocks, the posterior median and 68% central probability interval of the
698 density dependence parameter β do not differ much from those of the prior distribution.
699 We have identified two possible reasons for this. Firstly, most of the data points have been
700 collected when the stocks have been at low density and thus there was little information on
701 density dependence in the data. Secondly, the effects of ecosystem regime shifts may be
702 more likely to be transmitted to the S-R process through the α parameter than through the

703 β parameter. The β parameter is used to model density-dependent feedbacks on
704 recruitment success (e.g., cannibalism, effects of overcrowding and competition). These
705 effects can certainly be influenced by environmental changes (e.g., decreased abundance
706 of prey for adults, resulting in increased cannibalism; Hjermann et al. 2007). However,
707 direct effects of regime shifts (e.g., of changes in temperature or the abundance of prey,
708 competitors or predators of larvae and early juveniles) would be transmitted to the
709 recruitment process through the α parameter, unless incorporated directly as additional
710 terms in the recruitment model.

711

712 The model can produce a high posterior probability for a shift based on only one
713 observation that is not well explained by the posterior predictive distribution of the
714 previous regime. However, the posterior probabilities cannot tell if the latest observation is
715 the first observation from a new regime or an outlier produced by e.g. sampling error.

716 When more data is collected in the coming years, the smoothed run length probabilities
717 will retrospectively show which was the case. An outlier would be identified by finding a
718 huge discrepancy between the posterior and smoothed probabilities of a new run in the
719 particular year. In addition, even if the new observation actually comes from a new regime,
720 the regime-specific parameter estimates of the S-R relationship have to be very uncertain
721 since they are based only on one observation, and are heavily affected by the prior
722 distribution of the parameters. As an example of this, we point to the last two years in the
723 case of cod. Although the shift in 2013 seems obvious based on the smoothed run length
724 probabilities (Fig. 3), the posterior parameter estimates (Fig. 4), and by just looking at the
725 data (Fig. 6), it is highly questionable that the maximum recruit production per unit of
726 spawning stock biomass in 2014 is really more than eight times what it was in 2012. It

727 may well be that in both 2013 and 2014 surveys the recruitment was overestimated and/or
728 the spawning biomass underestimated. However, the small amount of data available for the
729 regime starting in 2013 results in high uncertainty in the carrying capacity (Fig. 5), and a
730 higher standard deviation (Fig. S3).

731

732 Even though the BOCPD modelling framework is theoretically sound, additional evidence
733 of the inferred shifts may be seen in the tendency of the constant parameter model
734 estimates to approach the BOCPD model estimates after a shift. This gives us even more
735 confidence stating that recruitment shifts have occurred for the stocks examined in this
736 study, and also that there is little reason to assume that shifts in S-R relationship would not
737 also happen in the future.

738

739 The assumption of time-invariant parameters is common when modelling complex
740 biological systems. However, as pointed out in this study, some parameters may well be
741 constant within some limited time range, but experience sudden and relatively strong
742 changes. In these cases, using constant model parameters may lead to serious over- or
743 underestimation of key population parameters and their uncertainty, subsequently resulting
744 in erroneous conclusions about the status of the population and forecasts of its future
745 development.

746

747 The stock-recruitment relationship plays a critical role in determining fisheries
748 management targets and limits (e.g., Shepherd 1982) and in population projections of
749 future biomass. Thus, the scientific advice provided to fisheries management would be
750 expected to be improved if it took into account effects of regime shifts on stocks (e.g.,

King et al. 2015). However, success depends on the ability to reliably identify the timing and extent of regime shifts (e.g., Basson 1999, King and McFarlane 2006). One approach has been to link a component of productivity (e.g., recruitment) to an environmental variable such as temperature and make projections or estimate reference points based on this relationship (Punt et al. 2014). Pitfalls of this approach include the possibility that these relationships are spurious, break down over time or change over time. A second approach attempts to identify regimes based on deviations (e.g., in annual recruitment) from the previous average value (e.g., STARS, Rodionov and Overland 2005) or potentially from model predictions (e.g., BOCPD).

760

The utility of incorporating information on recruitment regimes in fisheries management can be examined using Management Strategy Evaluation (MSE; Punt et al. 2014). In many cases evaluated using MSE, incorporating effects of regime shifts in management procedures failed to improve management performance (Punt et al. 2014; King et al. 2015). Reasons included high uncertainty in environmental and recruitment measurements (King et al. 2015), failure to detect regimes when they were present or detecting them when they were not (e.g., A'mar et al. 2009), and misidentifying regime timing combined with noisy estimates of management reference points due to the reduced sample size within regimes (Szuwalski and Punt 2013). However, use of BOCPD as the algorithm to detect regime shifts may improve performance due to its robust accounting of uncertainty and its probabilistic designation of regime shifts. Until information on regime shifts can be more reliably integrated directly into stock assessment models and estimation of biological reference points, King et al. (2015) suggest using this information in a supporting role. For example, biomass projections could be made assuming below average, average and above

775 average recruitment rates and advice based on these scenarios could be summarized along
776 with associated risks. In this case, BOCPD could be used to assign relative probabilities to
777 the various scenarios.

778

779 As pointed out by many fisheries scientists, establishing S-R relationships that are useful
780 in fisheries sciences is a difficult endeavor (Hilborn and Walters 1992, Subbey et al. 2014).
781 As the present study illustrates, incorporating the assumption of recruitment regimes in the
782 S-R models will bring us a step closer to understanding drivers of recruitment. However,
783 while recruitment is one of the most essential aspects of fish population dynamics, other
784 parts of the population dynamics could also experience shifts in the sense described in this
785 paper. Bayesian online change point detection offers a theoretically sound modular
786 framework for regime shift modelling to be used with any kind of a model relevant to fish
787 population dynamics.

788

789 **Supplementary material**

790 The following supplementary material is available on the journal Web site. Section A:
791 Derivations of the recursive computation of the run length posterior distribution and the
792 full posterior distribution of the parameters; Section B: Description of the prior sensitivity
793 analyses; Section C: Additional figures; Section D: Additional tables.

794

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952

953 **Table 1.** Model parameters for the study species: Atlantic cod (*Gadus morhua*), white
954 hake (*Urophycis tenuis*), American plaice (*Hippoglossoides platessoides*), and thorny skate
955 (*Amblyraja radiata*).

Species	a_R	α_{low}^R	α_{up}^R	β_{low}^R	β_{up}^R	σ_{low}^R	σ_{up}^R	α_{low}^{BH}	α_{up}^{BH}	β_{low}^{BH}	β_{up}^{BH}	σ_{low}^{BH}	σ_{up}^{BH}
cod	3	0.1	4	$5 \cdot 10^{-9}$	$10 \cdot 10^{-9}$	0.3	1.5	0.1	4	$10 \cdot 10^{-9}$	$20 \cdot 10^{-9}$	0.3	1.5
hake	2	0.1	6	$30 \cdot 10^{-9}$	$200 \cdot 10^{-9}$	0.3	1.5	0.1	6	$60 \cdot 10^{-9}$	$400 \cdot 10^{-9}$	0.3	1.5
plaice	4	0.2	6	$10 \cdot 10^{-9}$	$20 \cdot 10^{-9}$	0.3	1.5	0.2	6	$20 \cdot 10^{-9}$	$40 \cdot 10^{-9}$	0.3	1.5
skate	2	0.1	4	$400 \cdot 10^{-9}$	$2000 \cdot 10^{-9}$	0.3	1.5	0.1	4	$800 \cdot 10^{-9}$	$4000 \cdot 10^{-9}$	0.3	1.5

956

957 **Table 2.** RMSE of the posterior median estimates of parameters ($\hat{\alpha}$, $\hat{\beta}$ and $\hat{\sigma}$), derived
958 quantities ($\widehat{R_\infty}$ and $\widehat{R}$), and the median of the posterior predictive distribution ($\widehat{R_{t+1}}$) for
959 different noise levels ($\sigma \in \{0.3, 0.4, 0.5, 0.6\}$) for the change point model and constant
960 model. The three reported numbers are the 16th percentile, the median, and the 84th
961 percentile, respectively. The units for $\hat{\beta}$ are $\frac{10^{-9}}{\text{kg}}$, and for $\widehat{R_{t+1}}$ they are 10^6 of
962 individuals.

		σ	$\hat{\alpha}$				$\hat{\beta}$			$\hat{\sigma}$			$\widehat{R_\infty}/\widehat{R}$			$\widehat{R_{t+1}}$		
Beverton-Holt	BOCPD	0.3	0.24	0.44	0.57		1.76	2.64	4.11	0.056	0.073	0.091	18.4	28.7	45.0	3.3	9.0	16.3
		0.4	0.34	0.51	0.69		2.18	2.88	4.43	0.077	0.098	0.128	24.7	38.0	54.0	4.9	11.9	21.0
		0.5	0.39	0.60	0.79		2.26	2.95	3.98	0.097	0.133	0.162	26.5	41.6	60.2	5.9	14.6	27.8
		0.6	0.49	0.70	0.90		2.08	2.78	3.74	0.127	0.174	0.210	31.4	50.3	66.8	10.5	23.1	40.0
	Constant	0.3	0.53	1.02	1.67		1.72	2.74	5.08	0.148	0.238	0.287	49.2	81.1	123.3	15.1	35.4	61.7
		0.4	0.56	1.09	1.57		1.84	3.38	6.00	0.115	0.188	0.225	41.8	89.2	126.3	13.4	37.3	61.5
		0.5	0.52	1.04	1.57		1.74	3.41	5.16	0.106	0.141	0.164	38.1	76.7	120.4	11.2	36.0	65.6
		0.6	0.57	1.12	1.57		1.75	3.16	5.70	0.084	0.110	0.148	40.3	85.7	124.5	20.4	45.3	70.8
Ricker	BOCPD	0.3	0.34	0.49	0.67		0.88	1.17	1.67	0.059	0.070	0.090	11.6	17.6	29.6	2.0	6.8	14.3
		0.4	0.36	0.57	0.79		0.93	1.22	1.65	0.080	0.105	0.136	14.6	22.3	34.0	4.5	10.0	19.8
		0.5	0.44	0.69	0.91		1.10	1.46	1.98	0.093	0.123	0.153	18.4	28.5	41.6	6.3	12.0	23.9
		0.6	0.56	0.74	1.04		1.15	1.58	2.18	0.131	0.175	0.215	23.5	34.2	45.8	10.8	20.3	34.2
	Constant	0.3	0.51	1.04	1.60		0.76	1.11	1.76	0.133	0.226	0.292	23.4	51.6	84.4	8.8	25.8	51.1
		0.4	0.50	1.02	1.82		0.82	1.09	1.66	0.104	0.178	0.211	23.8	48.6	85.2	8.9	30.3	54.3
		0.5	0.49	0.98	1.71		0.80	1.36	1.93	0.097	0.131	0.161	22.6	46.9	82.0	9.7	27.3	62.7
		0.6	0.63	1.09	1.70		0.97	1.41	2.27	0.088	0.114	0.142	24.5	53.4	86.2	12.5	38.0	63.4

963

964

965 **Figure legends**

966

967 **Figure 1.** The results of the change point detection accuracy in the Beverton-Holt model
968 simulations for the four noise levels ($\sigma \in \{0.3, 0.4, 0.5, 0.6\}$). The vertical axis shows the
969 number of change points and the horizontal axis shows the absolute change in α^{BH}
970 parameter before and after the change point. Black color denotes the change points that
971 were inferred correctly, gray color denotes those change points that were detected but with
972 an error of ± 1 or ± 2 time steps, and white denotes the rest of the change points that we
973 considered as missed by our method. The corresponding figure for the Ricker model
974 simulations is found in the supplementary material.

975

976 **Figure 2.** Empirical cumulative distribution functions illustrating the accuracy of the
977 parameter estimates in the Beverton-Holt model simulations. The vertical axis shows the
978 proportion of time steps within a simulation case for which the true parameter value was
979 within the posterior central probability interval (CPI), whereas the horizontal line shows
980 the proportion of all the simulation cases. The dashed line denotes the BOCPD model and
981 the solid line denotes the model with time-invariant parameters. Different noise levels
982 ($\sigma \in \{0.3, 0.4, 0.5, 0.6\}$) are denoted with increasing darkness of the curves. The originally
983 staircase-like curves were smoothed to clarify patterns.

984

985 **Figure 3.** The smoothed run length probability distributions for the study species: Atlantic
986 cod (*Gadus morhua*), white hake (*Urophycos tenuis*), American plaice (*Hippoglossoides*
987 *platessoides*) and thorny skate (*Amblyraja radiata*). The left and right column show the
988 run length probabilities when the UPM is the Ricker model and Beverton-Holt model,

989 respectively. The red lines show the most likely segmentation of the data based on the
990 smoothed run length probabilities.

991

992 **Figure 4.** The sequential update of the posterior marginal densities of the maximum
993 number of recruits per unit of spawning stock biomass for the study species. Output for the
994 Ricker (α^R) and Beverton-Holt (α^{BH}) models are shown in left and right columns,
995 respectively. The colored solid lines denote the posterior median and the shaded areas
996 indicate the 68% central posterior probability interval. The regimes as identified using the
997 most likely segmentation of the data are denoted by the change in the color of the shading.
998 The black lines indicate the posterior median and 68% posterior probability interval of the
999 constant parameter model. The supplementary material includes figures for the posterior
1000 marginal densities of the density dependence parameter β (Fig. S3), and the standard
1001 deviation parameter δ_t (Fig. S4).

1002

1003 **Figure 5.** The sequential update of the posterior marginal densities of the carrying capacity
1004 for recruits $k = \frac{\alpha^R}{e\beta^R}$ in the Ricker model and the asymptotic maximum number of recruits
1005 $R_\infty = \frac{\alpha^{BH}}{\beta^{BH}}$ in the Beverton-Holt model. Medians and 68% central probability intervals are
1006 shown. Regimes are denoted with different colors. Constant parameter model fit is shown
1007 in black.

1008

1009 **Figure 6.** Medians of the posterior predictive distributions of R_t for the Ricker and
1010 Beverton-Holt S-R models using BOCPD (solid colored lines) and the constant parameter

1011 model (dashed black line). The data points belonging to each regime are colored using the
1012 same color as the median lines.
1013

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1014 Fig. 1

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1017 Fig. 2

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1020 Fig. 3

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1023 Fig. 4

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1026 Fig. 5

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1028 Fig. 6

1029

1 Examining non-stationarity in the recruitment
2 dynamics of fishes using Bayesian change point
3 analysis

4 *Supplementary material*

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6

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12 Section A: Derivations

13 The recursive computation of the run length posterior distribution

$$\begin{aligned}
 p(r_t | y_{1:t}, S_{1:t}) &= \frac{p(r_t, y_{1:t} | S_{1:t})}{p(y_{1:t} | S_{1:t})} = \frac{1}{p(y_{1:t} | S_{1:t})} \sum_{r_{t-1}=0}^{t-1} p(r_t, r_{t-1}, y_t, y_{1:t-1} | S_t) \\
 &= \frac{1}{p(y_{1:t} | S_{1:t})} \sum_{r_{t-1}=0}^{t-1} p(r_t, y_t | r_{t-1}, y_{1:t-1}, S_{1:t}) p(r_{t-1}, y_{1:t-1} | S_{1:t}) \\
 &= \frac{1}{p(y_{1:t} | S_{1:t})} \sum_{r_{t-1}=0}^{t-1} p(r_t | r_{t-1}, y_{1:t-1}, S_{1:t}) p(y_t | r_{t-1}, y_{1:t-1}, S_{1:t}) p(r_{t-1}, y_{1:t-1} | S_{1:t-1}) \\
 &= \frac{1}{p(y_{1:t} | S_{1:t})} \sum_{r_{t-1}=0}^{t-1} p(r_t | r_{t-1}) p(y_t | y_{(t-r_{t-1}):(t-1)}, S_{(t-r_{t-1}):(t-1)}) p(r_{t-1}, y_{1:t-1} | S_{1:t-1}) \\
 &= \sum_{r_{t-1}=0}^{t-1} \frac{p(r_t | r_{t-1}) p(y_t | y_{t-1}^{(r_{t-1})}, S_{t-1}^{(r_{t-1})}) p(r_{t-1} | y_{1:t-1}, S_{1:t-1}) p(y_{1:t-1} | S_{1:t-1})}{p(y_{1:t} | S_{1:t})} \\
 &= \sum_{r_{t-1}=0}^{t-1} \frac{p(r_t | r_{t-1}) p(y_t | y_{t-1}^{(r_{t-1})}, S_{t-1}^{(r_{t-1})}) p(r_{t-1} | y_{1:t-1}, S_{1:t-1})}{p(y_t | y_{1:t-1}, S_{1:t-1}, S_t)}
 \end{aligned}$$

14

15 The posterior density function of the parameters

$$\begin{aligned}
p(\alpha, \beta, \sigma | y_{1:t}, S_{1:t}) &= \sum_{r_t=1}^t p(\alpha, \beta, \sigma, r_t | y_{1:t}, S_{1:t}) \\
&= \sum_{r_t=1}^t p(r_t | y_{1:t}, S_{1:t}, r_t > 0) p(\alpha, \beta, \sigma | r_t, y_{1:t}, S_{1:t}) \\
&= \sum_{r_t=1}^t p(r_t | y_{1:t}, S_{1:t}, r_t > 0) p(\alpha, \beta, \sigma | y_{(t-r_t+1):t}, S_{(t-r_t+1):t}) \\
&= \sum_{r_t=1}^t p(r_t | y_{1:t}, S_{1:t}, r_t > 0) p(\alpha, \beta, \sigma | y_t^{(r_t)}, S_t^{(r_t)}).
\end{aligned}$$

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17 **Section B: Sensitivity analyses**

18 We tested how sensitive the results are for different change point prior probabilities and for
19 different choices for the supports of the parameters that were fixed when choosing the prior
20 distributions for the parameters. We will explain the sensitivity analyses below.

21 **The change point prior**

22 We rerun the analysis on all stocks and for both the Ricker and the Beverton-Holt models.

23 We explored eight choices for the prior probabilities $1/\lambda$, namely, the cases where the
24 hazard parameter $\lambda = \{5, 10, 20, 100, 200, 1000, 2000, 10000\}$. These choices cover a
25 broad range of choices from change point being a very common event (on average every 5
26 years) to an extremely rare event (on average every 10000 years) a priori.

27 The medians of the posterior predictive distributions of R_t at the end of the regimes for cod
28 using the Ricker model look identical for all the cases where $\lambda > 10$ (Fig. S10). For the case
29 where $\lambda = 10$, one extra regime was found, and for the case where $\lambda = 5$ two extra regimes
30 were found. Since three regimes were found even with the change point prior probability of
31 one in ten thousand years, it seems there is strong evidence that at least three regimes exist
32 for cod during this time period.

33 The smoothed run length probabilities show more difference so that with a higher prior
34 probability for a change point other runs than the dominant one also obtain more probability.
35 However, the change points in 1991 and 2013 were found in all cases (Fig. S11).

36 The sequential update of the parameter posterior marginal densities shows that the smaller the
37 change point prior probability the less year to year variation in the parameter posterior

distributions (for α see Fig. S12). However, the actual parameter posterior marginal distributions at the end of the regimes differed very little.

Other species and tests conducted using the Beverton-Holt model showed similar tendencies, and thus we have only included figures for cod using the Ricker model. The results for all cases are summarized in Table S2. The table lists all the change points detected in any of the sensitivity analysis runs, and the change points detected in a particular run are marked with an 'X'. In summary, it seems the method is quite robust regarding the change point prior and most of the change points found in the actual analyses were also found with a lot smaller prior probability.

The support of the parameter priors

Since, the choice for the support of the parameters was quite arbitrary, we also tested how it would affect the results if the width of the supports was doubled for some or all of the parameters. We tested all seven possibilities where the support for any of the parameters was doubled, the support for any two parameters was doubled, and the support for all three parameters was doubled. The wider supports used in the tests are reported in Table S3.

Since we had already restricted the parameter supports so that the correct parameter values seemed to be inside those supports, the only effect this test had was to give a lower value for the prior predictive density. For cod using the Ricker model the effect was that when two or more parameters had double supports, one less regime was found. Otherwise the resulting medians of the posterior predictive distributions at the end of the regimes were quite similar (Fig. S13). However, as shown by the smoothed run length probabilities, the differences in the run length distribution were minimal (Fig. S14), and the shifts in 1991 and 2013 were

60 found in all of the cases. The posterior marginal densities for α look almost identical (Fig.
61 S15). For the density dependence parameter β the posterior marginal densities look more
62 different when the support of β was doubled (Fig. S16). The higher uncertainty reflects the
63 fact that the data carried only little evidence about the density dependence, and the higher
64 prior uncertainty resulted in higher posterior uncertainty throughout the time series. The
65 sensitivity analyses for other stocks and using the Beverton-Holt model yielded similar
66 results. Mostly, the sensitivity tests did not affect the number or timing of the change points,
67 but for hake using the Ricker model one more change point was found in few cases, and for
68 plaice a new change point replaced the old ones in few cases (Table S2). All in all, the
69 method was quite robust regarding the support of the parameters.

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70 **Section C: Additional figures**

71

72 **Figure S1.** Stratification used in the September bottom-trawl survey of the southern Gulf of
73 St. Lawrence. Circles show the locations of fishing stations in the 1989 survey. “X” indicates
74 three strata added in 1984 and omitted from analyses of the survey data to maintain a
75 consistent survey area.

Figure S2. The sequential update of the posterior marginal densities of the density dependence parameters β^R of the Ricker model and β^{BH} of the Beverton-Holt model. The vertical axis has units $\frac{10^{-9}}{\text{kg}}$. Medians and 68% central probability intervals are shown. Regimes are denoted with different colors. The stationary model fit is shown in black.

81 **Figure S3.** The sequential update of the posterior marginal densities of the standard deviation
82 parameters δ_t^R of the Ricker model and δ_t^{BH} of the Beverton-Holt model. Medians and
83 68% central probability intervals are shown. Regimes are denoted with different colors. The
84 constant parameter model fit is shown in black.

Figure S4. Medians of the posterior predictive distributions of $\log(\frac{R}{SSB})$ at the end of the regimes for the study species. Regimes are denoted with different colors. The constant parameter model fit is shown in black.

89 **Figure S5.** The results of the change point detection accuracy in the Ricker model
90 simulations for the four noise levels ($\sigma \in \{0.3, 0.4, 0.5, 0.6\}$). The vertical axis shows the
91 number of change points and the horizontal axis shows the absolute change in α^R parameter
92 before and after the change point. Black color denotes the change points that were inferred
93 correctly, gray color denotes those change points that were detected but with an error of ± 1 or
94 ± 2 time steps, and white denotes the rest of the change points that we considered as missed
95 by our method.

96 **Figure S6.** Empirical cumulative distribution functions illustrating the accuracy of the
 97 parameter estimates in the Ricker model simulations. The vertical axis shows the proportion
 98 of time steps within a simulation case for which the true parameter value was within the
 99 posterior central probability interval (CPI), whereas the horizontal line shows the proportion
 100 of all the simulation cases. The dashed line denotes the BOCPD model and the solid line

101 denotes the model with time-invariant parameters. Different noise levels
102 ($\sigma \in \{0.3, 0.4, 0.5, 0.6\}$) are denoted with increasing darkness of the curves. The originally
103 staircase-like curves were smoothed to clarify patterns.

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Figure S7. The smoothed run length probability distributions for the adjusted and unadjusted data for thorny skate (*Amblyraja radiata*). The red lines show the most likely segmentation of the data based on the smoothed run length probabilities.

Figure S8. Medians of the posterior predictive distributions of R_t for the Ricker and Beverton-Holt S-R models for the adjusted and unadjusted data for thorny skate.

111 **Figure S9.** The sequential update of the posterior marginal densities of the maximum number
 112 of recruits per unit of spawning stock biomass α for the adjusted and unadjusted data for
 113 thorny skate for the study species. Output for the Ricker (α^R) and Beverton-Holt (α^{BH})
 114 models are shown in left and right columns, respectively. The colored solid lines denote the
 115 posterior median and the shaded areas indicate the 68% central posterior probability interval.
 116 The regimes as identified using the most likely segmentation of the data are denoted by the
 117 change in the color of the shading.

Figure S10. The smoothed run length probability distributions for different change point prior probabilities (shown on top of the panels) for cod using the Ricker S-R model. The red lines show the most likely segmentation of the data based on the smoothed run length probabilities.

Figure S11. The sequential update of the posterior marginal densities of the maximum number of recruits per unit of spawning stock biomass α for different change point prior probabilities (shown on top of the panels) for cod using the Ricker S-R model. The colored solid lines denote the posterior median and the shaded areas indicate the 68% central posterior probability interval. The regimes as identified using the most likely segmentation of the data are denoted by the change in the color of the shading.

Figure S12. Medians of the posterior predictive distributions of R_t at the end of the detected regimes for different change point prior probabilities (shown on top of the panels) for cod using the Ricker S-R model.

Figure S13. The smoothed run length probability distributions for different parameter prior supports for cod using the Ricker S-R model. The symbols above the panels indicate for which parameter the width of the support was doubled. The red lines show the most likely segmentation of the data based on the smoothed run length probabilities.

Figure S14. The sequential update of the posterior marginal densities of the maximum number of recruits per unit of spawning stock biomass α for different parameter prior supports for cod using the Ricker S-R model. The symbols above the panels indicate for which parameter the width of the support was doubled. The colored solid lines denote the posterior median and the shaded areas indicate the 68% central posterior probability interval. The regimes as identified using the most likely segmentation of the data are denoted by the change in the color of the shading.

145 **Figure S15.** The sequential update of the posterior marginal densities of the density
 146 dependence parameter β for different parameter prior supports for cod using the Ricker S-R
 147 model. The symbols above the panels indicate for which parameter the width of the support
 148 was doubled. The colored solid lines denote the posterior median and the shaded areas
 149 indicate the 68% central posterior probability interval. The regimes as identified using the
 150 most likely segmentation of the data are denoted by the change in the color of the shading.

Figure S16. Medians of the posterior predictive distributions of R_t for different parameter prior supports for cod using the Ricker S-R model. The symbols above the panels indicate for which parameter the width of the support was doubled.

Section D: Additional tables

Table S1a. Catch rates of Atlantic cod and white hake in the annual bottom-trawl survey of the southern Gulf of St. Lawrence. R is recruit abundance (fish/standard tow) and S is spawning stock biomass (kg/standard tow) in the year that the recruits were produced. Recruit abundance is at age 3 years for cod and 2 years for hake. Analyses used the age-based catch rates. Length-based catch rates are also included to show CVs to provide information on the uncertainty in the indices for each species. (CVs are not available for the age-based indices.)

Year-Class	Atlantic cod						White hake					
	Age-based		Length-based				Age-based		Length-based			
	R	S	R	cv	S	cv	R	S	R	cv	S	cv
1971	14.51	35.62	9.06	0.21	47.15	0.15	1.86	2.95	1.24	0.34	2.38	0.32
1972	6.27	36.02	5.49	0.32	54.61	0.12	8.26	3.58	4.81	0.47	4.07	0.40
1973	38.38	34.72	37.71	0.16	47.99	0.18	14.19	10.59	10.49	0.78	10.28	0.72
1974	26.55	33.65	20.65	0.21	45.62	0.15	12.79	15.11	8.90	0.59	16.62	0.50
1975	54.73	23.95	50.71	0.31	33.08	0.22	3.62	4.48	1.34	0.49	4.29	0.21
1976	31.85	22.56	31.76	0.15	32.00	0.22	8.93	3.29	6.29	0.42	3.37	0.19
1977	41.14	34.70	36.33	0.28	50.39	0.17	1.15	4.08	3.93	0.56	3.61	0.26
1978	21.92	56.34	21.01	0.18	97.20	0.37	0.45	11.48	1.02	0.63	11.59	0.27
1979	23.22	85.21	48.98	0.35	119.11	0.09	1.91	12.38	1.75	0.45	12.04	0.31
1980	53.29	91.86	72.58	0.12	137.01	0.16	1.10	14.12	0.36	0.36	13.21	0.16
1981	16.73	172.44	31.20	0.14	223.01	0.15	3.35	25.79	1.88	0.58	23.74	0.33
1982	38.91	141.13	43.38	0.12	177.66	0.18	1.98	7.95	1.32	0.27	6.75	0.39
1983	35.35	103.46	40.12	0.24	115.40	0.12	0.65	4.47	1.01	0.44	5.19	0.17
1984	25.03	83.91	34.54	0.15	96.41	0.09	1.73	7.93	1.63	0.25	8.45	0.19
1985	70.02	133.01	89.63	0.40	172.30	0.23	0.46	8.95	0.33	0.29	7.74	0.42
1986	34.63	116.14	42.09	0.22	131.76	0.10	1.56	10.69	1.22	0.34	9.42	0.17
1987	35.40	86.83	36.42	0.15	95.43	0.11	1.57	5.14	1.02	0.37	4.68	0.20
1988	15.89	120.92	23.39	0.22	139.65	0.11	2.08	5.61	2.29	0.47	5.12	0.16
1989	9.81	99.68	17.53	0.17	114.26	0.11	2.12	4.45	1.73	0.56	3.90	0.21
1990	9.17	53.83	13.15	0.21	66.66	0.10	1.50	4.68	0.96	0.38	3.89	0.19
1991	7.61	45.46	11.12	0.18	50.63	0.15	0.83	4.64	0.56	0.26	4.18	0.24
1992	5.86	19.61	7.26	0.16	23.29	0.13	0.98	2.16	0.68	0.52	1.50	0.23
1993	7.20	27.42	11.66	0.29	31.77	0.09	1.06	2.17	0.71	0.25	1.49	0.32
1994	5.54	28.24	5.62	0.15	33.17	0.11	1.17	1.60	0.68	0.23	1.48	0.29
1995	7.93	31.85	10.26	0.14	38.04	0.11	0.83	0.56	0.49	0.35	0.47	0.25
1996	8.70	40.36	12.87	0.28	49.33	0.15	1.45	0.74	1.08	0.26	0.54	0.22
1997	6.86	30.96	9.46	0.20	39.75	0.21	1.78	1.20	1.11	0.39	0.79	0.24
1998	4.38	32.03	5.30	0.14	37.87	0.14	4.43	0.94	3.32	0.42	0.70	0.26
1999	4.81	36.26	7.88	0.32	43.70	0.23	1.22	0.97	0.85	0.28	0.85	0.28
2000	NA	28.82	NA	NA	36.07	0.26	1.71	1.70	1.17	0.42	0.69	0.16
2001	12.92	26.81	17.83	0.33	34.86	0.28	NA	1.12	NA	NA	0.63	0.27
2002	6.27	47.03	13.14	0.37	53.34	0.34	0.56	0.60	0.35	0.31	0.47	0.29
2003	2.75	NA	4.10	0.25	NA	NA	2.51	NA	1.72	0.21	NA	NA
2004	4.11	29.90	5.00	0.30	32.75	0.36	0.73	0.57	0.48	0.27	0.52	0.25
2005	3.73	10.95	3.81	0.20	12.06	0.12	5.71	1.12	3.85	0.56	0.68	0.24
2006	10.39	16.55	17.48	0.52	22.27	0.29	1.07	0.37	0.75	0.27	0.26	0.28
2007	3.29	15.73	4.18	0.19	19.50	0.28	1.60	1.66	0.94	0.33	0.84	0.31
2008	3.89	20.64	4.14	0.38	23.18	0.41	2.19	1.01	1.38	0.29	0.56	0.25
2009	2.67	15.18	5.42	0.18	15.80	0.42	1.42	1.09	0.68	0.43	0.60	0.39
2010	20.78	8.80	23.17	0.51	10.48	0.25	1.86	0.89	1.22	0.52	0.64	0.21
2011	16.04	4.58	19.61	0.68	5.47	0.30	0.70	0.71	0.45	0.33	0.40	0.23

Table S1b. Catch rates of American plaice and thorny skate in the annual bottom-trawl survey of the southern Gulf of St. Lawrence. R is recruit abundance (fish/standard tow) and S is spawning stock biomass (kg/standard tow) in the year that the recruits were produced. Recruit abundance is at age 4 years for plaice and 2 years post-emergence (4 years after egg case deposition) for skate. Analyses used the age-based catch rates (except S of skate is length-based). Length-based catch rates are included to show CVs, providing information on the uncertainty in the indices for each species. (CVs are not available for the age-based indices.)

Year-Class	American plaice						Thorny skate					
	Age-based		Length-based				Age-based		Length-based			
	R	S	R	cv	S	cv	R	S	R	cv	S	cv
1971	79.41	32.55	88.20	0.33	31.29	0.20	0.049	-	0.091	0.42	1.354	0.18
1972	123.78	31.48	177.35	0.23	36.79	0.26	0.044	-	0.090	0.57	1.182	0.27
1973	190.24	41.36	268.20	0.19	38.28	0.23	0.136	-	0.275	0.42	2.183	0.23
1974	64.06	60.92	102.54	0.17	61.62	0.14	0.010	-	0.015	0.82	1.390	0.17
1975	50.52	56.41	141.58	0.17	61.49	0.16	0.038	-	0.055	0.30	0.954	0.23
1976	68.45	75.92	109.28	0.24	97.85	0.11	0.209	-	0.390	0.82	0.707	0.25
1977	54.32	71.26	103.64	0.31	86.21	0.17	0.079	-	0.160	0.34	1.563	0.34
1978	15.51	51.90	28.58	0.39	67.09	0.31	0.036	-	0.066	0.66	0.509	0.26
1979	25.95	79.70	39.32	0.21	90.59	0.14	0.026	-	0.049	0.40	1.434	0.20
1980	17.63	47.25	22.95	0.17	68.04	0.20	0.001	-	0.000	0.00	0.926	0.21
1981	17.39	50.46	27.88	0.43	58.56	0.23	0.051	-	0.104	0.27	0.999	0.27
1982	30.57	36.15	33.34	0.25	45.52	0.21	0.059	-	0.116	0.25	0.846	0.36
1983	30.45	39.56	34.33	0.22	39.69	0.19	0.067	-	0.128	0.21	0.684	0.28
1984	26.19	20.68	32.46	0.17	25.04	0.09	0.098	-	0.182	0.24	0.352	0.23
1985	27.31	27.89	38.16	0.13	30.39	0.09	0.119	-	0.222	0.18	0.321	0.20
1986	56.57	31.24	70.89	0.15	36.66	0.14	0.203	-	0.392	0.25	0.544	0.17
1987	51.17	26.22	51.05	0.17	31.72	0.13	0.146	-	0.284	0.24	0.526	0.31
1988	40.59	28.04	48.01	0.24	35.13	0.19	0.166	-	0.296	0.30	0.508	0.15
1989	39.14	21.36	44.27	0.13	26.91	0.12	0.099	-	0.195	0.23	0.238	0.23
1990	25.83	28.49	41.27	0.16	38.91	0.11	0.198	-	0.371	0.42	0.517	0.14
1991	29.24	35.99	36.96	0.10	48.28	0.12	0.133	-	0.241	0.30	0.381	0.17
1992	18.56	21.83	32.68	0.12	28.19	0.09	0.148	-	0.270	0.21	0.274	0.26
1993	19.48	17.34	26.67	0.13	22.05	0.10	0.156	-	0.295	0.29	0.283	0.27
1994	22.71	18.45	32.19	0.14	24.00	0.11	0.135	-	0.266	0.35	0.272	0.28
1995	23.29	16.29	28.85	0.10	19.11	0.09	0.055	-	0.094	0.27	0.236	0.36
1996	17.65	15.42	27.19	0.12	19.69	0.09	0.069	-	0.132	0.32	0.262	0.25
1997	17.46	9.17	22.88	0.10	12.94	0.08	0.040	-	0.074	0.28	0.149	0.20
1998	10.47	12.97	18.86	0.11	15.13	0.09	0.053	-	0.091	0.33	0.359	0.24
1999	NA	9.86	NA	NA	12.53	0.09	NA	-	NA	NA	0.191	0.24
2000	25.71	9.86	29.18	0.13	12.32	0.12	0.053	-	0.094	0.40	0.105	0.29
2001	19.07	8.20	33.60	0.18	11.89	0.13	0.048	-	0.085	0.39	0.179	0.26
2002	19.85	7.13	30.54	0.09	9.41	0.07	0.104	-	0.201	0.25	0.121	0.37
2003	14.19	NA	26.23	0.12	NA	NA	0.072	-	0.126	0.22	NA	NA
2004	17.94	8.76	27.28	0.10	8.93	0.10	0.138	-	0.262	0.29	0.073	0.30
2005	8.37	8.53	20.23	0.10	11.07	0.09	0.208	-	0.398	0.35	0.147	0.23
2006	29.18	9.43	49.09	0.10	10.19	0.09	0.210	-	0.395	0.34	0.074	0.38
2007	19.57	10.46	35.28	0.11	10.56	0.08	0.120	-	0.232	0.34	0.048	0.46
2008							0.152	-	0.270	0.50	0.070	0.50
2009							0.087	-	0.164	0.31	0.117	0.34
2010							0.084	-	0.159	0.48	0.043	0.54

Table S2. Summary of the sensitivity analyses. We have listed all years when a change point was found in any of the sensitivity test runs (columns) and marked whether the particular change point was found in a given sensitivity run (rows). The bolded rows show the parameterization used for the actual analyses. The third column from the left shows either the change point prior probability used or the symbol of the parameter whose support was doubled.

			cod				hake				plaice						skate						
			1976	1991	2001	2013	1979	1988	1993	1997	2013	1978	1982	1986	1994	2004	2010	1983	1988	1999	2006	2007	2013
Change point prior sensitivity	Ricker	0.0001		X		X																	
		0.0005		X		X																X	
		0.001		X		X																X	
		0.005		X		X				X			X								X		
		0.01		X		X	X			X			X								X		
		0.05		X		X	X			X			X						X	X	X		
		0.1	X	X		X	X			X			X						X	X	X		
		0.2	X	X	X	X	X	X		X	X		X			X	X	X	X	X	X		
	Beverton-Holt	0.0001		X		X															X		
		0.0005		X		X													X		X		
		0.001		X		X													X		X		
		0.005		X		X	X			X									X	X	X		
		0.01		X		X	X			X									X	X	X		
		0.05		X		X	X			X			X	X					X	X	X		
		0.1		X		X	X			X			X	X					X	X	X		
		0.2	X	X	X	X	X	X		X	X		X	X		X	X		X	X	X		X
Parameter support sensitivity	Ricker	Orig.	X	X		X	X			X			X					X	X	X			
		α	X	X		X	X			X			X					X	X	X			
		β	X	X		X	X		X	X			X					X	X	X			
		σ	X	X		X	X			X			X						X	X	X		
		α, β		X		X	X		X	X			X						X	X	X		
		α, σ		X		X	X			X			X						X	X	X		
		β, σ		X		X	X		X	X			X						X	X	X		
		α, β, σ		X		X	X		X	X			X						X	X	X		
	Beverton-Holt	Orig.		X		X	X			X			X	X					X	X	X		
		α		X		X	X			X		X							X	X	X		
		β		X		X	X			X			X	X					X	X	X		
		σ		X		X	X			X			X	X					X	X	X		
		α, β		X		X	X			X		X							X	X	X		
		α, σ		X		X	X			X		X							X	X	X		
		β, σ		X		X	X			X			X	X					X	X	X		
		α, β, σ		X		X	X			X		X							X	X	X		

178 **Table S3.** The wider parameter supports used in the sensitivity analyses.

	Ricker			Beverton-Holt		
	α	β	σ	α	β	σ
cod	[0.3, 2.7]	$[2.5 \cdot 10^{-9}, 12.5 \cdot 10^{-9}]$	[0.3, 2.7]	[0.1, 7.9]	$[5 \cdot 10^{-9}, 25 \cdot 10^{-9}]$	[0.3, 2.7]
hake	[0.1, 11.9]	$[10 \cdot 10^{-9}, 350 \cdot 10^{-9}]$	[0.3, 2.7]	[0.1, 11.9]	$[10 \cdot 10^{-9}, 690 \cdot 10^{-9}]$	[0.3, 2.7]
plaice	[0.1, 11.7]	$[5 \cdot 10^{-9}, 25 \cdot 10^{-9}]$	[0.3, 2.7]	[0.1, 11.7]	$[10 \cdot 10^{-9}, 50 \cdot 10^{-9}]$	[0.3, 2.7]
skate	[0.1, 7.9]	$[100 \cdot 10^{-9}, 3300 \cdot 10^{-9}]$	[0.3, 2.7]	[0.1, 7.9]	$[100 \cdot 10^{-9}, 6500 \cdot 10^{-9}]$	[0.3, 2.7]

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