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1 Detecting regime shifts in fish stock dynamics

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Draft

9 Abstract

10 Environmental factors such as the water temperature, salinity and the abundance of
11 zooplankton can have significant effects on certain fish stocks' ability to produce juveniles
12 and, thus, stock renewal ability. This variability in stock productivity manifests itself as
13 different productivity regimes. Here, we detect productivity regime shifts by analyzing
14 recruit-per-spawner time series with Bayesian online change point detection algorithm. The
15 algorithm infers the time since the last regime shift (change in mean or variance or both) as
16 well as the parameters of the data generating process for the current regime sequentially. We
17 demonstrate the algorithm's performance using simulated recruitment data from an
18 individual-based model, and further apply the algorithm to stock assessment estimates for four
19 Atlantic cod stocks obtained from RAM legacy data base. Our analysis shows that the
20 algorithm performs well when the variability between the regimes is high enough compared to
21 the variability within the regimes. The algorithm found several productivity regimes for all
22 four cod stocks, and the findings suggest that the stocks are currently in low productivity
23 regimes, which have started during the 1990s and 2000s.

24

25 Keywords: Atlantic cod, *Gadus morhua*, environmental change, productivity, recruitment, time
26 series

1. Introduction

Marine ecosystems can undergo rapid changes from one relatively stable state to another due to alterations in environmental conditions. These changes from one state to another are often called regimes shifts (Holbrook et al. 1997; Peterson and Schwing 2003; DeYoung et al. 2004). More rigorously, a regime shift can be defined as the event where some internal processes or external forcing drive the state of a system over a critical threshold after which the qualitative behavior of the system changes. From the modelling perspective, these shifts pose an interesting problem. Models often predict the behavior of the system relatively well only within a narrow range of previously observed behaviors, whereas sudden changes or regime shifts can be extremely difficult to predict. There are basically two ways to cope with regime shifts in models. The first is to increase the model complexity to better represent the actual dynamics of the system. This, however, might prove difficult due to the non-linear and chaotic nature of many natural systems, lack of direct observations of the system and high uncertainty about the model structure and parameters. The second way to deal with regime shifts is to use simple models but make them robust to sudden changes in the model parameters. Our present study falls into the latter category. We assume that the model structure is constant and define a regime shift as a sudden change in the model parameters, essentially assuming that the model describes the system well locally.

In the fisheries context, regime shifts can affect the stock productivity and further translate into changes in relative species abundances. For example in the central Baltic Sea, the late 1980s regime shift is believed to have contributed to decreased cod recruitment and thus to the lack of recovery of the declined Baltic cod stock. The low abundance of cod, in turn, translated into reduced predation pressure on sprat which together with favorable temperature

conditions drove the sprat stock to exceptionally high abundance (Alheit et al. 2005). Similarly, evidence of a regime shift affecting the organization of the fish community has been found in the North Sea. The 1980s regime shift increased the recruitment of flatfish whereas the recruitment of gadoids declined (Beaugrand 2004). Regime shifts in juvenile productivity are likely to substantially alter fish stock resilience to fishing and its ability to recover from overfishing. Therefore, detection of regime shifts is vital to adjust fisheries management to altered productivity conditions. Failure to do this can lead to overfishing and increase the risk of fish stock collapse. Such failure is argued to have happened in Newfoundland cod (*Gadus morhua*) fishery in Canada in the early 1990s, which led to the collapse of the cod stock and caused massive socio-economic costs (Biggs et al. 2009). On the other hand, an undetected shift to a higher productivity regime can lead to underfishing due to lower expectations of potential fishery yield.

The study of regime shifts can be roughly divided into three main problems. The first problem is to identify regime shifts in the past using historical data. This retrospective analysis aims at finding out when regime shifts have happened, how frequently regime shifts occur, and what is the magnitude of such shifts. The second problem is to estimate model parameters under the assumption of shifting regimes. The main idea is that if conditions have changed drastically, and the change has driven the system to a new regime, the old data that was produced under the old conditions should not affect the new estimates. The third problem is to produce predictions based on the belief about the current regime and about future regime shifts.

The recent attempts to study productivity regime shifts in fisheries context have been using frequentist methods, namely, STARS (Rodionov 2004). For example, Vert-pré et al. (2013) studied 230 fish stocks and found out that the productivity of 69.1% of the stocks was best explained by a model that took regime-like productivity into account. Similarly, Wayte

(2013) found a regime shift to lower productivity in south-eastern Australia jackass morwong (*Nemadactylus macropterus*) stock that happened in 1988. STARS uses sequential Student's t-test to find abrupt shifts in the mean level of the dataset, and reports the times of the regime shifts as well as the mean level of data in each regime. Another approach to solving the regime shift detection and parameter estimation problem is to use maximum likelihood methods. Maximum likelihood estimation is able to simultaneously detect shifts in the mean and variance, and it has been applied for change point detection in environmental monitoring (Liu 2010).

Bayesian statistics offer an attractive framework for regime shift research, since it can be used to detect shifts in the mean or the variance or any other parameter of the data generating process, the uncertainty about the parameter estimates can be included by the use of hyperparameters in hierarchical models, and predictions are easily produced by the posterior predictive distribution. There exist previous attempts to study fish productivity regime shifts within Bayesian statistical framework. The regime-specific parameters for a Ricker model for the Japanese sardine (*Sardinops melanostictus*) have been inferred using a Markov switching regression model with two regimes (Munch and Kottas 2009). Their analysis shows that the two-regime model outperforms a single-regime model, and they suggest that a shift to a lower productivity regime happened in 1988. The method is limited to only two regimes, although a similar approach may be adopted for models with multiple regimes.

The Bayesian online change point detection algorithm (BOCPD; Adams and McKay 2007) provides computationally efficient and exact recursive inference of the most recent regime shift. The algorithm updates the posterior probability distribution of the time since the latest regime shift together with the posterior probability distributions of the parameters of the data generating process sequentially. The number of possible regimes in the algorithm equals

the number of data points, since at each time step there is a small prior probability for the start of a new regime. BOCPD has been used earlier for example in satellite fault prediction (Turner 2010), detection of shifts between different brain states in epileptic patients (Malladi et al. 2013), radar tracking (Turner et al. 2013), detection of a tipping point in the amplitude of the annual cycle of Arctic sea ice area (Ditlevsen 2012), detection of change points in financial time series (Georgescu 2012) and bird song segmentation (Wang et al. 2013). The method has not, however, been used in the fisheries context.

In this study, we introduce the Bayesian online change point detection algorithm into the fisheries research context and utilize it to detect regime shifts in fish stock productivity by applying it to recruit-per-spawner time series. The method could be also used to detect shifts in recruitment, growth rates, carrying capacity, natural mortality, or any other estimated model parameters that could experience sudden shifts. Because of the probabilistic nature of the method, it calculates probabilities for new regimes given the input data and produces estimates and predictions that include the uncertainty about the regime shifts. We examine the posterior probabilities for the start of a new regime at each time step for early indication of regime shifts, and use smoothing to update our knowledge about the start of the regimes in the past based on the current data. We also calculate the posterior predictive distribution at each time step, which could be utilized in stock projections used to manage fisheries. We demonstrate the performance of the method through the model validation with simulated data, and provide empirical examples for regime shift detection in recruit-per-spawner estimate time series of four Atlantic cod stocks.

2. Methods

2.1. Model description

Bayesian online change point detection algorithm (BOCPD; Adams and McKay 2007) detects sudden changes in the parameters of a data generating process. Essentially the algorithm consists of sequential parameter estimations, hereafter denoted as ‘runs’, that are carried out in parallel. At each time step a new run starts and its parameters are estimated using the data obtained after the start of the run. Thus, at time t we have t competing runs that use different amount of data to make inference about the parameters of the data generating process. The runs are identified in the algorithm using their lengths, ‘run length’, i.e. the time since the run started, or equivalently, the number of data points used to calculate the parameters of the run. At each time step, the algorithm updates the parameter estimates of each run based on the latest data point, and calculates the probabilities of the different runs based on their probabilities at the previous time step and how well the predictive density of the given run explains the latest data point. Thus, the idea is that after a regime shift a new run would estimate the parameters of the new regime more accurately than any of the previously started runs, and by its better predictive performance would obtain high posterior probability. The posterior predictive density of the model is a weighted sum of different regime specific predictive densities and the weights are the posterior probabilities of the regimes. In the following, we provide a brief description of the algorithm.

Joint distribution of data and run length

The joint distribution of data $x_{1:t} = (x_1, \dots, x_t)$ and run length $r_t \in \{1, \dots, t\}$ at time t can be formulated recursively (for derivation see Appendix A)

$$p(r_t, x_{1:t}) = \sum_{r_{t-1}=0}^{t-1} p(r_t | r_{t-1}) p(x_t | x^{(r_{t-1})}) p(r_{t-1}, x_{1:t-1}), \quad (1)$$

where $p(r_t|r_{t-1})$ is the change point prior distribution that contains our prior belief of the probability of a regime shift. The underlying predictive model (UPM) $p(x_t|x^{(r_{t-1})})$ is the predictive density conditional on run length r_{t-1} , i.e. the predictive density using the latest r_{t-1} data points $x_{(t-r_{t-1}): (t-1)}$ denoted for clarity by $x^{(r_{t-1})}$. 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 data point. If the new data point is ‘far away’ from any of the predictive densities of the existing regimes, the prior predictive density $p(x_t|x^{(0)})$ will dominate, which serves as an indicator for a start of a new regime. The last term $p(r_{t-1}, x_{1:t-1})$ is the joint distribution of data and run length at the previous time step $t - 1$. The summation is carried out for all possible run lengths from 0 (new regime) to $t - 1$ (the longest possible regime so far). For simplicity, we assume that the first regime starts at the beginning of the time series, and initialize the run length distribution so that $p(r_0 = 0) = 1$.

Change point prior

The change point prior probabilities are defined using a constant probability of a change point

$$p(r_t|r_{t-1}) = \begin{cases} \frac{1}{\lambda}, & \text{if } r_t = 0 \\ 1 - \frac{1}{\lambda}, & \text{if } r_t = r_{t-1} + 1 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

which gives rise, a priori, to geometric inter-arrival times for regime shifts with expected length of $\lambda > 0$. 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.

Underlying predictive model

In the present study, we assume that the data-generating process is Gaussian with unknown mean and precision and place a normal-gamma prior on the parameters. The likelihood is

$$p(x_t|\mu, \tau) = \sqrt{\frac{\tau}{2\pi}} e^{-\frac{1}{2}\tau(x_t-\mu)^2}, \quad (3)$$

where μ denotes the mean and τ the precision (reciprocal of the variance) parameter. The normal-gamma prior density has the form

$$p(\mu, \tau) = \frac{\beta^\alpha \sqrt{\kappa}}{\Gamma(\alpha)\sqrt{2\pi}} \tau^{\alpha-\frac{1}{2}} e^{-\beta\tau} e^{-\frac{1}{2}\kappa\tau(\mu-\gamma)^2}, \quad (4)$$

where γ is the mean location parameter, κ is the mean scale parameter, α is the precision shape parameter, and β is the precision inverse scale parameter. The normal-gamma distribution is the conjugate prior for the normal likelihood, and it is particularly convenient in this context since the posterior distribution of the parameters conditional on run length r_t , $p(\mu, \tau|r_t, x_{1:t}) = p(\mu, \tau|x^{(r_t)})$, becomes also a normal-gamma distribution and its hyperparameters $\{\gamma_t^{(r_t)}, \kappa_t^{(r_t)}, \alpha_t^{(r_t)}, \beta_t^{(r_t)}\}$ can be updated recursively as new data arrives.

Moreover, these assumptions regarding the stochastic process for x_t , μ , and τ result in a UPM that is a non-standardized Student's t-distribution (Murphy 2007),

$$p(x_{t+1}|x^{(r_t)}) = t_{v_t^{(r_t)}}(x_{t+1}|\xi_t^{(r_t)}, \omega_t^{(r_t)}), \quad (5)$$

where the degrees of freedom $v_t^{(r_t)} = 2\alpha_t^{(r_t)}$, the location parameter $\xi_t^{(r_t)} = \gamma_t^{(r_t)}$, and the

scale parameter $\omega_t^{(r_t)} = \frac{\beta_t^{(r_t)}(\kappa_t^{(r_t)}+1)}{\alpha_t^{(r_t)}\kappa_t^{(r_t)}}$, can all be expressed in terms of the posterior

hyperparameters. The probability density function of the non-standardized Student's t-distribution is presented in Appendix A.

The hyperparameter update recursions are as follows. The mean location is a weighted average of the previous mean location and the newly obtained data point x_t

$$\gamma_t^{(r_t)} = \frac{\kappa_{t-1}^{(r_{t-1})} \gamma_{t-1}^{(r_{t-1})} + x_t}{\kappa_{t-1}^{(r_{t-1})} + 1}. \quad (6)$$

The mean scale is increased by the number of new observations ($= 1$)

$$\kappa_t^{(r_t)} = \kappa_{t-1}^{(r_{t-1})} + 1. \quad (7)$$

The precision shape is increased by one half times the number of new observations ($= \frac{1}{2}$)

$$\alpha_t^{(r_t)} = \alpha_{t-1}^{(r_{t-1})} + \frac{1}{2}. \quad (8)$$

The precision inverse scale is incremented by the squared difference of the previous mean location and the new data point scaled by one half of the ratio of the old and new mean scale parameters

$$\beta_t^{(r_t)} = \beta_{t-1}^{(r_{t-1})} + \frac{\kappa_{t-1}^{(r_{t-1})} (x_t - \gamma_{t-1}^{(r_{t-1})})^2}{2(\kappa_{t-1}^{(r_{t-1})} + 1)}. \quad (9)$$

Here the superscript (r_t) denotes the hyperparameters obtained by using the last r_t data points, i.e., the data belonging to the regime that started r_t time steps ago. The hyperparameter updating at each step depends only on the new data point and the previous hyperparameter values of the run, and is carried out sequentially when new data point arrives. The parameters are updated for every possible run length $r_t \in \{1, 2, \dots, t\}$, and thus each possible regime has different mean and precision. The hyperparameter updating is computationally fast since it requires only applying the four simple recursions t times. The initial values for the recursions

194 are the prior hyperparameters for a new regime at any time step t , $\{\gamma_t^{(0)}, \kappa_t^{(0)}, \alpha_t^{(0)}, \beta_t^{(0)}\} =$
 195 $\{\gamma^{(0)}, \kappa^{(0)}, \alpha^{(0)}, \beta^{(0)}\}$, which are given a priori as fixed parameters of the algorithm.

196

197 **Run length posterior**

198 The posterior run length probabilities, i.e. the probability of a run length conditioned on the
 199 data observed so far, can be computed from the joint distribution of data and run length

$$p(r_t | x_{1:t}) = \frac{p(r_t, x_{1:t})}{\sum_{r_t=0}^t p(r_t, x_{1:t})}. \quad (10)$$

200 The joint distribution is discrete for run length r_t with t states and, thus, the sum is cheap to
 201 compute. The run length posterior probabilities can be used as an early indicator of a regime
 202 shift. If the posterior probability that the current run length is one, $p(r_t = 1 | x_{1:t})$, is high, it
 203 means that the latest data point cannot be well predicted by the predictive density of the
 204 previous regime, thus suggesting that a regime shift has happened.

205

206 **Posterior predictive distribution**

207 The conditional probability distribution of a new data point at time $t + 1$, denoted by x_{t+1} ,
 208 conditioned on all the previous data points $x_{1:t}$, i.e. the posterior predictive distribution may be
 209 written as a weighted sum of conditional probability distributions of x_{t+1} conditioned on data
 210 points associated with the run length r_t , i.e. the last r_t observations $x_{(t-r_t+1):t}$ denoted by
 211 $x^{(r_t)}$ (for derivation see Appendix)

$$p(x_{t+1} | x_{1:t}) = \sum_{r_t=0}^t p(r_t | x_{1:t}) p(x_{t+1} | x^{(r_t)}). \quad (11)$$

The summation is carried out over all possible run lengths, and the weights are given by the posterior probabilities of the run lengths $p(r_t|x_{1:t})$. The posterior predictive distribution is used when making predictions about the future, and it is thus an integral quantity used to project stock development and produce management advice.

Smoothed run length distribution

It is possible that the latest data point is an outlier instead of the first data point in a new regime. In this case the posterior run length probabilities might indicate a regime shift even though no shift has actually happened. Conversely, because the posterior run length probability of a new regime depends on the often relatively small prior probability of a new regime and the prior predictive density of a new regime, the posterior run length probability may not react quickly enough to relatively small shifts. In both cases, the next data points might carry the necessary information to decide if a shift has occurred. Thus, it is of interest to also compute the smoothed run length distribution at each time step t . The smoothed run length distribution $p(r_k|x_{1:t})$ for any $k < t$ is calculated recursively using the following equations (Särkkä 2013):

$$p(r_{k+1}|x_{1:k}) = \sum_{r_k=0}^k p(r_{k+1}|r_k)p(r_k|x_{1:k}), \quad (12)$$

$$p(r_k|x_{1:t}) = p(r_k|x_{1:k}) \sum_{r_{k+1}=0}^{k+1} \frac{p(r_{k+1}|r_k)p(r_{k+1}|x_{1:t})}{p(r_{k+1}|x_{1:k})}. \quad (13)$$

The first equation calculates the one step forward predictions using the change point prior and the posterior probabilities. This equation can be also used sequentially to predict the run length distribution at any time step in the future. The second equation is the backward recursion to

compute the smoothed run length probabilities starting from the latest time step, i.e, $k + 1 = t$.

Choosing the prior hyperparameters

Usually in Bayesian context the prior distributions should encapsulate the available expert knowledge of the underlying phenomenon. The presented algorithm is very sensitive to the choice of prior hyperparameters. To make the parametrization of the prior more intuitive we specify the hyperparameters in terms that are more understandable and easier to elicit from experts. We use the upper limit of the variable of interest, $\tilde{u}$, the lower limit of that variable, $\tilde{l}$, the proportion of variance within the regime to the overall variance, $\tilde{\delta}$, and as a measure of uncertainty the coefficient of variation of the regime variance, $\tilde{c}$. By the tilde notation we stress that these quantities represent the expert knowledge and are not derived from data.

Since the mean of the next regime is unknown, we use a quite uninformative prior for the mean parameter. This is accomplished by choosing a small $\kappa^{(0)} = 0.05$. After choosing a small mean scale parameter the mean location parameter does not have much effect on the posterior distribution of the mean parameter but we set it to be the average of the upper and lower limits, $\gamma^{(0)} = \frac{1}{2}(\tilde{l} + \tilde{u})$. We cannot be as uninformative about the precision parameter, however. We model the expected variance of a regime as a proportion of the overall variance of the data. We do not know in advance what the variance of the data will be, so we make a crude estimate $\tilde{\sigma}_x^2 = \frac{1}{16}(\tilde{u} - \tilde{l})^2$, which corresponds to the range rule of thumb that says that the range is approximately four times the standard deviation. Using the results for the posterior hyperparameters after updating with n data points (see Murphy 2007), the definition of

coefficient of variation, and by approximating the expected variance with our crude estimate,
and assuming $\kappa^{(0)} \approx 0$, we can write

$$\alpha^{(0)} = \frac{1}{\tilde{c}^2} + 2 - \frac{n}{2} \quad (14)$$

and

$$\beta^{(0)} \approx \frac{1}{16}(\tilde{u} - \tilde{l})^2 \tilde{\delta} \left(\frac{1}{\tilde{c}^2} + 1 - \frac{n}{2} \right). \quad (15)$$

Next, we arbitrarily choose that the posterior distribution should coincide with the expert
opinion when four data points have been used to update the prior knowledge, i.e., set $n = 4$ to
obtain

$$\alpha^{(0)} = \frac{1}{\tilde{c}^2} \quad (16)$$

and

$$\beta^{(0)} = \frac{1}{16}(\tilde{u} - \tilde{l})^2 \tilde{\delta} \left(\frac{1}{\tilde{c}^2} - 1 \right), \quad (17)$$

where it is required that $0 < \tilde{c} < \sqrt{\frac{\tilde{\delta}}{2-\tilde{\delta}}}$ to ensure that $\beta^{(0)}$ is positive. In our numerical

examples, we chose the limits based on the data, and set $\tilde{\delta} = 0.25$ and $\tilde{c} = 0.1$.

Detecting regime shifts

Preliminary analyses showed that with a suitable choice of hyperparameters the method
performs well in producing the posterior predictive distributions and the run length
probabilities. However, due to the probabilistic nature of the algorithm, exact timings of the
regime shifts are not part of the algorithms output. If used for stock projections, the posterior
predictive distribution of BOCPD together with the change point prior hold all relevant
information for calculating future predictions, and it is not necessary to know the exact time of

the regime shifts. If the task of detecting the time of the shifts is of interest, we must choose a decision rule based on which the timings of the shifts are to be decided. We choose to give an early indication of a regime shift when the posterior probability of a new run exceeds a threshold of 0.5, i.e.

$$p(r_t = 1|x_{1:t}) > 0.5. \tag{18}$$

It is worthwhile to note here that the adopted regime shift indication scheme uses the new data point only to check if there is evidence for a regime shift happening from the previous time step to the current, and it does not update our belief about regime shifts in the past. However, we use the smoothed run length probabilities to check if our belief about regime shifts at time k in the past is updated by the current data point. We thus also indicate a regime shift whenever

$$p(r_k = 1|x_{1:t}) > 0.5 \tag{19}$$

and calculate the delay $t - k$. At the end of the time series we also check the most up to date smoothed run length distribution and use it to check for false alarms produced by the posterior or smoothed probabilities during the previous time steps.

2.2. Model validation with simulated data

To investigate the model performance, we simulated cod population dynamics under differing overall productivity regimes and then investigated whether the method was able to detect the change points between the regimes correctly. Cod population dynamics were simulated using an individual- and process-based model parameterized for Northern cod (Kuparinen et al. 2012a; Kuparinen and Hutchings 2012). The simulation model tracks a population through time and, at each time step (year), models the processes of natural mortality, growth, maturation, and reproduction for each individual. To incorporate demographic stochasticity to

the population dynamics, the outcomes of the processes are based on random numbers drawn from appropriate distributions. Egg production depended on female body size (May 1967) and was then tuned up or down depending on the population density and environmental year-to-year variability in recruit-per-spawner ratios (number of recruits divided by the spawning stock biomass, R/S). Environmental recruitment variability was modelled through normally distributed random numbers with mean zero and the standard deviation set to the average level of year-to-year variation across 18 cod stocks in the Northern Atlantic (Kuparinen et al. 2014; Keith and Hutchings 2012). Density-dependent recruitment variability was based on the same data, assuming compensatory dynamics. For further detail about the parameterization, see Kuparinen et al. 2014.

We simulated cod population dynamics under equilibrium conditions and at annual time steps recorded the recruit-per-spawner ratios. During the course of each 200 year long simulation, we introduced 11 productivity regimes the durations of which varied from 10 to 33 years. We further simulated four scenarios for the magnitude of the difference in overall productivity among the regimes, and repeated each scenario 50 times. Altogether we had 200 time series with 10 regime shifts in each. This allowed us to explore, how large the differences between the regimes need to be as compared with the demographic stochasticity within the regimes, to detect the shift between two consecutive regimes. We fixed the hazard rate in the change point prior to $\lambda = 10$.

Because we worked with simulated data we knew the true times of the shifts. Using this knowledge we were able to calculate different metrics to quantify the performance of the method. The known shifts were categorised into three categories based on the indicators produced by the method: 1) shifts that were detected and had their starting year timed correctly, 2) shifts that were detected but the starting year of the regime was timed incorrectly, and 3)

shifts that went completely undetected. Sometimes the last data points of a regime were by chance so close to the level of the next regime that the algorithm wrongly located the start of the next regime couple of time steps earlier and, since the following data points were adequately explained by the wrongly timed run, no other indication of the regime shift was produced. Thus, we included in the second category also shifts that were detected one or two time step before they actually happened. For any practical purposes such an error seems acceptable. Since many of the shifts were not detected immediately after the first data point of a new regime was analyzed, we also calculated the delay of the detection, i.e. how many data points from the new regime in addition to the first data point were needed to confirm that a shift had happened. All indications of a shift inside a regime for which the start had already been detected were regarded as false alarms.

Since the shifts varied in magnitude, we developed a measure for the “easiness” of detection. We computed the sample mean and sample standard deviation of each regime, and defined the easiness of detection of a shift as the absolute difference between the sample means of two consecutive regimes divided by the sample standard deviation of the previous regime,

$E_i = \frac{|\mu_{i+1} - \mu_i|}{\sigma_i}$. We divided the shifts into five categories based on their measure of easiness: 0 –

0.5, 0.5 – 1, 1 – 1.5, 1.5 – 2, and > 2.

2.3. Model application to empirical data

We further conducted the analysis of the productivity regime shifts using empirical cod productivity time series estimates available at RAM legacy stock assessment database (<http://ramlegacy.marinebiodiversity.ca>; Ricard et al. 2011). To this end, we investigated recruit-per-spawner estimate time series of four cod stocks that were chosen representative of

stocks that have potentially undergone drastic changes in their productivity. The chosen stocks were Northern cod (COD2J3KL), Southern Gulf of St. Lawrence cod (COD4TVn), North-East Arctic cod (CODNEAR), and North Sea cod (CODNS), and the assessment methods used to produce the recruit and spawning stock biomass estimates were SURBA, VPA/ADAPT, VPA/XSA, and SAM, respectively. We examined the stock assessment time series visually, and roughly estimated that the expected length of a regime would be 10 years. Thus, we fixed the hazard rate in the change point prior to $\lambda = 10$.

3. Results

3.1. Detection of shifts in simulated data

The method was able to detect shifts in the simulated R/S data. To give an example of the simulated R/S time series, and to illustrate how the posterior predictive distribution obtained during the forward filtering behaves in the model we have plotted the first 50 data points of a randomly chosen simulation time series (Fig. 1). It is easy to notice how the posterior predictive quickly reacts to the regime shifts, whereas the sample mean changes very slowly and is not very representative of the regimes after the shifts (Fig. 1a). To clarify the concept of the run length, we have also plotted the smoothed run length probabilities (Fig. 1b).

A summary of the method's performance is given in Table 1. The method produced 639 false alarms (33.1% of all indications). To illustrate how the easiness of the shift affects the method's ability to detect the shifts we have plotted the detection frequencies for each easiness category (Fig 2a). As expected, the detection frequency increases as the easiness of the shifts increases. We also plotted the detection delay as a function of the easiness measure (Fig 2b). The highest detection delays occur for the more difficult shifts. The median delay in the

simulations was one, and 76% of the delays were at most three. There are not many points on the far left since only few shifts having very low easiness measure were detected.

3.2. Detection of shifts in empirical data

The method was able to detect shifts in the empirical data. The posterior predictive distributions obtained during the forward filtering, and the probabilities for regime shifts are presented in Figure 1. For the Northern Cod the method found three shifts. The first shift was found in year 2000 with a three year delay. The second shift was found in real time in 2002 and the third in real time in 2006. After the whole time series was analyzed the final smoothing showed that only the shifts in 2002 and 2006 had higher probability than the set threshold of 0.5 (Fig 3a). To investigate how easy the shifts were in terms of the easiness measure, we calculated the easiness measure for each detected shift. The easiness for the shifts in Northern Cod time series were $E_1 = 3.2$ and $E_2 = 4.1$.

For the Southern Gulf of St. Lawrence cod, six shifts were found (Fig. 3b). The first shift in 1972 was found with a one year delay, the next shifts in 1973 and 1980 were found in real time. The next shift was found in 1992 with a two year delay, and the next shift in 1993 was found in real time. The last shift in 1996 was found with a six year delay. After the final smoothing only the shifts in 1973, 1980, 1993 and 1996 had higher probability than the set threshold, and the corresponding values of the easiness measure were $E_1 = 2.8$, $E_2 = 4.8$, $E_3 = 3.9$ and $E_4 = 3.8$, respectively.

Only two shifts were found for the North-east Arctic cod (CODNEAR). The shifts happened in 1965 and 1968 and were found in real time, and were still regarded as shifts after

the final smoothing (Fig. 3c). The easiness measures for the detected shifts were $E_1 = 8.2$ and $E_2 = 3.2$, respectively.

Fourteen shifts were found for the North Sea cod (CODNS) (Fig. 3d). The first two shifts in 1967 and 1969 were found with a one year delay, and the third shift in 1971 was found with a two year delay. The next six shifts in 1976, 1980, 1985, 1986, 1991 and 1993 were found in real time. The next shift in 1994 was found with a one year delay, and the last four shifts in 1996, 1997, 1999 and 2005 were found in real time. After the final smoothing only eight of the shifts (1976, 1980, 1985, 1986, 1991, 1994, 1996 and 1997) had higher probability than the threshold level of 0.5. In this case the parameterization of our method clearly failed since so many shifts were found so close to each other. Since our measure of easiness cannot be calculated for regimes of length one, we could not report those for the North Sea cod.

The easiness measures for the shifts found in the empirical data ranged from 2.8 to 8.2. Visual inspection of the time series does not suggest that any other shifts exist. So if this level of easiness is to be expected, the method will most likely find all the shifts. In light of this, most of the shifts in the simulated time series were more difficult to identify than in the empirical data.

4. Discussion

In the present study, we have used Bayesian online change point detection algorithm (Adams and MacKay 2007) to detect regime shifts in fish stock productivity. Most of the previous attempts to detect regime shifts in stock productivity have been based on frequentist methods (e.g., Vert-Pre et al. 2013; Wayte 2013). It is not clear, however, how these methods account

for the uncertainty in their estimated locations of the regime shifts or the uncertainty in the estimated parameters of each regime. Furthermore, it is not clear how these uncertainties would be accounted for in projections of the future state of the stock. In the Bayesian method presented in this study, the uncertainty is present in all of the parameter estimates, as well as in the locations of the shifts, and the uncertainties are represented by probability distributions that reflect the modeler's degree of belief. Projections of the stock would be carried out using the posterior predictive distribution, which incorporates all the aforementioned uncertainties. The uncertainties depend on the choice of the prior hyperparameters, the hazard rate, and the underlying predictive model, but all these assumptions are presented in a transparent manner and are subject to scrutiny. The difficulty with Bayesian methods arises when choosing the prior hyperparameters, since in many occasions the hyperparameters can be very difficult to interpret and to tune to the study in question. However, methods to estimate the hyperparameters from training data have also been developed (Turner et al. 2009).

4.1. Connections with previous work on cod productivity

The Northern cod has been shown to have collapsed solely because of overfishing in 1992 (Hutchings and Myers 1994), but migration due to changes in sea water temperatures and decline of capelin has been demonstrated to have co-occurred with the same event (Rose et al. 2000). Our dataset starts at 1991 and cannot answer any questions about the pre-collapse state of the stock. However, it seems that there was a shift in R/S to a higher level in 2002, but another shift has occurred in 2006 to very low levels of R/S.

The late 1980s regime shift in the Gulf of St. Lawrence ecosystem has been attributed to human exploitation of cod and redfish which resulted in a major perturbation of the structure

of the ecosystem from one previously dominated by demersal and small-bodied forage species to one now dominated by small-bodied forage species (Savenkoff et al. 2007). Previous analyses on productivity regimes in the Gulf of St. Lawrence cod have identified three productivity regimes spanning the years 1950-1972, 1973-1987, and 1988-2002 (Mohn and Chouinard 2007). Changes in the productivity of Gulf of St. Lawrence cod over the past few decades have been attributed to changes in natural mortality and growth (Chouinard et al. 2006). The production has been suggested to be linked to changes in the ambient temperature through declining size-at-age (Mohn and Chouinard 2004; Dutil et al. 1999). Also, size-selective fishing has been suggested to have caused genetic changes in growth in this population (Swain et al. 2007). Our analysis proposes that there was a shift to higher R/S regime in 1973, which is consistent with the findings of Mohn and Chouinard (2007). The second shift to a lower regime was found by our method in 1980, which is several years earlier than the low productivity regime proposed by Mohn and Chouinard (2007). Our method proposes that a shift to higher R/S regime happened also in 1993 but shift back to lower regime happened in 1996. It may be, however, questionable to define such a short period as a regime.

According to Brunel and Boucher (2007) the lower recruitment of North-east Arctic cod after the late 1980s could be attributed to elevated water temperatures. The recruitment of North-east Arctic cod has also been subject to earlier study (Godø 2003), which concluded that strong year-classes were produced in 1948-1950, 1963-1964, 1969-1970, and 1983. Godø (2003) suggests that the stock is affected by long-term fluctuations in the environment. Our method found shifts in R/S to a higher level in 1965 and back to a lower level in 1968. The findings correspond to the strong year-classes of 1966-1970 found by Godø (2003).

Positive correlation between the low recruitment of gadoids in the North Sea and strong positive northern hemisphere temperature anomalies after 1987 has been established

(Beaugrand 2004, O'Brien et al. 2000). The fluctuations in the abundance of plankton have been stated as one of the causes of long-term changes in cod recruitment (Beaugrand et al. 2003). Our analysis suggests that the North Sea cod stock entered a higher R/S regime in 1976, shifted back to a lower R/S regime in 1980, and has been fluctuating greatly during the period 1991—1996, and has been in a low R/S regime since 1997. However, our method essentially failed for the North Sea cod, mainly because the proportion of the within regime variance to the overall variance was underestimated while parameterizing the model.

4.2. On indicators of a regime shift

Characteristic to the Bayesian algorithms is that their output is a probability distribution as opposed to the point estimates produced by deterministic or frequentist methods. However, sometimes some kind of an indicator of the regime shifts is desirable. Adams and McKay (2007) did not discuss the problem of explicitly inferring the locations of the change points in the data. The algorithm solves the run length posterior probability distribution and the posterior probability distributions of the parameters for each run length, and if an indicator of a regime shifts is needed, it is up to the user to choose a utility function and find the decision ("regime shift occurred" or "no regime shift") that maximizes the expected utility. However, the development of a suitable utility function from management's perspective is out of the scope of this study. For simplicity, we use the posterior run length probabilities to give an early indication of a regime shift based on the newest data point and use the smoothed run length probabilities for retrospective regime shift indication. We indicate a regime shift when the probability of a run length of one is greater than a threshold value of 0.5. That is, the probability

that the data point of the particular time step is the first in a new regime is greater than the probability of the data point belonging to any of the possible previous regimes.

The success of early regime shift detection based on the posterior run length probabilities depends heavily on the prior hyperparameters, the hazard rate, and the threshold value. If the hyperparameters controlling the precision of a new regime are set so that the regime specific posterior predictive distributions become very narrow, even small deviations from the mean get interpreted as regime-shifts, and on the other extreme if the predictive distributions have very high uncertainty, even large deviations are accepted as belonging to the previous regime. Using the smoothed run length probabilities improves the accuracy of regime shift detection because it uses more data to evaluate the probabilities. Smoothing, however, can be only used to improve estimates of regime shifts in the past, and this introduces delay to the regime shift detection. In our simulations the median delay was one, and 76% of the delays were at most three.

4.3. Model limitations

In our case, the data generating process was Gaussian with unknown mean and variance. We recognize, however, that the Gaussian distribution cannot accurately model recruit-per-spawner data since it always has some probability mass on the negative real axis, and it is impossible for a stock to produce a negative number of recruits. We considered working with the log-normal distribution but the occasional years of zero recruitment in our simulation model made this impossible. Thus, we used Gaussian distribution and feel that it serves well for the purpose of demonstrating the method. The BOCPD algorithm works with any data generating process that is able to provide posterior predictive probabilities. If the

likelihood is in the exponential family and a conjugate prior is used, the posterior can be solved analytically and is computed by recursively updating the sufficient statistics since the last potential change point. This recursive approach has very low computation and memory requirements. Thus, other distributions belonging to the exponential family should be explored in the future to find the most realistic likelihood for the variable under investigation. Distributions not belonging to the exponential family might be also considered but they tend to lead to problems where the exact solution requires computationally expensive sampling methods, such as Markov Chain Monte Carlo. This is undesirable since many complex Bayesian stock assessment models already suffer from computational problems (Hilborn 2003; Kuparinen et al. 2012b), and integrating change point models into stock assessment models will further increase the amount of computation needed. However, variational approximations to non-exponential family change point models have been developed recently (Turner et al. 2013), and could also be explored.

We have used recruit-per-spawner ratios from existing model outputs to identify productivity regime shifts. This approach is very limited, since looking only at R/S does not take into account compensatory or depensatory effects. However, the widely applied Ricker stock-recruitment model can be formulated as a linear regression model that could be used as the data generating process with BOCPD to increase biological realism without sacrificing the analytical tractability of the algorithm. Moreover, productivity also depends on the mortality and growth of the population. We did not include them in our study, however, and believe that using this simple approach the operation of the methods is easier to present in an understandable format. However, as mentioned earlier, BOCPD works with any UPM, and in cases where the data model can be described as a linear regression, conjugate priors can be used to preserve the analytical tractability and computational efficiency of the algorithm. It is quite

straight-forward to extend the method for multi-dimensional data also to simultaneously analyze several variables for the same stock or to analyze several stocks at once to find temporal patterns across stocks. Moreover, our model does not include autocorrelation between consecutive R/S estimates, but instead assumes that they are mutually independent, and the parameters of the data generating process are constant within each regime.

We also acknowledge that the models that have produced the recruit-per-spawner estimates used in this study include their own assumptions about the dynamics of the population that can affect the estimates in form of biases and correlation between the estimates. For a detailed discussion about the pitfalls of post-hoc analyses of stock assessment model outputs see (Brooks 2015). Thus, given the aforementioned limitations of our approach, we propose not to take the results for the four cod stocks presented in this study as definitive proof of shifts in the productivity of these stocks, but rather as numerical illustrations of the BOCPD methodology which has not been used in fisheries research before.

In some ecosystems, it might be reasonable to model the system so that it switches between two or more reoccurring regimes, although we believe that the assumption that exactly the same conditions would repeat in reality are somewhat questionable considering the huge amount of different factors that affect the ecosystem. However, periodic recruitment has been observed for example in the Pacific mackerel fishery, and the periodicity has been contributed to periodically changing sea level, barometric pressure and sea surface temperature (Parrish and MacCall 1978). Our model is not designed for these kinds of situations since it is assumed that the parameters of the new regime depend only on the recent data and not on the data belonging to any previous regimes. Thus Markov switching regression models (Munch and Kottas 2009) will likely outperform BOCPD in cases where the system switches between reoccurring regimes. It is, however, possible to include our knowledge about the previous

regimes in the prior distribution for a new regime in our model. A straight-forward approach would be to use a mixture of previously identified regimes as the prior for new regime. The weights for each regime could indicate the relative frequencies of the different regimes, and as the hyperparameters we could use the posterior hyperparameters obtained for each regime earlier. This kind of mixture distribution approach would increase computation exponentially since at each time step each mixture component would essentially produce its own single component ‘path’ with equivalent complexity of the presented single component prior model. However, an approximate version where the components with very low probability would be ‘forgotten’ could be used to restrict the computational demand to acceptable levels. This approach has not been investigated yet but seems conceptually solid, and would probably improve regime shift detection considerably in systems where the regimes reoccur.

4.4. Implications for stock assessment

In this study, we focused on detecting productivity regime shifts in historical stock assessment data using estimates of the number of recruits and spawning stock biomass. Our approach was to inspect the posterior and smoothed run length probabilities for signs of regime shifts. This kind of an approach can provide valuable information about the magnitude and frequency of the productivity regimes experienced by a stock in the past, but it can also be used as a time series analysis tool to warn about coming regime shifts whenever new assessment data are available. However, we believe that the real potential of the method lies in incorporating the change point model of BOCPD directly into Bayesian stock assessment models. Any model parameter that is traditionally modeled as a stationary process but shows regime-type behaviour could be modeled as a change point process using the approach studied here.

Especially if there is considerable variation between regimes, the posterior predictive distribution of BOCPD model differs greatly from the posterior predictive distribution of a model that assumes no regime shifts, and is more up-to-date regarding the recent development in the stock status. Traditionally in stock assessment models, the density-dependent productivity is assumed constant across years, and the stock-recruitment model parameters are estimated using all available historical data (Hilborn 2003; Kuparinen et al. 2012b). Using change point models, the assessments may take into account the fact that under different productivity regimes the model parameters can change very rapidly and, thus, either restrict the use of the data to the current regime or simply use the posterior distribution of BOCPD, which implicitly accounts for the regime shifts. This should lead to better estimates of the model parameters because data from past regimes would not affect the estimates related to the current regime as much as when assuming stationary parameters. Implementation of such model changes is still an open problem and warrants for further research.

4.5. Implications for stock projections

In the recent assessments of all of the stocks chosen for this study the future projections are based on the recent estimates of the number of recruits or recruit-per-spawner ratios. In the 2012 assessment of cod in the Southern Gulf of St. Lawrence, the projections are based on an assumption of a linear stock-recruit relationship, and the slope of the relationship is chosen randomly from the R/S estimates for years 1994-2009 (Swain et al. 2012). The 2013 assessment of Northern Cod calculates projections to 2016 assuming that the future recruitment is the average of the past three years (DFO 2013). In the 2012 assessment of the North-east Arctic Cod, the projection for 2015 was carried out using the long-term arithmetic

mean of estimated recruitment (ICES 2012a). Whereas, in the 2011 assessment of the North Sea Cod, the future recruitment is re-sampled from the recruitment estimates of 1997 to the most recent year classes (ICES 2012b). All of these projections assume very little or no uncertainty at all in the predicted future recruitment, and implicitly assume perfect knowledge about the current regime and about its continuation in the near future. We believe that the methods proposed in this study could be immediately applied for stock projections by using the posterior predictive distribution of the latest year to predict the recruitment of the next year, and then by the sequential application of the one step forward predictions (13) calculate the predicted recruitment for the subsequent years. This would include a more realistic measure of uncertainty for developing future stock projections.

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Table 1. Summary of the regime shift detection in simulated Atlantic cod recruit-per-spawner time series. The reported quantities in each easiness class are the proportion of shifts detected at the correct time, the median detection delay for the correctly detected shifts, the proportion of shifts that were detected at a wrong time, the median error in time for the wrongly timed shifts, and the proportion of shifts that went undetected.

Easiness class	Correct time (%)	Median Delay	Wrong time (%)	Median Error	Missed (%)
0 – 0.5	1.3	1	20.4	5	78.3
0.5 – 1.0	11.1	3	26.7	3	62.2
1.0 – 1.5	25.3	2	25.0	2	49.7
1.5 – 2.0	41.5	2	33.1	2	25.4
> 2.0	81.0	1	12.1	1	6.9

744   **Figure 1.** Illustration of the method performance using the simulated recruit-per-spawner time
745   series. On the top row (panel a) we have plotted the recruit-per-spawner data (black dots), the
746   mean of the posterior predictive distribution of the current time step obtained during the
747   forward filtering (gray solid line), the 90 % probability interval of the posterior predictive
748   distribution (shaded gray area), the sample mean calculated by using all the data up to the
749   current time step (dashed black line), the years where a start of a new regime were found based
750   on the posterior run length probabilities (black triangles) or smoothed run length probabilities
751   (black triangles with a number on top indicating the detection delay), the years of actual regime
752   shifts (dashed vertical lines), the posterior probabilities for a start of a new regime (black bars),
753   the final smoothed probabilities for a start of a new regime after using all the data (light gray
754   bars), and the threshold probability level of 0.5 for the regime shifts (dashed horizontal line).
755   The second row (panel b) shows the final smoothed run length distribution. Darker color

756 indicates higher probability. The plot is cropped so that only run lengths up to 30 are shown.

757 Run lengths greater than 30 had negligible probabilities.

758

759 **Figure 2.** Examination of the performance of the method as a function of the easiness measure
 760 for the simulated recruit-per-spawner data (number of recruits divided by spawning stock
 761 biomass). The shifts are divided in four categories: the shifts that were detected correctly
 762 (lightest gray), the detected shifts for which the error in time was at most three time steps
 763 (medium gray), the detected shifts for which the error in time was greater than three time steps
 764 (darkest gray), and the shifts that were missed completely (black). The frequencies of each
 765 category are shown in panel a. The frequency data is grouped into five levels of easiness. Panel
 766 b shows the detection delay versus the easiness measure for the shifts that were detected
 767 correctly or with an error in time of at most three time steps.

768

Figure 3. Illustration of the method using the recruit-per-spawner estimates for four Atlantic cod stocks. The stocks used in the analysis are a) Northern Cod (COD2J3KL), b) Southern Gulf of St. Lawrence (COD4TVn), c) North-east Arctic (CODNEAR) and d) North Sea (CODNS). The year is shown on the horizontal axis and the recruit-per-spawner ratio (number of recruits divided by spawning stock biomass) on the vertical axis. We have plotted the recruit-per-spawner estimates (black dots), the mean of the posterior predictive distribution of the current time step obtained during the forward filtering (solid gray line), the 90 % probability interval of the posterior predictive distribution (shaded gray area), the years where a start of a new regime were found based on the posterior run length probabilities (black triangles) or smoothed run length probabilities (black triangles with a number on top indicating the delay), the posterior probabilities for a start of a new regime (dark gray bars), the final

780 smoothed probabilities for a start of a new regime after using all the data (light gray bars), and
781 the threshold probability level of 0.5 for the regime shifts (dashed horizontal line).

Draft

1 Appendix A

2 The recursive computation of the joint probability distribution of the run length and the 3 data

$$\begin{aligned}
 p(r_t, x_{1:t}) &= \sum_{r_{t-1}=0}^{t-1} p(r_t, r_{t-1}, x_t, x_{1:t-1}) = \sum_{r_{t-1}=0}^{t-1} p(r_t, x_t | r_{t-1}, x_{1:t-1}) p(r_{t-1}, x_{1:t-1}) \\
 &= \sum_{r_{t-1}=0}^{t-1} p(r_t | r_{t-1}, x_{1:t-1}) p(x_t | r_{t-1}, x_{1:t-1}) p(r_{t-1}, x_{1:t-1}) \\
 &= \sum_{r_{t-1}=0}^{t-1} p(r_t | r_{t-1}) p(x_t | x_{(t-r_{t-1}): (t-1)}) p(r_{t-1}, x_{1:t-1}) \\
 &= \sum_{r_{t-1}=0}^{t-1} p(r_t | r_{t-1}) p(x_t | x^{(r_{t-1})}) p(r_{t-1}, x_{1:t-1})
 \end{aligned} \tag{A1}$$

4 The probability density function of the non-standardized Student's t-distribution

$$t_v(x | \xi, \omega) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right) \sqrt{\pi v \omega}} \left(1 + \frac{(x - \xi)^2}{v \omega}\right)^{-\frac{v+1}{2}} \tag{A2}$$

5 The posterior predictive probability distribution

$$\begin{aligned}
 p(x_{t+1} | x_{1:t}) &= \sum_{r_t=0}^t p(x_{t+1}, r_t | x_{1:t}) = \sum_{r_t=0}^t p(r_t | x_{1:t}) p(x_{t+1} | x_{1:t}, r_t) \\
 &= \sum_{r_t=0}^t p(r_t | x_{1:t}) p(x_{t+1} | x_{(t-r_t+1):t}) = \sum_{r_t=0}^t p(r_t | x_{1:t}) p(x_{t+1} | x^{(r_t)}).
 \end{aligned} \tag{A3}$$

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