Decision Interval Cumulative Sum Harvest Control Rules (DI-CUSUM-HCR) for managing fisheries with limited historical information

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A R T I C L E   I N F O

Article history:
Received 20 March 2014
Received in revised form 5 September 2014
Accepted 6 September 2014
Handling Editor A.E. Punt
Available online 1 November 2014

Keywords:
Decision interval CUSUM
Indicator
Data poor
Fisheries management

A B S T R A C T

This study examines whether a fish stock can be managed using cumulative sum (CUSUM) control charts if limited historical information is available for the fish stock. We use the term ‘limited’ in the sense of having a minimal number of historical observations of relevant stock indicators and their respective control means (or reference points) that are aligned with the objectives of fisheries management. In the present study, a Decision Interval Cumulative Sum (DI-CUSUM) control chart was used to monitor two indices from a simulated fishery; the recruitment indicator and the large fish indicator (LFI). The fishery was subsequently managed using a harvest control rule (HCR) that triggered only when a significant deviation in the indicator trend was detected by the DI-CUSUM. The HCR was constructed using methods adopted from engineering process control theory where the adjustment in total allowable catch was determined by estimating the size of the shift in the indicator time series. We found that monitoring a combined indicator of both recruitment and LFI was more successful in controlling the fishery irrespective of the initial state of the fish stock. We discuss how DI-CUSUM could be incorporated into the management process for data poor fisheries.

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1. Introduction

Traditionally, fish stocks are assessed using analytical models where the state of the stock is predicted using quantitative estimates of spawning stock biomass and fishing mortality (Garcia, 1996). However, these models are generally data intensive, make numerous assumptions, and the validity of stock status estimates will depend upon the quantity, as well as the quality, of the data available for the fish stock (Kelly and Codling, 2006). Therefore, standard assessments cannot be completed for many fish stocks that have limited or poor data (Costello et al., 2012). In this context, various indicator-based methods and reference points have been suggested for monitoring the state of fish stocks (Rochet and Trenkel, 2003; Trenkel and Rochet, 2003; Caddy, 2004; Petitgas, 2009; Cope and Punt, 2009). However, there is currently a lack of quantitative methods that demonstrate how empirical indicators could be used to directly manage (rather than just monitor) a data poor fishery (O’Neill et al., 2010).

When the available data are insufficient or unreliable for conducting quantitative fish stock assessments, indicators based on landed catch or fishery independent research surveys are usually monitored for classifying the status of a fish stock (Trenkel et al., 2007; Cotter et al., 2009; Carruthers et al., 2012). The direction of indicator trends can be used for short term qualitative harvest decisions such as increasing or decreasing the relative catch (Jennings, 2005). However, there are two important challenges in the ‘indicator-based’ approach to fisheries management. First, the indicators should be sensitive as well as responsive to the changes in state of the stock (Rice and Rochet, 2005; Shin et al., 2005; Link et al., 2009; Shephard et al., 2011; Probst et al., 2012). Second, the trend detection methods should have a high classification result such that the probability of obtaining false alarms is minimized because the indicators may not indicate the true changes in state of the stock if they are inherently noisy or of poor quality (Jennings, 2005). A range of trend detection methods are available in the fisheries literature but so far, their applications are limited to qualitative fish stock assessments (e.g. Caddy, 1998; Cotter et al., 2009; Mesnil and Petitgas, 2009; Andersen et al., 2009; Honey et al., 2010).
Methods from statistical process control (SPC) theory such as the decision interval form of the cumulative sum (DI-CUSUM) control chart can effectively monitor the underlying trends when indicators are affected by internal (inherent to the system) or external (observation error) noise (Page, 1954). The key advantage of this approach is it can be implemented even when data are not available for a long historical period but yet hold the basic principles of a ‘traffic light’ approach fitted within a statistical framework (Scandol, 2003). The CUSUM techniques are mostly used in manufacturing industries as a monitoring tool to detect whether the state of a process (or stock in the context of fisheries management) is ‘in-control’ or ‘out-of-control’ (Montgomery, 1996). The DI-CUSUM raises an alarm to signal the out-of-control situations and calls for the response of process managers to undertake necessary corrective measures. Many authors have demonstrated the usefulness of DI-CUSUM as a fishery monitoring tool (Scandol, 2003, 2005; Petitgas, 2009; Mesnil and Petitgas, 2009), but their performance in directly managing a fishery has not been demonstrated so far.

Here, a simulated fishery was used to evaluate the performances of a DI-CUSUM integrated with a novel HRC (DI-CUSUM-HRC), where we implemented a quantitative approach to make relative adjustments in the fisheries catch based on the signals generated by the DI-CUSUM. We assumed that the time series of two stock indicators i.e. recruitment and the proportion of large fish individuals in the landed catch are available for a minimum of two years before the DI-CUSUM-HRC initiates. To compute the DI-CUSUM, we also assumed that the control means (or reference points) representing an in-control state of the fish stock are available for these indicators. However, no other biological information or scientific data were considered or used in this study. When an out-of-control situation is detected by the DI-CUSUM, it triggers the HRC to compute an adjustment factor (or multiplier) for updating the TAC using a carefully adapted method for determining the size of the shift in the indicator time series. We demonstrate the performance of DI-CUSUM-HRC under various scenarios, and show how the state of the stock can be regulated in a data poor fishery.

2. Methods

2.1. The operating model for fisheries dynamics

The present study adopted the operating model in Pzhayamadom et al. (2013), that has been used previously for testing the monitoring performance of a CUSUM based control chart (see Appendix B.1). The operating model simulated an age structured fish population, and the fishery dynamics consisted of four distinct phases. In the first phase, the population was simulated deterministically but without fishing, to grow and attain an equilibrium unfished stock biomass (\(B_{0\infty}\)). In the second phase, a fixed initial fishing mortality (\(F_{in\infty} = \frac{F_{MSY}}{5}\), Section 2.3) was applied and the model operated deterministically until the exploitable biomass converged to an equilibrium (\(B_{eq}\)). In the third phase, the model ran for 100 further years where random variability was introduced in the \(F_{in\infty}\) growth parameters (\(K \text{ and } L_{\infty}\), Eq. (B.1)) and stock-recruitment relationship to stabilize transient processes if any occurred (Eq. (B.4)). The recruitment to the stock was auto-correlated using an inter-annual dependency coefficient (\(p = 0.2\)) in the stock-recruitment relationship describing the dependency of recruitment in a given year with recruitment in the previous year. In the fourth phase, it was assumed that the indicator observations (Section 2.2) from the previous two years were available for the fish stock. The model ran for 20 further years during which the fishery was regulated using a DI-CUSUM-HRC. The DI-CUSUM-HRC computes an adjustment factor to increase, sustain or decrease the total allowable catch (TAC) depending on signals alarmed by the DI-CUSUM control chart.

2.2. The observation model and data collection

An estimate of the recruitment (\(R\)) and the proportion of large fish individuals in the catch (\(W_p\)) were the two indicators considered in the present study (Eqs. (B.9) and (B.10)). These indicators were measured annually during the fourth phase of the fishery simulation.

The ‘recruitment indicator’ provided an estimate of the abundance of zero age group individuals in the fish stock. Such indices are generally measured through scientific trawl research surveys and are used as a proxy for assessing the abundance of many real world fish stocks (Rochet et al., 2005; Wilderbuer et al., 2013; Fujino et al., 2013). However, an estimate of absolute recruitment is not necessary in this study because the indicator is treated in a relative sense so that even discards from a fishery can be used for monitoring the underlying trends of juveniles or young fish abundance. Such observations are extremely variable when surveys are not standardized on both temporal and spatial scales. Here, it was assumed that similar estimates were available for the recruitment indicator and were measured from the operating model using a coefficient of variation of 0.6 from the lognormal distribution (Eq. (B.9)).

Indicators based on size metrics are sensitive to fishing, and their importance has been highlighted by many authors from single species to ecosystem level research (Jennings and Dulvy, 2005; McGarvey et al., 2005; Shin et al., 2005; Cope and Punt, 2009). Recently, the large fish indicator (LFI) has been proposed as a useful community level indicator and is defined as the proportion (by number) of fish in the sample greater than a specified length (Greenstreet et al., 2011; Shephard et al., 2011). In the present study, a similar approach was used but at a single species level where the large fish individuals were classified as those which belong to age groups that are 95% or more vulnerable to fishing (\(\geq 55\%\), Step 7 in Appendix B.1). The LFI (\(W_p\)) indicator was computed from a random sample (\(n = 1000\) individual fish) of the fisheries catch and represented the proportion (by weight) of large fish individuals (Eq. (B.10)).

2.3. Monitoring indicators using DI-CUSUM control chart

The indicators measured in the fourth phase of the simulation were consistently monitored using a DI-CUSUM control chart. The DI-CUSUM is constructed by the cumulative sum of deviations of indicator observations from a reference point. To compute the DI-CUSUM, each observation in the indicator time series is first standardized (\(Z_i\)) using the control parameters such that,

\[
Z_i = \left( X_i - \bar{X} \right) \frac{1}{\sigma} ,
\]

where \(X_i\) is the \(i\)th indicator observation, \(\bar{X}\) is the control mean and \(\sigma\) is the control standard deviation. This procedure determines how far each indicator observation is from the control mean and also has the advantage of monitoring a variety of indicators combined since the deviations are expressed in standard deviation units. In the next step, a cumulative sum of \(Z_i\) is computed such that the positive indicator deviations (when \(Z_i > 0\)) and negative deviations (when \(Z_i < 0\)) are treated independently by computing two separate CUSUMs for each of them (Montgomery, 1996; Hawkins and Olwell, 1998). These are termed as the ‘Upper DI-CUSUM’ (\(\theta_{i+}^+\)) and ‘Lower DI-CUSUM’ (\(\theta_{i-}^-\)), respectively.

\[
\theta_{i+}^+ = 0 \quad \text{and} \quad \theta_{i-}^- = 0
\]
\[ \theta_i^+ = \max(0, \theta_{i-1}^+ + Z_i - k) \] and \[ \theta_i^- = \min(0, \theta_{i-1}^- + Z_i + k), \]

where 'k' is the allowance parameter, a threshold used for accommodating the common cause variability that may occur even when the state of the stock is in-control e.g. natural variability in recruitment. An out-of-control situation can be formally detected by DI-CUSUM using the 'control limit' \( (h) \). If the indicator is in an in-control state, all CUSUM observations will fall between \( h^+ \) and \( h^- \) and no management action is necessary. However, if the CUSUMs exceed these control limits, then the state of the stock is said to be in out-of-control state and a management action is required to bring the stock back to in-control. The out-of-control state of the stock can be mathematically expressed as:

\[ \theta_i^+ > h^+ \text{ or } \theta_i^- < h^- \]

The control mean \( (\bar{X}) \) should ideally represent an ‘in-control’ situation of the fishery (equivalent to a reference point in a fishery management context). In the present study, we assumed that \( \bar{X} \) is available for the fish stock and it corresponds to the indicator observation when the fishery is in equilibrium at 90% of the maximum sustainable yield (MSY). Previous studies have confirmed that this target is associated with long term yields for a wide range of stock sizes and are close to the optimal conservative level of harvest (Froese et al., 2011; Walters et al., 2008; Hilborn, 2010; Jensen, 2005). The control standard deviation \( (\bar{\sigma}) \) for DI-CUSUM was updated every year by computing the standard deviation of all indicator observations obtained until the most recent year. A ‘metric winsorization’ procedure was used to remove the effect of extreme outliers in the indicator if any (see Appendix A.1). A low allowance of \( k = 0.5 \) and \( h = 0.5 \) was used for monitoring the indicators in this study. However, the effects of using higher \( k \) or \( h \) limits were tested (see Appendix D).

2.4. Computing adjustment factor using engineering process control (EPC)

Once an out-of-control situation is detected, the next step is to estimate the shift that has occurred in the indicator. The advantage of this approach is that if such estimates are available, they can be used as a correction/adjustment factor for the control variable (TAC in this context) so that the next indicator observation will be closer to the control mean. Several methods are available for computing the adjustment factor \( (\hat{E}_i) \) in process regulation (Montgomery, 1996) and they are collectively termed as the engineering process control (EPC). These methods are based on numerical information from the CUSUM control charts i.e. standardized indicator \( (Z_i) \), CUSUM \( (\theta_i^\pm) \), O-counter \( (O^2) \), number of observations since \( |\theta| > 0 \) that led to the current out-of-control situation and H-counter \( (H_i^\pm) \), number of observations since \( |\theta| > |h| \) that led to the current out-of-control situation. Four types of EPC methods were used in the present study. They are:

1. Taguchi’s method (M1):
   \[ \hat{E}_i = Z_i \left( \theta_i^+ + k \text{ if } \theta_i^+ > h^+ \right) + \left( \theta_i^- - k \text{ if } \theta_i^- < h^- \right) \]

2. Montgomery’s method (M2):
   \[ \hat{E}_i = \frac{\theta_i^-}{\sigma_i} \text{ if } \theta_i^- < h^- \]

3. Grubbs’ harmonic rule (M3):
   \[ \hat{E}_i = \frac{\sum_{i=0}^{n} Z_i n_{i+1} \bar{X}_{i+1}}{\sum_{i=0}^{n} n_{i+1} \bar{X}_{i+1}} \text{ if } \theta_i^+ > h^+ \]
   \[ \hat{E}_i = \frac{\sum_{i=0}^{n} Z_i n_{i+1} \bar{X}_{i+1}}{\sum_{i=0}^{n} n_{i+1} \bar{X}_{i+1}} \text{ if } \theta_i^- < h^- \]

4. Using CUSUM observations (M4):
   \[ \hat{E}_i = (\theta_i^+ + \theta_i^-) \]

Taguchi (1985) proposed that an adjustment equivalent to the deviation of the last indicator observation from its control mean will be sufficient to bring the process back to its in-control state (M1, Eq. (2.3)). Montgomery (1996) proposed that the adjustment required can be estimated by dividing the current CUSUM \( (\theta_i^\pm) \) with the total number of observations since when the CUSUM was last detected equal to zero (M2, Eq. (2.4)). Grubbs (1983) suggested an adjustment equivalent to the Taguchi’s method but, progressively used smaller coefficients by dividing it with the total number of observations since the current out-of-control situation was detected. A modified form of Grubbs’ rule was implemented in the present study, where the correction in any year accounted for the cumulative sum of adjustments estimated previously in the immediate ‘out-of-control’ years (M3, Eq. (2.5)). Finally, the method based on CUSUM observations estimated the adjustment factor by summing up the upper and lower CUSUMs obtained for the last indicator observation (M4, Eq. (2.6)). All the above methods are demonstrated with worked examples in Appendix A.2.

2.5. Feedback regulation using DI-CUSUM Harvest Control Rule

To improve process control schemes, many researchers have integrated SPC and EPC; generally under the term ‘statistical process adjustment’ (SPA) such that an adjustment is not applied unless a significant deviation is detected by the DI-CUSUM (Box and Kramer, 1992; Montgomery et al., 1994; Vander Wiel et al., 1992). In the present study, the fishery was managed using a HCR in the fourth phase of the simulation where the TAC was updated only if an out-of-control situation is signalled by the DI-CUSUM. This can be mathematically expressed as

\[ \text{If } |\theta_i^\pm| > |h|, \text{ then } \]

\[ TAC_{i+1} = TAC_j + (TAC_j \times \hat{E}_i) \]

(2.7)

else,

\[ TAC_{i+1} = TAC_j. \]

(2.8)

where \( j \) is the year in which an in-control situation was last indicated by the DI-CUSUM. The \( \hat{E}_i \) is an adjustment factor computed using methods described in Section 2.4 to compensate for the shift that has occurred in the observed indicator. The formulation in Eq. (2.8) implies that when an in-control situation is signalled by the DI-CUSUM, the TAC from the previous year will be followed.

Since \( \hat{E}_i \) is a multiplier that makes relative adjustments to the TAC, the range of TACs could be extremely high if a large DI-CUSUM signal appears in the control chart (e.g. in the event of a recruitment failure). Similarly, the EPC methods may generate inaccurate estimates if a false alarm is signalled by the DI-CUSUM. Hence, an annual restriction in the TAC update was necessary to avoid stock collapse or closure of the fishery. The TAC\(_{i+1}\) was restricted using TAC\(_8\) such that it never dropped below TAC\(_i\) \times (1 − TAC\(_8\)) and never exceeded TAC\(_i\) \times (1 + TAC\(_8\)). For example if TAC\(_8\) = 30%, then TAC\(_{i+1}\) will remain between TAC\(_i\) \times 0.7 and TAC\(_i\) \times 1.3.

It is not uncommon to apply additional response levels for harvest strategies when there is high inter-annual catch variability with general lack of biological knowledge on the species (Dowling et al., 2008; Smith et al., 2008) e.g. a response when the current catch exceeds multiples of historically high catches (i.e. 0.5 \times, 1 \times, 2 \times). A similar approach was adopted in this study where the TAC at any point of time was not allowed to increase 1% more than the historical TAC maximum (i.e. TAC\(_\text{max}\) \times 1.01). A perfect implementation of the proposed TAC is not likely possible in the real world though we assume that the fishing was fully compliant with all regulations and the realized catch is a random but unbiased measure of the actual legal TAC. Hence, the fisheries catch (C\(_f\)) was computed by adding random errors using a coefficient of variation of \( cv = 0.1 \).
from the normal distribution, that is large enough to account for uncertainties in the actual catch taken (Edwards et al., 2011).

\[ C_i = \text{max}[0, -\text{normal} (\text{mean} = TAC_i, \text{cv} = 0.1)] \]  

(2.9)

2.6. Scenarios considered

Six fishery scenarios were constructed (Table 1) to compare the performances of the proposed DI-CUSUM-HCRs. These were based on the (i) type of indicator; (ii) type of estimation method; (iii) underestimation of control means in DI-CUSUM; (iv) life span of the species; (v) historical state of the stock and (vi) selectivity of the fishing gear. Additional scenarios were also constructed to evaluate other assumptions in this study and they are presented in Appendix D (Table D.1) i.e. (vii) overestimation of control means in DI-CUSUM; (viii) smaller catch sample for the LFI; (ix) higher constants for allowance (k); (x) higher constants for control limit (h); (xi) different inter annual TAC restrictions (TACo) and (xii) different coefficient of variation in the recruitment indicator.

In the first scenario, three stock indicators were used independently to manage fisheries using the DI-CUSUM-HCR i.e. the recruitment indicator (R), large fish indicator (WP) and a combined indicator of R and WP (RWp). An earlier study indicated that the large fish indicator (LFI) is more sensitive to fishing impacts on the stock biomass (Pazhayamadom, 2013). The combined indicator of recruitment and LFI may improve the overall sensitivity of DI-CUSUM because the former can account for impacts that are independent of fishing e.g. a recruitment collapse due to an environmental catastrophe. The combined indicator (RWp) was constructed by summing both R and WP, after standardizing them with their respective control means (Table A.1).

In the second scenario, the performances were measured when the adjustment factor in the DI-CUSUM-HCR (i.e. \( \hat{E}_1 \)) were computed using four EPC methods (M1–M4, Section 2.4). These methods used the information on standardized indicator time series (Zi) and their associated CUSUM values (\( \theta_i^r \) or \( \theta_i^o \)) for computing the adjustment factor for DI-CUSUM-HCR. The indicator control means for DI-CUSUM were assumed to be perfectly known in this study. However, in the real world, the indicator control means could be over- or under-estimated as they are more likely computed from historical observations (Scandol, 2003; Petitgas, 2009; Mesnil and Petitgas, 2009). In the third scenario, the performances of DI-CUSUM-HCR were measured when the control mean is under-estimated (similarly an over-estimated case is presented in Appendix D, see Table D.1).

The proposed harvest strategy should ideally manage a fishery irrespective of the life history characteristics of the species. In the fourth scenario, the HCR was evaluated for stocks with three life history traits i.e. short, medium and long lived species (Table 2). Most of the above scenarios were tested for a fishery where the stock is initially in an ‘in-control’ state. Again in the real world, fish stocks could be ‘out-of-control’ when the management plan is initiated. Hence in the fifth scenario, the HCR was evaluated for stocks at different historical states i.e. \( F_{\text{int}} = F_{50\% \text{ MSY}} \) (0.053) and \( F_{\text{int}} = F_{1.105 \text{ MSY}} \) (0.327). Fish stocks are frequently exploited using a wide range of gear types depending upon the size or behaviour of the species. Hence in the sixth scenario, the performance of DI-CUSUM-HCR was tested for different types of selectivity patterns. A logistic function was used to represent the selectivity-at-age of trawl nets with small, medium and large mesh size (increases with age giving a sigmoid shape). Similarly, a double-normal function was used to represent the selectivity-at-age of medium mesh size gill nets (increase up to a certain age and then decreases giving a dome shape). The equations and parameters used for simulating the selectivity patterns are presented in Appendix B.1.

In the base case scenario, the combined indicator (RWp) was monitored from a trawl net (medium mesh size) fishery for a medium life span species and the adjustment factor in DI-CUSUM-HCR was configured to operate using the Grubbs’ harmonic rule (M3) method. The simulations were iterated 1000 times in each scenario and the biomass, fishing mortality and total catch were recorded. The fishery simulations, indicator monitoring and the DI-CUSUM-HCR were carried out using codes written in the programming language R (R Core Team, 2013).

2.7. Performance measures for comparing scenarios

The performance of DI-CUSUM-HCR was first evaluated to detect whether the stock had collapsed in the fourth phase of the fishery simulation (probability of collapse – B01, Table 3). The stock in a given year was considered to be collapsed if the biomass was less than 10% of the un-fished stock biomass equilibrium (<0.1 × BMSY). The B01 is a proportion and hence the Pearson’s chi-squared test was applied for testing the equality of proportions. This test was employed using the prop.test function in R (R Core Team, 2013). If the performance of stocks within a scenario were found to be significantly different, multiple comparisons were made using the pairwise.prop.test function from the stats package (R Core Team, 2013).

The average stock biomass (B) obtained from the last 5 years of the simulation were assessed for their performances relative to the maximum sustainable yield (MSY) i.e. by dividing them with BMSY (relative stock biomass, Table 3) to evaluate the state of the stock further. The distribution of RSB was highly skewed since the stock collapsed in certain cases. The test for normality (Kolmogorov–Smirnov test) rejected the null hypothesis that these observations followed a normal distribution (ksnormTest function in fBasics package of R; Wuertz, 2013). Hence, a non-parametric Kruskal–Wallis test was applied to test whether the groups were significantly different from each other. Further, a multiple comparison post hoc test was applied using the kruskalwnc function in pgirmess package of R (Graudoux, 2013).

Since the same catch can be obtained for a wide range of fishing mortalities, measures on available fishing mortality (F) or average total catch (C) may not truly indicate the state of the fish stock. However, they are useful for performance comparison if the objective of fisheries management is to maximize the catch (see Appendix C).

3. Results

3.1. Illustration of DI-CUSUM-HCR

Results from the fishery simulations indicate that the DI-CUSUM-HCR was successful at regulating the state of the stock by sustaining the indicators at their respective control means. For illustration purposes, we provide an example iteration of the DI-CUSUM-HCR management from the fourth phase of the fishery simulation (Fig. 1). Fig. 1a and b displays the recruitment (R) and large fish indicator (WP) from the observation model. Fig. 1c shows the combined indicator (RWp) obtained by summing up the standardized indicator time series of R and WP (see Table A.1). Note that RWp represents the net positive or negative deviations from both indicators e.g. the negative drop of LFI in the 2nd observation and the positive peak of recruitment in the 17th observation.

Fig. 1d shows the DI-CUSUM generated using the combined indicator (RWp). Note that two historical indicator observations were available for the stock when the DI-CUSUM was initiated in the fourth phase of the simulation. A total of four signals were generated by the control chart, two from each of the upper and lower DI-CUSUMs. These signals display the most significant changes in
### Table 1
Scenarios considered for evaluating the performance of DI-CUSUM-HCR: the shaded areas highlight the differences when compared to the base case in scenario 1. The M1, M2, M3, M4 and M5 are the different types of EPC methods used for estimating the indicator shift in the time series (Scenario 2, see Appendix A.2). The LH1, LH2 and LH3 represent life history parameters of fish stocks with different life spans (Scenario 4, Table 2). The fishing mortality for different historical state of fish stocks i.e. below, at and above $F_{90\%\, MSY}$ were 0.053 yr$^{-1}$, 0.133 yr$^{-1}$ and 0.327 yr$^{-1}$ respectively (Scenario 5). The sigmoid and dome shape selectivity represents the trawl and gill net respectively (Scenario 6).

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Type of indicator</th>
<th>Estimation method</th>
<th>Under estimation of indicator control means</th>
<th>Life history species</th>
<th>Historical state of fish stock</th>
<th>Selectivity of the fishing gear</th>
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<tbody>
<tr>
<td>Scenario 1</td>
<td>Recruitment indicator (R)</td>
<td>M3</td>
<td>Not under estimated</td>
<td>LH2</td>
<td>At $F_{90%, MSY}$</td>
<td>Logistic (Medium mesh)</td>
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<td>Large Fish Indicator (Wp)</td>
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<td>Combined indicator (RWp)</td>
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<td>Scenario 2</td>
<td>Combined indicator (RWp)</td>
<td>M1, M2, M3, M4</td>
<td>Not under estimated</td>
<td>LH2</td>
<td>At $F_{90%, MSY}$</td>
<td>Logistic (Medium mesh)</td>
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<td>LH2</td>
<td>At $F_{90%, MSY}$</td>
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<td>Not under estimated</td>
<td>LH1, LH2, LH3</td>
<td>At $F_{90%, MSY}$</td>
<td>Logistic (Medium mesh)</td>
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<td>LH2</td>
<td>Below $F_{90%, MSY}$</td>
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<td>Above $F_{90%, MSY}$</td>
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<td>Scenario 6</td>
<td>Combined indicator (RWp)</td>
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<td></td>
<td>Logistic (Large mesh)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Double-Normal (Medium mesh)</td>
</tr>
</tbody>
</table>
Table 2
Parameters used for the simulation of different fish stocks: LH1 represents a Cod-like species (Family: Gadidae), LH2 represents a Herring-like species (Family: Clupeidae) and LH3 represents a Rockfish-like species (Family: Sebastidae). Parameters were determined from ICES fish stock summary database (ICES, 2010, 2011) and from the unpublished data in FishBase (Froese and Pauly, 2012).

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Life history 1 (LH1)</th>
<th>Life history 2 (LH2)</th>
<th>Life history 3 (LH3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Von Bertalanffy growth function</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic length (L∞)</td>
<td>129.1 cm</td>
<td>30 cm</td>
<td>49.2 cm</td>
</tr>
<tr>
<td>Age at length 0 (a0)</td>
<td>–0.82 yr</td>
<td>–1.6 yr</td>
<td>–2.19 yr</td>
</tr>
<tr>
<td>Growth coefficient (K)</td>
<td>0.14</td>
<td>0.41</td>
<td>0.07</td>
</tr>
<tr>
<td>Natural mortality (m)</td>
<td>0.21 yr⁻¹</td>
<td>0.23 yr⁻¹</td>
<td>0.15 yr⁻¹</td>
</tr>
<tr>
<td>Plus-group (n0)</td>
<td>10 yr</td>
<td>6 yr</td>
<td>30 yr</td>
</tr>
<tr>
<td>Length–weight relationship</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept (c)</td>
<td>0.0104</td>
<td>0.006</td>
<td>0.0113</td>
</tr>
<tr>
<td>Slope (d)</td>
<td>3</td>
<td>2.09</td>
<td>2.5</td>
</tr>
<tr>
<td>Re-parameterized Beverton–Holt recruitment function</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Steepness (z)</td>
<td>0.75</td>
<td>0.90</td>
<td>0.60</td>
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<tr>
<td>Maturity parameters</td>
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</tr>
<tr>
<td>Age at 50% maturity (M50%)</td>
<td>2.5 yr</td>
<td>1.8 yr</td>
<td>13 yr</td>
</tr>
<tr>
<td>Age at 95% maturity (M95%)</td>
<td>3 yr</td>
<td>3 yr</td>
<td>20 yr</td>
</tr>
</tbody>
</table>

Table 2 shows the tendency to increase since the TAC is not updated unless a signal is generated by the DI-CUSUM (Fig. 2b). As a result, the lower DI-CUSUM was comparatively larger in the initial years and once the catch was reduced, the upper DI-CUSUM increased during the final years of the fishery simulation (Fig. 2a and e). By the end of the fourth phase, the catch records obtained from all iterations corresponded to 90% MSY or below (Fig. 2c). Similarly, the stock biomass from all iterations in the fourth phase ended up at B∞ MSY or above (Fig. 2d).

Though the fishery was in-control for most of the iterations, the stock ended up with a small probability of stock collapse regardless of the EPC method used in DI-CUSUM-HCR (0.008% in base case). A comprehensive analysis showed that in all collapsed cases, the TAC in the initial year was set more than MSY of the fish stock (Fig. 3). Note that the initial TAC in the fourth phase was set equal to the catch in the previous year (from the third phase), that was generated using random errors from a normal distribution of F = F∞ MSY (different starting points for EPC methods in Fig. 3). This result shows that the DI-CUSUM-HCR may not sustain the stock at in-control state if such high initial TAC is used, generally for two reasons. First, there may be delay in the control chart raising a signal if there are not many historical observations available for the indicator. Second, the magnitude of the CUSUM observations will be small even if the control chart raises a signal during the initial years of the management phase. This essentially affects the accuracy of the indicator shift estimated by the EPC and thus results in a less effective adjustment of the TAC through DI-CUSUM-HCR. The probability of collapse may increase further if the TAC limit is allowed to increase more than 1% of the historical TAC maximum (Section 2.5), particularly if the fishery is already operating close to MSY.

3.3. Performance comparison with type of indicators

A comparison of performance measures indicated that using a combined indicator (RWp) is more precautionary since it resulted in a higher RSB with significantly low probability of stock collapse (Fig. 4a and b). This is because the RWp used a double proxy i.e. recruitment and large fishes in the stock to detect changes in age structure of the population. Hence the TAC will be reduced if a significant negative impact occurs to any of these indicators separately or combined, say for example, if the stock is severely overfished or in a depleted state.
Fig. 1. Graphical illustration of DI-CUSUM-HCR from single iteration of the base case: (a and b) The recruitment (R) and large fish indicator (Wp) with their respective control means; (c) the combined indicator obtained by summing up the standardized R and Wp; (d) DI-CUSUM generated from the combined indicator; (e and f) changes in catch, stock biomass and fishing mortality in response to the DI-CUSUM. A decrease in catch can be observed whenever DI-CUSUM raised negative signals and vice versa.
3.4. Performance comparison with type of estimation method

The estimates from all EPC methods were successful in sustaining the stock back at the in-control state. However, the Montgomery’s method (M2) and Grubbs’ harmonic rule (M3) were significantly different from other methods in terms of the probability of collapse (Fig. 4c). This is because these methods used all historical information since the last in-control signal, whereas the computation of M1 and M4 is based on the last indicator observation in the time series (see Appendix A.2). A comparison of the RSB showed that the method based on CUSUM observations (M4) gave the highest RSB in the present study (Fig. 4d). However, it is not feasible to apply the adjustment factor from M4 if the TAC is not updated on an annual basis (see Section 4).

3.5. Performance comparison with underestimated indicator control means

The performance measures are significantly different if the indicator control means in DI-CUSUM are underestimated (Fig. 4e and f). This is because the reference points in DI-CUSUM will get shifted away from the implied target i.e. 90% MSY at fishery equilibrium. In such scenarios, the upper DI-CUSUM will raise a large positive signal even if the recruitment or large fish individuals are too low. This eventually leads DI-CUSUM-HCR to make positive adjustments in the TAC, when in reality, a reduction of the same is required to sustain the stock at in-control state. Fig. 4f indicates that the probability of collapse is significantly higher when the control means are under-estimated.

3.6. Performance comparison with species having different life history traits

The probability of collapse depends on the longevity of the species, with the higher risk for species with the shortest life span (Fig. 5a). Since the number of cohorts in a short life span species is comparatively low, they are more responsive, dynamic and require quick management decisions which may otherwise lead to stock collapse. For the same reason, they will reach the reference point...
quicker than the long lived species if the alarm signals are not delayed (Fig. 5b). For long lived species, the fishing mortality for the younger age groups were low (Table 2) and hence their responses to fishing impacts were comparatively slow (Fig. 5b).

3.7. Performance comparison with different historical state of the stock

The probability of stock collapse will be greater if the stock is historically at a higher fishing mortality close to MSY or above (Fig. 5c). This is obvious because the chance of initiating DI-CUSUM-HCR with a TAC higher than MSY will be greater if the fishery is historically operated at these fishing mortalities. In out-of-control situations, a large DI-CUSUM signal will be already in place when the management initiates and thus a large positive or negative TAC adjustment occurs during the initial years. However, if the stock is historically in an in-control state, the TAC adjustments are gradual due to the absence of large DI-CUSUM signals. Thus a significantly low RSB was obtained for the base case (Fig. 5d).

3.8. Performance comparison with selectivity pattern of the fishing gear

There is no significant difference in the probability of stock collapse or RSB with selectivity pattern of the gear (Fig. 5e and f). However, the relative fishing mortality or average catch will be significantly low if a large mesh sized trawl net is used for fishing (see Appendix C). This is because comparatively smaller proportions of mature fishes are caught in a large mesh sized gear and thus providing them an opportunity to spawn and replenish the stock. A similar effect is expected for the dome shaped selectivity (e.g. gill net) since larger fishes are allowed to escape. The RSB for the dome shaped selectivity was higher, though not significantly so, when compared to the trawl nets (Fig. 5f).

4. Discussion

Only a few studies have demonstrated the use of empirical indicators with harvest control rules to manage fisheries (Little et al., 2011; Prince et al., 2011; Punt et al., 2012; Klaer et al., 2012). The Decision-Interval Cumulative Sum (DI-CUSUM) has been used in fisheries for monitoring such indicators (Campbell, 2004; Petitgas, 2009; Petitgas and Pouard, 2009; Lepage and Rochard, 2011) though their ability to directly control processes are limited to scientific discussions (Lee, 2000; Scandol, 2003; Pazhayamadom et al., 2013). The present study constructed a harvest control rule using DI-CUSUM and methods of EPC theory. The DI-CUSUM-HCR adjusted TAC by estimating the changes or shifts in the indicator time series. Results showed that the DI-CUSUM-HCR was successful in regulating the state of the fish stock. The DI-CUSUM-HCR approach can be implemented even if no biological information (other than the indicators with their respective control means) is available for the fish stock. This is a significant advantage over other harvest control rules that have been proposed so far in a data poor context (e.g. Cadin and Pastoors, 2008; Dowling et al., 2008; Smith et al., 2008). We now discuss the advantages and limitations of this approach for real world applications.

4.1. A catch control rule based on DI-CUSUM

The harvest strategy adopted in the present study belongs to a conditional constant catch control rule where the catch is set constant unless removing that amount would keep the CUSUM away from a predetermined maximum threshold (Hjorne and Hansson, 2001; Clark and Hare, 2004; Deroba and Bence, 2008). There are several advantages in this approach compared to other rules that are based on fishing mortality (F) or biomass (B). First, this is most suitable for managing fish stocks that have limited or poor data because estimating the “current” F or B will require more information from the stock. Secondly, a harvest control rule expressed as catch is much easier to develop support from the stakeholders.
Fig. 4. Performance of DI-CUSUM-HCR for different (a and b) types of indicators, (c and d) types of estimation methods and (e and f) under estimated indicator control means: (a, c and e) probability of stock collapse and (b, d and f) relative stock biomass obtained from the management phase of the fisheries simulation. Performance measures with the same letters in the plot indicate no significant difference between each other at $p \leq 0.01$. 
Fig. 5. Performance of DI-CUSUM-HCR for different (a and b) life history species, (c and d) historical state of the stock and (e and f) selectivity pattern of the fishing gear: (a, c and e) probability of stock collapse and (b, d and f) relative stock biomass obtained from the management phase of the fisheries simulation. Performance measures with the same letters in the plot indicate no significant difference between each other at $p \leq 0.01$. 
because the “out-of-control” situations are visually transparent in DI-CUSUM (Froese and Proelß, 2010). Thirdly, the problem of overfishing can be best addressed by regulating catch, as this quantity is directly interpretable in economic terms (Froese and Proelß, 2010). Harvesting a constant catch is more strategic and proactive, because a reduction or increase in TAC is not necessary unless there is sufficient evidence that indicates overfishing or economic inefficiency.

Setting a catch control rule in DI-CUSUM-HCR also has limitations in that an inter-annual TAC restriction (TAC\(^6\)) is necessary to avoid boom-or-bust situations (Garcia et al., 1989; Walters and Pearse, 1996; Lande et al., 1997). This is because the relationship between indicators with the underlying stock biomass is indirect and by setting TAC\(^6\), the DI-CUSUM-HCR ensures a risk-averse approach where huge fluctuations in harvest updates are penalized. However, it is important to ascertain that the TAC\(^6\) is effective in regulating the fishing mortality when a signal is raised by the DI-CUSUM. For example, setting a large TAC\(^6\) will reduce the risk of high relative fishing mortality but, by compromising with a low relative average catch (see Appendix D). We also found that the proposed scheme may result in a stock collapse, but this can be reduced substantially if the TAC in the initial year is set lower than the stock’s historical catch records (Kell et al., 2012) or alternatively below MSY if such information is available. This also implies that the DI-CUSUM-HCR can be applied in a developing fishery situation, particularly if the catch has been maintained historically low compared to MSY of the fish stock.

4.2. Indicators for DI-CUSUM-HCR approach

Many indicators have been found useful for detecting the changes in stock biomass due to fishing or other environmental factors (Probst et al., 2013). However, we restricted analysis to the recruitment (R) and large fish indicator (Wp) because the objective was to evaluate the performance of DI-CUSUM-HCR rather than determining the best plausible indicator itself for managing a data poor fishery. We demonstrated that DI-CUSUM-HCR could work regardless of the type of indicator but the sensitivity of DI-CUSUM and the accuracy of shift estimated by EPC methods may depend on the predictive power of the indicator (Scandol, 2005). By operating the DI-CUSUM-HCR with a combined indicator RWp and constant catch control rule, the method ensured that the harvest levels represented a fishing mortality (Lowe and Thompson, 1993; Beddington and May, 1977) or age structure corresponding to the reference point (Hightower and Grossman, 1987) used in this study i.e. 90% MSY.

In the real world, the recruitment index and large fish indicator may not be readily available for data poor fish stocks as presumed in this study. If only catch records are available for the fish stock, size based (age or length) empirical indicators can be computed representing the small and large fish individuals in the landed catch (Scandol, 2003, 2005). Similar indices can also be computed from fishery independent data or through discard monitoring if landed catch is not available for the fish stock (Shin et al., 2005; Kelly and Codling, 2006; Petitgas, 2009). However, such measurements could be noisier (due to observation errors) and may result in a loss of DI-CUSUM-HCR performance (see Appendix D). An improvised approach would be to use an absolute indicator (e.g. average length of the largest ‘n’ individuals) rather than a relative indicator (Wp in this study) for measuring the large fish component in the population since the latter is likely to be affected by the abundance of recruits or younger age groups (Probst et al., 2013).

4.3. The choice of CUSUM parameters

The in-control state of the system (or reference point) is defined using the control mean parameter in DI-CUSUM. The control mean was assumed to be perfectly known in the present study. In the real world, the control means are estimated from historical observations or other empirical assessments (Montgomery, 1996; Petitgas, 2009). However, if only a few historical observations are available, then a more precautionary approach should be adopted for calibrating the control means. Results from this study indicated that an overestimation of the control mean will significantly reduce the probability of stock collapse (see Appendix D). In practice, this can be approximated by using a higher percentile of the historical indicator distribution instead of using an average or other central tendency measures (Kell et al., 2012).

The sensitivity (probability of obtaining true positive signals) and specificity (probability of obtaining true negative signals) of DI-CUSUM are determined by the allowance parameter and control limit (Scandol, 2005). Fixing lower constants for allowance (k) and control limit (h) will increase the sensitivity of the DI-CUSUM, but decreases its specificity (Scandol, 2003; Mesnil and Petitgas, 2009; Pazhayamadom et al., 2013). However, using a low constant is more precautionary for the DI-CUSUM-HCR management because it ensures a proactive management where the TAC will be modified even if the indicator deviation is very small. This approach will significantly reduce the probability of stock collapse (see Appendix D).

4.4. The choice of EPC method

Our study indicated that all the four EPC methods were successful in regulating the state of the stock towards an in-control situation. However, these methods may provide strikingly different shift estimates if the fishery was not managed historically. In such instances, the methods M1 and M4 are highly unlikely to provide accurate estimates since they are based on the most recent observation in the time series. In particular, the performance of M4 (the method based on CUSUM observations) will depend on the catch restrictions (TAC\(^6\)) applied in the DI-CUSUM-HCR. This is because the magnitude of DI-CUSUM will continue to either increase or decrease if the TAC is not updated on an annual basis. The methods proposed by Montgomery (1996, M2) and Grubbs (1983, M3) use all out-of-control observations obtained until the most recent year to compute the adjustment factor and hence they are more pragmatic to apply to real world fish stocks.

If more historical data are available for the fish stock, other EPC estimation methods could be used for continuous process adjustment (Pan, 2002; Del Castillo, 2002). However, thorough evaluations are required to test whether they will perform better than the proposed schemes in this paper. An engineering industry standard version is the minimum mean square error (MMSE) controller where the adjustment factor is computed using an autoregressive moving average (ARMA) model estimator (Box et al., 1976; Anderson, 1976; MacGregor, 1990; Montgomery et al., 1994). Another widely used technique in the engineering discipline is the proportional-integral-differential (PID) control where the adjustment factor is computed using the present (most recent observation), past (historical observations) and future (prediction) shifts in the process indicator (Tsung and Shi, 1999). Both MMSE and PID controller have been found to be quite effective in a feedback regulated mechanism through statistical process control adjustment (Messina, 1992).

4.5. Application and future work

Several problems have been encountered while implementing the harvest strategy for data limited or poor fish stocks (the “tier 4” system in Australia) largely due to the absence of benchmarks indicating a target or limit reference point (Smith et al., 2008). The DI-CUSUM-HCR approach presented in this study is relevant
in such contexts because, the DI-CUSUM has a statistical approach in deciding the limit reference points by fixing the ‘control limit’ (Mesnil and Petitgas, 2009). The present study assumed that a target reference point (or control mean) is perfectly known for the fish stock. This issue can be overcome by employing a Self-Starting CUSUM (SS-CUSUM) chart instead, particularly if no historical indicator observations are available. In SS-CUSUM, the reference point (or a ‘running control mean’) can be calibrated from the indicator observations itself on an ongoing basis as the management scheme moves forward (see Pazhayamadom et al., 2013).

The present study explored how CUSUM techniques can be applied for managing a single fish stock in a data limited or poor situation. There are increasing calls to move away from single-species management towards an ecosystem approach to fisheries management – EAFM (Hall and Mainprize, 2004; Browman et al., 2004; Pikitch et al., 2004; Rice et al., 2005). Extending the application of CUSUM to an EAFM context will require (i) identifying relevant indicators that are sensitive to the changes in ecosystem; (ii) development of control chart schemes to monitor such indicators; (iii) performance evaluation of control chart schemes; and (iv) developing and testing management frameworks using SPA and harvest control rules.

Many of the initial steps have already been carried out by previous researchers i.e. identifying and testing candidate indicators (Nicholson and Jennings, 2004; Babcock et al., 2005; Blanchard et al., 2010; Jouffre et al., 2010; Shin et al., 2010). In particular, the usage of large fish indicators (LFIs) similar to the one used in our study has been tested widely in the context of CUSUM (Greenstreet et al., 2011; Shephard et al., 2012, 2013) and hence the DI-CUSUM-HCR approach can be easily transferred to a larger framework for managing multiple species or marine ecosystems. The CUSUM approach based on CUSUM can be extended further by monitoring multiple indicators in EAFM such as those characterizing the effect of pressure (e.g. fleet size, fishing mortality or fishing effort), current state (e.g. species abundance, mean body size), response of the ecosystem (e.g. rate of change in fishing mortality) through temporal and spatial scales (Jennings, 2005). For this, it is essential to develop HCRs that may consider multiple signals from several univariate DI-CUSUMs or alternatively develop a management scheme based on multivariate control charts, the latter being efficient in taking account of the correlation between indicators.

Acknowledgements

The authors would like to thank André Punt and one anonymous referee for their useful comments which have improved the manuscript. This work was carried out under the Sea Change strategy with the support of Marine Institute (Grant Aid Agreement No. PHD/FS/07/004) and the Marine Research Sub-programme of the National Development Plan 2007–2013, Ireland.

Appendix A.

A.1. Metric winsorization

Metric winsorization is one way of making DI-CUSUM robust to outliers in the indicator time series. In this approach, the deviation due to outlying observations are “edited” to more central values while updating the upper and lower CUSUMs using an additional parameter known as the winsorizing constant (w). Hence extreme changes in the indicator are not completely omitted but contributed to the CUSUM process. This is achieved by replacing the deviations obtained as a result of the extreme outliers by a cut-off threshold value known as the winsorizing constant (w) i.e., Z_i in Eq. (2.2) will be replaced by d_i in Eq. (A.1). A constant of w=2 was used in the present study since there is little loss of performance when CUSUM is updated with values of two standard deviations or above (Hawkins and Olwell, 1998; Pazhayamadom et al., 2013).

\[
d_i = \begin{cases} -w & \text{for } Z_i < -w \\
Z_i & \text{for } -w < Z_i < w \\
w & \text{for } Z_i > w 
\end{cases}
\] (A.1)

A.2. Computation of adjustment factor

Four types of EPC methods were used in the present study for estimating the shift in the indicator time series. These estimates were used as an adjustment factor for operating the DI-CUSUM-HCR. A numerical example is provided below using an example generated from a single iteration of the base case scenario (Table A.1 and Fig. 1).

A.2.1. Taguchi’s method

The Taguchi method is one of the conventional approaches used in process control theory (Taguchi, 1985). This method recommends a single step correction by using the opposite deviation of the last indicator observation obtained during the first out-of-control alarm i.e. –(X_i – μ) where μ is the control mean. However, conducting one step correction is insufficient to bring the process mean back to the in-control state (Wiklund, 1992, 1993). Hence, this method was applied sequentially on an ongoing basis i.e. for all years when CUSUM indicates an out-of-control situation. Since the indicator observations are already standardized in Eq. (2.1), the adjustment factor will be equal to the standardized indicator. Using Eq. (2.3), the adjustment factor computed in year ‘i= 22’ of Table A.1 will be,

\[
\hat{E}_{22} = Z_{22} = 1.70
\]

A.2.2. Montgomery’s method

According to Montgomery (1996), the CUSUM is a weighted average of the indicator deviations from the control mean, where the weights are stochastic or random. Using Eq. (2.4), the adjustment factor computed in year ‘i = 22’ of Table A.1 will be,

\[
\hat{E}_{22} = 0.69 - 0.5 = 0.60
\]

A.2.3. Grubbs’ harmonic rule method

The Grubbs’ harmonic rule estimation (Grubbs, 1983) is one of the classic methods used in process control theory (Del Castillo, 1998; Trietsch, 1998). Grubbs’ rule states that the correction required for the S_i out-of-control observation can be estimated as (X_i – μ)/S_i. However, the rule calls for sequential adjustments using progressively smaller coefficients of corrections as the process move forward. Hence, the Grubb’s harmonic rule was applied in a recursive manner such that, the correction required in year ‘i’ is a cumulative sum of estimates obtained from previous years since when the first alarm was raised by CUSUM that lead to the current out-of-control situation (Del Castillo, 2006). Using Eq. (2.5), the adjustment factor computed in year ‘i= 22’ of Table A.1 will be,

\[
\hat{E}_{22} = 0.59 + 1.33 - 0.65 - 0.31 + 1.70 = 1.30
\]

A.2.4. Method based on CUSUM observations

This method used the CUSUM values itself as an estimate for the required correction. This is a crude form of correction procedure because the absolute CUSUM will keep increasing even if the shift
very small. Hence, this method could be less useful as a quantitative method if the stock is left uncontrolled (or unmanaged) for several years. However, they are useful for making qualitative judgements such as whether to increase or decrease the fisheries catch. To test these effects, the adjustment factor was computed by summing up the upper and lower CUSUM values obtained in that particular year. Using Eq. (2.6), the adjustment factor computed in year ‘i = 22’ of Table A.1 will be:

\[ E_{22} = 0.69 + 0 = 0.69 \]

Appendix B–D. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fishres.2014.09.009.

References


