Self-Starting Cumulative Sum Harvest Control Rule (SS-CUSUM-HCR) for status-quo management of data limited fisheries

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Abstract: We demonstrate a harvest control rule based on the self-starting cumulative sum (SS-CUSUM) control chart that can be used to manage a fish stock with no historical data. The SS-CUSUM is an indicator monitoring tool and does not require long historical time series data or pre-defined reference points for detecting trends. The reference points in SS-CUSUM are calibrated in the form of 'running means' that are updated regularly when new observations become available. In this study, we simulated a data limited fishery and assumed that no historical data or life history parameters are available for the fish stock. The SS-CUSUM monitoring was initiated by measuring a combined index of recruitment and large fish indicator from the simulated fishery. The signals generated from SS-CUSUM triggered a harvest control rule (SS-CUSUM-HCR), where the shift that occurred in the indicator time series was estimated and used as an adjustment factor for updating the Total Allowable Catch (TAC). Our study showed that the SS-CUSUM-HCR can sustain the status-quo state of the fish stock but has limited scope if the stock is already in an undesirable state. However the approach via SS-CUSUM is adaptable to move beyond a status-quo management strategy, if some information on the desirable state of fisheries is available.

Introduction

For a wide range of fish stocks, the available data are inadequate for estimating reference points and assessing their relative stock status (Pilling et al. 2009). Such data limited situations can arise if the species concerned are not directly targeted by the fishery (by-catch), are prone to misidentification or if they lack catch and life history data (Reuter et al. 2010). If the federal or state agencies have insufficient financial or human resources to conduct appropriate fisheries monitoring, or if the number of different fish stocks is large, then these can also lead to data limited situations (Prince 2005). Hence there are growing concerns about improving existing methods and developing alternative ways for providing management advice for data limited fisheries (Kelly and Codling 2006; Punt et al. 2011; Pazhayamadom et al. 2013). When formal fish stock assessments cannot be completed, expert judgement can be made based on the trend of empirical stock indicators (Koeller et al. 2000). However, many existing methods require reference points and/or data from a reasonable number of years to detect these trends (Blanchard et al. 2010). Moreover, there is a lack of methods that give clear strategic direction as to how decision making should adapt and respond to indicators (Bentley and Stokes 2009).

The relationship between empirical indicators and the underlying abundance of the stock is not direct and can be affected by perturbations that may account for both transient and persistent effects (Scandol 2003; Dulvy et al. 2004; Scandol 2005). Methods from Statistical Process Control (SPC) theory such as the Decision Interval Cumulative Sum (DI-CUSUM) control charts are useful for classifying these effects and hold the basic principles of a 'traffic light' approach (Page 1954). The DI-CUSUM is a trend detection algorithm and raises an 'out-of-control' signal when a significant deviation occurs in the indicator time series ('in-control' if no deviation occurs). Pazhayamadom et al. (in press) constructed a harvest control rule (DI-CUSUM-HCR) based on DI-CUSUM and demonstrated that fisheries can be managed using the trend in empirical indicators. However, DI-CUSUM requires a control mean (or reference point) for computing the indicator deviations and hence they cannot be applied in situations when such information is not available (Pazhayamadom et al. in press).

In this study, we present the application of Self-Starting Cumulative Sum (SS-CUSUM), a variant of the DI-CUSUM where pre-determined reference points are not required for constructing the control chart (Hawkins 1987). In SS-CUSUM, a ‘running mean’ is generated (in place of a control mean) from regular indicator observations and is updated on an ongoing basis when new data becomes available (Hawkins and Olwell 1998; Pazhayamadom et al. 2013). Therefore SS-CUSUM can be initiated even when there are no historical data and if indicator observations can be made available in future (Hawkins and Olwell 1998). Inherently, the SS-CUSUM computation adapt its running mean to ‘status-quo’ conditions when the monitoring initiate but may shift eventually if a management response is not invoked at ‘out-of-control’ situations when they are signalled.

In Pazhayamadom et al. (2013), we showed that the SS-CUSUM is useful for detecting the impacts of fishing on stock biomass. In this study, we extend the application of SS-CUSUM to directly manage a data limited fishery using a harvest control rule i.e., SS-CUSUM-HCR. We assume that no biological information or life histories are available for the fish stock but only a few indicator observations so the SS-CUSUM monitoring can be initiated. We also assume that the fishery develops as the management moves on but no information on the Maximum Sustainable Yield (MSY) is available. Thus the objective of SS-CUSUM-HCR is to sustain the status-quo levels (biomass and catch) and implement a ‘stability management’ rather than ‘MSY management’. The performance of SS-CUSUM-HCR is evaluated under various biological and fishery scenarios. We discuss how the method can be applied in a data limited context, particularly when no historical data are available for the fish stock.

Materials and methods

Throughout this study, we assume that no biological information or pre-defined reference points are initially available for the fish stock (i.e. “no historical information”). The SS-

CUSUM is used to monitor a combined index of 1) the recruitment (which we assume is from an independent survey or similar), and 2) the large fish indicator (proportion of fishes greater than a certain age/ length from the catch), an indicator that has been found useful for operating CUSUM based management frameworks (Pazhayamadom et al. in press). Though SS-CUSUM does not require any historical observations for initiating the monitoring process, the earliest it could raise an 'out-of-control' signal is from the third year onwards since at least two data points are required for computing the initial running standard deviation (see Appendix A1). So we configured the SS-CUSUM-HCR management to operate only when two observations were available in the indicator time series. When an out-of-control situation is raised, the SS-CUSUM-HCR computes an adjustment factor to update the Total Allowable Catch (TAC).

The operating model for fisheries dynamics

We use a stochastic operating model to simulate a non-spatial age structured fish population (Pazhayamadom et al. in press, Appendix B). The fishery simulation consists of four distinct phases. In the first phase, the population is simulated to grow deterministically to reach an un-fished equilibrium stock biomass (B_{UF}). In the second phase, a fixed initial fishing mortality 'F_{int}' is applied so that the stock stabilizes at a fishery equilibrium biomass of B_{EQ} (F_{int}=$F_{50\%MSY}$ in the base case produce B_{EQ}=$B_{50\%MSY}$ with 50% of MSY; see Table 1 and Appendix B). At this point, it is assumed that the fish stock is in an 'in-control' situation representing a fishery with sustainable levels of harvest. This 'in-control' value of F_{int} is an important assumption in this study since the SS-CUSUM may not generate meaningful alarms if the fishery starts off from an undesirable state (thus a limitation as well if the stocks are already being overfished). In the third phase, the model runs for 100 further years where random variability is introduced in the growth, stock-recruitment and F_{int} (Appendix B). In the fourth phase, the only initial data available were two observations in the indicator time series. The indicators are monitored using SS-CUSUM and the fishery is managed using SS-

CUSUM-HCR for 20 further years. The biomass and catch from the fourth phase of the simulation is recorded for evaluating the performance of SS-CUSUM-HCR.

The observation model and data collection

Two types of stock indicators are measured in each year of the fisheries simulation. The first indicator is an empirical measure of recruitment (R) to the stock i.e., the number of zero age group individuals in the population (Appendix B). However, we consider the recruitment as a measure of small fish abundance which could be measured from fishery independent surveys, landed catch or discards (Rochet et al. 2005; Wilderbuer et al. 2013; Fujino et al. 2013). The recruitment indicator R was measured with an observation error using a coefficient of variation of 0.6 from the log-normal distribution. This is large enough to simulate the values observed in real world fish stocks (Sakuramoto and Suzuki 2012) though the effect of using relatively smaller or higher coefficients have been tested in later scenarios (see Appendix B). The second indicator we use is a large fish indicator (Wp) i.e., the proportion of large fish individuals by weight from the fisheries catch (Appendix B). Earlier studies have shown that similar indicators are useful for detecting the fishing impacts from single species to ecosystem level research (Shephard et al. 2011; Probst et al. 2013; Pazhayamadom et al. 2013). In the simulation, Wp is measured by taking a random sample of *n*=1000 individuals from the simulated fisheries catch (a smaller sample size is more realistic in data limited situations and their effects have been tested; see Appendix B). The large fish individuals are classified as those which belong to age groups that are 95% or more vulnerable to the fishing gear ($\geq S_{95\%}$; Table 2).

Monitoring the combined indicator using SS-CUSUM

The SS-CUSUM monitoring consists of three steps that are executed in each year of the fishery simulation. First, all observations in the indicator time series are transformed to a random variable (Z^R and Z^{W_p}) which involves updating the running parameters (running mean '$\overline{\mu_r}$' and running standard deviation '$\overline{\sigma_r}$') by including the most recent indicator observation and a standardization procedure to make them comparable to other indicators regardless of the unit of measurement (Appendix A1). In the second step, we construct a combined indicator (RWp) of both the recruitment and large fish indicator by summing the transformed time series observations (Z^{R} +$Z^{W_p} = Z^{RW_p}$). A detailed example of this step is provided in Table A1. In the third step, the RWp observations are used to compute an ‘Upper SS-CUSUM’ (θ^{+}, cumulative sum of $Z^{RW_p} > 0$) and ‘Lower SS-CUSUM’ (θ^{-}, cumulative sum of $Z^{RW_p} < 0$) separately (Appendix A2). If the SS-CUSUMs cross beyond a threshold limit ‘h’ ($\theta^{+} > +h$ or $\theta^{-} < -h$), then the control chart indicates an ‘out-of-control’ situation but if the SS-CUSUMs (θ^{+} and θ^{-}) are between $+h$ and -h, then it indicates an ‘in-control’ situation.

SS-CUSUM parameters

In SS-CUSUM, the running parameters are updated on an ongoing basis but only if the scheme signals an in-control situation. Thus the ‘out-of-control’ observations are not used for updating the running mean. However, occasional outliers may occur in the indicator time series and this could potentially contaminate the running mean (Hawkins and Olwell 1998). Therefore ‘metric winsorization’ is employed to replace the extreme outliers using a cut off threshold value known as the “winsorizing constant” (*w*; see Appendix A3). A *w*=1 is used in this study so that the running mean may not depart more than one standard deviation from its previous state. In addition to this, a parameter known as the allowance factor (*k*) is used in SS-CUSUM to make the scheme robust to inherent variability of the indicator (Mesnil and Petitgas 2009). This is employed in the computation of upper and lower CUSUMs where *k* is subtracted from the absolute transformed observations ($|Z^{RW_p}|$; eq. 15 in Appendix A2). In this study we use a high *k*=1.5 so that more in-control observations can be accommodated for the computation of running means (and the values may become closer to the status-quo). To detect out-of-control situations, a low *h*=0 is used in SS-CUSUM so that the probability of detecting true fishing impacts is high (Pazhayamadom et al. 2013). The effects of using different constants for *w, k* and *h* have been explored in Appendix B (see Table S1).

Adjustment factor for TAC

In our proposed SS-CUSUM-HCR, an adjustment factor is used to update the TAC from the previous year. Pazhayamadom et al. (in press) demonstrated that if the shift in the indicator (that resulted in an out-of-control signal) can be estimated, this could serve as an adjustment factor for TAC so that the next indicator observation may become closer to the reference point (here ‘running mean’) with the smallest variation. The shift in the indicator can be estimated using several methods in Engineering Process Control (EPC) theory but, we adapted a modified form of ***Grubbs harmonic rule*** (Grubbs 1983) for the following reasons. Firstly, this method has been found to be efficient in reducing the risk of stock collapse in a DI-CUSUM based management framework (Pazhayamadom et al. in press). Secondly, this method can estimate the indicator shift more accurately when compared to other techniques in EPC (Pazhayamadom 2013).Thirdly, this method holds fewer assumptions and requires the least number of historical observations to estimate the indicator shift (Kelton et al. 1990; Luceño 1992; Wiklund 1995). The modified form of Grubbs harmonic rule computes the indicator shift by constructing a harmonic series using all out-of-control observations such that the Z^{RW_p} is divided by progressively smaller coefficients (see Table A1). According to Grubbs harmonic rule, the proportional indicator shift in ith year ($\hat{E}_i$) can be estimated using the formula:

$$\hat{E}_i = \begin{cases} \sum_{t=1}^{H_i^+} \left(\frac{Z^{RWp}_{[i-H_i^+ + t]}}{t} \right) & \text{if } \theta_i^+ > h^+ \\ + & \\ \sum_{t=1}^{H_i^-} \left(\frac{Z^{RWp}_{[i-H_i^- + t]}}{t} \right) & \text{if } \theta_i^- < h^- \end{cases} \tag{1}$$

The condition $\theta_i^+ > h^+$ or $\theta_i^- < h^-$ indicates that the shift is estimated only if an out-of-control situation is signalled by the SS-CUSUM. The H-counter ($H_i^{\pm}$) indicates the number of observations since $|\theta| > |h|$ that led to the current out-of-control situation.

The SS-CUSUM-HCR

The SS-CUSUM-HCR is a catch based management procedure and is initiated in the fourth phase of the operating model. We assume that the catch from the last year of the indicator time series is available and is fixed as the initial TAC when the SS-CUSUM-HCR initiates (a feasible approach that can be applied in data limited situations). The adjustment factor ($\hat{E}_i$) updates the TAC only if two conditions are satisfied. First, the SS-CUSUM should raise an alarm indicating the "out-of-control" situation ($|\theta_i^{\pm}| > |h^{\pm}|$). Second, the absolute SS-CUSUM in the current year should be greater than the absolute SS-CUSUM in the previous year ($|\theta_i^{\pm}| > |\theta_{i-1}^{\pm}|$; progressing further away from zero), indicating that an adjustment in TAC is required to bring the observations (in future) closer to the running mean. The second condition is necessary because if the absolute SS-CUSUM stagnates or decreases (after raising an alarm), then it implies that the stock is already in the path back to its initial 'in-control' state and no further TAC adjustments are required to sustain the status-quo levels.

If SS-CUSUM indicates an in-control situation ($|\theta_i^{\pm}| < |h^{\pm}|$), then the HCR was designed to sustain TAC from the previous year. However, if SS-CUSUM is moving towards zero ($|\theta_i^{\pm}| < |\theta_{i-1}^{\pm}|$ at in-control situations), then the TAC is increased by a multiplier (TAC_{inc}) to simulate a developing fishery i.e., more catch is allowed as long as the SS-CUSUM indicates that the stock continues to remain in an 'in-control' state. This can be mathematically expressed as;

(2) If $|\theta_i^{\pm}| > |h^{\pm}|$ and $|\theta_i^{\pm}| > |\theta_{i-1}^{\pm}|$, $TAC_{i+1} = TAC_i + (TAC_i \times \hat{E}_i)$

(3) If $|\theta_i^{\pm}| > |h^{\pm}|$ and $|\theta_i^{\pm}| < |\theta_{i-1}^{\pm}|$, $TAC_{i+1} = TAC_i$

(4) If $|\theta_i^{\pm}| < |h^{\pm}|$ and $|\theta_i^{\pm}| > |\theta_{i-1}^{\pm}|$, $TAC_{i+1} = TAC_i$

(5) If $|\theta_i^{\pm}| < |h^{\pm}|$ and $|\theta_i^{\pm}| < |\theta_{i-1}^{\pm}|$, $TAC_{i+1} = TAC_i + (TAC_i \times TAC_{inc})$

A low TAC increment (TAC_{inc} =1% in the base case, eq. 5) is preferred to reduce the risk of overfishing if the fishery start off from an undesirable state (but we also explored the effect of using higher TAC_{inc}; see Appendix B). Also note that a low increment such as 1% becomes higher in absolute magnitude as the TAC moves closer to the MSY. We also apply an annual TAC restriction (TAC^R=10% in the base case; see Appendix B for the effect of using higher TAC^R) such that the TAC_{i+1} neither drops below $TAC_i \times (1 - TAC^R)$ nor goes above $TAC_i \times (1 + TAC^R)$. This is essential to avoid a stock collapse or fishery closure because the magnitude of adjustment factor ($\hat{E}_i$) will be high if a large SS-CUSUM signal appears in the control chart (e.g. in the event of a recruitment failure). Since there is no information on MSY of the stock, a catch higher than MSY is likely to be unsustainable. Therefore an additional response level is required where multiples of historical high catch (Dowling et al. 2008; Smith et al. 2009) may be used to minimize the TAC_{i+1} exceeding MSY. In this study, we used TAC_{lim} (1% in the base case) so the TAC was not allowed to increase more than a multiple of the historical TAC maximum (TAC_{max}) i.e., $TAC_{max} \times (1 + TAC_{lim})$. The effect of using higher TAC_{lim} have been explored and discussed in Appendix B. A perfect TAC implementation is also not likely possible in the real world so, the fisheries catch (C_i) is computed by adding random noise errors to the TAC_i using a coefficient of variation (*cv*) of 0.1 from the normal distribution.

(6) $$C_i = max[0, \sim normal\ (mean = TAC_i, cv = 0.1)]$$

The fishery simulations, indicator monitoring and SS-CUSUM-HCR computations were carried out using the programming language R (R Core Team 2014).

Scenarios considered

We consider four main scenarios to compare the performances of the SS-CUSUM-HCR (Table 1). These are based on (i) the number of historical observations available when the SS-CUSUM initiates (2, 4, 6 or 8 data points in the indicator time series); (ii) the state of stock when the management initiates (below F_{MSY}, at F_{MSY} or above F_{MSY}); (iii) the life span of the species (LH1, LH2 or LH3); and (iv) the selectivity of the fishing gear (trawl or gill net). We also considered other scenarios (see Appendix B) to test the effect of different (i) winsorizing constants (*w*); (ii) allowance constants (*k*); (iii) control limits (*h*); (iv) inter annual TAC restrictions (TAC^R); (v) coefficient of variation in the recruitment indicator (*cv*); (vi) sample size from the fisheries catch (*n*); (vii) TAC increments at in-control situations (TAC_{inc}) and (viii) restrictions on the maximum TAC allowed (TAC_{lim}).

Base case: We compare all scenarios with a base case (see Table 1) where the total number of historical observations available are the shortest plausible (two data points so that SS-CUSUM monitoring can be initiated, Pazhayamadom et al. 2013); the initial state of stock represent a developing fishery below the F_{MSY} i.e., at equilibrium levels of 50% MSY (to ensure that SS-CUSUM start off with the assumed "in-control" fishery where the status-quo catches are at sustainable levels given the inherent stock variations; Stefansson and Rosenberg 2005) and the model simulated a medium life span species (LH2; Table 2) with a fishery from medium mesh sized trawl net fishing gear (see Appendix B). Added to that, an observation error of *cv*=0.6 was used for the recruitment indicator and a sample size of *n*=1000 fish individuals were used for computing the large fish indicator. The SS-CUSUM parameters for the base case were *w*=1, *k*=1, *h*=0 and the SS-CUSUM-HCR parameters were $TAC^R = 10\%$, TAC_{inc} =1% and TAC_{lim} =1%. Each scenario was run for 1000 iterations and the biomass along with associated catch were recorded from the fourth phase of the simulation for evaluating the SS-CUSUM-HCR performance.

Scenario 1: In the operating model, only two historical observations are available for the indicators in the fourth phase when the SS-CUSUM-HCR initiates. However, the SS-CUSUM is generally recommended to start with a few more observations from the 'in-control' state so the running means may represent the status-quo levels and stabilize at the intended reference point. Hence in the first scenario, the performance of SS-CUSUM-HCR is tested for the effect of having more historical 'in-control' observations (Table 1).

Scenario 2: The SS-CUSUM-HCR should manage fisheries irrespective of the life history characteristics of the species because it is unlikely to have such information in a data limited context. Hence in the second scenario, we test the HCR for fish stocks with three different life history traits i.e., short lived (LH1; a Herring-like; Family: Clupeidae), medium lived (LH2; Cod-like; Family: Gadidae) and long lived (LH3; Rockfish-like; Family: Sebastidae) species. The life history parameters used for these fish stocks are provided in Table 2.

Scenario 3: We also consider situations where the stock is at different states when the management is initiated i.e., with relatively higher fishing pressure at or above F_{MSY} (Table 1). In these situations, we presume that the running mean may not stabilize at the intended reference point as the recruitment or large fish indicator will be relatively low at higher levels of fishing effort and the observations (including status-quo catch) may not represent a sustainable fishery given the inherent variation of stock dynamics. To test this assumption, we initiate the SS-CUSUM-HCR at F_{int}=0.227 (at F_{MSY}) and F_{int}= 0.327(above F_{MSY}).

Scenario 4: Indicators from landed catch are sensitive to the differences in selectivity pattern of the fishing gear (Shin et al. 2005). Hence, we compare the performance of SS-CUSUM-HCR across a trawl net (sigmoid shape selectivity for large, medium and small mesh sizes) and gill net (dome shape selectivity for medium mesh sizes) fishery. In trawl fisheries, we assume the fish become more vulnerable to fishing with increasing age (sigmoid shape selectivity) while in gill net, the vulnerability increases up to a certain age and then decreases (dome shape selectivity; see Appendix B).

Performance measures

The performance of SS-CUSUM-HCR is evaluated by computing the average ratio of stock biomass and total catch obtained in the fourth phase of the simulation (B_{HCR} and C_{HCR}) to their respective values at MSY i.e., the average B_{HCR} / B_{MSY} and C_{HCR} / C_{MSY} from all iterated simulations. Thus the outcomes can be compared to their MSY equivalents (a common reference point in fisheries; Froese et al. 2011) and mean status-quo levels i.e., values corresponding to the fishery equilibrium 'B_{EQ}' from the second phase of the simulation (to determine whether the stock has been sustained at its initial state). These performance measures are referred to as relative average biomass (RAB) and relative average catch (RAC) from here on. In certain cases, the stock collapsed and hence the performance measures (of biomass and catch) did not follow a normal distribution (Kolmogorov -Smirnov test using **fBasics** package of R; Wuertz 2013). Therefore, a non-parametric Kruskal-Wallis test is applied to find whether the performance measures within each scenario are significantly different from each other. If significant, a multiple comparison post hoc test was applied using the *kruskalmc* function from the **pgirmess** package of R (Giraudoux 2013).

A comprehensive study by Froese et al. (2011) showed that fish stocks with biomass levels below 0.5 B_{MSY} tend to impair recruitment and are unsustainable with a danger of collapse. Hence it is important to determine whether the SS-CUSUM-HCR management leads the stock to a state where the fishery is unsustainable. In our study, we consider the stock in a given year is at high risk if the biomass is less than 10% of the un-fished stock biomass equilibrium (<10%B_{UF}).This threshold correspond to 0.22 – 0.39 B_{MSY} of all the life history species used in this study with a biomass above 0.5 B_{MSY} when the SS-CUSUM-HCR initiates (Table 1; Appendix B). The proportion of biomass <10% B_{UF} (referred to as B_{10} from here on) is computed for each scenario from all iterated simulations of the fourth phase. Further, we employ the Pearson's chi-squared test using the *prop.test* function in R (R Core Team 2014), to test whether the B_{10} are equal for all stocks within each scenario. If the proportions are found to be significantly different, then the *pairwise.prop.test* function from the **stats** package (R Core Team 2014) is used for multiple comparisons.

Results

Illustration of SS-CUSUM-HCR

An example iteration of the SS-CUSUM-HCR management from the fourth phase of the fishery simulation is illustrated (Fig. 1). Figures 1*a* and 1*b* display the recruitment (R) and large fish indicator (Wp) from the observation model. In both cases, the running mean was stabilized very close to the intended reference point representing the mean status-quo state of the fish stock (but they may also stabilize at an inappropriate level which we discuss later on). The combined indicator (RWp) shows the net deviation obtained after summing up the transformed indicator time series of R and Wp, their trends being well represented in Fig. 1*c*. The SS-CUSUM generated using RWp (Fig. 1*d*; Table A1) shows a total of seven negative signals (14, 16 and, 18-22 observations). It is obvious in Fig. 1*e* that negative TAC adjustments were applied at out-of-control situations ($|\theta_i^{\pm}| > |h^{\pm}|$; *h*=0 in this case), whenever the absolute lower SS-CUSUM in a given year was higher compared to its previous year (observations at 14, 16 and 18-20th year). The TAC from the previous year was sustained (not updated) on the 21st and 22nd year because the SS-CUSUM is moving towards zero i.e., $|\theta_{22}^{-}| < |\theta_{21}^{-}| < |\theta_{20}^{-}|$ (Fig. 1*d*; Table A1). The associated changes in fishing mortality and the recovery of stock biomass are presented in Fig. 1*f*.

Output from the base case scenario

The shaded region in Fig. 2*a* shows the 5th and 95th percentile of upper and lower SS-CUSUMs obtained from all simulated iterations of the base case scenario. There are no signals during initial years because the earliest SS-CUSUM can raise an alarm is from the third year onwards (Fig. 2*a*) i.e., when the initial running parameters become available. Subsequently, the running means are updated but large departures from the existing mean is protected by the metric winsorization procedure. Figure 2*a* shows that alarms were raised by both the upper and lower SS-CUSUMs during the fourth phase of the simulation indicating that the algorithm was responding to changes in the status-quo state of the fish stock. Since the TAC was configured to increase by 1% at in-control situations, the fishing mortality becomes inflated occasionally (see Fig. 2*b*; the range of 5th-95th percentiles is large when compared to 25th- 75th percentiles) leading to out-of-control alarms from the lower SS-CUSUM (see the example in Fig. 1*e* and 1*f*). However, the median of fishing mortalities remained stable exactly at F=0.05 indicating that in most cases, the state of the stock was at in-control with mean status-quo levels (Fig. 2*b*). The range of stock biomass and total catch indicates that the SS-CUSUM-HCR sustained the fish stock with a stable median close to its initial years (Figs. 2*c* and 2*d*), though slightly below the mean status-quo reference points. Our study shows that choosing a low w=1 and high k=1.5 can adapt the running means moving closer to the mean status-quo reference points (Figs. 2*e* and 2*f*). Note that the mean status-quo levels marked in Figure 2 are values at fishery equilibrium conditions. The exact status-quo values are different in each iteration, given the inherent variation of stock dynamics and the observation or implementation errors applied.

The SS-CUSUM-HCR may also lead the stock to high risk conditions (B_{10}=0.008 in the base case scenario) if either one or both of the following situations occur. First, the signals from SS-CUSUM become meaningless if the running mean stabilizes far below or above the intended reference point, thus not representing the status-quo levels. Figure 3 shows an example situation where the fish stock ended up in a collapse. Here, the running mean of indicators was stabilized far below the mean status-quo levels (Figs. 3*a* and 3*b*) and raised disproportionate positive signals from the upper SS-CUSUM (Figs. 3c and 3*d*). This resulted in an increase in the TAC and F from the status-quo levels (Figs. 3*e* and 3*f*). It is unlikely that the running mean may stabilize exactly at the intended reference point but it is the extent to which the running parameters may depart from status-quo levels that determines the risk of the stock. However, this is a separate issue that require more research and is beyond the scope of the present study. Secondly, if the SS-CUSUM-HCR start-off with an initial TAC that is higher than the MSY (Fig. 3*e*), then the biomass cannot be sustained (Fig. 3*f*). Note that the 'in-control' condition of SS-CUSUM-HCR inherently assumes that the status-quo biomass and catch are at sustainable levels. In the example, the drop in large fish indicator was detected by SS-CUSUM after a delay due to the running mean stabilizing at lower levels (Figs. 3*b* and 3*d*). This initiated a negative TAC adjustment in later years (yet above the MSY) but was not early enough to rebuild the fish stock.

Performance comparison for stocks with more historical data

Results indicate that there is no significant difference in the performance measures (RAB ($p=0.06$); RAC ($p=0.002$); B_{10} ($p=0.004$)) if more historical data are available for the fish stock (Figs. 4*a*, 5*a* and 6*a*). Having more historical data means that the running means are expected to converge further towards the mean status-quo levels. However, no significant improvement was observed in the management performances. It is very obvious from Figs. 1*a*, 1*b*, 3*a* and 3*b* that the running means are more dynamic during initial years (in particular the first three data points) and the subsequent updates become smaller as more observations are added to the indicator time series. This essentially means that the quality of observations are more important than the length of the historical time series, because the first few observations largely determines whether the initial running mean and running standard deviation represents the status-quo state of the fish stock (see Discussion).

Performance comparison with species having different life history traits

All performance measures were significantly different for the three life history species ($p<0.001$). However, the values equivalent to B_{MSY} is different for each species and hence the RAB performances are similar if they are compared to their respective mean status-quo levels (Fig. 4*b*). There are clear differences in the performance of RAC and B10, the short life span species having the lowest relative catch and highest risk (Figs. 5*b* and 6*b*). Since only a few cohorts are present in a short life span species, they are relatively more responsive, dynamic and require quick management decisions to reduce the risk of stock collapse. The long lived species respond to fishing impacts relatively slow because of the large number of cohorts in their population and low fishing mortality applies to younger fish age groups (see the selectivity parameters, Table 2). In overall, the performances were better for the long lived species (LH3) since it gave the smallest spread of RAB distribution with least risk of stock collapse (Figs. 4*b* and 6*b*).

Performance comparison with different initial states of the stock

The performance measures were significantly different when SS-CUSUM-HCR was applied to stocks that are historically fished below F_{MSY}, at F_{MSY} and above F_{MSY} ($p<0.001$). However, the RAB performances were similar relative to their respective mean status-quo levels from where the SS-CUSUM-HCR started off (Fig. 4*c*). The catch performances were far below the status-quo levels for those with initial states at F_{MSY} or above F_{MSY} (Fig. 5*c*). Since the status-quo fishing mortality is relatively high in these cases, the probability of status-quo catch being above MSY is high and thus the fishery may not sustain for too long. This is more evident from the B_{10} performances which showed an increase with higher F_{int} i.e., at F_{MSY} and above F_{MSY} (Fig. 6*c*). Additionally if the fishery starts off from an undesirable state (e.g. above F_{MSY}), the SS-CUSUM-HCR may not sustain the status-quo because the initial years are not representative of the assumed 'in-control' fishery and thus leads to a running mean stabilizing at inappropriate levels.

Performance comparison with selectivity pattern of the fishing gear

The SS-CUSUM-HCR was tested for different types of selectivity patterns, under the assumption that the process was set-up for a large fish indicator from a medium mesh trawl net fishery. The performance measures were significantly different for all the selectivity patterns used in this study ($p<0.001$). However, the performances (of biomass and catch) compromised for each other such that a higher RAB leads to lower RAC or vice versa (Figs. 4*d* and 5*d*). This shows that the sensitivity of large fish indicator is affected by selectivity patterns, particularly if the (assumed) large fish age groups are not fully vulnerable to the fishing gear. For example, the age (*a*) at $S_{95\%}$ of the trawl net shifted from 5 to 7 when a large mesh size was used. This ended up catching smaller proportion of young fish ($a \leq 7$), and thus affecting the indicator sensitivity where true fishing impacts are not correctly detected. The performance of B_{10} was highest for the large mesh sized trawl net (Fig. 6*d*) with a RAC exceeding the mean status-quo levels (Fig. 5*d*).

Discussion

This study was conducted to assess whether a harvest strategy based on catch control rules and SS-CUSUM (SS-CUSUM-HCR) has the potential to manage data limited fish stocks. Though SS-CUSUM has been used previously for monitoring purposes (Lukas et al. 2008; 2009; Pazhayamadom et al. 2013), this is the first study demonstrating its potential to manage a population. The SS-CUSUM-HCR is fundamentally different in four ways when compared to the DI-CUSUM-HCR presented in Pazhayamadom et al. (in press). First, an indicator reference point is not required for SS-CUSUM-HCR to initiate the management process whilst, the DI-CUSUM-HCR requires observations from a reference period when the fishery was percieved to be stable (Scandol 2003; Jensen et al., 2006; Pazhayamadom et al, in press). Secondly, the recruitment and large fish indicator in SS-CUSUM-HCR are combined only after updating the running parameters with the most recent observation. In DI-CUSUM-HCR, the indicators can be combined immediately after standardizing them with the control parameters. Thirdly in SS-CUSUM-HCR, the adjustment factor is applied to the TAC from the previous year whilst in DI-CUSUM-HCR, the adjustment factor is applied to a historical TAC when the last 'in-control' situation was signalled (because the reference point is dynamic for SS-CUSUM and fixed for DI-CUSUM). Finally, DI-CUSUM-HCR responds to all out-of-control signals whereas SS-CUSUM-HCR consider the direction of CUSUMs to determine whether the TAC in the previous year should be sustained or not. This is important because the SS-CUSUMs could stop moving away from zero if the running mean has changed from its initial state (because the management affect future indicator observations and the updated running mean may not necessarily represent an in-control situation). Thus considering the direction of CUSUMs in SS-CUSUM-HCR is consistent with the objective i.e., to sustain the status-quo levels (biomass and catch). However, this objective restricts the possibility of providing sustainable high catches (equivalent to those of the MSY) because the threshold and direction of shift required in the running mean (or state of the stock) is unknown. The proposed SS-CUSUM-HCR sustained the status-quo fishery and state of the stock for a wide range of scenarios (see Table 1; Appendix B).

Comparison of SS-CUSUM-HCR with other management systems

Many authors have provided guidelines and examples for managing fisheries when data or information are limited (e.g. Froese et al. 2008; Dowling et al. 2008; Cope and Punt 2009; Wilson et al. 2010; Prince et al. 2011; Little et al. 2011; Cope 2013). However, these approaches are not fully comprehensive or adaptable in a data limited situation where no biological information or historical data are available for the fish stock. Many harvest strategies require a suite of indicators including catch rates or CPUE and appropriate reference points which may not necessarily be available for data limited fish stocks (Dowling et al. 2008; Wilson et al. 2010; Prince et al. 2011; Little et al. 2011). When compared to these strategies, the advantage of SS-CUSUM approach is the independence on the type of indicator that can be monitored (see Pazhayamadom et al. 2013). However, the chosen indicators should be sensitive and responsive to changes in state of the stock (Probst et al. 2012, 2013).

In Australia's Harvest Strategy Policy (HSP), for example, the harvest control rules are associated with 'tier-based' assessment systems (Smith et al. 2008; Reuter et al. 2010) where, the 'tier 4' category (Rayns 2007) is applied to fish stocks that have the least information. These control rules are based on target catch rates (catch per unit effort) and an adjustment is triggered when the indicator crosses the limit reference points. However, the 'tier 4' policy could not be applied to the Western Deepwater Trawl Fishery due to a lack of meaningful reference points (Smith et al. 2009; Smith et al. 2014). In such situations, the SS-CUSUM-HCR approach is feasible because the running mean and control limit could act as effective alternatives for the target and limit reference points respectively.

Advantages of SS-CUSUM based management in a data limited context

The foremost advantage of SS-CUSUM is the use of a running mean as the reference point for managing fish stocks. In the development of the Australian HSP (Dowling et al. 2008), to use the same example, the reference points were simply the "best guess" proxies informed through the participation, discussion and agreement of various industry stakeholders. The SS-CUSUM model is useful in such situations where the reference points corresponding to the current state of fishery can be informed by incorporating observations that are available so far. The second advantage is the use of the 'control limit' in SS-CUSUM, which provides a simple and explicit framework for defining trigger levels so that it informs the manager when a management response can be initiated (regardless of the choice of strategy such as the proposed SS-CUSUM-HCR in this paper). An example application is in the Australian HSP where multiple trigger levels are defined for data limited fish stocks, each one associated to higher data and analysis requirements (Dowling et al. 2008). The SS-CUSUM can be useful in these situations where the number of trigger levels can be reduced and no further data or assessment is required to initiate a management process. The third advantage is the simplistic nature of decision making when there are multiple indicators to be monitored. Previous studies have demonstrated TAC adjustment strategies based on multiple indicators (Wilson et al. 2010; Prince et al. 2011) but the control rules are overcrowded (one for each indicator) leading to complex decision trees. In SS-CUSUM-HCR, the information from all indicators is passed on to the control chart and TAC is adjusted only when the SS-CUSUM exceed control limits. If more indicators are available, then a multivariate self-starting control chart can be used (Sullivan and Jones 2002; Hawkins and Maboudou-Tchao 2007) instead of combining them individually (e.g. RWp indicator). Thus, the management approach based on SS-CUSUM is comparatively simple, pragmatic in real world situations, and can easily be understood by the fishers and other stakeholders (Scandol 2003; Kelly and Codling 2006).

The SS-CUSUM parameters

The allowance (*k*) and control limits (*h*) in CUSUM based control charts can be configured to obtain a fixed sensitivity (the probability of detecting an out-of-control situation when it occurs) or specificity (the probability of not detecting an out-of-control situation when it does not exist). Fixing a lower constant for *k* and *h* will increase the sensitivity of the SS-CUSUM, but decreases its specificity (Scandol 2003, 2005). In a previous study, Pazhayamadom et al. (2013) showed that the *k* or *h* constants required for achieving an equal trade-off between sensitivity and specificity will depend on the longevity of the species i.e., for fixed *k*, the *h* increases with longevity. This is because the response of size based indicators will depend on the number of cohorts within the population. For example, short lived species will usually have a small number of cohorts and hence the changes in population abundance are more dynamic. If the *h* is set too high, then the stock may collapse quickly giving no time for the SS-CUSUM to signal the out-of-control situation. Hence if no biological information is available for the species, a low constant should be chosen for the *k* and *h* (though a higher *k* converges the running mean to the intended reference point). This approach may increase the frequency of false positive signals in a long lived species but it will be more precautionary to adjust the TAC early so that the SS-CUSUM-HCR management is proactive (rather than not reacting until a signal is raised, see Appendix B).

Limitations and ways to improve the proposed SS-CUSUM-HCR approach

We demonstrated the status-quo management of SS-CUSUM-HCR in a data limited situation but, their application is limited if the stock is initially in an undesirable state (and the state could be unknown in the real world). In practice, a very large proportion of fisheries seem to exhibit fishing mortality rates excess of MSY levels (Froese et al. 2011; Costello et al. 2012). If SS-CUSUM-HCR starts off from an undesirable state, then a delay in response may occur and the reasons for this are inherent to SS-CUSUM. First, the observations from the first few years will be used to compute the running parameters and this may represent a fish stock that is already in an undesirable state. Secondly, the population should deplete further to generate meaningful alarms from SS-CUSUM via indicators. One solution is to configure the SS-CUSUM parameters (w, k and h) to generate signals at the earliest possible so the associated risks can be minimized (see Appendix B). However if more information on the desired state of the stock is available (a reference point), then the initial running parameters of SS-CUSUM can be adapted to stabilize at these levels (see below).

The second issue with the SS-CUSUM-HCR approach is its tendency of getting inappropriate running means (Fig. 3). This largely depends on the first three data points in the indicator time series and whether those observations really represent the actual state of the fish stock. This is because the first three observations are neither controlled by the winsorizing constant (the *w* which will avoid outliers if any) nor monitored by the SS-CUSUM (which will detect out-of-control situations if any) but instead, they are used to obtain an initial value for the running mean and running standard deviation. One solution to this problem is to use robust indicators that may not have large inherent variations, relative to the state of the stock (Essington 2010). To stabilize the indicator observations, it is useful to keep the catch constant for the first few years unless there is evidence indicating an increase in the fishing pressure (MacCall 2009). The initial observations in the time series can also be replaced with plausible values if an estimate of the reference point (or control mean indicating the desired state of stock) can be deduced from local fishers or scientists who are familiar with the fishery (Hawkins and Olwell 1998).

The third issue with SS-CUSM-HCR is the judgement on setting the initial TAC. Unless the initial TAC is conservative enough with regard to the MSY, then the stock may collapse (Fig. 3). If an estimate of the MSY of the fish stock is available then the control rules can be modified so that the catch never exceeds this threshold limit (Garcia et al. 1989; Walters and Pearse 1996; Lande et al. 1997). A second alternative is to configure the initial TAC to start off from a quantity that is significantly lower than the historical landings, so that the catches are likely sustainable with reduced risk of stock collapse (Kell et al. 2012; Pazhayamadom 2013). The harvest strategy can also be improved by monitoring indicators from fishery independent surveys and closing the fishery until an in-control situation is signalled by the SS-CUSUM. As more information becomes available, the TAC adjustment factors can also be computed using data rich methods that are available in the EPC theory (Tercero-Gómez et al. 2014; Luceño 1992; Box and Kramer 1992; Wiklund 1995).

Future developments

Data limited situations which can be inherently complex and highly uncertain in terms of the overall biomass, spatial extent and the ways in which they are harvested; may require more consideration. An example is the Coral Sea Fishery (CSF) in Australia where there is no information for multiple species regarding the size of the resource or exploitation rates, level of species misidentification and the variability of annual catches for individual species (Dowling et al. 2008). The indicators and estimation techniques appropriate for such scenarios will require further research. One potential approach is to extend the application of SS-CUSUM-HCR from a single-species basis to an ecosystem level.

Fishing can have a greater impact on slower growing, larger species with later maturity and thus reduces the mean body size within populations leading to an increase in the relative abundance of smaller species (Jennings et al. 1999). Small species may also proliferate when their larger predators are reduced (Dulvy et al. 2004). Hence species richness and other diversity indices are often proposed as indicators sensitive to ecological conditions of the marine habitat (Greenstreet and Hall 1996). Such ecosystem based approaches will require the monitoring of multiple indicators and thus require the development of HCRs based on multivariate control charts.

A key problem in multivariate control charts is the probability of false alarms if the indicators are autocorrelated. Hawkins and Olwell (1998) demonstrated how CUSUM can be adapted for monitoring an autocorrelated process using a Box-Jenkins autoregressive-moving average (ARMA) model. Similarly, Manly and Mackenzie (2000) also proposed a modified CUSUM using randomization tests to minimize the impact of serial correlation. Such models can be explored in future studies to improve the performance of the proposed management procedure. Nevertheless, our study suggests that the SS-CUSUM-HCR has great potential for managing data limited fisheries in a sustainable manner.

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References

Bentley, N., and Stokes, K. 2009. Contrasting paradigms for fisheries management decision making: how well do they serve data-poor fisheries? Mar. Coast. Fish. **1**: 391–401. doi: 10.1577/C08-044.1.

Blanchard, J.L., Coll, M., Trenkel, V.M., Vergnon, R., Yemane, D., Jouffre, D., Link, J.S., and Shin, Y.J. 2010. Trend analysis of indicators: a comparison of recent changes in the status of marine ecosystems around the world. ICES J. Mar. Sci. **67**: 732–744. doi: 10.1093/icesjms/fsp282.

Box, G., and Kramer, T. 1992. Statistical process monitoring and feedback adjustment – a discussion. Technometrics **34**: 251–267. doi: 10.1080/00401706.1992.10485271.

Cope, J.M. 2013. Implementing a statistical catch-at-age model (stock synthesis) as a tool for deriving overfishing limits in data-limited situations. Fish. Res. **142**: 3–14. doi: 10.1016/j.fishres.2012.03.006.

Cope, J.M., and Punt, A.E. 2009. Length-based reference points for data-limited situations: applications and restrictions. Mar. Coast. Fish. Dyn. Manag. Ecosyst. Sci. **1**: 169–186. doi: 10.1577/C08-025.1.

Costello, C., Ovando, D., Hilborn, R., Gaines, S.D., Deschenes, O., and Lester, S.E. 2012. Status and solutions for the world's unassessed fisheries. Science **338**: 517–20. doi: 10.1126/science.1223389.

Dowling, N.A., Smith, D.C., Knuckey, I., Smith, A.D.M., Domaschenz, P., Patterson, H.M., and Whitelaw, W. 2008. Developing harvest strategies for low-value and data-poor fisheries: case studies from three Australian fisheries. Fish. Res. **94**: 380–390. doi: 10.1016/j.fishres.2008.09.033.

Dulvy, N.K., Polunin, N.V.C., Mill, A.C., and Graham, N.A.J. 2004. Size structural change in lightly exploited coral reef fish communities : evidence for weak indirect effects **61**: 466–475. doi: 10.1139/F03-169.

Essington, T.E. 2010. Ecological indicators display reduced variation in North American catch share fisheries. Proc. Natl. Acad. Sci. U. S. A. **107**: 754–759. doi: 10.1073/pnas.0907252107.

Froese, R., and Pauly D. 2011. Editors, FishBase. World Wide Web electronic publication. www.fishbase.org, (06/2014).

Froese, R., Branch, T.A., Proelß, A., Quaas, M., Sainsbury, K., and Zimmermann, C. 2011. Generic harvest control rules for European fisheries. Fish Fish. **12**: 340–351. doi: 10.1111/j.1467-2979.2010.00387.x.

Froese, R., Stern-Pirlot, A., Winker, H., and Gascuel, D. 2008. Size matters: How single-species management can contribute to ecosystem-based fisheries management. Fish. Res. **92**: 231–241. doi: 10.1016/j.fishres.2008.01.005.

Fujino, T., Goto, T., Shimura, T., Yasuma, H., Tian, Y., Kidokoro, H., Masuda, S., and Miyashita, K. 2013. Decadal variation in egg abundance of a mesopelagic fish, *Maurolicus japonicus*, in the Japan sea during 1981-2005. J. Mar. Sci. Technol. **21**: 58–62.

Garcia, S., Sparre, P., and Csirke, J. 1989. Estimating surplus production and maximum sustainable yield from biomass data when catch and effort time series are not available. Fish. Res. **8**: 13–23. doi:10.1016/0165-7836(89)90037-4.

Giraudoux, P. 2013. pgirmess: Data analysis in ecology, http://CRAN.R-project.org/package=pgirmess.

Greenstreet, S.P.R., and Hall, S.J. 1996. Fishing and the ground-fish assemblage structure in the north-western North Sea: an analysis of long-term and spatial trends. J. Anim. Ecol. **65**: 577–598.

Grubbs, F.E. 1983. An optimum procedure for setting machines or adjusting processes. J. Qual. Technol. **15**: 186–189.

Hawkins, D.M. 1987. Self-starting cusum charts for location and scale. J. R. Stat. Soc. D **36**: 299–316.

Hawkins, D.M., and Maboudou-Tchao, E.M. 2007. Self-starting multivariate exponentially weighted moving average control charting. Technometrics **49**: 199–209.

Hawkins, D.M.,and Olwell, D.H. 1998. Cumulative sum charts and charting for quality improvement. Springer-Verlag, New York.

ICES. 2010. Report of the working group for the celtic seas ecoregion. ICES Document CM 2010/ACOM:12

ICES. 2011. Report of the herring assessment working group for the area south of 62 deg n (HAWG). ICES Document CM 2011/ACOM:06

Jennings, S., Greenstreet, S.P.R., and Reynolds, J.D. 1999. Structural change in an exploited fish community: a consequence of differential fishing effects on species with contrasting life histories. J. Anim. Ecol. **68**: 617–627. doi: 10.1046/j.1365-2656.1999.00312.x.

Jensen, W.A., Jones-Farmer, L.A., Champ, C.W., and Woodall, W.H. 2006. Effects of parameter estimation on control chart properties: a literature review. J. Qual. Technol. **38**: 349–364.

Kell, L.T., Mosqueira, I., Bruyn, P. De, and Magnusson, A. 2012. A kobe strategy matrix based upon probabilistic reference points: an example using a biomass dynamic assessment model. Collect. Vol. Sci. Pap. ICCAT **68**: 1030–1043.

Kelly, C.J., and Codling, E.A. 2006. “Cheap and dirty” fisheries science and management in the North Atlantic. Fish. Res. **79**: 233–238. doi:10.1016/j.fishres.2006.03.007.

Kelton, W.D., Hancock, W.M., and Bischak, D.P. 1990. Adjustment rules based on quality control charts. Int. J. Prod. Res. **28**: 385-400.

Koeller, P., Savard, L., Parsons, D.G., and Fu, C. 2000. A precautionary approach to assessment and management of shrimp Stocks in the Northwest Atlantic. J. Northwest Atl. Fish. Sci. **27**: 235–246. doi: 10.2960/J.v27.a20.

Lande, R., Sæther, B.-E., and Engen, S. 1997. Threshold harvesting for sustainability of fluctuating resources. Ecology **78**: 1341–1350. doi: 10.1890/0012-9658(1997)078[1341:THFSOF]2.0.CO;2.

Little, L.R., Wayte, S.E., Tuck, G.N., Smith, A. D.M., Klaer, N., Haddon, M., Punt, A. E., Thomson, R., Day, J., and Fuller, M. 2011. Development and evaluation of a cpue-based harvest control rule for the southern and eastern scalefish and shark fishery of Australia. ICES J. Mar. Sci. **68**: 1699–1705. doi: 10.1093/icesjms/fsr019.

Luceño, A. 1992. Performance of EWMA versus last observation for feedback control. Commun. Stat. - Theory Methods **22**: 241–255. doi: 10.1080/03610929308831016.

Lukas, J.M., Reneau, J.K., and Linn, J.G. 2008. Water intake and dry matter intake changes as a feeding management tool and indicator of health and estrus status in dairy cows. J. Dairy Sci. **91**: 3385–3394. doi:10.3168/jds.2007-0926.

Lukas, J.M., Reneau, J.K., Wallace, R., Hawkins, D., and Munoz-Zanzi, C. 2009. A novel method of analyzing daily milk production and electrical conductivity to predict disease onset. J. Dairy Sci. **92**: 5964–5976. doi:10.3168/jds.2009-2066.

MacCall, A. D. 2009. Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. ICES J. Mar. Sci. **66**: 2267–2271. doi: 10.1093/icesjms/fsp209.

Manly, B.F.J., and Mackenzie, D. 2000. A cumulative sum type of method for environmental monitoring. Environmetrics **11**: 151–166. doi: 10.1002/(SICI)1099-095X(200003/04)11:2<151::AID-ENV394>3.0.CO;2-B

Mesnil, B., and Petitgas, P. 2009. Detection of changes in time-series of indicators using CUSUM control charts. Aquat. Living. Resour. **22**: 187–192. doi: 10.1051/alr/2008058.

Montgomery, D.C. 1996. Introduction to statistical quality control. Third edition, Wiley, New York.

Page, E.S. 1954. Continuous inspection schemes. Biometrika **41**: 100–115.

Pazhayamadom, D. G. 2013. Application of signal detection methods to fisheries management. Ph.D. thesis, School of Biological, Earth and Environmental Sciences, University College Cork, Cork, Ireland.

Pazhayamadom, D.G., Kelly, C.J., Rogan, E., and Codling, E.A. 2013. Self-starting CUSUM approach for monitoring data poor fisheries. Fish. Res. **145**: 114–127. doi:10.1016/j.fishres.2013.02.002.

Pazhayamadom, D.G., Kelly, C.J., Rogan, E., and Codling, E.A. In press. Decision interval cumulative sum harvest control rules (DI-CUSUM-HCR) for managing fisheries with limited historical information. Fish. Res. doi: 10.1016/j.fishres.2014.09.009

Pilling, G.M., Apostolaki, P., Failler, P., Floros, C., Large, P.A., Morales-Nin, B., Reglero, P., Stergiou, K.I., and Tsikliras, A.C. 2009. Assessment and management of data-poor fisheries. *In* Advances in fisheries science: 50 years on from Beverton and Holt. *Edited by* A. Payne, J. Cotter and T. Potter. Wiley-Blackwell, pp. 280-305.

Prince, J. 2005. Combating the tyranny of scale for Haliotids: micro-management for microstocks. Bull. Mar. Sci. **76**: 557–578.

Prince, J.D., Dowling, N.A., Davies, C.R., Campbell, R.A., and Kolody, D.S. 2011. A simple cost-effective and scale-less empirical approach to harvest strategies. ICES J. Mar. Sci. **68**: 947–960. doi: 10.1093/icesjms/fsr029.

Probst, W.N., Stelzenmüller, V., and Fock, H.O. 2012. Using cross-correlations to assess the relationship between time-lagged pressure and state indicators: an exemplary analysis of North Sea fish population indicators. ICES J. Mar. Sci. **69**: 670–681. doi: 10.1093/icesjms/fss015.

Probst, W.N., Stelzenmüller, V., and Kraus, G. 2013. A simulation-approach to assess the size structure of commercially exploited fish populations within the European marine strategy framework directive. Ecol. Indic. **24**: 621–632. doi: 10.1016/j.ecolind.2012.08.026.

Punt, A.E., Smith, D.C., and Smith, A.D.M. 2011. Among-stock comparisons for improving stock assessments of data-poor stocks: the “Robin Hood” approach. ICES J. Mar. Sci. **68**: 972–981. doi: 10.1093/icesjms/fsr039.

R Core Team. 2014. R: A language and environment for statistical computing. R foundation for statistical computing, Vienna, Austria. Available from http://www.R-project.org/ [accessed 11 December 2014].

Rayns, N. 2007. The Australian government’s harvest strategy policy. ICES J. Mar. Sci. **64**: 596–598. doi: 10.1093/icesjms/fsm032.

Reuter, R.F., Conners, M.E., Dicosimo, J., Gaichas, S., Ormseth, O., and Tenbrink, T.T. 2010. Managing non-target, data-poor species using catch limits: lessons from the Alaskan groundfish fishery. Fish. Manag. Ecol. **17**: 323–335. doi: 10.1111/j.1365-2400.2009.00726.x.

Rochet, M.-J., Trenkel, V., Bellail, R., Coppin, F., Le Pape, O., Mahe, J.-C., Morin, J., Poulard, J.-C., Schlaich, I., Souplet, A., Verin, Y., and Bertrand, J. 2005. Combining indicator trends to assess ongoing changes in exploited fish communities: diagnostic of communities off the coasts of France. ICES J. Mar. Sci. **62**: 1647–1664. doi: 10.1016/j.icesjms.2005.06.009.

Sakuramoto, K., and Suzuki, N. 2012. Effects of process and/or observation errors on the stock-recruitment curve and the validity of the proportional model as a stock-recruitment relationship. Fish. Sci. **78**: 41–54. doi: 10.1007/s12562-011-0438-4.

Scandol, J.P. 2003. Use of cumulative sum (CUSUM) control charts of landed catch in the management of fisheries. Fish. Res. **64**: 19–36. doi:10.1016/S0165-7836(03)00104-8

Scandol, J.P. 2005. Use of quality control methods to monitor the status of fish stocks. *In* Fisheries assessment and management in data-limited situations. *Edited by* G.H.

Kruse, V.F. Gallucci, D.E. Hay, R.I. Perry, R.M. Peterman, T.C. Shirley, P.D. Spencer, B. Wilson, and D. Woodby. Alaska Sea Grant AK-SG-05-02. pp. 213-234.

Shephard, S., Reid, D.G., and Greenstreet, S.P.R. 2011. Interpreting the large fish indicator for the Celtic Sea. ICES J. Mar. Sci. **68**: 1963–1972. doi: 10.1093/icesjms/fsr114.

Shin, Y.-J., Rochet, M.J., Jennings, S., Field, J.G., and Gislason, H. 2005. Using size-based indicators to evaluate the ecosystem effects of fishing. ICES J. Mar. Sci. **62**: 384–396. doi: 10.1016/j.icesjms.2005.01.004.

Smith, A.D.M., Smith, D.C., Tuck, G.N., Klaer, N., Punt, A.E., Knuckey, I., Prince, J., Morison, A., Kloser, R., Haddon, M., Wayte, S., Day, J., Fay, G., Pribac, F., Fuller, M., Taylor, B., and Little, L.R. 2008. Experience in implementing harvest strategies in Australia's south-eastern fisheries. Fish. Res. **94**: 373–379. doi: 10.1016/j.fishres.2008.06.006.

Smith, D., Punt, A., Dowling, N., Smith, A., Tuck, G., and Knuckey, I. 2009. Reconciling approaches to the assessment and management of data-poor species and fisheries with Australia's harvest strategy policy. Mar. Coast. Fish. **1**: 244–254. doi: 10.1577/C08-041.1.

Smith, A.D.M., Smith, D.C., Haddon, M., Knuckey, I.A., Sainsbury, K.J., and Sloan, S.R. 2014. Implementing harvest strategies in Australia: 5 years on. ICES J. Mar. Sci. **71**: 195–203. doi: 10.1093/icesjms/fst158.

Stefansson, G., and Rosenberg, A.A. 2005. Combining control measures for more effective management of fisheries under uncertainty: quotas, effort limitation and protected areas. Philos. Trans. R. Soc. B Biol. Sci. **360**: 133–146.

Sullivan, J.H., and Jones, L.A. 2002. A self-starting control chart for multivariate individual observations. Technometrics **44**: 24–33. doi: 10.1198/004017002753398290.

Tercero-Gómez, V.G., Cordero-Franco, A., Pérez-Blanco, A., and Hernández-Luna, A. 2014. A self-starting CUSUM chart combined with a maximum likelihood estimator for the time of a detected shift in the process mean. Qual. Reliab. Eng. Int. **30**: 591–599. doi: 10.1002/qre.1511.

Walters, C., and Pearse, P.H. 1996. Stock information requirements for quota management systems in commercial fisheries. Rev. Fish Biol. Fish. **6**: 21–42. doi: 10.1007/BF00058518.

Wiklund, S.J. 1995. Process adjustment when using EWMA charts. Int. J. Qual. Reliab. Manag. **12**: 8–27. doi: 10.1108/02656719510080587.

Wilderbuer, T., Stockhausen, W., and Bond, N. 2013. Updated analysis of flatfish recruitment response to climate variability and ocean conditions in the Eastern Bering Sea. Deep Sea Res. Part II Top. Stud. Oceanogr. **94**: 157–164. doi: 10.1016/j.dsr2.2013.03.021.

Wilson, J.R., Prince, J.D., and Lenihan, H.S. 2010. A management strategy for sedentary nearshore species that uses marine protected areas as a reference. Mar. Coast. Fish. **2**: 14–27. doi: 10.1577/C08-026.1.

Wuertz, D. 2013. fBasics: Rmetrics - markets and basic statistics. Available from http://CRAN.R-project.org/package=fBasics [accessed 11 December 2014].

Appendix A. SS-CUSUM computation

A1. Indicator transformation

In self-starting CUSUM we assume that the indicator observations come from an in-control $N(\mu, \sigma^2)$ distribution (though it still worked when this assumption was violated). Now let:-

(6) $$W_n = \sum_{i=1}^{n}(X_i - \bar{X}_n)^2$$

Where, X_i is the indicator observation from year 'i', $\bar{X}_n$ is the running mean and W_n is the sum of squared deviations of the first 'n' year observations. The running standard deviation of the first 'n' observations is then given by

(7) $$S_n = \sqrt{W_n/(n-1)}$$

Standardizing each observation with the running mean and the running standard deviation obtained until the preceding observations gives:

(8) $$T_n = (X_n - \bar{X}_{n-1})/S_{n-1}$$

The exact cumulative distribution function of T_n is then given by:

(9) $$P_r[T_n < t] = f_{n-2}\left(t\sqrt{\frac{(n-1)}{n}}\right)$$

Where f_{n-2} stands for the cumulative distribution function of the Student's 't' distribution with *n-2* degrees of freedom. Taking an inverse normal function (Φ^{-1}) of f_{n-2} will transform the "studentized" CUSUM quantity T_n into a random variable Z_n for all $n>2$. Since Z_n is statistically independent of the standard deviation of indicator observations, by transforming T_n to their Z_n counterparts we get a sequence of independent $N(0,1)$ values to CUSUM.

(10) $$Z_n = \Phi^{-1}[f_{n-2}(a_n T_n)]$$

(11) $$a_n = \sqrt{(n-1)/n}$$

Once the Z_n are generated, they can be used in a Decision Interval form of Cumulative Sum (DI-CUSUM) control chart (Appendix A2). The updates for the running mean and variance can be simplified by the following calculation:

(12) $\bar{X}_n = \bar{X}_{n-1} + d_n/n$

(13) $W_n = W_{n-1} + (n-1)(d_n)^2/n$

Where, d_n is the deviation of X_n from the running mean $\bar{X}_{n-1}$

A2. Decision interval form of CUSUM

Standardized values of time series data are converted to upper and lower CUSUMs using the following equations (Montgomery 1996; Hawkins and Olwell 1998):

(14) $\theta_0^+ = 0$ and $\theta_0^- = 0$

(15) $\theta_n^+ = \max(0, \theta_{n-1}^+ + Z_n - k)$ and $\theta_n^- = \min(0, \theta_{n-1}^- + Z_n + k)$

Where, θ_n^+ and θ_n^- are upper and lower CUSUMs obtained respectively in the n^{th} year and *k* is the allowance parameter. The CUSUM signals an out of control situation when:

(16) $\theta_n^+ > +h$ or $\theta_n^- < -h$,

where, *+h and -h* are the control limits applied to both upper (θ_n^+) and lower (θ_0^-) CUSUMs respectively.

A3. Metric Winsorization

Metric winsorization can be applied to the formula for updating the running mean and standard deviation. The extreme outliers can be replaced with a cut off threshold value known as the winsorizing constant (*w*). Therefore extreme changes in the indicator are not completely omitted but contributed to the CUSUM process.

$$d_n = \begin{cases} -w & for \quad (X_n - \bar{X}_{n-1}) < -w \\ X_n - \bar{X}_{n-1} & for \quad -w < (X_n - \bar{X}_{n-1}) < w \\ w & for \quad (X_n - \bar{X}_{n-1}) > w \end{cases} \tag{17}$$

Appendix B. Supplementary data

Supplementary data associated with this article can be found in the online version

Table 1. Four types of fishery scenarios are considered for evaluating the performance of SS-CUSUM-HCR and they are based on (1) the number of historical data available for the indicators (when the SS-CUSUM-HCR initiate); (2) life history traits of the species (see Table 2); (3) state of the stock when the management initiated i.e., below F_{MSY}(F_{int}=0.053 yr^{-1}; B_{EQ}=0.69 B_{UF}), at F_{MSY}(F_{int}=0.23 yr^{-1}; B_{EQ}=0.27 B_{UF}), above F_{MSY}(F_{int}=0.327 yr^{-1}; B_{EQ}=0.16 B_{UF}); and (4) selectivity pattern of the gear used for fishing (sigmoid shape for trawl and dome shape for gill net; see Appendix B).

Scenario	Historical data available	Life history species	Initial state of the fish stock	Shape of gear selectivity
Scenario 1	2 years* 4 years 6 years 8 years	LH2*	Below F_{MSY}*	Sigmoid (Medium mesh)*
Scenario 2	2 years	LH1 LH2 LH3	Below F_{MSY}	Sigmoid (Medium mesh)
Scenario 3	2 years	LH2	Below F_{MSY} At F_{MSY} Above F_{MSY}	Sigmoid (Medium mesh)
Scenario 4	2 years	LH2	Below F_{MSY}	Sigmoid (Small mesh) Sigmoid (Medium mesh) Sigmoid (Large mesh) Dome (Medium mesh)

* Indicate the parameters used in the base case scenario

Table 2. Parameters used for the simulation of fish stocks and their fishery was determined from the ICES fish stock summary database (ICES 2010; ICES 2011) and the unpublished data in *FishBase* (Froese and Pauly 2011).

Parameters	**Life History 1 (LH1)** **Short life span**	**Life History 2 (LH2)** **Medium life span**	**Life History 3 (LH3)** **Long life span**
Von Bertalanffy growth function			
Asymptotic length (L_∞)	30 cm	129.1 cm	49.2 cm
Age at length 0 (a_0)	-1.6 yr	-0.82 yr	-2.19 yr
Growth coefficient (K)	0.41	0.14	0.07
Natural mortality (m)	0.23 yr^{-1}	0.21 yr^{-1}	0.15 yr^{-1}
Plus-group (a_{max})	6 yr	10 yr	30 yr
Length-Weight relationship			
Coefficient (c)	0.006	0.0104	0.0113
Exponent (d)	3.09	3	3.08
Re-parameterised Beverton-Holt recruitment function			
Steepness (z)	0.90	0.75	0.60
Maturity parameters			
Age at 50% maturity ($M_{50\%}$)	1.8 yr	2.5 yr	13 yr
Age at 95% maturity ($M_{95\%}$)	3 yr	3 yr	20 yr
Selectivity parameters (trawl)			
Age at 50% selectivity ($S_{50\%}$)	2.2 yr	3 yr	14 yr
Age at 95% selectivity ($S_{95\%}$)	2.6 yr	5 yr	17 yr

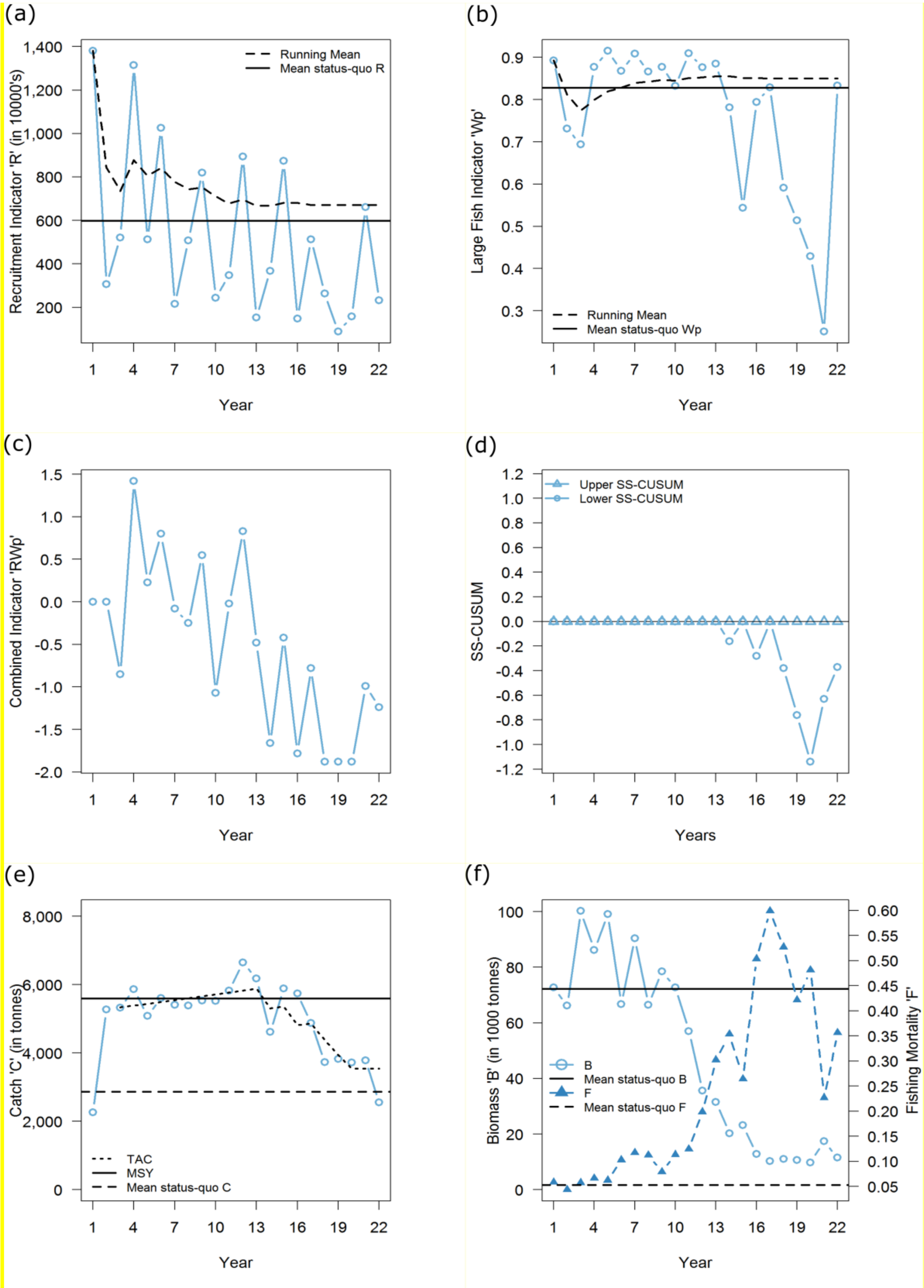


Fig. 1. Graphical illustration of SS-CUSUM-HCR from single iteration of the base case: (a) & (b) shows the recruitment and LFI with their respective running means; (c) shows the combined indicator obtained by summing up the transformed R and Wp; (d) SS-CUSUM generated from the combined indicator; (e) & (f) changes in TAC, catch, stock biomass and fishing mortality in response to the SS-CUSUM. The TAC was reduced on 14, 16 and 18-20th year of the fishery simulation due to a large negative signal from the SS-CUSUM.

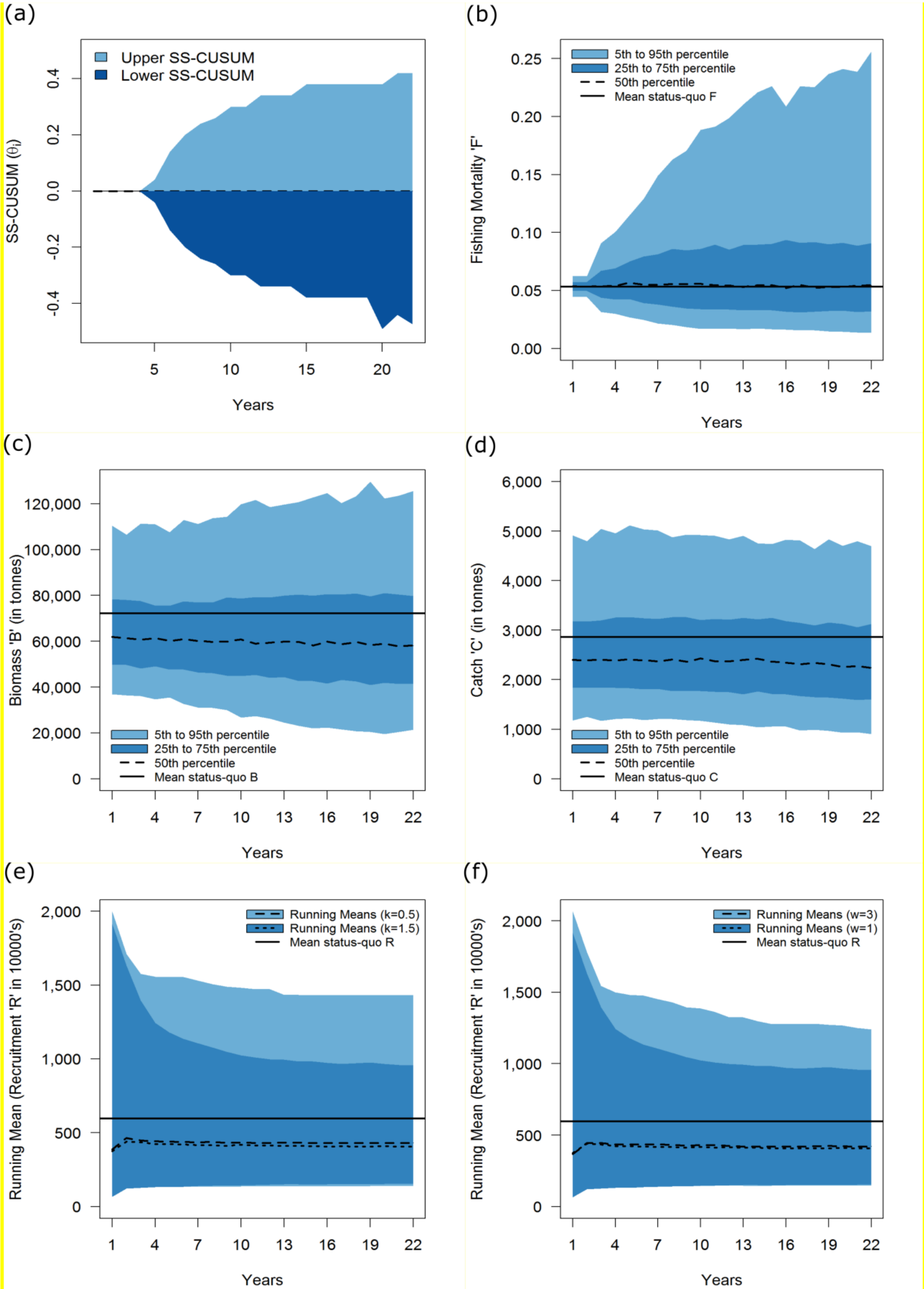


Fig. 2. Performance of SS-CUSUM-HCR from the base case indicating changes in: (a) SS-CUSUM; (b) stock biomass; (c) fishing mortality; (d) fisheries catch and (e & f) the dynamics of running means from all iterations of the fishery simulation. The state of the stock was sustained close to mean status-quo levels from where the SS-CUSUM-HCR stated off.

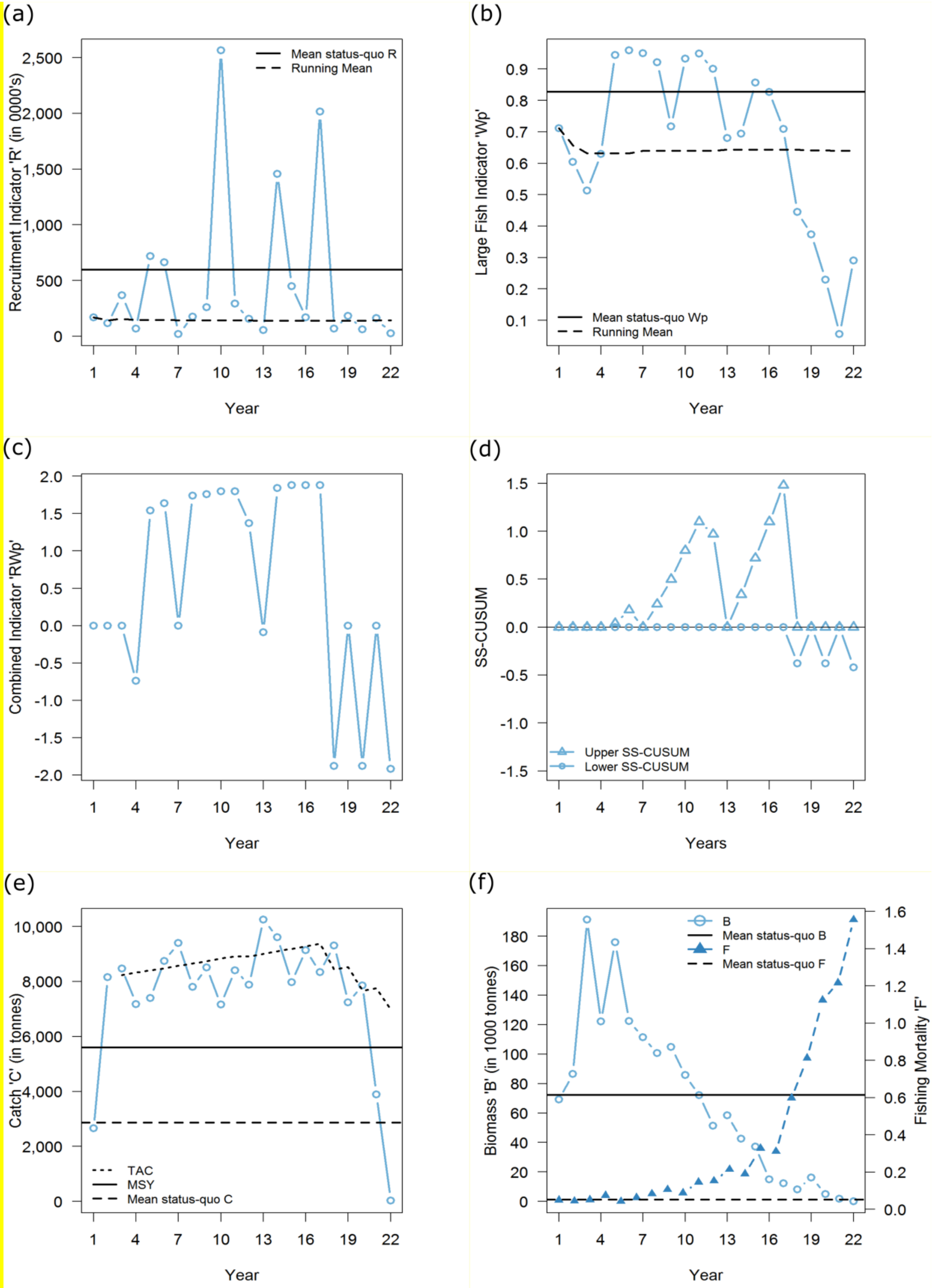


Fig. 3. Graphical illustration of a collapsed fish stock from the base case: (a & b) the running mean of recruitment and large fish indicator stabilizing far below the mean status-quo levels; (c & d) the combined indicator and SS-CUSUM with disproportionate signals; (e) resulting in an increase of the TAC from status-quo levels above MSY and (f) the deterioration of stock biomass leading to high levels of fishing mortality from status-quo.

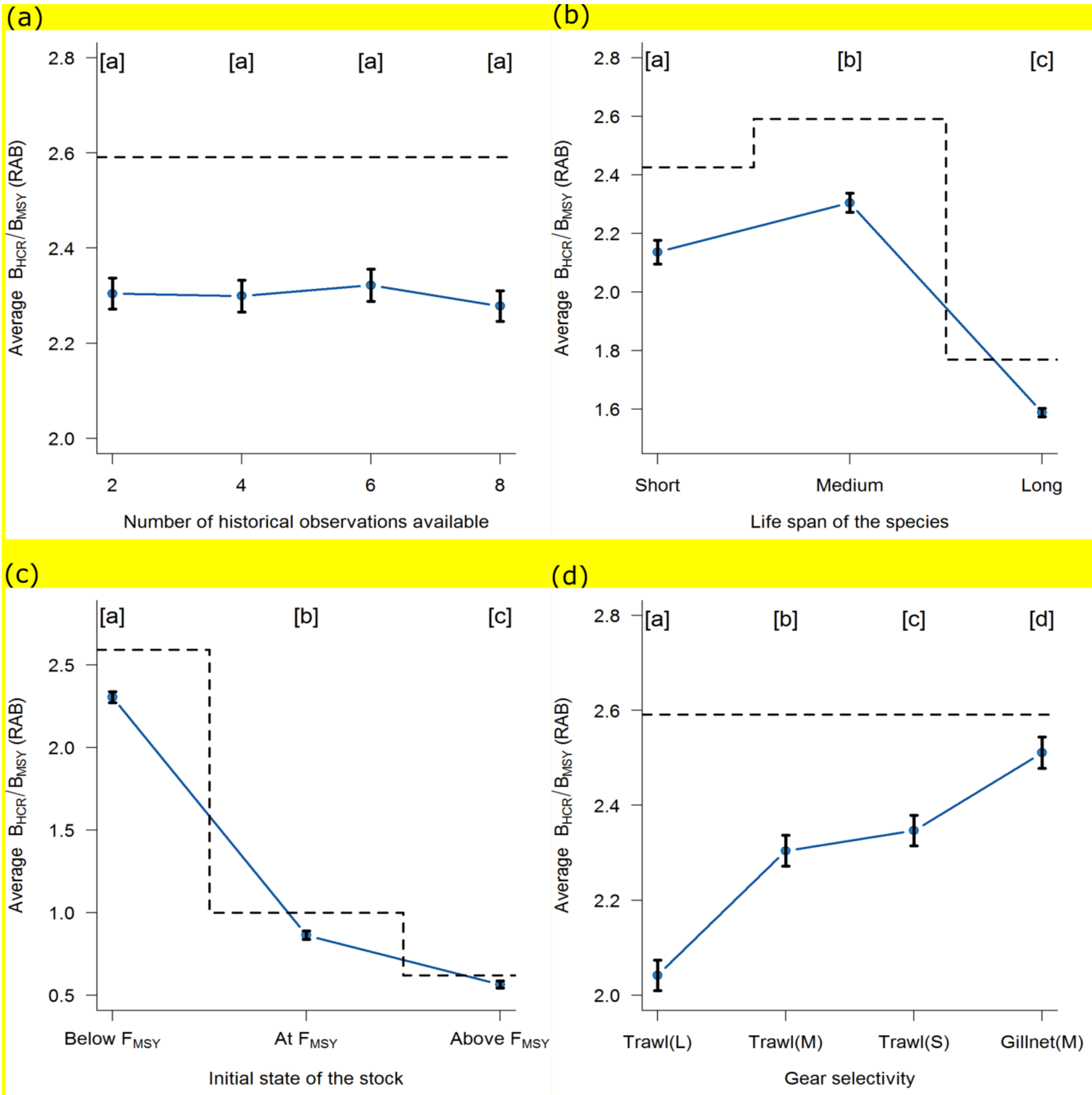


Fig. 4. Relative average biomass obtained for different scenarios: (a) number of historical observations available when the management initiated, (b) life span of the species, (c) state of the stock when the management initiated and (d) selectivity pattern of the fishing gear (L=large, M=medium and S=small mesh). The dashed line indicate mean status-quo levels and the performances with same letters in the square brackets indicate no significant difference between each other at p<0.001.

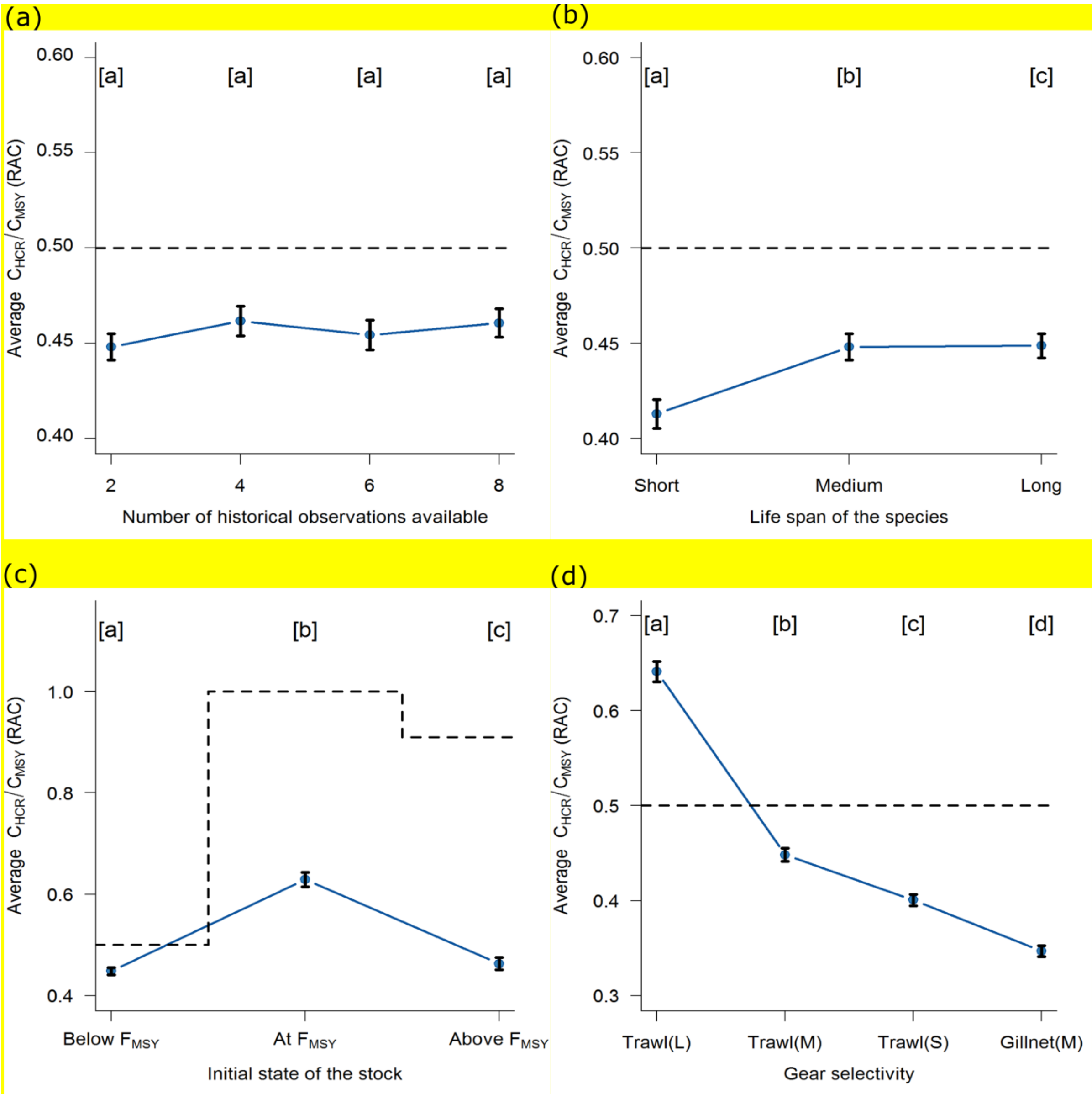


Fig. 5. Relative average catch obtained for different scenarios: (a) number of historical observations available when the management initiated, (b) life span of the species, (c) state of the stock when the management initiated and (d) selectivity pattern of the fishing gear (L=large, M=medium and S=small mesh). The dashed line indicate mean status-quo levels and the performances with same letters in the square brackets indicate no significant difference between each other at p<0.001.

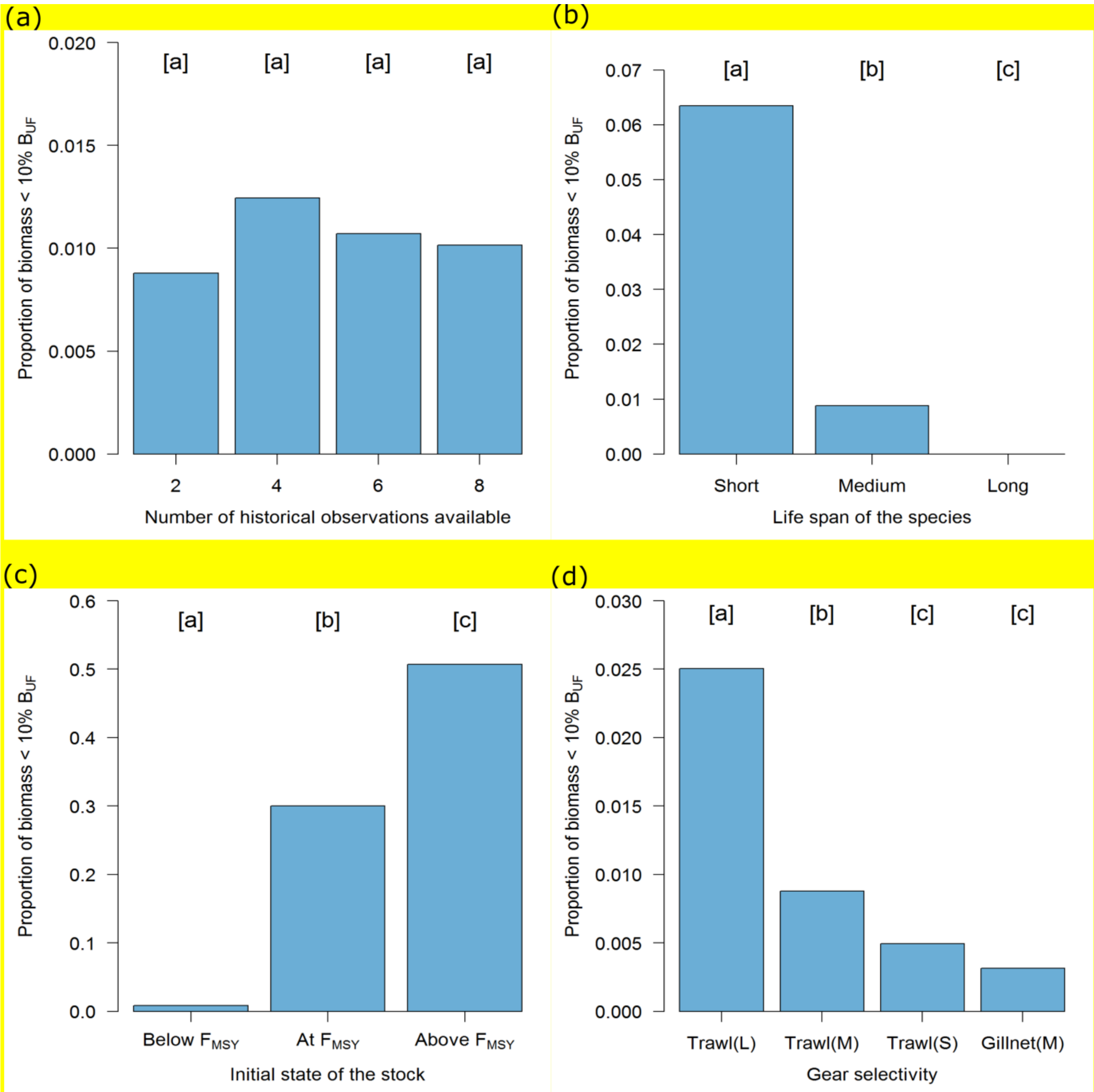


Fig. 6. The B_{10} performances obtained for different scenarios: (a) number of historical observations available when the management initiated; (b) life span of the species; (c) state of the stock when the management initiated and (d) selectivity pattern of the fishing gear (L=large, M=medium and S=small mesh). Performances with same letters in the square brackets indicate no significant difference between each other at $p<0.001$.

Table A1. This table shows the steps to be followed after indicator transformation in SS-CUSUM (*w*=1, *k*=1.5 and *h*=0); the H-counter indicates the number of observations since $|\theta_i^{\pm}| > |h|$ and in this example, no adjustment is applied to TAC in the 22nd year because the SS-CUSUM is moving towards zero ($\theta_{i=21}^{-} > \theta_{i=20}^{-}$).

$$\hat{E}_{21} = \frac{\theta_{i=18}^{-}}{H_{i=18}^{-}} + \frac{\theta_{i=19}^{-}}{H_{i=19}^{-}} + \frac{\theta_{i=20}^{-}}{H_{i=20}^{-}} = \frac{-0.38}{1} + \frac{-0.76}{2} + \frac{-1.14}{3} = -1.14$$

Year	Recruitment after indicator transformation	LFI after Indicator transformation	Combined Indicator	Upper SS-CUSUM	H-counter for θ_i^+	Lower SS-CUSUM	H-counter for θ_i^-
i	Z_i^R	Z_i^{Wp}	Z_i^{RWp} $(Z_i^R + Z_i^{Wp})$	θ_i^+	H_i^+	θ_i^-	H_i^-
1	0.00	0.00	0.00	0.00	0	0.00	0
2	0.00	0.00	0.00	0.00	0	0.00	0
3	-0.27	-0.58	-0.85	0.00	0	0.00	0
4	0.71	0.71	1.42	0.00	0	0.00	0
5	-0.54	0.77	0.23	0.00	0	0.00	0
6	0.37	0.43	0.80	0.00	1	0.00	0
7	-0.85	0.77	-0.08	0.00	0	0.00	0
8	-0.53	0.28	-0.25	0.00	0	0.00	0
9	0.16	0.39	0.55	0.00	0	0.00	0
10	-0.90	-0.17	-1.07	0.00	0	0.00	0
11	-0.83	0.81	-0.02	0.00	0	0.00	0
12	0.50	0.33	0.83	0.00	0	0.00	0
13	-0.92	0.44	-0.48	0.00	0	0.00	0
14	-0.74	-0.92	-1.66	0.00	0	-0.16	1
15	0.52	-0.94	-0.42	0.00	0	0.00	0
16	-0.94	-0.84	-1.78	0.00	0	-0.28	1
17	-0.45	-0.33	-0.78	0.00	0	0.00	0
18	-0.94	-0.94	-1.88	0.00	0	-0.38	1
19	-0.94	-0.94	-1.88	0.00	0	-0.76	2
20	-0.94	-0.94	-1.88	0.00	0	-1.14	3
21	-0.03	-0.96	-0.99	0.00	0	-0.63	4
22	-0.96	-0.28	-1.24	0.00	0	-0.37	5

Supplementary data

S1. The operating model

The current study used the following steps to simulate an age structured virtual fish stock. The recruits enter the fishery at age 0 in the operating model. The life history parameters for different fish stocks are provided in Table 2 of the main paper.

I. Weight at age 'a' in year 'i' (W_i^a) followed an isometric von Bertalanffy growth function (VBGF) of the form (Bertalanffy 1934):

(S.1) $$W_i^a \sim lognormal\left(mean = c(L_i^a)^d, cv = 0.2\right)$$

$$L_i^a = L_{\infty}{}_i^a\left[1 - exp^{-K_i^a\,(a-a_0)}\right] \ ,$$

$$K_i^a \quad \sim normal(mean = K, cv = 0.1),$$

$$L_{\infty}{}_i^a \ \sim normal(mean = L_{\infty}, cv = 0.1),$$

where *cv* is the coefficient of variation of the distribution, 'ln(c)' is the intercept, 'd' is the slope of length-weight relationship, L_i^a is the length at age 'a', $L_{\propto}$ is the asymptotic length, K_i^a is the growth coefficient and a_0 is the age when length is zero (Table 2). This equation was applied independently for each age group of the stock.

II. Maturity-at-age (M^a) was fixed throughout the years in the fishery simulation and was computed based upon the logistic function:

(S.2) $$M^a = (a, a_{50\%}, a_{95\%}) = \left[1 + exp\left(-ln19 \times \frac{a - a_{50\%}}{a_{95\%} - a_{50\%}}\right)\right]^{-1},$$

where $a_{50\%}$ and $a_{95\%}$ are the age groups for which 50% and 95% of the cohort are mature respectively.

III. Spawning stock biomass for year 'i' (SSB_i) was calculated as:

(S.3) $$SSB_i = \sum_{a=0}^{a_{max}}(M^a \times N_i^a) \times W_i^a \ ,$$

where N_i^a is the number of individuals with age 'a' in year 'i' within the fish stock.

IV. The recruits to the fish stock in year 'i' (R_i) followed a Beverton-Holt stock recruitment function (Beverton and Holt 1957) that had been re-parameterised to the steepness of the stock–recruitment relationship (z), initial biomass (B_0) and initial recruitment (r_0) as given by Mace and Doonan (1988):

(S.4) $r_i = [A \times SSB_{i-1}/(B + SSB_{i-1})] \times \exp(\upsilon),$

$A = 4zr_0/(5z-1);\ B = B_0(1-z)/(5z-1),$

$\upsilon = \varepsilon^i - 0.5\sigma_R^2,\ \varepsilon^i = \rho\varepsilon^{i-1} + \eta^i$ and $\eta^i \sim normal(0,\ [1-\rho^2]\sigma_R^2),$

where 'SSB' is the spawning stock biomass, ρ is the autocorrelation ($\rho = 0.2$) in the recruitment deviations (ε) and σ_R^2 is the variance of the log recruitment residuals ($\sigma_R^2 = 0.6$).

V. The population numbers at age 'a' for year 'i' (N_i^a) was updated by:

(S.5) $$N_i^a = \begin{cases} r_i & for \quad a = 0 \\ N_{i-1}^{a-1} e^{-(m+F_{i-1}^{a-1})} & for \quad 1 \le a < a_{max} \\ N_{i-1}^{a-1} e^{-(m+F_{i-1}^{a-1})} + N_{i-1}^{a} e^{-(m+F_{i-1}^{a})} & for \quad a = a_{max}, \end{cases}$$

where F_i^a is the fishing mortality for age 'a' in year 'i' and m=0.2 is the natural mortality of the fish population. The model was initialized with $N_0^a = r_0 exp(-m \times a)$ and $r_0 = 1000 \times 10^3$.

VI. The initial fishing mortality (F_{int}) for the three different life history species were configured to 50% MSY at fishery equilibrium i.e., F_{int}^{LH1} = 0.15 (F_{MSY}^{LH1} = 0.84), F_{int}^{LH2} = 0.05 (F_{MSY}^{LH2} = 0.23) and F_{int}^{LH3} = 0.04 (F_{MSY}^{LH3} = 0.20). These values lead to a biomass of 69% B_{UF} (2.6 B_{MSY}), 62% (2.4 B_{MSY}) and 82% (1.8 B_{MSY}) respectively at fishery equilibrium. The fishing mortality (F_i^a) at age for year 'i' was calculated as:

(S.6) $F_i^a = S^a \times \max[0, \sim normal(mean = F_{int}, cv = 0.1)]$

where S^a is the selectivity-at-age indicating the vulnerability to the fishing gear and the random multiplier is same across all age groups in a given year.

VII. Selectivity-at-age (S^a) was fixed throughout the years in the fishery simulation.

i) The S^a for trawl net followed the logistic function in eq. S.2 and gave a sigmoid shape selectivity pattern. The parameters used for the three life history species are $S_{50\%}^{a,LH1}$ = 2.2, $S_{95\%}^{a,LH1}$ = 2.6, $S_{50\%}^{a,LH2}$ = 3, $S_{95\%}^{a,LH2}$ = 5, $S_{50\%}^{a,LH3}$ = 14 and $S_{95\%}^{a,LH3}$ =

17. The base case represented a medium mesh size trawl net. Selectivity parameters for small mesh trawl net were $S^{a,LH2}_{50\%}$ = 2, $S^{a,LH2}_{95\%}$ = 3 and for large mesh trawl net were $S^{a,LH2}_{50\%}$ = 6, $S^{a,LH2}_{95\%}$ = 7.

ii) The S^a for gill net followed the double-normal function (Candy 2011) and gave a dome shaped selectivity pattern.

(S.7) $$S^a = \begin{cases} 2^{-\left[\frac{(a-\lambda)}{\sigma_L}\right]^2} & for \quad a_0 < a \leq \lambda \\ 2^{-\left[\frac{(a-\lambda)}{\sigma_U}\right]^2} & for \quad a > \lambda \\ 0 & for \quad a \leq a_0, \end{cases}$$

where λ is a cut-point parameter corresponding to the age at which $S^a = 1$, σ_L and σ_U are parameters denoting the standard deviations of the scaled normal density functions specifying the lower and upper arms of the function. In the present study, the parameters a_0, λ, σ_L and σ_U were set to 0, 5.5, 2 and 4 respectively so that 95% selectivity occurs at age 5 as used in the base case.

VIII. Baranov's catch equation (Baranov 1918) was used to calculate the catch numbers at age 'a' in year 'i' (C^a_i):

(S.8) $$C^a_i = N^a_i \times \frac{F^a_i}{F^a_i + m} \times \left[1 - exp^{-(F^a_i + m)}\right]$$

S2. The observation model

Two indicators were measured from the stock i.e., the number of individuals recruited to the zero age group (R) and the proportion of large fish individuals in the landed catch (Wp).

IX. The observed stock-recruitment in year 'i' (R_i) was measured using a coefficient of variation (*cv*) from the lognormal distribution:

(S.9) $$R_i \sim lognormal\ (mean = r_i, cv = 0.6)$$

X. The Wp was computed using a random sample of fish individuals from the landed catch (C^a_i). The *sample* function in R (R Core Team 2014) was used to draw 'n' individuals without replacement from the set of all individuals in the landed catch for the ith year. Further, the cumulative sum of individual weight was computed using those which belonged to age groups that were 95% or more selective to the fishing gear ($a \geq S_{95\%}$) i.e., the abundance of large fish individuals by weight. Their proportion to the total sample catch weight was the Wp indicator for year 'i'.

(S.10) $$Wp_i = \frac{\sum_{j=1}^{j=n} W_{i,j}^{a} \times I(a_j \geq S_{95\%})}{CW_i},$$

where 'j' indicate individual fish in the sample, CW_i is the total weight of the catch sample obtained in year 'i' and $I(.)$ denotes indicator function defined by

$$I(X) = \begin{cases} 1, & if\ X\ is\ true, \\ 0, & if\ otherwise. \end{cases}$$

S3. Additional scenarios for SS-CUSUM-HCR

Additional scenarios were used to evaluate the management based on SS-CUSUM-HCR (Table S1) and the performance measures are presented in Figs. S1 to S6.

Performance comparison with different winsorizing constants (*w*)

A higher *w* means that with subsequent updates, the deviation in observations will end up in larger steps taking the running mean far away from its initial state. This effect has been illustrated in Fig. 2*f* where the progression of running means remained farther away from the intended reference point when the constant was *w*=3. The RAB and RAC shows that the performances are significantly different if the choice is *w*=3 (Figs. S1*a* and S3*a*). The risk of stock collapse was also higher when *w*=3 though not significantly different when compared to lower constants (p=0.23; Fig. S5*a*). We found that a low constant such as *w*=1 in SS-CUSUM may provide relatively higher average catch performances (Fig. S3*a*).

Performance comparison with different allowance constants (*k*)

The allowance constant '*k*' is a threshold mechanism used in SS-CUSUM where a certain amount of indicator deviation (from the running mean) is considered inherent to the process and not due to factors such as fishing. Accounting such natural variability helps improve the specificity of SS-CUSUM-HCR i.e., responding only when the deviations are consistent and large. However, increasing the allowance could miss a signal if the indicator deviations are not consistent over time. Results show that *k*>1.5 could result in significantly lower RAB, higher RAC and higher B_{10} performances (p<0.001; Figs. S1*b*, S3*b* and S5*b*).

Performance comparison with different control limits (*h*)

The control limit '*h*' is a threshold mechanism used to decide whether the SS-CUSUM is large enough to raise an alarm. A higher '*h*' will only cause a delay in triggering the HCR and may affect the variability of catch. However, the adjustment factor is not affected as all indicator deviations are still accounted in SS-CUSUM even when a higher '*h*' is used (which is not the case when a higher '*k*' is used). The performance measures are significantly different with higher '*h*' (p<0.001; Figs. S1*c*, S3*c* and S5*c*) though the effects are not evident for values greater than *h*=1 (the latter may be the case where SS-CUSUM signals are large but the TAC adjustments are curbed by TAC^R configured in the SS-CUSUM-HCR).

Performance comparison with different TAC restrictions in SS-CUSUM-HCR

The SS-CUSUM-HCR was tested by relaxing the margin of inter annual TAC restrictions, thus allowing the method to make large adjustments in catch. Results show that increasing the TAC^R may result in relatively higher RAB and lower RAC (Figs. S1*d* and S3*d*), thus are useful to apply when a conservative approach is required. Results also show that this reduced the probability of stock depletion or collapse (Fig. S5*d*). However, relaxing the TAC restrictions should be adopted with caution in practice because the probability of stock collapse may increase if the fishery started off from an undesirable state (i.e., above F_{MSY}).

Performance comparison with observation errors in the indicators

The SS-CUSUM-HCR was tested for observation errors in recruitment (simulated using different coefficient of variation) and large fish indicator (using different sample size of the catch). Results in general show that higher observation errors in indicators may result in lower RABs and higher RACs (Figs. S2*a*, S2*b*, S4*a* and S4*b*). The performance measure of sample sizes in particular was significantly different only if they are very small such as n=10 individuals ($p<0.001$; Figs. S2*b* and S4*b*). In the real world, smaller sample sizes are realistic but may not represent a truly random catch sample and hence should be very cautious with the SS-CUSUM-HCR performance. The B_{10} performances indicate that there are no significant difference for observation errors in the indicator ($p<0.001$; Figs. S6*a* and S6*b*).

Performance comparison for TAC_{inc} and TAC_{lim} thresholds in SS-CUSUM-HCR

In this study, we assume that there is no information of MSY of the fish stock. Hence additional response levels are required in SS-CUSUM-HCR to reduce the chances of harvesting large unsustainable catches that are above MSY. In the base case, this was achieved by using a small multiplier such as 1% for TAC_{inc} and TAC_{lim}. Increasing these thresholds clearly showed that the performance measures are significantly different from the base case resulting in relatively lower RABs, higher RACs and higher proportion of stock depletions (Figs. S2*c*, S2*d*, S4*c*, S4*d*, S6*c* and S6*d*). If there is reliable information on MSY of the stock, then these thresholds can be replaced by MSY to avoid increasing the TAC above such levels or by a multiplier of MSY that may ensure long term sustainable yields.

References

Baranov, F.I. 1918. On the question of the biological basis of fisheries. Nauchn. Issled. Ikhtiol. Inst. Izv. **1**: 81–128.

Bertalanffy, L. von. 1934. Untersuchungen uber die Gesetzlichkeiten des Wachstums. 1. Allgemeine Grundlagen der Theorie. Roux' Arch.Entwicklungsmech. Org. **131**: 613–653.

Beverton, R.J.H., and Holt, S.J. 1957. On the dynamics of exploited fish populations. Fish. Invest. U.K. (Series 2.) **19**: 1–533.

Candy, S.G. 2011. Estimation of natural mortality using catch-at-age and aged mark-recapture data: a multi-cohort simulation study comparing estimation for a model based on the Baranov equations versus a new mortality equation. CCAMLR Sci. **18**: 1–27.

Mace, P. M., and Doonan, I. J. 1988. A generalised bioeconomic simulation model for fish population dynamics. New Zealand Fisheries Assessment Research Document 88/4: pp. 51.

Table S1. Six additional scenarios were considered for evaluating the performance of SS-CUSUM-HCR and they are based on different (1) winsorizing constants in SS-CUSUM (*w*); (2) allowance constants in SS-CUSUM (*k*); (3) control limits in SS-CUSUM (*h*); (4) annual TAC restrictions; (5) observation error in the recruitment indicator (using coefficient of variation of the log-normal distribution); (6) observation error in the large fish indicator (by changing the number of samples from the fisheries catch); (7) TAC increments when SS-CUSUM indicate "in-control" and (6) TAC_{lim} to restrict the maximum TAC allowed.

Scenario	w	k	h	Annual TAC restriction (TAC^R)	Observation error in R (cv)	Sample size (n)	TAC increment (TAC_{inc})	Maximum TAC restriction (TAC_{lim})
Scenario 5	w=1* w=2 w=3	k=1.5*	h=0.0*	TAC^R=10%*	cv=0.6*	n=1000*	TAC_{inc}=1%*	TAC_{lim}=1%*
Scenario 6	w=1	k=0.5 k=1.0 k=1.5 k=2.0	h=0.0	TAC^R=10%	cv=0.6	n=1000	TAC_{inc}=1%	TAC_{lim}=1%
Scenario 7	w=1	k=1.5	h=0.0 h=0.5 h=1.0 h=1.5	TAC^R=10%	cv=0.6	n=1000	TAC_{inc}=1%	TAC_{lim}=1%
Scenario 8	w=1	k=1.5	h=0.0	TAC^R=10% TAC^R=20% TAC^R=30% TAC^R=40%	cv=0.6	n=1000	TAC_{inc}=1%	TAC_{lim}=1%
Scenario 9	w=1	k=1.5	h=0.0	TAC^R=10%	cv=0.2 cv=0.4 cv=0.6 cv=0.8	n=1000	TAC_{inc}=1%	TAC_{lim}=1%
Scenario 10	w=1	k=1.5	h=0.0	TAC^R=10%	cv=0.6	n=1000 n=100 n=10	TAC_{inc}=1%	TAC_{lim}=1%
Scenario 11	w=1	k=1.5	h=0.0	TAC^R=10%	cv=0.6	n=1000	TAC_{inc}=1% TAC_{inc}=5% TAC_{inc}=10% TAC_{inc}=20%	TAC_{lim}=1%
Scenario 12	w=1	k=1.5	h=0.0	TAC^R=10%	cv=0.6	n=1000	TAC_{inc}=1%	TAC_{lim}=1% TAC_{lim}=5% TAC_{lim}=10% TAC_{lim}=20%

* parameters used in the base case scenario

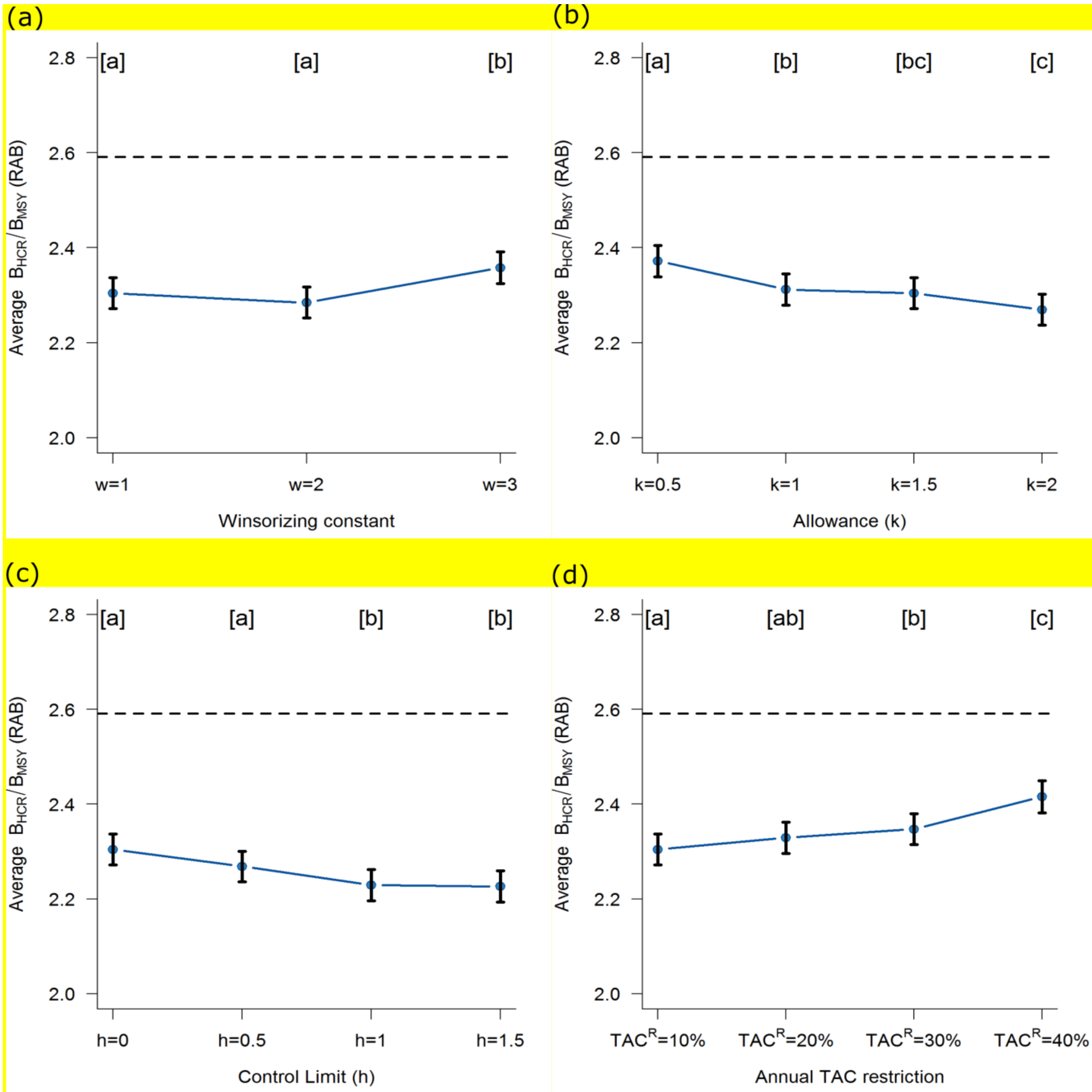
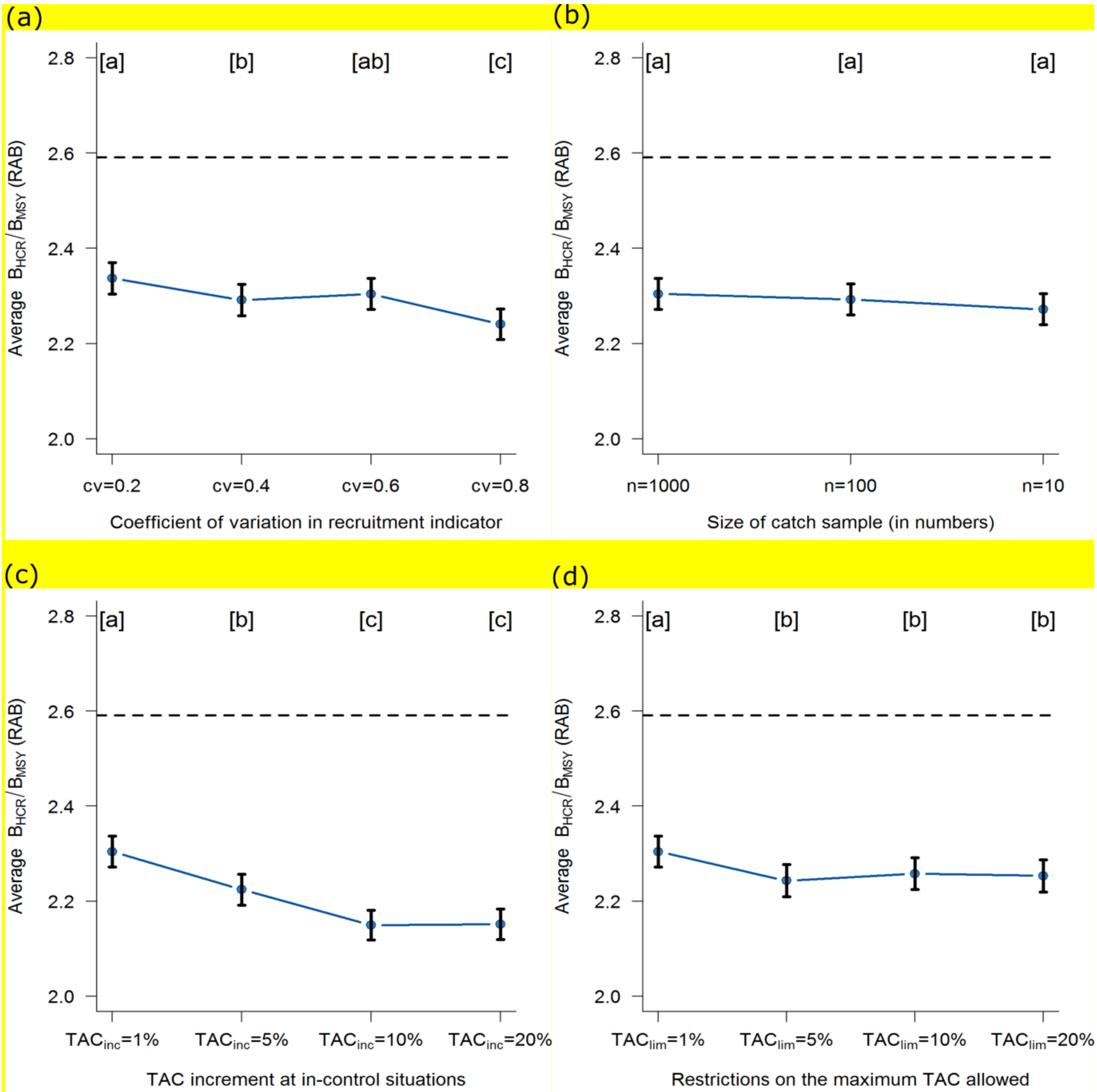


Fig. S1. Relative average biomass obtained for different (a) winsorizing constants in SS-CUSUM, (b) allowances in SS-CUSUM (c) control limits in SS-CUSUM and (d) inter-annual restrictions in total allowable catch. The dashed line indicate mean status-quo levels and the performances with same letters in the square brackets indicate no significant difference between each other at $p<0.001$.



1024 **Fig. S2.** Relative average biomass obtained for different (a) coefficient of variation in the
1025 recruitment indicator, (b) number of individuals used for the computation of large fish
1026 indicator, (c) TAC increments allowed at 'in-control' situations and (d) TAC_{lim} that restricted
1027 the maximum TAC in SS-CUSUM-HCR. The dashed line indicate mean status-quo levels
1028 and the performances with same letters in the square brackets indicate no significant
1029 difference between each other at p<0.001.

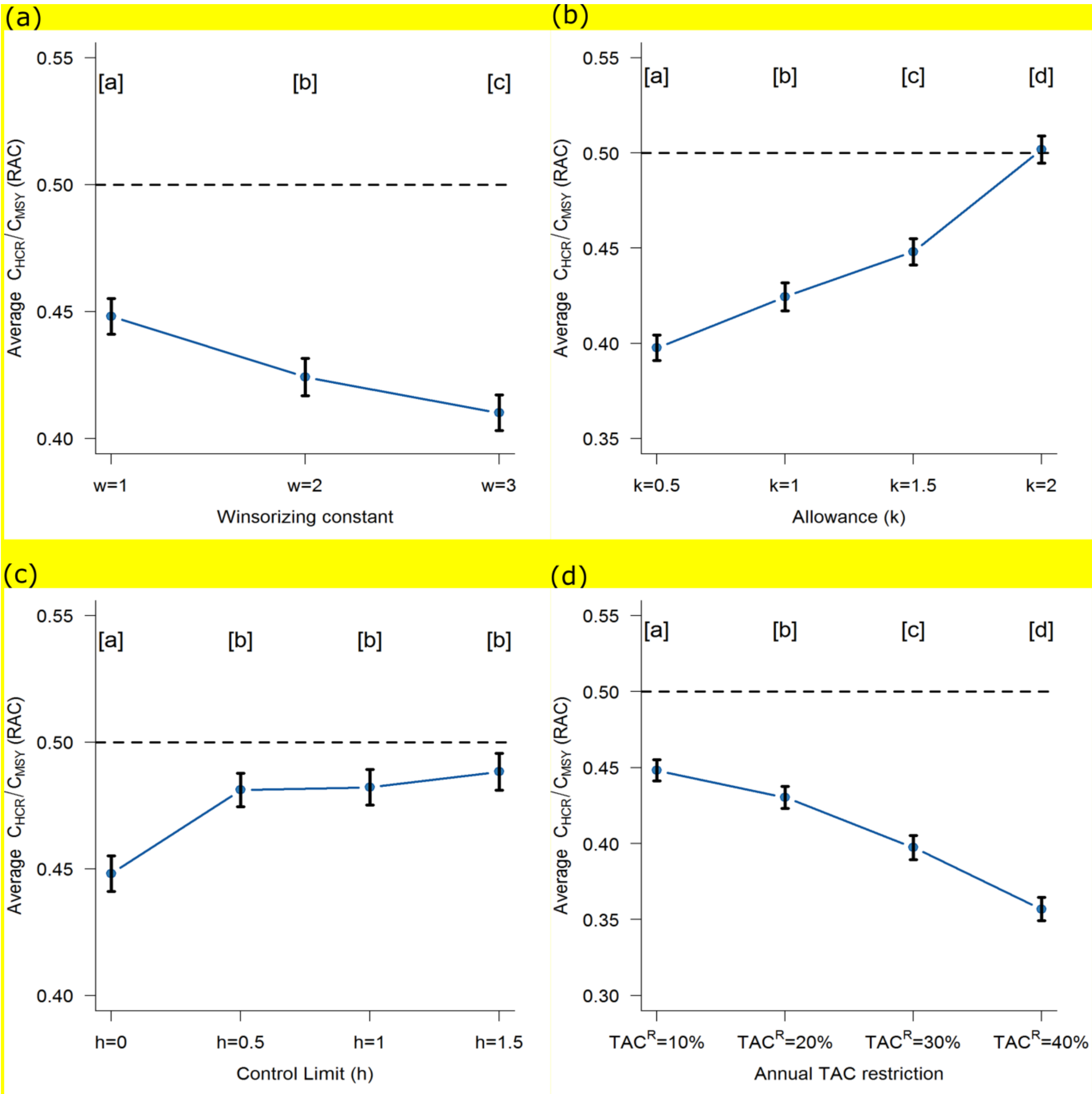


Fig. S3. Relative average catch obtained for different (a) winsorizing constants in SS-CUSUM, (b) allowances in SS-CUSUM (c) control limits in SS-CUSUM and (d) inter-annual restrictions in total allowable catch. The dashed line indicate mean status-quo levels and the performances with same letters in the square brackets indicate no significant difference between each other at p<0.001.

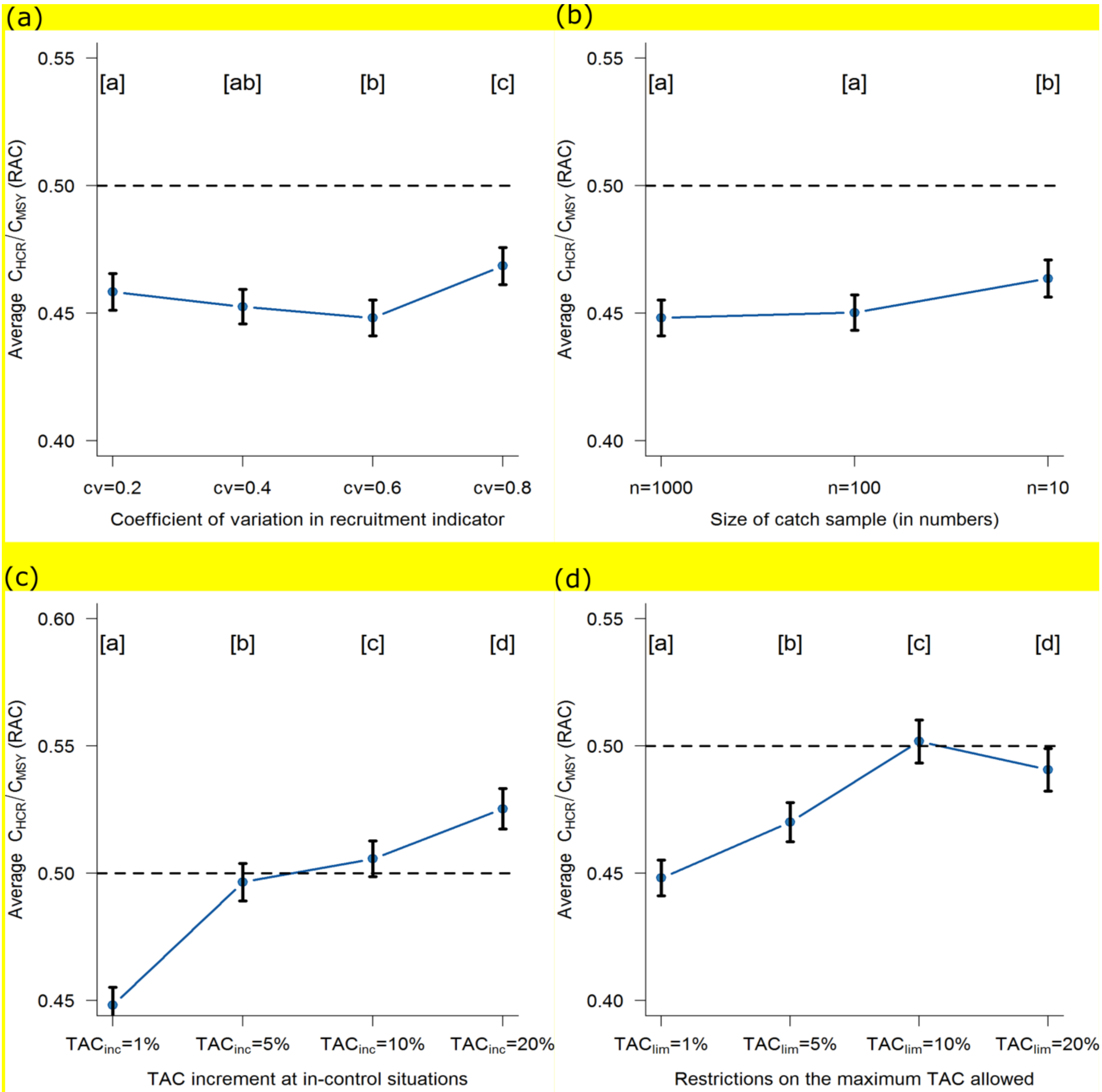


Fig. S4. Relative average catch obtained for different (a) coefficient of variation in the recruitment indicator, (b) number of individuals used for the computation of large fish indicator, (c) TAC increments allowed at 'in-control' situations and (d) TAC_{lim} that restricted the maximum TAC in SS-CUSUM-HCR. The dashed line indicate mean status-quo levels and the performances with same letters in the square brackets indicate no significant difference between each other at $p<0.001$.

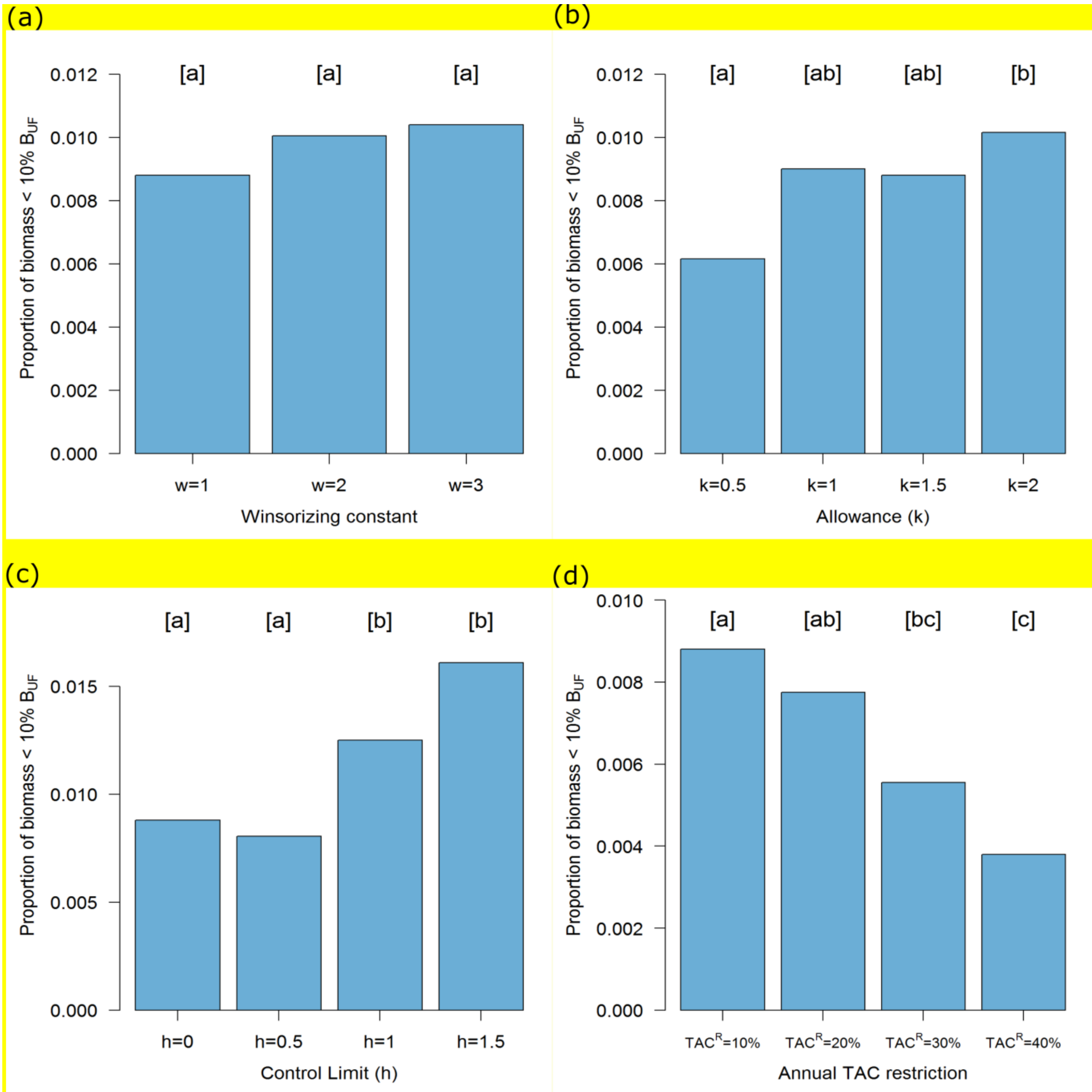


Fig. S5. The B_{10} performances obtained for different (a) winsorizing constants in SS-CUSUM, (b) allowances in SS-CUSUM (c) control limits in SS-CUSUM and (d) inter-annual restrictions in total allowable catch. Performances with same letters in the square brackets indicate no significant difference between each other at p<0.001.

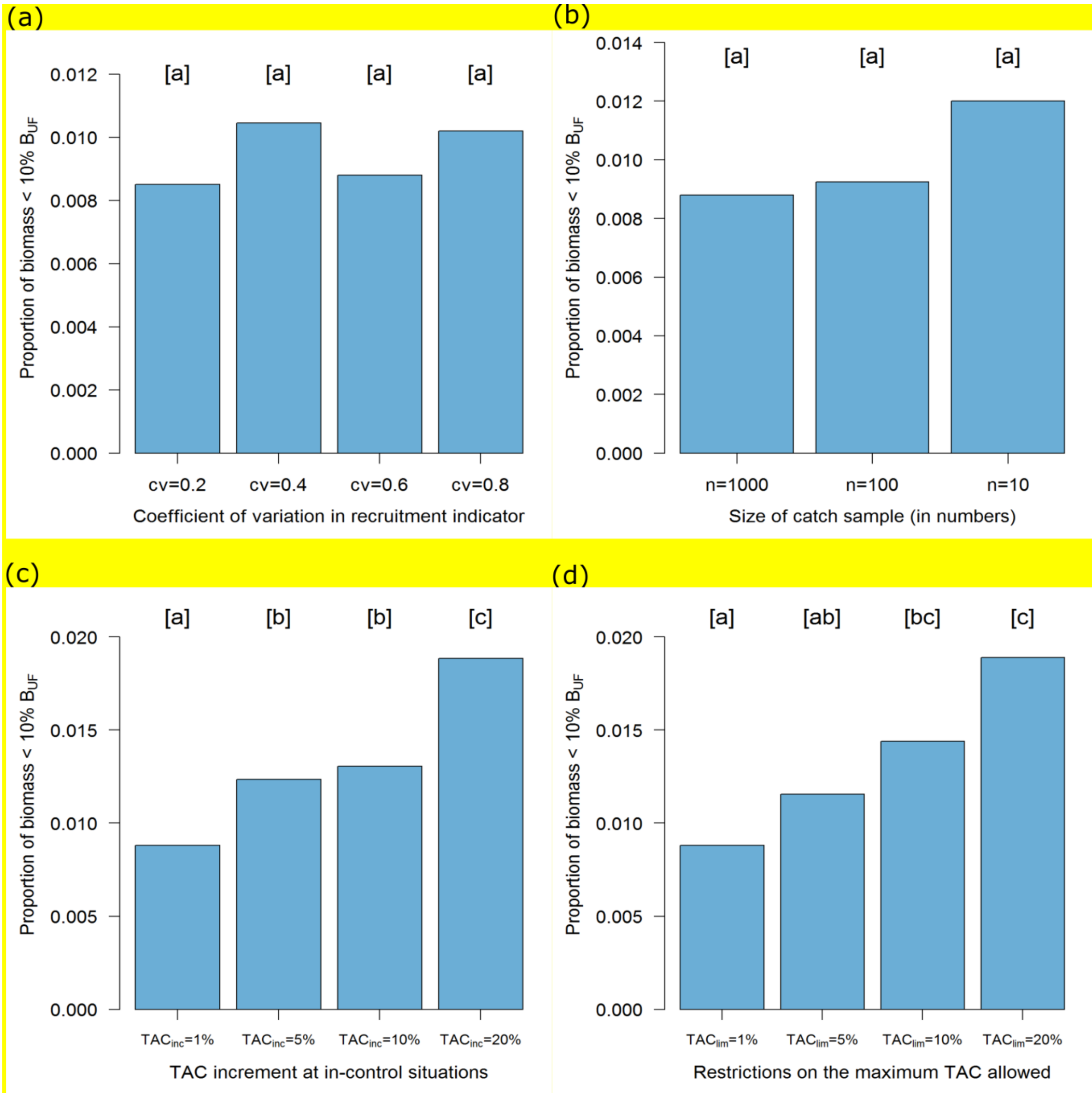


Fig. S6. The B_{10} performances obtained for different (a) coefficient of variation in the recruitment indicator, (b) number of individuals used for the computation of large fish indicator, (c) TAC increments allowed at 'in-control' situations and (d) TAC_{lim} that restricted the maximum TAC in SS-CUSUM-HCR. Performances with same letters in the square brackets indicate no significant difference between each other at $p<0.001$.