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Application of signal detection methods to fisheries management

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List of Symbols

Symbol	Description
a	Age of the fish
a_0	Age at length of zero centimetres (VBGF parameter)
a_{max}	Plus group or Maximum life span modelled
AW_a	Positive proportion of average catch weight at age 'a'(Indicator)
B	Stock Biomass
B_0	Virgin stock Biomass (unexploited)
B_{eq}	Stock Biomass at fishery equilibrium
B_{MSY}	Stock Biomass at MSY
C	Catch
CN_a	Catch numbers at age 'a'(Indicator)
CW_a	Catch weight at age 'a'(Indicator)
c	Intercept in length-weight relationship
cv	Coefficient of variation
d	Slope in length-weight relationship
d_n	Deviation of indicator from estimated control mean in CUSUM
e_M	Error in shift size estimates of stock biomass for M
F	Fishing Mortality
F_{int}	Initial fishing mortality to achieve fishery equilibrium
F_{MSY}	Fishing Mortality at MSY
F^+	False Positive outcome
F^-	False Negative outcome
i	Year
H	Number of years since when the CUSUM ($\|\theta\|$) was last lifted above or below zero
h	Control limit or Decision interval
K	Growth coefficient
k	Allowance parameter
L	Length of the fish
L_∞	Asymptotic length (VBGF parameter)
m	Natural mortality
M	Number of years since when the CUSUM ($\|\theta\|$) was last lifted above control limit ($\|h\|$)
M_a	Percentage of fully matured fish at age 'a'
$M_{50\%}$	Age group for which 50% of the cohort are fully matured
$M_{95\%}$	Age group for which 95% of the cohort are fully matured

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Symbol	**Description**
n	Number of samples or observations
N_a	Population numbers at age 'a'
O_n	Proportion of mature fish catch numbers (Indicator)
O_w	Proportion of mature fish catch weight (Indicator)
P_n	Proportion of large fish catch numbers (Indicator)
P_w	Proportion of large fish catch weight (Indicator)
PN_a	Positive proportion of catch numbers at age 'a'(Indicator)
PW_a	Positive proportion of catch weight at age 'a'(Indicator)
r	Recruitment numbers to the stock at age '$a = 0$'
R	Estimate of r
RP_n or RP_w	Combined indicator metric of estimated recruitment and LFI
s	Random sample of the fisheries catch
$\hat{S}$	Estimated shift size in stock biomass
$S_{50\%}$	Age group for which 50% of the cohort are vulnerable to fishing
$S_{95\%}$	Age group for which 95% of the cohort are vulnerable to fishing
T^+	True Positive outcome
T^-	True Negative outcome
TAC_r	Inter-annual restriction applied for the TAC update in percentage
U_n	Transformed indicator in SS-CUSUM
W	Weight of the fish
W_n	Running variance of SS-CUSUM
w	Winsorizing constant
X	Indicator observation
$\overline{X}$	Estimated in-control mean of DI-CUSUM
$\overline{X}_n$	Running mean of SS-CUSUM
Z	Standardized indicator observation
z	Steepness parameter in Beverton-Holt recruitment function
μ	In-control mean of DI-CUSUM
ρ	Coefficient of autocorrelation
σ	In-control standard deviation of DI-CUSUM
$\overline{\sigma}$	Estimated in-control standard deviation of DI-CUSUM
$\overline{\sigma}_n$	Running standard deviation of SS-CUSUM
σ_R^2	Variance of stock-recruitment
θ^+	Upper CUSUM
θ^-	Lower CUSUM

List of Abbreviations

Abbreviation	Description
ABI	Age Based Indicator
AFWG	Arctic Fisheries Working Group
ALK	Age-Length Key
ARMA	Autoregressive Moving Average
AUC	Area Under Curve
B01	Probability of stock collapse
CUSUM	Cumulative Sum
D1 to D6	Quantitative methods from EPC thoery used for estimating shift size in stock biomass
DI-CUSUM	Decision Interval Cumulative Sum
EAFM	Ecosystem Approach to Fisheries Management
EU	European Union
EPC	Engineering Process Control
EWMA	Exponentially Weighted Moving Average
HAWG	Herring Assessment Working Group for the area South of 62^0 North
HCR	Harvest Control Rule
I-ARL	In-control Average Run Length
ICES	International Council for the Exploration of Sea
LFI	Large Fish Indicators
LH1	Virtual fish type with life history parameters of Family: Gadidae
LH2	Virtual fish type with life history parameters of Family: Clupeidae
LH3	Virtual fish type with life history parameters of Family: Sebastidae
LRP	Limit Reference Point
MSY	Maximum Sustainable Yield
MFI	Mature Fish Indicators
MA	Mean Age (Indicator)
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
ML	Mean Length (Indicator)

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Abbreviation	Description
MW	Mean Weight (Indicator)
MI	Mean Indicators
MP	Management Procedure
O-ARL	Out-of-control Average Run Length
OP	Optimal Performance
PI	Proportional Indicator
PRP	Precautionary Reference Point
PDCA	The Deming (Shewhart) cycle
RAC	Relative Average Catch
RFM	Relative Fishing Mortality
ROC	Receiver Operator Characteristic curves
ROV	Relative Overall Variance
RSB	Relative Stock Biomass
SBI	Size Based Indicator
SSB	Spawning Stock Biomass
SPC	Statistical Process Control
SPA	Statistical Process Adjustment
SS-CUSUM	Self-Starting Cumulative Sum
TS	Tracking Signal
TAC	Total Allowable Catch
TRP	Target Reference Point
VAR	Overall Variance
VBGF	von-Bertalanffy Growth Function
VPA	Virtual Population Analysis
WGNSSK	Working Group on the Assessment of Demersal Stocks in the North Sea and Skagerrak
WGCSE	Working Group for the Celtic Seas Ecoregion
WKLIFE	Workshop on the Development of Assessments based on LIFE history traits and Exploitation Characteristics
XSA	Extended Survival Analysis

I, Deepak George Pazhayamadom, certify that this thesis is my own work and I have not obtained a degree in this university or elsewhere on the basis of the work submitted in this thesis.

Deepak George Pazhayamadom

Dedicated to my Grandparents

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Go raibh maith agaibh...!!!

Abstract

The abundance of many commercially important fish stocks are declining and this has led to widespread concern on the performance of traditional approach in fisheries management. Quantitative models are used for obtaining estimates of population abundance and the management advice is based on annual harvest levels (TAC), where only a certain amount of catch is allowed from specific fish stocks. However, these models are data intensive and less useful when stocks have limited historical information. This study examined whether empirical stock indicators can be used to manage fisheries. The relationship between indicators and the underlying stock abundance is not direct and hence can be affected by disturbances that may account for both transient and persistent effects. Methods from Statistical Process Control (SPC) theory such as the Cumulative Sum (CUSUM) control charts are useful in classifying these effects and hence they can be used to trigger management response only when a significant impact occurs to the stock biomass. This thesis explores how empirical indicators along with CUSUM can be used for monitoring, assessment and management of fish stocks.

I begin my thesis by exploring various age based catch indicators, to identify those which are potentially useful in tracking the state of fish stocks. The sensitivity and response of these indicators towards changes in Spawning Stock Biomass (SSB) showed that indicators based on age groups that are fully selected to the fishing gear or Large Fish Indicators (LFIs) are most useful and robust across the range of scenarios considered. The Decision-Interval (DI-CUSUM) and Self-Starting (SS-CUSUM) forms are the two types of control charts used in this study. In contrast to the DI-CUSUM, the SS-CUSUM can be initiated without specifying a target reference point ('control mean') to detect out-of-control (significant impact) situations. The sensitivity and specificity of SS-CUSUM showed that the performances are robust when LFIs are used. Once an out-of-control situation is detected, the next step is to determine how much shift has occurred in the underlying stock biomass. If an estimate of this shift is available, they can be used to update TAC by incorporation into Harvest Control Rules (HCRs). Various methods from Engineering Process Control (EPC) theory were tested to determine which method can measure the shift size in stock biomass with the highest accuracy. Results showed that methods based on Grubb's harmonic rule gave reliable shift size estimates. The accuracy of these estimates can be improved by monitoring a combined indicator metric of stock-recruitment and LFI because this may account for impacts independent of fishing. The procedure of integrating both SPC and EPC is known as Statistical Process Adjustment (SPA). A HCR based on SPA was designed for DI-CUSUM and the scheme was successful in bringing out-of-control fish stocks back to its in-control state. The HCR was also tested using SS-CUSUM in the context of data poor fish stocks. Results showed that the scheme will be useful for sustaining the initial in-control state of the fish stock until more observations become available for quantitative assessments.

Chapter 1

General Introduction

The application of Cumulative Sum (CUSUM) control charts in the fisheries management system is examined in this thesis. Specifically, four key questions are asked:-

1. Which catch-based indicators are useful for monitoring the state of a fish stock ?
2. Can fishing impacts on stock biomass be detected using CUSUM ?
3. Can the state of the stock be assessed using signals from CUSUM ?
4. Can fisheries be managed sustainably using signals from CUSUM ?

This chapter begins with a brief description about fisheries management and the problems and challenges that have led to the current focus of using signal detection methods in fisheries management systems. The potential use of indicators for monitoring and detecting the effects of fishing when high contrast data are not available for conducting a formal fish stock assessment are examined. Indicator trends can be monitored using a statistical framework like Cumulative Sum (CUSUM) control charts to obtain signals that are important for implementing management actions. The CUSUM control chart is a trend detection technique in Statistical Process Control (SPC) theory and has been widely applied in manufacturing industries for qualitative assessment of an ongoing process. The advantage of using CUSUM control charts, the application to fish populations and the concept of extending CUSUM control charts for monitoring, assessment and management of fisheries that have limited information is discussed. Finally, an outline of the key questions asked in other chapters of the thesis are presented. A number of terms are repeatedly used in this thesis and a summary of these terms and their definitions are given in Appendix A.

1.1 Fisheries management and fish stock assessments

In fisheries management, specifying clear objectives is important for judging the success or failure of a management strategy (Jennings et al., 2001). The objectives used in fisheries management can be broadly categorized into biological, economic, social or political aspects (Lane and Stephenson, 1995). Fisheries can be managed to increase food production, income, employment, support from fishers, or to conserve the target species (Jennings et al., 2001). However, none of these objectives are independent because maximizing one objective is likely to compromise others (William, 1998). Most managers deal with multiple objectives and fisheries management is often a trade-off between optimizing profits while maintaining the sustainability of the resource (Smith and Punt, 2001). Managers seek advice from scientists for recommended management actions to achieve these objectives and they are commonly implemented by either controlling the total catch or fishing effort (number of boats, fishers, days or duration). Other forms of management actions include mesh size restrictions (a larger mesh allow juveniles to escape), closed seasons (e.g. spawning periods), closed areas (e.g. breeding grounds) and closure of a fishery to rebuild depleted fish stocks (Cochrane, 2002).

The word 'stock' in fisheries management generally represents a fish population belonging to a single species that maintains and sustains itself over time in a definable area (Booke, 1981). The stocks will undergo many changes when they are harvested (or fished), such as their spatial distribution, numbers-at-age, numbers-at-size and total biomass. If the effort applied to fishing is uncontrolled, then this may result in stock collapse, economic inefficiency, loss of employment, habitat loss and/or reduction in abundance of rare species (Jennings et al., 2001). To regulate the fishing effort, it is important to understand the dynamics of exploited fish populations, how they respond to different levels of perturbations that are man-made (e.g. fishing) or environmental (e.g. impact of climate change). If this can be understood, it is assumed that the fisheries can be managed to achieve particular objectives (Haddon, 2011).

'Fish stock assessments' attempt to model the underlying cause of variation in a stock's production (yield) because this is a combined effect of variations in effort, stock-recruitment, natural mortality and growth (Sissenwine, 1984). Fishery scientists use mathematical approaches to understand these stock dynamics, estimate abundance, characterize the uncertainty involved in these estimates and predict responses for different levels of fishing pressure. The entire process is collectively termed as 'fish stock assessment' and the key goal is to provide advice on particular fishing or harvest levels so that the yields will be sustainable for a given future time. This is implemented using Harvest Control Rules (HCRs), which are a pre-agreed course of management actions as a function of the identified stock status and other economic or environmental conditions, relative to the agreed management objectives (Berger et al., 2012).

1.2 Problems in providing fisheries advice

Many commercially important fish stocks in the North Atlantic are currently managed using harvest policies that are based on trends in Spawning Stock Biomass and Fishing mortality (Probst et al., 2013*a*). The Spawning Stock Biomass (SSB) is the total weight of all mature fish individuals in the population and Fishing mortality (F) is the fraction of the average population taken by fishing per year expressed on a log scale. These parameters are traditionally derived using Virtual Population Analysis (VPA) models, where data from commercial catches and research surveys are combined to reconstruct stock sizes back in time. The management advice for these stocks are often based on Total Allowable Catch (TAC) recommendations corresponding to the level of F that ensures the SSB may remain above a threshold at which the stock-recruitment could be impaired (Kell et al., 2005*a*).

However, there is growing concern on overall effectiveness of such traditional approaches (Kelly and Codling, 2006) since there are clear indications of depletion in most commercial fisheries around the world (Caddy, 1999; Myers and Worm, 2003; Caddy and Seijo, 2005; Worm et al., 2009). This is because the traditional models are generally data intensive, make numerous assumptions and the trueness of estimates will depend upon the quality, as well as quantity, of data available for the fish stock (Kelly and Codling, 2006). Full stock assessments can be extremely costly due to these data requirements and hence are not an economically viable option for all exploited species in the ecosystem (Hilborn and Walters, 1992). Many fish stocks have unreliable catch data either due to misreporting or discards in the sea leaving the managers with little information upon which decisions can be based (ICES, 2010). Moreover, the monitoring, assessment and management of fish stocks are currently performed on a single-species basis. There are increasing calls in recent years for moving towards an ecosystem based fisheries management (Pikitch et al., 2004). Hence new alternative methods are required to provide better management of fish stocks worldwide (Myers and Worm, 2003).

In this context, "model-free" approaches such as those based on empirical indicators have been suggested for the assessment and management of fisheries (Rochet and Trenkel, 2003; Trenkel and Rochet, 2003; Caddy, 2004). Even when data are limited or unreliable, indicators such as the mean length or mean weight can be computed from fishery dependent or independent catch data (Kelly and Codling, 2006). Thus, changes in size composition of fish populations can be tracked and qualitative decisions can be made such as whether catch should be increased or decreased (Shin et al., 2005). One advantage of this approach is that the final advice does not have to rely completely on uncertain estimates of two numbers (SSB and F) but can be based on a variety of such empirical stock indicators (Trenkel et al., 2007).

1.3 Indicator based fisheries management

There are four elements to Indicator Based Fisheries Management:- (i) the selection of an indicator to be monitored; (ii) a target reference point corresponding to the management objective; (iii) precautionary reference points for triggering the management responses and (iv) decision rules to determine the management actions.

1.3.1 Indicators

Indicators are defined as variables, pointers or indices of a phenomenon and are extremely useful in a decision making process because they can be measured cost effectively even when the resources are limited (Garcia et al., 2000; Rice and Rochet, 2005). In fisheries management, various empirical indicators can act as proxies for describing the stock attributes that may not be directly measurable (Fulton et al., 2004; e.g., the pressure, state or response of the stock). This facilitates tracking them and assessing whether the current trend is progressing towards meeting the management objectives. The biggest advantage of indicators is that the fisheries impacts and the management processes can be communicated to a non-specialist audience by visualizing their trends (Rice, 2000; 2003; Rochet and Trenkel, 2003). This is illustrated using the Irish Sea Cod data (ICES, 2012*c*; *Gadus morhua* from the Celtic Sea) in figure 1.1 where the negative trend in catch numbers (of individuals above age 5 from observed landings) is similar to the trend of estimated SSB (from stock assessment models). This implies that the state of the stock can be qualitatively detected by simply monitoring empirical indicators when exhaustive data are not available for conducting quantitative stock assessments. Thus, they can be used for assessment and evaluation of stock responses to environmental effects or management actions (Rice and Rochet, 2005).

Desirable properties

Rice et al. (2005) describe the ideal properties of an indicator for fisheries management. First of all, indicators should be **interpretable**, so that a wide range of stakeholders can understand how they link to the management objectives. They should be **measurable** on both temporal and spatial scales, as needed for the management of the fish stocks concerned. In developing countries, a **cost-effective** option is to use an indicator which can be recorded using existing instruments, monitoring programmes and analytical tools. If the indicators can be computed from a time-series that is already available (e.g. commercial landings), then this will aid in interpreting the underlying trends and allow setting up management objectives that are more realistic. Above all, the indicators should be **sensitive**, as well as **specific**, to the properties that are intended to be measured. For example, to monitor the impact of fishing effectively, the indicator should

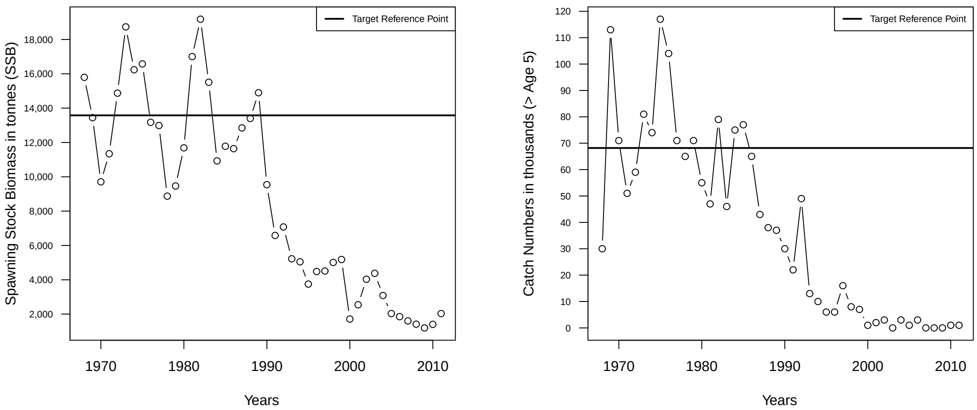
(*a*) Estimated indicator (*b*) Empirical indicator

Figure 1.1: **Comparison of trend in estimated and empirical indicators:** The figures are plotted using ICES data for the Irish Sea Cod between 1968-2011 (ICES, 2012*c*).

be sensitive to changes in the state of the stock and specific to the pressure applied to the stock. This implies that the indicators should have minimum or known bias and the trend should be distinguishable from underlying noise giving a higher probability of true signals (Jennings, 2005). Finally, the indicators should be **responsive** such that they provide rapid and reliable feedback on the consequences of management actions.

1.3.2 Target reference point

The target reference points (TRP) are defined as those indicator values that may permit long-term sustainable exploitation of the stocks, with the best possible catch (Cadima, 2003). The TRPs identify conditions at which management should aim and hence they are useful in understanding the current position (above or below TRP) and the direction in which the indicator moves (Punt et al., 2001; approaching or moving away from TRP). Traditionally, the spawning stock biomass (SSB) and fishing mortality (F) are monitored and hence the TRPs are fixed using values estimated from stock assessment models. However, for empirical indicators, TRPs based on empirically derived quantities will be required rather than the model-derived quantities such as F or SSB. I illustrate this in figure 1.2 using the example from Section 1.3.1, where the TRP for Irish Sea Cod data was computed by taking an average of the observations obtained between 1968-1988 (ICES, 2012*c*; since 1988, the stock is considered to be overfished). Indicator patterns will provide only abstract conclusions (negative trend, Figure 1.1), but fixing TRPs will provide a better resolution on years when the change occurred. Figure 1.2 shows a stable state stock until the late 80's and then the stock started to decrease from the target.



(*a*) Estimated indicator (*b*) Empirical indicator

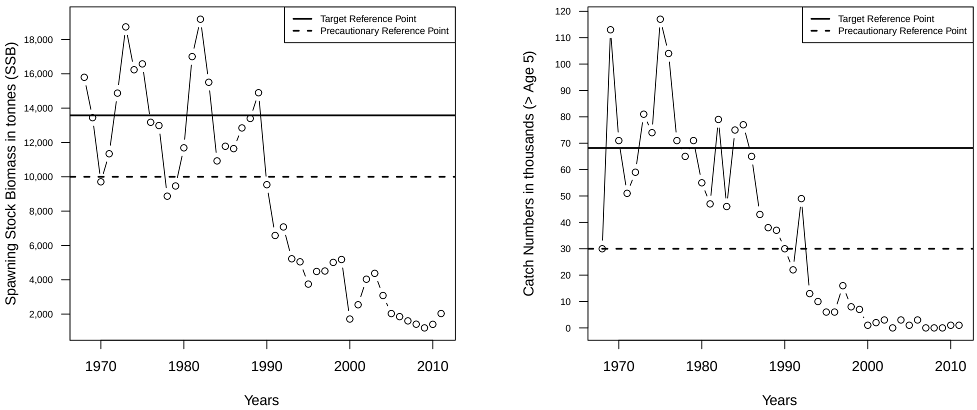
Figure 1.2: **Illustration of indicator trends using Target Reference Point (TRP):** The figures are plotted using the ICES data for the Irish Sea Cod between 1968-2011 (ICES, 2012*c*). For illustrative purposes, the TRP was computed by taking an average of the observations obtained between 1968-1988.

1.3.3 Precautionary and Limit reference points

In contrast to TRPs, the Limit Reference Point (LRP) indicates conditions to be avoided and which if exceeded, the stock may be subjected to serious or irreversible harm (Rice et al., 2005). However, the indicators are subjected to a variety of uncertainties such as the measurement or estimation errors and hence the underlying trend may provide a true or false indication of the stock state (Punt et al., 2001). To remain proactive and to avoid reaching the LRP, conventionally a precautionary reference point (PRP) is used for triggering the management responses. These reference points are considered more important than the TRPs because the latter are arguably more an issue for the industry and stakeholders than for fisheries biologists (Kaufmann et al., 1999; p.197). Figure 1.3 illustrates the PRPs used for the estimated and empirical indicator of Irish Sea Cod.

1.3.4 Decision rules

Broadly termed as 'reference directions', the indicator trends can be used as a guide to control the management actions (Link et al., 2002; Trenkel and Rochet, 2003). Though indicators are used to detect the state of the stock, management usually controls the fishing pressure (gear, boats or catch) and the response in the change of the state is measured (i.e. feedback mechanism). Hence it is extremely important to understand the relationship between indicator trends and the state of the stock, and how they are associated with meeting the management objectives (Jennings and Dulvy, 2005).



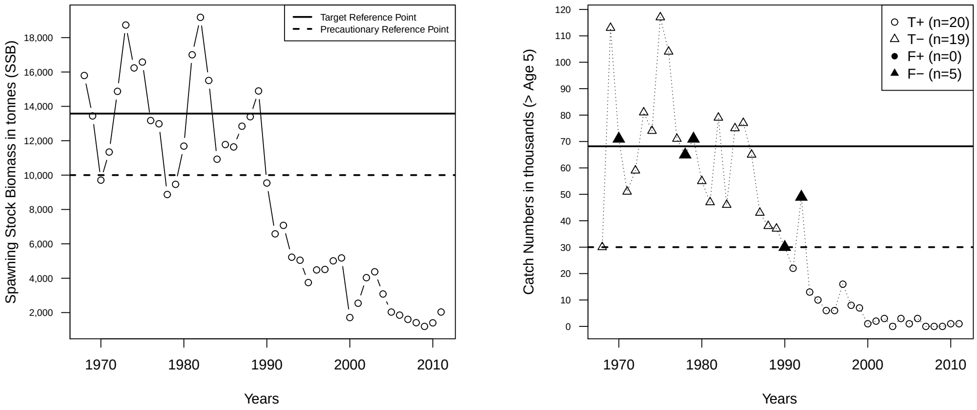
(*a*) Estimated indicator (*b*) Empirical indicator

Figure 1.3: **Illustration of fixing the Precautionary Reference Point (PRP):** The figures are plotted using the ICES data for the Irish Sea Cod between 1968-2011 (ICES, 2012*c*). To trigger the management responses, Precautionary Reference Points (PRPs) are fixed for the indicators conventionally. The figure 1.3a shows the PRP fixed for estimated SSB by ICES (ICES, 2012*c*; $B_{pa} = 10,000$tonnes). For illustrative purposes, an arbitrary threshold was chosen as PRP for the empirical indicator i.e., the observation in year 1990 (Figure 1.3b)

1.4 Signal detection theory

The variability of an indicator can be affected by internal (fishery independent) and/or external noise (fishery dependent). The internal noise can be due to biological or environmental factors while external noise originate during the measurement or detection process. Hence, nearly all reasoning and decision making takes place in the presence of some uncertainty. The principle behind signal detection theory is to increase the ability of detecting the true indicator signals from underlying noise and thereby reducing the probability of false alarms.

To illustrate, let's compare the detection outcomes from the empirical indicator in figure 1.3b with the estimated SSB of Irish Sea Cod, assuming that the latter represents the actual state of the stock. There are four possible outcomes: true-positive (T^+, state is below the PRP and this was correctly detected); true-negative (T^-, state is above the threshold and this was correctly detected); false-positive (F^+, state is above the PRP but this was incorrectly detected); and false-negative (F^-, state is below the PRP and this was incorrectly detected). These outcomes are marked in figure 1.4 and shows that there are 5 false negative alarms if the observation from 1990 is used as a decision criteria for determining the state of stock. In this example, it is clear that at least one false alarm could have been avoided by using a higher decision criteria i.e., the observation from 1989 (Figure 1.4b). However, indicators may also give responses that are early or too late due to time lagged relationship with the underlying stock abundance. In the above example, using a decision criteria equivalent to observation from 1987 generates F^+ signals though such a scheme will be useful in providing early alarms so that the stock depletion in later years can be avoided.



(a) Actual stock state (assumption) (b) Signal detection using indicator

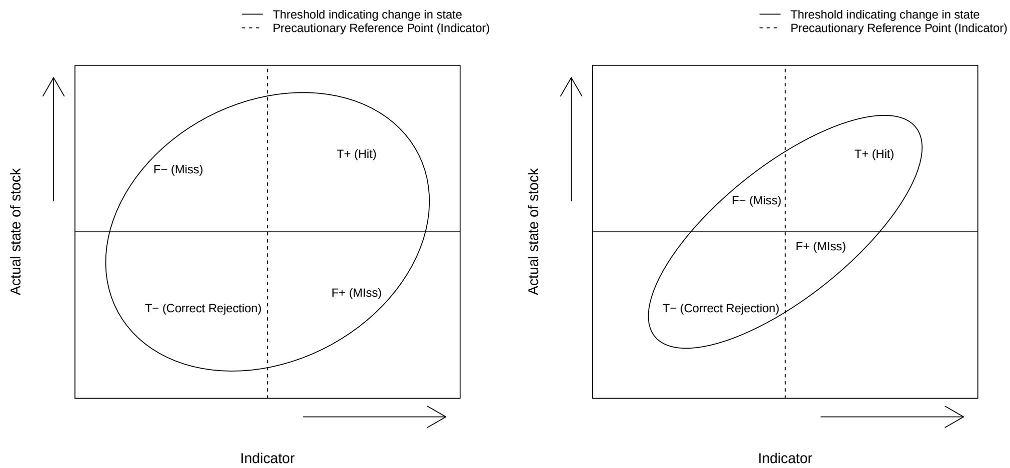
Figure 1.4: **Four possible outcomes in signal detection methods:** The ICES data for the Irish Sea Cod between 1968-2011 was used as an example to illustrate which years may indicate an out-of-control situation (ICES, 2012*c*). First, the estimated SSB was assumed to be the actual state of the stock (Figure 1.4a) and the empirical indicator was cross checked to see whether the observations are above or below the precautionary reference point (Figure 1.4b). The four possible outcomes are (i) true-positive (T^+, Hit); (ii) true-negative (T^-, Correct rejection); (iii) false-positive (F^+, Miss) and (iv) false-negative (F^-, Miss).

Nevertheless, the rate of false alarms will depend on how good the predictor (indicator) and the decision criteria are. This is illustrated using a Taylor-Russell diagram where the ellipse indicates the probability of outcomes (Figure 1.5a). On the vertical axis, we have the actual state of the stock (reality) and the region above the threshold (solid line) indicates when there is a shift. On the vertical axis, we have the indicator (predictor), and the precautionary reference point (dotted line) is the decision criteria used for determining whether a change occurred in the state of stock. Figure 1.5 shows the outcomes from two different decision criteria where the Scheme B performs better than Scheme A since the former gives a higher sensitivity (probability of T^+) and specificity (probability of T^-) by reducing the number of false alarms.

1.4.1 Statistical Process Control

In figure 1.4, it is obvious that the sensitivity and specificity of the detection scheme will depend on the Target Reference Point (TRP) and Precautionary Reference Point (PRP). However, some knowledge about the stock is required to fix these parameters and this forms an important challenge when historical data are limited, poor or uncertain.

Statistical Process Control (SPC) consists of methods where a statistical approach can be used for implementing the reference points without any prior knowledge of the



(*a*) Scheme A (*b*) Scheme B

Figure 1.5: **Illustration of the theory behind signal detection methods using a Taylor-Russell diagram:** The ellipse illustrating the uncertain relationship between an indicator and the actual state of a system. Here, it is assumed that the indicator moves in the same direction as in the state of the stock. There are four possible outcomes from a determination: true-positive (T^{+}) or true-negative (T^{-}) indicating correct detection and false-positive (F^{+}) or false-negative (F^{-}) indicating incorrect detection. *Source: Scandol (2003).*

system. They are generally visualized using control charts, which is a graphical representation of SPC computations showing how an indicator changes over time. Control charts will always have a central line indicating the TRP (termed as 'control mean', μ), an upper and lower line indicating the PRPs for positive and negative indicator deviations (termed as 'control limits', h). The data are compared with these control limits to draw conclusions on whether the indicator variability is consistent ('in-control' situation) or unpredictable ('out-of-control' situation). The state of the stock is considered to be stable as long as the control chart indicate an in-control situation. An example is illustrated using the Irish Sea Cod data in Figure 1.6 (ICES, 2012*c*).

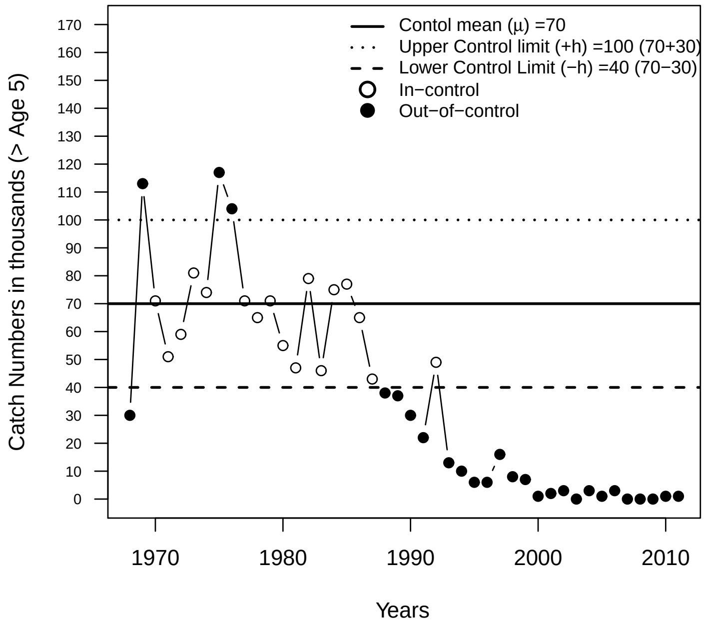
1.4.2 The principle behind SPC

Control charts are conventionally used in manufacturing industries for improving process stability so that the variability around product quality can be minimized (Montgomery, 1996). This is achieved by allocating the observed indicator variability to two categories of sources:

1. Common causes

2. Special causes

Common causes of variation are inherent and are always present in an indicator. An example in fisheries is the natural variability observed in stock-recruitment relationships.



Shewhart control chart

Figure 1.6: **Illustration of Statistical Process Control (SPC) using Shewhart chart:**

These variations are innate and are often not well understood due to the complex functional relationships within the population or ecosystem. If an indicator is affected only by common causes, then the state of the stock is said to be in-control. Indicator observations from an in-control state of stock vary within the control limits (h) around a central value, the control mean (μ). Using the example presented in figure 1.6, most of the indicator observations between 1968-1987 were around the control mean ($\mu = 70$), between the upper and lower control limits ($+h = 100$, $-h = 40$) showing that the state of the stock is in-control. A yearly management response is not required during this phase because essentially this would be reacting to a false-positive signal, an intervention which may induce more variability to the stock state resulting in economic loss.

Special causes of variation are occasional disturbances that may arise periodically or in an unpredictable fashion resulting in problems affecting the common cause variability of the indicator. An example is an increase in fishing pressure such that the catch obtained are not sustainable and unstable. If an indicator is affected by special causes, then the state of the stock is said to be out-of-control. Indicator observations from an out-of-control state of stock do not vary within the control limits (h), but instead deviate away from the control mean (μ). According to figure 1.6, most of the indicator observations after 1988 are outside the prescribed control limits (below the lower control limit $-h = 40$) showing that the state of the stock is out-of-control. Variations due to special causes are predictable, detectable and can be removed to bring the state of the stock back to the in-control state.

The principle behind SPC methods is to stabilize the process by improving the sensitivity and specificity of state detection schemes. This is achieved by not reacting to all types of indicator variability but instead triggering the management responses only when the indicator is affected by a special cause variation.

1.4.3 The statistical elements in SPC

The allocation of indicator variability into common and special causes has proven to be a powerful management concept in SPC (Kolesar, 1993). However, distinguishing between them in practice is not always easy and detecting an out-of-control situation is not trivial (Quesenberry, 1997). Hence, a statistical approach is required while using these control charts and the following aspects are generally considered:

1. It is assumed that the indicator observations (X) are statistically independent and identically distributed.
2. The control mean (μ) and standard deviation representing the in-control situation are known exactly.
3. The control limit (h) is fixed such that the detection scheme achieves a high In-control Average Run Length (I-ARL, the number of observations before the first $F+$) and a short Out-of-control Average Run Length (O-ARL, the number of observations before the first $T+$).

Some or none of these aspects can be guaranteed in the real world. It is not uncommon to have observations that are close together with some degree of association or serially correlated (Hawkins and Olwell, 1998). The control mean (μ) is generally estimated from historical observations though such data are not necessarily available (Jensen et al., 2006; e.g. data poor stocks). While fixing the control limit, there is a tendency to under-estimate the extent to which deviations from an expected value can be the result of a random process (De Vries, 2001). These issues will be discussed in various chapters of this thesis.

1.4.4 Types of special cause variation

All SPC methods are designed for detecting and diagnosing the special cause variability of indicators. However, there are two distinct types of special cause variability:

1. **Transient**: These special causes may affect the indicator for a short period and then disappear to reappear at some future time. An example is the short-lived invertebrate population outburst during years following the El-Niño, as an effect of replacing the relatively low abundance of Peruvian anchovies (*Engraulis ringens*) until they begin rebuilding in numbers/ biomass (Overland et al., 2010). Variability due to such effects may persist for a while and then go away, even if not treated.

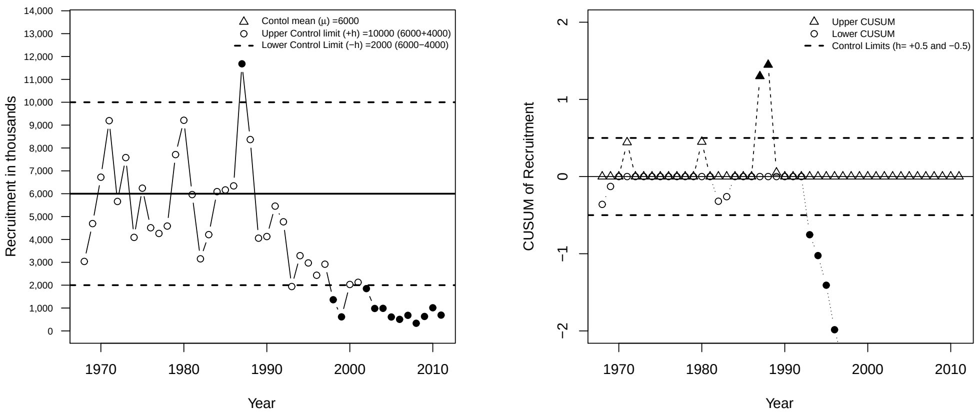
2. **Persistent:** The effect of these special causes will persist until the underlying problem is detected and diagnosed. The Irish Sea Cod data provided in figure 1.6 is an example of this effect where the stock is in an out-of-control state since 1988. The stock assessment reports indicate that the reason is an increased level of fishing which has to be reduced in the coming years to bring the stock back to in-control situation (ICES, 2012*c*).

To improve the stock stability, we may need good methodologies for detecting and removing both types of variabilities as soon as they occur. The two types of special causes have different effects on the stock and hence different methods are required to detect and diagnose them effectively (Hawkins and Olwell, 1998).

1.4.5 Shewhart and CUSUM control charts

The best-known and the most simple one is the **Shewhart control chart** which was introduced by Shewhart (1931; Figure 1.6). In this chart, the control limits are placed sufficiently far from the control mean so that very few samples should plot outside them if the indicator remains at its in-control distribution. This means that if an out-of-control situation is detected, necessary steps should be taken immediately to rectify the problem. Shewhart control charts are effective for detecting isolated special causes which are ***transient***, leading to occasional large shifts in the data. However, the chart has no memory and hence it is not effective in detecting moderate shifts that are gradual and persistent.

Cumulative sum control (CUSUM) charts were introduced as a resolution to the disadvantages of the Shewhart chart (Page, 1954). They accumulate information from successive observations by calculating their cumulative deviations from the control mean (see Chapter 3). Thus CUSUM keeps a memory of historical observations and are effective in monitoring gradual and ***persistent*** indicator shifts. To illustrate this, both the Shewhart and CUSUM control charts have been applied to the recruitment indicator for the Irish Sea Cod data (ICES, 2012*c*; Figure 1.7, the SSB is not a good example to illustrate because the shift is quicker). If the negative deviations are considered, the CUSUM raises an alarm 5 years earlier than the Shewhart control chart (Figure 1.7).



(a) Shewhart control chart (b) CUSUM control chart

Figure 1.7: **Comparison between Shewhart and CUSUM control chart:** Recruitment data for the Irish Sea Cod between 1968-2011 is used for the illustration (ICES, 2012*c*).

1.4.6 Advantages of CUSUM methods

Some of the key advantages of CUSUM techniques are that they are model free (Petitgas, 2009) and do not require any major investment. They are ideal for situations when there are short time series, low contrast data and hence have a great potential for developing low cost monitoring systems (Scandol, 2003; 2005). Another advantage of CUSUM is that a variety of indicators could be monitored and compared to each other. This is because the CUSUM is expressed in standard deviation units (Mesnil and Petitgas, 2009; Petitgas, 2009).

1.4.7 Application of CUSUM to fish populations

CUSUM control charts have been used previously for monitoring physical and environmental indicators (Mac Nally and Hart, 1997; Manly and Mackenzie, 2000; Barratt et al., 2007). However, only a few researchers have discussed the application of control chart techniques in fish populations (Anderson and Thompson, 2004).

The CUSUM was introduced in fisheries by Nicholson (1984) and this concept has been developed and applied in a small number of studies. Pettersson (1997) demonstrated how a multivariate control chart (Hotellings's T^2 method) can be used for monitoring the fish diversity of Lake MäIaren (Sweden) using catch data of commercially important freshwater species. Scandol (2003) showed how landed catch of marine fish populations can be monitored using CUSUM and he found that the method was able to detect the state of fish stocks with 60-80% probability. Scandol (2005) further evaluated the monitoring performance of CUSUM and found that catch indicators based on age and length samples gave the least probability of false alarms. Petitgas (2009) showed how the responses from multiple stock indicators (collection of univariate control charts) can be grouped to formulate a decision criteria for determining the state of fish stocks. Petitgas and Poulard (2009) demonstrated how changes in spatial patterns of an age-structured fish population can be detected using CUSUM by monitoring a multivariate spatial indicator obtained from research trawl surveys. Pazhayamadom et al. (2013) evaluated the performance of a Self-Starting CUSUM and demonstrated how they can be applied in a data poor situation, particularly when no historical data are available for the fish stock (see Chapter 5).

1.5 Thesis outline

There is a remarkable increase in computational speed in recent years and simulation models are increasingly used for evaluating the performance of monitoring, assessment and management of marine ecosystems (Hillary, 2009; Link et al., 2010; Lee et al., 2011; Thorson et al., 2012; Sebastián and McClanahan, 2013). All chapters in the present study used a non-spatial virtual fish population model for evaluating the applications of CUSUM control charts in a data poor context. In **Chapter 2** , I briefly explain the conceptual model used for simulating fish populations, fishery and computing various empirical indicators from the fish stock.

This study used two different types of CUSUM control charts, (i) Decision-Interval form of CUSUM (DI-CUSUM) and (ii) Self-starting CUSUM (SS-CUSUM). The DI-CUSUM requires the user to provide a reference point ('control mean') for detecting the trend in stock indicators. In contrast, the SS-CUSUM can be initiated with no historical data and hence the reference point ('running mean') is calibrated from the indicator observations. In **Chapter 3**, the steps (with equations) involved in computing these control charts and how such schemes can be made robust to outliers in the indicator time series are demonstrated.

The subsequent chapters in this thesis are structured following The Deming Cycle (Deming, 2000; Figure 1.8). The Deming (Shewhart) cycle (PDCA) advocated by Dr Deming in 1950 is a strategy used in many quality control activities for continuous improvement of a process. The cycle consists of four steps (i) **PLAN:** to study and improve the process by identifying potential indicators; (ii) **DO:** carry out the experimental test (monitoring); (iii) **CHECK:** analyse the results to determine the effects of change (assessment) and (iv) **ACT:** respond to correct the problem (implementing decisions). The CUSUM based fisheries management framework was developed following these steps i.e., identifying potential indicators (Chapter 4), indicator monitoring (Chapter 5), assessment (Chapter 6) and decision making (Chapter 7 and 8).

When limited data are available for a fish stock, it becomes necessary to use indica-

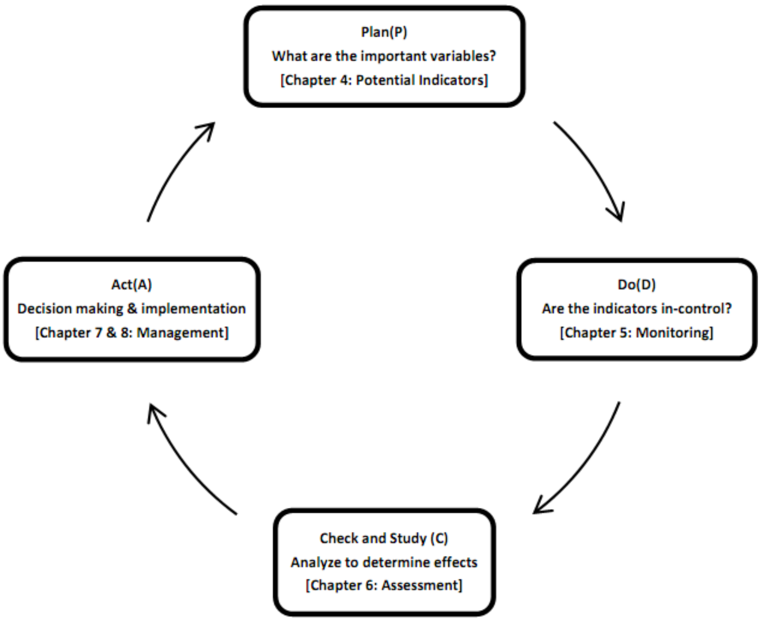


Figure 1.8: **The Deming Cycle outlining the structure of this thesis:**

tors based on empirically derived quantities such as the catch rates or size-frequency of catch, rather than on conventionally used model-derived quantities such as the fishing mortality or biomass to monitor the state of stock (Punt et al., 2001). In **Chapter 4**, many age-based catch indicators were compared with Spawning Stock Biomass (SSB) to evaluate their sensitivity and responsiveness to changes in the state of the stock. This study specifically tested the potential usefulness of indicators based on maturity (fully matured individuals, Mature Fish Indicators) and selectivity (fully vulnerable to fishing, Large Fish Indicators) of the fish stock.

Insight into the likely effects of management actions is possible only by realizing performance characteristics of the signal detection method (Rice and Rochet, 2005). The monitoring performance of DI-CUSUM has been previously tested using a simulated fishery for monitoring a variety of stock indicators and species with different life history characteristics (Scandol, 2003; 2005). However, the SS-CUSUM has not been applied to fisheries monitoring despite the advantage of requiring no historical indicator data. Therefore, in **Chapter 5**, the SS-CUSUM was evaluated for its monitoring capabilities in detecting the true effects of fishing using catch indicators that are likely to be available in a data poor fishery.

Once the CUSUM detects a meaningful deviation in the indicator (by raising an out-of-control alarm), the next step is to quantify how much shift occurred in the stock biomass (positive or negative) due to the fishing pressure. Various methods are available in Engineering Process Control (EPC) theory that can be used to determine the relative shift occurred in the mean of the indicator distribution. In **Chapter 6**, these were employed in a simulated fishery to determine which method gives the least bias and most precise estimates by comparing them with the actual shift that occurred in the underlying stock biomass.

The decision making process in fisheries management can be implemented using harvest control rules (HCRs) when specified deviations are observed in the indicators from their operational target (control mean). The combination of HCRs, assessment methods and data collection schemes are generally referred to as management procedures (MP). The MPs can be evaluated using simulation models to assess whether they are likely to achieve the management objectives (Punt, 2006). The MPs in **Chapter 7 and 8** contain a feed-back mechanism where the Total Allowable Catch (TAC) was modified using an adjustment factor when the CUSUM signals an out-of-control situation. In Chapter 7, a data limited fishery was tested to see if the MP could bring an out-of-control stock back to an in-control state using DI-CUSUM. Similarly in Chapter 8, the MP was applied in a data poor fishery to test whether it can sustain the initial state of the stock using SS-CUSUM.

Finally, **Chapter 9** summarizes the results, discusses the overall significance of the findings towards managing fish stocks that have limited information and suggests some directions for future work.

Chapter 2

Fisheries simulation

Simulations have been used in recent years to evaluate the performance of management strategies in fisheries because of their usefulness in considering a broad range of uncertainties in the biological characteristics of fish stocks (Ianelli et al., 2011; Szuwalski and Punt, 2012; Punt et al., 2013). For most chapters in this thesis, a simulation based framework was used for monitoring, assessment and management of virtual fish stocks. This chapter briefly explains the various life histories of the fish stocks modelled, the functions used for simulating fisheries and the stock indicators monitored for determining the state of the fish stock.

2.1 The conceptual simulation framework

The fisheries simulation framework in this thesis models both 'real' and 'perceived' systems (Kell et al., 2005*c*; Figure 2.1). The 'real' stock (the process of birth, growth, maturity and death) and fishery dynamics (the process of fishing and landing the catch) are represented as the '***operating model***'. The entire process in the real world is not known perfectly and hence stochastic elements were introduced for a variety of sources of variability. The 'perceived' system consists of an '***observation model***' where data are generated for fisheries monitoring and assessment. Due to measurement errors, there is an uncertainty in obtaining true observations from the real world fishery and hence variability was introduced while computing the required stock indicators. To evaluate management strategies, control measures were fed back into the 'real' system through a '***management procedure***', where the Total Allowable Catch (TAC) was regulated using Harvest Control Rules (HCRs).

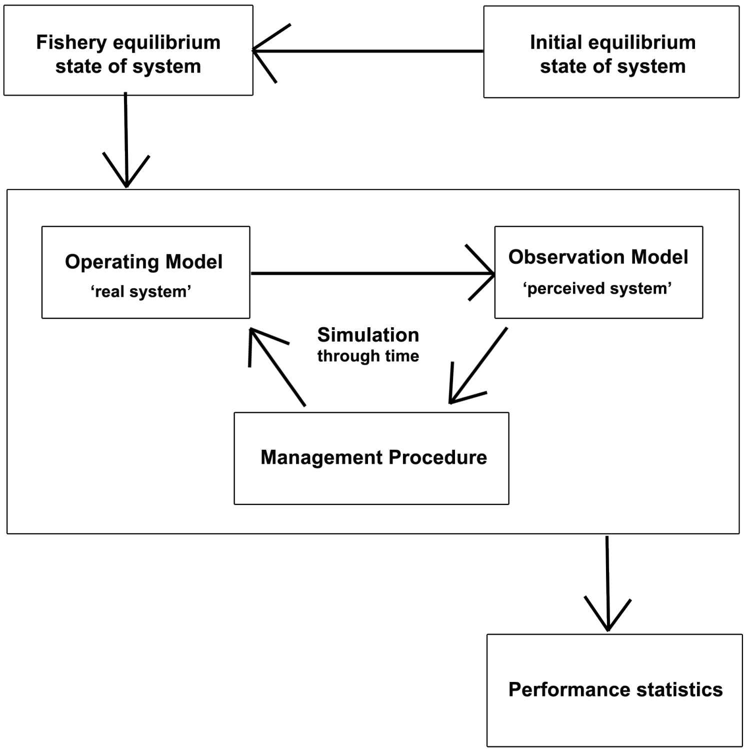


Figure 2.1: **Conceptual framework of fisheries simulation.** *Source: modified from Kell et al. (2005c).*

2.2 Life history species modelled

Three different fish species (virtual fish types) have been used in this thesis to test and evaluate the performance of CUSUM control charts. They are a cod-like species (Family: Gadidae) with a medium life span (LH1), a herring-like species (Family: Clupeidae) with a short life span (LH2) and a rock fish-like species (Family: Sebastidae) with long life span (LH3).

These fish stocks were chosen as they have three different life history characteristics i.e., they have high, medium and low resilience capacity or productivity. In general, short lived species are highly productive with large growth coefficients ($K > 0.3$). They are small in size, mature early and have greater fecundity because a large proportion of the energy resources are allocated to reproductive activities. In contrast, the long lived species have low resilience with small growth coefficients ($K < 0.15$), attain a larger size and have delayed maturation with low fecundity where most energy are spent for increasing individual fitness (Adams, 1980; King and McFarlane, 2003).

The base case model in this thesis uses a medium life span species (Cod like, Family: Gadidae) and the fishery was simulated using a medium mesh sized trawl net (Section 2.4.2). The life history traits and fishery parameters applied for the three fish species are presented in Table 2.1. These were determined from the ICES fish stock summary database (ICES, 2012*c*; 2011) and from unpublished data in FishBase (Froese and

Pauly, 2012).

Table 2.1: **Life history parameters of the fish stocks used:** Life history 1 represents a Cod-like species (Family: Gadidae) with medium life span. Life history 2 represents a Herring-like species (Family: Clupeidae) with short life span and life history 3 represents a Rockfish-like species (Family: Sebastidae) with a long life span.

Parameters	Life History 1 (LH1) Medium life span	Life History 2 (LH2) Short life span	Life History 3 (LH3) Long life span
von-Bertalanffy growth function			
Asymptotic length (L_∞)	129.10cm	30cm	49.2cm
Age at length 0 (a_0)	-0.82yr	-1.60yr	-2.19yr
Growth coefficient (K)	0.14	0.41	0.07
Natural Mortality (m)	0.21yr^{-1}	0.23yr^{-1}	0.15yr^{-1}
Plus group (a_{max})	10yr	6yr	30yr
Length-Weight Relationship			
Intercept (c)	0.0104	0.0060	0.0113
Slope (d)	3	3.090	3.08
Re-parameterised Beverton-Holt recruitment function			
Steepness (z)	0.75	0.90	0.60
Maturity parameters			
Age at 50% maturity ($M_{50\%}$)	2.5yr	1.8yr	13yr
Age at 95% maturity ($M_{95\%}$)	3yr	3yr	20yr
Selectivity parameters			
Age at 50% selectivity ($S_{50\%}$)	3yr	2.2yr	14yr
Age at 95% selectivity ($S_{95\%}$)	5yr	2.6yr	17yr

2.3 Equilibrium state of the system

2.3.1 The initial equilibrium

In an unexploited fish stock, the population achieves equilibrium when the rate of increase in stock biomass (by growth and reproduction) is compensated by the net decrease through natural mortality (by predation and death). To achieve this, first we have to estimate the starting numbers-at-age in the model for the initial year. This was generated based on the assumption that the age structure at equilibrium would be the result of natural mortality acting alone on average virgin levels of stock recruitment. Thus the relative population numbers (N_a^i) in each age class (a) in the initial year ($i = 0$) can be modelled as:

$$N_a^0 = \begin{cases} r^0 & \text{for} \quad a = 0, \\ N_{a-1}^0 e^{-(m)} & \text{for} \quad 1 \leq a \leq (a_{max} - 1), \\ N_{a_{max}-1}^0 e^{-(m)} / \left(1 - e^{-(m)}\right) & \text{for} \quad a = a_{max}, \end{cases} \tag{2.1}$$

where, m is the instantaneous rate of natural mortality and a_{max} is the maximum age modelled. The final component where $a = a_{max}$ is a plus group that combines ages a_{max} and all older ages. The model was initialized with a recruitment (r_0) of 1000×10^3 individuals.

Once the initial conditions are defined, the virgin biomass B_0 can be estimated by computing the cumulative biomass of all mature individuals in the stock. The population will grow over time following an exponential decay model (Section 2.4.1.1, Equation 2.3) and Beverton-Holt stock-recruitment relationship (Section 2.4.1.6) until the stock biomass stabilizes at an initial equilibrium state (Figure 2.2).

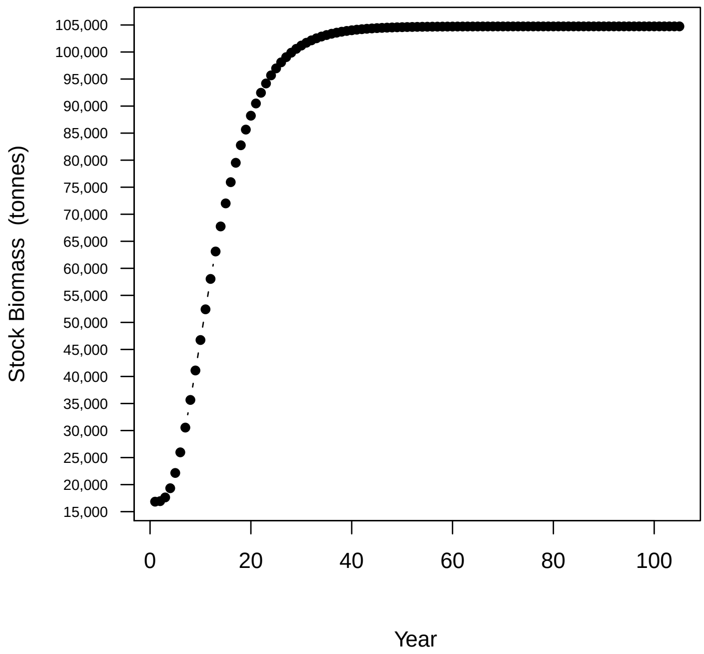
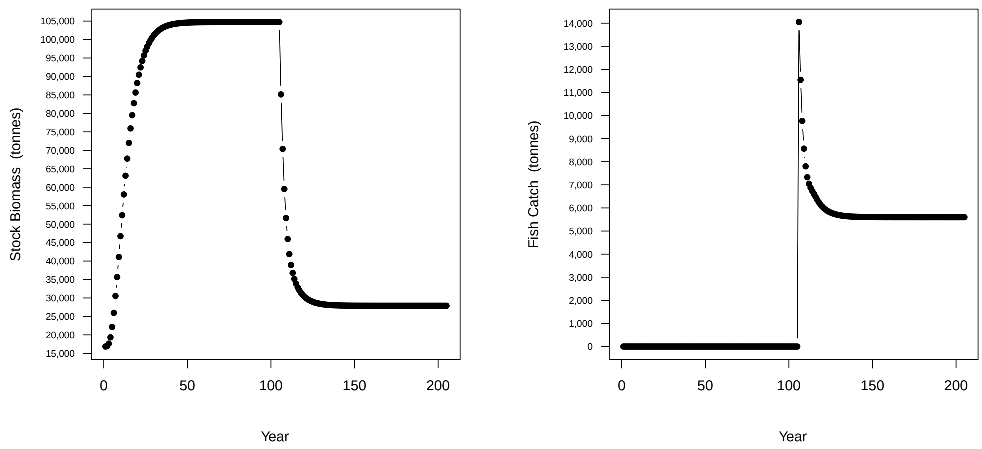


Figure 2.2: **The initial equilibrium state of fish stock:** The figure shows the initial equilibrium state of the base case species where the maximum age modelled was for 10 years.

2.3.2 The fishery equilibrium

When the stock achieves initial equilibrium (Section 2.3.1), a fixed initial fishing mortality (F_{int}) was applied to simulate the fishery dynamics deterministically. This means that no variability was introduced in the model while simulating the stock-recruitment relationship and applying fishing mortalities. For a given fixed level of F_{int}, the stock will become sustainable when there is a balance between the reduction (due to natural and fishing mortality) and increase (by reproduction and growth) in population biomass. Thus the biomass of the stock stabilizes (B_{eq}), a constant catch (C) is obtained and the state of the stock is said to be in fishery equilibrium (Figure 2.3).



(*a*) (*b*)

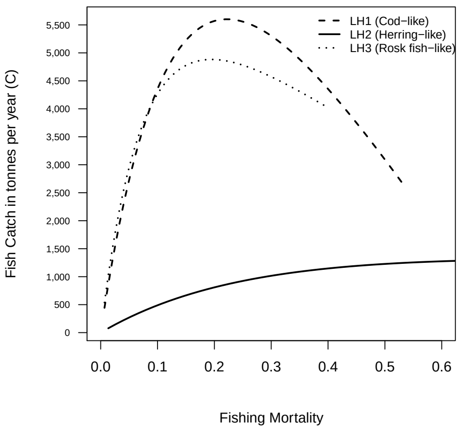
Figure 2.3: **The fishery equilibrium state of fish stock:** The figure shows **(a)** the biomass and **(b)** the catch obtained when the base case species (LH1, Cod-like) achieved the fishery equilibrium state. The model operated at a fishing mortality of $F_{int} = F_{MSY} = 0.227$ and simulated until the stock biomass stabilizes at a fishery equilibrium state where the net rate of growth in biomass equalled to the rate of mortality due to death, predation and fishing.

2.3.3 Computation of Maximum Sustainable Yield

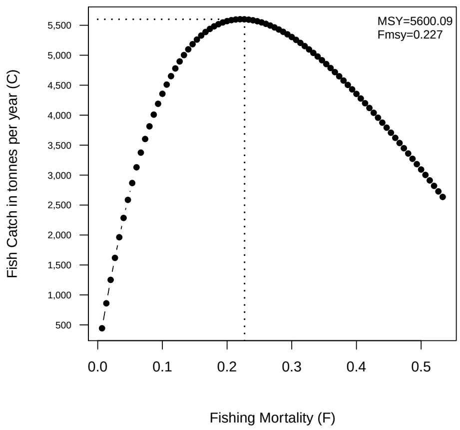
The procedure in section 2.3.2 was iterated for a range of fishing mortality i.e., from $F = 0.01$ with an increment of 0.01 until the observed catch (C) was maximised. The largest catch (C) that can be taken over the long-term without causing the population to collapse is termed as the Maximum Sustainable Yield (Jennings et al., 2001; MSY). The biomass (B) and fishing mortality (F) at MSY of the stock are designated as B_{MSY} and F_{MSY} respectively. The MSY obtained for the three different life history species (LH1, LH2 and LH3) are provided in Figure 2.4. The MSY curve of the fish stock becomes flatter if the productivity or compensation through stock-recruitment is strong (determined by a higher steepness parameter in the stock-recruitment relationship, see section 2.4.1.7) because there is reasonably little loss of yield when the fishing mortality is increased (Zhu et al., 2012; Figure 2.4a). Therefore, for species with different life history parameters, the MSY will be achieved at different fishing mortality rates (Figure 2.4bcd), with the highest F_{MSY} for species with stronger compensations (LH2).

2.4 The operating model

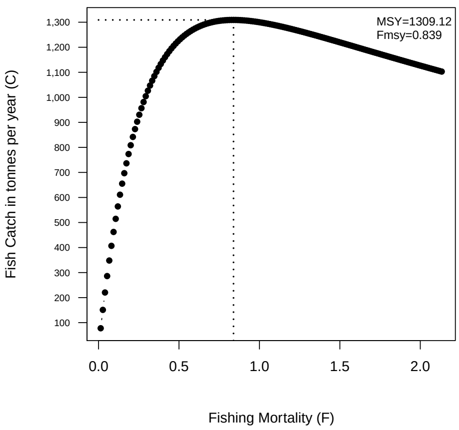
The operating model initiates from the state of fishery equilibrium (Section 2.3.2) and consists of two distinct phases. In the first phase, the model ran for 100 years with random variability in stock-recruitment (coefficient of variation (cv)= 0.6, log-normal distribution) and initial fishing mortality ($cv = 0.1$, normal distribution). The second phase of the operating model simulates the fishery dynamics using a fishing mortality



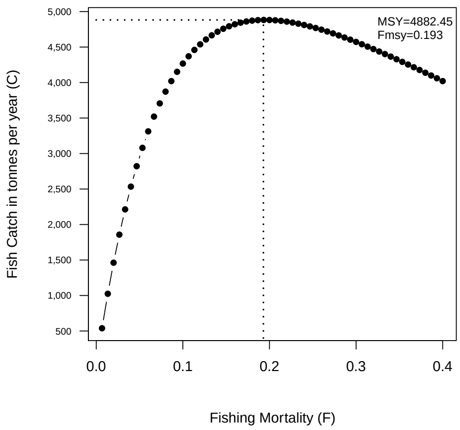
(a)All stocks



(b)LH1 (Base case, Cod-like, Family: Gadidae)



(c)LH2 (Herring-like, Family: Clupeidae)



(d)LH3 (Rock fish-like, Family: Sebastidae)

Figure 2.4: **The Maximum Sustainable Yield (MSY) obtained for different life history species:** **(a)** Shows the catch curve obtained for all species at fishery equilibrium. **(b), (c) & (d)** shows the catch curves obtained at fishery equilibrium for the three species with different life history parameters.

(F) that varied depending on the questions asked and are presented in each chapter.

2.4.1 Growth

2.4.1.1 Cohort dynamics: The exponential decay model

A 'cohort' is a batch of fish of the same age and belonging to the same stock. Each year, the number of survivors in the cohort decrease due to mortality (predation, death and fishing). According to the exponential decay model (Baranov, 1918), the numbers in each age class in each year depend on the numbers surviving from the preceding age class from the previous year. Hence the population numbers at age (N_a^i) for year 'i' is updated by:

$$N_a^i = \begin{cases} r^i & \text{for} \quad a = 0 \\ N_{a-1}^{i-1} e^{-(m+F_{a-1}^{i-1})} & \text{for} \quad 1 \leq a \leq (a_{max}-1) \\ N_{a-1}^{i-1} e^{-(m+F_{a-1}^{i-1})} + N_a^{i-1} e^{-(m+F_a^{i-1})} & \text{for} \quad a = a_{max} \end{cases} \tag{2.2}$$

However, note that the fishing mortality (F) is absent while simulating the initial equilibrium state of the fish stock. Hence the population numbers will be updated using only natural mortality (m) during this phase:

$$N_a^i = N_{a-1}^{i-1} e^{-(m)} \tag{2.3}$$

Figure 2.5 shows a family of exponential decay curves for different m-values. The higher the value of natural mortality (m), the faster the decrease in numbers and thus the lower the maximum age of survival. The effect will be similar if a fixed F is applied (when the stock is harvested through fishing) resulting in a combined total mortality of $m + F$ instead of the m acting alone.

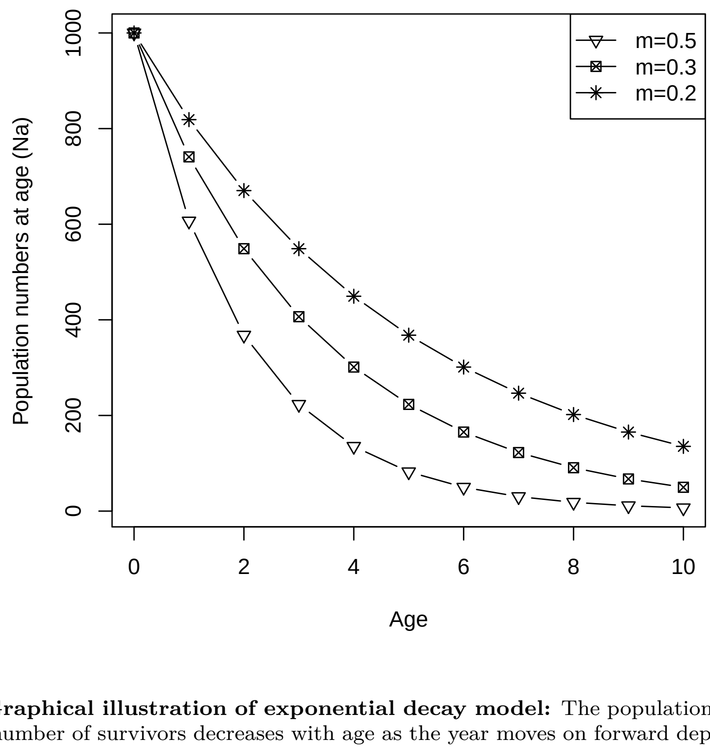


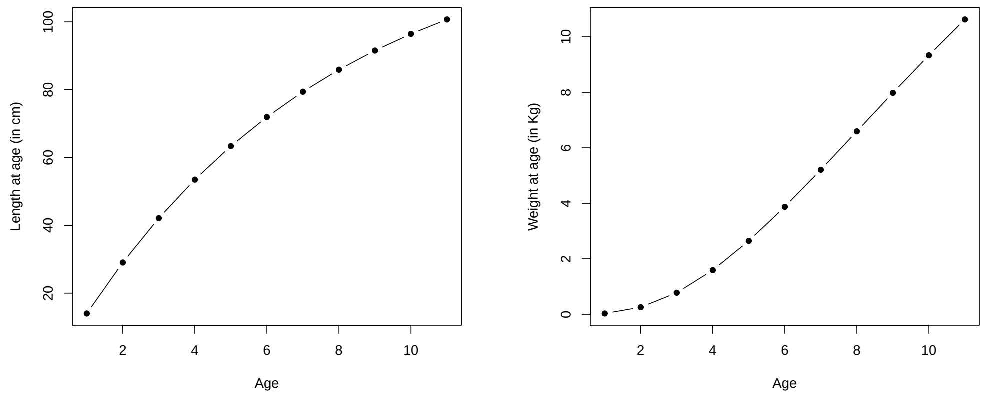
Figure 2.5: **Graphical illustration of exponential decay model:** The population numbers at age $a = 0$ is 1000 and the number of survivors decreases with age as the year moves on forward depending on the value of natural mortality applied to the stock.

2.4.1.2 The von Bertalanffy growth function

Bertalanffy (1934) developed a mathematical function for modelling the individual growth of fish in terms of its body size (length or weight) as a function of the age. This is known as the von Bertalanffy growth function (VBGF) and has been widely used in many complex models for describing the dynamics of fish populations (Sparre and Venema, 1999). In this study, the VBGF was used for determining the length and weight of cohorts in the stock.

1. Length at age 'a', (L_a) followed an isometric von Bertalanffy growth function (VBGF) of the form:
$$L_a = L_\infty [1 - \exp^{-K\ (a - a_0)}], \tag{2.4}$$
where, L_a is the length-at-age 'a', L_∞ is the asymptotic length, K is the growth coefficient and a_0 is the age when length is zero. The length-at-age of the base case species (Cod-like, LH1) is presented in Figure 2.6.

2. Weight at age 'a', (W_a) followed the length-weight relationship of the form:
$$W_a = c\,(L_a)\ ^d, \tag{2.5}$$
where, 'c' is the intercept, 'd' is the slope of the relationship. The weight-at-age of the species with increasing length is presented in Figure 2.6.



(a)Length of the fish (b)Weight of the fish

Figure 2.6: **Graphical illustration of the von Bertalanffy growth function (VBGF):** (a) length and (b) weight of the fish obtained at specific ages using the VBGF model. The parameters used are provided in Table 2.1.

2.4.1.3 Variability in length and weight

The results from the VBGF are deterministic (Section 2.4.1.2). This means all fish individuals with the same age in the stock (or cohort) will have the same length and weight. In real world, this does not occur due to individual variability and stochasticity (Le Cren, 1951). To obtain a realistic structure of length and weight distribution, variability was introduced using a coefficient of variation in key growth parameters of the VBGF model. Growth variability in length-at-age was introduced in the operating model by randomizing the growth coefficient (K) and asymptotic length (L_∞) parameters for each individual in the cohort in every consecutive year i.e., the growth varies within cohorts.

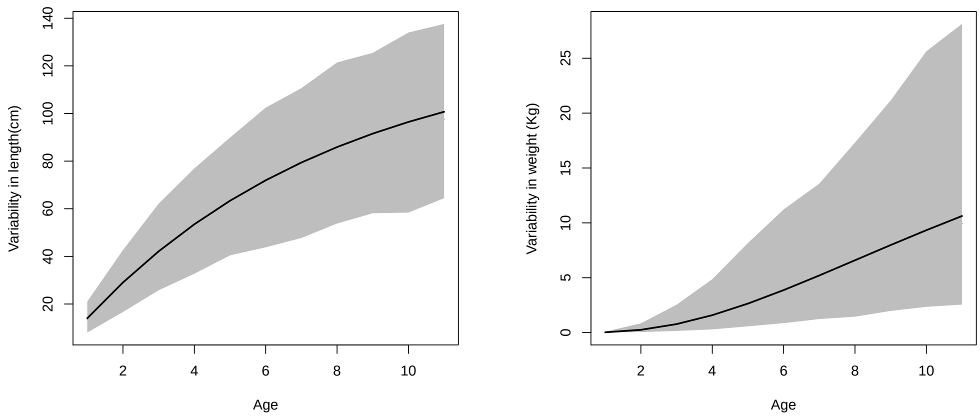
$$K_a^{i,g} \sim normal\ (mean = K, cv)\,, \tag{2.6}$$

$$L_{\infty a}^{\ i,g} \sim normal\ (mean = L_\infty, cv)\,, \tag{2.7}$$

For variability in weight-at-age, equation 2.5 was modified as:

$$W_a^{i,g} \sim lognormal\ \left(mean = c\,(L_a)^{\ d}, cv{=}0.2\right), \tag{2.8}$$

where, cv is the coefficient of variation of the distribution. Thus variability was introduced in the length and weight of each fish individual 'g' within each cohort 'a' in year 'i' using random values of $K_a^{i,g}$, $L_{\infty a}^{\ i,g}$ and $W_a^{i,g}$. An output obtained from 1000 years of the simulation is presented in Figure 2.7.



(a) (b)

Figure 2.7: **Variability in (a) length and (b) weight of the fish individuals:** The figure illustrates the variability introduced for length-at-age and weight-at-age of fish individuals in the stock (base case species). The gray shaded region indicates the 5^{th} and 95^{th} percentiles obtained for each age group of the stock during the simulated period. The thick black line indicates the deterministic values obtained from the VBGF in the operating model.

2.4.1.4 Maturity at age

For assessment purposes, maturity is assumed to be age dependent for many real world fish stocks (Köster et al., 2012). This means that the proportion of mature fish in a cohort increases with age and this is generally approximated using a logistic function. It is more realistic to assume that the time at which individual fish mature is not fixed and dependent on both the age and size (Stearns and Crandall, 1984). However for simplicity, the present study treated each cohort with a fixed proportion of fully matured individuals. Thus the maturity-at-age (M_a) in the operating model was modelled using the logistic function:

$$M_a = (a, a_{50\%}, a_{95\%}) = \left[1 + \exp\left(-\ln 19 \frac{a - a_{50\%}}{a_{95\%} - a_{50\%}}\right)\right]^{-1} \tag{2.9}$$

where, $a_{50\%}$ and $a_{95\%}$ are the age groups for which 50% and 95% of the cohort are mature. The maturity-at-age applied for the three life history species used in this study are presented in Figure 2.8.

2.4.1.5 Spawning Stock Biomass (SSB)

Spawning stock biomass (SSB) indicates the abundance of mature fish in the stock in terms of the total weight. The computation of SSB is important because the number of zero age group fishes in any particular year (recruits) will depend upon the SSB from the previous year. This can be computed by taking a cumulative sum of the weight of all mature fish individuals in each cohort of the stock. Thus the SSB for year 'i' (SSB^i) can be calculated as:

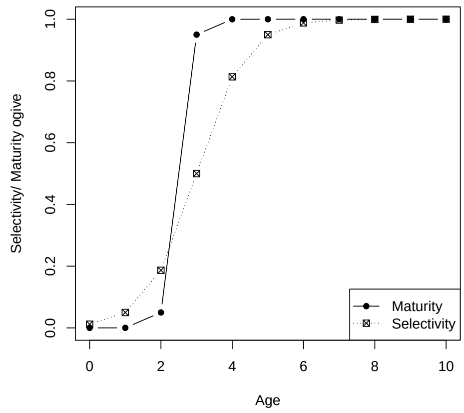
$$SSB^i = \Sigma_{a=0}^{a_{max}} (M_a \times N_a^i) \times W_a^i, \tag{2.10}$$

where, M_a, N_a and W_a are as previously defined (Section 2.4.1.4, 2.4.1.1 & 2.4.1.2).

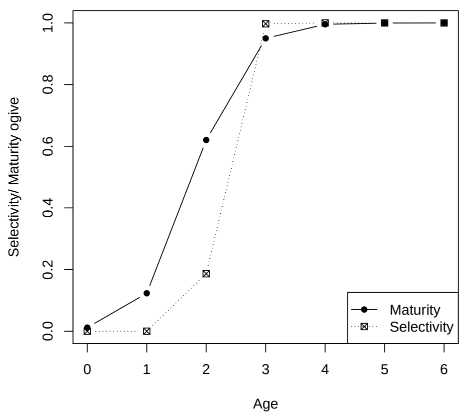
2.4.1.6 The Beverton-Holt stock recruitment function

The new recruits in year 'i' (r^i) followed a Beverton-Holt stock recruitment function (Beverton and Holt, 1957) and entered the stock at age $a = 0$. The Beverton-Holt model incorporates density-dependent effects by decreasing the survival rates of the larvae with increasing SSB and thus indicates the intra-cohort competition for critical resources. The Beverton-Holt stock recruitment function is given by:

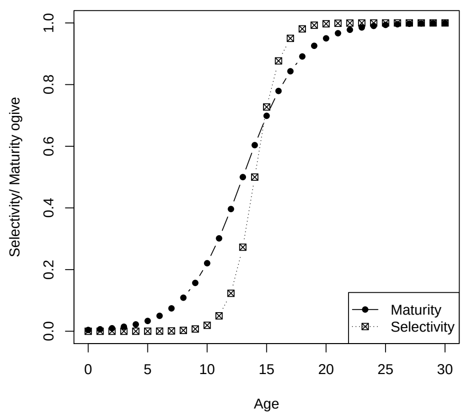
$$r^i \sim lognormal\left(mean = \left[\frac{A \times SSB^{i-1}}{B + SSB^{i-1}}\right], cv{=}0.6\right), \tag{2.11}$$



(*a*)LH1 (Base case, Family: Gadidae)



(*b*)LH2 (Family: Clupeidae)



(*c*)LH3 (Family: Sebastidae)

Figure 2.8: **Maturity and selectivity ogives applied to different life history species:** The figure shows the maturity-at-age and selectivity-at-age obtained for the **(a)** cod-like; **(b)** herring-like and **(c)** rock fish-like species using the logistic function given in Equation 2.9 and 2.14.

where, *cv* is the coefficient of variation used for introducing log normal errors between the relationship and observed data (Figure 2.9).

In equation 2.11, A is the maximum number of recruits produced (the asymptote) and B is the spawning stock required to produce, on average, recruitment equal to half maximum ($A/2$). If A is constant, then the number of recruits will be determined by B and captures the important behavioural aspects of the model (Figure 2.9a).

A stock is highly resilient if it can produce a higher number of recruits even with a low SSB. This can be visualized by the initial steepness of the Beverton-Holt curve (Figure 2.9b). If the initial steepness is very high, the asymptote (A) would be reached at a relatively small spawning stock sizes or B. In Figure 2.9b, the initial steepness increased with smaller values of B for a fixed constant of $A = 10,000$. Thus the steepness of the curve gives an indication of the resilience capacity of the species. By using different constants of A and B, the productivity of various life history species can be modelled.

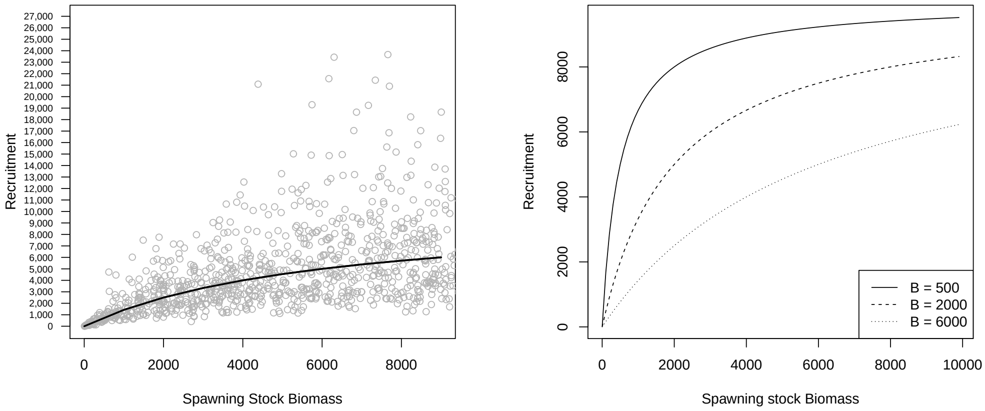


Figure 2.9: **Graphical illustration of the Beverton-Holt stock recruitment function: (a)** With a lognormal variation of $cv = 0.6$ ($A = 10,000$, $B = 6000$). The gray points are the recruits obtained for the base case fish species (LH1,Cod-like). **(b)** With no lognormal variation i.e., $cv = 0$. The maximum number of recruits or asymptote was fixed at a constant value of $A = 10,000$ while B is the average SSB required to produce $A/2$ (Equation 2.11).

2.4.1.7 Re-parameterized Beverton-Holt stock recruitment model

Mace and Doonan (1988) provided a biologically meaningful re-parametrization of the Beverton-Holt stock recruitment function in terms of steepness of the stock-recruitment curve (z), initial recruitment (r^0) and virgin biomass (B_0). This has the advantage of modelling recruitment with a single parameter i.e., steepness (z) instead of the two parameters i.e., A and B in the standard function (Equation 2.11).

Thus, if an un-fished or virgin population is assumed to be in equilibrium (Section 2.3.1), the parameters in equation 2.11 i.e., A and B can be replaced by:

$$A = \frac{4zr^0}{5z-1}\ ,\ B = \frac{B_0\,(1-z)}{5z-1} \tag{2.12}$$

The steepness parameter z is defined as the deterministic number of recruits that occurs at 20% of the virgin mature biomass level. By adjusting the steepness parameter, the resilience capacity of the fish stock can be altered to simulate real world fish stocks (Figure 2.10).

By definition, z can only have values between 0.2 and 1 (Michielsens and McAllister, 2004). If $z = 1$, recruitment is independent of biomass and if $z = 0.2$, then expected recruitment is proportional to biomass. Levels of steepness below 0.5 are not normally considered (Francis, 1993) because the population may not persist given the recruitment fluctuations observed in real world (He et al., 2006). The z values used for the three life history stocks in this study are provided in Table 2.1.

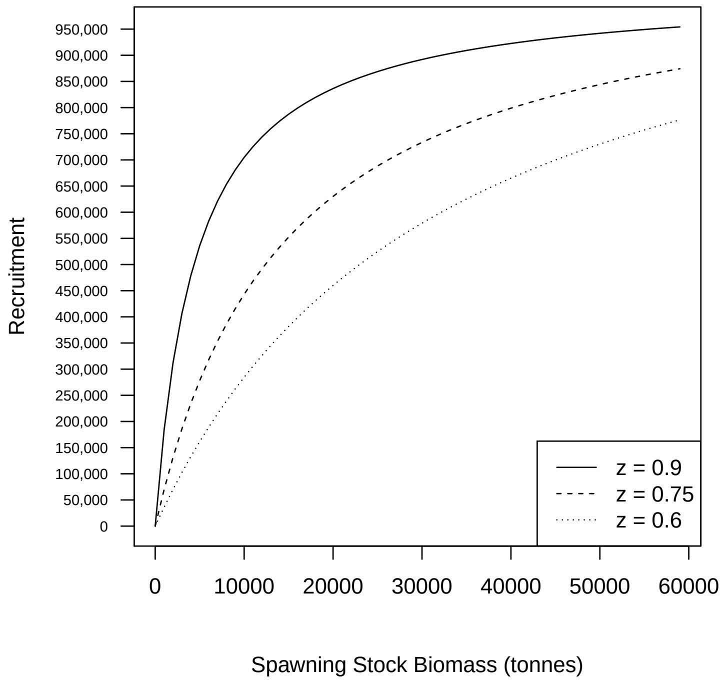


Figure 2.10: **Illustration of re-parametrized Beverton-Holt stock recruitment:** The steepness parameters used for the three life history species in this study were $z_{LH1} = 0.75$, $z_{LH2} = 0.9$ and $z_{LH3} = 0.6$

2.4.1.8 Autocorrelated stock-recruitment

It is crucial to understand to what extent recruitment depends on the underlying abundance of SSB because this relationship will determine the harvest sustainability for varying levels of fishing mortality (Sparholt, 1996). Survival of larvae is highly influenced by many environmental factors such as the temperature, salinity, current speed and direction resulting in considerable variation in the number of recruits, particularly when the stock biomass is very low (Brander, 2005). Previous research has shown that fish recruitment is significantly correlated with climatic variables (e.g., Sea Surface Temperature, Northern Hemisphere Temperature anomaly) and these time series are also often autocorrelated (Brunel and Boucher, 2007). Thus the positive autocorrelation observed in fish recruitment are due to persistent changes in environmental conditions. The range of autocorrelation for gadoid stocks (Family: Gadidae) has been reported to be between $\rho = -0.40$ to $\rho = +0.77$ (Fogarty et al., 2001). The negative autocorrelation reflects interaction among adjacent year classes (Fogarty et al., 2001) and this is already addressed in the model for stock-recruitment relationship (Section 2.4.1.6).

For autocorrelated recruitment, the Beverton-Holt stock-recruitment relationship was modified by an exponential multiplier (Kell et al., 2005*b*) i.e., $\exp(v)$:

$$r^i \sim lognormal\left(mean = \left[\frac{A \times SSB^{i-1}}{B + SSB^{i-1}}\right] \times \exp(v), \, cv{=}0.6\right), \tag{2.13}$$

$v = \varepsilon^i - 0.5\sigma_R^2$,

$\varepsilon^i = \rho\varepsilon^{i-1} + \eta^i$,

$\eta^i \sim normal\,(0, [1-\rho^2]\sigma_R^2)$,

Where, ρ is the coefficient of autocorrelation in the recruitment deviates (ε) and σ_R^2 is the recruitment variance. An illustration of the autocorrelation in stock recruitment data over 100 years is presented in Figure 2.11. The graph shows that the recruitment obtained in each year is more close to the numbers that occurred in the previous year when the coefficient of autocorrelation was increased from $\rho = 0.5$ (Figure 2.11a) to $\rho = 0.8$ (Figure 2.11b). This will have potential implications while modelling the stock-recruitment relationship. For example, a low stock-recruitment will be sustained for a few more years after the recovery of stock from its depleted state of biomass.

2.4.2 Fishery

2.4.2.1 Selectivity at age

Selectivity is generally understood as the capacity of a fishing method or gear to capture certain fractions or sections of the fish population based on their species, age, size or behaviour (FAO, 1984). However for simplicity, the present study considered gear selectivity only in the sense of mesh selectivity and operational method of the gear. Hence the fish become vulnerable to fishing depending upon the mesh size and type of fishing (trawl or gill net). Selectivity can be computed using an age dependent factor where the very young fish may escape if the mesh size of the fishing gear is too large. Thus the fishing mortality for different age groups in the stock can be modelled using a multiplier of selectivity-at-age (S_a, see Equation 2.16).

Trawl net

The selectivity of a trawl net depends on its mesh size and generally follows the logistic function as in equation 2.14 where the probability of capturing fish increases with higher age groups giving a ‘sigmoid’ shape:

$$S_a = (a, a_{50\%}, a_{95\%}) = \left[1 + \exp\left(-\ln 19 \frac{a - a_{50\%}}{a_{95\%} - a_{50\%}}\right)\right]^{-1} \tag{2.14}$$

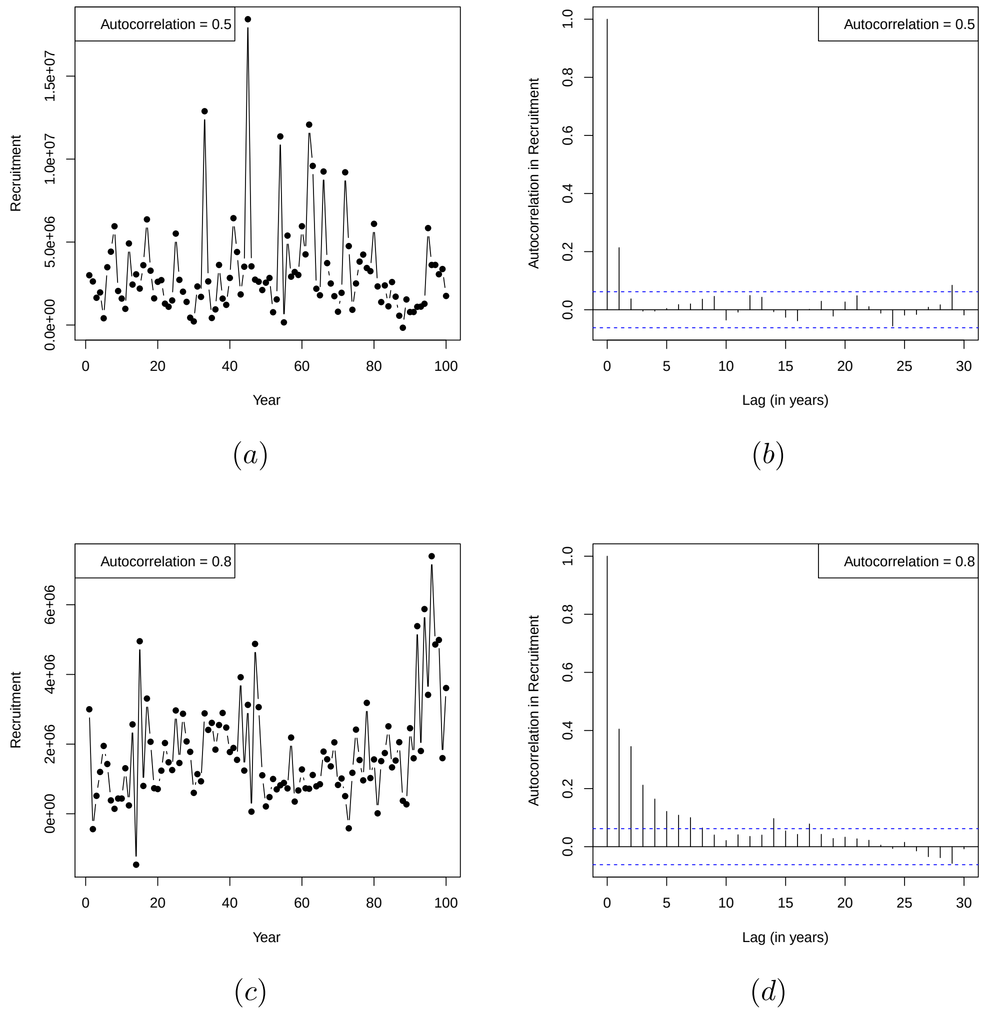


Figure 2.11: **Illustration of autocorrelated stock-recruitment:** A lognormal variation of $cv = 0$ and recruitment variance $\sigma_R^2 = 0.8$ was used for simulating the data. **(a) & (c)** Shows recruitment to the stock over 100 years with an autocorrelation coefficient of $\rho = 0.5$ and $\rho = 0.8$ respectively **(b) & (d)** Indicate the autocorrelation obtained with yearly lags for (a) and (c) respectively. The dotted lines indicate the 95% confidence interval of zero auto-correlation.

The $S_{50\%}$ and $S_{95\%}$ parameters indicate the age group for which 50% and 95% of the cohort is vulnerable to fishing. Selectivity parameters for the three life history species used in this study are given in Table 2.1 and their selectivity-at-age is graphically represented in Figure 2.8. The base case model used a medium mesh size trawl net with $S_{50\%} = 3$, $S_{95\%} = 5$.

The base case model was also explored for scenarios when the mesh size is too small or too large. The selectivity parameters for small mesh trawl net were $S_{50\%} = 2$, $S_{95\%} = 3$ and for the large mesh trawl net were $S_{50\%} = 6$, $S_{95\%} = 7$ (Figure 2.12).

Gill net

In contrast to trawling, gill netting is a passive fishing method where the fish swims

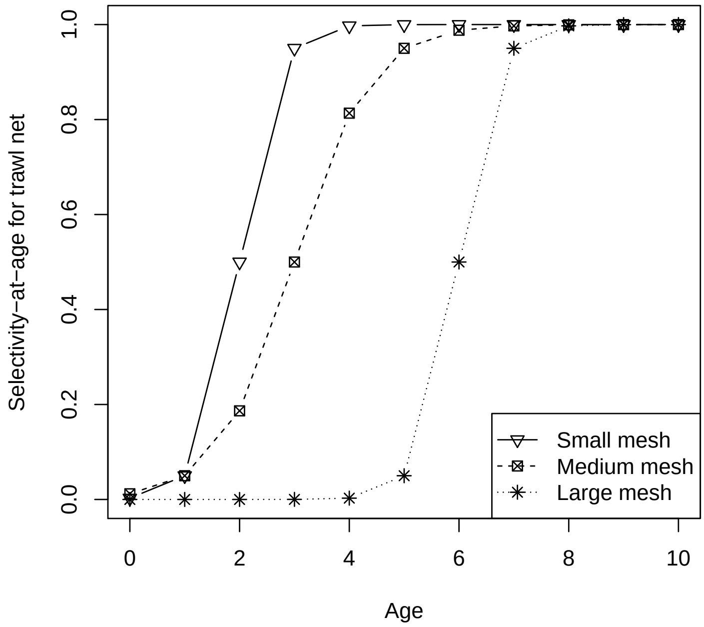


Figure 2.12: **Selectivity ogives applied to different types of trawl nets:** Indicating the selectivity-at-age obtained for trawl nets with small, medium and large mesh size when a fishery of the base case species (LH1,Cod-like) was simulated.

into the net and is wedged, gilled or tangled. Gill nets have a relatively high degree of size specific selectivity where fishes of only certain age groups are caught. Hence, the selectivity-at-age follows a double-normal function where the vulnerability of capture increases up to a certain age and then decreases giving a dome shape (Candy, 2011).

$$S_a = \begin{cases} 2^{-[(a-\lambda)/\sigma_L]^2} & \text{for} \quad a_0 < a \leq \lambda, \\ 2^{-[(a-\lambda)/\sigma_U]^2} & \text{for} \quad a > \lambda, \\ 0 & \text{for} \quad a \leq a_0, \end{cases} \tag{2.15}$$

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, respectively.

The fisheries simulations in this study used a gill net with medium mesh size. The parameters a_0, λ, σ_L and σ_U were set to 0, 5, 2 and 4 respectively (Figure 2.13).

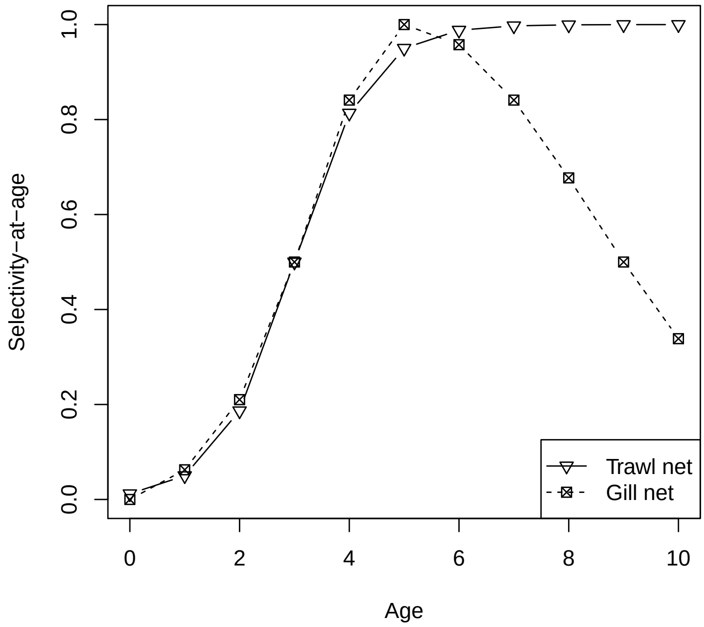


Figure 2.13: **Comparison of selectivity ogives used for trawl net and gill net:** Indicates the selectivity-at-age obtained for trawl nets and gill nets with the base case species (LH1,Cod-like). A logistic function was used for simulating the trawl net fishery (Sigmoid shape selectivity) while a double-normal function was used for the gill net fishery (Dome shape selectivity).

2.4.2.2 Fishing mortality at age

As mentioned previously (Section 2.4.2.1), each age group has a differential vulnerability to fishing through selectivity of the gear. Hence there is age dependent fishing mortalities within the stock. However, F can not be fixed in the real world due to fluctuations in the behaviour of the fishers and errors while implementing management strategies. Therefore, some noise was introduced using a coefficient of variation from the normal distribution. The fishing mortality at age (F_a^i) applied to the stock for year 'i' was calculated as:

$$F_a^i = max\left[0, \sim normal\left(mean = F^i, cv = 0.1\right)\right] \times S_a \tag{2.16}$$

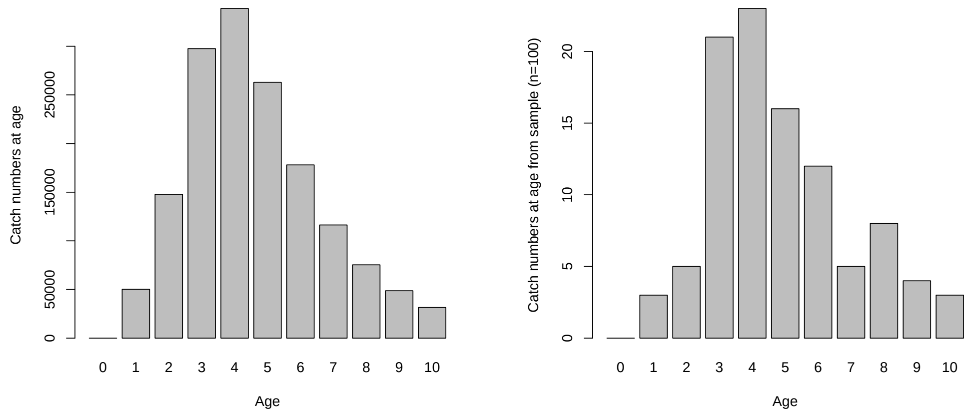
Where, cv is the coefficient of variation of the distribution.

2.4.2.3 Baranov's catch equation

The total fisheries catch (C) was computed by the cumulative sum of catch numbers obtained for each age group in the stock. The catch numbers at age (C_a^i) can be computed using Baranov's catch equation (Baranov, 1918). This is a fundamental equation commonly used in fish population models and assumes that fishing and natural mortalities (m and F) are constant over both age and time (Xiao, 2005). The catch numbers at age were modelled as,

$$C_a^i = N_a^i \times \frac{F_a^i}{F_a^i + m} \times \left[1 - \exp^{-(F_a^i + m)}\right] \tag{2.17}$$

Where N_a^i is the population numbers at age 'a' for year 'i' and 'm' is the natural mortality. The catch numbers at age obtained for the base case species (Cod-like, LH1) at fishery equilibrium of $F_{MSY} = 0.227$ is presented in Figure 2.14.



(a) (b)

Figure 2.14: **Catch numbers-at-age obtained using the Baranov's catch equation: (a)** For the base case species when simulated with a fishing mortality equivalent to the Maximum Sustainable Yield (F_{MSY}). **(b)** Shows the catch numbers-at-age obtained from the random sample of the fisheries catch (Sample size $n = 100$).

2.5 The observation model

The observation model consists of stock indicators that are commonly available during data limited situations. All indicators except the estimated recruitment (R^i) were computed from a random sample (without replacement) of the fisheries catch (Section 2.5.2).

2.5.1 Recruitment indicator

The term 'recruitment indicator' in this thesis represents an estimated value of the abundance of zero age group individuals in the stock. For the assessment of many fish stocks, scientific trawl research surveys are conducted with the primary purpose of providing abundance through recruitment indices (Rochet et al., 2005; Wilderbuer et al., 2013; Fujino et al., 2013; eggs or juveniles). The observations are extremely variable when surveys are not standardized both in temporal and spatial scales. It is assumed, for the purpose of this study, that similar estimates were available from fishery independent data and the variability was introduced using a *cv* from the log-normal distribution. Thus, the observed recruitment indicator (R^i) was approximated by:

$$R^i \sim lognormal \left(mean = r^i, cv \right) \tag{2.18}$$

where *cv* is the coefficient of variation of the log-normal distribution.

2.5.2 Catch-based indicators

Four categories of catch-based indicators were computed using a random sample (s^i) of the fisheries catch (C) from the operating model (Table 2.2). They are the (i) mean indicators (MI); (ii) age based indicators (ABI); (iii) mature fish indicators (MFI) and (iv) large fish indicators (LFI).

Random sampling of the fisheries catch

To simulate a random sample (s^i) of the fisheries catch, the *sample* function in R (R Development Core Team, 2012) was used to draw 'n' individuals without replacement from the set of all individuals in the total catch of the 'i^{th}' year. An illustration is provided in Figure 2.14 where a catch sample of size $n = 100$ is measured from a stock which is in equilibrium at F_{MSY}.

2.5.2.1 Mean indicators (MI)

Mean age (MA), mean length (ML) and mean weight (MW) are collectively termed as the 'mean indicators' in this study (Table 2.2). They are easy to measure and are commonly used for the purpose of monitoring, assessment and management of real world fish stocks (Smith, 1995; Armstrong et al., 2004; Guevara-Carrasco and Lleonart, 2008). The mean age (MA) was computed by taking the average numbers-at-age observations of all individuals in the fish sample. Similarly, the mean length (ML) was computed by taking the average length-at-age of all individuals in the fish sample. The individual length observations were drawn from a log-normal distribution with mean L_a of the cohort and coefficient of variation of 0.1. For obtaining the mean weight (MW), first the individual length observations were converted to weight using equation 2.5 and then their average was computed.

Table 2.2: **Formulas for the catch-based indicators used in this study:** The table provide equations for computing catch-based indicators from a random sample of the fisheries catch. Age based indicators are calculated for each age group in the catch sample. Mature fish individuals are those age groups for which at least 95% of the cohort is fully matured. Large fish individuals are those age groups for which at least 95% of the cohort is vulnerable to fishing. The sample size is 'n' and the year for which the indicators computed is denoted as 'i'.

Indicator	Symbol	Formula
Category 1: Mean Indicators (MI)		
Mean age	MA	$\frac{\sum_{j=1}^{j=n} a^j}{\sum_{a=0}^{a_{max}} CN_a}$
Mean weight	MW	$\frac{\sum_{j=1}^{j=n} W_a^j}{\sum_{a=0}^{a_{max}} CW_a}$
Mean length	ML	$\frac{\sum_{j=1}^{j=n} L_a^j}{\sum_{a=0}^{a_{max}} CN_a}$
Category 2: Age based indicators (ABI)		
Catch numbers at age 'a'	CN_a	From operating model
Catch weight at age 'a'	CW_a	From operating model
Positive proportion of catch numbers at age 'a'	PN_a	$\frac{\sum_{a}^{a_{max}} CN_a}{\sum_{a=0}^{a_{max}} CN_a}$
Positive proportion of catch weight at age 'a'	PW_a	$\frac{\sum_{a}^{a_{max}} CW_a}{\sum_{a=0}^{a_{max}} CW_a}$
Positive proportion of average catch weight at age 'a'	AW_a	$\frac{\sum_{a}^{a_{max}} CW_a}{\sum_{a}^{a_{max}} CN_a}$
Category 3: Mature fish indicators (MFI)		
Proportion of mature fish catch numbers	O_n	$\frac{\sum_{j=1}^{j=n} I(a^j > [M_{95\%}])}{\sum_{a=0}^{a_{max}} CN_a}$
Proportion of mature fish catch weights	O_w	$\frac{\sum_{j=1}^{j=n} W_a^j \times I(a^j > [M_{95\%}])}{\sum_{a=0}^{a_{max}} CW_a}$
Category 4: Large fish indicators (LFI)		
Proportion of large fish catch numbers	P_n	$\frac{\sum_{j=1}^{j=n} I(a^j > [S_{95\%}])}{\sum_{a=0}^{a_{max}} CN_a}$
Proportion of large fish catch weights	P_w	$\frac{\sum_{j=1}^{j=n} W_a^j \times I(a^j > [S_{95\%}])}{\sum_{a=0}^{a_{max}} CW_a}$

j : Individual fish in the random sample of landed catch

W_a : Weight of the fish at age 'a'

L_a : Length of the fish at age 'a'

I : Indicator function (If the condition satisfies, this will return a value of 1 otherwise 0)

2.5.2.2 Age based indicators (ABI)

Five types of ABIs were calculated for each age group in the fish sample (Table 2.2). They are catch numbers at age (CN_a), catch weight at age (CW_a), positive proportion of catch numbers at age (PN_a), positive proportion of catch weight at age (PW_a) and positive proportion of average catch weight at age (AW_a). The total number of indicators for any particular stock increases with the species longevity since they are age dependent. In a data limited or poor situation, it is more likely easier to obtain length based observations rather than those based on age. However for simplicity, ABIs were used because the overall interest of the study was to determine how useful the size based indicators are when they are used in a CUSUM based management framework.

2.5.2.3 Mature fish indicators (MFI)

Previous research has shown that age and length indicators based on mature fish individuals in the stock are promising for determining the changes in population abundances (Olsen et al., 2004; Froese, 2004; Fairweather et al., 2006; Vainikka et al., 2009). This is because such indicators will have more potential in predicting the changes in spawning stock biomass (SSB) with the least time lag response (in years). There is evidence that the maturity ogive of heavily exploited fish populations may shift to an earlier age and indicating that the stock is being severely depleted or may collapsed (Olsen et al., 2005). Research has also shown that the early maturation of fish stocks could occur due to shifts in environmental regimes and that the effect is not only dependent on the fishing pressure applied (Domínguez-Petit et al., 2008). Nevertheless, this means that a yearly assessment is required to update the maturity profile of fish populations in the stock. If such parameters are available, age or length based maturity indicators can be computed to detect shifts in SSB of the fish stock. In the present study, the fully matured fish individuals were classified as those belonging to age groups which are more than 95% mature ($M_{95\%}$) as specified in the operating model. If $M_{95}\%$ occurs at age 3, then all individuals in the sample from the 4^{th} age group onwards are considered as fully matured fish. Two types of mature fish indicators (MFI) were calculated. These are the proportion of mature fish by number and the proportion of mature fish by weight (Table 2.2). More details on the relevance and usage of such proportional catch indicators are discussed in Chapter 4.

2.5.2.4 Large fish indicators (LFI)

Indicators based on size metrics and their importance have 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). Fishing is size selective and overfishing changes the length frequency of populations in the catch by removing the older age classes of the stock (Froese, 2004; Shin et al., 2005; Perry et al., 2010). More recently, the large fish indicator (LFI) was suggested 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). Though LFI is an indicator calculated from all species in the catch, the principle could work even at single species level. In this study, the large fish individuals were classified as those age groups that are vulnerable to fishing for more than 95% (S_{95}%) of the population. If S_{95}% occurs at age 5, all individuals in the sample from the 6^{th} age group onwards are considered as large fish. Three types of large fish indicators (LFI) were calculated. These are the proportion of large fish by number, proportion of large fish by weight and the average weight of large fish in the sample (Table 2.2).

2.6 The management procedure

A variety of control measures are used to achieve the objectives in fisheries management e.g. by setting limits on the fishing effort (number of fleets, duration of fishing) or harvested biomass (landings, bycatch, discards). However, it is important to evaluate the risks and benefits associated with the choice of management measure e.g., choosing a Total Allowable Catch (TAC) to restrict the annual catch through commercial landings. This is because the control measures are advised based on stock assessments that are likely subject to considerable uncertainty if the indices used are noisy due to observation errors or inherent variation within the population. Hence a “management procedure” in this context means a rule for choosing a control measure and testing the consequences of following this rule regularly over time (Cooke, 1999). In particular, a management procedure is useful for quantifying the risks associated with a management strategy by considering the potential sources of variation in the observed data.

In the present study, the commercial landings from a fishery was regulated using TAC through harvest control rules (HCRs). However, the HCRs were applied only in certain scenarios where a management was required to test the hypothesis proposed in the chapter (see Chapter 4, 6, 7 and 8). The TAC for year ‘i’ was computed such that,

$$TAC^{i} = TAC^{i-1} + \left[TAC^{i-1} \times \left(\hat{f}\right)\right], \tag{2.19}$$

where $\hat{f}$ is a multiplier that may increase, decrease or sustain the TAC advised in the previous year. Since a perfect implementation is not possible in the real world, random noise errors were introduced using a cv of 0.1 from the normal distribution.

$$TAC^{i} = max\left[0, \sim normal\left(\text{mean} = TAC^{i}, cv = 0.1\right)\right] \tag{2.20}$$

2.7 Summary

- The fisheries simulation framework consists of three components: (i) an operating model characterizing the 'real world'; (ii) an observation model representing the 'perceived world' and (iii) a management procedure where regulations were implemented to control the fisheries.

- The operating model simulated the survival, growth, maturity, reproduction, mortality and fishery of an age structured non-spatial virtual fish stock.

- The various functions used for simulating the real world process were (i) *exponential decay model* for survival; (iii) *von Bertalanffy growth function* for growth; (iii) a *logistic function* for determining the maturity (iv) *Beverton-Holt stock recruitment* function for reproduction; (iv) a *logistic or double-normal function* for the fishing mortality and (v) *Baranov's catch equation* for the total catch.

- The observation model measured various indicators that are likely possible to obtain when limited information are available for fish stocks in real world.

- The various stock indicators observed in the perceived world were (i) estimated recruitment of zero age groups (R); (ii) mean indicators (MI); (iii) age based indicators (ABI); (iv) mature fish indicators (MFI); and (v) large fish indicators (LFI).

Chapter 3

Cumulative Sum control chart (CUSUM)

3.1 Introduction

Cumulative Sum (CUSUM) control chart is one of the process monitoring techniques in Statistical Process Control (SPC) theory. The methods based on SPC are useful for determining whether the current state of the stock is in an out-of-control situation i.e., whether a response is required to achieve the objectives of fisheries management. The most simple and widely applied SPC technique is the Shewhart control chart (Section 1.4.5, Figure 1.7). These charts are particularly efficient in detecting immediate and transient shifts in the indicator that may occur due to a special cause variation (Section 1.4.4). However, the Shewhart charts are inefficient for detecting shifts that are gradual and persistent (Section 1.4.5).

There have been numerous attempts to patch this deficiency by adding "supplementary runs rules" (Hawkins and Olwell, 1998). For example, an out-of-control situation is detected even if all indicator observations remain within the control limits but if two out of three successive observations are more than two standard errors away from the control mean. Such attempts were generally less successful than using methods that are inherently better in accumulating information from successive observations. The CUSUM control chart was developed based on such ideas where, instead of the indicator observations, their cumulative deviation from the control mean are used for detecting out-of-control situations (Page, 1954). Hence CUSUM have a memory of historical observations and are efficient for detecting special cause variability due to persistent shifts. Detection of indicator shifts that are persistent are more important than those which are transient because the former require a corrective action to bring the state of stock back to the in-control situation as defined by the management objectives.

3.2 Computation of CUSUM

The statistical model underlying CUSUM assumes that the indicator observations are independent of each other and follow a normal distribution. Essentially this means that the CUSUM is designed to detect the shift in mean of the indicator distribution rather than the absolute shift in the time series. Hence to use CUSUM control charts, the user must know (i) the true mean (μ) and (ii) the standard deviation (σ) of the indicator distribution that may characterizes the in-control state of the fish stock. However, these parameters are often not known perfectly and are estimated from historical data. In the following paragraphs, I illustrate how the cumulative sum technique was used to design a CUSUM control chart.

As stated previously, the underlying mechanism of CUSUM control charts is the accumulation of historical information. This is done by computing a cumulative sum of the indicator deviations from the estimated control mean ($\overline{X}$). If X_i is the indicator observation in the i^{th} year and 'n' is the number of observations in the time series, then the cumulative sum 'θ_n' is computed as:

$$\theta_n = \sum_{i=1}^{n} \left(X_i - \overline{X}\right) \tag{3.1}$$

The indicator deviations $\left(X_i - \overline{X}\right)$ will be zero if all observations are equal to the control mean ($\overline{X}$). This computation is illustrated in Table 3.1 (Column 6) using the example of Irish Sea Cod recruitment data (ICES, 2012*c*), where the control mean was set equivalent to an arbitrary value of $\overline{X} = 6000$. Though the observations between 1968-1990 were centred around $\overline{X}$ in the Shewhart chart (Figure 3.1a), the cumulative sum metrics shows that most of them were below the control mean (Figure 3.1b).

The 'θ_n' can be defined in two functionally equivalent ways. The first method (Method A) is by computing them in the original scale of the problem, which I have already demonstrated (Equation 3.1). The second method (Method B) involves an additional step where the indicator observations are first standardized to have zero mean and unit standard deviation before computing the cumulative sum metrics. This can be expressed as:

$$Z_i = (X_i - \overline{X})/\overline{\sigma} \tag{3.2}$$

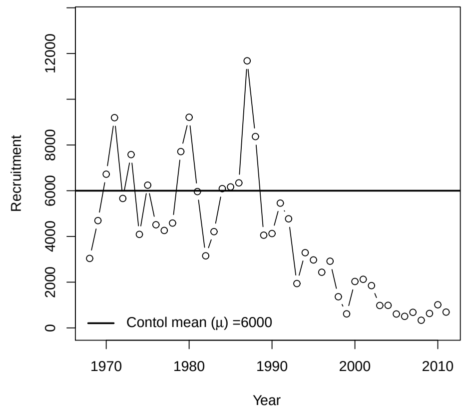
$$\theta_n = \sum_{i=1}^{n} Z_i, \tag{3.3}$$

Where $\overline{\sigma}$ is the estimated standard deviation of the in-control indicator distribution and Z_i is the standardized observation obtained for the 'i^{th}' year. The computation is illustrated in Table 3.1 (Column 7) and graphically shown in Figure (Figure 3.1c).

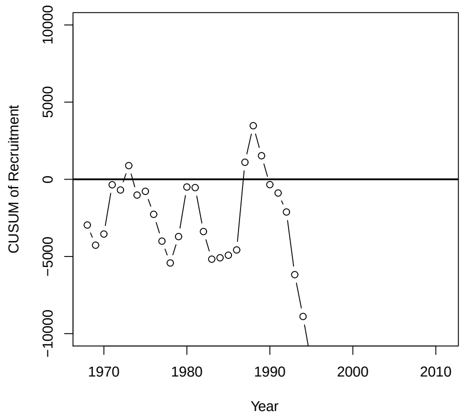
Table 3.1: **Computation of CUSUM using recruitment indicator of Irish Sea Cod (ICES, 2012*c*):**

	Year	Indicator			Method A	Method B	Upper CUSUM	Lower CUSUM	DI-CUSUM Signal
n	i	X_i	$\left(X_i - \overline{X}\right)$	$\frac{\left(X_i - \overline{X}\right)}{\overline{\sigma}}$	θ_i	θ_i	θ_i^+	θ_i^-	$h = \pm 0.5$
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
1	1968	3038	-2962	-0.98	-2962	-0.98	0.00	-0.28	NO
2	1969	4693	-1307	-0.43	-4269	-1.42	0.00	-0.02	NO
3	1970	6722	722	0.24	-3547	-1.18	0.00	0.00	NO
4	1971	9194	3194	1.06	-353	-0.12	0.36	0.00	NO
5	1972	5661	-339	-0.11	-692	-0.23	0.00	0.00	NO
6	1973	7580	1580	0.53	888	0.30	0.00	0.00	NO
7	1974	4090	-1910	-0.63	-1022	-0.34	0.00	0.00	NO
8	1975	6242	242	0.08	-780	-0.26	0.00	0.00	NO
9	1976	4511	-1489	-0.5	-2269	-0.75	0.00	0.00	NO
10	1977	4262	-1738	-0.58	-4007	-1.33	0.00	0.00	NO
11	1978	4585	-1415	-0.47	-5422	-1.80	0.00	0.00	NO
12	1979	7711	1711	0.57	-3711	-1.23	0.00	0.00	NO
13	1980	9212	3212	1.07	-499	-0.17	0.37	0.00	NO
14	1981	5962	-38	-0.01	-537	-0.18	0.00	0.00	NO
15	1982	3152	-2848	-0.95	-3385	-1.13	0.00	-0.25	NO
16	1983	4210	-1790	-0.6	-5175	-1.72	0.00	-0.14	NO
17	1984	6091	91	0.03	-5084	-1.69	0.00	0.00	NO
18	1985	6165	165	0.05	-4919	-1.64	0.00	0.00	NO
19	1986	6342	342	0.11	-4577	-1.52	0.00	0.00	NO
20	1987	11681	5681	1.89	1104	0.37	1.19	0.00	YES
21	1988	8368	2368	0.79	3472	1.15	1.28	0.00	YES
22	1989	4055	-1945	-0.65	1527	0.51	0.00	0.00	NO
23	1990	4127	-1873	-0.62	-346	-0.12	0.00	0.00	NO
24	1991	5457	-543	-0.18	-889	-0.30	0.00	0.00	NO
25	1992	4771	-1229	-0.41	-2118	-0.70	0.00	0.00	NO
26	1993	1940	-4060	-1.35	-6178	-2.05	0.00	-0.65	YES
27	1994	3290	-2710	-0.9	-8888	-2.95	0.00	-0.85	YES
28	1995	2972	-3028	-1.01	-11916	-3.96	0.00	-1.16	YES
29	1996	2434	-3566	-1.19	-15482	-5.15	0.00	-1.64	YES
30	1997	2917	-3083	-1.02	-18565	-6.17	0.00	-1.97	YES
31	1998	1363	-4637	-1.54	-23202	-7.71	0.00	-2.81	YES
32	1999	613	-5387	-1.79	-28589	-9.50	0.00	-3.90	YES
33	2000	2030	-3970	-1.32	-32559	-10.82	0.00	-4.52	YES
34	2001	2125	-3875	-1.29	-36434	-12.11	0.00	-5.11	YES
35	2002	1850	-4150	-1.38	-40584	-13.49	0.00	-5.79	YES
36	2003	981	-5019	-1.67	-45603	-15.16	0.00	-6.76	YES
37	2004	986	-5014	-1.67	-50617	-16.83	0.00	-7.72	YES
38	2005	608	-5392	-1.79	-56009	-18.62	0.00	-8.82	YES
39	2006	505	-5495	-1.83	-61504	-20.45	0.00	-9.94	YES
40	2007	681	-5319	-1.77	-66823	-22.22	0.00	-11.01	YES
41	2008	334	-5666	-1.88	-72489	-24.10	0.00	-12.20	YES
42	2009	632	-5368	-1.78	-77857	-25.88	0.00	-13.28	YES
43	2010	1012	-4988	-1.66	-82845	-27.54	0.00	-14.24	YES
44	2011	691	-5309	-1.77	-88154	-29.31	0.00	-15.30	YES
45	2012	12000	6000	1.99	-82154	-27.31	1.29	-12.61	YES

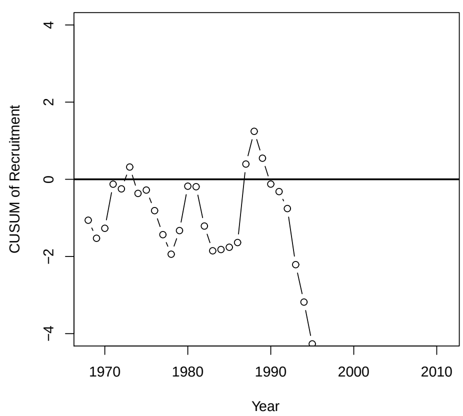
Note:
The control mean used was an arbitrary choice for illustration, where $\overline{X} = 6000$
The control standard deviation was computed from the whole time series, where $\overline{\sigma} = 3007.882$
The allowance parameter was an arbitrary choice to illustrate in-control and out-of-control, where $k = 0.7$
The metric winsorization was not applied in this example for simplistic illustration.
The observation in the highlighted row was introduced (unoriginal) to illustrate the advantage of DI-CUSUM.



(a)Shewhart chart



(b)CUSUM (Method A)



(c)CUSUM (Method B)

Figure 3.1: **Advantages of using cumulative sums instead of indicator observations:** The figure shows the recruitment indicator data of Irish Sea Cod (ICES, 2012*c*). **(a)** The Shewhart control chart were indicator observations are directly plotted for monitoring the underlying trend. **(b)** The cumulative sum indicating that most observations were less than the control mean i.e., $\overline{X}$=6000 (an arbitrary choice for illustration). **(c)** The cumulative sum after standardizing all indicator observations using the control mean $\overline{X}$=6000 and control standard deviation $\overline{\sigma} = 3007.882$ (see Table 3.1).

Both CUSUMs (Methods A and B) are identical except for the units in the vertical axis (Figure 3.1b,c). In Method A, the CUSUM will be measured in same unit of the indicator X and in Method B, the CUSUM will be in multiples of standard deviation of the data. However, statistically both CUSUMs contain the same information.

The advantage of Method B is that the units of CUSUM are always absolute irrespective of the unit in which the indicator observations are measured. Hence the CUSUMs obtained from Method B can be compared across various stock indicators. For example, the CUSUMs measured for mean length (in cm) and mean weight (in grams) can be plotted on the same chart if they are computed using Method B.

3.3 Decision Interval - Cumulative Sum (DI-CUSUM)

Regardless of the advantage demonstrated with Methods A and B, both have the weakness of delayed detection if the shift in indicator is immediate with a higher magnitude in the reverse direction from the previous CUSUM observation. For example, if there is an immediate positive shift in recruitment of Irish Sea Cod by 2012, Method A and B will use that information to compensate for the existing negative deviation in CUSUM rather than signalling the change immediately (Table 3.1).

This deficiency can be handled by using another algebraically equivalent version of CUSUM, which is the "decision interval" form of CUSUM (DI-CUSUM). This is the form used widely for process monitoring purposes and is comparatively more efficient in detecting immediate large shifts in the indicator time series. As can be seen from Table 3.1, a positive deviation was obtained in DI-CUSUM (θ_i^+, Column 8) due to an immediate large shift of recruitment in 2012. The DI-CUSUM has three additional modifications compared to the CUSUM computed by Method B. They are:

1. The positive and negative indicator deviations are computed independently
2. An allowance parameter (k) is used to accommodate common cause variation
3. A control limit ($\pm h$) is used to decide in-control and out-of-control situations

3.3.1 Upper and Lower CUSUMs

To improve the detection capabilities during large immediate shifts, 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 'Upper CUSUM' (θ^+) and 'Lower CUSUM' (θ^-), respectively. In the example provided in Table 3.1, this corresponds to Column 8 & 9. To compute these metrics, the CUSUMs are initially set to zero as:

$$\theta_{i=0}^{+} = 0 \text{ and } \theta_{i=0}^{-} = 0 \tag{3.4}$$

The upper and lower CUSUMs are further updated in each year as the monitoring process moves forward such that only positive deviations are used for updating the Upper CUSUM (θ^+) and only negative deviations are used for updating the Lower CUSUM (θ^-). This can be expressed as:

$$\theta_i^+ = \max\Big(0,\ \theta_{i-1}^+ + Z_i\Big) \text{ and } \theta_i^- = \min\Big(0,\ \theta_{i-1}^- + Z_i\Big) \tag{3.5}$$

3.3.2 The allowance parameter (k)

In Chapter 1, the common and special cause variations in indicator were discussed (Section 1.4.2). Variability due to common causes (such as the natural variation in stock-recruitment) are inherent to indicators and hence they occur even when the state of the stock is in-control. Indicator deviations resulting from common cause variability will not carry the CUSUM far away from the control mean. Hence it is important to identify which indicator deviations are meaningful enough for the fishery manager to investigate, and respond to, for correcting the underlying problem.

This can be accommodated in DI-CUSUM by assuming that a minimum threshold of the indicator deviation is due to common cause variability. This threshold is fixed as a chart constant 'k' while updating the CUSUMs and is known as the "allowance parameter". This can be mathematically expressed in CUSUM computation as:

$$\theta_i^+ = \max\left(0,\ \theta_{i-1}^+ + Z_i - k\right) \text{ and } \theta_i^- = \min\left(0,\ \theta_{i-1}^- + Z_i + k\right), \tag{3.6}$$

where in each year, the k constant is subtracted from positive indicator deviations and added to negative indicator deviations while updating the respective CUSUMs. The choice of 'k' is generally recommended to be set at half of the indicator shift that is likely to be detected by CUSUM control charts (Hawkins and Olwell, 1998). For monitoring indicators in fisheries, k will be useful for dealing with the variability inherent to fish populations. However, the choice of k constant is a subject that require more research and depends upon the objectives used while managing the fisheries.

3.3.3 The control limit (h)

The Upper and Lower CUSUMs alone are not useful since they will not indicate whether the indicator deviations obtained are significantly important to trigger a management action. Essentially, this means a criteria is required to classify whether the observed indicator deviation shows an in-control or out-of-control state of the fish stock.

This can be formally detected by using a CUSUM constant known as the 'control limit' (h). The 'h' is chosen so that if the indicator is in an in-control state, nearly all observations will fall between ^+h and ^-h. As long as the CUSUMs are within the $\pm h$ interval, it is assumed to be in control 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 (Table 3.1, Column 10). The out-of-control state of the stock can be mathematically expressed as:

$$\theta_i^+ >^+ h \quad \text{or} \quad \theta_i^- <^- h \tag{3.7}$$

3.3.4 Metric winsorization

The basic DI-CUSUM assumes that the data follow a normal distribution though there are situations when this assumption could fail (Hawkins and Olwell, 1998). Occasionally, outliers may appear in the time series if the actual distribution is heavier-tailed or a far-out value occurs as a result of an observation error. Such observations may affect the sensitivity and specificity of the outcomes from DI-CUSUM.

Metric winsorization is one way of making DI-CUSUM robust to such outliers. In this approach, the 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). This can be mathematically expressed as:

If $|Z_i| < w$ then

$$\theta_i^+ = \max\left(0, \theta_{i-1}^+ + Z_n - k\right) \text{ and } \theta_i^- = \min\left(0,\ \theta_{i-1}^- + Z_i + k\right) \tag{3.8}$$

If $|Z_i| > w$ then

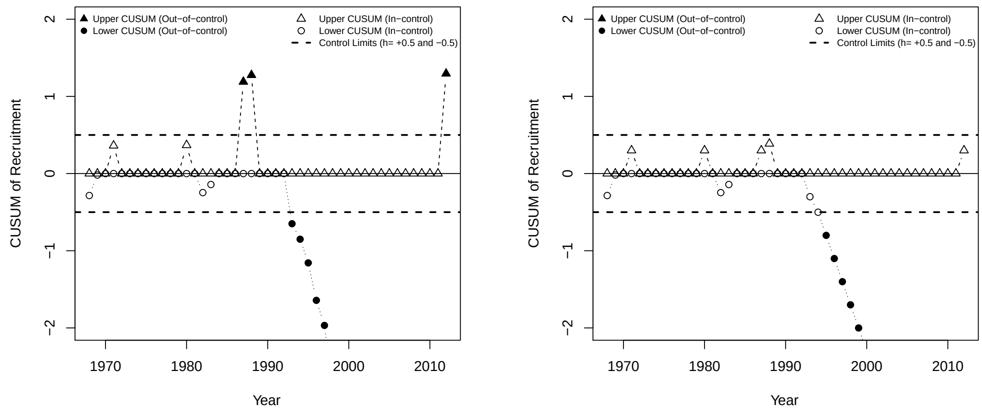
$$\theta_i^+ = \max\left(0, \theta_{i-1}^+ + w - k\right) \text{ and } \theta_i^- = \min\left(0,\ \theta_{i-1}^- - w + k\right) \tag{3.9}$$

Thus no matter how far the X_i is away from the control mean ($\overline{X}$), the Upper CUSUM will increase no more than $w - k$ and the Lower CUSUM will not decrease more than $-w + k$ for any given year. An example is illustrated in Figure 3.2 where the deviation in DI-CUSUM was more restrictive when a metric winsorization of $w = 1$ was applied.

3.4 Self-starting Cumulative Sum (SS-CUSUM)

One of the important assumptions in DI-CUSUM is the exact knowledge of the control mean (μ) and standard deviation (σ) for the indicator. In practice, these parameters are estimated ($\overline{X}$ and $\overline{\sigma}$) from extensive historical data sets and hence DI-CUSUM is inappropriate to use when there is poor data availability. Scandol (2003) and Petitgas (2009) suggested that a reference period from the stock history can be used to estimate these parameters. But this is obviously not a solution if no historical scientific data are available for the fish stock.

Self-starting CUSUM (SS-CUSUM) is one possible approach to get away from the estimation problem of the control mean (Hawkins, 1987; Quesenberry, 1997; Hawkins



(a) DI-CUSUM without winsorization (b) DI-CUSUM with winsorization ($w = 1$)

Figure 3.2: **Graphical illustration of DI-CUSUM with recruitment indicator of Irish Sea Cod (ICES, 2012*c*):** **(a)** Shows the DI-CUSUM without applying metric winsorization and **(b)** Shows the DI-CUSUM with metric winsorization ($w = 1$). The other parameters used in the DI-CUSUM were $\overline{X}$=6000, $k = 0.7$ and $h = 0.5$ such that the in-control or out-of-control situations can be illustrated.

and Olwell, 1998). SS-CUSUM is based on the idea of using regular indicator observations themselves to calibrate the control mean. Every new observation is standardized using the mean and standard deviation accumulated to date. So essentially, the $\overline{X}$ and $\overline{\sigma}$ are dynamic in SS-CUSUM and are referred to as the "running mean" ($\overline{X}_n$) and "running standard deviation" ($\overline{\sigma}_n$) respectively. These parameter estimates get closer and closer to the true values as more in-control observations are used for calibration. So eventually, a SS-CUSUM will behave in a similar manner to DI-CUSUM over time. This means that a long historical time series is not required to initiate the CUSUM monitoring process but can start with a few preliminary observations. However, this may expose the SS-CUSUM to the danger of contaminating the $\overline{X}$ and $\overline{\sigma}_n$ by including observations from out-of-control situations. Some precautions are required to avoid this happening and these are discussed in Section 3.4.3. The steps for computing a self-starting CUSUM are as follows:

3.4.1 Indicator transformation

In self-starting CUSUM we suppose that the indicator observations come from an in-control N(μ, σ^2) distribution. So the first step is to transform all indicator observations to a random variable that has an exact distribution of $\mathrm{N}(0, 1)$. Now let:-

$$W_n = \sum_{i=1}^{n} (X_i - \overline{X}_n)^2, \tag{3.10}$$

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

$$\overline{\sigma}_n = \sqrt{W_n/(n-1)} \tag{3.11}$$

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

$$T_n = \frac{(X_n - \overline{X}_{n-1})}{\overline{\sigma}_{n-1}}, \tag{3.12}$$

where, 'n' is greater than or equal to three (a minimum of two readings are required to get an initial mean and standard deviation). T_n follows a scaled Student's 't' distribution under a normal distribution assumption.

$$\sqrt{\frac{n-1}{n}}\, T_n \sim t_{n-2}$$

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

$$P_r[T_n < t] = f_{n-2}\left(t\sqrt{\frac{n-1}{n}}\right), \tag{3.13}$$

where f_{n-2} stands for the cumulative distribution function of the Student's 't' distribution with $n-2$ degrees of freedom. As $n \to \infty$, the 't' distribution gets closer and closer to the standard normal distribution. Taking an inverse normal function (ϕ^{-1}) of f_{n-2} will transform the "studentized" CUSUM quantity T_n into a random variable U_n that has an exact $N(0,1)$ distribution for all $n > 2$. Since U_n is statistically independent, by transforming T_n to their U_n counterparts we get a sequence of independent $N(0,1)$ values.

$$a_n = \sqrt{\frac{n-1}{n}} \tag{3.14}$$

$$U_n = \phi^{-1}\left[f_{n-2}(a_n T_n)\right] \tag{3.15}$$

Once U_n are generated, they can be handled exactly in the same way as how Z_i was used in the computation of DI-CUSUM (Section 3.3).

An example of the numerical computation with the recruitment indicator of Irish Sea Cod (ICES, 2012*c*) is provided in Table 3.2. They are graphically illustrated using control chart in Figure 3.3. Results in this illustration shows that the out-of-control years signalled by SS-CUSUM is equivalent to those which was obtained with DI-CUSUM (Figure 3.2a & 3.3a). This shows that the SS-CUSUM is a no lose proposition as a detection device, if the monitoring start with a few in-control observations. Figure 3.3c and 3.3e shows the progression of running mean and standard deviation as new observations become available. They are more dynamic during the initial years because only a few indicator observations are there in the time series. When the number of observations increased, the subsequent updates get smaller and eventually the running parameters become robust (Figure 3.3c,e).

3.4.2 Updating the running parameters in SS-CUSUM

The updates for the running mean and variance can be simplified by following equations:

$$\overline{X}_n = \overline{X}_{n-1} + \left(\frac{X_n - \overline{X}_{n-1}}{n}\right) \quad (3.16)$$

$$W_n = W_{n-1} + \left[\frac{(n-1)(X_n - \overline{X}_{n-1})^2}{n}\right] \quad (3.17)$$

3.4.3 Protecting SS-CUSUM from out-of-control observations

In SS-CUSUM, the running mean is updated on-line using future observations to detect the change in state of the stock from its initial state. Hence, it is important to protect the running mean from all observations that could result in an out-of-control signal. This can be achieved by rolling back the history to the last estimated running mean when the stock was in an in-control state as detected by the method.

An illustration of SS-CUSUM with the recruitment of Irish Sea cod (ICES, 2012*c*) is presented where the running mean and standard deviation are protected from observations that resulted in out-of-control signals (Figure 3.3 d,f). The first out-of-control signal from the lower SS-CUSUM was signalled in year 1993. From this year onwards, there were no in-control observations and hence the running parameters were not updated in the SS-CUSUM. This improved the signalling efficiency of the control chart because if the control limit is set equivalent to $h = \pm 2$, the signal will not be delayed for more than two additional years (Figure 3.3 b). Whilst for the unprotected SS-CUSUM, the signal will be delayed by five additional years (Figure 3.3 a). Hence, a protected SS-CUSUM is more reliable to apply, particularly when the user is uncertain about the choice of control limit (h).

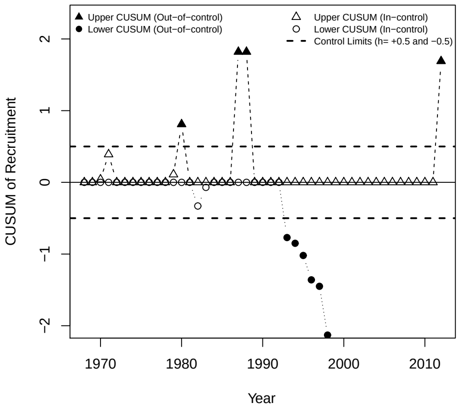
3.4.4 Protecting SS-CUSUM from outliers

It is also important to avoid the influence of isolated outliers in the time series which could eventually result in inflating the running standard deviation ($\overline{\sigma}_n$). This will reduce the potential of SS-CUSUM to detect the required mean shifts. How such observations can be handled in DI-CUSUM applying a metric winsorization procedure

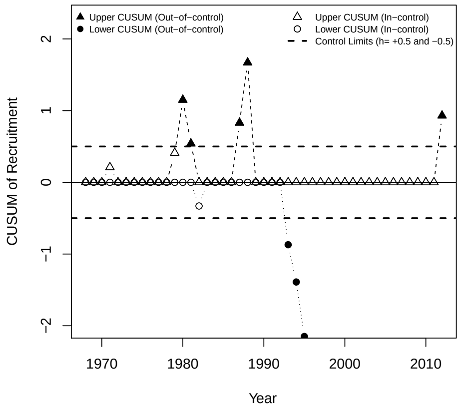
Table 3.2: **Computation of SS-CUSUM using the recruitment indicator of Irish Sea Cod (ICES, 2012*c*):** Columns [6-9] shows the metrics obtained during indicator transformation (Section 3.4.1). Column [12] tells whether the SS-CUSUM raised a signal i.e., when $\theta_i^+ > h$ or $\theta_i^- < -h$.

n [1]	Year i [2]	Indicator X_n [3]	Running Mean $\overline{X_n}$ [4]	Running SD $\overline{\sigma_n}$ [5]	T_n [6]	a_nT_n [7]	$F_{n-2}(a_nT_n)$ [8]	U_n [9]	Upper CUSUM θ_i^+ [10]	Lower CUSUM θ_i^- [11]	Signal $h = 0.5$ [12]
1	1968	3038	3038.00	NA	NA	NA	NA	NA	0.00	0.00	NO
2	1969	4693	3865.50	1170.26	NA	NA	NA	NA	0.00	0.00	NO
3	1970	6722	4817.67	1845.16	2.44	1.99	0.8518	1.04	0.04	0.00	NO
4	1971	9194	5911.75	2656.66	2.37	2.05	0.9116	1.35	0.39	0.00	NO
5	1972	5661	5861.60	2303.46	-0.09	-0.08	0.4706	-0.07	0.00	0.00	NO
6	1973	7580	6148.00	2176.44	0.75	0.68	0.7331	0.62	0.00	0.00	NO
7	1974	4090	5854.00	2133.65	-0.95	-0.88	0.2096	-0.81	0.00	0.00	NO
8	1975	6242	5902.50	1980.14	0.18	0.17	0.5647	0.16	0.00	0.00	NO
9	1976	4511	5747.89	1909.44	-0.70	-0.66	0.2652	-0.63	0.00	0.00	NO
10	1977	4262	5599.30	1860.55	-0.78	-0.74	0.2402	-0.71	0.00	0.00	NO
11	1978	4585	5507.09	1791.37	-0.55	-0.52	0.3078	-0.50	0.00	0.00	NO
12	1979	7711	5690.75	1822.65	1.23	1.18	0.8673	1.11	0.11	0.00	NO
13	1980	9212	5961.62	1999.75	1.93	1.86	0.9551	1.70	0.81	0.00	YES
14	1981	5962	5961.64	1921.30	0.00	0.00	0.5000	0.00	0.00	0.00	NO
15	1982	3152	5774.33	1988.46	-1.46	-1.41	0.0910	-1.33	0.00	-0.33	NO
16	1983	4210	5676.56	1960.44	-0.79	-0.76	0.2299	-0.74	0.00	-0.07	NO
17	1984	6091	5700.94	1900.85	0.21	0.21	0.5818	0.21	0.00	0.00	NO
18	1985	6165	5726.72	1847.33	0.24	0.24	0.5933	0.24	0.00	0.00	NO
19	1986	6342	5759.11	1800.83	0.33	0.32	0.6236	0.31	0.00	0.00	NO
20	1987	11681	6055.20	2196.76	3.29	3.21	0.9976	2.82	1.82	0.00	YES
21	1988	8368	6165.33	2199.81	1.05	1.03	0.8420	1.00	1.82	0.00	YES
22	1989	4055	6069.41	2193.44	-0.96	-0.94	0.1792	-0.92	0.00	0.00	NO
23	1990	4127	5984.96	2180.94	-0.89	-0.87	0.1971	-0.85	0.00	0.00	NO
24	1991	5457	5962.96	2135.73	-0.24	-0.24	0.4063	-0.24	0.00	0.00	NO
25	1992	4771	5915.28	2104.31	-0.56	-0.55	0.2938	-0.54	0.00	0.00	NO
26	1993	1940	5762.38	2204.26	-1.89	-1.85	0.0383	-1.77	0.00	-0.77	YES
27	1994	3290	5670.81	2213.21	-1.12	-1.10	0.1409	-1.08	0.00	-0.85	YES
28	1995	2972	5574.43	2230.92	-1.22	-1.20	0.1205	-1.17	0.00	-1.02	YES
29	1996	2434	5466.14	2267.01	-1.41	-1.38	0.0895	-1.34	0.00	-1.36	YES
30	1997	2917	5381.17	2275.68	-1.12	-1.11	0.1382	-1.09	0.00	-1.45	YES
31	1998	1363	5251.55	2350.94	-1.77	-1.74	0.0462	-1.68	0.00	-2.13	YES
32	1999	613	5106.59	2453.78	-1.97	-1.94	0.0309	-1.87	0.00	-3.00	YES
33	2000	2030	5013.36	2473.80	-1.25	-1.23	0.1140	-1.21	0.00	-3.21	YES
34	2001	2125	4928.41	2485.88	-1.17	-1.15	0.1293	-1.13	0.00	-3.34	YES
35	2002	1850	4840.46	2503.72	-1.24	-1.22	0.1156	-1.20	0.00	-3.54	YES
36	2003	981	4733.25	2550.15	-1.54	-1.52	0.0689	-1.48	0.00	-4.02	YES
37	2004	986	4631.97	2588.85	-1.47	-1.45	0.0780	-1.42	0.00	-4.44	YES
38	2005	608	4526.08	2635.74	-1.55	-1.53	0.0674	-1.50	0.00	-4.94	YES
39	2006	505	4422.97	2679.35	-1.53	-1.51	0.0698	-1.48	0.00	-5.42	YES
40	2007	681	4329.43	2710.14	-1.40	-1.38	0.0878	-1.35	0.00	-5.77	YES
41	2008	334	4231.98	2747.84	-1.47	-1.46	0.0762	-1.43	0.00	-6.20	YES
42	2009	632	4146.26	2770.38	-1.31	-1.29	0.1022	-1.27	0.00	-6.47	YES
43	2010	1012	4073.37	2778.62	-1.13	-1.12	0.1346	-1.10	0.00	-6.57	YES
44	2011	691	3996.50	2793.06	-1.22	-1.20	0.1184	-1.18	0.00	-6.75	YES
45	2012	12000	4174.36	3007.88	2.87	2.83	0.9965	2.69	1.69	-3.06	YES

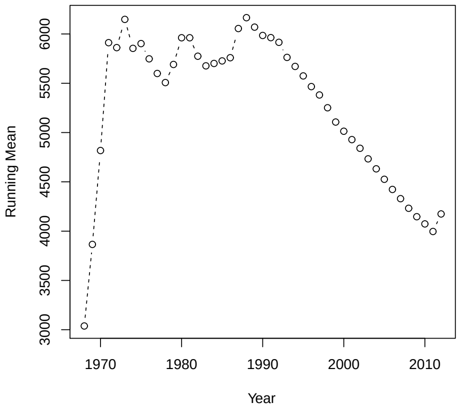
Note:
The allowance parameter was an arbitrary choice to illustrate in-control and out-of-control, where $k = 1$
The metric winsorization was not applied in this example for simplistic illustration (Figure 3.3 a, c & e).
The observation in the highlighted row was introduced (unoriginal).
NA indicate the slots where enough data are not available to compute the parameter.



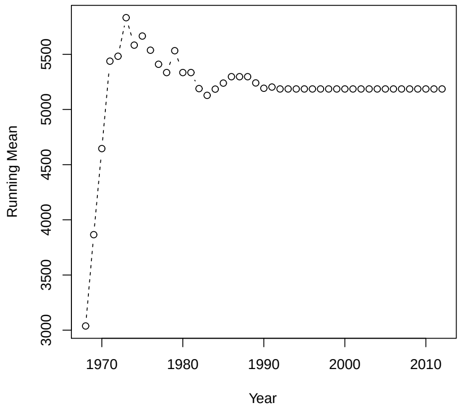
(a)Unprotected SS-CUSUM



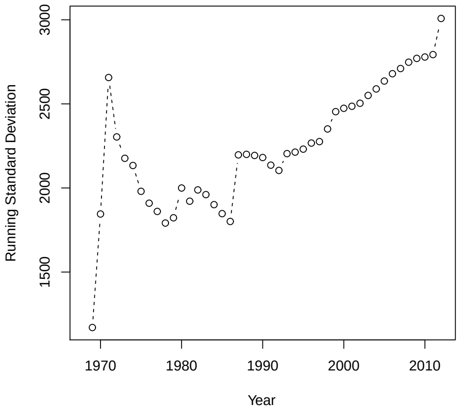
(b)Protected SS-CUSUM



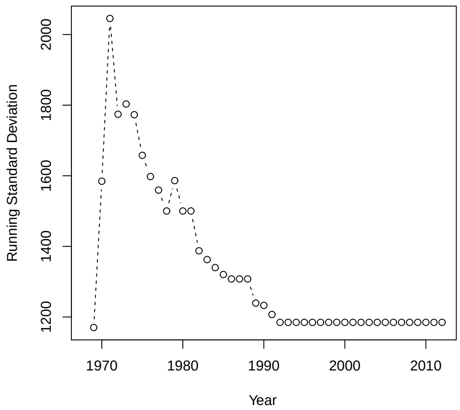
(c)Unprotected Running Mean



(d)Protected Running Mean



(e)Unprotected Running Standard Deviation



(f)Protected Running Standard Deviation

Figure 3.3: **Graphical illustration of SS-CUSUM with the recruitment indicator of Irish Sea Cod (ICES, 2012*c*): (a), (c) & (e)** Shows the classic SS-CUSUM where all observations are used for computing the running mean and standard deviation. **(b), (d) & (f)** Shows an SS-CUSUM with $w = 2$ where out-of-control observations were not used for updating the running parameters.

has already been discussed (Hawkins and Olwell, 1998; Section 3.3.4). This can be employed in SS-CUSUM as well by replacing the extremely large indicator deviations by a cut off threshold value known as the “winsorizing constant” (w). This can be easily applied to the formula for updating running mean and standard deviation (Equation 3.16).

$$\overline{X}_n = \overline{X}_{n-1} + \left(\frac{d_n}{n}\right) \tag{3.18}$$

$$W_n = W_{n-1} + \left[\frac{(n-1)\ d_n^2}{n}\right] \tag{3.19}$$

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

$$d_n = \begin{cases} -w & \text{for} \quad \left(X_n - \overline{X}_{n-1}\right) < -w \\ X_n - \overline{X}_{n-1} & \text{for} \quad -w < \left(X_n - \overline{X}_{n-1}\right) < w \\ w & \text{for} \quad \left(X_n - \overline{X}_{n-1}\right) > w \end{cases} \tag{3.20}$$

3.5 Summary

- CUSUMs are efficient for detecting persistent changes in stock indicators and they can be visualized using control charts.
- CUSUMs provide a statistical framework to determine whether the state of the stock is in-control (require no management response) or in an out-of-control (require a management action) situation.
- The CUSUM assumes that the indicator observations are independent and follows a normal distribution with mean (μ) and standard deviation (σ) regardless of the state of the stock.
- For the decision interval form of CUSUM (DI-CUSUM), the exact parameters should be known i.e., μ and σ. In practice, they are estimated from historical observations when the stock was perceived to be in-control.
- If the parameters are not available, then a self-starting CUSUM (SS-CUSUM) can be employed where the μ and σ will be calibrated from regular on-going observations itself as the monitoring process moves forward.

Chapter 4

Identifying potential indicators from fisheries catch data

4.1 Introduction

Indicators with their associated reference points are the key elements used for providing advice in fisheries management frameworks (Deriso and Quinn, 1998; FAO, 1999). In the precautionary approach of ICES, indicators such as spawning stock biomass (SSB) and fishing mortality (F) are monitored using limit reference points (B_{lim} and F_{lim}), where the objective is to maintain SSB above B_{lim} and F below F_{lim} (Dankel et al., 2008). Thus the Common Fisheries Policy of the EU currently confines fish stock assessments to the evaluation of SSB and F (ICES, 2013). However, management frameworks based on this approach are not always reliable since the operational advice is based on implicit sustainability objectives (De Lara et al., 2007). Added to that, the fishery models involved in scientific stock assessments are data intensive and require information on age or size structure, selectivity, maturity and other life history parameters (Schnute and Richards, 2001; Jennings et al., 2001; King, 2007). As data collection is expensive and labour intensive, many economically less important fish stocks have limited or poor data and hence such standard assessments cannot be completed (Kelly and Codling, 2006). In this paradigm, it is important to identify indicators that can explicitly track the state of the stock (Froese, 2004) so that reference directions can be established (Shin et al., 2005). For example, the declining trend in the mean size of the fish population can be related to a direct effect of the rate of increase in exploitation (Rochet et al., 2005; Clay et al., 1999). Trends in such indicators can be used to support harvest control rules and fisheries can thereby be managed in situations when data are unreliable or limited for conducting a formal fish stock assessment.

4.2 Objective of the study

A variety of indicators can be measured from the fisheries catch, but it is important to test how sensitive and specific they are to the changes in stock abundance for a given level of fishing pressure. It is difficult to measure these performances using real world datasets because the change in state of the stock can be due to pressures independent of fishing (Probst et al., 2013*b*). Previous research has shown that the relationship between the stock state and indicator responses can be affected by time lags of years (Greenstreet et al., 2011; Shephard et al., 2011; Probst et al., 2012). Hence the objective of the present study is:

- To identify a suite of age based catch indicators that are potentially sensitive and responsive to changes in abundance of spawning stock biomass of the fish population.

4.3 Background

A general objective of fish stock assessment is to estimate the current size of the stock and to predict future stock sizes based on a range of possible management measures e.g. catch quotas, effort limitation, closed areas or seasons (Clay et al., 1999). Spawning stock biomass is a well established state indicator for stock size and is the cumulative weight of sexually matured fishes in the population (Trippel, 1995; Probst et al., 2012). Since the proportion of mature individuals in the stock generally increases with length or age (Stearns and Koella, 1986), indicators based on the size structure may reveal critical information about the health status of the stock. For example, if the number of mature fish individuals are depleted, future recruitment to the stock is affected. The sensitivity of such size based indicators to changes in stock size can be assessed using their correlations with spawning stock biomass (Probst et al., 2012).

In this context, three simple catch indicators have been discussed by Froese (2004) that are based on species maturity and selectivity of a fishery. One of these indicators represented the mega spawners and was described as ‘large fish’, measured as the percentage of fish with a size greater than the length at which the catch biomass is maximum. Similar large fish indicators have recently gathered the attention of many fisheries scientists as a proxy to detect the impacts of fishing on stock abundance (Shephard et al., 2011; Greenstreet et al., 2011; Fung et al., 2012; Shephard et al., 2013). This is because the probability of a fish surviving beyond several years dramatically decreases if mortality due to fishing is high (as generally fishing is a size selective process) and effectively changes the stock abundance across age classes resulting in only a fewer mature fish individuals in the stock left to spawn (Trippel, 1995).

Commercial landings are usually recorded in many developing fisheries since they are more cost effective than any other fishery-dependent data (Scandol, 2003). Various size-based catch indicators can be computed if length frequencies or catch-at-age data are available for the fishery (Shin et al., 2005). The EU-Commission has proposed four indicators based on fisheries survey data and official landing statistics so they can be used for stocks where time-series for F and SSB are not available (EU-COM, 2010; Descriptor 3.3). One of the proposed indicators suggested is the use of size-based indicators (SBIs) based on proportions of old or mature fish in the catch statistics (PIs). Earlier Shin et al. (2005) proposed similar proportional indicators but also recommended that such assessments should be complemented with trends from recruitment abundance to facilitate proper diagnosis of the state of the stock. Probst et al. (2013*b*) tested a suite of SBIs and found that the relative SBIs (e.g. proportions based on size classes) are more sensitive to recruitment, but not to fishing pressure when compared to the absolute SBIs (e.g. maximum size observed in the catch).

In this study, an age structured stochastic fish population model was used to simulate a fishery similar to the real world. The approach of using fisheries simulation has the advantage of obtaining multiple replications of the same fishing scenarios. It was assumed that a time series of catch-at-age and weight-at-age data were available for the fish stock. Various age based catch indicators (including PIs) were computed and they were explored using correlations with the spawning stock biomass to predict which of those are potentially useful in characterizing the changes in state of the fish stock. Further, the usefulness of such indicators is tested in real world fish stocks from the North Atlantic using publicly available ICES data.

4.4 Methods

4.4.1 Fisheries simulation

A non-spatial age structured fish stock was simulated (Section 2.1) and fishery equilibrium was achieved with an initial fishing mortality of $F_{int} < F_{90\%MSY}$. The operating model included two distinct phases (Section 2.4). In the first phase, the model ran for 100 years with random variability in stock-recruitment and the initial fishing mortality to stabilize transient processes if any. In the second phase, the model ran for 30 further years during which an impact on the stock biomass was applied while various indicators were measured from the operating model and recorded for further analysis i.e., to correlate the indicators with SSB of the stock.

4.4.2 Indicators used

A total of four types of indicators were used in the present study. They were the age based indicators (ABI), mature fish indicators (MFI), large fish indicators (LFI) and mean indicators (MI). The indicators used were either relative, absolute or an average metrics based on the age groups in the fish stock. All indicators were computed using a random sample of 10,000 fish individuals from the fisheries catch. The description and formulas used for computation of these indicators are detailed in Section 2.5.

Various age based indicators (ABIs) were computed in each year from the operating model of the fishery simulation (Table 2.2). They are the catch numbers at age (CN_a), catch weights at age (CW_a), positive proportion of catch numbers at age (PN_a), positive proportion of catch weights at age (PW_a) and positive proportion of average catch weight at age (PA_a). These indicators were computed for each age group in the stock and hence the total number of ABIs will depend on the lifespan of the species. Age dependent indicators will be helpful in understanding how the species maturity and selectivity of the fishing gear affect their correlations with SSB.

The MFIs and LFIs used in the present study are essentially the proportional ABIs (PN_a and PW_a), but based on the age groups $a = M_{95\%}$ and $a = S_{95\%}$ in the operating model. These indicators were specifically used to test how the maturity and selectivity parameters affect indicator correlations with SSB. It was assumed that all age groups above $a > M_{95\%}$ were fully mature and those age groups above $a > S_{95\%}$ were fully selective to the fishing gear. Two mature fish indicators (MFIs) were used i.e., O_n and O_w which are the proportional catch indicators $PN_{a=M_{95\%}}$ and $PW_{a=M_{95\%}}$ respectively. Similarly, two large fish indicators (LFIs) were used i.e., P_n and P_w which are the proportional catch indicators $PN_{a=S_{95\%}}$ and $PW_{a=S_{95\%}}$ respectively.

Mean indicators (MI) were used in the present study for comparing their performances with ABIs because such indicators can be collected more easily in a data limited or poor fishery. The three MIs used in the present study were the mean length (ML), mean weight (MW) and mean age (MA) of all individuals obtained in the random sample of the fisheries catch. These indicators have previously proven to be useful in detecting the effects of fishing from environmentally induced impacts (Shin et al., 2005; Jennings, 2005; Froese, 2004; Piet and Jennings, 2005; Punt et al., 2001).

4.4.2.1 Scenarios considered for the simulated fishery

The stock indicators were computed from a range of fishery scenarios to evaluate their sensitivity and response towards changes in SSB. These scenarios were based on the (i) lifespan of the species; (ii) type of stock impact; and (iii) selectivity of the fishing gear

(Table 4.1). Additional scenarios based on growth variability, autocorrelated stock-recruitment and the number of catch samples are presented in Appendix B (Section B.1). Fish stocks with three different life history parameters were considered in this study i.e., cod-like (medium life span), herring-like (short life span) and rockfish-like (long life span) species. This was to determine whether the indicators are sensitive and responsive across a wide range of fish stocks that are usually observed in the real world. The life history parameters for these fish stocks are presented in Table 2.1.

Four types of impact scenarios were evaluated in the present study, where the stock (i) were persistently over-fished (increasing F); (ii) were persistently under-fished (declining F); (iii) experienced a recruitment crash and (iv) represented a well managed stable fishery (TAC management). For simulating a stock in the over-fished scenario, a compound fishing impact was applied by increasing the base fishing mortality (F) with a 5% step change per year (i.e. $F_{i+1} = 1.05F_i$, where 'i' is year, starting from the first year of the second phase) and a similar 5% annual step change reduction in F was applied in the under-fished scenario. The scenario representing a persistent recruitment crash was implemented using a fixed multiplier of 0.5 on the mean of the recruitment distribution (Equation 2.11) from the first year of the second phase, so that the expected number of recruits entering the stock in each subsequent year is halved. To simulate the scenario of a well managed stable stock fishery, a simple Harvest Control Rule (HCR) was applied such that the percentage change in Total Allowable Catch (TAC) in year 'i' is relative to the change occurred in SSB from the previous year (Equation 4.2).

$$TAC^i = TAC^{i-1} \times \left(\frac{SSB^i}{SSB^{i-1}} \right) \tag{4.1}$$

This can be rearranged in the form of Equation 2.19,

$$TAC^i = TAC^{i-1} + \left[TAC^{i-1} \times \left(-1 + \frac{SSB^i}{SSB^{i-1}} \right) \right] \tag{4.2}$$

Four different selectivity patterns were used to test whether the sensitivity and response of indicators are robust to the type of fishing gear used for obtaining the fisheries catch. The selectivity at age used a logistic function (Equation 2.14) to represent trawl nets with small, medium and large mesh sizes (which increases with age giving a sigmoid shape) or a double-normal function (Equation 2.15) representing medium mesh sized gill nets (increases up to a certain age and then decreases giving a dome shape). The base case scenario used a medium mesh size trawl net to simulate the fishery of a medium life span species where the stock was persistently overfished (Scenario 1, Table 4.1). All indicators were computed from a random sample of the fisheries catch from the second phase of the fishery simulation.

Table 4.1: **Scenarios used for correlating indicators with SSB of the simulated fishery:** Autocorrelated stock-recruitment and growth variability was absent in the base case (Scenario 1). The shaded areas highlight the differences compared to the base case parameters. The F_{inc} indicates the percentage step change in the base fishing mortality applied in each year during second phase of the fishery simulation.

Scenarios	Life History (LH, Life span)	F_{inc} (yr^{-1})	Selectivity function
1-Cod-like fishery*	LH1, Medium*		
2-Herring-like fishery	LH2, Short	5% increase*	Logistic*
3-Rockfish-like fishery	LH3, Long		
4-Under fishing		5% decrease	
5-Recruitment crash		5% increase	
6-Stable fishery	LH1	Regulated by TAC	Logistic
7-Trawl net (small mesh)			Logistic
8-Trawl net (large mesh)	LH1	5% increase	Logistic
9-Gill net			Double-Normal

*: Base case scenario

4.4.3 Statistical Analysis

4.4.3.1 Sensitivity

Pearson product-moment correlation coefficient was used to examine the relationship between each indicator and SSB. A t-test was used to test whether the correlations were significantly different from 0 at both the 95% and 99% confidence levels (null hypothesis being no significant difference). The significance of the indicator correlations depends upon the number of observations available in the time series i.e., small correlation coefficients are statistically significant if the time series are sufficiently long and *vice versa*. The length of the indicator time series was fixed in the simulated fishery i.e., 31 observations and hence the correlation coefficient required for rejecting the null hypothesis are 0.36 and 0.47 at the 95% and 99% confidence levels respectively. The scenarios in the simulated fishery were iterated 1000 times and the correlation coefficients were computed in each iteration of the simulation. The distribution of correlation coefficients obtained were tested to determine whether the median of indicator correlations were significantly greater than 0.36 or 0.47. A non parametric statistical test i.e., Wilcoxon signed-rank test was used for testing this hypothesis since the correlation distributions did not satisfy the assumptions for a parametric test.

4.4.3.2 Response

In medium and long lived fish stocks, the indicators and SSB may have time-lagged relationships due to delayed age at maturity. In order to fully compensate for such possible delayed relationships, cross-correlations with lags up to five years were considered between the stock indicator and the SSB time series i.e., the time lag for which the highest correlation with SSB was determined. Potentially useful indicators will give information about the present or future states of the stock (no lag or the SSB lagging the indicator) rather than previous states (indicator lagging the SSB). Thus, with cross correlations, the responsiveness of stock indicators to changes in SSB was assessed.

The 'most useful' type of indicators can be identified by considering its correlation with SSB (higher coefficient) and the time lag relationship ($\geq$0 years). The simulations, indicator correlations, cross-correlations and hypothesis testing were carried out using codes written in the programming language R (R Development Core Team, 2012).

4.4.4 Testing potential indicators using real world ICES fish stocks

The most useful indicators predicted from the simulated fishery were tested using historical fisheries catch data given in ICES Working Group reports (ICES, 2012a;b;c;d). These reports provide time series for spawning stock biomass (SSB), catch numbers at age (CN_a) and the mean weight at age. Note that these datasets consists of estimated values obtained as part of the assessment process using an extended survival analysis (XSA) based method (Shepherd, 1999; Darby and Flatman, 1994). However, the age based catch indicators (ABIs) were calculated (Table 2.2) assuming that the models used for generating catch numbers at age are reasonably realistic. Ideally in the real world, similar size based indicators could be generated using empirical catch data from fishery independent research surveys or samples collected from commercial fish landings. Thus the problems associated with using estimated values or assumptions in the assessment models can be avoided.

Five fish stocks consisting of species with different life history traits (short, medium and long lived), different habitats (pelagic and demersal) and different ICES regions (North sea, Celtic sea, Greenland sea and Norwegian sea) were used for the test (Table 4.2). Discarding is a problem in many EU fisheries, with commercial fish species being discarded because they were not targeted, below the minimum landing size, were damaged or there was no quota (Borges et al., 2005; 2006; Johnsen and Eliasen, 2011; Stockhausen et al., 2012). Therefore for all the real world fish stocks considered in this study, the catch-at-age observations were used rather than the landings-at-age since the former accounts for discard estimates if available for the fishery.

Due to differences in the length of indicator time series (Table 4.2), the significance of correlation coefficients obtained were assessed on a case by case basis. The MFIs were computed using the $M_{95\%}$ parameter from maturity estimates given in ICES working group reports (ICES, 2012a;b;c;d). The LFIs were computed by choosing the $S_{95\%}$ equivalent to the lowest age group for which the catch numbers indicates a decreasing trend as the fish gets older (Figure 4.5a). Among the mean indicators (MIs), only the mean weight (MW) was computed since the information on length and catch numbers at age above the plus group (a_{max}) were not available for these fish stocks.

Table 4.2: **Real world fish stocks used for age based indicator correlations with SSB:** The a_{max} indicates the plus group for which all individuals with age $a \geq a_{max}$ were considered as a single age group. The $M_{95\%}$ and $S_{95\%}$ are the parameters used for computing the MFIs and LFIs using equations given in Table 2.2.

Stock	ICES region(s)	Habitat	Years	Working Group Report	Plus group a_{max}	Estimated $M_{95\%}$	Assumed $S_{95\%}$
North Sea Herring (*Clupea harengus*)	Subarea IV	Pelagic	$1960 - 2011$ ($n = 52$)	HAWG, (ICES, 2012*b*)	8	3	1
Irish Sea Cod (*Gadus morhua*)	Division VIIa	Demersal	$1968 - 2011$ ($n = 44$)	WGCSE, (ICES, 2012*c*)	6	3	2
North Sea Plaice (*Pleuronectes platessa*)	Subarea IV	Demersal	$1957 - 2011$ ($n = 55$)	WGNSSK, (ICES, 2012*d*)	10	3	2
Greenland Halibut (*Reinhardtius hippoglossoides*)	Subareas I and II	Demersal	$1964 - 2011$ ($n = 48$)	AFWG, (ICES, 2012*a*)	15	13	7
Beaked red fish (*Sebastes mentella*)	Subareas I and II	Demersal	$1992 - 2011$ ($n = 20$)	AFWG, (ICES, 2012*a*)	19	16	15

4.5 Results

In general, the results from the simulated fishery indicate that no single stock indicator can ideally serve as an overall predictive variable for the state of the stock. However, the most sensitive indicators were the mean indicators (MIs) and proportional indicators (PN_a and PW_a) based on age groups $a \geq M_{95\%}$. A comparison between the mature fish indicators (MFI) and large fish indicators (LFI) showed that the former was more responsive i.e., minimum time lags. However, the MFIs are insensitive (non-significant correlations) if the mature fish age groups $a \geq M_{95\%}$ are not fully selected by the fishing gear. Across the range of scenarios tested, the correlations of MFIs or LFIs based on catch numbers were more robust than those based on catch weights. Historical analysis of ICES fish stocks showed that both the MFIs and LFIs gave positive correlations with the estimated SSB.

4.5.1 Indicator correlations from the simulated fishery

4.5.1.1 Sensitivity of indicators

The correlations obtained for various ABIs in the base case scenario are presented in Figure 4.1. Results show that the correlations of catch numbers-at-age (CN_a) and catch weights-at-age (CW_a) increased when they were computed for higher age groups in the stock. The correlations of proportional indicators (PN_a and PW_a) were also positive and significant for all age groups that were $a \geq M_{95}\%$. However, the correlations of proportional average catch weight (PA_a) decreased as they were computed for higher age groups in the stock.

Similar patterns were obtained in all scenarios and for the three life history types used in the present study (see Figure B.2 & B.3). Since all ABIs except PA_a were having positive and significant correlations with the plus group ($a = a_{max}$), only these

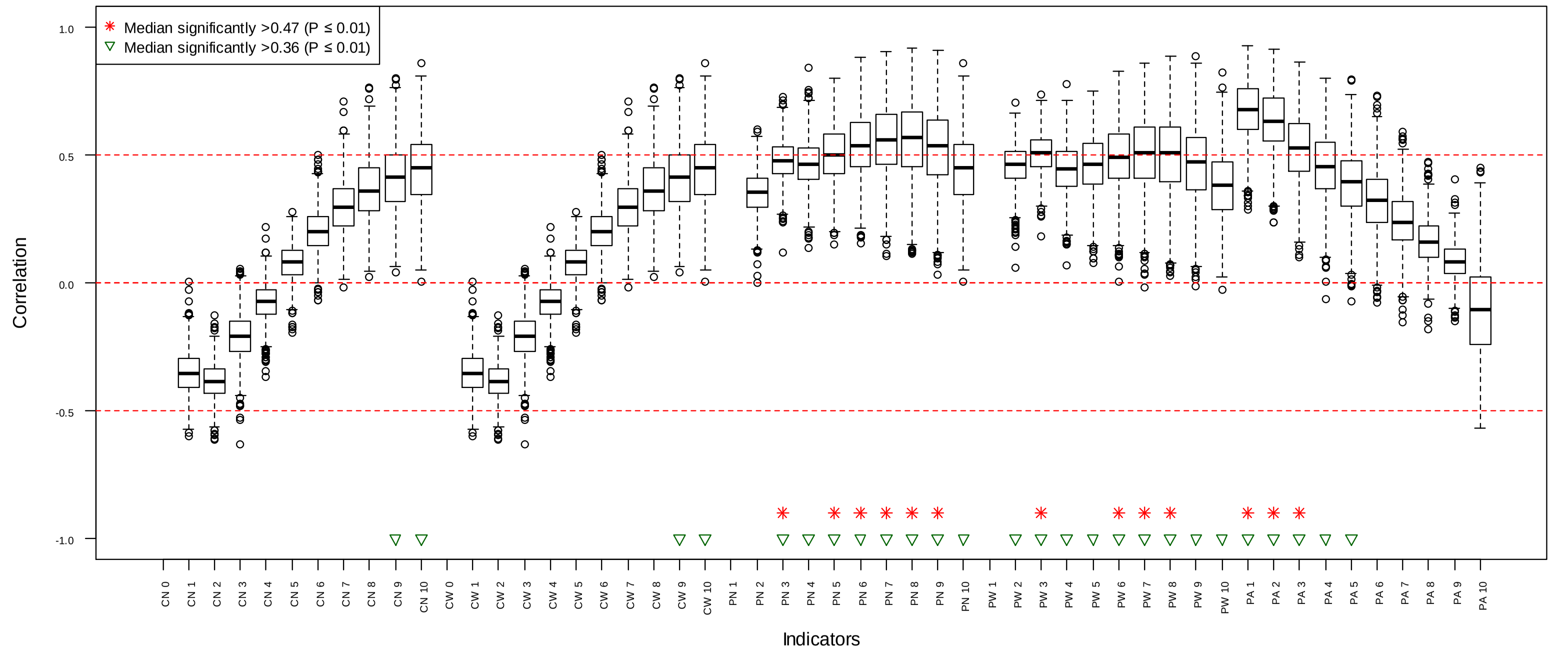


Figure 4.1: **Correlations of age based indicators (ABIs) with SSB of a medium life span species (Life History 1, Base case):** The coefficients obtained from 1000 iterations of the simulated fishery were tested to determine whether the median of the distribution has a significant correlation.

indicators are presented and discussed for the remaining scenarios. The highest correlation for PA_a was obtained for the lowest age group in the stock. This is essentially equivalent to the mean weight (MW) of the catch sample and hence they are not presented. The mature, large and mean indicators (MFIs, LFIs & MIs) gave significant correlations with SSB in the base case scenario (Figure 4.2a).

4.5.1.1.1 Effect of life span of the species

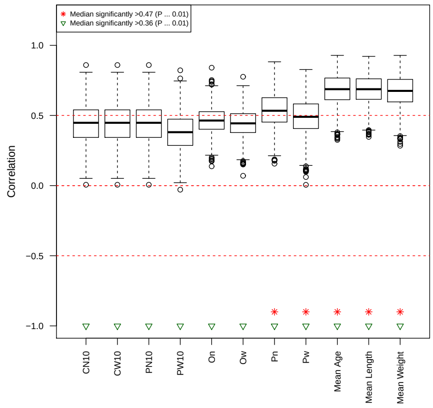
Results showed that the ABIs based on the plus group of the stock (CN_a, CW_a, PN_a and PW_a) were significantly correlated with SSB for all species used in the present study (Figure 4.2 a,b,c). The correlations of mature and large fish indicators were strong and more significant as the life span of the species increased (Figure 4.2 a,b,c). This is because the number of age groups representing fully matured individuals ($a_{max} - M_{95\%}$) increases with longevity of the species ($LH2 = 3$, $LH1 = 5$ and $LH3 = 10$). Moreover, the long life span species have slow growth, late age at maturity and display a slow turn over rate. This results in more conspicuous low frequency SSB fluctuations giving stronger trends when compared to the short life span species.

4.5.1.1.2 Effect of different stock impacts

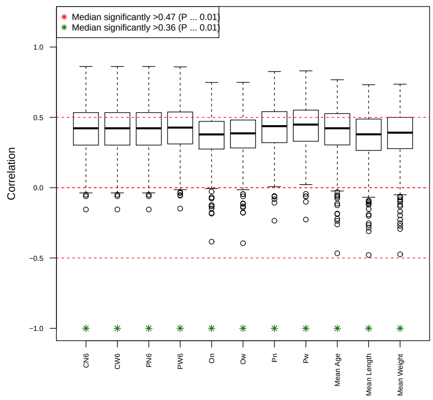
Results showed that none of the indicators were equally sensitive across all impact scenarios simulated in the present study. However, all indicators based on mature and large fish age groups were significantly correlated with SSB when the stock was persistently over-fished (Figure 4.3a). Fishing is size-selective and hence the SSB will decrease as more large and mature fishes are caught.

However when the stock was under-fished, all indicators except the MIs were not significantly correlated with SSB (Figure 4.3b). This is because the proportion of stock numbers in the age class structure become stagnant at higher stock abundances due to density dependent effects on the stock-recruitment relationship (Figure 2.9). Thus eventually the large fish indicators becomes less useful in predicting the improved state of the fish stock. However, the MIs will still be useful because fewer fishes are caught when the stock is under-fished resulting in consistently less numbers of large fish individuals in the catch sample.

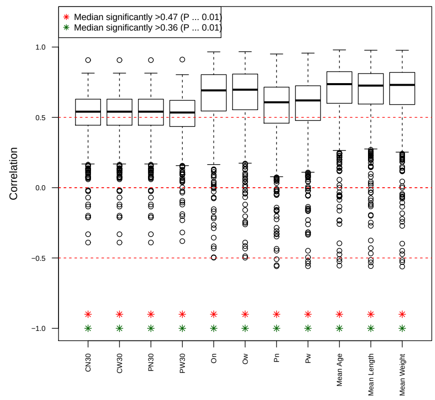
The proportional indicators based on mature or large fishes (MFI or LFI) have been reported as being sensitive to changes in recruitment (Probst et al., 2013*a*). In the recruitment crash scenario, the sensitivity of all indicators were affected. However, the MFI and LFI based on catch numbers were significantly correlated with the SSB (Figure 4.3c). Since the recruitment crash was simulated consistently for 30 years (three times the lifespan of the species), the negative trend eventually reflected in population numbers of the mature and large fish age groups in the stock. Hence intermittent spells



(a) Life History 1 (Base case)



(b) Life History 2



(c) Life History 3

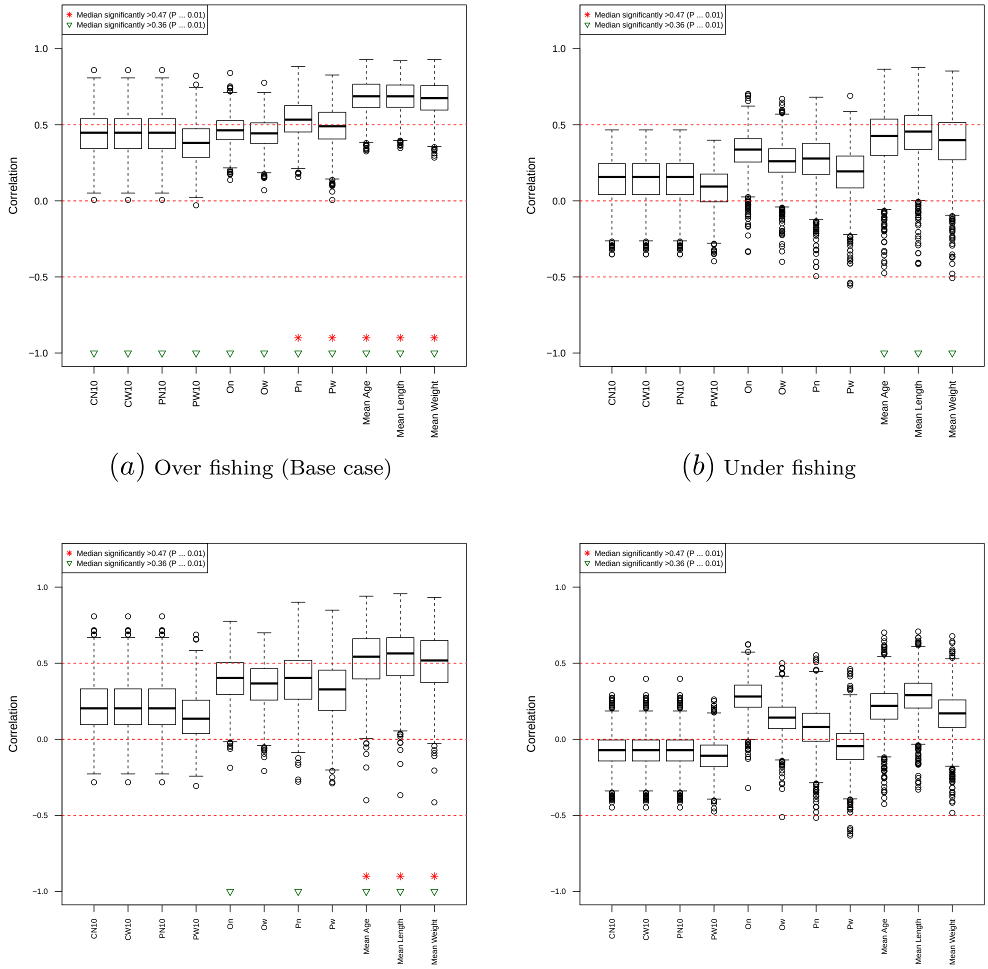
Figure 4.2: **Indicator correlations with SSB for different life history stocks:** The ABIs (CN_a, CW_a, PN_a and PW_a) represent the measures obtained from the plus group. Indicators from all life history species were found significantly correlated with the SSB.

of abundance in younger age classes may cause transient effects, but in longer term, the trend of proportional indicators are not affected if the stock impact is consistent.

In a stable and well managed fishery, the pressure applied through TAC is proportional to relative changes in SSB. As a result, the stock abundance will follow short cyclic trends. However, there will be a time lag between the trend in SSB and the catch indicators making them asynchronous because the latter is based only on large age groups in the stock. Hence none of the catch indicators based on mature or large fish gave significant correlations with SSB in this scenario (Figure 4.3d).

4.5.1.1.3 Effect of gear selectivity

All indicators gave significant correlations with SSB except for the scenario when a large mesh trawl net was used (Figure 4.4). In the large mesh scenario, only those ABIs based on the plus group of the stock gave significant correlations with SSB (Figure 4.4c).



(a) Over fishing (Base case)

(b) Under fishing

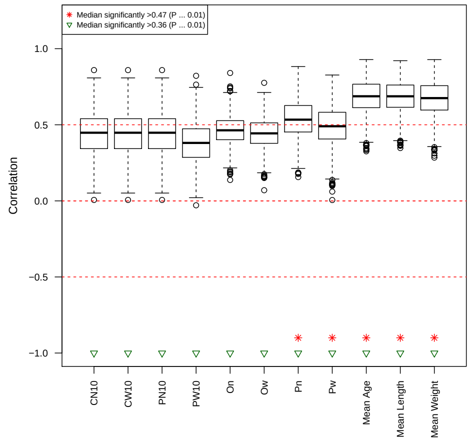
(c) Recruitment crash

(d) Stable fishery

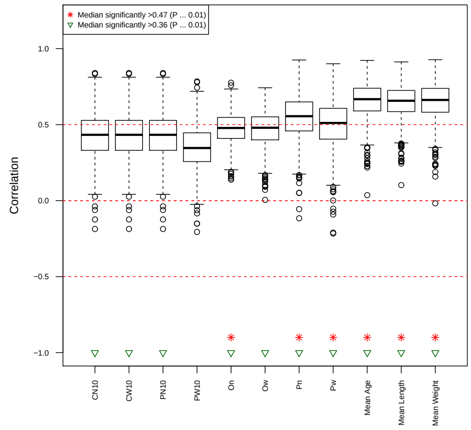
Figure 4.3: **Indicator correlations with SSB for different fishery scenarios:** The correlation of all indicators were non-significant in a well managed stable fishery. None of the indicators were equally sensitive to all impact scenarios.

This means that indicators based on large fish age groups was still useful in predicting the state of the stock. However, some knowledge of the fishing gear is required to classify the large fish samples. The LFIs in this scenario were computed based on the assumption that the selectivity parameter is $S_{95\%} = 5$ instead of the actual $S_{95\%} = 7$. As a result, neither P_n nor P_w gave any significant correlations with SSB.

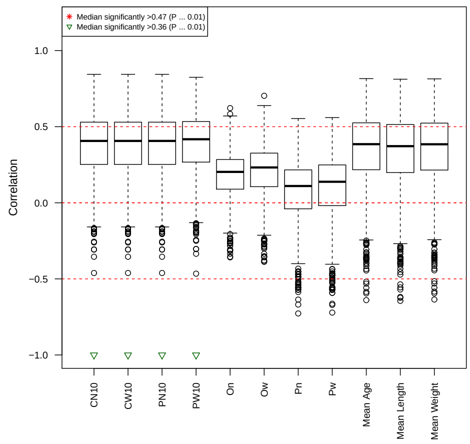
The MFIs in the large mesh scenario did not give any significant correlations because more mature fish individuals were allowed to escape. As a result, the SSB stabilized and continued to replenish the stock even when the F was increased. If the selectivity ogive is shifted to coincide with, or to exceed, the maturity ogive, then the population can sustain more exploitation (Brooks et al., 2010). In other words, the MFIs will be less useful if age groups based on $M_{95\%}$ are not vulnerable to fishing.



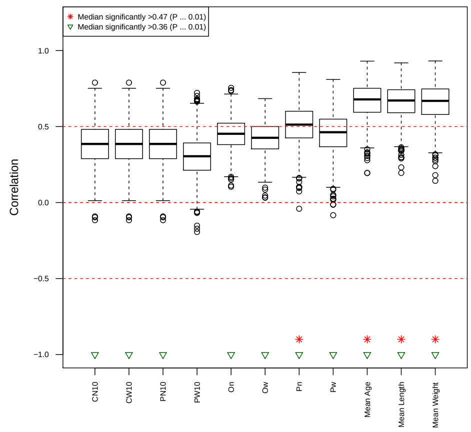
(*a*) Medium mesh trawl net (Base case)



(*b*) Small mesh trawl net



(*c*) Large mesh trawl net



(*d*) Medium mesh gill net

Figure 4.4: **Indicator correlations with SSB for different selectivity patterns:** All indicators except ABIs based on the plus group failed to produce significant correlations when a large mesh trawl net was used.

4.5.1.2 Response of indicators

The response was measured using the time lags obtained for the highest correlation coefficient when the indicators were cross-correlated with SSB. An indicator with a good response will have zero or minimum positive time lags. The median of the time lags (from 1000 iterations) obtained for each scenario is presented in Table 4.3. The choice of median over the mean values were to avoid the effect of outliers in the lag distribution. Results showed that in general, all the mean and mature fish indicators (MI and MFI) gave zero or positive time lags indicating their predictive nature in determining the current or future state of the stock (Table 4.3). The minimum positive time lag responses within a scenario were given by the mature and large fish indicators based on catch numbers (O_n and P_n).

Table 4.3: **Response of indicators from simulated fishery:** Shaded row indicate the response obtained from the base case scenario. The indicators with zero or minimum positive lags were determined as useful in predicting the state of the stock.

Scenarios	ABI ($a = a_{max}$)				MFI		LFI		MI		
	CN_a	CW_a	PN_a	PW_a	O_n	O_w	P_n	P_w	MA	ML	MW
1-Cod-like fishery	−4	0	−5	−5	3	3	2	−5	0	3	5
2-Herring-like fishery	3	3	3	3	2	2	3	3	2	2	2
3-Rockfish-like fishery	0	0	0	0	0	0	0	0	0	0	0
4-Recruitment crash	4	4	4	4	1	1	3	3	2	2	2
5-Under fishing	−5	0	−5	−4	3	4	4	−5	0	3	5
6-Stable fishery	5	5	5	5	1	1	3	3	2	2	2
7-Trawl (small mesh)	2	2	2	2	1	1	2	3	1	1	1
8-Trawl (large mesh)	0	0	0	0	1	2	3	3	4	4	4
9-Gill net	2	2	2	3	1	1	2	3	1	1	1

When different life history species are considered, the most immediate response was obtained for the long life span species (Table 4.3). This is because the change in SSB is slow due to the low selectivity applied to mature fishes in the younger age groups (see Figure 2.8). Scenarios based on selectivity patterns indicated that the time lag of ABIs based on the plus group were zero when a large mesh size gear is used (Table 4.3). This shows that the indicators based on the plus group can be used for determining the state of the stock if more mature fish individuals are allowed to escape.

4.5.2 Indicator analysis using real world ICES fish stocks

4.5.2.1 Sensitivity of indicators

The indicators which gave the highest correlations with SSB in the simulated fishery (Table 4.3) were tested for their usefulness in predicting the state of real world fish stocks. The sensitivity of these indicators were measured using their correlations with SSB and are presented in Table 4.4. Results show that the correlations are positive for the ABIs based on plus group, MFIs and LFIs. The correlations of MFIs were strong and significant when compared to other types of indicators (Table 4.4). This agree with the predictions from simulated fishery because the mature fish age groups are fully vulnerable to fishing ($M_{95\%} > S_{95\%}$) in all the selected real world ICES fish stocks (Table 4.2). This confirms that the indicators based on mature or large fish age groups are more likely useful in predicting the trend in underlying state of the stock. This is graphically illustrated in Figure 4.5b,c where the time series of MFI and LFI computed for the Irish Sea Cod (*Gadus morhua*) are plotted along with its estimated SSB (ICES, 2012*c*).

Table 4.4: **Sensitivity and response of indicators from real world fish stocks**

(a) Sensitivity: Shows the indicator correlations obtained with SSB.

Scenarios	ABI ($a = a_{max}$)				MFI		LFI		MI
	CN_a	CW_a	PN_a	PW_a	O_n	O_w	P_n	P_w	MW
Herring	0.51^S	0.50^S	0.55^S	0.50^S	0.63^S	0.64^S	0.63^S	0.63^S	0.61^S
Cod	0.82^S	0.83^S	0.62^S	0.61^S	0.50^S	0.57^S	0.15^N	0.35^S	-0.03^N
Plaice	0.16^N	0.17^N	0.08^N	0.09^N	0.25^N	0.29^S	0.18^N	0.21^N	0.04^N
Halibut	0.37^S	0.40^S	0.23^N	0.22^N	0.30^S	0.29^S	0.69^S	0.69^S	0.38^S
Rockfish	0.42^N	0.38^N	0.67^S	0.64^S	0.77^S	0.73^S	0.80^S	0.77^S	0.77^S

S : Correlation is significantly different from 0 with 95% confidence level
N : Correlation is not significantly different from 0

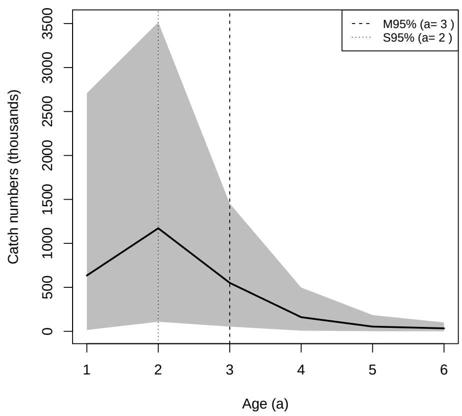
(b) Response: Time lag in years obtained when the indicators were cross-correlated with SSB.

Scenarios	ABI ($a = a_{max}$)				MFI		LFI		MI
	CN_a	CW_a	PN_a	PW_a	O_n	O_w	P_n	P_w	MW
Herring	2	2	5	5	2	2	2	3	2
Cod	1	1	1	2	1	1	0	1	−5
Plaice	5	5	5	5	2	2	4	3	5
Halibut	5	5	0	3	4	4	−3	−3	−3
Rockfish	1	1	1	1	1	1	1	1	1

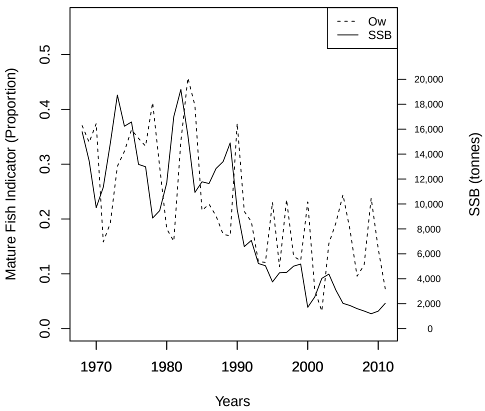
However, the mean weight (MW) indicator gave weak and non-significant correlations with the SSB for a few fish stocks (Table 4.4a). This shows that the indicators based on average metrics could be comparatively less useful in the real world because the impacts due to changes in fishing pressure are more dynamic and short term rather than consistent long term impacts as used in the simulated fishery. Hence such indicators will be more useful for short life span species (see the correlation of MW for Herring, Table 4.4). Large fishes in the stock are more sensitive to fishing and hence they can raise alarms earlier than the MIs (for the medium and long life span species).

4.5.2.2 Response of indicators

The indicators in Table 4.4a were tested for their responsiveness to changes in SSB using their cross-correlations. The time lags obtained in the results were either zero or positive for the ABIs based on plus group and the MFIs (Table 4.4a). A comparison with results from the simulated fishery (Table 4.3) shows that the responsiveness of MFIs and LFIs are consistent i.e., the direction of lags being positive or negative. The response of mean weight (MW) from ICES fish stocks were found to be the least useful since the range and direction of time lags obtained were large and inconsistent with the results from the simulated fishery (Table 4.3, 4.4b).



(a)



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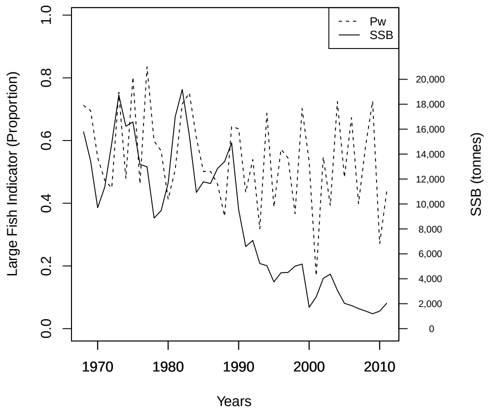


(c)

Figure 4.5: **Graphical illustration of MFI and LFI using Irish Sea Cod data**: **(a)** the shaded region indicates the range between 5th and 95th percentile of the catch numbers obtained in each age group between 1968-2011 (ICES, 2012*c*) **(b)** positive proportions of the catch weight computed for the age group $M_{95\%} = 3$ (MFI) **(c)** positive proportions of the catch weight computed for the age group $S_{95\%} = 2$ (LFI).

4.6 Discussion

The present study evaluated a variety of age based catch indicators using a simulated fishery to determine the most useful indicator in terms of their sensitivity and response towards changes in SSB. Similar studies have been done before by several researchers (Punt et al., 2001; Link et al., 2002; Trenkel and Rochet, 2003; Nicholson and Jennings, 2004; Fulton et al., 2005; Probst et al., 2012; 2013*a*), but these studies were more generally focussed on region specific fish stocks, survey indicators, community or ecosystems. The present study used a general approach across different life history species and real world fishery scenarios to determine whether any age based indicator from commercial fisheries catch could be used for detecting the state of the fish stock so they can be used for qualitative assessments when available data are unreliable or limited. In this study, the sensitivity of stock indicators were assessed using correlation coefficients and their response was evaluated by determining the time-lagged relationship with SSB. Correlation coefficients have been used before to assess the sensitivity of indicators in real world fish stocks and in simulated ecosystems (Fulton et al., 2005; Probst et al., 2012). The most useful indicator from the fisheries simulation was the LFI and the analysis on real world fish stocks showed that these results are consistent.

4.6.1 Indicators based on mean or age proportions?

Both mean and proportional indicators were found useful in the simulated fishery though the later was found more robust in real world fish stocks. Therefore, if catch at age or length data are available, proportional indicators based on mature or large fish individuals should be used. Similar large fish proportional indicators have been found useful in detecting the effects of fishing and are sensitive to changes in abundance of large predatory fish populations in ecosystems (Shephard et al., 2011; Greenstreet et al., 2011). Fishery independent effects on abundance of smaller age or length groups may affect the trend in such proportional indicators but can be resolved by using an absolute large fish indicator. For example, the average length of largest 10 individuals in the catch obtained during fisheries surveys has been found very promising to detect changes in size structure of the population (Piet and Doerner, 2010; Probst et al., 2013*b*).

Nevertheless, the most simple and cost effective metrics are the mean indicators because they can be measured easily even when the data are limited. Size-selective mortality is a fundamental response of fishing and hence the mean indicators (MIs) are sensitive towards changes in population abundances (Francis and Smith, 1995; Punt et al., 2001; Nicholson and Jennings, 2004). However, the estimates of MIs can be quite imprecise if the number of catch samples used are too small (Figure B.1d). For computing indicators such as the mean age, a reliable Age-Length Key (ALK) will be required which is not available for most data limited fisheries because they are costly, time consuming and laborious to produce (Campana et al., 1995; Officer et al., 1996). The age estimates for higher age groups are also likely to become inaccurate due to large overlaps between subsequent length classes because the growth rate generally diminishes with increasing age (Equation 2.4)

4.6.2 Indicators based on catch numbers or weight?

The differences in average weight-at-age reduces as the growth of fish reaches an asymptote and their variability will also increase with higher age groups (Equation 2.4 and 2.8). Therefore, the differences in population abundance of large fishes are better reflected in catch numbers than in catch weights. This is evident from the results (Table

4.3 & B.2) where the lags obtained for the indicator based on large fish catch weight (P_w) was higher than those based on catch numbers (P_n).

However, the application of indicators based on catch numbers will depend upon the practical feasibility of counting the catch (McGarvey et al., 2005). If an age-length key is available for the species, catch numbers at age can be sorted out based on their length. If not, age groups can be replaced by length classes which is a more viable option when only length frequency data are available for the fishery.

4.6.3 Indicators based on mature or large fishes?

In general, both mature and large fish indicators were sensitive to fishing but the former failed to give significant correlations with SSB in a large meshed trawl fishery. This indicates that MFIs will be less useful if the age group corresponding to $M_{95\%}$ parameter is not fully vulnerable to fishing. Thus linking broad suggestions of using the trend in MFIs into practical management advice (Froese, 2004) can be problematic if there is uncertainty in determining the interaction between maturity and selectivity of the stock (Cope and Punt, 2009).

Determining both $S_{95\%}$ and $M_{95\%}$ are challenging in a data limited fishery. The $M_{95\%}$ is generally estimated using a large number of individuals belonging to different age groups with an assumption that the samples used are an accurate representation of seasonal and regional distribution of the species in relation to their spawning activity (Murua et al., 2003). However, there is increasing evidence of fisheries-induced evolution in maturation patterns due to increased mortality at potential age or size at maturity (Trippel, 1995; Olsen et al., 2004). Research has shown that the changes in maturation schedule are not a result of phenotypic plasticity mediated through growth and survival but due to environmental effects through fishing (Olsen et al., 2005). The North Sea Plaice used in the present study is an example where early maturation at smaller sizes has been observed in recent years (Grift et al., 2003).

Information on selectivity parameters of the gear is essential to choose a size criteria for the minimum large fish age group. Estimating $S_{95\%}$ involves fishing experiments and is particularly difficult if the stock is exploited by multiple types of fishing gears. However, selectivity is relatively similar across multiple stocks if they are exploited by fleets using the same type of fishing gear. Hence selectivity parameters from other data rich stocks can be adopted if this information is not readily available (Punt et al., 2011). A second option is to identify those age or length classes for which the catch numbers or biomass in the subsequent classes follows a decreasing trend (Froese, 2004). This approach is used in the present study assuming that the concerned species represent a data-limited or poor fishery. However, this method is reliable only if the relative year class strength is consistent, at least for the last few years (Thurow, 1997).

4.7 Summary

The following conclusions can be drawn in determining the potential age based catch indicators that can be used for detecting the underlying state of a fish stock:

1. Indicators based on average (e.g., mean age of the catch) and proportional measures (e.g., positive proportion of catch above certain age) are sensitive to changes in SSB of the stock.

2. The sensitivity of mature or large fish proportional indicators (MFI or LFI) are more robust than those based on average measures e.g., mean indicators (MIs).

3. The mature or large fish indicators (MFIs or LFIs) based on catch numbers are more robust than those based on the catch weights because the weight of the fish becomes highly variable with increasing age.

4. The mature fish indicators (MFIs) are more responsive to changes in SSB than the large fish indicators (LFIs) because the MFIs account for more mature fish age groups in the stock.

5. The large fish indicators (LFIs) are more sensitive to fishing than the mature fish indicators (MFIs) because fishes bigger in size are more vulnerable to the fishing gear.

Chapter 5

Monitoring data poor fish stocks using SS-CUSUM

This chapter was published in a similar form in “Fisheries Research” under the reference: *Pazhayamadom, D. G., Kelly, C. J., Rogan, E. and Codling, E. A. 2013. Self-starting CUSUM approach for monitoring data poor fisheries. Fisheries Research 145: 114-127.*

5.1 Introduction

A data poor fish stock could be anything from having absolutely no data to poor quality data that are unreliable. The abundance of such stocks are difficult to monitor or assess using traditional methods because such models undertake numerous assumptions and are data intensive (Kelly and Codling, 2006). There is growing literature on developing alternative methods that would be cheaper and effective for monitoring the state of fish stocks with limited information (Smith et al., 2009; Honey et al., 2010). In this paradigm, methods based on sequential trend analysis of indicators have gained substantial attention (Andersen et al., 2009; Honey et al., 2010). Detection of trends or patterns in indicator time series are often used in data poor fisheries as a qualitative approach (Caddy, 1998). But many of the existing methods available require expert judgement, careful assumptions, robust estimates, reliable reference points or a reasonable number of years in the time series to detect an impact on the fishery (Honey et al., 2010). Moreover, the probability of detecting a trend is low for an indicator time series less than 10 years (Nicholson and Jennings, 2004; Blanchard et al., 2010). It is not consistent with the precautionary approach of fisheries management to wait until enough data are generated to apply a trend detection method since it will be too late to detect an impact if the stock is sensitive to fishing. But the question, “Can we manage a fishery if limited or no historical data are available?” remains unresolved.

This chapter presents a statistical approach to address this problem. Identifying anomalies is a pre-requisite to action plans in any management strategy. So a first step would be to evaluate monitoring schemes that require the least data to start with and detect anomalies correctly as soon as they occur. Methods from statistical process control (SPC) theory such as the cumulative sum control chart (CUSUM) are promising and hold the basic principles of a 'traffic light' approach but fitted within a statistical framework (see Chapter 3). Key advantages of these techniques are that they are model free and do not require any major financial or human resource investment (Scandol, 2003; Petitgas, 2009). Hawkins (1987) proposed Self-Starting CUSUM (SS-CUSUM) and demonstrated how a SPC method can be applied if no prior information about the process is available to estimate a reference point (Section 3.4). Application of the SS-CUSUM method would be ideal for situations where there is a short time series and/ or low contrast data, and hence has the potential scope for developing a low cost fishery monitoring system.

In the present study, a simulated fishery was used to evaluate performances of SS-CUSUM. We assume that the fish stock is historically in an 'in-control' state (steady and stable). No previous scientific data are available for the fish stock when the SS-CUSUM is initiated. A fishing impact was introduced to the stock by increasing the fishing pressure in an ongoing basis. The performance of SS-CUSUM is demonstrated under various scenarios and shows how significant changes in stock biomass due to a negative fishing impact can be detected using indicators from landed catch.

5.2 Objective of the study

Many data poor fish stocks do not have target or limit reference points due to the absence of biomass estimates and hence the management actions are usually triggered based on available information (Dowling et al., 2008; mostly limited to historical catch data). For example, in the Australian Harvest Strategy Policy (HSP), the triggers are based on multiple response levels, generally 0.5, 1.0, and 2.0$\times$ the highest recorded catches of key commercial species (Smith et al., 2009). The SS-CUSUM can be applied in such scenarios effectively since it has a statistical framework for determining the out-of-control situations using the allowance (k) and control limit (h) parameters (see Chapter 3). The objectives of the present study are:

- To determine the monitoring performance of SS-CUSUM with specific catch indicators from the fishery.
- What values should be used for the k and h to obtain signals with the required sensitivity or specificity?

5.3 Background

In a decision-interval form of CUSUM (DI-CUSUM), the user should know exactly the parameters of the in-control distribution i.e., the control mean and standard deviation for monitoring the indicator time series. SS-CUSUM has the advantage of using regular indicator measurements themselves to calibrate these parameters. In SS-CUSUM, every new observation is standardized using the mean and standard deviation accumulated to date. So essentially, the control parameters are dynamic in SS-CUSUM and they are referred to as the "running mean" and "running standard deviation" (see Section 3.4). These estimates get closer and closer to the true values as more observations are used for their calibration.

However, very careful attention is required when implementing a SS-CUSUM. The running mean of the indicator should be ideally based on observations when the stock is in an 'in-control' situation. The 'in-control' state of the stock will depend on the given management objectives but will usually correspond to when the stock is stable and being fished close to, or just below, the maximum sustainable yield. Hence the SS-CUSUM should begin with a few preliminary observations from the in-control state to calibrate the running mean. In this study it was assumed that the SS-CUSUM is started off in an in-control state. However, this is a limitation since in some data poor fisheries the state of the stock may initially be unknown or may be in an 'out-of-control' state. In such cases a SS-CUSUM may not be appropriate (see Section 5.6).

When no historical data are available, the running mean can be updated only with future observations to detect the deviation of fish stocks from its initial state. Hence, it is important to protect the running mean from all observations that could result in an out-of-control signal. This can be achieved by rolling back the history to the last estimated reference mean when the stock was in an in-control state as detected by the method (Section 3.4.3, Figure 3.3). Secondly, it is important to avoid the influence of isolated outliers in the data which could eventually result in inflating the running standard deviation. This will reduce the potential of SS-CUSUM to detect required mean shifts. This issue can be resolved by using "metric winsorization" where the deviation due to extreme outliers can be replaced by a cut-off threshold value known as the "winsorizing constant" (w) and thereby protecting the running mean and standard deviation (Section 3.4.4, Figure 3.2).

5.4 Methods

5.4.1 The operating model

This study used a stochastic operating model to simulate age structured fish stocks (see Section 2.4) and the fishery was simulated deterministically until the exploitable biomass converged to an equilibrium (B_{eq}, Section 2.3.2). The fishery equilibrium was achieved using a fixed initial fishing mortality ($F_{int} = 0.17$) that is close to, but below, the maximum sustainable yield ($F_{MSY} = 0.22$). Hence at this point, it was assumed that the stock is stable and sustainable ('in-control'). In the first phase, the model ran for 100 further years where random variability was introduced into the fishing mortality to stabilize any transient processes. In the second phase, a compound fishing impact was applied to the stock by increasing the base fishing mortality (F_i) with a 5% step change per year (i.e. $F_{i+1} = 1.05F_i$, where 'i' is year, starting from the first year of the second phase; a similar 5% annual step change reduction in F is applied in scenario 2).

5.4.2 Monitoring indicators from fisheries catch

A total of five catch-based indicators were generated from the second phase of the simulated fishery (Table 2.2) i.e., mean age (MA), mean length (ML), mean weight (MW), positive proportion of large fish individuals by catch number (P_n) and by catch weight (P_w). All indicators were calculated using a random sample (without replacement) of all fish individuals obtained in the fisheries catch. The P_n and P_w are the two large fish indicators (LFI) used in this study and they were collectively categorized as those age groups for which more than 95% of the cohort is vulnerable ($S_{95\%}$) to fishing (Section 2.5.2.4). All indicators were assumed to be representative of a data poor situation and they were monitored using SS-CUSUM for a 20 year period in the second phase of the fisheries simulation. Note that in the first year of the second phase, no historical indicator data are available for the fish stock (the only information available is that the stock starts off in an 'in-control' state).

5.4.3 Scenarios considered

Various scenarios were constructed to compare the monitoring performance of SS-CUSUM (Table 4.1). These scenarios were based on (i) the type of fishing impact (increasing or declining F); (ii) species with different life spans (short, medium or long); (iii) selectivity of the fishing gear (trawl or gill net); (iv) growth variability of the species (between or within the cohorts); (v) autocorrelation in recruitment deviates of the stock (medium or high) and (vi) number of catch samples used for indicator calculations ($n = 10000, 1000, 100$ or 10).

Table 5.1: **Scenarios used for evaluating the performance of SS-CUSUM:** F_{inc} is the percentage step change in the base fishing mortality each year in the second phase of the simulation. K and L_∞ are the growth coefficient and asymptotic length of the species respectively (Table 2.1). The shaded areas highlight the differences compared to the base case parameters.

Scenarios	F_{inc} (yr^{-1})	Life History	Selectivity function	Variability in K & L_∞	Autocorrelation (ρ)	Sample size (n)
1. Increasing F*	5% increase*	LH1*	Logistic*	Absent*	Absent*	10,000*
2. Decreasing F	5% decrease	LH1	Logistic	Absent	Absent	10,000
3. Life History 2	5% increase	LH2	Logistic	Absent	Absent	10,000
4. Life History 3	5% increase	LH3	Logistic	Absent	Absent	10,000
5. Trawl (small mesh)	5% increase	LH1	Logistic	Absent	Absent	10,000
6. Trawl (large mesh)	5% increase	LH1	Logistic	Absent	Absent	10,000
7. Gill net	5% increase	LH1	Double-Normal	Absent	Absent	10,000
8. Growth(between cohorts)	5% increase	LH1	Logistic	cv=0.2	Absent	10,000
9. Growth(within cohorts)	5% increase	LH1	Logistic	cv=0.2	Absent	10,000
10. Autocorrelation (ρ=0.5)	5% increase	LH1	Logistic	Absent	ρ=0.5	10,000
11. Autocorrelation (ρ=0.8)	5% increase	LH1	Logistic	Absent	ρ=0.8	10,000
12. 1000 samples	5% increase	LH1	Logistic	Absent	Absent	1000
13. 100 samples	5% increase	LH1	Logistic	Absent	Absent	100
14. 10 samples	5% increase	LH1	Logistic	Absent	Absent	10

* Base case scenario

The life history parameters used for three different species are given in Table 2.1. The selectivity-at-age used a logistic function (Equation 2.14) to represent trawl nets of small, medium and large mesh size (which increases with age giving a sigmoid shape) or double-normal function representing gill nets (which increases up to a certain age and then decreases giving a dome shape). Scenarios based on growth variability used a log normal error in the length weight relationship (Equation 2.8) and random noise errors in K and L_∞ in each year 'i', at age 0 (between cohorts, Equation 5.1 & 5.2) or all age groups (within cohorts, Equation 2.6 & 2.7).

$$K_{a=0}^{i,g} \sim normal\ (mean = K, cv{=}0.2), \tag{5.1}$$

$$L_{\infty}{}_{a=0}^{i,g} \sim normal\ (mean = L_\infty, cv{=}0.2) \tag{5.2}$$

A coefficient of variation of 0.2 was used for K and L_∞ which is an upper bound when compared to earlier studies (Shackell et al., 1997; Ratz et al., 1999; Armstrong et al., 2004). Autocorrelation in recruitment was introduced using an inter-annual dependency coefficient (ρ) in the stock-recruitment relationship describing the dependency of recruitment in a given year with recruitment of the previous year (Equation 2.13). The ρ value of 1 suggests a perfect autocorrelation of first order i.e., correlation of observations in year 'i' with those in year '$i-1$' (Kanaiwa et al., 2005). The ρ values used in the present study are potentially high considering the values observed in similar fish stocks (Fogarty et al., 2001). The base case considered an increasing F scenario with sigmoid shape gear selectivity on a medium life span species (Cod like, Family:

Gadidae).

For all scenarios, the winsorizing constant and allowance parameter of SS-CUSUM were kept constant (w=2, k=0.5). A w=2 is considered to be a good choice since this was found robust to outliers and equally sensitive to genuine shifts (Hawkins and Olwell, 1998). The method will be most sensitive when k is set at the minimum possible since this will produce responses even for small deviations from the running mean. Each scenario was iterated 1000 times in the second phase. The performance of SS-CUSUM was evaluated for h values ranging from 0 to 6 with 0.1 intervals (total 61). Note that fixing a value of h and varying k would produce qualitatively similar results and hence it is not necessary to consider a wide range of values for both parameters. The simulations and indicator monitoring using SS-CUSUM were carried out using codes written in the programming language R (R Development Core Team, 2012).

5.4.4 Performance measures

It is assumed that the fishery would require management action if the biomass in any given year (B_t) is 30% below (or above) the equilibrium biomass level (B_{eq}). This arbitrary threshold was chosen because the fluctuations of stock biomass in the second phase may not always correspond to the increment in fishing pressure but due to the variability introduced through random noise. Hence this approach has the advantage of determining which indicators are more likely to raise true signals with SS-CUSUM for the impacts due to fishing. Using a higher threshold (e.g., > 50%) is meaningless in the CUSUM context because these methods are designed for detecting persistent and gradual shifts in the indicator.

The years in which 'out-of-control' signals were generated by the SS-CUSUM from the second phase of the simulation were compared to the years in the operating model where biomass was 30% below (or above) the equilibrium level. An out-of-control signal is raised by the method when either the upper or lower SS-CUSUMs exceed the control limit (h). These signals can then be classified as either a true positive (T^+; $B_t < 0.7B_{eq}$ or $B_t > 1.3B_{eq}$) or a false positive (F^+; $0.7B_{eq} < B_t < 1.3B_{eq}$) situation. Alternatively, a true negative and false negative situation occurs when upper and lower SS-CUSUMs do not exceed the control limit (h) and hence there is no signal. If $0.7B_{eq} < B_t < 1.3B_{eq}$, then this is a true negative (T^-) but otherwise a false negative (F^-) case. If $P(T^+)$ is the probability of true positive results, sensitivity and specificity (Bland, 2000) is defined as:

$$Sensitivity = P(T^+)/\left[P(T^+) + P(F^-)\right]$$

$$Specificity = P(T^-)/\left[P(T^-) + P(F^+)\right]$$

For every h value, there is a pair of sensitivity and specificity measures. The full range of h values produced 61 pairs of sensitivity and specificity measures for each scenario. The discriminative power of a signal detection scheme is perfect if a h value gives 100% sensitivity and 100% specificity. However, this hardly happens while monitoring a stochastic process. Scandol (2005) constructed a 'receiver-operator curve' (ROC) to assess the discriminative power of CUSUM with fishery indicators. In a ROC curve, sensitivity is plotted against (1−specificity) for different h cut-off points. Hence, each point on the ROC curve represents a sensitivity and specificity pair with respect to a h threshold.

Both F^{+} and F^{-} are comparable to Type 1 and Type 2 errors in statistical testing. 'Optimal Performance' of the scheme was defined as when $P(F^{+}) = P(F^{-})$ (or when sensitivity equals specificity) since that would be the easiest way to interpret a trade-off between both types of errors (Scandol, 2003). However, this performance level is only theoretical and abstract since in a real fishery the optimality of a monitoring method may depend on management objectives (e.g. conservation or maximising catches).

A quantitative measure of overall performance of the scheme with an indicator can be represented as the area under the ROC curve (AUC). Generally AUC is used as a global index of diagnostic accuracy for comparative studies on the performance of a signal detection scheme with different indicators (Bamber, 1975). The area under the ROC curve (AUC) was calculated only up to the h value corresponding to optimal performance (i.e. for high values of sensitivity, low values of specificity) because beyond this point the ROC curves become noisy. Hence, these measures were used only for qualitative comparison in this study.

5.5 Results

5.5.1 Illustration of indicator tracking with SS-CUSUM

An illustration of SS-CUSUM with the large fish indicator (P_w) is presented here from the base case scenario. Figure 5.1 displays a window showing a single iteration from the second phase of the fishery simulation where a stable fish stock starts to become impacted due to the increasing F. Figure 5.1a shows the change in biomass of the stock over time and Figure 5.1b corresponds to the respective change in the P_w indicator. SS-CUSUM has two components, the upper SS-CUSUM tracks positive deviations of the indicator from the running mean and lower SS-CUSUM tracks negative deviations of the indicator. A negative trend in the large fish indicator is expected if the stock is overfished by an increasing F. In the following example, the lower SS-CUSUM started deviating after the second year of the second phase and the scheme signalled at year six when the control limit was set equivalent to $h = 1$ (Figure 5.1c).

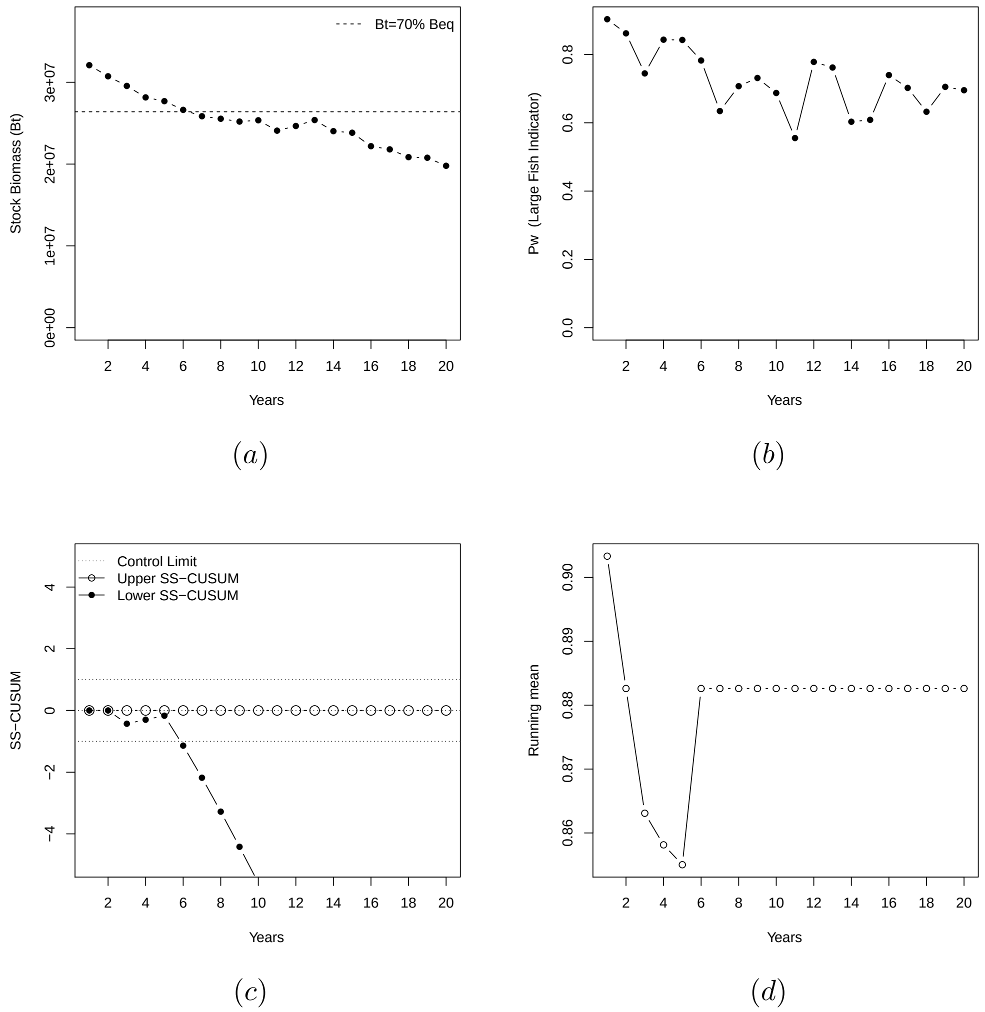
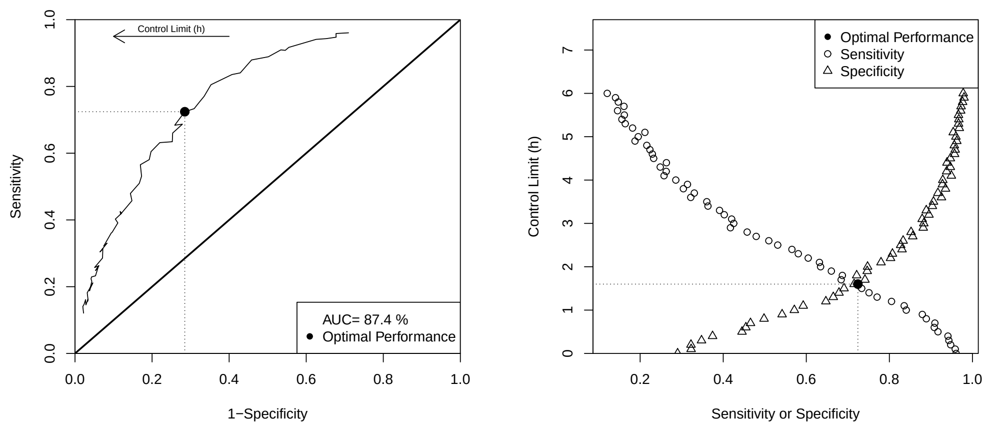


Figure 5.1: **Graphical illustration of indicator tracking with SS-CUSUM. a.** Degradation of stock biomass (B_t) in response to increasing fishing mortality (F). The change in stock biomass was greater than 0.3 B_{eq} after year 6. **b.** Movement of P_w indicator. **c.** Signals from SS-CUSUM method (k=0.5, h=1). **d.** Calibration of running mean by SS-CUSUM in real time. The scheme signalled at year 6 and the running mean was rolled back to year 2 when the stock was last perceived to be stable by the monitoring method.

Calibration of the running mean over time is shown in Figure 5.1d. The method signalled in year six and hence, the running mean was rolled back to the last estimated reference mean when the stock was in an in-control situation. The deviation which resulted in an out-of-control signal originated after the second year of the step change increase in F. Therefore the reference mean corresponding to the second year was used as the running mean from the sixth year of the simulation.

5.5.2 Illustration of the ROC curve

Figure 5.2 shows the performance measures of SS-CUSUM obtained while monitoring the P_w indicator. The closer the apex of the ROC curve towards the upper left corner, the better is the discriminative ability of the scheme (Figure 5.2a). SS-CUSUM is most sensitive and least specific when h=0. As h moves from 0 to 6, the sensitivity of the scheme decreases and the specificity will increase (Figure 5.2b). The optimal performance was achieved at h=1.6 with 72.42% sensitivity or specificity.



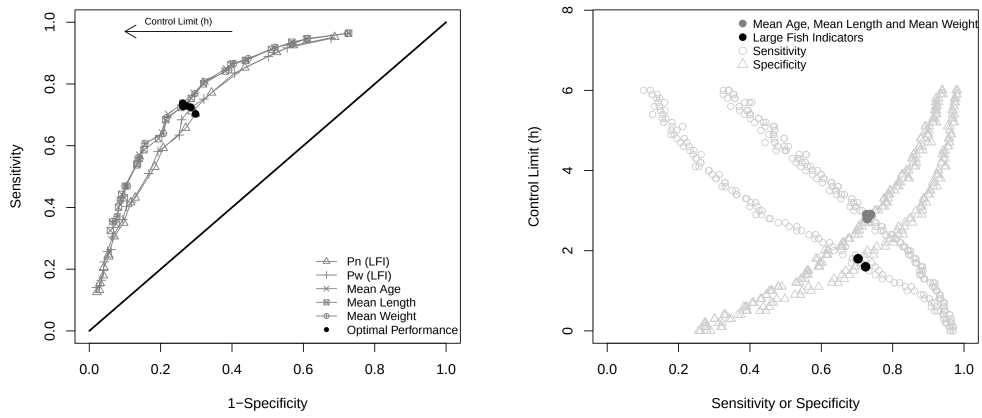
(a) (b)

Figure 5.2: **Graphical illustration of performance measures. a.** Receiver Operator Characteristic (ROC) curve for P_w indicator (other indices may perform better) constructed using sensitivity and specificity values obtained for different h thresholds (61 pairs). The area under the curve (AUC) is approximately 87.4% of the total area. **b.** Optimal performance (sensitivity equals specificity) was achieved when control limit (h) was 1.6.

5.5.3 Performance comparison with indicators

SS-CUSUM was successful in signalling a significant biomass change due to fishing impacts with all catch-based indicators (Figure 5.3). None of these indicators were considered poor with the method since ROC curves were above the diagonal line connecting (0, 0) and (1, 1).

Performance measures of SS-CUSUM with all indicators from the base case scenario are presented in Figure 5.3. The ROC curves of the scheme with large fish indicators were similar to those with traditional indicators i.e., mean age, mean length and mean weight (Figure 5.3a). For qualitative comparison, the AUC values for these indicators are given in Table 5.1. However, the large fish indicators were more responsive with the method. The optimal performance of SS-CUSUM with large fish indicators was achieved at a much lower h value compared to other indicators in the study (Figure 5.3b). So for any given h value below optimal performance, the scheme will have a greater sensitivity and specificity with large fish indicators. The sensitivity and specificity profile of catch-based indicators across all scenarios are graphically presented in Appendix C (Figure C.1). SS-CUSUM achieved optimal performances for all indicators with a sensitivity and specificity above 50%.



(*a*) (*b*)

Figure 5.3: **Performance measures of SS-CUSUM with different catch-based indicators. a.** ROC curve for indicators from the base case scenario. SS-CUSUM is more sensitive and specific when the apex of ROC curve is closer to the upper left corner. The ROC curves are similar for all indicators with the different h thresholds used in this study. **b.** Optimal performances of SS-CUSUM (sensitivity equals specificity). Optimal performance was achieved at lower h thresholds for large fish indicators. The P_n and P_w are the large fish indicators (Table 1).

5.5.4 Performance comparison with type of fishing impact

Performance measures from the base case scenario were used to check the consistency of the signal detection scheme to the type of fishing impact (increasing and declining F). ROC curves show that the method performed better in an increasing F scenario (Figure 5.4a). The area under ROC curves (AUC) can be used for qualitative comparison on performance of the method (Table 5.2). Only the large fish indicator (P_w) is presented graphically since the ROC curve for other indicators were qualitatively similar. The indicators used in this study are heavily influenced by the large fish component in the landed catch since fishing is size selective. Hence when F is increased, the impact to the stock will be more evident on the trend of these indicators. But when F is decreased, the relative changes in catch-based indicators will be comparatively less since the abundance of large adult fishes is controlled by density dependent effects on the stock recruitment relationship. However, the control limit at optimal performance of SS-CUSUM was consistent regardless of the type of fishing impact (Figure 5.4b). This means for any given h value, SS-CUSUM will be more efficient in picking up the true signals if the impact to the stock is due to an increasing F.

5.5.5 Performance comparison with life history traits

Performance of SS-CUSUM from the base case scenario was compared with a short lived (LH2, Herring-like, Family: Clupeidae) and long lived (LH3, Rock fish-like, Family: Sebastidae) species. The ROC curves show that SS-CUSUM performed better with a

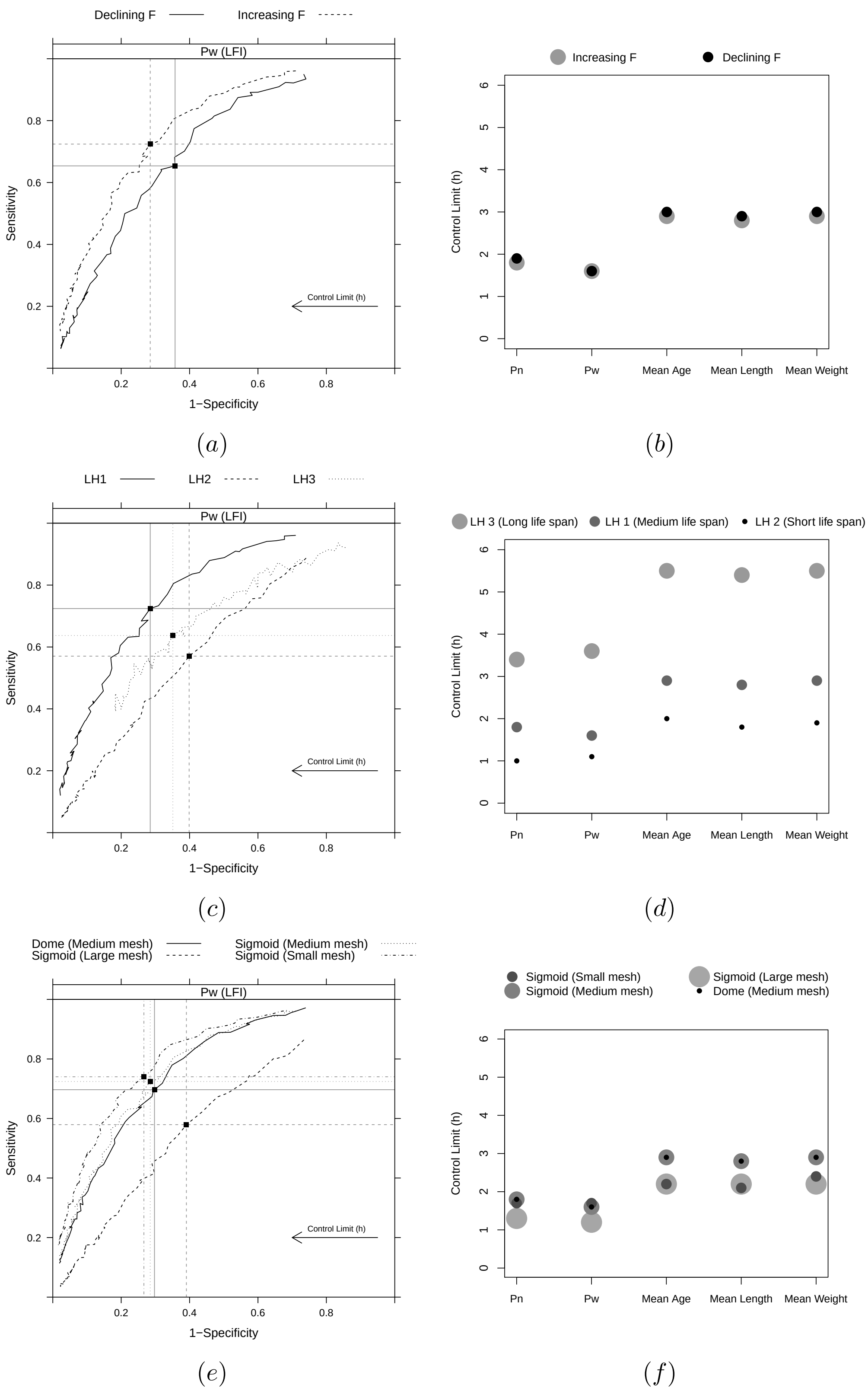


Figure 5.4: **Comparison of SS-CUSUM performance for type of fishing, life history traits and selectivity of the fishing gear. a,c & e** are the ROC curves for the P_w indicator. **b,d & f** are the control limits at which SS-CUSUM achieved optimal performance.

Table 5.2: **Area under ROC curves (AUC) obtained for SS-CUSUM with various catch indicators:** The AUC values for each indicator are represented as a relative proportion of the base case. The base case AUC values are P_n=0.877, P_w=0.874, MA=0.894, ML=0.896 and MW=0.893.

Scenarios	**Area Under Curve**				
	P_n	P_w	MA	ML	MW
1. Increasing F*	1.000	1.000	1.000	1.000	1.000
2. Decreasing F	0.961	0.970	0.964	0.960	0.969
3. Life History 2	0.859	0.842	0.870	0.853	0.858
4. Life History 3	0.915	0.913	0.911	0.906	0.907
5. Trawl (small mesh)	1.017	1.019	0.994	0.999	0.997
6. Trawl (small mesh)	0.864	0.829	0.887	0.883	0.888
7. Gill net	1.013	1.005	0.997	1.001	0.997
8. Growth (between cohorts)	0.878	0.856	0.853	0.854	0.846
9. Growth(within cohorts)	0.868	0.847	0.867	0.835	0.843
10. Autocorrelation ($\rho = 0.5$)	0.887	0.867	0.876	0.877	0.877
11. Autocorrelation ($\rho = 0.8$)	0.913	0.903	0.905	0.906	0.897
12. 1000 samples	0.998	0.997	1.000	0.996	1.002
13. 100 samples	0.972	0.999	0.976	0.974	0.980
14. 10 samples	0.835	0.968	0.924	0.960	0.963

* Base case scenario

species with medium life span (Figure 5.4c). However, a threshold of 30% change in stock biomass will not necessarily have the same magnitude of effect on the indicators of the three species considered in this study. Moreover, the stock biomass of a long lived species will take a longer period to have an impact of the specified threshold when compared to a short lived species. It would therefore be inappropriate to judge that SS-CUSUM works better with one life history type species over the other.

However, there was a marked difference in the control limit achieved by SS-CUSUM at optimal performance for species with different life histories. When h was increased, the sensitivity and specificity of the method changed more rapidly for short lived species and the optimal performance was achieved at very low h (Figure 5.4d). In contrast, the optimal performance for a long lived species was achieved at a higher h value. The catch-based indicators are more responsive in short lived species since the difference between recruitment and large fish age groups is small. Hence the choice of h in SS-CUSUM while monitoring catch-based indicators of a species is relative to its life span. A lower h value for short lived species and a higher h value for long lived species will reduce the risk of performance loss.

5.5.6 Performance comparison for selectivity pattern

Performance of SS-CUSUM from the base case scenario was compared with responses of indicators calculated from four types of fishing gear i.e., trawl nets with small, medium or large mesh size giving 'sigmoid shape selectivity' and gill net representing 'dome shaped selectivity'. In the 'dome shaped case', the selectivity for older age groups was low assuming that the gear was not efficient to catch large fish individuals. The ROC curves showed that the performance of SS-CUSUM is comparatively low if a large mesh trawl gear is used. Similar performances will be obtained for a large mesh gill net since fewer proportions of the mature adult fish are caught when the mesh size is large. Thus recruitment overfishing is reduced and the stock biomass gets replenished. However, more false positive signals are generated due to decreasing trends in the indicator (Figure 5.4e). The h values at optimal performance shows that the large fish indicators are more robust to the choice of control limit unless a large mesh size gear is used for fishing (this means the spread of h is minimum for LFIs, Figure 5.4f).

5.5.7 Performance comparison with variability in growth

Performance of SS-CUSUM from the base case scenario was compared with responses of indicators calculated from fish stocks where growth variability was introduced in two different ways i.e., between and within the cohorts. In the case of 'between cohorts', the K and L_∞ for each cohort was the same from birth to death but differed between consecutive generations. For the 'within cohort' case, these parameters were random in every consecutive year as the cohort become older. The ROC curves in Figure 5.5a show that the performance of SS-CUSUM was comparatively worse in both cases of growth variability. However, the ROC curves indicate good classification results (Fawcett, 2006) i.e., $P(T^+) > P(F^+)$ and hence SS-CUSUM can be used to monitor these indicators. Regardless of these differences, measures on optimal performance indicate that large fish indicators are more robust to the choice of h value and age based indicators will be more useful than those based on length or weight (see Figure 5.5b).

5.5.8 Performance comparison for autocorrelated stock-recruitment

Performance of SS-CUSUM from the base case scenario was compared with responses of indicators calculated from a fishery where the recruitment to stock was autocorrelated. Autocorrelation in recruitment variability may occur either due to life history traits (Korman et al., 1995) or environmental forcing conditions (Fogarty et al., 2001) and generate trends in abundance of age classes (Ottersen and Loeng, 2000). ROC curves showed a little loss of performance when autocorrelation was considered in the recruitment deviates (Figure 5.5c). The measures on optimal performance indicate that large fish indicators are robust to the choice of h value and will be more useful for monitoring fish stocks with significant autocorrelation in recruitment patterns (Figure 5.5d).

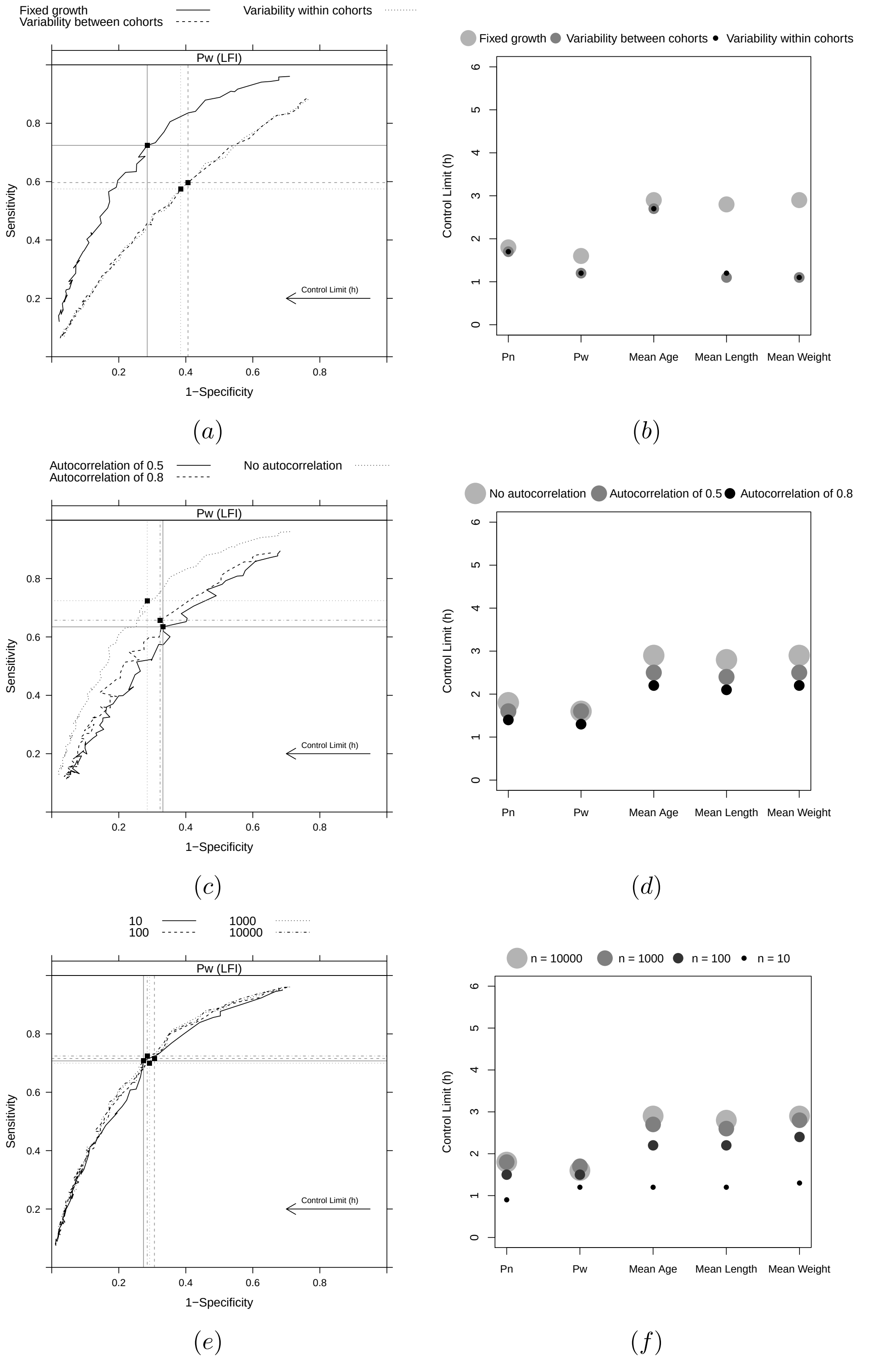


Figure 5.5: **Comparison of SS-CUSUM performance for growth variability, autocorrelation in recruitment and sample size used for indicator calculations. a,c & e** are the ROC curves for the P_w indicator. **b,d & f** are the control limits at which SS-CUSUM achieved optimal performance.

5.5.9 Performance comparison with samples of smaller size

Performance of SS-CUSUM from the base case scenario was compared with responses of indicators calculated from catch samples of smaller size (n =1000, 100 and 10). ROC curves showed that the number of catch samples did not affect the performance of the method (Figure 5.5e). However, the h values at optimal performance of the scheme were comparatively low for traditional indicators when a sample size of 10 was used (Figure 5.5f). The results show that the performance of the method is more robust to sample size when the large fish indicators are monitored.

The sensitivity and specificity values of SS-CUSUM at optimal performance for all indicators across the scenarios are given in Appendix C (Table C.1).

5.6 Discussion

Self Starting CUSUM, a method based on statistical process control, was tested for its detection capabilities in monitoring indicators from data poor fisheries. Application of SS-CUSUM has rarely been demonstrated in animal populations (Lukas et al., 2008; 2009). In the present study, a stochastic simulation was used to test and evaluate the performance of SS-CUSUM. Stochastic simulations are used to represent real world situations and are widely employed to evaluate the performance of SPC charts (Quesenberry, 1997; De Vries and Conlin, 2003; Scandol, 2003; De Vries and Conlin, 2005; Scandol, 2005). It was assumed that the fishery is historically ‘stable’ or ‘in-control’ up to the point where the monitoring method is initiated and no historical data for the stock are available but some catch based indicators could be obtained in the future. The indicators chosen for the study are typically available in a data poor situation, as they are based on direct observation of catches and do not rely on any other biological knowledge of the stock.

5.6.1 Running mean as reference point

The key advantage of SS-CUSUM as a trend detection method is that it does not require *a priori* knowledge of the reference mean, instead this can be calibrated from the regular indicator observations sequentially (running mean) as the monitoring process moves forward (Hawkins and Olwell, 1998). This is the novelty of the SS-CUSUM approach compared to a basic CUSUM which has been discussed previously in the context of fisheries assessment and management (Scandol, 2003; 2005; Mesnil and Petitgas, 2009; Petitgas, 2009). Hence SS-CUSUM is relevant and fits into a data poor context where a fishery manager could start monitoring the status of the stock with no previous scientific data.

It is generally advised to start SS-CUSUM with a set of observations obtained from a process that is within the control limits (for most fisheries this would be a stable stock state with $F < F_{MSY}$). In theory, the method would perform worst if the indicator mean shifts immediately after initiating the SS-CUSUM, and thereby not giving enough time to signal since the running mean adapts to the new level quickly. It is this feature that could possibly be the biggest weakness of the method as a signal detection scheme and its application to data poor fisheries. However, in this study a chronic change in fishing pressure was introduced from the same year in which the SS-CUSUM initiated the monitoring process and the method performed successfully for the simulated stocks. The method detected a change in stock status with all catch-based indicators used in this study. However, the earliest SS-CUSUM could detect is a change in the third year since at least two observations are required for an initial running mean.

5.6.2 Which values should be used for w and k?

The winsorizing constant and allowance parameter of SS-CUSUM were fixed in this simulation study (w=2, k=0.5) to make the comparison of performance measures easier. Metric winsorization makes SS-CUSUM more robust to outliers. A very small w would make the running mean insensitive to indicator observations while a large w would inflate the running standard deviation with noisy observations. This constant is typically set to a value in the range 1 to 3 standard deviations (Hawkins and Olwell, 1998). It was found that there is little loss of performance for values beyond 2 (Appendix C, Figure C.2a).

The choice of k depends on the nature of the fishery and how promptly the fishery manager would like to detect impacts. In this study, the simulations were run with low value of k=0.5 for a comparative assessment on performance of the method with various indicators. A low allowance (k) is important for proper judgement of the control limit (h) and ensures better performance measures (Appendix C, Figure C.2b).

5.6.3 A proposal for h

A rough guideline from the simulations suggest that h=1 is required if the quality of the indicator data available are unreliable since this will ensure the robustness of the method to variability that is independent of the fishery. But SS-CUSUM will be very sensitive in this case and more F^+ results are expected. It is important to note that using h=1 is limited to the application of SS-CUSUM with an allowance k=0.5.

If reliable data are available, judgement of the control limit (h) should consider the life span and resilience capacity of the species. This study was limited to three life history types. Performance measures showed that a short lived species will respond more rapidly compared to long lived species. Hence SS-CUSUM might perform better with a lower h for a short lived species. When long lived species are considered, they are larger in size, have advanced age maturity and hence they are less productive (Reynolds et al., 2005). From a management perspective, a very high h for long lived species could risk having more false negative cases and this might result in a delayed response by the fishery manager leading to stock collapse. A delayed response also means a delayed recovery of the stock from the fishing impact. The behaviour of stock indicators is also important while choosing h. Our study shows that SS-CUSUM with large fish indicators is more responsive to fishing compared to other traditional indicators. Hence for greater sensitivity and specificity of the method, a lower h is required when large fish indicators are used. Results from this study indicate that the h value for the large fish indicator while monitoring species with short, medium and long life span should be closer to 1, 2 and 3, respectively (Figure 5.4d). However h=1 should be used if fewer catch samples are available and if the variability in recruitment, fishery or growth of the stock are likely to be high (Figure 5.5b,d,f).

5.6.4 Choice of indicators and data availability

Careful attention is required while choosing which indicator to use for monitoring data poor fisheries. In this study, simple indicators were considered that could be calculated by sampling of commercial catches. However, using fishery dependent data may cause problems if there is any under- or over-reporting of catch. For instance, the estimated indicator values will be biased if there are trends in size-classes due to systematic discarding of a certain part of the stock e.g. young age classes (Borges et al., 2006). But if the bias is consistent (e.g. regular discarding of a certain age class or management regulations on a fishery), then this could be accounted for in the monitoring process.

If it is assumed that reliable indicator data are available for a data poor stock, then the most appropriate indicators to use depends on the species and the type of data available. If age and length samples from landings are available, using large fish indicators will be more useful since they are more responsive to fishing impacts when compared to other traditional indicators such as the mean age, mean length and mean weight. It is more reliable to use age based indicators if the variability in growth of the species is high. In a real fishery, information about the stock would also be required in order to define a criteria for the large fish component in the landed catch (i.e. we would need some basic biological knowledge about growth).

Alternatively, the indicators used in this study could be collected from fishery independent data through a standardized research survey or similar. However, the performances of such indicators are not comparable with results in this study since the indicator estimates from samples obtained will be different. For example, the scenarios used in this study will have more proportions of large fish in the landed catch as F is increased in the short term. This is because the stock is at an in-control state in the initial years and hence the catch numbers will increase with F until the large mature fishes are harvested. However, a negative trend will be obtained for the same indicator if fishery independent data are used because the indicators are measured with constant catchability (Arreguín-Sánchez, 1996; a term used for indicating the interaction between population abundance and gear efficiency). This means the catch numbers at age will increase only if the stock is abundant and not due to longer duration of fishing or improved selectivity of the gear used by the research vessels.

The ROC curves in this study indicate that SS-CUSUM is robust across the range of catch samples used for indicator calculations (Figure 5.5e). The performances for various scenarios are similar if indicators were computed from a sample size of 100 (Appendix C, Figure C.3 & C.4). However, when the sample size is too small, it is difficult to obtain a truly random sample in the real world. The measures of optimal performance indicate that a sample size less than 100 could affect the performance of the method if higher control limits are used in SS-CUSUM (Figure 5.5f).

5.6.5 Limitations and future work

Though this study focused on only a few case scenarios, the SS-CUSUM method can be applied to any short time data series particularly when it is not possible to conduct a full fish stock assessment. Self-starting control charts are no different from the principle of a time series trend detection method and have proved their application in manufacturing industries when no previous data are available to estimate a reference level (Li and Wang, 2010; Li et al., 2010). Data poor methods focus on making the most use of available information and reduce the risk in fisheries management (Honey et al., 2010). SS-CUSUM method conforms to this principle and parameters can be configured to obtain signals with required sensitivity and specificity. However this advantage could limit the application of the method since if the burden of proof to illustrate a sustainable fishery is on the industry, the method can be misused (e.g. using a higher h value would obtain a delayed signal or no signal at all).

It may also be possible to test and evaluate SS-CUSUM for a stock that starts in an 'out-of-control' situation. If the stock starts in an 'out-of-control' state then indicators are likely to respond more slowly and this will affect SS-CUSUM performance. For example, the mean weight of landed catch would be less useful for indicating an out-of-control situation if the SS-CUSUM was initiated at a later stage where the stock is already moving towards a collapse (since the age groups that are fully selected by fishing might have already depleted by this time). This also forms one of the important limitations in this study. If the stock is already at risk, it would be difficult to measure the magnitude of the out-of-control situation as there will be no observations available to calibrate the running mean relative to a stable in-control fishery.

Extending the application of a new method to real world fisheries is an evolving process that requires proper judgement. This study did not address all possible situations of a data poor stock since all indicators were based on landed catch or fishery dependent data and this might not necessarily be always available. Therefore, a proper evaluation of the signal responses would be required with preferred indicators before applying them to real world stocks. It is also important to understand in which context the method can be applied. SS-CUSUM qualitatively analyses potential risks in an ongoing system process. If sufficient data are available for quantitative fish stock assessments, SS-CUSUM signals should only be used to qualitatively support the decision rules such as whether the total catch for the next year can be increased or decreased. SS-CUSUM could also be useful for species where stock assessments and forecasts are treated qualitatively e.g. Plaice (*Pleuronectes platessa*) in the Eastern Channel, where reliable catch data are available for short time series e.g. Plaice in VIIh-k ICES area or where only landings data are available e.g. Pollack (*Pollachius pollachius*) in ICES subareas VI and VII. These issues and additional examples of data limited fisheries discussed in the WKLIFE report (ICES, 2012*e*) can be addressed using SS-CUSUM to monitor the stock-fishery dynamics.

An optimisation design can be developed for SS-CUSUM if the manager prefers to use signals from multiple indicators to manage a fish stock (Fulton et al., 2005; Rochet et al., 2005). For example, if more data are available, signal responses from indicators based on different age or length classes can be integrated to understand stock-fishery interactions and judge decision rules. If the various indicators are correlated to each other, they can be monitored by a multivariate self starting control chart (Hawkins and Maboudou-Tchao, 2007*a*). This approach has the added advantage of reducing the total false alarm rate that otherwise would have occur from a collection of unconnected univariate control charts. The multivariate method has potential application to fisheries when the objective is to monitor and manage a multi-species fishery in an ecosystem context.

In the present study, guidelines on choosing control limits (h) are proposed in order to develop an efficient monitoring system. However, successful management will also require corrective action to ensure successful replenishment of the fish stock when an out-of control situation is detected (Link, 2005). An important extension to the present work would be to develop management frameworks based on SS-CUSUM by integrating the method with harvest control rules (see Chapter 8).

5.7 Summary

- The Self-Starting CUSUM chart does not require reference points and hence can be used for monitoring indicators with no historical observations.
- The earliest SS-CUSUM can signal an out-of-control situation in the third year since the first two observations will be used to estimate an initial "running mean".
- SS-CUSUM gave good classification results with all indicators since the trade-off between F^+ & F^- (OP) was achieved with more than 50% sensitivity.
- The LFIs were found more useful to monitor with SS-CUSUM because the control limits (h) achieved at OP were robust for the range of scenarios tested.
- A lower k and h should be preferred for higher sensitivity of SS-CUSUM because both the short- and long-life span species will require early management responses to avoid stock depletion or collapse.

Chapter 6

Estimating the shift in biomass using CUSUM

6.1 Introduction

Assessments of data limited fish stocks are challenging since the results from most analytical models are useful only if the data are reasonably precise, reliable and accurate (Kelly and Codling, 2006). When data are limited, population changes are usually monitored using catch based indicators using samples from commercial fish landings or fishery independent research surveys (Koeller et al., 2000). In recent years, Size Based Indicators (SBI) such as the mean length and Large Fish Indicators (LFIs) are gaining attention for qualitative assessments (Greenstreet et al., 2011). The application of LFI in North Sea and Celtic Sea showed that their declining trends are due to direct effects of fishing (Shephard et al., 2011). However, many SBIs were found not specific though highly sensitive to fishing (Rochet et al., 2005; Shin et al., 2005; Link, 2005). For example, the decreasing trend in mean length of a fish population could be due to overexploitation or enhanced short term recruitment.

For proper diagnosis on the state of the stock, assessments can be complemented by monitoring a suite of indicators e.g. the trend in recruitment abundances (Shin et al., 2005). Trends from such relevant indicators can be combined to obtain an integral qualitative assessment for the stock (Rochet et al., 2005). Further, the status can be classified based on threshold reference points indicating whether a management action is required or not (Caddy, 2002). Previous studies have demonstrated a “traffic light” approach where responses from a group of indicators are mapped on a common colour scale to display whether reference points have been crossed (Caddy, 2002; 2004; Caddy et al., 2005). However, the interpretation of such assessments are so far based on logical reasoning, common sense and basic ecological theory (Rochet et al., 2005).

A statistical framework for the traffic light approach can be implemented using methods from process control theory such as CUSUM charts (Montgomery, 1996; Hawkins and Olwell, 1998). The CUSUM control chart monitors the cumulative deviation of indicator observations from their reference point and signals an out of control situation when they cross a pre-determined threshold (Section 3.3). A previous study by Scandol (2003), used CUSUM to monitor various catch based indicators from a simulated fishery and found that the method correctly classified the state of the stocks with 60%-80% probability. Petitgas (2009) demonstrated how the status of a stock can be determined using CUSUM responses from a group of indicators belonging to different stock attributes such as the length, maturity or mortality.

The sensitivity and specificity of CUSUM in monitoring fishery impacts to the stock biomass was studied by Scandol (2005) and Pazhayamadom et al. (2013). When a signal is raised by CUSUM, the usual recommendation is to "search for an assignable cause" or "take remedial action" which implies that a change in TAC should be considered through management (Kelton et al., 1990). Previous studies have recommended qualitative adjustments in TAC following the alarm signal i.e., increase, decrease or maintain the catch. **But there is no formal link between the detection and regulation processes for determining the size of TAC adjustment required in response to the observed changes in stock status** (Koeller et al., 2000). If the shift in stock biomass can be estimated quantitatively using CUSUM, relatively precise adjustments can be made in the TAC by incorporating such assessment methods into Harvest Control Rules (HCRs) and thus the risk to stock biomass due to management actions can be minimized.

In the present study, a simulated fishery was monitored using CUSUM to test a suite of quantitative methods for their predictive power in estimating the shift size in stock biomass. It was assumed that the stock is historically stable in an 'in-control' state and the indicator observations from two previous years are available for the fishery. A fishing impact was introduced to the stock by increasing the fishing pressure on an ongoing basis and various stock indicators were monitored using the CUSUM control chart. Once an out-of-control situation is signalled, various quantitative methods from the Engineering Process Control (EPC) theory were used to estimate the shift in stock biomass. The performances were evaluated in terms of bias, precision and accuracy of the shift size estimates by comparing them to the actual shift occurred.

6.2 Objective of the study

- To determine which methods in Engineering Process Control along with CUSUM control charts can accurately estimate the shift in the underlying stock biomass using various stock indicators.

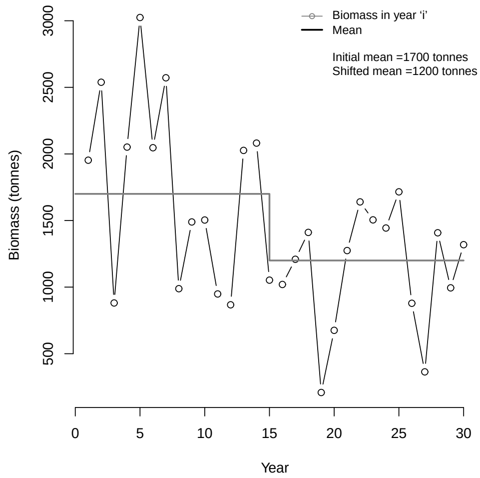
6.3 Background

The basic philosophy behind statistical process control (SPC) techniques is to maintain or improve the quality of a process by monitoring them relative to a Target Reference Point (TRP). In CUSUM, the control mean ($\overline{X}$) is equivalent to a TRP and it is assumed that the process is in an in-control state as long as the observations belong to a normal distribution with the process mean $\overline{X}$. If the observations start drifting, this essentially means that the current process mean ($\overline{X}_s$) has shifted by some unknown size (S) away from the control mean ($\overline{X}$) i.e., $\overline{X}_s = \overline{X} \pm S$. This is illustrated with an example in Figure 6.1 where the mean length of the fish was drifted from $\overline{X} = 17$cm to $\overline{X}_s = 12$cm due to the change in stock biomass, giving a shift in size of $S = -5$cm from the control mean. Note that the shift in underlying stock biomass is not directly observable. Secondly, previous studies in SPC have mostly focused on a step change problem in the process mean because this is more commonly confronted in manufacturing industries (Grubbs, 1983; Pan, 2002). In real world fish stocks, the changes in stock biomass are dynamic and do not necessarily follow a step change process shift.

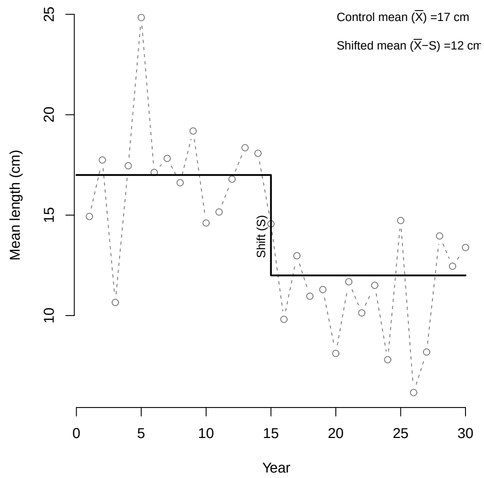
One of the basic challenges in fisheries data is the availability of a control mean (reference point) for the CUSUM chart. Ideally this should represent a stable state fishery so that meaningful signals on status of the fish stocks can be generated. Previous studies recommended the use of observations from a reference period during which the stock was perceived to be in an acceptable state (Scandol, 2003; Petitgas, 2009). Later Pazhayamadom et al. (2013) showed that a Self-Starting CUSUM (SS-CUSUM) can be used instead if a control mean is not available for the fishery (see Chapter 5). In SS-CUSUM, the control mean (termed 'running mean') can be calibrated from the indicator observations itself on an on-going basis.

The second most important parameter for CUSUM charts is the allowance (k) parameter (see Chapter 3). Choosing a particular k implies that the CUSUM responds only if there is a meaningful deviation in the process mean. This is because smaller shifts can occur if the observations are inherently noisy and thus being non-specific to fishing strategies (Hawkins and Olwell, 1998; Mesnil and Petitgas, 2009). A third parameter known as the control limit (h) is then applied to define the thresholds beyond which the CUSUM indicates an out-of-control situation (see Figure 6.1). Thus the sensitivity and specificity of CUSUM depends upon the choice of k and h (Chapter 3 and 5). The criteria for choosing k and h are beyond the scope of this study but these issues have previously been addressed (Scandol, 2003; Pazhayamadom et al., 2013). For the remainder of the chapter, the basic CUSUM control chart is referred to as DI-CUSUM (Hawkins and Olwell, 1998).

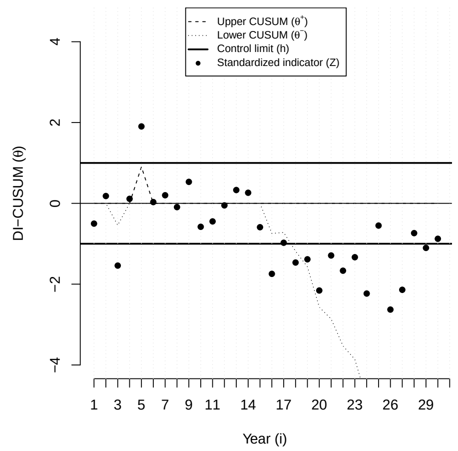
Once an out-of-control situation is detected (from the indicator), the next step is to estimate the actual shift occurred in the underlying process (Biomass). If reliable



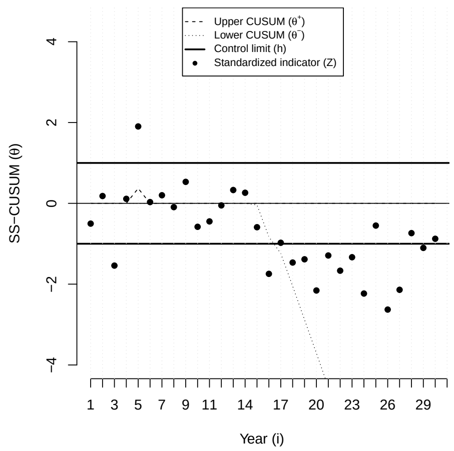
(a) Shift in Biomass



(b) Mean length (Indicator)



(c) DI-CUSUM of mean length



(d) SS-CUSUM of mean length

Figure 6.1: **Illustration of step change process shift in the mean of an indicator distribution:** **(a)** shift in the underlying stock biomass **(b)** step change in distribution of the mean length (ML) **(c) & (d)** indicator shift was detected by both DI-CUSUM and SS-CUSUM control charts. The ML were generated randomly using a coefficient of variation of $cv = 0.2$ from the normal distribution with $\overline{X} = 17$ and $\overline{X}_s = 12$. The biomass was modelled such that $Biomass \sim ML \times normal(mean = 1000, cv = 0.35)$.

estimates on shift sizes are available ($\hat{S}$), corrective adjustments can be introduced in the control variable (TAC in this context) so that the next indicator observation will be closer to the estimated control mean ($\overline{X}$). Estimation methods used in SPC charts are adopted from the Engineering Process Control (EPC) theory (see Section 6.6.1). Most of these methods apply regression or forecasting techniques on historical observations for estimating the shifted process mean (Kelton et al., 1990). For example, Luceño (1992) and Box and Kramer (1992) suggested an estimation procedure to obtain the minimum mean square error (MMSE) forecast from the exponentially weighted moving average (EWMA) statistic. Similarly, Wiklund (1995) proposed a maximum likelihood estimation method (MLE) from EWMA statistics based on a truncated normal probability density function. All these methods require an assumption on the smoothing constant (λ) as part of the EWMA for predicting the next indicator observation. With a focus on industrial applications, Kelton et al. (1990) and Ruhhal et al. (2000) suggested to make no adjustments up to the 10^{th} observation for obtaining an unbiased estimate of the shift size ($\hat{S}$). This waiting period is too large for many real world fish stocks because the fisheries data usually have only one observation per year and the generation time of fish species may be much shorter than 10 years.

In the present study, only a few selected estimation methods were considered because they generally hold comparatively fewer assumptions and require the least number of historical observations for computing the shift size (Taguchi, 1981; Grubbs, 1983; Montgomery, 1996). These procedures are detailed in Section 6.4.3 and most of them have been tested previously using a variety of control charts i.e., Shewhart, CUSUM and EWMA (Kelton et al., 1990; Luceño, 1992; Wiklund, 1995; Ruhhal et al., 2000; Pan, 2002). However, the differences between control charts are less substantial than those between the estimation strategies (Wiklund, 1995).

6.4 Methods

6.4.1 Operating model for the simulated fishery

An age structured fish stock was simulated using the operating model presented in section 2.1 and a fishery equilibrium was achieved with an initial fishing mortality of $F_{int} = F_{90\%MSY}$. In the first phase of the simulation, the model ran for 100 years where random variability was introduced in F_{int} ($cv = 0.1$) and the stock-recruitment relationship ($cv = 0.6$). At this point, the stock was assumed to be in-control (steady, stable and sustainable) and the biomass obtained at this level ($B_{90\%MSY}$) was considered as the reference point for the fish stock. It was also assumed that historical data from three previous years were available for the fishery since that is the earliest an SS-CUSUM can raise an alarm. In the second phase, the model ran for 30 further years and a fishing impact was applied to the stock using a 5% step change increase in fishing mortality per year ($F_{i+1} = 1.05F_i$, where 'i' is year). During this phase, stock indicators were measured and monitored using CUSUM control charts. Once an out-of-control situation is signalled, the shift in stock biomass was estimated using six different types of quantitative methods (Section 6.4.3). The simulation was iterated 1000 times and the actual shift in stock biomass along with estimated values were recorded for further analysis. The experiment was repeated for four different fishery scenarios (Section 6.4.4). The performance of each method was evaluated using the bias, precision and accuracy of the shift size estimates obtained in each scenario (Section 6.4.5).

6.4.2 CUSUM monitoring

The stock indicators were monitored using two types of control charts i.e., DI-CUSUM and SS-CUSUM. The former assumes that the indicator control means are available for the fishery while the later does not operate with that assumption. Apart from the control mean, three additional parameters were used in the CUSUM control charts. First, the winsorizing constant was fixed at $w = 2$ (two standard deviations) to protect the CUSUM from outliers in the time series (see Section 3.3.4). Second, the allowance was fixed at a low value of $k = 0.5$ to explore the full range of shifts in the underlying biomass i.e. small and large shift sizes. Third, the control limit was fixed at $h = 1$ so that all CUSUM deviations will not necessarily end up in an out-of-control situation. Fixing the CUSUM parameters was necessary to compare the performances of various estimation methods used in this study.

6.4.3 Methods used to estimate the shift in stock biomass

A total of six quantitative methods (D1, D2, D3, D4, D5 and D6) were used in this study (Table 6.2) to estimate the shift size in stock biomass ($\hat{S}$). Four methods (D1, D2, D3 and D4) were based on the direct indicator observations (X_i) and two methods (D5 and D6) were based on the CUSUM values ($\theta_i^{\pm}$) of the control chart.

A corrective adjustment in TAC through HCRs is required only if an out-of-control situation is signalled by the CUSUM. Hence for all the methods, the estimated shift ($\hat{S}$) was set equal to zero unless the CUSUM exceeds the control limit (h). Thus the estimated shift ($\hat{S}_i$) in year 'i' is:

$$\hat{S}_i = \begin{cases} 0 & \text{for} \quad \theta_i^+ < h^+ \text{ or } \theta_i^- > h^- \\ \hat{s}_i & \text{for} \quad \theta_i^+ > h^+ \text{ or } \theta_i^- < h^-, \end{cases} \tag{6.1}$$

where, θ_i^+ and θ_i^- are the Upper and Lower CUSUMs. For methods based on the indicators (D1, D2, D3 and D4), the indicators were first standardized using the control mean ($\overline{X}$) and the standard deviation ($\overline{\sigma}$) obtained from all observations available up to the most recent year in the second phase. Note that the control mean ($\overline{X}$) was assumed to be known while the control standard deviation ($\overline{\sigma}$) was updated in each year of the fishery simulation. As a result, the DI-CUSUM values were also updated as the monitoring process moves forward (Equation 3.2). Standardizing indicator observations have the advantage that the estimation methods can be compared across various indicators regardless of the unit in which they are measured. The standardized indicator (Z_i) in year 'i' of a time series with 'n' observations will be:

$$Z_i = \left(\frac{X_i - \overline{X}}{\overline{\sigma}_n} \right) \tag{6.2}$$

In SS-CUSUM, the indicator time series were first transformed into random variables of a normal distribution $N(0,1)$ i.e., U_i (Section 3.4.1). The transformed variables are already standardized in this process and hence the U_i were used instead of Z_i for all the computations related to SS-CUSUM.

6.4.3.1 D1: 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 signalled by the control chart i.e., $-(X_i - \overline{X})$.

However, this method is criticized for giving large and significantly biased shift estimates particularly when the actual shift size is really small (Pan, 2002). One of the major arguments from previous studies is that conducting only one step estimation is insufficient to bring the shifted process mean back to control (Wiklund, 1992; 1993). The method could also be misleading for small to moderate shift sizes in biomass particularly when the indicator observations are inherently very noisy (Adams and Woodall, 1989). A better estimation scheme would be to apply the method sequentially on an ongoing basis as the indicators are monitored by the control chart i.e., for all years when CUSUM indicates an out-of-control situation. Since all observations were first standardized (Equation 6.2), the estimated shift in biomass in year 'i' will be equal to the standardized indicator itself.

$$\hat{s}_i = Z_i, \tag{6.3}$$

6.4.3.2 D2: Grubb's harmonic rule

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 for the first out-of-control observation ($X_{i=1}$), the shift is estimated as equivalent to the full deviation of that observation from the control mean ($X_1 - \overline{X}$). For the second out-of-control observation ($X_{i=2}$), the estimated shift is only 1/2 of the deviation i.e., $(X_2 - \overline{X})/2$. In general, the estimated shift for X_i will be followed by $(X_i - \overline{X})/i$. Since standardized indicator observations were used in the present study, the $(X_i - \overline{X})$ can be replaced by Z_i (as both $(X_i - \overline{X})$ and Z_i will be zero when $X_i = \overline{X}$). Thus the rule calls for sequential adjustments using progressively smaller coefficients of corrections and the variance around the control mean is minimized as the process moves forward. If 'i' is the year and 'd' is the total number of observations in the time series, then the shift size estimate by Grubb's rule ($\hat{g}_i$) in each year is given by:

$$\hat{g}_i = \begin{cases} Z_1/1 & \text{for} \quad i = 1 \\ Z_2/2 & \text{for} \quad i = 2 \\ \ldots\ldots & \ldots\ldots \quad \ldots\ldots \\ Z_d/d & \text{for} \quad i = d \end{cases} \tag{6.4}$$

However, this method was designed for correcting the initial set-up errors in machines after their installation. So an adjustment is expected only during the start of the process. The method also makes an estimation for every single step (or year) regardless of whether a signal is raised by the control chart or not. The rule can be extended for SPC applications by estimating the shift only when a signal is produced by the control chart (Del Castillo et al., 2003; Del Castillo, 2006). So essentially the 'i' in equation 6.4 will be replaced by 'M' which is a counter (S-counter) giving the number of years since the first alarm was raised by the control chart. Thus the estimated shift in year 'i' will correspond to:

$$\hat{s}_i = \frac{Z_i}{M_i} \tag{6.5}$$

This is numerically illustrated in Table 6.1 where the upper and lower DI-CUSUMs indicates an out-of-control situation from year $i = 28$ onwards (Figure 6.2). The estimated shift in year $i = 30$ is computed by dividing the standardized indicator ($Z_{i=30}$) with the total number of out-of-control years (S-counter=3, Table 6.2).

6.4.3.3 D3: Recursive estimation using Grubb's harmonic rule

The third method extends the application of Grubb's harmonic rule in a recursive manner such that, the estimated shift in year 'i' is a cumulative sum of the estimated shifts obtained from the previous years when the first alarm was raised by CUSUM which lead to the current out-of-control situation (Del Castillo, 2006) i.e., for years in which the $|\theta_i| > |h|$ or $M_i > 0$ (Table 6.1 and 6.2). A simulation study based on a variety of SPC integrated estimation techniques showed that this method was better in minimizing the average squared deviation of a corrected process under management (Del Castillo, 2006; Pan, 2002). The estimated shift in year 'i' is given by:

$$\hat{s}_i = \left\{ \sum_{t=0}^{M_i-1} \frac{Z_{i+t}}{t+1} \quad \text{for} \quad M_i > 0 \right. \tag{6.6}$$

6.4.3.4 D4: Grubb's recursive estimation after allowance correction

This method essentially follows the same procedure as in D3, but extends it further by using an allowance corrected standardized indicator. Since the CUSUM signals an out-of-control situation after accounting for the noise in the indicator distribution,

Table 6.1: **Numerical illustration of signal counters using DI-CUSUM:** The table shows a numerical example of the control chart for obtaining the CUSUM counters (U-counter or L-counter) and the signal counters (S-counter). The U- or L-counters are the number of years since the CUSUM ($\theta_i^{\pm}$) was first lifted above or below zero for a given alarm ($\theta_i^{+} > h$ or $\theta_i^{-} < -h$). The signal counters are the number of years since the CUSUM was first lifted above the control limit for a given alarm. In the following example, the winsorizing constant (w), allowance (k) and control limit (h) was fixed at $w = 2$, $k = 0.5$ and $h = 3$.

Year (i)	Indicator (X_i)	$\left(\frac{X_i - \overline{X}}{\overline{\sigma}}\right)$ (Z_i)	UCUSUM (θ_i^{+})	U-Counter (H_i^{+})	LCUSUM (θ_i^{-})	L-Counter (H_i^{-})	Signal	S-Counter (M_i)
1	9.45	-0.48	0.00	0	0.00	0	NO	0
2	7.99	-1.74	0.00	0	-1.24	0	NO	0
3	9.29	-0.62	0.00	0	-1.36	0	NO	0
4	11.66	1.44	0.94	0	0.00	0	NO	0
5	12.16	1.87	2.31	0	0.00	0	NO	0
6	10.18	0.16	1.97	0	0.00	0	NO	0
7	8.04	-1.70	0.00	0	-1.20	0	NO	0
8	11.46	1.27	0.77	0	0.00	0	NO	0
9	9.20	-0.69	0.00	0	-0.19	0	NO	0
10	10.34	0.29	0.00	0	0.00	0	NO	0
11	9.03	-0.84	0.00	0	-0.34	0	NO	0
12	11.47	1.27	0.77	0	0.00	0	NO	0
13	10.51	0.44	0.72	0	0.00	0	NO	0
14	9.40	-0.52	0.00	0	-0.02	0	NO	0
15	10.08	0.07	0.00	0	0.00	0	NO	0
16	9.37	-0.55	0.00	0	-0.05	0	NO	0
17	10.62	0.54	0.04	0	0.00	0	NO	0
18	10.31	0.27	0.00	0	0.00	0	NO	0
19	8.52	-1.28	0.00	0	-0.78	0	NO	0
20	10.84	0.73	0.23	0	0.00	0	NO	0
21	10.90	0.78	0.51	0	0.00	0	NO	0
22	9.33	-0.58	0.00	0	-0.08	0	NO	0
23	12.29	1.99	1.49	0	0.00	0	NO	0
24	11.50	1.30	2.29	0	0.00	0	NO	0
25	10.60	0.52	2.31	0	0.00	0	NO	0
26	11.08	0.94	2.74	0	0.00	0	NO	0
27	10.38	0.33	2.57	0	0.00	0	NO	0
28	11.62	1.40	3.48	6	0.00	0	YES	1
29	11.31	1.14	4.11	7	0.00	0	YES	2
30	10.52	0.45	4.06	8	0.00	0	YES	3

Shaded areas indicate values used for estimating the shift in stock biomass (Table 6.2)

this method assumes that an accurate estimate of the shift can be obtained only by correcting the standardized indicator with the allowance used in CUSUM. Hence the shift size estimate in year 'i' is given by:

$$\hat{s}_i = \begin{cases} \displaystyle\sum_{t=0}^{M_i-1} \frac{max\,(0, Z_{i+t} - k)}{t+1} & \text{for} \quad \theta_i^{+} > h^{+} \\ \\ \displaystyle\sum_{t=0}^{M_i-1} \frac{min\,(0, Z_{i+t} + k)}{t+1} & \text{for} \quad \theta_i^{-} < h^{-} \end{cases} \tag{6.7}$$

6.4.3.5 D5: Rule based on CUSUM observations

This method used the CUSUM values itself as an estimate for the shift in stock biomass. This is a crude form of estimation because the absolute CUSUM will keep increasing even if this shift is small. For example, this method will be less useful if the stock is

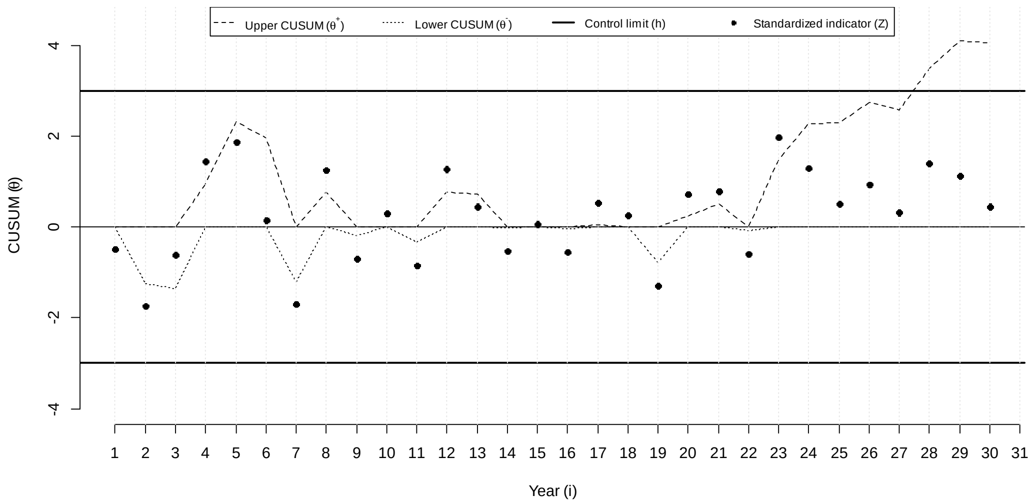


Figure 6.2: **Graphical illustration of signal counters with DI-CUSUM:** The figure shows a graphical illustration for the numerical example provided in Table 6.1.

left uncontrollable for several years. However, they can be useful if there are annual restrictions in the TAC adjustments. The CUSUM deviations can be used to detect the direction of the biomass shift that has occurred and thus some qualitative judgement can be made i.e., increase or decrease the TAC.

To test these effects, the shift in biomass for the i^{th} year was estimated by summing up the upper and lower CUSUM values obtained in that particular year (Table 6.2). The summation will give a net effective deviation of the shift, say if the change in biomass is large and immediate, then both the upper and lower CUSUM may raise alarms. Thus the estimated shift in year 'i'is given by:

$$\hat{s}_i = \left(\theta_i^+ + \theta_i^-\right) \tag{6.8}$$

6.4.3.6 D6: 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. Thus the shift occurred can be estimated as:

$$\hat{s} = \begin{cases} \dfrac{\theta_i^+}{H_i^+} + k & \text{if} \quad \theta_i^+ > h^+ \\ \quad + & \\ \dfrac{\theta_i^-}{H_i^-} - k & \text{if} \quad \theta_i^- < h^- \end{cases}, \tag{6.9}$$

where the CUSUM counters $\pm H_i$ (U-counter or L-counter, Table 6.1) are obtained by counting backward from the out-of-control signal to the time period when the CUSUM was first lifted above zero for that alarm. The illustrated example in Table 6.2, the $\hat{s}_{30} = 1.0075$ can be thought of as a weighted average in which equal weight is given to the last $H^+ = 8$ observations and weight zero to all other observations (Table 6.1).

Table 6.2: **Numerical example for methods used in estimating the shift in stock biomass:** The numerical example is based on the CUSUM control chart illustrated in Table 6.1. For the year '$i = 30$', the Z_i is the standardized indicator, $\theta_i^{\pm}$ is the CUSUM value, $k = 0.5$ is the allowance, $h = 3$ is the control limit, $\pm H_i$ is the CUSUM counter and M_i is the signal counter.

Methods	Formula	Example from Table 6.1
D1	$\hat{s}_i = Z_i$	$\hat{s}_{30} = 0.45$
D2	$\hat{s}_i = \dfrac{Z_i}{M_i}$	$\hat{s}_{30} = \dfrac{0.45}{3}$
D3	$\hat{s}_i = \sum_{t=0}^{M_i-1} \dfrac{Z_{i+t}}{t+1}$	$\hat{s}_i = \dfrac{1.4}{1} + \dfrac{1.14}{2} + \dfrac{0.45}{3}$
D4	$\hat{s}_i = \begin{cases} \sum_{t=0}^{M_i-1} \dfrac{max\,(0, Z_{i+t} - k)}{t+1} & \text{for} \quad \theta_i^+ > h^+ \\ \sum_{t=0}^{M_i-1} \dfrac{min\,(0, Z_{i+t} + k)}{t+1} & \text{for} \quad \theta_i^- < h^- \end{cases}$	$\hat{s}_i = \dfrac{1.4 - 0.5}{1} + \dfrac{1.14 - 0.5}{2} + 0$
D5	$\hat{s}_i = \left(\theta_i^+ + \theta_i^-\right)$	$\hat{s}_{30} = (4.06 + 0.00)$
D6	$\hat{s} = \begin{cases} \dfrac{\theta_i^+}{H_i^+} + k & \text{if} \quad \theta_i^+ >^+ h \\ + & \\ \dfrac{\theta_i^-}{H_i^-} - k & \text{if} \quad \theta_i^- <^- h \end{cases}$	$\hat{s}_i = \left(\dfrac{4.06}{8} + 0.5\right) + 0$

6.4.4 Scenarios considered

The four scenarios used in the present study were based on the (i) type of stock indicator; (ii) type of impact on the stock; (iii) lifespan of the species and (iv) historical state of the stock. Additional scenarios were simulated to test the effect of CUSUM parameters (w, k and h), selectivity of the fishing gear, autocorrelated stock-recruitment and a small number of samples from the fisheries catch. The results of these scenarios are presented in Appendix D.

The first scenario used four different types of stock indicators to estimate the shift in stock biomass (Table 6.4) i.e., mean age (MA), recruitment (R), positive proportion of the large fish catch numbers (P_n) and a combined indicator of R and P_n (RP_n). The MA and P_n were computed using a random sample of the catch from the operating model (Table 2.2). The estimation methods used in the present study were based on the sensitivity or specificity of the control chart and hence the estimated shift sizes are dependent on the predictive power of the stock indicator used. From Chapters 4 and

5, it is clear that large fish indicators are more sensitive to fishing impacts and are more useful in predicting the state of a stock, though their correlations with SSB were affected in a recruitment crash scenario (Figure 4.3b). To improve the sensitivity of P_n, a combined indicator (RP_n) was constructed by summing up both R and P_n, after standardizing them with their respective control means (Equation 6.2, Table 6.3).

Table 6.3: **Construction of the combined indicator using recruitment and LFI (RP_n):** The recruitment(R) and large fish indicator (P_n) are first standardized using their respective control means ($\overline{X}_R$, $\overline{X}_{P_n}$) and the standard deviation ($\overline{\sigma}_R$, $\overline{\sigma}_{Pn}$). The combined indicator RP_n is constructed by summing up the standardized values of recruitment (Z_R) and LFI (Z_{P_n}).

Year (i)	R_i [1]	Pn_i [2]	$Z_{R,i}$ [3]	$Z_{Pn,i}$ [4]	RPn_i [3] + [4]
1	4810865.21	0.75	-0.11	-0.27	-0.38
2	2118121.84	0.75	-0.50	-0.24	-0.74
3	6398135.40	0.61	0.12	-1.22	-1.10
4	2563852.47	0.79	-0.43	-0.00	-0.44
5	1188754.49	0.68	-0.63	-0.77	-1.41
6	23491655.23	0.68	2.61	-0.79	1.83
7	7293109.98	0.87	0.25	0.58	0.84
8	3239030.42	0.77	-0.34	-0.08	-0.42
9	11558320.95	0.79	0.87	0.01	0.88
10	31173409.00	0.53	3.73	-1.86	1.87
11	6843516.63	0.88	0.19	0.71	0.90
12	2226537.82	0.89	-0.48	0.73	0.24
13	2366271.62	0.83	-0.46	0.32	-0.14
14	6892554.43	0.80	0.20	0.10	0.29
15	9649123.35	0.94	0.60	1.09	1.69
16	9959509.97	0.91	0.64	0.87	1.51
17	8896535.39	0.65	0.49	-1.00	-0.51
18	2699680.55	0.84	-0.41	0.42	0.00
19	3287598.18	0.73	-0.33	-0.41	-0.74
20	4601911.06	0.80	-0.14	0.09	-0.05

The second scenario simulated four different types of impacts on the stock biomass (Table 6.4) where, the stock (i) is over-fished (increasing F); (ii) is under-fished (declining F); (iii) experiences a recruitment crash and (iv) represents a well managed stable fishery (TAC management). These stock impacts were simulated following the description provided in Chapter 4 (Section 4.4.2.1).

The third scenario tested whether the estimation methods are robust across the various life history species. Fish stocks with three different life spans were simulated in the third scenario i.e., Cod-like (LH1, medium life span), Herring-like (LH2, short life span) and Rockfish-like (LH3, long life span) species. The life history parameters for these fish stocks are provided in Table 2.1.

In chapter 5, it was concluded that the SS-CUSUM may not perform well if the fish stock is already in an overfished state. A fish stock was considered to be in an overfished state if the stock biomass is below B_{MSY} level (Froese and Proelß, 2010). To test whether it is possible to obtain accurate shift size estimates in such instances, the fourth scenario simulated fish stocks which were historically fished with $F_{int} = F_{100\%MSY}$ and

$F_{int} = F_{110\%MSY}$ (Table 6.4).

The base case scenario used the combined indicator (RP_n) of a medium life span species for estimating the shift size in stock biomass. The indicator was monitored using control charts with fixed CUSUM parameters i.e., $w = 2$, $k = 0.5$ and $h = 1$.

Table 6.4: **Scenarios used for estimating the shift in stock biomass:** The base case fish stock represented a medium life span species persistently overfished using a medium mesh sized trawl net (Scenario 1). The shaded areas highlight the differences compared to the base case parameters. The life history parameters used for simulating the three life history stocks i.e., LH1, LH2 and LH3 are provided in Table 2.1.

Scenarios	Indicators	Fishery scenarios	Life History (LH, Life span)	Historical state of stock
Scenario 1*	Mean Age (MA) Recruitment (R) Large Fish Indicator (P_n) Combined indicator (RP_n)*	5% increase in F*	LH1, Medium*	Below MSY*
Scenario 2	RP_n	5% decrease in F Recruitment crash Regulated by TAC	LH1, Medium	Below MSY
Scenario 3	RP_n	5% increase	LH2, Short LH3, Long	Below MSY
Scenario 4	RP_n	5% increase	LH1, Medium	At MSY Above MSY

*: Base case scenario

6.4.5 Performance measures: Bias, Precision and Accuracy

The performance of these methods was evaluated in terms of bias, precision and accuracy in the shift size estimates. The measure on bias gives the average difference between the estimated and true values. The precision shows how close the estimates are to each other. The accuracy tells how close the estimated values are to the actual shift.

To measure these performances, the actual shift in underlying biomass should be in standard deviation units so that the shift sizes are comparable. Hence, the biomass in each year (B_i) was standardized using $B_{90\%MSY}$ as the mean and standard deviation of all B_i observations obtained in the first phase of the simulation (σ_{B_n}). Thus the shift in underlying biomass ($\hat{B}_i$) was computed as:

$$\hat{B}_i = \left(\frac{B_i - B_{90\%MSY}}{\sigma_{B_n}} \right) \tag{6.10}$$

The error in shift size estimates can now be measured by taking the difference between the mean biomass shift and the mean estimated shifts occurring in each year i.e., $i = 1, 2, 3...31$. Thus the error in shift size estimates is measured as,

$$\overline{S_i} = \text{mean}\left(\hat{S}_i\right)$$

$$\overline{B_i} = \text{mean}\left(\hat{B_i}\right)$$

$$e_i = \overline{B_i} - \overline{S_i} \tag{6.11}$$

Thus the temporal variability of the error estimates can be assessed i.e., how the bias, precision and accuracy change in each year 'i'. This way the performance measures can be summarized with respect to the magnitude of biomass shift in temporal scale (shift increases with year since the stock was consistently overfished in the base case).

However, an alternative way is to find out the error estimates obtained in each signal counter instead of the year i.e., $M = 1, 2, 3...31$ by taking the difference between $\hat{B_M}$ and $\hat{S_M}$ (e_M). This approach was used in this study because it is important to understand how accurate the shift size estimates are if the control chart persistently raise alarms resulting in large CUSUM values. This means that if the estimates from one method are consistently accurate from $M = 1$ to $M = 31$, then this method will be useful for managing stocks with small or large biomass shifts.

6.4.5.1 Bias

In general, a method is less likely to be useful if the estimates are biased. However in fisheries management, the consequences of over or under estimating the biomass shifts are different. The risk of overfishing is less if the TAC is lowered proportionally more than the negative shift in stock biomass. This will correspond to a positive bias in the error estimates (e_M) when the stock is getting overfished (base case). Similarly, the risk of overfishing is less when the increment in TAC is proportionally smaller than the positive shift in stock biomass. This happens during under-fishing (Scenario 2) and indicates a negative bias in the error estimates (e_M).

Bias in the estimation methods were evaluated using the Tracking Signal (TS). This is a simple performance measure used for validating the bias in forecast models (Alstrøm and Madsen, 1996). The range of values are between -1 and $+1$ indicating 100% negative or positively biased estimates. A simple form of this measure is the ratio of the sum of errors from all signal counters to the average absolute errors (Brown, 1959). Thus it is given by:

$$\text{Tracking signal} = \frac{\sum (e_M)}{\text{mean}\left(|e_M|\right)} \tag{6.12}$$

A positive bias or no bias is desirable if F is increasing (except Scenario 2).

6.4.5.2 Precision

Precision reflects how consistent are the estimated shifts for a given change in biomass. This means that the spread of the distribution of the estimated shifts should be minimum.

However, the target is moving (the biomass continues to shift as F is increasing) in a stochastic manner and thus a superior precision is not expected. Therefore the relative performance of the overall variance was used to compare and evaluate the methods qualitatively. The variance was computed using the *var* function in the statistical package of R (R Development Core Team, 2012). The overall variance (VAR) for an estimation method was obtained by summing up the variances of the estimated shifts in each counter M.

Highly precise estimates will give minimum variance.

6.4.5.3 Accuracy

Commonly used accuracy measures are the Mean Square Error (MSE) and the Mean Absolute Percentage Error (MAPE). These are defined as:

$$\text{MSE} = \text{mean}\left(e_M^2\right), \ \text{M=1,2,3...31} \tag{6.13}$$

$$\text{MAPE} = \text{mean}\left(\left|e_M/\overline{B_M}\right|\right) \times 100, \ \text{M=1,2,3...31} \tag{6.14}$$

However, both measures were not found to be applicable in this study. Though popular, MSE is criticized for their sensitivity to outliers since the error measures are squared (Hyndman and Koehler, 2006). MAPE has the advantage of being scale independent but is undefined if $\overline{B_M}$ is zero i.e., if there is no shift in stock biomass. A better accuracy measure was found to be the Mean Absolute Deviation (MAD) which is given by:

$$\text{MAD} = \text{mean}\left(|e_M|\right), \ \text{M=1,2,3...31} \tag{6.15}$$

Accurate estimates will have the Mean Absolute Deviation close or equal to zero.

6.5 Results

6.5.1 Temporal variation of shift size estimates

In the base case scenario, a step change increase in F was applied to the fish stock and hence the biomass is expected to deplete over time (Figure 6.3a,b). The shift size in biomass was estimated using CUSUM control charts (DI-CUSUM and SS-CUSUM) and the average obtained from all the iterations showed that the accuracy of these estimates degraded over time as the shift in stock biomass increased (Figure 6.3a,b). The estimates from all the methods were close to each other for small biomass shifts in the initial years but diverged as the shift size in stock biomass increased (Figure 6.3a,b).

The errors (e_i) associated with these estimates can be used to assess whether these methods are useful for a wide range of shifts in stock biomass (Figure 6.3c,d). A positive error indicates that the estimates are precautionary since the estimated shift is more than the actual shift that occurred in the stock biomass. Estimates from three methods i.e, D3, D4 and D5 gave positive error estimates and hence were found useful to incorporate in HCRs for making TAC adjustments. The recursive estimation procedure by Grubb's harmonic rule (D4) was the most accurate among these methods since their estimates were comparatively closer to the base line indicating a true shift occurred in the underlying stock biomass (Figure 6.3c,d).

A comparison between DI-CUSUM and SS-CUSUM showed that the errors were high for the former but precautionary during the initial five years of the simulation (Figure 6.3c,d). However, an out-of-control situation is less likely to be obtained during these years because the stock was initially in an in-control state and hence the shift in stock biomass will be small. Thus comparatively fewer estimates will be available during these years. If the signals obtained during these years are transient due to the randomness in the indicator, then the estimates will be inaccurate (Figure 6.3c). However, this is less obvious in SS-CUSUM because during the initial years, the running mean is more dynamic and less robust to randomness due to their dependency on the indicator observations itself (Figure 6.3d).

6.5.2 Shift size estimates for M^{th} year of CUSUM signal

The errors obtained in the simulation study were sorted for each M counter to compare the accuracy of shift size estimates i.e., the number of years since the first CUSUM alarm occurred. The occurrence of first CUSUM signal is stochastic during the second phase of the simulation (not necessarily occur in the same year) and hence the errors are independent of the shift size in biomass (as the stock was depleting consistently). Results showed that the errors were negative for all methods in the first year of the CUSUM signal i.e., $M = 1$ (Figure 6.4a). However for methods D3, D4 and D5, they became positive by the second or third year of the CUSUM signal. Comparatively the most accurate estimates were given by D4, for which an allowance corrected standardized indicator was used in the estimation procedure (Figure 6.4a).

However, all methods showed a greater variability for smaller M (Figure 6.4b). The

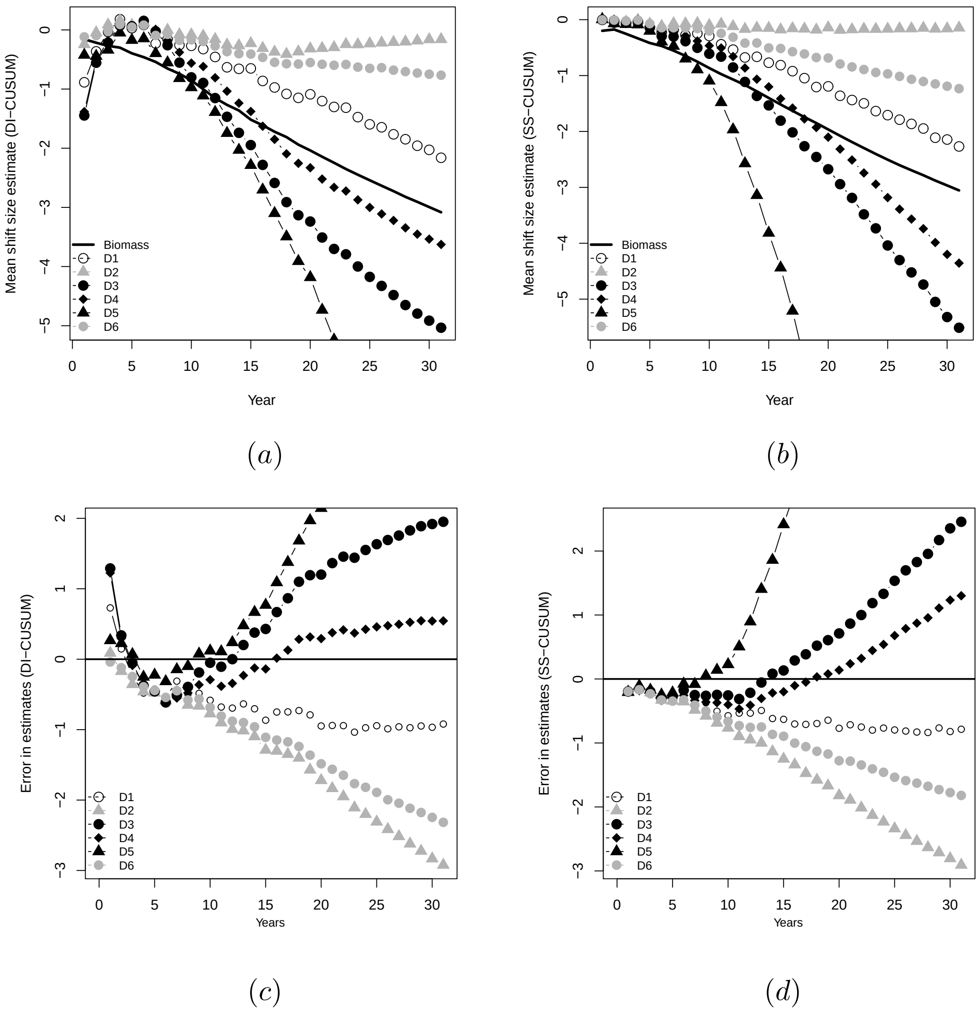


Figure 6.3: **Mean shift size in stock biomass estimated using CUSUM: (a) and (b)** shows the temporal variation of the estimates from DI-CUSUM and SS-CUSUM control charts. The actual shift in the underlying biomass is indicated by the black thick line and the estimates from various methods (D1 to D6) are indicated by symbols as shown in the legend. The values are presented in standard deviation units and hence if no shift has occurred, then the value is zero. The most accurate method will give estimates that are close to the shifted biomass. **(c) and (d)** shows the error in shift size estimates obtained from DI-CUSUM and SS-CUSUM. The estimated shifts are accurate if the error is close or equal to zero.

first CUSUM signal can occur at any point of time in the second phase of the simulation. This means the estimates for smaller M will represent a wide range of biomass shifts. However the shift size estimates for higher M will represent only when large shifts occur in the stock biomass. Hence the variability in shift size estimates was higher for the smaller M. A comparative analysis of the variances showed that the methods D3, D4 and D5 have greater variability when M is small (Figure 6.4b). This is because the computation procedure of these methods include a cumulative summation of estimates from the previous years.

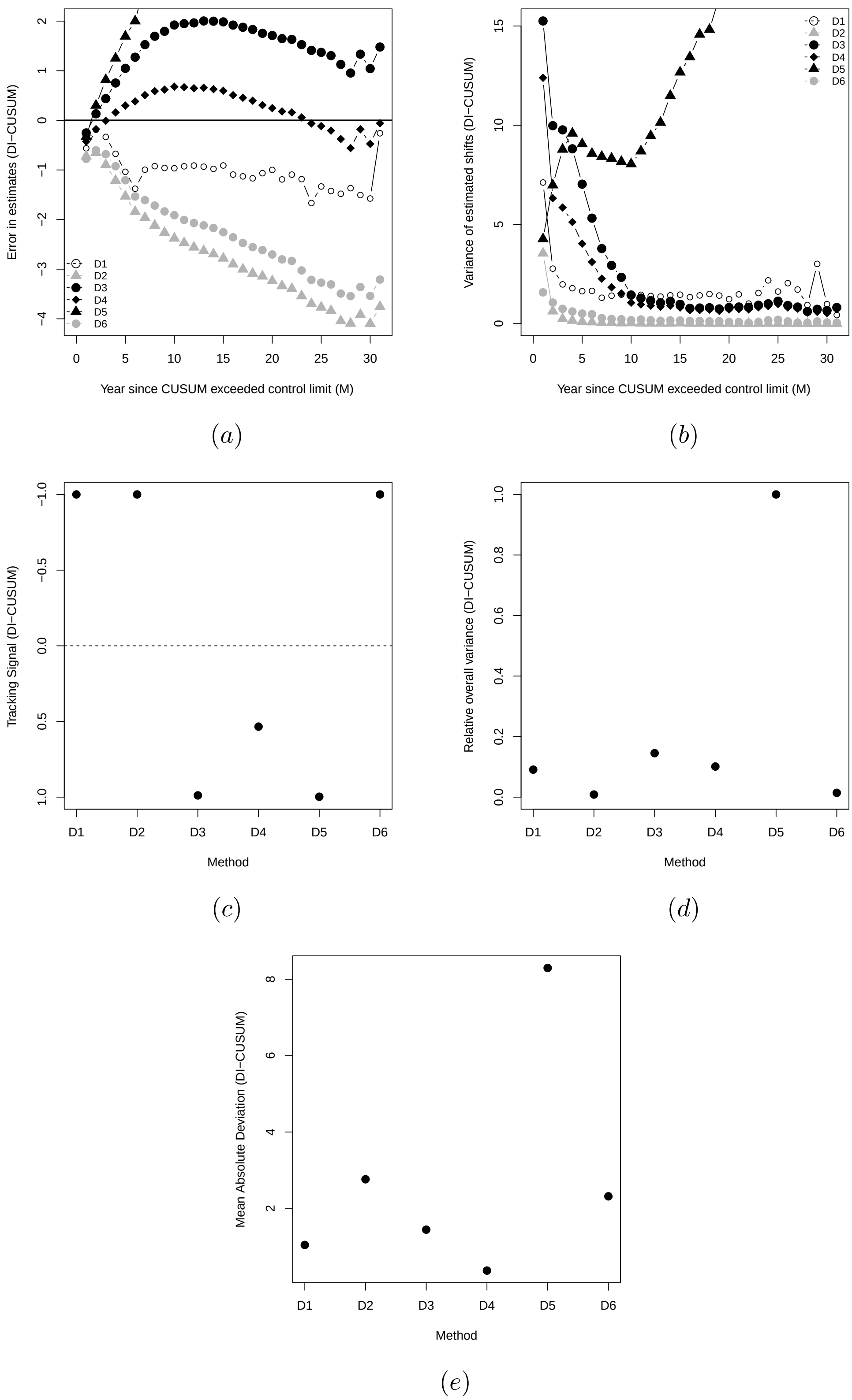


Figure 6.4: **Bias, precision and accuracy measures from the base case scenario:** The figure shows the performance measures obtained from DI-CUSUM in the base case scenario **(a)** Shows the error in shift size estimates **(b)** Shows the variance of shift size estimates **(c)** Shows the tracking signal (TS) as a measure of the bias in shift size estimates. The TS below the dotted line are negatively biased and precautionary **(d)** Shows the relative overall variance (ROV) as a measure of the precision. Estimates with minimum ROVs are comparatively more precise **(e)** shows the mean absolute deviation (MAD) as a measure of accuracy. The most accurate estimates will have MADs close to zero

6.5.3 Bias, precision and accuracy of shift size estimates

The performances were measured and evaluated in the order of bias, precision and accuracy of the shift size estimates. Estimates with negative errors may not be useful for managing fisheries since the adjustment in TAC will not be sufficient to avoid overfishing or stock collapse. So the first criteria of performance evaluation was to check which methods give zero or positive error in their estimated shift sizes as measured by the tracking signal. In figure 6.4c, we can see that only three methods i.e., D3, D4 and D5 give a positive bias in their estimates. The method D4 is more close to zero with a tracking signal of 0.5 indicating that at least 50% of the estimates are unbiased (Figure 6.4c).

The performance measures can now be compared between D3, D4 and D5 as other methods gave negatively biased estimates. The next performance measure is the relative overall variance of the shift size estimates to compare the precision of these methods. Despite being positively biased, method D5 gave the highest variance and this indicates that these estimates are unreliable (Figure 6.4d). However, the method could be still useful if appropriate annual catch restrictions are applied while adjusting the TAC for the stock. Both D3 and D4 methods were precise giving a smaller relative overall variance when compared to the estimates from D5 (Figure 6.4d).

The final performance measure is the accuracy of the shift size estimates and are measured by the mean absolute deviation (MAD). The method D4 was more accurate than D3 since the MAD for D4 was closer to zero (Figure 6.4e). However, both D3 and D4 are methods essentially based on the same principle (Grubb's harmonic rule). The estimates from D3 and D4 methods were reasonably precise and accurate across all scenarios (Figures 6.5 to 6.8 c,d,e,f).

6.5.4 Performance comparison for various stock indicators

A comparison of performance measures indicated that none of the methods are equally good for the range of stock indicators tested in this study. In Chapter 4, it was found that the performances are dependent on sensitivity and specificity of the stock indicator. In the present study, the accuracy of the D4 method was affected by negatively biased errors when a large fish indicator was used (Figure 6.5a,b). However, the estimates were positively biased when the combined indicator RP_n was monitored.

In SS-CUSUM, positively biased estimates were obtained only when the combined indicator (RP_n) was used (Figure 6.5b). Although the P_n gave good monitoring performances in Chapter 5, the deviation of indicator observations were not sufficiently good for predicting the shift size in stock biomass. This is because the running mean will be biased in the initial years by adapting to observations if no signals are raised by

SS-CUSUM. However this effect was nullified when both R and P_n were combined because both indicators are not equally affected unless the stock is in a severely depleted state. This means that if indicator control means are not available for the stock, then RP_n should be used for assessing the stock with SS-CUSUM control charts.

6.5.5 Performance comparison for various impact scenarios

Four types of impact scenarios were tested in this study. Note that in a declining F scenario, the stock biomass will increase and hence a negative bias should be preferred. In a stable state fishery, we do not require TAC adjustments and hence an unbiased shift size estimate is expected. In a recruitment crash scenario, a positive bias in shift size estimates are preferred because this is similar to the base case where the stock biomass declines.

In DI-CUSUM, both D3 and D4 gave shift size estimates with bias in the direction preferred for the given impact scenarios (Figure 6.6a). In SS-CUSUM, D3 and D4 gave positively biased errors for the under-fished scenario (Figure 6.6b). However, their shift size estimates were more accurate when compared to other methods used in this study (Figure 6.6b).

6.5.6 Performance comparison for various life history species

Results indicated that the estimates from both D3 and D4 methods were robust for all performance measures across the three life history species used in the present study (Figure 6.7). The results were similar in both DI-CUSUM and SS-CUSUM control charts. The estimates from D4 were more unbiased, precise and accurate when compared to the D3 method.

A comparison of the relative overall variance indicated that the precision of shift size estimates will depend upon the life span of the species. The variance was higher for a long lived species indicating comparatively less precise shift size estimates (Figure 6.7 c,d). This is in fact due to the slower response of long lived species, thus resulting in more out-of-control observations for small M values when compared to a short lived species.

6.5.7 Performance comparison for various historical state of the stock

Results indicated that the estimates from both D3 and D4 methods were robust for their bias and accuracy across the three historical states of fish stocks used in this study (Figure 6.8 a,b,e,f). The results were similar in both DI-CUSUM and SS-CUSUM

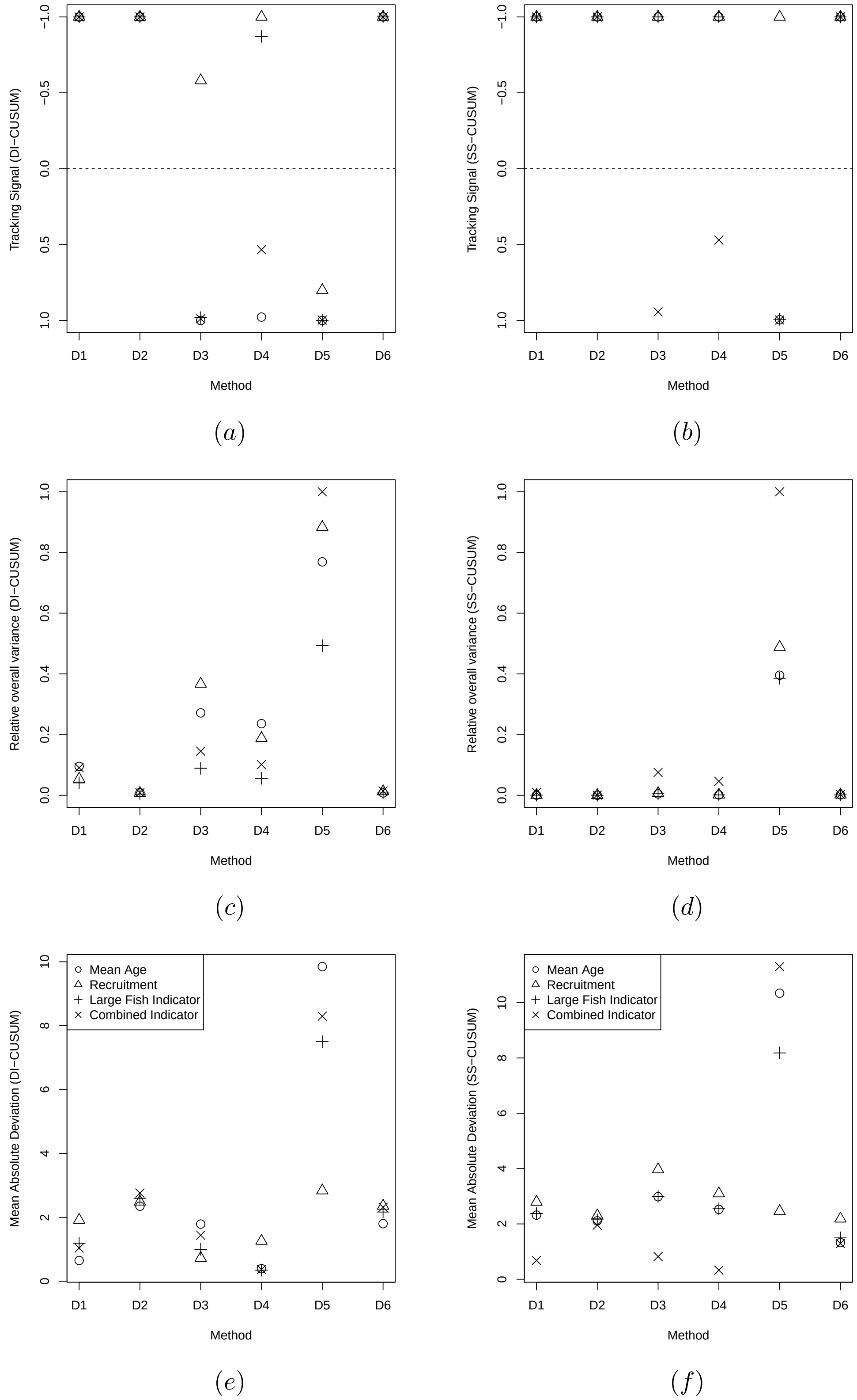


Figure 6.5: **Performance comparison for various stock indicators: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.

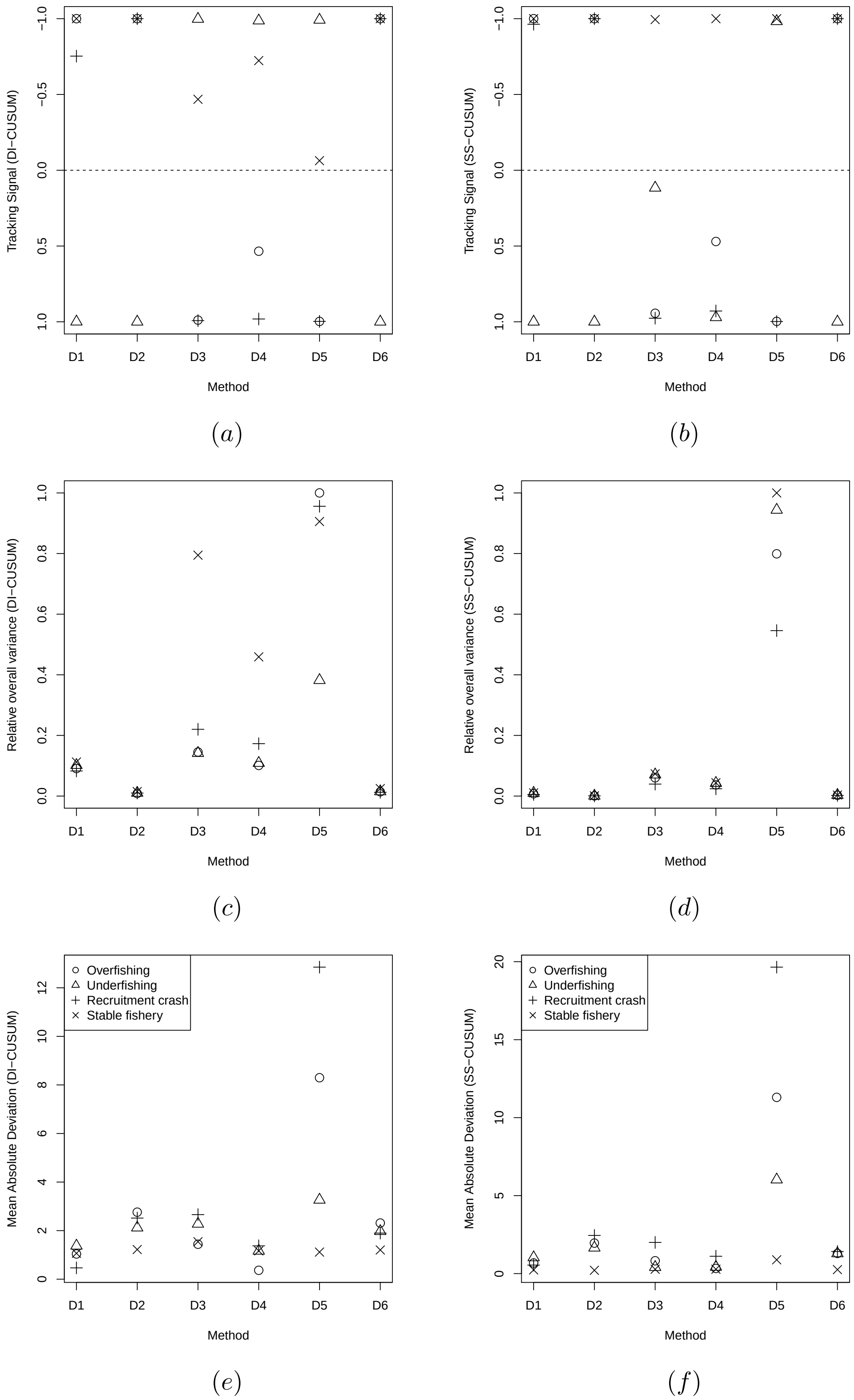


Figure 6.6: **Performance comparison for different fishery scenarios: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.

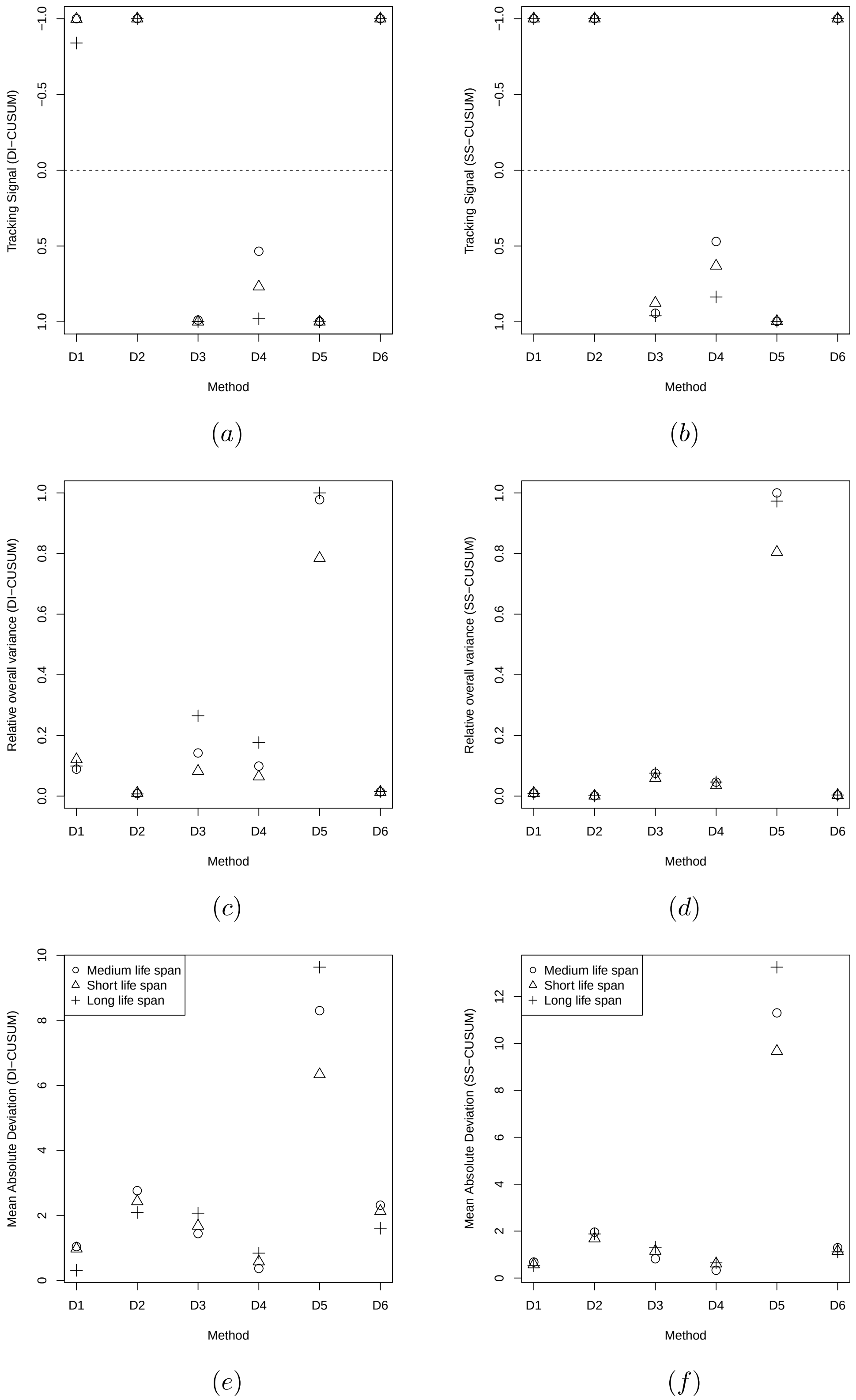


Figure 6.7: **Performance comparison for species with different life histories: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.

control charts. The estimates from D4 were more unbiased and accurate when compared to the estimates from D3 method.

A comparison of the relative overall variance in DI-CUSUM indicated that the precision of shift size estimates will depend upon the historical state of the fish stock. The variance was higher for the fish stock which was historically fished above MSY (Figure 6.7 c). This is expected as the range of shift size estimates will increase when the fish stock is historically exploited above the reference point (the biomass will be depleted more than the base case). Moreover, the methods may still give an estimate of smaller shift in stock biomass for low values of M if there are observation errors in the indicator.

However, this effect was absent in SS-CUSUM because the assumption used in this technique is to control the process with respect to its initial state. Therefore the reference point or 'running mean' will be equivalent to the initial state of the stock i.e., B_{MSY} for the stock that was historically fished at MSY and $B_{110\%MSY}$ for the stock that was historically fished above MSY.

6.6 Discussion

Conventionally, estimated indicators such as the SSB and F are monitored using reference points and the biomass is regulated by determining annual adjustments in TAC. The present study provides guidelines on how such adjustments can be implemented using CUSUM if data available for the fish stock are not sufficient for obtaining reliable estimates of SSB and F. In the context of 'indicator based fisheries management', many researchers have recommended monitoring the trend in various indicators from the fishery or stock. However, currently there is a lack of methodology that provides an explicit criteria for translating the indicator trends to harvest decisions. Most of the previous work has addressed this problem by advocating qualitative decisions i.e., increase or decrease catch (Trenkel et al., 2007; Koeller et al., 2000; Probst et al., 2013*a*), though no quantitative methods have been developed or proposed so far and that is the novelty of this study.

6.6.1 Statistical Process Adjustment (SPA) for regulating fisheries

The detection techniques from SPC have a long history of successful application in the manufacturing industries because they are efficient in detecting the defective products at the earliest possible moment in temporal scale (thus minimizing the cost in producing more defective products). Many manufacturing operations are continuous and hence it is important to sustain the quality (or process) of the product on an ongoing basis. To

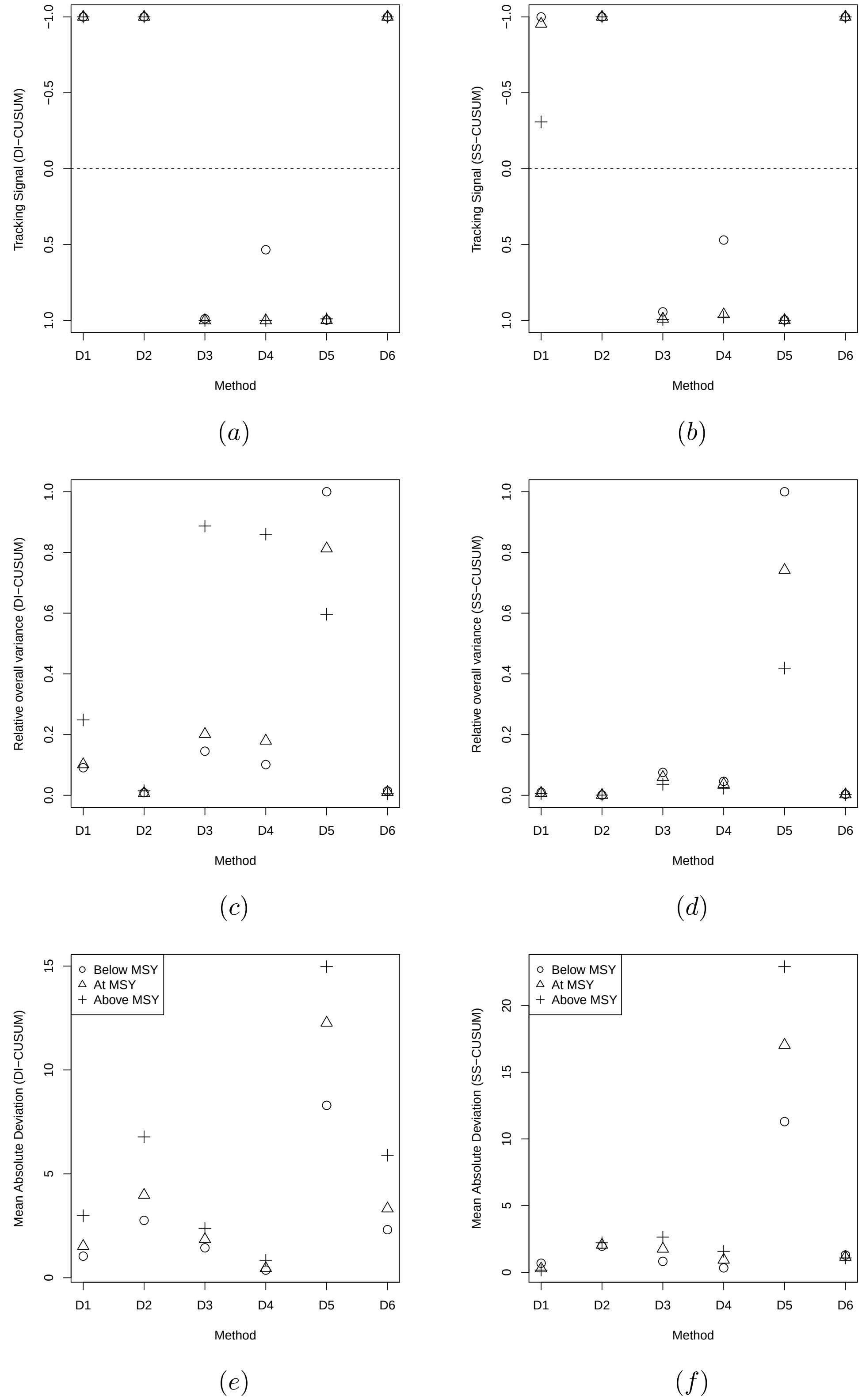


Figure 6.8: **Performance comparison for different historical states of stock: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.

keep the process (equivalent to stock biomass in this context) on target, the approach based on process regulation is used where some control variable (equivalent to TAC in this context) is manipulated by an adjustment scheme so that the variability of process around target is minimized. However, the adjustment schemes are effective only if accurate estimates are available for the shift that has occurred in the process mean. Several estimation procedures are used as adjustment schemes in process regulation and they are collectively termed as the engineering process control (Montgomery, 1996; EPC).

Both SPC and EPC were historically developed in different environments. The techniques in SPC are strategic in nature and popular among quality engineers, while the techniques in EPC are tactical in nature with more popularity among process engineers. However, both strategies share the common objective i.e., 'reduction of process variability'. Many previous research workers integrated these two strategies, generally under the term 'Statistical Process Adjustment (SPA)' for improving the adjustment schemes because EPC inherently assumes a dynamic process model with explicit links between the input and the output (Box and Kramer, 1992; Montgomery et al., 1994; Vander Wiel et al., 1992). Many adjustment schemes can not completely account for offsets in the process when there are external disturbances and as a result the process variability increases. By applying SPC in a specific way, adjustments can be applied only when there is significant deviation in the process mean.

The study presented here integrated CUSUM, a detection technique in SPC theory (for monitoring purposes) with various estimation techniques from the EPC theory (for adjustment purposes). The CUSUM control charts have been applied in fisheries so far only for monitoring purposes (Scandol, 2003; 2005; Petitgas, 2009) and hence this study is the first of its kind with a focus on discussing their possible extension in terms of stock assessment and management of a fishery. The purpose of this chapter was specifically to provide a preliminary evaluation on the efficiency of various estimation techniques for SPA in fisheries, particularly to determine which adjustment scheme is likely to perform better with HCRs if the available data are unreliable for conducting a formal quantitative fish stock assessment.

The two important steps in CUSUM following the detection of an out-of-control situation are "searching for an assignable cause" and "estimating the shift" that has occurred in the underlying process mean. The following discussion is based on these steps as they are important while applying SPAs to real world fish stocks.

6.6.2 Searching for an assignable cause

In Section 6.6.1, the point was raised that the ultimate goal of an SPC technique is the elimination of variability in the process. So it is important to understand the sources of variability that can perturb the stock indicator or the underlying stock biomass. Identifying these are critical for determining the nature of the corrective action required while managing the fishery. There are numerous sources of variability but they can generally be classified into three i.e., natural noise, fishery induced noise and observed errors.

The variability due to background noise is a cumulative effect of many small unavoidable causes that are inherent in the system and hence the process with such variabilities are considered to be in an in-control state (see Chapters 1 and 3). However, all natural variabilities are not necessarily beneficial to the fishery. There is evidence that for many fish stocks the variability in recruitment can be affected due to environmentally driven factors (Stenseth et al., 2002) e.g. the recruitment of cod in the North Atlantic is affected by sea temperature (O'Brien et al., 2000). If such effects persist for several years, the spawning stock biomass will be affected eventually.

The second source of variability is due to the nature of fishing activities on stock biomass. The size selective effects of fishing have previously been discussed in Chapters 4 and 5. Apart from that, the selectivity pattern of fishing gear can also affect the shift in stock biomass differentially and hence other estimation methods may perform better than D3 or D4 (see results from Scenario 8, Appendix D). Another source of variability is the misreporting of catch or if the indicators do not fully represent the fisheries catch e.g. the trend in stock indicators will be biased if the younger age classes are consistently discarded (Borges et al., 2006).

The choice of stock indicators should ideally be useful in identifying the source of variability that may drive the stock to an out-of-control situation. In the present study, a combined indicator of recruitment (R) and large fish positive proportion (P_n) was used for determining biologically plausible causes for the shift in stock biomass (Trenkel et al., 2007; Koeller et al., 2000; Probst et al., 2013*a*). Combining these two indicators (RP_n) are particularly robust when recruitment is affected by externally driven forces (Figure D.6). Moreover, the only useful indicator with SS-CUSUM chart was the RP_n i.e., when indicator control means are not available for the stock. The quantitative procedure of combining R and P_n indicator deviations is another novelty of this study.

The third source of variability that can arise are the observation errors while measuring or estimating the stock indicators. The present study tested the robustness of estimation methods to such sources of variability i.e., using fixed noise for recruitment ($cv = 0.6$) and a sample size of 10 fish individuals for computing the catch indicators (Scenario 9, Appendix D). Results showed that the estimates are robust for DI-CUSUM but a few more samples may improve the performance with SS-CUSUM as well (Results from Chapter 4 and 5 indicate that performances are robust for sample sizes of 100 fishes or more).

6.6.3 Estimating the shift in process mean

In the present study, performances of various estimation methods were evaluated without implementing a Harvest Control Rule (or adjusting the process). In the following section, I discuss how the proposed estimation methods are useful when applying them to real world fish stocks. The usefulness of an estimation method depends upon two aspects i.e., the amount of data available and the current state of the stock.

If no historical data are available, it is difficult to understand the current state of the stock. Results from additional scenarios showed that the estimates from method D3 (recursive estimation using Grubbs's rule) will be more precautionary if there is uncertainty in the choice of CUSUM parameters or if there is less information on the shift that has occurred in the underlying stock biomass (see Appendix D). However, if there is strong evidence that the stock is historically in an in-control state and only a small biomass shift has occurred, then the estimates from D1, D2 or D6 can be safely applied. This is because the estimates from these methods were comparatively more precise (less variance) and equally good when the shift in stock biomass is small. Note that the value of M will always be low for small biomass shifts. However more evaluations will be required to determine, for how long the estimates from D1, D2 and D6 can be safely applied because the magnitude of shift size will increase if the corrective actions are not effective due to observation errors.

The issue with the SS-CUSUM approach is that the fishery manager has to wait for at least three years to ensure the state of fish stock (Pazhayamadom et al., 2013). In such situations, the manager has to make sure that there is no further increase in catch or effort until enough data are available for SS-CUSUM (Walters, 1998). However, this approach may not guarantee a fixed F if the stock is already in an out-of-control state. This can be detected if the SS-CUSUM gives an alarm on the third year itself. If there is more information on the potential collapse of the stock (e.g. local fishers), then conservative strategies such as closed areas or seasons can be implemented and the indicators can ideally be monitored using fishery independent research surveys (Johannes, 1998).

If more than two years of data are available (as assumed in the present study), it is comparatively easier to determine the status of the stock since an alarm will be already raised if there is an out-of-control situation. If $M > 2$, then it is more precautionary to use the estimates from D3 or D4 because the shift in stock biomass could be sufficiently large by then (Figure 6.4a). If the objective of fisheries management is to maximize the catch, then estimates from method D4 could be more useful as they are comparatively more accurate. However, they should be used with more precaution since the method D4 is sensitive to the choice of CUSUM parameters (see Figure D.1, D.2 and D.3). Nevertheless, these estimation methods can also be used even in data rich stocks to qualitatively assess the relative shift occurred in SSB from a predefined reference point.

The most conservative option is to use method D5 where direct CUSUM values were used. This is because the direction of shift size estimates are unbiased though quantitatively inaccurate. Hence, they are only safe to use with appropriate upper and lower TAC limits (or inter-annual restrictions in TAC adjustment) which may otherwise result in stock collapse or extremely very low catches.

6.7 Summary

The present study was able to draw the following conclusions for estimating the shift in stock biomass using CUSUM control charts.

- The performance of various estimation methods are highly dependent on the sensitivity and specificity of the stock indicator.
- If reference points are not available, then the shift size estimates from a combined indicator (RP_n) of recruitment and large fish proportion will perform better than using them individually.
- The most precautionary shift size estimates were obtained by the procedure of recursive estimation using Grubbs' harmonic rule i.e., D3 method.
- The most accurate shift size estimates were obtained by using an allowance corrected standardized indicator i.e., D4 method. However, the risk of overfishing will increase if the w, k and h are not optimized for the management objective.
- Shift size estimates from D5 method are useful. However, they are only safe to apply with appropriate inter-annual restrictions in TAC adjustments.

Chapter 7

A fishery management procedure based on DI-CUSUM

7.1 Introduction

Indicators based on landed catch or fishery independent research surveys are monitored for classifying the status of a fish stock when the data available are unreliable or insufficient for conducting quantitative fish stock assessments (Cotter et al., 2009a; Carruthers et al., 2012). The direction of indicator trends can be used for short term qualitative decisions on harvesting such resources such as an increase or decrease in the catch (Jennings, 2005). A range of trend detection methods are available in the literature for monitoring and detecting impacts to the stock due to fishing (Cotter et al., 2009a; Mesnil and Petitgas, 2009). However the indicators will be noisy if the data available are of poor quality either due to measurement or estimation error (Jennings, 2005). One method that can effectively monitor the underlying trends in noisy observations is the decision interval form of the cumulative sum (DI-CUSUM) control chart (Page, 1954). They are mostly used in manufacturing industries as a monitoring tool to detect whether the state of a process is in-control or out-of-control (Montgomery, 1996). The DI-CUSUM raises an alarm to signal the out-of-control situations and call for the response of process managers to undertake necessary corrective measures. Many authors have previously demonstrated the usefulness of DI-CUSUM as a monitoring tool in fisheries management (Scandol, 2003; 2005; Petitgas, 2009; Mesnil and Petitgas, 2009), in particular, how DI-CUSUM can be used to monitor a variety of stock indicators and detect situations that require a management response. Once an out-of-control situation is detected, the fishery manager has to adjust the management policies to bring the stock back to the in-control state. Although this approach was mentioned in previous studies (Scandol, 2003; Pazhayamadom et al., 2013), the management performance of a fish stock using harvest control rules (HCRs) triggered by DI-CUSUM alarms have not been demonstrated so far.

The ICES provide scientific advice by recommending output controls in terms of total allowable catch (TAC) for the stocks in and around the North Atlantic. This means that the fishery will be closed once the cumulative catch for the year reaches the TAC. If the TAC is correctly specified and enforced, this method can maintain the stock biomass above a specific threshold as given by the management objective (Froese and Proelß, 2010; Beddington et al., 2007). The advice on TAC for the fish stocks are usually updated annually on an ongoing basis and this is based on the status of SSB and F estimated from data obtained during the previous year. But if sufficient data are not available for the fish stock for obtaining these estimates, then trends from the "indicator based" approach can be used to update the TAC. Previous research has provided guidelines on adjusting the TAC qualitatively though no quantitative methods are available so far demonstrating this approach (Trenkel et al., 2007; Caddy and Seijo, 2005).

In the present study, I will show how fish stocks can be managed by updating the annual TACs using a feedback mechanism triggered by DI-CUSUM. A combined metric of the estimated recruitment and large fish indicator was monitored using DI-CUSUM from a simulated fishery. In Chapter 6, the combined indicator was found more useful for estimating the shift in stock biomass (see Figure D.6). It was assumed that the fish stock is historically in an 'out-of-control' state and scientific data from the two previous years are available for the fish stock. When an alarm is raised by DI-CUSUM, the shift in the underlying stock biomass was estimated and the TAC was updated using a relative adjustment corresponding to the estimated shift. Performance was evaluated in terms of the risk associated with the stock biomass and whether the fishing mortality represents an 'in-control' state during the final years of the projected period.

7.2 Objective of the study

The application of DI-CUSUM to real world fish stocks are limited. Campbell (2004) used DI-CUSUM charts to monitor the performance of a long-line fishery off eastern Australia and found that the swordfish (*Xiphias gladius*) in the Brisbane Grounds region are "out-of-control". But the question is, how the harvest levels for such or similar fish stocks can be advised (through TAC) using CUSUM so they can be brought back to the "in-control" state? Hence the objective of the present study is:

- To bring an "out-of-control" fish stock back to the "in-control" state given that the indicator control mean ($\overline{X}$) for monitoring the estimated recruitment (R) and the large fish positive proportions (P_w) are available.

7.3 Background

There are five important parameters in a DI-CUSUM control chart. They are the control mean ($\overline{X}$), control standard deviation ($\overline{\sigma}$), winsorizing constant (w), allowance parameter (k) and the control limit (h). The equations for constructing DI-CUSUM control chart are provided in Section 3.3 (Figure 3.2).

The foremost assumption in DI-CUSUM is that the control mean ($\overline{X}$) and the control standard deviation ($\overline{\sigma}$) of the underlying indicator distribution are known. The control mean in DI-CUSUM refers to a fishery where the stock represents an in-control state (equivalent to a target reference point in fisheries management). Scandol (2003) provided three alternative strategies to specify these two parameters. First, they can be estimated from all available data until the most recent year. Second, they can be estimated from a window of historical data during which the stock was perceived to be stable or in an in-control state (Petitgas et al., 2009). Third, they can be simply specified as a managerial goal (e.g. equivalent to MSY of the stock).

The winsorizing constant (w) is used for making the DI-CUSUM robust to outliers or extreme observations in the indicator time series (see Section 3.3.4). In this approach, the outlying observations are "edited" to more central values by applying a threshold to the deviation of the indicator from their control mean (Hawkins and Olwell, 1998). This obviously reduces the sensitivity of DI-CUSUM for detecting genuine mean shifts but there is very little loss of performance for values of $w = 2$ and above (Hawkins and Olwell, 1998).

The sensitivity and specificity of detecting out-of-control situations will also depend upon the choice of allowance (k) and control limit (h). Choosing a particular k implies that the DI-CUSUM will respond only if there is meaningful deviation in the process mean. This is because it assumes that a certain amount of indicator variability is due to variation that is inherent to the system (Hawkins and Olwell, 1998; Mesnil and Petitgas, 2009; Chapter 3). Once the DI-CUSUM responds, the out-of-control situation is detected by monitoring the magnitude, whether it is above or below a threshold value known as the control limit (h). The value of h is usually set such that the probability of a false alarm is minimized. More details on the criteria of choosing these constants are provided in Chapters 3 and 5 (see Sections 3.3, 5.6.2 and 5.6.3).

An alarm from DI-CUSUM indicates that a significant shift occurred in the underlying biomass of the stock (positive or negative). If this shift can be estimated, then the risk of overfishing can be minimized by implementing a relative adjustment to the TAC through Harvest Control Rules (HCR). Essentially this implies that the stock abundance can be regulated by adjusting the removal due to fishing. For estimating the shift in stock biomass, the performance of six different quantitative methods (from engineering process control (EPC) theory) were tested in chapter 6 by integrating them with the DI-CUSUM control charts. This means that the shifts were estimated only when an alarm was raised by the DI-CUSUM. The approach of integrating both EPC and SPC method is generally termed as the **Statistical Process Adjustment (SPA)**. The results from chapter 6 indicate that the most accurate estimates were obtained from the method based on Grubb's harmonic rule (Grubbs, 1983; Del Castillo, 2006; See section 6.5.2).

7.4 Assumptions

In the present study, it was assumed that the fishery represents a data limited fish stock for which observations are available from the two immediate historical years. This minimum period was necessary to implement SPA since the fishery was regulated by updating the TAC from the previous year. It was also assumed that the stock is already in an out-of-control state so that it characterizes many real world fish stocks similar to the swordfish example provided in Section 7.2.

Secondly, it was assumed that the indicator control means are available for the fish stock. The present study followed the third strategy recommended by Scandol (2003) where a specific management goal was defined for the control means i.e., the indicator observations equivalent to 90% MSY at fishery equilibrium. 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). From this point onwards, the reference point will indicate quantities equivalent to a fishery equilibrium state of 90% MSY.

Thirdly, the study assumes that the fishery is regulated using TAC, but purely on the basis of signals from DI-CUSUM. This means that the management policies are not updated as more relevant information is available for the fish stock. Once the stock is back to the "in-control" state, the TAC was configured to remain at levels used in the previous year. In the real world, the fishing effort may increase at later stages to maximize the catch or profit.

7.5 Methods

7.5.1 Fisheries simulation

An age structured fish stock was simulated using the operating model presented in section 2.1 and a fishery equilibrium was achieved with an initial fishing mortality of

$F_{int} = F_{110\%MSY} = 0.33$. This F_{int} was applied to obtain a fish stock historically in an out-of-control state (the in-control state will correspond to $F_{int} = F_{90\%MSY} = 0.133$). The fisheries simulation consisted of two phases. In the first phase of the simulation, the model ran for 100 years where random variability was introduced in F_{int} ($cv = 0.1$) and the stock-recruitment relationship ($cv = 0.6$). In the second phase, it was assumed that the indicator observations from two immediate previous years are available for the fish stock. The model ran for 20 further years during which the stock indicators were monitored by DI-CUSUM and the fishery was regulated by TAC. Once an out-of-control situation is alarmed, the shift occurred in the underlying stock biomass was estimated (Section 6.4.3) and the fishery was managed by updating the TAC from the previous year using a relative adjustment corresponding to the estimated shift (Harvest control rule, Section 7.5.5). The simulation was iterated 1000 times and the experiment was repeated for five different fishery scenarios (Section 7.5.6). The performance measures in each scenario were computed to evaluate whether the stock has been brought back to the "in-control" state through the management process (Section 7.5.7).

7.5.2 Indicator used for DI-CUSUM monitoring

In the present study, the estimated recruitment (R) and the large fish positive proportion by catch weight (P_w) indicators were combined together to obtain the RP_w indicator (Similar to the approach used in table 6.3). For this, both the R and P_w were first standardized using their respective control means ($\overline{X}$) and standard deviation ($\overline{\sigma}$) obtained for observations until the most recent year in the time series (Equation 3.2). Since both indicators are in standard deviation units, they can be summed up together to obtain a net overall deviation in each year of the time series. The combined indicator (RP_w) have several advantages. First, the deviation in stock abundance is monitored from both ends of the age class structure, thus capturing the trend of new recruits entering the stock and removal of large fishes through the fishing process. Secondly, they can capture trends that are independent of the fishery e.g. recruitment crash due to an environmental catastrophe. These advantages are graphically illustrated in chapter 6 (see Figure D.6).

7.5.3 Monitoring the combined indicator RP_w using DI-CUSUM

The control means for the indicators R and P_w were set equivalent to the reference point of 90% MSY. These were obtained from a stock that was stabilized at a fishery equilibrium of $F_{int} = F_{90\%MSY}$ (Section 2.3.3). If both indicators represent an in-control state, then the net overall deviation of the combined indicator RP_w will be zero. The base case scenario was monitored using DI-CUSUM with parameters $w = 2$, $k = 0.5$ and $h = 0$. The winsorizing constant of threshold $w = 2$ is a good choice since the loss of performance in DI-CUSUM is small (Hawkins and Olwell, 1998; Equation 3.9). As the fish stocks are already in an out-of-control state, the DI-CUSUM should be set with the least possible k and h constants for obtaining the highest sensitivity. But both k and h can take values as low as zero which is effectively meaningless since the CUSUM scheme will not assume any inherent noise within the indicator observations. A plausible approach was to fix DI-CUSUM with $k = 0.5$ and $h = 0$. However, the performances for k and h with higher constants were evaluated in later scenarios (Scenarios 3 and 6, Table 7.1 & E.1).

7.5.4 Estimating the biomass shift using DI-CUSUM

In chapter 6, six different types of estimation methods were tested for their performances in obtaining the shift size in stock biomass ($\hat{S}$, Section 6.4.3, D1 to D6). Three methods were based on the last observation of the indicator time series (D1, D2 and D6) and three other methods were based on all observations that lead to the out-of-control situation (D3, D4 and D5). Results showed that the most reliable estimates were given by those in the latter category, in particular the method based on Grubb's harmonic rule (D3). The description and equations for all these methods are provided in section 6.4.3 (Table 6.2 & 6.2). However, the results obtained in chapter 6 were based on a fishery that was not regulated using SPA. The performances may differ if the indicator in year 'i' is a result of a fishery that was regulated using shift size estimates from the previous year '$i-1$'. Therefore, all the six estimation methods were used in the present study to evaluate their performances in a TAC regulated fishery (Scenario 1, Table 7.1). The method which gave the most accurate estimate was used as the base case for the later scenarios (Scenarios 2-12, Table 7.1 & E.1).

7.5.5 Harvest control rule using SPA

The TAC for year 'i' was updated based upon two conditions. First, the DI-CUSUM should raise an alarm indicating the "out-of-control" situation of the stock. Second, the CUSUM ($\theta_i^{\pm}$) in year 'i' should move further away from zero indicating that more adjustment in TAC is required to bring the stock back to the "in-control" state. If these two conditions are not satisfied, then the TAC from the previous year was followed.

If $|\theta_{i-1}^{\pm}| > |h|$ and $|\theta_{i-1}^{\pm}| > |\theta_{i-2}^{\pm}|$ then,

$$TAC^i = TAC^{i-1} + \left(TAC^{i-1} \times \hat{S}\right) \tag{7.1}$$

else,

$$TAC^i = TAC^{i-1} \tag{7.2}$$

Where $\hat{S}$ is the estimated shift in stock biomass (Section 6.4.3) and $\left(TAC^{i-1} \times \hat{S}\right)$ is the adjustment factor applied to update the TAC from the previous year. The range of shift size estimates were extremely high such that an annual restriction in TAC update was necessary which would otherwise result in stock collapse or closure of the fishery. The TAC^i was restricted using TAC_r such that it never dropped below $TAC^{i-1} \times (1 - TAC_r)$ and above $TAC^{i-1} \times (1 + TAC_r)$. For example if $TAC_r = 20\%$, then TAC^i is between $TAC^{i-1} \times 0.8$ and $TAC^{i-1} \times 1.2$.

A perfect implementation of the proposed TAC is likely not possible in the real world and hence random noise errors were added using a coefficient of variation of $cv = 0.1$ from the normal distribution.

$$TAC^i = max\left[0, \sim normal\left(\text{mean} = TAC^i, cv = 0.1\right)\right] \tag{7.3}$$

7.5.6 Scenarios considered

To compare the performances of the proposed Harvest Control Rule (HCR), five different fishery scenarios were constructed (Table 7.1). These were based on (i) the type of estimation method; (ii) underestimation of control means in DI-CUSUM; (iii) constants used for the allowance (k); (iv) constants used for restricting the TAC (TAC_r) and (v) life span of the species. Additional scenarios were also constructed and a comprehensive discussion of the key results is given in Appendix E.

In scenario 1, the performances were measured for six different types of estimation techniques (D1 to D6, section 6.4.3). These are the Taguchi's method (D1), Grubbs' harmonic rule (D2), recursive estimation using Grubb's harmonic rule (D3), Grubb's recursive estimation after allowance correction (D4), rule based on CUSUM observations (D5) and Montgomery's method (D6). They can be classified based on the (i) type of observations used and (ii) number of observations used for estimating the shift size in stock biomass. Methods D1 to D4 used indicator observations while methods D5 to D6 used the DI-CUSUM observations for computing the shift size in stock biomass. Three methods (D3, D4 and D5) used historical observations while the rest (D1, D2 and D6) used only the last observation in the time series for obtaining these shift size estimates.

In the present study, the indicator control means for DI-CUSUM were assumed to be perfectly known. However in the real world, the control means could be over or under-estimated as they are more likely computed from historical indicator observations. In scenario 2, the performances of HCR were measured for scenarios in which the control mean is under-estimated (similarly an over-estimated case is simulated in scenario 7, see Table E.1).

In scenario 3, the performance measures were evaluated for the effect of setting higher k constants in DI-CUSUM (Table 7.1). The criteria for choosing k has been already discussed in chapter 5 though it was specifically evaluated for monitoring purposes. The performance measures may differ if the fishery is regulated using feed back mechanisms through statistical process adjustment.

In scenario 4, the performance measures were evaluated for the effect of relaxing the inter-annual TAC restrictions (TAC_r). The range of shift size estimates from methods D1 to D6 are extremely high and hence the TAC_r are unavoidable (Chapter 6). But since the TAC update is applied consistently until the CUSUM start moving towards zero, this may likely result in an over or under-adjustment.

The proposed management procedure should ideally regulate a fishery irrespective of the life history characteristics of the species. In scenario 5, the HCR was evaluated for stocks with three different life history traits (short, medium and long lived species). The life history parameters for these fish stocks are provided in Table 2.1.

Most of the above scenarios tested the performance of HCR for stocks which were in out-of-control state. However in the real world, fish stocks could be in-control or much below the reference point when the management initiates. Hence in scenario 6, the HCR was evaluated for stocks which were in different historical states of fishery i.e., at $F_{90\%MSY}$ (0.133) and below $F_{90\%MSY}$ (0.013).

In the base case scenario, the fishery of a medium life span species (Cod-like, LH1) was simulated using a medium mesh sized trawl net. The combined indicator (RP_w) of the estimated recruitment (observation error of $cv = 0.6$) and the large fish positive proportion (from 10,000 fish individuals) was monitored using a DI-CUSUM configured with $w = 2$, $k = 0.5$ and $h = 0$. It was assumed that the indicator control means for DI-CUSUM are perfectly known. Once an out-of-control situation is detected, the fishery was managed using a harvest control rule (HCR) that updated the TAC from previous year using an adjustment factor relative to the shift size occurred in the underlying stock biomass. The shift size in stock biomass was estimated using the D2 method since that was found to be the most accurate in scenario 1. There was no variability in the growth of the species and the stock-recruitment was not autocorrelated.

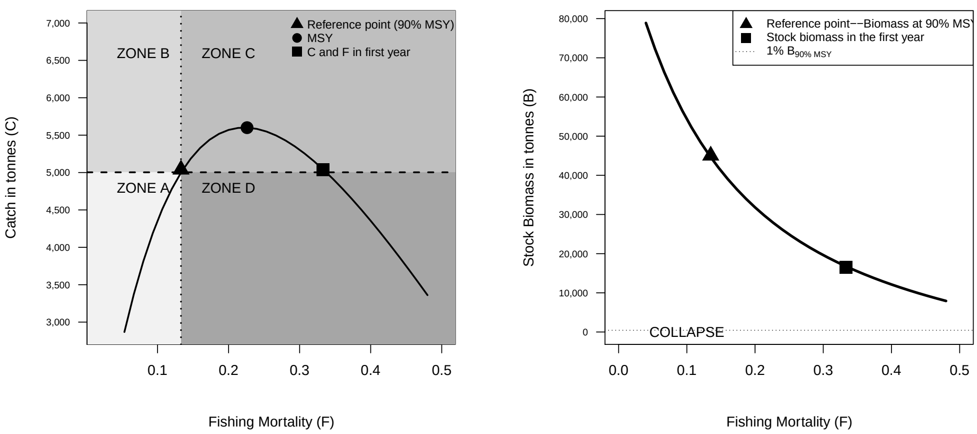
7.5.7 Performance measures

The performances were first evaluated to detect whether the stock was collapsed (Probability of collapse - B01, Table 7.2). For a given year 'i', the stock was considered to be collapsed if $B^i < (0.01 \times B_{90\%MSY})$. For example in the base case species, the probability of collapse is generally high if $F > 0.5$ (referred to as Zone D in Figure 7.1a,b).

Table 7.1: **Scenarios considered:** The following table shows the first six scenarios used for the present study (for additional scenarios, please see Table E.1). The shaded areas highlight the differences compared to the base case parameters.

Scenarios	Estimation method	Control mean for DI-CUSUM	Allowance (k)	TAC restriction	Lifespan of the species	Historical state of fish stock
Scenario 1	$D1$ $D2^*$ $D3$ $D4$ $D5$ $D6$	PK*	$k = 0.5^*$	$TAC_r = 20\%^*$	Medium (LH1)*	Above $F^*_{90\%MSY}$
Scenario 2	$D2$	PK UE by 5% UE by 10% UE by 25% UE by 50%	$k = 0.5$	$TAC_r = 20\%$	Medium (LH1)	Above $F_{90\%MSY}$
Scenario 3	$D2$	PK	$k = 0.0$ $k = 0.5$ $k = 1.0$ $k = 1.5$ $k = 2.0$	$TAC_r = 20\%$	Medium (LH1)	Above $F_{90\%MSY}$
Scenario 4	$D2$	PK	$k = 0.5$	$TAC_r = 10\%$ $TAC_r = 20\%$ $TAC_r = 30\%$ $TAC_r = 40\%$ $TAC_r = 50\%$	Medium (LH1)	Above $F_{90\%MSY}$
Scenario 5	$D2$	PK	$k = 0.5$	$TAC_r = 20\%$	Short (LH2) Medium (LH1) Long (LH3)	Above $F_{90\%MSY}$
Scenario 6	$D2$	PK	$k = 0.5$	$TAC_r = 20\%$	Medium (LH1)	Above $F_{90\%MSY}$ At $F_{90\%MSY}$ Below $F_{90\%MSY}$

* : Base case parameters
PK : Perfect Knowledge
UE : Under Estimated
D1 to D6 : Estimation methods (see Chapter 6, section 6.4.3)
LH1,LH2,LH3 : Life History stocks (Table 2.1)



(a) (b)

Figure 7.1: **Graphical illustration of 'in-control' state of the stock:** The figure shows the equilibrium points for catch and biomass with increasing constants of fishing mortality. **(a)** The 'in-control' state is represented by 90% MSY at fishery equilibrium (reference point). **(b)** The stock was considered to be collapsed if the biomass fell below 1% $B_{90\%MSY}$. This biomass level is represented by a dotted line in Figure 7.1b.

Table 7.2: **Performance measures used:** The following performance measures were computed from the second phase of the simulated fishery. Since the initial state of the stock was out-of-control, these measures were computed only for the last 5 years.

Performance Measures	Formula
Probability of collapse ($B01$)	$\frac{\sum_{q=1}^{q=1000}\sum_{i=16}^{i=20} I\left(B_q^i < [0.01 \times B_{90\%MSY}]\right)}{(i_{max} - i_{max-5}) \times q_{max}}$
Relative Stock Biomass (RSB)	$\frac{\left(\sum_{q=1}^{q=1000}\left[\frac{\sum_{i=16}^{i=20} B^i}{5}\right]\right)/q_{max}}{B_{90\%MSY}}$
Relative Fishing Mortality (RFM)	$\frac{\left(\sum_{q=1}^{q=1000}\left[\frac{\sum_{i=16}^{i=20} F^i}{5}\right]\right)/q_{max}}{F_{90\%MSY}}$
Relative Average Catch (RAC)	$\frac{\left(\sum_{q=1}^{q=1000}\left[\frac{\sum_{i=16}^{i=20} C^i}{5}\right]\right)/q_{max}}{C_{90\%MSY}}$

i : Year
q : Iteration
C_i : Fish catch in year 'i'
F_i : Fishing mortality in year 'i'
MSY : Maximum Sustainable Yield
$B_{90\%MSY}$: Stock biomass at reference point
$F_{90\%MSY}$: Fishing Mortality at reference point
$C_{90\%MSY}$: Total catch at reference point
I : Indicator function (If the condition satisfies, this will return a value of 1 otherwise 0)

To evaluate whether the stock was brought back to the in-control state, it was important to assess the stock biomass (B), fishing mortality (F) and the total catch (C) obtained during the terminal years of the fishery simulation. Hence, an average of these observations were recorded from the last 5 years of the second phase. Since the reference point was set equivalent to 90% MSY, the average B, F and C should correspond to $B_{90\%MSY}$, $F_{90\%MSY}$ and $C_{90\%MSY}$ if the stock was brought back to the "in-control" state. Hence their relative performances were used to assess the status of the fish stock (Table 7.2). If the stock is "in-control", then RSB, RFM and RAC will be close to 1. Thus the in-control state of fish stock corresponds to Zone A in figure 7.1a. In brief,

$$\text{Zone A (In-control):} \quad RFM < 1,\ RAC < 1 \text{ and } RSB > 1$$

The Zone B and C represent the fishery when harvests are close to the maximum sustainable yield (MSY), but with low and high F, respectively (Figure 7.1a). The state of the stock is generally unstable above the catch curve representing fishery equilibrium points. The MSY ($F_{MSY} = 0.226$ and $C_{MSY} = 5600.10$ tonnes) and the reference point ($F_{90\%MSY} = 0.13$ and $C_{90\%MSY} = 5003.10$ tonnes) used for base case species is graphically illustrated in figure 7.1a & 7.1b.

7.5.8 Statistical analysis

Performance measures in each scenario were statistically tested with the null hypothesis that there is no significant difference between stocks that used different parameters.

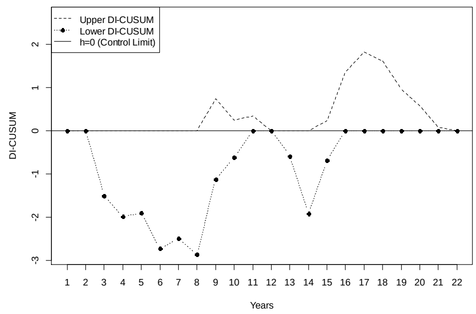
The performance measure on the probability of stock collapse (B01) is a proportion and hence the Pearson's chi-squared test was applied for testing the equality of proportions. The statistical test was omitted in certain cases when the proportions obtained were zero (no stock collapse). This test was employed using the *prop.test* function in R (R Development Core Team, 2012). If found significant, the multiple comparisons were made using the *pairwise.prop.test* function in **stats** package. The results from multiple comparison tests are marked in the summary plots of the performance measures (Figures 7.5 to 7.9).

The distribution of RSB, RFM and RAC were highly skewed in most scenarios since the stock collapsed for certain cases. Hence the test for normality rejected the null hypothesis that these observations followed a normal distribution (Wuertz, 2013; Kolmogorov -Smirnov test using *ksnormTest* function in **fBasics** package of R). Thus the non-parametric Kruskal-Wallis test was applied to find whether the groups are significantly different from each other. If found significant, a multiple comparison post hoc test was applied using the *kruskalmc* function in **pgirmess** (Giraudoux, 2013) package of R (R Development Core Team, 2012).

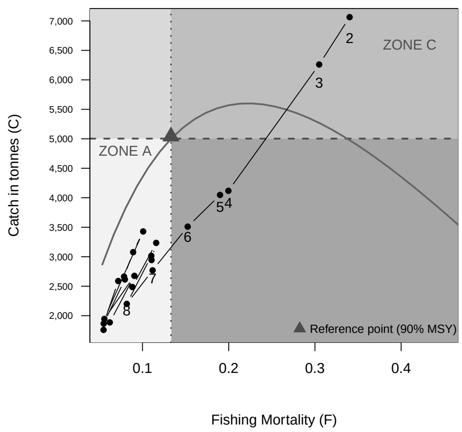
7.6 Results

7.6.1 Illustration of Statistical Process Adjustment (SPA)

Here I show an example of the SPA from the base case scenario. Figure 7.2 displays a window from a single iteration of the simulation in the second phase. In the first year, the stock was in an out-of-control state at $F^{i=1} = 0.34$ (Zone C, Figure 7.2b). The DI-CUSUM raised an alarm indicating the out-of-control situation in the third year of the time series (Lower DI-CUSUM $< -h$, Figure 7.2a). Note that two historical indicator observations were available for the stock when the DI-CUSUM was initiated. Following the alarm, the catch was adjusted (reduced) so that the state of the stock shifted to Zone A indicating an in-control situation (Figure 7.2b). As a result, the stock biomass increased and remained close to the reference point in the final year (Figure 7.2c).



(*a*)



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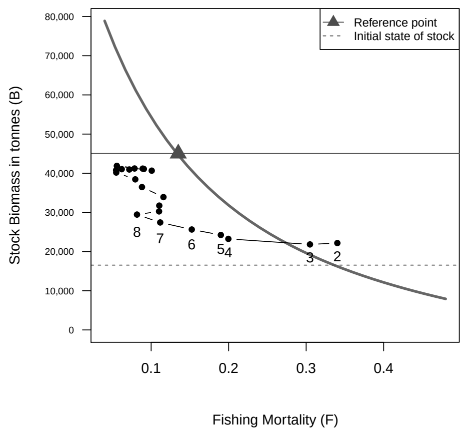


(*c*)

Figure 7.2: **Graphical illustration of SPA with DI-CUSUM:** The figures show an example obtained from the base case scenario**(a)** Shows the progression of DI-CUSUM. An out-of-control situation was alarmed for the third observation (first year of second phase). **(b)** Shows the progression of catch obtained in each year of the second phase. The fishing mortality was shifted from Zone C to Zone A and hence the stock was brought back close to the 'in-control' state. **(c)** Shows the progression of stock biomass in the second phase of the simulation. The stock biomass increased from its initial state and remained close to the reference point.

7.6.2 Output from the base case model

Figure 7.3a shows the temporal progression of average DI-CUSUM observations from all iterations in the second phase of the fishery simulation. The probability of getting an alarm from the upper DI-CUSUM is too low in the initial years. This is because the stock is already in an out-of-control situation. The stock biomass is below $B_{90\%MSY}$ and fishing mortality is above $F_{90\%MSY}$ in the initial year (Figure 7.3 c,d). Following the alarm from DI-CUSUM, the TAC was adjusted (reduced) so that a comparatively lower catch and fishing mortality was obtained in the final year of the second phase (Figure 7.3b,c). As a result the stock biomass increased from its initial state and crossed the reference point of $B_{90\%MSY}$ (Figure 7.3d).

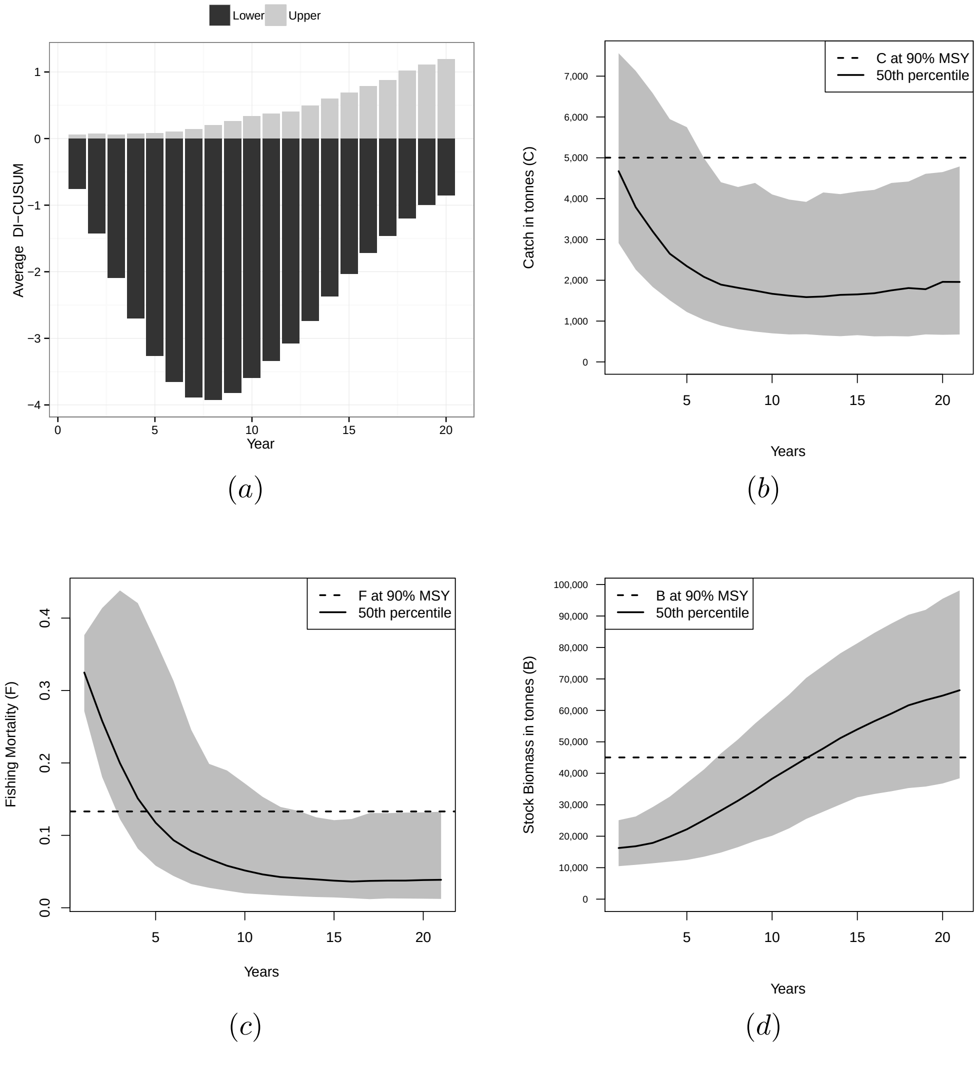
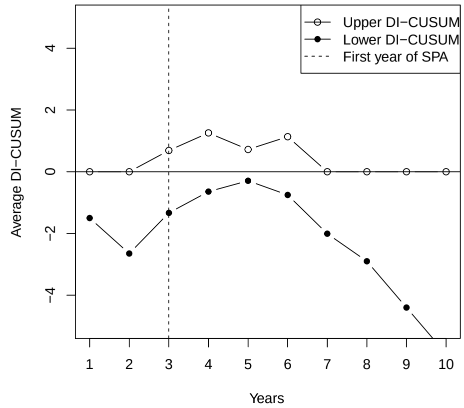


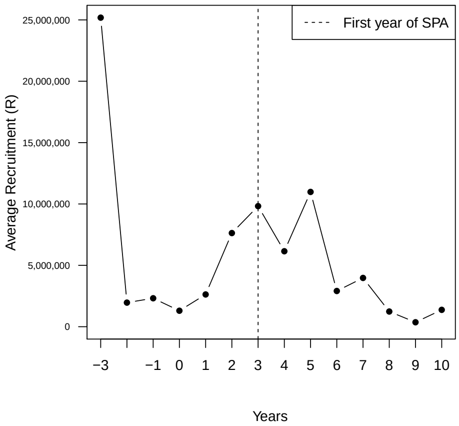
Figure 7.3: **Performance of HCR from the base case model:** The gray shaded regions indicate the range between 5^{th} and 95^{th} percentile of the observations obtained in each year during second phase of the fishery simulation. The figure shows the change in **(a)** Average DI-CUSUM **(b)** catch obtained from the fishery **(c)** fishing mortality and **(d)** biomass of the stock.

7.6.3 The rationale for stock collapse

The probability of stock collapse in the base case scenario was 0.005. The DI-CUSUM obtained from the collapsed stocks showed that the lower CUSUM was approaching zero in the first year of SPA (Figure 7.4a). Hence the TAC was not reduced in the following year (the lower CUSUM should move away from zero to reduce the TAC). A comprehensive analysis showed that the trend in the large fish indicator during the first year of SPA was affected by a large recruitment which occurred six years ago (Figure 7.4 b,c). Note that the P_w is based on the weight of all fish individuals with age $a > (S_{95\%} = 5)$ in the catch sample. Most scenarios in the present study gave a small probability of stock collapse due to the lack of indicator predictability as illustrated here. However, this will not have any significant effect on the performance measure of relative stock biomass (RSB). Scenarios which gave no significant differences between RSBs are presented in Appendix E.



(a)



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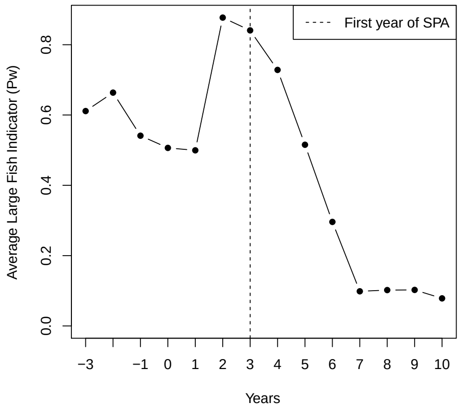


(c)

Figure 7.4: **Model output from the collapsed fish stocks in the base case scenario: (a)** Average DI-CUSUM of fish stocks that were collapsed in the base case. **(b) and (c)** Shows the average value of stock indicators from collapsed stocks in the base case model.

7.6.4 Performance comparison for estimation methods

Results showed that all estimation methods were successful in bringing the stock back to the in-control state. The estimation methods based on historical observations (D3, D4 and D5) were more precautionary since these methods gave positive errors in their shift size estimates (Figure 7.5a, Equation 6.11). Hence the TAC was reduced for more than the actual shift that occurred in the stock biomass. As a result the probability of stock collapse was relatively low for these methods (Figure 7.5c). An analysis of collapsed cases also indicated that the number of years since the first alarm signal (M) was large for stocks that used estimates from D2 and D3 (Figure 7.5b). This means that the stock collapse was due to the lack of indicator predictability (which occurred in the initial years) and not due to unreliable shift size estimates.

But once the stock is back in Zone A, the shift in stock biomass will become positive and the DI-CUSUM will raise alarms until the indicator means correspond to the reference point i.e., 90% MSY. These alarms will result in positive adjustment in the TAC update. However, the D3, D4 and D5 methods were insensitive to a positive shift in stock biomass and gave negative errors in the shift size estimates (Figure 7.5a). While the methods based on the last observation in the time series (D1, D2 and D6) were relatively more accurate and hence they gave the maximum relative average catch (Figure 7.5f). For later scenarios, the D2 method was used in SPA since they gave the most accurate estimates for both positive and negative shift in stock biomass (Figure 7.5a).

7.6.5 Performance comparison for biased indicator control means

Results indicate that the performance measures are significantly different if the control means are biased (Figure 7.6). The implied reference points in DI-CUSUM will be shifted away from the target (90% MSY) when the indicator control means are under or over-estimated. If the control means are underestimated, then an alarm signal from lower CUSUM will be raised only if the SSB and recruitment are too low (more false negative outcomes from DI-CUSUM). But instead, the upper CUSUM will indicate an increase in underlying stock biomass and eventually they will get depleted due to positive adjustments in TAC (Figure 7.6c,d). Figure 7.6a clearly indicates that the probability of collapse is significantly higher when the control means are under-estimated by 10% or above.

However if the control means are over-estimated, more false positive outcomes will be produced by the DI-CUSUM i.e., more signals from the lower CUSUM indicating a decrease in stock biomass. As a result, the probability of stock collapse are significantly reduced because the TAC reductions applied are unnecessary for sustaining the status of the fish stock. Hence the approach may not do any harm to the stock but could result in economic or financial loss to the fishers (Figure E.2). The performance measures for this scenario are provided in Appendix E.

7.6.6 Performance comparison for increasing allowance (k)

Results indicate that the probability of stock collapse may increase if a higher constant is used for the allowance (Figure 7.7a). When k is high, a bigger shift in stock biomass will be required to obtain the alarm signals in DI-CUSUM. Hence the stock may collapse before triggering the required adjustments in TAC. But if an alarm is raised, then a

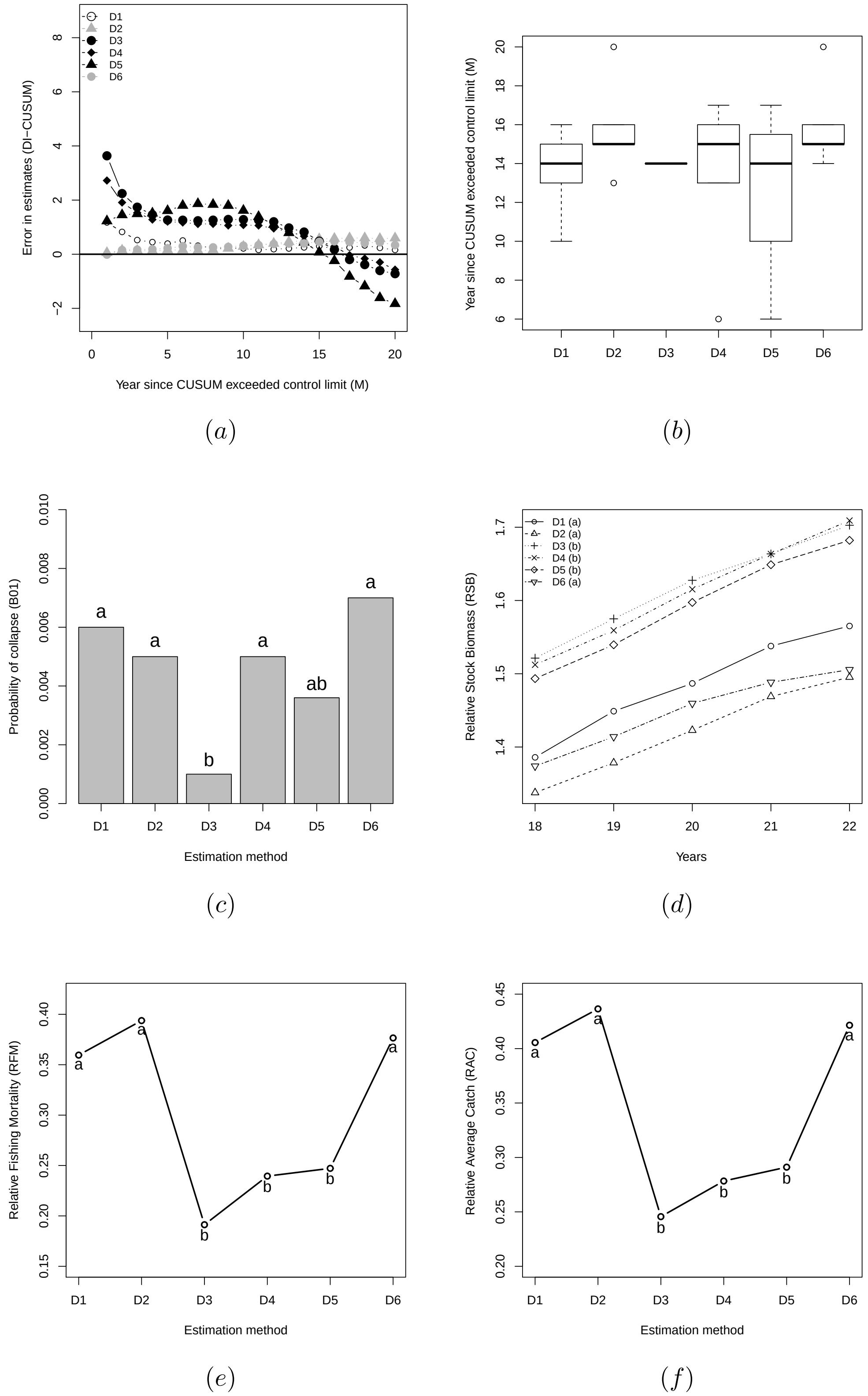


Figure 7.5: **Performance comparison for estimation methods: (a)** Shows the accuracy of mean shift size estimates from the estimation methods. The accuracy is expressed using mean absolute deviation (MAD, Equation 6.15) which will be zero if there is no error in the estimates. **(b)** Shows the year since the first alarm was raised in DI-CUSUM (M) for the collapsed stocks. **(c)** Shows the probability of collapse (B01).**(d), (e) & (f)** Shows the relative stock biomass (RSB), relative fishing mortality (RFM) and relative average catch (RAC) from the terminal years of the projection period. The same letters in the plots indicate no significant difference between each other at $p \leq 0.001$.

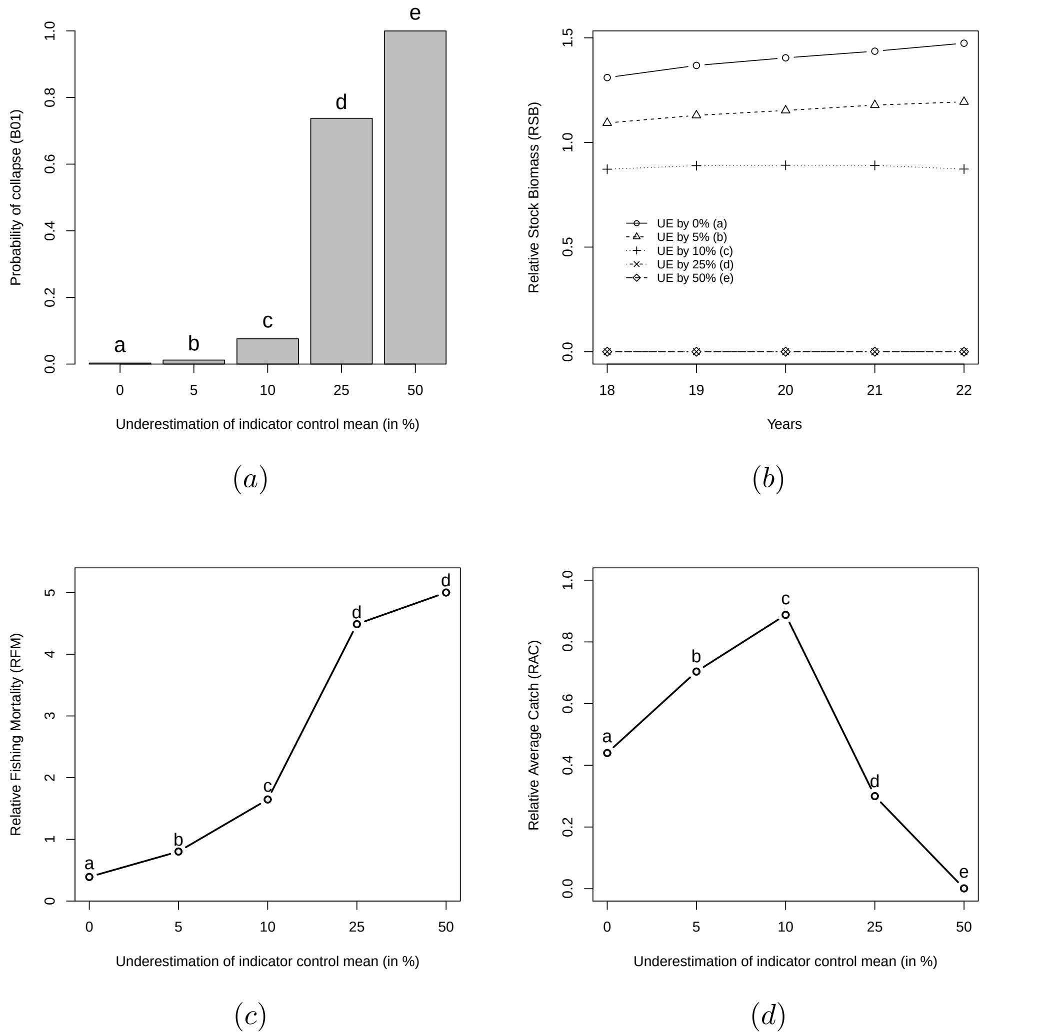


Figure 7.6: **Performance comparison for biased indicator control means:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

higher relative average catch will be obtained since the initial adjustment in TAC will be sufficiently large for the stock to reach the in-control state with a minimum number of time steps (Figure 7.7d).

When k is low, the TAC will be updated with small adjustments but for a longer period. In the present study, the probability of collapse increased up to 40% for $k = 2$ and the corresponding increase in catch was only 10% (Figure 7.7b,d).

Qualitatively similar results will be obtained for other species but the choice of k will depend on the life span of the species (Chapter 5). For short lived stocks, only a few cohorts exist and hence lower k constants should be preferred for quick management decisions. Delayed TAC adjustments may lead to stock collapse or depletion in such fish stocks.

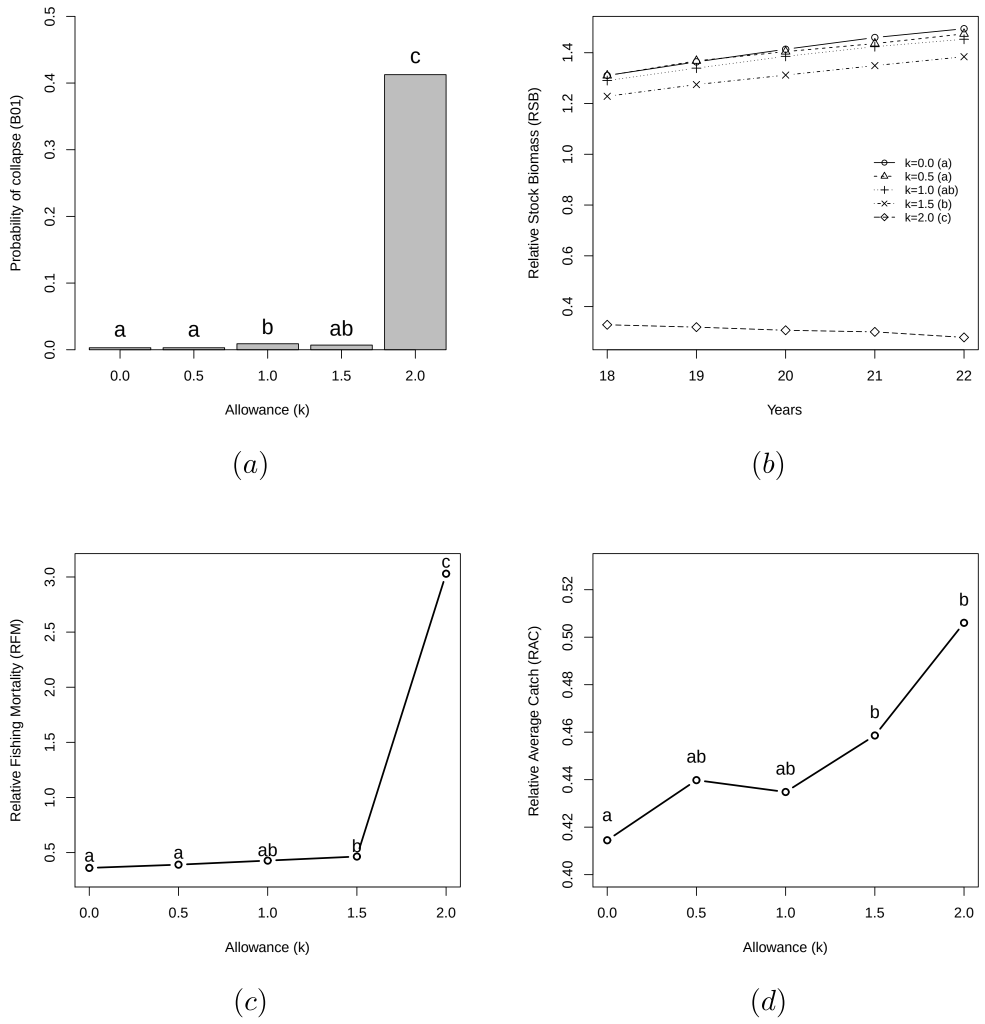


Figure 7.7: **Performance comparison for increasing allowance (k):** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

7.6.7 Performance comparison for relaxing TAC restrictions (TAC_r)

In the initial year, the TAC adjustment may exponentially decrease the catch due to large negative shift size estimates. However, such large catch variations are not necessary to bring the stock back to the in-control state. This is because, the $F_{90\%MSY} = 0.133$ can be achieved with roughly the same amount of catch at $F = 0.33$ (see Figure 7.1). The variability in catch can be significantly reduced by implementing inter-annual restrictions in the TAC (TAC_r). However, this will not guarantee that the F will be reduced since the stock biomass has to increase from its initial state. Results indicate that there is no significant difference in the probability of stock collapse for TAC_r greater than 10% (Figure 7.8a). This means that for TAC_r of 10% or below, the stock biomass may not increase sufficiently enough to reduce the fishing mortality. The optimal TAC_r threshold will be different for other species and this will depend upon the life history characteristics of the stock.

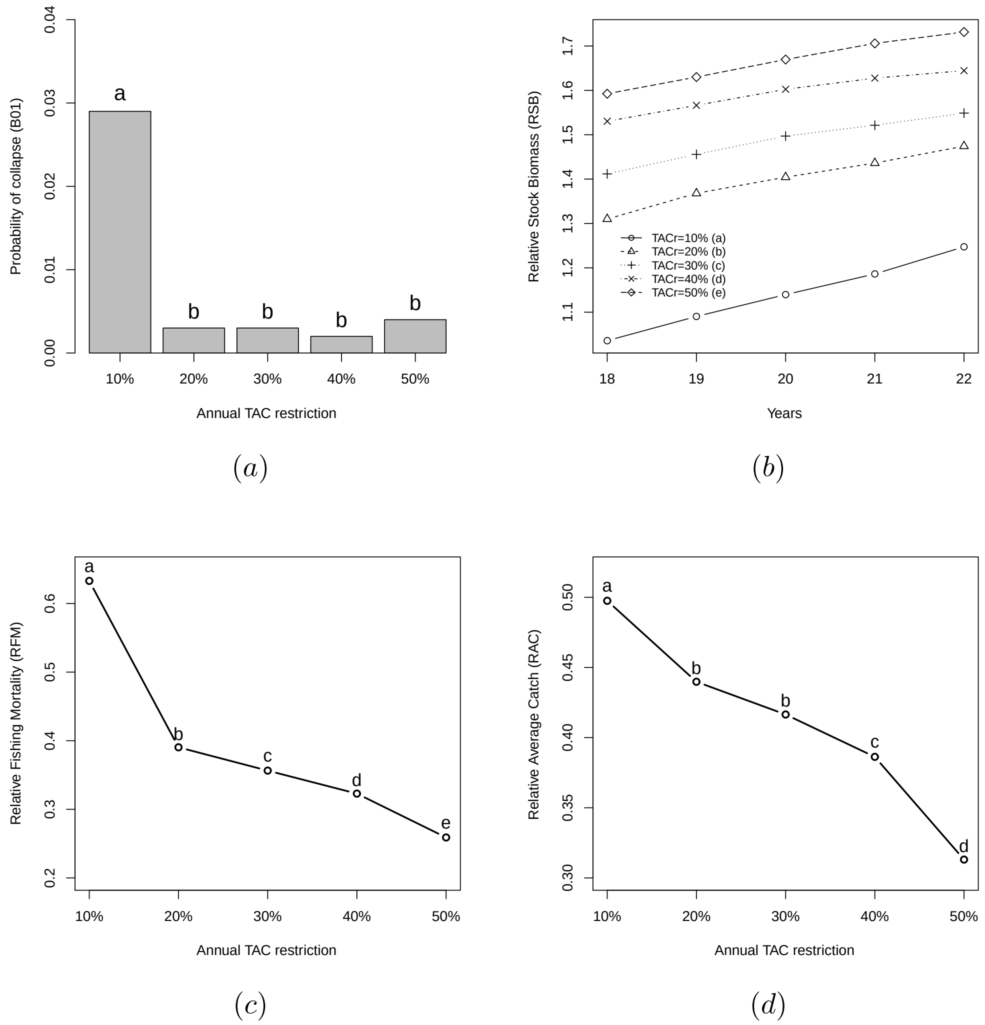


Figure 7.8: **Performance comparison for relaxing TAC restrictions (TAC_r):** Showing **(a)** probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) for the terminal years of the projection period.

But once the stock is in zone A (in-control state), there are two important differences in the TAC update. First, the direction of shift size estimates will change from negative to positive. Ideally this will occur when the stock biomass crosses the reference point of $B_{90\%MSY}$ (Figure 7.3d) or equivalently when $RSB > 1$ (Figure 7.8b). Second, the magnitude of shift size estimates (positive) are smaller during this phase when compared to the shift size estimates (negative) in the initial year and hence the TAC_r is less likely to be used for the update. Thus the performance measure of relative average catch will depend on the magnitude of the negative catch adjustment in the initial year. If the TAC_r is large, then the catch in the initial year will be reduced with a higher magnitude and eventually result in low relative average catch for the terminal years (Figure 7.8d).

7.6.8 Performance comparison for different life history species

Results showed that the probability of collapse will depend on species longevity, the higher risk being for species with shortest life span (Figure 7.9b). The number of cohorts in a short life span species is comparatively low. Hence they are responsive, dynamic and require quick management decisions which may otherwise lead to stock collapse (Figure 7.9a). If the alarm signals are not delayed, then they will reach the reference point relatively quicker than the long lived species (Figure 7.9d).

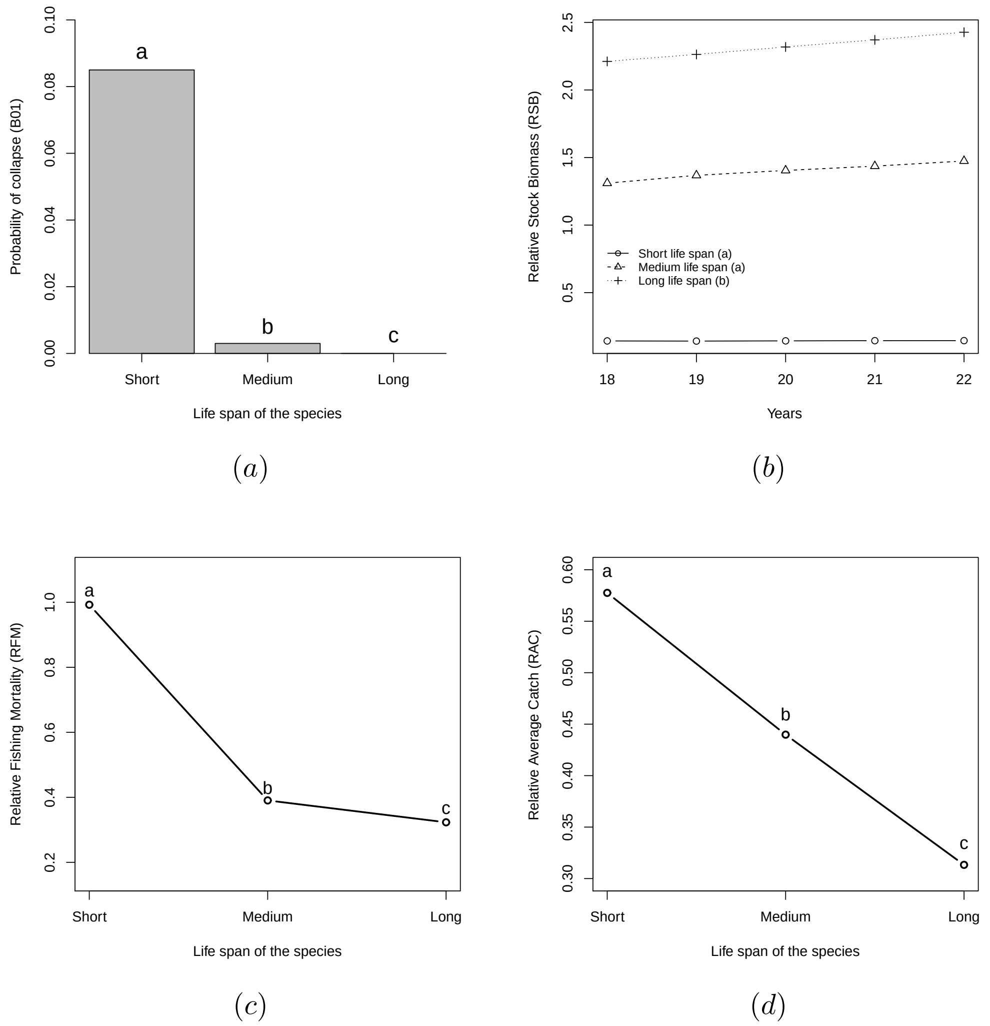


Figure 7.9: **Performance comparison for species with different life histories: (a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years.

The selectivity parameters for the long lived species indicate that they have very low fishing mortality for the younger age groups (Table 2.1, Figure 2.8c). Hence their response to fishing impacts will be slow when compared to other short lived species. This results in relatively low average catches in the terminal years of the projection period (Figure 7.9d).

7.6.9 Performance comparison for different historical states of stock

Results showed that the probability of collapse will be more if the stock is historically in-control i.e., at $F_{90\%MSY}$ (Figure 7.10a). The RFM and RAC indicates that the HCR made positive adjustments in TAC when stock was historically in-control and as a result the fishing mortality was increased (Figure 7.10c,d). Examining the direction of the trends in R and P_w from all collapsed cases showed that the large fish proportional indicator gave positive shifts (between 5-10 years) not because of an increase in abundance of the large fish population but as a result of a decreasing trend in the recruitment (Figure 7.10e,f). This effect will last only for a short period because eventually the trend in the large fish indicator will also decrease due to consistent lower recruitment. Note that a similar negative shift may also occur in the large fish proportional indicator if there is an increasing trend in R leading to extremely low catches by the HCR. Hence when the stock is historically in-control, the chances of getting misleading signals from RP_w will be greater as there is no true signals indicating strong negative or positive shifts in stock biomass.

7.7 Discussion

7.7.1 A harvest control rule based on indicator trends

Many biomass-based control rules have been developed in the context of a precautionary approach in fisheries management (Cadrin and Pastoors, 2008). Previous HCR evaluations assumed that the required estimates of stock status are available and biomass reference points are well established (Bence et al., 2008). However, it is commonly the case that many fish stocks do not have enough data for these estimates or reference points (Cadrin and Pastoors, 2008; Dowling et al., 2008; Smith et al., 2008). The management frameworks that have been developed so far do not fully accommodate the challenges in data-limited fish stocks and no prescriptive methods are available to ensure their precautionary management (Cadrin and Pastoors, 2008). In 2005, Australia adopted a “tier” based approach where the harvest strategy for each stock is chosen based on the type of data available so that the level of precaution can be scaled according to the amount of information available for the assessment of stock status (Smith et al., 2008). For data limited or poor fish stocks, the harvest strategy corresponds to the “tier 4” system in which the recent trends in commercial catch rates are used to update the total allowable catch (TAC). This strategy is implemented using a multiplier such that the catch levels will increase or decrease depending on the trend in ‘catch per unit effort’ (CPUE).

However, several problems were encountered while implementing this strategy and

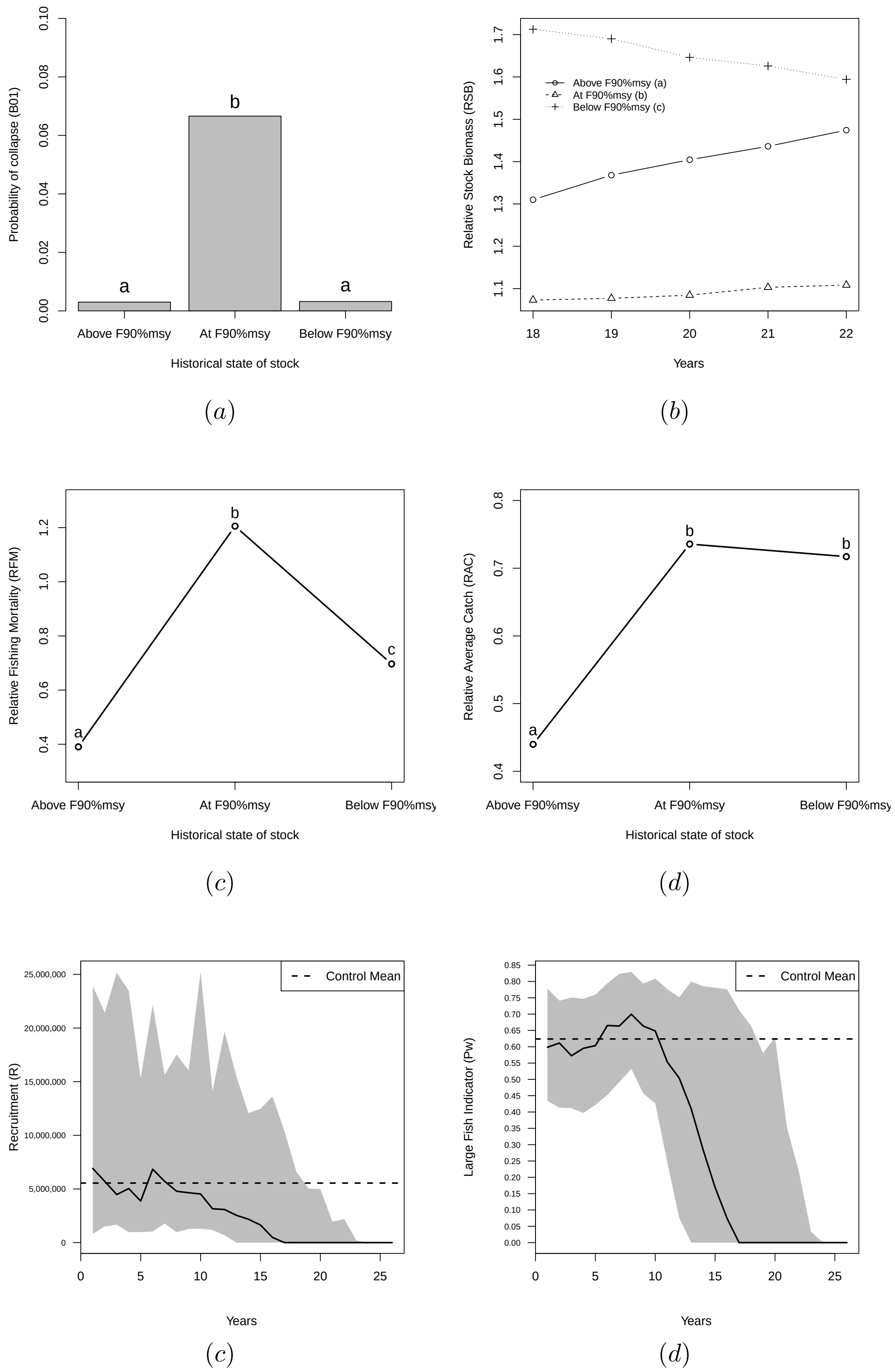


Figure 7.10: **Performance comparison for different historical states of stock:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) **(d)** relative average catch (RAC) from the terminal years **(e)** shows the decreasing trend in R from collapsed cases when stock was historically at $F_{90\%MSY}$ and **(f)** shows the positive pulse in proportion of large fish individuals between 5-10 years as a result of the decreasing trend in R.

they were generally due to the absence of benchmarks indicating a target or limit reference point. Within this context, the present study is relevant, as a decision-interval form of cumulative sum control chart (DI-CUSUM) could be applied for monitoring such indicators. The DI-CUSUM has a statistical approach in fitting the limit reference points for the stock indicators. However, the present study assumed that a target reference point is perfectly known for the stock. But this issue can also be dealt using a self-starting CUSUM chart where the reference point can be calibrated from indicator observations itself in an ongoing basis (see Chapter 5 & 8).

The present study explored the possibility of managing data limited fish stocks by linking indicator trends from DI-CUSUM with adjustment methods from the engineering process control (EPC) theory, the approach which is generally known as Statistical Process Adjustment (SPA). A harvest control rule (HCR) based on SPA was tested on a simulated fishery and the stock performances indicate that the management procedure was successful in bringing an out-of-control stock back to its in-control state. The term "out-of-control" refers to situations of managerial significance in which corrective measures are necessary to sustain the stock at a target reference point ("in-control"). The most important advantage of using a DI-CUSUM approach is that the "out-of-control" situations are visually transparent to the stakeholders in the industry. Thus the stakeholder engagement and participation can be promoted while developing harvest strategies to identify the most appropriate and acceptable management policies.

7.7.2 Control rules based on catch

Deroba and Bence (2008) reviewed the harvest control rules in fisheries and classified them into three main categories. Most control rules were either based on constant catch (Quinn and Deriso, 1999; regardless of F), constant fishing mortality (Quinn and Deriso, 1999; regardless of stock abundances) or constant escapement (Nøstbakken, 2006; intense harvest above a threshold biomass). An important variant of the first category is the conditional constant catch (CCC) control rule (Deroba and Bence, 2008). The harvest strategy used in the present study belongs to this type, where the catch is set as a constant unless removing that amount would deviate the indicator (or CUSUM) from a predetermined maximum threshold (Hjerne and Hansson, 2001; Clark and Hare, 2004). There are several advantages to this approach compared to other rules that are based on F or B. First, this is most suitable for managing fish stocks that have limited data. Estimating the "current" F or B will also require more information from the stock. Secondly, a harvest control rule expressed as catch is much easier to communicate and develop support from the stakeholders (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). Hence harvesting a constant catch is more strategic, and more proactive, because a reduction or increase in TAC is not necessary unless there is sufficient evidence that indicates overfishing or economic inefficiency.

7.7.3 The objective function of the "in-control" state

The choice of a control rule in a fishery generally depends upon the resource user and the broader societal goals. Hence the harvest control rules are evaluated using their relative performances for a given objective function. The most commonly used objective functions in control rules are centred around the fishery output, such as maximizing the catch, maximising the profit or maintaining the harvest at predetermined target levels. However, the objective functions that consider only harvest have raised criticisms (Deroba and Bence, 2008). First, the stock can get stabilized at two fishery equilibrium points with the same amount of catch, the one with the higher fishing mortality will result in lower equilibrium abundance. Second, the same harvest can be obtained for multiple age structures in an age-structured fish population. Maximizing or maintaining the harvest levels may increase the fishing mortality and results in declined stock sizes (Lowe and Thompson, 1993; Beddington and May, 1977). A solution to this problem is to simultaneously minimize the deviations of both harvest and biomass from their respective target levels (Hightower and Grossman, 1987). This is the approach used in the present study where the deviations in stock abundance were tracked using two key stock indicators (recruitment and large fish indicator) and the harvest levels were adjusted only when a significant change in the underlying stock biomass was detected.

The in-control state of the system is defined using the control mean parameter in DI-CUSUM. Two control mean parameters were necessary for the present study since the RP_w indicator was constructed by combining both the estimated recruitment and the large fish proportions. However these indicator control means were assumed to be perfectly known in the present study. In the real world, they will have to be estimated from historical observations or other empirical assessments. If the large fish indicator is reasonably stable during any historical years, this window could likely used as a reference period for calibrating the control means (recruitment estimates are generally noisy and hence they can be less useful in identifying the reference period). 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 indicate that an overestimation of these estimates will significantly reduce the probability of stock collapse. In practice, this can be approximated by using a higher percentile of the historical indicator distribution (instead of using an average or other similar measures).

7.7.4 Which estimation method follows the objective function?

A good estimation method will update the TAC in such a way that the mean of the indicator distribution during the terminal years will be equivalent to the control means used in the DI-CUSUM. Results indicated that all the six estimation methods were successful in bringing the out-of-control stock to the in-control state. However, estimation methods that are based on historical observations (D3, D4 and D5) were over precautionary in nature. Hence these methods are not required for achieving the management objectives in the present study. But this does not necessarily mean that they are less useful or unreliable. In the present study, the methods were evaluated only for a fishery in an already overfished state with a specific objective function. The performance characteristics may differ if the fishery is in an under-fished state and the management objective is to improve the fishery to a target reference point that may yield long term sustainable harvests. Hence more evaluations are required to test how efficiently these estimation methods perform in different fishery contexts.

The estimation methods can be evaluated with or without applying the feed back mechanism and hence this should be an important criteria while extending the SPA for further evaluations. When results from the previous chapter are compared (see chapter 6), the performance characteristics are strikingly different in both approaches. If the methods D1, D2 and D6 were more accurate with SPA (this chapter), the methods D3, D4 and D5 were more accurate without SPA (previous chapter). However, in both approaches, the methods performed similarly when the stock indicators represented a fishery that is being currently managed. Hence to extend these methods to real world fish stocks, future evaluations should include an integrative approach where the estimates from D3, D4 or D5 can be used for the initial adjustment in TAC (as they are accurate for large biomass shifts) and later on the choice of estimation method can be evaluated based on the robustness of D1, D2 or D6 method towards the uncertainties while implementing TAC updates.

If more data are available for the fish stock, other process control adjustment methods are available in the engineering literature but will require thorough evaluations to test whether they will perform better than the proposed schemes in this chapter. An industry standard version is the minimum mean square error (MMSE) controller where the adjustment factor is computed using an autoregressive moving average (ARMA) model (Montgomery et al., 1994; Anderson, 1976; Box et al., 1976; MacGregor, 1990). A 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 (Tsung and Shi, 1999). Both MMSE and PID controller have been found quite effective in a feedback regulated mechanism using statistical process control adjustment (Messina, 1992).

7.7.5 Remedial measures for stock collapse

The probability of stock collapse depends upon the choice of indicators, CUSUM parameters (k and h) and the control rules in SPA.

In the present study, the stocks collapsed when the trend in the large fish indicator (LFI) was affected by spasmodic recruitment. Large recruitment levels result in high stock numbers for a single cohort in the age class structure of the fish population. Since the LFI is a proportion, its trend will be affected as the cohort gets older. Hence a better approach will be to use an absolute measure of the large fish component such as the maximum length (L_{max}) in catch (Miller and Cury, 2003) or L_{max} of largest 'n' individuals (Probst et al., 2013a). These indicators are less likely to get affected by the abundance of other age groups.

In general, fixing a lower constant for the allowance (k) and control limit (h) is more precautionary since otherwise the probability of stock collapse may increase (Figure 7.7). Results also showed that higher constants for allowance (k) in DI-CUSUM has a greater effect on the performance measures when compared to the h (Figure 7.7 and E.1). This is because the k removes some minimum amount of indicator deviation in each time step assuming that they are due to inherent variation in the process (Equation 3.6). In contrast, h keeps the remaining deviations and monitors whether the cumulative sum crosses a benchmark indicating an out-of-control deviation or not. Choosing a low constant for k and h results in detecting the out-of-control situations with higher sensitivity leading to a more reactive fishery. But if the shift size estimates are accurate, then this is a safer option to choose from a precautionary point of view i.e., the probability of stock collapse will decrease but may result in an increased catch variability.

Another option to minimize the chances of stock collapse is to modify the control rules in SPA. The present study opted not to update the TAC if the DI-CUSUM starts approaching zero. This rule was based on the assumption that the adjustment factor applied in previous years is enough to bring the stock back to the in-control state. However, the collapsed cases from the base case showed that a negative signal was already in place though the HCR did not reduce the TAC since the CUSUM was approaching zero. Hence these collapses could have been avoided if the control rule was configured to reduce catch whenever the CUSUM is below $-h$.

If an approximation for MSY of the fish stock is already available, such estimates can be used to set an upper or lower bound for the TAC updates so they are never above or below the threshold limits. Such control rules are quite flexible to operate and ensure a risk-averse approach since the extreme harvest updates can be penalized to avoid boom-or-bust fisheries (Walters and Pearse, 1996; Lande et al., 1997; Garcia et al., 1989).

7.8 Summary

The present study was able to draw the following guidelines to manage data limited fisheries using a harvest control rule (HCR) based on statistical process adjustment (integrating DI-CUSUM with estimation methods from EPC theory).

- The statistical process adjustment (SPA) was successful in bringing an "out-of-control‘’ stock back to the "in-control state" and sustaining them at the specified target reference point (TRP).
- The estimation methods based on the last observation of the indicator time series (D1, D2 and D6) gave accurate shift size estimates and resulted in higher relative average catch. Methods based on historical observations (D3, D4 and D5) gave positive errors in shift size estimates and hence they were precautionary in nature resulting in the least probability of stock collapse.
- The stock may collapse if the indicator control means are under-estimated. In a precautionary approach, over-estimating the indicator control mean is more useful but may result in lower relative average catch.
- The probability of stock collapse depends on the choice of stock indicator, constants used in k or h and the control rule configured for implementing the SPA.
- The trend in the large fish indicator was affected by spasmodic stock-recruitment and this may lead to stock collapse. An absolute measure of the large fish individuals (instead of a proportion) may improve the proposed HCR.
- A low constant for k and h will be useful in a precautionary approach given that the biomass shift size estimates are accurate. This approach is particularly useful for species with short life spans (very responsive) and if the historical state of stock is unknown (works better in an out-of-control situation).
- If a reliable estimate of MSY of the stock is available, setting an upper bound for the TAC will ensure a risk-averse approach.

Chapter 8

A fishery management procedure based on SS-CUSUM

8.1 Introduction

For a wide range of fish stocks around the world, the data available are insufficient for estimating appropriate reference points to assess their relative stock status (Pilling et al., 2009). Such data poor situations can arise if the species concerned are not targeted by the fishery (by-catch), have low economic value, are prone to misidentification or if they lack catch and life history data (Reuter et al., 2010). When there are hundreds of individual stocks and if the federal or state agency do not have enough financial or human resources to conduct fisheries monitoring, then this will also lead to data poor situations (Prince, 2005). Hence there are growing concerns about improving existing methods and developing alternative ways for managing fisheries, particularly to undertake management decisions for data poor fish stocks (Dowling et al., 2008; Smith et al., 2009; Honey et al., 2010; Punt et al., 2011).

When formal fish stock assessments can not be completed, subjective decisions are made based on the trend in stock indicators. But this approach lacks clear strategic direction as to how decision making should adapt and respond to indicators (Bentley and Stokes, 2009). This is the context in which the Self-Starting cumulative sum (SS-CUSUM) control chart can be applied (Hawkins and Olwell, 1998). The SS-CUSUM is an indicator monitoring technique which raises alarms when out-of-control situations are detected so that a management response can be implemented. The key advantage of this approach is that it does not require a pre-determined reference point but instead the reference points are calibrated from the indicator observations on an ongoing basis (Section 3.4). This means that no previous scientific data are required to initiate the monitoring process. Pazhayamadom et al. (2013) tested its detection capabilities in a simulated fishery and found that the performances were robust for the large fish indicators (Chapter 5).

Most management procedures developed to date can be applied only for high-value, relatively data-rich fish stocks (Bentley and Stokes, 2009). The present study is an attempt to develop harvest control rules by integrating the SS-CUSUM approach so that fish stocks can be managed even in a data poor context. In the North Atlantic, the ICES provide scientific advice by recommending output controls in terms of total allowable catch (TAC). In this chapter, I will show how data poor fish stocks can be managed by updating the annual TACs using a feedback mechanism triggered by SS-CUSUM. In the fisheries simulation, it was assumed that at least two indicator observations are available for the stock when management is initiated. This is because the earliest SS-CUSUM could detect an out-of-control situation is on the third year of the time series (see Chapter 3). When an alarm is raised by SS-CUSUM, the shift in the underlying stock biomass is estimated and the TAC from the previous year is updated using a relative adjustment corresponding to the estimated shift. Performance of the scheme is evaluated to determine whether the state of stock during final years of the simulation represents a fishery as defined by the management objective (Section 8.2).

8.2 Objective of the study

Currently there is a lack of prescriptive methodology and a framework for providing scientific advice for the management of new and developing fisheries (Hilborn and Sibert, 1988). In such scenarios, the fishing pressure increases over time as the fishery becomes more profitable and the catches increase with high levels of effort. However, the high levels of effort may continue beyond the stage at which population productivity can compensate for the fishery removals and it eventually comes to the attention of fisheries managers (Perry et al., 1999). If the species has a high market value, the fishery will develop faster than the biology can be assessed, and the management actions will be delayed due to lack of adequate data (Gulland, 1971; Shephard and Rogan, 2006). Keeping these points in mind, the objective of the present study is:

- To sustain the state of the fish stock in a developing fishery at an “in-control” situation (as observed during initial years) until enough data are generated for conducting quantitative fish stock assessments given that the estimated recruitment (R) and the large fish indicator (P_w) are possible to measure in future.

8.3 Background

The most important feature of SS-CUSUM is the dynamic reference point which adapts as new observations are included in the indicator time series on an ongoing basis. This is termed as the "running mean ($\overline{X}_n$)" in the Statistical Process Control (SPC) literature (Hawkins and Olwell, 1998). In each time step, the running mean is computed by taking an average of the preceding indicator observations. Similarly a "running standard deviation ($\overline{\sigma}_n$)" is estimated by computing the standard deviation of all previous observations. Hence in SS-CUSUM, both $\overline{X}_n$ and $\overline{\sigma}_n$ are estimated recursively rather than the true parameter counter parts in DI-CUSUM (see Chapter 3). The first step in indicator monitoring is to standardize the observations and hence both $\overline{X}_n$ and $\overline{\sigma}_n$ are necessary to proceed further with constructing the SS-CUSUM (Section 3.4.1). The earliest SS-CUSUM could raise an alarm is on the third year since at least two observations are required to obtain an initial running mean and standard deviation. Obviously, the $\overline{X}_n$ and $\overline{\sigma}_n$ will be more dynamic in the initial years as only a few observations will be available. The estimates will get closer and closer to true values as more data are available for the fish stock.

However, using ongoing indicator observations may expose the SS-CUSUM to the danger of including data from out-of-control situations and thus contaminating the running means and standard deviations (Hawkins and Olwell, 1998). In such situations, the running mean may eventually catch up with the new shifted mean instead of stabilizing with true parameters representing the in-control distribution. Therefore, it is important to remove the "contaminated" data that lead to out-of-control situations before updating the running mean and standard deviation of SS-CUSUM. This can be employed by rolling the history back to the last estimated running mean when the SS-CUSUM indicated an in-control situation (see Figure 5.1d). However, this approach may not work if an out-of-control situation occurs very soon after the SS-CUSUM is initiated. In such cases, the running mean will quickly adapt to the new level, quite possibly before there is enough time to raise an alarm. For this reason, it is always recommended to start the SS-CUSUM responsibly, using a few indicator observations representing the "in-control" state (or the reference point defined by management objectives).

CUSUM control charts are applied to detect situations when there is a persistent and gradual shift in the mean of the indicator distribution. Hence SS-CUSUM assumes that the transient deviations in indicators are due to inherent variation in the system. This assumption is accommodated by including an allowance parameter (k) for which the choice of constant implies that the SS-CUSUM responds only if there is meaningful deviation in the mean of the indicator distribution (see Chapter 3). However, the choice of k will also affect the progression of the running mean in SS-CUSUM. A low

k will increase the sensitivity of SS-CUSUM but reduce the opportunity to update the running mean since only a few in-control observations will be available for this.

Another aspect that can affect the SS-CUSUM is the indicator outliers that may not end up in an out-of-control situation. The outliers will inflate the running standard deviation and thus the potential for identifying mean shifts or further outliers is weakened. One way to protect the $\overline{X}_n$ and $\overline{\sigma}_n$ are by metric winsorization where a winsorizing constant (w), usually in the range of 1 to 3 standard deviations are used to restrict the indicator deviations that goes into SS-CUSUM computation (see Chapter 3, Section 3.4.3). However, this approach has its own pros and cons. If the w is large, the running means will be updated with larger steps. If the indicator variability is too high, then more noisy observations will be used for the update and eventually the SS-CUSUM ends up with a running mean representing out-of-control situations.

Once an out-of-control situation is detected, the next step is to estimate the shift that has occurred in the underlying stock biomass (positive or negative). This can be used for updating the TAC applied in the previous year. Thus a feed back mechanism can be ensured where the harvests are regulated to control the stock biomass. In chapter 6, six different estimation methods from the Engineering Process Control (EPC) theory were tested and the methods based on Grubb's harmonic rules were found more reliable to use with CUSUM control charts. The process management method by linking SPC and EPC techniques is termed as Statistical Process Adjustment (SPA). In the present study, a Harvest Control Rule (HCR) based on SPA was tested and evaluated using data poor fish stocks. The TAC was updated only when an out-of-control situation is signalled by SS-CUSUM. Hence, the progression of the running mean will also depend on how TAC was updated in response to the deviation in stock indicators.

8.4 Assumptions

In the present study, it was assumed that the fishery represents a data poor fish stock for which observations are available from the two immediate historical years. There are two reasons for this assumption. First, at least two indicator observations are required for the initial running mean in SS-CUSUM. Secondly, the fishery was regulated by updating the TAC from the previous year. It was assumed that the stock indicators were possible to measure in the forthcoming years. The recruitment to the stock (R) was estimated using fishery independent research surveys and the large fish indicator was computed from samples of the fisheries catch (P_w, positive proportion of large fishes by catch weight) .

It was also assumed that management was initiated when the stock was in an "in-control" situation i.e., the stock is at a fishery equilibrium point of 50% MSY.

This assumption was necessary because the SS-CUSUM may not generate meaningful alarms if indicator observations from the initial years do not represent a fishery that is stable and sustainable (in-control). Note that both stock indicators have some inherent variation and hence this assumption will not completely avoid the possibility of having outliers or observations representing an out-of-control situation. To simulate a realistic scenario of developing fisheries, the TAC was increased by 1% per year whenever SS-CUSUM indicated an in-control situation.

8.5 Methods

8.5.1 Fisheries simulation

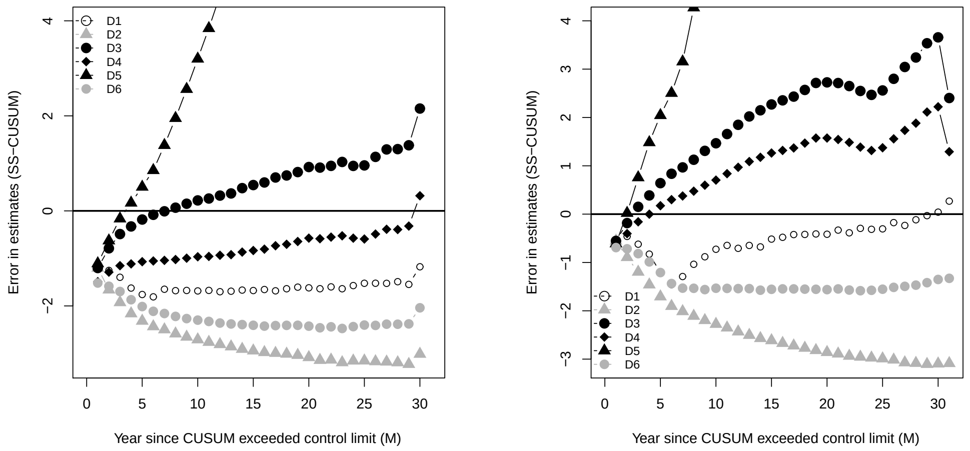
In the present study, an age structured fish stock was simulated using the operating model presented in section 2.1 and a fishery equilibrium was achieved with an initial fishing mortality of $F_{int} = F_{50\%MSY} = 0.053$. This F_{int} was applied to obtain a fish stock that is historically in-control representing stable and sustainable levels of harvests. The fisheries simulation consisted of two phases. In the first phase, the model ran for 100 years during which random variability was introduced into the F_{int} ($cv = 0.1$) and the stock-recruitment relationship ($cv = 0.6$). In the second phase, it was assumed that indicator observations from the two previous years are available for the fish stock. The model ran for 20 further years during which the stock indicators were monitored by SS-CUSUM and the fishery was regulated by TAC. Therefore, it is expected that the HCR based on SPA will sustain the future state of the stock at the fishery equilibrium point equivalent to 50% MSY because SS-CUSUM will raise an out-of-control alarm if it is otherwise. The TAC was increased by 1% from the previous year whenever SS-CUSUM indicated an in-control situation to simulate a developing fisheries. This also ensured a persistent and gradual negative shift in stock biomass (CUSUM control charts are not necessary to detect large and immediate shifts). Once an out-of-control situation is alarmed, the shift in the underlying stock biomass was estimated (Section 6.4.3) and the fishery was managed by updating the TAC using a relative adjustment corresponding to the estimated shift (Harvest control rule, Section 8.5.5). The simulation was iterated 1000 times and the experiment was repeated for five different fishery scenarios (Section 8.5.6). The performance measures in each scenario were evaluated to determine whether the fishery was sustained at the "in-control" state through the management process (Section 8.5.7).

8.5.2 Indicators used for SS-CUSUM monitoring

In the present study, the estimated recruitment (R) and the large fish indicator (P_w) were combined to obtain the RP_w indicator (Table 8.1). In Chapter 6, this indicator was found most useful in determining the shift in stock biomass using CUSUM control charts (Figure D.6). The R was measured from the operating model with random noise error of $CV = 0.6$ from the log-normal distribution (Section 2.5.1). The P_w is the positive proportion of large fish individuals in the commercial catch by weight computed from a random sample of 10,000 fish individuals (Section 2.5.2.4). The computation of the combined indicator RP_w is different compared to the method presented in Chapter 7 because in SS-CUSUM, they can be constructed only after updating the running mean using the observations obtained until the most recent year. Once the running mean is updated, both indicators are independently transformed into observations that are random variables (U_n^R and $U_n^{P_w}$) of the normal distribution $N(0,1)$ following the steps detailed in section 3.4.1. Further, both indicators were summed up to obtain the RP_w observations (Table 8.1). The advantages of using a combined indicator were detailed in chapter 6 and graphically illustrated in Figure D.6. However, it is arguable whether an average of R and P_w indicator time series can be used instead of the sum. For example, figure 8.1 shows a comparison of the error in shift estimates obtained when an average of R and P_w were used instead of their sum (Chapter 6). The errors were positive and comparatively more accurate for the latter method, particularly when M was small (Figure 8.1b).

Table 8.1: **Illustration of monitoring combined indicator RP_w with SS-CUSUM:** The RP_w observations were monitored using SS-CUSUM configured with $w = 1$, $k = 1.5$ and $h = 0$ (base case parameters). The number of observations since the CUSUM ($\theta_n^{\pm}$) was last lifted above or below the control limit is indicated by M.

Year (n)	R	P_w	$\overline{X}_n^R$	$\overline{X}_n^{P_w}$	U_n^R [1]	$U_n^{P_w}$ [2]	RP_w [1]+[2]	θ_n^+	θ_n^-	M	Signal
1	7910535.25	0.89	7910535.25	0.89	0.00	0.00	0.00	0.00	0.00	0.00	NO
2	8516739.21	1.00	8213637.23	0.95	0.00	0.00	0.00	0.00	0.00	0.00	NO
3	11077951.63	0.79	8356520.87	0.92	0.58	-0.58	0.00	0.00	0.00	0.00	NO
4	10435983.61	0.85	8454346.61	0.90	0.71	-0.71	0.00	0.00	0.00	0.00	NO
5	9802056.11	0.85	8529275.43	0.89	0.77	-0.66	0.11	0.00	0.00	0.00	NO
6	9548152.43	0.77	8590135.07	0.88	0.82	-0.82	0.00	0.00	0.00	0.00	NO
7	2985680.97	0.72	8590135.07	0.88	-0.85	-0.85	-1.70	0.00	-0.20	1.00	YES
8	17384476.38	0.74	8635012.61	0.87	0.87	-0.87	0.00	0.00	0.00	0.00	NO
9	4427445.59	0.73	8635012.61	0.87	-0.88	-0.88	-1.76	0.00	-0.26	1.00	YES
10	1562284.49	0.76	8635012.61	0.87	-0.90	-0.90	-1.80	0.00	-0.56	2.00	YES
11	1492257.71	0.82	8635012.61	0.87	-0.90	-0.90	-1.80	0.00	-0.86	3.00	YES
12	3429838.48	0.72	8635012.61	0.87	-0.92	-0.92	-1.84	0.00	-1.20	4.00	YES



(a) (b)

Figure 8.1: **Comparison of shift size estimates obtained by combining R and P_w using two different schemes:** The figure shows the error in shift size estimates obtained by combining R and P_w in two different ways (See equation 6.11). **(a)** the average of U_n^R and $U_n^{P_w}$ was used **(b)** the sum of U_n^R and $U_n^{P_w}$ was used.

8.5.3 Monitoring indicators using SS-CUSUM

The initial state of the stock was equivalent to 50% MSY at fishery equilibrium and hence in the longer term, the running means for R and P_w are expected to stabilize at values corresponding to this reference point. The base case model in this study monitored the RP_w indicator using SS-CUSUM with winsorizing constant $w = 1$, allowance $k = 1.5$ and control limit $h = 0$.

The low $w = 1$ will restrict the departure of the running mean to one standard deviation and thus preserves the robustness of the monitoring scheme. However if the observations in the initial years represent an out-of-control situation, then the scheme may fail to obtain running means equivalent to the in-control state (the parameters are less likely to change when more observations becomes available). Compared to chapter 7, the relatively higher allowance ($k = 1.5$) in SS-CUSUM was used to accommodate more observations so that the running means will adapt to values corresponding to the initial state of the fish stock. But this also involved the risk of using out-of-control observations since the TAC was configured to increase catch whenever SS-CUSUM indicated an in-control situation. In chapter 7, it was found that a lower h will be more precautionary, giving a low probability of stock collapse and hence this constant was retained for the present study. Nevertheless, the stock performances with different constants of w, k and h were evaluated in later scenarios (Scenarios 2, 3 and 6, Table 8.2) and the results are presented in Section 8.6.

8.5.4 Estimating the biomass shift using SS-CUSUM

In chapter 6, six different types of estimation methods were tested for their performances in obtaining the shift size in stock biomass ($\hat{S}$, Section 6.4.3, D1 to D6). Three methods were based on the last observation of the indicator time series (D1, D2 and D6) and three other methods were based on all observations that lead to the out-of-control situation (D3, D4 and D5). In chapter 7, these methods were evaluated using a HCR (SPA with DI-CUSUM) in a simulated fishery and the results showed that the most reliable and accurate estimates were given by the method based on Grubb's harmonic rule (D2). The description and equations for all these methods are provided in section 6.4.3 (Table 6.2 & 6.2). However, the performances may differ if they are implemented through a SS-CUSUM control chart. This is because the running mean is dynamic in nature and hence it is more precautionary to restrict enormous variations in TAC particularly when a new fishery is developed. Therefore, all the six estimation methods were used in the present study to test and evaluate their performances (Scenario 1, Table 8.2). The method which gave the least probability of stock collapse was used as the base case for the later scenarios (Scenarios 2-12, Table 8.2 & F.1).

8.5.5 Harvest control rule using SPA

Statistical process adjustment was used for implementing the Harvest Control Rules (HCRs) in the present study. Therefore, the TAC for year 'i' was updated only if two conditions were satisfied. First, the SS-CUSUM in year '$i-1$' should raise an alarm indicating the "out-of-control" situation. Second, the absolute CUSUM ($|\theta^{\pm}_{i-1}|$) in year '$i-1$' should be greater than the absolute CUSUM ($|\theta^{\pm}_{i-2}|$) in year '$i-2$'. This happens only if the CUSUM progress further away from the reference point indicating that more adjustment in TAC is required to bring the stock back to the "in-control" state. If these two conditions are not satisfied, then the TAC from the previous year was increased by 1% to simulate a developing fishery i.e., more catch is allowed as long as the SS-CUSUM indicate an "in-control" state. Note that the 1% increment becomes higher in magnitude as the TAC moves closer to Maximum Sustainable Yield (MSY).

If $|\theta^{\pm}_{i-1}| > |h|$ and $|\theta^{\pm}_{i-1}| > |\theta^{\pm}_{i-2}|$ then,

$$TAC^{i} = TAC^{i-1} + \left(TAC^{i-1} \times \hat{S}\right), \tag{8.1}$$

else,

$$TAC^{i} = TAC^{i-1} + \left(TAC^{i-1} \times 0.01\right), \tag{8.2}$$

where $\hat{S}$ is the estimated shift in stock biomass (Section 6.4.3) and $\left(TAC^{i-1} \times \hat{S}\right)$ is the adjustment factor applied to update the TAC from the previous year. The range of shift size estimates were extremely high such that an annual restriction in TAC update was necessary which would otherwise result in stock collapse or closure of the fishery. The TAC^i was restricted using TAC_r such that it never exceeded below $TAC^{i-1} \times (1 - TAC_r)$ and above $TAC^{i-1} \times (1 + TAC_r)$. For example if $TAC_r = 10\%$ (base case scenario), then TAC^i is between $TAC^{i-1} \times 0.9$ and $TAC^{i-1} \times 1.1$.

A perfect implementation of the proposed TAC is likely not possible in real world and hence random noise errors were added using a coefficient of variation of $cv = 0.1$ from the normal distribution.

$$TAC^i = max\left[0, \sim normal\left(\text{mean} = TAC^i, cv = 0.1\right)\right] \tag{8.3}$$

8.5.6 Scenarios considered

Six different fishery scenarios were constructed to compare the performances of the proposed HCR (Table 7.1). These were based on (i) the type of estimation method (D1 to D6); (ii) constants used for metric winsorization (w); (iii) constants used for the allowance (k); (iv) number of historical observations available (d); (v) historical state of the stock (Below MSY, at MSY or above MSY) and (vi) life span of the species (LH1, LH2 or LH3). Additional scenarios were also constructed but for comprehensive discussion on the key results, they are detailed in Appendix F.

In scenario 1, the performances were measured for six different types of estimation methods (D1 to D6, section 6.4.3). They are used for obtaining an estimate of the shift in the underlying stock biomass. More description about these methods are provided in chapter 6 (Table 6.2). The most important difference is the information used for computing these estimates. Three methods use all historical observations that lead to the out-of-control situation (D3, D4 and D5) while the rest use only the last observation in the time series (D1, D2 and D6). In chapter 7, the most accurate estimates were obtained for the method based on Grubb's harmonic rule (D2).

In scenario 2, performances were measured for the SS-CUSUM approach with higher winsorizing constants ($w = 1, 2$ or 3). The winsorizing constants decide whether observations that are far away from the current mean should be used for updating the running mean and standard deviations. Thus if the $w = 3$ is used, then the running mean will be updated with bigger steps by including observations that are 3 standard deviations away from the current running mean. Including extremely far observations may result in achieving an under- or over-estimated running mean relative to the reference point.

In scenario 3, performances were measured for the SS-CUSUM approach with different constants of the allowance parameter (k). A small allowance will raise early alarms and only a few observations will be used for updating the running mean. Hence increasing the k will allow more in-control observations to update the running mean but still limiting the extreme outliers by w standard deviations. However increasing k beyond a threshold may not improve the running mean but instead result in a stock that is under or overfished.

In scenario 4, the SS-CUSUM approach was tested to determine whether more historical observations representing an in-control state have any effect on the performance of the HCR. The SS-CUSUM is recommended to start with a few observations from the in-control situation since this will ensure that the adapted indicator running means represent the intended reference point. This scenario is unlikely to be realistic though the results may provide more insight in terms of the minimum number of in-control observations required for obtaining running means adapted to the reference point.

In scenario 5, the HCR was tested for stocks with three different historical states (Below $F_{MSY} = 0.053$, at $F_{MSY} = 0.226$, above $F_{MSY} = 0.326$). If the stock is historically overfished or in an out-of-control state (above F_{MSY}), the probability of obtaining an under-estimated running mean is high. This is because the recruitment and large fish indicators will be comparatively low at higher effort levels. Hence it is less likely to obtain any observations that may represent a stable or sustainable fishery in the initial years. In scenario 6, the proposed HCR was evaluated for stocks with three different life history traits (short, medium and long lived species). The life history parameters for these fish stocks are provided in Table 2.1.

In the base case model, a medium life span species (cod-like, LH1) was simulated and the RP_w indicator was monitored using SS-CUSUM configured with $w = 1$, $k = 1.5$ and $h = 0$. It was assumed that two historical observations were available for the fish stock when the management was initiated and the shift size in stock biomass was estimated using the D2 method (most accurate estimates obtained in scenario 1). Growth variability was absent for the species and the stock-recruitment was not autocorrelated.

8.5.7 Performance measures and statistical analysis

To ensure that the stock was sustained at the in-control state, the stock biomass (B), fishing mortality (F) and the total catch (C) were measured from the last 5 years of the projection period. The reference point was set equivalent to 50% MSY at fishery equilibrium point and hence if the stock is stabilized at the "in-control" state, then the B, F and C should correspond to $B_{50\%MSY}$, $F_{50\%MSY}$ and $C_{50\%MSY}$ respectively. The four performance measures used in the present study are provided in Table 8.3. They are the Probability of collapse (B01), Relative Stock Biomass (RSB), Relative Fishing Mortality (RFM) and Relative Average Catch (RAC).

Table 8.2: **Scenarios considered in the present study:** The following table shows the first six scenarios used in the present study (for additional scenarios, please see Table F.1). The shaded areas highlight the differences compared to the base case parameters.

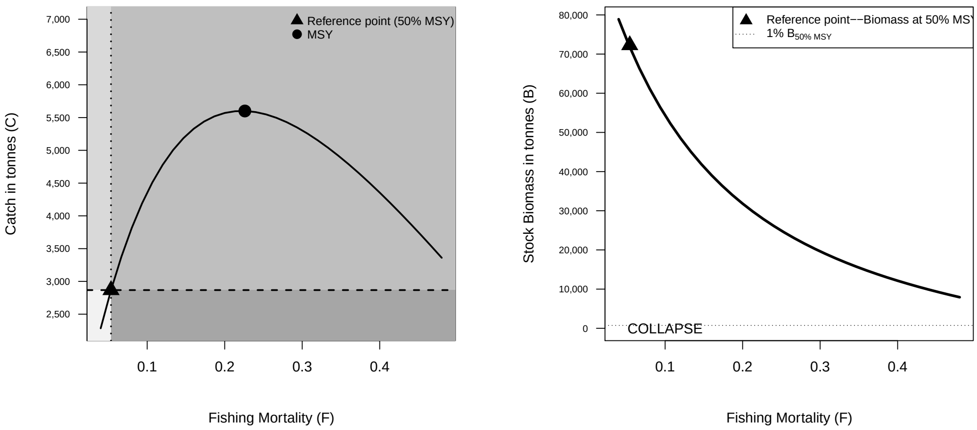
Scenarios	Estimation method	Winsorizing constant (w)	Allowance (k)	Historical data	Historical state of stock	Lifespan of the species
Scenario 1	$D1$ $D2^*$ $D3$ $D4$ $D5$ $D6$	$w = 1^*$	$k = 1.5^*$	2 years*	Below F^*_{MSY}	Medium (LH1)*
Scenario 2	$D2$	$w = 1$ $w = 2$ $w = 3$	$k = 1.5$	2 years	Below F_{MSY}	Medium (LH1)
Scenario 3	$D2$	$w = 1$	$k = 0.5$ $k = 1.0$ $k = 1.5$ $k = 2.0$ $k = 2.5$	2 years	Below F_{MSY}	Medium (LH1)
Scenario 4	$D2$	$w = 1$	$k = 1.5$	2 years 4 years 6 years 8 years 10 years	Below F_{MSY}	Medium (LH1)
Scenario 5	$D2$	$w = 1$	$k = 1.5$	2 years	Below F_{MSY} At F_{MSY} Above F_{MSY}	Medium (LH1)
Scenario 6	$D2$	$w = 1$	$k = 1.5$	2 years	Below F_{MSY}	Short (LH2) Medium (LH1) Long (LH3)

* : Base case parameters
D1 to D6 : Estimation methods (see Chapter 6, Section 6.4.3)
LH1,LH2,LH3 : Life History stocks (Table 2.1)

Table 8.3: **Performance measures used for the present study:** The initial state of the stock corresponds to 50% MSY at fishery equilibrium point and hence the performances were measured relative to this reference point.

Performance Measures	Formula
Probability of collapse ($B01$)	$\dfrac{\sum_{q=1}^{q=1000}\sum_{i=16}^{i=20} I\left(B_q^i < [0.01 \times B_{50\%MSY}]\right)}{(i_{max} - i_{max-5}) \times q_{max}}$
Relative Stock Biomass (RSB)	$\dfrac{\left(\sum_{q=1}^{q=1000}\left[\dfrac{\sum_{i=16}^{i=20} B^i}{5}\right]\right)/q_{max}}{B_{50\%MSY}}$
Relative Fishing Mortality (RFM)	$\dfrac{\left(\sum_{q=1}^{q=1000}\left[\dfrac{\sum_{i=16}^{i=20} F^i}{5}\right]\right)/q_{max}}{F_{50\%MSY}}$
Relative Average Catch (RAC)	$\dfrac{\left(\sum_{q=1}^{q=1000}\left[\dfrac{\sum_{i=16}^{i=20} C^i}{5}\right]\right)/q_{max}}{C_{50\%MSY}}$

i : Year
q : Iteration
C_i : Fish catch in year 'i'
F_i : Fishing mortality in year 'i'
MSY : Maximum Sustainable Yield
$B_{50\%MSY}$: Stock biomass at reference point
$F_{50\%MSY}$: Fishing Mortality at reference point
$C_{50\%MSY}$: Total catch at reference point
I : Indicator function (If the condition satisfies, this will return a value of 1 otherwise 0)



(a) (b)

Figure 8.2: **Graphical illustration of 'in-control' state of the stock:** The black solid line shows the equilibrium points for **(a)** catch and **(b)** biomass with increasing constants of fishing mortality. The 'in-control' state or reference point of the stock is represented by 50% MSY at fishery equilibrium (black triangle).

The maximum sustainable yield and the reference point used for the base case stock is graphically illustrated in figure 8.2. The performances were first evaluated to detect whether the stock was in a collapsed state. For a given year 'i', the stock was considered to be collapsed if $B^i < 1\% B_{50\% MSY}$. If the stock was sustained at the "in-control" state, then the relative measures of stock biomass (RSB), fishing mortality (RFM) and total catch (RAC) will be close or equal to 1. The performance measures in each scenario were statistically tested with the null hypothesis that there is no significant difference between the groups. The present study used the same statistical approach as detailed in chapter 7 since the fundamental reasonings were similar (Section 7.5.8).

8.6 Results

8.6.1 Illustration of Statistical Process Adjustment with SS-CUSUM

Figure 8.3 shows an example from a single iteration of the simulation in the second phase of the base case scenario. The HCR was successful in stabilizing the state of the stock close to the reference point of 50% MSY (Figure 8.3a,b). However, there are two significantly important aspects of SS-CUSUM in the graphical illustration. First, a signal is raised only if both the estimated recruitment and large fish indicator have trends moving in the same direction (either positive or negative relative to their respective running means). Second, the sequential adaptation of running mean in the initial years will depend upon the indicator variability during this period.

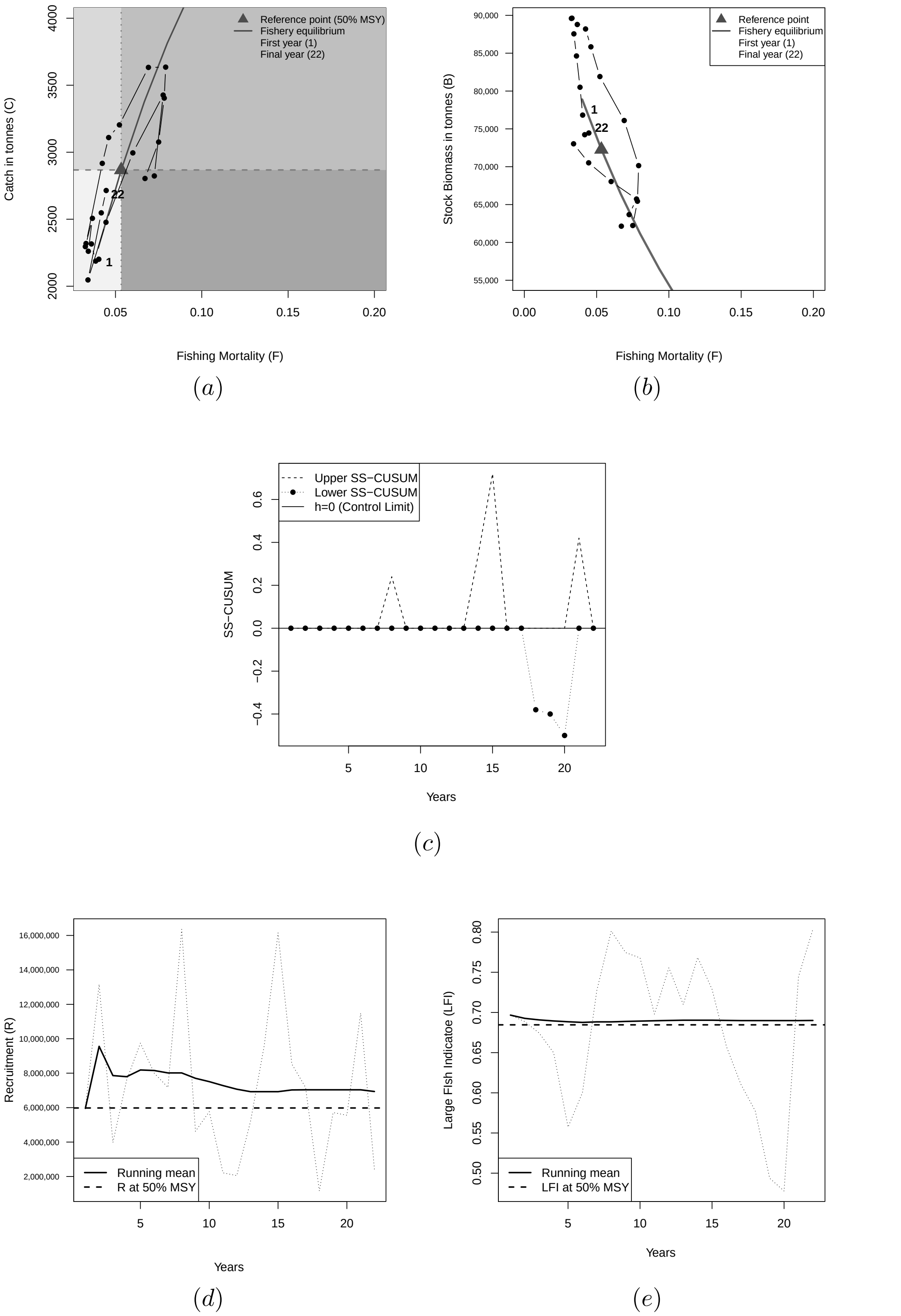


Figure 8.3: **Graphical illustration of SPA with SS-CUSUM:** The figures show an example iteration obtained from the base case scenario. **(a) & (b)** Indicate the changes in catch and stock biomass against fishing mortality. **(c)** Shows the progression of SS-CUSUM. **(c) & (d)** Shows the progression of running mean as new observations are added to the indicator time series.

8.6.1.1 Alarm signals in SS-CUSUM

In figure 8.3c, the SS-CUSUM raised a positive alarm on years 8, 14, 15 and 21. During these years, both the estimated recruitment and the large fish indicators were above their respective running means (Figure 8.3d,e). Similarly on year 18, 19 and 20, the SS-CUSUM raised negative alarms and both indicators were below their respective running means during this period (Figure 8.3d,e). This means that the SS-CUSUM was efficient in signalling events that require an important managerial response. For example, if the fishery is progressing towards a situation of stock collapse, both the recruitment and large fish indicator will show a negative trend. However, it is also obvious from figures 8.3d,e that SS-CUSUM may produce delayed or no alarm signals if the running means are substantially under or over-estimated.

8.6.1.2 Dynamics of running mean

The initial running mean ($\overline{X}_n$) and standard deviation ($\overline{\sigma}_n$) are obtained after the second observation in the time series. This means that the first two observations are neither monitored by SS-CUSUM nor restricted by winsorizing constant (w). From the third observation onwards, the metric winsorization is applied and the updates becomes smaller as the monitoring process move forwards. Any extreme departure or outliers in the first two observations may result in running means that are under or over-estimated. This effect is obvious for the estimated recruitment where the initial running mean (in the second year) was far away from the reference point and the subsequent updates ended up in a slightly overestimated running mean when compared to the large fish indicator (Figure 8.3d,e). Hence careful attention is required for the first two observations in SS-CUSUM, particularly when the indicator is inherently subject to high variability for a fixed status of the fish stock.

8.6.2 Output from the base case model

Figure 8.4a shows the temporal progression of average SS-CUSUM from all iterations in the second phase of the fishery simulation. The control limit for SS-CUSUM was $h = 0$ and the first signal was signalled in the 5th year and thereafter the absolute SS-CUSUM increased, particularly towards the negative direction. This is because the HCR was configured to increase TAC whenever SS-CUSUM indicates an in-control situation which eventually results in out-of-control alarms from the lower SS-CUSUM. The 50th percentile of catch (C) and stock biomass (B) shows that the stock was stabilized close to the reference point (Figure 8.4b,c). However the range of fishing mortalities (F) indicates that occasionally, the SS-CUSUM was not efficient in regulating the fisheries close to the intended reference point of $F_{50\%MSY}$ (Figure 8.4d).

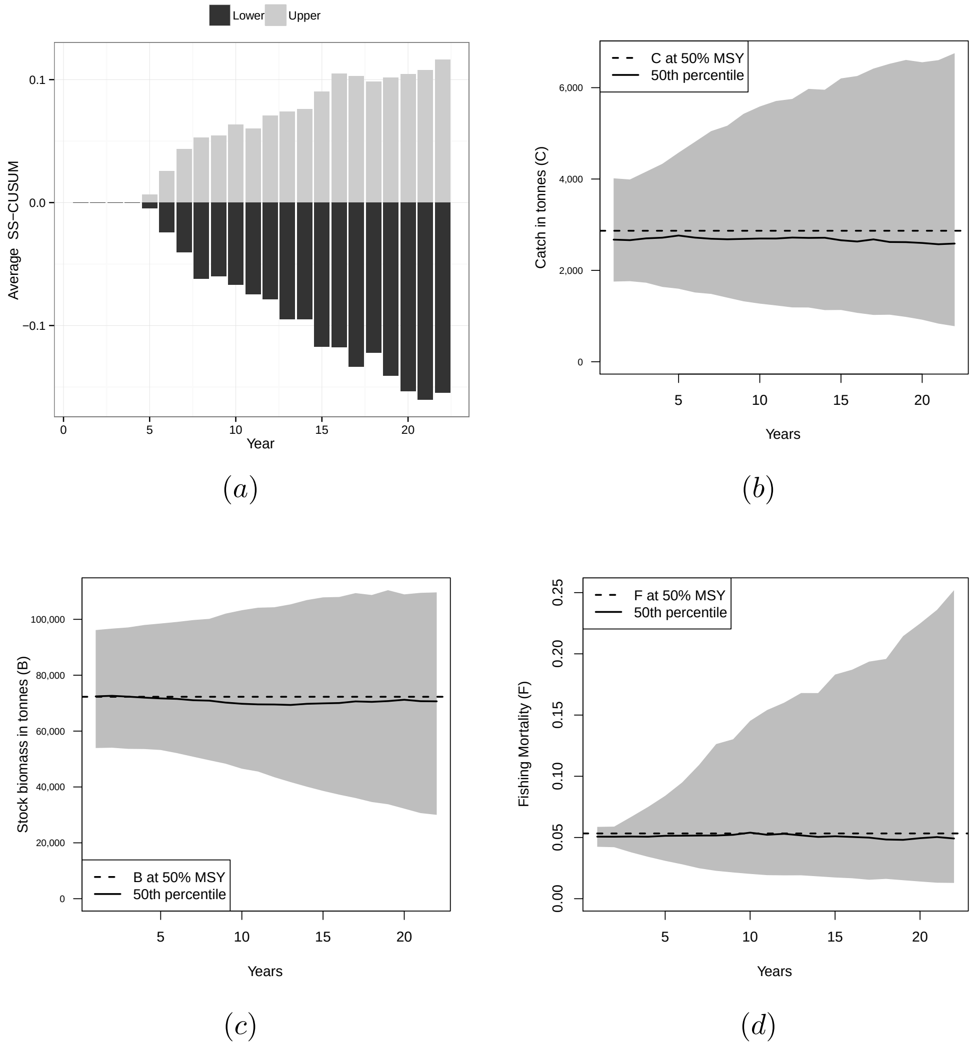


Figure 8.4: **Performance of HCR from the base case model: (a)** the average SS-CUSUM from all iterations in the second phase of the simulation. **(b), (c) and (d)** the change in catch, stock biomass and fishing mortality in response to the alarms raised by SS-CUSUM. The gray shaded regions indicate the range between 5^{th} and 95^{th} percentile of the observations obtained in each year.

8.6.3 Running parameter from the base case model

Figure 8.5a,b shows the sequential adaptation of indicator running means from all iterations in the base case model. The figure shows that the range was highest in the first year and they progressively reduced towards the final year. However, a few of them eventually resulted in an under or over-estimated running mean by end of the projection period. To understand how they relate to the state of the fish stock, the range of values obtained in the final year were highlighted on the catch curve representing fishery equilibrium points (Figure 8.5c,d). This figure shows that the running mean for both indicators represented a wide range of fishery states. However, the values achieved by the large fish indicator were comparatively more restrictive (Figure 8.5d).

The second parameter is the running standard deviation of the SS-CUSUM. Figure

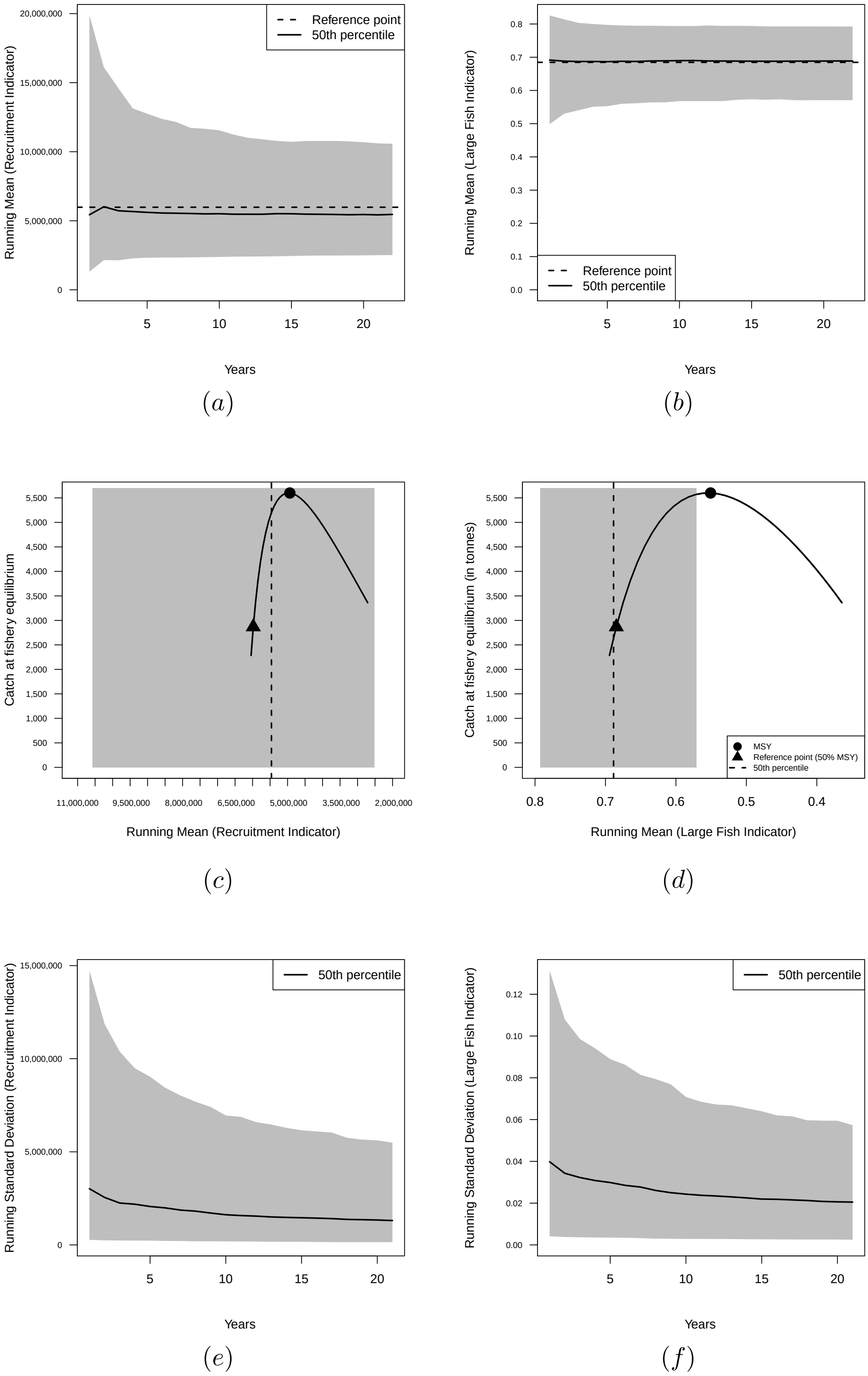


Figure 8.5: **Indicator running means obtained from the second phase of the simulation: (a) & (e)** shows the range of $\overline{X}_n$ and $\overline{\sigma}_n$ achieved by R **(b) & (f)** Shows the range of $\overline{X}_n$ and $\overline{\sigma}_n$ achieved by P_w **(c) & (d)** shows the fishery equilibrium state of the stock as represented by the running means obtained from the last year of the simulation. The gray shaded regions indicate the range between 5^{th} and 95^{th} percentile of the observations.

8.5e,f shows the sequential adaptation of running standard deviations from all iterations in the base case model. Similar to the running means, the range was highest in the first year and further they progressively reduced towards the final year. However if the difference between the first two observations is very close to zero, then the running standard deviation will remain close to zero when the monitoring process moves forward (Figure 8.5e,f). This is because the further updates of indicator deviations are restricted by winsorizing constants (see Equation 3.16 and 3.20). If the running standard deviation is unrealistically low, then the sensitivity of SS-CUSUM will increase by raising alarms for small indicator deviations from the running mean.

8.6.4 The rationale for stock collapse

The probability of stock collapse in the base case scenario was 0.008. An average of the running means obtained from collapsed stocks showed that they were under-estimated for both the estimated recruitment and the large fish indicator (Figure 8.6a,b). Hence, the SS-CUSUM raised positive alarms (Figure 8.6c) and the TAC was increased until the upper SS-CUSUM ceased moving further away from zero (Figure 8.6d). Average SS-CUSUM indicates that the TAC was reduced only after year 17 (Figure 8.6c) when the negative alarms were raised (the preceding negative signals from the lower SS-CUSUM may not reduce the TAC substantially since they will be compensated by the positive signals in upper SS-CUSUM). However, the biomass was severely depleted by year 17 and eventually the stock was collapsed (Figure 8.6e,f).

8.6.5 Performance comparison for estimation methods

Results showed that all estimation methods were successful in sustaining the stock at the in-control state. There was no significant differences in the performance measures between these methods (Figure 8.7a,b,c,d). However, all methods gave a small probability of stock collapse (Figure 8.7a). An analysis of collapsed cases indicated that the number of years since the first alarm signal (M) was small (1 to 8 years) for all the estimation methods (Figure 8.7e). This means the reason for stock collapses were similar to the case discussed in section 8.6.4, where the running means for both indicators were under-estimated.

The accuracy of these methods were analysed by looking at the errors in the shift size estimates of stock biomass (Figure 8.7f, Equation 6.11). These were computed with an assumption that the running means are stabilized at the intended reference point of 50% MSY. Results showed that the most inaccurate estimates were given by the D3 and D5 method with positive errors (both methods are based on historical observations, see Section 6.4.3 for more details). Positive errors indicate that the TAC will be updated

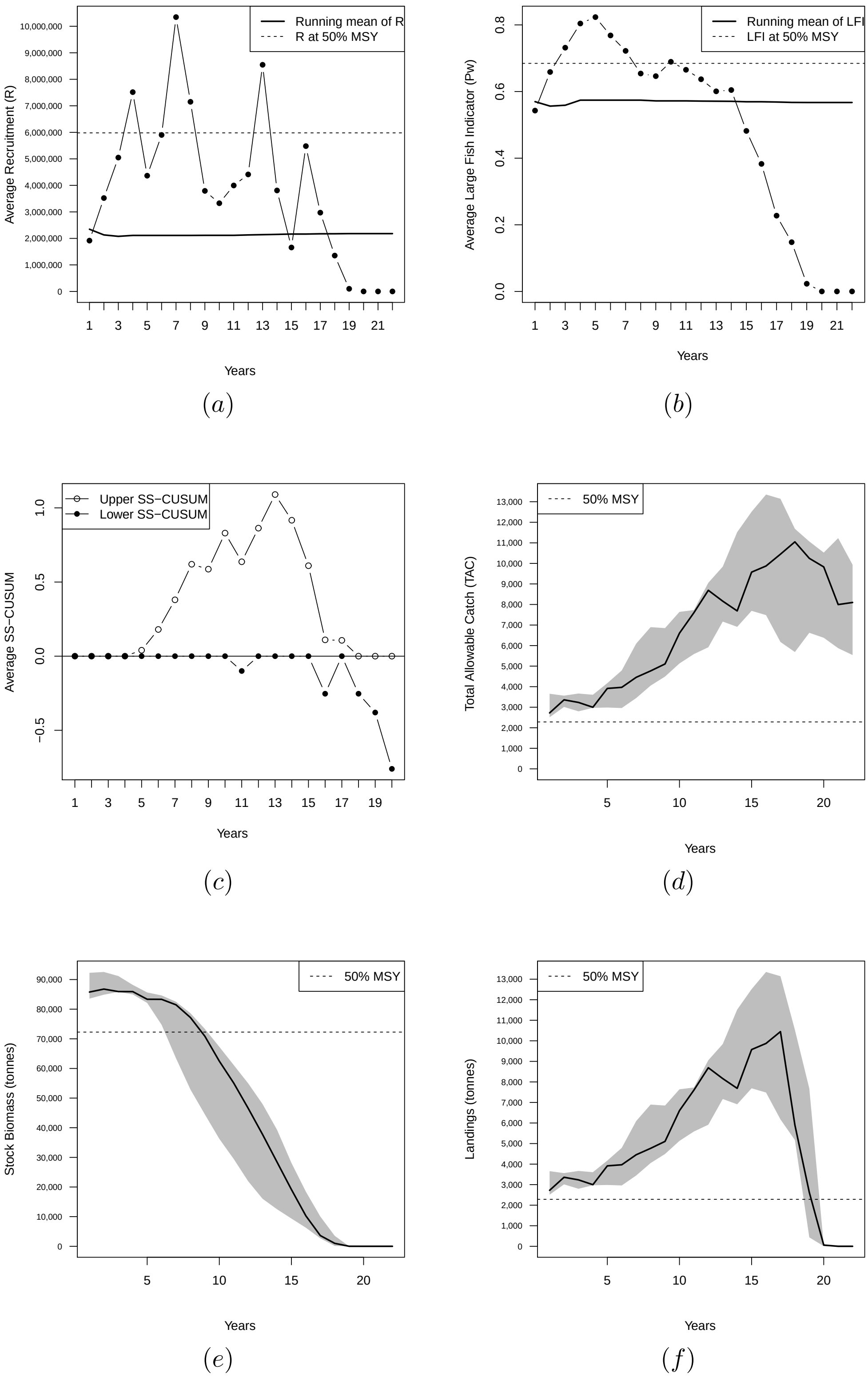


Figure 8.6: **Model output from the collapsed fish stocks in the base case scenario:** **(a) & (b)** shows the underestimated $\overline{X}_n$ obtained for R and P_w. **(c)** shows the average SS-CUSUM where positive alarms were raised due to underestimated indicator running means. **(d)** shows the progression of TAC where it was increased until the lower SS-CUSUM raised negative alarms.**(e)** shows that the stock biomass was already depleted when lower SS-CUSUM raised an alarm to reduce the TAC. **(f)** shows the fishery collapse when lower SS-CUSUM raised the first out-of-control alarm.

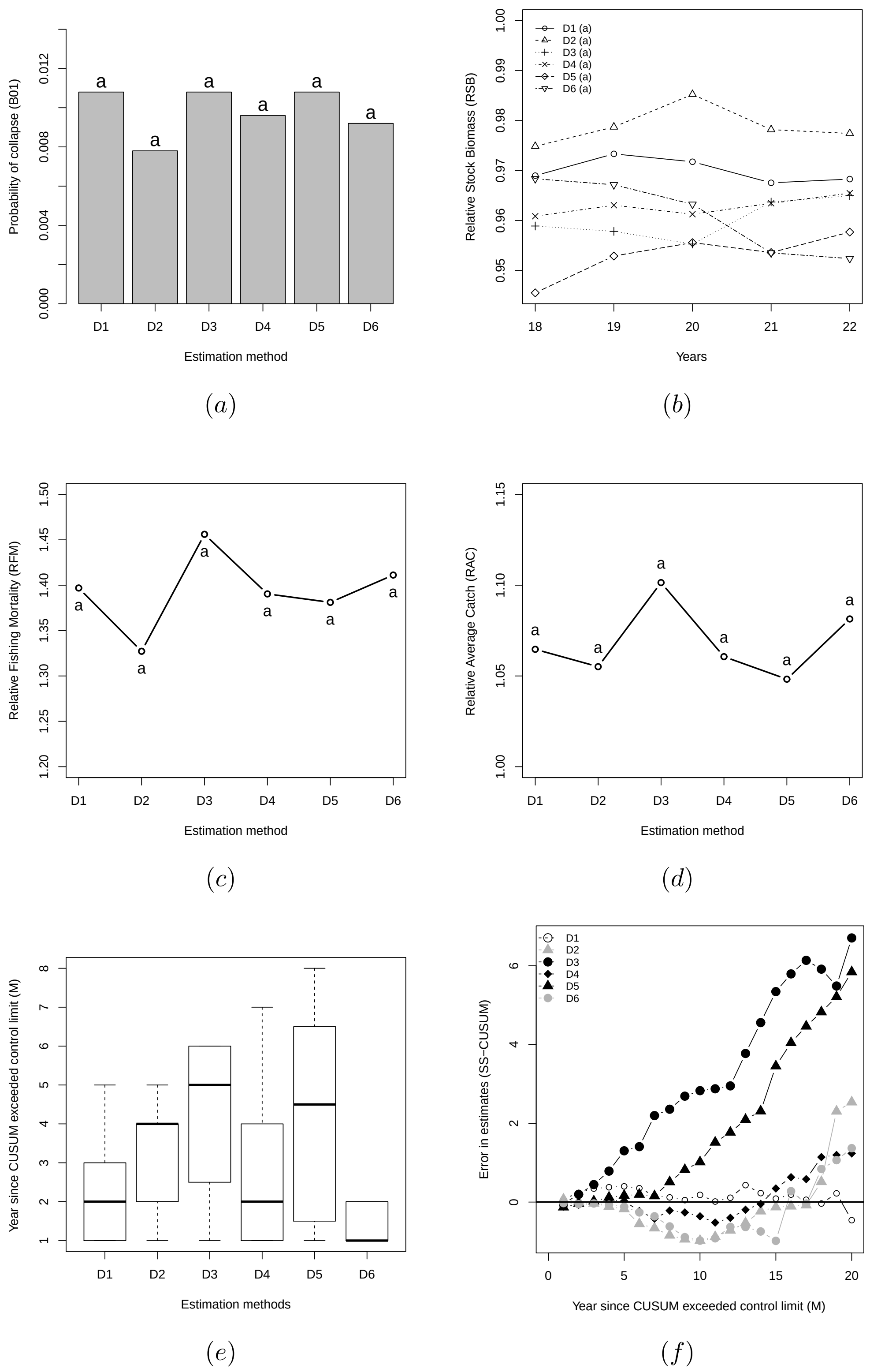


Figure 8.7: **Performance comparison for estimation methods:** The figures shows **(a)** the probability of stock collapse (B01).**(b)** the relative stock biomass (RSB), **(c)** the relative fishing mortality (RFM) and **(d)** the relative average catch (RAC). The same letters in the plots indicate no significant difference between each other at $p \leq 0.001$. **(e)** Indicate the M obtained for collapsed stocks when different estimation methods were used for the SPA in HCR **(f)** Shows the error in shift size estimates for all methods which will be zero if accurate.

with an adjustment factor more than the shift occurred in the underlying stock biomass. Hence the stock collapses were comparatively higher when D3 and D5 methods were used in the HCR (Figure 8.7a).

Results also indicated (Figure 8.7f) that shift size estimates were computed for alarm signals up to 20 years (M). However, figure 8.7e indicates that the maximum M obtained for the collapsed stocks (due to under-estimated running means) were not more than 8 years. This means that the running means were also over-estimated in certain cases because in such scenarios, the SS-CUSUM will continue raising negative signals until the TAC is reduced to extremely low catches.

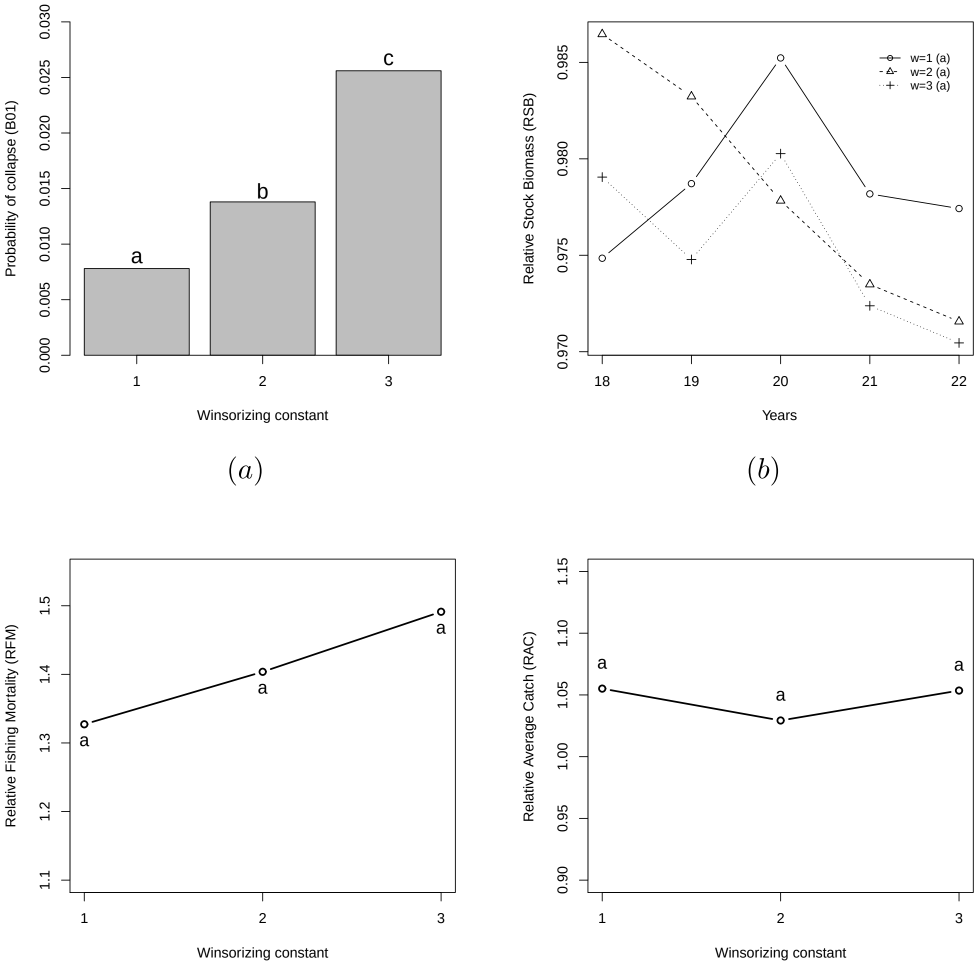
8.6.6 Performance comparison for winsorizing constants

In terms of sustaining the stock biomass, catch and fishing mortality, there was no significant differences in performances between stocks with constants of $w = 1, 2$ or 3 (Figure 8.8b,c,d). However, the probability of stock collapse increased with higher constants of w (Figure 8.8a). An increase in 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 value. This effect is illustrated with an example in figure 8.9a where you can see the progression of three running means (recruitment), each configured with $w = 1, 2$ and 3. All the running means started from more or less similar observations, but ended up with under-estimated values when $w = 2$ or 3.

8.6.7 Performance comparison for increasing allowance (k)

Results indicate that using a low allowance (k) will increase the probability of stock collapse (Figure 8.10). This is because the control chart will be more sensitive in such situations and consequently end up with more false positive alarms. Note that the running means will not be updated when alarms are raised. Thus the running means will be under or over-estimated if the initial observations belong to an out-of-control distribution (Figure 8.9b). Increasing the allowance will decrease the probability of false alarms and thus leads to a running mean closer to the intended reference point (Figure 8.9c).

If the allowance is too high, then the scheme may not raise any signals at all and the TAC will keep increasing the catch as configured in the harvest control rule. In the present study, the relative fishing mortality and average catch was higher for allowance $k > 1.5$ (Figure 8.10c,d). This means that the SS-CUSUM was not efficient in regulating the fishery close to the reference point when $k > 1.5$. Setting the allowance for SS-CUSUM will require careful attention since the trade-off between false positive and negative alarms are dependent on the life span of the species (see Chapter 5).

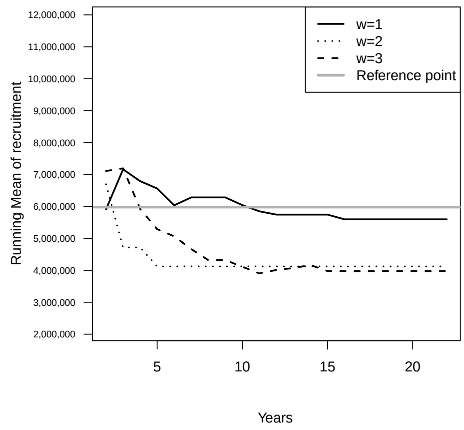


(a) (b) (c) (d)

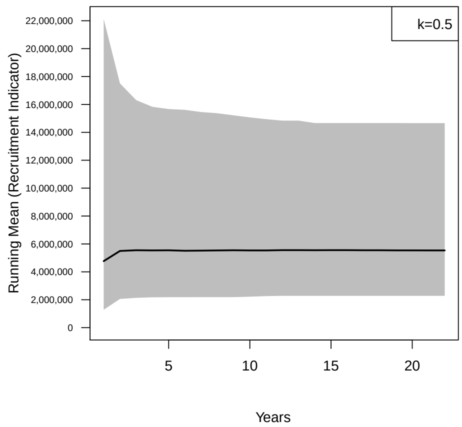
Figure 8.8: **Performance comparison for increasing winsorizing constants (w):** showing **(a)** the probability of stock collapse (B01) **(b)** the relative stock biomass (RSB) **(c)** the relative fishing mortality (RFM) and **(d)** the relative average catch (RAC) from the terminal years of the projection period.

8.6.8 Performance comparison for stocks with more historical data

Results indicate that there is no significant differences in the performances of RSB, RFM and RAC if more historical data are available for the fish stock (Figure 8.11b,c,d). However, the probability of stock collapse increased significantly (Figure 8.11a). This is because the stocks will start becoming overfished early in the time series if the running means are under-estimated. Note that the performance measures were computed only from the last 5 years of the projected period. This means that the quantity of historical observations does not matter but instead the quality, particularly the first three observations should be carefully used for adapting the running mean to the intended reference point of any given management objective.



(a)



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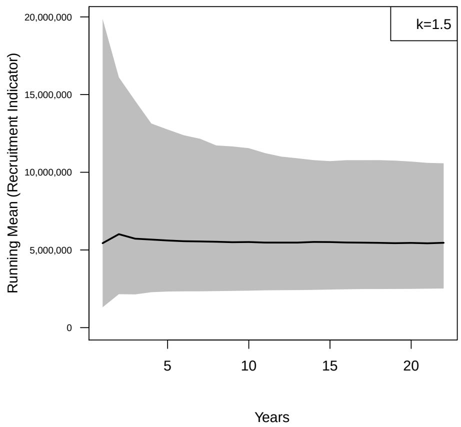


(c)

Figure 8.9: **Comparison of running means with different constants of w and k: (a)** the progression of running means from a single iteration of the simulation model using w = 1, 2 and 3. **(b) & (c)** the range of running means obtained in the third scenario with $k = 0.5$ and $k = 1.5$. The gray shaded regions indicate the range between 5^{th} and 95^{th} percentile of the observations obtained in each year. Results indicate that the running means adapt more closer to the intended reference point corresponding to the initial state of the stock if k is higher.

8.6.9 Performance comparison for different historical states of stock

Results indicate significant differences in the performance measures when the HCR was applied to stocks that were historically fished below F_{MSY}, at F_{MSY} and above F_{MSY}. The probability of stock collapse increased when the initial state of the stock shifted from left to right of the fishery equilibrium curve (Figure 8.12a). Hence the relative stock biomass from the terminal years reduced significantly (Figure 8.12b). When the stock is historically overfished (above F_{MSY}), the running mean will be computed only using observations from the out-of-control distribution. Thus the running mean will be underestimated and more false positive signals will be raised. This eventually results in an increase in the relative average catch and in fishing mortality (Figure 8.12c,d).

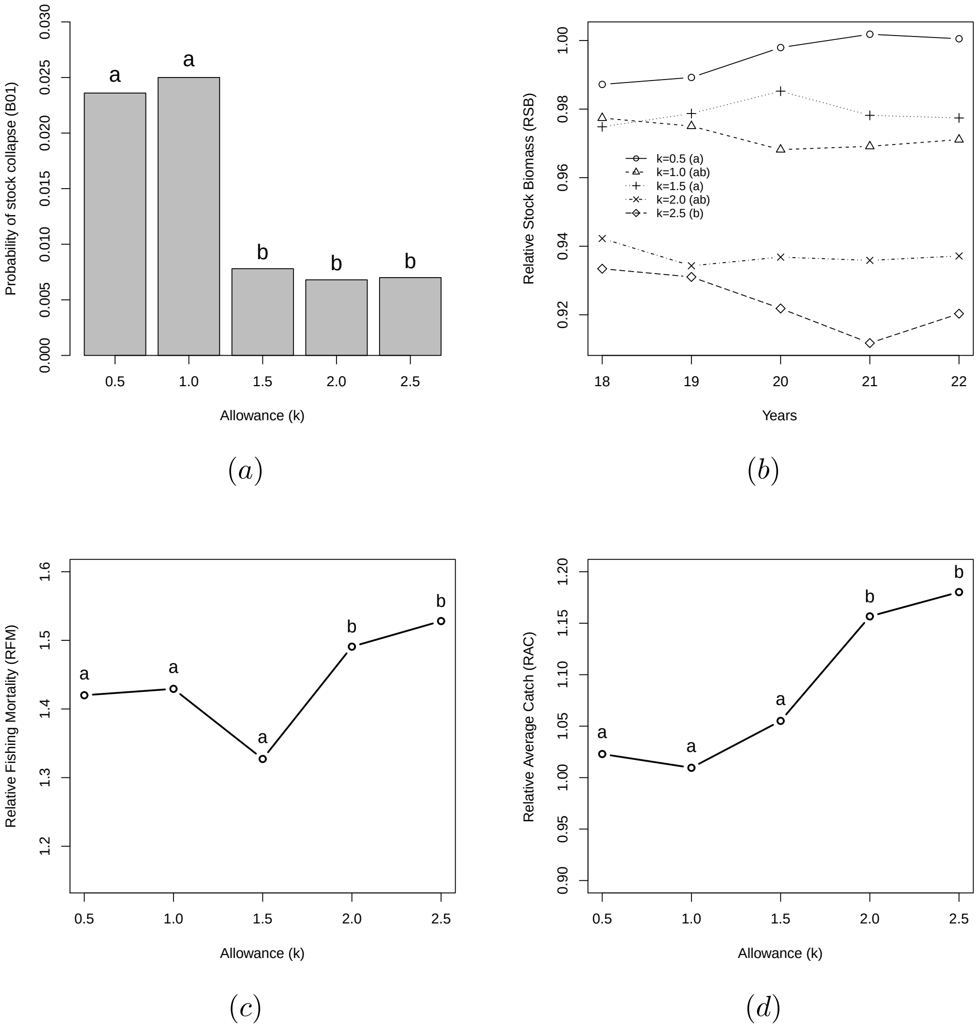


Figure 8.10: **Performance comparison for different allowance constants (k):** showing **(a)** the probability of stock collapse (B01) **(b)** the relative stock biomass (RSB) **(c)** the relative fishing mortality (RFM) and **(d)** the relative average catch (RAC).

8.6.10 Performance comparison for different life history species

The results obtained are similar to the effects observed in chapter 7 where the probability of stock collapse is higher for species with a shorter life span (Figure 8.13a). As mentioned previously, this is likely because the number of cohorts in a short life span species is low when compared to a long lived species. Short lived species are therefore responsive, dynamic and require quick management decisions which may otherwise lead to overfishing or stock collapse. Results also showed that the proposed statistical process adjustment optimizes a catch oriented performance rather than based on stock biomass or fishing mortality. Since the relative average catch for all life history species were close to 1 (Figure 8.13d) while the relative stock biomass and fishing mortality was dependent on the life span of the species (Figure 8.13b,c).

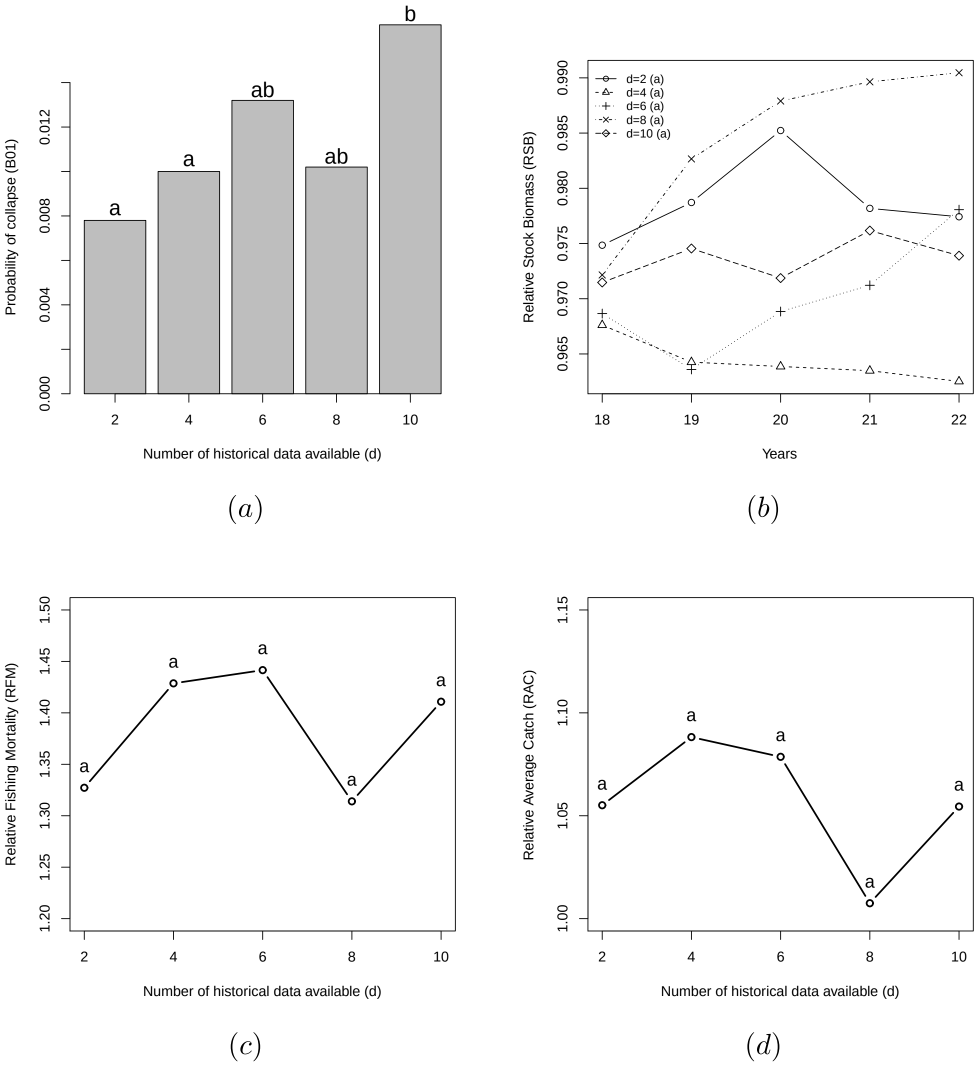


Figure 8.11: **Performance comparison if more historical data are available** (*d*)**:** showing **(a)** the probability of stock collapse (B01) **(b)** the relative stock biomass (RSB) **(c)** the relative fishing mortality (RFM) and **(d)** the relative average catch (RAC).

8.7 Discussion

A pilot study was conducted to assess whether a harvest strategy based on catch control rules and SS-CUSUM has the potential of managing data poor fish stocks, particularly if no historical scientific data are available. The objective of the harvest control rule was to sustain the state of stock as the fishery is in a developmental phase, as more data are required to conduct a formal fish stock assessment. Two stock indicators (recruitment and large fish indicator) were assumed to be available and the stock was managed based on the trend in these indicators. The overall stock performance shows that the proposed harvest strategy was successful in regulating fisheries with the given management objective across a range of stock perturbations, fishery dynamics and data errors (see Appendix F).

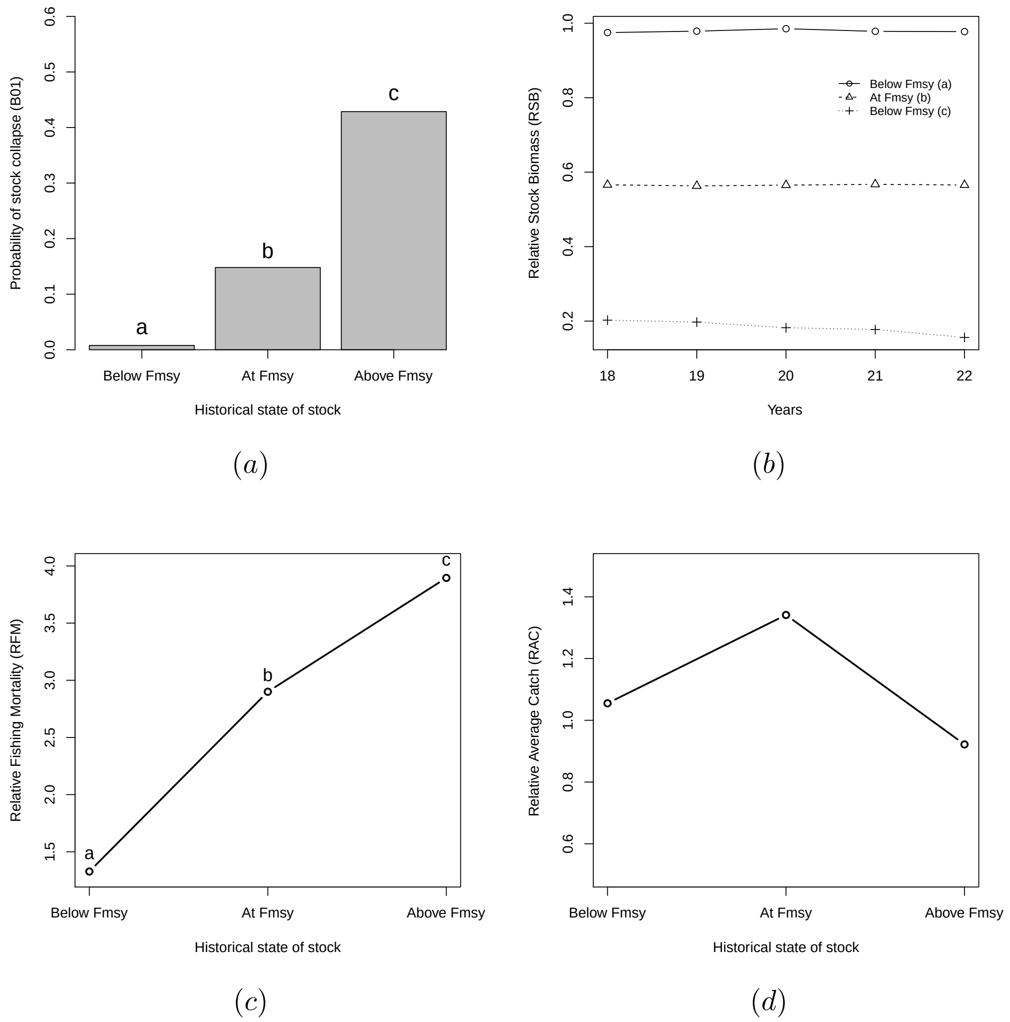


Figure 8.12: **Performance comparison for different historical states of stock:** showing **(a)** the probability of stock collapse (B01) **(b)** the relative stock biomass (RSB) **(c)** the relative fishing mortality (RFM) and **(d)** the relative average catch (RAC) from the terminal years of the projection period.

8.7.1 Comparison with other management systems

Most management strategies developed are for commercially important data-rich fisheries (Bentley and Stokes, 2009). Many harvest control rules were agreed upon by negotiation in committees and only a few of them have been evaluated through simulations (De Oliveira and Butterworth, 2004; De Oliveira, 2006; Rademeyer et al., 2008; De Moor et al., 2011). Hence there is no link between the method used to develop the scientific advice and the quality of the available data (Punt et al., 2013). The advantage of the proposed management procedure is that they are developed based on a method that require no historical data to start with. Hence they are useful to apply directly to data poor situations and the control rules can be modified as and when more information become available for the fish stock.

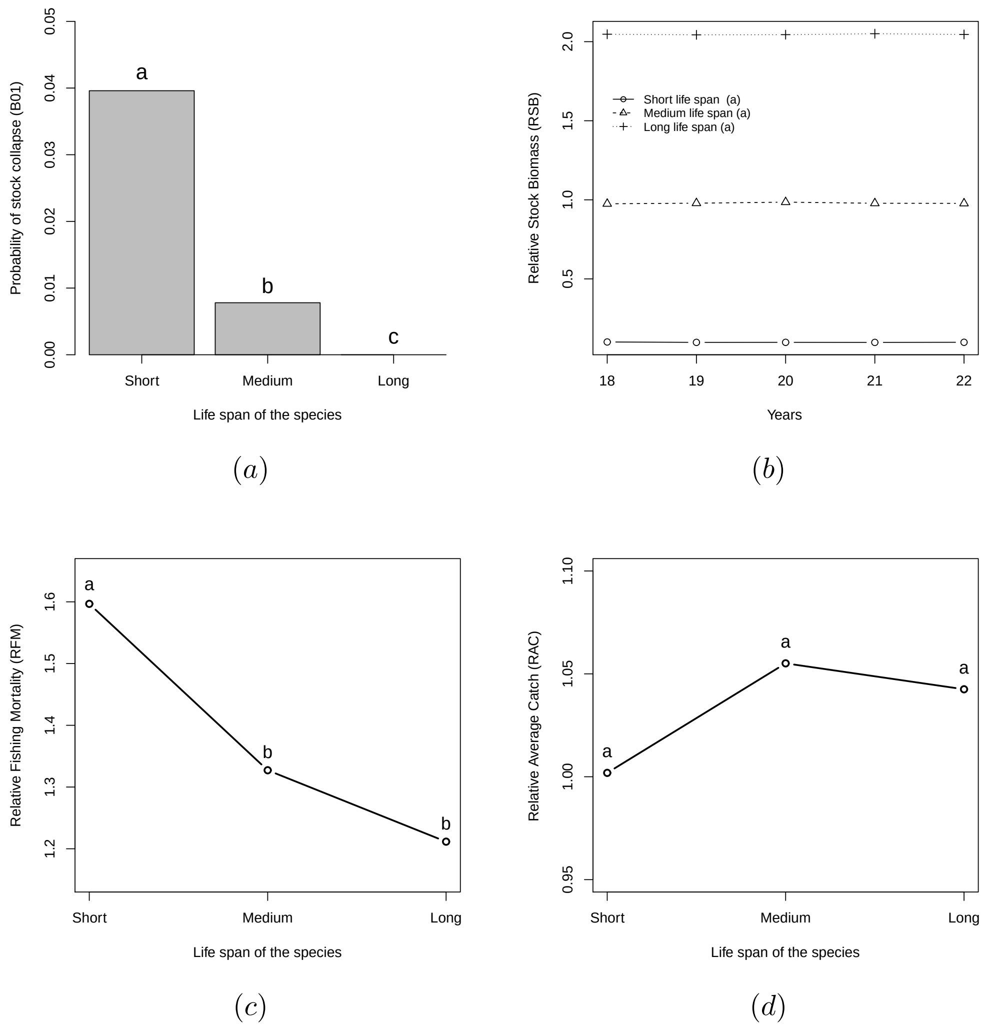


Figure 8.13: **Performance comparison for species with different life histories:** The figure shows the **(a)** probability of stock collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC).

Currently there two common ways of providing management advice for data poor fish stocks. They are (i) based on assessments by adopting parameters of a data-rich stock or species having the same dynamics (Punt et al., 2011; the "Robin Hood approach") and (ii) to use harvest strategies based on empirical decision rules (Smith et al., 2009; Wayte and Klaer, 2010). The second approach has been implemented in a few jurisdictions around the world mostly in the form of 'tier-based' assessment systems and associated harvest control rules (Smith et al., 2008; Reuter et al., 2010). In this approach, the choice of HCR has an increased level of precaution with increasing levels of uncertainty about stock status, such that the level of risk is approximately constant across the tiers. The 'tier 4' of Australia's Harvest Strategy Policy (Rayns, 2007) represent stocks that have the least information available, for which the targets and limits are based on historical standardized catch rates (catch per unit effort [CPUE]). The TAC advice for 12 data poor species in the Southern and Eastern Scalefish and

Shark Fishery (SESSF) is currently provided using the 'tier 4' approach. However, the Western Deepwater Trawl Fishery (WDTF) that operates off the Western Australian coast since 1987 is a multi-species and multi-gear fishery where a formal management plan has never been implemented. Unlike SESSF, there is very little information for the WDTF and consequently the control rules in tier 4 system were not applied since it was impossible to set any meaningful triggers (Smith et al., 2009). The results from this study suggest that it is feasible to implement management procedure based on SS-CUSUM in such situations since the priority will be to detect the impact due to changes in effort until more biological and scientific information becomes available for conducting quantitative assessments.

There are many examples from previous research on providing guidelines for managing fisheries with limited information though none of them are fully comprehensive nor adaptable in a data poor situation, particularly if no previous information is available for the fish stock (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). Most of these strategies require at least four observations to detect the trend and are based on the CPUE which is not necessarily available always for every data poor stock (Dowling et al., 2008; Wilson et al., 2010; Prince et al., 2011; Little et al., 2011). The advantage of the SS-CUSUM approach over these management procedures is its independence of the type of indicator that can be monitored (although this was not explicitly tested in the present study). More evaluations are required to understand which indicators are more likely to obtain robust stock performances for the given management objectives.

8.7.2 Credibility of SS-CUSUM in a data poor context

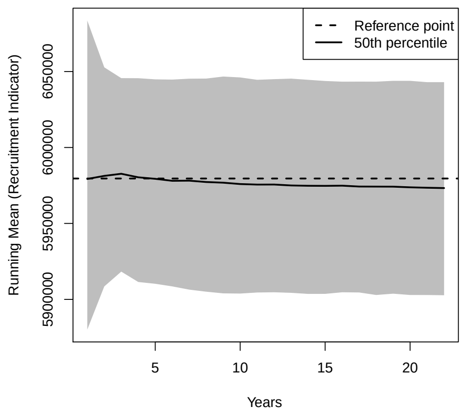
In this section, I will discuss what properties of the proposed approach makes it desirable to apply in a data poor context. The foremost advantage is the use of a running mean in SS-CUSUM as the reference point for managing fish stocks. It is easier to understand with the example of the steps involved in developing the Australian Harvest Strategy Policy (Dowling et al., 2008) where the reference points used were simply the "best guess" proxies informed through the participation, discussion and agreement of various stakeholders in the industry. The indigenous knowledge of local fishers may add subjectivity to the decision process. However, such information can not be completely ignored considering the uncertainty around limited historical data. The approach of SS-CUSUM can be used in such situations where the best guess reference points can be validated incorporating whatever data are so far available for the concerned stock.

The second important advantage of SS-CUSUM is the control limit which provides a simple and explicit framework of defining trigger levels to invoke a management response. In the example of Australian HSP for data poor fish stocks, multiple trigger levels were defined such that higher data and analysis requirements are associated with increasing levels of trigger response (Dowling et al., 2008). Using an SS-CUSUM approach can be advantageous in such instances since it reduces the number of trigger response levels. Thus a cost-effective management system can be implemented where the data analysis is required only if SS-CUSUM surpasses the control limits. Moreover, no additional data are required to implement the trigger response levels in SS-CUSUM (Australian HSP monitor CPUE and use historical catch records or biomass estimates for trigger response). Results from chapter 5 and the present study indicate that the range of h to detect meaningful impacts are between 0 to 3 (if $k = 0.5$) depending on longevity of the species.

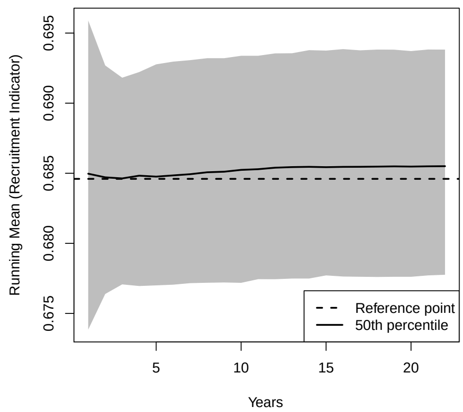
The third advantage of the proposed management strategy is the transparent nature of control rules where the annual TAC was updated only when an alarm was raised by SS-CUSUM. This means the catches will be relatively stable if no signals occurs. Wilson et al. (2010) and Prince et al. (2011) demonstrated how data poor fish stocks can be managed using empirical decision rules based on CPUE and size structure of the population. However, their approach consisted of decision rules with four levels where the TAC adjustment was based on (i) status of CPUE (ii) rate of change in CPUE (iii) status of old fish relative to the target and (iv) status of recruitment to the fishery. The overcrowded decision rule networks are simply because of the requirement of monitoring more than one indicator. In the present study, the management procedure was implemented by combining two plausible stock indicators (estimated recruitment and large fish indicator). If more indicators are available, a multivariate self-starting control chart can be used for detecting whether a management response is required or not (Sullivan and Jones, 2002; Hawkins and Maboudou-Tchao, 2007*b*). Hence, the approach based on SS-CUSUM is comparatively more simple, pragmatic in real world situations, easily understood by the fishers and hence has the advantage of gaining support through data collection activities.

8.7.3 How the proposed approach can be improved?

The major weakness of the SS-CUSUM approach is its tendency to under or over-estimate running mean compared to the initial state of the fish stock. Essentially this occurred only when the initial indicator observations were outliers, particularly the first two years represented a fishery that is unstable or in an out-of-control state. In the present study, the running mean of the estimated recruitment was under-estimated comparatively more than the large fish indicator (Figure 8.5cd). Hence one solution to this problem is to use more robust indicators which do not inherently have large variations relative to the state of the stock. It is also precautionary to keep the catch constant for the first few years unless there is an evidence indicating increase in the fishing pressure. The first few observations in the time series can be replaced with more realistic values if an estimate of the indicator control means are available for the fish stock. Figure 8.14 shows the range of running means obtained for the recruitment and large fish indicator using an example simulation where the first three observations were replaced with random values from the reference point of 50% MSY ($cv = 0.01$). Results show that the 50^{th} percentile of indicator running means (Figure 8.14a,b) were not under- or over-estimated (Compare with Figure 8.5a,b). The TAC was set constant in this example when an in-control situation was alarmed by the SS-CUSUM.



(*a*)



(*b*)

Figure 8.14: **Running means obtained with in-control observations during initial years**: **(a)** Shows the range of running means obtained for R ($\overline{X}_{n,R} = 5979577$) **(b)** Shows the range of running means obtained for P_w ($\overline{X}_{n,P_w} = 0.6846$). Shaded regions indicate the range between 5^{th} and 95^{th} percentile of the observations.

The results from different life history species (Scenario 5) showed that the proposed harvest strategy produced a catch oriented performance (Figure 8.13d). This means that the relative average catch was close to 1 while other performance measures were dependent on the species longevity (Figure 8.13a,b,c). This is because the large fish indicator was based on samples collected from the commercial catch. Alternatively an indicator of the stock abundance or samples from fishery independent surveys can be used to obtain a biomass oriented management performance.

The harvest strategy can also be improved by modifying the catch control rules in the statistical process adjustment. The catch rules could be as simple as halving the TAC from the previous year or closing the fishery if the SS-CUSUM crosses beyond the control limits. The catch rules can also be modified further as more information becomes available from the stock by computing the TAC adjustment factors based on other stock indicators (e.g. CPUE) or estimation methods (Tercero-Gómez et al., 2013). Once more observations are available, the shift in underlying stock biomass can be estimated using data rich methods in the Engineering Process Control (EPC) theory (Luceño, 1992; Box and Kramer, 1992; Wiklund, 1995).

In the present study, the management procedure based on SS-CUSUM was tested and evaluated in a scenario where it was assumed that the fish population belongs to a single stock with no spatial structure or movement dynamics and was harvested using a single type of fleet. Data poor situations can be quite complex as well as uncertain in terms of overall biomass, spatial extent of marine resources and the ways how they are harvested. 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, high levels of species misidentification and highly variable nature of annual catches for individual species (Dowling et al., 2008). The indicators and estimation techniques appropriate for such scenarios will require further research. Some example indicators could be changes in species composition of the fishery catch, spatial fishing patterns, declines in overall CPUE or overarching values for total catch (Dowling et al., 2008). The SS-CUSUM should be evaluated for its sensitivity and specificity with such ecosystem indicators before implementing them in real world scenarios. However, the initial evaluation of SS-CUSUM based harvest strategy suggests that it has the potential to produce management corrections across the range of scenarios tested in the present study.

The harvest strategy also needs to be robust to the high degree of uncertainty associated with existing information so that the outcome will not be disastrous even if the assumptions about the dynamics of the stock are incorrect (Perry et al., 1999). To assess the robustness of management strategies, Punt et al. (2013) suggested a consideration of the implications of plausible broad forecasts related to how biological parameters may change in the future. This can be incorporated by testing the HCR for uncertain or moderate-to-weak environmental relationships (De Oliveira et al., 2005) and by exploring the violations of assumptions used in the operating model (e.g. time and age-independent natural mortality and stationary stock–recruitment relationships).

8.8 Summary

The present study was able to draw the following guidelines to manage data poor fisheries using a harvest control rule (HCR) based on statistical process adjustment (integrating SS-CUSUM with estimation methods from EPC theory).

- The management procedure based on SS-CUSUM is simple and transparent compared to other management systems developed for data-poor fisheries.
- The statistical process adjustment (SPA) based on SS-CUSUM was successful in sustaining the stock in its initial “in-control‘’ state of fishery.
- The SS-CUSUM should be configured with w of one standard deviation to avoid contaminating the running mean with “out-of-control” observations.
- The SS-CUSUM can accommodate more indicator observations with higher allowance (k) and the initial running mean will get closer to the true reference point corresponding to the initial state of stock.
- The first two observations are not monitored by SS-CUSUM and hence any out-of-control observations in the initial years are likely to result in an under- or over-estimated running mean and the stock may become depleted or collapse.
- The running mean can be stabilized at the intended reference point by using robust stock indicators that have less variation relative to the state of the stock.
- The running mean can be stabilized at the initial state of the stock if the TAC is set constant unless there is evidence of an impact on the existing effort levels.

Chapter 9

General Discussion

The Cumulative Sum (CUSUM) control chart (Page, 1954) is a trend detection method from the Statistical Process Control (SPC) theory and is efficient at detecting gradual and persistent shifts in indicators (Hawkins and Olwell, 1998). However, their applications are so far limited in fisheries monitoring (Scandol, 2003; Petitgas, 2009). In the present thesis, I show how such models can be extended for assessment and management of fisheries when only limited historical information is available.

Development and evaluation of operational methods to achieve broad management objectives has achieved considerable progress in the last two decades, generally by implementing simulations of the fisheries management system as a whole (Sainsbury et al., 2000). In the present study, the application of CUSUM was tested and evaluated using a simulated fishery where a simple non-spatial age-structured virtual fish stock was modelled (see **Chapter 2**). The base case stock was exploited using a single type of fishing gear though the effect of other selectivity patterns were evaluated independently in later scenarios (Section 2.4.2.1). Various size-based catch indicators that are typically available from a data limited or poor fishery were computed from commercial catches (Section 2.5). The trend in these indicators was used for monitoring, assessment and management of various life history fish stocks (Table 2.1).

The steps involved in CUSUM are simple (see **Chapter 3**) where the cumulative sum of positive and negative indicator deviations are computed from a fixed reference point termed the 'control mean'. To accommodate the inherent variability of the indicator, a fixed 'allowance (k)' is deducted from the absolute CUSUM. A management response is evoked when the CUSUM is exceeded beyond a threshold, the 'control limit (h)' indicating an out-of-control situation (DI-CUSUM). A variant of DI-CUSUM is the self-starting CUSUM (SS-CUSUM) where indicators can be monitored without any prior knowledge of the control mean. In SS-CUSUM, a 'running mean' is calibrated from the ongoing indicator observations itself instead of the control mean.

The Statistical Process Adjustment (SPA) is an inter-disciplinary procedure used for process management in commercial industries where the monitoring methods in SPC theory are linked with adjustment methods in Engineering Process Control (EPC) theory (Del Castillo, 2006). The subsequent chapters in this thesis were developed following the basic steps in SPA. They are (i) identifying the potential output variables (**Chapter 4**); (ii) monitoring them for anomalies (**Chapter 5**); (iii) searching the reasons when alarms are raised (**Chapter 6**) and (iv) adjusting the input variable for process regulation (**Chapter 7 & 8**).

In **Chapter 4**, various age-based catch indicators from the fishery were analysed for their potential in detecting the state of stock. Results showed that the Mean Indicators (MI, Table 2.5.2) were most sensitive (strong correlation) in detecting the changes in the state of the stock while, the Mature Fish Indicators (MFI) were most responsive (least lag when cross-correlated). The Large Fish Indicators (LFI, based on proportion of large fish in the catch) were sensitive except when a recruitment crash scenario was simulated. In a data poor context, the MIs will be easier to obtain because the computation of MFI or LFI will require more information from the stock such as the maturity or selectivity parameters ($M_{95\%}$ and $S_{95\%}$). Similarly, indicators based on length or catch weight is a cost-effective option compared to those based on age or catch numbers (McGarvey et al., 2005). The sensitivity of LFI can be improved by computing an absolute measure instead of the proportions (Probst et al., 2013*b*; for example the mean length of largest 10 individuals from fishery independent surveys), thus reducing the effect of trends occurring in other age groups of the stock.

Once an appropriate indicator is identified, the next step is to monitor and detect the effects of fishing. The most important parameters in DI-CUSUM are the control mean and standard deviation representing the in-control indicator distribution i.e., the expected values in a fishery equilibrium state for given management objectives (reference point). In practice, these parameters are estimated using historical observations from a reference period or phase when the process (or stock) was in an in-control situation (Montgomery, 1996). However if no historical scientific data are available, particularly in the case of data poor stocks, then it is difficult to determine the appropriate control parameters for operating the DI-CUSUM. In such situations, the SS-CUSUM can be extremely useful since they can initiate monitoring without any prior knowledge of the control mean. In **Chapter 5**, the SS-CUSUM was evaluated for its detection capabilities in a fishery scenario where a stable state fish stock was exploited by a step change increase in fishing mortality per annum. The results showed that the SS-CUSUM was able to raise alarms as early as in the third year of the monitoring process (Pazhayamadom et al., 2013).

Scandol (2005) evaluated the monitoring performance of DI-CUSUM with a variety of stock indicators and the performances were measured by computing the area under receiver operator characteristic (ROC) curve, a larger area indicating better performance in detecting the true impact of fishing on the stock biomass (Section 5.4.4). A similar approach was used in **Chapter 5** for evaluating the monitoring performance of SS-CUSUM. Results from both studies showed that the ROC performances were similar for all age and length-based catch indicators. The variability in these indicators increased by reducing the sample size from 10,000 to 10 fish and the loss of performance was little (Scandol, 2005; Figure 5.5). This shows that the CUSUM approach is robust and flexible for monitoring catch-based indicators if extensive data are not available for fish stock assessments.

In the scenarios tested (**Chapter 5**), the SS-CUSUM performances were most robust with the LFI since the range of h values obtained at optimal performances (trade-off between false positive and negative outcomes) were minimum. Another advantage of the approach used is that their performance is not affected if the indicator variability is high. This is because the deviation of SS-CUSUM due to extreme outliers can be restricted by a fixed threshold w (winsorizing constant) and hence the optimal performances was achieved at lower h constants when compared to those obtained by Scandol (2003). For example, if length frequency data are available for the fish stock, then the LFI can be monitored using SS-CUSUM and the effect of variability due to inefficient sampling or other measurement errors can be controlled using the winsorizing constant (w). If selectivity parameters of the fishing gear are unknown, then large fish individuals can be sorted by identifying the length groups that are fully vulnerable to fishing. This is a similar to the approach used in the catch curve method for the estimation of total mortality (Pauly, 1983), where the assumption is that the decrease in observed numbers of individuals across the age or length structure of the population is the result only of total mortality.

Scandol (2003) tested DI-CUSUM with a variety of fish with different life histories for determining the allowance (k) and control limit (h) required for fisheries monitoring. However, the study gave mixed results where an appropriate combination of k and h was difficult to justify. This is because Scandol (2003) did not use a winsorizing constant (w) while testing them with indicators that have low and high catch variability. In **Chapter 5**, a similar study was conducted using SS-CUSUM but with w constants. The results showed that the k or h constants for achieving optimal performances will depend on the longevity of the species (for fixed k, the h increases with longevity). This is because the response of the indicators will depend on the number of cohorts within the population structure. Short lived species will usually have small number of cohorts and hence the changes in population abundance are more dynamic. As a result, the probability of signals due to true fishing impacts will be high when h is low. Hence the SS-CUSUM achieved optimal performances at lower h for the short lived species.

Once an alarm is raised by the CUSUM, the next step is to determine the extent of the shift that has occurred in the underlying stock biomass due to fishing. If this can be determined, a proportional amount of harvest can be reduced by decreasing the TAC in the subsequent year. A wide variety of methods are available in EPC for estimating the shift in mean of the indicator distribution and adjusting control variables for process regulation (Pan, 2002; Tercero-Gómez et al., 2013). In **Chapter 6**, a selection of these methods were tested with the objective to understand which method can accurately estimate the shift in the underlying stock biomass instead of the indicator monitored. In this study, a stable state fish stock was exploited by a step change increase in fishing mortality per annum (similar to the approach applied in Chapter 5) and the estimates obtained were compared with the actual shift that occurred in the stock biomass. Results showed that the estimates from methods based on Grubb's harmonic rule were accurate and precautionary in nature if all historical observations that lead to an out-of-control situation are considered (Grubbs, 1983; D3 and D4 method). However, the performance of these methods was dependent on the sensitivity and specificity of the indicator used for CUSUM monitoring. The most robust and accurate estimates were obtained when an estimated recruitment indicator (recruits entering the stock) was combined with the LFI (Figure 6.5). Combining these two indicators is a novel approach, where the overall net deviation indicates the direction of stock biomass changes in real time. Another advantage of this approach is its sensitivity towards fishery independent impacts on stock biomass such as the effect of environmental factors on the survival of juveniles or new recruits. This is also the first study which demonstrates a novel way of assessing relative stock status using indicator trends.

Once the shift in stock biomass has been quantified, the next step is to design empirical rules so that the fishery can be regulated towards given management objectives. In **Chapter 7**, a harvest control rule (HCR) was designed where the Total Allowable Catch (TAC) was updated with the objective to bring an 'out-of-control' (above F_{MSY}) fish stock back to the 'in-control' ($F_{90\%MSY}$) state. The HCR followed the principle behind Statistical Process Adjustment (SPA) such that the TAC was updated only when an alarm is raised by the DI-CUSUM. Results showed that the HCR was successful in bringing the stock back to the 'in-control' state (Figure 7.2). An analysis of the shift size estimates revealed that the most accurate method was the Grubb's harmonic rule based on the last observation in the indicator time series (D2 method). From the outset, this might seem to contradict the results obtained in Chapter 6. However, note that the fundamental difference of this study is that the shift in stock biomass was estimated when an ongoing management strategy was already in place. So if the stock is not regulated historically for longer period of time (thus resulting in a large shift in stock biomass or CUSUM), then the estimates from D3 or D4 method should be used. On the other hand, if the stock is already being managed and the shift in stock biomass is small, then the estimates from the D2 method will be more appropriate to use.

Though DI-CUSUM was found potentially useful for managing fisheries, two important aspects will need careful attention which may otherwise lead to stock depletion or collapse. First, the chosen indicators should not be affected by the trend in other age or length groups in the population structure. In **Chapter 7**, the stocks collapsed when the trend in the proportion of large fishes (LFI) was affected by a spasmodic pulse of historical stock-recruitment (Figure 7.4). Second, the control mean for indicators should be carefully used in DI-CUSUM. Results showed that the stocks may collapse if they are under-estimated (Figure 7.6). Scandol (2003) and Petitgas (2009) have provided some general recommendations on estimating the control mean from historical data. Later, Scandol (2005) used a simulated fishery to test the performance of DI-CUSUM, if the control parameters are computed from historical years during which various deleterious impacts were randomly imposed affecting the recruitment, fishing effort, catchability or natural mortality. His results indicated that large amounts of historical variation will degrade the performance of DI-CUSUM and hence in such situations it is better to estimate the control mean from a historical reference period during which the stock was perceived to be stable (Petitgas, 2009).

If no historical data are available for the estimation of the control mean, then the SS-CUSUM could be useful for managing the fishery. In **Chapter 8**, a new or developing fishery was assumed where SS-CUSUM (with SPA) was applied to regulate the fishery until enough information becomes available for conducting formal fish stock assessments. Results showed that the scheme was successful in sustaining the initial state of the stock (Figure 8.3). However, this management procedure may not work if the stock is historically in an overfished state (above F_{MSY}). This is because only out-of-control observations will be available to calibrate the running mean and eventually the stock may collapse. Results also indicated that the SS-CUSUM should be configured with $w = 1$ if the indicator variability (e.g. estimated recruitment) is inherently high for a relatively stable state of the stock. This is because the running mean is very dynamic in the initial years and if the future updates are configured for 2 or 3 standard deviations ($w = 2$ or 3), then the running mean will move far away from its initial value and end up with an under- or over-estimated value representing out-of-control situations (Figure 8.5). However, this problem can be resolved by either using carefully measured in-control observations in the initial years or by using more robust stock indicators.

To summarize, SS-CUSUM does not require a long in-control calibration sequence to estimate the control parameters. If one is available, then the SS-CUSUM may work better than the traditional method of fixing known parameters (DI-CUSUM) because the running mean and standard deviation will be more realistic compared to estimated values from a historical reference period (Hawkins and Olwell, 1998). Hence, SS-CUSUM can also be used in managing data-limited stocks and their possible application in the context of the WKLIFE categories (ICES, 2012*e*) is summarised in

Table 9.1.

Table 9.1: **Recommendations on using SS-CUSUM in various data limited situations:**

WKLIFE categories	Data availability	Application of SS-CUSUM
Category 1	Data rich stocks	Useful in supporting quantitative assessments and decision making.
Category 2	Discard species with negligible landings	Signals may reflect trends in stock-fishery interactions, market value and policy regulations rather than the impact on the stock itself.
Category 3	Quantitative assessments and forecasts treated qualitatively for variety of reasons	Appropriate for qualitative assessments and strategic decision making. Large fish indicators can be used with SS-CUSUM
Category 4	Stocks with survey indices - total mortality, CPUE, recruitment and biomass	Application requires careful attention since the precision of the signal depends on how well the indicators are standardized over temporal and spatial scales.
Category 5	Catch data available for short time series	Appropriate for qualitative assessments and decision making. If age or length at catch data is available, large fish indicators can be used for greater sensitivity and specificity.
Category 6	Only landings data are available	Appropriate for qualitative assessments and strategic decision making. However, overall landings indicator will be comparatively less sensitive and specific than the large fish indicators since they are an aggregate of all the age groups vulnerable to fishing.
Category 7	Stocks caught in minor amounts as by-catch	Signals do not necessarily detect fishing impacts since catch trends depend on the target species. However, application depends upon availability of appropriate indicator in relation to the management objective.

9.1 Limitations and future work

9.1.1 The base case model

The base case simulation model used in this study assumed that there is no growth variability for the species. It was also assumed that the recruitment to stock was not autocorrelated. These are quite unrealistic though the effect of such variabilities were independently evaluated in later scenarios and the loss of performance measures were marginal (Figure E.4, E.7, F.3 & F.4). The management procedures could have been tested by including all such variabilities. However, the present model was necessary to determine the reasons for stock collapse and the study demonstrated that the choice of indicators is extremely important in terms of predictability and variability about the state of the stock (Figure 7.4 & 8.9). Another limitation of this study is that the model has not considered individuals migrating between multiple stocks. For example, the concerned stock may get replenished by recruits from neighbouring spawning grounds. In such cases, the proposed method may fail to detect an increase in fishing effort.

9.1.2 Stock indicators

For most chapters in this thesis, an estimated recruitment was used as a measure of the new recruits entering the stock and it was assumed that recruitment can be estimated from fishery-independent research surveys (Section 2.5.1). However, recruitment can inherently exhibit large variations due to environmental factors (Daskalov, 1999; Planque and Frédou, 1999) and the observations are often noisy when measured from non-standardized research surveys (Cotter et al., 2009*b*). Moreover, the recruitment indicator may not be available for many data poor fish stocks, particularly in developing countries since additional financial and human resource investments are required to collect such data time series (Caddy, 2002). In such cases, the catch rates of younger age or length based groups can be used as a potential indicator of stock-recruitment (Willis, 1987; Prince et al., 2011).

The large fish indicator was computed from a random sample of the catch using individuals belonging to cohorts that are 95% vulnerable to fishing (based on $S_{95\%}$). However, it is arguable that a length-based indicator can be more realistic and easy to collect in a data limited or poor situation (Cope and Punt, 2009). For simplicity, the present study used an age-based indicator because the underlying objective was to test whether size-based indicators can potentially be used for managing fisheries. Moreover, age-based metrics will provide better diagnostic resolution in terms of determining the effect of external perturbations on the direction and change in indicator trends. For example, in Chapters 6 and 7, I showed how a recruitment crash scenario affected the trend in proportional catch-based indicators.

The management procedure presented in this study can be extended by replacing the recruitment and LFI indicators with other stock indicators available in real world fish stocks. An example is the empirical HCR discussed by Prince et al. (2011) as part of the Australian Harvest Strategy Policy for data poor stocks, where the CPUE indicator was monitored by categorizing them into three size classes representing small, medium and large fishes. However, before the scheme could be implemented as part of a fisheries advice framework, the SPA needs to be fully evaluated on a case specific basis ideally using management strategy evaluations (simulation of the whole management process).

9.1.3 The CUSUM parameters k and h

Traditionally k is fixed based on the shift in indicator mean (Δ) that is likely to be detected, such that $\Delta = 2k$ standard deviations. Similarly, h is fixed to obtain a long In-control Average Run Length (I-ARL, year with first false positive alarm) and a short Out-of-control Average Run Length (O-ARL, year with first true positive alarm) performance (Hawkins and Olwell, 1998). However in the context of fisheries management, the notion of detecting "meaningful impact", compromising "acceptable risk" and managing with "desired performance" are policy issues and have to be decided in partnership with managers and stakeholders (Mesnil and Petitgas, 2009). Nevertheless, what needs to be ensured is the avoidance of stock collapse.

So far, previous studies have focused on fisheries monitoring where CUSUM has been evaluated for its performance in detecting the effects of fishing (Scandol, 2003; 2005; Pazhayamadom et al., 2013). Mesnil and Petitgas (2009) and (Petitgas, 2009) conducted fisheries monitoring using indicators from research surveys and found that the k will generally take a value between 0.5-1.5. In Chapter 5, the results showed that for a fixed $k = 0.5$, the h will depend on the life span of the species. Hence, there is possibly sufficient information already for the range of possible k and h values that can be used for fisheries monitoring.

However to manage a fisheries, the k and h constants required will be different when compared to fisheries monitoring. This is because a management response for a specific k and h should ensure the "desired performance" pertaining to the given management objectives. Hence these constants will depend upon both the lifespan of the species and the HCR designed for implementing the SPA. Results from the base case model indicate that an allowance greater than 1.5 may increase the fishing pressure applied to the stock (Figure 7.7 & 8.10). However a better understanding is required in terms of detecting the maximum shift in stock biomass for which the proposed management procedure will ensure the "desired stock performances". Hence future studies should explore how CUSUM methods can be used to assess the risk involved while responding to the relative shift in stock biomass. This will possibly require developing an adaptive monitoring technique where the k and h changes in an ongoing basis, depending on the current state of the stock (Wu et al., 2009).

9.1.4 Monitoring autocorrelated observations

Most traditional SPC settings assume that the underlying stochastic process is univariate and stationary, producing uncorrelated observations. However previous research has found that fish recruitment time series is often autocorrelated, i.e. the value of current year depends on the value in previous years (Brunel and Boucher, 2007). Results from Chapter 7 and 8 showed that autocorrelated recruitment may have significant effects on the performance of the management procedure. Positive autocorrelation leads to a sharp increase in the number of false alarms. Negative autocorrelation will have less frequent false alarms but may result in reduced performance in detecting the true signal.

Hawkins and Olwell (1998) demonstrated how CUSUM can be adapted for monitoring an autocorrelated process through a model based approach where the dependence of the observations were described by a Box-Jenkins autoregressive-moving average (ARMA) process. However, the model based approach assumes that the monitored indicator will follow specific probability distributions. Recently, a Distribution Free Tabular CUSUM (DFTC) has been developed that can detect a mean shift in autocorrelated process quicker than other existing CUSUM charts (Kim et al., 2007). Such models can be explored in future studies to improve the performance of the proposed management procedure.

9.1.5 Monitoring multiple variables

Fisheries scientists most often monitor multiple indicators (e.g., spatial or survey indices, fishing or total mortality, length at first maturity, recruitment) and many sequential trend detection methods are not designed to use multivariate data. There are two different ways to monitor multiple indicators. One is to ignore how the indicators are inter-related and monitor them as a collection of unrelated univariate control charts. This approach was used by Petitgas (2009), where eight survey indicators belonging to five different attributes (abundance, length structure, maturity, mortality and spatial distribution) were monitored independently and the stock was classified as out-of-control when at least three attributes raise DI-CUSUM signals.

The second way is to process the collection of measures as a multivariate indicator and control it as such (Hawkins and Olwell, 1998). There are several types of SPC schemes that has been extended for monitoring multivariate indicators and are generally termed as “Multivariate Control Charts”. Such schemes are more sensitive to actual shifts than monitoring them as a collection of univariate control charts. Moreover, they are comparatively more specific while diagnosing the cause of an out-of-control situation. However, the most important aspect is to identify whether these indicators relate to the current state of stock. This is because the stock might be in out-of-control situation not because of problems in the current year, but because of problems created in earlier years (Hawkins and Olwell, 1998). Similarly, the change in indicator direction (relative to stock status) could be important because essentially the multivariate control chart considers the correlation between these indicators.

Anderson and Thompson (2004) developed a multivariate control chart for monitoring the temporal and spatial changes in species assemblages of coral reef fishes where the h limits were defined based on historical empirical knowledge of the system. Similar approaches can be used to develop multivariate schemes to monitor, assess and manage fish populations.

9.1.6 Managing a multi-species fishery or ecosystems

The present study explored how CUSUM techniques can be applied for fisheries monitoring, assessment and management of single species fish stocks. 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). The steps for extending the application of CUSUM to an EAFM should follow exactly what has been developed in this thesis, but with a wider perspective on (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; (iv) ecological or environmental impact assessment due to the effect of fishing and (v) developing and testing management frameworks using SPA through empirical control rules.

Much of the initial steps have already been done by previous research workers. Many candidate indicators that may support the EAFM objectives have been identified and tested. These include indicators from trawl surveys (Nicholson and Jennings, 2004; Jouffre et al., 2010), spatial components (Babcock et al., 2005), length structure of the populations (Greenstreet et al., 2011), mean trophic levels (Blanchard et al., 2010) and species life history characteristics (Shin et al., 2010). In an EAFM approach, more than one indicator will be required to characterize 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). Implicitly this means that the development of HCRs based on multivariate control chart is a pre-requisite for extending the application of proposed method from a single species level to EAFM.

Monitoring an ecosystem usually involves collecting data from several sites, locations or transects at intervals through time. Hence it is crucial to consider the spatial dynamics of indicator values over time. For example, how the spatial distribution of an age structured fish population or relative abundance of various species change over years (Anderson and Thompson, 2004; Petitgas and Poulard, 2009). In multivariate control charts, such indicators are analysed using dimension reduction techniques where the data are projected onto a lower-dimensional subspace with a few components containing most of the variance from the original data e.g. Principal Component Analysis (Nomikos and MacGregor, 1994), Multi Factor Analysis (Petitgas and Poulard, 2009). A key problem with this approach is the higher probability of false alarms when indicators are serially correlated in time or if they are spatially correlated between sites. Manly and Mackenzie (2000) proposed a modified CUSUM using randomization tests to minimize the impact of serial correlation. When indicators are spatially correlated between sites, the modified CUSUM can be applied to a reduced set of sites that are far enough apart to give effectively independent results (Manly and Mackenzie, 2003).

Fishing has greater effects 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). Monitoring such indicators using multivariate control charts will need careful attention because most dimension reduction techniques assume that indicators follow a normal distribution rather than a binomial distribution as observed in species presence-absence data. Robust non-parametric methods such as the distance based multivariate control charts can be used for monitoring changes in such indicators (Anderson and Thompson, 2004).

9.2 Conclusions

At the beginning of this thesis, four key questions were posed: to 1) identify catch-based indicators that are useful for monitoring the state of fish stocks; 2) detect the impacts of fishing on stock biomass using CUSUM; 3) assess the state of fish stocks using CUSUM and 4) manage fisheries using signals from CUSUM. All these questions were answered and the present study was able to draw the following general conclusions:

- The Cumulative Sum (CUSUM) control chart is a monitoring method in Statistical Process Control (SPC) theory and is efficient in detecting persistent and gradual trends in process indicators. The DI-CUSUM requires a few historical observations to determine the in-control state of the stock (reference point or 'control mean') and an out-of-control situation is detected when DI-CUSUM moves beyond a threshold known as the 'control limit'.
- Mean Indicators (MI), Mature Fish Indicators (MFI) and Large Fish Indicators (LFI) were found useful to monitor the change in the state of the fish stock. However to compute the MFI or LFI, more information will be required such as the maturity-at-age or selectivity-at-age of the stock.
- Self-starting CUSUM (SS-CUSUM) control chart does not require any historical data or reference points and hence can be used to monitor new indicators from data poor fish stocks. The performance of SS-CUSUM was robust when applied to monitor the LFI.
- The relative change in the state of the stock following an out-of-control alarm from CUSUM can be estimated using methods borrowed from Engineering Process Control (EPC) theory. The most accurate and reliable estimates of biomass shift sizes were obtained using the Grubbs' harmonic rule.

- The study introduced a novel approach of combining the estimated recruitment and large fish indicator for the assessment and management of data poor fish stocks. The combined metrics are extremely useful for estimating the shift in size of the stock biomass if no reference points are available for the fish stock (using SS-CUSUM).

- The present study developed a framework for managing data limited fisheries using Statistical Process Adjustment (linking methods in SPC and EPC) and simple empirical catch control rules. The scheme was successful in bringing an out-of-control stock back to its in-control state. The probability of stock collapse may increase if the indicator control means are underestimated.

- A similar framework was tested using SS-CUSUM for managing a new developing data poor fishery. The scheme was successful in sustaining the initial state of the stock. They are applicable only if there are sufficient evidence indicating that the current level of exploitation is much below the F_{MSY}. The stock may collapse if the first three indicator observations do not represent an in-control state.

- Future studies should consider multivariate control charts for extending the proposed CUSUM management framework with multiple state indicators and explore how such schemes can be used for providing management advice to multi-species resources or ecosystems.

Appendices

Appendix A

Chapter 1

A.1 Definitions

A.1.1 Recruitment

Recruitment is generally defined as the number of individuals that reach a specified stage of the life cycle (Jennings et al., 2001; e.g. metamorphosis, settlement or joining the fishery). However, the term 'recruitment' used throughout this thesis refer to the number of 0-age group individuals in the population of the stock. The number of recruits in an year depends on the total biomass of the mature fish individuals in the previous year. This is modelled by using a Beverton-Holt stock recruitment function (Section 2.4.1.6).

A.1.2 Data-limited stocks

"Data-limited" cases refer to those fish stocks for which a reliable indicator 'control mean' is either available or can be estimated from historical data of the fishery. The 'control mean' is an indicator value that represents a fishery where the yield is sustainable and the state of the stock is stable (equivalent to a reference point in fisheries management). This is the reference mean value used in DI-CUSUM for standardizing the indicator time series before computing the cumulative sum deviations. Hence, data-limited fish stocks are used in this thesis for evaluating the application of DI-CUSUM, wherever applicable.

A.1.3 Data-poor stocks

"Data-poor" cases refer to those fish stocks for which a reliable indicator 'control mean' is neither available nor can be estimated due to the lack of historical data. In such fish stocks, a SS-CUSUM can be used instead of the DI-CUSUM for monitoring the stock indicators. Here the 'control mean' is replaced by a 'running mean', which is calibrated from the indicators itself in an on-going basis and are updated as when new observations becomes available. Hence, data-poor fish stocks are used in this thesis for evaluating the application of SS-CUSUM, wherever applicable.

A.1.4 Signal

The term 'Signal' in this thesis refers to the condition when a control chart raises alarm indicating an out-of-control situation. This is when the statistic computed by an SPC method exceeds the control limits ($\pm h$) either due to a positive or negative deviation in the indicator variability.

Appendix B

Chapter 4

B.1 Additional scenarios considered

A total of four additional scenarios (10 to 13) were considered for evaluating the sensitivity and response of various age based catch indicators towards the changes in SSB of the fish stock. These scenarios were based on the (i) growth variability of the species; (ii) autocorrelation in the stock-recruitment relationship and (iii) number of samples from the fisheries catch.

The scenario based on growth variability used random noise errors to K and L_∞ (Equation 2.6 and 2.7) and a log normal error to the length weight relationship (Equation 2.8) in each year. A coefficient of variation of 0.2 was used for K and L_∞, which is an upper bound compared to the values observed in real world (Shackell et al., 1997; Ratz et al., 1999; Armstrong et al., 2004).

For the scenario based on autocorrelated stock-recruitment, an inter-annual dependency coefficient (ρ) was introduced which described the dependency of recruitment in a given year with the recruitment of the previous year (Equation 2.13). The ρ value of 1 suggests a perfect autocorrelation of first order (Kanaiwa et al., 2005) and the values used in the present study are potentially high considering the observed values of similar fish stocks (Fogarty et al., 2001).

The scenario based on catch samples computed the indicators from a medium and small sample of fish individuals ($n = 100$ or $n = 10$) because in data limited or poor situations, it is more likely to get only a few samples in the real world.

Table B.1: **Additional scenarios used for correlating indicators with SSB of the simulated fishery:** The shaded areas in scenarios 10-13 highlight the differences compared to the base case parameters. The K and L_∞ parameters are the growth coefficient and asymptotic length of the species used in von Bertalanffy growth function (Equation 2.4). The ρ and σ_R^2 are the autocorrelation coefficient and recruitment variance applied for simulating the autocorrelated stock-recruitment (Equation 2.13).

Scenarios	Variability in K and L_∞	Autocorrelation (ρ)	Sample size
10-Growth variability	$cv = 20\%$	Absent*	10,000*
11-Autocorrelated recruitment	No variability*	0.8 ($\sigma_R^2 = 0.6$)	10,000
12-Medium sample	No variability	Absent	100
13-Small sample	No variability	Absent	10

*: Base case scenario

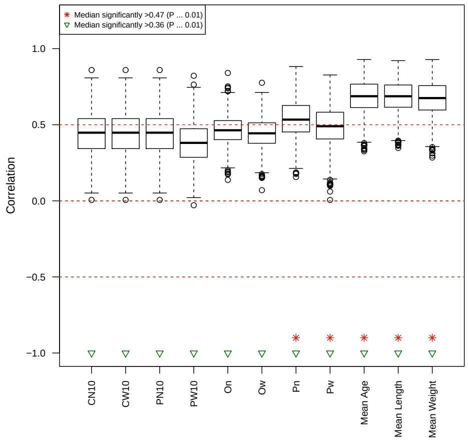
B.2 Additional results

Results show that the mean indicators (MI), mature and large fish proportional indicators based on catch at age numbers (O_n and P_n) were sensitive and robust to the different types of variability in the simulated fishery i.e., growth, autocorrelated recruitment and small sample from the fisheries catch (Figure B.1).

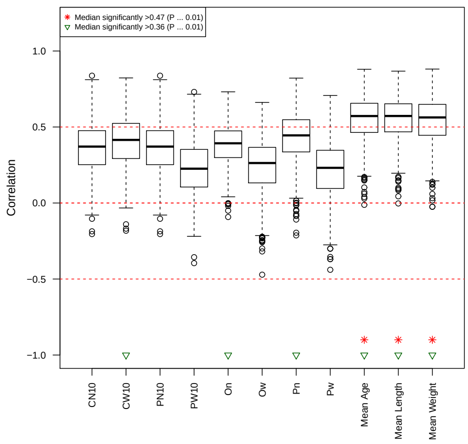
Higher growth variability changes the average weight-at-age of the fish stock and hence the indicators based on catch numbers (O_n and P_n) are more consistent than those based on catch weights (O_w and P_w).

Autocorrelated stock-recruitment was simulated to address the effect of environmental factors independent of the fishery and the results showed that the correlation distribution of mean, mature and large fish indicators were not affected (Figure B.1)c. This indicate that the changes in fishing pressure applied to the stock have a large and consistent impact to size based indicators than due to the changes in environment (Blanchard et al., 2010).

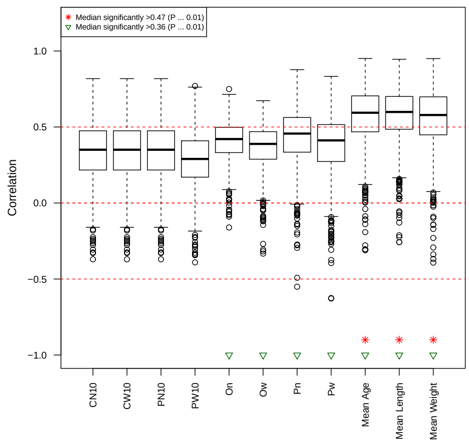
When catch samples are small (e.g. data poor fishery), the variability in catch-at-age numbers increase and hence they may not represent the actual population abundance in the stock. Results show that all stock indicators except the MI were not significantly correlated with SSB when the indicators were computed from $n = 10$ fish individuals (Figure B.1)d. However, the sensitivity of mean, mature and large indicators were not affected when they were computed from a sample size of $n = 100$ individuals (Figure B.1)d.



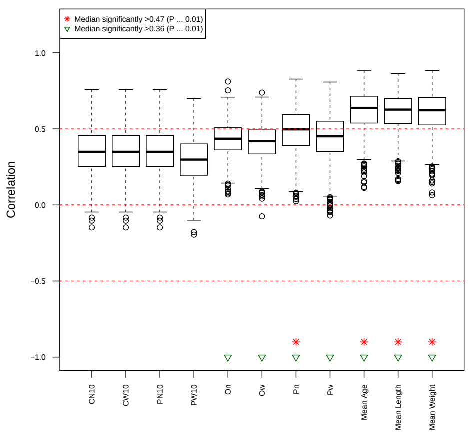
(*a*) No variability (Base case)



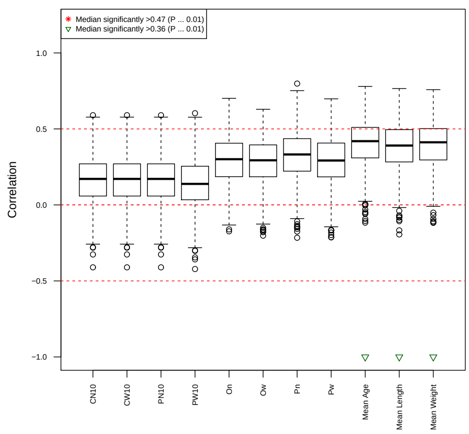
(*a*) Variability in growth



(*b*) Autocorrelated stock-recruitment



(*c*) Catch sample ($n = 100$)



(*d*) Catch sample ($n = 10$)

Figure B.1: **Indicator correlations with SSB for different types of variability:** The plot shows the correlation coefficient distribution obtained from 1000 iterations of the simulated fishery. Each indicator was tested to determine whether the median of the distribution satisfy a significant correlation at confidence level of 95% or 99% level.

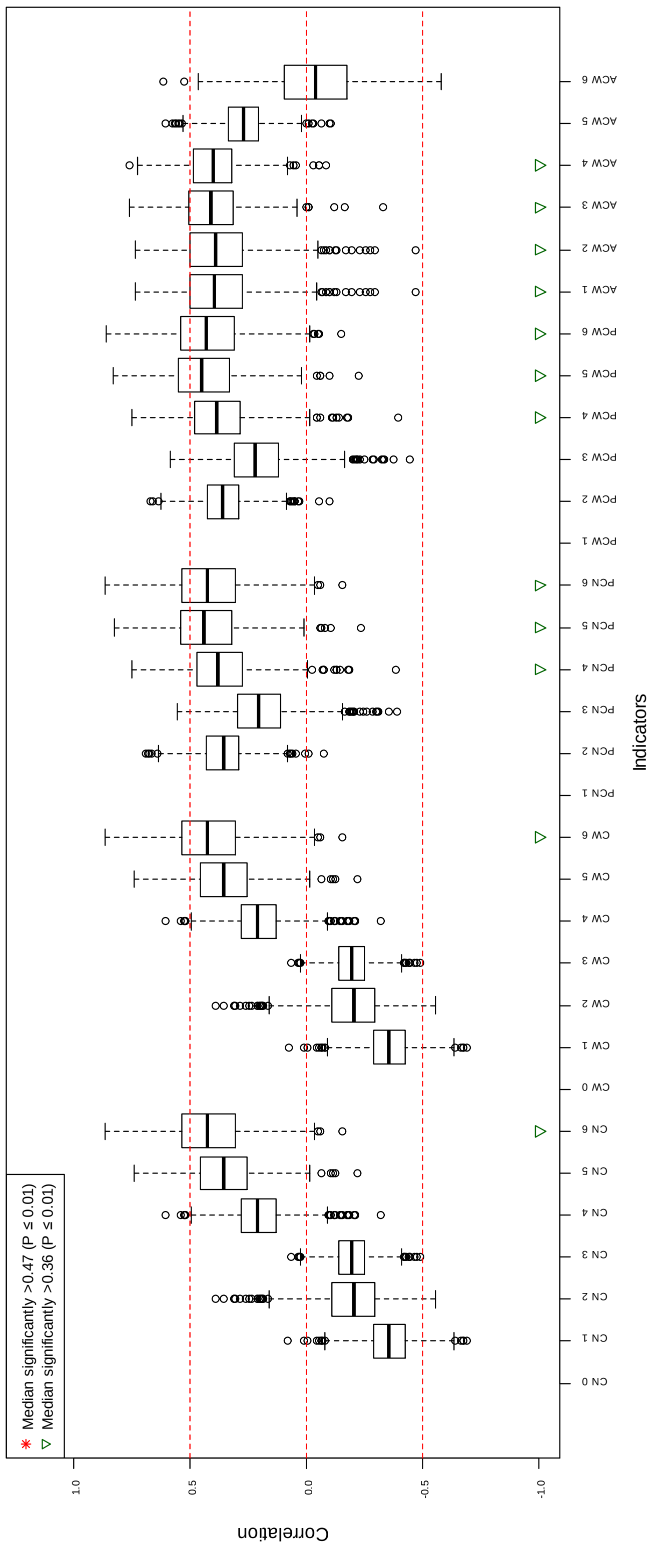


Figure B.2: **Correlations of age based indicators (ABIs) with SSB of a short life span species (Life History 2):** The ABIs were computed for each age group in the stock and the coefficients obtained from 1000 iterations of the simulated fishery were tested to determine whether the median of the distribution has a significant correlation.

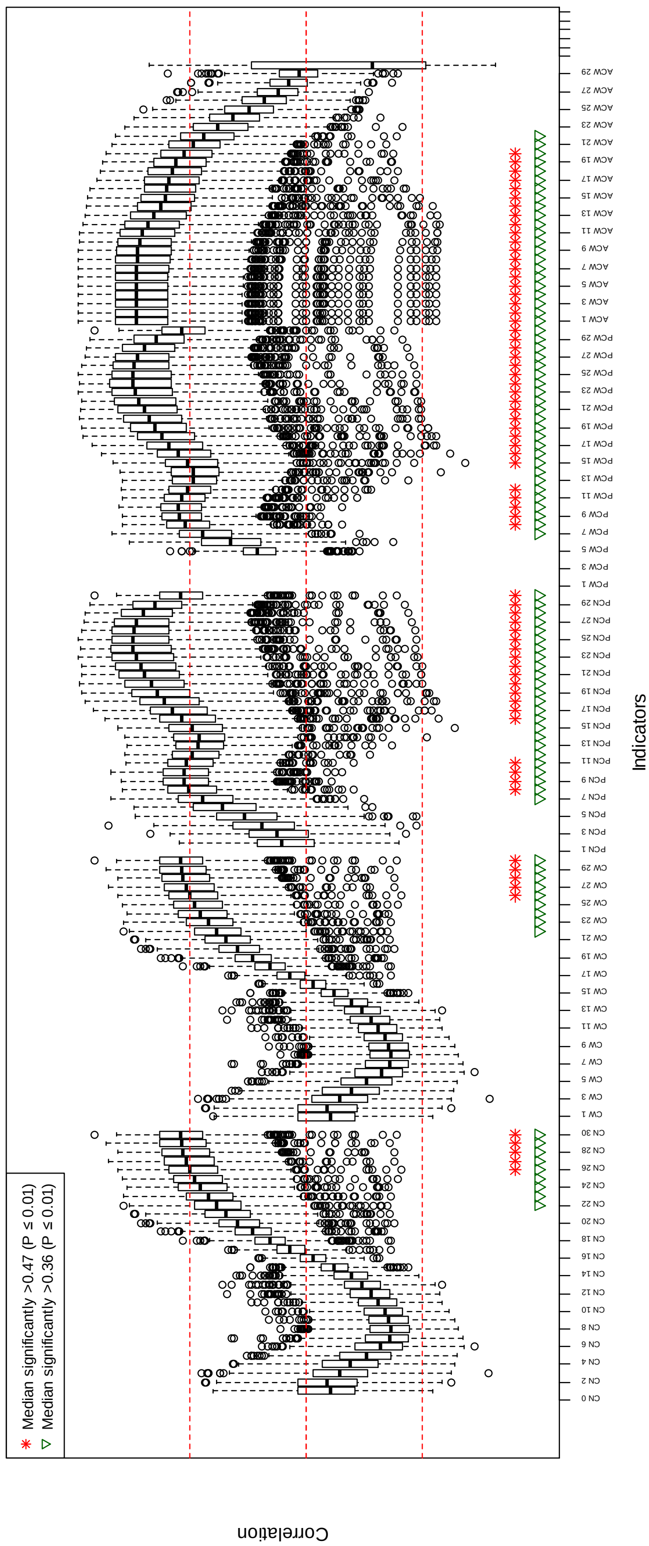


Figure B.3: **Correlations of age based indicators (ABIs) with SSB of a long life span species (Life History 3):** The ABIs were computed for each age group in the stock and the coefficients obtained from 1000 iterations of the simulated fishery were tested to determine whether the median of the distribution has a significant correlation.

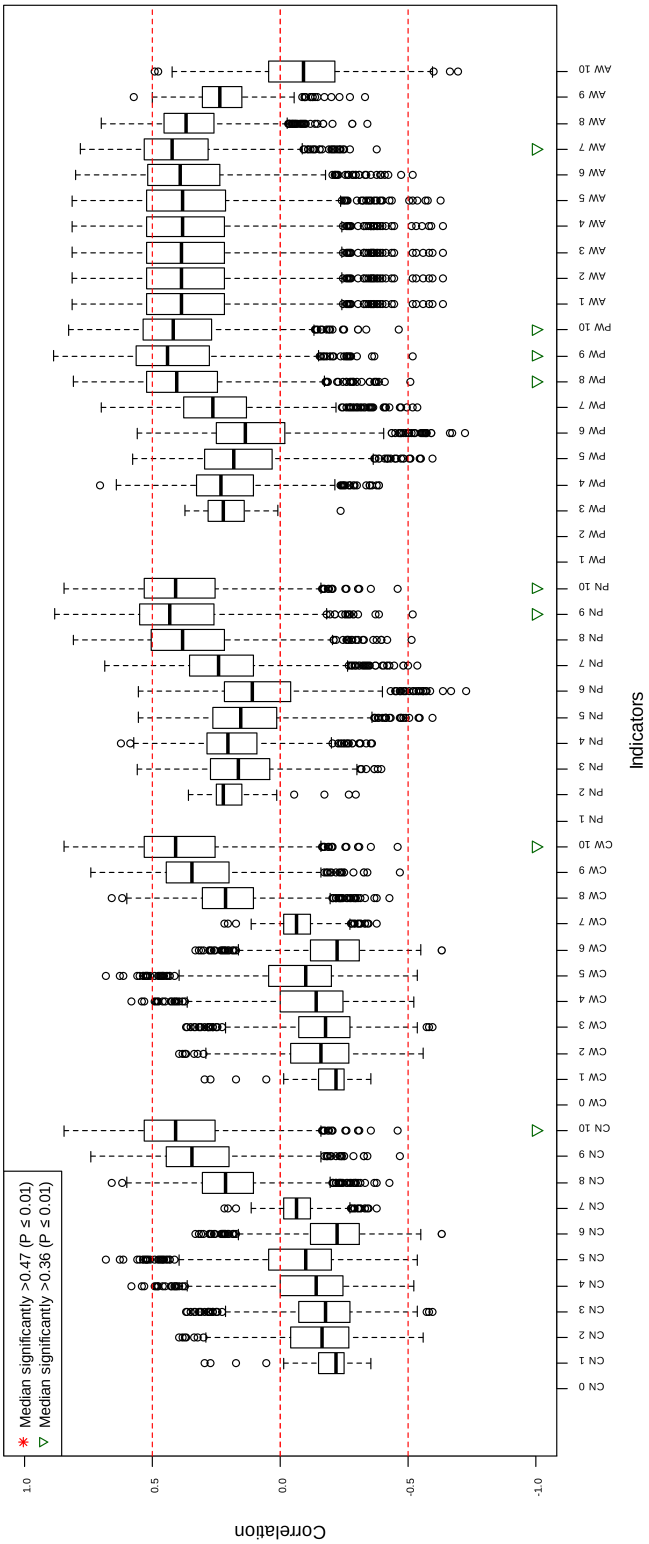


Figure B.4: **Correlations of age based indicators (ABIs) with SSB for a large mesh trawl fishery:** The plot shows the correlation coefficient distribution obtained for *ABIs* of the stock from 1000 iterations of the simulated fishery. The ABIs were computed for each age group in the stock and they were tested to determine whether the correlations with underlying SSB is significant or not.

Table B.2: **Response of indicators from simulated fishery:** The median of time lags (from cross-correlations with SSB) obtained from all iterations of the simulation is presented in the table. The indicators which gave zero or minimum positive lags were determined as useful for predicting the state of the stock.

Scenarios	ABI ($a = a_{max}$)				MFI		LFI		MI		
	CN_a	CW_a	PN_a	PW_a	O_n	O_w	P_n	P_w	MA	ML	MW
10-Growth variability	−2	0	−4	−3	2	2	2	−3	0	2	2
11-Autocorrelated recruitment	3	3	3	4	1	1	3	3	2	2	2
12-Medium sample	2	2	2	2	1	1	2	3	1	1	1
13-Small sample	2	2	2	2	1	1	2	3	1	1	1

Appendix C

Chapter 5

C.1 Additional results

Additional table and figures supporting the results are listed in this section. Table C.1 gives the sensitivity of self starting CUSUM (SS-CUSUM) at optimal performance for the scenarios used in this study. Figure C.1 shows the change in sensitivity and specificity of SS-CUSUM with various catch-based indicators when the control limit (h) was increased from 0 to 6. The winsorizing constant (w) and allowance (k) parameter for SS-CUSUM were fixed in this study and Figure C.2 details the reasoning for this. Figure C.3 & C.4 shows the performance of SS-CUSUM when indicators were computed from catch sample of 100 individuals.

Table C.1: **Sensitivity of SS-CUSUM at optimal performance with various indicators:** The sensitivity values for each indicator are represented as relative proportion of the base case. The base case values are LFI (P_n)=0.703, LFI (P_w)=0.724, Mean Age (MA)=0.738, Mean Length (ML)=0.729 and Mean Weight (MW)=0.727. A medium life span species (LH1, Cod like) with an increasing F scenario was considered as the base case.

Scenarios	P_n	P_w	MA	ML	MW
Increasing F - Base case*	1.000	1.000	1.000	1.000	1.000
Decreasing F	0.924	0.903	0.951	0.932	0.966
Short lived species (LH2)	0.848	0.788	0.825	0.836	0.846
Long lived species (LH3)	0.886	0.879	0.880	0.878	0.881
Small mesh sigmoid selectivity	1.070	1.022	1.016	1.045	1.037
Large mesh sigmoid selectivity	0.842	0.800	0.824	0.838	0.835
Medium mesh dome selectivity	0.992	0.962	0.970	1.003	0.981
Growth vary between cohorts	0.838	0.824	0.832	0.859	0.840
Growth vary within cohorts	0.850	0.794	0.820	0.794	0.847
Autocorrelated recruitment (ρ=0.5)	0.941	0.876	0.874	0.898	0.890
Autocorrelated recruitment (ρ=0.8)	0.948	0.908	0.921	0.924	0.931
Sample (n=1000)	0.994	0.966	1.011	1.018	1.022
Sample (n=100)	1.018	0.988	0.996	1.008	0.995
Sample (n=10)	0.946	0.977	0.953	0.988	0.960

10,000 catch samples (n) of a species with medium life span were used. Growth variability and autocorrelation in recruitment were absent. The fishing gear used has a medium mesh size with sigmoid selectivity.

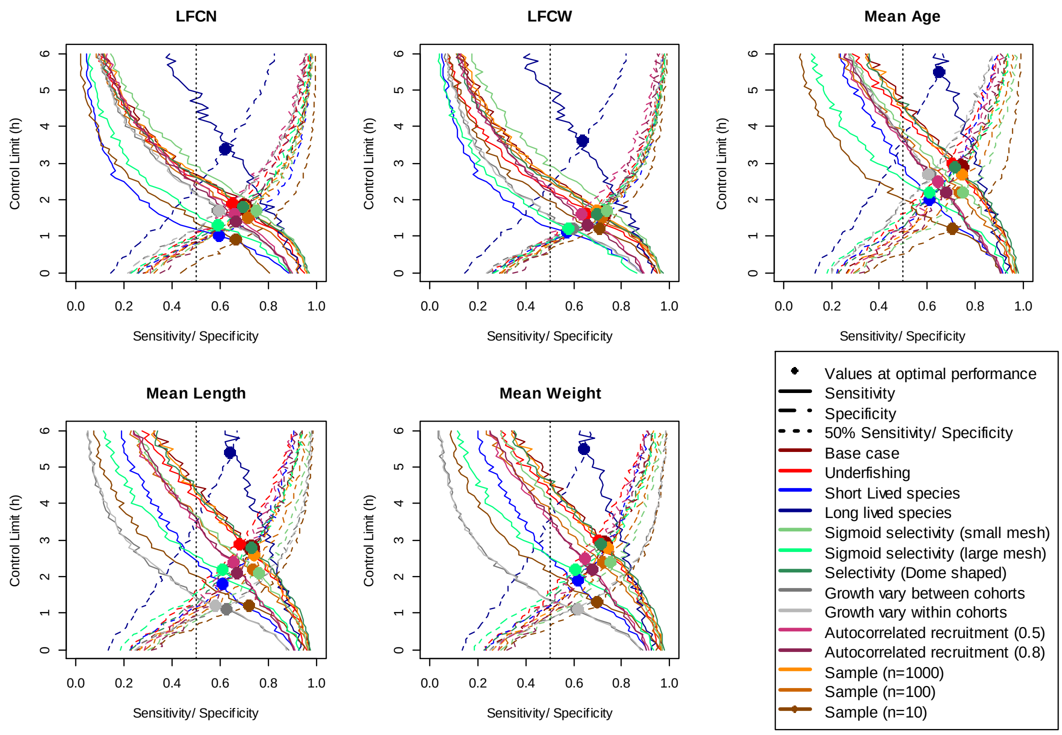
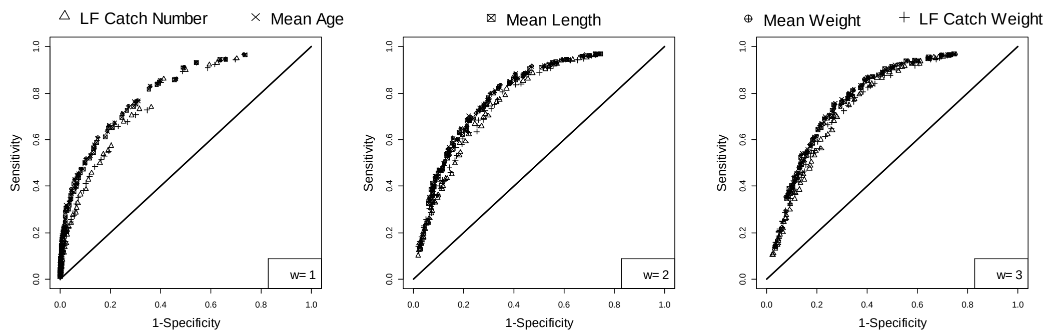
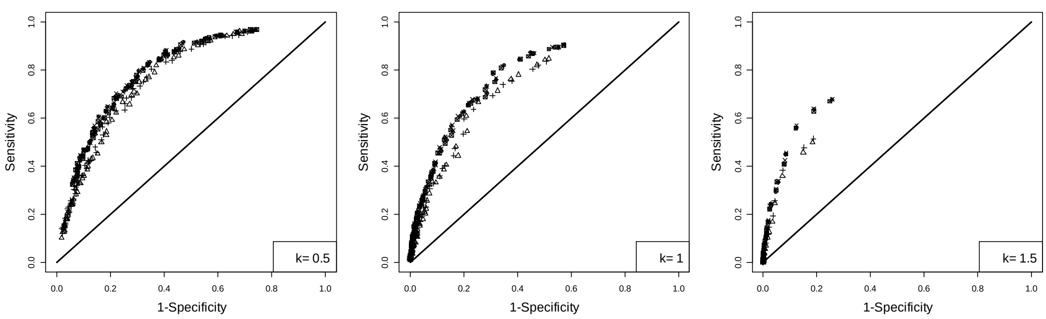


Figure C.1: **Sensitivity and specificity profile of SS-CUSUM from all scenarios:** As the h threshold is increased from 0 to 6, the sensitivity of the method degrades and the specificity increases. The optimal performance is achieved at an h threshold when sensitivity equals specificity. With all indicators, the method achieved optimal performance above 50% sensitivity (or specificity). The two large fish indicators used in the study are P_n and P_w (Table 2.2)



(a)



(b)

Figure C.2: **Effect of w and k parameter on SS-CUSUM performance: a.** The choice of w=2 was used in this study because the loss of performance is very little beyond this value. **b.** SS-CUSUM was approximately 100% sensitive with all catch-based indicators when k=0.5 while only 75% sensitive when k=1.5. A low allowance (k) was important in the present study for proper judgement on control limit (h) since this produced better performance measures with the indicators.

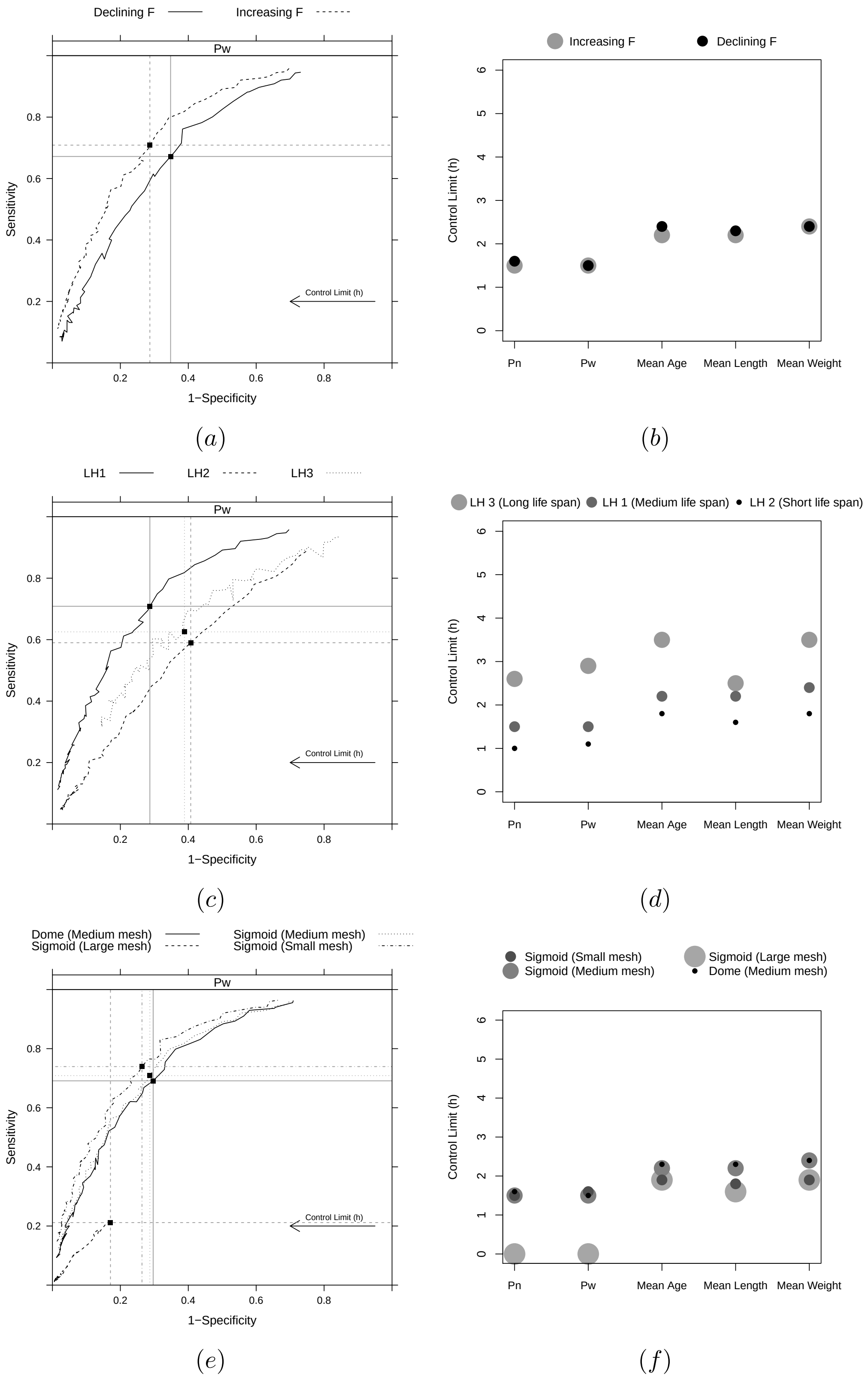


Figure C.3: **SS-CUSUM performance with indicators from 100 fish individuals: (a & b)** type of fishing impact; **(c & d)** life history traits of the species and **(e & f)** selectivity of the fishing gear. **(a,c & e)** are the ROC curves for the P_w indicator. **(b,d & f)** are the control limits at which SS-CUSUM achieved optimal performance.

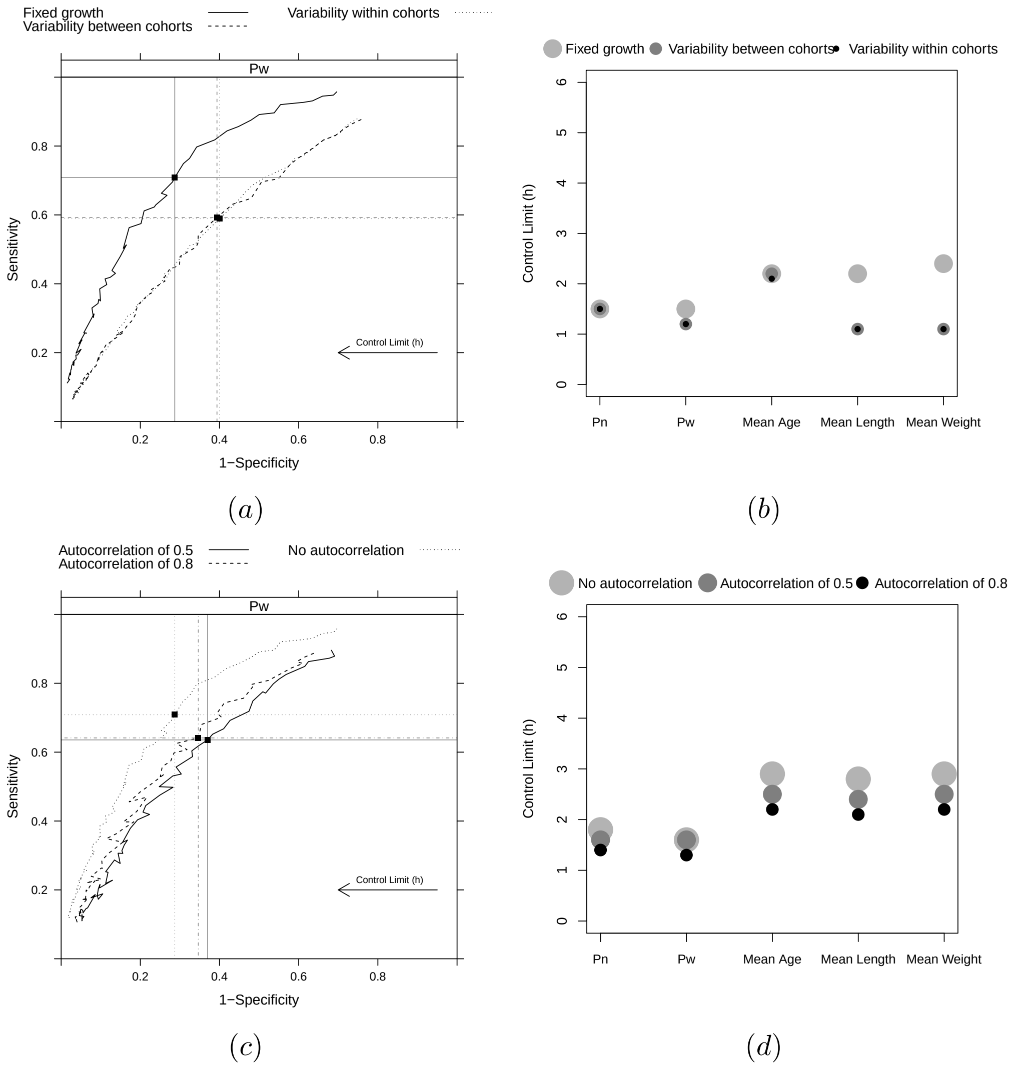


Figure C.4: **SS-CUSUM performance with indicators from 100 fish individuals: (a & b)** type of growth variability and **(c & d)** autocorrelated stock-recruitment. **(a & c)** are the ROC curves for the P_w indicator. **(b & d)** are the control limits at which SS-CUSUM achieved optimal performance.

Appendix D

Chapter 6

D.1 Additional scenarios considered

A total of five additional scenarios (5 to 9) were simulated (Table D.1) and they were based on (i) winsorizing constant (w); (ii) allowance parameter (k); (iii) control limit (h); (iv) selectivity of the fishing gear and (v) type of indicator variability.

The scenarios in 5, 6, and 7 tested the methods with different values for the CUSUM parameters w, k and h. The choice of winsorizing constant w will affect the magnitude of CUSUM values (Section 3.3.4) since it determines how robust the control chart is against outliers in the time series. A low allowance (k) will detect smaller shifts while a higher value will signal bigger shifts (Section 3.3.2). A good estimation method will produce estimates that are robust across a wide range of biomass shift sizes. The signal counters (M, Table 6.1) will depend on the constant used for h (Section 3.3.3) and hence the performances across various estimation methods can be compared to determine whether the choice of h is important for obtaining robust shift size estimates.

To test the effect of various selectivity patterns on the shift size estimates, four types of fishing gears were used in Scenario 8. These are (i) trawl nets with large, medium or small mesh and (ii) gill net with medium mesh. The equations and selectivity parameters used are presented in Section 2.4.2.1. In Scenario 9, three case studies where used where variability was introduced in the indicator using (i) growth variability (Section 2.4.1.3); (ii) autocorrelated stock-recruitment (Section 2.4.1.8) and (iii) observation errors in P_n by reducing the number of catch samples (Figure 2.14). Scenarios 8 & 9 were similar to those applied in chapter 4 and are detailed in section 4.4.2.1.

Table D.1: **Scenarios used for estimating shift size in biomass:** The shaded areas highlight the differences compared to the base case parameters. The K and L_∞ are the growth coefficient and asymptotic length used in von Bertalanffy growth function (Equation 2.4). The ρ is the coefficient of autocorrelation used for simulating the stock-recruitment relationship (Equation 2.13).

Scenarios	Winsorizing constant (w)	Allowance (k)	Control limit (h)	Selectivity function	Indicator variability
Scenario 5	$w = 1$ $w = 2^*$ $w = 3$	$k = 0.5^*$	$h = 1^*$	Logistic (medium mesh)*	No growth variability* Autocorrelation absent* Sample size (n)=10,000*
Scenario 6	$w = 2$	$k = 1$ $k = 1.5$	$h = 1$	Logistic(medium mesh)	No growth variability Autocorrelation absent Sample size (n)=10,000
Scenario 7	$w = 2$	$k = 0.5$	$h = 0$ $h = 2$	Logistic (medium mesh)	No growth variability Autocorrelation absent Sample size(n)=10,000
Scenario 8	$w = 2$	$k = 0.5$	$h = 1$	Logistic (small mesh) Logistic (large mesh) Double-Normal (gill net)	No growth variability Autocorrelation absent Sample size(n)=10,000
Scenario 9	$w = 2$	$k = 0.5$	$h = 1$	Logistic (medium mesh)	K and $L_\infty (cv = 20\%)$ Autocorrelation (ρ)=0.8 Sample size(n)=10

*: Base case scenario

D.2 Additional results

D.2.1 Performance comparison for various CUSUM parameters

Winsorizing constant (w): Results showed that the estimates from method D4 is most accurate for the range of winsorizing constants tested in this scenario. The precision and accuracy of these estimates were improved when $w = 1$ was used (Figure D.2 a,b). The estimates from D5 were inaccurate though useful in terms of their positive bias. The winsorizing constant make the control charts robust to extreme outliers and hence the estimates from D5 became more accurate when w was small.

Allowance (k): When a higher allowance is used, out-of-control situations will be raised for comparatively larger shifts in stock biomass. However, this will also reduce the number of observations available for computing the shift size estimates (only those when $|\theta| > |h|$ are used). Hence a higher allowance reduced the precision of estimates from method D3 and D4 (Figure D.2 c,d). A higher k will also reduce the magnitude of CUSUM values ($|\theta|$) and hence the estimates from method D5 improved in terms of their accuracy (Figure D.2 e,f).

Control limit (h): Increasing the constant of h will decrease the probability of signals due to common cause variability in the indicator that is inherent to the in-control state (see Chapter 3) and hence the precision of the shift size estimates increased (minimum variance, Figure D.3c). This means the shifts were estimated only when a

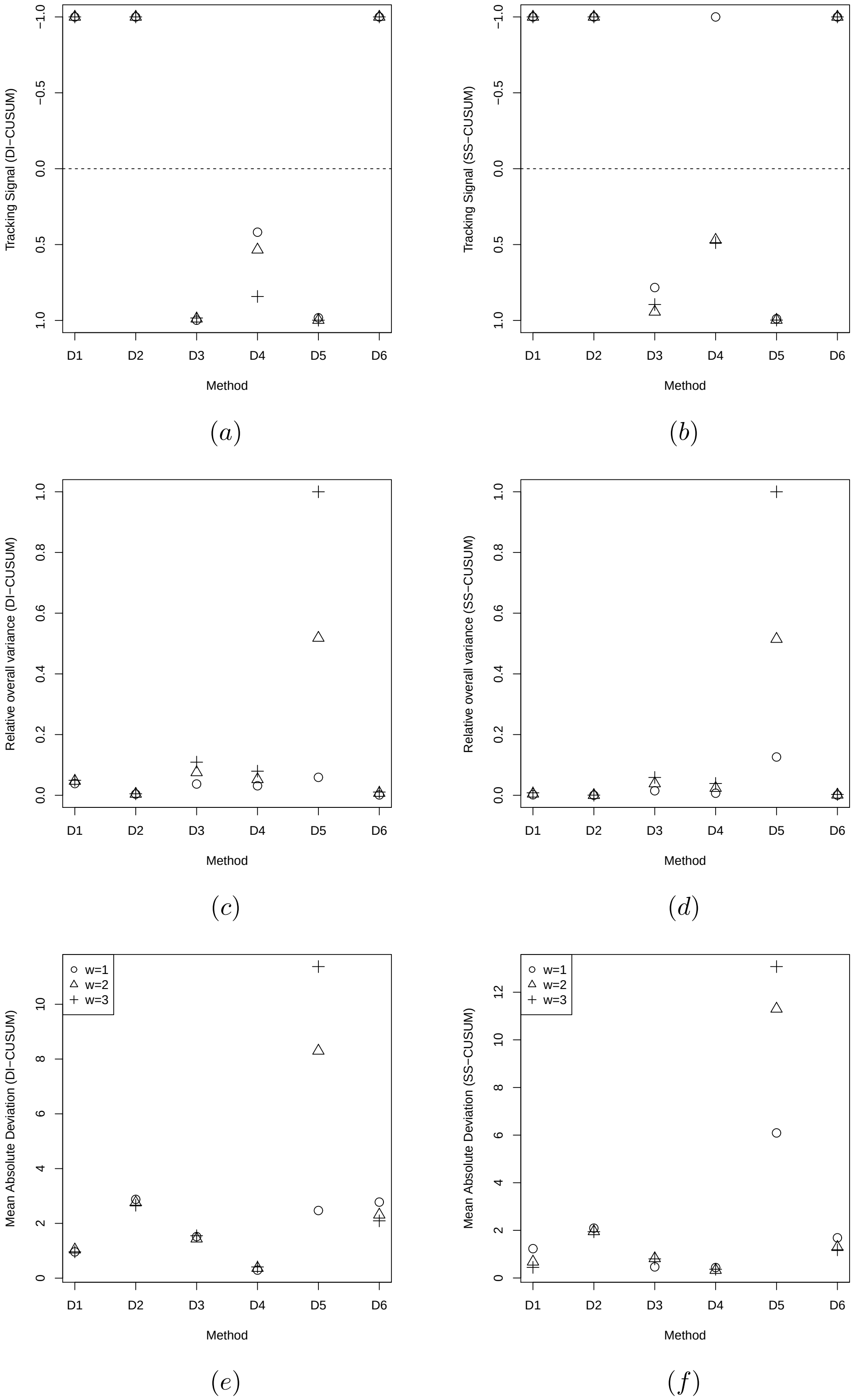


Figure D.1: **Performance comparison for winsorizing constants in CUSUM: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.

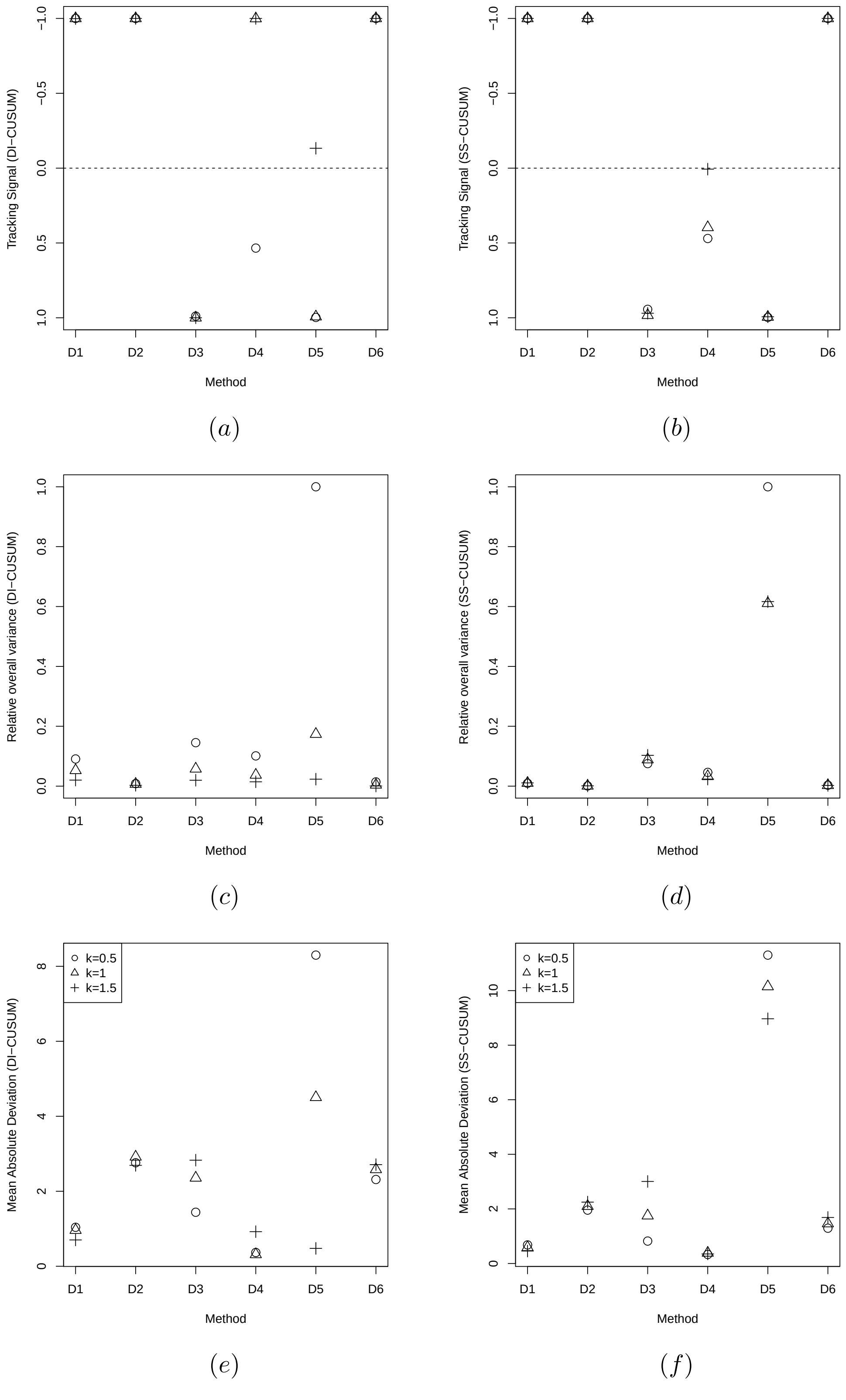


Figure D.2: **Performance comparison for increasing allowance in CUSUM: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.

true shift occurred in the underlying stock biomass. However, the accuracy of shift size estimates decreased as only fewer observations become available for the estimation process (Figure D.3a).

D.2.2 Performance comparison for various selectivity patterns

The performance measures from small, medium and large mesh trawl nets were similar in both CUSUM control charts (Figure D.4). However for the gill net, the estimates from Taguchi's method were more accurate and precise i.e., D1 (Figure D.4). In gill net, only a certain age groups were fully selective to the gear and most of the large mature fish were allowed to escape. Hence the stock biomass will not be depleted as much as in the trawl net fishery. The shift size estimates from Taguchi method were accurate because they are based on the last indicator observation in the time series and are generally small when compared to other methods. Though inaccurate, the shift size estimates from D3 and D4 were positively biased (Figure D.4 a,b) indicating that they are precautionary in nature and Taguchi's method should be preferred only if the selectivity of the fishery is known similar to the gill net.

D.2.3 Performance comparison for indicator variability

If both DI-CUSUM and SS-CUSUM are considered, none of the estimation methods were generally robust to all types of indicator variability. However, the most accurate and reliable estimates were obtained with the D4 method. For all methods except D3 and D4, the precision and accuracy of shift size estimates were affected by autocorrelated stock-recruitment (Figure D.5 c,d,e,f). This is because more false positive signals will be generated indicating an out-of-control situation when the stock is actually in an in-control state.

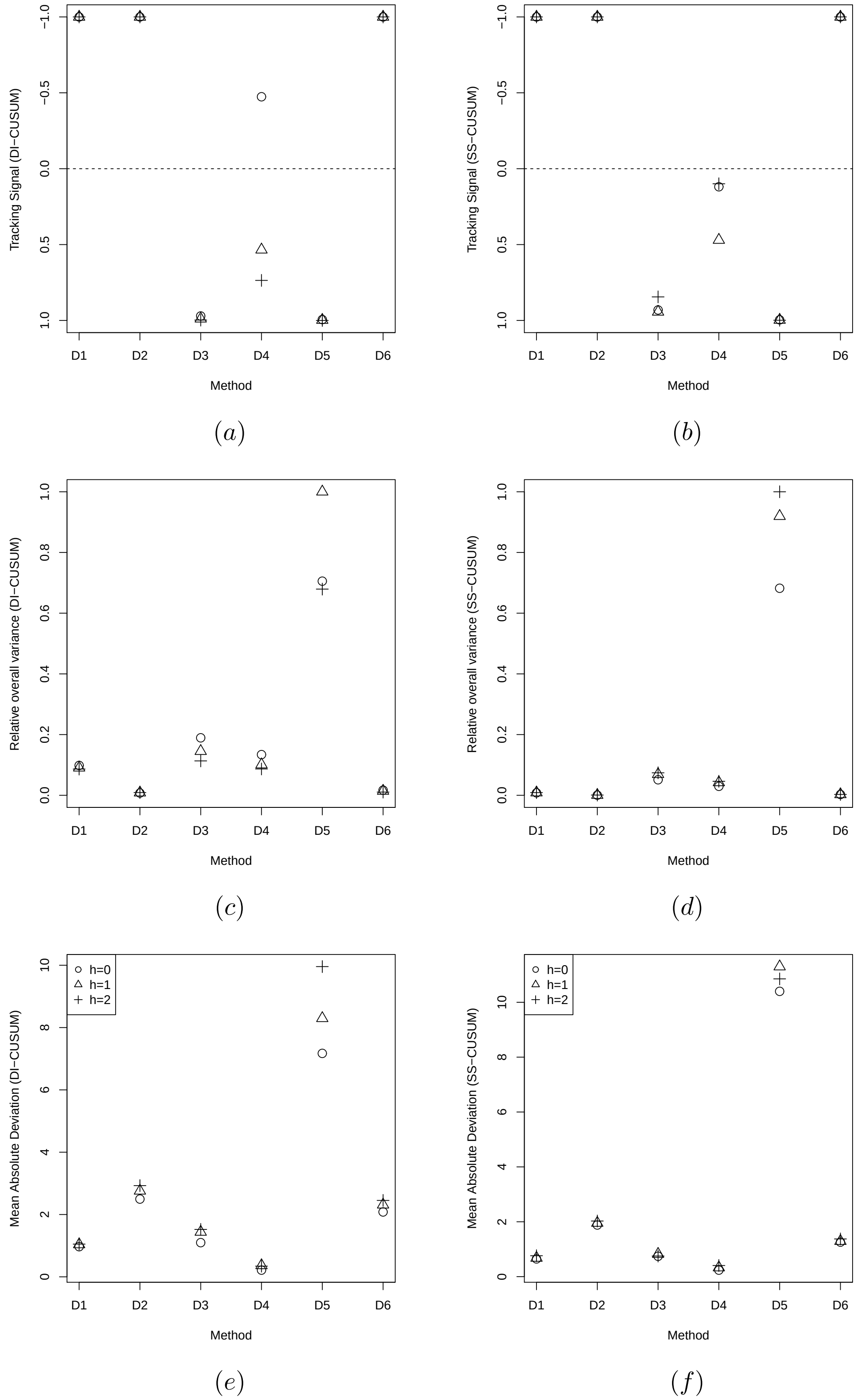


Figure D.3: **Performance comparison for the control limits in CUSUM: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.

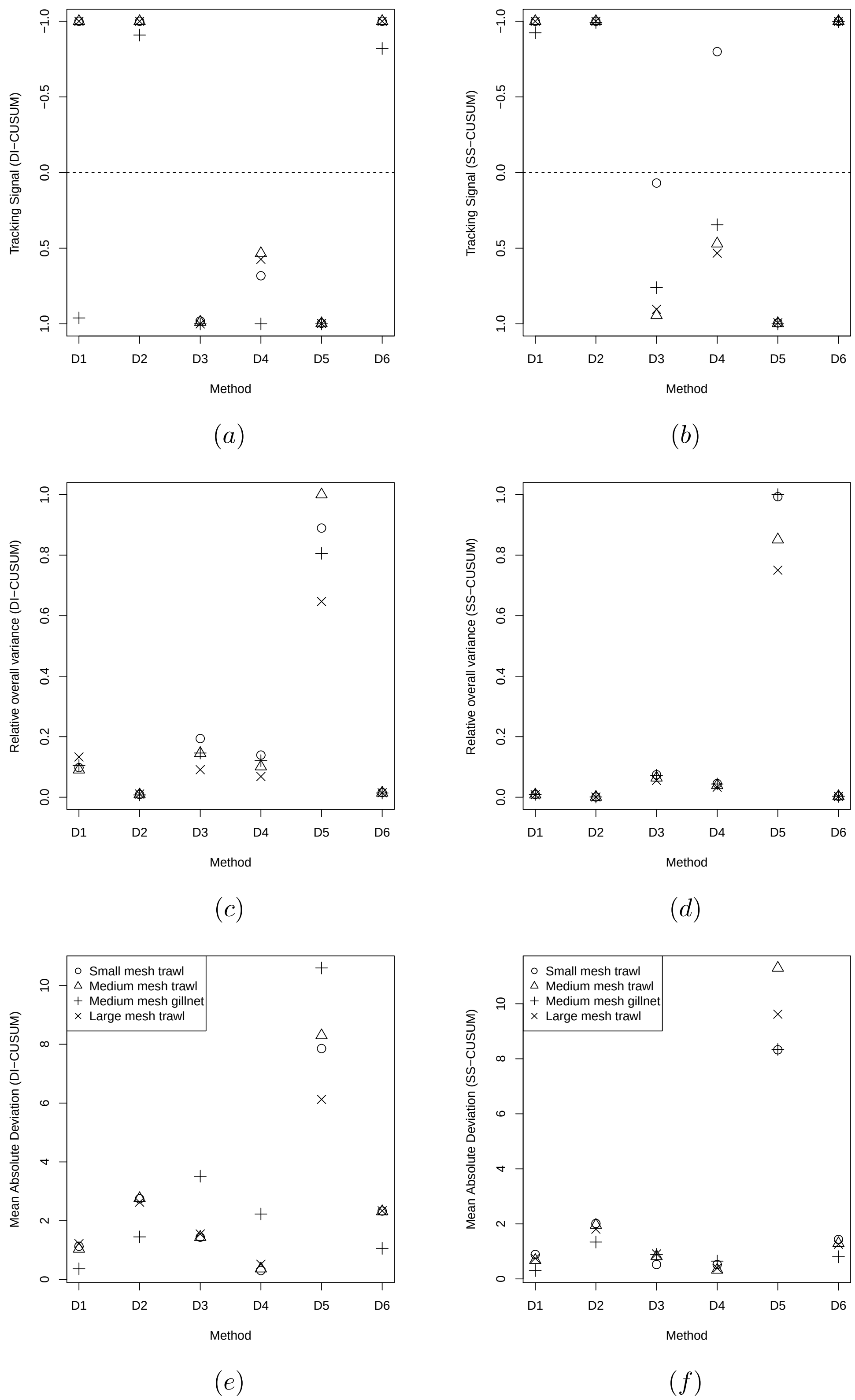


Figure D.4: **Performance comparison for selectivity patterns: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.

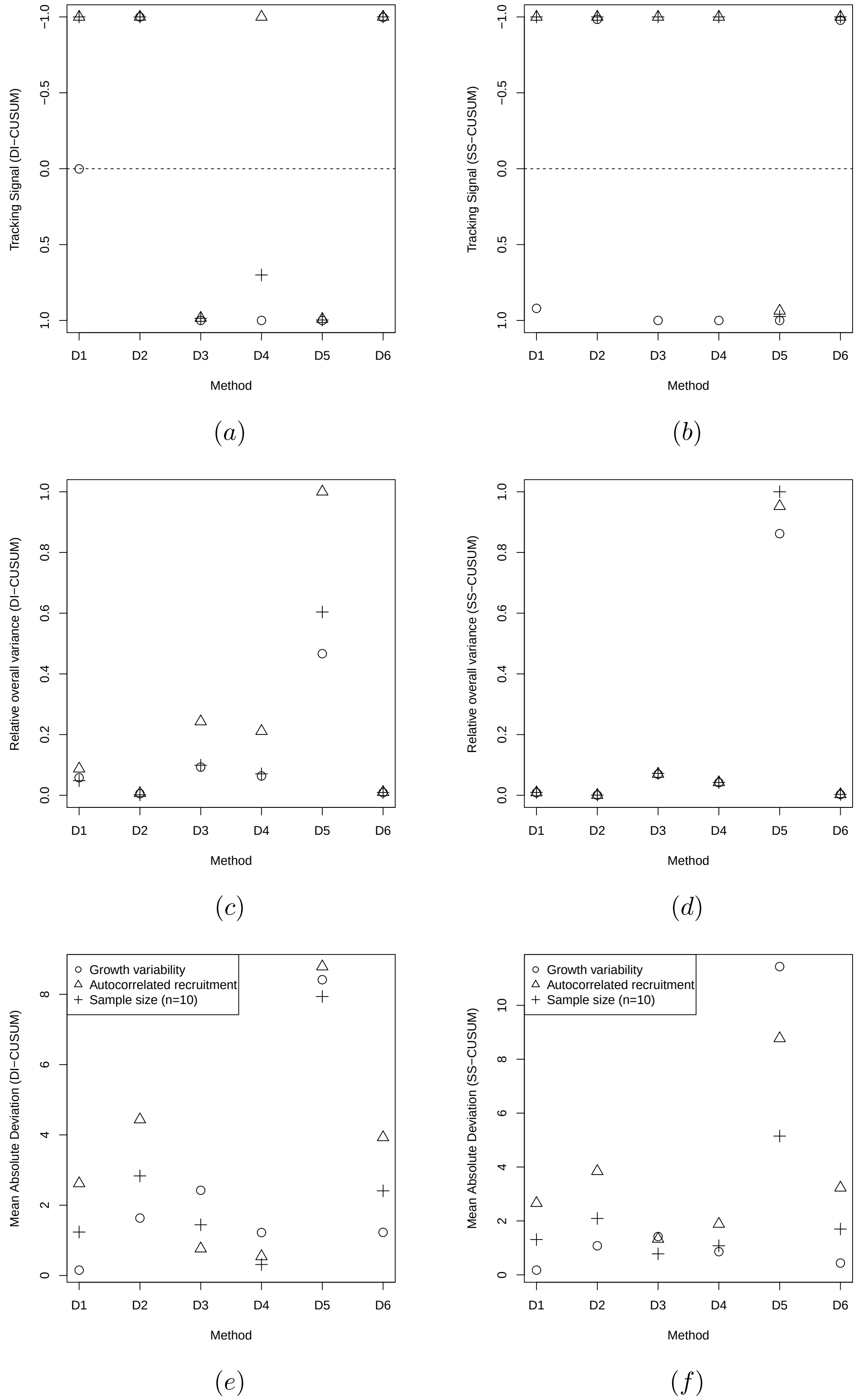
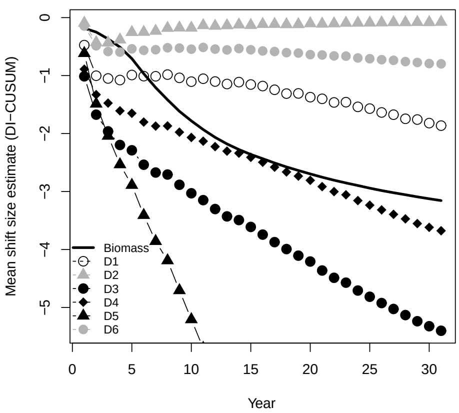
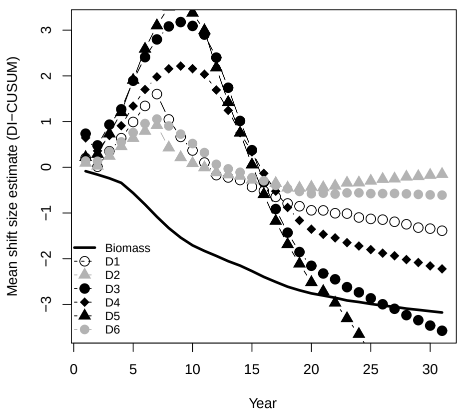


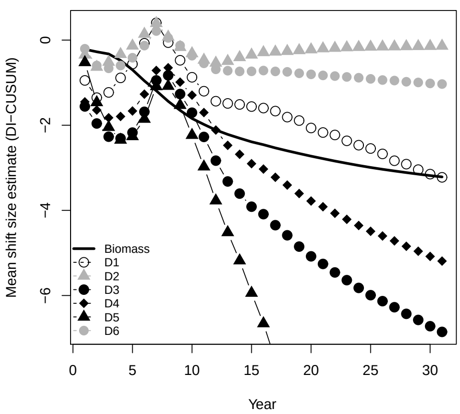
Figure D.5: **Performance comparison for growth variability: (a, c & e)** Shows the bias, precision and accuracy of shift size estimates from DI-CUSUM. **(b, d & f)** Shows the bias, precision and accuracy of shift size estimates from SS-CUSUM.



(a) Recruitment (R)



(b) Large fish indicator (P_n)



(c) Combined indicator(RP_n)

Figure D.6: **Advantage of combining estimated recruitment with the large fish indicator:** The figure shows the mean shift size estimates from a recruitment crash scenario **(a)** for the recruitment indicator (R) **(b)** for the large fish positive proportions indicator (P_n) and **(c)** for the combined indicator (RP_n). The estimated shift sizes were comparatively more accurate for the combined indicator RP_n.

Appendix E

Appendix - Chapter 7

E.1 Additional scenarios considered

A total of seven additional scenarios (6 to 12) were considered for evaluating the performance of the HCR (Table E.1). They were based on the (i) constants used for the control limit (h); (ii) overestimation of control means in DI-CUSUM; (iii) selectivity pattern of the fishing gear; (iv) autocorrelation in recruitment deviates of the stock; (v) observation errors in the estimated recruitment; (vi) observation error in the large fish indicator and (vii) growth variability of the species.

In scenario 7, the performance measures were evaluated for the effect of setting higher constants in h (Table E.1). In chapter 5, it was found that the optimal performances of the control chart (equal trade-off between false positive and negative outcomes) depend on the type of stock indicator and life span of the species. In statistical process adjustment (SPA), the choice of h will depend on the objective function of the control rule. For example, the DI-CUSUM can be configured with h that is more precautionary or optimal for yielding maximum relative average catches.

In the present study, the indicator control mean for DI-CUSUM was set equivalent to the reference point of 90% MSY at fishery equilibrium. However in the real world, the control means could be over or under-estimated. In scenario 8, the performance measures were evaluated for the effect of using an over-estimated control mean (Similarly an under-estimated case is presented in scenario 2 of the main chapter).

Indicators are sensitive to the differences in selectivity pattern of the fishing gear (Shin et al., 2005). Hence in scenario 9, the fishery was simulated for trawl nets with large, medium or small mesh sizes. The trawl net gives a sigmoid shape selectivity following the logistic function (increases with age). Similarly a medium sized mesh gill net fishery was also simulated in which a double-normal function was applied so that

Table E.1: **Additional scenarios considered:** The following table shows the additional scenarios used for the present study (please see table 7.1 for earlier scenarios used in the chapter). The shaded areas highlight the differences compared to the base case parameters.

Scenarios	Control limit (h)	Control mean for DI-CUSUM	Selectivity function	Autocorrelation (σ_r, ρ)	Observation error in R	Sample size (n)	Variability in K and L_∞
Scenario 7	0.0* 0.5 1.0 1.5 2.0	PK*	Logistic (Medium mesh)*	Absent*	$cv = 0.6^*$	10000*	Absent*
Scenario 8	0.0	PK OE by 5% OE by 10% OE by 25% OE by 50%	Logistic (Medium mesh)	Absent	$cv = 0.6$	10000	Absent
Scenario 9	0.0	PK	Logistic (Large mesh) Logistic (Medium mesh) Logistic (Small mesh) Double-Normal (Medium mesh)	Absent	$cv = 0.6$	10000	Absent
Scenario 10	0.0	PK	Logistic (Medium mesh)	Absent $\sigma_r = 0.2, \rho = 0.5$ $\sigma_r = 0.2, \rho = 0.8$ $\sigma_r = 0.6, \rho = 0.5$ $\sigma_r = 0.6, \rho = 0.8$	$cv = 0.6$	10000	Absent
Scenario 11	0.0	PK	Logistic (Medium mesh)	Absent	$cv = 0.2$ $cv = 0.4$ $cv = 0.6$ $cv = 0.8$	10000	Absent
Scenario 12	0.0	PK	Logistic (Medium mesh)	Absent	$cv = 0.6$	10000 1000 100 10	Absent
Scenario 13	0.0	PK	Logistic (Medium mesh)	Absent	$cv = 0.6$	10000	Absent $cv = 0.05$ $cv = 0.10$ $cv = 0.15$ $cv = 0.20$

* : Base case parameters
PK : Perfect Knowledge
cv : Coefficient of variation
σ_r : Recruitment variance
ρ : Coefficient of inter-annual dependency

the vulnerability to fishing increases up to a certain age and then decreases giving a dome shaped selectivity pattern (Equation 2.14 and 2.15).

Previous research has shown evidences for autocorrelation in the stock-recruitment of many fish stocks (Fogarty et al., 2001). In scenario 10, autocorrelation was introduced using an inter-annual dependency coefficient (ρ) in the stock-recruitment relationship describing the dependency of recruitment in a given year with the recruitment of the previous year (Equation 2.13).

In scenarios 11 and 12, the performance measures were evaluated for the effect of observation errors in stock indicators. The observation error in estimated recruitment was implemented using a coefficient of variation of $cv = 0.6$ from the log-normal distribution (Caputi, 1988; Scenario 11, Equation 2.18). In scenario 12, indicator variability due to inefficient sampling was introduced by reducing the number of catch samples. Size based indicators also exhibit variability in response to variations in growth (Willis et al., 1993; Blackwell et al., 2000). In scenario 13, growth variability was introduced by adding random noise errors to the growth parameters K and L_∞ (Equation 2.6 and 2.7) and log-normal errors to the length-weight relationship (Equation 2.8).

E.2 Additional results

E.2.1 Performance comparison for increasing control limits (h)

The present study showed that a higher constant will increase the probability of stock collapse (Figure E.1a). This is similar to the effect observed when the allowance (k) was increased in DI-CUSUM. For higher h constants, the signals are delayed and comparatively larger TAC adjustments are made in the initial year for bringing the stock back to "in-control". Hence a much lower fishing mortality and relative average catch was obtained in the terminal years (Figure E.1c,d). However, the results obtained are dependent on the allowance (k) used in DI-CUSUM. If a higher k is used, then the stock will collapse even if the $h = 0$.

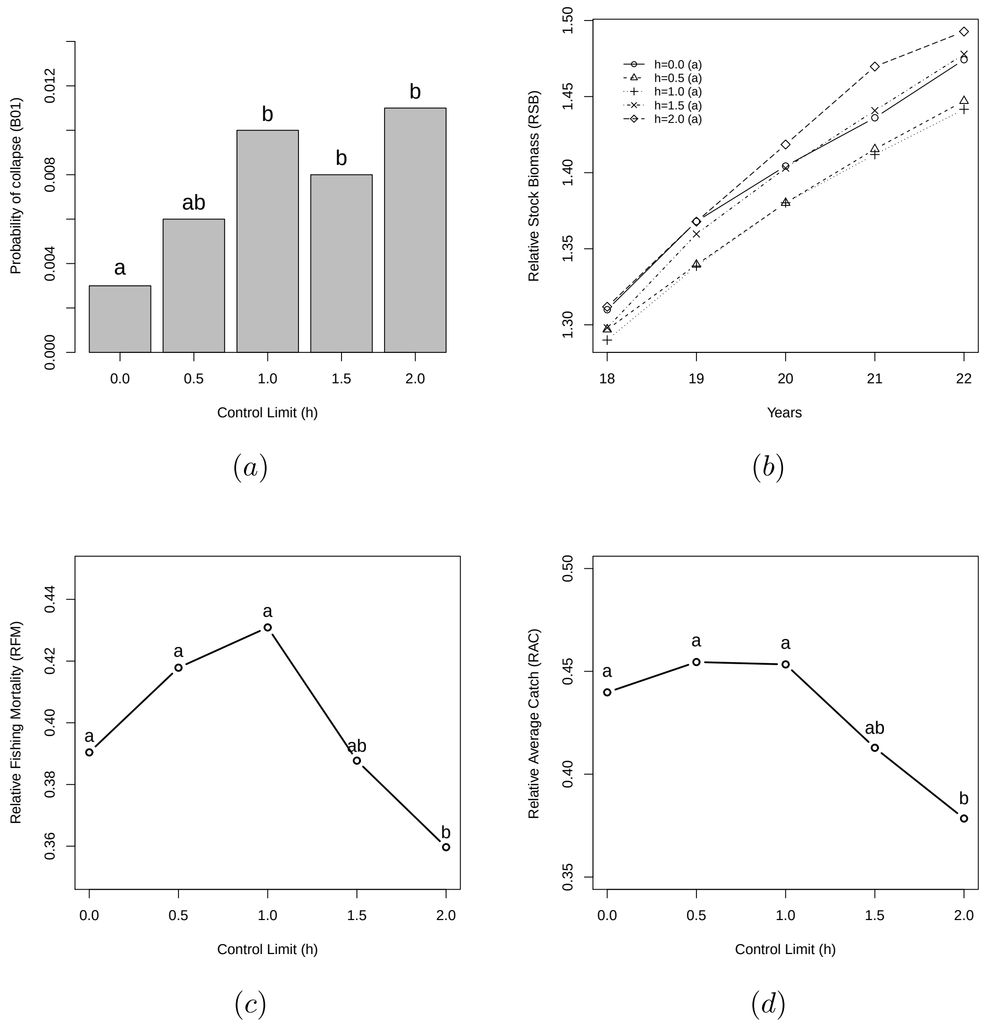


Figure E.1: **Performance comparison for increasing control limits:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

E.2.2 Performance comparison for overestimated control mean

When indicator control mean is overestimated, the implied reference point is shifted above the target of 90% MSY. This means that the control chart will raise alarms until higher recruitment and more large fish individuals are detected in the stock. To achieve this, the stock biomass has to increase by triggering a negative TAC adjustment and hence the performance measures of RFM and RAC decreased significantly when the control means were overestimated (Figure E.2c,d). In the present study, the stocks did not collapsed when the control means were overestimated for above 10% (Figure E.2b). This kind of approximation can be used for managing stocks with the precautionary approach but it may not benefit the fishery in financial or economical terms.

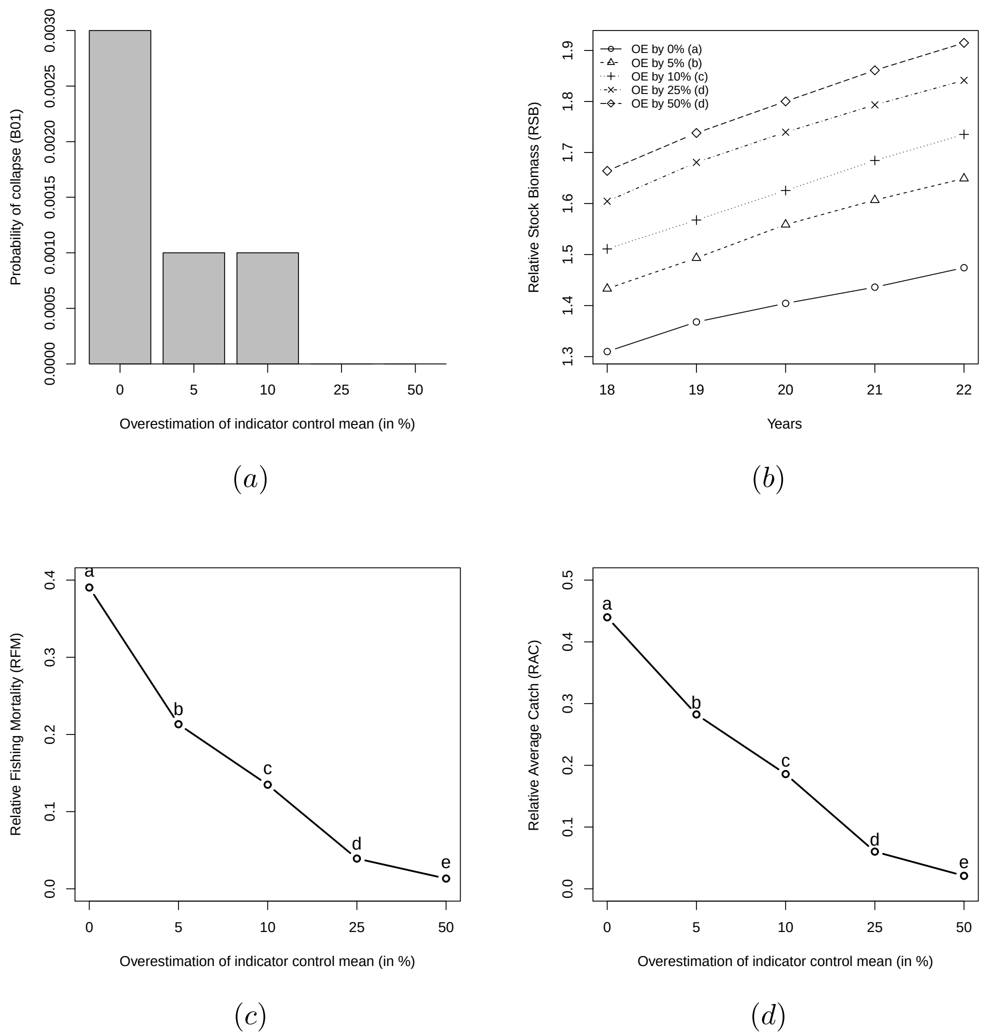


Figure E.2: **Performance comparison for overestimated control mean:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

E.2.3 Performance comparison for selectivity patterns

Results indicate that the probability of stock collapse is significantly higher for the large mesh sized fishing gear (Figure E.3a). This is because only a small proportion of the mature fishes are caught when a fishing gear with large mesh size is used. Hence in such scenarios, the large fish indicator is less likely useful in detecting whether the stock is overfished or not. Results also showed that the relative average catches were significantly different for the trawl and gill net fishery (Figure E.3d). For both fishing gears, the 95% selectivity parameter was set equal for the same age group ($S_{95\%} = 5$) and thus the sensitivity of large fish indicators was not affected. Hence the low average catch for gill net was due to the dome shaped selectivity pattern where only a few large fish individuals are caught (Figure E.3d).

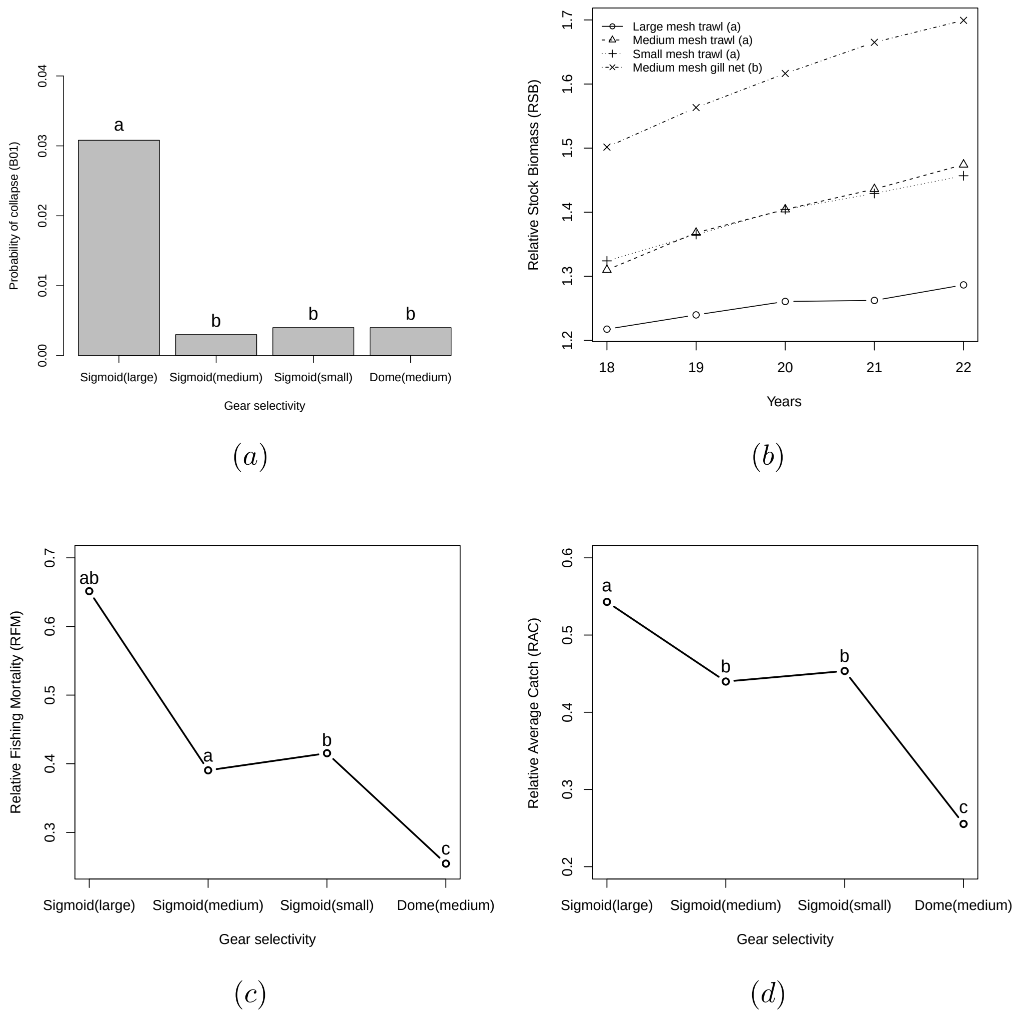
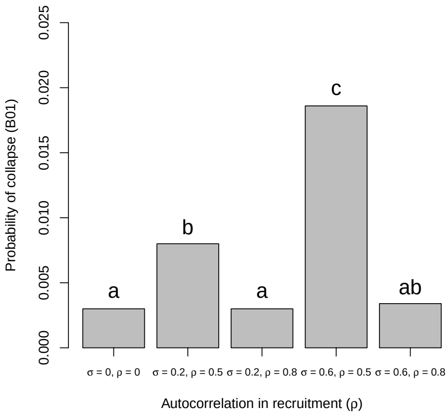


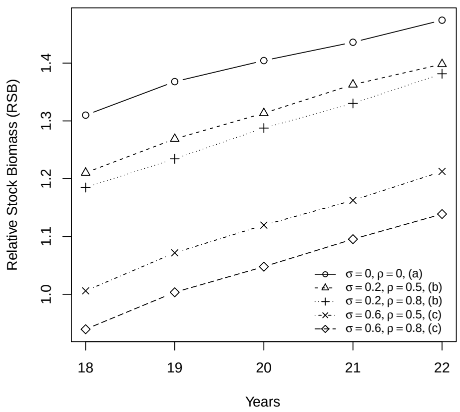
Figure E.3: **Performance comparison for selectivity patterns:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

E.2.4 Performance comparison for autocorrelated stock-recruitment

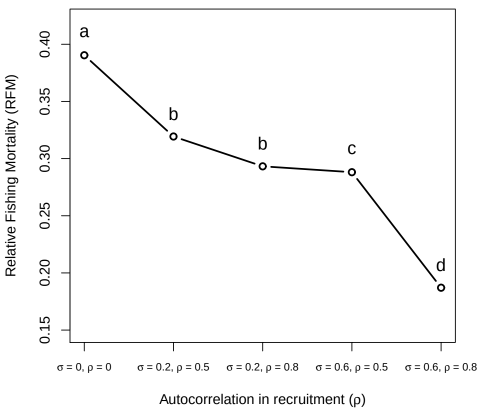
Results indicate two important effects to the performance measures of the HCR. High stochasticity in the recruitment deviates (σ_r) affects the predictability of the indicator. This results in the collapse of the stock if the alarm signals are delayed in the initial years (Figure E.4a,b). But once the stock is back to 'in-control' state, then the increment in catch will correspond to the positive shift in stock biomass. However, the response will be slower if the recruitment is autocorrelated (the number of recruits will be low since the stock is recovering) and hence results in low relative average catch in the terminal years of the projected period (Figure E.4d).



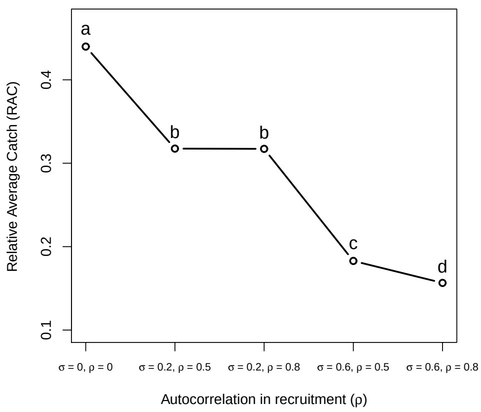
(a)



(b)



(c)



(d)

Figure E.4: **Performance comparison for autocorrelated stock-recruitment:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

E.2.5 Performance comparison for observation errors in recruitment

When the error in estimated recruitment is high, two things can go wrong. The out-of-control situations may not be signalled in the initial year and that eventually results in a stock collapse (Figure E.5a). But if the stock is back to the 'in-control' state, then the HCR will update TAC with positive shift size estimates due to the increase in stock biomass. But a higher relative average catch was observed with more observation errors in the estimated recruitment (Figure E.5c,d). This is because the TAC will keep increasing unless a bad recruitment is properly detected. For observations more than $cv = 0.6$, all performance measures were significantly affected (Figure E.5).

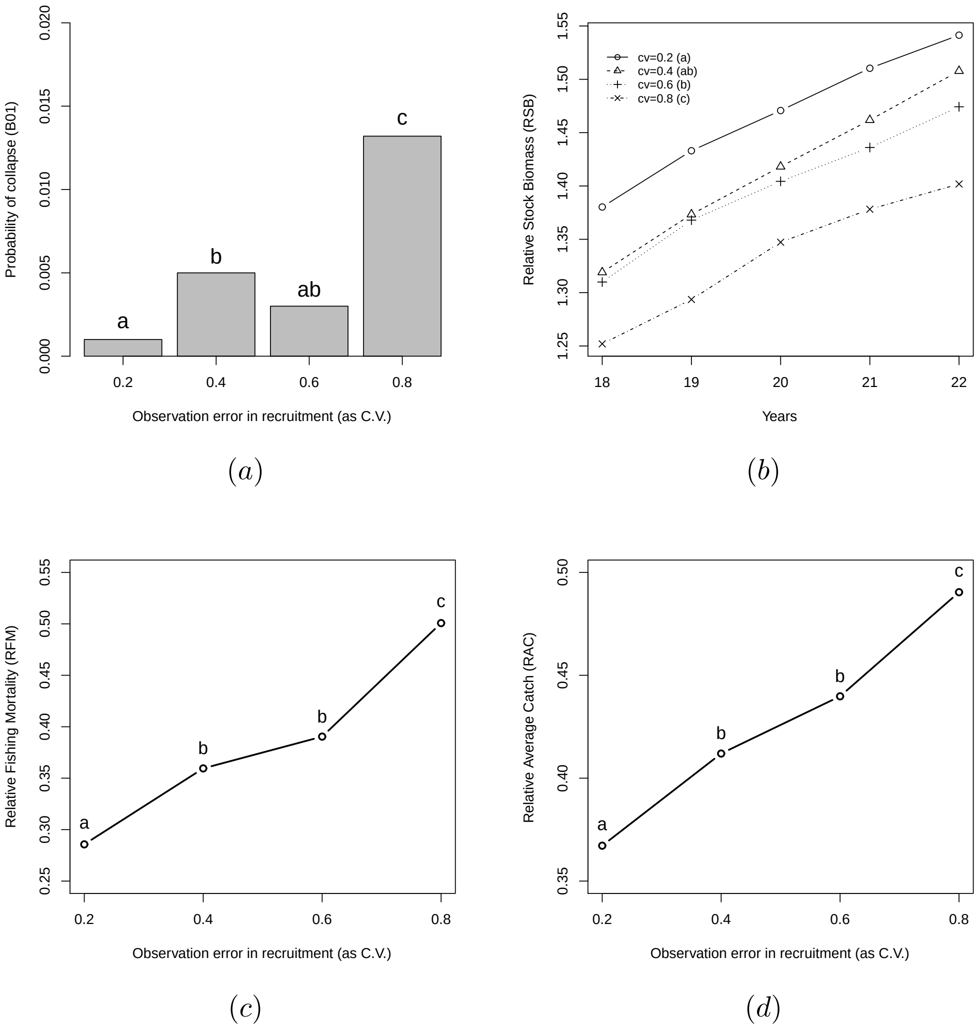


Figure E.5: **Performance comparison for observation errors in recruitment:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

E.2.6 Performance comparison for observation errors in LFI

The management procedure based on DI-CUSUM is most useful for stocks that are data limited or poor. Hence it is important have robust performances with small number of catch samples. Results indicate that the RSB and RFM are robust across the range of catch samples used in the present study since there are no significant difference between the groups (Figure E.6c). However, the probability of stock collapse indicates a significant increase in risk for catch samples with less than 1000 individuals (Figure E.6 a,b).

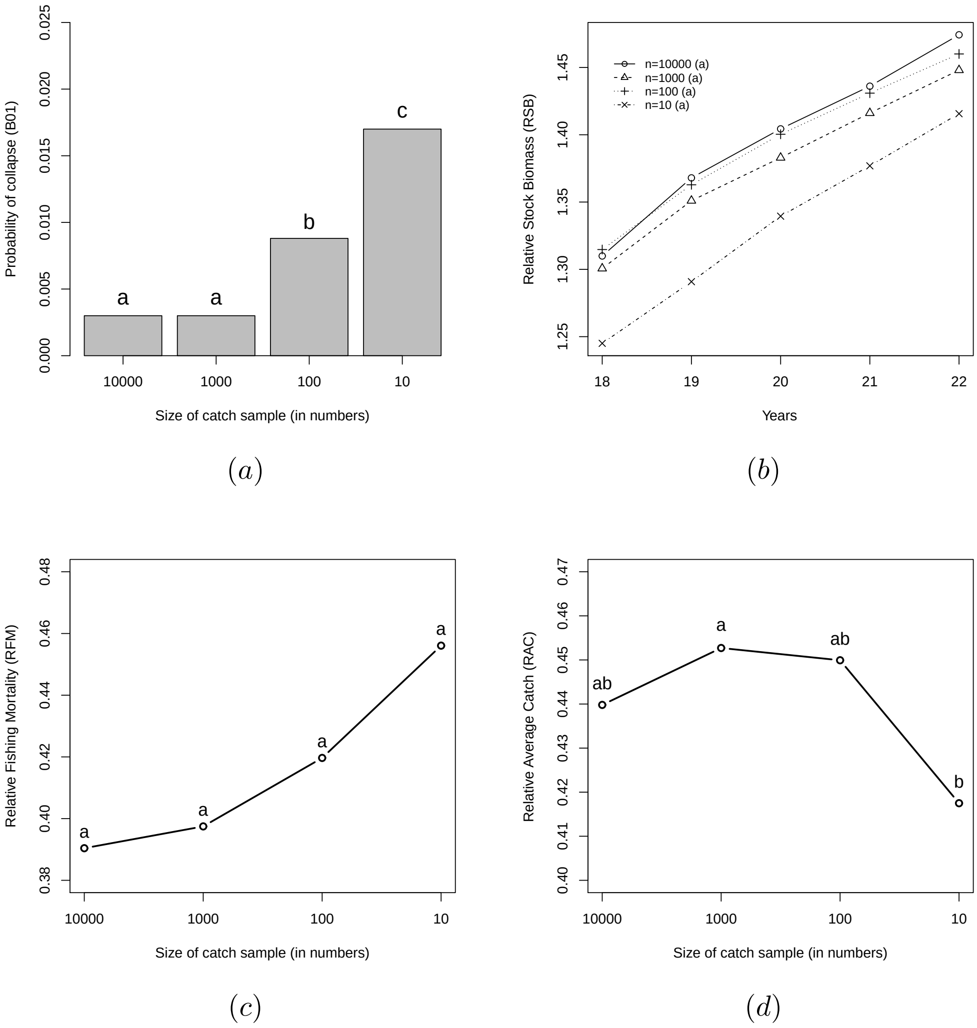
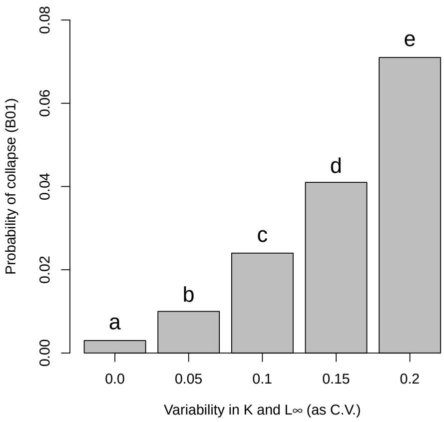


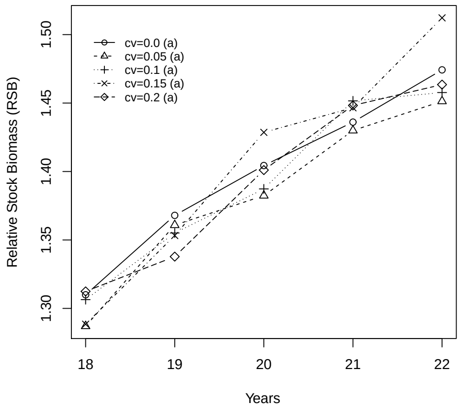
Figure E.6: **Performance comparison for observation errors in LFI:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

E.2.7 Performance comparison for growth variability

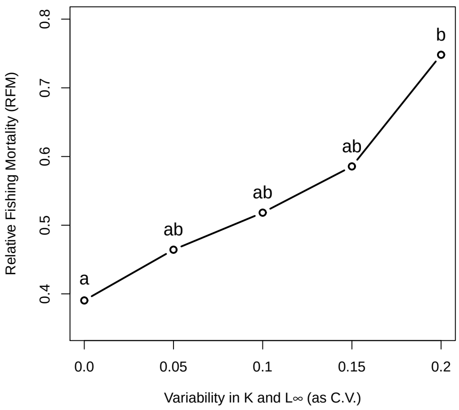
Performance measures indicate that the probability of stock collapse increase significantly with higher growth variability (Figure E.7a). However, there was no significant difference between groups for the performance measures of RSB and RAC (Figure E.7d). This indicates that for certain cases, the fish stock collapsed due to the failure in obtaining out-of-control signals in the initial year. Hence for stocks with high growth variability, a viable option is to choose indicators based on catch numbers or age. In chapter 5, the sensitivity and specificity for detecting out-of-control situations were found to be better for such stock indicators.



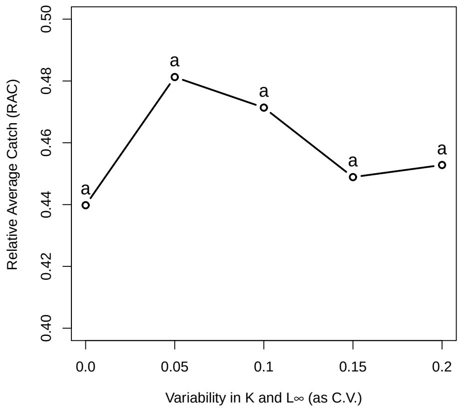
(*a*)



(*b*)



(*c*)



(*d*)

Figure E.7: **Performance comparison for growth variability:** The figure shows **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC) from the terminal years of the projection period.

Appendix F

Appendix - Chapter 8

F.1 Additional scenarios considered

The objective of the present study was to sustain the initial state of the fish stock using harvest control rules (HCRs) based on self-starting cumulative sum (SS-CUSUM) control chart. A total of seven additional scenarios (6 to 12) were considered in this study for evaluating the performance of HCR (Table F.1). They were based on the (i) constants used for inter-annual TAC restriction (TAC_r); (ii) selectivity pattern of the fishing gear; (iii) autocorrelation in stock-recruitment deviates; (iv) growth variability of the species; (v) observation errors in the estimated recruitment; (vi) observation errors in the large fish indicator and (vii) constants used for the control limit (h).

In scenario 6, the performance measures were evaluated for the effect of setting higher constants in the inter-annual TAC restriction (TAC_r). The TAC_r are useful for avoiding boom or bust fisheries because of the range of shift size estimates obtained from methods D1 to D6 were large (see Chapter 6). However, the objective of the present study was to sustain the initial state of the fish stock and hence only small biomass shifts are expected. But if the running means are under- or over-estimated, then these constants may have significant effects on the HCR performance.

The description and reasoning behind all remaining scenarios in the present study are explained in Chapter 7 (Scenarios 7-12, Section E.1).

Table F.1: **Additional scenarios considered:** The following table shows the additional scenarios used for the present study (please see Table 8.2 for earlier scenarios used in the chapter). The shaded areas highlight the differences compared to the base case parameters.

Scenarios	TAC restriction	Selectivity function	Autocorrelation (σ_r, ρ)	Variability in K and L_∞	Observation error in R	Sample size (n)	Control limit (h)
Scenario 6	$TAC_r = 10\%^*$ $TAC_r = 20\%$ $TAC_r = 30\%$ $TAC_r = 40\%$ $TAC_r = 50\%$	Logistic (Medium mesh)*	Absent*	Absent*	$cv = 0.6^*$	10000*	0.0^*
Scenario 7	$TAC_r = 10\%$	Logistic (Large mesh) Logistic (Medium mesh) Logistic (Small mesh) Double-Normal (Medium)	Absent	Absent	$cv = 0.6$	10000	0.0
Scenario 8	$TAC_r = 10\%$	Logistic (Medium mesh)	Absent $\sigma_r = 0.2, \rho = 0.5$ $\sigma_r = 0.2, \rho = 0.8$ $\sigma_r = 0.6, \rho = 0.5$ $\sigma_r = 0.6, \rho = 0.8$	Absent	$cv = 0.6$	10000	0.0
Scenario 9	$TAC_r = 10\%$	Logistic (Medium mesh)	Absent	Absent $cv = 0.05$ $cv = 0.10$ $cv = 0.15$ $cv = 0.20$	$cv = 0.6$	10000	0.0
Scenario 10	$TAC_r = 10\%$	Logistic (Medium mesh)	Absent	Absent	$cv = 0.2$ $cv = 0.4$ $cv = 0.6$ $cv = 0.8$	10000	0.0
Scenario 11	$TAC_r = 10\%$	Logistic (Medium mesh)	Absent	Absent	$cv = 0.6$	10000 1000 100 10	0.0
Scenario 12	$TAC_r = 10\%$	Logistic (Medium mesh)	Absent	Absent	$cv = 0.6$	10000	0.0 0.5 1.0 1.5 2.0

* : Base case parameters
PK : Perfect Knowledge
cv : Coefficient of variation
σ_r : Recruitment variance
ρ : Coefficient of inter-annual dependency

F.2 Additional results

F.2.1 Performance comparison for relaxing TAC restrictions (TAC_r)

Results indicate that relaxing TAC restrictions will increase the probability of stock collapse (Figure F.1a). This was expected because it is not precautionary to blindly follow a positive alarm signal if the running means are underestimated. Hence, the relative average catch declined when TAC_r was configured with higher constants (Figure F.1d). Results also indicated that the relative fishing mortality (RFM) reduced when TAC restrictions were 30% and above. It shows that the probability of getting an over-estimated running mean is higher than achieving an under-estimated case for large constants in TAC_r. Once the catch is reduced due to a negative signal (which is likely to raise in initial years due to the rule configured for in-control situations), the stock will take longer to reach its initial state of fishery since the restrictions are placed in terms of percentages. And as a result, the running mean will eventually adapt to an over-estimated value due to higher recruitment and large fish in the population.

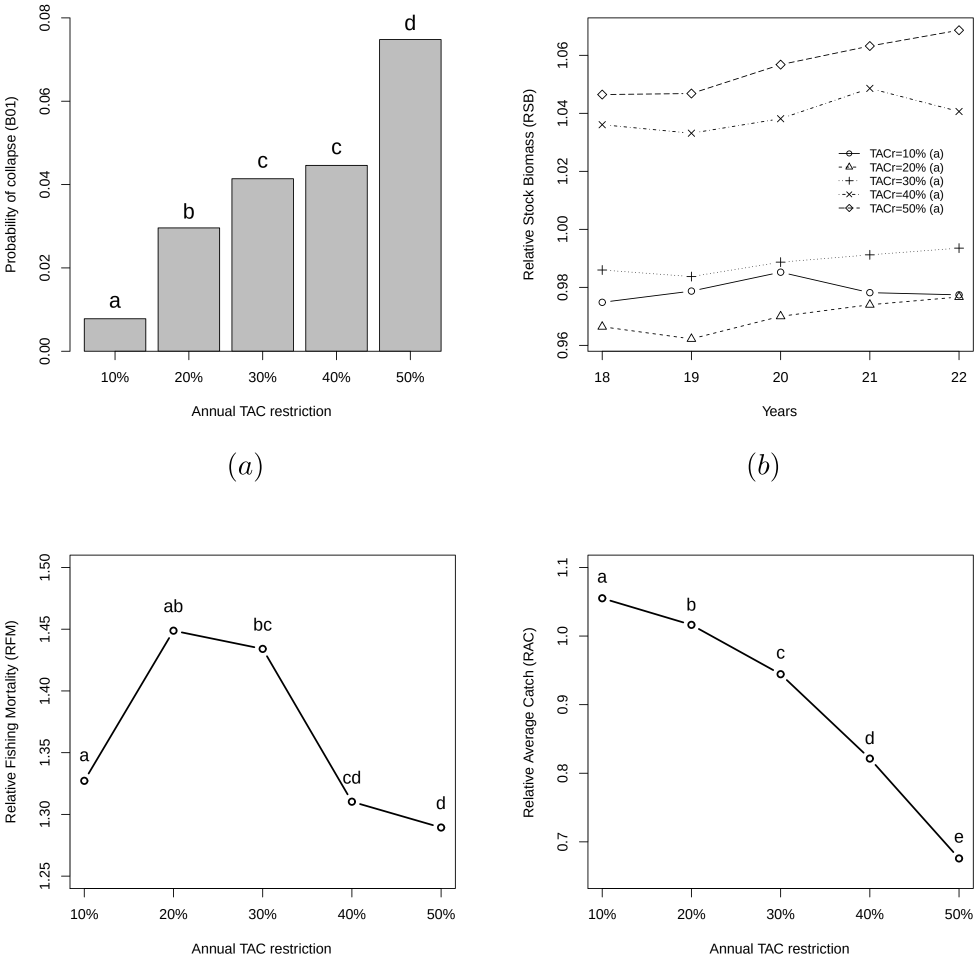


Figure F.1: **Performance comparison for relaxing TAC restrictions (TAC_r): (a)** the probability of collapse (B01) **(b)** the relative stock biomass (RSB) **(c)** the relative fishing mortality (RFM) and **(d)** the relative average catch (RAC) from the terminal years of the projection period. The same letters in the plots indicate no significant difference between each other at $p \leq 0.001$.

F.2.2 Gear selectivity

Results indicate no significant differences in the probability of stock collapse between fishing gears with different selectivity patterns (Figure F.2a). However, the relative stock biomass, average fishing mortality and catches were significantly different for gill nets (Figure F.2b,c,d). This is similar to the effect observed in chapter 7 (Section E) where only a few large fish are caught in the gill net due to the dome shaped selectivity pattern. In chapter 5, it was found the large fish indicator from a large mesh fishing gear is less likely useful in detecting whether the stock is getting overfished or not. However for the present study, the initial state of the fishery was well below the MSY and hence no significant difference was observed in the performance measures when compared to the base case (Figure F.2).

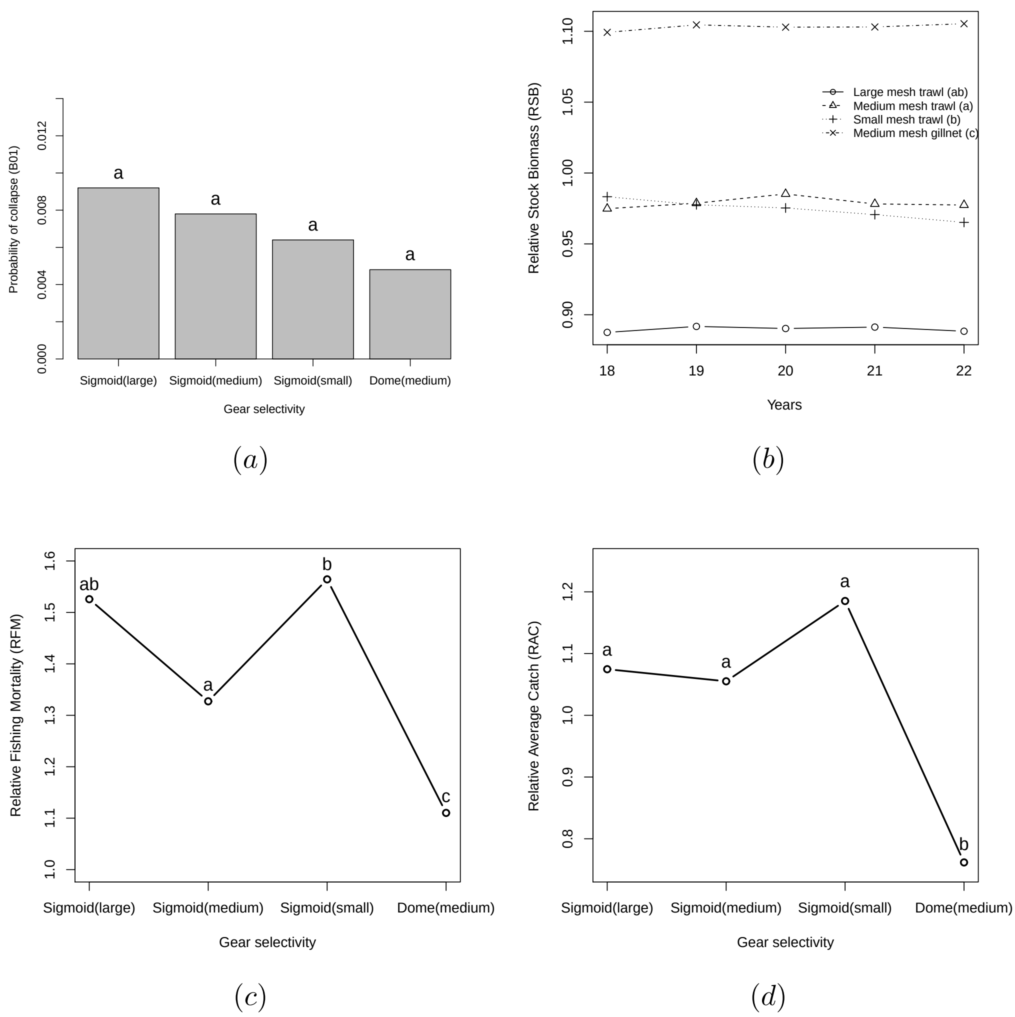


Figure F.2: **Performance comparison for selectivity patterns: (a)** the probability of collapse (B01) **(b)** the relative stock biomass (RSB) **(c)** the relative fishing mortality (RFM) and **(d)** the relative average catch (RAC).

F.2.3 Autocorrelated recruitment

When stock-recruitment is autocorrelated, gradual and short term trends will appear in the age groups of the stock. If recruitment is substantially lower in the initial years (compared to the state of stock), then this may end up in an under-estimated running mean depending on the underlying trend over the projected years. Positive autocorrelation results in delayed signals from SS-CUSUM and increases the rate of false alarms (Hawkins and Olwell, 1998). Results from the present study shows significant effects on performance measures with higher autocorrelation and stochasticity in the recruitment deviates (Figure F.3). This is similar to the effect observed in chapter 7 (Section E).

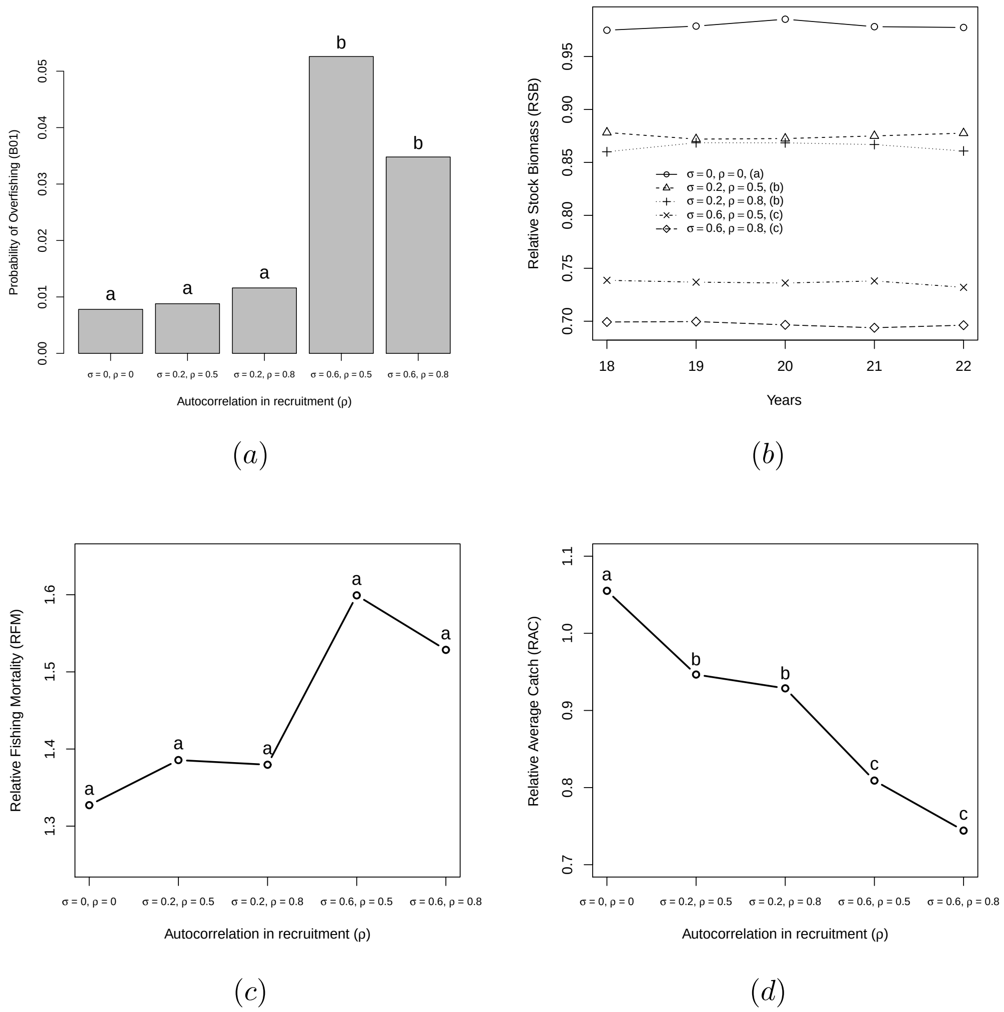


Figure F.3: **Performance comparison for autocorrelated stock-recruitment:** **(a)** the probability of collapse (B01) **(b)** the relative stock biomass (RSB) **(c)** the relative fishing mortality (RFM) and **(d)** the relative average catch (RAC).

F.2.4 Performance measures for scenarios 9-12

Scenarios 9 to 12 showed no significant differences between the groups in terms of achieving the relative stock biomass (RSB), fishing mortality (RFM) and average catches (RAC). These scenarios are based on higher growth variability (Figure F.4), observation errors in stock indicators (Figure F.5 and F.6) and control limits in SS-CUSUM (Figure F.7).

The probability of stock collapse was significantly higher when growth variability was more than $cv > 0.1$ for the K and L_∞ parameters (Figure F.4). In the present study, the large fish indicator was based on the proportions of catch weight and hence a higher growth variability may affect the sensitivity of such indicators.

The proposed harvest control rule showed that they are robust to observation errors

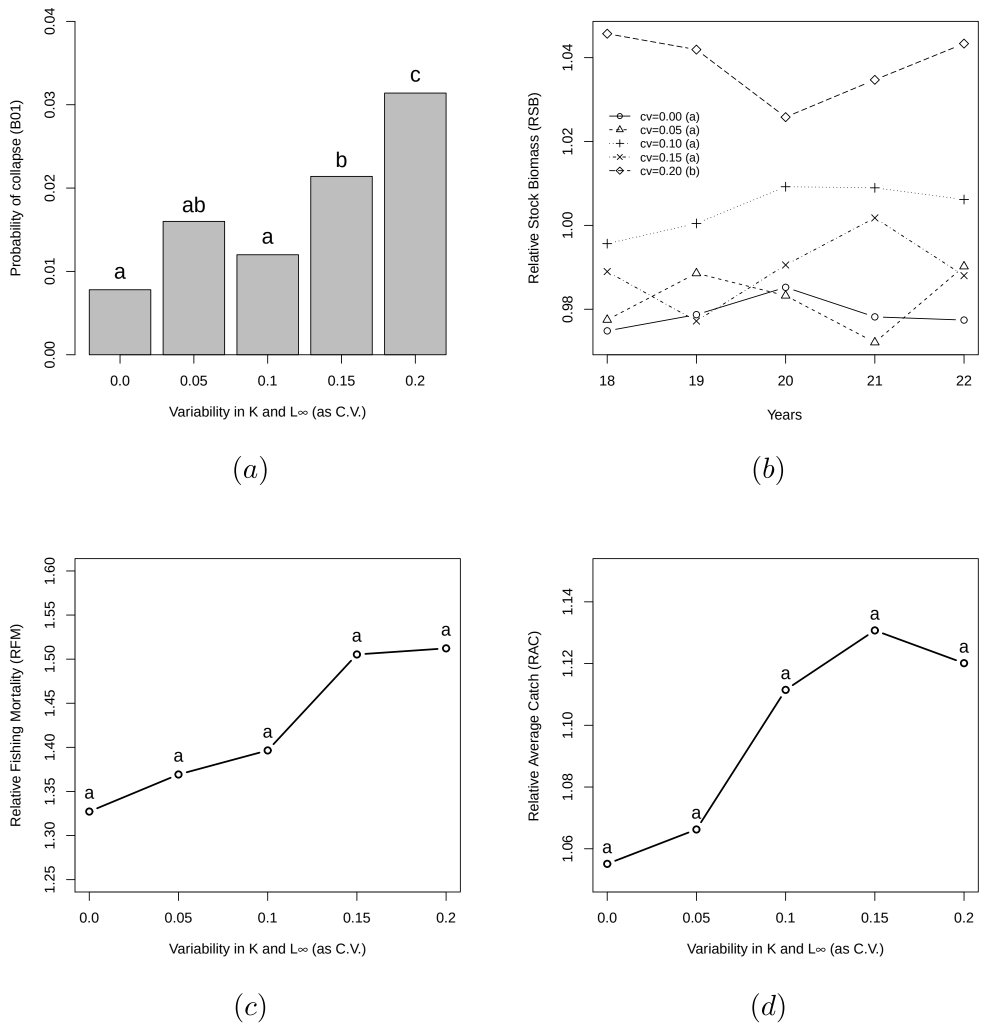


Figure F.4: **Performance comparison for growth variability: (a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC).

in the stock indicators. Recruitment to the fish stock is inherently noisy and are influenced by various environmental factors (Campana, 1996; Jenkins, 2005; Jenkins and King, 2006). Recruitment abundance of fish populations are estimated through fishery independent research surveys and such estimates are likely exposed to large variations due to measurement error or non-standardized statistical techniques (Dingsør, 2005). Results from the present study showed no significant differences in their performances for the noise introduced in the recruitment estimates (Figure F.5).

In a data poor situation, it is likely to have limited catch from the commercial fishing vessels. Results showed that the performances are not affected if the sample size is too small given that they are randomly selected. However, it will be challenging to obtain a true random sample in real world if only a few fish samples are available. Added to that, the performances may also be affected if there are consistent discards of a certain component in the commercial catch i.e., based on size or age group (Myers

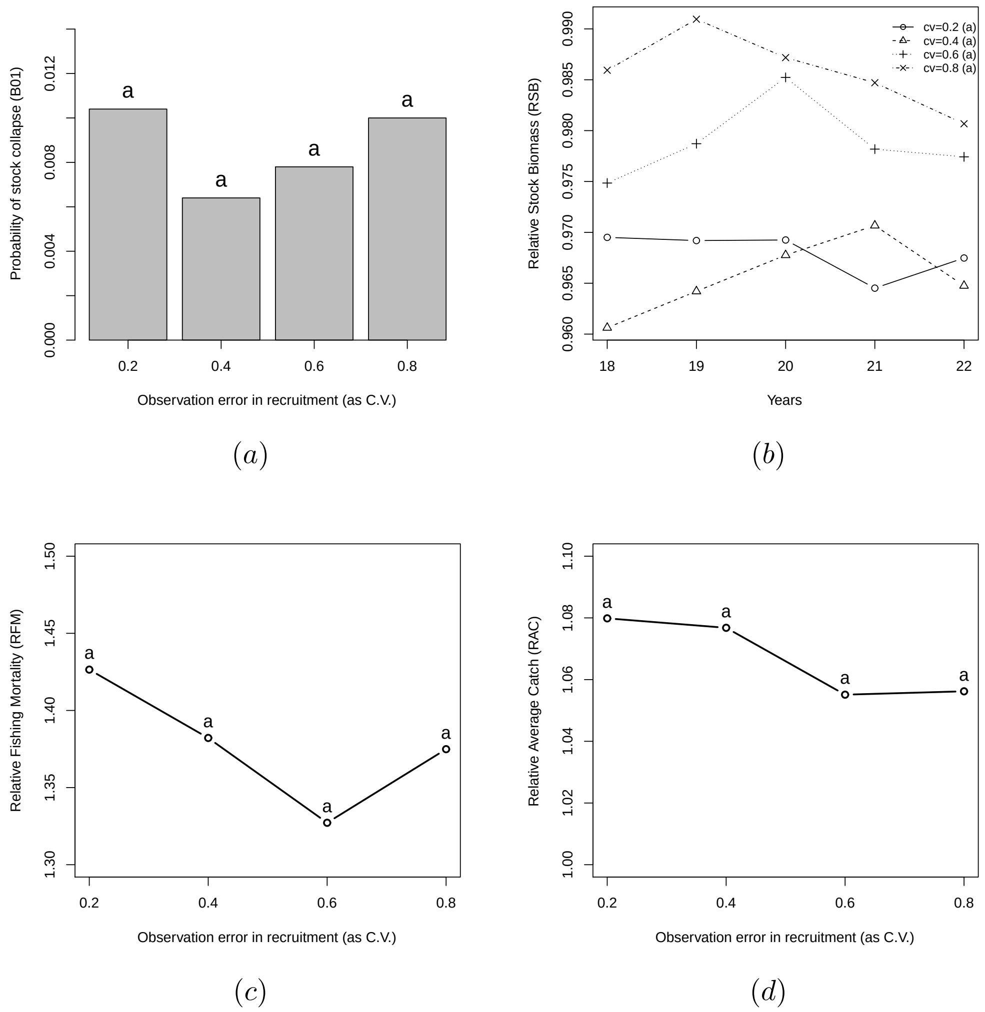


Figure F.5: **Performance comparison for observation errors in recruitment:** **(a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC).

et al., 1997; Borges et al., 2005). If juvenile or young fish are discarded consistently, this will affect the trend in the large fish indicator indicating more mature and adult fishes in the stock.

In scenario 12, the performances were measured for increasing constants of control limit. Results indicated that the probability of stock collapse decreased until $h = 1$ and then increased further. But, there was no significant effect on other performance measures in this scenario. This simply shows that the optimal performance (trade-off between false positive and negative signals) of SS-CUSUM was achieved when $h = 1$. As discussed in the previous chapter, the allowance and control limits in CUSUM charts act like the coarse and fine adjustment knobs of a microscope which can be optimized to obtain the required sensitivity and specificity.

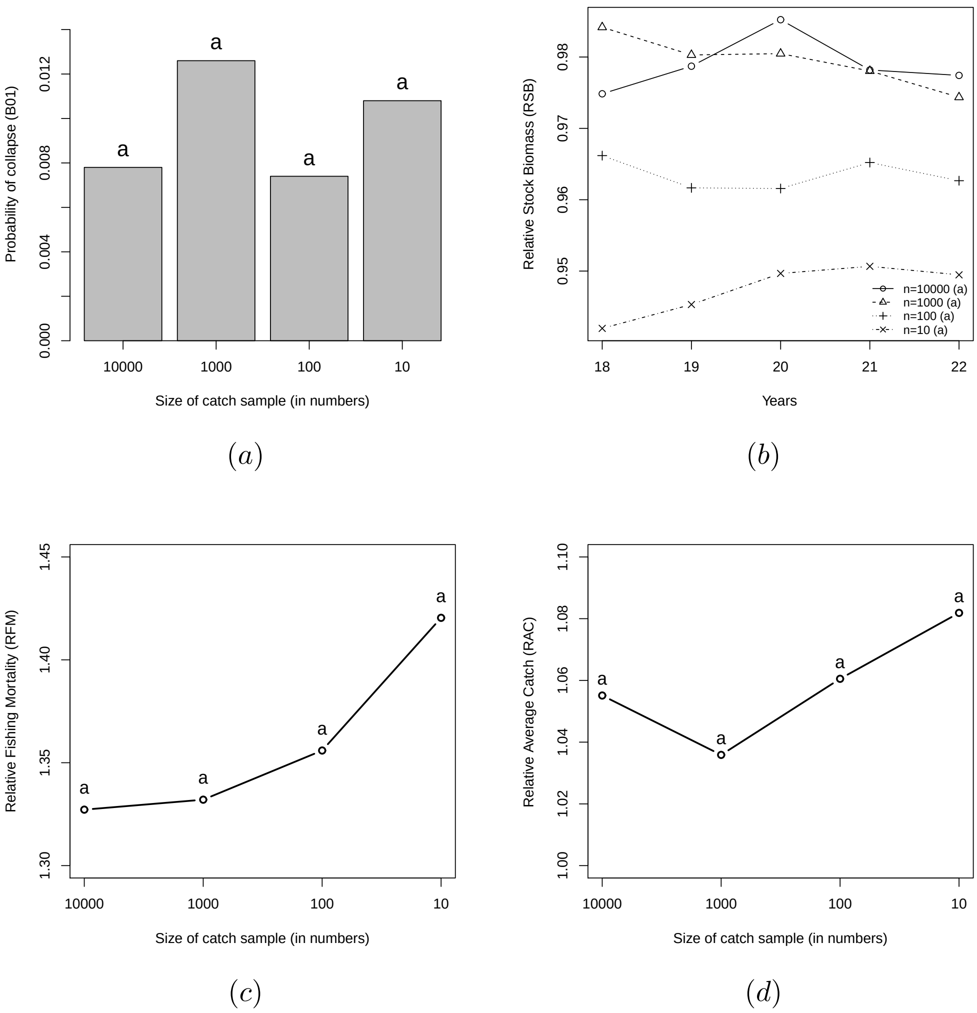


Figure F.6: **Performance comparison for observation errors in LFI: (a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC).

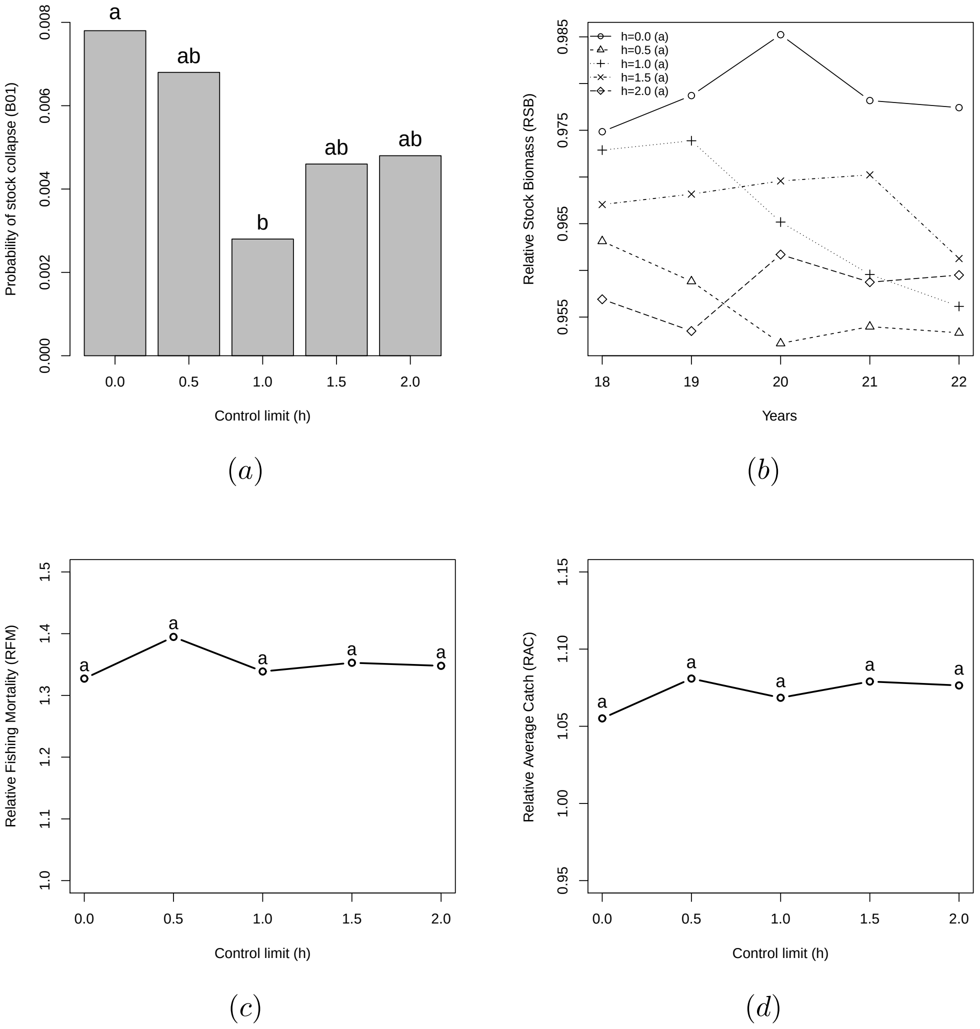


Figure F.7: **Performance comparison for increasing control limits (h): (a)** the probability of collapse (B01) **(b)** relative stock biomass (RSB) **(c)** relative fishing mortality (RFM) and **(d)** relative average catch (RAC).

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