Available online at www.sciencedirect.com

SCIENCE DIRECT®

Fisheries Research 64 (2003) 19–36

FISHERIES RESEARCH

www.elsevier.com/locate/fishres

Use of cumulative sum (CUSUM) control charts of landed catch in the management of fisheries

James P. Scandol*

Centre for Research on Ecological Impacts of Coastal Cities, Marine Ecology Laboratories A11, University of Sydney, Cronulla, NSW 2006, Australia

Received 27 September 2002; received in revised form 21 March 2003; accepted 28 March 2003

Abstract

This study examines the use and interpretation of landed catch as an indicator within fisheries management. A monitoring system has been designed to detect trends in time-series of commercial landings. This system was based upon cumulative sum (CUSUM) control charts and tested using simulated data from delay-difference models. Models were parameterised to represent a prawn fishery, a finfish fishery and an elasmobranch fishery. The performance of the scheme was measured by estimating of the probability of true-positive (sensitivity) and true-negative (specificity) outcomes from the signalling scheme. A true-positive outcome occurred when the exploitable biomass had fallen below a reference point and this situation was signalled as out-of-control. On the basis of simulations, the scheme correctly signalled the state of several fisheries with a probability of 60–80%. Sensitivity analyses of the important assumptions within the analysis are presented and examples of how the scheme would be applied to three species with varying life histories are included. Proximate causes of changes in landed catch will always require additional analysis. This scheme should only be used within the systematic prioritisation of stocks that require additional review and assessment. Precautionary management should not be subsumed into the signal detection algorithm but rather be integrated into the review and assessment process.

Keywords: Landed catch; CUSUM; Monitoring; Precautionary principle; Uncertainty; Impact; Indicators; Reference points; Data deficient

1. Introduction

1.1. Background

There are increasing calls for fisheries management agencies to monitor more and more species that are affected by fisheries. These demands can be based upon a desire for what is perceived to be a more ecosystem-based management or driven by concerns about rare or threatened species. While this trend is occurring, the practical reality is that many managerial agencies are expected to complete this work with limited resources. Given such changes, more research is required to develop and understand low-cost monitoring systems for fish stocks.

The quintessential low-cost index of abundance for fish stocks is commercial catch per unit effort (CPUE). This indicator is the basis for many assessment methods such as biomass-dynamic models (Hilborn and Walters, 1992), delay-difference models (Schnute, 1987), and is used to tune many other assessment methods (Megrey, 1989). The heterogeneous

* Present address: Cronulla Fisheries Centre, PO Box 21, Cronulla, NSW 2230, Australia. Tel.: +612-9527-8540; fax: +612-9527-8576.
E-mail address: james.scandol@fisheries.nsw.gov.au (J.P. Scandol).

0165-7836/$ – see front matter. Crown Copyright © 2003 Published by Elsevier Science B.V. All rights reserved.
doi:10.1016/S0165-7836(03)00104-8

nature of many fisheries has seen the development of procedures to standardise commercial CPUE data (e.g. Punt et al., 2000; Campbell, 1998). There is little doubt that the weakest component of CPUE data is the information about, and the interpretation of, fishing effort. Many fisheries have information about fishing effort that either lacks credibility or is simply not a good indicator of the effort actually applied. Even the simplest analyses or collation of data on effort can be time-confusing and, for some fisheries, a questionable use of resources. Of real concern is the mistaken conclusion that a CPUE time-series constructed from invalid effort data is an index of abundance for a stock when it simply is not.

Research presented here takes an alternative approach to the application of CPUE data by simply ignoring the effort data and exploring the possibility that catch data alone can be used as a low-cost indicator in the management of fisheries. Commercial landings are probably recorded more accurately and cheaply than any other fishery-dependent data and some research was necessary to understand the interpretive limits of this information. A time-series of landed catch is, however, a complex source of information. Annual landed catch is the aggregate of a large number of complex interactions between fishers and the stock. Some aspects of landed catch are biological phenomena (number and biomass of fish vulnerable to the gear), others are economic (market price of fish and the cost of applying effort), legal (regulations applied to fishing effort at that time) and some are behavioural (skill of the fisher that targeted the stock and accurate completion of catch records). Interpreting information about landed catch will always be awkward. At no point will it be suggested that landed catch is an indicator of the fish stock, but rather that it is a low-cost indicator of the fishery that could be used to prioritise further investigation. This scheme will not be suitable for fisheries under management using catch quotas.

1.2. *Previous uses of landed catch as an indicator*

Examples of where uncorrected commercial catch or landings have been used as an indicator within fisheries research and management are sparse. Two relevant types of these applications were found in the reviewed literature: qualitative or semi-quantitative indicators of stock or fishery status; and, use of catch data to determine appropriate total allowable catches (TACs) within quota management systems.

Caddy (1999) included trends in landings in a list of 30 qualitative and semi-quantitative criteria that could be used as a preliminary basis for precautionary fisheries management. For example, landings were coded as “green” (no trend), “orange” (upward trend) or “red” (declining trend) and combined with other information on the stock and the fishery to prioritise action. Some of this work was based upon Caddy and Gulland (1983) who had summarised the observed patterns in fish landings. Quantitative analyses of landings were not completed in Caddy (1999) and the research presented here is an extension of those ideas.

Since the gradual introduction of quota-managed fisheries there has been intensifying discussion about the appropriate methods used to determine what the level of the TAC should be (Walters and Pearse, 1996; Kaufmann et al., 1999) and the decision-making process used to set the actual value. The usual emphasis for the technical input is based upon the population dynamics of the stock (Walters and Pearse, 1996), but other inputs including economics have been considered (Lane and Kaufmann, 1993). Dew (2001) noted that many fisheries do not have reliable estimates of even the most rudimentary biological parameters (such as natural mortality) and developed a simple model that estimated TACs based upon historical catch data only. He suggested that “. . . TACs may be adjusted rather aggressively based upon previous catches to achieve a maximum sustainable yield (MSY) without significant risk to the fishery.” (Dew, 2001, p. 59).

A most interesting example of using catch data to estimate catch quotas was an article by Kesteven (1999). Kesteven briefly critiqued the definition, history and issues of “stock assessment” but he also argued that the TAC could be set more realistically and cheaply by looking at historical windows of catch history and recommending that a TAC be based upon average patterns within this catch history. After the TAC has been set, quotas could be adjusted according to information from inseason landings.

1.3. *Reference points, indicators, precaution and errors*

A fundamental difficulty with using commercial catch or landings as an indicator is the development of reference points or trigger points at which action should be taken. Conventional single-species limit reference points have been the focus of a great deal of research (Quinn and Deriso, 1999). These generally refer to fishing mortality or biomass, and are intended to maintain these at or below/above a level that will prevent recruitment overfishing (Caddy and Mahon, 1995). Limit reference points are now, however, normally associated with other trigger reference points. These reference points are used by undertaking previously agreed managerial responses if they are breached (FAO, 1995; Caddy and Mahon, 1995). Ideally, a management strategy should include multiple indicators, derived from independent data, with trigger reference points designed to “fire” or “trip” at roughly the same level of exploitation or risk (Seijo and Caddy, 2000). The other type of reference point is a target reference point. These represent an acceptable state of the fishery from which a measure of managerial performance can be defined.

Although reference points are generally accepted as a contemporary and effective way to approach the management of fisheries, several problems have been identified. One criticism is that most limit reference points are arbitrary, or based on arbitrary assumptions (Gilbert et al., 2000; Essington, 2001). Probably the most important criticism of limit reference points is that they rely too heavily on knowledge of stock abundance (Essington, 2001) which is extremely prone to error (Schnute and Richards, 2001; Hilborn, 2002). To circumvent issues such as uncertain estimates of stock size, various precautionary management strategies have developed that emphasise strategies to prevent overfishing, even in the absence of direct evidence that overfishing is occurring (Garcia, 1994; Francis and Shotton, 1997). There are now trigger reference points defined that are precautionary or risk-averse (FAO, 1995). The usual strategy to assess the performance of managerial systems based upon such trigger points is quantitative risk analysis (Francis and Shotton, 1997).

The approach presented here evaluates the performance of indicators and trigger points in a slightly different way. This method is equivalent to the power analysis of statistical tests (Peterman, 1990) and is a subset of quantitative risk analysis. Rather than estimating the probability of a stock recovering to a specified size or some other performance measure, this

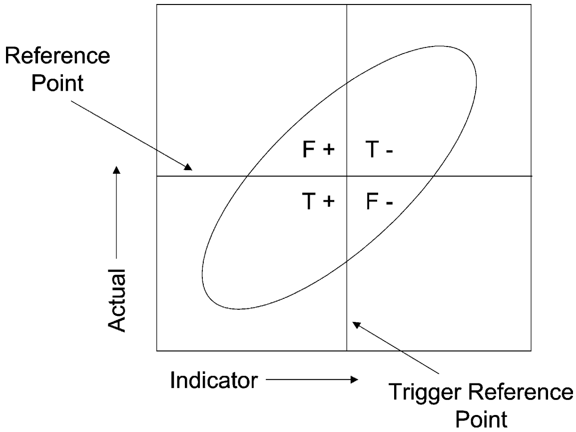

Fig. 1. A Taylor–Russell diagram, with the ellipse illustrating the uncertain relationship between an indicator and the actual state of a system. There are four possible outcomes from a determination: true-positive (state is below reference point, and this was correctly detected); true-negative (state is above the reference point, and this was correctly detected); false-positive (state is above the reference point and this was incorrectly detected); and false-negative (state is below the reference point and this was incorrectly detected).

analysis estimates the sensitivity and specificity of an indicator and a trigger point. Sensitivity is the probability of true-positive result when a test is applied to an indicator, whilst specificity is probability of a true-negative result.

False-positive and false-negative errors are fundamental to the understanding of any indicator and trigger point system. The so-called “duality of error” is illustrated in Fig. 1, a Taylor–Russell diagram (see Hammond, 1996) that represents the uncertain relationship between an indicator and the actual system state. Two threshold limits define the outcomes of a determination using that indicator. One, a threshold state or reference point of the system needs to be specified that should be acted upon (the horizontal line in Fig. 1). Two, a threshold value or trigger reference point on the indicator axis (the vertical line in Fig. 1) represents the indicated point when a determination is made. These two thresholds define the probabilities of the four possible outcomes of a decision (false-positive, false-negative, true-positive, true-negative). For a given relationship between an indicator and the actual system state, false-positive outcomes are traded off directly against false-negative outcomes. Precautionary decision-making based upon such a relationship would entail making false-positive errors in preference to false-negative errors (Peterman, 1990; Underwood, 1997).

2. Methods

2.1. Overview

This study used a different quantitative approach compared to stock assessment and risk analysis. Rather than estimating biomass or fishing mortality from data and then applying standard limit and trigger reference points for management, this study used landed catch and examined the performance of a trend detection algorithm to detect events of managerial importance. Errors associated with that interpretation were then explored.

An operating model approach was followed where a delay-difference simulation model (Hilborn and Walters, 1992, p. 330; Schnute, 1987) was defined that represented three different types of fish stocks: a prawn fishery; a finfish fishery and an elasmobranch fishery. Various impacts or failure scenarios were then simulated. Catch data generated from these models were analysed with cumulative sum (CUSUM) quality control algorithms and out-of-control patterns in landings identified. Replicate simulations were used to estimate the probability of false-positive and false-negative errors of the signal detection scheme.

2.2. The operating model

Growth of individuals was modelled using the recursive equation $w_a = \alpha + \rho w_{a-1}$, where w_a is the weight of an individual of age a, α and ρ are the intercept and slope of a Ford–Walford plot. These growth parameters were determined from available empirical data such as length-at-age plots and weight–length relationships.

Survival rate u_t at time t was determined from the natural survival rate S and the harvest rate h_t using $u_t = S(1 - h_t)$. Both the harvest rate and natural survival rate were also subject to impacts on the fishery described below. Landed catch C_t at time t was calculated using $C_t = h_t B_t$. A stock–recruitment relationship (see below) was used with the post-harvest biomass to estimate the number of recruits in κ years from t, $R_{t+\kappa}$. The mean weight of individual fish at time t was $\bar{w}_t$. Biomass before harvesting at time $t+1$ was determined with $B_{t+1} = u_t[\alpha N_t + \rho B_t] + w_k R_{t+1}$, where N_t is the number of individuals at time t and w_κ is the weight of fish at recruitment. Numbers of fish before harvesting at time $t + 1$ was calculated using $N_{t+1} = u_t N_t + R_{t+1}$.

These simulations were initialised with reasonable values of B_0 and N_0 (calculated using $N_0 = B_0/\bar{w}_0$) and iterated without variability until the biomass equilibrated to B_{eq}. After this transient period, there are two phases of the simulation: historical (from 1 to 20 years) and future (from 21 to 30 years). The historical phase reflects the period up to the notional “present” or “now”, whilst the 10 years in the future phase represents the time from “now” onwards.

The stock–recruitment relationship used was a Beverton–Holt model that had been re-parameterised to the steepness of the stock–recruitment relationship and the initial biomass/recruitment (see Haddon, 2001, p. 268). Thus

$$A^{\text{sr}} = \frac{B_0}{N_0}\left(1 - \frac{z - 0.2}{0.8z}\right),$$
$$B^{\text{sr}} = \frac{z - 0.2}{0.8zN_0} \quad \text{and} \quad \bar{R}_{t+\kappa} = \frac{B_t}{A^{\text{sr}} + B^{\text{sr}} B_t}$$

The parameter z is the steepness of the stock–recruitment relationship and A^{sr} and B^{sr} are the parameters of the standard Beverton–Holt stock–recruitment curve. There was a delay of κ years between spawning and recruitment into the exploitable population.

Process error is included in this operating model by rescaling the Beverton–Holt stock–recruitment with a lognormal random variable with a mean of 1 and co-efficient of variation R_{cv}. Standard algorithms are used to generate these variables so that if ε is a normally distributed random variate with mean zero and standard deviation one, then:

$$R_t = \bar{R}_t \exp\left(R_{\text{cv}}\varepsilon - \frac{R_{\text{cv}}^2}{2}\right)$$

Total catch was modelled as the sum of individual fisher activity. Instantaneous fishing mortality rate $f_{i,t}$ for fisher i was applied to the stock during year t of the simulation. That is, the total instantaneous fishing mortality rate F_t from all fishers during year t was $F_t = \sum_{i=1}^{m} f_{i,t}$. The rate $f_{i,t}$ is a random exponential variable with mean (and standard deviation) $\bar{f}$

Table 1
Summary of the elements that are used to define an impact upon a fishery

Element	Description
Recruitment failure	The actual number of recruits decreased after the failure occurred. This failure modified the values within the variable R_t
Survival failure	All sources of mortality, except for the commercial fishing responsible for the landings data, increased. Failure of survival could result from increased recreational fishing mortality or increased natural mortality. This impact caused a modification to the parameter S_t
Increasing fishing mortality	Average instantaneous fishing mortality per fisher ($\bar{f}_t$) increased in the fishery. There is no differentiation between the catchability or effort component of $\bar{f}_t$ as the cause of the increase

and m is the number of fishers in the fishery. The harvest rate for year t (or h_t) was calculated using $h_t = 1 - \exp(-F_t)$. Examination of the frequency distribution of catch per fisher in several fisheries in New South Wales (NSW), Australia, indicated that the exponential distribution was an appropriate choice for the random variable $f_{i,t}$. The additive operation used in this harvest algorithm caused the total fishing mortality to be gamma distributed (Bury, 1999). Variance of the harvest rate was thus a function of the number of fishers m and the variance (or mean) of the individual fisher's fishing mortality rate $f_{i,t}$. Final variability in the landed catch data was also dependent upon the variability in vulnerable biomass, which was subject to the process error of recruitment. A simple pattern of variance in simulated landed catch cannot, therefore, be expected. The frequency distribution was, however, always positive and approximately normal when a reasonable number of fishers (>100) were involved.

This analysis required a parsimonious mechanism to represent potential impacts on fisheries that might be detectable. Three elements (Table 1) were used to define an impact on the fishery and were applied at three levels of intensity: null, acute and chronic (Table 2). Impacts could be imposed in either the historical or future phases of the simulation. The eleven impact scenarios that were evaluated are summarised in Table 3. Variables within the model that were altered by an impact were appropriately rescaled at time t. The effect of the impacts was multiplicative, for example if there was x% per year impact imposed on recruitment at time t, then after n years $R'_{t+n} = R_{t+n}(1 - x/100)^n$. Similarly, impacts upon survival were calculated with $S'_{t+n} = S_{t+n}(1 - x/100)^n$. Impacts on fishing mortality were imposed by rescaling the mean rate per fisher after n years thus: $\bar{f}'_{t+n} = \bar{f}_{t+n}(1 - x/100)^n$.

Three different types of fisheries were represented with this model. An oceanic trawl fishery for the eastern king prawn (*Melicertus plebejus*) with approximately 500 fishers; a multi-gear fishery for yellowfin bream (*Acanthopagrus australis*) with approximately 1000 fishers; and a line fishery for scalloped hammerhead shark (*Sphyrna lewini*) with approximately 60 fishers. The models were not quantitatively calibrated to observations with optimisation methods, rather as many parameters as possible were determined from data available from publications (Glaister et al., 1987; Gordon et al., 1995; Gray et al., 2000), unpublished data from NSW Fisheries or *FishBase* (Froese and Pauly, 2001). Remaining parameters were tuned to generate simulated patterns that mimicked observed landings. For each fishery, a high and low variance model was specified so that the important characteristic of variability in landings could be evaluated. Table 4 summarises the parameter values used for the six simulated fisheries. Figs. 2a, 3a and 4a, illustrate

Table 2
Description of the quantitative effects of null, acute and chronic impacts

Impact intensity	Description
Null	There was no impact on recruitment, fishing mortality or survival
Acute	The impact occurred rapidly. Recruitment or survival decreased each year by 20%, or mean fishing mortality per fisher increased each year by 20%
Chronic	The impact occurred slowly. Recruitment or survival decreased each year by 5%, or mean fishing mortality per fisher increased each year by 5%

Table 3
Summary of the fishery impact scenarios[a]

Code	Impacts			Description
	Type	Historical	Future	
Null	Recruit Survival Fishing	Null Null Null	Null Null Null	The no impact scenario where nothing has happened to either recruitment, survival or fishing mortality
A1	Recruit Survival Fishing	Null Null Null	−Acute Null Null	The stock was historically stable but has now suffered acute recruitment failure
A2	Recruit Survival Fishing	Null Null Null	Null Null +Acute	The stock was historically stable but an acute increase in fishing mortality started to occur
A3	Recruit Survival Fishing	Null Null Null	−Acute −Acute Null	The stock was historically stable but then suffered acute recruitment and survival failure
A4	Recruit Survival Fishing	Null Null Null	Null −Acute +Acute	The stock was historically stable but acute survival failure has started to occur with an acute increase in fishing mortality
B1	Recruit Survival Fishing	Null −Chronic Null	−Acute −Chronic Null	The stock was experiencing and continued to experience chronic survival failure and then suffered acute recruitment failure
B2	Recruit Survival Fishing	Null Null +Chronic	−Acute −Chronic +Chronic	The stock suffered chronic fishing increase but is now subject to acute recruitment failure and chronic survival failure and increase in fishing pressure
C1	Recruit Survival Fishing	Null Null +Chronic	Null −Chronic +Chronic	The stock suffered a chronic increase in fishing (which continued) and now also experiences chronic survival failure
C2	Recruit Survival Fishing	Null −Chronic Null	Null −Chronic Null	The stock suffered chronic survival failure that continued
C3	Recruit Survival Fishing	Null Null Null	Null Null +Chronic	The stock has started to experience a chronic increase in fishing
C4	Recruit Survival Fishing	Null Null +Chronic	−Chronic −Chronic +Chronic	The stock was experiencing a historical increase in fishing (which continued) and then suffered chronic recruitment and survival failure

[a] Null, acute or chronic impacts could occur to recruitment, stock survival or fishing mortality in either the historical or future phases of the simulation. The ± sign on the impact indicates the direction of change.

observed catch data and simulated catch and biomass replicates for the three fisheries considered.

2.3. CUSUM control charts

CUSUM control methods are designed to detect persistent changes in observed processes. The underlying algorithm is a simple cumulative sum of the deviation of observations from the mean. Hawkins and Olwell (1997) presented a general analysis of the theory and application of CUSUM methods.

A search of the Aquatic Sciences and Fisheries Abstracts database revealed only one application of CUSUM charting in fisheries. Nicholson (1984) presented a paper at an ICES meeting in 1984. Manly (2001) promoted CUSUM methods for environmental

Table 4
Values of the model parameters for the six fisheries considered

Parameter	Prawn		Bream		Shark	
	Low	High	Low	High	Low	High
α (kg^{-1})	0.1	0.1	0.08	0.08	12	12
ρ	0.15	0.15	0.9	0.9	0.9	0.9
S	0.05	0.05	0.8	0.8	0.75	0.75
$\bar{w}_\kappa$ (kg)	0.03	0.03	0.3	0.3	10	10
$\bar{w}_0$ (kg)	0.05	0.05	0.5	0.5	60	60
B_0 (t)	4000	4000	1000	1000	50	50
B_{eq} (t)	2305	2305	2290	2290	39.3	39.3
R_{cv}	0.1	0.2	0.2	0.5	0.0	0.2
z	0.75	0.75	0.75	0.75	0.75	0.75
κ (years)	1	1	3	3	3	3
$\bar{f}$ (per year per fisher)	0.001	0.05	0.0002	0.001	0.001	0.03
m (fishers)	500	10	1000	200	300	10

monitoring in his recent book. Manly and MacKenzie (2000) developed a CUSUM Analysis Tool for the analysis of univariate and multivariate environmental datasets that was extended with permutation tests.

Pilot tests with typical time-series of landed catch from fisheries in NSW indicated that CUSUM methods were likely to generate credible results for this monitoring problem. The usual alternative to CUSUM charts for detecting persistent impacts are Geometrically Weighted Moving Average (GWMA) control charts, but the theory and applications for monitoring processes that are not normally distributed appear to be less developed than for the CUSUM approach (Derman and Ross, 1997). Like any statistical model, CUSUM algorithms have precise assumptions about the distribution and independence of the data. However, like many statistical applications, some of these assumptions will not be met and certain compromises are required.

The decision interval form of the CUSUM (Hawkins and Olwell, 1997) was used. Although CUSUM schemes usually require the assumption that observations are independent and identically distributed, these assumptions are only critical if analytical relationships for specifying an average run length, the number of events between false-positive signals, are to be applied (see Sparks, 2000). Observations in landed catch time-series are neither distributed normally nor independent, therefore an alternative scheme was required to specify the control parameters.

The second assumption about CUSUM methods is that the mean and standard deviation of the underlying normal distribution are known (hereafter referred to as the control mean and control standard deviation). There are three alternative strategies to specify these parameters. First, the parameters could be estimated from all data available (i.e. all years of landed catch available, including the most recent year). Second, the parameters could be estimated from a window of the available data (e.g. landings between 1984 and 1990). There would need to some justification of why this was an appropriate period to compare with future landings. Third, the controlling mean and standard deviation could simply be specified as a managerial goal.

These options increasingly demand additional judgements about the appropriate level of harvesting that, in an ideal world, might be based upon an independent analysis of the fishery (such as average annual catch at $F_{0.1}$). Relying on the argument that, "this fishery had stable landings between year x and y, therefore that level of catch is probably sustainable", might send shivers down the spine of many fisheries scientists, but is essentially what happens on an ad hoc basis for data-deficient fisheries anyway. Using particular years to define the controlling mean and variance simply formalises that process.

Once the controlling mean (μ) and standard deviation (σ) have been specified, catch data (C) within the time-series are standardised to z using: $z_t = (C_t -$

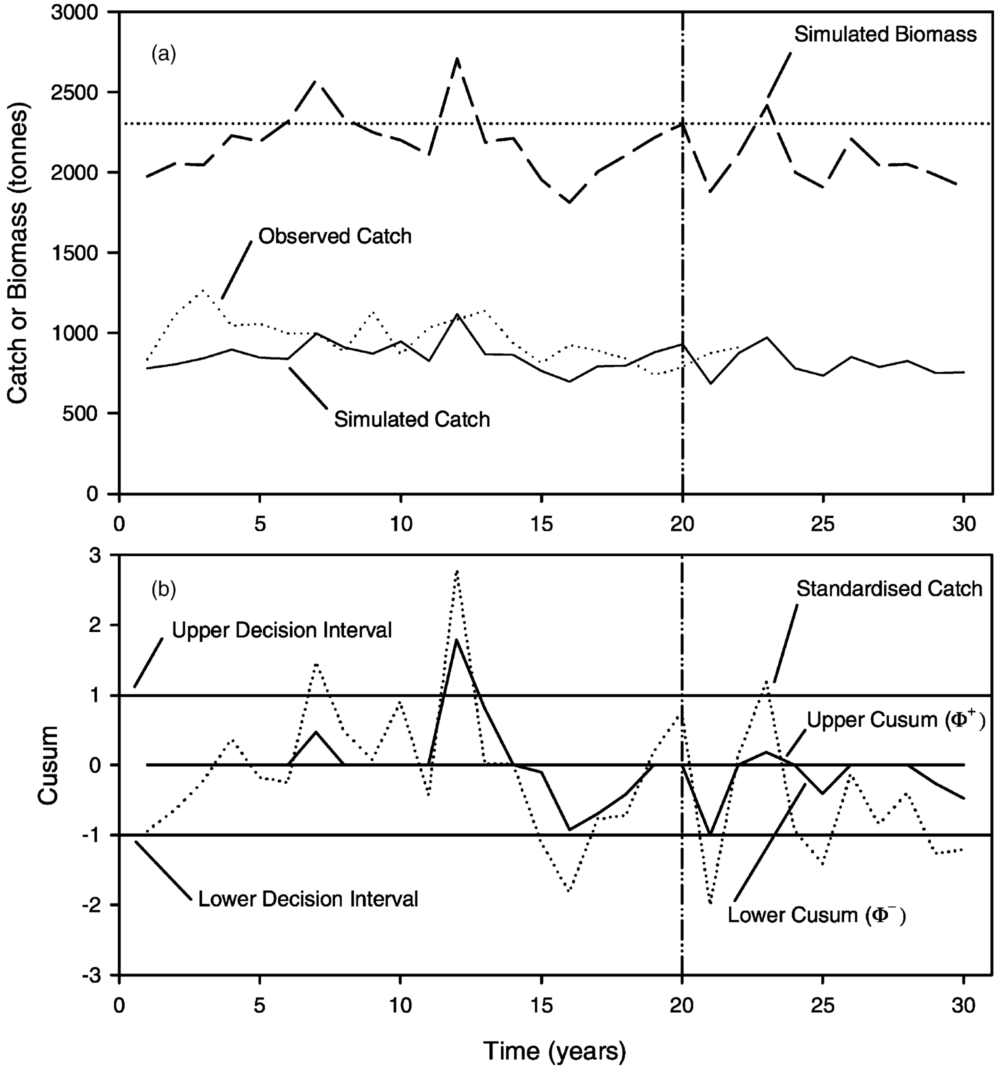

Fig. 2. (a) Observed catch for the eastern king prawn (*M. plebejus*) fishery in New South Wales (Australia) on a general time-scale, and output (biomass and catch) from a realisation of the simulated low variance prawn fishery experiencing impact C2. The dotted horizontal line is equilibrium biomass (B_{eq}). The vertical line indicates the threshold between historical and future events. (b) A CUSUM control chart for the catch realisation plotted in (a). The solid lines are the upper (>0) and lower (<0) CUSUMs. When either CUSUM breaches the decision interval ($\pm h$, respectively) then the process is out-of-control (for example, at time 12). Standardised catch data are also annotated on the plot.

$\mu)/\sigma$. These standardised values are converted to upper (Φ^+) and lower (Φ^-) CUSUMs using the following recursive equations (where k is the allowance):

$$\Phi_0^+ = 0 \quad \text{and} \quad \Phi_0^- = 0$$

$$\Phi_n^+ = \max(0, \Phi_{n-1}^+ + z_n - k)$$
$$\text{and} \quad \Phi_n^- = \min(0, \Phi_{n-1}^- + z_n + k)$$

A process is signalled as out-of-control at time n if (where $\pm h$ is the decision interval):

$$\Phi_n^+ > h \quad \text{or} \quad \Phi_n^- < -h$$

Two control parameters are included. Parameter k is the reference value or allowance of the control chart (Hawkins and Olwell, 1997). The parameter h defines

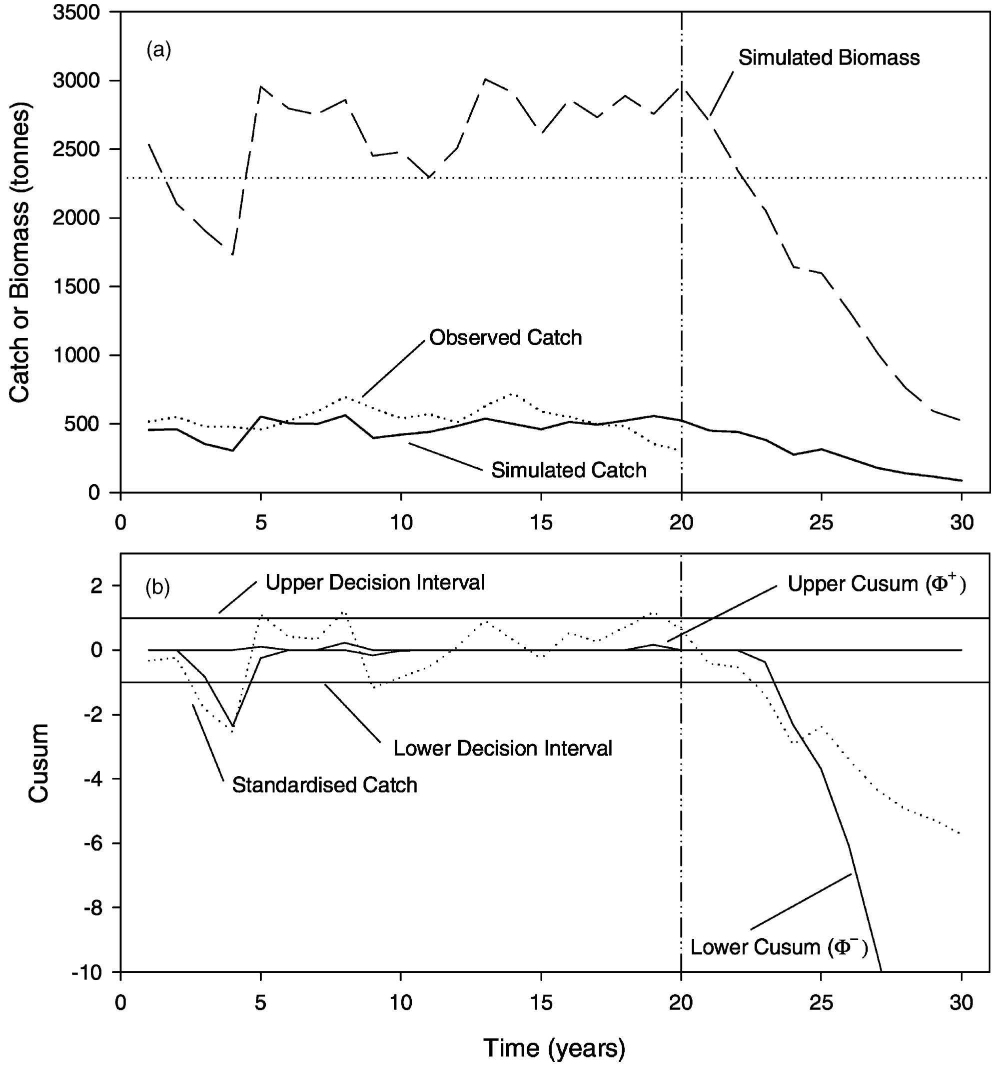

Fig. 3. (a) Observed catch for the yellowfin bream (*A. australis*) fishery in New South Wales (Australia) on a general time-scale, and output (biomass and catch) from a realisation of the simulated high variance bream fishery experiencing impact A1. The dotted horizontal line is equilibrium biomass (B_{eq}). The vertical line indicates the threshold between historical and future events. (b) A CUSUM control chart for the catch realisation plotted in (a). The solid lines are the upper (>0) and lower (<0) CUSUMs. When either CUSUM breaches the decision interval ($\pm h$, respectively) then the process is out-of-control (for example, at time 4). Standardised catch data are also annotated on the plot.

the decision interval. Once observations outside the allowance start to cumulate, the scheme is tripped or triggered once either CUSUM exceeds $|h|$.

2.4. Measurement of performance

When evaluating any signal detection scheme a threshold for an underlying problem must be defined. In this study, the reference point ϕB_{eq} (where ϕ = 50% by default) was used so that when $B_t < \phi B_{eq}$ a situation exists in the fishery that ought to be signalled. Three replicate simulations are illustrated in Figs. 2a, 3a and 4a, for the low variance prawn (impact C2), high variance bream (impact A1) and high variance shark (impact A4) fisheries, respectively. Corresponding diagrams in Figs. 2b, 3b and 4b, illustrate

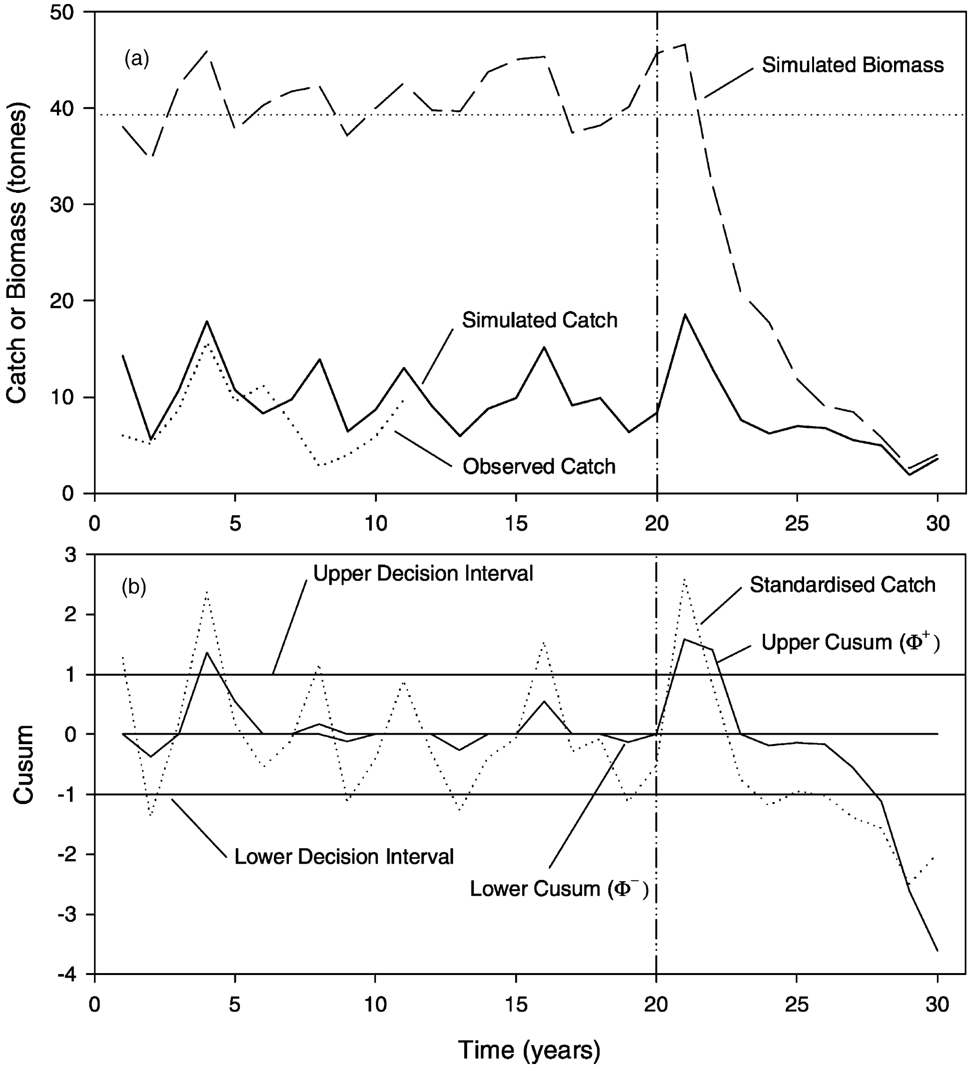

Fig. 4. (a) Observed catch for the scalloped hammerhead shark (*S. lewini*) fishery in New South Wales (Australia) on a general time-scale, and output (biomass and catch) from a realisation of the simulated high variance shark fishery experiencing impact A4. The dotted horizontal line is equilibrium biomass (B_{eq}). The vertical line indicates the threshold between historical and future events. (b) A CUSUM control chart for the catch realisation plotted in (a). The solid lines are the upper (>0) and lower (<0) CUSUMs. When either CUSUM breaches the decision interval ($\pm h$, respectively) then the process is out-of-control (for example, at time 28). Standardised catch data are also annotated on the plot.

how the CUSUM signal detection algorithm operates. When the upper CUSUM (Φ_t^+) exceeds the upper decision interval ($+h$) or the lower CUSUM (Φ_t^-) falls below the lower decision interval ($-h$) then an out-of-control signal is raised. If $B_t < \phi B_{eq}$, then this is a true-positive ($T+$) signal otherwise it is false-positive ($F+$) signal. Alternatively if $B_t \geq \phi B_{eq}$ and a signal is not raised a true-negative ($T-$) result occurs. Finally if $B_t < \phi B_{eq}$ and no signal is raised then a false-negative ($F-$) result is registered. Examples of some of these outcomes are illustrated in Figs. 2b, 3b and 4b, where the catch data are standardised using the controlling mean and standard deviation calculated from the historical data only. For these examples, the CUSUM is parameterised with $(h, k) = (1.0, 1.0)$.

The performance of the CUSUM algorithm was estimated in two steps. The first step was the estimation of signalling outcomes for each fishery and impact scenario over a range of values of h. For each combination of fishery and impact scenario, 1000 replicate simulations were calculated. The replicate simulations were processed using a fixed value of k (default 1.0) but varying the value of h from 0.1 to 10.0 (in increments of 0.1). The CUSUM was then repeatedly applied to the same replicate simulation for the 10 future years and the outcome recorded. Counts of these alternative outcomes from these 10 future years were collected over the 1000 replicates and then divided by the 10 000 to normalise the results and provide an estimate of the probability of the four possible signal outcomes. These estimates are not true probabilities because the results from one replicate simulation are dependent. This calculation accorded superior performance to parameter combinations that detected impact scenarios rapidly after the impact occurred because a greater proportion of the future years were signalled as true-positive signals.

The second step of the performance calculations required more judgements. Application of this scheme to actual data would be completed without knowledge of any underlying impact scenario. Any results presented with respect to the scenario are therefore somewhat synthetic. In contrast, the life history of the harvested species and the variation of catch history will be known so the reporting of performance with respect to the fishery is far more valuable. Results from the first step were thus averaged over all impact scenarios for each fishery for all values of the control parameter h. These consolidated results were then used to determine the optimal performance of the scheme and the value of h at that optimum. Optimal performance was defined as when $P(F+) = P(F-)$ because that provided the most easily interpreted result of the inevitable tradeoff between these two types of error. Alternatives such as the smallest value of $P(F-)$ when $P(F+) \leq 20\%$, were also considered but not presented.

These results were finally subject to sensitivity analysis. Analyses were completed on: the definition of acute and chronic changes; the value of the CUSUM allowance k; the parameter ϕ, the proportion of B_{eq} that defined the underlying reference point; and, the window of years used to standardise the records of landed catch.

3. Results

3.1. Simulated fisheries and impact scenarios

Fig. 5 illustrates the how the four signalling outcomes change as a function of the decision interval h for three particular fisheries and impact scenarios. Fig. 5a plots the results for the low variance prawn fishery with impact C2. This chronic impact on survival had little effect on the prawn stock because annual survival was so small after harvesting. There were, therefore, no situations where this impact caused $B_t < \phi B_{\mathrm{eq}}$, hence no true-positive or false-negative signals occurred (refer to Fig. 2a for an example). As the decision interval increased, the $P(F+)$ declined and the $P(T-)$ increased to 1.0.

In contrast, Fig. 5b and c illustrates results from the high variance bream fishery (impact A1) and high variance shark fishery (impact A4). Under these scenarios the biomass will fall below ϕB_{eq} (as illustrated in Figs. 3a and 4a) and true-positive signals should occur. From Fig. 5b, it can be seen that when $h \approx 0.2$, the sum of $P(T+)$ and $P(T-)$ is around 65%, but that comes at the expense of $P(F+) = 35\%$. Increasing the decision interval to 2 reduces this rate to 15% and the sum of true signals increases to 85%, but now there is a 1% chance of a false-negative result. The shark fishery exhibits a similar pattern in Fig. 5c, but in this case the $P(F-)$ is as high as 35% when $h = 2$.

3.2. Performance and sensitivity analysis of the scheme

Results for the optimal performance of the scheme are given in Table 5. This table gives the estimated values of the four outcomes of the signalling system at the optimal values when averaged over all scenarios and provides a simple interpretation of this study. In the simulated prawn fishery, the system registered reference point breaches 50% of the time. Of these 80% were correctly detected and 20% were missed. When the reference point was not breached, 80% of

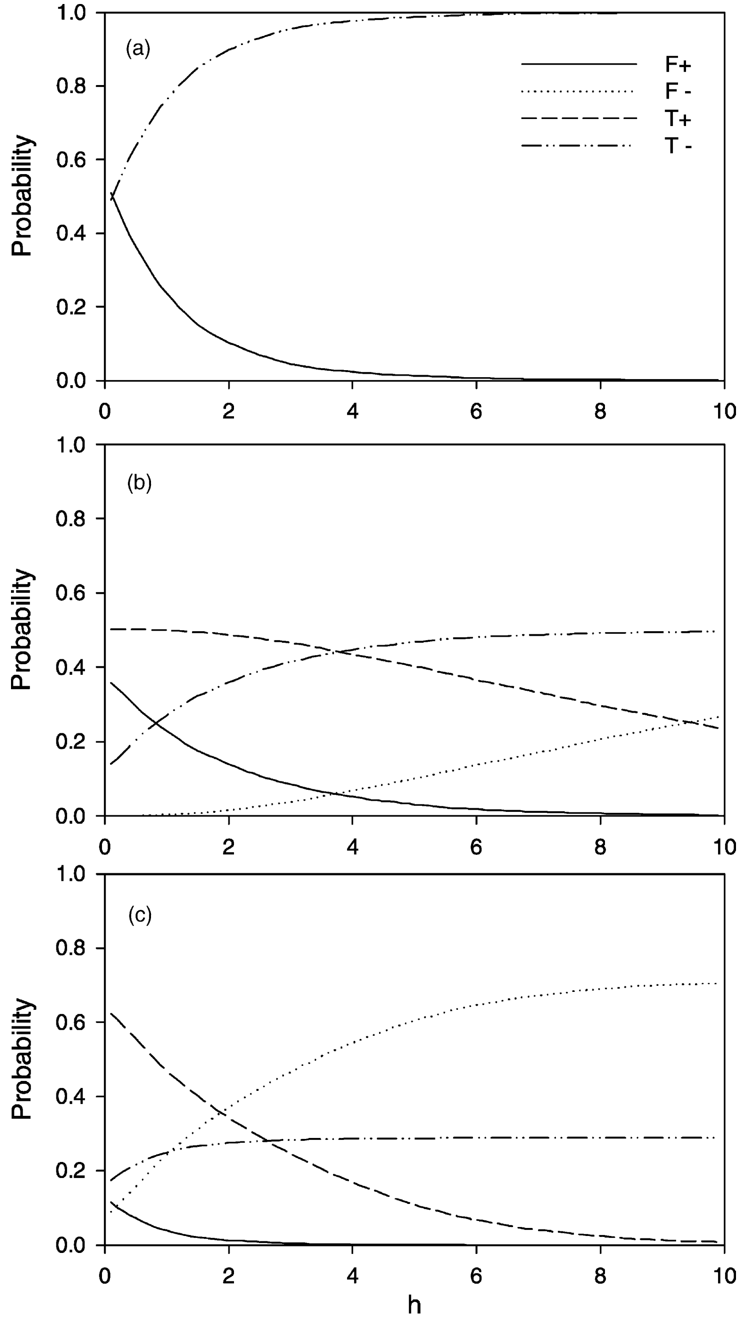

Fig. 5. The probabilities of false-positive ($F+$); false-negative ($F-$); true-positive ($T+$); and true-negative ($T-$) results for three simulated fisheries/impacts over a range of values of the allowance parameter h (when $k = 1.0$). (a) Low variance prawn fishery with impact C2. (b) High variance bream fishery with impact A1. (c) High variance shark fishery with impact A4.

Table 5
Optimal values of the CUSUM signal detection outcomes for the six simulated fisheries[a]

Fishery	$P(F-)$ (%)	$P(F+)$ (%)	$P(T-)$ (%)	$P(T+)$ (%)	$P(F-)+P(F+)$ (%)	$P(T-)+P(T+)$ (%)
Prawn (low)	9	9	42	40	18	82
Prawn (high)	11	10	40	39	21	79
Bream (low)	20	20	20	40	40	60
Bream (high)	19	18	22	40	38	62
Shark (low)	13	14	19	54	27	73
Shark (high)	13	12	22	54	25	75

[a] All parameters retain default values.

these events were correctly missed, but 20% indicated a breach when one had not occurred. Similar interpretations are available for the other fisheries.

Results of the sensitivity analyses are provided in Fig. 6 and Table 6. Fig. 6 provides the responses of the optimal value of $P(F-)$, whilst Table 6 gives the values of h at this optimum. Fig. 6a indicates that the performance is not greatly affected by altering the quantitative definitions of acute and chronic changes by ±20%. In contrast, Fig. 6b suggests that changing the allowance by ±0.5 has nominal effect on the prawn fisheries but that larger values of k seriously compromise the performance of the high variance shark fishery. Fig. 6c suggests that altering the window of years used to standardise the catch time-series has little effect on performance. In general, using only the historical years and excluding the future years of the simulation increases performance slightly. Fig. 6d indicates a mixed effect of the parameter ϕ that is used to define the reference point. For the prawn fisheries, smaller values of ϕ are associated with higher performance but the pattern is not consistent across the bream and shark fisheries.

Tabulated results have been provided for the associated h values of these optimal results because these are what will be required in any practical implementation of this approach. Table 6 illustrates that there is substantial variation in the values of h that should be used to optimise this scheme. There are, however, some simple generalisations that can be made including: the quantitative definition of acute and chronic change have little effect on the value of h at optimal performance; larger values of k require smaller values of h and vice versa; larger values of h can be used when standardising the catch data on a specific set of historical data rather than all years of data available;

Table 6
Results of the sensitivity analysis for various assumptions in the simulation study[a]

Consideration	Value	Prawn (low)	Prawn (high)	Bream (low)	Bream (high)	Shark (low)	Shark (high)
Change to	−20%	8.3	1.3	3.0	1.5	3.6	0.4
definition of	0%[b]	6.6	1.2	2.1	1.2	3.4	0.4
acute and chronic	+20%	6.9	1.3	1.6	1.0	3.4	0.4
Value of	0.5	9.1	2.7	5.4	3.9	7.4	1.9
allowance	1.0[b]	6.6	1.2	2.1	1.2	3.4	0.4
parameter k	1.5	4.7	0.3	0.6	0.1	1.4	0.1
Data used to	All	2.4	0.7	1.0	0.5	1.1	0.1
standardise catch	Historical[b]	6.6	1.2	2.1	1.2	3.4	0.4
Proportion (ϕ) of	30%	10.0	2.4	8.0	3.4	6.4	0.8
B_{eq} defining the	50%[b]	6.6	1.2	2.1	1.2	3.4	0.4
reference point	70%	3.2	0.5	1.1	0.4	2.7	0.1

[a] Numbers are the values of decision interval h that gave optimal results for the six simulated fisheries.
[b] Default values of the parameters are marked.

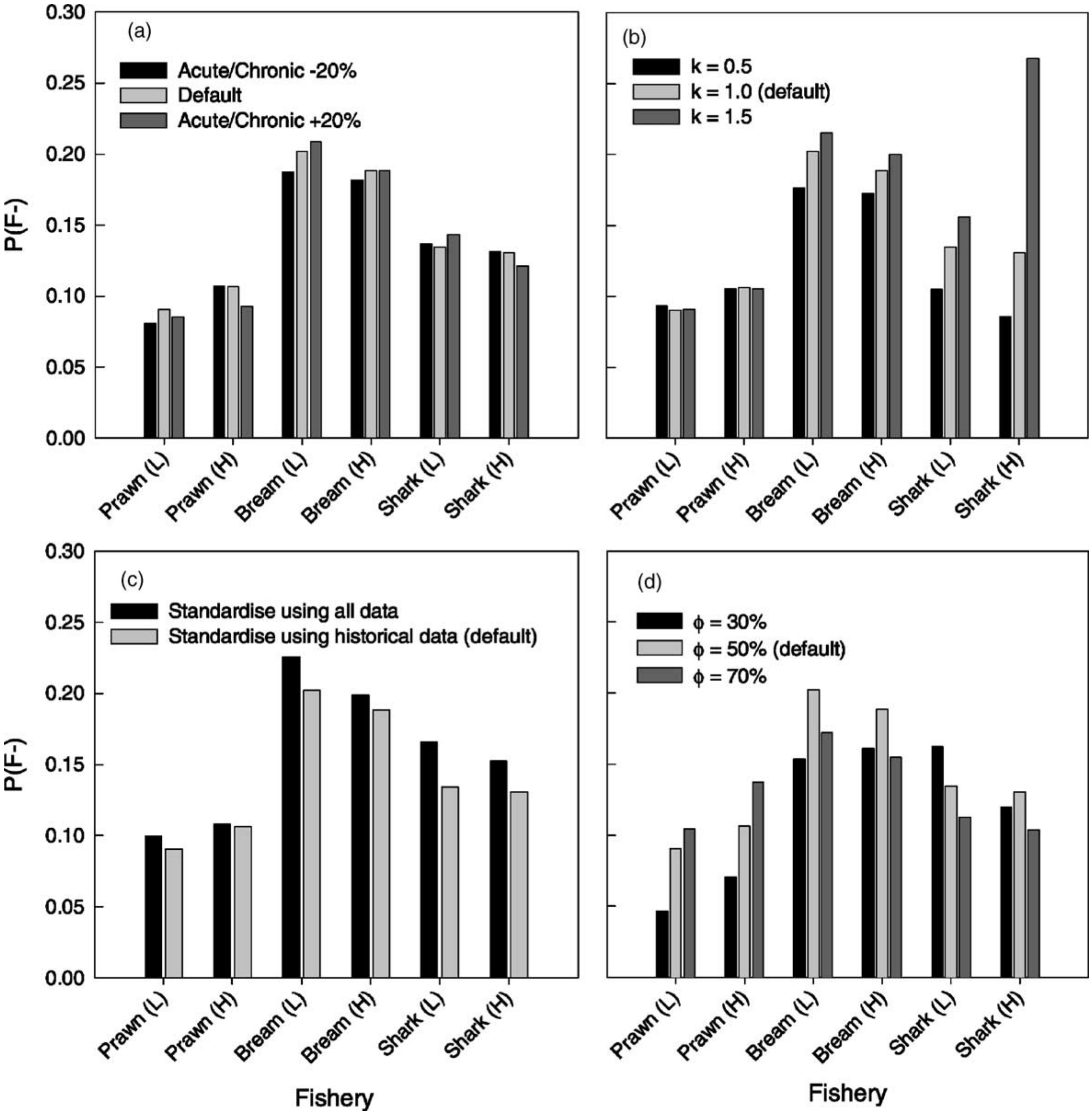

Fig. 6. Sensitivity analyses of the CUSUM impact detection scheme. Series representing the default values are shaded in light grey and the response variable is the optimal value of $P(F-)$. (a) Effect of the rate of change defining acute and chronic failure: the default definition has been altered by (−20, 0, +20). (b) Effect of the allowance parameter k: the default definition has been altered by (−0.5, 0.0, +0.5). (c) Effect of using two alternative methods for specifying the controlling mean (μ) and standard deviation (σ). Solid bars are results when all data are used, shaded bars are results when only the historical information is used (the default strategy). (d) Effect of the reference point parameter ϕ: the default definition has been altered by (−20, 0.0, +20%).

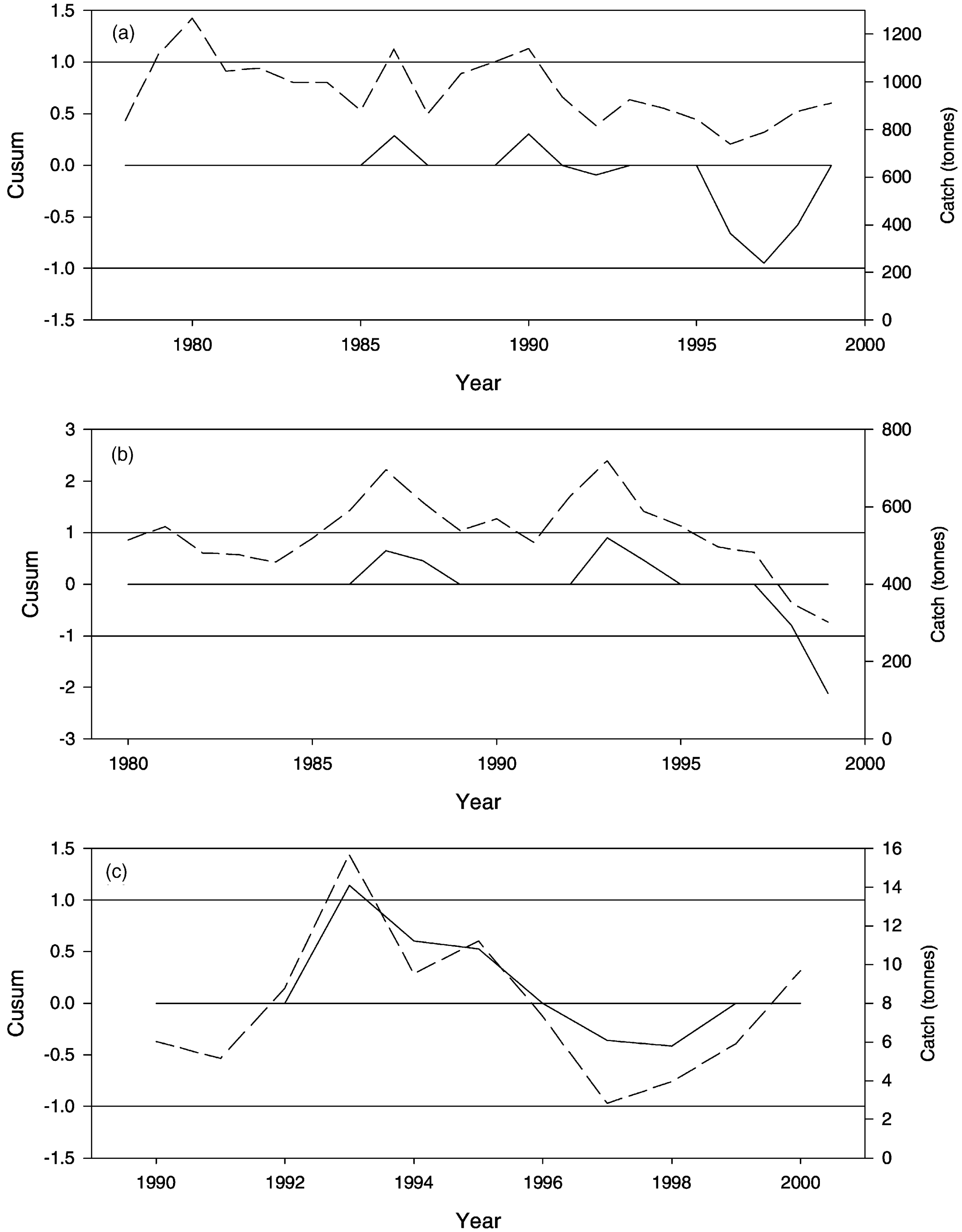

Fig. 7. CUSUM control charts for observed landings of the three species studied. The control mean and standard deviation are estimated from all years of data and the control parameters $(h, k) = (1.0, 1.0)$. Key: observed landed catch (dashed line, right axis); $\pm h$ decision interval (horizontal lines, left axis); CUSUM $\pm\Phi$ (solid lines, left axis). (a) Eastern king prawn (*M. plebejus*): landings are never out-of-control. (b) Yellowfin bream (*A. australis*): landings indicated a clear out-of-control signal by 1999. (c) Scalloped hammerhead shark (*S. lewini*): landings remained in-control except in 1993.

detecting smaller changes to biomass require smaller values of h and vice versa.

Issues surrounding the specification of the decision interval parameter h are considered in more detail in the discussion. The final results presented are an application of the scheme to the observed catch of the three case study fisheries. The control parameters (h, k) have been specified at (1.0, 1.0) for these examples.

3.3. Examples from actual fisheries

The fishery for eastern king prawn (*M. plebejus*) is valuable enough to justify more sophisticated strategies of assessment, but it is a useful exercise to complete a simple CUSUM analysis for landings of this species. Simple biomass models indicate the reference point of maximum sustainable yield for this stock is in the order of 900 t (Anon., 2000, based upon preliminary modelling completed by NSW Fisheries). We would therefore expect that the recent harvests of between 800 and 900 t per year to not cause major impacts on the stock.

Fig. 7a is the CUSUM control chart for eastern king prawn based upon the methods and parameters developed in this report. The controlling mean and standard deviation was estimated from all records to be $(\mu, \sigma) = (963, 135)$ t. The gradual decreasing trend (apparently) starting in 1990 almost caused a signal in 1997, but the process remained in-control for the entire time-series. This result is not unexpected nor unreasonable for this fishery.

There is a long time-series of catch records for yellowfin bream (*A. australis*) but only records of commercial landings from 1980 onward are considered reliable. Using the same parameter values as above and estimating the controlling $(\mu, \sigma) = (531, 99)$ t, from all records post 1980 (Fig. 7b), the decrease in the final year is clearly flagged as an out-of-control process. This large decrease in catch can probably be attributed to a reduction in effort in this fishery.

Landings of scalloped hammerhead shark (*S. lewini*) have also been evaluated using the above method and the results are presented in Fig. 7c. This analysis indicates that the landings can be considered to be in-control except in 1993 and landings are certainly back within the domain of historical variability by the year 2000.

4. Discussion

This study has developed and tested a new type of method for detecting important changes within time-series of landed catch. Operating models were constructed for three very different types of input-controlled fisheries and the performance of a CUSUM-based signal detection scheme was evaluated. Simulated results are, as always, somewhat difficult to relate to actual systems. The initial analysis measured the performance of the scheme for known systems, whilst the secondary analysis gave us examples of the same tool applied to actual, but essentially unknown, systems. The example given for the eastern king prawn fishery provided partial insight because there is some evidence from preliminary stock assessments that the fishery for eastern king prawn is relatively stable, a conclusion corroborated by the CUSUM analysis presented here. The positive signal from the observed bream data is probably true. Managerial changes in the NSW bream fisheries would be expected to have reduced landings.

Application of these CUSUM schemes requires several types of judgements. Firstly, and perhaps most importantly, is the credibility and representativeness of the commercial landings data used. Any obvious outliers in catch history need to be examined carefully as they will cause an overestimation of the control standard deviation that will reduce the sensitivity and specificity of the method. Misidentification of species, or confused nomenclature, can also cause substantial errors in landings data. Such issues will, however, affect any quantitative analysis of fisheries. For many data-deficient fisheries, landings data will usually be better quality than effort data, but that certainly does not mean that these data are error-free. This method works in a straightforward manner. If historical catches were stable, and the controlling mean and standard deviation are calculated using these records, then the scheme will have greater sensitivity and specificity than when the catches have been standardised using data with a historical trend. It is very important to recognise that this algorithm detects changes to the state of a system rather than indicating the absolute condition.

A second judgement required is the specification of the CUSUM parameters (h, k). This issue can be as complicated or as simple as required. A complex response would be to anguish over the very mixed results for the optimal h values presented in Table 6 and attempt to justify an appropriate combination from this information. A simple response would be to repeat the approach presented in Fig. 7 and use $(h, k) = (1.0, 1.0)$. These values reflect a sensible middle ground: the allowance (k) reflects the variability that will be accepted as background noise (one standard deviation); the decision interval ($\pm h$) a measure of acceptable run length. Using smaller values of h will generate more false-positive results while reducing false-negative responses. Larger values of h will do the opposite. This CUSUM approach is not designed to be a rigorous analytical method for elucidating casual processes in fisheries, it is simply to support the identification and prioritisation of systems that require further attention and analysis.

Agencies that have committed themselves to precautionary or risk-averse managerial strategies must recognise that any signalling system will generate false-positive as well as false-negative signals. Although false-positive errors are more "precautionary" than false-negative errors (Peterman, 1990; Underwood, 1997; Hall, 1999, p. 216), we must also note the important comment made by Hilborn (2002) that precautionary management is about decision-making process not reference points. This study supports that theme by recommending that simple assumptions be made when applying this method. Managers could then use these control charts and CUSUM signal results as one input (amongst many) into a deliberative process with explicit terms-of-reference for risk-aversion or the application of a precautionary approach.

Many jurisdictions land hundreds of species of fish. In many cases, there is not the information, expertise nor financial resources to complete quantitative stock assessments for these species. Nobody would be so naïve as to expect landings to be a robust indicator of stock status, but landed catch is an indicator of the status of a fishery. That, in itself, has made this quantitative analysis of landed catch data a valuable exercise and important extension to Caddy (1999).

This study did not consider the managerial response to signals from this scheme. An interesting extension would be to include the possible responses of a manager (for example reduce fishing effort, or do nothing and wait and see) into the dynamics of the system and then analyse the outcomes of such actions. Such an analysis would indicate what interpretation and actions are required when applying this method within risk-averse decision-making. Other extensions to this work would be the application of CUSUM or other quality control methods to: univariate indices of abundance and population structure; and, multivariate indicators of populations or ecosystems. Comparison of the performance of such quality control methods with conventional assessment methods would be a valuable and important exercise.

Acknowledgements

The author would like to thank Doug Ferrell, Charles Gray and Andrew Goulstone from NSW Fisheries for motivating this research. Keith Sainsbury, Bruce Mapstone, Geoff Gordon and two anonymous reviewers provided detailed and extremely valuable comments on earlier versions of this study and manuscript. Encouragement and assistance from Tim Glasby, Mike Holloway and Tony Underwood from the Centre for Research on Ecological Impacts of Coastal Cities is also acknowledged. NSW Fisheries funded this initial study and supported the author whilst he undertook necessary revisions.

References

Anon., 2000. Juvenile Prawn Summit: Summary of Proceedings. Cronulla Fisheries Centre, NSW Fisheries.

Bury, K., 1999. Statistical Distributions in Engineering. Cambridge University Press, Cambridge.

Caddy, J.F., 1999. Deciding on precautionary management measures for stock based on a suite of limit reference points (LRPs) as a basis for a multi-LRP harvest law. NAFO Sci. Coun. Stud. 32, 55–68.

Caddy, J.F., Gulland, J.A., 1983. Historical patterns of fish stocks. Mar. Pol. 7, 267–278.

Caddy, J.F., Mahon, R., 1995. Reference points for fisheries management. FAO Fish. Tech. Paper 347, 83.

Campbell, R., 1998. Catch and effort analysis with uncertain stock and effort dynamics: southern bluefin tuna longline. In: Funk, F., Quinn, T.J., Heifetz, J., Ianelli, J.N., Powers, J.E., Schweigert, J.F., Sullivan, P.J., Zhang, C.-I. (Eds.), Fishery Stock Assessment Models. University of Alaska, Fairbanks, pp. 75–95.

Derman, C., Ross, S.M., 1997. Statistical Aspects of Quality Control. Academic Press, London.

Dew, I.M., 2001. Theoretical model of a new fishery under a simple quota management system. Ecol. Mod. 143, 59–70.

Essington, T.E., 2001. The precautionary approach in fisheries management: the devil is in the details. TREE 16, 121–122.
FAO, 1995. Precautionary approach to fisheries. Part 1. Guidelines on the precautionary approach to capture fisheries and species introductions. FAO Fish. Tech. Paper 350.
Francis, R.I.C.C., Shotton, R., 1997. Risk in fisheries management: a review. Can. J. Fish. Aquat. Sci. 54, 1699–1715.
Froese, R., Pauly, D., 2001. FishBase. World Wide Web Electronic Publication. http://www.fishbase.org.
Garcia, S.M., 1994. The Precautionary principle: its implications in capture fisheries management. Ocean Coast. Manage. 22, 99–125.
Gilbert, D.J., Annala, J.H., Johnston, K., 2000. Technical background to fish stock indicators for state-of-environment reporting in New Zealand. Mar. Freshw. Res. 51, 451–464.
Glaister, J.P., Lau, T., McDonall, V.C., 1987. Growth and migration of tagged eastern Australian king prawns, *Penaeus plebejus* Hess. Aust. J. Mar. Freshw. Res. 38, 225–241.
Gordon, G.N.G., Andrew, N.L., Montgomery, S.S., 1995. Deterministic compartmental model for the Eastern King Prawn (*Penaeus plebejus*) fishery in New South Wales. Aust. J. Mar. Freshw. Res. 46, 793–807.
Gray, C.A., Pease, B.C., Stringfellow, S.L., Raines, L.P., Rankin, B.K., Walford, T.R., 2000. Sampling Estuarine Fish Species for Stock Assessment. NSW Fisheries, Cronulla.
Haddon, M., 2001. Modelling and Quantitative Methods in Fisheries. Chapman & Hall/CRC, London.
Hall, S.J., 1999. The Effects of Fishing on Marine Ecosystems and Communities. Blackwell Science Publications, Oxford.
Hammond, K.R., 1996. Human Judgment and Social Policy: Irreducible Uncertainty, Inevitable Error, Unavoidable Injustice. Oxford University Press, New York.
Hawkins, D.M., Olwell, D.H., 1997. Cumulative Sum Charts and Charting for Quality Improvement. Springer, New York.
Hilborn, R., 2002. The dark side of reference points. Bull. Mar. Sci. 70, 403–408.
Hilborn, R., Walters, C.J., 1992. Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Chapman & Hall, London.
Kaufmann, B., Geen, G., Sen, S., 1999. Fish Futures: Individual Transferable Quotas in Fisheries. Fisheries Economics, Research and Management, Canberra.
Kesteven, G.L., 1999. Stock assessment and the management of fishing activities. Fish. Res. 44, 105–112.
Lane, D.E., Kaufmann, B., 1993. Bioeconomic impacts of TAC adjustment strategies: a model applied to northern cod. Risk evaluation and biological reference points for fisheries management. Can. Spec. Publ. Fish. Aquat. Sci. 120, 387–402.
Manly, B.F.J., 2001. Statistics for Environmental Science and Management. Chapman & Hall/CRC, London.
Manly, B.F.J., MacKenzie, D., 2000. A cumulative sum type of method for environmental monitoring. Environmetrics 11, 151–166.
Megrey, B.A., 1989. Review and comparison of age-structured stock assessment models from theoretical and applied points of view. Am. Fish. Soc. Symp. 6, 8–48.
Nicholson, M.D., 1984. Some applications of CUSUM techniques in fisheries research. ICES CM 1984/D:5.
Peterman, R.M., 1990. Statistical power analysis can improve fisheries research and management. Can. J. Fish. Aquat. Sci. 47, 2–15.
Punt, A.E., Walker, T.I., Taylor, B.L., Pribac, F., 2000. Standardization of catch and effort data in a spatially-structured shark fishery. Fish. Res. 45, 129–145.
Quinn, T.J., Deriso, R.B., 1999. Quantitative Fish Dynamics. Oxford University Press, New York.
Schnute, J., 1987. A general fishery model for a size-structured population. Can. J. Fish. Aquat. Sci. 44, 924–940.
Schnute, J.T., Richards, L.J., 2001. Use and abuse of fishery models. Can. J. Fish. Aquat. Sci. 58, 10–17.
Seijo, J.C., Caddy, J.F., 2000. Uncertainty in bio-economic reference points and indicators of marine fisheries. Mar. Freshw. Res. 51, 477–483.
Sparks, R.S., 2000. CUSUM charts for AR1 data: are they worth the effort? Aust. NZ J. Stat. 42, 25–42.
Underwood, A.J., 1997. Environmental decision-making and the precautionary principle: what does this principle mean in environmental sampling practice? Lands. Urb. Plan. 37, 137–146.
Walters, C.J., Pearse, P.H., 1996. Stock information requirements for quota management systems in commercial fisheries. Rev. Fish Biol. Fish. 6, 21–42.