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Management Strategy Evaluation of Fisheries Resources in Data-poor Situations Using an Operating Model Based on a Production Model

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Abstract

The allowable biological catch (ABC) in Japanese fishery management is currently determined by applying harvest control rules, which are categorized into two types depending on whether or not stock-size information is available. We evaluate management procedures (MPs) in data-poor situations using an operating model (OM) based on a production model. The OM incorporates uncertainties regarding its assumptions and the process and observation errors of population dynamics and fishing processes, while the values of the MP parameters are determined to avoid stock collapses and low catches. We evaluated the MP formulation $ABC = \delta \times C_t \times \left(1 + k\frac{b}{\bar{I}}\right)$, where δ is a coefficient dependent on the stock status level on the stock size, C_t is the catch in year t, k is the weight coefficient, b reflects the trend in stock abundance index over time, and $\bar{I}$ is the mean of the stock abundance index I. This study shows that smaller values of k reduce the frequency of substantially low catches, particularly when there is significant uncertainty surrounding the stock status. In addition, the value of δ affects both the frequency of fishery collapse as well as stock and catch sizes. We conclude that more reliable stock abundance indices are necessary if the stock size and catch are to stabilize and MPs become more robust to uncertainties.

Discipline: Fisheries
Additional key words: harvest control rules, management procedure, population dynamics

Introduction

Important fisheries resources in Japan (e.g. jack mackerel, *Trachurus japonicus*, and walleye Pollock, *Theragra chalcogramma*) have been managed under the act of preservation and control of living marine resources[8]. The main tool for harvest control is the total allowable catch system, which has been implemented since 1997. In Japan, the total allowable catch is determined based on the allowable biological catch (ABC), which is calculated using data such as catch-at-age, catch per unit effort (CPUE), and biomass estimates from trawl surveys. The ABC is determined by harvest control rules[8], which are categorized into two types: those used for species whose stock size can be estimated based on virtual population analysis (VPA) or fishery-independent surveys (type I species), and those used for species whose stock size cannot be estimated due to a lack of reliable data (type II species). The purpose of this study is to evaluate the validity of the latter type of harvest control rule (i.e. for type II species) using the management strategy evaluation (MSE) approach. MSE involves developing an operating model (OM) to represent the underlying reality of the resource, and evaluating harvest control rules based on data simulated using the OM. MSE is undertaken to examine the robustness of candidate management procedures (MPs) to errors and uncertainties.

MPs for fisheries stocks have been proposed worldwide, and most have been developed using OMs[1,3]. In South Africa, MPs developed using OMs have been used to regulate the demersal fishery[14] and the pelagic fishery for sardines and anchovies[2,6]. In Japan, Watanabe et al.[19]

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evaluated the fishing impacts on the population dynamics of the Pacific chub mackerel (*Scomber japonicus*) using an age-structured OM. Horbowy[11] compared the management rules for Baltic cod stock using a similar OM. Punt and Smith[17] evaluated MPs for gemfish (*Rexea solandri*) in southeastern Australia and compared the performance of MPs based on estimates from VPA and from the Shaefer production model using age-structured OMs. Southern Bluefin tuna (*Thunnus maccoyii*) have been managed since 2011 based on an agreed MP developed using an OM[5,12]. These studies show that OMs are efficient approaches for developing MPs robust to uncertainties.

In this study, we developed an OM representing data-poor situations and used it to evaluate MPs. Stock assessment is often difficult when available data are insufficient. In Japan, one of two harvest control rules is currently used for type II species in data-poor situations depending on the availability of stock abundance indices. The harvest control formulae used in 2011[8] were:

$$ABC = \gamma \times C_y \qquad (1),$$

for stocks whose abundance indices were available, and

$$ABC = \delta \times C_{ave} \qquad (2),$$

for those with no available abundance indices (i.e. only catch data were available). In these formulae, ABC is the allowable biological catch, γ reflects the trend in the stock abundance index, δ is a weighted coefficient depending on stock status and catch trend, C_y is the catch in year y, and C_{ave} is the average catch in recent years. Normally, the ABC for year y is determined in year $y - 1$ using information available through year $y - 2$.

Although these harvest control rules have been applied to Japanese stocks since 1997, they have not yet been extensively or quantitatively evaluated. In 2004, Hiramatsu[10] recommended revising the rules (i.e. eqs. 1 and 2) based on an OM, and proposed an alternative harvest control formula:

$$ABC = \delta \times C_t \times \left(1 + k\frac{b}{\bar{I}}\right) \qquad (3),$$

where δ is a coefficient dependent on the stock status level, C_t is the catch in year t, k is a weight coefficient, b reflects the trend in the stock abundance index over time, and $\bar{I}$ is the mean of the stock abundance index I. Although Hiramatsu[10] showed that eq. 3 is superior to eq. 1, appropriate values for k and δ were not explicitly shown. In this study, therefore, we test the validity of this new harvest control rule (eq. 3), and explore appropriate values of k and δ for Japanese fishery stocks.

Materials and methods

1. Production model

The production-model-based OM structure as shown by Hiramatsu[10] is given by:

$$B_{y+1} = \left\{B_y + rB_y\left(1 - \frac{B_y}{K}\right)\right\}\hat{\varepsilon} - qX_yB_y \qquad (4),$$

where B_y is the biomass in year y, r is the intrinsic growth rate, K is the carrying capacity, q is the catchability coefficient, and X is the fishing effort. The parameter $\hat{\varepsilon}$ is the process error, defined as:

$$\hat{\varepsilon} = \exp\left(\sigma_R\varepsilon_y - \frac{1}{2}\sigma_R^2\right) \qquad (5),$$

where ε_y is described by a normally distributed random number with mean = 0 and standard deviation = 1, and σ_R is the scale of variance for the process error.

For this study, the carrying capacity K was assumed to be 10,000, and the intrinsic growth rate r was set at 0.3 or 0.5, based on age-specific survivorship, fecundity and mean generation time[20] of fish around Japan (Mito and Yatsu, pers. comm.). Maximum sustainable yield (MSY) was 750 (for $r = 0.3$) or 1250 ($r = 0.5$), and the stock size at MSY was 5000 for both cases. The total duration of the simulation was 50 years, consisting of the pre-management and management periods (20 and 30 years, respectively) (Fig. 1).

During the pre-management period, nine stock trajectory cases (e.g. from a high stock level [7500] to a low stock level [2500], and from mid-level [5000] to low) were assumed, to cover diverse stock change patterns (Figs. 1b and c). The ABC in year y was calculated using the catch in year $y - 2$ and the trend in the stock abundance index from years $y - 4$ to $y - 2$ during the management period (see eq. 3). The actual catch was assumed to be equal to the ABC during the management period. The stock abundance index at year y (I_y) is given by:

$$I_y = \frac{B_y + B_{y+1}}{2}\exp\left(\sigma_I\eta_y - \frac{1}{2}\sigma_I^2\right) \qquad (6),$$

where η_y is described by a normally distributed random number with mean = 0 and standard deviation = 1, and σ_I is the scale of variance for the observation error. The stock abundance indices during the management period were categorized into three levels — high, middle, and low — based on those during the pre-management period. This criterion is also used to judge the stock size for present stock assessments in Japan. The value for δ was determined during the management period according to the stock level. The maximum harvest rate was fixed at 70% to match the approximate observed maximum harvest rates around Japan[8,13], and the catch during the management period was assumed to be

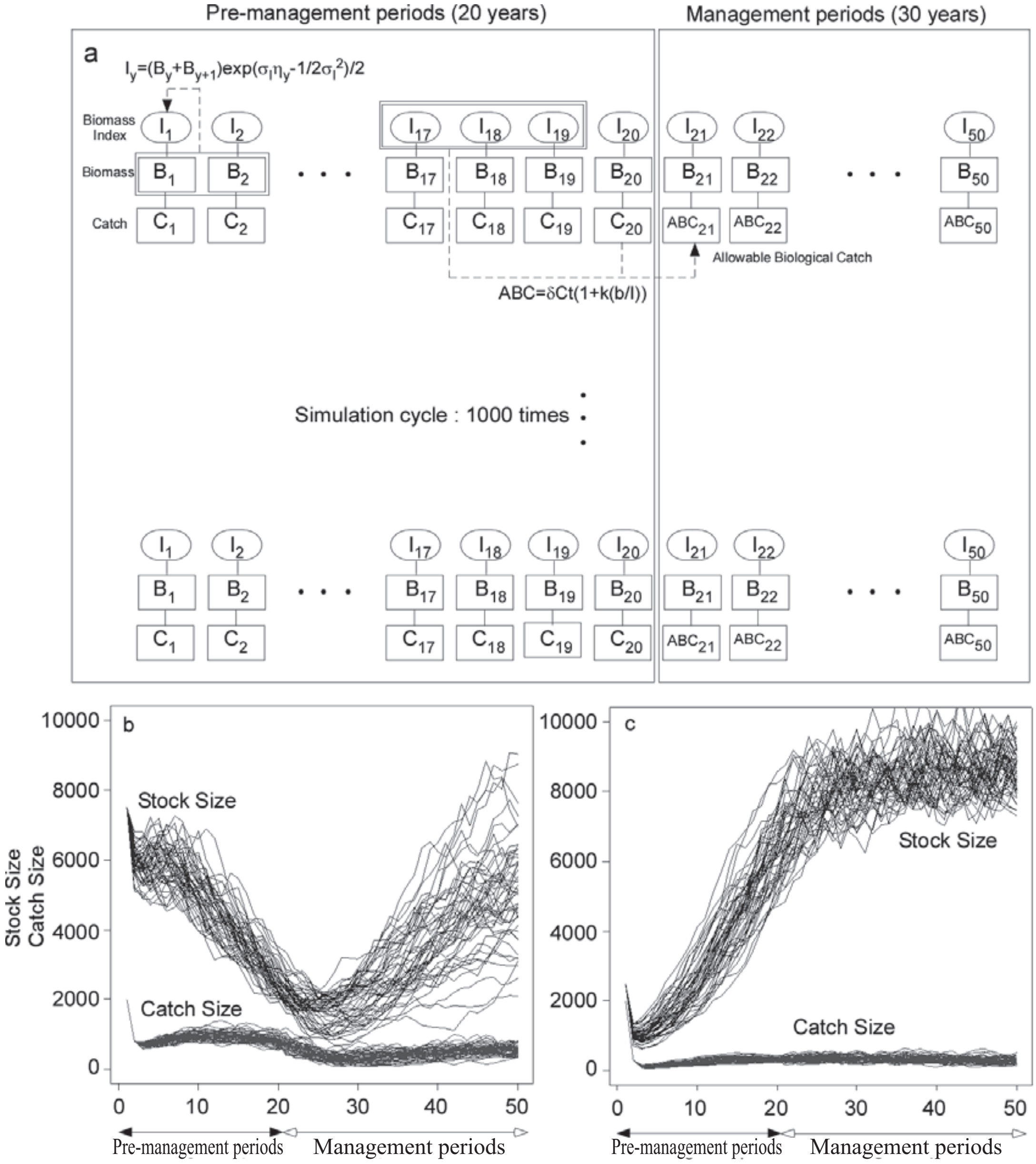

Fig. 1. Schematic representation of the management procedure evaluation using operating models in this study (a), and conceptual trajectories of the stock size and catch where the stock status is high to low (b) and low to high (c) during the pre-management period

0 when the ABC was 0 or less than 0.

This stochastic simulation was repeated 1000 times for each of the nine cases, for a total of 9000 simulations. In this study, the effect of observation errors is emphasized more than process errors. Therefore, σ_I was set at 0.2, 0.4 or 0.6, whereas σ_R was fixed at 0.05.

2. Parameter selection

To evaluate the performance of MPs with different parameter values, six performance statistics were formulated: the frequency of stock collapse, the frequency of management failure, mean stock size and catch, and the coefficient of variation (CV) of stock size and catch during the management period. Stock collapse and management failure were defined as low stock size (<20% of the carrying capacity)[9] and low catch (<1% of MSY) during the management period, respectively. The CV is given by

$$CV=\frac{\sqrt{\sigma^2}}{\bar{x}} \qquad (7),$$

where $\sqrt{\sigma^2}$ and $\bar{x}$ are the standard deviation and average, respectively. We first examined the effect of varying k, and subsequently the effect of the value of δ under the following six scenarios, assuming different combinations of values for

δ at high, middle and low stock status levels:

Scenario 1: high level, δ1.1;
middle level, δ 0.9; low level, δ 0.7
Scenario 2: high level, δ 1.1;
middle level, δ 0.8; low level, δ 0.6
Scenario 3: high level, δ 1.0;
middle level, δ 0.9; low level, δ 0.7
Scenario 4: high level, δ 1.0;
middle level, δ 0.8; low level, δ 0.6
Scenario 5: high level, δ 1.0;
middle level, δ 1.0; low level, δ 1.0
Scenario 6: high level, δ 1.0;
middle level, δ 1.0; low level, δ .9.

The number of stock collapses and fishery management failures for the nine cases was totaled, and the frequency calculated in terms of the total number of collapses and management failures divided by the total number of simulations. The mean stock size, catch and CV were calculated as averages in each case.

Results

1. Effects of *k* and σ_I

Frequencies (expressed as percentages) of stock collapse and management failure under scenario 3 are shown in Fig. 2a. For $k = 0.5$ and $\sigma_I = 0.2$, the frequency of stock collapse ranged from 19 to 31%. For $\sigma_I = 0.2$, the frequency of stock collapse decreased with increasing *k*. In contrast, management failures occurred more frequently with increasing *k* (Fig. 2b). Although the frequency of management failure was below 15% for $\sigma_I = 0.2$, it was observed more frequently for $k > 1.5$ and $\sigma_I = 0.4$ or 0.6, and exceeded 90% for $\sigma_I > 0.4$ and $k = 2.5$ (Fig. 2b).

The mean stock size, catch, and CVs of the stock size and catch during the management period are shown in Fig. 3. Mean stock sizes increased with increasing *k* (Fig. 3a). Mean stock sizes were higher at $\sigma_I = 0.6$ than at $\sigma_I = 0.2$ or 0.4 (Fig. 3a). Mean catch decreased with increasing *k* (Fig. 3b). The mean catch was lower at $\sigma_I = 0.6$ than at $\sigma_I = 0.2$ or 0.4 (Fig. 3b). Mean CVs of stock sizes were stable (Fig. 3c). Mean CVs of catch increased with increasing *k* (Fig. 3d), and the mean CV was higher at $\sigma_I = 0.6$ than at $\sigma_I = 0.2$ or 0.4.

2. Effects of δ

We compared the results from the scenarios with different combinations of δ. The frequency of stock collapse and management failure under the six scenarios when $\sigma_I = 0.4$ are shown in Fig. 4. The frequency of stock collapse was >10% for all of the scenarios (Figs. 4a and c). The

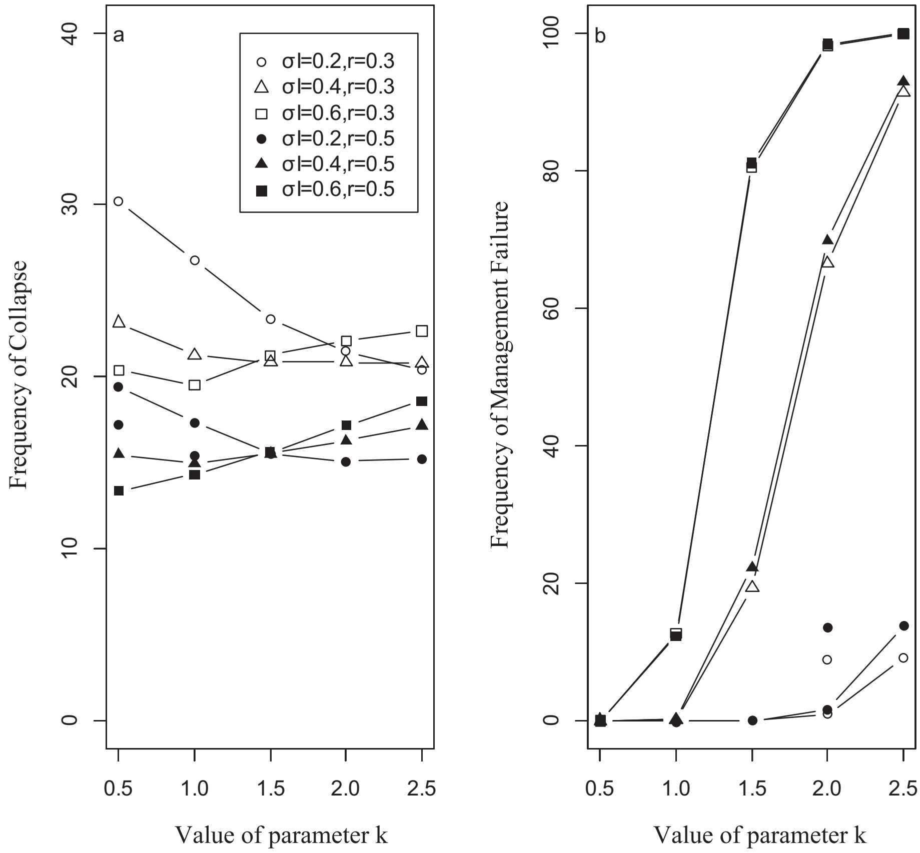

Fig. 2. Frequency of stock collapse (a) and fishery management failure (b) depending on parameter *k* for scenario 3

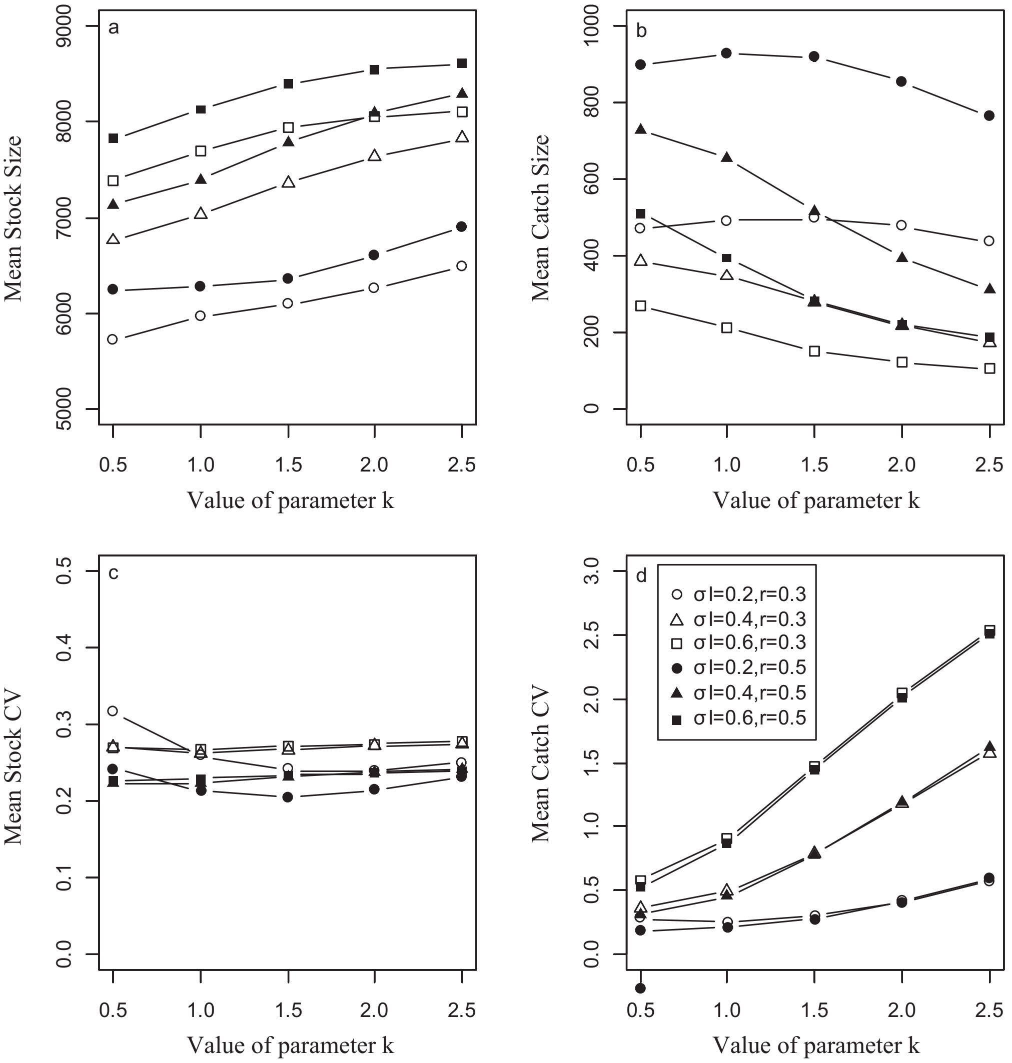

Fig. 3. Mean stock size (a), catch (b), mean CV of stock size (c) and CV of catch (d)

highest collapse frequency among all scenarios exceeded 40% under scenario 1 (Figs. 4a and c). In contrast, the lowest frequency of collapse was below 20% in scenario 4, irrespective of *k*. The frequency of stock collapse decreased under scenarios 1, 2, 5 and 6 with increasing *k*, whereas the frequencies were almost constant for scenarios 3 and 4 for all values of *k* (Figs. 4a and c). Management failures increased with increasing *k* (Figs. 4b and d).

The mean stock sizes and catches under scenarios with different δ are shown in Fig. 5. The largest mean stock size for all values of *k* was in scenario 4 (Figs. 5a and c). In contrast, mean stock sizes in scenarios 1, 5 and 6 were smaller than in the other scenarios although the mean stock size increased with increasing *k* (Figs. 5a and c). The mean catch was lower in scenario 4 for all values of *k* than the other scenarios (Figs. 5b and d). Overall in the present study, larger values of *k* led to a lower mean catch.

Discussion

This is the first study to evaluate risks such as the probabilities of stock collapse and fishery management failure for type II species in Japan. It is generally difficult to manage fisheries and stocks in data-poor situations, due to limited available information on stock status and only relative stock levels such as CPUEs are known. Under these circumstances, quantitative risk assessments e.g. involving estimation of stock depletion levels can be difficult. To overcome this limitation, it is necessary to develop MPs which are robust to various uncertainties, and confirm the robustness in advance of implementation using OMs. Although harvest control rules have been implemented in Japan, they have not been quantitatively validated.

The effects of uncertainties can be evaluated using OMs. Deroba and Bence[7] reviewed harvest policies for fishery management and concluded that most pre-1990s studies focused on evaluating harvest policies; assuming

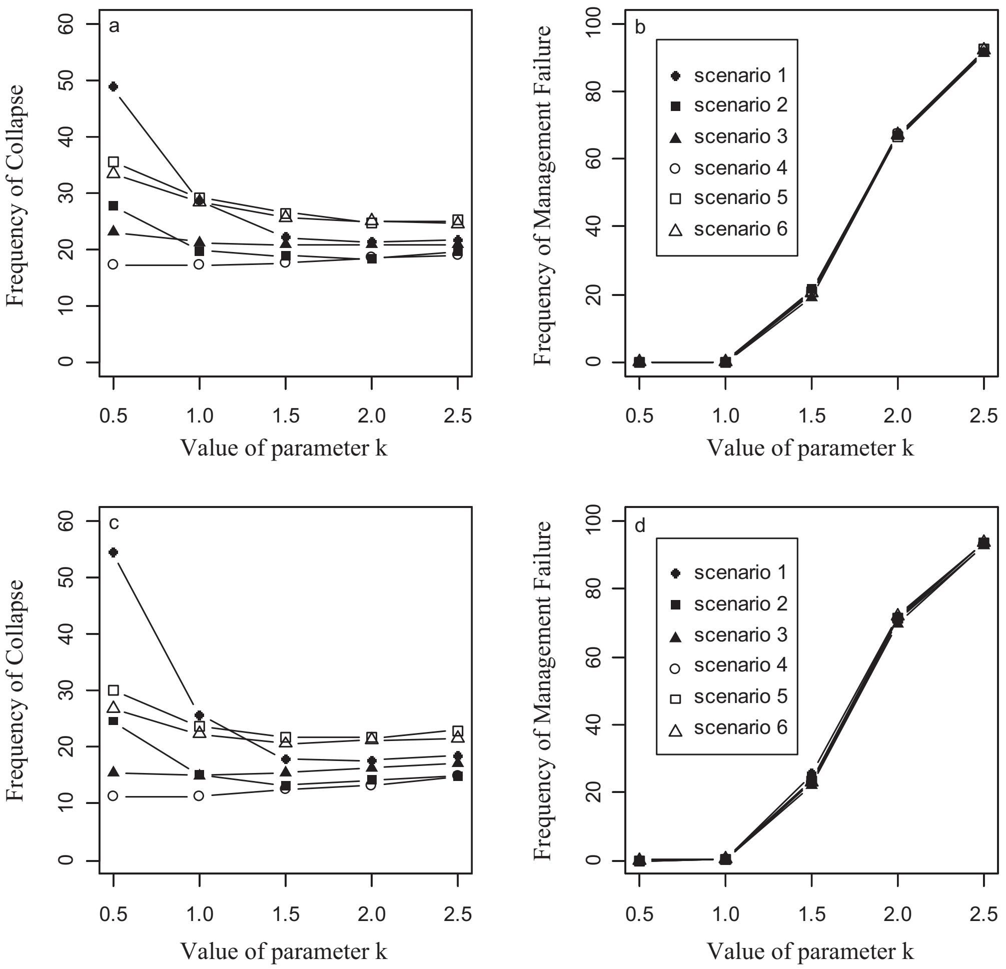

Fig. 4. Frequency of stock collapse (a: $r = 0.3$, c: $r = 0.5$), and management failure (b: $r = 0.3$, d: $r = 0.5$) when the value of σ_I is 0.4

ideal situations with accurate and reliable information (i.e. no uncertainty or errors). If information on population dynamics and stock abundance index were accurate, fisheries resources could be managed with few errors. However, various errors and biases in the processes of stock assessment and management implementation are unavoidable. Therefore, when decisions are made on the formulation of MPs and the values for their key parameters, these uncertainties need to be appropriately considered[15,16].

In this study we focused on determining the values of the key parameters (k and δ) of the MPs under circumstances where stock size could not be accurately estimated (i.e. for type II species). We evaluated MPs with different parameter values using an OM incorporating two types of error: process errors in population dynamics and observation errors in stock abundance indices. We assumed smaller process errors ($\sigma_R = 0.05$) than observation errors ($\sigma_I = 0.2$, 0.4 and 0.6). A preliminary analysis showed that large process errors led to significant variations in stock size, suggesting that fisheries might not be managed satisfactorily, regardless of which MP was applied. Therefore, future studies should comprehensively evaluate MPs under conditions with larger process errors.

If the sole objective of MPs were to increase stock abundance, their development could be simplified by simply selecting MPs yielding lower catches. However, from the perspective of fishery profitability, such MPs would be inappropriate. One requirement of harvest policies is transparency in the decision-making process, and the rules governing decisions about how the catch will vary should be evident in advance to all stakeholders. The harvest policy should be selected to optimally achieve management objectives, e.g. maximizing yield and minimizing risks of overexploitation and stock recovery time[7]. In the long term, it is generally unfeasible to simultaneously achieve large catches and large stock. We consider the first priority to be avoiding stock collapse rather than low catch levels (i.e. fishery management failure).

We tested parameters k and δ widely in the various scenarios of this study. Higher values of k led to lower probabilities of stock collapse and higher probabilities of management failure (Figs. 2 and 4). In particular, the fre-

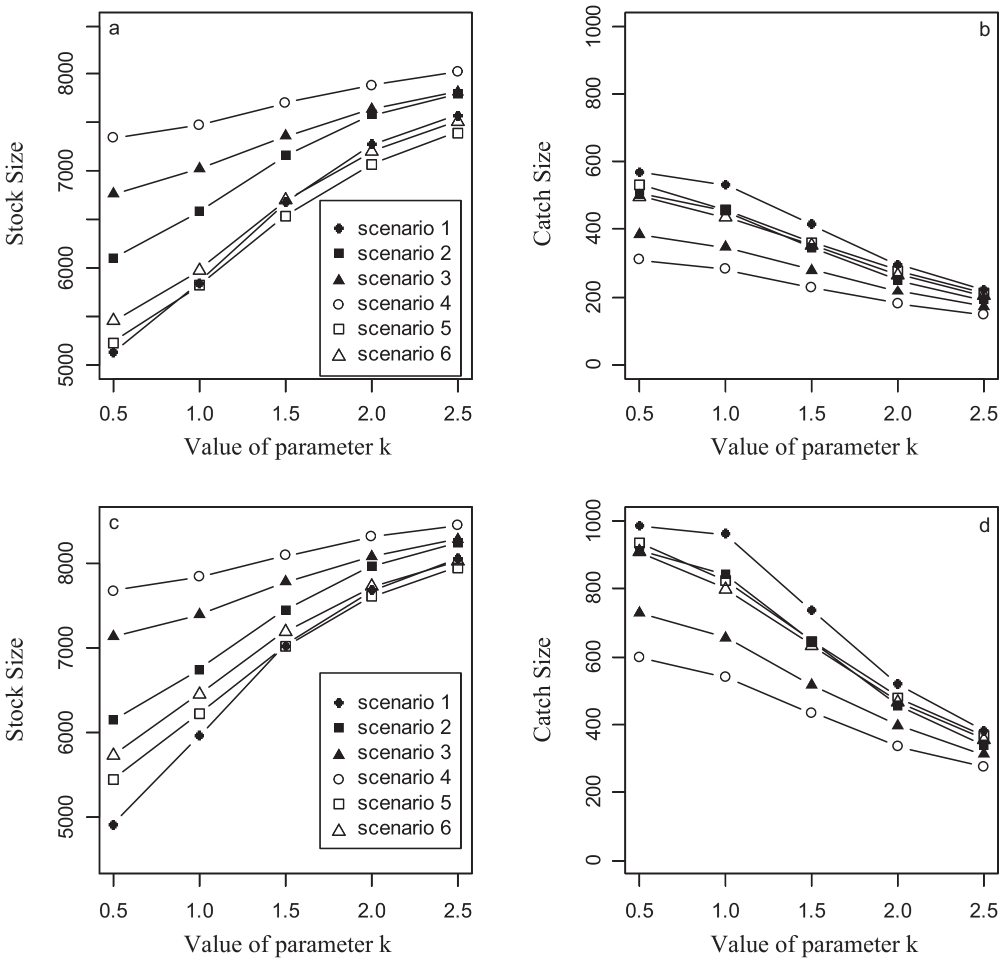

Fig. 5 Mean stock size (a: $r = 0.3$, c: $r = 0.5$), and mean catch (b: $r = 0.3$, d: $r = 0.5$) when the value of σ_I is 0.4

quency of management failure was very high (>90%) at $k = 2.5$ and $\sigma_I = 0.4$. For $k = 0.5$, the frequency of stock collapse peaked under scenario 1 (Figs. 4a and c). In contrast, the lowest frequencies of stock collapse were under scenario 4 (Figs. 4a and c). Our results suggest that conservative MPs that can avoid stock collapse as the first priority should be adopted in the event of limited available data. Based on this criterion we therefore conclude that the MP with the parameter values of scenario 4 is the most preferable.

The mean stock sizes during the management period increased with increasing *k* (Figs. 3a and c). A log-normal distribution was assumed for the observation error of the stock abundance index (σ_I in eq. 6), and large values of σ_I had the same effects as large values of *k*. The mean stock size was higher and the catch lower when σ_I was large (0.6), compared to when $\sigma_I = 0.2$ or 0.4 (Figs. 3a–d). This larger stock size led to a reduced frequency of stock collapse (Fig. 2a).

Larger catches were observed when observation errors were smaller. Additionally, the mean stock size was highest and the catch lowest under scenario 4 (Fig. 5). The mean CV of catch increased with increasing *k* (Fig. 3d), and was higher when $\sigma_I = 0.6$ than when $\sigma_I = 0.2$ or 0.4. A high catch CV would be undesirable for fishery stability. If observation errors are known to be large, *k* should be set to a low value to avoid a high catch CV and high frequency of management failure. This also shows the importance of minimizing observation errors, for example, by implementing intensive data collection.

The main purpose of this study was to revise the harvest control rules for type II species in Japan. We consider the MPs proposed here as feedback control rules that combine a constant proportion strategy (controlled by δ) and a slope strategy (controlled by *k*)[4]. Campbell and Dowling[4] reported on MSE for swordfish using the slope strategy, which was regarded as one of the feedback controls. In contrast, Roel and Oliveira[18] suggested that the constant proportion strategy might be more appropriate for western horse mackerel (*Trachurus trachurus*), which is characterized by spasmodic recruitment.

Punt[14] found that MPs based on stock assessments using a production model outperformed those based on VPA with ad-hoc tuning, mainly because the latter exhibited substantially larger inter-annual variability of the catch limit. In Japan, *F*-control rules based on biomass and mainly estimated using VPA are commonly applied to calculate ABCs for type I species. However, these *F*-control rules have not been closely evaluated using OMs, as in this study for type II species. We suggest that such evaluation of harvest control rules for type I species is necessary.

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