Initial developments of an empirical MP for Indian Ocean skipjack tuna

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Contents

Project Background and Objectives

Based on simulation evaluations of candidate harvest control rules by Bentley and Adam (Adam and Bentley, 2013, Bentley and Adam, 2014a,b, 2015, 2016), reviewed and endorsed by the Working Party on Tropical Tunas (WPTT), Working Party on Methods (WPM), and the Scientific Committee (SC), the IOTC adopted Resolution 16/02 "On Harvest Control Rules for Skipjack in the IOTC Area of Competence." This described the harvest control rule (HCR) to be used for setting a recommended catch for skipjack (SKJ) and stated that its first implementation will be based upon the 2017 stock assessment agreed by the WPTT and then endorsed by SC. Implementation of the HCR to give a recommended catch limit for 2018–2020 is described in IOTC (2017a). The Resolution also requested a further review and possible modification of the HCR to be conducted no later than 2021.

In 2018, the IOTC WPM noted that the SKJ HCR is not a fully specified Management Procedure (MP), since the underlying data required and assessment methodology are not defined (IOTC, 2018b). Hence the WPM suggested that a review and potential revision required under Resolution 16/02 be conducted with the aim of determining a fully specified MP for SKJ. This was noted by the SC in 2018 and provides the motivation and basis for the current work (IOTC, 2018a).

A fully specified MP is one that can be simulation tested, including at the least specification of the data inputs, a decision algorithm, and management outputs. Testing requires an accompanying operating model (OM) to describe dynamics of the resource under management and the generation of observational data for iterated application of the MP forward in time. The current report describes development of an empirical MP, which is tested using the OM developed by Edwards (2020b). Previous work towards a model-based MP has shown that a simple biomass dynamic model, on which the MP could be based, may not provide information on the stock depletion and it was noted by the WPM that an empirical MP may be more useful for SKJ (IOTC, 2021). The current report describes initial developments of an empirical MP based on CPUE inputs from the Maldivian Pole and Line (PL) and European Purse Seine Log-School (PSLS) fisheries.

1 Introduction

For a Management Procedure to be evaluated through simulation it needs to be specified fully in terms of: the data inputs; a decision algorithm; and management outputs. The decision algorithm includes a component for estimation of the stock status. For example a stock assessment model that may provide an estimate of the depletion. Conversion of the stock status into a management action takes place via a catch control rule (CCR), which describes a relationship between the status and either a fishing mortality or catch. If a fishing mortality is output, then it needs to be converted to a target catch using an estimate of the exploitable biomass. The decision algorithm may also contain meta-rules that limit the magnitude of the change in any given year, or exceptional circumstances that may be considered to invalidate the MP (Punt et al., 2016).

Under Resolution 16/02 the Indian Ocean SKJ fishery is currently managed using a CCR (or Harvest Control Rule) that is based on an estimate of the stock status and a target exploitation rate, which provide both the parameters needed to define the control rule and the stock status inputs required to implement it.

Although the product of substantial development work, the stock status estimator is not fully specified in 16/02 and it cannot therefore be formally tested through simulation. For example, between 2017 and 2020 there were changes in both the data inputs and the grid of SS III assessment runs. Periodic "benchmark" assessments of this type cannot, by their nature, be specified *a priori*. A much more parsimonious stock status estimator is needed, such as a two or three parameter biomass dynamic model. This kind of model has been developed for Indian Ocean BET (Kolody and Jumppanen, 2020). Given their relative simplicity, they can be fully specified and therefore tested. A biomass dynamic model has been applied to catch and abundance data from the 2017 SKJ assessment, and shown to provide reasonable estimates of the depletion (Edwards, 2020a). However the abundance indices have since been updated (Guery, 2020, Guery et al., 2020, Medley et al., 2020a,b), and are no longer informative for estimation of the depletion using this kind of model (IOTC, 2021). For this reason, it was noted by the WPM that an empirical approach should be investigated (IOTC, 2021).

An empirical MP is based on descriptive rather than process based models. This report describes development of such an MP, based on CPUE indices from the PL and PSLS fleets, which are both used routinely in assessments of the stock (Fu, 2017, 2020). The empirical MP is developed in parallel to a reference MP that assumes perfect knowledge of the resource biomass. Comparison of the two serves to demonstrate utility of the empirical approach. A summary of current management is first provided, before the empirical MP is described. A range of MPs are proposed based on two different CCRs, and tested using a SS III operating model. Because this represents an initial phase of the work, only simple evaluations are performed, based on the grid of single area runs used in the most recent stock assessment (Fu, 2020).

1.1 Current management

Based on the work of Bentley and Adam (Adam and Bentley, 2013, Bentley and Adam, 2014a,b, 2015, 2016) Resolution 16/02 was adopted in 2016 as a means of setting catch quotas for SKJ. It was implemented in 2017 to provide a recommended catch limit of 470,029 tonnes for the period 2018–2020 inclusive, and more recently in 2020 to recommend a preliminary catch limit of 513,572 tonnes for 2019–2023 (Table 1).

Using the terminology of Bentley and Adam (2016), the control rule outputs an intensity multiplier (I_y) as a function of the spawning stock biomass (SSB_y), using a step-linear relationship:

$$I_y = \begin{cases} 1 & \text{for } SSB_y \geq SSB_{40\%} \\ \frac{SSB_y - SSB_{10\%}}{SSB_{40\%} - SSB_{10\%}} & \text{for } SSB_{10\%} < SSB_y < SSB_{40\%} \\ 0 & \text{for } SSB_y \leq SSB_{40\%} \end{cases} \tag{1a}$$

Multiplication of the intensity by a target exploitation rate gives the realised exploitation rate:

$$E_y = I_y \times E_{40\%} \tag{1b}$$

The exploitation rate is defined as the catch over the vulnerable (selected) component of the biomass (Section 2.1.3, Bentley and Adam, 2016). However in the control rule itself the exploitation rate is implicitly re-defined as a proportion of the spawning stock biomass. Thus the recommended catch is set using the following relationship:

$$C_{y+1:3} = I_y \times E_{40\%} \times SSB_y \tag{1c}$$

The following additional meta-rules were also endorsed:

- The recommended catch limit should not exceed 900,000 tonnes;
- The change in recommended catch from the previous year should not exceed 30% unless $SSB_y \leq SSB_{10\%}$, in which case $C_{y+1:3}$ will always be zero.

Input values for the control rule ($SSB_{40\%}$, $SSB_{10\%}$, and $E_{40\%}$) are obtained as medians across estimated values from the grid of SS III assessment runs in the year in which the control rule is applied. In 2017, there were 36 alternative assessment model runs in the final grid (Fu, 2017, IOTC, 2017b), yielding the median values listed in Table 1a. Following implementation of the control rule, the catch in 2018 was approximately 607 thousand tonnes: 29% above the recommended catch limit; and in 2019 the catch was 547 thousand tonnes. Despite these high catches, the stock assessment in 2020, consisting of 24 grids (Fu, 2020, IOTC, 2020a), yielded a positive stock status (Table 1b).

1.2 Empirical MPs

Empirical MPs are based on descriptive models of the raw data, rather than the process based models applied in model-based MPs. For example, the mean length, or recent changes in an abundance index would provide the information needed to set a catch quota (e.g. Carruthers et al., 2016). Their main advantages are that they are simple to understand, apply and ultimately communicate. They are also more amenable to comprehensive evaluation and notwithstanding their simplicity have been shown to perform well in both simulation tests (Geromont and Butterworth, 2015a,b) and long-term observational studies (Breen et al., 2016).

A management procedure has three primary components, namely the data inputs, the decision algorithm (including the catch control rule) and management outputs (Punt et al., 2016). These are dealt with in reverse order here. Other components, such as meta-rules or the exceptional circumstances that may invalidate the MP, are left for future work and not considered in the current explorations. A glossary of terms used for description of the MPs is provided in Table 2.

Table 1: Derived quantities from the 2017 and 2020 SKJ stock assessments used by the control rule to recommend preliminary catch limits according to Resolution 16/02. Values are median and 80% quantiles across the grid of assessment model runs. Catch and biomass values are given in units of 1000 tonnes.

(a) SKJ 2017 stock assessment outputs Fu (2017), IOTC (2017b) yielding a recommended catch of 470,029 tonnes for 2018 – 2020 (IOTC, 2017a, 2018a).

Quantity	Median	80% quantiles
$C_{40\%}$	510.1	(455.9 – 618.8)
$E_{2016}/E_{40\%}$	0.93	(0.70–1.13)
$C_{2016}/C_{40\%}$	0.88	(0.72–0.98)
SSB_0	2,015.2	(1,651.2–2,296.1)
$SSB_{2016}/SSB_{40\%}$	1.00	(0.88–1.17)
SSB_{2016}/SSB_0	0.40	(0.35–0.47)
SSB_{2016}	796.7	(582.7–1059.4)
$E_{40\%}$	0.59	(0.53–0.65)
C_{2016}	446.7	
$C_{2012-2016}$	407.5	
$C_{2018-2020}$	470.0	

(b) SKJ 2020 stock assessment outputs Fu (2020), IOTC (2020a) yielding a recommended catch limit of 513,572 tonnes for 2021 – 2023 (IOTC, 2020b).

Quantity	Median	80% quantiles
$C_{40\%}$	536.0	(462.0 – 674.5)
$E_{2019}/E_{40\%}$	0.92	(0.67–1.21)
$C_{2019}/C_{40\%}$	1.02	(0.81–1.18)
SSB_0	1,992.1	(1,691.7–2,547.1)
$SSB_{2019}/SSB_{40\%}$	1.11	(0.95–1.29)
SSB_{2019}/SSB_0	0.45	(0.38–0.50)
SSB_{2019}	870.5	(660.4–1,253.2)
$E_{40\%}$	0.59	(0.53–0.66)
C_{2019}	547.2	
$C_{2015-2019}$	506.6	
$C_{2021-2023}$	513.6	

Table 2: Glossary of terms used for description of MPs.

Notation	Description
$C_{y+1:3}$	Total catch for years $y+1$ to $y+3$ recommended by the CCR
C_{TARGET}	Target catch for implementation of CCR1
C_{TAC}	Previous TAC for implementation of CCR2
I_y	Fishing intensity multiplier in year y
a_y	mean of the log-normalised PL and PSLS abundance indices per year
a_R, a_L	tuning parameters for index-based CCRs
SSD_y	depletion SSB_y/SSB_0
SSD_R, SSD_L	tuning parameters for SSB-based CCRs

1.2.1 Management outputs

In a catch controlled fishery, empirical MPs must output a catch. Since the stock biomass is unknown, a fishing mortality output could not be converted into a catch for management purposes.

1.2.2 Catch control rules

Calculation of a recommended catch from the data inputs occurs via a catch control rule. In the current context, the CCR calculates a fishing intensity multiplier I_y that represents a proportion of a known catch value (C^*). With analogy to Equation 1c, the recommended catch is then:

$$\mathrm{C}_{y+1:3} = \mathrm{I}_y \times C^*$$

If a stock is in reasonable condition then choice of C^* can be informed by recent catches and an MP can be constructed to maintain the catch and catch rates at or above their current levels via small adjustments in I_y. The recent assessments for SKJ suggest that the stock is healthy, with current catches close to the estimated target catch at $\mathrm{SSB}_{40\%}$ (Fu, 2017, 2020). Although there is concern that these catches may not be sustainable should environmental conditions change (IOTC, 2020a), they nevertheless provide an indicative starting point for management.

We consider here empirical MPs that depend on an index or indices of abundance. These provide either a trend in abundance or a status relative to a preferred index value (location). Either the trend or location are used to adjust I_y. For example, a typical trend-based MP will calculate the slope (λ) of the recent index values and use this to adjust the catch up or down:

$$\mathrm{I}_y = 1 + \kappa \cdot \lambda$$

with κ a tuning parameter chosen during the simulation evaluation process. A location based MP will use an abundance index a_y relative to a reference value a_R, which is perceived as a desirable catch rate for the stock:

$$\mathrm{I}_y = \frac{\mathrm{a}_y}{\mathrm{a}_\mathrm{R}}$$

If $\mathrm{a}_y > \mathrm{a}_\mathrm{R}$ then the catch is increased, if $\mathrm{a}_y < \mathrm{a}_\mathrm{R}$ then the catch is reduced. Rules of this type would usually include a lower limit a_L below which extreme management measures are taken (e.g. closure of the fishery):

$$\mathrm{I}_y = \begin{cases} \frac{\mathrm{a}_y - \mathrm{a}_\mathrm{L}}{\mathrm{a}_\mathrm{R} - \mathrm{a}_\mathrm{L}} & \text{for} \quad \mathrm{a}_y \geq \mathrm{a}_\mathrm{L} \\ 0 & \text{for} \quad \mathrm{a}_y < \mathrm{a}_\mathrm{L} \end{cases}$$

A characteristic of location based rules is that they are sensitive to fluctuations in the index due to observation error. This can be ameliorated by using an average of $(\mathrm{a}_y - \mathrm{a}_\mathrm{L})/(\mathrm{a}_\mathrm{R} - \mathrm{a}_\mathrm{L})$ over years, not just the current index. However this produces a lag that can potentially delay appropriate management action (Hoshino et al., 2020).

If a desirable target catch is reasonably well known, then a plateau at $\mathrm{I}_y = 1$ can be included for $\mathrm{a}_y > \mathrm{a}_\mathrm{R}$ to maintain the catch close that value, with a_R chosen to be low enough to ensure stability in I_y and high enough to ensure that it is sensitive to reductions in the stock abundance. This is the same functional form as Equation 1a. However if a desirable target catch is less well known, then it is possible to induce stability by updating the catch recursively using a weighted average:

$$\mathrm{I}_y = \begin{cases} \theta + (1-\theta) \cdot \left(\frac{\mathrm{a}_y - \mathrm{a_L}}{\mathrm{a_R} - \mathrm{a_L}}\right) & \text{for} \quad \mathrm{a}_y \geq \mathrm{a_L} \\ \theta & \text{for} \quad \mathrm{a}_y < \mathrm{a_L} \end{cases}$$

with $\theta = 0.5$ a typical value (e.g. Carruthers et al., 2016, Hoshino et al., 2020). This type of rule increases the catch for $\mathrm{a}_y > \mathrm{a_R}$ and decreases the catch for $\mathrm{a}_y < \mathrm{a_R}$, moving progressively towards a level where $\mathrm{a}_y \approx \mathrm{a_R}$.

We investigate both control rule types. For CCR1 we assume that the target catch is known from the benchmark assessment of Fu (2020). Specifically $\mathrm{C_{TARGET}}$ is set at a quantile of the target catch ($\mathrm{C}_{40\%}$) values estimated across the grid of assessment runs. The catch is then:

CCR1

$$\mathrm{C}_{y+1:3} = \mathrm{I}_y \times \mathrm{C_{TARGET}} \tag{2a}$$

The fishing intensity is adjusted using:

CCR1 (index)

$$\mathrm{I}_y = \begin{cases} 1 & \text{for} \quad \mathrm{a}_y \geq \mathrm{a_R} \\ \frac{\mathrm{a}_y - \mathrm{a_L}}{\mathrm{a_R} - \mathrm{a_L}} & \text{for} \quad \mathrm{a_L} < \mathrm{a}_y < \mathrm{a_R} \\ 0 & \text{for} \quad \mathrm{a}_y \leq \mathrm{a_L} \end{cases} \tag{2b}$$

For values of $\mathrm{a_L} < \mathrm{a}_y < \mathrm{a_R}$, the fishing intensity increases linearly to $\mathrm{I}_y = 1$ at $\mathrm{a}_y = \mathrm{a_R}$, so that $\mathrm{C}_{y+1:3} = \mathrm{C_{TARGET}}$. The recommended catch is constant for values of $\mathrm{a}_y > \mathrm{a_R}$. For $\mathrm{a}_y < \mathrm{a_L}$ the fishery is closed. During simulation testing a small constant catch of 100 tonnes is added during fishery closure so that index values continue to be simulated.

For comparative purposes, the equivalent "perfect information" rule is explored, which uses the known depletion (SSD_y) from the operating model.

CCR1 (SSB)

$$\mathrm{I}_y = \begin{cases} 1 & \text{for} \quad \mathrm{SSD}_y \geq \mathrm{SSD_R} \\ \frac{\mathrm{SSD}_y - \mathrm{SSD_L}}{\mathrm{SSD_R} - \mathrm{SSD_L}} & \text{for} \quad \mathrm{SSD_L} < \mathrm{SSD}_y < \mathrm{SSD_R} \\ 0 & \text{for} \quad \mathrm{SSD}_y \leq \mathrm{SSD_L} \end{cases} \tag{2c}$$

For CCR2 we update the previous TAC to provide a new recommendation using the weighted average approach:

CCR2

$$\mathrm{C}_{y+1:3} = \mathrm{I}_y \times \mathrm{C_{TAC}} \tag{3a}$$

CCR2 (index)

$$\mathrm{I}_y = \begin{cases} 0.5 + 0.5 \times \left(\frac{\mathrm{a}_y - \mathrm{a_L}}{\mathrm{a_R} - \mathrm{a_L}}\right) & \text{for} \quad \mathrm{a}_y \geq \mathrm{a_L} \\ 0.5 & \text{for} \quad \mathrm{a}_y < \mathrm{a_L} \end{cases} \tag{3b}$$

which includes a minimum fishing intensity multiplier $\mathrm{I}_y = 0.5$ at $\mathrm{a}_y < \mathrm{a_L}$. A constant catch recommendation is achieved at $\mathrm{a}_y = \mathrm{a_R}$, for which $\mathrm{I}_y = 1$, and $\mathrm{C}_{y+1:3} = \mathrm{C_{TAC}}$. However in

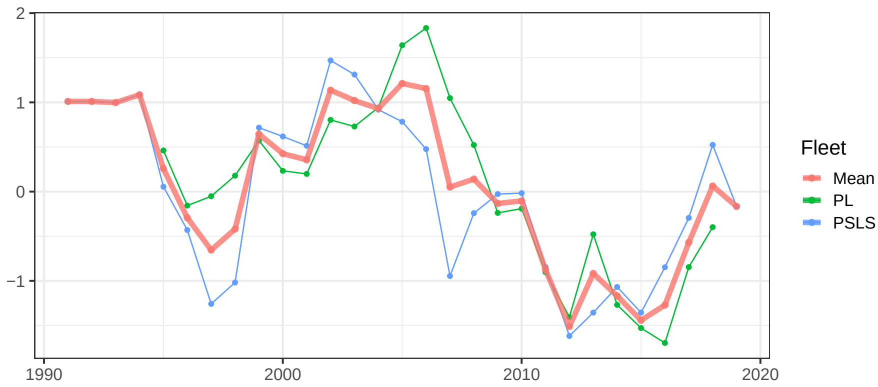


Figure 1: Annual log-normalised PL and PSLS indices. The mean value across indices is used as the input a_y for implementations of each MP.

contrast to CCR1, the recommended catch increases above the previous recommendation for values of $\mathrm{a}_y > \mathrm{a}_\mathrm{L}$. This could allow the rule to potentially exploit high levels of stock productivity, but likely at the expense of stability in the catches.

The equivalent perfect information rule is:

CCR2 (SSB)

$$\mathrm{I}_y = \begin{cases} 0.5 + 0.5 \times \left(\frac{\mathrm{SSD}_y - \mathrm{SSD}_\mathrm{L}}{\mathrm{SSD}_\mathrm{R} - \mathrm{SSD}_\mathrm{L}}\right) & \text{for} \quad \mathrm{SSD}_y \geq \mathrm{SSD}_\mathrm{R} \\ \quad 0.5 & \text{for} \quad \mathrm{SSD}_y < \mathrm{SSD}_\mathrm{L} \end{cases} \tag{3c}$$

In summary, two index-based catch control rules have been proposed (CCR1 and CCR2), each with equivalents based on the known SSD_y for comparison. For the CCR to be fully specified, the tuning parameters need to be defined, in this case values for a_R and a_L. These are considered next in relation to calculation of the CCR input value: a_y, including it's relation to the SSB.

1.2.3 Data inputs

To inform paramaterisation of the CCRs, we estimate the relationship between depletion ($\mathrm{SSD}_y = \mathrm{SSB}_y/\mathrm{SSB}_0$) and the stock status indicator in the previous year a_{y-1}. The status indicator is calculated from the log-normalised PL and PSLS abundance indices. These show similar trends over time (Figure 1), and we calculate a_y as the mean of the two log-normalised indices across all four seasons within the year. Using outputs from the stock assessment, we can plot the relationship between a_{y-1} and the depletion at the beginning of the following year. These are shown in Figure 2 for the twelve single area SS III models listed in IOTC (2020a). From linear regression fits for each model run, we can estimate the value of a_{y-1} associated with different depletion levels. The mean and minimum values for a_{y-1} taken across runs, are listed in Table 3. The full list of regression parameters is given in Table A1.

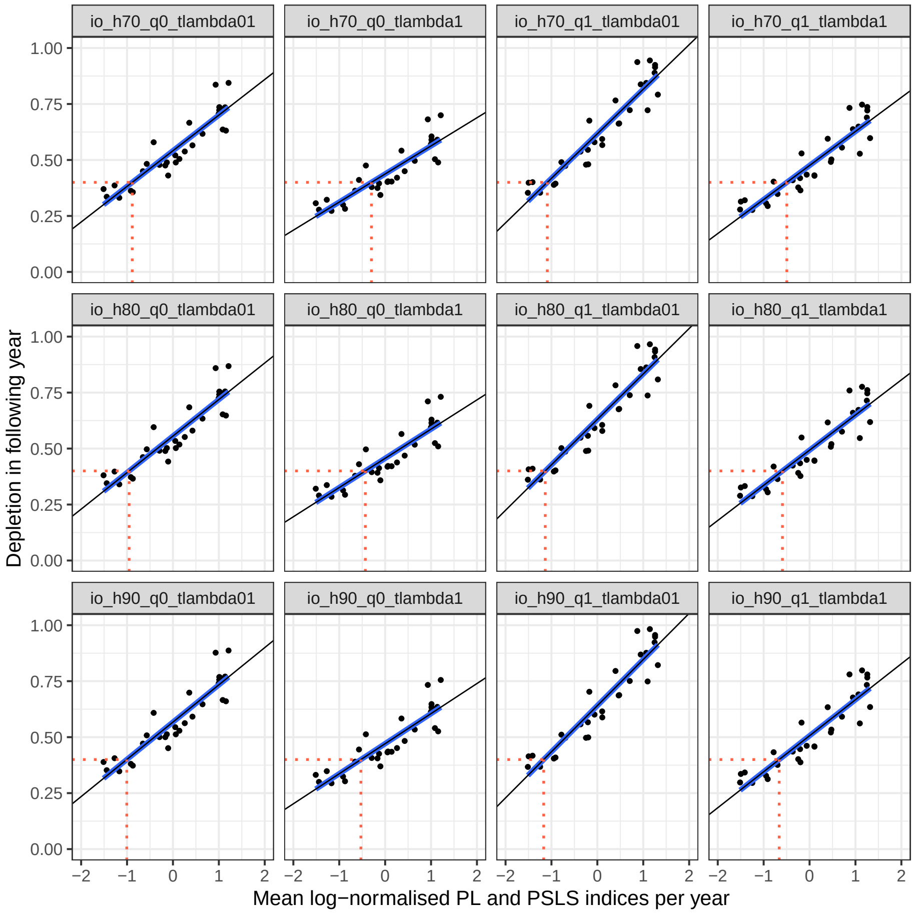


Figure 2: Relationships between the mean, within year log-normalised PL and PSLS indices, and the depletion at the beginning of the following year, estimated from the grid of stock assessment runs (Fu, 2020). Twelve single-area model runs are shown. The estimated linear relationship is shown in blue, with the index at $SSB_{40\%}$ marked in red.

Table 3: Estimated values for a_{y-1} at different depletion levels (left table), showing the mean and minimum values across runs (regressions used to calculate these values are shown in Figure 2 with a full list of parameters per run in Table A1). Minimum values were used to construct equivalent inputs for the SSB and index-based control rules shown in the right table.

SSD_y	Mean a_{y-1}	Minimum a_{y-1}
50%	-0.14	-0.68
40%	-0.77	-1.17
30%	-1.40	-1.65
20%	-2.03	-2.21
10%	-2.66	-2.81
0%	-3.29	-3.51

SSB-based inputs	Index-based inputs
$SSD_R = 0.5$	$a_R = -0.7$
$SSD_R = 0.4$	$a_R = -1.2$
$SSD_R = 0.3$	$a_R = -1.7$
$SSD_L = 0.2$	$a_L = -2.2$
$SSD_L = 0.1$	$a_L = -3.0$
$SSD_L = 0.0$	$a_L = -5.0$

From the relationships between SSD_y and a_{y-1} we can calculate equivalent values for the SSB-based, and index-based control rules. As an example, for CCR1 (SSB) we can investigate a control rule with values of $SSD_L = 0.1$ and $SSD_R = 0.4$. Using the minimum values listed in Table 3 (to make the control rule conservative), the equivalent inputs for CCR1 (index) are $a_L = -3.0$ and $a_R = -1.2$.

For CCR1, we are also required to choose a target catch value C_{TARGET}, which we fix at the 10%, 30% and 50% quantiles of the distribution of $C_{40\%}$ across model runs. These are 461215, 481523 and 521638 tonnes respectively. There were therefore a total of twleve CCR1 options investigated. For CCR2, the previous TAC is updated following each implementation of the control rule, starting at $C_{TAC} = 513572$ tonnes in 2024. There were therfore only four CCR2 options investigated. In addition, constant catch control rules (CCR0) were implemented, again using the 10%, 30% and 50% quantiles of $C_{40\%}$. These serve to illustrate the benefits of feedback control. The full list of CCR parameterisations is given in Table 4.

Table 4: List of CCR definitions. Each MP is referred to by the CCR, tuning parameter combinations and data inputs, e.g. CCR1A (index) and CCR1A (SSB).

	CCR0	CCR1			CCR2	
	C_{TARGET}	SSD_L (a_L)	SSD_R (a_R)	C_{TARGET}	SSD_L (a_L)	SSD_R (a_R)
A	461.2	0.0 (-5.0)	0.3 (-1.7)	461.2	0.0 (-5.0)	0.4 (-1.2)
B	485.1	0.0 (-5.0)	0.3 (-1.7)	481.5	0.1 (-3.0)	0.4 (-1.2)
C	521.6	0.0 (-5.0)	0.3 (-1.7)	521.6	0.0 (-5.0)	0.5 (-0.7)
D		0.1 (-3.0)	0.3 (-1.7)	461.2	0.1 (-3.0)	0.5 (-0.7)
E		0.1 (-3.0)	0.3 (-1.7)	481.5		
F		0.1 (-3.0)	0.3 (-1.7)	521.6		
G		0.0 (-5.0)	0.4 (-1.2)	461.2		
H		0.0 (-5.0)	0.4 (-1.2)	481.5		
I		0.0 (-5.0)	0.4 (-1.2)	521.6		
J		0.1 (-3.0)	0.4 (-1.2)	461.2		
K		0.1 (-3.0)	0.4 (-1.2)	481.5		
L		0.1 (-3.0)	0.4 (-1.2)	521.6		

2 Evaluation framework

The evaluation framework was based on a set of SS III operating models (Methot Jr. and Wetzel, 2013, version 3.30.16.02), called from within **R** (R Core Team, 2021) and making use of the `r4ss` **R**-package (Taylor et al., 2021). Justification for this approach was provided by

Edwards (2020b). Reference code developed for implementation of the current project is stored in `https://github.com/cttedwards/skj`.

2.1 Operating models

Operating models were based on the SKJ stock assessment of Fu (2020), covering the period 1950 to 2019 inclusive. The assessment included a grid of twelve single area SS III runs described in IOTC (2020a). Labels per run are listed in Table 5. The two-area model was not considered. Models were re-fitted for validation purposes, giving the results summarised in Table 6 (for comparison to Table 1b).

Table 5: List of single area SS III assessment runs used as operating models, reproduced from Table 2 of IOTC (2020a)

Label	Steepnes (h)	Catchability trend	Tag likelihood weighting (λ)
io_h70_q0_tlambda01	0.7	1.0000	0.1
io_h70_q0_tlambda1	0.7	1.0000	1.0
io_h70_q1_tlambda01	0.7	1.0125	0.1
io_h70_q1_tlambda1	0.7	1.0125	1.0
io_h80_q0_tlambda01	0.8	1.0000	0.1
io_h80_q0_tlambda1	0.8	1.0000	1.0
io_h80_q1_tlambda01	0.8	1.0125	0.1
io_h80_q1_tlambda1	0.8	1.0125	1.0
io_h90_q0_tlambda01	0.9	1.0000	0.1
io_h90_q0_tlambda1	0.9	1.0000	1.0
io_h90_q1_tlambda01	0.9	1.0125	0.1
io_h90_q1_tlambda1	0.9	1.0125	1.0

Recruitment deviations: An auto-regressive (AR1) time series model was fitted to the log-recruitment residuals estimated by SS III for the period 1983 to 2018. Recruitment for 2019 was estimated by the model as a free parameter. Recruitment deviations from 2020 onwards were generated using a auto-regressive random walk that was additive on the log-scale. Example recruitment deviations are shown in Figure 3.

Implementation of the catch: The catch in 2020 was set by SS III as equal to the estimated target fishing mortality per run ($C_{40\%}$). The TAC from 2021 to 2023 was fixed at 513,572 tonnes based on recommendation from IOTC (2020b). Thereafter the MP was used to set the catch. Annual, multiplicative catch deviations (implementation errors) were generated from a Gamma distribution with a mean of 1.10 and standard deviation of 0.05. A positive implementation error was assumed due to the observed overcatch of the TAC in 2018 and 2019 (Fu, 2020).

Observation: The last year of CPUE data was 2019. Future observations were generated from the exploitable biomass values predicted by SS III and the estimated catchabilities. Multiplicative observation errors were estimated from the log-residuals of the SS III model fits and applied to simulated index values using random numbers generated from a log-normal distribution. For runs assuming a constant catchability the observation errors had a mean of one. For runs with an increasing catchability (Table 5), the PSLS observation errors were assumed to have a mean that increased by 1.25% per year (Fu, 2020, IOTC, 2020a).

Table 6: Derived quantities from the twelve assessments used in the current application. Catch and biomass values are given in units of 1000 tonnes. Values are median and 80% quantiles reference point estimates across model runs, estimated using SS III

Quantity	Median	80% quantiles
$C_{40\%}$	521.8	(460.8 - 672.0)
$E_{2019}/E_{40\%}$	0.955	(0.69 - 1.20)
$C_{2019}/C_{40\%}$	1.049	(0.82 - 1.19)
SSB_0	1969.9	(1675.3 - 2555.6)
$SSB_{2019}/SSB_{40\%}$	1.14	(0.98 - 1.25)
SSB_{2019}/SSB_0	0.46	(0.39 - 0.50)
SSB_{2019}	879.3	(700.4 - 1252.3)
$E_{40\%}$	0.59	(0.53 - 0.64)
C_{2019}	547.2	

2.2 Dimensions

A total of twelve MPs using CCR1 and four MPs using CCR2, were tested (Table 4). Equivalent SSB and index-based runs were performed for each. For each MP, the twelve operating model variations were projected (Table 5), with ten stochastic iterations for each. To ensure comparability of the simulation results across MPs being applied to a particular operating model run, stochastic deviations and error values were generated for each iteration and the same values per iteration applied across all the MPs being tested. Each simulation projected the stock forward twenty years from 2020 to 2039 inclusive, with implementation of the MP every third year, starting in 2023 (to set the recommended catch for 2024 to 2026).

2.3 Diagnostics

A list of diagnostics with which to compare MPs was obtained from Bentley and Adam (2016). These are listed in Table 7.

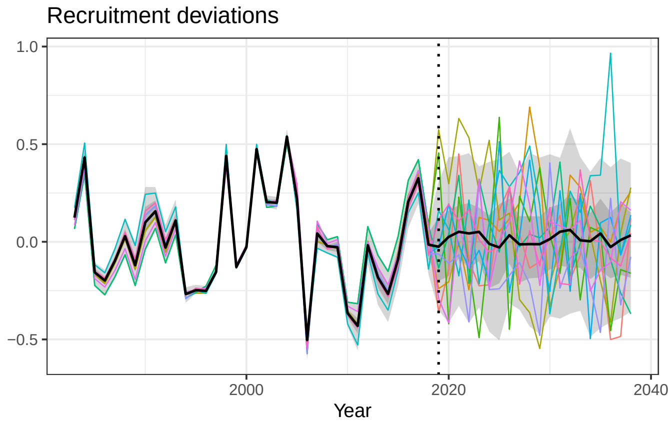


Figure 3: Example recruitment dynamics across model runs, used to evaluate different tuning parameters for CCR1 (index). Recruitment deviations are estimated by SS III between 1983 and 2019, and show a similar pattern across all models. The recruitment in 2019 is uninformed by the data and can therefore be considered a free parameter. Recruitment deviations from 2020 to 2039 were simulated from a fitted auto-regressive model. A sample of stochastic iterations is shown.

Table 7: Diagnostic outputs for MP evaluations. Each performance statistic is generated by first calculating the summary statistic per run and iteration across projection years, and then reporting the median and 80% quantiles across those values – unless the statistic is a probability, in which case it is calculated as a proportion across all projection years, runs and iterations simultaneously.

Performance Statistic	Description	Summary statistic
Catch		
C	Total catch	Mean
$C_{[PL]}$	Catch for PL fleet	Mean
$C_{[PSLS]}$	Catch for PSLS fleet	Mean
$C_{[PSFS]}$	Catch for PSFS fleet	Mean
$C_y/C_{40\%}$	Relative catch	Geometric mean
Catch stability		
Pr. $C_y = 0$	Closure	Probability
Pr. $> C_{y-1}$	Catch increase	Probability
Pr. $< C_{y-1}$	Catch decrease	Probability
$\lvert C_{y+1}/C_y - 1\rvert$	Catch change	Geometric mean
Catch rate		
$CPUE_{[PL]}$	CPUE for PL fleet	Geometric mean
$CPUE_{[PSLS]}$	CPUE for PSLS fleet	Geometric mean
Exploitation rate		
F_y	Exploitation rate	Geometric mean
$F_y/F_{40\%}$	Relative exploitation rate	Geometric mean
Stock biomass		
SSB_y	Stock biomass	Mean
SSB_y/SSB_0	Depletion	Geometric mean
SSB_{MIN}/SSB_0	Min. depletion	Minimum
Pr. $> SSB_{20\%}$	$SSB_y > SSB_{20\%}$	Probability
Pr. $> SSB_{10\%}$	$SSB_y > SSB_{10\%}$	Probability
Kobe Quadrants		
Pr. Red	$SSB_y < SSB_{40\%}$ and $F_y > F_{40\%}$	Probability
Pr. Green	$SSB_y > SSB_{40\%}$ and $F_y < F_{40\%}$	Probability

3 Results

Summary diagnostics for all MPs are shown in Figures 4 and 5, for the SSB-based and index-based MPs respectively. Both feedback control rules (CCR1 and CCR2) appear to perform better than the constant catch rule (CCR0), yielding similar catches but with a lower chance of excessive exploitation. Performance of the SSB and index-based MPs are similar, confirming utility of an index-based rule. However in both cases, at least for the tuning parameters explored here, CCR1 appears superior, with higher and less variable catches for equivalent levels of depletion and exploitation. This difference between CCR1 and CCR2 is more apparent for the index-based rules, with CCR2 having more variable catches and a higher chance of over-exploitation (Figure 5 and Table A4).

Noting the limited tuning parameterisations explored, the apparent superiority of CCR1 is further demonstrated by the trade off plots in Figure 6. For similar catches, the mean depletion is higher, the exploitation rate is lower, and the catches less variable.

Within the variations explored for CCR1, two options are selected for more detailed exposition, namely CCR1A and CCR1H, which both appear to perform well. Two dimensional histograms are plotted in Figure 7, illustrating how projected catches map to the control rule. The equivalent SSB and index-based rules also shown for comparison. Recommended catches are typically on the plateau of the rule, and actual catches slightly exceed the recommendation due to implementation error. Notably, the number of iterations on the slope of the rule is reasonably small, consistent with stability of the catch recommendations. Given that the operating model assumes stable dynamics over time, this is a desirable feature. Projections of the operating model dynamics under CCR1A (index) and CCR1H (index) are shown in Figures 8 and 9. Finally, the full suite of diagnostics is given in Table 8.

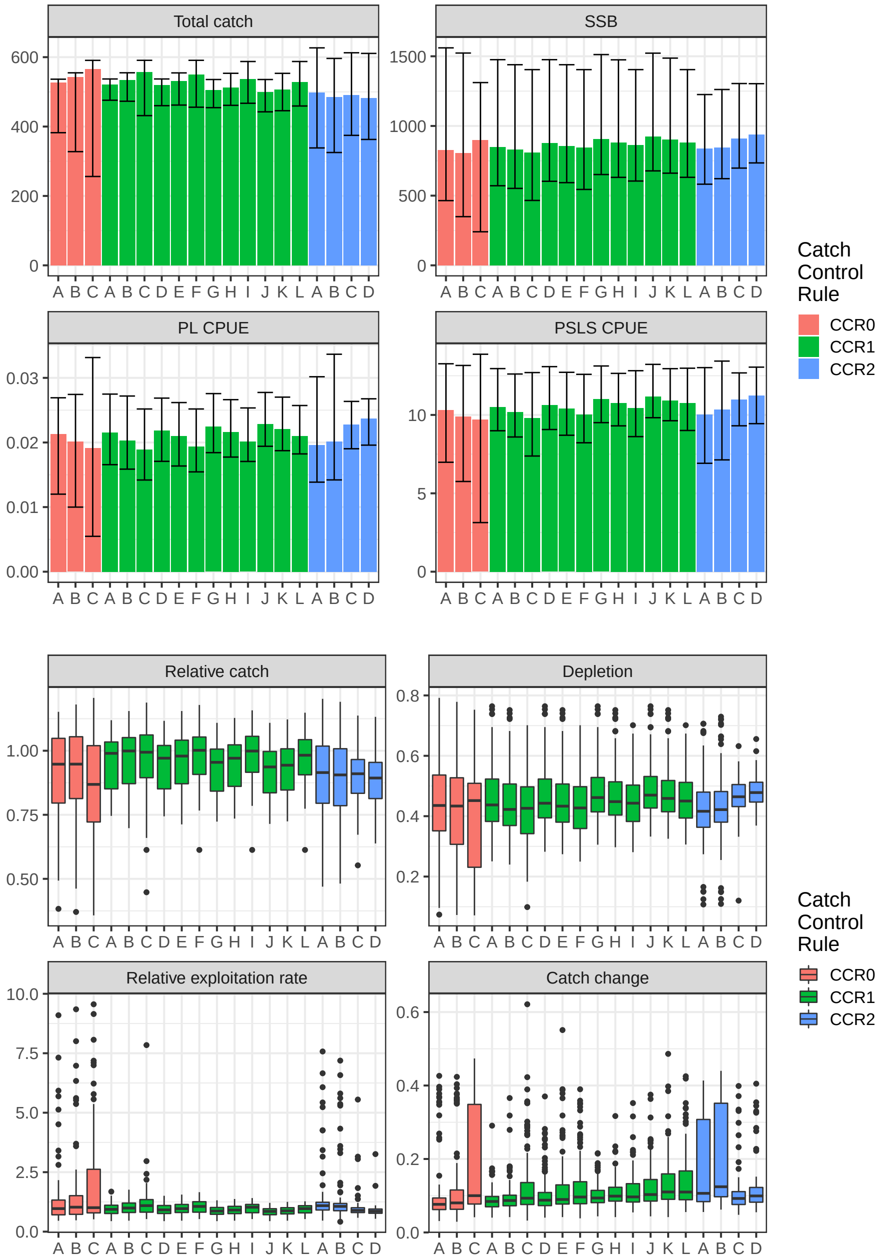


Figure 4: Diagnostic outputs for SSB-based MPs (Table 7). Each MP is referred to by the CCR definitions in Table 4.

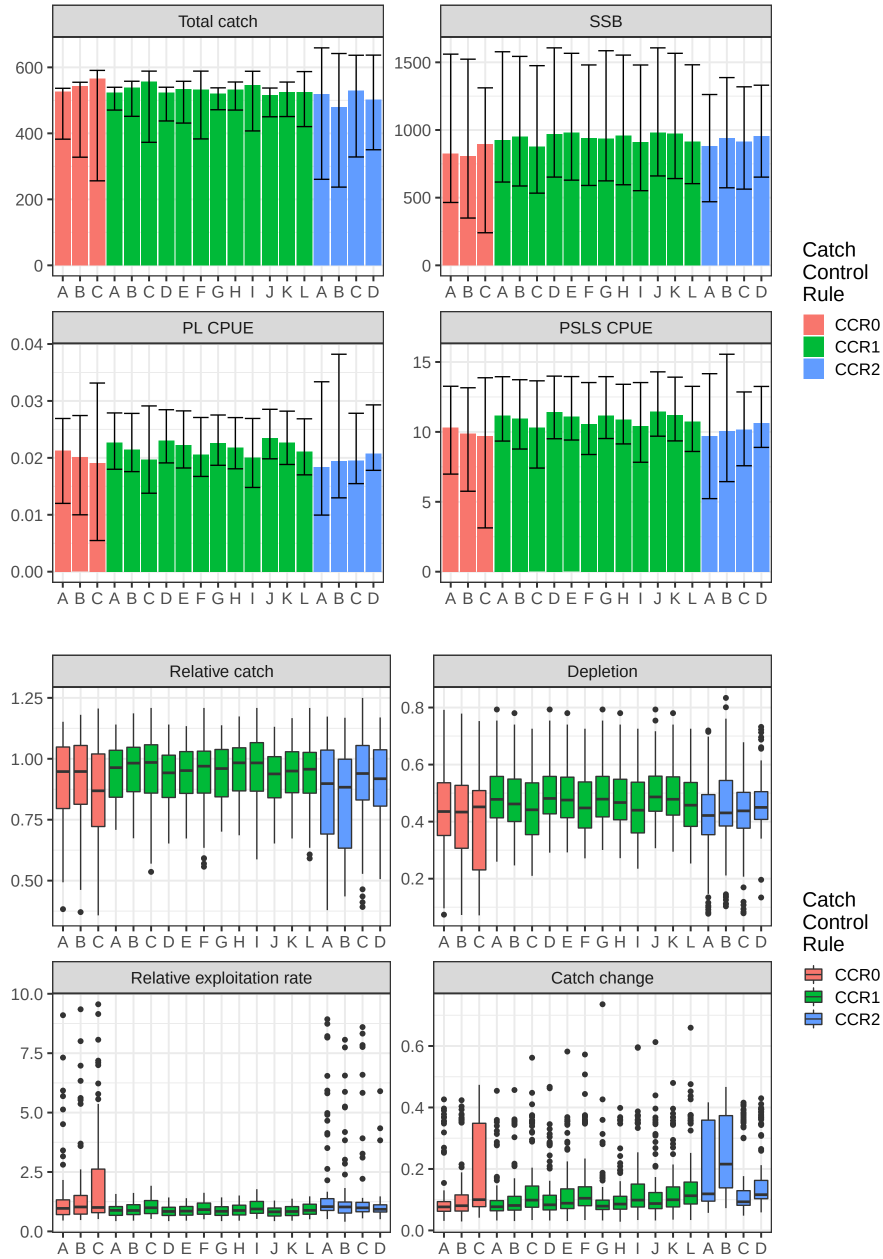
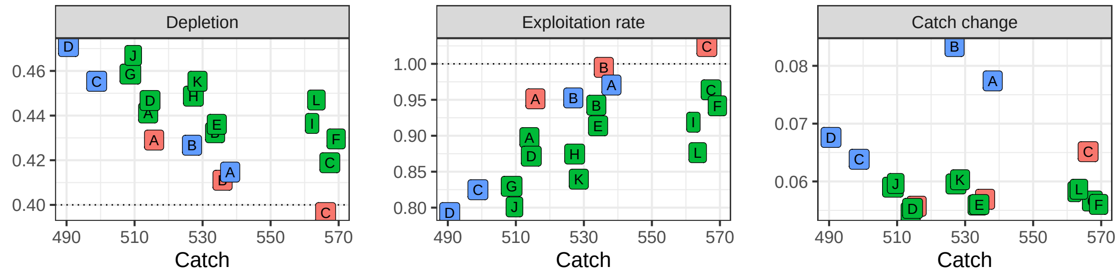


Figure 5: Diagnostic outputs for index-based MPs (Table 7). Each MP is referred to by the CCR definitions in Table 4.

(a) SSB-based MPs



(b) Index-based MPs

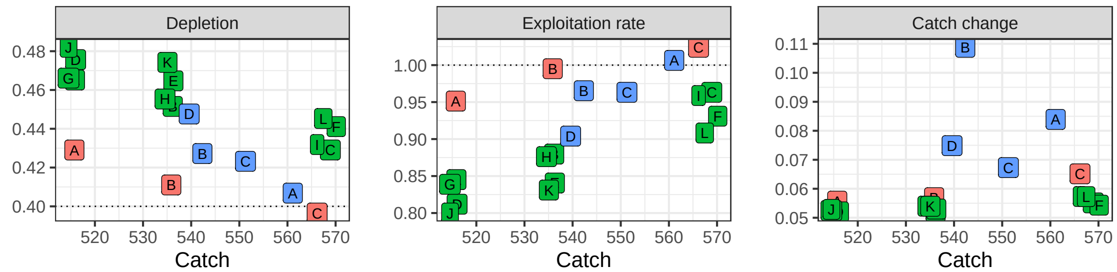


Figure 6: Tradeoff plots showing the total catch against: depletion relative to SSB_0; exploitation rate relative to $E_{40\%}$; and the catch change (see Table 7). Median values from Tables A3 and A4 are shown. Each MP is referred to by the CCR definitions in Table 4, with CCR0 in red, CCR1 in green and CCR2 in blue.

Table 8: Diagnostic outputs for comparison of selected MPs (see Table 4 for the list of MP definitions and Table 7 for a description of each diagnostic). Medians and 80% quantiles are reported for each statistic across runs and iterations. Probabilities are calculated across all runs, years and iterations simultaneously.

Statistic	CCR1A (SSB)	CCR1H (SSB)
C	521.4 (475.86 - 537.15)	512.79 (461.12 - 553.49)
$C_{[PL]}$	83.99 (77.34 - 86.65)	82.79 (75.36 - 88.74)
$C_{[PSLS]}$	200 (180.78 - 208.69)	197.11 (174.99 - 215.05)
$C_{[PSFS]}$	29.59 (27.13 - 31.43)	29.55 (26.38 - 32.32)
$C_y/C_{40\%}$	0.97 (0.76 - 1.07)	0.94 (0.78 - 1.04)
Pr. $C_y = 0$	0	0
Pr. $> C_{y-1}$	0.48	0.48
Pr. $< C_{y-1}$	0.52	0.52
$\|C_{y+1}/C_y - 1\|$	0.08 (0.06 - 0.13)	0.1 (0.07 - 0.16)
$CPUE_{[PL]}$	0.02 (0.02 - 0.03)	0.02 (0.02 - 0.03)
$CPUE_{[PSLS]}$	10.18 (8.53 - 12.68)	10.4 (9 - 12.33)
F_y	0.54 (0.33 - 0.73)	0.52 (0.33 - 0.65)
$F_y/F_{40\%}$	0.89 (0.57 - 1.22)	0.88 (0.59 - 1.1)
SSB_y	849.11 (571.13 - 1475.66)	881.9 (631.18 - 1474.45)
SSB_y/SSB_0	0.42 (0.32 - 0.58)	0.43 (0.35 - 0.57)
SSB_{MIN}/SSB_0	0.27 (0.15 - 0.4)	0.27 (0.18 - 0.38)
Pr. $> SSB_{20\%}$	0.97	0.98
Pr. $> SSB_{10\%}$	1	1
kobe_red	0.31	0.25
Pr. Green	0.57	0.58

Statistic	CCR1A (index)	CCR1H (index)
C	523.65 (470.54 - 539.65)	532.96 (470.58 - 555.6)
$C_{[PL]}$	84.58 (76.93 - 86.95)	86.1 (77.09 - 89.47)
$C_{[PSLS]}$	201.09 (178.35 - 209.1)	204.84 (178.37 - 215.25)
$C_{[PSFS]}$	29.94 (26.98 - 31.54)	30.42 (27.02 - 32.55)
$C_y/C_{40\%}$	0.95 (0.75 - 1.09)	0.96 (0.75 - 1.09)
Pr. $C_y = 0$	0	0
Pr. $> C_{y-1}$	0.47	0.47
Pr. $< C_{y-1}$	0.53	0.53
$\|C_{y+1}/C_y - 1\|$	0.08 (0.05 - 0.17)	0.09 (0.06 - 0.19)
$CPUE_{[PL]}$	0.02 (0.02 - 0.03)	0.02 (0.02 - 0.03)
$CPUE_{[PSLS]}$	10.86 (8.93 - 13.34)	10.61 (8.72 - 12.8)
F_y	0.48 (0.29 - 0.73)	0.49 (0.3 - 0.74)
$F_y/F_{40\%}$	0.81 (0.48 - 1.17)	0.82 (0.52 - 1.18)
SSB_y	927.14 (615.41 - 1578.04)	959.87 (595.26 - 1553.33)
SSB_y/SSB_0	0.46 (0.34 - 0.6)	0.45 (0.33 - 0.59)
SSB_{MIN}/SSB_0	0.29 (0.16 - 0.41)	0.28 (0.16 - 0.4)
Pr. $> SSB_{20\%}$	0.98	0.98
Pr. $> SSB_{10\%}$	1	1
Pr. Red	0.26	0.27
Pr. Green	0.63	0.59

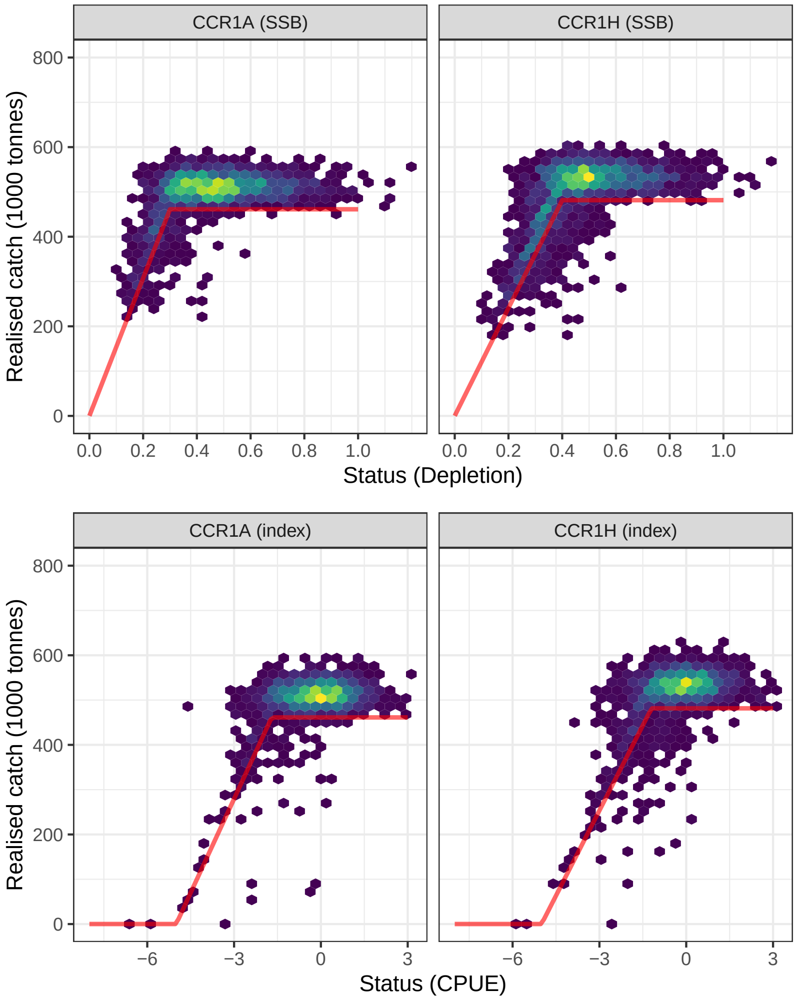


Figure 7: Relationship between the stock status, as measured by either the known SSB (top panel) or the mean log-normalised CPUE (bottom panel), and realised catches during the projection period for MPs: CCR1A and CCR1H. The CCR is shown for reference in each case. Colours represent a two-dimensional histogram of the number of samples across years, iterations and model runs that fall within each bin. Lighter colours indicate a higher frequency of counts.

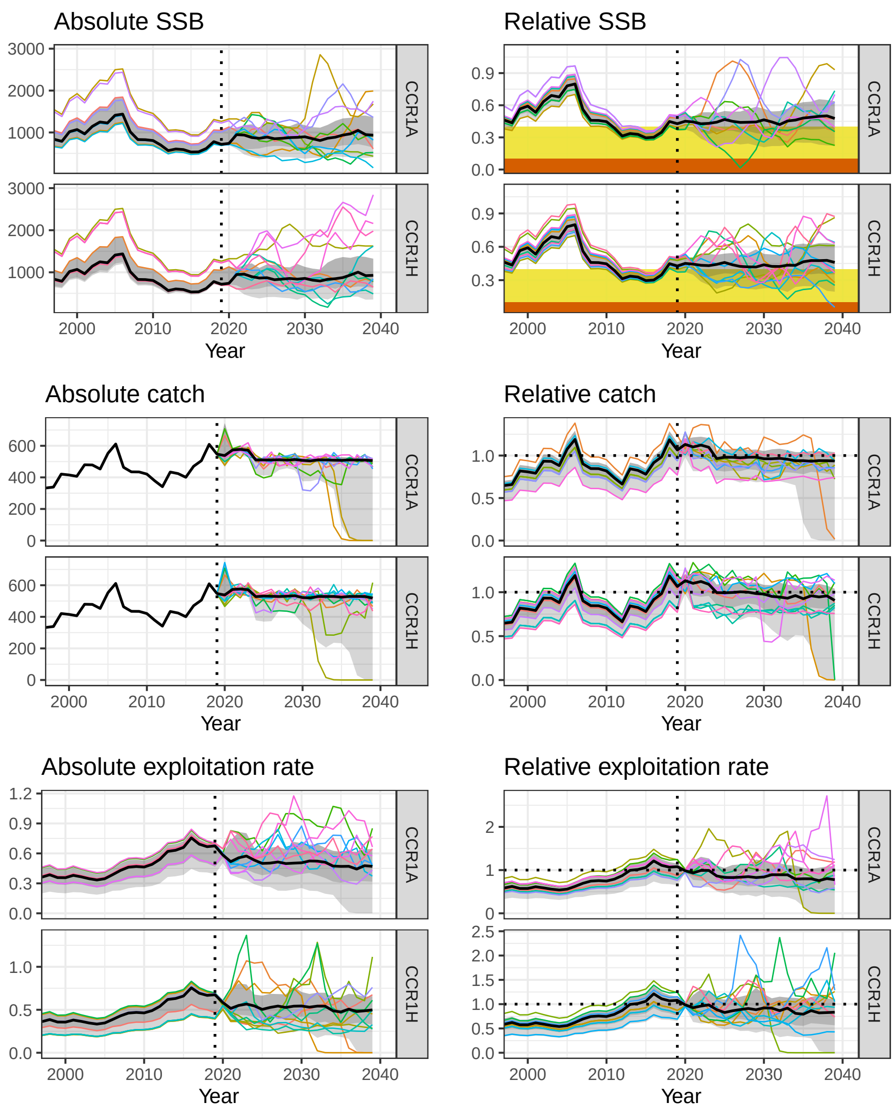


Figure 8: Dynamics following projection under CCR1A (index) and CCR1H (index). A sample of stochastic iterations is shown with 90% and 50% quantiles shaded in grey. Relative values are given according to SSB_0, $C_{40\%}$ and $E_{40\%}$ respectively. For the SSB, depletion values 10-40% are shown in yellow, and 0-10% in red.

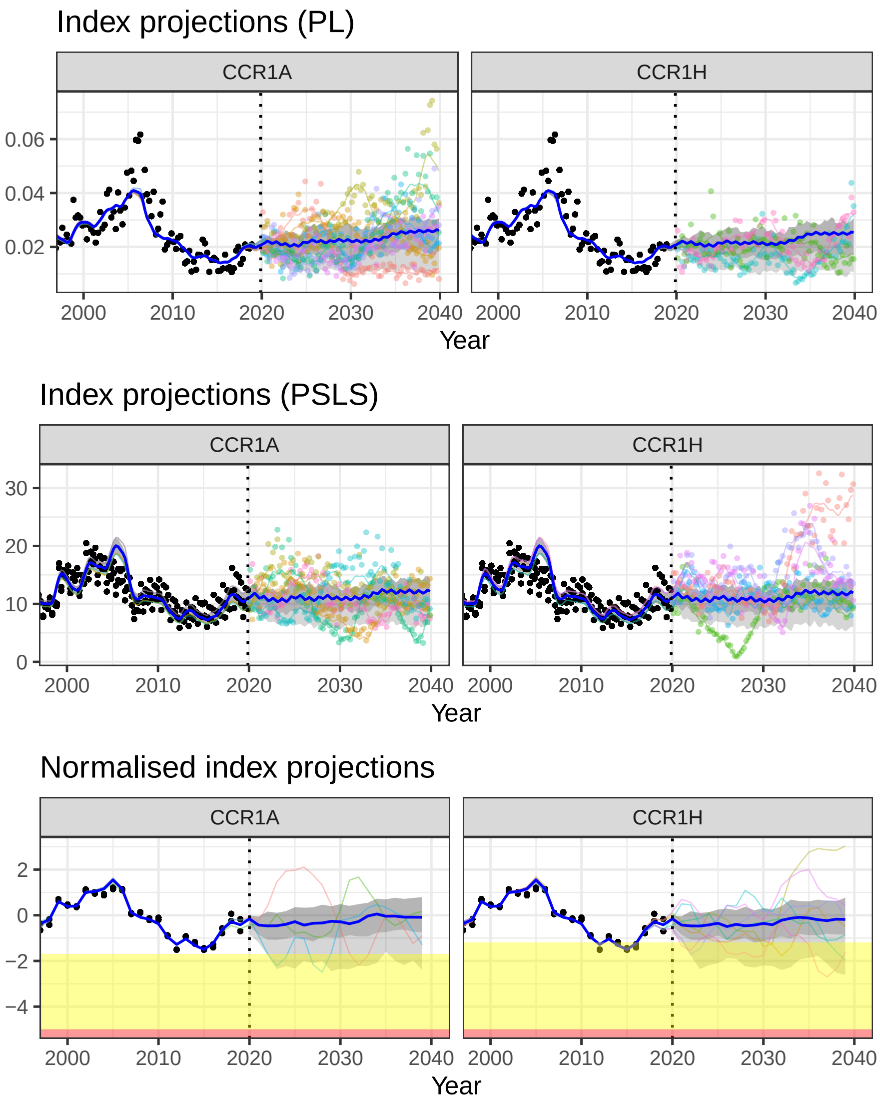


Figure 9: Index dynamics following projection under CCR1A (index) and CCR1H (index). A sample of stochastic iterations is shown with 90% and 50% quantiles shaded in grey. For the standardised indices tuning parameter values of $a_L < a_y < a_R$ are shown in yellow, and $a_y < a_L$ in red.

4 Summary and further work

The current work has proposed a set of empirical control rules for application to the Indian Ocean SKJ fishery, based on CPUE indices from the Maldivan PL and European PSLS fisheries. For the MP to be valid, generation of the PL and PSLS indices would have to be specified and maintained into the future.

Two control rule formulations were explored, with a step linear rule, similar in form to the current HCR, performing the best under the limited testing conducted. The most notable feature of the results is that an index-based rule can perform similarly to a rule that assumes perfect knowledge of the resource, provided equivalent parameterisations are used in each. This provides a useful justification for future developments of an empirical approach.

Since this work represents an initial step towards an empirical rule, the extent of simulation testing was limited in both the control rule parameterisations and OM configurations explored. The current OMs assume a relatively stable and productive stock. Clearly, a wider range of OMs will need to be included to ensure that the MPs being tested are able to recover the stock under less favorable conditions.

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A Appendix

Table A1: Regression parameters from relationship between the mean log-normalised PL and PSLS CPUE indices (a_{y-1}) and the estimated biomass depletion in the following year (Figure 2). Predicted values for a_{y-1} are shown for different depletion levels, estimated from the regression parameters.

Model run	Intercept	Slope	Predicted a_{y-1}					
			SSB 50%	SSB 40%	SSB 30%	SSB 20%	SSB 10%	SSB 0%
io_h70_q0_tlambda01	0.54	0.16	-0.26	-0.89	-1.51	-2.14	-2.77	-3.40
io_h70_q0_tlambda1	0.44	0.13	0.50	-0.30	-1.10	-1.89	-2.69	-3.49
io_h70_q1_tlambda01	0.62	0.20	-0.59	-1.09	-1.59	-2.10	-2.60	-3.10
io_h70_q1_tlambda1	0.48	0.15	0.16	-0.50	-1.15	-1.81	-2.47	-3.13
io_h80_q0_tlambda01	0.56	0.16	-0.34	-0.95	-1.57	-2.18	-2.79	-3.41
io_h80_q0_tlambda1	0.46	0.13	0.33	-0.43	-1.20	-1.96	-2.73	-3.50
io_h80_q1_tlambda01	0.63	0.20	-0.64	-1.13	-1.63	-2.12	-2.61	-3.11
io_h80_q1_tlambda1	0.49	0.16	0.05	-0.59	-1.23	-1.86	-2.50	-3.14
io_h90_q0_tlambda01	0.57	0.17	-0.40	-1.01	-1.61	-2.21	-2.81	-3.41
io_h90_q0_tlambda1	0.47	0.13	0.22	-0.53	-1.27	-2.02	-2.76	-3.51
io_h90_q1_tlambda01	0.64	0.21	-0.68	-1.17	-1.65	-2.14	-2.63	-3.11
io_h90_q1_tlambda1	0.51	0.16	-0.04	-0.66	-1.28	-1.90	-2.53	-3.15
Mean	0.53	0.16	-0.14	-0.77	-1.40	-2.03	-2.66	-3.29
Min.	0.44	0.13	-0.68	-1.17	-1.65	-2.21	-2.81	-3.51

Table A2: Diagnostic outputs for evaluation of constant-catch MPs (see Table 4 for the list of MP definitions and Table 7 for a description of each diagnostic). Medians are reported for each statistic across runs and iterations. Probabilities are calculated across all runs, years and iterations simultaneously.

Statistic	CCR0A	CCR0B	CCR0C
C	527.05	542.81	566.35
$C_{[PL]}$	84.99	87.76	91.42
$C_{[PSLS]}$	201.74	208.50	214.75
$C_{[PSFS]}$	30.23	31.15	32.50
$C_y/C_{40\%}$	0.94	0.92	0.86
Pr. $C_y = 0$	0.00	0.00	0.00
Pr. $> C_{y-1}$	0.45	0.44	0.41
Pr. $< C_{y-1}$	0.55	0.56	0.59
$\lvert C_{y+1}/C_y - 1\rvert$	0.08	0.08	0.10
$CPUE_{[PL]}$	0.02	0.02	0.02
$CPUE_{[PSLS]}$	9.85	9.62	9.18
F_y	0.57	0.55	0.57
$F_y/F_{40\%}$	0.92	0.97	0.94
SSB_y	825.68	806.11	897.05
SSB_y/SSB_0	0.41	0.40	0.41
SSB_{MIN}/SSB_0	0.25	0.24	0.21
Pr. $> SSB_{20\%}$	0.90	0.86	0.79
Pr. $> SSB_{10\%}$	0.94	0.92	0.86
Pr. Red	0.39	0.43	0.46
Pr. Green	0.52	0.46	0.44

Table A3: Diagnostic outputs for evaluation of SSB-based MPs (see Table 4 for the list of MP definitions and Table 7 for a description of each diagnostic). Medians are reported for each statistic across runs and iterations. Probabilities are calculated across all runs, years and iterations simultaneously.

Statistic	CCR1A	CCR1B	CCR1C	CCR1D	CCR1E	CCR1F	CCR1G	CCR1H	CCR1I	CCR1J	CCR1K	CCR1L	CCR2A	CCR2B	CCR2C	CCR2D
C	521.40	533.99	557.69	519.69	531.20	550.38	504.52	512.79	537.16	499.84	507.20	527.99	497.96	484.72	490.43	482.17
$C_{[PL]}$	83.99	85.97	90.25	83.73	85.67	88.48	81.15	82.79	86.55	80.27	81.90	85.40	79.96	78.93	79.45	78.23
$C_{[PSLS]}$	200.00	205.63	213.23	200.00	204.34	210.68	193.79	197.11	206.07	192.06	194.91	201.94	189.52	186.00	188.53	184.54
$C_{[PSFS]}$	29.59	30.50	31.94	29.51	30.36	31.72	28.86	29.55	31.06	28.59	29.18	30.59	29.33	28.66	28.32	27.92
$C_y/C_{40\%}$	0.97	0.98	0.96	0.94	0.95	0.93	0.92	0.94	0.97	0.90	0.91	0.94	0.89	0.88	0.89	0.87
Pr. $C_y = 0$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pr. $> C_{y-1}$	0.48	0.48	0.48	0.48	0.48	0.49	0.48	0.48	0.49	0.48	0.48	0.49	0.43	0.42	0.45	0.46
Pr. $< C_{y-1}$	0.52	0.52	0.52	0.52	0.52	0.51	0.52	0.52	0.51	0.52	0.52	0.51	0.57	0.58	0.55	0.54
$\|C_{y+1}/C_y - 1\|$	0.08	0.09	0.09	0.09	0.09	0.10	0.09	0.10	0.10	0.10	0.11	0.11	0.11	0.12	0.09	0.10
$CPUE_{[PL]}$	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
$CPUE_{[PSLS]}$	10.18	9.78	9.62	10.22	9.96	9.57	10.69	10.40	10.07	10.81	10.52	10.30	9.47	9.72	10.51	10.80
F_y	0.54	0.57	0.59	0.53	0.55	0.53	0.50	0.52	0.56	0.48	0.50	0.53	0.58	0.57	0.48	0.46
$F_y/F_{40\%}$	0.89	0.95	0.99	0.86	0.90	0.90	0.83	0.88	0.95	0.81	0.84	0.90	0.97	0.95	0.81	0.76
SSB_y	849.11	830.67	809.31	876.54	855.06	843.24	906.59	881.90	864.31	923.37	901.49	881.33	838.51	843.56	908.10	937.94
SSB_y/SSB_0	0.42	0.40	0.41	0.43	0.41	0.40	0.45	0.43	0.42	0.45	0.44	0.43	0.39	0.39	0.45	0.45
SSB_{MIN}/SSB_0	0.27	0.25	0.21	0.27	0.25	0.21	0.29	0.27	0.25	0.29	0.27	0.26	0.19	0.20	0.24	0.25
Pr. $> SSB_{20\%}$	0.97	0.95	0.90	0.97	0.96	0.92	0.99	0.98	0.96	0.99	0.99	0.97	0.89	0.89	0.95	0.96
Pr. $> SSB_{10\%}$	1.00	1.00	0.96	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.94	0.98	0.99
Pr. Red	0.31	0.35	0.38	0.28	0.32	0.33	0.22	0.25	0.31	0.19	0.22	0.26	0.39	0.36	0.26	0.23
Pr. Green	0.57	0.52	0.48	0.58	0.54	0.49	0.62	0.58	0.52	0.64	0.60	0.55	0.45	0.48	0.59	0.62

Table A4: Diagnostic outputs for evaluation of index-based MPs (see Table 4 for the list of MP definitions and Table 7 for a description of each diagnostic). Medians are reported for each statistic across runs and iterations. Probabilities are calculated across all runs, years and iterations simultaneously.

Statistic	CCR1A	CCR1B	CCR1C	CCR1D	CCR1E	CCR1F	CCR1G	CCR1H	CCR1I	CCR1J	CCR1K	CCR1L	CCR2A	CCR2B	CCR2C	CCR2D
C	523.65	539.18	556.22	523.23	533.86	532.88	520.55	532.96	546.47	516.11	525.49	524.82	518.95	476.70	529.05	502.99
$C_{[PL]}$	84.58	86.94	89.52	84.29	86.05	85.99	83.87	86.10	88.48	83.36	84.51	85.24	83.04	77.45	85.34	81.65
$C_{[PSLS]}$	201.09	207.08	213.30	200.84	204.25	203.73	200.17	204.84	210.08	198.38	201.74	201.26	196.17	180.87	202.01	191.97
$C_{[PSFS]}$	29.94	30.77	32.04	29.68	30.44	30.38	29.58	30.42	31.60	29.46	30.03	30.17	29.99	28.67	30.50	29.71
$C_y/C_{40\%}$	0.95	0.94	0.93	0.90	0.88	0.83	0.95	0.96	0.93	0.90	0.89	0.86	0.86	0.71	0.92	0.89
Pr. $C_y = 0$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pr. $> C_{y-1}$	0.47	0.47	0.46	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.42	0.40	0.45	0.47
Pr. $< C_{y-1}$	0.53	0.53	0.54	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.53	0.58	0.60	0.55	0.53
$\|C_{y+1}/C_y - 1\|$	0.08	0.08	0.10	0.08	0.09	0.14	0.08	0.09	0.10	0.09	0.10	0.14	0.12	0.22	0.09	0.12
$CPUE_{[PL]}$	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
$CPUE_{[PSLS]}$	10.86	10.60	9.96	10.93	10.64	10.20	10.86	10.61	10.13	11.10	10.83	10.23	9.18	9.48	9.77	10.04
F_y	0.48	0.48	0.49	0.44	0.44	0.37	0.47	0.49	0.52	0.44	0.45	0.41	0.56	0.52	0.55	0.49
$F_y/F_{40\%}$	0.81	0.81	0.82	0.75	0.77	0.64	0.81	0.82	0.85	0.75	0.75	0.69	0.97	0.88	0.93	0.83
SSB_y	927.14	950.59	877.85	967.89	980.77	940.01	936.45	959.87	910.05	981.56	975.20	914.27	879.84	931.94	913.61	954.19
SSB_y/SSB_0	0.46	0.45	0.42	0.47	0.46	0.42	0.46	0.45	0.42	0.47	0.46	0.44	0.39	0.40	0.41	0.43
SSB_{MIN}/SSB_0	0.29	0.27	0.21	0.29	0.28	0.21	0.30	0.28	0.21	0.30	0.28	0.22	0.18	0.16	0.22	0.21
Pr. $> SSB_{20\%}$	0.98	0.97	0.92	0.98	0.97	0.94	0.98	0.98	0.94	0.99	0.98	0.96	0.85	0.87	0.90	0.93
Pr. $> SSB_{10\%}$	1.00	0.99	0.99	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99	0.91	0.92	0.94	0.98
Pr. Red	0.26	0.29	0.36	0.22	0.25	0.31	0.24	0.27	0.35	0.20	0.22	0.28	0.42	0.36	0.38	0.29
Pr. Green	0.63	0.57	0.48	0.65	0.61	0.52	0.63	0.59	0.49	0.67	0.63	0.52	0.43	0.45	0.48	0.53