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Development and simulation testing of a Harvest Strategy for Redleg banana prawns in the NPF

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AFMA Project No. 2019/0819: Development and simulation testing of a Harvest Strategy for Redleg banana prawns in the NPF

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Version	Updates	Approver
Version 1	N/A	AFMA
Version 2	Edited for submission to NPRAG	AFMA
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Acronyms

AAV	Average Annual Variability
AFMA	Australian Fisheries Management Authority
BOM	Bureau of Meteorology
CPUE	Catch Per Unit Effort
CSIRO	Commonwealth Scientific and Industrial Research Organisation
HCR	Harvest Control Rule
HS	Harvest Strategy
MSE	Management Strategy Evaluation
NPF	Northern Prawn Fishery
NPFI	Northern Prawn Fishery Industry
NPRAG	Northern Prawn Fisheries Resource Assessment Group
OM	Operating Model
SOI	Southern Oscillation Index
RAG	Resource Assessment Group

Executive Summary

Redleg banana prawns (*Penaeus indicus*) are the target species of a sub-fishery of Australia's commercially important Northern Prawn Fishery (NPF) and are fished predominantly in the Joseph Bonaparte Gulf (JBG) in northern Australia. In 2015 and 2016, catch and effort were anomalously low and considered insufficient to reliably fit the assessment model. Low catch and effort, as well as low catch-per-unit-effort (CPUE) have, in part, been associated with environmental drivers. Research suggests that exceptionally good recruitment years and poor recruitment years may be explained by highly positive or negative values, respectively, of the Southern Oscillation Index (SOI) and the timing of rainfall, which is an important influencer of prawn recruitment. The increasing uncertainty in assessing the stock in years with insufficient data highlighted a gap in the harvest control rules (HCRs). The current Harvest Strategy (HS) inadequately accounts for risk to the stock in years with low fishing effort combined with low CPUE or years with environmental anomalies, such as El Niño years. To address this gap, there is a need to revise the HS and a Management Strategy Evaluation (MSE) approach is required to simulation-test the performance of any proposed revisions to the HCRs.

In this project, we developed a MSE framework that included a Reference Set of six Operating Models (OMs), to compare the performance of additional candidate HCRs using a suite of performance metrics (outputs from the operating models following the testing of each HCR). The OMs were chosen to best represent the underlying stock dynamics and account for uncertainty in both the dynamics and how the stock might behave. The base model (i.e. that which is most similar to the assessment model) was adapted from the stock assessment model and fitted to monthly CPUE data. Three variants of this model account for model structural uncertainty, specifically linking environmental variables (SOI and rainfall) to prawn recruitment or stock availability, while the last two models account for uncertainty in key model-estimated parameters. Harvest Control Rules were designed and selected through stakeholder engagement. Testing of the HCRs (simulation testing) was then carried out in the OMs by projecting forwards using simulated data (based on past observations) and applying the HCR to enforce a management response (e.g. fishery closure). A large number of stochastic replicates were projected forward in time and performance indicators, pre-determined through stakeholder consultation, were used to evaluate and compare the performance of each of the HCR candidates.

The MSE results were presented to stakeholders, who agreed that relative to the current HCR, three rules performed better than the others, namely HCR2, HCR3 and HCR4. HCR2, which prescribes a permanent closure of the first fishing season (April-June), achieved very low risk of fishery closure and risk to the stock, but reduced the occurrence of occasional very large catches. However, catch value in the second season was predicted to be good and catch variability the lowest amongst the options. The performance of HCR2 was fairly robust to uncertainties in the sensitivity testing and is logistically the easiest to implement and enforce, but prevents fishers from accessing the larger prawns that may be left over from the previous year. A closure of the first fishing season using an environmental trigger (HCR3) and an in-season CPUE trigger to pause fishing (HCR4) performed similarly to each other and the risk of fishery closure and the stock falling below BLIM were somewhat greater than HCR2, but considerably reduced compared with the current HCR1. Of the three preferred HCRs, the performance of HCR3 (particularly in terms of risk of depletion below the limit reference point) was the least robust to additional uncertainties as part of sensitivity testing. This is likely because it only pauses fishing if triggered by an El Niño year, but it nonetheless performed better than the current HCR1, whereas HCR4, which would pause fishing more frequently if needed, appeared to be most robust to uncertainties. HCR3, which relies on environmental data that are available from early March, would be logistically less demanding to implement than HCR4. HCR4 is reliant on adequate catch rate data and demands more time and effort from the scientific processes, Industry, and the management authority to implement and is thus logistically complex and more expensive, although may be most effective of the strategies in controlling total effort.

As is usually the case with the MSE approach, one HCR does not necessarily outperform another HCR and it is possible to achieve similar outcomes using different approaches. We recommend that stakeholders assess the trade-offs between the preferred HCR sub-set by considering the performance of each HCR (performance metrics), as well as the logistics of implementing each of the HCRs. The HCRs tested are assumed to be appropriate provided the stock and fishery dynamics are within the bounds of the variability tested, and it is anticipated there would be intermittent review as new data become available and stock assessment models are developed. If any substantial changes to the fishery or environment occur in the future, which have not been accounted for in the MSE testing, then there will be a need to review the HS.

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1 Background

Redleg banana prawns (*Penaeus indicus*) are a sub-fishery of Australia's commercially important Northern Prawn Fishery (NPF) and are fished predominantly in the Joseph Bonaparte Gulf (JBG) in northern Australia. Due to the extremely large tidal range in the JBG, fishing can only occur around neap tides, when tidal flows are reduced (Plagányi et al. 2020a). Additionally, the JBG is extremely remote and large distances need to be travelled by fishing vessels to reach the fishing grounds, which is costly both in terms of time and fuel. As such, fishery-independent data are not collected and thus data for this fishery are limited compared to other prawn species caught in the NPF and only fishery-dependent catch and effort data are available for the stock assessment model.

The assessment model for Redleg banana prawns in the JBG fishery, is a cohort aggregated production model, in which dynamics of the total recruited numbers, assumed mature, are represented over quarterly time steps (Plagányi et al. 2010). The model is fitted to available catch and effort data from the fishery, with an assumed growth curve (estimated from external data) that determines the approximate age and weight at recruitment to the fishery. The Harvest Strategy for the fishery is based on input controls, which dictate whether or not the fishery is open for any year, and whether it is open for the first season, using the fishery status from the previous year.

In 2015, the data were insufficient to reliably fit the model (Plagányi et al. 2015). Catch and effort were the lowest in the time series for the JBG and catch-per-unit-effort (CPUE) was anomalously low. Because of the limited data, the estimated status of the Redleg banana prawn fishery at the beginning of 2016 was highly uncertain. Consequently, no recommendation was made on a 2016 Total Allowable Effort for the fishery.

Several plausible reasons, not mutually exclusive, were proposed that might have caused the low level of fishing in the JBG in 2015. One possibility was that alternative fishing options were more attractive – in particular, the consistent, unusually high catch rates of tiger prawns elsewhere in the NPF. JBG Redleg banana prawn CPUE was low, and given the remoteness of the JBG area, there is a high logistic cost of fishing there and an opportunity cost of fishing in areas that are more accessible and that might provide a better return (Pascoe et al. 2020).

Environmental factors may have also led to low recruitment and/or availability of Redleg banana prawns in 2015. Like many other prawn species, the recruitment dynamics of *P. indicus* are complex, with their lifecycle dependent on tides, currents and river flows (Somers, 1994; Kenyon et al. 2004 and reviewed in Plagányi et al. 2020a) and the unusual tidal conditions and extreme temperature regime of 2015, were proposed by Plagányi et al. (2015) as two potential drivers of variation in both recruitment and availability of stock to the fishery.

Further research into the environmental drivers of variability in Redleg banana prawns in the JBG was carried out by Plagányi et al. (2020a). They suggested that exceptionally good recruitment years and poor recruitment years respectively (using August CPUE as an index) might plausibly be explained by highly positive or negative values of the Southern Oscillation Index (SOI) in January (i.e. 6-7 months earlier), which also correlates with sea level height. However, positive and negative values of the SOI do not always correlate with high and low rainfall respectively. The timing of rainfall is also important in influencing prawn recruitment. Hence, a second explanatory variable was proposed to further improve model predictions – namely the combined total rainfall during January and February (Plagányi et al. 2020a).

Given the number of recent uncertainties, the Northern Prawn Fishery Resource Assessment Group (NPRAG) have, for some time, been discussing additions and alterations that could be made to the NPF Redleg banana prawn Harvest Strategy to address the current uncertainties and ensure that the revised Harvest Strategy is appropriate and effective in achieving target sustainable harvest levels without undue risk to the fishery. This is challenging to operationalise due to limited available data and hence, it is necessary to simulation-test the performance of any proposed changes to the current Harvest Strategy.

2 Needs

The JBG Redleg banana prawn fishery is an input-controlled managed fishery. The current Harvest Strategy uses data on the effort (fishing boat days) and catch rate (kg per boat per day) from the previous year and estimated spawning biomass to determine whether the fishery will be open or closed during fishing seasons in the following year. However, because of recent declines in the fishery, the NPRAG has requested research into a more robust Harvest Strategy, one that has been simulation tested within a Management Strategy Evaluation framework.

3 Objectives

The objectives as specified in the original proposal are:

1. To develop a Management Strategy Evaluation (MSE) framework for the Redleg banana prawn fishery.

2. Simulation test the performance of alternative Harvest Strategies using components of the MSE framework.

3. Deliver to NPRAG output performance statistics for each alternative Harvest Strategy so that their relative performance can be evaluated.

4 Method

Management Strategy Evaluation (MSE) is the preferred tool to assess the performance of alternative Harvest Strategies (Rademeyer et al. 2007; Plagányi et al. 2018a). The MSE approach requires an Operating Model (or set of models) be developed to simulate behaviour of the fishery. These OMs are fitted to historical data and are then used to generate future data, typically assuming comparable levels of variability to that observed in the past. A set of Harvest Control Rules (HCRs) are then required for testing and are often designed and selected through stakeholder engagement, with tuning of parameters a part of the modelling process. Simulation testing of the HCRs is then carried out using the simulated data and applying the HCR to enforce a management response (e.g. fishery closure), which is carried out in the OM. This procedure is projected forward in time and performance indicators, pre-determined through stakeholder consultation, are used to evaluate and compare the performance of alternative HCRs.

4.1 Operating Model

A discrete population model, adapted from Plagányi et al. (2010), was constructed for Redleg banana prawns in the JBG (Appendix 1). The model has a monthly time-step and is fitted to fishery-dependent catch and effort data for the period 1980-2018. The number of prawns in year *y* and month *m* is given by:

$$N_{y,m+1} = N_{y,m} e^{-M_m} - C_{y,m} + R_{y,m+1} \tag{1}$$

Where $N_{y,m}$ is the number of recruited and mature prawns (those corresponding to a size large enough to be fished) at the start of month *m* in year *y* (a calendar year); $R_{y,m}$ is the number of recruits (number of 6-month old prawns) which are added to the population at the end of each month *m* in year *y*; M_m denotes the natural mortality rate during month *m* (assumed to be constant throughout the year); and computed by multiplying the weekly natural mortality rate estimate by 4 (weeks) to reflect a monthly mortality rate; and $C_{y,m}$ is the predicted number of prawns caught during month *m* in year *y*, with catches assumed taken as a pulse at the end of each month.

Six Operating Models (OMs) were developed for the MSE Reference Set (Figure 1). These models were chosen to best represent the underlying stock dynamics and account for uncertainty in how the stock might behave. OM1 is the base model, which is most similar to the stock assessment model (Plagányi et al. 2010) and three variants (OM2 – OM4) account for model structural uncertainty. While the last two (OM5 and OM6) were included to account for uncertainty in key parameters, namely *h*, the steepness parameter for the stock-recruitment relationship, and σ_R, the standard deviation associated with the recruitment deviations.

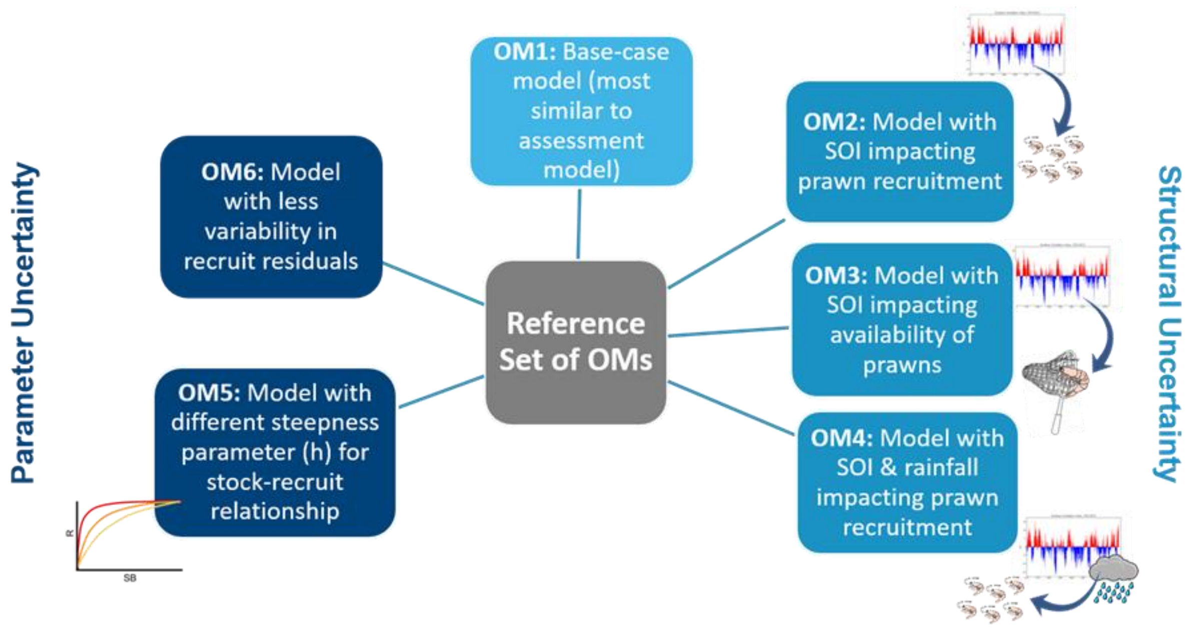

Figure 1: Overview of the six Operating Models (OMs) included in the Reference Set, showing those that account for structural and parameter uncertainty. SOI refers to Southern Oscillation Index.

The Six Operating Models are:

• OM1: Base-case model in monthly time-steps, with random future recruitment residuals assumed to be similar to historical recruitment residual patterns. Stock-recruitment parameter *h* = 0.6. Standard deviation σ_R = 0.8.

• OM2: Model as in OM1, but assumes that the Southern Oscillation Index (SOI) impacts prawn recruitment, such that variability in prawn recruitment is increased during El Niño (SOI < -7) and La Niña (SOI > 7) years. See details in Appendix 1.

- OM3: Model as in OM1, but assumes that the SOI (El Niño years only) impacts the availability of prawns – i.e. if SOI < -7, there is a change in the distribution of the stock which manifests on the catchability. See details in Appendix 1.

- OM4: Model as in OM1, but with lower standard deviation associated with the recruitment deviations (σ_R = 0.6) and assumes that both the Southern Oscillation Index (SOI) and rainfall impact prawn recruitment, such that variability in prawn recruitment is increased during El Niño (SOI < -7) years that have above average rainfall. See details in Appendix 1.

- OM5: Model as in OM1, but with a lower, more conservative steepness parameter (h=0.4).

- OM6: Model as in OM1, but with lower standard deviation associated with the recruitment deviations (σ_R = 0.6).

Each of the OMs were fitted to historical catch and effort data for the period 1980-2018 (Appendix 1). The models were implemented using AD Model Builder, which uses quasi-Newton automatic differentiation for statistical inference (Fournier et al. 2012). All graphical outputs were plotted in R 3.6.1 (R Core Team, 2019) using the packages dplyr (Wickham and Henry, 2019), ggplot2 (Wickham, 2016), gridExtra (Auguie, 2017), and tidyr (Wickham and Henry, 2019).

4.2 Future Projections

Each of the OMs were forward projected for 20 years to account for cyclical environmental drivers and for each OM, 200 replicates were run. Each OM used the same set of random numbers to generate the replicate simulations. The outputs from the six OMs were then combined, with equal weight accorded to each, giving a total of 1200 projection scenarios.

For each OM, future exploitable biomass was generated, and the future pattern of fishing effort per month was assumed to be similar to recent observed fishing effort distribution (i.e. the average of the last 5 years) and scaled so that the target fishing mortality per month m (F_m^{targ}) was approximately at a level that keeps the stock at B_{MEY}^{sp}. The future projected number of prawns caught each month could then be calculated using the fishing mortality and exploitable biomass under each alternative scenario. Uncertainty around the realised magnitude of future fishing effort (and hence catch) compared with target levels was captured through the inclusion of an implementation error (Appendix 1). Using the future generated monthly catch, the predicted economic value ($AUD) of prawns caught was calculated using an average price per size grade of prawn (Appendix 1).

Future CPUE data for the projection period were generated from the projected exploitable biomass, the catchability coefficient (q) and the future fishing power, which was assumed to increase linearly by a value 1.5 by the end of the 20-yr projection period. Uncertainty around the predicted CPUE was captured using an error (standard deviation) associated with future catch rates, input as 0.05 and increased to 0.2 in years with low CPUE (less than 400 kg/day) to account for increased error in years with few data (Appendix 1).

Future environmental data (January SOI and combined January and February rainfall) were generated using 200 random draws from past data (1969-2019), each 20 years in length. Historical rainfall data were obtained from the Australian Bureau of Meteorology (BOM) for the Lake Argyle Resort station (16.11°S, 127.74 °E; BOM station number 2044), which is located in the Ord river region and feeds into the Ord river and ultimately the JBG. Rainfall data for this station were used as a proxy for the river inflow into the JBG (important in the prawn's lifecycle) and a complete timeseries for the months of January and February were available from 1969. Data are available for other rainfall stations in a nearby catchment (e.g. Newry station, BOM station number 14820), as far back as the early 1900s. However, there are a number of gaps in this time series (including the second half of the 20th century) and thus, it was considered better to use a complete, but shorter time series for generating the future data. Additionally, these data were considered to most likely be more representative of future data than data from the first half of the 20th century. January SOI data were obtained from the BOM (http://www.bom.gov.au/climate/current/soi2.shtml) for the same historical period as the rainfall.

4.3 Management Reference Levels

Redleg banana prawns are a short-lived highly variable stock with recruitment dynamics driven by environmental factors. Hence, equilibrium-based concepts such as MSY are not that applicable to this stock, but are nonetheless required for reference purposes. Given the difficulties of analytically computing the MEY, in the stock assessment, a proxy is used that is based on a recent average computed over a period when industry were assumed to have been fishing at a level that maximises economic yield. Similarly, in the OMs, we therefore use a deterministic estimate of the biomass at which this level of fishing occurs (B_{MEY}) based on the average spawning biomass since 2000. In line with the Commonwealth Harvest Strategy, in cases where B_{MEY} is unknown, a proxy of 1.2B_{MSY} (or a level 20% higher than a given proxy for B_{MSY}) is to be used to approximate B_{MEY}. Hence, if B_{MEY} is known, then B_{MSY} is approximated as 0.8B_{MEY}. The limit reference level (B_{LIM}) is approximated as 0.5B_{MSY}. Reference levels for each of the OMs were calculated in this way (Table 1).

Table 1: Spawning biomass (tons) at which harvest levels produce the maximum economic yield (MEY) proxy and the maximum sustainable yield (MSY), and the biomass limit reference point B_{LIM} for all six operating models.

Model	B_{MEY}	B_{MSY}	B_{LIM}
OM1	2716	2263	1131
OM2	2701	2251	1125
OM3	2551	2126	1063
OM4	2429	2024	1012
OM5	2506	2088	1044
OM6	2429	2024	1012

4.4 Harvest Control Rules

The Redleg banana prawn fishery is currently managed using input controls, in which the Harvest Strategy (HS) includes a harvest control rule (HCR1 – outlined below) specifying closing the fishery in the following year if the estimated spawning biomass drops below the limit reference point (0.5B_{MSY}) for two consecutive years. Additional HCRs that could potentially be added to the HS to be tested in conjunction with the existing set of HCR were identified based on consultation with stakeholders and include the following:

- HCR1: Current rule in which the limit reference point B_{LIM} (0.5B_{MSY}) is the trigger. If the spawning biomass falls below this value for two consecutive years, then the fishery is closed the following year.
- HCR2: Current rule + permanent closure of the first fishing season (April –June).

- HCR3: Current rule + environmental (SOI) trigger to close the first season. If the SOI < -7 in January, then the first fishing season (April – June) is closed.
- HCR4: Current rule + a monthly CPUE trigger to close the fishery. If the monthly CPUE drops below 500 kg/day, the fishery closes for the rest of the season (either season 1 or season 2) and will re-open the following season.
- HCR5: As in HCR1, but with a more conservative limit reference point trigger of $0.6B_{MSY}$.

4.5 Performance Statistics

Model projections were run for 20 years, with 200 replicates run for each OM, giving a total of 1200 model runs. The same set of random numbers was used for setting model stochastic errors under each of the HCRs. The performance of the various HCRs are compared using key performance metrics, either displayed in the form of box-and-whisker plots (showing the median, 25th and 75th percentile as well as the range of the data, excluding outliers) or bar graphs (showing probabilities). It should be noted that the median does not represent an actual future trajectory, but rather it is similar to an average of all plausible scenarios. As such, examples of individual trajectories, similar to what could plausibly be observed in future, are also shown using worm plots, where each individual line is a possible outcome for the projected period. Key performance metrics include:

- B^{sp} : the projected average annual spawning biomass (tons year^{-1}) (to evaluate performance relative to pre-specified targets and limits)
- $B^{sp}_{2038} / B^{sp}_{2019}$: the spawning biomass at the end of the projection period relative to the start of the projection period
- $B^{sp}_{2038} / B^{sp}_{0}$: the spawning biomass at the end of the projection period relative to the start of the historical model period (i.e. 1980)
- Catch: the average annual catch (tons year^{-1})
- Catch Value: the value (AUD$ year^{-1}) of the average annual catch
- AAV: the average annual variability in catch over the 20-year period $\frac{1}{20}\sum\frac{|C_y - C_{y-1}|}{C_{y-1}}$

- Risk statistics: the probability of (1) the fishery closing completely in any given year, (2) B^{sp} falling below the limit reference point B_{LIM} (equal to 0.5 B_{MSY}) and (3) B^{sp} being at or above the target reference point B_{MSY}
- CPUE: the projected average catch-per-unit-effort (tons day^{-1})

4.6 Sensitivity Tests

The Reference Set of OMs is created to best represent the underlying stock dynamics, including consideration of some of the key structural and parametrisation uncertainties. Sensitivity tests are used to further account for uncertainties and highlight under what circumstances some strategies might perform poorly, to assess how robust individual HCRs under additional lower probability but plausible future scenarios. This more rigorous testing helps to further inform choice of a robust strategy that meets fishery objectives. Following consultation with stakeholders, we ran sensitivity tests (Table 2) on three of the preferred HCRs (HCR2, HCR3 and HCR4), relative to the current HCR.

Table 2: A list of sensitivity tests performed on three of the Harvest Control Rules (HCR2, HCR3 and HCR4).

Sensitivity	Description	Details
S1	Alternate fishing pattern (sensitivity to unusual 2019 observed fishing pattern)	Fishing 1st season only: *F* = scaled up by 1.5 in 1st season and implementation error doubled; *F* = 0 in 2nd season
S2	Increased fishing mortality	Fishing mortality *F* is doubled
S3	Alternate fishing power	Fishing power increases by 3.0 instead of 1.5 over 20-year period
S4	Alternate error associated with catch	Implementation error is doubled
S5	Increased recruitment variability	Recruitment variability for projection period scaled up by 1.5
S6	Autocorrelation in low recruitment years	Low recruitment years assumed to be autocorrelated: if recruitment residuals in year *y* < -0.6, then the same recruitment residual is given to year *y+1.*
S7	Delayed management response	If CPUE is low, then it is assumed that there are not enough data to reliably estimate the spawning biomass and hence a delay in management response occurs - i.e. HCR1 is not implemented. Additionally, it is assumed fishing mortality and the implementation error will increase. Thus if the average CPUE for April-June (1st season) or July-Sept (first half of 2nd season) in year *y* is < 0.4 tons day^{-1}, HCR1 in *y+1* is not implemented if spawning biomass < B_{LIM} for two years in a row and the fishing mortality *F* and implementation error are doubled the following year *y+1*.
S7b	Delayed management response - adjusted	As above, but the fishing mortality *F* and implementation error are doubled the following year *y+1*, for all years when the average CPUE for April-June (1st season) or July-Sept (first half of 2nd season) in year *y* is < 0.4 tons day^{-1}, and not just in years when HCR1 should have been, but is not implemented, due to low CPUE.
S8	Combination of autocorrelated recruitment & delayed management response	Combination of S6 and S7 - i.e. years with low recruitment are autocorrelated and there is a delay in management response if the average CPUE for April-June (1st season) or July-Sept (first half of 2nd season) is < 0.4 tons day^{-1}.

Sensitivity	Description	Details
S9	Recruitment variability more extreme in El Niño years (Applicable only to OM2 and OM4)	Increased variability in recruitment during El Niño Years - 1.5 x the environmental parameter

5 Results

5.1 Operating Models

Each OM was fit to monthly CPUE data for years and months for which there were enough data (in this case it was all months except February and March). In all OMs, model fits were reasonably good (Appendix 2, Figures A2.1-A2.6) and captured the broad patterns, including some of the peaks and thus were considered adequate for use as an OM.

Parameters estimated in the model included the pre-exploitation spawning biomass in the model start year, $K_{0,1}^{sp}$ (equivalent to $B_{0,1}^{sp}$), relative availability of the stock to fishing per quarter and per fishing period (as in Plagányi et al. 2010), recruitment residuals and an environmental parameter linked to either prawn recruitment (OM2 and OM4) or prawn catchability (OM3). In total, 47 parameters were estimated for OM1, OM5-OM6 and 48 parameters for OM2-OM4 (Appendix 2, Tables A2.1-A2.3). Parameter estimates were similar across all OMs and were mostly considered well estimated with reasonable standard deviations. However, some of the prawn availability parameters had to be fixed (kept constant) to allow a better fit of the model, or one or two with fairly large uncertainty (Appendix 2, Table A2.2). The model with the best AIC score among the comparable models was OM5 (73.85) followed by OM3 (77.61), OM1 (80.39) and OM2 (82.41). Of the models with reduced variability in recruitment, OM6 had a slightly better AIC (81.62) to OM4 (83.62) (Appendix 2, Table A2.3).

For models OM2 and OM4, it is notable that the model was able to reliably fit the environmental parameter estimate with fairly low associated standard deviations of 0.14 and 0.07, respectively (Appendix 2, Table A2.2). The OM2 AIC score was only slightly larger than the base model AIC. Hence these alternative models with an environmental link assumed are consistent with the historical data and are considered highly plausible alternative models (Appendix 2, Table A2.3). Similarly, the model estimate of the environmental-impact on the catchability parameter in OM3 was well-estimated with S.D. of 0.14 and a relatively better fit and lower AIC score compared to most of the other models, including the base model (Appendix 2, Table A2.3). The environment-recruitment and environment-catchability effects are confounded and there are no additional data that can be used to address the confounding within the model, which is why they are included as alternative plausible OMs.

5.2 Comparison with Stock Assessment Model

The OMs were adapted from the stock assessment model (Plagányi et al. 2018b) and of the six OMs, the base-case (OM1) is most similar to the assessment model because it doesn't explicitly include environmental drivers. One of the major differences in model structure between these two models is that the prawns are modelled in monthly time steps in the OM compared to quarterly time steps in the assessment model. As such, a larger standard deviation (compared with the 2019 stock assessment model, but same as the 2020 stock assessment) associated with the recruitment deviations (σ_R = 0.8) had to be used in OM1 to improve model fits to monthly CPUE data, which are more variable than the quarterly CPUE data, the latter having lost some of their variability when averaging across the months for each quarter. However, the 2020 stock assessment model that is used here in comparing outputs, also has σ_R=0.8 to capture the recent increased fishery variability. As expected, model fits in the OMs were not quite as good as in the assessment model, but they were nonetheless fairly good and considered acceptable for use as an OM, for which it is usually only necessary to use a loosely conditioned model (Punt et al. 2014). The pre-exploitation spawning biomass in the model start year, $K_{0,1}^{sp}$ differed substantially between OM1 and the latest assessment model (Plagányi et al. 2020b). This isn't surprising given limited information to inform on historical levels, but importantly, both the scale and pattern in the spawning biomasses were similar from 1990 onwards (Appendix 2, Figure A2.7a) and the commercially available biomasses were also very similar, for most of the model period (Appendix 2, Figure A2.7b). Reference levels differed somewhat as in each case they were scaled to the estimated biomass trajectories as described above. B_{MEY} and B_{LIM} for OM1 were estimated as 2716t and 1131t respectively, compared with the stock assessment estimates of 3275t and 1364t (Plagányi et al. 2020b).

5.3 Performance of Candidate Harvest Control Rules

Harvest Control Rule 1 (HCR1) is the rule that is currently used in the harvest strategy – i.e. if the spawning biomass is estimated to be less than the limit reference level (B_{LIM}, which is set at 0.5B_{MSY}) for two consecutive years, then the fishery is closed the following year. This HCR provides a baseline to which the other HCRs can be compared. A number of the performance metrics for HCR1 were similar to other HCRs, particularly HCR3, HCR4 and HCR5 (Figure 2 and Figure 3) but there was relatively more risk to the stock (probability of fishery closure and spawning biomass < B_{LIM}) under HCR1 compared to HCR2, HCR3 and HCR4 (Figure 2).

Harvest Control Rule 2 (HCR2) is the current rule plus the permanent closure of the first fishing season (April-June). This HCR achieves a greater average spawning biomass (indicated by the median) relative to other HCRs and there is a lower probability of extreme lower biomasses compared to HCR1. Depletion indices of the biomass in the final projected year (2038), as a proportion of the first project year (2019) and first modelled year (1980) are also slightly better compared to other HCRs. Although median catch is similar to all other HCRs, occasional large, extreme catches are not achieved under this rule, under the assumption that fishing effort is not substantially increased in the second season due to permanently closing the first season. Annual catch value tended to be greater (indicated by median estimate) under this HCR compared to all other HCRs and the variability in catch between years is less (Figure 2). Catch-per-unit-effort (CPUE) is relatively high under this HCR, and the extreme lower CPUEs are increased for Aug-Oct relative to HCR1 (Figure 3). This HCR suggests very little risk of fishery closure and little risk to the stock falling below the limit reference level B_{LIM}. It provides the greatest probability (75%) of the spawning biomass being at or above the target reference level B_{MSY} (Figure 2). To summarise, this HCR achieves very low risk of fishery closure and risk to the stock, but with an absence of occasional very large catches. However, catch value is predicted to be good because fishing is restricted to Season 2 when prawns are larger and annual average catch variance (AAV) is the lowest amongst the options (i.e. it has a narrow range), which is favourable to the fishery.

Harvest Control Rule 3 (HCR3) includes the current rule plus an environmental trigger to close the first fishing season. Under this HCR, spawning biomass is most similar to HCR1 (business as usual), but the small extreme biomasses are somewhat reduced (bottom whisker doesn’t extend as far down to the zero), similar to HCR2 and HCR4. Depletion indices, catch, catch value and catch variability are all similar to HCR1, but again don’t hit the lower extremes as much. CPUE is similar to that under HCR1, but there are relatively fewer extremely low CPUEs estimated for Aug-Oct relative to HCR1 (Figure 3). The risk of fishery closure is substantially reduced under HCR3 compared to HCR1, but not as reduced as under HCR2. Risk to the stock is approximately halved compared to HCR1, but isn’t as low as HCR2. The probability of the spawning biomass being at or above B_{MSY} is approximately 60%, a slight increase from HCR1, but not as great as HCR2 and only slightly better than HCR4 (Figure 2). To summarise, this HCR preforms very similarly to the current harvest control rule, except that risk to the stock and risk of fishery closure are reduced, although not as much as with HCR2.

Harvest Control Rule 4 (HCR4) includes the current rule plus a CPUE trigger to close the rest of the fishing season (season 1 or season 2). Under this rule, spawning biomass is similar to HCR1, HCR3 and HCR5, although the upper and lower extremes (top and bottom whiskers) are slightly reduced, meaning that there aren't as many instances of very large and very small biomass (Figure 2). A similar trend is seen in the depletion levels. Annual catches, catch value and catch variability are similar to HCR1 and HCR3, except that this rule hits the lower (zero) extremes more than HCR3. Under HCR4, the spread of the CPUE (i.e. the median, 25th and 75th percentiles or the "boxes") are similar to that under HCR1, but an advantage of this HCR is that it substantially decreases the probability of extremely low CPUEs (the lower whisker) for Aug-Oct relative to all other HCRs (Figure 3), because it pauses the fishery in response to low CPUE. The risk of fishery closure is reduced compared to HCR1 and is most similar to HCR3, although perhaps slightly reduced. Risk to the stock (biomass falling below B_{LIM}) is similar to HCR3 and approximately half that of HCR1. The probability of the spawning biomass being at or above B_{MSY} is similar to HCR1. To summarise, this rule performs similarly to HCR3, with risk of fishery closure being almost identical to HCR3. Risk of the stock falling below B_{LIM} is approximately double that of HCR2, but is similar to HCR3, and considerably reduced compared with the current HCR1.

Harvest Control Rule 5 (HCR5) is the current rule but uses a more conservative limit reference level to trigger closure of the fishery i.e. $B_{LIM} = 0.6B_{MSY}$ instead of the normal $0.5B_{MSY}$. This HCR performs similarly to HCR1 in almost all instances (Figure 2 and Figure 3), except that there is increased risk of fishery closure. This means that risk to the stock falling below the normal target reference level is reduced, but without any increased probability of the stock being at or above B_{MSY} compared with HCR1 (Figure 2). Given HCR5 doesn't perform any better than HCR1, it is not considered further when running sensitivity tests.

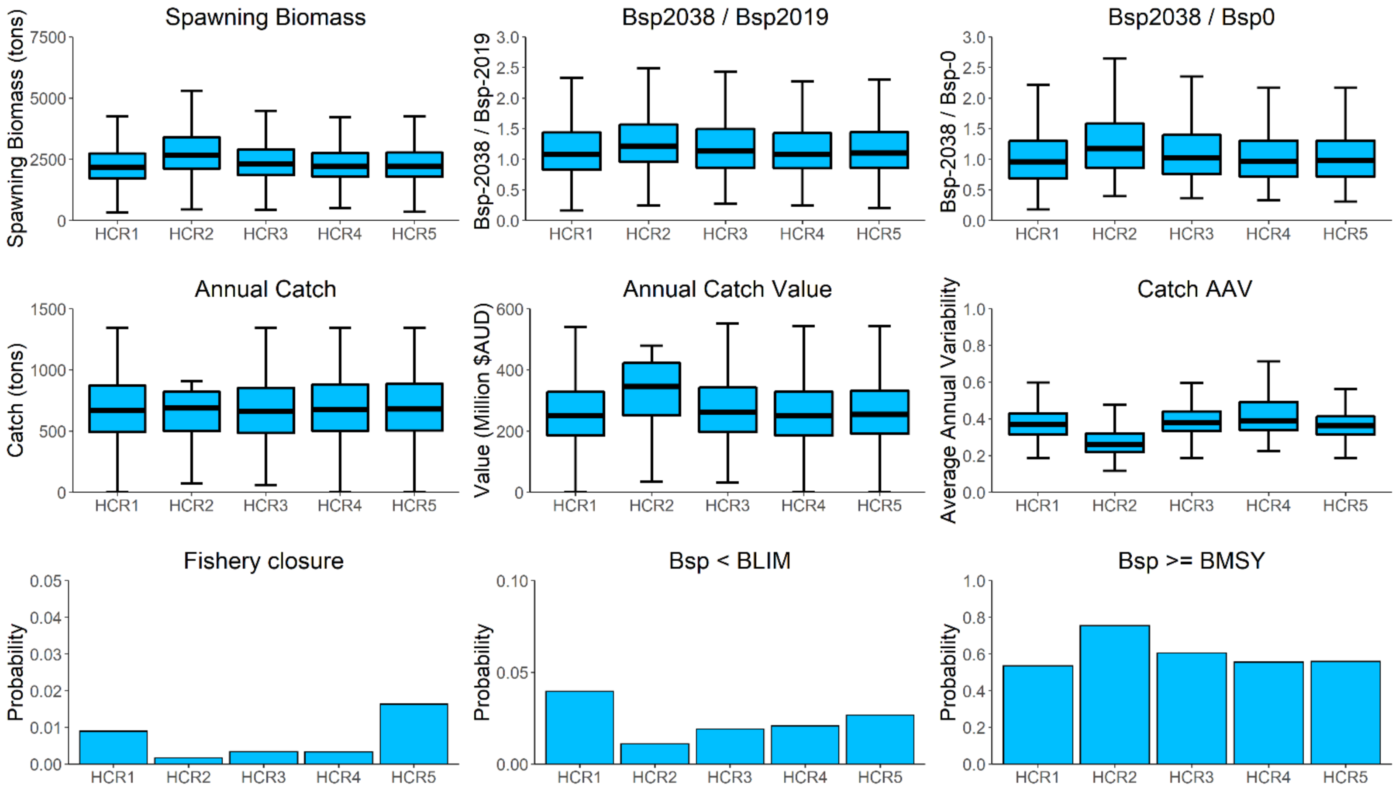

Figure 2: Key performance metrics across the five harvest control rules, for the reference set of Operating Models (i.e. averaged across all six OMs). Box and whisker plots (upper two panels) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

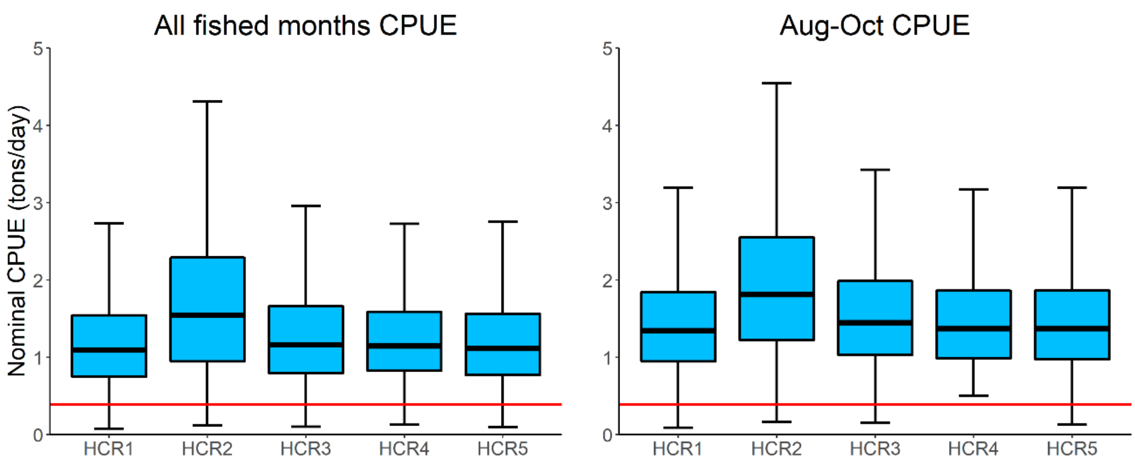

Figure 3: Catch-per-unit-effort (CPUE) across the five harvest control rules, for the reference set of Operating Models (i.e. averaged across all six OMs). Box and whisker plots show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers). The red horizontal line indicates the mean catch rate (390kg boat^{-1} day^{-1}) that is currently used as a trigger (as part of the current harvest strategy) to close the first fishing season of the following year, if catch rates fall below this level during Aug-Oct.

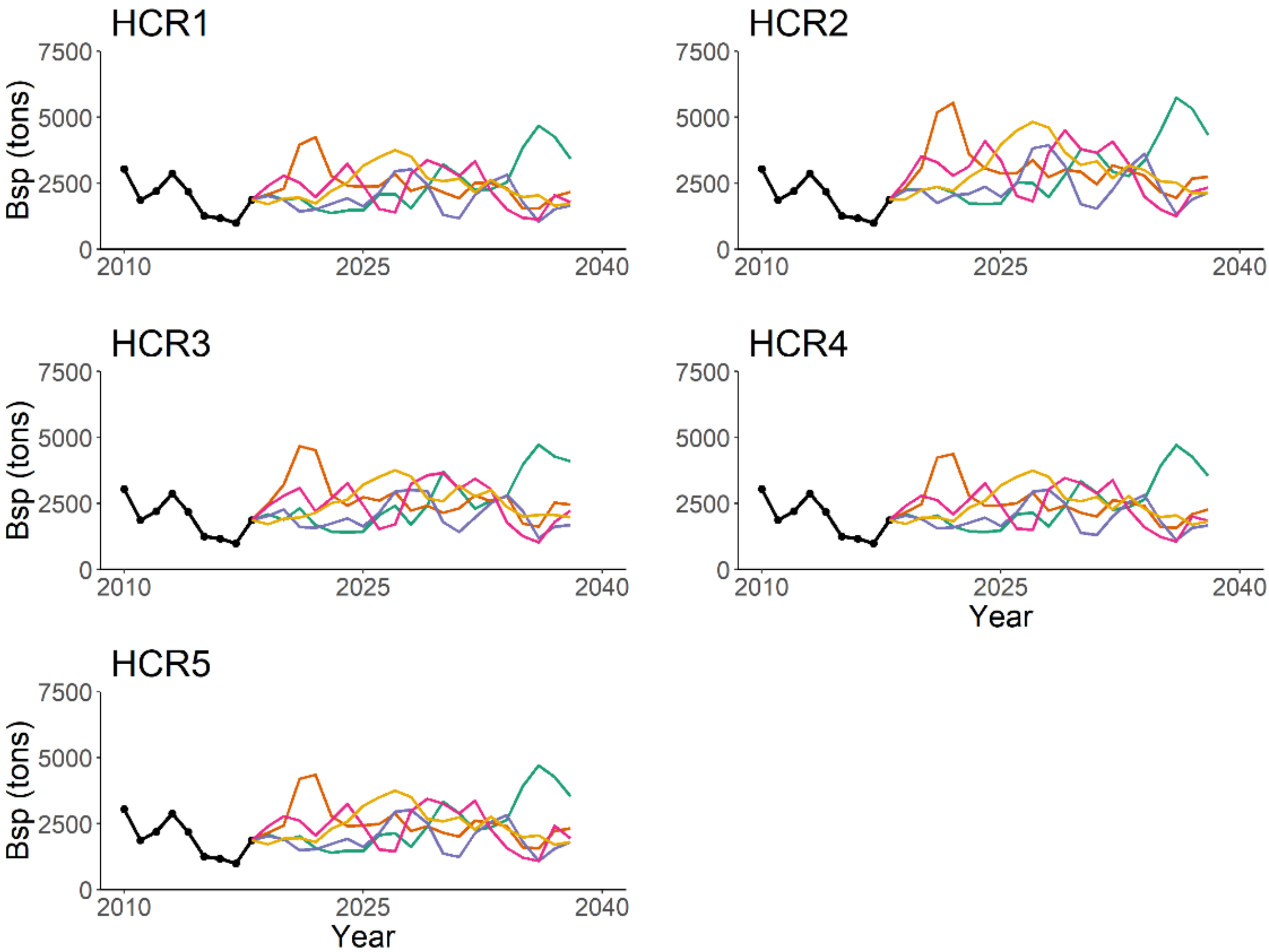

Figure 4: Examples of individual trajectories (worm plots) of spawning biomass (Bsp) projections for five random model runs (coloured lines) under HCR1, HCR2, HCR3, HCR4 and HCR5 using the Refence Set of Operating Models (i.e. averaged across all six OMs). These trajectories show five randomly selected possible outcomes. Black lines are the historical estimated spawning biomasses, averaged across OMs from 2010.

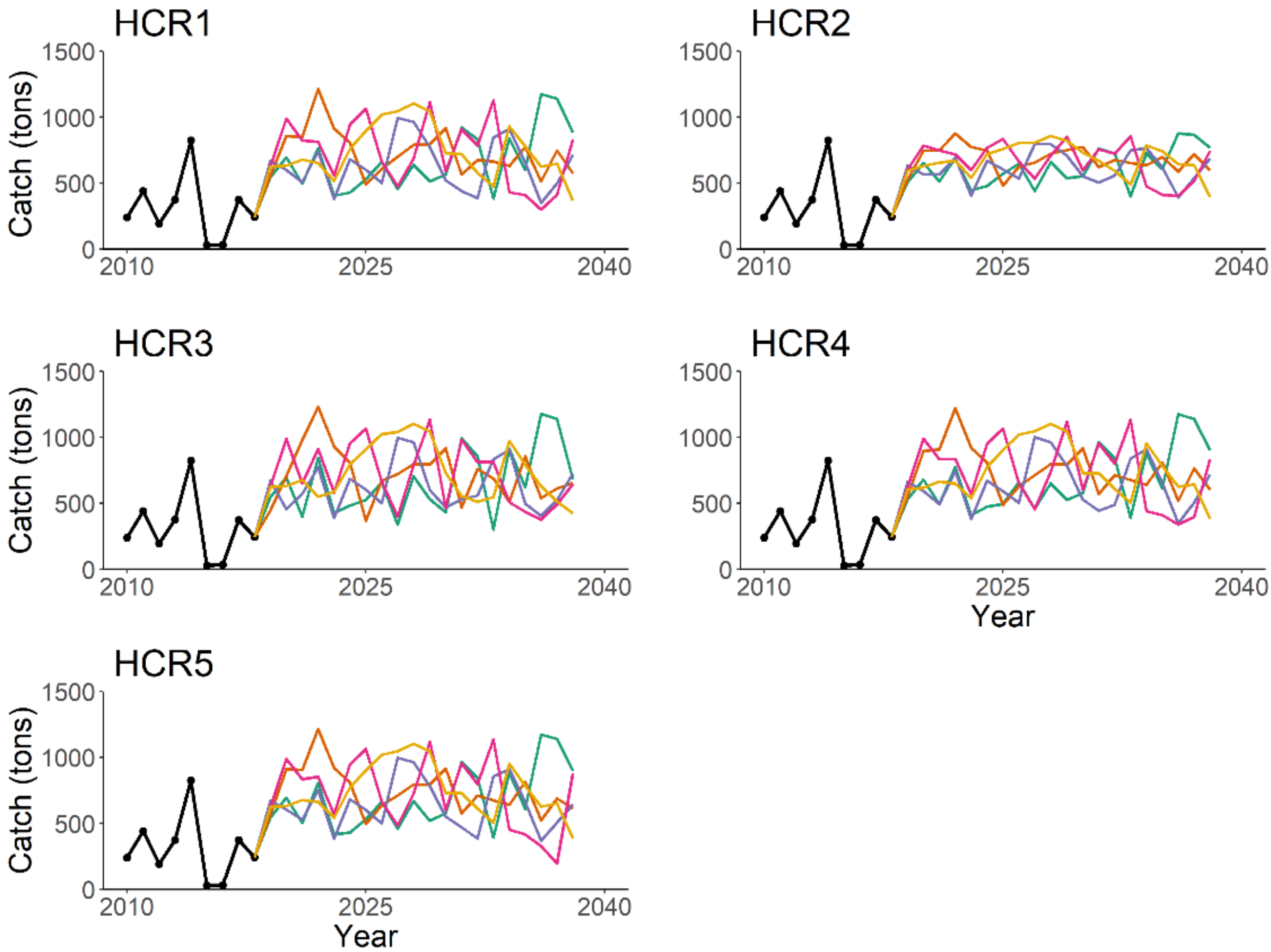

Figure 5: Examples of individual trajectories (worm plots) of catch projections for five random model runs (coloured lines) under HCR1, HCR2, HCR3, HCR4 and HCR5 using the Refence Set of Operating Models (i.e. averaged across all six OMs). These trajectories show five randomly selected possible outcomes. Black lines are the historical catches from 2010.

5.4 Performance of Harvest Control Rules using OM2 and OM4

The MSE results presented in Figures 2-5 were averaged over six alternative Operating Models, which represent alternative plausible parameterisations and functioning of the underlying system. Most of these OMs do not assume that environmental factors negatively impact stock recruitment (given that there is some, but inconclusive, evidence for this hypothesis currently). This does mean though that looking only at the average performance across all the OMs may confound interpretation of the relative performance of alternative HCR candidates. This is because there was no basis to objectively weight alternative OMs, as is sometimes done in MSE. Hence, here we show results for OM2 and OM4 only, because they are the two OM versions that incorporate the hypothesised link between environmental variables and stock recruitment. This relationship may well be validated (or strengthened) in the coming years, so it is also useful to analyse these results on their own too.

Figures 6 and 7 provide an example of how the HCRs perform under an OM that includes an environmental link to reduced recruitment (OM2 and OM4). Firstly, the number of fishery closures and risk to the stock under HCR1 is much greater for OM2 (Figure 6) and OM4 (Figure 7) compared to when the OMs were averaged (Figure 2), and the probability of the stock being at or above B_{MSY} is reduced. Secondly, while most of the trends in the performance metrics for OM2 (Figure 6) and OM4 (Figure 7) are similar to those when all the OMs are combined (Figure 2), under these two OMs, HCR2, HCR3 and HCR4 greatly reduce the number of fishery closures and risk to the stock, and to a lesser extent, increase the probability of the stock being at or above B_{MSY} (particularly HCR2, followed by HCR3).

Another example of how the HCRs compare, can be seen in Figures 8-11. They show five random model trajectories (coloured lines) for spawning biomass and catch respectively, for HCRs 1-4 using OM2 (Figure 8 and Figure 9) and OM4 (Figure 10 and Figure 11). These are examples of randomly selected trajectories (called worm plots) and are provided here as they illustrate the actual kinds of variability in catch and spawning biomass that may eventuate in future. The medians (not shown in figure) simply show the median value each year computed from all the individual simulated trajectories. Compared to the current rule (HCR1), the other three HCRs help to prevent the spawning biomass from dipping too low, and keep catches at reasonable levels, preventing any drastic declines in catch (as gauged by median values). While these figures don't necessarily show which of the HCRs performs better, they do show that either one of the three HCRs (HCR2, HCR3 or HCR4) can help prevent biomass and catches from dropping. The worm plots also show that catches in OM2 under HCR2 are much less variable compared to the other HCRs (Figure 9). This is largely because (1) fishing effort is focused solely on the second season and scaled accordingly to account for effort that would have occurred in the first season. (2) No fishing in the first season means that fishers miss out on any large prawns, and consequently large catches, left over from the previous year. (3) The HCR prevents the stock from depleting and as such catches don't drop as low.

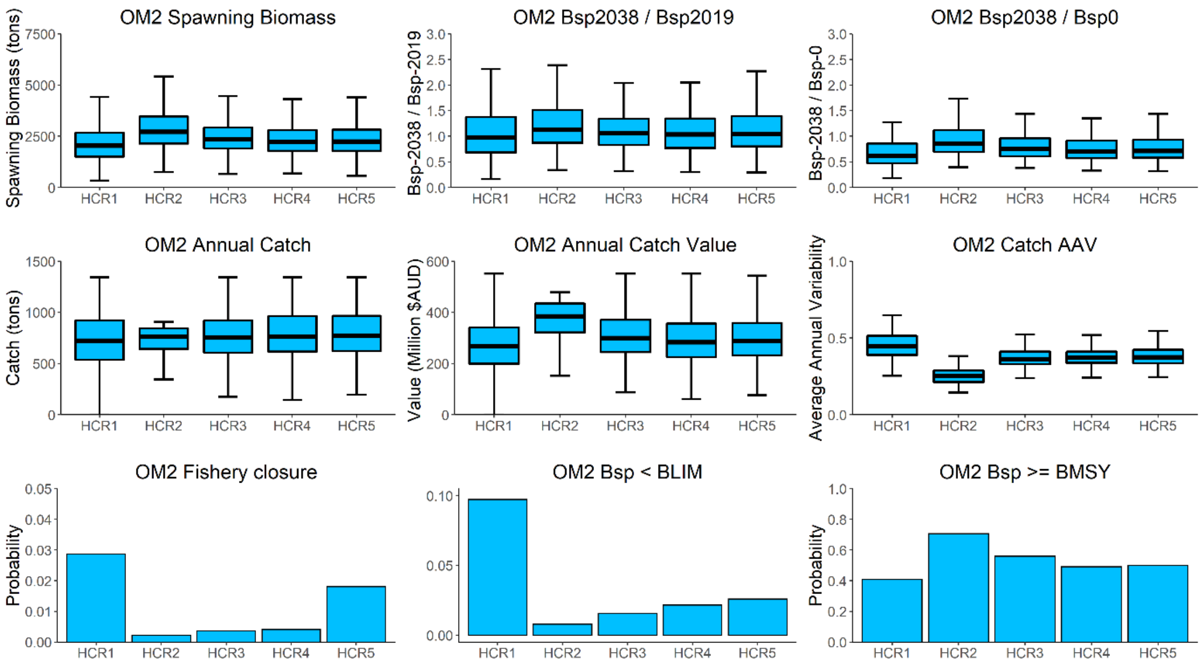

Figure 6: Key performance metrics across the five harvest control rules, for one of the more extreme OMs - Operating Model 2 (recruitment variability impacted by Southern Oscillation Index (El Niño and La Niña years)). Box and whisker plots (upper two panels) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

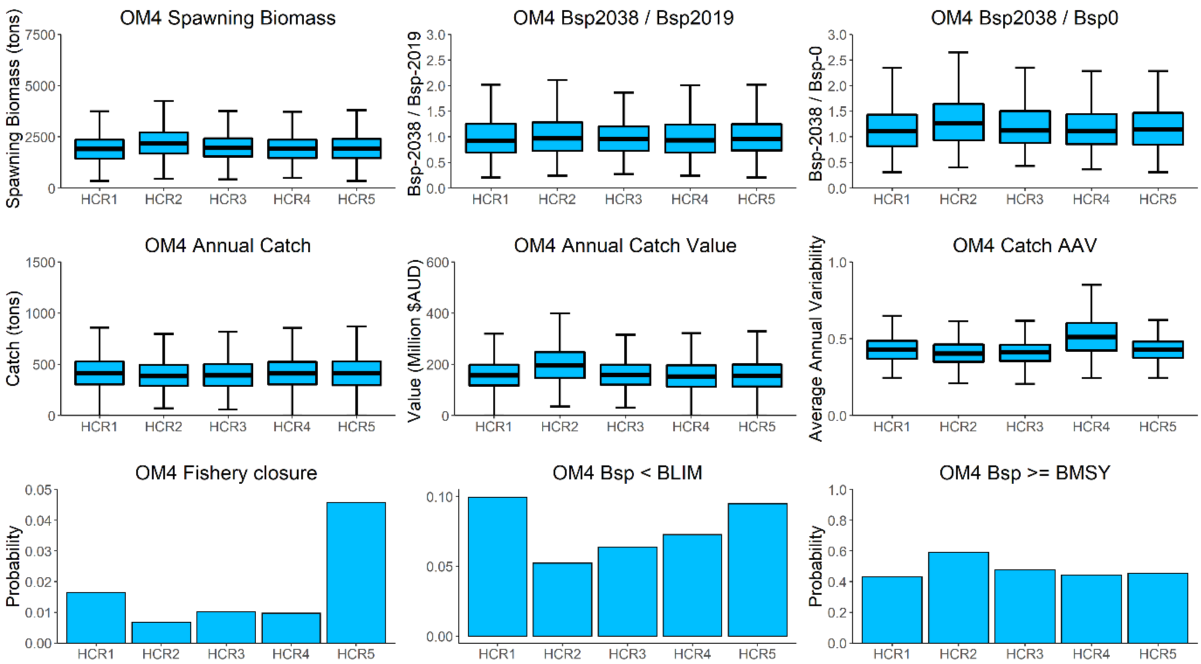

Figure 7: Key performance metrics across the five harvest control rules, for one of the more extreme OMs - Operating Model 4 (recruitment variability impacted by Southern Oscillation Index (El Niño years) and rainfall). Box and whisker plots (upper two panels) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

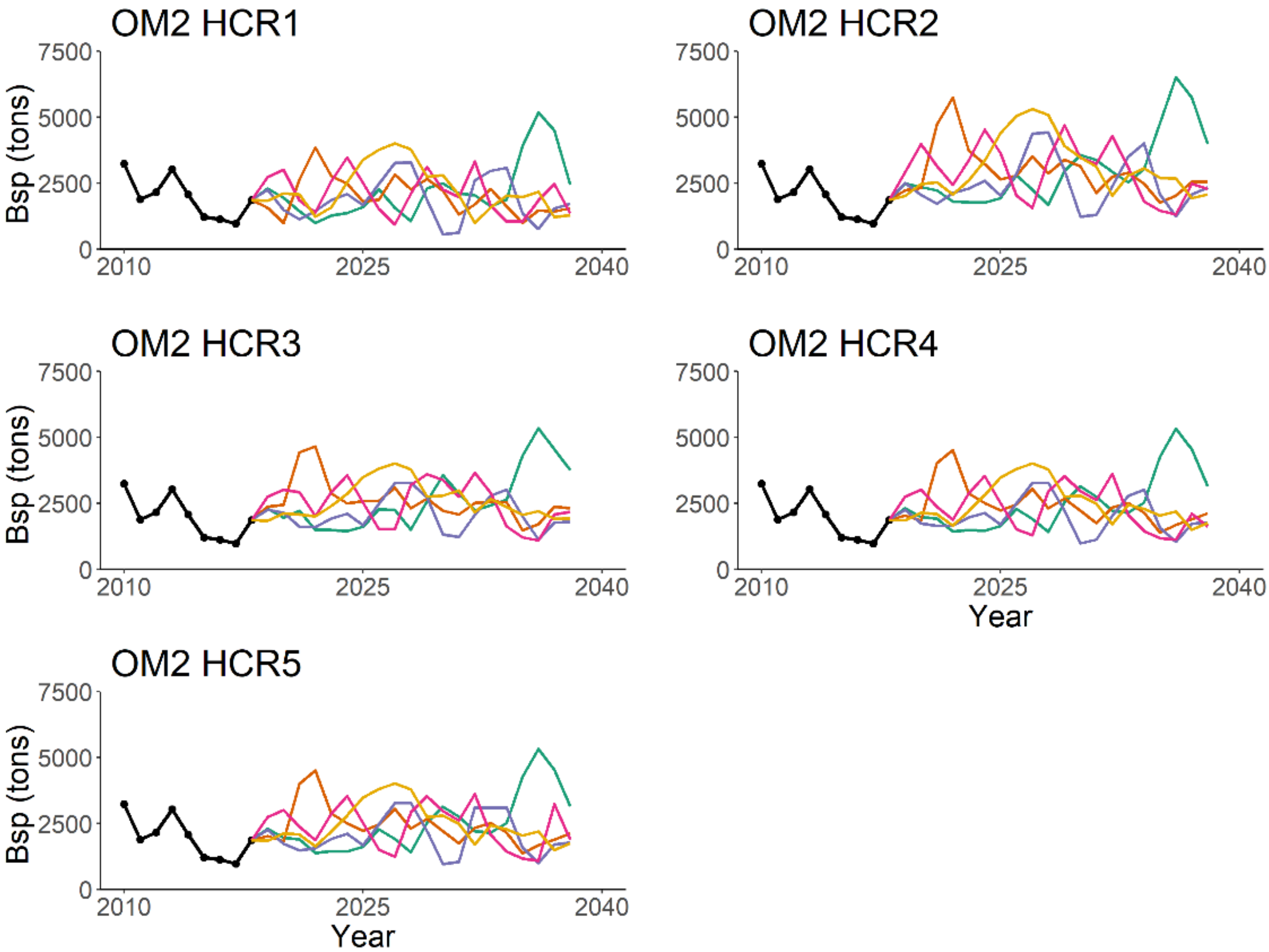

Figure 8: Examples of individual trajectories (worm plots) of spawning biomass projections for five random model runs (coloured lines) under HCR1, HCR2, HCR3, HCR4 and HCR5 using OM2. These trajectories show five randomly selected possible outcomes under this OM. Black lines are the historical estimated spawning biomasses from 2010.

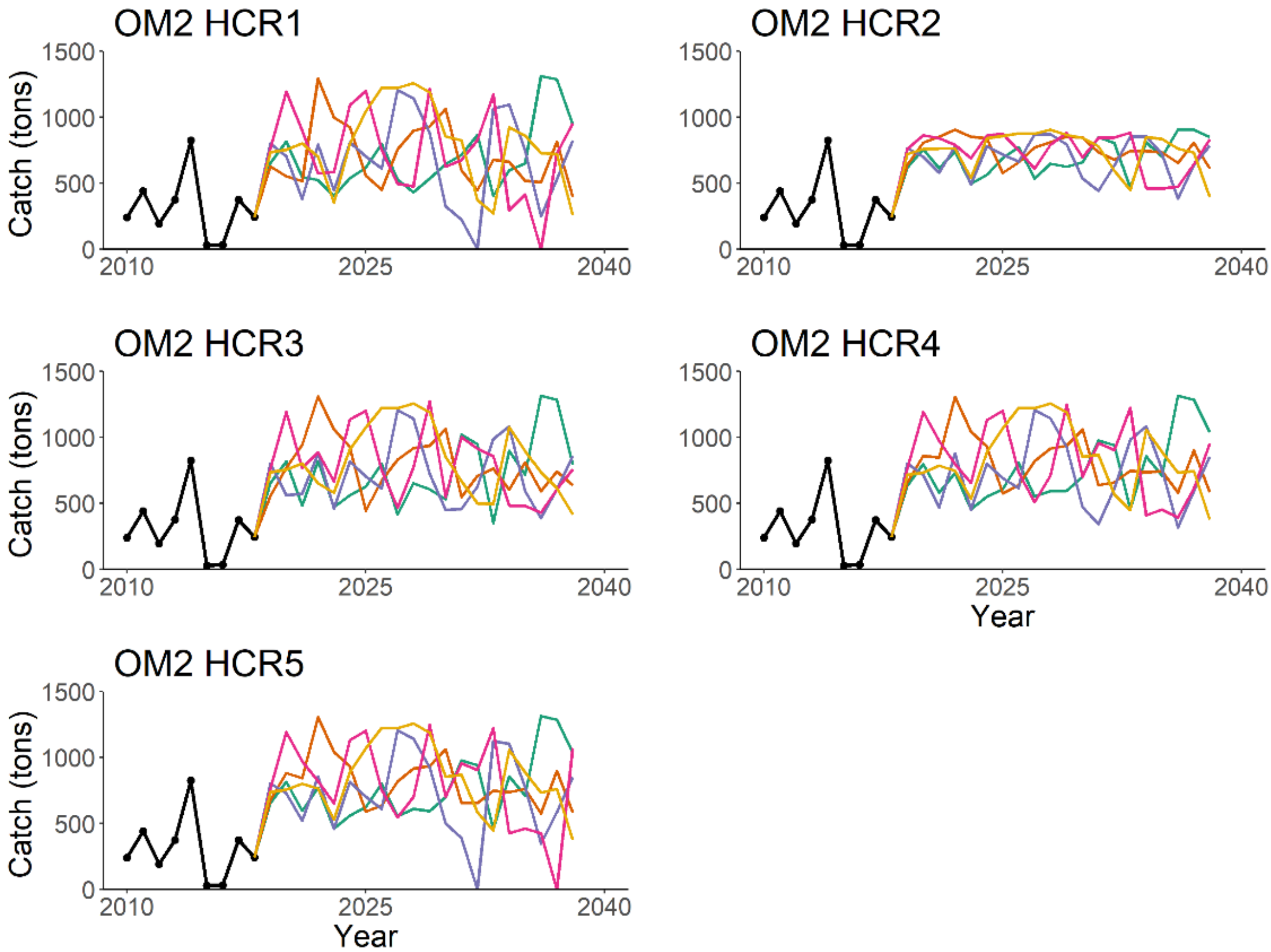

Figure 9: Examples of individual trajectories (worm plots) of catch projections for five random model runs (coloured lines) under HCR1, HCR2, HCR3, HCR4 and HCR5 using OM2. These trajectories show five randomly selected possible outcomes under this OM. Black lines are the historical catches, only shown from 2010.

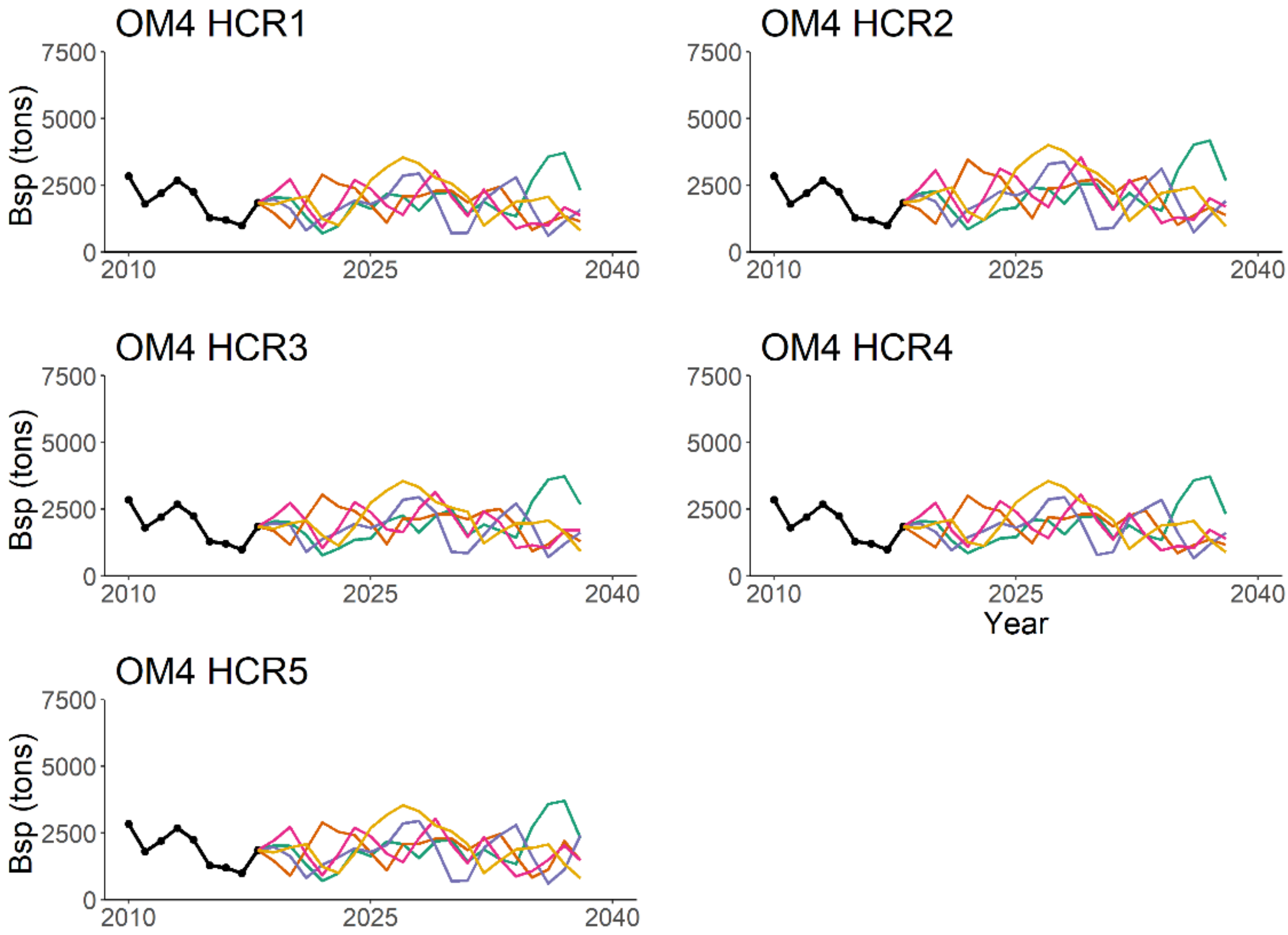

Figure 10: Examples of individual trajectories (worm plots) of spawning biomass projections for five random model runs (coloured lines) under HCR1, HCR2, HCR3, HCR4 and HCR5 using OM4. These trajectories show five randomly selected possible outcomes under this OM. Black lines are the historical estimated spawning biomasses, only shown from 2010.

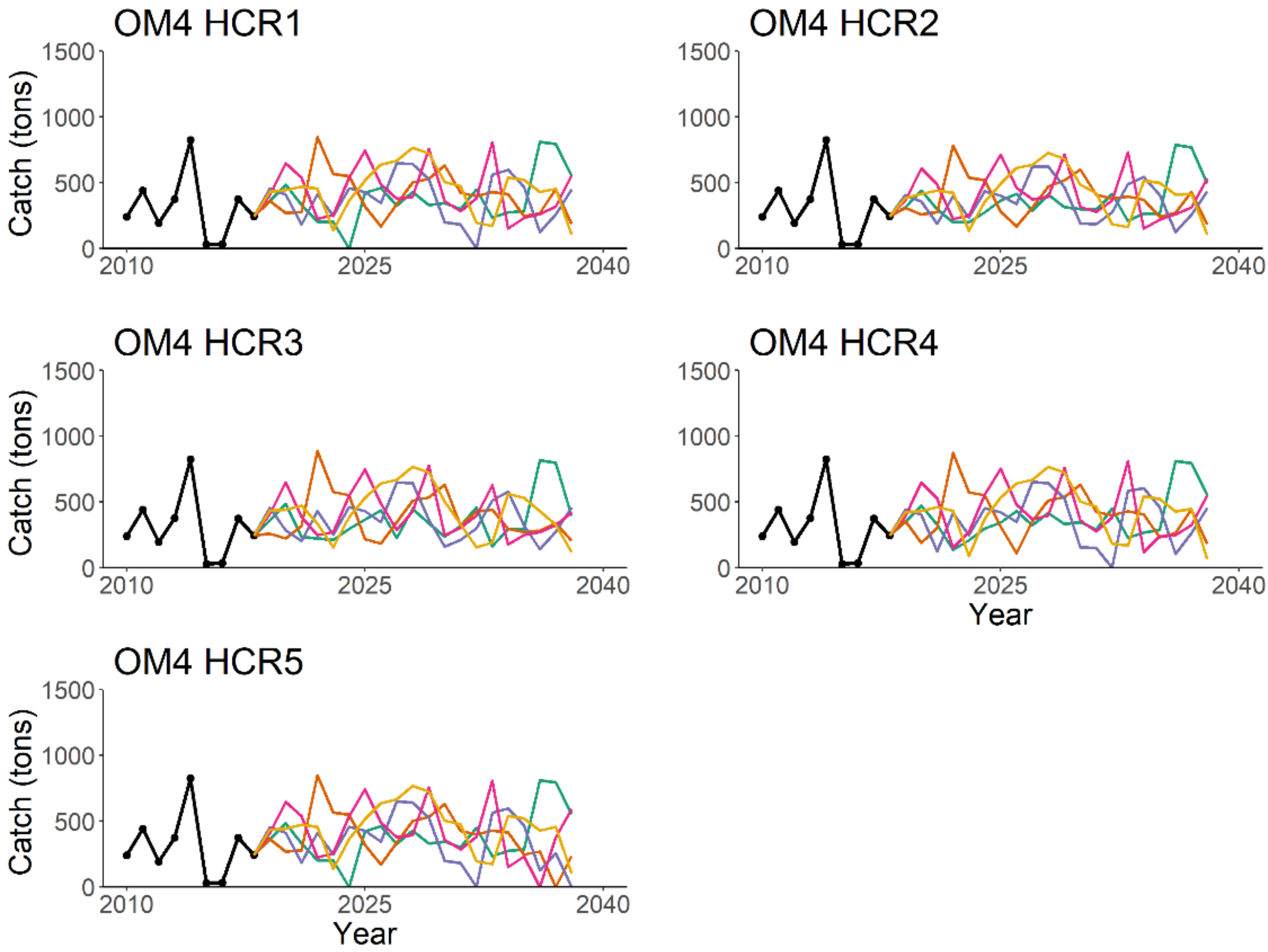

Figure 11: Examples of individual trajectories (worm plots) of catch projections for five random model runs (coloured lines) under HCR1, HCR2, HCR3, HCR4 and HCR5 using OM4. These trajectories show five randomly selected possible outcomes under this OM. Black lines are the historical catches, only shown from 2010.

5.5 Sensitivity Tests

Of the five HCRs that were tested, one of which was the current HCR (HCR1), three preferred rules (HCR2, HCR3 and HCR4) were identified by stakeholders during the NPRAG meeting. As such, sensitivity tests are presented for these three HCRs only and are discussed relative to each other and to HCR1 (Figure 12).

The performance of HCR2 was fairly robust to the sensitivity tests, with spawning biomass and catch showing similar medians and spread of the projected values (Figure 13). The exception was S1, which represents a change in fishing pattern (fishing in Season 1 only, as was the case in 2019), but does not apply to this HCR because HCR2 permanently closes the first season anyway. Hence, there is no catch and this sensitivity can be ignored under this rule. Sensitivity S4 (increased implementation error) resulted in a slightly greater catch variability, which is to be expected, and does not seem a major concern given performance across the other statistics. Sensitivities S2 (increased fishing mortality) and S6 (autocorrelation in low recruitment years), and to a lesser extent S5 (increased variability in recruitment) and S8 (autocorrelation in low recruitment years combined with a delay in management response due to low catch and effort data), resulted in an increase in the probability of fishery closures. Similarly, sensitivities S2, S6 and S8, and to lesser extent S5, resulted in a relatively greater risk to the stock dropping below B_{LIM} and a decline in the probability of the stock being at or above B_{MSY}, particularly for S2 (Figure 13). However, the risk is not considered unacceptable as the probability is less than 10%. These patterns were similar to HCR1, which was also sensitive to S2, S5, S6 and S8. However, HCR1 had a much greater and unacceptable risk (as per the guidelines in the Commonwealth Harvest Strategy) of fishery closures and risk to the stock under these sensitivity tests (Figure 12).

Under HCR3, spawning biomass, catch and catch variability were fairly robust to the sensitivity tests except for sensitivity S1 (change in fishing pattern to Season 1 only), which resulted in a substantially reduced catch and increase in the AAV, albeit with the trade-off of an increased spawning biomass (Figure 14). Sensitivity S2 greatly increased the probability of a fishery closure and risk of the stock being below B_{LIM} (over 20% probability, which is considered unacceptable as per the guidelines in the Commonwealth Harvest Strategy). Sensitivities S6, S5 and S8 also increased the probability of fishery closure and risk of the stock falling below B_{LIM}, but not as extreme as S2 (Figure 14). There was little risk of fishery closure or risk to stock under S1, but this could change if fishing effort was greatly increased in this season. Compared with HCR1, this HCR performed better across the sensitivities, except for S2 in which the risk of fishery closure and risk to the stock remained relatively high.

HCR4 was fairly robust to sensitivities and performed much better than HCR1, although as expected S1 resulted in greater spawning biomass but substantially reduced catch and catch variability (AAV) (based on the median estimates). Catch variability also increased under sensitivities S2-S4, but risk of fishery closure and risk to stock reduced to virtually zero for these sensitivities (Figure 15). As with other HCRs, there was an increase in the probability of fishery closure and risk of the stock falling below B_{LIM} for S5 (increased variability in recruitment) and S6 (autocorrelation in low recruitment years). There was also an increase in the risk of the stock falling below B_{LIM} for S8 (autocorrelation in low recruitment years combined with a delay in management response due to low catch and effort data), but not an increase in the probability of fishery closure for S8 given this sensitivity assumes a delay in management response (i.e. the fishery is not triggered to close if CPUE is below a threshold) (Figure 15). The risks of dropping below B_{LIM} thus remained within acceptable levels under all sensitivity tests that HCR4 was subjected to.

Focusing on an Operating Model with an environmental link to recruitment (OM2), the three HCRs showed similar patterns in sensitivity to those described above, with HCR2 and HCR4 most robust to sensitivities (Appendix 3 Figures A3.1-A3.3). Another sensitivity test (S9) was performed using only OM2 and OM4, in which recruitment was more strongly (negatively) impacted during El Niño years than in the Base models. All three of the HCRs were fairly robust to this sensitivity test (Appendix 3 Figures A3.1-A3.3 shows results for OM2 only), with HCR2 performing slightly better than HCR3 and HCR4, with relatively lower risk of fishery closure and stock dropping below B_{LIM}, as well as a greater probability of the stock being at or above B_{MSY}.

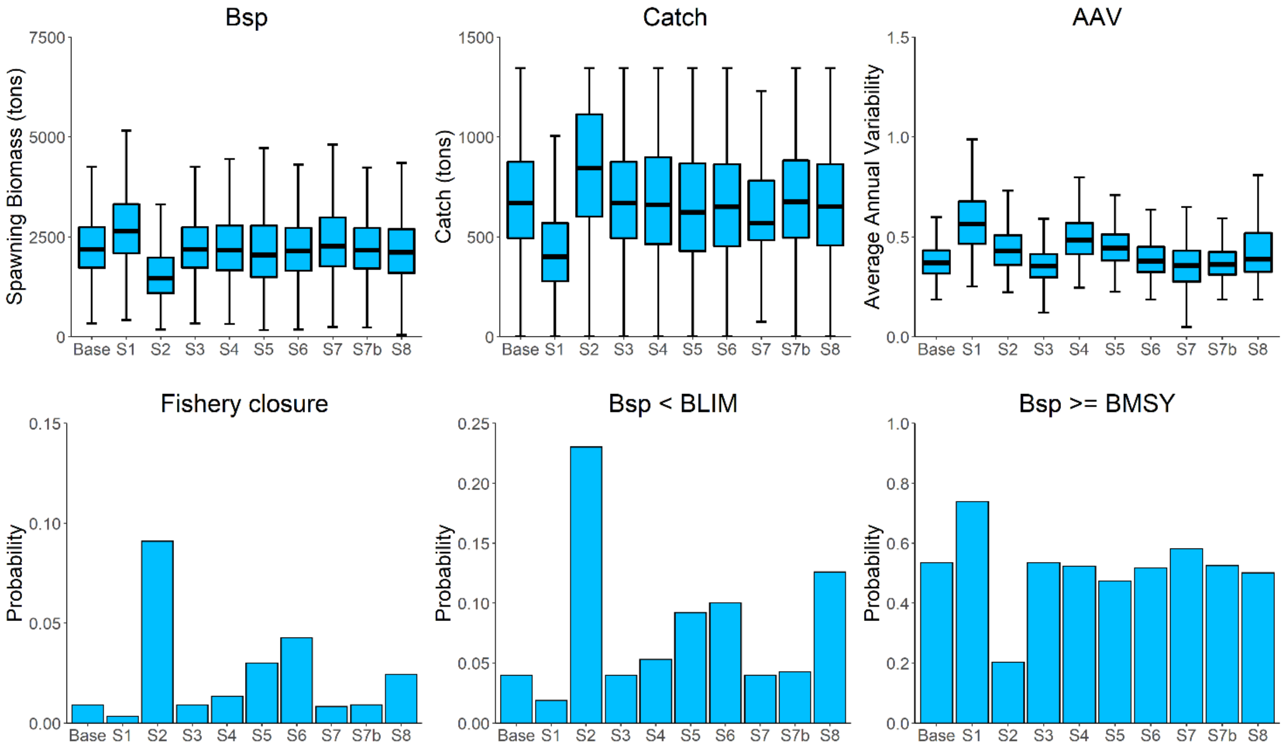

Figure 12: Selected performance metrics for sensitivity tests on HCR1 relative to the base HCR1 (all OMs combined). See Table 2 for a list of sensitivity tests. Box and whisker plots (upper panel) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

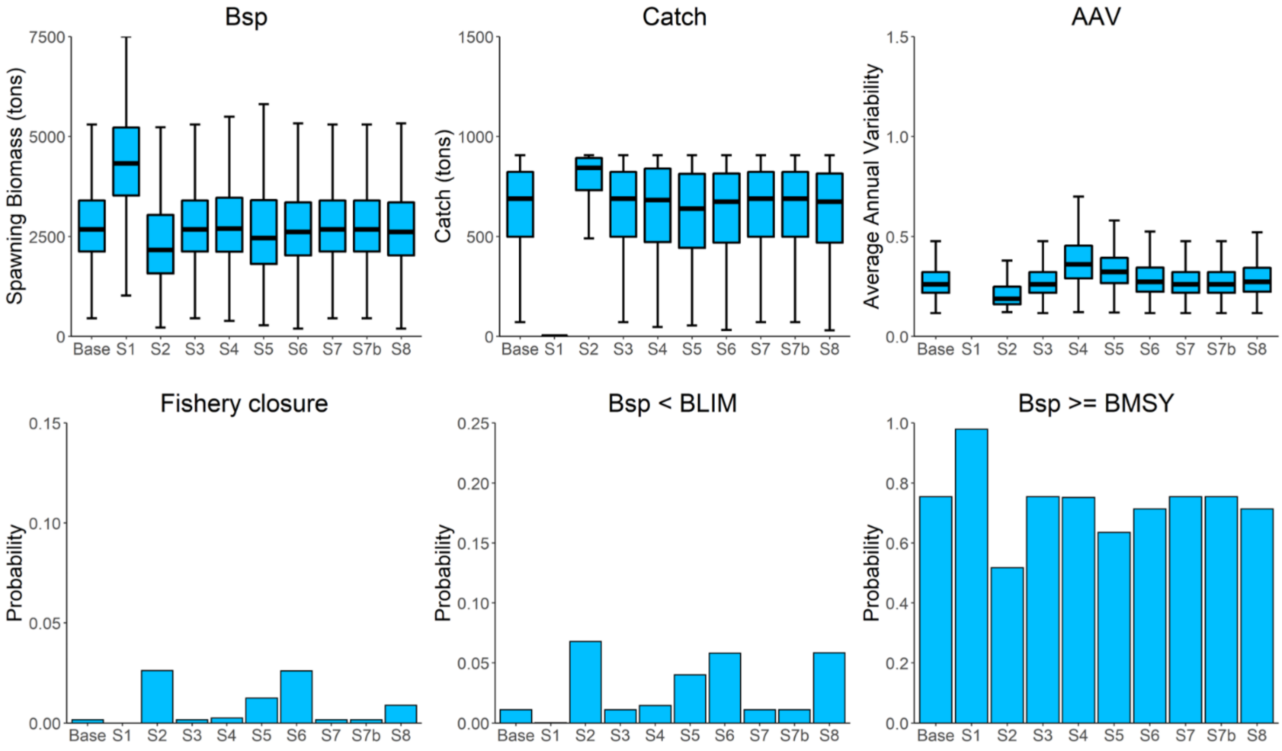

Figure 13: Selected performance metrics for sensitivity tests on HCR2 relative to the base HCR2 (all OMs combined). See Table 2 for a list of sensitivity tests. Box and whisker plots (upper panel) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

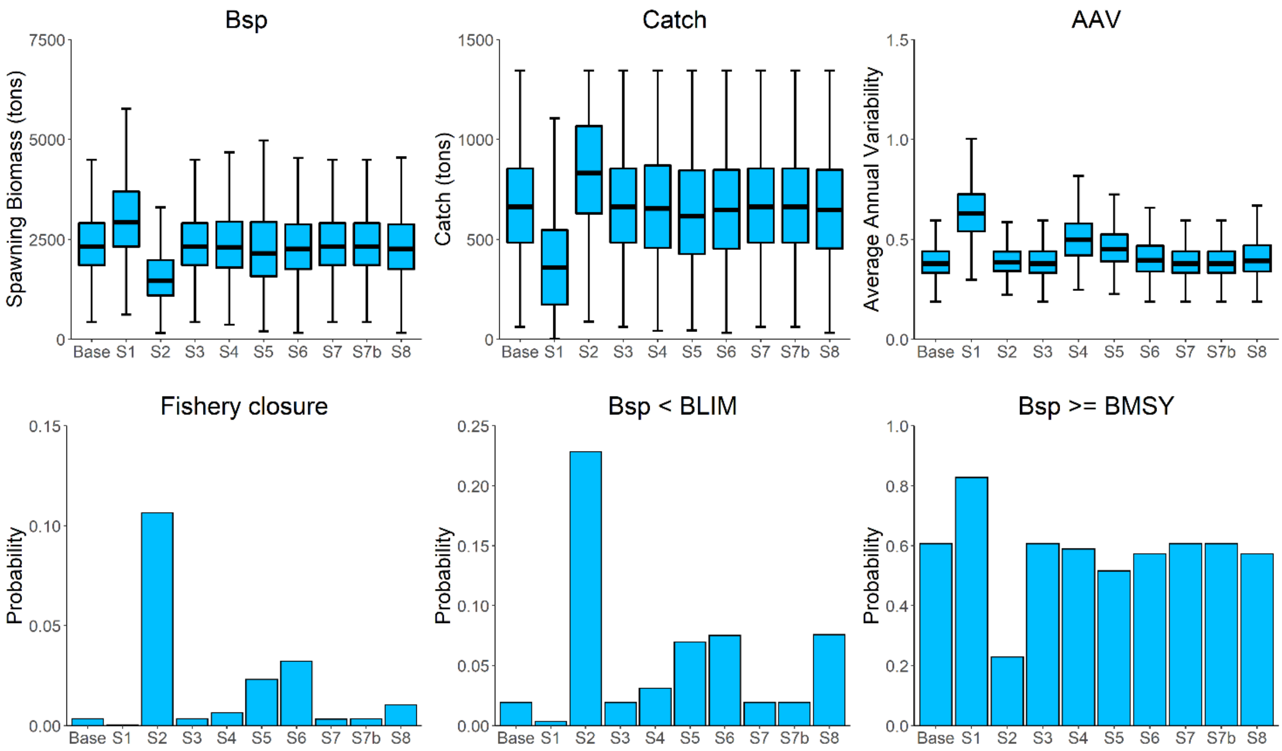

Figure 14: Selected performance metrics for sensitivity tests on HCR3 relative to the base HCR3 (all OMs combined). See Table 2 for a list of sensitivity tests. Box and whisker plots (upper panel) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

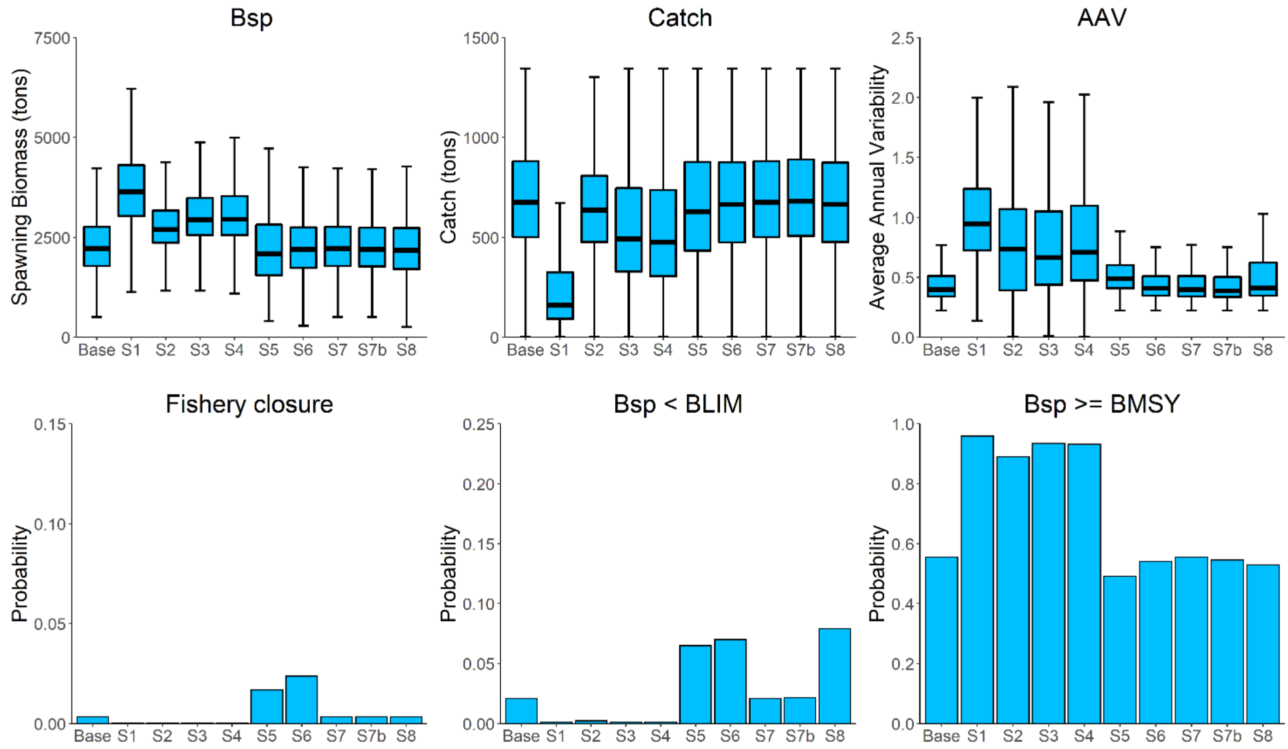

Figure 15: Selected performance metrics for sensitivity tests on HCR4 relative to the base HCR4 (all OMs combined). See Table 2 for a list of sensitivity tests. Box and whisker plots (upper panel) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

5.6 Logistics of Implementing Candidate Harvest Control Rules

In addition to assessing the trade-offs between the performance metrics for the candidate HCRs, the logistics of implementing the preferred rules also need to be considered. These are summarised below.

HCR2 is the "easiest" to implement and enforce and the management costs of implementing it are inexpensive compared to e.g. HCR4. The first season has been closed before for several years under the direction of the industry. Under this scenario, there is no direct reliance on environmental data and the assumptions around the impacts of El Niño events. Although, the science on the impact of environmental factors is continuing and will be able to be better appraised as further data are collected. Under HCR2, there is no need to collect catch rate data from the industry during the season (i.e. no trigger). As there is already an in-season trigger for Common[1] banana prawns, there is a risk that an additional in-season trigger for another species may cause confusion for fishers. Hence HCR2, which doesn't have an in-season trigger, is considered simpler to implement. In addition to safeguarding the prawn stock, it may also provide broader benefits in terms of bycatch reduction, given that no fishing would take place for Redleg banana prawns in the JBG during the first season. This could benefit vulnerable species in the region such as sawfish. HCR2 is the most cost-effective HCR in terms of long-term implementation, and because there is no option of possibly having the fishery open in this season (unlike HCR3 or HRC4), it is thus a more "stable" option and would help industry with their planning each year, specifically around the marketing and selling of prawns. However, some operators may consider it a negative that they are unable to fish for JBG Redleg banana prawns (and derive income) during the first season. This measure does also not require an assessment to be undertaken before the start of the first season. Therefore, it puts less pressure on the assessment team and fishing power analysis team (given the short time from when fishery data become available for analysis and the model outputs are needed to inform management recommendations). There are three main concerns however, in closing the first season. First, it would mean that industry cannot target large prawns left over from the last season and thus would miss out on those large catches. Second, it may force effort in the first season on to Common banana prawns and Redleg banana prawns that can be harvested outside of the JBG. In the longer term this may require that stocks of Redleg banana prawns outside of the JBG are assessed independently, and then managed as a separate stock. Last, if effort cannot be shifted on to other prawns e.g. in the event of a bad Common banana prawn season, then this HCR would lock out any effort for fishers in the first season, negatively impacting those that rely on income from fishing in the first season.

HCR3 relies on environmental data, namely the January SOI and the January-February combined rainfall. These data are available at the beginning of March. Hence, this rule can be straightforwardly implemented early in March. If a first season closure is triggered by the environmental rules, more time exists for the assessment. Whereas if the first season stays open, then as with the other rules below, it does put pressure on the system to

[1] Also known as White banana prawns (*Penaeus merguiensis*) although Common banana prawn is the name used by Industry.

deliver based on a tight time schedule. One advantage is that if there are successive poor years and few data to inform an assessment, there is less of a concern because the first season closure acts as a precautionary measure even in the absence of an assessment (provided there are no major changes in the fishery). This HCR does however, need industry buy-in and because it is unusual from other HCRs (i.e. rules that industry may be more familiar with and accepting of e.g. closed seasons and CPUE triggers), there is a risk that an environmental trigger in an already variable environment will not be trusted. Logistically, it is less demanding and cheaper than an in-season CPUE trigger (HCR4) as once the decision has been made to open or close the first season, then the logistics that follow and resources needed are minimal. Each year, as new data are collected, the relationship between these environmental variables and the CPUE of the stock will need updating. Thus, the key cut-off metrics may need to be re-evaluated down the track. For industry, which need to prepare vessels, obtain crew and prepare onboard stocks for heading to JBG fishing grounds, the timing of the final decision will be important. If this rule is adopted, then presumably as soon as the environmental data become available in early March, it would automatically trigger first season closure or opening. As per HCR2 above, a concern in closing the first season, is that industry cannot target large prawns left over from the previous season, and it may force effort in the first season on to Common banana prawns and Redleg banana prawns that can be harvested outside of the JBG. Again, as per the HCR above, in the longer term this may require that stocks of Redleg banana prawns outside of the JBG are assessed independently, and then managed as a separate stock.

HCR4 requires adequate CPUE data and puts the most pressure on both the scientific processes and Industry, and the management authority. As such, this HCR would be costly both in terms of time, resources and finances, which might be of concern given the relatively low economic value of the Redleg banana prawn fishery compared to other prawn sub-fisheries. An in-season trigger already exists for Common banana prawns (first season only), thus this HCR would need to be managed in parallel by industry each fishing season. Given this HCR uses a CPUE trigger, there will be a need to rapidly calculate a nominal CPUE average each month. However, this type of rule is already well-understood by fishers and managers who are used to providing monthly data and calculating an average CPUE each month, and thus might be better accepted over other HCRs. Of concern though is that this monthly CPUE might not be that easy to calculate and/or may not be a reasonable relative index of abundance. First, fishing occurs over neap tides, thus there may need to be some flexibility so the average CPUE sensibly reflects the monthly fishing activity, depending on the neap-tide cycles. Second, there may also need to be a lower limit set for how many boat days (e.g. minimum 5-10 boat days) are required to calculate the average CPUE and implement the rule to cover situations where a single vessel has done a couple of trials but the season has not fully commenced or other unusual fishing patterns. Another consideration is whether fishers may alter their fishing pattern in response to minimum boat days (e.g. more effort in JBG at the beginning of the season), or other unintended consequences of implementation. These considerations will need to be thoroughly discussed before any uptake of this HCR. The actual trigger limit will need to be reviewed every few years because it will necessarily be based on a nominal (i.e. not standardised) CPUE and is a less reliable index of relative stock abundance over time (compared to a standardize time series), and will need to be calibrated against the current estimates of biomass from the stock assessment. Alternatively, the trigger could also be changed (upwards only) to meet economic objectives. Although this approach does not directly use the environmental variables, scientific research will continue in parallel on risks of shocks from climate change. Thus, there is still the option to reconsider explicitly accounting for the impact of the environment in the future (noting HCRs should ideally be put in place for a considerable amount of time).

Another concern with HCR4 is that it could potentially be a costly option for industry, given the JBG is so remote and fishing vessels must travel considerable distances (time and fuel costs) to reach the fishing grounds. If vessels have already travelled to the JBG and started fishing and the HCR comes into effect early in the season, this would result in wasted time and fuel costs for industry. However, this may be a risk that industry is willing to take given they (1) wouldn’t travel to the JBG from the GoC if early reports of catches were poor in the JBG or (2) if they did travel to the JBG, they would normally stop fishing anyway and return to the GoC if catches were found to be poor.

Aside from being more logistically complex and expensive than the other HCRs, a big positive of this in-season trigger approach is that it is a rapid adaptive feedback approach that will limit effort whenever there are indications that the stock biomass is reduced or CPUE is less favourable, and hence it is the most effective of the strategies in controlling total effort. It does, however, assume that the nominal CPUE data in any given year are adequate as an indicator of relative Redleg banana prawn abundance.

6 Discussion

The 2015-2016 declines in Redleg banana prawn catch and CPUE affected the ability to assess the stock, highlighting a gap in the harvest strategy to adequately account for risk to the stock in years with low fishing effort combined with low CPUE or years with environmental anomalies. Before revising the HS, there is a need to first simulation-test the performance of any proposed revisions. Management Strategy Evaluation is a useful tool to test how well different rules perform, allowing for transparency of the trade-offs between alternative rules. Here we discuss (1) some of the limitations to the study and (2) how the three key project objectives were met.

6.1 Limitations related to Assumptions of Future Projections

- The future pattern of fishing effort per month was assumed to be similar to recent observed fishing effort distribution (e.g. the average of the last 5 years) and scaled so that the target fishing mortality per month was approximately at a level that kept the stock at B_{MEY}. In the future though, fishers may well be forced to change their fishing pattern and effort, for example, due to availability of prawns, economic considerations or under a changing climate. We considered both an alternative fishing pattern and increased fishing mortality through sensitivity testing. Of these, the HCRs, particularly HCR3, were most sensitive to an increase (doubling) in fishing effort. There was not much sensitivity to shifting fishing effort entirely to the first season (quarter 2; as was observed in 2019), although this scenario assumed there would not be a massive increase in the level of effort that is all concentrated over a shorter time period. There are other implications that need be considered e.g. the lack of catch rate data for season 2 (particularly quarter 3), which the stock assessment model requires for a reliable estimate of the spawning biomass. An absence of these data could lead to a delay in management response. Whereas we did test a delay in management response, the MSE framework could in future also consider a sensitivity test that incorporates a combination of a change in fishing effort and a delay in management response/increased error around the following year's catch.
- We assumed that there would be inter-annual differences between the actual future projected number of prawns caught and the model-estimated target catch (based on the target effort level) – i.e. the implementation error (see Appendix 1). The magnitude of the implementation error was approximated by comparing predicted versus realised

catches from the last few years in the historical model and a sensitivity test was carried out in which this error was doubled. The current rule (HCR1) showed some, albeit little, sensitivity to this, which is not surprising because we assumed a normally distributed error, which is not consistently biased upwards and thus on average, fishing is still at target levels. The three preferred rules (HCR2-HCR4) all performed well with regards to increased error around catch, although we note this was assuming errors were normally distributed. If future errors have a consistent bias or are larger than those we simulated, then our model predictions would be limited

- In the model projections, future fishing power was assumed to increase over time using a simple linear increase (based on the overall increase in historical fishing power). In reality, the increase in historical fishing power has been variable, whereby it could increase or decrease in any given year despite the overall trend being an increase. We included a sensitivity test using a future fishing power with a larger linear increase and all three of the preferred rules performed well, showing little if any sensitivity to this increase. Given more time though, it would be useful to include a future fishing power that increases with variability similar to historical fishing power, randomized for each model run.
- The catch rate index used in the models is based on a minimum of five days per month, with anything less than this excluded from the CPUE time-series. This minimum effort is quite low and the CPUE therefore might not be accurately representative of prawn abundance. Ideally it would have been better to use a minimum of 10 boat days per month, however it meant that we would not have been able to fit the model to the index of abundance for some key periods for which some months had few values. Instead we chose to retain a minimum effort of 5 boat days but acknowledged the uncertainty in the CPUE when effort was low by increasing the standard deviation of the randomly-generated annual error associated with future catch rates (see Appendix 1) to account for increased error in years with few data.

6.2 Achievement of Objectives

Objective 1: To develop a Management Strategy Evaluation (MSE) framework for the Redleg banana prawn fishery.

This objective has been achieved, with a Redleg banana prawn MSE framework developed consisting of a Reference Set of six OMs, that have been used to test five

HCRs using a suite of performance metrics and sensitivity tests. The base-case OM was adapted from the assessment model developed by Plagányi et al. (2010) and fitted to monthly CPUE data. Fitting to monthly CPUE data proved more challenging than fitting to quarterly CPUE data (as in the assessment model) given the monthly data included more extreme peaks than when averaged out across a quarter. Despite this, model fits were relatively good and considered adequate for use as an OM, but would need more careful evaluation if they were to be considered for use as an assesment model.

Objective 2: Simulation test the performance of alternative harvest strategies using components of the MSE framework.

We simulation-tested the performance of five different HCRs using the MSE framework, one of which was the current HCR (for comparison). Sensitivity tests were then performed on selected candidates to assess the robustness of each rule. Further robustness tests could be conducted once the preferred HCR is selected if there are any additonal concerns raised by stakeholders as to scenarios which they feel haven’t been adequately considered.

Objective 3: Deliver to NPRAG output perfomance statistics for each alternative harvest strategy so that their relative performance can be evaluated.

Performance metrics for each of the HCRs were presented to the NPRAG and a summary document of the preferred candidate rules was then produced so that the relative performance of these HCRs can be evaluated. In summary, stakeholders found that relative to the current HCR, three rules performed better than the others. These are summarised below.

- HCR2 achieves very low risk of fishery closure and risk to the stock, but with an absence of occasional very large catches. However, catch value is predicted to be good and catch variability is the lowest amongst the options, which is favourable to the fishery. HCR2 is fairly robust to uncertainties in the sensitivity testing and is logistically the easiest to implement and enforce, but prevents fishers from accessing the larger prawns that are left over from the previous year, and could potentially lock any effort out for some fishers if catches were poor for other stocks e.g. Common banana prawns during the first season.
- HCR3 performed similarly to HCR4 and risk of fishery closure and the stock falling below B_{LIM} are somewhat greater than HCR2, but considerably reduced compared

with the current HCR1. Of the three preferred HCRs, HCR3 was the least robust to uncertainties in the sensitivity testing but performed better than the current HCR1. HCR3, which relies on environmental data that are available from early March, is logistically less demanding to implement than HCR4, and means that fishing in the first season isn't permanently closed, as in HCR2. However, industry may be wary of an environmental trigger-based HCR given their unfamiliarity with this type of trigger and the natural variability in the environment.

- HCR4 performed similarly to HCR3 and the risk of fishery closure and the stock falling below B_{LIM} are somewhat greater than HCR2, but considerably reduced compared with the current HCR1. This HCR appears to be most robust to a broad range of uncertainties as investigated using sensitivity testing. While it is the most effective of the strategies in controlling total effort, HCR4 is logistically complex and expensive to implement compared with the other HCRs, and demands more time, effort and resources from the scientific processes, Industry, and the management authority. It also relies on adequate CPUE data in any given year. Given the relatively small economic value of the Redleg banana prawn fishery compared to other prawn sub-fisheries in the NPF, the trade-offs between cost and effectiveness of implementation need to be carefully considered.

The performance and trade-offs between the different HCR options are recommended as a basis for informing final choice by members of the NPRAG as to which HCR to adopt.

7 Benefits and Adoption

The results herein have been presented at two NPRAG meetings in 2020 (teleconference – March 11th and full RAG web-conference on the 20th and 21st May). Previous progress was presented to a series of NPRAG meetings in 2019 prior to these two recent RAG meetings. The research presented in this report has demonstrated its value via its acceptance at NPRAG meetings.

The benefits are clear as the research presented in this project is leading to the future adoption of a single HCR from the list evaluated within this project. There was an expectation that a single HCR would be endorsed at the May 2020 NPRAG meeting; however the industry and the NPRAG agreed that a subset of HCRs would be presented at a future Industry meeting (June/July 2020) and following consultation with Industry members, a review of options would be communicated with NORMAC. As this involves future decisions and adoption by the co-management fora, the work in this report is current up to date of submission (30th May 2020).

8 Further Development & Planned Outcomes

After the endorsement of a HCR there is the option to consider future updates to the annual stock assessment to make any changes that may be necessary in light of changes to the HS. Given there are ongoing changes in the environment and climate change is likely to exacerbate future environmental anomalies, there exists the opportunity for the research to be updated (and informed by the data) over the coming years. In terms of planned outcomes, the endorsement and acceptance of a new HCR will lead to a planned update of the Harvest Strategy for Redleg banana prawns which meets the requirements of the Commonwealth Harvest Strategy Policy. This will represent a beneficial and valuable outcome in terms of the biological and economic sustainability of this fishery.

9 Conclusion and Recommendations

As is usually the case in testing alternative HCR candidates, there is no obvious ‘best-case scenario’ as more than one strategy can achieve pre-specified objectives. However, the MSE testing makes transparent what the trade-offs are between various performance metrics such as total catch, stock depletion targets and risk to the stock as a basis for stakeholders to evaluate these trade-offs and select a preferred option. There may also be additional logistical considerations that may inform the final choice between the subset of strategies that appear to perform satisfactorily. The MSE testing also assists in removing alternative candidate HCRs that don’t perform well, as well as highlighting the potential pitfalls in some strategies. The proposed HCRs were tested under a wide range of plausible future scenarios, such as under assumptions of greatly increased future catches or more negative environmental impacts, and the final choice of HCR should ensure that it is robust across these uncertainties.

It is important to remember that one HCR does not necessarily outperform another HCR and it is possible to achieve similar outcomes using the different approaches. Going forward, we provide the following recommendations:

- Stakeholders need to assess the trade-offs between the preferred HCRs by considering the performance of each HCR (performance metrics), but also considering the logistics of implementing each of the HCRs.
- The HS that is implemented based on MSE testing is assumed to be appropriate provided the stock and fishery dynamics are within the bounds of the variability tested – hence meta-rules usually stipulate that there is to be a deviation from the pre-agreed HS only if there is an extremely anomalous event that is outside the range of variability that was tested. However, it is anticipated there would be intermittent review as new data become available and stock assessment models are developed.
- If any changes to the fishery or environment occur in the future that have not been accounted for in the MSE testing, then there will be a need to review the MSE and HS.

We acknowledge the support of AFMA, and industry and look forward to some measures evaluated herein being adopted as part of the NPF Harvest Strategy for Redleg banana prawns.

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Appendices

Appendix 1 Model Equations

Base-Case Model

A discrete population model was constructed for Redleg banana prawns in the JBG as follows. The model time-step is monthly, with the number of prawns in year *y* and month *m* ($N_{y,m}$) given by:

$$N_{y,m+1} = N_{y,m}\, e^{-M_m} - C_{y,m} + R_{y,m+1} \qquad \text{for } m = 1 \text{ to } 11 \qquad \text{(A1)}$$

and

$$N_{y+1,1} = N_{y,12}\, e^{-M_{12}} - C_{y,12} + R_{y+1,1} \qquad \text{for } m = 12 \qquad \text{(A2)}$$

where

$N_{y,m}$ is the number of recruited and mature prawns (those corresponding to a size large enough to be fished) at the start of month *m* in year *y* (which refers to a calendar year),

$R_{y,m}$ is the number of recruits (number of 6-month old prawns) which are added to the population at the end of each month *m* in year *y*,

M_m denotes the natural mortality rate during month *m* (assumed in the Reference case to be constant throughout the year), and computed by multiplying the weekly natural mortality rate estimate by 4 (weeks) to reflect a monthly mortality rate; and

$C_{y,m}$ is the predicted number of prawns caught during month *m* in year *y*, with catches arbitrarily assumed taken as a pulse at the end of each month.

Given catches are recorded in units of mass, the predicted number of prawns caught during month *m* in year *y* is computed from the following relationship:

$$C_{y,m} = A_{y,m} F_{y,m} N_{y,m} e^{-M_m} \qquad \text{(A3)}$$

where

$A_{y,m}$ is the relative availability for month *m* and for year *y*, with one availability vector being applied to the early period 1980-1987, another vector to the period 1988-2006 (i.e. post end of year NPF closure) another to 2007-2010 (first season closure) period and another to post-2011 period; and

$F_{y,m}$ is the fished proportion in month *m* and year *y* of a fully selected age class.

The fished proportion reflects the catch by mass ($C_{y,m}^{mass}$) in month m and year *y* as a proportion of the exploitable ("available") component of biomass:

$$F_{y,m} = C_{y,m}^{mass} / B_{y,m}^{ex} \qquad \text{(A4)}$$

with

$$B_{y,m}^{ex} = w_m N_{y,m} e^{-M_m} A_{y,m} \qquad \text{(A5)}$$

where

w_m is the average mass of prawns during month *m*.

One of the biggest challenges in constructing a realistic model of *P. indicus* relates to improved information on growth, and in particular monthly changes in growth. Length frequency data that span a number of periods through the year are needed to better inform this aspect of the model. This model used the female (because the male growth is too slow on its own) von Bertalanffy growth parameters and assumed that individual mass increases through the year (see Plagányi et al. 2010 for details). An average length and mass of prawns was thus calculated for each month, assuming a median birth date of October.

The number of recruits at the end of month *m* in year *y* is assumed to be related to the spawning stock size six months previously by a Beverton-Holt stock-recruitment relationship (Beverton and Holt, 1957), allowing for annual fluctuation about the deterministic relationship for each month:

$$
\begin{aligned}
R_{y,1} &= \frac{\alpha B^{sp}_{y-1,m}}{\beta + \left(B^{sp}_{y-1,m}\right)} e^{\left(\varsigma_y - (\sigma_R)^2/2\right)} && m = 7 \\
R_{y,m+1} &= \frac{\alpha B^{sp}_{y-1,m+7}}{\beta + \left(B^{sp}_{y-1,m+7}\right)} e^{\left(\varsigma_{y,} - (\sigma_R)^2/2\right)} && m = 1-5 \\
R_{y,m+1} &= \frac{\alpha B^{sp}_{y,m-5}}{\beta + \left(B^{sp}_{y,m-5}\right)} e^{\left(\varsigma_y - (\sigma_R)^2/2\right)} && m = 6-11
\end{aligned}
\qquad \text{(A6)}
$$

Where α and β are spawning biomass-recruitment relationship parameters, $\varsigma_{y,m}$ reflects fluctuation about the expected recruitment for year *y* and month *m*, which is assumed to be normally distributed with standard deviation σ_R (which is input in the applications considered here); these residuals are treated as estimable parameters in the model fitting process, and a single set of residuals is estimated for each year. In OM2, the January southern oscillation index (SOI) is assumed to impact Redleg banana prawns (see Plagányi et al. 2020a) and we model this by increasing the variability in prawn recruitment during El Niño (SOI < -7) and La Niña (SOI > 7) years (based on the January SOI index only), such that we define a new parameter $\varsigma^{e}_{y=ElNino}$ as an environmental effect on prawn recruitment in all El Niño and La Niña years so that fluctuation about the expected recruitment is now given by $\varsigma^{e}_{y=ElNino} * \eta + \varsigma_{y,m} - (\sigma_R)^2/2$ where $\varsigma^{e}_{y=ElNino} = 0$ in neutral years otherwise a common parameter is estimated within the model in El Niño and La Niña years. The parameter η is set = -1 in El Niño years and = 1 in La Niña years. In OM4 both the southern oscillation index (SOI) and rainfall are assumed to impact prawn recruitment, such that variability in prawn recruitment is increased during El Niño (SOI < -7) years with below average rainfall and thus for years where January SOI < -7 and rainfall is below the median rainfall for January and February combined, fluctuation around the recruitment is now given by $\varsigma^{e}_{y=ElNino} * (\eta + \frac{\rho_y - \rho_{median}}{\rho_{median}}) + \varsigma_{y,m} - (\sigma_R)^2/2$, where ρ_y is the combined January and February rainfall for year *y* and ρ_{median} is the median rainfall for January and February, recorded at the BOM Lake Argyle Resort station.

$B^{sp}_{y,m}$ is the spawning biomass at the start of month *m* in year *y*, computed as:

$$B^{sp}_{y,m} = f_m \cdot w_m \cdot N_{y,m} \tag{A7}$$

where

f_m is a relative index of the amount of spawning during month *m*.

It follows that total spawner stock size and recruitment for calendar year *y* are given respectively by:

$$B^{sp}_{y} = \sum_m B^{sp}_{y,m} \tag{A8}$$

$$R_y = \sum_m R_{y,m} \tag{A9}$$

In order to work with estimable parameters that are more meaningful biologically, the stock-recruitment relationship is re-parameterised in terms of the pre-exploitation equilibrium spawning biomass, B^{sp}_o, and the "steepness", *h*, of the stock-recruitment relationship, which is the proportion of the virgin recruitment that is realized at a spawning biomass level of 20% of the virgin spawning biomass. In OM1 – OM4 and OM6 *h* is input as 0.6. In OM5 *h* is input as 0.4.

$$\beta = \frac{(B^{sp}_0)(1-5h)}{5h-1} \tag{A10}$$

and

$$\alpha = \frac{\beta + \left(B^{sp}_0\right)}{SPR_0} \tag{A11}$$

where

$$SPR_0 = \frac{B_0^{sp}}{R_0} \tag{A12}$$

The total pre-exploitation spawning biomass B_0^{sp}, is given by:

$$B_0^{sp} = \frac{\sum_m f_m \cdot w_m \cdot R_{0,m}}{\left(1-e^{-M_m}\right)} \tag{A13}$$

And R_0 is the total recruitment in the first year, calculated by summing monthly recruitment for that year:

$$R_0 = \sum_m R_{0,m} \tag{A14}$$

The resource is assumed to be at the deterministic equilibrium (corresponding to an absence of harvesting) at the start of 1980, the initial year considered here. The model sets the starting spawning biomass in the first month $B_{0,1}^{sp} = K^{sp}$, from which the initial recruitment can be calculated for each month in the starting year:

$$\begin{aligned} R_{0,m} &= \left(1-e^{-M(m)}\right) \cdot B_{0,m}^{sp} / \left(f_m \cdot w_m \right) \qquad && m = 1 \\ R_{0,m} &= \left(1-e^{-M(m-1)}\right) \cdot N_{0,m-1} \qquad && 1 < m \leq 12 \end{aligned} \tag{A15}$$

With starting numbers $N_{0,m}$ in the first year calculated as follows:

$$\begin{aligned} N_{0,m} &= B_{0,m}^{sp} / \left(f_m \cdot w_m \right) \qquad && m = 1 \\ N_{0,m} &= N_{0,m-1} e^{-M_{m-1}} \qquad && 1 < m \leq 12 \end{aligned} \tag{A16}$$

Likelihood function

The model is fitted to all available CPUE data for each month, except months 2 and 3 for which there are no/insufficient data. The likelihood contribution is calculated assuming that the observed abundance index is log-normally distributed about its expected value:

$$I_y^m = \hat{I}_y^m e^{\varepsilon_y^m} \qquad \text{or} \qquad \varepsilon_y^m = \ln(I_y^m) - \ln(\hat{I}_y^m) \tag{A17}$$

where I_y^m is the abundance index (with fishing power effect added) for year *y* and quarter *m*,

$\hat{I}_y^m = q^m B_{y,m}^{ex}$ is the corresponding model estimated value, where $B_{y,m}^{ex}$ is the model value for exploitable resource biomass corresponding to month *m*, given by equation (A5) and q^m is the catchability coefficient, which is assumed to be the same for each month and ε_y^m from $N\left(0,\left(\sigma_y^m\right)^2\right)$

In OM3, environmental conditions are assumed not to influence the overall stock recruitment (as is the case in OM2), but rather to change the distribution of the stock such that the effect is manifest on the catchability. Hence we define a new parameter $q_{y=ElNino}^e$ as the environmental effect on catchability in all El Niño years (defined for current purposes simply as years where the January index <-7), and we assume that the same parameter applies to all months for which we fit to standardised (i.e. accounting for fishing power) CPUE data. We also start with the simplest possible model, which is to assume that the change in catchability in El Niño years is the same in all of the El Niño years, such that a single common parameter is estimated for each of the 9 past El Niño years since 1983 and up until 2018. Hence, we modify the relationship between the CPUE index and model estimates as follows:

$$\hat{I}_y^m = q^m \cdot q_{y=ElNino}^e \cdot B_{y,m}^{ex} \tag{A18}$$

where the default value of $q_{y=ElNino}^e = 1$ for all non-El Niño years, otherwise $q_{y=ElNino}^e = par\_qe$ which is a parameter estimated within the model and is bounded in the range 0 to 1.

The contribution to the negative of the log-likelihood function is given then by:

$$-\ln L = \sum_y \left[\sum_m \ln \sigma_y^m + \left(\varepsilon_y^m\right)^2 / 2\left(\sigma_y^m\right)^2 \right] \qquad \text{(A19)}$$

with the standard deviation of the residuals for the logarithms of the abundance series assumed to be independent of *y*, and set in the fitting procedure by its maximum likelihood value:

$$\hat{\sigma}^m = \sqrt{\frac{1}{n} \sum_y \sum_m \left(\ln I_y^m - \ln \hat{I}_y^m\right)^2} \qquad \text{(A20)}$$

where n is the number of data points across all years and months. As there are unequal data for the different months and to prevent some months overfitting, $\hat{\sigma}^m$ was constrained using a lower bound of 0.25 (as much lower $\hat{\sigma}^m$ values are not considered realistic) and this allowed a better trade-off in terms of fitting to all the data.

The catchability coefficient q^m is also estimated using maximum likelihood:

$$\ln \hat{q}^m = \frac{1}{n} \sum_y \sum_m \left(\ln I_{y,m}^m - \ln \hat{B}_{y,m}^{ex}\right) \qquad \text{(A21)}$$

Stock-recruitment function residuals

The stock-recruitment residuals are assumed to be log-normally distributed. Thus, the contribution of the recruitment residuals to the negative of the (now penalised) log-likelihood function is given by:

$$-\ell n L^{pen} = \sum_{y=y1+1}^{y2} \left(R_{y,m}\right)^2 \Big/ 2\sigma_R^2 \qquad \text{(A22)}$$

where

σ_R is the standard deviation of the log-residuals, which is input as 0.8 except in OM4 and OM6, in which it is reduced to 0.6.

Future projections

Resource biomass was projected forward for 20 years under each of the alternative scenarios.

The future pattern of fishing effort per month is assumed to be similar to recent observed fishing effort distribution (e.g. the average of the last 5 years) and scaled so that the target fishing mortality per month *m* (F_m^{targ}) is approximately at a level that keeps the stock at B_{MEY}^{sp} .

The future projected number of prawns caught during month *m* in year *y* is therefore computed from the following relationship:

$$\hat{C}_{y,m} = F_m^{targ} \cdot \hat{B}_{y,m}^{ex} \cdot e^{\varepsilon_y^I}, \quad \varepsilon_y^I \ from\ N\left(0, \sigma_I^2\right) \tag{A23}$$

Where σ_I controls the magnitude of the implementation error, that is the error that captures the difference between the target effort level and hence target catch, and the actual realised catch. The magnitude of the implementation error was approximated by comparing predicted vs realised catches from the last few years in the historical model. As such, σ_I is input at 0.2 and random errors generated accordingly for each of the future projection years.

The predicted economic value of prawns caught can be calculated as follows:

$$\hat{V}_{y,m} = \hat{C}_{y,m} \cdot p_m \tag{A24}$$

where

p_m is the average price per prawn in month *m*

Future CPUE was calculated as follows:

$$\hat{I}_y^m = q^m \cdot \theta_y \cdot \hat{B}_{y,m}^{ex} \cdot e^{\varepsilon_y^{CPUE}}, \quad \varepsilon_y^{CPUE} \ \textit{from}\ N\left(0,\sigma_{CPUE}^2\right) \qquad \text{(A25)}$$

where θ_y is the future fishing power for year *y*, which is assumed to increase linearly by a value 1.5 by the end of the 20-yr projection period. σ_{CPUE} is the standard deviation of the randomly-generated annual error associated with future catch rates, which is input as 0.05 and increased to 0.2 in years with low CPUE (less than 400 kg/day) to account for increased error in years with few data. As described above (equation A18), for OM3 we assume that there is a change in catchability in El Niño years ($q_{y=ElNino}^e$) as follows:

$$\hat{I}_y^m = q^m \cdot q_{y=ElNino}^e . \theta_y \cdot \hat{B}_{y,m}^{ex} . e^{\varepsilon_y^{CPUE}} \qquad \text{(A26)}$$

An estimate of the predicted fishing effort (days) for each future year *y* and month *m* can thus be calculated as follows:

$$\hat{E}_{y,m} = \frac{\hat{C}_{y,m}}{q^m . \theta_y . \hat{B}_{y,m}^{ex} . e^{\varepsilon_y^{CPUE}}} \qquad \text{(A27)}$$

Appendix 2 Model Fits and Parameter Estimates

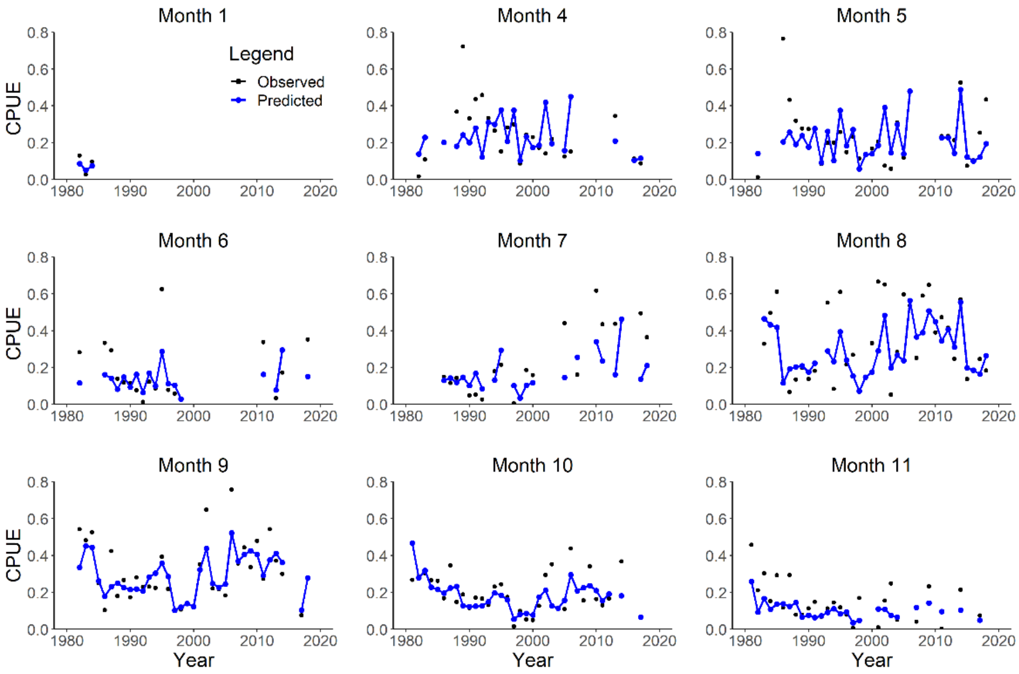

Figure A2.1: Observed (black dot) vs predicted (blue line) CPUE (tons day^{-1}) for OM1 for the model period 1980-2018. The model was fit to CPUE data for all months except February and March (insufficient data). Model fits for December are not shown.

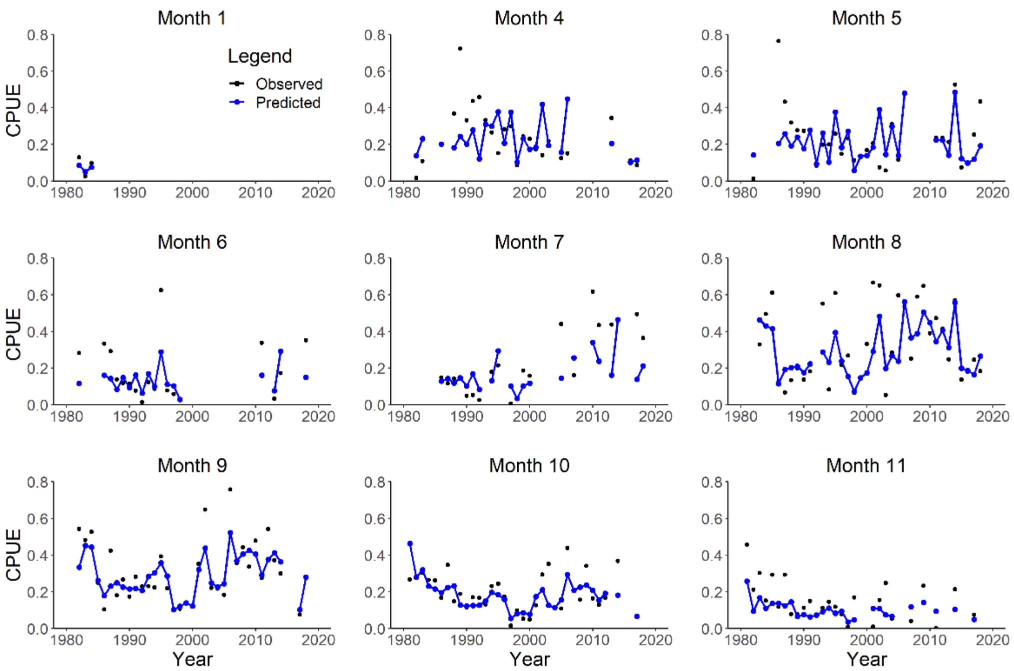

Figure A2.2: Observed (black dot) vs predicted (blue line) CPUE (tons day^{-1}) for OM2 for the model period 1980-2018. The model was fit to CPUE data for all months except February and March (insufficient data). Model fits for December are not shown.

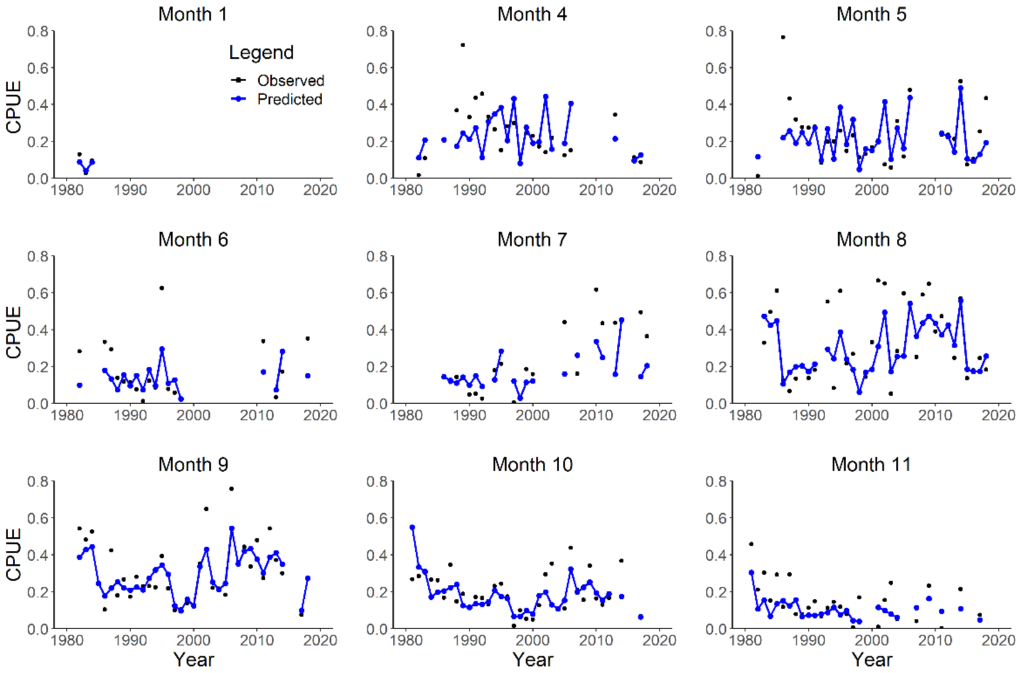

Figure A2.3: Observed (black dot) vs predicted (blue line) CPUE (tons day^{-1}) for OM3 for the model period 1980-2018. The model was fit to CPUE data for all months except February and March (insufficient data). Model fits for December are not shown.

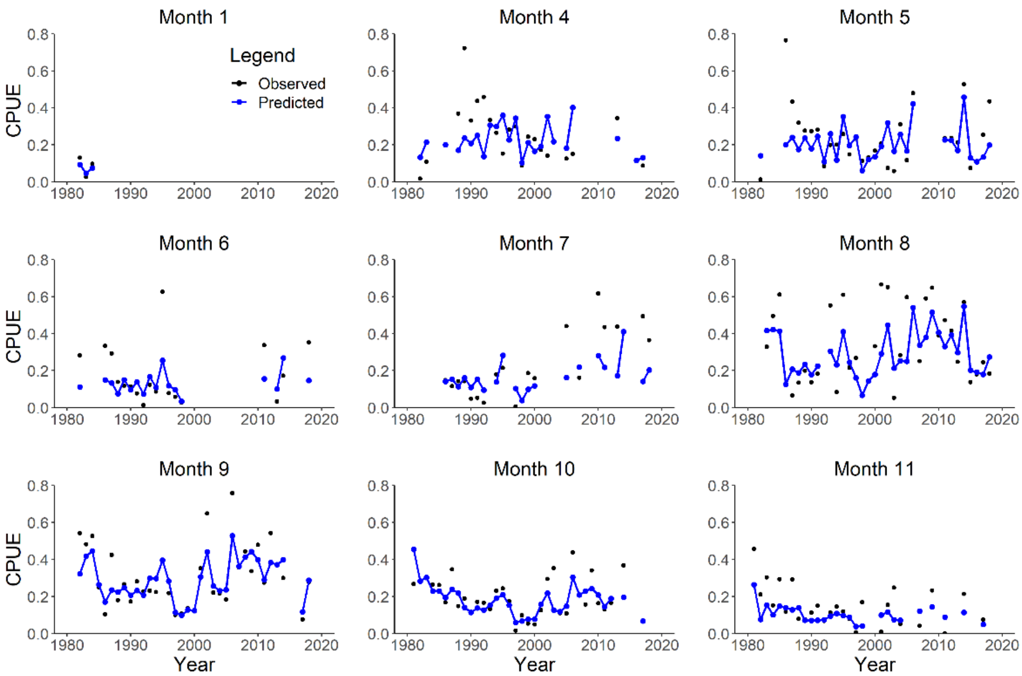

Figure A2.4: Observed (black dot) vs predicted (blue line) CPUE (tons day^{-1}) for OM4 for the model period 1980-2018. The model was fit to CPUE data for all months except February and March (insufficient data). Model fits for December are not shown.

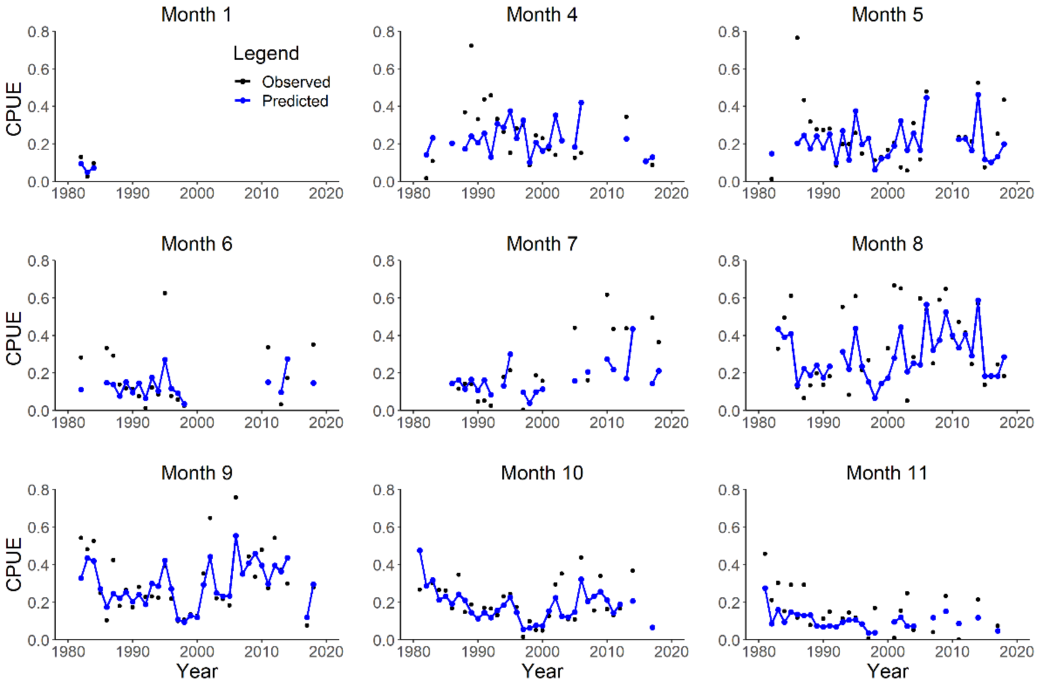

Figure A2.5: Observed (black dot) vs predicted (blue line) CPUE (tons day^{-1}) for OM5 for the model period 1980-2018. The model was fit to CPUE data for all months except February and March (insufficient data). Model fits for December are not shown.

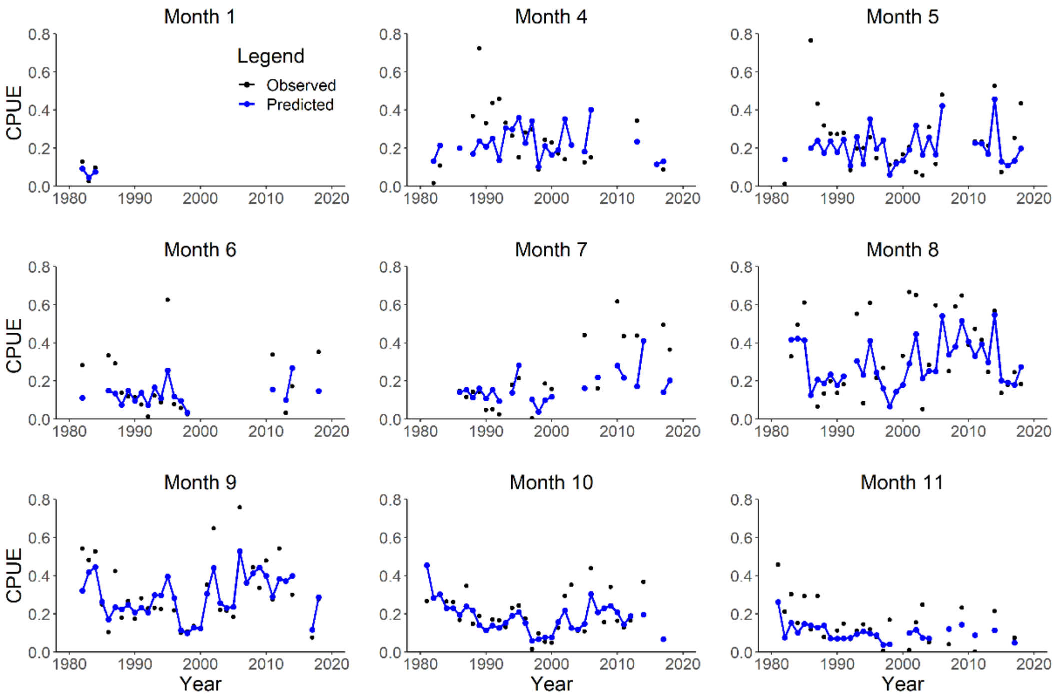

Figure A2.6: Observed (black dot) vs predicted (blue line) CPUE (tons day^{-1}) for OM6 for the model period 1980-2018. The model was fit to CPUE data for all months except February and March (insufficient data). Model fits for December are not shown.

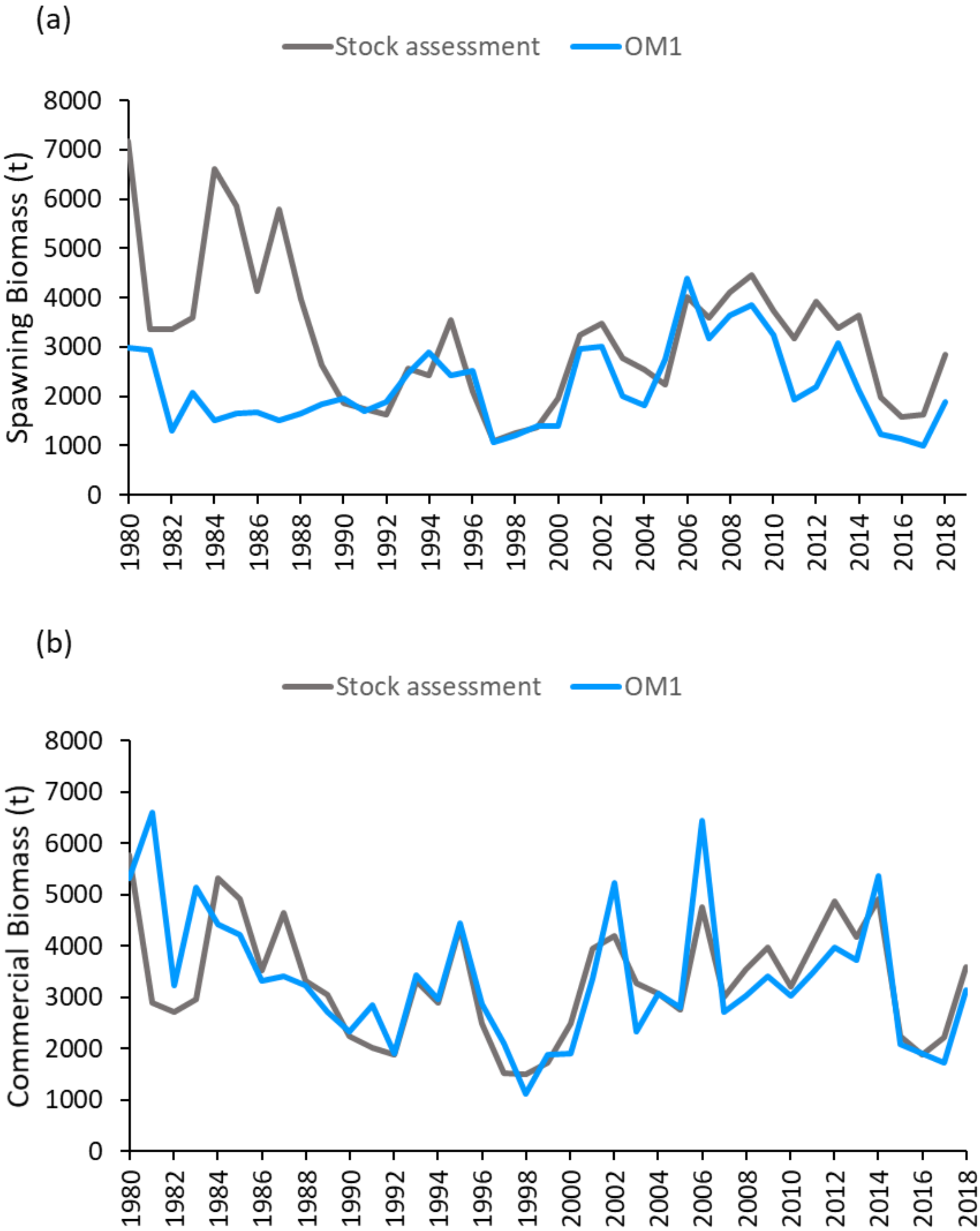

Figure A2.7: (a) Spawning biomass (tons) and (b) commercially available biomass (tons) for OM1 and the stock assessment model (Plagányi et al. 2020) for the model period 1980-2018.

Table A2.1: Parameters used to describe the population dynamics of the six Operating Models (OMs). Where relevant, parameter estimates are shown in Table A2.2.

Parameter	OM1	OM2	OM3	OM4	OM5	OM6
Pre-exploitation spawning biomass in month 1, $K_{0,1}^{sp}$ (or $B_{0,1}^{sp}$)	Estimated (see Table A2.2)	Estimated (see Table A2.2)	Estimated (see Table A2.2)	Estimated (see Table A2.2)	Estimated (see Table A2.2)	Estimated (see Table A2.2)
Natural mortality, M	0.2 (fixed, from Die et al. 2002)	0.2 (fixed, from Die et al. 2002)	0.2 (fixed, from Die et al. 2002)	0.2 (fixed, from Die et al. 2002)	0.2 (fixed, from Die et al. 2002)	0.2 (fixed, from Die et al. 2002)
Von Bertalanffy parameters	Loneragan et al. (2002)	Loneragan et al. (2002)	Loneragan et al. (2002)	Loneragan et al. (2002)	Loneragan et al. (2002)	Loneragan et al. (2002)
Length-weight relationship	Loneragan et al. (1997)	Loneragan et al. (1997)	Loneragan et al. (1997)	Loneragan et al. (1997)	Loneragan et al. (1997)	Loneragan et al. (1997)
Stock-recruit 'steepness' parameter, h	0.6 (fixed)	0.6 (fixed)	0.6 (fixed)	0.6 (fixed)	0.4 (fixed)	0.6 (fixed)
Recruitment residuals	38 estimated for period 1981-2018	38 estimated for period 1981-2018	38 estimated for period 1981-2018	38 estimated for period 1981-2018	38 estimated for period 1981-2018	38 estimated for period 1981-2018
Recruitment variability σ_R	0.8 (fixed)	0.8 (fixed)	0.8 (fixed)	0.6 (fixed)	0.8 (fixed)	0.6 (fixed)
Stock- recruitment parameters α and β	Calculated using pre-exploitation biomass K^{sp} and h	Calculated using pre-exploitation biomass K^{sp} and h	Calculated using pre-exploitation biomass K^{sp} and h	Calculated using pre-exploitation biomass K^{sp} and h	Calculated using pre-exploitation biomass K^{sp} and h	Calculated using pre-exploitation biomass K^{sp} and h
Proportion of Bsp spawning each month, f_m	Jan-Mar: 0.3 Apr-Sep: 0.05 Oct-Dec: 0.6	Jan-Mar: 0.3 Apr-Sep: 0.05 Oct-Dec: 0.6	Jan-Mar: 0.3 Apr-Sep: 0.05 Oct-Dec: 0.6	Jan-Mar: 0.3 Apr-Sep: 0.05 Oct-Dec: 0.6	Jan-Mar: 0.3 Apr-Sep: 0.05 Oct-Dec: 0.6	Jan-Mar: 0.3 Apr-Sep: 0.05 Oct-Dec: 0.6
Availability for quarters S1-S4 for 1st period 1980-1987	S1_1: Fixed (1) S2_1: Est. S3_1: Est. S4_1: Est.	S1_1: Fixed (1) S2_1: Est. S3_1: Est. S4_1: Est.	S1_1: Fixed (1) S2_1: Est. S3_1: Est. S4_1: Est.	S1_1: Fixed (1) S2_1: Est. S3_1: Est. S4_1: Est.	S1_1: Fixed (1) S2_1: Est. S3_1: Est. S4_1: Est.	S1_1: Fixed (1) S2_1: Est. S3_1: Est. S4_1: Est.
Availability for quarters S1-S4 for 2nd period 1988-2006	S1_2: 0 S2_2: Est. S3_2: Est. S4_2: Est.	S1_2: 0 S2_2: Est. S3_2: Est. S4_2: Est.	S1_2: 0 S2_2: Est. S3_2: Est. S4_2: Est.	S1_2: 0 S2_2: Est. S3_2: Est. S4_2: Est.	S1_2: 0 S2_2: Est. S3_2: Est. S4_2: Est.	S1_2: 0 S2_2: Est. S3_2: Est. S4_2: Est.
Availability for quarters S1-S4 for 3rd period 2007-2010	S1_3: 0 S2_3: 0 S3_3: S3_2 S4_3: S4_2	S1_3: 0 S2_3: 0 S3_3: S3_2 S4_3: S4_2	S1_3: 0 S2_3: 0 S3_3: S3_2 S4_3: S4_2	S1_3: 0 S2_3: 0 S3_3: S3_2 S4_3: S4_2	S1_3: 0 S2_3: 0 S3_3: S3_2 S4_3: S4_2	S1_3: 0 S2_3: 0 S3_3: S3_2 S4_3: S4_2

Table A2.1 cont.: Parameters used in the population dynamics of the six Operating Models (OMs). Where relevant, parameter estimates are shown in Table A2.2.

Parameter	*OM1*	*OM2*	*OM3*	*OM4*	*OM5*	*OM6*
Availability for quarters S1-S4 for 4th period 2011-2018	S1_4: 0 S2_4: Est. S3_4: Fixed (0.9) S4_4: Est.	S1_4: 0 S2_4: Est. S3_4: Fixed (0.9) S4_4: Est.	S1_4: 0 S2_4: Est. S3_4: Fixed (0.9) S4_4: Est.	S1_4: 0 S2_4: Est. S3_4: Fixed (0.9) S4_4: Est.	S1_4: 0 S2_4: Est. S3_4: Fixed (0.9) S4_4: Est.	S1_4: 0 S2_4: Est. S3_4: Fixed (0.9) S4_4: Est.
Catchability co-efficient q	Calculated (see Eqn A21)	Calculated (see Eqn A21)	Calculated (see Eqn A21)	Calculated (see Eqn A21)	Calculated (see Eqn A21)	Calculated (see Eqn A21)

Table A2.2: Estimated parameter values and associated Hessian-based standard deviations for the six Operating Models (OMs). $B_{0,1}^{sp}$ is the estimated spawning biomass at the start of the model in month 1 and B_0^{sp} is the spawning biomass for the model start year. A_S is the quarterly availability of prawns for the respective time periods and $\varsigma_{y=ElNino}^{e}$ and $q_{y=ElNino}^{e}$ are the environmental parameters linked to recruitment variability and prawn catchability respectively.

	OM1		OM2		OM3		OM4		OM5		OM6	
Parameter	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**
Spawning Biomass												
$\ln(B_{0,1}^{sp})$	1.67	0.00	1.67	0.00	1.58	0.00	1.58	0.00	1.82	0.00	1.58	0.00
$B_{0,1}^{sp}$ (tons)	5.32		5.32		4.84		4.86		6.15		4.87	
B_0^{sp} (tons)	2981.69		2981.67		2685.58		1560.23		1972.93		1561.37	
Availability per quarter_period												
A_{S2_1} (1980-1987)	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
A_{S3_1} (1980-1987)	0.90	3.32	0.87	0.63	0.97	0.99	1.00	0.02	0.91	0.26	1.00	0.07
A_{S4_1} (1980-1987)	0.69	1.04	0.69	0.36	1.00	0.01	0.76	0.49	0.74	0.21	0.76	0.21
A_{S2_2} (1988-2007)	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
A_{S3_2} (1988-2007)	0.63	1.35	0.62	0.28	0.60	0.27	0.70	0.13	0.68	0.19	0.70	0.13
A_{S4_2} (1988-2007)	0.30	0.06	0.30	0.11	0.37	0.08	0.30	0.20	0.32	0.08	0.30	0.10
A_{S2_4} (2011-2018)	1.00	0.00	1.00	0.01	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
A_{S4_4} (2011-2018)	0.42	0.92	0.43	0.27	0.53	0.34	0.36	0.25	0.39	0.17	0.36	0.15
Recruitment Residuals												
RecPar01	-0.69	0.72	-0.69	0.31	-0.88	0.22	-0.50	0.20	-0.55	0.23	-0.50	0.18
RecPar02	0.10	0.60	0.10	0.27	0.46	0.37	0.17	0.21	0.26	0.05	0.17	0.19
RecPar03	-0.15	0.57	0.65	0.33	-0.48	0.38	1.05	0.26	-0.05	0.26	-0.05	0.25
RecPar04	-0.14	0.56	-0.13	0.25	-0.12	0.24	-0.01	0.19	0.04	0.21	-0.01	0.19
RecPar05	-0.20	0.20	-0.20	0.15	-0.10	0.13	-0.06	0.15	-0.05	0.16	-0.06	0.15

Table A2.2 cont.: Estimated parameter values and associated Hessian-based standard deviations for the six Operating Models (OMs). $B_{0,1}^{sp}$ is the estimated spawning biomass at the start of the model in month 1 and B_0^{sp} is the spawning biomass for the model start year. A_S is the quarterly availability of prawns for the respective time periods and $\varsigma_{y=ElNino}^{e}$ and $q_{y=ElNino}^{e}$ are the environmental parameters linked to recruitment variability and prawn catchability respectively.

	OM1		OM2		OM3		OM4		OM5		OM6	
Parameter	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**
RecPar06	0.15	0.49	-0.64	0.23	0.14	0.17	0.24	0.12	0.28	0.14	0.24	0.12
RecPar07	-0.18	0.20	-0.18	0.17	-0.13	0.14	-0.11	0.16	-0.10	0.17	-0.11	0.16
RecPar08	0.16	0.36	0.16	0.18	0.22	0.18	0.33	0.17	0.36	0.19	0.33	0.17
RecPar09	-0.23	0.26	-1.02	0.23	-0.18	0.20	-0.14	0.18	-0.15	0.20	-0.14	0.19
RecPar10	0.22	0.23	0.22	0.16	0.19	0.16	0.23	0.16	0.27	0.22	0.23	0.20
RecPar11	-0.91	0.79	-0.91	0.37	-0.46	0.24	-0.65	0.29	-0.72	0.38	-0.65	0.28
RecPar12	0.39	0.27	1.19	0.22	0.61	0.26	1.48	0.19	0.53	0.19	0.46	0.16
RecPar13	0.11	0.11	0.90	0.16	0.02	0.14	0.59	0.13	0.17	0.14	0.18	0.13
RecPar14	0.40	0.23	0.40	0.18	0.38	0.33	0.42	0.17	0.45	0.30	0.42	0.17
RecPar15	-0.42	0.31	-0.42	0.28	-0.42	0.57	-0.29	0.23	-0.32	0.56	-0.29	0.23
RecPar16	0.44	0.06	-0.35	0.01	0.57	0.13	0.42	0.10	0.43	0.18	0.42	0.09
RecPar17	-0.71	0.01	-0.71	0.01	-0.61	0.11	-0.54	0.11	-0.48	0.10	-0.54	0.10
RecPar18	0.36	0.00	1.15	0.10	0.40	0.07	1.68	0.11	0.49	0.11	0.46	0.09
RecPar19	-0.21	0.16	-1.01	0.18	-0.21	0.25	-0.06	0.13	-0.02	0.15	-0.06	0.13
RecPar20	-0.14	0.27	-0.14	0.27	-0.11	0.30	0.06	0.22	0.10	0.23	0.06	0.22
RecPar21	0.46	0.27	-0.33	0.27	0.47	0.23	0.36	0.22	0.40	0.22	0.36	0.21
RecPar22	-0.72	0.39	-0.72	0.40	-1.03	0.47	-0.48	0.31	-0.53	0.33	-0.48	0.31
RecPar23	0.18	0.22	0.18	0.21	0.55	0.23	0.12	0.20	0.17	0.21	0.12	0.20
RecPar24	-0.61	0.41	0.18	0.34	-0.67	0.41	-0.06	0.24	-0.29	0.25	-0.29	0.24
RecPar25	0.64	0.26	0.63	0.23	0.47	0.29	0.58	0.21	0.64	0.22	0.58	0.21
RecPar26	-0.33	0.40	-1.12	0.44	0.20	0.42	-0.41	0.32	-0.50	0.35	-0.41	0.31
RecPar27	-0.16	0.40	0.63	0.37	-0.13	0.45	0.96	0.30	-0.07	0.42	-0.10	0.29
RecPar28	0.17	0.47	-0.62	0.33	-0.17	0.41	0.25	0.25	0.28	0.25	0.25	0.25
RecPar29	0.14	0.50	-0.65	0.33	0.60	0.32	-0.01	0.26	-0.04	0.28	-0.01	0.26
RecPar30	-0.45	1.25	0.33	0.39	-0.63	0.38	0.55	0.25	-0.34	0.28	-0.32	0.24
RecPar31	-0.16	1.36	-0.96	0.40	-0.20	0.31	-0.06	0.24	-0.04	0.25	-0.06	0.24
RecPar32	-0.35	0.33	-1.14	0.28	-0.31	0.25	-0.16	0.23	-0.18	0.22	-0.16	0.23
RecPar33	0.64	0.52	0.63	0.18	0.60	0.16	0.62	0.14	0.66	0.13	0.62	0.14
RecPar34	-1.02	0.80	-1.82	0.48	-0.69	0.55	-0.92	0.37	-1.10	0.41	-0.92	0.37
RecPar35	-0.85	0.68	-0.06	0.40	-0.63	0.41	0.24	0.32	-0.64	0.34	-0.67	0.32

Table A2.2 cont.: Estimated parameter values and associated Hessian-based standard deviations for the six Operating Models (OMs). $B_{0,1}^{sp}$ is the estimated spawning biomass at the start of the model in month 1 and B_0^{sp} is the spawning biomass for the model start year. A_S is the quarterly availability of prawns for the respective time periods and $\varsigma_{y=ElNino}^{e}$ and $q_{y=ElNino}^{e}$ are the environmental parameters linked to recruitment variability and prawn catchability respectively.

	OM1		OM2		OM3		OM4		OM5		OM6	
Parameter	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**	**Value**	**SD**
RecPar36	-0.65	0.44	0.14	0.27	-0.77	0.29	0.61	0.21	-0.38	0.21	-0.44	0.20
RecPar37	-0.01	0.40	-0.01	0.24	-0.04	0.41	0.15	0.20	0.21	0.20	0.15	0.20
RecPar38	-0.19	1.82	-0.99	0.64	-0.14	1.06	-0.08	0.53	-0.15	0.78	-0.08	0.53
Environmental												
$\varsigma_{y=ElNino}^{e}$	–	–	0.79	0.11	–	–	0.92	0.06	–	–	–	–
$q_{y=ElNino}^{e}$	–	–	–	–	0.64	0.09	–	–	–	–	–	–

Table A2.3: Negative log likelihood (-InL) contributions to the overall negative log likelihood, number of parameters estimated and AIC scores for the six Operating Models (OMs). Note the OM4 and OM6 AICs are comparable with each other, but not the other OMs as these models used a different σ_R.

	OM1	OM2	OM3	OM4	OM5	OM6
CPUE -InL	-12.786	-12.796	-15.658	-13.403	-14.664	-13.405
Recruitment residuals -InL	5.984	5.999	6.465	7.213	4.848	7.216
Overall -InL	-6.803	-6.797	-9.193	-6.190	-10.075	-6.190
No. parameters Estimated	47	48	48	48	47	47
AIC	80.39	82.41	77.61	83.62	73.85	81.62

Appendix 3 Outputs from Sensitivity Tests

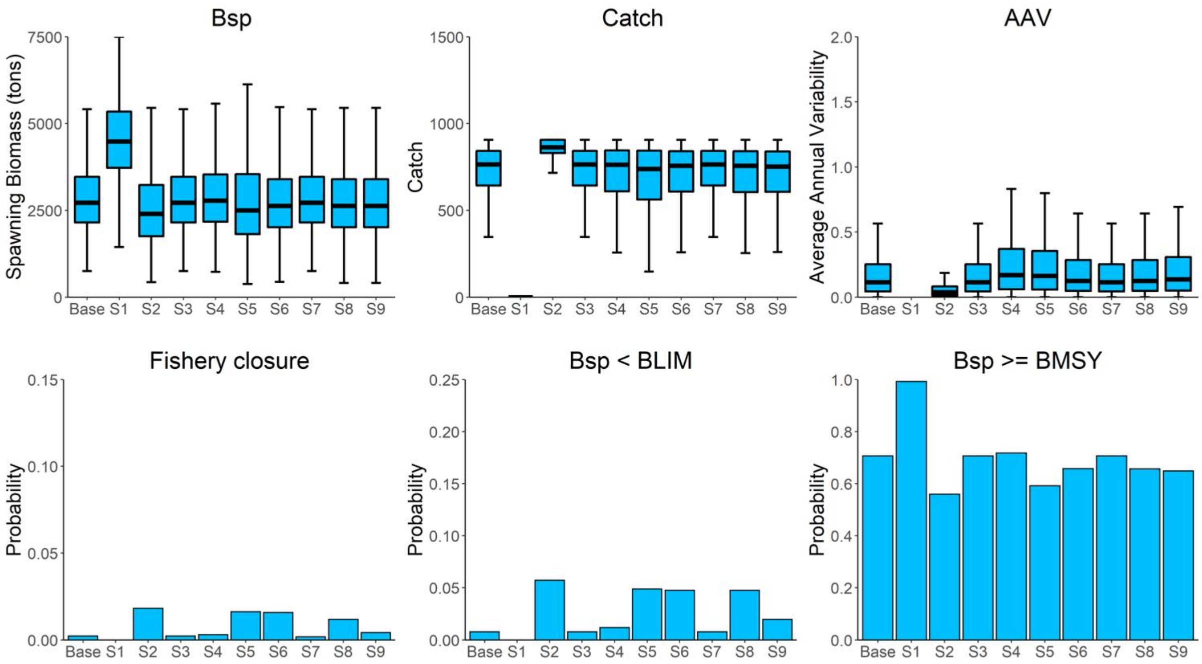

Figure A3.1: Selected performance metrics for sensitivity tests on OM2 HCR2 relative to the base HCR2. See Table 2 for a list of sensitivity tests. Box and whisker plots (upper panel) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

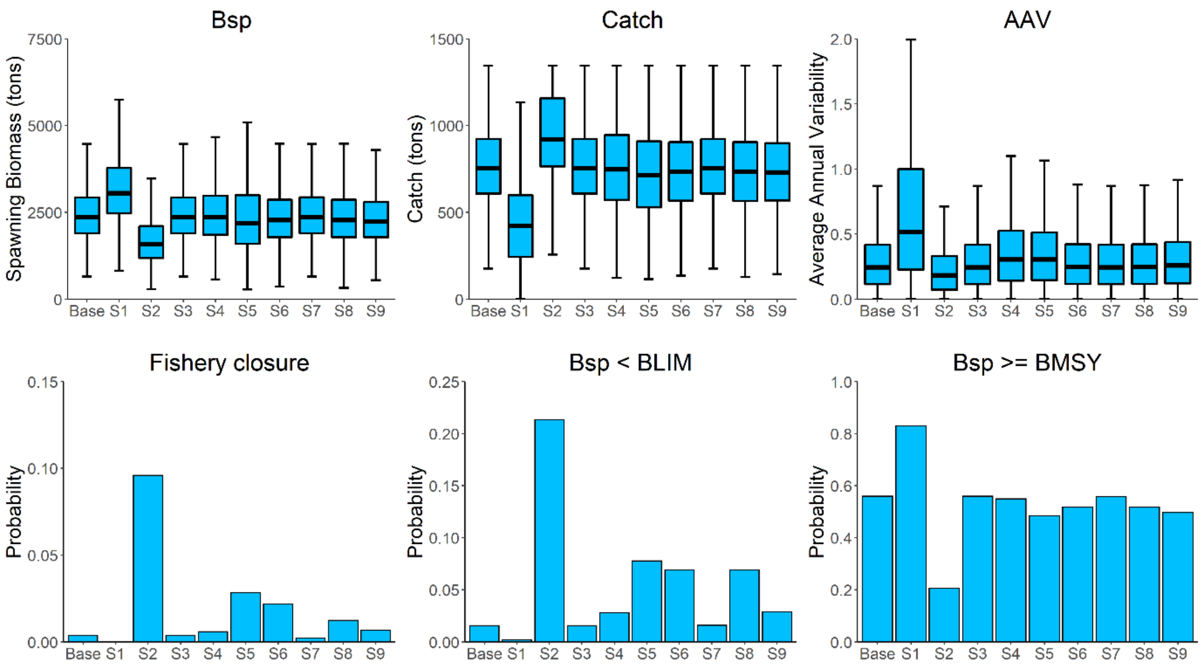

Figure A3.2: Selected performance metrics for sensitivity tests on OM2 HCR3 relative to the base HCR3. See Table 2 for a list of sensitivity tests. Box and whisker plots (upper panel) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

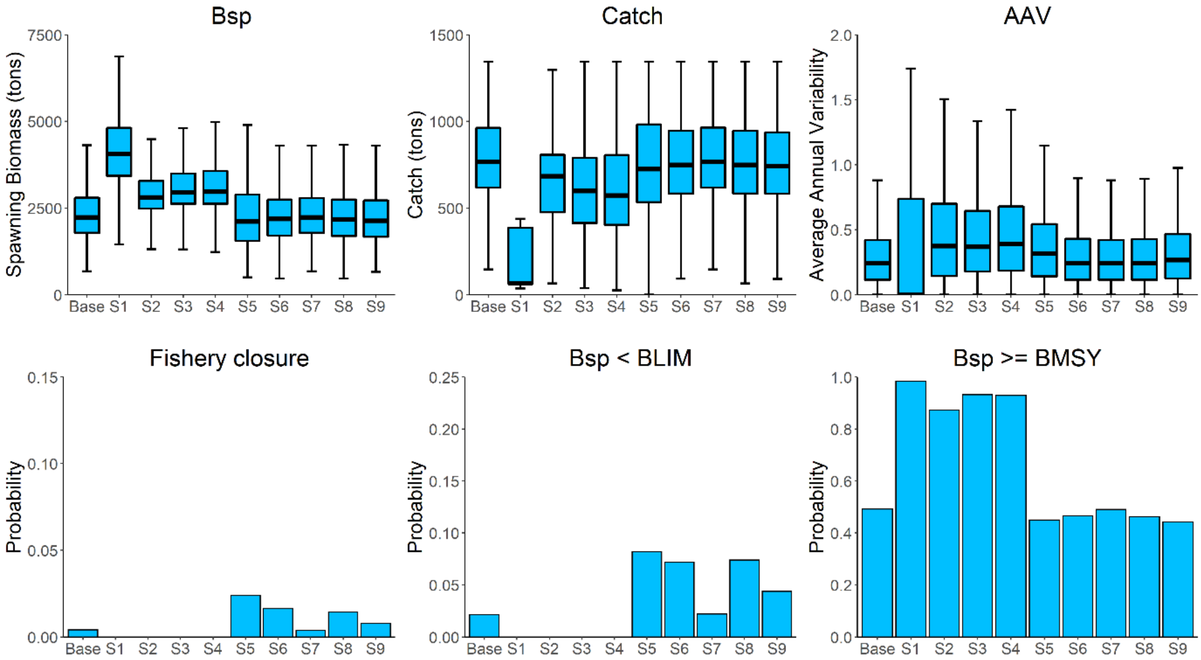

Figure A3.3: Selected performance metrics for sensitivity tests on OM2 HCR4 relative to the base HCR4. See Table 2 for a list of sensitivity tests. Box and whisker plots (upper panel) show the median (central bold line), the 75th and 25th percentiles (the blue box) and the range of projected values, excluding outliers (the whiskers).

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