Conditioning of an operating model grid for South Pacific jack mackerel

Working Document SCW   -Doc04

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SPRFMO Jack Mackerel Benchmark Workshop (SCW16), 18-22 May 2026

The current approach employed to condition operating models (OMs) for the management strategy evaluation (MSE) of Chilean Jack Mackerel (CJM) is described. The document outlines the modelling approaches currently implemented, the associated inputs and assumptions, the principal axes of uncertainty presently explored and potential axes of uncertainty that can be explored. It also illustrates how OM configurations may influence stock dynamics and projections. The primary purpose of the document is to support discussions during the CJM stock assessment benchmark process by documenting the current OM framework and identifying areas where additional information, hypotheses, parameterisations, or model developments could be incorporated into future OM implementations.

Introduction

In fisheries science, Management Strategy Evaluation (MSE) is a simulation framework used to evaluate the performance of fishery management systems under uncertainty.

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Within an MSE framework, the Operating Model (OM) represents the underlying "true" system driving the simulations, including population dynamics, fishery processes, environmental variability, and observation and implementation error.

The development and conditioning of OMs are a fundamental part in the MSE process, taking three out of seven of the basic steps commonly followed (Punt et al. 2014). The choices made when conditioning OMs determine what key sources of uncertainty are represented when testing candidate management procedures, and thus the robustness of the MSE analysis.

In this context, the present document describes the current implementation of Operating Models for the MSE of Chilean Jack Mackerel (CJM). The document outlines the modelling approaches currently implemented, the associated inputs and assumptions, the principal axes of uncertainty presently explored and potential axes of uncertainty that can be explored. It also illustrates how OM configurations may influence stock dynamics and projections.

The primary purpose of the document is to support discussions during the CJM stock assessment benchmark process by documenting the current OM framework and identifying areas where additional information, hypotheses, parameter sets, or model developments could be incorporated into future OM implementations.

Material and Methods

Data input

The data used in the CJM MSE correspond to those fitted within the JJM stock assessment model. Input data are divided into three main categories: fishery-dependent data, CPUE indices, and survey indices. The temporal coverage of the different data sources is shown in Figure 1.

Scenario sets

The Operating Models (OMs) are defined under three sets: reference set, robustness set and sensitivity tests. The definition of these sets is still open to the exploration of

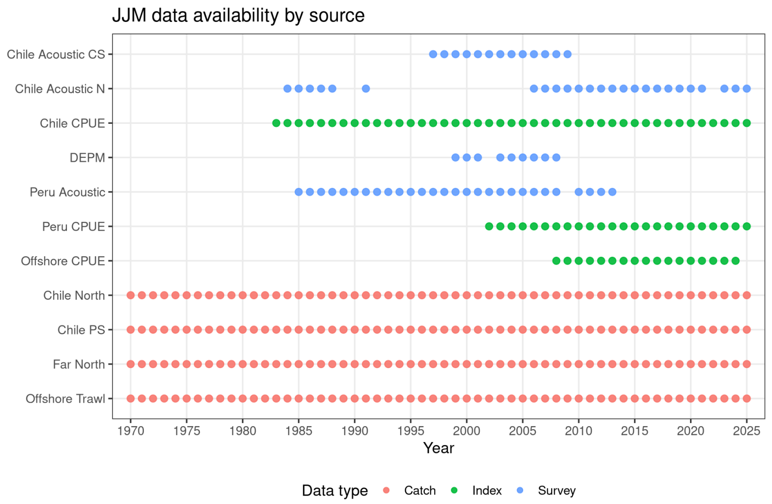

Figure 1: Data sources and availability for the conditioning of the OMs.

alternative assessment models to be carried out by the benchmark.

The reference set is meant to represent the current understanding of the most likely stock dynamics, fishery processes, and observation system. This reference configuration provides the baseline for the tuning and testing of management procedures. Candidate management procedures are either tuned to each model in this this set, or required to perform to a high standard when tested against them.

The robustness set of OMs is developed to represent plausible alternative hypotheses that expand the range of uncertainties covered in the reference set. Procedures under evaluation are expected, once tuned under the reference set, to perform sufficiently well under this set. Results of these tests might lead to changes in the procedures to ensure their robustness under the possible realities contained in this set.

Sensitivity tests may also be conducted to explore the influence of specific assumptions or modelling choices on model behaviour and projections. In contrast to the robustness set, sensitivity tests are not necessarily intended to represent fully plausible alternative operating conditions, but rather to investigate the response of the system to targeted perturbations or structural uncertainties. The aim of the sensitivity tests is to identify sources of model sensitivity to inform one on potential OM development and conditioning. The can also prove useful at establishing limits to the successful application of MPs that should be considered when specifying exceptional circumstances provisions.

Grid of Operating Models (OM)

The uncertainties to be explored in the conditioning of Operating Models (OMs) will ultimately be determined by the CJM working group. However, several major axes of uncertainty can already be identified for consideration within the MSE framework. These include uncertainties related to stock-recruitment dynamics, survey and fishery selectivity, model conditioning under alternative data inputs, and potential ENSO-related scenarios, including climate-induced trends in stock productivity or growth.

The current implementation of OMs explores a subset of these uncertainties, including alternative stock-recruitment relationships, one- and two-stock hypotheses, stock movement dynamics, and alternative selectivity assumptions for fisheries and surveys. The presently implemented OM configurations are summarized in the following table.

OM name	Base model	Stock recruitment	Stock movement	Selectivity	Set
OM 1.1	h1_1.14	SR1 (h=0.65)	NA	2016-2025	TBD
OM 1.2	h1_1.14	SR2 (h=0.80)	NA	2016-2025	TBD
OM 2.1	h2_1.14	SR1 (h=0.65)	no mvt	2016-2025	TBD
OM 2.2	h2_1.14	SR2 (h=0.80)	no mvt	2016-2025	TBD
OM 3.1	h2_1.14	SR1 (h=0.65)	mvt	2016-2025	TBD
OM 3.2	h2_1.14	SR2 (h=0.80)	mvt	2016-2025	TBD

Version 1 OMs correspond to the one-stock hypothesis. Version 2 OMs correspond to the two-stock hypothesis without stock movement, while Version 3 OMs correspond to the two-stock hypothesis including movement dynamics between stocks.

These OM configurations represent an initial implementation framework and are intended to support further discussion on the range of uncertainties and hypotheses that should be incorporated into future OM development and conditioning.

Operating Model conditioning

Uncertainty

A key component of the MSE framework is the representation of uncertainty in stock status and fishing pressure estimates. In the current implementation, parameter estimation uncertainty is quantified using a No-U-Turn Sampler (NUTS) algorithm applied to the stock assessment model.

These uncertainties are propagated into the Operating Models (OMs) through the generation of replicate model trajectories using a Markov chain Monte Carlo (McMC) process. The resulting McMC samples provide plausible realizations of stock dynamics and fishing history, so called stock replicates. Example replicate stock trajectories is shown in Figure @ref(fig:data-om11_indRep).

To investigate the effect of the number of stock replicates on projection stability, stock projections at $F = F_{MSY}$ were conducted using 500 replicates. Sub-samples of these replicates were then bootstrapped 50 times to compute long-term performance metrics (2039–2050) across a range of replicate sizes, from 50 to 450 replicates in 50 replicates steps.

This analysis allows evaluation of whether projected performance metrics remain stable as the number of replicates increases, and therefore whether the selected number of replicates is sufficient to adequately represent uncertainty within the OMs.

The results are shown in Figure 3 and indicate that the use of 500 replicates appears sufficient to provide statistically stable projections and performance estimates. However, additional testing using larger numbers of replicates would be required to allow to more appropriate combinations and to fully validate the adequacy of the selected sample size.

Biological parameters

Biological parameters used in the Operating Models include natural mortality, stock weight-at-age, and maturity-at-age, and are provided in Table 2. These parameters are assumed to be time invariant and are carried forward unchanged throughout the projection period.

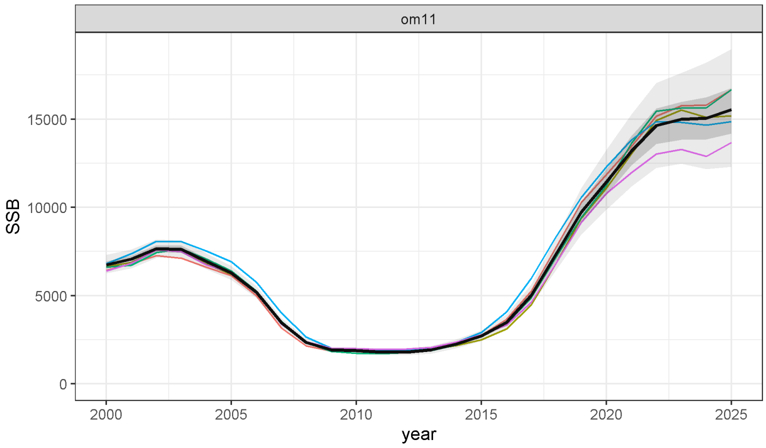

Figure 2: Historical stock trajectory since 2000 with 5 stock replicates. The OM used is OM1.1 (h1_1.14, h=0.65)

Landing weights-at-age by fleet are shown in Figure 4. For projections, landing weights are assumed to remain constant and are specified as the average values over the period 2016–2025.

Stock recruitment

Simulating recruitment into the future is a key component of the MSE exercise, as recruitment assumptions strongly influence projected stock trajectories and, consequently, the ability of the stock to sustain higher or lower levels of fishing mortality. For CJM, recruitment in the stock assessment is represented using a Beverton–Holt stock–recruitment relationship of the form:

$$R = \frac{4hR_0\,SSB}{SSB_0(1-h) + SSB(5h-1)}$$

where R is the recruitment, SSB is the spawning stock biomass, R_0 is the unfished equilibrium recruitment, SSB_0 is the unfished spawning stock biomass, and h is the steepness parameter. The steepness parameter defines the proportion of unfished recruitment produced when the stock is at 20% of unfished spawning biomass.

To date, the recruitment scenarios considered include two alternative steepness assumptions, $h = 0.65$ and $h = 0.80$, which remain fixed at those values in different runs. All

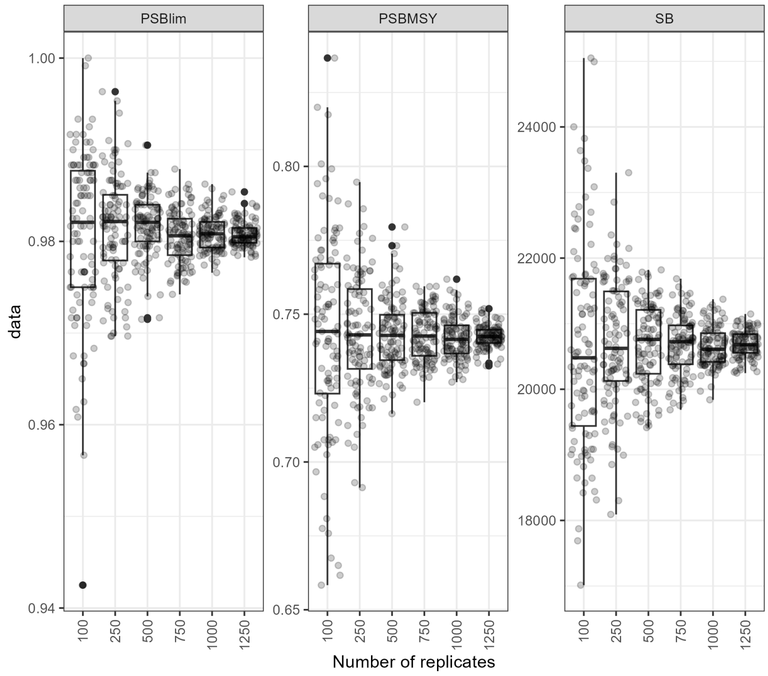

Figure 3: Results of bootstraping of stock replicates of stock projections at F=F_{MSY}. A total of 1500 replicates are bootstrapped 100 times to compute performance metrics in the long term (2039-2050) across 100 to 1250 replicates. The OM used is OM1.1 (h1_1.14, h=0.65). Performance metrics investigated are Spawner biomass (SB), Probability of SB greater or equal to SBMSY ($P(SB \geq SB_{MSY})$) and Probability that spawner biomass is above SBlim ($P(SB \geq SB_{lim}$)

other parameters of the stock–recruitment relationship are estimated independently for each replicate, thereby propagating parameter uncertainty into the Operating Models.

The uncertainty associated with the stock–recruitment relationship across replicates for the one-stock hypothesis is shown in Figure 5, while the corresponding functions for the two-stock hypothesis are shown in Figure 6. Considerable variability can be observed among replicates, resulting in a broad range of potential recruitment dynamics across the OM ensemble, but most notable at low population sizes.

The stock–recruitment relationships are used to generate recruitment during the projection period. In addition, stochastic recruitment deviations are applied multiplicatively to account for interannual variability not explained by spawning biomass alone. These deviations are predefined for each replicate and are generated from a lognormal distribution with AR1 autocorrelation. The base case parametrization of the lognormal distribution is estimated empirically from the residual variability of the fitted stock–recruitment

Table 2: Biological parameters: natural mortality, stock weight and maturity at age.

age	m	wt	mat
1	0.28	0.1815	0.52
2	0.28	0.2303	1.00
3	0.28	0.3025	1.00
4	0.28	0.3820	1.00
5	0.28	0.5268	1.00
6	0.28	0.7345	1.00
7	0.28	0.9226	1.00
8	0.28	1.1060	1.00
9	0.28	1.3435	1.00
10	0.28	1.5135	1.00
11	0.28	1.6205	1.00
12	0.28	1.8285	1.00

relationship for each replicate. Alternative recruitment are generated by specifying lower or higher mean levels or variability, for the whole time period of projection or following some other pattern. Cyclic patterns in recruitment due to ENSO can be constructed in this way.

The resulting base case recruitment deviations for the different OMs are shown in Figure 7 and Figure 8 for the one-stock and two-stock hypotheses, respectively.

Fishing selectivity

Fishing selectivity is a potential source of uncertainty for the CJM stock. Figure 9 shows the historical selectivity patterns from the JJM model by 10-year intervals. In the projections, selectivity is gradually transitioned during the first 10 years of the projection (2026-2035). The selectivity applied after this transition period can be customized under a range of alternative assumptions. The baseline scenario assumes future selectivity will follow the average selectivity estimated over the final 10 historical years (2016–2025).

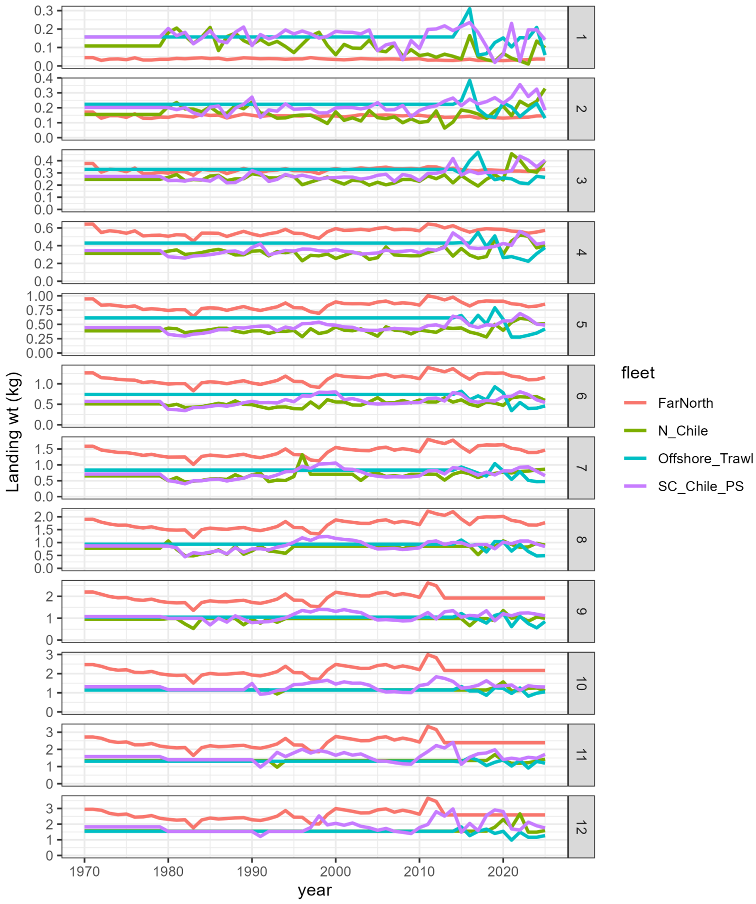

Figure 4: Landing weight at age in the different fleets.

Projection dynamics of the Operating Models

Projections for the OMs are conducted using the FLR FLasher package (F and I (2016), https://flrproject.org/FLasher), which allows the specifications of a range of targets and limits and for OMs consisting of one or more stock, and single or multiple fisheries. The basic mechanism of the `fwd()` method is to find the fishing mortality (F) that achieves a specified target (e.g., catch, biomass, or exploitation rate) in a given time step and for each fishery. The necessary change in effort by fishery from that applied in the previous time step that would result in the desired outcome is found across all fisheries simultaneously by applying the effort-based catch equation:

$$F_{f,t,a} = E_{f,t} \times S_{f,t,a} \times \alpha_{f,t}$$

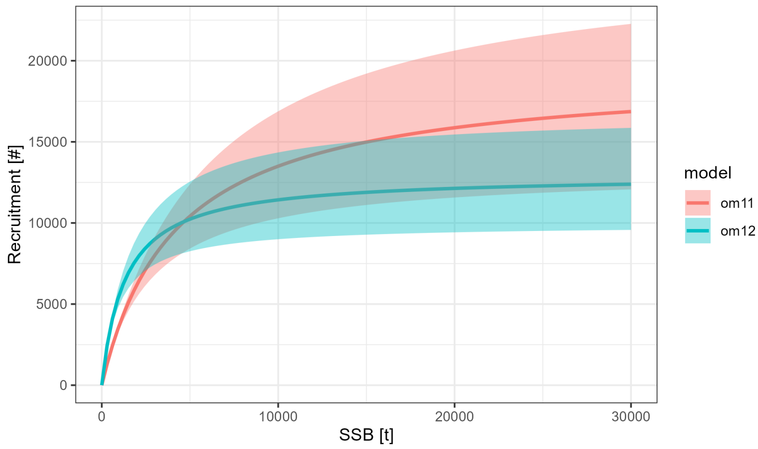

Figure 5: Stock recruitment relationships in the case of the single stock hypothesis (h=0.65 for OM1.1 and h=0.80 for OM1.2).

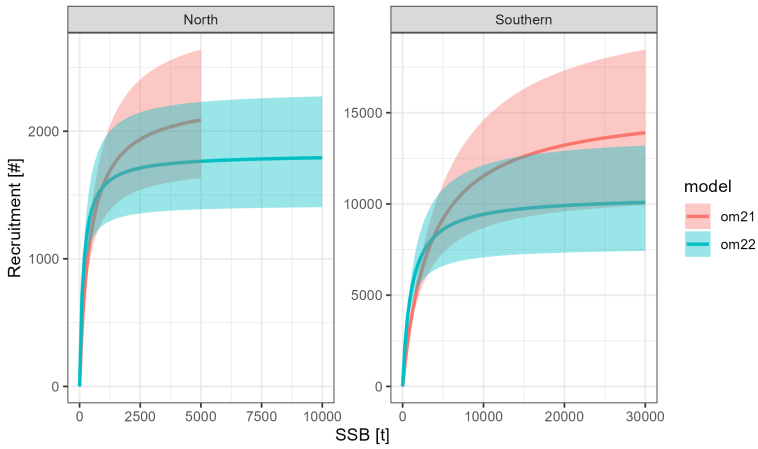

Figure 6: Stock recruitment relationships in the case of the two stocks hypothesis (h=0.65 for OM2.1 and h=0.80 for OM2.2).

where the fishing mortality F by fishery f, time step t and age a is obtained from effort E, selectivity S and catchability α for each fishery, time step and age. The resulting F is applied to the standard Baranov equation to obtain the corresponding catches by fishery and the resulting abundances by stock.

The application of this methodology to the CJM OMS is carried out through two methods. For the OMs comprised of one stock, or two independent stocks, the default method is used, while for the stock movement scenarios, the `fwd()` method is applied after to corresponding movements across stocks by age, as defined by the given movement matrix, have been computed.

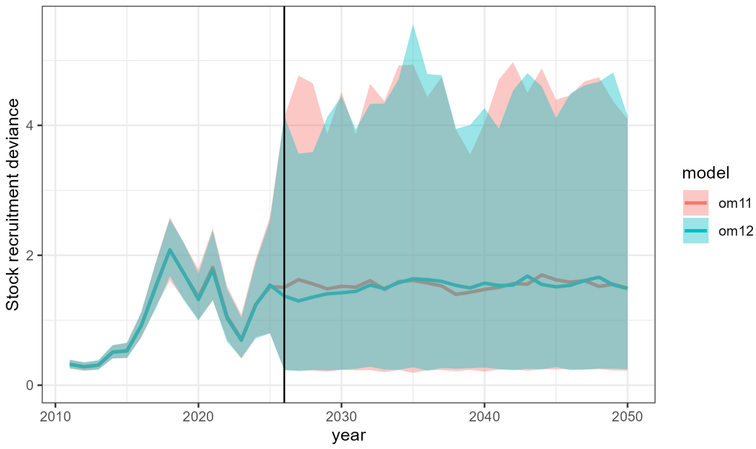

Figure 7: Stock recruitment deviances in the case of the single stock hypothesis (h=0.65 for OM1.1 and h=0.80 for OM1.2).

Observation Error Model (OEM)

In the projections, new catch and survey data are generated and provided to the MP by the Observation Error Model (OEM).

The observed catch-at-age is generated from that present in the OM by applying the deviances to each fishery catch-at-age as:

$$C^{\mathrm{obs}}_{a,y,f} = C^{\mathrm{OM}}_{a,y,f} \times \mathrm{dev}^{C}_{a,y,f}$$

where $C^{\mathrm{obs}}_{a,y}$ is the observed catch at age a in year y for fishery f. $C^{\mathrm{OM}}_{a,y,f}$ is the catch at age generated by the operating model (OM) projection, and $\mathrm{dev}^{C}_{a,y,f}$ is the observation error deviance applied to catch at age a in year y for fishery f. These observation deviances are generated from a lognormal distribution with sdlog = 0.2 across all four fisheries.

Similarly, the survey indices are generated as:

$$I_{a,y,i} = q_{a,i}\, N_{a,y}\, e^{-t_i Z_{a,y}}\, \mathrm{dev}^{I_i}_{a,y}$$

where $I_{a,y,i}$ is the survey index for age a, year y, and survey i, $q_{a,i}$ is the catchability coefficient at age, $N_{a,y}$ is the population abundance at age, t_i is the timing of survey i

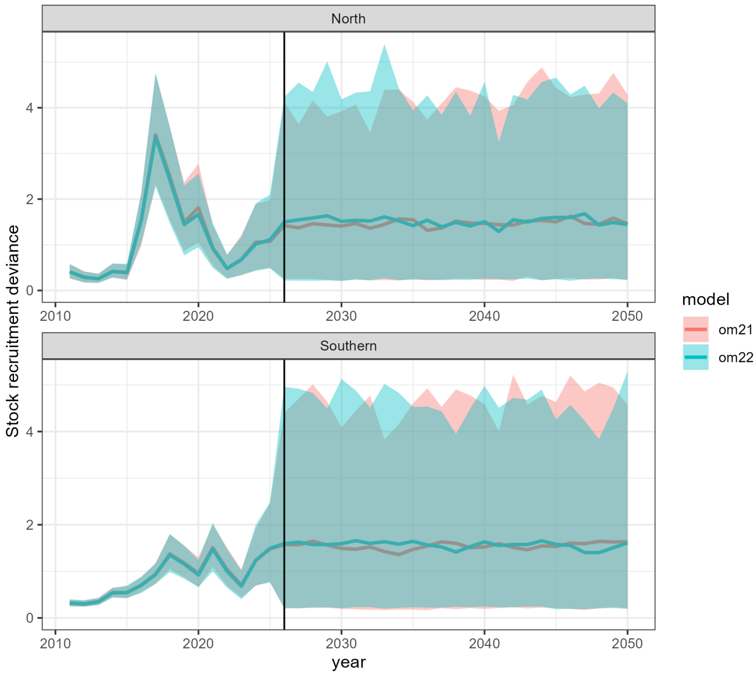

Figure 8: Stock recruitment deviances in the case of the two stocks hypothesis (h=0.65 for OM2.1 and h=0.80 for OM2.2).

as a proportion of year, $Z_{a,y}$ is the total mortality at age a in year y, and $\text{dev}^{I_i}_{a,y}$ is the observation error deviance applied to survey i at age a in year y.

The observation deviances applied to biomass indices are generated from an AR1 auto-correlated lognormal distribution. The parameters of the distribution (sdlog and ρ) are estimated post-hoc. The resulting time series of deviances are shown in Figure 11.

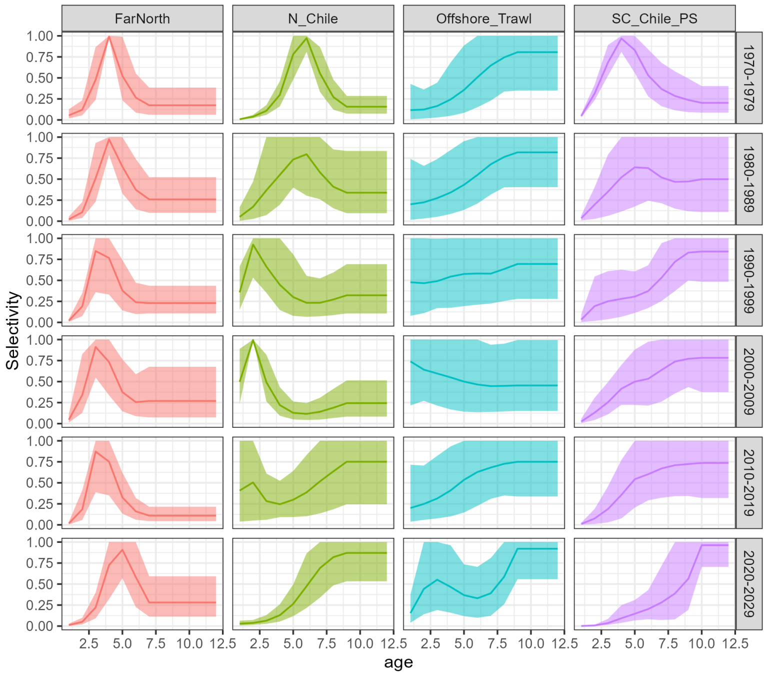

Figure 9: Fishing selectivity out of the jjm model for OM1.1 (h1_1.14, h=0.65). Ribbons are the 5th and 95th quantiles

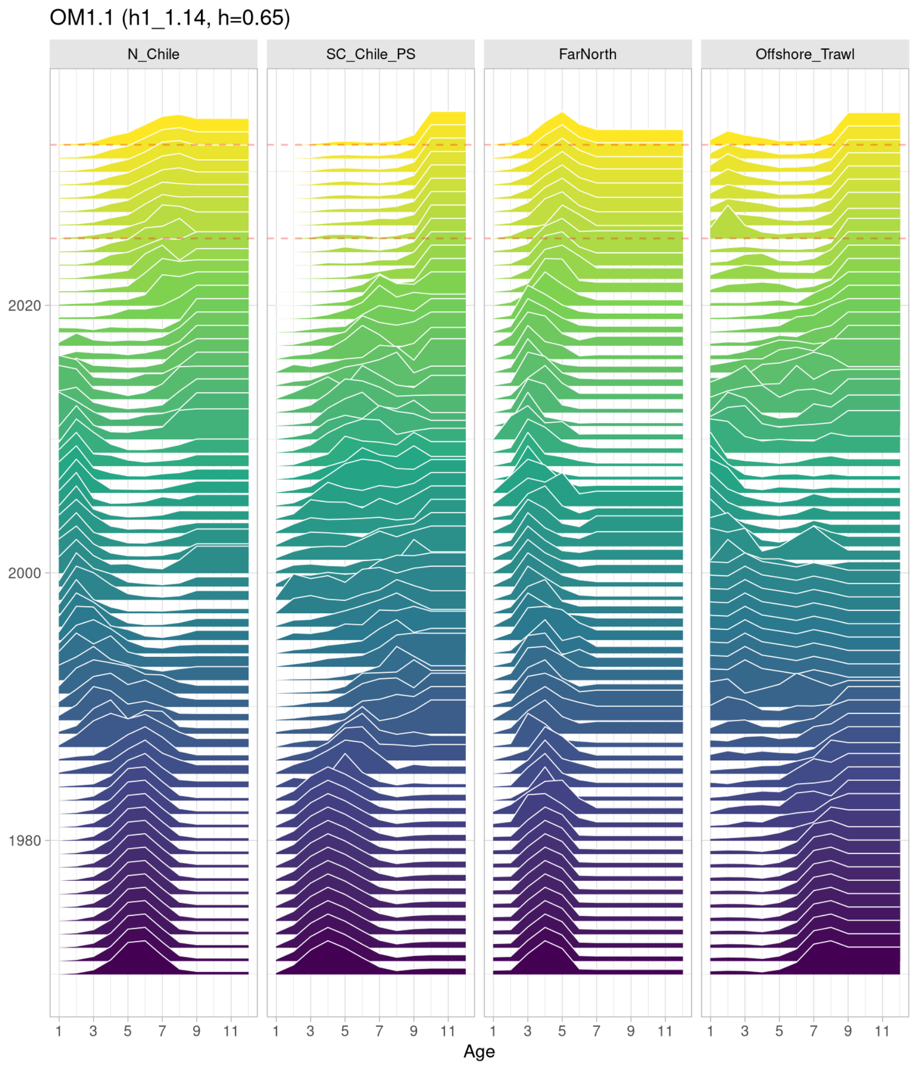

Figure 10: Estimated selectivity at age over time for the four fleets in OM 1.1 (h1_1.14, h=0.65). Dashed horizontal lines indicate the start of projections (2026) and the end of the transitional period (2032).

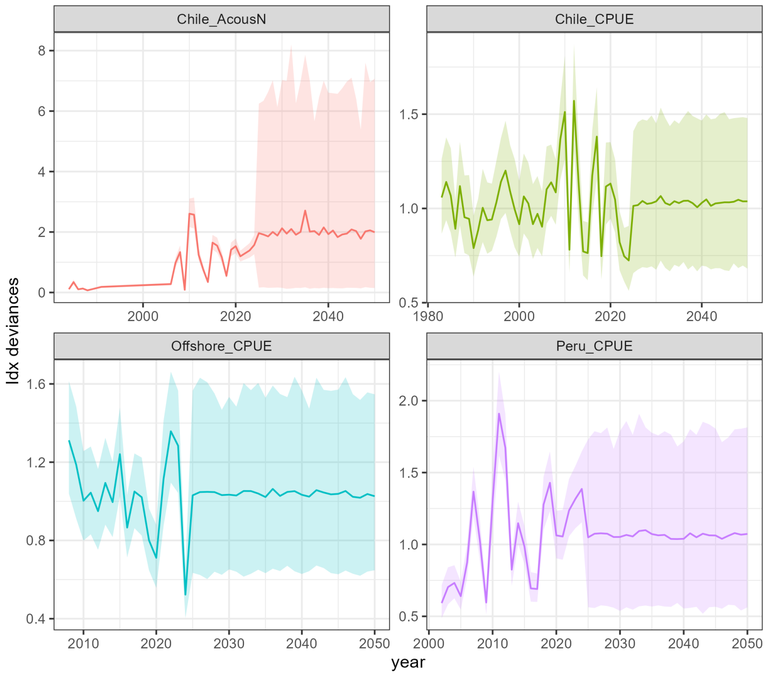

Figure 11: Historical and projected index deviances for OM1.1 (h1_1.14, h=0.65).

Results

OM trajectories and stock status

Historical stock trajectories are generated using 500 replicates derived from the JJM stock assessment model. Parameter uncertainty is estimated using a No-U-Turn Sampler (NUTS), with replicate trajectories generated through a Markov Chain Monte Carlo (MCMC) process.

The resulting historical trajectories for the one-stock and two-stock hypotheses are shown in Figure 12 and Figure 13, respectively. For each hypothesis, model fits corresponding to different values of the stock–recruitment relationship (SRR) steepness parameter are presented.

Across the historical period, the fitted trajectories and associated uncertainty envelopes are broadly similar among steepness assumptions, indicating that the historical fit is relatively insensitive to the alternative SRR formulations considered.

The corresponding stock status trajectories for the one-stock and two-stock hypotheses under the $h = 0.65$ steepness assumption are shown in Figure 14 and Figure 15, respectively. The results indicate that the stock has remained predominantly within the Kobe green quadrant in recent years.

Fit of indices

The performance of the different indices is evaluated over the historical period using the sampled uncertainty across stock replicates, including uncertainty in stock numbers, fishing mortality, and individual index selectivities and catchabilities. For each OM replicate, a corresponding index time series is generated, allowing the uncertainty associated with each biomass index to be characterized across replicates. The generated indices are subsequently compared with the raw observed indices.

The resulting time series are shown in Figure 16. The performance of each individual index is further summarized using their Receiver Operating Characteristic (ROC; Figure 17) and Area Under the Curve (AUC; Figure 18) diagnostics. In these diagnostics, higher

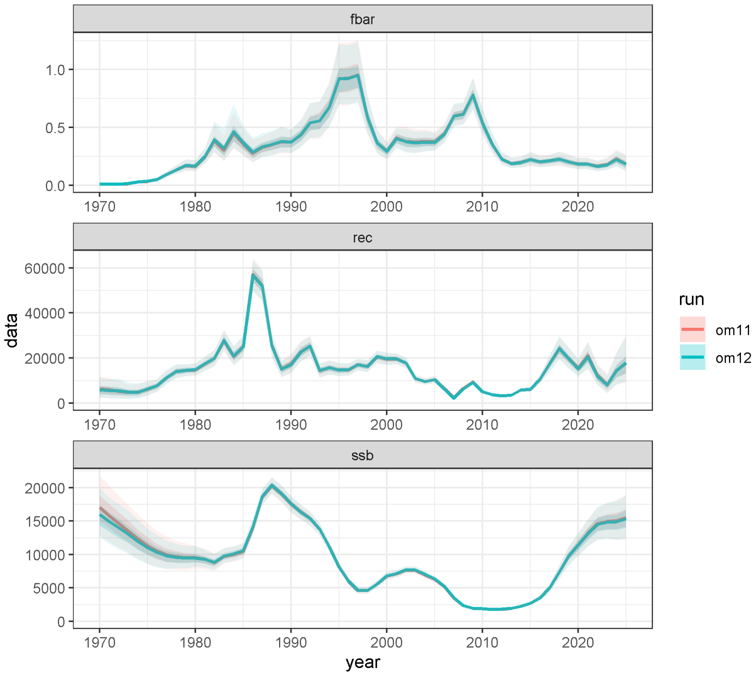

Figure 12: Timeseries of average fishing mortality (fbar), recruitment (rec) and spawning biomass (ssb), for the one-stock hypothesis OMs, with different values for the SRR steepness paramater (h=0.65 for OM1.1 and h=0.80 for OM1.2).

AUC values indicate a greater ability of the index to track changes in spawning stock biomass (SSB).

The results indicate that the `Chile_AcousN` index performs the poorest, both over the full time series and during the recent period (2006–2025). This finding suggests that further investigation of the `Chile_AcousN` index may be warranted. In contrast, the `Offshore_CPUE` index shows the strongest ability to track SSB trends for the shoerter time period of its existence.

Reference Points

Reference points are estimated within the JJM stock assessment model. These are dynamic reference points, estimated independently for each historical year and replicate.

The distributions of the resulting reference points under the two alternative stock–recruitment relationship (SRR) scenarios are shown in Figure 19 and Figure 20 for the one-stock and two-stock hypotheses, respectively.

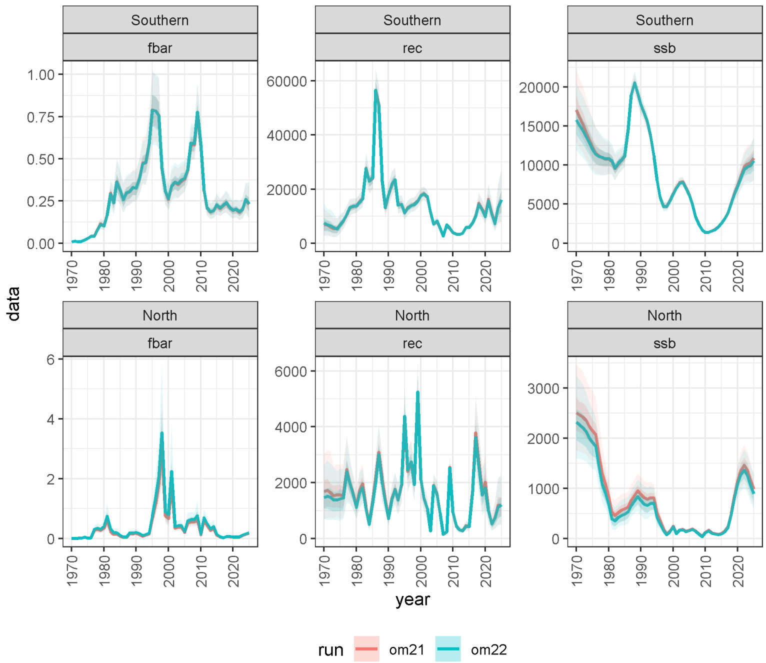

Figure 13: Timeseries of average fishing mortality (fbar), recruitment (rec) and spawning biomass (ssb), for the two-stocks hypothesis OMs, with different values for the SRR steepness paramater (h=0.65 for OM2.1 and h=0.80 for OM2.2).

OM Projections

F=0 projections

Figures 25 and 26 show stock projections under $F = 0$ for the one-stock and two-stock hypotheses, respectively. These projections highlight clear contrasts between the alternative stock–recruitment relationship (SRR) assumptions considered for both stock hypotheses. As expected, the higher steepness scenario (h=0.80) results in greater rebuilding potential and leads to substantially higher projected biomass levels over the projection period compared to the lower steepness scenario (h=0.65).

Impact of selectivity patterns

To illustrate the effect of varying fishing selectivity patterns, average selectivity patterns from recent years are applied during the projection period following a 10-year transition phase. Stock projections are subsequently performed under a constant fishing mortality corresponding to $F = F_{MSY}$.

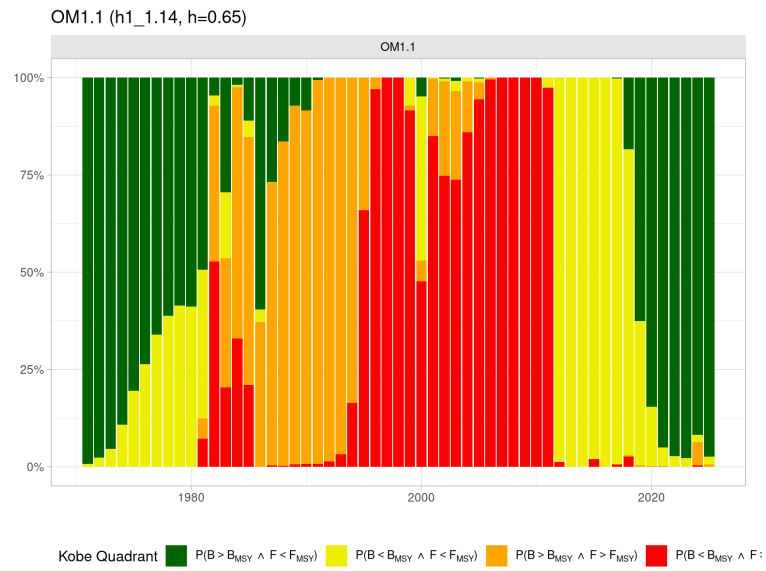

Figure 14: Time series of Kobe quadrant probabilities for OM 1.1 (h1_1.14, h=0.65). Bars represent the probability of the stock falling within each of the four Kobe quadrants.

The resulting projections are shown in Figure 27, including the distribution of spawning stock biomass (SSB) in 2040. The results demonstrate that alternative selectivity assumptions can substantially influence both the central tendency and spread of the projected SSB distribution, as reflected by changes in the mode and overall variability of the distribution.

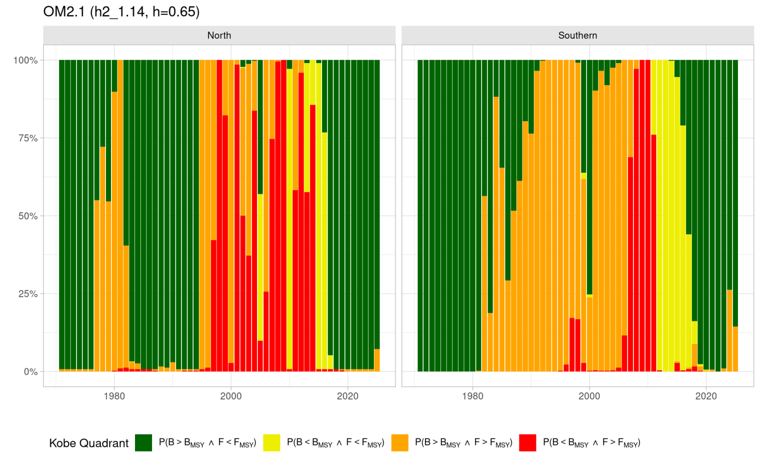

Figure 15: Time series of Kobe quadrant probabilities for OM 2.1 (h2_1.14, h=0.65). Bars represent the probability of the Southern and Northern stocks falling within each of the four Kobe quadrants.

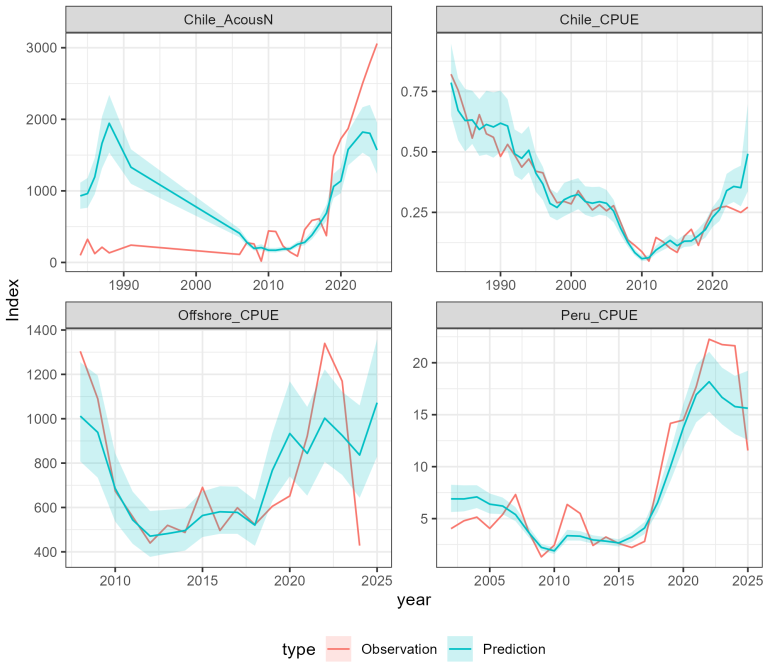

Figure 16: Time series of observed and OEM-predicted indices for OM 1.1 (h1_1.14, h=0.65).

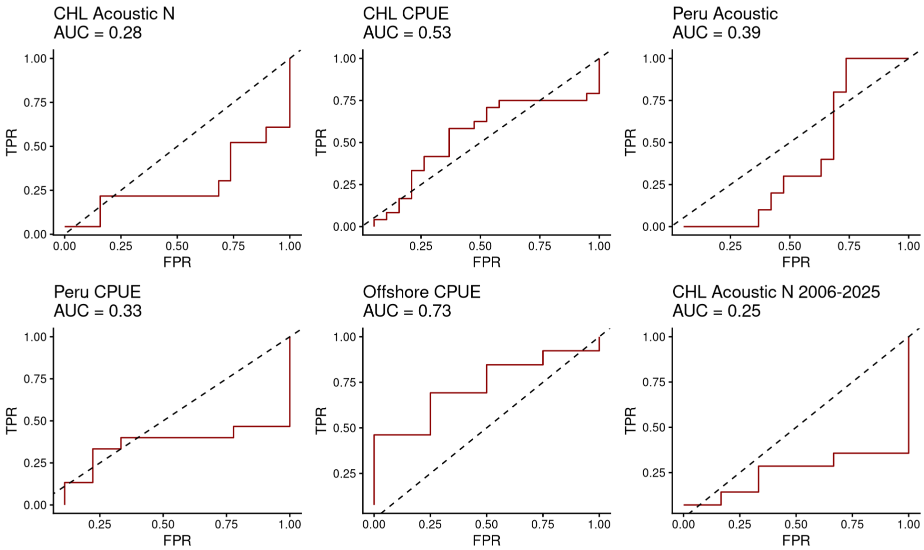

Figure 17: Receiver Operating Characteristic (ROC) curves for the different abundance indices as indicators of changes in spawning stock biomass (SSB), defined as $\frac{SB_y}{SB_{y-1}}$, for the h1_1.14 JJM stock assessment run. The corresponding area under the curve (AUC) is shown.

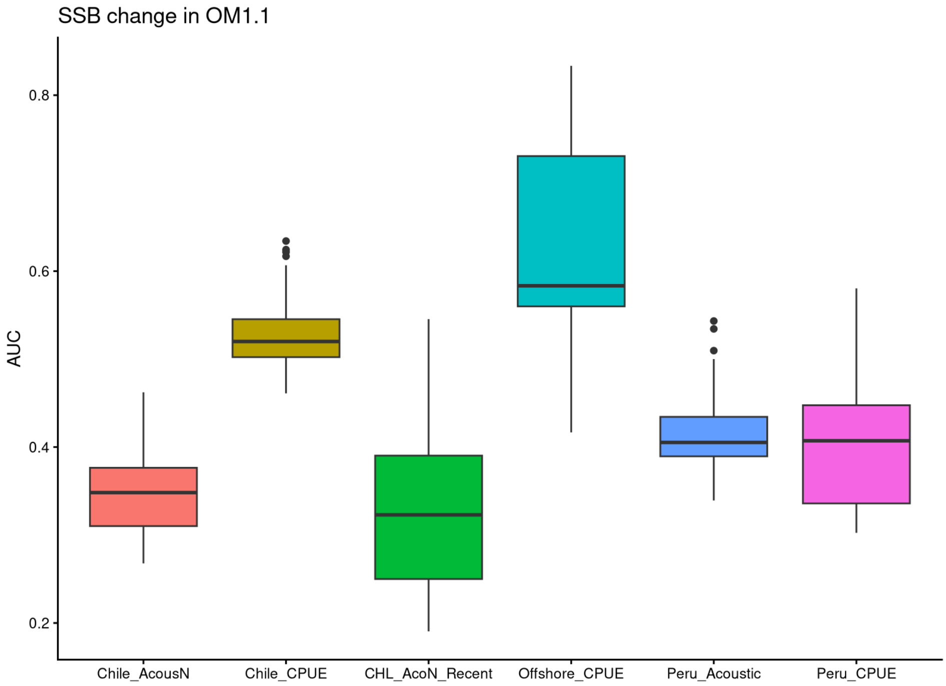

Figure 18: Distribution of Receiver Operating Characteristic (ROC) Area Under the Curve (AUC) values for the different abundance indices as indicators of changes in spawning stock biomass (SSB), defined as $\frac{SB_y}{SB_{y-1}}$, across all iterations of OM 1.1 (h1_1.14, h=0.65).

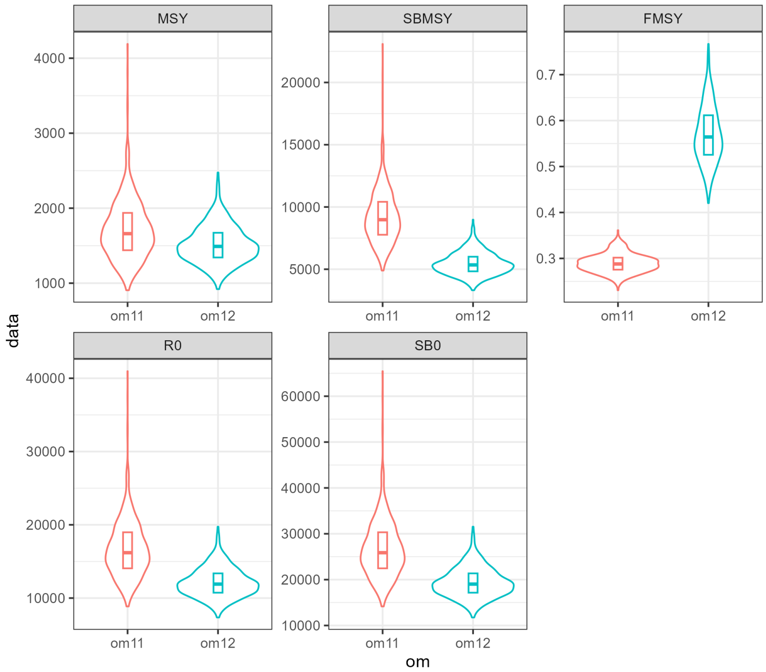

Figure 19: Distribution of reference points in the case of the single stock hypothesis (h=0.65 for OM1.1 and h=0.80 for OM1.2).

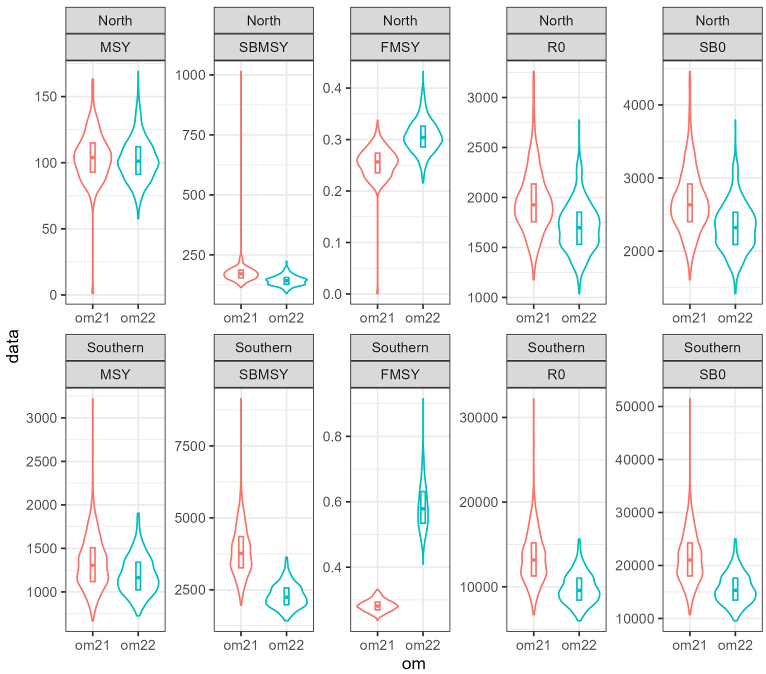

Figure 20: Distribution of reference points in the case of the two stocks hypothesis (h=0.65 for OM2.1 and h=0.80 for OM2.2).

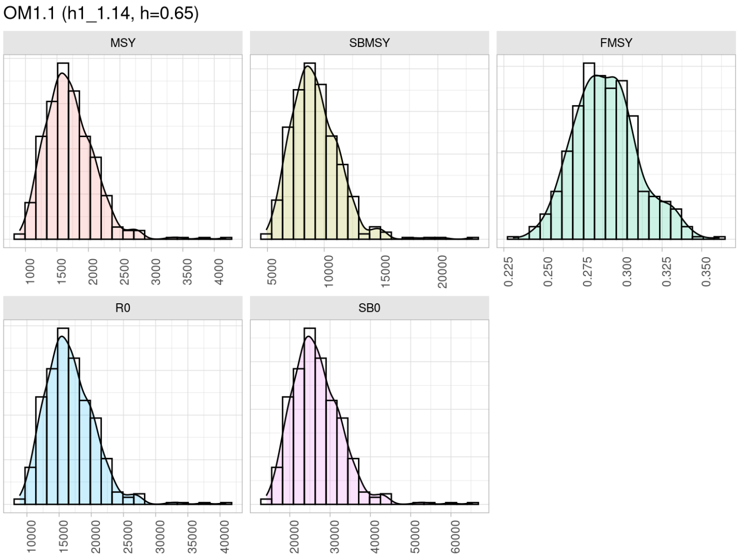

Figure 21: Sample distributions and kernel densities of reference point values for OM 1.1 (h1_1.14, h=0.65).

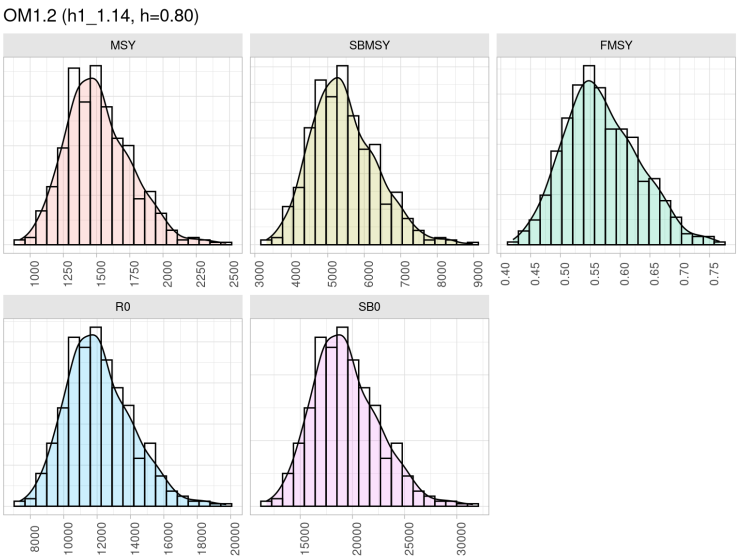

Figure 22: Sample distributions and kernel densities of reference point values for OM 1.2 (h1_1.14, h=0.80).

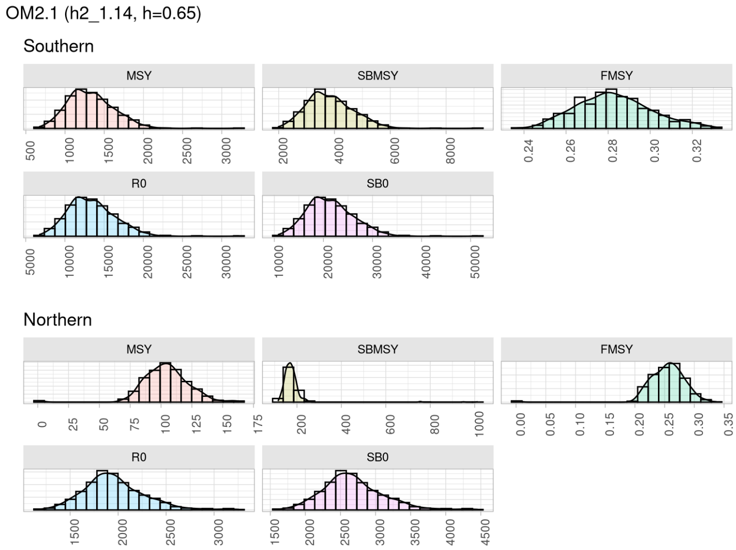

Figure 23: Sample distributions and kernel densities of reference point values for OM 2.1 (h2_1.14, h=0.65), and for the Southern and North stocks.

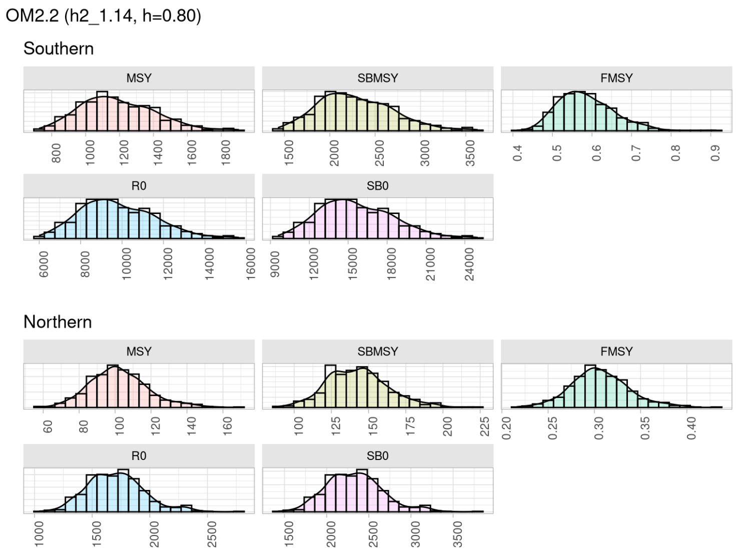

Figure 24: Sample distributions and kernel densities of reference point values for OM 2.2 (h2_1.14, h=0.80), and for the Southern and North stocks.

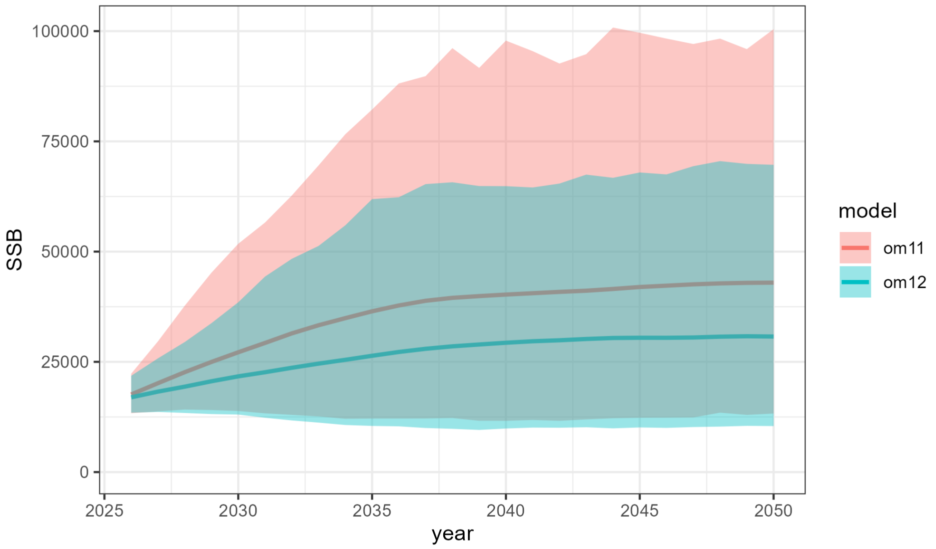

Figure 25: Projections at F=0 for the one-stock hypothesis (h=0.65 for OM1.1 and h=0.80 for OM1.2).

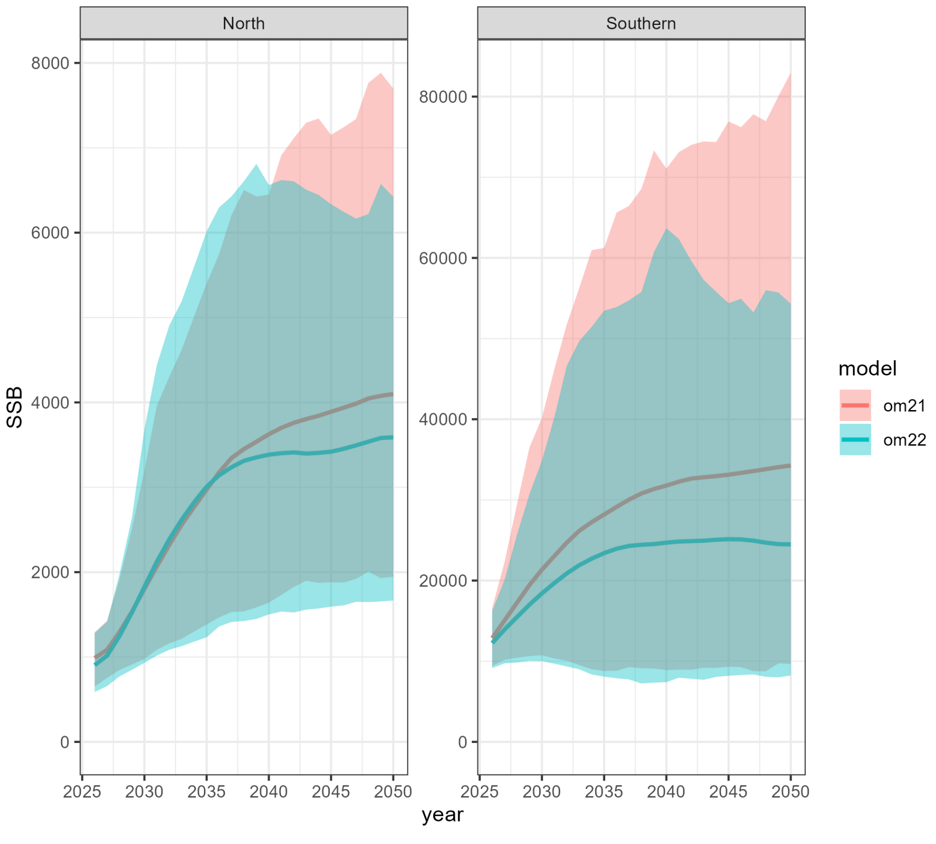

Figure 26: Projections at F=0 for the two-stock hypothesis (h=0.65 for OM2.1 and h=0.80 for OM2.2).

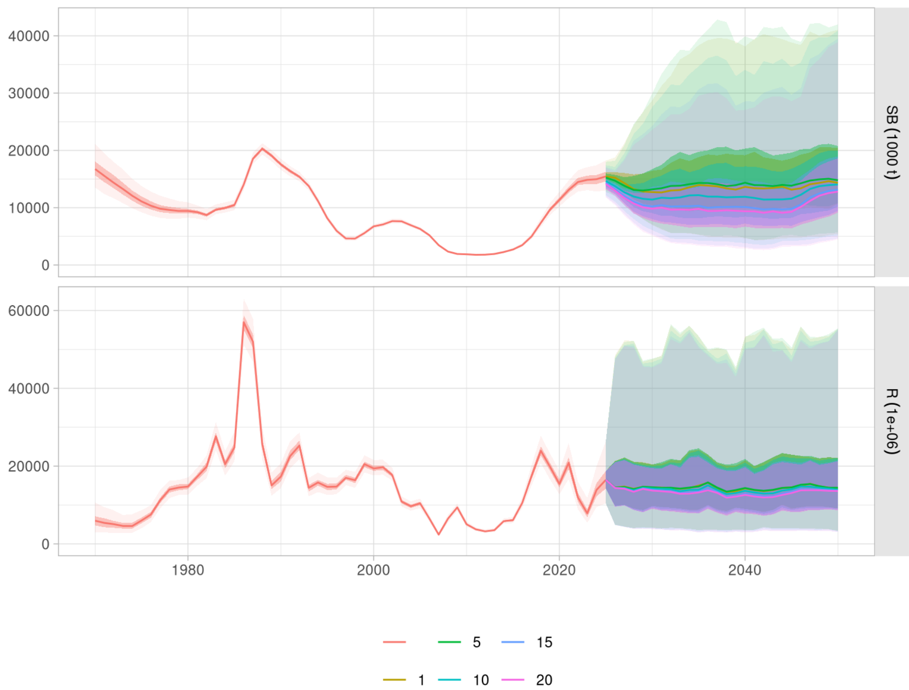

Figure 27: Forecasts for OM 1.1 (h1_1.14, h=0.65) under a fishing mortality equal to F_{MSY} and alternative future selectivity patterns. Future selectivity patterns following the transition period (2026-2032) are defined by averaging selectivity over different numbers of recent historical years.

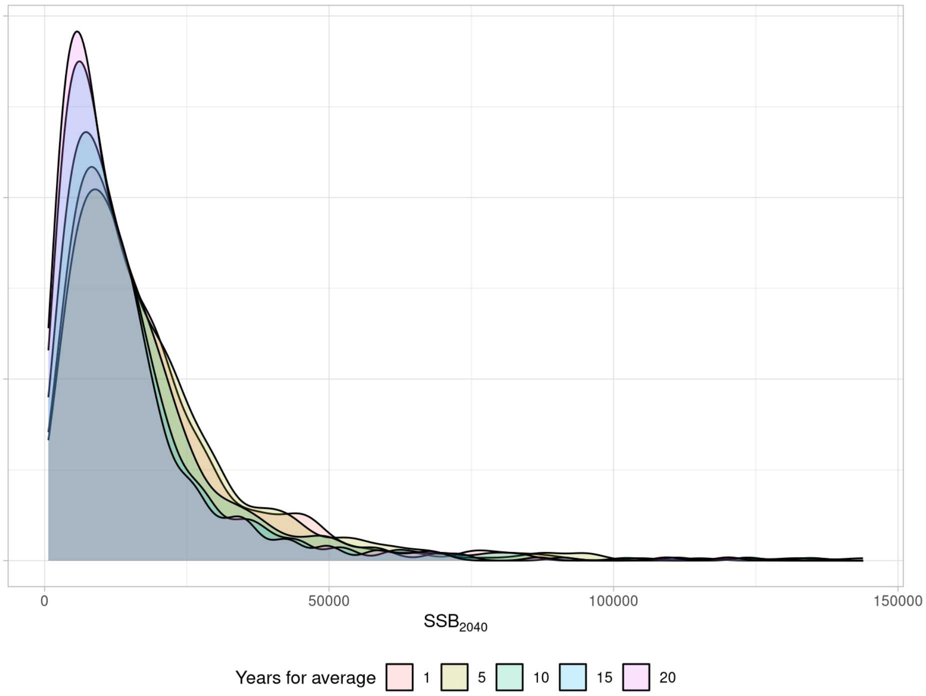

Figure 28: Distribution of spawning stock biomass (SSB) values in 2040 after 15 years of projection under alternative future selectivity patterns for OM 1.1 (h1_1.14, h=0.65) and a fishing mortality equal to F_{MSY}. Future selectivity patterns are defined by averaging fishery-specific selectivity over different numbers of recent historical years.

Summary and recommendations

This document presents the current conditioning framework for the operating model (OM) grid intended to support future management strategy evaluation (MSE) analyses for the CJM stock. The analyses and assumptions presented here should be considered open in light of the progress and discussion to be held during the benchmark process. Further refinement of the OM grid will depend on future input, feedback, and decisions from the group. The code developed to condition the OMs through the NUTS sampler, load the result, generate the corresponding FLR objects, and set the various options on future dynamics, has been made more flexible and will allow a final OM grid to be created rapidly after the benchmark meeting.

The current OM framework explores several important sources of uncertainty, including alternative stock hypotheses, stock–recruitment relationship (SRR) assumptions, fishing selectivity patterns, observation error processes, and biological reference points. Stock structure is the essential uncertainty to be considered when assessing management procedures for this stock. Alternative stock-recruitment relationship assumptions are also critical to explore, given their strong influence on projected stock trajectories and rebuilding potential. Scenarios on recruitment variability and their environmental drivers, such as ENSO, should also be explored to further expand the range of recruitment dynamics represented in the OMs. An agreed ENSO robustness test will form an important part of the OM set.

Fishing selectivity is another important source of uncertainty that can substantially influence the result of future projections, both directly and through its relationship with reference points employed to evaluate performance.

The analysis of survey index performance suggest differing abilities among indices to track stock dynamics. In particular, the North Chile Acoustic index shows weak tracking performance relative to other indices. This is unfortunate given than it is the only current fishery-independent index. But the potential effects of various unaccounted-for factors in the ability of this index to track the population, the relatively narrow range of ages it covers, anf the large impact it has on both assessment and OM conditioning results, suggest that some consideration should be given to strategies to incorporate this source of uncertainty. On the OM conditioning step, scenarios not including or that allow larger variance in its likelihood contribution could be explored. On the MSE step, MPs including multiple indices could provide a more robust performance.

The following areas are proposed for further exploration and discussion during the benchmark so that they can be agreed upon for the upcoming OM conditioning process:

- Consider the need for further exploration of SR uncertainty, by defining an aghreed range of recruitment scenarios that consider the potential effects of environmental drivers, such as ENSO, on recruitment dynamics, and possible low recruitment robustness tests.
- Include a wide investigation of fishing selectivity assumptions, including alternative model runs and the use of different historical periods to define future selectivity patterns.
- Incorporate to the OM grid robustness models that include different levels of reliability to different indices of abundance, particularly to the Chile Acoustic North index, given its influence on the perception of current stock status.
- Develop a final set of ENSO-related scenarios, including potential effects on growth, natural mortality, maturity, selectivity, and recruitment processes

Despite the obvious limitations on time, some level of interactivity should still be available so that a final set of OM scenarios can be assembled, tested and refined following the benchmark process, so that the final operating model set adequately captures the key uncertainties relevant to future management evaluations.

References

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