An update of the IPHC Secretariat MSE Program of Work for 2026-2028

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***Outcome sought**: DISCUSS the updated MSE framework and operating model for 2026 and preliminary outcomes; provide further DIRECTION to the Secretariat for specific management procedures and scenarios to evaluate.*

PURPOSE

To provide the IPHC's Scientific Review Board with a response to recommendations and requests made during SRB028 (IPHC-2026-SRB028-R) and an update on progress of the Management Strategy Evaluation (MSE) Program of Work for 2026, including methods used for projections and preliminary results from the updated MSE framework.

1 INTRODUCTION

The International Pacific Halibut Commission (IPHC) adopted the IPHC Harvest Strategy Policy (HSP) at the 101st Session of the IPHC Interim Meeting (IM101; IPHC-2025-IM101-R, para. 25) and requested a number of items to be added to the MSE Program of Work for 2026 (IPHC-2025-IM101-R, para. 26). The Commission noted priority items for the 2026 MSE Program of Work at the 102nd Session of the IPHC Annual Meeting (AM102):

> **IPHC-2026-AM102-R, para. 56**: *The Commission **NOTED** that the 2026 MSE and HSP Program of Work will include the following high priority topics:*
>
> *a) Update and recondition the MSE Operating Model in accordance with the schedule defined in the Harvest Strategy Policy;*
> *b) Evaluate a range of SPR values to determine if the optimal reference coastwide fishing intensity is different than the current reference fishing intensity (F43%) defined in the HSP;*
> *c) Investigate productivity regimes to determine how the Pacific halibut population and fisheries respond to different productivity regimes, if the optimal reference fishing intensity differs across productivity regimes, and how productivity regimes may be incorporated into a Management Procedure;*
> *d) Further develop the Depleted concept and identify a limit reference point below which recovery of the Pacific halibut population would be uncertain.*

Furthermore, the SRB reviewed 2025 MSE results and the initial conditioning of the 2026 operating model (OM) at the 28th Session of the SRB (SRB028). The following requests and recommendations were made:

> **IPHC-2026-SRB028-R, para 27 (SRB028–Rec.01):** *The SRB **NOTED** that a single control rule based on relative biomass is unlikely to reach the ramp (descending limb) where reduction in F are triggered. Therefore, the SRB **RECOMMENDED** investigating HCRs based on absolute biomass.*

IPHC-2026-SRB028-R, para 23 (SRB028–Req.05): *The SRB **REQUESTED** that the Secretariat investigate, via the MSE, control rules based on changes to the risk of overfishing (often referred to as p*, see Shertzer et al. 2008).*

IPHC-2026-SRB028-R, para 25 (SRB028–Req.06): ***RECALLING** that at SRB026, the SRB made the following recommendation,*

> *IPHC-2025-SRB026-R, SRB026–Rec.07 (para. 24) "The SRB **RECOMMENDED** that recruitment projections in the stock assessment and Management Strategy Evaluation (MSE) incorporate a random-walk starting from the most recent reliable recruitment estimate to constrain expected short-term recruitment around recent estimates rather than immediately reverting to the stock-recruitment relationship."*

*and **NOTING** the update provided by the Secretariat at SRB028, the SRB **REQUESTED** an analysis of projecting recruitment via projections in environmental drivers (Pacific Decadal Oscillation) in addition to autocorrelated recruitment, which tends to rapidly revert to the mean.*

This paper presents an update on progress for the Commission's high priority topics and the SRB028 recommendations and requests. Each section below represents a high priority topic and responses to the SRB are presented accordingly within each section.

2 Condition the Operating Model and update the MSE framework

The MSE framework consists of the operating model (OM) conditioned to past observations and estimates, the operating model projecting forward in time, the variability associated with the historical conditioning and the future projections, the integration of the management procedure (MP), and the process for running simulations. The OM was conditioned to recent observations and the 2025 stock assessment, the process to project future variability in weight-at-age and recruitment was revised, and the code to run simulations made more efficient.

The MSE operating model (OM) consists of four individual models based on the four models in the stock assessment ensemble, which includes new updates made during the full stock assessment in 2025. The models in the stock assessment ensemble are an areas-as-fleets (AAF) long time-series model (longAAF), an AAF using a short time-series starting in 1992 (shortAAF), a coastwide (CW) long time-series model (longCW), and a CW short time-series model (shortCW). Recent updates to the stock assessment that were incorporated into the MSE OM included updating the time-series information for the Pacific Decadal Oscillation, re-tuned recruitment variability, and an updated maturity ogive to reflect the recent histology-based estimates produced by the IPHC's Biological and Ecosystem Sciences Branch.

Each individual model in the MSE OM begins in 1952 to avoid technical challenges associated with highly uncertain but low spawning biomass and population dynamics bottlenecks in the 1920s and 1930s. This later start date, however, still captures important historical changes in the Pacific halibut stock. The parameters and assumptions from each stock assessment model were used to initialize the associated individual regional MSE model while unfished equilibrium recruitment, movement, and recruitment distribution parameters were estimated during the conditioning process to best fit the estimated spawning biomass from the associated assessment model, the stock distribution estimated from the FISS, and the age compositions estimated from the FISS. Variability was added by sampling from the multivariate normal distribution of parameters to produce 125 individual trajectories for each of the four models. The MSE OM integrates over these four models to include parameter and structural uncertainty. Details of the conditioning are provided in IPHC-2026-SRB028-08 Rev_1.

The median integrated spawning biomass for the 2026 MSE OM along with 5th and 95th percentiles are shown in Figure 1. The estimated spawning biomass from the ensemble stock assessment, shown in blue for comparison, is similar when comparing the medians but has less variability for most of the time-series. The MSE OM is designed to represent additional uncertainties to ensure that the best performing management procedures (MPs) are robust to many sources of uncertainty.

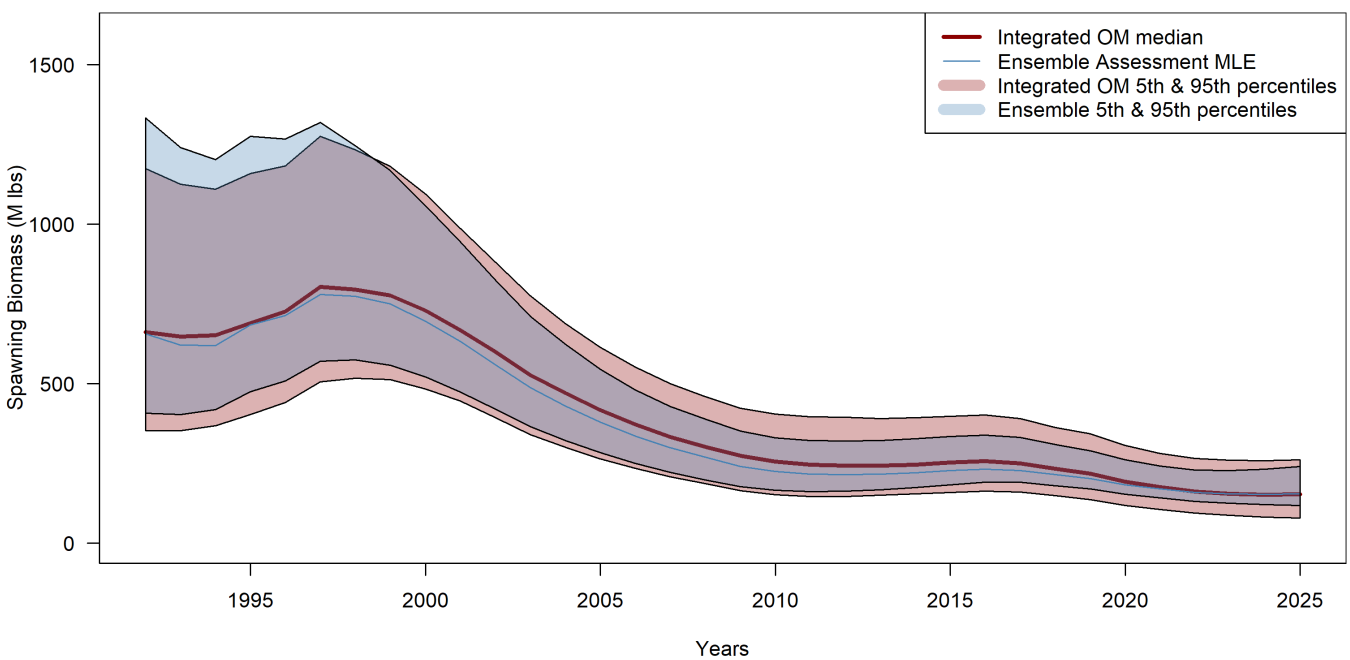

Figure 1. Integrated conditioned spawning biomass for the MSE Operating Model in 2026. The red line shows the median and the red polygon encompasses the 5th and 95th percentiles of the 500 simulated trajectories integrated over the four individual models. The blue line and polygon show the median and 5th and 95th percentiles from the stock assessment ensemble for comparison.

2.1 Projections with the MSE framework

An additional component of conditioning the OM is to simulate variability into the future. Each individual trajectory characterizes parameter and structural uncertainty in the OM, and variability is also simulated for future weight-at-age, recruitment, and fishery selectivity. Along with fishing mortality, weight-at-age and recruitment are the biggest factors influencing the biomass of the stock in the past and the future.

2.1.1 Weight-at-age projections

A new analysis of weight-at-age was conducted that provided insight into some of the factors influencing weight-at-age. Using modern random effects models (Cheng et al. 2023) year, age, and cohort effects were examined. The models incorporating cohort effects did not perform well because estimates of mean weight-at-age for older fish were often much greater than expected and additional work by the Secretariat is needed for their development. However, simply including year and age effects, as described by Xu et al. (2019), can serve as a proxy for cohort specific differences in weight-at-age (Figure 2). Additional research to specifically incorporate cohort effects will continue as time allows.

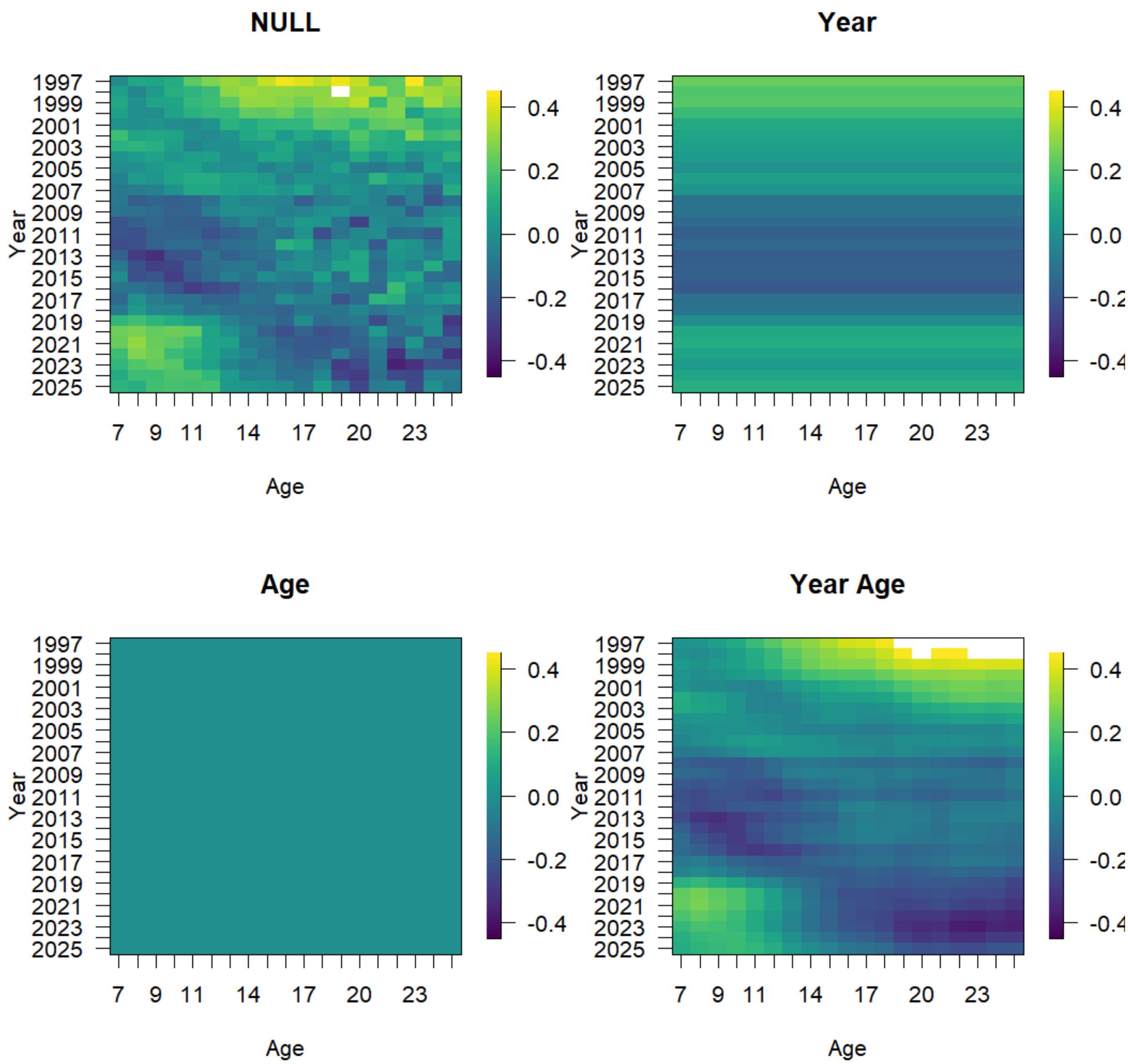

Figure 2. Models with estimated year and age effects for coastwide female Pacific halibut weight-at-age showing deviations from an overall mean weight at each age. The NULL model estimates a deviation for each year/age combination as a random effect. Blue colours indicate low weight-at-age and yellow colours indicate high weight-at-age. White regions are outside of the range indicated by the scale. Consistent coloration along a diagonal suggests that a cohort experienced similar low or high weight-at-age across its lifetime.

The model used to predict weight-at-age is a state-space model written in RTMB (Kristensen et al. 2016) and estimates a global mean weight-at-age (μ_a) and year and age deviations ($\varepsilon_{a,y}$) from those global means in the process model.

$$W_{a,y} = e^{\ln(\mu_a)+\varepsilon_{a,y}}$$

where *a* is age, *y* is year, and $\varepsilon_{a,y}$ is a matrix of age and year deviations simulated as a two-dimensional (2D) AR(1) process:

$$\boldsymbol{\varepsilon} \sim MVN(0, \sigma_\varepsilon^2 \boldsymbol{\Sigma})$$

The correlation matrix ($\boldsymbol{\Sigma}$) is equal to the Kronecker product ($\otimes$) of the two correlation matrices representing among-age and among-year AR(1) processes:

$$\boldsymbol{\Sigma} = \boldsymbol{R}_{a,a'} \otimes \boldsymbol{R}_{y,y'}$$

$$[\boldsymbol{R_a}]_{a,a'} = \rho_a^{|a-a'|}$$

$$[\boldsymbol{R_y}]_{y,y'} = \rho_y^{|y-y'|}$$

Therefore, $\boldsymbol{\Sigma}$ is a matrix of dimensions $n_y n_a \times n_y n_a$ where each element of the $n_y \times n_y$ block matrix is an $n_a \times n_a$ age matrix scaled by the corresponding year correlation. The inverse of the correlation matrices ($\boldsymbol{R}^{-1}$) is defined as a tridiagonal matrix, thus the precision matrix ($\boldsymbol{\Sigma^{-1}}$) is a sparse matrix. RTMB leverages these assumptions to create a fast and efficient random effects model. The marginal process variance of every year-age combination is σ_ε^2 because the AR(1) components are stationary with unit marginal variance.

$$Var(\varepsilon_{a,y}) = \sigma_\varepsilon^2$$

However, the variability of $W_{a,y}$ increases with age because $\varepsilon_{a,y}$ is lognormal.

A parametric process, such as the von Bertalanffy growth equation, was tested but was not used because the weight-at-age for older Pacific halibut is highly variable and nearly linear across all ages modelled (i.e. did not show a strong asymptote, as shown in Figure 3). Other formulations to force monotonically increasing weight-at-age were also tested but also showed poor convergence behaviour, sensitivity to starting values, and large departures from some observed median weight-at-age calculated across years. Therefore, the overall log mean weight-at-age was estimated freely for each age class.

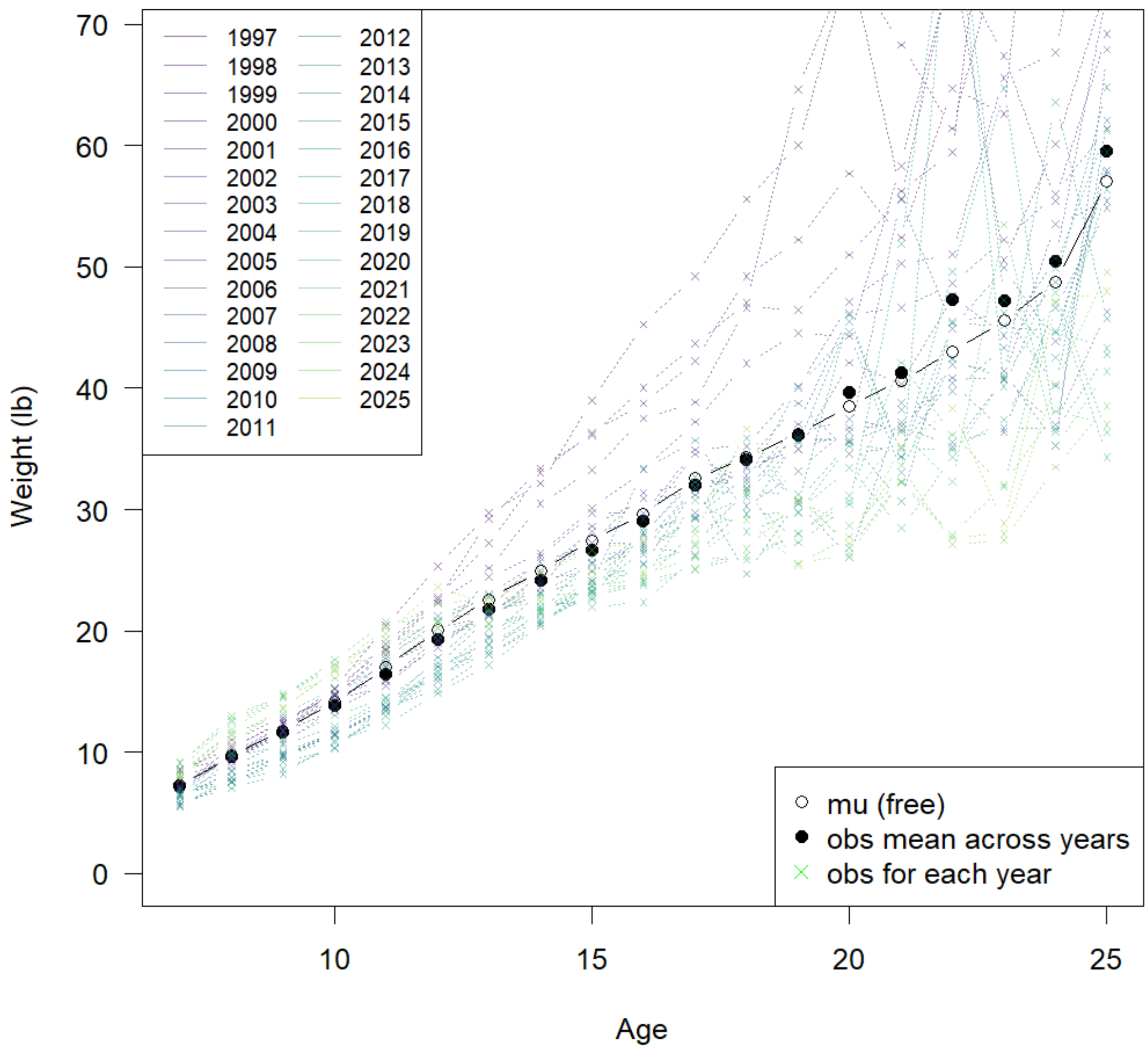

Figure 3. Observed female weight-at-age from coastwide FISS samples for each year from 1997–2025 (x's and dotted lines) with the observed mean across all years (black points). Estimated mean weight-at-age from which year and age effects apply are shown as open circles.

The observation model relates the observed mean weight-at-age to the unobserved mean weight-at-age from the process model.

$$\widehat{W}_{a,y} = W_{a,y} + e^{\tau_{a,y}}$$

$$\tau_{a,y} \sim N(0, \sigma^2_{\tau,a,y})$$

Parameters estimated included the log of the overall mean weight-at-age, the correlation for age, the correlation for year, and the variance of $\varepsilon_{a,y}$ (Table 1). Initial tests determined that also estimating the observation variance ($\sigma^2_{\tau,a,y}$) was not feasible, even if assuming it was constant across years, thus was determined from bootstrapping individual observations for each age and year and calculating the variance of the mean weight-at-age for each year.

Table 1. Estimated parameters and transformations used for the weight-at-age models.

Estimated Parameter	Model Transformation
$\ln(\mu_a)$	$\mu_a = e^{\ln(\mu_a)}$
$\ln(\sigma_\varepsilon^2)$	$\sigma_\varepsilon^2 = e^{\ln(\sigma_\varepsilon^2)}$
θ_a	$\rho_a = \text{logit}^{-1}(\theta_a) = \frac{1}{1+e^{-\theta_a}}$
θ_y	$\rho_y = \text{logit}^{-1}(\theta_y) = \frac{1}{1+e^{-\theta_y}}$

Seven (7) different models were fit to observations from the IPHC Fishery-Independent Setline Survey for the years 1997–2025 because that was a complete and consistent dataset that included individual observations from which to calculate observation error. Observations less than 7 years old were limited due to selectivity of the gear and observations older than 25 were sparse, therefore only ages 7 through 25 were used. Likelihoods and AIC from the seven (7) different model specifications, incorporating age, year, and cohort effects, were determined for model selection. As noted previously, the models with cohort effects, using a different estimation routine, did not perform well due to unexpectedly high estimated mean weight-at-age for older fish, thus were rejected due to uncertainty in producing consistent and reasonable results for forward projections. The AIC for each of four models incorporating year and/or age effects and using all sex-specific data coastwide or sex-specific data only within one of the four Biological Regions was always lowest for the model with both year and age effects (Table 2).

Year and age were important effects to predict weight-at-age, which suggests that fish in the same cohort experience a similar trajectory of weight-at-age being below or above average over their lifetime, with some variability (Figure 2). The NULL model (no year or age effects but estimating deviations for each year/age combination as a random effect) shows patterns in low and high weight-at-age, which are diagonal indicating that a deviation from average weight-at-age is apparent when the cohort is young and has not experienced much fishing pressure, and tends to remain through the life of a cohort. The NULL model is useful to understand these patterns, but is not useful to project weight-at-age into the future, which is the goal for the MSE. Year-effects alone showed changes in weight-at-age over time, but could not explain these cohort specific deviations. Age-effects alone explained very little variation in weight-at-age because the majority of the variation across age is explained by the estimated mean weight-at-age parameters. However, estimating year- and age-effects together was able to explain much of the cohort patterns apparent in the NULL model. It is uncertain if a cohort-effect may improve model.

The estimated relationships in the random effects model were used to simulate weight-at-age in the future with variability, which was the goal of this analysis for the MSE. The following objectives were used to tune the projections: 1) simulate weight-at-age covering the entire range of observed weight-at-age from 1950 to 2025, 2) mimic slow changes in weight-at-age over decadal time-scales, 3) implement a slow increase in weight-at-age from current conditions, 4) have the median of the simulated weight-at-age 70 years in the future be approaching the median observed weight-at-age from 1950 to 2025, and 5) simulate mean weight for ages 1 to 30. To achieve these objectives, the estimated parameters for the mean weight-at-age, the process error, and the correlation across years were adjusted because the analysis was based on the years 1997 to 2025 which showed a reduced range of weight-at-age relative to the longer time-series (for which individual observations are not available). Future analyses could be improved by incorporating all the data, which would require stitching summarized datasets together and determining observation error for all years. For most historical years, individual observations are not available, which will make determining the appropriate level of observation error to use challenging.

Table 2. AIC for sex-specific models with different combinations of year and age effects using coastwide data and region-specific data. The NULL model estimates a deviation for each year/age combination as independent random effects. The lowest AIC is shown in italics.

Model	**Coastwide**		**Region 2**		**Region 3**		**Region 4**		**Region 4B**	
	F	**M**	**F**	**M**	**F**	**M**	**F**	**M**	**F**	**M**
No year or age (NULL)	-177	-464	-398	-528	128	-345	-38	-211	-169	-421
Year	842	-749	-150	-794	1179	-979	4	-750	54	-810
Age	5051	6003	1020	649	3661	3449	1788	1962	913	1294
Year & Age	*-1133*	*-1795*	*-958*	*-1200*	*-556*	*-1510*	*-719*	*-1157*	*-351*	*-1118*

Projections for one-hundred (100) years were completed for each sex/region/fleet combination. First, the medians of the mean weight-at-age for ages 1 to 30 were determined using observations from all years (1950–2025) and stitched together from multiple data sources (as used in the stock assessment). The medians were then lightly smoothed across ages to reduce the variability in the median weight-at-age seen at older age classes due to the paucity of observations. The median was used to provide a central point of the extended time-series to project deviations from and avoid influence from unbalanced low and high periods. Sigma was increased using a multiplier to allow coverage over the range of historical observed weight-at-age. The year correlation parameter was increased to 0.98 to produce a slow increase, decadal oscillations, and a median that approaches the central point after approximately 70 years of projections. The first deviation to begin the process was calculated from the difference between the 2025 and 2024 observed weights-at-age (in natural log scale). The minimum and maximum projected weight-at-age was bounded by 5% beyond the minimum and at the maximum observed weight-at-age observed over the entire time-series. The same seed for the standard normal deviations was used so that each fleet and sex showed consistent increases and decreases across time, but at different magnitudes.

Tuning these parameters was done ad hoc after looking at summaries of the trajectories for different fleets and sexes. The objectives were challenging to meet for all ages and fleets, and projections tended to show a smaller median weight-at-age than observed values over the full time-series. An example for population weight-at-age for females in region 2 is shown in Figure

4. The Secretariat determined these to be reasonable, especially given the priority of the Commission to consider current conditions for managing Pacific halibut. Figure 5 shows three examples of simulated weight-at-age and how they compare to historical weight-at-age. The main objective was to capture the oscillations in weight-at-age over decadal time scales.

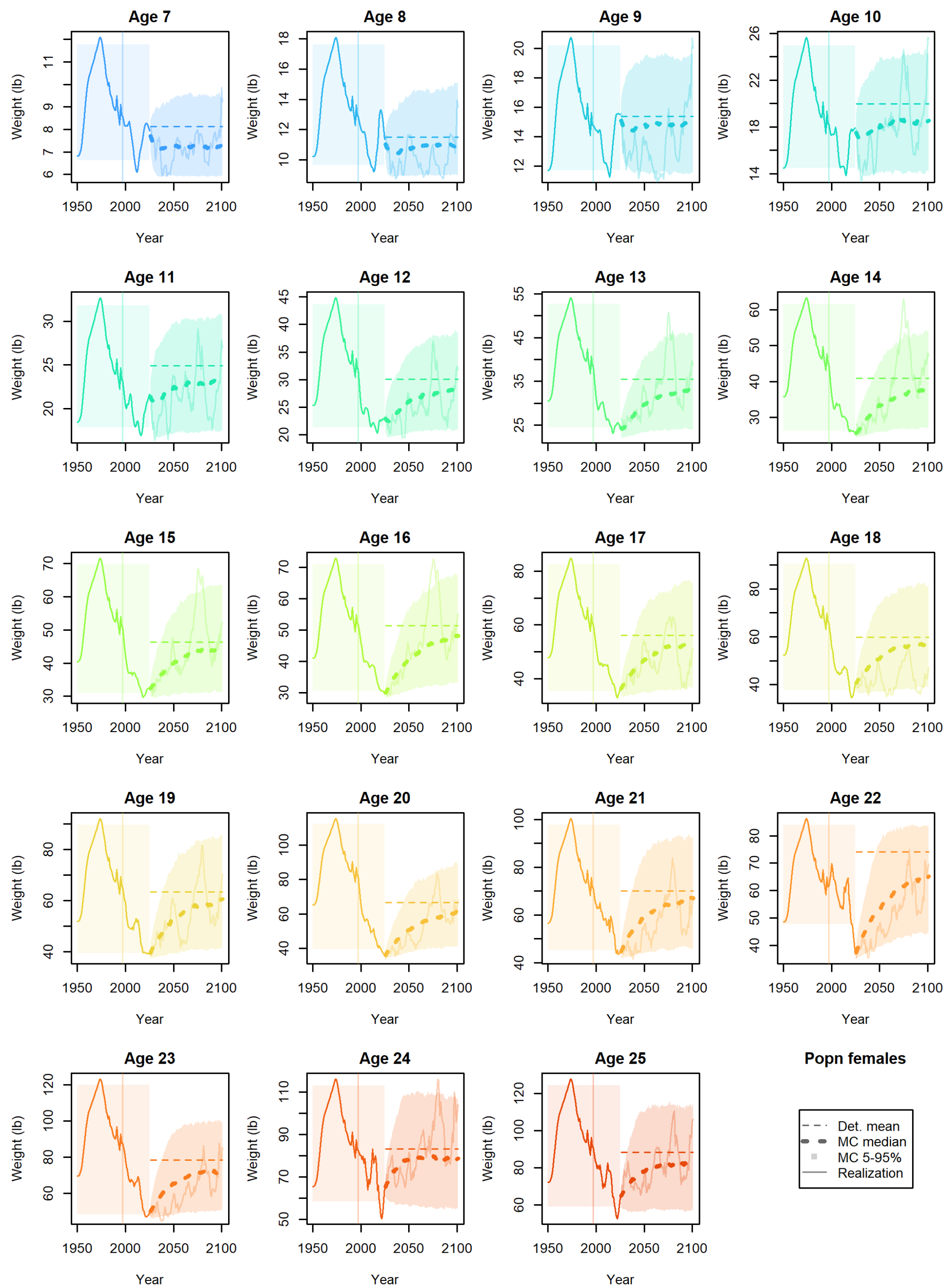

Figure 4. Historical mean weight-at-age with a shaded region between the 5th and 95th percentiles calculated across the years 1950–2025, and the median projected weight-at-age with a shaded region between the 5th and 95th percentiles calculated for each projected year (2026–2125) using 1000 simulations. The thin dashed line is the median of the historical period. One example projection realization is shown as a light line in the projection period.

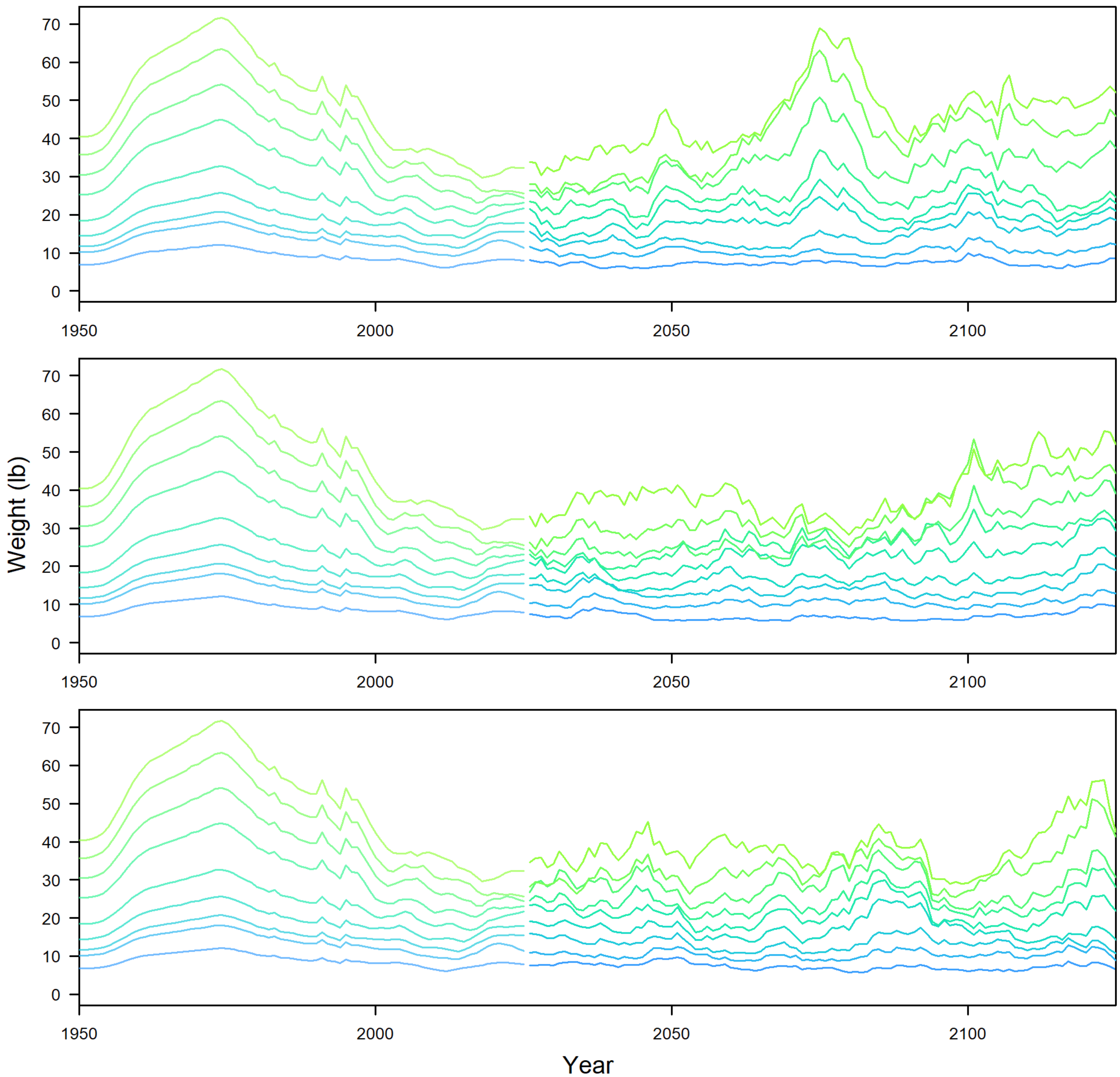

Figure 5. Historical weight-at-age and three examples of simulated weight-at-age for female Pacific halibut in Region 2 for ages 7 to 15 using a random effects model with year and age effects. The break in the time-series between 2025 and 2026 represents the transition from estimated to simulated trends.

2.1.2 Recruitment projections

Recruitment was simulated into the future with annual random deviations representing a departure from average recruitment determined from the stock-recruit relationship. Average recruitment is dependent on the PDO regime, where high average recruitment occurred in high PDO regimes, and low average recruitment occurred in low PDO regimes. The difference in average recruitment between the two regimes was determined from the stock assessment models where high average recruitment was about 1.5 times greater than low average recruitment.

The PDO regime was simulated as high or low with a typical period of 10-20 years before switching to the opposite regime. This was done by modelling a probability of switching to the opposite regime which increases, following a logistic curve, as the length of the current regime (i.e. run) increases.

$$P(\text{switch}) = \frac{1 - y_{\text{int}}}{1 + e^{-k(\text{run} - y_{\text{mid}})}} + y_{\text{int}}$$

where y_{int} is the probability when the length of the run is zero, k controls the steepness of the curve, and y_{mid} is the run length at which the probability of switching is halfway between y_{int} and 1. The values for y_{int}, y_{mid}, and k were 0, 0.2, and 20, respectively, resulting in the curve shown in Figure 6. The proportion positive, determined from 125 simulated trajectories, begins at 0 in 2026 because monthly PDO values have been negative in 2026, and increases from 0.5 in 2027 to nearly 1 in 2030 because the probabilities of switching from the current negative regime to positive in 2027, 2028, and 2029 are fixed at 0.5, 0.7, and 0.8, respectively, to encourage a more gradual switch to a positive PDO in the near-term (Figure 7). Without this constraint, following the 28 year period of low PDO values there would be a very rapid projection of switching regimes, leading to an immediate disconnect with current conditions. Years beyond 2029 show a decline in the proportion of positive PDOs that oscillates around 0.5 and dampens quickly.

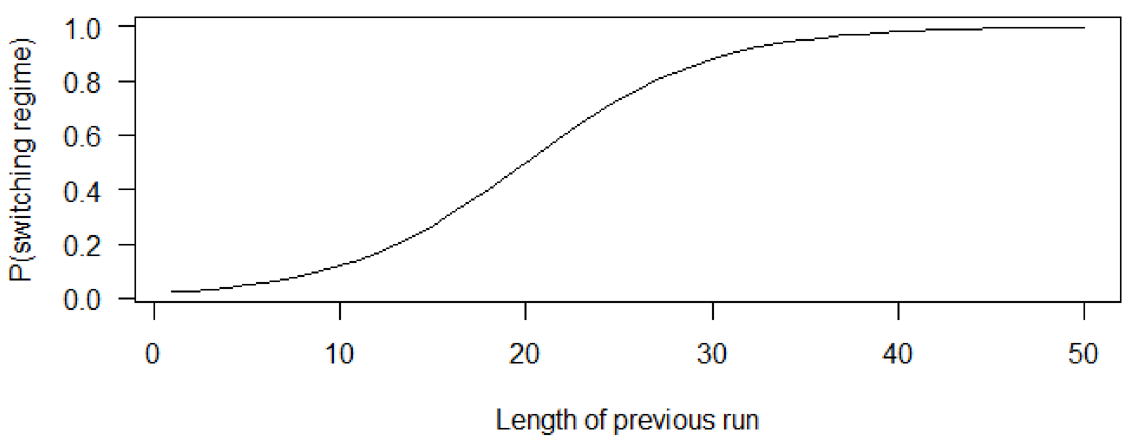

Figure 6. Modelled probability of switching the PDO regime based on the length of the current PDO regime in the simulations.

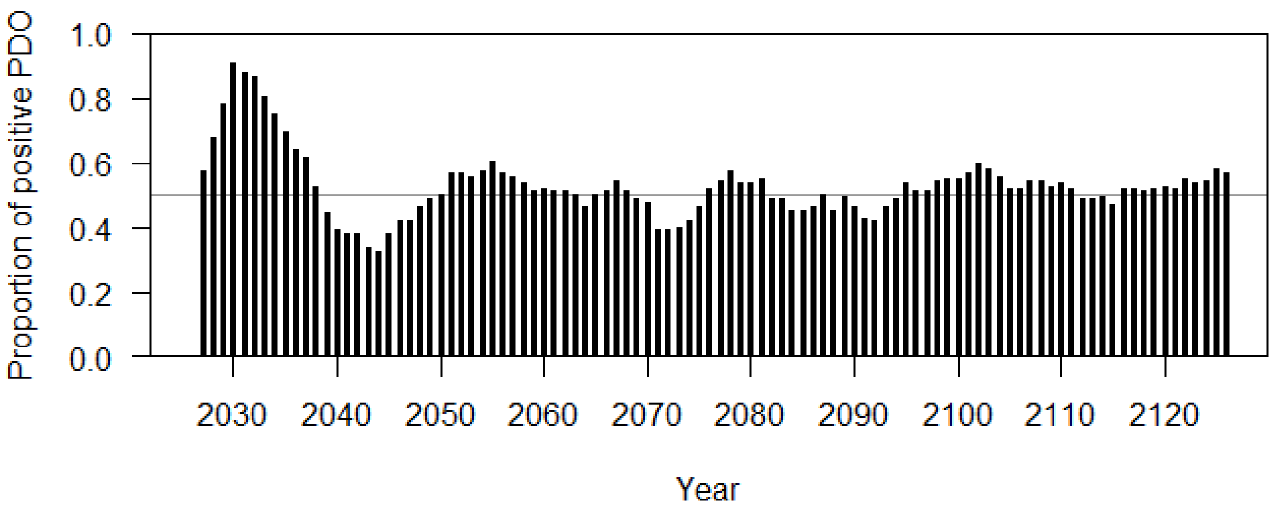

Figure 7. The proportion of simulated positive PDO values by year over 125 realizations. The year 2026 is set to zero because Monthly PDO values in 2026 has been negative. The PDO values for 2027, 2028, and 2029 have specified probabilities of being positive equal to 0.5, 0.7, and 0.8, respectively. Other years use the length of the previous run (**Figure 6)** to determine the probability of switching.

This semi-Markovian approach to simulating the PDO into the future was used because the goal was not to predict the specific future PDO transitions, but to integrate over runs of negative and positive PDO in the projections. In response to **SRB028-Req.06**, the Secretariat implemented the above method with ad hoc fixed probabilities in the first four years of the simulations to slowly move out of the current negative PDO regime. There was a small amount of evidence of autocorrelated recruitment from previous investigations, which had minor effects on the MSE results. However, instead of autocorrelated recruitment, the new MSE simulations implement this slower transition to a positive PDO regime to reflect the recent period of low mean recruitment. These will affect short-term and medium-term performance metrics from the MSE simulations, while long-term performance metrics will equally integrate over low and high regimes.

Additionally, relating the PDO to environmental variables and predicting regime shifts has been challenging because the PDO represents a combination of processes that span a wide area (Newman et al. 2016; Qin et al. 2023). It is possible that PDO regime shifts may be predicted from climate models (Newman et al. 2016), although the relationship of the PDO to other environmental variables seems to be changing in recent years (Litzow et al. 2020) and it is unknown if it will remain a good predictor of differences in Pacific halibut mean recruitment in the future.

2.1.3 Projection results

The parameter and structural uncertainty along with the variability in weight-at-age and recruitment results in a considerable amount of uncertainty in the spawning biomass, especially when projected 70 years into the future (Figure 8). This is consistent with the estimated dynamics and past observations of Pacific halibut, and the newly conditioned OM reflects the current understanding of the Pacific halibut stock while also incorporating an appropriate and scientifically based range of variability for the robust evaluation of MPs.

The range of projected spawning biomass is narrower when compared to the simulation results from 2025 (using the previously conditioned OM), which is mostly due to updated methods to simulate weight-at-age and average recruitment (Figure 8). At the beginning of the projections, the median spawning biomass and the median TCEY remain low, representing the persistence of low productivity in the short-term. At the end of the time-series, the median spawning biomass and median TCEY are similar to previous results, but the variability is narrower, representing the improved method to model weight-at-age where extreme high and low weight-at-age (e.g. levels that have been recently experienced) have lower chances of occurring compared to the methods used in 2025. Figure 9 shows that fixing weight-at-age at levels seen in the last five years and keeping the projected PDO in the low regime results in a similar spawning biomass and TCEY levels in short-term projections, but lower levels in the long-term compared to the simulations integrating over those factors. These results highlight the importance of evaluating results for specific weight-at-age and PDO scenarios to understand the effect these have on the outcomes (also see below).

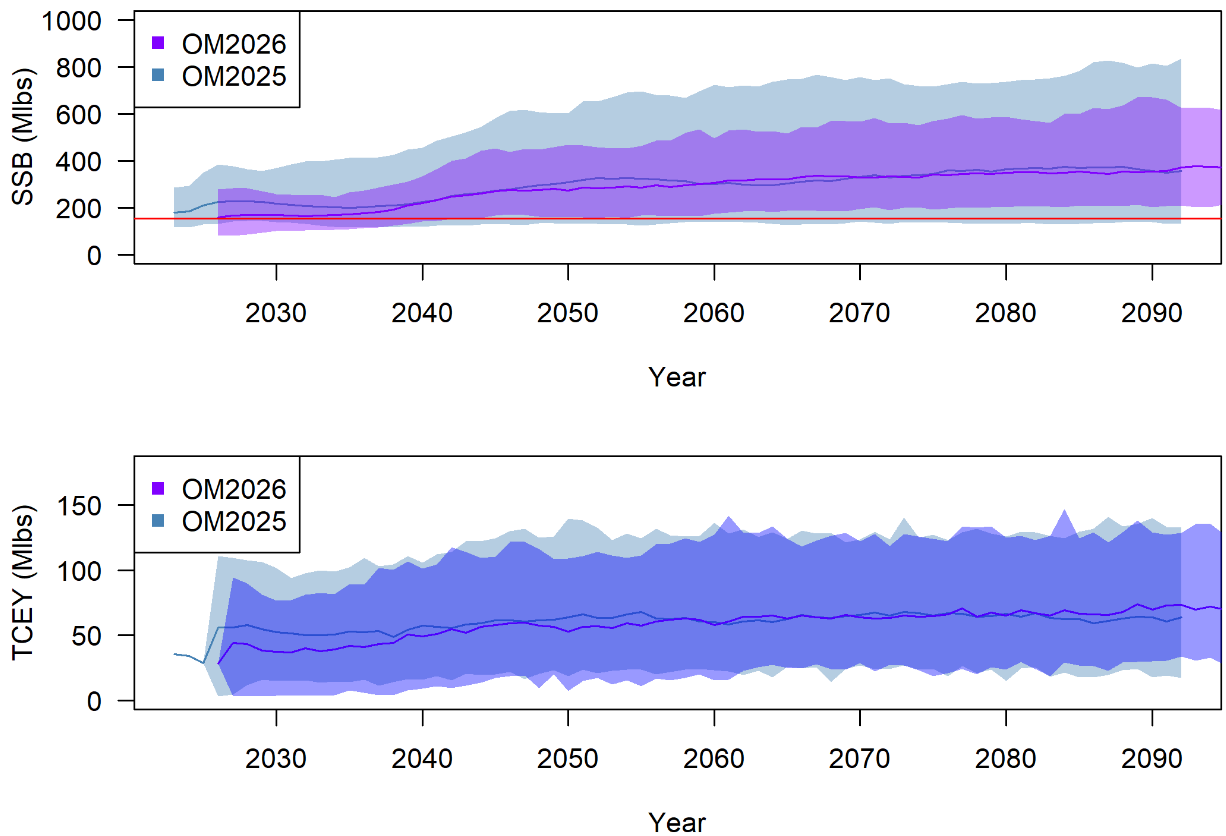

Figure 8. Projected spawning biomass (top) and the corresponding TCEY (bottom) based on harvesting at an SPR of 43%. Simulations include decision-making variability, estimation error, and observation uncertainty. Results using the updated simulation framework for 2026 are shown in purple (OM2026) and the results using the 2025 framework with the same options are shown in blue (OM2025). The red horizontal line is at a spawning biomass of 153 Mlbs to reflect the lowest estimated spawning biomass (2024) from the recent stock assessment.

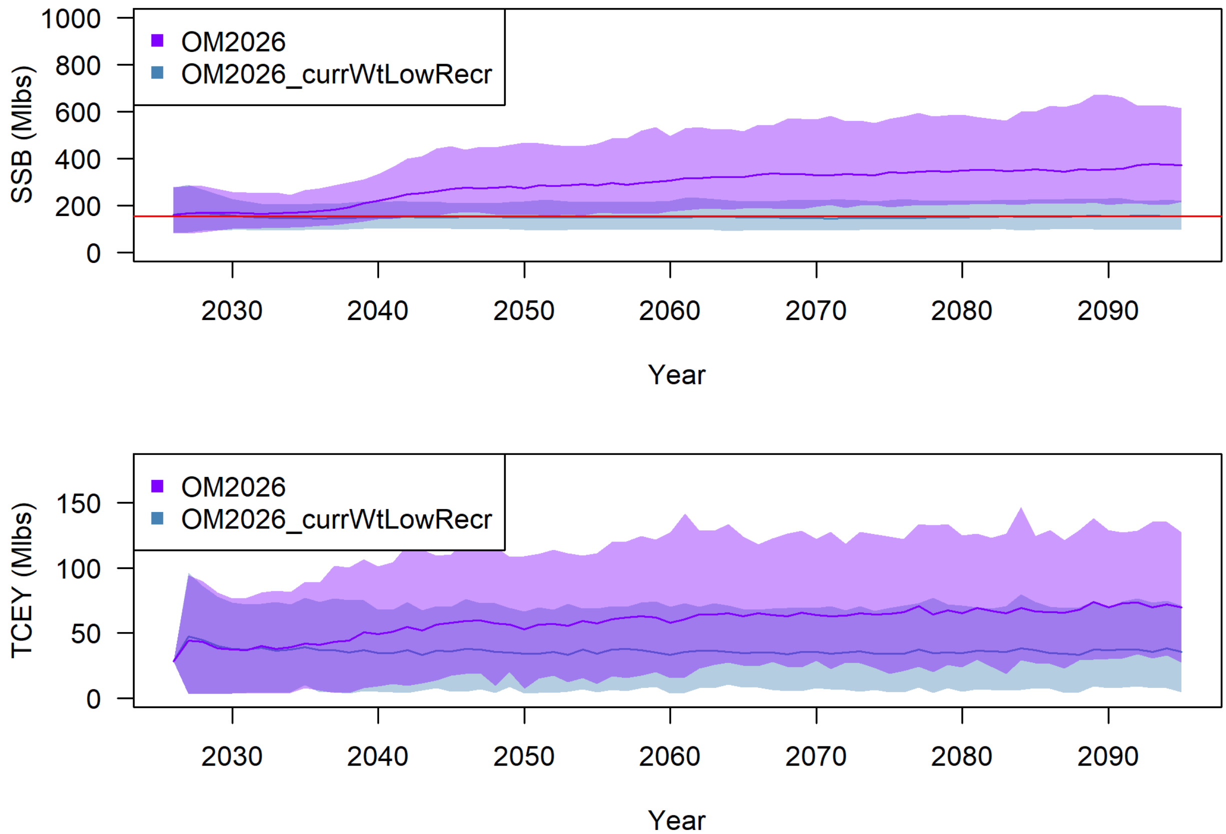

Figure 9. Projected spawning biomass (top) and the corresponding TCEY (bottom) based on harvesting at an SPR of 43%. Simulations include decision-making variability, estimation error, and observation uncertainty. Results using the updated simulation framework for 2026 are shown in purple (OM2026) and the results when fixing weight-at-age at recent levels seen in the last five years and keeping the projected PDO at low values are shown in blue (OM2026_currWtLowRecr). The red horizontal line is at a spawning biomass of 153 Mlbs to reflect the lowest estimated spawning biomass (2024) from the recent stock assessment.

3 EVALUATE A RANGE OF SPR VALUES

Simulations across a range of spawning potential ratio (SPR) values (i.e. different fishing intensities) are currently in progress to determine outcomes that can be evaluated against the Commission's objectives. Although considerable improvements to the simulation code were made to speed up the simulations, this remains a time-consuming process and the full set of results are currently not available. The MSE Explorer (https://apps.iphc.int/MSE-Explorer/) will be updated as results are available and a full report will be provided at IM102.

The Management Strategy Advisory Board (MSAB) made a number of requests related to the investigation of MPs during its recent 22nd Session of the MSAB meeting in May 2026. These included:

IPHC-2026-MSAB022-R, para. 37 (MSAB022–Req.06): *The MSAB **REQUESTED** further evaluations of the following MP elements:*

a) fishing intensities including, but not limited to, SPRs of 40%, 43%, 46%, 49%, 52%, 55%, and 100% (no fishing), as well as no directed fishing (e.g. bycatch only);
b) a triennial assessment frequency with various empirical rules to determine the reference coastwide TCEY in non-assessment years.

IPHC-2026-MSAB022-R, para. 38 (MSAB022–Req.08): *The MSAB **REQUESTED** evaluating constraints and smoothers, along with MP elements listed in para. 37, that would potentially reduce the interannual variability in the TCEY, including:*

a) a 3-year rolling average (arithmetic or geometric) on the FISS O32 WPUE used in the empirical rule in a triennial stock assessment frequency;
b) constraints applied only to non-assessment years and/or applied only to assessment years;
c) a phase-in approach for the change in TCEY in assessment years.

Given preliminary results, the performance metrics associated with the Commission's priority objectives from the 2026 OM show some slight differences when compared to those determined in 2025 for an SPR of 43% (Table 3). The new results show a slightly higher probability of exceeding the 36% relative spawning biomass (RSB) threshold (0.5). The median TCEY is slightly lower and the AAV quite a bit larger. These differences are mostly due to updates in the understanding of Pacific halibut population dynamics (e.g. maturity and natural mortality) and to weight-at-age projections. Additionally, the short-term probability that the spawning biomass is less than the 2023 estimated spawning biomass is greater because the 2026 OM has a more gradual increase away from recent low productivity.

Table 3. Performance metrics from 2025 simulations (OM2025) and new simulations (OM2026) for an SPR value of 43%, comparing a scenario integrating over changes in weight-at-age and cyclical PDO and a recent (i.e. currently low) productivity scenario (i.e. current weight-at-age and negative PDO). A green colour indicates that the performance metric passes and red indicates that it does not, which applies to only the probabilistic long-term objectives.

		Integrated (low & high) Productivity			Recent (low) Productivity	
		OM2025	**OM2026**		**OM2025**	**OM2026**
	SPR (%)	**43**	**43**		**43**	**43**
Long-term	**P(RSB<20%)**	<0.001	<0.001		<0.001	<0.001
	P(RSB<36%)	0.195	0.263		0.462	0.629
Short-term	**Median TCEY**	52.0	42.2		41.2	36.7
	AAV	26.3%	36.2%		28.3%	36.0%
	P(SB < SB_{2023})	0.350	0.578		0.543	0.744

The performance metrics for the 2026 simulations with the newly conditioned OM and updated MSE framework show that when integrating over low and high productivity the long-term spawning biomass objectives are met with any fishing intensity from an SPR of 43% to 52%, and it is likely that higher fishing intensities would also meet these objectives (Table 4). Short-term TCEYs ranged from 35 Mlbs to 42 Mlbs. The AAV ranged from 32% to 36% and decreased most rapidly when changing from an SPR of 43% to an SPR of 46%. The probability that the short-term spawning biomass is less than the 2023 spawning biomass is not a priority objective, but it is reported for reference. This probability was greater than 0.5 for an SPR of 43% and about equal to 0.5 at an SPR of 46%.

The performance metrics showed similar patterns but different values when assuming constant low productivity (Table 4). The objective to remain at or above 36% relative spawning biomass was not met at an SPR of 43%. TCEYs were approximately 4 Mlbs less than when integrating over low and high productivity and the AAVs were similar. The probability that the short-term spawning biomass would be less than the 2023 spawning biomass was greater than 0.5 across all of the SPR values evaluated.

Table 4. Performance metrics from 2026 simulations for SPR values from 43% to 52%, comparing a scenario integrating over changes in weight-at-age and cyclical PDO (top) and a recent (i.e. currently low) productivity scenario (i.e. current weight-at-age and negative PDO; bottom). A green colour indicates that the performance metric passes and red indicates that it does not, which applies to only the probabilistic long-term objectives.

	Integrated (low & high) productivity				
	SPR (%)	**43**	**46**	**49**	**52**
Long-term	**P(RSB<20%)**	<0.001	<0.001	<0.001	<0.001
	P(RSB<36%)	0.263	0.088	0.015	0.001
Short-term	**Median TCEY**	42.2	40.2	37.5	34.8
	AAV	36.2%	33.7%	32.2%	31.9%
	$P(SB < SB_{2023})$	0.578	0.498	0.420	0.350

	Low (current) Productivity				
	SPR (%)	**43**	**46**	**49**	**52**
Long-term	**P(RSB<20%)**	<0.001	<0.001	<0.001	<0.001
	P(RSB<36%)	0.629	0.421	0.219	0.081
Short-term	**Median TCEY**	36.7	34.8	33.0	30.5
	AAV	36.0%	33.4%	33.2%	34.1%
	$P(SB < SB_{2023})$	0.744	0.666	0.610	0.544

3.1 Alternative control rules

SRB recommendation **SRB028-Rec.01** and request **SRB028-Req.05** list control rules based on absolute spawning biomass and the risk of overfishing. With the conditioning of the OM and specification of the MSE framework completed, investigation of these and other elements of management procedures will be increased in priority.

4 INVESTIGATE PRODUCTIVITY REGIMES

Pacific halibut experience variable productivity over time, which is important to capture in the MSE projections. However, it is also useful to examine simulations where productivity is fixed in the future to better understand the importance of environmental influences on important outcomes, such as mortality limits. Six scenarios defined by low, high, and current weight-at-age crossed with low or high PDO (affecting average recruitment, movement, and age-0 distribution) were simulated for comparison to the fully integrated results. The MSAB was also interested in these investigations.

> **IPHC-2026-MSAB022-R, para. 38 (MSAB022–Req.09):** *The MSAB **REQUESTED** conducting simulations assuming the following productivity regimes with a subset of the MPs from paras. 37 and 38 and all other sources of variability:*
>
> *a) low recruitment and low weight-at-age;*
> *b) low recruitment and current weight-at-age (the current perceived productivity regime);*
> *c) high recruitment and low weight-at-age.*

Three levels of weight-at-age were chosen to capture the high and low periods, but to also capture the differences in younger and older age classes during the low periods in recent years (Figure 10). The Low period (2011–2015) captures smaller young fish and larger old fish, while the Current period (2021–2025) captures larger young fish and smaller old fish, when compared to each other. The High period (1971–1975) shows average weight-at-age up to four times greater than in 2025 for the older age classes.

The productivity has a very large effect on the outcomes of the simulations with regard to spawning biomass and mortality limits. The median average long-term TCEY when integrating over all types of productivity and managing with an SPR of 43% was 70 Mlbs. If productivity was to remain as we have seen in the last five years (current weight, low PDO) the median average long-term TCEY managing with an SPR of 43% would be 36 Mlbs. The performance metrics associated with the Commission's priority objectives, including short-term fishery objectives, are less different for the low productivity scenario because the integrated results gradually increase from current conditions (Table 4). Figure 9 shows the projected spawning biomass and projected TCEY when integrating over productivity and when assuming current productivity.

It is important to note that the future is uncertain and productivity will certainly not remain constant, which is why it is integrated into the MSE simulations. Even though what was experienced in the past may not be experienced in the future, the integrated simulations provide a range of possibilities for strategic planning, and the specific scenarios ensure that the evaluation of all candidate management procedures is robust to a wide range of stock conditions.

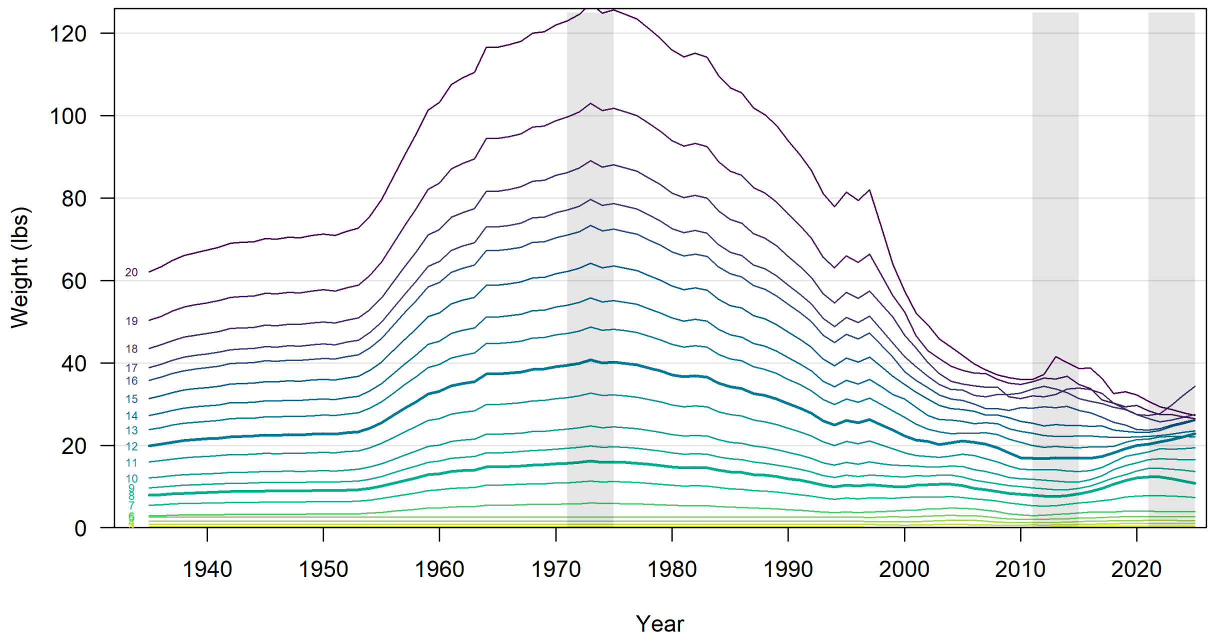

Figure 10. Average historical weight-at-age for Pacific halibut showing three different weight-at-age scenarios defined by the average over 5-year time-periods. High is from 1971–1975, Low is from 2011-2015, and Current is from 2021-2025.

5 Further develop the depleted concept

The IPHC HSP describes two reference points related to spawning biomass:

- **Overfished**: the female dynamic spawning biomass level where the ecological risk to the population and the risk to the health of the fisheries is regarded as unacceptable.
- **Depleted**: the female absolute spawning biomass level below which the potential for recovery is uncertain.

The overfished level is defined as when the estimated probability that coastwide female relative spawning stock biomass is below the limit reference point (RSB20%) is greater than 50%. Depleted does not have a definition and is currently being investigated.

Overfished implies that fishing was the cause of a low biomass state, whereas a depleted condition could be caused by fishing or other factors. Both definitions are important to fisheries management because managers control fishing to avoid precariously low biomass, but the population may be at low biomass for reasons that cannot be controlled by management yet may require management action to increase the chance of recovery. The use of dynamic reference points allows for the separation of fishing effects from other effects on population size, and, a dynamic relative spawning biomass (as currently used by IPHC) is appropriate to determine if the population is overfished. An absolute spawning biomass is appropriate to determine if the population is at a low population state from which recovery could be compromised. Both concepts are shown in Figure 11 with an example level for Depleted shown, as it is not currently defined. Overfished is currently defined as 20% of unfished spawning biomass and changes over time when calculated as an absolute spawning biomass, depending on current stock conditions. Depleted is a constant absolute spawning biomass and varies in terms of relative spawning biomass.

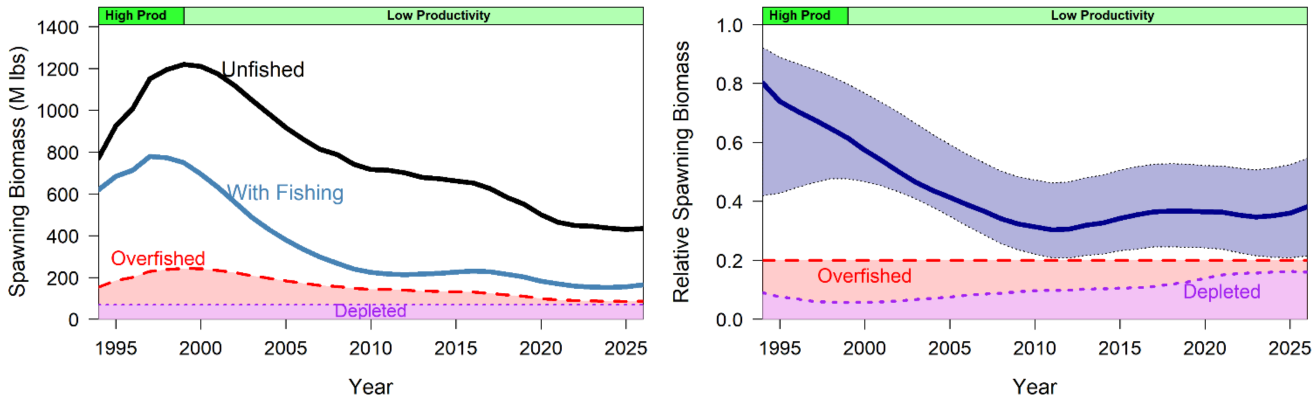

Figure 11. Estimated spawning biomass (left) if fishing had not occurred (unfished) and estimated spawning biomass from the 2025 stock assessment (with fishing). The Overfished threshold of 20% of unfished spawning biomass is shown as a dashed line and changes over time. An example "Depleted" threshold is shown as a straight horizontal line, assuming that it is defined as a constant absolute spawning biomass. The relative spawning biomass ("with fishing" divided by "unfished") is shown on the right with a 95% credible interval (accounting for the covariance in the biomass estimated with and without fishing). The Overfished threshold is shown at 20% and the example Depleted value mapped onto the relative spawning biomass scale is shown in purple.

Absolute spawning biomass is an appropriate measure for a depleted reference point because it directly relates to fecundity (i.e. egg production). The current understanding of Pacific halibut egg production is that it is directly related to body size. For example, a 100-pound mature female Pacific halibut produces four times more eggs than a 25-pound mature female Pacific halibut. Therefore, absolute spawning biomass is a measure of reproductive potential for the stock, and if reproductive potential approaches or drops below a critical level, management response would be warranted. Current research on fecundity by the Secretariat (IPHC-2026-SRB029-05) may suggest using reproductive output instead of spawning biomass to account for potential nonlinear reproductive potential over different sizes of Pacific halibut; it would be an easy switch to account for this but would have important effects on estimated reference points.

The Secretariat has currently identified three possible approaches to identify an appropriate absolute spawning biomass reference point for defining a depleted stock condition.

1. Use the lowest spawning biomass observed in the estimated time series from the stock assessment, which is 153 Mlbs in 2024 according to the 2025 stock assessment. The estimated spawning biomass in the 1970s may have been at similar levels seen in recent years, but recent levels are estimated to be low with much greater certainty due to data available from the IPHC's Fishery Independent Setline Survey (FISS).
2. Use a low spawning biomass level that was associated with a high recruitment event. This could be 215 Mlbs that produced the 2012 year-class, according to the 2025 stock assessment.
3. Use simulation (via the MSE framework) to determine an absolute spawning biomass reference point where the potential for recovery is uncertain based on our scientific understanding of biological and reproductive dynamics. This would involve simulating the Pacific halibut population forward at a high fishing rate for many years under a 'worst-case' scenario (e.g. low weight-at-age, low PDO) and then transition to simulating without fishing. A bifurcation point in the spawning biomass where trajectories either recover or

stabilize and those that continue to decline could indicate an appropriate depleted threshold that accounts for uncertainty.

The Secretariat will continue to work with the SRB to refine these approaches and determine an appropriate depleted reference point.

6 AI ASSISTANCE

The results in this document were prepared with AI assistance. All code and content have been reviewed and verified by A. Hicks. AI contribution: coding assistance. This disclosure is made in accordance with the IPHC's Artificial Intelligence Usage Policy.

7 RECOMMENDATION/S

That the SRB:

a) **NOTE** paper IPHC-2026-SRB029-07 which provides an update on progress for the MSE Program of Work in 2026 and preliminary results from the updated MSE framework.
b) **NOTE** that the MSE operating model (OM) has been reconditioned for 2026 using updated stock assessment inputs and improved weight-at-age and recruitment simulation methods, resulting in a more gradual increase away from current productivity and a narrower range of projected spawning biomass than the 2025 OM.
c) **NOTE** that simulations across a range of SPR values and productivity scenarios are underway and a full report is to be provided at IM102.
d) **NOTE** that productivity has a large effect on long-term projected outcomes.
e) **NOTE** that the Secretariat has identified three candidate approaches for defining an absolute spawning biomass reference point for Depleted and will continue to work with the SRB on this topic.
f) **REQUEST** any management procedures and scenarios to evaluate before IM102, including the outstanding recommendation (**SRB028-Rec.01**) and request (**SRB028-Req.05**) from SRB028.
g) **REQUEST** any analyses to be provided at SRB030.

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