INTER-AMERICAN TROPICAL TUNA COMMISSION

SCIENTIFIC ADVISORY COMMITTEE

17TH MEETING

La Jolla, California (USA)
08-12 June 2026

DOCUMENT SAC-17-05

MANAGEMENT STRATEGY EVALUATION FOR BIGEYE TUNA IN THE EASTERN PACIFIC OCEAN

Haikun Xu and Mark N. Maunder

CONTENTS

SUMMARY

This report presents the results of a Management Strategy Evaluation (MSE) developed to support the adoption of a harvest strategy for bigeye tuna in the eastern Pacific Ocean (EPO). The MSE uses a closed-loop simulation framework to evaluate eight candidate harvest control rules (HCRs) under a wide range of biological, fishery, observation, and implementation uncertainties. These simulations build on the improved scientific foundation provided by the 2024 benchmark stock assessment and risk analysis, which includes an ensemble of thirty-six operating models representing plausible states of nature for bigeye tuna. The objective of the MSE is to quantify how well alternative harvest strategies meet potential management objectives related to safety, status, stability, yield, effort, and abundance.

Across all candidate HCRs, the stock is projected to be rebuilt rapidly in the early years of the simulation. This response reflects both a strong recruitment in 2023 and the reduction in juvenile fishing mortality following the implementation of the individual vessel threshold (IVT) measure to reduce bigeye catches beginning in 2022. All HCRs perform well relative to candidate limit reference points, with near-zero probabilities of breaching the two "hard" limit reference points (7.7%S_0 and 50%S_{MSY}) and low probabilities of falling below the "soft" limit reference point (20%dS_0). Similarly, the probability of remaining in the green Kobe quadrant is high for all HCRs, ranging from about 90% for the less conservative HCRs to about 95% for the more conservative ones.

While performance related to safety objectives is similar across HCRs, differences arise in tradeoffs between fishery utilization and stock conservation objectives. Less conservative HCRs provide higher purse-seine catches and shorter fishery closures but result in slightly lower probabilities of meeting stock status objectives. More conservative HCRs provide improved safety and status outcomes but at the cost of longer closures and lower purse-seine catches. These tradeoffs are central for management decision-making and illustrate the value of the MSE framework in providing transparent, quantitative comparisons across strategy options.

A robustness test examining the staff-proposed (least conservative) HCR under a hypothetical 25% persistent reduction in recruitment regime showed that the harvest strategy remained precautionary, with very low probabilities of breaching candidate limit reference points even under long-term adverse environmental conditions. Nonetheless, several technical limitations, including assumptions about fishing mortality changing linearly with the number of closure days, lack of implementation of longline catch limits in the simulations, constant fishery selectivity, and simplified representation of CPUE uncertainty, highlight areas for continued improvement. Overall, the results demonstrate that all eight candidate HCRs can maintain the bigeye tuna stock at sustainable levels, and the selection among them will depend primarily on policy preferences regarding the balance between conservation performance, catch rate, and fishery yield.

1. INTRODUCTION

The primary objective of fishery management is the sustainable exploitation of fishery resources, ensuring the long-term viability of both fish stocks and of the fisheries and associated human activities that depend on them. Fishery management represents a complex interplay among multiple stakeholders with potentially diverse interests, roles, and objectives. These stakeholders typically include fishers, industry representatives, managers, conservation organizations, members of the public, and fishery scientists. The relative roles and levels of involvement of these stakeholders vary depending on cultural, institutional, financial resources, and historical contexts. Traditionally, fisheries scientists have played a central role in supporting management decision-making by conducting quantitative analyses to inform assessments of stock status and trends, both historical and projected under alternative management scenarios. The provision of scientific advice for fishery management can take many forms, depending on the characteristics of the fishery, its historical development, the availability and quality of data, analytical capacity, financial and human resources, and the prevailing management framework.

The traditional approach to providing management advice has typically relied on a single "best" assessment model that integrates available data (e.g., catches, indices of relative abundance, and size compositions), external estimates of biological processes (e.g. growth), and assumptions regarding parameters (e.g. natural mortality) and structures (e.g. stock/fishery structure) that are difficult or not possible to estimate. This approach has been problematic because assessment outcomes can be sensitive to the changes in data types, analytical methods, or model structure and parameter assumptions. Since assessment outputs are commonly used within a harvest control rule (HCR) that specifies management actions based on estimated stock status relative to estimated reference points, uncertainties and biases in the assessment can propagate into management actions. Additional shortcomings of the traditional approach include limited consideration of mid- to long-term trade-offs (e.g., between exploitation levels and biological risk), a tendency to emphasize short-term management outcomes (e.g., annual total allowable catch or effort limits) rather than the robustness of the decision-making framework itself, a tendency towards minimal management changes under uncertain, and incomplete treatment of uncertainty, which is often restricted to assessment uncertainty alone.

Management strategy evaluation (MSE) is widely recognized as the most robust framework for evaluating trade-offs among alternative harvest strategies while explicitly accounting for multiple sources of uncertainty. Harvest strategies comprise integrated combinations of data inputs, analytical methods, and the HCR that collectively determine management actions, such as catch quotas or seasonal closures. A fundamental distinction between the traditional assessment-based approach and MSE lies in the treatment of uncertainty: whereas the former typically focuses primarily on assessment uncertainty (and sometimes model assumptions), MSE explicitly integrates additional uncertainties, including management implementation, future sampling, and projection uncertainties. Furthermore, MSE evaluates risk through closed-loop simulation that captures the feedback between management actions and system dynamics, thereby differentiating it from conventional stock assessments, which may overestimate risk by failing to consider management responses to future information.

MSE is a simulation-based framework that evaluates candidate harvest strategies using performance indicators linked to explicit management objectives. Importantly, MSE extends beyond pure technical exercise, requiring active engagement of stakeholders in defining objectives, selecting performance indicators, and formulating candidate harvest strategies. While the technical aspects of MSE - such as model development and simulation - are primarily conducted by scientists, effective MSE depends strongly on stakeholder participation. These technical and participatory components should evolve simultaneously to ensure a transparent, credible, and policy-relevant evaluation process. MSE has been widely applied both nationally and internationally, including by all five tuna regional fisheries management organizations

(IATTC, IOTC, WCPFC, ICCAT, and CCSBT), each of which is at a different stage of MSE development and implementation.

An ongoing MSE process for tropical tunas in the eastern Pacific Ocean (EPO) has been initialized, with an initial focus on bigeye tuna (*Thunnus obesus*). This process includes both a dialogue component and a technical component. The MSE dialogue component has involved five IATTC workshops on MSE, organized by the staff and conducted from 2019-2025, aimed at familiarizing stakeholders with MSE concepts and eliciting input on management objectives, performance indicators, and harvest strategies. More recently, the dialogue component was strengthened throughout the establishment of the IATTC *Ad Hoc Working Group to Strengthen the Dialogue among Scientists, Managers and other Stakeholders on MSE,* which has held three WG meetings since May 2025. Since 2025, the MSE technical component has focused on developing and customizing simulation code, conditioning alternative operating models that represent plausible biological and fishery dynamics, and constructing online tools to communicate MSE results and facilitate stakeholder engagement.

This report presents the technical aspects of the MSE for bigeye tuna in the EPO. The second section summarizes bigeye tuna fisheries, current management measures, proposed harvest control rules which have emerged out of the dialogue process, and the performance indicators used to evaluate them. The third section explains the construction of the operating, sampling, and estimation models, the treatment of uncertainty, and the procedures used to simulate management decisions and conduct a robustness test. The fourth section presents the results on the performance of eight candidate harvest control rules across biological, fishery, and stability objectives. The final section highlights key uncertainties in modeling assumptions and data inputs that should be considered when interpretating the MSE results.

2. BACKGROUND

2.1. Fisheries

Bigeye tuna is a tropical tuna species inhabiting tropical and temperate waters of the Pacific, Atlantic, and Indian Oceans (Collette, Reeb et al. 2001). In the EPO, bigeye tuna is exploited by multiple fishing gears, primarily longline and purse-seine fisheries. Since the 1970s, bigeye tuna has been the principal target species of the longline fishery, driven by its high commercial value in the global sashimi market (Matsumoto 2008). Prior to 1993, distant-water longline fleets accounted for the majority of bigeye catches in the EPO, with average annual landings of approximately 88,000 metric tons during 1985–1992 (IATTC 2021).

In contrast, purse-seine fisheries predominantly harvest juvenile bigeye tuna (Okamoto and Bayliff 2003, Xu, Maunder et al. 2020). The three main types of purse-seine fisheries in the EPO include sets made on free-swimming tuna schools (NOA), on tunas associated with dolphin herds (DEL), and on tunas associated with floating objects (OBJ) (Lennert-Cody and Hall 2000, Maunder and Harley 2006). Among these, OBJ sets historically accounted for relatively minor bigeye catches prior to 1993, when the fishery relied mainly on natural drifting objects (Lennert-Cody and Hall 2000). Annual bigeye catches from floating-object sets during this period averaged approximately 5,000 metric tons, much lower than the level of longline catches (about 80,000 metric tons).

Following the widespread adoption of fish aggregation devices beginning in the early 1990s, the OBJ fishery expanded rapidly and replaced the longline fishery as the dominant contributor to bigeye tuna catches in the EPO (Xu, Maunder et al. 2020, IATTC 2021). During the same period, NOA and DEL sets contributed minimally to bigeye tuna catches in the EPO (Figure 1). Fish Aggregation Devices are man-made floating objects placed in the water to attract tunas. They are commonly equipped with an echo-sounder to measure fish abundance and a GPS to report their geographic locations (Hall and Roman 2013). This expansion extended the fishery from coastal waters of the American continent to offshore areas beyond the western management boundary (150°W) (Lennert-Cody and Hall 2000). The resulting increase in juvenile bigeye mortality substantially affected stock dynamics and longline yields (Okamoto and Bayliff 2003, Matsumoto 2008, Sun, Maunder et al. 2019). Consequently, the proportion of total bigeye tuna catch attributed to longline fleets declined from 88% in 1993 to a historically low level of 23% in 2020 (IATTC 2021). Since 2022, implementation of the individual vessel threshold (IVT) measure to reduce bigeye catches has contributed to reductions in OBJ catches of bigeye tuna (Figure 1).

In the 2024 benchmark assessment, twenty-two fishery fleets were defined for bigeye tuna in the EPO, classified by gear type (purse-seine or longline), purse-seine set type (OBJ or NOA), spatial operation area (Figure A1), and longline catch unit (numbers or weight). These fleets comprise fourteen longline fleets, five floating-object fleets, one floating-object discard fleet, and two non-associated fleets. Due to limited length composition data and negligible contributions to total catch, pole-and-line and dolphin-associated sets were pooled into the non-associated category.

2.2. Management

Management advice for EPO tropical tuna fisheries in the IATTC has traditionally been based on applying the interim harvest control rule (Resolutions C-16-02 and C-23-06) using a "best" assessment approach. Formal stock assessments were conducted for bigeye and yellowfin tuna, whereas the status of skipjack tuna was historically inferred indirectly. Recognizing limitations in assessment reliability, particularly for bigeye (2018) and yellowfin (2019), IATTC staff concluded that these assessments were insufficient as sole bases for management advice. While stock status indicators were used to support management deliberations they were not formally embedded within operational HCRs, resulting in the absence of a quantitative default management framework when assessments are unreliable.

To address these challenges, IATTC staff proposed a weighted multi-model risk analysis framework incorporating uncertainty in both parameters and model structure (SAC-11-08). While this represented an improvement over prior approaches by explicitly incorporating uncertainty into management advice, substantial unresolved uncertainties remained regarding stock dynamics and fishery interactions. Consequently, IATTC has emphasized two complementary pathways: continued improvement of stock assessments and advancement of MSE as a central element of its Strategic Science Plan. Although interim strategies have been adopted for tropical tunas in the EPO, several components (e.g., specificity of management objectives, probability of being above target reference points) require further refinement to constitute a fully specified strategy (SAC-15-08).

Management of tropical tunas in the EPO relies primarily on purse-seine fishery closures and longline catch limits. Closure duration is determined based on the stock requiring the most restrictive management, historically, in most years, bigeye tuna. Assuming a linear relationship between fishing effort and fishing mortality, closure duration is calculated as a function of the ratio of current fishing mortality to that corresponding to maximum sustainable yield (MSY). Since 2022, the IVT measure has been implemented to further reduce bigeye mortality in the OBJ fishery.

2.3. Candidate harvest control rules

In 2025, the staff proposed a single HCR for bigeye tuna (SAC-16-06). In addition, thirteen candidate HCRs were proposed during WSMSE-05 and these were discussed and expanded during the 1st meeting of the WG to Strengthen the Dialogue on MSE (see appendix 2 in MSEWG-01). Due to computational and logistical constraints, and following a review of preliminary MSE results at the second MSEWG meeting, the WG agreed to remove six candidate HCRs from the prioritized list, as they were considered redundant (MSEWG-02). As a result, the present MSE evaluates the performance of the staff's proposed HCR alongside seven alternative HCRs selected by the MSEWG. Eight candidate HCRs were evaluated in the MSE for bigeye tuna (Table 1 and Figure 2).

All eight candidate HCRs rely on two biomass-related inputs: dynamic spawning biomass ratio (dSBR) and its associated control point ($S_{control}$). Here, dSBR is defined as the ratio of current spawning biomass to unfished spawning biomass. The term "dynamic" reflects that recruitment variability is explicitly incorporated into the estimation of spawning biomass ratio. $S_{control}$ is defined as the threshold for dSBR below which fishing mortality decreases in response to stock depletion. These inputs are estimated using a simplified version of the base stock assessment model employed in the most recent benchmark assessment (SAC-15-02) to reduce computation time (see section 3.3 for details on the estimation model). Each HCR prescribes a fishing mortality rate for the subsequent management cycle based on the estimate of dSBR relative to $S_{control}$ at the end of the current management cycle. The fishing mortality specified by the HCR is then translated into the number of fishery closure days, assuming a linear relationship between fishing mortality and the number of days the fishery is open (i.e., 365 minus the number of closure days).

The eight candidate HCRs share a common structural form (Table 1 and Figure 2). In all cases, fishing mortality remains at the level (F_{target}) corresponding to the target dSBR when dSBR is estimated to exceed the $S_{control}$ and decreases linearly to zero at zero biomass as a function of dSBR when it falls below $S_{control}$.

In addition, all HCRs impose identical constraints on interannual management adjustments:

- when dSBR is estimated to be above $S_{control}$, the change in closure duration between successive management cycles is limited to ±10 days;
- when dSBR is estimated to be below $S_{control}$, closure increases and decreases between successive management cycles are capped at 20 and 10 days, respectively.

This asymmetric management restriction described above has been shown in preliminary analyses to allow faster responses to stock depletion while preserving management stability (MSEWG-03-04). Under each HCR, biomass is expected to move asymptotically towards the level corresponding to F_{target}, so F_{target} should be set based on the target biomass level. For example, under a fishing mortality of $F_{30\%}$ the spawning biomass is expected to reach asymptotically towards 30% of unfished spawning biomass.

The eight candidate HCRs differ in the target biomass levels and threshold biomass control points (Table 1 and Figure 2). The staff's proposed HCR is the least conservative among the eight, specifying a relatively high target fishing mortality ($F_{target} = F_{30\%}$) and a low threshold biomass level ($S_{control} = 20\%$). In contrast, the seven HCRs proposed by the MSEWG are more conservative, featuring lower F_{target} values, higher $S_{control}$ values, or both. Collectively, the eight candidate HCRs span three target fishing mortality levels ($F_{target} = F_{40\%}$, $F_{35\%}$, and $F_{30\%}$) and four threshold biomass levels ($S_{control} = 20\%, 25\%, 30\%,$ and 40%). The most conservative HCR specifies both a low target fishing mortality ($F_{target} = F_{40\%}$) and a high threshold biomass level ($S_{control} = 40\%$). For clarity and consistency throughout this document, HCRs are denoted using the format F_{target} - $S_{control}$. For example, the staff HCR and the most conservative HCR mentioned above are hereafter referred to as HCR F30-S20 and HCR F40-S40, respectively.

2.4. Management objectives and performance indicators

Although the IATTC has not formally adopted management objectives for the tropical tuna fishery in the EPO, a set of management objectives for bigeye tuna in the EPO were identified and discussed during the MSE dialogue process. They can be classified into six categories (Table 2): safety, status, stability, yield, effort, and abundance. To quantitatively evaluate and compare the performance of the eight candidate HCRs with respect to these objectives, one or more preliminary performance indicators were proposed for each objective. These indicators are described in detail below and are also summarized in Table 2.

2.4.1. Safety

A safety objective proposed during the MSE dialogue process is to maintain the stock above candidate limit reference points (LRPs). Three alternative limit reference points were proposed for testing in the MSE, each corresponding to a distinct performance indicator:

1. LRP at 20% of dSBR (0.2dSBR), which is the limit reference point adopted for most tropical tuna stocks in the western and central Pacific Ocean. This limit reference point is intended to ensure a degree of consistency between the management of bigeye tuna stocks across the Pacific Ocean.
2. LRP at 7.7% of SBR (0.077SBR), which represents the interim LRP for tropical tunas in the EPO, corresponding to a less than 10% probability of being breached. This value is derived from the SBR level associated with a 50% reduction in recruitment, assuming a stock–recruitment steepness of 0.75 (SAC-05-14).
3. LRP at 50% of S/S_{MSY} ($0.5S_{MSY}$), where S_{MSY} denotes the spawning biomass corresponding to MSY.

Participants in the MSEWG proposed treating 0.2dSBR as a soft limit, with a relatively low probability of breach (e.g., <20%), and 0.077SBR and $0.5S_{MSY}$ as hard limits, with a very low probability of breach (e.g., <1%) (MSEWG-02). Accordingly, the three performance indicators are defined as the probability that the spawning biomass exceeds each of these candidate limit reference points across all simulation years, operating models (OMs), and iterations.

2.4.2. Status

A proposed status objective arising from the MSE dialogue process is to maintain the stock within the green quadrant of the Kobe plot, defined by $S > S_{MSY}$ and $F < F_{MSY}$. The corresponding performance indicator is the probability that the stock remains within this green Kobe quadrant across all simulation years, OMs, and iterations.

2.4.3. Stability

The stability objective proposed during the MSE dialogue process is to limit the magnitude of average interannual variation in both catch and fishing effort. The primary performance indicator for catch stability is the average annual variability in total bigeye catch. It is defined as the ratio of average year-to-year change in the catch to average catch. For fishing effort, managers have expressed that it is undesirable for the purse-seine fisheries in the EPO to experience large fluctuations in fishery closures, which apply uniformly across all three purse-seine set types. Regardless of the HCR applied, the maximum increase in closure duration is constrained to 20 days when the spawning biomass is estimated to fall below the control point. The probability that the closure will increase by the maximum of 20 days in response to stock depletion is therefore calculated as the performance indicator for effort stability.

2.4.4. Yield and effort

The yield and effort objectives proposed during the MSE dialogue process aim to maintain both catch and fishing effort at high levels. To evaluate yield performance, the average annual bigeye catches for the purse-seine and longline fisheries, and both gears combined are calculated. Fishing effort is assumed to be proportional to the number of days the fishery remains open, such that the average annual number of closure days serves as the performance indicator for effort (lower average closure durations correspond to higher fishing efforts).

2.4.5. Abundance

The abundance objective proposed during the MSE dialogue process is to maintain average longline catch-per-unit-effort (CPUE) at or above the level observed during the reference period 2017–2019, the socalled status quo period when bigeye was evaluated to be in a healthy condition. The associated performance indicator is defined as the ratio of average longline CPUE across all simulation years to the mean CPUE observed during the 2017–2019 period. Because the longline fishery in the EPO predominantly targets adult bigeye tuna, longline CPUE is considered a reliable proxy for spawning biomass and, thus, a meaningful indicator of stock abundance.

3. MSE FRAMEWORK

3.1. Operating models

Operating models (OMs) represent hypotheses about the true population dynamics of bigeye tuna and the associated fisheries, including uncertainty in biological processes (e.g., growth, natural mortality, stock-recruitment steepness, recruitment regime) and fishery processes (e.g., selectivity and catchability).

Reliable stock assessments suitable for use as operating models are fundamental to the MSE process. The assessment for bigeye tuna has evolved substantially over time, with major methodological improvements implemented in recent years. The 2020 benchmark assessment exhibited significant uncertainties, including a bimodal pattern in key management quantities and an apparent regime shift in recruitment coincident with the expansion of the floating-object purse-seine fishery in the 1990s (SAC-11-06). Although this assessment encompassed a broad range of uncertainties, the resulting operating models may not have been optimal for selecting robust management strategies. In contrast, the 2024 benchmark assessment resolved many of these structural issues, enabling the development of a more reliable suite of operating models (SAC-15-02). These improvements, together with evolving perspectives on appropriate target reference points for tropical tunas in the EPO, motivated a revision of the MSE workplan, replacing the original operating models with a new ensemble derived from the 2024 risk analysis and incorporating alternative HCRs and reference points.

The OM ensemble used in the MSE consists of the thirty-six reference models developed for the 2024 risk analysis, which collectively represent an ensemble of stock assessment models. Detailed descriptions of these models are provided in the report of the most recent benchmark assessment (SAC-15-02). All OMs were implemented in Stock Synthesis (Methot and Wetzel 2013). Both parameter uncertainty and structural uncertainty are incorporated in the development of OMs, which are weighted using model grids representing alternative structure assumptions. For the purposes of the MSE, the reference models were updated in 2025 by incorporating an additional year (2024) of data, allowing the OMs to more accurately reflect current stock status and fishery conditions.

The thirty-six reference models address three major sources of uncertainty within a hierarchical framework:

1. Uncertainty in the misfit to the length-composition data for the longline fishery under the assumption of asymptotic selectivity;
2. Uncertainty in the rate of effort creep (increase in catchability) in the longline fishery; and
3. Uncertainty in the steepness of the stock–recruitment relationship.

Level 1 Uncertainty: Four alternative model structures are used to address the misfit to the longline composition data under the assumption of asymptotic selectivity (hypotheses names in parentheses): ignoring the misfit (Fix); estimating the growth curve with a prior on L_{inf} (Gro); estimating dome-shape selectivity curve for the longline fishery that is assumed to have asymptotic selectivity (Sel); and estimating a scaler for the natural mortality vector (Mrt). Each model structure is equally weighted.

Level 2 Uncertainty: Three annual rates of increase in longline catchability (0%, 1%, and 2%) are considered to represent uncertainty in effort creep. Because bigeye tuna is the primary target species of the Japanese longline fleet in the EPO, catchability is expected to increase over time as fishing skill and technology improve. Based on recommendations from the review panel (RVMTT-01-RPT), a 1% annual increase was suggested, with 0% and 2% included to bracket this uncertainty. Each annual rate is equally weighted.

Level 3 Uncertainty: Three steepness values (1.0, 0.9, and 0.8) are included to address the uncertainty in the shape of the Beverton-Holt stock-recruitment relationship. The three steepness values are weighted by 0.46, 0.32, and 0.22, respectively, based on expert judgement from the risk analysis for the last benchmark assessment (SAC-11 INF-F).

3.2. Sampling model

The sampling model defines how data – including catches, size compositions, and CPUE - are collected from the thirty-six operating models, accounting for observation error, measurement uncertainty, and bias. Simulated data for catches, longline indices of abundance, and length compositions are generated using the bootstrap feature in Stock Synthesis, the platform on which both the OMs and the estimation model are implemented.

An iteration-specific random seed is applied to the bootstrap procedure to ensure that observation errors are identical across all HCRs within each iteration. Catch observations are assumed to have negligible measurement error (coefficient of variation, CV = 0.01). The CV of the longline abundance index is set equal to the average value observed during 2021–2023. The effective sample sizes for longline length-composition data are set equal to those observed during 2017–2019, as no longline length compositions were collected during the COVID-19 period.

3.3. Estimation model

The estimation model (EM) uses simulated fishery and abundance index data to estimate perceived stock status and trends, which are used to implement management actions according to the specified HCRs.

Three candidate EMs were evaluated during the early phase of MSE development:

1. The ASPM_Rdevs+ version of the base reference model (Fix-1-1);
2. The ASPM_Rdevs+ version of the tuned base reference model; and
3. The ASPM_Rdevs+ version of the ensemble reference model.

ASPM_Rdevs+ refers to an age-structured production model that includes estimated recruitment deviations and is fitted to the abundance index as well as length composition data for the abundance index (assuming dome-shaped selectivity) and for one longline fishery (assuming asymptotic selectivity). It is worth noting that the selectivities for the two fleets are estimated and those for all other fleets are fixed in the model. This simplified framework was adopted because replicating the full benchmark stock assessment within the MSE would be computationally prohibitive.

The tuning was achieved by bias-adjusting estimates of fishing mortality and dSBR using terminal-year values from the EM and OM ensemble estimated from the historical data (Table 3). Specifically, scaling factors of 0.833 and 1.163 are applied to the estimates of fishing mortality and dSBR from the EM, respectively, when implementing the HCR. These scalers represent the ratio of the weighted terminal estimates from the OM ensemble to the corresponding EM estimates, ensuring consistency between the EM and the OM ensemble.

Comparative testing indicated that the ASPM_Rdevs+ version of the tuned base reference model achieved both computational efficiency (a limitation of the ensemble EM) and reliable asymptotic convergence of simulated biomass toward the HCR-defined target (a limitation of the untuned base model) (Figure A2). Consequently, this model was selected as the EM for the MSE.

The parameters estimated in the EM include initial and main recruitment deviations, the unfished recruitment level (R_0), two initial fishing mortality rates (one for purse-seine and one for longline), and six parameters for the two estimated longline selectivity curves. On average, each EM run requires approximately 12 minutes to obtain the maximum likelihood estimate (MLE). Convergence is assumed when the maximum gradient component is less than 0.01. Due to computational constraints, determining whether the Hessian matrix was positive definite was not evaluated.

3.4. MSE specifications

3.4.1. General specifications

The OMs are "conditioned" on fishery data collected in 1979-2024, as data for 2025 are incomplete. They are projected into the future for twenty-one years (2025-2046) using closed-loop simulations where management actions are updated according to the HCR and EM-derived biomass estimates. This projection horizon represents a trade-off between computational feasibility and the need to capture long-term stock dynamics. Each management cycle where management is held constant spans three years, yielding seven complete management cycles. Given that bigeye tuna in the EPO reaches maturity at approximately 3.5 years, the simulations encompass roughly six generations of bigeye tuna.

To account for stochasticity in recruitment, observation processes, and management implementation, each combination of Level 1 and Level 2 uncertainty includes 100 iterations with unique random seeds. These iterations are allocated across the three steepness hypotheses in proportion to their weights (46, 32, and 22 iterations for steepness values of 1.0, 0.9, and 0.8, respectively). Given four Level 1 hypotheses and three Level 2 hypotheses, each HCR is evaluated using a total of 1,200 unique iterations (4 × 3 × 100).

Future recruitment is modeled as lognormally distributed with zero bias and a standard deviation of 0.6, consistent with assumptions used in the OMs. Iteration-specific random seeds are applied to recruitment generation to ensure that identical recruitment deviations are shared across all HCRs within each iteration.

3.4.2. Management module

The management module translates EM estimates into fishery closure decisions based on the specific HCR. The procedure involves the following seven steps for a three-year management cycle:

1. Run the EM to get the estimates of current F/F_{target} and dSBR
2. Tune these estimates using pre-defined scalers (0.833 for F/F_{target} and 1.163 for dSBR)
3. Apply the HCR to calculate the target number of closure days:
$$Closure_{HCR} = 365 - (365 - Closure_{current}) \times \frac{\max(1, SBR/S_{control}) \times F_{target}}{F}$$
where $Closure_{current}$ is the closure duration in the current management cycle
4. Reset the new closure based on the management restriction if the new closure duration calculated in step 3 requires a management change larger than the limit (ten days if $dSBR > S_{control}$ or if $dSBR < S_{control}$ and $Closure_{HCR} < Closure_{current}$; twenty days if $dSBR < S_{control}$ and $Closure_{HCR} > Closure_{current}$)
5. Compute the relative change in fishing mortality between the current and new management cycle:
$$F_{ratio} = \frac{365 - Closure_{current}}{365 - Closure_{HCR}}$$
6. Calculate the current fishing mortality in the OM ($F_{current}$)
7. Derive the fishing mortality under which the OM projects for the next management cycle:
$$F_{HCR} = F_{current} \times F_{ratio}$$

Due to technical limitations regarding the projection feature in Stock Synthesis, fishery closures are assumed in the management module to have the same proportional impact on purse-seine and longline fishing mortalities. Considering that the dSBR is mainly impacted by the purse-seine fishery (Figure A3), this assumption is not expected to substantially bias dSBR trajectories. Similar constraints prevent direct implementation of the longline catch limit specified in Resolution C-21-04. The implications of excluding this limit are discussed in subsequent sections.

3.4.3. Implementation error

In the MSE, fishing mortality is assumed to be proportional to the number of open fishing days, reflecting the current effort control framework for purse-seine fisheries in the EPO. However, factors such as fleet capacity, the individual threshold (IVT) measure to reduce bigeye catches, skipjack abundance, and the number of active fish aggregating devices can generate deviations from this idealized linear relationship. To capture these deviations, implementation error is incorporated as a stochastic component. Because fishing mortality is influenced by factors beyond formal management measures (i.e., fishery closure), including implementation error enhances the realism and robustness of MSE outcomes.

Specifying an appropriate magnitude of implementation error for the MSE is however challenging. The contrast in the fishery closure of the past decade or so is small, precluding the possibility of estimating a reliable magnitude of implementation error using historical observations. In addition, the introduction of the IVT is expected to influence the magnitude of implementation error, and it will take years before this influence can be quantitatively evaluated. Since the implementation error in this MSE is applied to a fishing mortality that is assumed to be constant within each three-year management cycle, it is modeled as a lognormally distributed error, constant over the three years of the management cycle, with no bias and a standard deviation of 0.1. Preliminary results showed that adding this implementation error to the MSE results in more variable trajectories of dSBR (Figure A4).

3.4.4. Robustness test

The staff also conducted a robustness test to evaluate the performance of the candidate HCRs for bigeye tuna in the EPO under a hypothetical extreme scenario: a sustained 25% reduction in recruitment beginning in 2025. This scenario is intended to assess HCR behavior under adverse conditions (e.g., climate change) that substantially reduce stock productivity.

Except for the imposed regime shift in recruitment, all simulation specifications for the robustness test were identical to those used in the base-case MSE. Due to time constraints, the robustness test was conducted only for the least conservative candidate HCR, F30–S20, which is expected to be most vulnerable to declines in recruitment.

3.5. MSE algorithm

The computational workflow of the MSE comprises the following steps:

1. Fit the thirty-six OMs to historical data from 1979-2024, generating fixed parameter estimates for simulation.
2. Compile the historical data and structural specifications required by the EM.
3. Project the OMs forward for one management cycle (three years) using simulated data, recruitment deviations, and HCR-derived management actions. This updates the stock trajectory for 3 years.
4. Update OM data files by:
    a. Extending the terminal year by three years;
    b. Inserting projected catches from step 3 for the updated three years of “historic” catch;

    c. Incorporating random recruitments into the updated three years; and
    d. Adding dummy CPUE and length composition data for the updated three years.
5. Bootstrap perceived observations (catch, CPUE, and length compositions) for the entire period and replace only the newly bootstrapped data for the updated three years.
6. Repeat step 2-5 seven times to generate twenty-one years of closed-loop simulations
7. Repeat steps 2–6 across 100 stochastic iterations using consistent recruitment deviations and bootstrap seeds for each OM scenario.

All simulation is coded by R (R Core Team 2025) and associated package r4ss (Taylor, Doering et al. 2021).

4. RESULTS

The MSE for bigeye in the EPO evaluates eight candidate HCRs. Each HCR is tested across 36 operating models, with 1,200 unique stochastic iterations per HCR representing possible future scenarios. For each iteration, the MSE is simulated for 21 years, corresponding to seven three-year management cycles. In total, the MSE simulations include 57,600 ($8 \times 1200 \times 6$) EM runs, noting that the first management cycle does not require an EM run. Based on the convergence criterion of a maximum gradient component less than 0.01, all EM runs are considered to have convergence successfully. Across the 57,600 runs, the largest maximum gradient is 0.005, while the median maximum gradient was 0.0003. We developed a R-shiny app (https://haikun-xu.shinyapps.io/MSE_BET_EPO/) that provides an interactive way to present all results described in this section.

Because both the target biomass and control point for the HCRs are defined in terms of dSBR, the trajectories of dSBR are first examined to evaluate the impact of each candidate HCR on stock depletion. Considerable uncertainty is associated with future dSBR trajectories, and this uncertainty increases slightly over time (Figure 3). The mean trajectory across iterations represents the expected stock condition under each HCR. Regardless of the HCR implemented, the mean dSBR increases sharply from approximately 0.25 to above 0.35 within the first management cycle (Figure 4). This rebuilding trend can be attributed to a reduction in the fishing mortality on juvenile bigeye following the implementation of the IVT measure in 2022. As a result, the benefits of this reduction begin to be reflected in the spawning biomass when these juveniles start to reach maturity around 2025.

4.1. Safety

Three performance indicators are calculated for the safety objective, each associated with a different candidate limit reference point. The first reference point is treated as a soft limit, which should have a low probability of being breached. Specifically, the probability that dSBR falls below 0.2 ranges from 1.2% under HCR F40-S40 to 3.5% under HCR F30-S20 (Table 4 and Figure 5).

The second and third reference points are treated as hard limits, which should have very low probabilities of being breached. Regardless of the HCR implemented, the probability that SBR falls below 0.077 is less than 0.1% (Table 4 and Figure 6), and the probability that spawning biomass falls below $0.5S_{MSY}$ is also less than 0.1% (Table 4 and Figure 7).

4.2. Status

The probability that the stock is in the green Kobe quadrant is calculated for the status objective. Overall, this probability is high across all HCRs (Table 4 and Figure 8). The less conservative HCR (F30-S20) has the lowest probability, 89.6%, while the most conservative HCR (F40-S40) has the highest probability, 95.5%. As expected, both higher target biomass and higher control points improve stock status with respect to the probability of remaining in the green Kobe quadrant.

4.3. Stability

Average annual variability in annual total catch is calculated to quantify the degree of stability in the EPO bigeye fisheries. Differences among HCRs are minor: all HCRs exhibit variability between 7.2% and 7.3% (Table 4; Figure 9). This similarity likely reflects the fact that all HCRs share the same management constraint, which limits changes in fishery closure between management cycles to ±10 days when the spawning biomass exceeds the control point and -10 and +20 days when the biomass is below the control point.

Large changes in management actions are undesirable; therefore, the probability that the fishery closure increases by the maximum allowed amount (20 days) is calculated as an additional measure of stability. This probability is primarily influenced by the control point of the HCR and how close the control point is to the target biomass (Table 4; Figure 10). When the control point is 20%, the probability is negligible (less than 0.8%). Under a 25% control point, the probability increases slightly to 1.9%. When the control point is 30% or higher, the probability becomes more substantial, ranging from 7.7% to 17.6% for a control point of 30%, and reaching 28.9% for a control point of 40%.

4.4. Yield

Average annual catches for both purse-seine and longline fisheries are calculated for the yield objective. The average annual purse-seine catch stabilizes between 46,000 and 51,000 metric tons (Table 4; Figure 11). This level is comparable to catches observed during the early expansion of the floating-object fishery in the EPO between 1995 and 2000 but remains substantially lower than the average purse-seine catches observed since 2000.

The average annual longline catch is projected to be highly stable and show little variation across HCRs, ranging from 50,000 mt and 52,000 mt (Table 4 and Figure 12). It should be noted that the longline catch increases substantially in the first year and then becomes stable. The annual average exceeds any longline catch observed since 2005. Moreover, the 80% confidence interval suggests a substantial probability that future longline catches will exceed the current total longline limit specified in Resolution C-21-04.

4.5. Effort

The average number of fishery closure days is used to represent the trend in fishing effort. Longer closures correspond to lower fishing effort, while shorter closures correspond to higher fishing effort. Substantial differences among HCRs are observed, largely driven by the target biomass level (Table 4). The two HCRs with a 30% target dSBR (F30-S20 and F30-S30) correspond to the shortest closures, averaging 43 and 46 days, respectively. In contrast, the three HCRs with a 40% target dSBR produce the longest closures, ranging from 77 to 89 days. The three HCRs with a 35% target dSBR fall between these extremes, with closures ranging from 52 to 75 days.

All eight candidate HCRs display a decreasing trend in the closure after the first management cycle, and less conservative HCRs are tend to associated with faster decreases than more conservative HCRs (Figure 13). Differences among HCRs are primarily determined by the initial closure adjustment during the first management cycle. This sensitivity arises because the stock is currently rebuilding from a relatively low depletion level (dSBR ≈ 0.2 at the start of 2024) to a moderate level (dSBR ≈ 0.25 at the start of 2025), reflecting the lagged effect of the IVT on spawning biomass recovery.

At this moderate depletion level, the initial closure recommended by an HCR depends strongly on both the target and control points. Three HCRs (F30-S20, F35-S20, and F35-S25) recommend an initial closure of 62 days, representing a 10-day reduction from the from 72 days, the closure in place during the terminal 3-year period (2022-2024) in the update assessment used for the MSE. F30-S30 recommends a 64-day closure, corresponding to an 8-day reduction. F40-S20 recommends 82 closure days, representing a 10-

day increase. The remaining HCRs (F35-S30, F40-S30, and F40-S40) recommend 92 closure days, corresponding to a 20-day increase.

Over time, the projected closure trajectories become increasingly variable due to stochastic recruitment and implementation error (Figure 14). Closure projections are relatively precise during the first three management cycles but become substantially more uncertain during the later cycles. This uncertainty is, however, much smaller when measuring in the number of days the fishery is open.

4.6. Abundance

The ratio of longline CPUE to the historical average observed during 2017-2019 is calculated to quantify longline catch rate. Owing to the combination of strong recent recruitment (the 2023 cohort) and the implementation of the IVT since 2022, longline CPUE is projected to increase rapidly to more than twice the 2017–2019 level within the first management cycle (Figure 15). Across the seven simulated management cycles, longline CPUE is projected to reach between 226% (under HCR F30-S20) and 251% (under HCR F40-S40) of the 2017–2019 level (Table 4).

4.7. Tradeoff in management actions

Trade-offs arise when the management objectives associated with different performance indicators conflict. For example, safety objectives aim to maintain the stock at high biomass levels, whereas yield objectives seek to maintain high harvest levels. Consequently, no HCR performs best across all performance indicators (Table 4).

In general, HCRs with lower target fishing mortality perform better with respect to safety and stock status but perform worse with respect to yield and fishing effort. Similarly, HCRs with higher control points tend to perform better in terms of safety, but at the cost of poorer stability performance. The ability to quantify such trade-offs is one of the key advantages of the MSE framework.

Because differences among HCRs in the three safety indicators are relatively small, the status indicator (probability of remaining in the green Kobe quadrant) is used as one dimension of the trade-off analysis. Since fishing effort influences the catch of all three tropical tuna species in the EPO, the effort indicator (average fishery closure) is used as the second dimension. The yield indicator (average annual purse-seine catch) is represented by the color scale of the trade-off points (Figure 16).

The resulting trade-off plot clearly illustrates the relationship between effort and stock status (Figure 16). Shorter closure durations are associated with lower probabilities that the stock remains in the green quadrant of the Kobe plot. Shorter closures are also associated with higher average annual purse-seine catches.

4.8. Robustness test

The results indicate that HCR F30–S20, the least conservative of the eight candidate HCRs, is relatively robust to the simulated 25% downward regime shift in recruitment. Under this scenario, the probability that the soft limit reference point is breached (dSBR < 0.2) remains low, with the spawning biomass exceeding this threshold in more than 95% of simulation outcomes. Similarly, the probabilities of breaching the two hard limit reference points — SBR < 0.077 and S < $0.5S_{MSY}$ — are extremely small, with the stock remaining above these limits in more than 99% of simulations (Table 5). The probability that the stock remains in the green Kobe quadrant is also high, at 88.5%, and the average fishery closure is projected to be 38 days.

The trajectory of dSBR is not expected to be strongly affected by the 25% reduction in recruitment regime because, by definition, dSBR accounts for fluctuations in recruitment (Figure 17). Since both the target biomass and the control point of the HCR are defined in terms of dSBR, the resulting management action—expressed as in fishery closure—responds only modestly to recruitment variability (Table 5).

In contrast, the trajectory of SBR is more sensitive to the recruitment regime shift than that of dSBR (Figure 18). Nevertheless, even under the reduced recruitment scenario, more than 99% of simulated SBR trajectories remain above 0.077, the hard limit reference point for SBR (Table 5), indicating that the stock remains well above critical biological thresholds under this scenario.

5. DISCUSSION

The MSE clearly shows the tradeoffs in the management of EPO bigeye tuna. Higher F_{target} is associated with less days of closure but lower biomass. High $S_{control}$ is associated with high probability of 20-day increases in the closure. It is also noted that catch is less sensitive than days open (365 minus days of closure) due to the shape of the yield curve.

Several key limitations were identified in the MSE for bigeye in the EPO. These limitations are ranked below according to their potential influence on the reliability of the MSE outcomes.

a) Simplified representation of fishing mortality responses to fishery closure:

In the current framework, fishing mortality rates for both the purse-seine and longline fisheries are assumed to respond linearly to fishery closure. In reality, fishery closures are intended to influence only the purse-seine fishery. Due to technical constraints within the modeling framework, however, the MSE cannot represent separate trends in fishing mortality for purse-seine and longline fisheries. Furthermore, it is uncertain whether the relationship between purse-seine fishing mortality and fishery closure remains linear following the implementation of the IVT measure. As the fishing mortality increases due to the reduced closure days, vessels are more likely to reach their threshold, which would limit the amount that the fishing mortality increases. Therefore, the simulations, which don’t include the IVT measure, would over-estimate the fishing mortality and under-estimate the real population abundance.

b) Absence of a longline total catch limit in the simulations

The longline fishery is not constrained by a total catch limit in the current simulations (actual catches would be more restricted due to the limits being CPC specific and limits on the transferability). As a result, there is a significant probability that simulated longline catches exceed the limit specified in Resolution C-21-04 (55,131 mt). This limitation arises from the same technical constraints described above, which prevent the implementation of the longline catch limit within the MSE framework. The absence of the longline catch limit in the MSE means that true population trajectory in the future will likely be more optimistic than that simulated in the MSE.

c) Assumptions regarding uncertainty in Japanese longline CPUE

The Japanese longline CPUE index is assumed to have the same level of uncertainty (coefficient of variation, CV) as the average observed during 2022–2024. In the estimation model—an age-structured production model—the Japanese longline CPUE index and its associated uncertainty have a substantial influence on estimates of current stock status. However, the uncertainty in this index has increased considerably since 2011 due to reductions in both fishing effort and the spatial coverage of the Japanese longline fishery. There is also uncertainty in the amount of effort creep used in the OMs.

d) Assumption of constant selectivity

Selectivity for all fisheries is assumed to remain constant at current levels throughout the simulations. In practice, selectivity can change over time in response to variations in fleet operations, gear configurations, and targeting strategies. The assumption of constant selectivity may therefore limit the ability of the MSE to capture potential future changes in fishery dynamics.

It should also be noted that the harvest strategies are based on current purse-seine fishing capacity. Any changes in fishing capacity would require the days open to be adjusted appropriately to achieve the desired fishing mortality.

Acknowledgement

The authors express their sincere appreciation to Dr. Juan Valero for his contributions in leading the early phase of the MSE dialogue process at the IATTC and for his initial work on developing components of the MSE framework. The authors further thank Dr. Desiree Tommasi for providing technical assistance and valuable insights during the coding phase of this project. Gratitude is also extended to the participants of the *ad hoc* MSE dialogue working group for their constructive comments and suggestions, which contributed meaningfully to the improvement of this work. Special recognition is due to the co-chairs of the *ad hoc* MSE dialogue working group, Dr. Juan-Carlos Quiroz and Ms. Shana Miller, for their dedicated efforts in organizing multiple working group meetings, which greatly facilitated communication among IATTC staff, CPC scientists, and stakeholders. Finally, the authors wish to thank Dr. Alexandre Aires-da-Silva for his thorough review of this document.

6. REFERENCES

Collette, B. B., et al. (2001). "Systematics of the tunas and mackerels (Scombridae)." Fish physiology **19**: 1–33.

Hall, M. and M. Roman (2013). "Bycatch and non-tuna catch in the tropical tuna purse seine fisheries of the world." FAO fisheries and aquaculture technical paper(568): I.

IATTC (2021). "The tuna fisheries in the eastern Pacific Ocean." Inter-Amer.Trop. Tuna Comm., 12th Scient. Adv. Com. Meeting: SAC-12-03.

Lennert-Cody, C. and M. Hall (2000). The development of the purse seine fishery on drifting Fish Aggregating Devices in the eastern Pacific Ocean: 1992-1998. Pêche thonière et dispositifs de concentration de poissons, Caribbean-Martinique, 15-19 Oct 1999 15-19 octobre 1999.

Matsumoto, T. (2008). "A review of the Japanese longline fishery for tunas and billfishes in the eastern Pacific Ocean, 1998-2003." Bull IATTC **24**: 1–187.

Maunder, M. N. and S. J. Harley (2006). "Evaluating tuna management in the eastern Pacific Ocean." Bulletin of Marine Science **78**(3): 593–606.

Methot, R. D. and C. R. Wetzel (2013). "Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management." Fisheries Research **142**: 86–99.

Okamoto, H. and W. H. Bayliff (2003). "A review of the Japanese longline fishery for tunas and billfishes in the eastern Pacific Ocean, 1993-1997." Inter-American Tropical Tuna Commission Bulletin **22**(4): 221–431.

R Core Team (2025). "R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.".

Sun, C.-H., et al. (2019). "Increasing the economic value of the eastern Pacific Ocean tropical tuna fishery: Tradeoffs between longline and purse-seine fishing." Deep Sea Research Part Ii: Topical studies in Oceanography **169**: 104621.

Taylor, I. G., et al. (2021). "Beyond visualizing catch-at-age models: Lessons learned from the r4ss package about software to support stock assessments." Fisheries Research **239**: 105924.

Xu, H., et al. (2020). "Bigeye tuna in the eastern Pacific Ocean, 2019: benchmark assessment." Inter-Amer.Trop. Tuna Comm., 11th Scient. Adv. Com. Meeting: SAC-11-06.

TABLES

Table 1. The eight candidate harvest control rules compared in this management strategy evaluation.

Component	Staff	WG1	WG2	WG3	WG4	WG5	WG6	WG7
HCR number	1	2	3	4	5	6	7	8
F_{target}	$F_{30\%}$	$F_{35\%}$	$F_{40\%}$	$F_{30\%}$	$F_{35\%}$	$F_{35\%}$	$F_{40\%}$	$F_{40\%}$
$S_{control}$	20%	30%	20%	30%	20%	25%	30%	40%
Range for closure change (day): $S > S_{control}$	-10 to 10	-10 to 10	-10 to 10	-10 to 10	-10 to 10	-10 to 10	-10 to 10	-10 to 10
Range for closure change (day): $S < S_{control}$	-10 to 20	-10 to 20	-10 to 20	-10 to 20	-10 to 20	-10 to 20	-10 to 20	-10 to 20
HCR Name	F30-S20	F35-S30	F40-S20	F30-S30	F35-S20	F35-S25	F40-S30	F40-S40

Table 2. The management objectives and the associated performance indicators included in this MSE for evaluating the performance of candidate harvest control rules.

Management objective	Performance indicator	Unit	Description	Note
Safety	$p(dSBR < 0.2)$	%	The probability that dynamic spawning biomass ratio falls below 0.2	A dynamic spawning biomass ratio of 0.2 is the limit reference point for bigeye in the WCPO
	$p(SBR < 0.077)$	%	The probability that equilibrium spawning biomass ratio falls below 0.077	An equilibrium spawning biomass ratio of 0.077 is the interim limit reference point for tropical tunas in the EPO
	$p(S/S_{MSY} < 0.5)$	%	The probability that spawning biomass falls below 50% of the spawning biomass at the maximum sustainable yield	
Status	$p(Kobe\ in\ green)$	%	The probability that the stock is in the green Kobe quadrant plot	The definition of the green quadrant of the Kobe plot is that $SB > SB_{MSY}$ and $F < F_{MSY}$
Stability	$AAV(catch)$	%	Average annual variability in annual bigeye catch	
	$p(closure + 20)$	%	The probability that the closure increases by 20 days	20 days is upper bound for the increase in fishery closure per management cycle
Yield	$PS\ catch$	ton	Average annual purse-seine bigeye catch	
	$LL\ catch$	ton	Average annual longline bigeye catch	
Effort	$closure$	day	Average fishery closure	
Abundance	$CPUE$	%	The ratio of average longline CPUE to the average level for 2017-2019	Longline CPUE reflects the abundance of adult bigeye

Table 3. Comparison of estimated fishing mortality relative to $F_{30\%}$ (the fishing mortality that results in a dynamic spawning biomass ratio of 30%) for 2022-2024 and estimated dynamic spawning biomass ratio for the first quarter of 2025 between the thirty-six operating models and the estimation model.

Type	Model	Effort creep	Steepness	$F_{2022-2024}/F_{30\%}$	$dSBR_{2025}$
OM	Fix	0%	1	0.852	0.227
	Fix	0%	0.9	0.863	0.214
	Fix	0%	0.8	0.866	0.205
	Fix	1%	1	0.960	0.192
	Fix	1%	0.9	0.975	0.177
	Fix	1%	0.8	0.980	0.168
	Fix	2%	1	1.071	0.164
	Fix	2%	0.9	1.099	0.145
	Fix	2%	0.8	1.111	0.135
	Gro	0%	1	0.732	0.266
	Gro	0%	0.9	0.750	0.252
	Gro	0%	0.8	0.767	0.240
	Gro	1%	1	0.817	0.231
	Gro	1%	0.9	0.842	0.214
	Gro	1%	0.8	0.863	0.201
	Gro	2%	1	0.908	0.199
	Gro	2%	0.9	0.945	0.179
	Gro	2%	0.8	0.973	0.165
	Sel	0%	1	0.539	0.364
	Sel	0%	0.9	0.551	0.353
	Sel	0%	0.8	0.563	0.343
	Sel	1%	1	0.654	0.298
	Sel	1%	0.9	0.672	0.283
	Sel	1%	0.8	0.689	0.271
	Sel	2%	1	0.773	0.245
	Sel	2%	0.9	0.801	0.226
	Sel	2%	0.8	0.824	0.212
	Mrt	0%	1	0.566	0.383
	Mrt	0%	0.9	0.591	0.360
	Mrt	0%	0.8	0.616	0.336
	Mrt	1%	1	0.703	0.305
	Mrt	1%	0.9	0.737	0.278
	Mrt	1%	0.8	0.768	0.254
	Mrt	2%	1	0.851	0.241
	Mrt	2%	0.9	0.896	0.212
	Mrt	2%	0.8	0.932	0.189
EM	Fix	0%	1	0.964	0.212

Table 4. The table of performance indicators summarized across iterations, simulation years, and operating models for the eight candidate harvest control rules. From left to right: HCR name, probability of dynamic spawning biomass ratio < 0.2 (%), probability of spawning biomass ratio < 0.077 (%), probability of spawning biomass < 50% spawning biomass at the maximum sustainable yield (%), probability of in the green Kobe quadrant (%), average annual variability in annual total catch (%), probability of fishery closure increases by 20 days between two management cycles (%), average annual catch of bigeye by purse-seine (mt), average annual catch of bigeye by longline (mt), average fishery closure (day), and the average ratio of longline CPUE to the historical average for 2017-2019.

HCR	Prob dSBR < 0.2	Prob SBR < 0.077	Prob $S/S_{MSY} < 0.5$	Prob Kobe = green	AAV in catch	Prob change = 20	Annual PS catch	Annual LL catch	Fishery closure	CPUE ratio
F30-S20	3.5	0.1	0.1	89.6	7.3	0.8	50722	51663	43	2.26
F30-S30	3.3	0.1	0.1	90.0	7.3	7.7	50384	51509	46	2.28
F35-S20	2.5	0	0	91.6	7.3	0.4	49785	51277	52	2.31
F35-S25	2.5	0	0	91.6	7.3	1.9	49746	51250	52	2.31
F35-S30	1.7	0	0	94.0	7.2	17.6	47514	50533	75	2.44
F40-S20	1.5	0	0	94.6	7.2	0.1	47221	50258	77	2.45
F40-S30	1.3	0	0	95.2	7.2	16.3	46456	49966	84	2.49
F40-S40	1.2	0	0	95.5	7.3	28.9	45911	49624	89	2.51

Table 5. The table of performance indicators summarized across iterations, simulation years, and operating models for the staff-proposed harvest control rule under a hypothetical 25% reduction in future recruitments. The columns have the same meanings as those in table 4.

HCR	Prob dSBR < 0.2	Prob SBR < 0.077	Prob $S/S_{MSY} < 0.5$	Prob Kobe = green	AAV in catch	Prob change = 20	Annual PS catch	Annual LL catch	Fishery closure	CPUE ratio
F30-S20	4.6	1.0	0.2	88.5	7.2	1.5	38646	41096	38	1.76

FIGURES

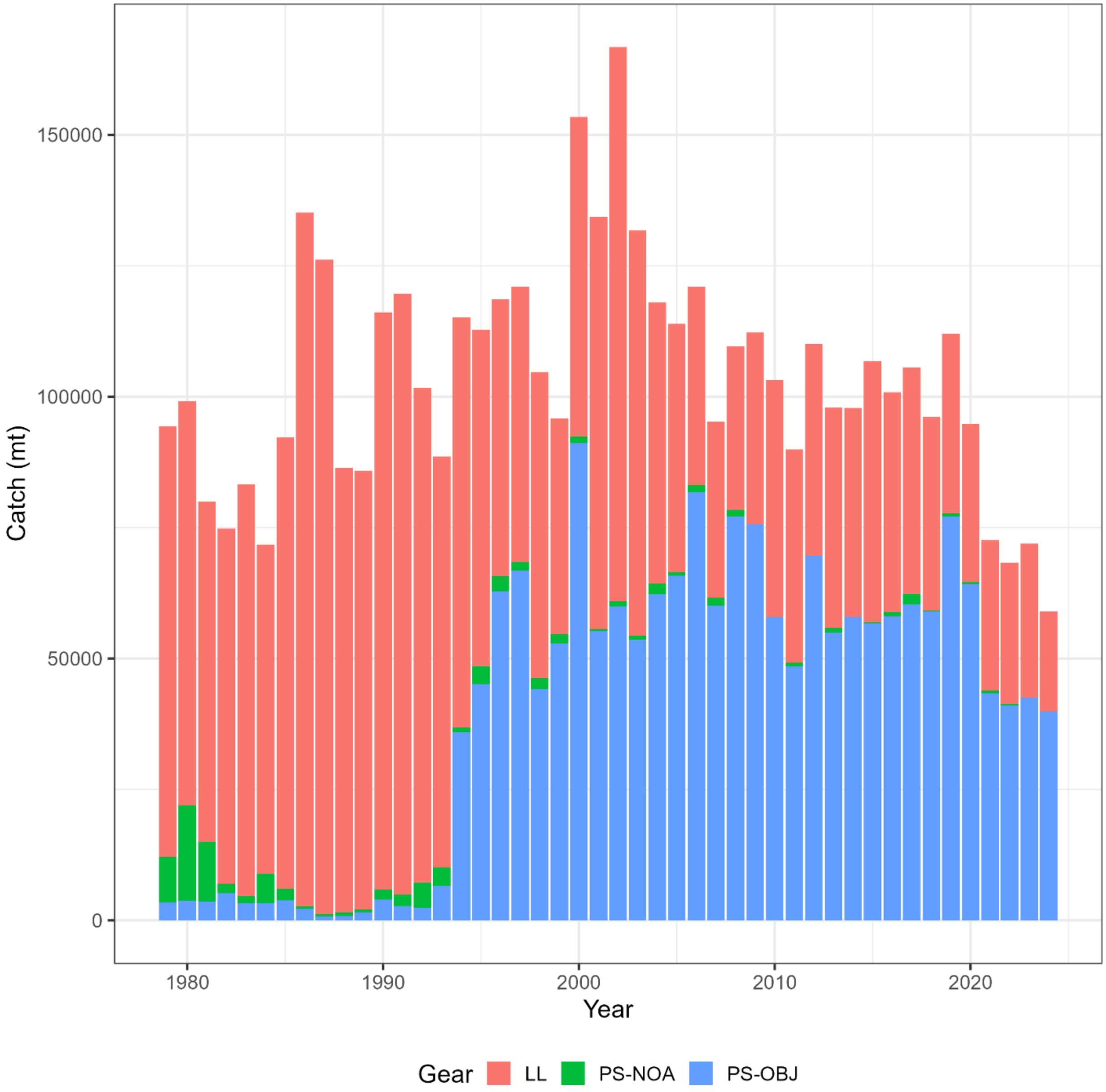

FIGURE 1. Annual catches (metric tons) of bigeye tuna in the eastern Pacific Ocean by gear and set type in 1979-2024.

FIGURA 1. Capturas anuales (toneladas métricas) de atún patudo en el Océano Pacífico oriental, por tipo de arte, en 1979-2024.

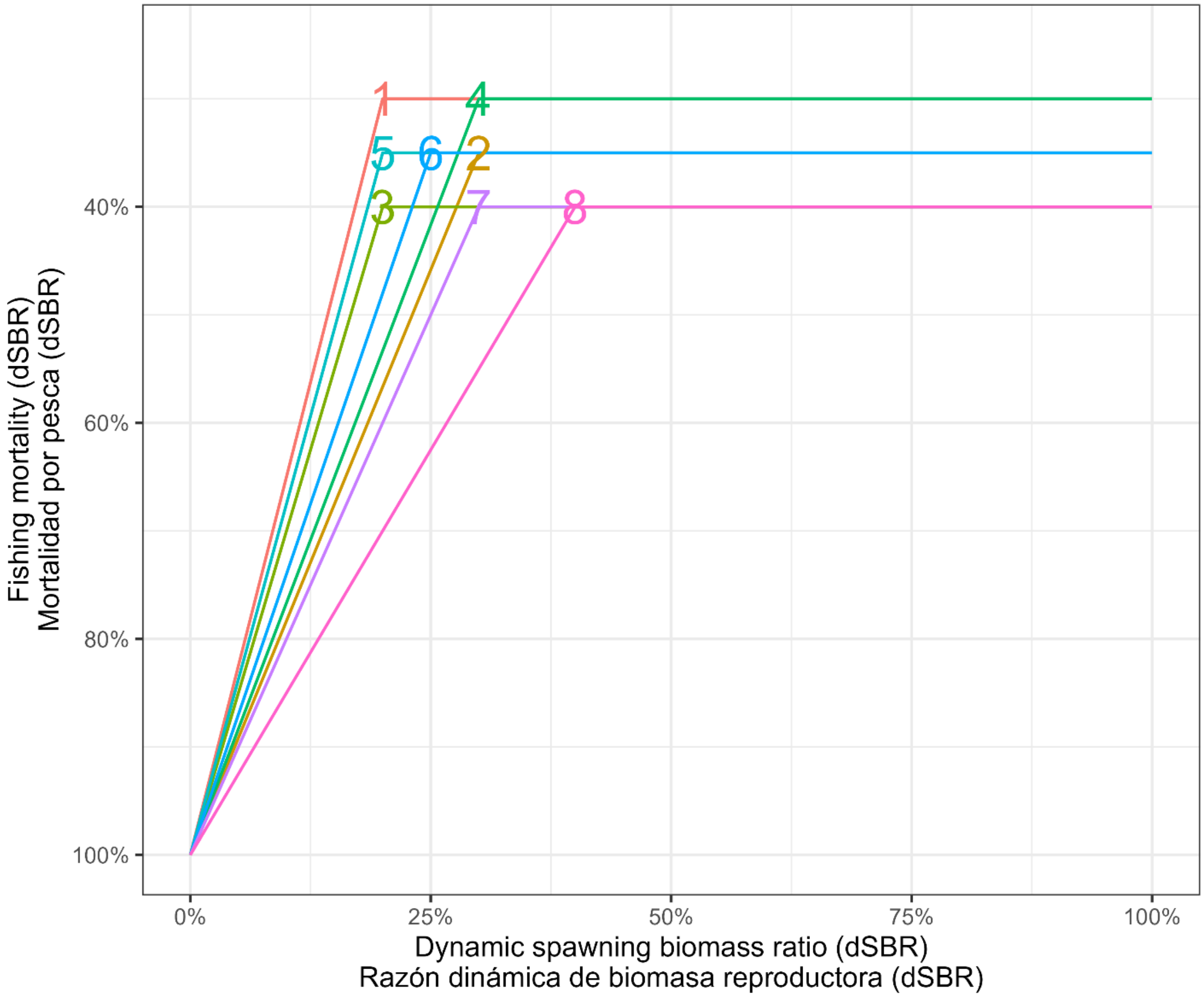

FIGURE 2. The eight candidate harvest control rules compared in this management strategy evaluation.

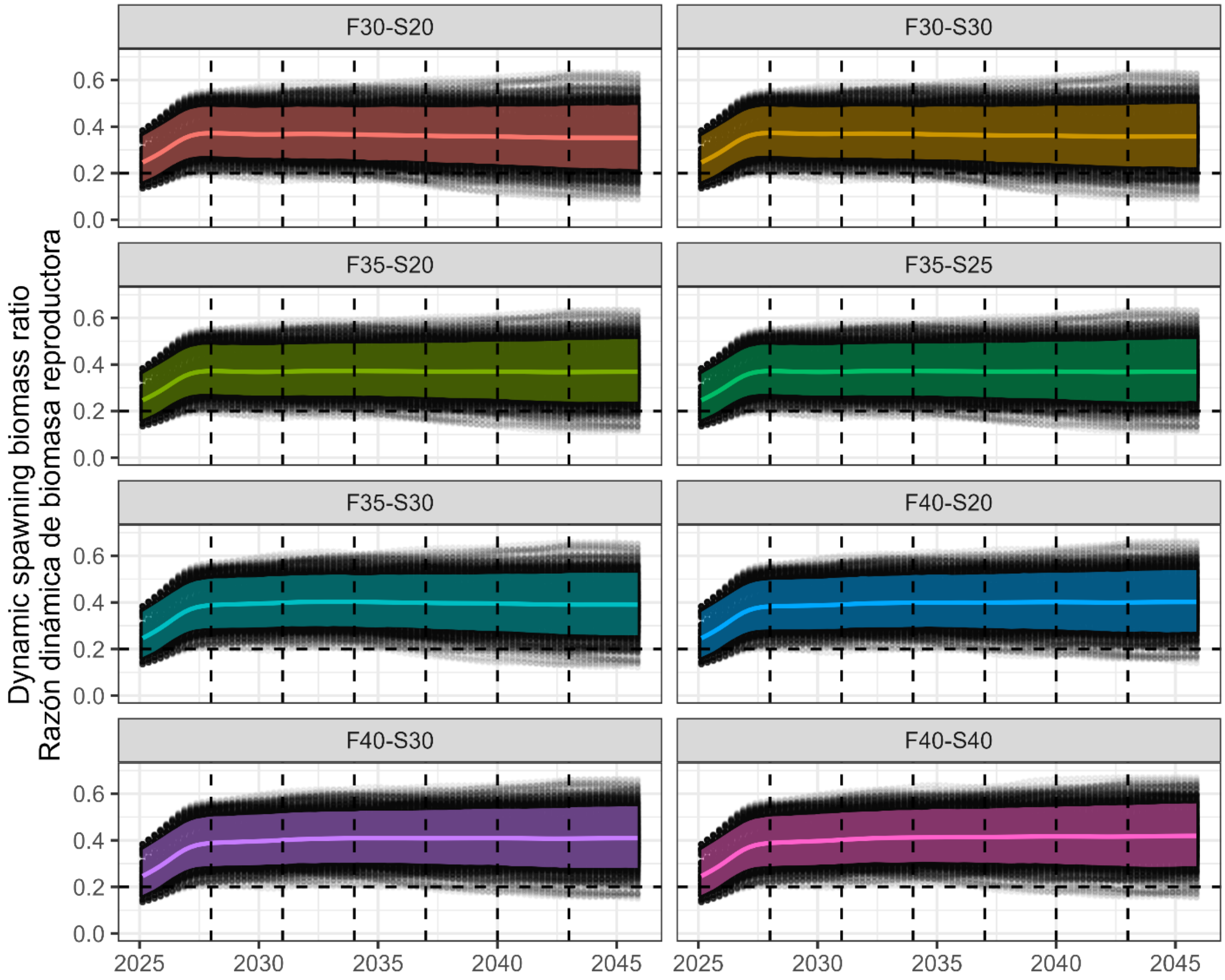

FIGURE 3. Dynamic spawning biomass ratio simulated under each candidate harvest control rule. The black dots are for individual iterations, and the color line and color ribbon represent the mean and 80% confidence interval, respectively.

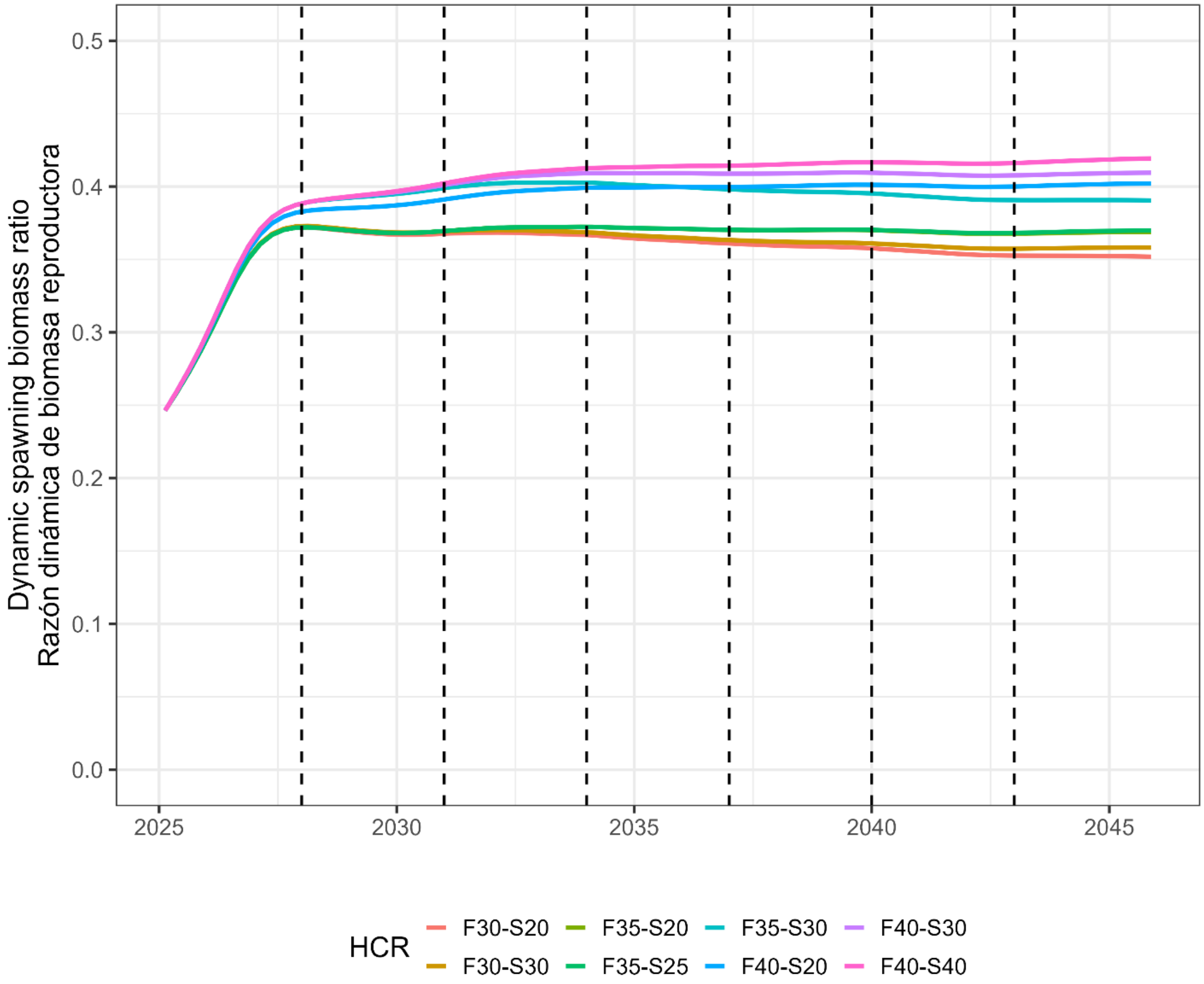

FIGURE 4. Comparison of mean spawning biomass ratio simulated under each candidate harvest control rule.

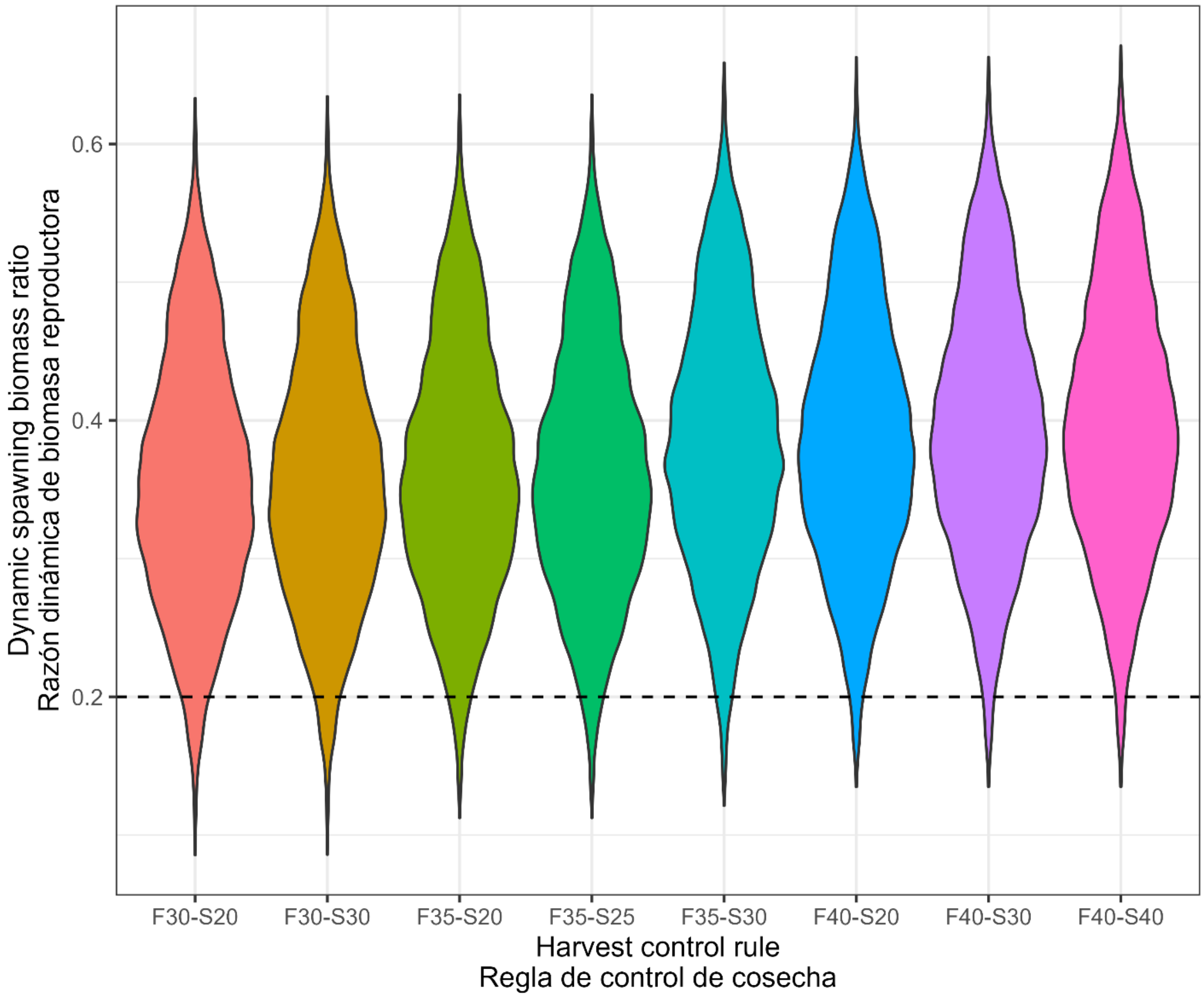

FIGURE 5. The violin plot for dynamic spawning biomass ratio simulated under each candidate harvest control rule. The horizontal dashed line represents the soft limit reference point of 0.2.

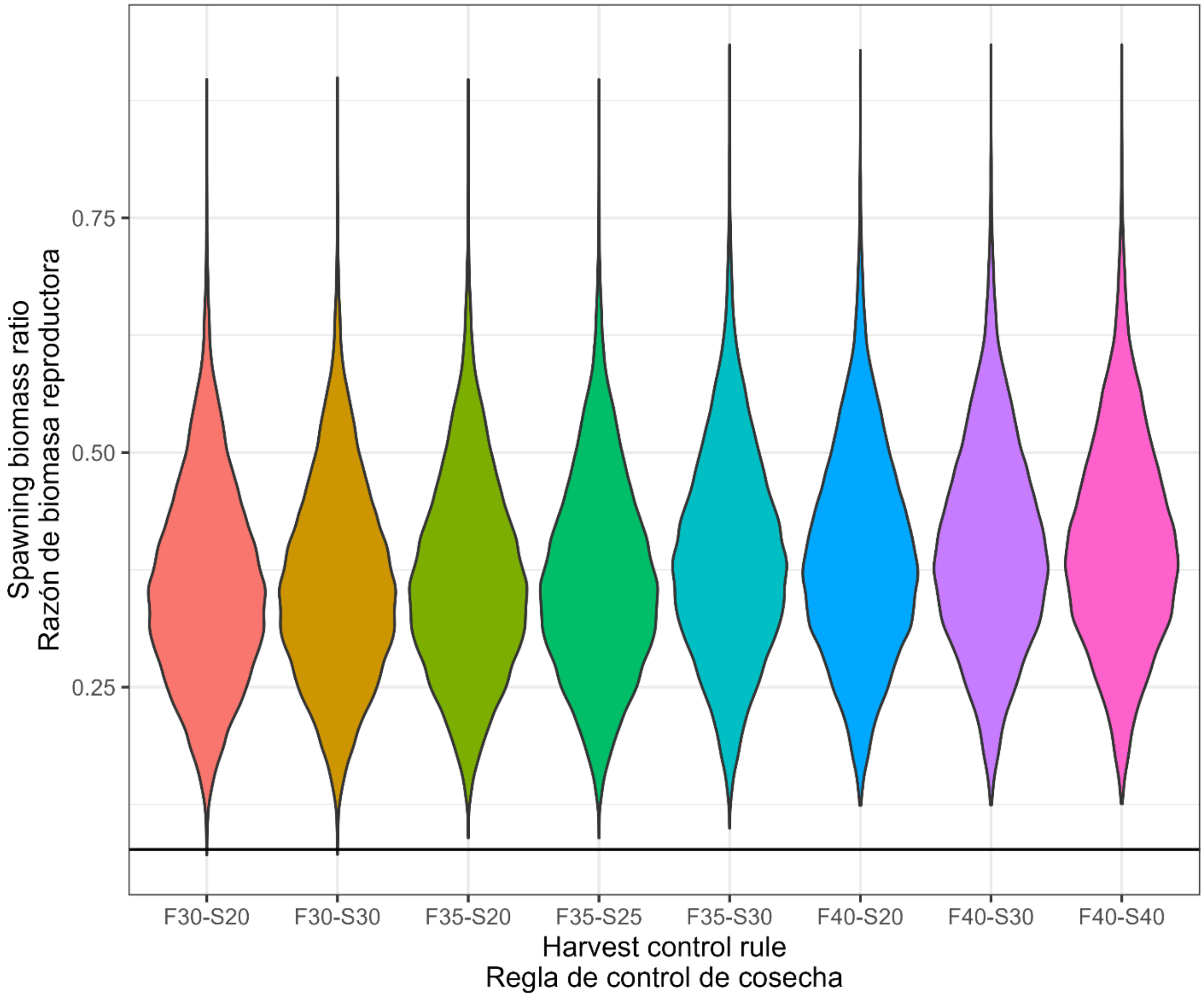

FIGURE 6. The violin plot for spawning biomass ratio simulated under each candidate harvest control rule. The horizontal solid line represents the hard limit reference point of 0.077 for spawning biomass ratio.

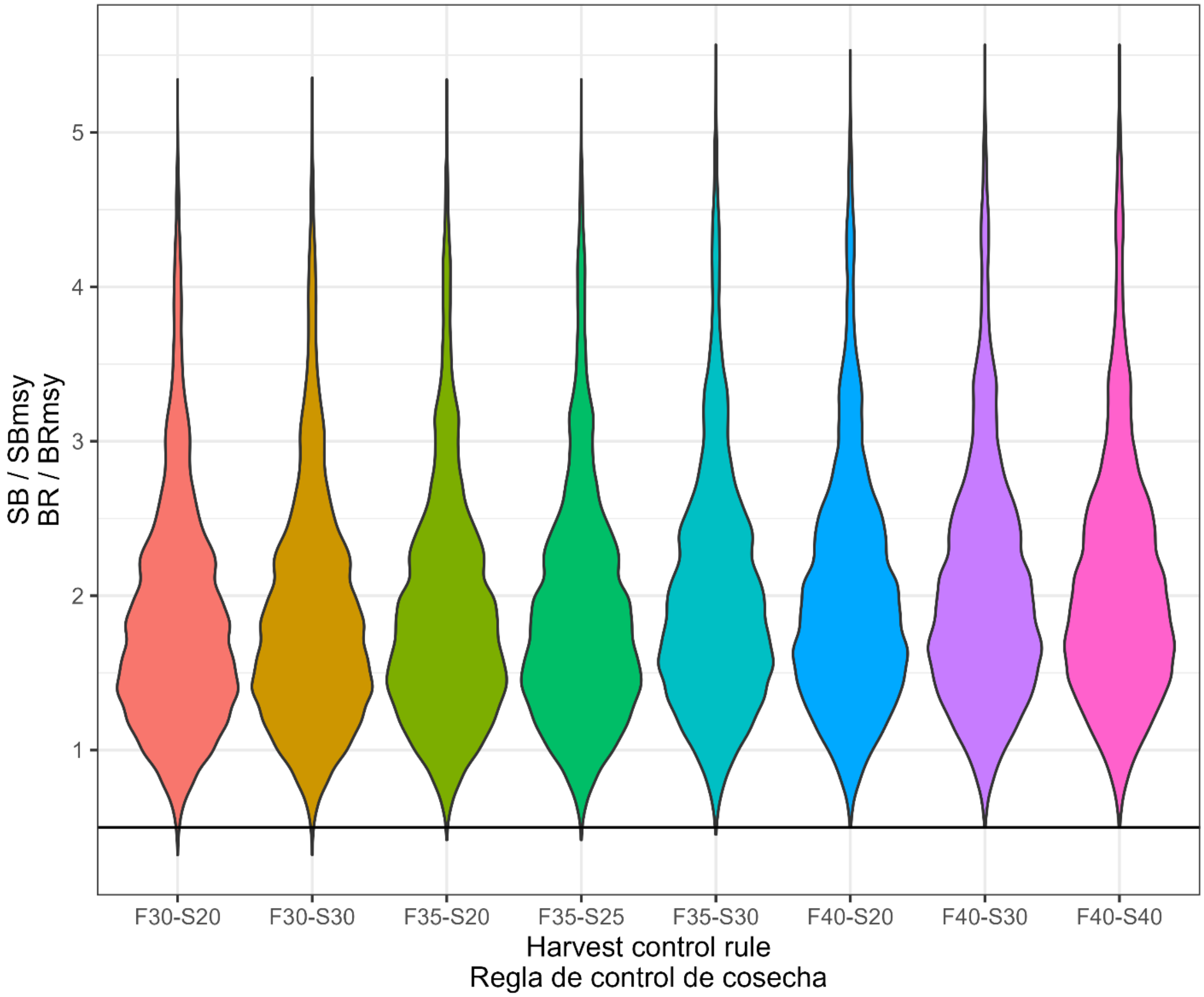

FIGURE 7. The violin plot for the ratio of spawning biomass to spawning biomass at the maximum sustainable yield simulated under each candidate harvest control rule. The horizontal solid line represents the hard limit reference point of 0.5 for spawning biomass.

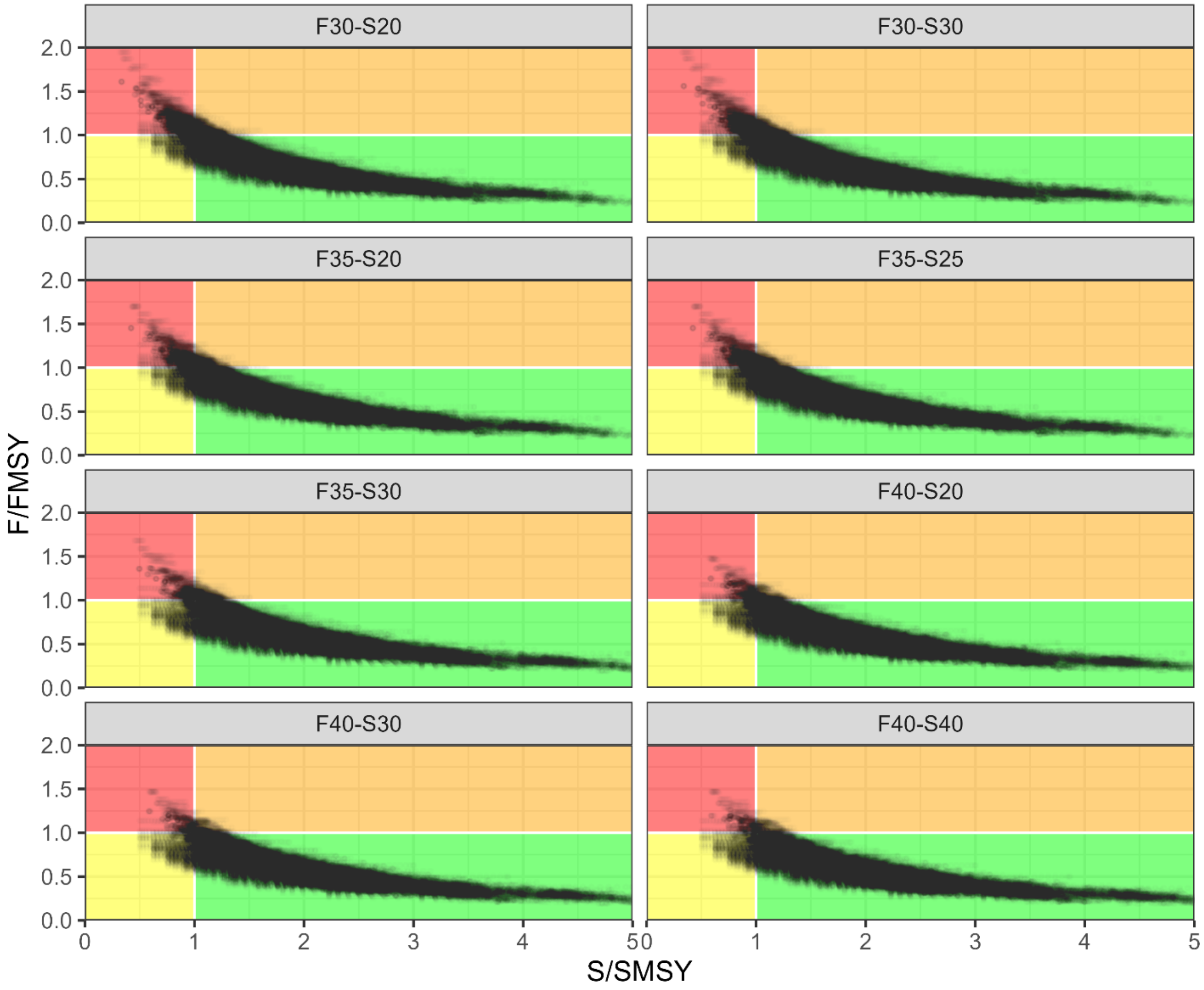

FIGURE 8. The Kobe plot for the stock simulated under each candidate harvest control rule. Each dot represents a quarterly stock status between 2025 and 2045.

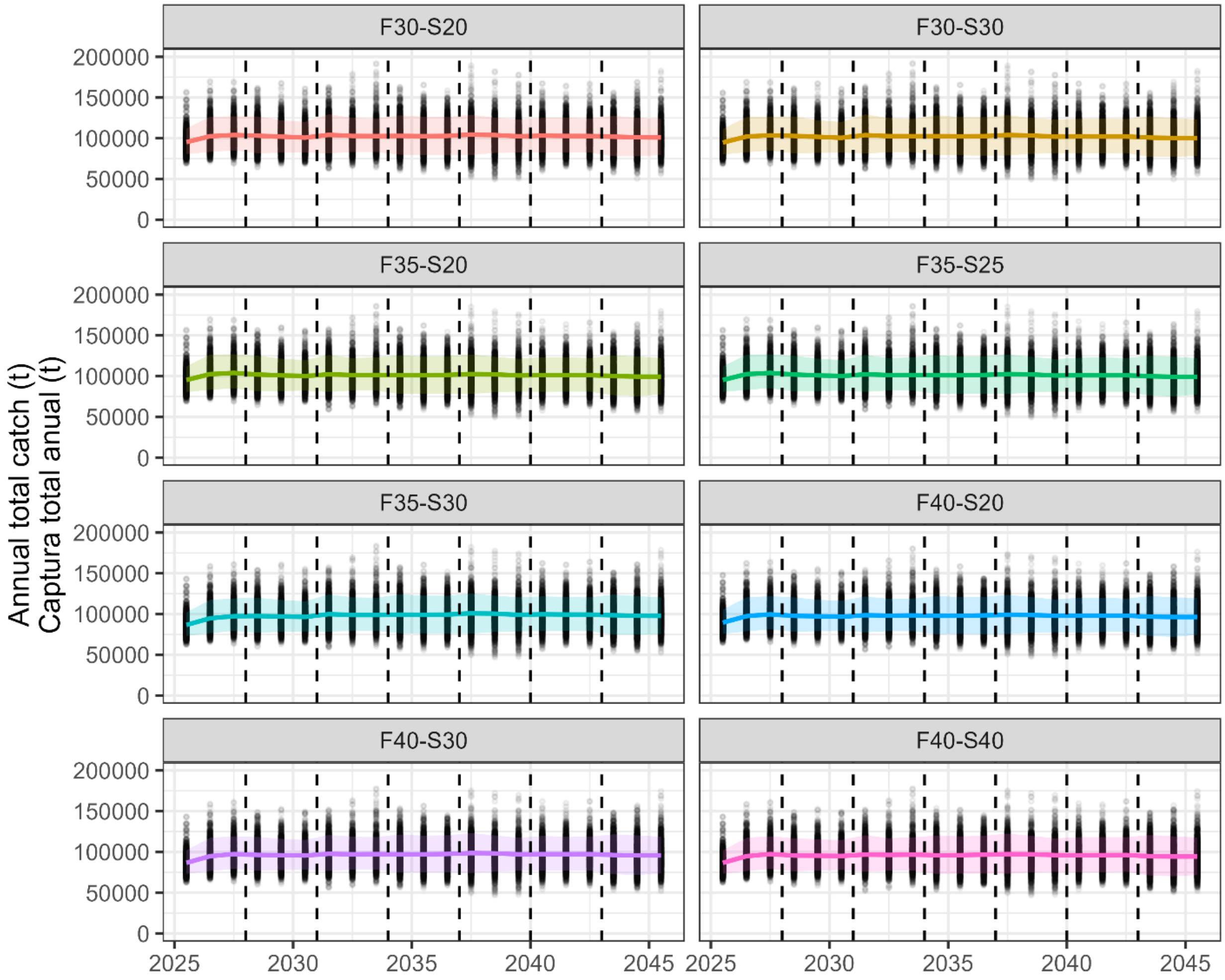

FIGURE 9. Annual total bigeye catch (mt) simulated under each candidate harvest control rule. The black dots are for individual iterations, and the color line and color ribbon represent the mean and 80% confidence interval, respectively.

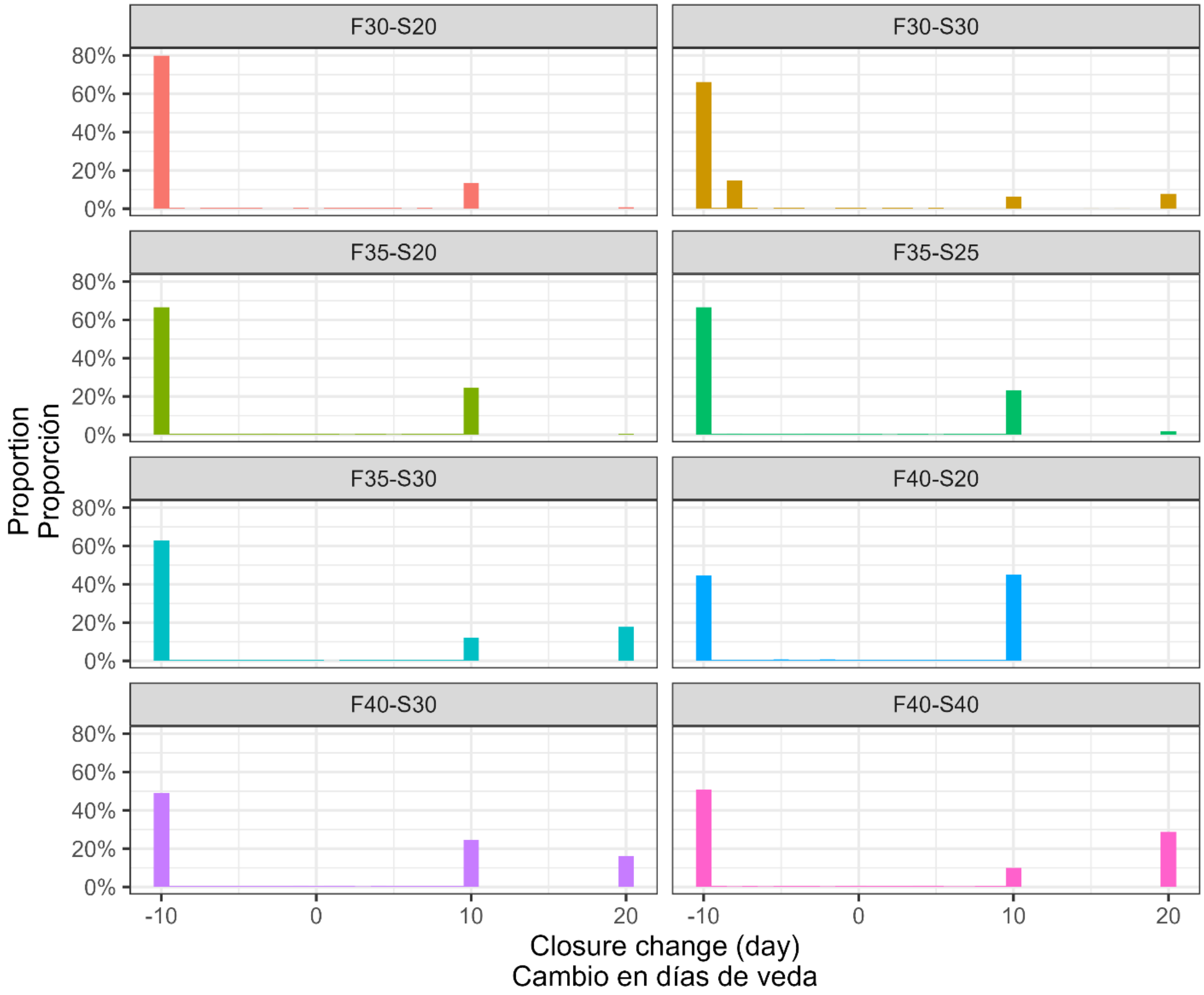

FIGURE 10. The histogram for the between-cycle change in the fishery closure simulated under each candidate harvest control rule

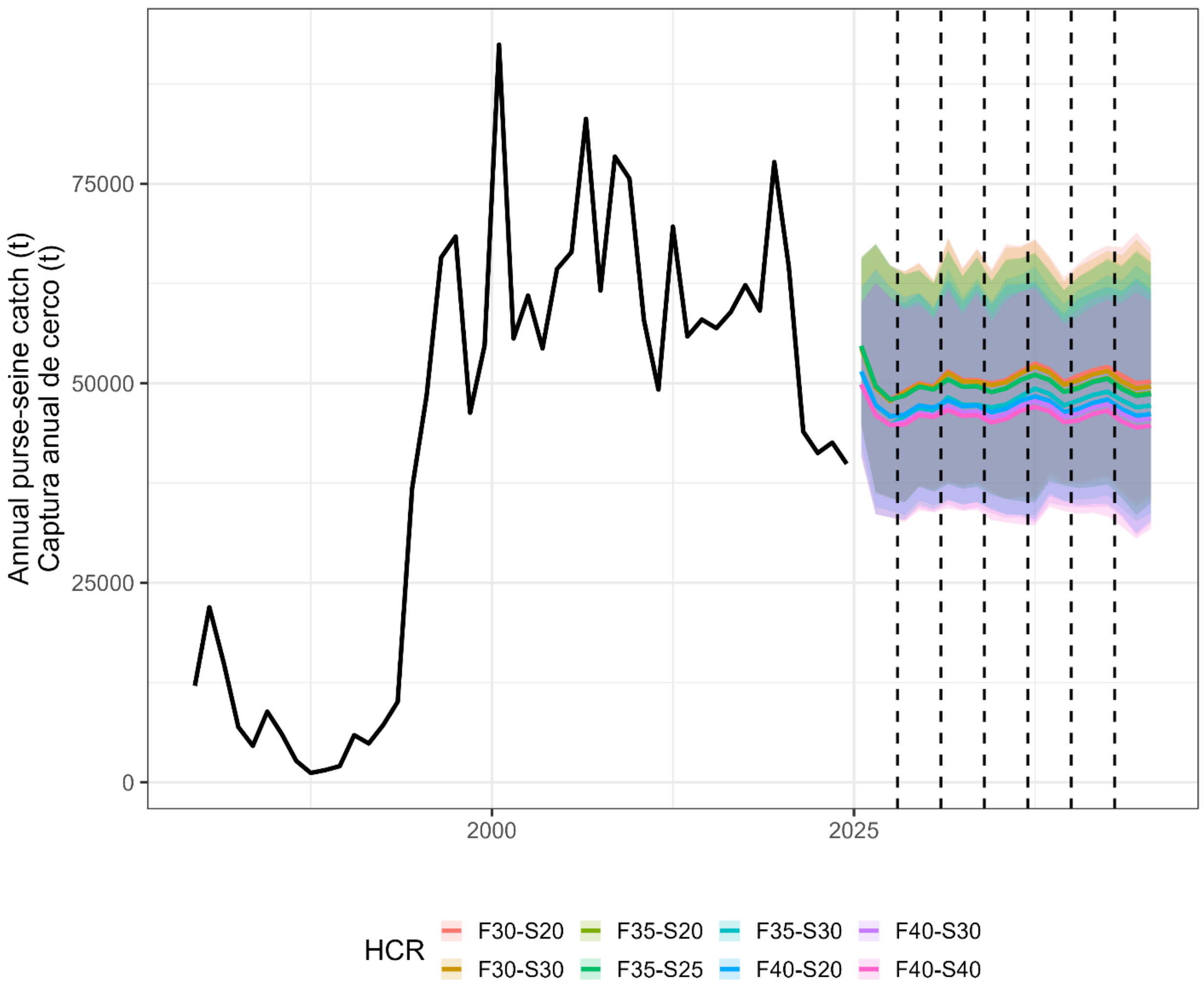

FIGURE 11. The time series of mean annual total bigeye catch (mt) simulated under each candidate harvest control rule

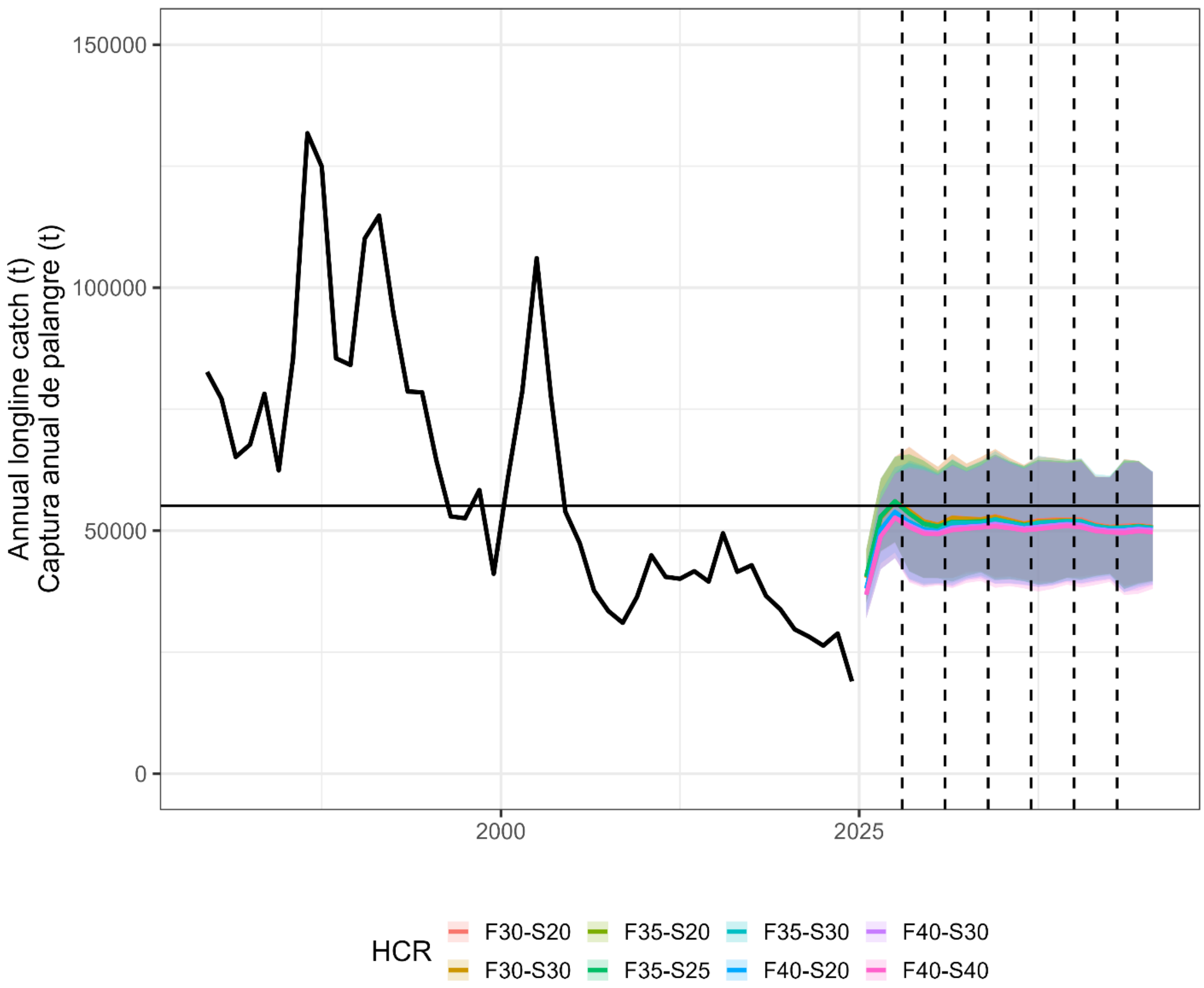

FIGURE 12. The time series of mean annual total bigeye catch (mt) simulated under each candidate harvest control rule

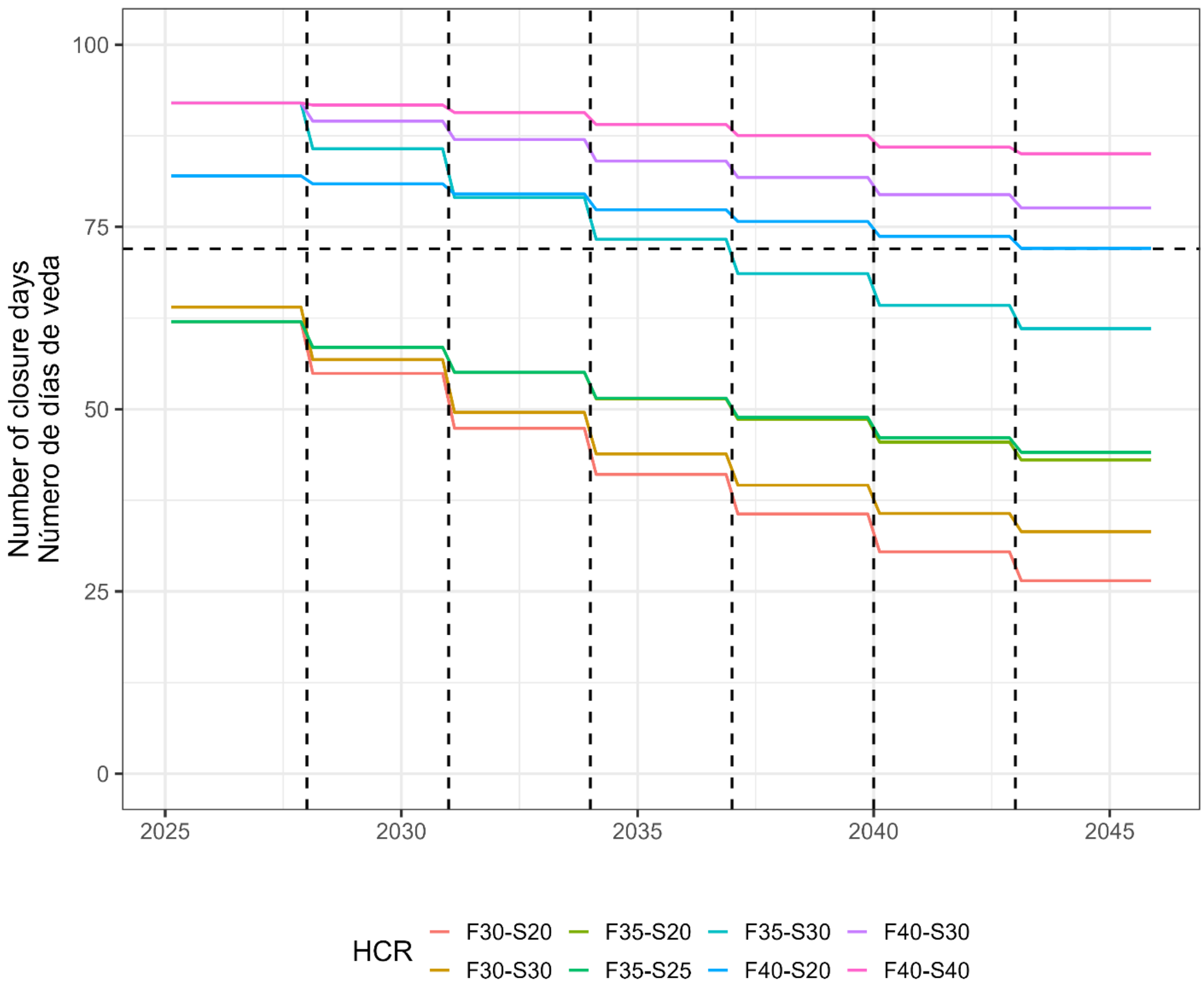

FIGURE 13. Time series of average fishery closure (day) simulated under each candidate harvest control rule.

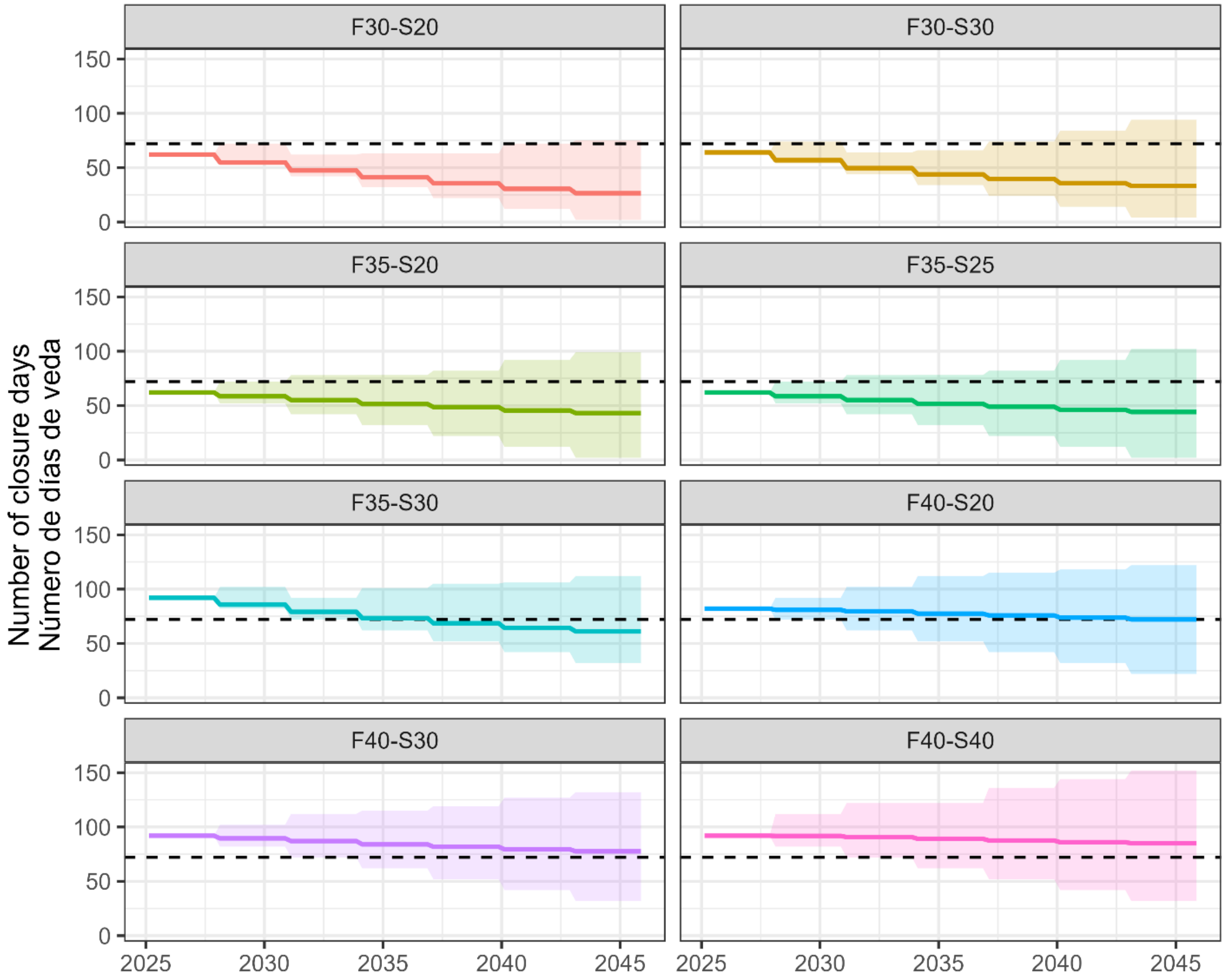

FIGURE 14. Fishery closure (day) simulated under each candidate harvest control rule. The color line and color ribbon represent the mean and 80% confidence interval, respectively.

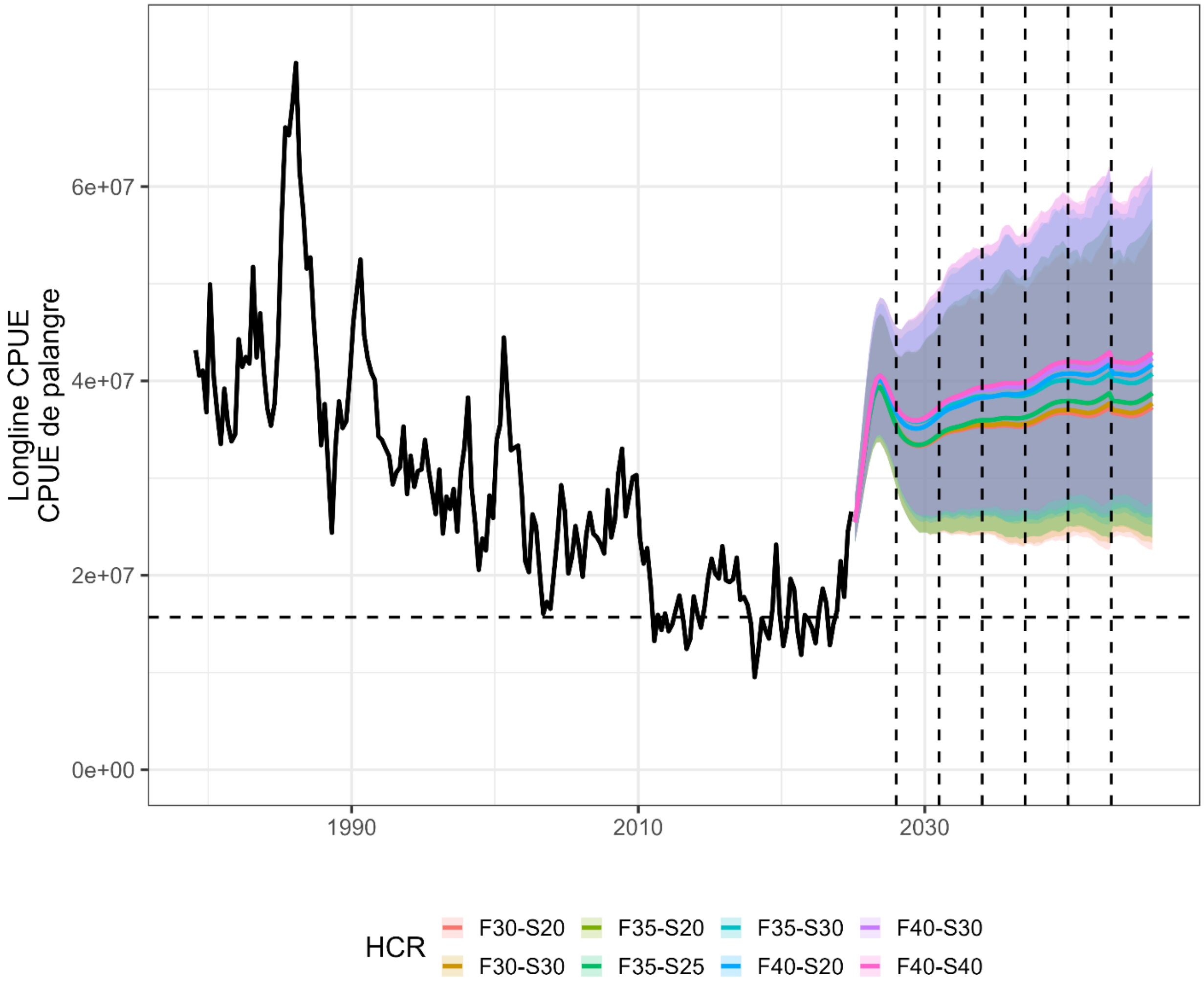

FIGURE 15. The Japanese longline CPUE for bigeye tuna in the eastern Pacific Ocean. The black line represents historical estimates and the color lines represent the mean predictions simulated under each candidate harvest control rule. The horizontal dashed line marks the average level observed in 2017-2019.

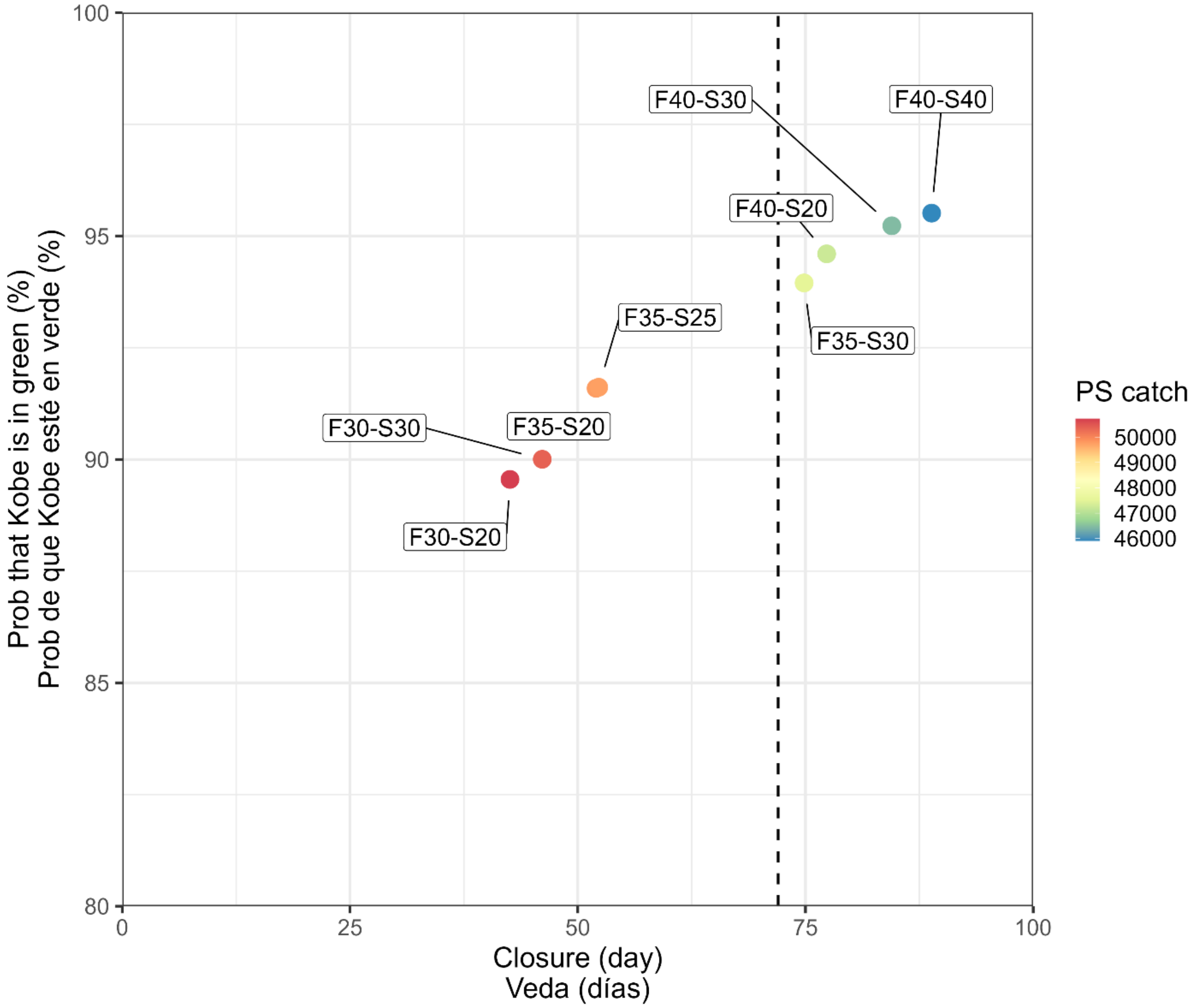

FIGURE 16. The probability that the stock is in the green quadrant of the Kobe plot versus the average number of closure days simulated under each candidate harvest control rule. The color represents the average annual bigeye catch (mt) made by the purse-seine fishery in the EPO.

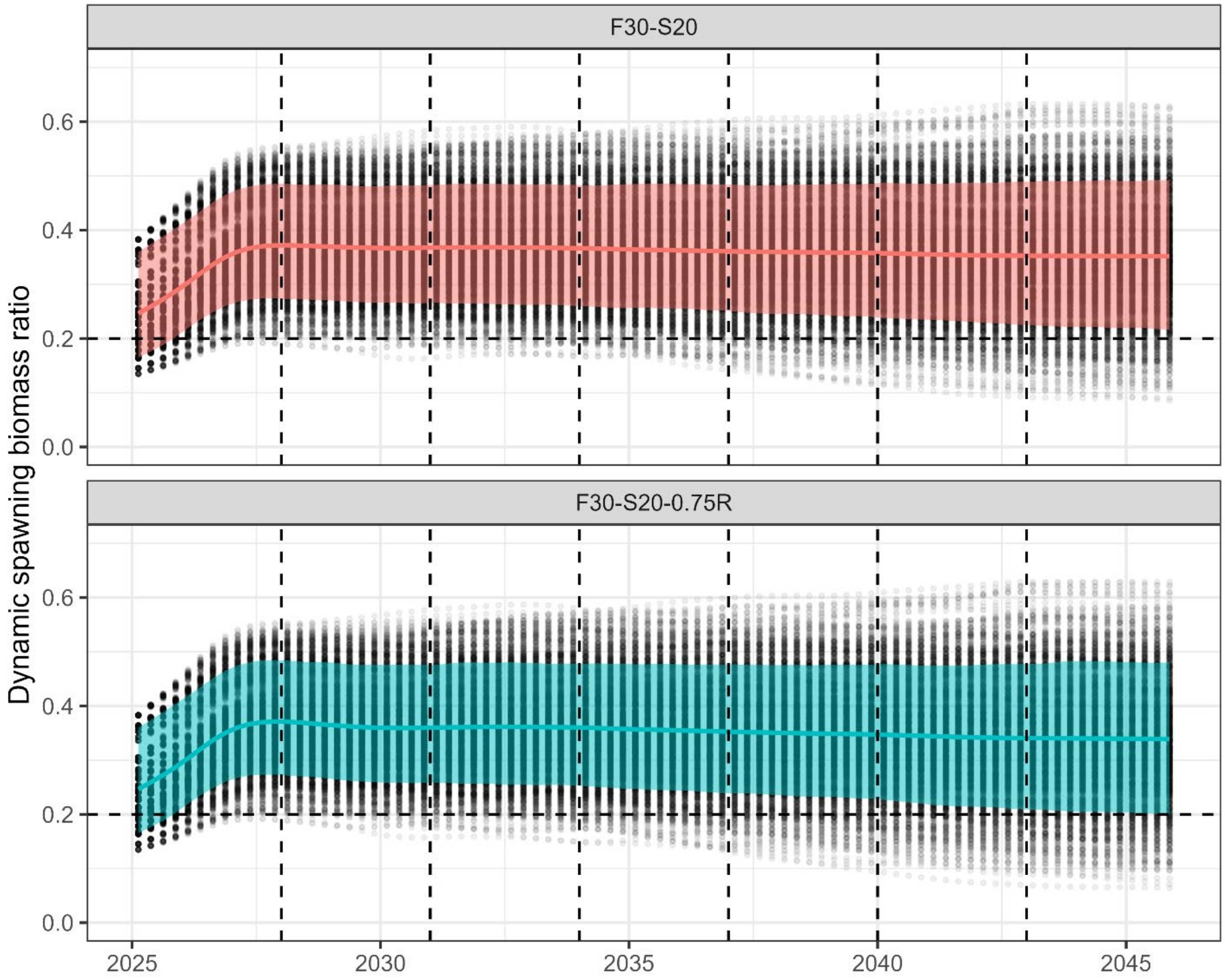

FIGURE 17. Dynamic spawning biomass ratio simulated under the staff-proposed harvest control rule with (blue) and without (red) a 25% drop in future recruitments. The black dots are for individual iterations, and the color line and color ribbon represent the mean and 80% confidence interval, respectively.

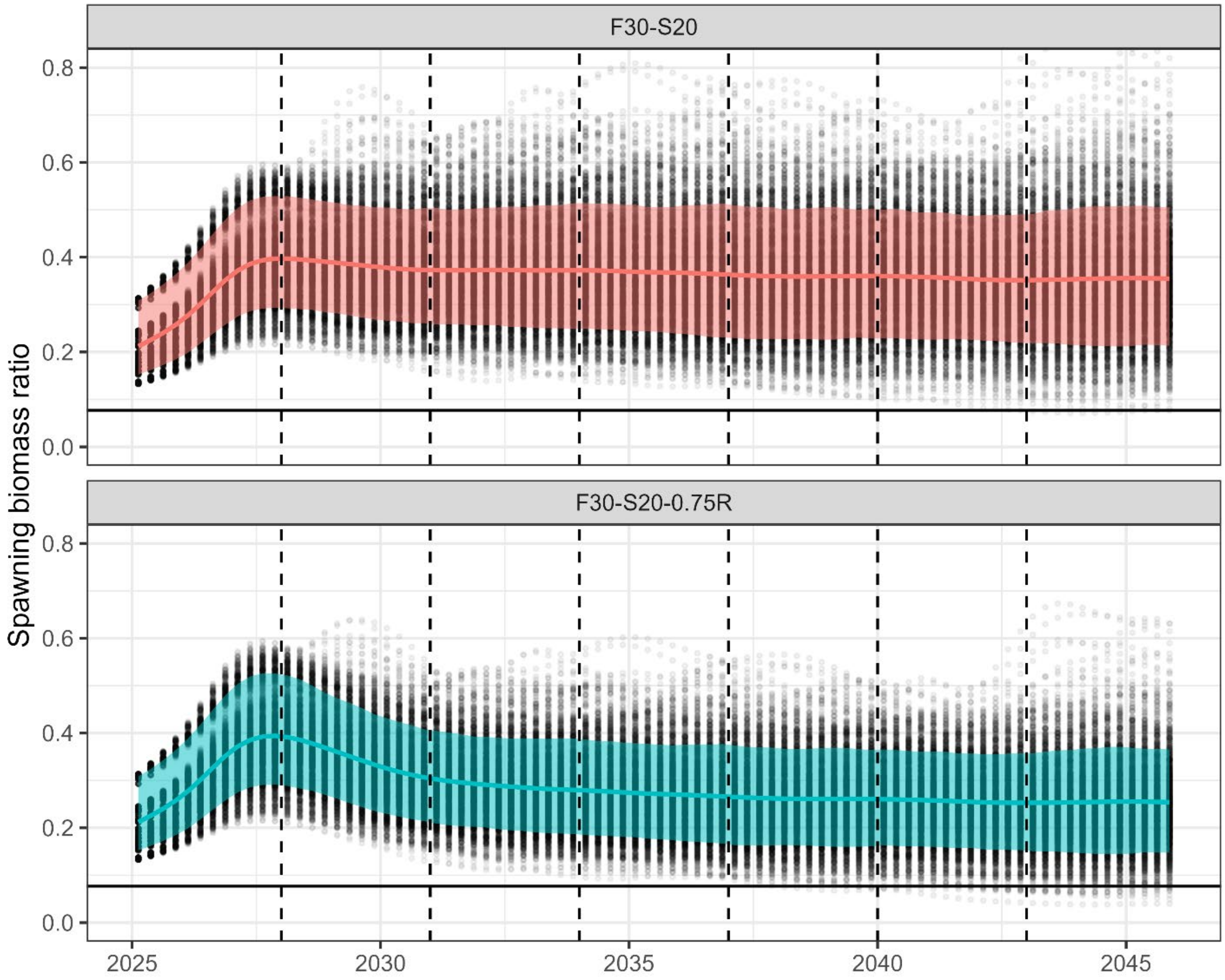

FIGURE 18. Spawning biomass ratio simulated under the staff-proposed harvest control rule with (blue) and without (red) a 25% drop in future recruitments. The black dots are for individual iterations, and the color line and color ribbon represent the mean and 80% confidence interval, respectively.

APPENDIX

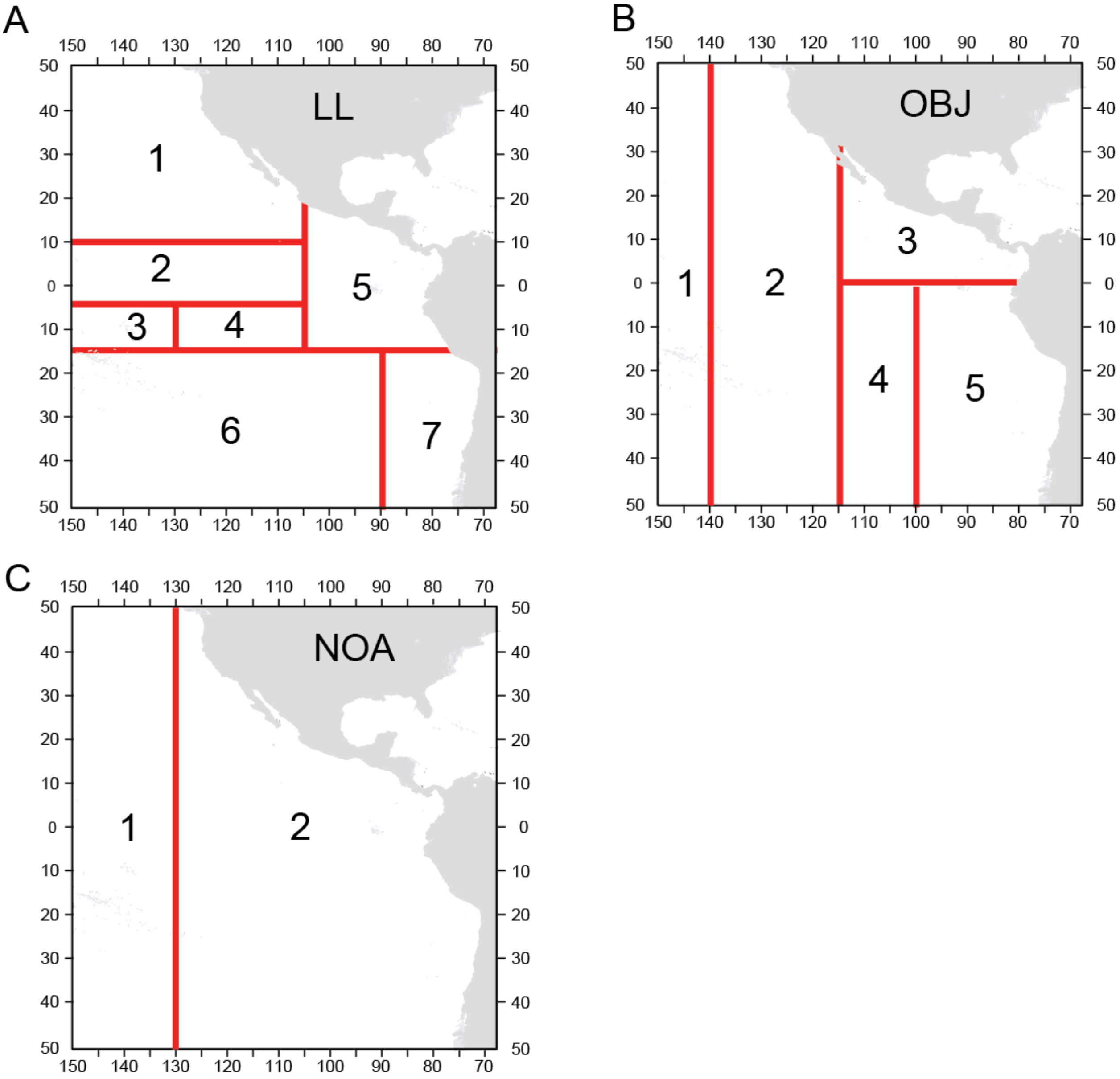

FIGURE A1. Summary of area definitions for the longline (LL), floating-object (OBJ), and unassociated (NOA) fishery fleets in the stock assessment of bigeye tuna in the EPO.

FIGURA A1. Resumen de las definiciones de áreas para las flotas de las pesquerías palangrera (LL), sobre objetos flotantes (OBJ) y no asociada (NOA) en la evaluación del atún patudo en el OPO.

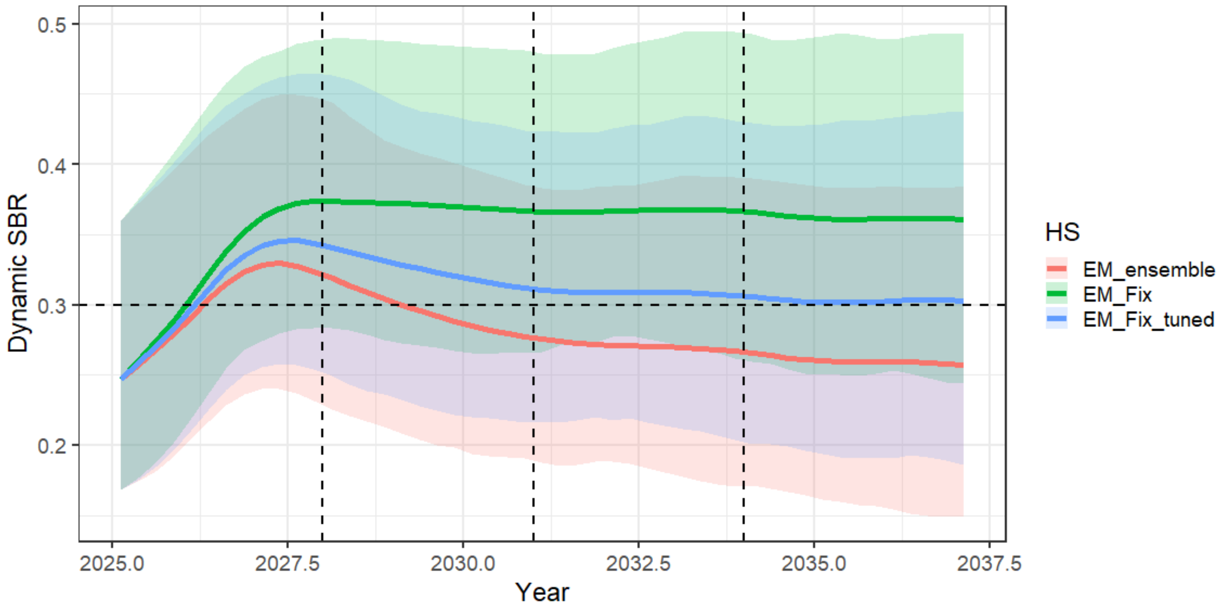

FIGURE A2. Dynamic spawning biomass ratio simulated under the staff using the three candidate EMs. The color line and color ribbon represent the mean and 80% confidence interval, respectively.

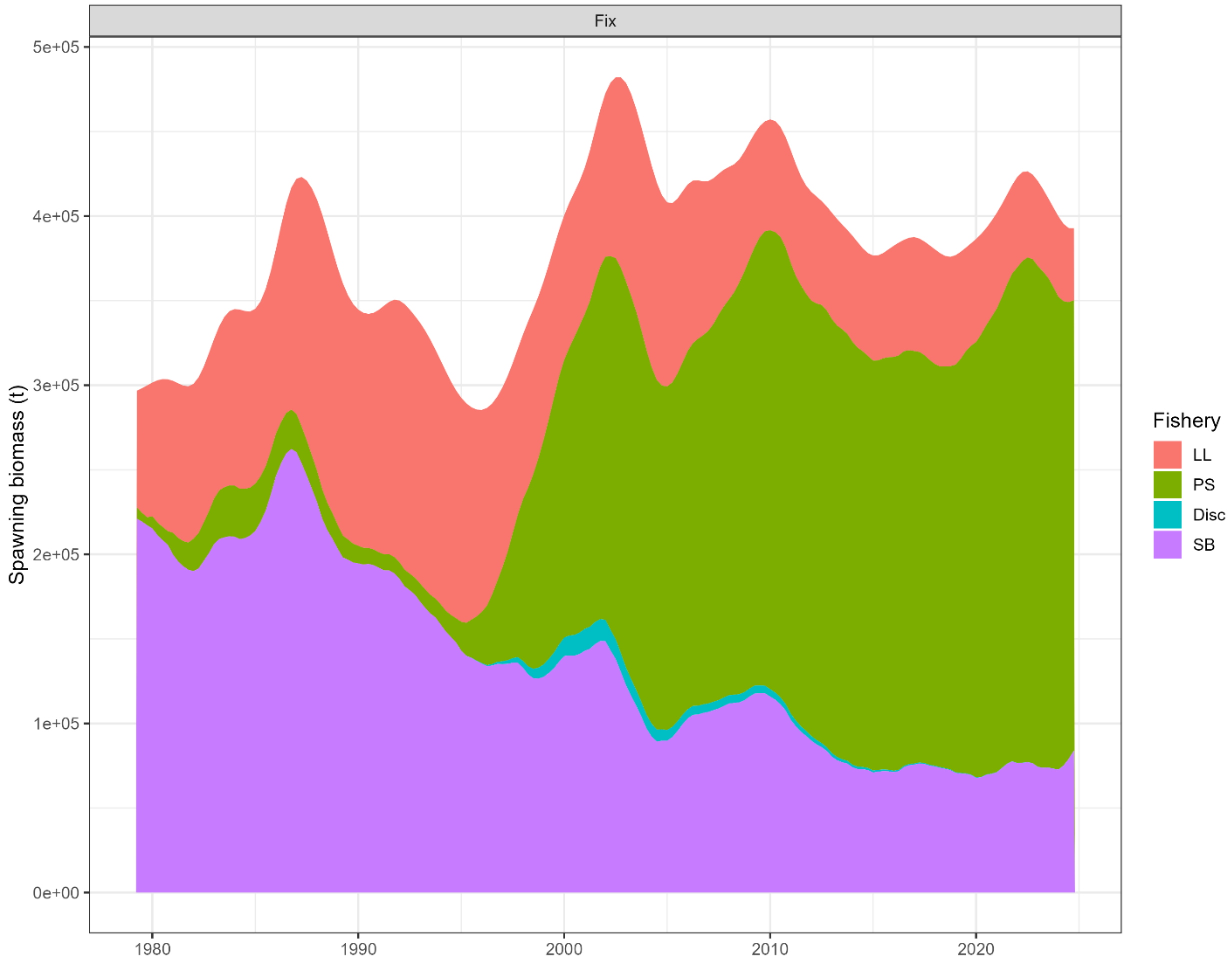

FIGURE A3. Comparison of spawning biomass trajectory of a simulated population of bigeye tuna that was never exploited (top line) and that predicted by the stock assessment model (bottom line). The shaded blue, green, and red areas show the proportional impact of the discard, purse-seine, and longline fishery, respectively.

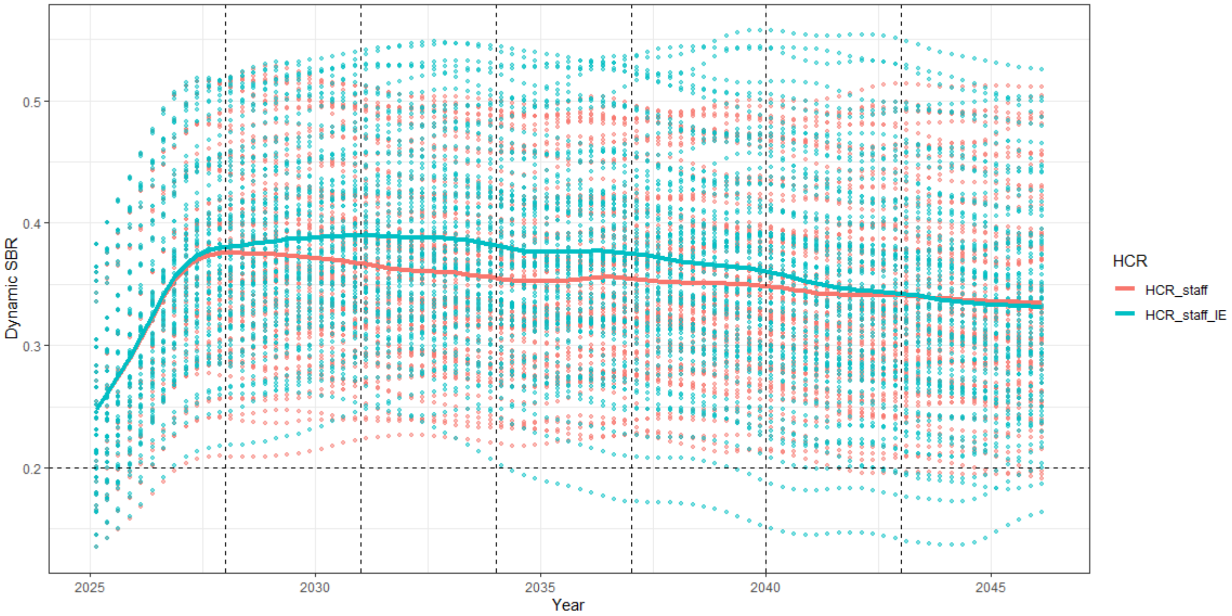

FIGURE A4. Dynamic spawning biomass ratio for bigeye in the eastern Pacific Ocean simulated under identical harvest control rule and recruitment deviations with (blue) and without (red) implementation error. Doted lines represent individual iterations and solid lines represent the average across all iterations.

FIGURA A4. Cociente de biomasa reproductora dinámica para el patudo en el Océano Pacífico oriental simulado bajo reglas de control de extracción idénticas y desviaciones de reclutamiento con (azul) y sin (rojo) error de implementación. Las líneas punteadas representan iteraciones individuales y las líneas continuas

Table A1: Glossary of acronyms

Acronym	Full Term
AAV	Average Annual Variability
ASPM	Age-Structured Production Model
S_{MSY}	Spawning biomass at Maximum Sustainable Yield
CCSBT	Commission for the Conservation of Southern Bluefin Tuna
CPC	Cooperating non-member Party, Entity, or Fishing Entity
CPUE	Catch Per Unit Effort
CV	Coefficient of Variation
DEL	Dolphin-associated purse-seine sets
dSBR	Dynamic Spawning Biomass Ratio
EM	Estimation Model
EPO	Eastern Pacific Ocean
FAO	Food and Agriculture Organization (of the United Nations)
F_{MSY}	Fishing Mortality at Maximum Sustainable Yield
GPS	Global Positioning System
HCR	Harvest Control Rule
IATTC	Inter-American Tropical Tuna Commission
ICCAT	International Commission for the Conservation of Atlantic Tunas
INF	Information document (IATTC document type)
IOTC	Indian Ocean Tuna Commission
IVT	Individual Vessel Threshold
LL	Longline
LRP	Limit Reference Point
MLE	Maximum Likelihood Estimate
MSE	Management Strategy Evaluation
MSEWG	Management Strategy Evaluation Working Group
MSY	Maximum Sustainable Yield
NOA	Non-associated purse-seine sets (free-swimming schools)
OBJ	Object-associated purse-seine sets (floating objects/FADs)
OM	Operating Model
PS	Purse-seine
R_0	Unfished Recruitment Level
SAC	Scientific Advisory Committee (of the IATTC)

SBR	Spawning Biomass Ratio
WCPFC	Western and Central Pacific Fisheries Commission
WCPO	Western and Central Pacific Ocean