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A probabilistic risk-analysis framework for reconciling competing stock assessments

CALAMASUR

A probabilistic risk-analysis framework for reconciling competing stock assessments

Method and application to jumbo flying squid (*Dosidicus gigas*) in the South-East Pacific (SPRFMO)

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Abstract A risk-assessment framework is presented to identify sustainable management actions for the jumbo flying squid (*Dosidicus gigas*) in the South-Eastern Pacific Ocean. It applies reference-point-based management quantities inside a probabilistic setup that accommodates multiple, competing hypotheses drawn from the current stock-assessment models developed under the umbrella of the South Pacific Regional Fisheries Management Organisation (SPRFMO). By explicitly quantifying uncertainty instead of relying on point estimates from a single "best" assessment model, the framework reconciles the tension between competing candidate models used for inference and decision-making. Risk is defined, following FAO guidelines, as "the probability of something undesirable happening" — here, exceeding the reference points that trigger management action. The framework is demonstrated on the three stock-assessment methodologies presented for jumbo flying squid to the 2025 Scientific Committee, treated here as archetypes of competing model architectures rather than as the positions of the parties that submitted them: a two-stage depletion model, the most mechanistic, operating at monthly time steps and explicitly modelling fleet-specific depletion and fishing operations before scaling up to a production model; a continuous-time surplus-production model, more data-modest, relying on annual CPUE indices and frequentist maximum likelihood; and a fully Bayesian state-space model, standardising CPUE via GAM before incorporating it into the population dynamics. These assessments arrive at markedly different conclusions despite using overlapping data from the same fishery. The framework yields probabilistic statements about whether feasible reference points have been, or are likely to be, exceeded, tying together three actionable components: identifying alternative hypotheses about population dynamics, weighting them by model reliability and expert judgement, and combining the resulting distributions into probability statements that can directly inform harvest control rules.

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1 Introduction

The jumbo flying squid (*Dosidicus gigas*) supports the world's largest invertebrate fishery — over one million tonnes in recent years, the fifteenth largest of all fisheries — prosecuted by a multinational jigging fleet distributed across the Eastern Pacific from Central America to southern Chile (Rosa et al., 2013). The species is endemic to the Eastern Pacific, with fishing grounds concentrated off Peru (2–10°S) and on the high seas off Peru (3–18°S) and Central America (5–10°N), and it has undergone a recent poleward range expansion (Waluda & Rodhouse 2005; Rosa et al. (2013)). Habitat-modelling studies show that suitable habitat expands during spring–autumn and contracts sharply in winter off Peru, with catch-per-unit-effort (CPUE) closely tracking habitat suitability (Yu et al., 2019). Its short, semelparous life cycle, fast growth, and strong sensitivity to environmental variation — particularly the El Niño–Southern Oscillation (ENSO) — make it both economically important and unusually difficult to assess (Gilly et al., 2006; Ibáñez et al., 2016).

The fishery is managed within the South Pacific Regional Fisheries Management Organisation (SPRFMO). Current conservation and management measures rely on effort- and capacity-based controls (vessel-number and gross-tonnage caps). However, jigging efficiency is strongly environment-driven — modulated by upwelling, sea-surface temperature, and ENSO phase — so capping the size of the fleet does not translate directly into a cap on fishing pressure (Fang et al., 2023; Yu & Chen, 2018). This motivates complementary catch-based, environment-aware measures.

A more immediate obstacle to management advice is that the science itself does not speak with one voice. Three SPRFMO parties presented stock assessments for jumbo flying squid to the 13th meeting of the SPRFMO Scientific Committee (SC13; 8–13 September 2025, Wellington, New Zealand). Although all three assess the same species, the same region (South-East Pacific / FAO Area 87), and broadly the same catch data updated to 2024 — including a sharp ~52% drop in landings in 2024 — they reach different verdicts on stock status. The divergence comes almost entirely from model architecture and from how each model treats the 2024 catch decline and environmental variability, not from the underlying data. Point estimates from any single "best" model cannot express the resulting uncertainty, and picking one model discards defensible alternatives.

This working paper presents a probabilistic multi-model risk-analysis framework — adapted from the reference-point-based approach developed for tropical tunas by the Inter-American Tropical Tuna Commission (IATTC) (Aires-da-Silva et al., 2020; Maunder et al., 2020) — for turning a set of competing stock assessments into management-relevant probability statements. The three SC13 assessments provide the worked case. They are identified individually only where each is described; thereafter they are referred to by their defining architecture — the *depletion* model, the *continuous-time* model, and the *Bayesian* model — which is the level at which the framework operates and at which the method generalises to any set of competing assessments.

2 Three competing model architectures

All three architectures share the same catch history to 2024, including the 2024 landings decline (Figure 1), and the same broad understanding that the stock is strongly modulated by the ENSO cycle. They differ in model family, estimation paradigm, time step, use of fishing effort, and how — if at all — the environment enters the population dynamics.

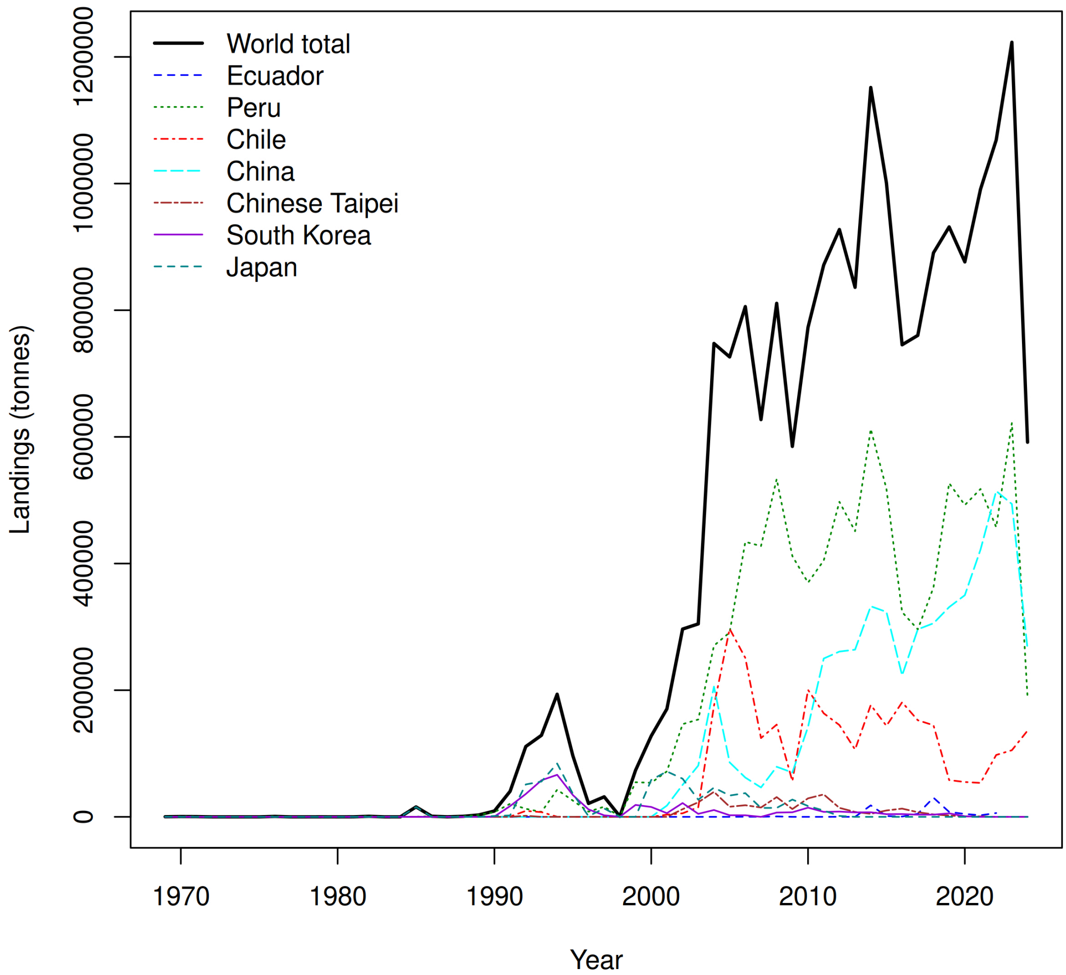

Figure 1: Annual landings of *Dosidicus gigas* in the South-East Pacific, showing the sharp ~52% reduction in 2024 that is central to the differing verdicts of the three assessments.

2.1 Two-stage environment-driven depletion + production model

The **depletion** assessment (Roa-Ureta & Wiff, 2025), submitted by CALAMASUR as observer paper SC13-Obs03, is the most mechanistic of the three. It is a two-stage, environment-driven approach spanning 1990–2024. Stage 1 fits multi-annual, multi-fleet generalized depletion models to a monthly database (January 2012–December 2024) of total catch, fishing effort, and mean weight for three fleets (Peruvian, Chilean, Asian), covering >99% of regional landings. Stage 2 then drives a Pella-Tomlinson surplus-production model with El Niño/La Niña transitions (NOAA's Oceanic Niño Index; 10 transitions over 1990–2024), testing 16 hypotheses about how carrying capacity, production symmetry, and intrinsic growth rate change with the environment.

Crucially, the depletion stage is effort-driven rather than CPUE-driven, so the assessment does not rely on a standardized CPUE series as an index of abundance — an assumption widely questioned for fast-growing, highly migratory squid. Natural mortality is estimated *inside* the model at ≈0.17/month (≈2.0/yr), consistent with the species' short life cycle. The best-supported environmental hypothesis is that only the intrinsic growth rate r varies with the environment — higher in El Niño (2.93/yr) than in La Niña (0.48/yr). The compiled ADMB production model (a two-regime Pella-Tomlinson fit) estimates a carrying capacity K ≈ 10.85 million tonnes and a shape parameter $p \approx 1.97$.

The estimated biomass fluctuates widely (maxima an order of magnitude above minima) but shows no sustained downward trend, with the highest peaks before 2019; exploitation rates have risen since 2020 but remain mostly below 40% (Figure 2). The main conclusion is that the stock is not overfished, though it may be undergoing overfishing. Because the stock has entered a regime of strong environment-driven fluctuations, MSY and B_{MSY} are judged inadequate reference points, a standard Kobe plot cannot be built, and estimates of sustainable harvest rates (mean latent productivity) remain statistically imprecise.

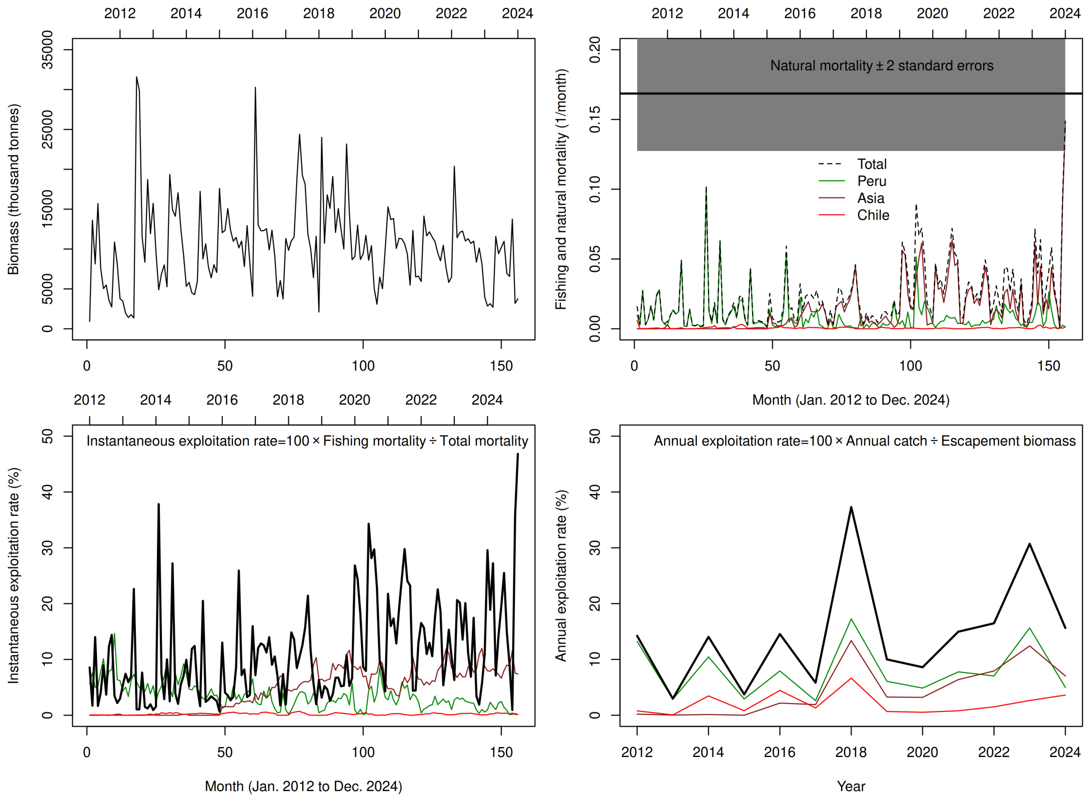

Figure 2: Estimated trajectories of biomass, mortality, and exploitation rate from the two-stage depletion model. Biomass fluctuates widely without a sustained trend, while the exploitation rate has risen since 2020 but remains mostly below 40%.

2.2 Continuous-time state-space surplus-production model (SPiCT)

The **continuous-time** assessment (Payá, 2025), submitted by Chile (IFOP) as SC13-SQ06, applies the Stochastic Production model in Continuous Time (SPiCT) — a state-space Pella-Tomlinson surplus-production model that separates process from observation error and can be run at monthly / quarterly steps — to *D. gigas* in FAO Area 87. Its main advance over previous assessments is the use of data up to 2024, reducing the two-year lag of earlier work. Six country CPUE indices were compiled (two Chinese fleet indices, Chinese Taipei, Korea, Chile, Peru), and a sensitivity analysis of seven cases tested a single global index versus six country indices, a fixed Schaefer curve, and a prior on *r*, over two data spans (2001–2024 and 2012–2024).

Catch fell by ~52% in 2024, and the abundance indices show a general decreasing trend. MSY converges around ~950 kt (906–950 kt across cases). The 2025 status is uncertain — of seven cases, four fell in the Kobe red zone, one yellow, two green — but the cases fitted to the six country indices, and in particular Case 7 (free productivity curve, six indices, *r* prior) with the best retrospective pattern, place the 2025 stock in the Kobe red zone, with a 2026 TAC of ~467 kt (comparable to the 2024 catch). TAC advice under F_{MSY} ranged widely, from 267 kt to 989 kt across cases. This is a notable contrast with the "healthy" 2022 status discussed in 2024, and the reversal is driven by a 52% catch drop and declining indices. The authors caution that SPiCT assumes indices are unbiased indicators of the whole stock, and recommend standardising CPUE and accounting for the three *D. gigas* phenotypes and environmentally driven variability.

2.3 Bayesian state-space model with explicit ENSO regimes

The **Bayesian** assessment (Li & Chen, 2025), submitted by China (Shanghai Ocean University) as SC13-SQ07, is a state-space surplus-production (Pella-Tomlinson) model fitted in WinBUGS via MCMC, with an explicit test of how the ENSO cycle affects population dynamics. Four abundance indices were used: Peruvian and Chilean CPUE from CALAMASUR, plus the Chinese squid-jigging CPUE standardized with a Generalized Additive Model (GAM) using environmental covariates (SST, chlorophyll-*a*, salinity, Niño 1+2) and spatiotemporal terms. Seven environment-dependent models were tested, letting carrying capacity K, growth rate r, and shape s vary between El Niño and La Niña phases.

The GAM confirmed year, month, and salinity as the main CPUE drivers, with standardized CPUE peaking in 2015 and lowest in 2024. Among the seven models, the "Kr" model (both K and r vary with ENSO) had the lowest DIC and was best supported. Base-scenario MSY ≈ 1.19–1.35 Mt (traditional model), rising to ~1.3–1.6 Mt under the environment-dependent model. Kobe diagnostics indicate the stock has been sustainable since 2013 — neither overfished nor undergoing overfishing — with a terminal-year probability of healthy status of 70.9–88.3% under the environment-dependent model (58.6–73.1% under the traditional one). Notably, despite the sharp 2024 landings decline, the stock stayed healthy, a pattern the authors attribute to El Niño's influence on population dynamics rather than to depletion.

3 Model comparison: how architecture drives the verdict

Table 1 summarises the three approaches. The single biggest structural difference is whether biomass is inferred from an abundance index or reconstructed from effort: the continuous-time and Bayesian models both fit a surplus-production model directly to catch and a CPUE abundance index, inferring biomass from the relationship between catch and a relative abundance signal, whereas the depletion model first fits an effort-driven depletion model and feeds its biomass series into a production model. This matters because production models assume the CPUE index is proportional to true abundance — questionable for this species — while the depletion design avoids that reliance and estimates M internally.

Table 1: Comparative overview of the three competing model architectures for SPRFMO jumbo squid.

Dimension	Continuous-time production (SPiCT) (Payá, 2025)	Bayesian state-space (Li & Chen, 2025)	Two-stage depletion + Pella-Tomlinson (Roa-Ureta & Wiff, 2025)
Model family	Surplus production (Pella-Tomlinson), **continuous time**, state-space	Surplus production (Pella-Tomlinson), **discrete/annual**, state-space	**Two-stage**: monthly *depletion* → Pella-Tomlinson production
Estimation	Maximum likelihood (TMB)	Bayesian MCMC (WinBUGS)	Non-Bayesian hierarchical (ADMB)
Time step	Continuous	Annual	Stage 1 monthly; Stage 2 annual
Data used	Catch + 6 country CPUE indices	Catch + 4 fleet indices	Monthly catch, **effort** & mean weight (3 fleets) + FAO landings
Uses fishing **effort**?	No (index-based)	No (index-based)	**Yes** — depletion is effort-driven
Environment in model	Not explicit (caveat)	**Explicit** — K, r, s vary by ENSO; 7 models	**Explicit** — r varies by El Niño/La Niña; 16 hypotheses
Time span	2001–2024 (and 2012–2024)	2012–2024	2012–2024 (Stage 1); 1990–2024 (Stage 2)
Terminal verdict	Kobe **red zone** (best case)	**Healthy** since 2013 (71–88% prob.)	**Not overfished**, possibly overfishing

The three models also differ in how the environment enters. The Bayesian and depletion models build the ENSO cycle *into* the model, letting productivity switch between regimes — the former favouring both K and r varying, the latter finding support for only r varying (Figure 3). The continuous-time model does not encode the environment explicitly, flagging it instead as a caveat.

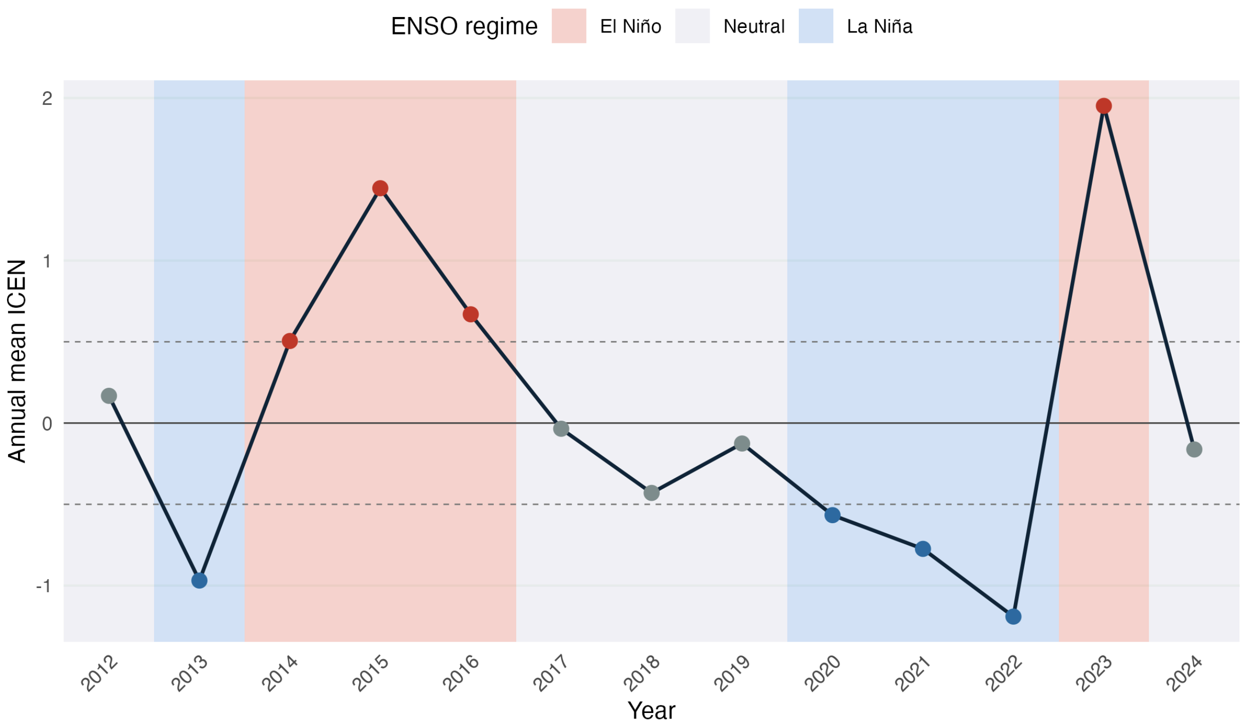

Figure 3: El Niño–Southern Oscillation signal over the assessment period, shown as the annual mean of the Índice Costero El Niño (ICEN; monthly data 2012–2024). The shaded background classifies each year into an ENSO regime using the standard ±0.5 thresholds (El Niño ≥ 0.5, La Niña ≤ −0.5, Neutral between; dashed lines). The Bayesian and depletion models let population productivity parameters switch between these El Niño and La Niña phases.

Most consequentially, the models differ in what they make of the 2024 catch drop:

– The Bayesian model interprets a healthy stock *despite* the 2024 decline as evidence of an El Niño effect on availability, not depletion → still healthy.
– The depletion model sees a stock in a regime of wide fluctuations with no sustained downward trend and exploitation mostly below 40% → not overfished, but rising exploitation means overfishing *may* be occurring.
– The continuous-time model reads the 52% catch reduction plus declining abundance indices as a genuine downturn → 2025 in the Kobe red zone.

The spread of verdicts is best understood as a model-structure spectrum rather than a data dispute: the more a model trusts declining CPUE as a direct abundance signal (here, the continuous-time model), the more pessimistic the status; the more it attributes the 2024 drop to environment/availability (the Bayesian model), the more optimistic; and the more it relies on effort-based depletion and treats MSY as unreliable under fluctuations (the depletion model), the more it lands on a cautious middle. Despite the different headlines, the three converge on several points: the stock is strongly influenced by ENSO; biomass fluctuates widely rather than trending; exploitation has been rising; and the standardized CPUE indices need improvement. No single model is definitively “right” — each encodes a different, defensible hypothesis about *why* catches fell in 2024, which is precisely why the SPRFMO Squid Working Group runs them in parallel.

4 A probabilistic risk-analysis framework for competing assessments

Rather than choose among the competing architectures, we adopt a risk analysis that carries a suite of plausible models, weights them by plausibility, and produces probability statements about whether reference points have been or are likely to be exceeded. The method is stated generally — it requires only a set of candidate assessments, their estimated quantities of interest, and a defensible weighting — and is then instantiated on the three architectures described above. The approach is adapted from the reference-point-based framework developed for eastern Pacific tropical tunas (Aires-da-Silva et al., 2020; Maunder et al., 2020), where IATTC staff concluded that "best assessment" results were too sensitive to new data to support management advice — a situation closely mirrored by jumbo squid, where the 2024 catch drop swings the verdict from "healthy" to "red zone" depending on the model.

Following FAO guidelines (FAO, 1995), risk is defined as "the probability of something undesirable happening" — here, exceeding a target or limit reference point. Because status is judged relative to reference points, the quantities of interest are ratios (e.g. F_{cur}/F_{MSY}, B_{cur}/B_{MSY}), and the framework concentrates on two categories of uncertainty: parameter uncertainty within a model, and model-structure uncertainty across the competing candidate models. A fully Bayesian solution integrating all models is idealised but impractical, so a pragmatic approach is used — a deliberate compromise among computational demand, complexity, and statistical rigour. Figure 4 summarises the end-to-end procedure.

Figure 4: The pragmatic multi-model risk-analysis workflow adapted from the IATTC SAC-11 framework, from probabilistic problem framing through hypothesis definition, model weighting, distribution combination, and management presentation.

The procedure has five main steps.

Step 1 — A hierarchy of hypotheses and models. Candidate hypotheses about the state of nature are represented by stock-assessment models arranged in a three-level tree: *Level 1* overarching hypotheses (weighted by expert opinion only), *Level 2* data-distinguishable hypotheses, and *Level 3* sub-hypotheses evaluated so as to limit the influence of data. For jumbo squid the natural Level-1 hypotheses concern the interpretation of the 2024 decline (environmental availability vs. genuine depletion) and stock structure (single stock vs. the three phenotypes); Level-2 hypotheses map directly onto the three architectures of Table 1 and their environmental treatments.

Step 2 — A weighting system. Each model's weight is the product of several metrics, drawn from four discrete categories (None = 0, Low = 0.25, Medium = 0.5, High = 1.0) to contain subjectivity:

$$W(\text{model}) = \prod_{k \in \mathcal{M}} W_k,$$
$$\mathcal{M} = \{\text{Expert, Convergence, Fit, Plaus. params, Plaus. results, Diagnostics}\}$$

Model fit (a liberal, AIC-based criterion) is only *one* metric among many; convergence failure (e.g. a non-positive-definite Hessian) zeroes the product and eliminates the model. The diagnostics term is itself a sum of sub-weights (retrospective behaviour, index and process residuals, production-function diagnostics) so that no single diagnostic dominates. Weights are then rescaled to sum to one conditionally along the branches of the tree, turning the flow chart into a probability tree so that a hypothesis does not gain weight merely by being represented by more models.

Step 3 — Per-model distributions. For each retained model, the probability distribution of the quantity of interest (a ratio) is approximated from the estimated standard error (frequentist/normal approximations standing in for a full per-model posterior) and rescaled to a proper density, $P(\text{Quantity} \mid \text{Model} = m)$.

Step 4 — Combine across models (model averaging). The per-model densities are combined by weighted model averaging (Buckland et al., 1997; Hoeting et al., 1999):

$$P(\text{Quantity}) = \sum_m P(\text{Quantity} \mid \text{Model} = m)\, P(\text{Model} = m)$$

evaluated over a grid fine and wide enough to resolve the tails — which matter because harvest control rules turn on tail probabilities such as $P(F > F_{LIMIT})$. The cumulative distribution is then used to read off reference-point exceedance probabilities.

Step 5 — Present the risk analysis. Results are presented as probability densities and CDFs of the ratios, Kobe phase plots placing each model and the combined result relative to reference points, and decision tables giving the exceedance probability for each candidate management action (e.g. alternative TACs or season closures) under each state of nature, with a weighted-average column. Sensitivity of the advice to the (subjective) weights is reported explicitly.

What makes this framework more viable for jumbo squid than a generic ensemble or model-averaging exercise (Deroba & Schueller, 2013; Punt et al., 2016) is that it ties three concrete, actionable components together: identifying alternative hypotheses about population dynamics, weighting them by model reliability and expert judgement, and combining the resulting distributions into probability statements that can directly inform harvest control rules or other management decisions. It also inherits the tuna framework's honest limitations: pervasive subjectivity in hypothesis choice and weighting (contained, not eliminated, by discrete categories and sensitivity analysis); an internal tension between treating parameter uncertainty with standard machinery while handling structural uncertainty by judgement; and the risk of bimodality when the data cannot distinguish an optimistic from a pessimistic cluster of models — a real possibility here, given how sharply the three current verdicts diverge (Runge et al., 2011).

5 Discussion: management implications

Two management messages follow. First, effort- and capacity-based controls are insufficient on their own. Jigging efficiency responds strongly to upwelling, SST, and ENSO phase (Fang et al., 2023; Weiguo, 2012; Yu & Chen, 2018), so a fixed cap on vessels or tonnage does not fix fishing pressure; realised mortality can rise under favourable environmental conditions even as the fleet stays within its cap. This argues for complementing capacity limits with catch-based measures and for environment-aware reference points that acknowledge productivity is not stationary.

Second, because MSY and B_{MSY} are unreliable under strong environment-driven fluctuations — a point on which the depletion model is explicit, and which the divergence among the three models illustrates — management advice should be framed probabilistically rather than around a single point estimate or a single "best" model. The risk-analysis framework does exactly this: it turns three irreconcilable headline verdicts into a weighted probability statement about reference-point exceedance, which can seed a harvest control rule and, ultimately, Management Strategy Evaluation (Punt et al., 2016). Natural mortality, estimated internally at ≈2.0 / yr, and its plausible spatial variation across Peru, Chile, and the high seas (Stock et al., 2021) are among the parameters whose uncertainty most deserves to be carried explicitly.

6 Way forward and conclusions

Priorities for improving the assessment and the risk analysis are: (i) extending the depletion model to four fleets and three natural-mortality zones (Peru, Chile, high seas); (ii) moving the surplus-production stage to a continuous, monthly ONI-driven time step; (iii) improving and standardizing the CPUE abundance indices to incorporate spatiotemporal structure and the different squid sizes across regions; and (iv) accounting for the three *D. gigas* phenotypes, which likely differ in growth and carrying capacity (Ibáñez et al., 2016; Park et al., 2015). The weighted model set assembled for the risk analysis can be reused directly as the operating models for a future MSE.

In summary, the three 2025 SPRFMO assessments of jumbo flying squid disagree not because of the data but because of how each model is built and how each treats the 2024 catch decline and environmental variability. A probabilistic, reference-point based risk-analysis framework — carrying the competing models as weighted hypotheses rather than selecting one — offers a defensible, management-ready way to reconcile them, and directly supports the shift toward catch-based, environment-aware management measures for this exceptionally variable fishery. The framework itself is not specific to this stock: it applies wherever competing assessment architectures produce divergent status advice for the same resource, and the jumbo squid case is presented here as a demanding instance of that general problem.

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