SPRFMO
South Pacific Regional Fisheries Management Organisation

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Standardization of Catch-per-unit-effort (CPUE) for jack mackerel (2015-2025) in Peruvian national jurisdictional waters

by

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IMARPE

This report contains information on the jack mackerel fish stock and fishery in Peruvian jurisdictional waters that, we reiterate, the delegation of Peru, in use of its discretionary powers, voluntarily provides for the purpose of information and support to the scientific research work within the Scientific Committee of the SPRFMO. In doing so, while referring to Article 5 of the Convention on the Conservation and Management of High Seas Fishery Resources in the South Pacific Ocean and reiterating that Peru has not given the express consent contemplated in Article 20 (4) (a) (iii) of the Convention, Peru reaffirms that the decisions and conservation and management measures adopted by the SPRFMO Commission are not applicable within Peruvian jurisdictional waters.

2026

ABSTRACT

The catch per unit effort (CPUE) of jack mackerel (*Trachurus murphyi*) in Peruvian jurisdictional waters was standardized for the period 2015–2025 using generalized additive models (GAMs). The information was updated by incorporating improvements to the database through the recovery of spatial information, latitude and longitude, and an effective effort measure based on trip duration. Different GAMs were evaluated using catch per trip as the response variable and temporal factors, year and month, operational factors, hold capacity and fleet type, spatial variables, latitude, longitude, and distance to the coast, and environmental variables, sea surface temperature and salinity, as covariates. Trip duration was included as an offset term to represent effective fishing effort. The results showed that models incorporating hold capacity as a continuous variable and a two-dimensional spatial structure had the best statistical performance. The selected model, A2, explained 60.9% of the deviance and included significant temporal, spatial, and environmental effects. The standardized CPUE series showed high interannual variability, with marked increases in 2017 and especially between 2022 and 2024, followed by a decrease in 2025.

1. INTRODUCTION

Relative abundance indices based on catch per unit effort (CPUE) are a key tool in stock assessment, particularly when fishery-independent information is not available. However, for CPUE to represent a reliable indicator of abundance, standardization procedures must be applied to remove or reduce the influence of factors other than biomass that affect catchability (Hilborn & Walters, 1992; Maunder & Punt, 2004; Harley et al., 2001). The selection of the methodological approach and the covariates to be included depends on aspects such as the biology of the species, the dynamics of the fishery, data quality, and the objectives of the analysis. Commonly used approaches include generalized linear models (GLMs), generalized additive models (GAMs), delta or hurdle models, as well as more recent approaches that incorporate spatio-temporal structures (Maunder & Punt, 2004; Zuur et al., 2009; Thorson et al., 2015).

In the South Pacific, jack mackerel (*Trachurus murphyi*) is one of the pelagic resources of greatest ecological and fishery importance, characterized by its broad geographic distribution and marked interannual variability (Serra, 1991; Cubillos et al., 2008). Several studies have addressed the standardization of CPUE for this species within the framework of the South Pacific Regional Fisheries Management Organisation (SPRFMO), mainly using GLM- and GAM-based approaches, while progressively incorporating more complex methodologies. These studies have highlighted the importance of accounting for spatial heterogeneity, temporal variability, and changes in fishing efficiency in order to obtain more representative abundance indices.

In Peru, monitoring of jack mackerel has shown fluctuations in its availability associated with both oceanographic variability and the dynamics of fishing effort (IMARPE, 2016; 2019; 2023). Currently, CPUE standardization is mainly carried out using generalized additive models (GAMs), incorporating operational variables, such as number of trips and hold capacity, and temporal variables, such as month and year. However, since 2019, a sustained increase in CPUE has been observed, becoming more pronounced from 2022 onward. This has generated uncertainty as to whether these variations reflect real changes in the abundance of the resource or limitations in the measurement of nominal effort, specifically the number of trips, particularly in a context of changes in fleet structure and efficiency, operational strategies, and the spatial distribution of fishing areas.

In this context, the present study aims to standardize the CPUE of jack mackerel (*Trachurus murphyi*) in the Peruvian sea for the period 2015–2025 through the application of generalized additive models (GAMs) that incorporate operational, temporal, spatial, and environmental variables, in order to obtain a robust relative abundance index for use in the stock assessment of jack mackerel.

2. MATERIAL AND METHODS

2.1. FISHERY DATA

The information used in the present study comes from the Pelagic Fisheries Monitoring Program of the Peruvian Marine Research Institute (IMARPE), which continuously collects data on fishing fleet operations in the Peruvian sea. Records corresponding to fishing trips targeting jack mackerel (*Trachurus murphyi*) during the period 2015–2025 were used, with each trip considered as an independent observation.

The database used is comparable to that employed in jack mackerel stock assessments in Peruvian waters; however, in this version, improvements were incorporated to strengthen the quality, consistency, and level of detail of the information. These improvements include the recovery and integration of the spatial component of fishing operations, latitude and longitude, and an effective effort measure based on trip duration.

Each record included operational, temporal, and spatial information, such as fleet type, vessel hold capacity (m^3), departure and arrival dates and ports, total jack mackerel catch, expressed in tonnes, trip duration, in days, and the geographic position, latitude and longitude, associated with the fishing operation. In addition, distance from the Peruvian coast, in nautical miles, was estimated from the geographic position.

The vessels used purse seine fishing gear, with nets having a mesh size of 38 mm, 1½ inches, and were classified according to their structural and operational characteristics as follows:

- **Industrial fleet:** composed of vessels with a hold capacity greater than 36.2 m^3, equipped with RSW (Refrigerated Sea Water) refrigeration systems.
- **Artisanal fleet:** composed of vessels with a hold capacity of less than 32.6 m^3, mainly built of wood and designed to transport boxes with ice as a refrigeration system.

Likewise, hold capacity was categorized using a combination of statistical and operational criteria. For this purpose, the `rpart()` algorithm was applied independently to the artisanal and industrial fleets, and the results were subsequently contrasted with information on the jack mackerel fishery in Peru. As a result, cut-off points of 15 and 25 m^3 were defined for the artisanal fleet, and 300, 400, 500, and 600 m^3 for the industrial fleet, establishing the following categories: a = <−Inf, 15>, b = <15, 25>, c = <25, 300>, d = <300, 400>, e = <400, 500>, f = <500, 600>, and g = <600, Inf>.

Finally, trip duration was estimated as the difference between the arrival and departure dates, expressed in effective fishing days. Latitude and longitude information corresponded, in most cases, to the geographic location of the last set with jack mackerel catch, which was used as an approximation of the effective fishing area.

2.2. ENVIRONMENTAL DATA

Given that the population dynamics and distribution of jack mackerel (*Trachurus murphyi*) may be influenced by environmental conditions (Dioses T., 2013; Espino M., 2013; Ñiquen M. et al., 2013), oceanographic variables were incorporated into the analysis, specifically sea surface temperature (SST) and salinity (SO). These data were obtained from the Copernicus Marine Service platform at daily resolution and at a depth of 0.49 m. For each observation, the environmental variables were associated using the trip arrival date and the corresponding geographic location. Both sea surface temperature and salinity were extracted at a spatial resolution of 0.083° × 0.083°.

2.3. DATA PREPARATION

The generated information consisted of 24 687 fishing trips. During the data preparation and model-fitting process, records with missing values in the environmental variables used in the analysis, specifically sea surface temperature (SST) and salinity (SO), were excluded. After this data-cleaning procedure, the final database used for model estimation consisted of 24 122 trips, equivalent to 97.7% of the original records.

When disaggregated by fleet type (Table 1), missing values were observed to be concentrated exclusively in the artisanal fleet, with percentages close to 2.5% (565 records), whereas the industrial fleet did not present incomplete records for these environmental variables. In addition, missing values for temperature and salinity occurred simultaneously in all identified cases, with no cases in which only one of the two variables was missing.

Considering the low proportion of excluded records and their relatively homogeneous distribution across years, it was assumed that removing these data did not introduce relevant bias into the estimation of the standardized CPUE or affect the representativeness of the artisanal fleet within the analysis.

Table 1. Missing data by fleet type and environmental variable.

Type of fleet	Original N	Cleaned N	Percentage (%)
Artisanal	22495	21930	-2.5
Industrial	2192	2192	0
Total	24687	24122	-2.5

3. RESULTS

3.1. DESCRIPTION OF THE DATA

For this study, a total of 24,122 fishing trip records were available, of which 90.9% corresponded to the artisanal fleet and 9.1% to the industrial fleet (Figure 1). The annual distribution of the number of trips shows a marked predominance of the artisanal fleet throughout the analyzed period. The participation of the industrial fleet was null between 2015 and 2017, due to the low availability of jack mackerel (*Trachurus murphyi*) in the operating areas of this fleet and the shift in target species toward chub mackerel (*Scomber japonicus*). Subsequently, from 2018 onward, the participation of the industrial fleet increased progressively, reaching its highest relative proportions in 2019 and 2020, with 17.7% and 19.9% of the total number of trips, respectively (Table 2). Likewise, an important increase in the number of fishing fleet trips was observed from 2023 onward, reaching the highest number of records in 2024.

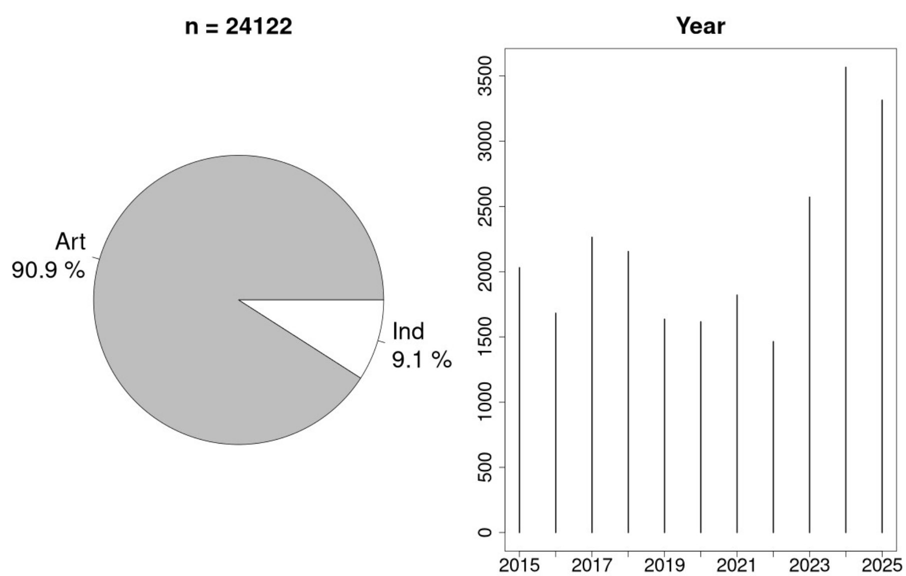

Figure 1. Distribution of jack mackerel fishing trip records by fleet type and year.

Table 2. Number of trips by year, vessel type, and total.

Year	Artisanal	Industrial	Total	%Artisanal	%Industrial
2015	2031	0	2031	100	0
2016	1682	0	1682	100	0
2017	2264	0	2264	100	0
2018	2019	136	2155	93.7	6.3
2019	1346	290	1636	82.3	17.7
2020	1295	321	1616	80.1	19.9
2021	1611	210	1821	88.5	11.5
2022	1258	206	1464	85.9	14.1
2023	2177	394	2571	84.7	15.3
2024	3266	301	3567	91.6	8.4
2025	2981	334	3315	89.9	10.1
Total	21930	2192	24122	90.9	9.1

3.2. DISTRIBUTION OF FISHING OPERATIONS

The spatial distribution of jack mackerel fishing trips showed marked differences between the artisanal and industrial fleets throughout the analyzed period (Figure 2). The artisanal fleet exhibited a predominantly coastal distribution, concentrating its fishing operations near the Peruvian coastline, whereas the industrial fleet showed a more oceanic distribution farther from the coast, particularly in the central-southern area of Peru.

Between 2015 and 2017, the fishing trip records corresponded to the artisanal fleet, which showed more restricted spatial coverage closer to the coast, with no industrial fleet operations observed. From 2018 onward, the participation of the industrial fleet in the jack mackerel fishery was recorded again, with fishing operations located in areas farther offshore. Between 2023 and 2024, broader spatial coverage of fishing operations was observed, particularly in the central-southern region of the Peruvian sea. Overall, these results show temporal changes in the spatial distribution of fishing activity, possibly associated with variations in resource availability, environmental conditions, and the fleet's operational strategies.

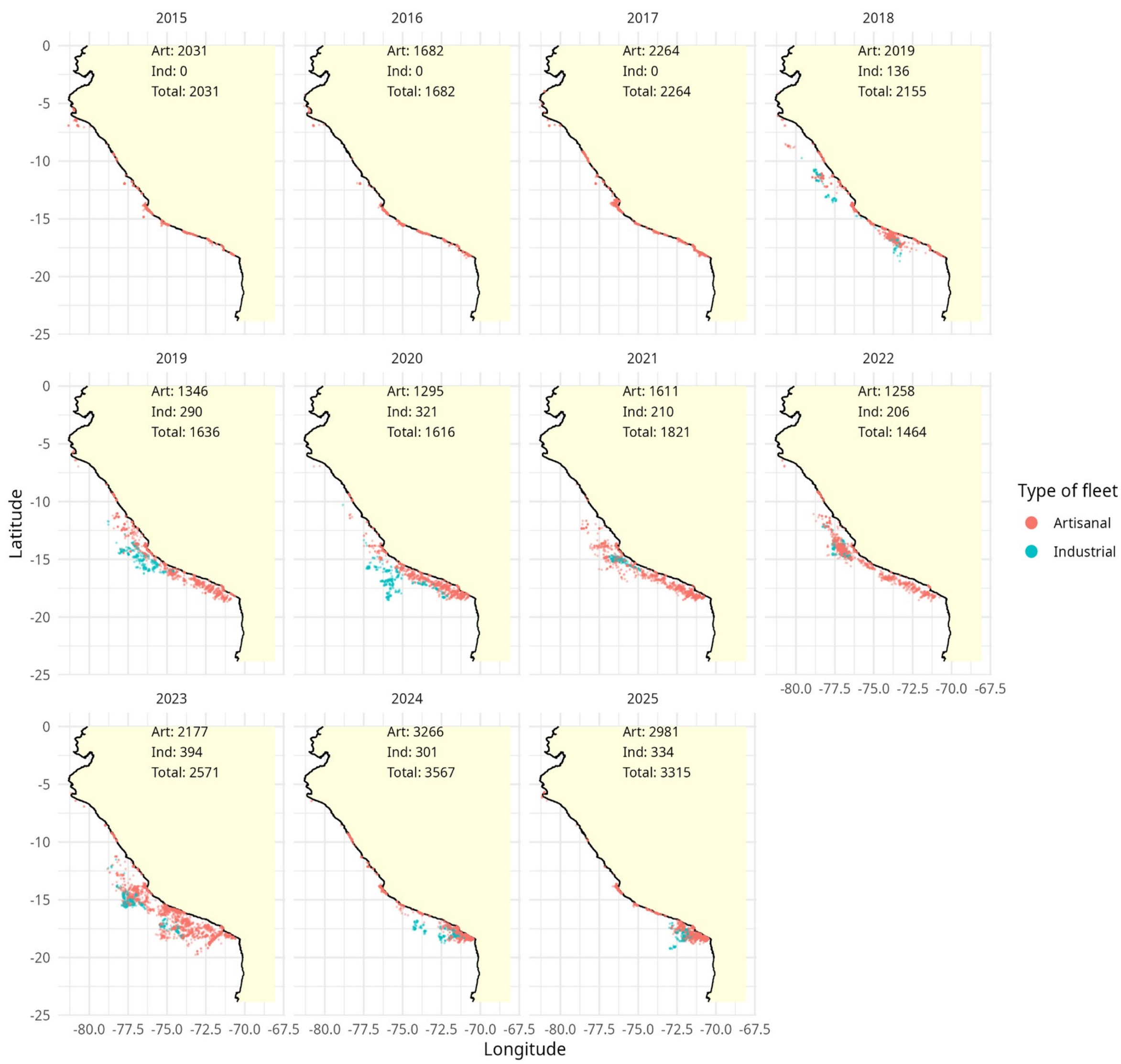

Figure 2. Distribution of jack mackerel fishing trips by vessel type (industrial vessels in blue and artisanal vessels in red) and by year.

3.3. EXPLORATORY ANALYSIS OF CPUE

Figure 3 presents the bivariate exploratory analysis of nominal CPUE, expressed on a logarithmic scale as log(catch/trip duration), in relation to the main covariates considered in the study. The CPUE histogram shows a unimodal distribution, with a high concentration of observations at intermediate values and marked asymmetry toward low values, indicating the presence of tails and a non-normal distribution of the response variable. This pattern supports the use of flexible models, such as generalized additive models (GAMs), which are capable of representing nonlinear relationships and asymmetric distributions.

The temporal variables show variability in nominal CPUE throughout the analyzed period. At the annual level, a progressive increase in CPUE is observed toward recent years, particularly between 2022 and 2024, coinciding with greater resource availability and an increase in fishing effort, measured as the number of trips. In contrast, the monthly pattern does not show a clearly defined seasonality, although some months, such as February, present greater dispersion and variability in CPUE values. These results suggest that interannual variability has a more important influence on catch than intra-annual variability.

The spatial variables show clearly nonlinear effects on expected CPUE. The partial effect of longitude shows lower values around −80°; however, these should be interpreted with caution due to the limited number of observations available in those areas. Subsequently, the effect increases, reaching maximum values between −78° and −77°. In the case of latitude, a decrease in the effect is observed in the northern region, although this pattern could also be influenced by the limited spatial coverage of the data in those areas, followed by increases at intermediate latitudes, with relative maxima around −11° and −15°. Similarly, distance to the coast shows a nonlinear relationship: CPUE is relatively low near the coastline, increases rapidly in intermediate areas, and decreases toward distances close to 150 nautical miles. Afterwards, a new increase is observed, although this behavior in more oceanic areas could be conditioned by the low frequency of fishing operations recorded at those distances. Overall, these patterns reflect marked spatial heterogeneity in both resource availability and the distribution of fishing operations.

Operational variables also show important effects on CPUE. The industrial fleet presents higher nominal CPUE values than the artisanal fleet, which probably reflects differences in autonomy, operational capacity, and fishing efficiency. Likewise, hold capacity shows a positive relationship with CPUE in both its continuous and categorical representations, with important increases in expected catch values as vessel size increases.

Finally, the environmental variables, sea surface temperature (SST) and salinity (SO), also show nonlinear relationships with CPUE. In both cases, increasing trends are observed within certain environmental ranges, suggesting that specific oceanographic conditions may favor greater availability or aggregation of the resource. Overall, the results of the exploratory analysis highlight the complexity of the factors affecting CPUE and justify the use of GAMs to adequately represent the observed nonlinear effects.

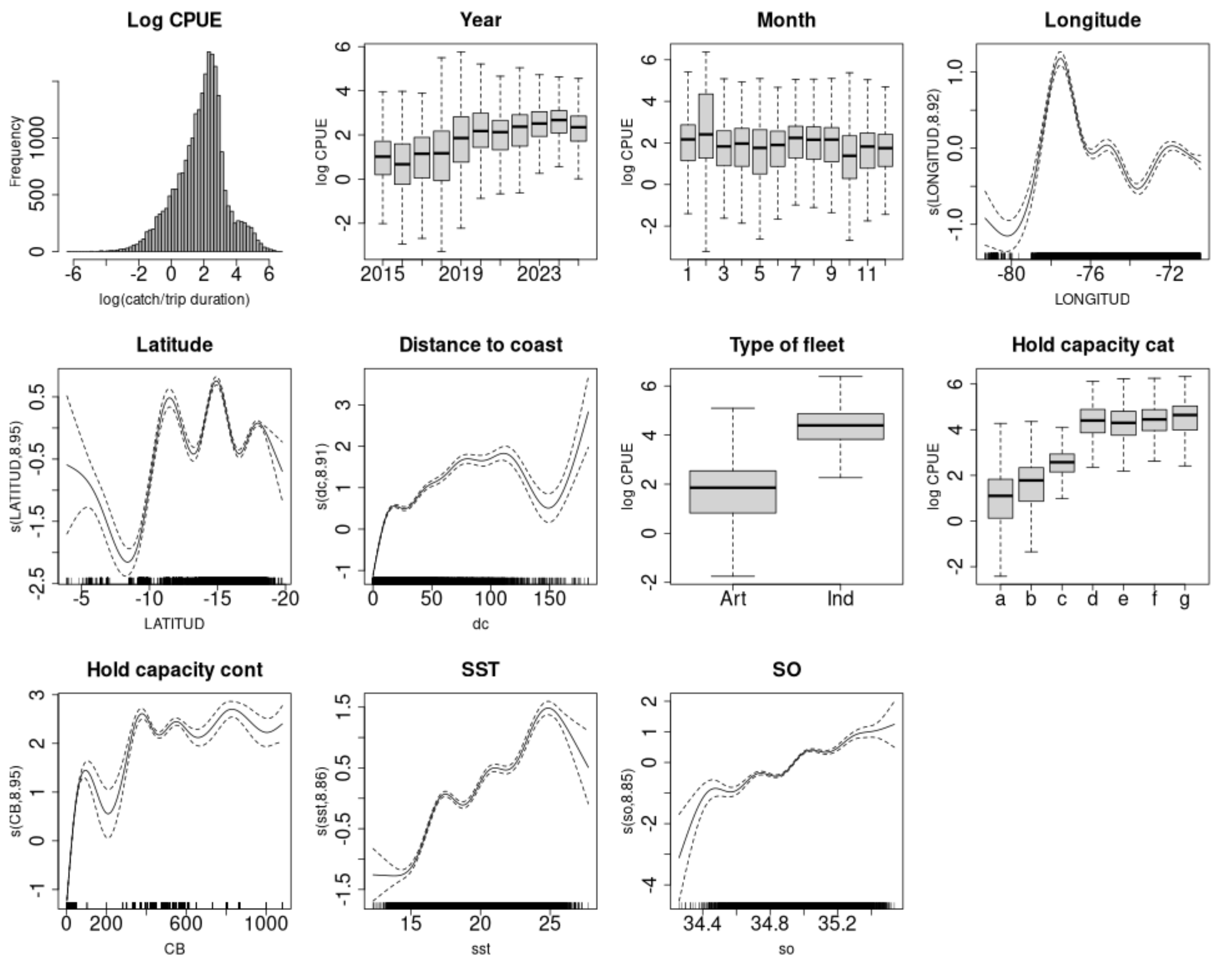

Figura 3. Bivariate exploratory analysis of CPUE.

3.4. CPUE MODELING

3.4.1. EVALUATED MODELS

Generalized additive models (GAMs) were used due to the nonlinear relationships observed between CPUE and the covariates during the bivariate exploratory analysis. To evaluate different representations of the operational structure of the fleet, three model families were implemented and compared. In the first, hold capacity was considered as a continuous variable (Family A); in the second, as a categorical variable (Family B); and in the third, fleet type was included, excluding hold capacity (Family C).

In all cases, the response variable corresponded to jack mackerel catch per trip (`catch`), which was assumed to be a positive and continuous variable and was modeled using a Gamma distribution with a logarithmic link function. Likewise, trip duration (`n_days`) was incorporated as an offset term and interpreted as a measure of effective fishing effort. In general, the models are expressed as:

$$E[catch] = \eta_{\square} + offset(\log(N\_days)),$$

where η represents the linear or additive predictor associated with the model covariates. In this way, the model allows the expected catch to be estimated after adjusting for trip duration.

The analysis began with a base model that included year and month as explanatory factors, as well as spatial, operational, and environmental variables, such as latitude, distance to the coast (`dc`), hold capacity (`hc`), sea surface temperature (`sst`), and salinity (`so`).

Models - Family A

```
catch ~ year + month + s(lat) + s(dc) + s(HC) + s(sst) + s(so) + offset(log(n_days))
```
(Model A1)

```
catch ~ year + month + te(lon, lat) + s(HC) + s(sst) + s(so) + offset(log(n_days))
```
(Model A2)

```
catch ~ year + month + te(dc, lat) + s(HC) + s(sst) + s(so) + offset(log(n_days))
```
(Model A3)

```
catch ~ year + month + te(dc, lat) + s(HC) + te(sst, so) + offset(log(n_days))
```
(Model A4)

Models - Family B

```
catch ~ year + month + s(lat) + s(dc) + HC_cat + s(sst) + s(so) + offset(log(n_days))
```
(Model B1)

```
catch ~ year + month + te(lon, lat) + HC_cat + s(sst) + s(so) + offset(log(n_days))
```
(Model B2)

```
catch ~ year + month + te(dc, lat) + HC_cat + s(sst) + s(so) + offset(log(n_days))
```
(Model B3)

```
catch ~ year + month + te(dc, lat) + HC_cat + te(sst, so) + offset(log(n_days))
```
(Model B4)

Models - Family C

```
catch ~ year + month + s(lat) + s(dc) + type_fleet + s(sst) + s(so) + offset(log(n_days))
```
(Model C1)

```
catch ~ year + month + te(lon, lat) + type_fleet + s(sst) + s(so) + offset(log(n_days))
```
(Model C2)

```
catch ~ year + month + te(dc, lat) + type_fleet + s(sst) + s(so) + offset(log(n_days))
```
(Model C3)

```
catch ~ year + month + te(dc, lat) + type_fleet + te(sst, so) +
offset(log(n_days))
```
(Model C4)

3.4.2. MODEL COMPARISON AND SELECTION

Table 3 presents the comparison of the candidate GAMs using the Akaike Information Criterion (AIC), together with the percentage of deviance explained, the effective degrees of freedom, and ΔAIC. The models in Family A, in which hold capacity was incorporated as a smoothed continuous variable, generally showed better statistical performance than those in Families B and C. Model A2 obtained the lowest AIC value (158,780.93), explaining 60.92% of the total deviance. This model included a two-dimensional spatial structure based on longitude and latitude through a tensor smooth `te(lon, lat)`, as well as smoothed effects for hold capacity and the environmental variables.

Models A3 and A4 showed similar performance to the selected model, although with slightly higher AIC values. The models in Family B, which treated hold capacity as a categorical variable, presented a poorer fit compared with the models in Family A, suggesting that the continuous representation of this variable better describes the variability associated with fishing efficiency. In turn, the models in Family C, based only on fleet type, showed lower deviance explained and considerably higher AIC values, indicating a lower capacity to represent operational differences among fishing trips. Overall, these results highlight the importance of incorporating continuous capacity variables and explicit spatial components in the standardization of jack mackerel CPUE.

Table 3. Comparison of candidate GAM models based on AIC.

Ranking of candidate GAM models

Model	Model structure	AIC	Deviance explained (%)	Total EDF	N	Residual DF	Rank	ΔAIC
A2	**year + month + te(lon, lat) + s(HC) + s(sst) + s(so)**	**158,780.93**	**60.92**	**70.16**	**24122**	**24,051.84**	**1**	**0.00**
A1	year + month + s(lat) + s(dc) + s(HC) + s(sst) + s(so)	158,972.06	60.63	65.69	24122	24,056.31	2	191.14
A3	year + month + te(dc, lat) + s(HC) + s(sst) + s(so)	158,988.85	60.66	71.40	24122	24,050.60	3	207.92
A4	year + month + te(dc, lat) + s(HC) + te(sst, so)	158,991.35	60.72	77.86	24122	24,044.14	4	210.43
B2	year + month + te(lon, lat) + HC_cat + s(sst) + s(so)	159,286.78	60.45	67.45	24122	24,054.55	5	505.85
B3	year + month + te(dc, lat) + HC_cat + s(sst) + s(so)	159,481.10	60.17	68.92	24122	24,053.08	6	700.17
B4	year + month + te(dc, lat) + HC_cat + te(sst, so)	159,493.65	60.22	75.34	24122	24,046.66	7	712.72
B1	year + month + s(lat) + s(dc) + HC_cat + s(sst) + s(so)	159,541.72	60.07	55.20	24122	24,066.80	8	760.79
C2	year + month + te(lon, lat) + type_fleet + s(sst) + s(so)	161,992.27	56.35	62.03	24122	24,059.97	9	3,211.34
C3	year + month + te(dc, lat) + type_fleet + s(sst) + s(so)	162,003.67	56.42	62.90	24122	24,059.10	10	3,222.74
C4	year + month + te(dc, lat) + type_fleet + te(sst, so)	162,024.49	56.48	69.58	24122	24,052.42	11	3,243.57
C1	year + month + s(lat) + s(dc) + type_fleet + s(sst) + s(so)	162,155.53	56.15	57.46	24122	24,064.54	12	3,374.61

Models ranked from lowest to highest AIC. Best-supported model highlighted in green.

Figure 4 shows the time series of standardized CPUE obtained from the different GAMs evaluated, grouped into Families A, B, and C. The series were normalized by dividing their values by the corresponding maximum value of each model. In general, all series show a consistent temporal pattern, characterized by a decrease between 2015 and 2016, followed by a pronounced increase in 2017. Subsequently, they decrease between 2018 and 2019 and remain relatively stable during the 2019–2021 period. From 2022 onward, a sustained increase is observed, reaching maximum values in 2024, followed by a decrease in 2025.

Differences among models are mainly observed in the relative magnitude of the indices. Models from Families A and B show very similar trajectories throughout the entire period. In contrast, models from Family C show relatively lower indices between 2015 and 2021, suggesting a lower capacity to capture the heterogeneity associated with fishing efficiency.

Overall, the temporal consistency observed among models suggests that the main signal of interannual CPUE variation is robust to different parameterizations of effort and fleet structure. Nevertheless, the better statistical performance of model A2 indicates that the explicit incorporation of the two-dimensional spatial structure and hold capacity as a continuous variable allows the processes affecting resource catchability to be represented more adequately.

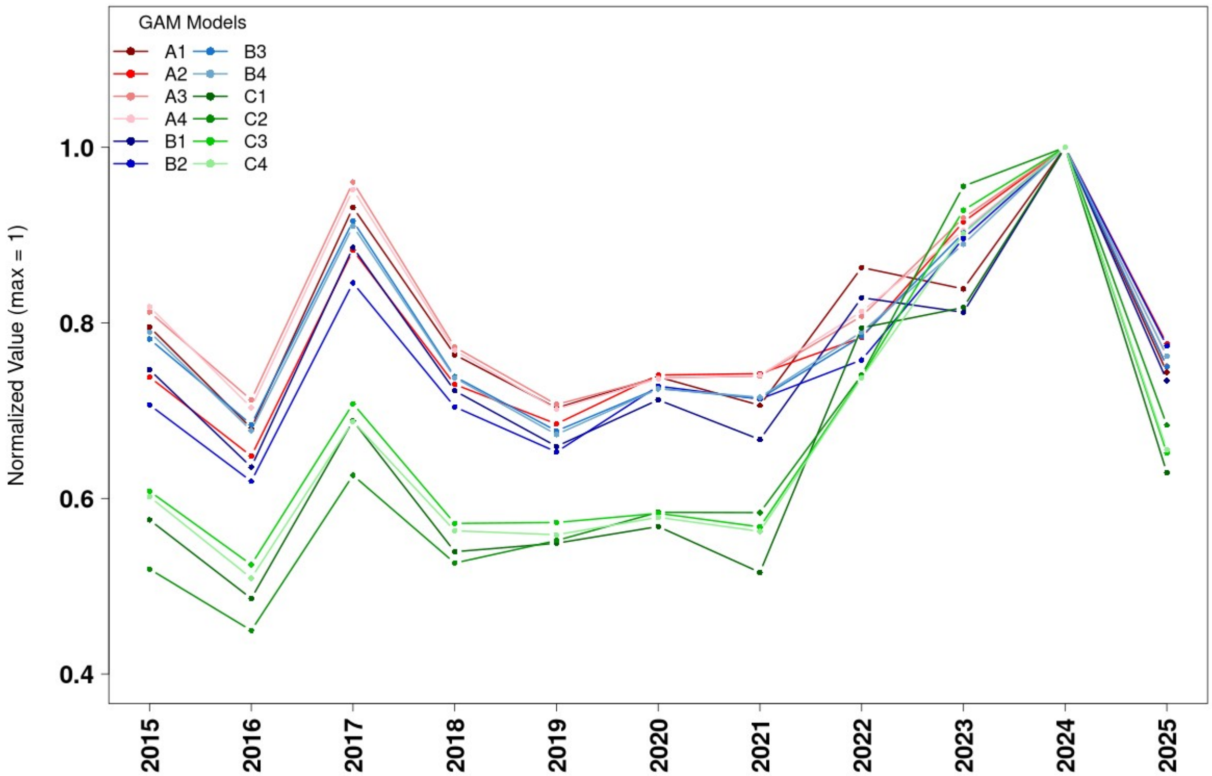

Figure 4. Comparison of normalized standardized CPUE indices estimated from candidate GAM models.

3.4.3. DIAGNOSTICS OF THE FINAL MODEL

In terms of AIC, model A2 was selected as the best-performing model among the candidates evaluated. This model explained 60.92% of the total deviance, with the largest contribution associated with the year effect (20.92%), followed by hold capacity (17.31%) and the spatial effect (13.51%). The month effect also contributed substantially to the model fit (9.03%), whereas the environmental variables showed a comparatively small contribution (Table 4).

Table 4. Contribution of each predictor to the explained deviance of model A2.

GAM A2	
Variable	% Explained
Year	20.92
Month	9.03
Spatial effect	13.51
Hold capacity	17.31
SST	0.09
Salinity	0.08
Total	**60.92**

Figure 5 shows the diagnostic plots for model A2. Overall, the model provides a reasonable fit. Residuals follow the expected distribution mainly in the central range, with deviations at the extremes. Some structure and dispersion are observed in the residuals, but no severe lack-of-fit pattern is evident. The model captures the general trend in catches, although variability increases at higher fitted values.

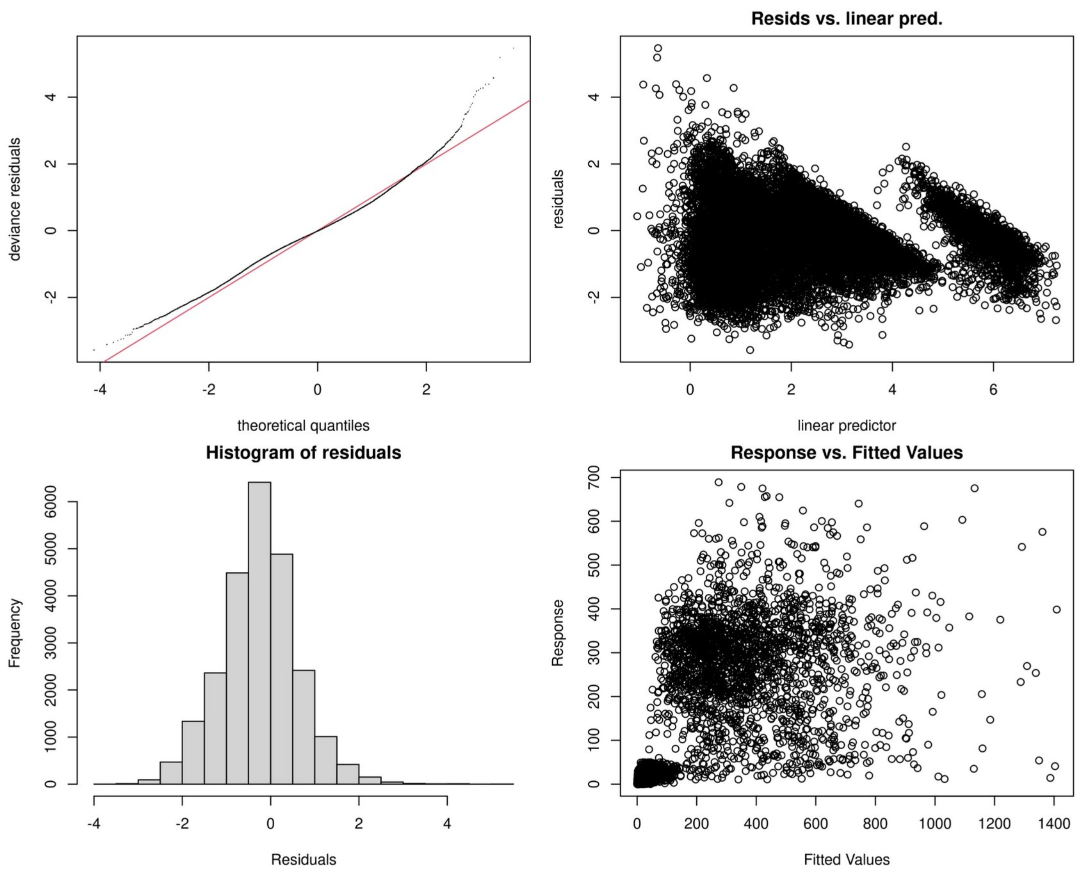

Figure 5. Diagnostic plots of the selected GAM A2 model.

The results in Table 5 show that both the parametric and smoothed terms of the final model were highly significant ($p < 0.001$). The year and month effects indicate an important temporal influence on CPUE. Among the smoothed terms, the two-dimensional spatial component `te(LONGITUDE, LATITUDE)` showed a complex and highly significant spatial structure, while hold capacity had the largest relative contribution to the model, indicating a strong relationship between vessel size and fishing efficiency. The environmental variables, sea surface temperature and salinity, were also significant, although their contribution was smaller compared with the operational and spatial variables.

Tabla 5. Anova results for final model A2.

```
Family: Gamma
Link function: log

Formula:
catch ~ year + month + te(lon, lat) + s(HC) + s(sst) +
    s(so) + offset(log(n_days))

Parametric Terms:
     df     F p-value
year 10 31.32  <2e-16
month  11 13.38  <2e-16

Approximate significance of smooth terms:
                        edf Ref.df        F p-value
te(lon,lat) 22.680 22.935   48.921  <2e-16
s(HC)                8.926  8.998 1022.249  <2e-16
s(sst)               8.366  8.891    5.595  <2e-16
s(so)                8.192  8.795    5.332  <2e-16
```

3.4.4. PARTIAL EFFECTS OF THE FINAL MODEL

Figure 6 shows the partial effects estimated by model A2. The annual effect shows low values in 2016, an increase in 2017, and a marked rise during 2023–2024, followed by a decrease in 2025. The monthly effect suggests higher CPUE at the beginning of the year and lower values between August and November.

The spatial component shows stronger positive effects in the central-southern area of the Peruvian sea. Hold capacity shows a positive nonlinear relationship with CPUE, tending to stabilize for vessels with larger capacities. SST showed moderate changes, with a decrease toward higher temperatures, while salinity showed weaker effects at low values and greater stability at intermediate and high ranges.

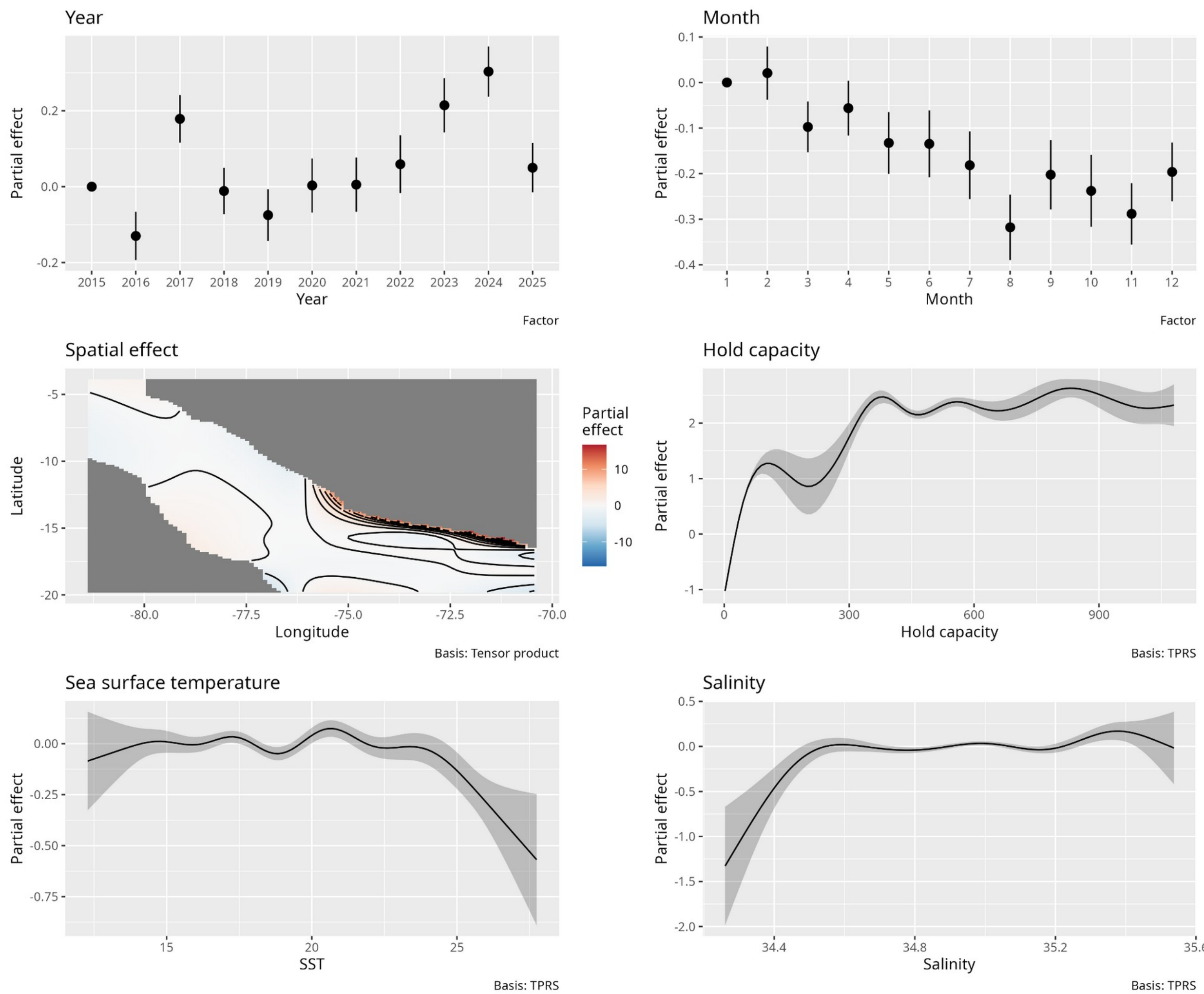

Figure 6. Partial effects of model A2.

3.4.5. FINAL STANDARDIZED CPUE INDEX

The final standardized CPUE index obtained from model A2 is presented in Figure 7. After adjusting for temporal and spatial effects, hold capacity, environmental variables, and trip duration as effective effort, the series shows low values at the beginning of the period, an increase in 2017, relative stability between 2018 and 2021, and a sustained rise from 2022 to 2024, followed by a decrease in 2025. This pattern is consistent with the recent expansion of fishing operations toward more oceanic areas of central-southern Peru.

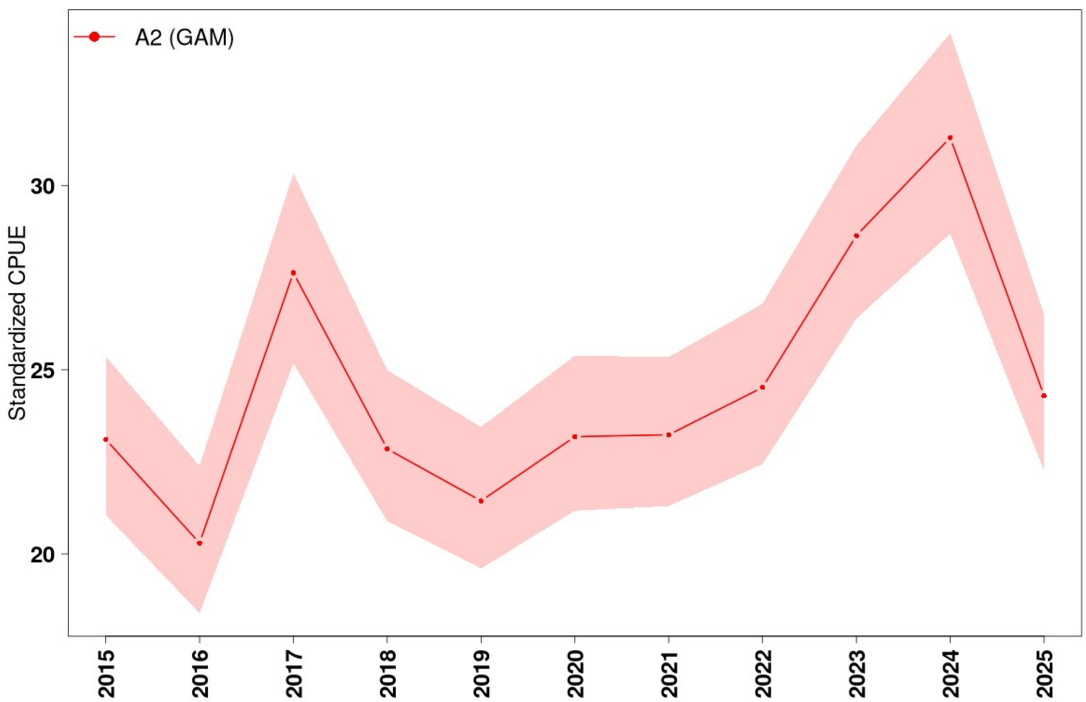

Figure 7. Standardized CPUE from the final A2 model.

The comparison between the standardized CPUE from model A2 and the series used in the national stock assessment of jack mackerel was based on values normalized by the maximum of each series (Figure 8). During the overlapping period 2015–2025, important differences are observed between the two series: the A2 index shows relatively high values from 2015 and a more stable trajectory, whereas the previous series shows low values until 2018 and a sharper increase from 2019 onward. Although both series reach high values in recent years and decrease in 2025, differences in their relative behavior suggest that the incorporation of spatial information and trip duration as effective effort modifies the estimated relative abundance signal.

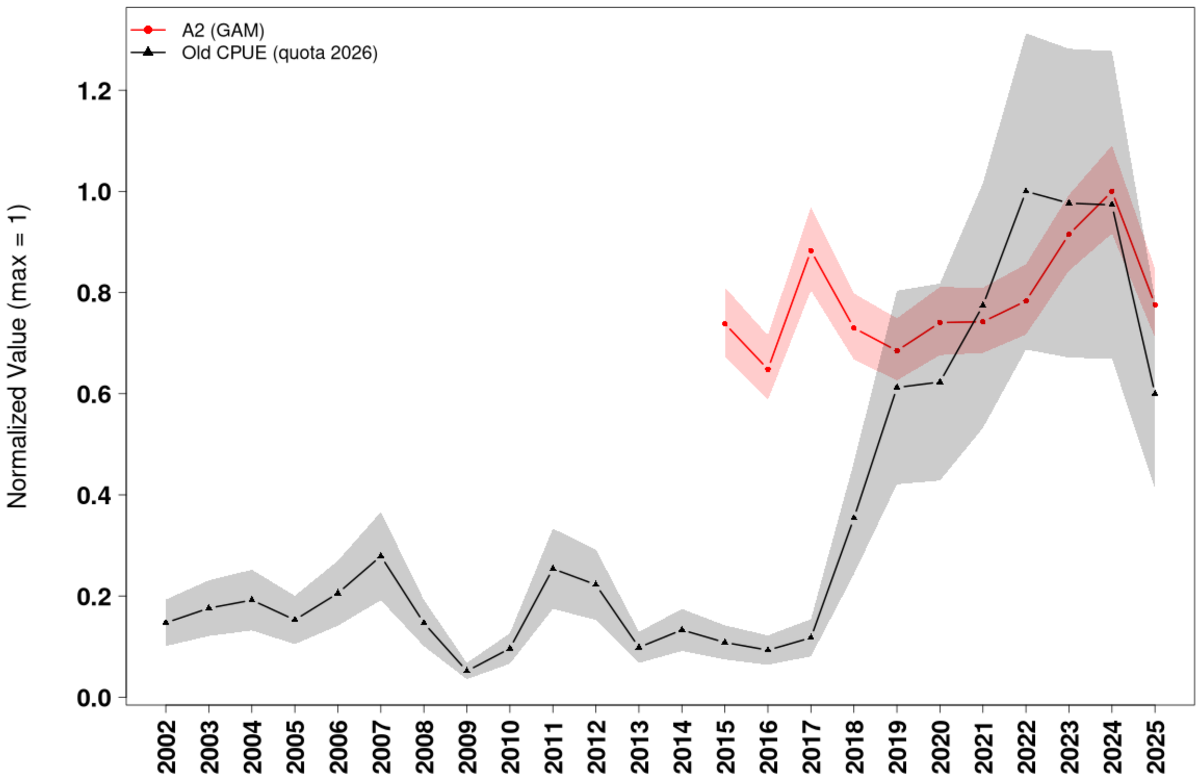

Figure 8. Standardized CPUE from model A2 and previous CPUE series up to November 2025 used in the national stock assessment for the 2026 quota.

3.5. About national stock assessment (Far-north stock)

Several model configurations were evaluated to assess the impact of the new CPUE index on the jack mackerel stock assessment for the Far-north stock using the JJM model. The evaluated models were:

- **Mod0.0**: Same as the 2026 quota model, corresponding to the 2025 stock assessment, with information up to November 2025.
- **Mod1.0**: Same as Mod0.0, but with updated catches and length-frequency data up to December 2025.
- **Mod2.0**: Same as Mod1.0, but including three abundance indices: the acoustic index, the old CPUE series for 2002–2014, and the new standardized CPUE series for 2015–2025.
- **Mod3.0**: Same as Mod2.0, but using the new standard errors.

Model Mod0.0 represents the jack mackerel stock assessment conducted in November 2025 for the establishment of the 2026 quota for the Far-north stock. This model uses catch information from 1970 to 2025, length-frequency data from 1980 to 2025 in total length (TL), an acoustic echo-abundance index for 1985–2008 and 2010–2013, and a CPUE index for 2002–2025.

Model Mod1.0 is equivalent to Mod0.0, but updates the catches and length-frequency data to December 2025. Model Mod2.0 is equivalent to Mod1.0, but considers three abundance indices: the acoustic index, the old CPUE series for 2002–2014, and the new standardized CPUE obtained from model A2 for 2015–2025. In addition, this model considers two CV blocks: block 1, with CV = 0.2 for 2002–2017, and block 2, with CV = 0.3 for 2018–2023. Finally, model Mod3.0 is equivalent to Mod2.0, but replaces the CV values with the estimated standard errors.

Figure 9 shows the biological time series resulting from the model fits: biomass (a), spawning biomass (b), recruitment (c), and fishing mortality (d). Updating the catch and length-frequency data to December 2025 (Mod1.0) does not produce noticeable changes relative to Mod0.0. However, under the configuration with three abundance indices (Mod2.0), increases in biomass are observed in the years prior to 2000 and after 2010, consistent with the reduction in fishing mortality during those periods. When the standard errors are included (Mod3.0), the increase in biomass and spawning biomass becomes more pronounced, although both series show a decline after 2020. Recruitment shows similar trends among models up to 2010, with greater differences observed in the more recent period

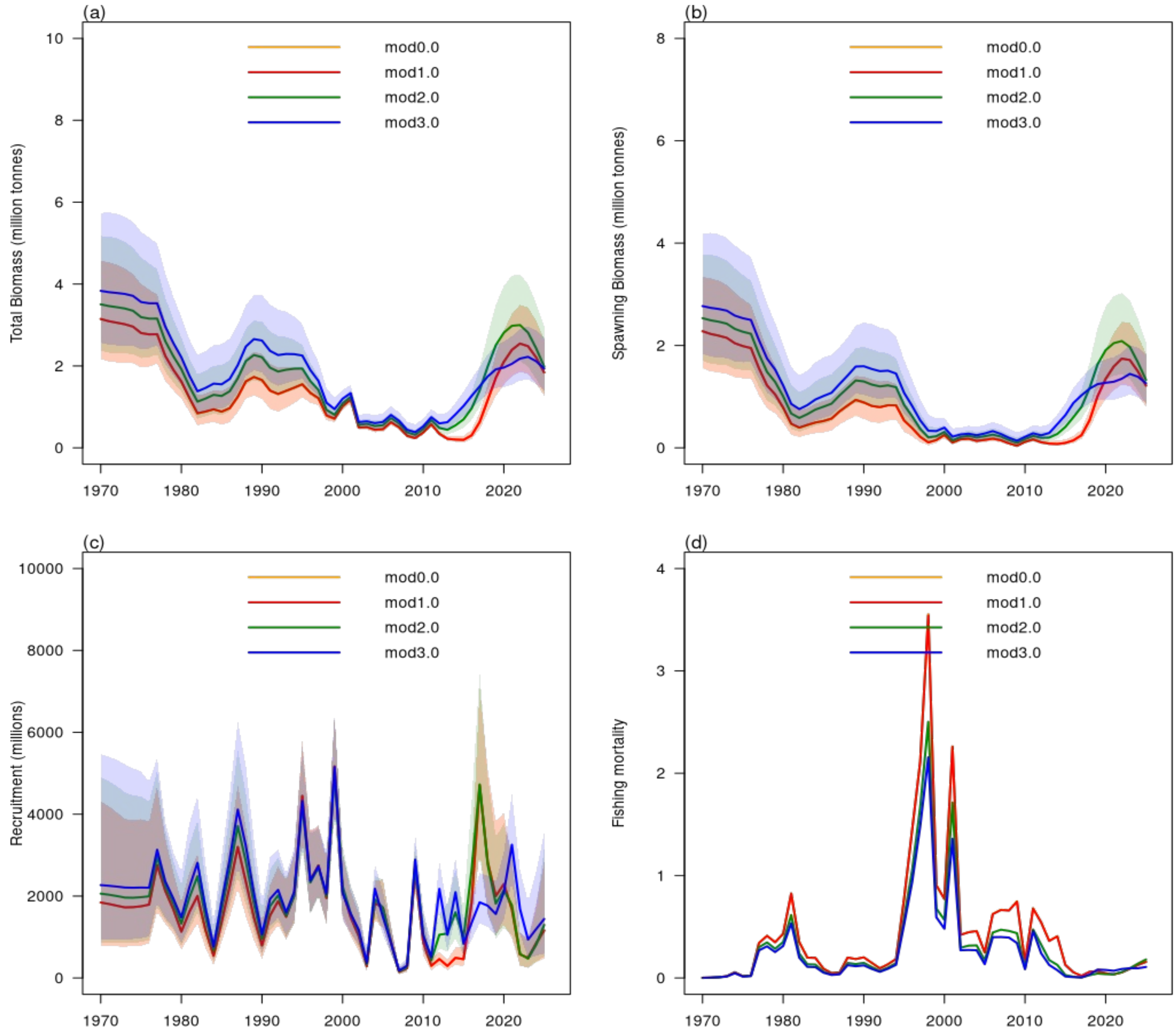

Figure 9. Biological time series for all model configurations.

Tables 6 and 7 show that Mod0.0 and Mod1.0 produce very similar results, both in terms of reference points and objective function components. In contrast, when the new standardized CPUE series is incorporated in Mod2.0 and Mod3.0, higher values of MSY and BMSY are observed, together with lower values of FMSY.

The objective function values, expressed as negative log-likelihood, also increase in Mod2.0 and Mod3.0, mainly due to the length-composition component. However, the recruitment component shows a positive contribution to the likelihood, partially compensating for this increase.

Table 6. Comparison of biological reference points among model configurations.

	MSY	Bmsy	Fmsy
mod0.0	108.5607	171.3867	0.3089178
mod1.0	108.5758	171.6350	0.3084322
mod2.0	141.8781	248.7763	0.2764119
mod3.0	142.1437	283.4693	0.2494133

	MSY_last	Bmsy_last	Fmsy_last	Capt. Fmsy
mod0.0	103.6826	174.3801	0.30567	216.698
mod1.0	103.6913	174.6235	0.30517	219.342
mod2.0	135.2025	251.9360	0.27374	183.896
mod3.0	135.6407	285.6519	0.24800	252.904

Table 7. Objective function components for each model configuration.

	mod0.0	mod1.0	mod2.0	mod3.0
catch_like	0.93	0.93	0.66	0.86
age_like_fsh	0.00	0.00	0.00	0.00
length_like_fsh	452.32	451.74	479.43	561.57
sel_like_fsh	11.60	11.60	11.45	10.16
ind_like	58.07	58.09	66.91	56.87
age_like_ind	0.00	0.00	0.00	0.00
length_like_ind	0.00	0.00	0.00	0.00
sel_like_ind	0.00	0.00	0.00	0.00
rec_like	26.75	26.56	15.40	4.13
fpen	0.06	0.06	0.03	0.03
post_priors_indq	0.04	0.04	0.04	0.04
post_priors	0.00	0.00	0.00	0.00
residual	0.17	0.17	0.07	0.07
total	549.96	549.20	574.00	633.72

4. CONCLUSIONS

- The standardization of jack mackerel CPUE in Peruvian waters for the period 2015–2025 showed that temporal, spatial, and operational effects explain an important part of the observed variability in catch per unit effort. Among the variables evaluated, year, month, hold capacity, and the spatial component showed the largest contributions to the final model.
- The GAM models from Family A showed the best statistical performance compared with Families B and C, indicating that the continuous representation of hold capacity and the explicit incorporation of spatial structure improve the predictive capacity and biological interpretation of CPUE. Based on the model selection criteria, model A2 was identified as the most suitable model.
- The standardized CPUE series derived from model A2 maintained a signal consistent with the recent dynamics of the fishery, particularly the increase observed between 2022 and 2024. In addition, the differences observed relative to the series currently used in the national stock assessment suggest that a better definition of fishing effort and the spatial structure of the fishery can modify the estimated signal and provide a more appropriate representation of the relative variability in resource abundance.
- The incorporation of the new CPUE series into the Far-north stock assessment produced changes in the estimates of biomass, spawning biomass, and fishing mortality, indicating that the assessment results are sensitive to how the abundance index is defined and standardized.

5. PERSPECTIVES

As future work, continued recovery and compilation of historical information for the period 2002–2014 is proposed, with the aim of constructing a homogeneous standardized CPUE time series for 2002–2025. In addition, more advanced spatio-temporal models should be evaluated to explicitly represent spatial and temporal variability in the availability of jack mackerel in Peruvian waters.

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