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Standardization of Commercial CPUE for Chilean Jack Mackerel in Central-Southern Chile Using Hierarchical Bayesian Spatio-Temporal Models

Chile

Standardization of commercial CPUE for Chilean jack mackerel in central-southern Chile using hierarchical Bayesian spatio-temporal models

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Abstract

Catch per unit effort (CPUE) standardization is essential for deriving fishery-dependent indices of relative abundance, particularly for pelagic stocks characterized by strong spatial dynamics and changes in fishing behavior. We applied a hierarchical Bayesian spatio-temporal framework implemented through the Integrated Nested Laplace Approximation (INLA) to standardize commercial CPUE of Chilean jack mackerel (Trachurus murphyi) in central-southern Chile from 1994 to 2026. Set-level catch and fishing-location data were combined with seasonal and operational covariates, and alternative spatial and spatio-temporal structures were evaluated.

Models allowing the spatial CPUE field to vary among years substantially outperformed a temporally constant spatial formulation. Independent year-specific spatial fields provided a parsimonious representation of the pronounced redistribution of fishing activity and CPUE, while environmental covariates produced only marginal improvements in model performance. The resulting standardized index showed marked interannual variability, characterized by relatively high values during the mid-2000s, a decline to a minimum around 2011, and a recovery toward predominantly above-average levels after 2019. Retrospective analysis indicated high temporal stability of the index, with small terminal-year revisions and a Mohn's ρ of 0.025. Influence diagnostics showed that fishing duration and the year-specific spatial field produced the largest temporal adjustments to nominal CPUE, whereas seasonal effects and vessel capacity had comparatively smaller influences. In 2026, the standardized index increased relative to 2025 despite negative contributions from fishing duration and the year-specific spatial field.

These results demonstrate that explicitly accounting for annual spatial redistribution and changes in fishing operations can substantially improve the interpretation of commercial CPUE in highly dynamic pelagic fisheries. The proposed framework provides a reproducible and operational approach for updating the Chilean jack mackerel CPUE series and supports its evaluation as a fishery-dependent abundance index for stock assessment.

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1. Introduction

The standardization of catch per unit effort (CPUE) is essential to obtain reliable indices of relative abundance in fisheries. Traditional approaches, such as Generalized Linear Models (GLM) and Generalized Additive Models (GAM), typically account for operational and environmental effects but often do not explicitly model spatio-temporal interactions. This can lead to biased indices when the spatial distribution of the stock changes over time.

To address this limitation, a Bayesian Hierarchical Spatio-Temporal Modeling (BHSTM) framework implemented through the Integrated Nested Laplace Approximation (INLA) (Rue et al., 2009) was previously developed for the Chilean jack mackerel (*Trachurus murphyi*) fishery in central-southern Chile (Vásquez et al., 2023). This approach explicitly accommodates spatial and temporal variation, along with operational and environmental covariates.

In this work, we apply this framework to standardize CPUE for the period 1994–2026. The objectives are (i) to evaluate and select the most appropriate model structure using historical data, and (ii) to update the standardized CPUE index by incorporating data from 2026 using the selected model.

2. Methodology

2.1. Data

The analysis is based on fishery-dependent data from the purse seine fleet targeting Chilean jack mackerel (*Trachurus murphyi*) in central-southern Chile, covering the main fishing grounds of the fleet over the period 1994–2026. The dataset includes observations at the level of individual fishing sets, comprising catch, geographic location, and timing (year and quarter).

Operational variables included vessel hold capacity and fishing trip duration. Environmental covariates, including sea surface temperature, sea surface temperature anomaly, and chlorophyll concentration, were additionally evaluated as potential predictors during model selection. Only positive catches were retained, and the response variable was defined as the logarithm of catch per set, representing CPUE conditional on presence.

To provide a general overview of the operational characteristics of the fishery, mean annual values of key variables are summarized in Table 1, including distance from port, fishing trip duration, catch per set, vessel hold capacity, and the proportion of total catch represented within the study area.

These variables reflect substantial temporal changes in fishing behavior, fleet capacity, and spatial coverage of the dataset. In particular, the progressive increase in vessel capacity and variability in fishing distance and trip duration suggest shifts in fleet dynamics over time. Additionally, the increasing proportion of catch represented within the study area highlights changes in the spatial representativeness of the data, which is relevant for the interpretation of long-term CPUE trends.

These patterns illustrate substantial changes in the operational and spatial characteristics of the fishery over time, emphasizing the need to account for relevant operational and spatial effects when standardizing CPUE.

Table 1: Summary of the mean annual records of fishing sets: distance from the port (km), duration of the fishing trip (days), catch per haul (tons), vessel hold capacity (m^3), percentage of the jack mackerel catch spatiotemporally referenced and number of fishing sets in central-southern Chile, period 1994–2026

Year	Distance from port [km]	Fishing trip duration [days]	Catch per set [tons]	Vessel hold capacity [m3]	Catch proportion referenced ST [%]	Number of fishing sets
1994	161.9	2.2	177.2	847	0.3	69
1995	205.6	2.0	143.5	959	0.9	268
1996	381.9	3.2	171.2	1073	1.9	397
1997	192.6	2.7	118.5	1188	2.0	468
1998	222.4	2.6	153.5	1389	8.6	883
1999	197.4	2.6	148.7	1354	11.4	893
2000	224.9	2.6	181.1	1484	13.8	832
2001	180.6	2.4	174.8	1367	30.2	2407
2002	270.5	3.4	174.4	1243	24.6	1970
2003	413.0	3.3	164.6	1228	19.8	1534
2004	447.9	3.3	225.1	1272	44.9	2578
2005	483.2	3.5	220.5	1251	43.6	2504
2006	284.8	2.5	244.6	1299	7.7	388
2007	448.7	4.1	192.0	1357	14.5	854
2008	947.0	7.2	189.6	1346	39.1	1505
2009	845.4	7.2	165.3	1375	36.8	1557
2010	970.2	9.2	151.3	1395	46.0	897
2011	769.1	8.4	95.9	1532	32.6	732
2012	253.3	3.6	125.5	1438	76.5	1293
2013	331.7	3.9	141.9	1468	56.4	853
2014	300.2	5.7	114.5	1577	21.2	471
2015	541.7	6.2	111.6	1518	40.3	901
2016	355.6	4.3	159.9	1626	29.2	531
2017	286.5	4.0	157.8	1614	23.3	449
2018	281.9	3.8	152.7	1674	16.8	455
2019	196.2	2.6	211.2	1561	41.2	823
2020	204.5	2.4	253.8	1564	50.9	1036
2021	185.0	2.5	247.6	1564	69.7	1596
2022	122.1	2.3	242.9	1585	80.9	2001
2023	136.8	1.6	252.9	1578	83.4	2379
2024	196.9	2.8	232.7	1583	92.4	5237
2025	375.0	3.8	233.1	1608	88.8	4163
2026	291.2	4.2	222.3	1589	76.5	1427

2.2. Spatial framework

The study area extends from 22.9°S to 46.3°S in latitude, and from the coastline to 99.3°W in longitude. Geographic coordinates were projected to a UTM coordinate system, and a spatial mesh was constructed to represent the study domain (Figure 1). The mesh was designed to ensure adequate spatial resolution in areas with high sampling density while maintaining computational efficiency.

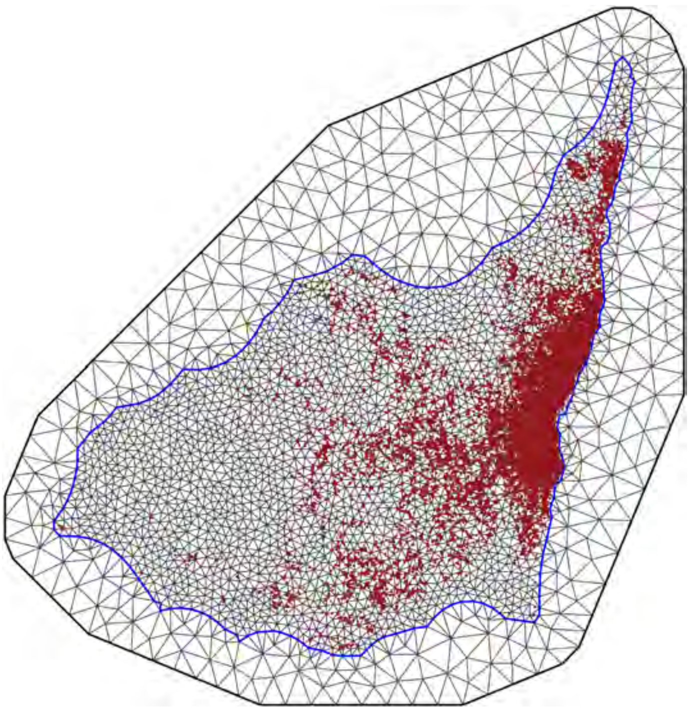

Figure 1: Spatial mesh used to approximate the Gaussian random field under the SPDE framework, overlaid with fishing set locations. The mesh defines the spatial resolution of the model and ensures adequate coverage of the study domain.

The spatial random field was modeled using the stochastic partial differential equation (SPDE) approach, assuming a Matérn covariance structure.

2.3. Model formulation

Let i index fishing sets. The response variable is defined as $y_i = \log(CPUE_i)$ and is assumed to follow a Gaussian distribution:

$$y_i \sim \mathcal{N}(\eta_i, \sigma^2). \tag{1}$$

The linear predictor is defined as:

$$\eta_i = \beta_0 + \beta_{Year(i)} + \beta_{Quarter(i)} + f(logCB_i) + \beta_{DFP}\, logDFP_i + s(\mathbf{x}_i, t_i), \tag{2}$$

where β_0 is the intercept, β_{Year} and $\beta_{Quarter}$ are categorical effects, $f(\cdot)$ represents a nonlinear effect of vessel capacity modeled as a second-order random walk (RW2), and $s(\mathbf{x}_i, t_i)$ is a spatial or spatio-temporal random effect at location $\mathbf{x}_i$ and time t_i.

The spatial component is modeled as a Gaussian random field with Matérn covariance, implemented through the SPDE approach.

Three alternative model structures were evaluated:

Model 1 (spatial).

$$s(\mathbf{x}_i, t_i) = s(\mathbf{x}_i), \tag{3}$$

a single spatial field assumed constant in time.

Model 2 (replicated spatial fields).

$$s(\mathbf{x}_i, t_i) = s_{t_i}(\mathbf{x}_i), \tag{4}$$

independent spatial fields estimated separately for each year.

Model 3 (spatio-temporal AR1).

$$s_t(\mathbf{x}) = \rho\, s_{t-1}(\mathbf{x}) + \epsilon_t(\mathbf{x}), \tag{5}$$

where $|\rho| < 1$ is the temporal autocorrelation parameter and $\epsilon_t(\mathbf{x})$ is a spatial Gaussian field.

All models were fitted using the Integrated Nested Laplace Approximation (INLA).

2.4. Model selection

Models were compared using the Watanabe–Akaike Information Criterion (WAIC). The selection focused on identifying a model that adequately captured spatial and temporal variability while maintaining parsimony.

2.5. Index estimation

Predictions from the selected model were generated on a regular spatial grid covering the study area, using common reference values for the operational covariates. Predicted CPUE was back-transformed to the original scale and averaged across space and quarters to obtain an annual standardized index. Uncertainty was quantified from posterior samples, from which 95% credible intervals and coefficients of variation were calculated.

2.6. Update for 2026

The selected model structure was applied to an updated dataset including 2026. The model was re-fitted without modifying its structure, allowing a consistent extension of the standardized CPUE index in an operational context.

2.7. Retrospective analysis

The temporal stability of the standardized CPUE index was evaluated through a retrospective analysis based on sequential truncation of the most recent years of the dataset. The selected model was repeatedly re-fitted after removing terminal years, while retaining the same model structure, covariates, and spatial framework used in the final analysis.

For each truncated dataset, the standardized annual CPUE index was estimated following the same prediction and spatial integration procedure applied to the full model. Retrospective estimates were then compared with those obtained from the complete time series over their overlapping years. This analysis was used to assess whether the estimated historical trajectory was sensitive to the progressive addition of recent observations and to identify potential changes in the perception of relative abundance near the terminal years of the series.

2.8. Influence diagnostics

To evaluate how individual components of the standardization affected the temporal CPUE trajectory, influence diagnostics were adapted from the framework proposed by Bentley et al. (2012). These diagnostics were applied after model selection and were intended to characterize the contribution of operational, seasonal, and spatio-temporal components to differences between observed and standardized CPUE, rather than to provide an additional model-selection criterion.

First, a stepwise diagnostic was constructed by sequentially adding model components while retaining the same response distribution and general model formulation. The sequence included year, quarter, fishing trip duration, vessel hold capacity, and the replicated annual spatial field. Annual effects from each successive model were expressed on a relative scale, allowing changes in the temporal trajectory associated with the inclusion of each component to be visualized.

Annual influence was subsequently quantified from the selected model by evaluating the contribution of each covariate to the linear predictor under the observed annual composition of the fishery. For component k, annual influence was defined as

$$I_{k,t} = \exp\left(\overline{\eta}_{k,t} - \overline{\eta}_k\right), \tag{6}$$

where $\overline{\eta}_{k,t}$ is the mean contribution of component k to the linear predictor for fishing sets observed in year t, and $\overline{\eta}_k$ is its mean contribution across the complete dataset. Values of $I_{k,t}$ greater than one therefore indicate that the annual composition of that component was associated with higher predicted CPUE relative to the overall reference, whereas values below one indicate a negative relative contribution.

Influence was evaluated for quarter, fishing trip duration, and vessel hold capacity. For continuous or nonlinear terms, contributions were calculated on the linear-predictor scale using the corresponding estimated model effects. Complementary coefficient–distribution–influence (CDI) diagnostics were used to distinguish the estimated effect of each covariate from temporal changes in its observed distribution, thereby identifying whether annual influence resulted primarily from the magnitude of the estimated effect, changes in fleet composition or fishing behaviour, or a combination of both.

Because the selected model includes year-specific spatial random fields, the influence framework was extended to quantify the contribution of the year-specific spatial component. For each fishing set, the posterior mean of the annual spatial field was projected from the SPDE mesh to the observed fishing location using the corresponding projection matrix. The year-specific spatial contribution for observation i was therefore calculated as:

$$\eta_i^{ST} = \mathbf{A}_i \mathbf{w}_{t_i}, \tag{7}$$

where $\mathbf{A}_i$ is the SPDE projection vector for fishing set i and $\mathbf{w}_{t_i}$ represents the posterior mean of the spatial field for year t_i.

Annual influence of the year-specific spatial field was then calculated using the same relative formulation applied to the other model components:

$$I_t^{ST} = \exp\left(\overline{\eta}_t^{ST} - \overline{\eta}^{ST}\right). \tag{8}$$

This diagnostic characterizes whether fishing observations in a given year were associated, on average, with relatively higher or lower values of the estimated year-specific spatial CPUE field compared with the overall reference. Because this quantity reflects both the annual spatial field and the locations sampled by the fleet, it was interpreted as a measure of spatio-temporal influence on the observed CPUE rather than as a direct measure of stock abundance or spatial displacement.

3. Results

3.1. *Spatio-temporal distribution of fishing activity and catch*

The spatio-temporal distribution of fishing activity and catch exhibited strong interannual variability over the study period (Figure 2). Fishing sets were predominantly concentrated along the continental shelf and slope, although both the spatial extent and the location of high catch areas varied substantially between years.

During the mid-1990s, fishing activity was largely concentrated in coastal areas off central Chile, associated with high total catches exceeding 3000×10^{3} tons. In contrast, the late 1990s and early 2000s showed a progressive offshore expansion of fishing grounds, with a more dispersed spatial footprint.

Between approximately 2007 and 2012, the fishery exhibited a marked contraction in both spatial extent and total catch, with fishing activity becoming fragmented and shifting further offshore. This period corresponded to the lowest observed catches in the time series.

In more recent years (post-2015), fishing activity became increasingly concentrated again along the continental margin, accompanied by a gradual recovery in total catch and a reduction in the spatial footprint of the fishery.

Overall, these patterns highlight substantial shifts in both the intensity and spatial distribution of fishing effort and catch. These dynamics suggest that ignoring spatio-temporal structure may confound temporal changes in CPUE with changes in the spatial distribution of fishing activity, particularly during periods of expansion or contraction of fishing grounds.

3.2. *Model selection*

Model comparison based on WAIC (Table 2) showed a clear improvement when incorporating spatio-temporal structure relative to purely spatial formulations. Static spatial models (m1 and m1s) presented substantially higher WAIC values, indicating limited ability to capture temporal variability in CPUE.

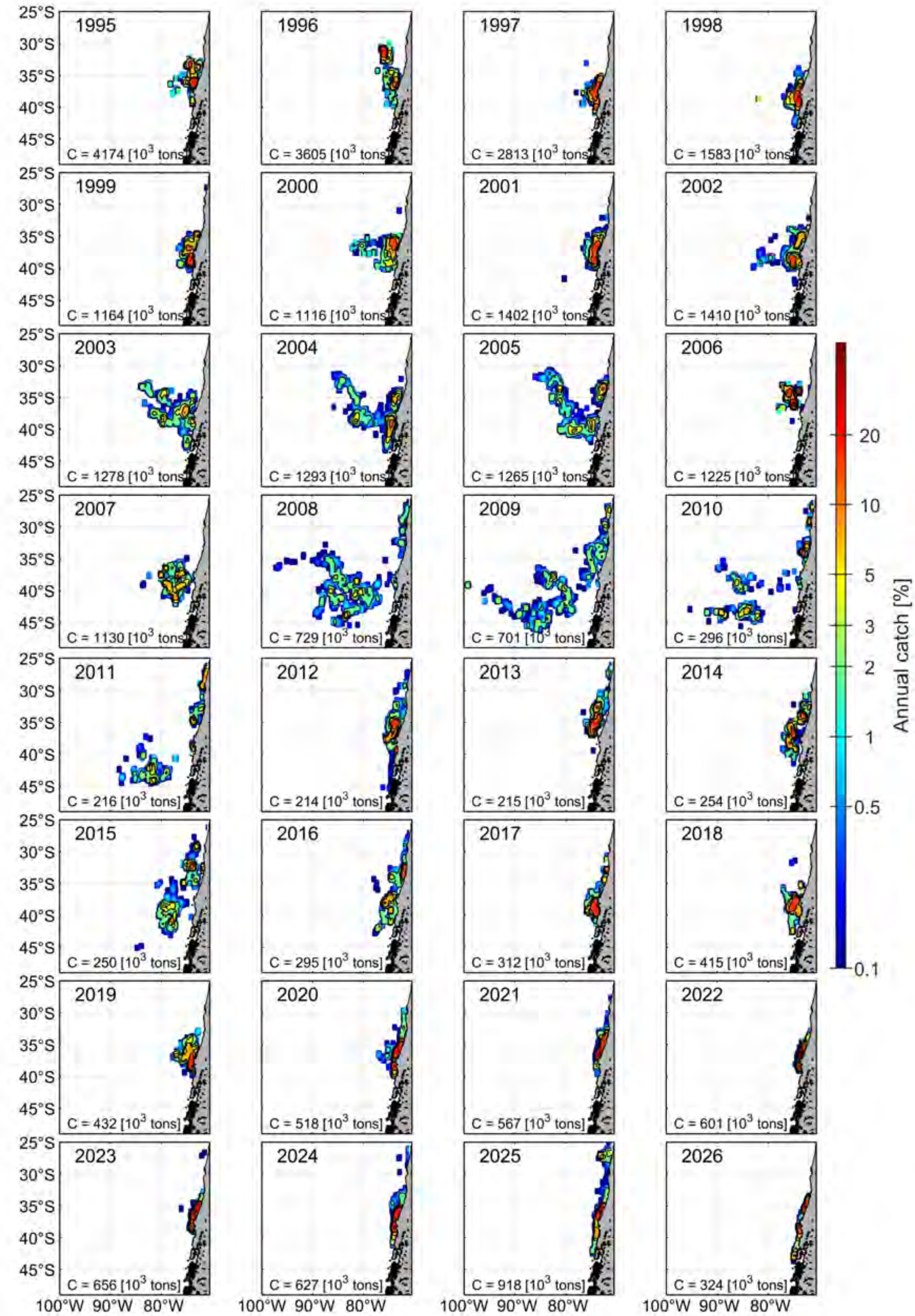

Figure 2: Interannual spatial distribution of fishing sets and relative catch (%) for Chilean jack mackerel (*Trachurus murphyi*) in central-southern Chile (1995–2026). Colors indicate the percentage contribution to annual catch (log scale), and total annual catch (C, 10^3 tons) is shown in each panel. Strong interannual shifts in the spatial extent and intensity of the fishery are evident.

Table 2: Model comparison based on DIC, WAIC, ΔWAIC, and LCPO for alternative spatial and spatio-temporal formulations. Lower values indicate better model fit. Models with independent year-specific spatial fields (m2–m6) outperformed static and AR1 formulations, with minimal differences among models m2 and m4–m6.

Model	Description	DIC	WAIC	ΔWAIC	LCPO
m1	Static spatial field, linear logCB	103210.5	102947.2	1857.5	-51234.8
m1s	Static spatial field, nonlinear logCB (RW2)	103050.7	102813.3	1723.6	-50890.3
m2	Independent year-specific spatial fields	101310.3	101090.1	0.4	**-49512.6**
m3	Year-specific spatial fields with AR1 temporal correlation	101350.6	101112.9	23.2	-49601.3
m4	m2 + sea surface temperature (SST)	101320.4	101093.4	3.7	-49540.8
m5	m2 + SST anomaly (SSTA)	101318.9	101092.4	2.7	-49540.8
m6	m2 + chlorophyll concentration	**101305.8**	**101089.7**	**0**	-49510.9

The model based on independent year-specific spatial fields (m2) provided a strong improvement in model fit. The AR1 spatio-temporal model (m3) did not outperform this formulation, indicating that allowing spatial structure to vary independently among years provided a better-supported representation than imposing temporal autocorrelation among annual spatial fields.

The inclusion of environmental covariates such as SST, SST anomalies, and chlorophyll concentration resulted in only marginal improvements in WAIC. The model including chlorophyll (m6) achieved the lowest WAIC, but the improvement relative to m2 was negligible (ΔWAIC $= 0.4$), indicating little support for the additional environmental covariate.

Based on these results, model m2 was selected as a parsimonious and robust framework for CPUE standardization.

3.3. Spatio-temporal structure of CPUE

The estimated spatial fields revealed a highly heterogeneous distribution of CPUE across the study domain, with persistent areas of elevated predicted CPUE associated with the main fishing grounds along the continental shelf and slope (Figure 3). The year-specific spatial formulation allowed these patterns to vary among years, capturing shifts in both the location and intensity of high-CPUE areas. In particular, the model reproduced periods of spatial expansion and contraction that were broadly consistent with the observed distribution of fishing activity (Figure 2).

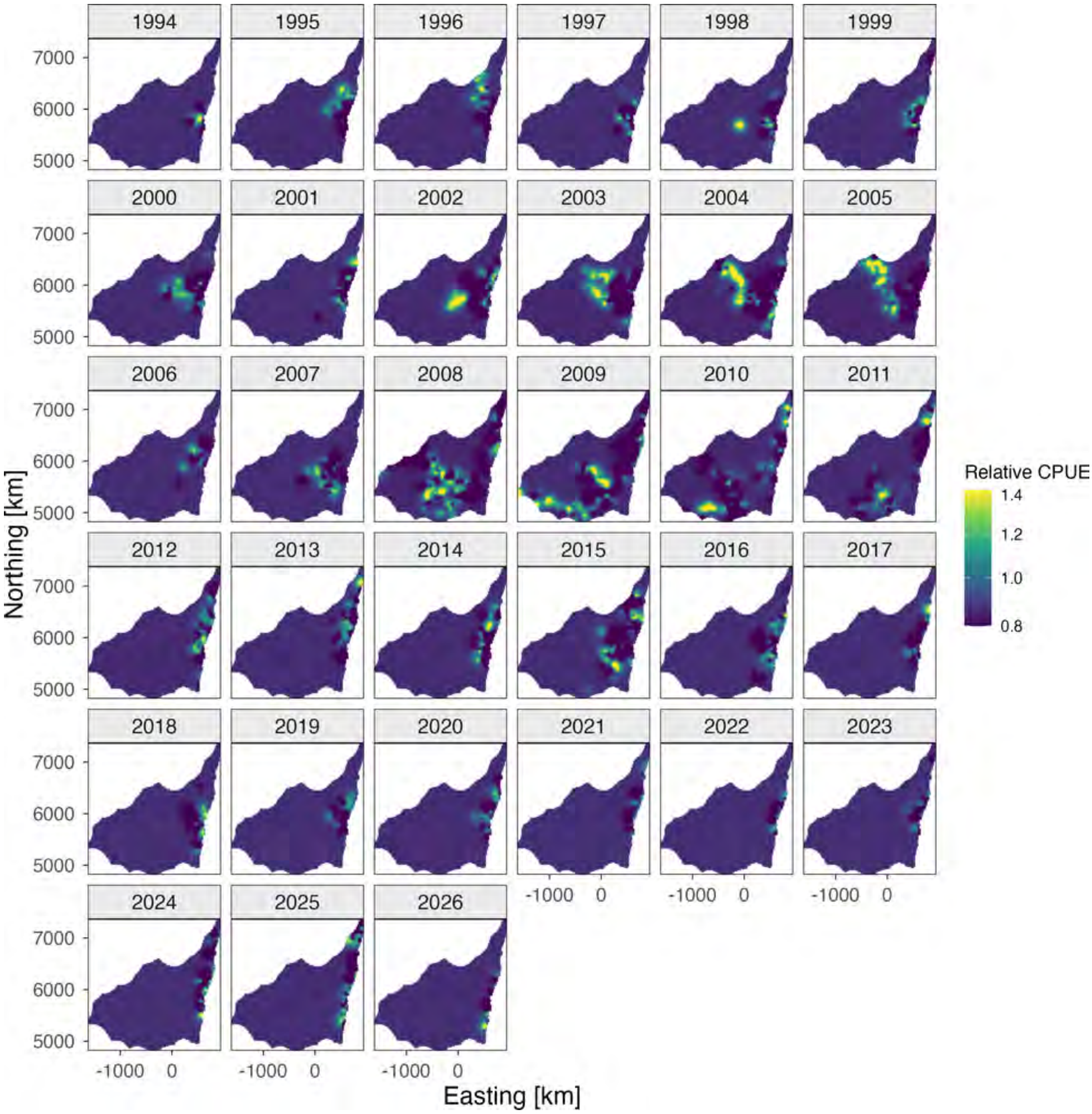

Figure 3: Spatio-temporal predictions of relative CPUE derived from the selected INLA model. Panels show the spatial distribution of predicted CPUE over the 1994–2026 period.

To further highlight deviations from the long-term mean spatial pattern, anomalies of the predicted CPUE were computed by subtracting the average spatial field across the study period from each yearly prediction. This representation emphasizes relative increases and decreases in CPUE, facilitating the identification of spatial expansion and contraction processes that are less apparent in the absolute predictions (Figure 4).

These results highlight the importance of accounting for spatial redistribution of the fishery-dependent CPUE signal, as changes in the spatial overlap between fishing activity and areas of high CPUE may otherwise influence temporal trends in the index. The anomaly patterns are consistent with the observed shifts in fishing activity (Figure 2), reinforcing the importance of accounting for spatio-temporal variability when standardizing CPUE.

3.4. Standardized CPUE index

The standardized CPUE index exhibited pronounced interannual variability over the period 1994–2026, reflecting changes in the fishery-dependent CPUE signal after accounting for operational and spatio-temporal effects (Figure 5).

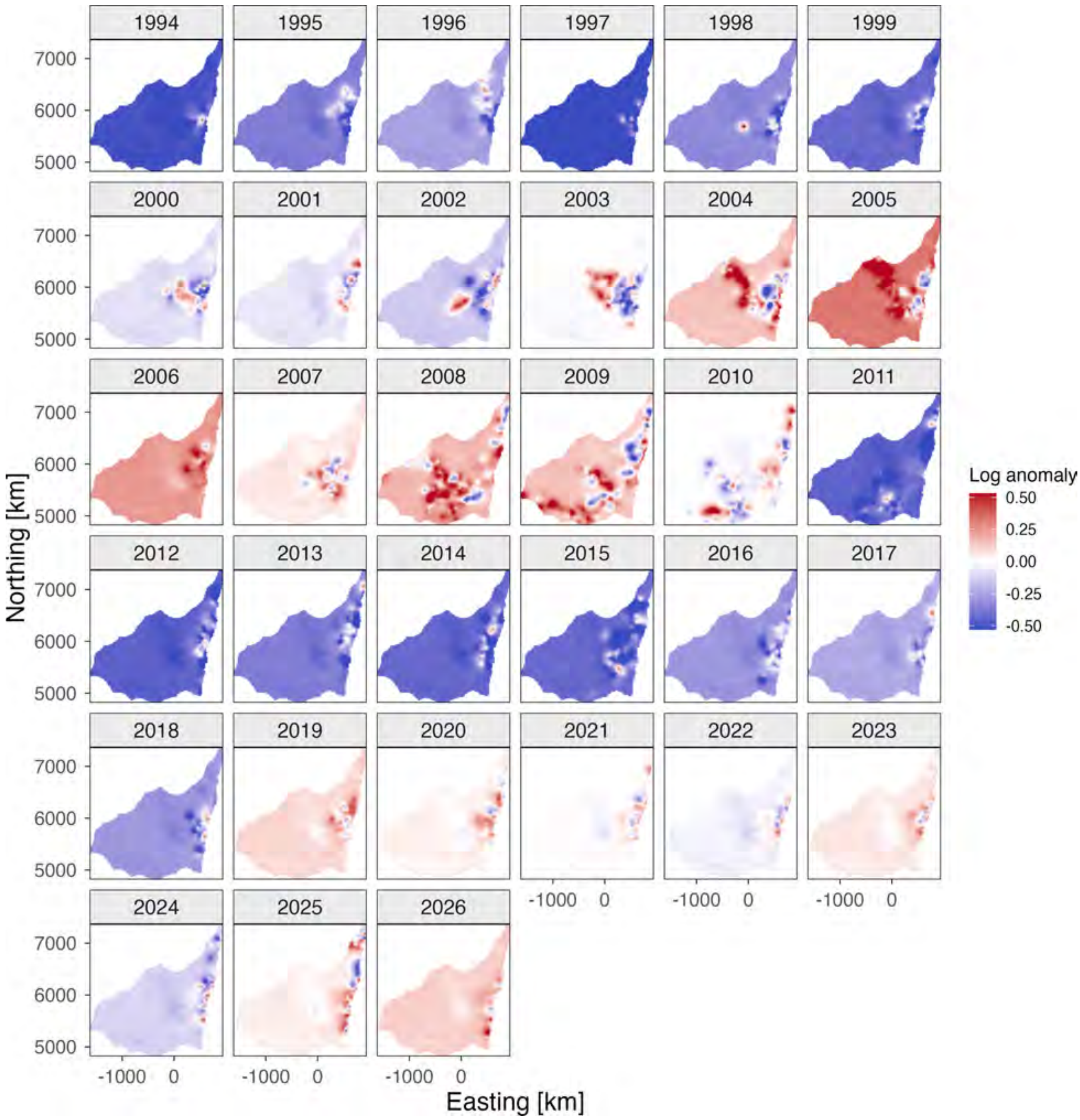

Figure 4: Spatio-temporal anomalies of predicted CPUE relative to the long-term mean. Positive values indicate areas with higher-than-average CPUE, while negative values represent below-average conditions. The anomaly fields highlight interannual shifts in the spatial distribution of predicted CPUE, including periods of expansion, contraction, and displacement of high-CPUE areas.

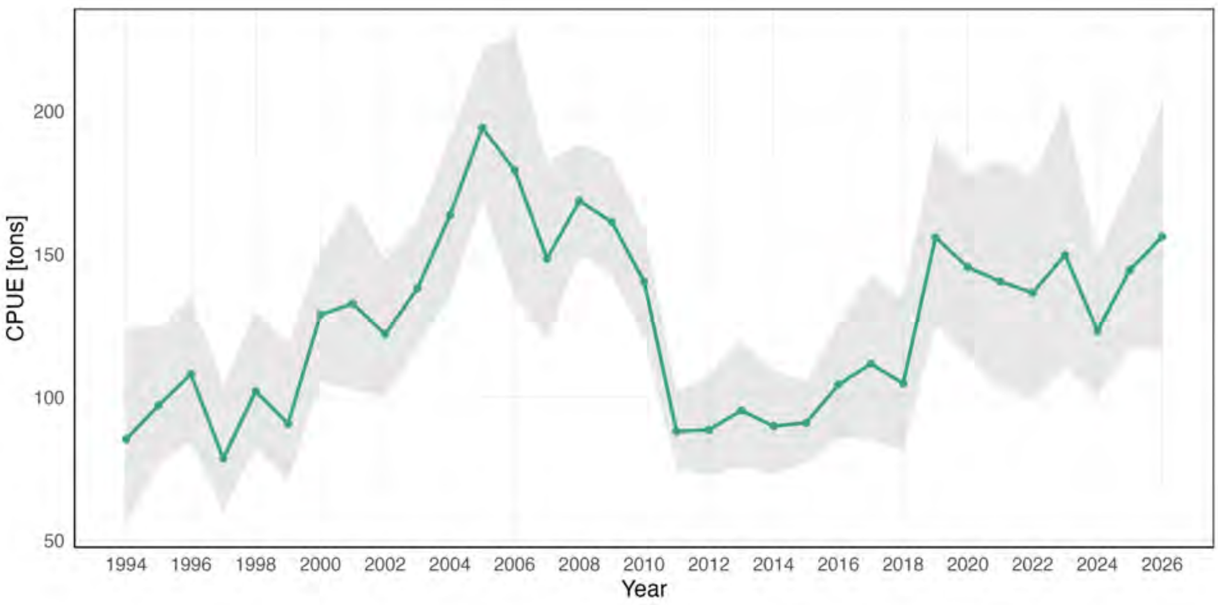

Figure 5: Standardized CPUE index (in tons per set) for Chilean jack mackerel (*Trachurus murphyi*) in central-southern Chile over the period 1994–2026. The solid line represents the posterior mean estimate derived from the selected spatio-temporal model, and the shaded area indicates the 95% credible interval. The index exhibits pronounced interannual variability while accounting for operational and spatio-temporal effects.

Compared to the observed CPUE, the standardized index showed smoother temporal dynamics after accounting for variability associated with fishing behavior, fleet characteristics, and spatial distribution.(Figure 6). Uncertainty estimates derived from posterior distributions showed wider credible intervals during periods of reduced sampling intensity or increased spatial dispersion of fishing activity.

For reproducibility and potential use in stock assessment applications, the annual standardized CPUE estimates derived from the selected model are summarized in Table 3.

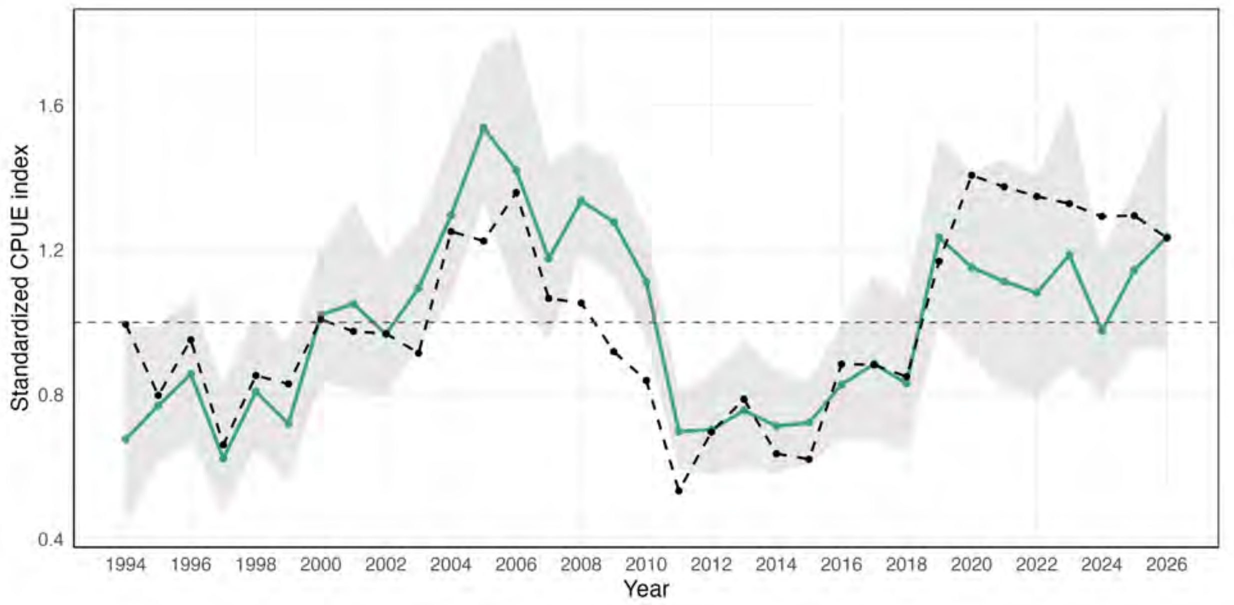

Figure 6: Comparison between observed and standardized CPUE for Chilean jack mackerel (*Trachurus murphyi*) in central-southern Chile (1994–2026). The standardized CPUE (solid line) represents the model-based estimate, while the observed CPUE (dashed line) corresponds to the mean catch per positive set. The shaded area denotes the 95% credible interval of the standardized index. Differences between both series reflect the influence of operational, spatial, and temporal effects accounted for in the model, highlighting periods in which nominal CPUE was particularly sensitive to changes in fleet behavior or spatial distribution.

3.5. Update for 2026

The inclusion of the most recent fishing data extended the standardized CPUE series to 2026 while retaining the model structure and standardization procedure used in the previous assessment. The updated model estimated a further increase in standardized CPUE in 2026 relative to 2025, following the recovery from the lower value observed in 2024. The 2026 estimate reached a level comparable to that estimated in 2019 and remained above the long-term mean. This increase contrasts with the decline observed in the unstandardized CPUE between 2023 and 2024 and its subsequent recovery, indicating that changes in the raw fishery-dependent signal over the terminal years were partly associated with changes in the operational and spatio-temporal characteristics of the fishery.

The predicted spatial distribution for 2026 was characterized by a relatively restricted coastal pattern, with the highest relative CPUE concentrated along the eastern portion of the study domain. This configuration continues the predominantly coastal distribution observed during recent years, particularly since 2018, and contrasts with the broader and more offshore distributions estimated during periods such as 2003–2011. Despite these changes in spatial configuration, the 2026 standardized index increased relative to the two preceding years, emphasizing the importance of accounting for spatial heterogeneity and temporal changes in fishing operations when interpreting recent CPUE trends. The stability of this terminal estimate and the contribution of individual standardization components were further evaluated through retrospective and influence diagnostics.

Table 3: Time series (1994–2026) of standardized CPUE for Chilean jack mackerel estimated from the selected hierarchical Bayesian model for the central-southern Chilean fishery. Mean posterior estimates, 95% credible intervals (Low and Upp), and coefficients of variation (CV) are reported.

Year	Mean	Low	Upp	CV
1994	85.4	68.1	102.7	0.2027
1995	97.1	84.2	110.1	0.1332
1996	108.1	95.5	120.6	0.1162
1997	78.6	67.3	90.0	0.1444
1998	102.0	89.7	114.4	0.1214
1999	90.8	78.2	103.4	0.1384
2000	128.8	116.3	141.3	0.0968
2001	132.7	115.5	149.8	0.1293
2002	122.1	110.0	134.1	0.0986
2003	138.1	126.6	149.7	0.0835
2004	163.6	150.5	176.7	0.0802
2005	194.2	179.8	208.6	0.0741
2006	179.4	155.3	203.4	0.1341
2007	148.5	132.0	165.0	0.1111
2008	168.7	158.3	179.1	0.0616
2009	161.3	150.6	171.9	0.0660
2010	140.4	129.6	151.1	0.0764
2011	88.1	80.9	95.2	0.0809
2012	88.6	79.6	97.7	0.1024
2013	95.4	84.6	106.2	0.1132
2014	89.9	79.9	100.0	0.1117
2015	91.1	83.5	98.7	0.0835
2016	104.4	93.6	115.2	0.1034
2017	111.7	96.8	126.5	0.1327
2018	104.9	90.9	118.9	0.1334
2019	155.9	137.0	174.8	0.1215
2020	145.4	129.2	161.7	0.1120
2021	140.5	120.0	160.9	0.1456
2022	136.5	115.8	157.2	0.1514
2023	149.8	126.6	173.0	0.1548
2024	123.2	110.6	135.9	0.1024
2025	144.5	129.7	159.3	0.1023
2026	156.1	133.6	178.6	0.1441

3.6. Retrospective analysis

The retrospective analysis showed a high degree of consistency in the estimated temporal trajectory of standardized CPUE (Figure 7). Sequentially truncating the time series from 2025 back to 2020 produced only minor revisions to the historical index and preserved its main temporal features, including the high values observed during the mid-2000s, the decline during the early 2010s, and the subsequent increase from 2019 onwards.

Terminal-year deviations relative to the corresponding estimates from the full model ranged from -0.19% to $+5.41\%$. The two most recent peels showed particularly small deviations ($+0.50\%$ for 2025 and -0.19% for 2024), whereas progressively larger positive deviations were observed for the earlier terminal years, reaching $+5.41\%$ for the model ending in 2020. Mohn's rho across the six retrospective peels was 0.025, indicating a small positive retrospective tendency, whereby truncated models tended to estimate their terminal-year CPUE slightly higher than the corresponding estimates obtained after incorporating subsequent years of information. Overall, the low magnitude of Mohn's rho and the close agreement among retrospective trajectories indicate that the historical standardized CPUE series is relatively insensitive to the sequential addition of recent years.

Figure 7: Retrospective analysis of the standardized jack mackerel CPUE index. Lines represent estimates from the full model ending in 2026 and retrospective fits obtained by sequentially truncating the time series at terminal years from 2020 to 2025. All retrospective fits retained the same model structure, covariates, spatial framework, and standardization procedure. The dashed horizontal line indicates the long-term mean of the relative index (1.0). Mohn's rho calculated from six retrospective peels (2020–2025) was 0.025.

3.7. Influence diagnostics

The stepwise influence analysis showed that the year-only model closely reproduced the unstandardized geometric CPUE series, with both trajectories being virtually indistinguishable (maximum absolute difference < 0.0001; Figure 8). Differences therefore emerged only after additional standardization components were incorporated. Despite these adjustments, the main temporal structure of the series remained consistent, including the increase during the early 2000s, the peak in 2005–2006, the decline to a minimum in 2011, and the subsequent recovery to predominantly above-average values after 2019.

The magnitude of the index was progressively modified by quarter, fishing duration, vessel hold capacity, and the year-specific spatial field. The latter produced additional interannual adjustments, particularly during the recent period. In 2024, incorporation of the year-specific spatial field reduced the relative index towards the long-term mean, while the fully standardized index subsequently increased in 2025 and 2026. Overall, the broad temporal signal was robust to the sequential standardization, while seasonal, operational, and spatio-temporal components affected the magnitude of individual annual estimates.

The terminal year showed a particularly informative response to standardization. While the 2026 index remained relatively high across model configurations, incorporation of the year-specific spatial field reduced its magnitude relative to the preceding model step. Nevertheless, the fully standardized index increased from 2025 to 2026, indicating that the terminal increase was not driven by a positive contribution of the year-specific spatial field. The factors underlying this pattern are further examined through the annual influence diagnostics.

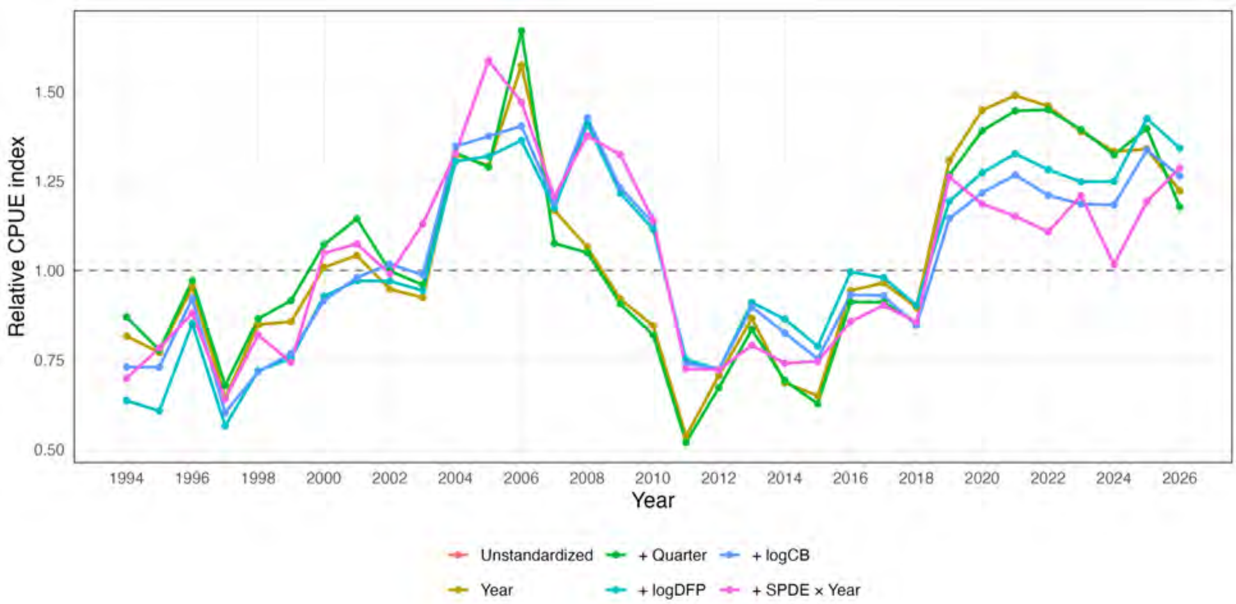

Figure 8: Stepwise influence of model components on the temporal trajectory of the relative jack mackerel CPUE index. Lines show the index obtained as successive components were incorporated into the standardization model, including Year, Quarter, fishing trip duration (logDFP), vessel hold capacity (logCB), and the year-specific spatial field (SPDE × Year). All series were normalized to their respective long-term means. The dashed horizontal line represents a relative index of 1.

Annual influence diagnostics revealed marked differences among model components in both the magnitude and temporal variability of their effects (Figure 9). Fishing duration showed pronounced temporal variation, with positive influence during the early years and again during 2019–2024, contrasting with a pronounced negative influence during 2008–2015. Quarter and vessel capacity showed comparatively smoother patterns, with influences generally close to neutral and only moderate departures from 1.0. In contrast, the year-specific spatial field exhibited substantial interannual variability, alternating between positive and negative influence throughout the series. This indicates that the spatial configuration of fishing activity relative to the estimated CPUE field contributed differently to the standardized index among years.

In 2026, fishing duration and the year-specific spatial field both showed negative influence, whereas quarter and vessel capacity had small positive effects. Consequently, the relatively high standardized CPUE estimated for 2026 cannot be attributed to favorable effects of fishing duration or the year-specific spatial field. Together with the stepwise analysis, this indicates that the terminal increase primarily reflects the underlying annual signal after accounting for these standardization effects.

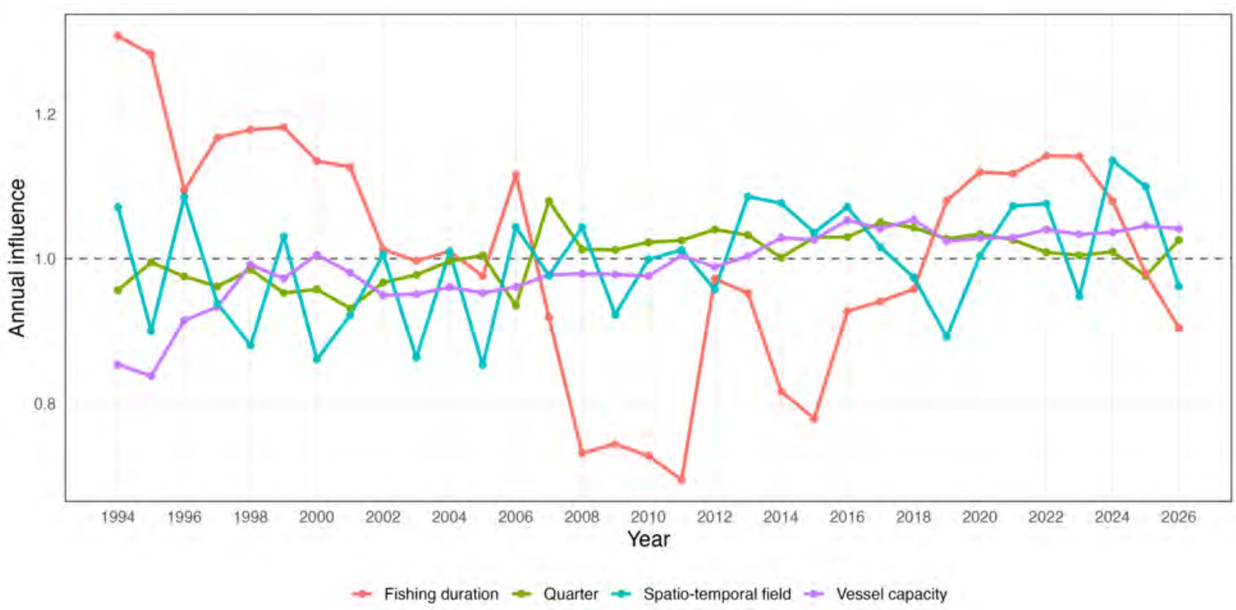

Figure 9: Annual influence of seasonal, operational, and year-specific spatial components on the standardized jack mackerel CPUE index. Values above 1 indicate annual conditions associated with higher predicted CPUE relative to the reference distribution, whereas values below 1 indicate conditions associated with lower predicted CPUE. The dashed horizontal line represents neutral influence (1.0).

3.8. *Concluding remarks*

- This study demonstrates that accounting for annual spatial variability is critical for standardizing commercial CPUE of Chilean jack mackerel. Year-specific spatial fields substantially improved model performance, whereas temporal autocorrelation and environmental covariates provided limited additional improvement.

- Despite substantial changes in fishing behavior and spatial distribution, the standardized index retained a coherent long-term pattern, with high values during the mid-2000s, a minimum around 2011, and predominantly above-average levels since 2019. The 2026 estimate further highlights the importance of accounting for operational and spatio-temporal variation when interpreting recent CPUE trends.

- The low retrospective bias (Mohn's $\rho = 0.025$) and limited revisions of historical estimates support the temporal stability of the standardized series. Influence diagnostics further identified fishing duration and the year-specific spatial field as important sources of adjustment to nominal CPUE.

- Overall, the hierarchical Bayesian framework provides a robust and reproducible approach for updating the commercial CPUE series. Continued annual updates and comparison with fishery-independent abundance indices will help evaluate its long-term performance and potential contribution to jack mackerel stock assessment.

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