Standardization of Chilean jack mackerel CPUE fishery in central-southern Chile using Hierarchical Bayesian Models (INLA)

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Abstract

The standardization of catch per unit effort (CPUE) is essential for deriving reliable indices of relative abundance, particularly in fisheries with strong spatial dynamics. In this study, we apply a hierarchical Bayesian spatio-temporal modeling framework based on the Integrated Nested Laplace Approximation (INLA) to standardize CPUE of the Chilean jack mackerel (*Trachurus murphyi*) fishery in central-southern Chile over the period 1994–2026. The model explicitly accounts for spatial and temporal dependence, as well as operational and environmental covariates, using fishing set-level data.

Alternative model structures were evaluated using information criteria, with a formulation based on independent spatial fields replicated by year providing the best balance between model fit and parsimony. Results reveal strong interannual variability in both the spatial distribution of CPUE and the standardized index. The inclusion of 2026 data allowed a consistent extension of the time series without modifying the model structure, demonstrating the operational robustness of the approach.

Overall, the framework provides a flexible and robust method for CPUE standardization in highly dynamic pelagic fisheries, improving the interpretation of abundance indices by accounting for spatio-temporal variability in stock distribution and fishing behavior.

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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 incorporates spatial and temporal dependence, 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 such as vessel hold capacity and fishing trip duration were considered, along with environmental covariates including sea surface temperature and chlorophyll concentration. 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 operational and sampling-related factors may influence observed CPUE independently of stock abundance and are therefore explicitly accounted for in the standardization model.

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), and percentage of the jack mackerel catch spatiotemporally referenced 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 [%]
1994	161.9	2.2	177.2	847	0.3
1995	205.6	2.0	143.5	959	0.9
1996	381.9	3.2	171.2	1073	1.9
1997	192.6	2.7	118.5	1188	2.0
1998	222.4	2.6	153.5	1389	8.6
1999	197.4	2.6	148.7	1354	11.4
2000	224.9	2.6	181.1	1484	13.8
2001	180.6	2.4	174.8	1367	30.2
2002	270.5	3.4	174.4	1243	24.6
2003	413.0	3.3	164.6	1228	19.8
2004	447.9	3.3	225.1	1272	44.9
2005	483.2	3.5	220.5	1251	43.6
2006	284.8	2.5	244.6	1299	7.7
2007	448.7	4.1	192.0	1357	14.5
2008	947.0	7.2	189.6	1346	39.1
2009	845.4	7.2	165.3	1375	36.8
2010	970.2	9.2	151.3	1395	46.0
2011	769.1	8.4	95.9	1532	32.6
2012	253.3	3.6	125.5	1438	76.5
2013	331.7	3.9	141.9	1468	56.4
2014	300.2	5.7	114.5	1577	21.2
2015	541.7	6.2	111.6	1518	40.3
2016	355.6	4.3	159.9	1626	29.2
2017	286.5	4.0	157.8	1614	23.3
2018	281.9	3.8	152.7	1674	16.8
2019	196.2	2.6	211.2	1561	41.2
2020	204.5	2.4	253.8	1564	50.9
2021	185.0	2.5	247.6	1564	69.7
2022	122.1	2.3	242.9	1585	80.9
2023	136.8	1.6	252.9	1578	83.4
2024	196.9	2.8	232.7	1583	92.4
2025	375.0	3.8	233.1	1608	88.8
2026	221.8	3.9	238.8	1584	81

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.

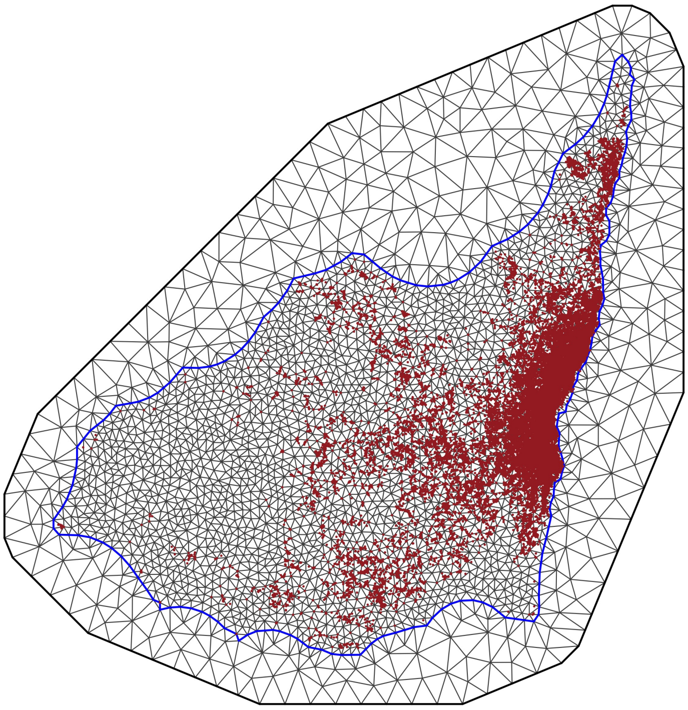

Figure 1: Spatial mesh used to approximate the Gaussian random field under the SPDE framework, overlaid with fishing set locations. The mesh defines the spatial resolution of the model and ensures adequate coverage of the study domain.

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:

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

The linear predictor is defined as:

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

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 replicated 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 were obtained on a regular spatial grid covering the study area. CPUE was back-transformed to the original scale and averaged across space and quarters to obtain an annual standardized index. Uncertainty was quantified using posterior sampling.

Observed CPUE was defined as the mean catch per positive set, ensuring consistency with the model formulation.

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.

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.

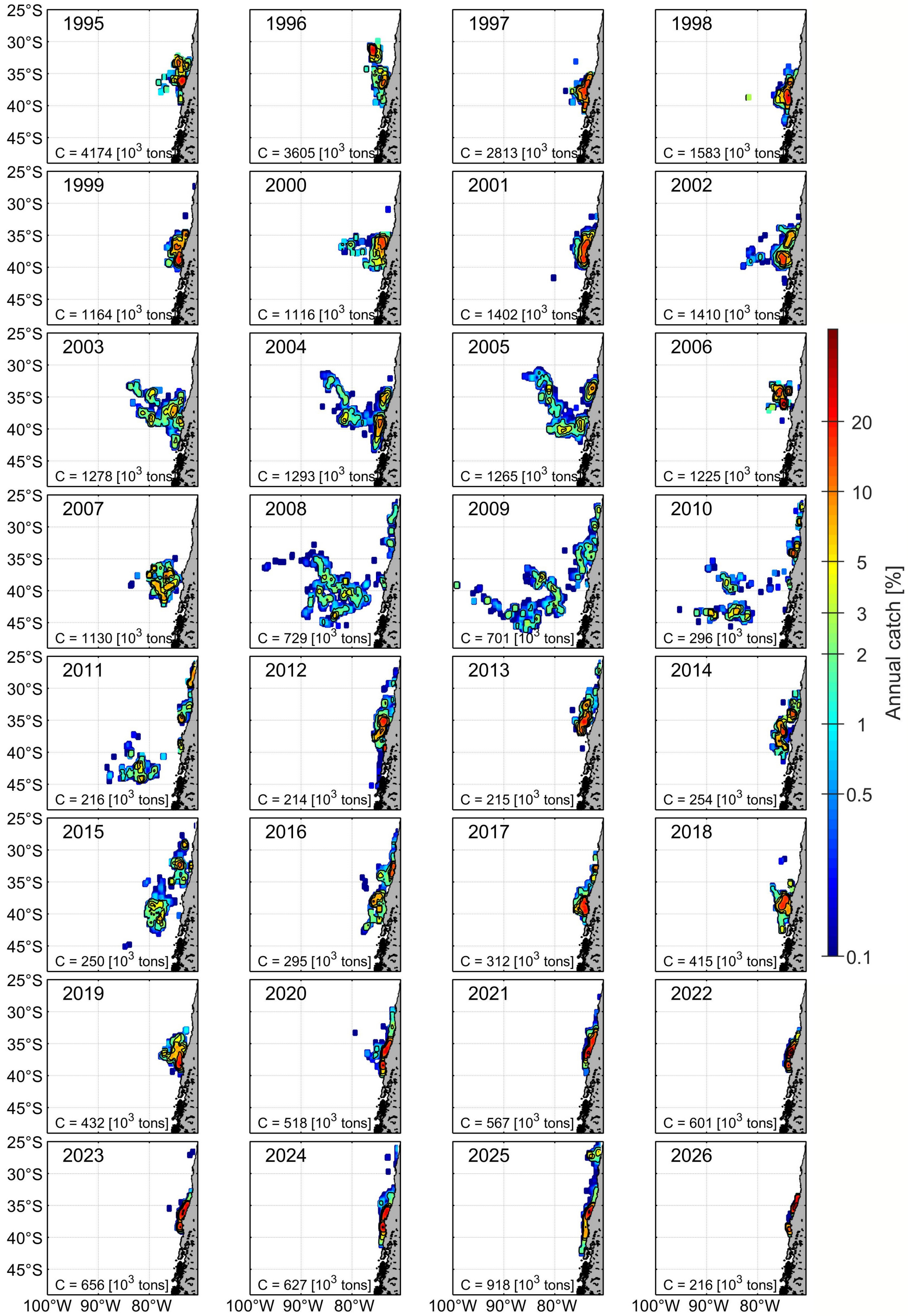

Figure 2: Interannual spatial distribution of fishing sets and relative catch (%) for Chilean jack mackerel (Trachurus murphyi) in central-southern Chile (1995–2026). Colors indicate the percentage contribution to annual catch (log scale), and total annual catch (C, 10^3 tons) is shown in each panel.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

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 lead to biased CPUE indices, 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.

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 replicated spatial fields by year (m2–m6) outperformed static and AR1 structures, with minimal differences among them.

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	Spatio-temporal independent spatial fields replicated by year	101310.3	101090.1	0.4	**-49512.6**
m3	Spatio-temporal spatial fields with AR1	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 spatial fields replicated by year (m2) provided a strong improvement in model fit. The AR1 spatio-temporal model (m3) did not outperform this formulation, suggesting that temporal dependence is better captured through year-specific spatial effects rather than through a structured temporal autocorrelation process.

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 difference relative to m2 was negligible (WAIC 0), indicating that most of the variability is already explained by the spatio-temporal structure.

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 relative abundance associated with the main fishing grounds along the continental shelf and slope (Figure 3). The spatio-temporal formulation allowed these spatial patterns to dynamically evolve across years, capturing shifts in both the location and intensity of high CPUE areas. In particular, the model reproduced periods of spatial expansion and contraction consistent with the observed distribution of fishing activity. These predicted patterns are consistent with the observed distribution of fishing activity (Figure 2), indicating that the model adequately captures the main spatial dynamics of the fishery.

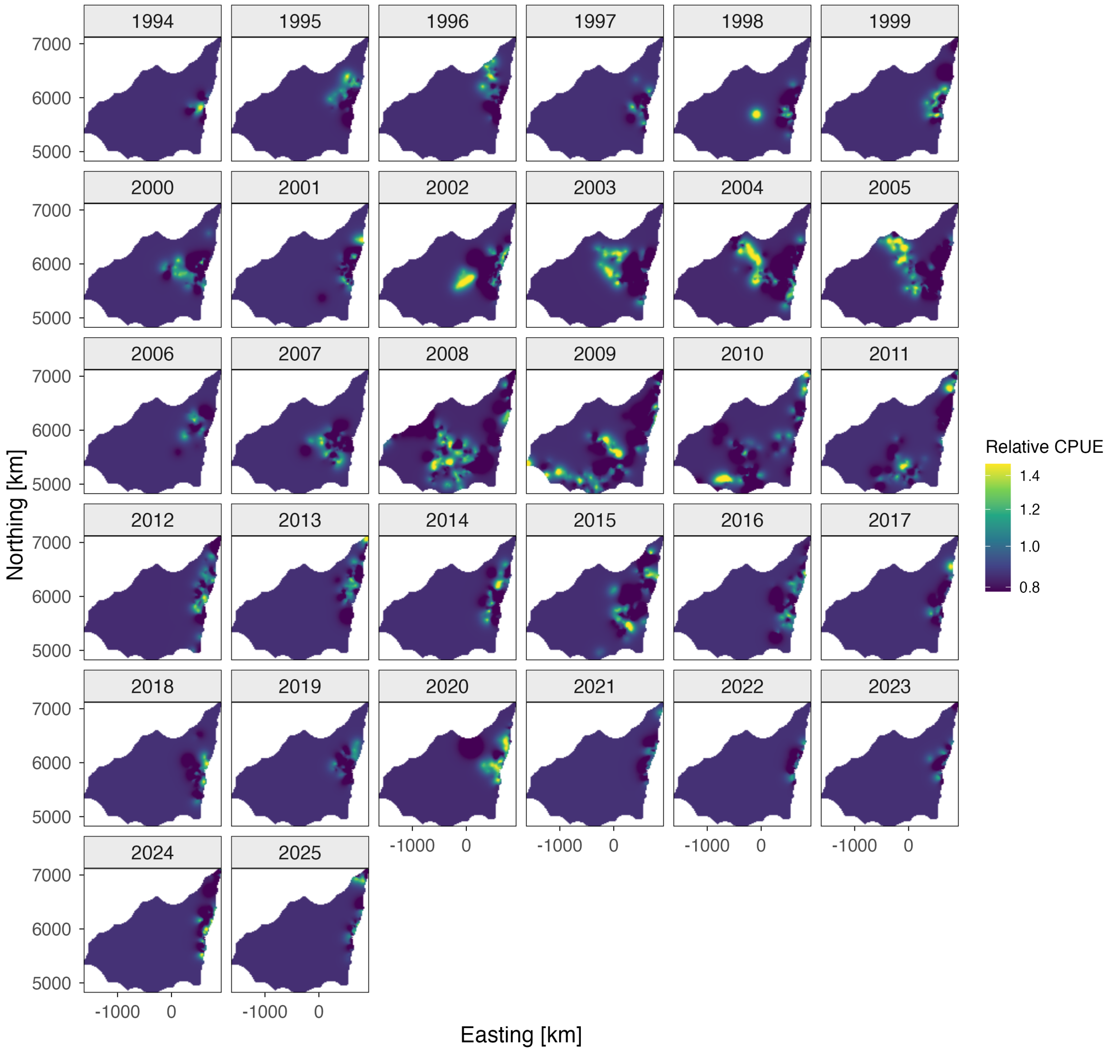

Figure 3: Spatio-temporal predictions of relative CPUE derived from the selected INLA model. Panels show the spatial distribution of predicted CPUE for selected years (or mean conditions).

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).

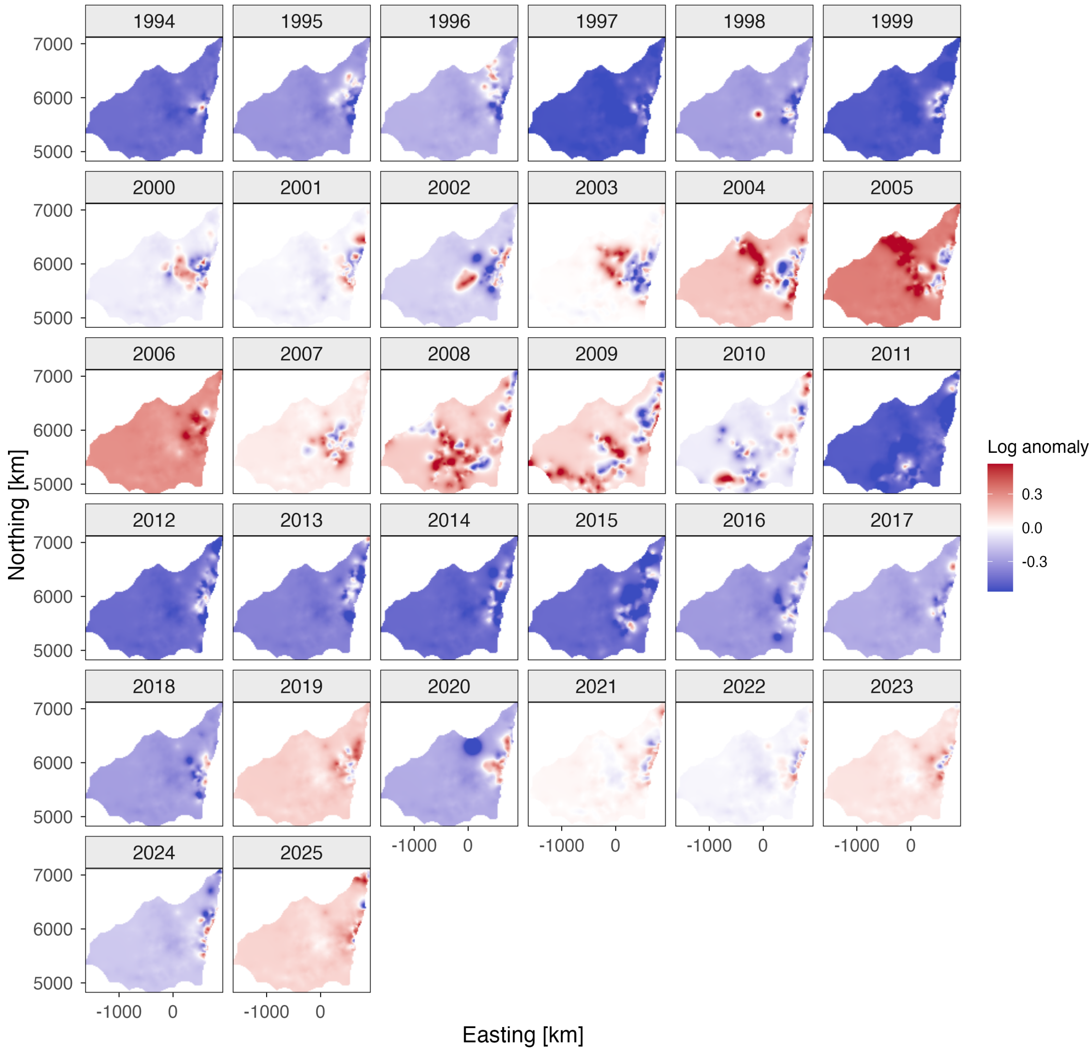

Figure 4: Spatio-temporal anomalies of predicted CPUE relative to the long-term mean. Positive values indicate areas with higher-than-average CPUE, while negative values represent below-average conditions. The anomaly fields highlight interannual shifts in the spatial distribution of the stock, including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

These results highlight the importance of accounting for spatial redistribution of the stock when standardizing CPUE, as changes in availability may otherwise be confounded with changes in abundance. These anomaly patterns are consistent with the observed shifts in fishing activity (Figure 2), reinforcing the importance of accounting for spatio-temporal variability when interpreting CPUE trends.

3.4. Standardized CPUE index

The standardized CPUE index exhibited pronounced interannual variability over the period 1994–2025, reflecting both changes in stock availability and shifts in spatial distribution (Figure 5).

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, indicating that the model effectively accounted for variability associated with changes in fishing behavior, fleet distribution, and environmental conditions (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 1.

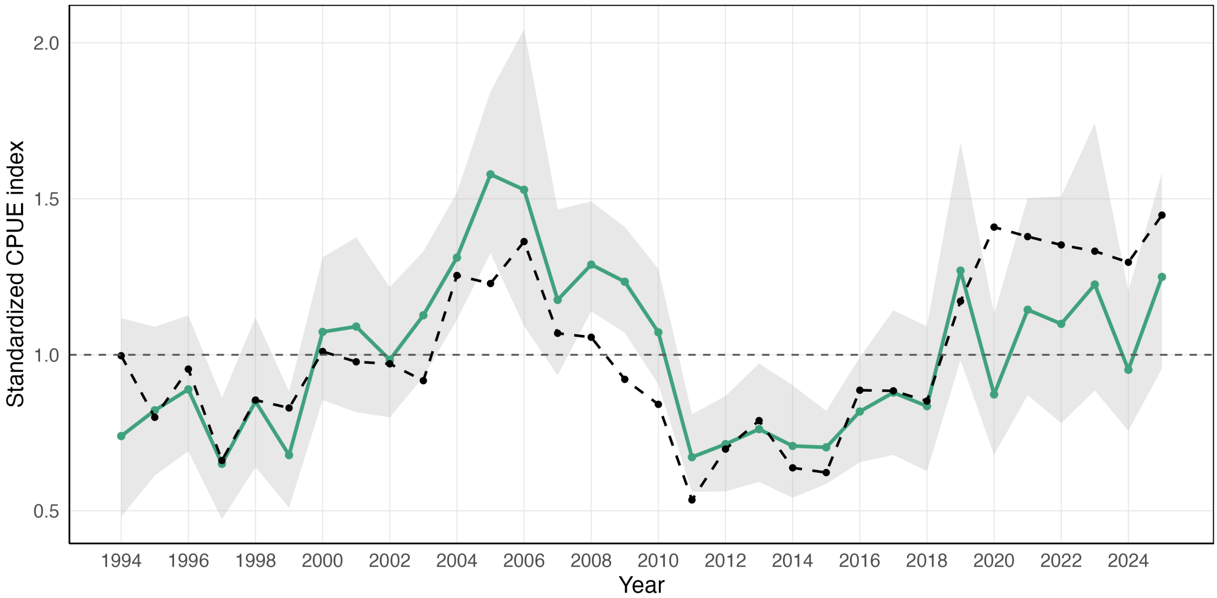

Figure 6: Comparison between observed and standardized CPUE for Chilean jack mackerel (*Trachurus murphyi*) in central-southern Chile (1994–2026). The standardized CPUE (solid line) represents the model-based estimate, while the observed CPUE (dashed line) corresponds to the mean catch per positive set. 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 where raw CPUE may be biased due to changes in fleet behavior or spatial distribution.

3.5. Update for 2026

The selected model was applied to the updated dataset including 2026, allowing a consistent extension of the standardized CPUE time series. The incorporation of the new data did not require modification of the model structure, demonstrating the operational robustness of the framework. The 2026 estimate was consistent with recent trends, although associated uncertainty remains relatively high due to the limited data available for the most recent year (Figure 7).

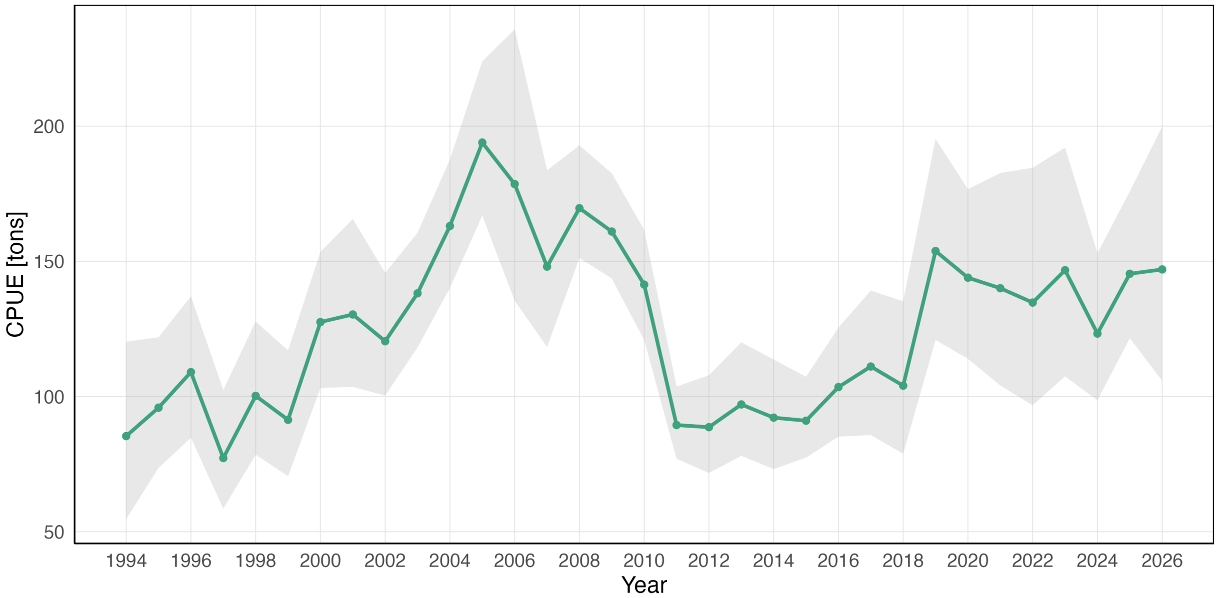

Figure 7: Extension of the standardized CPUE index (in tons per set) for Chilean jack mackerel (*Trachurus murphyi*) in central-southern Chile over the period 1994–2026. The solid line represents the posterior mean estimate derived from the selected spatio-temporal model, and the shaded area indicates the 95% credible interval. The inclusion of 2026 allows a consistent continuation of the time series without modifying the model structure, demonstrating the operational robustness of the framework. The 2026 estimate is broadly consistent with recent trends, although uncertainty remains relatively high due to the limited data available for the most recent year.

The spatial prediction for 2026 (Figure 8) is consistent with recent years, showing a concentration of relative CPUE along the continental margin, although with increased uncertainty associated with the most recent observations.

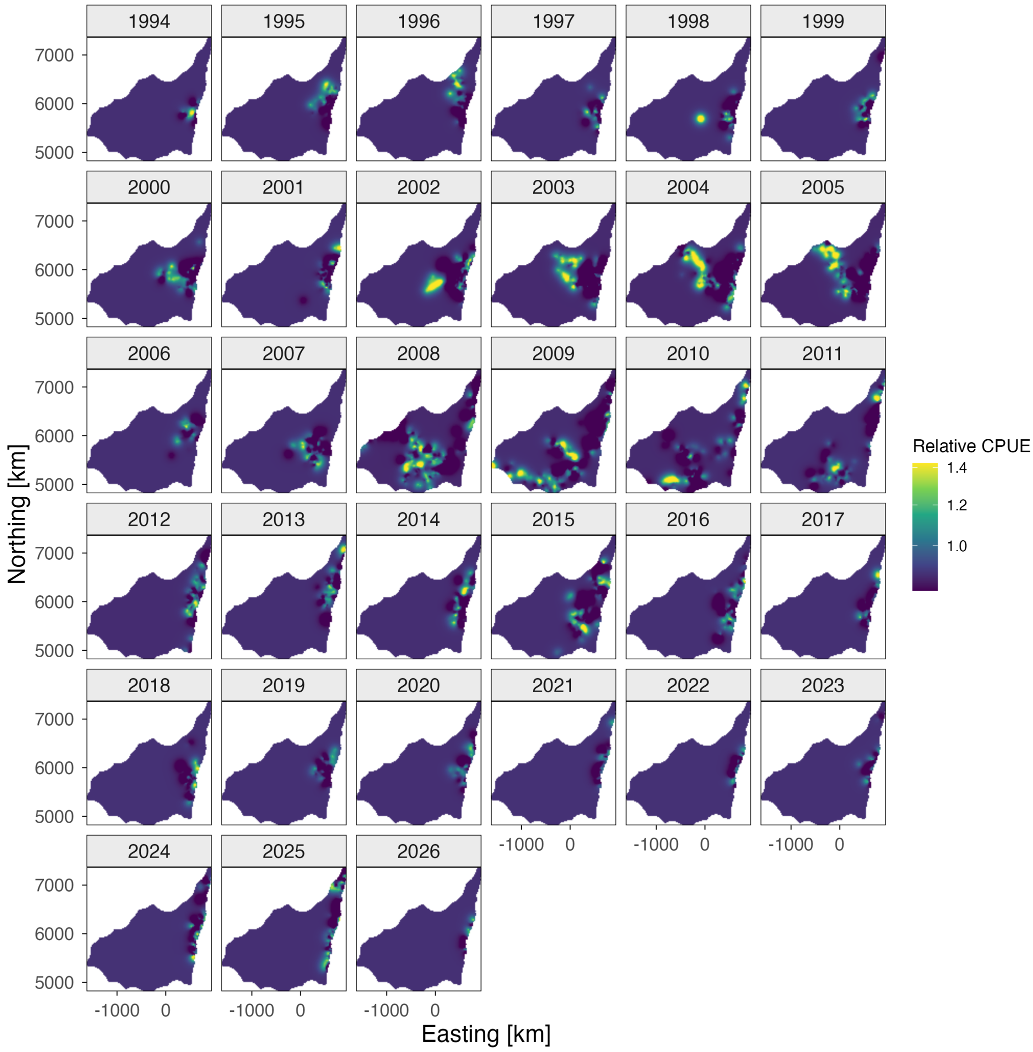

Figure 8: Spatial prediction of relative CPUE for Chilean jack mackerel (*Trachurus murphyi*) in central-southern Chile for 2026. The map shows the predicted distribution derived from the selected spatio-temporal model, highlighting a concentration of relative CPUE along the continental margin. This spatial pattern is consistent with recent years, although uncertainty is higher due to the limited data available for the most recent period.

3.6. Concluding remarks

Concluding remarks

- The inclusion of spatio-temporal structure substantially improved model performance compared to purely spatial formulations, highlighting the importance of accounting for distributional shifts in pelagic fisheries.

- A model based on independent spatial fields replicated by year provided a parsimonious and robust representation of CPUE dynamics, outperforming more complex temporal structures such as AR1.
- The standardized CPUE index revealed smoother temporal dynamics than the observed series, indicating that a significant fraction of variability is driven by changes in fleet behavior and spatial sampling rather than stock abundance alone.
- Spatial predictions and anomaly patterns highlighted pronounced interannual shifts in the distribution of Chilean jack mackerel, reinforcing the need to interpret CPUE in a spatially explicit context.
- The extension of the index to 2026 without modifying the model structure demonstrates the operational applicability of the framework for routine updates in an assessment context.
- These results support the use of spatio-temporal CPUE standardization as a robust input for stock assessment and fisheries management.

Table 3: Time series (1994-2026) of the CPUE of Chilean jack mackerel estimated using spatio-temporal Bayesian models in the central-southern Chile fishery.

Year	Mean	Low	Upp
1994	85.4	54.6	120.3
1995	95.9	73.6	121.9
1996	109.0	84.8	137.1
1997	77.2	58.6	102.4
1998	100.3	78.5	127.7
1999	91.4	70.5	117.1
2000	127.6	103.2	153.5
2001	130.4	103.6	165.7
2002	120.5	100.4	145.7
2003	138.2	118.2	160.6
2004	163.1	140.2	187.7
2005	193.9	167.0	224.0
2006	178.6	135.5	235.8
2007	148.1	118.4	183.7
2008	169.7	151.3	192.9
2009	161.0	143.7	182.5
2010	141.4	121.0	161.6
2011	89.5	77.0	103.7
2012	88.7	71.7	107.9
2013	97.1	78.1	120.0
2014	92.2	73.2	113.7
2015	91.1	77.4	107.3
2016	103.5	85.2	125.5
2017	111.1	85.8	139.2
2018	104.0	78.9	135.2
2019	153.8	120.9	195.3
2020	144.0	114.0	176.7
2021	140.1	104.1	182.7
2022	134.8	96.8	184.6
2023	146.7	107.5	192.1
2024	123.3	98.6	153.0
2025	145.4	121.6	175.8
2026	147.0	105.8	199.8

References

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