South Pacific Regional Fisheries Management Organisation

11th MEETING OF THE SCIENTIFIC COMMITTEE

11 to 16 September 2023, Panama City, Panama

SC11 – JM07
A Bayesian spatio-temporal approach for the standardization of CPUE in the *Trachurus murphyi* fishery of central-southern Chile

Republic of Chile

A Bayesian spatio-temporal approach for the standardization of CPUE in the Chilean jack mackerel (*Trachurus murphyi*) fishery of central-southern Chile

Sebastián I. Vásquez[a,b,], Luis Cubillos[c], Aquiles Sepúlveda[a]

[a] *Instituto de Investigación Pesquera, Talcahuano, Chile*
[b] *Programa de Doctorado en Oceanografía, Universidad de Concepción, Chile*
[c] *Departamento de Oceanografía, Universidad de Concepción, Chile*

Abstract

The spatial distribution and the habitat selection are key factor in population dynamics of pelagic fish stocks, but are often not explicitly included in ecological studies or age- or size-structured stock assessment models (SAMs). The main types of data commonly used in SAMs are catch, composition (e.g. age/length, sex and weight) and indices of relative abundance. Fishery-independent indices from standardized surveys are often difficult to obtain for logistic and funding reasons or occur during a specific season. Therefore, many SAMs rely on indices of relative abundance based on fishery catch-per-unit-of-effort (CPUE) which can be influenced by several factors that promote its spatial variation challenging its standardization (e.g. environmental-conditions, fishing methods, season/area fished and vessel-size). This study standardized the data of Chilean jack mackerel fishery-dependent CPUE from central-southern Chile for the period 1994-2023 using Bayesian hierarchical spatio-temporal models with the integrated nested Laplace approximation (INLA). Jack mackerel CPUE was best explained by vessel hold-capacity, days at the sea, quarter, year, the spatio-temporal component and environmental conditions (here sea surface temperature and chlorophyll-a). In terms of spatio-temporal distribution, jack mackerel biomass prediction maps showed a variable interannual pattern with two periods of coastal concentration (1995-2001 and 2012-2023) and one of offshore expansion (2002-2011). The standardized series of CPUE suggested a stable period of high biomass that reached its maximum in 2006, from when it declined steadily. Then, since 2015, an increase in the CPUE is observed, which was associated with a greater availability of fishing close to the main fishing ports. In addition, the included environmental variables showed an improvement in the goodness-of-fit of the standardization model, suggesting a habitat-based aggregation of jack mackerel biomass. This approach provides a new spatio-temporal standardized jack mackerel CPUE series that could be used in the Joint-Jack-Mackerel-SAM.

Email address: svasquez@inpesca.cl (Sebastián I. Vásquez)

1. Introduction

Scientific advice on fisheries management is generally based on the results of the application of some form of stock assessment technique (Hilborn & Walters, 2013). Size- or age- structured population dynamics models are fit to different data sets to estimate model parameters and associated derived management quantities. Three primary types of data are commonly used in fish stock assessment models: catch, indices of relative abundance and composition data representing the proportions of the sampled population within different age, length, sex, and/or weight categories (Maunder et al., 2020). While indices provide information on trends in abundance, the composition data provide information on the component of the population represented by the index, and the size or age of the fish removed by the fishery. Indices based on fishery-independent data from standardized scientific surveys are often difficult to collect for economic and technical reasons (Maunder & Punt, 2004). Furthermore, scientific surveys usually occur during specific months or seasons, and provide no information about the stock during the rest of the year. For this reason, many stock assessments rely on indices of relative abundance based on fishery catch-per-unit-of-effort (CPUE) data (Maunder et al., 2006), which can be influenced by several factors, including environmental conditions, fishing methods, season, area fished, vessel size, fishing restrictions, and economics that may invalidate the assumption that the index is proportional to abundance (Hilborn & Walters, 2013; Thorson et al., 2016). For this reason, it becomes necessary to standardize the CPUE index in an effort to eliminate the effects of these factors (Hilborn & Walters, 2013)

The standardization of CPUE can be challenging and frequently involves separate steps, in which the standardization process and population dynamics are fitted independently (Maunder, 2001). Various methods are used to standardize CPUE, of which Generalized Linear Models (GLM) are the most common to account for linear relationships between the response variable and the covariates (Maunder & Punt, 2004; Lynch et al., 2012; Payá, 2022) and Generalized Additive Models (GAM) which also allow for fitting non-linear relationships between variables. Most of these methods commonly incorporate location as a factor without an additional term for time-space interaction. This approach implicitly assumes that the estimated time effect (i.e., the temporal trend, commonly interannual), which is assumed to be a proxy of relative abundance, is the same in each spatial stratum, and that only the average CPUE differs among strata (Maunder et al., 2020). The assumptions underlying this approach can lead to bias in the estimated index of relative abundance in several situations, including when the spatial distribution of the stock changes over time (Punt et al., 2000). Thus, both spatial and temporal correlation must be considered during the modelling process because observations of species at geographically close locations are subject to similar life habits and environmental characteristics (Thorson & Barnett, 2017). Commonly, commercial fishery data are records of a specific vessel at a given time and location. For this type of nested data, spatial models using hierarchical approaches are known to perform well (Izquierdo et al., 2022). Recently, several authors have used Bayesian Hierarchical Spatio-Temporal models (BHSTM) fitted through the integrated nested Laplace approximation (INLA) (Rue et al., 2009) in single-species CPUE standardization (e.g. (Cao et al., 2011; Zhou et al., 2019; Ijima & Koike, 2021; Izquierdo et al., 2022)). BHSTM have an advantage over common CPUE standardization models (e.g. GLM or GAM) by accounting for spatio-temporal autocorrelation through spatially structured random effects and autoregressive terms, thereby reducing uncertainty of estimated biomass indices (Cosandey-Godin et al., 2015; Izquierdo et al., 2022). It is worth to note that BHSTM also allow the inclusion of linear or smoothed (non-linear) terms for environmental covariates, which can be key to explain spatio-temporal distribution of species biomass (Munoz et al., 2013; Paradinas et al., 2017; Izquierdo et al., 2022)

Chilean jack mackerel (CHJM; *Trachurus murphyi*, Nichols) a transboundary pelagic species that is widely distributed in the southeastern Pacific ocean off Chile and Peru, reaching across to New Zealand and Tasmania (Bailey, 1989; Grechina et al., 1998). The wide distribution of this species and its highly migratory behavior make it difficult to gather evidence supporting specific hypotheses about its spatial dynamics and population structure.

Furthermore, due to its transzonal nature, CHJM is caught by several fleets that operate in different areas of its global distribution, with the purse seiner fleet from central-southern Chile as the most important in terms of landings. The biomass index based on the CPUE standarization of the central-southern Chilean purse seiner fleet is one of the main indices used in the SPRFMO joint jack mackerel (JJM) stock assessment model which is standardized by traditional methods (i.e. GLM, (Payá, 2022)). However, in this region the spatial distribution of the CHJM has changed over time (Figure 1), which poses difficulties for the standardization of the CPUE and can lead to biases in its estimation. This contribution aims to assess the spatio-temporal variability of CHJM distribution in central-southern Chile and to derive a standardized CPUE index that could be used as input to JJM stock assessment model. To this end, we apply BHSTM via INLA to map CHJM biomass accounting for vessel-related variables, spatio-temporal autocorrelation, and possible relationships with environmental covariates, such as Sea Surface Temperature and Chlorophyll-a. The presented approach enables the inclusion of different variables through various types of random effects and to consider spatio-temporal dependence for data sets with consecutive time units (e.g. quarters or years).

2. Methods

2.1. CHJM Purse-seine fishery data

This study analysed data from the Chilean jack mackerel purse-seine fishery off central-southern Chile. As we were interested in long-term variability in CHJM index of biomass, the period 1994–2023 were selected, a period with availability of reliable data on the position and date of individual fishing sets that were the basis of the analysis. The data set comes from a joint effort of the two main Chilean fisheries research institutes focused on CHJM (IFOP and INPESCA), which developed a unique data set for the CHJM fishing sets referenced in time and space. Number of records, operational details of the fishing activity and technical characteristics of the vessels are summarized in Table 1. One of the limitations of the data set that emerges is the imbalance in the proportion of the catch effectively referenced spatio-temporally, which has increased steadily in the last decade with the implementation of electronic logs. However, we consider that both the technical characteristics and the fishing locations are representative of the fishing activity of each year and support their spatio-temporal evaluation.

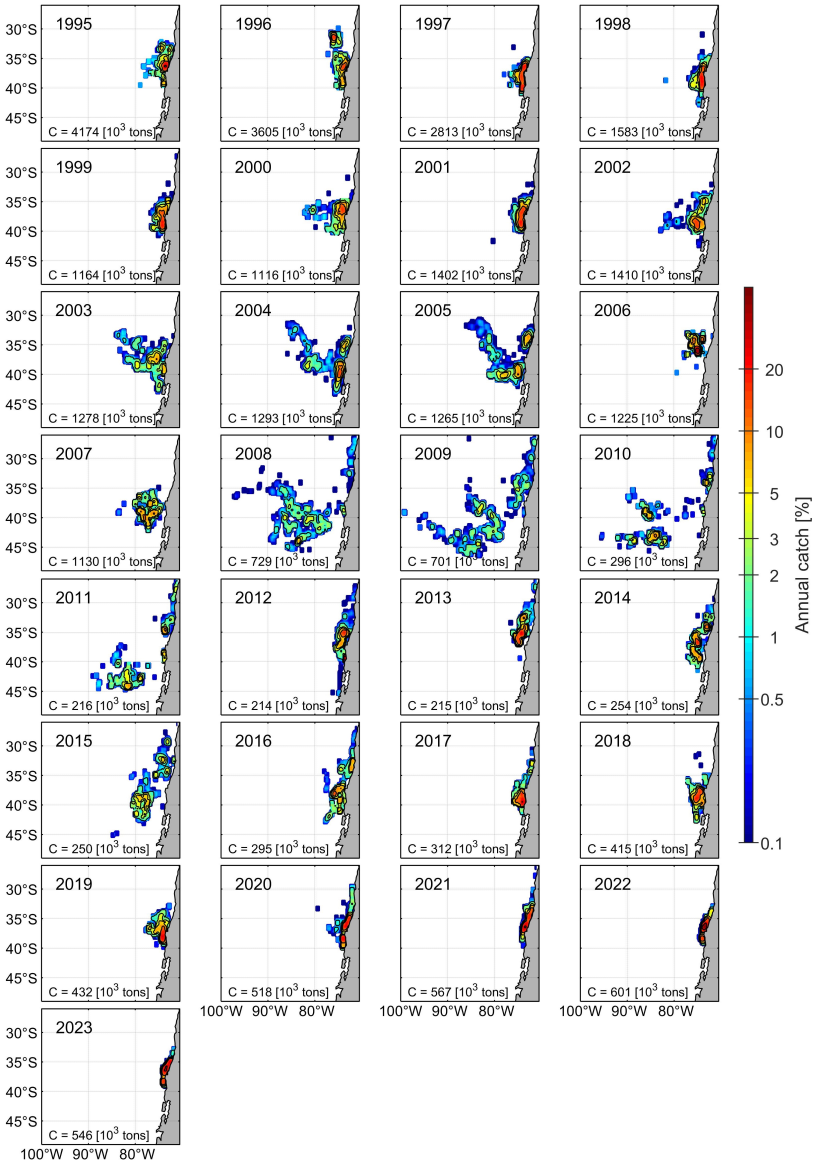

Figure 1: Spatio-temporal variability of the Chlean jack mackerel catch in the purse-seine fleet of central-southern Chile, period 1994-2023.

Table 1: Summary of the proportion of the catch referenced spatiotemporally per year, operational details of the fishing activity and technical characteristics of the vessels for BH modelling of CPUE in CHJM fishery of central-southern Chile.

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	1.8	252.9	1578	83.4

2.2. Environmental variables

Environmental variables influence habitat preferences, which in turn influence catchability (Arreguín-Sánchez, 1996). To asess the relationship between CHJM catch, locations, and habitat conditions at these locations, we considered two environmental variables: Sea Surface Temperature (SST in °C) and Chlorophyll-a (Chl-a). These variables were selected for analysis because they were shown to be related to CHJM habitat preferences (Núñez et al., 2004). Daily satellite fields of SST and Chl-a were retrieved from the Copernicus program (https://www.copernicus.eu/es) at a spatial resolution of 4 x 4 km. Finally, the values of the environmental variables at each fishing set location were extracted from the corresponding daily variable maps.

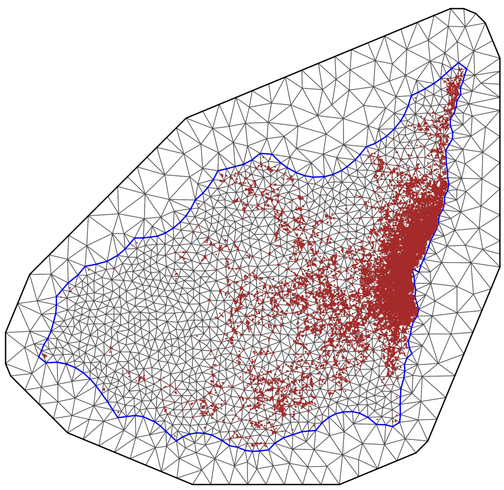

Figure 2: Delaunay triangulation used to calculate the Gaussian Markov random field for the SPDE approach. Historical observations of Chilean jack mackerel fishing sets are shown in red dots.

2.3. CPUE modelling process

Total CHJM catch (tons) from a single fishing set per trip was used as the response variable to characterize spatio-temporal CHJM biomass. We utilized the Integrated Nested Laplace Approach (INLA) of Rue et al. (2009) and the Stochastic Partial Differential Equations (SPDE) approach of Lindgren et al. (2011) to model a Gaussian spatio-temporal process with Matérn covariance. The INLA SPDE module allows the construction of a Delaunay triangulation covering the region of interest for the estimation (Figure 2). Once the estimation is performed in the observed location, there are additional functions that linearly interpolate the results within each triangle into a finer regular grid. The CPUE (catch per vessels hold capacity and days at sea) observed at locations s_i with $i = 1, ..., n$ was assumed to be a realization of a Gaussian Field (GF) at locations s_i and measured error. Moreover, the spatial process was assumed to be stationary and isotropic, meaning that the covariance between any two points only depends on their distance. The SPDE approach is a GF solution with Matérn correlation when > 0. A two-dimensional space triangulated domain represented the spatial process defined using nodes of a mesh. A projector matrix links the spatial GF to the locations of the observed data. The CPUE data had a lognormal distribution, i.e.,

$$f(y) = \frac{1}{y\sqrt{2\pi}}\sqrt{\tau}(-\tau(log(y) - \mu)^2/2),$$

where μ is the mean and linked to the linear predictor $g = \mu$, and $\tau > 0$ is the precision parameter and it is an hyperparameter represented by $\theta = log(\tau)$. According to Paradinas et al. (2017), we estimated and constant spatial effect model (Model 1), a yearly changing spatial realization model (Model 2), a yearly correlated or progressive spatial model (Model 3). The models were fitted with INLA with the intercept added as a covariate term in the list of effects, i.e.,

Model 1: $log(y_{s,t}) = \beta_0 + T_{s,t} + Q_{s,t} + log(H_{s,t}) + log(E_{s,t}) + V_s$

Model 2: $log(y_{s,t}) = \beta_0 + T_{s,t} + Q_{s,t} + log(H_{s,t}) + log(E_{s,t}) + V_{s,t}$

Model 3: $log(y_{s,t}) = \beta_0 + T_{s,t} + Q_{s,t} + log(H_{s,t}) + log(E_{s,t}) + V_{s,t} + \sum_K^{k=1} \rho_k V_{s(t-k)}$

where β_0 is the intercept, $T_{s,t}$ is a year effect, $Q_{s,t}$ is a seasonal effect represented by quarter, $log(H_{s,t})$ is the logarithm of hold capacity of a given vessel operating in location s

and year t, $log(E_{s,t})$ is the logarithm of the days at sea of a given fishing vessel in location s and year t. The term $V_{s,t}$ is a random spatial effect represented by $V_{s,t} = w_{s,t}$.

The Deviance Information Criterion (DIC) (Spiegelhalter et al., 2014), the Watanabe-Akaike (WAIC) information criterion (Watanabe & Opper, 2010) and Log-Conditional Predictive Ordinations (LCPO) (Roos et al., 2011) were used to compare the alternative models. The best compromise between fit, parsimony and predictive quality is the smaller the WAIC, DIC and LCPO values are. Once the best model was selected, we added Sea Surface Temperature (SST) and Chlorphyll-a (Chl-a) to the linear predictor (Model 4). All models were fitted using the Integrated Nested Laplace Approximation (INLA) via the R-INLA environment (https://www.r-inla.org/).

3. Results

The best model for standardizing Chilean jack mackerel included the logarithm of the vessels hold capacity, the logarithm of the days at sea (included as an offset), the spatio-temporal component, ear, and quarter (Table 2). In Model 4 that included the environmental variables (SST and Chl-a) as linear predictors, a small improvement in goodness of fit over the model 3 was observed. In Model 3 the greatest reduction in DIC, WAIC, and LCPO was associated with the inclusion of the spatio-temporal component. Figure 3 shows the marginal posterior distribution of the hyperparameters and the fixed effects of Model 4. The mean posterior value for the spatial effect range was 121.1 km, while the standard deviation was 0.526. The presence of an autoregressive spatio-temporal term indicated a relative degree of temporal persistence in the spatial distribution of adult CHJM over the study area. The medium temporal correlation parameter ρ of the progressive spatio-temporal structure (0.562) suggested these results.

Table 2: Model selection process for the Chilean jack mackerel *Trachurus murphyi* CPUE standardization in the fishery of central-southern Chile within the period 1994–2023

Selection of models	DIC	WAIC	LCPO
Model 1	90082.6	90395.9	1.375
Model 2	88305.1	88521.9	1.343
Model 3	88097.8	88391.1	1.341
Model 4	88041.3	88327.2	1.340

As can be seen in Figure 3, the posterior distribution of the environmental effects suggests that both covariates (Sea Surface Temperature, $\beta 1$ and Chlorophyll-a, $\beta 2$) have a significant influence on driving the CHJM biomass distribution, positively influencing the CPUE. Thus, these results indicate that the CHJM biomass tends to be higher in warmer regions with higher chlorophyll-a concentration.

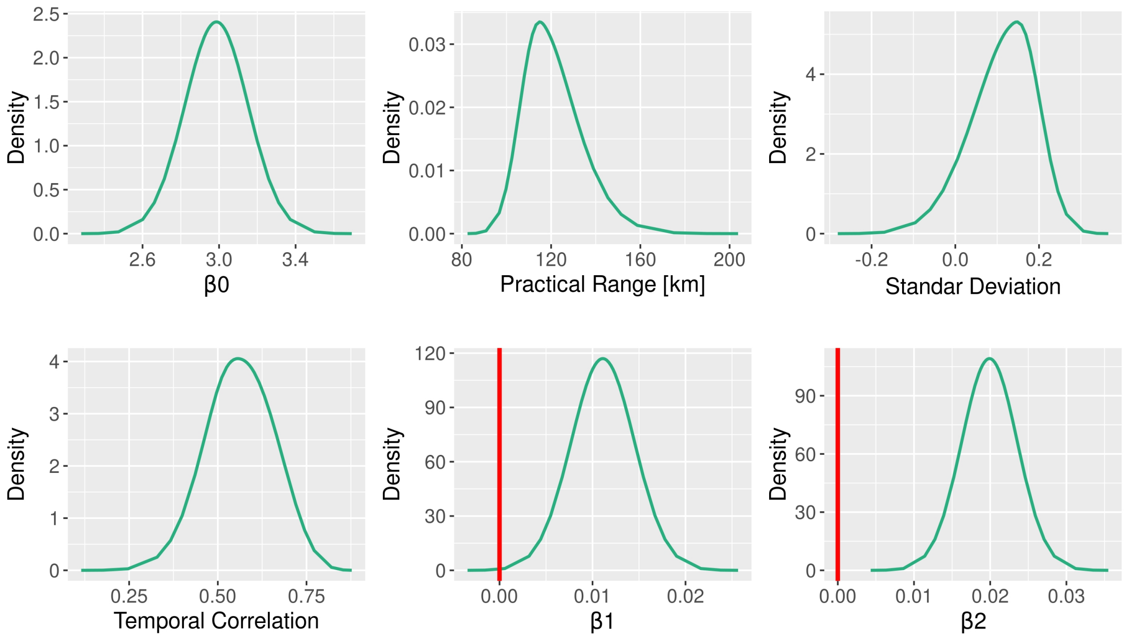

Figure 3: Marginal posterior distribution for the practical range (top-middle), standard deviation of the Gaussian field (top-rigth), the temporal correlation (bottom-left), the sea surface temperature (β_1, fixed effects; bottom-middle), the chlorophyll-a (β_2, fixed effects; bottom-rigth)

The linear effect for the variable vessel hold capacity showed that the relationship between catch biomass and vessel hold capacity was not strictly linear, for vessels over 1000 m^3 where the catch seems to reach an asymptotic level (Figure 4). This relationship should be carefully analyzed due to the influence of changes in fishing tactics that have occurred in recent years. The linear effect for quarter captured well the temporal cyclic trend throughout the year, with a minimum effect in the fourth quarter and a maximum effect in second quarter (Figure 4).

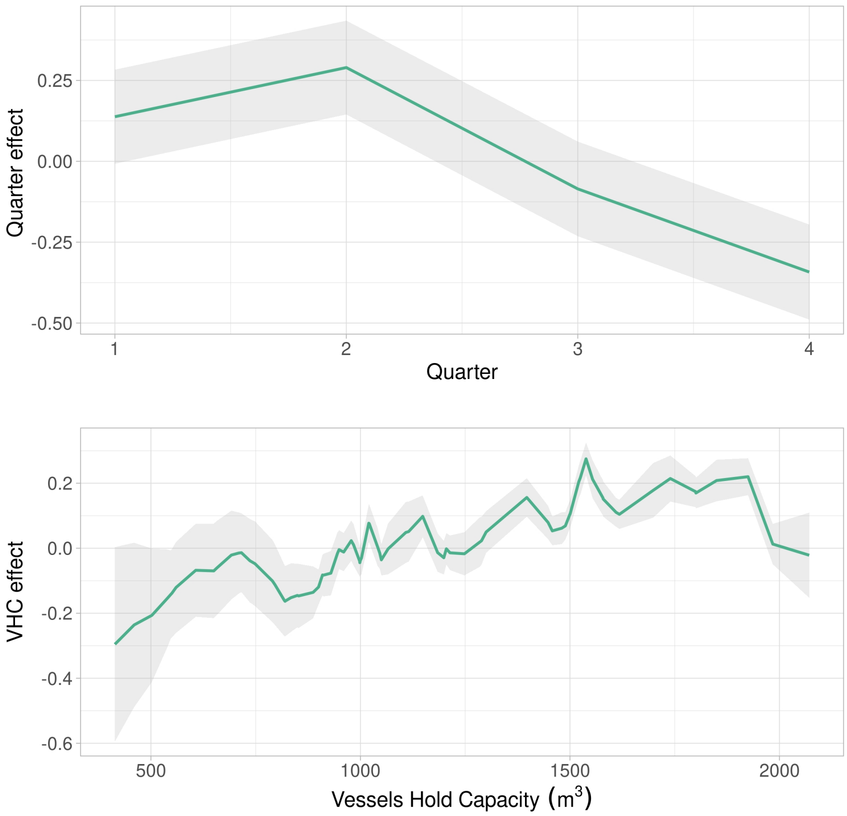

Figure 4: Marginal linear effects of vessel hold capacity and quarter on the linear predictor scale (logarithmic link) of the Chilean jack mackerel (CPUE) best model. Shaded regions represent the approximate 95% credibility interval.

The mean of the posterior predictive distribution for CHJM CPUE revealed areas with a persistent high concentration of fish in coastal regions during 1994-2001 period, being the central coastal near to Talcahuano port the one with maximum values, whereas a low biomass area is predicted offshore (Figure 5). During the period 2000-2007 the distribution becomes more opportunistic, with non-persistent high CPUE areas located both in coastal and oceanic regions (Figure 5). Subsequently, a period of low CPUE is observed between 2008 and 2015 where the biomass was recorded dispersed without areas of high concentration and a non-persistent distribution of CPUE. Finally, the most recent period, 2016-2023, has been characterized by an increasing trend in CHJM biomass with a persistent distribution of high CPUE in the coastal region (up to 200 km offshore) where biomass has been concentrated in locations close to the Talcahuano fishing port (Figura 5).

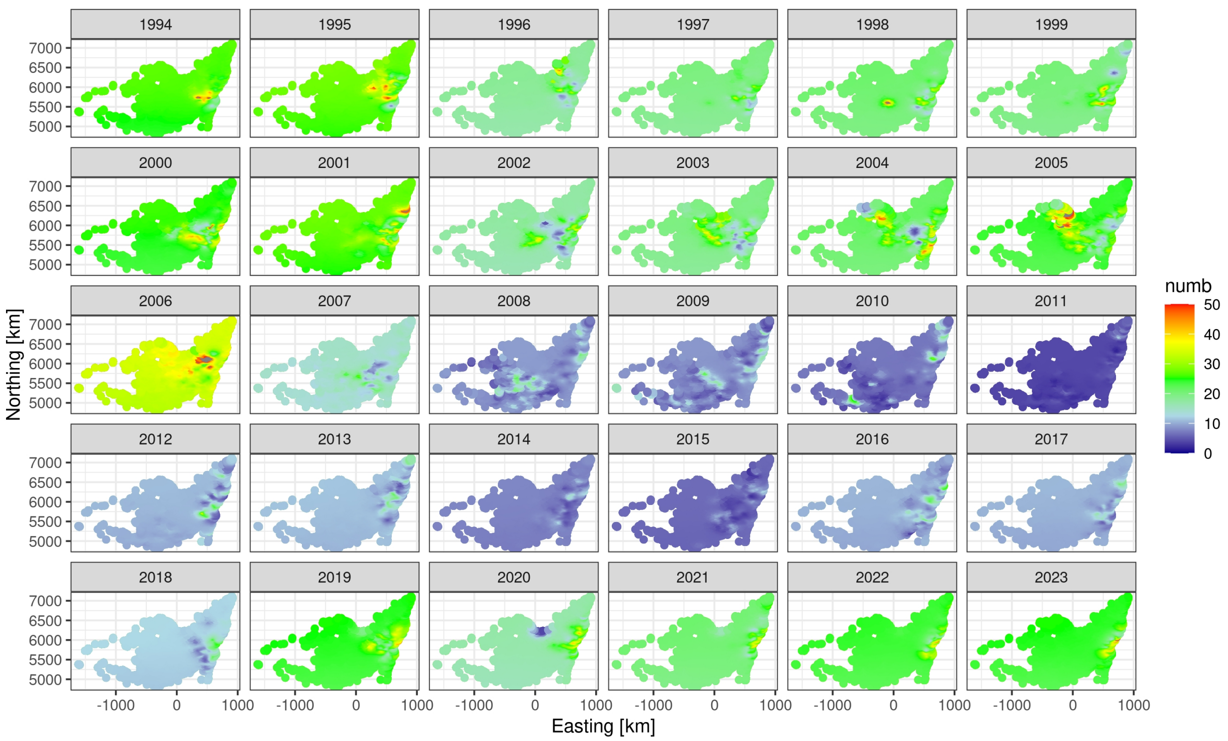

Figure 5: Estimates of the spatio-temporal mean for the CPUE of Chilean jack mackerel in central-southern Chile.

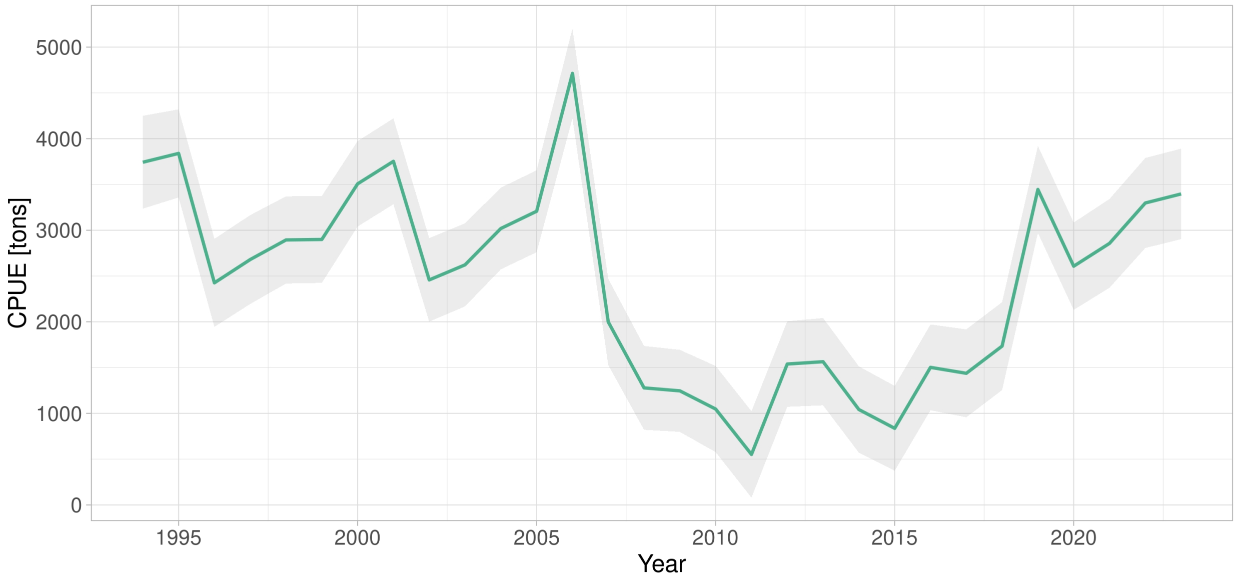

Figure 6: Spatio-temporal predicted biomass (CPUE) index of Chilean jack mackerel (*Trachurus murphyi*) fishery of central-southern Chile. Shaded lower and upper limits represent the standard deviation of the prediction. This time-series has been obtained from the mean of the predicted biomass (CPUE) yearly maps.

Finally, derived spatio-temporal predicted CPUE time-series was obtained from the mean of the predicted biomass (CPUE) yearly maps and is showed in Figure 6. The interannual variability in the CPUE shows an initial period with high values that reach a historical maximum in 2006. Afterwards, a sustained fall is observed until reaching the lowest value in the time series in 2011. The period 2011-2017 was characterized by low CHJM CPUE values. Since 2015, a increasing trend has been observed that partially breaks in 2020 with a specific decline. The last period, 2020-2023, is characterized by a moderate upward trend associated with a greater concentration and availability of fishing in localities close to fishing ports.

4. Concluding remarks

1. The spatial distribution of jack mackerel in central-southern Chile has changed over time, which imposes a limitation for the estimation of the CPUE by means of traditional methods (e.g. GLM, GAM).

2. Bayesian hierarchical spatio-temporal models have an advantage over traditional CPUE standardization models by accounting for spatio-temporal autocorrelation through spatially structured random effects and autoregressive terms, thereby reducing uncertainty of estimated biomass indices.

3. A database of individual fishing sets from the CHJM purse-seine fishery generated from the joint effort of IFOP and INPESCA was used. One of the limitations of the data set that emerges is the imbalance in the proportion of the catch effectively referenced spatio-temporally, which has increased steadily in the last decade with the implementation of electronic logs.

4. The best model for standardizing Chilean jack mackerel included the logarithm of the vessels hold capacity, the logarithm of the days at sea (included as an offset), the spatio-temporal component, year and quarter.

5. The linear effect for the variable vessel hold capacity showed that the relationship between catch biomass and vessel capacity was not strictly linear, for vessels over 1000 m^3 where the catch seems to reach an asymptotic level.

6. The posterior distribution of the environmental effects suggests that Sea Surface Temperature and Chlorophyll have a significant influence on driving the CHJM biomass distribution, positively influencing the CPUE.

7. The mean of the posterior predictive distribution for CHJM CPUE revealed areas with a persistent high concentration of fish in coastal regions during 1994-2001 period. During the period 2000-2007 the distribution becomes more opportunistic, with non-persistent high CPUE areas located both in the coastal and oceanic regions. A period of low CPUE is observed between 2008 and 2015 where the biomass was recorded dispersed without areas of high concentration and a non-persistent distribution of CPUE. The most recent period, 2016-2023, has been characterized by an increasing trend in CHJM biomass with a persistent distribution of high CPUE in the coastal region (up to 200 km offshore).

8. The interannual variability in the CPUE reveals an initial period with high values that reach a historical maximum in 2006. Afterwards, a sustained fall is observed until reaching the lowest value in 2011. The period 2011-2017 was characterized by low CHJM CPUE values. Since 2015, a increasing trend has been observed that partially breaks in 2020 with a specific decline. The last period, 2020-2023, is characterized by a moderate increasing trend associated with a greater concentration and availability of fishing in localities close to fishing ports.

References

Arreguín-Sánchez, F. (1996). Catchability: a key parameter for fish stock assessment. *Reviews in fish biology and fisheries*, *6*, 221–242.

Bailey, K. (1989). Description and surface distribution of juvenile peruvian jack mackerel, trachurus murphyi, nichols. *Fishery Bulletin*, *87*, 273.

Cao, J., Chen, X., Chen, Y., Liu, B., Ma, J., & Li, S. (2011). Generalized linear bayesian models for standardizing cpue: an application to a squid-jigging fishery in the northwest pacific ocean. *Scientia Marina*, *75*, 679–689.

Cosandey-Godin, A., Krainski, E. T., Worm, B., & Flemming, J. M. (2015). Applying bayesian spatiotemporal models to fisheries bycatch in the canadian arctic. *Canadian Journal of Fisheries and Aquatic Sciences*, *72*, 186–197.

Grechina, A., Núñez, S., & Arcos, D. (1998). Biología reproductiva del jurel (trachurus symmetricus murphyi) en el pacífico sur. *Biología y ecología del jurel en aguas chilenas*, (pp. 77–79).

Hilborn, R., & Walters, C. J. (2013). *Quantitative fisheries stock assessment: choice, dynamics and uncertainty*. Springer Science & Business Media.

Ijima, H., & Koike, H. (2021). *CPUE Standardization for Striped Marlin (Kajikia audax) using Spatio-Temporal Model using INLA*. Technical Report ISC/21/BILLWG-03/01.

Izquierdo, F., Menezes, R., Wise, L., Teles-Machado, A., & Garrido, S. (2022). Bayesian spatio-temporal cpue standardization: Case study of european sardine (sardina pilchardus) along the western coast of portugal. *Fisheries Management and Ecology*, *29*, 670–680.

Lindgren, F., Rue, H., & Lindström, J. (2011). An explicit link between gaussian fields and gaussian markov random fields: the stochastic partial differential equation approach. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *73*, 423–498.

Lynch, P. D., Shertzer, K. W., & Latour, R. J. (2012). Performance of methods used to estimate indices of abundance for highly migratory species. *Fisheries Research*, *125*, 27–39.

Maunder, M. N. (2001). A general framework for integrating the standardization of catch per unit of effort into stock assessment models. *Canadian Journal of Fisheries and Aquatic Sciences*, *58*, 795–803.

Maunder, M. N., & Punt, A. E. (2004). Standardizing catch and effort data: a review of recent approaches. *Fisheries research*, *70*, 141–159.

Maunder, M. N., Sibert, J. R., Fonteneau, A., Hampton, J., Kleiber, P., & Harley, S. J. (2006). Interpreting catch per unit effort data to assess the status of individual stocks and communities. *Ices Journal of marine science*, *63*, 1373–1385.

Maunder, M. N., Thorson, J. T., Xu, H., Oliveros-Ramos, R., Hoyle, S. D., Tremblay-Boyer, L., Lee, H. H., Kai, M., Chang, S.-K., Kitakado, T. et al. (2020). The need for spatio-temporal modeling to determine catch-per-unit effort based indices of abundance and associated composition data for inclusion in stock assessment models. *Fisheries Research*, *229*, 105594.

Munoz, F., Pennino, M. G., Conesa, D., Lopez-Quilez, A., & Bellido, J. M. (2013). Estimation and prediction of the spatial occurrence of fish species using bayesian latent gaussian models. *Stochastic Environmental Research and Risk Assessment*, *27*, 1171–1180.

Núñez, S., Letelier P, J., Donoso Q, D., Sepúlveda O, A., & Arcos R, D. (2004). Relating spatial distribution of chilean jack mackerel eggs and environmental factors in the oceanic waters off chile. *Gayana (Concepción)*, *68*, 444–449.

Paradinas, I., Conesa, D., López-Quílez, A., & Bellido, J. M. (2017). Spatio-temporal model structures with shared components for semi-continuous species distribution modelling. *Spatial Statistics*, *22*, 434–450.

Payá, 2022 (2022). *High fish concentrations close to the coast in recent years could affect the Jack Mackerel CPUE abundance index in south-central Chile: proposal of a correction procedure*. SC10-JM05, South Pacigic Regional Fisheries management Organisation.

Punt, A. E., Walker, T. I., Taylor, B. L., & Pribac, F. (2000). Standardization of catch and effort data in a spatially-structured shark fishery. *Fisheries Research*, *45*, 129–145.

Roos, M., Held, L. et al. (2011). Sensitivity analysis in bayesian generalized linear mixed models for binary data. *Bayesian Analysis*, *6*, 259–278.

Rue, H., Martino, S., & Chopin, N. (2009). Approximate bayesian inference for latent gaussian models by using integrated nested laplace approximations. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *71*, 319–392.

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Linde, A. (2014). The deviance information criterion: 12 years on. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *76*, 485–493.

Thorson, J. T., & Barnett, L. A. (2017). Comparing estimates of abundance trends and distribution shifts using single-and multispecies models of fishes and biogenic habitat. *ICES Journal of Marine Science*, *74*, 1311–1321.

Thorson, J. T., Fonner, R., Haltuch, M. A., Ono, K., & Winker, H. (2016). Accounting for spatiotemporal variation and fisher targeting when estimating abundance from multispecies fishery data. *Canadian Journal of Fisheries and Aquatic Sciences*, *74*, 1794–1807.

Watanabe, S., & Opper, M. (2010). Asymptotic equivalence of bayes cross validation and widely applicable information criterion in singular learning theory. *Journal of machine learning research*, *11*.

Zhou, S., Campbell, R. A., & Hoyle, S. D. (2019). Catch per unit effort standardization using spatio-temporal models for australia's eastern tuna and billfish fishery. *ICES Journal of Marine Science*, *76*, 1489–1504.