
Small Pelagic Fish:
New Frontiers in Science and Sustainable Management
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Centre of Mathematics (CMAT), University of Minho

Spatio-temporal variability of the distribution and abundance of small pelagic fish off the Portuguese continental coast and relationship with environmental drivers

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Scope of the work

Loss of marine biodiversity

Improve the knowledge about population dynamics of main fishing resources

Restoration of marine biodiversity

Spatio-temporal analysis of abundance indexes

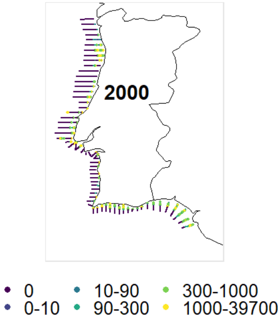
Motivating data

PELAGO surveys

Estimate the abundance of sardine inhabiting the Portuguese shelf.

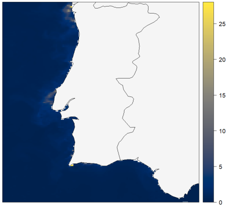
Database

Time:	20 annual surveys from 2000 to 2020, except 2012.
Study region:	Portuguese continental coast and Gulf of Cadiz.
Interest:	Biomass index (NASC, $n^2\ nm^{-2}$).
Geographic information:	Latitude and longitude.
Additional information:	Sectors and geographical areas.

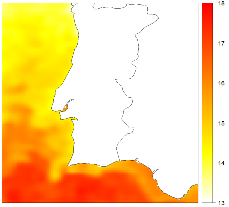


Environmental data

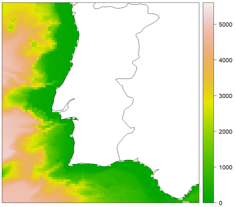
Chlorophyll



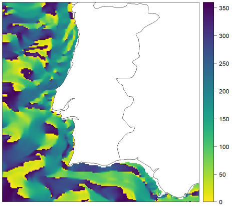
Temperature



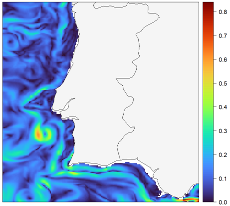
Bathymetry



Direction of ocean currents



Intensity of ocean currents



Problem and Objective

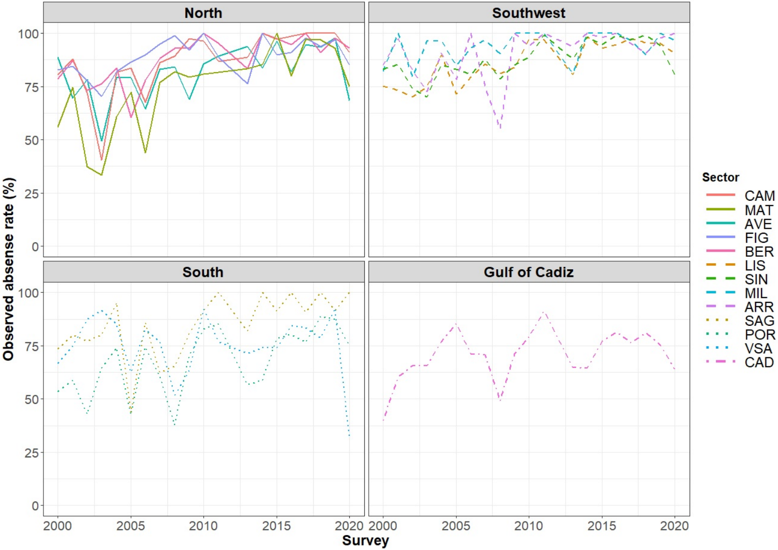
Species Distribution Data often implies residual **spatial autocorrelation**

- **Non-consideration** of important environmental conditions.
- **Intrinsic factors**: competition, dispersal, aggregation, etc.

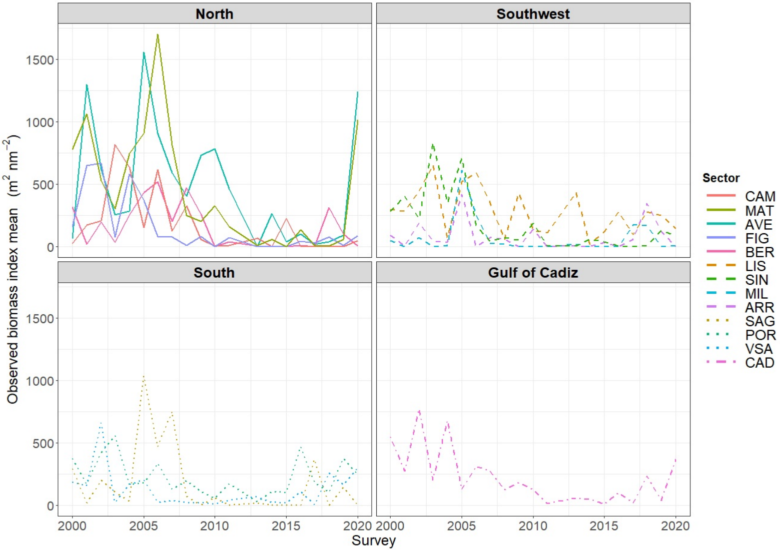
↓

Geostatistics

Problem and Objective



Problem and Objective



Problem and Objective

Main aims

- Estimate the **spatio-temporal distribution** of sardine in western and southern Iberian waters.
- Understand sardine dynamics over time and space.
- Identify the **main drivers** of sardine spatial dynamics.

To consider:

- Complex spatio-temporal dynamics.
- Excess of zeros.
- Difference between occurrence process and biomass process under occurrence.
- Relationship between response and **environmental conditions with a time lag**.

Two-part model

Hierarchical model

Series of levels linked by probability functions.

Y_{st} - **Biomass process** at location s and time t
Z_{st} - **Occurrence sub-process**

Distribution of biomass index

$$
\begin{aligned}
[Y_{st}] &= [Z_{st}]\,[Y_{st}|(Z_{st}=1)] \\
&= \begin{cases} 1-\pi_{st}, & y_{st}=0 \\ \pi_{st}\,[Y_{st}|(Z_{st}=1)], & y_{st}>0 \end{cases}
\end{aligned}
$$

such that:

$$
\begin{aligned}
Z_{st} &\sim Bernoulli(\pi_{st}) \\
Y_{st}|(Z_{st}=1) &\sim Gamma(a_{st}, b_{st})
\end{aligned}
$$

Two-part model

Two-part model can be defined by:

$$log(\mu_{sti}) = \alpha + \sum_{j=1}^{p} \mathbf{f}(K(X_{jsti}, c, l)) + \gamma_t + W_{st}$$

$$logit(\pi_{sti}) = \alpha' + \sum_{j=1}^{p'} \mathbf{f}'(K(X'_{jsti}, c, l)) + \gamma'_t + kW_{st}$$

time lag $c + l$ in days from i^{th} day of the survey in year t,
smoother function $\mathbf{f}$ of the j^{th} covariate X_{jsti},
spatio-temporal structure W_{st},
unstructured temporal effects γ_t and γ'_t.

Spatio-temporal structure with AR(1) process

$$W_{\mathbf{s}t} = \delta W_{\mathbf{s}(t-1)} + \xi_{\mathbf{s}t}$$

1. $|\delta| < 1$
2. $\xi_{\mathbf{s}t}$ is is a zero-mean GF with spatio-temporal covariance:

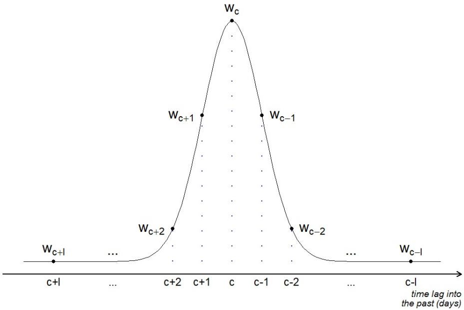
$$Cov(\xi_{\mathbf{s}t}, \xi_{\mathbf{u}j}) = \begin{cases} 0 & if \quad t \neq j \\ Cov(\xi_{\mathbf{s}}, \xi_{\mathbf{u}}) & if \quad t = j \end{cases}$$

such that $Cov(\xi_{\mathbf{s}}, \xi_{\mathbf{u}})$ is given by **Matérn spatial covariance** with partial variance σ^2 and range ϕ.

Kernel application $K(.,.,.)$

$$K(X_{jsti}, c, l) = \sum_{q=-l}^{l} w_{c-q} X_{jst(i-(c-q))}$$

- $w_{c-q} = \frac{1}{\sqrt{2\pi}} exp\left\{-\frac{q^2}{2h^2}\right\}$
- $X_{jst(i-(c-q))}$ - jth covariate observed in day $i-(c-q)$ of year t
- On the i^{th} day, the maximum effect of X_j occurs for lag c

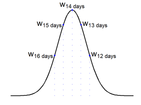


Examples of Kernel application

Presence/absence modelling:

$$logit(\pi_{sti}) = \alpha_1 + \sum_{j=1}^{p'} \mathbf{f}(K(X'_{jsti}, c, l)) + \gamma'_t + kW_{st}$$

1. If the biomass **is only affected by chlorophyll on the same day**, then $K(CHL_{sti}, 0, 0) = CHL_{sti}$
2. If the biomass **is affected by chlorophyll 14 days ago**, then $K(CHL_{sti}, 14, 0) = CHL_{st(i-14)}$
3. If the biomass **is affected by chlorophyll 14 days earlier and 2 days before and after**, then $K(CHL_{sti}, 14, 2) = w_{16}CHL_{st(i-16)} + w_{15}CHL_{st(i-15)} + w_{14}CHL_{st(i-14)} + w_{13}CHL_{st(i-13)} + w_{12}CHL_{st(i-12)}$



Bayesian perspective

Advantages

- It allows to **incorporate prior information**.
- **Information and uncertainty** about all the unknown can be better (and easily) **expressed in terms of probability distributions**.
- It might more **easily handle with inference and prediction** (Banerjee, Carlin, and Gelfand 2004).

Inference method

INLA approach was used to approximating the posterior marginals of the latent GF (Rue, Martino, and Chopin 2009).

https://www.r-inla.org/

Some highlights

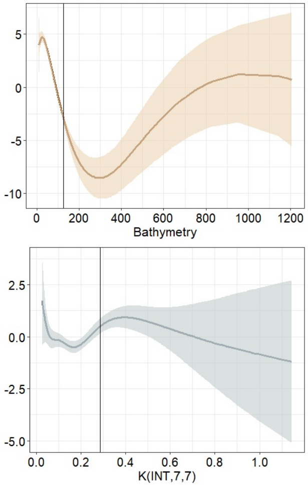
- Various **combinations of c and l** were tested.

- Data from the west and south Iberian coasts are **studied separately**.

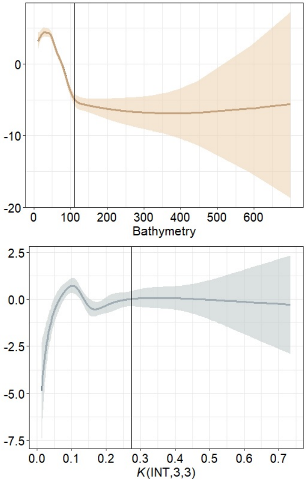
- Spatial predictions over the entire study region were obtained **for a "representative day"** of each survey for the total 21 years.

Results: Environmental effects for the presence

Effects on west coast



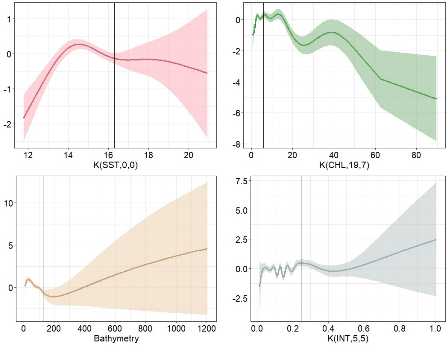
Effects on south coast



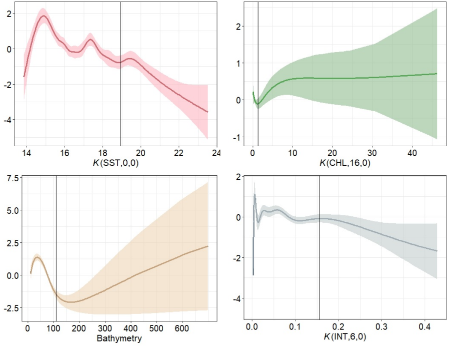
**vertical line - quantile 80%*

Results: Environmental effects for the biomass

Effects on west coast

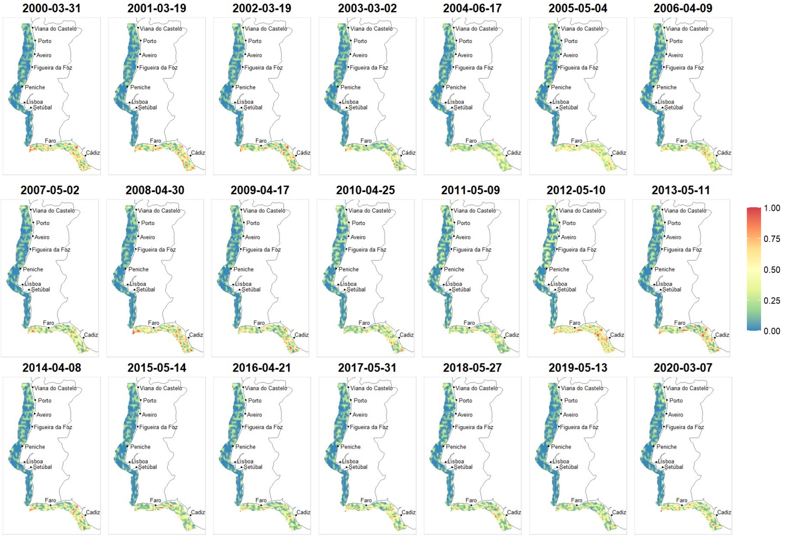


Effects on south coast

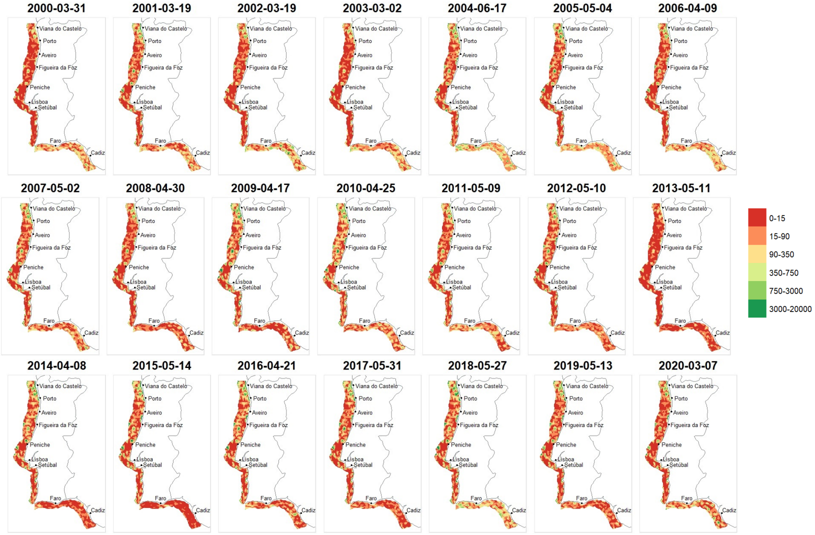


**vertical line - quantile 80%*

Results: Predicted occurrence



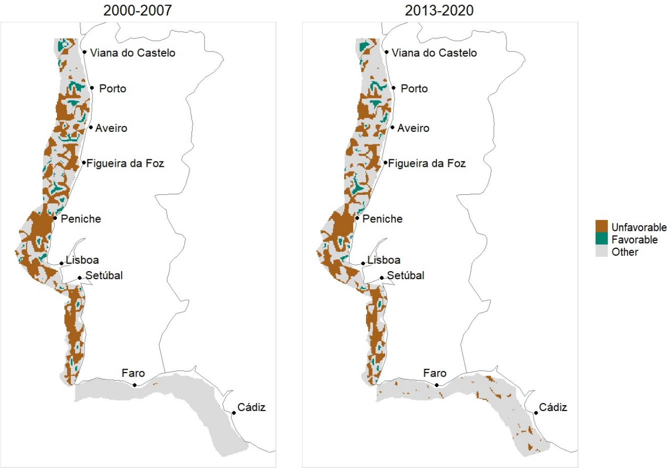
Results: Predicted biomass



Results: Occupancy areas

Results: Favourable and unfavourable zones

Persistent rare (unfavourable) and preferred (favourable) zones



On going and Future work

On going work

- Apply this methodology to the **anchovy data**.

Future work

- Model the spatio-temporal distribution of sardine from data obtained from commercial fisheries, taking into account **preferential sampling**.
- **Joint modelling** fishery-dependent and fishery-independent data.

Thank you for your attention!

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