Spatio-temporal models for a marine spatial planning in fisheries.

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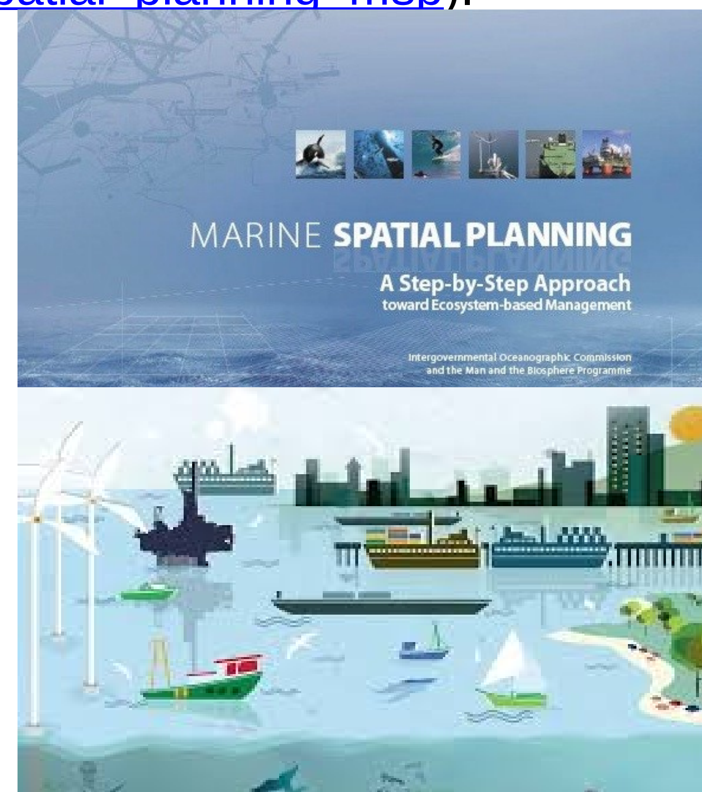
Marine Spatial Planning (MSP)

- Marine spatial planning is a public process of analyzing and allocating the spatial and temporal distribution of human activities in marine areas to achieve ecological, economic, and social objectives that usually have been specified through a political process (http://www.unesco-ioc-marinesp.be/marine_spatial_planning_msp).

- Characteristics of marine spatial planning include ecosystem-based, area-based, integrated, adaptive, strategic and participatory.

- Marine spatial planning is not only conservation planning. It seeks to balance economic development and environmental conservation, and not focus on only on the goals of conservation or protection.



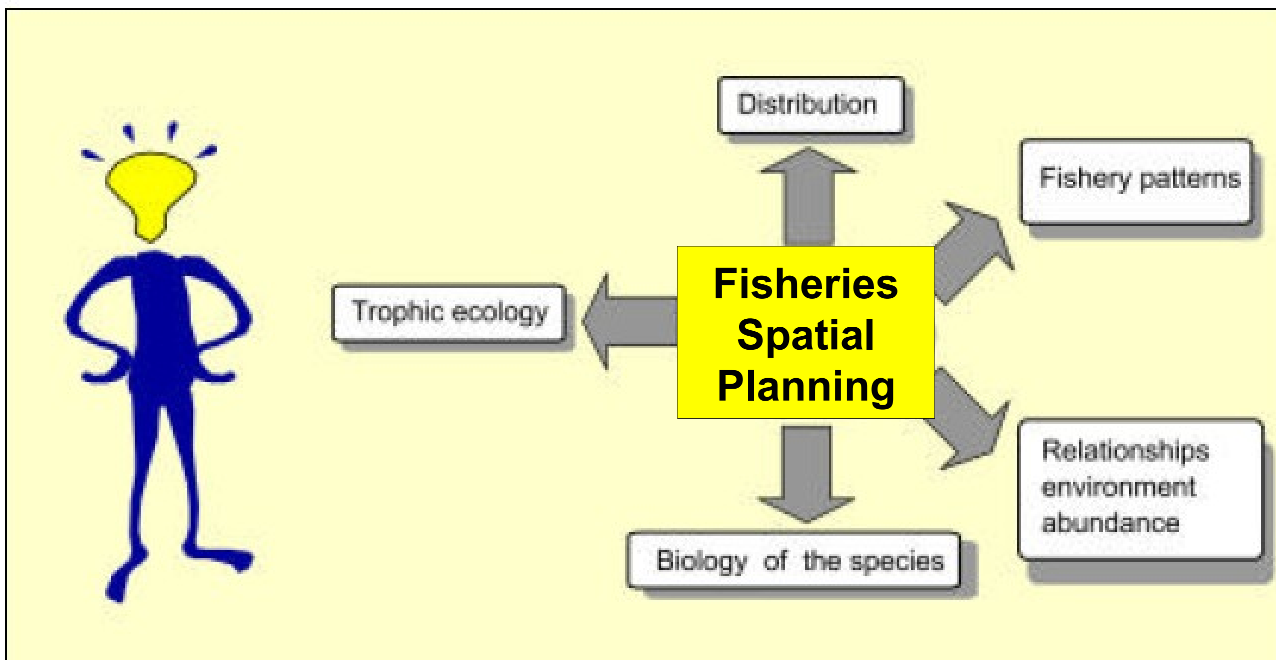
Marine spatial planning in fisheries

- The implementation of a Marine Spatial Planning to fisheries management requires the understanding of marine biological processes at a spatial scale.

- However, quantifying the ecological importance of an area is a challenging task because of the inherent constrains of sampling at sea.

- Spatial patterns geographical sce fisheries resource

- Marine Planning spatial scenario f



A Bayesian spatio-temporal approach

- In order to identify and locate potential spatio-temporal closures, a solid knowledge of species-environment relationships is needed, as well as a spatial identification of fish nurseries applying robust analyses.

- One way to achieve knowledge of fish nurseries is to analyse the persistence of recruit hot-spots. In this study, we propose the comparison of different spatio-temporal structures to assess the persistence of a spatial process.

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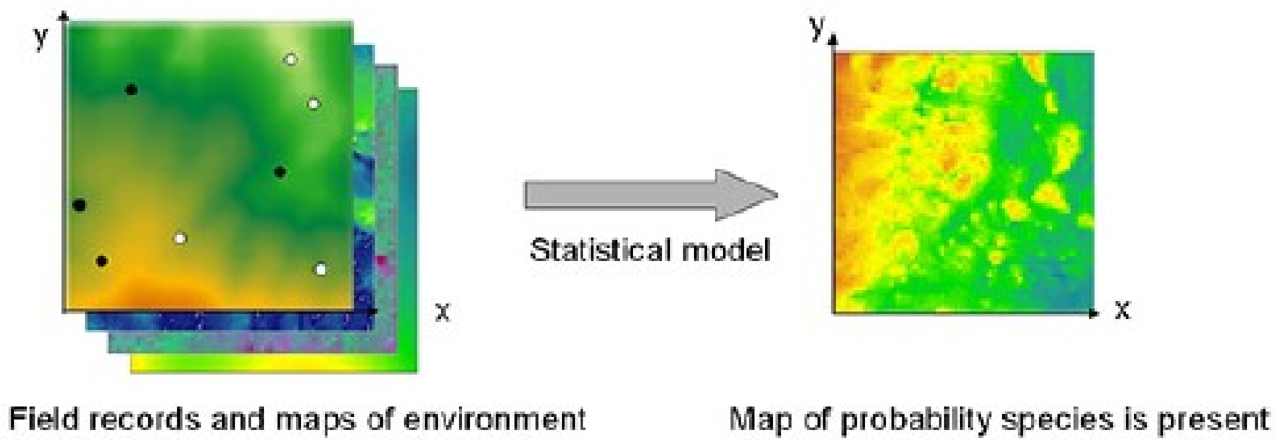

Data

- Most of the available data come from the designed field-based biodiversity monitoring programmes.

- In our case, hake recruits were collected during the EU-funded MEDIterranean Trawl Survey (MEDITS) programme, Spanish part.

- Two types of information:
  - Presence/absence of hake recruits, and
  - total weight of recruits (abundance).

- Covariates: bathymetry, type of substratum, sea surface temperature, and the chlorophyll-a concentration.

Previous approaches vs our approach

- Some previous approaches: GLM, GAM, Species envelope models, Multivariate adaptive regression splines (MARS).
  - Mostly explanatory. Few studies are predictive.
  - Typically assume that observations are independent.
  - But, species distribution data are often inclined to spatial and temporal autocorrelation.

- Our approach: Propose hierarchical Bayesian geostatistical models both for the occurrence and the abundance of hake recruits, while
  - incorporating the available environmental covariates, and
  - accounting for spatial and temporal autocorrelation.

- Use them to identify nursery areas persistent over time.

Implementation/computational issues

- The key idea: these hierarchical models can be seen as a particular case of Structured Additive Regression Models. Specifically as latent Gaussian models. As usual in Geostatistical problems, and following Lindgren et al. (2011), we approximate the resulting continuously indexed Gaussian Field by a Gaussian

- Posterior distribution of the parameters and posterior predictive distributions can be approximated with INLA (Rue et al., 2009).
  - Fast accurate approximation to posterior marginals.
  - Predictive distributions in unsampled locations.
  - Various measures for model comparison, DIC and LCPO.

- Markov random field using the Stochastic Partial Differential Equation approach. The Markov property makes the precision matrix involved sparse, which allows the use of faster numerical algorithms.

Modelling the presence/absence

- Distribution of the presence/absence at location i of year j is modelled by:

$$Z_{ij} \sim \mathrm{Ber}(\pi_{ij}).$$

- Probability of occurrence

$$\mathrm{Logit}(\pi_{ij}) = X_i\beta + u_{ij} \quad i = 1, \ldots, n$$

- Structure 1: $u_{ij} = w_{ij} + v_i$.
  - *w* represents a unique spatial random effect for all observations
  - v_i represents an independent random effect for year.

- Structure 2: uij = wij
  - *wi* represents a different spatial random effect for each specific year *j*, This structure is more flexible as it allows to capture different structures of ocurrence for each year.

Modelling the abundance

- Our next interest is to model the absolute abundance of recruits in those places where the fish is present. We made a two-step model (presence then abundance) because the high numbers of zero observations. A zero-inflated model was not considered as a zero probability of hake presence at a location is far from an ecological reality.

- Hierarchical Bayesian spatio-temporal modelling, although instead of using a Bernouilli distribution for the presence, we now use a Gamma distribution for the Catch Per Unit Effort (measure of abundance).

$$Z_{ij} \sim \Gamma a(a_{ij}, b_{ij}), \forall i, j$$

$$\log(\mu_{ij}) = X_{ij}\beta + u_{ij}$$

$$\beta_k \sim N(\mu_{\beta k}, \sigma_{\beta k}),$$

- where $\mu_{ij} = a_{ij}/b_{ij}$, $X_i\beta$ represents the linear predictor and u_{ij} represents the two different spatio-temporal structures of random effects previously introduced (Structure 1 and 2)

Model selection

- All the resulting models obtained by combining environmental variables (bathymetry and type of substratum) with the different decompositions of the spatio-temporal structures were fitted and compared. The DIC and the logarithmic score (LCPO) were used as measures of goodness-of-fit and predictive quality of the models, respectively. Selected models are those suggesting persistence of th

Model comparison for the Bernoulli response variable

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Summary of the fixed effects for the occurrence model.

	mean	sd	$Q_{0,025}$	$Q_{0,5}$	$Q_{0,975}$
(Intercept)	2.07	0.814	0.469	2.07	3.67
Depth	1.82e-02	6.86e-03	5.04e-03	1.81e-02	3.20e-02
Depth^2	-6.43e-05	1.38e-05	-9.25e-05	-6.39	-3.83e-05

Model comparison for the Gamma response variable

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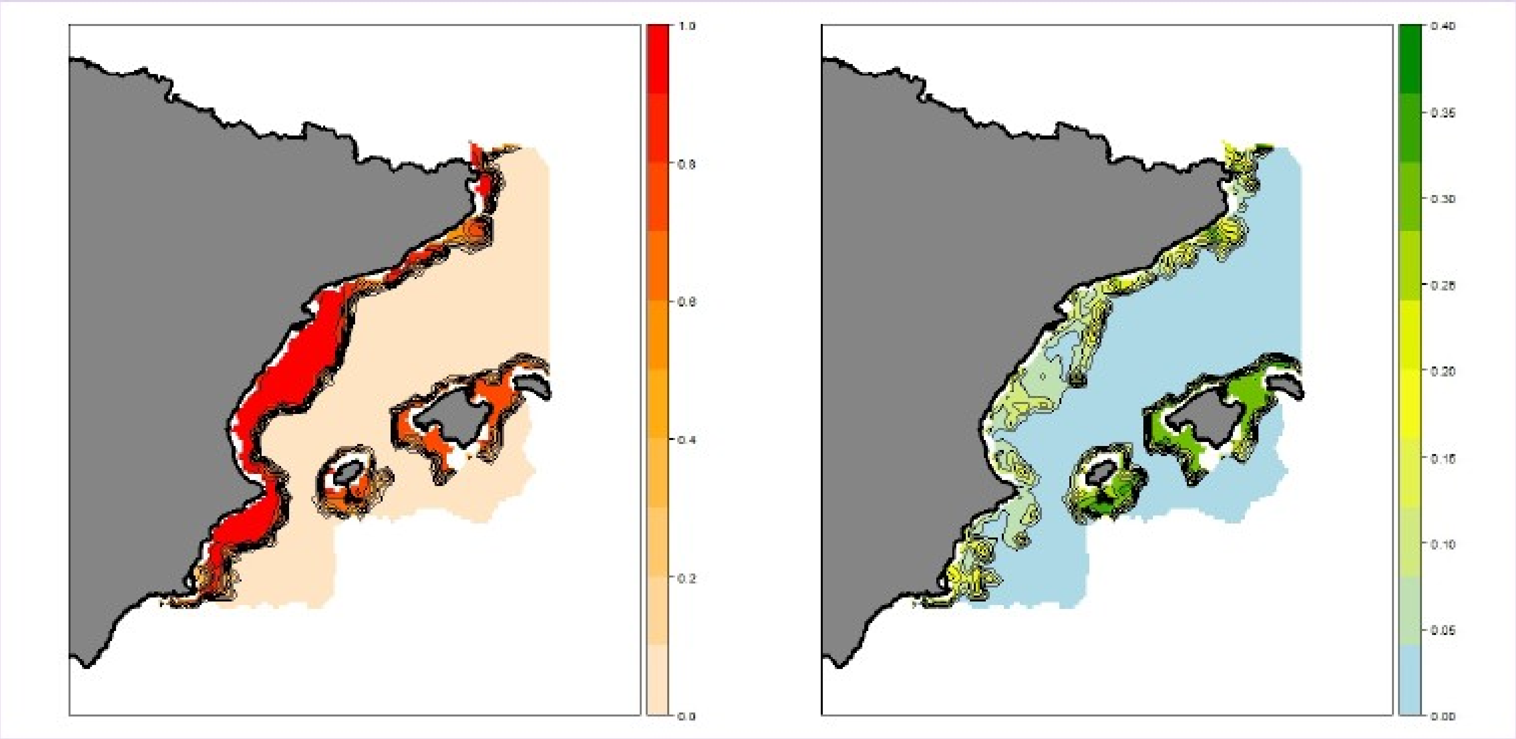
Summary of the fixed effects for the abundance model.

	mean	sd	$Q_{0,025}$	$Q_{0,5}$	$Q_{0,975}$
(Intercept)	-0.392	.316	-1.01	-0.39	0.231
Depth	6.79e-03	2.83e-03	1.18e-03	6.80e-02	1.23e-02
Depth^2	–3.14e-05	5.35e-06	-4.17e-05	-3.14e-05	-2.07e-05

Occurrence probability

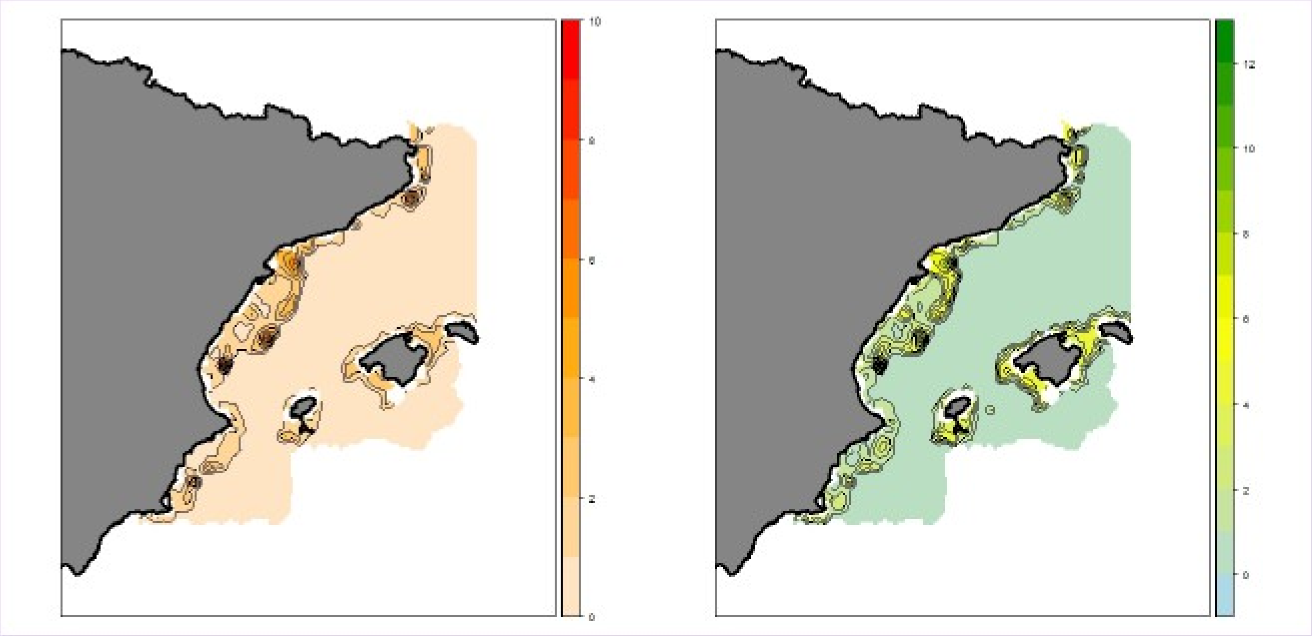
Posterior mean (left) and standard deviation (right) for the occurrence probability.



- Spatial effect jointly with the bathymetry explains the behaviour of the ocurrence. The selected model reveals highest probability of presence along the continental shelf and the upper slope.

Abundance estimates

Posterior mean (left) and standard deviation (right) for the abundance.



- Again, highest abundance areas are located along the continental shelf and the upper slope, coinciding with the estimated effect of the bathymetry. Quadratic term for bathymetry estimates a peak abundance around 50-150 m. However, these abundance hot-spots are much more localised than the occurrence: size of these areas are around 10 km in diameter.

Conclusions

- Spatial planning can provide further insights in fishery management, considering the spatial scenario where natural populations and fishing take place.

- Modelling, both explanatory and/or predictive, is necessary for designing and forecasting such as spatial scenario.

- Our approach makes use of advanced statistical tools to identify nursery areas persistent over time. These areas are good candidates for fishing protection by a network of Marine Fishery Reserves. They can be dynamic and adaptable to the natural movements of the fishing resources.

- According to our model, the size of these hot-spots are around 10 km in diameter. This size can be a proxy for Marine Fishery Reserves.

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Thanks for your attention

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Bayesian spatio-temporal approach to identifying fish nurseries by validating persistence areas

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