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Incorporating the spatial dependence with physical barriers in a bayesian spatio-temporal model to obtain a relative index of abundance

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Introduction

For modelling a particular fishery population it is necessary to consider the proper features at the moment to build a representative model. A specific case is the estimation of the relative abundance index (≈CPUE) for benthic resources. Since these populations present a high sensitivity to the local oceanographic variations and spatial gradients, these might affect directly the natural process of growth, recruitment and mortality.

Since benthic populations are characterized by a spatial density-dependence (larval dispersion between fishing sites), population decay associated with resource abundance, is very complex to measure. This is due to the difficulty of determining whether if each fishing site present an increase or decrease of individuals across time.

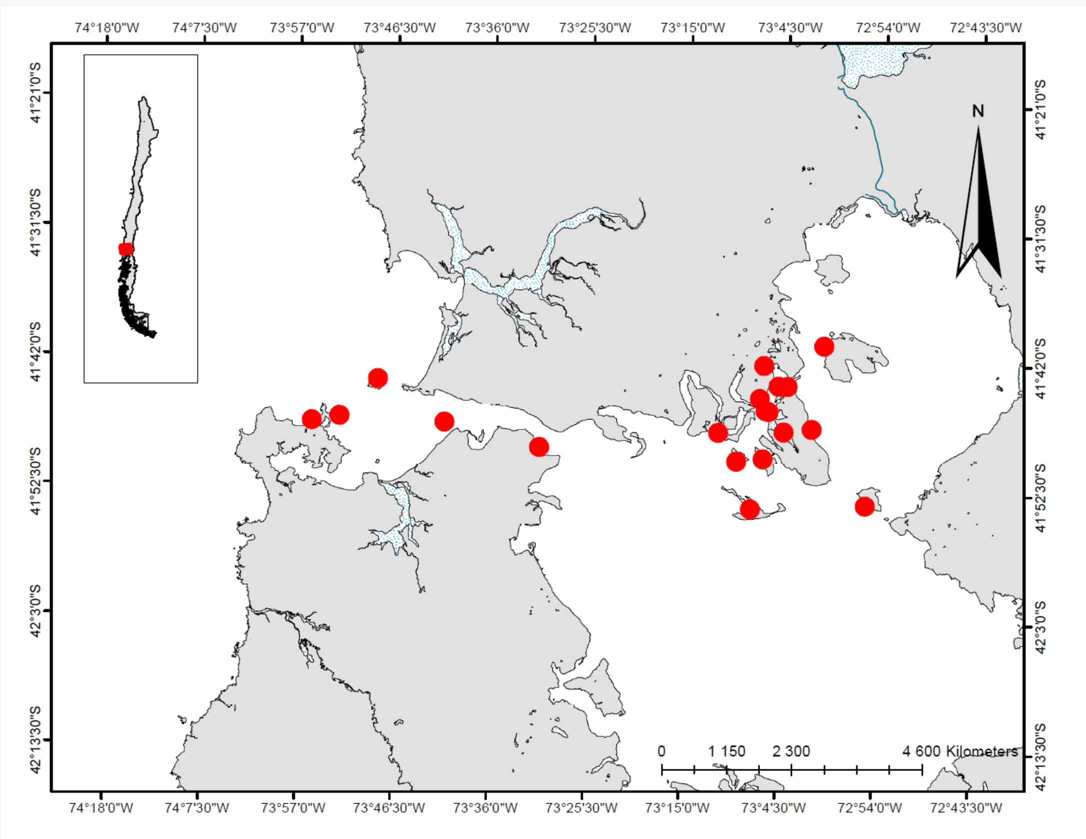

Figure 1: Sites of fishing for the Sea urchin (*Loxechinus albus*) in Chile

Materials and Methods

We propose a spatio-temporal model which incorporates abundance variations in time, and also, we incorporate the density-dependence by Gaussian Markov random field (GMRF) with physical environmental constraints. We use template model builder (TMB) platform for modelling and the inference was implemented with Stan (`tmbstan`) to obtain relative abundance index. The study case is based on the benthic fishery of sea urchin (*Loxechinus albus*) in south of Chile, having spatially referenced data for its principal fishing sites, measured between 1996 and 2018.

Model specification

$$y_i \mid \theta \sim Gamma(a_i, b_i) \quad (1)$$
$$\eta_i = \alpha + x_i\beta + s_i \quad (2)$$
$$s_i \sim \mathcal{N}(0, Q^{-1}(\kappa, \tau)) \quad (3)$$
$$log(\kappa) \sim \mathcal{N}(m_\kappa, q_\kappa^{-2}) \quad (4)$$
$$log(\tau) \sim \mathcal{N}(m_\tau, q_\tau^{-2}) \quad (5)$$

where i = 1, ..., n, where n is the number of observations, x is the vector of covariables, s_i is the latent field (GMRF) and $\theta = \{\alpha, \beta, \kappa, \tau\}$ is the vector of all parameters. m_κ is chosen automatically such that the range of the field is 20% of the diameter of the region, while m_τ prior values used for the range. q_κ^{-2} are the marginal variance equal 1 and q_τ^{-2} = 1 – 0.5. *We will evaluate another distributions also (log-normal and Inverse Gaussian and, to compare different model, we will use* $\hat{R}$*)*

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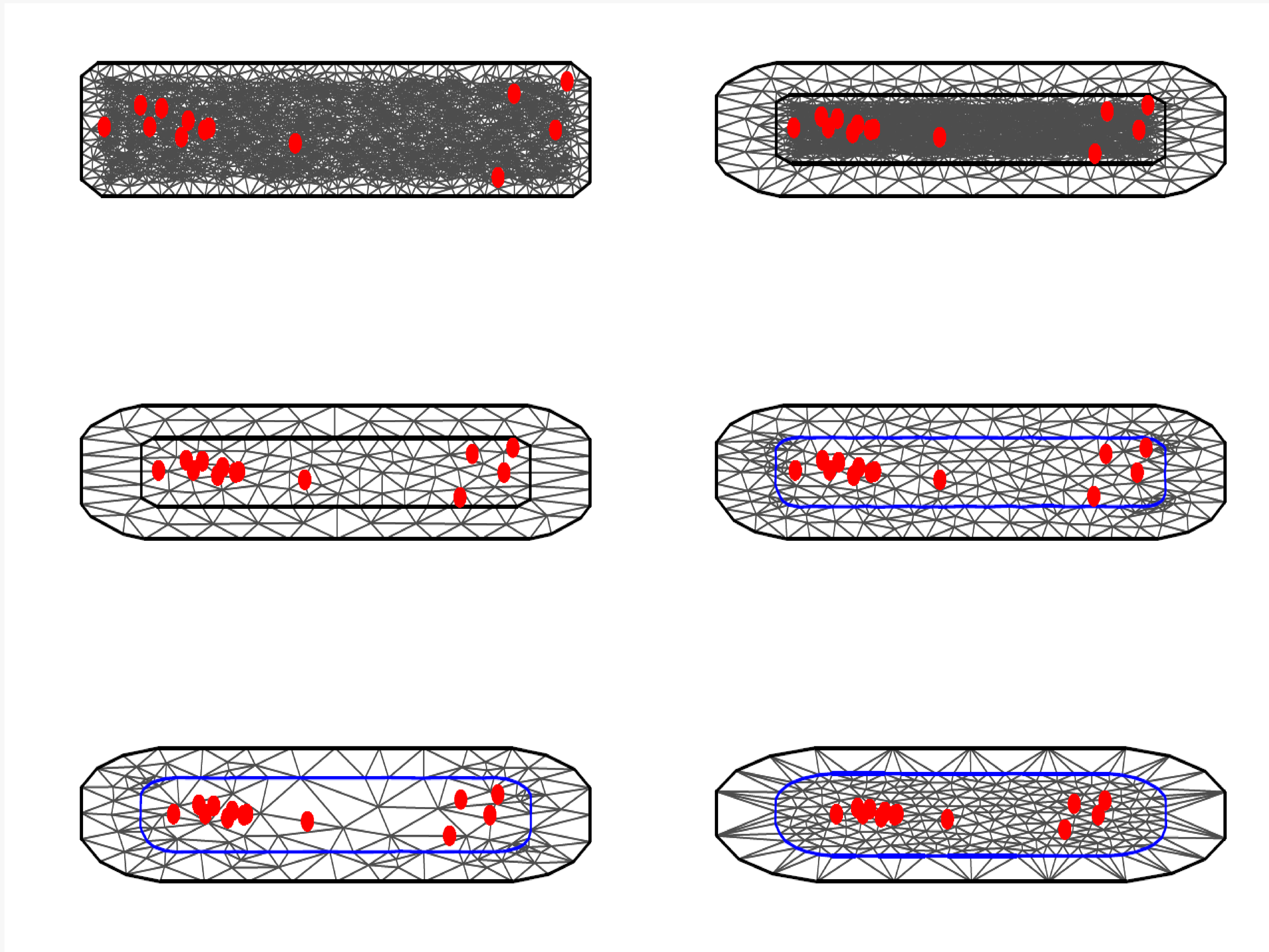
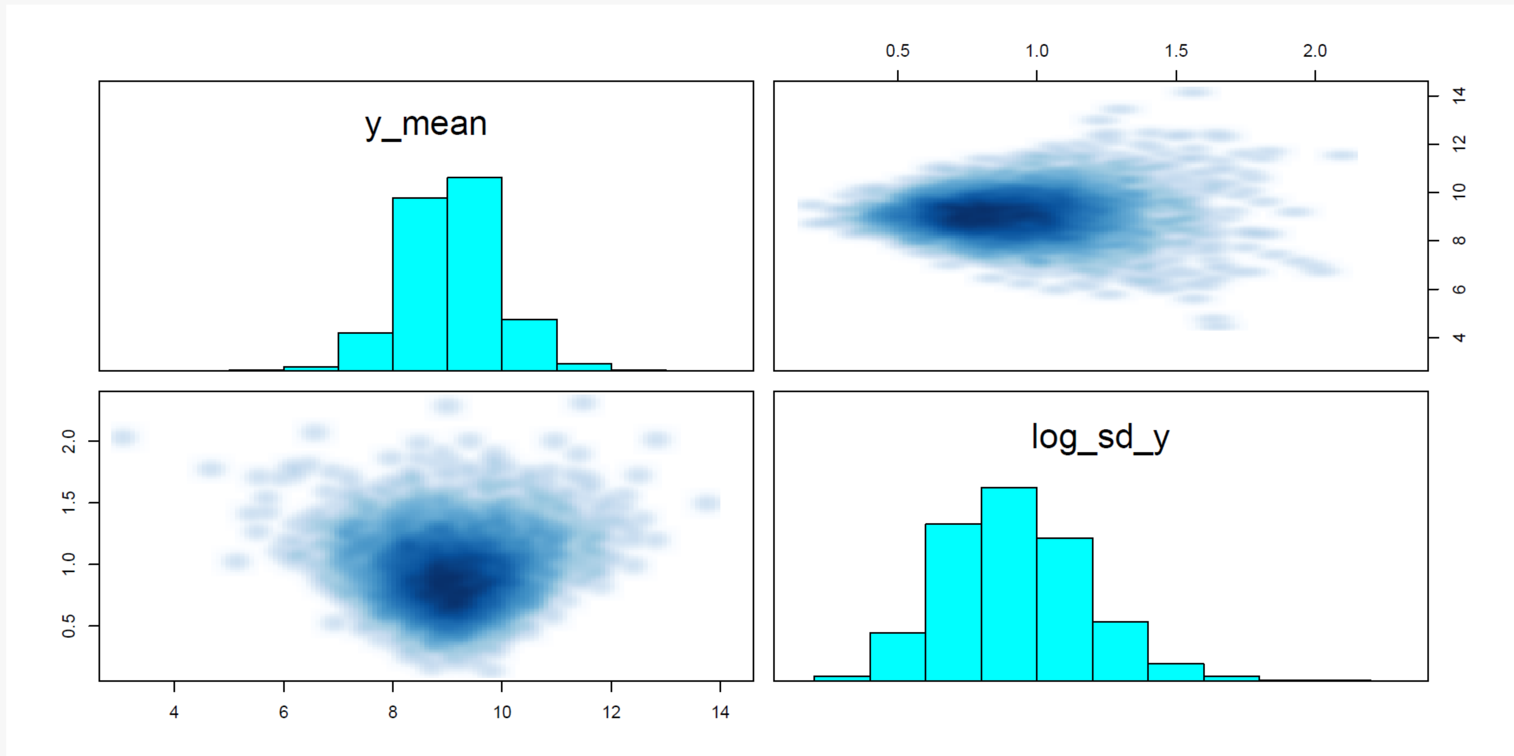
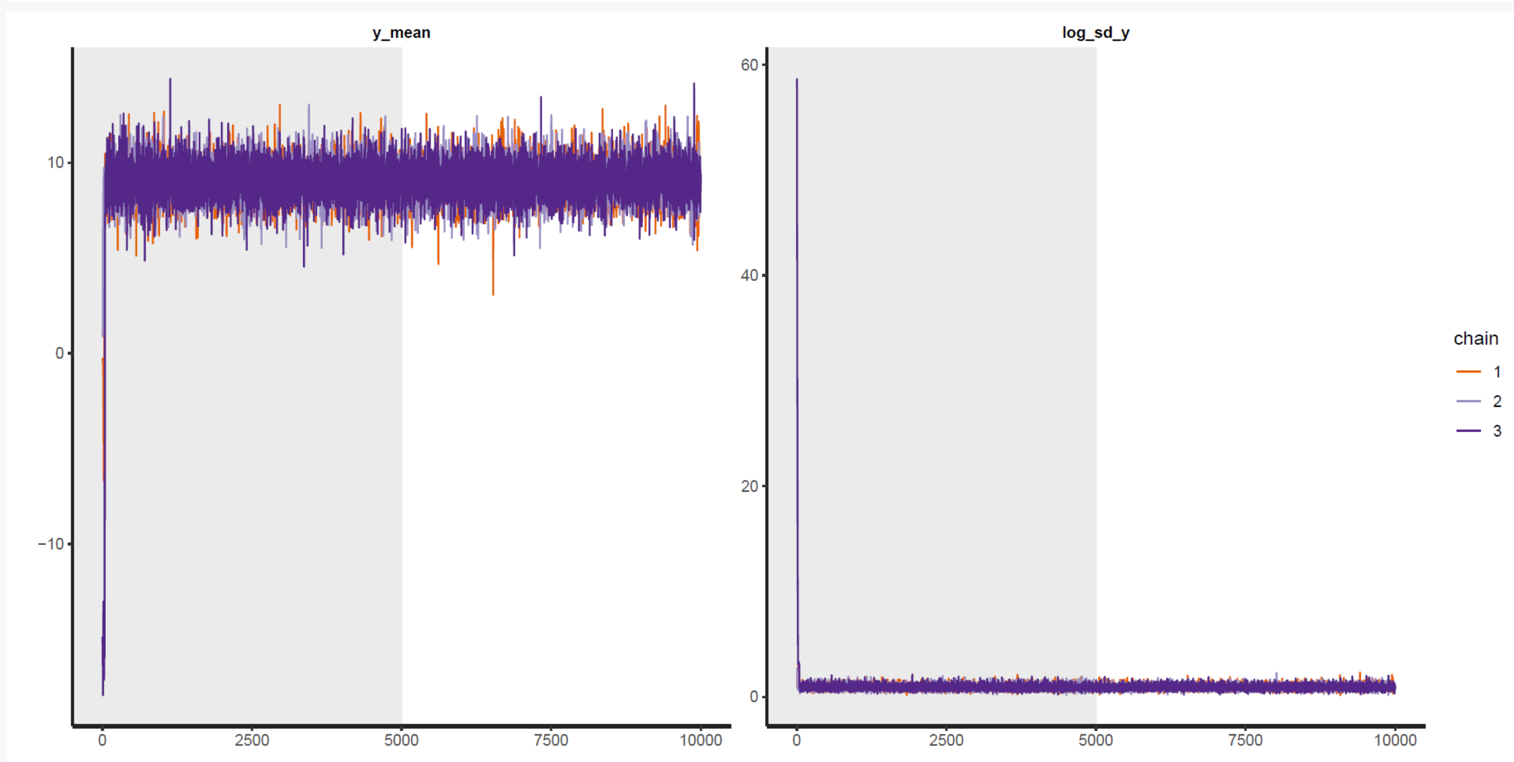
Preliminary analysis

I. Construction of the mesh for the spatial points



II. Experimental hierarchical model with sites of fishing as "Random Effects" in TMB and doing the inference with `tmbstan` (simulated data)





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