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Using a spatio-temporal Bayesian approach to estimate the relative abundance index of yellow squat lobster (*Cervimunida johni*) off Chile

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ABSTRACT

Estimating relative abundance indexes based on spatio-temporal variations in fishing effort has been one of the greatest challenges in fisheries sciences. Obtained from the catch per unit of effort (CPUE), such indexes are generally used within evaluation models as "relative" to the stock abundance. Herein, a Bayesian spatio-temporal model was used to obtain an index for yellow squat lobster (*Cervimunida johni*) between the III and IV regions of Chile based on CPUE data (Kg/h.a) from fishing logs. The spatial field was approximated by a GMRF using the SPDE method and posterior distributions of interest were approximated using the Integrated Nested Laplace Approximation (INLA). By taking into account the distributional assumption of the CPUE the proposed model showed a good fit to the observed data. The proposed method allowed obtaining a relative index of abundance which could be included within the classic stock assessment models.

1. Introduction

Yellow squat lobster (*Cervimunida johni*) is an endemic species, distributed over Chile's continental shelf and upper slope from 23°00′S to 38°20′S and at depths of 150 to 400 m (Bahamonde, 1965; Bahamonde et al., 2003). The spatial distribution of the yellow shrimp is characterized by aggregations and discrete foci persistent over time, although with important interannual variations in its surface (area). (Canales and Arana, 2012). This benthic demersal species lives over gravel and mud bottoms and occasionally around rocky areas (Ahumada et al., 2013). The yellow squat lobster found off northern Chile is one of the nation's few fishing resources that is not overexploited (Cavieres et al., 2017). Thus, in order to maintain fishery sustainability, it is extremely important to protect current abundance levels in that area, which is currently certified by the Marine Stewardvessel Council (MSC).

Fisheries sciences generally assume that the catch per unit of effort (CPUE) is proportional to the relative abundance index. However, the assumption of proportionality does not hold when factors that affect catchability but not abundance are not accounted for (Harley et al., 2001; Maunder et al., 2006). Therefore, a wide part of methodological literature describes how to decrease the influence of these factors, including "CPUE standardization" (Maunder and Punt, 2004). Generally, the CPUE is standardized through generalized linear models (GLM); these incorporate factors such as the fishing area, the months in which the fishery is concentrated, the depth at which the catches are recorded, etc.

Different statistical tools have been proposed for modeling the CPUE by considering the variables that explain their behavior. For example, Lo et al. (1992) used the Delta method (also known as a Hurdle model) to model the CPUE, by estimating the probability of obtaining catches when the record is 0 (without fishing) and 1 (with fishing). Since a recurring problem when having CPUE observations is to have observations with value 0 within the data, Shono (2008) modeled the CPUE using the Tweedie distribution, which allows to obtain an index and model all the observations simultaneously. One of the methodologies used to model CPUE are the so-called generalized additive models (GAM's, Hastie et al., 2001), which are an extension of a GLM where the linear predictor is replaced by a non-linear additive function (Maunder and Punt, 2004).

An extension of generalized linear models are mixed generalized linear models (GLMMs, Pinheiro and Bates, 2000), which are also used to standardize CPUE. These models have three main characteristics: they can model a response variable by assuming a non-Gaussian distribution, they allow generating a linear structure between the mean and the predictors through a link function and can establish some correlation between the data through the covariance matrix of the error. A detailed description of all these models and their applications

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in various fisheries can be reviewed in Maunder and Punt (2004). More recently, Thorson and Ward (2014) used a Delta-GLMM model to differentiate the fishing power between vessels and estimating an index of relative abundance (Lo et al., 1992; Stefánsson, 1996)

To model observations measured in a delimited space, Lindgren et al. (2011) approximated a Gaussian Field (GF) to a Gaussian Markov Random Field (GMRF). This allowed to achieve efficiency in the computational cost of the estimation process without losing the consistency of the estimates of the involved parameters.

Recently, Thorson et al. (2015) modeled the density of individuals at a given sampling station through Gaussian Markov random fields (GMRF) in order to approximate a continuous spatial field and reduce the computational cost. Kallasvuo et al. (2016) modeled distribution and even predicted larval dispersion in three commercially important fish species in the Baltic Sea. Those authors concluded that, compared with the entire habitat of a population, fish production can be concentrated in a very limited space. Monnahan and Stewart (2018) standardized the CPUE in order to obtain a relative abundance index, considering the effect of hook spacing on longline catch rates as random effects. Those authors modeled the CPUE with Template Model Builder (TMB; Kristensen et al., (2016)), which allows the incorporation of a GMRF as the correlated spatial effect and "Years" as a random effect.

In this work, the CPUE is modeled through spatio-temporal GMRF models in a hierarchical Bayesian framework (Rue et al., 2009) using some exogenous variables such as the year and the number of vessels This approach takes into account proposals by Rue and Martino (2007), Cameletti et al. (2011) and Martins et al. (2013) with the main aim to obtain a relative abundance index in a given time series.

2. Materials and methods

2.1. Data

The data used in this work are part of the "Monitoring of demersal crustacean fisheries" program that is executed annually by the Instituto de Fomento Pesquero (IFOP) and were collected through the fishing logbooks of the vessels that were operating in the fishery between the period 1988 and 2017 spanning from 26° 03′to 30° 30′ LS (Fig. 1).

The greatest number of observations were collected in the year 2000 with 2292 records, while the year with the lowest was the 2017 with only 18 (although this information corresponds to the month of June of the year 2017). The number of vessels presented a variation over the years in the operative term, starting with 7 vessels in the 1988 and reaching a maximum of 20 vessel in 1999 (Fig. 2).

In order to select the variables which could be the predictors of the CPUE in the spatio-temporal framework we implemented a linear model for each series using the “Year” and “Vessel” as covariates (Cavieres et al., 2017). Fig. 3 shows the distribution of the CPUE respect these variables.

2.2. Gaussian Markov random fields (GMRF)

A Gaussian random field, with observations in a continuous domain, assumes that the entire collection of random variables comes from a normal multivariate process. Specifically, if the process is defined in space, then we have $D \subset R^d$, a subset of the spatial domain of interest, where d is generally of the second or third order (if defined in space, this is determined by latitude-longitude coordinates). The above allows us to say that a random field$\{x(s): s \in D \subset R^d\}$, for each finite subset of locations, $\{s_1, \ldots\ldots, s_n\}$, is Gaussian if:

$$(x(s_1), \ldots\ldots, x(s_n)) \sim N_n(\mu, \Sigma) \tag{1}$$

where N_n is the normal multivariate distribution with a mean $\mu = (\mu(s_1), \ldots\ldots, \mu(s_n))$, covariance matrix Σ, and $n \geq 1$. The covariance matrix at i and j is given by the elements (i,j) of the covariance matrix $\Sigma_{i,j} = Cov\{x(s_i), x(s_j)\}$. A random field that is assumed to be stationary would also be invariant to translations. Moreover, if this is second-order stationarity, the mean and variance would not depend on the location. If $Corr\{x(s_i), x(s_j)\} = \rho(|s_j - s_i|)$, then the field would be isotropic. The dependence of the spatial structure is built through the covariance function which is generally modeled by a Matérn’s function.

Rue and Held (2005) proposed using a Gaussian Markov Random Field (GMRF) instead of a GF in order to decrease the computational cost of estimation. A GMRF is a Gaussian spatial process with Markovian properties, where these properties are mainly associated to its correlation structure. The main characteristic of the GMRF is that it uses a conditional dependency structure through the precision matrix $Q(Q = \Sigma^{-1})$.

2.3. The SPDE (Stochastic partial differential equation) approach

Lindgren et al. (2011) introduced a new approach for modeling data indexed in space. This is based mainly on the approximation of a GRF with a Matérn covariance function through stochastic partial differential equations (SPDE):

$$(\kappa^2 - \Delta)^{\alpha/2}(\tau x(s)) = W(s) \tag{2}$$

where $x(s)$ is a Gaussian random field, $W(s)$ is a Gaussian white noise, α is a smoothing parameter (differentiable) of the spatial process, τ is the parameter that controls the variance of the Gaussian random field, and $\kappa > 0$ is a scale parameter. In summary, a GMRF is constructed from a GRF$x(s)$ by means of SPDE without specifying an explicit covariance structure. The direct implication of this, is a decrease in the computational burden from $O(n^3)$for the GRF to $O(n^{3/2})$ for GMRF, where the region is discretized into a triangular mesh. The primary contribution of the SPDE approach is to allow one to construct a sparse precision matrix on a continuously-indexed region in a way that approximates a Matern field. The triangulation of the CPUE (Kg/h.a) observations generated by the GMRF is shown in Fig. 4.

2.4. Integrated nested laplace approximation (INLA)

Given x, which is a latent Gaussian field (GMRF); θ, the vector of the all parameters; and y, a vector of observations, INLA uses the joint posterior distribution (Rue et al., 2009) given by:

$$\pi(x, \theta|y) \propto \pi(\theta)\pi(x|\theta)\prod_{i\in I}\pi(y_i|x_i, \theta) \tag{3}$$

to find the marginal posterior of θ

$$\tilde{\pi}(\theta|y) \propto \frac{\pi(x, \theta, y)}{\tilde{\pi}_G(x|\theta, y)}\Big|_{x=x*(\theta)} \tag{4}$$

where $\tilde{\pi}_G(x|\theta, y)$ is the Gaussian approximation for the joint conditional of $x$and $x^*(\theta)$ is the mode of the full conditional for a given value of θ. In order to approximate the marginal posterior of the GMRF we start from $\tilde{\pi}_G(x|\theta, y)$ and approximate the density of $x_i|\theta, y$ with the marginal Gaussian coming from $\tilde{\pi}_G(x|\theta, y)$, that is:

$$\tilde{\pi}(x_i|\theta, y) = N\{x_i; \mu_i(\theta), \sigma_i^2(\theta)\} \tag{5}$$

where $\mu(\theta)$ is the mean of the Gaussian approximation vector, $\sigma^2(\theta)$ is the vector corresponding to the marginal variances. The numerical approximation with respect to θ for obtaining the marginal posteriors of the GMRF is given by

$$\tilde{\pi}(x_i|y) = \sum_k \tilde{\pi}(x_i|\theta_k, y) \times \tilde{\pi}(\theta_k|y) \times \Delta_k \tag{6}$$

The sum is above the values of θ with Δ_k (Rue and Martino, 2007; Rue et al., 2009; Bivand et al., 2015).

2.5. Model selection

INLA offers a criterion that can be seen as an improvement over the

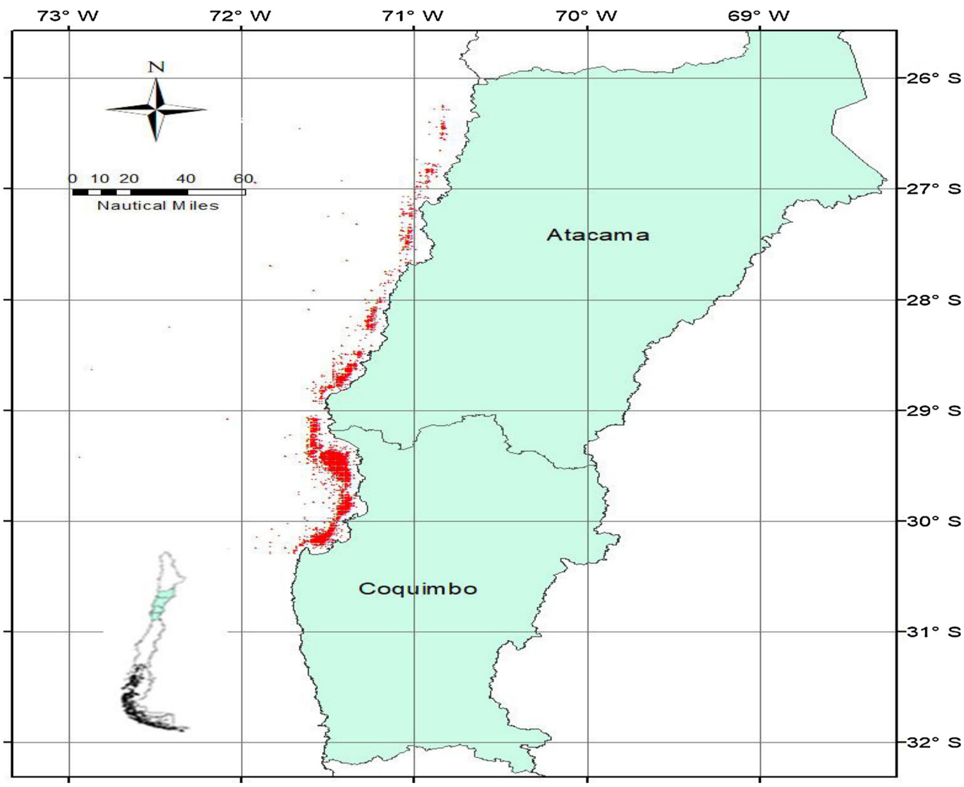

Fig. 1. Spatial distribution of CPUE (kg/h.a) for yellow squat lobster.1988–2017.

DIC for Bayesian models: the Watanabe-Akaike (WAIC, Watanabe, 2010). This criterion has a much closer approximation to the Bayesian cross-validation than the DIC and is invariant to parameterization since it can work for singular models (Vehtari et al., 2016). To calculate the WAIC, it is necessary to obtain a value for the positive predictive density on a logarithmic scale, that is:

$$lpd = \sum_{i=1}^{n} \log p_{post}(y_i) = \sum_{i=1}^{n} \int p(y_i|\theta) p_{post}(\theta) d\theta \tag{7}$$

To calculate lpd, expectations need to be evaluated using samples from $p_{post}(y_i)$through a subsequent simulation, known as θ^S, where $s = 1, \ldots, S$. Thus:

$$\hat{lpd} = \sum_{i=1}^{n} \log\left(\frac{1}{S} \sum_{s=1}^{S} p(y_i|\theta^S)\right) \tag{8}$$

and WAIC is a convenient computational interpretation approximated to the cross-validation defined as:

$$\hat{elpd} = \hat{lpd} - \hat{p}_{WAIC} \tag{9}$$

and can be calculated by:

$$WAIC = -2\hat{elpd}_{WAIC} \tag{10}$$

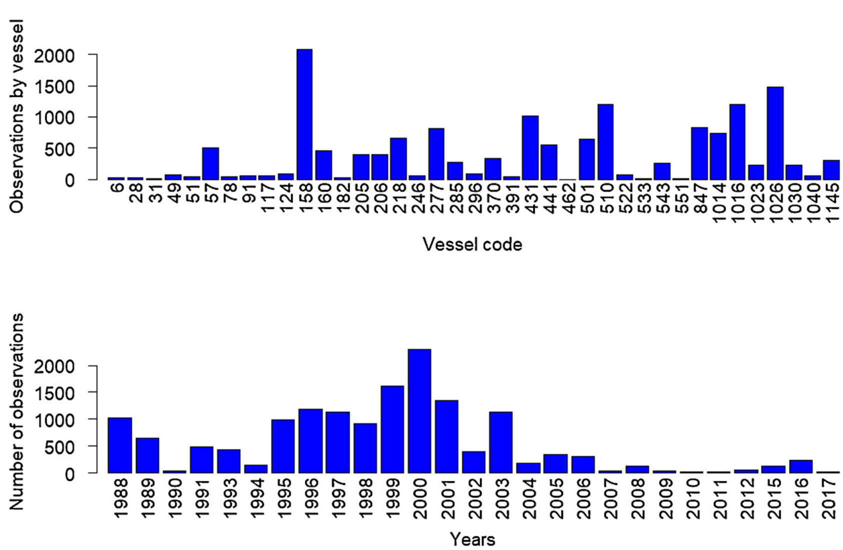

Fig. 2. Number of total observations per vessel (upper) and number of vessels for year (lower).

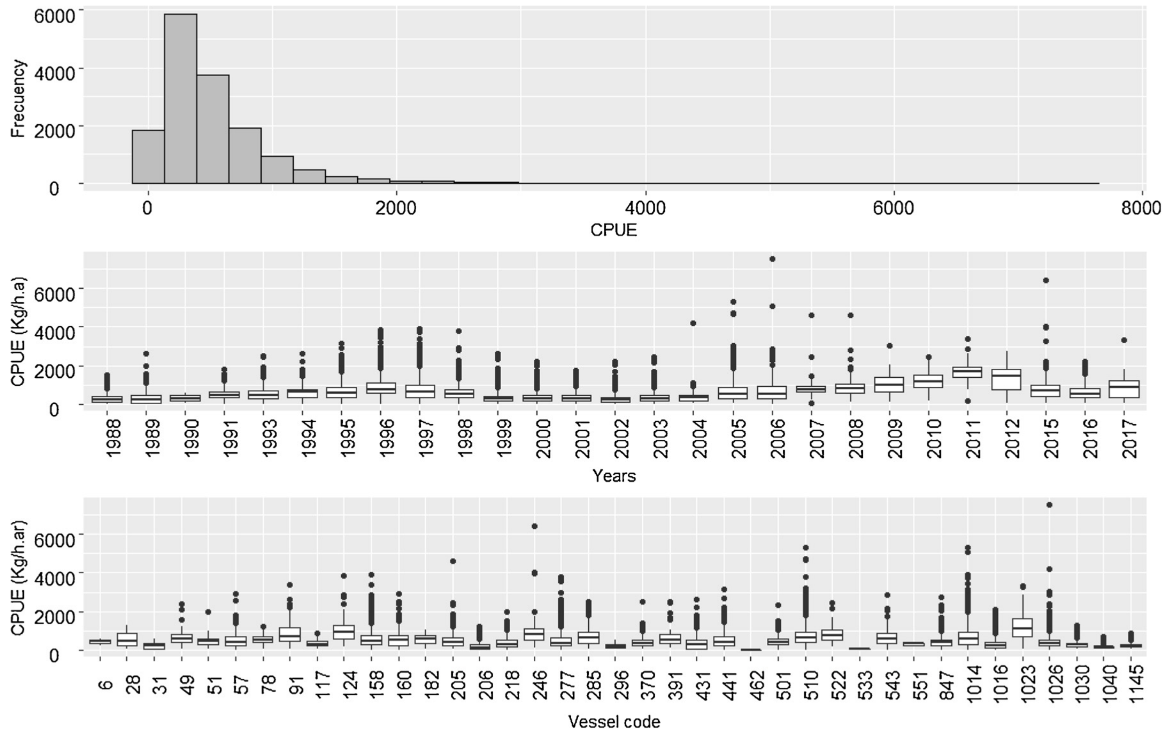

Fig. 3. Histogram of yellow squat lobster CPUE (upper) and boxplots by year (middle) and vessel (lower) during the period.1988–2017.

2.6. Model for the data

The general structure for CPUE modeling (Kg/h.a) was constructed according to the data presented in Section 2.1 and the structure of the hierarchical Bayesian model shown in Section 2.4. Observations in space were related to the nodes (885 nodes) created from the SPDE, and temporal observations were made between 1988 and 2017. Given the above, the general structure of the model is as follows:

$$y_i|\theta \sim Gamma(a_i, b_i) \tag{11}$$

$$\eta_i = \alpha + c_i\beta + x_i$$

$$x_i \sim N(0, Q^{-1}(\kappa, \tau)) \tag{12}$$

$$\log\kappa \sim N(m_k, q_k^{-2}) \tag{13}$$

$$\log\tau \sim N(m_\tau, q_\tau^{-2}) \tag{14}$$

where $i = 1, ..., n$, where n is the number of observations, $c_i$es the vector of covariables, x_i is the latent field (GMRF) and $\theta = \{\alpha, \beta, \kappa, \tau\}$is the vector of all parameters. m_k is chosen automatically such that the range of the field is about 20% of the diameter of the region, while $m_\tau$is

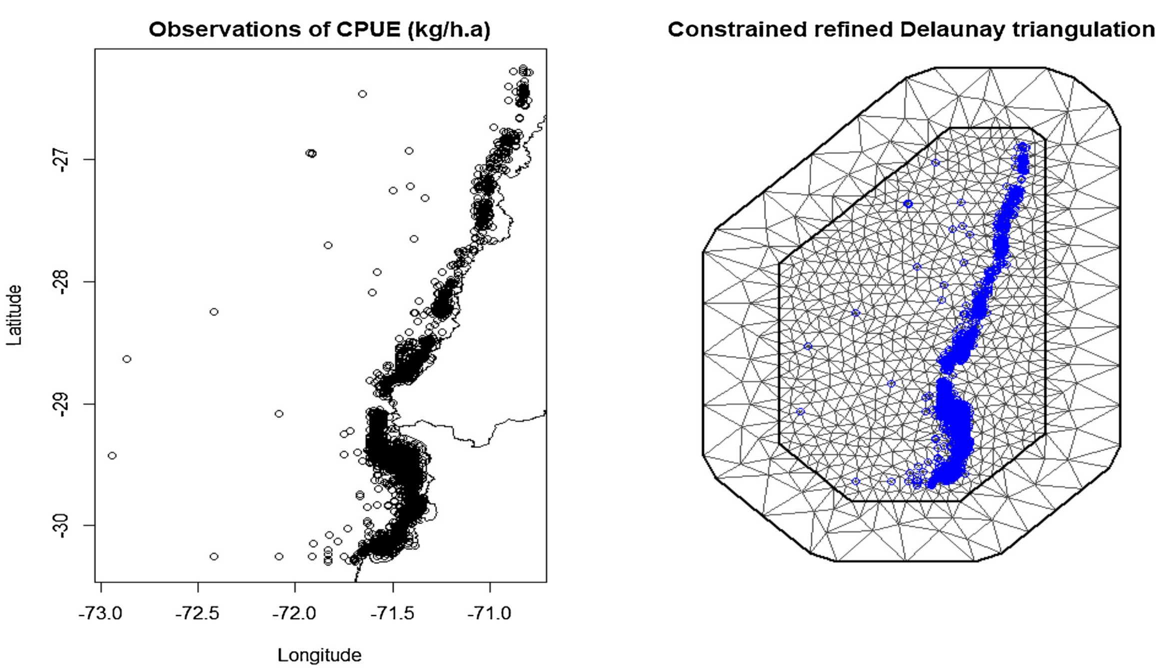

Fig. 4. Spatial distribution of the CPUE observations (Kg/h.a) (left) and discretization of the continuous space towards a GMRF (right).

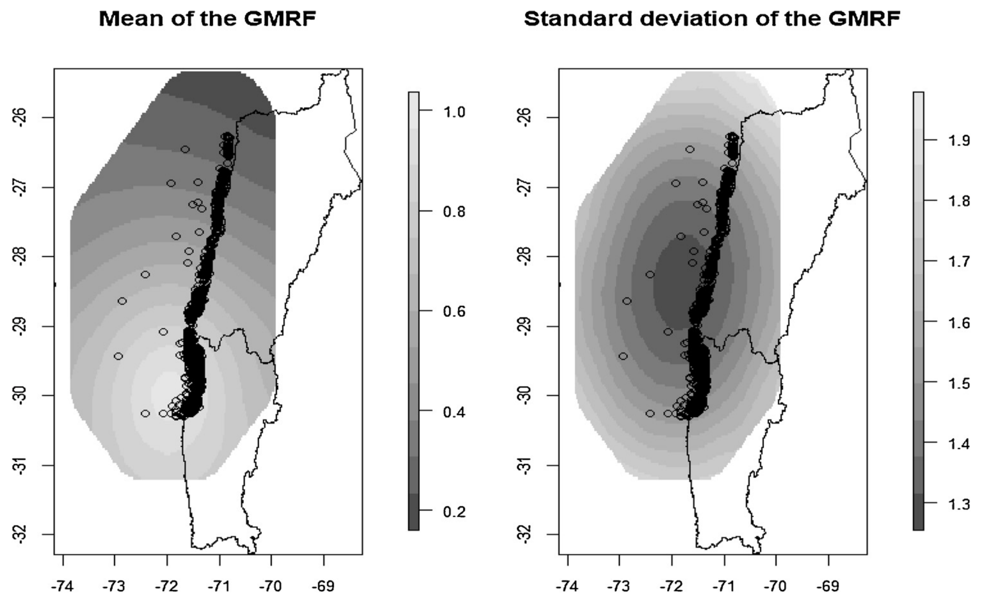

Fig. 5. Mean of the GMRF (left) and its standard deviation (right) estimated from the CPUE observations in space and time.

Table 1
Models proposed to modelling CPUE (Kg/h.a) for yellow squat lobster.

Model	Covariable	Random effects	Description
M1	Year + GMRF	Yes	Year is a “iid”
M2	Year + GMRF	Yes	Year is a “rw1”
M3	Year + Vessel + GMRF	Yes	Year and Vessel is “iid”
M4	Year + Vessel + GMRF	Yes	Year is “iid” and Vessel is “rw1”
M5	Year + Vessel + GMRF	Yes	Year is “rw1” and Vessel “iid”
M6	Year + Vessel + GMRF	Yes	Year is “rw1” and Vessel “rw1”

iid = independently and identically distributed and rw1 = random walk of the variable within the predictor.

chosen so that the corresponding variance of the field is 1.

2.7. Choice of priors

In general, for a Bayesian model to present a good estimate, it is necessary to provide reasonable a priori distributions for the hyperparameters. The SPDE methodology is characterized mainly by the parameters τ and $\varkappa$, where τ is the parameter of the Matérn covariance function and $\varkappa$ is a differential operator. The INLA library has the option to use the marginal standard deviation $\sigma$and the range $r = \sqrt{8\nu/\varkappa}$ proposed by Lindgren et al. (2011) as input information. Fuglstad et al. (2018) developed a joint principle for the parameters $r$and$\varkappa$ using the methodology proposed by Simpson et al. (2017), successfully applied to practical problems (Wakefield et al., 2018; Bakka et al., 2018). The prior values used for the range and the marginal variance are $q_k^{-2} = 1 - 0.5$and $q_\tau^{-2} = 1 - 0.5$, respectively (Simpson et al., 2017).

3. Results

The mean and standard deviation of the CPUE estimated by GMRF is shown in Fig. 5. From this figure we can note that the highest values of the estimated CPUE are distributed along the coast of the southern part of the considered area corresponding to the Coquimbo region of Chile.

Different alternatives were modeled to estimate the annual index of relative abundance (≈CPUE); six different models were constructed (see Table 1).

Tables 2 show the model estimates and standard deviations for fixed and random effects. As can be seen, the spatio-temporal model offers a good estimate of the average of the random effect "Year", a value of interest, and estimations based on the credible quartiles of the parameters showed a certain consistency when assuming a GMRF for the CPUE. The measurement of the posterior of the fixed effects varied slightly; the mean of M4 was 6.328 and the average standard deviation was 0.084.

Fig. 6 shows the estimation of the indices for each of the proposed models along with their respective credible intervals. The trends in all the models were very similar, and the variation was high for periods lacking information. Nonetheless, the spatio-temporal model captured the behavior throughout the series as would a generalized linear model with the factor "Year" in the predictor. Based on WAIC, the model with the lowest score was chosen (Table 2) for the purpose of estimating the index of relative abundance.

Table 2
Posterior measures of the fixed effect (intercept), random effect “Year”, parameter of dispersions and criteria WAIC for the proposed spatio-temporal models. The shaded color indicates the chosen model.

Models	Intercept (±SD)	Year (mean ±SD)	Range (*mean ±SD*)	GMRF σ_x (mean ±SD)	WAIC
M1	6.464 (0.121)	3.272 (0.939)	0.135 (0.023)	0.351 (0.030)	214060
M2	6.462 (0.049)	14.290 (4.341)	0.135 (0.019)	0.355 (0.040)	214061
M3	6.338 (0.015)	5.224 (1.505)	0.131 (0.024)	0.353 (0.028)	212893
M4	6.328 (0.028)	4.923 (1.458)	0.136 (0.026)	0.364 (0.033)	212891
M5	6.346 (0.071)	17.023 (5.481)	0.131 (0.023)	0.354 (0.030)	212896
M6	6.334 (0.058)	16.694 (5.475)	0.136 (0.025)	0.364 (0.025)	212894

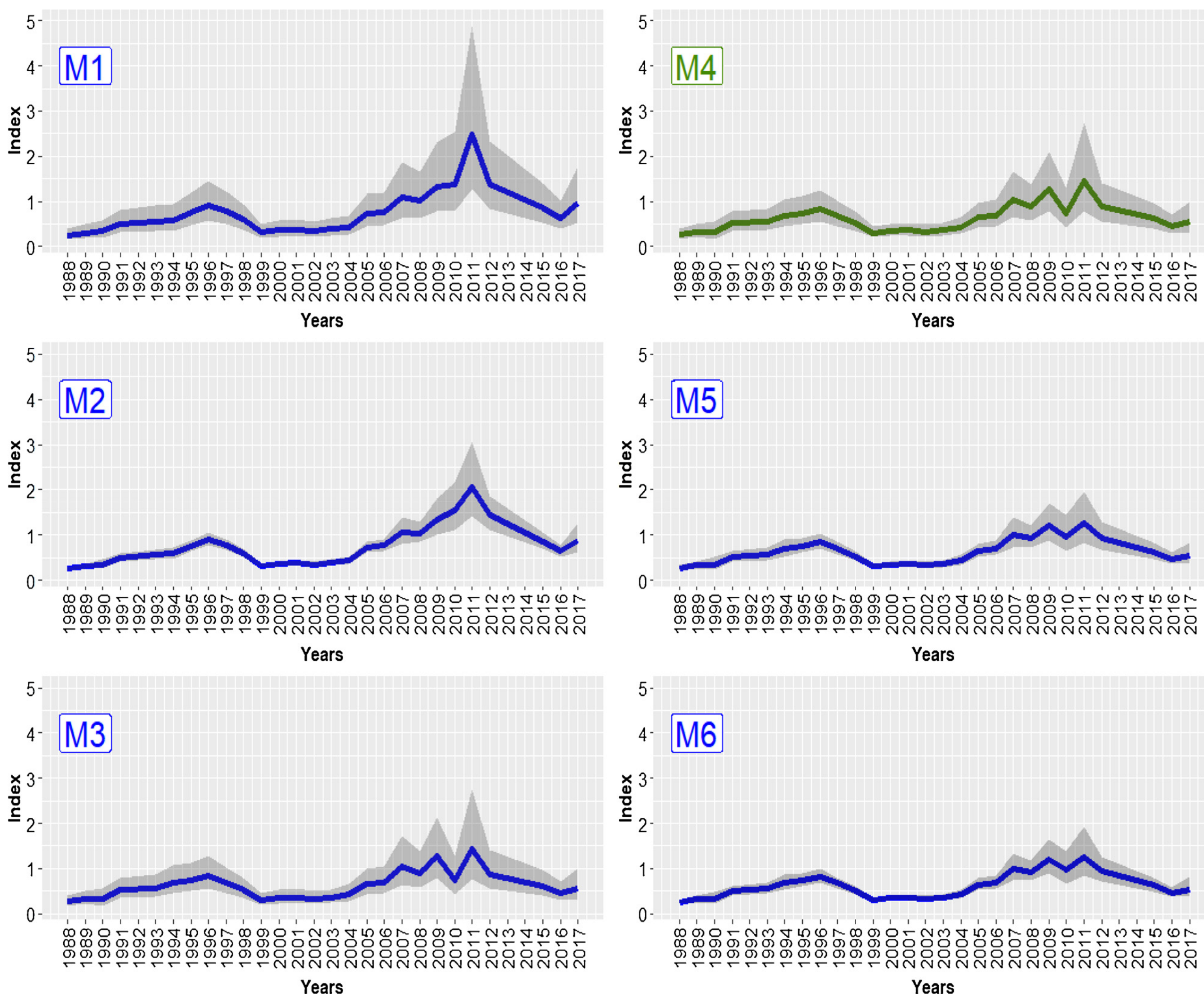

Fig. 6. Estimation of the random factor, year, as relative abundance index for the different models proposed for yellow squat lobster off Chile, 1988–2017. The box marked in the legend indicates the model with the best performance (M4) according to the selection criteria WAIC.

Fig. 7 shows the marginal posterior distributions for the hyperparameters of the chosen model (M4). As you can see, after executing the model once, obtaining the results and then again executing with the outputs of the values obtained for the hyperparameters, adequate results are achieved if the distribution of the posterior density for each of them is taken into account. they. The estimated average values for σ_ε, σ_x, and the range are respectively 2.315, 0.135 and 0.363.

Fig. 8 shows the posterior mean of the random field and its standard deviation. Concentrations were highest from -29 °S to -31 °S. The variability estimated for the random field showed a greater deviation in the same area with a more concentrated field as a function of its mean, decreasing - but not greatly - northward.

4. Discussion and conclusion

Spatio-temporal models may improve the approximation of fishing effort that is a function of the population dynamics of yellow squat lobster, this based on spatial and temporal variations within its distribution.

However, in the classical GLMs, a statistical arrangement allows incorporating the spatial variation of the fishing effort in a simple way, that is, declaring as factors "fishing zones" within a particular spatial domain. A comparison for the standardization of CPUE between a classic GLM and the temporal space model that is presented in Fig. 9. In these models, the same covariables (Year and Vessel), the same distribution of the response variable (Gamma), and the same link function have been used for the linear predictor (log).

Standardizing the CPUE with a GLM model is simpler than doing it with a temporary space model in terms of theory and structure. However, the true variations of the relative index are not of such magnitude as the classic GLM presents, with notable positive and negative anomalies between years, but rather it presents variations in a lower level of scale, as it is shown by fitting a spatio-temporal model (Fig. 9).

The spatio-temporal model explicitly integrates spatial and temporal variation, allowing the best fit to observations. For this reason, modeling CPUE through GMRF has good statistical properties, especially when the data comes from well-defined geographic spaces (Lindgren et al., 2011). One of them is the imputation of resource abundance in areas where there are no catches, and therefore no records of fishing effort. Hence, if a fishery has been subjected to intense fishing mortality and shows strong signs of spatial expansion, this may be masking large population declines that a traditional GLM is not able to detect (Carruthers et al., 2010).

On the other hand, the relative abundance index is generally considered to be a source of information related to the impact of fishing on marine populations (Francis, 2011). This index is used to model the population dynamics of marine species, both those that have extensive

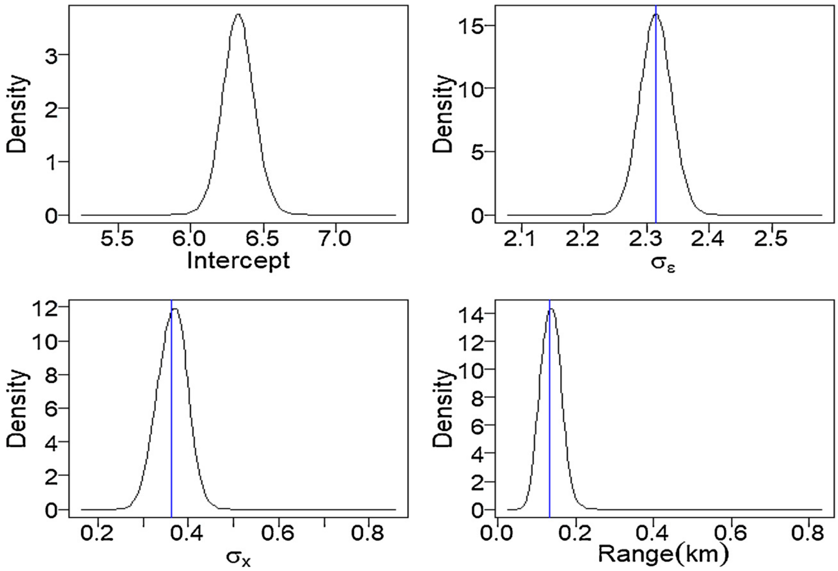

Fig. 7. Marginal posterior distributions for: the intercept (upper left), the variance of the Gamma observations (upper right), the marginal variance of the GMRF (lower left), and the range (lower right). The blue lines represent the initial values of the hyperparameters in each case. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

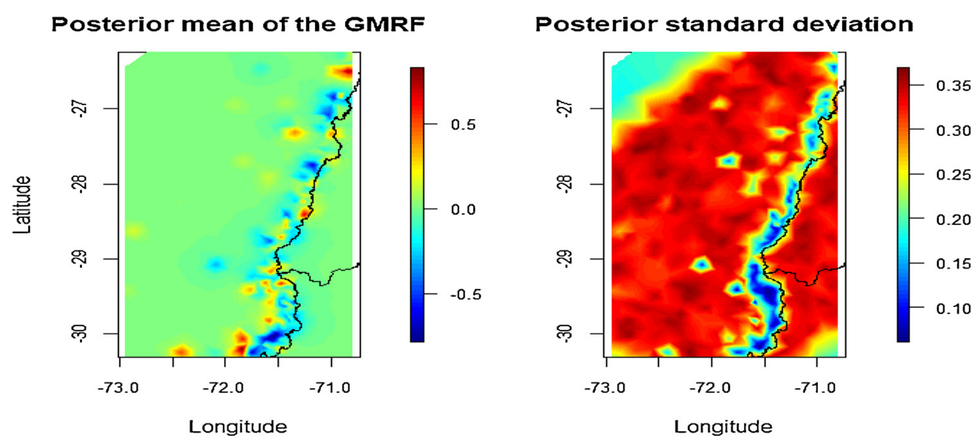

Fig. 8. Posterior mean of the GMRF (left) and posterior standard deviation (right) of the random field estimated by the model.

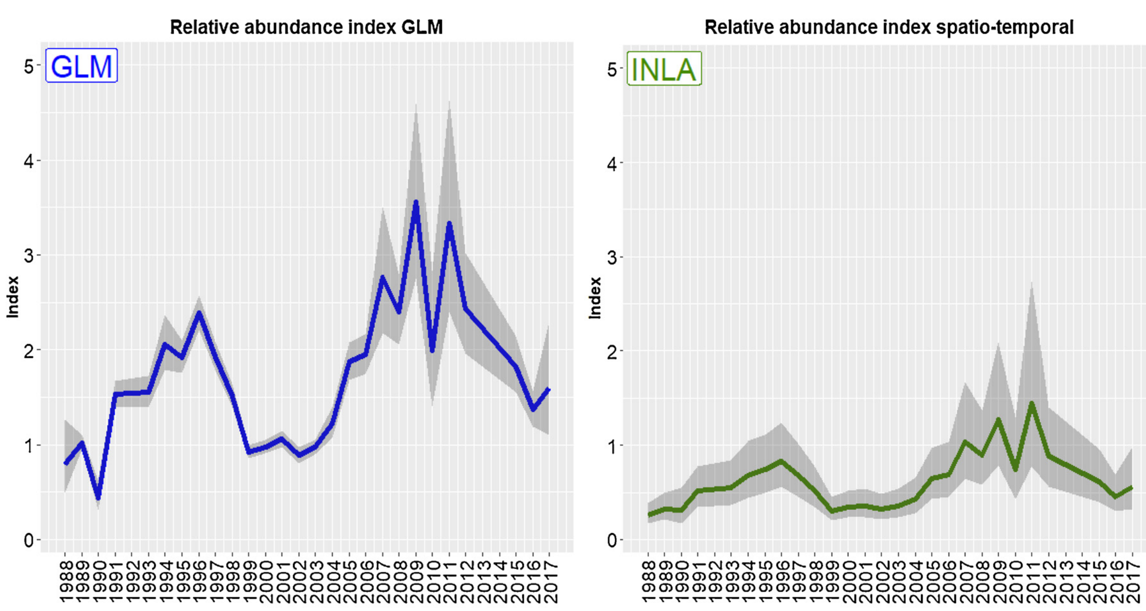

Fig. 9. Relative abundance index with GLM and Relative abundance index with INLA.

data ("data-rich") and those with a paucity ("data-limited") (Methot et al., 2014). However, this index is obtained from spatially stratified models, which produces skewed estimates (Thorson et al., 2015). Spatially explicit models allow other sources of information to be summarized within the stock evaluation models (Thorson et al., 2015). In contrast and as noted earlier, the explicit declaration of the displacement of the fleet, the distribution of effort, and changes in the CPUE over the years might not imply a notable change in the trends of the analyzed series.

The assumptions of GMRFs for unobservable processes may be a matter of discussion, but GMRFs are widely used in geostatistics (Diggle et al., 1998). The construction of the GMRF is simple through stochastic partial differential equations, but it can only be solved, to date, within the family of Matérn covariances. The use of an explicit covariance function can be done through the composite likelihood method and with a reasonable estimation time, according to the model that is to be implemented (Lindsay, 1988; Varin, 2008). With the Bayesian hierarchical model, a structure of spatial dependence given dynamic interactions over time can be generated through the partial stochastic equations used to obtain the GMRF. It is also possible to integrate a large amount of data into these models, and it is very computationally efficient to obtain the posterior marginals.

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