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Abstract Spatial management of discards has recently been proposed as a useful tool for the protection of juveniles, by reducing discard rates and can be used as a buffer against management errors and recruitment failure. In this study Bayesian hierarchical spatial models have been used to analyze about 440 trawl fishing operations of two different metiers, sampled between 2009 and 2012, in order to improve our understanding of factors that influence the quantity of discards and to identify their spatio-temporal distribution in the study area. Our analysis showed that the relative importance of each variable was different for each metier, with a few similarities. In particular, the random vessel effect and seasonal variability were identified as main driving variables for both metiers. Predictive maps of the abundance of discards and maps of the posterior mean of the spatial component show several hot spots with high

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discards concentration for each metier. We argue how the seasonal/spatial effects, and the knowledge about the factors influential to discarding, could potentially be exploited as potential mitigation measures for future fisheries management strategies. However, misidentification of hotspots and uncertain predictions can culminate in inappropriate mitigation practices which can sometimes be irreversible. The proposed Bayesian spatial method overcomes these issues, since it offers a unified approach which allows the incorporation of spatial random-effect terms, spatial correlation of the variables and the uncertainty of the parameters in the modelling process, resulting in a better quantification of the uncertainty and accurate predictions.

Keywords Bayesian kriging · Bayesian hierarchical models · Fishery Discards · GSA06 South area · Trawl fishery

1 Introduction

Discarding is currently one of the most important issues in fisheries management, both from economic and environmental points of view (Bellido et al 2011). Discard occurs for a range of reasons and it is influenced by an even more complex array of factors that remain still poorly understood due to, among other things, incomplete knowledge on the spatio-temporal pattern of discards (Feekings et al 2012).

There are indications that the practice of discarding has altered the ecosystem functioning at several levels, causing cascading effects throughout the trophic chains (Valeiras 2003; Jenkins et al 2004). However, not all of the biological or ecological impacts of discards are considered negative (Zhou 2008). Hill and Wassenberg (1990) and Votier et al (2004), for example, discuss that discarding from trawls transfers large quantities of biological material from the bottom to the surface, making otherwise inaccessible food available to surface scavengers such as sea-birds.

All these trends are the manifestation, expressed by the European Union, that there is need to quantify discards to understand their causes and effects in order to manage them effectively. Consequently, data on discards have become more widely available, opening a door for the development of discard management plans (Viana et al 2013).

The literature on discards has mainly been descriptive, with a focus on understanding discard rates of specific species (Welch et al 2008), estimating the amount or proportion of total catch discarded from particular fisheries (Rochet et al 2002), as well as global discard assessments (Alverson 1994; Kelleher 2005). These studies fail to acknowledge that discards are dynamic in time and space.

However, some studies that provide spatio-temporal estimations of discard rates are emerging (Catchpole et al 2011; Feekings et al 2012; Madsen et al 2013; Feekings et al 2013; Viana et al 2013) and spatial management of discards has recently been proposed as a very useful tools for discard reduction strategies, jointly with the technical measures (Dunn et al 2011; Viana et al 2013).

The use of spatial modelling approaches to discard data provides the chance to estimate which factors could influence in the discard process. In addition, it offers important insights to predict future catches and discards both in quantity and location.

The main goal of this study is to address the discard issue by examining the data collected in the GSA06 (Geographical Sub-Areas) South area, identifying the factors that influence discards within the Spanish trawling fleet and their spatio-temporal distributions.

On-board sampling of the fishery is directly related to fishing strategy. Therefore, the data collected are useful for analysing discard trends (Essington 2010). Two different metiers were analyzed, the bottom otter trawls demersal species metier (OTB-DES) and the bottom otter trawl deep-waters species metier (OTB-DWS). Firstly, we have analyzed discards of both metiers in order to understand their quantity and species composition. Secondly, we have focused our analysis on factors influencing discards to identify their spatio-temporal patterns in the study area.

In the last decade, various methodologies were developed to independently investigate spatio-temporal effects, *e.g.* GAMs, kriging for spatial patterns, and various time-series analyses such as autoregressive components that deal with time effects (Brockwell and Davis 2002; Viana et al 2013). Models which integrate space and time are sparse and only began to emerge recently in ecology (Banerjee et al 2004). In addition, two important issues that have to be addressed are the estimation of the uncertainties in the parameters of interest, and the computational time required to fit such models, especially for large data sets.

In this study we overcome these problems implementing Bayesian hierarchical spatio-temporal models using the integrated nested Laplace approximation (INLA) methodology and software (http://www.r-inla.org).

Indeed, Bayesian models are appropriate to spatial hierarchical analysis as they allow both the observed data and model parameters to be considered as random variables, resulting in a more realistic and accurate estimation of uncertainty (Banerjee et al 2004). This is essential in a study like this, where the main goal is to identify discard hot spots and to verify their persistence over the time, with the least possible error. Bayesian spatial models may also aid data analyses with geographically uneven levels of survey effort, as such bias can be incorporated within the spatial random-effect term, which reduces its influence on estimates of the effects of environmental variables (Gelfand et al 2006). Particularly, by treating spatial effect as a variable of interest, hierarchical Bayesian spatial models are able to improve model fit and to identify the existence of area effects that may affect discard abundance.

In addition, the great bonus of our application is the possibility to use INLA, which provides accurate approximations to posterior distributions of the parameters, even in complex models, in a fast computational way (Rue et al 2009).

Finally, few models, like these, offer, in addition to an estimation of the processes that drive the distribution of discards, a predictive spatial abundance of discards in unsampled areas. Using Bayesian kriging we have generated predictive maps, obtaining a posterior predictive distribution of the discard abundance for each location of the study area. This means that for each posterior distribution, unlike the mean and confidence interval produced by classical analyses, we are able to make explicit probability statements about the estimation, implying a more accurate estimation of the uncertainty.

It is finally worth noting that a detailed knowledge of the spatio-temporal discard patterns could allow further development of spatial fishery management. Predictive maps could provide an essential tool for identifying areas where discard is high and facilitate the move to discard free fisheries as part of the proposed reforms of the Common Fisheries Policy (CFP).

2 Materials and Methods

2.1 Discard Data

Under the European Union Data Collection Framework (EC Regulation 199/2008), EU members are obliged to collect biological data including discards. Sampling of discards by the *Instituto Español de Oceanografía* (IEO, Spanish Oceanographic Institute) is based on a metier approach, that is a formal segmentation of a fishery by vessel types characterised by the same fishing gear, fishing area and target species assemblage.

Discards are sampled at a haul level, by randomly collecting one box of discarded catch from as many hauls as possible during each trip. For each observed haul, an estimate of the total weight discarded is made by the fishermen and the on-board observer, by subtracting the landings from the total catch, both directly weighing. The discard weight of the fish species in the sample is then multiplied by the total discarded weight of the haul recorded to obtain the total weight of fish discarded per haul (Damalas and Vassilopoulou 2013).

The discard sample is sorted by the observer into species. Total weights and numbers of each discarded species in the subsample are determined and based on the total approximated discarded weight.

On-board sampling is not mandatory for skippers and they may decline participation in the discard sampling programme, resulting in a quasi-random sampling of the fishery. Nevertheless, in order to obtain a representative sample of the studied fisheries, a random rotation of all the vessels available to be sampled is made during the entire period of activity of a given fishery.

The reference fleet for this study was the trawl fleet which operates in the GSA06 South area (Figure 1). This trawl fleet has been divided into two different types of metiers, the bottom otter trawls demersal species metier (OTB-DES) and the bottom otter trawl deep-waters species metier (OTB-DWS).

The OTB-DES includes trawlers that usually operate in waters from the continental shelf (from 50-200 m. depth) with European hake (*Merluccius merluccius*) and the Octopus (*Octopus vulgaris*) as target species. They make short hauls of about 2-4 hours, comprising about 2-3 fishing hauls per trip.

The OTB-DWS involves trawlers that usually operate on deep-waters (from 400-1000) with red shrimp (*Aristeus antennatus*) as target species. They generally make a unique haul per trip about 5-6 hours. The monthly sampling frequency usually consists in about 2-3 trips for the OTB-DES metier, and about 1 trip for the OTB-DWS metier.

In this study, 343 OTB-DES hauls and 97 OTB-DWS hauls, sampled from 2009 to 2012, were analyzed. Log-transformed discards per unit effort (DPUE) were used to downweight extreme values, to improve normality and ensuring a better fit of the models. For each metier, DPUE was calculated as discard weight per haul duration (kg/h).

2.2 Modelling discard abundance

Hierarchical Bayesian spatio-temporal models were used to account for discards dependency with respect to explanatory variables, as well as to describe the main spatial distribution changes over time (Muñoz et al 2013).

The expected values of DPUE in each haul (μ_{DPUE}) were related to the spatial, temporal, technical and environmental covariates, according to the general formulation,

$$\mu_{DPUE_{ijk}} = X_{ij}\beta + Y_j + Z_k + W_i \,, \tag{2.1}$$

where β represents the vector of the regression coefficients, X_{ij} is the vector of explanatory covariates at year j and location i, Y_j is the component of the temporal unstructured random effect at the year j, Z_k is the random effect of the vessel, and W_i represents the spatially structured random effect at location i.

In our case, from the on-board observer dataset we have extracted the spatial location, year, quarter, moon phase, day light and the CPUE of the observed hauls. All these variables have been introduced in the analyses in order to capture the variation on DPUE due to particular fishing characteristics such as, among others, the fishing ground selection. In particular, the moon phase has been added in order to reflect the sea tides. As aforementioned with DPUE, we have used a log-transformation of the CPUE variable, computed from the total catch per haul duration (kg/h). With respect to the quarter variable (which indicates the period when the haul was sampled), it has been introduced in order to verify intra-annual variations on the discard abundance.

On-board observer dataset also has information about the characteristics of sampled vessels. Among power, gross register tonnage (GRT) and length, and through the application of a Principal Components Analysis, the vessel's length was selected as the most relevant one to be included in the analysis. Indeed, a correlation of 0.67 was found between the GRT and the length and about 0.58 between the GRT and the power variable. In addition, the PCA shows that the vessel's length explains by itself about 73% of the variability of the data. The PCA was performed using the *prcomp* function of the *stats* package of the R software (R Development Core Team 2013).

Bathymetry and type of substratum data have also been included in the model. They were obtained from the IEO geoportal, accessible by the website of the Spanish Institute of Oceanography (`http:\www.ieo.es`). Moreover, slope and orientation have also been included, the information being derived from the bathymetry map, using the *Slope Spatial Analyst* and *Orientation Analysis Tools (OATools)* tools of the ArcGIS 10.0 (`http:\webhelp.esri.com/arcgisdesktop/10`). In order to make it possible to work in the R framework maps have been transformed into *SpatialPolygonsDataFrame* objects using the *sp* R package.

As a result, a total of nine potential fixed-effects have been considered for each of the models (for each metier) and they are listed in Table 1.

The remaining potential source of variation on discards used has been the existing differences among vessels. These differences can be caused by a skipper effect or

Table 1 Summary of variables included in Bayesian Models as potential fixed-effects influencing discard.

Variable	Description	Units
Depth	Mean fishing depth of haul	In meters
Slope	Seabed slope in the fishing location	In meters
Orientation	Seabed aspect in the fishing location	In degrees
Type of Seabed	Seabed sediment types in the fishing location	Sand, Mud, Rock, Gravel
Moon	Moon Phase of the trip day	New, Full, Crescent,Waning
Log(CPUE)	Log-transformed catch per unit effort of all species	In Log-kilograms/hour
Light	Day light when the haul was sampled	Yes/No
Quarter	Quarter when haul was sampled	1,2,3,4
Vessel length	Vessel's length overall	In meters

unobserved gear characteristics. Ignoring such non-independence in the data may lead to invalid statistical inference. Then, in order to remove bias caused by vessel-specific differences in fishing operation, we have included a vessel effect. And, since we are not interested in knowing the specific nature of the observed vessels, we have included this vessel effect as a random effect.

2.3 Bayesian inference

Once the model is determined, the next step is to estimate its parameters. Following Bayesian reasoning, the parameters are treated as random variables, and prior distributions have been assigned for each parameter.

In particular, we have used vague Gaussian distributions for the parameters involved in the fixed effects $\beta \sim$ N(0, 100), in order to allow empirically derived distributions.

For the spatial component, we have used the Stochastic Partial Differential Equation module (SPDE), which allows us to fit the particular case of continuously indexed Gaussian Fields by INLA (Lindgren et al 2011). This component is defined in terms of two hyperparameters, κ and τ which are related with the range and scale of the spatial effect. We have assumed prior Gaussian distributions with mean of zero and a covariance matrix dependent of each of the hyperparameters.

Moreover, for the temporal effect we have assumed, following Rue and Held (2005), LogGamma prior distribution on the log-precision λ_y (a=1, b= 5e -05).

As usual in this context, the resulting hierarchical Bayesian model containing all the information about the system has no closed expression for the posterior distribution of all the parameters, and so numerical approximations are needed. One possible choice for doing this would be using Markov Chain Monte Carlo (MCMC) methods. This could be done using WinBUGS (Spiegelhalter et al 1999), flexible software for performing the Bayesian analysis of complex statistical models. Nevertheless, as Rue et al (2009) state implemeting MCMC methods can be done but they are not without problems, in terms of both convergence and computational time. In fact, using their own words, "in some practical applications, the extent of these problems is such that MCMC sampling is simply not an appropriate tool for routine analysis". They introduced the use of an integrated nested Laplace approximation (INLA) that allows to directly compute very accurate approximations. Here we use INLA to approximate the posterior distribution of all the parameters in order to benefit both from their computational and generality (Rue et al 2009).

All the resulting models obtained from combining the mentioned variables and the respective interactions were fitted and compared. The Deviance Information Criterion (DIC) (Spiegelhalter et al 2002) was used as a measure for the goodness-of-fit. The smaller the DIC, the better the compromise between fit and parsimony.

Additionally, in order to have a measure of the predictive quality of the models, we have used the Conditional Predictive Ordinate (CPO, Geisser 1993; Gneiting and Raftery 2007), which is defined as the cross-validated predictive density at a given observation. This measure is usually express via its logarithmic score (LCPO). Lower values of LCPO indicate a better predictive model.

2.4 Bayesian kriging

Once the inference is carried out, the next step is to predict the DPUE in the rest of the area of interest, especially in unsampled locations. Here, we adopted a Bayesian kriging approach to calculate posterior predictive distributions of the DPUE for the whole region. Using Bayesian kriging, we incorporated parameter uncertainty into the prediction process by treating the parameters as random variables.

A common method for performing predictions with Bayesian kriging is to take observations and construct a regular lattice over them. In this study, we have considered a more computationally efficient approach. Using the INLA SPDE module we have created a triangulation around the sampled points in the region of interest (Figure 2). As opposed to a regular grid, a triangulation is a partition of the region into triangles, satisfying constraints on their size and shape in order to ensure smooth transitions between large and small triangles. Initially, observations are treated as vertices for the triangulation, and extra vertices are added heuristically to minimize the number of triangles needed to cover the region subject to the triangulation constraints. These extra vertices are used as prediction locations. The triangulation approach has several advantages over a regular grid. First, the triangulation is denser in regions where there are more observations and consequently there is more information, and more detail is needed. Second, it saves computing time, because prediction locations are typically much lower in number than those in a regular grid. Third, it is possible take into account the boundary effects generating a mesh with small triangles in the domain of interest, and use larger triangles in the extension used to avoid boundary effects.

Once the prediction is performed in the sampled fishing location, INLA provides additional functions that linearly interpolate the results to the whole area. As a result of the process, for each point of the area we obtain a predictive posterior distribution of the discard abundance. This means that for each posterior distribution, unlike the mean and confidence interval produced by frequentist analyses, we are able to make explicit the probability statements about the estimation. Thus, the region bounded by the 0.025 and 0.975 quantiles of the posterior distribution has an intuitive interpre-

Table 2 The five most discarded and caught species for the two different sampled metiers, with the respective quantity discarded and caught during the time series.

metier	Discarded species	Discards (kg.)	Catch (kg.)	Caught species	Discards (kg.)	Catch (kg.)
OTB-DES						
	B. boops	6,497	6,731	*B. boops*	6,497	6,731
	P. acarne	3,043	4,895	*O.vulgaris*	191	5,583
	S. canicula	2,303	3,244	*P. acarne*	3,043	4,895
	P. erythrinus	1,304	2,592	*M. poutassou*	787	4,438
	T. trachurus	1,165	3,742	*T. trachurus*	1,165	3,742
OTB-DWS						
	L. crocodilus	578	578	*A. antennatus*	8,8	3,893
	G. melastomus	471	1459	*G. melastomus*	471	1,459
	L. caudatus	218	218	*M. poutassou*	18	1,291
	S. canicula	191	422	*P. blennoides*	79	1,279
	E. spinax	164	165	*G.longipes*	25	1,037

tation: under the model, the unknown discard estimation is 95% likely to fall within this range of values.

Interestingly, INLA performs simultaneously the prediction with the inference, considering the prediction locations as points where the response is missing (see the INLA web page for more details).

For each metier, maps of the posterior mean from the predictive distribution were plotted to illustrate the predicted DPUE in this area. In addition, the posterior mean and standard deviation of the spatial component were displayed to detect hidden spatial patterns.

3 Results

A total of 440 hauls (343 OTB-DES and 97 OTB-DWS) were analysed over the period 2009 to 2012 in the study area. For the OTB-DES the total catch in the entire time series is about 81,126 kg. with a total discard about 27,406 kg., which is equivalent to a proportion of 34%. This proportion is about 20% for the OTB-DWS, with 15,158 kg. of total catch and about 3,100 kg. of total discards.

In the Table 2 are listed the five most discarded and caught species (in terms of weight), for the two different metiers, with the respective quantity discarded and caught during the time series.

For the OTB-DES metier, the bogue (*B. boops*) represents about the 23% of the total discards between the 2009 and 2012, followed by the axillary seabream (*P. acarne*) with a 11% and the small-spotted catshark (*S. canicula*) with a 8%. In addition to being the most discarded species, the bogue is also the most caught species, representing the 8% of the total catch of the OTB-DES. The common octopus, which is one of the target species of this metier, is the second species most captured, representing the 7% of the total catch and with only a 3% of discards. The axillary seabream is the third species most captured, about the 6% of the total catch of this metier. Catch of European hake, which is one of the main target species of this metier, are only tenth in abundance, accounting for approximately 4% of the total catch.

For the OTB-DWS metier, the jewel lanternfish (*L. crocodilus*) accounts for the 19% of the total discards, followed by the blackmouth catshark (*G. melastomus*) with a 15% and the silver scabbardfish (*L. caudatus*) with a 7%. The red shrimp is the target species of this metier and the most caught, representing the 26% of the total catch and only a 0.3% of the discards. Blackmouth catshark is the second species most captured, in addition to being the second most discarded species. It represents the 10% of the total catch for this metier and is discarded with a 32%. Blue whiting (*M. poutassou*) is the third most caught species for this metier, accounting for 9% of the total catch. For both metiers the large proportion of catch and discards is represented by non-target and species of low commercial value.

Bayesian models showed that the relative importance of each variable was different for each metier, with a few similarities.

As shown in Tables 3 and 5, both measures agree on the same model, with a reasonable predictive quality. It is worth mentioning that only some of the fitted models (the most relevant) are presented for space reasons.

For both metiers, no relevant inter-annual differences were found in this area for the discard variability. All models with the temporal effect, show higher DIC with respect to those without it.

Table 3 Model comparison for the OTB-DES metier. The acronyms are: D= Depth, S= Slope, O= Orientation, TS= Type of Seabed, M= Moon, L(C)= Log(CPUE), L= Light, V= Vessel effect, VL= Vessel's length, Q= Quarter, $\boldsymbol{\theta}$ = Spatial effect, Y = temporal effect.

	Model	LCPO	DIC
1	$(1 + D + S + O + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta} + Y)^2$	0.76	568
2	$1 + D + S + O + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta} + Y$	0.54	378
3	$1 + D + S + O + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta}$	0.50	353
4	$1 + D + S + O + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta}$	0.67	325
5	$1 + D + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta}$	0.47	320
6	$1 + D + TS + M + L(C) + V + VL + Q + \boldsymbol{\theta}$	0.45	310
7	$1 + D + TS + M + L(C) + V + Q + \boldsymbol{\theta}$	0.39	302
8	$1 + D + M + L(C) + V + Q + \boldsymbol{\theta}$	0.34	298
9	$1 + D + M + L(C) + V + Q$	0.28	292
10	$1 + D + M + L(C) + V + Q + \boldsymbol{\theta}$	0.23	286

In the OTB-DES metier, the model selected for its best fitting (based on the lowest DIC and LCPO) (Table 3) includes the bathymetry, the log-transformed CPUE, the moon phase, the quarter of the year and the vessel random effect as covariates, plus a stochastic spatial component that accounts for the residual spatial autocorrelation. Table 4 presents a numerical summary of the posterior distributions of the fixed effects for this final model.

Among the environmental variables, slope, orientation and the type of the seabed were found to be irrelevant on the variability of DPUE abundance. No difference was found between day and night trawling. The vessel random effect was relevant for all models, while the vessel's length was not relevant.

Results showed a negative relationship between bathymetry and the DPUE: the posterior mean being -0.22 and the 95% Credible Interval being [-0.35,-0.09] (inter-

Table 4 Numerical summary of the posterior distributions of the fixed effects for the OTB-DES metier.

Predictor	Mean	Sd	$Q_{0.025}$	$Q_{0.5}$	$Q_{0.975}$
(Intercept)	-2.54	0.48	-3.48	-2.54	-1.60
Moon(Full)	-0.25	0.16	-0.56	-0.25	0.06
Moon(Crescent)	0.17	0.16	-0.14	0.17	0.48
Moon(Waning)	0.10	0.16	-0.21	0.10	0.41
Depth	-0.22	0.07	-0.35	-0.22	-0.09
Log(CPUE)	1.43	0.05	1.34	1.43	1.52
Quarter 2	1.85	0.55	0.78	1.85	2.92
Quarter 3	1.55	0.57	0.43	1.55	2.67
Quarter 4	0.16	0.55	-0.92	0.16	1.25

pretation of this regression coefficient is the usual one: an increase in depth of $100m$ implies that the expected value of discards will be reduced in exp(2.2) = 9.03 *kg*.). Conversely, the log-transformed CPUE showed a positive relation with respect to the amount of DPUE (posterior mean = 1.43; 95% CI = [1.34,1.52]).

The full moon phase shows a lower estimated DPUE (posterior mean = -0.25; 95% CI = [-0.56,0.06]) with respect to the reference level (new moon). Also, waning moon showed a lower estimated coefficient than the reference level (posterior mean = 0.10; 95% CI = [-1.21,0.41]), leaving the crescent moon as the lunar categories with the highest estimated DPUE abundance for the OTB-DES metier (posterior mean = 0.17; 95% CI = [-1.14,0.48]).

All the estimated coefficients of the quarters of the year show higher DPUE than the reference level (first quarter). In particular, the second quarter shows the highest estimated DPUE (posterior mean = 1.85; 95% CI = [0.78,2.92]) with respect to the baseline.

Higher values of DPUE in the OTB-DES metier are on shallow waters, on the crescent moon and in the second quarter of the year, and when the CPUE is higher.

Figure 3 shows the predictive spatial distribution of discards, influenced by the relevant factors, in the GSA06 South area. Discards of the OTB-DES metier show a longitudinal gradient, with the highest values in the central western part of the GSA06 South, along the coastline.

Figure 4 displays the posterior mean and standard deviation of the spatial component. The effect of the spatial component was consistent for all models. This component shows different marked hot spots with positive values in the western part, near the coast, and sporadic areas that show negative values.

The best model fitting for the OTB-DWS metier includes the log-transformed CPUE, quarter of the year, moon phase, vessel length and type of substratum as relevant covariates together with the vessel and spatial random effects (Table 5).

Moon effects change smoothly declining from full moon (posterior mean = -0.07; 95% CI = [-0.50,0.35]) through to waning moon phase (posterior mean = -0.28; 95% CI = [-0.69,0.12]) with respect to the reference level (new moon)(Table 6).

As in the OTB-DES metier, the log-transformed CPUE shows a positive relationship with respect to the DPUE abundance (posterior mean = 1.09; 95% CI = [0.93,1.24]).

Table 5 Model comparison for the OTB-DWS metier. The acronyms are: D= Depth, S= Slope, O= Orientation, TS= Type of Seabed, M= Moon, L(C)= Log(CPUE), L= Light, V= Vessel effect, VL= Vessel's length, Q= Quarter, $\boldsymbol{\theta}$ = Spatial effect, Y = temporal effect.

	Model	LCPO	DIC
1	$(1 + D + S + O + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta} + Y)^2$	0.69	408
2	$1 + D + S + O + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta} + Y$	0.45	389
3	$1 + D + S + O + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta}$	0.50	353
4	$1 + D + S + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta}$	0.47	325
5	$1 + D + TS + M + L(C) + L + V + VL + Q + \boldsymbol{\theta}$	0.47	320
6	$1 + D + TS + M + L(C) + V + VL + Q + \boldsymbol{\theta}$	0.45	310
7	$1 + TS + M + L(C) + V + VL + Q + \boldsymbol{\theta} + Y$	0.39	312
8	$1 + TS + M + L(C) + V + VL + Q + \boldsymbol{\theta}$	0.43	305
9	$1 + TS + M + L(C) + V + VL + Q$	0.28	298
10	$1 + TS + M + L(C) + V + VL + Q + \boldsymbol{\theta}$	0.16	158

Table 6 Numerical summary of the posterior distributions of the fixed effects for the OTB-DWS metier.

Predictor	Mean	Sd	$Q_{0.025}$	$Q_{0.5}$	$Q_{0.975}$
(Intercept)	0.05	0.23	-0.41	0.05	0.51
Moon(Full)	-0.07	0.22	-0.50	-0.07	0.35
Moon(Crescent)	-0.12	0.20	-0.51	-0.12	0.28
Moon(Waning)	-0.28	0.21	-0.69	-0.28	0.12
Log(CPUE)	1.09	0.08	0.93	1.09	1.24
Vessel length	0.06	0.03	0.01	0.06	0.12
Seabed(Mud)	0.12	0.19	-0.26	0.12	0.49
Seabed(Rock)	-0.07	0.35	-0.75	-0.07	0.60
Quarter 2	0.13	0.15	-0.16	0.13	0.42
Quarter 3	0.10	0.16	-0.22	0.10	0.41
Quarter 4	-0.02	0.15	-0.32	-0.02	0.29

Regarding seabed, the rock substratum shows the lowest estimated DPUE (posterior mean = -0.07; 95% CI = [-0.75,0.60]) with respect to the reference level (sand substratum). Muddy substrata showed a higher estimated coefficient than the reference level (posterior mean = 0.12; 95% CI = [-0.26,0.49]).

In this case the depth is not relevant, and neither are the slope and orientation of the seabed, as in the OTB-DES metier. Nor in this metier the presence or absence of light during the hours of trawling was found relevant for the DPUE.

The second quarter of the year shows the highest estimated DPUE (posterior mean = 0.13; 95% CI = [-0.16,0.42]) with respect to the reference level (first quarter), while the fourth quarter show the lowest estimated coefficient (posterior mean = -0.02 ; 95% CI = [-0.32,0.29]).

The vessel random effect and the vessel's length were relevant for all the fitted models. In particular, longer vessels show higher DPUE values (posterior mean =0.06; 95% CI = [0.01,0.12]).

The higher values of DPUE of the OTB-DWS metier are recorded for longer vessel, on muddy substrata, in the second quarter of the year, when the moon phase is new and the CPUE is higher.

Both, the map of the predictive spatial DPUE values, and the map the posterior mean of the spatial effect (Figure 5 and 6a) show a patchy distribution of the DPUE of the OTB-DWS metier. In particular, Figure 5 and 6 show three marked hot spots with higher DPUE values.

4 Discussion

Estimation of discards and knowledge about the reasons why the discard process occurs, have been recognized to be crucial for improving stock assessments and exploring the impacts of fishing on the ecosystem (Tsagarakis et al 2012). The latter has gained attention during the last decade since ecosystem approach to fishery management (EAFM) has been established as a priority in fishery science (Bellido et al 2011). Solving the problem of discards is quite complex, since discards show high variability across time, space and metiers due to the numerous factors affecting them, including, among others, technical characteristics, environmental conditions and species composition (Rochet and Trenkel 2005).

It is known that, among different fishing gears, the trawl is responsible for most fisheries discards (Tsagarakis et al 2008). In the Mediterranean, the discarded fraction of otter-trawl catches ranges from 20 to 70% by weight (Carbonell et al 1998; Machias et al 2001; Kelleher 2005). In our study area, for the whole sampled fleet of trawlers, the discarded fraction accounted for 31% of the total catch, specifically a 34% of own total catch for OTB-DES and 20% for OTB-DWS metier.

Similar studies on demersal trawls, in a broad scale, reported a higher discard ratios, such as in the northeastern Mediterranean sea (38-49%; (Machias et al 2001; Tsagarakis et al 2008)). However, the discard ratio of the OTB-DES and OTB-DWS in the study area was higher than that of mid-water trawls in the Turkish Black Sea (5.1%; (Kelleher 2005)) and the Adriatic (up to 15%; (Santojanni et al 2005)).

From a point of view of the species composition, the results show that the large proportion of catch and discards is represented by non-target and non-commercial species. In particular, in the OTB-DES metier, bogue and axillary seabream are the most discarded and caught species, representing up to a 32% of total discards. In the OTB-DWS metier the species most captured corresponds with the target species (red shrimp) of this metier, unlike the OTB-DES where the main target species are european hake, which is the tenth most captured species. Among the high commercial value species, such as the red shrimp and octopus, their discards are negligible for both metiers (respectively 0.3% and 3%). Moreover, a large fraction of the discards of both metiers (10%), consists of elasmobranch species, which are considered vulnerable species due to their biology and K-selection life-history traits (Pennino et al 2013). Discard non-target species may have negative consequences for both commercial and non-commercial species owing to the effects on species interactions and cascading effects throughout the trophic web.

Previous studies that have investigated the spatio-temporal variability and factors influencing discards have focused only on target species or species with a high commercial value, as well as global discard estimates. To investigate only the spatio-temporal variability and quantity of the target species discards could lead to underestimated and biased conclusion about this fleet.

In order to overcome this problem, and to understand which factors influence the variability of the discards, the DPUE of each haul, shared by metier, has been modeled with respect to environmental and technical characteristics of fishing operations for each metier.

Our analysis, performed using Bayesian methods, showed that the relative importance of each variable was different for each metier, with a few similarities. Interestingly, for both metiers, the discarded quantities were not found to be related to factors such as day light of the haul or environmental factors such slope and orientation of seabed.

Only for OTB-DWS metier, the vessel length influences the DPUE. Longer vessel implies greater catch and implicitly a higher discard fraction. Indeed, one of the main driving variables that explain the discard variability is the abundance of catch. Our results show a direct and positive relationship between the CPUE and the DPUE, more catch involve an increase on DPUE for both metiers.

Surprisingly, for both metiers, moon phase has been relevant on discard variability. As mentioned previously, a considerable part of discard consists of elasmobranch species, whose distribution has been related by several studies with the lunar phases (Poisson et al 2010; Cuevas-Zimbrón et al 2011).

The type of seabed was only relevant for the OTB-DWS metier. The muddy substratum are those with a higher amount of DPUE. A recent study (Pennino et al 2013) of the sensitive habitats for the three most frequently captured species (*Scyliorhinus canicula*), *Galeus melastomus*, *Etmopterus spinax*), which coincides with the most discarded ones, has found that the habitat preference of these species is for hard and sandy substrates with respect to muddy seabeds in this area. Then the relationship between the type of seabed and the discard abundance probably reflect the selection of the fishing grounds by fishermen and the distribution of the target species of the metier. Indeed, as mentioned before, the target species of the OTB-DWS metier is the red shrimp (*Aristeus antennatus*) that is commonly associated with dense, muddy bottoms (Guijarro et al 2008).

Another factor that influences the DPUE in the OTB-DES metier is the depth. As also highlighted by Lorance (1998) and Blasdale et al (1998), the depth-related variations of discard rates and quantities are linked to differences in species composition of the fish communities and in the length–frequency distribution of some species (Allain et al 2003). Species replace each other according to their bathymetric and geographical preferences. Thus, the bogue, which is the most discarded and caught species of this metier, is particularly abundant between 50 and 200 m., which explains the increase of both discard rate and fish biomass in the shallow waters. This results from an overlap between target and non-target species. Indeed, the European hake and the Octopus, that are the target species of the OTB-DES metier, share the same bathymetric prevalence of the bogue (Abella et al (2008).

Furthermore, discarding is a process decided on board based on the specific fisherman behaviour that could be influenced by the size of the catch, market prices of species and/or takes into account legal constraints. In our results, the random vessel effect should collects this hidden variability that, other way could not be analyzed.

Discards fluctuated greatly in each metier, but did not show any relevant temporal trends among years. On the contrary, intra-annual variability was a relevant variable for both metiers. In particular, the second quarter of the year is the period which recorded highest abundance of discards for both metiers. This is probably due to the recruitment of most species occurs during this period, as well as of the absence of trawling in the previous months (Abella et al (2008). These seasonal discard process can be attributed to the targeting behaviour of the fishermen and the condition/behaviour of species during different seasons.

The spatial effect explained much of the variability in DPUE quantities for both metiers. The spatial random component may reflect the effect of other hidden factors, such as community composition, distance from the coast, productivity gradients etc., and can contribute to making a good estimate of discards. Maps show a clear spatial longitudinal gradient for the OTB-DES metier, with highest discards in the central western part of the study area, along the coastline. This trend is confirmed by the relevant negative relationship between the abundance of discards and the fishing depth variable. The DPUE is higher on shallow waters, along the coastline and may reflects the selection of fishing grounds of this metier.

The map of the spatial component of the OTB-DES metier shows several hot spots with high discard values and sporadic areas with lower discard abundance. Probably, this trend reflects the resources distribution, and it is very useful to identify sensitive areas that could be avoided by fisheries in order to decrease discards.

Moreover, the spatial predictive discard map and the spatial effect map of the OTB-DWS metier, highlight clear hot spots of DPUE.

The identification of these areas of high concentration of discards could be an important benefit for the spatial management of the fleet. The inter-annual/spatial effects could potentially be exploited in an overall strategy of the spatial management to reduce discard rates, providing the necessary economic incentive for fishermen to adopt selective temporal rotation of fishing grounds. Our findings show that the spatial variability in the discard rates can potentially be exploited in a general strategy to reduce discards. A similar approach was proposed for the USA mixed species otter trawl fisheries of the Georges Bank-Southern New England region. By limiting directed fishing to times and places where resources are segregated, the quantity of unintended catch could potentially be reduced (Murawski 1996). To achieve these purposes, predictive spatial maps, like the ones our approach generates, could be essential tools to implement an efficient spatial management and control schemes to reduce discards.

5 Conclusions

Spatial fisheries ecology has a direct applied relevance to resource management, but it also has a broad ecological significance. Our results identify that a large fraction of the discards of both metiers are represented by elasmobranchs species. The assessment of elasmobranch discard hotspots is an important first step towards the development of a management program to ensure the sustainability of vulnerable species and the discard reduction. Although it may be complicated to define the boundaries of these hotspots combined with an efficient fishery management that recognizes the importance of such areas, this represents the first step towards facilitating an effective Ecosystem Approach to Fishery Management. However, misidentification of hotspots and uncertain predictions can culminate in inappropriate mitigation practices which can sometimes be irreversible. The proposed Bayesian spatial method overcomes these issues, since it offers a unified approach which allows the incorporation of spatial random-effect terms, spatial correlation of the variables and the uncertainty of the parameters in the modelling process, resulting in a better quantification of the uncertainty and accurate predictions.

However, there are two issues that still need to be addressed. Firstly, discards and environmental data are sampled during a limited period of time and space and so, models fitted can reflect only a snapshot view of the expected relationship. Future studies should compare the temporal and spatial trends of discards from additional sources of data with a widest spatial and temporal coverage (Cao et al 2011).

Secondly, the model developed in this study is a Linear Mixed Model (LMM), which assumes linearity between the dependent and explanatory variables. However, many studies suggest that functional relationships between CPUE or DPUE and environmental variables are likely to be non-linear suggesting the use of a General Additive Model (GAM). However, over-fitting can be a problem with GAMs, which often make the fitted relationship perform less well on the data set used for model fitting (Everitt 2002).

Finally, we would like to mention that the Bayesian analytical approach we used here to document the spatial patterns of the trawl fleet of the study area, can be extended to different metier or specific species in an easy way and in order to improve knowledge of the discard process.

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Figure legends

Figure 1: Map of the study area with the sampling locations indicated by black dots.

Figure 2: Fishing locations of the OTB-DES metier (•) and the OTB-DWS metier (•) in the GSA06 South; each mesh vertex is either an observed point or a prediction point.

Figure 3: Posterior mean of the predictive discard abundance of the OTB-DES metier. This prediction has been obtained with the model selected for its best fitting, which includes the bathymetry, the log-transformed CPUE, the moon phase, the quarter of the year and the vessel random effect as covariates, plus a stochastic spatial component that accounts for the residual spatial autocorrelation.

Figure 4: The posterior mean (A) and standard deviation (B) of the spatial effect of the OTB-DES metier. The spatial component represents the intrinsic spatial variability of the data without variables.

Figure 5: Posterior mean of the predictive discard abundance of the OTB-DWS metier. This prediction has been obtained with the best model fitting, which includes the log-transformed CPUE, quarter of the year, moon phase, vessel length and type of substratum as relevant covariates together with the vessel and spatial random effects

Figure 6: The posterior mean (A) and standard deviation (B) of the spatial effect of the OTB-DWS metier. The spatial component represents the intrinsic spatial variability of the data without variables.

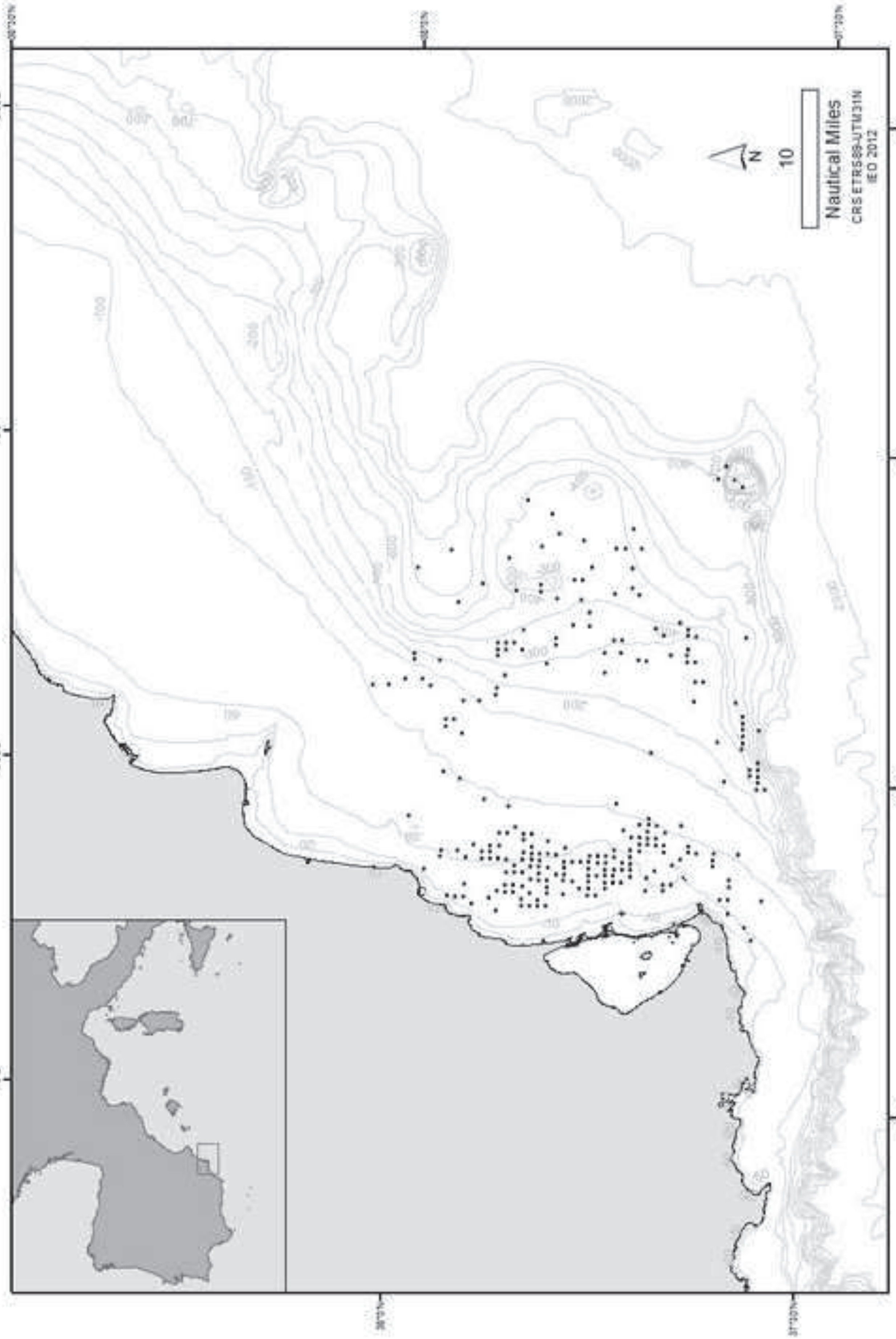


Fig.1

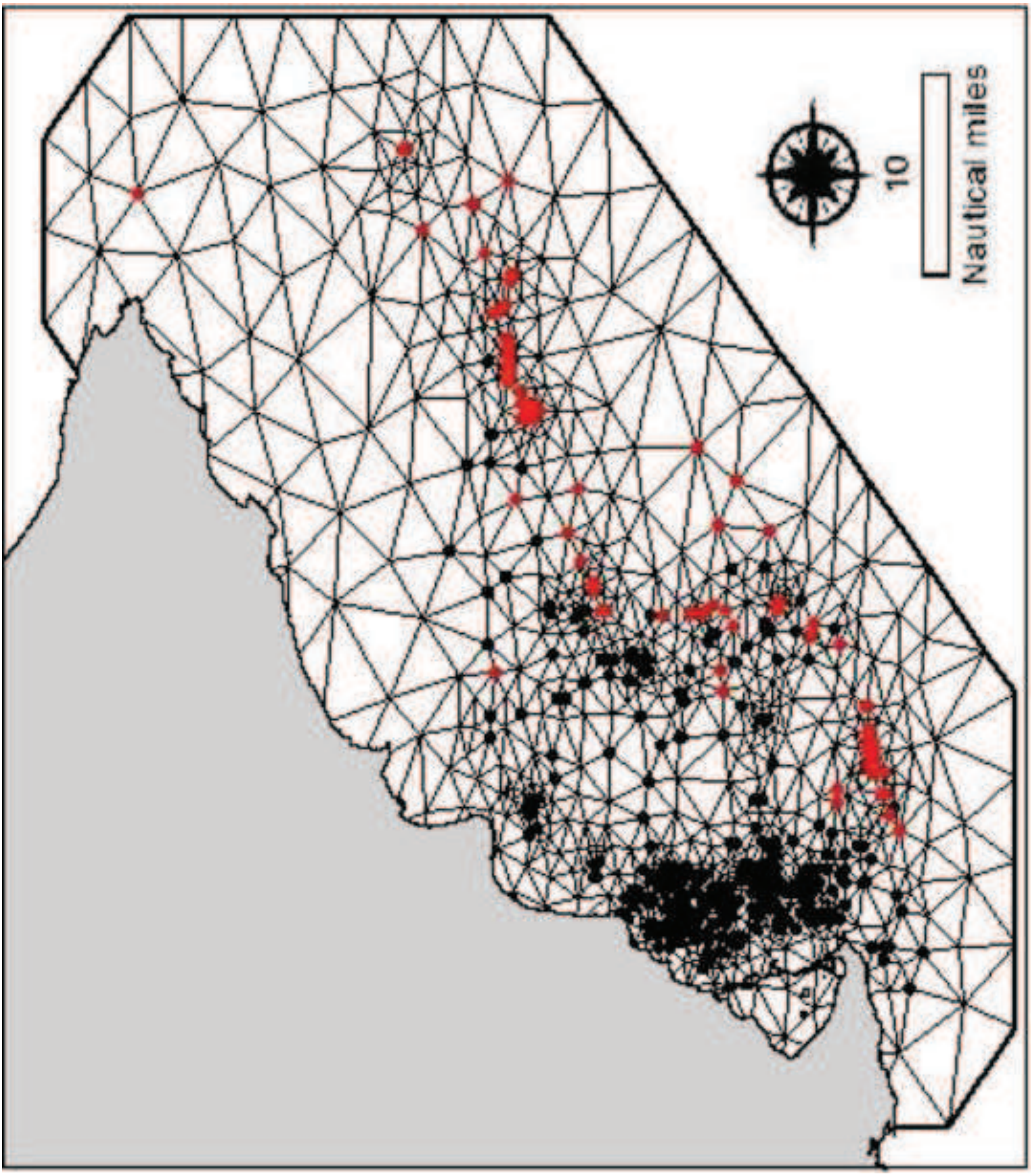
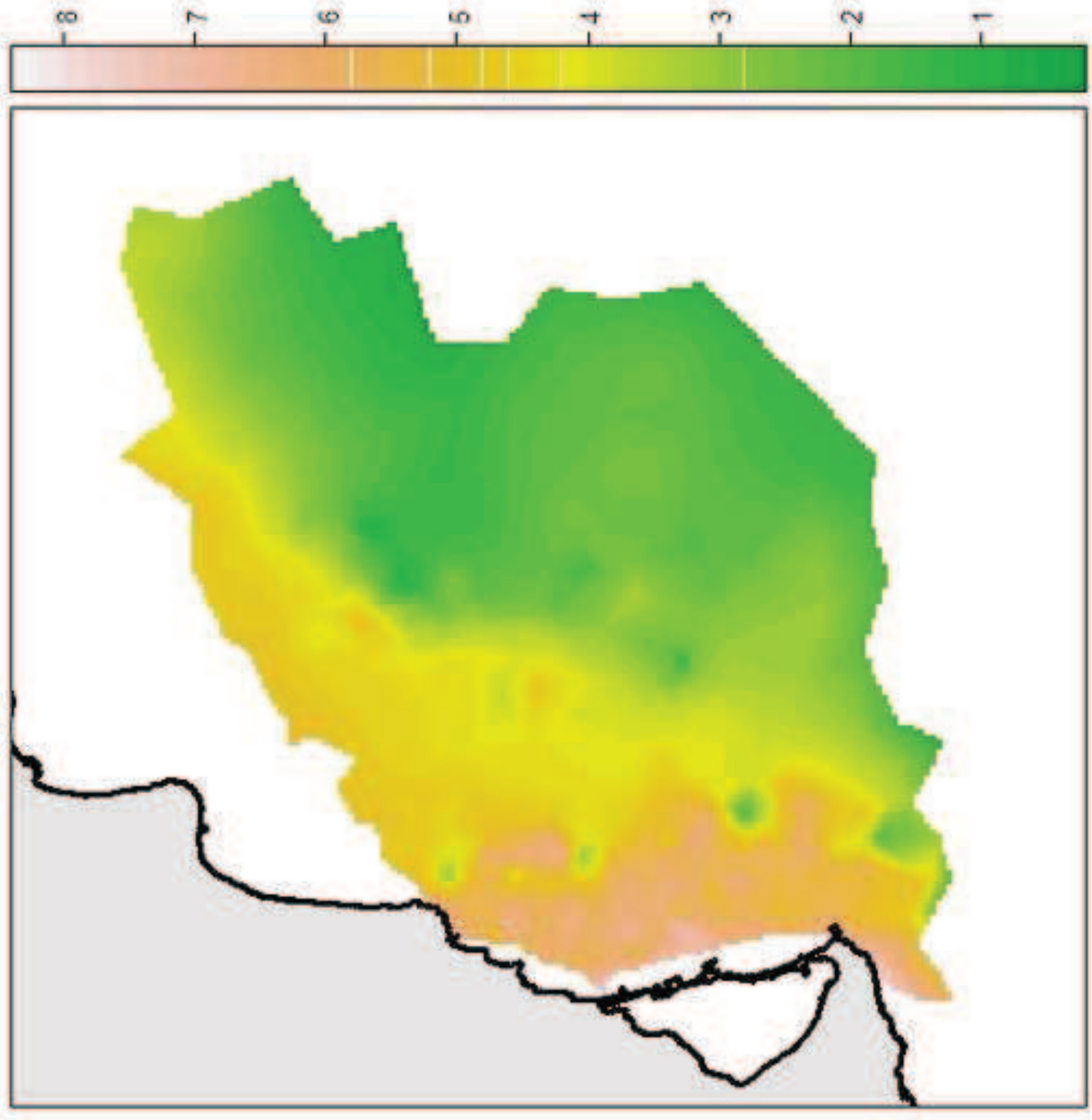


Fig.2



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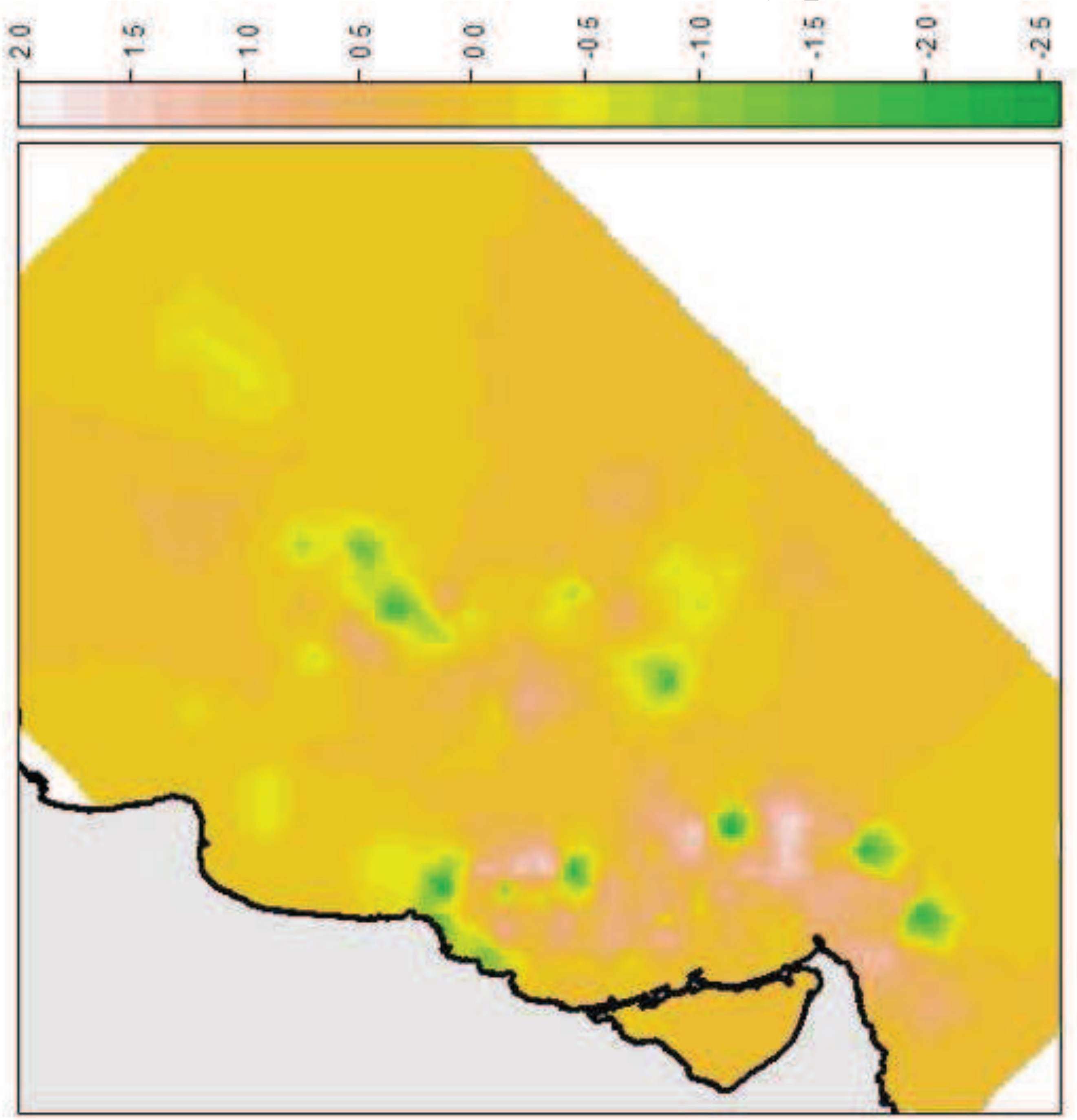

Fig.4a

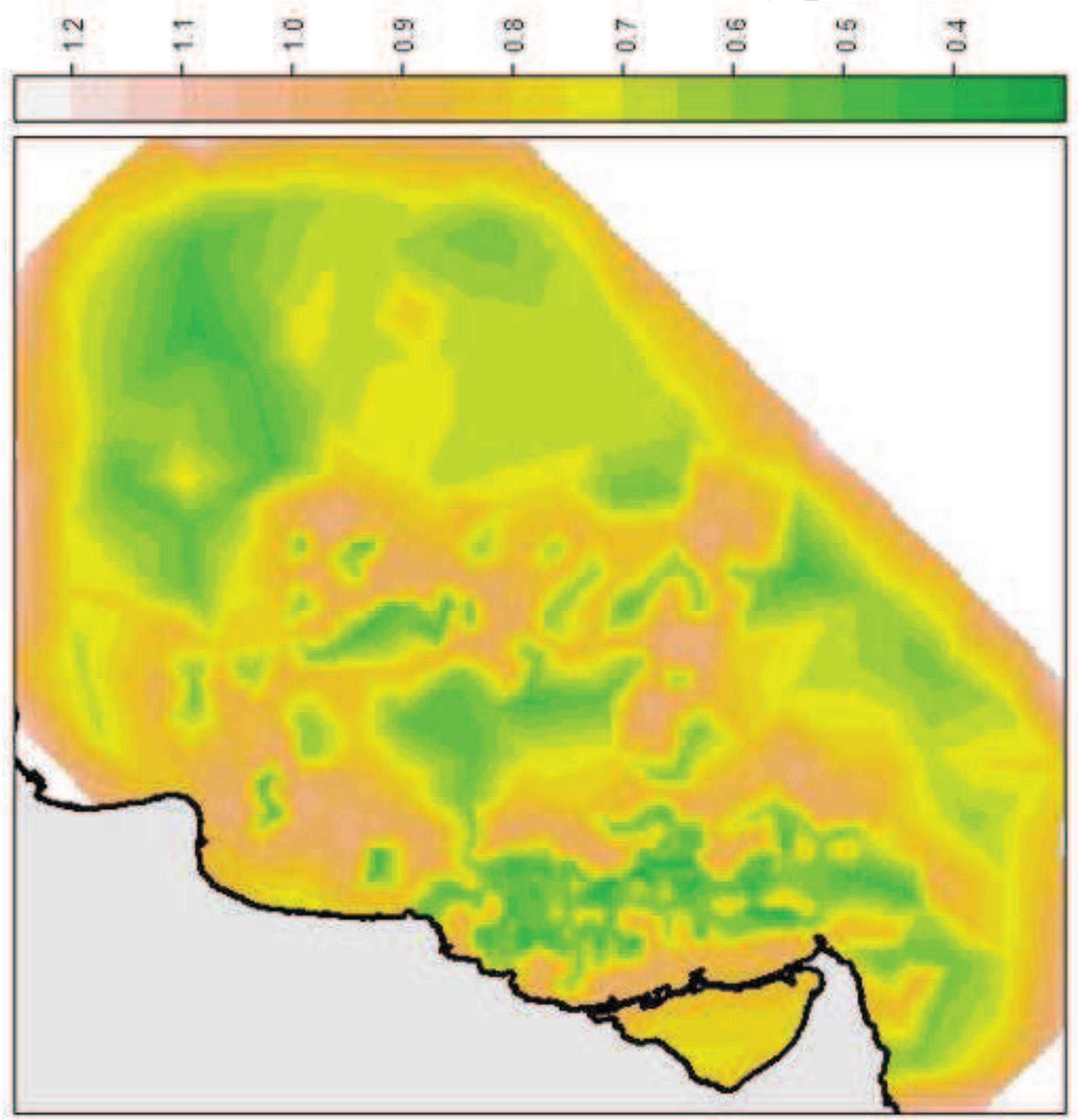

Fig.4b

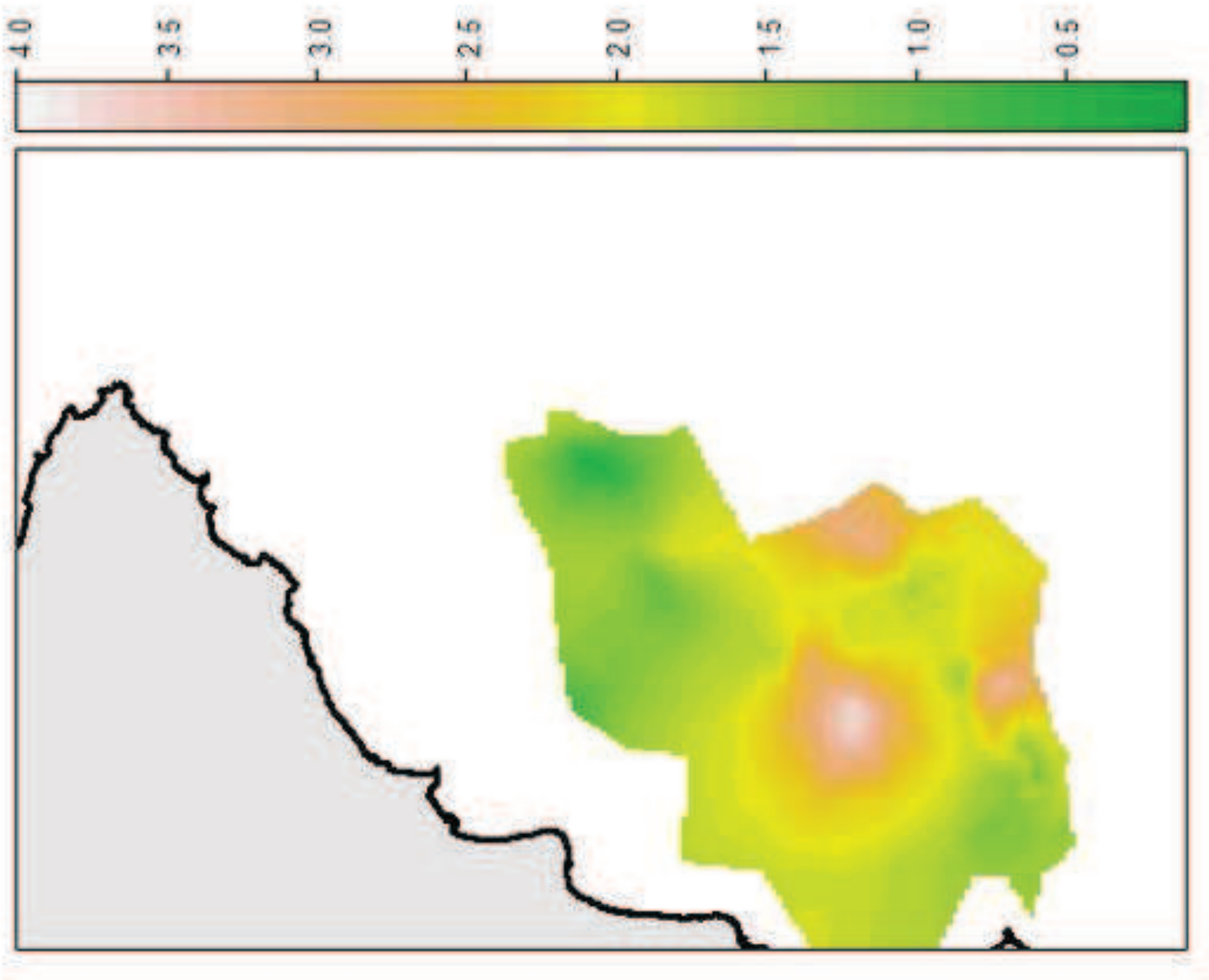

Fig.5

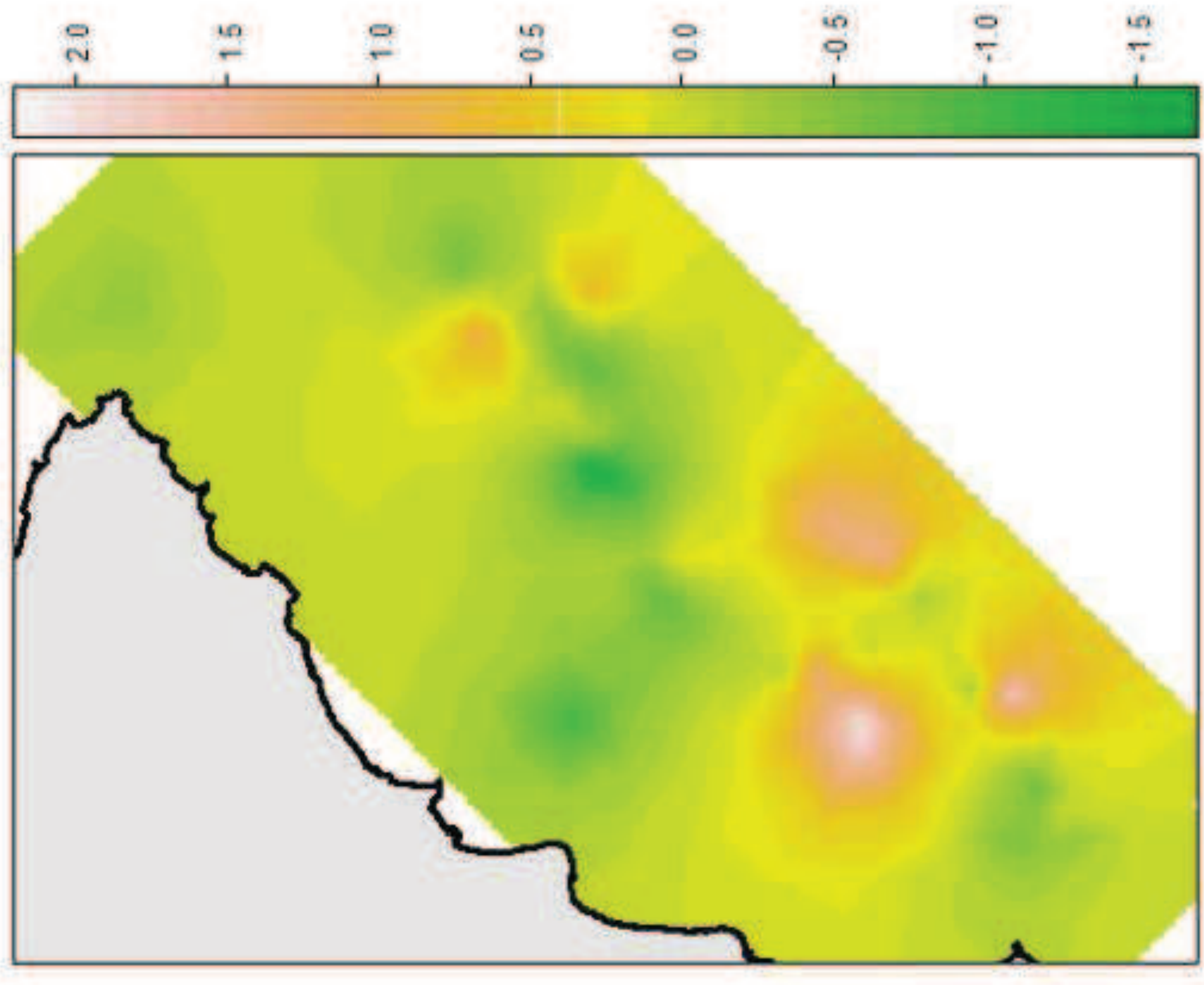

Fig.6a

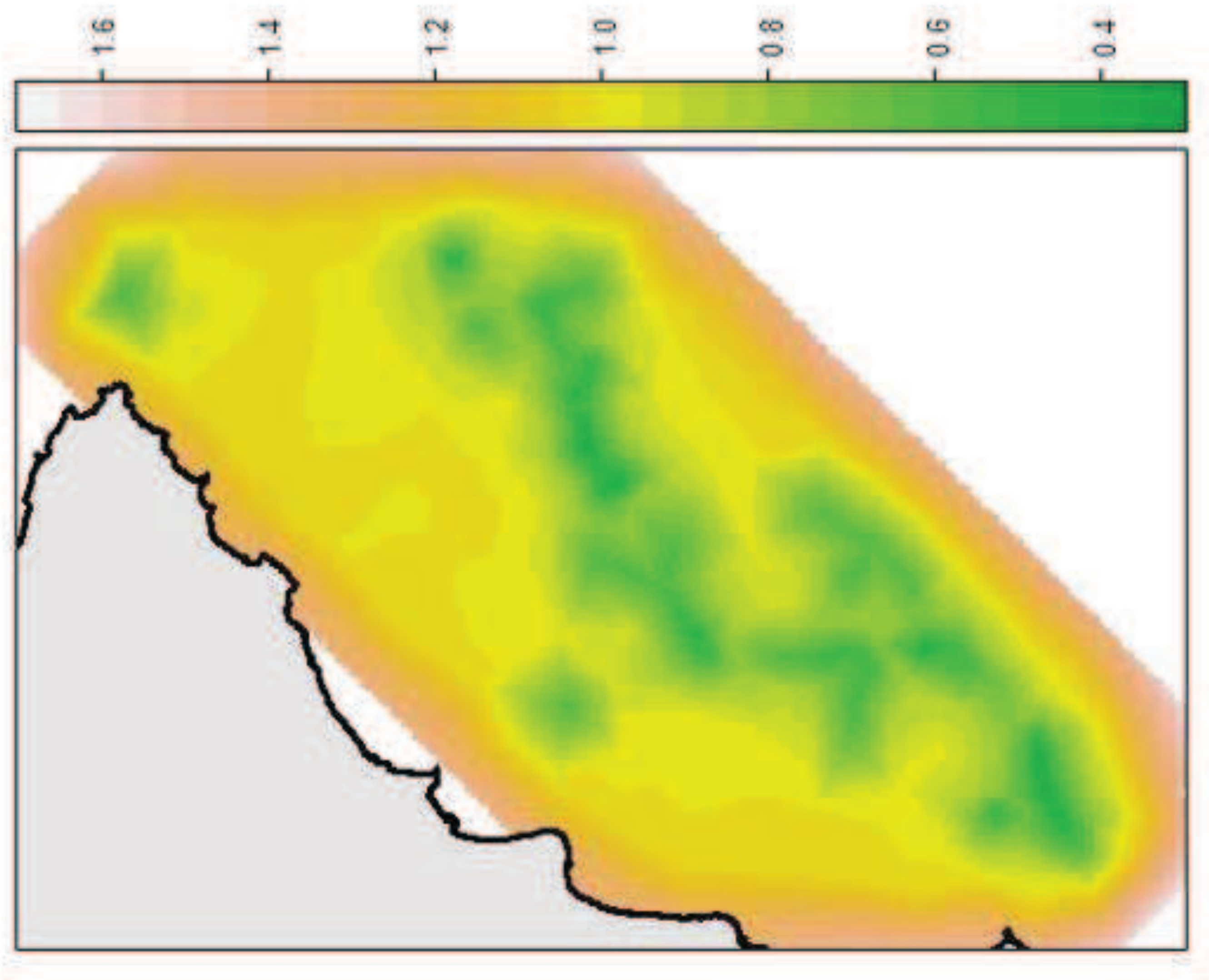

Fig.6b

Highlights

Bayesian models have been used to identify the spatio-temporal discard distribution.

Discards are influenced by different factors that are similar for both metiers.

Spatial predictive maps highlight clear hot spots of discard abundance.

The 10% of the discards aggregated in specific hot spots are elasmobranchs.

The identification of these areas could be an essential tool for the MSP.