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Integrating spatial management measures into fisheries: The *Lepidorhombus* spp. case study

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ABSTRACT

Most fisheries management systems rely on a set of regulatory measures to achieve desired objectives. Controls on catch and effort are usually supplemented with gear restrictions, minimum landing sizes, and in the framework of the new common fisheries policy, limitation of discards and by-catch. However, the increasing use of spatial management measures such as conservation areas or spatial and temporal area closures faces new challenges for fishery managers. Here we present an integrated spatial framework to identify areas in which undersized commercial species are more abundant. Once these areas are identified they could be avoided by fishers, minimizing the fishing impact over the immature fraction of the stocks. In particular we applied this methodology to two species of megrim, *Lepidorhombus whiffiagonis* and *L. boscii*, in North Atlantic Iberian waters (ICES Divisions 8c and 9a), analyzing fishery-independent data provided by bottom-trawl surveys and environmental data through Bayesian spatial models. Results show that species exhibit species-specific spatial patterns, and we identified sensitive areas that could be used for conservation purposes. We discuss integrating technical measures together (e.g. Minimum Conservation Reference Size and spatial closures) could be a more effective approach for fishery management and this case study could be extended to other species.

1. Introduction

Since 2015, a series of new management measures have been progressively implemented with a view to minimizing the discards of commercially valuable species in European Union (EU) fisheries [1–3]. These actions have been developed under the Landing Obligation (LO) mandate, established in Article 15 of EU Regulation 1380/2013 (European Common Fisheries Policy, CFP). The LO prohibits the discarding of species which are subject to catch limits (TAC and quotas) and those which are subject to minimum landing sizes (MLS) in the Mediterranean. European Union fishing vessels shall bring and retain on board, record, land and count the unwanted catch against the quotas [3]. This political decision is one of the most important shifts in EU fisheries harvest rules in recent decades and it will determine the future of fishing exploitation with several important socio-economic implications; economic incentives for advancement in gear selectivity, changes in fishing behavior, and an expected decrease in benefits per fishing effort, among others yet to be established [1].

An adaptive response will be required from fishers and stakeholders under this new CFP in order to avoid the loss of legitimate catch. For this reason, fishers, stakeholders and also policy makers are now demanding more effective tools that can be used to facilitate this adaptation. In particular, the use of spatial tools could be very useful within this framework [4–6]. Indeed spatial management measures such as conservation areas or spatial and temporal area closures, as opposed to the classic set of regulatory and technical actions, could improve not only the protection of vulnerable zones such as nurseries and spawning habitats, but also the socio-economic trade-off of CFP implementation.

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In the context of LO, these spatial techniques could help to identify and avoid high-intensity discard zones [6,7], even in real-time [8] and could have a role to play in a more effective assessment of whether and where undersized species are aggregated. Once identified, these areas could be avoided by fishers, thus minimizing the fishing impact on the immature fraction of the stocks and their ecosystem [5,8]. Indeed, one of the main reasons for discarding commercial species is that the individuals caught are below Minimum Conservation Reference Size [1,9], previously known as minimum landing size. In addition, other problems derived from discarding undersized individuals may have further side effects such as high-grading and the choke species effect. High-grading refers to the practice of retaining larger individuals while discarding the smaller ones even if they are above the Minimum Conservation Reference Size [10]. The choke effect implies that for the species with Total Allowable Catch (TAC), undersized catches must be landed under the LO and this proportion will count against the quota but cannot be sold for direct human consumption [11].

As previously mentioned, the LO brings with it a series of changes that will represent a challenge for fishermen and the industry, potentially involving additional costs in fishing operations in terms of time and work [3] and that would be potentially reduce commercial-size catch that can be sold. Within this context and in order to minimize this impact, the objective of this paper is to present a tool that facilitates the selection of fishing areas where the abundance of undersized individuals is lower. The integrated spatial framework to identify these areas using a Bayesian spatial model with environmental and bottom trawl survey data would provide assistance in the management of commercial species under LO in addition to other possible actions such as an improvement in fishing device selectivity.

As a case study to develop this tool, two flatfish species have been used, namely the whiff megrim (*Lepidorhombus whiffiagonis*) and the four-spot megrim (*L. boscii*) in North Atlantic Iberian waters (ICES divisions 8c and 9a). Indeed, for these species [12], reported that the principle reason for discarding is not reaching Minimum Conservation Reference Size (MCRS), which is 20 cm for both stocks. In fact, more than 90% of discards in weight were for this reason between 2011 and 2013 [12].

Previous studies show that the distribution of these species depends on environmental variables. *L. boscii* seem to be more abundant in deeper waters than *L. whiffiagonis* [13,14]. They seem to present a relation to the type of bottom, *L. whiffiagonis* preferred fine-medium sandy and *L. boscii* fine sandy sediments because of its different diets in adult stages [14]. Also, juveniles of both species can be present at deeper areas than other flatfish because they feed on detritivore crustaceans instead of zooplankton [13], being more accessible to the trawl fishery.

Throughout the last decade, megrim discards have been fluctuating in the area studied, from 10 to 47% of the total catch in individuals for *L. whiffiagonis* and between 39 and 67% for *L. boscii* [15], which represent very high percentages across all the European fisheries [2].

Given this significant percentage, effective technical measures based on the spatial distribution of these undersized fish could help to minimize the effects of the implementation of LO for the *Lepidorhombus* stocks.

2. Materials & methods

2.1. Megrim fisheries and stock status

Megrims are caught in mixed fisheries of bottom trawlers from Portuguese and Spanish fleets, generally targeting a heterogeneous group of demersal white fish and operating on the continental shelf and upper slope [13]. This fishing tactic does not show clear seasonality and megrim appear in most of the hauls. The target species are a number of valuable fish including European hake (*Merluccius merluccius*), anglerfish (*Lophius budegassa*), megrims (*Lepidorhombus boscii* and *L. whiffiagonis*), horse mackerel (*Trachurus* sp.), blue whiting (*Micromesistius poutassou*) and Norway lobster (*Nephrops norvegicus*) [16]. Megrim represent 5% of the total landings of the whole fishery and they have significant commercial value in the Spanish market. The more abundant of the two megrim species is the Four-spot megrim (*L. boscii*), representing 63%–94% between 1986 and 2017 (the entire period for which data are available) [15]. These species mature early and reach legal size at approximately age 2 [15].

These species are regulated in the area by a TAC quota system, both stocks sharing the same TAC. Over recent decades, this value has only been slightly exceeded by landings in one 3-year period (Fig. 1).

It is important to mention that these stocks are in accordance with the Maximum Sustainable Yield (MSY) target of the CFP in the latest scientific advice [17,18] with a sustainable fishing mortality below F_{MSY} (fishing mortality that produces the maximum sustainable yield) and the spawning stock biomass above the MSY $B_{trigger}$. These stocks are category 1, 'advice-rich' species, which means they undergo a complete analytical assessment and the biological reference points are defined.

2.2. Area studied

The area of interest of this study is the northern continental shelf of the Iberian Peninsula (i.e. ICES divisions 8c and the northern part of 9a). The continental shelf in this area has an extension ranging between 10 km and 60 km, with a total surface area of almost 18,000 km^2 [19]. A bottom-trawling fleet operates in these waters exploiting the rich fishing grounds.

The type of seabed on the inner shelf is mainly composed of rocky or sandy substrata in the Cantabrian Sea, mud and muddy sand bottoms in Galician waters, sandy grounds in Galicia and muddy ones in the Cantabrian Sea along the outer shelf [13,20]. The area is characterized by a significant and marked hydro dynamism. Winter fluxes from the warm poleward current result in a convergent front between coastal and oceanic waters [21]. Consequently, seasonal coastal upwelling (spring and summer) combined with hydrographic meso-scale activities along the northwestern shelf-break have a strong influence on the primary production of the area [22].

2.3. Lepidorhombus spp. data

Megrim data were collected during the scientific survey series "DEMERSALES" carried out in autumn (September to October) from 1993 to 2017 by the "Instituto Español de Oceanografía" (IEO). This bottom-trawl survey makes use of a stratified sampling design based on depth with three main bathymetric strata: 70–120 m, 121–200 m and 201–500 m (Fig. 2).

The sampling design used is proportional to the stratum surface area, and the number of ship-days available is also taken into consideration, which result in approximately 128 hauls (minimum 119 and maximum 141) per survey. Trawling operations were performed by day at a speed of 3 knots. Hauls lasted 30 min using the baka 44/60 gear and following the ICES IBTS protocols [23].

The total number of individuals caught per 30 min of trawling was used as a species abundance index for each sampling location. The species abundance of each megrim species was divided into two different categories, namely "undersized" and "commercial size". The criterion used to disaggregate the megrim categories has been to consider all specimens of less than 19 cm in length as undersized and the rest as commercial size.

2.4. Environmental variables

Both topographic (i.e., depth, slope, rugosity and type of seabed) and oceanographic variables (i.e., sea bottom temperature and sea bottom salinity) were used as predictors for megrim hot-spot areas. In particular, depth and parameters of seafloor complexity were identified as key

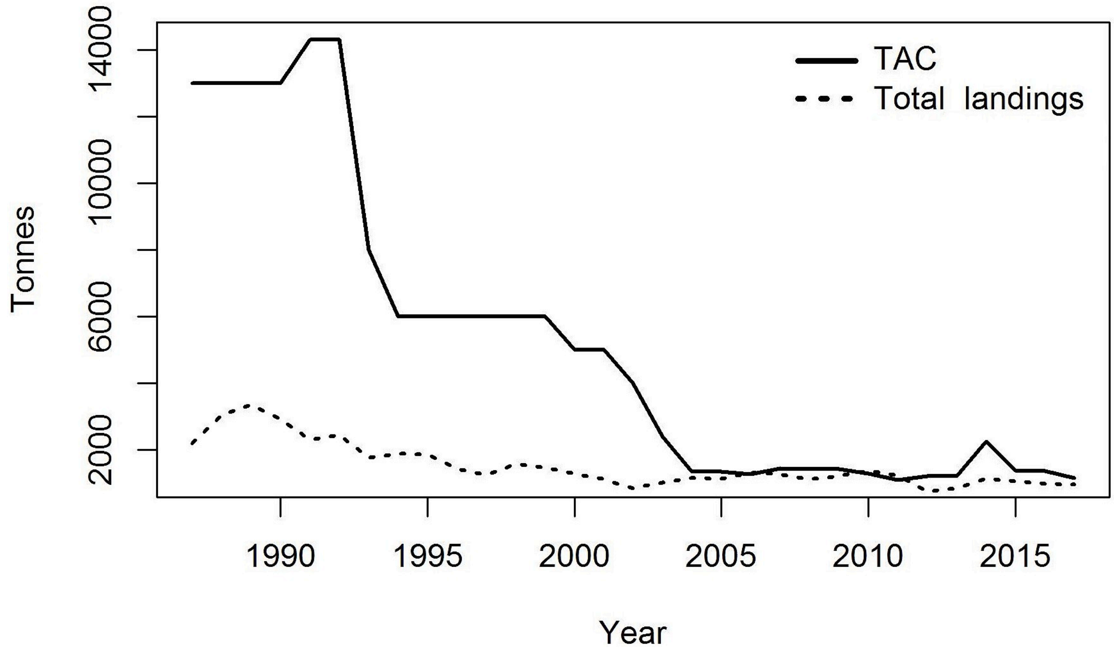

Fig. 1. Annual landings of *Lepidorhombus* spp. in ICES divisions 8c and 9a for Spain and Portugal and corresponding annual TAC (total allowable catch).

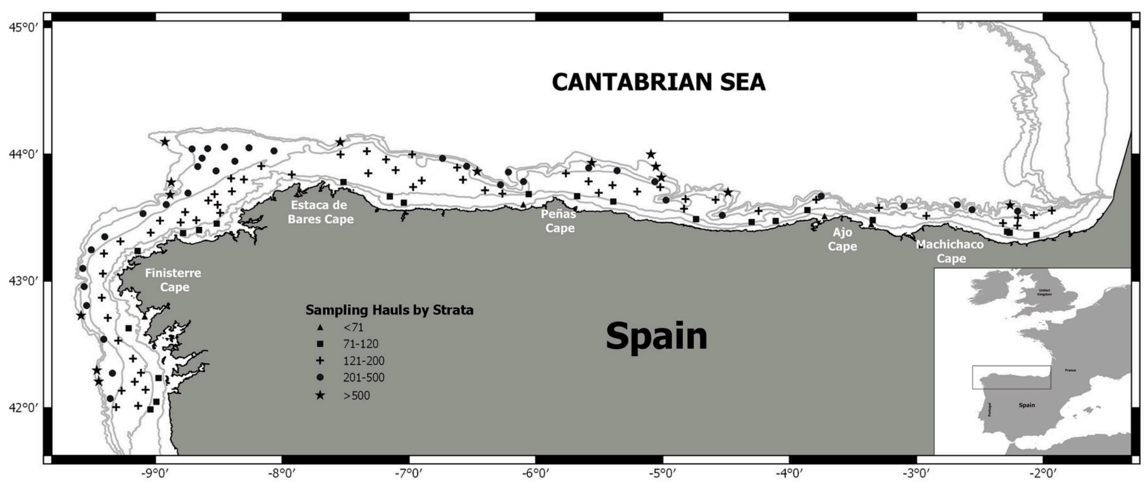

Fig. 2. Study area on the northern continental shelf of the Iberian Peninsula. Color lines represent sampling locations by depth strata.

predictors to determine the demersal species distribution of many species and marine communities [24,25].

A bathymetry map obtained from the European Marine Observation and Data Network (EMODnet, http://www.emodnet.eu/) with a spatial resolution of 0.02 × 0.02 decimal degrees (~200 m) was used. Similarly, a seabed substrate classification consisting of five groups (mud to sandy mud; sand; coarse sediment; mixed sediment and rock and boulders) was extracted from the same website. Slope and rugosity were derived from the bathymetric map using the "Slope" and "Terrain Ruggedness Index (TRI)" tools of the "Terrain Analysis" module in SAGA-GIS 3.0.0. The slope computes the rate of maximum vertical change for each cell of surface [26] while the TRI measures the three-dimensional depth variation of grid cells within a neighborhood. This method effectively captures variability and seabed aspect into a single indicator [27].

Sea Bottom Temperature (SBT in °C) and Sea Bottom Salinity concentration (SBS in PSU) were added to the analysis as they are strongly related to marine system productivity, affecting nutrient availability and water stratification [24,28]. SBT and SBS values were collected during the survey with a CTD (conductivity, temperature and depth) sounding at different random sampling points of the study area. Monthly SBT and SBS maps of the entire area were obtained for each year of the period studied with the RBF tool in ArcGIS 10.1.

In order to ensure the same spatial resolution, all environmental data were aggregated to the lower spatial resolutions (0.02 × 0.02 decimal degrees, ~200 m) using the '*raster*' package [29] in the R software [30].

All covariates were analyzed for collinearity, outliers and missing values before their use in the models [31]. As no collinearity, outliers and missing values were found, all covariates were all used in the models together. Finally, the explanatory variables were standardized (difference from the mean divided by the corresponding standard deviation) to facilitate visualization and interpretation [32].

2.5. Statistical models

An exploratory analysis showed that megrim abundance data possess two main characteristics; strong spatial dependence and high proportions of zero. Thus, a two-step Bayesian spatial model (also known as hurdle model) was implemented providing the basis to simultaneously account for the spatial autocorrelation, excess of zeros and uncertainties associated with the sampling process [5].

Specifically this type of model combines two structures: (i) modeling presence/absence of the species in order to predict the probability of occurrence of the species and (ii) modeling the conditional-to-presence abundances (number of individuals) of the species studied to predict the probability of abundance. A binomial distribution was implemented with a logit link function for the first model, while species abundance was fitted using a Poisson distribution and a log link function. Thus, the abundance process will depend on the occurrence process. More specifically, it follows:

$$\begin{aligned} \textit{Occurrence process}: \quad & Z_{ij} \sim \text{Bernoulli}(\pi_{ij}) \\ & \text{logit}(\pi_{ij}) = \alpha^{(Z)} + X_{ij}\beta + W_i^{(Z)} + Y_j \end{aligned}$$

$$\begin{aligned} \textit{Abundance process}: \quad & Y_{ij} \sim \text{Poisson}(t_{ij}, \lambda_{ij}) \\ & \text{lo}(\lambda_{ij}) = \alpha^{(Y)} + X_{ij}\beta + W_i^{(Y)} + Y_j \end{aligned}$$

where π_{ij} represents the probability of occurrence at location *i* and year *j*, while λ_{ij} the intensity of the conditional-to-presence abundance at location *i* and year *j*. The linear predictors containing the effects to which these parameters π_{ij} and λ_{ij} are linked are formed with: $\alpha^{(Z)}$ and $\alpha^{(Y)}$, the terms representing the intercepts for each variable; β is the vector of regression parameters; X_i is the matrix of the explanatory covariates at location *i* and year *j*; $W_i^{(Y)}$ and $W_i^{(Z)}$ refer to the spatial structure of the occurrence and conditional-to-presence abundance respectively; and the final terms Y_j is the temporal unstructured random effect at the year *j*.

Bayesian parameter estimates and predictions were obtained through the Integrated Nested Laplace Approximations (INLA) approach [33] and package (http://www.r-inla.org/) which is implemented in the R software.

The spatial effects ($W_i^{(Y)}$ and $W_i^{(Z)}$) were modeled as using the INLA Stochastic Partial Differential Equations (SPDE) approach [33], that involves the approximation of a continuously indexed Gaussian Field with a Matérn covariance function by a Gaussian Markov Random Field. In particular, a prior Gaussian distribution with a zero mean and covariance matrix was assumed for the spatial component which depend on the hyperparameters k and τ, which determined its variance and range, respectively (see Ref. [34], for more detailed information about spatial effects).

Temporal component was modeled as a random unstructured effect and a LogGamma prior distribution on the log-precision λ ($a = 1$, $b = 5e{-}05$) has been assigned [35]. Non-linear relationships between species and environmental variables were modeled using second order random walk (RW2) latent models that perform as Bayesian smoothing splines [36].

All possible combinations of the candidate covariates were tested using both backwards and forwards approaches in order to select the relevant ones. We selected the model which had the lowest Watanabe-Akaike information criterion (WAIC) [37], Log-Conditional Predictive Ordinates (LCPO) [38] and containing only relevant predictors (i.e., those predictors with 95% credibility intervals not including the zero). Specifically, WAIC was used as a measure for goodness-of-fit, while the LCPO was used for predictive quality as it is a "leave-one-out" cross-validation index that assess the predictive power of the model.

INLA performs the prediction simultaneously with the inference, considering the prediction locations as points where the response is missing. With the INLA SPDE module the region of interest for the prediction is covered through Delaunay triangulation [34]. This has at least three advantages over a regular grid. Firstly, the triangulation is denser in regions where there are more observations and consequently there is more information. Secondly, it saves computing time, because prediction locations are typically much lower in number than those in a regular grid. Thirdly, it is possible to take boundary effects into account by generating a triangulation with small triangles in the domain of interest, and using larger triangles in the extension used to avoid boundary effects. Once the prediction is performed in the observed locations, there are additional functions that linearly interpolate the results within each triangle into a finer regular grid. As a result of the process, a faceted surface prediction is obtained which approximates to the true predictive surface.

Hot-spots were identified from the predicted posterior mean using a threshold set at 95% superior CI of the predicted range.

Occurrence models were tested for prediction performance by using the area under the receiver-operating characteristic curve (AUC) [39] and the "True Skill Statistic" (TSS) [40]. Both prediction measures range from 0 to 1, where values close to 1 indicate better predictions. Moreover, abundance model predictions were evaluated by computing the Spearman's rank correlation test (r_s) between observed and predicted values.

3. Results

3.1. Four-spot megrim (*Lepidorhombus boscii*)

The four-spot megrim showed an increase in both undersized and commercial size abundance from about 2004 (1993–2017) (Fig. 3). For the undersized category the last year of the time series were the one with the highest species abundance (4778 individuals per haul, CI = [3785,5771]), while 2003 was the lowest (1013 individuals per haul, CI = [20,2006]). For the commercial size category 2012 was the year with highest species abundance (4538 individuals per haul, CI = [3544,5532]), while 1993 was the lowest (1015 individuals per haul, CI = [21,2009]). Overall the mean of individuals caught was of 2988 for the undersized category and 2207 for the commercial one.

The frequency of occurrence by depth stratum in the survey shows a significant increase in the 70–120 m strata from the beginning of the time series (1983–2017) (Fig. 4).

3.1.1. Undersized category

The final hurdle model selected for the undersized category explained the 65.4% of the variability of the species. The binomial model retained SBT, depth and TRI as relevant predictors (based on the lowest WAIC and LCPO) rather than the spatial and temporal effects (Table S1 Supplementary materials). Slope, type of seabed and SBS were not relevant for the probability occurrence of this species (Table S1 Supplementary materials). All variables required smoothing splines for this final model (Fig. S1 Supplementary material). In particular, the probability of occurrence of undersized four-spot megrim showed an increasing trend with SBT from 11 °C to 12.5 °C, while above this temperature the probability of occurrence seemed to gradually decrease (Fig. S1 Supplementary materials). The probability of occurrence of the undersized categories of this species increased on the inner shelf until 350 m and then declined in deeper waters (Fig. S1 Supplementary materials). A higher probability of occurrence was noted with consolidated seafloors (i.e. coarse and mixed sediment) (Fig. S2 Supplementary materials). Prediction evaluation measures showed that the binomial model performed well achieving good AUC and TSS values (0.82 and 0.63 respectively). The predictive map of the probability of occurrence from 2003 to 2017 highlighted that the envelope of presence of this species is on the outer shelf, between depths of 100 m and 350 m (Fig. S2 Supplementary materials).

Undersized four-spot megrim abundance was mainly explained by depth, SBT, SBS and the spatial and temporal effects, according to the model with the best fit (Table S1 Supplementary materials).

All retained variables required smoothing splines (Fig. 5). Slope, type of seabed and TRI were not relevant for the abundance of this species (Table S1 Supplementary materials). Similarly to the occurrence pattern, the preferred habitat of the undersized four-spot megrim category is between depths of 100 m and 350 m, with 11 °C and 12 °C of SBT

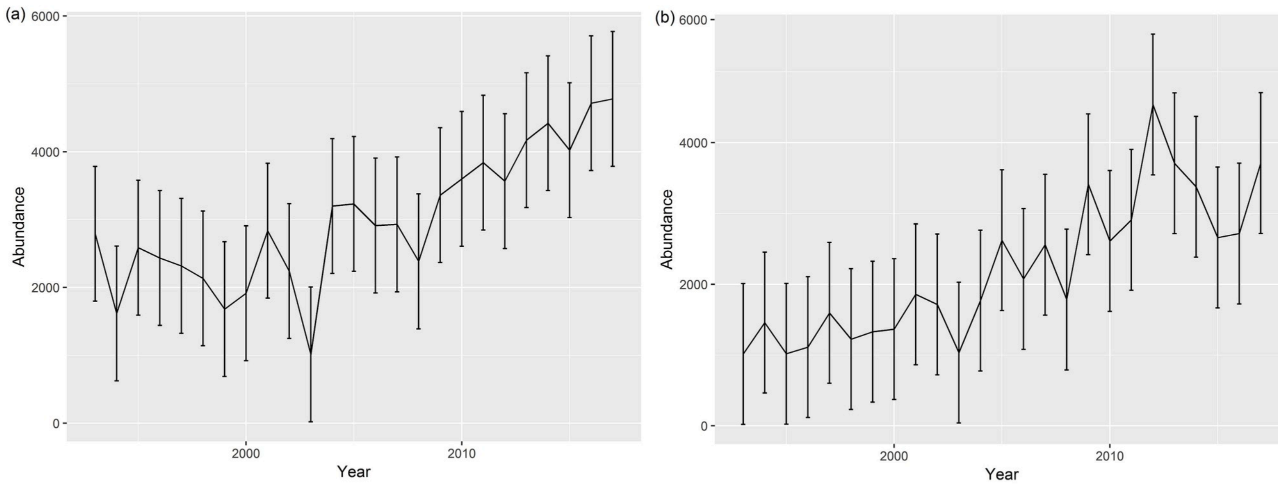

Fig. 3. Annual variability of undersized (smaller than 19 cm) (a) and commercial size (larger than 19 cm) (b) categories of the four-spot megrim (*Lepidorhombus boscii*).

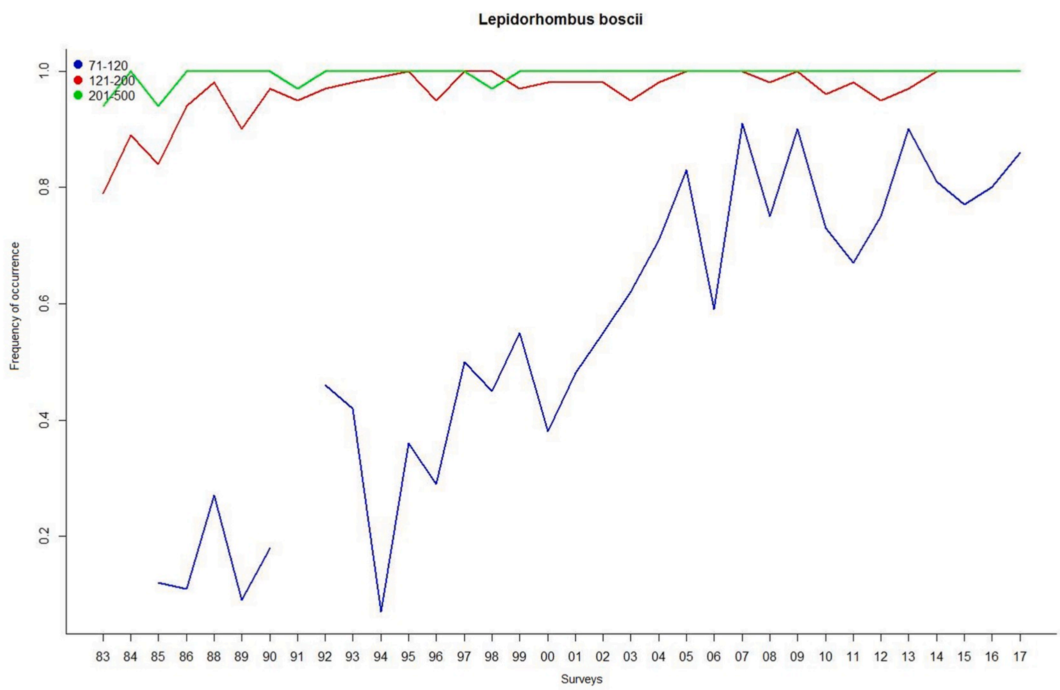

Fig. 4. Frequency of occurrence of *L. boscii* by depth stratum in the time series of the Demersales survey (1983–2017).

and more than 35.6 PSU of SBS (Fig. 5).

The selected model presented a good prediction power, as demonstrated by the high values of the Spearman's correlation coefficient (0.75, p-value = 0.01).

The posterior predictive map (1993–2017) highlighted two main hot-spots on the western coast of the area studied (Fig. 6), identified using the 95% superior CI of the predicted abundance mean, corresponding to an abundance of more than 300 individuals.

Specifically, from south to north, the first was located off the Rias of Pontevedra and Vigo and the second off La Coruña.

3.1.2. Commercial size category

The Bayesian hurdle model explained overall the 66.3% of the variability of the four-spot megrim species for the commercial category. Depth, SBT, SBS and the spatial and temporal components were selected as relevant variables for the final four-spot megrim binomial model of the commercial size category (Table S2 Supplementary materials). Smoothing splines were implemented for all predictors, highlighting a negative relationship with bathymetry, SBT, SBS and the probability of occurrence of this category (Fig. S3 Supplementary materials). Specifically, higher probability of occurrence was found between depths of 300 m and 500 m, between 11 °C and 13 °C of SBT and with SBS values of less than 35 PSU (Fig. S3 Supplementary materials). Prediction measures showed a good performance of the model with an AUC of 0.86 and TSS of 0.64. The predictive probability occurrence highlighted a wide envelope of presence of this species in the area (Fig. S4 Supplementary materials).

As in the case of the undersized category, depth, TRI and SBS together with the spatial and temporal components were the predictors that better explained the variability of the abundance model of the commercial size category (Table S2 Supplementary materials). Specifically, the abundance of the commercial size of four-spot megrim

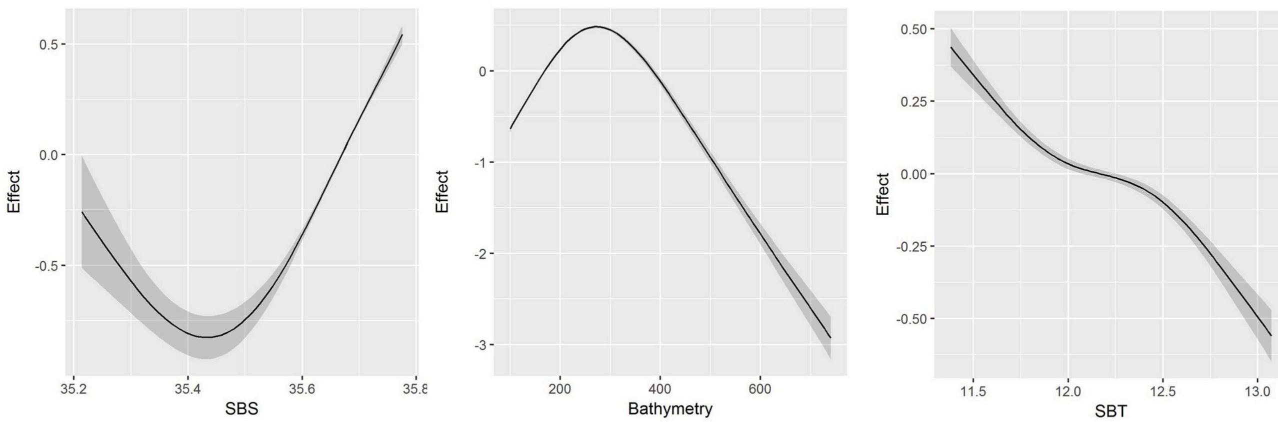

Fig. 5. Functional response of depth, Sea Bottom Temperature (SBT) and Sea Bottom Salinity (SBS) with the predicted abundance of the undersized four-spot megrim (*Lepidorhombus boscii*). Grey shades indicate the 95% Bayesian credible intervals.

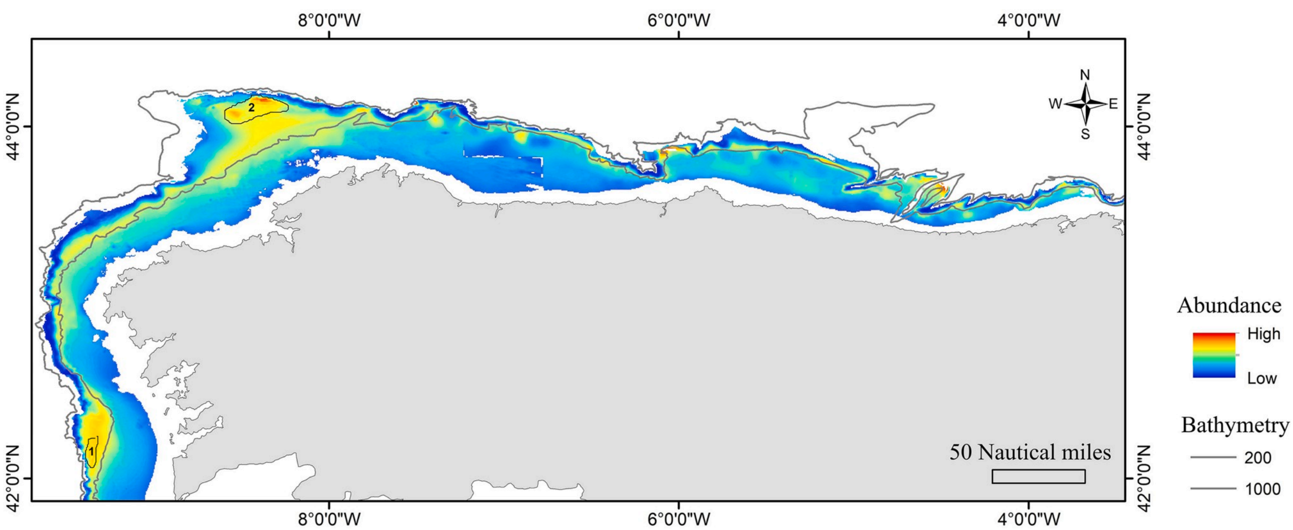

Fig. 6. Spatial-temporal abundance model output for the undersized four-spot megrim (*Lepidorhombus boscii*) category showing average posterior mean abundance estimates (1993–2017) and the two persistent hot-spots identified.

decreased from a depth of 350 m, on unconsolidated substrata (i.e. low values of TRI) and more than 35.2 PSU of SBS (Fig. 7).

The abundance model showed a good prediction performance with a Spearman's correlation coefficient of 0.71 (p-value = 0.001).

Four main hot-spots were identified in the area studied (Fig. 8). Specifically, from south to north, the first was located off the Ria of

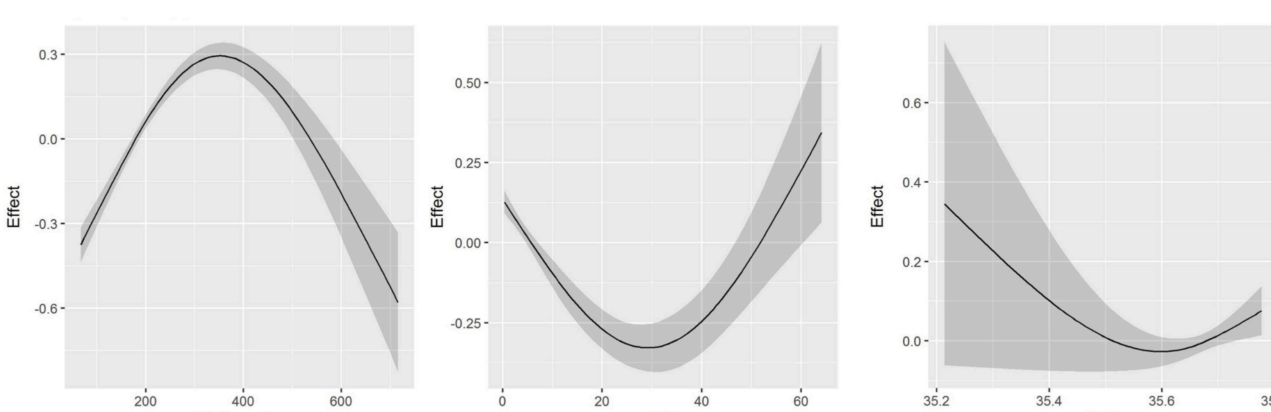

Fig. 7. Functional response of depth, rugosity (TRI) and Sea Bottom Salinity (SBS) with the predicted abundance of the commercial size four-spot megrim (*Lepidorhombus boscii*). Grey shades indicate the 95% Bayesian credible intervals.

Pontevedra and Vigo, the second one off the Costa de la Muerte, the third and largest of these covered most of the Artabrian gulf off La Coruña, and the fourth (a small one) was located off Santander (Fig. 8).

3.2. Megrim (*Lepidorhombus whiffiagonis*)

The time trend is similar across both undersized and commercial-sized megrim (Fig. 9).

For the undersized category, the year with the highest abundance along the time series was the 2016 with 1743 individuals per haul (CI = [1247,2239]). All the other years had very low abundance, although the 2008 was the lowest with only 25 individuals per haul (CI = [-471,521]). For the commercial size category the 2010 was the year with the lowest abundance (429 individuals per haul, CI = [-121,979]), while 2017 was the highest (2809 individuals per haul, CI = [2259,3359]). Overall the average of the individuals caught was of 462 for the undersized category, and 1037 for the commercial one.

As with abundance, no clear trend can be observed in the frequency of occurrence by depth stratum in the survey, although the decade near the 2000's seems to experience a decline in occurrence in most depths and an increase in recent years. (Fig. 10).

3.2.1. Undersized category

This final Bayesian hurdle model explained the 67.2% of the variability of the megrim species in the undersized category. Depth and SBS were retained as relevant predictors for the final binomial model in addition to the spatial and temporal effects (Table S3 Supplementary materials). Both predictors required smoothing splines, showing a negative relationship with the probability of occurrence of the *L. whiffiagonis* undersized category (Fig. S5 Supplementary materials). The probability of occurrence of the undersized megrim category is higher in shallow waters on the inner shelf with values of SBS between 35.2 and 35.5 PSU (Fig. S5 Supplementary materials). Prediction indicators showed a good performance of the binomial model (AUC = 0.80; TSS = 0.59). The map of the probability of occurrence highlighted that the envelope of presence is in the central part of the area from the waters off La Coruña to Bilbao (Fig. S6 Supplementary materials).

According to the model with the best fit, the abundance variability was mainly explained by depth, SBT, SBS and the spatial and temporal effects (Table S3 Supplementary materials). Slope, type of seabed and TRI were not relevant for the abundance of this species. All retained variables required smoothing splines (Fig. 11). Results showed higher abundances in waters between 120 m and 200 m of depth, with temperatures between 11 °C and 12 °C of SBT and with SBS lower than 35.5 (Fig. 11). The final abundance model presented a good prediction performance, showing a Spearman's correlation value of 0.73 (p-value = 0.01).

The only hot-spot was located off Santander and was identified using the 95% superior CI of the predicted abundance mean, corresponding to an abundance of more than 50 individuals per 30 min of trawling (Fig. 12).

3.2.2. Commercial size category

This final Bayesian hurdle model explained the 66.6% of the total species variability in the commercial size category. The probability of occurrence of commercial size megrim was mainly explained by depth, SBT, SBS and spatial and temporal effects (Table S4 Supplementary materials). As in the case of undersized megrim for this model, type of seabed and slope were not relevant. Only depth and SBS required a smoothing spline, while the SBT presented a linear relationship with the response variables (posterior mean = −0.12, IC 95% [-0.09 to −0.94]), i.e. higher probability in colder waters. Similarly, depth and SBS showed a negative relationship with the probability of occurrence (Fig. S7 Supplementary materials). In particular, the probability of occurrence decreased from a depth of 250 m and 35.5 PSU of SBS (Fig. S7 Supplementary materials). As for the other models, reasonably high values of AUC and TSS were obtained (0.86 and 0.59 respectively). Similarly to the case of the undersized category, the map of the probability of occurrence highlighted that the envelope of presence is in the central part of the area from the waters off La Coruña to Bilbao (Fig. S8 Supplementary materials).

SBS, depth, and the spatial and temporal effects were retained as predictors for the final abundance model (Table S4 Supplementary materials). None of the others variables were relevant. Both selected predictors required smoothing splines and showed a negative relationship with the response variables (Fig. 13). In particular, abundance decreased from 35.3 PSU of SBS and at depths of below 250 m.

The correlation between observed and predicted values was about 0.79, highlighting the good performance of the model. Similarly to the undersized category, the final prediction map identified only one hot-spot off Santander (Fig. 14).

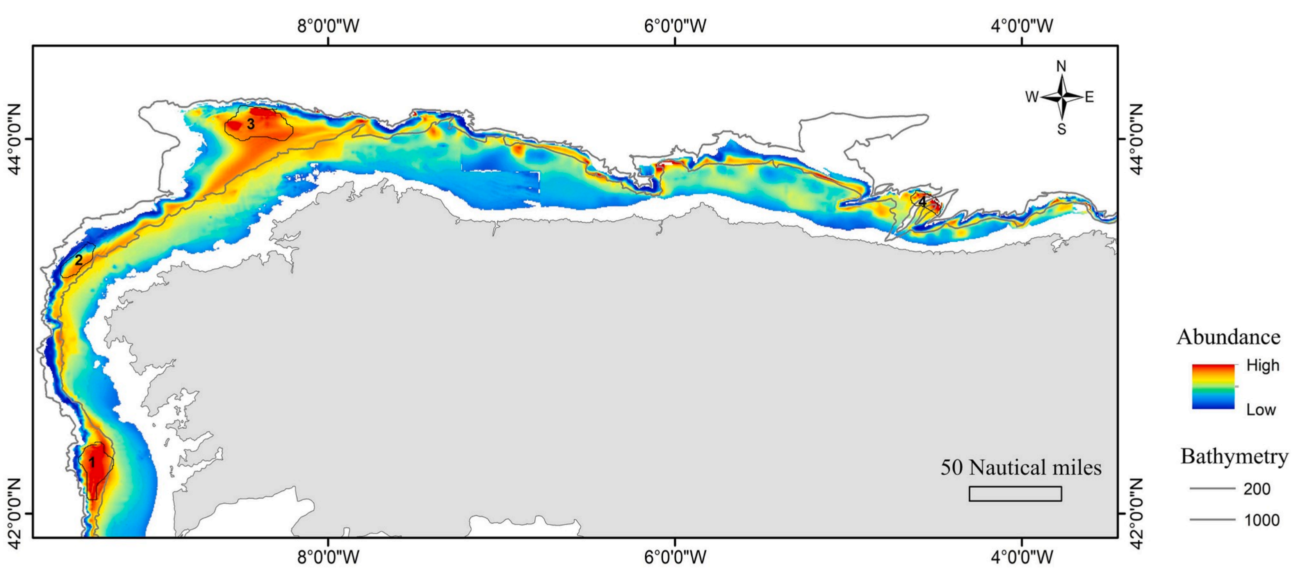

Fig. 8. Spatial-temporal abundance model output for the four-spot megrim (*Lepidorhombus boscii*) commercial size category showing average posterior mean abundance estimates (1993–2017) and the four persistent hot-spots identified.

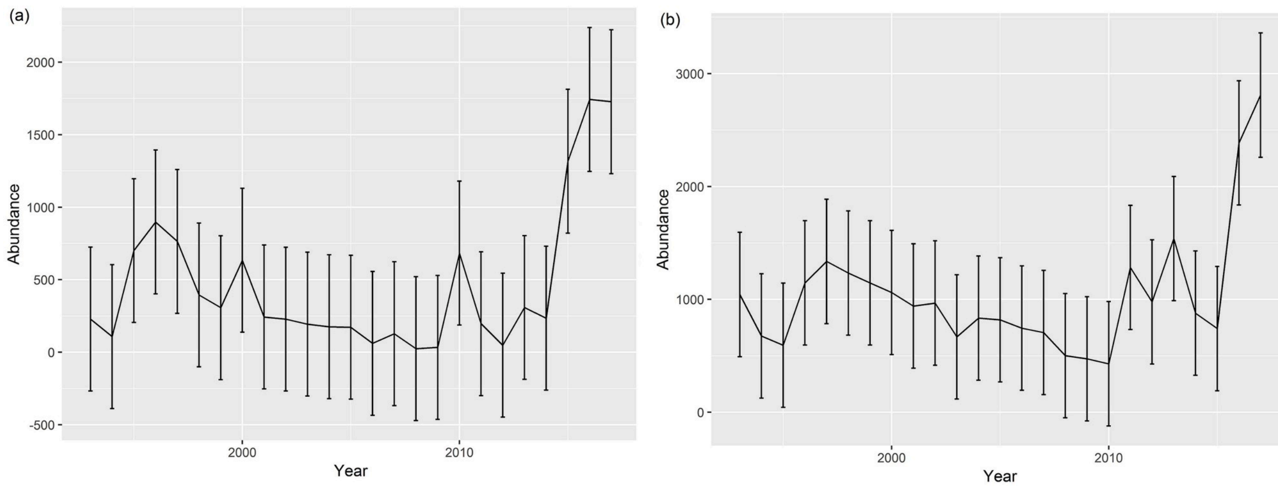

Fig. 9. Annual variability of undersized (smaller than 19 cm) (a) and commercial size (b) categories (larger than 19 cm) of the megrim (*Lepidorhombus whiffiagonis*).

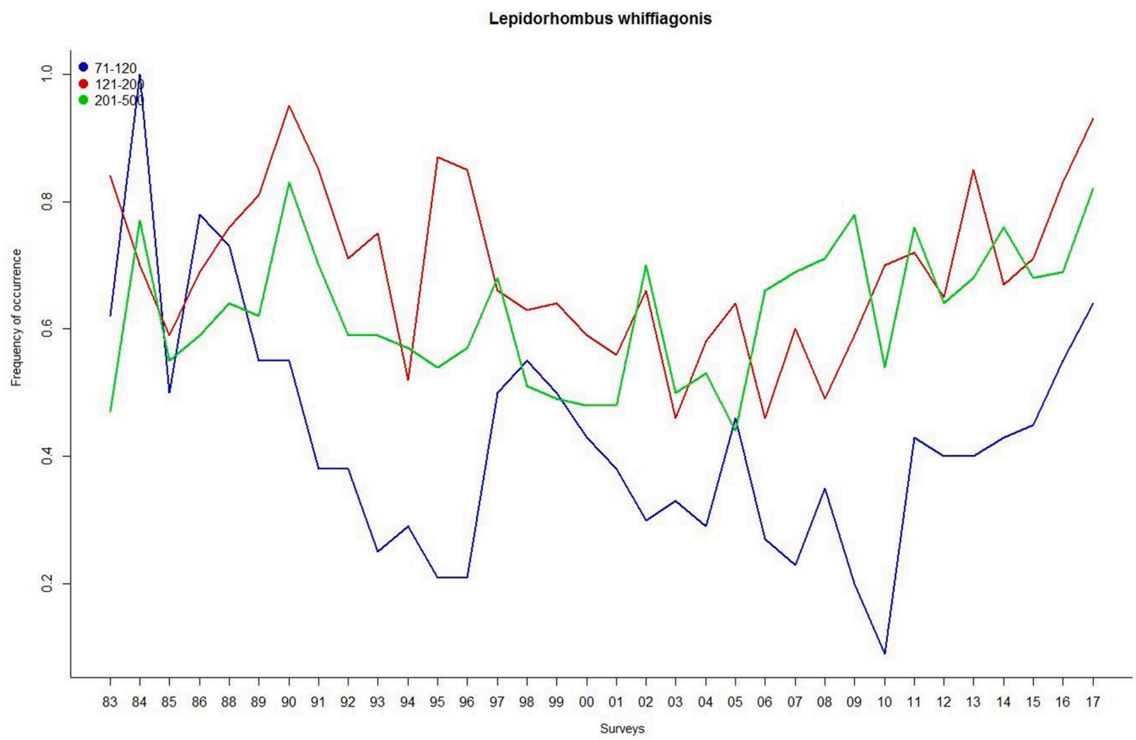

Fig. 10. Frequency of occurrence of *L. whiffiagonis* by depth stratum in the time series of the Demersales survey (1983–2017).

4. Discussion

The new obligation to land all catches for species under a TAC quota in European Seas may have adverse ecological and socio-economic impacts, such as high-grading and the choke species effect. To avoid these impacts, a combination of different possible solutions could be applied, such as the use of more selective gears that catch a smaller number of undersized individuals, and/or identifying areas with a higher concentration of small individuals in order to develop fishing strategies that might reduce their catches.

In this study, a methodology has been proposed to identify these areas with a view to developing protective spatial measures. This could benefit not only the resources and the habitat where undersized individuals dwell but also the fishers exploiting such resources.

4.1. Biological results

Our results showed that the two species have different preferential habitats, although inter-species similarities were found in the two categories studied. In particular, *L. boscii* seems to be more abundant in the northwestern part of the area studied with two main hot-spots of undersized individuals located off the Rias of Pontevedra and La Coruña. There are four main hot-spots of commercial individuals, two of them overlapping with the undersized individuals hot-spots, and the others located off the Ria of Muros and the Artabrian gulf.

On the contrary, the *L. whiffiagonis* is more abundant in the eastern part of the study area with only one hot-spot located off Santander.

These findings are in accordance with the known distribution of the *Lepidorhombus* genus that shows a spatial segregation between the two species on the border between the ICES divisions 8c and 9a [13,14].

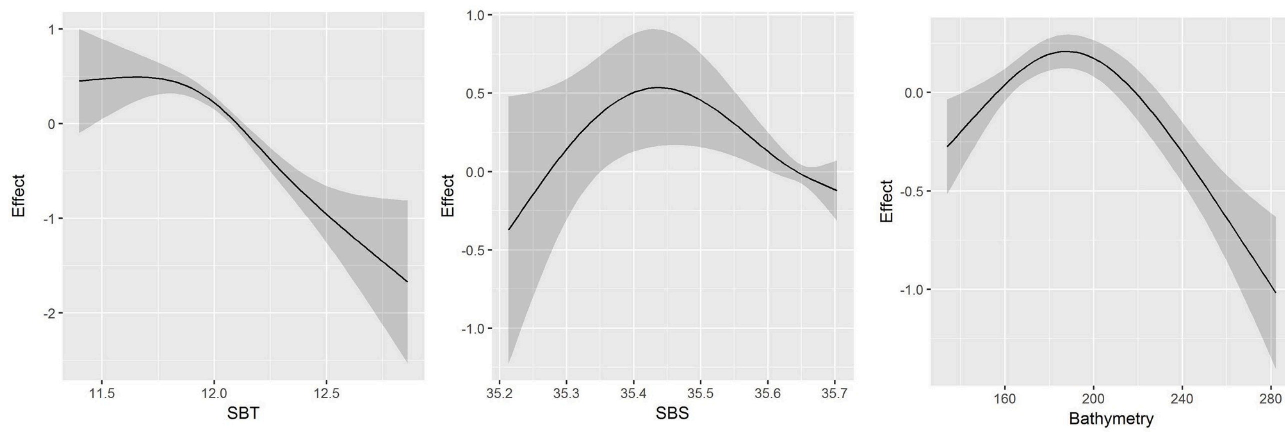

Fig. 11. Functional response of depth, Sea Bottom Temperature (SBT) and Sea Bottom Salinity (SBS) with the predicted abundance of undersized megrim (*Lepidorhombus whiffiagonis*). Grey shades indicate the 95% Bayesian credible intervals.

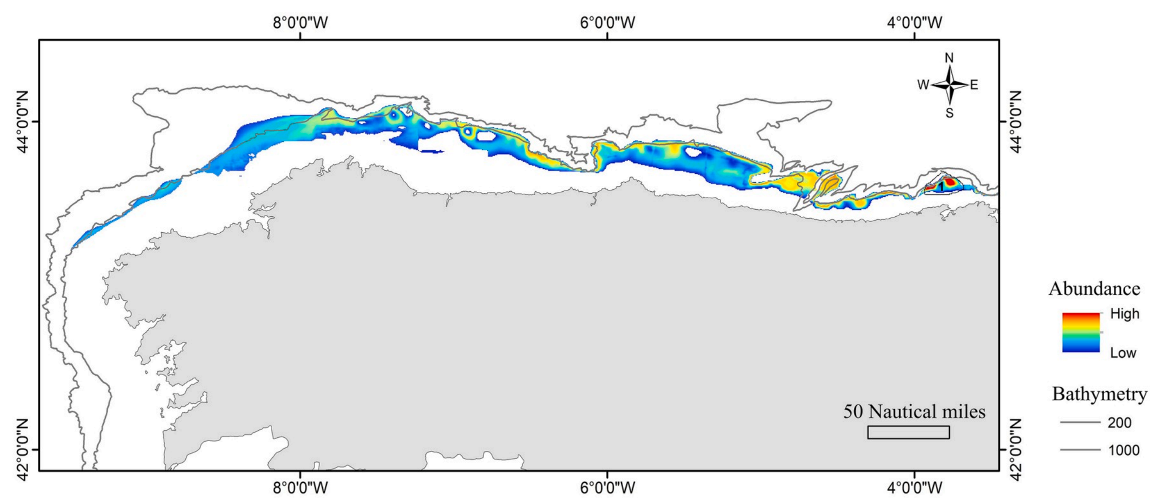

Fig. 12. Spatial-temporal abundance model output for the undersized megrim (*Lepidorhombus whiffiagonis*) category showing average posterior mean abundance estimates (1993–2017) and the persistent hot-spot identified.

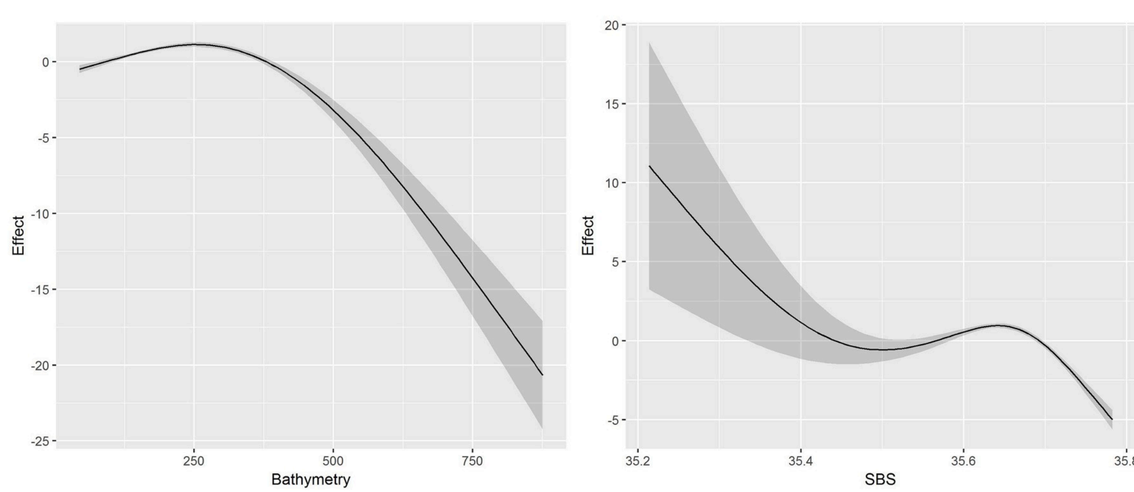

Fig. 13. Functional response of the Sea Bottom Salinity (SBS) and depth with the probability of occurrence of the commercial size megrim (*Lepidorhombus whiffiagonis*).Grey shades indicate the 95% Bayesian credible intervals.

This segregation could be due to different environmental variables. Indeed, there is a certain bathymetric segregation between the two species of megrim. *L. boscii* has a preferential depth range from 100 m to 450 m and *L. whiffiagonis* from 50 m to 300 m [13]. Overall, this is in line with our findings although for both species a narrower preferential bathymetric range was found (i.e., 100–350 m for *L. boscii* and

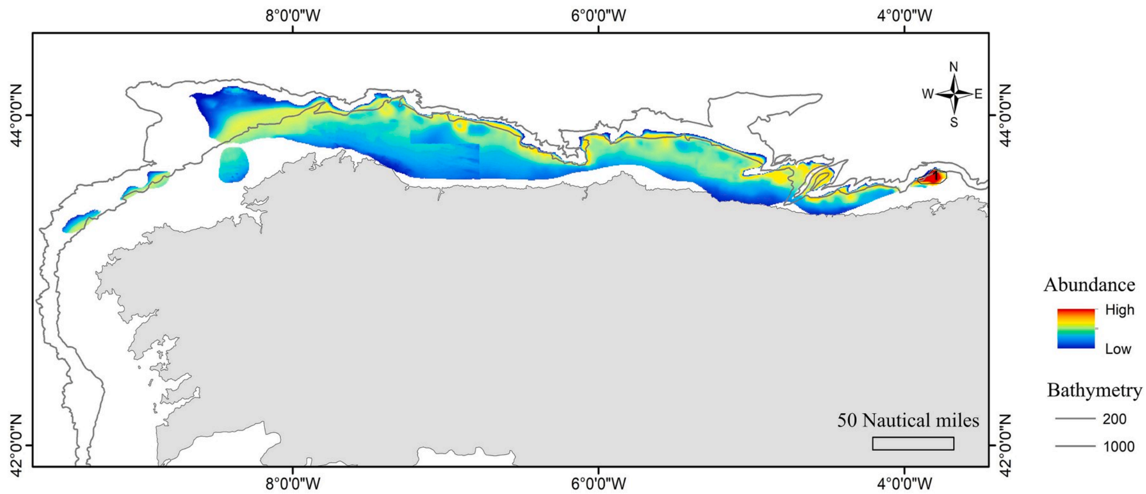

Fig. 14. Spatial-temporal abundance model output for the megrim (*Lepidorhombus whiffiagonis*) commercial category showing average posterior mean abundance estimates (1993–2017) and the persistent hot-spot identified off Santander.

100–200 m for *L. whiffiagonis*). Depth was one of the main predictors for both species and categories, and indeed, depth has amply proved to be one of the main structuring factors for marine, and particularly demersal, species in this area [20,41].

Sea bottom salinity seems to be another important factor that defines distribution and abundance of megrims. *L. boscii* showed a positive relationship with saltier waters from 35.5 PSU, while *L. whiffiagonis* has low tolerance to changes in salinity, highlighting a negative relationship. Previous studies on megrim species show that they generally occurred outside zones with hydrographical instabilities that foster the vertical interchange of organic matter [42] and disappear at the mouths of the most important rivers [43]. Furthermore, this factor could be another ecological barrier that separates the two species in the area studied. On the contrary, the SBT showed a similar range of preference for both species in the undersized category, highlighting similarities in the genus when the species are in the first life-stages.

With respect to species distribution, it should be noted that the spatial component was one of the most important variables selected by the models in the case of both species and categories. This component indicates the intrinsic spatial variability of the data after the exclusion of the environmental variables, drawing attention to the fact that other important spatial processes which have not been taken into account in the model could be affecting the distribution and abundance of these species, Indeed, in demersal species such as megrims, the role of other abiotic factors such as the type of sediment affects their spatial distribution [14] as it was previous mentioned in this work. It is known that most of the spatial distribution of demersal species is directly related to the spatial structure of their habitats [6]. This feature is also directly related to other factors, for example the type of prey and biotic processes such as competition, predation and recruitment that are also spatially structured [44].

From a temporal point of view, *L. boscii* presented an increasing pattern throughout the time series in both categories, while *L. whiffiagonis* has a stable pattern. However, it is worth noting that the lowest abundance of *L. boscii* in the time series was in 2003 and could probably be related to the Prestige oil spill that occurred in Galician waters in November 2002. After the spill, a spatial-temporal closure of fishing activity was established with numerous fishing restrictions [45, 46]. This spill particularly affected the area where *L. boscii* is more abundant and the survey index for 2003, the post spill year, showed a significant decline [46].

This general pattern over time is observed by Ref. [47] for the two species. In the case of *L boscii*, an increase in frequency in stratum 70–120 m (Fig. 4) increases the probability of being captured. In the case of *L. whiffiagonis*, the pattern is stable at all depths (Fig. 10). In this case, these authors attribute these changes, along with other species, to the possible effects of global warming on demersal ecosystems, phenomena already observed in other sites such as the North Sea [48] or in the Baltic [49]. These changes in the distribution of species and modifications in the recruitment processes due to these environmental phenomena can generate mid-term uncertainty in the processes of space management such as the ones proposed here.

4.2. *Fishery management*

Different management options could be applied with varying levels of overlap between undersized and commercial categories to reconcile conservation measures with fishers' interests. For example, when there is a partial overlap, as is the case of *L.boscii*, for which two of the four commercial hot-spots are also undersized aggregation zones, restricted spatial-temporal closures could be implemented.

[50] reported that conservation areas need to cover at least 20–30% of the area of interest to provide effective protection. In the L.*boscii* case, this would imply the closures of two of the four identified commercial size hot-spots, which would have only a minor impact on fishers as they would avoid landing minimum size individuals.

It is known that discards present a spatial pattern and their management should be at a regional level [51], although this issue might be simplified by the presence of a unique hot spot which coincides for both categories of *L. whiffiagonis* and the commercial category of *L. boscii*. However, it is worth mentioning that the data comes from a survey performed in autumn and to define the persistence of the hot-spot throughout the year and to study the intra-annual variance of the abundances, a survey with larger seasonal coverage would be needed [6]. In any case, a set of spatial-seasonal closures could be proposed for this area during the autumn season, as avoiding unwanted catch of undersized individuals will benefit fishers' revenues as well.

In the framework of the mixed fisheries, which are strongly represented in the area, these closures could also benefit other target species. In other areas, associations of juveniles of white-bellied anglerfish, hake and megrim have been detected [52]. Future studies similar to the one presented in this work including more species could be interesting. Determining potential closures according to the presence of undersized individuals of several species could solve this common problem suffered by stocks which are simultaneously exploited by this kind of fishery. Shifts in spatial fishing patterns will help in the implementation of the LO [52]. It is important to take into account in other studies the effects derived from this measure, which can be positive but also negative in biological, ecological and socioeconomic aspects [45,53].

Fishers' perception is another issue that can influence the success of any management rule and contribute in the case of a spatial-seasonal closure, as they might be able to provide up-to-date information on changes in the distribution and abundance of fish [10]. In fact, it was previously mentioned that a strategic combination of different measures would be the most effective policy to deal with the landing obligation and to reduce the unwished adverse effect derived from an unique procedure [53]. If some areas are protected to avoid hot-spots of undersized individuals and gear selectivity is increased, these measures should lead to more responsible fishing, minimizing the economic impact of the discard ban [2].

In addition, it seems proven that similar closure measures in other areas have led to an increase in the abundance of commercial lengths of both target and non-target species in relation to adjacent areas [4]. However, if the optimal yield is the only management objective, we are focusing the Ecosystem-Based Fishery Management exclusively on sustainable fishery harvest limits while disregarding other elements [54]. The Marine Spatial Planning approach needs to go further, not only increasing fish biomass but also protecting their habitats [4,5].

The landing obligation will be fully implemented in 2019. It is time to decide how the whole ecosystem is going to benefit from this situation, making the right choices to preserve resources, the environment and society.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.marpol.2019.103739.

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