Evidence for spatiotemporal shift in demersal fishery management priority areas in the western Mediterranean

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Abstract

Marine protected areas (MPAs) are a promising management tool for the conservation and recovery of marine ecosystems, as well as fishery management. MPAs are generally established as permanent closures but marine systems are dynamic, which has generated debate in favour of more dynamic designs. As a consequence, the identification of priority areas should assess their persistence in space and time. Here, we develop a step-by-step approach to assess the spatiotemporal dynamics of fishery management priority areas using standard fishery-independent survey data. To do so, we fit Bayesian hierarchical spatiotemporal SDM (species distribution model) models to different commercially important demersal species and use the resulting maps to fit different spatial prioritisation configurations. The proposed method is illustrated through a western Mediterranean case study using fishery-independent trawl survey data on six commercially important species collected over 17 years. We use these results to assess the spatiotemporal dynamics of fishery priority areas. We identified two fishery priority area patterns in the study area, each predominant during a different time period of the study, asserting the importance of regularly reassessing MPA designs.

Résumé

Les aires marines protégées (AMP) constituent un outil de gestion prometteur pour la conservation et le rétablissement des écosystèmes marins, ainsi que pour la gestion des pêches. Si les AMP sont généralement établies comme zones interdites à la pêche permanentes, le caractère dynamique des systèmes marins est à l'origine d'arguments en faveur d'une conception plus dynamique de ces aires. La délimitation de secteurs prioritaires devrait ainsi comprendre une évaluation de leur persistance dans l'espace et le temps. Nous présentons une approche par étape pour évaluer la dynamique spatiotemporelle de secteurs prioritaires pour la gestion des pêches qui fait appel à des données d'évaluation indépendantes des pêches standards. Pour ce faire, nous ajustons des modèles de répartition d'espèces (MRE) spatiotemporels hiérarchiques bayésiens à différentes espèces démersales d'importance commerciale et utilisons les cartes ainsi produites pour ajuster différentes configurations de priorisation spatiale. La méthode proposée est illustrée par une étude de cas de l'ouest de la mer Méditerranée qui fait appel à des données de relevés au chalut indépendantes de la pêche pour six espèces d'importance commerciale, recueillies sur 17 années. Nous utilisons ces résultats pour évaluer la dynamique spatiotemporelle de secteurs prioritaires pour la pêche. Nous cernons deux motifs de secteurs prioritaires pour la pêche dans la région d'étude, chacun étant prédominant durant différentes périodes de l'étude, ce qui souligne l'importance d réévaluer régulièrement la conception des AMP. [Traduit par la Rédaction]

1. Introduction

Large-scale implementation of marine protected areas (MPAs) is expected worldwide in the near future. Different international agreements concur on protecting 10% of coastal and marine areas (CBD Aichi target 11, UN sustainable development goal 14, EU Common Fisheries Policy target 14.5, etc.) and nearly 200 governments committed to meet this goal by 2020 (Tittensor et al. 2014). Post-2020 global conservation targets have increased this target to 30% by 2030 and to 50% by 2050 (O'Leary et al. 2016; Baillie and Zhang 2018; Dinerstein et al. 2019).

MPAs are a promising management tool for the conservation and recovery of marine ecosystems (Leenhardt et al. 2015; Giakoumi et al. 2017), as well as for fishery management (Kaiser et al. 2007; Di Franco et al. 2016; Petza et al. 2017, 2021; Fraschetti et al. 2018). MPAs protect fish stocks in the no-take zone, promote greater reproductive output (Kaiser et al. 2007), and therefore sustain density-dependent

spill-over (Di Lorenzo et al. 2016) enhancing fishery catches in the buffer zone and outside the MPAs (Hilborn et al. 2004; Kerwath et al. 2013; Ovando et al. 2016).

Most MPAs are established as permanent closures (Game et al. 2009), but marine systems are dynamic in space and time (Halpern et al. 2015; Gordon et al. 2018; Kroeker et al. 2020), which has generated arguments in favour of more dynamic and adaptive MPA designs (Grafton and Kompas 2005; Hobday and Hartmann 2006; Hughes et al. 2007). Therefore, the assessment of new MPAs should quantify the spatiotemporal dynamics of priority areas.

A long-standing approach in designing MPAs is to use numerical spatial prioritisation algorithms such as Marxan (Ball and Possingham 2000), Zonation (Moilanen et al. 2009), or prioritizr (Hanson et al. 2019), which identify priority areas that cost-effectively optimise ecological objectives based on several species-specific distribution maps and a set of user-defined conditions. The quality and resolution of species distribution maps vary from the most basic species range maps, based on presence data and (or) expert opinion, to the more sophisticated species distribution maps produced by species distribution models (SDMs). SDMs are particularly useful to conservation biology (Rodríguez et al. 2007) and the selection of protected areas (Seo et al. 2009). In the spatiotemporal framework, SDMs usually apply either generalized spatiotemporal additive mixed models or spatiotemporal geostatistical models to produce a series of maps. To account for the spatiotemporal dimension in the prioritisation exercise, users may optimise a single area solution using the full time series together or produce a set of optimised areas disaggregated by time, i.e., monthly, seasonally, yearly, etc. These results provide different information that users can employ to investigate the spatiotemporal dynamics of priority areas.

Within this context, the purpose of this study was to identify priority areas for the management of the most economically important demersal species in the western Mediterranean Geographical subarea (GSA) 06, with particular emphasis on nursery areas. The western Mediterranean fishing fleet is characterised by small vessels, multiple landing sites, and multispecies catches that sell for relatively high prices (Lizaso et al. 2020). Approximately 90% of assessed stocks are exploited above the maximum sustainable yield (MSY) limits (Raicevich et al. 2018) and it has the highest percentage of unsustainable fished stocks among the 16 major seas in the world (FAO 2000). The socioeconomic models by Sola et al. (2020) suggest that to achieve an MSY level of vulnerable stocks requires 80% reduction of fishing effort following the current spatial planning, which in practice seems to be unrealistic (Maynou 2014; Martín et al. 2019).

In this article, we identify and assess the spatiotemporal dynamics of fishery management priority areas based on standard fishery-independent survey data. To do so, we first apply Bayesian hierarchical spatiotemporal SDMs to different commercially important demersal species (Section 2.1). Then, we use SDM results to fit different spatial prioritisation configurations (Section 2.3) and assess the spatiotemporal dynamics of fishery management priority areas through a number of steps.

Fig. 1. Sampling locations (black dots) of the MEDITS surveys (2000–2016). Bathymetric lines indicate the 200 m isobaths. Coastline is extracted from the European Environmental Agency. Bathymetry was extracted from the EMODnet Bathymetry portal. Map projection is WGS 84—UTM zone 31N.
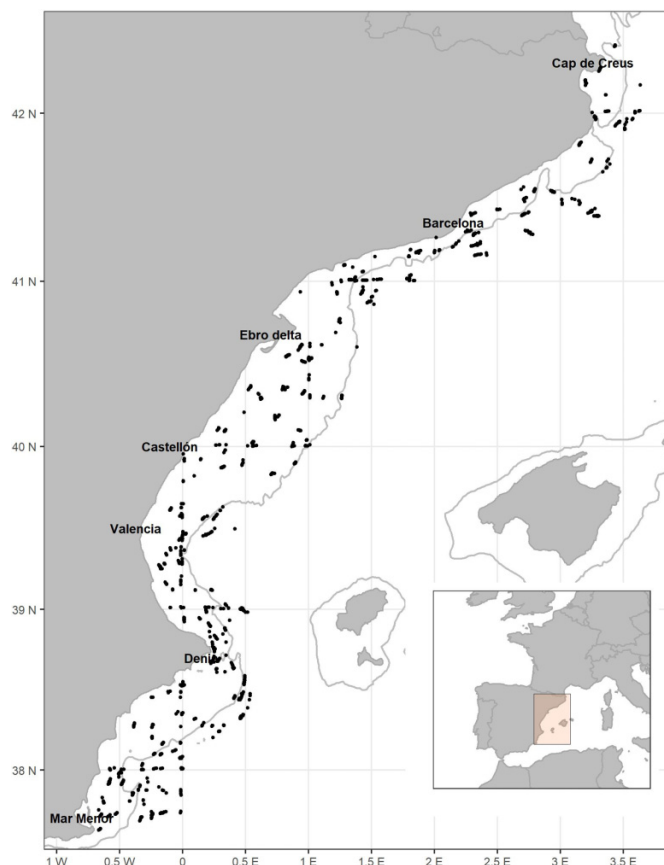

2. Material and methods

The data for this study come from the fishery-independent Mediterranean trawl survey (MEDITS) project (Bertrand et al. 2002) carried out from April to June between 2000 and 2016. The MEDITS uses a stratified sampling design, where strata are defined by bathymetry. Sampling stations were initially placed randomly within each stratum at the beginning of the project and trawl hauls were performed in similar geographical locations every year. This study concerns the trawlable grounds of GSA06, which borders the northern Iberian Mediterranean coast, from Cap de Creus in the north to Cabo de Palos in the south (Fig. 1). The data for this study comprise six species: red mullet (*Mullus barbatus*), striped red mullet (*Mullus surmuletus*), shortfin squid (*Illex coindetii*), European hake (*Merluccius merluccius*), monkfish (*Lophius piscatorius*), and blackbellied monkfish (*Lophius budegassa*). European hake and both monkfish species abundances were segregated into recruits and non-recruits. The MEDITS survey only samples the non-recruit stages of red mullet, striped red mullet, and squid. Table 1 summarises the data comprised in the study.

Table 1. Overall presence probability and conditional-to-presence catch quantiles per species and life stage in the western Mediterranean MEDITS survey data from 2000 to 2016.

Species	Life stage	Presence probability	$Q_{0.25}$	$Q_{0.5}$	$Q_{0.75}$
Merluccius merluccius	Recruits	0.73	14	47	106
Merluccius merluccius	Non-recruits	0.77	2	5	10
Lophius piscatorius	Recruits	0.12	1	1	2
Lophius piscatorius	Non-recruits	0.15	1	1	1
Lophius budegassa	Recruits	0.20	1	1	2
Lophius budegassa	Non-recruits	0.55	1	2	5
Illex coindetii	Non-recruits	0.66	3	9	30
Mullus barbatus	Non-recruits	0.55	5	18	45
Mullus surmuletus	Non-recruits	0.38	1	2	6

Fig. 2. Calculating the predictive posterior distribution of hurdle models using *Mullus barbatus* results for the year 2000. From left to right, top panels represent the mean occurrence probability posterior distribution, the conditional-to-presence mean abundance posterior distribution, and the predictive delta abundance posterior distribution at a particular location. Solid vertical lines represent the mean of the distribution. Bottom panels show mean probability, conditional-to-presence mean abundance, and mean hurdle model abundance maps. Bathymetry and coastline sources as in Fig. 1.
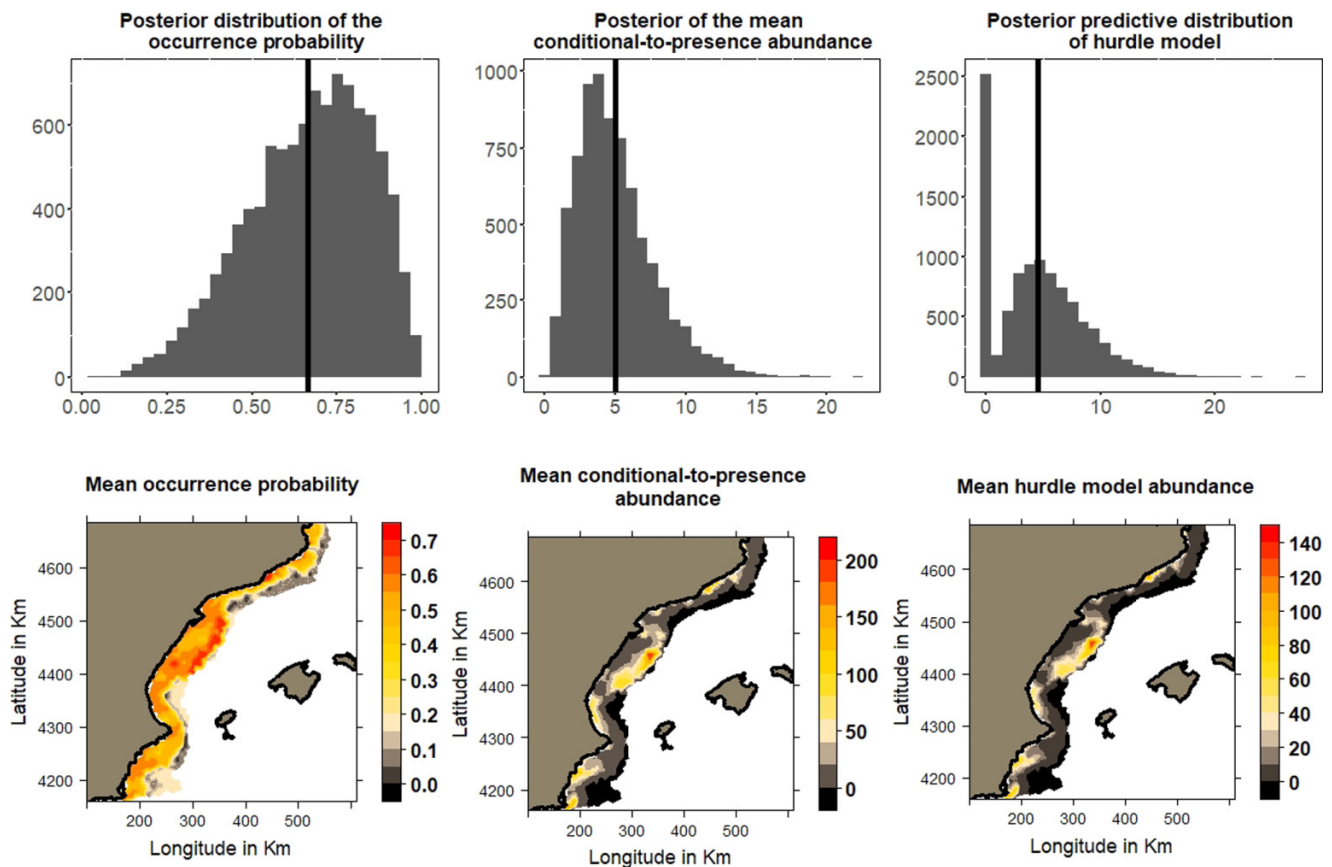
2.1. Spatiotemporal fishery SDMs

To deal with zero catch observations and the interaction between space and time, we fitted Bayesian spatiotemporal two-part or hurdle models. Hurdle models break the data into two and fit separate models to the occurrence and the abundances (Stefánsson 1996; Maunder and Punt 2004; Martin et al. 2005).

Our proposed spatiotemporal structure comprised a geostatistical spatial field that evolved through a first-order autoregressive temporal effect. Autoregressive effects contain a correlation parameter, namely ρ, that infers level of correlation or similarity between subsequent spatial distributions. Therefore, ρ provides important information on the degree

of persistence in the process. The closer the ρ value is to one, the more temporally persistent the process (i.e., very high correlation between subsequent years), whereas ρ values closer to zero suggest more opportunistic distributions (i.e., uncorrelated distributions). See Paradinas et al. (2017, 2020), Martínez-Minaya et al. (2018), and Izquierdo et al. (2021) for further information on persistent, progressive, and opportunistic spatiotemporal fish distributions.

Our spatiotemporal proposal also included a marginal temporal trend and a nonlinear bathymetric explanatory effect, both fitted through second-order Random Walks (RW2), which perform as Bayesian smoothing splines (Fahrmeir and Lang 2001; Lang and Brezger 2004). RW2 models do not allow shape constraints, and therefore we visually confirmed that fitted bathymetric effects were sensible. In particular, if $Z_{s,t}$ and $Y_{s,t}$ are, respectively, the occurrence and the abundance at location s and time t, our proposed model can be formulated as follows:

$$
\begin{aligned}
(1) \quad & Z_{s,t} \sim \mathrm{Be}\left(\pi\left(s, t\right)\right) \\
& Y_{s,t} \sim \mathrm{NB}\left(\mu\left(s, t\right), \phi\right) \\
& \mathrm{logit}\left(\pi\left(s, t\right)\right) = \alpha_Z + f_Z\left(d_s\right) + V_Z\left(s, t\right) + f_Z\left(t\right) \\
& \log\left(\mu\left(s, t\right)\right) = \alpha_Y + f_Y\left(d_s\right) + V_Y\left(s, t\right) + f_Y\left(t\right) \\
& V\left(s, t\right) = W_t\left(s\right) + \rho V\left(s, t - 1\right) \\
& \boldsymbol{W} \sim \mathrm{N}\left(0, \boldsymbol{Q}\left(r, \sigma\right)\right)
\end{aligned}
$$

where Be and NB stand for the Bernoulli and Negative binomial distributions, respectively; $\pi(s, t)$ represents the probability of occurrence at location s at time t; and $\mu(s, t)$ and ϕ are the mean and variance of the conditional-to-presence abundance, respectively. The linear predictors, which contain the effects linked with the parameters $\pi(s, t)$ and $\mu(s, t)$, include α_Z and α_Y, terms that represent the intercepts of each respective variable; $f()$ represent RW2 functions with hyperparameters γ, i.e. the variance of the RW2 model, and parameterised as unknown values $f = (f_0, \ldots, f_{i-1})^T$ at $i = 25$ equidistant values of d_s for the bathymetry and at $i = 17$ year values of t for the marginal temporal trend. $V(s, t)$ refers to a spatiotemporal field that evolves through time given the correlation parameter ρ. Finally, $\boldsymbol{W}$ is a geostatistical field with a covariance function defined by range r and standard deviation σ. Note that the Be and NB processes present different $V(s, t)$ fields, $V_Z(s, t)$ and $V_Z(s, t)$, respectively.

We used the INLA package (Martins et al. 2013) for R (R Core Team 2021) that allows relatively fast spatial and spatiotemporal modelling (Lindgren et al. 2011). The Bayesian approach requires specification of the prior distributions for the parameters and hyperparameters of the model. We used R-INLA default vague prior distributions for the dispersion of the conditional-to-presence abundance and the fixed effects. The hyperparameters of the spatiotemporal fields and the γ hyperparameters of the RW2 were set using penalized complexity (PC) priors as described by Simpson et al. (2017) and Fuglstad et al. (2019). Specifically, we used PC priors that followed the following criteria: (a) the probability that the spatial effect range was smaller than 150 km was 0.15, to avoid very small spatial autocorrelation ranges, (b) the

probability that the spatial effect variance was greater than 1 was 0.20, to avoid masking the bathymetric effect through the spatial effect, and (c) the probability that γ was greater than 0.5 in the occurrence model and greater than the observed conditional-to-presence abundance standard deviation in the conditional-to-presence model were 0.01.

2.2. Quantity of interest

Hurdle models provide two estimates for every location s and time t: a probability of occurrence ($\pi(s, t)$) and a conditional-to-presence abundance ($\mu(s, t)$). While both estimates provide important information for the spatiotemporal characterisation of a species, it is common to work with the mean of a hurdle model, which can be obtained by multiplying the probability of presence and the conditional abundance (Stefánsson 1996; Maunder and Punt 2004; Zuur et al. 2009; Lecomte et al. 2013). The analytical estimation of the variance is slightly more complicated, and it varies depending on the likelihood of $\mu(s, t)$ (e.g., see Lecomte et al. (2013) for the case of delta–gamma and Poisson–gamma models). However, within the Bayesian paradigm, we can easily approximate hurdle model posterior distributions by resampling from the marginal distributions of $\pi(s, t)$ and $\mu(s, t)$. To do so, we first predict n presence–absence values from $\pi(s, t)$, which generates m presences and l absences. Then, we sample m times from $\mu(s, t)$ and combine it with the absences to produce hurdle model posterior distributions. Figure 2 shows an example using *Mullus barbatus* results for the year 2000.

2.3. Fishery management priority area identification

Spatial prioritisation algorithms use several species distribution maps to optimise priority areas based on user-defined conservation objectives, constraints, and penalisations. Conservation objectives set the expected ecological targets to meet. Constraints establish a set of prerequisites to the solutions to ensure that solutions exhibit specific properties (e.g., select specific planning units for protection), and penalisations to penalise solutions according to specific metrics (e.g., connectivity).

This study identified demersal fishery management priority areas minimising the size of the area required (penalising area as a proxy of cost) to protect a minimum set objective, similar to the Marxan's decision support tool (Ball et al. 2009). The prioritisations were solved to within 1% of optimality using Gurobi (version 8.1.0; Bixby 2007) and the prioritizr R package (Hanson et al. 2017). We were particularly interested in protecting nursery grounds, so we set our protection targets to 20% of recruits and 10% of non-recruits. We hypothesized that recruit and non-recruit priority areas could be significantly different; thus, we fitted three different scenarios based on these targets: one that met both objectives, one that met recruit protection targets alone, and another that only met non-recruit protection targets.

In fisheries, fishing effort may be regarded as a proxy to economic impact, and therefore it is common to include

Fig. 3. Difference between the overall map (left) and frequency map (right). These results are then used to assess the spatiotemporal dynamics of priority areas. Dashed lines represent the use of a spatial prioritisation algorithm.
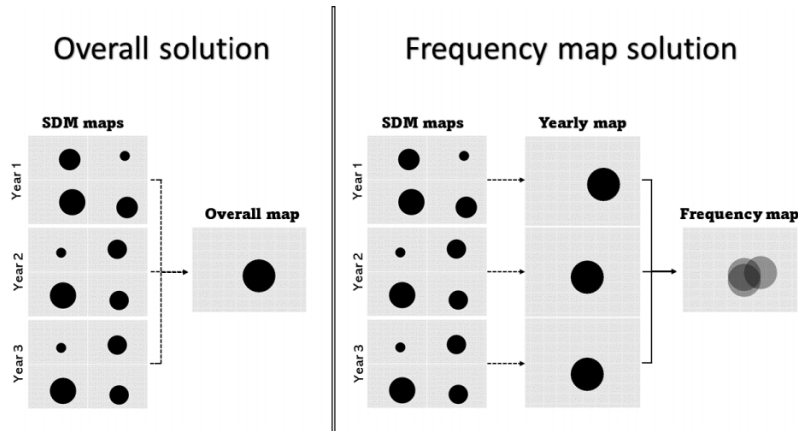
Table 2. Summary of fitted species-specific spatiotemporal pattern.

Species—life stage	ρ Occurrence	ρ NPUE
Merluccius merluccius—R	0.98 (0.02)	0.98 (0.03)
Merluccius merluccius—J/A	0.96 (0.04)	0.83 (0.08)
Lophius piscatorius—R	0.48 (0.18)	—
Lophius piscatorius—J/A	0.51 (0.19)	—
Lophius budegassa—R	0.23 (0.15)	0.42 (0.26)
Lophius budegassa—J/A	0.92 (0.06)	0.74 (0.06)
Illex coindetii—A	0.89 (0.06)	0.83 (0.07)
Mullus barbatus—A	0.98 (0.01)	0.97 (0.01)
Mullus surmuletus—A	0.96 (0.02)	0.97 (0.02)

Note: R and J/A stand for recruits and non-recruits, respectively. ρ is the temporal autocorrelation parameter of the spatiotemporal structure and the value within the parenthesis is the associated standard deviation. NPUE is number per unit effort.

Vessel Monitoring System (VMS)- or Automatic Identification System (AIS)-derived data as a penalisation in the spatial prioritisation algorithm (Afán et al. 2018; Giménez et al. 2020). However, the current overexploitation of fishery resources is driven by an excess of fishery effort (Brochier et al. 2018), and therefore we decided to identify the most productive fishery areas for protection, regardless of the impact on the fishery.

2.3.1. Persistence of priority areas

Marine ecosystems and fish assemblages change in space and time (Halpern et al. 2015; Gordon et al. 2018; Kroeker et al. 2020), which has generated arguments in favour of dynamic MPA designs (Grafton and Kompas 2005; Hobday and Hartmann 2006; Hughes et al. 2007). As a result, we assessed

the spatiotemporal dynamics of priority areas. To do so, we compared two spatiotemporal optimisations that provided valuable information about the level of spatial persistence of priority areas (see Fig. 3). One optimisation included all available maps together (i.e., every time event in the series) to optimise an overall priority area. The overall priority area solution can be regarded as a temporally averaged solution. The other optimisation fitted different priority areas to every time event in the series, providing a temporal series of priority area maps. These maps were then summarised into a frequency map (i.e., a map that overlaps the number of times an area has been selected as a priority area over the time series). The results from these two optimisations were then used to assess the suitability of fixed, progressive, or other types of dynamic MPA designs in the study area.

2.3.1.1. Persistent priority areas

Persistence was assessed by comparing the selected areas in the overall priority area solution and the temporal frequency map solution. High similarity between them implies that yearly priority areas do not differ much from the overall selected priority area, suggesting that priority areas are persistent and therefore a fixed MPA design would be effective. In contrast, divergence in priority areas between the two solutions may suggest a dynamic scenario that requires further considerations and more flexible designs.

2.3.1.2. Progressive priority areas

A difference between the overall priority area solution and the temporal frequency map solution suggests some sort of spatiotemporal variability in priority areas. Progressive priority area drifts were assessed using the Cohen's kappa coefficient, which measure inter-rater reliability for qualitative data (Landis and Koch 1977; McHugh 2012), and help us assess the similarity between different priority area maps (Ban et al. 2009). By doing a pairwise comparison across every map in the time series, we produced a kappa matrix that summarises all the pairwise coefficients and follow the categorisation proposed by Landis and Koch (1977): 0, "No agreement"; 0–0.2,

Fig. 4. Averaged spatial distributions of the different species and life stage abundances between 2000 and 2016. Units are in specimens per hour of trawl fishing using MEDITS gear. Visit tinyurl.com/42hy9e8m for yearly maps. R and J/A stand for recruits and non-recruits, respectively. Bathymetry and coastline sources as in Fig. 1.
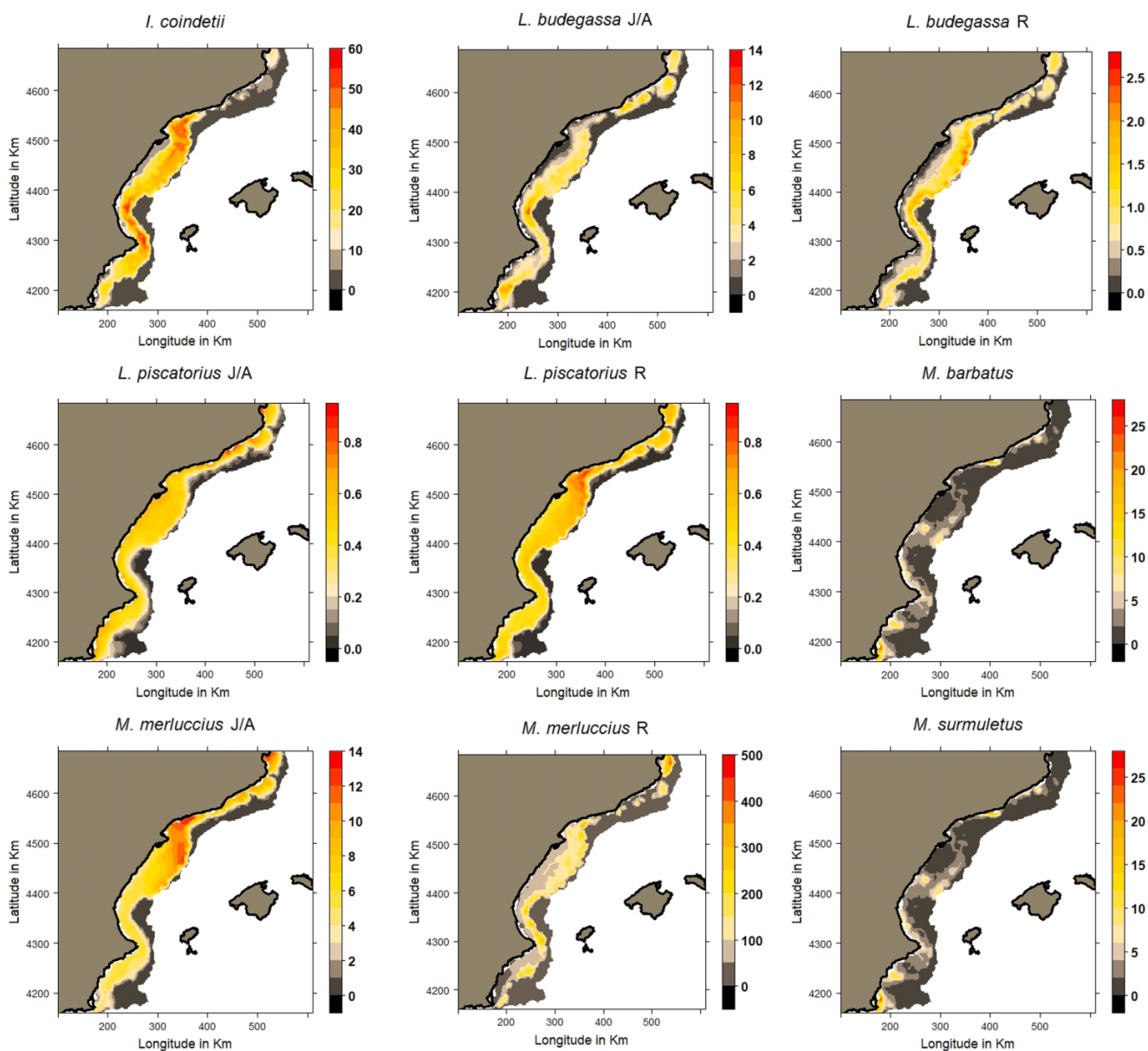
"Slight agreement"; 0.2–0.4, "Fair agreement"; 0.4–0.6, "Moderate agreement"; 0.6–0.8, "Substantial agreement"; and 0.8–1.0, "Almost perfect agreement". We particularly looked at the diagonal of the kappa matrix because it indicates the similarity between successive yearly priority areas. Therefore, a kappa matrix with consistently high diagonal values manifests a progressive evolution in the distribution of priority areas, and therefore, new MPA designs could be informed progressively based on the last fishery-independent survey data.

2.3.1.3. Other priority area dynamics

Inconsistent Cohen's kappa matrix diagonal values imply more flexible priority area dynamics. Under such a situation, it is useful to identify patterns that help us further understand the spatiotemporal process under study. While humans are able to extract patterns from maps, quantifying similarities and dissimilarities among them can be quite challenging, especially when working with several maps. In this regard, we used multivariate methods to help us identify recurrent spatial patterns from the series of maps. Specifically, we used ordination plots and cluster dendrograms to evaluate similarities between spatial prioritisation solutions (Linke et al. 2011). Non-metric multidimensional scaling procedure (NMDS) allowed us to visualise similarities among different solutions in several dimensions with the advantage that the relative differences between solutions were conserved, so it reflected true dissimilarities. In contrast, clustering methods quantify distance between solutions and allowed us to organise them into a dendrogram to help us choose the number of groups.

Fig. 5. Fitted nonlinear bathymetric effects for each of demersal species considered. *Y*-axis values were standardized to be between 0 and 1 for the sake of comparability. Each boxplot corresponds to an approximately 20 m depth interval. Each box represents the interquartile range of the mean fitted values, the central bold line represents the median value, and dots represent fitted values above 1.5 times and below 3 times the interquartile range beyond either end of the box. R and J/A stand for recruits and non-recruits, respectively.
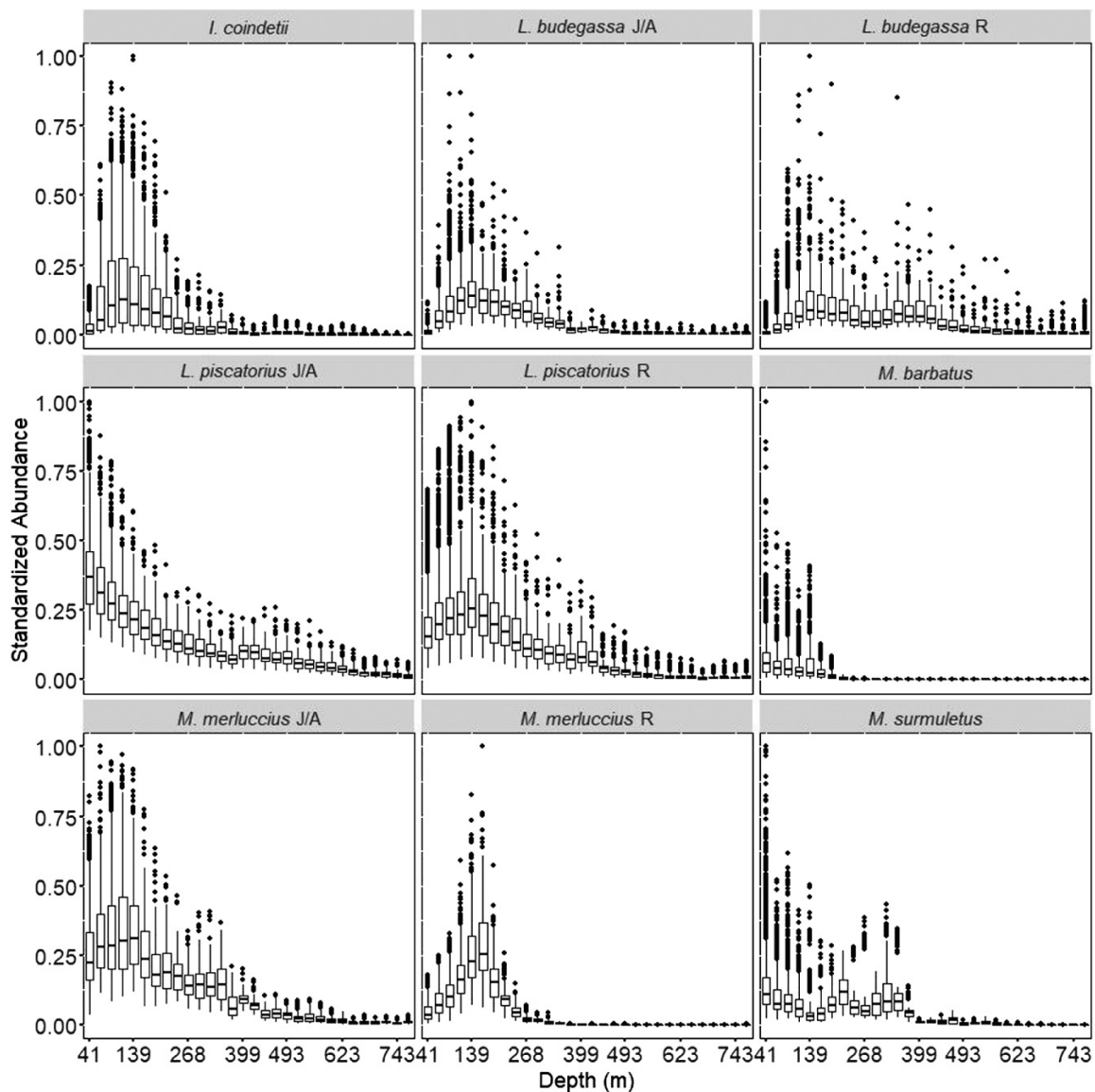
3. Results

SDM results are summarised in Table 2 and reveal rather persistent distributions ($\rho > 0.9$) for *Mullus barbatus*, *Mullus surmuletus*, and *Merluccius merluccius* recruits and non-recruits, suggesting that the spatial distribution of these species and life stages did not vary much from year to year. *Illex coindetii* and *Lophius budegassa* non-recruits showed smooth spatial distribution changes. *Lophius budegassa* recruit and *Lophius piscatorius* recruit and non-recruit distributions changed very abruptly from year to year, falling in the opportunistic distribution category. Figure 4 visualises the average spatial distribution of each species and life stage from 2000 to 2016 (visit tinyurl.com/42hy9e8m for the full time series of maps). Figures 5 and 6 present the fitted bathymetric distribution

and overall population size trends for each species and life stage, respectively.

Figure 7 presents the overall priority areas solution and priority frequency maps for the three different scenarios considered in this study. These results provided two important conclusions for decision making. On the one hand, priority areas that met both recruit and non-recruit protection targets were very similar to the areas that met recruit protection targets alone. In other words, by optimising the protection of 20% of recruits, we also protected 10% of non-recruits in the study area. As a consequence, from this point forward, the study focused on the scenario that combined the 20% recruit and 10% non-recruit protection targets altogether. On the other hand, the overall priority area solution and yearly priority area solution were substantially different, implying non-persistent

Fig. 6. Each species and life stage temporal trends from 2000 to 2016 in the study area. Solid lines represent the mean effect in the linear predictor, and dotted lines represent the 95 credibility interval. R and J/A stand for recruits and non-recruits, respectively.
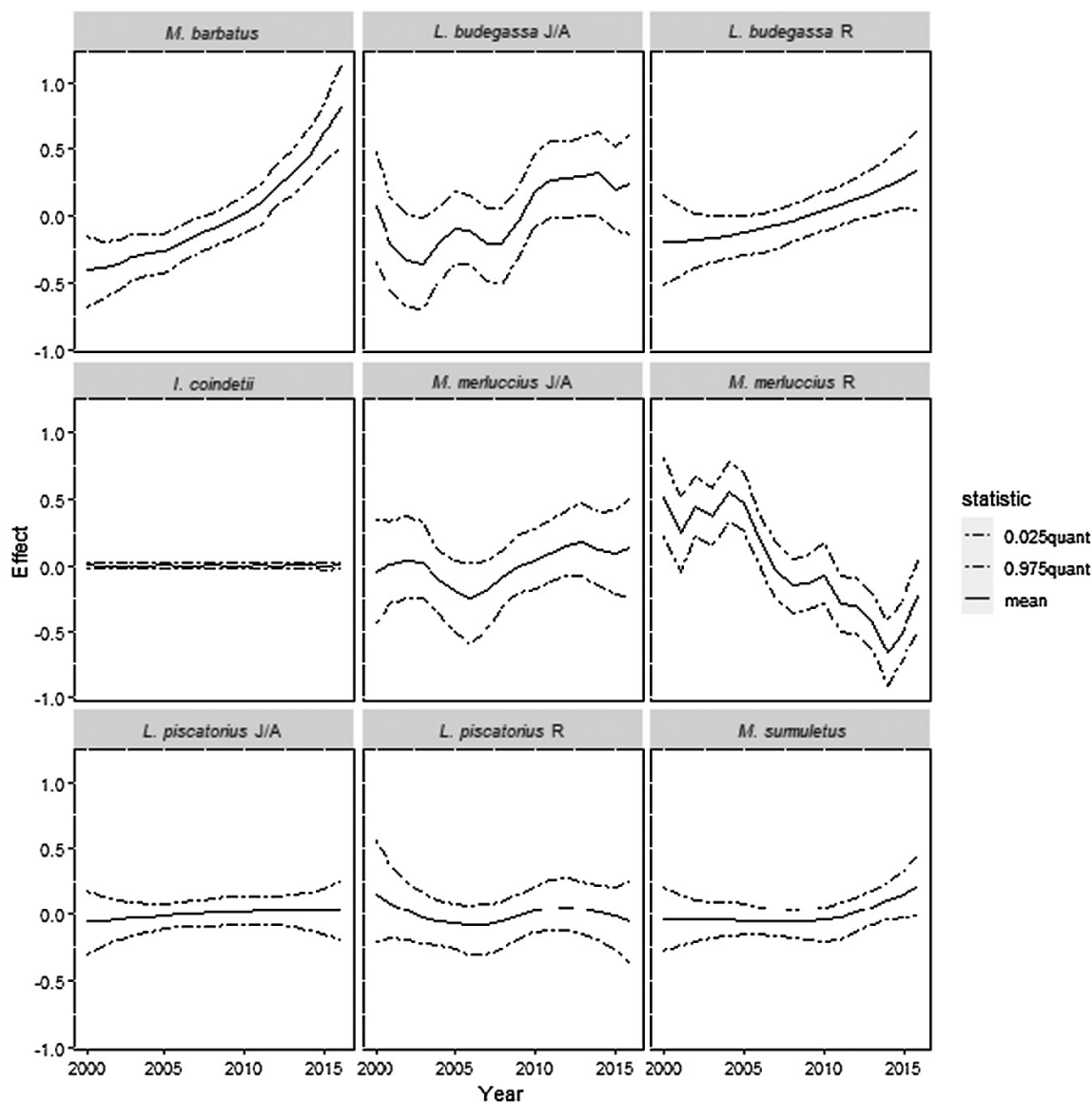
priority areas during the study period. Therefore, we deduced that a fixed MPA design could be ineffective and decided to further explore the spatiotemporal dynamics of priority areas.

Cohen's kappa matrix diagonal indicated that the similarity between temporally subsequent priority areas was rather inconsistent (Fig. 8). Therefore, we deduced that a progressive MPA design based on the previous year's survey result would not be very effective.

NMDS and hierarchical clustering results suggested the presence of either two or four patterns (Fig. 9). After carefully visualizing the maps obtained selecting two and four clusters, and consulting local fishery scientists about better representation of the results, we decided to select two clusters as highlighted by the different colours (see Appendix A for a visualization of the maps obtained by selecting four

clusters). Interestingly, there seems to be a clear temporal pattern between these two clusters, one cluster occurring during the first part of the series and the other one in the second part (see the right panel in Fig. 9). We used these results to create new frequency maps based on these two clusters.

In the end, we obtained a portfolio of priority area maps (Fig. 10) containing: an overall solution map (top left panel); an overall frequency map (top right panel); and a set of frequency maps for the selected number of clusters (bottom panels). The different maps in Fig. 10 consistently identified a number of priority areas. From north to south: (A) the area around Cap de Creus; (B) the end of the continental shelf around the Ebro delta; and (C) the shelf break in front of Valencia. Lastly, despite the lower consistency of priority areas in the south, the zone in front of Mar Menor seemed to be

Fig. 7. Overall priority areas and priority area frequency maps for the different conservation targets. Blue lines represent the 90th percentile contour lines. Coastline source as in Fig. 1. [Colour online.]
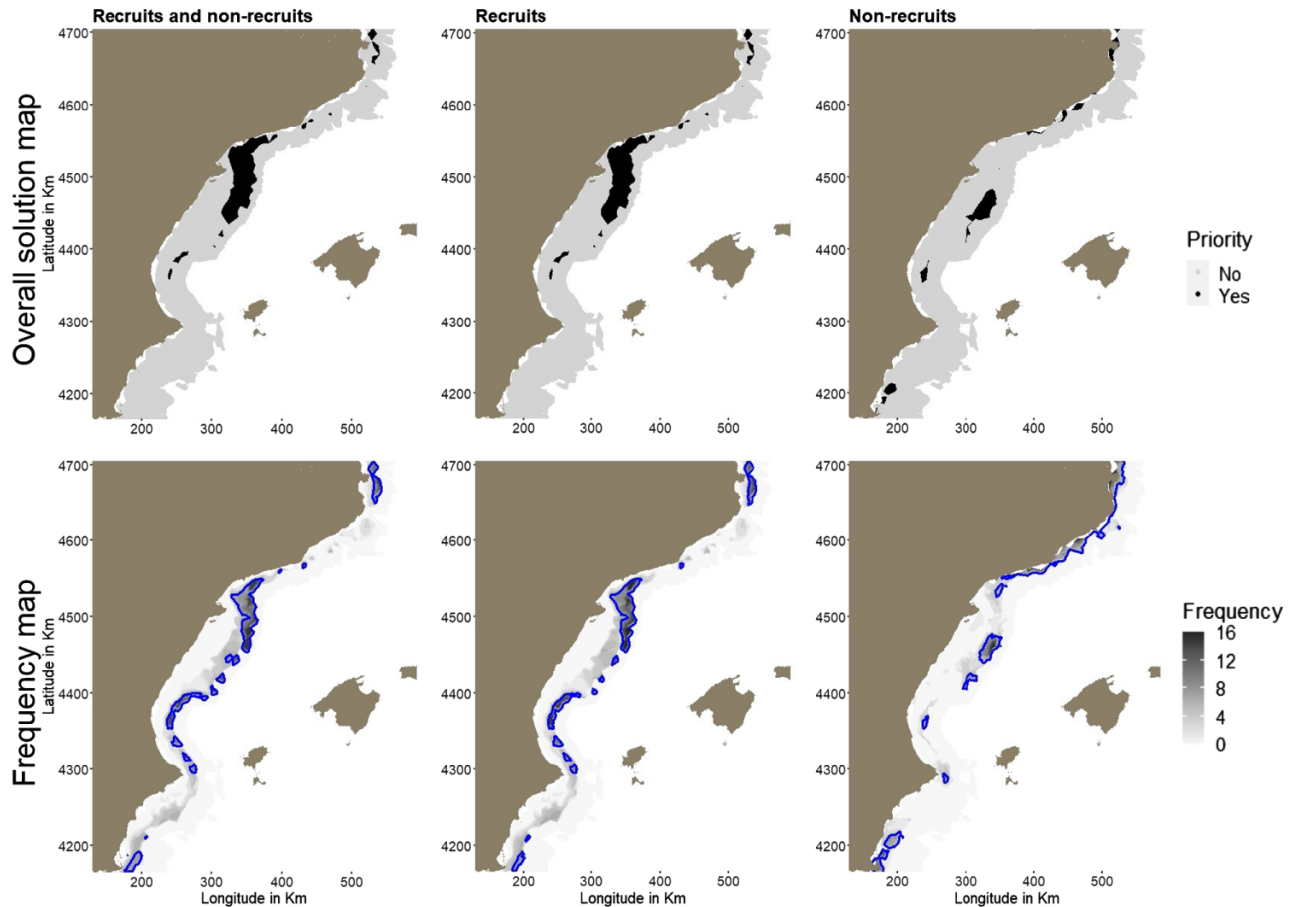
a relatively important ecological area during the second half of the time series (Cluster 1).

4. Discussion

This study assessed the spatiotemporal dynamics of fishery priority areas using spatiotemporal SDMs; different spatiotemporal prioritisation configurations; and a small set of simple metrics and multivariate methods. The method was applied over a western Mediterranean case study, and results identified two temporally structured priority area patterns: one occurring during the first half of the time series and another during the second half. Identifying the drivers behind these patterns was beyond the scope of this study, but could indicate the presence of a large-scale driver such as the western Mediterranean oscillation or the impact of fishing pressure in fish distribution patterns.

Species distribution maps represent the baseline unit for the identification of fishery priority areas. Therefore, good spatiotemporal SDMs are essential to adequately assess the spatiotemporal dynamics of fishery priority areas. There is a wide range of spatiotemporal SDM software available. In fisheries, INLA (Cosandey-Godin et al. 2015; Paradinas et al.

2020), VAST (Thorson 2019), and mgcv (Schmiing et al. 2013; Parra et al. 2017) may be the most widely used R packages in fisheries. We provide R scripts (link) to fit generic spatiotemporal hurdle SDMs using INLA so that other users may apply them in other case studies and areas of interest. It is important to note that our SDMs did not include spatiotemporally changing habitat variables (e.g., temperature, salinity, etc.), so these models provide a good view of what happened in the past but are not appropriate to predict the spatiotemporal distribution into the future.

Our spatial prioritisation optimisations did not include fishery effort as a penalization and identified fishery priority areas based on conservation objectives alone. Far from considering the impact on fishers unimportant, given the overexploitation levels in the Mediterranean (FAO 2000; Sola et al. 2020), our objective was to identify the most important areas for the species under study. In fact, the socioeconomic impact may be assessed afterwards by calculating the amount of fishing activity that would need to be relocated in other areas using VMS- or AIS-derived data.

Our case study constitutes a clear example where fishery priority areas change in space and time. Non-spatiotemporal SDMs and (or) prioritisations would have ignored such vari-

Fig. 8. Cohen's kappa statistic matrix comparing pairwise yearly priority area maps. Of special interest is the diagonal of the kappa matrix, which indicates the similarity between temporally subsequent priority areas. A scenario where kappa matrix diagonal values are consistently high manifests a progressive evolution in the priority areas. [Colour online.]
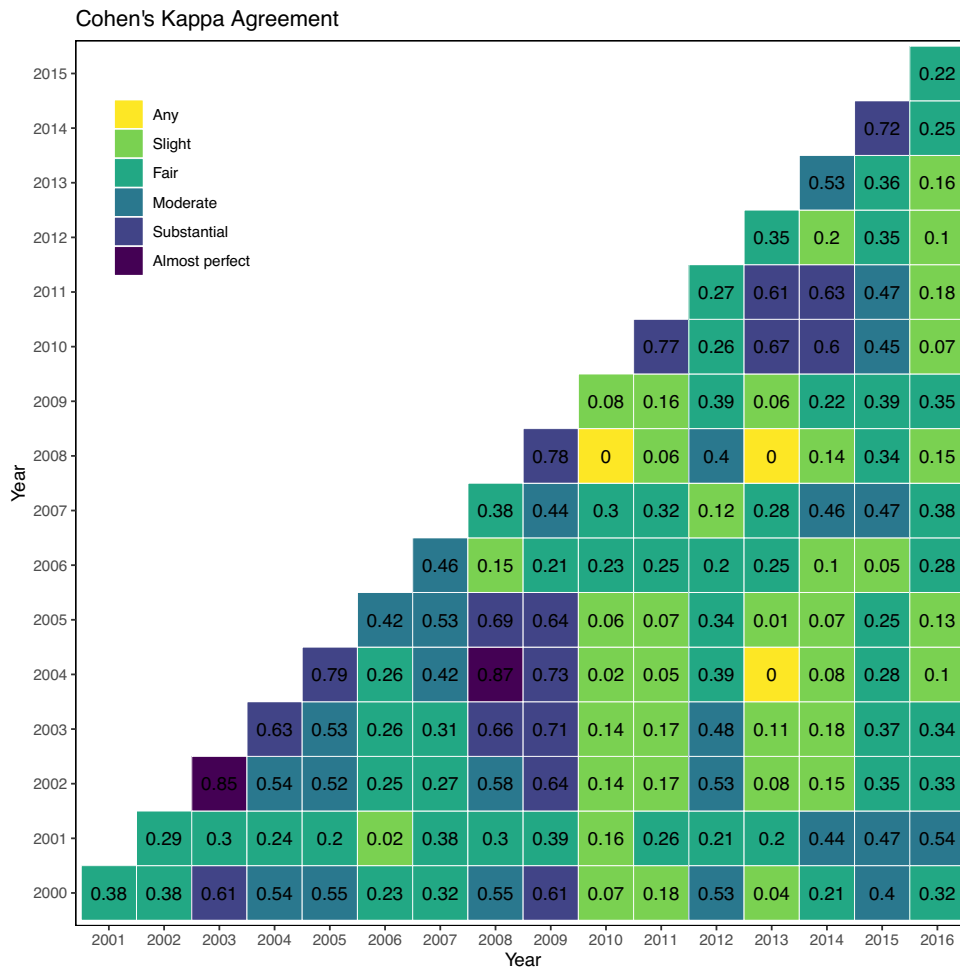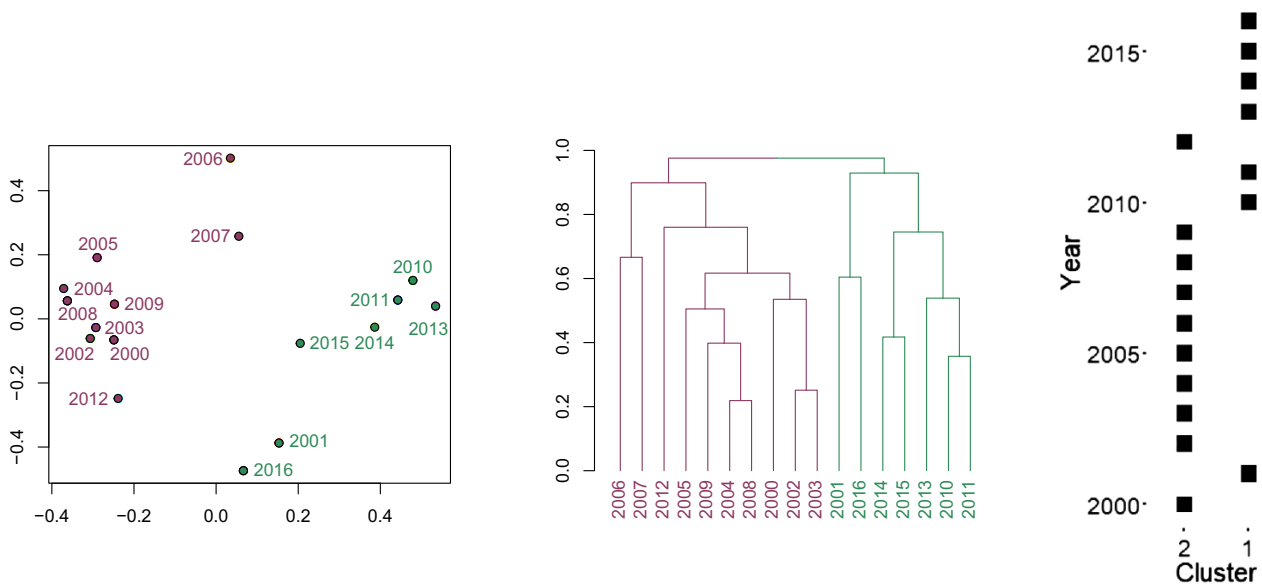
Fig. 9. NMDS scatterplot (left panel) and hierarchical clustering dendrogram (centre panel) of yearly priority area results. The right panel shows the time series of the selected clusters. [Colour online.]

Fig. 10. Portfolio of proposed solutions to assess the spatiotemporal distribution of multispecies hotspots as described in Section 2.3.1. The top left and top right panels represent the overall solution map and the overall priority area frequency map, respectively. The bottom panels show the clustered frequency maps. A, B, and C point at areas that were consistently identified as priority areas across solutions. Coastline source as in Fig. 1.
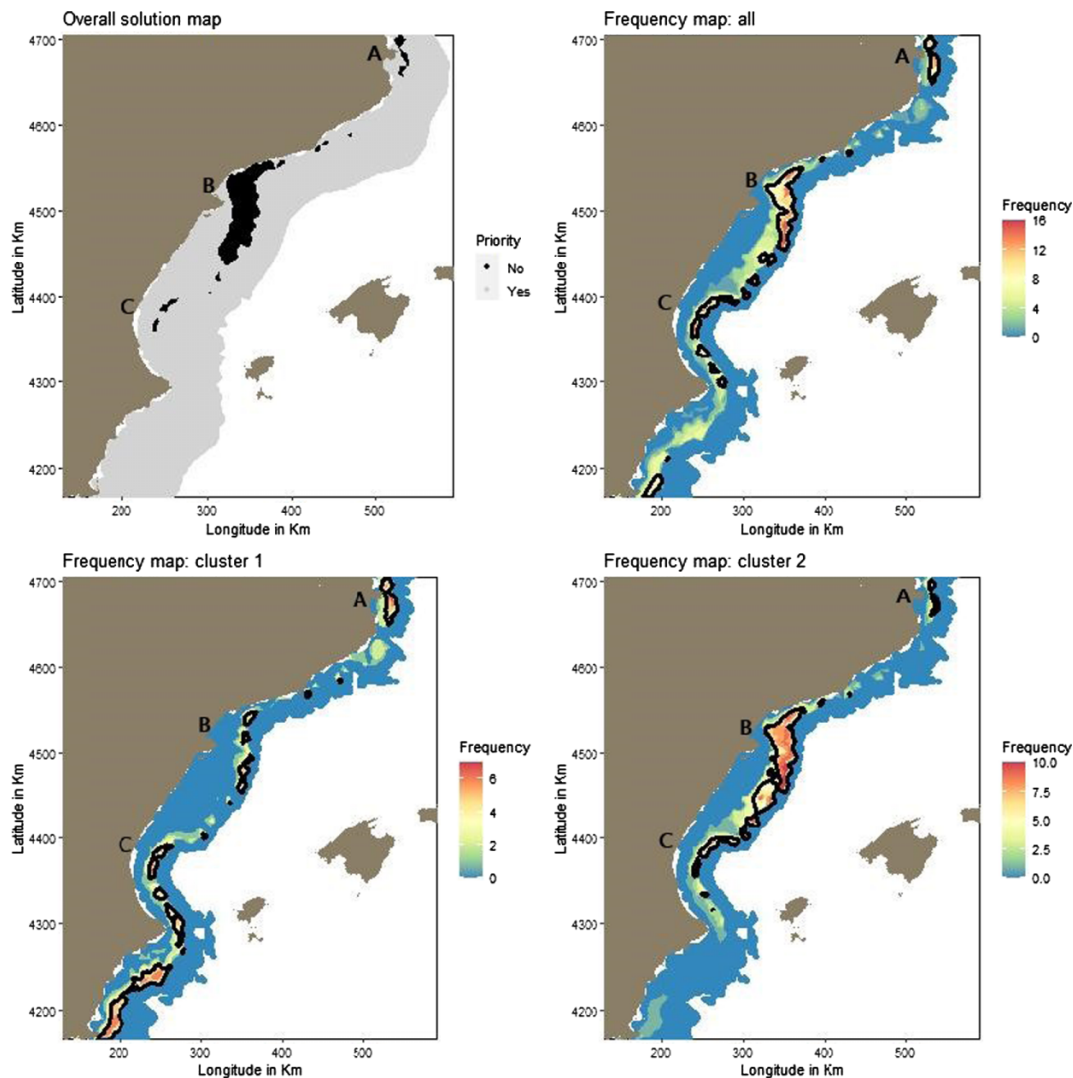
ability, potentially reducing the conservation impact. In this regard, long-term surveys are essential to predict the spatiotemporal distribution of species and assess the spatiotemporal variability of priority areas. Similarly, intraannual temporal resolution is key to assess year-round persistence of priority areas. Unfortunately, fishery-independent surveys are generally programmed once or twice a year, and identified conservation priority areas may not be representative of all seasons. Fishery-dependent data could complement survey data, but its spatial coverage is not always scalable to survey data and target species estimates are affected by the preferential sampling bias (Diggle et al. 2010; Pennino et al. 2018). Another relatively cheap option to complement fishery-independent surveys could be to seek the collaboration of the fishery sector to scientifically sample the ocean in different seasons. The Norwegian reference fleet (Nedreaas et al. 2006) constitutes an excellent example of co-operation between fishers and scientists.

The described procedure follows a clear step-by-step approach to assess the spatiotemporal dynamics of conservation priority areas. A good implementation requires high-quality and long-term fishery data; on-site fishery knowledge to select key conservation objectives; expertise to fit robust spatiotemporal SDMs; spatial planning software skills; and basic multivariate analysis understanding. While this method has been developed for fishery management, it is also applicable to other multispecies systems that evolve with time, no matter marine or terrestrial. Clearly, there is still a considerable challenge ahead to collect quality fishery data to inform the intra-annual dynamics of conservation priority areas. Lastly, we would like to suggest that, given the spatiotemporal dynamics of marine systems and fishery markets, existing MPA designs should go through cyclical and iterative reassessments that incorporate new information and adapt their objectives and measures according to the evolution of the socio-ecological system.

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Notes

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Data availability

The data that support the findings of this study are available from IEO-CSIC (http://www.ieo.es/) upon reasonable request.

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IP, DC, and ALQ contributed to the funding acquisition. IP and JG contributed to the conceptualization and the formal analysis. IP and MGP contributed to the writing of the original draft and all authors contributed to the reviewing and editing all the versions of the manuscript.

Competing interests

The authors declare there are no competing interests.

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Appendix A

In this appendix, we present the frequency maps that we would have obtained if four clusters were selected (as opposed to the two clusters that we present in the results) after the NMDS exercise. The maps presented on the left-hand side of Fig. A1 constitute a single cluster in the article (cluster 1), while the maps on the right-hand side constitute another cluster (cluster 2 in Fig. 10). While there are certain differences, we finally decided that a two-cluster representation was better. We used local fishery scientist opinion to decide whether a four-cluster representation made a significant difference from the two-cluster representation. We finally decided that the two-cluster representation was a smoother description of the results.

Fig. A1. Visualization of the frequency maps that would have been obtained if we selected four clusters after the NMDS exercise over the spatial prioritisation solutions. Coastline source as in Fig. 1. [Colour online.]