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Designing fisheries restricted areas using standard fishery survey data: a novel multilevel spatio-temporal approach†

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Abstract

Fishery restricted areas (FRAs) are pivotal for the mitigation of fishery impacts, but the designation of optimum FRAs is complex, and currently there is no quantitative guideline to assess the spatio-temporal variability of conservation priority areas. Fishery systems are naturally dynamic, and shifts may at two different levels, the species level and the community level. As a consequence, the identification of optimum FRAs using standard fishery data should follow a spatiotemporal procedure that accounts for both levels of dynamism. Here, we describe an approach to optmise the location of FRAs assessing the spatiotemporal dynamism of conservation priority areas at both the species and the multi-species level. To do so, we first assess species-specific dynamisms through Species Distribution Models (SDMs). Then, we use SDM results to explore different spatial prioritisation software configurations to assess the suitability of fixed, progressive, or more complex fishery restricted area designs. Finally, we assess the ecologic and socioeconomic impact of FRA candidates based on our SDM estimates and fishery footprint data, respectively. The proposed method is illustrated through a western Mediterranean case study using scientific trawl survey data on six commercially important species collected over 17 years. Following this approach, we identified two main priority area patterns in the study area. Each pattern is predominant during a different period of the study, constituting a clear example of the importance of regularly re-assessing FRA designs. We conclude that a spatiotemporal assessment of conservation priority areas using long-term data is essential to inform the location of new FRAs.

KEYWORDS:
conservation planning, marine protected area design, marine spatial planning, spatial prioritisation, species distribution model

1 | INTRODUCTION

Marine protected areas are a promising strategy for fisheries management (Hilborn et al. 2004; Rodríguez-Rodríguez, Rodríguez, Malak, Nastasi, & Hernández 2016). In the past, there was a distinction between marine protected areas that aimed for the protection of biodiversity and those that aimed for fisheries management, but currently it is argued that they provide both biodiversity and fishery benefits (Dimarchopoulou, Dogrammatzi,

† Fishery priority areas in space and time

Karachle, & Tsikliras 2018; Fraschetti et al. 2018; Gell & Roberts 2003b 2003a; Petza et al. 2017; Roberts, Hawkins, & Gell 2005). Fisheries restricted areas (FRA) are a particular case of marine protected areas where all or certain fishing activities are temporarily or permanently banned or restricted to improve stock status and long term sustainability (Jonas, Barbuto, Jonas, Kothari, & Nelson 2014; Petza et al. 2017). 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 have already committed to meet this goal by 2020 (Tittensor et al. 2014). Future prospects may raise this number to 30% by 2030 (Dinerstein et al. 2019).

Marine systems are dynamic in space and time (Halpern et al. 2015; Kroeker et al. 2020), making long-term datasets essential to assess spatiotemporal changes in ecological communities and inform effective marine spatial planning consequently (Magurran et al. 2010; Proença et al. 2017). The spatiotemporal dynamism of productive areas may arise at two different levels, the species level and the community level. As a consequence, an appropriate assessment of spatiotemporal FRA designs requires good species-specific spatiotemporal Species Distribution Model (SDM) predictions to feed a spatiotemporal priority area assessment.

The quality and resolution of species distribution maps vary from the most basic species range maps, based on occurrence data and/or expert opinion, to the more accurate species distribution maps produced by SDMs. There is a wide range of different SDMs and data sources (Dormann et al. 2012; Martínez-Minaya, Cameletti, Conesa, & Pennino 2018) that may produce different results (Williams et al. 2014). Most fishery-independent survey data share common features: spatially sampled; performed periodically in the same area; collect both count (n. of individuals) and biomass measurements (weight of individuals); and species-specific datasets commonly have large proportions of zeros observed at unfavourable conditions. Despite the fairly homogeneous characteristics of fishery-independent survey data, applied methods range from the simplest linear model to generalized spatio-temporal additive mixed models (GAMMs) and hurdle geostatistical models, i.e., a two-part model that specifies one process for zero observations and another process for positive observations. Latest fishery distribution models apply spatiotemporal geostatistical hurdle models (Brooks et al. 2017; Cao, Thorson, Punt, & Szuwalski 2020; Paradinas, Conesa, López-Quílez, & Bellido 2017). In this regard, both the integrated nested Laplace approximation (INLA) (Rue et al. 2009) and template model builder (TMB) (Kristensen, Nielsen, Berg, Skaug, & Bell 2016) packages for R (R Core Team 2018) provide very flexible and robust approaches to deal with spatiotemporal hurdle models that effectively deal with the complexities of fishery survey data.

A long-standing approach in designing protected areas is to use numerical spatial prioritisation algorithms such as Marxan (I. Ball & Possingham 2000), Zonation (Moilanen, Kujala, & Leathwick 2009), or prioritizr (J. O. Hanson, Fuller, & Rhodes 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. In the spatiotemporal framework, 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 dynamism of productive areas.

The aim of this article is to propose a spatiotemporal and statistically sound protocol (Figure 1) to appropriately assess the suitability of different FRA designs using standard fishery survey data. Our proposal first applies spatiotemporal Bayesian hurdle models (base code provided) to create species-specific spatiotemporal abundance maps. Then, we apply different spatial prioritisation algorithms to assess the spatiotemporal dynamism of conservation priority areas. Finally, we assess the projected ecologic and socioeconomic impact on each of them.

Sustainable fisheries management seeks a balance between fisheries conservation and fishers' economic well-being. As a consequence, it is common to include the economic impact as a penalisation in the optimisation problem (Mazor, Giakoumi, Kark, & Possingham 2014). In fisheries, fishing effort may be regarded as a proxy to economic impact, and therefore it is common to include Vessel Monitoring System (VMS) or Automatic Identification System (AIS) derived data as a penalisation in the spatial prioritisation algorithm (Afán, Giménez, Forero, & Ramírez 2018; Giménez et al. 2020). However, we argue that including the fishery footprint as a penalisation may be counter effective. The current overexploitation of fishery resources is partly driven by an excess of fishery effort (Brochier et al. 2018); thus FRAs should prioritise the protection of ecologically important areas over the distribution of fishery effort. In fact, heavily fished areas may coincide with high productivity areas and minimising the impact on fishers could displace selected areas for conservation to areas that are seldom fished, projecting little ecological impact.

The reminder of this article is structured in such a way that we progressively present our results along with the description of each methodological step. As a consequence, we first introduce our case study followed by the proposed methodology along with the obtained results. After the methodological section we present a short results section with our proposed FRA network design and finally discuss the main steps of this approach, including some suggestions for a better assessment in the future.

2 | WESTERN MEDITERRANEAN CASE STUDY

The objective of this case study was to propose a FRA network design that accounts for the sustainability of the most economically important demersal species in the western Mediterranean Geographical subarea GSA06, with particular emphasis on nursery areas. The data come from the EU-funded Mediterranean trawl survey (MEDITS) project (Bertrand, de Sola, Papaconstantinou, Relini, & Souplet 2002) carried out from spring to early summer (April to June) between 2000 and 2016. The MEDITS uses a stratified sampling design based on different bathymetric strata. Sampling stations were placed randomly within each stratum at the beginning of the project and 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. The data comprise a total of six species: red mullet (*Mullus barbatus*); striped red mullet (*Mullus surmuletus*); and the shortfin squid (*Illex coindetii*); European hake (*Merluccius merluccius*) disaggregated in recruits (less than 16cm length) and non-recruits; angler (*Lophius piscatorius*) and blackbellied angler (*Lophius budegassa*) disaggregated in recruits (less than 17cm and 20cm length respectively) and non-recruits. Unfortunately, red mullet, striped red mullet, and squid recruits are not collected during the MEDITS survey. Table 1 summarises the data comprised in the case study.

The western Mediterranean fishing fleet is characterised by small vessels, multiple landing sites, multi-species catches, and relatively high prices (Lizaso, Sola, Guijarro-García, Bellido, & Franquesa 2020). Excessive fishery effort seems to be driving the over-exploitation of most Mediterranean commercial species (Da-Rocha, García-Cutrín, Prellezo, & Sempere 2017), with about 90% of assessed stocks exploited above the maximum sustainable yield limits (Raicevich, Alegret, Frangoudes, Giovanardi, & Fortibuoni 2018). The Food and Agriculture Organization (FAO) stated that the Mediterranean and Black Seas had the highest percentage of unsustainable fished stocks among the 16 major seas in the world (FAO 2000) . In particular, the demersal fishery management of the Mediterranean GSA 06 is based on a multi-annual plan (Commission 2019). Fishing activity is not permitted on weekends and the vessels are forced to return to base port with a maximum of 12 fishing hours per day (Bellido, Sumaila, Sánchez-Lizaso, Palomares, & Pauly 2020; Lleonart & Maynou 2003). There are minimum landing sizes for most target species exploited by demersal fleets; however they are not fully enforced, which contributes to the low economic efficiency of fisheries exploitation (Colloca et al. 2013; Sola, Maynou, & Sánchez Lizaso 2020). Some other spatial and spatiotemporal restrictions are in place, but they are currently rather small and localised. The socioeconomic models by Sola et al. (2020) suggest that the maximum sustainable yield level of vulnerable stocks should be achieved soon. However, this goal requires 80% reduction of fishing effort following the current spatial planning, which in practice seems to be unrealistic (Martín, Maynou, Garriga-Panisello, Ramírez, & Recasens 2019; Maynou 2014).

Since 2006, eight FRAs have been established to ensure the protection of deep-sea sensitive habitats and of essential fish habitats (EFH) in well-defined sites by the General Fisheries Commission for the Mediterranean (GFCM). In addition, in 2005, the GFCM prohibited the use of towed dredges and trawl nets in all waters deeper than 1000 metres to protect little-known deep-sea benthic habitats in the Mediterranean. In 2016, this large protected area below 1000 metres was officially declared a FRA by the Commission.

3 | MODELLING SPATIOTEMPORAL FISH DISTRIBUTION USING STANDARD SURVEY DATA

In general, three main characteristics determine the structure of a fisheries spatiotemporal SDM: the nature of the fishery data, the type of environmental covariates included in the model, and the spatiotemporal autocorrelation of the data given the covariates.

3.1 | Zero inflation in fishery data

Fishery data are always positive and may be measured either as number of specimens or biomass. Surveys sample at different marine environments, which often results in not observing any species-specific specimens at unfavourable conditions (Martin et al. 2005; Maunder & Punt 2004). As a consequence, standard fishery survey species-specific datasets typically result in zero-inflated datasets. In our western Mediterranean case study for example, overall zero probabilities varied from 0.88 in *Lophius piscatorius* recruits to 0.23 in *Merluccius merluccius* non-recruits (See Table 1 for a summary of the data).

A number of approaches have been proposed to deal with zero inflation in either continuous biomass data (Maunder & Punt 2004; Thorson 2018) or discrete data (Martin et al. 2005), but the most common approach to deal with the excess of zeros in fisheries is to use a particular type of zero-inflated model known as hurdle model, delta model, or two-part model (Maunder & Punt 2004). These models break the data in two (Equation 1) and fit separate models to the occurrence and the abundances (Equation 2) (Martin et al. 2005; Maunder & Punt 2004; Stefánsson 1996). In particular, if $U(s,t)$ represents a zero inflated random variable observed in location s and time t, then:

$$\begin{aligned} Z(s,t) &= \begin{cases} 1, & \text{if } U(s,t) > 0 \\ 0, & \text{otherwise} \end{cases} \\ Y(s,t) &= \begin{cases} \texttt{NA}, & \text{if } U(s,t) = 0 \\ U(s,t), & \text{otherwise} \end{cases} \end{aligned} \tag{1}$$

where $Z(s,t)$ is a presence-absence process, and $Y(s,t)$ stands for a conditional-to-presence abundance process. $Z(s,t)$ is commonly modelled through a Bernoulli and $Y(s,t)$, through any convenient distribution for the type of observed abundance, either a gamma or lognormal distribution for biomass data, and Poisson or negative binomial for count abundance data. Therefore, hurdle models assume that species occurrence and abundance are different processes that may be driven by completely different predictors.

3.2 | Including covariates

An essential step in SDMs is to gather relevant environmental data that may help us understand and thus predict the distribution of the species under study. Once these data are collected, it is crucial to assess their relevance to avoid including unrealistic environmental relationships into our models (Elith & Leathwick 2009). Early SDMs were based on linear covariate effects using generalized linear models. As nonlinear species responses to environment were recognised (Austin, Nicholls, & Margules 1990; Pulliam 2000; Sinclair, White, & Newell 2010), more studies included quadratic, cubic, or other parametric transforms as well as semi-parametric splines. Currently, the use of smoothing splines is a common approach through generalized Additive Models in the frequentist field (Wood & Augustin 2002) and Random Walk effects in the Bayesian field (Lang & Brezger 2004).

In line with equation 1, a purely covariate driven hurdle model could be written as follows:

$$\begin{aligned} Z(s,t) &\sim \mathrm{Be}(\pi(s,t)) \\ \mathrm{logit}(\pi(s,t)) &= \alpha_Z + \sum_{i=1}^{I} f_i(X_i(s,t)) \\ Y(s,t) &\sim \mathrm{Ga}(\mu(s,t), \phi) \\ \log(\mu(s,t)) &= \alpha_Y + \sum_{j=1}^{J} f_j(X_j(s,t)) \end{aligned} \tag{2}$$

where $\pi(s,t)$ represents the probability of occurrence included through a logit link at location s at time t, and $\mu(s,t)$ and ϕ are the mean and dispersion of the conditional-to-presence abundance (modelled in this case through a gamma distribution and a logarithmic link function). The linear predictors containing the effects to which these parameters $\pi(s,t)$ and $\mu(s,t)$ are linked are formed with α_Y and α_Z, the terms representing the intercepts for each variable, and $f()$, which represents any function applied to our environmental variables X_i.

Assessing the relevance of environmental covariates is critical to every SDM. There is a wide range of model selection scores available in the SDM literature (Robinson, Nelson, Costello, Sutherland, & Lundquist 2017). Unfortunately, these metrics are generally unable to identify u-shaped curve and/or multimodal process-environment relationships, which are not common in nature. In contrast, ecological niche theory expects unimodal relationships with respect to environmental gradients (Hutchinson 1957). Therefore, it may be important to use shape-constrained effects (Citores et al. 2020) and/or visual confirmation to make sure that our SDMs fit meaningful relationships (Elith & Leathwick 2009).

Our case study used second order Random Walk effects to fit the bathymetric distributions of each species and life stage. We used visual validation to assess the biological meaning of fitted effects and also performed sensitivity analyses to test that different priors resulted in similar effects. Figure 2 presents the fitted bathymetric distribution of each species and life stage.

3.3 | Accounting for spatiotemporal autocorrelation

Purely covariate-driven SDMs residuals are often spatially or spatiotemporally correlated due to missing key environmental predictors (Legendre 1993; Whitehead 2001). Ignoring these spatial or spatiotemporal dependencies not only restricts their predictive capacity, but it may also lead to incorrect results (Fortin & Dale 2009; Legendre et al. 2002). A spatial autocorrelation term includes spatial dependency among neighbouring locations based on the principle that close locations have more in common than distant ones (Tobler 1970), resulting in better predictions at unsampled locations (Krige 1951). Overall, there are two main approaches to address continuous spatial autocorrelation: fitting 2D contours using splines (Späth 1993) or applying geostatistics (Krige 1951), i.e. a spatial interpolation technique based on a covariance function that relates the similarity of two locations based on distance (see (Stein 2005) for a full review of covariance functions).

Most fishery surveys are repeated periodically to monitor the temporal evolution of fish populations. As with the spatial domain, temporally close observations tend to be more related than temporally distant observations (Cressie & Wikle 2015). As a consequence, including temporal autocorrelation in our spatial models is likely to improve both model fit and prediction. A spatiotemporal model ($V(s,t)$) assumes that observations are part of a spatial process that changes with time. Mathematically, space and time should be treated as different dimensions, thus $V(s,t) \in \mathbb{R}^2 \times \mathbb{R}$. Within the geostatistical approach, we usually deal with a Gaussian random field that is specified by its mean and spatiotemporal covariance function $\mathrm{Cov}(V(s,t), V(s',t')) = \sigma^2 \omega((s,t),(s',t'))$, defined for each (s,t) and (s',t') in $\mathbb{R}^2 \times \mathbb{R}$. In our study, ω represents the Matérn covariance function.

In addition to the spatiotemporal correlation effect $V(s,t)$, marginal temporal trend effects may be of great interest. A marginal temporal effect can be regarded as a standardised indicator of population size in function of time (Maunder & Punt 2004; Paradinas et al. 2020). Therefore, even a non-relevant marginal temporal effect provides important information for stock assessment, which is that the overall population size has not changed with time.

In line with this, spatiotemporal effects and independent marginal temporal trends can be included in Equation 2 as:

$$\begin{aligned} \mathrm{logit}(\pi(s,t)) &= \alpha_Z + \sum_{i=1}^{I} f_i(X_i(s,t)) + V_Z(s,t) + f_Z(t) \\ \log(\mu(s,t)) &= \alpha_Y + \sum_{j=1}^{J} f_j(X_j(s,t)) + V_Y(s,t) + f_Y(t) \end{aligned} \tag{3}$$

where $V(s,t)$ and $f(t)$ refer, respectively, to possible spatiotemporal autocorrelation structures and marginal temporal effects.

In our case study, spatiotemporal effects comprised a geostatistical spatial field that evolved through a first order autoregressive temporal effect. Autoregressive effects contain a correlation parameter, namely ρ, that helps us assess the 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 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) and Martínez-Minaya et al. (2018) for further information on persistent, progressive, and opportunistic spatiotemporal fish distributions.

This case study used the R-INLA package software (Martins, Simpson, Lindgren, & Rue 2013) that allows relatively fast spatial or spatiotemporal Bayesian inference exploiting stochastic partial differential equations (Lindgren, Rue, & Lindström 2011). Results are summarised in Table 2 and reveal rather persistent distributions for *M. barbatus*, *M. surmuletus*, *L. budegassa* recruits and *M. merluccius* recruits and non-recruits, suggesting that the spatial distribution of these species and life stages did not vary much from year to year. *I. coindetii* and *L. piscatorius* recruits and non-recruits showed smooth spatial distribution changes. *L. budegassa* non-recruit distribution changed very abruptly from year to year, falling in the opportunistic distribution category. Figure 3 visualises the average spatial distribution of each species and life stage from 2000 to 2016 (Visit app for the full time series of maps of each species and life stage) and Figure 4 presents the fitted marginal temporal trends using second order random walk models.

3.4 | Quantity of interest in hurdle models

Hurdle models provide two estimates for every location s and time t, a probability of occurrence, and a conditional-to-presence abundance. While both estimates provide important information for the spatiotemporal characterisation of a species, it could be more useful to work with the mean of a hurdle model, which can be obtained by multiplying the probability of presence and the conditional abundance (Lecomte et al. 2013; Maunder & Punt 2004; Stefánsson 1996; Zuur, Ieno, Walker, Saveliev, & Smith 2009). The estimation of the variance is slightly more complicated, and it varies depending on the likelihood of $\mu(\mathrm{s}, \mathrm{t})$ (e.g. see (Lecomte et al. 2013) for the case of a delta-gamma and Poisson-gamma models). In our case study, as we are within the Bayesian paradigm, we used resampling from our posterior distributions of the parameters to approximate the posterior predictive distribution of the hurdle model, not only its mean and variance. To do so, we combined the conditional-to-presence model mean abundance posterior distribution with the posterior distribution of the mean of the occurrence model as illustrated in Figure 5 .

4 | ASSESSING SPATIOTEMPORAL PRIORITY AREAS

spatial prioritisation algorithms such as Marxan (I. Ball & Possingham 2000), Zonation (Moilanen et al. 2009), and prioritizr (J. O. Hanson et al. 2019) 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 metric (e.g. connectivity). In marine spatial planning, it is common to use fishery footprint as a proxy to the socioeconomic impact on fishers (Giménez et al. 2020; Klein, Steinback, Watts, Scholz, & Possingham 2010). However, minimising the impact on fishers may be counter effective as it can displace important conservation areas and prioritise other areas that are seldom fished, projecting little ecological impact. The current overexploitation of fishery resources is partly driven by an excess of fishery effort (Brochier et al. 2018), thus placing a FRA in a non-fished area will inevitably have no effect as it does not reduce fishing effort in conservation hot-spots. We believe that this is a strong argument against the use of fishery footprint as a penalisation, and we argue that this impact should be assessed a posteriori.

4.1 | Priority area identification

We generated prioritisations using the minimum set objective (similar to the Marxan decision support tool, (I. R. Ball, Possingham, & Watts 2009)). We minimised the cost of the solution whilst ensuring that all targets were met (Rodrigues, Orestes Cerdeira, & Gaston 2000). Specifically, the prioritisations were generated using area as a proxy of cost. prioritisations were solved to within 1% of optimality using Gurobi (version 8.1.0) (Bixby 2007) and the prioritizr R package (J. Hanson et al. 2017).

FRAs may target several ecological objectives such as the preservation of recruits and spawners, the reduction of discards, and the conservation of specific biodiversity indexes, etc. In particular, our case study targeted the protection of 20% of recruits and 10% of the juveniles and adults, demonstrating our first prioritisation process was fitted to meet these two targets. However, we also fitted prioritisations that met single target

solutions in order to better understand what specific areas are important to meet each specific objective. As a result, in total we performed three different prioritisations: one that targeted both recruits and non-recruits protection levels; another that targeted only recruits protection; and one that targeted non-recruits protection. The difference obtained targeting only recruits or non-recruits is compelling (see Figure 6). However, the solutions that target the protection of only recruits and both recruits and non-recruits are very similar. In other words, by optimising the protection of 20% of recruits, we also protected 10% of non-recruits in the study area; thus, the case study focused on the overall 20% recruits and 10% non-recruits prioritisation.

4.2 | Spatiotemporal optimisation

Marine ecosystems and fish assemblages change in space and time (Gordon et al. 2018). As a result, the spatiotemporal identification of priority areas is pivotal to an effective FRA design. Our case study only accounts for six commercially exploited species, which means that results may not represent ecosystem or community shifts, but we intend to use these data to illustrate the multi-specie spatiotemporal pattern identification approach that we propose. Our proposed approach compares two spatiotemporal optimisations that can provide important information about the level of spatial persistence of priority areas. Assessing the level of spatial persistence is key to decision making because it will assess the suitability of fixed FRA designs.

One approach includes all available maps together (i.e. every time event in the series) to optimise an overall priority area (Solution A hereafter). Solution A can be regarded as a temporally averaged solution, or a merely spatial solution. The other approach optimises different priority areas to every time event in the series, providing a temporal series of priority area maps. These maps can be summarised into a frequency map (Solution B hereafter), which is a map that overlaps the number of times an area has been selected as a priority area over the time series. The visualisation of solution B can be improved by selecting an upper percentile to select the percentage of area to be protected. For example, a 90th percentile cut-off selects the 10% most productive areas in the time series. Figure 6 presents solutions A and B for the different protection targets described in the previous Section 4.1.

4.2.1 | Persistent priority areas

Temporally persistent priority areas may be assessed by comparing the selected areas in solutions A and B. High similarity between them implies that a fixed FRA design will be effective given the data, i.e., we deduce that priority areas have been persistent so far. In contrast, divergence in priority areas between solutions A and B may suggest a dynamic scenario that requires further considerations and more flexible designs (i.e. dynamic FRAs). In our case study, a visual comparison of solutions A and B in Figure 6 displays a substantial divergence, suggesting that an averaged or purely spatial prioritisation, i.e. solution A, should not be advised. As a result, we decided to further explore the spatiotemporal dynamism of priority areas.

4.2.2 | Progressive priority areas

Differences between solutions A and B suggest spatiotemporal variability in priority areas. Under such situations, Cohen's kappa coefficient may be a useful statistic. Cohen's kappa coefficient is a statistic that is used to measure inter-rater reliability for qualitative data (Landis & Koch 1977; McHugh 2012) and it can help us asses the similarity between different priority area maps (Ban, Picard, & Vincent 2009). By doing a pairwise comparison across every map in the time series, we can produce a kappa matrix that summarises all the pairwise coefficients. The extent of agreement was given following Landis and Koch (1977): 0, "No agreement"; 0-0.2, "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." 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, so FRAs could be informed progressively based on the last fishery survey's solution.

In our case study, Cohen's kappa diagonal matrix showed relatively inconsistent values when targeting both recruits and non-recruits conservation levels (Figure 7). Therefore, we discarded the use of progressive FRA designs based on the previous year's survey results.

4.2.3 | Other dynamisms in priority areas

Inconsistent Cohen's kappa matrix diagonal values imply more flexible priority area dynamisms. Under such a situation, it is useful to identify patterns that help us further understand the spatiotemporal process under study. Whilst humans are able to extract patterns from maps, quantifying similarities and dissimilarities amongst them can be quite challenging, especially when working with several maps. In this regard, multivariate methods provide appropriate statistical techniques to identify recurrent spatial patterns from a series of maps. Ordination plots and cluster dendrograms are useful tools to evaluate similarities between spatial prioritisation solutions (Linke, Watts, Stewart, & Possingham 2011). Non-metric multidimensional scaling procedure (NMDS) allow us to visualise similarities among different solutions in several dimensions with the advantage that the relative differences between solutions is conserved, so it reflects true dissimilarities. In contrast, clustering methods quantify distance between solutions and allow us to organise them into a dendrogram to help us chose the number of groups. While a number of quantitative approaches exist to select the number of groups or patterns, fishery expertise is always desirable in this stage.

In our case study, NMDS and clustering results (Figure 8) suggested either two or four groups. After carefully looking at the solutions and getting the opinion of fishery experts', we decided to separate two groups as seen in Figure 8 . Interestingly, these two clusters were quite clearly separated in time, one cluster mainly occurring during the first part of the times series and the other one in the end (See right panel in Figure 8). Once the number of clusters or patterns were selected, we created new frequency maps to obtain a more informative set of solution B maps. As a result we obtained a portfolio with an overall solution map; an overall frequency map; and a set of frequency maps for the selected number of patterns Figure 9 .

4.3 | Impact assessment

An appropriate FRA network design must take into account both expected ecological targets and the expected socioeconomic impact on fishers. Table 3 summarises the impact assessment of the highlighted frequency contours in Figure 9 . We used the predicted delta abundance distributions in Section 3.4 to calculate the protection levels of each species and life stage that would have been protected. Similarly, we used fishery footprint maps to assess the socioeconomic impact. In particular, we used AIS Fishery footprint maps (Kroodsma et al. 2018) sourced online from the Global Fishing Watch website (GFW: http://globalfishingwatch.org/; accessed on August 2017). GFW estimates daily fishing effort for five complete years (2012-2016) by combining scores for all fishing vessels operating in the area. In turn, the fishing score model computes the probability that a vessel is fishing based on its AIS track data. Fishing is defined as the period that a vessel spends away from shore in which it is not transiting to and from the fishing grounds. We focused in the fishing activity of trawlers because this is the main gear fishing the species under study, but information for long liners and purse seiners is also available.

5 | DISCUSSION

Designing fisheries restricted areas (FRA) is a complicated task. Fish populations and fish assemblages change in space and time (Mason & Brandt 1999; Rogers & Ellis 2000); therefore, the design of new FRAs should consider the spatiotemporal dynamism of species-specific distributions and multi-species hotspots. Here, we describe a procedure to identify multi-species hotspots using Species Distribution Models (SDMs) and spatial prioritisation algorithms. We used two main R libraries, R-INLA (Martins et al. 2013) to fit SDMs and prioritizr (J. O. Hanson et al. 2019) to identify priority areas but other software may be as valid to produce similar results. All the software is open source and we provide R scripts to fit generic spatiotemporal hurdle SDM using R-INLA. Prioritzr R code is also available at the developpers page.

Spatiotemporal SDMs allow us to infer species-specific distributional changes using standard survey data as described in Section 3. spatial prioritisation algorithms assist us on the prioritisation of areas that meet expected protection targets using SDM estimates (Section 4). In Section 4.2 we describe an approach to assess the spatiotemporal behaviour of priority areas using different prioritisation strategies and multivariate techniques. Lastly, we use SDMs estimates to calculate the conservation impact of FRAs, and fishery footprint maps to calculate the percentage of effort

that would need to be relocated as a proxy to the socioeconomic impact (Section 4.3). Our impact assessment was performed over the different proposed solutions. However, these areas may not constitute a good balance between conservation and socioeconomic impact, neither may be spatially balanced, which means our results only provide information to assist decision makers and should not be regarded as a final solution to a FRA design. In fact, a competent FRA network design should result from an iterative discussion between the scientific community, the fishery sector, and policy makers to enact law that ensure the conservation of fishery important areas while balancing the socioeconomic impact on the fishing sector (Caveen, Polunin, Gray, & Stead 2014; Lubchenco et al. 2019).

Our case study has shown a clear example where fishery priority areas change in space and time. A purely spatial prioritisation would have suggested different FRA locations, potentially reducing conservation impact. Therefore, we argue that a spatiotemporal priority area evaluation is essential to adequately assess effective FRA designs. In this regard, Section 4.2 explores different priority area results to assess the suitability of fixed, progressive, or more complex FRA designs. Fixed FRA designs are assessed by comparing the similarity between an overall priority area solution and yearly priority area solutions (Section 4.2.1). High similarity between these two implies effective fixed FRA designs, while differences suggest spatiotemporal priority area changes. Progressive FRA designs imply priority areas that evolve progressively through time. These are assessed calculating Cohen's kappa coefficient between consecutive years optimised priority areas. Consistently high kappa coefficient values manifest a progressive evolution in priority areas, which means FRAs could be progressively re-designed based on the last fishery survey's solution. In contrast, inconsistent kappa values imply more complex and flexible systems where multivariate statistical methods can assist us to identify recurrent priority area patterns. In particular, the western Mediterranean has been characterised by two main priority area patterns. One pattern was predominant during the first half of the time series and another on its second half, suggesting a shift in productive areas. While future studies should investigate the drivers behind this shift (climate change, chlorophyll concentration levels, fronts, etc), this case study constitutes a clear example why FRA designs should be regularly re-assessed.

Long-term fishery-independent surveys are pivotal to the spatiotemporal assessment of FRA designs. Our western Mediterranean case study constitutes a clear example where a shorter time series could have produced completely different results, concluding that conservation priority areas were persistent as opposed to the two clear patterns identified. Similarly, intra-annual temporal resolution is key to assess year around FRA designs. Unfortunately, fishery-independent surveys are generally programmed once or twice a year, and as such, FRA designs may not represent conservation priority areas at unsampled 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, Menezes, & Su 2010; Pennino et al. 2018). Another relatively cheap option to complement fishery surveys could be to seek the collaboration of the fishery sector to scientifically sample the ocean in different seasons. The Norwegian reference fleet (Nedreaas, Borge, Godøy, & Aanes 2006) constitutes an excellent example of co-operation between fishers and scientists. Similarly, while this case study seems sufficient to illustrate the proposed approach, the relatively small spatial coverage of the study is a clear shortfall and we suggest to expand this study to the whole Mediterranean sea with the co-operation of the General Fisheries Commission for the Mediterranean and other institutions of competence.

Current overexploitation of fishery resources is partly driven by an excess of fishery effort (Brochier et al. 2018), thus FRAs should prioritise the protection of ecologically important areas over the fishery (Kenchington 2017). Therefore, our FRA optimisation approach did not include the fishery footprint as a penalisation in the spatial prioritisation algorithm. This decision was taken in the interest of prioritising ecological targets over the minimisation of the socioeconomic impact. In fact, minimising the socioeconomic impact may result in prioritising large areas of little interest, and most importantly, it may not displace much fishery effort in ecologically important areas.

The described procedure follows a clear step-by-step approach to assess the spatiotemporal dynamism of conservation priority areas. An adequate implementation of this method requires: a high-quality and long-term fishery dataset; 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 fisheries management, it is also applicable to other marine and terrestrial systems. Clearly, there is still a considerable challenge ahead to collect quality fishery data to inform the intra-annual dynamism of conservation priority areas. Lastly, we would like to

remark that, given the spatiotemporal dynamism of marine systems and fishery markets, existing FRA designs should go through cyclical and iterative re-assessments that incorporate new information and adapt their objectives and measures according to the evolution of the socio-ecological system.

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6 | FIGURES

7 | TABLES

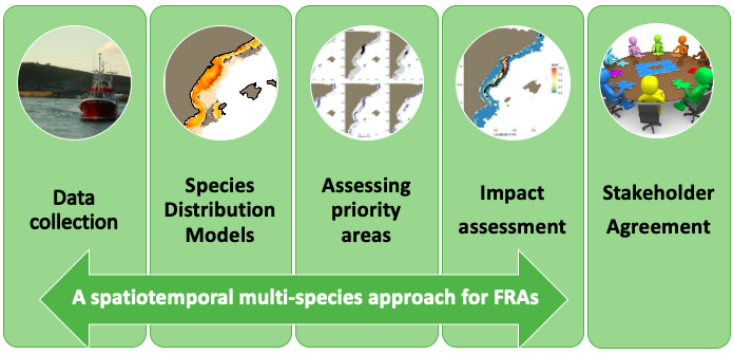

FIGURE 1 Graphic flowchart describing the proposed spatiotemporal FRA assessment approach.

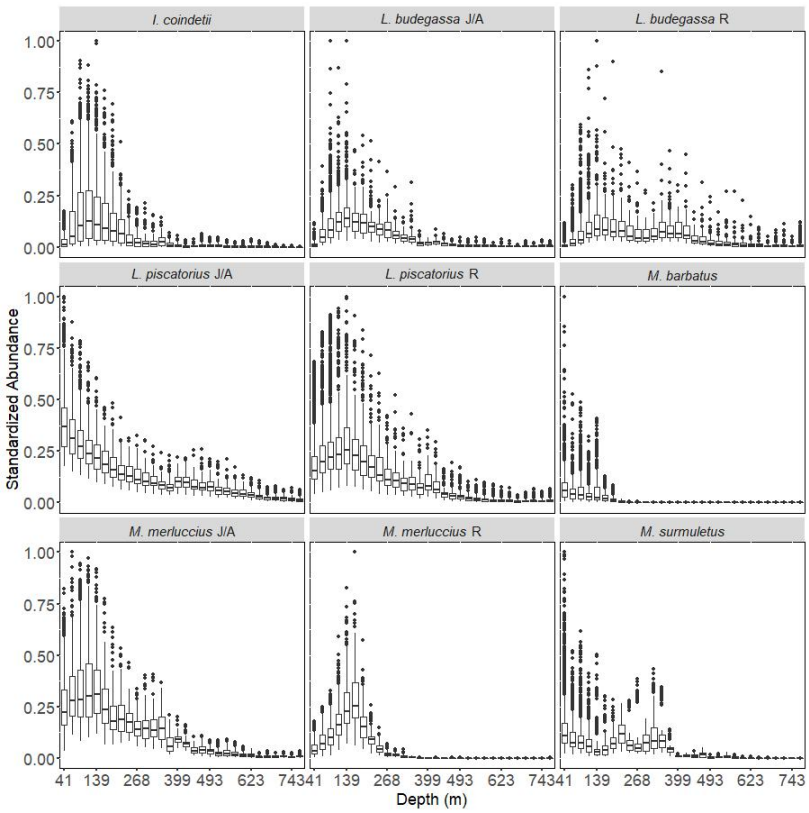

FIGURE 2 Fitted non-linear bathymetric effects for each of demersal species considered. Each boxplot corresponds to an approximately 20 m depth interval. Each box represents the interquartile range of the mean fitted values, the central bold line represents the median value, and dots represent fitted 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.

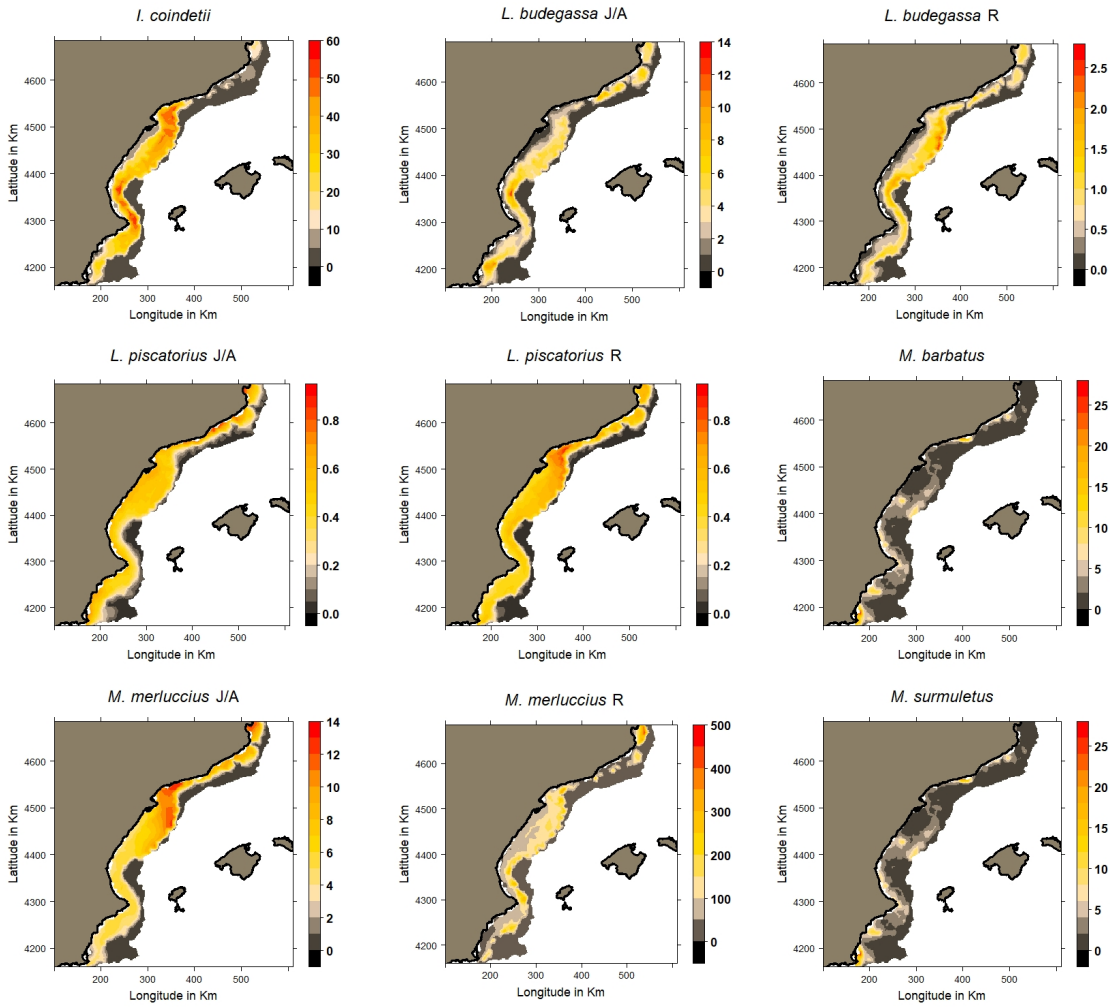

FIGURE 3 Average spatial distribution of the different species and life stage abundances between 2000 and 2016. Visit app for yearly maps. R and J/A stand for recruits and non-recruits respectively.

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

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.

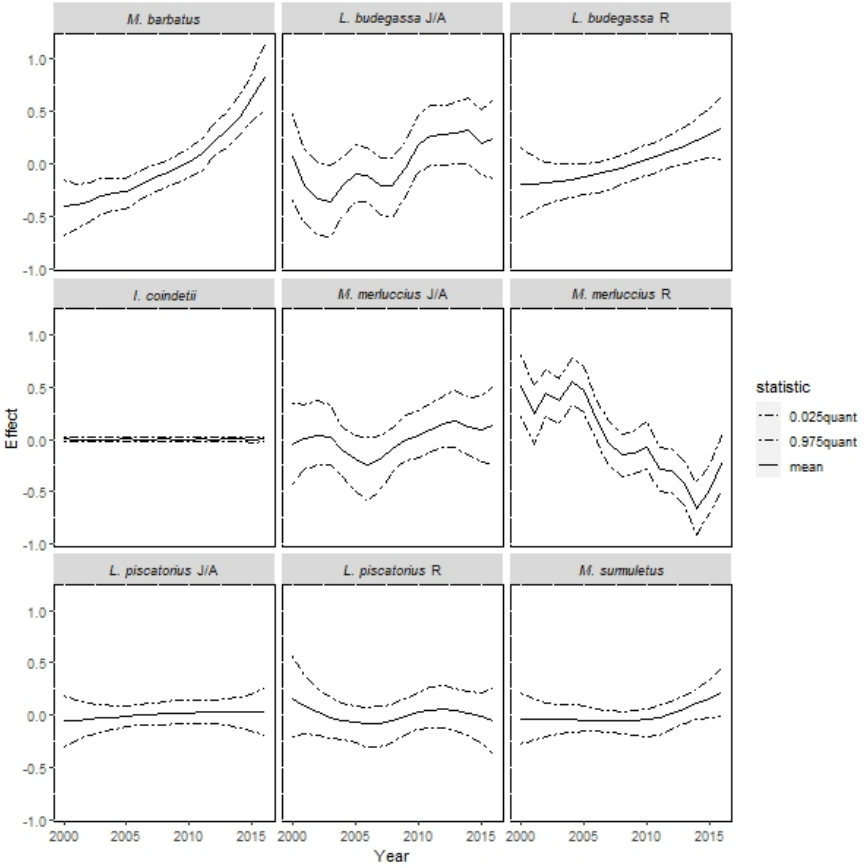

FIGURE 4 Each species and life stage temporal trends from 2000 to 2016 in the study area. Solid lines represent the mean effect in the linear predictor, and dotted lines represent the 95 credibility interval. R and J/A stand for recruits and non-recruits, respectively.

Species - Life stage	ρ Occurrence	ρ NPUE
M. merluccius R	0.98 (0.02)	0.98 (0.03)
M. merluccius J/A	0.96 (0.04)	0.83 (0.08)
L. piscatorius R	0.48 (0.18)	-
L. piscatorius J/A	0.51 (0.19)	-
L. budegassa R	0.23 (0.15)	0.42 (0.26)
L. budegassa J/A	0.92 (0.06)	0.74 (0.06)
I. coindetii A	0.89 (0.06)	0.83 (0.07)
M. barbatus A	0.98 (0.01)	0.97 (0.01)
M. surmuletus A	0.96 (0.02)	0.97 (0.02)

TABLE 2 Summary of fitted species-specific spatiotemporal pattern. 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.

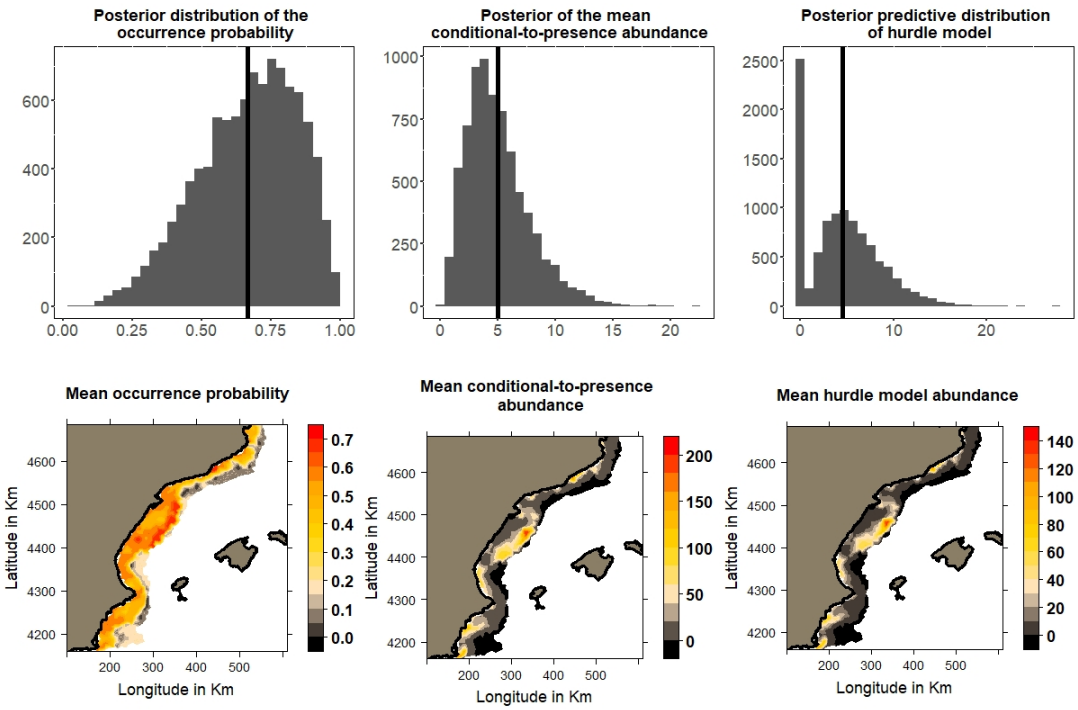

FIGURE 5 Calculating the predictive posterior distribution of hurdle models using *Mullus barbatus* results for the year 2000. From left to rigH, top panels represent the mean occurrence probability posterior distribution, the conditional-to-presence mean abundance posterior distribution, and the predictive 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.

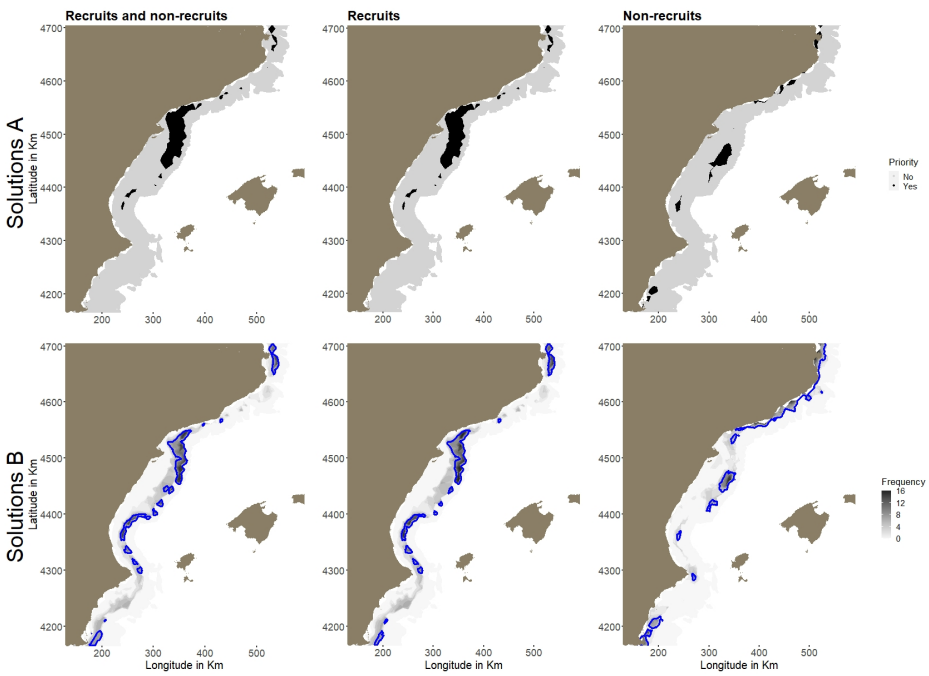

FIGURE 6 Overall priority areas (solution A) and priority frequency maps (solution B) for the different conservation targets. Blue lines represent the 90th percentile contour lines.

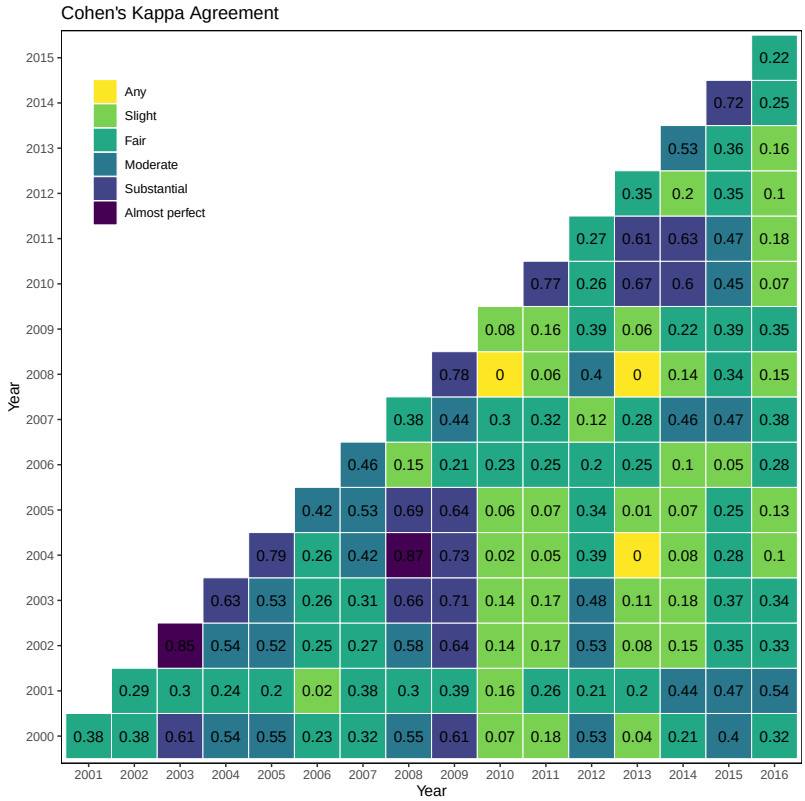

FIGURE 7 Cohen's kappa statistic matrix comparing pairwise yearly priority area maps. Of special interest is the diagonal of the kappa matrix, which indicates the similarity between temporally subsequent priority areas. A scenario where kappa matrix diagonal values are consistently high manifests a progressive evolution in the priority areas.

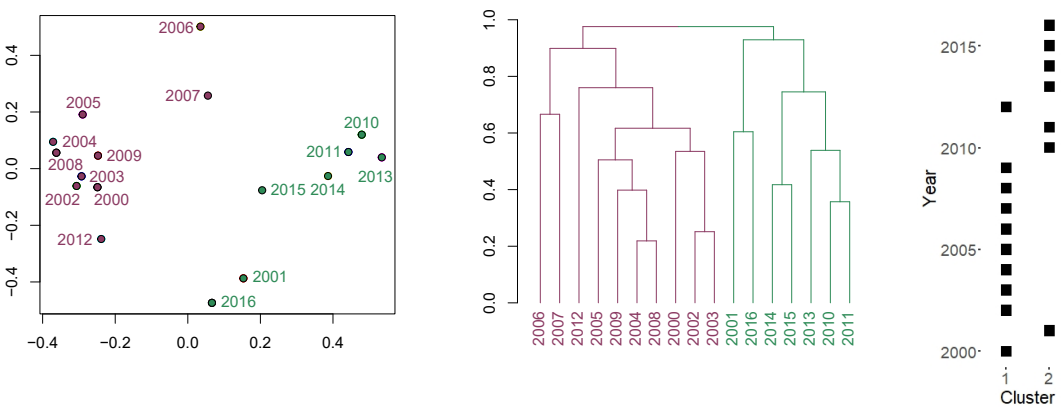

FIGURE 8 NMDS scatterplot (left panel) and clustering dendrogram (centre panel) of yearly priority area results. The right panel shows the time series of the selected clusters.

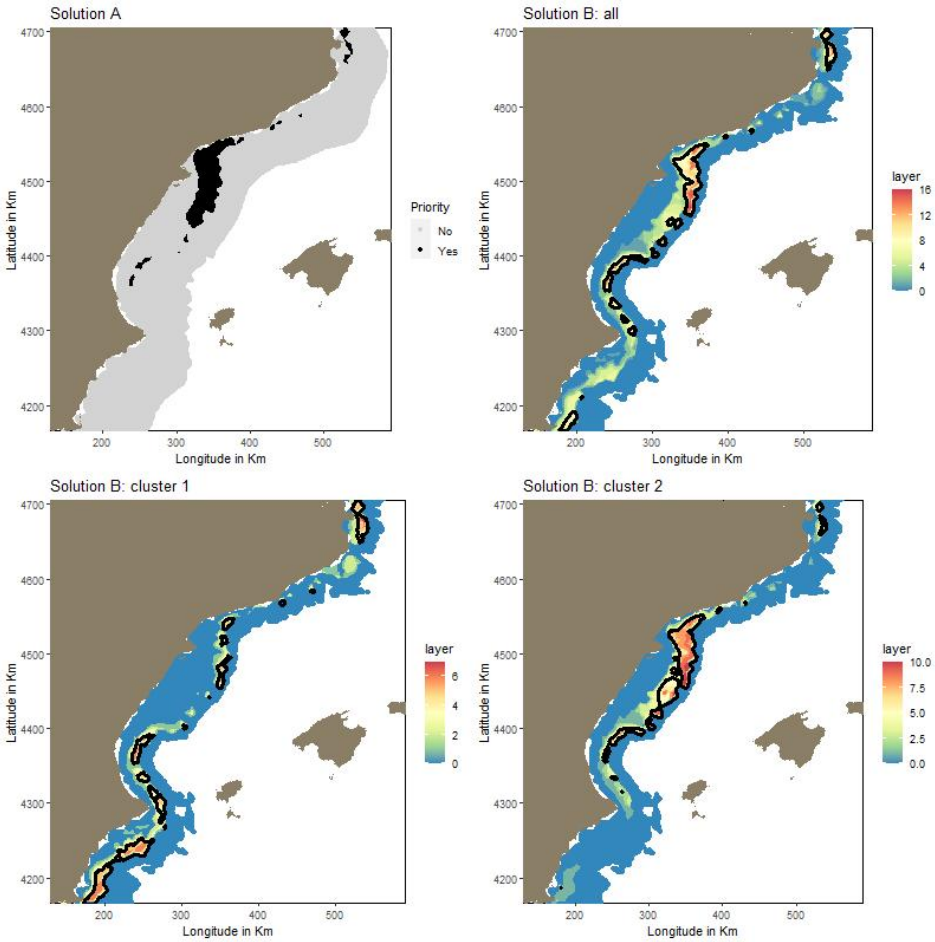

FIGURE 9 Portfolio of proposed solutions to assess the spatiotemporal distribution of multi-species hotspots as described in Section 4.2. The top-left and top-right panels represent the overall solution map and the overall priority area frequency map respectively. The bottom panels show the clustered frequency maps.

	Solution A	Solution B: cluster 1	Solution B: cluster 2	Solution B: all
M. merluccius J/A	26.4	11.4	17.5	15.2
M. merluccius R	27.8	19.2	20.8	20.9
L. budegassa R	22.1	15.6	17.2	17.0
L. budegassa J/A	20.5	16.5	15.2	15.4
L. piscatorius R	22.6	12.6	15.5	14.3
L. piscatorius J/A	17.1	9.4	11.1	9.9
I. coindetii A	29.3	17.7	22.3	20.0
M. surmuletus A	12.0	9.9	10.1	8.6
M. barbatus A	21.1	12.8	18.2	14.8
Fishery effort	10.3	7.5	7.0	7.1

TABLE 3 Impact assessment of the highlighted frequency contours in Figure 9 . Values represent the percentage of fish or fishery effort that is contained within the contour lines of the different solutions in Figure 9 .