# Discard ban: a simulation-based approach combining hierarchical Bayesian and food web spatial models

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## Abstract

Discarding is one of the most important topics in fisheries management, both for economic and ecological reasons. The European Union has included, through the current EU Common Fisheries Policy (CFP) Regulation, a discard ban with a quite controversial instrument: to enforce the landing of unwanted catch as a measure to promote their reduction. This management decision may condition the future of the fishing exploitation in European Sea. Within this context, both stakeholders and policy makers are now claiming for more effective tools that can be used to support the decision-making framework. In this study, we propose a simulation-based approach combining hierarchical Bayesian Spatial Models (H-BSMs) with the spatial-temporal module of Ecopath with Ecosim (EwE) approach, Ecospace, in the North Western Mediterranean Sea. In particular, we firstly assessed high-density discard areas using H-BSMs with fisheries and environmental data, and secondly, we simulated potential management options to identify the trade-offs of the discard ban application within these areas using EwE. We argue that coupling novel methods, as the ones used in this study, could be a decisive step to identify the best management action among a set of different scenarios within the context of the discard ban application in European Seas.

**Keywords:** Bayesian model, discards, Ecospace, food web model, landing obligation, Mediterranean Sea, spatial ecology.

## Introduction

Worldwide discarding is one of the most important issues in fisheries management as it has negative impacts on ecosystems, the economy, and society [1, 2]. Indeed, discards represent a wasteful use of resources and, consequently, generate future economic losses for fisheries, populations, communities and ecosystems [3].

There is an increasing effort to understand the complex array of factors that influence the discard process [4:6] and to assess the spatial-temporal dynamics surrounding this process [7:10].

Within the European Union (EU hereafter) waters, a number of factors are responsible for the high level of discards, including the use of non-selective fishing gear, lack of market value for certain species, minimum landing size restrictions, and the overlap between fishing grounds and species home range [11]. One of the most important recent changes regarding discard management is the shift in focus to what is caught rather than what is landed [12, 13]. The European Common Fisheries Policy (CPF) introduced a 'discard ban' measure between January 1, 2015 to the January 1, 2019 for all regulated species in EU waters (Article 15, EU Regulation 1380/2013), which determined that all catches of regulated commercial species be landed and counted, and compared against their quota. This management strategy, should it be extended, could determine the future of fishing exploitation in European seas with short-term and long-term socio-economic and ecological implications. For these reasons, stakeholders and policy makers alike now demand more effective tools to support the decision-making framework.

To explore alternative management options and to identify the ecological trade-offs of the discard ban, a simulation-based approach that couples species distribution models, specifically the hierarchical Bayesian Spatial Models (H-BSMs), with ecosystem models, using the food-web model Ecopath with Ecosim (EwE), might offer an innovative approach. H-BSMs are particularly appropriate to identify discard hotspots as they can explicitly model the spatio-temporal variability of discards [14]. When geo-referenced discard data are analyzed, it is common to include geographic coordinates (latitude and/or longitude) in the models as continuous explicative variables [15, 16], given that fixed effects and, therefore, the spatial dependency of observations is not considered. Similarly, a non-random spatial variable [17] or geographic fishing boundaries [18] can be included as predictors in models to try to capture spatial discard trends [7]. However, only geostatistical techniques intrinsically incorporate a component to account for spatial autocorrelation [19, 20]. H-BSMs extend the concept of spatial autocorrelation in multilevel structures, including a spatial random effect that is a stochastic process indexed in space, which represents all spatially explicit processes that may influence the discard pattern. By applying H-BSMs to discard data the multiple sources of uncertainty associated with both the observed data and the discard process can be included in the analysis to generate a more robust statistical inference. Moreover, H-BSMs is not only better able to identify discard hotspots, but also predict them and, therefore, contribute to better spatial management planning [21, 7, 8, 10, 22].

Ecological processes and human activities, in addition to environmental factors, can indeed affect the discard phenomena and need to be explicitly considered in process-based oriented modelling, such as Ecopath with Ecosim food-web modelling (EwE) [23]. EwE is an ecosystem modelling approach that builds food-web models by describing the ecosystem through energy flows between functional groups with similar functional and ecological traits. Within EwE, Ecospace is a spatial-temporal dynamic module that represents temporal and spatial 2D dynamics of trophic web components [24, 25]. This approach has been widely used to quantify the spatial impact of fisheries on marine species [26], to analyse the impact of management scenarios such as the establishment of marine protected areas [27], to develop spatial optimization routines [28], and to assess the impact of climate change on marine ecosystems [29, 30]. EwE has also been used to model the ecological impacts of changes in fishing gear, for example to measure the ecological consequences of reducing discarding from bottom trawling in the NW Mediterranean Sea [31]. Recently a new Ecospace module has been implemented that integrates niche modelling into the food web modelling approach [32: 36]. This new tool, combined with the spatial-temporal framework module of EwE [30], bridges the gap between envelope environmental models and food web models [32].

In this study, we apply Bayesian spatial modelling with ecological modelling techniques to analyze fishery discard and environmental data in the Southern Catalan Sea ecosystem. First, the Bayesian approach is used to model the amount and distribution of discards in the study area. Next, we use the EwE approach to evaluate the ecological consequences of discards on commercial and non-commercial species under different degrees of the discard ban by examining a broad number of ecological indicators related to trophic network dynamics. Finally, we reflect on how the simulation-based coupling framework tested here can provide a new and useful tool to explore management strategies that benefit fishers and possibly improve economic revenues while reducing the ecological impacts and pressure on non-target species.

## Material and Methods

### *Study area*

The study was carried out in the Southern Catalan Sea (Figure 1), an area of relatively high productivity due to a joint effect of the Northern current and the run-off of the Ebro and Rhone rivers [37, 38]. The continental shelf in this area is narrow, with the northern current flowing south-westwards along the continental slope toward the wider continental shelf surrounding the Ebro Delta River. This area is an important fishing ground for both small pelagic and demersal species [39, 40], as well as at risk predatory marine species, such as marine mammals and seabirds [41].

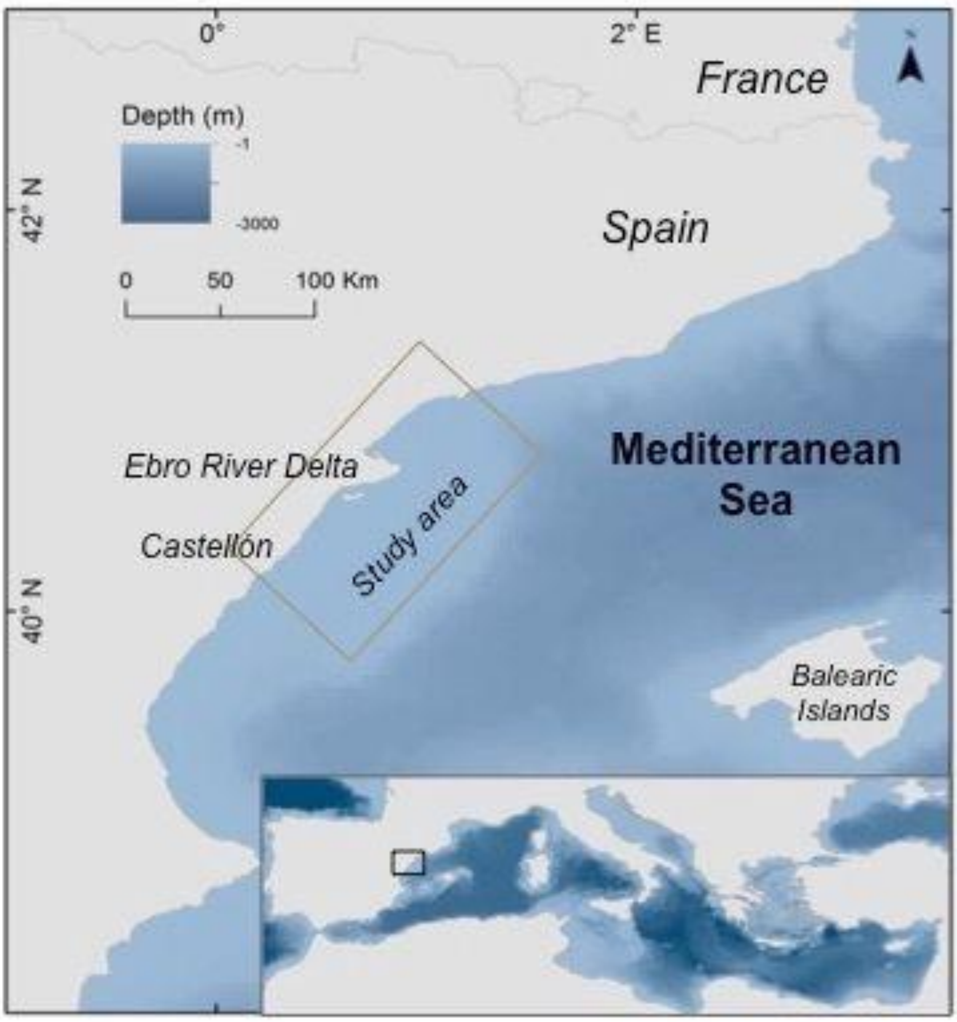


*Figure 1: Study area located in the North-western Mediterranean Sea.*

***Discards, landings and fishing effort datasets***

Catch and discards data from 2009 to 2016 were collected by the Instituto Español de Oceanografía (IEO, Spanish Oceanographic Institute), under the EU Data Collection Framework (EC Regulation 199/2008) [42]. A *métier* approach was used in the sampling design, which is a method that formally segments fisheries by vessel type, gear, fishing grounds and target species [8]. On-board observers collected monthly discards data for each sampled haul as estimation between landings and the total catch. The reference fleet for this study was the bottom otter trawl fleet that operates in the Southern Catalan Sea (Geographical Sub Area 06 North), which targets a mixed species *métier* (hereafter OTB-MIX). The OTB-MIX includes trawlers that usually operate in the continental shelf waters (from 50 to 200 m depth) with different target species. European hake (*Merluccius merluccius*), red mullet (*Mullus barbatus*), Norway lobster (*Nephrops norvegicus*), and octopus (*Octopus vulgaris*), are the most common species. These trawlers make short hauls of about 2-4 hours with about 2-3 fishing hauls per trip and land in Castellón and Tarragona harbours, the two main fishing ports in the study area.

Since the catch and discard statistics varied markedly among vessels, catch per unit effort (CPUE) and discards per unit effort (DPUE) were calculated by the catch and discard weight per haul duration (kg/h). Two CPUE variables were calculated: one of the total discards (hereafter $CPUE_{tot}$), and the other of the regulated species (hereafter $CPUE_{reg}$) defined in Annex III of Regulation (EC) No 1967/2006 (see Appendix 1 for the specific regulated species). Similarly, two DPUE response variables were created: one representing total discards in order to assess the overall ecological impact of the fishery (hereafter $DPUE_{tot}$), and the other representing the discards of regulated species, which have a minimum landing size (hereafter $DPUE_{reg}$). Finally, all DPUE measures were log-transformed to down weight extreme values, to achieve normality and ensure a better fit of the models (Shapiro and Kolmogorov-Smirnov tests, p-values $< 0.05$). Landing datasets collected in the fishery harbours located in the studied area where the OTB-MIX métier land were provided by the General Secretariat of Fisheries of the Spanish Ministry of Agriculture, Food and Environment (MAPAMA).

***Environmental data***

To predict DPUE we included both oceanographic variables (i.e., Sea Surface Temperature (SST), Sea Bottom Temperature (SBT), Sea Surface Salinity (SSS), Sea Bottom Salinity (SBS), Primary Production (PP)) and physical descriptors (i.e., bathymetry and type of the seabed) as possible predictors in the models (Table 1).

Oceanographic variables were derived for the entire study area from a regional application of the

ROMS model [43] which is coupled with a biogeochemical nitrogen-based plankton model [44] already tested for spatial applications in the Mediterranean Sea [45, 33, 36]. Implementation of the ROMS was adapted to the Catalan Sea with a grid of 2 x 2 km resolution and a vertical resolution of 40 levels. Climatologies were used as boundary conditions and were derived from the NEMO model (available from http://www.nemo-ocean.eu) [46], following the same procedure used in Coll et al., [47]. Bathymetry and the types of seabed were obtained from the European Marine Observation Data Network (EMODnet Bathymetry Consortium (2018): EMODnet Digital Bathymetry (DTM), http://doi.org/10.12770/18ff0d48-b203-4a65-94a9-5fd8b0ec35f6).

Specific values for the environmental variables In each fishing location were extracted using the "extract" function of the "raster" package [48] in the R software [49].

Both physical and oceanographic variables were explored for correlation, collinearity, outliers, and missing data before they were included in the model. Correlation among variables was checked by performing a Spearman's correlation test with the "cor.test" function of the R software. Collinearity was tested by computing the generalized variance-inflation factors (GVIF), which are the corrected VIF values by the number of degrees of freedom of a predictor variable [50]. The GVIF was assessed using the "corvif" function in R software. All variables used in the models have a GVIF lower than 3 and a Spearman's correlation lower than 0.70 (p-value >0.05). Outliers and missing data were checked using the procedure elaborated by Zuur et al. [51].

Environmental predictors, as well as the computed CPUEs measures, were standardized (difference from the mean divided by the corresponding standard deviation) to facilitate visualization and interpretation.

***Modelling high density DPUE areas***

Hierarchical Bayesian spatial models (H-BSMs) were used to identify the high-density DPUE areas for both total discards and discard of regulated species. Specifically, the expected values of DPUE in each haul (μDPUE) were related to the spatial, temporal and environmental covariates according to the general formulation,

$$\mu DPUE_{ijk} = X_{ij}\, b + Y_j + W_i + Z_k \qquad \text{(Eq. 1)}$$

where β represents the vector of the regression coefficients, $X_{ij}$ is the vector of explanatory covariates listed in Table 1 at year *j* and location *i*, $Y_j$ is the component of the temporal unstructured random effect in year $t_j$,, $W_i$ represents the spatially structured random effect at location *i*, and $Z_k$ is the random effect of the vessel. The remaining potential source of DPUE variability could be due to differences among vessels caused by a skipper effect or unobserved gear characteristics. To remove bias caused by vessel-specific differences in fishing operation, we included a vessel effect. In addition to the environmental variables, CPUE measures ($CPUE_{tot}$ and $CPUE_{reg}$) for each fishing haul were included as possible predictors of DPUE variability, as well as a month factor to assess intra-annual variations.

H-BSMs were fitted using the Integrated Nested Laplace Approximation (INLA) package [52] in the R environment. INLA performs Stochastic Partial Differential Equations (SPDE) [53] for the spatially structured random effect, which approximates a continuously indexed Gaussian Field (GF) with a Matérn covariance function by a Gaussian Markov Random Field (GMRF). The spatial effect is a numeric vector that links each observation to a spatial location and, thus it accounts for independent region-specific noise that cannot be explained by the available covariates [54]. This component is defined in terms of two hyperparameters, κ and τ, that are related to the range and scale of the spatial effect [55]. A multivariate Gaussian distribution with a mean of zero and a Matérn spatially-structured covariance matrix were assumed for the spatial component (see [54] for more information about how to express prior knowledge of spatial effects).

A vague Gamma prior distribution with shape and scale parameters of 1 and 5e-05, respectively, was assumed for the precision parameter γ of the temporal component. Vague prior distributions with a zero-mean and a standard deviation of 100 were used for all the fixed effects since no prior information was available.

Model selection was performed by testing all possible combinations among the non correlated variables considering the Watanabe Akaike Information Criterion (WAIC) [56] for goodness of fit and the Log-Conditional Predictive Ordinates (LCPO) [57] for predictive quality measures.

***Ecopath with Ecosim modelling approach***

The basic routine of *Ecopath* is to provide a snapshot of the structure and flows of a food web and describe the balance between production of functional groups and consumption within an ecosystem. Each functional group can represent a species, a sub-group of a species (e.g., juveniles and adults) or a group of species with functional and ecological similarities. Ecopath is the starting point to develop temporal and spatial-temporal modelling approaches using Ecosim and Ecospace [22]. A description of the EwE methodology, main applications and limitations can be found in the literature [23, 58, 59, 60].

The Ecopath model uses a system of linear equations to describe the average flows of mass and energy between these groups during a specific period of time, (normally a year). The flow to and from each group is described by the following equation:

$$B_i \cdot (P/B)_i = \sum B_j \cdot (Q/B)_j \cdot DC_{ij} + Y_i + E_i + BA_i + B_i \cdot (P/B)_i \cdot (1 - EE_i) \qquad \text{(Eq. 2)}$$

where $B_i$ is the biomass of group *i*, $(P/B)_i$ is the production per unit of biomass, $Y_i$ is the total fishery catch rate, $E_i$ is the net migration rate (emigration−immigration), $BA_i$ is the biomass accumulation rate, $EE_i$ is the ecotrophic efficiency, which is defined by the proportion of production that is utilized in the system, $B_j$ is the biomass of consumers or predators *j*, $(Q/B)_j$ is the consumption per unit of biomass *j*, and $DC_{ij}$ is the fraction of *i* in the diet of *j*.

For each functional group *i*, at least three of the four basic parameters are required: biomass ($B_i$), consumption rates $(Q/B)_i$ and production rates $(P/B)_i$, and ecotrophic efficiency ($EE_i$). The fourth parameter is estimated in the model [23]. Diet composition ($DC_{ij}$) and fishing yields and other exports ($Y_i$ and $E_i$) are also needed.

Ecosim is a temporal dynamic module that is able to simulate ecosystem effects of (mainly fishing) mortality changes and environmental forcing over time [23, 24, 25]. The model uses a system of time-dependent differential equations from the baseline mass-balance model (see Eq. 3), where the biomass growth rate is calculated as:

$$dB_i/dt = g_i \cdot \sum Q_{ji} - \sum Q_{ij} + I_i - (M_i + F_i + e_i) \cdot B_i \qquad \text{(Eq. 3)}$$

where $dB_i/dt$ represents the biomass growth rate of group $i$ during the time interval $dt$, $g_i$ is the net growth efficiency (production/consumption ratio, $P/Q$), $M_i$ is the natural mortality rate ($(P/B)_i \cdot B_i(1-EE_i)$), $F_i$ is the fishing mortality rate, $I_i$ is immigration rate, and $e_i$ is emigration rate. The two sums from equation 3 estimate consumption rates. The first expresses total consumption by group $i$, and the second predation by all predators in the same group $i$. The consumption rates, $Q$, are calculated based on the 'foraging arena' concept, where $B_i$'s are divided into vulnerable and non-vulnerable components [61].

The set of Ecosim equations are used in the spatial routine Ecospace, the spatial-temporal model of *EwE,* which predicts the biomass dynamics in a two-dimensional space [24]. 'Water' cells in Ecospace can be assigned to contain one or more habitat types and species can be assigned preferred habitats [23]. Fishing fleets can be limited to fish in specific habitats and can be subjected to zonal fishing regulations (no take zones) [24]. The model further incorporates organism dispersal rates and other behavioural parameters [23].

In this study, the ecosystem model of the Southern Catalan Sea that was developed with Ecopath with Ecosim (EwE) [62, 63, 64] was run to analyze the spatial-temporal dynamics of marine resources and the ecosystem under different discard ban policy scenarios. This model, previously fitted to 1978- 2010 time series [65] includes 40 functional groups and four fishing fleets (bottom trawling, purse seining, long lining and tuna fishing), and covers an area of 5,000 km$^2$ with depths from 50 to 400 m [66]. A previous Ecospace model, which was developed to evaluate the combined effects of environmental conditions and fishing in the ecosystem dynamics of the Southern Catalan Sea, was used as a starting point with the original configuration as the default setting [66]. The environmental variables used to parameterize the Ecospace model were the same as those used for the H-BSMs. The primary production spatial pattern was used to drive the dynamics of the phytoplankton group (through the variation of the initial P/B value) of the food web model [64].

***Ecosystem simulations and analyses***

Starting from the original Ecosim model and previously developed Ecospace configurations [64, 65, 66], a series of spatial-temporal simulations were run and compared against a non-discard ban scenario. Spatial-temporal simulations were developed for the period 2016 to 2020 and the model was let to keep running until 2030 (Table 2). EwE version 6.6 and the spatial-temporal framework module of *EwE* [30] were used to implement the discard ban scenarios at specific points in time and space.

A first group of simulations was carried out and ran until 2030 using an Ecosim temporal dynamic model and did not include spatial information:

S0: Baseline simulation - the original Ecosim model fitted to time series from 1978 to 2010 was used and ran to 2030 and did not include implementation of a discard ban policy.

S1: total implementation of the discard ban on regulated species, i.e., 100% reduction of discards of these species in the entire study area from 2016 to 2020 and run to 2030.

S2: total implementation of the discard ban on all discarded species (both regulated and not regulated species), i.e., 100% reduction of all discards in the entire study from 2016 to 2020 and run to 2030.

In a second group of simulations, spatial-temporal scenarios were developed, which integrated the H-BSMs outputs in the spatial-temporal model Ecospace [47], and reduced 100% of discards from 2016 to 2020, while running to 2030:

S3: total implementation of the discard ban (100% reduction of discards) of regulated species in the entire study area.

S4: total implementation of the discard ban for total discarded species in the entire study area.

S5: total implementation of the discard ban for the regulated species only in the high intensity $DPUE_{reg}$ areas identified by H-BSMs.

S6: total implementation of the discard ban for total discarded species only in the high intensity $DPUE_{tot}$ areas identified by the H-BSMs.

***Ecological indicators***

Results from scenarios were compared by using a set of selected ecological indicators that were calculated for three different years: the year the discard ban policy started (2016), the year set for full policy implementation (2020), and 10 years after full implementation of the ban (2030) (Table 3).

The ecological indicators that were chosen were divided into two categories: (1) biomass and catch-based indicators, such as total catch, total catch of important commercial species (such as hake, red mullets, Norway lobster, anchovy, sardine, flatfish and demersal species), total biomass of exploited species, total biomass of important commercial species, total invertebrates over fish biomass, total demersal over pelagic biomass, predatory biomass; and (2) ecosystem and biodiversity-based indicators, such as, Kempton's Q biodiversity index, marine trophic index (MTI), Trophic level of the catch (TLc) and TLco 3.25. These are all common indicators that are regularly extracted from EwE modelling [64, 65, 67]. The Kempton's Q index was calculated as a relative index of biomass diversity based on the Kempton's Q index developed for expressing species diversity [61]. This index includes those species or functional groups with a TL ≥ 3, so an increase in this index implies an increase in the biomass of various high TLs organisms. The TLc was used to describe how the fishery and ecosystem might interact because of modelled policy measures [23].

## Results

A total of 201 fishing hauls were sampled in the study area over the period 2009 to 2016. Total catch and discards for that period were 49,517 kg and 12,720 kg respectively, which is equivalent to 26% of all fisheries catch during that period. Overall, the most discarded species were *Scyliorhinus canicula* (726.93 kg), *Engraulis encrasicolus* (631.78 kg) and *Galeus melastomus* (604.97 kg). Among the regulated species, the most discarded were *Engraulis encrasicolus, Sardina pilchardus* (356.19 kg) and *Pagellus acarne* (148.24 kg).

### *Hierarchical Bayesian spatial models*

SSS was highly correlated to SBS (r>0.80) and SST was highly correlated to SBT (r>0.80). Moreover, the variables SSS and SST have a Generalized Variance Inflation Factors of (GVIF)>3. Given this, separate H-BSM runs were performed and each run included only one of the highly correlated variables to determine which one would explain the most discard variance.

For total discards, the selected predictors (based on the lowest WAIC and LCPO values) were $CPUE_{tot}$, month, SBT, PP and the vessel random effect, plus a stochastic spatial component that accounts for the residual spatial autocorrelation. No relevant inter-annual differences were found in this area for the $DPUE_{tot}$ variability. Indeed, all H-BSMs that contained the temporal effect revealed higher WAIC and LCPO values that those lacking.

The findings showed a positive relationship between $CPUE_{tot}$ and $DPUE_{tot}$ (posterior mean= 1.65; 95% CI= [0.96; 1.84]). Conversely, both SBT and PP presented negative relationships with $DPUE_{tot}$ variability (posterior mean= -0.65; 95% CI= [-0.33; -0.10]; posterior mean= -1.15; 95% CI = [-1.19; -0.53], respectively). Thus, higher values of $DPUE_{tot}$ were found in colder waters with lower concentrations of PP. The months with higher estimated coefficients than the reference level (January) were February and May (posterior mean = 1.23; 95% CI= [0.41; 1.92]; posterior mean= 1.05; 95% CI = [0.34; 1.52], respectively). By contrast, September was found to be the month with the lowest $DPUE_{tot}$ values.

Maps of the $DPUE_{tot}$ revealed latitudinal patterns, and the highest values were reached in the southern part of the study area (Figure 2) where the continental shelf is wider. The spatial component effect was consistent and revealed a similar pattern (Figure 3).

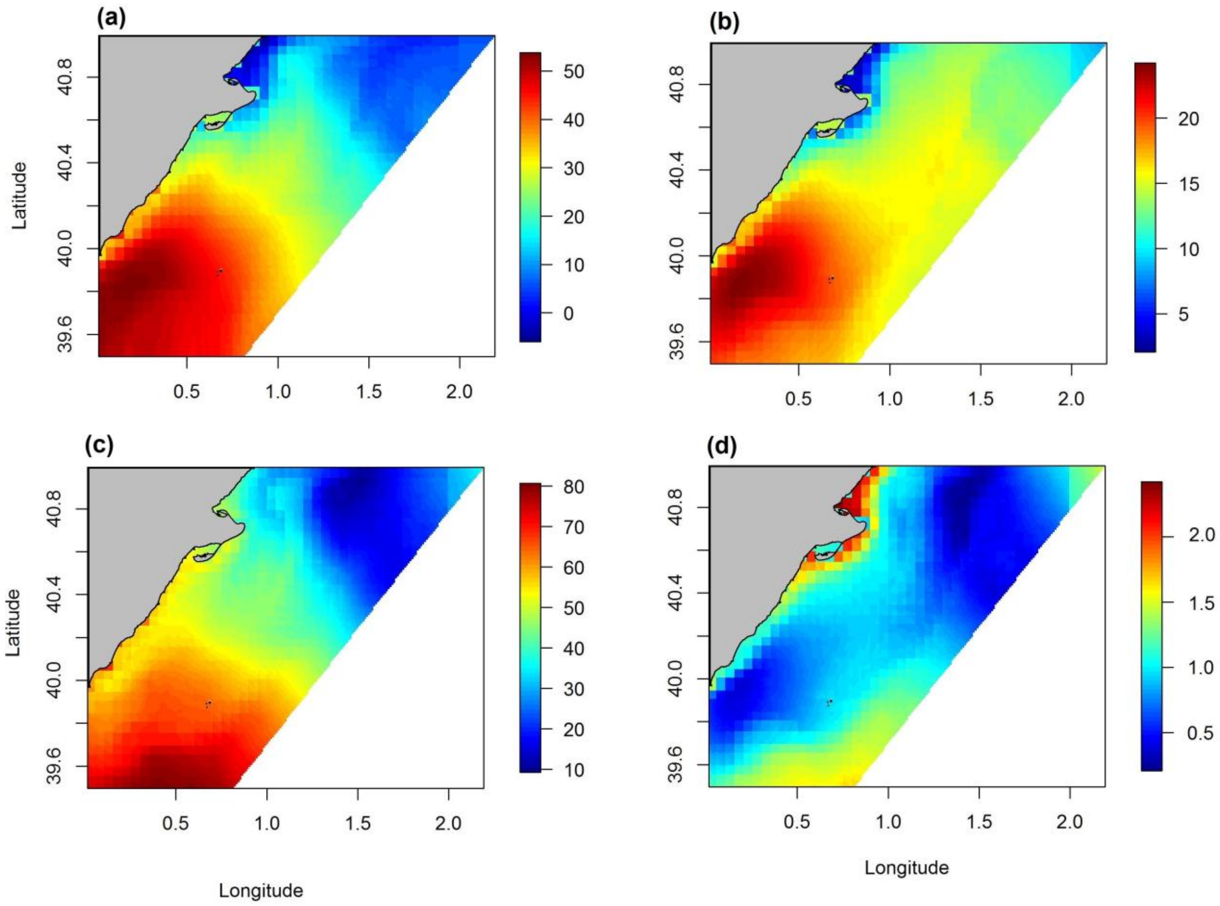


*Figure 2: Posterior predictive distribution of the $DPUE_{tot}$: mean (a); 95% credible intervals with the first (b) and third (c) quantiles and the standard deviation (d).*

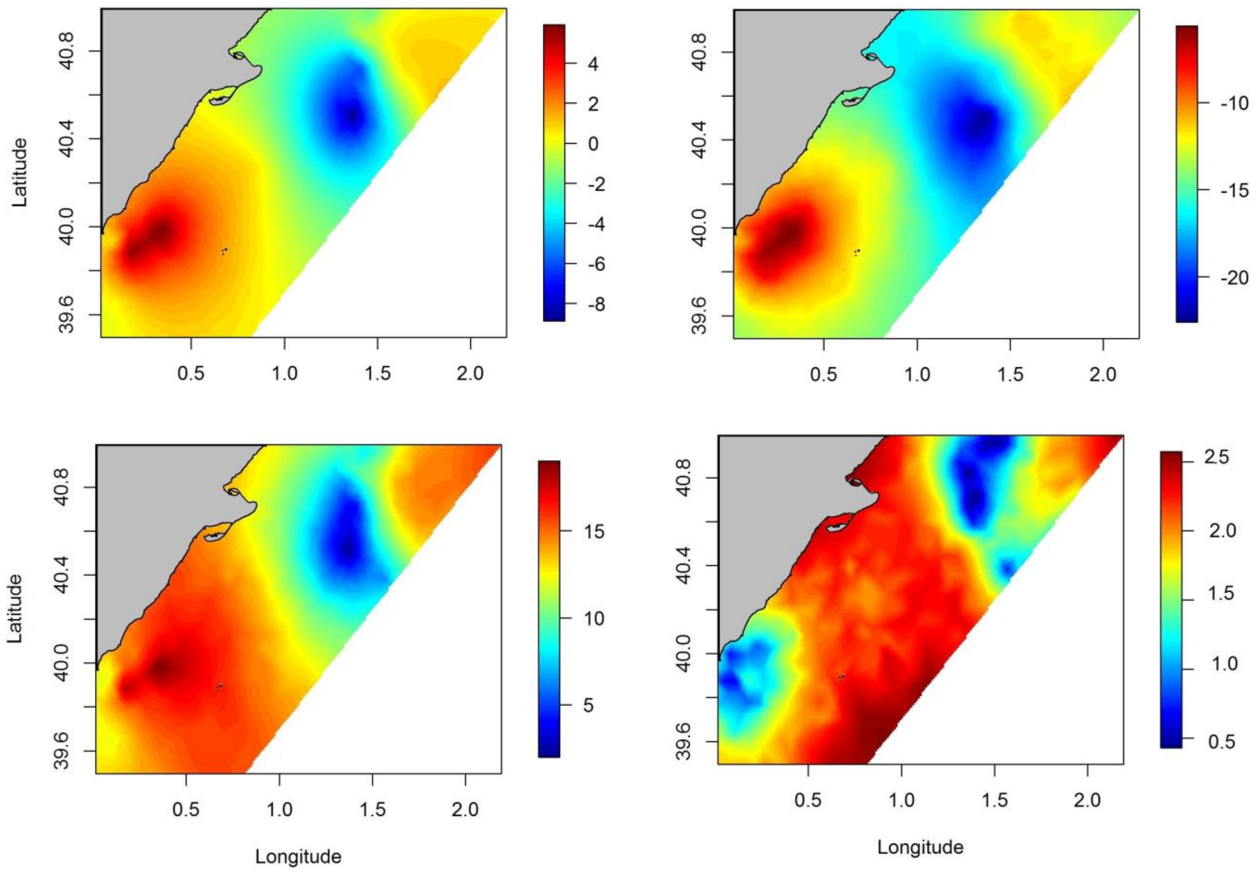


*Figure 3: Posterior distribution of the spatial effect of the DPUE$_{tot}$: mean (a); 95% credible intervals with the first (b) and third (c) quantiles and the standard deviation (d).*

With respect to DPUE$_{reg}$, the relevant covariates for the best model were CPUE$_{reg}$ bathymetry and PP together with the vessel and spatial random effects. As for the DPUE$_{tot,}$ no inter-annual variability was identified for the DPUE$_{reg}$. Moreover, no monthly variation was found for DPU$_{reg}$. A positive relationship was found between DPUE$_{reg}$ and the bathymetry, (posterior mean= 1.42; 95% CI= [0.74; 2.01]), and between DPUE$_{reg}$ and CPUE$_{reg}$ (posterior mean= 1.84; 95% CI= [1.02; 2.34]). By contrast, a negative relationship was found between PP and DPUE$_{reg}$ (posterior mean= -0.49; 95% CI= [-0.53; -0.09]).

Both the predictive spatial DPUE$_{reg}$ values map and the posterior mean of the spatial effect map (Figures 4 and 5) demonstrated that the southern part of the study area has the highest DPUE$_{reg}$ concentrations. A specific marked hotspot with higher DPUE$_{reg}$ was identified in waters located off

Castellón.

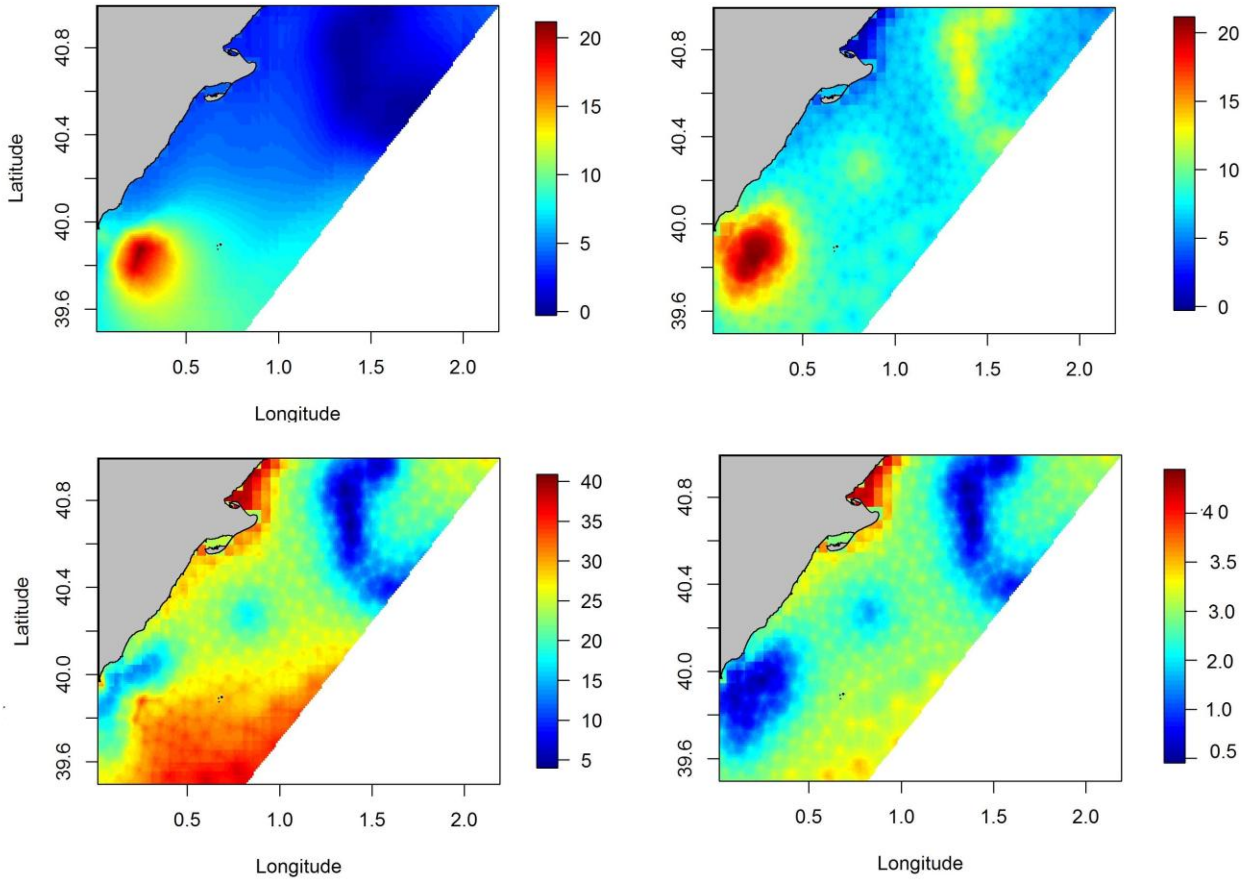


*Figure 4: Posterior predictive distribution of the $DPUE_{reg}$: mean (a); 95% credible intervals with the first (b) and third (c) quantiles and the standard deviation (d).*

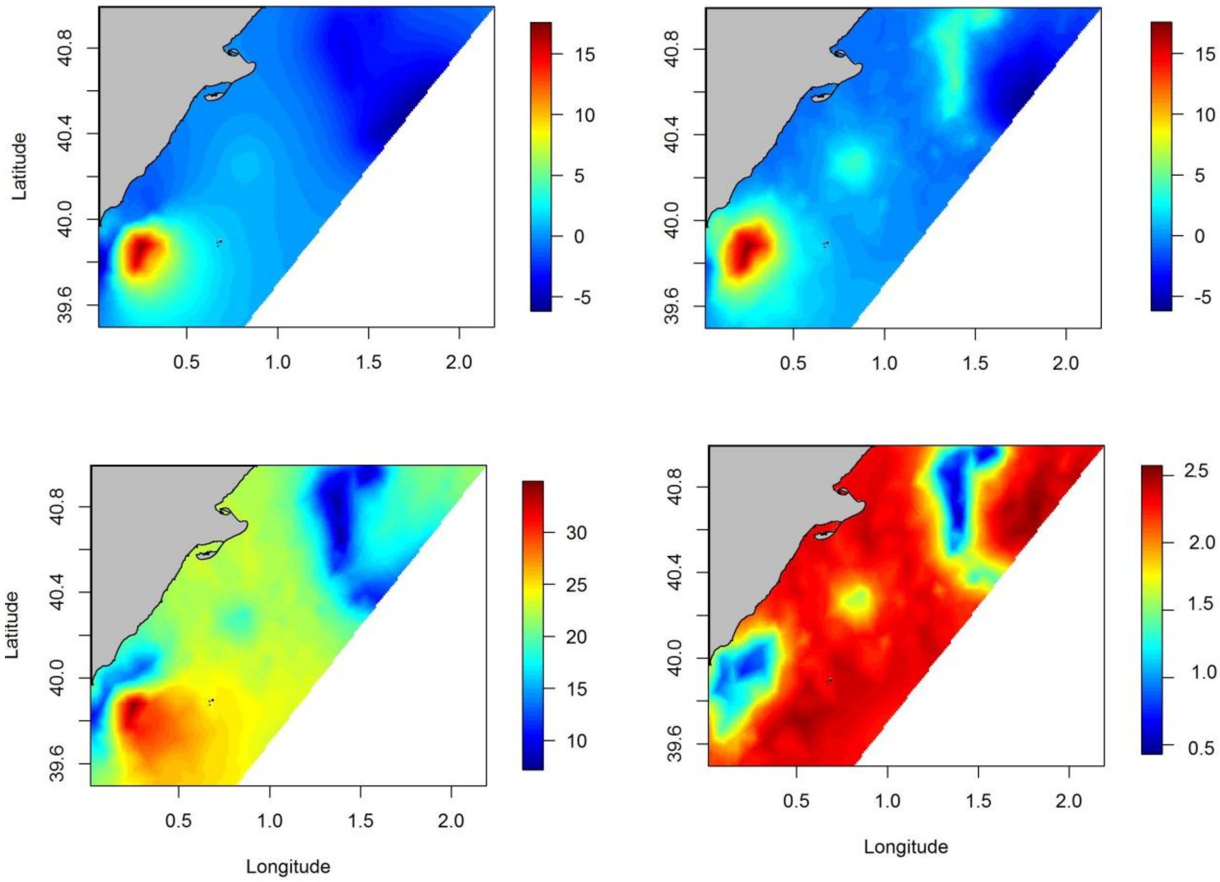


*Figure 5: Posterior distribution of the spatial effect of the $DPUE_{reg}$: mean (a); 95% credible intervals with the first (b) and third (c) quantiles and the standard deviation (d).*

### ***Ecosystem scale simulations of the discard ban impact***

Compared to the baseline scenario of no discard ban, the simulations performed with the ecosystem EwE model that considered regulated species predicted that the biomass and hake catch would increase, especially when submitted to spatial-temporal effects. (Table 4 and Figure 6a). These increases were higher in simulations that extended the discard ban to all discarded species, not just regulated ones. Results for Norway lobster showed that biomass increased when compared to the baseline scenario (Figure 6b), although there were no clear increases in catches. On the contrary, anchovy and sardine biomass and catches either slightly declined or increased depending on the simulation. For anchovy, the discard ban on all species had a larger negative effect than it did on the discard ban for only regulated species, whereas similar results were observed for sardine in both simulations of the discard ban. Result for flatfish species were contrasting. A discard ban on regulated species was shown to have large positive effects, whereas a discard ban on all discarded species predicted negative results, both in terms of biomass and catch (Table 4).

Simulations with the ecosystem EwE model predicted slight declines (mostly < 1%) of total catch and total biomass in both 2020 and 2030 under the different simulations tested in the study, when compared to 2016 (Table 5). Overall, the discard ban is predicted to have moderate positive effects on demersal fish catch and biomass, a slight negative impact on invertebrates (less than 1% change) and a slight negative impact on total fish biomass (less than a 2% change). Changes to the total invertebrates/total fish biomass were also predicted to be small, and results were contrasting: positive results were obtained when the discard ban was simulated on regulated species, and negative results were obtained when the discard ban was simulated on all discarded species. Biomass results for other predatory species contrasted between temporal simulations (which revealed a notable increase in biomass) and spatial-temporal simulations (which revealed either a slight increase or decline) (Table 5). The Kempton's Q index mainly revealed slight positive increases in the simulation of the discard ban on retained species, but slight negative increase was observed when all species were banned from discarding. A similar behaviour was observed with the MTI indicator, whereas the TLc slightly increased in all simulations, including the baseline (Table 5).

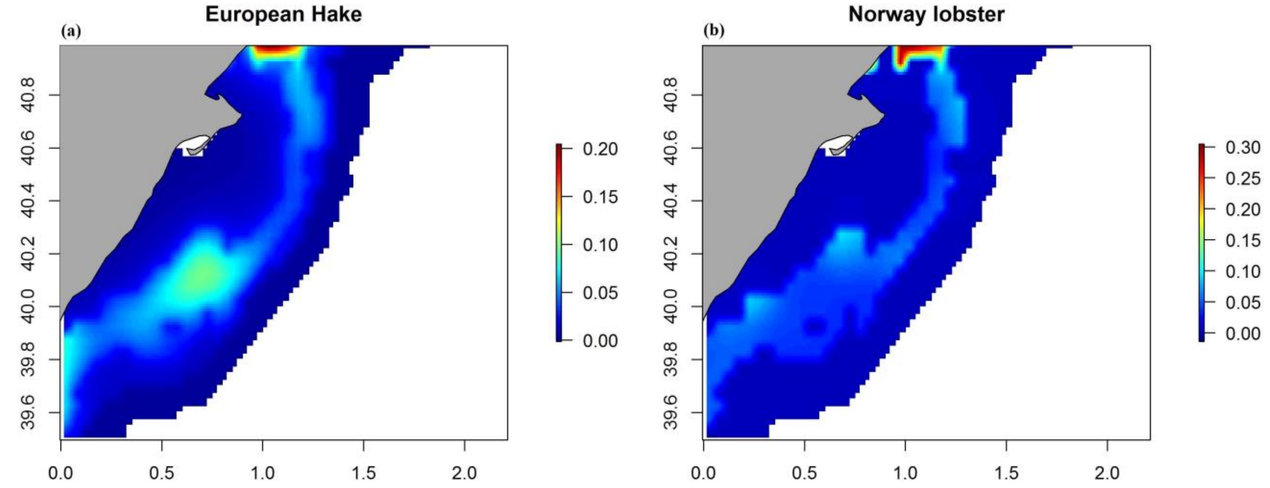


*Figure 6: Ecospace predicted distribution of biomass (log(t·km$^{-2}$)) for European hake (a) and Norway Lobster (b) in the study area under Scenario 6 of discard banning (Table 2)*

## Discussion

Solving the discards problem is an urgently need to better manage fisheries. However, it is quite a complex issue given that discards vary substantially over time and space and are due to numerous factors, including environmental conditions and species composition, as well as fisheries and economic characteristics [7, 8]. The new obligation to land discards in European Seas may have unpredictable and unwished ecological, socio-economic and operational impacts [2, 68]. For these reasons we tested a simulation-based approach that combined H-BSMs with spatial-temporal EwE modelling to assess the potential effects of implementing the ‘landing obligation’ in a highly exploited ecosystem in the North Western Mediterranean Sea. Overall, we found that the amount of discard in our study area between 2009-2016 accounted for 26% of the total catch. Similar studies on demersal trawls reported higher discard ratios, such as in the north-eastern Mediterranean Sea (38-49%) [69:71] and in the south Spain area (31-34%) [7]. However, the discard ratio in our study area was higher than the ratio reported for mid-water trawls in the Turkish Black Sea (5.1%) [72] and in the Adriatic Sea (up to 15%) [73].

From a species composition point of view, a large portion of discard was of the elasmobranch species, which are considered vulnerable species due to their biology and K-selection life-history traits [74]. Discard non-target vulnerable species may have negative consequences for both commercial and non-commercial species owing to the effects on species interactions and cascading effects throughout the trophic web.

Our findings did not identify any relevant temporal trends over the years in either DPUE measures. On the contrary, intra-annual variability was a relevant factor for the $DPUE_{tot}$. February and May, specifically, were the months that recorded the highest DPUE values. This could be attributed to the fisher targeting behaviour during these months [75], and in general due to spatial seasonal patterns of the marine community [76, 77].

Furthermore, discarding is a decision taken on board and based on a given fisher's discarding pattern, which is influenced by different factors, such as market dynamics for a given species or other legal and regulatory constraints. Indeed, for both DPUE measures, H-BSMs identified the random vessel effect to be a relevant variable that could affect the discard amount. This effect should collect this hidden variability that otherwise could not be analyzed.

Moreover, for both DPUE measures, results showed a direct and positive relationship between the CPUE and the DPUE, meaning that more catches lead to more discard. This result is in line with other studies that found the same relationship in other exploited areas [6, 8].

In terms of which variables could be driving the spatial distributions and discard abundance, some differences were found between total discards and regulated species discards. For example, bathymetry was only an important factor influencing the DPUE variability for regulated species. This result is in line with other discard studies that highlighted depth-related variations of DPUE quantities as this is linked to differences in species composition and in the length-frequency distribution of some particular species as the *Boops boops* [6, 78].

Both total discards and regulated species discards were affected by the primary production concentration (PP). Waters with lower concentrations of PP recorded higher DPUE values. Similarly, the sea bottom temperature (SBT) was negatively related to the DPUE of total discards.

Thus, areas with colder and less productive waters were also the areas with high discard abundances. These results can potentially be explained by two different hypotheses or a combination of both: 1) the "environmental hypothesis" whereby these environmental variables are directly correlated to the habitat preferences of *métier* target species (i.e., European hake, red mullet, Norway lobster), which are also favourable to the organisms that are part of the discard; 2) the "effort hypothesis" whereby fishing is more intense in areas with these characteristics and where the stock of target species is more abundant.

The spatial effect, which indicates the intrinsic spatial variability of the discards after excluding explicative variables, was relevant for both DPUE measures (total species and regulated species). This result could reflect the effect of other hidden factors, such as community composition or biological interactions, on the total values of DPUE Maps show a clear latitudinal pattern with a specific DPUE hotspot of regulated species in waters located in front of Castellón. The identification of these spatial-temporal trends and in particular of the DPUE hotspots can be particularly useful for spatial management of the analyzed fleet. The intra-annual/spatial effects could potentially be exploited in a spatial management strategy to reduce DPUE quantities, providing there are necessary economic incentives for fishers to adopt selective temporal rotation of fishing grounds.

According to the simulations from the ecosystem modelling exercise, the ecological benefits of the discard ban would be mainly positive on European hake, a vulnerable and highly exploited or overexploited species [79, 80], and on Norway Lobster, a highly exploited invertebrate [81, 82] in the Mediterranean Sea. These impacts would be larger if the discard ban were extended to the entire list of discarded species, instead of just the regulated ones. However, other regulated species would show contrasting results. Likely, due to their role as prey and competitor species, smaller species that mainly play a prey role in the ecosystem may be negatively affected by the recovery of their predators (such as European hake as predator and anchovy as prey) or recovery of competitors (such as demersal fish and flatfishes that can compete for similar preys). These results highlight that considering inter-specific food-web dynamics are essential to identifying the ecological consequences [68] and trade-offs of fisheries management and exploitation alternatives [83].

Ecosystem simulations also illustrated that the impact of the discard ban on the ecosystem may be limited and only a slight recovery of the ecosystem structure may be achieved by a discard ban. Some indicators showed a partial recovery of the ecosystem health with the implementation of the discard ban, such as demersal fish biomass. However, most of them did not show clear signs of recovery [67]. This can be related to the fact that the study exclusively simulated a discard ban of bottom trawling and did not include other measures or fleets. Additional fleets, such as purse seiners and small-scale fisheries, also have a large negative effect on marine resource and thus an intervention on these fleets may be needed to recover highly exploited Mediterranean species and communities, such as a reduction of fishing effort or total closure of sensitive areas (e.g., nurseries, spawning areas or aggregation areas). Due to the poor situation of many exploited stocks (such as European hake, European sardine and European anchovy) and ecosystems in the Mediterranean Sea [80] this study highlights that more drastic measures may be needed to yield clearer results in terms of recoveries of stocks and communities in Southern European Seas, in addition to a full implementation of the discard ban.

Finally, our results highlight that the choice of modelling framework used to analyse the discard ban outcomes is important because in some cases our modelling results contrasted when implementing a temporal or a spatial-temporal approach. This is mainly because fishing effort, catch and discarding generation show heterogeneous spatial patterns.

Bayesian spatial models can be a powerful approach to identifying discard hotspots given that they quantify both the spatial magnitude and the different sources of uncertainty. However, these models often include only implicit biotic interactions (such as competition, predation etc.) and simulation of future management scenarios are not performed straightforwardly. By contrast, these options are available with the *EwE* approach, which did not include an explicit spatial component to account for the spatial autocorrelation and a quantification of the uncertainty. By combining these two techniques we can gain clear advantages for the exploration of management strategies and, specifically, assess possible discard ban implementations and consequences. This approach could be extended to others case study in others European fishing areas using similar data to test similarity and possible difference in the discard ban implementation.

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*Appendix 1: List of the regulated species in the Mediterranean Sea as defined in Annex III to Regulation (EC) No 1967/2006 that shall be brought and retained on board the fishing vessels, recorded, and landed, when the landing obligation will be implemented. The length (cm) refers to the Minimum Landing Size. Acronyms are: TL= total length and CL = carapace length.*

| Species | Length (cm) |
|---|---|
| *Dicentrarchus labrax* | *25* |
| *Diplodus annularis* | *12* |
| *Diplodus puntazzo* | *18* |
| *Diplodus sargo* | *15* |
| *Diplodus vulgaris* | *15* |
| *Engraulis encrasicolus* | *9* |
| *Epinephelus spp.* | *45* |
| *Lithognathus mormyrus* | *20* |
| *Merluccius merluccius* | *20* |
| *Mullus spp.* | *11* |
| *Pagellus acarne* | *12* |
| *Pagellus bogaraveo* | *33* |
| *Pagellus erythrinus* | *15* |
| *Pagrus pagrus* | *18* |
| *Polyprion americanus* | *45* |
| *Sardina pilchardus* | *11* |
| *Scomber* spp. | *18* |
| *Solea vulgaris* | *20* |
| *Sparus aurata* | *20* |
| *Trachurus* spp. | *15* |
| *Homarus gammarus* | *30 TL, 10,5 CL* |
| *Nephrops norvegicus* | *7 TL, 2 CL* |
| *Palinuridae* | *9 CL* |
| *Parapenaeus longirostris* | *2 CL* |
| *Pecten jacobeus* | *10* |
| *Venerupis* spp. | *2.5* |