



A Bayesian model of fisheries discards with flexible structure and priors defined by experts



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ARTICLE INFO

Article history:

Received 26 July 2017

Received in revised form 11 October 2017

Accepted 13 October 2017

Available online 27 October 2017

Keywords:

Unwanted catches

Spatial modelling

Trawl fishery

Mediterranean sea

Local ecological knowledge

ABSTRACT

Minimizing the probability of discards is an important step in mitigating environmental impacts of fishing activities and maximizing economic gains from fish stocks. Although several discard models have been recently developed, current approaches are still unable to robustly adjust to different circumstances (e.g. fishery target species, geographical location), and lack a closer interaction with stakeholders. Here, we present a novel approach consisting of a modular Bayesian model, which can incorporate any relevant explanatory variable, independently of data availability. The relationships between the variables and discard rates are initially delineated by stakeholders through surveys, and included to the model as priors. The priors are then used together with observed data for estimating posterior distributions of discard probability. We test this approach in two study areas at the Mediterranean Sea: the Ligurian and Tyrrhenian Seas in Italy, and the Greek part of the Aegean Sea. For each site, we evaluated the model for estimating discards from bottom trawl fishery associated with European minimum conservation reference size regulations, as well as discards caused by the low economic value of catches.

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1. Introduction

Unwanted catches and discards represent major economic and environmental problems in the maritime fishery sector (Komoroske and Lewison, 2015; Sigurdardóttir et al., 2015). Unwanted catch is hereby defined as incidental catch of organisms that cannot be commercialized due to low or no economic value, or due to legal requirements (e.g. Minimum Conservation Reference Size, MCRS, provisions). Discards refer to the portion of the catches that is returned to the sea, either dead or alive (Feekings et al., 2012; Viana et al., 2013b). Discard patterns are affected initially by catch compositions, which are determined by environmental factors, relationships between species and their habitat, the fishing gear, fishing tactics, and ultimately by fishermen behaviour. The decision of which parts of the catch has to be retained is influenced by both market and regulatory conditions, and constrained

by storage space onboard the vessel and sorting time (Catchpole et al., 2014). Hence, discards are a result of deliberate choices made by fishers during the fishing process (Eliassen et al., 2014).

Discarding leads to a waste of natural resources that negatively affect the sustainable exploitation of marine ecosystems and the economic gains of fisheries (Paradinas et al., 2016; Viana et al., 2013b). Unwanted catches related to MCRS can be particularly harmful to the productivity of stocks, by killing young individuals before their optimum production potential is achieved. Likewise, fishing gears with low selectivity can be detrimental to threatened species, which are unintentionally caught and released with low chances of survival (Snape et al., 2013; Tudela et al., 2005). Furthermore, food subsidies between marine and terrestrial ecosystems can alter trophic webs (Oro et al., 2013). From an economic perspective, unwanted catches reduce fishery efficiency, by making activities more laborious and time consuming, because of the substantial time spent to sort out catches (Macher et al., 2008).

Discards vary from 20 to 60% of total catch in weight in the Atlantic (STECF/SGMOS, 2008) and between 10 and 35% in the Mediterranean (Sánchez et al., 2007; Tsagarakis et al., 2014). Dis-

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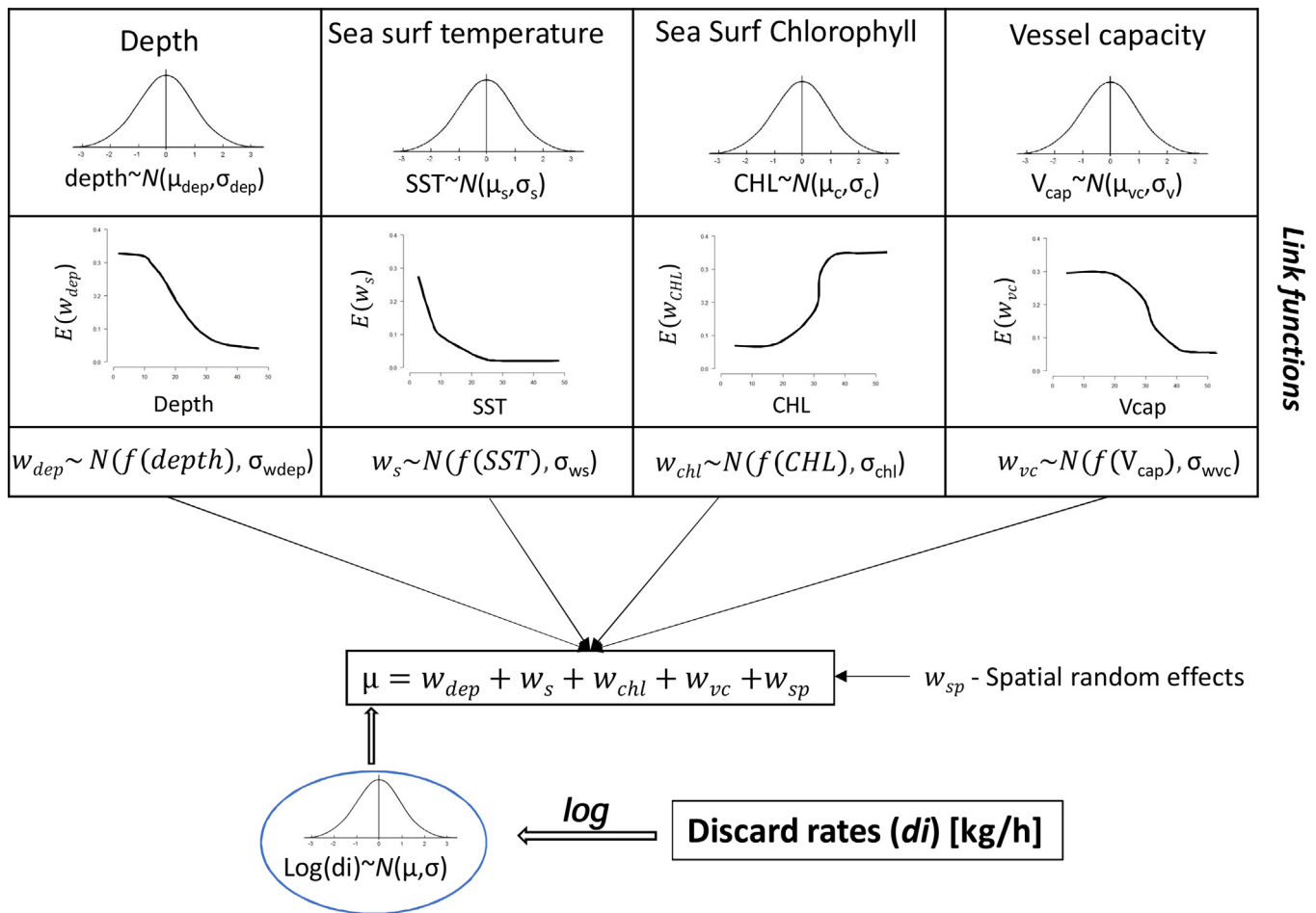


Fig. 1. Graphical illustration of the Bayesian model of fishery discards.

cards in the Mediterranean present a high diversity of species and a wide size range, which makes discards mitigation by using only fishing gear selectivity difficult. Out of the 300 species caught in the Mediterranean bottom trawl fisheries, only around 10% are consistently marketed and 30% are occasionally retained (depending on the sizes and market demands), whereas up to 60% are always discarded.

European fisheries are transitioning to new rules aiming at reducing discards and mandatorily bringing all catches to land ("discard ban" or "landings obligation": Art. 15 of the new Common Fisheries Policy, CFP, EU Regulation 1380/2013). These new rules are likely to significantly affect fishery activities in Europe. Given the impossibility to completely avoid unwanted catches and the fact that CFP will progressively phase out discards of regulated species (i.e., those subject to quota, and species with MCRS in the Mediterranean; see Reg. EC 1967/2006), it is essential to develop new technological solutions, along with economic and social incentives, to gradually reduce unwanted catches. In this context, combining technical solutions and economic incentives of discards-free fishing has the potential to considerably reduce unwanted catches and facilitate a more ecologically sound harvesting regime.

Mathematical models can have a key role in the transition for these new rules, as they may assist managers and fishermen in identifying areas with lower probability of unwanted catches. Moreover, models can be used to estimate the impacts of discarding on population productivity. Although modeling tools to address these problems are not abundant in the literature, several models have been developed in recent years for assessing

bycatches/discards, using a variety of methods and parameterization strategies. For instance, Sims et al. (2008) developed a Bayesian hierarchical model framework for mapping bycatch of marine mammal and seabird, using data collected from the United States gill net fishery for groundfish in the northwest Atlantic. They concluded that models represent an important tool for understanding spatial variations in bycatch, being able to generate alternative summaries of bycatch, and having considerable promise for bycatch management and mitigation (Sims et al., 2008).

Madsen et al. (2013) applied generalized additive models (GAM) to analyze factors driving discards of plaice (*Pleuronectes platessa*) under MCRS in the Danish part of North Sea. They identified mesh size and geographical location as significant factors defining discard volumes. Pennino et al. (2014) developed Bayesian hierarchical models to analyze trawl fishing operations in the Spanish Mediterranean Sea. They argued that the Bayesian spatial approaches have the advantage of allowing the incorporation of spatial random-effects and uncertainty about the parameters in the modeling process, resulting in clearer uncertainty estimates and improved predictions (Pennino et al., 2014). Nonetheless, they point out that the model developed in their study was based on linear mixed models, and therefore could only account for linear relations between the dependent and explanatory variables.

Although these previous approaches have significantly improved our knowledge on the factors driving discards, many bottlenecks still restrict the use of models for effectively managing this issue. For instance, in most cases, models are designed to conform to data availability. This means that the variables driving the model do not always have a direct causal relationship with

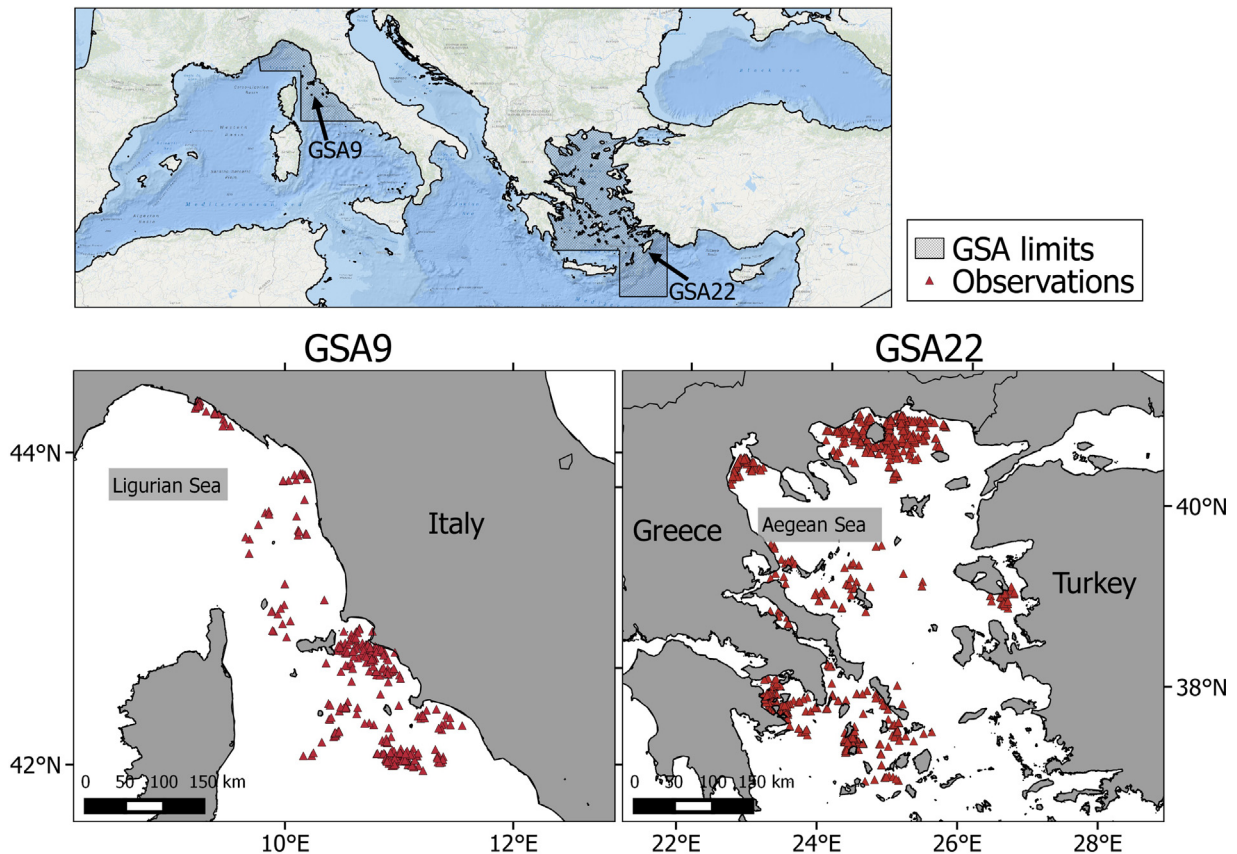


Fig. 2. Limits of the Geographical Sub Areas (GSA) 9 and 22 (top side) and location of the discard observations in the Ligurian sea (GSA 9, bottom left) and Aegean Sea (GSA 22, bottom right).

discards, while the model cannot account for other factors that are indeed considered relevant by experts or other stakeholders. In these cases, a valuable two-ways flow of information that could take place between modelers and stakeholders (including fishermen), is unfortunately lost or neglected. Several studies have shown that the use of Local Ecological Knowledge (LEK) can foster conservation and environmental management approaches (Bender et al., 2014; Wilson et al., 2006). However, the use of stakeholders' knowledge for improving the performance of discard models has not yet been comprehensively explored.

Another known problem with traditional discard modelling approaches is that explanatory variables and the general model structure tend to be area specific. Previous assessments have shown that the effects of imperfect fisheries selectivity are specific to each type of fishery and regional sea (STECF/SGMOS, 2008). This makes imperative a case-by-case approach that proposes technically feasible, cost-effective solutions agreeable to fish producers, consumers and policy makers. Additionally, current fishing methods and practices in Europe have indirect effects on components of exploited marine systems (habitats, sensitive species) which threaten fisheries sustainability and reduce the societal value of marine ecosystems (Suuronen et al., 2012). Hence, developing different models for each of these varying conditions can be challenging and, in some cases, counterproductive, given the lack of harmonization between assessments.

Finally, it is crucial for modelling approaches to account for spatial auto-correlation in the input data, which may lead to spatial and temporal uncertainties in discard estimates. Studies have shown that the misidentification of bycatch hotspots can result in erroneous mitigation practices, which can be irreversible (Viana et al., 2013a). Hence, models should be able to sequentially update

parameters as new data becomes available, as well as account for new knowledge input from literature, experts and stakeholders.

The objective of this study was to develop a spatial Bayesian model of fishery discards that can incorporate field knowledge from experts for identifying the relevant explanatory variables, as well as the characteristics of their relationship with discards rates. We present our approach through case studies in two Geographical Sub-Areas (GSA) in the Mediterranean Sea: the Ligurian and northern Tyrrhenian Seas (GSA9) and the Aegean Sea (GSA22). For both sites, we evaluate the model for estimating bottom trawl fishery discards associated with MCRS regulations, as well as discards of individuals that cannot be commercialized due to low or no economic value. The aim of these case studies is not to optimize prediction accuracies for each case, but to provide an overview on how the model can be used for combining stakeholders knowledge and field data, leading to a better understanding of the factors driving the temporal and spatial distribution of discards.

2. Model design

A Bayesian model was developed for describing the spatial probability of discard rates in bottom trawl fishery. A graphical concept of the model is presented in Fig. 1. The model is driven by a set of explanatory variables, each of them having its independent probability distribution. In the example presented in Fig. 1, four explanatory variables were chosen: bottom depth, sea surface temperature (SST), sea surface chlorophyll (CHL) and vessel capacity (see Section 3.2 for more details). The model can accommodate spatial and non-spatial variables equally. Furthermore, the model structure allows the addition or removal of any explanatory variable desired by the user.

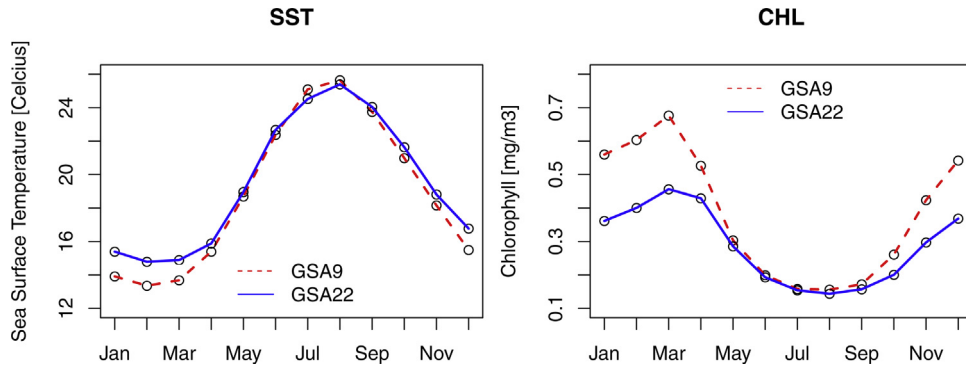


Fig. 3. Seasonal variation of sea surface temperature (SST) (left) and sea surface chlorophyll (CHL) (right), averaged within the Ligurian and northern Tyrrhenian Seas (GSA9) and the Greek part of Aegean Sea (GSA22). Monthly averages were calculated using observations from 2003 to 2014.

The discard rates (d_i) at location i are transformed to natural logarithm ($\log(d_i)$). Unexplained random variation around the model prediction μ_i is represented in the model by a normal distribution ($\sim N$) with variance σ^2 :

$$\log(d_i) \sim N(\mu_i, \sigma^2) \tag{1}$$

The value of μ_i is determined by the sum of weights $w_{v,i}$, where v represents the different explanatory variables, and a spatial random effects component ($w_{sp,i}$):

$$\mu_i = w_{sp,i} + \sum w_{v,i} \tag{2}$$

The relationship between $w_{v,i}$ and the explanatory variable value V is then described by a link function (Fig. 1):

$$E(w_{v,i}) = f(V_i) \tag{3}$$

The link functions provide a simple and graphical way of representing the influence of different driving factors on discard volumes. These functions can be designed independently for each explanatory variable. The existing knowledge about parameters of each link function is formalized using normal distributions. For instance, in the case of a simple linear function, given by $w_{v,i} = \beta_v + \alpha_v \times V_i$, the knowledge about coefficients is represented as:

$$\alpha_v \sim N(\mu_{\alpha,v}, \sigma_{\alpha,v}^2) \tag{4}$$

$$\beta_v \sim N(\mu_{\beta,v}, \sigma_{\beta,v}^2) \tag{5}$$

where $\mu_{\alpha,v}$ and $\sigma_{\alpha,v}^2$ denotes the mean and variance of the α_v prior distribution. The spatial random effects ($w_{sp,i}$) account for spatial correlation within the variation that remains unexplained by the included predictors. The inclusion of the spatial random effects decreased the residual deviance of the model, leading to improvements in the model performance, in comparison with a non-spatial approach. Here we use a Gaussian process with exponential decay spatial correlation function, written as $w_{sp,i} \sim N(0, \sigma_w^2 \rho_w)$, with ρ_w for a location s given by:

$$\rho_w(s; \varphi) = \exp[-d_s \times \varphi] \tag{6}$$

where σ_w^2 is the spatial variance, φ is the decay parameter and d is the distance between observations.

2.1. Using experts and stakeholders knowledge as priors to the model

Priors obtained from experts or stakeholders may be used to fit the model in two cases. First, in the absence of observed data for one or more explanatory variables, priors for the parameters of the probability distributions may be provided by external input (e.g.

Based on your experience, how do you think haul **depth** affect discards volumes?

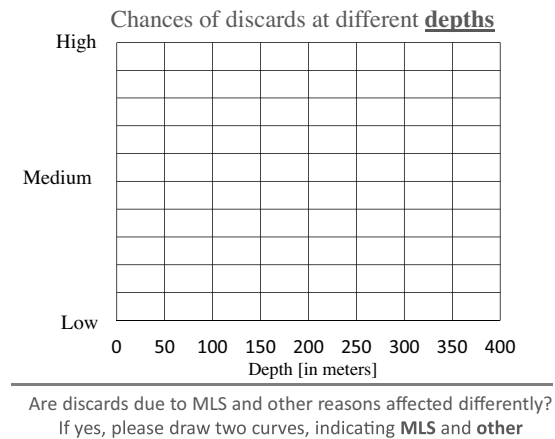


Fig. 4. Example of chart filled by stakeholders, aiming to provide priors for the Bayesian modelling framework.

through interviews or online forms). In this case, for example, the interviewed individual may be asked for the average and range of the explanatory variable in question. This information may be also obtained through literature review, i.e. meta-analysis.

Second, external knowledge can be used for obtaining priors for the parameters defining the shape of the link functions. A simple way of performing this task, is to ask the priors' provider to describe a curve that best represent the influence of the variable on discard rates. With this curve in hands, the modeler can apply statistical methods to fit the best equation to the curve, or adjust the parameters of a pre-defined function to better describe the curve given by the priors' provider. The main advantage of this method is that stakeholders or experts can participate in the modelling process without needing to have knowledge on the mathematical aspects of the model. In other words, they only need to have a preconceived knowledge on how different variables affect discards.

3. Case studies

The Ligurian and northern Tyrrhenian Seas are defined and included by the General Fisheries Commission for the Mediterranean (GFCM) in the Geographical Sub-Area (GSA) 9 (Fig. 2). The fishing fleet operating in GSA9 is characterised by a high proportion of small-scale artisanal vessels, which accounts for about three quarters of the boats. Nevertheless, fishing vessels equipped with trawl nets provide the highest landings and turnover sales levels. In 2015, the trawl fleet in GSA 9 consisted of 320 vessels. The

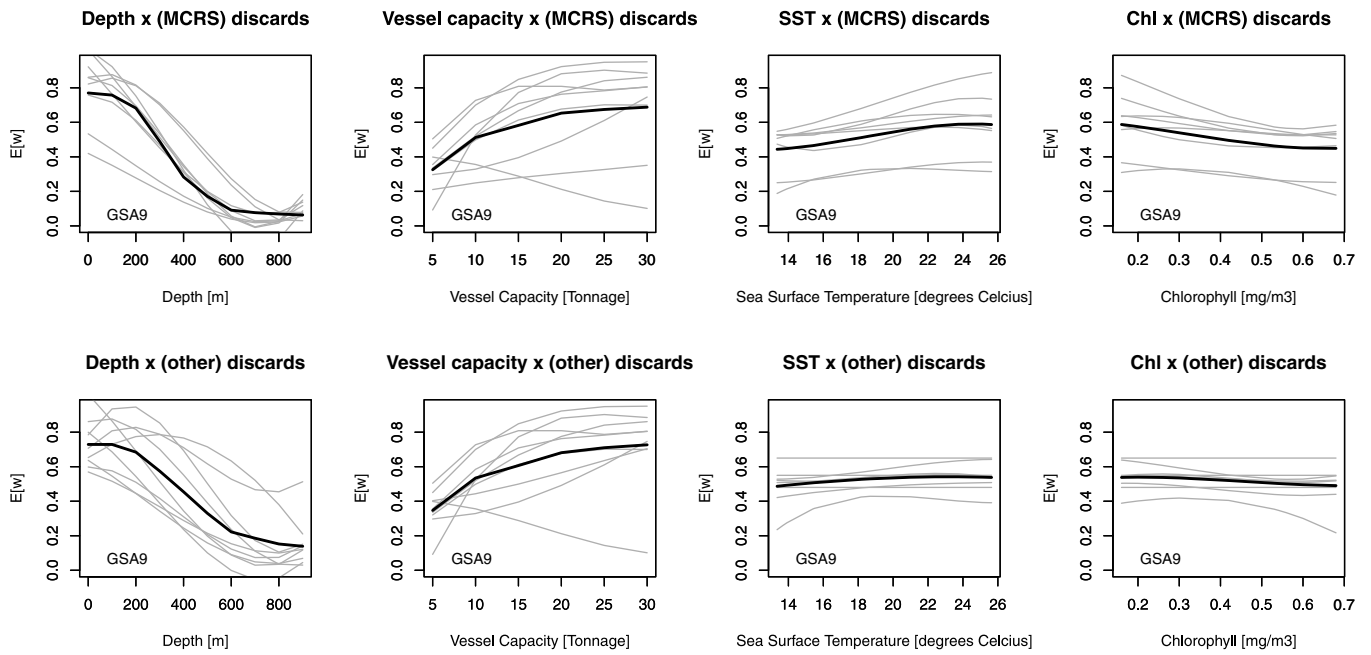


Fig. 5. Prior link functions fitted using information obtained from questionnaires filled by stakeholders in GSA9. The gray lines represent individual answers, the solid black line represent the average.

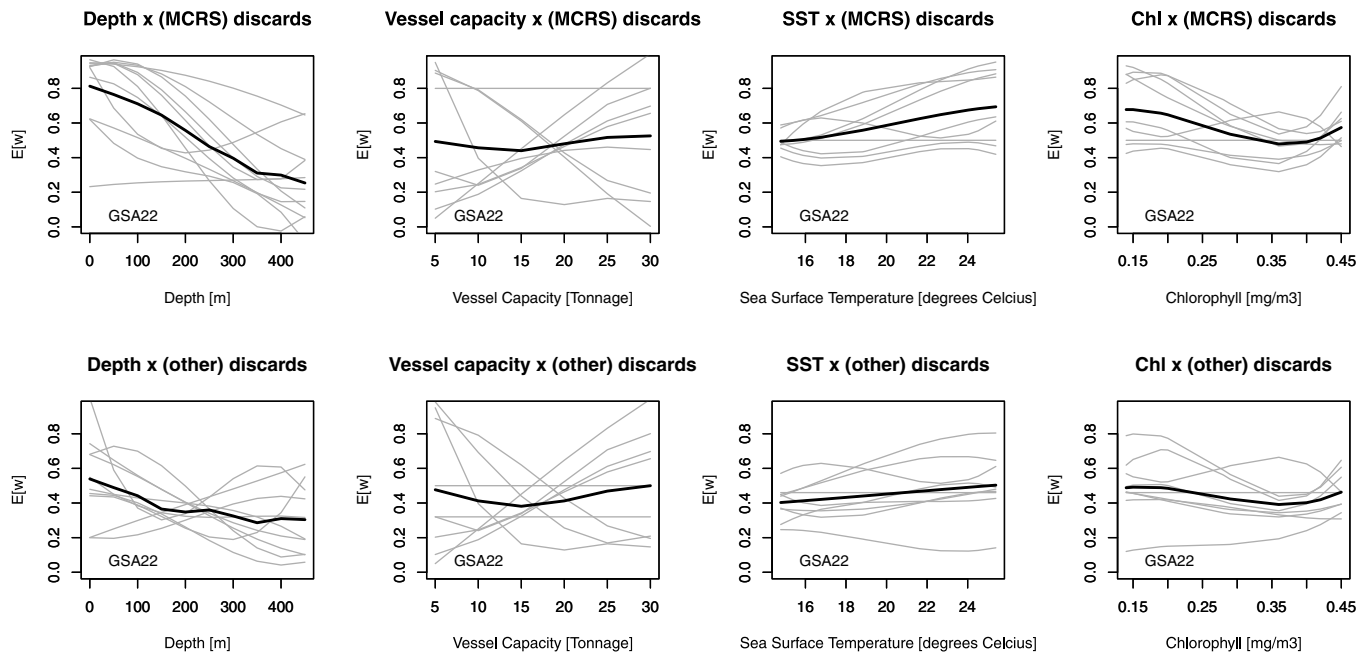


Fig. 6. Prior link functions obtained from questionnaires filled by stakeholders in GSA22. The gray lines represent individual answers, the solid black line represent the average.

landings due to trawlers were about 7500 t, approximately 40% of the total landings in GSA9. The highest contribution is due to the trawlers involved in the demersal species fishery, which are followed by those involved in the deep water species fisheries targeting crustaceans (Sbrana et al., 2003). The production of trawlers is characterized by a high proportion of fish (60%), followed by mollusks (30%) and crustaceans (15%) (Ligas et al., 2010; Sbrana et al., 2006).

The fishing effort exerted by trawlers is not uniformly distributed throughout GSA9. In the northwestern part of the area, there is little fishing activity on the shelf, due to its limited extension, and many vessels concentrate their activity on bathyal

bottoms targeting blue and red shrimp (*Aristeus antennatus*) (Orsi Relini et al., 2013). Along the central and southern coasts of GSA9, the shelf is wider, and important trawl fleets operate in those areas, targeting European hake (*Merluccius merluccius*), red mullet (*Mullus barbatus*), horned octopus (*Eledone cirrhosa*), common octopus (*Octopus vulgaris*), mantis shrimp (*Squilla mantis*), and deep-water rose shrimp (*Parapenaeus longirostris*) (Ligas et al., 2010; Sbrana et al., 2006). Discards are mainly made by non-commercial species (principally invertebrates). Discard of commercial species is less important and is due mainly to specimens below the MCRS or to species without market value. The European hake represents the target species of the bottom trawl fishery in this area and it accounts

Table 1
Prior parameters of the link functions for MCRS discards.

	β_0		β_1		β_2		β_3	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
MCRS discards GSA9								
Depth	8,02E-01	2,06E-01	-4,08E-04	8,24E-04	-3,01E-06	2,18E-06	2,88E-09	1,57E-09
Vessel capacity	6,74E-02	2,75E-01	6,31E-02	5,53E-02	-2,28E-03	2,28E-03	2,90E-05	3,10E-05
SST	1,18E+00	1,74E+00	-1,46E-01	2,62E-01	8,92E-03	1,31E-02	-1,62E-04	2,12E-04
CHL	6,15E-01	2,54E-01	-2,73E-02	8,02E-01	-1,09E+00	1,36E+00	1,14E+00	9,95E-01
MCRS discards GSA22								
Depth	7,72E-01	2,65E-01	-1,43E-03	2,31E-03	-3,42E-06	1,46E-05	8,39E-09	2,16E-08
Vessel capacity	6,63E-01	6,56E-01	-3,31E-02	9,81E-02	1,28E-03	5,00E-03	-1,85E-05	7,76E-05
SST	2,31E+00	5,69E+00	-2,79E-01	8,96E-01	1,37E-02	4,54E-02	-2,14E-04	7,50E-04
CHL	2,48E-01	7,11E-01	4,98E+00	1,06E+01	-2,31E+01	4,52E+01	3,03E+01	5,68E+01

Table 2
Prior parameters of the link functions for other discards.

	β_0		β_1		β_2		β_3	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
other discards GSA9								
Depth	7,37E-01	1,44E-01	1,95E-04	1,24E-03	-3,24E-06	2,58E-06	2,56E-09	1,73E-09
Vessel capacity	9,22E-02	2,94E-01	6,19E-02	5,65E-02	-2,19E-03	2,39E-03	2,77E-05	3,24E-05
SST	2,75E-01	1,47E+00	2,01E-02	2,06E-01	-2,39E-04	9,73E-03	-5,57E-06	1,51E-04
CHL	5,06E-01	1,14E-01	3,52E-01	3,97E-01	-1,10E+00	1,14E+00	8,02E-01	1,12E+00
other discards GSA22								
Depth	6,35E-01	3,13E-01	-2,03E-03	3,82E-03	4,36E-06	1,97E-05	-3,38E-09	2,66E-08
Vessel capacity	7,37E-01	6,73E-01	-4,49E-02	9,53E-02	1,56E-03	4,82E-03	-1,71E-05	7,81E-05
SST	-1,90E+00	3,65E+00	3,33E-01	6,02E-01	-1,56E-02	3,22E-02	2,46E-04	5,52E-04
CHL	1,26E-01	8,65E-01	5,08E+00	1,22E+01	-2,10E+01	4,96E+01	2,53E+01	6,00E+01

for the highest discard rate. This is due to the combination of low selectivity of trawl nets and the high concentration of juveniles in this zone. In fact, some of the most important nursery areas of European hake in the Mediterranean can be found in GSA9 (Colloca et al., 2009; Ligas et al., 2015; Orsi Relini et al., 2002).

The second case study was developed in the Greek part of the Aegean Sea (GSA 22) (Fig. 2). Here, the main fishing activity is represented by the bottom trawl fishery. This fleet includes trawlers that usually operate in waters from 50 to 300 m depth with European hake, red mullet and deep-water rose shrimp as target species. The species composition of the landings, bottom trawling is a typical multi-species fishery and past studies have shown that their landings include around to 70 fish, crustacean and cephalopod species (Stergiou et al., 2003). The majority of the fishers make short hauls of about 2–4 h, comprising 2–3 fishing hauls per trip. In 2013, the trawl fleet in GSA22 consisted of around 280 vessels. The majority is registered in the North Aegean sea (41.61%), and together with the vessels of the Central Aegean constitute 60.25% of the total number of bottom trawlers that operate in the Greek waters. The bottom trawl fishery is prohibited in the Greek national waters from June to September (4 months). The annual discard ratio of the bottom trawl fishery, in terms of biomass, ranges from 28 to 35% depending on the area and the season (Tsagarakis et al., 2014). The contribution of bottom trawlers to the total production is rather stable in the last few years of the examined period (1991–2009) fluctuating between 27 and 30%. The most important fishing grounds are located at the northern part of the Aegean Sea whereas fishing effort reaches up to 45% of the total, in terms of GT*days at sea. On the continental shelf (depths <200 m) it was recorded the 76% of the total fishing effort.

3.1. Observed data

Discard data used in this study were collected by on board observers from year 2003–2015. Observers, which generally have

a scientific background, participated to different surveys, both fishery-dependent and fishery-independent survey, collecting data about the fishing operations. Scientific observers performed 120 fishing trips (for a total of 336 trawling hauls sampled) on board of commercial bottom trawls in GSA9 and 303 fishing trips (for a total of 844 hauls sampled) in the Greek part of GSA 22. Trips were performed in a seasonal basis. In all cases during the fishing trips there was no interference with the habitual “modus operandi” of the fishermen. For each sampling haul several types of information such as date and time of sampling, longitude and latitude, swept area, length of the wraps, depth, haul duration and species composition were recorded by the on board observers. Catch data were divided into unwanted catch and landings per species. Unwanted catch was sampled at a haul level, by randomly collecting two boxes of discarded catch from all hauls held during each trip. The species composition of the discarded catch was determined and total weight and number of individuals of each taxon was recorded. In addition, for each recorded haul, an estimate of the total weight discarded is made by the fishermen and the on-board observer. The discarded weight of the species in the sample is then multiplied by the total discarded weight of the haul in order to obtain the total weight of the species discarded per haul (Damalas and Vassilopoulou, 2013). Subsequently, unwanted catch was divided into the biomass of species a) with MCRS and b) without MCRS (other discards). Discard rates were obtained by dividing the total discards [kg] by the haul duration [h].

3.2. Explanatory variables

The explanatory variables for the model were chosen based on literature review, as well as the opinion of scientists and stakeholders working in GSA9 and the Greek part of GSA22. From the variables mentioned in the literature, three were considered highly relevant for our study: bottom depth, vessel capacity and season of the year. Although a much higher number of explanatory vari-

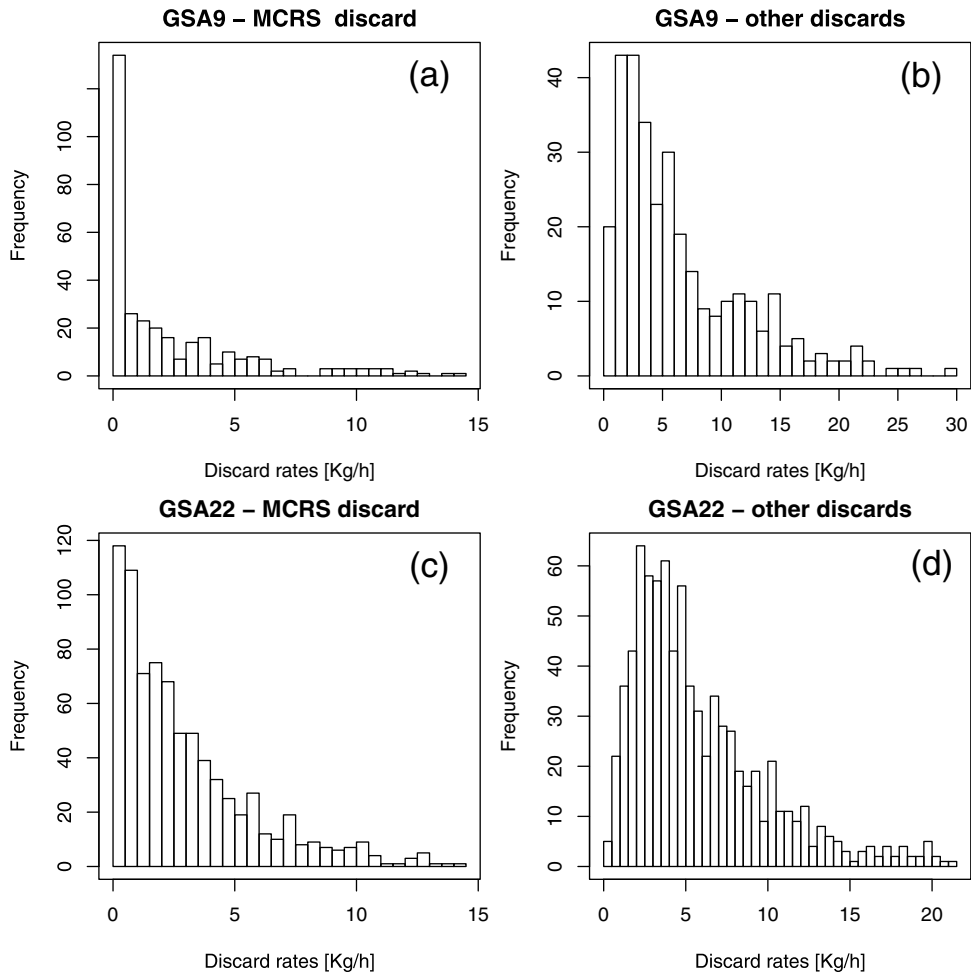


Fig. 7. Distribution of observed discard rates within GSA9 and GSA22. (a) MCRS discards at GSA9; (b) other discards in GSA9; (c) MCRS discards in GSA22 and; (d) other discards in GSA22.

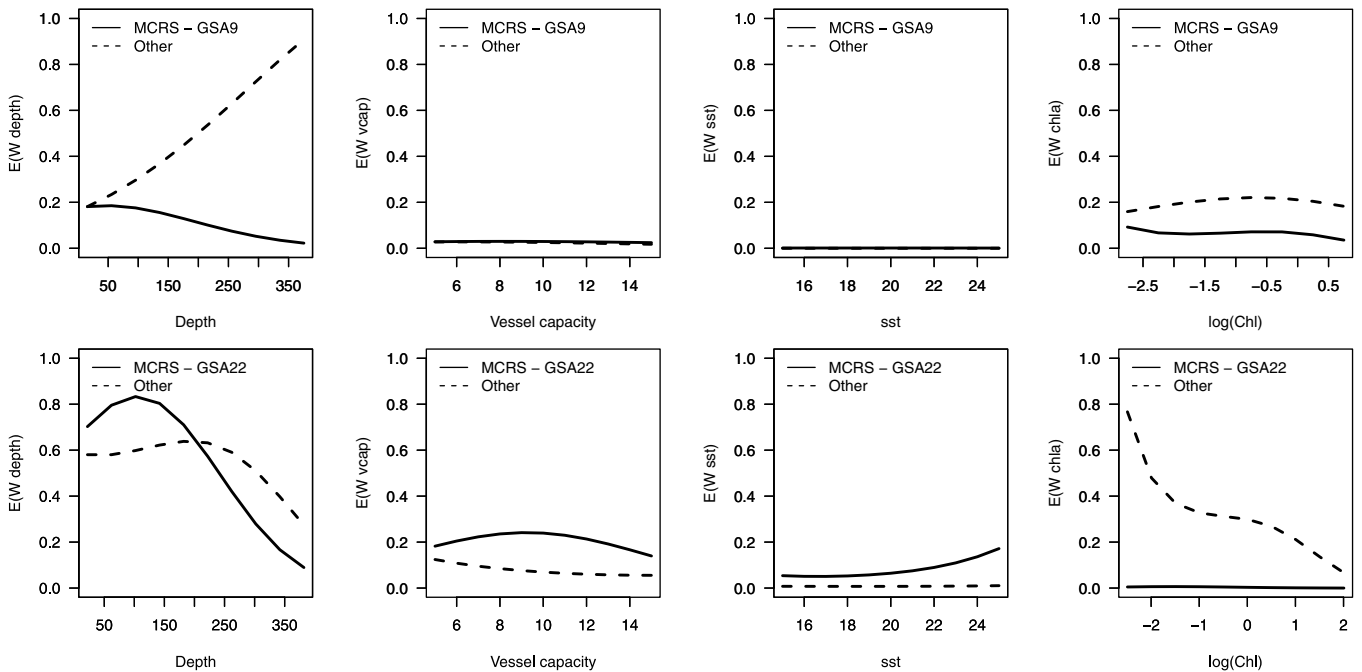


Fig. 8. Link functions fitted using posterior parameters for GSA9 (top) and GSA22 (bottom).

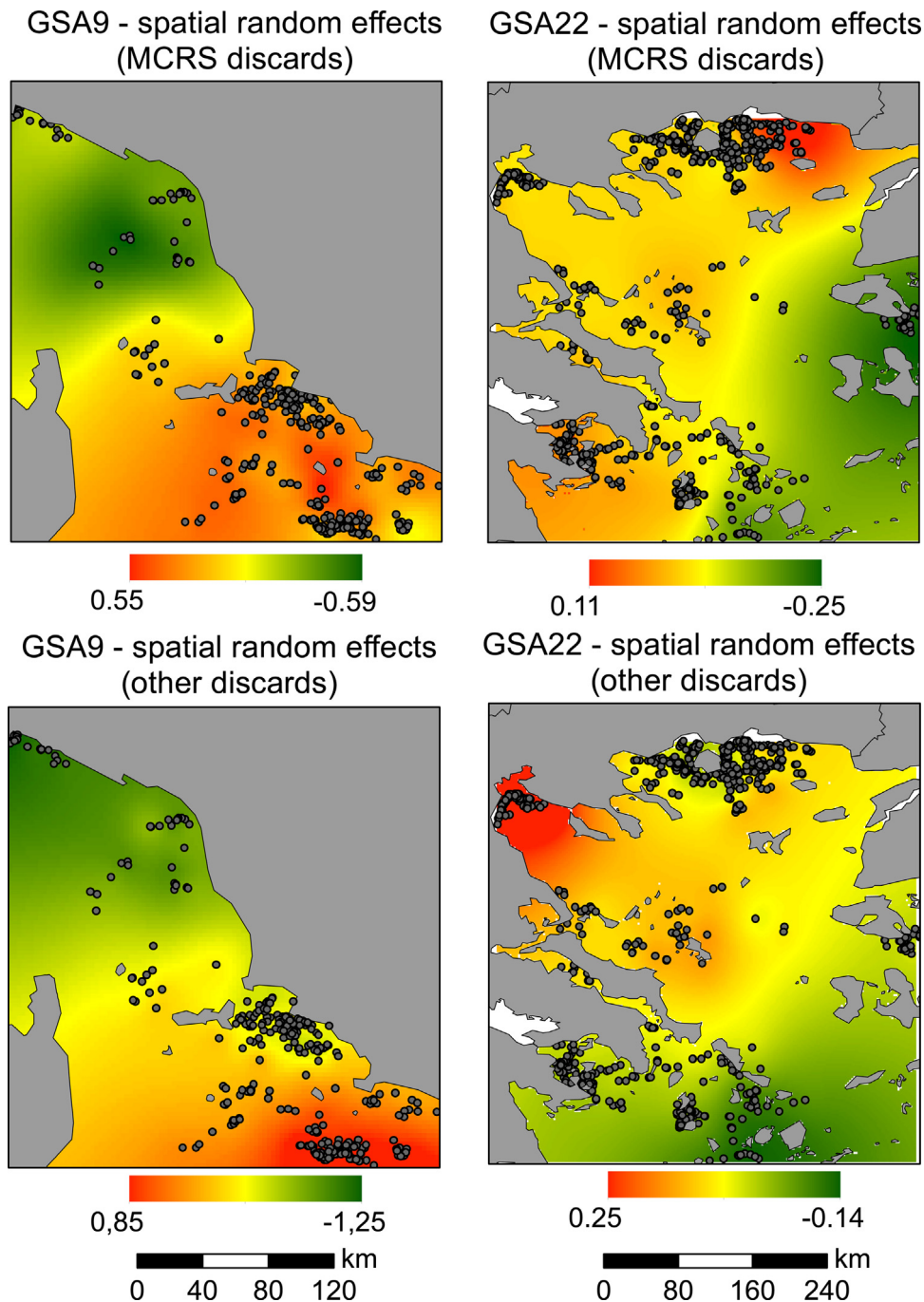


Fig. 9. Posterior means of spatial random effects surface for GSA9 and GSA22.

ables were mentioned in the literature and by experts, the number of inputs for the model was kept small for an easier interpretation of the results and evaluation of the model. Furthermore, some variable considered relevant in previous studies were not included due to autocorrelation with the variables included in the model or lack of importance from a practical management point of view. For instance, although mesh size is recognized as an important factor affecting discard rates and characteristics (Rochet and Trenkel, 2005), there are no foreseeable policies aiming to change this factor in the near future. A correlation matrix with all the variables considered for this study is presented in the supplementary material (Fig. S1).

From the chosen variables, bottom depth has been pointed out by several studies as having significant influence on unwanted

catch amounts, rates and species composition (Allain et al., 2003; Sánchez, 2004). For this study, we used the gridded ocean depth data from the general bathymetric chart of the oceans (GEBCO) (Becker et al., 2009). The original data were obtained in netCDF format, with 30 arc-second spatial resolution.

Vessel capacity has also been consistently mentioned in previous studies and by our local stakeholders as having important impact on unwanted catch. One argument is that vessel holding capacity limits the storage of fishing products and the proportion of discards increases with trip duration as storage becomes limiting (Rochet and Trenkel, 2005). However, a counter argument states that larger vessels have higher capacity to catch biomass, and therefore higher capacity may lead to higher discards, assuming that discards are proportional to catch volumes.

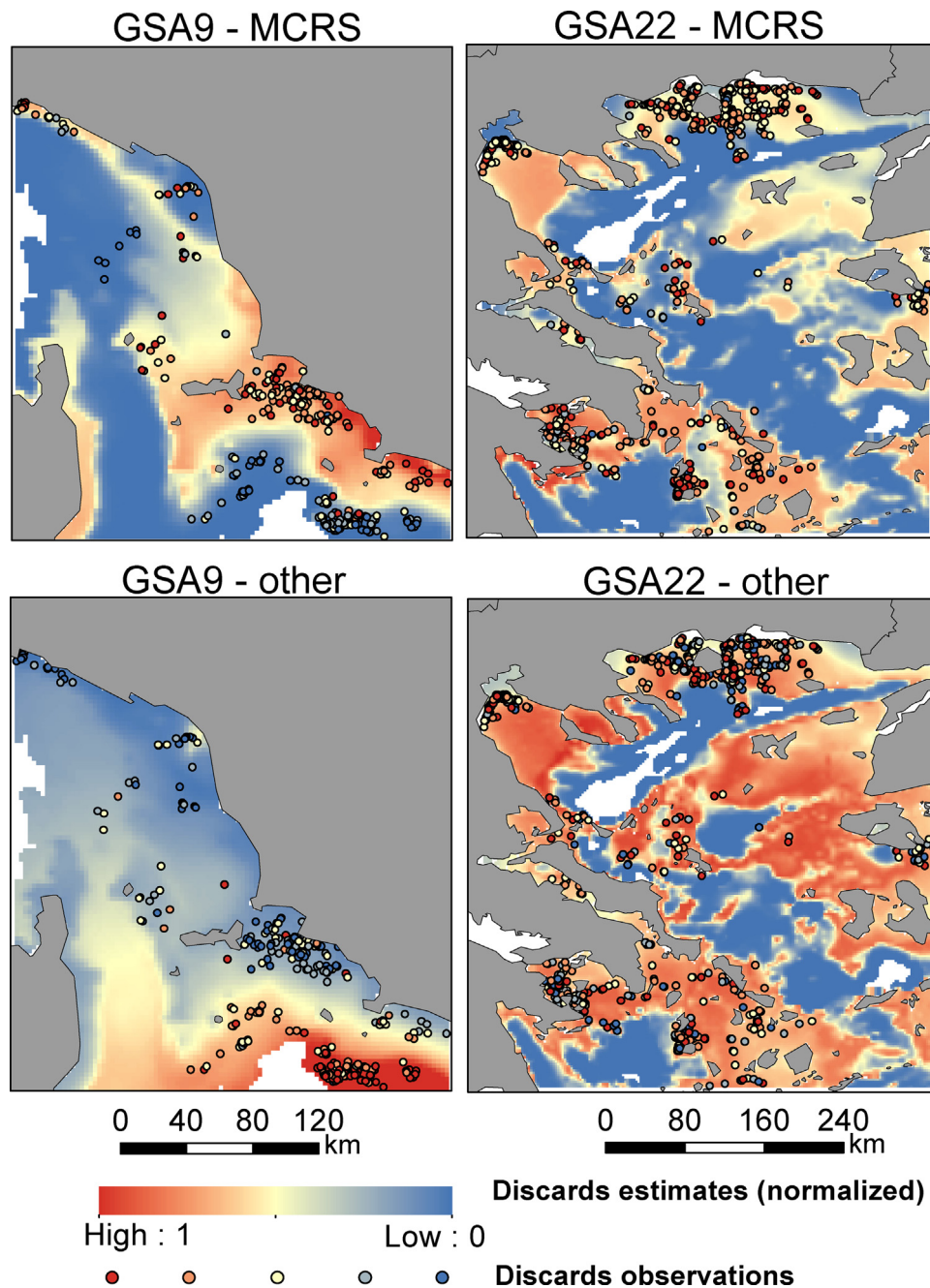


Fig. 10. Maps of the mean values of the estimates for MCRS discards and other discards, across GSA9 (left side) and GSA22 (right side).

Given that vessel capacity data were not available, this explanatory variable was added into the Bayesian model as a normally distributed prior:

$$V_{cap,i} \sim N(\mu_{vcap}, \sigma_{vcap}^2) \quad (7)$$

where $V_{cap,i}$ is the vessel capacity expressed in gross tonnage, which is how fishing capacity has been historically measured in EU (Pascoe and Gréboval, 2003).

Finally, the season of the year has been shown to affect unwanted catch rates and characteristics, given intra-annual variations in key environmental variables for fish stocks. To capture this seasonal information in a quantitative and spatially explicit manner, we included two other explanatory variables into the model: the sea surface temperature (SST) and the sea surface chlorophyll (CHL).

The seasonal variation of average SST and CHL across GSA9 and the Greek part of GSA22 is presented in Fig. 3. These two variables are intrinsically related to seasonal variations in fish population dynamics. For instance, CHL provides a proxy of productivity, which may help identifying nursery hotspots.

Both, SST and CHL data, were obtained from remote sensing measurements acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS), onboard the TERRA and AQUA satellites (Bailey and Werdell, 2006). CHL estimates were obtained from the MODIS Chlorophyll-a concentration product, which provides near-surface concentration of chlorophyll-a (mg m^{-3}), calculated using an empirical relationship derived from in situ measurements of CHL and remote sensing reflectance. SST was obtained from MODIS level-3 sea surface temperature product (Kilpatrick et al., 2015). These satellite variables were used at their best available resolution provided by the online satellite data distribution archives

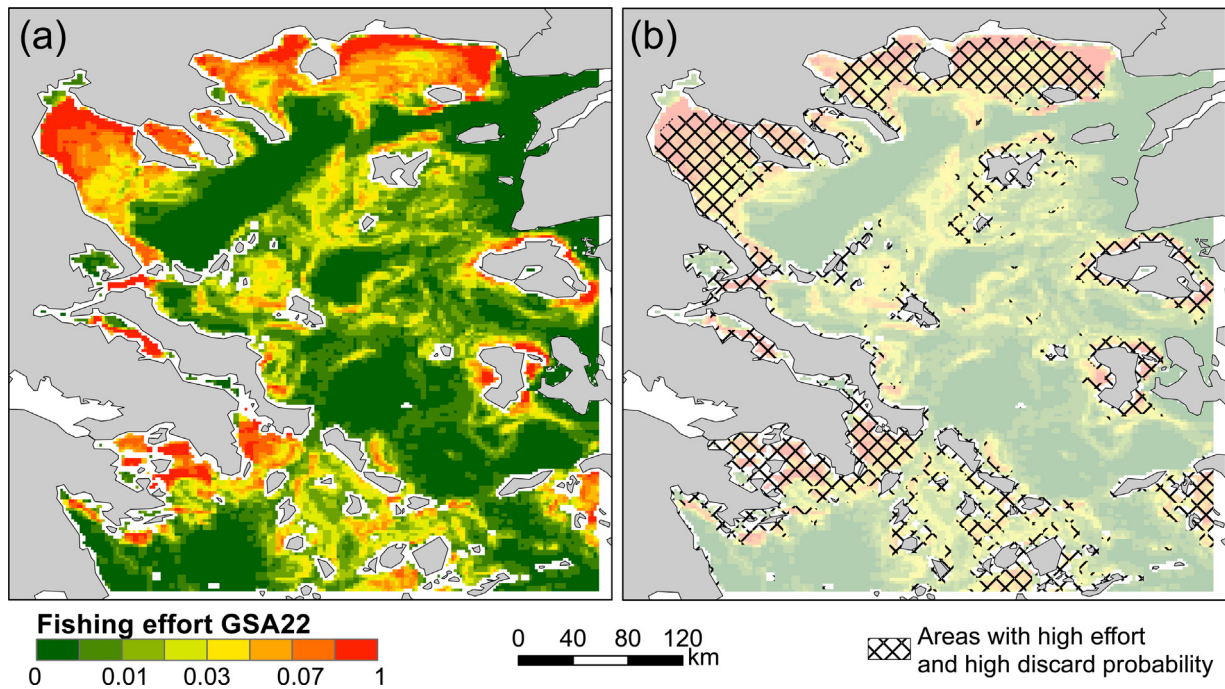


Fig. 11. a) Fishing effort at the Aegean Sea (GSA22). Values are normalized from zero (no effort) to 1 (maximum effort). b) Overlap between areas with high fishing effort and high discard probability.

(oceancolor.gsfc.nasa.gov) in order to obtain values at each sampling point. This results in an average spatial resolution of 1.5 km, adequately defining environmental spatial heterogeneity and the best available resolution of the explanatory environmental variables.

3.3. Stakeholder survey and link functions

Priors for the link functions were obtained through forms filled by different stakeholders, including fishermen, vessel observers, and scientists, working in GSA9 and GSA22. A total of 10 forms were used for each site. No personal information of the participants were collected or stored at any moment, and the forms had the solely objective of obtaining a general overview of the stakeholders' opinion about the factors affecting discards. Hence, no ethical issues were raised in this process. Although the number of forms for each site was not large, they provided enough knowledge for delineating informative priors. In the future, as more forms become available, the priors can be iteratively updated, leading to better estimates of the discards characteristics.

The forms were designed to enquire, in a simple way, how each of the explanatory variables affect discard rates. They consisted of empty charts, with the explanatory variable in the horizontal axis, and the level of importance of this variable in the vertical axis, varying from "low" to "high". An example of these charts, for the variable "depth", is presented in Fig. 4, and a sample of a filled form is available in the supplementary material. The stakeholders were then asked to draw a line on the chart to represent the relationship between the explanatory variable and discards.

Two categories of bottom trawl discards were assessed in our study. The first type were discards of undersized individuals, below the MCRS (or minimum landing size, MLS) as defined by EU regulations (Reg. n. 1967/2006). This category is hereby classified simply as "MCRS discards". The second discard category comprised individuals of species of low or no economic value. This latter category is hereby classified as "other discards". Hence, if a certain explanatory variable would affect differently MCRS and other discards, the

individuals filling the forms were asked to draw one line for each category.

After all forms were filled, the charts were digitalized and the vertical axis of the plots was re-scaled according to the historical discard rate characteristics of each site, as described in the observed dataset. For this procedure, the minimum discard rate was set to zero, and the maximum rate was defined as the 95th percentile of all observed discards in the respective GSA. Once the curves were digitalized and scaled, third degree polynomial models were fitted to the curves, as follows:

$$E(w_i) = \beta_0 + (\beta_1 \times V_i) + (\beta_2 \times V_i^2) + (\beta_3 \times V_i^3) \quad (8)$$

where β_0 , β_1 , β_2 and β_3 are the coefficients of the polynomial equation. Polynomial models were chosen due to its simplicity and flexibility in describing different curve's shapes. Nonetheless, any type of mathematical model, such as exponential or logit models, could have been used to better fit the shape of the curves. The coefficients of the models were then recorded for each independent form, and their mean and standard deviation used as priors for the fitting the Bayesian model.

3.4. Model fitting and evaluation

A model for each discard category and GSA was separately fitted, totaling four models. The sampling of values from the joint posterior distribution of parameters was performed through the Markov chain Monte Carlo (MCMC) algorithm, implemented using JAGS (Just Another Gibbs Sampler, [Plummer, 2003](#)). The number of MCMC chains used to fit the model was 2 and the number of iterations was 100 000. Given that parameter inference from posterior samples can only be made when the MCMC chains have converged, we perform the Gelman-Rubin diagnostic ([Brooks and Gelman, 1998](#)), which evaluates the difference between multiple Markov chains (see supplementary material, Figs. S1–S4). The convergence is assessed by comparing the estimated between-chains and within-chain variances for each model parameter, with large differences between these variances indicating non convergence ([Brooks and Gelman, 1998](#)). Once the link function parameters have

been inferred, spatial predictions of mean discard rates were carried out for each discard category and GSA.

To assess the potential of these predictions in guiding future discard mitigation actions, we evaluated the spatial distribution of discard predictions against current fishing effort maps at GSA22. The estimation of fishing effort was computed as the amount of transmitted signals (also known as “ping”) deployed by vessel monitoring system (VMS) in each spatial cell (i.e. 3×3 grid cell size) of a given space partitioning. Common errors and outliers in the VMS dataset were filtered out and removed based on Maina et al. (2016) and Russo et al. (2014). Speed thresholds for bottom trawlers were used to define “fishing” activity. It was considered that VMS readings of speed lower than 4 knots corresponded to “fishing”, otherwise the signals were classified as “steaming”. VMS data were enhanced using interpolation techniques (Russo et al., 2014). Since the standard frequency of the native dataset was around 2 h and the frequency of the interpolated dataset was increased at 10 min, estimation of fishing hours by grid cell (Fhc) calculated as the total number of fishing signals with 10 min frequency divided by 6. Finally the fishing effort expressed in fishing hours was transformed in an index (FEi) expressed in values from 0 to 1 (i.e. $FEi = Fhc / MAX(Fhc)$).

Greek bottom trawlers are equipped with VMS since 2009. Thus it was not possible to find a fishing effort dataset to match the catch and environmental dataset. We assumed that the spatial distribution of the bottom trawlers has not changed substantially within the last five years. The fishing effort analysis was performed on annual basis for the year 2012, considering it as representative snapshot of the spatial distribution of fishing effort to compare with model output.

4. Results

The adjusted link functions obtained from the forms filled by stakeholders from GSA9 and GSA22 are presented in Figs. 5 and 6, respectively. The mean and standard deviation of the polynomial coefficients of the functions, which were used as priors for fitting the Bayesian model, are presented in Table 1, for MCRS discards, and Table 2, for other discards.

In GSA9 (Fig. 5), depth variation was considered to have strong influence on both MCRS (Fig. 5, top panel) and other discards (Fig. 5, bottom panel). Higher discard rates were associated with lower depths (0–200 m), decreasing steadily until approximately 600 m depth. Chances of MCRS discards were considered to decrease faster with increasing depth, in comparison with other discards. Vessel capacity was considered to affect MCRS and other discards in a similar way, with increasing chances of discard with higher vessel capacity. On the other hand, seasonal changes, as described by SST and CHL, were considered to slightly affect MCRS discards, but with small or no influence on other discards. Chances of MCRS discard were considered higher at higher SST and lower CHL concentration.

In GSA22 (Fig. 6), a larger variance was observed on the answers obtained from stakeholders, particularly the ones related to bottom depth and vessel capacity. Despite this higher variance, the average link function for depth showed the same pattern as observed in GSA9, that is, higher discard chances at lower depths. Note that fishing trawls in GSA22 have a lower range, with maximum depths at around 500 m. Chances of MCRS discards were considered to reach the lower values at approximately 300 m, after which values were stable. The probability of other discards, however, decreased faster, getting stable at around 150 m. On average, vessel capacity variability showed no clear influence on discards. Nonetheless, the opinion on this matter varied greatly among stakeholders: some answers indicated higher discard with larger vessel capacities, other answers indicated the opposite. This inconsistency may

be caused by different interpretations of the charts, which in future studies need to be clarified through more interactions with stakeholders. The average link function for SST and CHL showed small variation, indicating that, according to stakeholders, variations of these environmental variables do not critically affect discard rates. It is however important to note that, at GSA22, bottom trawlers are not allowed to fish within territorial waters between the 1st of June and 1st October, a fact that can decrease the influence of seasonality on stakeholder’s perception. Temporal fishing closure in GSA9 is only 30–40 days, generally in from September to October, thus not affecting the seasonality of fishing activities.

The frequency of discard rates observed in GSA9 from 2003 to 2015, and in the Greek part of GSA22 from 2003 to 2014, are presented in Fig. 7. For easier visualization, outliers were removed using a 95th percentile threshold. In both areas, the frequency distribution of MCRS discards were strongly skewed to the left, with most observations between zero and 5 kg h^{-1} . In GSA9, the frequency of MCRS discards between 5 and 10 kg h^{-1} were much lower than in GSA22, and in both areas discard rates higher than 10 kg h^{-1} were rarely observed. The frequency distribution of other discards had a higher mode, at approximately 2.5 kg h^{-1} , in both areas. In GSA9, most other discard observations were between zero and 5 kg h^{-1} , but the proportion of discards between 5 and 20 kg h^{-1} were higher in comparison with MCRS discards. The same could be observed in GSA22.

Having the link function priors and observed data in hands, the Bayesian models were fitted for providing posteriors inference. The link functions constructed with the mean posterior coefficients are presented in Fig. 8, and a full analysis of the convergence of models’ parameters are presented in the supplementary material. In GSA9, depth was the main variable driving discard rates (Fig. 8, top panel). Interestingly, the influence of depth on MCRS and other discards were inverse. That is, higher MCRS discards were expected at lower depths, while other discards were more likely at deep waters. Vessel capacity and SST did not show clear influence on discards GSA9, for both discard categories. CHL, however, was shown to slightly affect MCRS discards, with lower chances of MCRS discards at higher CHL concentration. This result is somehow counterintuitive, given that one would expect that nurseries are concentrated in areas with higher productivity (i.e. higher CHL concentration). This might indicate that this relationship is not causal, and may be due to lower CHL concentration at higher depths. In general, depth seems to be the dominant variable driving the mean probability of both discard categories GSA9.

In GSA22, lower depths were associated with increasing probability of both MCRS and other discards. The influence of depth on MCRS discards was stronger at shallow waters, between 50 and 200 m. Vessel capacity had a stronger relative influence on MCRS discards, although no clear increasing or decreasing pattern in discards rate is observed with varying vessel capacity. It is worth mentioning that in this case study, vessel capacity data was not available, and this information was inserted as a normally distributed prior. SST showed a slightly positive correlation with MCRS discards, while it did not affect other discards. CHL showed a strong influence on other discards, with decreasing discard rates at higher CHL concentrations. MCRS discards were not affected by CHL concentration in GSA22.

As stated in equation 2, the mean discard rate at a certain point in space and time is defined by weights determined by the link functions, and corrected for spatial dependence biases by adding a spatial random effects component (w_{sp}). The spatial random effect surfaces for each case are presented in Fig. 9. Positive values suggest an adjustment towards a higher probability of discards than described by the explanatory variables alone. On the other hand, negative values suggests an adjustment towards a lower probability of discard. It is interesting to note that the spatial patterns of

w_{sp} varies considerably among discard categories, even though the location of the observations is the same. This result highlights the importance of the model capacity to account for different scenarios, fishery characteristics and objectives.

The spatial prediction of mean discard rates (μ), for average SST and CHL conditions, are presented in Fig. 10. Values in the figure have been normalized from zero to 1 for easier comparison among regions and discard categories. Fig. 10 also shows, as dots, the location and magnitude of observed discard rates. As expected from the posterior link functions (Fig. 8), in GSA9 MCRS discards and other discards show an inverse pattern. That is, areas with high chances of MCRS discards have lower chances of other discards. Chances of MCRS discards are shown to be higher at the vicinities of the southeastern coast of GSA9, and around the island of Portoferraio. Lower MCRS discard probabilities were observed at the northeastern coast of GSA9, as well as at high depth locations (>200 m). Chances of other bycatches in GSA9 were higher in the southern border of the GSA, where depths are generally higher.

In GSA22 (Fig. 10, right side), MCRS discards and other discards followed a similar spatial pattern. Generally, discard chances were higher closer to the coastlines, decreasing towards more remote and deeper areas. Nonetheless, several exceptions were observed, where lower discard probabilities take place at coastal areas, for instance across some northern bays of the Aegean Sea (e.g. Strymonikos Gulf). The most noticeable difference between MCRS and other discards in GSA22 is that chances of MCRS discard decrease faster when moving towards deeper areas, whereas the distribution of other discards are more homogenous across shallow areas (0–300 m).

The contrasts between the two study areas and the discard categories nicely show the flexibility of the model. Namely, with the same structure the model could adapt to these different situations, while accounting for local knowledge for improving predictions. Although optimizing prediction accuracy is not the main scope of the study, we can observe that the spatial patterns of predictions at GSA9 closely followed those of observed data for both discard categories (Fig. 10). The spatial patterns of the observed discard rates are not as evident in GSA22, where in the same clusters it is possible to observe high and low discard rates. Nonetheless, the model was still able to identify borderlines between high and low discard probabilities that nicely agrees with those in the observed data.

To demonstrate the potential of this tool for policy guiding, we evaluate our discard estimates in contrast to a fishing effort map for GSA22 (Fig. 11). It is interesting to note that the spatial patterns of the fishing effort map (Fig. 11a) closely resembles those of the discard probability map (Fig. 10), indicating that generally high fishing effort is undertaken in areas with high discard chances. Nonetheless, these results demonstrate that spatial modeling may foster the identification of hotspots, as high fishing effort areas can be seen in locations with low discard probability. Fig. 11b shows the overlap of areas with high effort and high discard probability, which are here defined as areas with values higher than the mean for the entire area. From the figure it is clear that areas with high effort are still observed in regions with discard chances lower than average, indicating potential sites for maximizing landings while reducing chances of discards. It is however worth highlighting that the fishing effort dataset used in this study was obtained using VMS data from only one year (2012). Hence, the spatial patterns of fishing effort can vary from year to year.

5. Discussion

A major advantage of the modelling framework proposed in this study is the possibility to integrate stakeholders' knowledge to better shape the relationships between explanatory variables and

discard probability. Involving stakeholders has advantages not only in improving model predictions, but also in tightening relations between modelers and end-users, which can facilitate the integration of such tools in guiding policies and fishery management. Studies have demonstrated that stakeholder engagement through dialogue and interactions are beneficial for scientists and the fishing industry alike (Sampedro et al., 2016). Furthermore, integrating scientific research and stakeholder knowledge can lead to stronger legitimacy of actions and more effective implementation of regulations (Sampedro et al., 2016).

Despite many benefits, a few challenges were identified in integrating stakeholders' inputs into the model during the two case studies. In some cases, the explanatory variables included in the forms, although based on an extensive literature review (e.g. Feekings et al., 2012; Komoroske and Lewison, 2015; Madsen et al., 2013; Pennino et al., 2014), were not fully appropriate for these specific cases. This has led to minor mismatches in the expectation of scientists, and the real knowledge available to stakeholders to fill the questionnaires. For instance, on board observers from GSA22 could not give a precise indication of seasonal discards variation between June and end of September, since fishery activities do not take place during this period in the Aegean Sea. Similarly, although mesh size is broadly considered as an important factor affecting discard rates (Feekings et al., 2012; Rochet and Trenkel, 2005), stakeholders from GSA9 and GSA22 had little experience in using different mesh sizes and, therefore, were not confident in providing answers for this variable.

In Bayesian inference, posterior probabilities are obtained as a function of priors, here provided by stakeholders, and the likelihood, here provided by observed discard data. Hence, it is interesting to evaluate similarities and discrepancies when comparing the shape of the posterior link functions (Fig. 8) with those of the priors (Figs. 5 and 6), as delineated by stakeholders. For instance, although stakeholders from GSA9 indicated that depth would have similar influence on MCRS and other discards, the posteriors show the opposite i.e. other discards increase in deeper areas. In this context, the Bayesian approach is a strong advantage of the method, as these discrepancies can be clarified and the distributions of the model parameters can be sequentially updated when more evidence becomes available. As more knowledge from stakeholders is gathered through new questionnaires, uncertainties in the prior and posterior distributions tend to decrease.

Previous studies have shown that one of the main difficulties in developing models for estimating discards is the high variability between fisheries, gears, geographical location, hauls, among other factors (Rochet and Trenkel, 2005; Tsgarakis et al., 2014). Although the model structure used in our study was the same for both study areas and discard categories, the posterior parameters defining the shape of the link functions varied significantly. Hence, our results confirm the case specific character of discard rates, as well as the importance of accounting for local and expert's knowledge for choosing the explanatory variables. Since the proposed modelling framework does not rely on any fixed assumptions, it has adequate flexibility to be applied under a large range of condition.

As expected, our results indicate that a model calibrated for a certain geographical area should not be applied for a different location without adjustments in the model's parameters. The same assumption is valid when analyzing different discard categories inside the same area. However, an important strength of the Bayesian approach proposed in this study is the possibility of using the posterior distribution of parameters from one area as priors for modeling discards in a different location. When data becomes available in the new location, the priors can be sequentially adjusted. The same concept can be applied for assessing discards of a different target species at a same location. For instance, the posterior

link functions obtained for total discard rates can later be applied as priors for assessing discards of a given species.

Another important benefit in using a Bayesian approach lays in the better assessment of uncertainties associated with model parameters and the model outcomes (Pennino et al., 2014). For instance, besides estimating the spatial distribution of discard rates, it is possible to evaluate its corresponding standard errors and generate alternative summaries of discards, such as threshold probabilities, to be used in multi-taxa analyses (Sims et al., 2008). Furthermore, the spatial random effects (Fig. 9) allow a more robust assessment of spatial dependence biases on discard, leading to more realistic estimates.

The incorporation of the link functions for describing the relationship between the explanatory variables and discard rates (Fig. 1) is another important improvement of our approach. Previous studies have shown that models developed based on linear mixed models can only account for simple linear relations between the dependent and explanatory variables (Pennino et al., 2014). The link functions not only allows the description of non-linear relationships, such as the influence of depth on discard rates (Fig. 8), but also facilitates the interpretation of these relationships by stakeholders (Figs. 5 and 6).

A recent study by Komoroske and Lewison (2015) has identified six factors currently hindering actions for reducing unwanted catches: lack of data, uncertainty of population level effects of bycatch, poor understanding of the ecological effects of bycatch, uncertainties on how to address bycatch within ecological and social systems, the need to address the linked socio-ecological factors govern bycatch, and the importance of fostering stakeholder engagement in the development of sustainable bycatch reduction strategies and actions. Although these barriers are still present, and addressing them remain challenging, technological tools, such as the one presented in this study, represent important steps forward in tackling these issues. For instance, the capability of this tool to provide iterative updates of posteriors as new data becomes available, friendly interface with stakeholders, flexibility to modify covariates and easier interpretation of uncertainties, can all provide contributions for better assessing the impacts of current and future policies on discards.

Further studies applying this tool in the assessment of discards reduction policies can benefit from a more comprehensive analysis of discard volumes in relation to total catch biomass. Previous studies indicate that the ratio between discards and total catches is a good alternative to discards per unit effort, as used in this study, given that it provides an indication whether or not the amount of discards is disproportionate to the catch (Paradinás et al., 2016). The presented modelling framework could be easily applied in this context, as it can be also used for constructing spatial probabilities of total catches, and then combined with discard probabilities. Such an approach will be particularly useful in preparation for the discard ban rule under new EU regulations, given the increased interest in reducing the proportion of discards in relation to commercial landings. Future assessments should also evaluate how to incorporate parameters related to fishers' behavior, reflecting market demands and legal constraints. In fact, discards in the Greek trawl fishery were found to be driven mostly by an absence of market, corresponding to species of no commercial value, market inconsistencies (i.e. species that were discarded when the catch exceeded local market demand) and legislation (MCRS) (Catchpole et al., 2014). Moreover, further assessments are needed to describe the influence of physical barriers in the probability of discards. For instance, in the case of GSA22, the presences of a large number of islands is likely to affect the duration of trips, and therefore play a role in the spatial patterns of discards probability.

Finally, the next step towards the development of this model will be to optimize model predictions for specific cases. This must

include a full assessment of parameters convergence, as well as the assessment of the accuracy and reliability of predictions. This will require a more extensive interaction with stakeholders, aiming to better select explanatory variables that altogether complies with stakeholders' believe, model technical capability and realistic relationships.

6. Conclusions

This study proposes a new approach for modelling the spatial probability of discards. The method is based on a Bayesian modelling framework, in which the input explanatory variables can be easily chosen by experts, independently of current data availability. Priors describing the influence of each covariate on discard rates are obtained through questionnaires, which are filled by fishermen, fleet observers and local scientists. Hence, the framework account for a close and active participation of stakeholders. Observed discards data is used to fit the model, and iteratively update the posterior probabilities. The spatial distribution of observed data is also used for accounting for spatial random effects, and therefore correct spatial dependence biases. We tested the approach in two case studies in the Mediterranean Sea, and in each site we accounted for two discard categories from bottom trawl fishery. The interaction with stakeholders, through questionnaires, was shown to be a useful tool for better understanding the factors driving discard dynamics. Nonetheless, minor challenges were faced while obtaining priors from stakeholders, indicating that repeated two-ways interactions are needed for harmonizing the modelers' expectation and stakeholders' field knowledge. The model output provided spatial maps of discard probabilities, as well as an ample set of graphics (i.e. link functions) describing the influence of different explanatory variables on discard chances. Hence, the approach was shown to provide a comprehensive tool for testing hypothesis, assessing new policies and management strategies. Combining the model output with fishing effort map obtained using VMS showed good potential of the spatial probability maps in identifying areas with lower discard/total catch ratio. Moreover, the close participation of stakeholders is more likely to lead to an easier integration and stronger legitimacy of the tool at local levels. Further studies should be undertaken to quantitatively assess the accuracy of model predictions for specific target species.

Acknowledgements

This research has received funding from the European Commission's Horizon 2020 Research and Innovation Programme under Grant Agreement No. 634495 for the project Science, Technology, and Society Initiative to minimize Unwanted Catches in European Fisheries (MINOUW).

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.ecolmodel.2017.10.007>.

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