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Bayesian spatio-temporal discard model in a demersal trawl fishery

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ABSTRACT

Spatial management of discards has recently been proposed as a useful tool for the protection of juveniles, by reducing discard rates and can be used as a buffer against management errors and recruitment failure. In this study Bayesian hierarchical spatial models have been used to analyze about 440 trawl fishing operations of two different metiers, sampled between 2009 and 2012, in order to improve our understanding of factors that influence the quantity of discards and to identify their spatio-temporal distribution in the study area. Our analysis showed that the relative importance of each variable was different for each metier, with a few similarities. In particular, the random vessel effect and seasonal variability were identified as main driving variables for both metiers. Predictive maps of the abundance of discards and maps of the posterior mean of the spatial component show several hot spots with high discard concentration for each metier. We argue how the seasonal/spatial effects, and the knowledge about the factors influential to discarding, could potentially be exploited as potential mitigation measures for future fisheries management strategies. However, misidentification of hotspots and uncertain predictions can culminate in inappropriate mitigation practices which can sometimes be irreversible. The proposed Bayesian spatial method overcomes these issues, since it offers a unified approach which allows the incorporation of spatial random-effect terms, spatial correlation of the variables and the uncertainty of the parameters in the modeling process, resulting in a better quantification of the uncertainty and accurate predictions.

1. Introduction

Discarding is currently one of the most important issues in fisheries management, both from economic and environmental points of view (Bellido et al., 2011). Discard occurs for a range of reasons and it is influenced by an even more complex array of factors that remain still poorly understood due to, among other things, incomplete knowledge on the spatio-temporal pattern of discards (Feekings et al., 2012).

There are indications that the practice of discarding has altered the ecosystem functioning at several levels, causing cascading effects throughout the trophic chains (Jenkins et al., 2004; Valeiras, 2003). However, not all of the biological or ecological impacts of discards are considered negative (Zhou, 2008). Hill and Wassenberg (1990) and Votier et al. (2004), for example, discuss that discarding from trawls transfers large quantities of biological material from the bottom to the surface, making otherwise inaccessible food available to surface scavengers such as sea-birds.

All these trends are the manifestation, expressed by the European Union, that there is need to quantify discards to understand their causes and effects in order to manage them effectively. Consequently, data on discards have become more widely available, opening a door for the development of discard management plans (Viana et al., 2013).

The literature on discards has mainly been descriptive, with a focus on understanding discard rates of specific species (Welch et al., 2008), estimating the amount or proportion of total catch discarded from particular fisheries (Rochet et al., 2002), as well as global discard assessments (Alverson, 1994; Kelleher, 2005). These studies fail to acknowledge that discards are dynamic in time and space.

However, some studies that provide spatio-temporal estimations of discard rates are emerging (Catchpole et al., 2011; Feekings et al., 2012, 2013; Madsen et al., 2013; Viana et al., 2013) and spatial management of discards has recently been proposed as a very useful tool for discard reduction strategies, jointly with the technical measures (Dunn et al., 2011; Viana et al., 2013).

The use of spatial modeling approaches to discard data provides the chance to estimate which factors could influence in the discard process. In addition, it offers important insights to predict future catches and discards both in quantity and location.

The main goal of this study is to address the discard issue by examining the data collected in the GSA06 (Geographical Sub-Areas) South

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area, identifying the factors that influence discards within the Spanish trawling fleet and their spatio-temporal distributions.

On-board sampling of the fishery is directly related to fishing strategy. Therefore, the data collected are useful for analyzing discard trends (Essington, 2010). Two different metiers were analyzed, the bottom otter trawl demersal species metier (OTB-DES) and the bottom otter trawl deep-water species metier (OTB-DWS). Firstly, we have analyzed the discards of both metiers in order to understand their quantity and species composition. Secondly, we have focused our analysis on factors influencing discards to identify their spatio-temporal patterns in the study area.

In the last decade, various methodologies were developed to independently investigate spatio-temporal effects, e.g. GAMs, kriging for spatial patterns, and various time-series analyses such as autoregressive components that deal with time effects (Brockwell and Davis, 2002; Viana et al., 2013). Models which integrate space and time are sparse and only began to emerge recently in ecology (Banerjee et al., 2004). In addition, two important issues that have to be addressed are the estimation of the uncertainties in the parameters of interest, and the computational time required to fit such models, especially for large data sets.

In this study we overcome these problems implementing Bayesian hierarchical spatio-temporal models using the integrated nested Laplace approximation (INLA) methodology and software (http://www.r-inla.org).

Indeed, Bayesian models are appropriate to spatial hierarchical analysis as they allow both the observed data and model parameters to be considered as random variables, resulting in a more realistic and accurate estimation of uncertainty (Banerjee et al., 2004). This is essential in a study like this, where the main goal is to identify discard hot spots and to verify their persistence over the time, with the least possible error. Bayesian spatial models may also aid data analyses with geographically uneven levels of survey effort, as such bias can be incorporated within the spatial random-effect term, which reduces its influence on estimates of the effects of environmental variables (Gelfand et al., 2006). Particularly, by treating spatial effect as a variable of interest, hierarchical Bayesian spatial models are able to improve model fit and to identify the existence of area effects that may affect discard abundance.

In addition, the great bonus of our application is the possibility to use INLA, which provides accurate approximations to posterior distributions of the parameters, even in complex models, in a fast computational way (Rue et al., 2009).

Finally, few models, like these, offer, in addition to an estimation of the processes that drive the distribution of discards, a predictive spatial abundance of discards in unsampled areas. Using Bayesian kriging we have generated predictive maps, obtaining a posterior predictive distribution of the discard abundance for each location of the study area. This means that for each posterior distribution, unlike the mean and confidence interval produced by classical analyses, we are able to make explicit probability statements about the estimation, implying a more accurate estimation of the uncertainty.

It is finally worth noting that a detailed knowledge of the spatio-temporal discard patterns could allow further development of spatial fishery management. Predictive maps could provide an essential tool for identifying areas where discard is high and facilitate the move to discard free fisheries as part of the proposed reforms of the Common Fisheries Policy (CFP).

2. Materials and methods

2.1. Discard data

Under the European Union Data Collection Framework (EC Regulation 199/2008), EU members are obliged to collect biological data including discards. Sampling of discards by the *Instituto Español de Oceanografía* (IEO, Spanish Oceanographic Institute) is based on a metier approach, that is a formal segmentation of a fishery by vessel type characterized by the same fishing gear, fishing area and target species assemblage.

Discards are sampled at a haul level, by randomly collecting one box of discarded catch from as many hauls as possible during each trip. For each observed haul, an estimate of the total weight discarded is made by the fishermen and the on-board observer, by subtracting the landings from the total catch, both directly weighing. The discarded weight of the fish species in the sample is then multiplied by the total discarded weight of the haul recorded to obtain the total weight of fish discarded per haul (Damalas and Vassilopoulou, 2013).

The discard sample is sorted by the observer into species. Total weights and numbers of each discarded species in the subsample are determined and based on the total approximated discarded weight.

On-board sampling is not mandatory for skippers and they may decline participation in the discard sampling program, resulting in a quasi-random sampling of the fishery. Nevertheless, in order to obtain a representative sample of the studied fisheries, a random rotation of all the vessels available to be sampled is made during the entire period of activity of a given fishery.

The reference fleet for this study was the trawl fleet which operates in the GSA06 South area (Fig. 1). This trawl fleet has been divided into two different types of metiers, the bottom otter trawl demersal species metier (OTB-DES) and the bottom otter trawl deep-water species metier (OTB-DWS).

The OTB-DES includes trawlers that usually operate in waters from the continental shelf (from 50 to 200 m depth) with European hake (*Merluccius merluccius*) and the Octopus (*Octopus vulgaris*) as target species. They make short hauls of about 2–4 h, comprising about 2–3 fishing hauls per trip.

The OTB-DWS involves trawlers that usually operate on deep-waters (from 400 to 1000) with red shrimp (*Aristeus antennatus*) as target species. They generally make a unique haul per trip in about 5–6 h. The monthly sampling frequency usually consists in about 2–3 trips for the OTB-DES metier, and about 1 trip for the OTB-DWS metier.

In this study, 343 OTB-DES hauls and 97 OTB-DWS hauls, sampled from 2009 to 2012, were analyzed. Log-transformed discards per unit effort (DPUE) were used to downweight extreme values, to improve normality and ensure a better fit of the models. For each metier, DPUE was calculated as discard weight per haul duration (kg/h).

2.2. Modeling discard abundance

Hierarchical Bayesian spatio-temporal models were used to account for discard dependency with respect to explanatory variables, as well as to describe the main spatial distribution changes over time (Muñoz et al., 2013).

The expected values of DPUE in each haul (μ_{DPUE}) were related to the spatial, temporal, technical and environmental covariates, according to the general formulation,

$$\mu_{DPUE_{ijk}} = X_{ij}\beta + Y_j + Z_k + W_i, \tag{2.1}$$

where β represents the vector of the regression coefficients, X_{ij} is the vector of explanatory covariates at year j and location i, Y_j is the component of the temporal unstructured random effect at the year tj, Z_k is the random effect of the vessel, and W_i represents the spatially structured random effect at location i.

In our case, from the on-board observer data set we have extracted the spatial location, year, quarter, moon phase, day light and the CPUE of the observed hauls. All these variables have been introduced in the analyses in order to capture the variation on DPUE due to particular fishing characteristics such as, among others, the fishing ground selection. In particular, the moon phase has been added in order to reflect the sea tides. As aforementioned with DPUE, we have used a log-transformation of the CPUE variable, computed from the total catch per haul duration (kg/h). With respect to the quarter variable (which