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REPORT OF THE WORKSHOP ON MODELLING CATCH-PER-UNIT-EFFORT (WKCPUE)

Rui Coelho, Ana Cláudia Fernandes, Hugo Mendes, Teresa Moura, Bárbara Serra-Pereira, Andreia V. Silva, Cristina Silva, Manuela Azevedo

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REPORT OF THE WORKSHOP ON MODELLING CATCH-PER-UNIT-EFFORT (WKCPUE)

Rui Coelho[1], Ana Cláudia Fernandes[2], Hugo Mendes[2], Teresa Moura[2], Bárbara Serra-Pereira[2], Andreia V. Silva[2], Cristina Silva[2], Manuela Azevedo[2]

[1] Instituto Português do Mar e da Atmosfera (DivRP), Av. 5 de Outubro s/n, 8700-305 Olhão.

[2] Instituto Português do Mar e da Atmosfera (DivRP), Rua Alfredo Magalhães Ramalho 6, 1495-165 Algés.

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RESUMO

A Captura por Unidade de Esforço (CPUE) estandardizada de pescarias comerciais, ou seja, dados de capturas comerciais modelados estatisticamente para remoção dos efeitos dependentes da pesca, são por vezes utilizados como indicadores indiretos de abundância e de biomassa na avaliação de stocks. Neste trabalho, reportamos os resultados de um workshop de modelação de CPUEs que teve lugar virtualmente nos dias 3-5 Novembro 2020 e 6-7 Janeiro 2021, organizado pelo IPMA e integrado no âmbito do PNAB/DCF (Programa Nacional de Amostragem Biológica). Apresentamos um sumário dos métodos usados, focando sobretudo Modelos Lineares Generalizados (GLM) usando distribuição Tweedie para tratamento de capturas zero. Providenciamos exemplos de casos-estudo desenvolvidos e discutidos no workshop, nomeadamente lagostim (*Nephrops norvegicus*) capturado pela frota de arrasto de crustáceos, tamboril-sovaco-preto (*Lophius budegassa*) capturado pela frota polivalente, rejeições de cavala (*Scomber colias*) e pescada (*Merluccius merluccius*) capturados pela frota Portuguesa de arrasto. As discussões relativas à exploração dos dados e ajuste dos modelos resultou em algumas recomendações para trabalho futuro, sumarizadas no final deste relatório.

Palavras-chave: Captura-Por-Unidade-Esforço (CPUE), indicadores de abundância e biomassa, padronização de captura-por-unidade-esforço, dados dependentes da pesca, avaliação de stocks.

ABSTRACT

Title: Report of the workshop on modelling Catch-Per-Unit-Effort (WKCPUE). Standardized Catch-Per-Unit-Effort (CPUE), i.e., data from commercial fisheries that have been statistically modelled to remove fishery dependant effect, are often used in stock assessments as indicators of abundance and biomass. Here we report the outcomes of the workshop on modeling CPUEs that took place virtually on the 3-5 November 2020 and 6-7 January 2021 organized by IPMA and integrated in PNAB/DCF (National Program of Biological Sampling). We provide a summary of the methods used, focusing particularly on Generalized Linear Models (GLM) with Tweedie distributions for treatment of zero captures. We provide examples of case-studies developed and discussed, namely Norway lobster (*Nephrops norvegicus*) caught by crustacean trawlers, black-bellied anglerfish (*Lophius budegassa*) caught by the polyvalent fleet, chub mackerel (*Scomber colias*) discards and hake (*Merluccius merluccius*) caught by the Portuguese trawl fleet. The discussions on the exploration of input data and model fitting resulted in some recommendation for future work, summarized at the end of the report.

Keywords: Catch-Per-Unit-Effort (CPUE), indicators of abundance and biomass, standardization of catch-per-unit-effort, fishery-dependent data, stock assessment.

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1 INTRODUCTION

1.1 Terms of reference

The Workshop on Modelling Catch-per-Unit-Effort (WKCPUE), chaired by Rui Coelho met virtually on the 3-5 November 2020 and the 6-7 January 2021, to explore and discuss the application of methods for estimating trends in relative abundance and biomass based on standardized Catch-Per-Unit-Effort (CPUE) and for estimating Discard-Per-Unit-Effort (DPUE) to derive total discards, with focus on fishing effort data sets with a high mass of zero catches of a selected number of case-studies.

The workshop was organized within the scope of the National Programme for Biological Sampling (PNAB/DCF) co-financed by National funds and the European Maritime and Fisheries Fund (EMFF).

1.2 Background

CPUE is used in many stock assessments assuming that CPUE is proportional to stock abundance and biomass. Several methods are regularly applied to reduce the influence of factors affecting the estimate of CPUE, such as generalized linear models (GLM), generalized linear mixed models (GLMM), generalized additive models (GAM), regression trees (RTs) and machine learning techniques (e.g., Maunder and Punt, 2004; Hoyle et al., 2014; Forrestal et al., 2019; Yang et al., 2020). Among these, the application of GLM is the approach mostly followed to estimate standardized abundance indices. However, when dealing with bycatch species or with species not frequently discarded, it is common to have data sets with high mass of zero catches despite non-zero effort records. In this case, GLM model fitting based on log-transformed data (adding a constant to the response variable) or by collapsing strata to eliminate the zero catch observations may not be appropriate. In fact, the log-transformation procedure may induce bias in the estimate of the year effect while the strata combination procedure may mask information contained in levels of explanatory variables not related to the collapsed strata which may be important to explain the annual relative levels of abundance (year effect).

To overcome these issues in the estimation of the fishery-dependent abundance or biomass indices, the delta, zero-inflated and hurdle models have been used (e.g., Lo et al., 1992, Campbell, 2004, Coelho et al., 2011). The delta approach is a two step-method which combines the modelling of the zero catches with the modelling of the positive catches. Zero-inflated models are typically used if the data contains an excess of structural and sampling zeros, whereas hurdle models are generally used when there is only an excess of sampling zeros. Another way of dealing with a high mass of zero catches is to use a statistical distribution that allows for zero observations, such as the Tweedie family of distributions (Dunn and Smyth, 2008). Therefore, the Tweedie method (e.g., Shono, 2008; Coelho et al., 2020), having the advantage of handling the zero catch data in a unified way, was selected for the exploration of CPUE and DPUE standardization of the species showing high mass of zero catches, used as case-studies during the workshop.

1.3 Conduct of the workshop

The four case-studies selected for the workshop were:

- **CS1**: Norway lobster (*Nephrops norvegicus*) caught by the Portuguese crustacean trawl fishery (Cristina Silva and Bárbara Serra-Pereira);
- **CS2**: Black anglerfish (*Lophius budegassa*) caught by the Portuguese polyvalent fleet (Teresa Moura);
- **CS3**: Chub mackerel (*Scomber colias*) discards by the Portuguese the trawl fishery (Ana Cláudia Fernandes and Manuela Azevedo);
- **CS4**: Hake (*Merluccius merluccius*) caught by the Portuguese trawl fishery (Hugo Mendes and Andreia Silva).

Previous to the workshop the chair made available to participants a data set with swordfish (*Xiphias gladius*) and blue marlin (*Makaira nigricans*) data, simulating a longline fishery and an R code for data exploration and model fitting. The swordfish data set included few zero catch, simulating data from a target fishery while the blue marlin data set had many zero observations, simulating an occasional bycatch species. The workshop had two meetings. The November meeting started with the introduction to CPUE standardization and a training session using the swordfish and blue marlin simulated data sets, with model fitting, analysis of fitting diagnostics and discussion of results. The training session was followed by the presentation of the data available for each case-study, the discussion of the criteria for data selection, including likely reasons for the zero observations, and the preliminary analysis for CPUE (CS1, CS2) and DPUE (CS3) standardization. Discussions focused on further exploration of the data sets and model fitting and a plan was settled for the work to be carried out for the second workshop meeting, in January 2021, when the CS4 was also addressed.

It is noted that while the workshop introduction and example provided was mainly focused on one particular type of analysis (Tweedie distribution, that can model CPUE data that includes discrete zeros as well as continuous non-zeros), the Case Studies were developed by the respective modellers considering the specificities of each particular case.

1.4 Structure of the report

The structure of the report is as follows:

- Section 2 describes the background material and the training session.
- Section 3 describes the work developed and discussed during the workshop for CS1.
- Section 4 describes the work developed and discussed during the workshop for CS2.
- Section 5 describes the work developed and discussed during the workshop for CS3.
- Section 6 documents the method currently used to estimate the standardized CPUE for hake in the Portuguese trawl fishery and for providing estimates of the year effect (CS4).
- Section 7 summarises the workshop conclusions and recommendations for future work.
- Annex 1 provides a description of the Tweedie distribution and its characteristics.
- Annex 2 provides additional analysis for CS3
- Annex 3 provides the list of participants

Note that the references cited are provided at the end of each section.

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2 WORKSHOP PRESENTATIONS AND EXAMPLES

2.1 Introduction

In this section we report the first part of the workshop where two theoretical presentations and one practical example were provided. Specifically, on section 2.2 we describe the theoretical background and workshop presentations, and then on section 2.3, a practical example is provided with R code using simulated datasets. This last component of the practical exercises was based on datasets that were built and used by Forrestal *et al*. (2019) in a CPUE simulation study.

2.2 Presentations on CPUE standardization

2.2.1 Why do we need indices of abundance?

Stock assessment models reconstruct population history and keep track of abundance over time. Those models describe the fish population dynamics and their interaction with the fisheries and need guidance to tell if abundance (biomass) is increasing or decreasing or stable at any point in time. As such, indices of abundance are needed and commonly used for stock assessment models. Ideally, fishery independent indices are used, but that is not always possible. In some cases, there is the need to explore and apply fisheries-dependent indices to assessment models.

2.2.2 The CPUE as an index of abundance

The most used index of abundance in species exploited by commercial fisheries is the catch-per-unit-effort (CPUE). Examples of CPUEs used in tuna and tuna-like fisheries are numbers or biomass of fish per 1000 hooks (e.g., longline fisheries), metric tons per day (e.g., pole and line fisheries) or per trip (e.g., oceanic gillnet fisheries).

Assuming that the biomass of fish caught per unit of fishing effort is proportional to the abundance of the fish, we have:

$$\frac{C}{E} = q * B$$

where C is catch, E is effort, q is catchability and B is biomass

The catch rate directly estimated from the fishery data (nominal CPUE) can be an index of abundance only if q is constant over time. However, q usually changes over time due to many variables, as for example: 1) changes in fishing methods and techniques;

2) changes in biological and environmental factors and, 3) changes in the fishing effort with different catchability characteristics.

A simple example is when the depth of the gear operation changes at some point in time and the fishery explores depths where the resource is more abundant, meaning that the catch rates change but the biomass has not changed. In such cases, the raw (nominal) CPUE is not an appropriate index of abundance.

As such, we need to make sure that any changes in catchability are estimated and accounted for, implying the removal of the impact on catch rates of factors other than abundance. This process is usually referred to as "CPUE standardization".

2.2.3 CPUE standardization models

The most common method used for CPUE standardization is the Generalized Linear Model (GLM) (McCullagh and Nelder, 1989; Agresti, 2002). However, other models have also been applied, as, for example, Generalized Additive Models (GAMs) and Generalized Linear Mixed Models (GLMMs).

The general approach to fitting the standardization models involves: 1) choosing the response variable, 2) choosing the error distribution and the link function, 3) selecting a set of appropriate explanatory variables, 4) extract the standardized time series, 5) producing and analyzing diagnostics to answer if the model is adequate and for selecting between alternative models.

Within the sets of possible explanatory variables, the main effects usually explored and considered are 1) Year (primary time unit of interest), 2) Area and 3) Season. Other variables of interest that are commonly explored are 1) Gear characteristics (e.g., depth, bait, hook-type), 2) Vessel characteristics (e.g., size, technology, skipper experience) and 3) Environmental characteristics. Additional issues that need to be considered are if those explanatory variables are continuous *vs.* categorical, and the possible use of interaction terms in the model.

2.2.4 What to do with the 0 catches

Having datasets with zero (0) catches in some of the fishing sets is very common in fisheries data (Coelho, 2013). There are various reasons for the occurrence of such zeros, such as, 1) species not being targeted, 2) species having a patchy distribution, and 3) logbooks omissions. This means that the first step is to explore and analyze the data in order to understand the origin and quantity of zeros(Zuur et al., 2012).

Depending on the structure and quantity of zeros in the dataset, , the options are then to: 1) remove the zeros, 2) replace with a small constant, 3) use distributions that can account for zeros (e.g., Tweedie), 4) use a two-step process to model the zero and positive catches separately (e.g., delta or hurdle models) or 5) use zero-inflated models (for more extreme cases). This workshop concentrated on option 3, where we use the Tweedie distribution that can take into account the discrete and continuous features of such data, namely the discrete point of zeros as well as the continuous values for the non-zeros positive component of the data (see Annex 1).

2.2.5 Selection of explanatory variables

There are several options for the selection of explanatory variables within the models. The approach used in the workshop followed a stepwise approach, as recommended by Hosmer and Lemeshow (2000). In this approach, the univariate significance of each explanatory variable is determined by the Wald statistic and by the likelihood ratio tests, comparing each univariate model with the null model. The significant variables are then used to construct a simple effect multivariate GLM, with the non-significant variables (at the 5% level) eliminated consecutively from the model. At this stage, the variables that had been eliminated in the first step are further tested, in order to determine an eventual significance within the framework of a multivariate model. Once a final multivariate simple effects model is obtained, each pair of possible 1^{st} degree interactions is tested, and are considered for inclusion in the final model if significant at the 1% level.

In terms of the GLM assumptions regarding the explanatory variables, the assumption of linearity (in the continuous variables) with the linear predictor is assessed by creating and analyzing GAM plots. If evidence of non-linearity is present, then multivariate fractional polynomial transformations are carried out, and the transformed explanatory variables are used in the final models (as described by Royston and Altman, 1994).

2.2.6 Model validation

Models should be assessed by analyzing the residuals to determine visually if major problems are taking place, such as overdispersion problems, the presence of outliers or influential observations. In general, the deviance residuals should be used (Zuur et al., 2009). However, in the case of the Tweedie models the quantile residuals are used, as recommended by Dunn and Smyth (1996).

For each model, the values of the AIC - Akaike Information Criterion (Akaike, 1974), and the pseudo R^2 - Nagelkerke coefficient of determination (Nagelkerke, 1991) are also calculated. Those are especially useful for model comparison in terms of goodness-of-fit and to choose between alternative models.

2.3 Example of CPUE standardisation using a simulated dataset

2.3.1 Descriptive analysis

The data used in the workshop exercise was a simulated blue marlin (*Makaira nigricans*) CPUE obtained from a simulated fishery, to which a simulated swordfish (*Xiphias gladius*) was added. The idea was to include one main target species with very little occurrence of zeros (swordfish) and one bycatch species with a high occurrence of zeros (blue marlin). The data from the blue marlin component was built and used by Forrestal *et al.* (2019) in a simulation blind study on CPUE standardization. All analyses were performed in R version 3.6.1. (R Core Team, 2019).

The simulated dataset contained information usually obtained from commercial logbooks, in this case from oceanic pelagic longline fisheries, to which some environmental variables were added (Table 2.1).

Table 2.1. Example of the simulated dataset used. Each row represents one longline fishing set, where lat=latitude, long=longitude, SST = sea surface temperature, surface_DO = Dissolved oxygen at the surface, hbf = hooks between floats used as a proxy for depth/targeting, SWO = catch of swordfish in number, BUM = catch of blue marlin in number.

lat	lon	year	month	SST	surface_DO	light	fleet	hooks	BUM	bait	hbf	area	SWO
1.5	-28.5	2000	1	27.94	4.53	4	1	750	0	2	3	5	8
3.5	-28.5	2000	1	27.71	4.61	2	1	1036	0	5	4	5	4
18.5	-49.5	2000	1	25.36	4.68	4	1	824	1	2	4	5	2
19.5	-50.5	2000	1	25.18	4.69	4	1	801	2	2	3	5	7
19.5	-46.5	2000	1	25	4.75	4	1	900	1	2	3	5	5
21.5	-68.5	2000	1	24.94	4.74	3	1	400	0	2	4	5	2
21.5	-67.5	2000	1	24.97	4.78	3	1	484	1	2	4	5	4
21.5	-67.5	2000	1	24.97	4.78	3	1	484	0	2	4	5	3
21.5	-66.5	2000	1	25.02	4.85	3	1	472	0	2	4	5	4
25.5	-88.5	2000	1	23.68	4.76	2	1	600	1	2	4	1	4
25.5	-75.5	2000	1	23.31	4.9	3	1	360	0	5	3	4	3
26.5	-87.5	2000	1	23.3	5.01	3	1	800	0	2	4	1	4
26.5	-86.5	2000	1	23.18	5.09	3	1	800	0	2	4	1	6

After loading the dataset, the first step was to analyze and describe the data. There are multiple ways to achieve that, and during the workshop some ideas and options were discussed and provided. One possibility to start is to check if there are sufficient datapoints for all the combinations of the various variables that could be incorporated in the models by using mosaic plots, with one example provided in Figure 2.1.

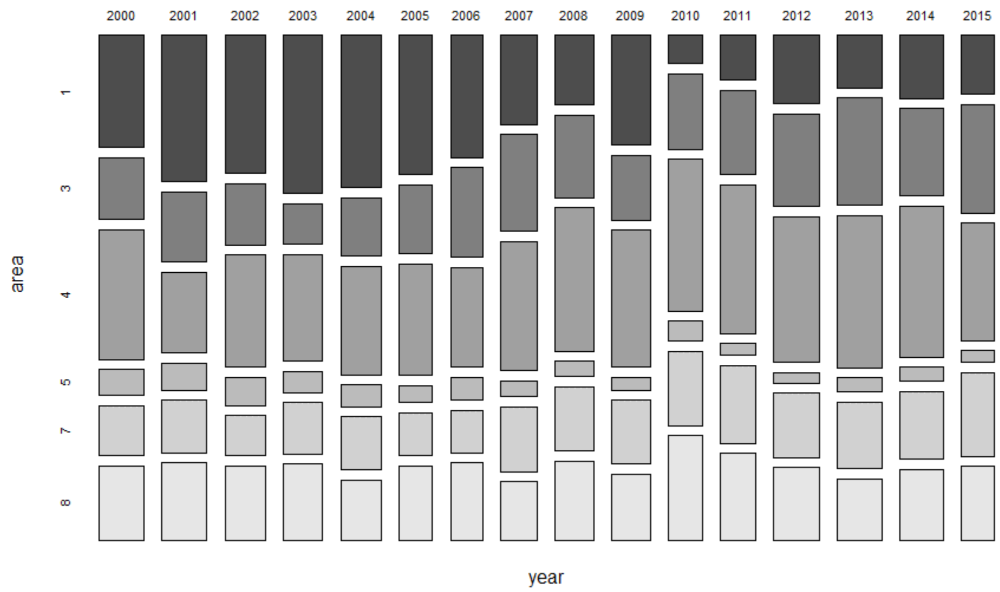

Figure 2.1. Mosaic plot for describing the quantity of datapoints in the dataset, in this case for each combination of area along the various years.

Using maps to evaluate the geographical distribution and extent of the data is also very useful. In the exercise, we provided examples on how to build effort distribution maps (Figure 2.2) and mean CPUE distribution maps (Figures 2.3 and 2.4).

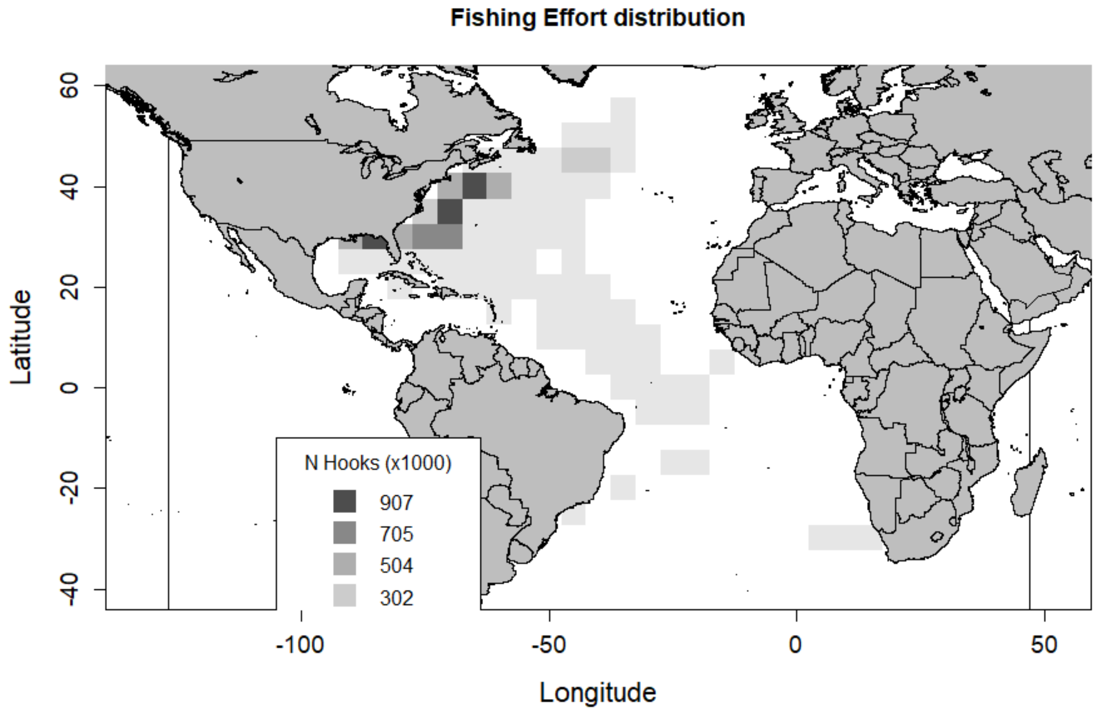

Figure 2.2. Effort distribution map of the simulated pelagic longline dataset.

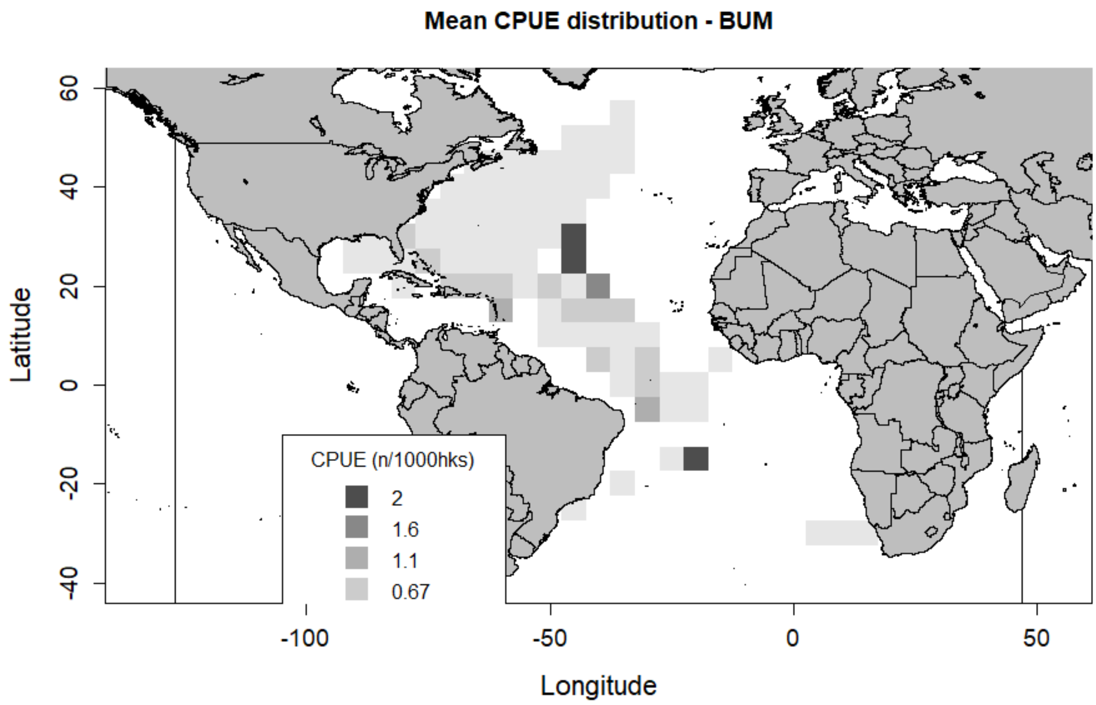

Figure 2.3. Mean CPUE distribution map of the simulated pelagic longline data, in this case specifically for the bycatch species (BUM = blue marlin).

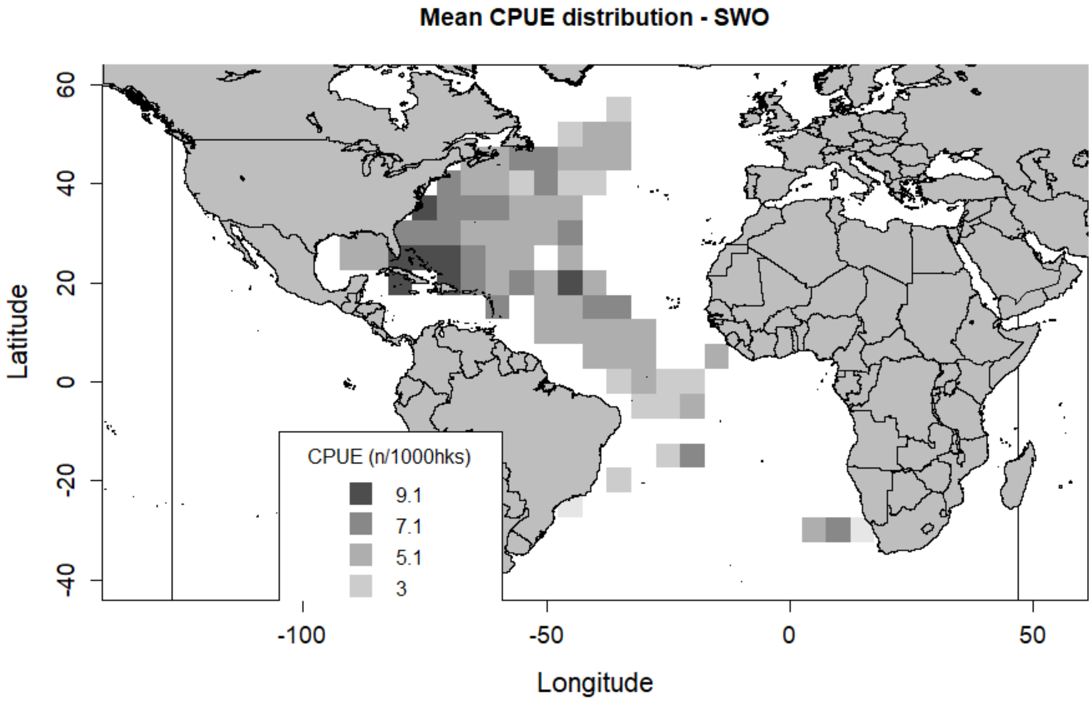

Figure 2.4. Mean CPUE distribution map of the simulated pelagic longline data, in this case specifically for the main target species (SWO = swordfish).

It is then important to explore the shape of the distribution of the response variable that will be modeled, in this case the CPUEs of the target and bycatch species. Figures 2.5 and 2.6 provide the examples specifically for the blue marlin and swordfish datasets. As expected from a bycatch species, the blue marlin data has a very high concentration of zeros, which is not the case of the swordfish as the main target species.

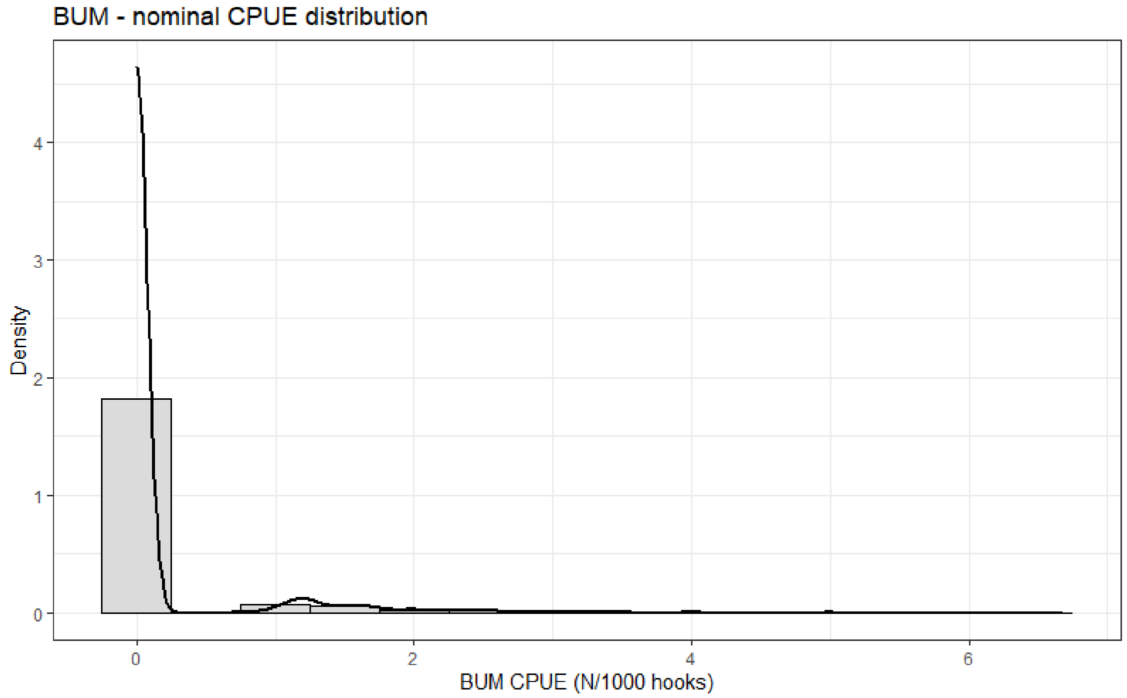

Figure 2.5. Shape of the distribution of the CPUE data for the blue marlin (BUM).

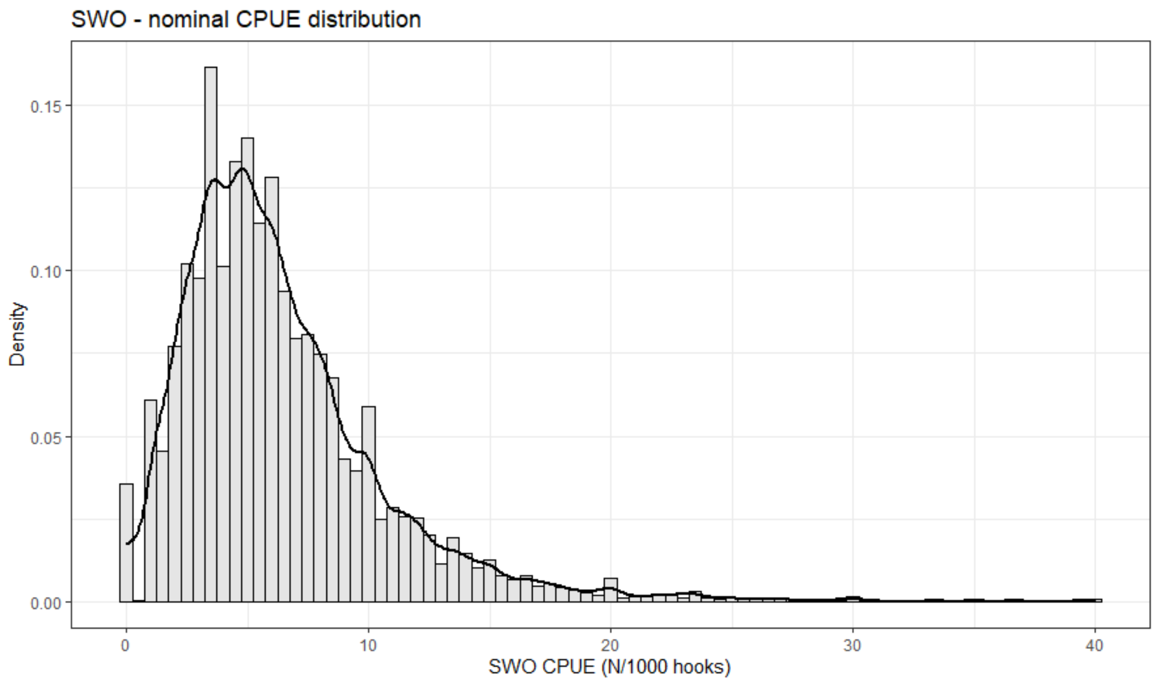

Figure 2.6. Shape of the distribution of the CPUE data for swordfish (SWO).

We can then look into the time series and trends of the nominal (i.e., fishery dependent) CPUEs, which are represented in Figures 2.7 and 2.8.

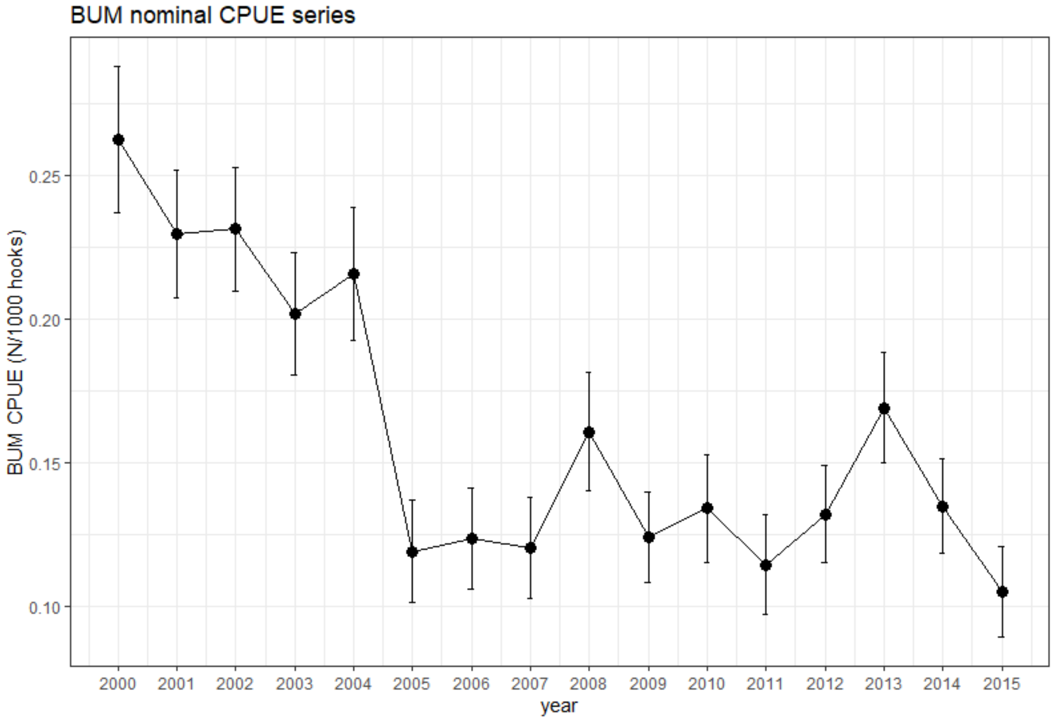

Figure 2.7. Time series of the nominal CPUE data from the blue marlin (BUM). The dots represent the mean nominal yearly CPUE and the error bars represent the standard error.

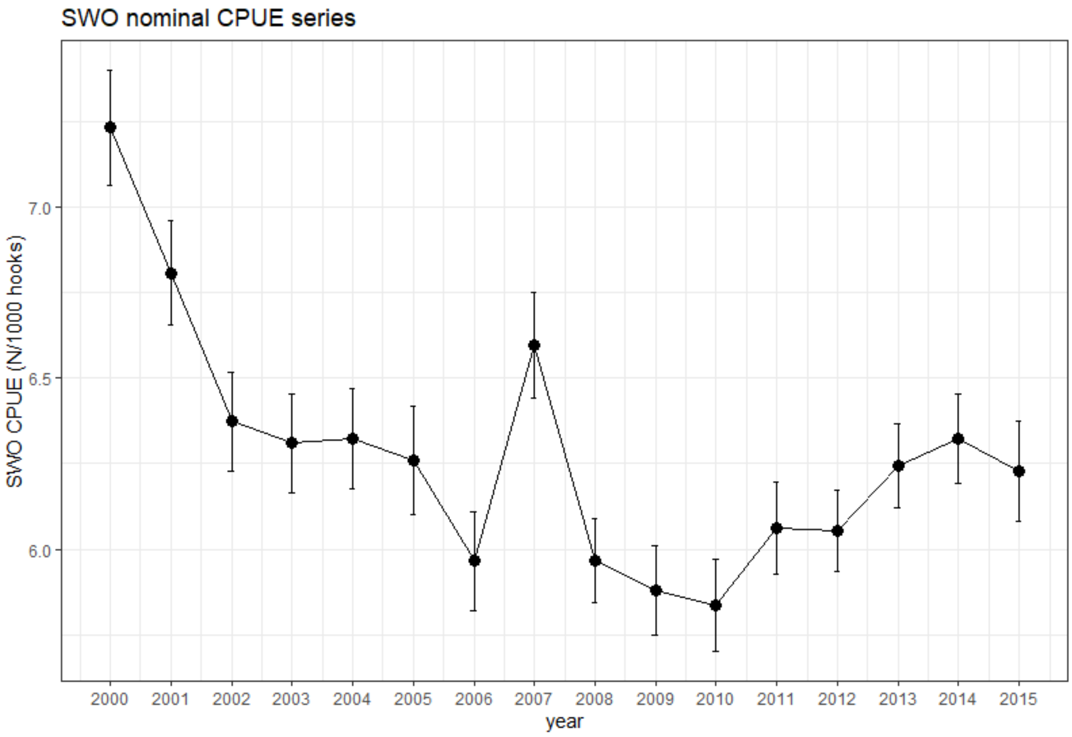

Figure 2.8. Time series of the nominal CPUE data from the swordfish (SWO). The dots represent the mean nominal yearly CPUE and the error bars represent the standard error.

2.3.2 CPUE standardization model

The case of blue marlin, a bycatch species with a high percentage of zeros (90.7% of the fishing sets) was the example provided for CPUE standardization modelling.

The first step was to estimate the p-index of the Tweedie distribution that best fits the data (Figure 2.9). The p-index in this case was estimated at 1.155 and produced the distribution that is indicated in Figure 2.10. This distribution could account for 90.6% of zeros, which is a very good approximation of the actual zeros in the dataset (i.e., 90.7%).

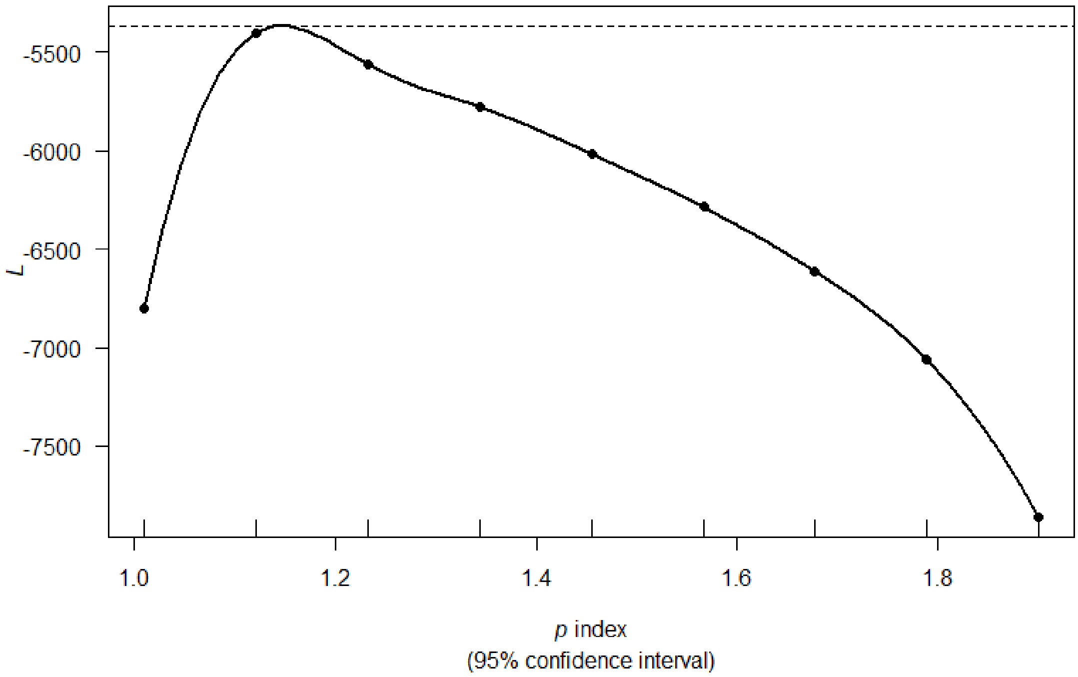

Figure 2.9. Maximum likelihood estimation of the p-index value of the Tweedie distribution for the blue marlin CPUE data.

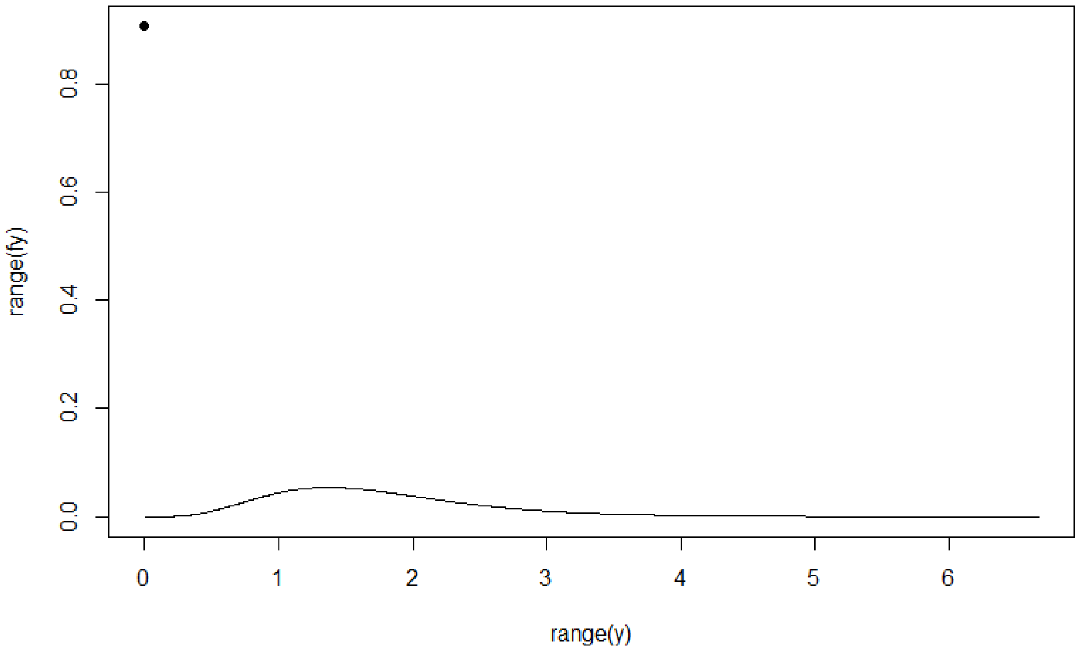

Figure 2.10. Tweedie distribution defined to model the blue marlin CPUE data. The point represents the mass of zeros (90.6%) and the line represents the continuous distribution for the non-zeros.

The possible explanatory variables to model the blue marlin CPUE were tested in simple univariate models and then the following simple effects model using only categorical variables was created:

$$BUM\ cpue \sim year + month + light + bait + hbf + area$$

Note that *hbf* stands for “hooks-between-floats” and is used as a proxy for targeting based on the fishing gear depth.

This preliminary first model had an AIC of 16517.7 and a pseudo R^2 of 13.3%. The residuals are shown in Figure 2.11.

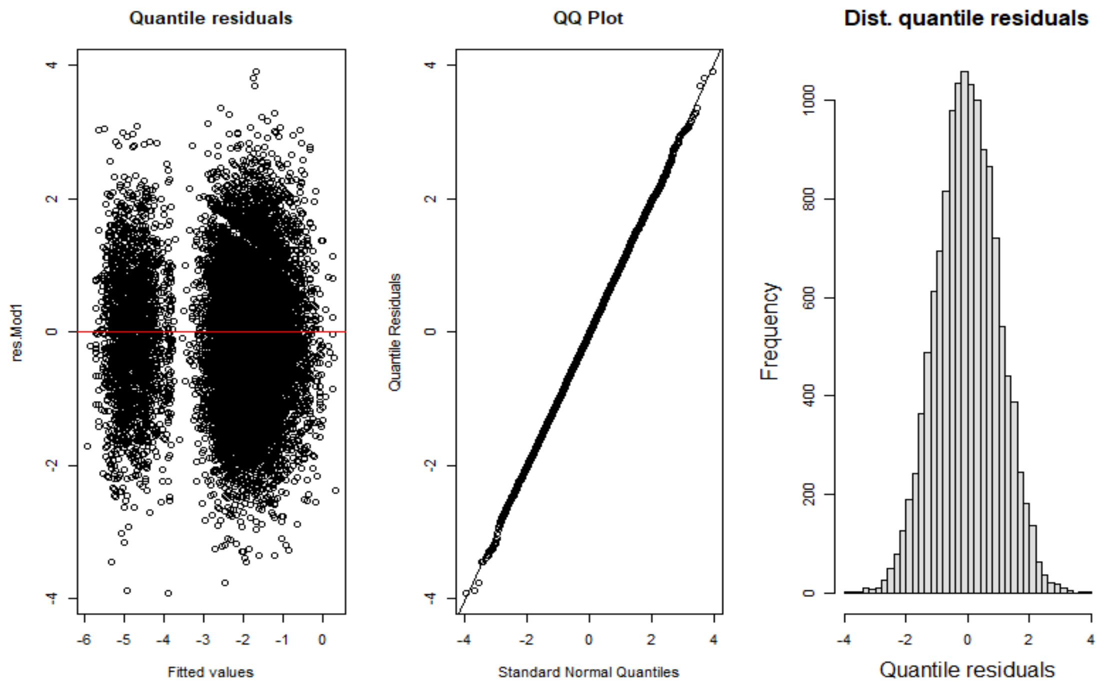

Figure 2.11. Residuals of the first simple effects model using only categorical variables for the blue marlin CPUE.

The next step was to explore the incorporation of some continuous variables, in this case two environmental variables, namely Sea surface temperature (SST) and dissolved oxygen at the surface. Their shape is described in Figure 2.12, where especially for the dissolved oxygen there is a clear non-linear trend.

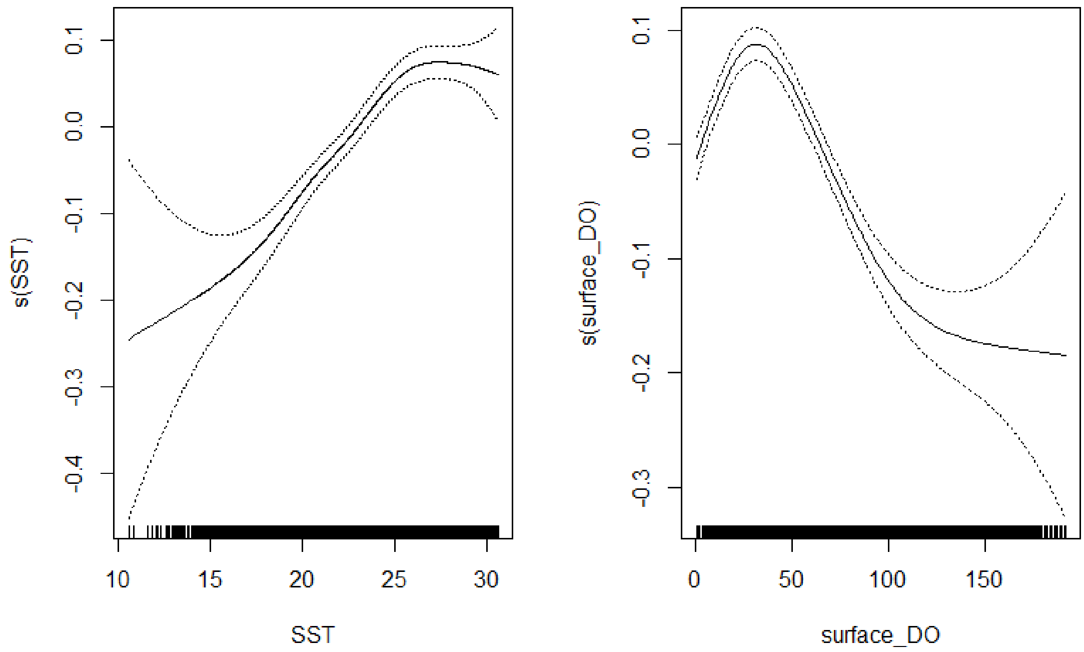

Figure 2.12. Shape of the continuous explanatory variables considered for incorporation in the blue marlin model, in this case sea surface temperature (SST) and dissolved oxygen at the surface (surface_DO)

We then used multivariate fractional polynomials to transform the variables. For the SST only a scale transformation was performed, while for the dissolved oxygen polynomials transformations were used:

SST: I((SST/10)^1)

surface_DO: log((surface_DO/100))+I((surface_DO/100)^0.5)

With those transformed variables a new model was created, which is represented below:

BUMcpue ~ year + month + light + bait + hbf + area+ I((SST/10)^1) + log((surface_DO/100)) + I((surface_DO/100)^0.5

This updated model had an AIC = 13413.9 and a pseudo R^2 = 15.9%. In this particular case, the AIC is not comparable with the previous model using only categorical variables, as this model had less data (due to lack of environmental variables in some years of the dataset). However, the residuals of this updated model, plotted in Figure 2.13, show an improvement compared to the previous model residuals.

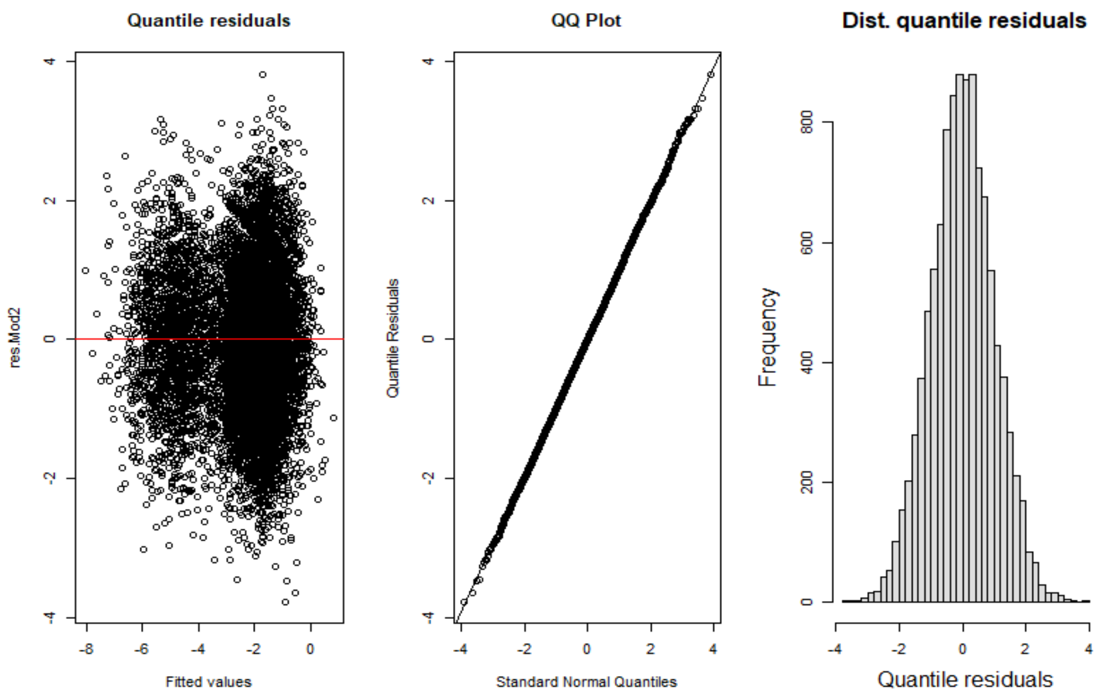

Figure 2.13: Residuals of the updated model using categorical and continuous (environmental) variables transformed with fractional polynomials, for the blue marlin CPUE.

Finally, the marginal means of the year effect were calculated, in order to provide the standardized CPUE series. A potential difficulty in extracting the year effect is that each explanatory variable will have multiple levels (for categorical variables) and values (for continuous variables) during each year (Maunder and Punt, 2004). In this case, the year effects are calculated as the predicted values averaged across all levels of all other variables. Those standardized CPUEs, both from the simpler model using only categorical variables and from the final model using categorical and continuous variables, are represented in Figure 2.14.

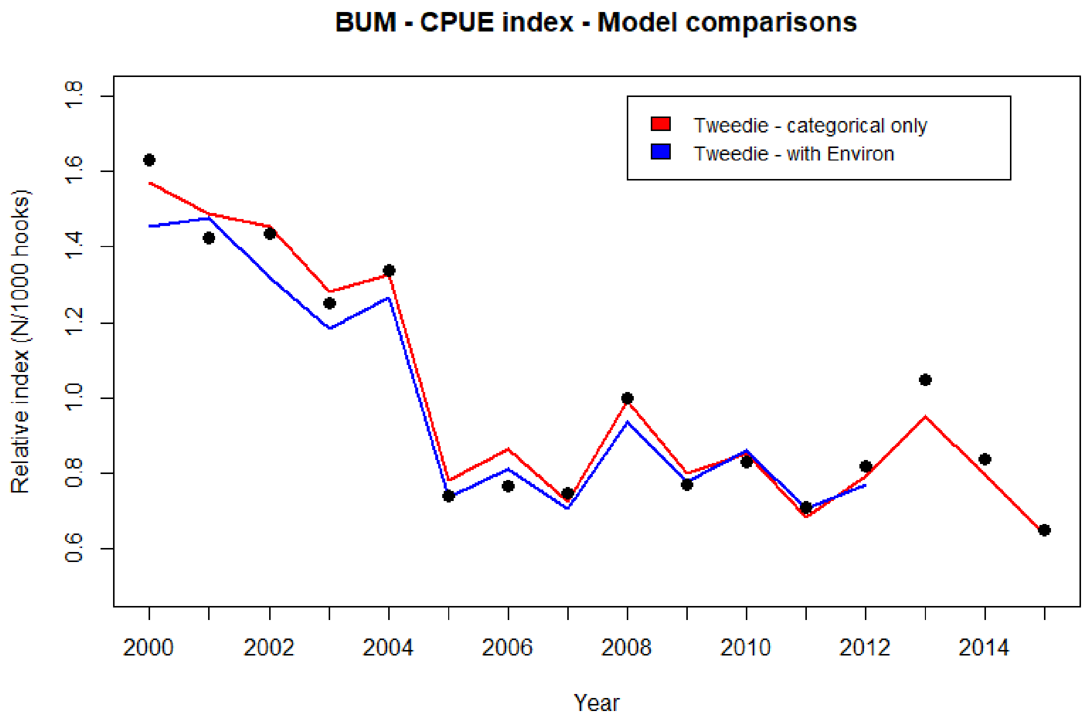

Figure 2.14. Nominal CPUE (black dots) and standardized CPUEs (lines) for the blue marlin CPUE dataset.

2.4 Additional introductory notes

Some additional notes with regards to recommendations for future work are presented later in Section 7 of this report. Here, we provide some additional introductory notes that are common to the methods used and important to introduce here.

In terms of estimation of the year effect, the assumption made is that after removing all fishery-dependent variables (all explanatory variables used in the models), the remaining year effect will be proportional to species abundance, and therefore can be used as a proxy of species abundance in stock assessment models. Recent simulation work has been conducted, showing that it is possible to reconstruct the true underlying annual abundance trends with these methods (Forrestal et al., 2019).

One important initial consideration for the analysis is the choice of distribution for the models, that should take into account the type and shape of the distribution of the data being modeled. For that reason, an initial descriptive analysis as introduced here is very important. A discrete distribution, such as the Poisson or Negative Binomial, can be appropriate if the catch is recorded and modelled in number of individuals (discrete distribution), while a continuous distribution such as the Gamma is more appropriate if the data modeled is continuous, such as CPUE data (Maunder and Punt, 2004).

This point is linked on how the effort is introduced in the models. Usually, the approach chosen is to use the effort included in the response variable, in the form of CPUE data, in which case using a continuous distribution can be appropriate. However, another possibility is to use the effort as an offset variable, in which case the response variable should be the catch in numbers or biomass (Maunder and Punt, 2004). As we have seen, the Tweedie distribution is a compound distribution that can model the discrete point of zeros and the continuous component for the non-zeros, which is a common feature of many CPUE datasets.

Finally, another important point for the analysist to consider is model development and the selection of the explanatory variables. The approach introduced in this workshop follows the stepwise approach recommended by Hosmer and Lemeshow (2000) (see Section 2.2.5 for the procedure steps), but it is noted that there are now multiple packages available in statistical software that can conduct variable selection automatically (usually based on AIC). However, the more manual approach introduced here, that starts with univariate models, then builds a multivariate model, and finally tests for interactions, allows the analysist to better understand the process of variable selection and be fully aware of the decisions that are made.

2.5 References

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3 CASE STUDY 1: NORWAY LOBSTER (*Nephrops norvegicus*)

3.1 Introduction

Norway lobster (*Nephrops norvegicus*) is distributed along the continental slope off the southwest (FU 28) and south (FU 29) Portuguese coast, at depths ranging from 200 to 800 m. Its distribution is limited to muddy sediments with 10–100% silt and clay content, required to excavate burrows (Bell et al., 2013).

The area of distribution of Norway lobster in these functional units (FUs), includes ICES rectangles 03E, 04E0 and 05E0 in FU 28 and rectangles 02E0, 02E1, 02E2 and 01E2 in FU 29 (Figure 3.1). Although FUs 28 and 29 are different stocklets, landing records are not differentiated by FU and are assessed together.

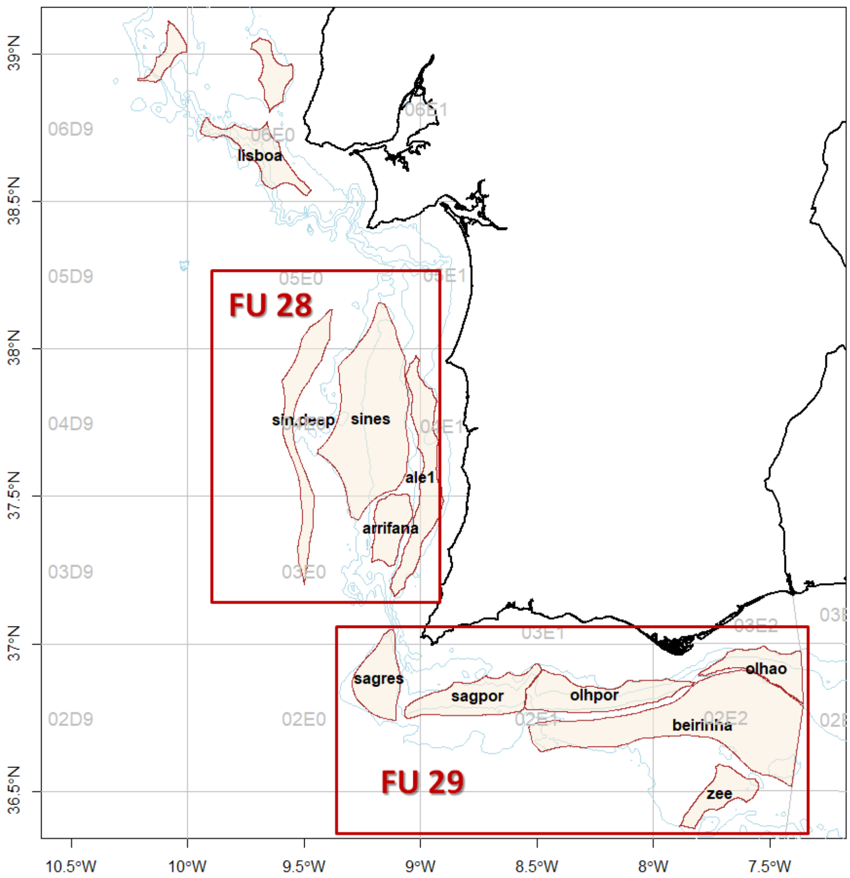

Figure 3.1. *Nephrops* in FUs 28-29 (SW and S Portugal). Fishing grounds overlaying ICES statistical rectangles.

Norway lobster is a very valuable and important resource for the demersal trawl fisheries operating in the region. Together with the deepwater rose shrimp (*Parapenaeus longirostris*), Norway lobster constitutes the main target species of the majority of the crustacean trawl fleet and is not generally caught as bycatch in other fleets. These two species have a different but overlapping depth distribution: the deepwater rose shrimp occurs at the depth range of 100–350 meters whereas Norway lobster is distributed from 200 to 800 meters (Sobrino at al., 2005). The number of fishing trips directed to one species or to the other depends on the abundance of these species each year.

The Portuguese trawl fleet comprises two components, namely the trawl fleet targeting demersal fish and the trawl fleet targeting crustaceans. The trawl fleet targeting demersal fish operates off the entire Portuguese coast while the trawl fleet directed to crustaceans operates mainly in Southwest and South Portugal and at deeper waters (≥ 200 m), where the crustacean species are more abundant. The fish trawlers are licensed to use a mesh size ≥ 65 mm and the crustacean trawlers are licensed for two different mesh sizes, 55 mm for catching shrimp and ≥ 70 mm for Norway lobster. Demersal fish trawlers that regularly land *Nephrops*, do in fact target this resource, which in terms of overall profit, represents a significant additional income.

The number of trawlers targeting crustaceans has been fixed at 35 since the early 1990s. However, in late 1990s, some vessels have been replaced by new ones, better equipped and more powerful, and the number of crustacean trawlers was then reduced to 30. In the last decade (2010s), the fishery in FUs 28 and 29 was mostly conducted by the Portuguese crustacean fleet composed by an average of 23 vessels (18 – 29 m of overall length and 220 – 450 kW) and up to 5 Spanish trawlers licensed for this fishery under a bilateral agreement.

The fishery takes place throughout the year, with the highest landings usually being made in spring and summer. The main bycatch species are blue whiting, hake and anglerfish (Abad et al., 2007). Discards are considered negligible, based on the results obtained from the DCF discard sampling program onboard the Portuguese crustacean trawlers, since 2004. When occurring, discards of *Nephrops* are not related to size but mainly related to quality (i.e., broken or soft shells).

Considered as an ICES data-limited category 3 stock (ICES, 2015), the advice for this stock has been based on the trends of a standardized CPUE, used as a biomass index. The effort estimated using this standardized CPUE has been used as a measure of fishing pressure. The CPUE standardization model had only considered the positive catches of *Nephrops*, based on the assumption that this is a target fishery. A GLM with Gamma distribution and log link was used with the following predictor factors: year, month, depth interval (100 – 400 m, 400 – 800 m, 800 – 1600 m), log catch classes of deepwater rose shrimp (corresponding to low and high catches), proportion of *Nephrops* in the total catch of crustaceans (<25%, ≥25%) and vessel category (categories A, B and C, based on their productivity compared to a reference vessel).

The classes of rose shrimp log catches and the classes of proportion of *Nephrops* were used as target fishing proxies.

For this workshop, an alternative to the current model standardization procedure was explored, taking into account also the null catches of *Nephrops*.

3.2 Exploratory data analysis

The data used in the model included daily catches from logbooks linked to VMS fishing positions, for 44 crustacean trawlers in the period 1998 – 2019. Trawling activity was assigned to VMS records based on the speed profile of the vessels. The time difference between two contiguous VMS records was assigned to the second record as fishing time. Records with duration greater than two hours were removed. Depth and subarea were identified by superimposing the VMS fishing records over a depth layer and over the fishing grounds represented in Figure 3.1. Daily catches of each vessel were distributed by the daily VMS records of the vessel weighted by the fishing time of each record.

The number of records available for the analysis (Figure 3.2) was not evenly distributed over the years, with lower number of records in the period 1998-2001 and in 2004, when information available was provided by the GeoCrust project (Afonso-Dias, 2002) for some of the vessels, with the addition of extra data in 2001 and 2004. Over the months, the records were almost evenly distributed with the exception for January, due to a fishing closure set experimentally in 2003 and permanently since 2005 (Portaria no. 1557-A/2002, 30th December2002; Portaria no. 1142, 13th September 2004; Portaria no. 43/2006, of 12th January 2006), and in February in 2005 and 2016 when the seasonal closure was extended for one month (Portaria no. 8-A/2016, of 28th January 2016). *Nephrops* fishing was also restricted in the period September to mid-November in the years 2014-2017 due to quota reduction resulting from the application of the Recovery Plan for Southern Hake and Iberian Norway lobster stocks (Council Regulation (EC) no. 2166/2005). In terms of subareas (i.e., fishing grounds) and depth intervals there is also some asymmetry on the information available in result of the fishing strategy, size and depth of the fishing grounds, and target species distribution, with less records in Arrifana and ZEE and in depths deeper than 800 m (Figure 3.2). To note that in this new approach the depth intervals considered in the analysis were narrower than those in the previous CPUE model.

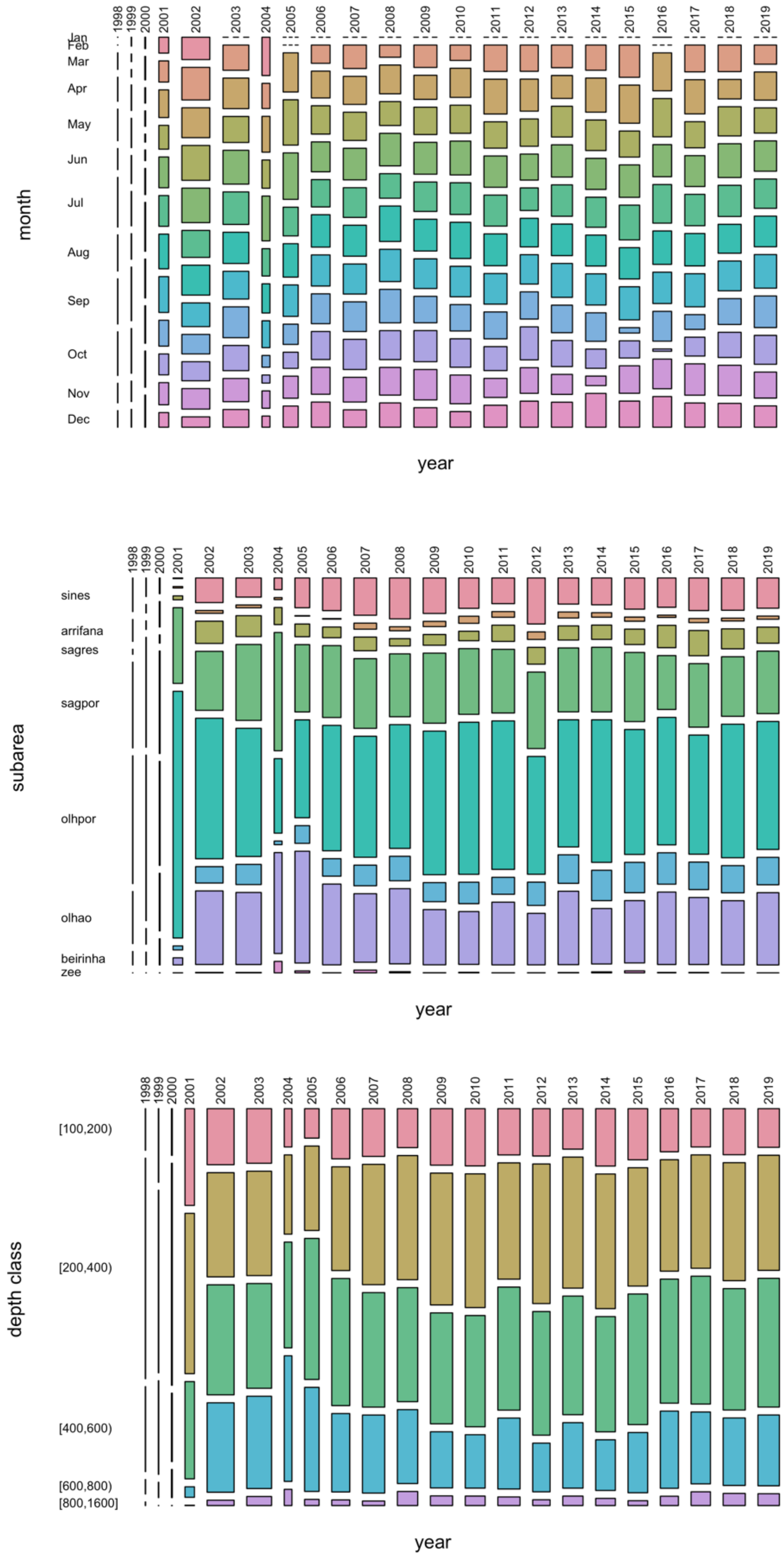

Figure 3.2. Distribution of the number of records through the time series by month (top), subarea (middle) and depth classes (bottom).

An exploratory data analysis was conducted to evaluate the proportion of zero catches of *Nephrops* in the data set and its behaviour against some of the possible explanatory variables, namely subarea and depth interval (Figure 3.3). Lower proportion of zeros (and therefore, higher proportions of positive catches) were found, in depths between 400 m and 800 m and in subareas Sines, Sagres, Sagres-Portimão (sagpor) and Beirinha.

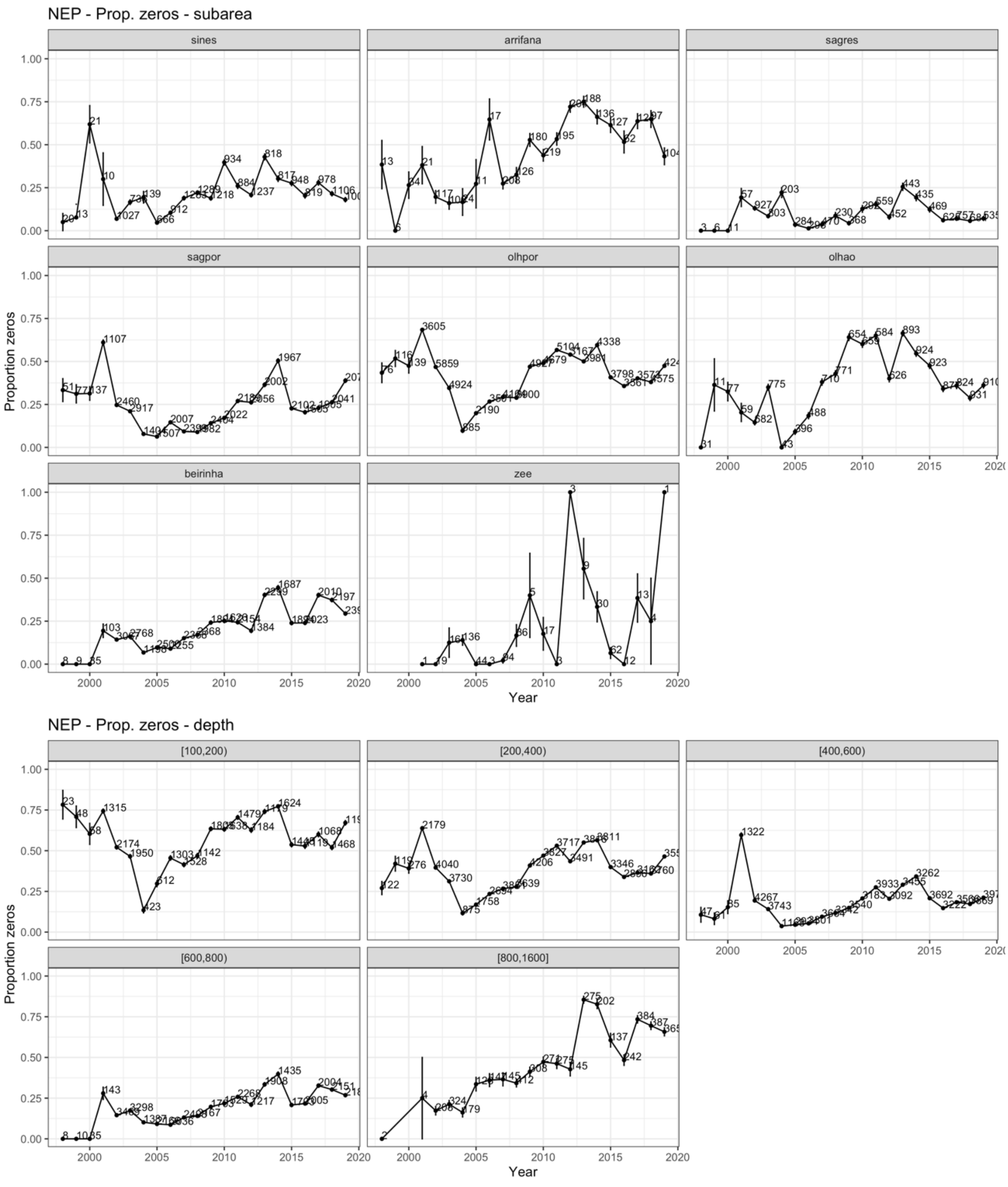

Figure 3.3. Proportion of zero catches of *Nephrops* by year in each subarea (upper panel) and depth interval (lower panel).

3.3 Model fitting and diagnostics

Generalized linear models were fitted to the data, considering the *Nephrops* CPUE as the response variable. The *Nephrops* CPUE is a continuous variable with a discrete mass of zeros, therefore a Tweedie distribution with a log link was assumed (Dunn, 2009). The power-index parameter (*p*) was determined using the package *'tweedie'*.

Initially, univariate models were applied for each explanatory variable candidate. The same categorical variables used for the previous model were tested, with some new formulations explained next, and adding a new variable, the subarea.

Depth was tested either as a continuous variable transformed with multivariate fractional polynomials (MFP), using package *'mfp'* (Benner, 2015), or as a factor but with more detailed levels than in the previous model for positive values, i.e. [100, 200[, [200, 400[, [400, 600[, 600, 800], [800, 1600] m. Details on the polynomial terms obtained are presented in the results section.

The factor vessel (*cfr*) was tested with all levels (44 vessels) and grouped in 3 levels as before. Another option was to include the vessel as a random variable, but there was no time during the workshop to test this approach.

Considering that one of the proxies for target fishing, the proportion of *Nephrops* in the total catch of crustaceans, was not truly independent from the response variable, a cluster analysis was performed to identify clusters of target fishing. The categorical variable *cluster* replaced in the final model the referred predictor and the log catch classes of deepwater rose shrimp, also a proxy for target fishing used in the initial model. A non-hierarchical clustering technique, CLARA (Clustering LARge Applications) based on the k-medoid approach (Kaufman and Rousseeuw, 1990; Struyf et al., 1996), was applied to the catch composition matrix, using the *'cluster'* package (Maechler et al., 2019). The matrix contained the proportion in weight per hour of the five main crustacean species caught by the fishery in each record in relation to the total weight per hour of crustaceans. The species considered were: Norway lobster, deepwater rose shrimp, blue and red shrimp (*Aristeus antennatus*), giant red shrimp (*Aristaeomorpha foliacea*) and scarlet shrimp (*Plesiopenaeus edwardsianus*). The CLARA analysis was based on 100 data samples, each comprising 1000 records. The optimal number of k clusters was selected by iterative maximization of the Average Silhouette Width (ASW). The outcomes of the CLARA analysis are presented in the results section of this report.

All significant variables ($p \leq 0.05$) were retained for a GLM with multiple explanatory variables. The best model was selected based on the explained deviance, the Akaike Information Criterion (AIC) and residual diagnostics. The mean estimates of the standardized CPUE of *Nephrops* from each model were obtained with least-squares means (Lenth, 2016).

3.4 Results and Discussion

3.4.1 Extra analysis on the exploratory variables

3.4.1.1 Target fishing

In the CLARA analysis used to identify clusters of target fishing, although the highest *Average Silhouette Width* (*ASW*) was obtained for *k = 2* clusters (*ASW = 0.62*), it was concluded that this number of clusters could be limitative to describe the target fishing. Therefore, the scenario using *k = 4*, the second largest value obtained (*ASW = 0.57*), was also considered (Figure 3.4). Figure 3.5 shows the silhouette plot for these two cases.

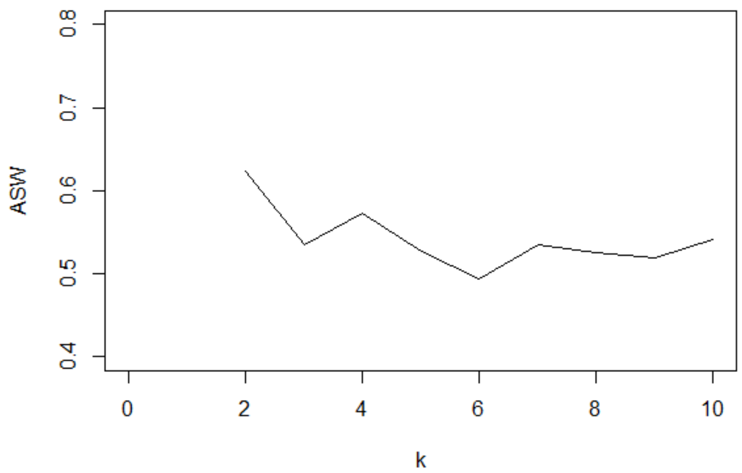

Figure 3.4. Average Silhouette Width (ASW) obtained for different number of clusters of the target fishing in the crustacean trawl fishery catching *Nephrops*.

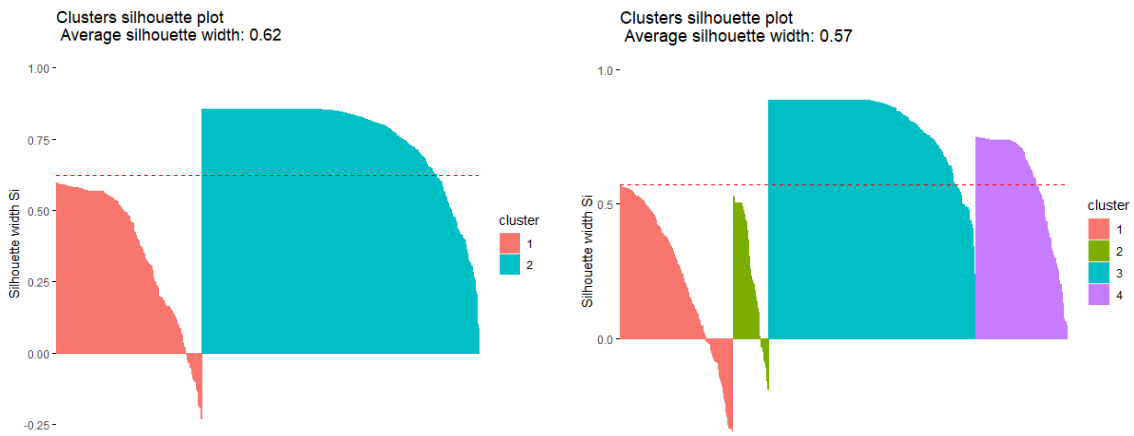

Figure 3.5. Silhouette plot for two (left) and four clusters (right).

Figure 3.6. Proportion in weight of the five crustacean species by cluster for two clusters (upper panel), and four clusters (lower panel). ARA: blue and red shrimp (*Aristeus antennatus*), ARS: giant red shrimp (*Aristaeomorpha foliacea*), DPS: deepwater rose shrimp (*Parapenaeus longirostris*), NEP: Norway lobster (*Nephrops norvegicus*), SSH: scarlet shrimp (*Plesiopenaeus edwardsianus*).

For the scenario *k = 2*, the cluster characterization with the species proportion by year (Figure 3.6, upper panel) led to identify one cluster (cluster 2) with a high proportion of deepwater rose shrimp (95%) and the other (cluster 1) with a higher diversity of species, being *Nephrops* the dominant one (67%). For the scenario *k = 4* (Figure 3.5, lower panel), apart from a deepwater rose shrimp cluster (100%, cluster 3), one can be considered a *Nephrops* cluster (86%, cluster 4), another with a mixture of those two main species but with higher proportion of deepwater rose shrimp (66%, cluster 1) and a fourth one (cluster 2) containing more deep-water species like blue and red shrimp (56%) and scarlet shrimp (11%). Clusters 3 and 4, targeting rose shrimp or *Nephrops* each, have silhouette coefficients greater than 0.50 (Figure 3.5), thus considered as having a reasonable to strong structure (Kaufman and Rousseew, 1990). Also, the different depth ranges associated to each cluster seem to be better explained in the k = 4 scenario and result on a better segregation of the target species (Figure 3.7).

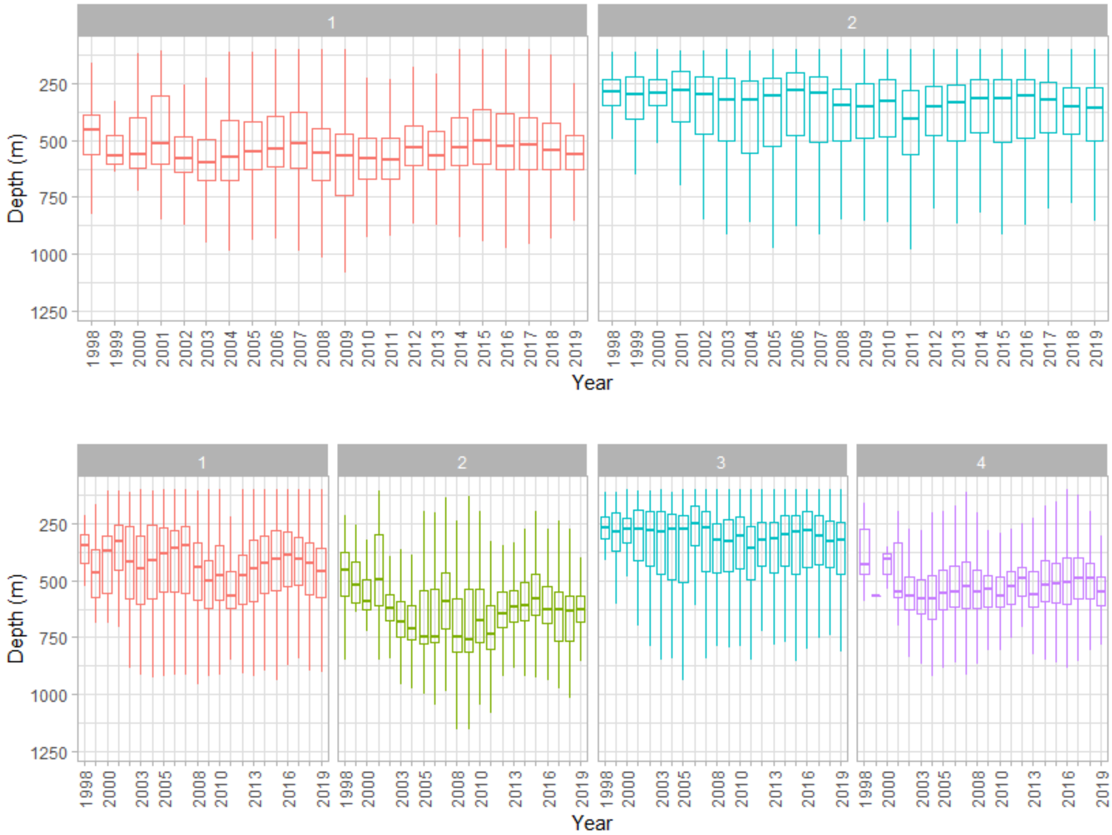

Figure 3.7. Depth range by cluster for k = 2 clusters (upper panel) and k = 4 clusters (lower panel).

3.4.1.2 Depth

To include depth as a continuous variable in the GLM, a transformation was conducted with MFP, as linear models assume explanatory variables to be linearly associated with the response variable and depth has a non-linear behaviour (Figure 3.8). The MFP which best predicted the depth variable was:

$$I((depth/1000)^2) + I((depth/1000)^3).$$

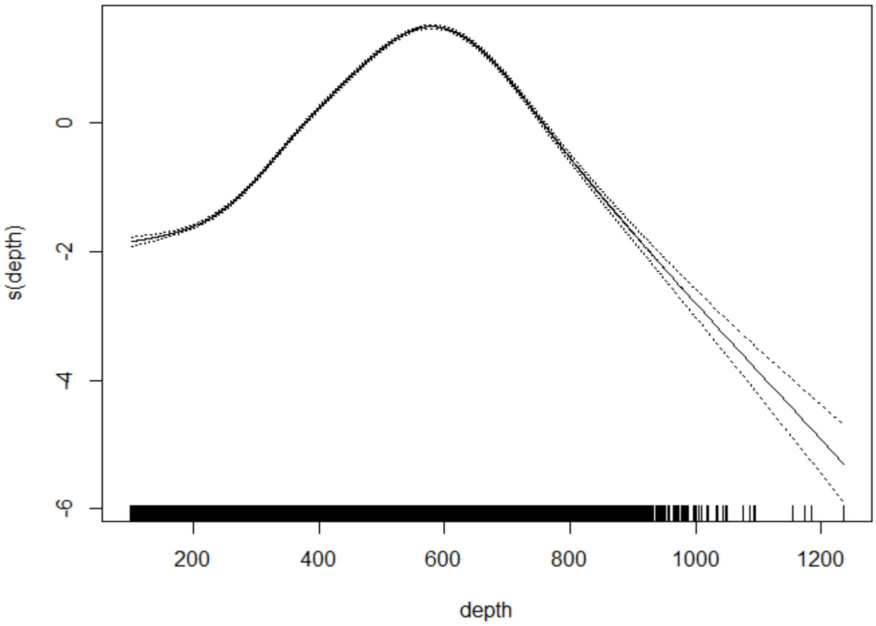

Figure 3.8. Variability of *Nephrops* CPUE with depth

3.4.2 *Models results*

3.4.2.1 Estimation of power parameter

The p-index was estimated by maximizing the profile log-likelihood across the grid values of *p* (Figure 3.9) in the range of $1 < p < 2$. The estimated value was $p = 1.517$.

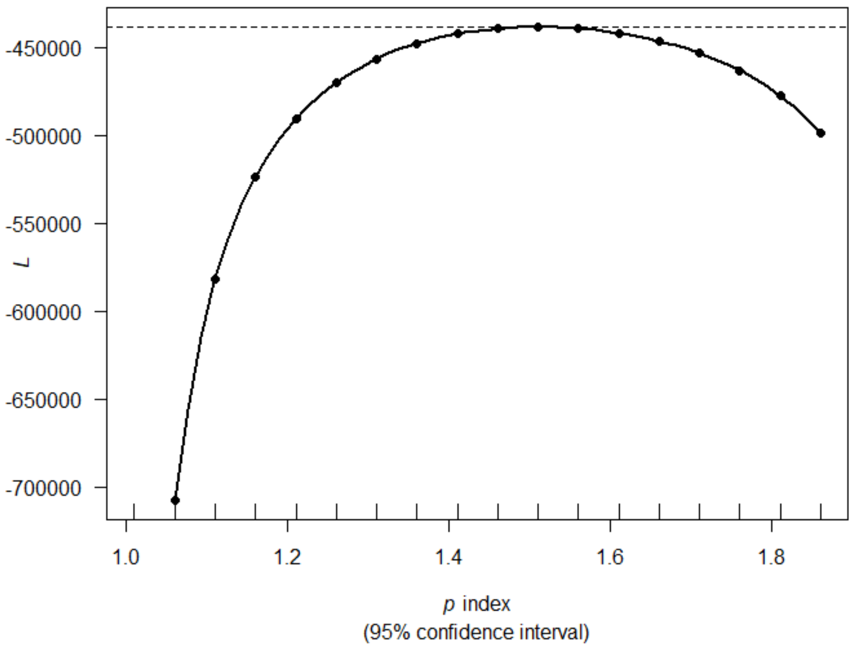

Figure 3.9. Value of log-likelihood function (*L*) changing the power-parameter (*p*) of the Tweedie model for *Nephrops* CPUE standardization (*p-index = 1.517*, phi-method = *'mle'*)

3.4.2.2 Model fitting

Modelling was performed with all significant variables. Table 3.1 summarizes the results of different combinations of predictors tested during the workshop. Taking into account the lower number of records for the years 1998-2000, some models were tested with a shorter time series (2001-2019). As the differences were very small, these models were discarded (represented with grey background in Table 3.1). The variables year, month and subarea were included in all models.

Table 3.1. Summary of GLM models: explained deviances and value of the Akaike Information Criterion (AIC). Models using only years 2001-2019 with grey background.

		Explanatory Variables										
Model name	year	year	month	subarea	depth (pol)	depth.class1	clstr_k2	clstr_k4	cfr (44 lvl)	cfr (3lvl)	Expl dev %	AIC
Mod0.k2	1998-2019	8.2%	5.6%	5.9%	1.6%		18.2%				39.5%	768,031.7
Mod01.k2	2001-2019	7.8%	5.6%	5.9%	1.6%		18.3%				39.2%	766,953.2
Mod0.k4	1998-2019	8.2%	5.6%	5.9%	0.5%			32.7%			52.9%	719,185.4
Mod01.k4	2001-2019	8.2%	5.6%	5.9%	0.5%			32.6%			52.8%	718,447.4
Mod1.k2	1998-2019	8.2%	5.6%	5.9%			18.2%				37.9%	773,278.4
Mod1.k4	1998-2019	8.2%	5.6%	5.9%				32.7%			52.4%	721,113.8
Mod2.k2	1998-2019	8.2%	5.6%	5.9%		2.4%	16.8%				38.9%	769,940.1
Mod2.k4	1998-2019	8.2%	5.6%	5.9%		2.4%		30.6%			52.7%	719,966.4
Mod3.k2	1998-2019	8.2%	5.6%	5.9%	3.3%		16.5%		1.7%		41.1%	762,452.6
Mod3.k2.cat	1998-2019	8.2%	5.6%	5.9%	3.3%		16.5%			1.2%	40.6%	764,081.3
Mod3.k4	1998-2019	8.2%	5.6%	5.9%	3.3%			29.9%	1.2%		54.1%	714,462.9
Mod3.k4.cat	1998-2019	8.2%	5.6%	5.9%	3.3%			29.9%		0.6%	53.5%	716,749.3
Mod3.1.k4	2001-2019	7.8%	5.6%	5.9%	3.3%			30.0%	1.2%		53.9%	713,730.2
Mod3.1.k4.cat	2001-2019	7.8%	5.6%	5.9%	3.3%			30.0%		0.6%	53.3%	716,020.5

The best models were obtained with *depth* as continuous variable and target fishing explained by 4 clusters. The variable *cluster* is the most important of the explanatory variables. The CPUE year trends obtained for the models with higher explained deviance and lower AIC (models Mod3.k4 and Mod3.k4.cat) are plotted together with nominal CPUE trend in Figure 3.10, for comparison. Mod3.k4 (with 44-level vessel factor) has a slightly higher explained deviance and wider confidence limits than Mod3.k4.cat (with 3-level vessel factor) with a loss of higher number of degrees of freedom. Details from the model Mod3.k4 and Mod3.k4.cat are presented in Table 3.2 and Figure 3.11.

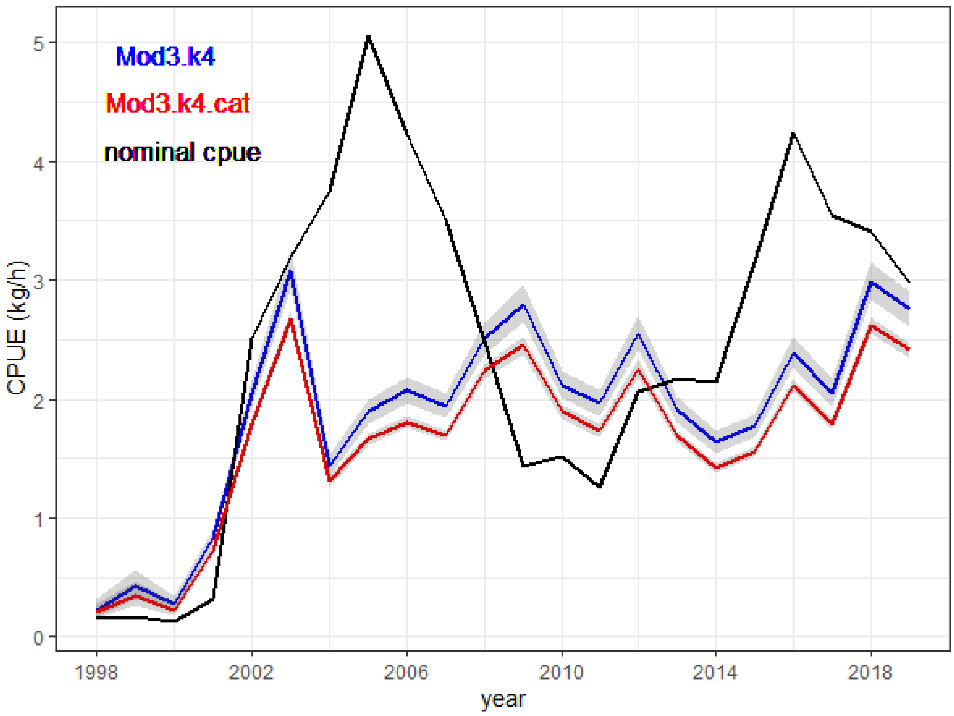

Figure 3.10. Standardized CPUE trends for the best GLM models compared to nominal CPUE of *Nephrops* in FU 28-29, in the period 1998-2019. Confidence intervals represented in grey.

Table 3.2. Deviance tables from models Mod3.k4 (upper table) and Mod3.k4.cat (lower table).

Mod3.k4	Df	Deviance	Resid. Df	Resid. Dev	F	Expl Dev
NULL			193318	702962		
year	21	57917	193297	645045	1492.1	8.2%
month	11	39102	193286	605943	1923.14	5.6%
subarea	7	41510	193279	564433	3208.2	5.9%
I((depth/1000)^2	1	410	193278	564023	221.87	0.1%
I((depth/1000)^3	1	22803	193277	541220	12336.7	3.2%
clstr4	3	209996	193274	331224	37870.2	29.9%
cfr	43	8477	193231	322747	106.65	1.2%
AICtweedie =		714462.9				54.1%

Mod3.k4.cat	Df	Deviance	Resid. Df	Resid. Dev	F	Expl Dev
NULL			193318	702962		
year	21	57917	193297	645045	1444.01	8.2%
month	11	39102	193286	605943	1861.16	5.6%
subarea	7	41510	193279	564433	3104.82	5.9%
I((depth/1000)^2	1	410	193278	564023	214.72	0.1%
I((depth/1000)^3	1	22803	193277	541220	11939.1	3.2%
clstr4	3	209996	193274	331224	36649.8	29.9%
cfr_cat	2	4320	193272	326904	1130.82	0.6%
AICtweedie =		716749.3				53.5%

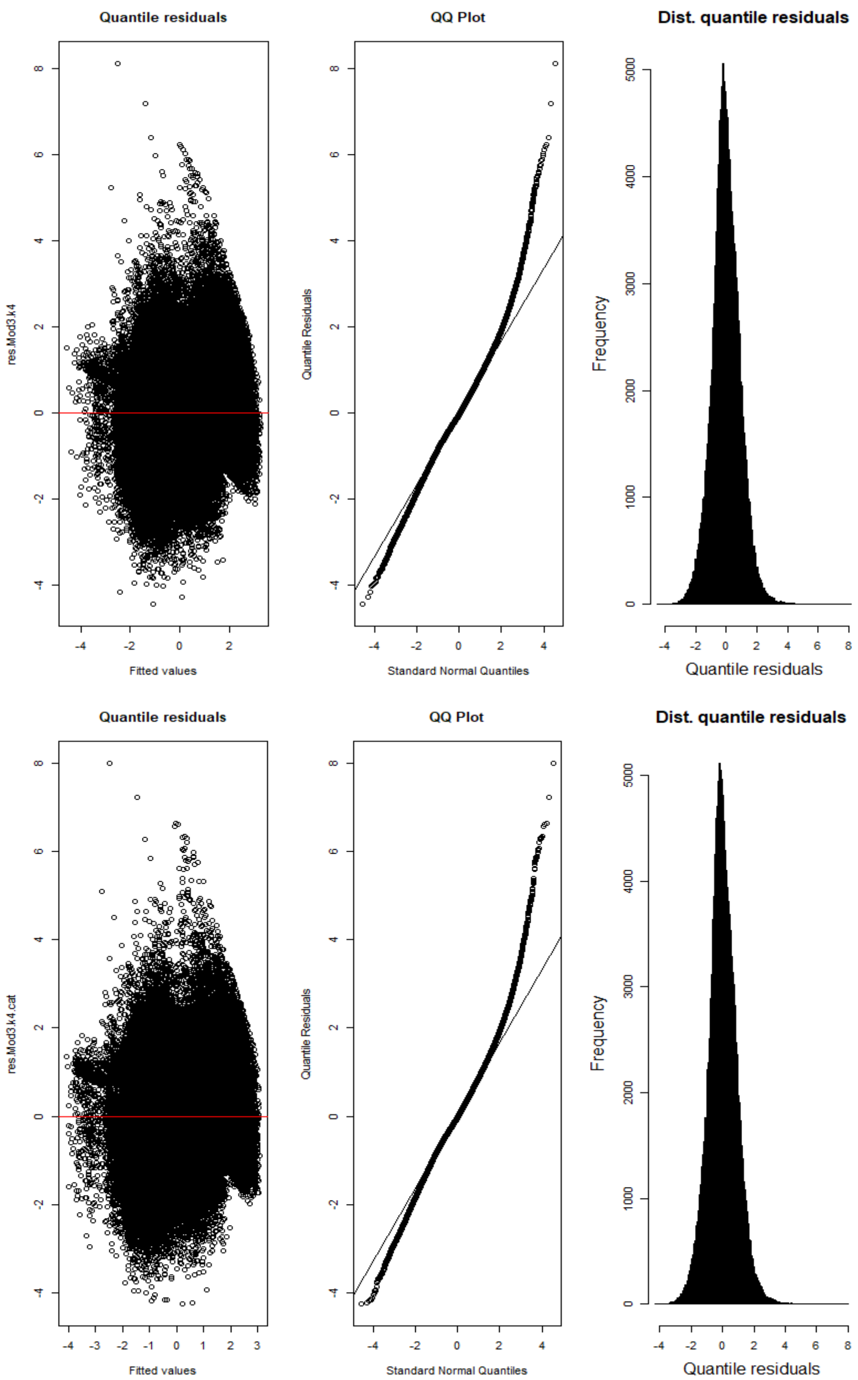

Figure 3.11. Mod3.k4 (upper panel) and Mod3.k4.cat (lower panel) residuals diagnostics.

3.5 Conclusions and Recommendations

The GLM assuming a Tweedie distribution with a log-link seems to be adequate to explain the *Nephrops* CPUE trends, considering also the species spatial and depth distribution. Although Mod3.k4 provided a better fit, taking into account the complexity of the model (considering 44 different vessels) and the aim of standardized CPUE series, i.e. to be used in the assessment of *Nephrops* FU 28-29, it was concluded that the best candidate model to explain the trend of *Nephrops* CPUE was the Mod3.k4.cat, although with slight worst fitting results than Mod3.k4. Nevertheless, as an alternative to Mod3.k4 it was suggested, as future work, that this model could be improved, using mixed effects models (e.g., GLMM or GAMM) with the vessel as a random effect, avoiding the loss of degrees of freedom. The further development of this work was presented to the ICES Benchmark Workshop on MSY Advice using SPiCT (WKMSYSPiCT) (ICES, 2021) and the final model was considered for the assessment of the *Nephrops* FU 28-29 stock under the Working Group for the Bay of Biscay and the Iberian Waters Ecoregion (WGBIE) in 2021.

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4 CASE STUDY 2: BLACK-BELLIED ANGLERFISH (*Lophius budegassa*)

4.1 Introduction

The white anglerfish *Lophius piscatorius* Linnaeus, 1758 and the black-bellied anglerfish *Lophius budegassa* Spinola, 1807 have traditionally been caught by two fleets in Portugal mainland: the bottom otter trawl and the polyvalent, which represented 11-38% and 62-89% of the national landings of both species from 1984 to 2019, respectively. The polyvalent fleet refers to multi-gear/multi-species fisheries, and involves a large group of vessels, from various sizes, usually licensed to operate with more than one fishing gear (most commonly gill and trammel nets, longlines and traps), that can be deployed in the same trip, targeting different species. Given the nature of these fisheries, selecting the species to target depends not only on species abundance, but also on other factors such as the area of exploitation, market prices, IVQ - individual vessel quotas (to hake) or season (among others) (Moura *et al.*, 2016). As a consequence, landing profiles are quite diverse within and among vessels, since their activity is ruled by a multitude of factors that are measured in order to maximize fishermen profit (Christensen and Raakjaer, 2006).

Within the polyvalent fleet, anglerfish are mostly caught by trammel nets (75-90% of annual national landings of the polyvalent fleet recorded in logbooks), all along the Portuguese coast and target fisheries are known to occur. This section presents a CPUE model for the black-bellied anglerfish in Portuguese waters using data for the trammel net fisheries reported in logbooks. This fishery represents an average of 72% and 22% of the national and total international landings of the stock, respectively.

4.2 Exploratory data analysis

4.2.1 Logbook data

Logbook data (2002-2019) was provided by Direcção Geral de Recursos Naturais, Segurança e Serviços Marítimos (DGRM), the national fisheries administration, under established protocols. Logbook reports have, in theory, more precise information on landings, with catches being reported by day of catch, ICES rectangles (or geographical coordinates in case of electronic logbooks), and fishing gear. Hauls conducted with trammel nets and with reported catches of anglerfish species (irrespective of the species reported) were selected from the overall dataset. The reason to select only hauls with anglerfish catches and not all hauls assigned to trammel nets is related to the polyvalent nature of this fleet: vessels can deploy trammel nets with different mesh sizes or at fishing grounds other than those usually used to target anglerfish. By including these hauls, different fisheries would be considered, and “false zeros” (hauls without catches of anglerfish as a result, for example, of fishing operations outside distribution area of the species or inadequate gear or mesh size) would be included in the analysis. As a consequence, the analysis does not include the “true zeros”, i.e., hauls where anglerfish could be potentially caught but were not present. It should be remarked that, in the case of target fisheries to anglerfish, the effect of not considering the “true zeros” is likely low since fishermen will not opt by this fishery when yields are low. Future work will be developed in order to consider targeting effects and this issue may be minimized.

Due to the possible misidentification of *Lophius* species within logbook data, the proportion of each species on market samples were used to estimate a catch value for each *Lophius* species by year and by landing port. It was assumed that the landing port nearest to the fishing ground reported (ICES rectangle) could inform on species composition of the catch. Such approach led to the occurrence of zeros in the data, i.e., when landings in a particular landing port are attributed to a single species.

4.2.2 Data cleaning and selection

Abnormal values in the number of hauls or reported catches were identified and removed from the dataset.

After inspection of the data, it was decided to exclude data reported for the northern area. Despite having important fishing grounds for *Lophius* spp., most of the estimated catches in this area are attributed to *L. piscatorius*. *Lophius budegassa* has low levels of catches and CPUE in the northern area (ICES statistical rectangles 08, 09, 10, 11 and 12; Figures 4.1 and 4.2).

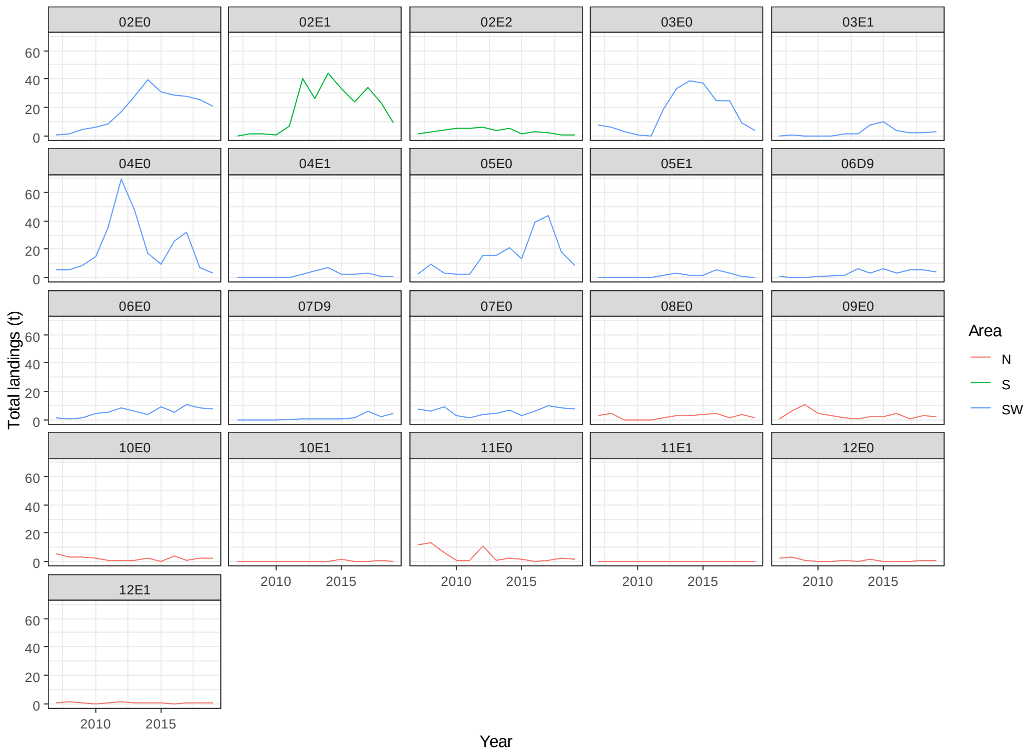

Figure 4.1. PT-GTR total catches of *Lophius budegassa* by ICES rectangle as reported in logbooks (2008-2019).

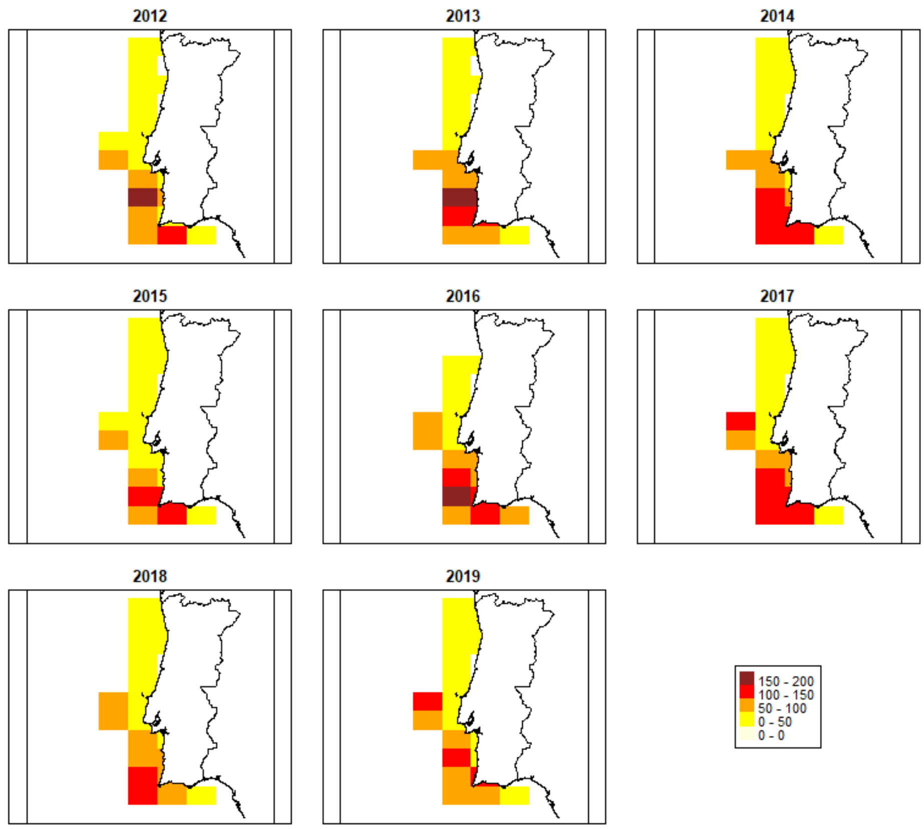

Figure 4.2. Number of hauls with catches of *Lophius budegassa* (logbook data from 2012-2019).

Due to misreporting and poor quality of the report, only data from 2008 onwards were considered for modelling. Months from January and February were also excluded from the dataset due to the prohibition of *Lophius* landings (national regulation: Portaria n.º 315/2011 - Diário da República n.º 249/2011, Série I de 2011-12-29).

Since catches by species are estimated based on the proportion of each species in the nearest landing port, hauls with zero catches of *L. budegassa* (see last paragraph of section 4.2.1.) were removed, as those would only correspond to a fraction of the "true zeros".

4.2.3 Variables selected for analysis

The "Duration" field available in logbooks was considered not reliable. Therefore, CPUE was estimated as the catches of *L. budegassa* by haul. The following variables were also selected for modelling: Year, Month and Area (ICES rectangle).

Observer data collected during a Data Collection Framework pilot study developed to collect information on the trammel net fishery targeting anglerfish in Portuguese waters, showed that 92% of the hauls targeting anglerfish (*Lophius* spp.) returned landings >50% in weight of these species (Moura et al., 2016). So, a new variable (binary) was added to the dataset, specifying if the haul was likely to have targeted anglerfish (*Lophius* spp.) or not. Target hauls were those with catches of *Lophius* spp. ≥0.4 of the total catch.

Table 4.1. summarizes the information selected for modelling, by year. The variation of catches by year, month, ICES rectangle and target is presented in Figure 4.3.

Table 4.1. Summary of the information selected for modelling. ANK, *Lophius budegassa*; GTR, trammel net hauls.

Year	Hauls	Vessels	Areas	Months	Target hauls	Proportion of ANK catches (GTR)	
	n	n	n	n	n	All hauls	Target hauls
2008	670	47	10	8	297	0.63	0.49
2009	627	40	8	6	257	0.54	0.44
2010	1270	39	11	8	499	1.00	0.87
2011	878	38	8	6	363	0.98	0.91
2012	2392	50	13	10	1330	0.99	0.94
2013	2073	45	12	10	1212	0.99	0.94
2014	2310	50	12	10	1336	1.00	0.91
2015	2325	60	13	10	1467	0.99	0.92
2016	1874	53	13	10	1356	1.00	0.93
2017	2263	50	13	10	1547	0.98	0.89
2018	1637	39	13	10	1114	0.99	0.92
2019	1125	34	13	10	696	1.00	0.90

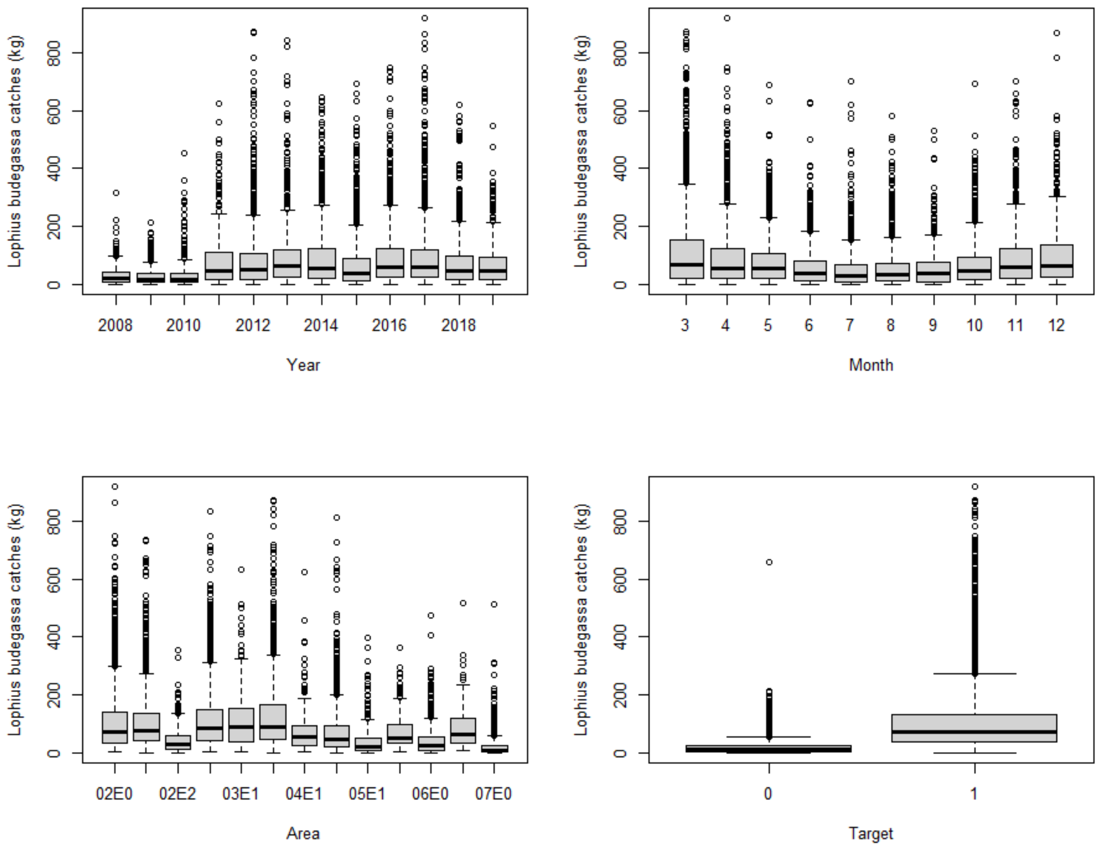

Figure 4.3. CPUE variation by levels of each factor selected for analysis.

4.3 Model fitting and diagnostics

Initial models were tested using a GLM, using the same variables as the final model: Year, Month, Area, Vessel and Target. In addition, initial analyses tested models with data from different groups of vessels, selected by applying thresholds to the frequency of anglerfish catches in each year and to the persistency of catches along the years. Such methodology was followed to ensure that the variable Vessel was informative and adequate to be included in the model since several vessels did not exhibit a persistent pattern in anglerfish catches neither over the years nor along the year.

To overcome this deficiency of data, it was suggested to apply a generalized linear mixed model (GLMM), with the variable Vessel as random variable. GLMMs combine the properties of linear mixed models (which incorporate random effects) and generalized linear models (which handle non normal data by using link functions and exponential family) (Bolker *et al.*, 2009).

The following model was fitted to the response variable CPUE (catches of *L. budegassa* by haul):

GLMM: (log(ANK) ~ Year + Month + Area + Target, random=Vessel)

considering as independent variables: Year, Month, Area (ICES statistical rectangle) and Target. The vessel identity (Vessel) was considered as the random variable, due to the high number of levels and relatively little data on most levels.

All the independent variables were modelled as categorical variables. Modelling was conducted in R software, using package “glmmTMB” (Brooks *et al.*, 2017). *Lophius budegassa* catch data was log transformed and modelled assuming the gaussian probability distribution. Tests with a gamma distribution and log link function (and no transformation of the variable CPUE) were also conducted. Model´s adequacy was checked based on residual analysis. The package “effects” (Fox and Weisberg, 2019) was used to visualize graphical effects of the predictors included in the model. Estimated marginal means for the variable year were extracted using package “emmeans” (Lenth, 2020).

4.4 Results and Discussion

Residual analyses showed better fits with a gaussian distribution after log transforming the CPUE data instead of a gamma distribution (Figure 4.4). Results will be presented for the first condition.

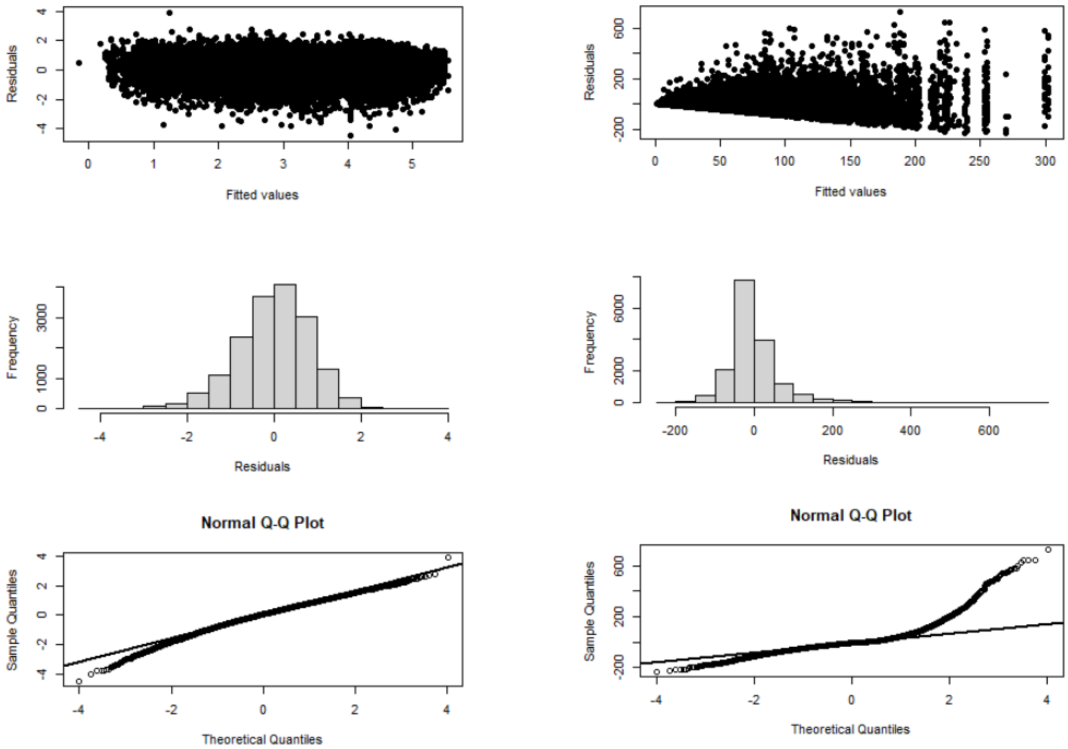

Figure 4.4. Standardized CPUE index (kg.haul-1) for the Portuguese trammel net fishery (2008-2019): Model residuals. Top: fitted vs residuals; middle: residuals distribution plot; bottom: Q-Q plot. Left: model with gaussian distribution (and log transformation of the CPUE); right: model with gamma distribution and log link function.

All variables were significant in the GLMM model. Effects of each variable are presented in Figure 4.5. Standardized values are presented in Table 4.2 and Figure 4.6. As shown above, model residuals suggest a relatively good fit (see also Figure 4.7).

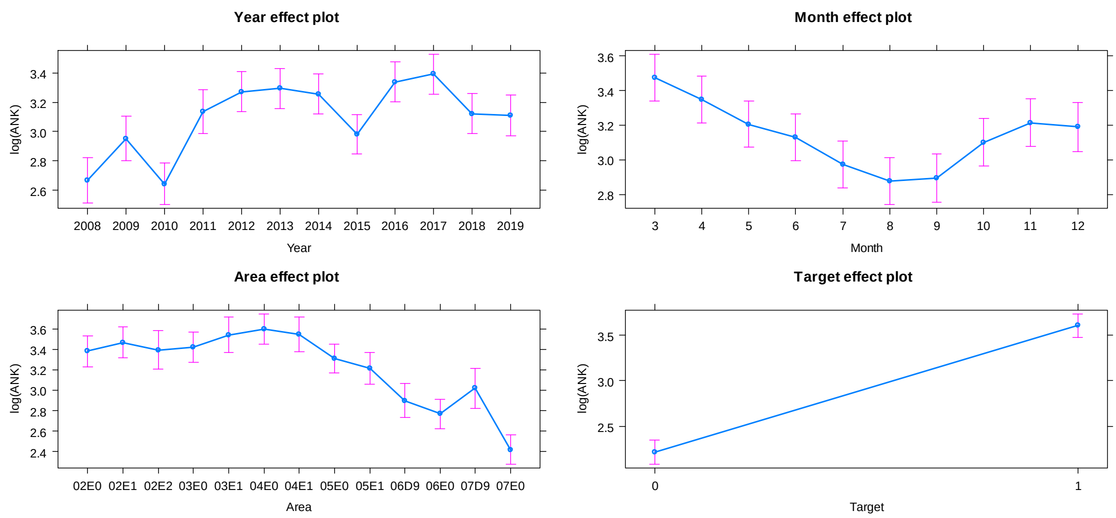

Figure 4.5. Effects of the variables Year, Month, Area and Target.

Table 4.2. Standardized CPUE index of *L. budegassa* and respective standard error (se) for the Portuguese trammel net fishery (2008-2019).

Year	CPUE (kg/haul)	se
2008	11.54	0.91
2009	15.34	1.19
2010	11.26	0.83
2011	18.45	1.41
2012	21.12	1.47
2013	21.59	1.51
2014	20.80	1.44
2015	15.82	1.09
2016	22.55	1.57
2017	23.80	1.64
2018	18.16	1.27
2019	17.95	1.29

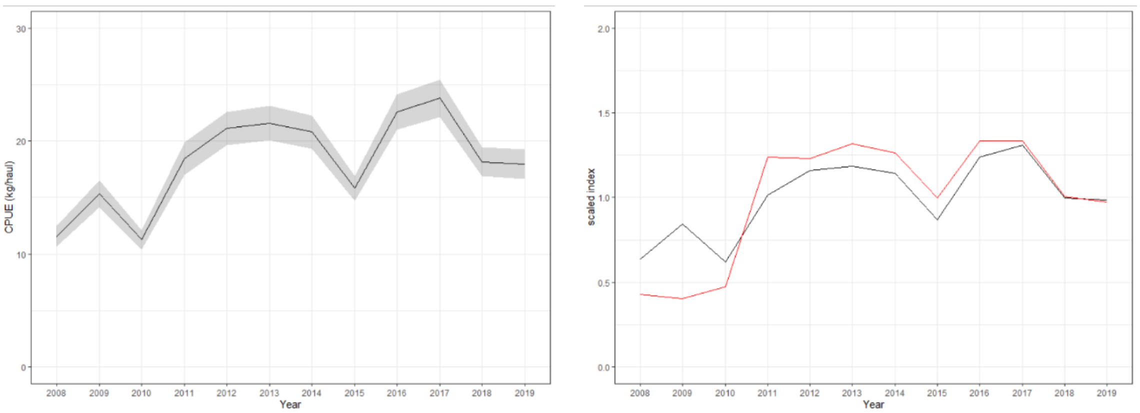

Figure 4.6. Standardized CPUE index (kg.haul^{-1}) of *L. budegassa* for the Portuguese trammel net fishery (2008 – 2019). Left: model results with standard errors (shaded grey area). Right: comparison between the standardized CPUE (black solid line) and the non-standardized series (red solid line).

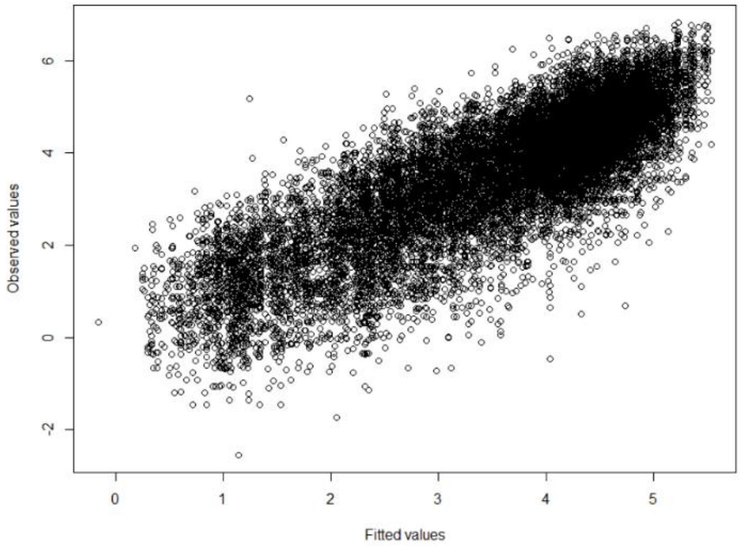

Figure 4.7. Standardized CPUE index (kg.haul^{-1}) for the Portuguese trammel net fishery from (2008-2019): fitted vs observed values.

4.5 Conclusions and Recommendations

The CPUE trajectory obtained for the trammel net fleet shows an increasing trend (with fluctuations) from 2010 to 2016-2018, similarly to the trends from the commercial series for the Portuguese trawl fleets (Figure 4.8).

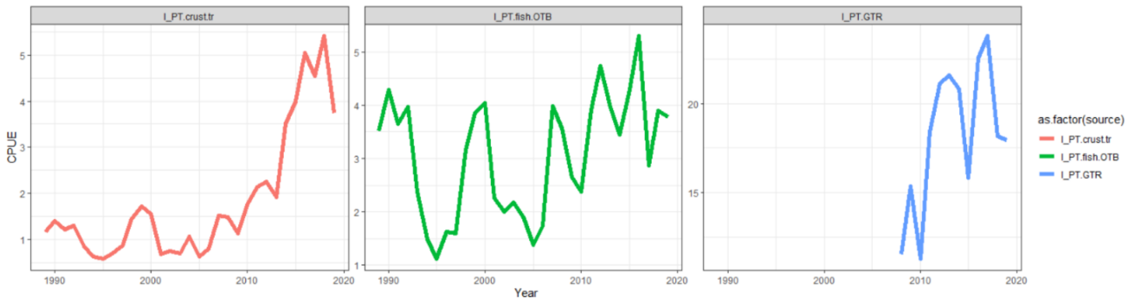

Figure 4.8. Non-standardized CPUE for the Portuguese trawl fleet targeting crustaceans (left; I_PT.crust.tr; 1989-2019), Portuguese trawl fleet targeting fish (middle; I_PT.fish.OTB; 1989-2019) and standardized CPUE for the Portuguese trammel net fishery targeting anglerfish (right; I_PT.GTR; 2008-2019). CPUE values in kg.h-1 and kg.haul-1 for the trawl and trammel net fleets, respectively.

Despite being the most abundant *Lophius* species in Portuguese landings, *L. budegassa* is landed together with *L. piscatorius*. It is recognized that an improvement in landings assignment to species denominations has occurred in the last couple of years, but such success cannot be attributed, at the moment, to all landing ports. It should thus be remarked that a correct identification of species in landings is essential, especially for species whose assessment relies on fisheries dependent data, as the case of *L. budegassa*.

Results from this study will be presented to the ICES Benchmark Workshop on MSY Advice using SPiCT (WKMSYSPiCT). This work will be further developed considering conclusions from WKMSYSPiCT and to better accommodate issues related to limitations of the data and targeting effects. The knowledge achieved for this stock will be extended for *L. piscatorius* which is also yearly assessed by ICES.

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5 CASE STUDY 3: CHUB MACKEREL (*SCOMBER COLIAS*) DISCARDS

5.1 Introduction

The extent and patterns for discarding is determined by a combination of regulations, environmental conditions, fishers' preferences and market forces. The effect and relative importance of these factors will vary for different species, vessels, *métiers* and fleets and will fluctuate over time (Catchpole *et al*., 2011).

The estimation of discards is essential for assessing the full impact of fisheries upon fish population and upon the ecosystem in which they operate (Borges *et al.*, 2005). Because discarding can be a substantial component of the fishing mortality, it is important to take it into account for the stock assessment. Discards' information can also be used in fisheries management, e.g., for evaluating conservation measures or for identifying the characteristics and behaviour of the fishing fleets.

Discard observer programs are an important key to obtain information on species abundance and distribution, particularly concerning non-commercial species and it may also provide valuable biological information on geographical areas and wide temporal trends.

The objective of the Portuguese onboard sampling program is to estimate the composition, volume, lengths and age of catches (landings + discards) taken by the Portuguese bottom otter trawl fleet (OTB) operating in the Portuguese area of ICES Division 27.9.a. This fleet is generally engaged in mixed fisheries, where a variety of species contribute to the output of the fishery. These species differ in habitat requirements and in their seasonal migration pattern, hence the species composition of catches will vary in space and time (Poos *et al.*, 2010). Consequently, also discard patterns can be highly variable due to changing economic, environmental and social factors (Catchpole *et al.*, 2005). Knowledge on the retained and discarded catch compositions of a fishery and how these vary spatially, temporally and among different fishing operations is then necessary for identifying the potential impacts of fishing on stocks assessment and ecosystems (Gray *et al.*, 2005).

Discards of *Scomber colias* are mainly related to market motives (volume vs commercial value) rather than regulatory motives (e.g., minimum length of reference for landing) (Fernandes *et al.*, 2015). This fact is reflected in the irregular discard pattern of the species occurrence and volume observed between years and areas. For these reasons, discard estimates using the routine design-based discard raising algorithm (Jardim and Fernandes, 2013) are only provided when the frequency of occurrence of the species in the sampled hauls is above 30%. Also, the large variability of discarded volumes between hauls/trips, that may be linked to several factors (e.g.

area, species price, etc), may result in biased estimates. The high proportions of zeros in the discards (more than 30%) of this species in several years creates a difficulty in obtaining precise overall discard rates, possibly due to the negative relation observed between frequency of occurrence and coefficient of variation estimates (Fernandes *et al.*, 2021).

In this work, it is presented an exploratory analysis of the relationship between discards per-unit-effort (DPUE) and several technical and environmental variables in order to obtain standardized series of DPUEs. The goal of this work is to obtain standardized discard estimates to be used to estimate annual discards with a model-based raising procedure. The modelled and observed discards are compared and the differences in the annual discards obtained from the design- and model-based approaches are evaluated.

5.2 Exploratory data analysis

5.2.1 Data

The analysis is performed for the period 2004-2019 using data collected by the Portuguese Onboard Sampling Programme (PNAB/EU DCF) and the sales records information provided by the Portuguese Administration (DGRM). This program uses a stratified random sampling and the vessel selection, with fleet region and quarter as strata, is based on an opportunistic sampling of cooperative commercial vessels. The bottom otter trawl fleet (OTB_DEF) is the selected fleet of this study. The sampling protocol used in the onboard sampling is summarized. Observers are deployed in a fishing trip to sample hauls selected systematically – either odd or even hauls are sampled after a random start. On each selected haul, observers take a sample from the catch, sort the specimens into retained and discarded fractions according to the crew's criteria, do the species identification and record the weight and length composition. Concurrently, observers also collect auxiliary fishery-related information such as effort, geographical and environmental data. From 2004 to 2010 the onboard sampling protocol suffered only minor changes and adaptations but from 2011 onwards the size of the catch samples was doubled (from 1 to 2 boxes of catch) and the within-trip selection of hauls was standardized to "at-least every other haul", while before 2011 all possible hauls were sampled.

The case-study focused on *Scomber colias* (VMA) which can be occasionally discarded in the OTB_DEF. *Scomber colias* is a species with an irregular discard pattern both because it is not frequently discarded in some of the sampled years (<30%) and some of the haul/trip occurrences may present very high discard weights. Table 5.1 summarizes the information on the sampling effort including the number of sampled trips, number of sampled hauls, hauls with the presence of the species in the catch and in each sampled fraction (landings and discards), along with the frequency of occurrence in the discards of sampled hauls, in the period 2004-2019 (Table 5.1).

Table 5.1. Sampling effort information for the OTB_DEF fishery, with the number of sampled trips, hauls and with the presence of *Scomber colias* in the catch and in each fraction, and the frequency of occurrence in discards, for the period 2004-2019.

Year	Nb Trips	Nb Hauls sampled	Nb Haul with species	Nb Hauls with species landings	Nb Hauls with species discards	Frequency of occurrence in discards (%)
2004	24	125	88	59	47	38
2005	39	159	127	100	57	36
2006	42	194	124	73	88	45
2007	38	162	137	88	111	69
2008	34	128	109	62	96	75
2009	38	135	110	31	95	70
2010	31	116	89	26	78	67
2011	30	83	74	33	59	71
2012	31	60	33	27	14	23
2013	27	50	36	20	22	44
2014	24	52	23	18	6	12
2015	24	48	15	10	5	10
2016	29	61	28	13	19	31
2017	32	69	45	26	30	43
2018	21	47	25	11	15	32
2019	23	45	23	12	12	27

The information collected onboard at haul level included coordinates, date, depth, total catch and discard percentage. Additional information on daily market value of the species, landings value of the haul and cumulative value for the hauls in the same trip was also collected, using the sales records. The analysed dataset consisted of 1537 observations on the response and on the predictors.

Spatial distribution of the observed fishing effort, catches, discard rates and DPUE of *S. colias* is presented in Figure 5.1. Mean values for the period 2004-2019, by 0.1° Latitude x 0.1° Longitude grid cell, are presented. It is shown that the spatial distribution of fishing effort and total catches (upper panel) for the whole period present a similar pattern indicating the strong relation between these two variables. The spatial distribution of the total discards percentage and of *S. colias* DPUE (lower panel) are probably more related to the species composition of catches in the first case, and to the species abundance vs price, in the second case. The annual variation of total catches and discards percentages between areas is presented in Figure 5.2.

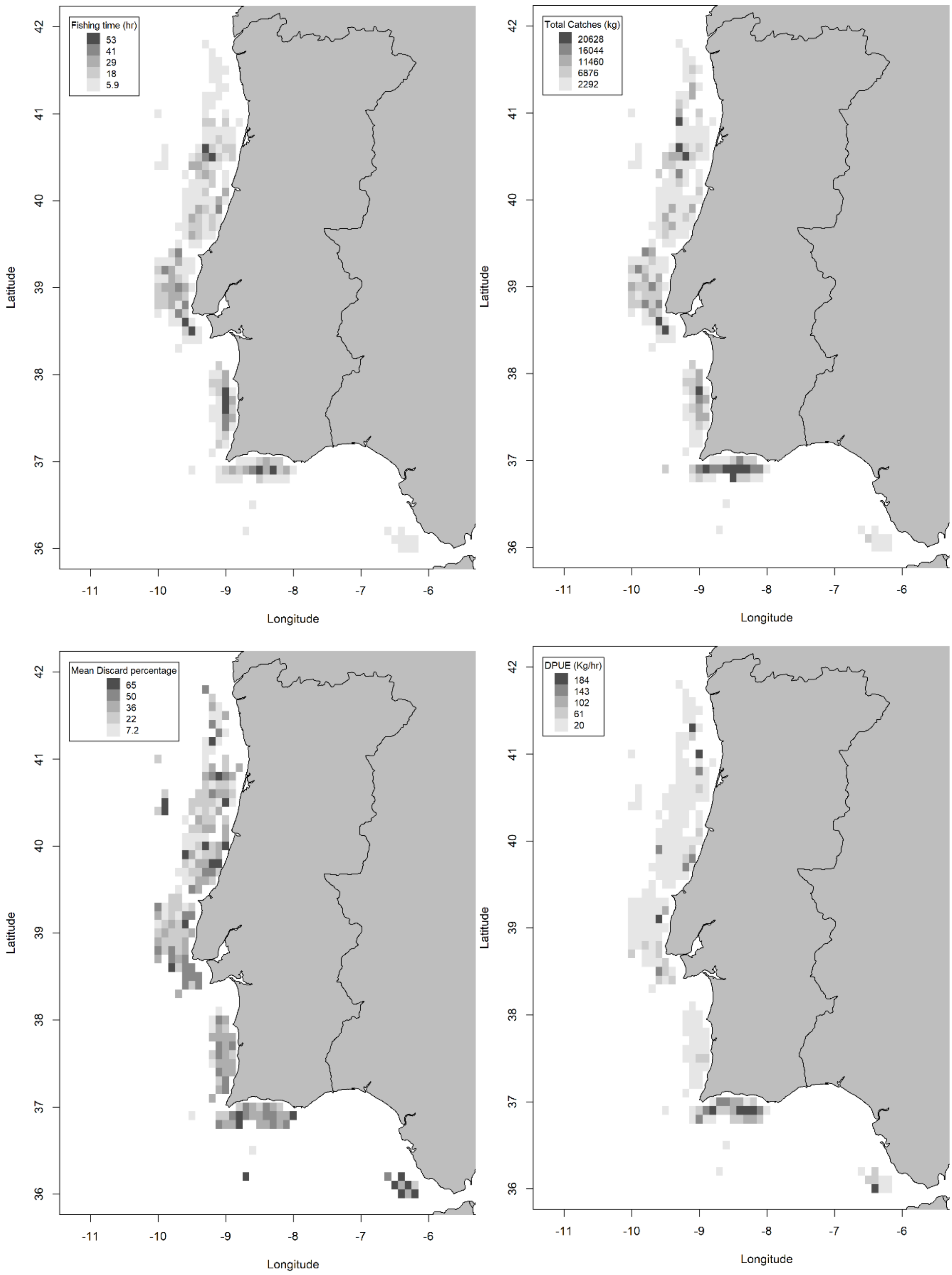

Figure 5.1. Spatial distribution of the fishing effort (upper panel left), total catch (upper panel right), discard percentage of all species (lower panel left) and *S. colias* (VMA) DPUE (lower panel right), in the sampled hauls of bottom trawl for demersal species (OTB_DEF) during the period 2004-2019. Resolution of 0.1º Lat x 0.1º Long.

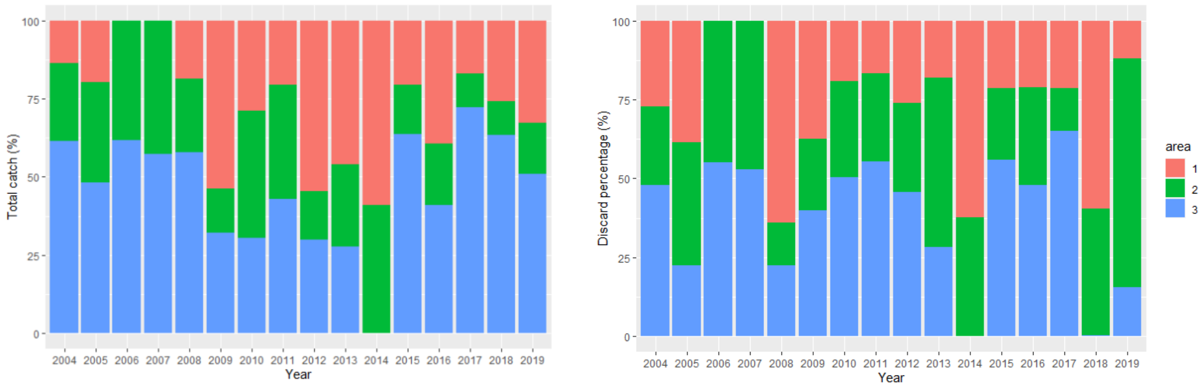

Figure 5.2. Annual variation of total catches (left panel) and discards (right panel) by area, observed in the sampled hauls of bottom trawl for demersal species (OTB_DEF) during the period 2004-2019 (1 – NW; 2 - SW; 3 - S).

5.2.2 Discards-per-unit-effort - DPUE

DPUE presented a wide range of values due to the large variability of this species discards, hence the distribution of the species nominal DPUE was not easy to interpret. The distribution of the log-transformed non-zero DPUE (Log DPUE) is also presented (Figure 5.3). This Log DPUE is also used in several other analyses presented in this work.

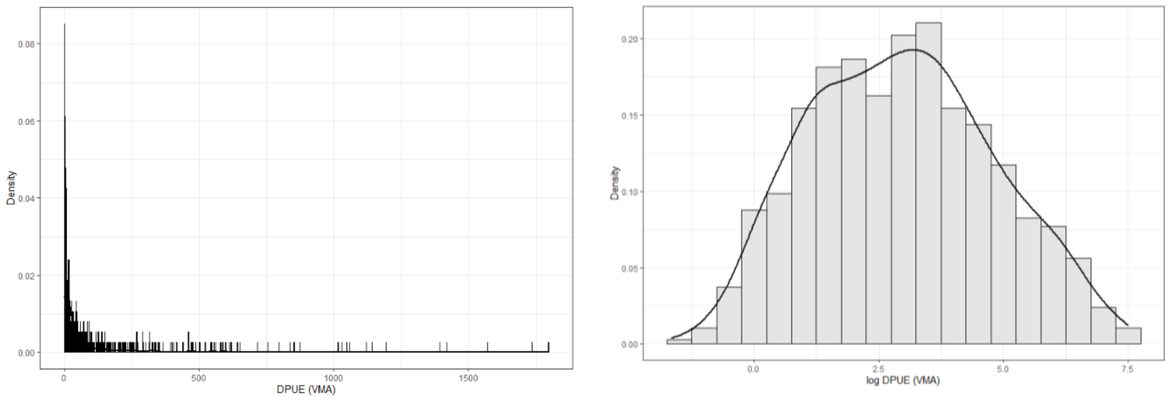

Figure 5.3. Density plot of *S. colias* nominal DPUE (left panel) and log-transformed of non-zero DPUE (right panel) in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019.

The annual variation of nominal DPUE, using mean DPUE estimates and their standard error, is presented in Figure 5.4 (left panel). The graphical analysis of the zeros proportions of the species against mean DPUE by year is presented in Figure 5.4 (right panel). The mean DPUE presented a high variability between years, suggesting two main periods, one from 2004 to 2010 presenting an increasing trend to the highest values (2008 and 2010), and another, after 2011, with the lowest values in 2014-2015 and a decreasing trend in most recent years (Figure 5.4 left panel). There is a linear relationship between mean DPUE and the percentage of the zeros, showing a decreasing trend of mean DPUE with increasing percentage of zeros (Figure 5.4 right panel).

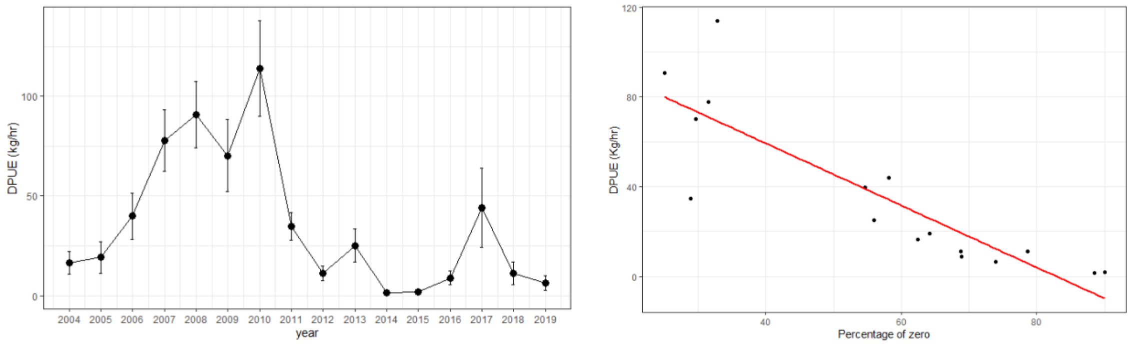

Figure 5.4. Mean DPUE (±1 SE) of *S. colias* (left panel) and annual percentage of zeros in the data against mean DPUE (right panel), in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019. Linear model (red line) fitted to the data points. Correlation index is -0.8609 (p-value = 1.852e-05) (right panel).

5.2.3 Potential predictor variables

Besides year, seven other potential predictor variables were explored to evaluate how they are related to the response variable, DPUE of VMA (Table 5.2). The continuous variables latitude and longitude were used to assign the fishing area along the Portuguese coast. Predictor variables year, quarter and area were categorical. Predictor variables depth and discard of all species, excluding VMA were treated both as continuous and as categorical. The predictors catch of all species excluding VMA, market value of VMA and haul income by trip were all continuous.

Table 5.2. Description of the predictor variables used in the exploratory analysis.

Predictor	Abbreviation	Type	Description
Year	Year	Categorical	16 levels: 2004-2019
Season	Quarter	Categorical	4 levels: Quarters: January-March(Q1); April-June (Q2); July-September (Q3); October-December (Q4)
Fishing area	Area	Categorical	Defined by trip coordinates; 3 levels: NW (Caminha-Nazaré); SW (Nazaré-Sagres); S (Sagres – V.R.S António)
Depth	Depth	Continuous Categorical	Depth (m) of the bottom of the trawl net; Categorical: 4 levels: [0,100[; [100-150[; [150-200[; [200,+∞[
Total discard other	DOther	Continuous Categorical	Discard (%) of all species except VMA; Categorical: 4 levels: 0-25; 25-50; 50-75; 75-100
Total catch other	COther	Continuous	Catch of all species (kg) except VMA, by haul
Market value	Price	Continuous	Market value (euro) of VMA
Income	Income	Continuous	Haul cumulative landings income (euro) of all species except VMA, by trip

Correlation analyses between the continuous predictor variables used to depict collinearity between predictors, are presented in Figure A2.4 (Annex 2). It shows that the stronger correlation occurs between price and income variables (0.43). The relation between species DPUE and the explanatory variables is analysed accounting for the proportion of zeros and the distribution of the positive DPUE by variable. Assuming the possibility of nonlinearity of the data, a smooth curve (loess: locally weighted smoothing, span=0.75) and a linear model were fitted to the scatter plot. Linearity between the continuous explanatory variables and the response variable was analysed by fitting GAM model with Gaussian distribution.

In order to evaluate which variables should be included in the model development, an exploratory analysis was performed guided by the following questions and rationales.

5.2.3.1 Has percentage of zero DPUE and positive DPUE changed along the 2004-2019 period?

Rationale: It is expected that zero proportions of DPUE are linked to the positive DPUE variation among years.

The percentage of zero DPUE decreased from 2004-2006 (62%-55%) to the lowest values between 2007-2011 (25%-29%). The highest values were observed in 2014-2015

(88%-90%), decreased until 2017 (58%) and then increased until the end of the period (2019: 74%) (Figure 5.5, left).

The positive DPUE highlight the relationship between the percentage of zeros and positive DPUE (Figure 5.5, right). The median of the positive DPUE were higher between 2007-2011 and decreased in the period 2017-2019.

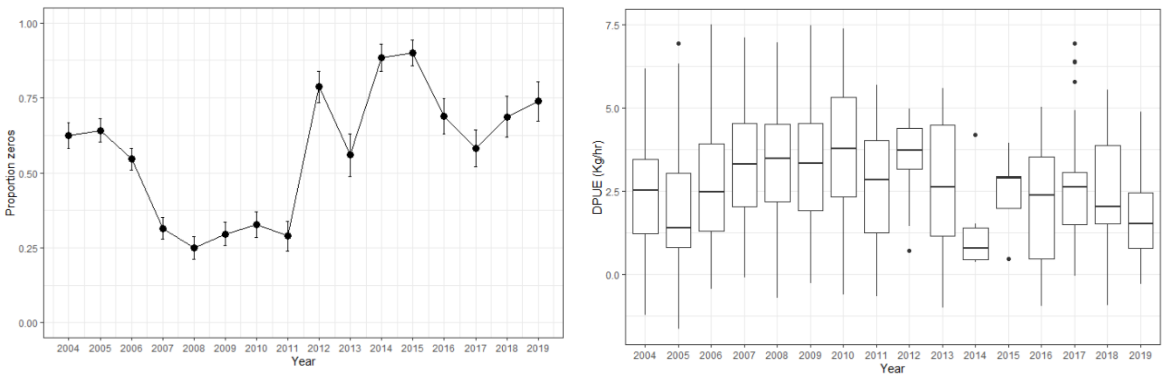

Figure 5.5. Proportion of zero DPUE of *S. colias* per year (left panel) and boxplot of non-zero log-transformed DPUE (right panel) by year, in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019.

5.2.3.2 Does percentage of zero DPUE and positive DPUE vary with time of the year (quarter)?

Rationale: Evaluate possible seasonality of the species DPUE.

Both proportion of zeros and positive DPUE do not vary among quarters of the year (Figure 5.6). The ‘Quarter’ won’t be included as an explanatory variable in the model.

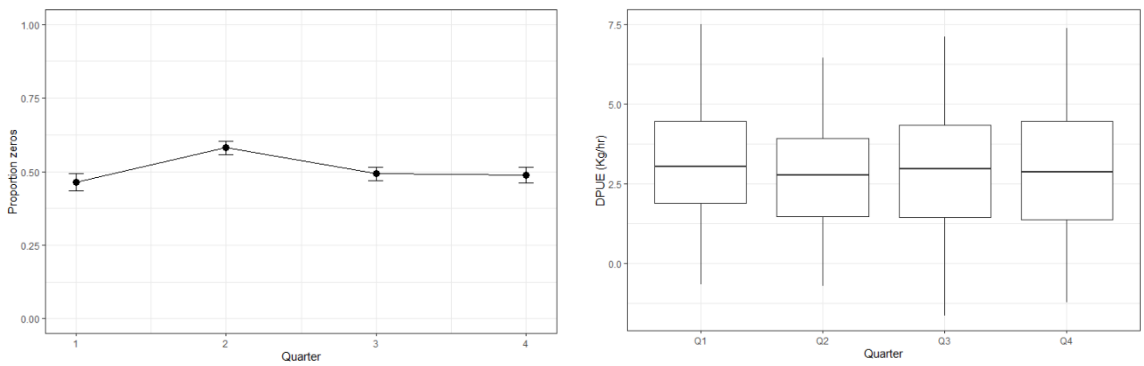

Figure 5.6. Proportion of zero DPUE of *S. colias* per quarter (left panel) and boxplot of non-zero log-transformed DPUE (right panel) by quarter, in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019.

5.2.3.3 Does percentage of zero DPUE and positive DPUE vary along the coast?

Rationale: The spatial distribution of the species differs along the coast, with predominance in the S and SW areas.

There is evidence of a decrease in the proportion of zeros from Northwest (NW) to the South (S) while positive DPUE is similar between NW and the Southwest (SW) areas and higher in the S for the whole period 2004-2019 (Figure 5.7). Figure 5.8 shows that *S. colias* Catch per-unit-effort (CPUE) for the whole period presented higher values in the South (left panel) and that annual DPUE estimates also occur in high percentages in the southern area for the main part of the period (right panel). 'Area' should be included in the model as an explanatory variable. An interaction term Year*Area was not considered in model configuration because there are combinations of Year*Area with no observations.

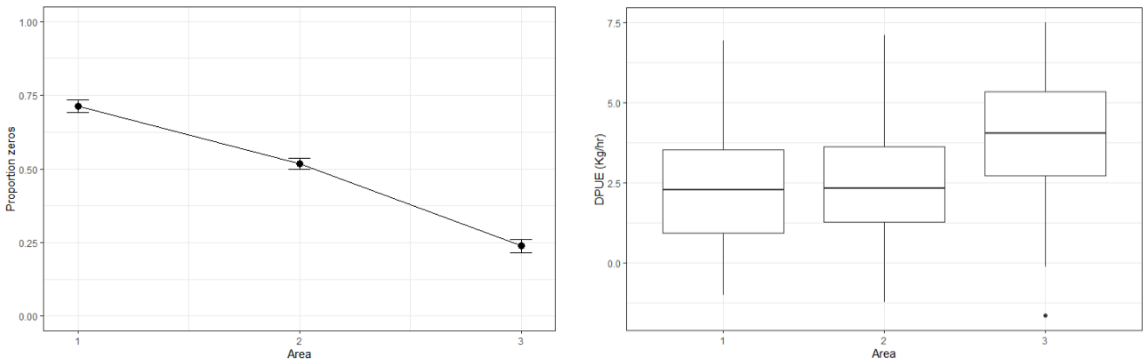

Figure 5.7. Boxplot of *S. colias* proportion of zero DPUE (left panel) and non-zero log-transformed DPUE (right panel) by area (1: NW; 2: SW; 3: S), in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019.

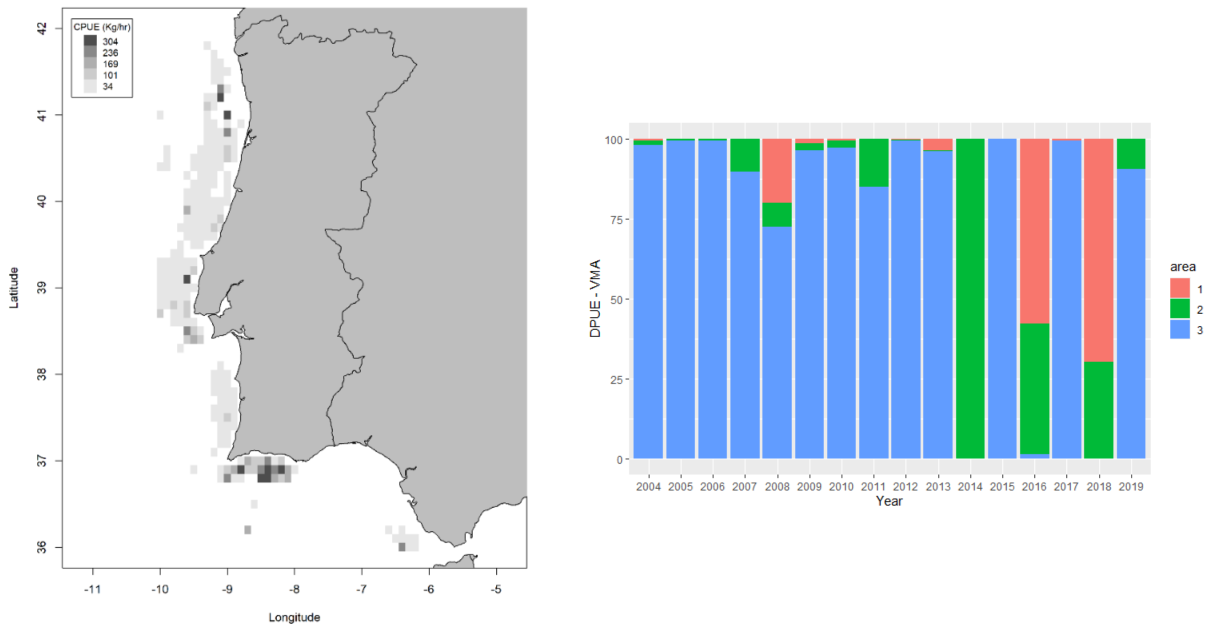

Figure 5.8. Spatial distribution of the *S. colias* CPUE (resolution of 0.1º Lat x 0.1º Long) (left panel) and percentage of *S. colias* DPUE by area (1 – NW, 2 – SW, 3 - S) (right panel), in the sampled hauls of bottom trawl for demersal species (OTB_DEF) during the period 2004-2019.

5.2.3.4 Does percentage of zero DPUE and positive DPUE vary with fishing depth?

Rationale: At depths above 200 m there is lower probability of catching *S. colias*, or its catches are composed of bigger individuals, which may not be discarded because they may have higher market value.

There seems to be a slight increasing trend between the mean proportion of zero DPUE and depth (Figure 5.9, left). The decreasing linear relationship observed for DPUE is mainly conditioned by the three observed values at depths above 400 m (Figure 5.9, right). The shape of the variable depth obtained from a GAM plot suggested violation of the assumption of linearity, hence a polynomial transformation of the variable was adopted (Figure 5.10). DPUE model development should evaluate the inclusion of the explanatory variable 'depth' both in absolute values and with the polynomial transformation.

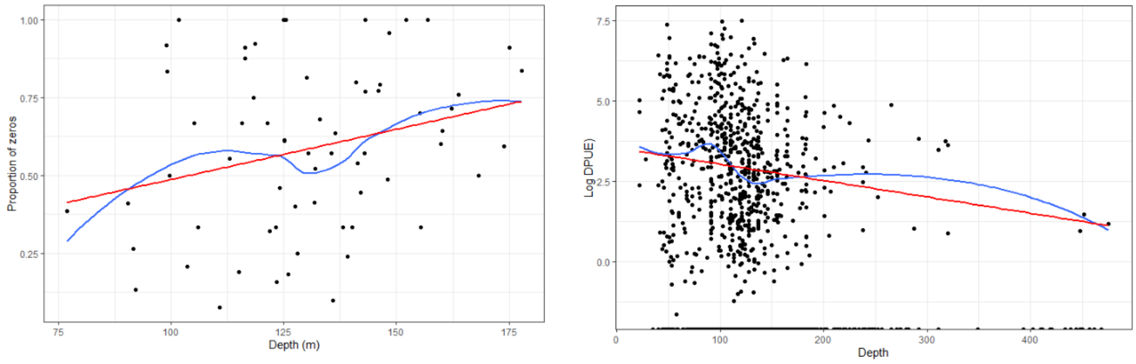

Figure 5.9. Mean proportion of zero DPUE against depth by year and quarter (left panel) and non-zero log-transformed DPUE (right panel) against depth, in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019. Linear model (red line) and 'loess' smooth (blue line) fitted to the data points.

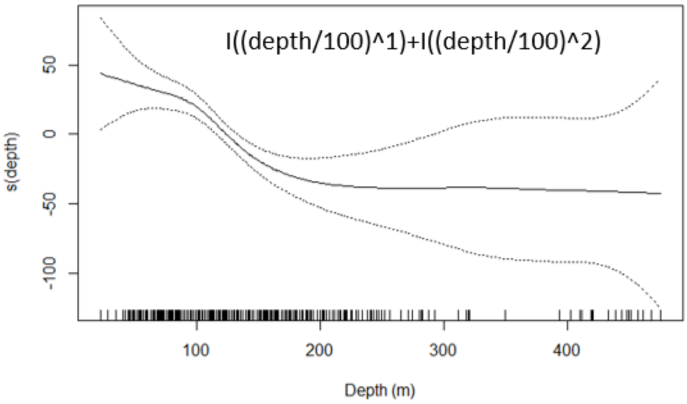

Figure 5.10. Shape of the continuous variable 'depth' with the polynomial transformation considered for model evaluation.

5.2.3.5 Is the discard percentage of all other species related to VMA discards?

Rationale: High discards of other species (e.g., blue whiting, blue jack mackerel) could indicate fishing hauls in fishing grounds with low co-occurrence of *S. colias*, hence low catch and discards of VMA.

Contrary to the rationale, the higher is the mean total discard percentage the lower is the mean proportion of zero VMA DPUE, suggesting co-occurrence of the *S. colias* with other discarded species (Figure 5.11, left). As a result, there is tendency of increasing positive DPUE with increasing total discards (Figure 5.11, right). The explanatory variable discard percentage without VMA ('DOther') should be included in the DPUE model development. There was no evidence of non-linearity of the variable DOther (Figure A2.1, in Annex 2) and no transformation was considered for this variable.

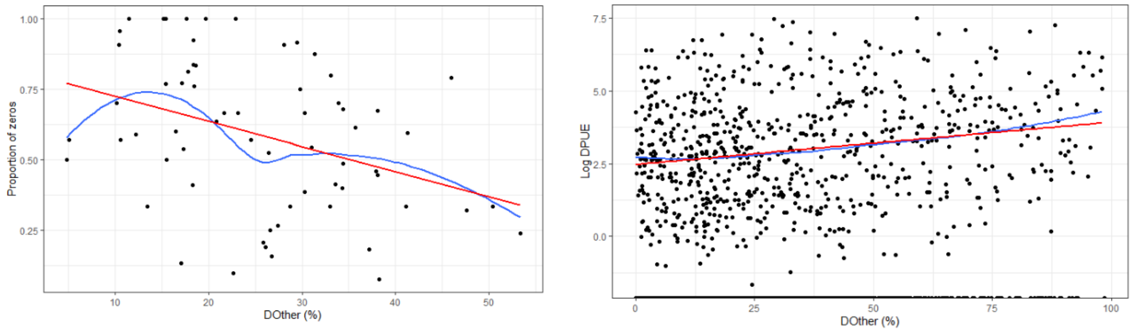

Figure 5.11. Mean proportion of zero DPUE against total discard percentage (without VMA) by year and quarter (left panel) and non-zero log-transformed DPUE (right panel) against discard percentage (without VMA), in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019. Linear model (red line) and 'loess' smooth (blue line) fitted to the data points.

5.2.3.6 Does percentage of zero DPUE and positive DPUE vary with total catch (without VMA)?

Rationale: Since chub mackerel, VMA, is a bycatch species of this fishery, it is likely that the higher the catches of main/target species the higher the discard of VMA.

The scatterplots do not show evidence that total catch influence the mean proportion of zero (Figure 5.12, left). However, the positive DPUE seems to show an increasing trend with positive catches without VMA (Log COther) (Figure 5.12, right). Model development will consider the inclusion of the explanatory variable 'COther'. There was no evidence of non-linearity of the variable COther (Figure A2.2, in Annex 2) hence variable transformation was not considered necessary.

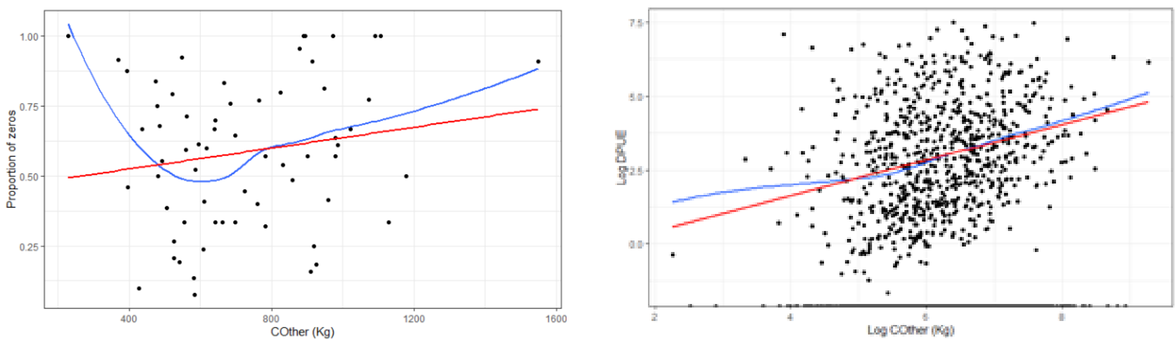

Figure 5.12. Mean proportion of zero DPUE against total catch (without VMA) by year and quarter (left panel) and non-zero log-transformed DPUE (right panel) against log-transformed total catch (without VMA), in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019. Linear model (red line) and 'loess' smooth (blue line) fitted to the data points.

5.2.3.7 Does percentage of zero DPUE decrease and positive DPUE increase with landings income?

Rationale: High landing income could be an incentive to discard *S. colias* since, besides horse mackerel, which is the main target species of this fishery, species composition of the landing has high commercial value (e.g., hake, anglerfish).

The cumulative haul value in the trips (excluding VMA income) is used in the analysis. In accordance to the rational, the proportion of zero DPUE seems to decrease with the mean cumulative haul value (Figure 5.13, left). However, a slight decrease of the positive DPUE with the increasing cumulative value is also observed (Figure 5.13, right), suggesting that lower discard volumes of the species seem to occur with the increasing value of the hauls. For these reasons, DPUE model development should evaluate the inclusion of the explanatory variable 'cumulative haul value'. There was no evidence of non-linearity of the variable 'Income' (Figure A2.3, in Annex 2) and variable transformation was not considered necessary.

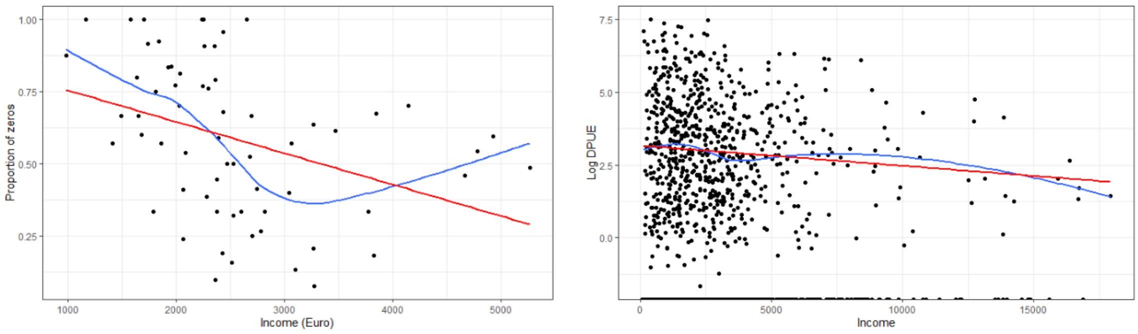

Figure 5.13. Mean proportion of zero DPUE against landing income, in euro by year and quarter (left panel) and non-zero log-transformed DPUE (right panel) against landing income, in euro, in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019. Linear model (red line) and 'loess' smooth (blue line) fitted to the data points.

5.3 Model fitting and diagnostics

Generalized linear models (GLM) with log-link function as a Tweedie regression model were used to estimate the standardized DPUE year trend. The Tweedie distribution can handle zero-data uniformly (Dunn and Smyth, 2008) which is appropriate for the *S. colias* case-study given the high rate of zero observations in the data set. The power index parameter of the Tweedie distribution was determined using the inversion method for computing the (log-) likelihood function. Model fitting considered a full-fixed effect structure with predictors year and area as factors, depth, DOther, COther, price and income as continuous variables. Model fitting was also performed with depth and DOther as factors. Model simplification was explored. The test of the goodness-of-fit between models was performed using the likelihood ratio test (LRT). The approach used to evaluate alternative models was based on the analysis of residual distribution patterns, the relationship between predicted and observed DPUE, the deviance explained and also on the value of the Akaike Information Criterion (Burnham *et al.*, 2011). The mean estimates of the standardized DPUE of VMA were computed with least-square means.

Analyses were conducted in R (R Core Team, 2020) using the packages 'grid' (R Core Team, 2020), 'mapplots' (Gerritsen, 2018), ' maptools' (Bivand and Lewin-Koh, 2020), 'mapdata' (Brownrigg, 2018) and 'maps' (Minka and Deckmyn, 2018) for map plots, 'Tweedie´ (Dunn, 2017; Dunn and Smyth, 2005, 2008) to determine the power index parameter of the Tweedie distribution, "statmod" (Dunn and Smyth, 1996) for the Tweedie family functions and GLM model fitting and diagnostics, 'gam' (Hastie, 2020) for the GAM models, 'mfp' (Axel, 2015) for the multivariate fraction polynomials, 'PerformanceAnalytics' (Peterson and Carl, 2020) for analytics and correlation plots, 'car' (Fox and Weisberg, 2019) for collinearity tests and "lsmeans" (Lenth, 2016) to compute the mean estimates of the standardized DPUE.

5.4 Results and Discussion

Figure 5.14 (left) presents the power index parameter of the Tweedie distribution, of 1.74 ($1 < p < 2$), that can be represented as Poisson mixtures of gamma distributions and are mixed distributions with mass at zero and with support on the non-negative reals (Dunn and Smyth, 2005). The percentage of zeros to be explained were around 53% (Figure 5.14, right).

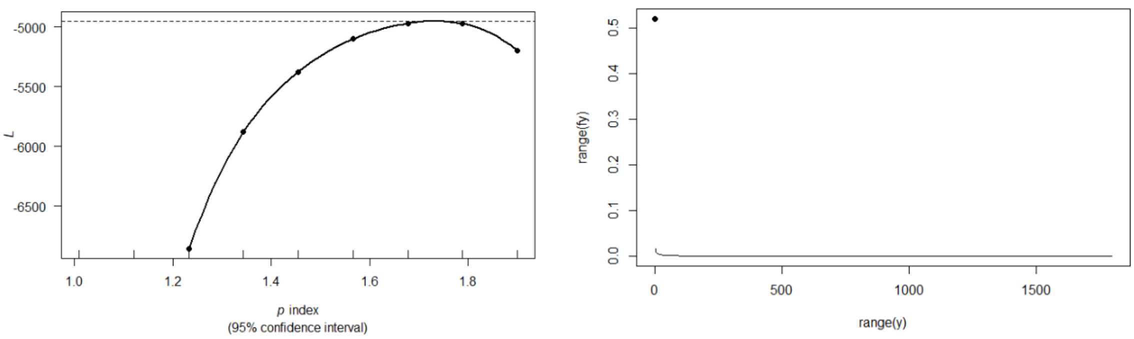

Figure 5.14. Fit of the Tweedie distribution; p-max = 1.74 using 'mle' method (left panel) and Plot of the Tweedie distribution (point: indicates the proportion of zeros in the data – 52.15%; line: shows the distribution of the continuous component of the model) (right panel).

Thirteen different models were produced and explored (Table 5.3). The first six are simple univariate models for each of the selected explanatory variable, while the other six include simple effects model starting with all the predictors together and then removing a continuous variable sequentially. A model was produced with all the categorized variables (model 12), and also a last model, with the same variables of model 8 but using the transformed depth, was considered. The table includes the results obtained from the test of the goodness-of-fit between models performed between the simple model and each of the model (LRT (Pr(>F))), the deviance explained by the model, the indication of the analysis of residual patterns and the AIC value. For the residual pattern analysis three different outputs were produced: a) residuals obtained from the model (Quantile residuals, QQ plot and Distribution of the quantile residuals); b) Fitted vs observed and; c) the residuals from the variables included in the model.

The analysis of the results, summarized in Table 5.3, indicates that all the models explored presented significant improvements (Pr(>F) < 0.005) over the simple model. Models 6 and 7 showed however no convergence of the GLM fit and they were further investigated. Firstly, the variable 'Income' is the continuous variable present in both models (univariate model 6 and multivariate model 7). The data exploration showed the presence of five extreme values for 'Income'. Also the fact that model 8 (without 'Income', with 'COther') and model 9 (with 'Income', without 'COther') showed no convergence problems gave some indications that a possible collinearity could exist between 'Income' and 'COther'. However, they presented a very low correlation between them (0.11%, Figure A2.4, in Annex 2) and also the collinearity tests performed using the Variance Inflation Factor (VIF) showed no collinearity issues regarding all variables included in those models. Models 6 and 7 were re-run using the same dataset but without the extreme values of 'Income' and they revealed no convergence problems. The deviance explained by this 'new' model 7 (30%) is the same of the one obtained for the model 8 when running both with the same data subset and with the full dataset. Therefore, the between model comparison was performed for the simple effect models 8 to 12 (Table 5.4, model 8 with full dataset in Figure 5.15-5.17 and models 9, 10, 11 and 12 in section C of the Annex 2). It indicates that, although the patterns of the residuals present slight differences between models, they are in general acceptable for all (normality and independence of errors, homoscedasticity, absence of outliers) despite higher dispersion around the diagonal line in the predicted *vs* observed plot. Model 8 and 13 outperformed the other models in terms of deviance explained, of 30%, and lower AIC, of 8814 and 8859, respectively. Since the transformation of the variable depth in model 13 didn't present much improvement when compared to model 8, the model 13 was excluded from the model comparisons. Models 9, 10 and 12 presented lower deviance explained (27%) while model 11 had the lowest value (25%) among the explored models. Model 8 was adopted to estimate total annual discards.

Table 5.3. Summary of results from the fitted models (ns – not significant; nc – not comparable; Residuals patterns: QQ-plot; Fitted vs observed; residuals variables; '+' - OK; '±' - high dispersion; fact – variable converted to factor; T – variable transformed with fractional polynomials)

Model code	Variables	LRT (Pr(>F))	Deviance explained (%)	Residual patterns	AIC	Comment
Mod 1	DPUE ~ Year	8.21e-14	12	-	-	-
Mod 2	DPUE ~ Area	< 2.2e-16	15	-	-	-
Mod 3	DPUE ~ Depth	9.54e-14	7	-	-	-
Mod 4	DPUE ~ DOther	4.31e-4	2	-	-	-
Mod 5	DPUE ~ COther	< 2.2e-16	35	-	-	-
Mod 6	DPUE ~ Income	7.722e-05	2	-	-	Subset without 5 'Income' outlier values
Mod 7	DPUE ~ year + area + depth + DOther + Income + COther	< 2.2e-16	30	-	nc	Subset without 5 'Income' outlier values ns: Income
Mod 8	DPUE ~ year + area + depth + DOther + COther	< 2.2e-16	30	+; ±; +	8814	-
Mod 9	DPUE ~ year + area + depth + DOther + Income	< 2.2e-16	27	+; ±; +	8853	ns: Income
Mod 10	DPUE ~ year + area + depth + DOther	< 2.2e-16	27	+; ±; +	8852	-
Mod 11	DPUE ~ year + area + depth	< 2.2e-16	25	+; ±; +	8884	-
Mod 12	DPUE ~ year + area + fact(depth) + fact(DOther)	< 2.2e-16	27	+; ±; +	8859	-
Mod 13	DPUE ~ year + area + T(depth) + DOther + COther	< 2.2e-16	30	+; ±; +	8859	-

Table 5.4. presents the detailed results obtained for Model 8 (DPUE ~ year + area + depth + DOther + COther) and Figures 5.15-5.17 the residual plots.

Table 5.4. Analysis of deviance table for the Tweedie Model 8.

Model 8	Df	Deviance	Resid. Df	Resid. Dev	F	P(F)	Deviance explained (%)
Null			1464	22949			
Year	15	2833.75	1449	20115	9.3142	< 2.2e-16	12
Area	2	2495.77	1447	17619	61.5247	< 2.2e-16	11
Depth	1	534.21	1446	17085	26.3381	3.256e-07	2.3
DOther	1	432.99	1445	16652	21.3477	4.172e-06	1.9
COther	1	510.66	1444	16141	25.1773	5.878e-07	2.2

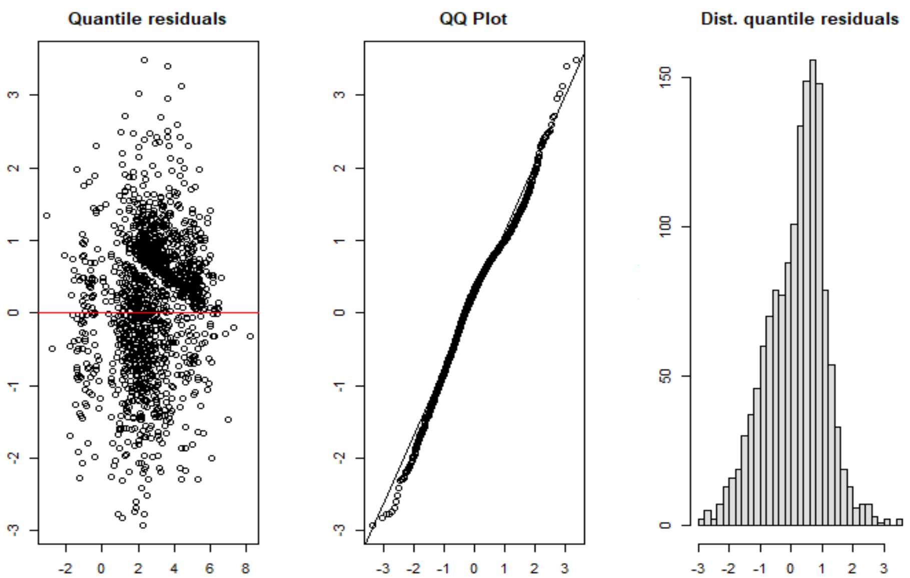

Figure 5.15. Scatterplot of the residuals vs. fitted values (left panel); normal probability plot of residuals (middle panel); distribution of the quantile residuals (right panel) obtained in Model 8.

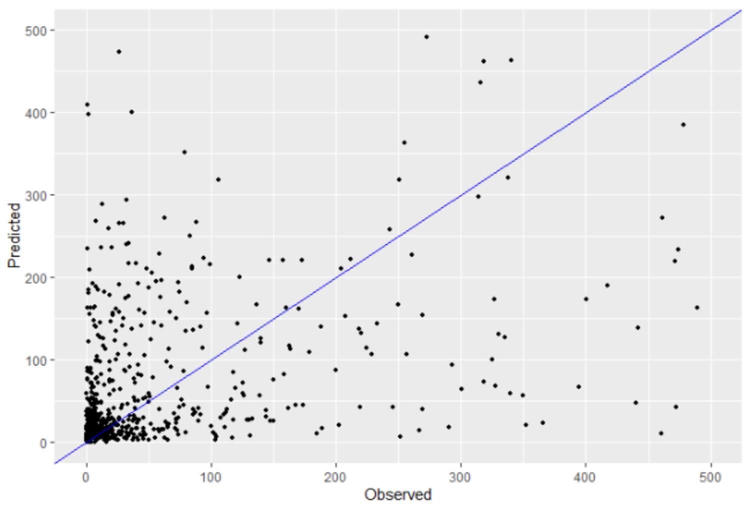

Figure 5.16. Scatterplot of the predicted values against the observed DPUE for Model 8.

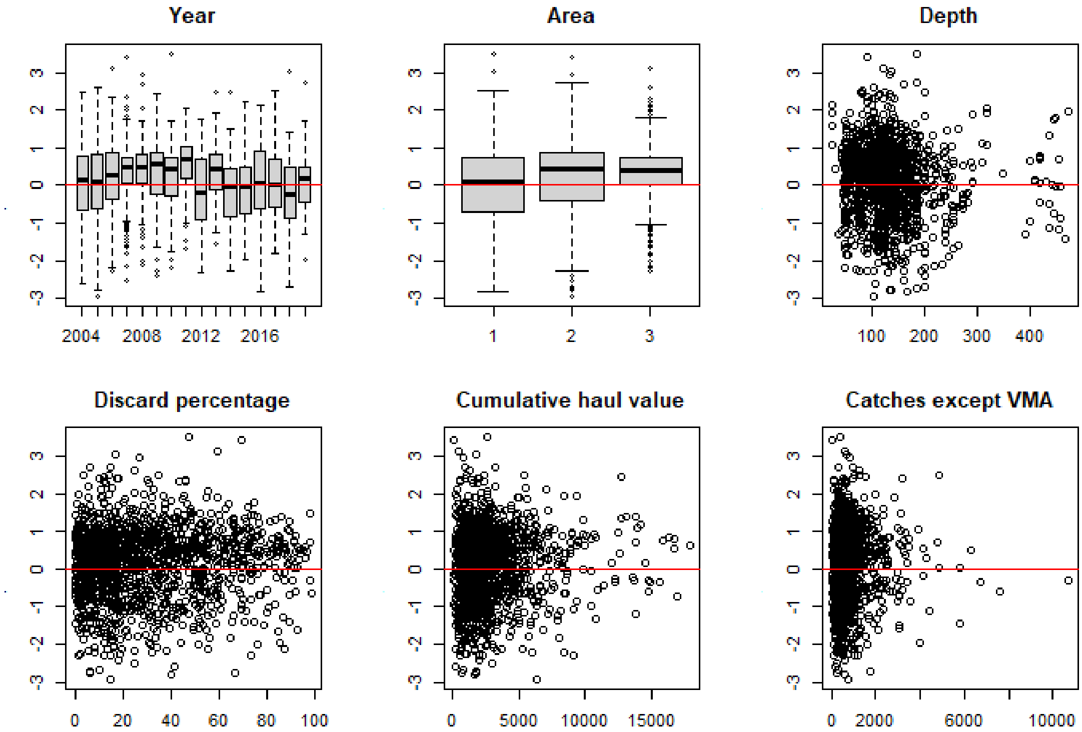

Figure 5.17. Scatterplots of the residuals for each explanatory variable included in Model 8.

The comparison performed between model index values and the nominal series did not include Model 11 because it presented the lowest deviance explained (25%) nor Model 13 given that its results were very similar to Model 8. For each model considered (Models 8, 9, 10 and 12), the DPUEs were scaled by the mean value of the model to remove the year effect and facilitate the comparison. The results are presented in Figure 5.18 and show three different trends. One that comprises models 9, 10 and 12 that, having the same deviance explained, also present overlapping trends, another for the nominal series and at last the model 8 trend that is placed between the other two in the periods 2005-2011 and 2016-2018 and is very similar in the remaining periods.

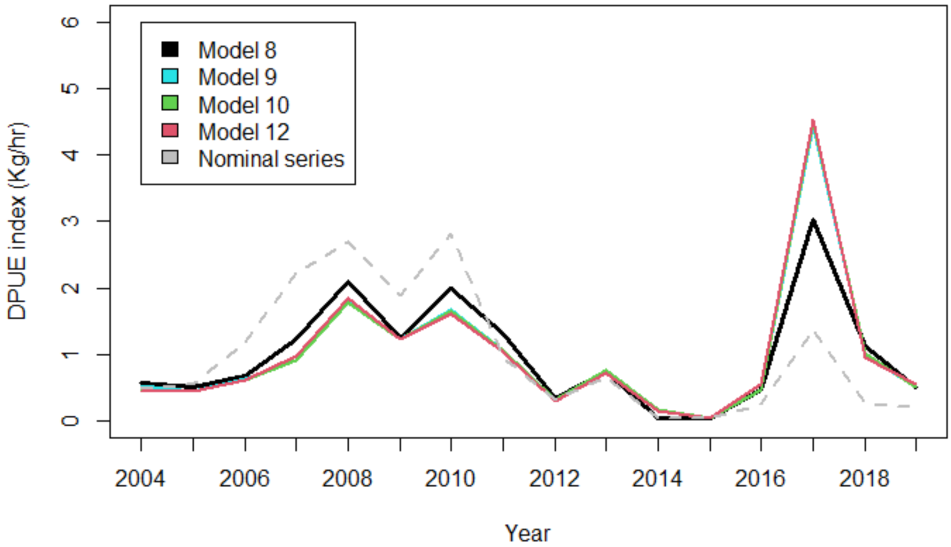

Figure 5.18. Standardized DPUEs of *S. colias* obtained from each of the models (8, 9, 10, 12) and of the nominal series, obtained for the bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019.

5.5 Total annual discards

The standardized DPUE series obtained from model 8 was used to estimate annual discards. A simple discard raising procedure where the annual mean DPUE is multiplied by the fleet effort (total fishing hours) was used, instead of the design-based discard estimation procedure routinely used (Jardim and Fernandes, 2013). In this procedure, a mean DPUE per trip is raised to the reported fishing effort weighted by trip duration (logbooks) and then summed to obtain the annual estimate. Also, the stratified cluster discard estimates resulting from the approach presented in Fernandes *et al.* (2021) for the period 2012-2015 - where a similar design-based estimation is performed but with a cluster stratified mean DPUE instead - are included for comparison among approaches (Figure 5.19).

The annual discard estimates obtained from the model-based approach (standardized DPUE from model 8) present a similar variation in most years when compared to the fleet-based estimates (Figure 5.19). Differences can be observed for the years 2004-2005, 2011 and in 2017, where the fleet-design based approach doubled the discard volume of the one obtained with the model-based approach. Regarding the stratified cluster design-based estimation, which was considered the best discard raising procedure (Fernandes *et al.*, 2021), the period with discard estimates currently available (2012-2015) shows the same pattern but with lower discard values.

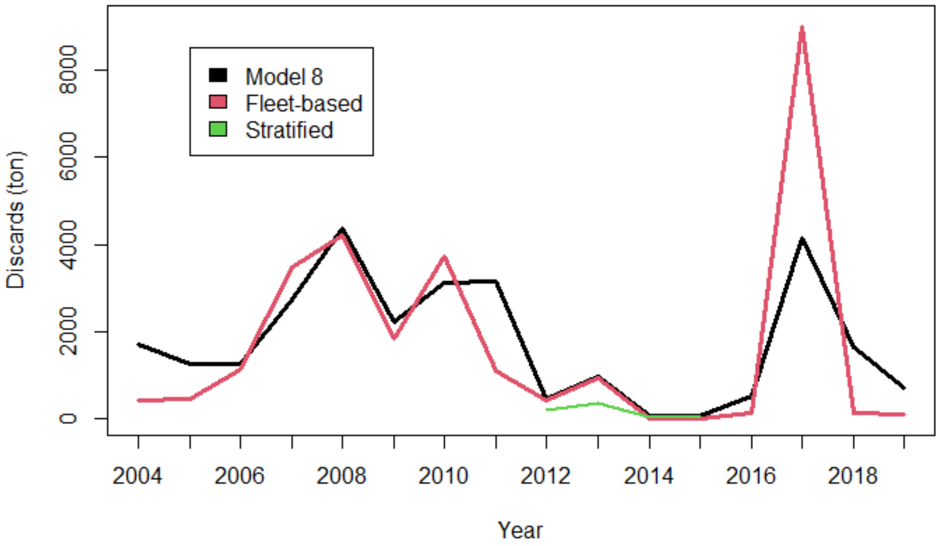

Figure 5.19. Annual discard estimates obtained from the discard raising procedures using standardized DPUE from Model 8 (black line), annual fleet-based (red line), reported in several working groups, and stratified cluster-based discard estimates (green line), reported in Fernandes *et al.* (2021).

5.6 Conclusions and Recommendations

- The DPUE standardization using the Tweedie distribution seems to be a good approach for deriving annual discard estimates when large number of zeros are present in the data.
- Improvements on annual discard estimates can be obtained using the model-based approach when dealing with occasionally discarded species (high percentage of zeros in the dataset)
- More models can be explored, considering different combinations of predictors or including other new predictors, to evaluate further improvements in the outputs.
- A factor relating each haul to the trip duration in the model-based approach (number of days as used in the design-based approaches) should be included to improve the precision and accuracy of the model-based annual discard estimates.
- The comparison among the three discard raising approaches (fleet design-based, cluster stratified design-based and model-based) for obtaining annual discards should account for the precision and accuracy of the estimates, especially in what relates to less frequent or rare species.
- The cross-validation procedures should be performed for evaluating the performance of the three different methods used in the discard raising at fleet level.

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6 CASE STUDY 4: EUROPEAN HAKE (*MERLUCCIUS MERLUCCIUS*)

6.1 Introduction

Southern hake *Merluccius merluccius* stock comprises the Atlantic coast of Iberian Peninsula corresponding to the ICES Divisions 8.c and 9.a. This stock is one of the most important target species for the fleets operating in the Atlantic coast of the Iberian Peninsula and is caught in a mixed fishery by the Spanish and Portuguese fleets that include trawls, pair-trawls, gillnetters, longliners and artisanal fleets. In the Portuguese continental waters (Division 9.a) hake is caught by the Portuguese fleet in the trawl and artisanal mixed fisheries together with other fish species and crustaceans. These include horse mackerel, anglerfish, megrim, mackerel, chub mackerel, blue whiting and the crustacean red shrimp, rose shrimp and Norway lobster. The Portuguese trawl fleet comprises two distinct components - the trawl fleet catching demersal fish (55 mm mesh size) and the trawl fleet targeting crustaceans (70 mm mesh size). The fleet targeting fish species operates along the entire Portuguese coast mostly at depths between 100 and 200 m. The trawl fleet targeting crustaceans operates mainly in the southwest and south in deeper waters, from 100 to 750 m. Historical information and details on the southern hake catches by country and gear for the period 1972-2019 is available at ICES (2020).

In 2003, the International Council for the Exploitation of the Sea (ICES) classified the stock as being outside safe biological limits and advised a rebuilding plan. Accordingly, a recovery plan was introduced by the European Commission in 2006 aiming at rebuilding the stock to safe biological limits. After a recovery plan that improved the spawning-stock biomass to levels above the B_{pa} and $MSY_{Btrigger}$ biological reference points, the stock is currently managed under the EU multiannual plan for Western Waters and adjacent waters (EU, 2019). The plan predicts the use of the concept of "Pretty Good Yield" (Hilborn, 2010), materialized by a range around F_{MSY} that would also allow for more flexibility in mixed fisheries management with advised hake catches between the estimated F_{MSY} ranges.

Since 2010, based on the decisions of ICES (2010,2014) a length-based model with GADGET ("Globally applicable Area Disaggregated General Ecosystem Toolbox") is used to perform the stock assessment. The model uses the Spanish and the Portuguese IBTS ("international Bottom Trawl Surveys) surveys to tune the model, by fitting the model estimates to the observed length proportions and abundance trends. In addition, two CPUE series are also used as relative abundance indices to tune the model. The two fleets included in the assessment model are the Coruna trawlers CPUE (from 1985 to 2012) and the Portuguese trawlers standardized CPUE (from 1989 to 2019).

In 2019, the GADGET model showed a more severe non-precautionary retrospective bias – overestimation of the spawning stock biomass and underestimation of the fishing mortality – and, in 2020, it was not accepted for stock assessment and advice this year. Without an analytical assessment, the Spanish IBTS survey and the Portuguese LPUE were the only series available to make an ICES Category 3 advice calculation, that requires a stock-size indicator with representative trends having, at least, the last 5 years available (ICES, 2019). The Portuguese IBTS survey index was not considered because the survey was not conducted in the last two years. These circumstances promoted the Portuguese LPUE series as one of the main trend series to guide the scientific advice for this important stock.

Following the previous work of Cardador and Jardim (2010), we re-evaluate the current LPUE methodology used for advice and provide guidance on additional methodologies for estimating an abundance index based on commercial catch-effort data, namely the use of the Least-Square means method (LS means) providing an alternative prediction from the standardized LPUE series.

6.2 Exploratory data analysis

In this study the LPUE – referred in this section as CPUE – is estimated based on the effort data (tow duration in hours) and respective landings series (in kg) collected from Portuguese logbooks and compiled by IPMA from 1992-2019. This latest series used in the present study is based on a renewed extraction of the complete logbook dataset housed in the DGRM (Portuguese administration) databases, which includes both paper and e-logbooks. From 2003 discards on this species are also available from the work of the Portuguese Discard Sampling Programme, based on a quasi-random sampling of co-operative commercial vessels from the crustacean and fish trawl fleets. Discard data were not evaluated and therefore not included in the CPUE analysis.

The logbooks selected are those from trawlers with at least one hake catch record and including all the other species caught. The removal of hauls with zero catch, contrasts with the methodologies described in the other sections of this report (e.g., see section 2.2.4) and decreased the logbook entries available for analysis from more than 500,000 to n=71,015. The daily records include the ICES statistical rectangles from a spatial grid (with intervals 30´ latitude and 1º longitude) covering the Portuguese continental coast. ICES rectangles were assigned to geographical zones: North, Southwest and South (Figure 6.1) and missing rectangles were assigned to an area designated by “x”.

Additionally, data on the main characteristics of each trawler are also selected for the CPUE standardization model: engine power (xpot in kW), gross registered tonnage

(GRT in tonnes), length-over-all (m). On each record, trawling hours (hours), total catch, catch of hake, catch of hake/total catch (phke) are computed per day and a metier type (HOM, CEF, WHB and MIX) is also assigned to each record, following the methodology in Silva et al. (2009).

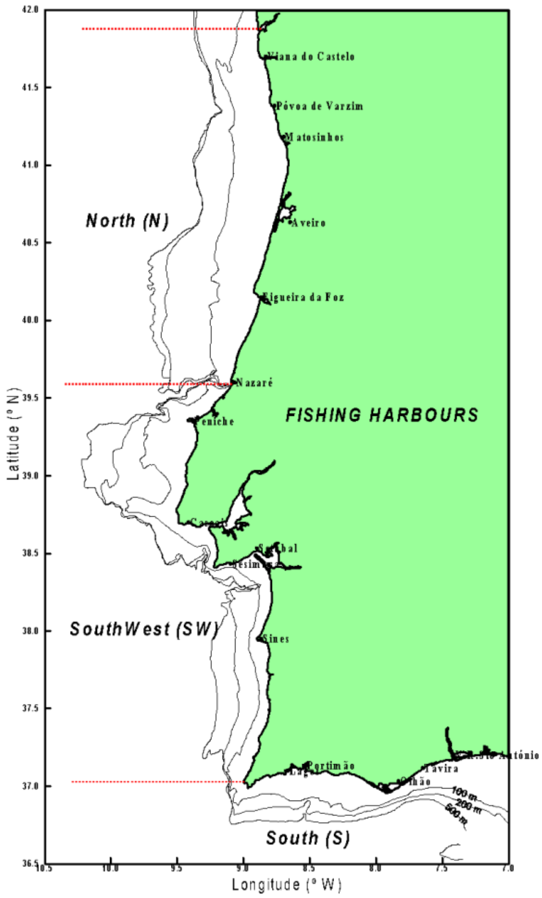

Figure 6.1. Geographical areas in Portuguese continental coast (adapted from Cardador and Jardim, 2010).

Explanatory variables were analysed (e.g., significance, collinearity) and Cardador and Jardim (2010) decided to use engine power as the main factor that influence the catchability of the vessel, as this variable is also highly correlated with gross tonnage and length overall (LOA). Following the exploratory analysis, the selected variables were categorized with the following levels:

Year – 1989 : 2019

Zone – n, sw, s and x

Cla.xpot (kW) – (500,600], (600,700], (700,800], (800,900]

Metier – HOM, CEF, WHB, MIX

cat_phke – 0-10%, 10-25%, 25-100%

cat_catch (kg) – (1, 150], (150, 400], (400, 1000], (1000, 3000], (3000, 8000], >8000 kg

cat_hours – (1-4], (4-8], (8-12], (12-16], (16-20]

Figure 6.2 shows the CPUE distribution across all levels of the relevant factors; engine power (cla_xpot), métier type, fishing zone, percentage of hake (cat_phke) and tow duration (cat_hours). Very high CPUE values are observed in 2013 to 2015 when compared with the rest of the dataset (Figure 6.2a). The engine power time series indicates a major increase in recent years for levels (500-600]kW, (700-800]kW and (800,900]kW (Figure 6.2b). Considering the fishery type, hom and mix métiers have the biggest CPUE values along the time series (Figure 6.2c). At the beginning of the series and until 2005, area n showed higher CPUE values when compared with the other areas, however in recent years, areas S and SW showed a significant increase, reaching maximum CPUE values (Fig. 6.2d). The percentage of hake in the catch shows an increasing trend along the years, with (0-10]% and (10-25]% the levels with the biggest CPUEs values (Fig. 6.2e). The trawling hours category has considerable variation among levels. The level (0-4]hour has the higher mean value along the time series and shows a significant peak in 1990 (Fig. 6.2f).

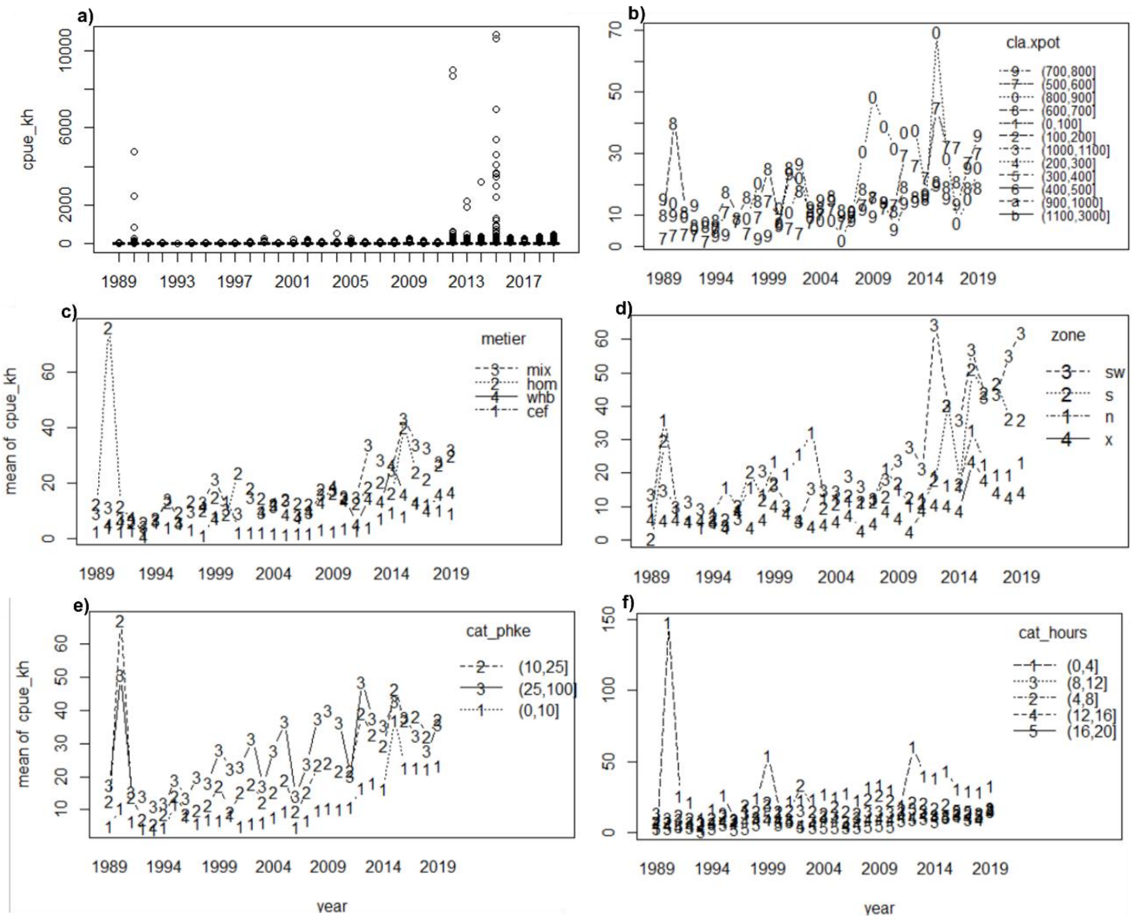

Figure 6.2. Interaction plots of CPUE (kg/hr) by (a) year, (b) category of engine power (cla.xpot) (c) métier, (d) fishing areas (zone), (e) percentage of hake in the catch (cat_phke) and (f) tow duration (cat_hours).

6.3 Model fitting and predictions

The hake standardized CPUE from the Portuguese bottom-trawl fleet targeting roundfish has been routinely calculated each year in the advice working group by fitting a Generalized Linear Model (GLM, annex 1) to logbook data on landings and effort, following the methods described in Cardador and Jardim (2010). Modelling was performed in the R environment (V.4.0.3, http://www.r-project.org/) using the glm routines (R Core Team, 2020).

The nominal hake CPUE distribution is highly skewed, and the standard deviation increases with the mean approximately proportionally. In these circumstances, the gamma distribution with a log link function was found to be appropriate for the response variable. The modelling strategy consisted of a stepwise procedure that started by testing the significance of the explanatory variables followed by the inclusion of first order interactions. The variables (and potential interactions) retained were those with more than 1% contribution to the overall variance. The final standardized CPUE GLM with the gamma distribution and log link function is expressed as:

ln [E (CPUE)] ~ year + zone + clax.pot + metier + cat_phke + cat_catch + cat_hours

The model fitted to the full 1989-2019 dataset with the following parameter estimates (the model intercept represents the overall mean referred to the first level of each factor):

```
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.732545   0.082850   8.842  < 2e-16 ***
year1990            -0.059733   0.096825  -0.617   0.5373
year1991            -0.164278   0.133412  -1.231   0.2182
year1992            -0.232976   0.097827  -2.382   0.0172 *
year1993            -0.423818   0.107624  -3.938 8.23e-05 ***
year1994            -0.230437   0.118796  -1.940   0.0524 .
year1995             0.003298   0.106847   0.031   0.9754
year1996            -0.091263   0.113535  -0.804   0.4215
year1997             0.065934   0.121321   0.543   0.5868
year1998            -0.097101   0.102482  -0.947   0.3434
year1999             0.091480   0.093557   0.978   0.3282
year2000            -0.244676   0.137024  -1.786   0.0742 .
year2001             0.003899   0.117409   0.033   0.9735
year2002            -0.014132   0.088730  -0.159   0.8735
year2003            -0.103363   0.075907  -1.362   0.1733
year2004            -0.105174   0.074841  -1.405   0.1599
year2005            -0.034807   0.075470  -0.461   0.6447
year2006            -0.101339   0.088753  -1.142   0.2535
year2007            -0.147173   0.072141  -2.040   0.0413 *
year2008             0.036093   0.072535   0.498   0.6188
year2009            -0.027032   0.074146  -0.365   0.7154
year2010            -0.025281   0.075026  -0.337   0.7361
year2011            -0.016675   0.078340  -0.213   0.8314
year2012             0.156956   0.073918   2.123   0.0337 *
year2013             0.100625   0.074307   1.354   0.1757
year2014             0.079381   0.075539   1.051   0.2933
year2015             0.353386   0.075103   4.705 2.54e-06 ***
year2016             0.072427   0.075054   0.965   0.3345
year2017             0.007444   0.075736   0.098   0.9217
year2018             0.033540   0.075300   0.445   0.6560
year2019             0.059481   0.075204   0.791   0.4290
zones                0.194395   0.021898   8.877  < 2e-16 ***
zonesw               0.262188   0.017927  14.625  < 2e-16 ***
zonex               -0.137733   0.025434  -5.415 6.14e-08 ***
cla.xpot(600,700]    0.040103   0.020321   1.973   0.0484 *
cla.xpot(700,800]   -0.054629   0.023262  -2.348   0.0189 *
cla.xpot(800,900]    0.201360   0.039202   5.137 2.81e-07 ***
metierhom            0.241728   0.035908   6.732 1.69e-11 ***
metiermix            0.283914   0.033891   8.377  < 2e-16 ***
metierwhb           -0.170927   0.072516  -2.357   0.0184 *
cat_phke(10,25]      1.016013   0.016165  62.852  < 2e-16 ***
cat_phke(25,100]     1.776858   0.023196  76.602  < 2e-16 ***
cat_catch(5,6]       0.881720   0.030014  29.377  < 2e-16 ***
cat_catch(6,7]       1.699591   0.030343  56.012  < 2e-16 ***
cat_catch(7,8]       2.388133   0.032527  73.419  < 2e-16 ***
cat_catch(8,9]       2.835697   0.038843  73.004  < 2e-16 ***
cat_catch(9,12]      3.188370   0.087372  36.492  < 2e-16 ***
```

```
cat_hours(4,8]     -0.865484   0.024028 -36.020  < 2e-16 ***
cat_hours(8,12]    -1.262385   0.026796 -47.112  < 2e-16 ***
cat_hours(12,16]   -1.596604   0.031288 -51.029  < 2e-16 ***
cat_hours(16,20]   -1.888436   0.037823 -49.929  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null deviance: 90376  on 71015  degrees of freedom
Residual deviance: 28941  on 70965  degrees of freedom
AIC: 492030
```

The model fitted explains 68% of the overall variability, total catch factor has the highest contribution, followed by trawling hours, zone and percentage of hake. The metier and engine power have the lower contribution in the variability explained. These results are very similar to the ones observed in Cardador and Jardim (2010).

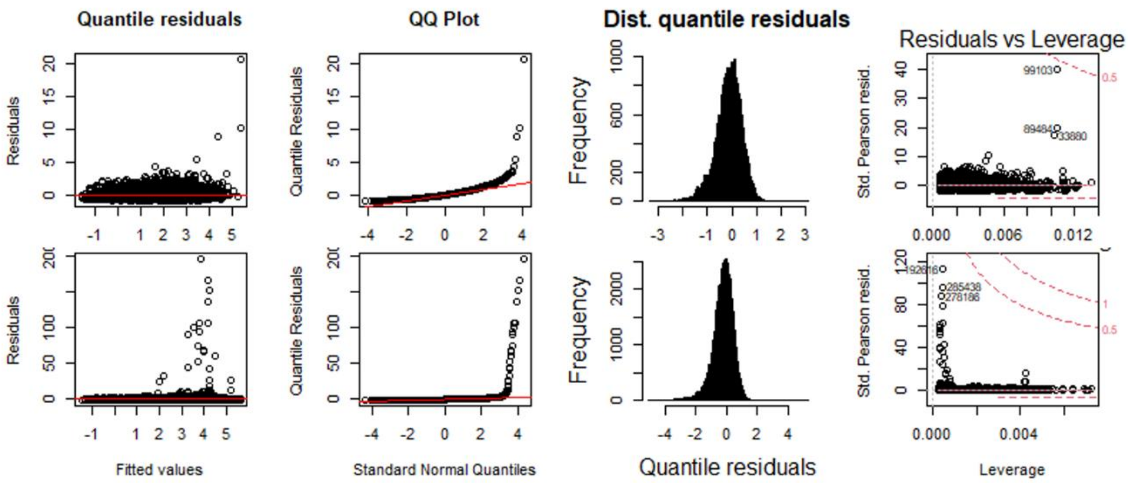

Figure 6.3. Residual analysis. On the upper panels, the residuals of the GLM model using the 1989-2008 dataset as fitted by Cardador and Jardim (2010) and on the bottom the residual analysis of the full dataset GLM fit. The plot on the left represents the values of the residuals along the predicted (log) values, followed by the quantile-quantile plot, the distribution of quantile residuals and the plot on the right represent the leverage analysis of the residuals.

The residuals of the GLM model using the 1989-2008 dataset as fitted by Cardador and Jardim (2010) are shown in the upper panels of Figure 6.3 and the residuals of the GLM fit with the complete dataset (1989-2019) are shown in the lower panels of Figure 6.3. In terms of model validation, the residual analysis, including the residuals distribution along the fitted values and the quantile-quantile (QQ) plots, showed that the 1989-2008 GLM model is in general adequate, although with a presence of some potential outliers. However, according to the leverage analysis these are not influential observations on the overall fit. The residual analysis of the model with the complete dataset shows a bigger number of potential outliers (mainly the 2013-2015 observations as indicated in Figure 6.2), however these observations do not seem to influence the overall fit of the model. Although the model assumption seems to agree, the scale of these larger residuals have a visual impact on the model diagnostics, the removal of these observations (not shown) significantly improved the visual shape of the residuals distribution along the fitted values and the QQ plots for both dataset fits.

Reference "fleet" prediction *vs.* LS means prediction

Following the previous work of Cardador and Jardim (2010), we re-evaluate the proposed methodology that uses the predictions from a reference "fleet" on the standardized model to estimate the CPUE. The annual CPUE for advice is estimated from the predicted model considering a reference "fleet". This "fleet" is in fact a combination of reference levels in each factor of the GLM model and are as follows: zone = north, clax.pot = (500,600]kW, cat_phke = (10,25]%, cat_catch = (400,1000]kg, hours = (1-4) and metier = mix.

For comparison purposes with the reference "fleet" methodology, we also used the Least-Squares means method where predictions from the model are adjusted for the effects of year averaged over all the levels the selected variables. The Least-Squares means for the GLM were estimated using the *lsmeans* package (v. 2.30-0, Lenth, 2016) and *doBy* (v. 4.6.8, Højsgaard et al., 2014). The plots were designed using library *ggplot2* (v. 3.3.3 Wickham, 2009).

Table 6.1 summarizes the parameters (effects) estimated by the GLM procedure used for the predictions in the reference "fleet" method and using the LS means method. The effects from all the level/factors are lower in the LS means, indicating that the chosen "fleet" reference levels are above average when compared to the other levels for each factor. The factors cat_phke, metier and cat_catch achieved the higher differences.

Figure 6.4 shows the predicted CPUE with 95% confidence intervals using the LS mean method and the reference "fleet" estimated effects. The prediction in LS means has a significantly lower mean value, which can be explained by the combination of lower estimated effects in the factors with a higher contribution for the variability explained in the model. It is also noticeable that despite the difference in scale, the trajectory of the CPUE series is comparable and both series indicate similar temporal trends in the relative abundance of the stock.

Table 6.1. Parameter effects for the reference levels estimated by the standardized GLM model procedure and using the LS means method (year effect not shown).

Factor/level	Reference "fleet" prediction effects	LS means prediction effects
Zone n	0.733	0.250
cla.xpot(500,600]	0.733	0.250
metier mix	1.016	0.250
cat_phke(10,25]	1.749	0.333
cat_catch(0,5]	0.733	0.167
cat_hours(1,4]	0.733	0.200

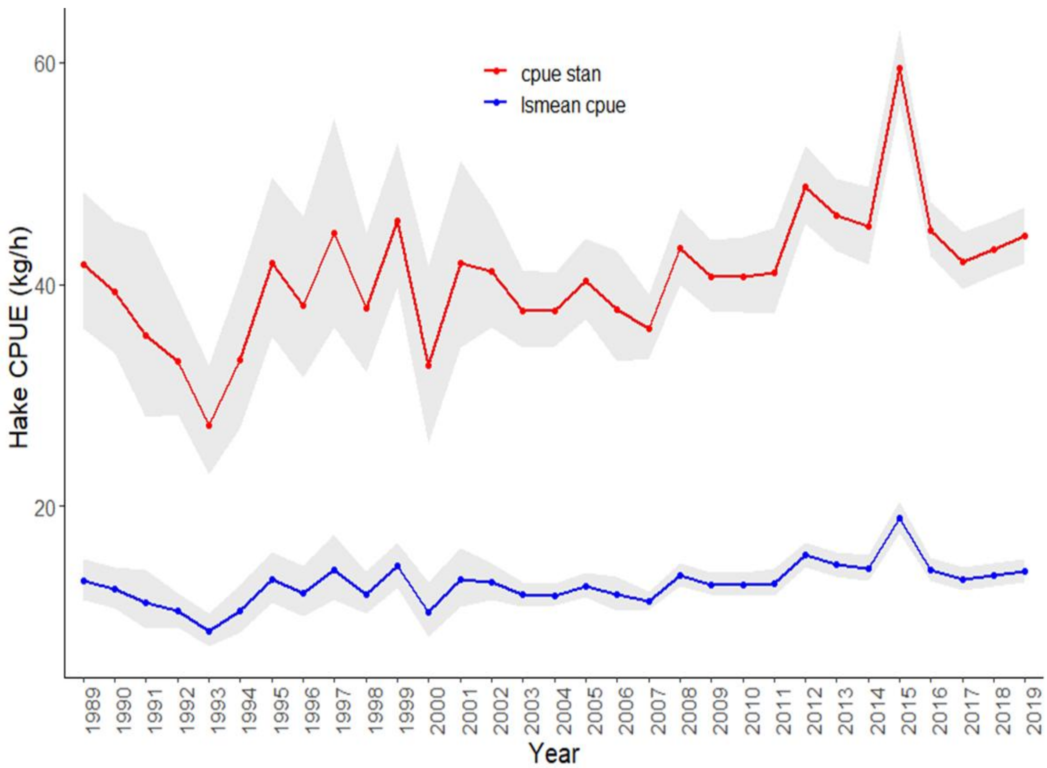

Figure 6.4. The red line indicates the CPUE estimated from the reference level/factors and the blue line the CPUE estimated by the lsmeans method with 95% confidence intervals (shaded area).

6.4 Discussion

This study re-evaluated with new data from 2009-2019, the work developed by Cardador and Jardim (2010) to build a standardised hake CPUE for the Portuguese trawl fleet between 1989 and 2008. The applied method of predicting the CPUE using reference levels from the variable factors of the standardized CPUE GLM model is not very common in the literature. Recent advances in modelling techniques have also enabled the possibility of applying more complex models and statistical distributions that allows for frequent zero-value observations which are very common in commercial-catch logbook data.

The rationale behind the chosen reference levels is not entirely clear and some inconsistencies can be found in the available R script in the document and the proposed reference levels. However, Cardador and Jardim (2010) performed extensive analysis on the statistical differences and effects on the CPUE for each level/factor arrangement. The proposed reference levels suggest a combination of expert judgment and the level/factor with more representation in the 1989-2008 dataset (e.g. zone north, metier mix) to allow the abundance index to be estimated with more data. It was argued that the chosen reference levels better describe the relevant trip strategies (e.g. inclusion of a percentage of hake factor) and improved the adjustment of the main effects model and CPUE comprehension. Additionally, correlations were found between the CPUE series and the biomass indices from the Portuguese Winter and Autumn groundfish surveys, which also gave confidence that the predicted CPUE using reference levels was reflecting the abundance of hake in Portuguese waters.

In this study we also used the LS means method to predict from the standardized CPUE GLM model. When comparing the CPUE series estimated by the predictions from the reference "fleet" and the LS means method, there were noticeable differences in the mean value. These differences were to be expected given the different levels used for predictions in both methods but also amplified by some changes in the fleet behaviour between 2009-2019 (increased importance of area SW and S when compared to North). Interestingly enough and despite having larger differences in the mean, both CPUE series have very similar temporal trends that are probably explained by the chosen reference levels which seems to be representative of the overall effects of the factors total catch, percentage of hake and trawling hour, factors which also have larger contributions in the explained model variability. If using the LS means, the annual series would show an intermediate prediction compared to all possible combinations when using reference levels.

The CPUE is a relative abundance index, where the dynamics of the series is more important than the magnitude, and despite the changes in the fleet behaviour, the chosen reference level/factor are still capable to capture the abundance dynamics of hake.

6.5 Conclusions and Recommendations

One interesting feature of the methodology developed by Cardador and Jardim (2010) re-evaluated in this study, is the inclusion of reference levels in the selected variable factors of the standardized CPUE GLM model. This methodology is not very common in the literature and recent advances in modelling techniques, computational power and optimization routines have enabled the possibility of applying more complex models and statistical distributions that allows for frequent zero valued observations which are very common in commercial-catch logbook data. These new techniques and advances, suggest the exploration of alternative methods to estimate an abundance index for hake, where the information provided by the zero valued observations can be taken into account.

The recent changes in the hake spatial distribution of catches and fleet behaviour suggest that the reference level/factors should be updated if using the current advice CPUE reference “fleet” methodology.

6.6 References

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7 RECOMMENDATIONS FOR FUTURE WORK

The following recommendations for CPUE standardization and future work are provided:

- Model diagnostics: Model diagnostics are fundamental to validate and compare models. In the work provided here we explore some diagnostics including goodness-of-fit measures and residual analysis. Future work could explore additional diagnostics, such as for example cross validation procedures to determine the predictive capacity of the models;

- Environmental variables: The inclusion of environmental variables in the CPUE standardization contributes to improving the models, which has been shown in simulation work for oceanic species. As such, future work could be to explore the feasibility of including such variables in the case studies that are now being developed mostly for coastal species;

- Targeting effects: Catch related explanatory variables, not truly independent from the response variable, should be avoided as e.g. proxies of target fishing based on the actual catch numbers or proportions of the species in the response variable. Instead, it might be possible to explore clustering methods using the catch composition by species to find fishing clusters that may be used as covariates in model fitting;

- Model complexity: Increasing model complexity by including many variables should be avoided. Expert knowledge of the data and the fishery should be used to consider testing only variables for which there is a good reason *a priori* to expect a relationship with the response variable.

8 ANNEX 1: GLM AND GLMM MODELS WITH THE TWEEDIE DISTRIBUTION

GLM model

The GLM model (McCullagh and Nelder, 1989; Agresti, 2002) can be noted as:

$$\eta(Y_i) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_k x_{k,i} + \varepsilon_i$$

Where η represents the link function, x_i the model variables, *β* the model coefficients (estimated by maximum likelihood), and *ε* represents the errors.

GLMM model

The GLMM model can be defined as:

$$\eta(Y_{ij}) = \beta_0 + \beta_1 x_{1,ij} + \beta_2 x_{2,ij} + \cdots + \beta_k x_{k,ij} + a_j + \varepsilon_{ij}$$

Where η represents the link function, x_i the model fixed effects variables, *β* the model coefficients (usually estimated by penalized quasi-likelihood (Venables and Ripley, 2002) or Laplace approximations (Bolker et al., 2008)), *a* represents the random variable with a distribution defined by $a \sim N(0, \sigma^2)$, and *ε* represents the errors.

Tweedie distribution

The Tweedie distribution is part of the exponential family of distributions (Dunn, 2004), and is defined by:

$$E(Y)=\mu$$

$$Var(Y)=\varphi \times \mu \hat{} p$$

In which *φ* is the dispersion parameter and *p* is the index parameter.

When the index (*p*) parameter has values between 1 and 2, the distribution is continuous for positive real numbers, but has an added discrete mass at 0, which seems appropriate to model CPUE data (continuous data with an added mass of zeros). In this case, the distribution is also called a compound Poisson-Gamma distribution. To define this, the index parameter is calculated externally to the models, by maximizing the likelihood profile function of possible values of *p* between 1 and 2. The Figure 1 below provides the shapes of some Tweedie distributions for different p-indices, including cases with the p-index between 1 and 2 (examples of compound Poisson-

Gamma) and with p-index values higher than 3 (example of a positive stable distribution).

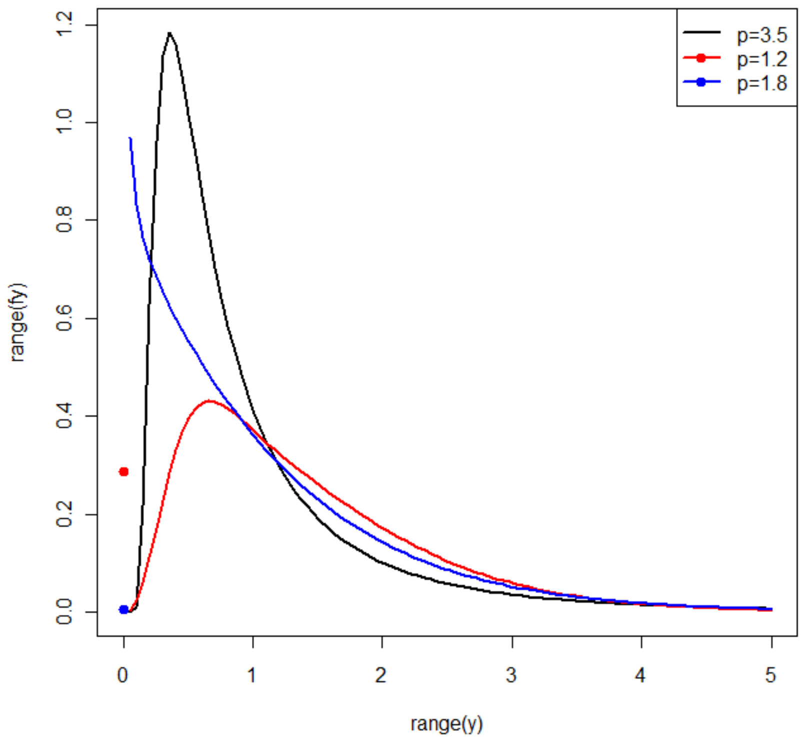

Figure A1.1. Shape of several Tweedie distributions for various p-index values (as defined inside the figure legend). In this figure, the other parameters are kept constant on all distributions (μ =1, φ =1).

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9 ANNEX 2: ADDITIONAL MATERIALS FROM CS3

Section A - GAM plots for the explanatory continuous variables selected for the model evaluation

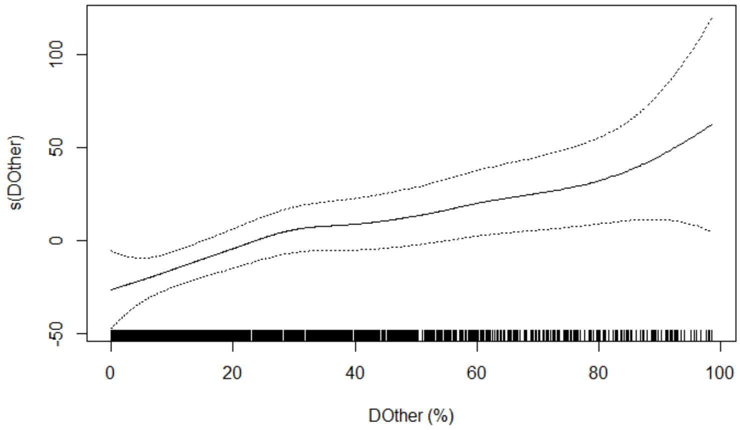


Figure A2.1. Shape of the explanatory variable 'DOther' obtained from the GAM using a Gaussian distribution

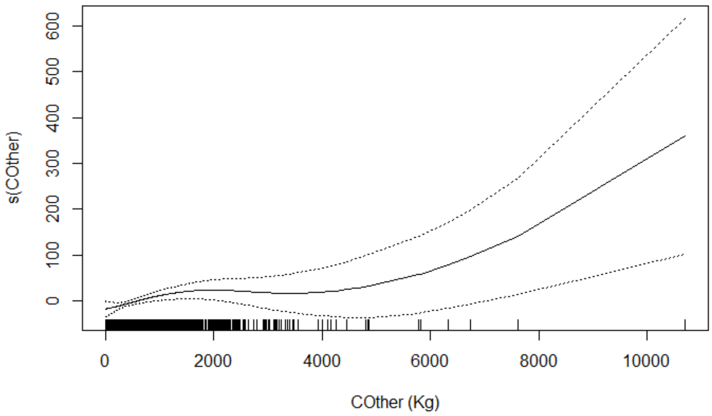


Figure A2.2. Shape of the explanatory variable 'COther' obtained from the GAM using a Gaussian distribution.

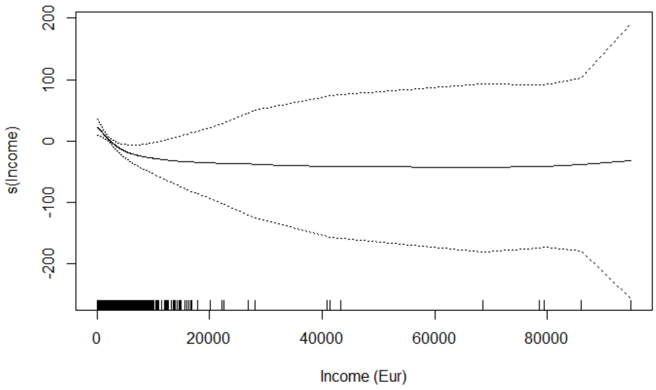


Figure A2.3. Shape of the explanatory variable 'Income' obtained from the GAM using a Gaussian distribution.

Section B - Correlation plot for the explanatory variables evaluated for the modelling

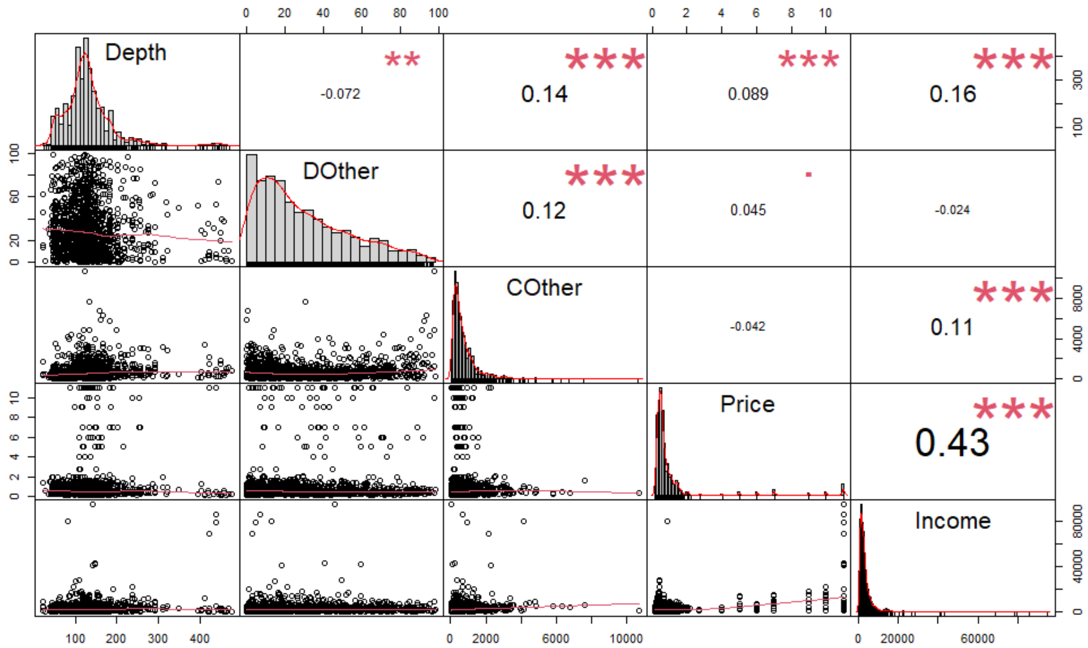


Figure A2.4. Correlation between continuous variables depth, discard percentage without VMA (DOther), catches without VMA (COther), VMA price (Price), cumulative haul value per trip (Income), in the sampled hauls from bottom trawl targeting demersal species (OTB_DEF), in the period 2004-2019. (symbols represent p-values: "***" - 0; "**" - 0.001; "*" – 0.05; ".": 0.1; and " ": 1).

Section C - Results obtained in the non-selected models

Model 9: *DPUE ~ year + area + depth + DOther + Income*

Table A2.1. Analysis of deviance table for the Tweedie Model 9.

Model 9	Df	Deviance	Resid. Df	Resid. Dev	F	P(F)	Deviance explained (%)
Null			1464	22949			
Year	15	2833.75	1449	20115	9.2099	< 2.2e-16	12
Area	2	2495.77	1447	17619	60.8356	< 2.2e-16	11
Depth	1	534.21	1446	17085	26.0431	3.783e-07	2.3
DOther	1	432.99	1445	16652	21.1085	4.718e-06	1.9
Income	1	14.86	1444	16637	0.7245	0.3948	0.6

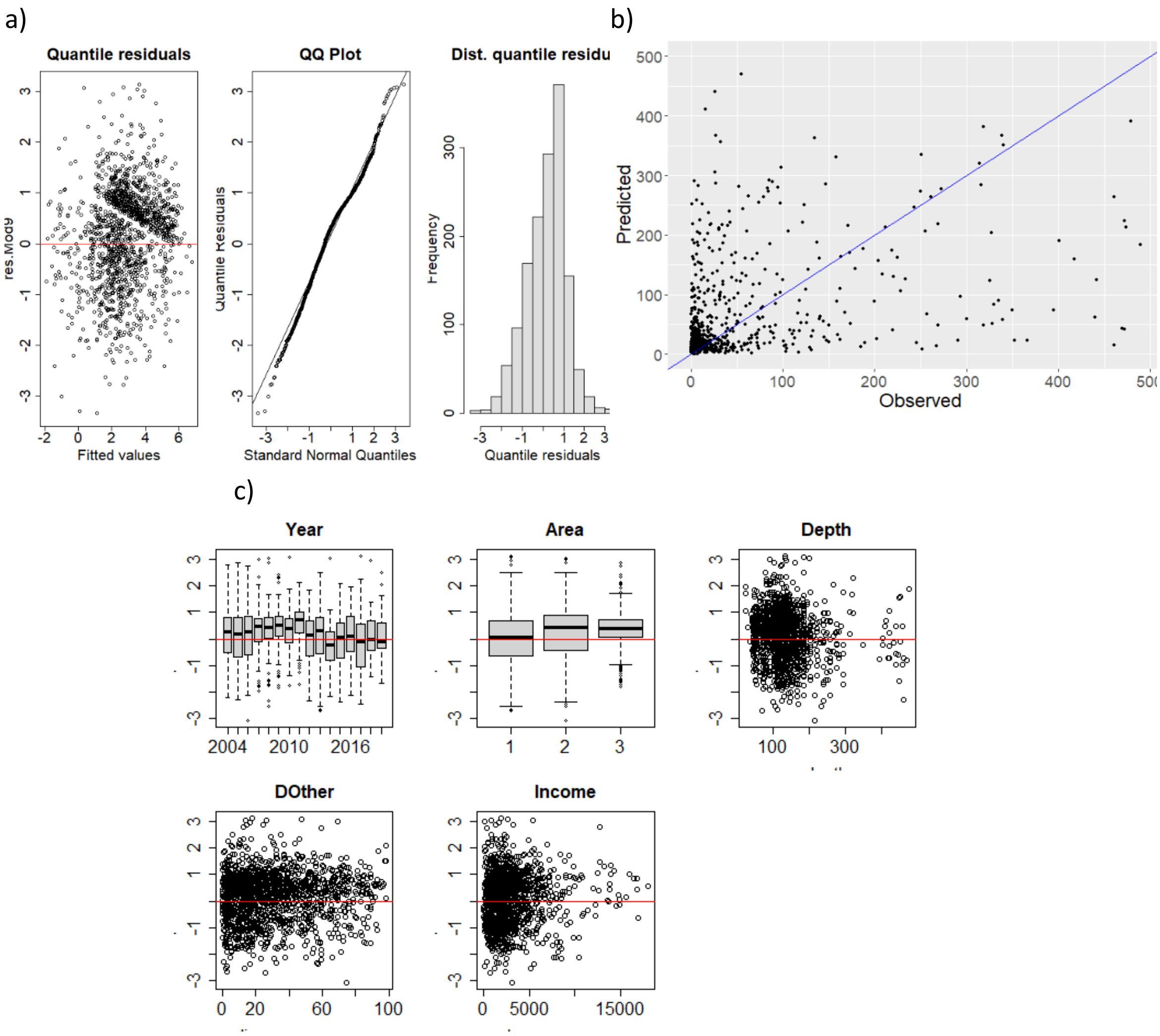


Figure A2.5. Outputs from the Model 9 analysis: a) Scatterplot of the residuals vs. fitted values (left panel); normal probability plot of residuals (middle panel); distribution of the quantile residuals (right panel); b) Scatterplot of the predicted from the model fit and the observed DPUE; c) Scatterplots of the residuals for each explanatory variable included in Model 9.

Model 10: *DPUE ~ year + area + depth + DOther*

Table A2.2. Analysis of deviance table for the Tweedie Model 10.

Model 10	Df	Deviance	Resid. Df	Resid. Dev	F	P(F)	Deviance explained (%)
Null			1464	22949			
Year	15	2833.75	1449	20115	9.147	< 2.2e-16	12
Area	2	2495.77	1447	17619	60.420	< 2.2e-16	11
Depth	1	534.21	1446	17085	25.865	4.141e-07	2.3
DOther	1	432.99	1445	16652	20.964	5.081e-06	1.9

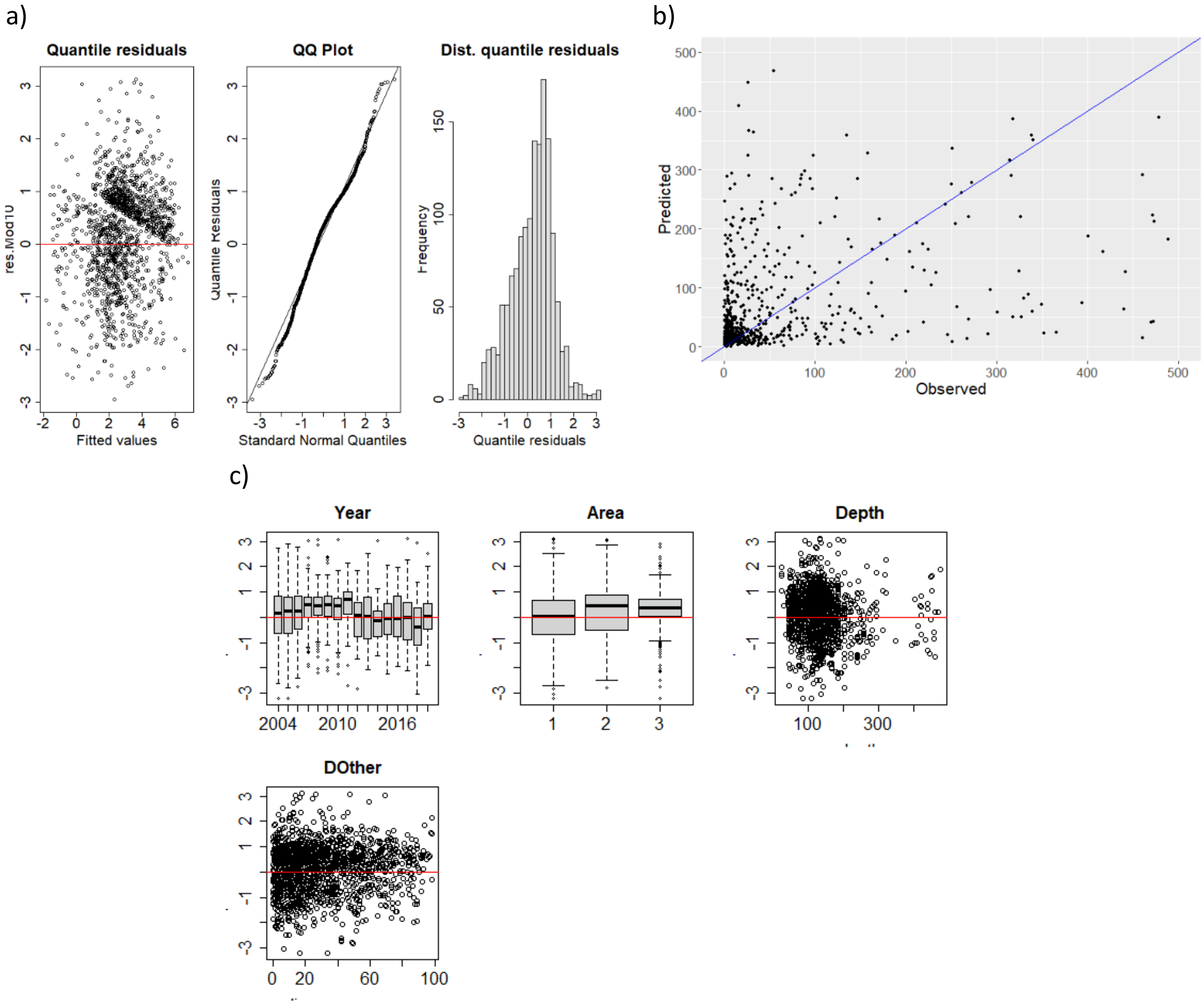


Figure A2.6. Outputs from the Model 10 analysis: a) Scatterplot of the residuals vs. fitted values (left panel); normal probability plot of residuals (middle panel); distribution of the quantile residuals (right panel); b) Scatterplot of the predicted from the model fit and the observed DPUE; c) Scatterplots of the residuals for each explanatory variable included in Model 10.

Model 11: *DPUE ~ year + area + depth*

Table A2.3. Analysis of deviance table for the Tweedie Model 11.

Model 11	Df	Deviance	Resid. Df	Resid. Dev	F	P(F)	Deviance explained (%)
Null			1464	22949			
Year	15	2833.75	1449	20115	8.906	< 2.2e-16	12
Area	2	2495.77	1447	17619	58.831	< 2.2e-16	11
Depth	1	534.21	1446	17085	25.185	5.855e-07	2.3

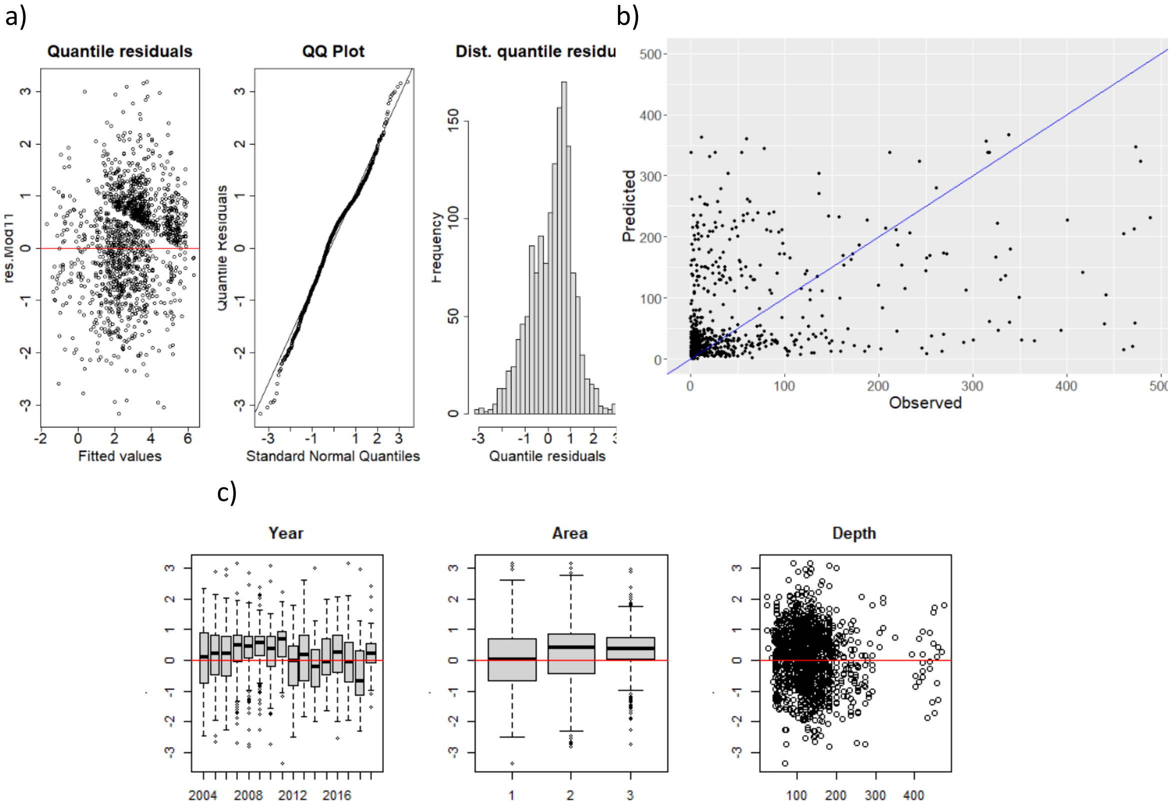


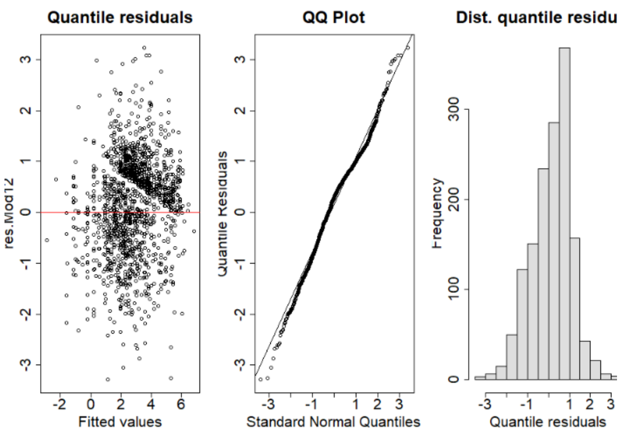
Figure A2.7. Outputs from the Model 11 analysis: a) Scatterplot of the residuals vs. fitted values (left panel); normal probability plot of residuals (middle panel); distribution of the quantile residuals (right panel); b) Scatterplot of the predicted from the model fit and the observed DPUE; c) Scatterplots of the residuals for each explanatory variable included in Model 11.

Model 12: *DPUE ~ year + area + fact(depth) + fact(DOther)*

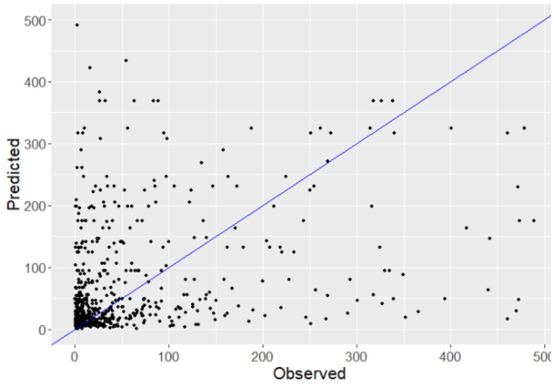
Table A2.4. Analysis of deviance table for the Tweedie Model 12.

Model 12	Df	Deviance	Resid. Df	Resid. Dev	F	P(F)	Deviance explained (%)
Null			1464	22949			
Year	15	2833.75	1449	20115	9.210	< 2.2e-16	12
Area	2	2495.77	1447	17619	60.836	< 2.2e-16	11
Fact(depth)	1	625.38	1444	16994	10.1628	1.264e-06	2.7
Fact(DOther)	1	366.03	1441	16628	5.9482	4.973e-04	1.6

a)



b)



c)

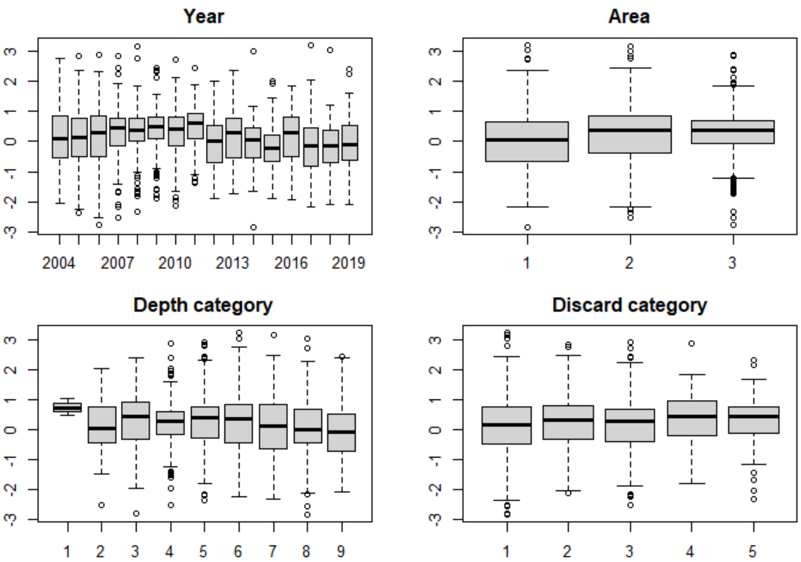


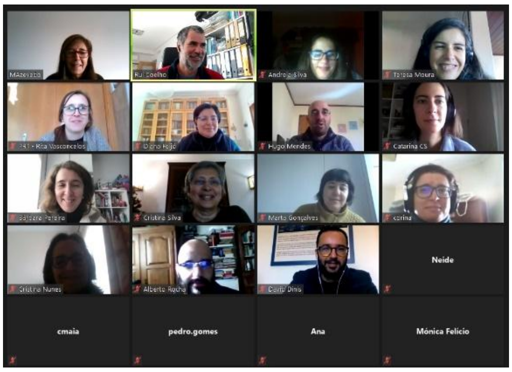
Figure A2.8. Outputs from the Model 12 analysis: a) Scatterplot of the residuals vs. fitted values (left panel); normal probability plot of residuals (middle panel); distribution of the quantile residuals (right panel); b) Scatterplot of the predicted from the model fit and the observed DPUE; c) Scatterplots of the residuals for each explanatory variable included in Model 12.

10 ANNEX 3: LIST OF PARTICIPANTS

CPUE Workshop Participant	E-mail
Alberto Rocha	arocha@ipma.pt
Alexandra Silva	asilva@ipma.pt
Ana Cláudia Fernandes	acfernandes@ipma.pt
Ana Moreno	amoreno@ipma.pt
Andreia V. Silva	avsilva@ipma.pt
Bárbara Serra-Pereira	bpereira@ipma.pt
Catarina Maia	cmaia@ipma.pt
Catarina C. Santos	catarina.santos@ipma.pt
Corina Chaves	corina@ipma.pt
Cristina Nunes	cnunes@ipma.pt
Cristina Silva	csilva@ipma.pt
Daniela Rosa	daniela.rosa@ipma.pt
David Dinis	david.dinis@ipma.pt
Diana Feijó	dfeijo@ipma.pt
Hugo Mendes	hmendes@ipma.pt
Inês Farias	ifarias@ipma.pt
Ivone Figueiredo	ifigueiredo@ipma.pt
Laura Wise	lwise@ipma.pt
Manuela Azevedo	mazevedo@ipma.pt
Marta Gonçalves	mgoncalves@ipma.pt
Monica Felicio	mfelicio@ipma.pt
Neide Lagarto	nlagarto@ipma.pt
Patricia Gonçalves	patricia@ipma.pt

Pedro Duarte Gomes	pedro.gomes@ipma.pt
Pedro Lino	plino@ipma.pt
Rita Vasconcelos	rita.vasconcelos@ipma.pt
Ruben Lechuga	ruben.lechuga@ipma.pt
Rui Coelho	rpcoelho@ipma.pt
Teresa Moura	tmoura@ipma.pt

IPMA, 3-5 November 2020 and 6-7 January 2021



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