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Application of Generalized Linear Models and Generalized Estimation Equations to model at-haulback mortality of blue sharks captured in a pelagic longline fishery in the Atlantic Ocean

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ABSTRACT

At-haulback mortality of blue shark (*Prionace glauca*) captured by the Portuguese pelagic longline fishery targeting swordfish in the Atlantic was modeled. Data was collected by onboard fishery observers that monitored 762 fishing sets (1 005 486 hooks) and recorded information on 26 383 blue sharks. The sample size distribution ranged from 40 to 305 cm fork length, with 13.3% of the specimens captured dead at-haulback. Data modeling was carried out with Generalized Linear Models (GLM) and Generalized Estimation Equations (GEE), given the fishery-dependent source of the data. The explanatory variables influencing blue shark mortality rates were year, specimen size, fishing location, sex, season and branch line material. Model diagnostics and validation were performed with residual analysis, the Hosmer–Lemeshow test, a receiver operating characteristic (ROC) curve, and a 10-fold cross validation procedure. One important conclusion of this study was that blue shark sizes are important predictors for estimating at-haulback mortality rates, with the probabilities of dying at-haulback decreasing with increasing specimen sizes. The effect in terms of odds-ratios are non-linear, with the changing odds-ratios of surviving higher for the smaller sharks (as sharks grow in size) and then stabilizing as sharks reach larger sizes. The models presented in this study seem valid for predicting blue shark at-haulback mortality in this fishery, and can be used by fisheries management organizations for assessing the efficacy of management and conservation initiatives for the species in the future.

1. Introduction

In the Atlantic Ocean several pelagic shark species are common bycatch on pelagic longline fisheries (e.g. Buencuerpo et al., 1998; Petersen et al., 2009; Simpfendorfer et al., 2002) but information on their life history, population parameters and the effects of fisheries on these populations is still limited. Generally, elasmobranchs have K-strategy life cycles, characterized by slow growth rates and long lives, and reduced reproductive potential with few offspring and late maturity. The natural mortality rates are usually low, and increased fishing mortality may have severe consequences on these populations with declines occurring even at relatively low levels of fishing mortality (Smith et al., 1998; Stevens et al., 2000). Of the several elasmobranch species caught in surface pelagic longline fisheries, the blue shark (*Prionace glauca*, L. 1758), is the most frequently caught species, and can represent more than 50% of the total fish catch, and 85–90% of the total elasmobranch catch (Coelho et al., 2012a).

Previous studies have focused elasmobranch mortality during fishing operations, with many carried out for coastal species caught in trawl fisheries (e.g. Mandelman and Farrington, 2007; Rodriguez-Cabello et al., 2005). For pelagic elasmobranchs, Campana et al. (2009) analyzed blue sharks captured by the Canadian pelagic longline fleet and studied both the short term mortality (recorded at-haulback) and the longer term mortality (recorded with satellite telemetry). Also for the NW Atlantic, Diaz and Serafy (2005) worked with data from the U.S. pelagic fishery observer program and analyzed factors affecting the live release of blue sharks. Additionally, several authors have addressed the possible effects of gear modifications such as hook style and leader material on both the catch rates and mortalities of pelagic elasmobranchs (e.g. Afonso et al., 2011, 2012; Kerstetter and Graves, 2006; Yokota et al., 2006).

Knowledge on the at-haulback mortality (recorded at time of fishing gear retrieval) can be used to evaluate conservation and management measures that include the prohibition to retain particular vulnerable species, such as those recently implemented

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by some tuna Regional Fisheries Management Organizations (tRFMOs). In particular and for the Atlantic Ocean, the International Commission for the Conservation of Atlantic Tunas (ICCAT) has recently implemented mandatory discards for the bigeye thresher (ICCAT Rec. 09-07), the oceanic whitetip (ICCAT Rec. 10-07), hammerheads (ICCAT Rec. 10-08) and silky sharks (ICCAT Rec. 11-08). However, at-haulback fishing mortality remains largely unknown, and therefore the efficiency of such measures also remains unknown. Considering that all specimens of these particular species are now being discarded, fishing mortality is still occurring due to at-haulback mortality, as part of the catch is already dead at time of fishing gear retrieval and is therefore being discarded dead (Coelho et al., 2012b).

At-haulback mortality studies are also important as they can be incorporated into stock assessments, such as the study by Cortés et al. (2010), which used an ecological risk assessment analysis for eleven species of elasmobranchs captured in pelagic longlines in the Atlantic Ocean. With this analysis, both the susceptibility and the productivity of each species are analyzed in order to rank and compare their vulnerability to the fishery. One of the parameters that can be included in the susceptibility component is the probability of survival after capture, which can in part be calculated from the mortality at-haulback.

This study had two main objectives: (1) to predict at-haulback mortality of blue sharks captured in the Portuguese pelagic longline fishery targeting swordfish in the Atlantic Ocean, comparing GLM and GEE models and, (2) to identify and interpret variables that significantly influence the blue shark at-haulback mortality rates.

2. Materials and methods

2.1. Data collection

Data for this study was collected by fishery observers from the *Portuguese Sea and Atmospheric Research Institute* (*IPMA*, *I.P.*) placed onboard Portuguese longliners targeting swordfish along the Atlantic Ocean. The fishing gear typically used by this fleet consists of a standard monofilament polyamide mainline set for fishing at depths of 20–50 m below the surface. Usually the line is set with five branch lines between pairs of buoys, with each branch line having approximately 18 m in length and a hook in the terminal tackle. The hooks used by the fleet are typically stainless steel J-style hooks, baited either with squid (*Illex* spp.) or mackerel (*Scomber* spp.). Both monofilament and multifilament wire branch lines are used, but only one type is used per fishing set. Gear deployment traditionally begins at around 17:00, with haulback starting the next day from about 06:00. Data was collected between August 2008 and December 2011, and during that period information from a total of 762 longline sets, corresponding to 1 005 486 hooks, was collected. The study covered a wide geographical area (from both hemispheres) of the Atlantic Ocean (Fig. 1).

For every specimen caught, the onboard fishery observers recorded the species, specimen size (FL, fork length measured to the nearest lower cm), sex and at-haulback condition (alive or dead at time of fishing gear retrieval). The condition of the sharks at fishing gear retrieval (alive or dead) was categorized based on any responsiveness from the sharks indicating that specimens were alive. For each longline set carried out some additional information was recorded, including date, geographic location (coordinates: latitude and longitude), number of hooks deployed in the set, and branch line material used (monofilament or wire). Sea Surface Temperature (SST) was interpolated from satellite data using the known date and location of each fishing set, applying the algorithm described by Kilpatrick et al. (2001), and using the Marine Geospatial Ecology Tools (MGET) developed by Roberts et al. (2010).

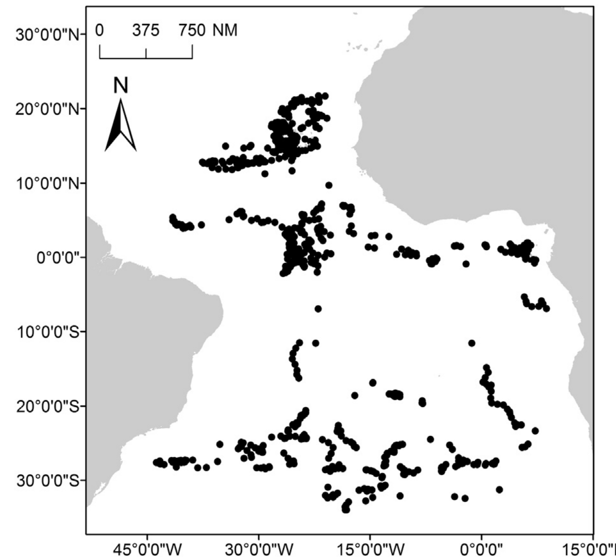

Fig. 1. Location of the longline fishing sets analyzed in this study along the Atlantic Ocean. The scale bar is represented in nautical miles (NM).

2.2. Description of the data

The length frequency distribution of male and female blue sharks was analyzed, and compared with a 2-sample Kolmogorov–Smirnov test and a Mann Whitney rank sum test. Those non-parametric tests were chosen after calculating the skewness and kurtosis coefficients, and confirming that the data were non-normal with a Lilliefors test. The proportions of dead and alive blue sharks were calculated for each level of each categorical variable (trip, sex, year, quarter, vessel, branch line material), and the differences in the proportions were compared with contingency tables and chi-square statistics (using Yates' continuity correction in the cases of 2×2 tables). For this preliminary contingency table data analysis, the continuous variables FL, latitude, longitude and SST were categorized by their quartiles.

2.3. Data modeling

Generalized Linear Models (GLMs) and Generalized Estimation Equations (GEEs) were used to model blue shark at-haulback mortality, and compare the odds of a shark being dead at-haulback given the various variables considered. The response variable was the condition of the specimens at time of haulback (Y_i: binominal variable, i.e., dead or alive), and for this study we considered that the event occurred if the shark died during the fishing operation. Therefore, the response variable was coded with 1 for sharks dead at-haulback and with 0 for sharks alive at-haulback.

Each captured shark (Y_i) follows a Bernoulli distribution with p_i (probability of success/dying at-haulback = π_i), and can be specified as:

$$Y_i \sim B(1, \pi_i)$$

With the expected value and the variance defined by:

$$E(Y_i) = \pi_i$$

$$Var(Y_i) = \pi_i \times (1 - \pi_i)$$

The relationship (link function) between the mean value of Y_i and the model covariates considered for this model was the logit, and the model was therefore defined by:

$$logit(\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_k x_{k,i}$$

where x_i are the model covariates and β are the coefficients that were estimated by maximum likelihood.

The explanatory variables initially considered were the specimen size (FL in cm), specimen sex, fishing location (latitude and longitude in decimal degrees), year (2008–2011), quarter of the year (4 quarters), vessel identity, branch line material (wire or monofilament) and SST (decimal degrees in °C).

The first modeling approach was carried out with GLMs. The univariate significance of each explanatory variable was determined by the Wald statistic and with likelihood ratio tests, comparing each univariate model with the null model. The significant variables were 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 covariates that had been eliminated in the first step were further tested, in order to determine an eventual significance within the framework of a multivariate model, as recommended by Hosmer and Lemeshow (2000). Once a final multivariate simple effects model was obtained, each pair of possible first degree interactions was tested. The interactions were considered for inclusion in the final model if comparison of models with and without interaction were significant at 1% level, using Wald statistics and likelihood ratio tests.

The GLM assumptions in terms of both the continuous and categorical explanatory variables were assessed. Regarding the continuous variables, GLMs assume that those are linear with the predictor (in this case the *logit*) and such linearity was assessed by categorizing the continuous variables by their quartiles, as described by Hosmer and Lemeshow (2000), and by analysing GAM plots. If evidences of non-linearity were present, then multivariate fractional polynomial transformations were calculated and the transformed variables were used in the models instead of the original values, following the methods developed by Royston and Altman (1994) and recommended by Hosmer and Lemeshow (2000). Regarding the categorical variables, GLMs assume that all levels of the categorical covariates have sufficient information in the binomial response to allow contrasts in the data and achieve model convergence. These assumptions follow the contingency tables and chi-square tests assumptions, in which the contingency tables should not have cells with zero values, or more than 25% of the cells with predicted values lower than 5. These assumptions were validated by building contingency tables for all categorical variables considered.

Another assumption in the GLM modeling approach is that the data in the sample is independent, in this case that the Y_i correspond to a succession of independent Bernoulli trials. Given that the data used in this study are fisheries-dependent (collected from the commercial fishery), it is plausible to consider that this assumption was not validated. Therefore, an alternative modeling approach with Generalized Estimation Equations (GEE) models was considered, as this technique allows for a working correlation to be calculated within the data. Within this GEE model framework the fishing sets were considered as the grouping variable, meaning that the data could be considered to be clustered and not independent within each fishing set. This allowed for a model formulation in which the blue shark at-haulback mortality data recorded within each fishing set carried out by each particular vessel in each particular fishing trip did not require the assumption of independence. With this GEE model formulation, the correlation structure of the data within each set was assumed to be of the type exchangeable, as this seems to be the most adequate correlation structure for clustered data (Halekoh et al., 2006).

The final GLM and GEE models were calculated, and an example of interpretation is presented for the probabilities of a shark dying at-haulback with varying specimen sizes, as well as for the odds-ratios of at-haulback mortality for increasing specimen sizes by 10 cm FL classes. The probabilities were calculated as the *inverse-logit* functions of the final equations considered, and the odds-ratios as the exponential values of the differences (in 10 cm FL sizes) in the *logits*. Both the point estimates and the 95% confidence intervals are presented. For these examples, all other variables, including the interactions with FL, were considered to be on their baseline levels.

2.4. Diagnostics and goodness-of-fit

A residual analysis using Pearson and Deviance residuals was used to search for outliers, and the Cooks distances and DfBetas were used to identify eventual values with influence in the estimated parameters. Model goodness-of-fit was assessed with the Hosmer and Lemeshow test, that groups the observations into 10% quantiles (deciles) according to their predicted values, and uses a chi-square test for comparing the observed versus predicted values in each group (Hosmer and Lemeshow, 2000). Additionally, the Nagelkerke coefficient of determination (R^2) (Nagelkerke, 1991) was also calculated. The discriminative capacity of the models was determined by the Area Under the Curve (AUC) value of the Receiver Operating Characteristic (ROC) curves, with the calculation of the model sensitivity (capacity to correctly detect the event = mortality at-haulback), and model specificity (capacity to correctly exclude sharks not dead at-haulback).

Cross validation was carried out with a k-fold cross validation procedure (with $k = 10$) to estimate the expected level of fit of the models to new data, and to assess eventual over-fitting problems. Because the models in this study are of the binomial type, the cross validation procedure was used to estimate the misclassification error rate, with the procedure randomly partitioning the original sample into k-subsamples, and then retaining one subsample as the validation dataset and using the remaining $k - 1$ subsamples as training datasets to build the models. The cross-validation procedure was repeated k times, with each of the k subsamples used one time as the validation dataset, and the use of $k = 10$ was chosen as this seems to be an adequate value for models using large datasets (Fushiki, 2011). Finally, a bootstrapped cross validation procedure was also used to calculate new AUC values, that were compared to the original AUC calculated using the entire dataset.

All statistical analysis for this study was carried out with the R Project for Statistical Computing version 2.14.1 (R Development Core Team, 2011). Many functions are available directly in the core R Program, but some analysis required additional libraries, including library "gmodels" (Warnes, 2011a) for the contingency table analysis, library "gplots" (Warnes, 2011b) for some of the graphics produced, library "moments" (Komsta and Novomestky, 2012) for data summaries including the kurtosis and skewness coefficients, library "gam" (Hastie, 2011) for the GAM models and plots, library "mfp" (Ambler and Benner, 2010) for the multivariate fractional polynomials transformations, library "geepack" (Halekoh et al., 2006) for the GEE models, library "Epi" (Carstensen et al., 2011) for the ROC curve plots, and library "boot" (Canty and Ripley, 2011) for the cross validation procedure.

3. Results

3.1. Description of the catches

A total of 26 383 blue shark specimens were captured and recorded during the sampling period. Of those, complete capture information including at-haulback condition, size, sex, date and coordinates of the capture was available for 24 958 specimens (94.6% of the blue shark catch) and the analyses were therefore performed on those specimens. Of the specimens analyzed, 54.2% were females, with the remaining 45.8% corresponding to males. The females mean size in the sample was 199.5 cm FL (SD = 31.7) with the size distribution ranging from 40 to 305 cm FL, while the males had a mean size of 194.5 (SD = 36.9) and the size distribution ranged from 69 to 295 cm FL. The size distribution of males and females was significantly different (2-sample K–S test: D = 0.06, p-value < 0.001). Likewise, the ranks of the sizes of males and females were also significantly different (Mann–Whitney test: W = 7.9e + 7, p-value = 0.002). The non-normality in the size data was confirmed with a Lilliefors test (D = 0.030, p-value < 0.001), with the data having a skewness coefficient of −0.41 (negatively asymmetrical) and a kurtosis coefficient of 4.99 (leptokurtic data).

3.2. Proportions of at-haulback mortality

In general terms 13.3% of the blue shark specimens that were captured during this study were dead at-haulback. In terms of the categorical variables, the proportions of alive:dead blue sharks were significantly different between all levels of the covariates that were considered, specifically fishing trip (chi-square = 2092.5, df = 13, p-value < 0.001), sexes (chi-square = 94.4, df = 1, p-value < 0.001), year (chi-square = 1191.2, df = 3, p-value < 0.001), quarter (chi-square = 193.8, df = 3, p-value < 0.001), vessel (chi-square = 181.3, df = 1, p-value < 0.001) and branch line material (chi-square = 39.4, df = 1, p-value < 0.001) (Fig. 2).

Regarding the continuous variables, and considering the data grouped by the quartiles, the proportions of alive:dead sharks were significantly different between sizes (chi-square = 833.5, df = 3, p-value < 0.001), latitude (chi-square = 643.2, df = 3, p-value < 0.001) and longitude (chi-square = 323.3, df = 3, p-value < 0.001), but not when considering SST (chi-square = 2.8, df = 3, p-value = 0.419) (Fig. 2). Moreover, the SST was also found to be correlated with latitude (Pearson correlation: r = 0.605, p-value < 0.001; Spearman correlation: ρ = 0.581, p-value < 0.001), and with longitude (Pearson correlation: r = −0.363, p-value = 0.001; Spearman correlation: ρ = −0.353, p-value < 0.001), which could create multicollinearity problems if both the SST and the geographical coordinates were used in the multivariate models. Since geographical coordinates were available for all fishing sets while SST was only available for part of the sets, the SST variable was discarded and not used in the final models.

3.3. Simple effects GLM and GEE models

In the simple effects multivariate GLM all the variables initially considered were significant at the 5% level, except the vessel effect that was not significant. For the variable quarter, the overall effect was significant but no differences were found between quarters 1 and 2 (Wald statistic: z = −0.323; p-value = 0.747) and quarters 1 and 4 (Wald statistic: z = 0.578; p-value = 0.563). Therefore, this variable was simplified into a binomial variable, coded with: season 1 = quarter 3; season 2 = quarters 1, 2 and 4.

By analysing the functional form of the continuous explanatory variables with GAM plots it was possible to see that at-haulback mortality tended to decrease with increasing specimen size, toward

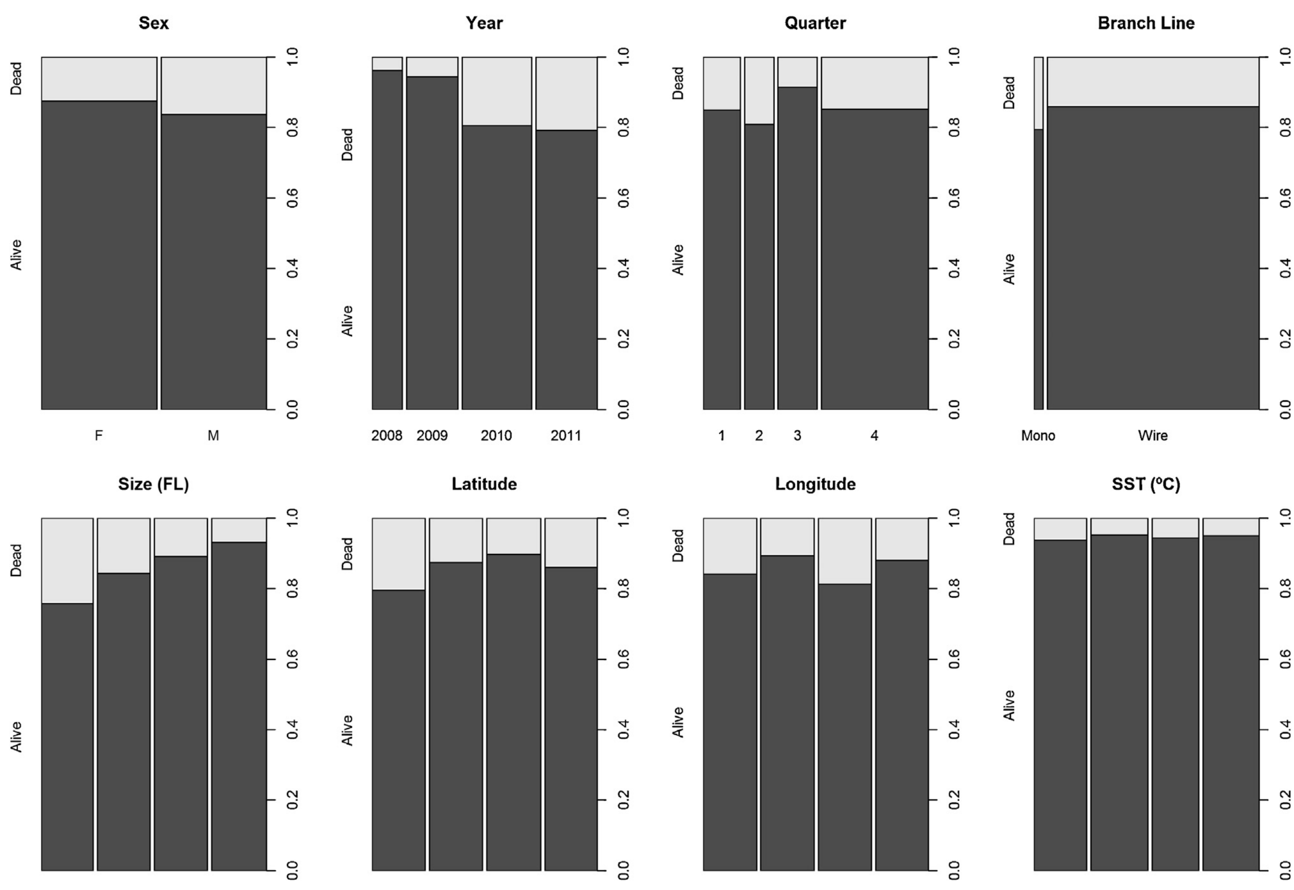

Fig. 2. Proportions of blue sharks at-haulback condition (alive vs. dead) with the various categorical and continuous explanatory variables considered in this study. The continuous variables are categorized by their quartiles.

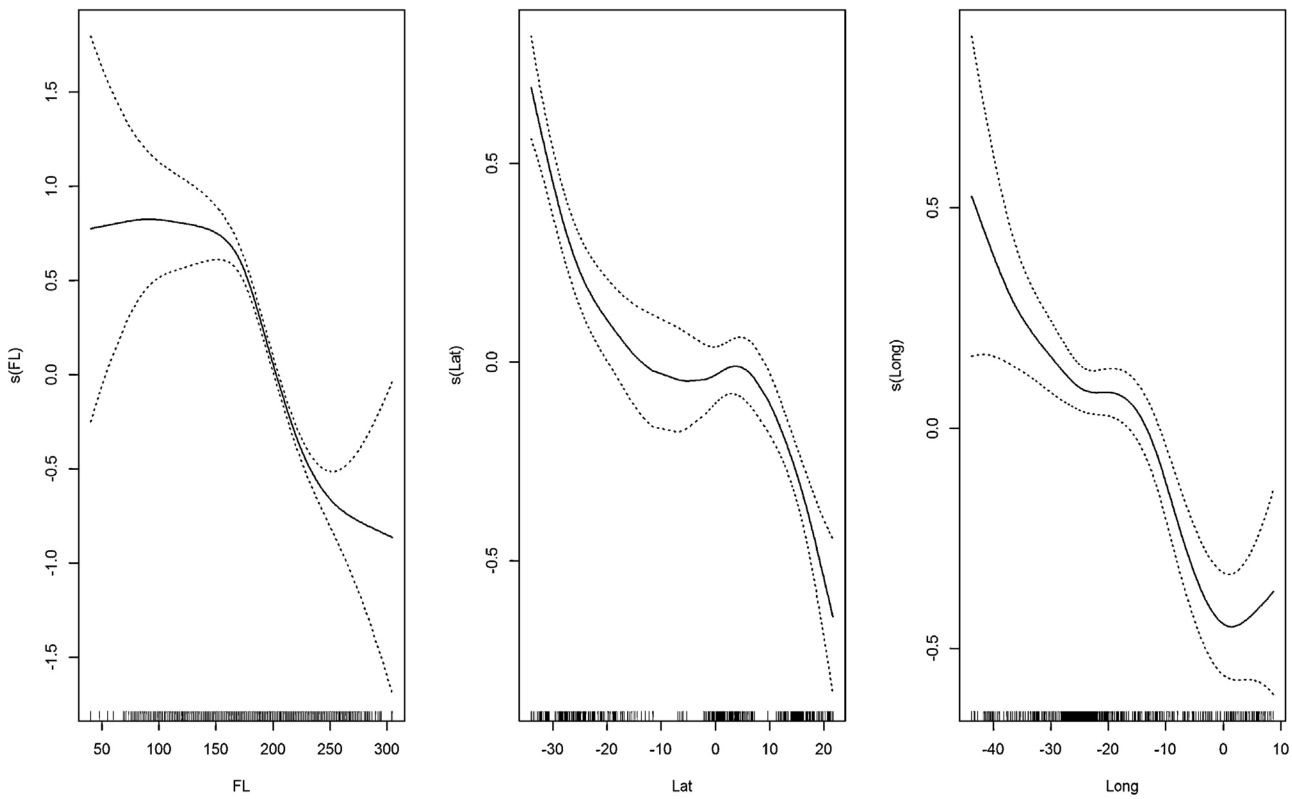

Fig. 3. Generalized Additive Model (GAM) plots with the shape of the continuous explanatory variables (FL, latitude and longitude) for modeling blue shark at-haulback mortality.

northern latitudes and eastern longitudes (Fig. 3). The non-linearity of those continuous variables was verified with multivariate fractional polynomials models, and in those only the longitude was significantly linear, while the specimen size and latitude were non-linear variables that needed to be transformed before being included in the GLM and GEE models. By applying the multivariate fractional polynomial transformations to those three continuous variables, the best candidate alternatives to the transformations of the functional forms were:

$$\text{Size} \quad (\text{FL}): \quad \left(\frac{\text{FL}}{100}\right)^{-0.5} + \log\left(\frac{\text{FL}}{100}\right)$$

$$\text{Latitude}: \quad \log\left(\frac{\text{Lat}+34.1}{10}\right) + \left(\frac{\text{Lat}+34.1}{10}\right)^{3}$$

$$\text{Longitude}: \quad \left(\frac{\text{Long}+43.8}{10}\right)$$

The transformation regarding the longitude is a simple scale transformation, while the transformations for specimen size and latitude refer to transformations in the functional form. These transformed variables were used in the models instead of the original values.

The results of the simple effects GLM parameters in terms of significance are given in the analysis of deviance presented in Table 1, where it is possible to see the contribution of each parameter for explaining part of the deviance observed in the blue shark at-haulback mortality. The parameters that are contributing more for the model deviance explanation are the effects of the year and specimen size, followed by the geographical location of the capture. Finally, the effects of season, branch line material and sex are contributing less for the blue shark at-haulback mortality deviance explanation, but are still significant variables in the model (Table 1).

When applying GEE models to those variables, and considering the fishing sets as the grouping (cluster) variable, the estimated correlation value was low (alpha = 0.058, SE = 0.019), and the estimated parameters were very similar between the GLM and GEE models, with only some minor differences (Table 2). The overall parameter interpretation would be similar with both modeling approaches, given that the parameters were consistently positive or negative when comparing the models. The only major difference in these multivariate simple effects models was that the effect of sex was significant in the GLM but not significant (at the 5% level) within the GEE framework (Table 2).

3.4. Models with interactions

Several possible 1st degree interactions between the variables were significant at the 1% level, and therefore a GLM with significant interactions was created. In this model, year and specimen size were still the most important explanatory variables, followed

Table 1
Deviance table for the simple effects GLM for the binomial response (alive or dead) status of blue sharks at-haulback. Resid.DF are the residual degrees of freedom and Resid.dev is the residual deviance. Significance of the terms is given by the *p*-values of the chi-square test. The ".t" notations after the continuous variables (FL, Lat and Long) represent the utilization of the transformed variables in the models.

Parameter	Df	Deviance	Resid.DF	Resid.dev	*p*-Value
Null			24 957	19 561	
FL.t	1	645.24	24 956	18 915	<0.001
Latitude.t	1	273.10	24 955	18 642	<0.001
Longitude.t	1	251.79	24 954	18 390	<0.001
Year	3	908.63	24 951	17 482	<0.001
Season	1	11.06	24 950	17 471	<0.001
Branchline	1	7.07	24 949	17 464	0.008
Sex	1	12.71	24 948	17 451	<0.001

Table 2
Multivariate simple effects GLM and GEE model parameters (coefficients and standard errors) for the binomial response (alive or dead) status of blue sharks at-haulback. Significance of the explanatory variables is given by the Wald statistic with the respective *p*-values. The ".t" notations after the continuous variables (FL, Lat and Long) represent the utilization of the transformed variables in the models.

Variable	Generalized Linear Model				Generalized Estimating Equation			
	Estimate	SE	Wald	*p*-Value	Estimate	SE	Wald	*p*-Value
Intercept	3.952	0.347	11.4	<0.001	4.297	0.493	75.9	<0.001
FL.t	−4.186	0.226	−18.5	<0.001	−4.295	0.343	156.4	<0.001
Lat.t	−0.007	0.000	−14.5	<0.001	−0.007	0.001	60.0	<0.001
Long.t	−0.252	0.024	−10.4	<0.001	−0.211	0.048	19.5	<0.001
Year2009	0.508	0.109	4.7	<0.001	0.411	0.178	5.3	0.021
Year2010	1.604	0.096	16.8	<0.001	1.340	0.175	58.6	<0.001
Year2011	1.796	0.092	19.5	<0.001	1.702	0.159	114.3	<0.001
Season2	−0.196	0.065	−3.0	0.003	−0.230	0.101	5.2	0.023
BranchWire	−0.199	0.087	−2.3	0.022	−0.281	0.119	5.6	0.018
SexMale	0.148	0.041	3.6	<0.001	0.059	0.046	1.7	0.197

by location, season, branch line material and sex. In terms of interactions, specimen size was significantly interacting with longitude and year; specimen sex was interacting with longitude and season; longitude was interacting with season; and branch line material was interacting with year (Table 3). The interactions between longitude and season, and between year and branch line material seem to be particular significant in this model, with relatively high values of deviance (Table 3).

With regards to the multivariate GEE using interactions (again using the fishing set as the grouping variable), and similarly to what had been observed in the simple effect GEE, the correlation within the fishing sets were low (alpha = 0.051, SE = 0.022), and the parameters estimated with both the GLM and GEE models were similar, with consistently positive or negative parameters (Table 4). In this case, the major differences between using GLM or GEE approaches were the loss of significance of the interactions between season and sex, and between size and longitude (Table 4).

By using significant interactions, the interpretation needs to take into account the effects of the main variable and the interacting variable at the same time. Regarding the interaction between size and year, the at-haulback mortality for all size classes tended to increase along the years, but the relative increase was different between sizes, with the smaller specimens having a sharper increase in mortality for the more recent years (Fig. 4a). In terms of the relation between size and longitude, the at-haulback mortality remained at relatively low levels for the larger size classes throughout the entire longitude range, while a peak of at-haulback mortality was observed for the smaller size classes toward the eastern longitudes (Fig. 4b). The sex was significantly interacting with season and longitude, and on both cases the mortality of males tended to be higher than for females, but with small differences in the changing patterns (Fig. 4c and d). There was also an interaction between season and longitude, with changes in the mortality rates along the longitude gradient during the seasons of the year (Fig. 4e). The last 1st degree interaction considered was between branch line material and year, where it was possible to see that in general the at-haulback mortality when using monofilament remained relatively high between 2008 and 2011 (except for 2010, when a decrease was observed), while an increasing trend along the time period was observed for wire branch lines (Fig. 4f).

By using the final GLM for prediction and interpretation of the effects of specimen size on the mortality rates, it was possible to see that the probabilities of a specimen dying at-haulback decrease with increasing specimen size, but the rate at which the probabilities decrease is higher for smaller specimens (Fig. 5). By interpreting the odds-ratios (in this case calculated for an increase of 10 cm FL in specimen size), it is possible to see that as a shark increases in size the odds of dying decrease, but these odds are non-linear and vary with the size. For example, for a blue shark close to the size of birth (e.g. 50 cm FL) an increase of 10 cm FL in size would result in the odds of dying decreasing by 22%, with 95% CI varying between 14% and 30% (Fig. 5). On the other hand, for a larger adult blue shark with 250 cm FL, an increase of 10 cm FL in size would result in the odds of dying decreasing by only 11%, with 95% CI varying between 7% and 15% (Fig. 5).

Table 3
Deviance table for the GLM model with significant 1st degree interactions for the binomial response (alive or dead) status of blue sharks at-haulback. Resid.DF are the residual degrees of freedom and Resid.dev is the residual deviance. Significance of the terms is given by the *p*-values of the chi-square test. The ".t" notations after the continuous variables (FL, Lat and Long) represent the utilization of the transformed variables in the models.

Parameter	Df	Deviance	Resid.DF	Resid.dev	Pr (>Chi)
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Year	3	908.63	24 951	17 482	<0.001
Season	1	11.06	24 950	17 471	0.001
Branch line	1	7.07	24 949	17 464	0.008
Sex	1	12.71	24 948	17 451	<0.001
FL.t:Long.t	1	13.62	24 947	17 437	<0.001
FL.t:Year	3	41.96	24 944	17 395	<0.001
Long.t:Season	1	71.25	24 943	17 324	<0.001
Long.t:Sex	1	15.06	24 942	17 309	<0.001
Year:Branch line	3	80.81	24 939	17 228	<0.001
Season:Sex	1	8.71	24 938	17 220	0.003

3.5. Diagnostics and goodness-of-fit

The final validation with the residual analysis did not show any values that could be significant outliers. The Cooks distances identified a few data points with values relatively higher than the remaining, but those points did not had an impact in the estimated model parameters and therefore were not removed from the final model.

In terms of model goodness-of-fit, both the simple effects and the GLM with interactions passed the Hosmer and Lemeshow test, with the simple effects GLM having chi-square = 11.8 (*p*-value = 0.162) and the model with interactions having a slightly better fit (chi-square = 9.6, *p*-value = 0.295). The same type of improvement was observed for the Nagelkerke R^2 values, with the simple effects GLM having an R^2 of 0.149 and the model with interactions producing a higher R^2 of 0.165. Finally the discriminative capacity of the models also improved by adding the interactions, with the simple effects GLM having an AUC of 0.741, and the model with interactions a higher AUC value of 0.750 (IC95% = 0.742, 0.758), with a sensitivity of 74% and a specificity of 65%, for a cut point of 0.144 (Fig. 6). Those ranges of AUC discriminative values are considered acceptable, according to Hosmer and Lemeshow (2000).

Table 4
Multivariate GLM and GEE parameters of the models with significant 1st degree interactions (coefficients and standard errors) for the binomial response (alive or dead) status of blue sharks at-haulback. Significance of the explanatory variables is given by the Wald statistic with the respective *p*-values. The ".t" after the continuous variables (FL, Lat and Long) represent the utilization of the transformed variables in the models.

Variable	Generalized Linear Model				Generalized Estimating Equation			
	Estimate	SE	Wald	*p*-Value	Estimate	SE	Wald	*p*-Value
Intercept	3.90	1.26	3.1	0.002	2.50	1.39	3.2	0.073
FL.t	−4.24	0.88	−4.8	<0.001	−3.21	0.98	10.8	0.001
Lat.t	−0.01	0.00	−13.4	<0.001	−0.01	0.00	52.8	<0.001
Long.t	−0.96	0.29	−3.3	0.001	−0.50	0.42	1.4	0.231
Year2009	7.85	1.67	4.7	<0.001	6.49	1.90	11.6	0.001
Year2010	2.32	1.34	1.7	0.083	2.61	1.58	2.7	0.100
Year2011	5.70	1.35	4.2	<0.001	5.52	1.44	14.6	<0.001
Season2	0.85	0.18	4.7	<0.001	0.78	0.27	8.3	0.004
BranchWire	−1.26	0.21	−6.0	<0.001	−1.25	0.27	22.3	<0.001
SexMale	0.17	0.17	1.0	0.301	0.30	0.16	3.6	0.056
FL.t:Long.t	0.83	0.20	4.1	<0.001	0.51	0.30	2.9	0.087
FL.t:Year2009	−5.47	1.19	−4.6	<0.001	−4.51	1.37	10.8	0.001
FL.t:Year2010	−1.85	0.94	−2.0	0.050	−2.07	1.10	3.5	0.060
FL.t:Year2011	−3.61	0.96	−3.8	<0.001	−3.52	1.03	11.8	0.001
Long.t:Season2	−0.49	0.05	−9.0	<0.001	−0.44	0.09	21.9	<0.001
Long.t:SexMale	−0.12	0.04	−3.0	0.003	−0.13	0.04	12.1	0.001
Year2009: BranchWire	0.04	0.29	0.1	0.894	0.01	0.37	0.0	0.983
Year2010: BranchWire	2.12	0.30	7.0	<0.001	1.94	0.42	21.3	<0.001
Year2011: BranchWire	1.42	0.24	6.0	<0.001	1.41	0.30	22.1	<0.001
Season2:SexMale	0.36	0.12	3.0	0.003	0.14	0.12	1.5	0.226

The 10-fold cross validation procedure resulted in an estimated prediction error of 13.4% for the multivariate simple effects GLM, and a similar prediction error of 13.3% for the model with interactions. The bootstrapped cross-validation procedure resulted in an AUC = 0.748, which is very similar to the original AUC using the entire dataset (0.750) and also validates the models. Additionally, all bootstrapped GLM also passed the Hosmer and Lemeshow test (p-value > 0.05 on all cases) for model goodness-of-fit.

4. Discussion

This study focused on the parameters affecting blue shark at-haulback mortality in a large scale swordfish pelagic longline fishery in the Atlantic Ocean. In general, 13.3% of the blue shark capture was dead at-haulback, but it was possible to determine that several variables had significant effects on this mortality rates and a predictive statistical model was produced.

Several studies have previously addressed blue shark at-haulback mortality in pelagic longline fisheries, including the works of Diaz and Serafy (2005) and Campana et al. (2009) in the Atlantic, and Moyes et al. (2006) in the Pacific. For the Canadian fleet in the northwest Atlantic, Campana et al. (2009) estimated the blue shark at-haulback mortality in the 12–13% range as measured by fishery observers, which is relatively similar to the 13.3% estimated in our study. However, using telemetry technology to account for the post-release mortality, Campana et al. (2009) also reported that the actual mortality values could be closer to 20% due to the added post-release mortality. In the Pacific Ocean, Moyes et al. (2006) also addressed post-release mortality using satellite telemetry, and in the case of blue shark noted that the survivorship of sharks landed in an apparently healthy condition was likely to be high. This means that our estimates of 13.3% mortality probably represent accurately the at-haulback mortalities of blue shark in the Portuguese pelagic longline fishery, but at this stage the total mortalities (that also need to account for post release mortality) still remain unknown.

The most significant factors affecting mortality in our study were the year effect, followed by specimen size. The yearly variations may be related with inter-annual variability inherent to the species or the fishery spatial/seasonal patterns, or eventual changes in the fishery that may be contributing to changes in these rates. It should be mentioned, however, that the data analyzed in this study was collected by the fishery observer program that tries to cover the geographical/seasonal variability of the fleet in terms of catch rates, but it is a fishery-dependent source of data that cannot cover those geographical/seasonal patterns in a truly balanced design.

With regards to the specimen size, the probabilities and odds-ratios show that the larger specimens have lower probabilities of being dead at-haulback than the smaller specimens. However, these effects are non-linear, with the odds-ratios of surviving higher for the smaller specimens (as they grow in size) and then tending to stabilize as the sharks reach larger sizes. Some previous studies had already looked into effects of specimens sizes in the mortality rates (e.g. Diaz and Serafy, 2005; Campana et al., 2009), and similar results were reached, with decreasing probabilities of at-haulback mortality as the specimens increase in size. These results have a direct effect on eventual management and conservation initiatives such as the establishment of minimum and/or maximum landing sizes, as the efficiency of such measures will have specific effects depending on the shark sizes. For example, the establishment of a minimum landing size would have a limited conservation effect, as the smaller specimens are the ones that have higher probabilities of dying due to the fishing process, and would therefore tend to be discarded already dead.

Even though the models created and presented seem to be valid and perform well for predicting blue shark at-haulback mortality rates (as verified by the residual analysis, goodness-of-fit, and cross-validation procedures), some limitations need to be addressed and considered. One characteristic of our study was that the hook style effect was not considered, mainly because the Portuguese longline fleet uses exclusively J-style hooks. Therefore, the values reported in our study refer specifically to fisheries using this type of hooks, while other pelagic longline fleets may use different hooks such as circle and/or tuna hooks. Some previous studies have reported that blue shark mortality rates were higher with J-style hooks when compared to circle hooks (Carruthers et al., 2009), while on the other hand Coelho et al. (2012a) reported that for the elasmobranch species more commonly discarded (e.g. bigeye thresher and crocodile shark) the hook style (J-style vs. circle hooks) seemed unrelated to at-haulback mortality. Likewise, Kerstetter and Graves (2006) also showed that even though several target and bycatch species seemed to have higher rates of survival at-haulback with circle hooks, the effects were not statistically significant for

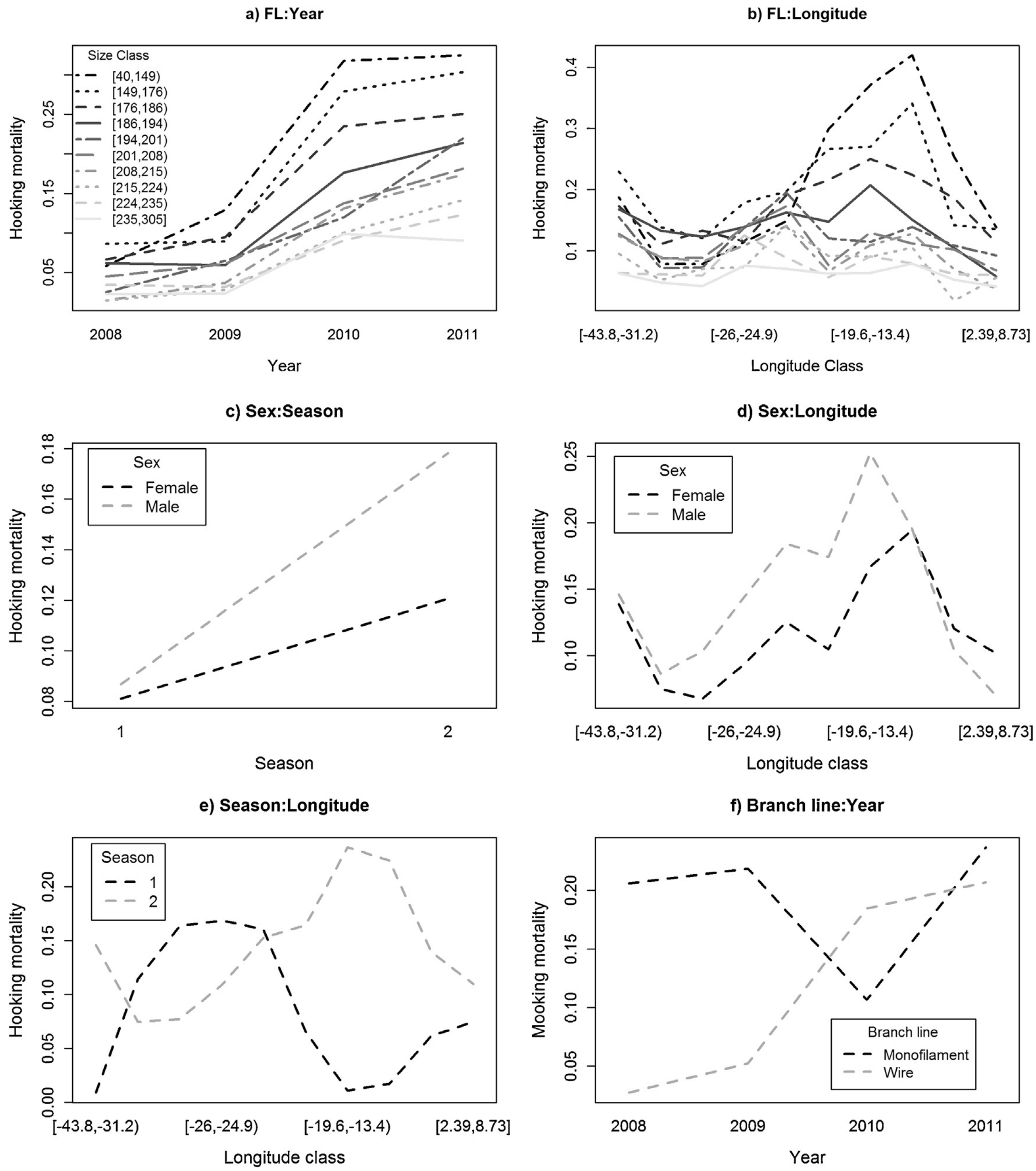

Fig. 4. Interactions plots (from the GLM) between (a) specimen size (FL) with year; (b) specimen size with longitude; (c) sex with season; (d) sex with longitude; (e) season with longitude and (f) branch line material with year. The specimen sizes are categorized by the deciles and the longitudes are categorized by the quartiles.

most species. On the contrary, Afonso et al. (2011) compared J-style with circle hooks in the south-western Atlantic Ocean and concluded that circle hooks were efficient in reducing the mortality rates of most species caught, both in pelagic and coastal longline fisheries, observing at the same time that the catch rates of some species, including the blue shark, were higher with circle hooks. In the North Pacific Ocean, however, Yokota et al. (2006) showed that the hooks (circle vs. tuna hooks) had little effect on the catch rates and mortalities of blue shark. This variability in results seems to support the fact that specific studies and assessments should be carried out specifically for each fishery and fleet in question.

One possible shortcoming in our study was the fact that the fishing gear soaking time was not considered, with several previous studies (e.g. Campana et al., 2009; Diaz and Serafy, 2005; Morgan and Burgess, 2007) having demonstrated that the soaking time was a significant variable for predicting at-haulback mortality on elasmobranchs. Besides the fishing gear soaking time, Morgan and Carlson (2010) also demonstrated that the capture time (measured with hook timers) was also influential in the mortality rates of some demersal shark species captured in bottom longline fisheries. Finally, and even though in our study the gangion material had a relatively small effect on the mortality rates, other authors have shown that some components of longline gear may interact to influence catch rates and relative mortality estimates (e.g. Afonso et al., 2012; Ward et al., 2008). As suggested by these authors, it could be hypothesized that nylon leaders could catch relatively more dead blue sharks than wire leaders because healthy and robust specimens, which would be more likely to be alive at gear retrieval, may have more chances of biting through the nylon and escaping.

The logistic models used in our study seem adequate to evaluate the contribution of potential explanatory variables to blue shark at-haulback mortality, as the response variable is binomial (dead vs.

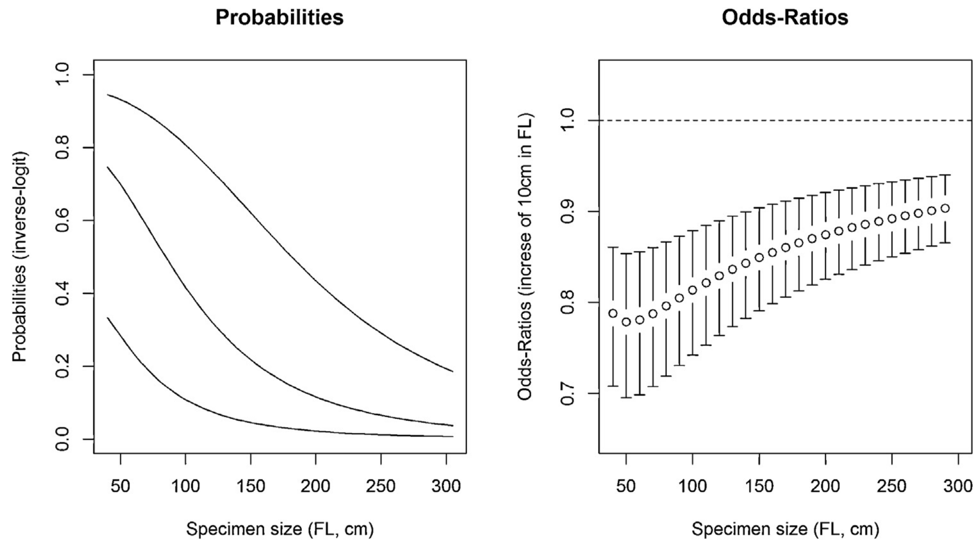

Fig. 5. Probabilities of a blue shark dying at haulback with varying specimen size (left), and the odds-ratios of a blue shark dying at-haulback (for an increase of 10 cm FL in specimen size) along the size ranges of the captured specimens. The predictions presented were made from the final GLM, considering all other variables on their baseline levels.

alive sharks at fishing gear haulback). The models created used both biological factors such as specimen size and sex, as well as fishery operational factors such as geographical location and branch line material. In our study the vessel effect was tested but not considered significant, while a previous study by Campana et al. (2009) had verified that the vessel effect was significant. One important difference between the two studies is in the number of vessels monitored that was much larger in the Campana et al. (2009) study. Eventual differences between different vessels can hypothetically be due to: (1) vessels (in different trips and sets) targeting different species, and using therefore different gear specifications, such as monofilament vs. steel branch line materials; (2) vessels with different crews that may handle the sharks in different ways; (3) vessels using different fishing *metiers* that can result in different soak times of the fishing gear, which will be influent in the mortality rates. Such possibilities are hypothesis that cannot be easily verified at this stage, but it is feasible to consider that a correlation in the mortality data within vessels, fishing trips or fishing sets may exist in those fishery-dependents datasets.

For addressing such eventual lack of independence in the sample, the ideal scenario would be to collect fishery-independent data, but for the large pelagic species such data would be extremely costly, and therefore fisheries-dependent data (either logbooks or fishery observers datasets) is usually the only available data for such analysis, However, models such as GLMs or GAMs assume that the data is independent, and therefore making inference from such

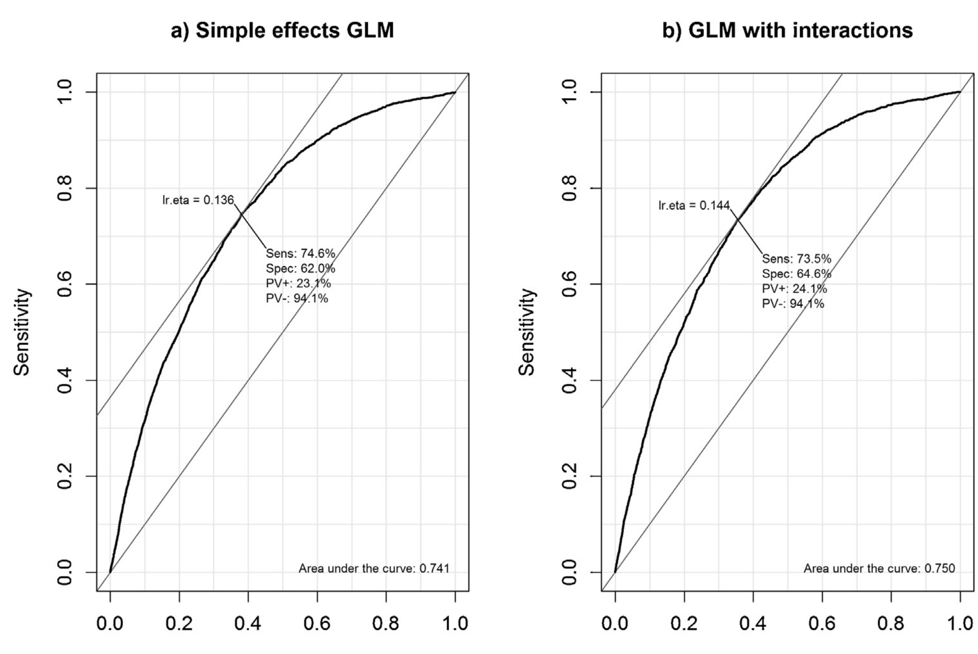

Fig. 6. Receiver Operating Characteristic (ROC) curves for the multivariate GLM using simple effects (a) and considering interactions (b), for the binomial response (alive or dead) status of blue sharks at-haulback. The Area Under the Curve (AUC) values are given, as well as the sensitivity (Sens), specificity (Spec) and predictive values (PV) at the optimal response cut-points (lr.eta).

data with such models may result is biased results. For such cases, the use of Generalized Estimating Equations (GEE) might be a valid alternative approach, as this modeling technique calculates a working correlation matrix that approximates the true correlation on the observations (Wang and Carey, 2003). Therefore, in our study we opted for a methodology of comparing GLM with GEE models, using the fishing sets as the grouping variable in the GEE models, and assuming therefore a possible lack of independence of data within each fishing set. With the GEE models a working correlation matrix is estimated, that is then used to correct the model parameters. However, the estimated correlation parameters were low, meaning that this lack of data independence between fishing sets does not seem to be significantly affecting the GLM, which could thus be considered also valid for predicting blue shark mortality rates.

This paper presents new and important information on the impacts of this pelagic longline fishery on blue shark populations in a wide Atlantic area. The results can be used to predict the effect of the fishery on blue shark mortality, and specifically on how several factors are contributing to this mortality rates. One immediate application is, for example, to determine the efficiency of eventual future management and conservation initiatives such as the establishment of minimum and/or maximum landing sizes. The results can also be incorporated into future stock assessment models, including ecological risk assessment analysis carried out regularly by tRFMOs for bycatch species.

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