CATCH PROBABILITIES OF SAILFISH (*Istiophorus platypterus*) BASED ON ENVIRONMENTAL FACTORS IN SOUTHWESTERN ATLANTIC OCEAN

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**SUMMARY**

Generalized Analysis and Spatial Predictions (GRASP) method was used to obtain a spatial prediction map of catch probabilities for sailfish (*Istiophorus platypterus*) for the Atlantic Southwestern area. The prediction model was fitted to CPUE data assuming a quasi-Poisson distribution and the predictors were Sea Surface Temperature, Chlorophyll-α concentration, distance from continental coast or from the nearest oceanic island, month and year. The results showed that Sailfish spatial distribution is closely related to warmer surface temperatures and oligotrophic waters. Two separated groups were identified, the first one was strongly associated with coastal area and oceanic Island surroundings and the second one presented a more oceanic distribution. These groups were contrasted with spatial size data distribution suggesting wider limits to migration pattern of the southwest Atlantic sailfish.

**KEYWORDS**

GAM, environmental effects, billfish

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1. Introduction

The relationship between the distribution of fisheries resources and environmental variables is one of the main factors affecting catchability, being, therefore, very important to take it into account in fisheries management models (Miller, 2007; Zagaglia et al. 2004, Bigelow et al., 1999). Unfortunately, however, these relationships are often found to be non-linear and, therefore, difficult to predict and to be explained by statistical analysis alone (Hazin and Erzini, 2008). Modeling spatial prediction, thus, can be a useful tool for better understanding the influence of ecosystems on species distribution and, consequently, for the implementation of management and conservation measures. The use of prediction maps may facilitate the comprehension of spatial distribution, because it not only reveals the relationship between species distribution and the set of environmental variables, but also allows the identification of areas of high abundance (Zheng et al 2002).

Nevertheless, the employment of spatial prediction techniques based on the interpolation algorithms are generally highly data intensive, requiring large amount of well distributed data. This requirement is barely attainable by fisheries data, especially when the species of interest is not the target one. This problem was partially overcome by Lehmann et al. (2002) with the development of the method “generalized regression analysis and spatial prediction” (GRASP). This method uses statistical models to determine the relationship between the response and predictors and then uses the spatial pattern of the predictor surfaces to predict the response in geographic space. In the present paper we tried to apply the GRASP method to the catch and effort data for sailfish (Istiophorus platypterus) from the Brazilian tuna longline fleet in order to better understand the relationship between catch distribution and environmental factors.

2. Material and methods

2.1 Catch and size data

The catch and effort data, from 1999 to 2006, were obtained from logbooks of Brazilian tuna longline fleet (national and chartered vessels) which operated in the southwestern Atlantic, between 10°N to 45°S and from 50°W to 10°W. The data were grouped in 1° x 1° quadrants by month and year, whilst the catch per unit of effort was calculated based on the number of the fish caught per 1,000 hooks. A high number of sets with no sailfish catch was observed (78%), which stemmed from the by-catch nature of the species in the tuna longline fishery. The analysis was restricted to 12º (about 1,550 km) from the coastline of the continent or of oceanic islands, because of the very low fishing effort beyond such distance (Figure 1).

In order to incorporate size frequencies in the spatial prediction, lower jaw to fork length (LJFL) measurements, obtained from the Brazilian Longline Observer Program, from 1999 to 2007, were included in the analysis.

2.2 Environmental data

The temporal series for sea surface temperature (SST) was obtained from the satellite sensors from the Physical Oceanography Distributed Active Archive Center (PODAAC)- Jet Propulsion Laboratory/ NASA. These data had an original resolution of 0.5 x 0.5° and were aggregated to 1° x 1° quadrants by month and year. The Chlorophyll-α concentration (CLR) data were obtained from SeaWiFS images, provided by “SeaWiFS Project” from Goddard Space Flight Center/NASA. These images were turned into numerical data with the GDRA2XYZ program provided by the Phoenix Training Consultants. Their initial resolution of 9 km x 9 km resolution was aggregated to 1° x 1° quadrants by month and year. The distance from Brazilian coast or oceanic islands (DIS) was calculated based on the numeric coastline provided by NOAA/NGDC Marine Geology and Geophysics Division.
2.3 GRASP

Spatial prediction was done using the grasp function v3.3 (Lehmann et al., 2002), which basically consists in using Generalized Additive Models (GAMs) to generate predictions in grid format. Predictors variables were selected according to an F-test (p value = 0.05). The relationship between selected predictors and the CPUE was analyzed considering the plot of the partial residuals (Neter et al., 1989), including the 95% confidence intervals, as well as tick marks on the abscissa showing the location of data points.

The consistency of the final model was evaluated using two methods: the first method used linear regression between randomly chosen observed values of relative abundance and those generated by the model using the included independent variables as input (simple validation). The second one was a cross-validation method, which assessed the goodness of fit of a Poisson model by calculating the correlation between the observed and predicted values using the Pearson correlation coefficient.

3. Results and discussion

The GAM was fitted assuming a quasi-Poisson distribution for the CPUE data. The final model explained approximately 11% of total deviance, including SST, CLR and DIS as continuous variables, inserted in the model with a smoothing function, and Year and Month as factors (Table 1). Its equation can be expressed as:

$$\text{CPUE} = a + s(\text{SST}, 8) + \text{Year} + s(\text{CLR}, 8) + s(\text{DIS}, 8) + \text{Month} + e.$$  

Where: “a” is a constant, “SST”, “Year”, “CLR”, “DIS” and “Month” are the variables taken into the model, “s” is the smooth function “Spline” (cubic smoothing spline) and “e” is the error function.

The contribution from each variable when they all are included in the model are shown in Figure 2. The SST was the most important factor followed by CLR, Year, DIS and Month. The SST was expected to contribute significantly to the model; due to the shallow distribution of sailfish (Hoolihan, 2004). Moreover, the temperature not only influences the physiology of fishes but is also related to other environmental factors that affect fish distribution, such as upwelling and climatic events (Hazin, 1994). Figure 2 also shows the drop in the explained deviance when a particular variable is removed from the model and finally the potential contribution from each variable if they were considered alone. The factor Year was the most important in these analyses reflecting the high inter-annual variability of fisheries data.

Figure 3 shows the partial residuals plots of the variables considered in the model. Lower temperature values exhibited negative effect on sailfish CPUE, but this effect disappeared for temperatures between 25 and 30º C. The sailfish preference for this temperature interval was already reported by other studies, based on PSAT and ultrasonic telemetry (Hoolihan and Luo, 2007; Hoolihan, 2004). The preference for near surface and warmer waters was also reported for other Istiophoridae fishes in the Atlantic Ocean (white marlin, *Tetrapturus albidus*; Horodysky et al., 2007; and Horodysky and Graves 2005; blue marlin, *Makaira nigricans*; Graves et al. 2002; and Kerstetter et al., 2003).

The positive effect of CLR was higher for the lowest values of chlorophyll-α concentration. This relationship might be explained by the preference of sailfish for warmer waters, which are, in most cases, more oligotrophic. The Month factor presented its higher positive effects on CPUE between June and September. As the majority of the fishing sets took place northward of 20ºS, this pattern can be related to the increase in sailfish abundance near the northeast Brazilian coast during the third quarter of the year (Hazin et al., 1994) (Figure 3).

The DIS effect presented two positive peaks, the first one in areas no farther than 1º (~111 km) from coast line and the second one in areas between 4 and 6º (~444 to 667 km). After the second peak, there was a strong negative shift around 8º (~889 km) of distance from coast. The CPUE spatial predictions map (Figure 4) shows

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3 Details on this function are provided on Lehmann et al 2002 and in the website: http://www.unine.ch/cscf/grasp/
that the spatial catch probabilities are closely related to the DIS predictor, with two separated areas of higher catch probabilities. The first one is closer from coast and includes all oceanic southwest Atlantic Islands, agreeing with the known sailfish preferences for coastal areas and oceanic Islands surroundings (Nakamura, 1985; De Sylva 1974). The second area is located in a more oceanic region and it is separated from the first one by the 8–10º range of distance from coast (Figure 4).

When high catch probabilities areas are compared to size data, it is possible to see that the specimens found in the first area are smaller than those found in the more oceanic region. Figure 5 shows the mean LJFL of sailfishes caught by chartered vessels between 2005 and 2007, grouped by 10º of Latitude and 5º of DIS. In the first two DIS classes (0º–5º and 5–10º) the mean LJFL (161.3 and 160.8 cm) were very close, with a slight trend to increase southward, while in the last two DIS classes (10º–15º 15º–20º) the mean size were larger (171.8 and 175.9 cm), with a trend to increase northward (Figure 5). According to Mourato et al. (2008), the sailfish starts its reproductive migration from Brazilian northeast coast to southeast on mid September remaining near southeast coast until early March. This group, composed of young and adult individuals, could be associated to the coastal area of high CPUE probabilities presented in this work. Based on the distribution pattern presented here, it is likely that the second area of high CPUE probabilities is formed by a group of larger specimens, which tend to be distributed in more oceanic areas, probably moving there after the spawning season, following the South Atlantic Subtropical Gyre (Pettersson and Stramma, 1991).

In conclusion, the present work provided some insight about the Sailfish distribution in the South Atlantic as a function of environmental data. The residual plots and the prediction map indicated that sailfish seems to be associated to warmer, tropical and coastal waters. In spite of the typical association of sailfish to coastal areas and Island surroundings, the Grasp showed that size segregation may occur, with a group of larger animals being found in more distant and oceanic areas.

Acknowledgements

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References


Table 1 – Deviance, validation and cross validation values for the GAM used for the catch probabilities.

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Figure 1- Distribution of fisheries sets made by Brazilian longline fleet, sailfish presence is represented by crosses and absences by circles. The contour lines represent the distance from coast isolines (in degrees) and the bold line shows the prediction’s limits.
Figure 2- Contributions from each predictor variable. (a) explained deviance lost if dropped of the model, (b) inside the model, and (c) explained deviance if the variable is the only one considered in the model.
Figure 3- Partial response curves for all predictors variables considered in the GAM.
Figure 4- Predicted sailfish CPUE (catch per 1000 hooks). The contour lines represent the distance from coast isolines.
Figure 5 – Sailfish LJFL means by Latitude. Each column color represents a different distance from coast or oceanic Islands interval and numbers over columns represents the numbers of measured fishes.