Effects of environmental factors on catch rates of FAD-associated yellowfin (*Thunnus albacares*) and skipjack (*Katsuwonus pelamis*) tunas in the western Indian Ocean

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Abstract

Understanding the relationship between environmental variables and tuna concentrations is important for fishery management. The present study analyzes the relationship between the skipjack (*Katsuwonus pelamis*) and yellowfin tuna (*Thunnus albacares*) spatio-temporal distribution and the environmental conditions in the western Indian Ocean. Data from logbooks, remotely sensed data, ocean circulation model and *in situ* observations for three consecutive years (2006-2008) were used in the analyses. Generalized additive models (GAMs) were applied to examine the relative influence of various factors on tuna catch per unit effort (CPUE). The relationships were examined for the following oceanographical variables: temperature at surface, at 30m and at 75m depth, chlorophyll concentration the same day of the fishing event and 18 days before, sea-level anomaly, mixed layer depth, and gradient of the thermocline. Additionally, geographical location, fishing vessel and month were also used as explanatory variables. The results obtained show that highest CPUEs of both skipjack and yellowfin tuna occurred above 15°N (Somalia upwelling region) and below 15°S (towards the Mozambique Channel), characterized by high chlorophyll-α concentration, and reduced thermocline. However, these relationships are relatively weak suggesting that tropical tuna dynamics are highly complex and may also be influenced by factors not included in this study.

Key words: *Thunnus albacares*, *Katsuwonus pelamis*, GAM, Indian Ocean, habitat

1 Introduction

Tuna and tuna-like species are high valued commercial fish for worldwide fisheries. Skipjack tuna, *Katsuwonus pelamis*, and yellowfin tuna, *Thunnus albacares* are often referred to as the "tropical tunas", due to their distribution range throughout the tropical and sub-tropical waters. Skipjack and yellowfin tuna, the most important species of Indian Ocean tuna catches, are fished throughout the equatorial waters of the Indian Ocean with the majority of the catch being taken in the western areas, from about 20°N to 20°S (Fig. 1). Skipjack and yellowfin tunas are mainly caught by purse seine fleet, but also by longline and gillnet fisheries. These two species together comprise the most important component of Indian Ocean tuna catches. Total annual catches of skipjack tuna averaged 494,100 t between 2004 and 2008. During the same time period, yellowfin tuna was the second most important, with total annual catches of 413,100 t. Over 40% and 80% of purse seine yellowfin and skipjack catches are taken in log-schools (associated with floating objects) respectively (IOTC-2009-WPTT). The floating objects tend to concentrate large pelagic fish under them. In consequence, a worldwide fishery has been developed over these floating objects. Fishing over artificial floating objects, so-called FADs (Fish Agregating Devices) was developed between the mid eighties and the early nineties, increasing purse-seine efficiency and subsequently the catches (Fonteneau et al. 2000; Fron and Dagorn 2000; Delgado et al., 2005). Currently, tuna aggregations around FADs provide about half of worldwide tuna catches (Fonteneau et al. 2000). In spite of the economical importance of fish aggregations around FADs, the knowledge of their role and the relation between tuna aggregations and the environment around these floating objects is still scarce.

Several biotic and abiotic factors influence the distribution and local concentrations of these species. Although there are many published studies on tropical tuna, the interaction of FAD-associated tuna aggregations with their local environment is still unclear. In a recent study, Doray et al. (2009) analyzed the temporal dynamics of tuna biomass around a FAD deployed in the western tropical Atlantic in relation to its local biotic and abiotic environment. The environmental factors included in their analysis could explain 66% of the tuna biomass variability around the FAD, consisting mainly of skipjack, yellowfin and blackfin tuna. A similar conclusion reached Fonteneau et al. (2008), who analyzed catch rates of the purse seiner fleet operating in the western Indian Ocean in February 2005, when one of the major tuna concentration event occurred. The authors related this "extreme fishing event" with high concentration of chlorophyll that occurred 18 days before in the same area. Several researchers have identified correlations between tuna populations processes and environmental factors (e.g. Lehodey et al., 1998, Bertignac et al., 1998; Goñi et al., 2005), and some hypotheses have been suggested for the underlying causes of these correlations. However, no clear relationship has been determined between local abundance, migration patterns and oceanographic conditions; and there are still large uncertainties concerning the environmental mechanism capable of explaining such biological tuna concentrations. Taking into account that ocean circulation models can provide predictions for some oceanographic variables, the relationship between tuna populations and oceanographic conditions can be used to predict potential hotspots in the future.

In the present study, we focus on the relationship between abundance of tuna aggregated around floating objects, and local biotic and abiotic environment. To solve such questions, we analyzed up to three years of log books data containing the location and catch per unit effort (CPUE) of sixteen fishing vessels operating in the Indian Ocean, and the environmental variables corresponding to the catch day and site. The analysis of three consecutive years enables interannual comparison of abundance and their relation with the oceanographic conditions. Generalized Additive Models (GAMs) have been applied in order to assess the effects of environmental factors on tuna aggregations. Due to the flexibility of GAMs to model relationships between biomasses and variables describing their environment, they are increasingly been applied to investigate the relation between environmental factors and marine organisms (e.g. Maravelias, 1999, 2001; Maury et al., 2001; Denis et al., 2002; Katsanevakis et al., 2009; Murase et al., 2009, Sagarminaga and Arrizabalaga, 2005). Two aspects of the ecology of tropical tunas, spatio-temporal distribution (presence/absence data) and local abundance (given its presence), were examined in this study. The considered species are yellowfin (*Thunnus albacares*) and skipjack tuna (*Katsuwonus pelamis*), as these are the most important species of Indian Ocean tuna catches.

2 Material and Methods

2.1 Data

2.1.1 Fisheries data

The compilation of logbooks data from sixteen Biscayan purse seiners for the period of 2006 to 2008 operating in the western Indian Ocean (30°N-30°S, 30°-80°E) was examined.The sixteen fishing vessels use the same fishing gear and have similar technical characteristics (length, weight and material). Therefore, we assumed that the average CPUE represented a similar density of fish. No survey data are available for the study area so that commercial fishery data are therefore the only source of information of tuna distribution. This dataset covers the western part of the Indian Ocean (Fig. 1 and 2), one of the most important regions for tropical tuna fisheries. Fishing events that were performed using natural floating objects (generally logs or similar) were used for model development. In order to use an independent dataset to compare model results and original data, catch rates employing artificial FADs were used to illustrate the correspondence between model predictions and observations. The CPUE is the daily catch rate (in tonnes), which is interpreted as a measure of relative abundance. Including the parameters influencing local catchability in the GAMs, such as geographical location and month, enables to interpret daily catches as a local abundance index (Maury et al., 2001).

2.1.2 Environmental data

For each fishing event, the following oceanographic data were used: temperature at surface, at 30m and at 75m depth (further referred to as SST, T_{30} and T_{75}), chlorophyll-α concentration the same day of the fishing event and 18 days before (Ch-α and Ch-α_{18}, respectively), sea-level anomaly (departures of the sea surface from long term mean, SLA), mixed layer depth (TD), and gradient of the thermocline (TG). Oceanographic information of the covered region and time was provided by the NASA Moderate Resolution Imaging Spectroradiometer (MODIS, http://modis.gsfc.nasa.gov/). The fishing vessel, year and month were also used as explanatory variables.

2.2 GAMs

2.2.1 Presence-absence analysis

In a first stage, skipjack and yellowfin tuna presence-absence was analyzed. The presence was modelled as a binomial variable (i.e. positive catches interpreted as presence vs null catches interpreted as absence), through a Generalized Additive Model (GAM). GAMs use smoothing curves to model relationships between response variable and the explanatory variables. They allow for non-linear relationships, a very common feature in ecological processes, and therefore are a very flexible tool to build complex, non-linear general models (Hastie and Tibshirani, 1990). For this first qualitative analysis, a binomial error distribution and logit-link function (relationship between the response and the additive predictor) were used to model the relation between presence-absence of tuna and environmental conditions.

2.2.2 Quantitative analysis

To link tuna distributions with habitat parameters, we assumed that habitats with higher CPUE would also have greater habitat suitability for that particular species. With this approach, CPUEs (given tuna presence) were modelled as a function of the environmental variables. A Gamma error distribution with a log-link function was found to be adequate for the data modelled here. In order to remove the effects of catchability variability, the parameters that are supposed to influence catchability were systematically added in each model.
In a preliminary analysis, an important number of environmental variables appeared to have a significant effect. To reduce the number of parameters in the analysis (generally fewer parameters is better as long as we do not

loose too much information), a principal component analysis (PCA) was used to describe the linear relationships between the explanatory variables (Fig. 3). Absolute value of latitude was also included in this PCA. The first two components derived from this PCA were then used as synthetic environmental variables in further analysis, instead of using the original environmental variables themselves (Dim_1 and Dim_2). This avoided overestimating the significance of environmental effects of tuna catch rates, due to possible collinearities in the environmental variables.

2.2.3 Model selection

Models were fitted in a forward stepwise manner. To find the optimal set of explanatory variables, the AIC (Akaike Information Criteria) method was used to measure the goodness of fit (Akaike, 1974). The AIC can be calculated for each possible combination of explanatory variables and the model with the smallest AIC can be selected as the "optimal model". A forward stepwise model selection was applied to select the variables. In each step of forward selection, the degree of smoothing was chosen by cross-validation, which is a process that automatically determines the optimal amount of smoothing. The detailed methodology of GAMs is described in Hastie and Tibshirani (1990). All GAMs were performed using the mgcv 1.3-30 package of R 2.9.0 free software (R Development Core Team, 2009).

3 Results

3.1 Data exploration

For data exploration, CPUEs have been transformed in order to down-weight the influence of outliers. Generally, skipjack catches are higher than yellowfin catches for all years, but this difference was more pronounced in 2006 (Fig. 4). During 2006, skipjack catch rates were considerably higher than in the following two years. In a preliminary analysis, The Pearson correlation coefficient (indicator of linear relationship) between daily catches (indicator of species local abundance) and environmental variables was calculated to detect relationships between variables and possible collinearities among explanatory variables (Table.1). The Pearson correlation coefficients reveals that there might be an effect of temperature, chlorophyll-α concentration (18 days before) and depth of thermocline in the abundance of yellowfin and skipjack tuna. Year may also be an important factor when analyzing fishery data. Skipjack tuna catches are also correlated with the yellowfin catches (R=0.39). The highest collinearity was found between temperature at 75m depth and thermocline depth (R=0.61). We decide to drop off the variable T_{75} for further analysis, as it is meaningless to use a model where some of the explanatory variables mirror the same information.

A principal component analysis (PCA) was used to describe the relationships between the environmental variables (Fig. 3). PCA takes a set of variables and defines new variables that are linear combinations of the initial variables. The first two axis of the PCA are then used as explanatory variables in future analysis. The x-axis (Dim_1) is interpreted as indicator of well mixed waters of the southern part of the Indian Ocean, with high chlorophyll concentrations, low SST and a deep thermocline with low gradient. Y-axis (Dim_2) represents cyclonic condition, with positive sea-level anomaly and high sub-surface temperatures. The position of the two investigated species in relation to the environmental variables is illustrated in the same graph. These two axis of the PCA are used as explanatory variables to build the model, achieving a considerable reduction in dimensionality whilst still accounting for a large proportion of original variation (more than 60%).

3.2 GAMs

In a first stage the presence-absence of tropical tunas has been modeled using environmental factors as explanatory variables. For skipjack tuna, a forward selection criterion gave a model where space and time (absolute value of latitude and month), thermocline depth, chlorophyll-α concentration and the interaction between gradient of thermocline and chlorophyll-α concentration 18 days before the fishing event were selected. All the other parameters are not significant. Assuming a binomial error distribution and logit-link function the optimal model was:

$$p/a_{sk} = c + s(Lat) + factor(Month) + s(TD) + s(Ch{-}\alpha\ ) + \mathrm{s}(\text{Ch-}\alpha_{18}, TG) \quad (1)$$

c is the intercept and $s(x)$ the smoothing function. The estimated parameters and p-values are given below (Table 2). The model can explain 21.8% of the variance with a R^2 of 0.142. The partial fits in Fig. 5a show the contribution of the individual explanatory variables. The cross-validation estimated 1 degree of freedom for the smoother of chlorophyll_α and thermocline depth. This means that a linear relationship exist between presence of skipjack tuna and these two environmental variables. Chlorophyll_α has a positive relationship with skipjack abundance: the higher the chlorophyll concentration is, more skipjack tuna are present. In contrast, depth of thermocline is inversely related to skipjack abundance. The estimated smoother for the variable 'Latitude' shows a non-linear pattern. The results for the nominal variable 'Month' indicates that there were significantly less skipjack tunas in April and July than in January, which is the baseline value (90% and 99% of confidence level respectively). For the rest, the difference respect to the baseline (January) was not significant. In a second stage, the CPUE of skipjack tuna was modelled. In this case, the explanatory variables that constitute the optimal model are:

$$CPUE_{sk} = c + s(Lat) + s(Lon) + s(Dim_1) + s(Dim_2) + factor(Month) + factor(Vessel) \tag{2}$$

Dim_1 and Dim_2 correspond to the first two axis of the PCA analysis (Fig. 3). Dim_1 represents well mixed waters of the southern part of the Indian Ocean, with high chlorophyll concentrations, low SST and a deep thermocline with low gradient. Dim_2 is interpreted as indicator cyclonic condition, with positive sea-level anomaly and high sub-surface temperatures. The model can explain 40.7% of the variation found in our dataset with a R^2 of 0.274. The shape of the smoothers and their contribution is illustrated in Fig. 5a. Additionally, standard graphical output for validation of GAMs is shown in Fig. 6. None of the panels show serious problems, except the response against fitted values, which should ideally show a straight line.
The same procedure has been used to select the "optimal" model for yellowfin tuna. The variables that best explain the data were fishing vessel and year, sea-level anomaly, chlorophyll concentration and location (longitude).

$$p/a_{ye} = c + factor(Vessel) + factor(Year) + s(SLA) + s(Ch\alpha) + s(Lon) \tag{3}$$

All these variables are significant within a 95% of confidence level. The cross-validation estimated 1 degree of freedom for 'Longitude', indicating that a linear relationship exist between yellowfin presence and longitude. Sea-level anomaly and chlorophyll concentration present a non-linear relationship with yellowfin presence (Fig. 7a). As the interval of 95% confidence level is very wide in both edges of the x-axis, we focus on the central part of the plot, where most of the data-points lie and the confidence bands are narrower. The probability of yellowfin presence peaks around zero values of sea-level anomaly, and it is minimum at values of chlorophyll around $0.1 mg/m^3$. Longitude presents a weak negative slope, meaning that in the western part of the studied area the probability of yellowfin presence is slightly higher than in the eastern part. In the second stage, the first two axis of the PCA analysis together with 'Longitude' and the nominal variables 'Month' and 'Vessel' were chosen as the best explanatory variables. The deviance explained for first and second stage was, respectively, 25.6% and 43.3%

$$CPUE_{ye} = c + s(Lon) + s(Dim_1) + s(Dim_2) + factor(Month) + factor(Vessel) \tag{4}$$

The partial fits in Fig. 7b show the contribution of the individual smoothers, while taking into account the other variables in the model. The cross-validation estimated 1 degree of freedom for Dim_1 and Dim_2 (linear relationship), whereas the smoother 'Longitude' has a nonlinear shape (6.69 degrees of freedom). The partial fit of Dim_1, indicator of productive waters of the southern part of the Indian Ocean, has a positive slope, indicating that yellowfin is more abundant at high latitudes, with a deep thermocline and high chlorophyll concentration. In contrast, Dim_2, indicator of cyclonic conditions is negatively related to yellowfin abundance. The model validation includes QQ-plots and histogram of residuals, residuals versus fitted values and model fit (fitted values versus observed values). The first three do not show any problem. The last panel, response versus fitted values, should ideally lie on a straight line.

3.3 Prediction

The distribution of the GAM-estimated local abundance index of skipjack and yellowfin tunas has been compared to monthly fishery data (Fig. 9 and 10). For the comparison, we used an independent dataset based on fishing events that were performed using artificial FADs. In order to prevent trends due to different number of observations per month, a mean catch rate has been calculated for each month. The mean catch rate is then used as an indicator of fishing intensity during that month. During the months with high catches (between August and November), the predicted value is also larger (clearly noticeable in case of skipjack tuna). The main activity of the selected fleet is directed to skipjack tuna, and consequently, CPUEs of yellowfin tuna present discontinuities within the studied period. Consequently, these discontinuities in fishing events make the comparison between observed and predicted values difficult. Moreover, the monthly catches using artificial and natural FADs differ considerably in magnitude.

For skipjack tuna, a noteworthy seasonal pattern can be discerned in both observed data and GAM-based predictions. This seasonal pattern using artificial FADs for fishing is similar to that derived from catches using natural FADs. Maximum CPUEs of skipjack tuna based of natural FADs occurred in September (Fig. 4), whereas with the use of artificial FADs occurs between August and November (Fig. 9).The order of magnitude of the predicted values are rather lower than those from logbooks data. However, the maxima predicted for August-November in consecutive years are consistent with observed values.

4 Discussion

Although tropical tunas are a very important economical resource for the purse seiners fleet operating in the Indian Ocean, there is little detailed information on their biology and ecological preferences. The present study has showed the existence of environmental and habitat association of tropical tunas in the

western Indian Ocean using two-stage GAMs.
Dorey et al. (2008) have demonstrated that fish abundance decreased with the distance from the head of the FAD, suggesting that environmental descriptors are not directly forcing the FAD tuna concentration, but might be indicative of migratory patterns. The depth and gradient of thermocline together with the chlorophyll concentration seem to be the most important factors controlling the presence of skipjack tuna. The geographical location however influences its local abundance (directly related to CPUE). PCA allowed the complex oceanographic environment to be represented by a small set of predictors, while preserving most of the original variance. The first two components of the PCA significantly influence the CPUE of both skipjack and yellowfin tunas. in the range where interval of confidence is narrowest a positive relation exist between skipjack CPUEs and Dim_1, which represents cold and well mixed waters, with high chlorophyll concentration from the southern part of the Indian Ocean. Tuna may have preference for these conditions to feed on the trophic chain generated by the high primary productivity. The negative relation between Dim_2 and tuna CPUEs suggest that cyclonic conditions are not a suitable habitat for skipjack tuna. This is consistent with previous studies showing that tuna biomass decreased under the presence of an eddy in a moored FAD deployed in the Caribbean (Doray et al., 2009).
The predictions carried out with an independent fishery dataset in order to test the model are much lower than those reported by the logbooks. Nevertheless, the models can capture the high peaks occurring between August and November, related to large tuna aggregations (CPUEs per fishing event are also larger during these month). It is therefore useful to find potential hotspots for tuna aggregations.

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5 Figures and Tables

Table 1
Pearson correlation coefficients (indicator of linear relationship) between skipjack (SK) (K*atsuwonus pelamis*) and yellowfin (YE) (*Thunnus albacares*) tuna catches and the selected environmental variables for the Indian Ocean: Temperature at surface (SST), and in the water column (T_{30} and T_{75}), chlorophyll concentration at the time of fishing (Ch-α) and 18 days before (Ch-α_{18}), thermocline depth (TD) and gradient (TG), sea-level anomaly (SLA), year, month and location (absolute latitude and longitude).

	SK	YE	SST	T_{30}	T_{75}	Ch-α	Ch-α_{18}	TD	TG	SLA	Year	Month	Long
YE	0.39												
SST	0.11	0.23											
T_{30}	0.24	0.32	0.49										
T_{75}	0.24	0.18	<0.1	0.51									
Ch-α	<0.1	0.13	0.50	0.39	<0.1								
Ch-α_{18}	0.19	0.27	0.54	0.48	<0.1	0.54							
TD	0.19	<0.1	0.54	<0.1	**0.61**	0.46	0.30						
TG	<0.1	<0.1	0.30	<0.1	0.45	0.19	0.35	0.23					
SLA	0.13	0.19	<0.1	0.38	0.41	<0.1	0.15	0.38	0.11				
Year	0.23	0.21	<0.1	0.31	0.27	0.12	0.25	0.22	<0.1	0.25			
Month	<0.1	0.12	0.41	0.31	<0.1	0.36	0.39	0.27	0.24	0.34	0.31		
Long	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1	0.10	<0.1	<0.1	0.31	0.48	
Lat	<0.1	<0.1	<0.1	<0.1	0.11	<0.1	0.11	<0.1	0.18	0.20	0.55	0.43	0.53

Table 2
Summarized results for the optimal GAMs selected for skipjack and yellowfin tunas caught in the western Indian Ocean. In a first-stage presence/absence of tuna has been analyzed, and in the secong stage their abundance (given presence).

	Skipjack tuna (*Katsuwonus pelamis*)				**Yellowfin tuna (*Thunnus albacares*)**			
	Presence-absence		**CPUE**		**Presence-absence**		**CPUE**	
Family	Binomial		Gamma		Binomial		Gamma	
Link-function	Logit		Log		Logit		Log	
Adjusted R^2	0.142		0.274		0.265		0.217	
Deviance esplained (%)	21.8		40.7		25.6		43.3	
	Edf.	**p-value**	**Edf.**	**p-value**	**Edf.**	**p-value**	**Edf.**	**p-value**
factor(Month)	1	1	11	$4.1 \cdot 10^{-6}$	-	-	11	$5.48 \cdot 10^{-5}$
factor(Vessel)	-	-	15	$2 \cdot 10^{-16}$	15	$2.05 \cdot 10^{-12}$	15	$8.75 \cdot 10^{-5}$
factor(Year)	-	-	-	-	2	$5.92 \cdot 10^{-5}$	-	-
s(Latitude)	4.32	$1.12 \cdot 10^{-3}$	5.544	$3.68 \cdot 10^{-6}$	-	-	-	-
s(TD)	1.00	$7.66 \cdot 10^{-3}$	unused	unused	-	-	unused	unused
s(Ch-α)	1.00	0.05874	unused	unused	6.367	0.03652	unused	unused
s(Ch-α,TG)	15.1	0.0731	unused	unused	-	-	unused	unused
s(Long)	-	-	8.238	$2.59 \cdot 10^{-5}$	1	0.0466	6.686	$6.03 \cdot 10^{-5}$
s(SLA)	-	-	-	-	6.445	$1.21 \cdot 10^{-3}$	-	-
s(Dim$_1$)	unused	unused	3.695	$1.41 \cdot 10^{-3}$	unused	unused	1	$1.83 \cdot 10^{-5}$
s(Dim$_2$)	unused	unused	2.358	$7.7 \cdot 10^{-7}$	unused	unused	1	$2.28 \cdot 10^{-6}$

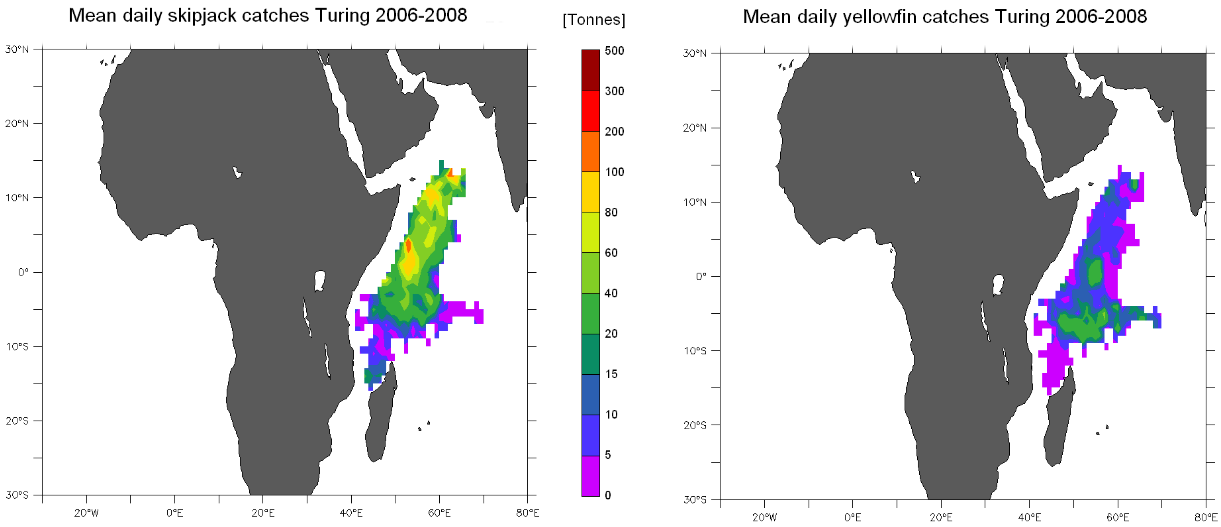

Fig. 1. Mean daily catches of skipjack and yellowfin tunas in the western Indian Ocean by the Biscayan fleet during the period 2006-2008. Original dataset has been gridded in a 1°x 1°array and smoothed for the purpose of better visualization.

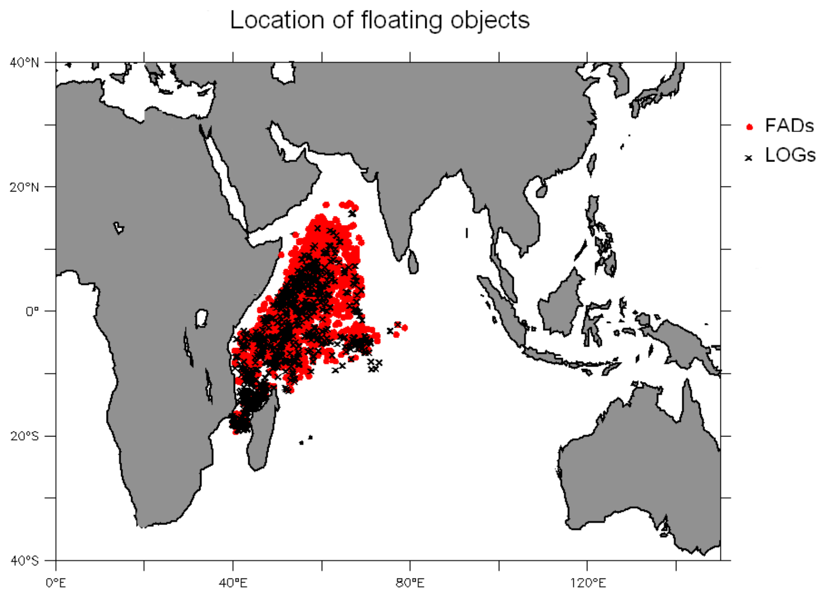

Fig. 2. Location of natural floating objects (LOGs) and artificial devices (FADs) used in this study

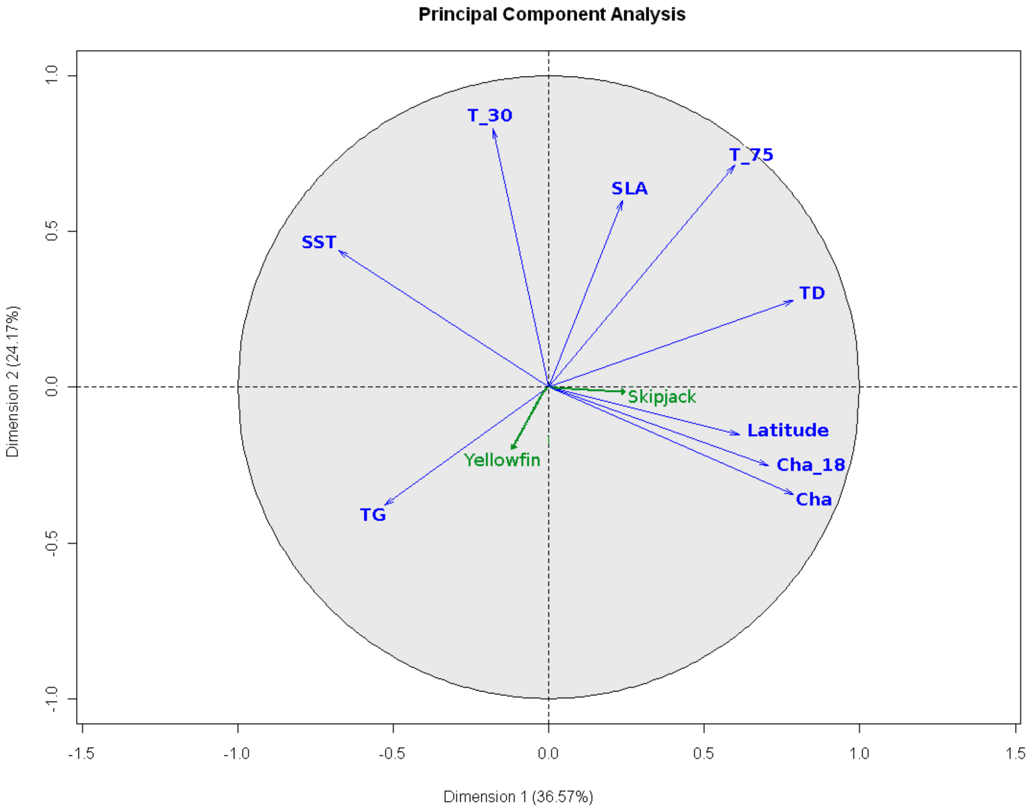

Fig. 3. First two axis of obtained by PCA for the environmental variables: temperature at surface (SST), and in the water column (at 30m and at 75m depth), chlorophyll concentration at the time of fishing (Ch-α) and 18 days before ($Ch\alpha_{18}$), thermocline depth (TD) and gradient (TG), sea-level anomaly (SLA), and latitude (absolute value). The position of the two investigated species in relation to the environmental variables is printed in green.

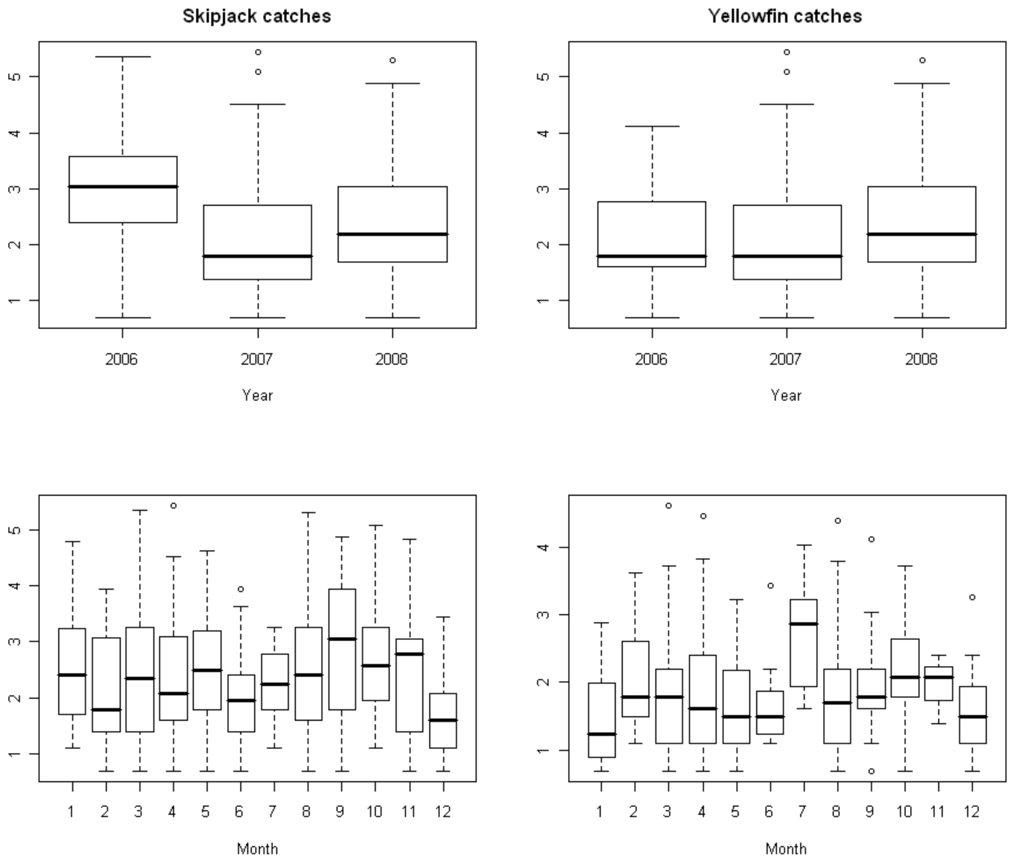

Fig. 4. Boxplot of logarithmic transformed CPUEs for the two tuna species: Skipjack (*Katsuwonus pelamis*) and yellowfin tuna (*Thunnus albacares*). Comparison between years (upper panels) and between months (lower panels). The 25% and 75% quartiles define the end of the boxes, and points outside these values are potential outliers.

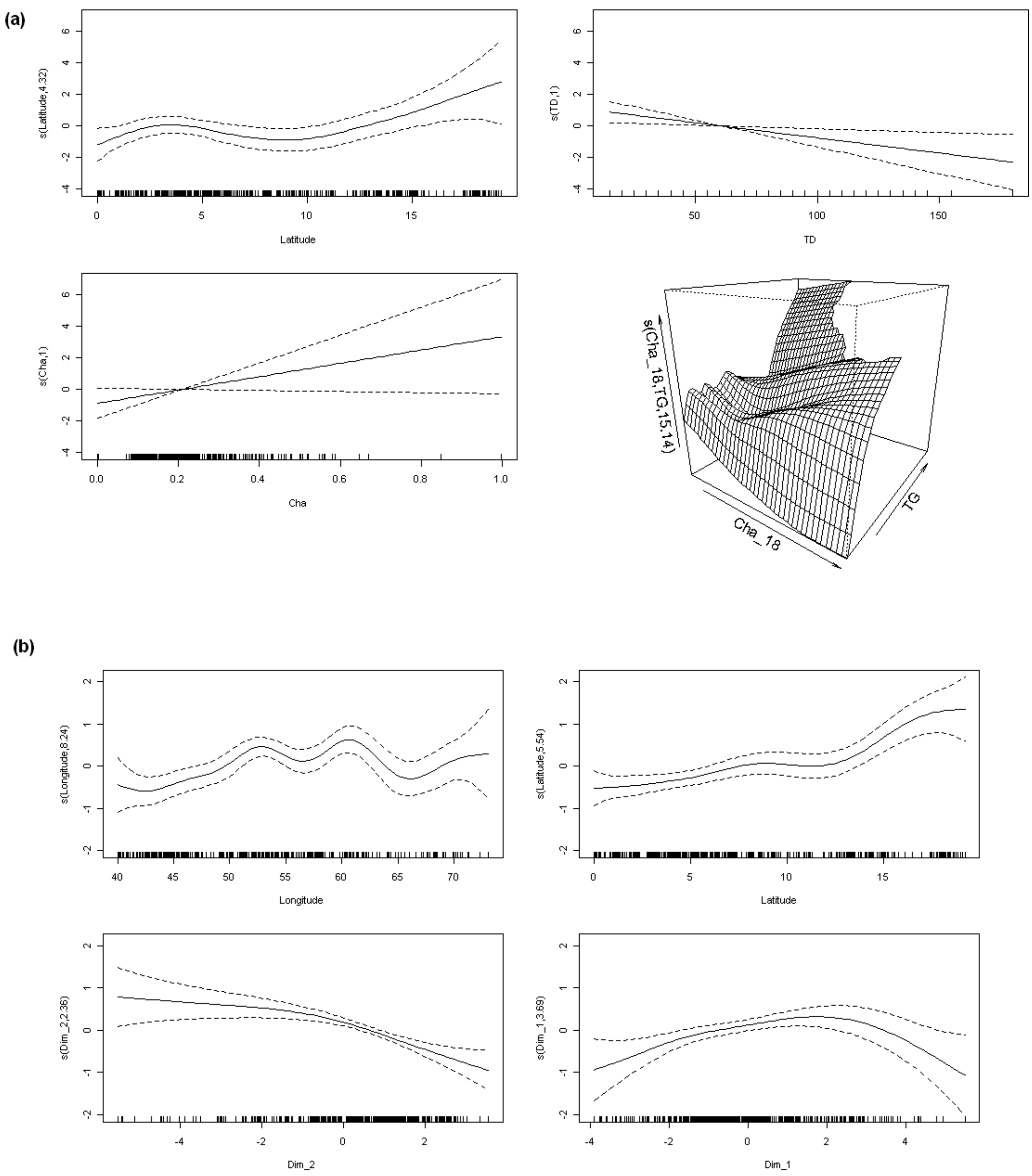

Fig. 5. **(a)**: Estimated smoothing curves obtained by the GAM applied to presence-absence data of skipjack tuna. **(b)**: Estimated smoothing curves obtained by the GAM applied to positive CPUE data of skipjack tuna using the first two dimensions of the PCA as explanatory variables. The x-axis shows the values of the explanatory variables (TD: depth of thermocline; (Ch-α): Chlorophyll concentration) and the y-axis the contribution of the smoother to the fitted values. The dashed lines represent 95% confidence bands. The tick marks along the x-axis indicate the values of the observed data-points.

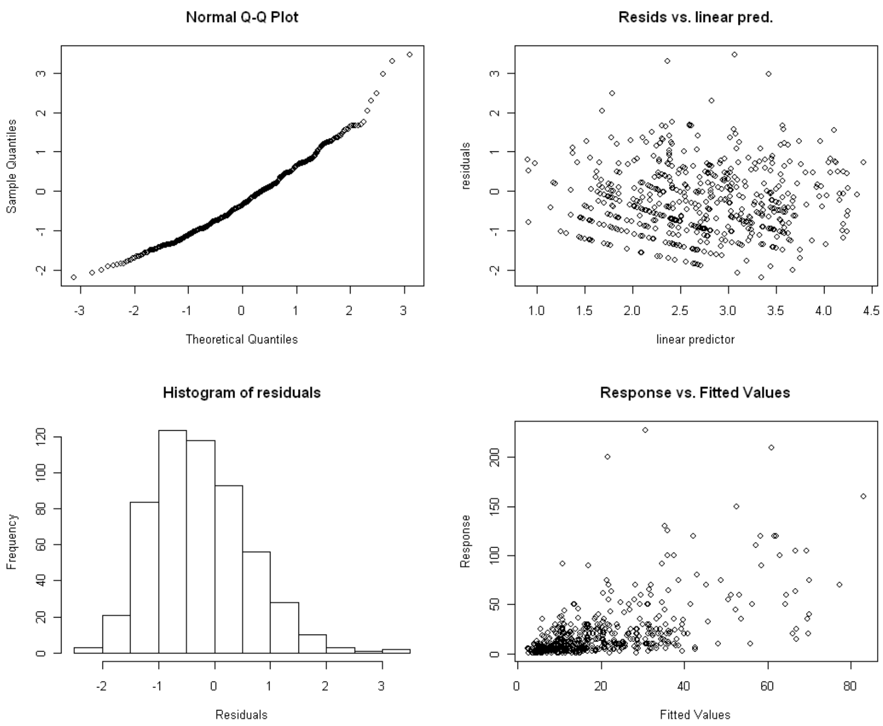

Fig. 6. Diagnostic plots for the GAM model for skipjack tuna when fitting non-zero catch rates. The QQ-plot and the histogram of the residuals are used to verify normality. The plot of standardized residuals against fitted values assesses homogeneity.

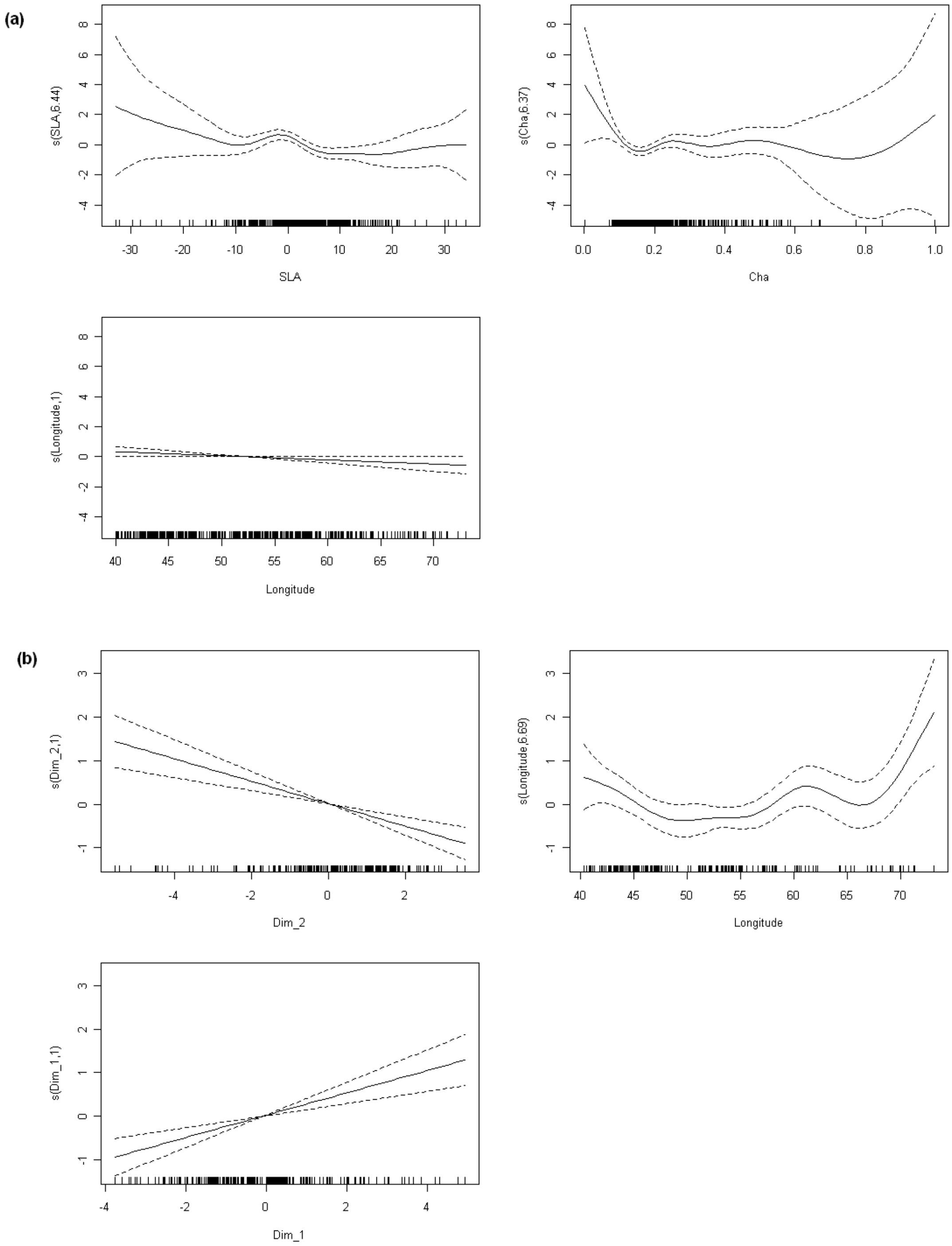

Fig. 7. **(a)**: Estimated smoothing curves obtained by the GAM applied to presence-absence data of yellowfin tuna. **(b)**: Estimated smoothing curves obtained by the GAM applied to abundance data of yellowfin tuna using the first two dimensions of the PCA as explanatory variables. The x-axis shows the values of the explanatory variables (SLA: Sea-level anomaly; Cha: Chlorophyll concentration) and the y-axis the contribution of the smoother to the fitted values. The dashed lines represent 95% confidence bands. The tick marks along the x-axis indicate the values of the observed data-points.

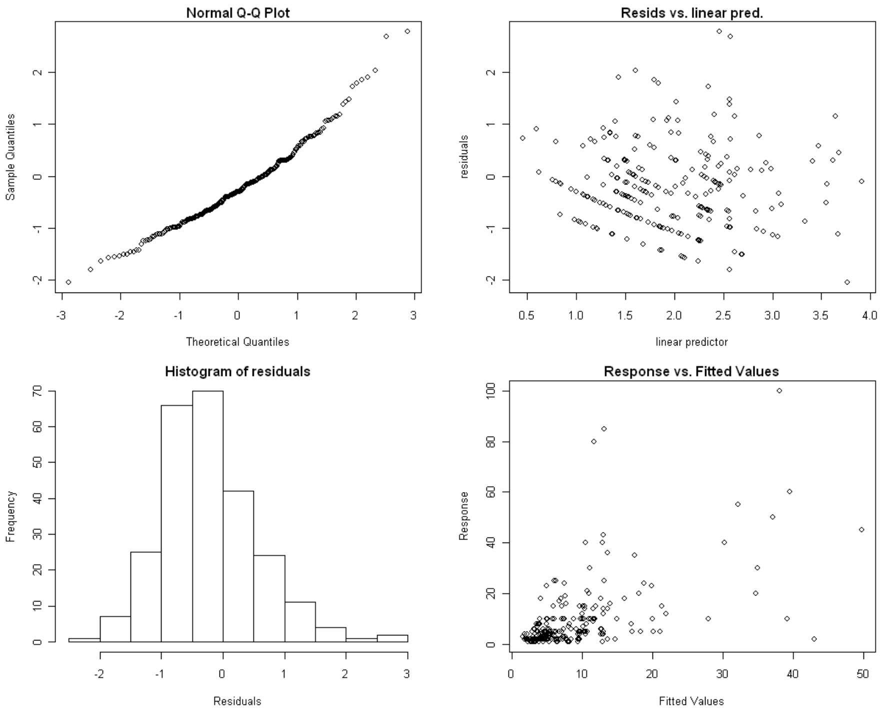

Fig. 8. Diagnostic plots for the GAM model for yellowfin tuna when fitting non-zero catch rates. The QQ-plot and the histogram of the residuals are used to verify normality. The plot of standardized residuals against fitted values assesses homogeneity.

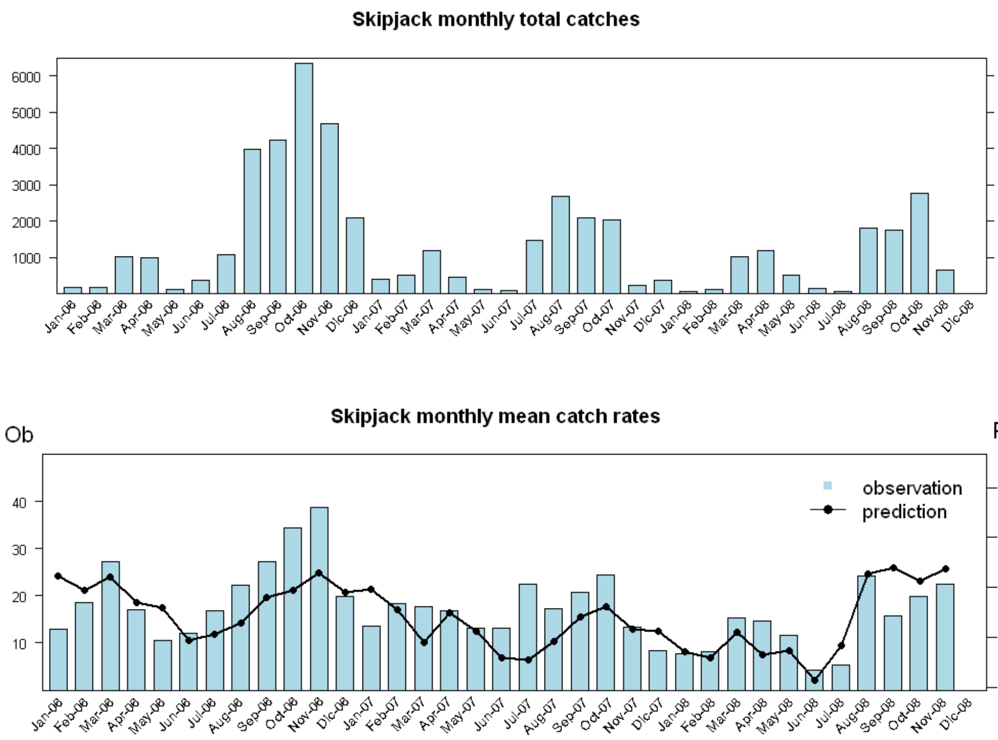

Fig. 9. Temporal evolution of mean catch rates during the studied period for skipjack tuna (*Katsuwonus pelamis*) employing artificial FADs. The upper panel represents total monthly catches (tonnes), whereas the lower panel reproduces average CPUE (tonnes per fishing event). Observed values (blue) versus GAM predicted values (black).

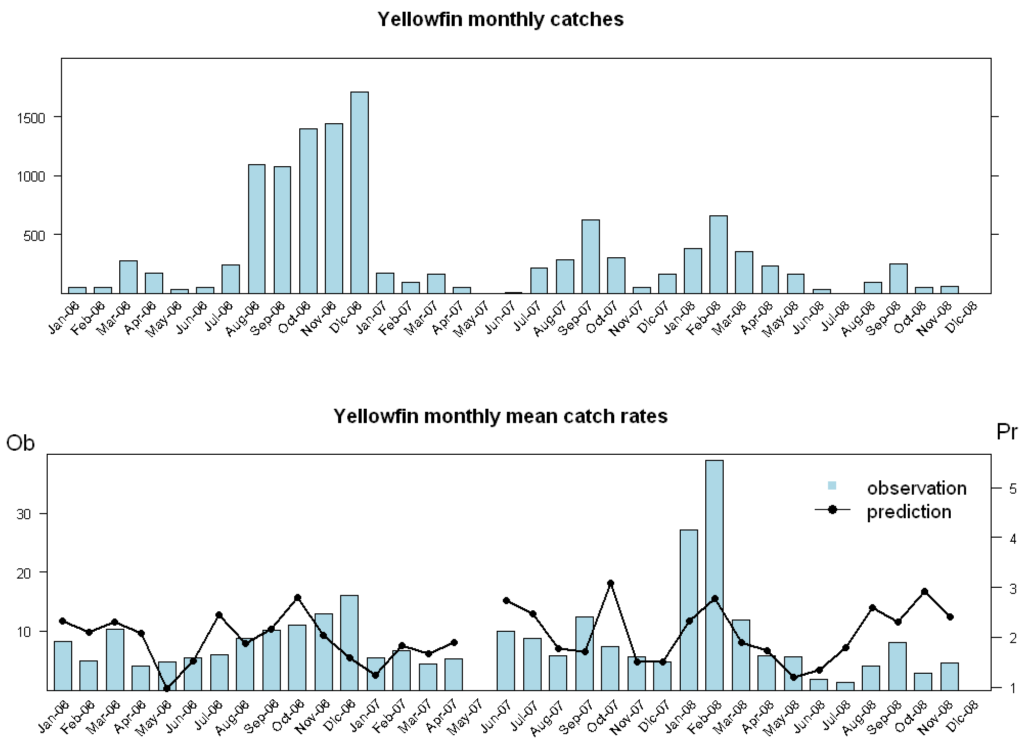

Fig. 10. Temporal evolution of mean catch rates during the studied period for yellowfin tuna (*Thunnus albacares*) employing artificial FADs. The upper panel represents total monthly catches (tonnes), whereas the lower panel reproduces average CPUE (tonnes per fishing event). Observed values (blue) versus GAM predicted values (black).