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Standardized CPUE of porbeagle shark (*Lamna nasus*) caught by the Uruguayan pelagic longline fleet in the Southwestern Atlantic Ocean (1982-2012)

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STANDARDIZED CPUE OF PORBEAGLE SHARK (*LAMNA NASUS*) CAUGHT BY THE URUGUAYAN PELAGIC LONGLINE FLEET IN THE SOUTHWESTERN ATLANTIC OCEAN (1982-2012)

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1. Introduction

This study represents a contribution by Uruguay to the Southern Hemisphere Porbeagle Shark Stock Status Assessment, reporting the standardized catch rate of porbeagles captured by the Uruguayan longline fleet in the Southwestern Atlantic Ocean between 1982 and 2012.

2. Materials and methods

2.1 Fleet description

The Uruguayan tuna fleet operated continuously between 1981 and 2012, but in two separate phases. Between 1981 and 1991, the fleet was composed entirely of large-scale freezing vessels operating with a Japanese-style multifilament longline (averaging 2,000 hooks per set), reaching a total of 15 vessels at its peak in 1984. After 1992 the majority of these vessels were replaced by small-scale fresh-fishing vessels that utilized an American-style monofilament longline (averaging 1,000 hooks per set), with the exception of two vessels that utilized Spanish-style multifilament longline (averaging 2,200 hooks per set) (Mora and Domingo 2006, Domingo *et al.* 2008). All vessels in the last period (both the American and Spanish-type) set their fishing gears at shallower depths than their Japanese-style counterparts in the first period.

2.2 Database

Data were obtained from the logbooks of the Uruguayan longline fleet that operated in the South Atlantic Ocean between 1981 and 2012 (**Figure 2**). Date, geographic position (latitude and longitude) and sea surface temperature (SST in Celsius degrees) at the beginning of the set, effort (number of hooks) and gilled and gutted weight (GWT) of *L. nasus* captured were recorded for each set.

Given the change in the fleet in 1992, standardization analyses were performed both considering the time series as a whole (1982-2012) and as two distinct periods according to fishing gear characteristics: 1982-1992 and 1993-2012.

2.3 Data filtering

A total of 20,906 sets were deployed between 1981 and 2012. Eighty percent of the sets were considered for the standardization. The other 20% were eliminated for several reasons, such as missing information about geographic position and/or SST; and missing capture information, with all shark captures grouped as ‘sharks’. All 1981 sets were eliminated because the fleet did not operate until late September. In addition, since porbeagle sharks have a southern distribution and were only captured within a restricted subset of the total fishing distribution of the Uruguayan tuna fleet, we only used data in the area south of 34ºS. We also omitted sets east of longitude 39º W, as there was little effort in this area. Overall, we analyzed a total of 16,741 fishing sets deployed between 1982 and 2012 in the area located between 34-48º S and 60-39º W (**Figure 1**), representing a total effort of 23,952,386 hooks.

2.4 Variables used

Nominal CPUE was calculated as kilograms of porbeagle (GWT) per 1,000 hooks. Seasons (*Quarter*) were considered as quarters: 1st (January-March), 2nd (April-June), 3rd (July-September) and 4th (October- December). Sea surface temperature (*SST*) and *Latitude* were fitted as continuous variables to facilitate identification of the relationships. Vessel identity (*Vessel*) was fitted as a categorical variable.

To account for the variability among operations in the Uruguayan tuna fleet we also considered three categories of vessel based on a cluster analysis performed by Pons et al. (2012) to group them according to similar characteristics (*i.e.* length, motor power and gross register tonnage). Storage characteristics affect the vessel's autonomy and effective days of fishing per fishing trip, and may also affect the species targeted due to their effects on fish quality and marketability, so we also considered two vessel categories according to the type of storage utilized, namely, frozen storage or fresh storage.

Table 1 summarizes the explanatory variables used for the standardization.

2.5 Delta-lognormal Model

Many species, especially non-target species (or bycatch) have a high proportion of zero catches with positive effort. In order to deal with this type of data, methods such as the *Delta-Lognormal* (Pennington, 1996, Lo *et al.*, 1992; Stefansson, 1996, Ortiz and Arocha, 2004) have been applied. *Delta* or *hurdle* methods analyze separately the probability that a null or positive observation occurs, and the positive observations. The approach employs two models, the first part assuming a binomial distribution, and the second part a positive distribution such as the lognormal or gamma.

In preliminary and exploratory analyses on the full dataset we fitted the catch rate data with generalized linear models, using the function *glm*() in R (R Core Team 2016) and the *influ* library (Bentley et al. 2011). The *influ* package is a useful resource for model exploration that is currently only available for glm. Models were fitted using *Year*, *Quarter*, and *Vessel* as categorical variables, and *Latitude* and *SST* as continuous variables using cubic splines with 5 degrees of freedom.

For the final analyses with the dataset separated into two periods, we used generalized additive mixed models, implemented with the functions *gam* and *gamm* from the package *mgcv* (Wood 2011). The mixed modelling approach is more flexible than generalized linear modeling. For example, vessel effects can be included as random effects, which reduces problems with inestimable parameters. The *gam* function was used to implement simple mixed models and allowed easier hypothesis testing, while adding correlation structure required the *gamm* function. Given that both functions involve generalized additive mixed models, we refer to both using the term *gamm*.

Models were fitted using *Year*, *Quarter*, and *Vessel* as categorical variables, and *Latitude* and *SST* as continuous variables using smooth terms with the function *s*(). Interactions between smooth terms were implemented with the function *te*(), to allow the degrees of freedom to vary by parameter.

We used AIC for both components of the *gamm* Delta Model to determine the set of explanatory factors and interactions that explained most of the variability in the data. Hypothesis testing was carried out for the fixed effects component after fitting models with maximum likelihood (ML), and for the random effects after fitting with restricted maximum likelihood (REML).

Autocorrelation in the residuals was explored using *gamm* models and an autoregressive process of order 1, which was grouped by vessel and implemented using the correlation structure class 'corAR1'.

Q-Q plots are presented for the log-transformed residuals of the lognormal components of the full period, and for each of the split periods.

CPUE indices were estimated by predicting the proportion of positive sets and the catch rate in positive sets for each year, at the median of all covariate values for continuous variables, and the mode for categorical variables. Confidence intervals for each year were based on 2 standard errors of the lognormal component of the delta lognormal model.

3. Results and discussion

A total of 737.637 tons of porbeagle sharks were registered during 1982-2012 in the analyzed area. The maximum number of sets occurred in 1984, which corresponds with the period when the most vessels were operating (n=12 after data filtering). Between 1984 and 1993 the number of sets decreased, and subsequently increased again to a second smaller peak in 2005. From this year onwards the number of sets per year declined (**Figure 2**). The percentage of positive captures among the total sets was 16.4% for the entire period with a maximum of 57.2% in

1982 and a minimum of 0.9% in 2000. **Figure 2** shows the percentage of positive sets and total effort (in number of sets) for each year between 1982 and 2012.

3.1 Whole period (1982-2012)

Model comparisons for the Binomial and Lognormal models are shown in **Table** . For both the mean catch rates in the positive sets and for the proportion of positives/total sets the factors *Year, Quarter, SST, Latitude,* and *Vessel* were significant, with significant interactions between *SST* and *Quarter*. For the binomial model there was also a significant interaction between *Latitude* and *Quarter*. *Storage factor* (frozen vs. fresh) and *Vessel Category* were also explored and found to explain less variation than *Vessel*. Interactions with the Year effect were not considered, due to low sample sizes, lack of balance in the data across *Year*, and the need to estimate the *Year* effects. Results are also presented for a model without interaction terms.

The factors selected for the Lognormal and Binomial components were:

Binomial Model: *positive/total = Year + Quarter + Vessel + ns(Latitude, df=5)*Quarter + ns(SST,df=5)*Quarter*

Lognormal Model: *log (CPUE) = Year + Quarter + Vessel + ns(Latitude, df=5)*Quarter + ns(SST,df=5)*

Diagnostic plots for both the Lognormal GLM models with and without interactions terms confirmed model assumptions of homogeneity of variance and lognormal distribution of the CPUE (Error! Reference source not found.).

The influence plots demonstrate the sizes and patterns of variable effects on catch rates (**Figures 4** and **5**). They indicate a strong effect of latitude, with much higher catch rates further south even after accounting for SST. Note that the increase in nominal CPUE in 2010-2012 appears to be due to fishing further south. SST also has a strong effect on catch rate, with much lower catch rates at higher temperatures. Catch rates vary by quarter, which is consistent with seasonal movements of vessels with the fishery, and porbeagle sharks by season. Vessel effects are very influential, with large differences between individual vessels.

3.2 Split periods (1982-1992 and 1993-2012)

Comparisons of the fixed effects in the Binomial and Lognormal models are shown in **Table** . For each period, and for both the mean catch rates in the positive sets and for the proportion of positives/total sets the factors *Year, Quarter, SST and Latitude* were significant, with significant 3-way interactions between *SST, Quarter and Latitude*. Vessel does not appear in this table because it was fitted as a random effect. For each model component and period, the models including Vessel as a random factor had lower AIC values than those without random effects (**Table 4**). However, the results of interest were very similar for the model without random effects and these are presented in the figures for clarity. Results are also presented for a model without interaction terms.

The fixed factors selected for the Lognormal and Binomial components were:

Lognormal: *log (CPUE)=Year + Quarter + te(Latitude, SST, by = Quarter, k = c(10,10)) + s(Vessel, bs = "re")*

Binomial: *positive/total=Year + Quarter + te(Latitude, SST, by = Quarter, k = c(10,10)) + s(Vessel, bs = "re")*

Diagnostic plots for both the final Lognormal additive models with and without random effects confirmed model assumptions of lognormal distribution of the CPUE (**Figure** 2).

The autocorrelation plots indicate some autocorrelation for data from the same vessels (**Figure 7**), supporting its inclusion in the model. However, it has only a small effect on variable pattern plots and very little effect on indices.

The gamm plots show similar patterns to the influence plots, but the confidence intervals on the smooth terms demonstrate the low confidence for estimates at extreme values of *SST* and *Latitude* (**Figures 8, 9, 10** and **11**). The Latitude effect for the early period surprisingly declines south of 38 °S, but is uncertain and based on very little fishing effort (see **Figure**). The binomial effect plots show stronger patterns than the lognormal plots (**Figures 8, 9, 10** and **11**). There appears to be more information in the presence and absence of porbeagles in the catch than in the weight of sharks caught per positive set.

Standardized indices and confidence intervals for both periods are presented in **Table 5** and **6**. Standardized CPUE values increase over most of the first part of the time series, when catch rates are higher (**Figures 12** and **13**). In the second part of the time series, after the fleet changed its fishing gear from a Japanese-Style to an American-Style longline, catch rates are in general much lower, apart from a few of the early index values for the new fleet. There is no evidence of change in the catch rate from 1998-2012, but catch rates are very low and variability in the indices is very high, so the information content may be limited. Although using a different standardization method and based on observer program data instead of logbooks, Pons & Domingo (2010) also found no apparent trend in porbeagle catch rates between 1998 and 2012.

These results provide useful information about factors affecting catch rates of porbeagle sharks, showing important effects of SST, Latitude and Vessel. The substantial changes in catch rate after the transformation of the fleet from Japanese style to American-style longlines are independent of SST and Latitude, suggesting that fishing method factors such as set depth or bait type may affect porbeagle catch rates. We did not have the data to standardize for these factors, but Japanese-style longlines typically operate at deeper depths than American-style longlines (Domingo et al. 2014). Thus it is possible that fishing depth may affect porbeagle catch rates. Reporting reliability may also be significant in differences among vessels.

4. References

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Table 1. Summary of independent variables used in the GLM models. The numbers in parentheses refer to the number of categories in each variable. ** L=length, HP= engine power (in horse power), GRT= gross registered tonnage, see SCRS/2011/114.

Variable	**Type**	**Observations**
Year	Categorical (31)	Period: 1982-2012
Quarter	Categorical (4)	Quarter 1: January-March Quarter 2: April-June Quarter 3: July-September Quarter 4: October-December
Latitude	Continuous	34-47°S
Sea Surface Temperature (SST)	Continuous	Range: 8 to 29° 95% interval: 13 to 24.8°
Vessel cluster	Categorical (3)	1: Mean L 51 m; Mean HP 1256; Mean GRT 322 ** 2: Mean L: 36 m; Mean HP 923; Mean GRT 286 ** 3: Mean L: 21 m; Mean HP 350; Mean GRT 110 **
Storage	Categorical (2)	C: frozen storage of catch F: fresh storage of catch
Vessel	Categorical(45)	Unique vessels, 21 in the first period, and 28 in the second period

Table 2. Table of models for proportion of positive sets (Binomial) and positive catch rate (Lognormal) models for the period 1982-2012. 'd.f.' refers to degrees of freedom of the model components; 'deltaAIC' is the difference in AIC from the best model, which is indicated with deltaAIC of 0.

Model structures and AIC for proportions of non-zero sets

Model #	Model	AIC	deltaAIC	df
1	Yr + ns(SST)	7345.4	717.4	36
2	Yr + Vessel + ns(SST)	7011.8	383.7	64
3	Yr + Vessel + ns(Lat) + ns(SST)	6890.2	262.2	68
4	Yr + Vessel_cat + C_vs_F + ns(SST)	7286.2	658.2	39
5	Yr + Qtr + Vessel + ns(Lat) + ns(SST)	6742.2	114.1	71
6	Yr + Qtr + Vessel + ns(Lat) * Qtr + ns(SST)	6699.5	71.4	83
7	**Yr + Qtr + Vessel + ns(Lat) * Qtr + ns(SST) * Qtr**	**6628.0**	**0.0**	**98**

Model structures and AIC for positive catch rates

Model #	Model	AIC	deltaAIC	df
1	Yr + ns(SST)	8364.6	230.8	37
2	Yr + Vessel + ns(SST)	8275.0	141.2	66
3	Yr + Vessel + ns(Lat) + ns(SST)	8160.1	26.3	70
4	Yr + Vessel_cat + C_vs_F + ns(SST)	8311.2	177.4	40
5	Yr + Qtr + Vessel + ns(Lat) + ns(SST)	8152.4	18.6	73
6	**Yr + Qtr + Vessel + ns(Lat) * Qtr + ns(SST)**	**8133.8**	**0.0**	**85**
7	Yr + Qtr + Vessel + ns(Lat) * Qtr + ns(SST) * Qtr	8138.4	4.6	100

Table 3: Table of models for proportion of the periods 1982-1992 and 1993-2012, for the proportions of non-zero sets (binomial distribution) and positive catch rate (lognormal distribution). 'd.f.' refers to degrees of freedom of the model components; 'deltaAIC' is the difference in AIC from the best model, which is indicated with deltaAIC of 0.

Pd	Type	#	Model	AIC	Delta-AIC	df
1982-1992	Bin	5	Year + Qtr + s(SST, k = 12) + s(Lat, k = 9)	3894.0	79.5	33.3
		6	Year + Qtr + s(SST, k = 20) + s(Lat, by = Qtr, k = 9)	3867.1	52.6	39.4
		7	Year + Qtr + s(SST, by = Qtr, k = 12) + s(Lat, k = 9)	3852.7	38.2	48.6
		8	Year + Qtr + s(SST, by = Qtr, k = 12) + s(Lat, by = Qtr, k = 9)	3834.5	19.9	53.8
		9	**Year + Qtr + te(Lat, SST, by = Qtr, k = c(10,10))**	**3814.6**	**0.0**	**122.2**
	Logn	5	Year + Qtr + s(SST, k = 12) + s(Lat, k = 9)	6032.7	35.7	29.4
		6	Year + Qtr + s(SST, k = 20) + s(Lat, by = Qtr, k = 9)	6038.4	41.3	34.7
		7	Year + Qtr + s(SST, by = Qtr, k = 12) + s(Lat, k = 9)	6027.1	30.0	32.4
		8	Year + Qtr + s(SST, by = Qtr, k = 12) + s(Lat, by = Qtr, k = 9)	6032.1	35.1	44.3
		9	**Year + Qtr + te(Lat, SST, by = Qtr, k = c(10,10))**	**5997.1**	**0**	**81.1**
1993-2012	Bin	5	Year + Qtr + s(SST, k = 12) + s(Lat, k = 9)	2584.3	79.0	55.1
		6	Year + Qtr + s(SST, k = 20) + s(Lat, by = Qtr, k = 9)	2574.3	69.0	61.6
		7	Year + Qtr + s(SST, by = Qtr, k = 12) + s(Lat, k = 9)	2557.1	51.8	65.4
		8	Year + Qtr + s(SST, by = Qtr, k = 12) + s(Lat, by = Qtr, k = 9)	2546.9	41.6	72.8
		9	**Year + Qtr + te(Lat, SST, by = Qtr, k = c(10,10))**	**2505.3**	**0.0**	**127.8**
	Logn	5	Year + Qtr + s(SST, k = 12) + s(Lat, k = 9)	2059.5	52.5	57.5
		6	Year + Qtr + s(SST, k = 20) + s(Lat, by = Qtr, k = 9)	2040.9	33.8	64.7
		7	Year + Qtr + s(SST, by = Qtr, k = 12) + s(Lat, k = 9)	2046.9	39.8	69.0
		8	Year + Qtr + s(SST, by = Qtr, k = 12) + s(Lat, by = Qtr, k = 9)	2029.1	22.0	71.5
		9	**Year + Qtr + te(Lat, SST, by = Qtr, k = c(10,10))**	**2007.1**	**0**	**87.6**

Table 4: AIC estimates for *gamm* models fitted with and without random effects for Vessel. To compare random effects, the models are fitted using REML. Each set of results comes from *gamm* model 9.

Period	**Distribution**	**Model**	**df**	**AIC**	**dAIC**
1982-1992	Binomial	No RE	61.5	3911.8	60.2
		With RE	62.2	3851.6	
1993-2012	Binominal	No RE	71.4	2658.9	114.6
		With RE	88.6	2544.2	
1982-1992	Lognormal	No RE	56.0	6037.5	11.4
		With RE	62.8	6026.1	
1993-2012	Lognormal	No RE	61.0	2117.3	79.9
		With RE	77.7	2037.4	

Table 5: Indices for the period 1982-1992, including 95% confidence intervals. Each set of results comes from gamm model 5.

Year	Index	2.5% CI	97.5% CI
1982	1.86	1.86	1.86
1983	0.65	0.51	0.83
1984	0.20	0.15	0.25
1985	0.60	0.46	0.78
1986	0.40	0.30	0.54
1987	0.62	0.46	0.83
1988	0.98	0.73	1.31
1989	1.46	1.09	1.97
1990	2.10	1.54	2.86
1991	0.83	0.52	1.34
1992	1.30	0.88	1.93

Table 6: Indices for the period 1993-2012, including 95% confidence intervals. Each set of results comes from gamm model 5.

Year	Index	2.5% CI	97.5% CI
1993	2.37	2.37	2.37
1994	7.67	2.88	20.43
1995	0.35	0.08	1.57
1996	2.72	1.05	7.05
1997	1.09	0.39	3.07
1998	0.22	0.07	0.68
1999	0.98	0.34	2.83
2000	0.12	0.03	0.55
2001	0.31	0.09	1.09
2002	0.21	0.07	0.60
2003	0.92	0.37	2.29
2004	0.12	0.04	0.35
2005	0.33	0.13	0.87
2006	0.53	0.21	1.35
2007	0.06	0.02	0.21
2008	0.69	0.26	1.84
2009	0.04	0.01	0.12
2010	0.72	0.23	2.29
2011	0.20	0.07	0.58
2012	0.33	0.11	1.00

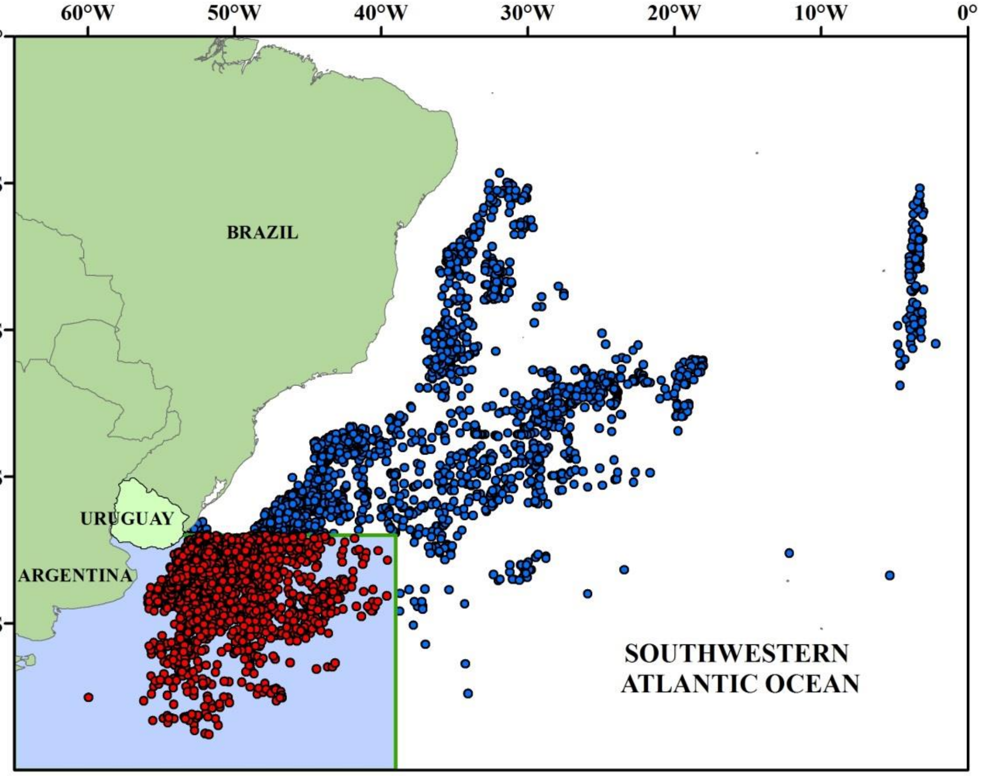


Figure 1. Total distribution of the Uruguayan pelagic longline fleet (blue dots), and selected sets for standardization of *Lamna nasus* captures (red dots).

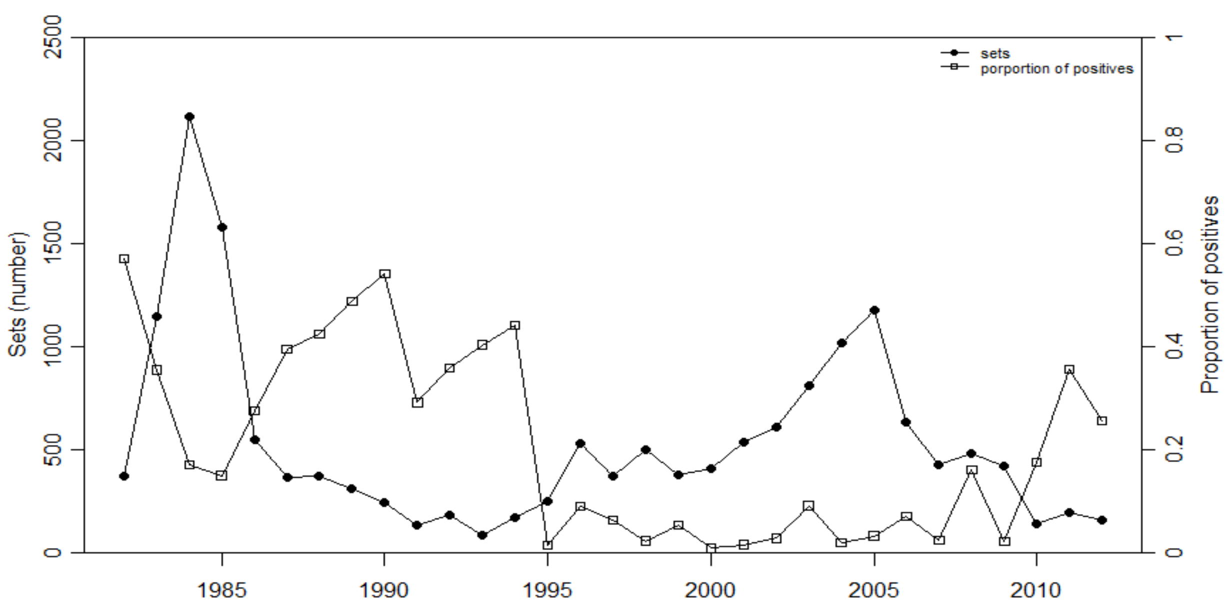
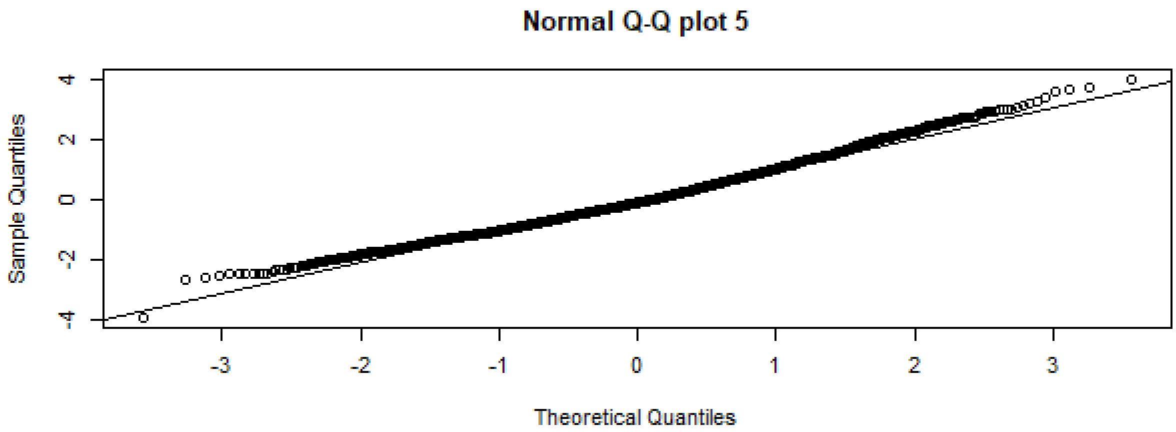
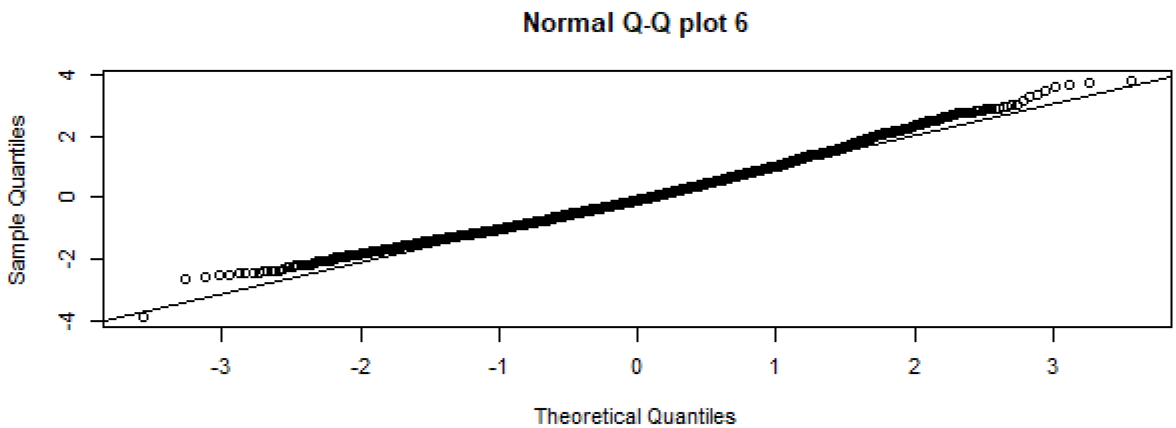


Figure 2. Proportion of porbeagle positive sets (open squares) and total effort in number of sets (solid circles) for the period 1982-2012.





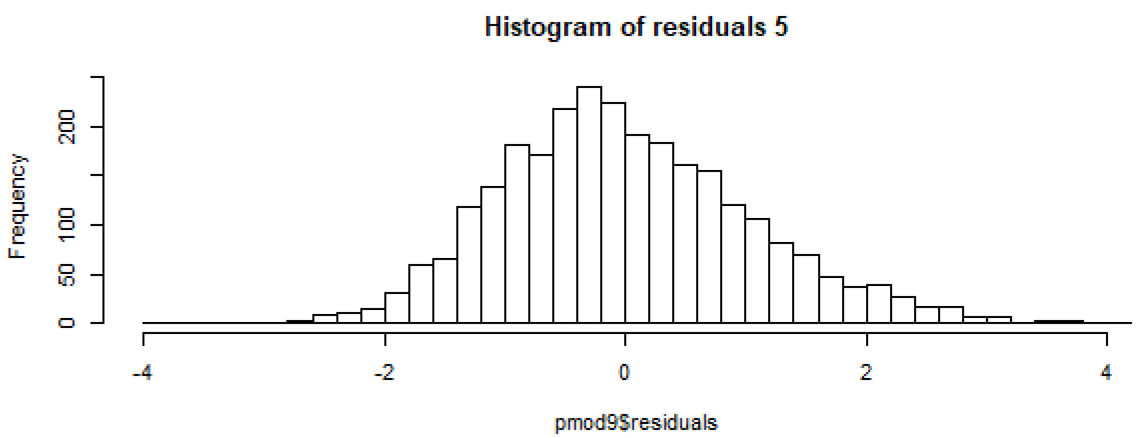


Figure 3: Plots of residuals from CPUE standardized using glm models 5 and 6, for positive sets of porbeagles caught by the Uruguayan longline fishery for the period 1982-2012. The top Q-Q plot is for glm model 5, the middle Q-Q plot is for glm model 6, and the lower residual histogram is for glm model 5.

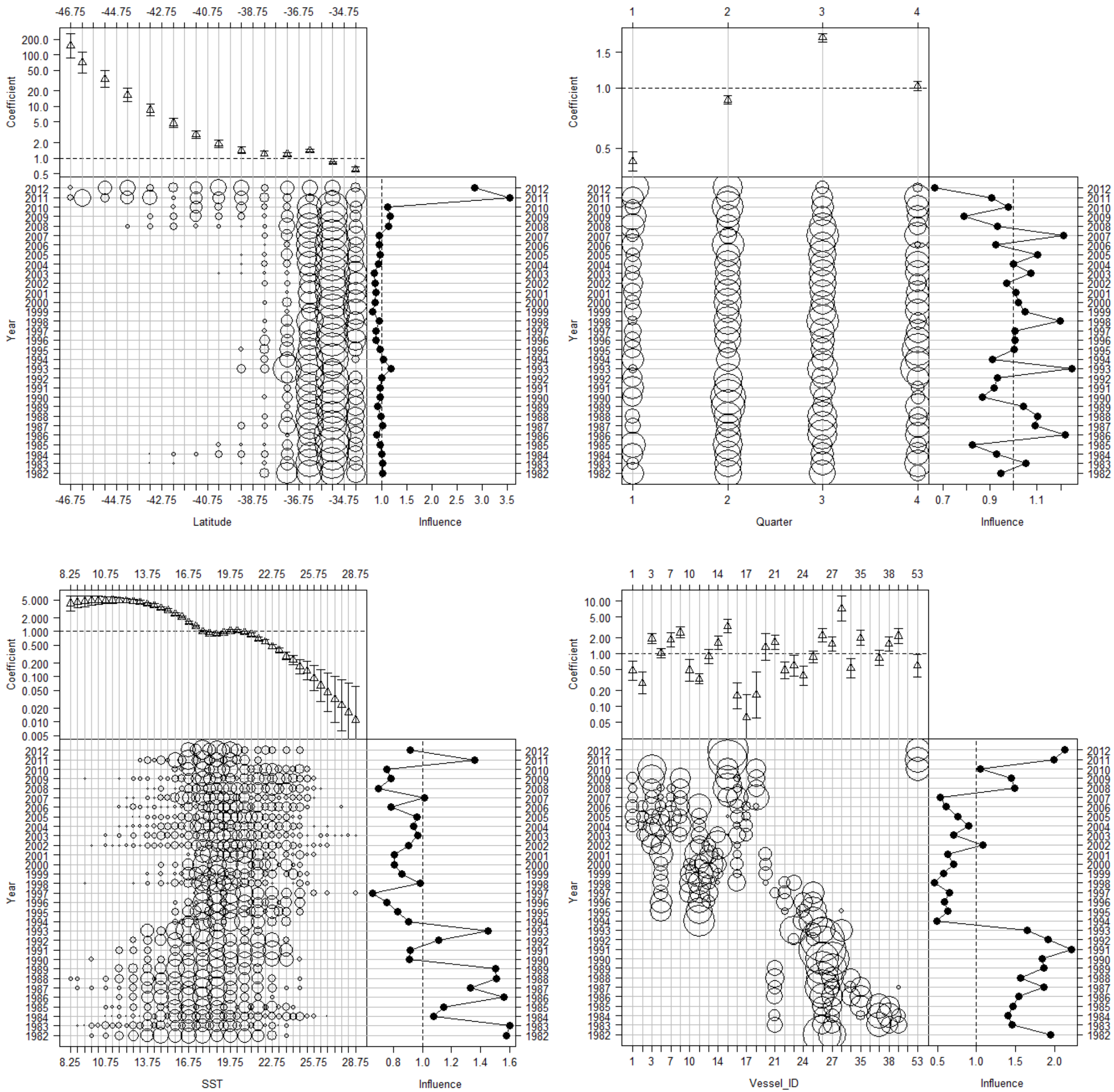


Figure 4: Influence plots for binomial glm Model 5 (without interactions), showing the distributions of parameter values by year and their influence on the predicted probability per set of catching porbeagle sharks. Influence plots are shown for latitude, quarter, SST, and Vessel.

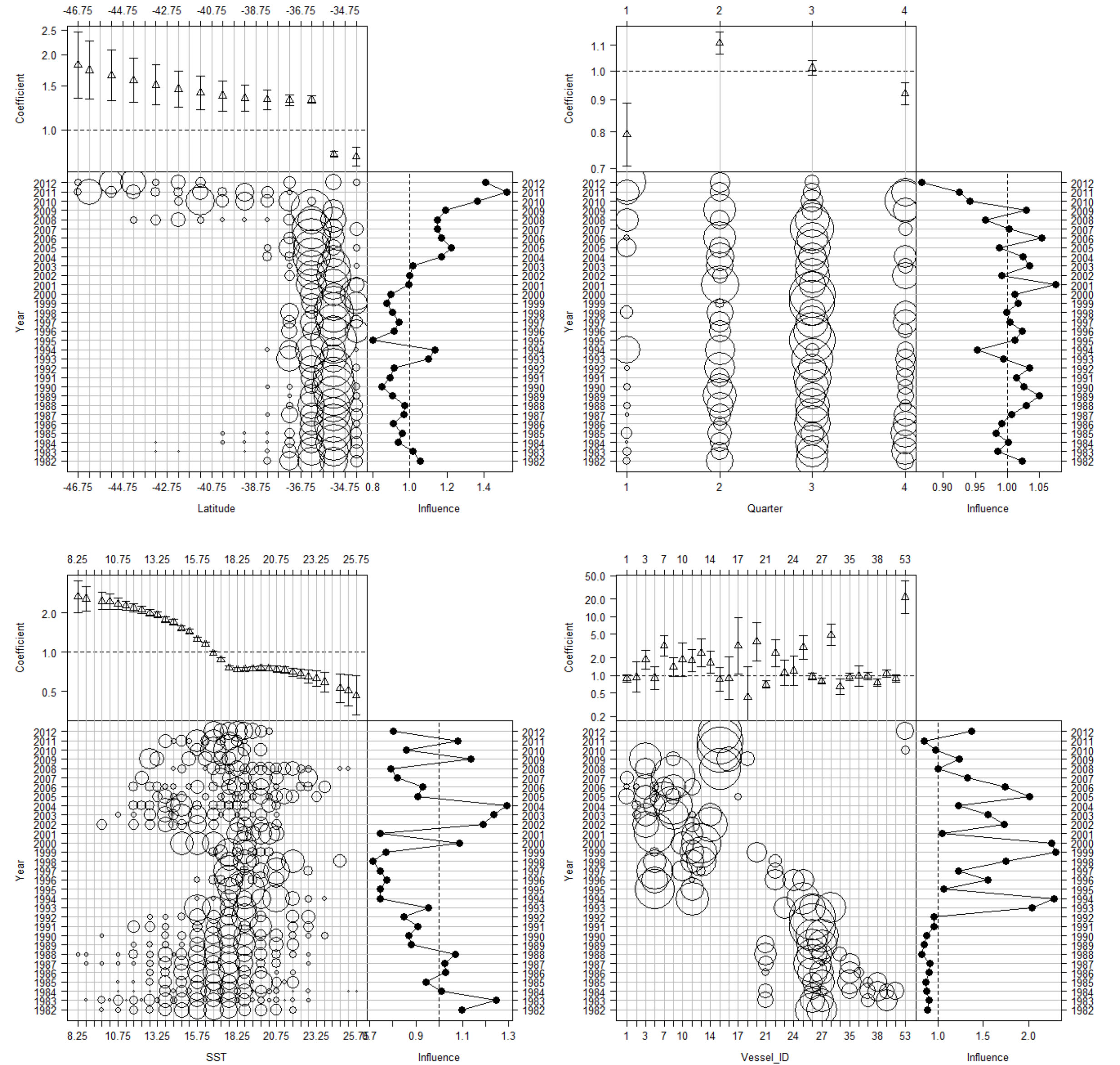


Figure 5: Influence plots for positive glm Model 5 (without interactions), showing the distributions of parameter values by year and their influence on the predicted catch per set. Influence plots are shown for latitude, quarter, SST, and Vessel.

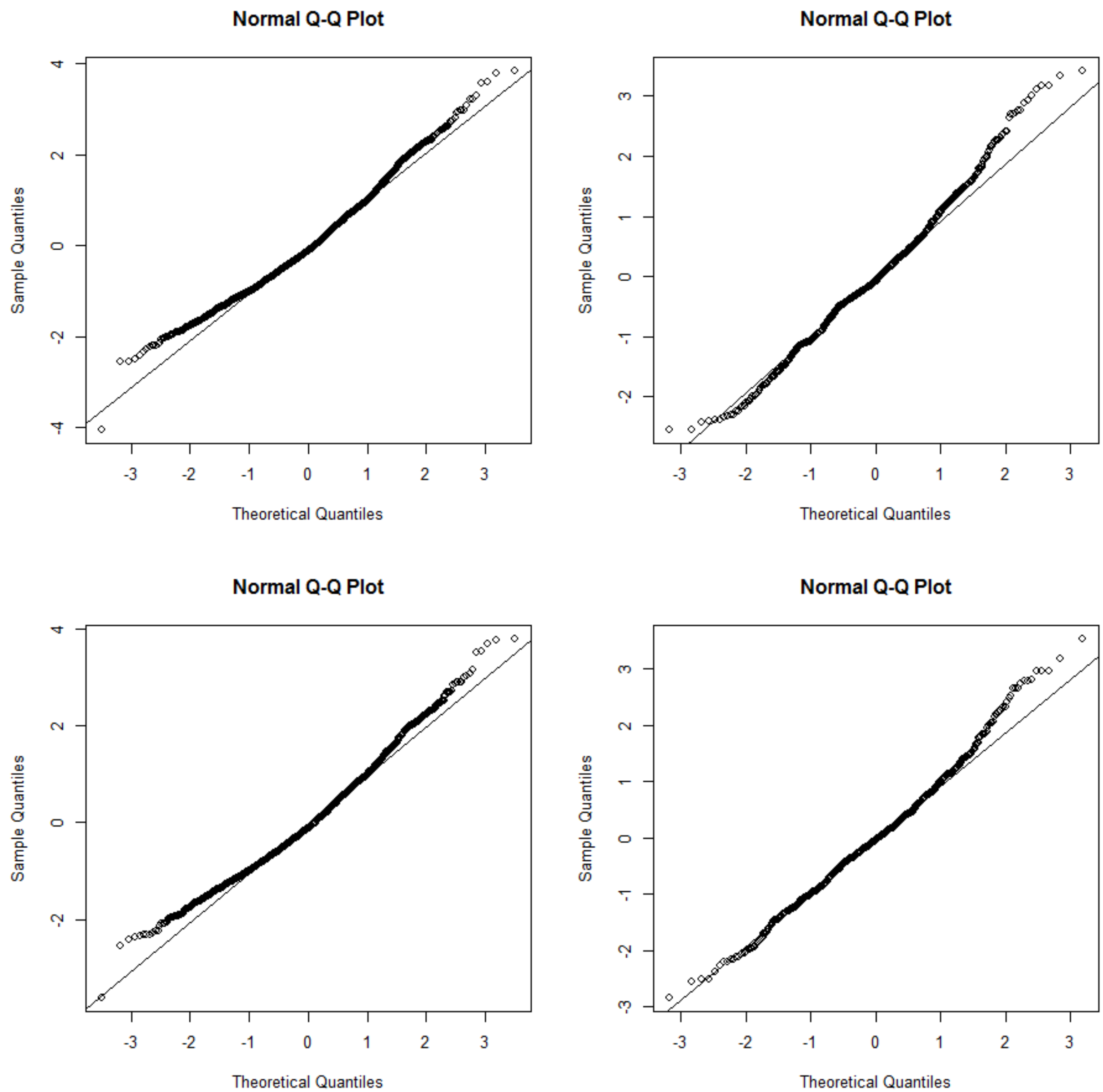


Figure 2. Q-Q plots of residuals from standardized CPUE for positive sets of porbeagles caught by the Uruguayan longline fishery for the periods 1982-1992 (left) and 1993-2012 (right). The plots above and below are for gamm models considering and not considering interaction terms, respectively.

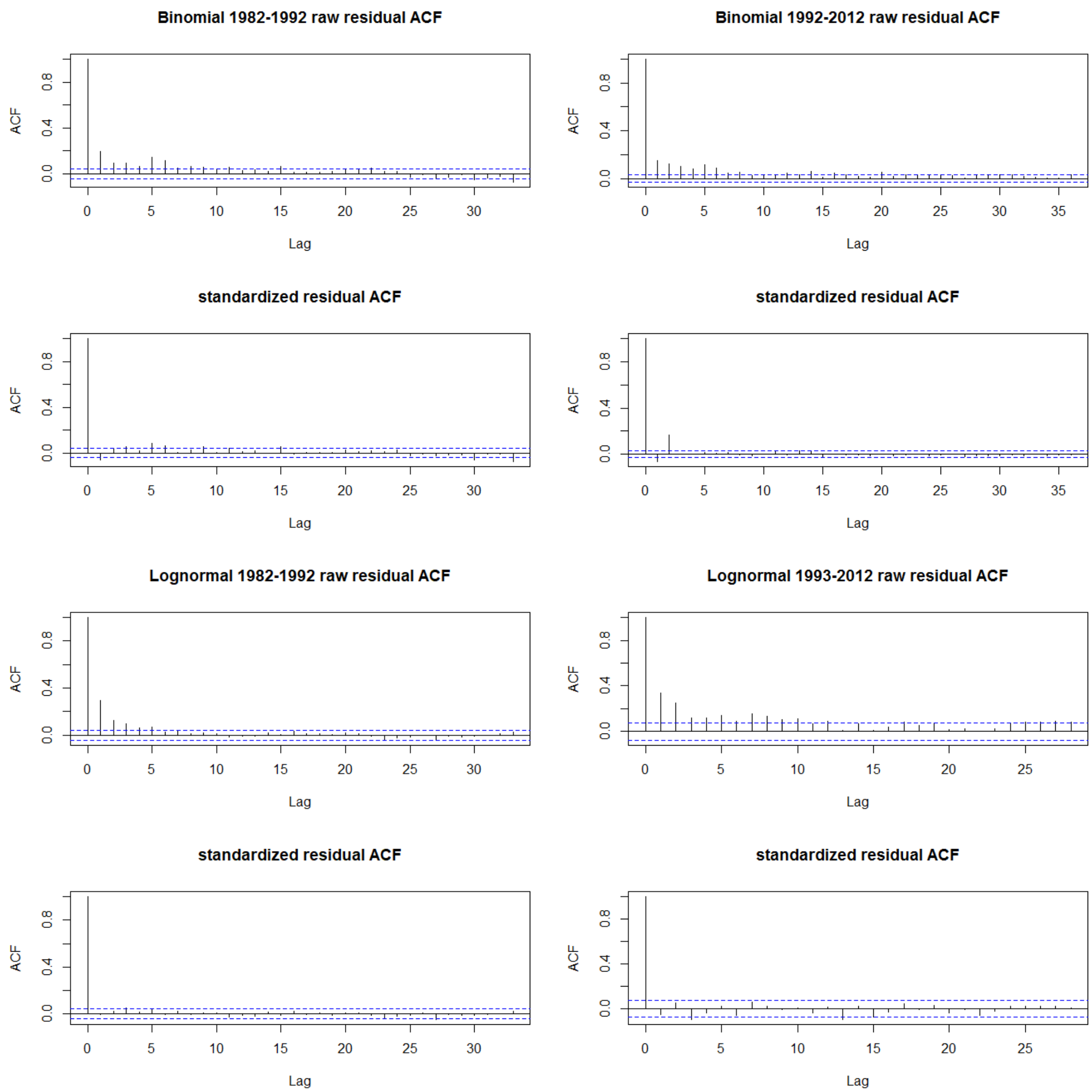


Figure 3: Autocorrelation plots showing the effects of adjustment for autocorrelation on the best fitting gamm models, which was model 9 in each case. Two plots are shown for each of the four models. Models for 1982-1992 are on the left, and 1993-2012 on the right. Binomial models are above and lognormal models below.

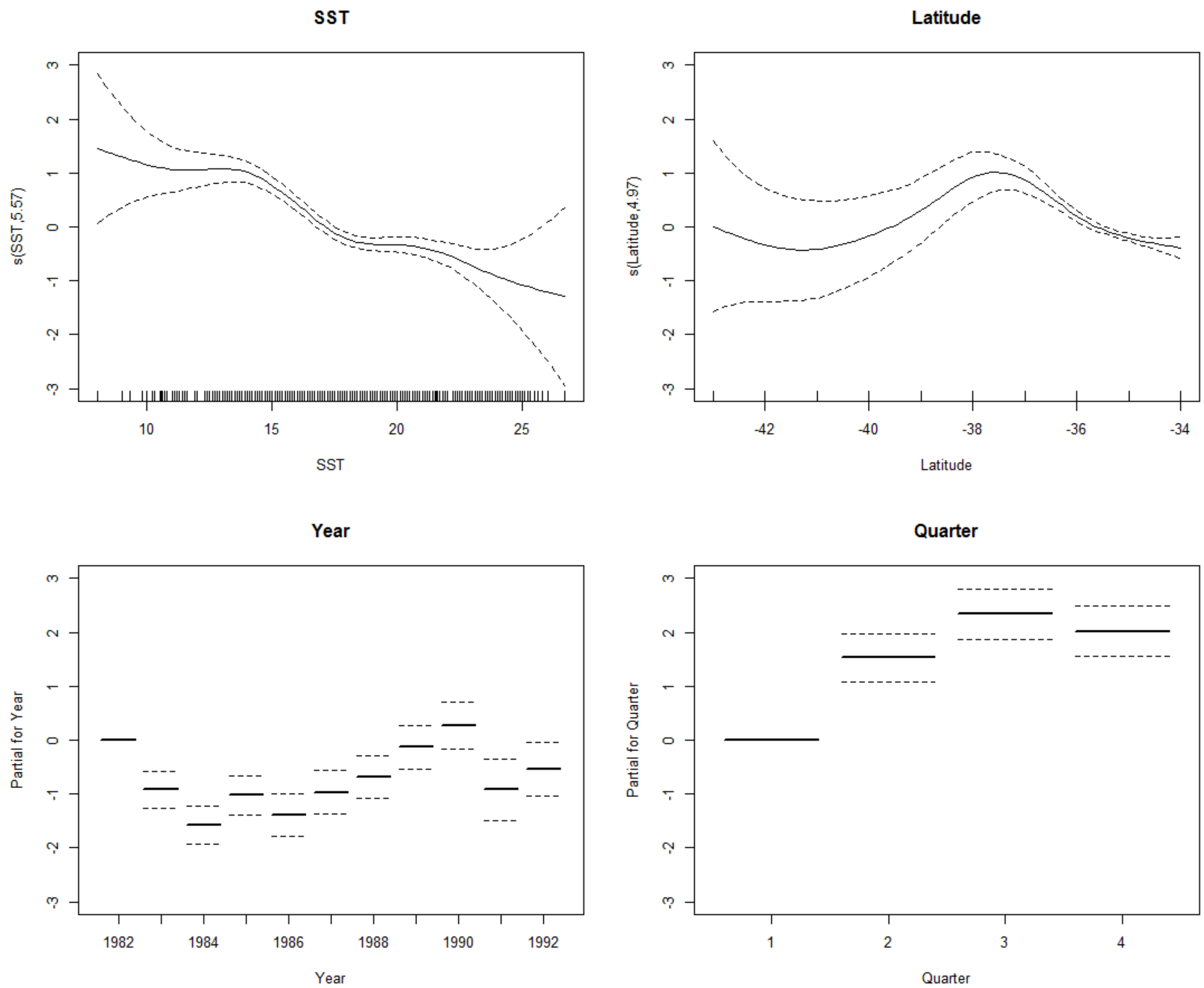


Figure 8: Plots of effects for gamm model analysis of the proportions of non-zero sets in the period 1982-1992. Dashed lines correspond to the 95% confidence interval of the estimated effect size.

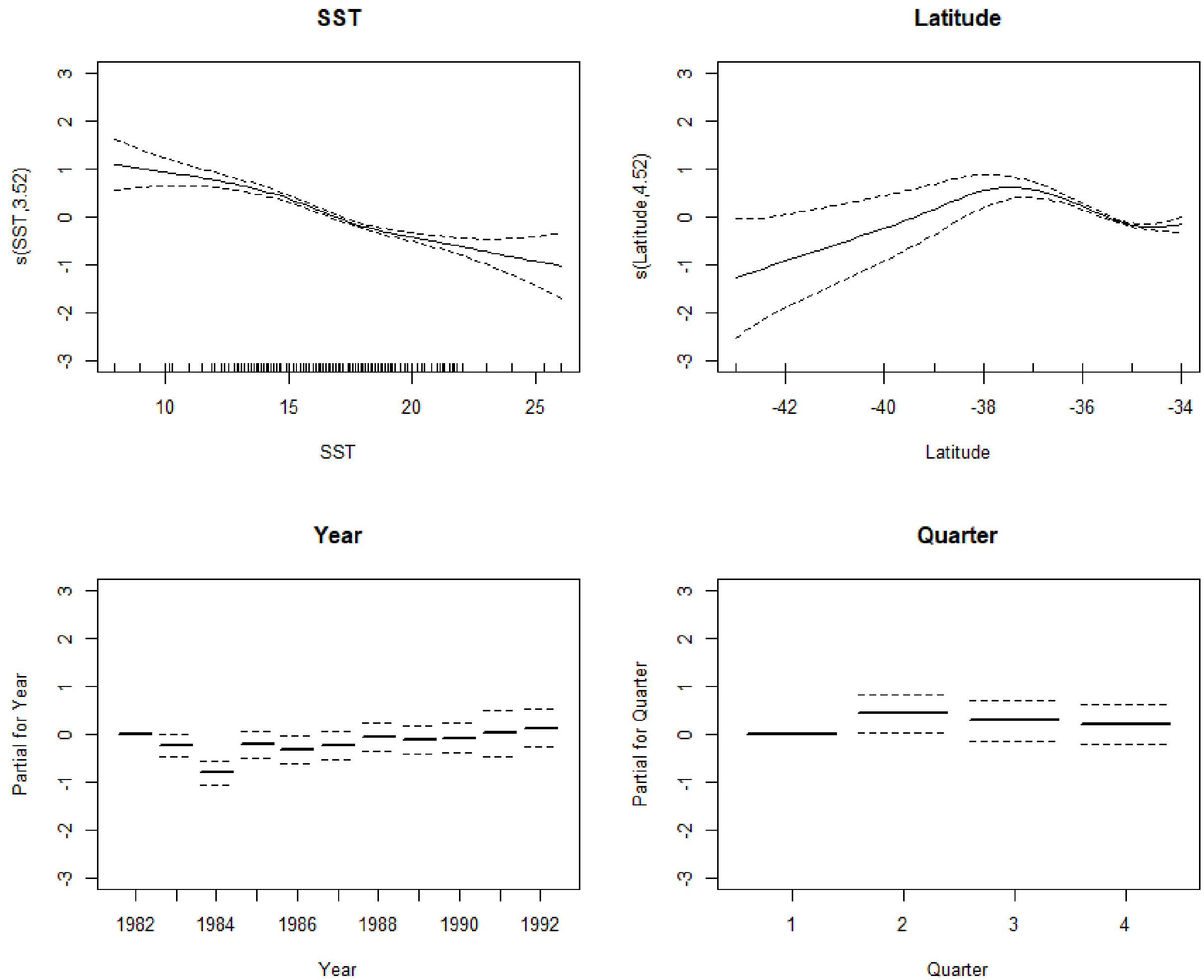


Figure 9: Plots of effects for gamm analysis of the catch rates in non-zero sets in the period 1982-1992. Dashed lines correspond to the 95% confidence interval of the estimated effect size.

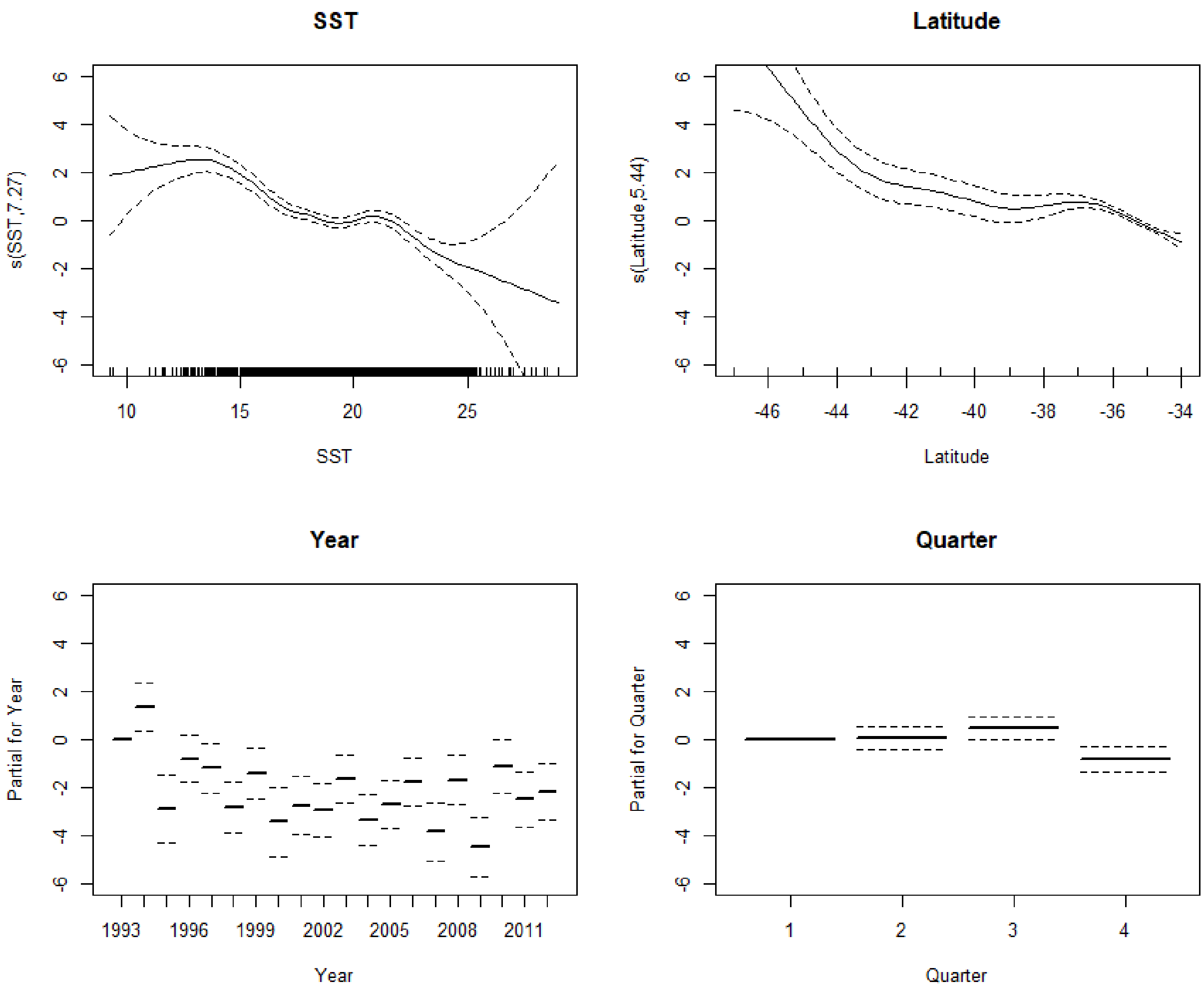


Figure 10: Plots of effects for gamm analysis of the proportions of non-zero sets in the period 1993-2012. Dashed lines correspond to the 95% confidence interval of the estimated effect size.

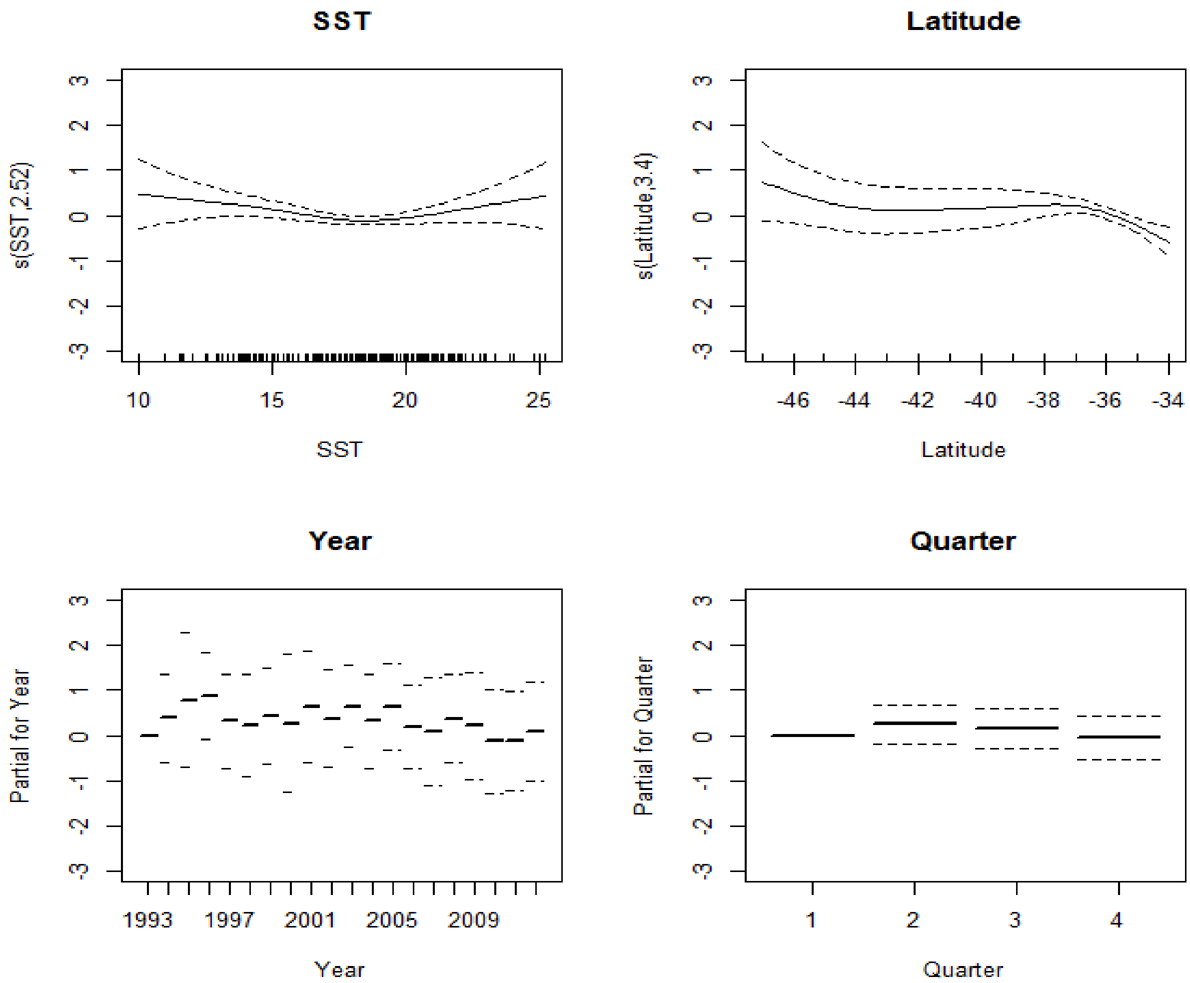


Figure 11: Plots of effects for gamm analysis of the catch rate in non-zero sets in the period 1993-2012. Dashed lines correspond to the 95% confidence interval of the estimated effect size.

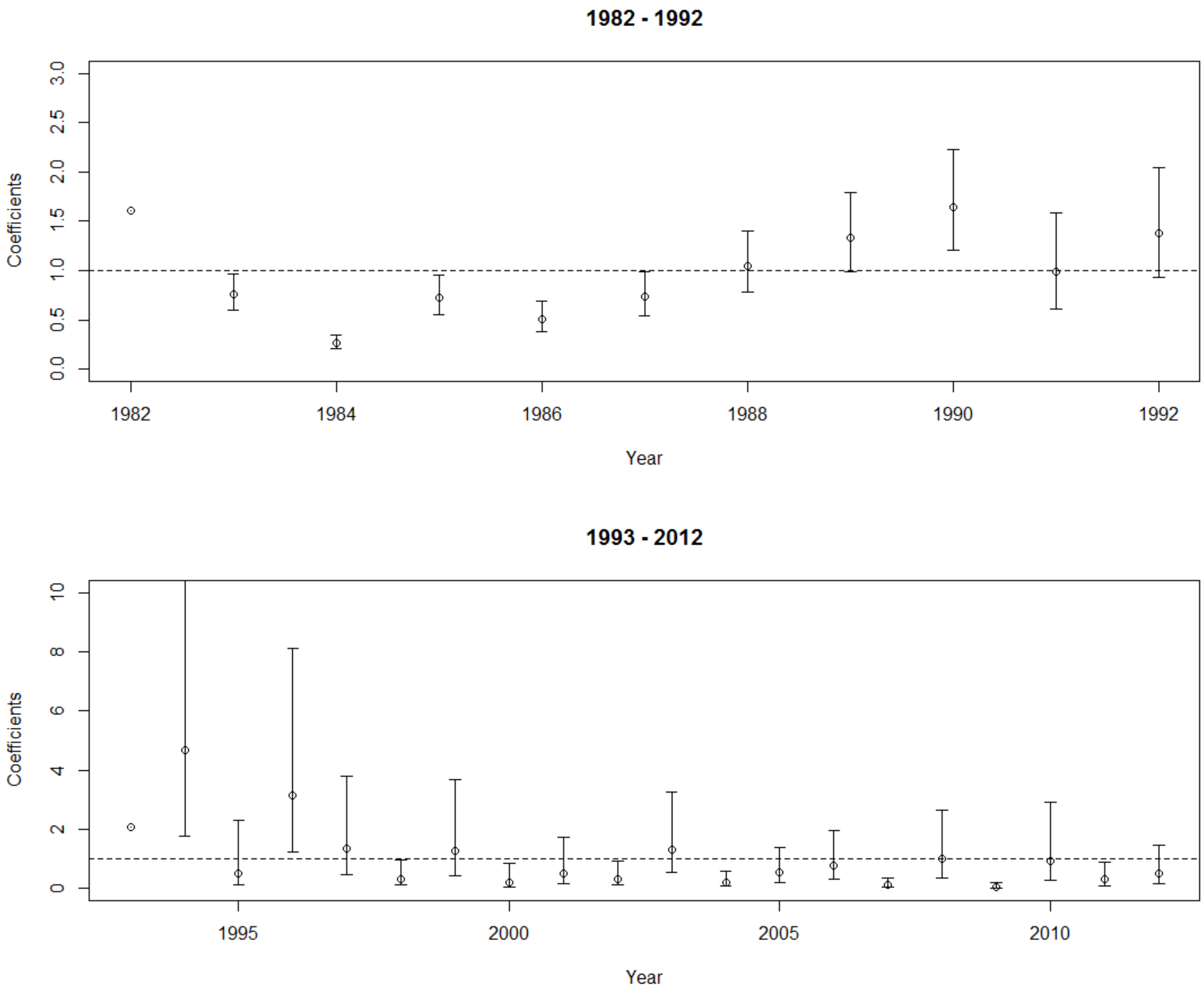


Figure 12: Normalized standardized indices of abundance in biomass for porbeagle caught by the Uruguayan pelagic longline fleet. The upper (1982 - 1992) and lower (1993 – 2012) indices are on different scales. Intervals represent the 95% confidence interval from the lognormal part of the analysis. Each set of results comes from gamm model 5 (without interactions).

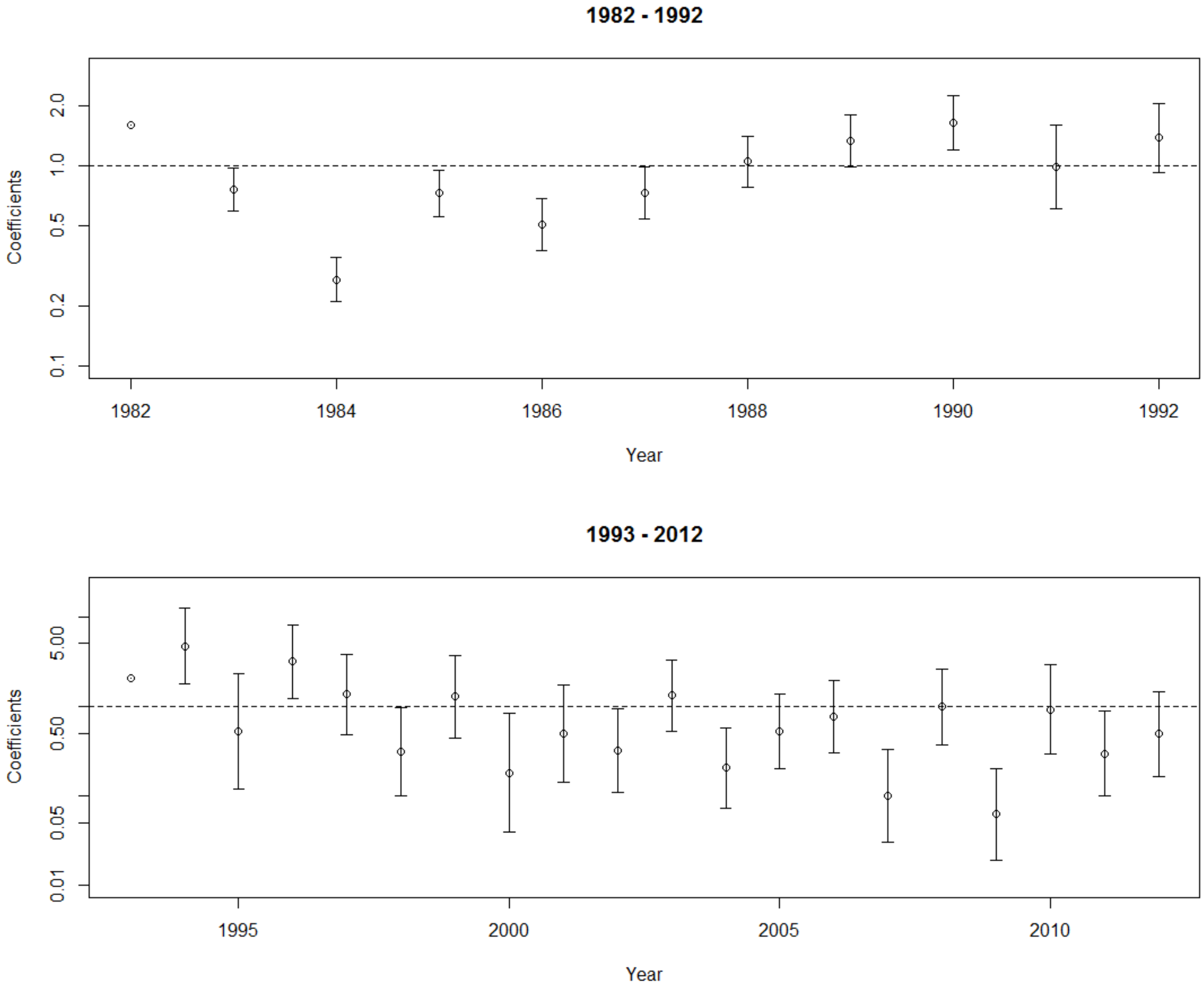


Figure 13: Normalized standardized indices of abundance in biomass for porbeagle caught by the Uruguayan pelagic longline fleet, with y axis on log scale. The upper (1982 - 1992) and lower (1993 – 2012) indices are on different scales. Intervals represent the 95% confidence interval from the lognormal part of the analysis. Each set of results comes from gamm model 5 (without interactions).

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