# Update on standardized catch rates for mako shark (*Isurus oxyrinchus*) in the 2006-2016 Mexican Pacific longline fishery based upon a shark scientific observer program[1]

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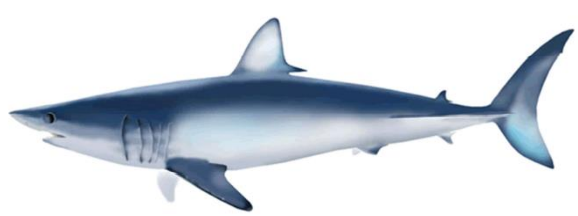

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## SUMMARY

Abundance indices for mako shark (*Isurus oxyrinchus*) in the northwest Mexican Pacific for the period 2006-2016 were estimated using data obtained through a pelagic longline observer program, updating a similar analysis made in 2014. Individual longline set catch per unit effort data, collected by scientific observers, were analyzed to assess effects of environmental factors such as sea surface temperature, distance from mainland coast and time-area factors. Standardized catch rates were estimated by applying two generalized linear models (GLMs). The first model (using a quasi-binomial likelihood and a complementary log-log link function) estimates the probability of a positive observation and the second one estimates the mean response for non-zero observations, using a lognormal error distribution. The importance of factors included in the models is discussed. The results of this analysis point at the abundance index trends being close to stability in the analyzed period, but particularly in the last 4 years.


## INTRODUCTION

The presence of more than 100 species of sharks in Mexican waters has allowed the development of commercial fisheries in both coastal and oceanic waters (Castillo-Géniz *et al.* 1998). The main Mexican shark fisheries are the coastal artisanal fishery (along both Pacific and Gulf of Mexico coastlines) and the pelagic longline fisheries using medium size vessels in the northern Pacific region (Castillo-Géniz *et al.* 2008).

The average annual Mexican shark production (including small sharks, called “cazones”) from 1976 to 2014 (most recent official data) was 28,248 t, which places Mexico as one of the top shark producer nations in the world according to Musick and Musick (2011). In 2014 the total domestic shark production reached 29,436 t, (2.2% of the total national fisheries production), with a market value of more than three hundred million pesos. The average annual shark production in Mexican Pacific for 1976-2014 was 20,053 t. In 2014 the Pacific shark production reached 24,845 t which comprised 84% of the total Mexican shark production.

Pelagic shark fisheries in the Mexican Northwest Pacific began in the mid 80's with the creation of an industrial fishing fleet. That was the result of the successful driftnet fishery in California, which began in 1978, originally targeting the common thresher shark (*Alopias vulpinus*) and shortfin mako (*Isurus oxyrinchus*, locally known as bonito shark).

In 1986 a small fleet of driftnet vessels appeared in northern Baja California, Mexico. This fishery was stimulated both by the reduction in longline permits and by the local abundance of swordfish and other marketable by-catch products, including several species of large pelagic sharks. These vessels were fiberglass or steel built, with an overall length of 18-25 m and a fish hold capacity of 50-70 t.

The number of vessels had grown to 20 by 1990, and to 31 by 1993 (Holts and Sosa-Nishizaki 1998). These vessels operated out of Ensenada, Baja California, and were similar in design and size (18-25 m) to the U.S. driftnet vessels, operating just 100 km to the north. This fleet targeted sharks, swordfish, tuna, and other pelagic fish. Sosa-Nishizaki *et al.* (1993), Holts *et al.* (1998), Ulloa-Ramirez *et al.* (2000), and Sosa-Nishizaki *et al.* (2002) described in detail the growth of swordfish and sharks fishery along the west coast of Baja California (BC).

During the first 20 years, this fleet used surface gillnets as its primary fishing gear. The Mexican Official Standard NOM-029-PESC-2006 (DOF 2007) banned driftnets in medium-size vessels (10-27 m length). By the end of 2009, all vessels switched to longlines and the operational dynamics of the fleet changed drastically. The main shark species caught were blue (*Prionace glauca*), short-fin mako (*Isurus oxyrinchus*) and thresher (*Alopias vulpinus*) sharks.

In the last decade, the Mexican shark fisheries conducted by medium size commercial longliners from Ensenada, Baja California and particularly from Mazatlán, Sinaloa had expanded its fishery operations towards more oceanic waters in the Mexican Pacific Economic Exclusive Zone (EEZ).

## Management of Mexican shark fisheries

Shark fisheries in Mexican waters are managed mainly through three instruments:

1) The Mexican Official Standard NOM-029-PESC-2006. Shark and Ray Responsible Fisheries. Specifications for Their Exploitation;
2) The National Fisheries Chart (Carta Nacional Pesquera, CNP) and
3) The Shark and RayFishery Closure Agreements for both coastlines.

The NOM-029 (DOF 2007) established numerous regulations for shark and ray fisheries in order to achieve sustainability, among them the establishment of specific fishing zones according to vessel characteristics, refuge zones, specifications for fishing gears, mandatory participation in the satellite vessel tracking program (Vessel Monitoring System, VMS), the banning of gillnets on medium size boats and the implementation of a scientific observer program on a voluntary basis.

The National Fisheries Chart includes the description and the current exploitation status of shark populations as well as their availability in Mexican waters. At present, all shark fisheries are considered to be fully exploited (DOF 2010).

Finally, the fisheries authority has established closed seasons for shark and ray fisheries in the Pacific and only for sharks in the Gulf of Mexico, with the aim of protecting the main reproductive season for most species (DOF 2012 and 2014). Those closed periods include shark by-catch in other fisheries. The closed season in the Mexican Pacific was established between May 1st and July 31st.

## Mexican shark fishery scientific observer program

The shark scientific observer program (SSOP) was established in August 2006 by the Fisheries and Aquaculture Commission (CONAPESCA), in offshore and pelagic waters of the Mexican Pacific, as established in the Shark and Ray Responsible Fisheries Mexican Official Standard NOM-029-PESC-2006. The SSOP was designed by Mexico's National Fisheries Institute (INAPESCA) and implemented by the National Research Trust for the National Program for Tuna Utilization and Dolphin Protection and Other Programs Related to Protected Aquatic Species (FIDEMAR). The shark scientific observers, trained by INAPESCA shark biologists and technicians, record numerical catches by species and operational details (e.g. time, geographical position, number of sets per trip, number of hooks per set, setting times, target species, bait type), catch and by-catch composition and catch trends of species caught by shark vessels. They also collect biometric (size and sex) and biological data (maturity stage) of shark target species. INAPESCA is responsible for analyzing data generated by the SSOP.

Boat participation in the observer program is voluntary so fishing trips with observer onboard are conducted according to the availability and willingness of fishing companies. The sampling coverage of fishing trips by the SSOP has been very variable, with a maximum of 20% in 2007 and a minimum of 1% in 2012 (Castillo-Géniz *et al.* 2014).

## Evolution of the catch

Swordfish landings from Mexican driftnet vessels were first reported in 1986. They increased steadily to a high of 831 t in 1991, and averaged 535 t in 1988-93. The low catch in 1993 forced some fishing vessels to look for alternate resources, including coastal and pelagic sharks, in the Gulf of California. The number of vessels operating driftnetting for swordfish in the first half of 1994 fell to 16 (Holts and Sosa-Nishizaki 1998).The information recorded by the Federal Fisheries Delegation in Baja California for 1990-1999 indicated an average catch per boat of 15.3 t and an average catch per trip of 2.73 t for the whole driftnet and longline fleet.

Recently, Corro-Espinosa (unpublished data) conducted an analysis of the comercial logbooks from the Mazatlan longline fleet for years 2009-2012. Corro-Espinosa documented a total catch of 182,482 sharks from 11 species, caught in 8,447 sets. Blue shark (*P. glauca*) 64.6%, thresher (*A. vulpinus*) 9.4%, bigeye thresher (*A. superciliosus*) 9.3%, pelagic thresher (*A. pelagicus*) 7.7% and mako (*I. oxyrinchus*) 1.7% were the most frequently caught pelagic sharks. With a similar approach, Ortega-Salgado *et al.* (unpublished data) examined the commercial logbooks of 124 fishery trips and 1,404 longline sets from the swordfish and shark fleet of Ensenada conducted during 2001-2013. The logbooks reported a capture of 42,814 sharks belonging to six shark species, with blue (86.5%), mako (11.9%) and thresher (0.73%) sharks being the most abundant species.

## Catch composition

In the period 2006-2014 sharks comprised 94.3% and 97.4% of the catch in longline and driftnet sets, respectively. Shark catch from all fleets with both fishing gears included 32 species from eight families and five orders. Longline shark catch composition was made up by brown smoothhound (*Mustelus henlei*, 42.5%), blue shark (*P. glauca*, 33.9%) and angel shark (*Squatina californica*, 5.4%), with mako shark (*I. oxyrinchus*) accounting for 1.6%. The dominance of *M. henlei* in the observed total longline sets was the result of catches obtained in the upper Gulf of California by a fleet based in Puerto Peñasco, Sonora.

Driftnet shark catch was made up by 23 shark species from 7 families and 4 orders, with *S. californica* (26.1%), *M. henlei* (26.0%) and the Pacific sharpnose shark *Rhizoprionodon longurio* (19.7%) being the most abundant. The mako shark accounted for 4.2% in total driftnet catches (Castillo-Géniz *et al.* 2014).

Longline and driftnet catches also included 10 species of the genus *Carcharhinus*.

## Catch rate standardization

The primary indices of abundance for many of the world's valuable and vulnerable species are based on catch and effort. These indices, however, should be used with care because changes over space and time in catch rates can occur because of factors other than real changes in abundance (Gavaris 1980, Walters 2003, Maunder and Punt 2004, Haggarty and King 2006, Campbell 2015). Nominal catch rates obtained from fishery statistics or observer programs require standardization to correct for the effect of factors not related to regional fish abundance but assumed to affect fish availability and vulnerability, usually by using statistical regression methods (Bigelow *et al.* 1999, Ortiz and Arocha 2004).

Generalized Linear Models (**GLM**, Nelder and Wedderburn 1972, McCullagh and Nelder 1989) are the most common method for standardizing catch and effort data and their use has become standard practice because this approach allows identification of the factors that influence catch rates and calculation of standardized abundance indices, through the estimation of the year effect (Goñi *et al.* 1999, Maunder and Punt 2004, Brodziak and Walsh 2013). GLMs are defined mainly by the statistical distribution for the response variable (in this case, catch rate) and the relationship of a linear combination of a set of explanatory variables with the expected value of the response variable. Its use is based upon the assumption that the relationship between a function of the expected value of the response variable and the explanatory variables is linear. A variety of error distributions of catch rate data have been assumed in GLM analyses (Lo *et al.* 1992, Bigelow *et al.* 1999, Punt *et al.* 2000, Goñi *et al.* 2004, Maunder and Punt 2004).

Catches of non-target species are relatively unusual (resulting in many catch records being zero, even though effort is recorded to be non-zero) and catch and effort data are often characterized by left-skewed distributions, with a high proportion of zero catches, and few observations with high catch rates that resemble the distributions of highly aggregated species. The presence of a high proportion of zeros can invalidate the assumptions of the analysis and make inferences based on them dubious. The presence of zeros can also result in computational difficulties, as the logarithm of zero is undefined (Maunder and Punt 2004, Ortiz and Arocha 2004).

Alternatives to deal with this kind of data can include using zero-inflated models (Minami *et al.* 2007, Zuur *et al.* 2009), models based on the Tweedie distribution (Tweedie 1984, Shono 2008), or hurdle (or zero-altered models) modeling separately the probability of obtaining a positive catch and the catch rate, given that the catch is non-zero, using a standard distribution defined for positive values (Pennington 1983, as proposed by Lo *et al.* 1992, Harding and Hilbe 2012). The probability of obtaining a positive observation is usually modeled using the binomial distribution (Stefansson 1996, Maunder and Punt 2004), with logit or probit link when assuming approximately an equal number of zeros and ones (positive observations) or complementary log-log (c log-log) when there is a predominance of negative or positive observations (Myers *et al.* 2002, Zuur *et al.* 2009). A variety of distributions could be used to model the catch rate given that it is non-zero (Dick 2004). Most commonly selected distributions are the log-normal (Brown 1998, Porter *et al.* 2003), Gamma (Punt *et al.* 2000), poisson (Ortiz and Arocha 2004), negative binomial (Punt *et al.* 2000) and inverse gaussian (Walker *et al.* 2012).The final index of abundance is the product of the back transformed year effects from the two GLMs (Lo *et al.* 1992, Stefánsson 1996).

## MATERIAL AND METHODS

This study is focused on the longline component of the shark fishery with medium size vessels in the northwest region of the Mexican Pacific. Driftnet operations were banned in 2009, while longline fishing has prevailed through the years of operation of the scientific observer program, so the longline time series June 2006-December 2016 is complete. In particular, only data from the Ensenada and San Carlos longline fleets were used in the analysis, as they are the ones with better observer coverage and operating within the main mako shark distribution area in the Mexican Pacific. In this first stage, many zero-catch data –belonging to fleets operating outside this area or scarcely sampled– were excluded from the analysis. Then, data were subjected to a preliminary analysis, looking for missing values, incomplete information and inconsistencies. In this way, from an initial total of 5,766 longline sets, just 2,183 validated sets were retained to be used in the analysis. The proportion of zero-catch sets in this subsample was 44.75%, pointing to the use of a two-part, Delta model for the analysis, with a c log-log link for the binomial GLM.

After an initial exploratory analysis, factors which were considered as having a posible influence on the response variables of the binomial or lognormal models (CTCHPROB: catch probability or CTCHRATE: logarithm of catch rate of makos, respectively) were selected for the analyses, like mean sea surface temperature (TF as a two level factor), distance from the starting point of each fishing set to the nearest point in the continental coast (DF as a two level factor) and time-area factors such as YEAR, QUARTER and fishing area (ZONE). Mean sea surface temperature was calculated for each set as the average of temperature data measured *in situ*, at the beginning and the end of both gear setting and retrieval. TF levels were defined as PR (preferential, >=18.0°C and <=21.0°C), and NP (not preferential, <18.0°C or >21°C), on the basis of the mean sea surface temperature in which all validated sets of the Ensenada and San Carlos fleets were performed, and matching the limits of the preferential range (18-21°C) of sea surface temperatures for shortfin makos (Castro 2011). Distance from the starting point of each fishing set to the nearest point in the continental coast was calculated using the raster package for R (Hijmans, 2016). TF levels were defined as N (near, <=100 km), and F (far, >100 km), based upon examination of a LOWESS smoother on a scatterplot of catch rate against distance. Three fishing areas (ZONE) were defined as NORTH (>30° LN), CENTRAL (>=28° LN and <=30° LN) and SOUTH (<28° LN), based upon the latitude of the beginning of gear setting (Figure 1). Catch probability and catch rates were modeled as a function of these factors, in the programming language and environment *R* version 3.4.0 (*R* Core Team 2017).

Standardized indices of relative abundance of mako shark were developed based on two generalized linear models (GLMs). The first model estimates the probability of a positive observation using a quasi-binomial likelihood to model any potential bias because of overdispersion (phi<>1), and a complementary log-log (c log-log) link function. The second model (the "positive" model) estimates the mean response for those non-zero observations, assuming that the error distribution is (in this case) lognormal. The final index is the product of the backtransformed year effects from the two GLMs. The Delta model was set with the Delta-GLM function in *R* from SEDAR (2006).

The predictor variables QUARTER, TF, DF and ZONE were included initially in both GLM models as a set of main (direct) effects and interactions. Although we are conscious that inter annual variations in spatial or temporal patterns could occur (*v. gr.* the species and/or effort distribution, seasonal changes in temperature or other factors among years), we preferred not including interactions involving the factor YEAR at this stage of the analysis with fixed effects models. Including interactions involving the factor YEAR, as well as treating it as a random factor by using Generalized Linear Mixed Effects Models (GLMMs) as suggested by Maunder and Punt (2004) and Campbell (2015), could be considered at later stages of the analysis.

The formulas of the maximum (initial) models were:

CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:ZONE + DF:ZONE

CTCHRATE ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE

Variables to be kept in the final model were examined through hypothesis testing procedures, using deletion of one variable at a time in order to prevent the potential effects of colinearities, as described by Crawley (2009). The effect of the term was determined to be significant at least at the alpha = 0.05 level based on an F test for both the quasi-binomial and lognormal GLM models. Standard errors and coefficients of variation for the standardized abundance indices were estimated with a jackknife.

## RESULTS AND DISCUSSION

Spatial-temporal heterogeneity in the marine environment greatly affect the biology, dynamics, and availability of fish stocks, as well as their vulnerability to fishing gear, thus introducing a source of variability in nominal catch rates (Bigelow *et al.* 1999).

Sea surface temperature is one of the most important physical factors because it modifies the geographical and vertical aggregation patterns of fishes, through its effect on feeding, reproductive and migratory behavior, and body thermoregulation (Fonteneau 1998). The importance of sea surface temperature as an explanatory variable in the present analysis points to the potential utility of exploring other possible relationships between probability of catch or catch rate and mesoscale oceanic features by including thermal gradients in the model in further analysis.

It is possible, however, that the relationships found between probability of catch or catch rate and temperature may not only be due to specific temperature preferences by mako shark, especially because most of the sets analyzed occurred in waters with surface temperatures below 28°C, considered to be the thermal maximum for the distribution of this species (Castro 2011).

Detection of a significant relationship between probability of catch and the quarter:temperature interaction (Table 1) was due –at least in part– to the space-time microscale approach used and it could be explained in terms of seasonal temperature variations that could affect the spatial distribution of the species.

Similarly, the interaction between the factors QUARTER and ZONE (Tables 1 and 2) could involve a spatial component in those variations (*v. gr.* one zone having a seasonal pattern different from the other one).

In this updating, similar to an analysis made in 2014 (González-Ania *et al.* 2014), we included the distance to the closest continental shore that previously showed to have a significant relationship with blue shark catch rate (Fernández-Méndez *et al.*, 2016). In this analysis the interaction DF:ZONE had a significant relationship both with catch probability and catch rate pointing to the importance of specific areas, relatively near to the shore, of the Baja California peninsula. The importance of temperature in specific geographic areas in relationship with catch rate (hinted by the interaction TF:DF:ZONE) should be taken into account but the effect of other factors (such as primary productivity in a coastline characterized by local upwellings) should be investigated in further analysis.

It is possible that the biggest inter-annual differences observed in the abundance index (for example in the years 2006 and 2012, Tables 3 and 4, Figures 2 and 3) could be a result, at least in part, from inter-annual differences in sample sizes. Taking into account the uncertainty, the results of this analysis point at the abundance index trends being close to stability in the analyzed period, in particular since the year 2013.

Variability in probability of catch or nominal catch rates can also be related to other physical, chemical, and biological processes or factors in the ocean (e.g. water transparency, circulation patterns, frontal zones, salinity, plankton, nekton), which together with temperature define the identity, structure, and interaction of water masses and can affect the availability of potential prey and the capture efficiency of predatory fishes (Laurs *et al.* 1984, Bigelow *et al.* 1999). Fishery-related factors like hook size and type, fishing depth or bait type were not included in this analysis, as data on these factors were not available in the data set we used but could be available in the observer data base. Other factors, like moon phase during the fishing set, could be included in a more detailed further analysis.

The present study is the result of work recently initiated, aiming to merge fishery and environmental information from the distribution range of the shortfin mako, and other shark species, in the Mexican Pacific, to estimate the best available relative abundance indices, and model recent trends in CPUE. Results may be improved by adding other predictor variables to the model, extending the time series, and taking into account the size-age structure and sex of the catches. Variable transformation and use of generalized additive models (GAMs) may also increase the explanatory power of the model, due to the likely nonlinearity of many of the functional relationships between probability of catch or catch rate and the predictor variables.

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## Table 1.- Deletion tests for the quasi-binomial GLM model[1].

```
> ModBin2 <- update(ModBin1, . ~ . -DF:ZONE)
>
> anova(ModBin1, ModBin2, test= "F")
Analysis of Deviance Table

Model 1: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE
Model 2: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    QUARTER:ZONE + TF:DF + TF:ZONE
  Resid. Df Resid. Dev Df Deviance      F    Pr(>F)
1      2148     2676.7
2      2150     2699.5 -2  -22.836 11.158 1.511e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModBin2 <- update(ModBin1, . ~ . -TF:ZONE)
>
> anova(ModBin1, ModBin2, test= "F")
Analysis of Deviance Table

Model 1: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE
Model 2: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    QUARTER:ZONE + TF:DF + DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F  Pr(>F)
1      2148     2676.7
2      2150     2682.4 -2    -5.68 2.7752 0.06256 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModBin3 <- update(ModBin2, . ~ . -TF:DF)
>
> anova(ModBin2, ModBin3, test= "F")
Analysis of Deviance Table

Model 1: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    QUARTER:ZONE + TF:DF + DF:ZONE
Model 2: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    QUARTER:ZONE + DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      2150     2682.4
2      2151     2683.4 -1  -1.0648 1.0378 0.3084
>
>
> ModBin4 <- update(ModBin3, . ~ . -QUARTER:ZONE)
>
> anova(ModBin3, ModBin4, test= "F")
Analysis of Deviance Table

Model 1: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    QUARTER:ZONE + DF:ZONE
Model 2: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F    Pr(>F)
1      2151     2683.4
2      2157     2713.4 -6   -29.94 4.8852 5.722e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
```

**Table 1.- (Cont.)[1].**

```
> ModBin4 <- update(ModBin3, . ~ . -QUARTER:DF)
>
> anova(ModBin3, ModBin4, test= "F")
Analysis of Deviance Table

Model 1: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:DF +
    QUARTER:ZONE + DF:ZONE
Model 2: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:ZONE +
    DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      2151     2683.4
2      2154     2687.5 -3  -4.0972 1.3371 0.2606
>
>
> ModBin5 <- update(ModBin4, . ~ . -QUARTER:TF)
>
> anova(ModBin4, ModBin5, test= "F")
Analysis of Deviance Table

Model 1: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:ZONE +
    DF:ZONE
Model 2: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:ZONE + DF:ZONE
  Resid. Df Resid. Dev Df Deviance     F    Pr(>F)
1      2154     2687.5
2      2157     2704.8 -3  -17.235 5.634 0.0007624 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModBin5 <- update(ModBin4, . ~ . -YEAR)
>
> anova(ModBin4, ModBin5, test= "F")
Analysis of Deviance Table

Model 1: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:ZONE +
    DF:ZONE
Model 2: CTCHPROB ~ QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:ZONE +
    DF:ZONE
  Resid. Df Resid. Dev  Df Deviance      F    Pr(>F)
1      2154     2687.5
2      2164     2807.3 -10  -119.78 11.746 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
```

[1]**Note:** What is being shown in this table is the automatic output for this routine. The response variable for the Binomial GLM (CTCHPROB) is treated as a presence/absence variable. What is modeled in this part of the model is the probability of catch being not zero. Model terms not assessed with deletion tests are a part of significant interaction terms and most be kept to ensure model stability (Crawley 2009).

## Table 2.- Deletion tests for the positive GLM (Lognormal)[1].

```
> ModLognorm2 <- update(ModLognorm1, . ~ . -TF:DF:ZONE)
>
> anova(ModLognorm1, ModLognorm2, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + QUARTER:TF:DF +
    QUARTER:TF:ZONE + QUARTER:DF:ZONE + TF:DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + QUARTER:TF:DF +
    QUARTER:TF:ZONE + QUARTER:DF:ZONE
  Resid. Df Resid. Dev Df Deviance    F  Pr(>F)
1      1155     939.77
2      1157     946.03 -2  -6.2652 3.85 0.02155 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
>
> ModLognorm2 <- update(ModLognorm1, . ~ . -QUARTER:DF:ZONE)
>
> anova(ModLognorm1, ModLognorm2, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + QUARTER:TF:DF +
    QUARTER:TF:ZONE + QUARTER:DF:ZONE + TF:DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + QUARTER:TF:DF +
    QUARTER:TF:ZONE + TF:DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      1155     939.77
2      1161     945.66 -6  -5.8883 1.2061 0.3004
>
>
> ModLognorm3 <- update(ModLognorm2, . ~ . -QUARTER:TF:ZONE)
>
> anova(ModLognorm2, ModLognorm3, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + QUARTER:TF:DF +
    QUARTER:TF:ZONE + TF:DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + QUARTER:TF:DF +
    TF:DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      1161     945.66
2      1166     953.12 -5  -7.4661 1.8332 0.1035
>
>
> ModLognorm4 <- update(ModLognorm3, . ~ . -QUARTER:TF:DF)
>
> anova(ModLognorm3, ModLognorm4, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + QUARTER:TF:DF +
    TF:DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      1166     953.12
2      1169     956.97 -3  -3.8495 1.5698  0.195
>
```

## Table 2.- (Cont.)[1].

```
> ModLognorm5 <- update(ModLognorm4, . ~ . -QUARTER:ZONE)
>
> anova(ModLognorm4, ModLognorm5, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F   Pr(>F)
1      1169     956.97
2      1175     971.42 -6  -14.444 2.9408 0.007482 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModLognorm5 <- update(ModLognorm4, . ~ . -QUARTER:DF)
>
> anova(ModLognorm4, ModLognorm5, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
  Resid. Df Resid. Dev Df Deviance     F Pr(>F)
1      1169     956.97
2      1172     968.33 -3  -11.354 4.623 0.0032 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModLognorm5 <- update(ModLognorm4, . ~ . -QUARTER:TF)
>
> anova(ModLognorm4, ModLognorm5, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:DF +
    QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      1169     956.97
2      1172     958.22 -3   -1.246 0.5074 0.6773
>
>
> ModLognorm6 <- update(ModLognorm5, . ~ . -YEAR)
>
> anova(ModLognorm5, ModLognorm6, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:DF +
    QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
Model 2: log(CTCHRATE) ~ QUARTER + TF + DF + ZONE + QUARTER:DF + QUARTER:ZONE +
    TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE
  Resid. Df Resid. Dev  Df Deviance      F    Pr(>F)
1      1172     958.22
2      1182     990.01 -10   -31.79 3.8883 3.256e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
```

[1]**<u>Note</u>:** What is being shown in this table is the automatic output for this routine. The response variable for the Lognormal GLM is treated as a continuous variable. What is modeled in this part of the model is the mean response for non-zero observations. . Model terms not assessed with deletion tests are a part of significant interaction terms and most be kept to ensure model stability (Crawley 2009).

## Table 3.- Results of the delta-Lognormal model fit.

Lognormal distribution assumed for positive observations.
Formula for quasibinomial GLM: CTCHPROB ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF + QUARTER:ZONE + DF:ZONE
Formula for gaussian GLM: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE + TF:DF:ZONE

| | index | jack.mean | jack.se | jack.cv |
|---|---|---|---|---|
| 2006 | 2.10948722102668 | 2.10954233952392 | 0.417860853147948 | 0.198086458634519 |
| 2007 | 1.0223889668765 | 1.02239257101898 | 0.167706269332573 | 0.164033723725455 |
| 2008 | 0.762683412578975 | 0.762675267712553 | 0.148926027506528 | 0.195265853498691 |
| 2009 | 2.2983421396293 | 2.2983692508074 | 0.413496930027806 | 0.179910955335178 |
| 2010 | 1.58308697902089 | 1.58309737511694 | 0.254656152672139 | 0.160860493483206 |
| 2011 | 1.71340913152416 | 1.71341458984515 | 0.323456247459811 | 0.188779341436147 |
| 2012 | 3.08271540310026 | 3.08285025107149 | 0.929976704264155 | 0.301674524780616 |
| 2013 | 1.38773382546969 | 1.38774941975503 | 0.246697311387261 | 0.177769905769763 |
| 2014 | 1.4284126682387 | 1.42840626119716 | 0.255522778744605 | 0.178885825102403 |
| 2015 | 1.3258311106343 | 1.32584665859942 | 0.238971580019195 | 0.180242851523424 |
| 2016 | 1.44934696040606 | 1.44936891067864 | 0.313410812494627 | 0.216242777648507 |

| QUARTER | |
|---|---|
| 1 | 1.94032568489828 |
| 2 | 1.52954297271011 |
| 3 | 1.86901419623449 |
| 4 | 1.09474824908285 |

| TF | |
|---|---|
| NP | 2.04346905222379 |
| PR | 1.20383519847457 |

| DF | |
|---|---|
| F | 1.5063049098123 |
| N | 1.62678505071586 |

| ZONE | |
|---|---|
| CENTRAL | 1.93105397730979 |
| NORTH | 1.76437569921249 |
| SOUTH | 1.12607427942362 |

| V1 | |
|---|---|
| AIC.binomial | NA |
| AIC.lognormal | 5735.24114655366 |
| sigma.mle | 0.89137103264421 |

**Table 4.- 95% confidence intervals of the estimated indices for the delta - lognormal model and re-scaled values.**

| | Estimated index | LCI* | UCI* |
|---|---|---|---|
| **2006** | 2.1094872 | 1.2904959 | 2.928479 |
| **2007** | 1.0223890 | 0.6936776 | 1.351100 |
| **2008** | 0.7626834 | 0.4707874 | 1.054579 |
| **2009** | 2.2983421 | 1.4879052 | 3.108779 |
| **2010** | 1.5830870 | 1.0839538 | 2.082220 |
| **2011** | 1.7134091 | 1.0794369 | 2.347381 |
| **2012** | 3.0827154 | 1.2600537 | 4.905377 |
| **2013** | 1.3877338 | 0.9042051 | 1.871263 |
| **2014** | 1.4284127 | 0.9275878 | 1.929238 |
| **2015** | 1.3258311 | 0.8574482 | 1.794214 |
| **2016** | 1.4493470 | 0.8350640 | 2.063630 |

*Approximate 95% lower and upper confidence intervals.

| | Re-scaled index | LCI* | UCI* |
|---|---|---|---|
| **2006** | 1.2775313 | 0.7815401 | 1.7735224 |
| **2007** | 0.6191713 | 0.4200997 | 0.8182429 |
| **2008** | 0.4618904 | 0.2851146 | 0.6386662 |
| **2009** | 1.3919041 | 0.9010936 | 1.8827146 |
| **2010** | 0.9587368 | 0.6564557 | 1.2610180 |
| **2011** | 1.0376615 | 0.6537202 | 1.4216028 |
| **2012** | 1.8669301 | 0.7631039 | 2.9707564 |
| **2013** | 0.8404286 | 0.5475977 | 1.1332595 |
| **2014** | 0.8650642 | 0.5617585 | 1.1683698 |
| **2015** | 0.8029395 | 0.5192811 | 1.0865979 |
| **2016** | 0.8777422 | 0.5057250 | 1.2497595 |

*Approximate 95% lower and upper confidence intervals.

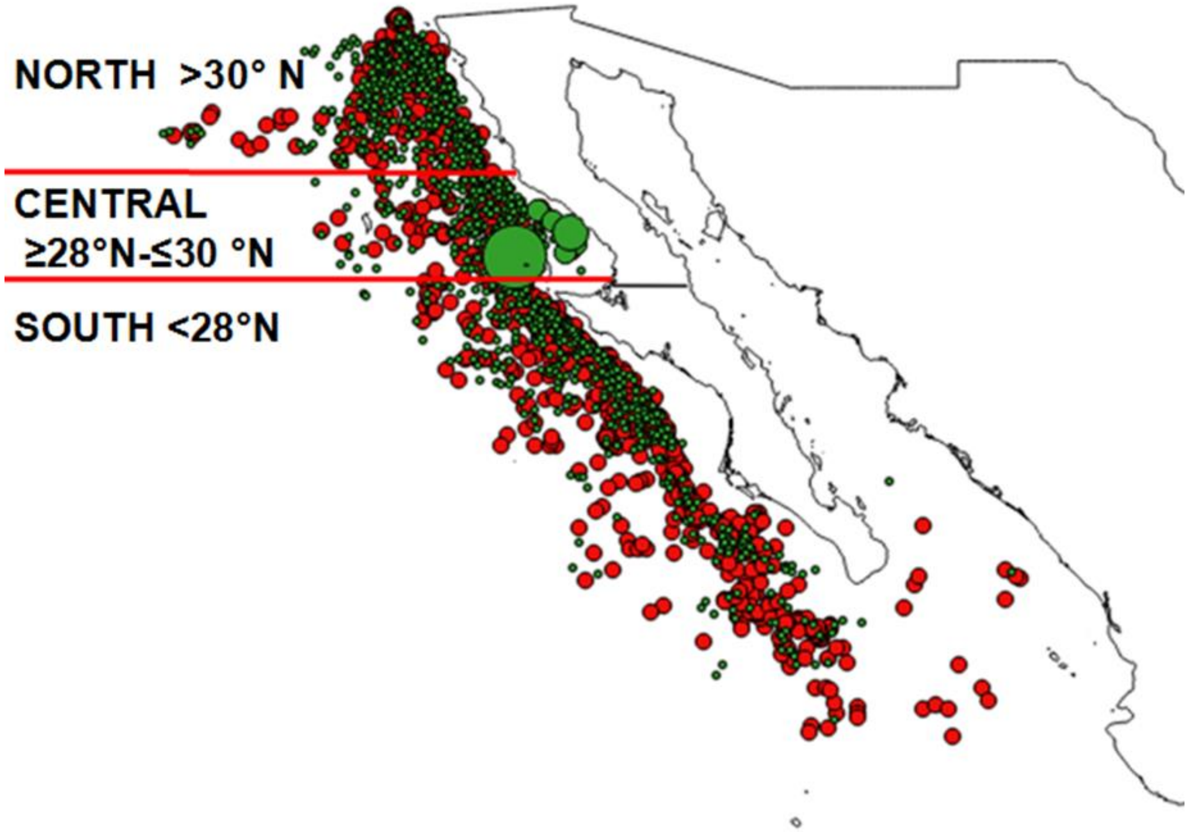


Figure 1.- The zones used in the analyses. Sets positive for shortfin mako are shown with green circles. Negative sets are shown by red circles.

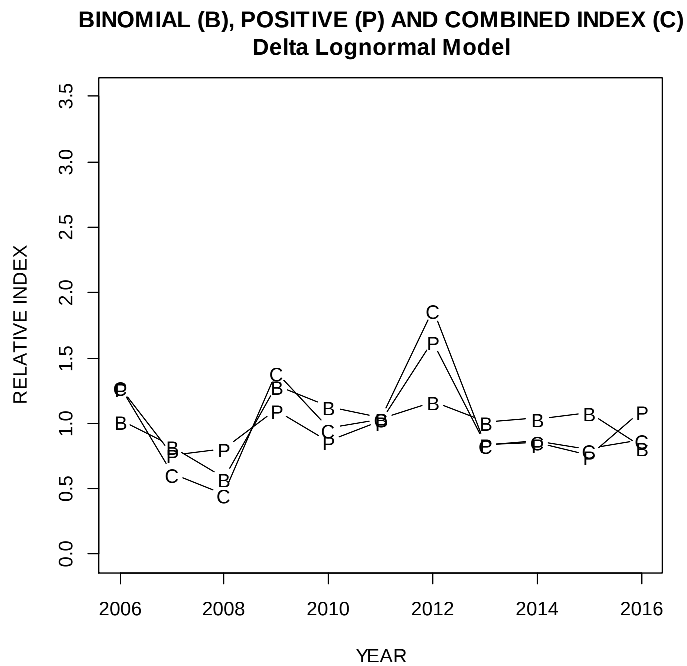


Figure 2.- Quasi-Binomial, Positive and Combined indices for mako shark 2006-2016.

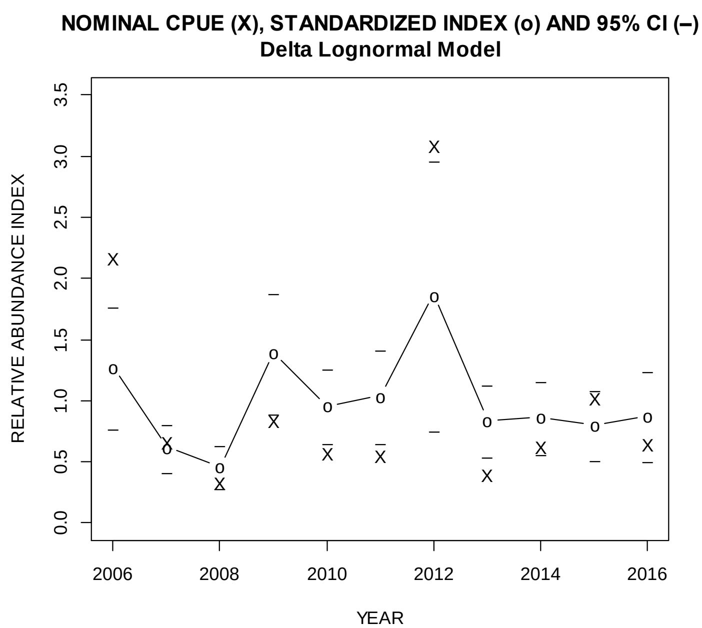


Figure 3.- Relative abundance indices for shortfin mako with approximate 95% confidence intervals. Delta-lognormal model for years 2006-2016.

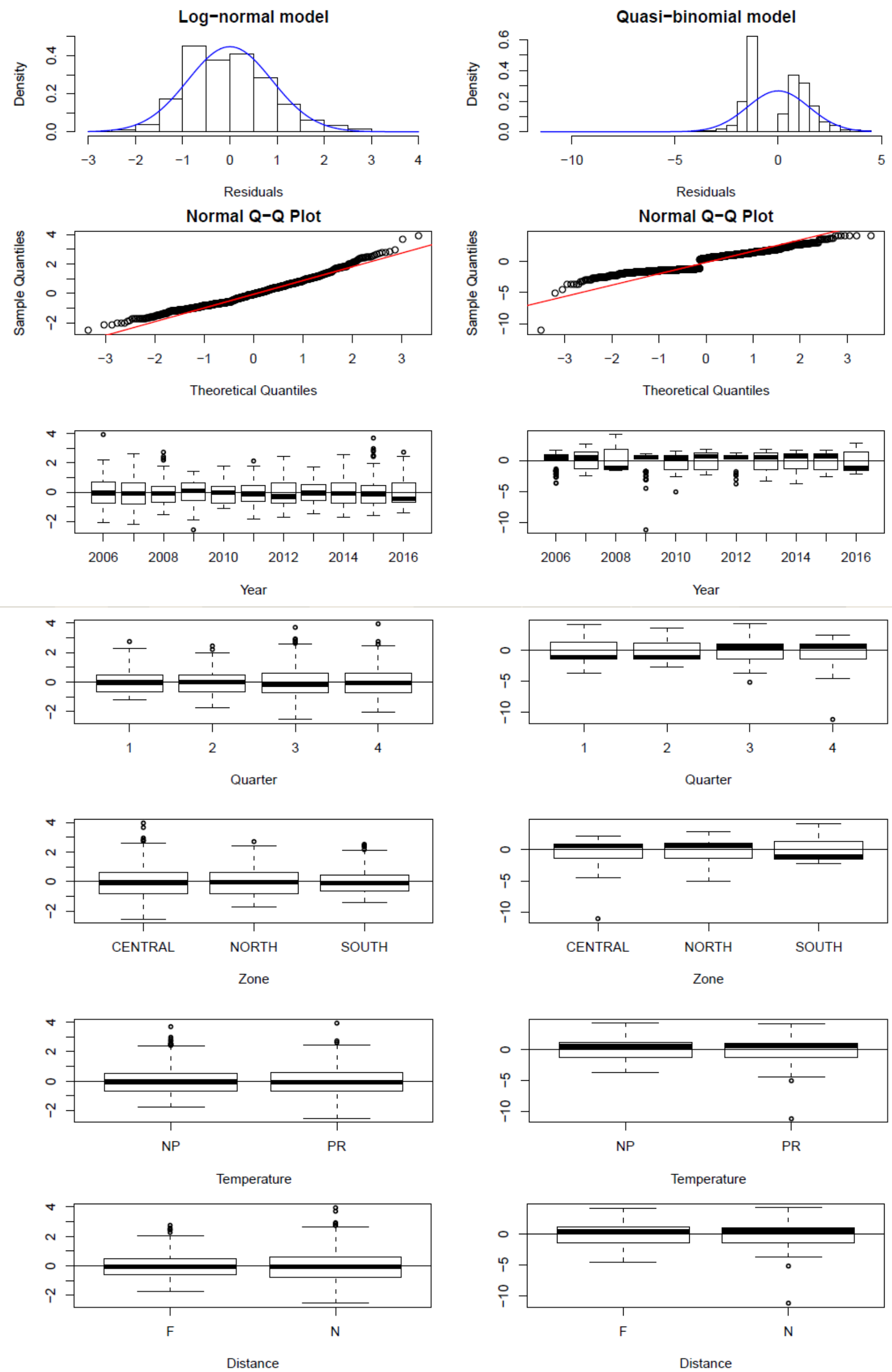


Figure 4.- Residuals and Marginal-model plots of the log normal (left) and quasi-binomial (right) GLMs. The residuals for the log normal GLM are close to normal. The pattern of the residuals of the quasi-binomial GLM, although close to the plot's central line, show a clear two-bands pattern, typical of the models with a binary response (Christensen 1997, Zuur *et al.* 2009).