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Standardized catch rates for mako shark (*Isurus oxyrinchus*) in the 2006-2014 Mexican Pacific longline fishery based upon a shark scientific observer program[1]

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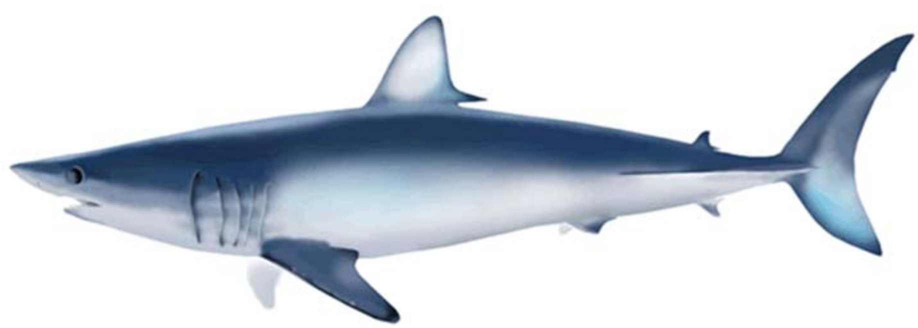

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SUMMARY

Abundance indices for mako shark (*Isurus oxyrinchus*) in the northwest Mexican Pacific for the period 2006-2014 were estimated using data obtained through a pelagic longline observer program. 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 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. Sea surface temperature, year, area fished and quarter were all significant factors included in the model.

INTRODUCTION

The driftnet fishery off the coast of southern California began in 1978, originally targeting the common thresher shark (*Alopias vulpinus*) and shortfin mako (*Isurus oxyrinchus*, locally known as bonito shark). Almost immediately swordfish (*Xiphias gladius*) became an important component of the catch. The early success of the fishery was attributed to the abundance of Pacific swordfish and pelagic sharks in coastal waters and popular consumer acceptance of both swordfish and sharks, together with lower operating expenses in comparison with the swordfish harpoon fishery (primarily due to greater fuel efficiency). Driftnet vessels landing swordfish in California numbered 173 in 1991, 169 in 1992, and 162 in 1993 (Holts and Sosa-Nishizaki 1998).

Stimulated by the successful driftnet fishery in California, 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 and were similar in design and size (18-25 m) to the U.S. driftnet vessels, operating just 100 km to the north. The nets were similar in design to the U.S. drift nets, although they might be up to 4.5 km long, whereas U.S. nets were limited to 1 nm (1.8 km).

At the end of the 1990’s decade, because of the high by-catch of marine mammals and marine turtles in the operations of the driftnets, the Ensenada-based swordfish fleet began a fishery gear transition to a more selective, pelagic longline.

The Mexican Official Standard NOM-029-PESC-2006 banned driftnets in medium-size vessels (10-27 m length). By the end of 2009, all vessels switched to longline and the operational dynamics of the fleet changed drastically. Blue shark (*Prionace glauca*) and shortfin mako became the most abundant catch in terms of numbers in the longline fishery along the west and south coast of the Baja California peninsula. 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).

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 commercial 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.

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, on a voluntary basis, 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),recording 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.

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 (see details in working paper ISC/14/SHARKWG-3/02 entitled “Catch data for shortfin mako shark reported by fishery observers from Mexican shark longline and driftnet fisheries in the North Pacific in 2006-2014” by Castillo-Géniz *et al.*, this meeting).

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 fishery 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. Mako accounted for 4.2% in total driftnet catches (see details in working paper ISC/14/SHARKWG-3/02 entitled “Catch data for shortfin mako shark reported by fishery observers from Mexican shark longline and driftnet fisheries in the North Pacific in 2006-2014” by Castillo-Géniz *et al.*, this meeting).

Longline and driftnet catches also included 10 species of 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).

For non-target species, catches are relatively unusual (in many records catch is 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 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). The probability of obtaining a positive observation is usually modeled using the binomial distribution (Stefánsson 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-April 2014 is complete. In particular, only data from the Ensenada longline fleet were used in the analysis, as it is the one with better observer coverage 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 8,389 longline sets, just 1,145 sets were retained to be used in the analysis. The proportion of zero-catch sets in this subsample was 41.5%, 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 possible influence on the RESPONSE variables of the binomial or lognormal models (catch probability or logarithm of catch rate as number of makos per 100 hooks, respectively) were selected for the analyses, like mean sea surface temperature (MEANTEMP as a two-level factor) and time-area factors such as YEAR, QUARTER and fishing area (ZONE). Mean sea surface temperature (MEANTEMP) 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. MEANTEMP levels were defined as LOW (<=18.5°C), and HIGH (>18.5°C), on the basis of the mean sea surface temperature in which all validated sets of the Ensenada fleet were performed, and matching approximately the lower limit of the preferential range (18-21°C) of sea surface temperatures for shortfin makos (Castro 2011). Two fishing areas (ZONE) were defined as NORTH (>27° LN) and SOUTH (<=27° LN), based upon the central latitude of the fishing area (Figure 1). Catch probability and catch rates were modeled as a function of these factors.

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 overdispersion, 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 back-transformed year effects from the two GLMs. The analyses were performed using the R language/environment version 3.0.1 (R Core Team 2013). The Delta model was set with the Delta-GLM function from SEDAR (2006).

The predictor variables QUARTER, MEANTEMP and ZONE were included initially in both GLM models as a set of direct effects and their two-way 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 formula of the maximum (initial) models was:

RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP + QUARTER:ZONE + MEANTEMP:ZONE

They were assessed through tests of hypothesis to assay each potential term one at a time, using deletion tests 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. A weight vector based on the annual variances of nominal catch rates was also included in the positive model (lognormal), to indicate that the catch rates of different years have different dispersions, with the values in the vector of annual weights being inversely proportional to the dispersions (i.e., observations in the year with the least variance in catch rates has weight = 1). Standard errors and coefficients of variation for the standardized abundance indices were estimated with a jackknife routine.

RESULTS AND DISCUSSION

The quasi-binomial GLM presented a very small over dispersion (dispersion parameter = 1.020). The results of the tests of hypothesis (deletion tests) of the factors and interactions included in the quasi-binomial GLM, are shown in Table 1. The minimum adequate (final) model was:

RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP + QUARTER:ZONE

The results of the tests of hypothesis (deletion tests) of the factors included in the positive GLM of the lognormal model are shown in Table 2. The final model was:

RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP

The results of the relative abundance analyses for shortfin mako (2006-2014) from the delta-lognormal model are shown in Table 3. Figure 2 shows the quasi-binomial index, together with the positive and combined indices. Table 4 and Figure 3 show the estimated values of the relative index of the combined model and their 95% confidence intervals.

Figure 4 shows the residuals of the quasi-binomial (right) and log normal (left) GLMs as well as the marginal-model plots for each factor. 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 that is typical of the models with a binary response as their residuals are not asymptotically normal (Christensen 1997, Zuur *et al.* 2009). Diagnostic plots showed good agreement with model assumptions and there were no clear systematic patterns in the residuals.

Spatial-temporal heterogeneity in the marine environment is believed to 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. Detection of a stronger relationship between probability of catch and the quarter*temperature interaction was due –at least in part– to the space-time microscale approach used.

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). The interaction between the factors QUARTER and MEANTEMP 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 could involve a spatial component in those variations (*v.gr.* one zone having a seasonal pattern different from the other one).

It is possible that the biggest inter-annual differences observed in the abundance index 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.

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 or distance from the coast, that could be included in a more detailed analysis, were not considered at this stage due to time constraints.

The present study represents the first attempt to merge fishery and environmental information from the distribution range of the shortfin mako in the Mexican Pacific, 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].

```
> ModQBin2 <- update(ModQBin1, . ~ . -QUARTER:MEANTEMP)
>
>anova(ModQBin1, ModQBin2, test= "F")
Analysis of Deviance Table

Model 1: RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
QUARTER:ZONE + MEANTEMP:ZONE
Model 2: RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:ZONE
+  MEANTEMP:ZONE
Resid. DfResid. Dev Df Deviance      F   Pr(>F)
1      1124     1379.9
2      1127     1394.4 -3  -14.512 4.7481 0.002694 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModQBin2 <- update(ModQBin1, . ~ . -QUARTER:ZONE)
>
>anova(ModQBin1, ModQBin2, test= "F")
Analysis of Deviance Table

Model 1: RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
QUARTER:ZONE + MEANTEMP:ZONE
Model 2: RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
MEANTEMP:ZONE
Resid. DfResid. Dev Df Deviance      F   Pr(>F)
1      1124     1379.9
2      1127     1392.6 -3  -12.693 4.1531 0.006142 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModQBin2 <- update(ModQBin1, . ~ . -MEANTEMP:ZONE)
>
>anova(ModQBin1, ModQBin2, test= "F")
Analysis of Deviance Table

Model 1: RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
QUARTER:ZONE + MEANTEMP:ZONE
Model 2: RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
QUARTER:ZONE
Resid. DfResid. Dev Df Deviance      F  Pr(>F)
1      1124     1379.9
2      1125     1383.8 -1  -3.8931 3.8213 0.05085 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModQBin3 <- update(ModQBin2, . ~ . -YEAR)
>
>anova(ModQBin2, ModQBin3, test= "F")
Analysis of Deviance Table

Model 1: RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
QUARTER:ZONE
Model 2: RESPONSE ~ QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP
+ QUARTER:ZONE
Resid. DfResid. Dev Df Deviance      F    Pr(>F)
1      1125     1383.8
2      1133     1446.6 -8  -62.797 7.6923 4.509e-10 ***
---
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. Internally, the response variable for the Binomial GLM is treated as a presence/absence variable. What is modeled in this part of the model is the probability of catch being not zero.

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

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

Model 1: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
QUARTER:ZONE + MEANTEMP:ZONE
Model 2: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:ZONE +  MEANTEMP:ZONE
Resid. DfResid. Dev Df Deviance      F  Pr(>F)
1       649     204.14
2       652     206.97 -3  -2.8274 2.9963 0.03018 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModLognorm2 <- update(ModLognorm1, . ~ . -QUARTER:ZONE)
>
>anova(ModLognorm1, ModLognorm2, test= "F")
Analysis of Deviance Table

Model 1: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
QUARTER:ZONE + MEANTEMP:ZONE
Model 2: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
MEANTEMP:ZONE
Resid. DfResid. Dev Df Deviance      F  Pr(>F)
1       649     204.14
2       652     206.12 -3  -1.9778 2.0959 0.09952 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModLognorm3 <- update(ModLognorm2, . ~ . -MEANTEMP:ZONE)
>
>anova(ModLognorm2, ModLognorm3, test= "F")
Analysis of Deviance Table

Model 1: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP +
MEANTEMP:ZONE
Model 2: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + ZONE
+ QUARTER:MEANTEMP
Resid. DfResid. Dev Df Deviance      F  Pr(>F)
1       652     206.12
2       653     207.16 -1  -1.0445 3.3039 0.06957 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModLognorm4 <- update(ModLognorm3, . ~ . -ZONE)
>
>anova(ModLognorm3, ModLognorm4, test= "F")
Analysis of Deviance Table

Model 1: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + ZONE
+ QUARTER:MEANTEMP
Model 2: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + QUARTER:MEANTEMP
Resid. DfResid. Dev Df Deviance      F    Pr(>F)
1       653     207.16
2       654     218.03 -1  -10.865 34.249 7.675e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModLognorm4 <- update(ModLognorm3, . ~ . -YEAR)
>
>anova(ModLognorm3, ModLognorm4, test= "F")
Analysis of Deviance Table

Model 1: log(RESPONSE) ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP
Model 2: log(RESPONSE) ~ QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP
Resid. DfResid. Dev Df Deviance      F   Pr(>F)
1       653     207.16
2       661     214.24 -8  -7.0787 2.7891 0.004841 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
```

[1]**Note:**The response variable for the Lognormal GLM is treated as a continuous variable.

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

Lognormal distribution assumed for positive observations.

Formula for quasi-binomial GLM:
RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP + QUARTER:ZONE

Formula for gaussian GLM:
RESPONSE ~ YEAR + QUARTER + MEANTEMP + ZONE + QUARTER:MEANTEMP

	index	jack.mean	jack.se	jack.cv
2006	0.253049411618264	0.253051696677215	0.0517664468582902	0.204570508689355
2007	0.119516792032309	0.119517027350201	0.0203981294942961	0.17067166167564
2008	0.092401485052865	0.0924021205846411	0.0176309651471418	0.190808244446014
2009	0.177544680253138	0.177545650255557	0.0311649469434794	0.175532980763182
2010	0.13990322923433	0.139905471469418	0.0264182009901829	0.188831960025268
2011	0.201419582053638	0.201421367132468	0.0509040937462057	0.252726637734012
2012	0.324606815130658	0.324617795419286	0.0957985276865822	0.295121738734974
2013	0.155154357057024	0.15515612591302	0.0293375623970172	0.189086294149218
2014	0.191015600777476	0.191019283344254	0.0437745461261511	0.229167387103352

QUARTER	
1	0.133803775808748
2	0.151907093791985
3	0.226076063167899
4	0.184303548614367

MEANTEMP	
H	0.178811325643948
L	0.168992482716388

ZONE	
N	0.226761020423412
S	0.135581406019589

	V1
AIC.binomial	NA
AIC.lognormal	532.916982035871
sigma.mle	0.556054952140217

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

	Estimated index	LCI*	UCI*
2006	0.253049412	0.151587176	0.354511647
2007	0.119516792	0.079536458	0.159497126
2008	0.092401485	0.057844793	0.126958177
2009	0.177544680	0.116461384	0.238627976
2010	0.139903229	0.088123555	0.191682903
2011	0.201419582	0.101647558	0.301191606
2012	0.324606815	0.136841701	0.512371929
2013	0.155154357	0.097652735	0.212655979
2014	0.191015601	0.105217490	0.276813711

*Approximate 95% lower and upper confidence intervals.

	Re-scaledindex	LCI*	UCI*
2006	1.376422248	0.824534465	1.928310031
2007	0.650092686	0.432625984	0.867559387
2008	0.502603262	0.314637604	0.690568921
2009	0.965726205	0.633473278	1.297979132
2010	0.760981486	0.479334140	1.042628832
2011	1.095589957	0.552895815	1.638284099
2012	1.765647426	0.744328787	2.786966065
2013	0.843937584	0.531166604	1.156708563
2014	1.038999146	0.572313896	1.505684397

*Approximate 95% lower and upper confidence intervals.

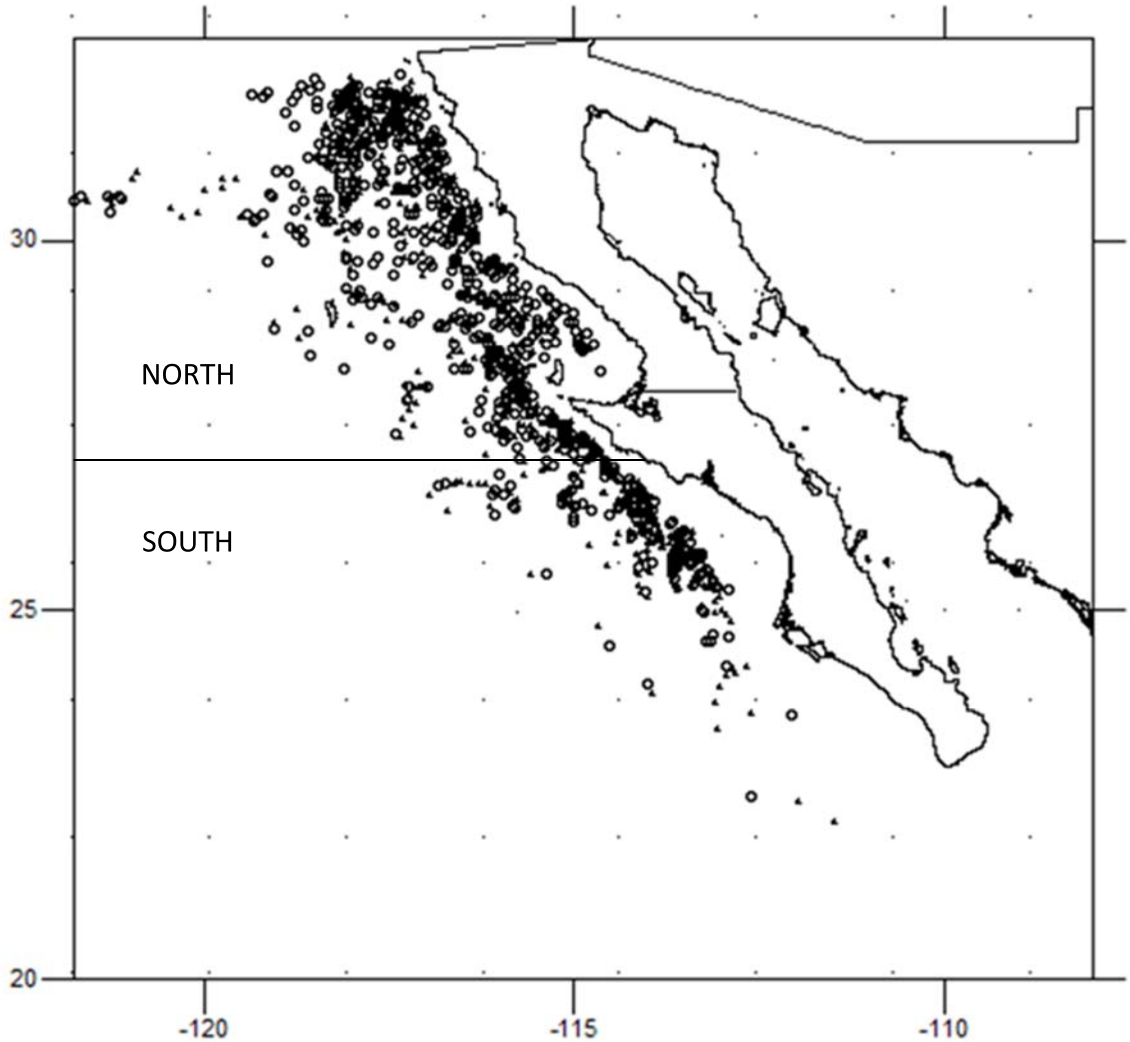

Figure 1.- The zones used in the analyses. Sets positive for shortfin mako are shown with a circle. Negative sets are shown by small triangles.

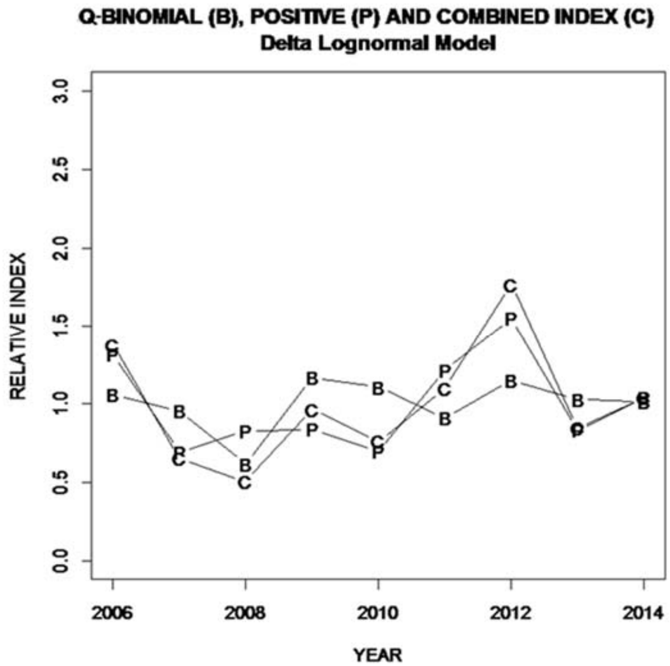

Figure 2.- Quasi-Binomial, Positive and Combined indices for mako shark 2006-2014.

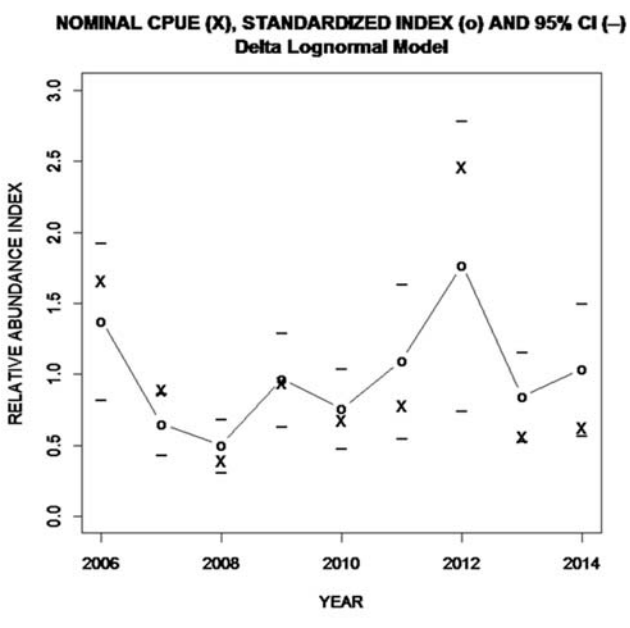

Figure 3.- Relative abundance indices for shortfin mako with approximate 95% confidence intervals. Delta-lognormal model for years 2006-2014.

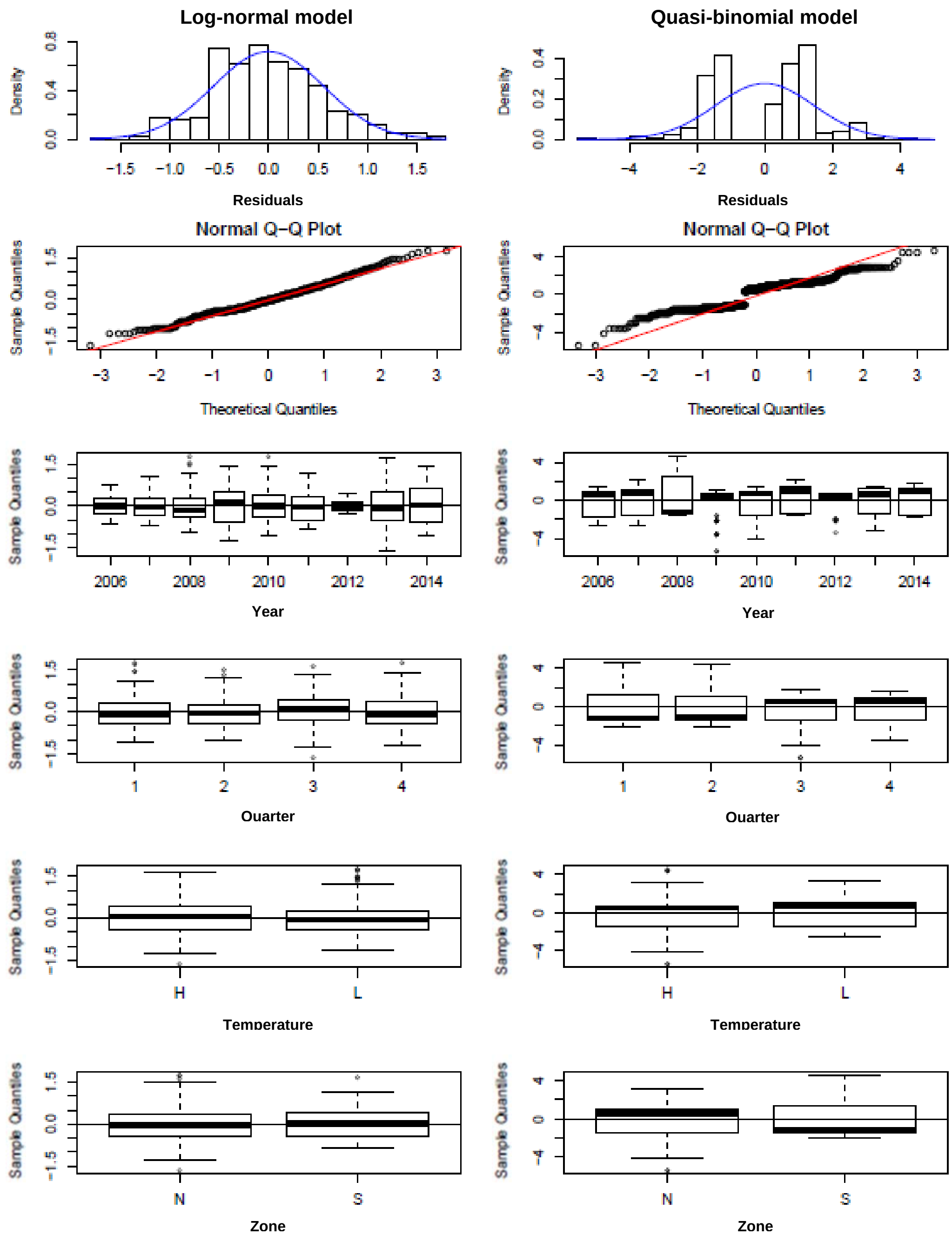

Figure 4.- Residuals and Marginal-model plots of the log normal (left) and quasi-binomial (right) GLMs. The residuals for the log normal GLM are close to normal. The pattern of the residuals of the quasi-binomial GLM, although close to the plot's central line, show a clear two-bands pattern, typical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