ISC/21/SHARKWG-1/07

Update on standardized catch rates for mako shark (*Isurus oxyrinchus*) in the 2006-2019 Mexican Pacific longline fishery based upon a shark scientific observer program[1]

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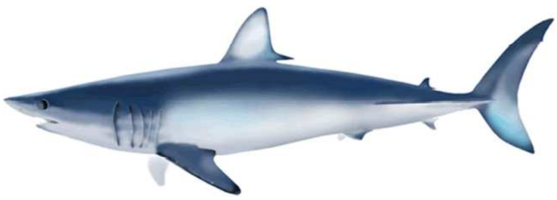

[1] Working document submitted to the ISC Shark Working Group Workshop, 22 – 26 February, 2021, videoconference. **Document not to be cited without author's permission.**

SUMMARY

Abundance indices for mako shark (*Isurus oxyrinchus*) in the northwest Mexican Pacific for the period 2006-2019 were estimated using data obtained through a pelagic longline observer program, updating similar analyses made in 2014 and 2017. 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.

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, Del Moral-Flores *et al*. 2015). 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 2018 (most recent official data) was 29,464 t, which places Mexico as one of the top shark producer nations in the world according to Musick and Musick (2011). In 2018 the total domestic shark production reached 47,873 t, (2.8% 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 1976-2018 was 21,344 t. In 2018 the Pacific shark production reached a historical peak with 38,573 t which comprised 80.5% of the total Mexican shark production (SADER-CONAPESCA, 2020).

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 (BC), Mexico. This fishery was stimulated 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, BC, 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-Ramírez *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.

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*) and short-fin mako (*Isurus oxyrinchus*) (Godinez-Padilla *et al*. 2016).

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

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 Ray Fishery 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 National Aquaculture and Fisheries 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 Institute for Fisheries and Aquaculture (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.

Although participation of vessels in the observer program should be mandatory, fishing trips with observers 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.

Corro-Espinosa (unpublished data) conducted an analysis of the commercial logbooks from the Mazatlan longline fleet for years 2009-2012, documenting 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.

In 2016 Godinez-Padilla *et al*. carried out a study on the composition and diversity of species and the relative abundance of oceanic sharks caught by the Ensenada longline fleet based on the analysis of 683 fishing logs from the period 2011-2015. The authors reported the presence of 18 shark species in the catches without any significant change in the annual diversity between fishery zones (north-south) and an apparent positive trend in the nominal CPUE (not standardized).

Catch composition

Godinez-Padilla *et al.* (2016) reported the species composition by numbers from the catches of the Ensenada longline fleet for the period 2011-2015: blue shark, *P. glauca* (89.25%), short-fin mako, *I. oxyrinchus* (7.77%), thresher, *A. vulpinus* (1.06%), silky shark, *Carcharhinus falciformis* (0.63%), scalloped hammerhead, *Sphyrna lewini* (0.51%) and pelagic thresher, *A. pelagicus* (0.19%), followed by a shark ten-species group with 0.28%, of the total numerical catches in five years.

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 middle-size 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*.

Short-fin mako Mexican Pacific commercial landings

Shortfin mako sharks are caught mainly in the western coast of the Peninsula of Baja California, and waters off the mouth of the Gulf of California (Godinez-Padilla, *et al*. 2016, Sosa-Nishizaki *et al*. 2017). During the second half of the 1990s up to 2013 catches increased to a level around 700 t. However, in 2014 they doubled and reached a level of around 1,400 t, in 2016 catches decreased around a level of 700 t (Sosa-Nishizaki *et al*. 2017). The average annual production of shortfin mako shark in the Mexican Pacific for the period 1976-2019 was 488 t. By 2019 the catches of *I. oxyrinchus* reached a historical peak of 1,795 t. The catches of this species for 2017, 2018 and 2019 were provided by the

General Direction of Planning, Programming and Evaluation of the National Aquaculture and Fisheries Commission of Mexico (CONAPESCA).

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.* 1999, 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 (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-December 2019 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, just 2,589 validated sets were retained to be used in the analysis. The proportion of zero-catch sets in this subsample was 46.3%, 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 (CTCHPROB: catch probability or log(CTCHRATE): logarithm of positive 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 each starting point of fishing sets 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 positive 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 back-transformed 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:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE

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

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 (2013). 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 affects 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 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).

In addition to temperature, other environmental factors can affect the distribution and abundance of mako shark in the area of study. High primary productivity on the Pacific coast of the Baja California Peninsula is usually related to coastal upwelling activity that injects nutrients into the euphotic zone. The upwelling intensity changes in accordance with local combinations of wind conditions and bottom topography, modulated by the influence of mesoscale meanders of the California Current (Zaytsev *et al*. 2003). As upwelling results in the appearance on the surface of cold water masses from the bottom, water temperature is indirectly related to these local high productivity areas but no direct causal relationships exist between these two factors.

The coastal nature of upwellings could explain, at least in part, the significance of terms containing the distance to the coast (DF). In this updating, similar to analyses made in 2014 and 2017 (González-Ania *et al.* 2014, 2017), 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).

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

In spatial terms, a significant relationship between probability of catch and the distance to the coast:zone (DF:ZONE) interaction could be explained in terms of the variations of coastal upwelling patterns due to the local combinations of wind conditions and bottom topography mentioned above.

Similarly, the significance of the relationship of probability of catch and the interaction between the factors quarter and temperature (QUARTER:TF, Table 1) could involve a spatial component in those variations (*v. gr.* one zone having a seasonal pattern different from the other one).

In this analysis, the interactions QUARTER:DF, QUARTER:ZONE, DF:ZONE had a significant relationship with catch rate pointing to the importance of specific seasons and areas of the Baja California peninsula, relatively near to the shore.

The lack of significance of the terms containing temperature (TF) in relationship with catch rate could be related with situations like a possible collinearity of the variables temperature and distance to the coast (that could be expected in a coastline characterized by local upwellings) and should be investigated in further analysis. Despite this lack of significance, temperature as main effect (TF) was retained in the model to allow the calculations involving the effects of the two models to proceed.

As a result of what has been discussed in the paragraphs above, variability in probability of catch or nominal catch rates can be related to physical, chemical, and biological processes or factors in the ocean (e.g. water transparency, circulation patterns, frontal zones, salinity, plankton, nekton) not included in this analysis, 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). However, the availability and spatial and temporal resolution of data related to those factors would limit the possibility of their inclusion in future analysis.

In addition, 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 time of the day and moon phase during the fishing set, could be included in a more detailed future 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.

The results of this analysis point at the abundance index trends being close to stability in the analyzed period, taking into account the uncertainty involved.

The present study is the result of recently initiated work, 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      2551     3120.5
2      2553     3143.3 -2  -22.795 11.053 1.661e-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      2551     3120.5
2      2553     3125.4 -2  -4.9311 2.3911 0.09174 .
---
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      2553     3125.4
2      2554     3126.5 -1  -1.0275 1.0077 0.3155
>
>
> 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      2554     3126.5
2      2560     3172.8 -6  -46.372 7.5743 4.509e-08 ***
---
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      2554     3126.5
2      2557     3132.2 -3   -5.789 1.8911 0.1289
>
>
> 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      2557     3132.2
2      2560     3150.7 -3  -18.464 6.0566 0.0004177 ***
---
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 must be kept to ensure model stability (Crawley 2013).

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      1334     1068.5
2      1336     1070.6 -2  -2.0365 1.2712 0.2808
>
>
> ModLognorm3 <- update(ModLognorm2, . ~ . -QUARTER:DF: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 + QUARTER: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
  Resid. Df Resid. Dev Df Deviance      F  Pr(>F)
1      1336     1070.6
2      1342     1079.8 -6  -9.2681 1.9277 0.07322 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
>
> ModLognorm4 <- update(ModLognorm3, . ~ . -QUARTER:TF:ZONE)
>
> 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 +
    QUARTER:TF: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
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      1342     1079.8
2      1348     1087.6 -6   -7.749 1.6051 0.1421
>
>
> ModLognorm5 <- update(ModLognorm4, . ~ . -QUARTER:TF: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 + QUARTER:TF:DF
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + TF:ZONE + DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      1348     1087.6
2      1351     1090.0 -3  -2.4384 1.0074 0.3885
>
```

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

```
> ModLognorm6 <- update(ModLognorm5, . ~ . -DF:ZONE)
>
> anova(ModLognorm5, ModLognorm6, 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
Model 2: log(CTCHRATE) ~ 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      1351     1090.0
2      1353     1108.7 -2  -18.655 11.561 1.051e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
>
> ModLognorm6 <- update(ModLognorm5, . ~ . -TF:ZONE)
>
> anova(ModLognorm5, ModLognorm6, 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
Model 2: log(CTCHRATE) ~ 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      1351     1090.0
2      1353     1091.9 -2   -1.897 1.1756 0.3089
>
>
> ModLognorm7 <- update(ModLognorm6, . ~ . -TF:DF)
>
> anova(ModLognorm6, ModLognorm7, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + TF:DF + DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F  Pr(>F)
1      1353     1091.9
2      1354     1094.1 -1  -2.2089 2.7371 0.09827 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
>
> ModLognorm8 <- update(ModLognorm7, . ~ . -QUARTER:ZONE)
>
> anova(ModLognorm7, ModLognorm8, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F   Pr(>F)
1      1354     1094.1
2      1360     1111.5 -6  -17.413 3.5915 0.001547 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
```

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

```
> ModLognorm8 <- update(ModLognorm7, . ~ . -QUARTER:DF)
>
> anova(ModLognorm7, ModLognorm8, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:ZONE + DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F    Pr(>F)
1      1354     1094.1
2      1357     1109.1 -3  -14.978 6.1784 0.0003609 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
>
> ModLognorm8 <- update(ModLognorm7, . ~ . -QUARTER:TF)
>
> anova(ModLognorm7, ModLognorm8, test= "F")
Analysis of Deviance Table

Model 1: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:TF +
    QUARTER:DF + QUARTER:ZONE + DF:ZONE
Model 2: log(CTCHRATE) ~ YEAR + QUARTER + TF + DF + ZONE + QUARTER:DF +
    QUARTER:ZONE + DF:ZONE
  Resid. Df Resid. Dev Df Deviance      F Pr(>F)
1      1354     1094.1
2      1357     1098.8 -3  -4.6914 1.9352  0.122
>
```

[1]**Note:** What is being shown in this table is the automatic output for this routine. The response variable for the Lognormal GLM [log(CTCHRATE)] 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 must be kept to ensure model stability (Crawley 2013), or must be kept to estimate the effects of predictors in the delta-Lognormal model.

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 + DF:ZONE

	index	jack.mean	jack.se	jack.cv
2006	3.00819890518209	3.00825664575932	0.574690476989173	0.191041382270028
2007	1.58236629053556	1.58237909019254	0.250777707715835	0.158482716180055
2008	1.12889621151301	1.12889985779287	0.204894522872182	0.181499876412527
2009	3.39477378624525	3.39480745329843	0.543706080472253	0.160159738087766
2010	2.25488151406975	2.25490483777222	0.343041250919596	0.152132716854134
2011	2.34545891169168	2.34547105449751	0.425711178225517	0.181504428026185
2012	4.17992082065563	4.18003030070387	1.307355343107360	0.312770360779777
2013	1.88658059520543	1.88659585007131	0.295812686115663	0.156798329669797
2014	2.10489364722024	2.10489919763245	0.329527015441756	0.156552810103701
2015	1.92427917013240	1.92430405260025	0.303304195952434	0.157619643064351
2016	2.07394800181778	2.07397680789425	0.423004399034374	0.203960947267538
2017	1.32755907916664	1.32756515477591	0.256538887772648	0.193241032959292
2018	1.14010105549989	1.14011776653596	0.319549783534567	0.280281982016460
2019	5.32125685582325	5.32130648160065	0.938741698382479	0.176413528573645

QUARTER	
1	2.24884775107576
2	2.34792324858915
3	3.23740784015816
4	1.43878058097730

TF	
NP	2.38809683135661
PR	2.07205890165634

DF	
F	1.92340124050747
N	2.57927947518076

ZONE	
CENTRAL	2.55167060131815
NORTH	2.74579015803775
SOUTH	1.57843959329313

	V1
AIC.binomial	NA
AIC.lognormal	6612.130926601650
sigma.mle	0.889426339603184

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

	Estimated index	LCI*	UCI*
2006	3.008198905	1.88180557	4.13459224
2007	1.582366291	1.09084198	2.07389060
2008	1.128896212	0.72730295	1.53048948
2009	3.394773786	2.32910987	4.46043770
2010	2.254881514	1.58252066	2.92724237
2011	2.345458912	1.51106500	3.17985282
2012	4.179920821	1.61750435	6.74233729
2013	1.886580595	1.30678773	2.46637346
2014	2.104893647	1.45902070	2.75076660
2015	1.924279170	1.32980295	2.51875539
2016	2.073948002	1.24485938	2.90303662
2017	1.327559079	0.82474286	1.83037530
2018	1.140101055	0.51378348	1.76641863
2019	5.321256856	3.48132313	7.16119058

*Approximate 95% lower and upper confidence intervals.

	Re-scaled index	LCI*	UCI*
2006	1.25069465	0.78238316	1.71900615
2007	0.65788770	0.45353059	0.86224481
2008	0.46935209	0.30238489	0.63631929
2009	1.41141778	0.96835527	1.85448029
2010	0.93749394	0.65795188	1.21703600
2011	0.97515258	0.62824334	1.32206182
2012	1.73785204	0.67249677	2.80320732
2013	0.78436843	0.54331262	1.02542425
2014	0.87513469	0.60660529	1.14366409
2015	0.80004207	0.55288147	1.04720266
2016	0.86226867	0.51756517	1.20697218
2017	0.55194856	0.34289670	0.76100041
2018	0.47401064	0.21361162	0.73440966
2019	2.21237614	1.44740170	2.97735059

*Approximate 95% lower and upper confidence intervals.

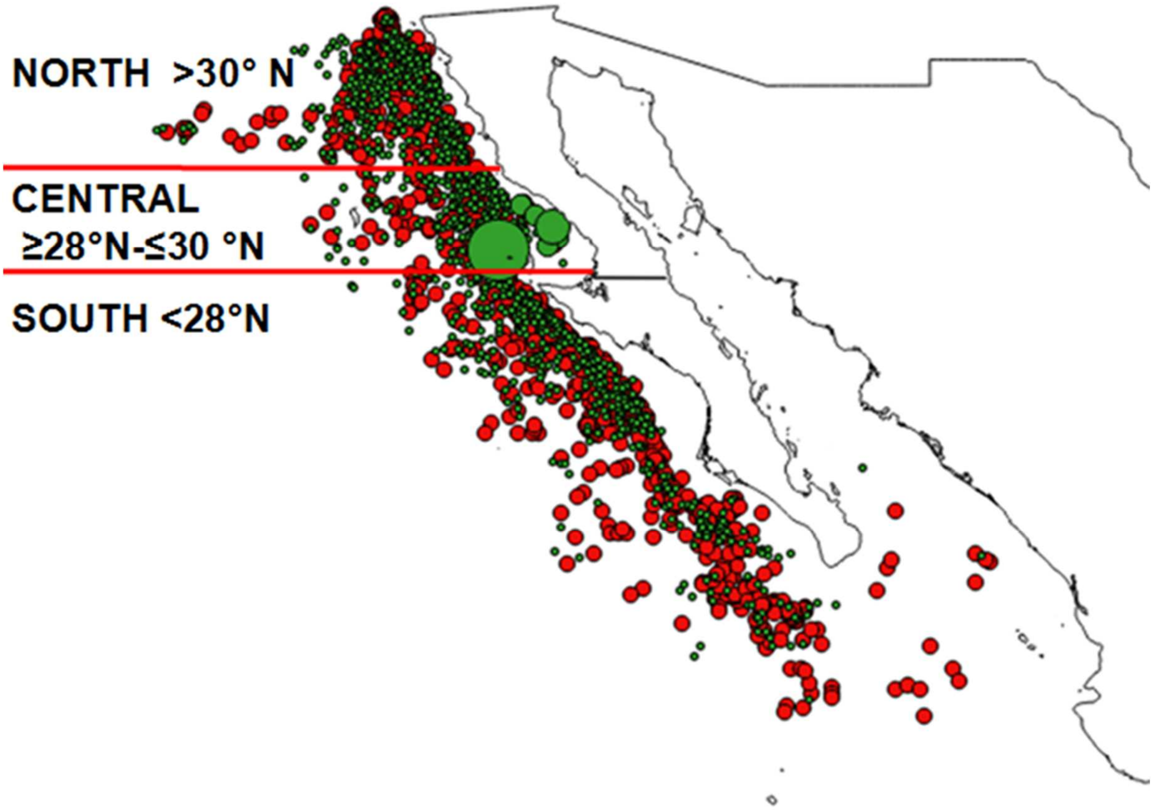

Figure 1.- The zones used in the analyses. Sets positive for shortfin mako are shown with green circles. Negative sets are shown by red circles.

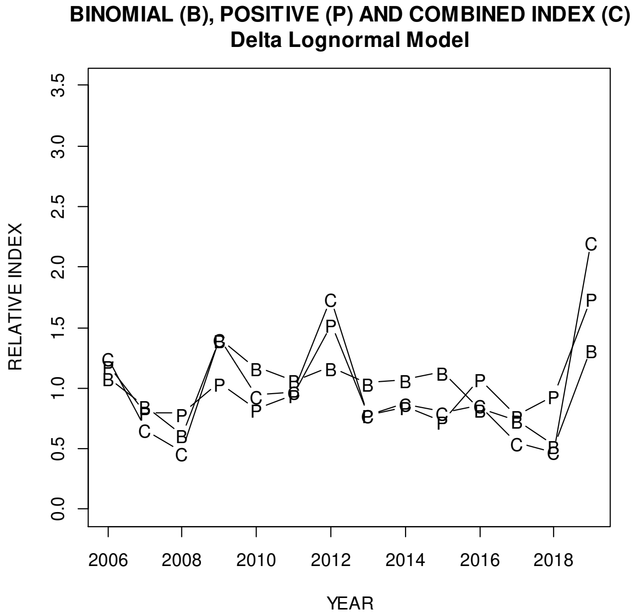

Figure 2.- Quasi-binomial, positive and combined indices for mako shark 2006-2019.

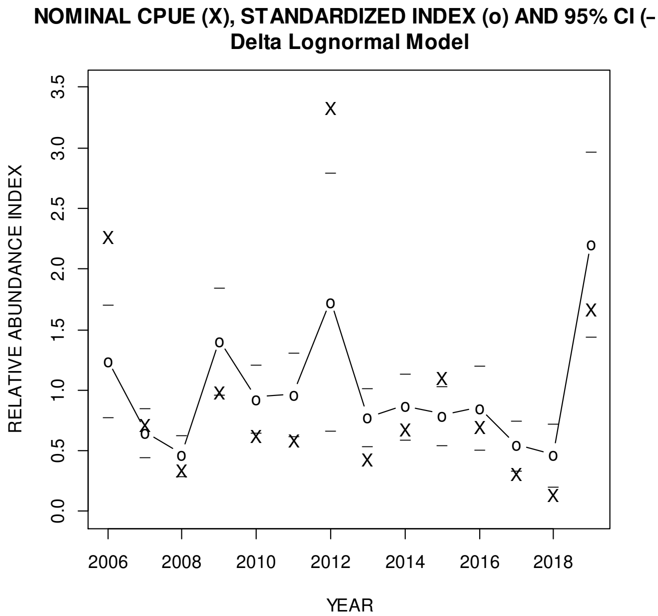

Figure 3.- Relative abundance indices for shortfin mako with approximate 95% confidence intervals. Delta-Lognormal model for years 2006-2019.

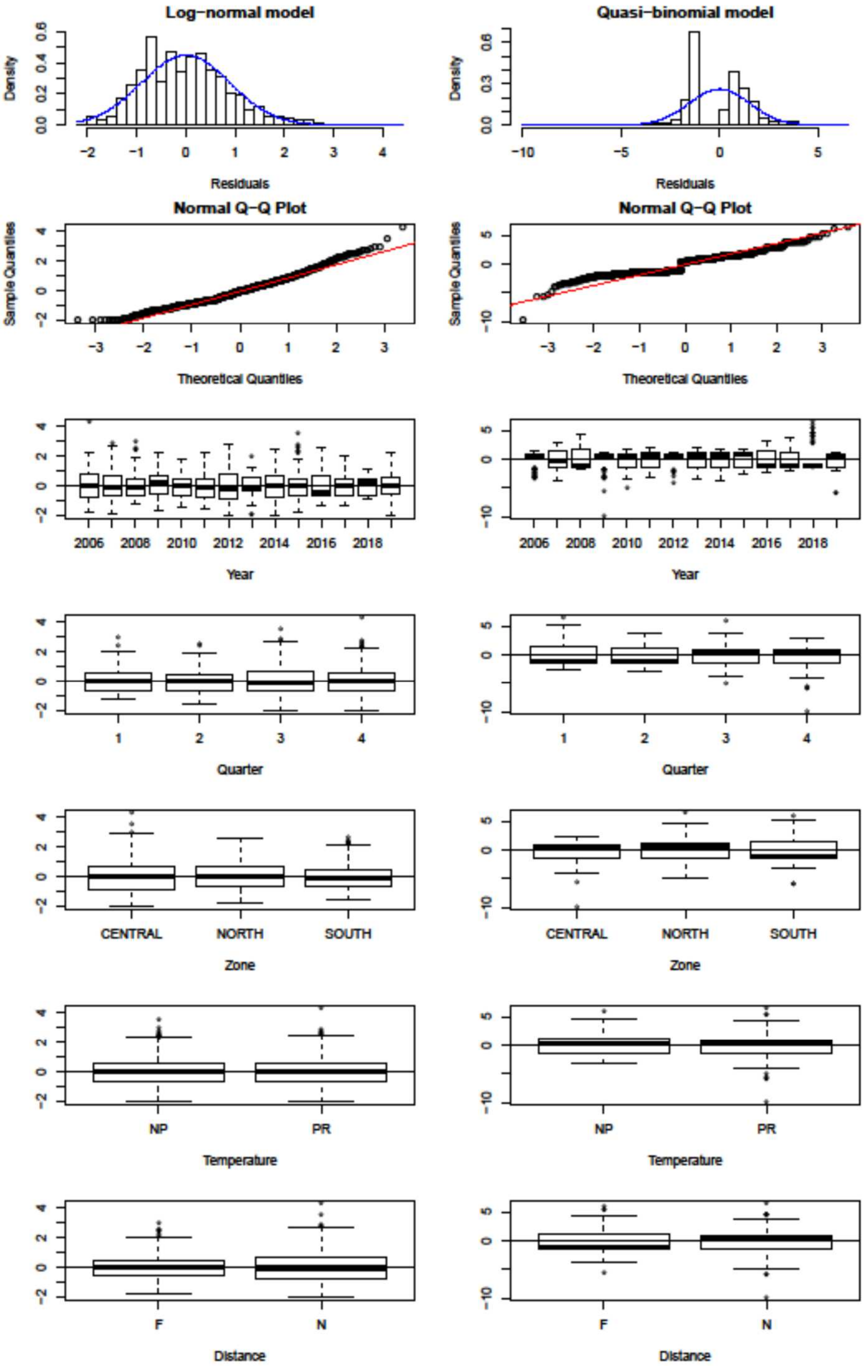

Figure 4.- Residuals and Marginal-model plots of the log normal (left) and quasi-binomial (right) GLMs. The residuals for the log normal GLM are close to normal. The pattern of the residuals in the quasi-binomial GLM, although close to the plot's central line, shows a clear two-band pattern, typical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