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PRELIMINARY STANDARDIZED CATCH RATES FOR PELAGIC AND LARGE COASTAL SHARKS FROM LOGBOOK AND OBSERVER DATA FROM THE NORTHWEST ATLANTIC

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SUMMARY

The purpose of this paper is to investigate all available U.S. and Canadian observer and logbook data to detect trends in abundance for pelagic and large coastal shark species in the Northwest Atlantic. We found that it was very difficult to obtain long terms trends from a combined analysis of the U.S. and Canadian observer data sets because of very limited overlap among the datasets. We found that the most useful data set was the U.S. logbook data if it was analyzed using assumptions that were likely to be true. For example, we assumed only that if sharks were reported that the number caught was approximately correct, but not that sharks were always reported. Our results indicate that the hammerhead, white, and blue sharks may have undergone declines since 1986. The U.S. logbook data also suggests a decline in the thresher, mako, and tiger sharks.

RÉSUMÉ

Le présent document a pour but d'examiner toutes les données disponibles des carnets de pêche et des observateurs américains et canadiens pour rechercher la tendance de l'abondance des espèces de requins pélagiques et de grands requins côtiers dans l'Atlantique nord-ouest. Il s'est avéré très malaisé d'obtenir la tendance à long terme d'une analyse des jeux de données d'observateurs américaines et canadiennes du fait du chevauchement très limité entre les jeux de données. Nous avons trouvé que le jeu de données le plus utile était celui des carnets de pêche américains s'il était utilisé en formulant des postulats vraisemblables. Par exemple, nous avons supposé seulement que si les requins étaient déclarés le nombre capturé était à peu près correct, mais non que les requins étaient toujours déclarés. Nos résultats indiquent que les requins-marteaux, le grand requin blanc et le requin peau bleue auraient pu souffrir une baisse depuis 1986. Les carnets de pêche américains suggèrent aussi une diminution des requins-renards, des requins-taupes et du requin-tigre commun.

RESUMEN

El propósito de este documento es investigar todos los datos disponibles de los cuadernos de pesca y de los observadores de Canadá y de Estados Unidos para detectar las tendencias en la abundancia de especies de tiburones pelágicos y grandes tiburones costeros del Atlántico noroeste. Hemos llegado a la conclusión de que resulta muy difícil obtener tendencias a largo plazo si se parte de un análisis combinado de los datos de los observadores de Canadá y Estados Unidos debido a un solapamiento muy limitado de los grupos de datos. Descubrimos que el grupo de datos más útil era el procedente de los cuadernos de pesca de Estados Unidos, analizándolos bajo el supuesto de que es probable que sean fidedignos. Por ejemplo, hemos partido del supuesto de que cuando se comunican las capturas de tiburones el número de capturas comunicadas es correcto, pero no de que se comuniquen todas las capturas. Nuestros resultados indican que las poblaciones de peces martillo, tiburón blanco y tiburón azul pueden haber experimentado descensos desde 1986. Los datos de los cuadernos de pesca de Estados Unidos también sugieren la existencia de un descenso en zorros, Isurus spp y tintorera tigre.

KEYWORDS

Longlining, Logbooks, Observer, Bycatch, Catch/effort, Time series analysis, Tuna fisheries, Swordfish fisheries

1. INTRODUCTION

There has been considerable concern about the conservation of pelagic shark species affected by longline and gillnet fisheries (Camhi et al. 1998; Musick 1999), however, there is little consensus on the status of these species.

For example, an analysis of the U.S. logbook data claims that most pelagic shark species are decreasing (Cramer 1997) while (Hoey et al. 1999) believe, based upon an analysis of observer data, that blue sharks in the Atlantic have increased in spite of intensive fishing mortality.

The purpose of this paper is to investigate all available U.S. and Canadian observer and logbook data to detect trends in abundance for large pelagic shark species in the Northwest Atlantic. We present a preliminary analysis of standardized catch rates for six species groups of sharks using U.S. logbook data, and explain difficulties inherent in using U.S. and Canadian observer datasets for this purpose.

2. METHODS

2.1 CPUE Data

We had access to logbook and observer CPUE data from both the U.S. and Canada. Data sources varied in quality and comparability, and are described below. Note that we divided the data analysis into the 11 regions used by the U.S. Pelagic Observer Program (Figure 1).

2.1.1 Observer Data

The U.S., Canada, and some other countries have carried scientifically trained observers on commercial fishing vessels. These programs began to monitor foreign, usually Japanese vessels, fishing within the EEZ of the coastal state, and later expanded to cover a portion (typically around 5%) of the domestic fishery. In the U.S. and Canada these programs began a year after the declaration of the 200 nautical mile EEZ, i.e. in 1978. These programs have moderately reliable species identifications, but in the early U.S. data sharks are not identified to species. In the U.S. EEZ foreign fisheries were not allowed to retain swordfish, billfish, or sharks (although their status (dead or alive) was recorded). In the Canadian EEZ foreign fishers were allowed to fish only if they had quota for species under quota regulations. For this reason, the Japanese fishery was excluded from the Canadian EEZ in 2000 because they lacked swordfish quota.

Four types of U.S. and Canadian observer data were used in this analysis:

- U.S. observers on Japanese boats fishing within the U.S. EEZ (1978-1988)
- U.S. observers on U.S. boats fishing within the U.S. EEZ (1985-1999). The U.S. domestic fishery observer program included the Domestic (DOM) Program from 1985-1988, the Louisiana State University (LSU) Program from 1992-1997, and the Pelagic Observer Program from 1992 onwards.
- Canadian observers on Japanese boats fishing within the Canadian EEZ (1979-1984, 1986-2000)
- Canadian observers on Canadian boats fishing within the Canadian EEZ (1979-2000)

2.1.2 Logbook Data

The U.S. and Canadian logbook program contains data that is very useful for some purposes. The fishers who fill out these logs are primarily concerned with fishing, and cannot be expected to identify rare species correctly. However, this data is extremely useful for determining trends in commonly caught species. We analysed only the U.S. logbook data here. Since 1986, fishers have been required to keep logbooks of their catch. However, our interest here is in the shark species that are not the prime focus of the fishers or the regulators that require the logbooks to be kept. U.S. logbook data were available for fishing vessels that land swordfish from the U.S. Atlantic, the Gulf of Mexico and the Caribbean from 1986 to 1999. Pelagic and large coastal sharks are primarily taken as a bycatch, but are also occasionally targeted by these fisheries.

2.2 Species considered

The species identification from the observer data is reasonably reliable. However, for the logbook data, this cannot be assumed for all species. Furthermore, the species that have been recorded have changed over time. In the U.S. logbook data, 6 species or species groups have been recorded since 1986 (blue *Prionace glauca*, white *Carcharodon carcharias*, tiger *Galeocerdo cuvieri*, mako *Isurus paucus, I. oxyrinchus*, thresher *Alopias superciliousus, A. vulpinus* and hammerhead sharks *Sphyrna mokarran, S. lewini, S. zygaena*). After 1992, bignose, blacktip, dusky, night, oceanic whitetip, porbeagle, silky, and spinner sharks were also recorded. Unidentified sharks were recorded as 'other shark'. In this report, we examined the 6 species groups recorded since 1986. For each species, sharks caught are the total number of sharks reported kept, discarded dead or discarded alive.

2.3 Analysing CPUE data

Determining the changes in abundance of sharks is hampered by the lack of direct research surveys. Here we discuss the use of generalized linear models applied to observer and logbook data to overcome many of these problems.

Despite well-known difficulties with catch per unit effort data (Hilborn and Walters 1992), it is often still essential for the management of many fisheries. One problem with such data is standardization, i.e. there are many factors that affect catch rate that must be taken into account before CPUE has any chance of corresponding to true abundance. Probably the most widely used approach for the standardization is a multiplicative model, which assumes that true abundance, and factors that affect catchability, e.g. size of fishing boat, can be multiplied together to reconstruct true abundance. In this approach, catch rate data is broken into categories, e.g. year, season, area, and the catch rate for that category is calculated. The resulting estimates are then log transformed and are analyzed using a general linear model, usually in the form of an ANOVA (Gavaris 1980). The "year effects" in this type of model are then interpreted as indices that are proportional to the true abundance in a year.

While this approach is often very useful, there are several limitations to this approach. First, it is well known that CPUE is often a concave function of true abundance, and thus may be a misleading measure of abundance (Hilborn and Walters 1992). We will not consider this important effect here. Second, log transformation will not work if there are zero catches in a particular category. Third, if there are many factors in the model, a very large number of unconstrained estimates may be required to be made. For example, if individual fishing boats are considered, then estimating a factor for each one may cause the model to be overparametrized. The second problem can be overcome by using a generalized linear or generalized additive model with a log link and a discrete error distribution, e.g. Poisson, extra-Poisson, or negative binomial. The third problem can be overcome with a mixed effect model, in which the number of factors can be greatly reduced by allowing them to be random variables in a mixed effect or hierarchical Bayes model. Such an approach has greatly improved statistical properties and is more robust than fitting data sets individually (Richardson and Welsh 1995; Barrowman 2000). These last two approaches can be combined in a generalized linear mixed effect model (Wolfinger and O'Connell 1993). This provides a more reliable estimator under a wide range of conditions (Robinson 1991). Also, in this approach the estimates are consistent, while the fixed effect model is not. Kiefer and Wolfowitz (1956) noted that in estimation situations where the number of parameters increases to infinity, maximum likelihood parameter estimates are not consistent, but by treating parameters as coming from a distribution—that is, as random effects—consistency could be obtained.

2.3.1 Analysing the observer data

Consider a longline set, i, using gear type g in stratum si at day of year di of year yi in which Hi hooks are set. We are interested in estimating the relative abundance of animals alive in year y_i. To estimate this, we predict the number of animals of a given species caught in that set, Ci,g We assume this is a function of the true abundance of the species at the location and time the set is made, Ni, and the selectivity and catchability of the gear.

We will initially assume that there is no hook saturation or other factors that make CPUE non-proportional to the true abundance. The expected value of the catch, $E[C_{i,g}]$, is

$$E[C_{i,g}]=N_{yi}P_{si,di}H_{i,g}S_g$$

where $C_{i,g}$ is the product of the true abundance, the number of hooks, and the catchability of the gear. N_{yi} is the number of fish in the population in year y_i, $P_{si,di}$ is the proportion of fish in stratum s_i at day d_i, and S_g is the combined availability and vulnerability of each species to the gear (or catchability). The selectivity of gear type will be scaled so that the largest selectivity will be 1. The simplest model for the probability of catching $C_{i,g}$ fish is a Poisson distribution. This is not a realistic model, however, because fish usually aggregate (i.e. in schools) and, as such, are not captured independently. Also, habitat within a stratum is not equally suitable. An over-dispersed, i.e. extra-Poisson model, is preferred in which over-dispersion is modeled using a scale factor for the variances (McCullagh and Nelder 1989). We consider alternative models, e.g. the negative binomial and a variety of quasi-likelihood model. The scale factor only affects the variance, but not the parameter estimates. The data can be analyzed in terms of a generalized linear model (GLIM) with a log link. The main assumption of this model is that an equal proportion of fish will be in each stratum in all years. We will test this assumption by examining time trends in CPUE for each stratum separately.

The simplest model for the capture probabilities is a multiplicative model. Letting lower case letters represent the log of a value, e.g., s_g=log (Sg), we have

$$\log(E[C_{i,g}])=n_{yi}+p_{si,di}+h_{i,g}+S_{g}.$$

In the above model, the parameter of primary interest is n_{yi} but the seasonal distribution in each stratum $p_{si,di}$ will also be of interest. The number of hooks is known and will be treated as an "offset" (McCullagh and Nelder 1989), and the catchability, S_g will be estimated as a nuisance parameter.

A mean seasonal cycle was determined for each stratum from the data by a fit to the exponentiation of a series of sines and cosines. Up to 4 periods of 1, ½ 1/3 and ¼ years were fitted in the generalized linear model

$$\hat{p}_{s,d} = m_s + \sum_{i=1}^{4} [V_{s,i}\cos(2\pi i d/365.25) + s_{s,i}\sin(2\pi i d/365.25)],$$

where d is the sequential day of the year. The fitted parameters are the mean for the stratum and the coefficients $V_{s,i}$ and $s_{s,i}$. The amplitude and phase of the i^{th} period are $(V_{s,i}^2 + s_{s,i}^2)^{1/2}$ and $\tan^{-1}(s_{s,i}/V_{s,i})$ respectively. For strata with relatively few observations, we only fit the first two components.

Differences among models were tested using standard likelihood ratio tests and by looking at the deviance. The deviance, $d_{i,s}$, is defined to be twice the difference between the maximum likelihood achievable in a saturated model, in which there is one parameter fit per observation, and that achieved by the model under investigation. This procedure is similar to a standard analysis of variance method but is appropriate for count data observed for longline fisheries.

2.3.2 Analysing the logbook data: Estimating trends when zeros cannot be distinguished from missing values

In the logbook data, where zeros are not recorded, it is difficult to distinguish real zeros from missing values or censored observations. Here, we examine an approach for obtaining unbiased estimates of abundance and trends in the U.S. logbook data when missing values cannot be distinguished from zeros, and the ratio of the two has changed over time. We aim to infer total abundance and trends from this data with maximum efficiency and minimum bias.

The analysis of the data is only possible by making reasonable assumptions, and fitting models, which allow the reality of these assumptions to be tested. Essentially, the problem can be thought of as an extrapolation of the number of real zeros that would have been observed (if those data were present). Such an extrapolation is inherently difficult. We examine strategies to make reliable inferences when zeros cannot be distinguished from missing values, and test their robustness to violations of the model assumptions.

One possibility is to rely solely upon the positive (non-zero) observations and ignore entirely the zero observations. The basic difficulty with this approach is that as the population decreases, the proportion of zero observations increases, and the relative bias in using the mean of the positive values to approximate the true mean will increase (see below). Thus, a model is needed to obtain reasonable interpretation of the remaining values.

We begin with a model in which we do not know how many of the reports of zero catches are missing values. In order to begin an analysis we begin with two assumptions:

1. If the number of animals caught in a set is recorded, it is the true number
2. The probability of catching x animals in a set follows a negative binomial distribution

We will investigative alternative assumptions later.

If under the same conditions, e.g. number of animals present, the catch follows a negative binomial distribution then the probability of observing x animals, given that on average the catch would be μ is

(1)
$$p(x\,|\,u,k)=\frac{\Gamma(k+x)}{\Gamma(k)\Gamma(x+1)}\left(\frac{u}{k+u}\right)^{x}\left(\frac{k}{k+u}\right)^{k}\text{ for } x=0,1,2,...,$$

where k is the dispersion parameter. As $k\rightarrow\infty$ then the negative binomial distribution becomes the Poisson, which should occur if there was no heterogeneity in catches and if the catch of each animal was independent of all others. However, we cannot use the zero catches, since under assumption 1, we only have reliable information for the positive observations. We thus assume the nonzero catches follow a zero truncated negative binomial, which is simply the above equation without zero, rescaled so that it sums to one. That is, the zero truncated negative binomial is

(2)
$$p(x\,|\,u,k)=\frac{\dfrac{\Gamma(k+x)}{\Gamma(k)x!}\left(\dfrac{u}{k+u}\right)^{x}\left(\dfrac{k}{k+\grave{\imath}}\right)^{k}}{1-\left(\dfrac{k}{k+\grave{\imath}}\right)^{k}}\text{ for } x=1,2,...,$$

We first model the mean, μ, using a model that predicts the number of animals that are caught using only those sets with nonzero catches of the species of interest. The mean of the zero truncated negative binomial is

(3) $$\mu_c = \mu \Bigg/ \left(1 - \left(\frac{k}{k+\mu}\right)^k\right)$$

It is also necessary to estimate k. The simplest assumption is to use maximum likelihood to estimate a constant k for all the data. Alternatively, k could be estimated as a function of the mean. Here we have used a constant value of k=1. We will estimate alternate k values later.

For each model that is estimated, the same mean can be estimated as for a model with the zeros present. If the negative binomial assumption is correct, then the model using data with the correct number of zero observations (Eq. 1) and the model with censored zeros (Eq. 2) should both be asymptotically unbiased if maximum likelihood is used.

It is useful to examine the bias in the positives, if the zeros are ignored, and the proportion of zeros under reasonable values of k (Figure 2). We examine the relative bias, i.e. $\left(\frac{\mu_c - \mu}{\mu}\right)$. Only examining the positive values, without a correction, will lead to an overestimation of abundance at low population size.

In practice, we also have the number of hooks, h, that are set. In this case, this information can be included in the model by estimating μ, but fitting to hp, where p is interpreted as the mean per hook. The log likelihood is then

(4)
$$l(p,k \mid x) = \log\Gamma(k+x) - \log\Gamma(k) - \log x! + x\log\left(\frac{hp}{k+hp}\right) + k\log\left(\frac{k}{k+hp}\right) - \log(1 - \left(\frac{k}{k+hp}\right)^k),$$

where the log likelihood is summed over all observations.

The truncated negative binomial is a member of the exponential family of distributions, when k is known, and thus model-fitting can proceed using software for fitting generalized linear models (McCullagh and Nelder, 1989).

We present truncated negative binomial models here for each of the 11 areas using year and hooks sets as variables. Models presented here are preliminary in that they include only year and hooks, but do not include operational variables. We are investigating all other potential confounding variables to determine if changes in the fishery could be biasing our results. We have used the day of year, estimated depth, a categorical variable that identified the use of light sticks, and a categorical variable that identified if a set was during the night or day. Target species were recorded from 1991 onwards. We are also using target species as a variable. These models will be presented in future work.

3 RESULTS

3.1 Trends from the observer data

We have expended considerable efforts in producing a standardized abundance from the Canadian and U.S. observer program. In doing so, there have been considerable technical difficulties. The most important difficulty is that the four types of observations are from fisheries that are not constant, and may operate in very different manners. Specifically, there is almost no overlap between the first two data sets (U.S. observers on Japanese boats, U.S. observers on U.S. boats), and they operate in very different manners. The Japanese boats were not allowed to retain swordfish while swordfish was the main target of the U.S. fishery. Furthermore, there is insufficient data to obtain trends in abundance from these two time series separately because of the small number of samples. For example, the data from the U.S. domestic observer program is not sufficient to detect any but the largest trends in abundance for blue shark and yet the data for blue shark is much better than the data for other sharks because it is relatively common (Figure 3). The same difficulty exists for the data on the Japanese fishery within the U.S. EEZ for the blue shark and other species. The data from the Canadian observers on Canadian boats is also too sparse to be used for this purpose. Thus, if the observer data is to be used to detect trends in abundance, longer time series must be used.

The Japanese fishery in the Canadian EEZ could potentially serve as a long-term source, but this fishery has drastically changed its targeting over time. Prior to 1986, the median depth of the fishery was around 60 meters, but from 1987 to 1996 the median depth increased to 140 meters, and after 1998 decreased to 100 meters. This increased depth of the sets probably reflects the targeting of bigeye tuna; however, information on the species being targeted is not recorded in the Canadian observer data. We have been unable to standardize the data from Canadian observers on Japanese boats to obtain trends.

3.2 Changes in the fishery according to logbook data

The number of hooks per set has increased substantially in the U.S. fishery during the 14-year time period examined (Figure 4).

3.3 Patterns of targeting according to logbook data

In order to help us understand the patterns in the U.S. logbook data we display the changes in target ing between 1991 and 1999, the period when such data exists (Figure 5). For this plot we have eliminated the sets in which no target was reported. Note that more than one target per set is often recorded, and thus the proportions do not sum to 1. The most important point for our purposes here is to note the large increases in directed shark sets between 1991 and 1994, and the subsequent decline. This is particularly true in the South Atlantic Bight, the Mid Atlantic Bight, and the Northeast Coastal region.

3.4 Trends from the logbook data

For the 6 major species groups we (i) plotted the mean and median positive catches per 1000 hooks for each of the 11 U.S. fishing areas, and all areas combined; (ii) modelled trends in the catch and year effect in each area and in all areas combined, using the truncated negative binomial model; (iii) plotted the proportion of positive sets in each area and in all areas combined.

3.4.1 Blue sharks

The most common shark species caught, as bycatch, is the blue shark (Figure 6). For this species, there is a large decline over time in the mean and median CPUE for positive observations. We note two exceptions to this pattern. In the Northeast distant area, the CPUE increases around 1991. This increase is not seen in other areas. It could represent a change in fishing strategies, or perhaps improved technology to find concentrations of swordfish, which may also increase catch of blue shark. A second anomaly is the very high CPUE for 1993 in the Gulf of Mexico. This primarily represents the activity of one vessel that had very high catch rates of blue sharks in 1993 in that area, greater then has been seen before or after 1993. This suggests a decline in blue sharks in the region, but that the 1993 point was particularly high because of the activity of one vessel.

The truncated negative binomial models for blue shark catch for all areas combined shows a 2.5-fold decline during the 14-year period examined. Declines are evident in all areas, except for the two discussed above, and for the North Central Atlantic. The proportion of sets in which blue sharks were caught has remained relatively constant over time (Figure 7). However, considering that the number of hooks per set has doubled in this time period, this indicates a decline in abundance of blue sharks. Our preliminary conclusion is that overall blue sharks may have declined in the Northwest Atlantic since 1986.

3.4.2 Hammerhead sharks

The third most common shark species group caught as bycatch are the hammerhead sharks. For this species, there is a large decline over time in the mean and median CPUE for positive observations in all areas (Figure 8). In some areas, e.g. the Northeast distant and Sargasso regions, no hammerheads have been caught in the U.S. longline fishery in recent years. The preliminary truncated negative binomial models for hammerhead sharks show substantial declines in each of the 11 areas and a decline of 75% in all areas combined. The proportion of sets in which hammerhead sharks were caught has also declined slightly over time, despite the increase in hooks per set. Our preliminary conclusion is that hammerhead sharks have declined in the Northwest Atlantic.

3.4.3 White sharks

The great white shark was caught in relatively large numbers in the late 1980's from the Gulf of Mexico, and along the east coast of the U.S. (Figure 10). Since 1990, the catch per 1000 hooks (when the species was caught) has been greatly reduced. For all areas combined, the mean catch per 1000 hooks (when the species was caught), was around 10 in the late 1980's and only around 2 in recent years. In some areas, e.g. the Northeast distant, no great white sharks have been caught in the U.S. longline fishery in recent years.

The model for all areas combined indicates that overall the white shark has declined since 1986. The models indicate declines in the Caribbean, Gulf of Mexico, Florida East Coast and the South Atlantic Bight. Due to small sample sizes, the 95% confidence intervals for most other areas are very wide, and thus a reliable trend cannot be detected. The proportion of sets in which white sharks were caught has declined over time, from 1.4% between 1986 and 1991 to 0.4% between 1992 and 1999. Furthermore, there have been no sets reported with white sharks in Northeast Coastal and Northeast Distant since the early 1990s. We conclude that the great white shark has likely declined in the Northwest Atlantic.

3.4.4 Thresher sharks

Thresher sharks appear to be declining in most regions, but this decline is not as great as seen for the 3 species groups discussed above (Figure 12). Exceptions to the decline occur particularly in the Mid Atlantic Bight region in the 1990's. In this region, the mean, but not the median, positive CPUE increased in this region. This may be caused by the increase in the directed shark fishery in that region (Figure 5). There has been no evidence of any significant decline in the Northeast Distant fishery. The truncated negative binomial model for all areas combined indicates that overall thresher sharks have declined from 4.5 per 1000 hooks in 1986 to about 1.5 per 1000 hooks in 1999. Furthermore, the proportion of non-zero sets for thresher sharks declined slightly overall during this time period (Figure 13). In certain areas (Florida East Coast, Northeast Coastal) the proportion of sets with thresher sharks declined considerably.

3.4.5 Tiger sharks

There is some evidence for a decline in tiger sharks in most regions, but this decline (if it is real) does not appear to be as large as the previous groups discussed (Figure 14). Again, exceptions to the decline occur particularly in the Mid Atlantic Bight region in the 1990's. This may again be caused by the increase in the directed shark fishery in that region (Figure 5).

In the models, slight declines are evident in the Caribbean, Gulf of Mexico and Florida East Coast. The model for all areas combined shows a slight increase, which is driven by the apparent increase in the South Atlantic Bight and the Mid Atlantic Bight. Overall, the proportion of sets in which tiger sharks were caught has remained fairly constant over time (Figure 15). Considering the increase in hooks per set, the overall pattern indicates a decline in abundance of tiger sharks. We conclude that tiger sharks may have declined slightly in the Northwest Atlantic.

3.4.6 Mako sharks

The interpretation of any trend for the mako sharks is confounded by the relatively recent increase in shark-targeted sets (in the South and Mid Atlantic Bight regions). Thus, the data for this species is difficult to interpret (Figure 16). Again, exceptions to the general decline occur particularly in the Mid Atlantic Bight region in the 1990's where the mean, but not the median, CPUE increased. Again this may be due to the directed shark fishery in that region (Figure 5). The model for all areas combined indicates an overall decline in mako sharks since 1986. The proportion of non-zero sets for mako sharks also declined slightly overall during this time period (Figure 17).

3.5 Factors affecting the CPUE

There are several key factors that make it difficult to interpret the logbook data (the same problems exists for any commercial longlining CPUE). The most important of these are discussed below.

3.5.1 Improved efficiency in established fisheries

Improved efficiency of catch rates in established directed fisheries for targeted species or for bycatch species that are strongly associated with the directed species. There is continuous improvement in the ability of longline fishers to detect oceanographic features that may concentrate their prey, e.g. the use of improved satellite imagery and analysis and drifters that can detect convergence zones. Even though sharks are not necessarily targeted, they can be attracted to the same features as a target species. For example, this may occur in the Northeast distant U.S. swordfish fishery, where blue sharks are strongly associated with swordfish. This may account for the increase in CPUE for blue shark in this region in the 1990's, which does not occur in any other region.

3.5.2 New directed fisheries

There are many examples in fisheries of how misleading CPUE is as an index of abundance for newly established fisheries (Hutchings and Myers 1994; Myers, Hutchings, and Barrowman 1997). When a new directed fishery occurs, the capture efficiency should increase drastically over the first few years of the fishery as fishers learn to fish the target species. The interpretation of the catch rates during these years is extremely problematic, and usually renders such CPUE indexes impossible to interpret. This is probably a key problem with any interpretation of the mako CPUE's (see the mean for the positive observation in Figure 16) in the mid Atlantic Bight, because directed shark fisheries increased greatly in the region in the early 1990's. The increase in the mean CPUE for positive observations in this region is not seen in areas with little or no directed mako fishery, e.g. the Northeast distant fishery. Thus we strongly recommend that CPUE data from newly established directed fisheries not be included in any shark assessment.

3.6 Modeling the Role of Targeting

We examined the role of targeting in the U.S. logbook data and found that this is not the same for all areas. For example, in the Northeast Distant blue shark fishery, CPUE for blue sharks is strongly positively related to swordfish targeted sets.

3.6.1 Robustness

We have carried out extensive checks on the robustness of our results, and will carry out more as we investigate different models that include fishery dependent variables (e.g. light sticks, depth). One potential problem with our analysis is that some confounding variable may cause a decreasing change in the average number of sharks per hooks that does not correspond to an actual decrease in abundance. We investigated that the increase in the number of hooks per set over time is a potential factor causing this problem. However, if we divided the data into groups of relative constant hooks per set, the declines remained approximately the same for each group.

4 DISCUSSION

Of the species groups that we have investigated, blue, hammerhead and white sharks show substantial declines. In almost all cases, these declines are seen in all areas. There may also have been declines in thresher, tiger and mako sharks. We have not been able to determine any variable that could be causing a significant bias in our results; however, we are investigating several potential sources of bias. We are concerned that there may be situations where the increase in hooks per set in the U.S. fishery may cause our estimates to be biased. Although we have not demonstrated this, it is being investigated.

Our results are consistent with previous analyses of the U.S. logbook data using different methods, i.e. the delta lognormal model (Cramer 1997). However, our results are not consistent with one previous analysis of the combined U.S. and Canadian observer data (Hoey et al. 1999). We have attempted to replicate the analysis of Hoey using an updated data set, but have not been able to. The problem appears to be that the U.S. observer program consists of two types of data: U.S. observers on Japanese boats and U.S. observers on U.S. boats. There is almost no overlap between these two data sets, and they operated in very different ways, since they targeted different species. The only way that these data sets can be joined is by the use of an independent data set. We attempted to use the Canadian observers on Japanese boats for this comparison. However, the amount of overlap between this dataset and the two U.S. observer sets is limited since this fishery takes place in only one area, and only in the late fall and winter. Furthermore, it has undergone drastic changes in targeting and in how it operates. We were not able to construct time series of abundance from this data because of the very limited data collected by the Canadian observers and the large changes that have taken place.

The observer data clearly shows different trends among areas for some species in the raw CPUE over time. These differences appear to be due to changes in targeting over time. In some cases, these changes may be disentangled using available data, but in others they cannot. Unless the differences can be resolved, then it is unwise to use a multiplicative model that assumes that the relative abundance among areas remains constant over time. The best way forward in these cases, if the changes in targeting cannot be resolved, is to use the subset of areas where the targeting has not changed.

4.1 Interpreting declines in CPUE

In order to determine the significance of a decline in CPUE we must have some point of reference. Two assumptions that are likely to underestimate the risk to a population are (1) CPUE is proportional to abundance, and (2) the population was in a virgin state at the start of our time series of CPUE indices. Even with these assumptions, for species such as porbeagle sharks, a decline in CPUE of greater than 40% is likely to result in a population that is below the biomass that will produce the maximum sustainable yield (Campana et al. 2001). For species that mature earlier than porbeagles (13 years of age) and produce more than 4 pups per year, this threshold is likely to be higher. Without accurate details of important life-history parameters for a species, we would consider a decrease in CPUE (assumed proportional to abundance) of greater than 50% to most likely result in a population reduced to a level below that which would produce the maximum sustainable yield. Greater declines, as seen here in the overall truncated negative binomial models for blue shark, hammerhead sharks, white sharks and thresher sharks, could suggest a population is in critical danger.

4.2 Future work

The results presented here are part of ongoing research to determine trends in abundance for pelagic and large coastal shark species in the Northwest Atlantic. We are continuing to check the robustness of the generalized linear models with the truncated negative binomial distribution, by (i) including fishery related model variables (day of year, light sticks, depth, surface temperature, target species (from 1991) etc.) and (ii) determining the maximum likelihood estimate for the dispersion parameter, k. We are also checking the robustness of the results from these models by running additional models that use different distributions and require more assumptions about the data.

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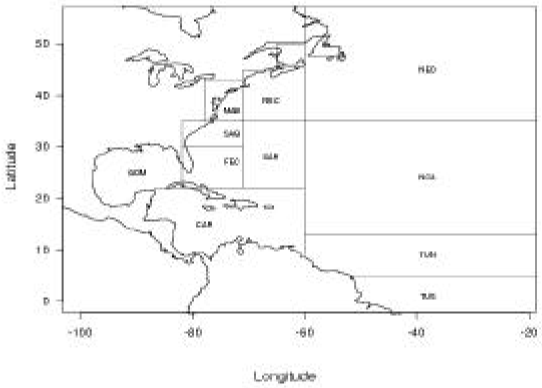

Figure 1. The 11 regions used by the U.S. pelagic observer program.

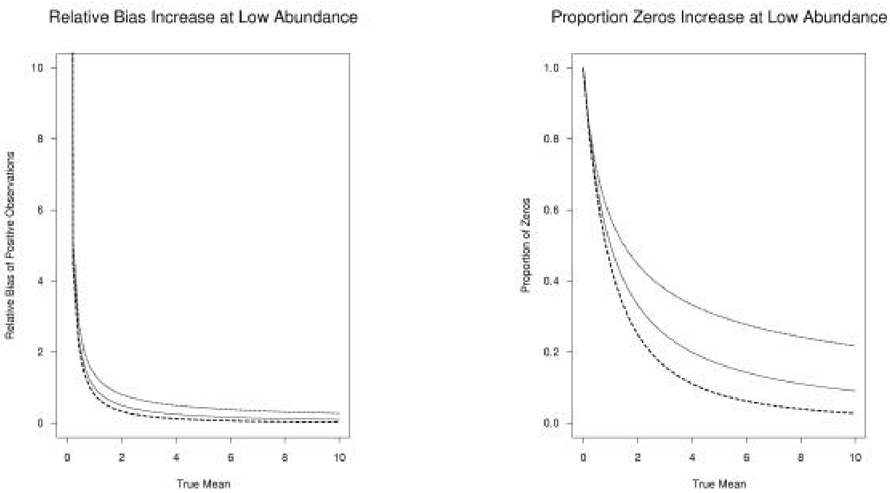

Figure 2: (Left Figure) The relative bias as a function of the true abundance for k 1 (solid line), k 2 (dashed line), and k 0 5 (dotted line). (Right Figure) Proportion zeros for the three vales of k.

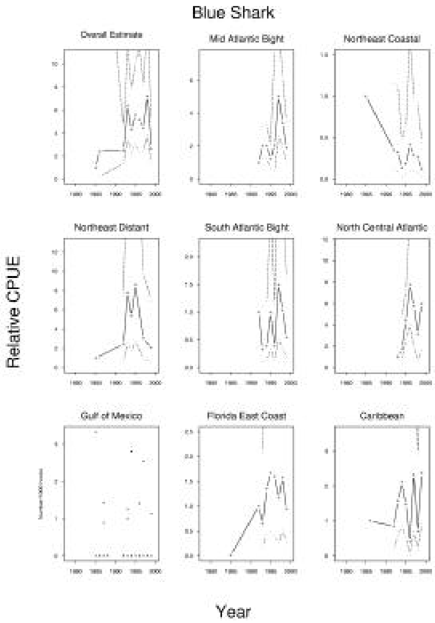

Figure 3: Estimates of standardized blue shark catch per 1000 hooks from the U.S. observer program on U.S. boats. Standardized CPUE is estimated overall, and for each of the 8 regions with the most data separately, from a quasi-likelihood model with extra Poisson variability. Also included is an overall estimate under the assumption that the relative abundance among regions remains constant among years. The models include estimates for the seasonal cycle in each area and the target species. Note that the overall estimates of the confidence regions are much too wide to detect any but the largest trends in abundance. The estimates of the confidence region in this type of model are conservative, i.e. the true uncertainty is usually much larger.

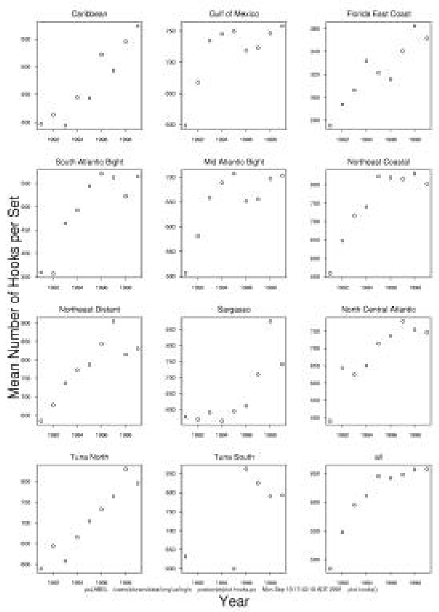

Figure 4: The mean number of hooks per set (circles).

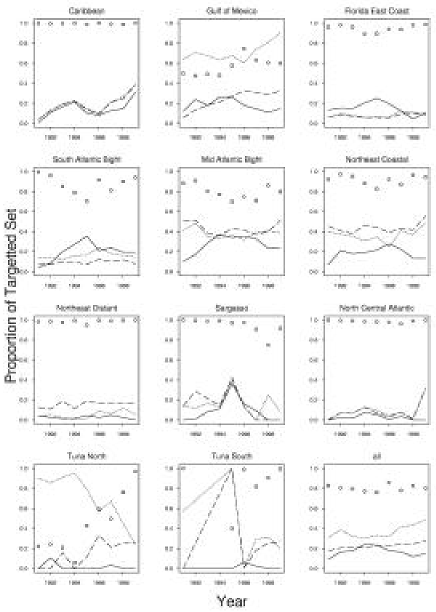

Figure 5: The proportion of sets targeting swordfish (circles), sharks (solid lines), yellow fin tuna (dotted line), and bigeye tuna (dashed line).

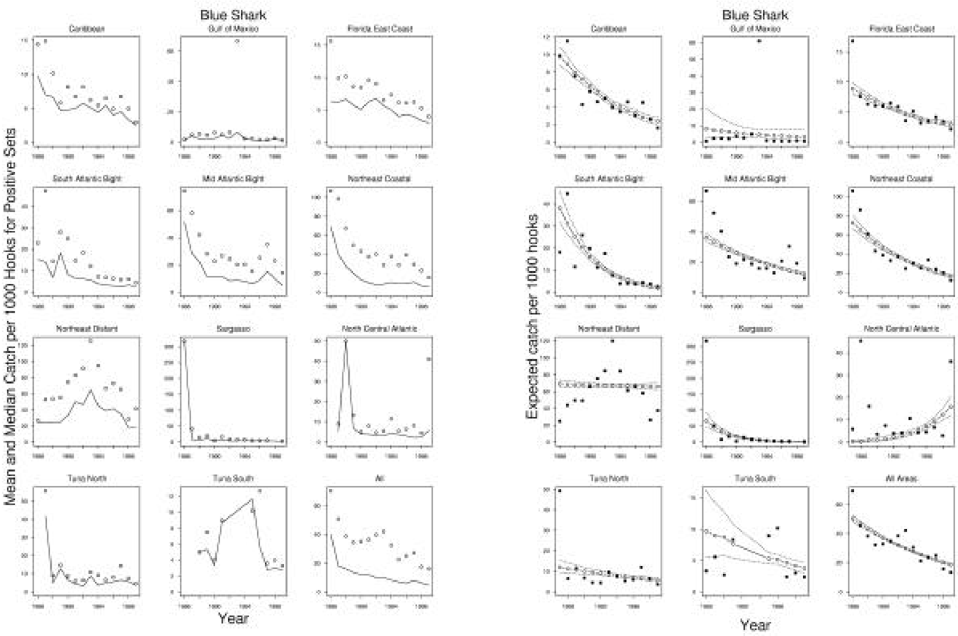

Figure 6: (Left Figure) The mean (circles) and median (lines) number of blue sharks caught per 1000 hooks, if any were reported in a set, for each year and region. (Right Figure) The trend (solid line with 95% confidence region) and year effect estimates (points) for the overall model of blue shark abundance for the truncated negative binomial model for each area, and all areas combined.

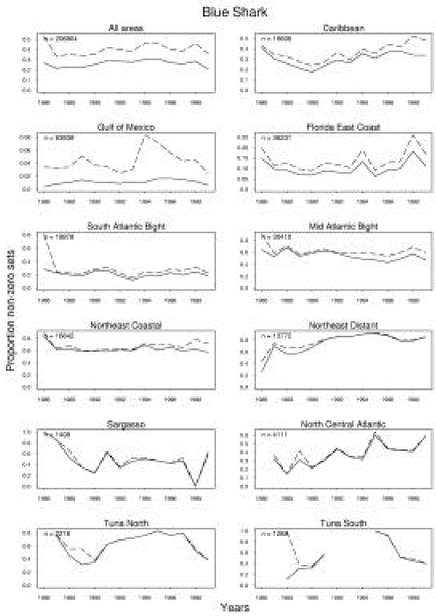

Figure 7: The proportion of non-zero sets for all sets (solid line) and only sets where a vessel had reported at least one individual during that year (dashed line) by region and year. The total number of sets in each region is given. A combined plot for all years is also provided.

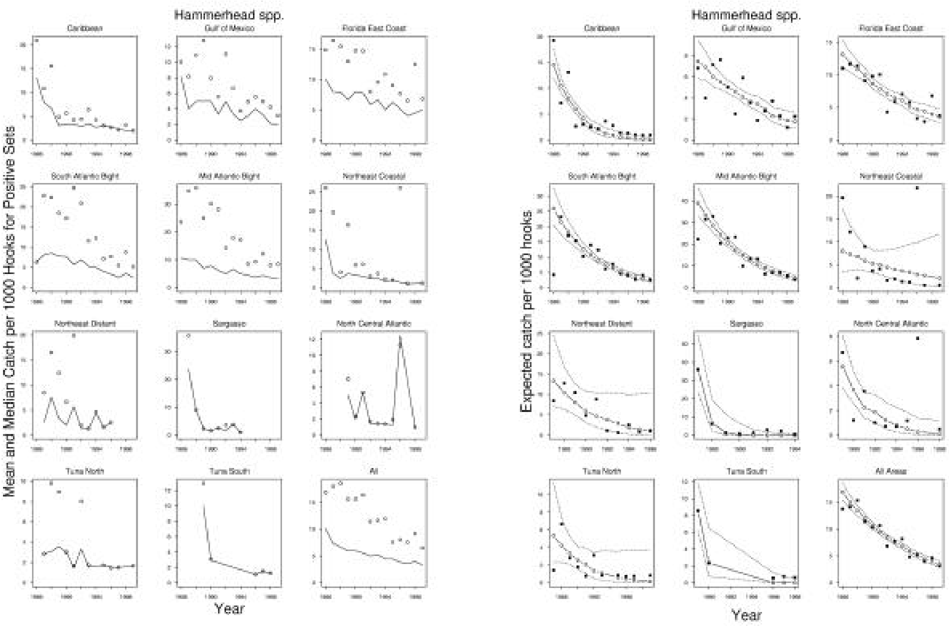

Figure 8: The mean (circles) and median (lines) number of hammerhead sharks caught per 1000 hooks, if any were reported in a set, for each year and region. (Right Figure) The trend (solid line with 95% confidence region) and year effect estimates (points) for the overall model of hammerhead shark abundance for the truncated negative binomial model for each area, and all areas combined.

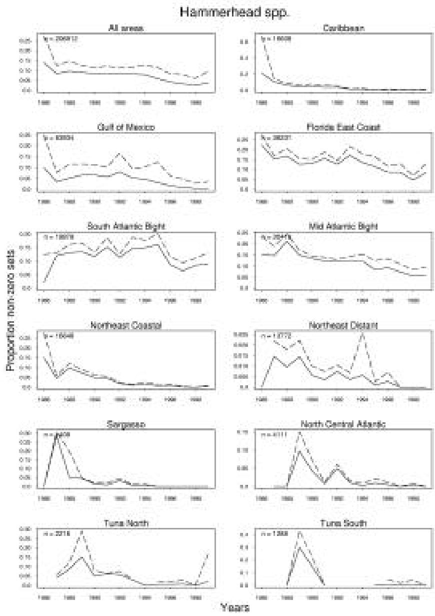

Figure 9: The proportion of non-zero sets for all sets (solid line) and only sets where a vessel had reported at least one individual during that year (dashed line) by region and year. The total number of sets in each region is given. A combined plot for all years is also provided.

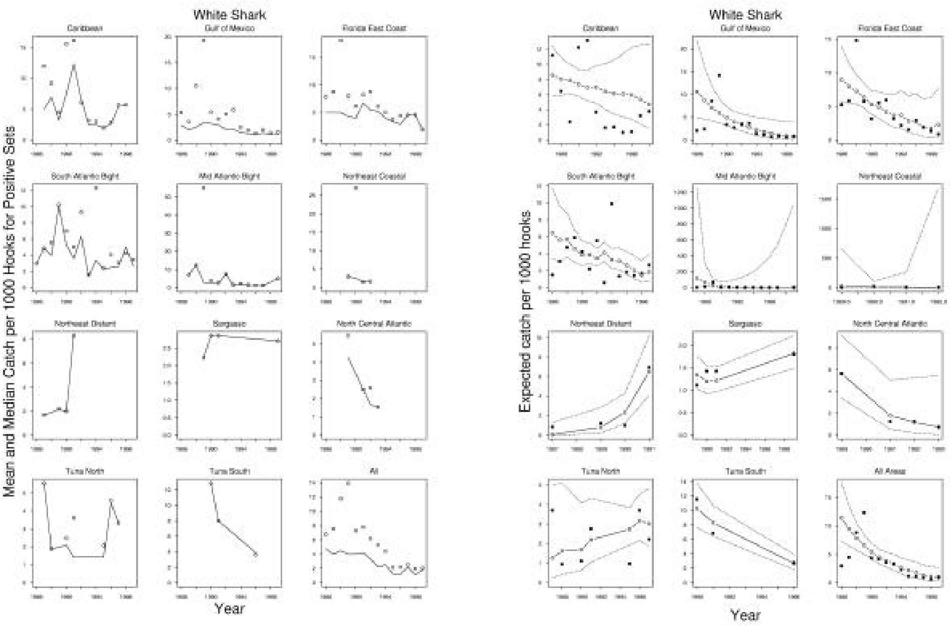

Figure 10: The mean (circles) and median (lines) number of white sharks caught per 1000 hooks, if any were reported in a set, for each year and region. (Right Figure) The trend (solid line with 95% confidence region) and year effect estimates (points) for the overall model of white shark abundance for the truncated negative binomial model for each area, and all areas combined.

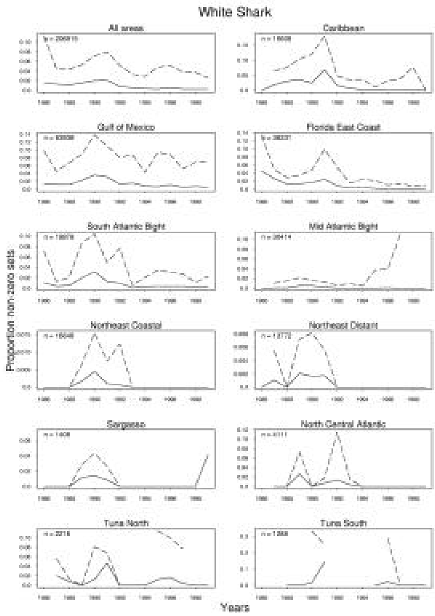

Figure 11: The proportion of non-zero sets for all sets (solid line) and only sets where a vessel had reported at least one individual during that year (dashed line) by region and year. The total number of sets in each region is given. A combined plot for all years is also provided.

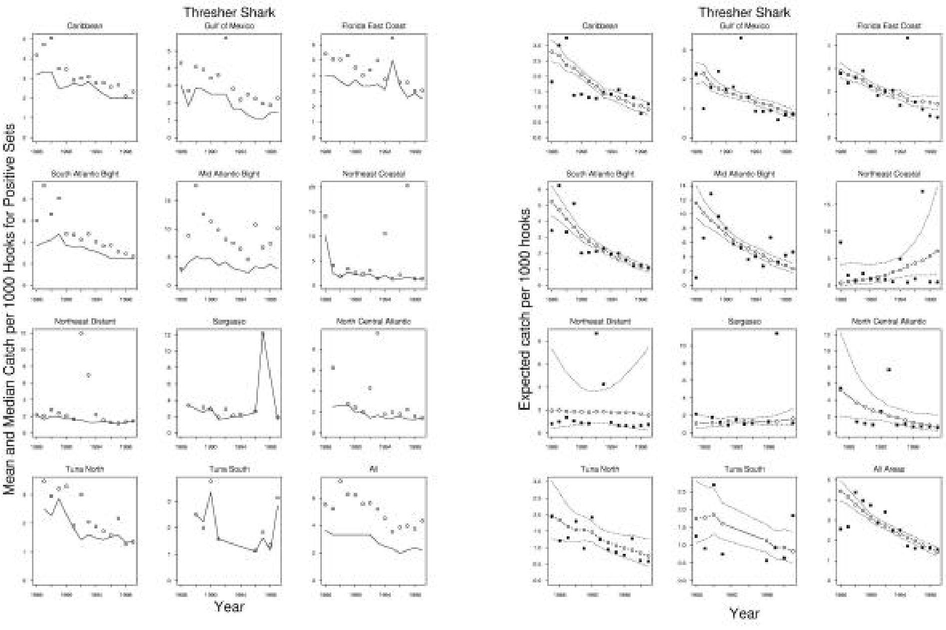

Figure 12 The mean (circles) and median (lines) number of thresher sharks caught per 1000 hooks, if any were reported in a set, for each year and region. (Right Figure) The trend (solid line with 95% confidence region) and year effect estimates (points) for the overall model of thresher shark abundance for the truncated negative binomial model for each area, and all areas combined.

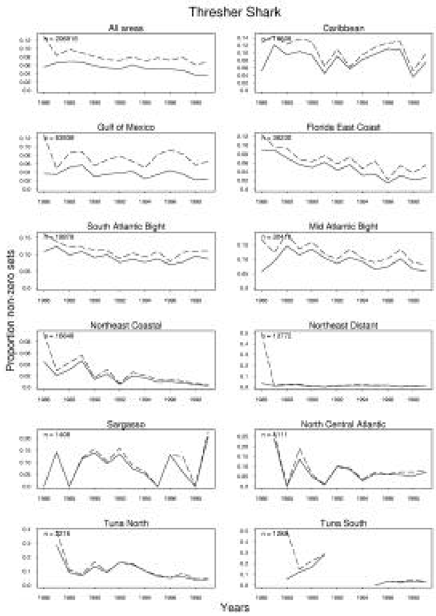

Figure 13: The proportion of non-zero sets for all sets (solid line) and only sets where a vessel had reported at least one individual during that year (dashed line) by region and year. The total number of sets in each region is given. A combined plot for all years is also provided.

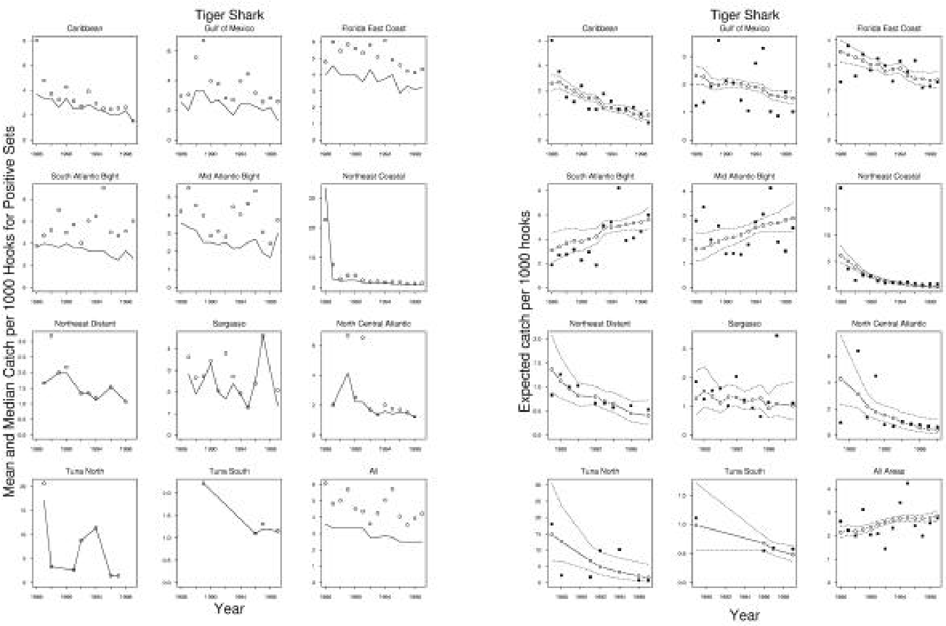

Figure 14: The mean (circles) and median (lines) number of tiger sharks caught per 1000 hooks, if any were reported in a set, for each year and region. (Right Figure) The trend (solid line with 95% confidence region) and year effect estimates (points) for the overall model of tiger shark abundance for the truncated negative binomial model for each area, and all areas combined.

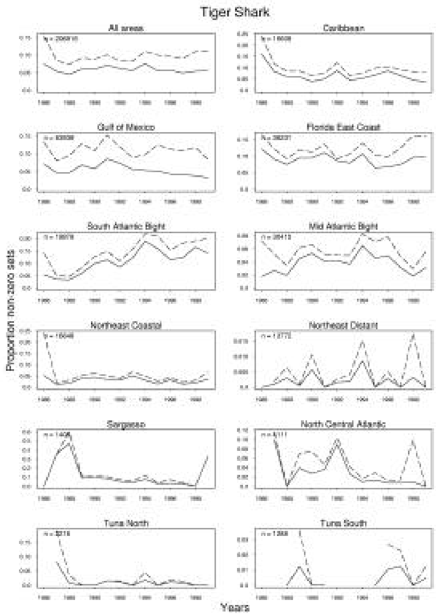

Figure 15: The proportion of non-zero sets for all sets (solid line) and only sets where a vessel had reported at least one individual during that year (dashed line) by region and year. The total number of sets in each region is given. A combined plot for all years is also provided.

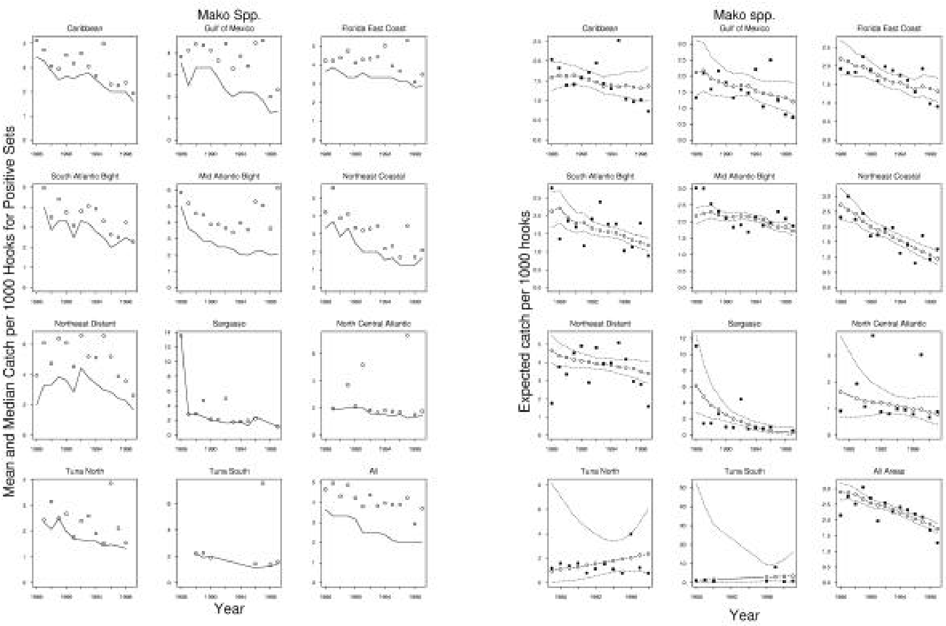

Figure 16: The mean (circles) and median (lines) number of mako sharks caught per 1000 hooks, if any were reported in a set, for each year and region. (Right Figure) The trend (solid line with 95% confidence region) and year effect estimates (points) for the overall model of mako shark abundance for the truncated negative binomial model for each area, and all areas combined.

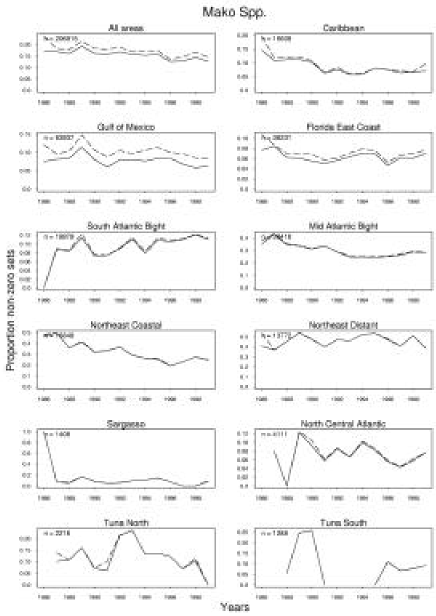

Figure 17: The proportion of non-zero sets for all sets (solid line) and only sets where a vessel had reported at least one individual during that year (dashed line) by region and year. The total number of sets in each region is given. A combined plot for all years is also provided.