Supporting Online Material

Trends Analysis Methods

Our goal was to obtain reliable unbiased estimates of trends in abundance for the recorded shark species. We assumed that the true distribution of shark catches follows a negative binomial distribution. In the logbook data, only the positive catches are recorded making zeros indistinguishable from missing values. Hence, we modeled only the positive catches using the zero-truncated negative binomial distribution (see e.g. *S1-S3*). The log likelihood is given by

$$l(\mu : y_t) = \log\left(\frac{\Gamma(y_t + \theta)}{\Gamma(\theta) y_t!}\right) + y_t \log\mu + \theta\log\theta - (y_t + \theta)\log(\mu + \theta) - \log\left(1 - \left(\frac{\theta}{\theta + \mu}\right)^{\theta}\right),$$

for $y_t = 1,2,\ldots,\infty$, where θ indicates the amount of overdispersion relative to the Poisson distribution. The log-likelihood is parameterized in terms of the mean of the untruncated distribution. When θ is known this distribution is a member of the one-parameter exponential family of distributions. This allows us to utilize the generalized linear model (GLM) framework (*S4*). In the GLMs we model the truncated means, μ_t, not the untruncated means, μ, where $\mu_t = \dfrac{\mu}{1 - \left(\dfrac{\theta}{\theta + \mu}\right)^{\theta}}$

Since we are interested in making inference about the untruncated means, not the truncated means, we must solve the function for μ, not μ_t. For most values of θ, there is no exact solution, and a numerical root finder must be employed.

To use GLMs we must specify a link and a variance function. The canonical link for the zero-truncated negative binomial, $\log\left(\frac{\mu}{\mu + \theta}\right)$, is not easily interpretable and is parameterized in terms of the untruncated means. Instead, we use the link function log (μ_t – 1) = η, as this ensures that $1 \leq \mu_t \leq \infty$. The variance function,

$$V(Y_t) = \frac{\mu + \frac{\mu^2}{\theta} + \mu^2}{1 - \left(\frac{\theta}{\theta + \mu}\right)^{\theta}} - \left(\frac{\mu}{1 - \left(\frac{\theta}{\theta + \mu}\right)^{\theta}}\right)^2,$$

is derived from the truncated distribution. Note that the variance function is also parameterized in terms of the untruncated means, and requires transforming the estimated truncated means at each iteration of the weighted least squares algorithm used in fitting a GLM (*S4*).

Estimating θ

In order to use the GLM framework, the overdispersion parameter θ is assumed to be known. In reality, θ must be estimated, as the resultant estimates of μ depend upon the value of θ. To estimate θ, we constructed likelihood profiles, finding the values of μ that maximized the likelihood at each value of θ by fitting a GLM. When θ is 1, computation is greatly eased because the transformation from the truncated means to the untruncated means is exact: $\mu = \mu_t - 1$. Thus, we elected to fix θ at a value of 1 (see Trends Analysis Robustness section).

Trends Analysis Robustness

We carried out extensive data checks, and tested the robustness of our main results by examining the model assumptions and by performing six additional analyses. We demonstrate that our results are robust across a suite of models and explain why the truncated negative binomial models are preferred. Our conclusions are not dependent on our choice of model.

Data Checking

It is unlikely that fishers identified all sharks correctly to species. To address concerns about misidentifications, we first compared catch rates for each species to those recorded in the observer program. Catch rates by area were comparable between the two data sets for each of the shark species recorded from 1986, but differed for the coastal species recorded from 1992, likely because these species are similar looking congenerics. Hence we grouped these six species. In the logbook data, until 1992, fishers recorded scalloped, smooth and great hammerheads grouped as hammerheads; bigeye and common thresher as threshers; and shortfin and longfin makos as makos. We kept these groupings. In each case we analyzed the data for both the individual species and the groups. We presented only the results of models for the shark groups because we believe them to be more defensible.

Of the recorded species, the only other species likely to be mistaken for one another are the shortfin mako and porbeagle sharks. There was a gross imbalance in sample size for these two species: the shortfin mako is the second most commonly caught species (n>32,000 observations), while the porbeagle (found primarily in Areas 6 and 7) was the least commonly recorded species (n=338 observations). As such, results for the mako sharks were robust, whereas small changes in the misidentification rate had a strong effect on model results for the porbeagle shark. Consequently we have not presented models for the porbeagle. A recent assessment of this species indicates that it is severely overfished (*S5*).

Many sharks were not recorded to species, but rather in the categories 'Other sharks' (1986-1999), 'Other pelagic sharks' (1995-2000), or 'Other coastal sharks' (2000). We examined these categories together from 1992 onwards (since recording of many species changed that year from these categories to individual species), and found declines of about 70%. These declines are comparable to those found for the species presented. The overall trend in abundance for all recorded sharks combined has been a decline of 67% (95% CI: 65 - 69%) since 1986.

Prior to analysis, the values and ranges of all analyzed variables were checked. For independent variables, once obvious recording errors were corrected, any remaining implausible values were excluded from the analyses. Unrealistically high catches in the data suggest overreporting or recording errors. To decide on a cutoff level for these catches we examined the output for models where sets in which catch/hook>=0.6, 0.5 and 0.4 were removed. Models for most species were robust to the different cutoff levels; declines in white sharks were slightly smaller when lower cutoffs were used. We present the results of models for a cutoff of catch/hook>=0.5 for blue sharks (the most commonly caught species) and the coastal group (a category that includes 6 species), and for catch/hooks>=0.4 for all other species.

We developed the truncated negative binomial models to address the fact that fishers probably did not always record sharks. It is also possible that fishers may have underreported sharks, and that the declines in the estimated catch rates reflect an increase in underreporting. If this were true, one might expect that fishers would be more likely to underreport large catches of sharks (large relative to what is commonly caught). To investigate this potential bias, we repeated our analysis without the largest catches, using several different cutoffs for each shark species. Excluding the largest catches is preferable to reassigning large catches to some average catch level because it requires fewer assumptions. Note that the latter method would only result in intermediate values between excluding the large catches and leaving them in the analysis. In general, our results were not significantly affected; tiger sharks declined less as more catches were removed (see Table S1). Thus, it does not seem likely that a change in the reporting rates of large catches can account for the observed trends.

Model Assumptions

We present models in which θ is set to 1. Examining the likelihood profiles for θ suggested a maximum below one for all species, and often very close to 0. A 90% likelihood interval, however, always included 1 and the estimated trends did not differ much for values of θ between 0.3 and 1.

We explored the effect of changes in the fishery on the year estimates. We ran many different models with operational variables, including use of light sticks, depth, number of hooks between floats, target species, and set time. In general these variables had little effect on the estimated year effects; area, season, and year were always more important. As such, results are presented for a base model that included main effects of area, season, use of light sticks, temperature, and year and area*season, area*light interactions. We also examined the consequence of including a random year effect to account for any unexplained heterogeneity in catch among years. Results were very similar to the base model for all shark groups, (with the exception of white sharks, who showed a steeper decline), though with larger standard errors for the slope estimates.

A further concern was that fishing methods might have changed over time. Changes to monofilament line and the use of artificial light sticks occurred prior to the start of the dataset examined. During the time period examined (1986-2000), however, the number of hooks per set doubled. We examined the possibility of 'gear saturation', where catches are maximized at a hook level less than the actual number set. We tested this hypothesis and found that modeling hooks in a non-proportional relationship (whereby the fishing gear tended to saturate with increasing number of hooks) to catches resulted in statistically significant, but smaller declines. However, the year and hook variables are confounded. To overcome this, we consulted an independent analysis using a different longline dataset in which the time each hook was in the water was recorded (*S6*). This analysis demonstrated that soak time had a positive affect on the catch rates per hook of most shark species taken by longliners in the Pacific Ocean. The positive correlation between hooks set and soak time observed in the logbook data provides evidence that gear saturation does not occur. Instead, we would expect shark catch rates to increase as a result of the increase in hooks set.

Alternative Models

The truncated negative binomial analysis is advantageous over other types of analyses for the logbook data because it makes the fewest assumptions about the data. This approach may be criticized however, because it ignores much of the data (i.e. the inferred zeros). As an example, oceanic sharks were recorded on between 3.4% (for oceanic whitetip) and 26.0% of sets (for blue sharks), while coastal sharks were recorded less often, between <1% (for white sharks) and 5.9% (for hammerhead sharks). Though it appears that the truncated models ignore the vast majority of the data, it is important to keep in mind that the sets where sharks were not recorded are not necessarily useful data, since we can't distinguish zeros from missing values. Nonetheless, as a comparison, we included the inferred zeros in two additional analyses, the first using the negative binomial distribution and the second, the delta-lognormal method (*S7*). In the latter method, the proportion of positive sets is modeled assuming a binomial error structure, and the mean catch rate of positive sets is modeled assuming a lognormal error distribution. The standardized index is the product of these two components. For both of these methods, we analyzed (i) the full dataset, and subsetted datasets that only included sets from vessels that had either (ii) recorded a given species at least once or (iii) recorded a given species in a given year.

We found declines for all species for each model and dataset tested (Fig. S1). Estimated declines for these models were consistently more extreme for hammerhead (A), white (B), coastal (D) and mako (G) sharks than in the truncated negative binomial models. If the rate of unreporting has increased in recent years, then the analyses that include the inferred zeros would overestimate the true declines. This hypothesis is consistent with the results for these four categories of sharks where the truncated models resulted in smaller declines. Further support for this hypothesis comes from observing that the overestimation of the untruncated relative to the truncated models is less substantial for vessels that consistently reported sharks over the period (Models 4 & 7). Estimated declines for thresher (E) and blue (F) sharks were very similar for all models (annual rate of change varied by ±1-2). For tiger (C) and oceanic whitetip sharks (H) the truncated models give slightly larger declines than all other model and data combinations. This could occur if reporting rates had increased in recent years, or if the shark distribution became less aggregated with decreasing abundance. We find neither argument compelling, and the results of these models rest on assumptions more tenuous than our primary method.

Analysing all data requires the unrealistic assumption that all missing values are in fact true zeros. Although subsetting attempts to eliminate some of these missing values, by excluding data from vessels that did not report sharks, there is no way of verifying the assumed vessel recording tendencies. In reality, no method can overcome logbook unreporting. However, we believe that our method is the most defensible.

Closed-Area Methods

We analyzed swordfish-targeted longline sets from both U.S. Atlantic observer (n=1,946 longline sets) and logbook data (n= 82,754) to determine how redirected effort from year long spatial closures to the longline fishery could change catches of those species that are of conservation concern (Table S2). Swordfish-targeted sets account for about three quarters of the U.S. pelagic longline fishery. Data were pooled over the period 1992-99. We estimated the ratio of the catch for each species to the target catch (in this case swordfish) from the observer data, because when pooled these observer data provide reliable catch rate estimates for each individual species, particularly non-target species. Observers were randomly assigned to swordfish longlining vessels throughout areas and seasons to obtain a representative sample of all areas.

Let $C_{i,s,j}$ be the catch of species *s* and let $S_{i,j}$ be the swordfish catch for set *j* in area *i*, as determined by scientific observers. We estimated the ratio of each species caught per swordfish caught as

(1) $R_{i,s} = \frac{\sum_j C_{i,s,j}}{\sum_j S_{i,j}}$.

We scaled up the catch ratio $R_{i,s}$ to calculate the total catch for each species in each area $C'_{i,s}$ based on the total swordfish catch S'_i in that area as reported in the logbook data

(2) $C'_{i,s} = R_{i,s} \cdot S'_i$.

because these data represent the best estimate of total swordfish catch for each area. The catch per unit effort for swordfish in each area U_i was determined by dividing the total swordfish catch by fishing effort, that is the total number of hooks H'_i in that area as reported in the logbook data

(3) $U_i = \frac{S'_i}{H'_i}$.

Under both the "constant-quota" and "constant-effort" scenarios, we allocated effort from the closed area *x* to the remaining open areas $i \neq x$ based on the proportion of total swordfish catch $P_{i,x}$ caught in area *i*, if area *x* is closed, i.e.

(4) $P_{i,x} = \frac{S'_i}{\sum_{i \neq x} S'_i}$.

(i) Constant-quota scenario

Under this scenario, we calculated the extra swordfish catch $S^*_{i,x}$ allocated to each remaining open area, if area *x* is closed, as

(5) $S^*_{i,x} = S_x \cdot P_{i,x}$.

The new effort H_i^* was calculated as

(6) $$H_{i,x}^* = \frac{S_i + S_{i,x}^*}{U_i}$$

The new catch for each species $C_{i,s,x}^*$ in area *i* during the closure of area *x* was determined as (7) $C_{i,s,x}^* = U_i \cdot H_{i,x}^* \cdot R_{i,s}$.

The proportional change in catch $Z_{x,s}$ for a given species and area closure is given by

(8) $$Z_{x,s} = \frac{\sum_{i \neq x} C_{i,s,x}^* - \sum_i C_{i,s}^{'}}{\sum_i C_{i,s}^{'}},$$

where $\sum_i C_{i,s}^{'}$ is the original catch of a species over all areas.

(ii) Constant-effort scenario

Under this scenario, the new fishing effort $H_{i,x}^*$ that occurs in each area during the closure of area *x* was calculated as

(9) $$H_{i,x}^* = (H_x^{'} \cdot P_{i,x}) + H_i^{'}.$$

The new effort was then used in Eq. (7) to determine the new catch. This new catch was incorporated into Eq. (8) to determine the proportional change in catch for each species. Results of the constant-quota scenario are shown in Fig. 4 and Fig. S2. Results of the constant-effort scenario are shown in Fig. S3.

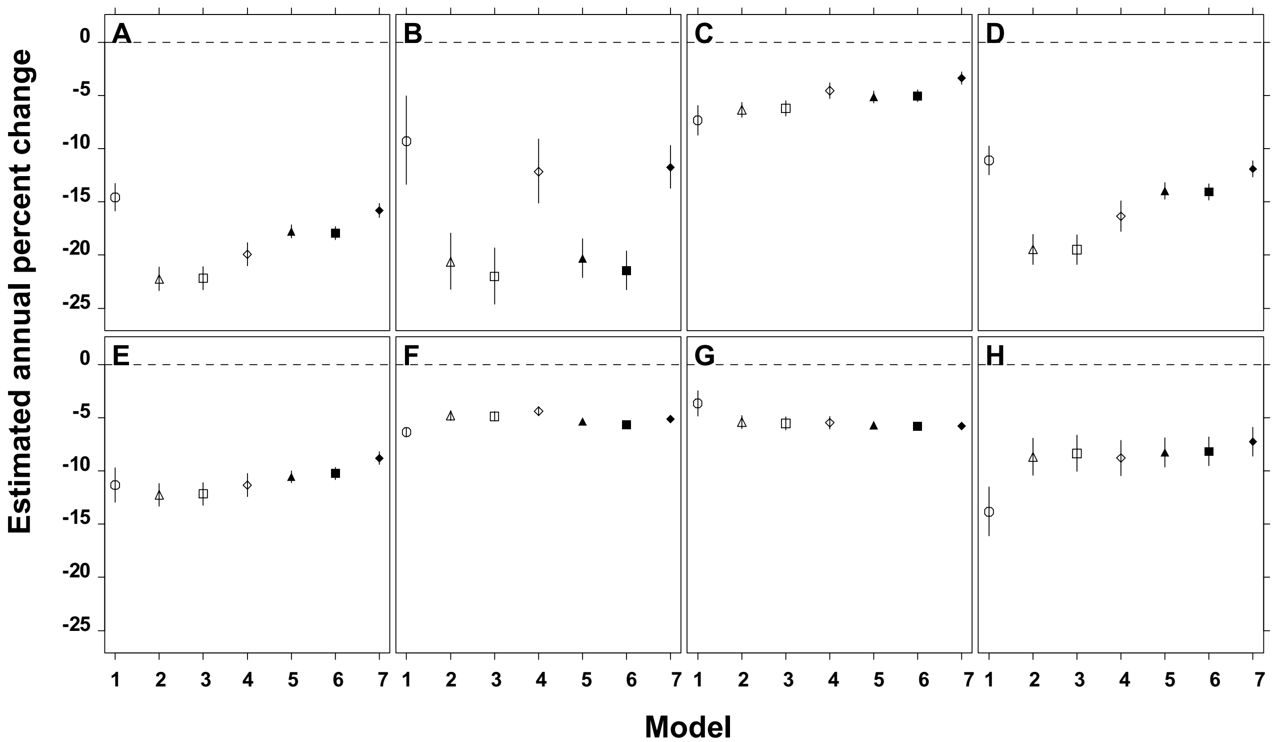

Figure S1. The annual rate of decline (± 95% CI) for all areas combined estimated from the following models: (1) truncated negative binomial; (2) negative binomial on full dataset; (3) negative binomial on data subsetted for vessels that recorded the species at least once; (4) negative binomial on data subsetted for vessels that recorded the species in a given year; (5) delta-lognormal on full dataset; (6) delta-lognormal on data subsetted for vessels that recorded the species at least once; (7) delta-lognormal on data subsetted for vessels that recorded the species in a given year. Models are presented for coastal shark species: (A) hammerhead, (B) white, (C) tiger, (D) coastal shark species identified from 1992 onwards; and oceanic shark species: (E) thresher, (F) blue, (G) mako, (H) oceanic whitetip.

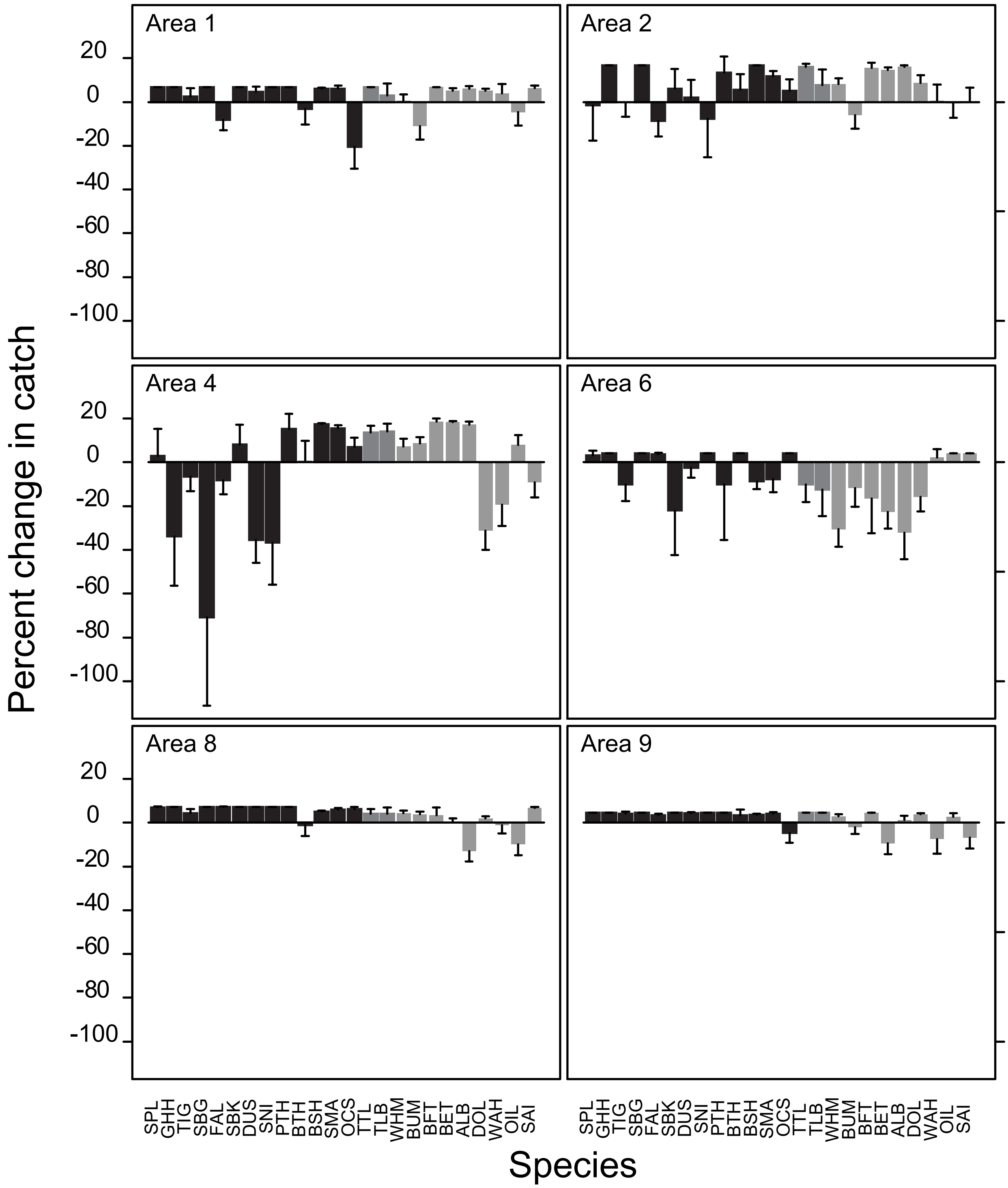

Fig. S2. Results from closed-area model showing predicted changes in catch as caused by year-round longline closure of the remaining areas (Areas 1, 2, 4, 6, 8, and 9). Negative values refer to reductions in catch. Error bars are 95% bootstrap confidence intervals, accounting for the uncertainty in the observer estimates of species composition. Black bars represent sharks (SPL=scalloped hammerhead, GHH=great hammerhead, TIG=tiger, SBG=bignose, FAL=silky, SBK=blacktip, DUS=dusky, SNI=night, PTH=common thresher, BTH=bigeye thresher, BSH=blue, SMA=shortfin mako, OCS=oceanic whitetip), dark bars represent sea turtles (TTL=loggerhead, TLB=leatherback), and light grey bars represent finfish (WHM=white marlin, BUM=blue marlin, BFT=bluefin tuna, BET=bigeye tuna, ALB=albacore tuna, DOL=common dolphinfish, WAH=wahoo, OIL=oilfish, SAI=Atlantic sailfish).

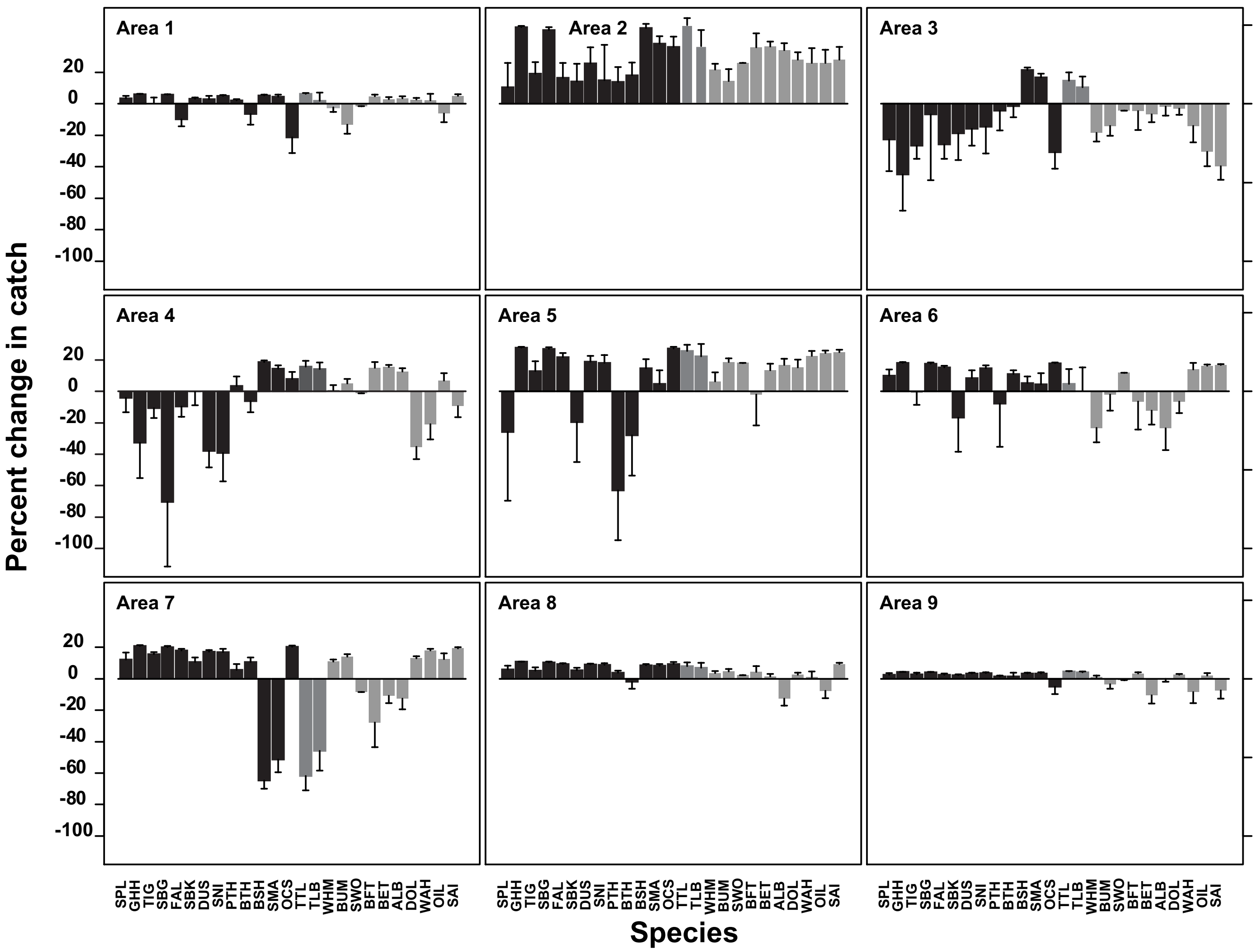

Fig. S3. Results from closed area model under constant-effort scenario showing predicted changes in catch as caused by year-round longline closure of each area (Area 1-9). Negative values refer to reductions in catch. Error bars are 95% bootstrap confidence intervals, accounting for the uncertainty in the observer estimates of species composition. Black bars represent sharks (SPL=scalloped hammerhead, GHH=great hammerhead, TIG=tiger, SBG=bignose, FAL=silky, SBK=blacktip, DUS=dusky, SNI=night, PTH=common thresher, BTH=bigeye thresher, BSH=blue, SMA=shortfin mako, OCS=oceanic whitetip), dark bars represent sea turtles (TTL=loggerhead, TLB=leatherback), and light grey bars represent finfish (WHM=white marlin, BUM=blue marlin, BFT=bluefin tuna, BET=bigeye tuna, ALB=albacore tuna, DOL=common dolphinfish, WAH=wahoo, OIL=oilfish, SAI=Atlantic sailfish).

Table S1. Models testing the robustness of the trend estimates (% change/year) to removal of the largest catches, for each species and species group presented. The percent of observations removed by each cutoff is also given.

Coastal Species	Cutoff (catch≤)	% removed	Trend estimate	Pelagic Species	Cutoff (catch≤)	% removed	Trend estimate
Hammerheads	-	0	-0.147	Threshers	-	0	-0.110
	150	0.1	-0.146		70	<0.1	-0.112
	100	0.3	-0.140		55	0.1	-0.111
	50	0.9	-0.131		35	0.3	-0.106
	25	2.5	-0.118		20	1	-0.099
White	-	0	-0.117	Blue	-	0	-0.064
	100	0.2	-0.117		400	<0.1	-0.065
	80	0.3	-0.117		300	0.3	-0.066
	20	0.8	-0.105		200	0.8	-0.068
	15	0.9	-0.100		199	1.3	-0.067
Tiger	-	0	-0.073	Makos	-	0	-0.033
	20	<0.1	-0.070		100	<0.1	-0.033
	15	0.2	-0.066		50	<0.1	-0.032
	10	0.3	-0.059		25	0.2	-0.033
	7	0.9	-0.052		20	0.3	-0.033
Coastal	-	0	-0.111	Oceanic Whitetip	-	0	-0.138
	150	0.1	-0.112		15	0.3	-0.121
	75	0.3	-0.108		10	0.7	-0.125
	50	0.7	-0.103		9	1.1	-0.124
	25	2.3	-0.098				

Table S2. Conservation status of species that were included in the closed-area analysis.

Acronym	Common Name	Scientific Name	IUCN [1)]	U.S. [2)]
SPL	scalloped hammerhead shark	*Sphyrna lewini*	LR/nt	OF
GHH	great hammerhead shark	*Sphyrna mokarran*	DD	OF
TIG	tiger shark	*Galeocerdo cuvieri*	LR/nt	OF
SBG	bignose shark	*Carcharhinus altimus*		OF/P
FAL	silky shark	*Carcharhinus falciformis*		OF
SBK	blacktip shark	*Carcharhinus limbatus*	VU [3)]	OF
DUS	dusky shark	*Carcharhinus obscurus*	VU [4)]	OF/P
SNI	night shark	*Carcharhinus signatus*		OF/P
PTH	common thresher	*Alopias vulpinus*	DD	DD
BTH	bigeye thresher shark	*Alopias superciliosus*		OF/P
BSH	blue shark	*Prionace glauca*	LR/nt	DD
SMA	shortfin mako	*Isurus oxyrinchus*	LR/nt	DD
OCS	oceanic whitetip shark	*Carcharhinus longimanus*	LR/nt	DD
TTL	loggerhead turtle	*Caretta caretta*	EN	TH
TLB	leatherback turtle	*Dermochelys coriacea*	CR	EN
WHM	white marlin	*Tetrapturus albidus*		OF [7)]
BUM	blue marlin	*Makaira nigricans*		OF
SWO	swordfish	*Xiphias gladius*	EN [5)]	OF
BFT	bluefin tuna	*Thunnus thynnus*	CR [6)]	OF
BET	bigeye tuna	*Thunnus obesus*	VU	OF
ALB	albacore tuna	*Thunnus alalunga*	VU [5)]	OF
DOL	common dolphinfish	*Coryphaena hippurus*		DD
WAH	wahoo	*Acanthocybium solandri*		DD
OIL	oilfish	*Ruvetus pretiosus*		DD
SAI	Atlantic sailfish	*Istiophorus platypterus*		OF

Notes for Table S2.

1) Status as reported by the International Union for the Conservation of Nature (*S8*): LR/nt=lower risk/near threatened, VU=vulnerable, TH=Threatened, EN=endangered, CR=critically endangered, DD=data deficient/unknown.
2) Status as reported by United States National Marine Fishery Service (*S9*, *S10*) and the United States Federal Wildlife Service (URL: http://endangered.fws.gov/wildlife.html): OF=overfished, OF/P=overfished and prohibited to retain, TH=Threatened, EN=endangered DD=data deficient, but caught in large numbers with great uncertainties about stock status. A stock is considered overfished when the biomass level (B) falls below a specified minimum stock size threshold (MSST). All species in this analysis of status OF and OF/P also have further overfishing occurring, which means that the current fishing mortality rate (F) exceeds the maximum fishing mortality threshold (MFMT).
3) Northwest Atlantic Stock
4) Northwest Atlantic and Gulf of Mexico stocks
5) North Atlantic Stock
6) Western Atlantic Stock
7) White Marlin is under consideration for listing under the US Endangered Species Act.

References and Notes

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S9. NMFS, *Stock Assessment and Fishery Evaluation for Atlantic Highly Migratory Species 2002* (National Marine Fisheries Service, Highly Migratory Species Management Division, Silver Spring, MD, USA, 2002).

S10. NMFS. *Final Fishery Management Plan for Atlantic Tuna, Swordfish, and Sharks* (National Marine Fisheries Service, Highly Migratory Species Management Division, Silver Spring, MD, USA, 1999).