Historical standardized CPUEs of the Indian Ocean shortfin mako (*Isurus oxyrinchus*) for 1966 through 1989 with catch estimation

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Abstract

We used an historical longline survey from 1966 to 1989 in the Indian Ocean basin to calculate standardized CPUEs for the endangered shortfin mako shark (*Isurus oxyrinchus*). CPUEs were generated using a zero-inflated negative binomial (ZINB) generalized additive model (GAM). These CPUEs represent an important basin-wide baseline for shortfin mako abundance at the start of industrialization of Indian Ocean fisheries. We also demonstrate how they can be used in combination with effort data to generate estimates of catch. Regressed with CPUEs from other fleets, we demonstrate a significant decline in shortfin mako abundance from the 1960s to present. Finally, we show a decline in median fork length between the USSR and IOTC data.

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Introduction

The shortfin mako is a globally endangered species (Rigby et al., 2019). Like many other shark species, it suffers from a lack of historical baseline data. Further, the Indian Ocean is one of the least studied ocean sectors for shark exploitation and bycatch (Molina & Cooke, 2012). These spatial and temporal phenomena compound into a significant management challenge for sharks in the Indian Ocean region.

To address this issue, we utilize data from a scientific longline survey conducted throughout the region from 1966 to 1989 to reconstruct trends of shark abundance (Fig. 1). The historical longline survey was conducted by USSR scientists using gear targeting tuna (Romanov, Sakagawa, Marsac, & Romanova, 2006), making the data comparable to that recorded by modern commercial longline fleets reporting to the IOTC. Shortfin mako stocks in the Indian Ocean were thought to be near-pristine in 1971, five years after the start of the USSR survey (Brunel et al., 2018). While Japan and Taiwan started exploiting these waters in a limited capacity shortly before the survey began, the USSR survey period covers twenty other nations joining the longline fishery (Fonteneau, 2017), along with significant improvements in longline gear and refrigeration technology (Ward & Hindmarsh, 2007), the introduction of industrial purse seining (Fonteneau, 2017), and the start of direct targeting of sharks due to increased global demand for shark fins (Camhi, Valenti, Fordham, Fowler, & Gibson, 2009; Fabinyi, 2012). Thus, the USSR survey reflects shark populations at pre-industrial fishing levels.

Methods

Datasets used

USSR survey data

We estimated historical catch rates from a scientific longline survey carried out by the former Soviet Union (USSR). Longline sets (n = 4,678) were cast throughout the Indian Ocean between 1961 and 1989 as part of the Soviet Indian Ocean Tuna Longline Research Programme (SIOTLLRP) (Romanov et al., 2006). Scientists aboard the ship identified the sharks to species or genus level and measured fork length. We discarded data collected prior to 1966 due to concerns with the reliability of species identification.

SIOTLLRP surveyors recorded for each longline set: date, latitude, longitude, start and end of longline setting and hauling, number of hooks set, basket length, buoyrope length, hookline length, number of baskets, number of hooks per basket, estimated depth of each hook in a basket, and hook number for each capture (Romanov et al., 2006). From these, we derived: soak time, haul time, mean number of hooks per basket, ocean depth, distance from coast, and Longhurst biogeographical province (Bart, 2012), using the "marmap" package to calculate depth and distance to the nearest coast (Pante & Simon-Bouhet, 2013). Month was input into the model as the sum of a sine and cosine transform to linearize the cyclical nature of the seasons (Ferretti, Osio, Jenkins, Rosenberg, & Lotze, 2013). This yielded 14 explanatory variables for shark abundance, which we tested for collinearity using the variance inflation factor (VIF) (Faraway, 2016).

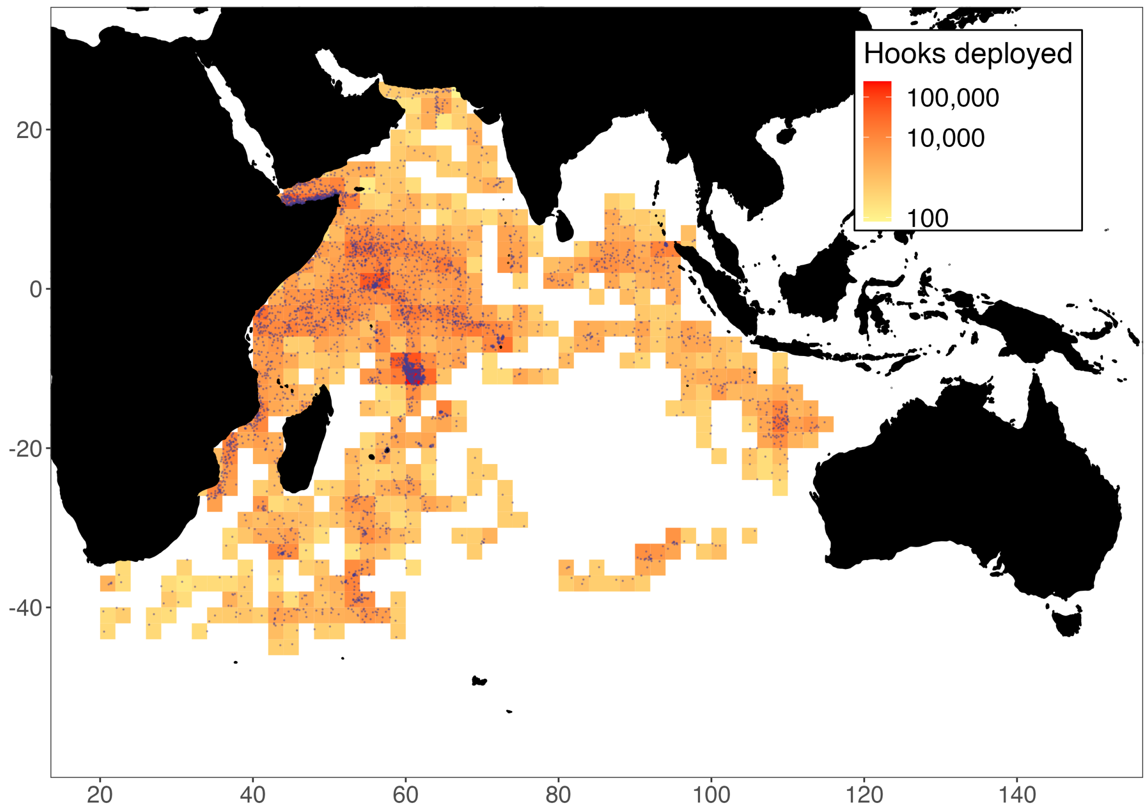

Fig. 1. USSR survey effort by number of hooks (2° by 2° resolution). Purple dots are locations of longline sets.

IOTC data

We used effort data from the Indian Ocean Tuna Commission's (IOTC's) publicly available catch and effort database (Commission, 2021).

CPUE standardization

We used a frequentist statistical modeling approach to produce standardized CPUEs (individuals per 1000 hooks deployed) from the USSR data. Our modeling approach consisted of three stages: statistical distribution and model framework selection, variable selection, and simulation. We used the blue shark as a model species owing to its status as the most abundant species in the dataset (n = 1,156) and one of the most commonly caught shark species in the Indian

Ocean (Tsai & Liu, 2018). We used the blue shark catch data to choose a statistical distribution and model framework to use for all species, but variable selection and simulation were performed for each species for which we produced standardized CPUEs.

We considered 14 statistical distributions and modeling frameworks commonly used in the literature for CPUE standardization (Table 1). We selected the zero-inflated negative binomial (ZINB) generalized additive model (GAM) based on its low Akaike information criterion (AIC) value relative to other models (Table 1) (Akaike, 1998) and the ability of GAMs to model non-linear trends in the data.

Table 1. AIC values of candidate models for catch rate standardization. Selected statistical distribution and model framework is in bold.

Model	AIC	R function
Poisson GLM	9066.62	glm()
Negative binomial GLM	7124.69	glm.nb()
Zero-inflated Poisson GLM	8488.14	zeroinfl()
Zero-inflated negative binomial GLM	7013.7	zeroinfl()
Poisson GAM	9066.62	gam()
Negative binomial GAM	7120.81	gam()
Zero-inflated Poisson GAM	8171.72	zipgam()
Zero-inflated negative binomial GAM	**7034.77**	**zinbgam()**
Zero-inflated Poisson GLMM	Did not converge	glmmTMB()
Zero-inflated negative binomial GLMM	Did not converge	glmmTMB()
Tweedie GLM	Did not converge	glm()
Tweedie GAM	7837.2	gam()
Tweedie GLMM	Did not converge	glmmTMB()
Delta-lognormal	7424.85	deltaLN()

The ZINB GAM is a mixture model with two component models: a negative binomial GAM predicting counts and a binomial GAM predicting the probability of a false zero. We used the "zigam" package in R to fit ZINB GAM models (Wotherspoon & Burch, 2017). We modified the package's source code to produce confidence intervals for predicted values using a Monte Carlo approach (Preacher & Selig, 2012).

For variable selection, we followed Babyak's (Babyak, 2004) rule of having at least 10 non-zero counts in the data for each variable. To select variables under this limit, we conducted variable selection in two steps, first permuting the variables to find which produced the best models, and then determining whether any of those variables could be dropped from a preliminary model. For the first step, we tried all possible combinations of the 14 candidate variables in a process known as dredging (Barton, 2020). We tested the component models of the ZINB GAM separately and used GLMs because of the computationally expensive nature of dredging. Variables appearing in every model in the 95th percentile confidence set of model performance were then considered for their respective component of the ZINB GAM model. In our second step, to reduce the risk of overparameterization, we tested the negative binomial and binomial GAMs to see if any variables could be removed without significant ($> 1\%$) loss of $\%$ deviance explained.

In our final step of model development, we performed simulations to test the statistical power of our ZINB GAM and its ability to capture the underlying biological processes in the data. We generated simulated counts for the survey data using the ZINB distribution from the model 100 times. A new model was fit to each simulated dataset and the coefficients of the variables recorded. We plotted a histogram of each coefficient for each variable and examined the distribution for approximate normality. If the coefficients were not centered on the estimate generated from the real data, we concluded that the model did not successfully capture the process of the data. In cases where this was true, we added or removed variables until the coefficient distributions were centered and approximately normal. The final parameterization of the shortfin mako ZINB GAM was:

Count process: $count \sim year + lat + depth_n + lhprovince + hookdmin + lenbasket +$

$offset(log(nhooks))$

Zero process: $w \sim year+lat+lon+hookdmin+lhprovince+lenbasket+offset(log(nhooks))$

Multiple CPUE series regression

To construct a longer-term trend, we combined our CPUEs with those published by Japan (Kai & Semba, 2019) and Taiwan (Tsai, Wu, & Liu, 2019). We excluded CPUEs from Spain and Portugal because these fleets target swordfish in the Indian Ocean, as opposed to tuna. From the CPUE series, we created a generalized linear mixed-effects (GLMM) model using the ”glmmTMB” package in R (Brooks et al., 2017). We used year as a fixed effect and fleet as a random effect to account for differences between fleets. We used the inverse of the standard error of the CPUE estimate as the weight.

Catch estimation

We followed a procedure similar to (Shea, Gallagher, Bomgardner, & Ferretti, 2023)'s Monte Carlo method of estimating shark catches from standardized CPUEs and fishing effort data. We used the IOTC's catch and effort database and cropped it to the time frame and bounding box covered by the USSR survey. All data from this time period was reported at a 5° by 5° resolution and includes data from Japan, Taiwan, South Korea, and the Seychelles.

We first randomly sampled a point from each grid cell at a 1° by 1° resolution. We used this point to predict a CPUE using the model we developed from the USSR survey data. We multiplied this CPUE by the number of hooks deployed in the grid cell to give an estimate of sharks caught, and totaled these catches for each year. We repeated this process 1,000 times, deriving a catch estimate from the median catch each year, and a confidence interval from the 2.5-th and 97.5-th percentiles.

Results

Standardized CPUEs

A total of 1,080 shortfin mako sharks were caught throughout the USSR survey. Figure 2 and Table 2 show the standardized CPUEs for shortfin makos from the USSR survey. There were three years in which an insufficient number of sets caught a shortfin makos to generate a CPUE: 1966, 1974, 1975. Residual plots can be found in the Appendix.

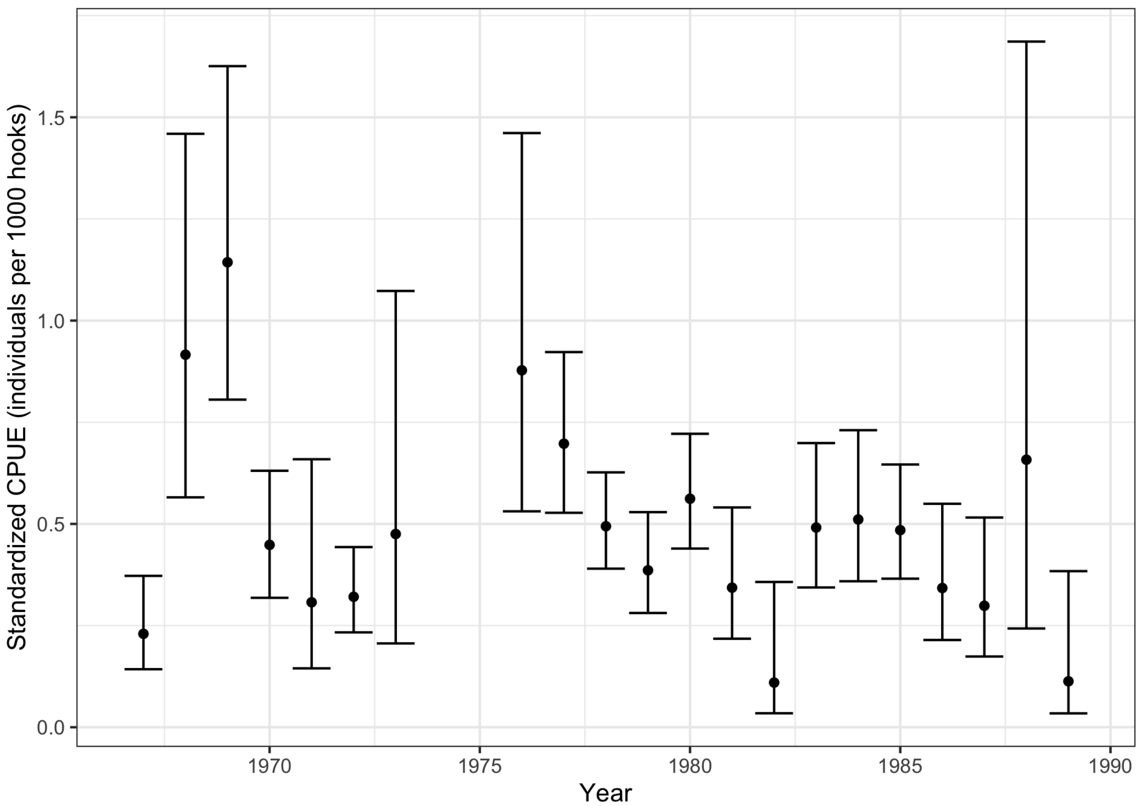

Fig. 2. Standardized CPUEs of the shortfin mako with 95% confidence intervals.

Table 2. Standardized CPUEs of the shortfin mako with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1967	0.2297	0.1427	0.3723
1968	0.9161	0.5653	1.4594
1969	1.1435	0.8057	1.6258
1970	0.4484	0.3183	0.6307
1971	0.3073	0.1448	0.659
1972	0.3208	0.2333	0.4431
1973	0.4752	0.2061	1.0729
1976	0.8777	0.531	1.4612
1977	0.6973	0.5274	0.9226
1978	0.4942	0.39	0.6268
1979	0.3859	0.281	0.529
1980	0.562	0.4394	0.7216
1981	0.3432	0.2177	0.5405
1982	0.1098	0.0344	0.3572
1983	0.4911	0.3437	0.6988
1984	0.511	0.359	0.7305
1985	0.4847	0.3653	0.6461
1986	0.3423	0.2145	0.5495
1987	0.2987	0.1739	0.5157
1988	0.6579	0.2429	1.6862
1989	0.113	0.0341	0.3839

Long-term CPUE trend

From 1966 through 2019, we estimate that the shortfin mako experienced a statistically significant decline of 83.9% (95% CI 43.0% - 95.4%). This decline is shown in Figure 3 on a natural scale and in Figure 4 on a log scale.

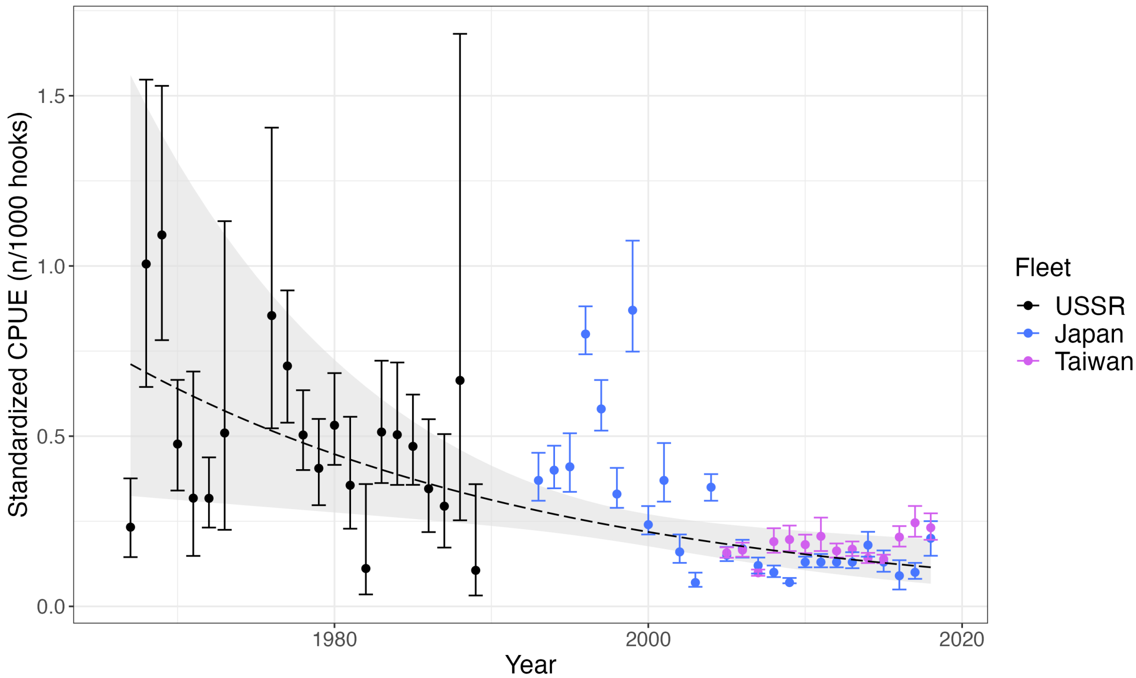

Fig. 3. Long-term trend in shortfin mako CPUEs shown on a natural scale.

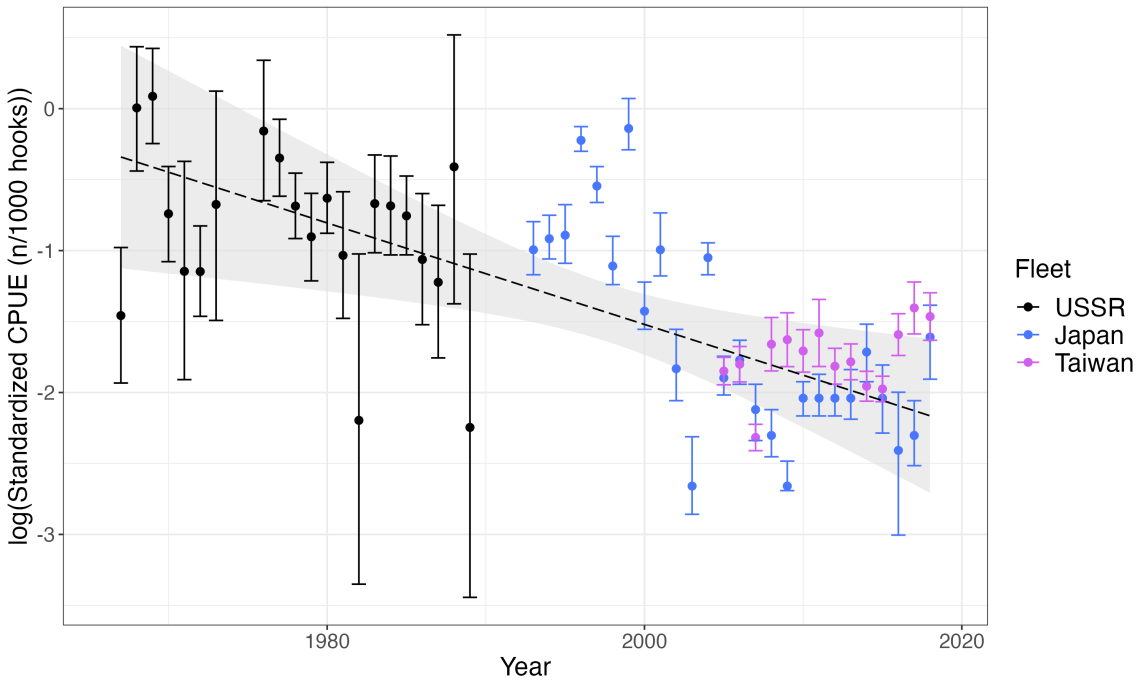

Fig. 4. Long-term trend in shortfin mako CPUEs shown on a log scale.

Catch estimation

Table 3 shows the estimated catches of shortfin mako sharks from the publicly available IOTC longline catch and effort data from 1967 through 1989. These data are also illustrated in Figure 5.

Table 3. Estimates of shortfin mako catch with 95% confidence intervals.

Year	Catch estimate	Lower bound	Upper bound
1967	31968	30687	33435
1968	135438	128156	142721
1969	170075	163993	178193
1970	54106	51132	58559
1971	34916	33329	36692
1972	27999	26654	29654
1973	36004	33167	38457
1976	72513	67476	77173
1977	69568	66356	72545
1978	66967	63762	69971
1979	52038	49538	54174
1980	86592	83304	90266
1981	50739	48165	52973
1982	19884	19138	20750
1983	102047	97067	107179
1984	95343	90887	99820
1985	82792	79722	86496
1986	75206	72345	78366
1987	65442	63088	67848
1988	121660	116831	126025
1989	23444	22244	24514

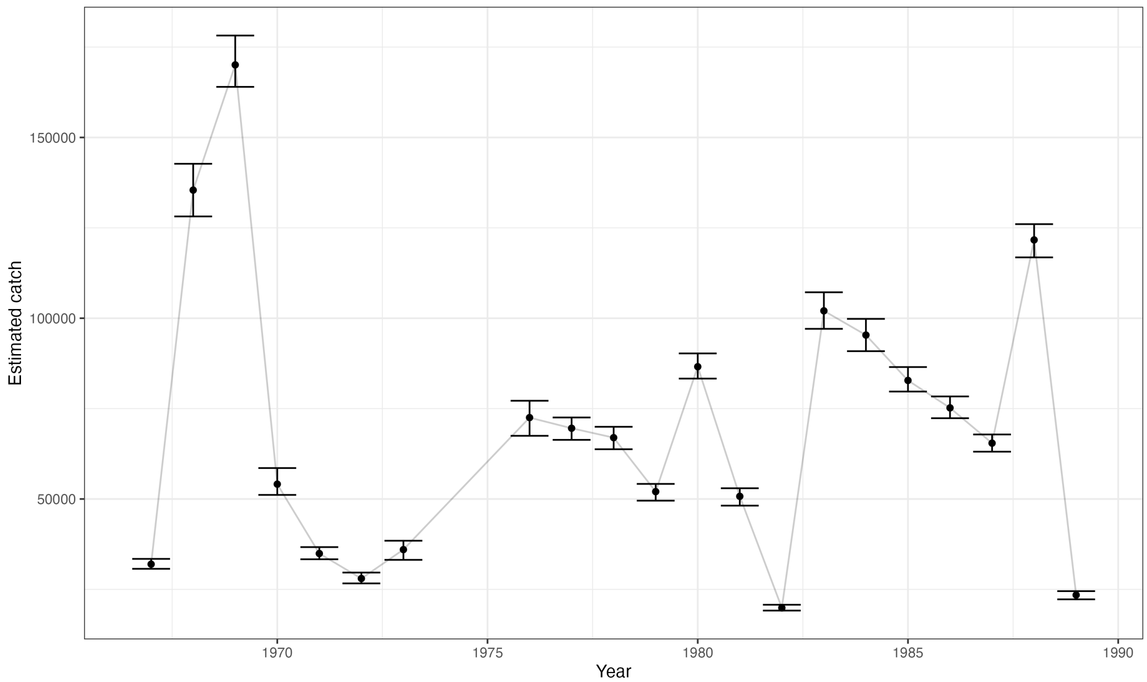

Fig. 5. Estimates of shortfin mako catch with 95% confidence intervals.

For reference, hooks deployed in the IOTC database over the same time period is shown in Figure 6.

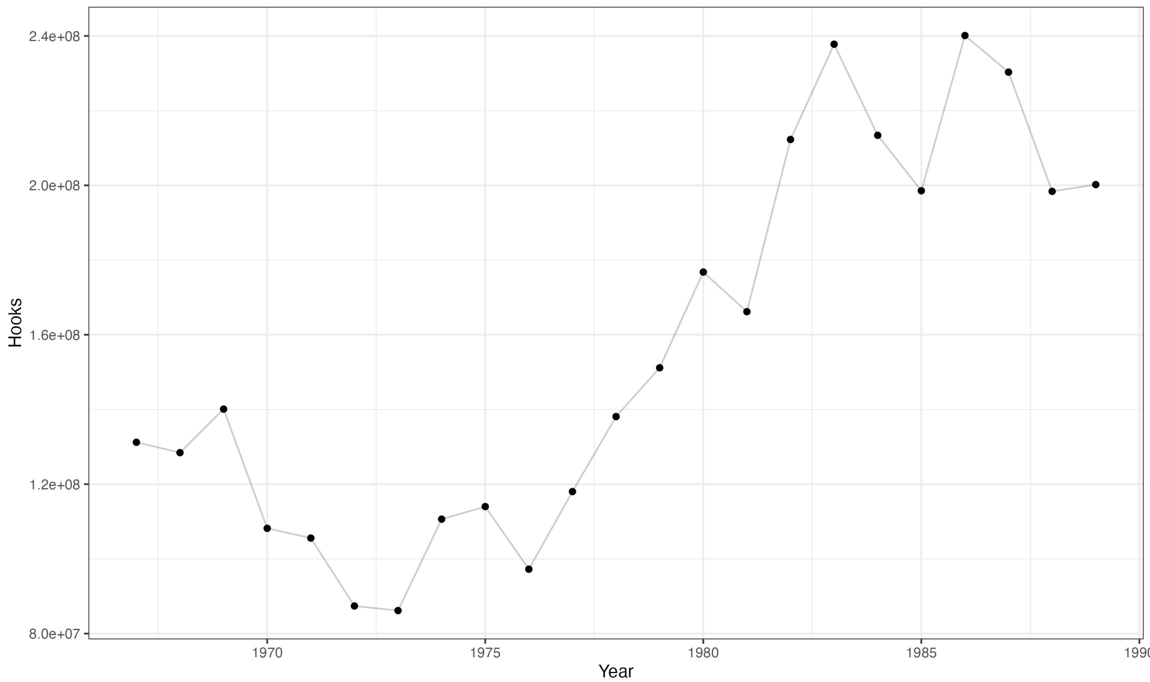

Fig. 6. Longline hooks deployed from 1967 through 1989 from the IOTC catch and effort database.

Size

Median shortfin mako fork length declined from 185 cm during the USSR survey (n = 1,059) to 167.5 cm in the IOTC data (n = 7,589). Fork lengths in the IOTC data also follow a narrower distribution than the USSR data (Fig. 7).

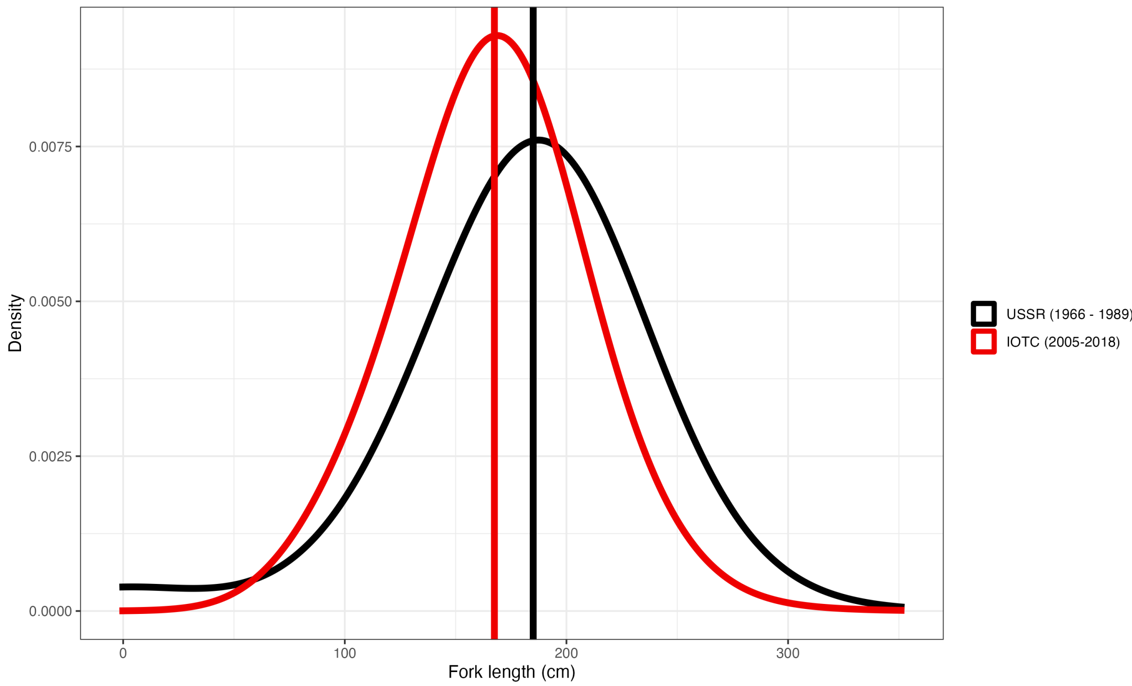

Fig. 7. Distribution of recorded fork lengths in the USSR data and publicly available IOTC size data.

Discussion

A USSR survey that spanned 24 years provided a rare record of shark initial abundances in the Indian Ocean. Combined with other published CPUEs, it indicates a clear downward trend in shortfin mako abundance. This contradicts findings from the preliminary stock assessment conducted in 2018, which found that biomass only began decreasing in the 1990s (Brunel et al., 2018). We find that the shortfin mako has been decreasing in abundance since the start of industrial-scale fishing in the Indian Ocean. The patterns we have identified demonstrate an urgent need for conservation and protection for this species. A formalized stock assessment should be conducted next to identify appropriate management measures.

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Acknowledgments

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Appendix

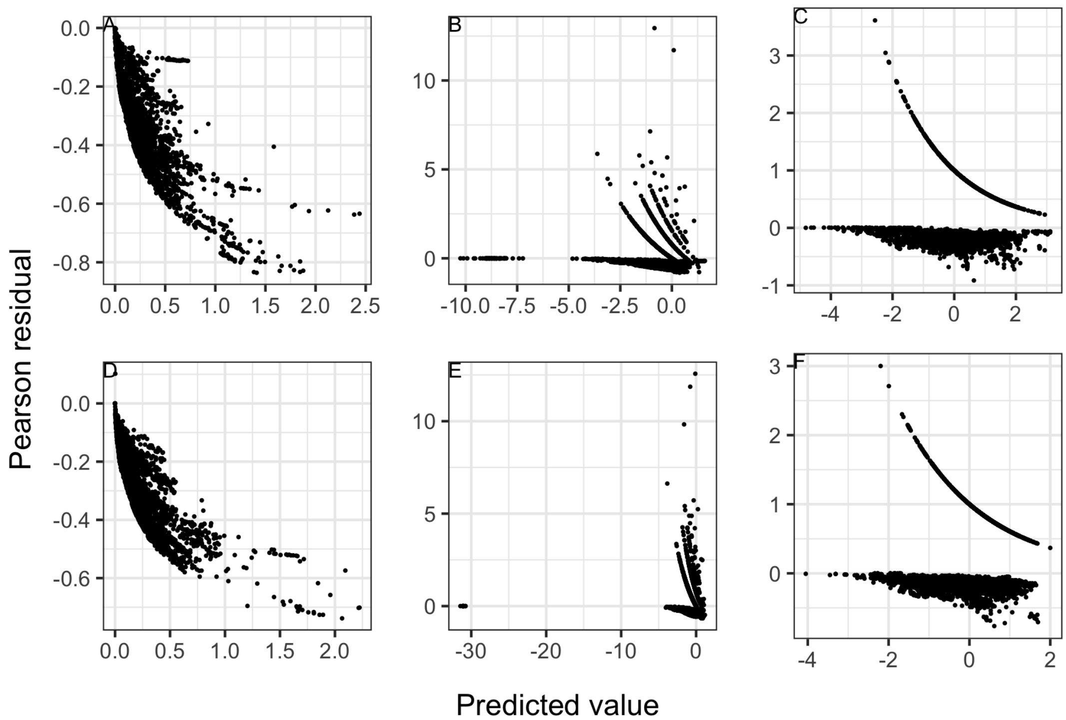

Fig. S1. Residuals of (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the shortfin mako.