Historical standardized CPUEs of seven shark species in the Indian Ocean with preliminary 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 blue shark (*Prionace glauca*), silky shark (*Carcharhinus falciformis*), tiger shark (*Galeocerdo cuvier*), silvertip shark (*C. albimarginatus*), sandbar shark (*C. plumbeus*), oceanic whitetip (*C. longimanus*), and shortfin mako (*Isurus oxyrinchus*), as well as the genera *Sphyrna, Alopias, Isurus,* and *Carcharhinus*. Twelve other shark species were recorded in the survey, but were not caught frequently enough to create standardized CPUEs. We use the standardized CPUEs of the blue shark to estimate catches by the Taiwanese longline fleet from 1977 - 1989. These CPUEs represent an important basin-wide baseline for shark 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 catches for use in stock assessment models. Additionally, we present standardized CPUEs for the porbeagle (*Lamna nasus*) derived from the IOTC's publicly available catch and effort data.

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Introduction

Having received attention in fisheries management and conservation only in recent decades (Ferretti, Worm, Britten, Heithaus, & Lotze, 2010), shark management continues to suffer from a lack of historical and species-specific data. Sharks are caught throughout a vast and difficult-to-manage seascape, and can be difficult to identify to the species level even when fisheries monitoring efforts are put into place. As a result, shark populations are largely not managed at levels that ensure sustainable exploitation (Davidson, Krawchuk, & Dulvy, 2016; Dulvy et al., 2017).

Further, the Indian Ocean is one of the least studied ocean sectors for shark exploitation and bycatch (Molina & Cooke, 2012), despite being bordered by four of the top ten shark-fishing countries border the Indian Ocean (Brautigam, 2020). A recent synthesis of global oceanic shark trends (Pacoureau et al., 2021) had large taxonomic and spatial gaps in the Indian Ocean, as it relied heavily on spatially limited datasets from South Africa and Western Australia. The countries bordering the Indian Ocean are home to a third of the world's population and are especially reliant on their fisheries, as many are developing nations that depend on seafood as a primary source of protein (Roy, 2019). Sustainable fisheries management in the Indian Ocean is thus imperative to achieving nutrition security and food justice as well.

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. Pelagic shark 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 and their responses to large-scale fishing pressure.

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. 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).

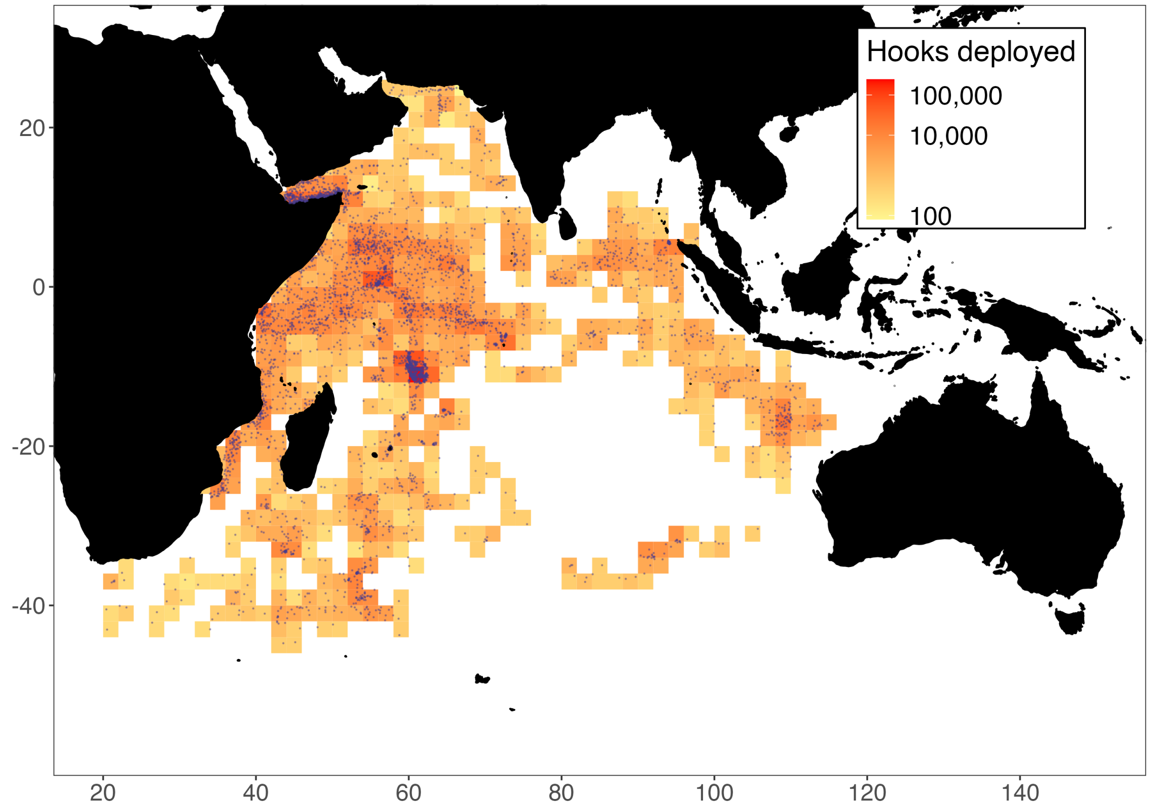

Fig. 1. USSR survey effort by number of hooks (2° by 2° resolution). Purple dots are locations of longline sets.

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 discarded species that were caught in fewer than three years.

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) (appendix).

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.

To produce standardized CPUEs for a genus, we aggregated the catches of all species in the genus and added them the catch numbers only identified to genus level. Due to our threshold of having 10 positive counts per variable and the fact that year in the USSR dataset has 24 levels when treated as a factor, we only produced standardized CPUE series for species that were caught at least 250 separate times. For all other species, we only produced a model with year treated as a continuous variable. We used these models to quantify the trajectory of the species over time using the estimated effect of year on abundance. When reporting the year effect estimates, we used only the parameter estimate of the year effect for the NB model, since this was assumed to be proportional to population abundance.

We followed the same steps to produce standardized CPUEs for the porbeagle from the IOTC's catch-effort data (Commission, 2021). South Korea and Japan were the two fleets who report their effort in hooks who also reported porbeagle catches. Since the data are reported on a grid, we used the average depth and distance to coast of the grid cell. To derive a trend from the two sets of CPUEs, we used a linear mixed-effects (LME) model with fleet as a random effect (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2018).

Catch estimation

Using the blue shark as a model species, 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 Taiwan's fishing effort data from the IOTC's catch and effort database because it had the greatest temporal overlap with the USSR survey. In the database, Taiwan's fishing effort is reported on a 5° by 5° grid. 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 abundance trends

Seven species and four genera were caught frequently enough in the USSR survey to produce a standardized catch per unit effort (CPUE) time-series.

Blue shark

Figure 2 and Table 2 show the standardized CPUEs for blue sharks from the USSR survey. Residual plots can be found in the appendix.

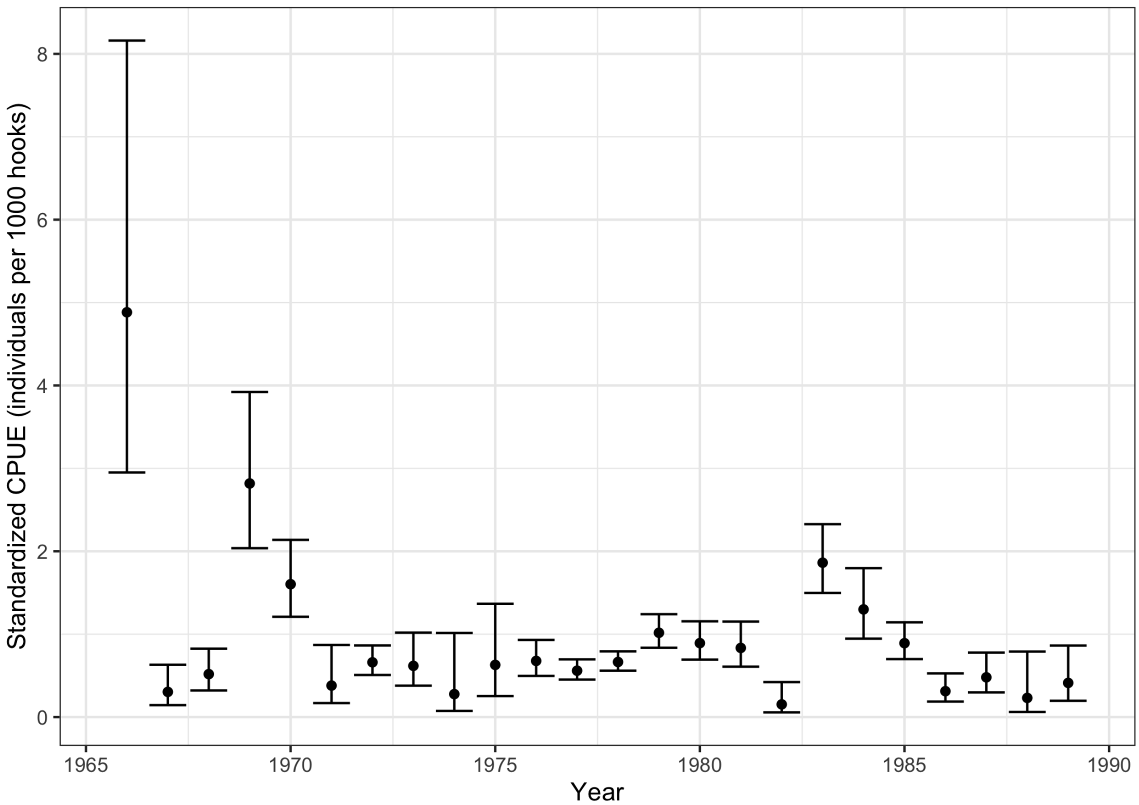

Fig. 2. Standardized CPUEs of the blue shark with 95% confidence intervals.

Table 2. Standardized CPUEs of the blue shark with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1966	4.883	2.9506	8.1605
1967	0.3036	0.144	0.6311
1968	0.5181	0.3211	0.825
1969	2.8179	2.0372	3.9215
1970	1.6027	1.2097	2.1377
1971	0.3798	0.1687	0.8696
1972	0.6605	0.5077	0.8641
1973	0.6179	0.3789	1.0185
1974	0.2771	0.074	1.0146
1975	0.6294	0.2532	1.3667
1976	0.6773	0.4965	0.9305
1977	0.5595	0.4524	0.6959
1978	0.6644	0.5596	0.7926
1979	1.017	0.8361	1.2409
1980	0.8922	0.693	1.1553
1981	0.8341	0.6078	1.1518
1982	0.1531	0.0567	0.4219
1983	1.8621	1.4973	2.3268
1984	1.299	0.9458	1.7962
1985	0.8914	0.6993	1.143
1986	0.3122	0.187	0.5269
1987	0.4795	0.2974	0.7779
1988	0.2312	0.0615	0.7903
1989	0.4122	0.1963	0.8628

Silky shark

Figure 3 and Table 3 show the standardized CPUEs for silky sharks from the USSR survey. Residual plots can be found in the appendix.

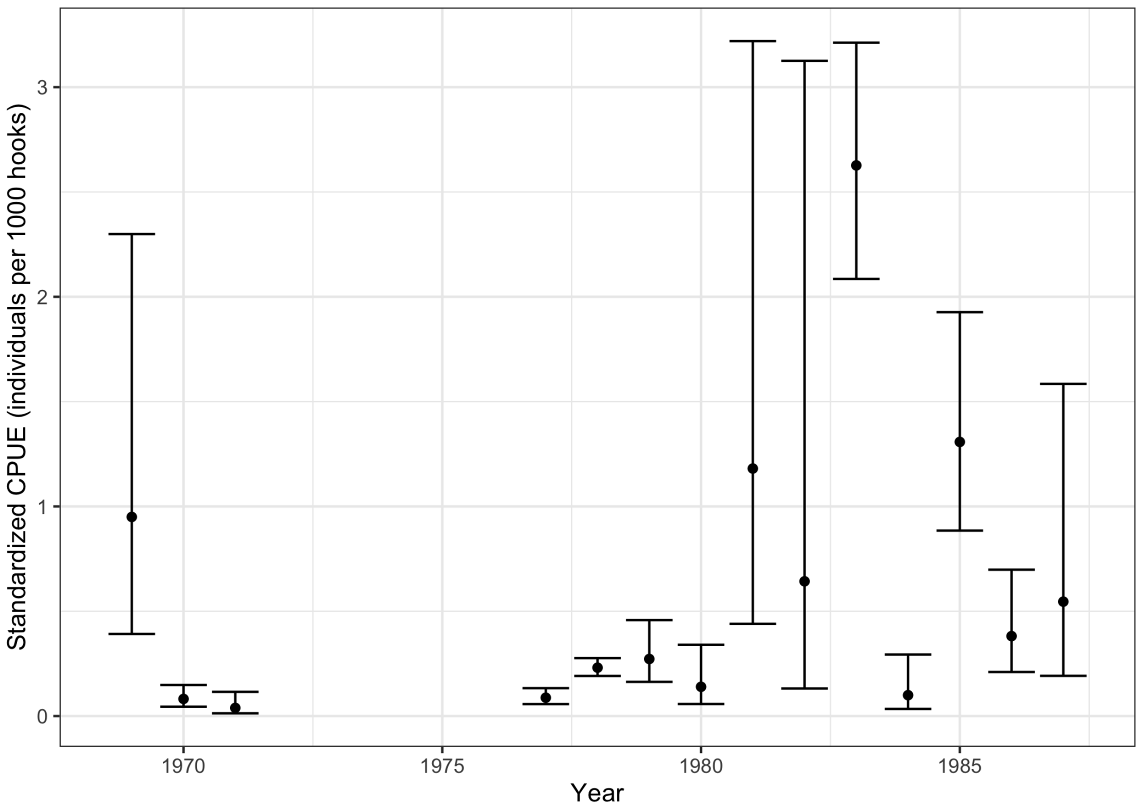

Fig. 3. Standardized CPUEs of the silky shark with 95% confidence intervals.

Table 3. Standardized CPUEs of the silky shark with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1969	0.2535	0.1376	0.474
1970	0.0187	0.0077	0.0462
1971	0.0103	0.0026	0.0414
1977	0.0646	0.0257	0.1657
1978	0.3861	0.2654	0.5647
1979	0.3536	0.2355	0.5359
1980	0.2085	0.0886	0.4903
1981	0.7271	0.4709	1.1348
1982	0.9021	0.2653	3.0026
1983	1.4695	0.975	2.23
1984	0.2719	0.0888	0.8304
1985	2.1329	1.3978	3.2772
1986	0.6759	0.3331	1.379
1987	0.5241	0.3263	0.8505

Oceanic whitetip shark

Figure 4 and Table 4 show the standardized CPUEs for oceanic whitetips from the USSR survey. Residual plots can be found in the appendix.

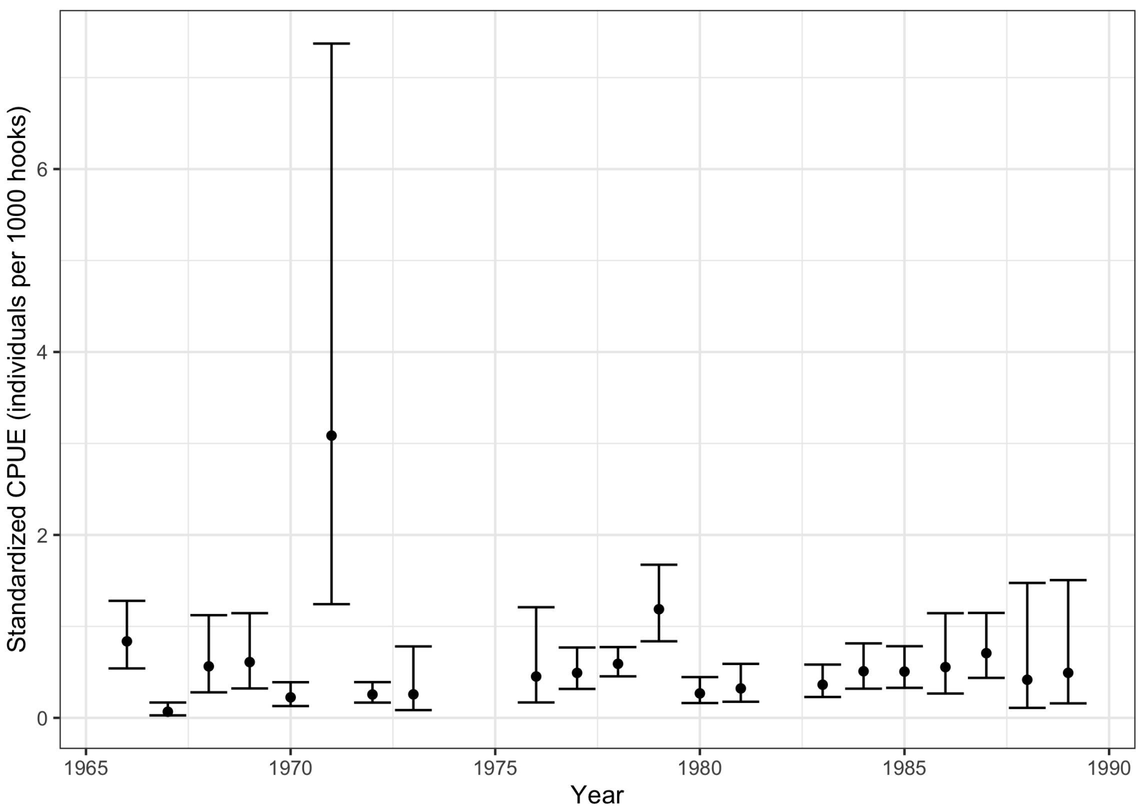

Fig. 4. Standardized CPUEs of the oceanic whitetip with 95% confidence intervals.

Table 4. Standardized CPUEs of the oceanic whitetip with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1966	0.8366	0.5405	1.2794
1967	0.0672	0.0273	0.1677
1968	0.5632	0.2791	1.1227
1969	0.6097	0.3217	1.1447
1970	0.2245	0.1293	0.3896
1971	3.0858	1.2431	7.3717
1972	0.2554	0.1668	0.3906
1973	0.2571	0.0849	0.7811
1976	0.4523	0.1685	1.2096
1977	0.4915	0.3165	0.7692
1978	0.5908	0.4539	0.7737
1979	1.1877	0.8373	1.6741
1980	0.2676	0.1623	0.4458
1981	0.3218	0.1762	0.5905
1983	0.3626	0.2283	0.5825
1984	0.5098	0.319	0.8143
1985	0.5058	0.3282	0.7833
1986	0.5549	0.266	1.1444
1987	0.7074	0.4372	1.1473
1988	0.4166	0.1093	1.4751
1989	0.492	0.1586	1.506

Shortfin mako shark

Figure 5 and Table 5 show the standardized CPUEs for shortfin makos from the USSR survey. Residual plots can be found in the appendix.

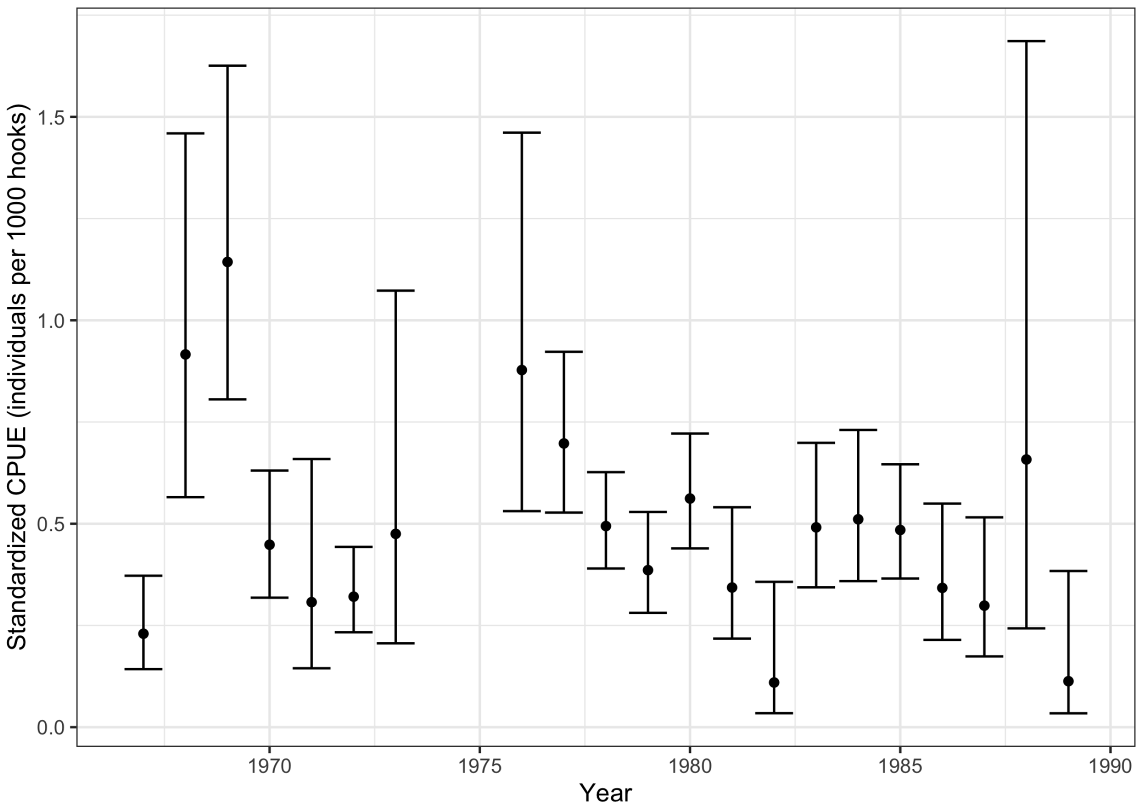

Fig. 5. Standardized CPUEs of the shortfin mako with 95% confidence intervals.

Table 5. 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

Tiger shark

Figure 6 and Table 6 show the standardized CPUEs for tiger sharks from the USSR survey. Residual plots can be found in the appendix.

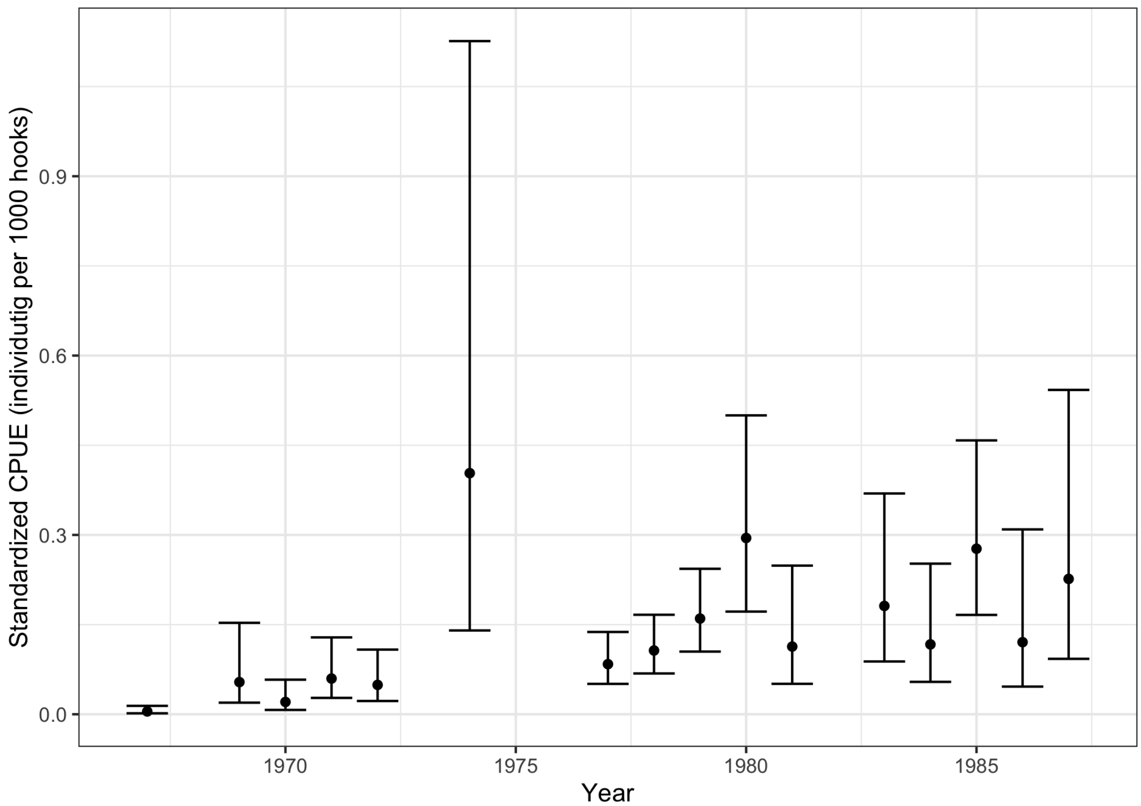

Fig. 6. Standardized CPUEs of the tiger shark with 95% confidence intervals.

Table 6. Standardized CPUEs of the tiger shark with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1967	0.0048	0.0016	0.0141
1969	0.0538	0.0194	0.153
1970	0.0206	0.0073	0.0579
1971	0.0597	0.0274	0.1286
1972	0.0492	0.0222	0.1082
1974	0.4033	0.1402	1.126
1977	0.0839	0.0508	0.1377
1978	0.1067	0.0683	0.1665
1979	0.1601	0.1049	0.2434
1980	0.2949	0.1718	0.5
1981	0.1132	0.0509	0.2487
1983	0.1812	0.0883	0.3693
1984	0.1169	0.0542	0.2519
1985	0.2769	0.1662	0.4581
1986	0.1206	0.0463	0.3092
1987	0.2264	0.0927	0.5426

Silvertip shark

Figure 7 and Table 7 show the standardized CPUEs for silvertip sharks from the USSR survey. Residual plots can be found in the appendix.

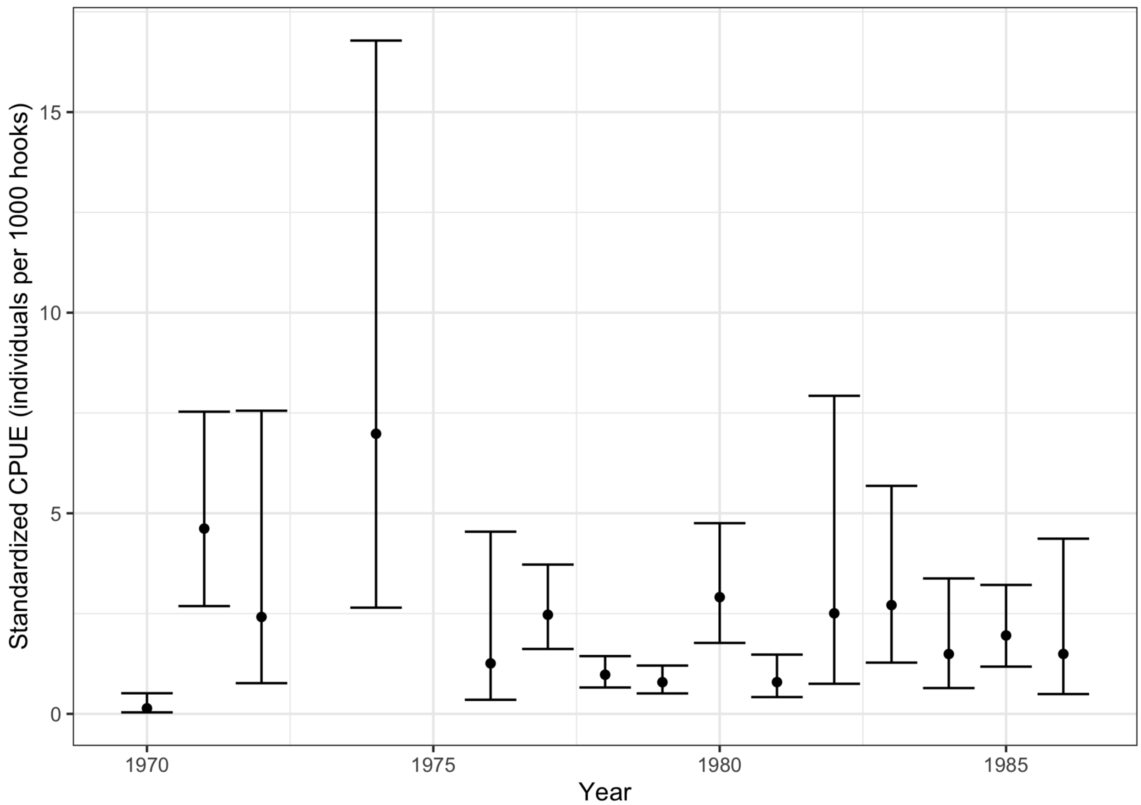

Fig. 7. Standardized CPUEs of the silvertip shark with 95% confidence intervals.

Table 7. Standardized CPUEs of the silvertip shark with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1970	0.1387	0.0375	0.5141
1971	4.6186	2.6866	7.5329
1972	2.4157	0.7654	7.5562
1974	6.9829	2.648	16.7831
1976	1.2583	0.3514	4.541
1977	2.4705	1.6177	3.7212
1978	0.9758	0.6573	1.4393
1979	0.7895	0.5097	1.2039
1980	2.9091	1.7685	4.7537
1981	0.7917	0.4188	1.4773
1982	2.5065	0.7502	7.928
1983	2.7115	1.2776	5.6831
1984	1.4916	0.6433	3.3757
1985	1.9546	1.1778	3.2143
1986	1.4932	0.4938	4.3667

Sandbar shark

Figure 8 and Table 8 show the standardized CPUEs for sandbar sharks from the USSR survey. Residual plots can be found in the appendix.

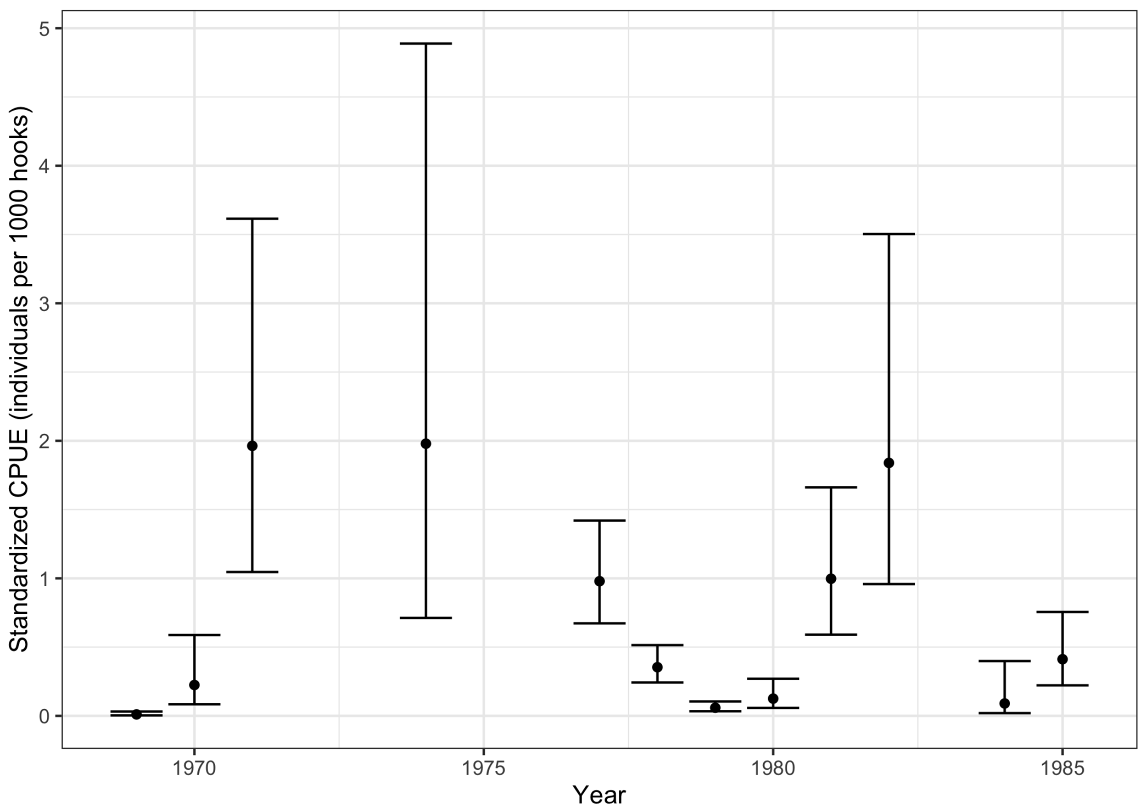

Fig. 8. Standardized CPUEs of the sandbar shark with 95% confidence intervals.

Table 8. Standardized CPUEs of the sandbar shark with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1969	0.0108	0.0037	0.0317
1970	0.2246	0.0844	0.5881
1971	1.9634	1.0461	3.615
1974	1.9792	0.7123	4.8883
1977	0.9793	0.6727	1.4202
1978	0.3538	0.2429	0.5144
1979	0.0592	0.0336	0.1048
1980	0.1255	0.0579	0.27
1981	0.9972	0.5905	1.6615
1982	1.8395	0.9584	3.5035
1984	0.0904	0.02	0.3986
1985	0.4119	0.222	0.7556

***Sphyrna* spp.**

Figure 9 and Table 9 show the standardized CPUEs for the genus *Sphyrna* from the USSR survey. Residual plots can be found in the appendix.

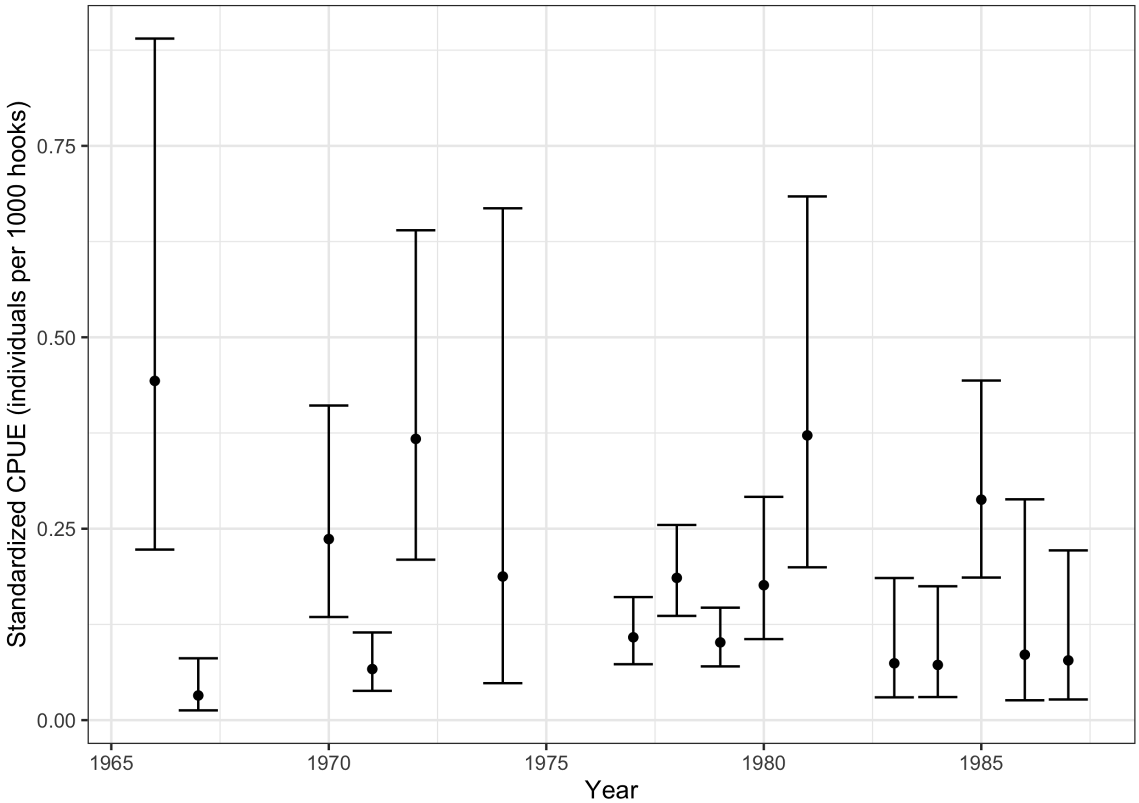

Fig. 9. Standardized CPUEs of the *Sphyrna* spp. with 95% confidence intervals.

Table 9. Standardized CPUEs of the *Sphyrna* spp. with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1966	0.443	0.2228	0.8901
1967	0.0322	0.0128	0.0808
1970	0.2365	0.1347	0.4109
1971	0.0667	0.0383	0.1145
1972	0.3673	0.2096	0.6397
1974	0.1876	0.0483	0.6684
1977	0.1082	0.073	0.1607
1978	0.1858	0.1361	0.2549
1979	0.1015	0.0702	0.1469
1980	0.1762	0.1058	0.2916
1981	0.3719	0.1996	0.6839
1983	0.0742	0.0298	0.1856
1984	0.0721	0.0301	0.1748
1985	0.2879	0.1862	0.4435
1986	0.0855	0.0259	0.2883
1987	0.078	0.027	0.2217

***Carcharhinus* spp.**

Figure 10 and Table 10 show the standardized CPUEs for the genus *Carcharhinus* from the USSR survey. Residual plots can be found in the appendix.

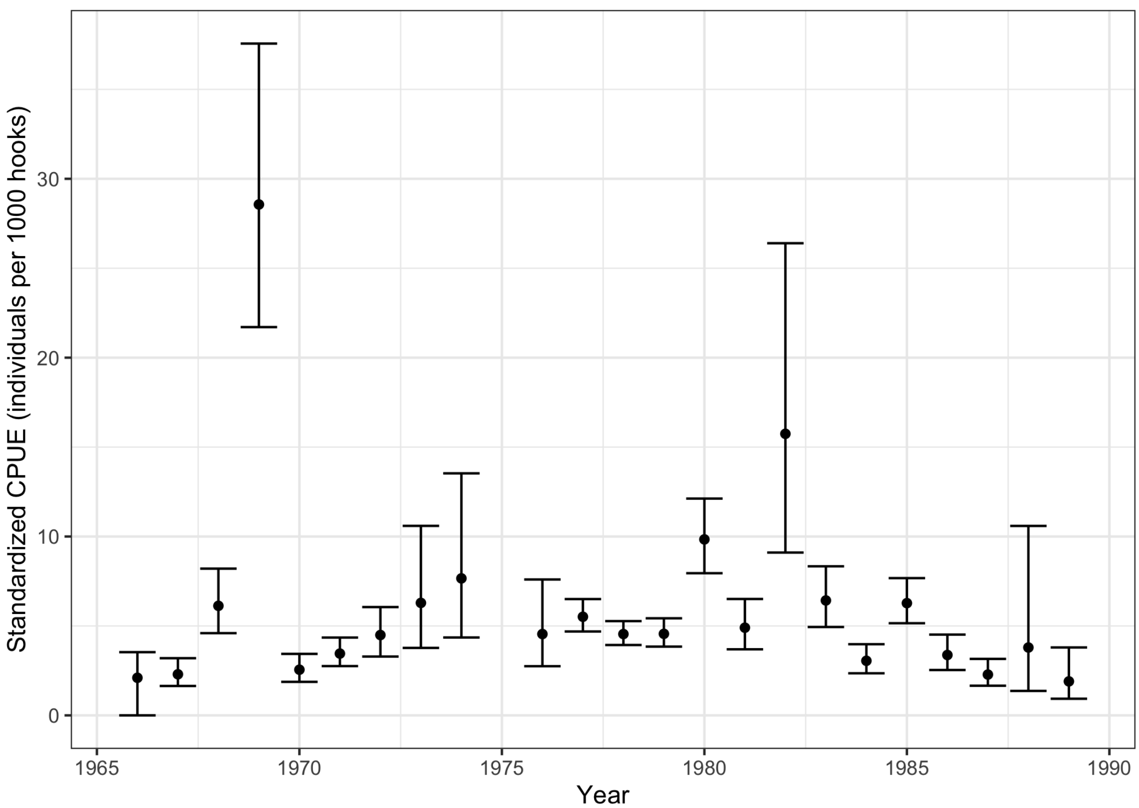

Fig. 10. Standardized CPUEs of the *Carcharhinus* spp. with 95% confidence intervals.

Table 10. Standardized CPUEs of the *Carcharhinus* spp. with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1966	2.1016	0	3.5344
1967	2.2975	1.6437	3.1963
1968	6.1245	4.5963	8.2043
1969	28.5637	21.7079	37.56
1970	2.5534	1.8739	3.4372
1971	3.4547	2.7553	4.3507
1972	4.4916	3.2884	6.055
1973	6.2885	3.772	10.5954
1974	7.6588	4.3543	13.5319
1976	4.5465	2.7489	7.5974
1977	5.5128	4.6895	6.5027
1978	4.5465	3.9339	5.2703
1979	4.5586	3.8441	5.4274
1980	9.8387	7.9479	12.1213
1981	4.9018	3.6936	6.5072
1982	15.7419	9.1029	26.3974
1983	6.4245	4.9406	8.3342
1984	3.0512	2.3529	3.9786
1985	6.2748	5.1513	7.6733
1986	3.3753	2.5361	4.5158
1987	2.2814	1.6579	3.1569
1988	3.7936	1.3663	10.592
1989	1.9007	0.9296	3.7969

***Alopias* spp.**

Figure 11 and Table 11 show the standardized CPUEs for the genus *Alopias* from the USSR survey. Residual plots can be found in the appendix.

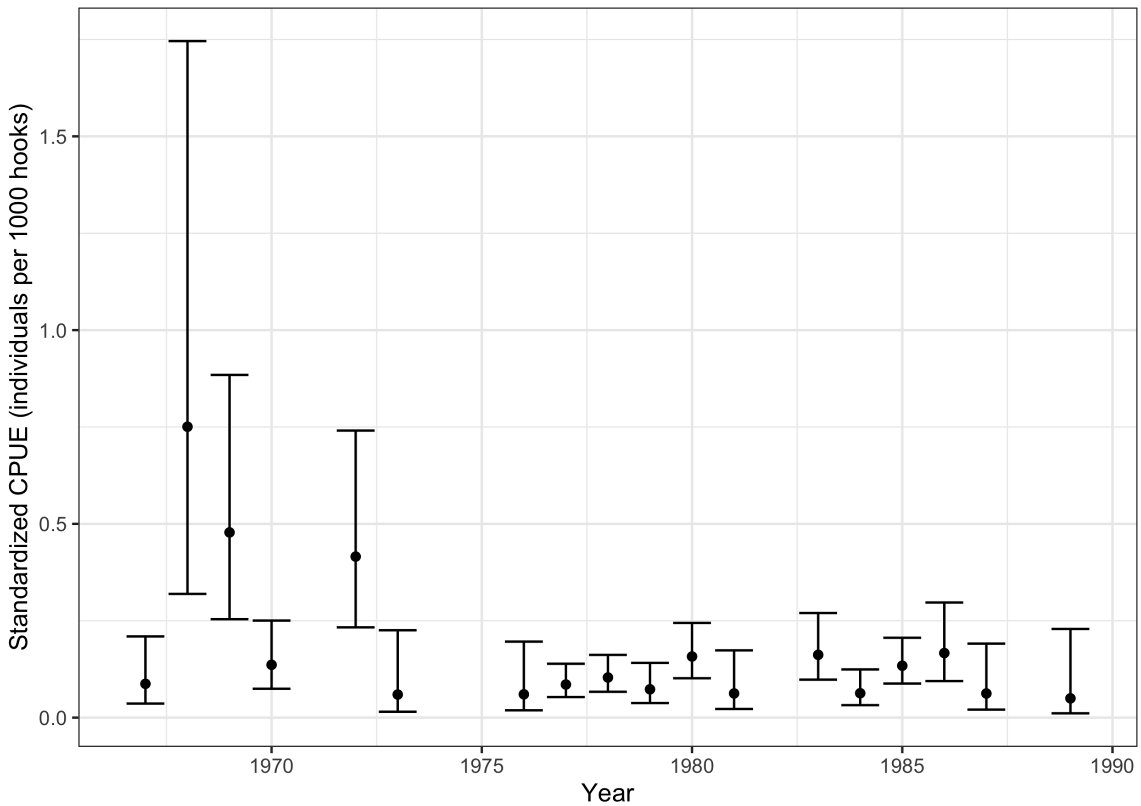

Fig. 11. Standardized CPUEs of the *Alopias* spp. with 95% confidence intervals.

Table 11. Standardized CPUEs of the *Alopias* spp. with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1967	0.0873	0.0363	0.2096
1968	0.7507	0.3193	1.7458
1969	0.478	0.254	0.8843
1970	0.1363	0.0745	0.2505
1972	0.4156	0.233	0.7408
1973	0.0596	0.0153	0.2255
1976	0.0601	0.0189	0.1961
1977	0.0854	0.0531	0.139
1978	0.1035	0.0667	0.1619
1979	0.0731	0.0376	0.1412
1980	0.1577	0.1016	0.2444
1981	0.0624	0.0223	0.1736
1983	0.1621	0.098	0.27
1984	0.0629	0.0322	0.1244
1985	0.1339	0.0879	0.2061
1986	0.1666	0.0943	0.297
1987	0.0623	0.0207	0.191
1989	0.0498	0.0112	0.2288

***Isurus* spp.**

Figure 12 and Table 12 show the standardized CPUEs for the genus *Isurus* from the USSR survey. Residual plots can be found in the appendix.

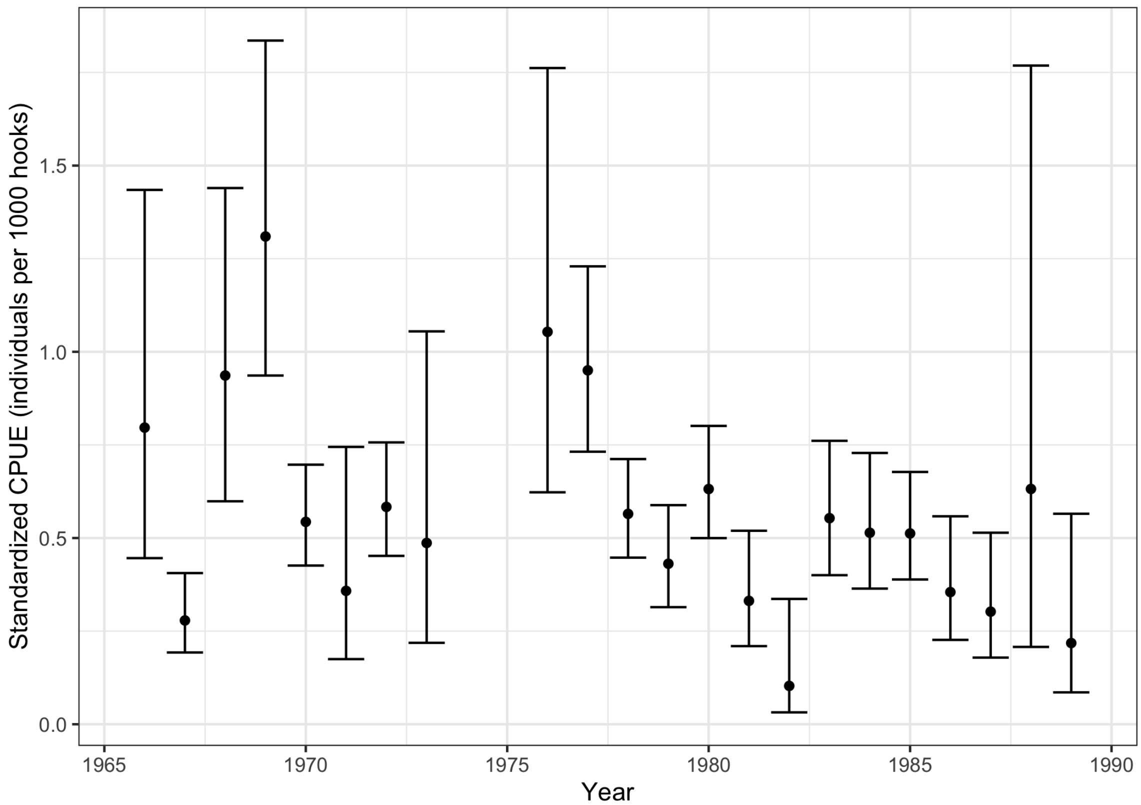

Fig. 12. Standardized CPUEs of the *Isurus* spp. with 95% confidence intervals.

Table 12. Standardized CPUEs of the *Isurus* spp. with 95% confidence interval bounds.

Year	Standardized CPUE	Lower Bound	Upper Bound
1966	0.7965	0.446	1.4347
1967	0.2787	0.1927	0.4059
1968	0.9363	0.5987	1.4397
1969	1.3096	0.9363	1.8356
1970	0.5434	0.4261	0.6969
1971	0.3581	0.1749	0.7446
1972	0.5836	0.452	0.7567
1973	0.4867	0.2186	1.0548
1976	1.0536	0.6228	1.7619
1977	0.9502	0.7318	1.2294
1978	0.5649	0.4474	0.712
1979	0.431	0.3144	0.5883
1980	0.6316	0.4998	0.801
1981	0.3313	0.2098	0.5195
1982	0.103	0.0319	0.3365
1983	0.5533	0.4002	0.761
1984	0.5141	0.3642	0.7284
1985	0.5123	0.3887	0.6774
1986	0.3548	0.2265	0.5583
1987	0.3023	0.179	0.5143
1988	0.6318	0.2076	1.7685
1989	0.218	0.0856	0.5652

Abundance trends

Twelve species were not caught often enough in the survey to generate standardized CPUEs. For all species, we took the count process as a proxy of abundance, and its instantaneous rate of change (IRC) over time (the model's year coefficient) as a proxy of the species' change in abundance over the survey period. Of the 19 total species, five had a significantly positive IRC in the count process, nine had significantly negative IRCs, and five had a non-significant IRC (Fig. 13). Four of the five species with positive IRCs were not commonly caught in the survey, except the silky shark. The porbeagle appears to have declined in abundance over the USSR survey, though not to a statistically significant extent.

The thresher shark *Alopias* and mako shark *Isurus* genera declined significantly over time. The two carcharhiniform genera, the requiem sharks *Carcharhinus* and hammerheads *Sphyrna*, had abundance trends that were not statistically significant.

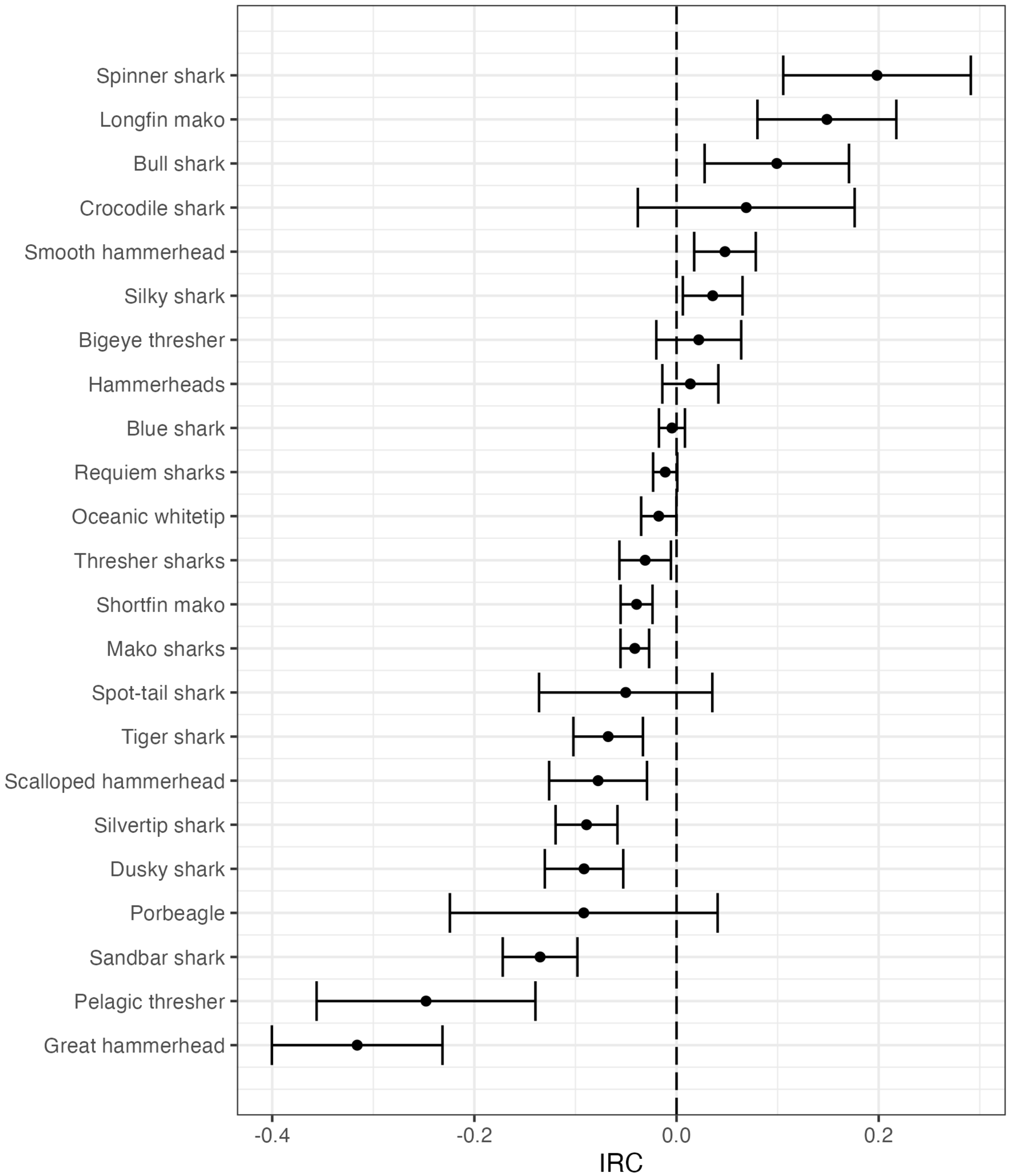

Fig. 13. Change in abundance over time for all species and genera identified in the USSR survey.

Porbeagle

IOTC catch-effort data of the porbeagle are available from two fleets, South Korea and Japan, for the time period of 2009 through 2018. The catchability of the porbeagle appears to have declined significantly over this period.

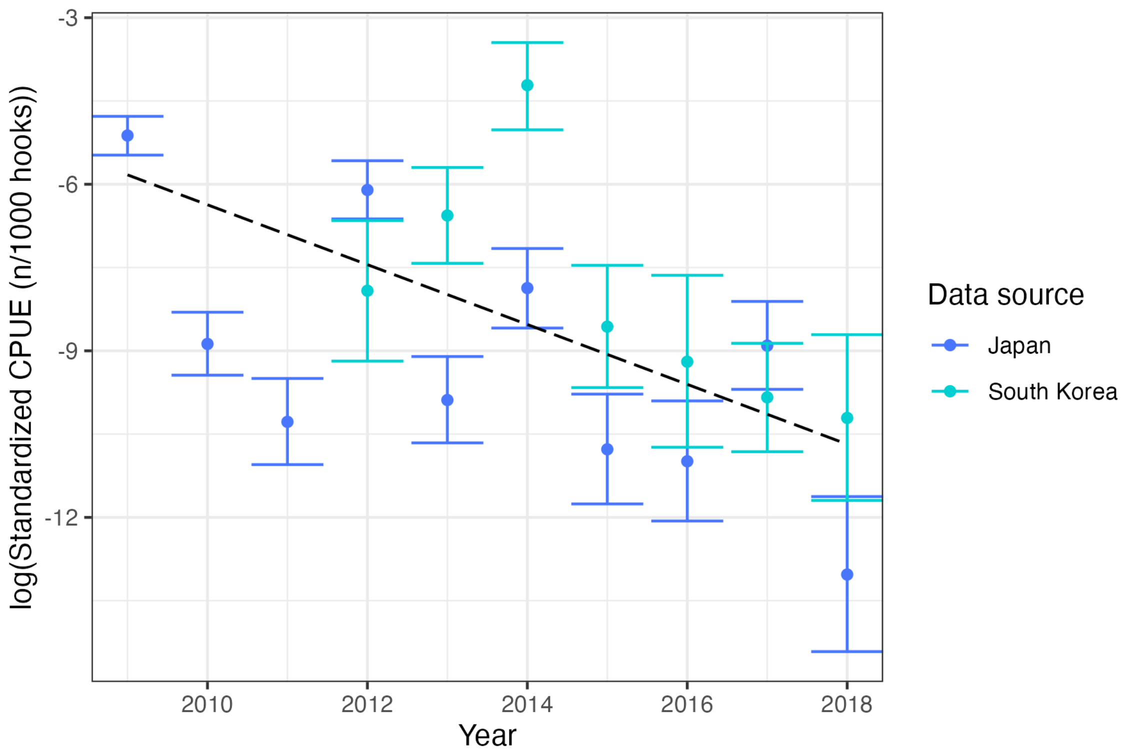

Fig. 14. Trend over time in standardized CPUEs of the porbeagle, derived from IOTC catch-effort data.

Tables 13 and 14 list the standardized CPUEs from the South Korean and Japanese fleets, respectively.

Table 13. log(Standardized CPUE) of the porbeagle derived from South Korea's catch and effort data in the IOTC database.

Year	log(Standardized CPUE)	Lower Bound	Upper Bound
2012	-7.9181	-9.1856	-6.6548
2013	-6.5632	-7.4237	-5.6987
2014	-4.2157	-5.0201	-3.4484
2015	-8.5649	-9.6622	-7.4601
2016	-9.1963	-10.7368	-7.6395
2017	-9.8381	-10.817	-8.8646
2018	-10.2091	-11.6935	-8.7091

Table 14. log(Standardized CPUE) of the porbeagle derived from Japan's catch and effort data in the IOTC database.

Year	log(Standardized CPUE)	Lower Bound	Upper Bound
2009	-5.1227	-5.475	-4.7771
2010	-8.876	-9.4392	-8.3049
2011	-10.2796	-11.049	-9.4978
2012	-6.1036	-6.6245	-5.5762
2013	-9.8866	-10.6584	-9.1034
2014	-7.8704	-8.5897	-7.1571
2015	-10.7741	-11.7578	-9.7794
2016	-10.9899	-12.0654	-9.9021
2017	-8.9067	-9.6937	-8.1108
2018	-13.0292	-14.4172	-11.6249

Catch estimation

Table 15 shows the estimates catches of blue sharks by the Taiwanese longline fleet for 1977 - 1989.

Table 15. Estimates of blue shark catch by the Taiwanese longline fleet with 95% confidence intervals.

Year	Number of hooks	Estimate	2.5 Percentile	97.5 Percentile
1977	33,880,700	55,451	53,938	56,992
1978	36,647,400	87,634	85,476	89,611
1979	57,891,600	170,182	166,095	173,776
1980	60,096,020	113,108	111,339	115,028
1981	52,502,148	115,583	113,385	117,815
1982	79,779,449	38,036	37,212	38,786
1983	87,070,117	374,996	368,239	381,781
1984	82,531,240	307,166	299,589	315,086
1985	65,443,162	78,960	77,267	80,704
1986	86,358,796	41,616	40,876	42,406
1987	109,042,240	80,607	79,075	82,231
1988	123,571,979	44,828	43,757	45,949
1989	133,521,215	155,758	150,801	160,746

Discussion

A USSR survey that spanned 24 years provided a rare record of shark initial abundances in the Indian Ocean and showed that initially species' trajectories were variable, experiencing both significant upwards and downwards trends. However, publicly available catch data for most of these species does not exist for more recent decades. Given the large shifts in Indian Ocean fishing that occurred in the latter part of the USSR survey, this leaves the current status of these species unknown. While this study provides an important first step in establishing a baseline, the current status of most species cannot be assessed because of a lack of specific data.

We demonstrated how the CPUEs we generated can be used to estimate catches given fleet effort data. Our hope is that these estimates can be used to expand the IOTC's suite of stock assessments for sharks, as the blue shark is currently the only one with a full stock assessment (IOTC, 2017). However, this effort is again limited by the availability of more recent specific data. Sharks are an essential part of ocean ecosystems (Heupel, Knip, Simpfendorfer, & Dulvy, 2014). Shark declines can cause trophic cascades (Myers, Baum, Shepherd, Powers, & Peterson, 2007; Baum & Worm, 2009), and make ecosystems more vulnerable to regime shifts (Möllmann & Diekmann, 2012). Their sustainable management will be increasingly important in an ocean facing climate change and biodiversity loss.

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We thank the work of YugNIRO scientists in collecting the historical survey data on sharks in the Indian Ocean funded by the Ministry of Fisheries of the former USSR. Additionally, we thank the work of the IOTC in collecting and compiling fisheries data for the region.

Appendix

The residual plots for the ZINB GAM models of the USSR data are shown below.

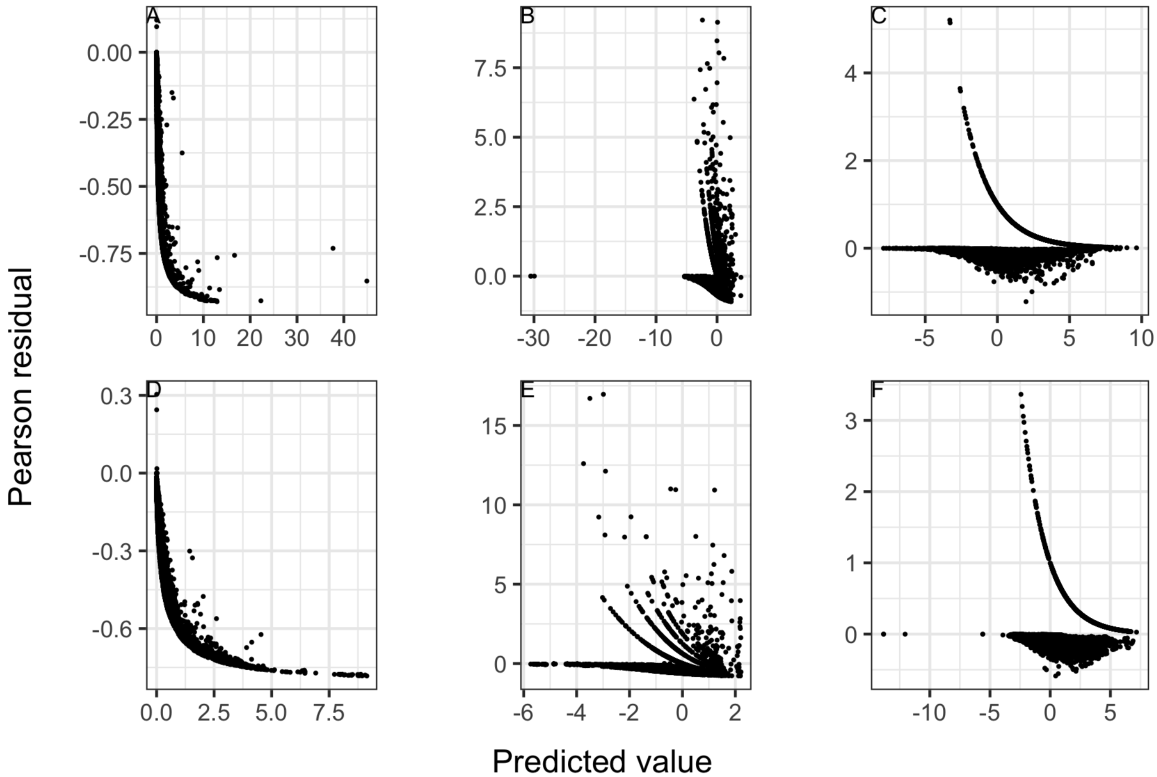


Figure S1. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR blue shark data.

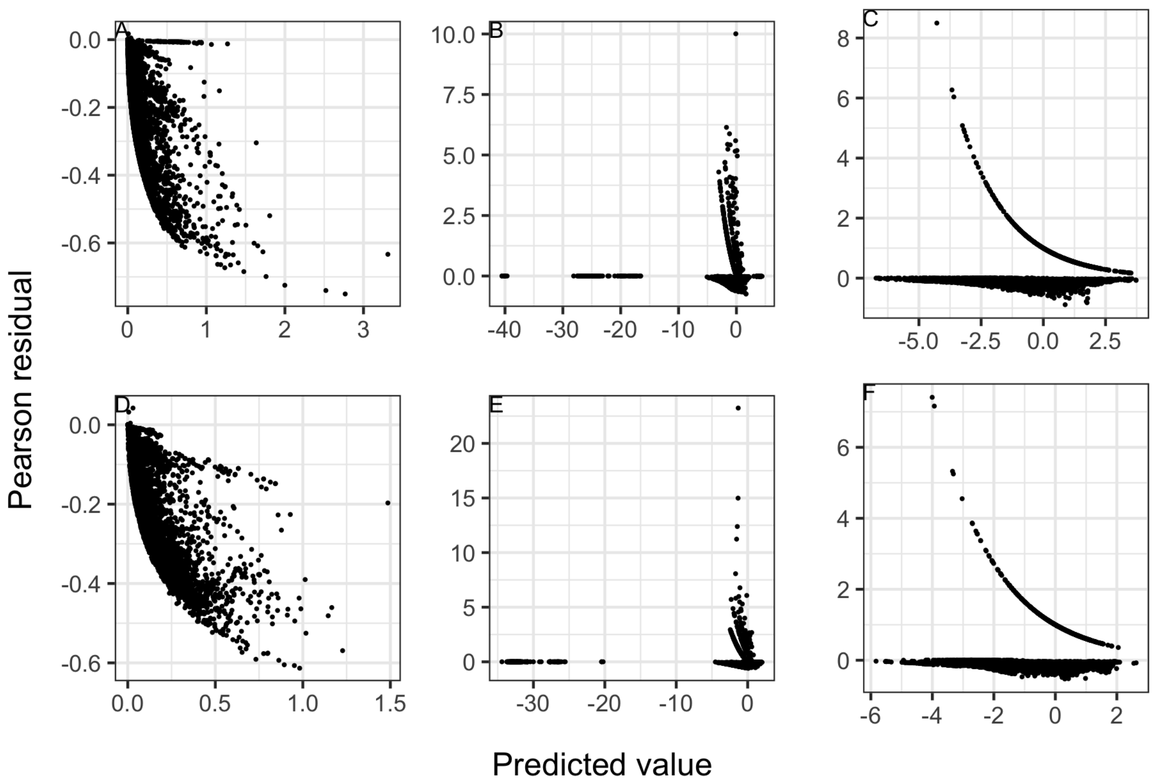


Figure S2. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR oceanic whitetip data.

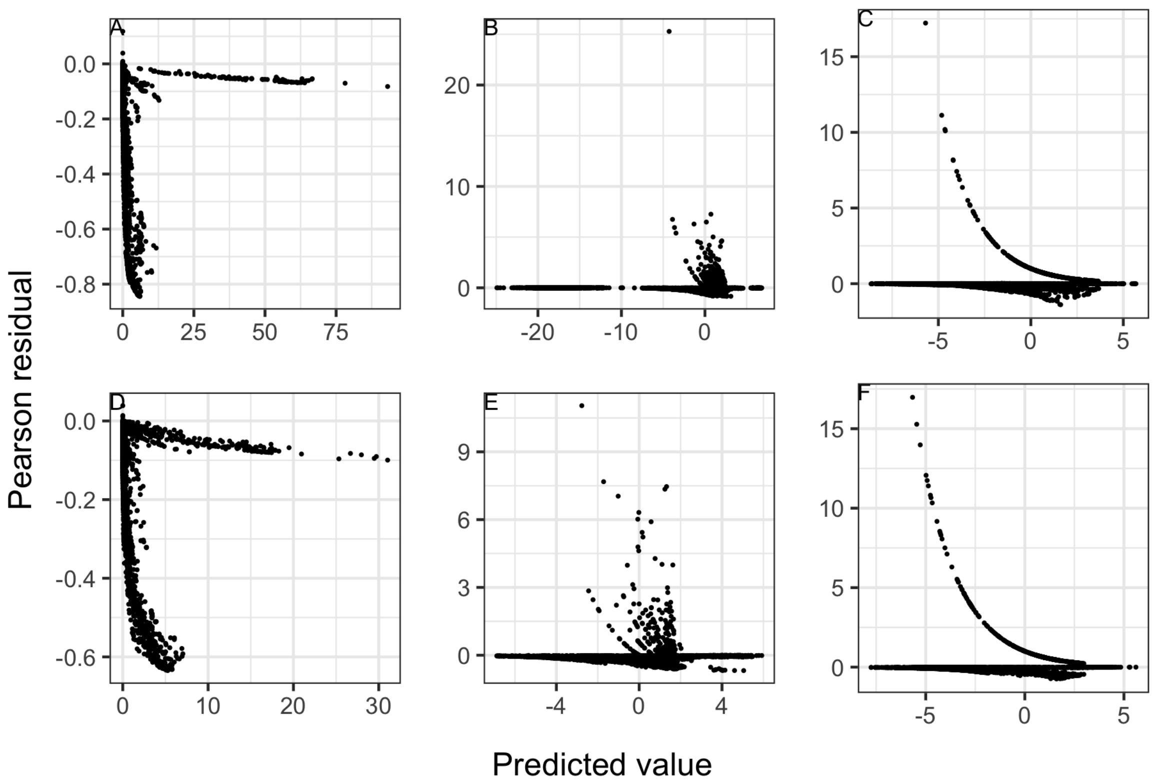


Figure S3. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR sandbar shark data.

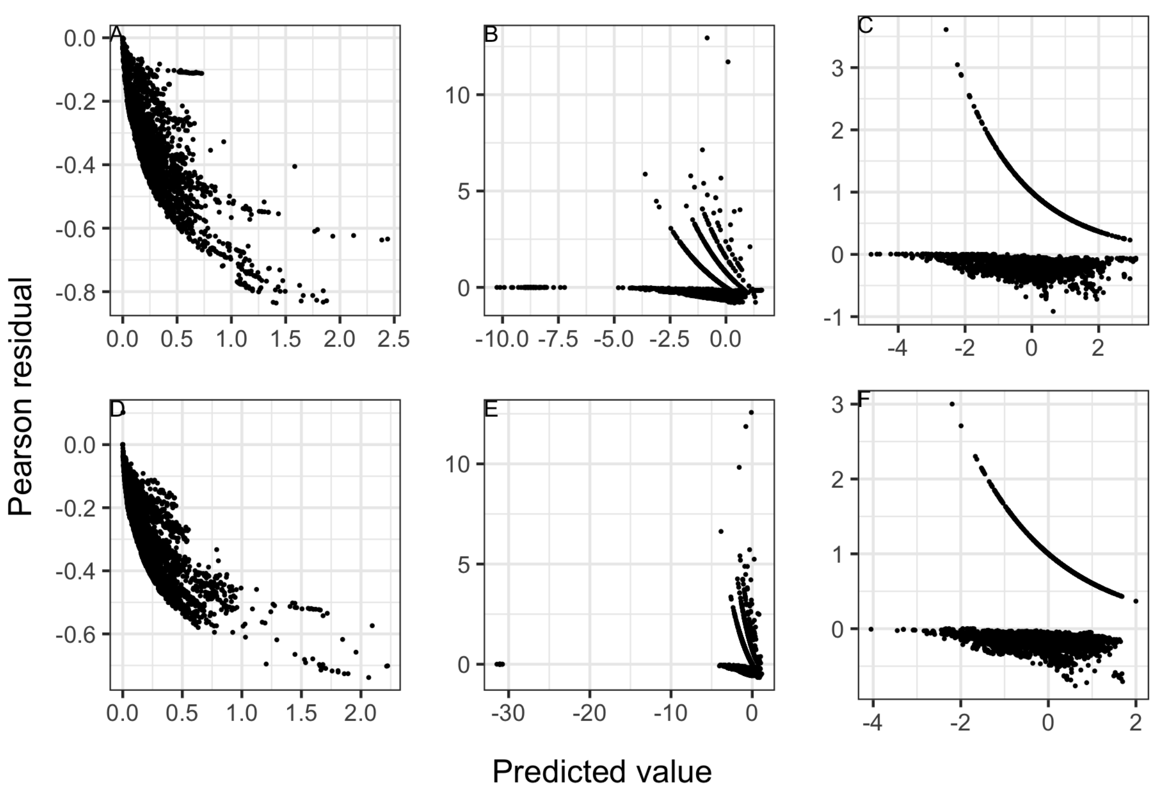


Figure S4. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR shortfin mako data.

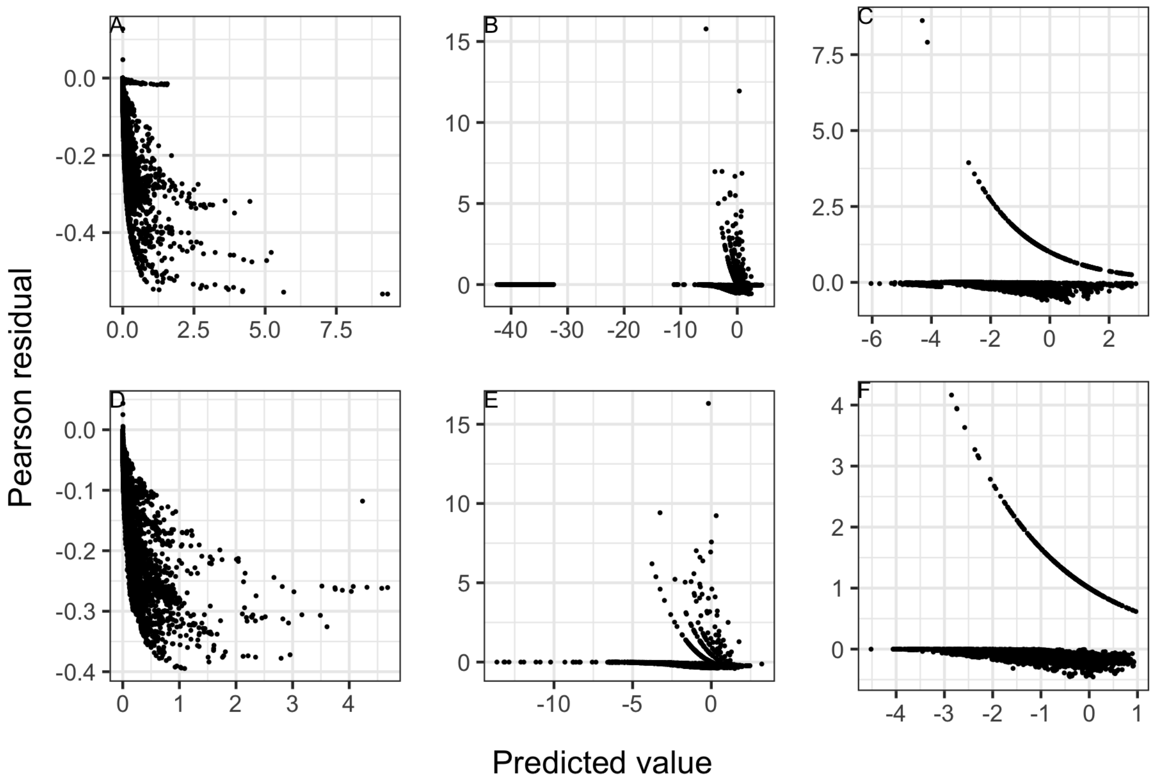


Figure S5. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR silky shark data.

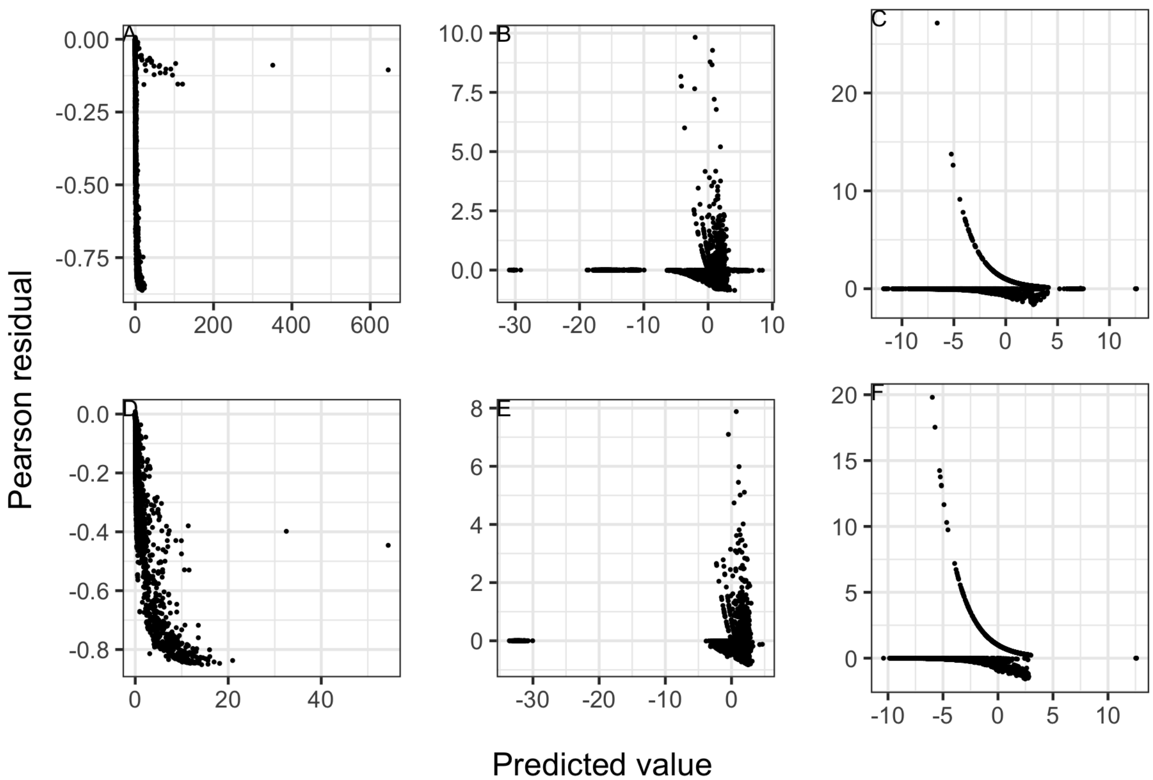


Figure S6. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR silvertip shark data.

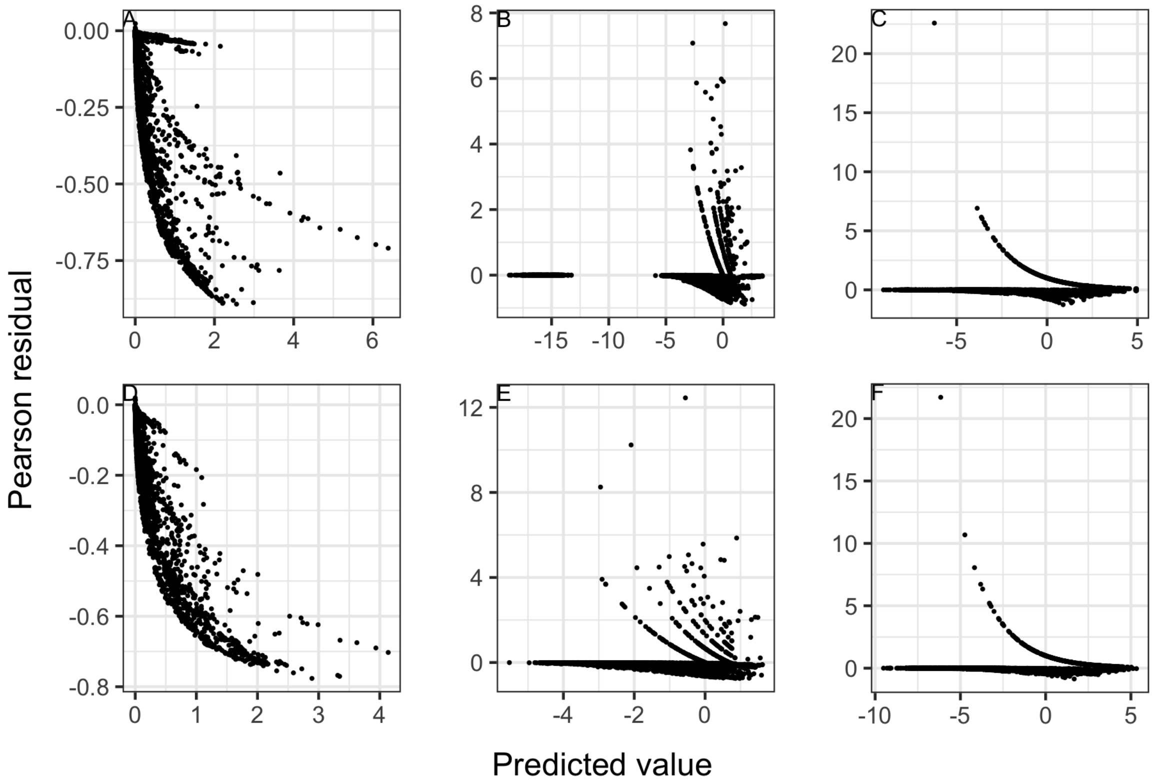


Figure S7. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR tiger shark data.

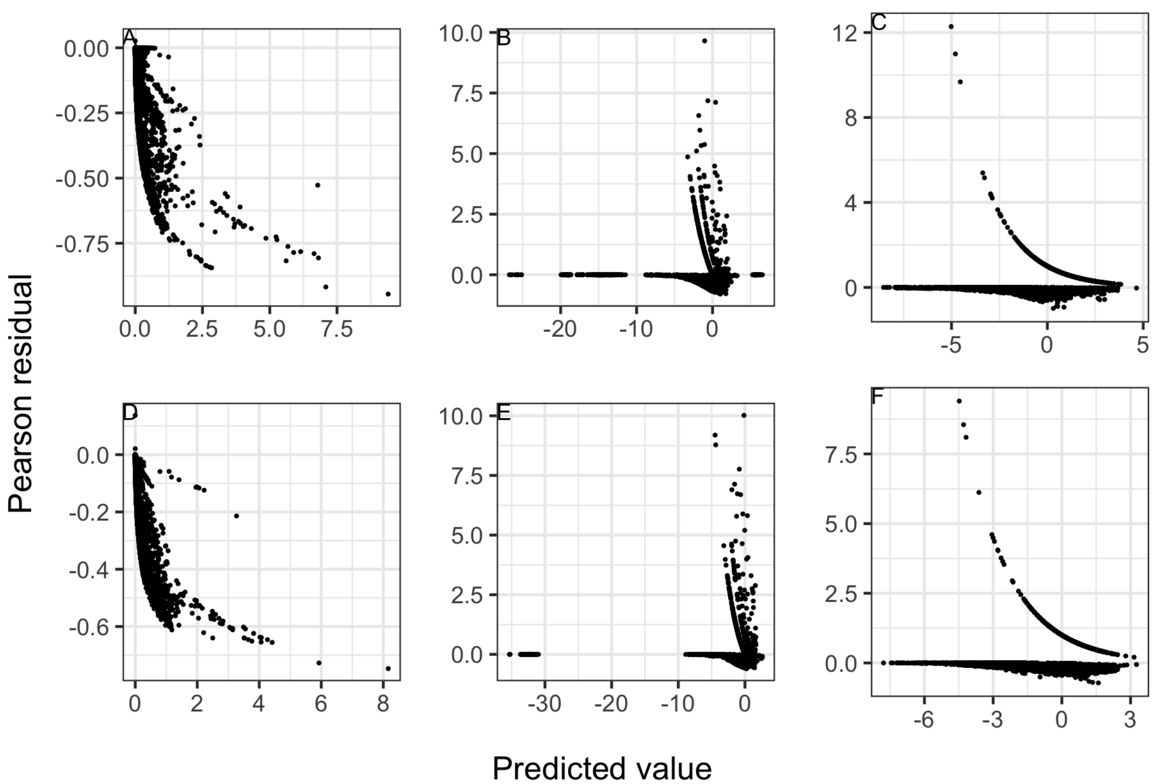


Figure S8. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR Thresher sharks data.

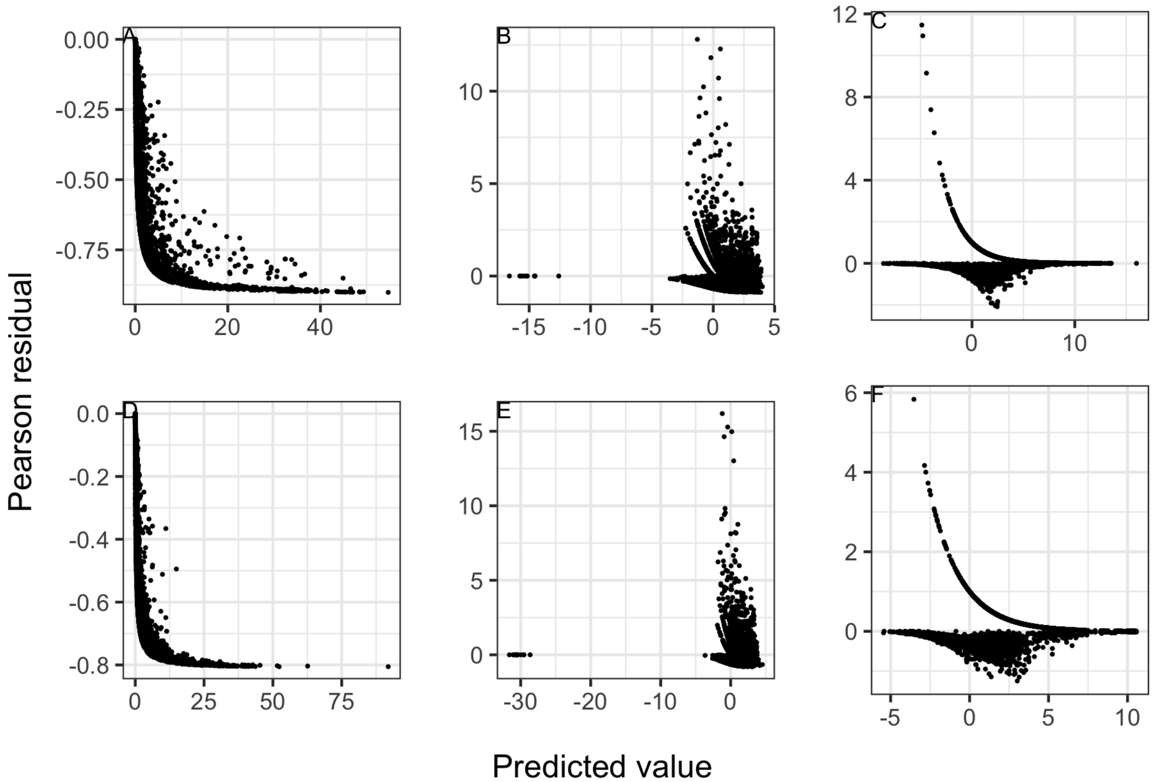


Figure S9. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR Requiem sharks data.

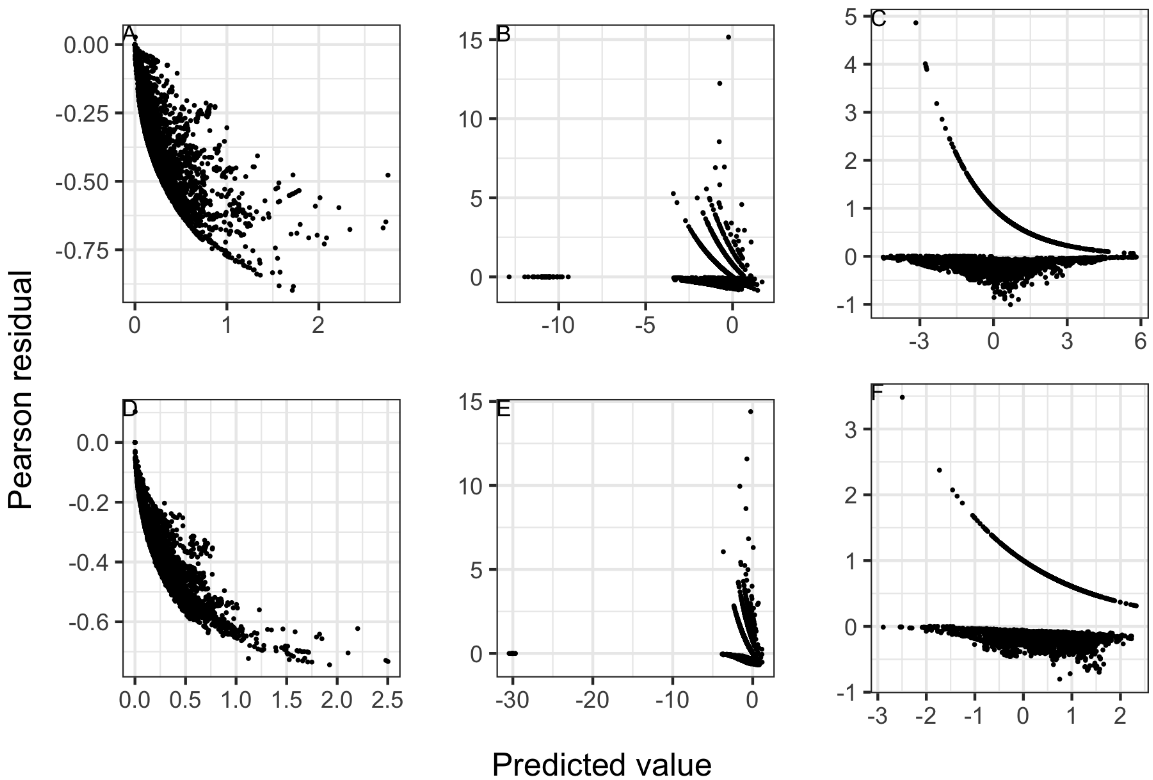


Figure S10. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR Mako sharks data.

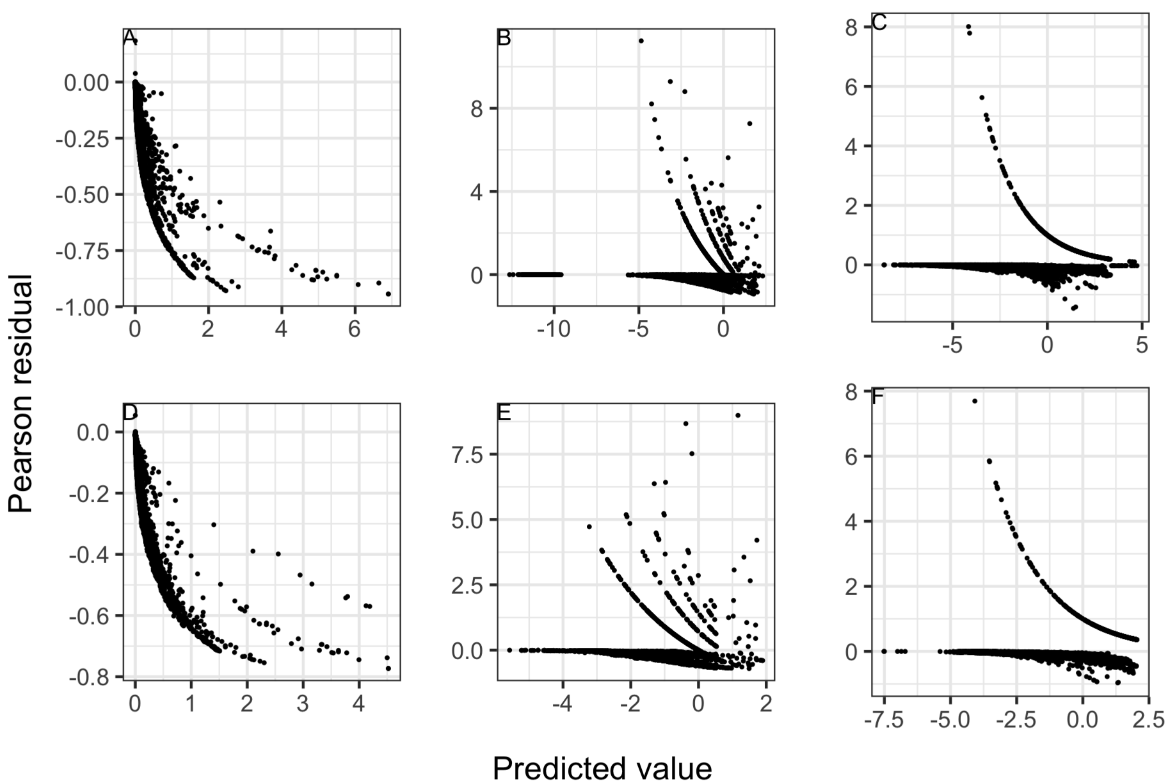


Figure S11. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, (C) the zero process with year as a factor, (D) the whole model with year as a continuous variable, (E) the count process with continuous year, and (F) the zero process with continuous year for the USSR Hammerheads data.

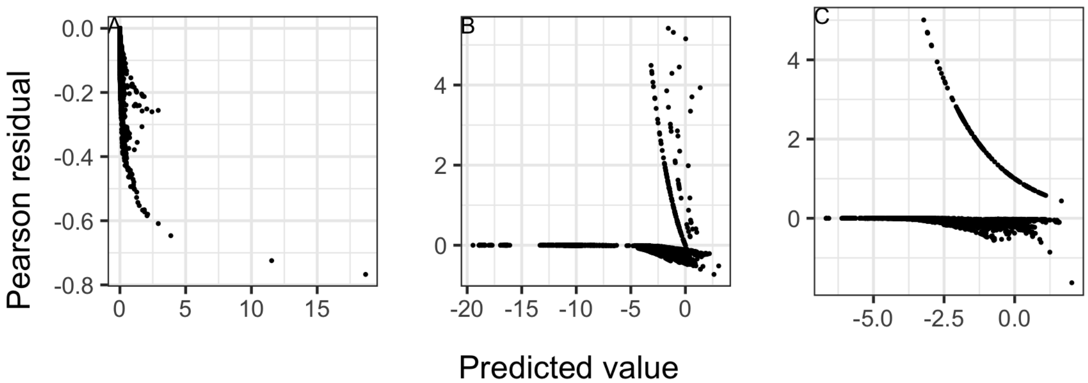


Figure S12. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR bigeye thresher data.

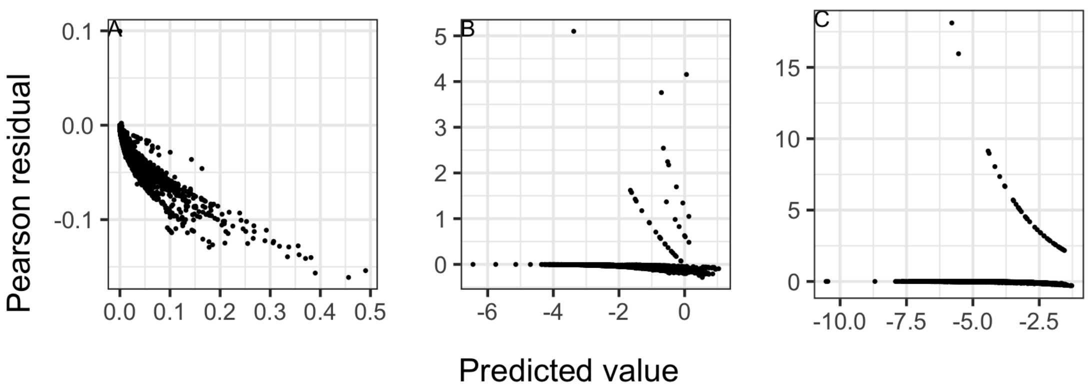


Figure S13. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR bull shark data.

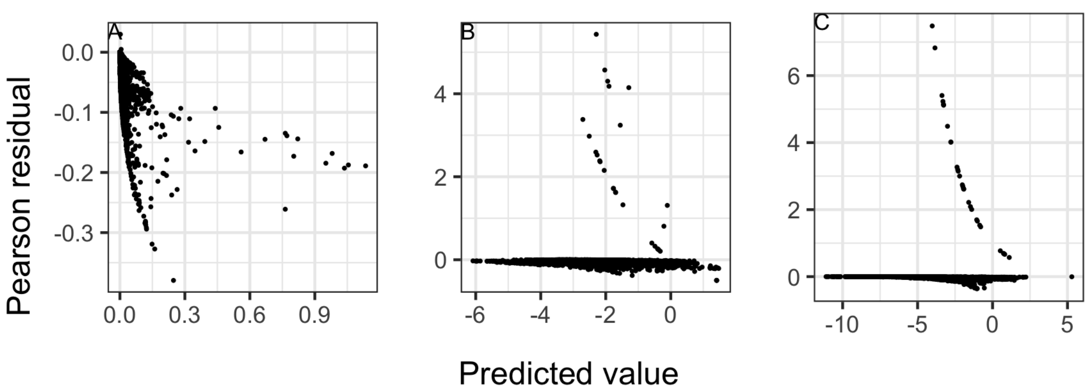


Figure S14. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR crocodile shark data.

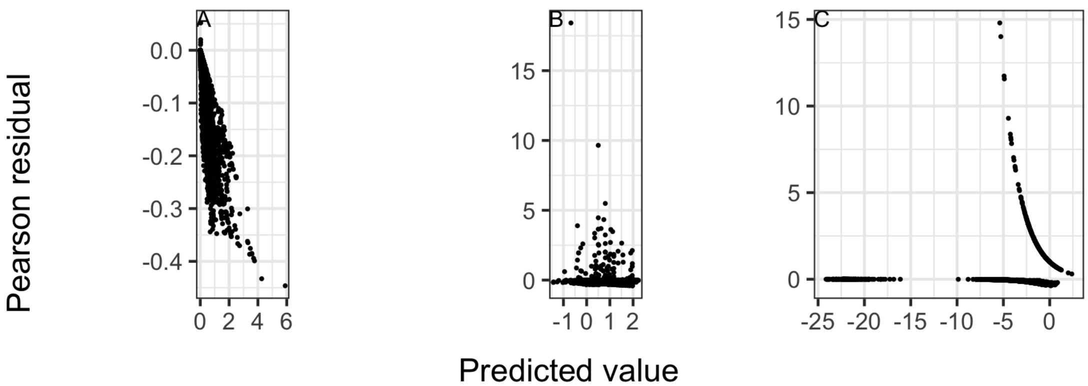


Figure S15. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR dusky shark data.

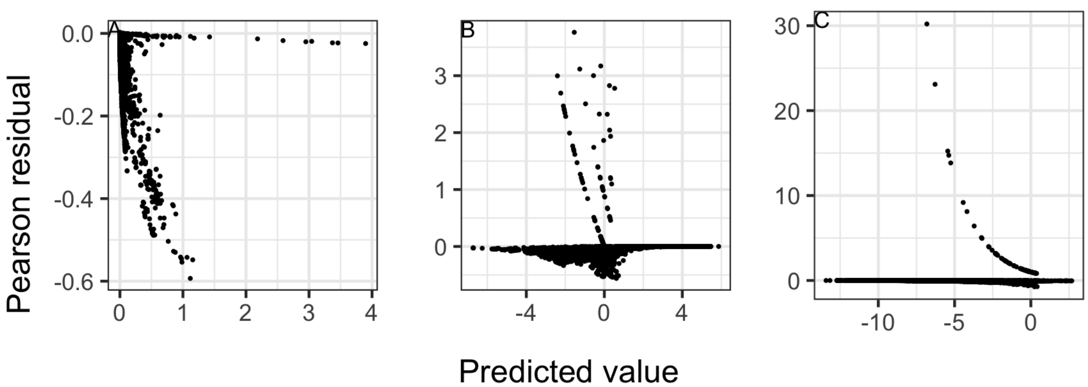


Figure S16. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR great hammerhead data.

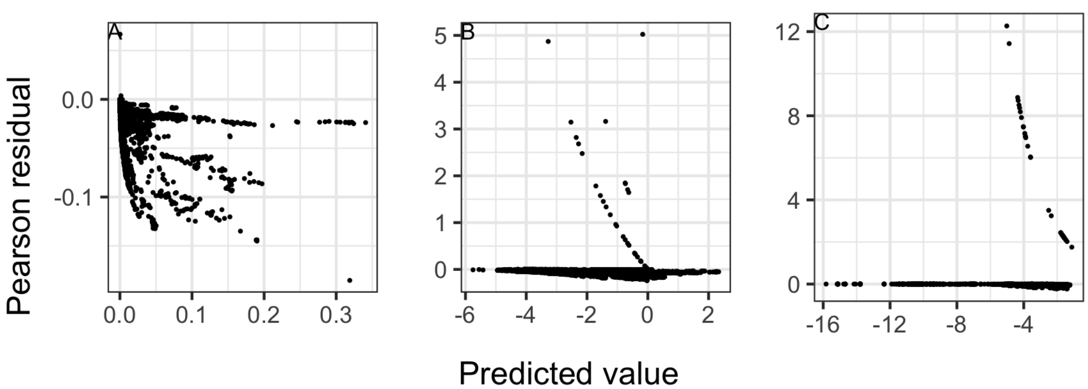


Figure S17. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR longfin mako data.

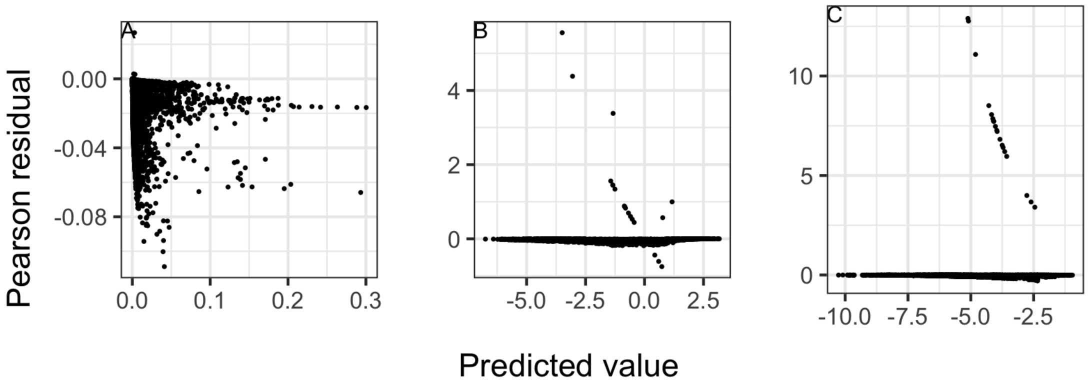


Figure S18. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR pelagic thresher data.

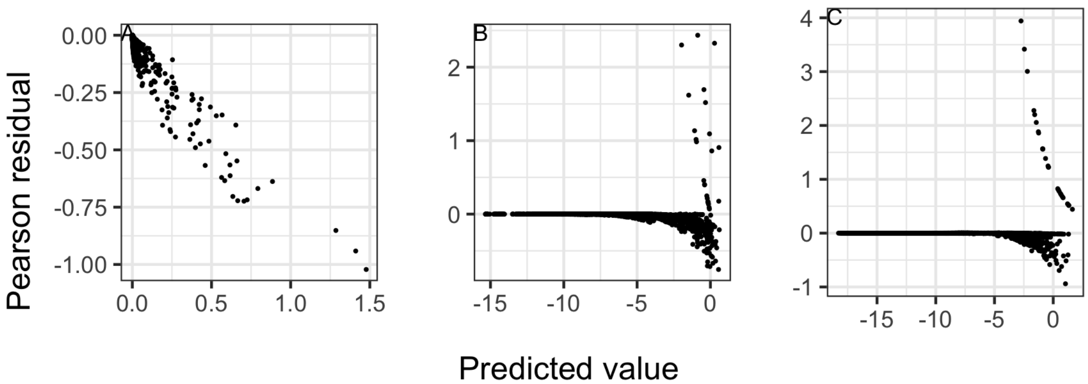


Figure S19. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR porbeagle data.

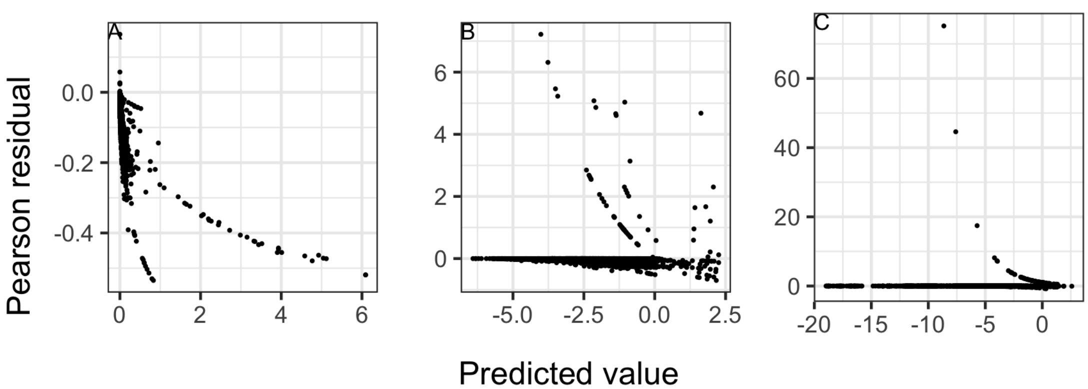


Figure S20. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR scalloped hammerhead data.

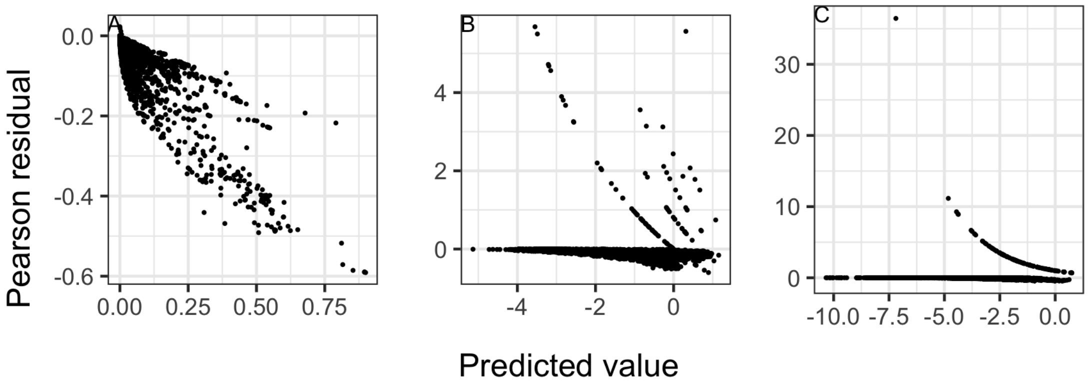


Figure S21. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR smooth hammerhead data.

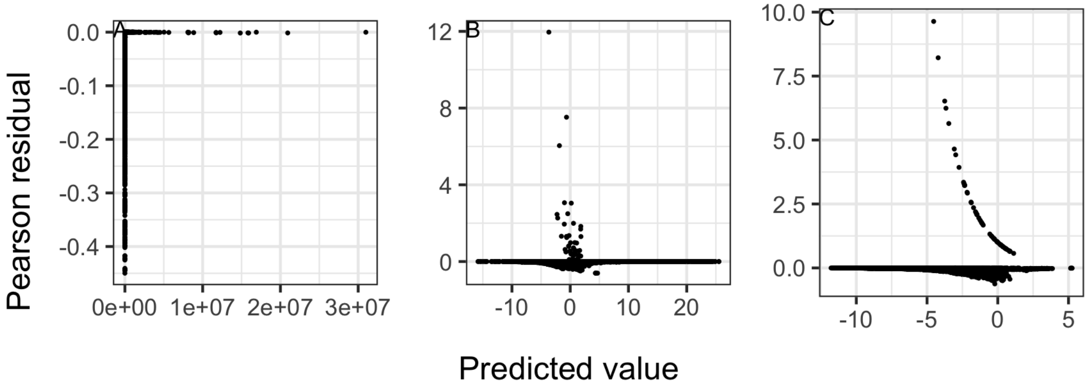


Figure S22. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR spinner shark data.

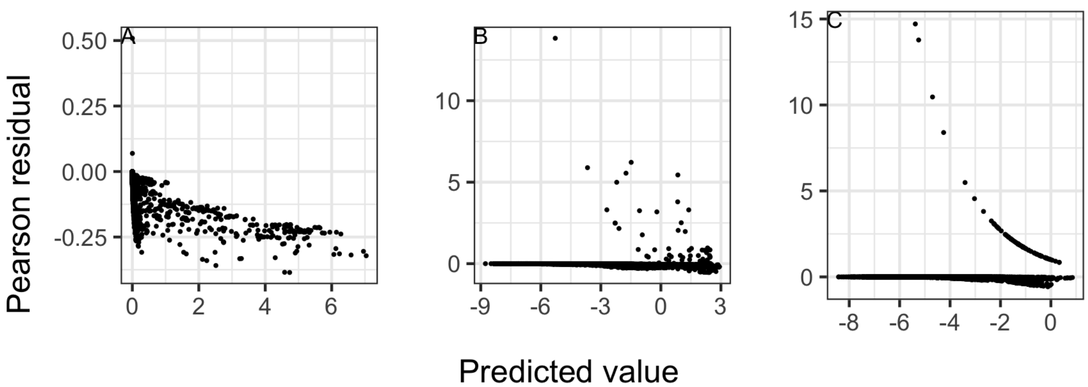
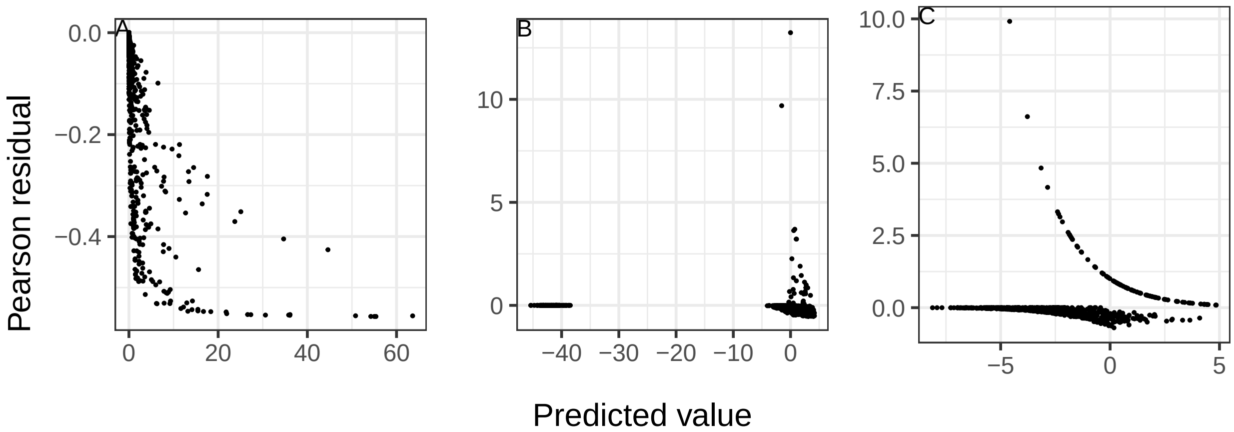


Figure S23. Residual plot for (A) the whole model with year as a continuous variable, (B) the count process with continuous year, (C) the zero process with continuous year for the USSR spot-tail shark data.



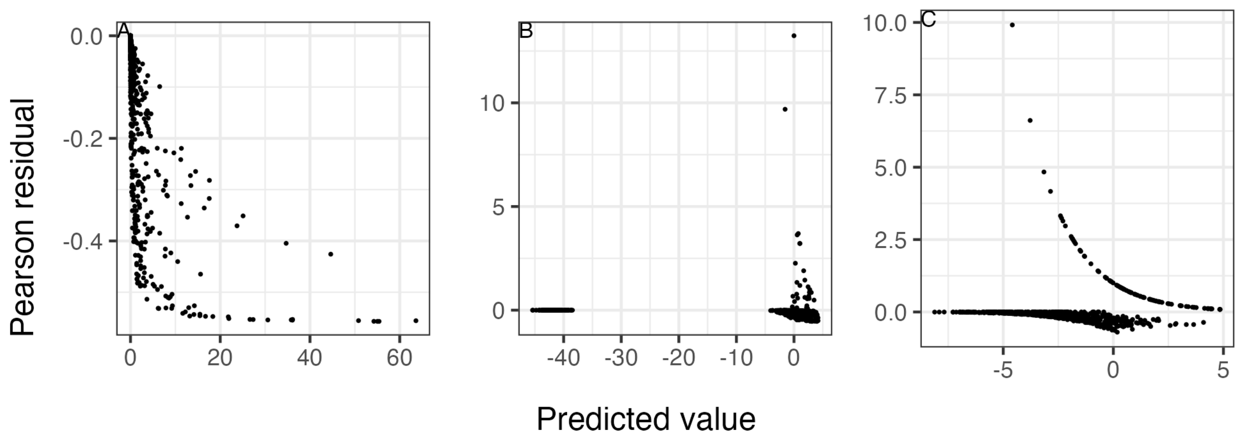
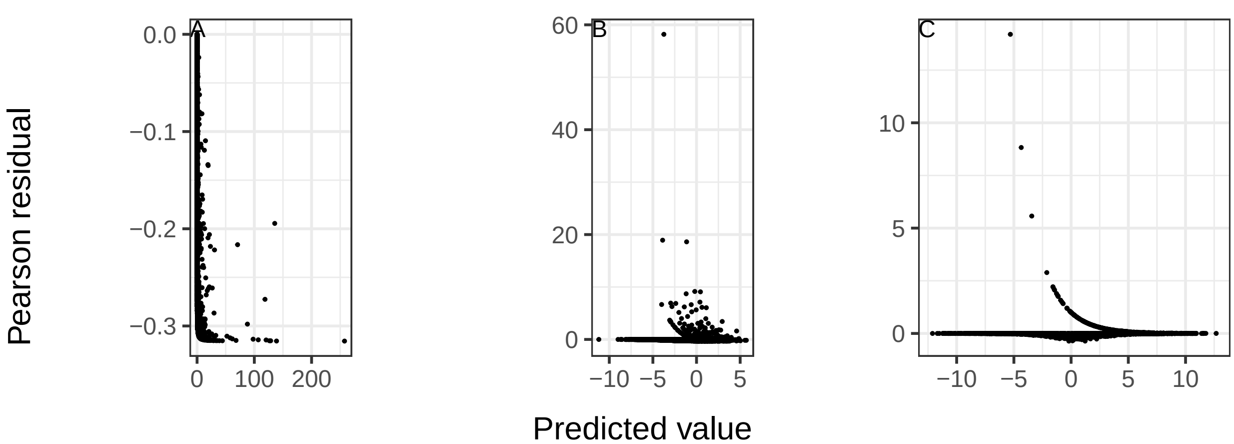


Figure S24. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, and (C) the zero process with year as a factor IOTC porbeagle data.



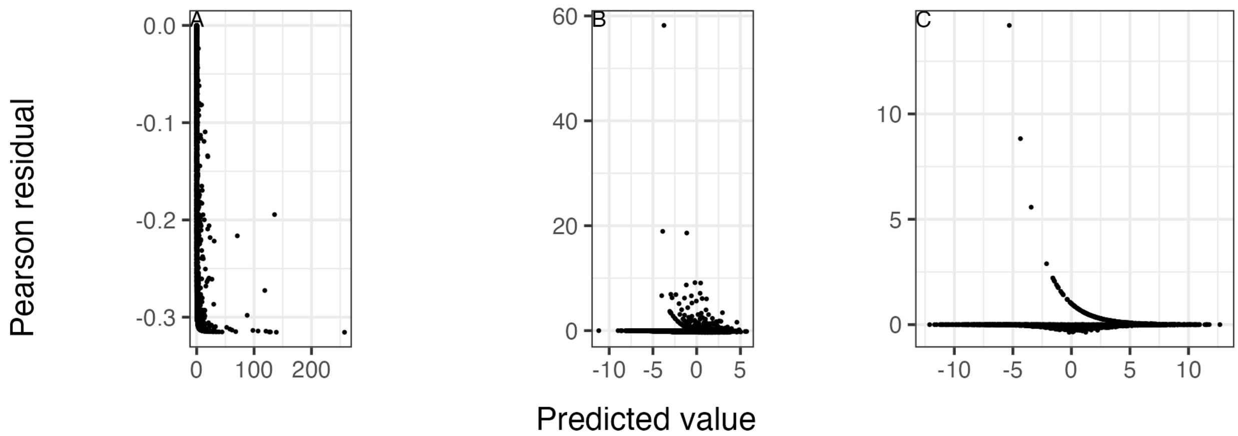


Figure S25. Residual plot for (A) the whole model with year as a factor, (B) the count process with year as a factor, and (C) the zero process with year as a factor IOTC porbeagle data.

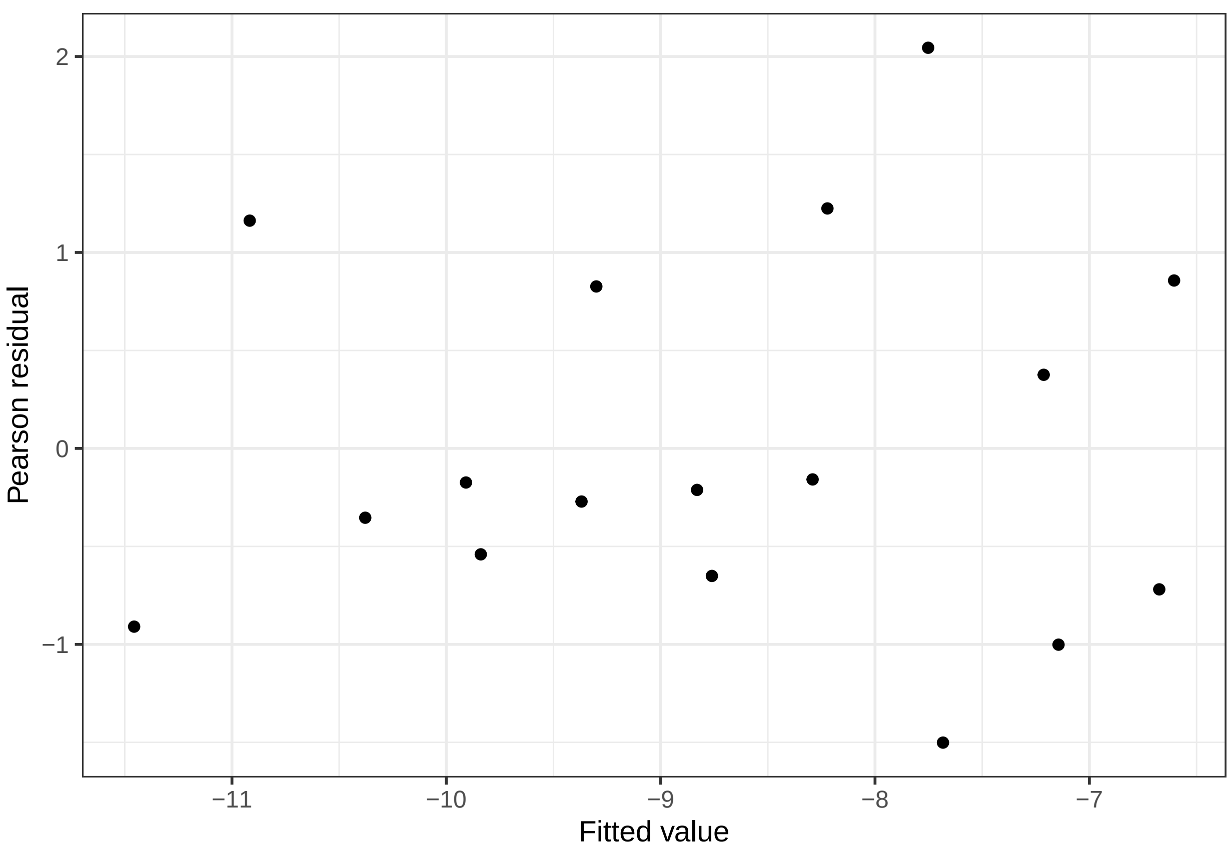


Figure S26. Residual plot for the multiple timeseries regression of the porbeagle.