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Billfish CPUE standardization in the Hawaii longline fishery: Model selection and multimodel inference

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ABSTRACT

This paper presents catch per unit effort (CPUE) standardizations and model selection procedures for four billfish species (Family Istiophoridae) caught primarily as bycatch in the Hawaii-based pelagic longline fishery during 1995–2011: Blue marlin *Makaira nigricans*; Striped marlin *Kajikia audax*; Shortbill spearfish *Tetrapturus angustirostris*; and Sailfish *Istiophorus platypterus*. The first three species were analyzed on a fishery-wide basis. For sailfish, the fishery data came exclusively from tuna-targeted longline sets in the deep-set sector of the Hawaii-based fishery. We used fishery observer data from the NOAA Fisheries Pacific Islands Regional Observer Program to fit the CPUE standardization models. In this context, our objective was to investigate the quality of model fit for five types of generalized linear models (GLMs: Poisson; negative binomial; zero-inflated Poisson; zero-inflated negative binomial; delta-Gamma). Each of these models represented a different hypothesis about the capture process for a bycatch species for which the catch data primarily consisted of zero catch observations. The five GLMs were fitted by forward entry variable selection, and the best fitting GLM for each species was selected on the basis of Akaike Information Criterion values and calculated Akaike weights. The best-fitting model selected for each species was a zero-inflated negative binomial GLM (ZINB). The ZINB model was comprised of a negative binomial counts model for expected zero catch sets and a positive catch per set distribution along with a binomial inflation model to account for excess zeros. For each species, the important explanatory variables for standardizing CPUE were fishing year, fishing (i.e., calendar) quarter, and fishing region. The best-fitting models indicated that standardized CPUE for striped and blue marlins decreased significantly during the study period. Because the ZINB model was selected as the best fitting model for all species, we suggest that longline CPUE for incidentally caught billfishes is best represented as a process characterized by zero inflation and overdispersion in the positive catches and expected zero catches. We therefore recommend that ZINB models be considered as an *a priori* model for CPUE standardizations of billfishes and other bycatch species in longline fisheries.

1. Introduction

Population status of billfishes (Class Actinopterygii; Division Teleostei; Order Perciformes; Suborder Xiphioidei; Family Istiophoridae), as with many other non-target species, is often inferred from time series of standardized catch rates because costs associated with fishery-independent surveys are prohibitive (Lynch et al., 2012). Even in this context of reliance upon fishery-dependent data, where non-random sampling, fishermen's behavior, and gear selectivity may adversely affect sample representativeness (Jennings et al., 2001), billfishes present at least three additional, potentially serious challenges. First, their migratory behaviors may not coincide with those of target species. Second, large numbers of zero catches are common (Lynch et al., 2012). Third, the external morphological similarities that have long caused taxonomic confusion among marlin species (Royce, 1957) continue to engender species misidentifications, as documented for marlins in the Hawaii-based pelagic longline fishery (Walsh et al., 2005, 2007) and spearfishes along the mid-Atlantic coast of the United States (Shivji et al., 2006).

Catch per unit effort (CPUE) standardization analyses for bycatch species caught in low numbers, such as billfishes, were reviewed by Maunder and Punt (2004). Their recommendations for standardizing such catches included use of mixture models that analyze the proportions of zeros and the positive catch rates separately (i.e., Delta distribution models) or use of zero-inflated models.

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Brodziak and Walsh (2013) presented a model selection and multimodel inference procedure (Burnham and Anderson, 2002; Zuur et al., 2009) for standardizing catch per unit of effort (CPUE) of bycatch species. The procedure was applied to standardize CPUE of oceanic whitetip shark *Carcharhinus longimanus* in the Hawaii-based pelagic longline fishery during 1995–2010. Brodziak and Walsh (2013) investigated the use of zero-inflated models and selected a zero-inflated negative binomial model (ZINB) for CPUE standardization. This zero-inflated model is comprised of a counts model that allows for overdispersion in both the zeros and positive catches and a binomial model that allows for "extra" zeros (Zuur et al., 2009, 2012; Brodziak and Walsh, 2013), with the latter defined as a higher frequency of zeros than expected under the Poisson, negative binomial, or other count distributions (Zuur et al., 2009). This paper presents a new application of the model selection and multimodel inference procedure to four billfishes caught in the Hawaii-based pelagic longline fishery during 1995–2011.

These incidentally-caught billfishes (Walsh et al., 2007) and the oceanic whitetip shark taken as bycatch (Brodziak and Walsh, 2013) had similarly high proportions of zero catches, but differed in productivity and resilience. Further, the ecology, life histories, behavior, and distributions of the billfishes (Royce, 1957; Strasburg, 1970; Nakamura, 2001; Kitchell et al., 2006) are far better known than those of the oceanic whitetip shark, a species that has never been thoroughly studied despite its formerly high level of abundance (Strasburg, 1958; Bonfil et al., 2008). Thus, it was possible to test a larger suite of explanatory variables in the CPUE standardization models than had been possible for the oceanic whitetip shark. Catch and operational data from Hawaii longline fishery observers for blue marlin *Makaira nigricans*, striped marlin *Kajikia audax*, and shortbill spearfish *Tetrapturus angustirostris* on a fishery-wide basis and sailfish *Istiophorus platypterus* from the deep-set (i.e., tuna-targeted) sector were used in the analyses.

Our analytical objective was to standardize CPUE using five types of GLMs (see below) for each billfish species and then apply model selection and multimodel inference procedures to identify the best-fitting GLM. We were particularly interested in determining whether the ZINB model previously selected for oceanic whitetip shark would also be selected for any of these incidentally caught billfishes.

The primary impetus for this research was generated by studies of the population status of the two marlin species in the fishing grounds exploited by the Hawaiian pelagic longline fishery. A recent stock assessment for striped marlin in the western and central North Pacific Ocean for 1975–2010 concluded that this species is overfished and subject to overfishing (Lee et al., 2012a). A second stock assessment for blue marlin concluded that this species is neither overfished nor subject to overfishing, but the stock is nearly fully exploited and stock biomass underwent a period of decline that began in the mid-1970s and continued for about three decades until stabilizing about 10 years ago (Lee et al., 2012b). Finally, knowledge about the relative abundance of shortbill spearfish is limited, other than a recent analysis presented by Gilman et al. (2012), and there is no information about sailfish population status in this fishery. This paper presents new information about billfish catch rates and abundance trends in the Hawaii-based pelagic longline fishery in 1995–2011 and also contributes to the understanding of catch rate standardization with incidentally caught billfishes.

2. Methods

2.1. Fishery description

The Hawaii-based longline fishery is managed in two fishing sectors, defined as deep-set (≥15 hooks per float) and shallow-set longline operations (<15 hooks per float). The target species for the deep-set sector is usually bigeye tuna *Thunnus obesus* while the shallow-set sector predominantly targets swordfish *Xiphias gladius*. Deep sets are generally deployed around dawn and hauled in near dusk; shallow sets are generally deployed after dusk, use about half as many hooks as deep sets, and are hauled in around dawn. For the last decade, shallow-set activity has been concentrated at relatively high latitudes (ca. 30°N) in the first and fourth quarters (Walsh et al., 2009). Deep-set activity extends southward to waters near the equator with considerable fishing activity throughout the year. Gilman et al. (2012) provide a detailed description of the deep-set fishery sector.

2.2. Data sources

Fishery observers from the Pacific Islands Regional Observer Program (PIROP) recorded species-specific catch tallies and operational descriptors (e.g., geographic position, number of hooks deployed, set and haul times) according to protocols in a field manual (Pacific Islands Regional Office, 2009). This catch and operational data set was used by Brodziak and Walsh (2013), but with 2011 fishery observer data added to make a 17-year time series (N = 51,515 observed longline sets). We used fishery observer data to avoid problems with species misidentifications that complicate use of logbook data.

Two environmental predictors and fishing vessel size were evaluated as possible continuous explanatory variables in the analyses; these were sea surface temperature and the Multivariate El Niño/Southern Oscillation Index. Sea surface temperature (SST°C) data were weekly mean values measured by an advanced, very high resolution radiometer borne by a NOAA satellite (Walsh et al., 2007). Numerical values of the Multivariate El Niño/Southern Oscillation Index (MEI) were obtained from the NOAA Earth System Research Laboratory Physical Sciences Division (http://www.esrl.noaa.gov/psd/enso/mei/). The sizes of fishing vessels (hull length, feet) were obtained from the NOAA Fisheries Office of Science and Technology (http://www.st.nmfs.noaa.gov/st1/CoastGuard/VesselByName.html).

2.3. CPUE standardizations

Five distributional assumptions for billfish CPUE standardization were investigated. These included distributions that could exhibit overdispersion and underdispersion, as well as zero-inflation. The five distributions were: delta-Gamma; Poisson; negative binomial; zero-inflated Poisson; zero-inflated negative binomial (ZINB). Full details of GLM fitting procedures and the theory underlying these models are presented in Brodziak and Walsh (2013). Details of model structure, including the probability function, expected value, variance, and the variance to mean ratio are compared in Table 1.

The models were fitted by step-wise variable selection, beginning with the factor variables, followed by the continuous variables, interactions between factors, and interactions between factors and continuous variables. Factor variables tested for inclusion were the 17 fishing years, four calendar quarters, two set types, eight fishing regions (Region 1: 0–10°N, east of 160°W; Region 2: 0–10°N, west of 160°W; Region 3:10–20°N, east of 160°W; Region 4: 10–20°N, west of 160°W; Region 5:20–30°N, east of 160°W; Region 6:20–30°N, west of 160°W; Region 7: above 30°N, east of 160°W; Region 8: above 30°N, west of 160°W) six bait types, three leader materials, and four hook types (See Chapter 6 of the Hawaii Longline Observer Manual for descriptions of bait types, hook types and leader materials). Continuous variables tested were the SST, the MEI, the begin-set time (HST), the illuminated fraction of the face of the moon, and the soak duration. Year–quarter, year–region, quarter–region, set type–hooks per float, set type–vessel length,

Table 1
Probability models and hypotheses about the capture probability of catch (C) for CPUE standardization, including the probability mass or density function for catch, the hypothesis about catch rates, and the variance to mean ratio (*VMR*) for the Poisson, negative binomial, zero-inflated Poisson, zero-inflated negative binomial, and delta-gamma distributions, where π is the probability of an extra zero catch per set, p is the probability of a positive catch per set, and μ, k and λ are parameters.

Probability model	Probability Function	Hypothesis	Variance to mean ratio
Poisson	$Pr(C=c)=\mu^c \times \exp(-\mu)/c!$	Catch rates are neither overdispersed or underdispersed	1
Negative Binomial	$\Pr(C=c)=\left((c+k)!/k!(c+1)!\right)\left(k/k+\mu\right)^k\left(\mu/k+\mu\right)^c$	Catch rates are overdispersed	$1+\mu/k$
Zero-inflated Poisson	$Pr(C=0)=\pi+(1-\pi)\exp(-\mu)$ $Pr(C=c\vert c>0)=(1-\pi)\left(\mu^c \times \exp(-\mu)/c!\right)$	Catch rates are overdispersed	$1+\pi\mu$
Zero-inflated negative binomial	$Pr(C=0)=\pi+(1-\pi)\left(k/k+\mu\right)^k$ $Pr(C=c\vert c>0)=(1-\pi)\left((c+k)!/k!(c+1)!\right)\left(k/k+\mu\right)^k\left(\mu/k+\mu\right)^c$	Catch rates are overdispersed	$1+\left(\mu/k\right)+\left(\mu\pi(1+\pi)/(1-\pi)\right)$
Delta-Gamma	$Pr(C=0)=1-p$ $Pr(C=c\vert c>0)=p\times\left(\lambda^k c^{k-1}\times\exp(-\lambda c)/\Gamma(k)\right)$	Catch rates are either overdispersed or underdispersed	p/λ

and year–MEI interactions were also tested, but we found that all GLMs with year-region interactions did not numerically converge. For this reason, year-region interactions do not appear in the results.

The reductions in the residual deviance (if available), Akaike Information Criterion (AIC), or both were calculated after each entry. Chi-squared tests were computed at each entry stage to evaluate the statistical significance of explanatory variables.

Our analytical approach was to test specific hypotheses to include only significant and informative explanatory variables in the standardization models. Because temporal trends were of primary interest, yearly and quarterly effects were the initial entries. Spatial effects were expected to be important so the fishing regions were then entered. The set types were then tested because these represent the basis for management of this fishery. The bait types, hook types, and leader materials were then tested as factor variables because recently published studies (Curran and Bigelow, 2011; Gilman et al., 2012) reported that catch rates for several fishes varied significantly by hook types. The sea surface temperature (SST) was expected to exert strong effects as a continuous variable (Walsh et al., 2005, 2007; Su et al., 2008), so it was tested as a linear, parabolic, or polynomial term as an index of habitat suitability. The MEI was tested because the deepening of the thermocline during El Niño events may affect the catchability of ordinarily surface-associated species with longline gear (Su et al., 2008). The begin-set time was tested to indicate whether gear deployment had proceeded normally. The interaction between the set types and the number of hooks per float was tested because use of many hooks per float on deep sets would be expected to sink the longline gear beneath the habitat of surface-associated species. The interaction between the set types and vessel length was tested because large vessels in the deep- and shallow-set sectors may fish in equatorial waters and in the North Pacific transition zone, respectively, whereas smaller vessels may be incapable of such long trips. An intercept for the zero inflation model was included at every fitting stage with the zero inflated models; e.g., the null zero-inflated Poisson model included two intercepts.

The sample size of observed longline sets during 1995–2011 was relatively large ($N = 51{,}515$). As a result, some explanatory variables were expected to be statistically significant but of little practical importance. In an attempt to minimize this concern, we required that an explanatory variable yield a reduction of at least 5 AIC units per degree of freedom to be retained in a fitted GLM. Some numerical convergence problems had also been encountered during preliminary attempts to fit models with numerous predictors, particularly interactions. Although chosen arbitrarily, use of this value (5 AIC units/df) generally sufficed to eliminate lack of convergence and the signs and magnitudes of coefficients in fitted models seemed reasonable.

Each longline set was considered to be an independent fishing operation, as in Brodziak and Walsh (2013). We took this approach because within-trip relationships among the individual sets might exert positive, negative, or indirect effects. Examples of negative or positive effects included movements away from areas with low catches of target species but high catches of bycatch species or vice versa. Indirect effects included private at-sea communications among cooperating vessels leading to ensuing movements to higher catch rate areas. Overall, using this approach may underestimate the uncertainty about standardized billfish CPUE of vessels for which within-trip catch correlations were important and lead to selection of overly complex models.

2.4. Model selection

The model selection procedures were based upon use of the Akaike Information Criterion (AIC) and AIC weights as described in Brodziak and Walsh (2013). The fit of each model was evaluated on the basis of its AIC, residual deviance and *pseudo*-coefficient of determination (*pseudo*-R^2) if available, as well as residual patterns.

2.5. Computations

All GLM computations were performed in R Version 2.14.1 for Windows or R Version 2.10.0 or 2.15 for Linux (R Development Core Team, 2008). The significance criterion for statistical tests was $P < 0.05$. The zero-inflated and negative binomial models were computed with the “pscl” and “MASS” libraries, respectively.

Unique indices of relative abundance were computed by applying the “predict” function provided by the R software to the selected GLMs. Some of the best-fitting GLMs to standardize CPUE included an interaction term between the year and quarter factors. In this case, standardized annual CPUE in a given year Y (CPUE_Y) was computed using an effort-weighted average of the standardized CPUE estimates by year and quarter ($\mathrm{CPUE}_{Y,Q}$) as $\mathrm{CPUE}_Y = \sum_Q p_{Y,Q} \times \mathrm{CPUE}_{Y,Q}$ where $p_{Y,Q}$ was the annual proportion of longline sets that captured the species of interest in quarter Q.

3. Results

3.1. Descriptive catch statistics

PIROP fishery observers recorded catch and operational data at sea during 3824 trips by 183 Hawaii-based commercial longline vessels that deployed over 94 million hooks in 1995–2011 (Table 2).

Table 2
Summary of observed fishing effort in the Hawaii-based pelagic longline fishery during 1995–2011. Results are pooled and also presented by fishery sectors. Operational parameters are means (upper entries) and standard deviations (lower parenthetical entries).

Sector	Vessels	Trips	Sets	Total hooks	Hooks per set	Hooks per float	Mean latitude	Mean longitude
Both	183	3824	51,515	94,394,621	–	–	–	–
Deep	175	3125	39,885	84,013,461	2,106.4 (402.1)	26.6 (3.1)	20.8°N (5.9°)	158.3°W (5.9°)
Shallow	74	706	11,630	10,381,160	892.6 (170.2)	4.5 (0.8)	30.1°N (3.8°)	157.7°W (8.3°)

Striped marlin (Table 3) had the highest values of mean catch per set, nominal CPUE, percentage of sets with positive catches, percentage of sets with multiple catches, and variance:mean ratio, as well as the lowest percentage of zero catches among the four billfishes. Over half (51%) of the positive catch sets yielded more than one striped marlin, and a few (0.6%) yielded relatively large catches (10–35 fish) that comprised 9% of the total striped marlin catch. The corresponding shortbill spearfish values approached those of striped marlin. Over half (54%) of the positive catches consisted of one shortbill spearfish, but a very small fraction of the sets (0.3%) yielded relatively large catches (10–25 fish) that comprised 5% of the total catch. Blue marlin had higher percentages of both zero catches (74%) and single catches (72%) among the positive catch sets. Twelve sets took 10–15 blue marlin that comprised 1% of the catch. Sailfish were caught far less frequently than the other species, with 98% zero catches.

The frequencies of incidental billfish catches differed between the fishery sectors. In the deep-set sector, 32.5% of all sets yielded zero billfish catches and 23.1% yielded one billfish, but 6.8% yielded multiple catches of both striped marlin and shortbill spearfish. In the shallow-set sector, however, 67.9% of all sets yielded zero billfish catches, 15.6% yielded one billfish, and 0.8% yielded multiple catches of both striped marlin and shortbill spearfish. Overall, the frequency of zero-catch sets was in the shallow-set sector was approximately twice that in the deep-set sector.

3.2. Spatial and seasonal catch distributions

Spatial patterns of billfish catches varied by quarter and by fishery sector. An overview of the distributions of quarterly billfish and target species catches in 2007–2011 shows the typical patterns of variation (Fig. 1). In the deep-set sector (Fig. 1a), striped marlin and shortbill spearfish were similarly distributed, with most caught in Regions 3–6 during the first, second, and fourth quarters (striped marlin: 88%; shortbill spearfish: 89%). Blue marlin were caught in substantial numbers in Region 4 year-round (48% of the deep-set total catch), with an additional 19% of the deep-set blue marlin catch taken in Regions 3 and 5 during the third and fourth quarters. Most (55%) sailfish were caught in Regions 4 and 5 in the second, third, and fourth quarters. Bigeye tuna, the target species, comprised 18.5% of the total observed deep-set sector catch, whereas the billfishes comprised 4.4%.

There were marked differences in observed billfish catch rates by species and by fishery sector. Most (77%) of the observed longline sets were in the deep-set sector, so the blue and striped marlin catches were greater than those in the shallow-set sector, but their nominal CPUE values were greater in the shallow-set sector (striped marlin: deep-set = 0.48/1000 hooks; shallow-set = 0.62/1000 hooks; blue marlin: deep-set = 0.13/1000 hooks; shallow-set = 0.18/1000 hooks). Shortbill spearfish differed, with a nominal deep-set sector CPUE that exceeded the shallow-set sector mean by more than 3-fold (deep-set = 0.41/1000 hooks; shallow-set = 0.12/1000 hooks). In the shallow-set sector (Fig. 1b), the incidental catch of bigeye tuna exceeded that of billfishes by 46%, with almost half (49%) of these bigeye tuna taken in Regions 6 and 7 during the first quarter. Swordfish and the billfishes comprised 34.2% and 2.4% of the total observed catch in the shallow-set sector, respectively.

Table 3
Summary of incidental billfish catches in the Hawaii-based pelagic longline fishery during 1995–2011. Catch per set and nominal CPUE values are sample means and standard deviations (parenthetical entries). Blue marlin, striped marlin, and shortbill spearfish results are presented fishery-wide and by fishery sectors; sailfish results are from the deep-set sector only.

Fishery statistics: Fishery-wide and by fishery sectors (PIROP observer data)		Species			
		Blue marlin	Striped marlin	Shortbill spearfish	Sailfish
Catch	Both	12,403	45,567	34,685	930
	Deep-set	10,594	39,148	33,456	930
	Shallow-set	1809	6419	1229	–
Catch per set	Both	0.241 (0.679)	0.885 (1.747)	0.673 (1.395)	0.023 (0.177)
	Deep-set	0.266 (0.682)	0.982 (1.827)	0.839 (1.528)	
	Shallow-set	0.156 (0.662)	0.552 (0.387)	0.106 (0.447)	
Nominal CPUE	Both	0.145 (0.498)	0.514 (1.099)	0.345 (0.730)	0.011 (0.085)
	Deep-set	0.134 (0.376)	0.482 (0.919)	0.411 (0.766)	
	Shallow-set	0.183 (0.782)	0.622 (1.561)	0.120 (0.531)	
Sets with zero catches	Both	83.6%	62.4%	67.0%	98.0%
	Deep-set	81.4%	58.9%	59.7%	
	Shallow-set	90.9%	74.1%	92.1%	
Sets with positive catches	Both	16.4%	37.6%	33.0%	2.0%
	Deep-set	18.6%	41.1%	40.3%	
	Shallow-set	9.1%	25.9%	7.9%	
Sets with multiple catches	Both	4.6%	19.3%	15.0%	0.3%
	Deep-set	5.1%	21.6%	19.0%	
	Shallow-set	3.0%	11.7%	1.6%	
Variance: mean (catch per set)	Both	1.92:1	3.45:1	2.89:1	1.34:1
	Deep-set	1.75:1	3.40:1	2.78:1	
	Shallow-set	2.82:1	3.49:1	1.89:1	

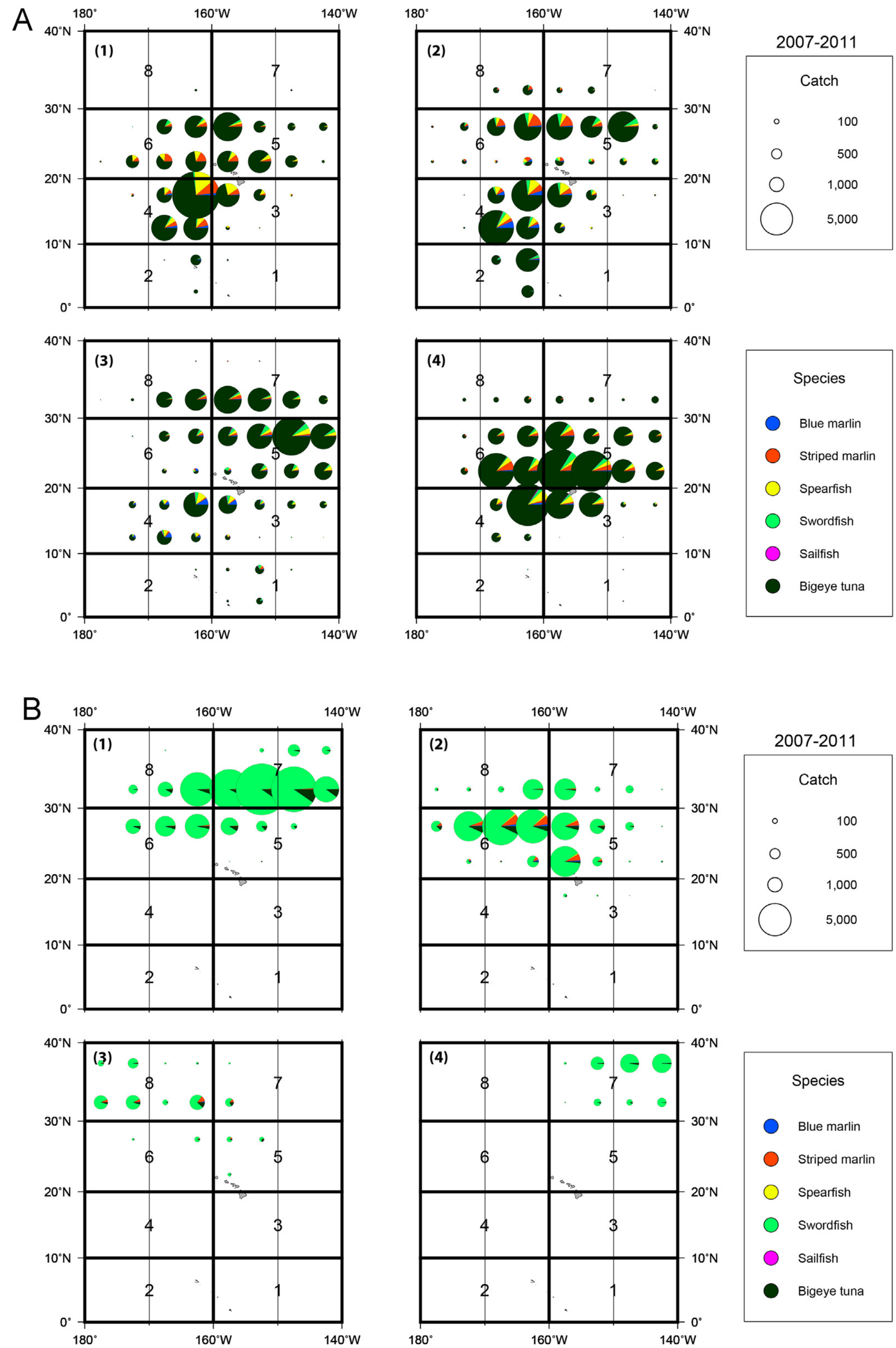

Fig. 1. Incidental catches of billfishes and swordfish *Xiphias gladius* as well as target species bigeye tuna *Thunnus obesus* catches, and incidental catches of billfishes and bigeye tuna as well as target species swordfish catches, as reported by PIROP fishery observers in the deep-set (a) and shallow-set sectors (b), respectively, of the Hawaii-based pelagic longline fishery during 2007–2011. Eight fishing regions are defined by 10° latitudinal increments and a longitudinal separation at 160°W. The Main Hawaiian Islands (grey shading) are centered near 19°34′N and 155°30′W (Hawai'i) to 21°54′N and 160°10′W (Ni'ihau).

3.3. Model selection

Alternative GLM models were compared using differences in goodness-of-fit. Fitted AIC values differed among the various alternatives models but exhibited a consistent pattern across species. The model selection results (Table 4) showed that the zero-inflated negative binomial model provided the best fit to the billfish catch per set data for each species. This model had the

Table 4
Summary of model selection information from GLM analyses for billfishes in the Hawaii-based pelagic longline fishery during 1995–2011. The GLM hypothesis, model structure, Akaike Information Criterion value (AIC), and Akaike weight are presented for each model by species. Results for the best-fitting models are in boldface type.

Species	GLM Hypothesis	Model structure	AIC	Akaike weight
Blue marlin	Poisson	Counts	53,983.78	0.00
Blue marlin	Negative binomial	Counts	52,587.78	0.00
Blue marlin	Zero-inflated Poisson	Binomial and counts	52,872.81	0.00
Blue marlin	**Zero-inflated negative binomial**	Binomial and counts	**52,394.92**	1.00
Blue marlin	Delta-Gamma	Binomial and continuous	54,325.85	0.00
Striped marlin	Poisson	Counts	124,809.7	0.00
Striped marlin	Negative binomial	Counts	113,504.0	0.00
Striped marlin	Zero-inflated Poisson	Binomial and counts	117,714.6	0.00
Striped marlin	**Zero-inflated negative binomial**	Binomial and counts	**113,021.3**	1.00
Striped marlin	Delta-Gamma	Binomial and continuous	116,974.4	0.00
Shortbill spearfish	Poisson	Counts	106,297.6	0.00
Shortbill spearfish	Negative binomial	Counts	98,199.93	0.00
Shortbill spearfish	Zero-inflated Poisson	Binomial and counts	101,433.9	0.00
Shortbill spearfish	**Zero-inflated negative binomial**	Binomial and counts	**97,788.0**	1.00
Shortbill spearfish	Delta-Gamma	Binomial and continuous	101,928.8	0.00
Sailfish	Poisson	Counts	8282.37	0.00
Sailfish	Negative binomial	Counts	7949.11	0.00
Sailfish	Zero-inflated Poisson	Binomial and counts	7955.40	0.00
Sailfish	**Zero-inflated negative binomial**	Binomial and counts	**7914.55**	1.00
Sailfish	Delta-Gamma	Binomial and continuous	8063.03	0.00

lowest AIC for each species, and except for sailfish, the negative binomial had the second lowest. In comparison, the Poisson model had the highest AIC among the five models, except for blue marlin. The within-species differences between the zero-inflated Poisson and Poisson AIC values were much greater than those between the zero-inflated negative binomial and negative binomial models. The Akaike weights and evidence ratios represented overwhelming evidence supporting selection of the zero-inflated negative binomial model for each species.

3.4. CPUE standardizations

The forward selection entry procedures for all species (Appendix A: Tables A1a–d) yielded the zero-inflated negative binomial models that accounted for 14.7%, 12.7%, 10.9%, and 14.0% of the null zero-inflated model AIC values for blue marlin, striped marlin, shortbill spearfish, and sailfish, respectively. Full fitting details are presented in these tables.

The predictive variables selected for inclusion in the models differed among species (Table 5). The zero-inflated negative binomial model for blue marlin included six factors, three continuous predictors, and four interactions in the counts model, and two continuous predictors in the zero-inflation model. The striped marlin model included one less factor in the counts model but two more continuous variables in the zero-inflation model. The shortbill spearfish zero-inflated negative binomial model included six factors, two continuous predictors, and four interactions in the counts model, and two continuous predictors in the zero-inflation model. An SST effect was a continuous predictor in the counts models for each of these species.

Table 5
Summary of the predictor variables in the best-fitting standardization models for billfish catches per longline set in the Hawaii-based pelagic longline fishery in 1995 – 2011.

Species	Model	Component	Factor variables	Continuous variables	Interactions
Blue marlin	Zero-inflated negative binomial	Binomial model	–	SST (parabolic) Hooks per float	–
		Counts model	Year Quarter Region Bait types, Hook types, Leader types	SST (parabolic) Lunar illumination Vessel length	Year–Quarter Quarter–Region Set type–Hooks per float Set type–Vessel length
Striped marlin	Zero-inflated negative binomial	Binomial model	–	SST (linear) Hooks per float Lunar illumination Soak duration	–
		Counts model	Year Quarter Region Bait types, Hook types	SST (linear)	Year–Quarter Quarter–Region Set type–Hooks per float Year–MEI
Shortbill spearfish	Zero-inflated negative binomial	Binomial model	–	SST (linear) Hooks per float	–
		Counts model	Year Quarter Region Bait types, Hook types, Leader types	SST (linear) Lunar illumination Vessel length	Year–Quarter Quarter–Region Set type–Hooks per float Set type–Vessel length
Sailfish	Zero-inflated negative binomial	Binomial model	Quarter	SST (linear)	–
		Counts model	Year Region	Hooks per float MEI	–

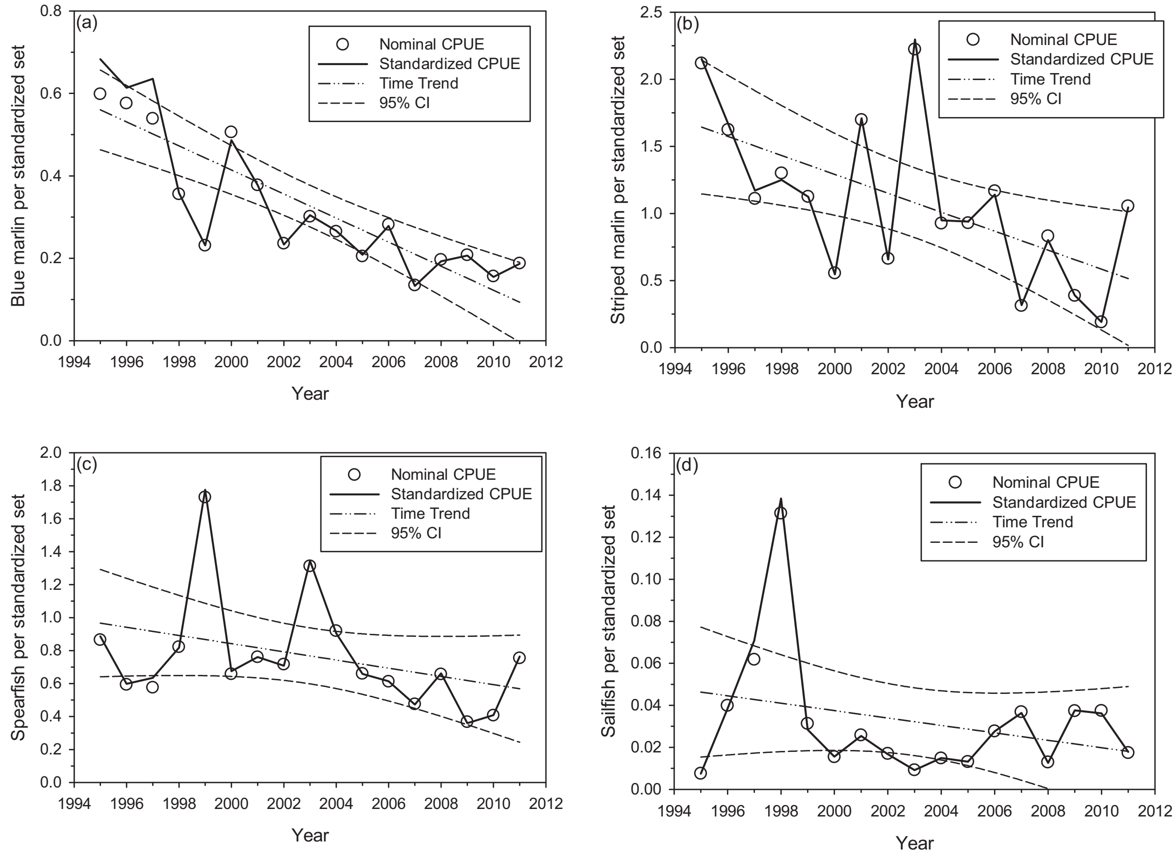

Fig. 2. Standardized catches per set for blue marlin *Makaira nigricans* (a), striped marlin *Kajikia audax* (b), shortbill spearfish *Tetrapturus angustirostris* (c), and sailfish *Istiophorus platypterus* (d) in the Hawaii-based pelagic longline fishery during 1995–2011. The time trend regression lines (dot-dot-dash) and the associated 95% confidence intervals (short dash) are included.

The sailfish zero-inflated negative binomial model included fewer and different predictive variables than the models for the other species. This model included only two factors and two continuous variables in the counts model, one factor and one continuous variable in the zero-inflation model, and no interactions in either the counts or zero-inflation models. None of the zero-inflation models for the other species included factor variables. The sailfish model was also unique in that SST was only included in the zero-inflation model.

The annual, quarterly, and regional effects yielded large AIC reductions for blue marlin, striped marlin, and shortbill spearfish (Tables A1a–d). The annual effects reductions per degree of freedom were always least among the three. SST, quarterly, and regional effects yielded large AIC reductions for blue marlin and striped marlin, with stronger quarterly than regional effects per degree of freedom in striped marlin, but less of a difference in blue marlin.

3.5. Standardized CPUE trends

The annual mean standardized CPUE with 95% confidence intervals and the annual nominal mean CPUE values were similar for all four billfishes (Fig. 2). Linear regression analyses indicated that the trends for blue and striped marlins were negative and statistically significant (blue marlin: $F_{1,15}=36.289$, $R^2=0.708$, $P<0.001$; striped marlin: $F_{1,15}=8.007$, $R^2=0.348$, $P=0.013$), but those for shortbill spearfish and sailfish were not (shortbill spearfish: $P=0.147$; sailfish: $P=0.271$).

4. Discussion

This paper has presented CPUE standardizations for four billfishes comparing five types of catch rate GLMs. The results indicated that the zero-inflated negative binomial model provided the best fit to the catch per set data for each species. Brodziak and Walsh (2013) presented a multimodel inference study of CPUE standardization for oceanic whitetip shark and this study is a logical extension of the previous work because we evaluated the same types of models and because the oceanic whitetip shark and the incidentally caught billfishes had similarly large fractions of zero catch sets.

The combined results of the two studies demonstrated that both the zero-inflated negative binomial and Poisson models fit the catch per set data better than the corresponding non-inflated models, and the zero-inflated negative binomial fit the data better than the zero-inflated Poisson model. Thus, the frequencies of zero catches exceeded those expected with either the Poisson or negative binomial distribution, and the positive counts and true zeros exhibited overdispersion.

4.1. Species comparisons

Three studies have recently assessed catch rate trends in the deep-set sector of the Hawaii-based pelagic longline fishery (Polovina et al., 2009; Gilman et al., 2012; Polovina and Woodworth-Jefcoats, 2013). However, our work differed from these studies with respect to the data sources, time series durations or both, and in our use of parametric (i.e., GLMs) versus

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semiparametric models (generalized additive and generalized additive mixed models; GAMs, GAMMs).

Polovina et al. (2009) presented an analysis of logbook data from the deep-set sector of this fishery in 1996–2006, whereas our analyses were conducted with PIROP fishery observer data over a longer time series (1995–2011). The logbook data, moreover, include large numbers of billfish misidentifications (Walsh et al., 2005, 2007), the result of which is that their estimated annual linear decreases in striped marlin and shortbill spearfish CPUE of −4.8% and −3.3%, respectively, are characterized by downward bias and probably excessively pessimistic.

Gilman et al. (2012) analyzed observer data from the deep-set sector of this fishery using GAMMs using Poisson error structures and reported significant nonlinear decreasing CPUE trends for striped marlin and shortbill spearfish. These authors also documented interspecific differences in responses to the El Niño/La Niña cycles, with shortbill spearfish catch rates affected positively after the strong El Niño event of 1997–1998, but negatively affected by the following moderate La Niña plase of 1998 to mid-2000 and the minor La Niña plase of late-2000 to mid-2001, whereas striped marlin exhibited opposite effects. Finally, these authors identified significant effects of other variables that were included and significant in our analyses (e.g., hook and bait types), although most of the effects of these variables on catch rates were of relatively minor practical importance.

Most recently, Polovina and Woodworth-Jefcoats (2013) presented a size-based analysis of CPUE trends in the deep-set sector of this fishery in 1996–2011. They reported strong declines in relative abundance of blue marlin, striped marlin, and shortbill spearfish of (−4.2% to −5% per year), but their weight data for these species were more than double previously reported weights (Walsh et al., 2007; Nakamura, 2001), which would bias results of weight-based CPUE analyses.

4.2. Catch rate standardizations

Temporal and spatial factors were important for explaining billfish catch rates, which supported our hypotheses that they would exert strong effects. However, we had no *a priori* expectations about the relative strength of these effects, so their interspecific variation was noteworthy (Tables A1a–c). In the blue marlin counts model, the AIC reductions per degree of freedom for the regional and quarterly effects were considerably greater than that for the annual effects (Table A1a). Striped marlin differed, with a greater AIC reduction per degree of freedom for the quarterly than for the regional or annual effects (Table A1b). The AIC reduction per degree of freedom for the regional effect in the shortbill spearfish counts model was considerably greater than that for the quarterly effects, which in turn exceeded that for the annual effects (Table A1c). In all three species, however, the AIC reduction per degree of freedom for the annual effects was the least among these three factors.

SST effects on billfish catch rates also varied among species, but this was expected. Walsh et al. (2007) presented GAM analyses in which the SST effect on blue marlin catch rates was strongly positive and roughly linear from 22 °C to 28 °C, while those for striped marlin and shortbill spearfish were dome-shaped with a maximum at 26 °C and nearly flat from 23°C to 28 °C, respectively. The effects of SST on blue marlin catch rates were expressed as parabolic terms with positive and negative coefficients, respectively, in the counts and zero-inflation models, which indicated that SST effects on the most tropical istiophorid (Nakamura, 2001) were curvilinear across the range encountered in this fishery. Shortbill spearfish differed from the two marlins, with strong regional effects on catch rates but a weak SST effect. Strong regional effects may have been related to habitat preferences, fleet dynamics, or both. The catches from Regions 3 and 4 in the first, second, and fourth quarters comprised 49% of the shortbill spearfish catch. This may have reflected habitat preference, but 35% of the bigeye tuna catch also came from these regions at these times. Hence, large shortbill spearfish catches may simply have coincided with productive fishing for the target species in suitable, but not necessarily preferred habitat. The weak SST effect in the counts model with its negative coefficient also differed from blue and striped marlin, with strong positive parabolic and linear effects, respectively. We could not identify a physiological or ecological basis, but differences in behavioral responses to temperature as a directive factor (Fry, 1971) could serve to reduce interspecific competition during the early winter to spring months when both shortbill spearfish and striped marlin are relatively common in waters near Hawaii.

Inclusion of the interaction of set types with hooks per float in the counts models was preferable to use of a set type main effect to explain billfish catch rates. This differed from our expectations, but was comprehensible. Significant differences between coefficients from the deep- and shallow-set sectors reflect the fact that by definition the ranges of hooks per float in the two sectors do not overlap, and there is no limit in the deep-set sector.

The significant interactions between fishing years and the MEI in the blue marlin, striped marlin, and shortbill spearfish counts models were not surprising. Gilman et al. (2012) described departures from predictions of GAMM analyses during various phases of the El Niño/La Niña cycle; we obtained comparable results using parametric tests. Similarly, the significant coefficient for this interaction in the blue marlin counts model for 1997 represented a positive influence of the El Niño phase on catch rates, as has been reported by Su et al. (2008, 2011). The interaction between fishing years and the MEI may have been a more useful predictor of billfish catch rates than a continuous effect of the MEI because the onsets, durations, and intensities varied among the events.

The zero-inflation models included only continuous variables, except in sailfish which included a quarterly effect as a factor. In blue and striped marlins, the SST coefficients were positive in the counts models but negative in the zero-inflation models. This indicated that catches would vary directly, but the probabilities of extra zeros would vary inversely with SST. Shortbill spearfish differed, however, with negative coefficients for SST in both the counts and zero-inflation models. Hence, this species may be adapted to relatively cool conditions and more stenothermal than either marlin because both catches and the probability of extra zeros were inversely related to SST. Alternatively, these results may reflect fleet dynamics targeting bigeye tuna. Moreover, the two possibilities are not mutually exclusive.

The number of hooks per float was the other important continuous variable in the zero-inflation models for blue marlin, striped marlin, and shortbill spearfish. The coefficients were negative, which represented an inverse relationship between the probability of extra zeros and the depth of the longline gear as influenced by the number of hooks per float.

4.3. Indices of relative abundance

Lynch et al. (2012) recently evaluated the performance of several CPUE standardization methods used for highly migratory species (HMS). They simulated a 53-year time series similar to historical patterns of Japanese longline fishing in the Atlantic Ocean, generating 150 scenarios from 50 biomass trajectories and three temperature profiles representing shallow, intermediate, and deep thermocline depths. The delta-GLM analysis that incorporated detailed vertical habitat information provided the most accurate estimates of HMS relative abundance. They also determined that when vertical catchability is greatest near the surface, all methods yielded upwardly biased estimates of abundance early in the time series but negatively biased estimates later when catch rates declined with altered fishing strategies. Both findings pertain to our results because these billfishes are surface-associated species and because this fishery underwent substantial changes in strategies and operations during the study period.

Lynch et al. (2012) proffered three important recommendations for CPUE standardization research and our results are consistent with those recommendations. Treatment of zero catches was not the focus of their work, but based largely on simulation results that the highest proportions of zeros were associated with the surface peak in catchability, they specifically recommended studies of the influence of zero observations on methods used to estimate indices of abundance. We did so with species all of which had higher proportions of zeros than their maximum (0.41). They also recommended studies using discrete distributions that do not require data alteration; four of the five we evaluated were discrete. Finally, they recommended studies of model selection criteria. We have incorporated model selection in this study and in previous work (Brodziak and Walsh, 2013) and intend to expand this aspect in our future work.

4.4. Conclusions

Our analyses demonstrated that zero-inflated negative binomial models provided the best fit to catch per longline set data for incidentally caught billfishes in the Hawaii-based pelagic longline fishery in 1995–2011. Because we evaluated models that represent various hypotheses about the capture process (Brodziak and Walsh, 2013) and obtained results consistent with our previous study of the oceanic whitetip shark taken as bycatch (Brodziak and Walsh, 2013), we conclude that zero inflation as well as overdispersion in the counts may be typical of catch per set data for highly migratory, non-target pelagic fishes. Hence, zero-inflated analyses should be considered for catch rate standardization in such circumstances. Further, it is recommended that future research consider more general count distributions such as the zero-inflated negative binomial-negative binomial (Okamura et al., 2012) to account for expected patterns of overdispersion in catch rates.

Blue and striped marlins exhibited decreases in standardized catch rates during the study period that may have reflected population decline, operational changes, or both, because these possibilities are not mutually exclusive. Shortbill spearfish and sailfish, however, did not exhibit linear temporal trends in standardized catch rates, and other results suggested that environmental conditions, particularly the El Niño/La Niña cycle, can strongly affect billfish catch rates. As such, we conclude that standardized catch rates did not indicate that billfishes in the aggregate are in decline in the Hawaii-based pelagic longline fishery.

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Appendix A.

Table A1. Analysis of deviance tables summarizing the zero-inflated negative binomial variable selection procedures for four billfishes in the Hawaii-based pelagic longline fishery in 1995–2011. Table entries at each fitting step include the degrees of freedom (Df), significance of the chi-squared test ($\Pr > |\chi^2|$), reduction in the AIC (ΔAIC), percent reduction of the null model AIC, reduction in the AIC per degree of freedom, median Pearson residual, and the dispersion parameter. A zero-inflation model intercept was included at each step in the counts model.

Tables A1a.
Tables A1b.
Tables A1c.
Tables A1d.
Fig. A1

Table A1a
Blue marlin: Counts model.

Parameter	Df	$\Pr > \|\chi^2\|$	ΔAIC	%AIC	ΔAIC/Df	Median Pearson residual	k
Intercept	1	<0.0001	–	–	–	−0.3710	0.3120
Fishing years	16	<0.0001	−1427.23	2.32	−89.20	−0.3629	0.3735
Fishing quarters	3	<0.0001	−1355.61	2.21	−451.87	−0.3392	0.4316
Fishing regions	7	<0.0001	−3207.37	5.22	−458.20	−0.3023	0.6586
Bait types	6	<0.0001	−995.56	1.62	−165.93	−0.2984	0.7892
Leader types	2	<0.0001	−65.64	0.11	−32.82	−0.2996	0.8075
Hook types	3	<0.0001	−66.77	0.11	−22.26	−0.2983	0.8185
SST (parabolic)	1	<0.0001	−676.95	1.10	−676.95	−0.2947	0.9150
Vessel length	1	<0.0001	−62.74	0.10	−62.74	−0.2929	0.9259
Moon fraction	1	0.0001	−12.38	0.02	−12.38	−0.2925	0.9324
Years × quarters	48	<0.0001	−365.91	0.60	−7.62	−0.2886	1.0317
Quarters × regions	21	<0.0001	−271.90	0.44	−12.95	−−0.2890	1.0986
Set types × hooks per float	2	<0.0001	−221.00	0.36	−110.50	−0.2892	1.1557
Fishing years × MEI	17	<0.0001	−103.05	0.17	−6.06	−0.2891	1.1941

Blue marlin: Zero-inflation model

Parameter	Df	$\Pr > \|\chi^2\|$	ΔAIC	%AIC	ΔAIC/df	Median pearson residual	k
Intercept	1	<0.0001	–	–	–	−0.2891	1.1941
Hooks per float	1	<0.0001	−8.31	0.01	−8.31	−0.2894	1.2484
SST (parabolic)	1	<0.0001	−205.81	0.33	−205.81	−0.2884	1.3289

Table A1b
Striped marlin: counts model <0.0001.

Parameter	Df	Pr > |χ^2|	ΔAIC	%AIC	ΔAIC/Df	median Pearson residual	*k*
Intercept	1	<0.0001	–	–	–	−0.4727	0.4076
Fishing years	16	<0.0001	−6036.33	4.66	−377.27	−0.4292	0.5744
Fishing quarters	3	<0.0001	−1655.54	1.28	−551.85	−0.4296	0.6350
Fishing regions	7	<0.0001	−2765.91	2.14	−395.13	−0.4147	0.7497
Bait types	6	<0.0001	−873.83	0.67	−145.64	−0.4185	0.8002
Hook types	3	<0.0001	−25.81	0.02	−−8.60	−0.4177	0.8017
SST	1	<0.0001	−761.55	0.59	−761.55	−0.4117	0.8361
Fishing years × fishing quarters	48	<0.0001	−2142.92	1.65	−44.64	−0.4024	0.9726
Fishing quarters × fishing regions	21	<0.0001	−1140.19	0.88	−54.29	−0.3863	1.0400
Set types × hooks per float	2	<0.0001	−388.89	0.30	−194.45	−0.3864	1.0727
Fishing years × MEI	17	<0.0001	−174.52	0.13	−10.27	−0.3861	1.0899

Striped marlin: Zero-inflation model

Parameter	Df	Pr > |χ^2|	ΔAIC	%AIC	ΔAIC/Df	Median Pearson residual	*k*
Intercept	1	<0.0001	–	–	–	−0.3861	1.0899
SST	1	<0.0001	−151.64	0.12	−151.64	−0.3846	1.2345
Hooks per float	1	<0.0001	−319.05	0.25	−319.05	−0.3821	1.1893
Moon fraction	1	<0.0001	−28.42	0.02	−28.42	−0.3819	1.1870
Soak duration	1	<0.0001	−18.48	0.01	−18.48	−0.3817	1.1857

Table A1c
Shortbill spearfish: counts Model.

Parameter	Df	Pr > |χ^2|	ΔAIC	%AIC	ΔAIC/Df	Median Pearson residual	*k*
Intercept	1	<0.0001	–	–	–	−0.4576	0.4867
Fishing years	16	<0.0001	−1838.34	1.67	−114.90	−0.4588	0.5470
Fishing quarters	3	<0.0001	−1007.23	0.92	−335.74	−0.4715	0.6051
Fishing regions	7	<0.0001	−5792.14	5.28	−827.45	−0.3382	0.8483
Bait types	6	<0.0001	−1426.32	1.30	−237.72	−0.3315	0.9434
Hook types	3	<0.0001	−71.85	0.07	−23.95	−0.3323	0.9489
Leader types	2	<0.0001	−19.84	0.02	−9.92	−0.3309	0.9502
Moon fraction	1	<0.0001	−19.71	0.02	−19.71	−0.3303	0.9514
SST	1	<0.0001	−31.92	0.03	−31.92	−0.3319	0.9493
Fishing years × fishing quarters	48	<0.0001	−850.05	0.77	−17.71	−0.3292	1.0160
Set types × hooks per float	2	<0.0001	−136.96	0.12	−68.48	−0.3270	1.0330
Set types × vessel length	2	<0.0001	−161.03	0.15	−80.52	−0.3231	1.0455
Fishing years × MEI	17	<0.0001	−139.64	0.13	−8.21	−0.3230	1.0611

Shortbill spearfish: Zero-inflation model

Parameter	Df	Pr > |χ^2|	ΔAIC	%AIC	ΔAIC/df	Median Pearson residual	*k*
Intercept	1	<0.0001	–	–	–	−0.3230	1.0611
SST	1	<0.0001	−51.93	0.05	−51.93	−0.3228	1.1141
Hooks per float	1	<0.0001	−444.384	0.40	−444.384	−0.3281	1.0955

Table A1d
Sailfish: counts model.

Parameter	Df	Pr > |χ^2|	ΔAIC	%AIC	ΔAIC/Df	Median Pearson residual	*k*
Intercept	1	<0.0001	–	–	–	−0.1319	0.072
Fishing years	16	<0.0001	−157.559	1.85	−9.847	−0.1223	0.0919
Fishing regions	7	<0.0001	−343.162	2.52	−49.023	−0.1171	0.1314
Hooks per float	1	<0.0001	−140.303	1.64	−140.303	−0.1202	0.1242
MEI	1	0.003	−6.687	0.08	−6.687	−0.1198	0.1260

Sailfish: Zero-inflation model

Parameter	Df	Pr > |χ^2|	ΔAIC	%AIC	ΔAIC/df	Median Pearson residual	*k*
Intercept	1	<0.0001	–	–	–	−0.1198	0.1260
Fishing quarters	3	<0.0001	−172.134	2.02	−57.378	−0.1142	0.2444
SST	1	<0.0001	−78.048	0.91	−78.048	−0.1128	0.3028

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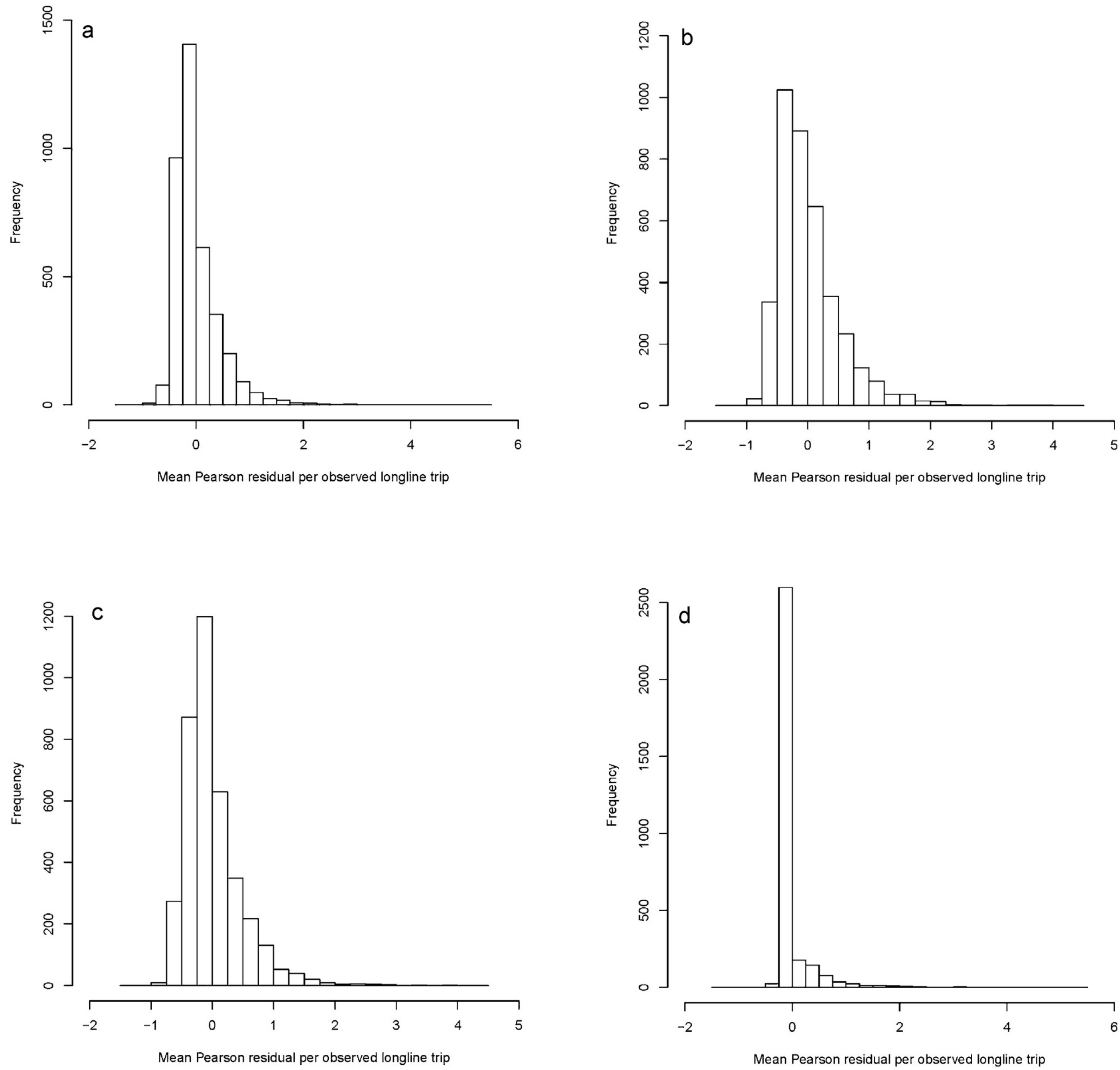

Fig. A1. Histograms of Pearson residuals from the blue marlin (a), striped marlin (b), shortbill spearfish (c), and sailfish (d) zero-inflated negative binomial models. The values are the mean Pearson residuals per observed longline trip.

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