0.1 Introduction

Note: The current analysis does not construct inputs to use for stock assessments or catch estimates. Our goal is to highlight general trends in population abundance over time, to be interpreted together with other indicators as outlined above. We recommend that catch rates standardization for stock assessments or catch estimates be conducted independently.

Catch-per-unit-effort data (CPUE) are commonly used as an index of abundance for marine species. However, multiple factors—fishing technique, season, bait type, etc.—can alter the relationship between CPUE and abundance, especially in complex fisheries systems comprising of several fleets and spanning large spatial and temporal scales. Nominal catch rates must thus be standardized to account for changes in the relative prevalence of these factors over time. This is typically done *via* the use of models in the GLM family, which allows us to model the relationship of CPUE *vs.* a set of explanatory variables to be standardized against, but these variables must be defined for each observation. The dataset used in the current analysis provides many such candidate variables, but, given the diversity of observer programs represented, few had enough coverage to be retained in the final models. The available variables are described in Table **??** (see also Table 2 in **?** for an overview of the use of variables in shark CPUE standardizations).

CPUE data for species such as sharks often have a large proportion of observations (sets) with zero catch, while at the same time also including instances of large catches ('long tails'). These uncommon instances of high catches can occur when areas of high shark densities are accidentally encountered, but also when fishing vessels engage in anecdotal shark targeting behaviour. The co-existence of both high proportions of zero catches *and* long tails resuls in over-dispersed data, and is typical of bycatch species (**?**). These features are challenging to account for from a statistical point of view, and have been reviewed at length in the literature on by-catch analyses (Bigelow et al. 2002; Campbell 2004, Ward and Myers 2005; Minami et al. 2007).

Error distributions for by-catch species have been discussed at length in previous publications as these data are notoriously hard to model properly due to the high proportion of zeroes (**?**). We achieved significant improvements in model diagnostics by allowing multiple parameters in the error distribution to be fit. This is because accounting for the large amount of zeroes in shark CPUE catch data often comes at the expense of modelling large catch events, since the dispersion parameter which controls the length of the tail is assumed to be constant over all factors. This is especially a problem when the mean of the distribution is close to zero or one, as in those instances the probability of getting large events if mostly controlled by the dispersion parameter (unlike when the mean is larger and the tail is not as pronounced). However, whenever conditions are good for sharks or targeting takes place, larger catch events can happen and not modelling them properly means we are missing important drivers. Typically, this can seen as a bump in the right-hand side of qqnorm plots. This approach is similar in spirit to the zero-inflated-neg-bin that has been advocated by multiple authors (brodziak) but is less computationally intensive. The main advantage of the zero inflated approach is that these techniques can model the overdispersion in both the zeros and the counts as opposed to just the counts (negative binomial) and deal with overdispersion better than other models (such as the quasi-Poisson). A drawback of the zero inflated approach is that it is data intensive and the models often fail to converge.

Further, catch data for non-target species (and sharks in particular) often contain large numbers of observed zeros as well as large catch values which need to be explicitly modelled More on data issues: Recent work by **?** noted gaps in observer data in terms of time and space continuity, reporting rate, and identification with respect to sharks.

Standardized CPUE series for the longline bycatch fisheries were developed using generalized linear models. We did not generate indices from purse-seine observer data. The number of hooks in a longline set was used as a measure of effort. See also Clarke et al., (2011, 2011b), Walsh and Clarke (2011), Rice and Harley (2013) for past work on shark CPUE standardization in the Western Central Pacific.

0.2 Methods

0.2.1 Stock definition for the purpose of the analysis

Silky and oceanic white tip sharks are observed mainly in the equatorial waters in the purse seine fishery (Figure **??**), and from about -25° S to 25° N in the longline fishery (Figure 1). Silky and oceanic white tip sharks have been assessed (**??**) as a single stock in the WCPO, and are presented in this analysis as a single stock. Thresher, mako and blue sharks occur more frequently in cold, temperate waters, and generally believed to be separated into northern and southern stocks. For instance, blue sharks in the North Pacific have been subject to multiple stock assessments as a single stock (**?**). These temperate species will thus be analysed as individual stocks. Porbeagle sharks are only found in the southern hemisphere and will also be analysed as a single stock. Hammerheads

To further define the expected geographic range, we defined a coarse climate 'envelope' based on sea surface temperature. This aid in distinguishing between zero catches in areas where the species does not occur from zero catches in areas where the species occurs but was not caught. Temperature data were downloaded from the GODAS database (**?**) and matched to the observer data on a set by set basis. The temperature range of a species was defined as the minimum and maximum of the monthly mean sea surface temperatures (SST) of cells with positive catches for that species (see Table **??**). SST was measured as the temperature predicted by GODAS at the 5 meters depth. Only cells for which all mean monthly temperatures fell within this range were retained. Looked at range of SST where positive catches occured, selected cells where median falls within this range.

0.2.2 Data trimming

Data were cleaned following the general method outlined in Appendix section **??**. Records from the US observer programs (Hawaii and American Samoa) were excluded from the analysis as they were only available up to 2011. Records from the Papua New Guinea observer program were removed as vessels in the fleet frequently target sharks. We also removed records from any observer programs for which we had less than 100 sets. Extreme catch events greater than the 97.5^{th} quantile were also removed. Finally, year effects were only estimated if there were at least 50 sets observed in that year.

Although a much smaller proportion of the overall dataset (6.5% of the sets), the targeting sets represent significant shark catch (82% of the total silky shark catch). Therefore the dataset was examined with respect to variables relating to whether sharks were the intentional target of the set.

Shark targeting sets were deemed to be sets where the observer had marked that the set was intentionally targeting sharks of any species, whether shark bait was used, or whether shark lines were used . We also removed the data from the PGOB because of frequent shark targeting.

The results of these filtering rules are listed by species in Table **??**.

0.3 Additional categorical variables

1. Day category 2. HPBCAT

0.4 Overview of GLM Analyses

0.4.1 Notes on error distributions:

The filtered datasets were standardized using generalized linear models (McCullagh and Nelder 1989) using the software package R (www.r-project.org). Multiple assumed error structures were tested including the delta lognormal approach (DLN) (Lo et al. 1992, Dick 2006, Stefansson 1996, Hoyle and Maunder 2006), zero-inflated poisson and negative binomial models, the tweedie distribution (cite), and negative binomial models with mu and sigma modelled. Due to its superior performance both in run time and model diagnostics, we retained the latter and only present those results here. The negative binomial (Lawless 1987): is typically more robust to issues of overdispersion (overdispersion can arise due to excess zeros, clustering of observations, or from correlations between observations) was also used. This model has been advocated as a model that is more robust to overdispersion than the Poisson distribution (McCullagh and Nelder 1991), and is appropriate for count data (Ward and Myers 2005), but does not expressly relate covariates to the occurrence of excess zeros (Minami et al. 2007).

0.4.2 Procedure for model selection

Because flag and observer programs are highly correlated, we used observer program as an explanatory categorical variable as it tended to explain a higher proportion of the data when used on its own than flag (except in the case of XXXX and XXXX where flag explained the most). We also explored adding an interaction between year and observer program, as for some species of less mobile sharks we could expect to see local trends in annual abundance that are reflected in the observer program data. We checked for the relevance of including interactions early in the model selection process but did not proceeded with an interaction for the remaining of the model selection.

0.4.3 Calculation of year indices and confidence intervals

Year effects could be extracted as is from the model output as there were no interactions between year and other variables, and year was not included as an explanatory variable for the σ models. Confidence intervals were computed with the function `confint` in `gamlss`.

0.5 Results

Blue shark (*Prionace glauca*), north Pacific Both the standardized and nominal CPUEs of blue shark in the north Pacific show a declining trend starting in 1999 and 1998, respectively. Data points for 2011 and 2012 are unavailable due to low sample size.

Blue shark (*Prionace glauca*), south Pacific Both the standardized and nominal CPUEs for blue shark in the south Pacific show declines in the initial 1995-2003 and late 2010-2015 periods, with relatively stable CPUEs between 2004 and 2009.

Mako shark (*Isurus oxyrinchus* and *Isurus paucus*) in the north Pacific The standardized and nominal CPUEs share the same trajectories (Figure **??**), but on a slightly different scale for the first 6 years (1995-2001). The largest difference in the nominal and standardized CPUE is in the final year, where the standardized CPUE declines sharply in contrast to the nominal, but years 2011 and 2012 were excluded from the standardization due to poor sample sizes (Figure **??**).

Mako shark (*Isurus oxyrinchus* and *Isurus paucus*) in the south Pacific The standardized CPUEs show a more stable trend in relative abundance than the nominal CPUEs, although both have low points in 2002 and 2014. In addition, the standardized CPUE peaks in 2010, whereas the nominal is the highest in 1996.

Oceanic whitetip shark (*Carcharhinus longimanus*) The standardized oceanic whitetip shark trend decreases steadily over 1995-2014. The standardized trend shows a slightly steeper decline than the nominal, with the most noticeable departure from the nominal being the large decrease from 2013-2014 in the standardized CPUE.

Silky shark (*Carcharhinus falciformis*) Standardized silky shark trends in the WCPO showed high inter-annual variability with an initial decline from 1995-2000 followed by a slight increase until 2010, followed by a steep decline. This mirrors the trends seen in the nominal CPUE, albeit with a lesser variability.

Thresher sharks (*Alopias superciliousus, vulpinus, & pelagicus*) Standardized CPUE values for thresher sharks were similar to the nominal CPUE except for additional variability in the nominals. They both rise for the first 6 years of the series (1995-2001) but diverge afterwards. For the years 2002-2014, the standardized CPUE is less variable showing a slightly decreasing CPUE from 2003-2011. The last three years of both the standardized and nominal CPUEs show a steep decline. The CPUE from the thresher complex (bigeye, common and pelagic) is difficult to interpret as the second most commonly reported thresher species is the general "thresher shark" category.

Hammerhead sharks (*Sphyrna mokarran, lewini, zygaena, & Eusphyra blochii*) Standardized CPUE for the hammerhead complex shows a large increase from the 3rd to the 6th year of the study period (1997-2001), with a relatively stable CPUE thereafter (2002-2013, regions 3 and 5 in the longline database). Similar to the thresher shark complex, the CPUE series representing the hammerhead complex are difficult to interpret because more than half of the observations in the study period (1995-2014) were made to a generic "hammerhead" category.

Porbeagle shark (*Lamna nasus*) The standardized CPUE for porbeagle shark was close quite similar to the nominal CPUE, showing an increase in the first three years of the time series, followed by a decline from 1999 to 2003, and a monotonic increase thereafter.

0.6 Conclusions

Table 1: Summary of temperature ranges by species used as filters for cells to retain in the CPUE analysis.

Species	Minimum T(° C)	Maximum T(° C)
Blue shark	10	30
Hammerhead sharks	13	30
Mako sharks	11	30
Oceanic whitetip shark	18	30
Porbeagle shark	10	26
Silky shark	18	30
Thresher sharks	11	30

Variable name	Symbol	Explanation	% records present
Year	β_Y	Required to estimate year effect	100
Month	β_M	Captures seasonal variability	100
Observer program	β_O	Country hosting the observer program	100
Vessel flag	β_F	Note: correlated with observer program	100
Hooks-beween-floats	β_{HBF}	Indicator of catchability for surface-dwelling species	
Shark bait			
Shark target		Sharks explicitly defined as targets?	
SST	SST	100	
Day category		Day or night, before or after sunrise/sunset?	100

0.7 Model structure by species

in appendix: summarize proportion of data removed for each species (temperature, observer, quantile), e.g. North Mako: removing HW removes a lot of data!! check for catches...

0.8 Model diagnostics

Used quantile residuals.

0.9 Conclusions

The signals from the nominal CPUE data can be heavily influenced by factors other than abundance and therefore a procedure to standardize CPUE data for changes in factors that do not reflect changes in abundance is usually recommended.

Table 2: Summary of number of records removed by filter type for each species before GLM analyses. HW/AS and PG refer to the Hawaai/American Samoa and the Papua New Guinea observer programs. OB sampling refers to records removed from observer programs with few records. See summary in section **??**

Species	Hemisphere	SST range	max quantile	HW/AS	PG	OB sampling	# rows left
Blue shark, south	41276	1234	309	3449	571	21	19660
Blue shark, north	25244	0	805	36818	0	35	3618
Hammerhead sharks	0	4999	12	41072	571	21	19845
Mako sharks, south	41276	1419	130	3359	571	21	19744
Mako sharks, north	25244	0	97	37536	0	35	3608
Oceanic whitetip shark	0	10266	171	38532	570	21	16960
Porbeagle shark	41276	18038	78	0	0	122	7006
Silky shark	0	10266	127	38563	563	21	16980
Thresher sharks	0	1419	290	40860	571	21	23359

Table 3: Summary of model structures retained for CPUE standardization of each species

Species	Model μ	model σ	% deviance
Blue shark, northern stock	year + program + HPBCAT2 + month + sharkbait	program + HPBCAT2 + month	
Blue shark, southern stock	year + flag + HPBCAT2 + month + sharkbait		
Mako, southern stock	year + program + HPBCAT2 + month + sharkbait	program + month	—
Mako, northern stock	year + program + month + sharkbait	HPBCAT2	
Oceanic white tip	year + program + HBPCAT2 + month + sharkbait	program	
Thresher sharks	year + program + HPBCAT2 + month	program + HBPCAT2	
Hammerheads	year + program + HPBCAT2 + month + sharkbait	sharkbait	
Oceanic whitetip shark	year + program +HBPCAT2 + month + sharkbait	program	
Silky shark	program + year + HPBCAT2 + month + sharkbait	program + sharkbait + month	
Porbeagle	year + flag + HPBCAT2 + month	flag + month	

Table 4: AIC improvement over null model for BSH.north from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
yy	319.76	216.04
program_code	212.51	198.47
flag	105.54	195.94
mm	56.57	52.05
daycat	11.17	19.95
HPBCAT2	10.07	53.88
sharkbait	8.29	10.80
HPBCAT	8.20	54.58

Table 5: AIC improvement over null model for BSH.south from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
flag	11043.90	4626.32
program_code	9971.76	4152.00
HPBCAT2	6048.07	2829.18
daycat	4346.51	2116.94
yy	2943.03	1860.51
mm	2803.40	749.34
HPBCAT	2709.55	2295.09
sharkbait	298.24	8.37

Table 6: AIC improvement over null model for FAL from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
program_code	2401.27	1256.90
flag	2084.24	1052.85
yy	745.86	265.08
daycat	240.04	82.13
HPBCAT	202.88	42.80
HPBCAT2	201.02	41.61
sharkbait	62.96	33.48
mm	22.92	31.98

Table 7: AIC improvement over null model for HHD from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
program_code	385.38	-4.39
flag	384.82	98.17
HPBCAT2	151.90	10.83
HPBCAT	102.78	-1.37
daycat	66.76	4.51
yy	33.71	31.08
mm	26.11	3.39
sharkbait	15.37	21.94

Table 8: AIC improvement over null model for MAK.north from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
yy	68.41	42.54
flag	41.17	-72.56
program_code	37.21	8.88
daycat	14.17	0.75
mm	6.12	-15.83
sharkbait	4.87	-1.39
HPBCAT	-1.18	1.10
HPBCAT2	-1.18	8.03

Table 9: AIC improvement over null model for MAK.south from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
flag	2405.90	543.71
program_code	2007.09	656.44
HPBCAT2	1477.37	269.01
daycat	544.87	70.17
yy	535.65	359.67
mm	473.91	251.28
HPBCAT	310.63	186.70
sharkbait	55.88	5.94

Table 10: AIC improvement over null model for OCS from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
program_code	999.45	192.55
yy	792.33	181.77
flag	627.40	69.86
HPBCAT2	71.93	-3.52
sharkbait	70.89	4.42
daycat	53.56	0.70
HPBCAT	50.80	-1.94
mm	28.96	11.17

Table 11: AIC improvement over null model for POR from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
yy	1007.71	376.45
flag	602.59	825.49
daycat	328.52	374.34
program_code	265.33	223.13
mm	241.27	383.30
HPBCAT2	39.12	165.32
HPBCAT	9.18	149.03
sharkbait	-0.85	-0.85

Table 12: AIC improvement over null model for THR from a single explanatory variable

Variable	AIC.diff	AIC.diff.sigma
program_code	3583.25	1213.50
flag	2832.48	934.07
yy	1049.10	434.79
mm	111.10	32.01
HPBCAT	13.59	256.75
HPBCAT2	12.85	264.39
sharkbait	7.09	25.92
daycat	0.27	280.76