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.

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

Standardized CPUE series for the longline bycatch fisheries were developed using generalized linear models. The number of hooks in a set was used as a measure of effort.

0.2 Stock definition for the purpose of the analysis

JR Recent work by Clarke et al. (2011) noted gaps in observer data in terms of time and space continuity, reporting rate, and identification with respect to sharks. Silky and oceanic white tip sharks are observed mainly in the equatorial waters in the purse seine fishery (Figure 1), and from about -25??S to 25??N in the longline fishery (Figure 1). Silky and oceanic white tip sharks have been assessed (Rice et al 2012, Rice et al 2013) as a single stock in the WCPO, and are presented in this analysis ass one stock (not regionally). Thresher, mako and blue sharks are more common in cold and temperate waters, and generally believed to constitute two seperate stocks, in the north and south. Blue shark in the north pacific have been subject to multiple stock assessments as a single stock. These temperate species stocks will be presented as individual stocks.

0.3 Methods

The SPC longline observer database contains records from 1985 to recent years, however silky sharks were not routinely identified to species until 1995, hence the dataset used in this analysis spans the years 1995-2014. This analysis follows the work of Clarke et al., (2011, 2011b), Walsh and Clarke (2011), Rice and Harley (2013) however the regions for this study differ slightly. Because silky sharks are tropical species this led to the analysis being considered for one region, from 25??S to 25??N and bordered on the east and west by the WCPFC Statistical Area.

To distinguish between zero catches in areas where the species does not occur with zero catches in areas where the species occurs but was not caught, we defined a coarse climate envelope model based on sea surface temperature. Temperature data were downloaded from the GODAS database (**?**) and matched to the observer data on a set by set basis.

The data were validated and trimmed (records with missing values for key explanatory variables removed) to include only relevant data from the species 'core' habitat. This was done to reduce the already excessive number of zeros in the data, i.e. zero catch where you would not reasonably expect to catch silky sharks.

Because silky sharks are an epi-pelagic tropical species, all sets that occurred in water colder than 25%??C were discarded, this left 95% of the sets with a non-zero catch (Figure 2). The effect of hooks between floats (a proxy for depth) was investigated independently and sets with greater than 30 hooks between floats were discarded, this left 90% of the sets with a non-zero catch (Figure 2). National affiliation of the fishing vessel was included in the data set, and only those nations that had greater than 100 sets since 1995 were used. The last variable that resulted in a culling of the data set was that based on non-zero CPUE for unidentified sets (sets where the target is marked as unidentified) as a function of national affiliation. Flagged vessels where the average positive CPUE was 3 times larger than the mean CPUE for all other nations combined were removed from the bycatch longline data under the premise that these vessels were targeting sharks.

Latitude and longitude were truncated to the nearest 1%??; this location information was used to calculate the set specific association with a 5??square (referred to hereinafter as cell). Date of set was used to calculate the year, month, quarter and trimester of the set. Set time was used to calculate the time category of the day in sixths starting at midnight. A non-target data set was created as a result of filtering data sets according to the above rules as well as filtering sets where sharks were the intentional target. This was done under the premise that the factors leading to non-zero catch rates when targeting sharks would be different than factors that lead to non-zero catch rates when not targeting sharks.

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. Silky shark CPUE was plotted as a function of the variables sharkline, shark bait, shark target against date of set (Figure 3). Inspection of these covariates led to the separation of shark-targeting sets and non-targeting (bycatch) sets.

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 **??**.

Overview of GLM Analyses

0.3.1 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): this approach is a special case of the more general delta method (Pennington 1996, Ortiz and Arocha 2004), and uses a binomial distribution for the probability w of catch being zero and a probability distribution f(y), where y was log(catch/hooks set), for non-zero catches. An index was estimated for each year, which was the product of the year effects for the two model components,

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). 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.

0.4 Results

0.4.1 Blue Shark

0.4.2 Mako Shark

0.4.3 Silky Shark

0.4.4 Oceanic Whitetip Shark

0.4.5 Thresher Shark

0.5 Conclusions

1 Methods for standardized indices of abundance

1.1 Stock definition for CPUE analysis

Porbeagle not found in north so removed hemi Mako + blue south and north stocks (see Clarke 2011... or other refs)

1.2 Selection of cells within shark distribution

Looked at range of SST where positive catches occured, selected cells where median falls within this range

1.3 Procedure for model selection

Variable name	Symbol	Explanation	% records present
Year	β_Y	Require 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			
Number of shark lines			
Lighsticks			
Shark target		Sharks explicitly defined as targets?	
SST	SST	Moon frac	

1.3.1 Note on interactions between year and observer program

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. 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, and proceeded with an interaction for the remaining of the model selection if the AIC score when interactions are allowed is at least 50 lower than with additive effects only.

1.4 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...

1.5 Model diagnostics

Used quantile residuals.

1.6 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 1: 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 2: 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 3: 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 4: 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 5: 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 6: 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 7: 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 8: 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 9: 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 10: 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