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 preser
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

1.4 Notes on the use of error distributions

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 often accounting for the large amount of zeroes in shark CPUE catch data comes at the expense of modelling large catch events, since the dispersion is assumed to be constant for 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.

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.

Hooks-between-floats on its own explains little variation, probably because it only matters when looked at within specific levels of other factors (see Fig ... – panel observers).

1.5 Model structure by species

North Mako: removing HW removes a lot of data!! check for catches...

Species	Model μ	mo
South mako: program + hbp2 + yy + mm	program code + month	
North mako:		
South Blue shark: year + program code + hpbcat + mm + shark bait	program + hbpcat + mm	
North Blue shark: year + program + mm	program + mm + hpbcat	
Thresher:		
Hammerheads:		
Oceanic whitetip:		
Silky: program + year +		
Porbeagle:		

1.6 Model diagnostics

Used quantile residuals.

Table 1: 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 2: 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 3: 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 4: 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 5: 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 6: 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 7: 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 8: 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 9: 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