

## **Spatial and temporal predictions of inter-decadal trends in Indian Ocean whale sharks**

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### **Supplement. Model predictors: Step 1**

Here we re-fitted the whale shark distribution model for autumn (Sequeira et al. 2012), using generalized linear mixed-effects models estimated with a Laplace approximation to the likelihood (lmer function; Bates et al. 2011) rather than using a penalized quasi-likelihood approach (glmmPQL function in R; Venables & Ripley 2002) as used by Sequeira et al. (2012). Using the lmer approach, we can now obtain information criteria output to rank models. When re-running the autumn spatial model, we also used a different response variable for these models by increasing the pseudo-absence:presence ratio from 1:1 (Sequeira et al. 2012) to 1:10 to ensure that the variable coded as a random effect (spatially aggregated cells) contained at least 1 point for the analysis. We included an additional quadratic term for ‘depth’ (bathymetry), because although whale sharks spend most of their time at the surface (Sleeman et al. 2010b), they frequently make sub-surface dives (Wilson et al. 2006). Including this quadratic term tests the hypothesis that sightings occur mostly in locations where depth is within a specific range. Moreover, depth can also be viewed as a proxy for a set of environmental conditions differentiating the conditions encountered in shallow versus deep habitats (e.g. upwelling and primary productivity, hydrodynamics), which could play a role in influencing whale shark occurrence at the surface. We also standardized some explanatory variables used by Sequeira et al. (2012) to stabilize parameter estimation within the lmer function: we centred ‘depth’ and mean ‘sea surface temperature’, and log-transformed mean ‘chlorophyll *a*’, ‘distance to shore’, ‘slope’ and ‘effort’ (i.e. autumn mean value; Table S1). In this model update, we have included ‘effort’ (autumn mean value) as an offset term to account directly for the proportional increase in sightings with proportional increases in spatial fishing effort.

Table S1. Treatment given to each explanatory variable (standardization) used to obtain the spatial predictor ('SpatialP'; Sequeira et al. 2012) for the first step of our temporal models; SST: sea surface temperature; chl *a*: chlorophyll *a*

Variable	Treatment	Range	Mean
Depth	Centred	-3754.8 – 2444.4	0.00
Slope	Log	-5.21 – 3.43	-1.25
Distance to shore	Log	0.10 – 14.17	12.61
Mean SST	Centred	-3.97 – 2.40	0.00
Mean chl <i>a</i>	Log	-2.63 – 2.91	-1.93
Effort	Log (used as an offset)	-0.18 – 7.56	3.30

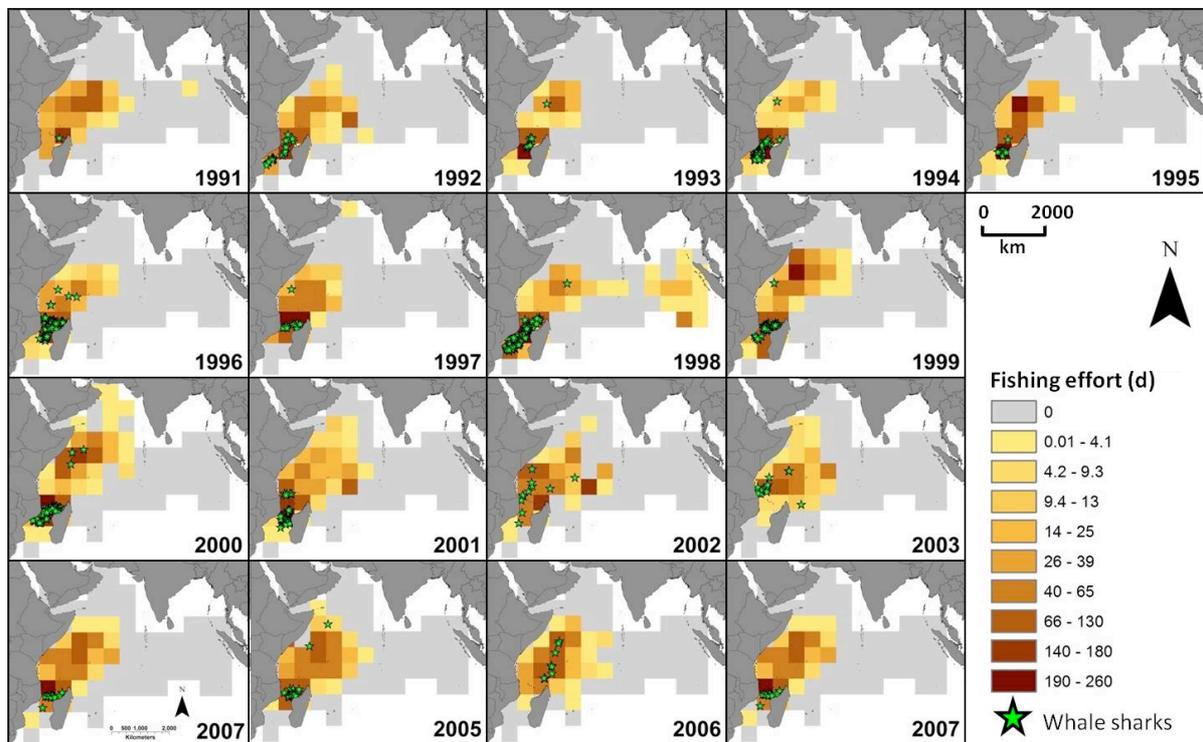


Fig. S1. Purse-seiner fishing effort (in days) during autumn for each year from 1991 to 2007

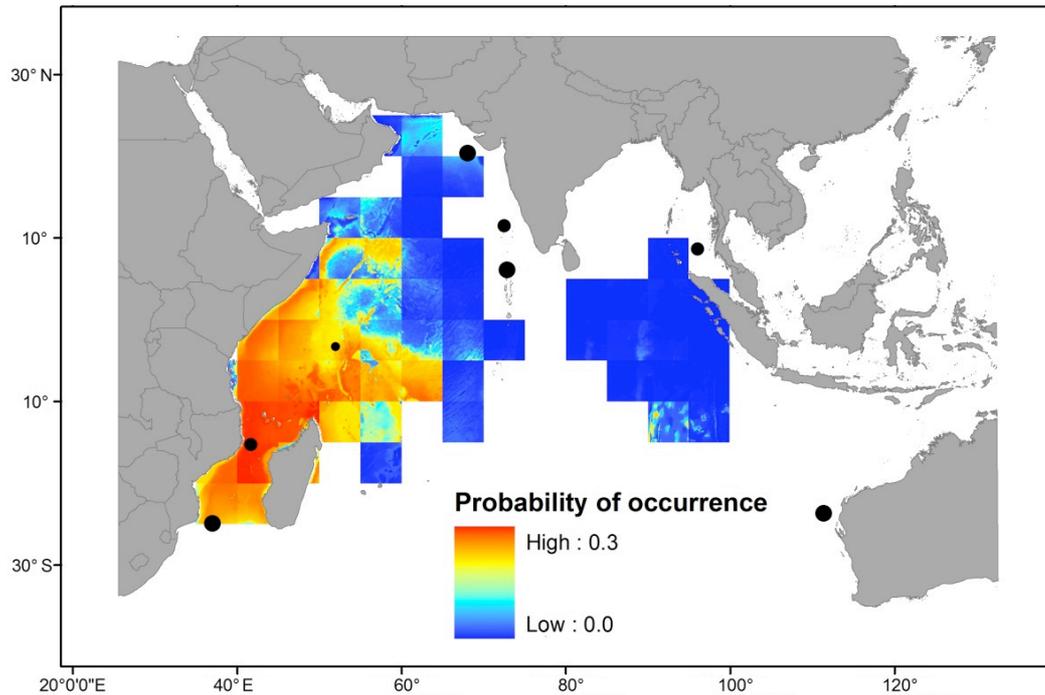


Fig. S2. *Rhincodon typus*. Habitat suitability of whale sharks in the Indian Ocean during autumn; updated model from Sequeira et al. (2012) (see Methods in the main text for details). Areas with higher probability of whale shark sightings are similar to the ones previously described and show that mostly the western Indian Ocean, specifically the Mozambique Channel, is more suitable for whale sharks in autumn, although lower probabilities ( $\sim 0.3$ ) were obtained when compared to the results of Sequeira et al. (2012). ●: known occurrences (Rowat 2007), with size representing strength of occurrence (i.e. larger dots correspond to a higher number of expected sightings)

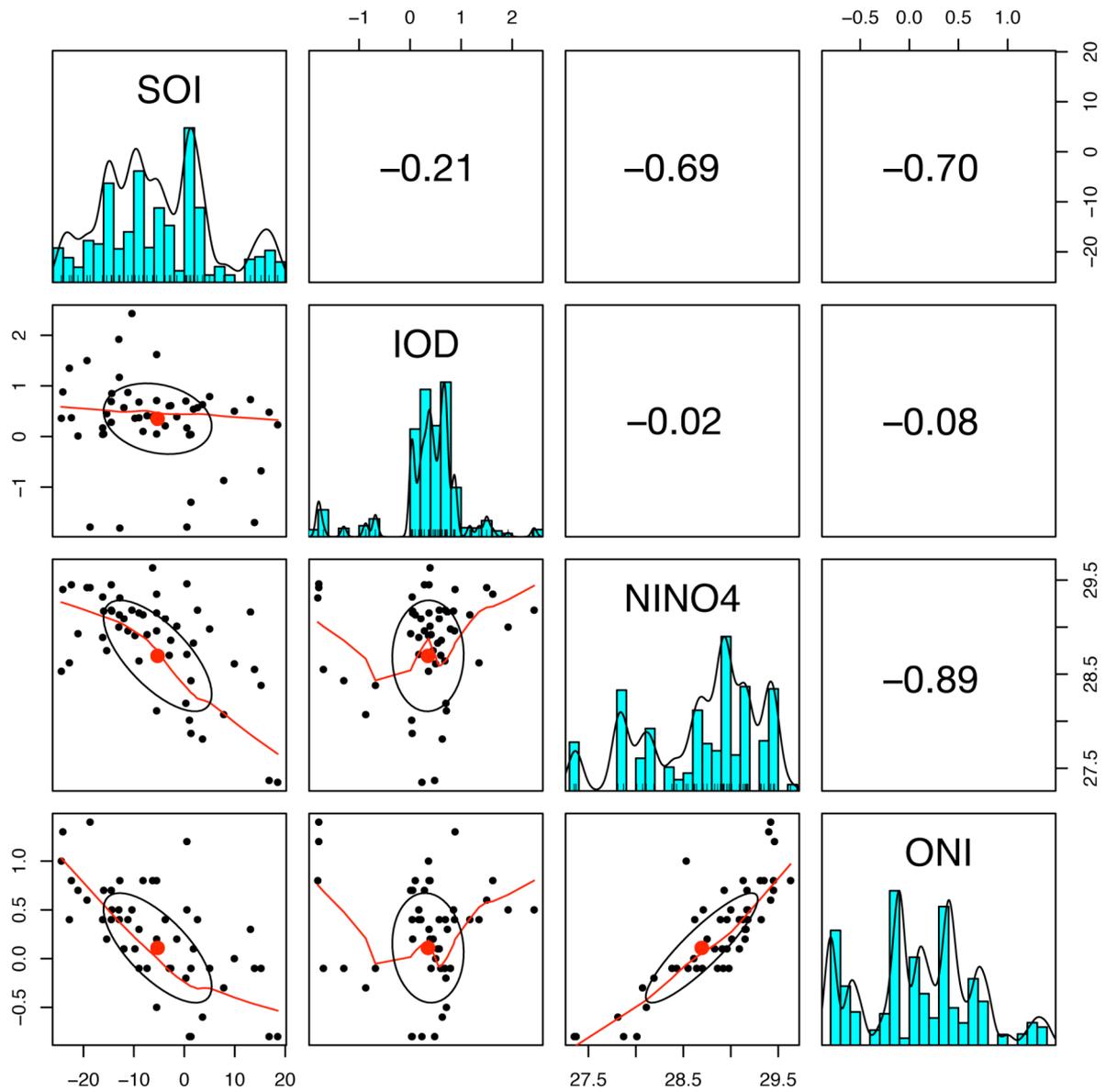


Fig. S3. Correlation between climatic predictor variables, showing: the histograms for each predictor considered in the diagonal, the bivariate scatter plots with linear fits and correlation ellipses below the diagonal, and the Pearson's correlation results above the diagonal. SOI: Southern Oscillation Index, IOD: Indian Ocean Dipole, NINO4: El Niño variation in the central Pacific Region 4, ONI: Oceanic Niño Index

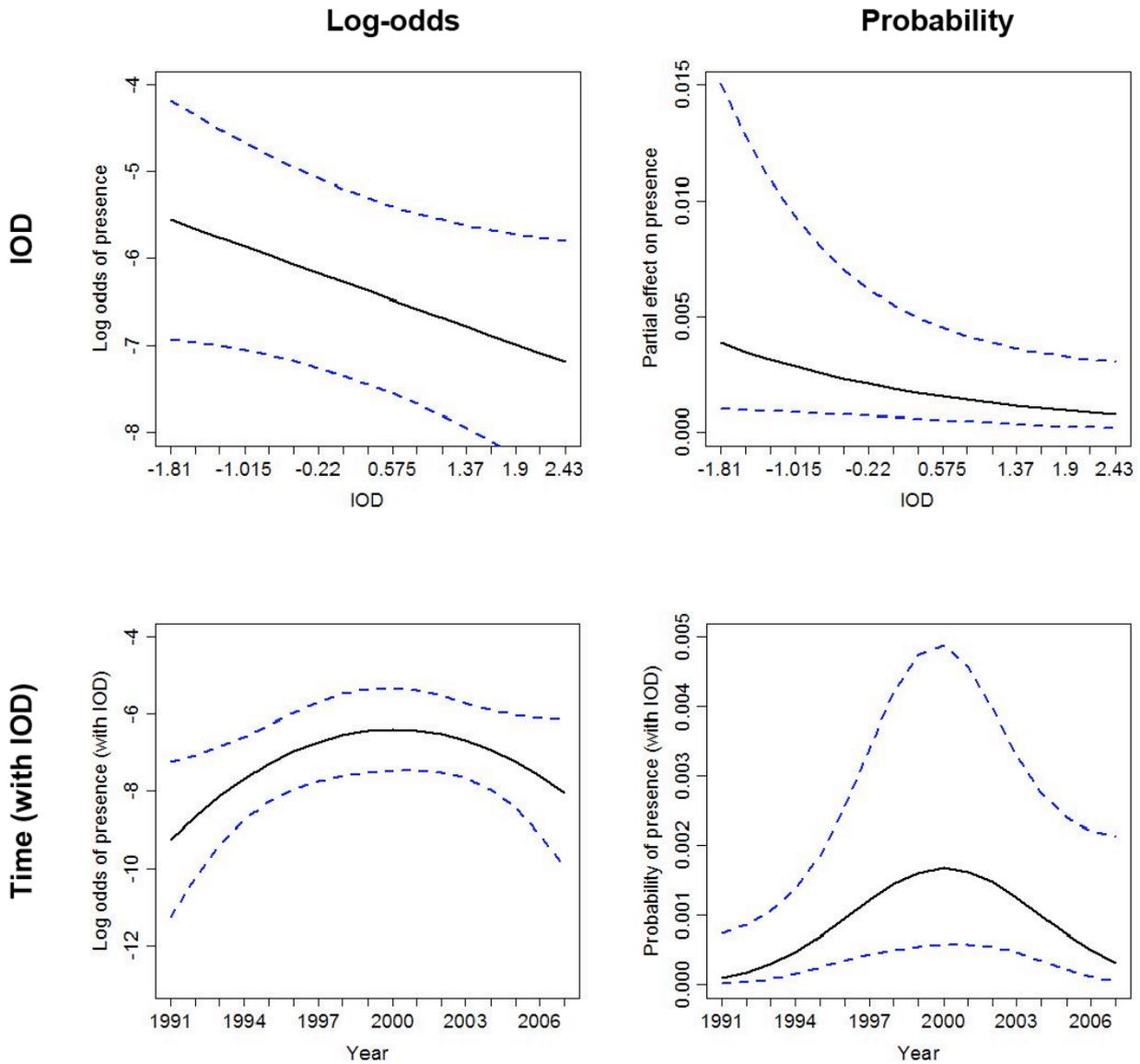


Fig. S4. *Rhincodon typus*. Top row: Partial effect of the Indian Ocean Dipole (IOD; Saji et al. 1999) on the probability of whale shark sightings. IOD reflects anomalies in the sea surface temperature in the equatorial area of the Indian Ocean between 50 to 70° E, 10° N to 10° S and 90 to 110° E, 0° N to 10° S. Bottom row: Partial effect of 'Time' after accounting for climatic contributions to whale shark sighting probability. Dashed lines: 95% CI