Supporting Information

Queiroz et al.

Contents   page no.

1. Supporting Methods

1.1. Study animals and tagging methods

Overall, 113 sharks were tagged between 2006 and 2012; however, since 14 tags reported poor data, we restricted our analysis to 99 tracks collected over 7,990 cumulative days and representing six species: blue (*Prionace glauca*) $n = 38$ individuals; shortfin mako (*Isurus oxyrinchus*) $n = 14$; longfin mako (*Isurus paucus*) $n = 1$; tiger (*Galeocerdo cuvier*) $n = 32$; great hammerhead (*Sphyrna mokarran*) $n = 12$, and scalloped hammerhead (*Sphyrna lewini*) $n = 2$. Figure S1 shows the tagging locations and numbers of sharks tagged at each location. Table S1 provides summary information of individuals tagged including size, sex, and tag type.

At coastal locations in the north-eastern Atlantic (southern England and mainland Portugal) capture and tagging methods of blue sharks followed Queiroz *et al*. (1, 2). Briefly, sharks were captured using rod and line and brought on-board for body-length measurement and tagging. Pop-off satellite-linked archival transmitter tags (PSATs; models PAT4 and PAT-Mk10, Wildlife Computers, Redmond, WA, USA) were attached via a monofilament tether (250 lb test) connected to a 5-cm long stainless steel T-bar arrowhead or an 'umbrella' type nylon dart. Tags were inserted into the dorsal musculature at a 45° angle to a maximum depth of 10 cm. Argos satellite platform transmitter terminals (PTTs) (Smart position-only tags, SPOT; model SPOT5, Wildlife Computers, Redmond, WA, USA) were attached to the first dorsal fin with stainless steel bolts, neoprene and steel washers, and steel screw-lock nuts. In the north-western Atlantic, tiger and hammerhead capture and tagging methods followed Hammerschlag *et al*. (3, 4). Sampling was conducted within the U.S. east coast (southern Florida) and off the Bahamas (Grand Bahamas). Sharks were captured using standardised circle hook drumlins, each consisting of a submerged weight base tied to a line running to the surface by means of an attached, visible float. Captured sharks were secured alongside the boat or on a partially submerged platform. A seawater hose was placed in the sharks' mouth, permitting oxygenation of the gills while the shark was temporarily immobilised. SPOT tags were affixed to the first dorsal fin using titanium bolts, neoprene and steel washers, and high-carbon steel nuts. A subset of tiger shark data published previously (3) was analysed differently in this study.

At oceanic locations blue and mako sharks were captured on baited longlines deployed from a commercial fishing vessel. Sharks were brought alongside the vessel in the beginning

of the gear-hauling phase, lifted and tagged while suspended against the vessel's side in the vertical position. PSAT tags were rigged with a monofilament tether covered with silicone tubing and looped through a small hole made in the base of first dorsal fin; SPOT tagging at oceanic locations followed a similar procedure to coastal deployments.

All shark tagging procedures undertaken in this study were approved by institutional ethical review committees and completed by licensed, trained and experienced personnel. The procedures used by the UK personnel were licensed by the UK Home Office under the Animals (Scientific Procedures) Act 1986.
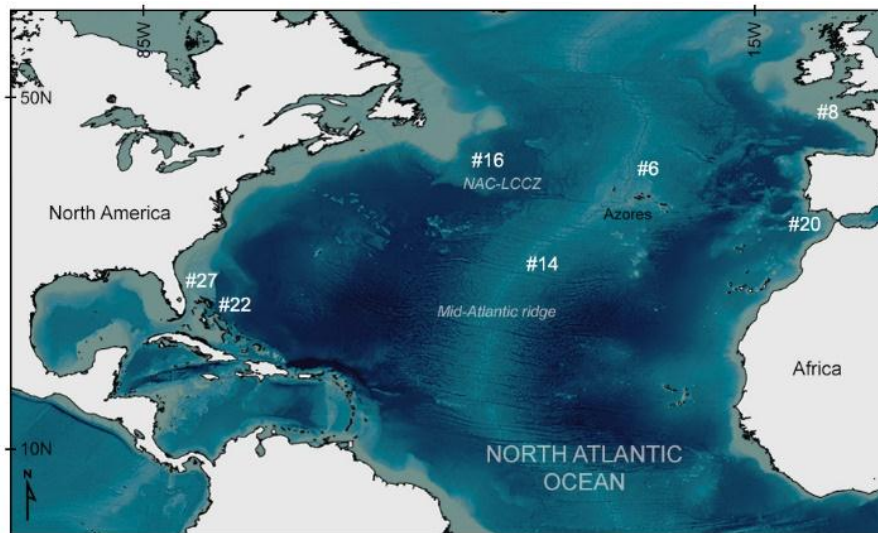

Fig. S1. Shark tagging locations showing the number of tags (#) deployed at each location. NAC-LCCZ denotes the North Atlantic Current – Labrador Current convergence zone.

Table S1. Summary data for satellite tagged sharks; F – female; M – male; * poor transmission.

Shark ID	PTT ID	Species	Fork length (cm)	Sex	Tag type	Location tagged	Tagging date	Days-at-liberty
Shark 1	40390	*Prionace glauca*	210	F	SPOT5	Oceanic	29 Aug. 2011	46
Shark 2	40406	*Prionace glauca*	150	F	PAT-Mk10	England	21 Aug. 2007	69
Shark 3	40421	*Prionace glauca*	180	F	PAT-Mk10	Portugal	04 Jun. 2008	11
Shark 4	40461	*Prionace glauca*	180	F	PAT-Mk10	Portugal	04 Jun. 2008	50
Shark 5	49022	*Prionace glauca*	199	F	PAT4	England	06 Jul. 2006	29
Shark 6	66935	*Prionace glauca*	200	F	PAT-Mk10	Portugal	03 Jun. 2008	28
Shark 7	66936	*Prionace glauca*	95	F	PAT-Mk10	Portugal	10 Oct. 2006	19
Shark 8	66938	*Prionace glauca*	199	M	PAT-Mk10	Oceanic	17 Jun. 2007	23
Shark 9	66940	*Prionace glauca*	130	F	PAT-Mk10	England	01 Aug. 2007	12
Shark 10	66942	*Prionace glauca*	115	F	PAT-Mk10	Portugal	04 Oct. 2007	41
Shark 11	66945	*Prionace glauca*	153	F	PAT-Mk10	England	21 Jul. 2006	19
Shark 12	66946	*Prionace glauca*	130	F	PAT-Mk10	England	08 Aug. 2006	20
Shark 13	66951	*Prionace glauca*	186	F	SPOT5	England	15 Aug. 2006	8
Shark 14	66952	*Prionace glauca*	170	F	SPOT5	England	18 Aug. 2006	14
Shark 15	66954	*Prionace glauca*	160	F	SPOT5	England	31 Aug. 2007	21
Shark 16	66955	*Prionace glauca*	145	F	SPOT5	Portugal	01 Jun. 2009	23
Shark 17	66957	*Prionace glauca*	220	M	SPOT5	Portugal	01 Jun. 2009	102
Shark 18	66963	*Prionace glauca*	90	M	SPOT5	Portugal	10 Oct. 2006	23
Shark 19	66967	*Prionace glauca*	130	F	SPOT5	Portugal	06 Jun. 2008	101

Shark ID	PTT ID	Species	Fork length (cm)	Sex	Tag type	Location tagged	Tagging date	Days-at-liberty
Shark 20	66969	*Prionace glauca*	130	M	SPOT5	Portugal	17 Jun. 2008	112
Shark 21	84174	*Prionace glauca*	190	F	SPOT5	Oceanic	30 Aug. 2011	18
Shark 22	84175	*Prionace glauca*	220	F	SPOT5	Oceanic	02 Sep. 2011	33
Shark 23	85136	*Prionace glauca*	260	M	PAT-Mk10	Oceanic	21 Aug. 2011	91
Shark 24	85140	*Prionace glauca*	250	M	PAT-Mk10	Oceanic	22 Aug. 2011	119
Shark 25	85693	*Prionace glauca*	240	M	PAT-Mk10	Oceanic	26 Aug. 2011	81
Shark 26	85697	*Prionace glauca*	200	M	PAT-Mk10	Oceanic	26 Aug. 2011	119
Shark 27	86395	*Prionace glauca*	185	M	PAT-Mk10	Oceanic	26 Jun. 2010	88
Shark 28	86396	*Prionace glauca*	192	F	PAT-Mk10	Oceanic	27 Jun. 2010	56
Shark 29	86403	*Prionace glauca*	125	F	PAT-Mk10	Portugal	26 May 2009	120
Shark 30	91026	*Prionace glauca*	240	F	PAT-Mk10	Oceanic	21 Aug. 2011	89
Shark 31	91658	*Prionace glauca*	260	F	PAT-Mk10	Oceanic	26 Aug. 2011	121
Shark 32	96034	*Prionace glauca*	260	F	PAT-Mk10	Oceanic	29 Jun. 2010	119
Shark 33	96035	*Prionace glauca*	240	F	PAT-Mk10	Oceanic	30 Jun. 2010	26
Shark 34	96036	*Prionace glauca*	200	M	PAT-Mk10	Oceanic	25 Jun. 2010	13
Shark 35	96037	*Prionace glauca*	210	M	PAT-Mk10	Oceanic	25 Jun. 2010	7
Shark 36	96039	*Prionace glauca*	235	M	PAT-Mk10	Oceanic	25 Jun. 2010	179
Shark 37	107084	*Prionace glauca*	220	F	PAT-Mk10	Oceanic	27 Aug. 2011	119
Shark 38	107085	*Prionace glauca*	220	F	PAT-Mk10	Oceanic	28 Aug. 2011	93
Shark 39	40392	*Isurus oxyrinchus*	210	F	SPOT5	Oceanic	05 Sep. 2011	58

Shark ID	PTT ID	Species	Fork length (cm)	Sex	Tag type	Location tagged	Tagging date	Days-at-liberty
Shark 40	40393	*Isurus oxyrinchus*	200	M	SPOT5	Oceanic	08 Sep. 2011	50
Shark 41	86399	*Isurus oxyrinchus*	140	M	PAT-Mk10	Oceanic	25 Jun. 2010	59
Shark 42	86400	*Isurus oxyrinchus*	125	M	PAT-Mk10	Oceanic	23 Apr. 2009	29
Shark 43	86401	*Isurus oxyrinchus*	220	M	PAT-Mk10	Oceanic	30 Jun. 2010	86
Shark 44	86402	*Isurus oxyrinchus*	170	F	PAT-Mk10	Oceanic	24 Apr. 2009	59
Shark 45	86407	*Isurus oxyrinchus*	130	M	PAT-Mk10	Oceanic	03 Jul. 2010	89
Shark 46	86408	*Isurus oxyrinchus*	180	M	PAT-Mk10	Oceanic	27 Jun. 2010	113
Shark 47	96030	*Isurus oxyrinchus*	130	F	PAT-Mk10	Oceanic	04 Jul. 2010	117
Shark 48	96031	*Isurus oxyrinchus*	165	F	PAT-Mk10	Oceanic	05 Jul. 2010	117
Shark 49	98334	*Isurus oxyrinchus*	270	F	SPOT5	USA	13 Nov. 2010	150
Shark 50	107089	*Isurus oxyrinchus*	220	F	PAT-Mk10	Oceanic	21 Aug. 2011	119
Shark 51	107090	*Isurus oxyrinchus*	255	F	PAT-Mk10	Oceanic	22 Aug. 2011	119
Shark 52	107091	*Isurus paucus*	245	F	PAT-Mk10	Oceanic	30 Aug. 2011	49
Shark 53	107092	*Isurus oxyrinchus*	170	M	PAT-Mk10	Oceanic	03 Sep. 2011	119
Shark 54	33992	*Galeocerdo cuvier*	203	F	SPOT5	USA	26 May 2010	34
Shark 55	34020	*Galeocerdo cuvier*	164	M	SPOT5	USA	26 May 2010	41
Shark 56	34021	*Galeocerdo cuvier*	217	F	SPOT5	USA	26 May 2010	25
Shark 57	34029	*Galeocerdo cuvier*	205	F	SPOT5	USA	26 May 2010	191
Shark 58	34203	*Galeocerdo cuvier*	210	F	SPOT5	USA	13 Nov. 2010	47
Shark 59	55494	*Galeocerdo cuvier*	210	F	SPOT5	USA	10 Jun. 2010	96

Shark ID	PTT ID	Species	Fork length (cm)	Sex	Tag type	Location tagged	Tagging date	Days-at-liberty
Shark 60	55495	*Galeocerdo cuvier*	206	F	SPOT5	USA	09 Jun. 2010	129
Shark 61	68471	*Galeocerdo cuvier*	245	F	SPOT5	USA	29 Jan. 2011	28
Shark 62	68477	*Galeocerdo cuvier*	201	M	SPOT5	USA	29 Oct. 2010	128
Shark 63	68485	*Galeocerdo cuvier*	162	F	SPOT5	Bahamas	19 Feb. 2011	95
Shark 64	68486	*Galeocerdo cuvier*	280	F	SPOT5	Bahamas	20 Feb. 2011	99
Shark 65	68488	*Galeocerdo cuvier*	267	F	SPOT5	Bahamas	20 Feb. 2011	252
Shark 66	68494	*Galeocerdo cuvier*	245	F	SPOT5	Bahamas	19 Feb. 2011	191
Shark 67	68495	*Galeocerdo cuvier*	306	F	SPOT5	Bahamas	20 Feb. 2011	232
Shark 68	68496	*Galeocerdo cuvier*	271	F	SPOT5	Bahamas	20 Feb. 2011	217
Shark 69	68529	*Galeocerdo cuvier*	232	F	SPOT5	Bahamas	19 Feb. 2011	551
Shark 70	68554	*Galeocerdo cuvier*	271	F	SPOT5	Bahamas	19 Feb. 2011	185
Shark 71	68555	*Galeocerdo cuvier*	340	F	SPOT5	Bahamas	20 Feb. 2011	253
Shark 72	68556	*Galeocerdo cuvier*	237	F	SPOT5	Bahamas	20 Feb. 2011	240
Shark 73	98332	*Galeocerdo cuvier*	269	F	SPOT5	USA	12 Nov. 2010	85
Shark 74	105594	*Galeocerdo cuvier*	148	F	SPOT5	Bahamas	19 Feb. 2011	10
Shark 75	105595	*Galeocerdo cuvier*	315	F	SPOT5	Bahamas	22 Feb. 2011	35
Shark 76	105599	*Galeocerdo cuvier*	271	F	SPOT5	Bahamas	19 Feb. 2011	9
Shark 77	106660	*Galeocerdo cuvier*	285	M	SPOT5	Bahamas	10 Apr. 2011	53
Shark 78	106661	*Galeocerdo cuvier*	167	F	SPOT5	Bahamas	10 Apr. 2011	49
Shark 79	112986	*Galeocerdo cuvier*	267	F	SPOT5	Bahamas	23 Jul. 2012	25

Shark ID	PTT ID	Species	Fork length (cm)	Sex	Tag type	Location tagged	Tagging date	Days-at-liberty
Shark 80	112987	*Galeocerdo cuvier*	204	F	SPOT5	Bahamas	22 Jul. 2012	26
Shark 81	113534	*Galeocerdo cuvier*	246	F	SPOT5	Bahamas	15 Dec. 2011	33
Shark 82	113536	*Galeocerdo cuvier*	268	F	SPOT5	Bahamas	15 Dec. 2011	86
Shark 83	113537	*Galeocerdo cuvier*	254	F	SPOT5	Bahamas	05 Feb. 2012	72
Shark 84	115906	*Galeocerdo cuvier*	290	M	SPOT5	USA	27 May 2012	40
Shark 85	115907	*Galeocerdo cuvier*	162	M	SPOT5	Bahamas	10 Feb. 2012	24
Shark 86	33933	*Sphyrna mokarran*	204	M	SPOT5	USA	04 Jun. 2010	20
Shark 87	33938	*Sphyrna mokarran*	193	M	SPOT5	USA	12 Mar. 2010	42
Shark 88	33994	*Sphyrna lewini*	155	F	SPOT5	USA	17 Mar. 2010	23
Shark 89	68472	*Sphyrna mokarran*	212	F	SPOT5	USA	29 Jan. 2011	26
Shark 90	68480	*Sphyrna mokarran*	196	F	SPOT5	USA	29 Jan. 2011	116
Shark 91	68481	*Sphyrna mokarran*	218	F	SPOT5	USA	29 Jan. 2011	101
Shark 92	98328	*Sphyrna mokarran*	173	M	SPOT5	USA	20 Feb. 2010	10
Shark 93	98329	*Sphyrna mokarran*	184	M	SPOT5	USA	20 Feb. 2010	62
Shark 94	105597	*Sphyrna mokarran*	255	M	SPOT5	Bahamas	19 Feb. 2011	49
Shark 95	106662	*Sphyrna lewini*	197	M	SPOT5	USA	30 Apr. 2011	65
Shark 96	106663	*Sphyrna mokarran*	199	F	SPOT5	USA	13 Jul. 2011	156
Shark 97	106895	*Sphyrna mokarran*	204	F	SPOT5	USA	05 Aug. 2011	32
Shark 98	106896	*Sphyrna mokarran*	222	M	SPOT5	USA	18 Jul. 2011	4
Shark 99	111550	*Sphyrna mokarran*	195	M	SPOT5	USA	12 Sep. 2011	53

Shark ID	PTT ID	Species	Fork length (cm)	Sex	Tag type	Location tagged	Tagging date	Days-at-liberty
Shark 100*	40460	*Prionace glauca*	140	M	PAT-Mk10	Portugal	09 Jun. 2008	–
Shark 101*	40462	*Prionace glauca*	200	F	PAT-Mk10	Portugal	06 Jun. 2008	–
Shark 102*	40463	*Prionace glauca*	200	M	PAT-Mk10	Portugal	11 Jun. 2008	–
Shark 103*	66937	*Prionace glauca*	110	F	PAT-Mk10	Portugal	12 Oct. 2006	–
Shark 104*	66962	*Prionace glauca*	90	F	SPOT5	Portugal	10 Oct. 2006	–
Shark 105*	66964	*Prionace glauca*	90	M	SPOT5	Portugal	10 Oct. 2006	–
Shark 106*	66965	*Prionace glauca*	95	M	SPOT5	Portugal	11 Oct. 2006	–
Shark 107*	66966	*Prionace glauca*	120	F	SPOT5	Portugal	12 Oct. 2006	–
Shark 108*	66968	*Prionace glauca*	120	F	SPOT5	Portugal	12 Jun. 2008	–
Shark 109*	85698	*Prionace glauca*	240	M	PAT-Mk10	Oceanic	27 Aug. 2011	–
Shark 110*	86406	*Prionace glauca*	165	F	PAT-Mk10	Oceanic	25 Jun. 2010	–
Shark 111*	107088	*Prionace glauca*	220	F	PAT-Mk10	Oceanic	29 Aug. 2011	–
Shark 112*	34107	*Galeocerdo cuvier*	210	F	SPOT5	USA	25 May 2010	–
Shark 113*	98331	*Sphyrna mokarran*	185	F	SPOT5	USA	07 Feb. 2010	–

1.2. Track processing

1.2.1. Pop-off Satellite Archival Transmitters (PSAT)

The movement of PSAT-tagged sharks was estimated using either satellite relayed data from each tag or from archival data after the tags were physically recovered. Positions of each shark between attachment and tag pop-up were reconstructed using software provided by the manufacturer (WC-GPE, global position estimator program suite), where daily maximal rate-of-change in light intensity was used to estimate local time of midnight or midday for longitude calculations, and day-length estimation for determining latitude. Anomalous longitude estimates resulting from dive-induced shifts in the estimated timings of dawn and dusk from light curves were automatically discarded from the dataset using software provided by the manufacturer (WC-GPE); latitude estimates were subsequently iterated for the previously obtained longitudes. An integrated state-space model [unscented Kalman filter – UKFSST (5); using spatially complete NOAA Optimum Interpolation Quarter Degree Daily SST Analysis data] was then applied to correct the raw geolocation estimates and obtain the most probable track. A regular time-series of locations was then estimated using a continuous-time correlated random walk Kalman filter, CTCRW (6) performed in R (*crawl package*). UKFSST geolocations were parameterised with standard deviation (SD) constants (K) which produced the smallest mean deviation from concurrent Argos positions (7).

1.2.2. Argos Satellite Transmitter tags

Location class (LC) Z data (failed attempt at obtaining a position) were removed from the dataset. The remaining raw position estimates (LC 3, 2, 1, 0, A and B) were analysed point-to-point with a 3 m s^{-1} speed filter to remove outlier locations. Subsequently, the CTCRW state-space model was applied to each individual track, producing a single position estimate per day. Argos positions were parameterised with the K error model parameters for longitude and latitude implemented in the *crawl package* (6).

1.3. Spatial density analysis and statistics

As described above, to obtain unbiased estimates of shark space use, gaps between consecutive dates in the raw tracking data were interpolated to one position per day. However, and even though the frequency of long temporal gaps (> 20 days) in the dataset

10

was small (Table S2), any tracks with gaps exceeding 20 days were split into segments prior to interpolation, thus avoiding the inclusion of unrepresentative location estimates (8).

Table S2. Number of temporal gaps of a given length per track for the different species and tag type.

| Species | Tag type | Frequency of gaps; mean (± SD) | | | Number of tracks |
		> 5d	> 10d	> 20d	
Prionace glauca	PAT-Mk10	4.3 (4.2)	0.9 (1.1)	0.1 (0.3)	27
	SPOT5	1.4 (1.7)	0.3 (0.6)	0.0	11
Isurus spp.	PAT-Mk10	4.2 (3.9)	1 (1.4)	0.1 (0.3)	12
	SPOT5	0.0	0.0	0.0	3
Galeocerdo cuvier	SPOT5	3.9 (2.4)	1.4 (2.2)	0.1 (0.4)	32
Sphyrna spp.	SPOT5	2.6 (4.5)	0.5 (0.9)	0.1 (0.3)	14

To account for the spatial error around real individual geolocations, these were randomly resampled (100 times) along tag-specific longitudinal and latitudinal Gaussian error fields (7, 9). To reduce tagging location and track length bias, the number of resampled positions per grid cell were normalised by the number of individual sharks within each grid cell (10); thus, an effort-weighted index of residence per unit area (number of mean days per grid cell) was calculated from the initial resampled geolocations using ArcGIS geographical information system (ESRI Inc., CA, USA) (see Fig. S2). We then applied a spatial hotspot analysis, the Getis-Ord Gi* hotspot analysis (11), implemented in ArcGIS to identify objectively the patterns of spatial significance. For a set of weighted features, this analysis identifies clusters of points with higher (hotspot) or lower (coldspot) values in magnitude than expected by random chance (12). Briefly, the procedure analyses spatial data and determines the correlation of a given data point value (in our case mean days per grid cell) with the values in surrounding (neighbour) areas, automatically performing a test of significance (z-score) for each area. At a significance level of 0.05, a z-score would have to be smaller than -1.96 or greater than 1.96 to be statistically significant. Hence, hotspots and coldspots of shark geolocations were defined as high (above the resampled mean days) and low (below the resampled mean days) space use areas, respectively. In the analysis the spatial relationship was conceptualised through a fixed distance band and importantly, the appropriate value was objectively calculated within ArcGIS (*spatial statistics tool*). To test whether serial

correlation was an issue in the performed analysis, we applied a spatial hotspot analysis using every fifth location in the observed tracks (Fig. S3).
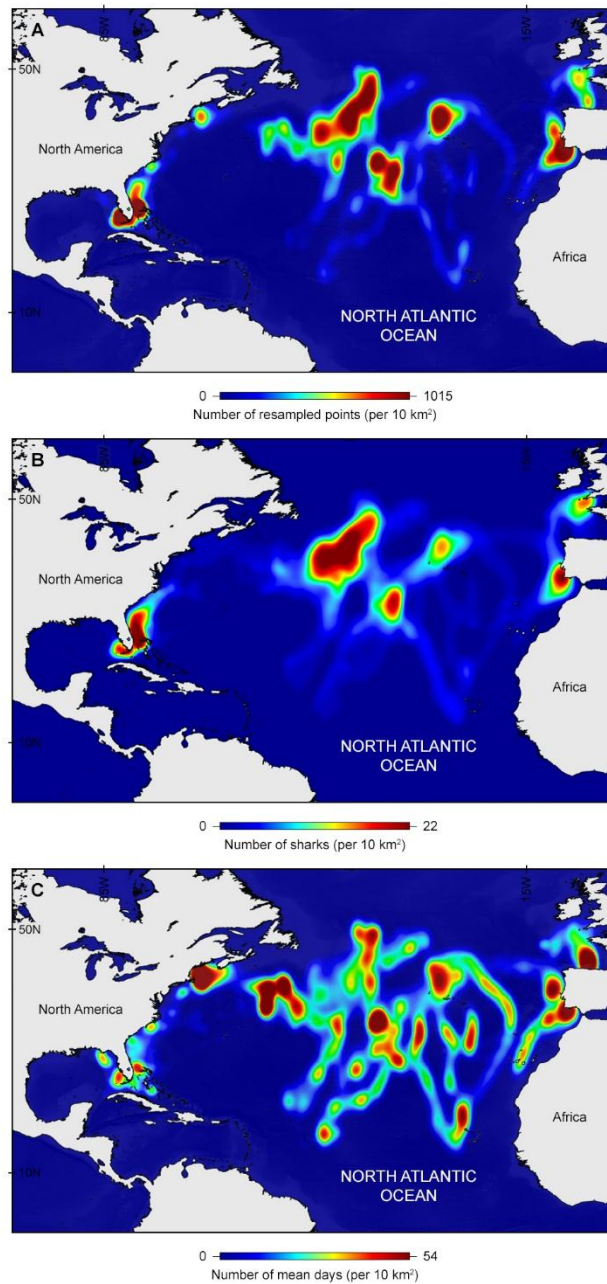

Fig. S2. Tagging location and track length bias reduction procedure; the number of resampled positions per grid cell (A) were normalised by dividing it by the number of tracked sharks (B), thus calculating the number of mean days per grid cell (C); the kernel smoothing parameter was calculated using a smooth cross validation procedure in R and was kept constant to enable the visual comparison of residence probabilities.
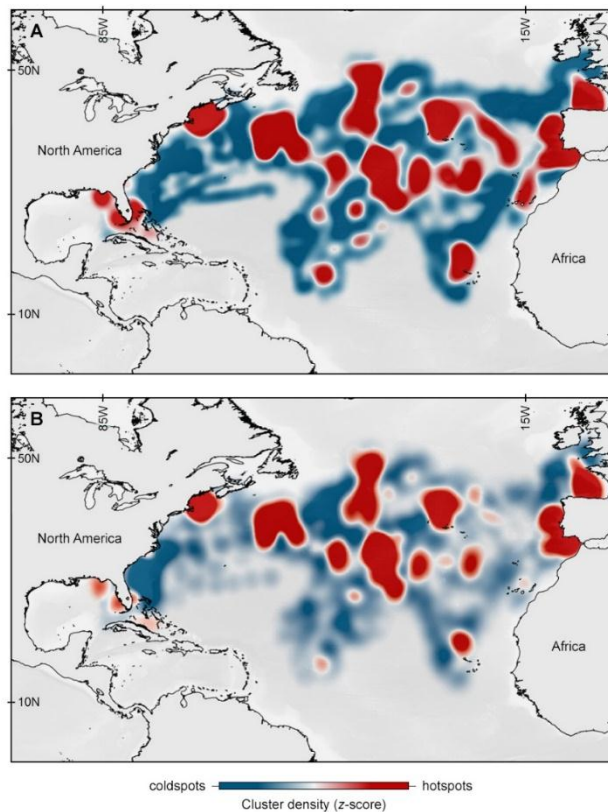
Fig. S3. Map of the estimated high (hotspot; red) and low (coldspot; blue) use habitats of sharks using daily (A) or every fifth location (B).

1.4. Vessel monitoring system data

Vessel monitoring system (VMS) data from 186 Spanish and Portuguese longliners (> 15 m length) operating in the north-east Atlantic were obtained from the respective national fisheries monitoring centres. The Spanish dataset spanned from January 2005 to December 2009, whereas the Portuguese data ranged from January 2003 to December 2005 and January 2009 to December 2011. Each record contained the Global Positioning System (GPS) position of the vessel (accurate to < 500 m), time stamp, and a vessel identification number. All records were anonymous with respect to the vessel registration number, dimensions and administrative ports. Received data duty cycle/reporting frequency ranged from 10 min to two hours. To determine the actual fishing locations where each individual longline was deployed, we developed an algorithm which detected sharp turning angles (> 130º), considered to be the point between longline deployment and retrieval (see Fig. S4). When a possible turn point was found, the inbound leg was retraced until the distance travelled

exceeded the longline length (between 80 and 100 km); the prior point was then taken as the start of deployment and the outbound leg was traced until the end-of-deployment point was determined in a similar fashion. A further check was undertaken that the endpoints were within a short distance of each other to confirm that a proper 'V' shape was defined. Subsequently, all movements between fishing locations were ignored (including trips to and from fishing ports), retaining only data pertaining to fishing activity ($n = 1,063,861$ data points). To estimate longliner space-use, fishing data were first normalised by calculating daily centroids and then mapped onto a grid at a spatial resolution of $1° × 1°$ with fishing effort computed as the number of vessels in each grid cell per day (Fig. 3).
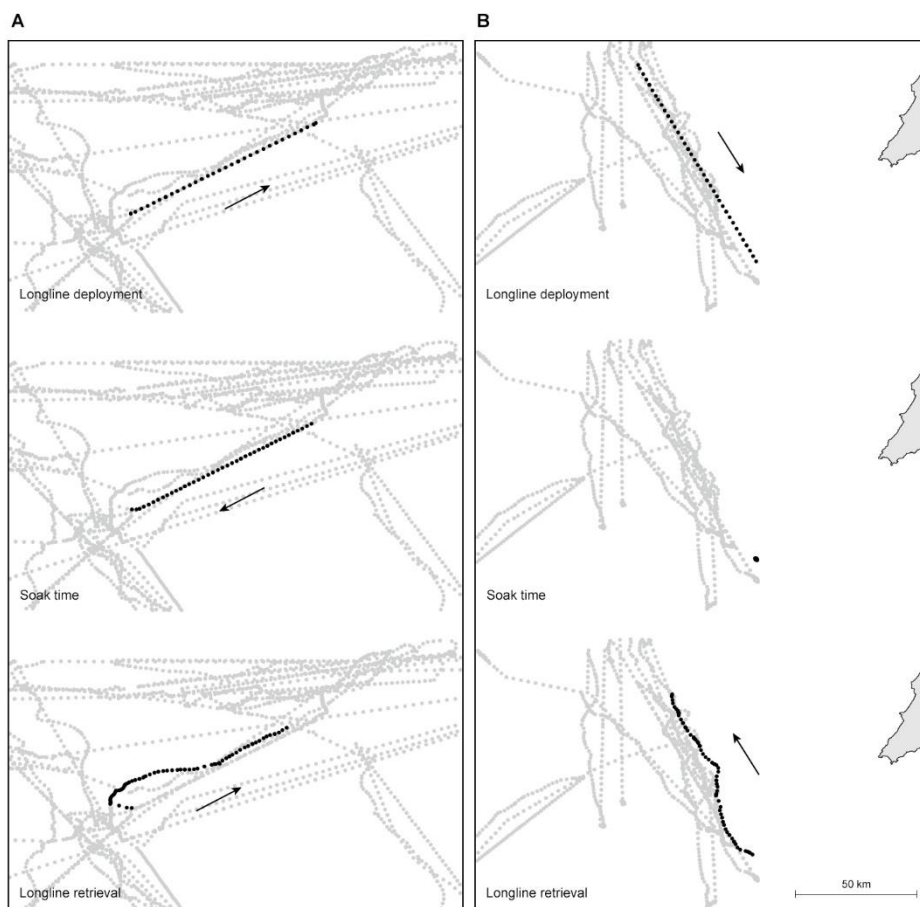
Fig. S4. Examples of area restricted searches with distinct soak time phases in tracked surface longliners, in areas with low (A) and high (B) abundance of targeted prey.

For a subset of 50 longliners, fishing data was further analysed to identify areas of restricted search, or spatial clusters of longline deployment locations. Briefly, when searching for fish species, longliners move from and back to the start position in three distinct phases:

line deployment, soak time and line retrieval (Fig. S4A). However, when sufficient numbers of target fish are found, the vessel remains stationary during soak time, thus allowing the longliners to target the same areas repeatedly (Fig. S4B), which results in (i) higher spatial concentration of fishing locations (data points), (ii) a higher number of turn points per grid cell, and (iii) increased number of hours between turn points, which were identified by the filtering algorithm as area-restricted spatial clusters. Environmental field data (section 1.5) were then extracted for the spatial clusters (see Fig. S5).
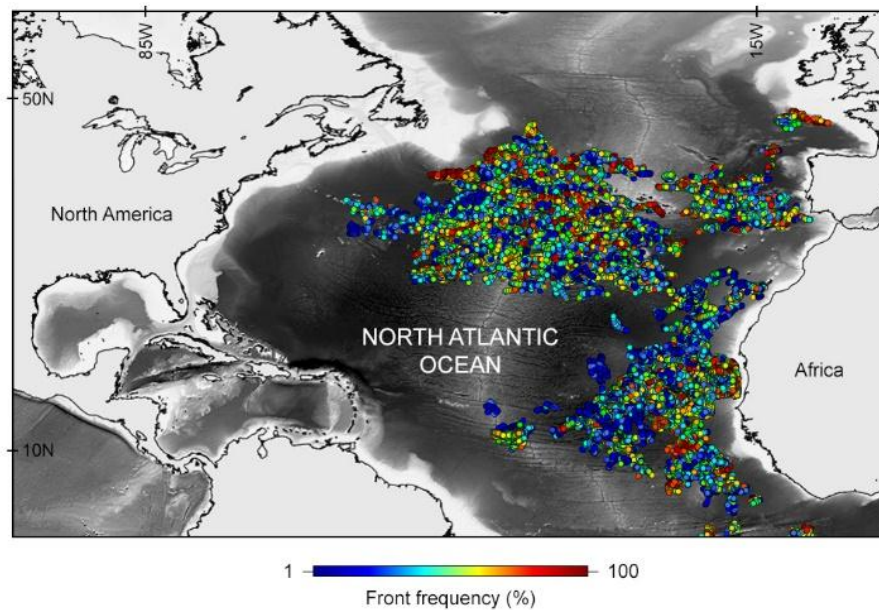
Fig. S5. Area restricted searches spatial clusters of longline deployment locations associated with frontal boundaries in the ocean.

1.5. Null model simulations and environmental preferences

1.5.1. Simulations of shark movements

To test shark associations with oceanographic features (a measure of habitat selection) quasi-realistic 'null' shark tracks, based on a random-walk model, were generated using custom-written R code. At the start of each simulated track, the null shark was placed at a random position within the actual tagging location error field (7, 9) and the initial turning angle derived from a 360º uniform distribution. The movement path of each shark comprised a sequence of discrete steps (each representing one day) and turning angles, with the former limited by the actual number of individual steps recorded for each real shark. In each iteration, the step length and angle were drawn from species-specific step length/angle

15

distributions estimated from the tracked sharks, and a move was performed. After computing a new position, a check was made to ensure that it did not fall within land masses, in which case the position was rejected and a new step length and angle were redrawn. The simulated walks were also restricted to occur within the area defined by the minimum convex polygon (MCP) that encompassed all observed locations of each species.

For each tracked shark a total of 200 simulation runs were completed (for examples see Fig. S6). Simulated random walks were then combined with satellite-derived environmental data. The environmental data used were daily (i) sea surface temperature, SST and (ii) SST anomalies derived from NOAA Optimum Interpolation Quarter Degree Daily SST Analysis (OISST) data; based on the OISST data we also calculated (iii) daily SST maximum gradient maps by calculating for each pixel a geodetic–distance-corrected maximum thermal gradient (ºC/100 km), and (iv) thermal front frequency (Ffreq) seasonal maps (0.1º spatial resolution), derived from a front-following algorithm (13); (v) monthly merged chlorophyll *a* levels (0.25º spatial resolution), acquired from GlobColour (European Space Agency − ESA); and finally, (vi) weekly merged sea surface height (SSH) anomalies (0.33º spatial resolution) obtained from AVISO satellite altimetry data. To determine the optimal number of simulated pseudo-absences we calculated, for each environmental variable, the mean and standard deviation of increasing numbers of 'null' tracks were computed. Calculated statistics stabilised with sample sizes of about 50 to 75 simulated tracks for each observed track (Fig. S7A-D), and thus, we set our sample size at 75 'null' tracks per shark track.

Oceanographic variables were also sampled for real tracks; however, to account for estimated error distribution around individual geolocations, we calculated a spatially weighted average of the environmental data for each location using 75 randomly resampled locations (from section 1.3).
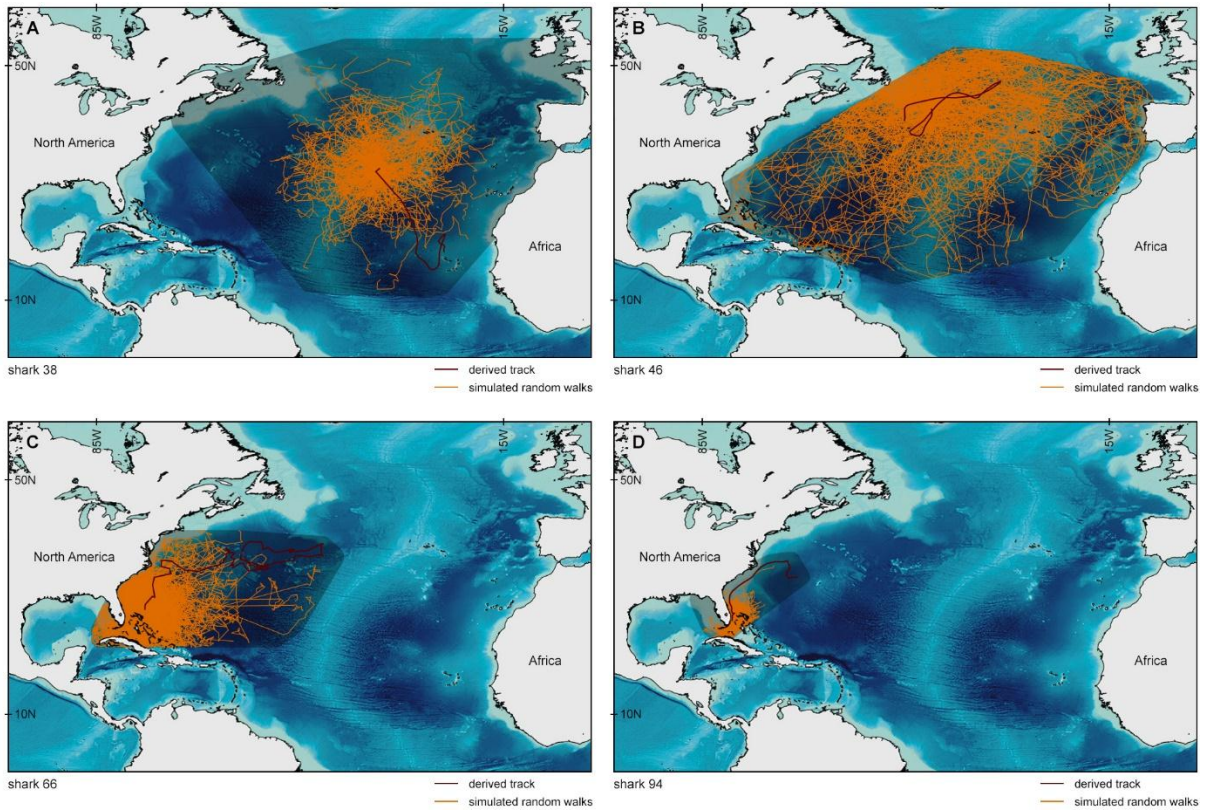
Fig. S6. Examples of random walk simulations for the different shark species; blue (A), mako (B), tiger (C) and hammerhead (D). Red lines are tagged shark movements; orange lines are 75 replicate random-walk model sharks.
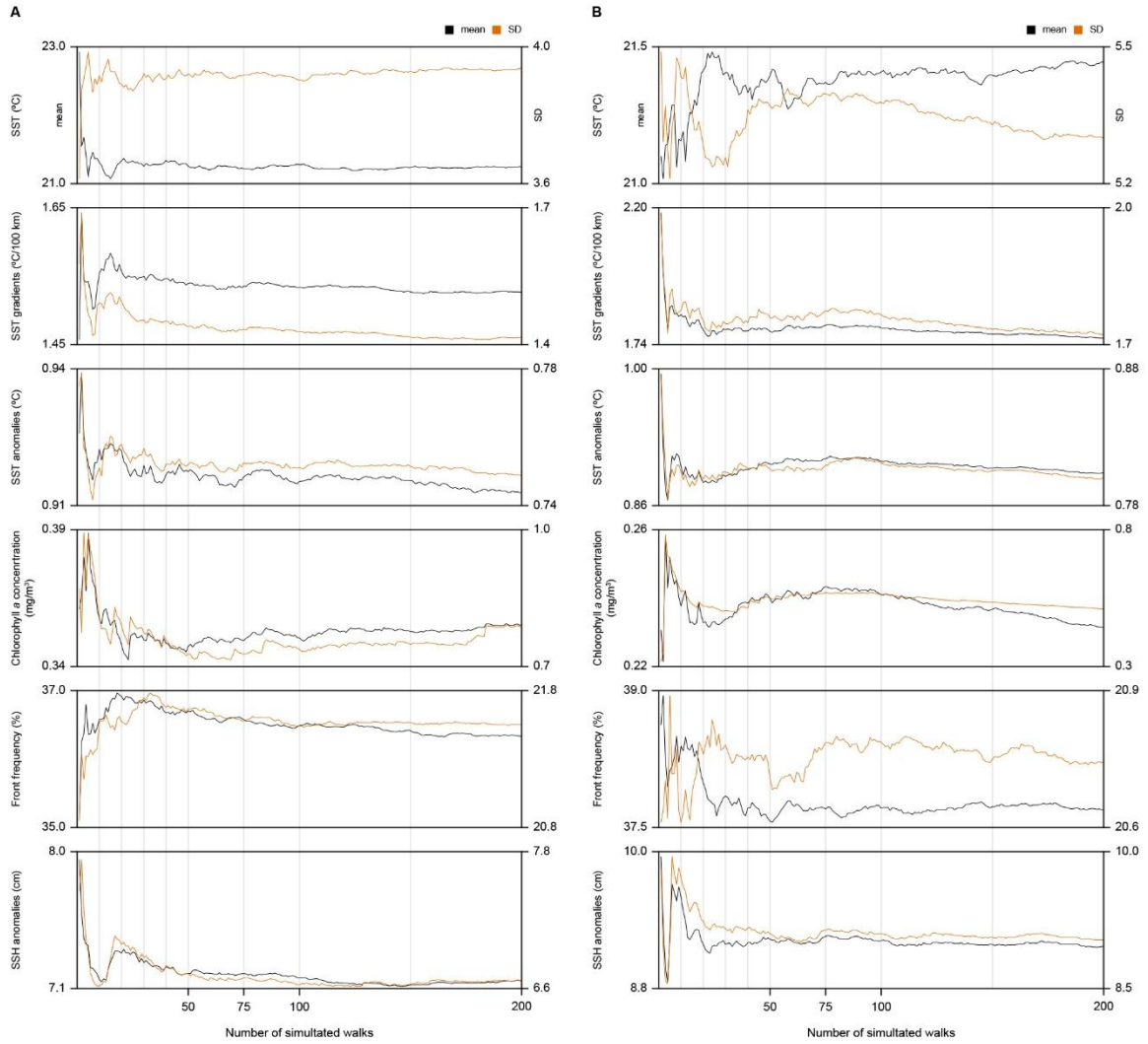
Fig. S7. Effects of different number of pseudo-absence locations on the mean and SD variation for the different environmental variables, shark species and longliners; blue (A), mako (B), tiger (C), hammerhead (D) and longliners (E); SST, sea surface temperature; SSH, sea surface height.
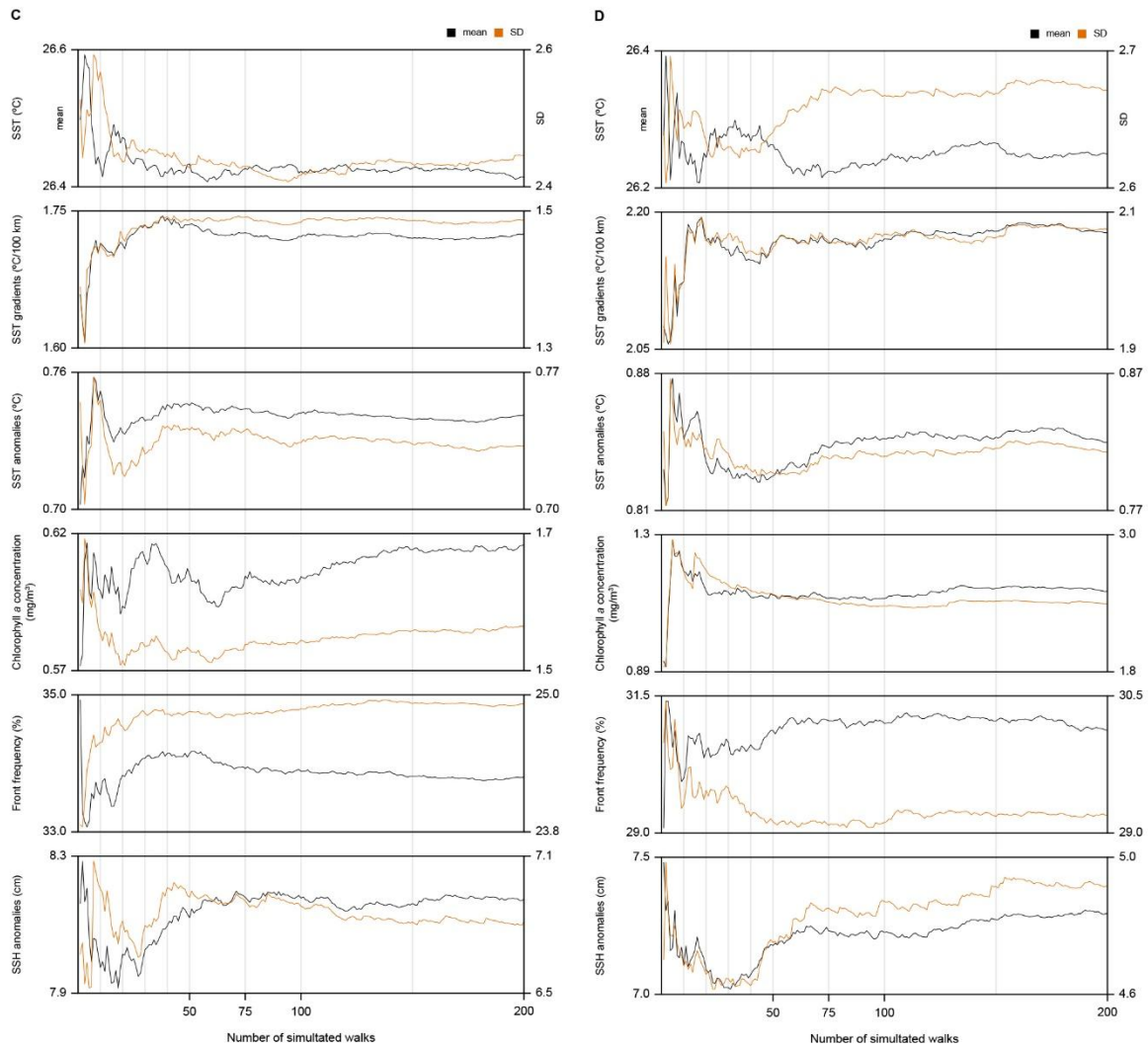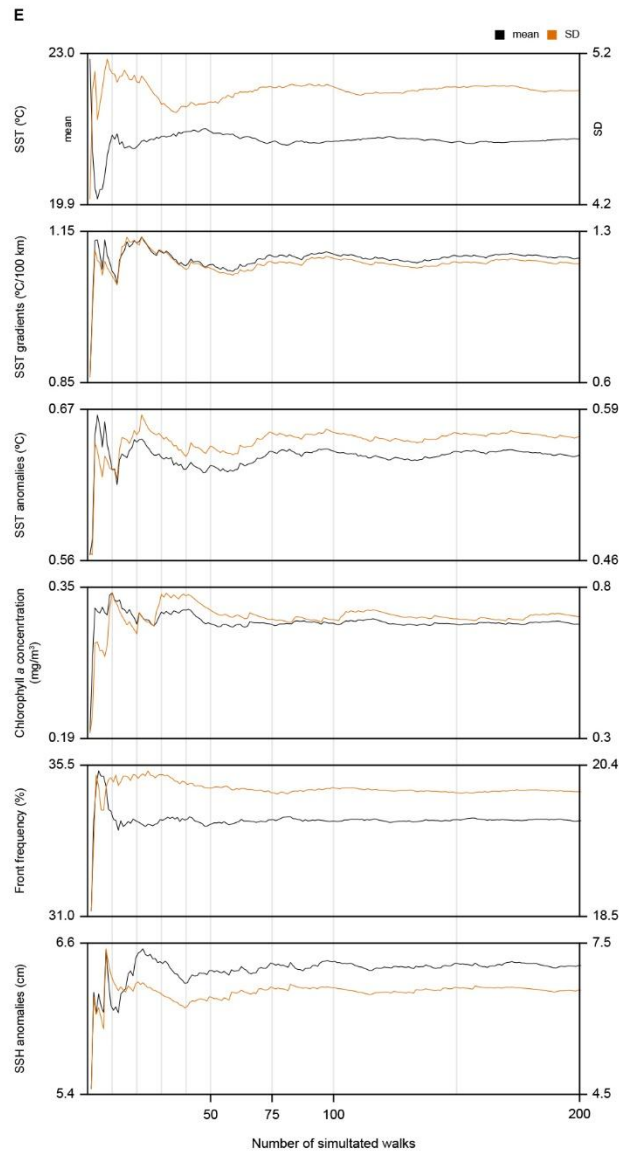
Fig. S7 (cont'd). Effects of different number of pseudo-absence locations on the mean and SD variation for the different environmental variables, shark species and longliners; blue (A), mako (B), tiger (C), hammerhead (D) and longliners (E); SST, sea surface temperature; SSH, sea surface height.

Fig. S7 (cont'd). Effects of different number of pseudo-absence locations on the mean and SD variation for the different environmental variables, shark species and longliners; blue (A), mako (B), tiger (C), hammerhead (D) and longliners (E); SST, sea surface temperature; SSH, sea surface height.

1.5.2. Simulations of longliner movements

Similarly, to test longliner associations with oceanographic features quasi-realistic 'null' vessel tracks were generated for a subset of 300 vessel/year combinations [selected amongst the vessels with both (i) the highest number of data points (days) in a year and (ii) largest fishing area]. At the start of each simulated track, the null vessel was placed at a random position within the daily estimated standard deviation of fishing locations (latitude SD: 0.19º; longitude SD: 0.30º) and the initial turning angle derived from a 360º uniform distribution.

20

All subsequent simulation steps were similar to those described in section 1.5.1 with simulated tracks also restricted to occur within defined MCP area defined by all observed longliner locations (for examples see Fig. S8). Given that environmental statistics for vessels also stabilised at about 75 simulated tracks (Fig. S6E) we set our sample size at 75 'null' tracks per vessel.

Oceanographic variables were sampled for both the simulated and real tracks; however, to account for the daily dispersion in fishing locations, we averaged the environmental data for all fishing points in a given day, and assigned the mean value to the daily centroid (calculated in section 1.4).
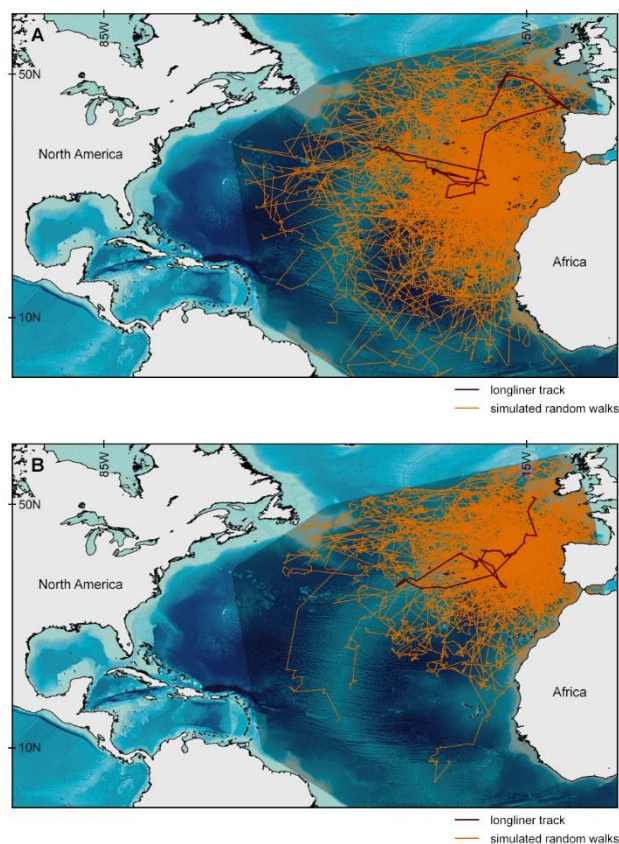

Fig. S8. Examples of random walk simulations for two different longliners.

1.5.3. Habitat modelling

To investigate habitat preferences we tested associations of individual sharks and vessels with oceanographic features by comparing real with simulated random tracks using Resource Selection Probability Functions (RSPFs; 14, 15, 16, 17). Before running the analyses, records with incomplete environmental information, e.g. where remotely sensed data were not

available due to cloud cover, were removed from the datasets. Also, to avoid pseudo-replication and spatial auto-correlation of oceanographic data, locations within a radius of 0.33^o (lowest spatial resolution of satellite-derived environmental data – AVISO SSH anomalies) of the previous position were removed. Predictor variables were subsequently checked for co-linearity using Spearman's rank correlation matrix; however, none of the variables exceeded the 0.75 correlation coefficient (18; see also Table S3) and thus all variables were considered in the same candidate model.

RSPFs are models used to compare the amount of used habitat with the amount of available habitat (15). Furthermore, logistic regression has become one of the most common statistical approaches to estimate habitat selection models (19). We estimated logistic RSPF models [implemented in R (*ResourceSelection package*); (16, 17)] under a use-availability framework. The obtained variable estimates were post-hoc standardised based on standard deviations (20) which allowed for comparisons between the relative influence of variables and habitat use, regardless of the measurement scale quantifying the resource. As a result, the explored habitat (defined by used/real locations) was analysed in contrast to available (random) locations. RSPF models were estimated using maximum likelihood methods with the final model form and covariates selected using Bayesian information criterion (BIC). Habitat modelling can be affected by serial correlation in telemetry data (21). However, the 0.33^o spatial reduction performed previously, also resulted in significant sub-sampled temporal datasets (mean temporal gaps in real tracks: 5.02 days; mean temporal gaps in simulated tracks: 5.64 days). Therefore no further temporal sub-sampling was performed.

Table S3. Spearman's rank correlation coefficient matrix for predictor variables; SST – sea surface temperature; Chl. *a* conc. – chlorophyll *a* concentration; SSH – sea surface height.

Species	Variable	SST gradients	SST anomalies	Chl. *a* conc.	Front frequency	SSH anomalies
Prionace glauca	SST	-0.37	-0.11	-0.36	-0.11	0.04
	SST gradients	–	0.18	0.20	0.20	0.09
	SST anomalies	–	–	0.07	0.06	0.13
	Chl. *a* conc.	–	–	–	-0.15	-0.07
	Front frequency	–	–	–	–	0.02
Isurus sp.	SST	-0.35	-0.18	-0.29	-0.27	0.04
	SST gradients	–	0.33	0.20	0.29	0.09
	SST anomalies	–	–	0.18	0.14	0.15
	Chl. *a* conc.	–	–	–	0.04	-0.01
	Front frequency	–	–	–	–	0.00
Galeocerdo cuvier	SST	-0.42	-0.30	0.01	-0.11	-0.04
	SST gradients	–	0.39	0.12	0.15	0.00
	SST anomalies	–	–	0.21	0.01	0.00
	Chl. *a* conc.	–	–	–	-0.04	-0.07
	Front frequency	–	–	–	–	0.02
Sphyrna sp.	SST	-0.45	-0.54	-0.05	-0.22	-0.19
	SST gradients	–	0.53	0.15	0.21	0.10
	SST anomalies	–	–	0.32	0.14	0.09
	Chl. *a* conc.	–	–	–	-0.11	0.00
	Front frequency	–	–	–	–	0.06
longliners	SST	-0.29	-0.12	-0.15	-0.24	-0.01
	SST gradients	–	0.32	0.19	0.26	0.18
	SST anomalies	–	–	0.10	0.11	0.17
	Chl. *a* conc.	–	–	–	0.04	0.00
	Front frequency	–	–	–	–	-0.01

1.6. Overlap between sharks and longlines

The spatial overlap (%) between sharks and longliners irrespective of time was calculated by counting the total number of $1^{\circ} \times 1^{\circ}$ grid cells where both sharks and longliners occurred at least once, as a function of the total number of grid cells. To quantify the spatial and temporal

co-occurrence of longlines and sharks in the same geographic grid cell at the same time, the sum of the number of days with shared occupancy (overlap frequency, i.e. presence of both vessels and sharks in a 1º × 1º grid cell on the same day) was determined. A fixed 1º × 1º geographic grid cell was chosen because it encompassed the length of the longlines which typically range between 80 and 100 km in total length. Because there was a mismatch between Portuguese and Spanish data and both fleets target different oceanic regions, VMS data was reorganised in a total of 30 fishing scenarios which resulted from all the possible combinations of five years of Spanish with six years of Portuguese fishing data. The different fishing scenarios enabled descriptive statistics (e.g. mean, standard deviation) to be calculated for temporal co-occurrence for each scenario allowing us to confirm the similarity in estimates of overlap frequency between scenarios. Specifically, within each scenario, and for each day of the analysis, each vessel track was examined to determine whether a longline fishing point existed for that date. If so, grid coordinates were calculated and the grid cell vessel count updated. If the next point in the vessel track was one day later, then the vessel was considered to be fishing for the 24 h between those points and therefore all grid cells encountered while moving between the start and end fishing points were updated. Once all vessel tracks were processed, shark tracks were analysed in a similar way, with interpolated grid cells updated with occupancy and with counts made of the number of cells containing both longlines and sharks from which the numbers of 'days-at-risk' for each shark were calculated.
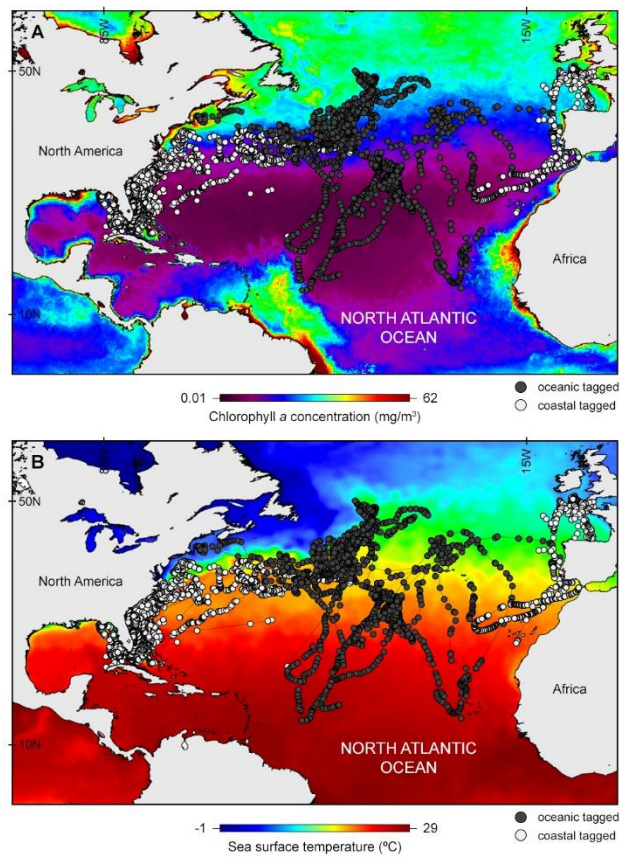
2. Supporting Results and Discussion

Fig. S9. Processed satellite tag geolocations of six pelagic sharks overlaid on a six-year average of chlorophyll *a* concentration (A) and sea surface temperature (B).
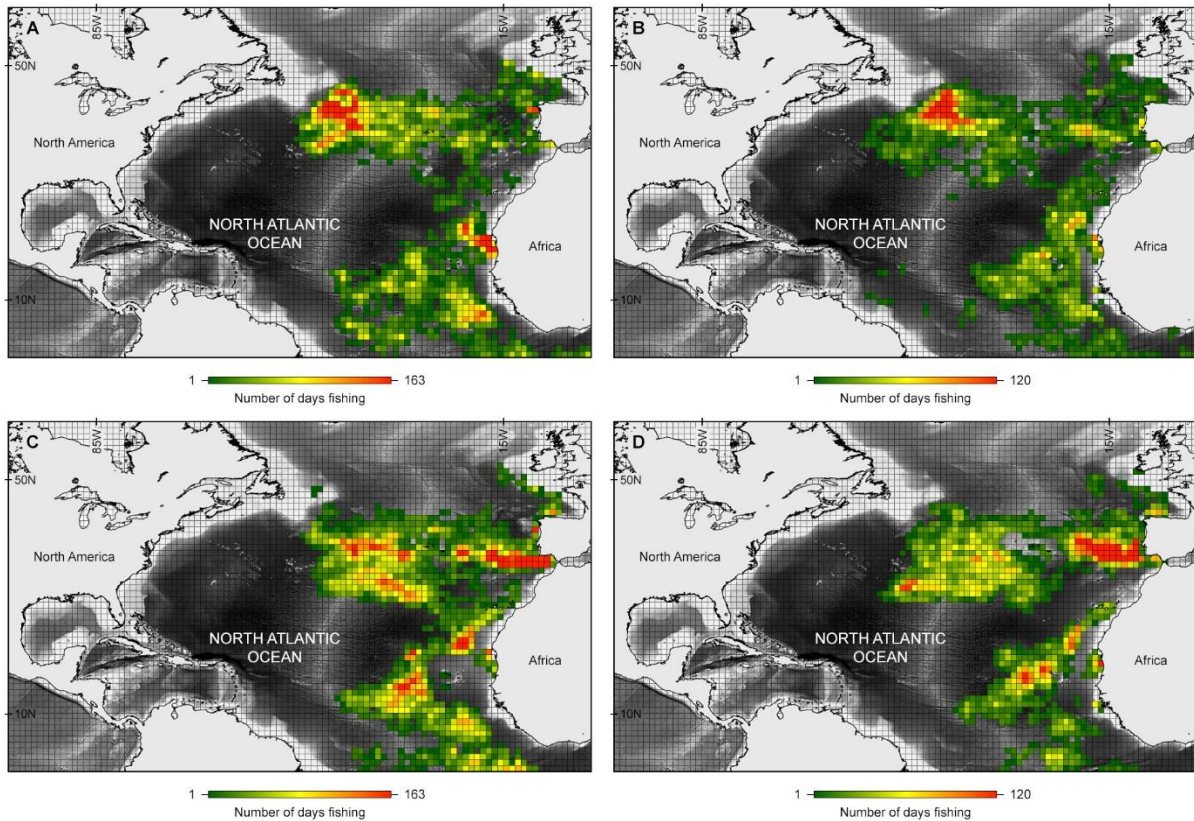
Fig. S10. Temporal persistence in fishing patterns. Spatial distribution of longline fishing intensity is conserved between seasons across years: (A) summer (Jun – Aug) 2005 and (B) summer 2009; and (C) autumn (Sep – Nov) 2005 and (D) autumn 2009. (B).

2.1 Reducing hotspot bias

Defining space use 'hotspots' of sharks is one way of exploring shark/environment relationships, however, designating spatial hotspots can be biased due to several factors. For instance, a hotspot could be inaccurately assigned from tracking data if tags are deployed at a single location, the tracks are all of short duration, and no account is taken of re-weighting the geolocations with respect to tagging locations. In the present study we attempted to reduce each of these potential spatial biases. First, we spread deployments of tags across seven release locations spanning the North Atlantic (Fig. S1), and with tags attached to all species (except the one longfin mako tagged) in multiple locations (Table S1). Our efforts to spread tagging locations is consistent with other broad-scale tracking studies of large pelagic fish where hotspots and interactions have been investigated (e.g. 8, 22). Secondly, to our knowledge we have tagged the largest number of sharks in a single electronic tagging study to be undertaken in the North Atlantic Ocean (*n* = 113). Tagging this number of sharks for 3 months on average per individual broadens the range of possible shark habitats recorded so

that the spatial 'hotspot' analysis may be more representative of actual shark space use patterns. Lastly, and as with other similar studies (8, 10), we used a hotspot mapping technique that statistically assigns greater weight on tag geolocations that are further away from tagging locations to further reduce the effects of tagging bias. Whilst it would be desirable to track many more sharks for longer periods to define hotspots even more accurately, it should be recognised that our study is a first step in exploring fine-scale shark/environment/fishery spatial and temporal co-occurrence across the broad scale.

2.2. Species-specific high-use areas

The tagging location and track length bias-reduction procedure was applied to tracking data of each species separately, to evaluate the presence of species-specific high-space-use areas and their contribution to the identification of hotspots (Fig. 1D). Even though tagged sharks generally occupied large oceanographic regions limited by temperature (Fig. 2B), areas with high shared space-use were observed (Fig. S10), for example in the western and eastern coastal and continental shelves of the North Atlantic (including the Canary and Cape Verde islands) and oceanic areas including the Gulf Stream, NLCZ and west and south-west of the Azores. These regions were also identified as areas of high seasonal fishing effort (Fig. 3) and were also where the highest shark-vessel overlap frequencies were observed (Fig. 4).

Noticeably, areas of high blue shark residency were observed south of Nova Scotia (Gulf Stream) and south of the Azores (Fig. S10A), which were also classified as hotspots (Fig. 1D). Likewise, higher space-use/abundance of mako sharks in the Gulf Stream, the NLCZ and the Azores and mid-Atlantic Ridge areas were also identified with tracking data (Fig. S10B). The distribution of tiger and hammerhead sharks was generally restricted to coastal shelf areas (Fig. S10C,D) which contributed to the identification of coastal hotspots (Fig. 1D).
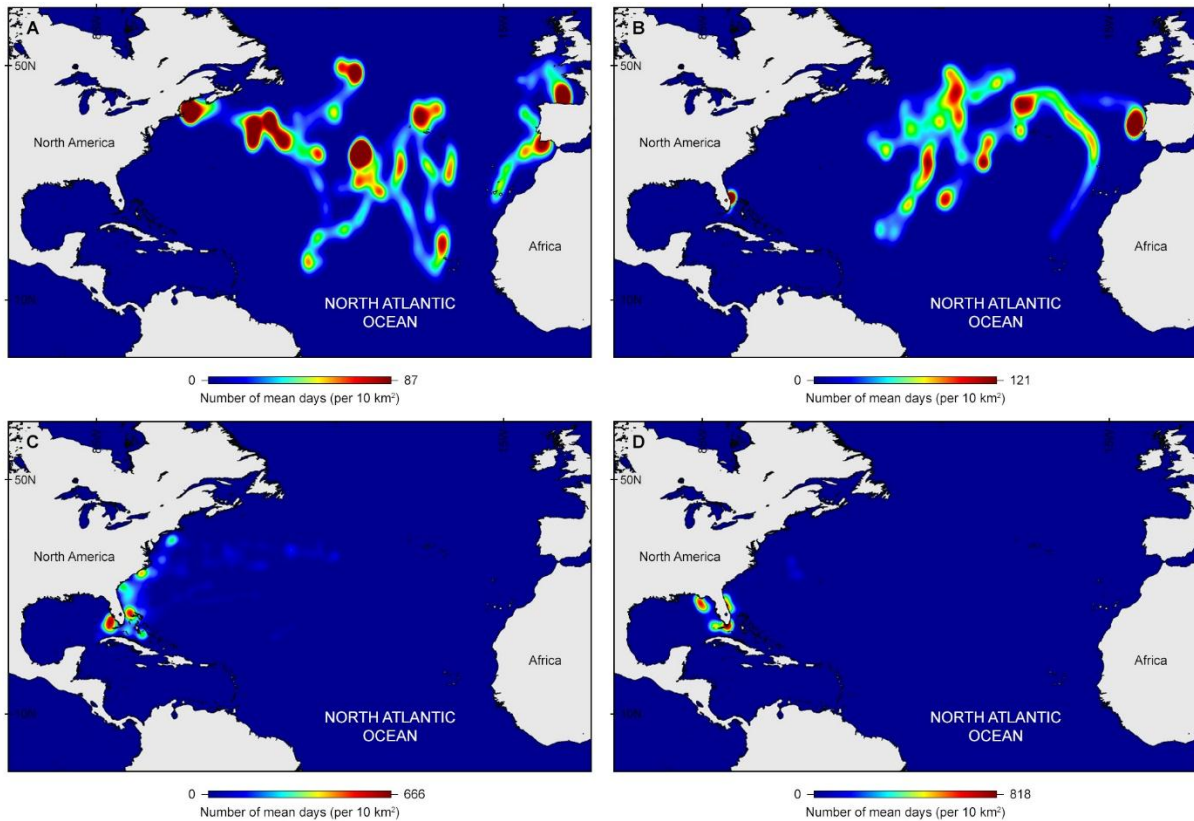
Fig. S11. High species-specific space-use areas calculated for blue (A), mako (B), tiger (C) and hammerhead (D) sharks. The kernel smoothing parameter was kept constant to enable the visual comparison of residence probabilities.

2.3. Environmental preferences

As previously mentioned (section 1.5.3), we used RSPF models to test associations of individual sharks with oceanographic features. The analysis showed that, overall, sharks prefer frontal boundary habitats characterised by steep temperature or productivity gradients (from remote-sensing images of sea surface temperature, SST, or Global colour, Chl 'a') (see Fig. 1). Preferences for areas identified with the thermal front frequency (Ffreq) algorithm were, when significant, low. It is possible that (i) the seasonal scale of the Ffreq metric calculation and/or (ii) the 76.5 km spatial scale of the smoothing Gaussian Ffreq filter were inadequate for comparing with shark tracks, since daily position estimates were used in the analysis. This seems to be supported by general higher preferences observed for the daily, higher spatial resolution, SST thermal gradient fields we used. Therefore, it seems likely that tagged sharks were responding at a smaller temporal and spatial scale than possible to measure with the automated front detection filter we implemented, whereas longliners

28

selected SST and productivity boundaries with much greater temporal persistence, i.e. front frequency (Fig. 2). The use of a higher resolution front frequency product may have further improved indication of shark habitat preferences for the movement analysis (e.g. 23).

We found that the risk from fisheries differed between tagged blue and mako sharks, with blue sharks spending on average 2.6 days-at-risk/month and makos 3.0 days-at-risk/month (Mann-Whitney U-test = 163.5; $p < 0.05$), which was likely related to differing habitat preferences in mako sharks. For example, RSPF analysis shows that longliners prefer productive habitats characterised by high frontal frequencies, thermal and SSH anomalies for longline deployment (Fig. 2). Hence, similar habitat preferences of sharks and longliners are likely driving co-occurrence, potentially leading to higher probability of shark capture on longlines through increased encounter rates (see also Figs. 4, 5E,F).

Even though tiger and hammerhead sharks displayed similar overall levels of environmental preferences to oceanic sharks, their high space-use of coastal and shelf areas (Fig. S10C,D) – where they were tagged – meant that no overlap with the longlining fleets for which we have data, was observed for hammerhead sharks. In addition, for only two tiger sharks (#66 and #67; Table S1) was co-occurrence recorded during offshore movements into deep water (west of the Azores). Both sharks spent on average 0.4 and 1.0 days-at-risk during the 309 and 122 d tracks, respectively.

2.4 Species-specific differences and exploitation

Species differences in habitat selection and a high degree of spatio-temporal overlap between sharks and longliners combined with different life-history traits may help in part to explain observed pelagic shark catch trends. For example, we found that shortfin mako sharks actively select frontal habitats and overlap the most with longliners. Moreover, they have amongst the lowest fecundity of any shark (~10-12 young every second or third year). In contrast, blue sharks are not only less strongly associated with steep SST gradients thereby overlapping less with longliners, but it also has relatively high fecundity (~80 young per year). This predicts greater susceptibility of makos for capture by longliners compared with blues, and consequently due to lower fecundity, a more rapid potential decline of mako population abundance compared with blue sharks in the North Atlantic. However, although regional analyses of catch per unit effort (CPUE) data from U.S. longliners in the western

north Atlantic indicates significant declines for both species, declines were apparently greater for blues than makos (24). The 2009 Atlantic shark stock assessments do not provide any support for regional declines previously reported; they suggest that current North Atlantic blue shark biomass appears to be well above the biomass that would support maximum sustainable yield and close to an unfished biomass (25, 26), whereas despite initially reporting declines for makos, recent estimates now show no evidence for declines (27). These trends are clearly at odds with reported regional declines for blue and mako sharks (24, 28, 29) and in addition with species predictions arising from our space use study. Overall the apparent contradictions in CPUE trends of some oceanic sharks and with our predictions argue for full disclosures of accurate spatial catch data because without them sustainable management will not be possible. Many countries exploiting North Atlantic oceanic habitats do not make, or do not have, full high-quality catch or landings data available for scientific assessments (30). Hence, CPUE trends for blue and mako sharks in the North Atlantic are difficult to interpret because despite VMS technology, the precise location and composition of catches is lacking, therefore it is challenging to determine if the observed trend variability is more closely related to variations in the area targeted or the changing sharks' spatial distributions.

3. References

1. Queiroz N, Humphries NE, Noble LR, Santos AM, Sims DW (2010) Short-term movements and diving behaviour of satellite-tracked blue sharks *Prionace glauca* in the northeastern Atlantic Ocean. *Mar. Ecol. Prog. Ser.* 406:265-279.

2. Queiroz N, Humphries NE, Noble LR, Santos AM, Sims DW (2012) Spatial dynamics and expanded vertical niche of blue sharks in oceanographic fronts reveal habitat targets for conservation. *PLoS One* 7:e32374.

3. Hammerschlag N, Gallagher AJ, Wester J, Luo J, Ault JS (2012a) Don't bite the hand that feeds: assessing ecological impacts of provisioning ecotourism on an apex marine predator. *Funct. Ecol.* 26:567-576.

4. Hammerschlag N, Luo J, Irschick DJ, Ault JS (2012b) A comparison of spatial and movement patterns between sympatric predators: bull sharks (*Carcharhinus leucas*) and Atlantic tarpon (*Megalops atlanticus*). *PLoS One* 7:e45958.

5. Lam C, Nielsen A, Sibert J (2008) Improving light and temperature based geolocation by unscented Kalman filtering. *Fish. Res.* 91:15-25.

6. Jonsen ID, Flemming JM, Myers AE (2005) Robust state-space modeling of animal movement data. *Ecology* 86:2874-2880.

7. Sippel T, Holdsworth J, Dennis T, & Montgomery J (2011) Investigating behaviour and population dynamics of striped marlin (Kajikia audax) from the southwest Pacific Ocean with satellite tags. PLoS One 6(6):e21087.

8. Block BA, et al. (2011) Tracking apex marine predator movements in a dynamic ocean. *Nature* 475:86-90.

9. Patterson TA, McConnell BJ, Fedak MA, Bravington MV, Hindell MA (2010) Using GPS data to evaluate the accuracy of state–space methods for correction of Argos satellite telemetry error. *Ecology* 91:273-285.

10. Walli A, et al. (2009) Seasonal movements, aggregations and diving behavior of Atlantic bluefin tuna (*Thunnus thynnus*) revealed with archival tags. *PLoS One* 4:e6151.

11. Getis A, Ord JK (1992) The analysis of spatial association by use of distance statistics. *Geo. Analysis* 24:189-206.

12. Robinson PW, et al. (2012) Foraging behaviour and success of a mesopelagic predator in the northeast Pacific Ocean: insights from a data-rich species, the northern elephant seal. *PLoS One* 7:e36728.

13. Miller P (2009) Composite front maps for improved visibility of dynamic sea-surface features on cloudy SeaWiFS and AVHRR data. *J. Mar. Syst.* 78:327-336.

14. Boyce MS, McDonald LL (1999) Relating populations to habitats using resource selection functions. *Trend Ecol. Evol.* 14:268-272.

15. Manly BFJ, McDonald LL, Thomas DL, McDonald TL, Erickson WP (2002) *Resource selection by animals: statistical design and analysis for field studies*. Springer, Dordrecht.

16. Lele SR, Keim JL (2006) Weighted distributions and estimation of resource selection probability functions. *Ecology* 87:3021-3028.

17. Lele SR (2009) A new method for estimation of resource selection probability function. J. Wildlife Manage. 73:122-127.

18. Žydelis R, et al. (2011) Dynamic habitat models: using telemetry data to project fisheries bycatch. *Proc. R. Soc. Lond. B* rspb.2011.0330

19. Hebblewhite M, Merrill EH, McDonald TL (2005) Spatial decomposition of predation risk using resource selection functions: an example in a wolf/elk predator/prey system. *Oikos* 111:101-111.

20. Marzluff, JM, Millspaugh JJ, Hurvitz P, Handcock MS (2004) Relating resources to a probabilistic measure of space use: forest fragments and Steller's Jays. Ecology 85:1411-1427.

21. Aarts G, MacKenzie M, McConnell B, Fedak M, Matthioloulos J. (2008) Estimating space-use and habitat preference from wildlife telemetry data. *Ecography* 31**:**140-160.

22. Block BA, et al. (2005) Electronic tagging reveals population structure and behaviour of bluefin tuna. *Nature* 434:1121-1127.

23. Miller PI, Scales KL, Ingram SN, Southall EJ, Sims DW (2015) Basking sharks and oceanographic fronts: quantifying associations in the north-east Atlantic. *Funct. Ecol.* 29:1099-1109.

24. Baum JK, et al. (2003) Collapse and conservation of shark populations in the northwest Atlantic. *Science* 299:389-392.

25. International Commission for the Conservation of Atlantic Tuna (ICCAT) (2005) Report of the 2004 Inter-sessional Meeting of the ICCAT Sub-committee on By-catches: Shark Stock Assessment. *Collect. Vol. Sci. Pap. ICCAT* 58:799-890.

26. International Commission for the Conservation of Atlantic Tuna (ICCAT) (2009) Report of the 2008 Shark Stock Assessment Meeting. *Collect. Vol. Sci. Pap. ICCAT* 64:1343-1491.

27. International Commission for the Conservation of Atlantic Tuna (ICCAT) (2012) Report of the 2012 Shortfin Mako Stock Assessment and Ecological Risk Assessment Meeting. Olhão, Portugal. http://www.iccat.int/Documents/Meetings/Docs/2012_SHK_ASS_ENG.pdf

28. Baum JK, Myers RA (2004) Shifting baselines and the decline of pelagic sharks in the Gulf of Mexico. *Ecol. Lett.* 7:135-145.

29. Ferretti F, Myers RA, Serena F, Lotze HK (2008) Loss of large predatory sharks from the Mediterranean Sea. *Conserv. Biol.* 22:952-964.

30. Dulvy NK, et al. (2014) Extinction risk and conservation of the world's sharks and rays. *eLife* 3:e00590.

4. Data Access

The Vessel Monitoring System (VMS) data used in this paper are freely available for non-profit, scientific use from the national government departments given below.

Access to the Portuguese VMS data should be directed to:

Direção Geral de Recursos Naturais, Segurança e Serviços Marítimos

www.dgrm.mam.gov.pt/

Av. Brasilia

1449-030 LISBOA - PORTUGAL

Phone: +351 21 3035700

Fax: +351 21 3035702

dgrm@dgrm.mam.gov.pt

Access to the Spanish VMS data should be directed to:

Ministerio de Agricultura, Alimentación y Medio Ambiente

www.magrama.gob.es

Pº Infanta Isabel, 1

28014 MADRID - SPAIN

Phone: +44 91 347 45 80

Fax: +44 91 347 55 80

gprensa@magrama.es