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Ship strike risk assessment and mitigation solutions for Arabian Sea humpback whales

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ABSTRACT

Over eighty percent of the world's commercially traded goods are transported by sea and increasing levels of vessels traffic in whale habitats are resulting in threats to many large whale populations. Where these overlaps occur the incidence of ship strikes resulting in injury and mortality are being reported. Approaches to model anthropogenic space use and the spatial distribution of species are increasingly being used to identify mitigation solutions in important habitat for large whales. We developed an Ensemble Ecological Niche Model (EENM) using satellite telemetry data from Arabian Sea humpback whales (*Megaptera novaeangliae*; IUCN Endangered) and combined this with satellite derived

Automatic ship Identification System (s-AIS) tracking data to understand the risk of ship strike within the North Indian Ocean (NIO) and Important Marine Mammal Areas (IMMAs) therein. Areas of increased relative risk to Arabian Sea humpback whales (ASHW) from commercial shipping traffic were identified close to core habitat along the Arabian Sea coast of Oman. Rerouting vessels 40 nmi (nautical miles) further offshore could reduce the risk of strike by as much as 88%. Mortalities of large whales from ship strikes and other anthropogenic causes (fisheries entanglement) are unstudied in large part because they are difficult to detect. Estimates of the potential biological removal (PBR) reveals that the ASHW population cannot sustain the human induced death of more than one animal every four years, and that the current level of threat to ASHWs from shipping is likely unsustainable, particularly for a relict population at risk of extinction. As such, development of mitigation measures is urgently required by coastal states and industry stakeholders including support from the International Maritime Organisation (IMO). Initial management measures for shipping should be expedited where threats exist within core areas of habitat and in the long-term should be implemented in parallel with a broader suite of marine spatial planning activities that accounts for the livelihoods of coastal communities and projected growth of industrial maritime activities.

KEYWORDS: ARABIAN SEA HUMPBACK WHALE, ENSEMBLE ECOLOGICAL NICHE MODELLING, SHIP STRIKE, RISK ASSESSMENT, MITIGATION, VESSEL ROUTING.

INTRODUCTION

The relative importance of non-hunting threats to great whales from anthropogenic activities has become a growing area of interest within the international scientific community since the moratorium on whaling came into effect and has provided the opportunity for research and management initiatives to address new priorities (Burns and Wandesforde-smith, 2002, Johnson et al. 2022). Addressing population-level threats has been of particular importance in the cases when post whaling recovery has not occurred.

Over eighty percent of the world's commercially traded goods are transported by sea, with the industry witnessing a 300% increase in the volume of shipping traffic between 1992 and 2013 (UNTCAD, 2013, UNTCAD, 2022). The risks of strike from commercial shipping is considered one of the most serious global anthropogenic threats to large whales along with entanglement in fishing gear (Thomas et al., 2016). The threat has resulted in studies to assess risks and provide mitigation solutions (Minton et al., 2021). Ship strike records of northern right whales (*Eubalaena glacialis*) were used to develop a model describing the increased probability of a lethal strike with vessel speed (Vanderlaan and Taggart, 2007, Conn and Silber, 2013). This lethal strike probability model has been combined with spatial models of vessel traffic and surface density models of whales to produce maps of relative ship strike risk across selected study areas (Redfern et al., 2013, Smith et al., 2020, Wiley et al., 2011, Chion et al., 2018, Rockwood et al., 2020).

The IWC and the International Maritime Organisation (IMO) recommend the adoption of such approaches to identify priority areas for the development of mitigation measures (IMO, 2009, Silber et al., 2012, Cates et al., 2017). Avoiding whale habitat has been promoted as one of the most effective ways of minimising risk, and where this is not possible voluntary or mandatory speed restrictions are also considered effective, with a recommended upper threshold of 10 knots (Constantine et al., 2015, Laist et al., 2014, Ritter and Panigada, 2018, IWC et al., 2019).

Mapping the distribution of cetacean habitat is logistically and financially challenging (Redfern et al., 2006, Redfern et al., 2013), but considered a prerequisite for accurately assessing shipping and fisheries related threats. The development of technical approaches, such as ecosystem niche modelling (Redfern et al., 2013, Smith et al., 2020), and the emergence of collaborative frameworks to map cetacean habitat, such as Important Marine Mammal Areas

(IUCN Marine Mammal Protected Areas Task Force, 2018), have become leading biocentric approaches to help address place-based cetacean resource management (Notarbartolo di Sciara and Hoyt, 2020, IWC et al., 2019).

In the north Indian Ocean (NIO), the Endangered Arabian Sea humpback whale has been described as a 'canary in a coalmine' for the plight of baleen whales in the region (Baldwin et al., 2010). Almost extirpated by Soviet whaling in the mid-60s (Mikhalev, 1997), and genetically isolated (Pomilla, Amaral et al. 2016), the population was last estimated to number 82 individuals (CI 95% 60-111) (Minton et al. 2008). The extent of ASHW known habitat brings the population into proximity with commercial shipping routes (Johnson et al., 2022). Investigating habitat preference and location of ASHW's across their range using ecosystem niche modelling approaches has been identified as a priority by the international scientific community to identify areas for field-based studies and address management concerns (Minton et al., 2015, CMS, 2017).

Here we develop an ensemble ecological niche model (EENM) of ASHW distribution derived from satellite telemetry data collected between 2014 and 2018 together with satellite-derived vessel Automatic Identification System data (s-AIS) collected between December 2015 and May 2016, to produce a ship strike risk assessment for the NIO. These results are used to evaluate speed and ship routing control measures as mitigation solutions. The areas of high habitat suitability from EENM are spatially referenced to the location of IMMAs in the region and are flagged for the focus of general conservation management efforts beyond shipping.

MATERIALS AND METHODS

ASHW are thought to range within the EEZs of at least 10 countries bordering the NIO (Minton et al., 2008a). Of these 10 countries, dedicated cetacean research that have yielded direct observations and detailed data on humpback whale distribution has only been conducted in the Sultanate of Oman. As such, understanding the relationship between ASHW distribution and vessel activity from direct observations over an extent as large as the NIO is not feasible. To gain a relative overview of risk from shipping activity, our method was comprised of five stages; (1) developing an EENM using data derived from the tracked movements of ASHW that were instrumented with satellite tags, (2) processing AIS data to produce rasters of shipping traffic and associated vessel speeds, (3) developing an additional raster to include a model for probability of lethal strike (based on vessel speed) , (4) combining the EENM and lethal strike raster to create a strike risk model, and (5) using the strike risk model to investigate mitigation scenarios in a selected area of interest.

Developing the EENM

A workflow plan was developed before initiating the EENM process (**Supplementary Information, Figure S1**).

Occurrence data

Thirteen ASHW were instrumented with 14 Wildlife Computers SPOT5 and SPLASH10 satellite tags (Redmond, WA, USA) between February 2014 and November 2018 (9 males, 2 females and 2 of unknown sex; Willson et al., in prep). Occurrence data for the EENM was generated from location data processed in a switching space state model (SSSM; Breed et al., 2009) to address serial autocorrelation and reduce the potential bias caused by behavioural shifts of animals as described by Aarts et al. (2008). The majority of telemetry data was generated between December and May, which coincides with the ASHW breeding period (Mikhalev 1997). Oceanographic conditions during this period are dominated by the prevailing north east monsoon (Bruce et al., 1994). Review of the telemetry data in each month of the year together with consideration of the seasonality of oceanographic processes and biological processes provided a rationale to produce a model representing the months between December and May. This approach makes the assumption that habitat utilisation will likely be different outside of the breeding season and during the southwest monsoon period when strong upwelling influences productivity, and likely drives shifts in ASHW movements and distribution linked to foraging opportunities.

Recent and historical data on ASHW occurrence and distribution guided the spatial extent of the modelling environment and environmental co-variate data (**Figure 1**; 31˚N, 32˚E, 83˚W and 2˚S) including the northern Red Sea (Notarbartolo Di Sciara et al., 2017), Arabian/ Persian Gulf (Dakteh et al., 2017), Somalia and Gulf of Aden (Mikhalev, 1997), Gulf of Mannar (Whitehead, 1985) and Pakistan coast (Moazzam et al., 2019).

Selecting environmental covariates

Physical and biological covariate data were selected based on suitability as detailed in other studies (Fiedler et al., 2018, Becker et al., 2016, Redfern et al., 2017) and also on spatial and temporal concordance with the telemetry data. Seabed depth, seabed slope and distance from the shelf break (as defined by the 200m depth contour) were selected as static physical covariates based on the previous ASHW telemetry studies (Willson et al., in press) and additional studies on humpback whale breeding and foraging related depth preferences (Moore et al., 2002, Moors-Murphy, 2014, MacKay et al., 2016).

Chlorophyll-α, and a derivative, net primary productivity (NPP), were initially selected as temporally dynamic covariates and drivers of habitat use related to prey availability. Sardines and euphausiids were found in the stomachs of humpback whales examined in the Soviet catch from the Arabian Sea (n=85) (Mikhalev, 1997a) and sardines were the predominant prey observed in whales taken off the coast of Oman. Sardine species in Oman primarily feed on phytoplankton (Randall, 1995) with fisheries landings correlated to chlorophyll-α concentrations off the northern coast of Oman (Piontkovski et al., 2014). The distribution of euphausiids in relation to environmental covariates is less well studied in the region although the proximity to the shelf edge is considered an important variable in the concentration of krill (Harris et al., 2014). Other satellite telemetry studies of humpback whales have found an association between elevated levels of chlorophyll-α and slower swimming speeds and inferred that this slow swimming is indicative of whales foraging on zooplankton during migratory periods (Trudelle et al., 2016). Sea surface temperature was also included as a remaining dynamic covariate due to its importance in models generated for humpback whale breeding and nursery habitats (Smith et al., 2012).

Bathymetric data (DEPTH; m) were sourced through gebco.net. Seabed slope (SLOPE; ^{o}) was derived from the Gebco seabed depth data. Bathymetry data were also used to create a distance to shelf edge data layer (DIST; km). For this study the shelf edge was taken to be 200 m depth contour.

Covariate data sources and processing

Satellite co-variate data were accessed for the period between 2003 and 2016. Chlorophyll- α (CHLO; mg m^{-3}) and night sea surface temperature (NSST; ˚C) data were accessed from MODIS Aqua (Moderate-Resolution Imaging Spectrometer) L3 using MATLAB (The MathWorks, Natick, MA, USA) to extract and archive monthly TIF files for the study area (NASA) Ocean Color Group (http://oceancolor.gsfc.nasa.gov).Net primary productivity data (NPP; mg C m^{-2} day^{-1}) were accessed as a separate remote sensing product (http://sites.science.oregonstate.edu/ocean.productivity/standard.product.php).

Satellite environmental data were processed within R (R Development Core Team 2013) to create monthly climatology rasters. These included the sum, mean, minimum and maximum values for each co-variate from the 10-year period. All bathymetry and satellite data were geo-spatially aligned to a 9km x 9km grid according to the coarsest co-variate grid (NPP). To address issues related to overfitting of models due to pseudo-replication correlation tests were performed between covariates using the 'COR.TEST' package. This was based on extraction of data from rasters using 100 random points (**Supplementary Information Table S1**). We decided to eliminate use of NPP given its highly significant correlation with CHLO (R^2=0.938 p-value=$2.2x10^{-16}$) and other covariates, including NSST (R^2=0.671 p-value=$2.17x10^{-14}$). We set an acceptable upper limit for an R^2 threshold value of 0.6 based on the threshold presented by Bombosch et al. (2014) in another humpback whale modelling study. After elimination of NPP all covariates were geo-spatially aligned to a 4 x 4 km grid based on the higher resolution images associated with other covariate layers.

Modeling framework development

We used the EENM approach to identify habitat suitability for ASHW (Araujo and New, 2007, Loyola and Dias, 2012) within the Biomod2 package (R Development Core Team 2008, (Thuiller et al., 2009). Combinations of models and covariates were run in a series of iterative experiments to provide a refined and identical modelling framework for occurrence/ presence data. The model was configured to run response variables in a binary format with presence data together with an equal number of randomly selected pseudo-absence location points to represent background environmental characteristics of the study area (Pikesley et al., 2013). Experiments were conducted in consideration of spatial bias caveats related to this pseudo-absence technique (Phillips et al., 2009) and specifically to large whales where the process presents the ability to produce patterns of occurrence but not density or abundance distributions (Fiedler et al., 2018). Our patterns of occurrence were represented by an environmental suitability index. This was produced as raster outputs for each model run, and scored from 0 to 1, with 1 a perfect score indicating greatest habitat suitability, 0.5 areas of typical suitability and 0 an absence.

Models evaluated included generalised linear model (GLM), generalised additive model (GAM), generalised boosted model (GBM), multivariate adaptive regression splines (MARS) and maximum entropy (MAXENT). Models were run using a 10-fold cross validation with a 75/25% random split of location data for calibration and model testing (Pikesley et al., 2013). Three metrics were used for evaluation of model experiments and scaled between 0 to 1. The true skill statistic (TSS) was used to determine the accuracy of the models in predicting the correct category relative to that of random chance. A measure of resolution in discriminating between two alternative events or potential usefulness was performed by the receiver operating characteristic (ROC). Cohen's Kappa coefficient (Heidke skill score; KAPPA) was also used as a measure of agreement occurring by chance and inter-raster agreement for categorical quantitative items. The mean scores of each model type and mean of means from all runs during an experiment were used for performance assessment of each experiment. GAM and MAXENT models were removed from initial experiments based on returning the lowest mean values for each test.

The relative importance of environmental variables in their contribution to the modelling process was also calculated for each model that was run using a randomisation process (Thuiller et al., 2009, Pikesley et al., 2013). Low correlations were considered important for the model. The relative importance of each variable was calculated from the mean of the correlation coefficient over multiple runs followed by subtracting these means from 1.

GLM, MARS and GBM models were subsequently run within a series of experiments of which Experiment 1, Experiment 3 and Experiment 4 were selected for review. Refinements were made in each successive experiment by reducing the number of environmental covariates. Preference was associated to the covariates with highest scores whilst considering results of correlation coefficient tests between each variable. Model rasters from successful experiments were reviewed within ArcGIS. The Moran's I Test for spatial autocorrelation was the final step in validating models. Ensemble results with z-score values between <1.65 and >-1.65 describe random association between occurrence data and model rasters and qualify the results as not experiencing spatial autocorrelation to invalidate results. Maps of the coefficient of variation (SD of model surface/ Mean of model surface) were produced from the final model outputs; values closer to zero represent areas of relative agreement between the ensembles of models.

Area of interest coverage assessment

Area coverage assessment of EENM surface found within Exclusive Economic Zones (EEZs) (Flanders Marine Institute, 2019) and Important Marine Mammal Areas (IMMAs) (IUCN, 2019), was calculated for selected environmental suitability index ranges of >0.5, >0.75 and >0.9. Raster counts of EENM coverage were expressed as percentages within each area of interest and comparatively as the percentage of coverage across the study area.

Processing AIS Data

Producing ship strike risk rasters

Range-wide assessment of risk to whales from ship strike referred to as a ship strike risk index (SSRI) was conducted by adapting methods presented by Redfern et al. (2013) and Smith et al. (2020). These authors used a spatially explicit estimate of species distribution (from EENM) multiplied by a shipping traffic density raster, as a measure of co-occurrence. Shipping traffic density was defined by cumulative vessel transit distance through each grid cell of a raster (Leaper and Panigada, 2011). A factor defining the probability of lethal strike related to vessel speed was applied to the shipping traffic density rasters to reflect the increasing chance of being struck by faster moving vessels and the increased probability of the strike resulting in a lethal injury (Conn & Silber, 2013).

S-AIS data sourced from exactEarth Ltd UK covered a six-month period coincident with the presence data from our EENM results between 1st December 2015 and 31st May 2016. To translate records of individual ship AIS locations into a regional risk assessment framework we retained AIS records with Maritime Mobile Service Identity (MMSI) data representing the country codes for commercial shipping (codes between 200 and 800). Records were also retained for AIS message types including class 'A' position reports, static and voyage related data, addressed safety related messages, channel management and position reports for long range application (highlighted elements in **Supplementary Information Table S2**). Navigation status assignments were further used to retain records for vessels underway using engine, not under command, restricted manoeuvrability, engaged in fishing and underway sailing (highlighted elements in **Supplementary Information Table S3**). S-AIS location records for consecutive locations common to unique MMSI identifiers were used to produce daily line segments for each vessel with a speed attributed to each segment. Segments were summed (total distance) within raster cells at a resolution of 4 x 4 km. Each raster represented predefined transit speeds. Mean, maximum and standard deviation values were calculated from all cells within each raster, and a sum of all rasters was also calculated to denote the total transit distance (irrespective of speed) through each cell. Rasters were multiplied by an index value representing the probability of lethal strike according to their associated speed range (**Supplementary Information Table S4**) (Conn & Silber, 2013). The sum of these stacked rasters was multiplied by the environmental suitability index values from the EENM raster to produce the final SSRI raster. Port locations including a relative index for port size (defined by a range of criteria including quay length, maximum draft and infrastructure facility attributes) were sourced and used to contextualise nodes of shipping (World Food Program, 2017).

Area-based assessment and industry trends

To provide additional insight on the relationship between shipping traffic and marine mammal species in general (not just for ASHW) we referenced our shipping traffic density data to the location of IMMAs within the NIO, (IUCN MMPAFT, 2020). We also obtained research agreements for third party data to characterise the volumes and type of traffic passing through IMMAs from a global study evaluating exactEarth AIS data from 1st September 2018 and 1st September 2019 (OceanMind et al., 2020). Annual container traffic data were extracted to identify the annual trend of freight volumes passing through countries in the study area with container trade volumes measured according to the twenty-foot equivalent unit (TEU), where one 20-foot-long container is equivalent to 1 TEU, and summary data accounts for units passing between land and sea and vice-versa (WTO, 2020).

Mitigation simulation

Rasters of environmental suitability, probability of lethal strike and SSRI were used in a mitigation simulation of ship strike risk reduction based on vessel speed and route transit options through the Oman Arabian Sea IMMA along the coast of southern Oman. Raster cell values were extracted and summed along simulated vessel transits. Two mitigation scenarios were referenced to a primary transit route that reflects the current dominant passage of traffic, which was overlaid on the ship strike risk raster through cells with the highest values (<75th percentile). The two alternative transit routes were set parallel to the primary route at 20 nmi increments offshore and hence at increasing distance from the higher relative risk areas. Risk simulations for these routes were prepared using the extracted environmental suitability index values multiplied by the probability of lethal strike index values (Conn and Silber, 2013). Estimated transit times were also calculated for each speed and route options for rasters representing speeds at 2 knot increments ranging between 10 and 30 knots.

Potential Biological Removal

To understand the tolerance of the ASHW population to suffer human induced mortalities, such as those from ship strikes, the potential biological removal (PBR) framework was used (Wade, 1998).). The formular accounts for the product of a minimum population estimate, half of the maximum productivity rate for the species and a recovery factor, as detailed below:

$$PBR = Nmin \ ½Rmax \ Fr$$

Where Nmin = the minimum population estimate, ½Rmax = half the maximum theoretical or estimated net productivity rate and Fr the recovery factor (between 0.1 and 1). For Arabian Sea humpback whales we selected Nmin as 60 (Minton et al., 2008), Rmax as 0.08 for humpback whales (Wade, 1998). A range of Fr values were applied including the recognised value of 0.1 as defined for vulnerable populations where N <1500 (Taylor et al;. 2003) and values of 0.5 and 1 to demonstrate the full potential range.

RESULTS

EENM

Model test metrics and selection

A total of 1822 SSSM location points was reduced to 1526 after filtering according to the selected 6-month season (beginning of December to end of May) and removal of location points that were located in covariate raster cells where data was absent (**Figure 1**).

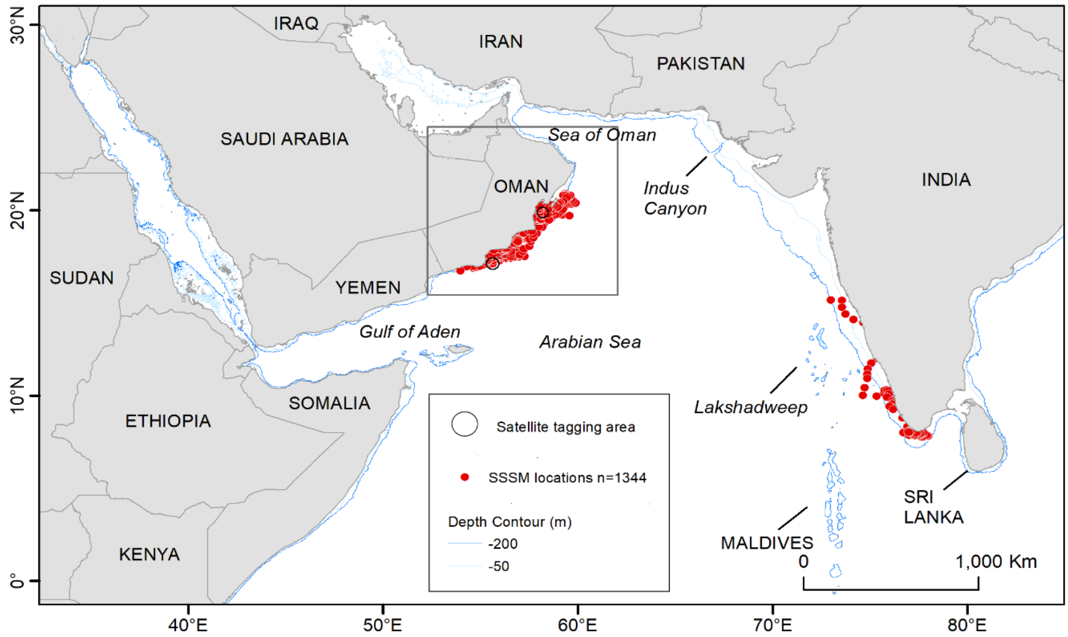

Figure 1 Study areas in Oman and available ASHW presence data. Full extent of study area and selected SSSM estimated locations between 2014 and 2018 after filtering for season and spatial cooccurrence with valid data within selected covariate raster plots

Test statistics for the 10-fold cross validation of the models scored within satisfactory limits (<0.8) for GLM, MARS and GBM models in all experiments (**Supplementary Information Table S5**). In modelling refinements, SLOPE was eliminated as a covariate based on results in Experiment 1. Whilst this covariate was not significantly correlated with any other covariates ($R^2 < 0.21$, $p > 0.05$), it contributed least to model performance, as detailed in the summaries of variable importance, with a mean value of 0.02 (SD= 0.01) (**Supplementary Information Table S6**). DEPTH and DIST both significantly correlated with each other, (R^2 =0.559, p-value= $1.5x10^{-9}$). The later performed best in variable importance and therefore was retained as the preferred static variable in Experiment 4 (**Supplementary Information Table S6**). NSST and CHLO were significantly correlated (R^2 = -0.528, p-value= <0.01), although both scored below an R^2 threshold value of 0.6 and therefor were retained for Experiment 4 given their representation of thematically different dynamic oceanographic data sources.

For our final set of experiments (Experiment 4 a, b and c), DIST, NSST and CHLO values were extracted from rasters using occurrence data to evaluate characteristics of environmental covariates (**Supplementary Information Figure S2**). Covariate summary data was represented by median values for DIST of 30.66km (IQR= 40.4), NSST 24.7 ºC (IQR= 0.53ºC) and chlorophyll-α of 4.12 mg m^{-3} (IQR= 7.9 mg m^{-3}), (**Supplementary Information Table S7**).

In Experiment 4a occurrence data failed validation (Moran's I test for spatial correlation), scoring significant z-score values above the accepted threshold (z= 2.216, p=0.027). Spatial autocorrelation of SSSM data were addressed in subsequent runs by thinning occurrence data to two locations every 24 hours (Experiment 4c) and one SSSM location every 24 hours (Experiment 4b) and keeping the number of pseudo-absence location points at the same value as previous model experiments. The refinement resulted in failed validation for Experiment 4c (z= 2.210, p=0.027) but a random association between SSSM data and the final model for Experiment 4b (z= 0.044 p-value=0.965), (**Supplementary Information Table S8**). Experiment 4b was selected as the preferred model (**Table 1**). Metrics demonstrated a suitable level of agreement between GLM, GBM and MARS models used in the ensemble approach, with a coefficient of variation >0.5 for areas of environmental suitability with index values >0.75 (**Supplementary Information Figure S3**).

Table 1 Summary of ecological niche modelling evaluation metrics for 10-fold cross validation. Experiment 4b was the final selected model.
Abbreviations: Generalised Linear Model (GLM), Multivariate Adaptive Regression Splines (MARS) and Generalised Boosted Model (GBM) from Experiment 4 performed in the Biomod2 R package.

SSSM Experiment 4b						
Model Experiment Run	**Model Test**	**GLM**	**MARS**	**GBM**	**Mean**	**SD**
1	ROC	0.967	0.981	0.982	0.977	0.008
	KAPPA	0.824	0.868	0.896	0.863	0.036
	TSS	0.845	0.895	0.905	0.882	0.032
2	ROC	0.978	0.991	0.984	0.984	0.007
	KAPPA	0.856	0.906	0.890	0.884	0.026
	TSS	0.878	0.925	0.917	0.907	0.025
3	ROC	0.968	0.986	0.984	0.979	0.010
	KAPPA	0.805	0.875	0.849	0.843	0.035
	TSS	0.841	0.920	0.893	0.885	0.040
4	ROC	0.965	0.983	0.983	0.977	0.010
	KAPPA	0.812	0.885	0.901	0.866	0.047
	TSS	0.823	0.897	0.913	0.878	0.048
5	ROC	0.964	0.984	0.989	0.979	0.013
	KAPPA	0.792	0.866	0.904	0.854	0.057
	TSS	0.802	0.907	0.924	0.878	0.066
6	ROC	0.973	0.989	0.989	0.984	0.009
	KAPPA	0.843	0.894	0.913	0.883	0.036
	TSS	0.851	0.918	0.918	0.896	0.039
7	ROC	0.968	0.985	0.988	0.980	0.011
	KAPPA	0.816	0.873	0.881	0.857	0.035
	TSS	0.826	0.912	0.906	0.881	0.048
8	ROC	0.977	0.989	0.992	0.986	0.008
	KAPPA	0.851	0.898	0.924	0.891	0.037
	TSS	0.870	0.920	0.932	0.907	0.033
9	ROC	0.960	0.986	0.988	0.978	0.016
	KAPPA	0.796	0.909	0.880	0.862	0.059
	TSS	0.810	0.927	0.912	0.883	0.064
10	ROC	0.969	0.990	0.989	0.983	0.012
	KAPPA	0.783	0.902	0.896	0.860	0.067
	TSS	0.827	0.920	0.901	0.883	0.049
Model Performance Summary	ROC	0.969	0.986	0.987	0.981	0.010
	KAPPA	0.818	0.888	0.893	0.866	0.042
	TSS	0.837	0.914	0.912	0.888	0.044
	Mean	0.875	0.929	0.931	0.912	0.032
	SD	0.082	0.051	0.049	0.061	0.018
Model Variable Importance	DIST	0.624	0.224	0.363	0.404	0.034
	SST	0.008	0.265	0.262	0.179	0.020
	CHLO	0.368	0.510	0.375	0.418	0.031
Moran's I Spatial Auto-correlation	Index			0.011		
	z-score			0.044		
	p-value			0.965		

Habitat suitability and area based assessments

Raster outputs of the final model revealed habitat suitability of >0.75 located around the periphery of the NIO to the north of 15°N, with distribution mostly concentrated along the continental shelf of Oman, Iran, Pakistan and northern India (**Figure 2(A)**). Habitat suitability scores between 0.5 and 0.75 were revealed off the southwest coast of India, Maldives and Lakshadweep. Similar suitability scores were identified in the southern Red Sea (Eritrea and Saudi Arabia). Habitat suitability values >0.5 were not found in the Arabian Gulf.

Of the three models, GBM was the most conservative in the predicted extent of suitable habitat (**Supplementary Information Figure S4**). GLM provided a broader distribution with habitat extended into southern portions of the Red Sea. MARS revealed greatest suitability along the coast of western India and around Sri Lanka. The coefficient of variation indicates best agreement between the models along the coast of Oman, Iran and Pakistan. The models are most contradictory in the Red Sea, along the coast of Yemen, Somalia and around the Lakshadweep territory (**Supplementary Information Figure S3**).

The EENM rasters provided a fit with observation data from cetacean surveys and opportunistic sightings (ESO, 2020) and Soviet whaling locations (Mikhalev, 1997, Allison, 2013) along the coast of Oman for both seasons for environmental suitability cell index values of >0.5 (**Figure 2**). For season 1 (December to May) sightings data collected by Pakistani fishing fleets from, 2015-2019 (Moazzam et al., 2020) fell within areas with an EENM suitability >0.75 around the Indus Canyon and across to India and the Gulf of Kutch (**Figure 2 (A)**). However, the model for season 2 (June to November) does not reflect the occurrence of ASHW in the area as reported by the Pakistan fishing fleet or from Soviet whaling locations (**Figure 2 (B)**). It is noted that the season 2 raster surface uses the EENM product produced from occurrence data in season 1 and is projected using the environmental co-variate layers from season 2. Soviet and Pakistan data have no accompanying observer effort and therefore inferences related to their relationship with the EENM should also be treated with caution.

A comparison of the total EENM surface coverage between EEZs across the study area for an environmental suitability index >0.75 was attributed to Oman (42%) and Pakistan (36%). Iran and India ranked third (12%) and fourth (7%), respectively (**Supplementary Information Table S9**). At environmental suitability index value >0.9, 56% of the area was attributed to Oman. Evaluation of the percent of EEZ surface covered by an index value >0.75 within each country's EEZs revealed Pakistan's EEZ to have the highest proportion of area covered at 39% (cell count n= 11341) in comparison to the Oman EEZ at 19% (cell count n=27523).

The Oman Arabian Sea IMMA and the Northeast Arabian Sea IMMAs were attributed the highest coverage across the study area for environmental suitability index >0.75 with 39% and 35% respectively (cell count n=32096) (**Supplementary Information Table S10**). The remaining coverage was distributed between the Gulf of Masirah and Offshore Waters, Muscat Coastal Waters and Offshore Canyons, Dhofar, and Gulf of Mannar and Palk Bay IMMAs. For index values >0.9 the Oman Arabian Sea IMMA contained 46% of raster cells across the study area. Of these areas the Gulf of Masirah and Offshore Waters and the Muscat Coastal Waters and Offshore Canyons had 100% of the area associated with index cell values >0.75 (cell counts n=1185 and 240 respectively).

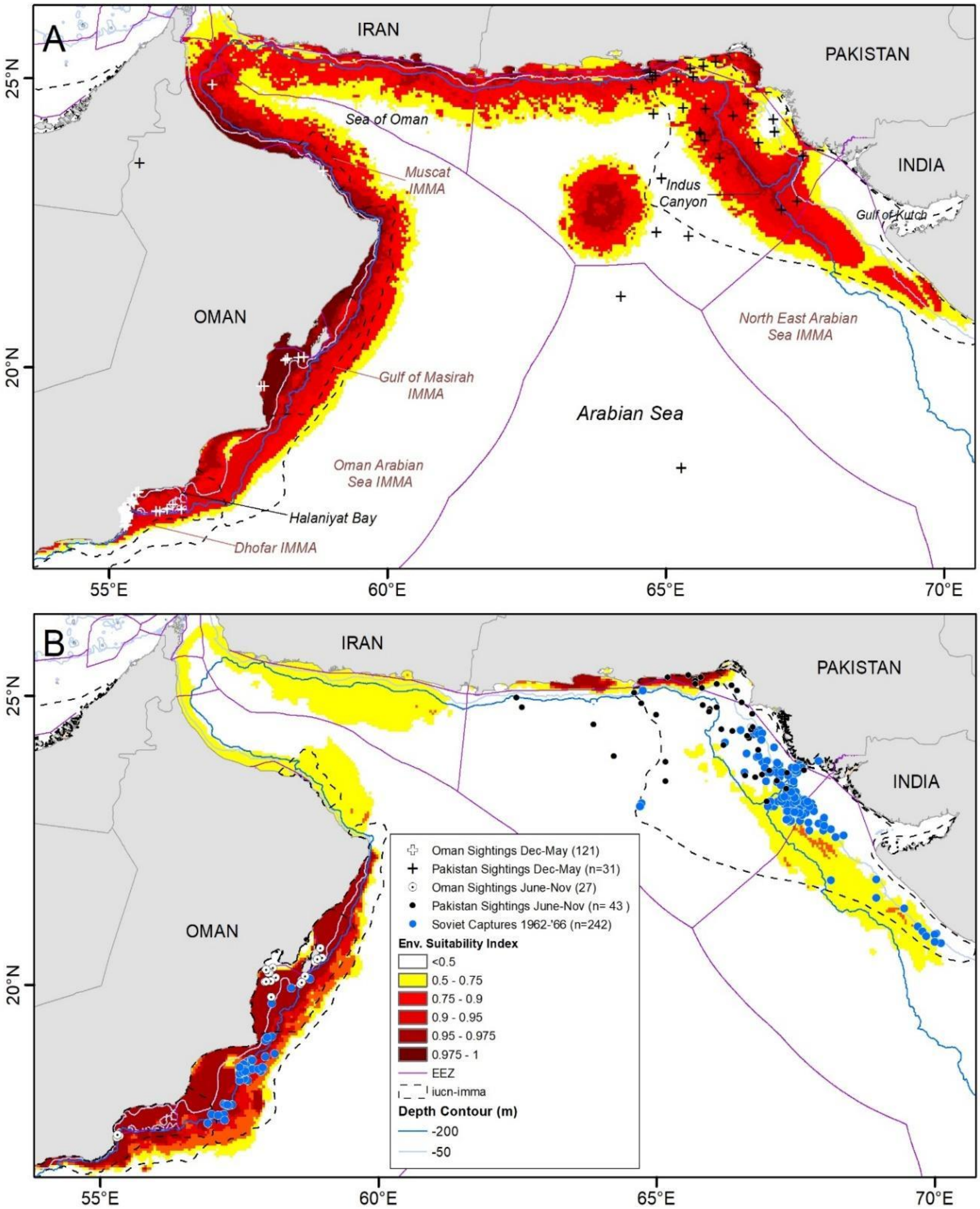

Figure 2 Detailed EENM results produced from satellite telemetry work in Oman overlaid with recent sightings from Season 1 (Dec-May) (A), and Season 2 (June-Nov) (B). Overlays include Pakistan Sightings documented by a fisheries observer programme (2015-2019) (Moazzam et al. 2019), Soviet Captures of humpback whales in the Northern Indian Ocean as documented in Soviet whaling (1962- 1966) (Mikhalev, 2000; IWC Catch Database, extracted 25 October 2013) and Oman Sightings taken from all humpback whale encounters during dedicated humpback whale surveys in Oman (2000-2017).

Vessel traffic distribution

Total traffic passage distance varied with speed, for example 40,456,767 km were transited by vessels moving at 12-14 knots, in comparison to 13,918 km of passage at 40-50 knots (**Supplementary Information Figure S5**). The sum of total transit distance for each speed category between 2 and 22 knots presents a near normal distribution, with transits within the 12-14 knot speed range representing 34% of the total distance travelled within the study area (n=120,946,750 km) (**Supplementary Information Figure S5** and **Table 2**). The mean transit distance of cells in the 12-14 knot speed bin raster was 47 km (SD=257.2). The maximum cell transit distance, from transits summed across the entire dataset, was 20,629 km and occurred in waters adjacent to the Port of Fujairah (United Arab Emirates).

Table 2 Summary statistics derived from processed s-AIS data for the northern Indian Ocean between December 2015 and May 2016.

Speed category (knots)	Sum of total transit distance at given speed (km)	Percentage of summed distance (%)	Mean distance travelled within cells at given speed category (km)	Standard deviation of distance travelled within cells at given speed category (km)	Maximum cell value for transit distance at given speed category (km) (km)
2 to 4	1,443,028	1.2	2.1	46.1	16226
4 to 6	1,524,207	1.3	2.6	48.9	15221
6 to 8	3,275,173	2.7	5.4	82.1	20629
8 to 10	5,653,973	4.7	8.9	93.9	16722
10 to 12	21,199,419	17.5	26.0	155.9	10252
12 to 14	40,456,767	33.5	46.6	257.2	10992
14 to 16	20,270,097	16.8	24.5	151.8	9795
16 to 18	13,038,158	10.8	15.4	101.7	5971
18 to 20	10,554,845	8.7	12.5	98.2	6088
20 to 22	3,279,426	2.7	4.1	35.4	3555
22 to 24	149,643	0.1	0.2	2.7	524
24 to 30	58,503	0.0	0.1	1.2	270
30 to 40	29,593	0.0	0.0	0.4	37
40 to 50	13,918	0.0	0.0	0.2	18
sum	120,946,750	100.0			
mean	8,639,054	7.1			
sd	11,739,008	9.7			

Areas of high relative shipping traffic moving at speeds >10 knots included the Red Sea, Gulf of Aden, eastern approaches of the Arabian/Persian Gulf (Straits of Hormuz) and Laccadive Sea (between southern Sri Lanka and southern India) (**Figure 3**). Transoceanic passages in the NIO predominantly connect between these three nodes. Other isolated areas of high relative traffic density included the Gulf of Kutch, waters near Mumbai (Eastern Indian coast), a transit route through the Lakshadweep Archipelago and approaches to ports of Gulf States and along the western coastline of Iran. Transit speeds above 40 knots were observed in the southern Red Sea, Sea of Oman, Gulf of Aden and Laccadive Sea, although these are infrequent and represent <0.1% of the dataset.

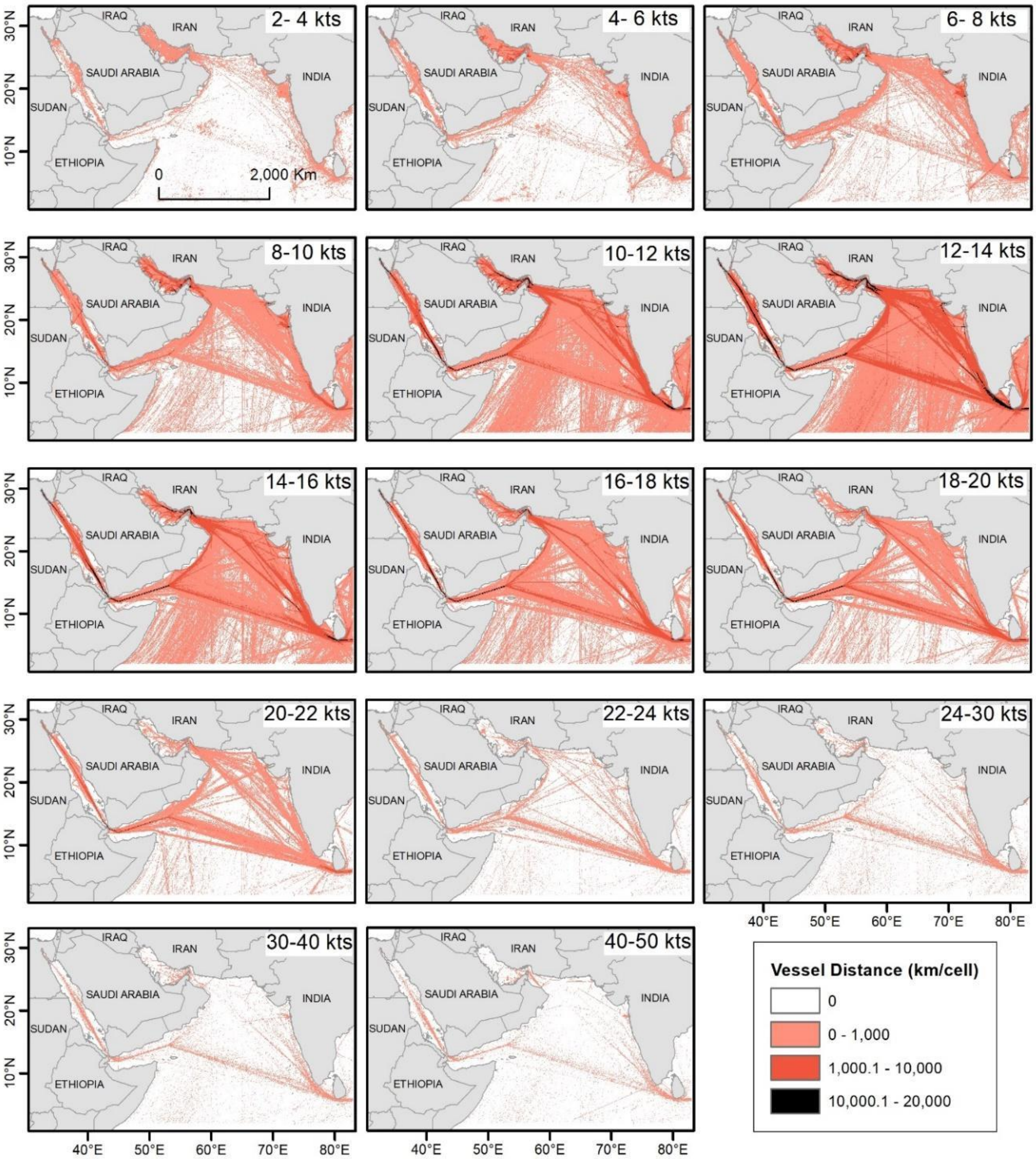

Figure 3 Distribution of vessel traffic defined by s-AIS data and grouped by speed categories. Distance traversed by vessels (km/cell) at given speed categories (a-m) derived from s-AIS data for December 2015 to May 2016 for the Northwest Indian Ocean.

Risk from commercial vessels

Shipping corridors representing a high probability of lethal strike (cell values > 0.015, 75th percentile value) were described for central parts of the NIO between nodes at the approaches to the Gulf of Aden, Straits of Hormuz and the Lakshadweep Archipelago, and between the same locations but along the coastlines of Oman, India and Sri Lanka (**Figure 4(B)**). Areas of high strike risk were also located along the Arabian Sea coastline of Oman, the Sea of Oman coastline of Oman, UAE and Iran and the routes transecting east west from Mumbai and Karachi (**Figure 4 (C)**). Additional areas of high strike risk were also detected around the southern coast of Sri Lanka and the northern reaches of the Laccadive Sea along the southwest coast of India (southern extent of the Gulf of Mannar). Areas of moderate risk (index values 75th-25th percentile) are found between areas of higher risk along the west coast of India and

Pakistan (**Figure 4 (C)**). Areas of high risk intersect with the Oman Arabian Sea and Northeast Arabian Sea IMMAs (IUCN MMPAFT, 2020).

The Oman Arabian Sea IMMA also includes the extents of the Dhofar and Gulf of Masirah IMMAs that are underpinned by evidence of ASHW breeding and foraging habitat, occurrence of blue whales in the former (*Baleanoptera musculus*), and Bryde's whales (*Baleanoptera edeni*) in both IMMAs. High risk areas throughout the Oman Arabian Sea IMMA correspond to transits of vessels along the coast between routes into the Gulf of Aden and Sea of Oman, whereas the high-risk areas in the North East Arabian Sea project outwards into the Arabian Sea from ports of Karachi (in Sindh Province, Pakistan) and Kandia (located in the Gulf of Kutch / State of Gujarat, India).

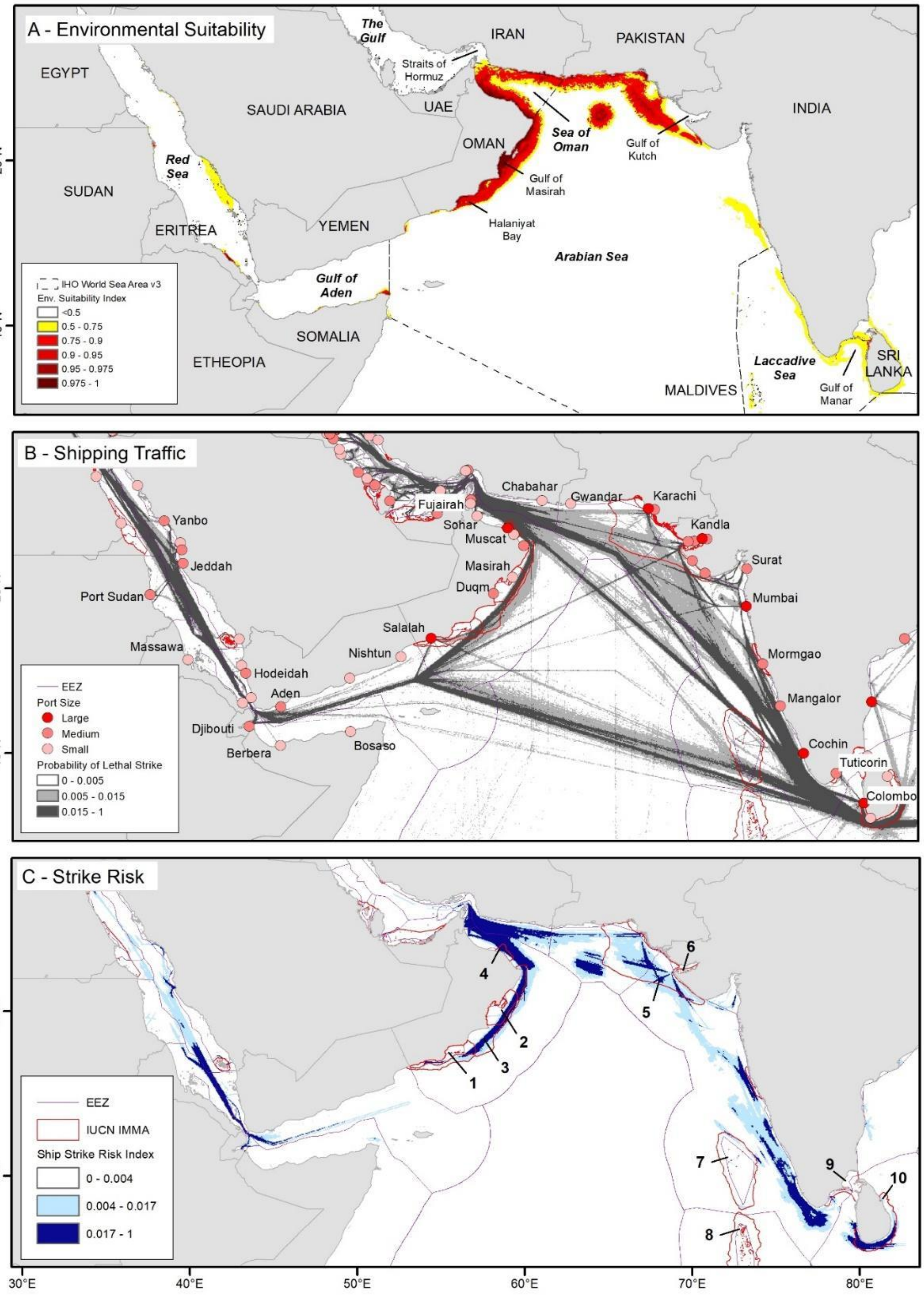

Figure 4 Strike risk framework components and important maritime features.

(A) Ensemble ecological niche model (EENM) of environmental suitability for ASHWs (source: Chapter 3), (B) probability of lethal strike, and (C) ship strike risk index (SSRI; A x B) Important Marine Mammal Areas (IMMAs; red empty polygon). IMMAs are labelled as 1) Dhofar, 2) Gulf of Masirah and Offshore Waters, 3) Oman Arabian Sea, 4) Muscat Coastal Waters and Offshore Canyons, 5) North East Arabian Sea, 6) Gulf of Kutch, 7) Lakshadweep Archipelago, 8) Maldives Archipelago, and Adjacent Oceanic Waters, 9) Gulf of Mannar and Palk Bay and 10) South West to Eastern Sri Lanka.

Mitigation Scenarios

The development of two mitigation solutions was guided by shipping industry trend data (**Supplementary Information; Table S11, Table S12 and Table S13**), where cargo vessel traffic was the most prolific of vessel categories representing 45% of traffic volume (unique vessel IDs= 43,229), and considered trends in overall shipping traffic, which increased 35% between 2008 and 2018 (increase = 5.7% per annum, SD= 3.7).

Shipping route assessment through important whale habitat off the coast of Oman demonstrated ship strike risk reduction could be achieved by routing vessels further offshore. Alternative route options (options 2 and 3 in Figure 5) located 20 and 40 nmi offshore from the primary route (the central line of current shipping transits) led to transects that were 28 nmi and 59 nmi longer respectively (**Figure 5 and Table 3**). The sum of strike risk index values for route 3 (the furthest offshore) (strike risk = 0.921) was approximately 88% less than the risk along the current primary transit route (route A; strike risk = 7.595).

Shipping route simulations run with speeds between 10 and 30 knots revealed that there were marginal differences in transit times between the three routes, with just over 3 hours difference between route 1 and 3 at 10 knots and just over 1 hour at 30 knots (**Figure 5 and Table 3**). Of interest, the strike risk along route 3 for a vessel traveling at 30 knots (strike risk index value = 46.645) was just less (by 5%) than the strike risk of a vessel traveling at 10 knots along route 1 (strike risk index value = 49.599), with the former having a transit time saving of approximately 14 hours (Figure 4-4, Table C 7). The risk of ship strike along route 3 can be further reduced by 72% by transiting through this area at 10 knots (strike risk index = 12.9) instead of 30 knots (strike risk index = 46.6).

The top three flag states associated with passing through Oman's EEZ include the Marshall Islands, Liberia and Panama and accounts for 35% (n=2530) of unique vessel identification numbers recorded from the area (total n= 7231) (Table 4-3). The full listing includes 91 flag states (**Table S13**).

Potential Biological Removal

Our calculation for PBR referred to the lower bounds of the ASHW population estimate (N= 60, Minton et al. 2008), and an Rmax value of 0.08 (Wade,1998). Based on the Fr values of 0.1, 0.5 and 1 the values for potential biological removal were calculated at 0.24, 1.2 and 2.4 whales per year respectively.

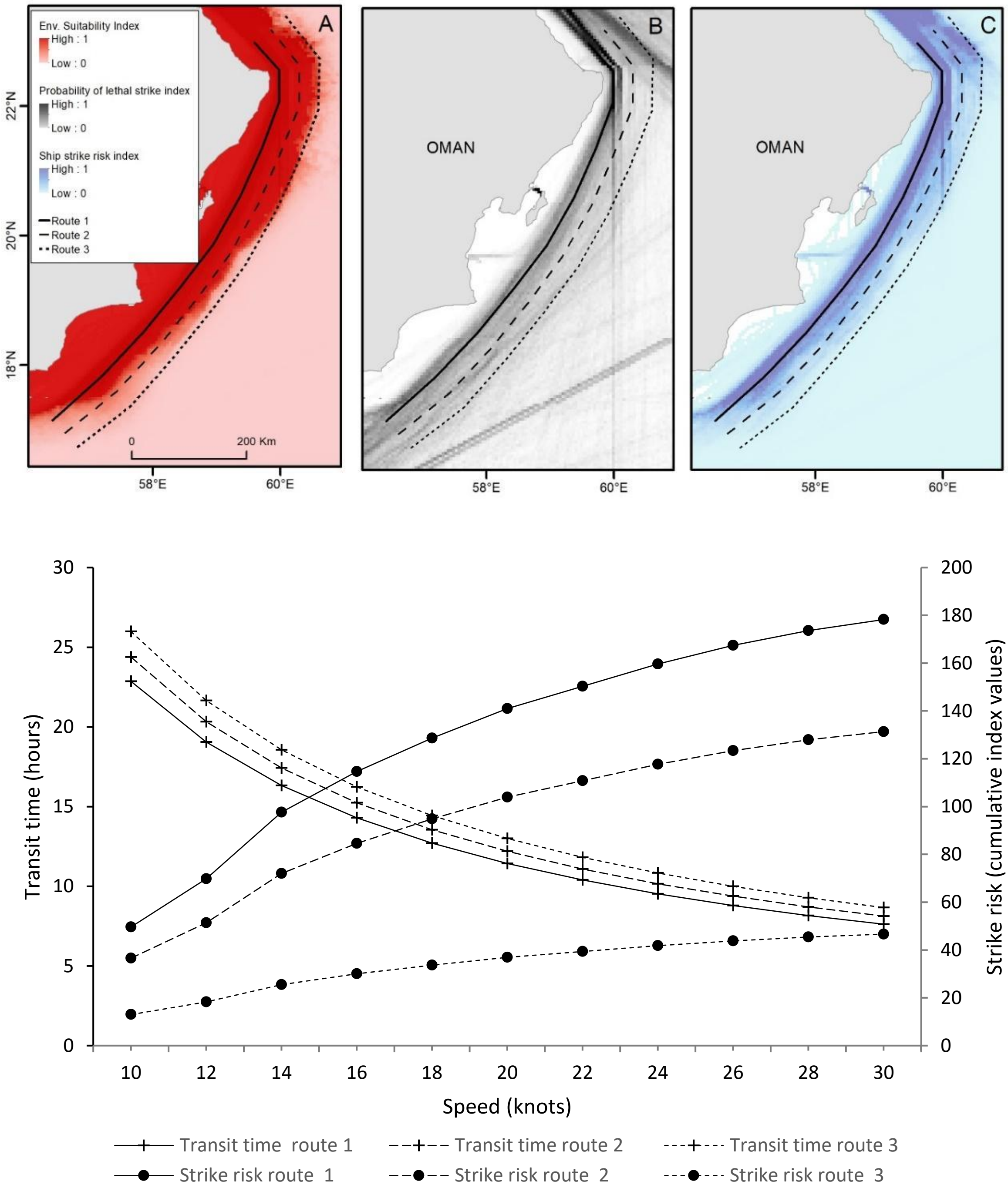

Figure 5 Transit simulation along the Arabian Sea coast of Oman to evaluate strike risk and passage time parameters according to different route and speed options. (A) Environmental suitability derived from ensemble ecological niche model (EENM) of environmental suitability (Chapter 3), (B) probability of lethal injury and (C) strike risk derived from multiplication of EENM and probability of lethal injury rasters. Route 1 represents present dominant shipping route with routes 2 and 3 selected as alternative scenarios to reduce putative strike risk and at 20 and 40 nmi from the Omani coast respectively. (D) The cost-benefit graph presents re-calculated strike risk for each route (based on EENM values multiplied by probability of lethal strike (Conn and Silber, 2013)) and the transit time in hours at predefined speeds of 2 knot increments between 10 and 30 knots.

DISCUSSION

Understanding the range-wide habitat utilisation of ASHW in the NIO is a management priority for this Endangered population (CMS, 2017), although this priority is challenged by a paucity of field-based studies across the suspected range (Minton et al., 2015). Evaluation of data on vertical space-use from ASHW equipped with biologging devices has revealed they spend 82% of time within 20m of the surface (Willson et al. in press), thus placing them within a depth range which exposes ship strike for much of the time (McKenna et al., 2015).

Our study successfully used satellite telemetry data coupled with an EENM framework to describe the relative habitat suitability across the suspected range. The EENM results together with a speed-weighted s-AIS model revealed that the highest risk of ship strike occurred around the periphery of the NIO. High risk areas (in the > 75th percentile of all risk values) were most pronounced within the Oman Arabian Sea IMMA and in the North East Arabian Sea IMMA. Referencing data external to this study, the majority of the traffic (45%) was attributed to cargo vessels (unique vessel IDs =43,299) (IUCN MMPATF, 2020), and is a concern given the 5% annual increase in traffic in the NIO between 2008 and 2018 (WTO, 2020). The preliminary mitigation simulation exercise in this study supports an approach to re-route vessels by 40 nmi further offshore from existing preferred existing routes to reduce the ship-strike risk to ASHW by 88%.

Consequences of ASHW population level impacts

Of 93 live ASHW examined in a visual health assessment, 10% showed signs of ship strike with two showing severe injuries or deformation attributed to fishing or shipping (Minton et al. 2022). A further 66% had scaring consistent with fisheries interactions. Ship strikes are considered to have a low detection rate and modelling has demonstrated that mortality from ship strikes to be significantly higher than the number of events that can be detected from strandings (Rockwood et al., 2017). The reduced number of animals likely to strand and be accessible to evaluation after decomposition also make it difficult to assign ship strike to the cause of mortality (Williams et al., 2016). As considered elsewhere, the absence of evidence of ship strike (based on observed carcasses) should not be considered as a proxy for the extent of the problem (Williams et al., 2011). Our results revealed ship strike risk is greatest along the Oman Arabian Sea coastline. Using the detection of beach strandings as an indicator of lethal ship strikes in this area is likely to be constrained by the cross-shore or offshore winds that prevail for 72% of the year (Supplementary Information Figure S6, Global Wind Atlas, 2019). These offshore winds are dominant between March and October.

Although our study is devoid of an ASHW surface density model to calculate the probability of a ship strikes, applying the concept of potential biological removal (PBR) to our situation revealed there is limited tolerance for human induced mortality where, according to recognised calculation parameters for small populations, loss of an estimated one whale every four years to human induced causes should not be exceeded. The PBR value is a concern particularly considering the cumulative influence of the range-wide threats presented by fisheries (Minton et al. 2022, Johnson et al., 2022) and the 5% annual increase in commercial shipping traffic in the NIO over the last decade (WTO, 2020). These compounding threats render the population vulnerable to further decline and highlight the urgent requirement to work with industry to evaluate all options for reducing threats.

Mitigation approach for commercial shipping

Our study adopts recommended approaches for ship strike risk assessment detailed by the IWC and IMO (Cates et al., 2017, Silber et al., 2009). This assessment together with the evaluation of mitigation options aligns our study with 'Stage 3' of the IWC ship strike risk assessment framework. The next stage in the framework involves engagement with stakeholders to assess and optimise risk reduction measures. From an IMO perspective, the coastal member states of the IMO exercise primary jurisdiction over vessel routing within their own EEZ, and therefore the member states should be considered as a first point of approach for discussion of mitigation proposals. However, the IMO can be called to administer such a process given that rerouting options (that this study describes) may also have a bearing on safety and antipollution regulations which flag states of IMO are bound to under international law (IMO, 2014b). The southern coastline of Oman is already recognised for its importance by the IMO as a 'Special Area' under MARPOL guidelines (IMO, 2020) and the adoption of a PSSA would provide the opportunity to develop associated protective measures for a broader array of the Sultanate's coastal and marine natural resources that are worthy of protection.

It is recognised that rerouting will also have a bearing on the operational measures of vessels and therefore also requires support of representatives from the shipping industry to ensure measures will be acceptable. This has been addressed as a first step by consultation of the World Shipping Council within this study.

Limitations of the EENM approach

Highest environmental suitability (≥0.75) and the most expansive areas of habitat were identified along the southern coast of Oman and marine waters between Pakistan and India. The agreement of our habitat suitability model with the location of Soviet ASHW catch positions, recent Pakistani fishing observer data, Oman vessel survey data and core home range analysis (defined by satellite telemetry data; Willson et al., in press), suggests that the important areas of habitat may have remained consistent over the last 50 years.

The EENM work addressed the importance of refining occurrence data selection and elimination of environmental covariates to use within the modelling framework. It also promoted compliance with pre-defined statistical parameters for each model run. Although not spatially independent, or able to provide absence data for a niche modelling environment, the satellite telemetry studies provided superior spatial and temporal extents of empirical data on whale occurrence than could be obtained from small vessel surveys (Corkeron et al. 2011). Furthermore, use of the SSSM approach is known to reduce issues related to serial autocorrelation in tracking data (Edelhoff et al., 2016), however, our SSSM data still required thinning to gain sufficient spatial independence between the locations for autocorrelation not to be detected when compared with the final model. This also has its constraints in limiting the availability of information for the modelling process (Aarts et al., 2008, Rooney et al., 1998).

It is important to bear in mind that the telemetry work did not proportionally sample the ASHW population across the known geographical range (Willson et al. in press). Our presence-only occurrence datasets relied on the incorporation of randomly generated pseudo-absences to produce the modelled surfaces. Use of pseudo-absence assumes no bias in presence sampling, and therefore a sampling bias may be present in our model (Fiedler et al., 2018). As a result, the relative importance of habitat utilisation across the range may not be well defined. Such caveats are understood to compromise the use of such models for risk management purposes (Guillera-Arroita et al., 2015, Fiedler et al., 2018). However, the cross reference with vessel-based occurrence data (from Soviet whaling data and Pakistani fisher sightings) has proven useful as an independent means of coarsely evaluating our model.

Our final modelling outputs were further restricted by seasonal constraints on tag deployment and longevity. This resulted in a temporally restricted dataset to apply to the modelling environment. The occurrence data we selected for the model represents an important period relating to the annual breeding cycle, however a gap remains in describing the habitat utilisation of ASHW during the rest of the year, particularly during the southwest monsoon.

The good fit with alternative occurrence data off the coast of Oman but poor reflection of habitat suitability off the coast of Pakistan for season 2 demonstrates the requirement for season-specific models to utilise presence data collected from the same period and across a broader extent of the Arabian Sea.

The biological covariate in our EENM model (chlorophyll-α) is used as a proxy for suitable foraging habitat. We believe this should be improved in future modelling exercises through generating covariate surfaces that more directly reflect the ecological niche of prey species, as it has for North Atlantic right whales (*Eubalaena glacialis*) (Pendleton et al., 2012). This may be a challenge due to the multi-prey diet of ASHW's (Mikhalev, 1997) but should allow for dynamic data to be used for seasonal or near real-time definition of environmental suitability. With conservation management a priority for the population, a more dynamic approach to understanding habitat utilisation (e.g., Maxwell et al., 2015, Hazen et al., 2018) is deemed necessary given observed ecosystem state change and concern for future biological productivity in the region (Goes et al., 2020).

Limitations of the ship strike risk assessment

Our EENM and s-AIS source data generalise space use patterns over a 6-month period. Between December and May ASHW move between different areas along the coastline of southern Oman (Willson et al. in press), but there are insufficient data to understand inter- or intra-annual variation of movements within this area. From a management perspective, the risk described by our study in this area is considered to be consistent year-round given the relative seasonal consistency of shipping traffic (Oceanmind et al. 2020) and the combined evidence of year-round ASHW presence in the Arabian Sea evidenced by Soviet whaling activities (Mikhalev, 1997), small vessel surveys (Minton et al., 2011, Willson et al., 2013), passive acoustic monitoring (Cerchio et al., 2016a) and satellite telemetry (Willson et al. in press). Whilst more complex dynamic ship strike management tools (accounting for dynamic oceanographic variables and near real-time AIS data) have been developed for assessing strike in multispecies environments (Becker et al., 2016, Hazen et al., 2017), the static spatial management measures applied in this study have still proven effective in these same areas where there is consistency of whale distribution and vessel movement (Redfern et al., 2020).

Environmental suitability described by the EENM was likely underestimated in waters of the eastern Arabian Sea and Laccadive Sea, particularly in areas where there was less convergence in model predictions. Evidence that suggests ASHW are using this habitat, include an ASHW satellite track along the southwest coast of India (Willson et al. in press), acoustic detections made off Cochi and Goa (Mahanty et al., 2015, Madhusudhana et al., 2019, D'Souza et al., in press) and the sightings of ASHW in the Gulf of Mannar (Whitehead and Moore, 1982, Reeves et al., 1991). As such, we consider the ship strike risk assessment in the eastern Arabian Sea to be an underestimate. Further studies of whale distribution in these areas will allow for refined EENMs to be developed.

Our study adopted a model for calculating lethal injury that was sensitive to speeds greater than 20 knots. This has been considered to generate estimates of instantaneous strike rates that can be misleading (Leaper, 2019). As such we accounted for potential over-prediction of the instantaneous strike rate by capping the index value for the probability of lethal injury for speeds above 22 knots (value = 1.006). However, we consider the influence of this capped value to be negligible in our overall strike risk assessment given that <0.1% of transits through raster cells occurred at speeds above 22 knots. The relationship used to estimate probability of lethal injury from vessel speed was derived from strike risk assessments developed for North Atlantic right whales, and whilst there was unlikely to be substantial difference in the severity of injury at different speeds between different species of large whales, there may be differences in response time and swim speeds to approaching vessels (Leaper, 2019).

Although large industrial vessels (>300 tonne) should be captured within our s-AIS dataset, many of the fishing fleets in the region are dominated by the artisanal sector, such as in Oman where 99% of the fleet is represented by small artisanal vessels (fibreglass skiffs < 13m overall length and capable of speeds >20 knots) that account for 96% of the total number of registered vessels (n= 22,673) (Ministry of Agriculture and Fisheries Wealth, 2018). The associated risk from this fleet is as likely to be associated with injury to the occupants or damage to the vessel from hull strike as it is from risk to the whales (Winkler et al., 2020). Larger multi-day artisanal and semi-industrial fishing vessels (of higher displacement) also exist throughout the region, although little information is available regarding the characteristics of these vessels that would be necessary to make an assessment of what risk they might present. Further marine spatial planning work should also consider the overlap between commercial shipping and artisanal fisheries with respect to risk of collisions or losses to gear (e.g. Guzman et al., 2020).

Our approach also neglects to evaluate the impact of noise generated by vessel traffic (commercial or otherwise). Masking from vessel noise has been linked to changes in animal's communication space (Clark et al., 2009). This is of concern given that increased noise from vessel traffic in the presence of large whales has been associated with reduced foraging behaviour, changes to social communication (surface generated sounds), changes to call rates and frequency, reduced social interaction (joining between different groups) (Blair et al., 2016, Dunlop et al., 2010, Parks et al., 2014, Rolland et al., 2012). Reduction of noise from shipping is attracting attention of international governance (IMO, 2014a, IWC, 2018) and studies have shown that reduction of speed by 10% (from 15 knots) can reduce sound energy at the source by as much as half (Leaper, 2019). These stated reductions indicate that speed reduction measures are worth considering for areas of important habitat, even where re-routing measures are also advised. In consideration of IMO non-mandatory noise reduction measures and IWC recommendations we suggest noise modelling and monitoring is conducted for important whale habitat to provide comprehensive recommendations of speed and re-routing mitigation options (IMO, 2014a, IMO, 2018).

The future for ship strike risk assessment in the NIO

Future risk assessment work should account for seasonal variability of shipping and whale movements using dynamic environmental information~~,~~ (Redfern et al., 2020), and also introduce presence-absence abundance data collection for whales, based online transect methodology, to allow the interactions to be assessed within a modelling framework for estimating dynamic habitat suitability (Abrahams et al., 2018). This approach has been applied to a near real-time blue whale (*Balaenoptera musculus*) density prediction tool in the Eastern North Pacific and is used to inform resource managers of the temporal and spatial components of ship strike and bycatch risks in the Californian Current (Hazen et al., 2017, Hazen et al., 2018). Approaches such as these are considered more suitable for addressing ecological and economic objectives that are associated with the emerging field of dynamic ocean management (Maxwell et al., 2015).

The Oman Arabian Sea IMMA includes the extents of the Dhofar and Gulf of Masirah IMMAs. The IMMAs were identified on the basis of evidence of ASHW breeding and foraging habitat, as well as the regular presence of blue whales (*Baleanoptera musculus*), Bryde's whales (*Baleanoptera edeni*) and sperm whales (*Physeter macrocephalus*) within their extents (IUCN MMPAFT, 2020). The evidence of ship strikes of blue whales off southern Sri Lanka has also been well documented (de Vos et al., 2013, de Vos et al., 2016, Priyadarshana et al., 2016). Development of a regional multispecies ship strike assessment would be a logical next step, particularly given the availability of species distribution models that have already been developed for blue whales and sperm whales within the NIO (Redfern et al., 2016, Letessier et al., 2023).

Conclusions

Our EENM model development and validation process has produced a final EENM that can be used to inform ASHW conservation management. Its use should consider the model constraints (Guillera-Arroita et al., 2015) including the potential spatial bias that may result from seasonally constraints and patterns of relative occurrence that result from tagging locations being restricted to the western Arabian Sea. To help address these current potential shortfalls, we advise use of the model in guiding the design of future field surveys in eastern Pakistan and northern India within the North East Arabian Sea IMMA to understand habitat utilisation of ASHW in greater detail, and support efforts to track the conservation status of the population (CMS, 2017, IUCN MMPAFT, 2020).

Areas not detected with high environmental suitability (areas of < 0.75) known to host ASHW, (such as along the western and southern coasts of India and the Gulf of Aden) should receive similar attention. These areas are currently classified as 'Areas of Interest' within the IMMA classification framework (IUCN MMPATF, 2020) and require further evidence of habitat utilisation to be considered for full IMMA status.

The risk of ASHW ship strikes is likely to escalate given the annual increases in shipping traffic throughout the NIO and projected global increase of 2.1 % per year between 2023 and 2027 (UNTCAD, 2022). We have outlined evidence to support uptake of mitigation measures subject to further review from the commercial shipping industry, the International Whaling Commission and member states of the International Maritime Organisation. The successful implementation of these measures will require continuous engagement through dedicated communication strategies used by the industry (Guzman et al., 2020). The effective management of ship strikes also needs to be coupled with assessments of underwater noise associated with vessel traffic and the interaction of ASHW with fishing fleets (and associated gear). Based on our review of potential biological removal of ASHW and consideration of the cumulative impacts from anthropogenic industries we recommend that the next steps towards mitigation are taken up with immediate effect. These should be integrated within a marine spatial planning framework that will ensure the ecological and economic security of a broader range of interests including the livelihoods of coastal communities and growth of other industrial maritime activities including fisheries and offshore energy production.

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SUPPLEMENTARY INFORMATION

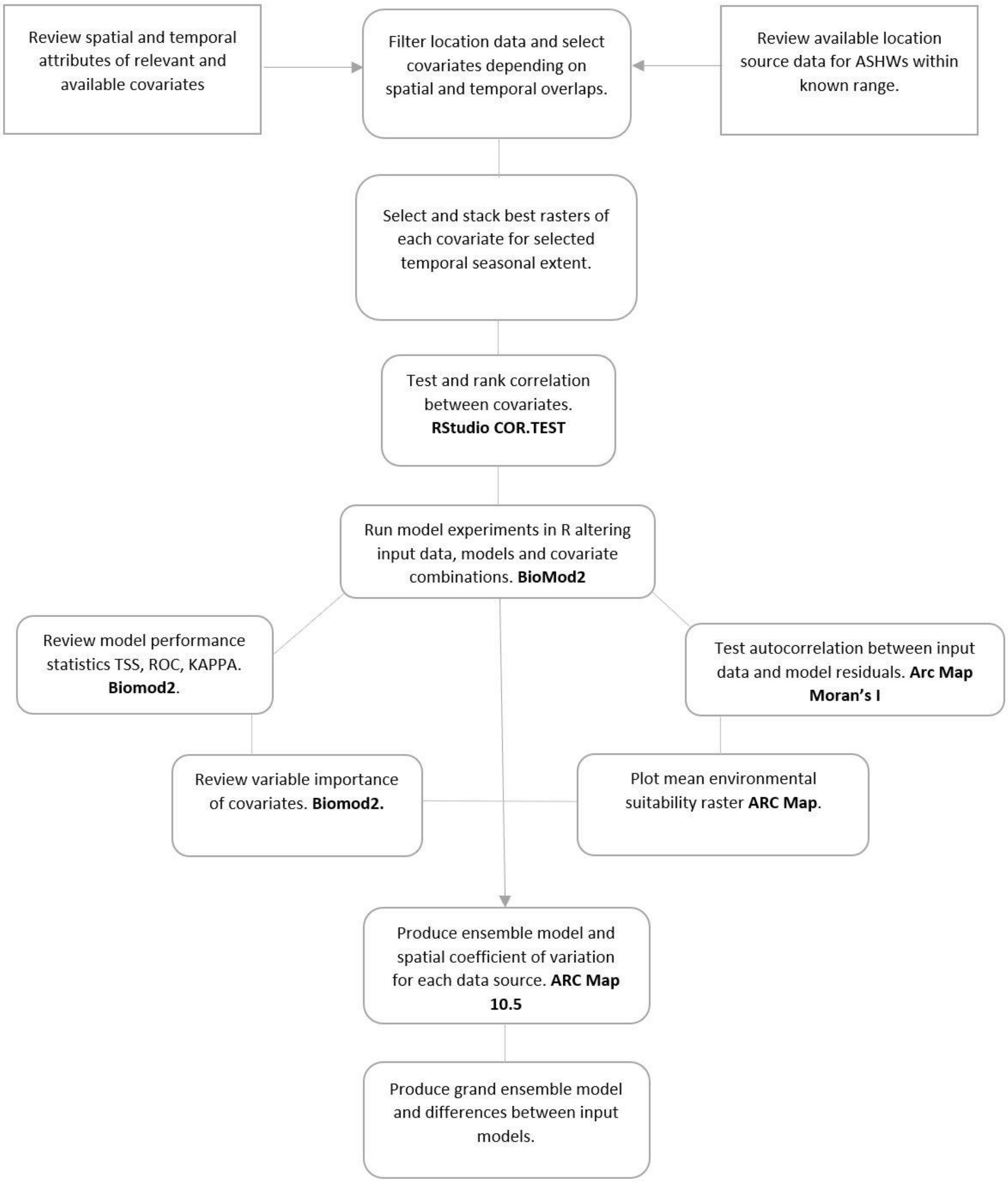

Figure S1 Overview of the workflow used for the EENM study.

The workflow includes incorporating the vessel based sightings and satellite telemetry data of ASHWs into ensemble ecological niche models in the 'Biomod2' package in *R*.

Table S1 Summary of tests for covariate correlation (R^2) and strength of correlation (p-value).

Values extracted from 100 random points applied to all rasters layers in ArcGIS 10.5 and tested in R using the 'COR.TEST' package.

Selected Covariates	R2	p-value
slope v nsst	0.020	0.846
slope v dist	-0.061	0.547
depth v slope	0.152	0.130
slope v chlo	-0.179	0.074
slope v npp	-0.208	0.038
dist v chlo	-0.218	0.029
dist v nsst	0.292	0.003
depth v chlo	0.400	0.000
depth v npp	0.528	0.000
nsst v chlo	-0.528	0.000
depth v dist	-0.559	0.000
depth v nsst	-0.598	0.000
nsst v npp	-0.671	0.000
nsst v npp	-0.671	0.000
chlo v npp	0.938	0.000

Table S2 Summary of AIS message types and code.
S-AIS records were retained for those message types highlighted in yellow.
(Source: https://web.nlcindia.com/gpsd/gpsd-3.1/www/AIVDM.txt)

```
Message types
[width="50%",frame="topbot"]
|=======================================================
|01 |Position Report Class A
|02 |Position Report Class A (Assigned schedule)
|03 |Position Report Class A (Response to interrogation)
|04 |Base Station Report
|05 |Static and Voyage Related Data
|06 |Binary Addressed Message
|07 |Binary Acknowledge
|08 |Binary Broadcast Message
|09 |Standard SAR Aircraft Position Report
|10 |UTC and Date Inquiry
|11 |UTC and Date Response
|12 |Addressed Safety Related Message
|13 |Safety Related Acknowledgement
|14 |Safety Related Broadcast Message
|15 |Interrogation
|16 |Assignment Mode Command
|17 |DGNSS Binary Broadcast Message
|18 |Standard Class B CS Position Report
|19 |Extended Class B Equipment Position Report
|20 |Data Link Management
|21 |Aid-to-Navigation Report
|22 |Channel Management
|23 |Group Assignment Command
|24 |Static Data Report
|25 |Single Slot Binary Message,
|26 |Multiple Slot Binary Message With Communications State
|27 |Position Report For Long-Range Applications
|=======================================================
```

Table S3 Summary of AIS navigation status codes.
S-AIS records were retained for those codes highlighted in yellow. (Source: https://web.nlcindia.com/gpsd/gpsd-3.1/www/AIVDM.txt)

```
Navigation Status
[width="50%",frame="topbot"]
|=================================================================
|0 | Under way using engine
|1 | At anchor
|2 | Not under command
|3 | Restricted manoeuvrability
|4 | Constrained by her draught
|5 | Moored
|6 | Aground
|7 | Engaged in Fishing
|8 | Under way sailing
|9 | Reserved for future amendment of Navigational Status for HSC
|10| Reserved for future amendment of Navigational Status for WIG
|11| Reserved for future use
|12| Reserved for future use
|13| Reserved for future use
|14| Reserved for future use
|15| Not defined (default)
|=================================================================
```

Table S4 Probability of lethal strike adapted from Conn and Silber (2013). The probability of lethal strike (P^{LS}) is derived from the estimated probability of lethal injury (Mv) multiplied by the instantaneous rate at which whales are struck (log(λ)). Highlighted rows represent P^{LS} values capped after the 20-22 knot speed bin to account for the absence of supporting empirical data informing the instantaneous strike rate (log(λ)).

Selected Raster Speed Bin (knots)	Selected speed value (knots)	Mv	log(λ)	P^{LS}
	1	0.156	-0.310	-0.048
	2	0.187	-0.009	-0.002
2 to 4	3	0.222	0.167	0.037
4 to 6	5	0.306	0.389	0.119
6 to 8	7	0.405	0.535	0.217
8 to 10	9	0.512	0.644	0.330
10 to 12	11	0.618	0.732	0.452
12 to 14	13	0.714	0.804	0.574
14 to 16	15	0.794	0.866	0.688
16 to 18	17	0.856	0.921	0.788
18 to 20	19	0.902	0.969	0.874
20 to 22	21	0.934	1.012	0.946
22 to 24	23	0.956	1.052	1.006
24 to 30	24	0.965	1.070	1.006
30 to 40	35	0.997	1.234	1.006
40 to 50	45	1.000	1.343	1.006

Table S5 Means of modelling test statistics including ROC, KAPPA and TSS from experiments performed in the Biomod2 R package.

The means of each experiment are derived from ten runs for each model (GLM, MARS, GBM) with vessel sightings and satellite telemetry data.

Env. Cov.	Model Test Stats	SSSM Models					
		Loc. Point Count	GLM	MARS	GBM	Mean	SD
EXP 1 Depth Slope Dist200m NSST CHLO	ROC	1526	0.975	0.987	0.991	0.984	0.008
	KAPPA		0.859	0.927	0.949	0.912	0.047
	TSS		0.836	0.921	0.947	0.901	0.058
	Mean		0.890	0.945	0.962		
	SD		0.074	0.036	0.025		
EXP 3 Depth Dist200m NSST CHLO	ROC	1526	0.977	0.990	0.993	0.987	0.008
	KAPPA		0.874	0.936	0.951	0.920	0.041
	TSS		0.851	0.930	0.950	0.910	0.053
	Mean		0.901	0.952	0.965		
	SD		0.067	0.033	0.024		
EXP 4a Dist200m NSST CHLO	ROC	1526	0.972	0.989	0.990	0.984	0.010
	KAPPA		0.847	0.921	0.926	0.898	0.044
	TSS		0.846	0.922	0.927	0.898	0.045
	Mean		0.888	0.944	0.948		
	SD		0.072	0.039	0.037		
EXP 4b Dist200m NSST CHLO	ROC	509	0.969	0.986	0.987	0.981	0.010
	KAPPA		0.818	0.888	0.893	0.866	0.042
	TSS		0.837	0.914	0.912	0.888	0.044
	Mean		0.875	0.929	0.931		
	SD		0.082	0.051	0.049		
Exp 4c Dist200m NSST CHLO	ROC	763	0.970	0.987	0.988	0.982	0.010
	KAPPA		0.837	0.897	0.904	0.879	0.037
	TSS		0.838	0.917	0.924	0.893	0.048
	Mean		0.881	0.934	0.939		
	SD		0.077	0.047	0.044		

Table S6 Summary of variable importance of environmental covariates from experiments in the Biomod2 R package. Variable importance presented for sightings and satellite telemetry data.
Results show means for each experiment where five, four and three covariates were tested in a process of elimination according to rank determined by variable importance. Means are determined from 10 model runs for each model (GLM, MARS and GBM). Relative importance of environmental covariates was determined by ranking of sightings and telemetry means of means.

Exp No.	Env. Cov.	SSSM Varaible Importance					
		Loc. Point Count	GLM	MARS	GBM	Mean of Means	Mean of SDs
EXP 1	DEPTH	1526	0.10	0.10	0.15	0.12	0.04
	SLOPE		0.05	0.02	0.01	0.02	0.01
	DIST		0.58	0.21	0.32	0.37	0.05
	SST		0.01	0.21	0.25	0.15	0.03
	CHLO		0.27	0.47	0.27	0.34	0.06
EXP 3	DEPTH	1526	0.15	0.14	0.29	0.19	0.19
	DIST		0.54	0.29	0.26	0.36	0.36
	SST		0.01	0.26	0.26	0.18	0.18
	CHLO		0.31	0.31	0.19	0.27	0.27
EXP 4a	DIST	1526	0.62	0.33	0.34	0.43	0.04
	SST		0.00	0.23	0.28	0.17	0.02
	CHLO		0.38	0.44	0.37	0.40	0.04
EXP 4b	DIST	509	0.6238	0.2244	0.3625	0.4036	0.0345
	SST		0.008	0.2653	0.2622	0.1785	0.0204
	CHLO		0.3682	0.5103	0.3752	0.4179	0.0314
EXP 4c	DIST	763	0.64	0.2242	0.3462	0.4034	0.0156
	SST		0.0008	0.268	0.3112	0.1933	0.01
	CHLO		0.3592	0.5078	0.3426	0.4032	0.021

Table S7 Quartile statistics for environmental covariate raster surfaces extracted for sightings and SSSM data in Arc GIS 10.5.

Depth and slope parameters (in grey) were eventually eliminated as selected covariates for the final EENM model.

	Quartile	**depth (m)**	**slope (degrees)**	**dist (km)**	**sst (°C)**	**chlo (mg m^{-3})**
SSSM	lower	-132	0.09	11.81	24.69	1.90
	median	-40	0.25	30.66	24.97	4.12
	upper	-22	2.76	52.22	25.39	9.78
	IQR	110	2.67	40.40	0.70	7.88
	mean	-275	2.01	31.85	25.24	6.29
	sd	592	3.07	21.82	1.11	5.02

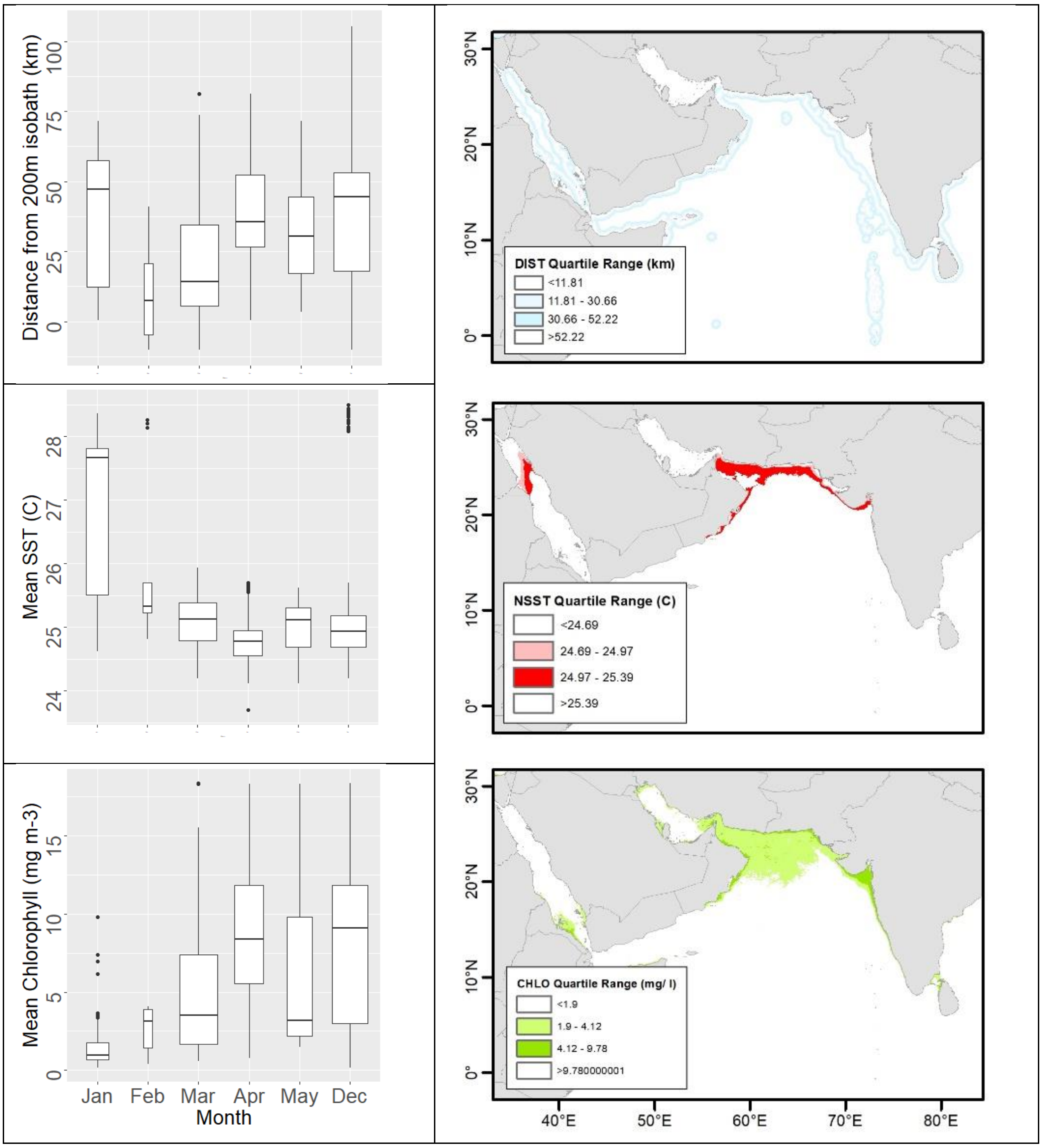

Figure S2 Plots of data extracted from environmental covariate rasters.

Left and middle: Box plots (with outliers) for median and inter-quartile ranges for environmental covariates extracted from December to May for satellite telemetry SSSM data. Variables include; (a) mean distance from the 200m isobath (km) (DIST), (b) mean night time sea surface temperature (NSST) (°C) (c) chlorophyll- α (CHLO) (mg C m-3). Box plot upper and low hinges set at interquartile ranges (25% and 75%), and box width proportional to the square root of the number of observations in the groups. Whisker plots are set within no more than 1.5 x the inter-quartile range and remaining outlying data represented by points. Right: Environmental covariate rasters of distance from 200m contour (DIST), night sea surface temperature (NSST) and chlorophyll- α (CHLO). Scales for covariate values adjusted to interquartile ranges (Supplementary Information, Table 8).

Table S8 Results of Morans I spatial autocorrelation test conducted on raster outputs of EENM experiments.
Test conducted in Arc Map 10.7. P-values <0.05 indicate that features are spatially autocorrelated.

Exp. No.	SSSM Morans I Test		
	Index	z-score	p-value
Exp 1	0.180	2.175	0.030
Exp 3	0.158	1.911	0.056
Exp 4a	0.184	2.216	0.027
Exp 4b	0.011	0.044	0.965
Exp 4c	0.318	2.210	0.027

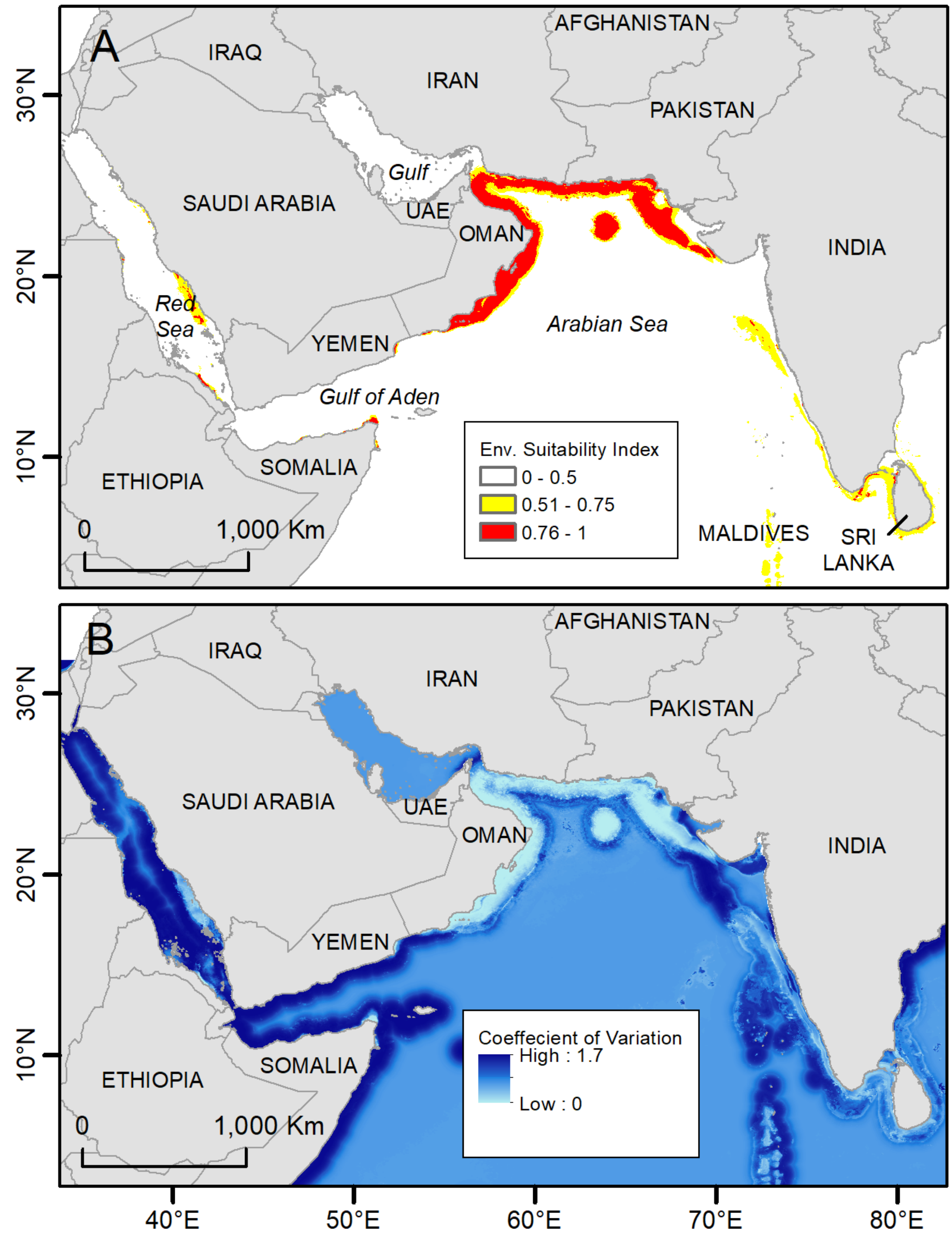

Figure S3 Ensemble ecological niche models for Arabian Sea humpback whales.

(A) Environmental suitability index derived from SSSM location estimates (2014-2018). (B) Spatial coefficient of variation from all model outputs (GLM, GBM, MARS). Agreement across models is indicated by lower values for the coefficient of variation (lighter shading), with high values indicating lack of agreement in model predictions.

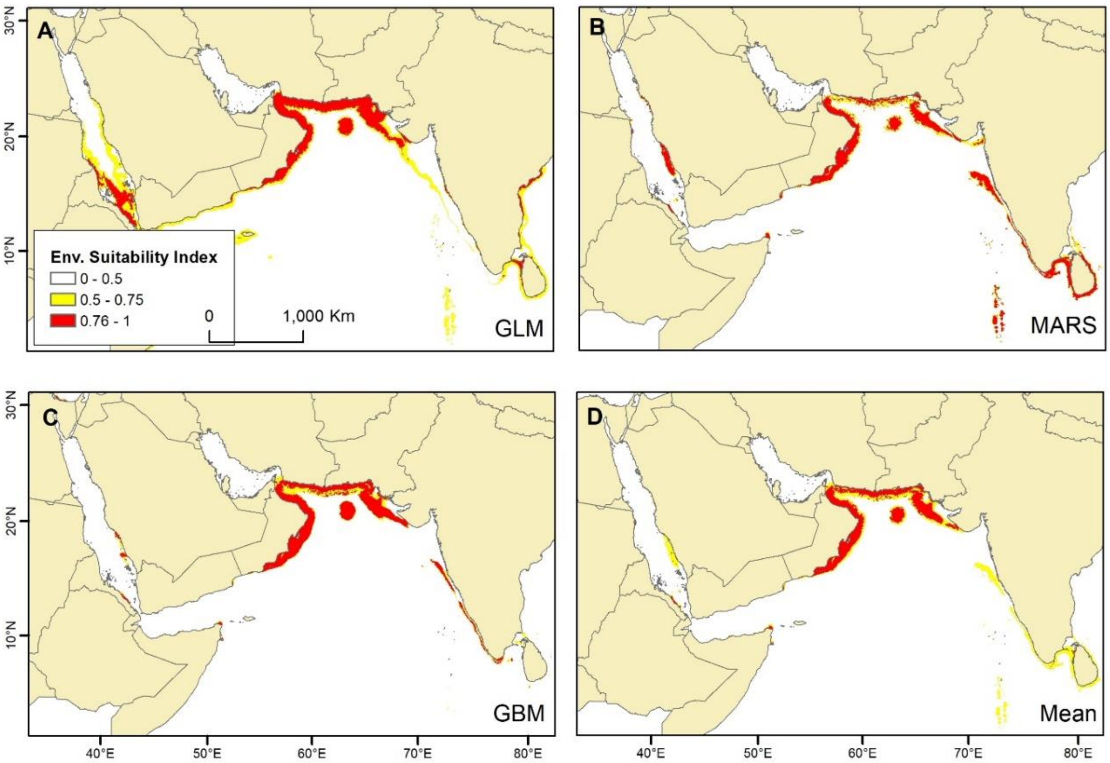

Figure S4 Environmental suitability EENM rasters generated from satellite telemetry data.
Rasters produced using satellite telemetry data from the months of December to May extracted from data collected between February 2014 and December 2017. Rasters presented for (a) General Linear Model, (b) Multivariate Adaptive Regression Splines, (c) Generalised Boosted Model (d) Ensemble. Model algorithms used from the 'Biomod2' package (R Development Core Team, 2008; R package: biomod2; Thuiller et al., 2013).

Table S9 Extent of EENM within Exclusive Economic Zones (EEZ) of Arabian Sea humpback whale range states. Assessment according to EENM raster counts of environmental suitability index values (ESI) of >0.5, >0.75 and >0.9 within EEZs. Countries ranked by percent of EEZ surface covered by EENM relative to other areas for ESI values >0.75.

		Count (n)				Perc. surface within area (%)			Perc. of surface relative to other areas (%)		
Area Type	Area of Interest	Raster Count	0.5	0.75	0.9	ESI >0.5	ESI >0.75	ESI >0.9	ESI >0.5	ESI >0.75	ESI >0.9
EEZ	Oman	27523	6455	5153	3666	23	19	13	28	42	56
	Pakistan	11341	6453	4406	2033	57	39	18	28	36	31
	Iran	8119	2351	1485	491	29	18	6	10	12	8
	India	62233	4144	805	136	7	1	0	18	7	2
	United Arab Emirates	2610	225	153	74	9	6	3	1	1	1
	Eritrea	3758	181	86	49	5	2	1	1	1	1
	Federal Republic of Somalia	36851	227	81	39	1	0	0	1	1	1
	Sri Lanka	17049	1332	63	12	8	0	0	6	1	0
	Saudi Arabia	11249	1070	31	1	10	0	0	5	0	0
	Sudan	3114	46	25		1	1	0	0	0	0
	Yemen	25269	85	25	6	0	0	0	0	0	0
	Bahrain	383				0	0	0	0	0	0
	Djibouti	346				0	0	0	0	0	0
	Egypt	4451	34			1	0	0	0	0	0
	Iraq	53				0	0	0	0	0	0
	Israel	81				0	0	0	0	0	0
	Jordan	2				0	0	0	0	0	0
	Kenya	21				0	0	0	0	0	0
	Kuwait	586				0	0	0	0	0	0
	Maldives	39538	727			2	0	0	3	0	0
	Qatar	1614				0	0	0	0	0	0
	Seychelles	3582				0	0	0	0	0	0

Table S10 EENM extent within Important Marine Mammal Areas (IMMAs) of Arabian Sea humpback whale range states. Assessment according to EENM raster counts of environmental suitability index values (ESI) of >0.5, >0.75 and >0.9 within IMMAs. Countries ranked by percent of EEZ surface covered by EENM relative to other areas for ESI values >0.75**.**

		Count (n)				Perc. surface within area (%)			Perc. of surface relative to other areas (%)		
Area	Area of Interest	Raster	ESI	ESI	ESI	ESI	ESI	ESI	ESI	ESI	ESI
IMMA	Oman Arabian Sea IMMA	4745	3671	3303	2560	77	70	54	30	39	46
	North East Arabian Sea IMMA	6572	4425	2940	1254	67	45	19	36	35	22
	Gulf of Masirah and Offshore Waters IMMA	1185	1185	1185	1090	100	100	92	10	14	20
	Dhofar IMMA	937	769	650	479	82	69	51	6	8	9
	Muscat Coastal Waters and Offshore Canyons IMMA	240	240	240	199	100	100	83	2	3	4
	Gulf of Mannar and Palk Bay IMMA	954	608	64	0	64	7	0	5	1	0
	Indus Estuary and Creeks IMMA	102	29	17	0	28	17	0	0	0	0
	Sindhudurg-Karwar IMMA	186	60	10	1	32	5	1	0	0	0
	Farasan Archipelago IMMA	278	38	8	1	14	3	0	0	0	0
	Southern Egyptian Red Sea Bays, Offshore Reefs and Islands	986	3	3	0	0	0	0	0	0	0
	South West to Eastern Sri Lanka IMMA	1346	606	1		45	0	0	5	0	0
	Miani Hor IMMA	1	1	1	1	100	100	100	0	0	0
	Gulf of Salwa IMMA	538	0	0	0	0	0	0	0	0	0
	Gulf of Kutch IMMA	130	0	0	0	0	0	0	0	0	0
	Lamu Offshore IMMA	538	0	0	0	0	0	0	0	0	0
	Lakshadweep Archipelago IMMA	4130	22	0	0	1	0	0	0	0	0
	Nakhiloo Coastal Waters IMMA	18	0	0	0	0	0	0	0	0	0
	Northern Gulf and Confluence of Tigris, Euphrates and Kuran	172	0	0	0	0	0	0	0	0	0
	Northern Red Sea Islands IMMA	111	0	0	0	0	0	0	0	0	0
	Southern Gulf and Coastal Waters IMMA	1306	0	0	0	0	0	0	0	0	0
	Maldives Archipelago and Adjacent Oceanic Waters IMMA	7621	728	0	0	10	0	0	6	0	0

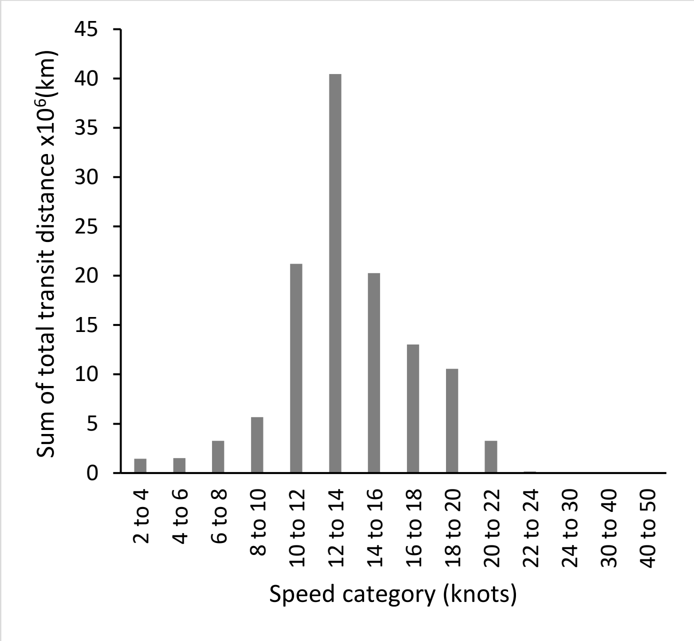

Figure S5 Sum of total transit distance within each speed category for processed s-AIS data in the Northern Indian Ocean from December 2015 to May 2016.

Table S11 Counts of vessels (by type) found within Important Marine Mammal Areas (IMMAs) of the north Indian Ocean.

Counts derived from s-AIS unique vessel IDs (MMSI numbers) and the percentage of counts from each vessel category of the total number of detected unique vessel IDs. Assessment includes IMMAs associated with large whale habitat.

Vessel category		Fishing	Fish	Fish	Fishing	Cargo	Hazardous	Passenger	Pleasure	Unknown	Other	Total
Dhofar IMMA	Counts of Unique Vessel IDs	27	1	2	2	1066	790	53	73	28	181	2223
Gulf of Mannar and Palk Bay IMMA		112	0	0	0	385	111	9	11	28	90	746
Gulf of Masirah and Offshore Waters IMMA		13	1	0	1	1053	716	50	41	28	200	2103
Lakshadweep Archipelago IMMA		313	9	0	8	3117	3093	45	30	355	192	7162
Maldives Archipelago and Adjacent Oceanic Waters		292	13	0	7	933	626	35	85	54	125	2170
Muscat Coastal Waters and Offshore Canyons IMMA		17	3	3	2	1802	1989	59	53	36	234	4198
North East Arabian Sea IMMA		99	1	2	2	2597	2521	28	36	187	343	5816
Oman Arabian Sea		42	3	3	3	1991	1871	72	94	77	293	4449
South West to Eastern Sri Lanka IMMA Vessel		1475	8	0	53	5816	4625	106	115	1647	516	14361
Dhofar IMMA	Percentage of vessel categories	1	0	0	0	48	36	2	3	1	8	
Gulf of Mannar and Palk Bay IMMA		15	0	0	0	52	15	1	1	4	12	
Gulf of Masirah and Offshore Waters IMMA		1	0	0	0	50	34	2	2	1	10	
Lakshadweep Archipelago IMMA		4	0	0	0	44	43	1	0	5	3	
Maldives Archipelago and Adjacent Oceanic Waters		13	1	0	0	43	29	2	4	2	6	
Muscat Coastal Waters and Offshore Canyons IMMA		0	0	0	0	43	47	1	1	1	6	
North East Arabian Sea IMMA		2	0	0	0	45	43	0	1	3	6	
Oman Arabian Sea		1	0	0	0	45	42	2	2	2	7	
South West to Eastern Sri Lanka IMMA Vessel		10	0	0	0	40	32	1	1	11	4	
Mean		5	0	0	0	45	36	1	2	3	7	
SD		6	0	0	0	4	10	1	1	3	3	

Source: WWF-IUCN-IWC-OceanMind, (2020). A Geospatial Analysis of Vessel Traffic in Important Marine Mammal Areas; Using the Automatic Identification System to Monitor the Important Marine Mammal Areas (01Sep2018-01Sept2019).

Table S12 World Trade Organisation container port traffic data for selected countries surrounding the north Indian Ocean from 2000 to 2018.
Summary statistics calculated for the increase in TEU traffic since the beginning of records for each country.

Country Name	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Perc. Increase from the beginning of recrds (%)
India	2,450,656	2,764,757	3,208,380	3,916,814	4,332,863	4,982,092	6,141,148	7,398,211	7,672,457	8,014,487	8,922,576	9,922,786	10,072,000	10,626,000	11,323,000	11,882,003	12,086,010	15,426,000	16,382,600	85
Saudi Arabia	1,502,893	1,676,991	1,958,570	2,440,327	759,769	3,732,706	3,863,202	4,208,854	4,652,022	4,430,676	5,810,404	7,001,000	7,949,000	7,811,139	7,446,762	7,567,862	7,578,862	8,082,000	8,670,000	83
Qatar	na	na	na	na	na	na	na	350,000	400,000	410,000	420,000	420,001	420,001	420,001	462,000	568,000	568,000	1,267,000	1,835,000	81
Kuwait	na	na	na	na	na	673,472	750,000	900,000	961,684	854,044	950,000	950,000	950,000	950,000	1,050,000	1,035,000	1,262,174	984,000	3,099,345	78
Sri Lanka	1,732,855	1,726,605	1,764,720	1,959,354	2,220,525	2,455,297	3,079,132	3,687,338	3,687,465	3,464,297	4,100,000	4,260,000	4,321,000	4,310,000	4,908,000	5,185,000	5,550,000	6,200,000	7,000,000	75
Egypt, Arab Rep.	1,625,601	1,708,990	1,336,040	1,579,530	2,959,895	4,031,114	5,372,832	5,181,581	6,099,218	6,250,443	6,833,009	6,514,020	7,434,989	7,345,189	7,897,189	7,186,489	7,377,489	6,151,900	6,151,900	74
United Arab Emirates	5,055,801	5,081,964	5,872,240	6,955,202	8,661,636	9,851,709	10,967,048	13,182,412	14,756,127	14,425,039	15,177,436	16,866,912	18,120,112	18,693,112	20,223,612	21,233,200	20,613,200	19,128,300	19,054,000	73
Pakistan	na	878,892	na	787,559	1,269,373	1,686,355	1,776,939	1,935,882	1,938,001	2,058,056	2,149,000	2,278,000	2,222,000	2,262,000	2,534,600	2,755,600	2,755,600	3,275,000	3,275,000	73
Oman	1,161,549	1,331,686	1,415,500	2,264,826	2,515,546	2,748,584	2,620,363	2,876,969	3,427,990	3,768,045	3,943,835	3,749,817	4,330,000	4,024,400	3,886,000	3,569,000	4,075,000	4,784,712	4,223,712	72
Djibouti	na	na	na	na	na	na	na	294,902	356,462	519,500	600,000	634,200	659,600	660,000	736,000	910,000	987,000	928,000	847,000	65
Yemen, Rep.	248,177	377,367	na	na	na	na	na	773,016	775,165	639,671	640,076	619,694	569,694	559,694	496,000	377,000	375,000	535,000		54
Maldives	na	na	na	na	na	na	na	47,703	53,650	56,000	49,627	53,062	54,820	79,712	83,777	83,778	81,744	86,730	88,898	46
Bahrain	na	na	na	na	na	na	na	238,624	269,331	279,799	269,331	269,331	269,331	269,331	269,331	269,331	269,331	400,300	432,200	45
Iran, Islamic Rep.	na	na	805,860	1,090,212	1,177,265	1,325,643	1,528,518	1,722,513	2,000,230	2,206,476	3,045,500	3,426,000	2,656,000	2,129,000	2,270,000	2,165,250	2,555,063	3,093,400	2,378,600	44
Sudan	na	na	na	na	na	na	na	342,152.00	391,139.00	431,232.00	430,000.00	430,000.00	441,000.00	447,495.00	434,445.00	481,815.00	465,355.00	487,331.00	551,900.00	38
																			Mean	66
																			SD	16

Table S13 Summary of World Trade Organisation container port traffic data for the north Indian Ocean study area between 2009 and 2018. Summary statistics calculated for the percent increase relative to 2009 and the annual percent increase. Summary data includes countries selected in **Error! Reference source not found.**.

Statistical Summary	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Total (TEU)	47,807,765	53,340,794	57,394,823	60,469,547	60,587,073	64,020,716	65,269,328	66,599,828	70,829,673	73,990,155
Mean (TEU)	3,384,038	3,779,342	4,068,916	4,287,753	4,295,684	4,541,877	4,627,680	4,723,891	5,024,453	5,649,097
StDev (TEU)	3,996,636	4,284,412	4,753,070	5,130,507	5,300,923	5,678,390	5,919,202	5,785,058	5,811,812	5,963,136
Percent increase relative to 2009 (%)	0	10	17	21	21	25	27	28	33	35
Percent increase annualy since 2009 (%)	0	10	7	5	0	5	2	2	6	11
							Mean annual increase			5.47
							StDev of annual increase			3.74

Source: The World Bank, World Development Indicators (2020). Container port traffic (TEU: 20 foot equivalent units) [API_IS.SHP.GOOD.TU_DS2_en_excel_v2_1217940]. Retrieved from https://data.worldbank.org/indicator/IS.SHP.GOOD.TU (Accessed 21/07/2020)

Table S13 Ranked counts of unique vessels assigned to the 20 most frequent flag states passing through Oman's EEZ.

Counts derived from from s-AIS MMSI data between January 2015 and May 2016.

Country	MMSI Counts	Rank
Marshall Islands (Republic of the)	895	1
Liberia (Republic of)	867	2
Panama (Republic of)	768	3
Hong Kong (Special Administrative Region of China)	499	4
Singapore (Republic of)	369	5
Unassigned	353	6
Bahamas (Commonwealth of the)	273	7
Malta	238	8
Greece	190	9
India (Republic of)	183	10
United Kingdom of Great Britain and Northern Ireland	144	11
Iran (Islamic Republic of)	133	12
Antigua and Barbuda	129	13
Norway	124	14
Cyprus (Republic of)	103	15
United Arab Emirates	90	16
Cayman Islands	79	17
Saudi Arabia (Kingdom of)	78	18
Denmark	61	19
China (People's Republic of)	60	20

Degrees	Frequency
30	0.01
60	0.05
90	0.12
120	0.07
150	0.04
180	0.04
210	0.12
240	0.43
270	0.08
300	0.02
330	0.02
360	0.01
On-shore frequency	0.28
Cross shore frequency	0.72

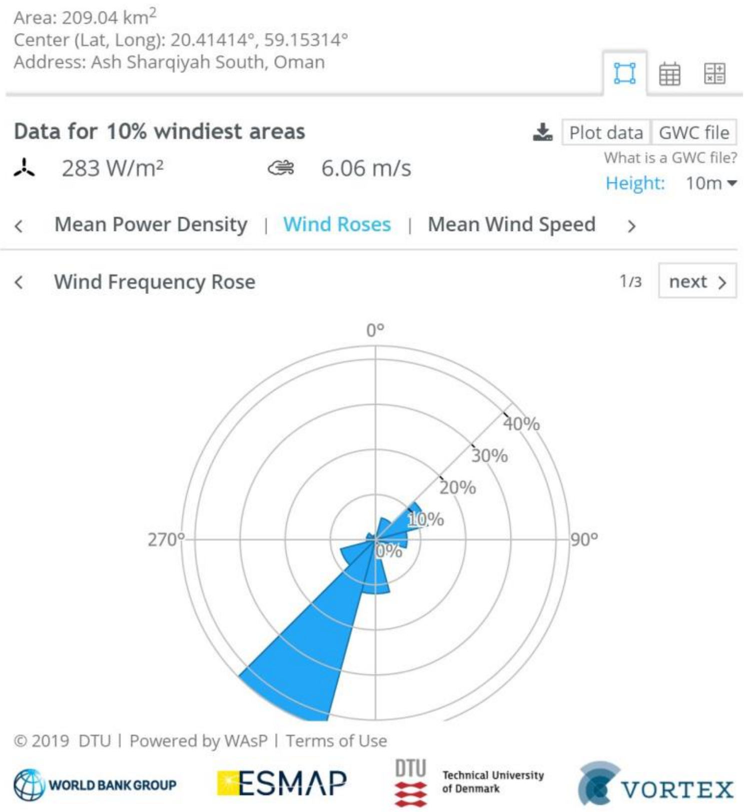

Figure S6 Annual Wind frequency data from offshore of Masirah aligned with shipping route A.
Statistics demonstrate the frequency of time surface winds (10m) are prevailing onshore or offshore. (Source: *Global Wind Atlas 3.0, a free, web-based application developed, owned and operated by the Technical University of Denmark (DTU). The Global Wind Atlas 3.0 is released in partnership with the World Bank Group, utilizing data provided by Vortex, using funding provided by the Energy Sector Management Assistance Program (ESMAP). For additional information: https://globalwindatlas.info*)