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Modeling habitat and bycatch risk for dugongs in Sabah, Malaysia

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ABSTRACT: Bycatch of marine megafauna in fishing gear is a problem with global implications. Bycatch rates can be difficult to quantify, especially in countries where there are limited data on the abundance and distribution of coastal marine mammals, the distribution and intensity of fishing effort, and coincident interactions, and limited bycatch mitigation strategies. The dugong *Dugong dugon* is an IUCN-listed Vulnerable species found from the eastern coast of Africa to the western Pacific. As foragers of seagrass, they are highly susceptible to bycatch in small-scale fisheries. To address the knowledge gaps surrounding marine mammal bycatch, we used existing survey and fishing effort data to spatially characterize the risk of bycatch for this species. Using Sabah, Malaysia, as a case study, we employed presence-only modeling techniques to identify habitat associations of dugongs using a maximum entropy distribution model (MaxEnt) based on published sightings data and several geophysical parameters: coastal distance, depth, insolation, and topographic openness. Model outputs showed distance from the coast as the highest-contributing variable to the probability of dugong presence. Results were combined with previously published fishing effort maps of this area to develop a predictive bycatch risk surface. Our analyses identified several areas of high risk where dugong surveys were conducted, but also identified high-risk areas in previously unsurveyed locations. Such methods can be used to direct field activities and data collection efforts and provide a robust template for how existing sightings and fishing effort data can be used to facilitate conservation action in data-limited regions.

KEY WORDS: Dugong · *Dugong dugon* · Habitat modeling · Spatial analysis · Fisheries · Bycatch · MaxEnt · Malaysia

INTRODUCTION

The unintentional catch of non-target marine mammals in fishing gear, termed bycatch (Reeves et al. 2013), is a global problem. While commercial and industrial fisheries bycatch has been the target of many conservation efforts, small-scale fisheries bycatch is, based on available data, substantial and more difficult to regulate (Moore et al. 2010). According to the Food and Agriculture Organization (FAO), over 90% of the 436 million vessels active in the world can be classified as small-scale fishers (Béné 2005). Small-scale fisheries support up to 22 million fishers, which represents more than 40% of fishers in primary production (Teh & Sumaila 2013). Despite their prevalence, understanding the impacts of small-scale fisheries on megafaunal bycatch is difficult. The distribution and intensity of small-scale fishing effort, gear use, and incidences of species interaction are hard to monitor and even harder to manage. Limited governmental oversight and infrastructure are realities for the majority of small-scale

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fisheries worldwide, which constrains the ability to characterize the number of boats and the amount of fishing gear being deployed. Likewise, the distribution of marine mammals in most coastal areas where small-scale fisheries are prevalent is unknown. Given this absence of information, developing mitigation or avoidance strategies can be challenging (Moore et al. 2010, Murray & Orphanides 2013).

Even with these substantial knowledge gaps, interaction with fisheries is considered the single greatest threat to marine megafaunal populations (see Lewison et al. 2004, Read 2008, Grech et al. 2011, Reeves et al. 2013). Marine mammals, like other marine megafauna, have long life histories that make them particularly vulnerable to the effects of bycatch (Lewison et al. 2004). Coastal marine mammal species, such as the dugong *Dugong dugon*, are some of the most at-risk species.

Although advancements in biologging technologies have aided in the monitoring of species movement and distribution, in many ocean regions these high-resolution data are not available. As a result, conservation scientists have begun to explore indirect methods for collecting crucial fisheries data (Soykan et al. 2014). In many areas, spatial data rely heavily on interviews, sightings, or expert surveys. Yet, these data have been traditionally underutilized, especially with respect to using bycatch rates towards conservation and management strategies. Most recently, Dunn et al. (2010) and Stewart et al. (2010) undertook a comprehensive, multi-year study to quantify the spatial extent of fishing effort and density in several coastal regions of the world's oceans. One of these regions, Southeast Asia, is a region of high species biodiversity coupled with high fishing density (Roberts et al. 2002, Stewart et al. 2010). This region is home to many threatened and endangered marine mammals, one of which is the dugong.

The dugong is a herbivorous marine mammal found in the coastal waters of the tropical and subtropical Indo-West Pacific (Grech et al. 2011). As obligate foragers of coastal seagrass beds, dugongs have historically exhibited a wide distribution. However, remnant populations are patchy over broad spatial scales. This specialized yet patchy distribution makes the dugong especially vulnerable to the effects of increasing habitat fragmentation and interaction with fisheries (Hines et al. 2012a). We have limited knowledge of dugong population numbers and distribution throughout most of Asia (Hines et al. 2012a), particularly in countries such as Malaysia, where the majority of our information comes from incidental sightings and reports by fishers (Hines et al. 2012b). Yet, the life history patterns of this K-selected species and increased interaction with anthropogenic threats have led to its Vulnerable status on the IUCN Red List (Marsh 2008). Once thought to be extinct off peninsular Malaysia, dugongs are still fragmented in distribution and believed to be decreasing in abundance (Rajamani et al. 2006, Jaaman et al. 2009, Rajamani & Marsh 2010).

In some developed countries such as Australia, dugong monitoring and conservation programs have been ongoing for the past 20 yr (see Marsh 1999, 2002, 2005, Grech & Marsh 2007, Grech et al. 2011). The outputs of such research initiatives have been applied to the development of federally enforced Marine Protected Areas (Grech et al. 2011). While localized efforts do exist in other countries such as Malaysia, these are also the places experiencing some of the highest global levels of resource use, population growth, and development (Hines et al. 2012a). In Sabah, Malaysia, the dugong is protected by the Wildlife Conservation Enactment of 1997 and the Fisheries Act of 1985 (Department of Fisheries Malaysia 1985, Sabah Wildlife Department 1997), yet the species remains highly threatened by anthropogenic demands, to the extent that populations are declining (Rajamani 2013). Incidental entanglement in fishing nets and coastal development and habitat destruction are the primary threats to this species; however, destructive fishing practices (i.e. 'blast' fishing), directed take, and vessel strikes from tourism vessels all contribute to dugong mortality (Rajamani 2009, Rajamani & Marsh 2010).

Defining the overlap between key habitats and fisheries threats has been one of the most important topics of marine conservation research (Lefebvre et al. 2000). While dugongs frequently occur in shallow coastal waters, they have also been observed in deeper waters further offshore, where the continental shelf is wide and remains relatively shallow and protected (Rajamani 2009). Although they are seagrass specialists, dugongs have been shown to prefer some seagrass beds and avoid others, presumably making foraging decisions at a range of spatial scales (Anderson & Cribble 1998, Preen 1995b, Sheppard et al. 2006, 2009, 2010). For this reason, understanding the spatial dynamics of foraging habitat is essential for predicting patterns of use by selectively feeding dugongs and for the effective management of seagrass resources (Sheppard et al. 2007).

The incorporation of spatial risk into studies of species distribution has aided in the qualitative and quantitative assessment of the impact and distribution of multiple anthropogenic activities (Grech et al.

2011, Hobday et al. 2011, D'Souza et al. 2013). Current methodologies in species habitat modeling, which have been useful to understand species–environment relationships and habitat preference, have been combined with fisheries effort and interaction rates to produce spatial risk assessments for species such as seabirds (Cuthbert et al. 2005, Žydelis et al. 2011), sea turtles (Murray & Orphanides 2013), and marine mammals (Goldsworthy & Page 2007, Grech et al. 2008). A recently published study by D'Souza et al. (2013) showed long-term trends of heightened risk of dugong extinction by anthropogenic factors in areas historically known as optimal foraging habitat.

At present, there are no robust, quantitative estimates of dugong population size or distribution for the Malaysian Peninsular region (Rajamani 2009, 2013). While it may be unreasonable to protect a species by restricting human-induced threats along an entire coastline, it may be feasible to target specific areas where the species is abundant and/or the risk of interaction is greatest (Grech & Marsh 2008). The goal of this paper is to examine to what extent an observed species distribution derived from low spatial and temporal resolution data can be used to inform our understanding of the overlap between dugongs and fishing boats. Specifically, we aim to generate a spatially explicit risk surface that captures the relationships between marine mammal distribution and fishing effort. Our approach addresses a crucial knowledge gap for our study area and demonstrates the utility of this approach for other similarly data-limited regions.

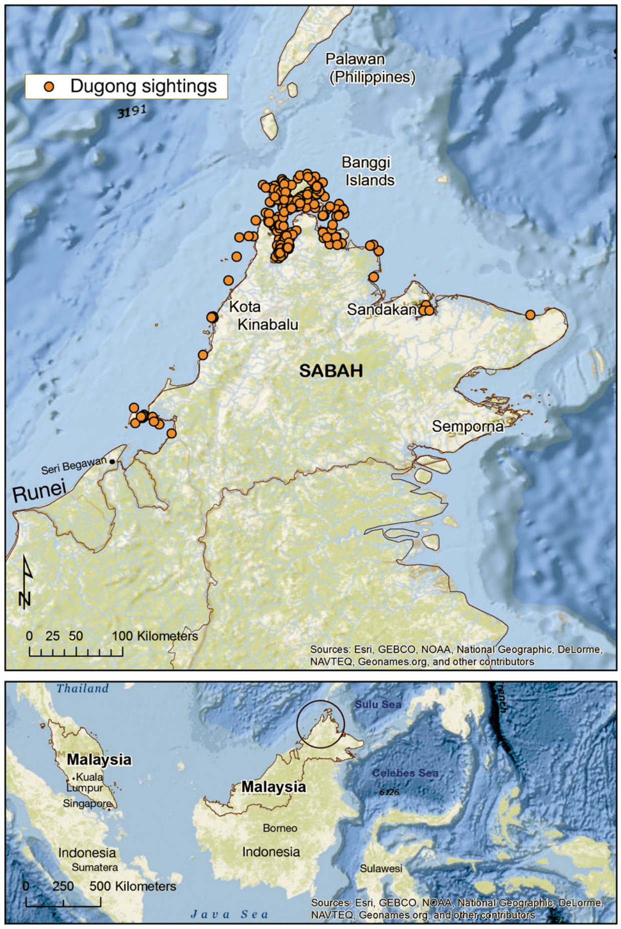

Fig. 1. Sabah, Malaysia, study area (circled in bottom panel) with dugong sightings by interview surveys (top panel). Data from Rajamani & Marsh (2010) and the Marine Research Foundation (unpubl. data)

MATERIALS & METHODS

Study area

Sabah is the easternmost state of Malaysia, located on the northern tip of the island of Borneo (Fig. 1). Bordered by the South China and Sulu Seas, Sabah covers an area of 74 500 km^2. Sabah's coastline stretches over 1400 km (Sabah ICZM Spatial Plan 1999, Rajamani & Marsh 2010).

Dugong sightings

Dugong sightings were collected as part of 2 independent dugong assessment projects. Fig. 1 shows the location of all 318 dugong sightings used in this study, relative to the Sabah coastline. Sightings data were based on fisher interviews and community monitoring programs conducted by L. Rajamani (see Rajamani & Marsh 2010, Rajamani 2013) and the Marine Research Foundation (MRF) (MRF unpubl. data, www.mrf-asia.org). Data from L. Rajamani included individual and group interviews conducted with 40 fishers from 12 villages in northern Sabah. Interviews included recent and historical dugong sightings (Rajamani 2013). Interview data from the MRF were collected throughout 2012. Both interview and monitoring surveys relied on qualitative assessments of dugong sightings, strandings, and hunting incidences (Rajamani & Marsh 2010, Pilcher & Kwan 2012).

Environmental data

A number of environmental variables were considered for inclusion in the habitat suitability analysis. Given the scarcity of environmental data in this region, some variables that have been known to correlate with dugong habitat selectivity, including seagrass distribution, nutrient concentration, salinity, turbidity and water currents (see Coles et al. 2007, Sheppard et al. 2007, Grech & Coles 2010), were unavailable.

High-resolution seagrass distributions have been mapped in Australia (e.g. the Great Barrier Reef) (Grech & Coles 2010) and the Mediterranean Sea (Pasqualini et al. 2005); however, current seagrass data sets are incongruent and spatially restrictive for Malaysia. Depth, coastal proximity, and solar accessibility and intensity are all factors in seagrass growth and productivity (see Coles et al. 2007, Ralph et al. 2007, Grech & Coles 2010). This includes the 2 dominant species of seagrass favored by dugongs: *Halodule uninervis* and *Halophila ovalis* (De Iongh et al. 2007, Yaakub et al. 2014). Because direct measurements of seagrass distribution were not available for the study area, we used several proxy parameters known to be favorable for seagrass growth, and thus dugong foraging. These include: depth (m), distance from coast (m), seafloor slope (°), solar radiation (W m^{-2}), and topographic 'openness' (degrees). Positive openness is a measure of the 'openness of the terrain to the sky', and is calculated as an average of zenith angles in all 8 compass directions at a specified distance (Yokoyama et al. 2002).

We obtained 30 arc-second global bathymetry data from the General Bathymetric Chart of the Oceans (GEBCO, www.bodc.ac.uk/projects/international/gebco/gebco_digital_atlas). In order to maximize variation related to slope aspect, total solar radiation was calculated for the late afternoon during the winter solstice (Fu & Rich 2002). Distance from coast was calculated in ArcGIS (v.10.1, ESRI 2013) as the Euclidean distance from an individual raster cell center to the coast.

Fisheries effort

We used data compiled from an extensive fishing effort database by Stewart et al. (2010) that sought to quantify fishing effort in several high-use/data-poor coastal areas, which included Southeast Asia. The Stewart et al. (2010) data set has spatial extent and fishing effort for each gear type, including number of boats, length of boats, and spatial boundary of the fishery. Using this information, Stewart et al. (2010) created a spatial analysis envelope (FEET) to map fishing effort density, measured as boat-meters per square kilometer, for 3 broad fishing gear categories: gillnets, longlines, and trawls. These 3 gear categories are general and encompass different subtypes within each category (e.g. trawls includes bottom trawls and mid-water trawls).

Habitat suitability

Presence-only modeling techniques have been used in a variety of marine mammal distribution and conservation studies (Kaschner et al. 2006, Best et al. 2007, Becker et al. 2012, Bestley et al. 2013). Many of these modeling methodologies require a set of known occurrences, or sightings, coupled with predictor variables that are relevant to habitat suitability (static and dynamic). Given the limitations of data with presence-only models (e.g. sample size, location bias, and availability of environmental factors), results may yield very different predictions (Pearson et al. 2006, Randin et al. 2006, Kumar & Stohlgren 2009). For this reason, it is important to review and consider all possible outcomes of the predictive distribution models when choosing the most accurate model for a given data set. Guisan & Zimmermann (2000) and Elith et al. (2006) provide comprehensive reviews of distribution modeling techniques to predict suitable habitat for a species (Phillips & Dudík 2008, Kumar & Stohlgren 2009).

In the present study, we used MaxEnt (v.3.3.3) to identify suitable habitat for the 318 dugong sightings off the northern coast of Sabah, Malaysia. The MaxEnt model estimates the probability distribution for a species' occurrence based on environmental constraints (Phillips et al. 2006, Kumar & Stohlgren 2009). The environmental conditions at a given species location are sampled and are used to develop suitable habitat for the entire study region. MaxEnt has been shown to perform well against a variety of modeling methods when based on predictive accuracy, especially when sample sizes remain small (Elith et al. 2006, Pearson et al. 2007), and has been a commonly used method in the conservation biology field to understanding species distribution models (Franklin 2009, Merow et al. 2013). For data preparation purposes into MaxEnt, the environmental layers were first mapped in ArcGIS (v10.1, ESRI 2013). All environmental grids were resampled and clipped to the same geographic extent and cell size of 1.2 km^2, the largest spatial resolution between the data sets. Slope data were log-transformed. All other parameters were normally distributed.

Model validation is a necessary component used to assess the predictive performance of the model

(Kumar & Stohlgren 2009). In our study, 75% of the sightings (presences) were used as training data. The remaining 25% were used as test data. Like Friedlaender et al. (2011), we used the replication function to randomly sample occurrences from each training run, and used the remaining occurrences to test the model. For our models, we chose to run 10 replications, or 'iterations', similar to Phillips et al. (2006) and Friedlaender et al. (2011). This type of cross-validation technique addresses the effects of spatial autocorrelation. Each model iteration was run with all background points available in the study area. The mean of the 10 replicates was then computed for the model output.

MaxEnt also outputs a cumulative threshold table, which shows how any environmental variable(s) that are statistically significant contribute to the fit of the model, and by how much (percent contribution). It is important to note that percent contribution values are heuristically defined, in that they depend on the particular algorithm used in MaxEnt, and that given highly correlated environmental variables, these contribution percentages are subject to caution (Phillips et al. 2006). The resulting output of the MaxEnt model generated a correlation estimate of probability of presence of the species that varies from 0 to 1, with 0 being the lowest and 1 the highest probability.

Mapping fishing activity

The spatial distribution of fishing activities in the study area was defined as a function of 2 terms: fishing effort and the relative impact from each gear type on dugongs. Fishing effort was described by the spatial extent, the gear type, and the measured intensity of fishing effort. These data were originally published in Dunn et al. (2010) and Stewart et al. (2010), who used empirical data to generate spatial estimations of fishing activity in 6 large marine regions. These fishing effort metrics were compiled and processed into regional- and country-specific GIS map layers (see Dunn et al. 2010, Stewart et al. 2010). For our analyses, we extracted spatial data on effort (boat-meters km^{-2}) and gear type. Each of these spatial data sets was clipped to the same cell size and resolution as the habitat suitability layer.

The relative impact of each gear type describes the degree to which dugongs were likely to be affected by a gear type, i.e. their vulnerability to a particular gear (Table 1). We generated relative impact ranks for 5 gear types that were reported to occur within the projected range of dugongs – gillnet, hook and line, purse seine, trawl and mixed. The mixed gear category represents the fishers that use more than one type of gear (alternately or simultaneously), depending on the season, conditions, and location (Jaaman et al. 2009, Moore et al. 2010). The ranks were based on documented bycatch from the region from both published and grey literature. This included a marine mammal bycatch database developed by Project GLoBAL (http://bycatch.env.duke.edu), which synthesized all reported bycatch (not including strandings) information from 1990 to present, as well as published literature (Read et al. 2006, Marsh 2008, Jaaman et al. 2009, Moore et al. 2010, Reeves et al. 2013). Based on this information, our relative impact ranks (from high to low) were gillnet, mixed, trawl, hook and line, and purse seine. In the supporting documents, gillnets were found to have the highest rates of bycatch in this and other regions. Gillnets are also associated with high rates of mortality for entangled animals (Lewison et al. 2004). We assumed that mixed gear included gillnets, an assumption supported by empirical data (Jaaman et al. 2009, Moore et al. 2010).

Table 1. Relative impact of fishing effort by gear type (4 is the highest impact)

Gear type	Relative impact ranking	Relative impact justification
Purse seine	1	Reported in Jaaman et al. (2009) to only catch cetaceans
Hook and line	1	No bycatch reported for this region
Trawl	2	Dugong bycatch was reported in trawl vessels in shallow water in this region (Jaaman et al. 2009)
Mixed	3	This gear type often includes gillnets plus additional gears
Gillnet	4	Documented dugong bycatch was reported to yield the highest relative number of bycatch events (Marsh 2008, Jaaman et al. 2009, Moore et al. 2010)

Spatial risk assessment

Spatial risk was determined based on spatial layers of dugong habitat suitability and fishing activity by each gear type. Fishing effort metrics originally compiled and processed by Dunn et al. (2010) and Stewart et al. (2010) were imported into ArcGIS as regional- and country-specific map layers. Spatially explicit data on effort (boat-meters km^{-2}) and the 5 gear types described in the previous sub-section were extracted for Sabah, Malaysia. An impact by gear type layer was created by assigning the numeric value associated with relative gear impact (Table 1). Effort and impact layers were masked and clipped to the same cell size and resolution as the habitat suitability layer. Polygon shapefiles for measured fishing effort, relative impact by gear type, and suitable habitat were converted into 1.2 km grid cell rasters. Fishing activity was calculated for each cell based on the product of measured effort by gear type. Spatial risks were calculated for each cell based on the product of fishing activity by likelihood of dugong habitat.

RESULTS

Habitat suitability

Fig. 2 shows the modeled probability of suitable habitat conditions, based on dugong presence data. The MaxEnt model predicted the most suitable dugong habitat to be in shallow coastal waters. Distance from shore was considered the largest overall contributor to the model (81.8%), followed by depth (10.7%). The model indicated a high probability of dugong presence closest to shore along the entire study region. The likelihood of dugong presence decreased as distance from shore increased. Other variables contributed far less to the model: slope (6.3%), topographic openness (1.1%), and solar radiation (0.1%). The averaged area under the curve (AUC) value derived from the 10 replicated MaxEnt models was 0.88 (±0.04), indicating that the model performed well (Table 2, Figs. S1 & S2 in the Supplement at www.int-res.com/articles/suppl/n024p237_supp.pdf).

Fishing activity

Fishing effort by gear type for gillnets, mixed gear, and trawls is shown in Fig. 3. Hook and line and purse seine efforts were ranked as having the lowest relative impact by gear type, and were therefore not included in Fig. 3. Off the coast of Sabah, the most heavily used gear type is a composite of mixed gear, which covers the largest spatial extent of coastal fishing effort. Gillnets and trawling efforts overlap along

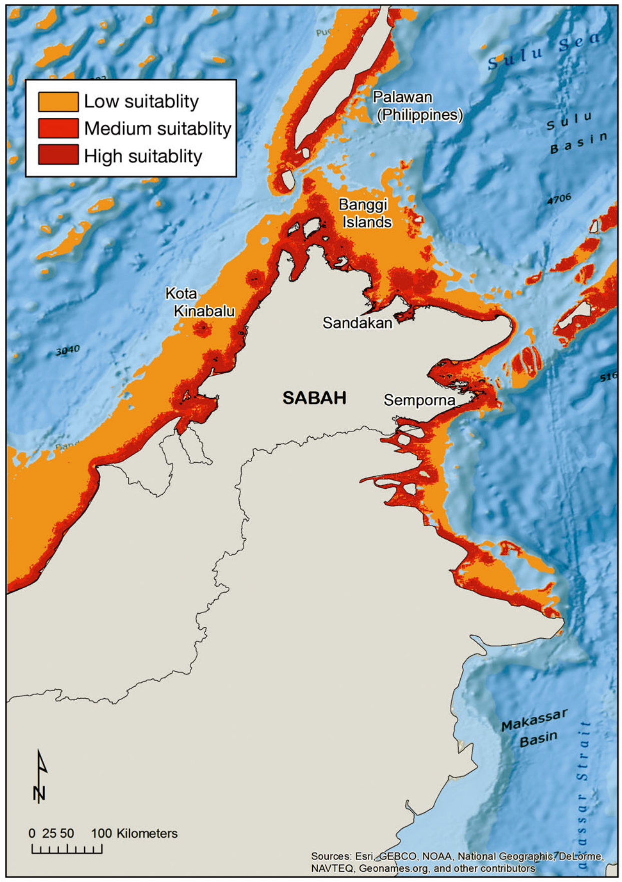

Fig. 2. MaxEnt prediction of suitable habitat for dugongs along the Sabah, Malaysia, coast

the west and northern peninsula; however, fishing effort is higher for gillnets.

The map of fishing activity (Fig. 4) shows the weighted product of measured fishing effort by the impact of a given gear type. The areas of greatest fishing activity occurred along the southeastern coast of Sabah, Malaysia, and the area to the north of the peninsula, around Palawan Island (Philippines). In these areas, fishing activity is predominantly mixed gear (north of Sabah) and mixed gear and purse

Table 2. Percent contribution of each variable to the MaxEnt model. This model had a mean ± SE area under curve (AUC) of 0.88 ± 0.04; the AUC generally provides a measure of overall accuracy ranging from 0 to 0.1

Variable	Percent contribution
Distance	81.8
Depth	10.7
Slope	6.3
Openness	1.1
Solar radiation	0.1

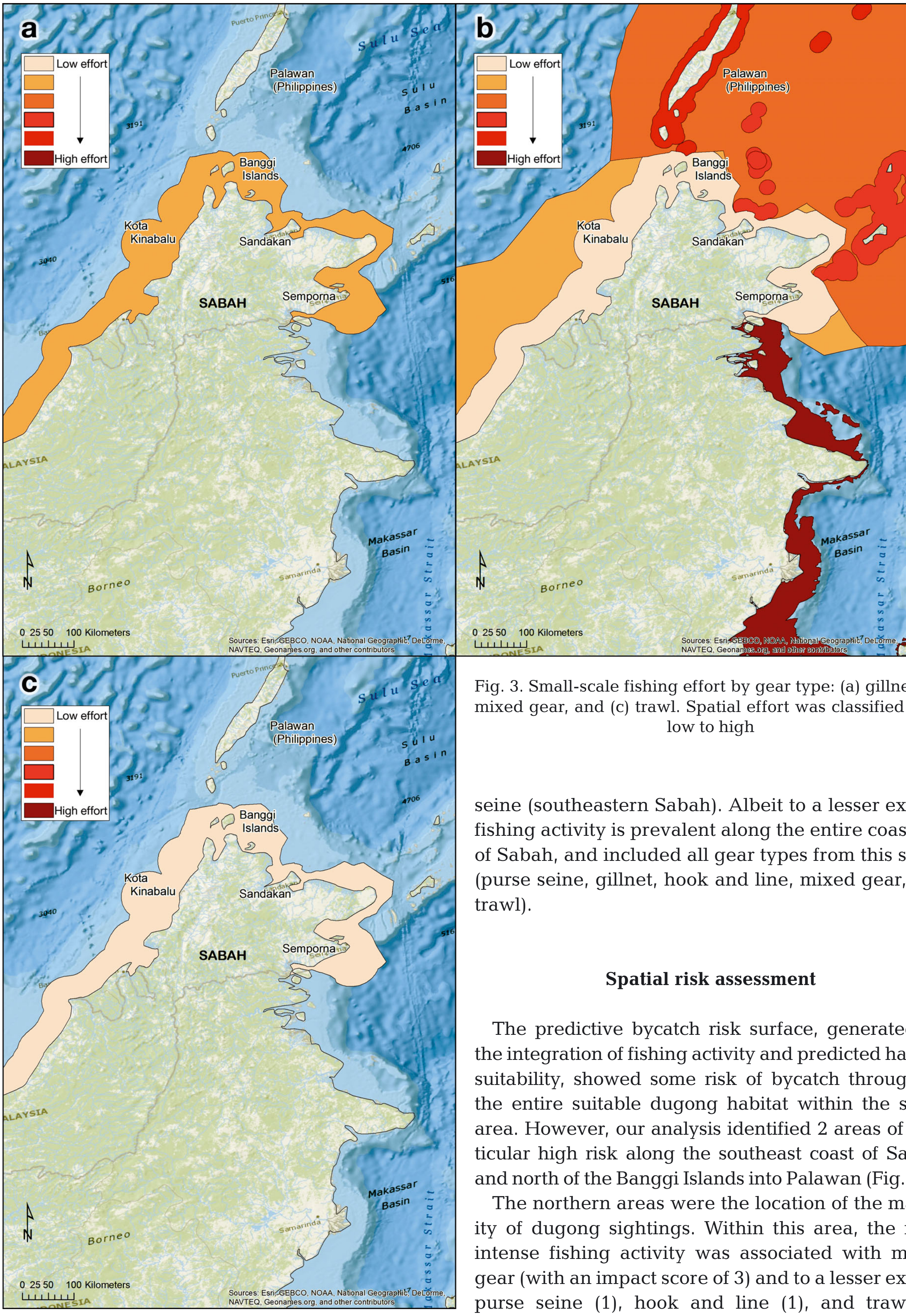

Fig. 3. Small-scale fishing effort by gear type: (a) gillnet, (b) mixed gear, and (c) trawl. Spatial effort was classified from low to high

seine (southeastern Sabah). Albeit to a lesser extent, fishing activity is prevalent along the entire coastline of Sabah, and included all gear types from this study (purse seine, gillnet, hook and line, mixed gear, and trawl).

Spatial risk assessment

The predictive bycatch risk surface, generated by the integration of fishing activity and predicted habitat suitability, showed some risk of bycatch throughout the entire suitable dugong habitat within the study area. However, our analysis identified 2 areas of particular high risk along the southeast coast of Sabah, and north of the Banggi Islands into Palawan (Fig. 5).

The northern areas were the location of the majority of dugong sightings. Within this area, the most intense fishing activity was associated with mixed gear (with an impact score of 3) and to a lesser extent, purse seine (1), hook and line (1), and trawl (2)

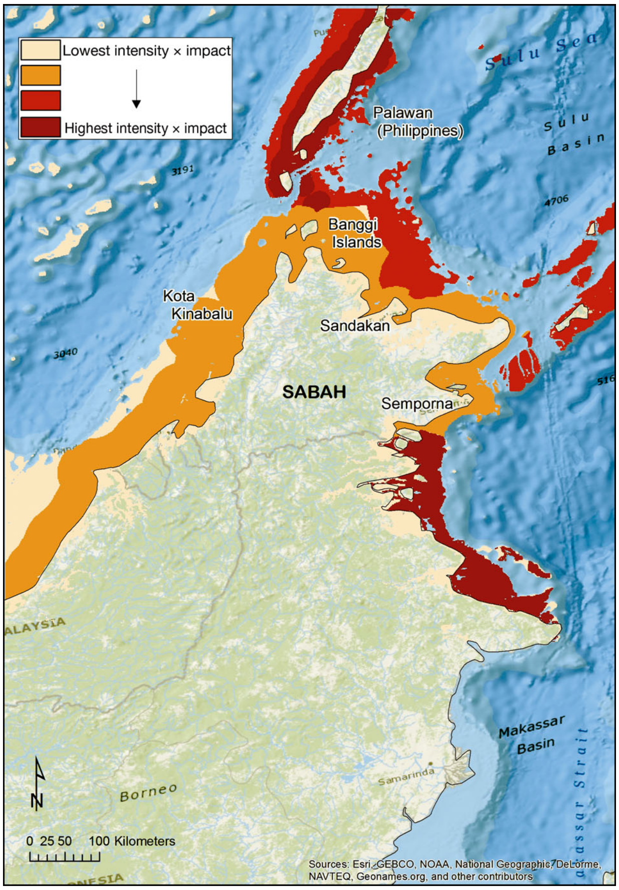

Fig. 4. Fishing activity, a measured product of small-scale fishing effort (boat-meters km^{-2}) by gear-type impact. Fishing activity impacts were classified from low to high intensity

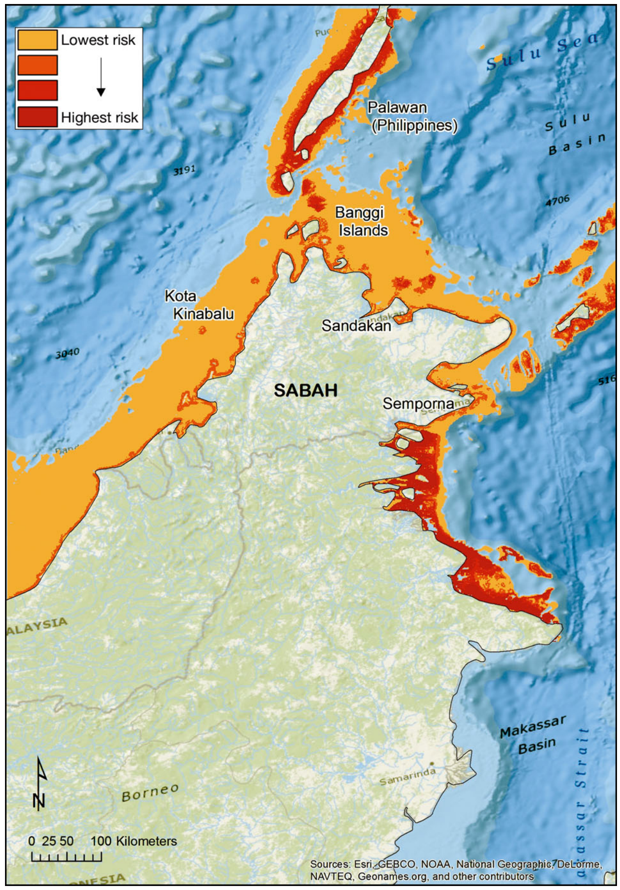

Fig. 5. Risk of bycatch based on fishing activity and likelihood of dugong encounters along Sabah, Malaysia. Spatial risk was classified from low to high

(Table 1). There was small spatial overlap with gillnets, which carry the highest impact score. However, it should be noted that gillnet use is also incorporated within the mixed gear category, increasing the spatial risk associated with this gear type.

Along the southeast coast of Sabah, high risk was associated with only 2 gear types, mixed gear and purse seine, with impact scores of 3 and 1, respectively. There were no dugong sightings associated with this area, but it is within the predicted boundaries of suitable habitat.

DISCUSSION

Given the challenges associated with mitigating marine mammal bycatch in many data-limited regions, there is a clear need to develop approaches that use best-available data to inform conservation and management. By combining a habitat distribution model based on sightings with fishing effort data, we present one approach that demonstrates how spatial risk assessments can be conducted even in the absence of high-resolution spatial information.

Using all available sightings for the study area, our predictive model identified all shallow, proximal to shore waters as potential habitat for dugongs along peninsular Malaysia. This finding is corroborated by previous research, which has demonstrated that dugongs selectively feed within coastal seagrass habitat (Preen 1995a,b, Marsh et al. 2002, 2003, Sheppard et al. 2007, Rajamani 2009). In a localized study in northern Sabah, Rajamani (2009) noted high concentrations of seagrass communities in waters within the intertidal zone and dugong feeding trails less than 1 km from shore.

While spatially and temporally dynamic, many tropical seagrass communities thrive in shallow reef flats, where sunlight is obtainable in the water column and turbidity is low (Short et al. 2007).

Although dugongs may be widely distributed in this area, our results indicate a few areas where the risk of dugong–fisheries interactions is particularly high: north of Sabah and nearby islands, and southeastern Sabah. These areas are characterized by high levels of fishing activity using gillnets and fishers with mixed gear, which typically include gillnets. Worldwide, gillnets have been recognized as the primary cause of cetacean and dugong bycatch (Perrin et al. 1994, 2005, Marsh et al. 2002, Jaaman et al. 2009). Cheap, easy to operate, and highly effective, gillnets are widely used by fishers to catch high-value fish species (Perrin et al. 1994, Jaaman et al. 2009). The fact that our analysis identified a potential high-risk area along the southeast coast suggests that there may be other unmonitored coastal areas where dugong and coastal fishers frequently co-occur, which demonstrates the utility of spatially explicit risk maps. This is especially useful in highlighting key areas of focus, as conservation funds and monitoring efforts may be limited.

Current challenges to spatial risk assessment

While our outcomes represent a novel approach to a global problem where data are lacking, we acknowledge the current challenges associated with risk assessment. Given that this was a static study, our risk surface may not fully capture the dynamic relationships between the dugong and its environment. Seagrass communities are known to shift in space and time, depending on several abiotic parameters, which may affect the abundance and distribution of community grazers. At present, knowledge of seagrass distribution remains limited, often scaled to and identified within local communities. A more complete map of seagrass distribution and productivity would greatly enhance predictive capacity.

The use of interview-based sighting data can also lead to bias. Observations can only occur in areas where fishers visit, which may be non-uniform. Interview-based data also require disclosure of a sighting event, which fishers may be reluctant to do given local prohibitions on capture or consumption of dugongs (Jaaman et al. 2009).

To date, the majority of dugong studies have been in coastal waters where shallow depths allow for greater sighting opportunities from boats and aerial surveys, and generally when environmental conditions are favorable (Chilvers et al. 2004, Pollock et al. 2006). However, dugongs are known to track seagrass meadows as deep as 30 m as they undergo large-scale migrations between habitats (Chilvers et al. 2004), and such behavior increases vulnerability to bottom-set nets and should be included in management strategies. Given that our study relies heavily on nearshore observations, we recognize such spatial bias inherent in our data set. Hagihara et al. (2014) recently introduced promising methodologies to reduce availability bias and improve population estimates for dugongs.

Despite these potential drawbacks, protection of species through fishery independent and dependent data can be used to assess the spatial risk associated with bycatch encounter (Murray 2011). Along the Malaysian peninsula, even a coarse scale of fisheries-related risk can be informative for bycatch mitigation and management strategies for dugongs, as well as other charismatic megafauna that utilize these coastal waters (e.g. dolphins, sea turtles, whales, and whale sharks).

In developing countries, interview-based survey techniques are often the most cost-effective and practical (Aragones et al. 1997). While data gaps and other limitations present analytical challenges, the availability of low-resolution data presents an excellent opportunity to create a scientifically defensible approach to assess spatial bycatch risk for coastal species of conservation concern even in the absence of detailed information on species distribution, abundance, and encounter rates. Through this analysis, we demonstrate how to utilize low-resolution data to develop a predictive bycatch risk surface that can inform conservation management strategies. Our analyses fill an important knowledge gap for our case study area and also provide a template technique for ways in which similar low-resolution data can be used to facilitate conservation action where other species–coastal fisheries interactions occur.

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