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Research article

Predicting coastal fishing community characteristics in Tanzania using local monitoring data

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ABSTRACT

Small-scale marine fisheries in Tanzania provide the main source of subsistence for coastal communities, yet due to poor management, they have been overexploited for decades. These coastal fisheries have historically been described as homogeneous in gear-use and fish community makeup. Yet, regional and local variability in the characteristics of these fishing communities was recently identified with community-based fisheries-dependent data. We proposed a flexible modeling approach that incorporated local monitoring data with spatial data to predict the spatial characteristics of the marine fisheries in Tanzania. The spatial models identified relationships between fishery landings and coral reef, seagrass, and mangrove habitat patch attributes, along with fisher density and a hydrologic index. Furthermore, the predicted spatial characteristics matched previously reported fishery characteristics in both districts. The maps developed by our modeling process provide a means for stakeholders and managers to understand the spatial distribution of their fisheries and in turn, focus on explicitly managing what, how, and where fishers operate. Overall, the flexible modeling approach developed here may act as a first step in incorporating local monitoring data into co-management frameworks, which may promote more sustainable fisheries management strategies in data-poor regions.

1. Introduction

Fisheries co-management has become increasingly common in recent decades. It was developed in response to a lack of financial resources for—and the perceived failure of—conventional fisheries management (i.e. the population dynamics approach; Berkes, 2003) in promoting sustainable fisheries in developing countries (Allison and Ellis, 2001; Cinner et al., 2009; Evans et al., 2011; Johannes, 1998). Fisheries co-management is defined by the collaboration of stakeholders with government and research institutions at various levels to regulate fishery resources (Armitage et al., 2007). One of the main strengths of co-management is its focus on integrating data and knowledge from institutions and stakeholders at varying levels of the management structure (Berkes, 2009; Raymond et al., 2010). While this aspect of co-management is often viewed as a pre-requisite for the production of sustainable fishing practices (Zermoglio et al., 2005), many systems struggle to integrate information from stakeholders, which can ultimately disrupt the efficacy of management (Nunan et al., 2015; Robertson et al., 2018).

Creating an effective system of fisheries management for small-scale fisheries in particular has been described as a wicked problem (i.e. difficult to define & have no full solution; Jentoft and Chuenpagdee, 2009). Small-scale fisheries are composed of subsistence based fishers who generally use traditional or simple gears, on foot or in small boats (Chuenpagdee et al., 2006) and as a result, these fisheries have complex boundaries between governing bodies (Jentoft and Chuenpagdee, 2015). The complexity involved in defining an appropriate management scale for small-scale fisheries has led to many of these fisheries lacking the financial (Jacquet and Pauly, 2008) and technical ability to monitor their available stocks (Gillett and Lightfoot, 2001; Mills et al., 2011). However, the ability to quantitatively monitor a resource is required for policy-makers to assess whether conservation and management goals are being met (Campos-Silva et al., 2017; Danielsen et al., 2005). Various co-management programs have begun to use local volunteers to monitor their fishery resources (Castello, 2004; Cohen and Steenbergen, 2015; Dobbs et al., 2016; Saunders and Xuereb, 2016) and when used effectively, local monitoring can be a reliable, cost-effective solution for monitoring fishing activity (e.g. Tanzania and Kenya [Obura et al., 2002], Brazil [Campos-Silva and Peres, 2016; Castello et al., 2009], Philippines [Uychiaoco et al., 2005]). Furthermore, local monitoring can involve different levels of relative involvement of local stakeholders and researchers, depending on the intended goals and

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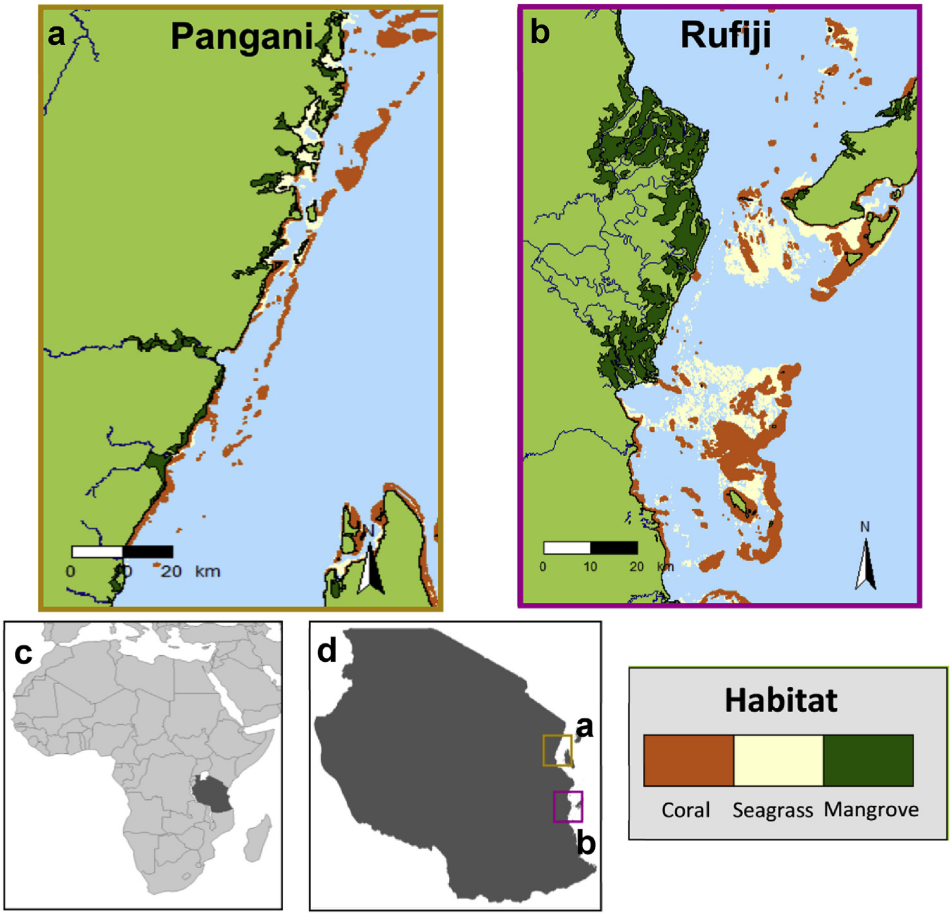

Fig. 1. Pangani district (a) and Rufiji district (b) maps. The location of Tanzania in Africa (c). The relative location of each district along the Tanzanian coast is represented by colored boxes within the map of the Tanzanian coast (d). Dark blue lines in the district maps represent relative river position (not scaled to represent river width; data not available). A description for the sources of the spatial data represented here can be found in Section 2.3. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

available economic resources (Danielsen et al., 2008; Obura et al., 2002). The collation of data from local sources by research and government institutions in co-management systems can allow for an analysis of fishery harvest trends at multiple spatial scales (Robertson et al., 2018).

Information and monitoring data on fisher behavior—i.e. the decisions that fishers make about when, how, and where they will fish—may be used to inform co-management in small-scale fisheries (Naranjo-Madrigal et al., 2015; Thiault et al., 2017). Previous research has established that fisher behavior is particularly important in defining the dynamics and distribution of fishing effort (Fulton et al., 2011; Hilborn and Walters, 1992; Salas and Gaertner, 2004). Furthermore, these behaviors are known to be influenced by the geomorphic and socioeconomic settings of the region (Abernethy et al., 2007; Berkes, 2003; Salas and Gaertner, 2004; Salas et al., 2004; Smith and Hanna, 1993). For example, the characteristics of the Itaipu Reservoir fishery in Brazil (i.e. gear and vessel-use patterns) were described by using a longitudinal gradient between the lentic and lotic conditions of the reservoir, which explained the distribution of the three main target species (Okada et al., 2005). Alternatively, the spatial fishing effort allocation of a cockle fishery in Ila Costa Rica, Ecuador was defined, in part, by a combination of individual preference, territoriality, and mutual respect between fishers (Beitl, 2014). Hence, it has been hypothesized that identifying the ecological and socioeconomic drivers of fisher behavior may provide further insight on how, when, and where fishers will allocate their effort.

Using marine fisheries in Tanzania as a model system, the present study aimed to examine the connection between fishery data from local monitoring and spatial habitat characteristics, hydrology, and fishing pressure data. The marine fisheries in Tanzania are a source of protein and income for over nine million people along the coast (Hamidu, 2012), yet these fisheries have shown signs of overexploitation for decades (Berachi, 2003; Jacquet and Zeller, 2007; Mapunda, 1983). Since 2003, these fisheries have been ostensibly managed by a co-management program that incorporates local fishing community groups (Beach Management Units—BMUs; Sobo, 2012). A primary purpose of these BMUs has been to use local fishers to collect data on fishing trips (e.g. port, date, number of fishers, gear, vessel) and their associated landings (e.g. taxa, biomass, number of fish, value of catch) throughout the coast (Sobo, 2016). The management framework for Tanzanian fisheries was designed to promote information sharing upwards (i.e. BMUs to districts, regions, and the national government) and downwards (i.e. from the national government to regional, district, and BMUs), but these interactions have not operated effectively (Onyango, 2015). The creation of a conceptual framework where fishery characteristics along the coast can be related to spatial attributes and mapped will promote a greater understanding of the relevant scales for local fishery management.

Here, we propose a flexible modeling approach that uses trends in local BMU monitoring data to predict the spatial characteristics of small-scale fisheries. Using the context of the small-scale behaviors for the coastal fishery in Tanzania described in Robertson et al. (2018), we generated regional models to predict the location of areas with coral reef-associated and estuary-associated fishery characteristics. The parameterizations of these models were then applied to the entire Tanzanian coast and compared against national catch data to identify the efficacy of extrapolating small-scale drivers of fishery characteristics to larger spatial scales. The discussion then provides an overview of the performance, management applicability, and limitations to our modeling framework. Overall, the study objective was to examine whether locally recorded landings data of taxa that were associated with coral reef or estuarine fishing characteristics would be related to seascape habitats, fisher density, and/or hydrology.

2. Methods

2.1. Study site description

This study focused on nine villages—five in the Pangani district and four in the Rufiji district of coastal Tanzania (Note: villages are the smallest spatial unit, they are nested within districts, which are nested within regions in Tanzania [Fig. 1]). Pangani is a northern district that covers approximately 1800 km^2 and is characterized by an arid climate, many coral reef fringed islands (Samoilys and Kanyange, 2008), and is home to around 55,000 people (TZNBS, 2013). Rufiji is a southern district characterized by its large river delta (the largest in East Africa; Caras, 2001). The Rufiji River Basin extends approximately 177,000 km^2 and contains the largest mangrove wetland (~53,000 ha) area in Eastern Africa (Turpie, 2000). Due to high river discharge (mean ~ 800 m^3s^{-1} [Duvail and Hamerlynck, 2007]), nutrients, and silt, the majority of the shelf surrounding the Rufiji delta lacks coral reefs (Richmond et al., 2002). However, there are some reefs located on the southern delta sub-region surrounding Simaya Island and near Pombwe village (Richmond et al., 2002). Many of the people in both districts mostly rely on marine fishery resources for their food and livelihoods.

Using BMU fishery records, Robertson et al. (2018) identified that marine fisher behaviors and characteristics varied at the local and regional scale along the Tanzanian coast, likely because of the socio-economic and ecological context in which fishing was occurring. Fishers tended to target certain taxa with distinct vessels and gears (i.e. specialization) in the Pangani district (Northern Tanzania), which has a dense human population and nearshore coral reefs. In contrast to the Pangani district, fishers used a wide variety of vessels and gears to catch many taxa (i.e. generalization) in the Rufiji district (Southern Tanzania), which has a less dense human population inhabiting the largest deltaic system in East Africa.

2.2. Landings data

Species capture data for the villages in the Rufiji and Pangani districts came from historical BMU catch-assessment survey records that were collected in 2016 and 2017. The records in Rufiji district encompassed the period between 2014 and 2016 while the records in Pangani district included data from 2016 to 2017. BMU catch-assessment surveys are conducted by BMU enumerators who record information based on an interview of a fisher who took part in a fishing trip. The type of vessels used within the fisheries are small, and therefore, the number of fishers per boat (trip) is typically low (1–5 fishers). As a result, the unit of inference is based on individual fishing trips (n = 1160), irrespective of the number of fishers involved. All catch-assessment surveys had approximately the same templates (see Robertson et al., 2018 for an example). Data entry included: village, port, BMU enumerator name, date, fisher village of origin, gear (type and number), vessel used, vessel registration, location of catch, departure time, return time, trip recentness, taxa (type, weight, number, and value). However, for the purposes of this model we only examined the taxa composition by trip.

BMU surveys are fishery-dependent data, collected without the intent to characterize species diversity. Thus, we used the term “taxon” to define each grouping (e.g. Octopus, Prawn, Mullet, etc.). Local fishers are able to identify the most commonly landed species (Berkes et al., 2001); however, a consistent identification of less common species can be difficult (May, 2005). Certain Swahili words used to identify species could not be matched to any taxonomy, and in other cases, species were binned into different taxa groupings as there was no apparent distinction among their definitions. Additionally, the composition of species differed between regions, yet the majority of taxa identifications were regarded as accurate based on the analysis of the original data sets.

Coral reef and estuary-associated fishing characteristics are typified by the capture of taxa that are known to inhabit those two habitats (Robertson et al., 2018). Data was compiled in the BMU data to describe the proportion of taxa associated with coral reef, estuary, or a combination of coral and estuary habitats that were captured on each trip for each village. The proportion value is the proportion of taxa captured in a trip, not the proportion of weight or number of fish captured per taxon. Taxa were associated with coral reef, estuary, or coral and estuary habitats by using an FAO field guide to commercial marine and brackish-water species of Tanzania (Blanchi, 1985). The FAO field guide listed the habitat(s) in which each species could be found. Because BMU data record the capture of taxa (where a taxon is often a combination of species) rather than species, we aggregated habitat data from the FAO field guide for each taxon. A taxon with species exclusively found in estuaries or coral reefs were described to be associated with each specific habitat. Any taxa that had species assigned to use both habitats were defined as mixed-habitat. While there are species and habitat use patterns that are likely not described in the FAO field guide, this is the only comprehensive reference available for Tanzanian fishes' habitat use patterns. Furthermore, the observed pattern described using this method was able to bin the regional fisheries (Fig. 2) into groups that matched past research (Robertson et al., 2018) and can therefore be regarded as accurate for the purposes of this study.

We opted to use the proportion of taxa rather than a more traditional measure (e.g. abundance). Although the relative abundance of each species almost certainly plays a role in fisher behavior in these systems, the allocation of effort for BMU surveys and fishing trips was uneven, as was the abundance between species due to life-history traits (e.g. prawns and sharks), therefore any abundance calculations would have been prone to high levels of uncertainty. The current metric acts more as a presence/absence indicator for whether fishers are landing particular species, and we felt that this was appropriate for our objectives. However, future iterations of the model could use any metric that the modelers feel is appropriate.

2.3. Spatial metrics

Measures of landscape/seascape connectivity are important to evaluate how habitat types and habitat patches are interlinked (Nagelkerken, 2009; Taylor et al., 1993). High measures of connectivity describe areas where animals may be able to easily move among different habitat types and patches without having to travel large distances or be impeded by landscape/seascape structure. There are multiple ways of calculating habitat connectivity: yet, a relatively simple and interpretable metric involves identifying locations that have various types of habitat in close proximity to one another (i.e. structural connectivity; Grober-dunsmore et al., 2009). To calculate this metric, we used rasters for the three habitat types of interest—mangrove forests, seagrass beds, and coral reefs. Habitat patches were defined using the Queen's case in which cells adjacent to any part of another cell (eight possible adjacencies) of the same habitat type were considered part of the same patch (Hijmans, 2016). In this study, connectivity was measured as the Euclidean distance of the centroid of every raster cell in the model's extent to the nearest habitat patch boundary of each habitat patch. This procedure allowed for individual habitat patch characteristics (e.g. area, perimeter, etc.) to be examined in the context of the distance from each habitat patch to each village. The mangrove forest habitat data was derived from ground verified Landsat-7 ETM + data created in 2002 for FAO Africover (Wang et al., 2003). The seagrass layer was generated by Landsat-8 OLI Sensor data at 30-m resolution (USAID-NASA, 2015). Finally, the coral reef layer was obtained from a compilation of various sources using multispectral Landsat-7 sensor data at 30-m resolution (UNEP-WCMC, WorldFish-Centre, WRI, and TNC, 2010).

In addition to considering habitat connectivity, we examined habitat patch size and density. The three metrics for each habitat

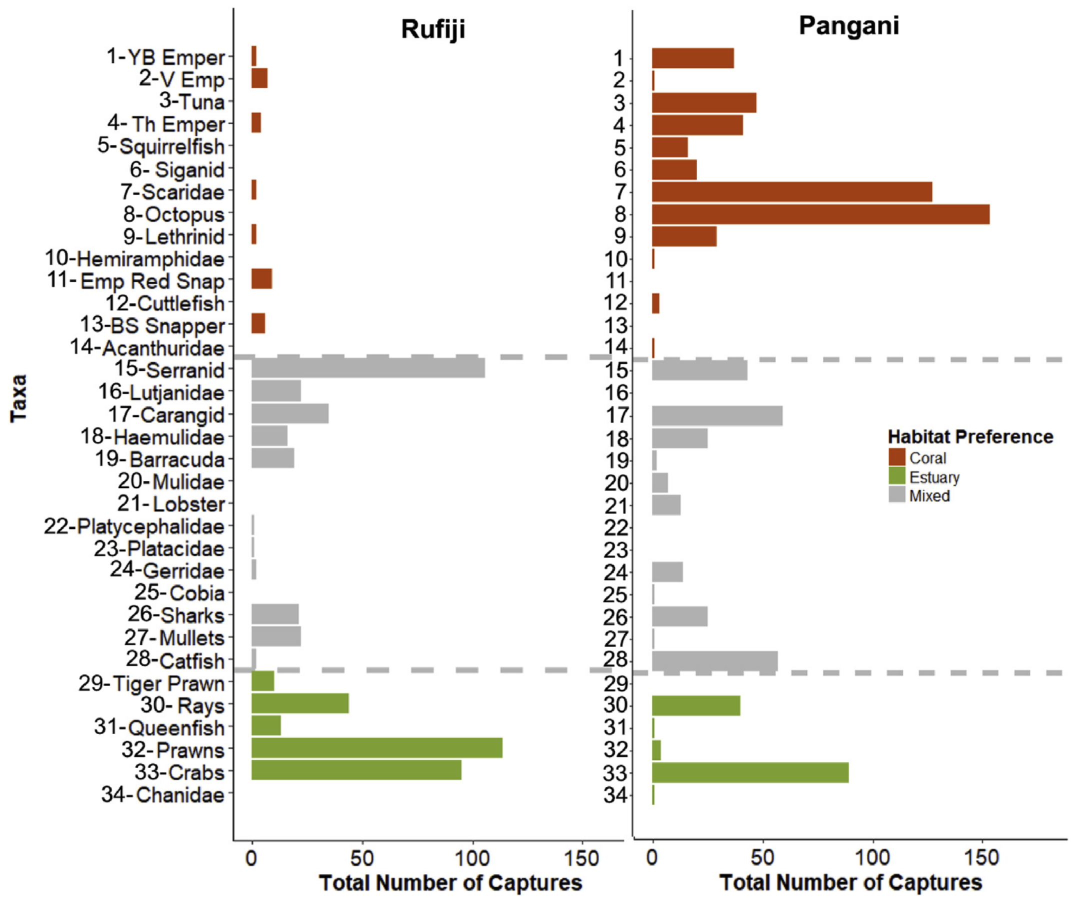

Fig. 2. The total number of captures (i.e. at least 1 fish of that taxon landed on a trip) of every taxon in Rufiji and Pangani, Tanzania. The number next to each bar on the *y*-axes are used for ease of visualization so that each taxon can be related between the two *y*-axes; the numbers were assigned in an arbitrary order. The color of bars and the order of taxa on the *y*-axis is based on the Blanchi (1985) description of habitat usage. A count was made of the number of species that used estuaries in a taxa grouping and the number of species that used coral reef habitat (species could be found in both) in each taxon grouping. The number of species that used estuaries was subtracted from the number of species that used coral reefs for each taxon This number was then divided by the sum of those values, such that taxa which used estuaries exclusively had a value of -1, taxa which used coral reefs exclusively had a value of 1, and those that could be found in either habitat had a value somewhere between -1 and 1 depending on which habitat they were more likely to be found in. The grey dashed lines indicate the division between taxa which were coral reef (1) or estuary (-1) associated and taxa which were associated with mixed-habitats ($-1 < x < 1$). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

(distance, area, and density) were compared visually to assess similarities and differences between Pangani and Rufiji districts. Metrics that provided multiple unique values within a district and described a clear contrast between districts were modeled against catch. The metrics that fit these criteria were: 1) area (km^2) of the largest mangrove patch within 10 km of a village, 2) area (km^2) of the largest coral reef patch within 15 km of a village, and 3) the number of seagrass patches within 10 km with an area > 0.5 km^2.

The local hydrologic influence was also incorporated into the models. Available hydrologic data included a GIS layer for mean rainfall (based on rainfall patterns from 2002 [Kariuki, 2002]) and a layer for Tanzanian rivers (Africover, 2007). The river layer consisted of lines that denoted the location of every river in Tanzania, all lines were of equal width, and had no description of river size or discharge. To approximate the hydrologic/estuarine influence, a buffer was created for areas where rivers connected with the ocean. All rivers within ten kilometers of the coastline were selected and each river was given a five-kilometer buffer. The area within the buffer would presumably be influenced by the river discharge. This buffer was then matched to annual rainfall estimates to define the influence of each river based on estimated discharge. Because there were only three unique rainfall measurements that described the estuaries (1200, 1000, and 800 mm yr^{-1}), the rainfall estimates were matched to the values 1, 0.8, and 0.6, respectively, and will henceforth be described as a hydrologic index. Finally, it is worth noting that because the rainfall data were only available for a single year they are prone to a relatively high level of uncertainty. Rainfall patterns are heavily influenced by a number of annual and multi-year variations (e.g. El Niño) that should be accounted for; however, this was the only data available for coastal Tanzania and was therefore the best available estimate.

One of the most common ways of including the local socioeconomic influence on small-scale fisheries in spatial models involves a calculation of fishing density (Ban et al., 2009; Hutchison et al., 2015; Jennings and Polunin, 1996; Stewart et al., 2010). This variable can be described by both population density, fisher density, or a combination of both. An estimate of fisher density was calculated through a combination of data from the Tanzanian Fisheries Annual Statistics Report (FSS, 2014), Population Census (TZNBS, 2013) and a GIS layer of Tanzanian wards (TZNCB, 2006). Fisher density can provide a better estimate of fishing effort than population density alone, as it accounts for the importance of fishing to the target location (Thiault et al., 2017). The Fisheries Annual Statistics Report only provided an estimate of the number of fishers at the regional level. Thus, to further estimate fishing effort at the district level (the highest resolution possible with available data) the number of fishers in each region was divided by the proportion of the population of each district within its respective region. A three-kilometer buffer was then created along the coastline to act as an estimate of the area where marine fishing households can aggregate. The number of fishers per district was then divided by the area that the buffers covered within each district to calculate the density of coastal fishers per district. This extrapolation should provide a better estimate of fishing pressure than by using district population or regional fisher density alone, although there are potential problems with this approach (see Section 4.2). When this variable was incorporated in the model, the fisher density values were applied to a 10 km buffer along the border of each district, so that the value of the buffer was equal to the fisher density per district. This buffer was masked to remove any sections where the buffer overlaid areas where water depth was > 200 m. The majority of fishing pressure off of the coast of Tanzania occurs in water no deeper than 40 m (Jacquet and Zeller, 2007); however, there is no available data for this isobath therefore the next shallowest isobath (200 m) was used.

2.4. Model parameterization

Spatial metric values were extracted at the location of each of the nine villages examined in this study. The spatial data was then compared against the proportional catch per habitat in comparison to all other taxa captured on each individual fishing trip ($n = 1160$). Estuary and mixed-habitat taxa were combined because the capture of taxa that used both habitats occurred most commonly in villages with estuary-associated fishing characteristics. Because the catch values (i.e. response data) were proportional (within the interval [0,1]), a beta distribution was deemed most appropriate (Fig. 3; Ferrari and Cribari-Neto, 2004). Beta distributions are naturally heteroskedastic, asymmetric (Cribari-Neto and Zeileis, 2009), and therefore flexible enough to accommodate proportional response data. Because, our data included zeros and ones, which are not within the interval associated with the beta distribution (0,1), we transformed the response data by

$$y = \frac{[y_i(n-1) + 0.5]}{n} \tag{1}$$

which centers each proportion by a small fraction to allow for the inclusion of the extreme values (i.e. 0 and 1) without affecting model outcomes (Smithson and Verkuilen, 2006). Upon visual inspection of the relationship between the response data and the five potential spatial metrics it became clear that some relationships took on a linear shape while others appeared to be best defined by a logistic shape. Therefore, depending on the spatial metric of interest, a simple linear or logistic-shape relationship (Fig. 3) was evaluated as the linear predictor for the beta-regressions. For both model types, the response was modeled as

$$y = Beta(\alpha, \beta) \tag{2}$$

$$\alpha = \mu \times \varphi \tag{3}$$

$$\beta = (1 - \mu) \times \varphi \tag{4}$$

where α and β are the shape parameters that describe the beta distribution, μ is the expected value of y (i.e. $E(y)$), and ϕ is the dispersion parameter (Ferrari and Cribari-Neto, 2004). μ and ϕ are used to calculate both shape parameters, and as a result the shape parameters can co-vary.

For simple linear relationships, the logit expectation of y (μ) was described with a linear predictor

$$logit(\mu) = \delta_0 + \delta_1 \times x_i \tag{5}$$

where δ_0 is the intercept, δ_1 is the slope, and x_i is the spatial metric of interest. For logistic-shape relationships, the logit expectation of y (μ) was described with a logistic function

$$logit(\mu) = \frac{1}{1 + e^{(-\gamma_0 * (x_i - \gamma_1))}} \tag{6}$$

where γ_0 is the steepness of the curve, γ_1 is the inflection point and x_i is the spatial metric of interest.

Villages were treated as fixed factors in the models because each village corresponded to one value for each spatial metric. Districts were also treated as fixed factors because most villages within districts had relatively similar values to one another for each spatial metric. Therefore, the variability that would have been accounted for by a within group (i.e. district) structure was low.

A Bayesian framework was adopted for analysis to allow the response data to be modeled with a beta distribution and for the model to take non-linear forms. In these models, the parameters δ_0, δ_1, γ_0, γ_1, and

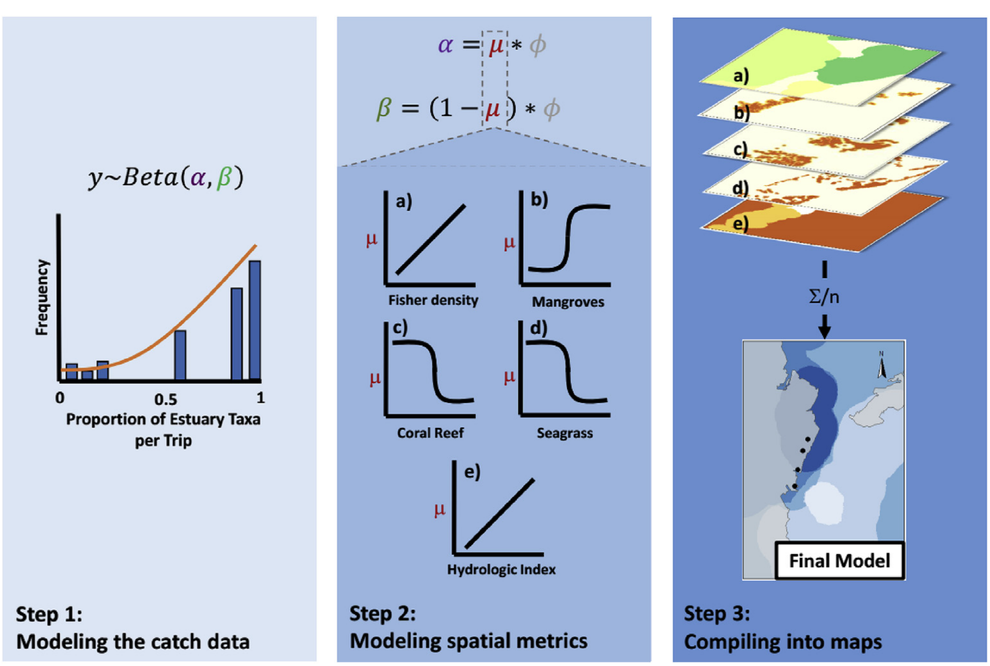

Fig. 3. Concept diagram of the modeling process. Step 1: the dependent data (proportion of estuary or coral reef taxa captured per trip) was beta-distributed (within the interval (0,1)), and therefore described by Eqn (2) (example probability density function shown in orange). Step 2: the beta-distribution is composed of two shape parameters, α and β, which are modeled with Eqn (3) and Eqn (4), respectively. Both equations rely on the μ and ϕ parameters; ϕ is based on the dispersion of the data and is therefore not modeled explicitly, while independent data is used to predict μ. The prediction of μ is completed with monotonic functions (a–e). Step 3: the output of the beta-regression for each type of independent data is then used as the input for each spatial metric (letters indicate the connection between beta-regressions and spatial metrics). The spatial metrics are then summed together and divided by the number of suitability layers (n) that were used to generate the final model of fishery characteristics. The beta-regression process is completed twice—once for coral-associated landings and once for estuary-associated landings. The beta-regressions are then each used to create a spatial model in both districts (Rufiji and Pangani), resulting in four total spatial models. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Spatial metrics modeled with beta-regressions and the posterior means (95% credible intervals) for each parameter included in the model. γ_0 and γ_1 parameters indicate metrics that were fit with Eqn (6). δ_0 and δ_1 parameters indicate metrics that were fit with Eqn (5). NA's represent relationships with poor model fit (see section 2.4).

Spatial Metric	Coral Model	Estuary Model
Number of Seagrass Patches (> 0.5 km^2) within 10 km	γ_0 = 84.191 (6.865, 229.155)	γ_0 = −82.763 (−222.553, −9.296)
	γ_1 = 3.080 (2.166, 3.961)	γ_1 = 1.422 (1.025, 1.911)
Largest Coral Reef Patch (km^2) within 15 km	γ_0 = 34.234 (0.751, 165.781)	γ_0 = −84.213 (−228.687, −6.293)
	γ_1 = 22.515 (15.989, 23.484)	γ_1 = 12.210 (10.325, 14.177)
Largest Mangrove Patch log(km^2) within 10 km	γ_0 = −104.954 (−240.068, −30.153)	γ_0 = 68.122 (7.499, 213.126)
	γ_1 = 3.076 (2.997, 3.186)	γ_1 = 4.867 (4.619, 5.017)
Fisher Density	NA	δ_0 = −1.592 (−1.798, −1.381)
	NA	δ_1 = 1.082 (0.946, 1.213)
Hydrologic Index	γ_0 = 49.012 (8.746, 172.518)	NA
	γ_1 = 0.052 (0.004, 0.213)	NA

ϕ were all given diffuse normal priors. We ran three Markov chains with each chain beginning with randomly selected values. From a total of 20,000 iterations the first 5000 iterations of each chain were discarded as burn-in and further thinned by retaining every third value for a total of 5000 iterations per chain for analysis. Final posterior distributions were assessed for convergence both visually, as well as with the Brooks-Gelman-Rubin statistic, $\hat{R}$, with values < 1.1 indicating convergence. All analyses were performed in JAGS in R (R Core Team, 2017) using the package *R2jags* (Su and Yajima, 2015).

Beta-regressions for each of the five spatial metrics were run for the two spatial models—one model for coral-reef associated fishery landings and one for estuary-associated landings—resulting in ten total beta-regressions. Both spatial models were created for the Pangani district and the Rufji district spatial extents, using the same parameterization (based on the five beta-regressions used for that spatial model) in both districts. The cell values from the raster files of the five spatial metrics were then used as the independent variable (x) in each respective monotonic function (parameterized from the associated beta-regression posterior estimates [see Table 1]) to generate distinct suitability layers (Fig. 3). These layers were bound such that any suitability layer value > 1 or < 0, were made equal to 1 or 0 respectively. Spatial metrics that did not fit to the response data of a model (see NAs in Table 1) were not transformed into a suitability layer for that specific model. As a result, both the coral and the estuary models were composed of four suitability layers. These suitability layers were then summed and divided by the number of suitability layers used (4) to generate the final models (Fig. 3), with values within the interval [0,1]. Finally, to ensure that fishing characteristics were only occurring in areas where small-scale fishing was likely to occur, final model suitability values were cropped to fall within 10 km of the coastline and only in areas with water < 200 m deep, as had been done for the fisher density data in section 2.3.

To generate an easily interpretable output that may be useable by stakeholders, we simplified the model output of both models into a single map for each region. These models were simplified by removing all data that did not have a high level of certainty (index value > 0.7). The raster cells with index values > 0.7 for both the estuary and coral reef models were then mapped together in both regions such that locations with values from either model that were > 0.7 were described as preferring either coral or estuary fishing characteristics. Areas that did not have an index value > 0.7 for either model were described to have uncertain fishing characteristic preferences. There were no areas where modeled values were > 0.7 for both the coral and estuary model in either district. All models were created in R (R Core Team, 2017) using the *sp* (Pebesma and Bivand, 2005) and *raster* (Hijmans, 2016) packages, maps were created using the *tmap* package (Tennekes, 2017).

2.5. Model comparison

Aggregated national catch statistics are available for the proportion of landings (based on biomass) for certain taxa in each coastal Tanzanian district (TZNBS, 2014). To identify how the models would compare to national statistics, we associated the proportion of landings data of each district to its respective polygon for all taxa that were associated with a model. Country-wide landings data were available for the following coral-associated taxa: Acanthuridae, Hemiramphidae, Lethrinidae, Octopus, Scombridae, and Siganidae. Country-wide landings data were also available for the following estuary and mixed-habitat taxa: Ariidae, Carangidae, Chanidae, Gerridae, Haemulidae, Mugilidae, Mullidae, Prawns, Rays, Serranidae, and Sharks. We then generated the coral associated and estuary associated models for the entire Tanzanian coast using the same methods that had been used for the Pangani and Rufiji districts (see section 2.4). To compare the modeled catch per estuary and coral reef associated taxa to actual recorded catch we extracted all modeled index values within five km of the district bounded coastlines and calculated the median modeled index value for each district. The buffer along the coast was used to delineate fishing locations that would likely have distinct associations with the political boundaries used within the aggregated statistics. The median modeled index was calculated rather than the mean because the median describes the central tendency of non-normally distributed data more accurately. Finally, the catch data and the median modeled index values were compared using a beta-regression with a simple linear shape, following the same methods as described in section 2.4.

3. Results

The beta-regression models described different relationships between each spatial metric and the capture of coral associated or estuary and mixed-habitat taxa (Table 1). The slope and mid-point of all relationships were credibly (95%) different from zero, indicating that there were relationships between the spatial metrics and taxa captured (Table 1). Coral associated catch was highest when mangrove patches near villages (within 10 km) were small (< 3.076 log(km^2)), coral reef patches near villages (within 15 km) were large (> 22.515 km^2), there were > 3 large seagrass patches (> 0.5 km^2) within 10 km of the village, and when the hydrologic index values were small (< 0.052). Estuary associated and mixed-habitat taxa catch were highest when mangrove patches near villages (within 10 km) were large (> 4.867 log (km^2)), coral reef patches near villages (within 15 km) were small (< 12.21 km^2), there were < 2 large seagrass patches (> 0.5 km^2) within 10 km of the village, and the fisher density was high (> 1.5 fishers km^{-2}).

The coral fishery model in the Pangani district predicted that coral associated fishes would be caught throughout most of the district (coral fishery index values > 0.7; Fig. 4a). Areas near estuaries in the Pangani district showed the lowest likelihood of coral associated fish capture (coral fishery index values < 0.7) in the district. Specifically, the estuary that surrounds Pangani Mashariki and Pangani Magharibi (the two northernmost villages in Fig. 4a) was the least likely area to capture

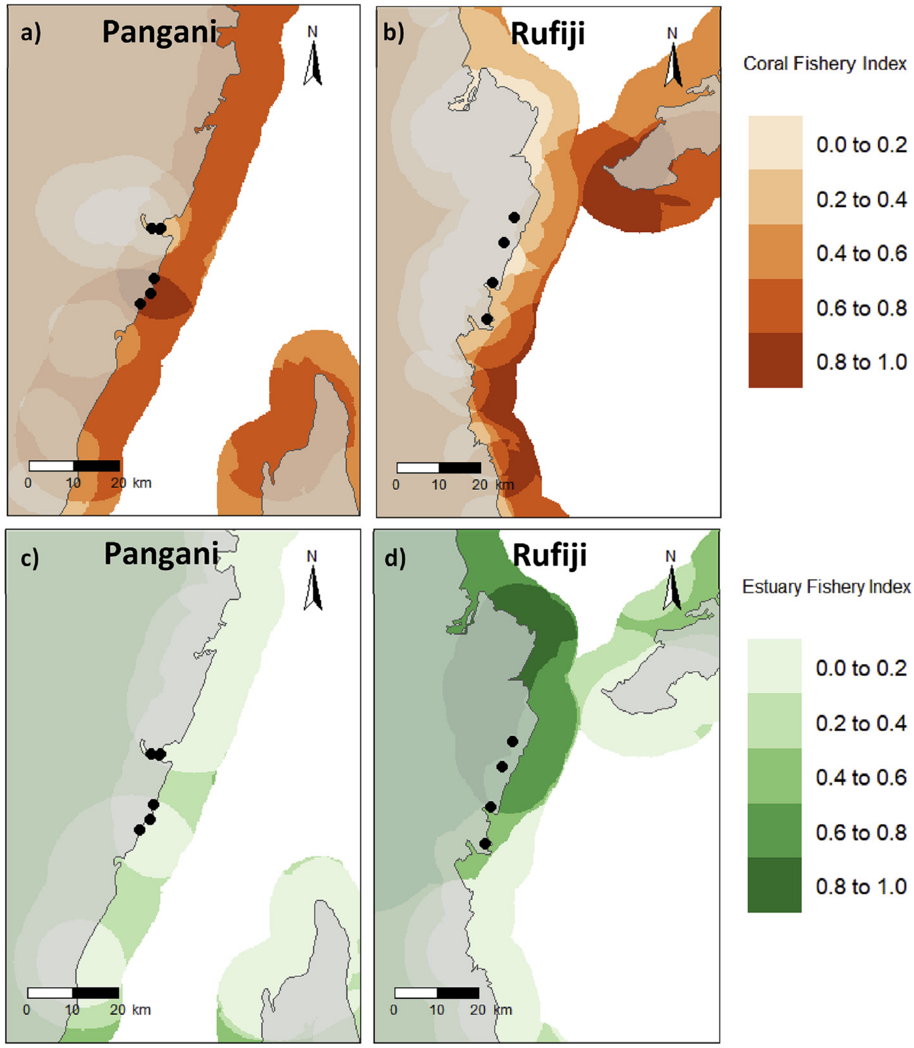

Fig. 4. Maps of model results for the coral fishery characteristic model in a) Pangani and b) Rufiji and the estuary fishery characteristic model in c) Pangani and d) Rufiji. Black dots represent the location of villages with BMU data used to parameterize the models.

coral associated fishes (coral index values < 0.2) in the district. The coral model in Rufiji predicted that few coral associated fishes would be caught along the delta region (coral fishery index values < 0.4; Fig. 4b). To the south of the delta region and in offshore locations, coral fish were predicted to be caught often (coral fishery index values > 0.7). The estuary fishery model did not predict the capture of many estuary associated fishes anywhere in Pangani (estuary fishery index values < 0.4; Fig. 4c). In Rufiji, the same model predicted that estuary associated fishes would be captured often (estuary fishery index values > 0.7) throughout the delta area, with the highest values (> 0.8) appearing in the northern half of the delta (Fig. 4d).

The simplified model output shows areas with high model certainty in preferred fishing characteristics, where managers may be able to apply similar strategies across areas with the same preferred characteristics. Most of the Pangani district and northern Zanzibar coastlines had coral fishing characteristics, although there are a few regions lacking these attributes (Fig. 5a). Specifically, the area near Pangani Mashariki and Pangani Magharibi (the two northernmost villages in Fig. 5a) had uncertain fishing characteristics. No locations in Pangani district had preferred estuary characteristics. The simplified model output for Rufiji district shows areas with coral, estuary, and uncertain fishery characteristics (Fig. 5b). Estuary characteristics were present throughout the central and northerly latitude areas of the Rufiji delta, while coral characteristics were present in the southern half of the Rufiji coastline and around most of the southern coast of Mafia island.

There was not a relationship between the whole-coast estuary model and the proportion of estuary taxa captured in each district. When the whole-coast estuary model was modeled against the proportion of estuary taxa captured using the beta-regression, the slope (0.755 [-1.979, 3.267]) was not credibly [95%] different from zero, however, the intercept was (−1.448 [-2.340, −0.547]). Furthermore, the model expected far lower capture of estuary-associated fishes than were present in the national catch statistics. There was a relationship between the whole-coast coral model and the proportion of coral taxa captured in each district, in this case the slope (4.180 [0.492, 7.898]) was credibly different from zero but not the intercept (−0.259 [-14.703, 5.258]). In contrast to the estuary model, the coral model over predicted the capture of coral-associated fishes in comparison to the national catch statistics.

4. Discussion

This study demonstrates that in management-limited areas, basic local monitoring data along with spatial metrics can predict the local characteristics of small-scale fisheries. Our models show that in coastal Tanzania the capture of coral and estuarine associated fishes was related to nearby habitat type, river discharge, and socio-economics. The simplified outputs of our models provide an easy method of visualizing the variability in fishery characteristics in a way that may be useful for local fishery managers and stakeholders. By providing a means to understand and assess how the local socio-ecological environment and fisheries interact, we feel that our model may serve as a baseline assessment capable of initiating further local monitoring data collection and hopefully, improved management. Furthermore, the framework of our model was designed with flexibility in mind and is capable of integrating a variety of data-types, making it potentially applicable for a wide-variety of data-poor, small-scale fisheries.

4.1. Model performance

The models generated maps of the spatial variability of fishing characteristics throughout the Tanzanian coast. The models for the Pangani district identified the majority of the Pangani coastline to be driven by coral fishing characteristics (i.e. specialized gear-use, vessel-use, and taxa captured). Although some locations along the Pangani coast had higher coral index values than others (e.g. more evidence for coral fishery characteristics in that location), there were no locations along that coast that showed high estuary fishery index values. One study on the habitat types frequented by fishers in the Tanga region (which encompasses Pangani district) found that < 15% of fishers frequently visited estuaries (Katikiro, 2014). Other studies of the fisheries in Pangani district and the Tanga region also show that fishing activity focused around coral habitats (Anderson, 2004; Horrill, 1999; McClanahan et al., 1999; Robertson et al., 2018; Samoilys and Kanyange, 2008; Turque and Casper, 2016; Wells et al., 2010). When both the coral and estuary fishing models were combined, there were multiple locations along the Pangani coast characterized by uncertain fishing characteristics. Two of the three regions with uncertain characteristics were located near an estuary (Fig. 5), one was located around Pangani Mashariki and Pangani Magharibi; two villages located near the Pangani river. Fishing trips from Pangani Magharibi have been associated with some of the lowest levels of coral associated fishing characteristics among the villages in the Pangani district (Robertson et al., 2018). Therefore, while not yet validated, the maps produced by our models match our current understanding of the fisheries in Pangani district (Robertson et al., 2018).

The model results for the Rufiji district identified that most of the inshore waters around the Rufiji delta were driven by estuarine fishing characteristics (i.e. generalist gear-use, vessel-use, and taxa captured). The most prominent feature of the Rufiji district is its large deltaic system. This geomorphic feature influences the fisheries near the delta to such a degree that the majority of landings are comprised of freshwater and estuarine finfish, as well as prawns, and the models were able to identify this pattern (Mwakosya et al., 2010; Richmond et al., 2002; Silas, 2011). Additionally, there were locations to the south of the delta, and along the coast of Mafia island where the model predicted coral fishing characteristics. One of the villages with landings data from the southern delta, Pombwe, had less prominent estuary associated fishing characteristics than the other three villages with data in the Rufiji district. Pombwe is specifically known to be closer to coral reef habitat than most villages in the delta region (Richmond et al., 2002), and sightings of the seagrass associated dugong (*Dugong dugon)* are relatively common there (Muir et al., 2003; West, 2011). Furthermore, other studies show that Mafia island supports coral reef fish populations and a coral associated fishery (Dorenbosch et al., 2005; Garpe and Öhman, 2003; Guard and Mgaya, 2002; Kamukuru, 2005). Therefore, similar to the results from Pangani district, it appears that the model results for the Rufiji district are supported by previous studies.

The full coast model results were compared to the proportion of coral taxa landings in the national fishery statistics but were not related to the proportion of estuary taxa landings. This may have been because the estuarine areas tended to promote localized fisheries that may not be well described when fishery characteristics are aggregated to the district scale. Additionally, the national statistics for landings data were derived from BMU data from 32 randomly selected villages throughout the coast (Sobo, 2016). For the most recent national fisheries statistics (TZNBS, 2014), only one landing site (out of 32) matched the landing sites examined here (Sobo, 2016). The national datasets are aggregated and then expanded for all districts along the coast; however, the specific methods for this aggregation are not documented in further detail. Due to the intrinsic problems with the BMU data (Robertson et al., 2018), the potential bias of sites where BMU data is obtained for national analysis (Sobo, 2016), and the uncertainty around the methodology for the calculation of the national data, it is possible that these data do not describe the fisheries characteristics accurately. However, we still think that the extrapolation of our model to the entire coast is worthwhile because requiring data prior to making management decisions in small-scale fisheries is not always practical (Johannes, 1998). Therefore, the creation of tools that can estimate useful information in data-less locations may provide the initial information that is needed to push those areas towards data-collection and management change. Furthermore, our models are not an endpoint for understanding fishery-environment relationships; there is nothing preventing the improvement of our models as more and better information is obtained.

4.2. Management applicability

Historically, fisheries management has focused on identifying what

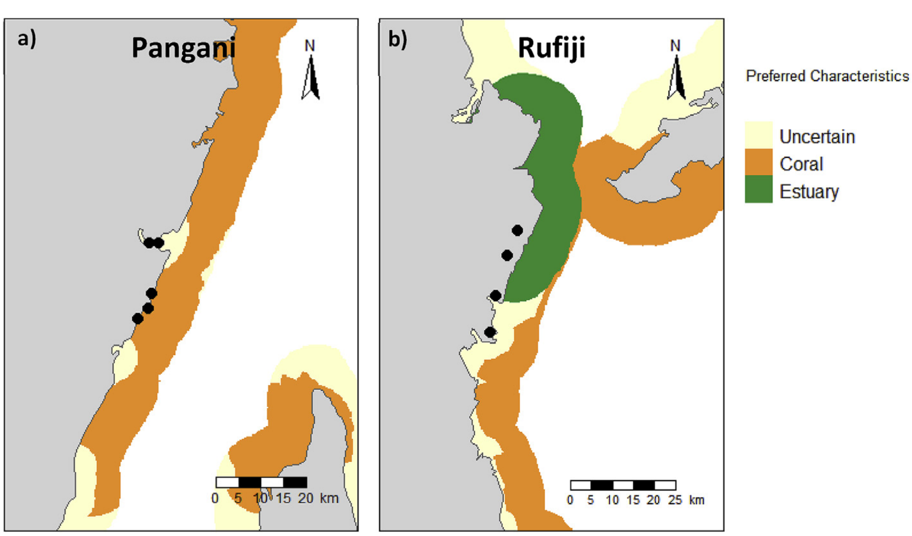

Fig. 5. Maps of preferred fishery characteristics in a) Pangani district and b) Rufiji district based on locations with index values > 0.7 from the coral and estuary characteristic models within 5 km of the coast. Any areas that had index values < 0.7 in both models are described to be uncertain. There were no areas that had index values > 0.7 in both the coral and estuary characteristic models. Black dots represent the location of villages with BMU data that were used to parameterize the models.

level of harvest is sustainable (Caddy and Mahon, 1995) rather than managing how, when, and where fishing is occurring (Salas and Gaertner, 2004). This can be problematic for small-scale fisheries because they are often not inventoried in a way that allows for the exclusion of certain individuals or forms of harvest when fishing effort exceeds levels of sustainability (Berkes et al., 2001). The proposed modeling framework may promote a basic understanding of how and where fishing is occurring. Although the models were parameterized based on landings data for coral associated and estuary associated taxa (i.e. what is actually caught), the capture of these taxa have been related to other fishing characteristics, including vessel-use, gear-use, and the level of specialization of fishers along the Tanzanian coast (i.e. how fishing is occurring; Robertson et al., 2018). While this methodology does not inventory the fishery completely, it does present the spatial distribution of broad characteristics, allowing managers to adapt regulations to match the fishery of concern. Furthermore, using relationships between what is caught and how it is being caught to understand fisheries may be particularly useful in many developing countries, where access to consistent fishery monitoring data can be problematic (Gillett and Lightfoot, 2001; Jacquet et al., 2010; Mills et al., 2011) and enforcement of harvesting regulations can be difficult (Berachi, 2003; Fulton et al., 2011; Kanyange et al., 2014).

In addition to the broad characterization of local fisheries, our models may provide a framework from which local monitoring data can be examined by individual local management institutions (e.g. BMUs). For example, a specific village in the Rufiji district (Kiechuru) may have driven the relationship between fisher density and the capture of estuarine associated fishes. Fishers in Kiechuru had the widest diversity of gears used by any village in Rufiji (Robertson et al., 2018). These fishers captured high-value species (prawns, crabs, and groupers) more often than any other species, yet, the mean biomass per-trip in Kiechuru (1.5 kg $trip^{-1}$) was significantly lower than any other village in Rufiji ($> =11$ kg $trip^{-1}$) which led to lower total value captured per trip as well (Robertson et al., 2018). The use of many different gears may increase the overall selectivity of a fishery beyond the point of sustainability (McClanahan and Mangi, 2004). Therefore, implementation of gear-based management, as has been advocated by others in the region (Chande et al., 2019) may be a worthwhile step forward for Kiechuru, and potentially other estuary-associated fishing villages as well. This example shows that by examining the specific modeled relationships alongside summary local monitoring data, villages may be able to glean detail that would be unavailable if viewing model output or local monitoring data alone.

The design of institutions required for sustainable management is believed to depend on resource monitoring (Ostrom, 1990), and local monitoring data has filled this role for other small-scale fisheries in the past. One recent example is the arapaima fishery in the Mamirauá reserve in Brazil that underwent a rapid recovery over the past 20 years (Campos-Silva and Peres, 2016). This recovery involved a greatly improved institutional framework that was based around local community involvement, and specifically local fishermen conducting count-based surveys of arapaima (Castello et al., 2009). The multi-species, multi-gear fisheries of coastal Tanzania may not be able to assess their fishery in the same way. However, if managers are capable of identifying the main issue affecting a local community's fishery (e.g. gear diversity in Kiechuru), local monitoring data and regulations could be focused toward that particular issue. It is likely that having communities focus their effort on localized issues that can be monitored and assessed will improve local management success.

Top-down decision making is prevalent in certain co-management institutions, including many in Africa (Hara and Nielsen, 2003). A recent review of the social, ecological, and economic success of global fisheries co-management, concluded that one of the main causes of low success was the mismatch between scales of fish population distribution, the fishing process, and the management system (Gutierrez et al., 2011). In co-management frameworks the problem of appropriate management scale is reliant on the cooperation and integration of knowledge at each scale of governance (Jentoft et al., 1998; Wilson, 2003). As such, models like the one developed here that use local monitoring data to develop an understanding of the local variability in fishery characteristics and how this variability may affect the fishery at larger scales may be able to improve co-management decisions in two distinct ways. First, if the structure of the government is unwilling to allow for greater direct communication between levels of governance, the promotion of indirect communication of local level fishery characteristics and trends through local monitoring data acquisition and analysis may serve as a step in the right direction. Second, if higher level governance institutions acknowledge that their success is based on improving their understanding of fisheries at a smaller-scale, then they are more likely to take part in and promote discussions with stakeholders and institutions at the regional and local scale (see Castello et al., 2009). For scale appropriate management to be possible, both the higher level institutions and local scale stakeholders need to understand the benefits of working together to understand their fisheries (Ostrom, 2009).

The models used in this study predicted the spatial distribution of coral and estuary fishing characteristics, thus showing that the proposed framework for these models is flexible and could be used as a tool for other forms of spatial modeling in data-poor fisheries. There have been various attempts to spatially model fishing effort in data-poor fisheries (Leopold et al., 2014; Moreno-Báez et al., 2010; Naranjo-Madrigal et al., 2015; Pennino et al., 2016; Stewart et al., 2010). While useful for their target fisheries, many of these models still require significant amounts of data or are not explicitly developed to act as tools for future analyses (but see Kavadas et al., 2015; Thiault et al., 2017). We feel that our modeling framework is able to address both of these issues. For example, the environmental and socio-economic variables used to evaluate spatial relationships could be altered to fit the data availability of different fisheries. Countries with access to large amounts of data and finances are likely to use other modeling frameworks, yet this framework could be useful for fisheries that are truly data poor.

Our models experienced several limitations. The data used to parameterize the models (BMU data) are the only available landings data for small-scale coastal fisheries in Tanzania. These data have various issues including, but not limited to, the lack of temporally consistent recording, unequal data records between districts and villages, the absence of effort to inform catch, and the potential bias of fishers when describing their catch (Robertson et al., 2018). In addition, the association of taxa to habitat types was based on one reference (i.e. Blanchi [1985]). This field guide is over 30 years old, and the methods used to establish connections between fishes and their habitats is not explicitly described. Yet, Blanchi (1985) is the only comprehensive guide to fish habitat use in this coastal region.

The classification of the habitat data types used in the models is of low resolution, since it described the broadest habitat types (i.e. coral reef, seagrass, mangrove). Furthermore, some of the habitat data is relatively old (up to 15 years) and therefore may be incorrect due to environmental and/or anthropogenic changes. Another potential limitation is that fisher density was the only socio-economic variable that was included in this study. Although fishing pressure has been used in the past to describe fisher spatial allocation (Thiault et al., 2017), the inclusion of additional socio-economic variables (e.g. market access, development) would likely describe the variability of fishery characteristics more accurately (Brewer et al., 2012). Furthermore, the method used here for calculating fisher density assumes that population density and the regional number of fishers calculated in the census (the only available data) are accurate estimates of fishing pressure. This may be problematic as not all fishers are equal, and it is likely that the composition of fisher type (e.g. full-time, part-time, migrant) in a village would affect local fishing pressure.

Despite these limitations, our models used the best available data for this data-poor coastal fisheries region. Furthermore, all data used here, other than the landings data, were freely available online and are therefore likely to exist in similar forms in other data-limited, small scale fisheries. Additionally, although the landings data were not freely available, they were voluntarily recorded and therefore, future study locations could fulfill all data requirements at very low cost. Due to the relatively low data requirements, we believe that it is possible that models based on the framework developed here could be applied to other data-limited fisheries, particularly in developing countries. Additionally, this modeling approach can help prioritize research needs and data collection. These tasks will contribute to improvements in the sustainability of these fisheries.

5. Conclusions

The modeling approach developed here may act as a first step in incorporating local monitoring data into co-management frameworks. The models were able to describe relationships between socio-ecological variables and the capture of estuary and coral associated taxa. These relationships were explicitly modeled spatially so that the spatial characteristics of coastal fisheries in Tanzania could be projected into areas lacking available catch data. The maps developed by the modeling process provide a means for stakeholders and managers to understand the spatial distribution of their fisheries. If communities are capable of identifying the main issues affecting their fisheries, they should be able to focus on monitoring and creating improved institutional frameworks to deal with those problems. Furthermore, the integration of local data into management plans would inherently invoke discussions between top-down institutions and stakeholders. The ability for different levels of the management framework to discuss and share information, data, and knowledge should promote more successful management, not only through an improved understanding of the fisheries, but also through an increased involvement by all participants.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.05.082.

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