Using Local Fishery Monitoring to Understand Small-Scale Coastal Fisheries in Tanzania

Matthew Robertson
mrob122@lsu.edu

Follow this and additional works at: https://digitalcommons.lsu.edu/gradschool_theses

Part of the Aquaculture and Fisheries Commons, Marine Biology Commons, and the Oceanography Commons

Recommended Citation
https://digitalcommons.lsu.edu/gradschool_theses/4782

This Thesis is brought to you for free and open access by the Graduate School at LSU Digital Commons. It has been accepted for inclusion in LSU Master's Theses by an authorized graduate school editor of LSU Digital Commons. For more information, please contact gradetd@lsu.edu.
USING LOCAL FISHERY MONITORING TO UNDERSTAND SMALL-SCALE COASTAL FISHERIES IN TANZANIA

A Thesis

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Master of Science

in

The Department of Oceanography and Coastal Sciences

by

Matthew Robertson
BSc, Dalhousie University, 2016
December 2018
ACKNOWLEDGMENTS

I would like to thank Dr. Stephen Midway for serving as my major professor during my time at Louisiana State University. His dedication to my improvement as a scientist and a professional has been tremendously appreciated. Dr. Midway allowed my work to be my own, but was always there when I went off course to push me in the right direction. I would also like to thank my committee members Dr. James H. Cowan Jr., Dr. Victor Rivera-Monroy, and Dr. Michael Polito. Dr. Cowan provided valuable insight into fisheries oceanography and management, Dr. Rivera-Monroy taught me many valuable lessons about being a better scientist and to never forget about the scale of your system, and finally, Dr. Polito was a great source of ecological knowledge and unending positivity. I want to thank all of my committee members for the time and effort that they have given to my thesis. Additionally, I would like to acknowledge the National Science Foundation (CNH-S Grant #1518471) and Louisiana State University Office of Research and Economic Development for providing funding for the project, as well as the Department of Oceanography and Coastal Sciences at Louisiana State University for providing funding for my graduate assistantship.

This thesis would not have been possible without the help, support, and friendship of my fellow lab mates Shane Flinn and Lucas Pensinger. In addition, I would like to thank my fellow graduate student Mario Hernandez for his assistance throughout my time at LSU and for being an excellent travel companion to Tanzania. I would also like to thank Tanya Prystay for her unending support, insight, and patience throughout the last two years. Finally, I would like to thank my family for their love and support, and for teaching me to be curious about the world and to pursue my dreams.
TABLE OF CONTENTS

ACKNOWLEDGMENTS .............................................................................................................. ii

LIST OF TABLES ......................................................................................................................... iv

LIST OF FIGURES ......................................................................................................................... v

ABSTRACT ........................................................................................................................................ vi

CHAPTER 1. GENERAL INTRODUCTION .................................................................................. 1
  1.1. Small-Scale Fisheries ............................................................................................................. 1
  1.2. Fisheries Co-Management ................................................................................................. 2
  1.3. Small-Scale Fishery Monitoring .......................................................................................... 4
  1.4. Tanzanian Fisheries ............................................................................................................ 5
  1.5. Thesis Goals and Objectives .............................................................................................. 6
  1.6. References .......................................................................................................................... 6

CHAPTER 2. FISHERY CHARACTERISTICS IN TWO DISTRICTS OF COASTAL TANZANIA ................................................................. 11
  2.1. Introduction .......................................................................................................................... 11
  2.2. Methods .............................................................................................................................. 15
  2.3. Results .................................................................................................................................. 19
  2.4. Discussion ............................................................................................................................ 33
  2.5. References .......................................................................................................................... 41

CHAPTER 3. PREDICTING COASTAL FISHING COMMUNITY CHARACTERISTICS IN TANZANIA USING LOCAL MONITORING DATA .......................................................... 48
  3.1. Introduction .......................................................................................................................... 48
  3.2. Methods ............................................................................................................................... 51
  3.3. Results .................................................................................................................................. 64
  3.4. Discussion ............................................................................................................................ 69
  3.5. References .......................................................................................................................... 80

CHAPTER 4. GENERAL DISCUSSION ..................................................................................... 92
  4.1. Summary and Synthesis ...................................................................................................... 92
  4.2. References .......................................................................................................................... 95

APPENDIX A. CHAPTER 2 SUPPLEMENTARY MATERIAL ...................................................... 98

APPENDIX B. CHAPTER 3 SUPPLEMENTARY MATERIAL ...................................................... 106

APPENDIX C. COPYRIGHT INFORMATION ............................................................................. 109

VITA .................................................................................................................................................. 112
LIST OF TABLES

Table 2.1. Vessel type and descriptions for all vessels included in the BMU data. ....................... 21

Table 2.2. Model equations, test statistics, and p-values for all t-tests and ANOVAs used throughout the results. ...................................................................................................................................... 32

Table 3.1. The spatial metrics that were modeled with beta-regressions and the posterior means (95% credible intervals) for each parameter in those beta-regression models. ........................................ 66
LIST OF FIGURES

Figure 2.1. Map of Tanzanian coastline, Pangani District, and Rufiji District.......................... 17

Figure 2.2. The recorded fishing trips in the eight villages with the most data in Pangani and Rufiji by month, season, and year................................................................. 20

Figure 2.3. The proportional use of the ten most frequently used gear types within Pangani and Rufiji, Tanzania, 2014–2017................................................................. 23

Figure 2.4. The ten most commonly caught taxa in Rufiji and Pangani, Tanzania, 2014–2017.. 24

Figure 2.5. The total number of trips which landed each of the ten most frequently landed taxa in Rufiji and Pangani, Tanzania 2014–2017................................................................. 25

Figure 2.6. The total value of landings by the number of recorded fishing trips in each village within Pangani and Rufiji, Tanzania, 2014–2017................................................................. 27

Figure 3.1. Pangani District and Rufiji District maps............................................................ 53

Figure 3.2. 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................................................................. 58

Figure 3.3. Concept diagram of the modeling process............................................................. 62

Figure 3.4. Maps of model results for the coral fishery characteristic model in Pangani and Rufiji and the estuary fishery characteristic model in Pangani and Rufiji ....................... 67

Figure 3.5. Maps of preferred fishery characteristics in Pangani district and Rufiji district based on locations with index values >0.7 from the coral and estuary characteristic models within 5 km of the coast ................................................................. 68
ABSTRACT

Nearshore marine fisheries provide the main source of protein for nearly 9 million people in the coastal villages of Tanzania, yet for decades the fisheries have shown signs of overexploitation. These fisheries are small-scale and co-managed by local coastal communities in groups known as Beach Management Units (BMUs). BMUs monitor individual fishing trip data (e.g. gear, vessel, taxa); however, these data have only been analyzed in nationally aggregated statistics and to our knowledge, are not presently used in management decision making. The present thesis aimed to identify the forms of data and information that local fishery monitoring can record about small-scale marine fisheries in Tanzania, and how that local monitoring data may be related to the spatial socio-ecological context of those fisheries. We collected all available fishing trip data from 2014 to 2017 from BMUs in fourteen villages in two spatially, socially, and ecologically distinct districts (Pangani and Rufiji) of the country. Our results found that each village had unique patterns of vessel-use, gear-use, and taxa landed, and that every village was specialized in some measure. Specifically, two villages in Pangani district landed octopus or parrotfish almost exclusively, suggesting potential trophic cascades after years of overexploitation. We then proposed a flexible modeling approach which incorporated the BMU landings 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, this thesis has
shown that the catch data collected by BMUs were able to generate the first descriptions of village-based Tanzanian fishery characteristics. Thus, it is possible that the collection and analysis of local monitoring data can be used to promote the application of fishery regulations that are relevant to their socio-ecological context.
CHAPTER 1. GENERAL INTRODUCTION

1.1. Small-Scale Fisheries

Small-scale fisheries (SSF) exist in at least 140 countries, are estimated to directly and indirectly employ more than 138 million people globally (Bene, Macfadyen, and Allison, 2007), and provide two-thirds of the global fish catches used for direct human consumption (FAO, 2015). The definition for SSF varies dramatically with location, however, in general they are described to be mainly subsistence-based with fishers mostly consisting of those who use traditional or simple gears, on foot, or in small boats (<15 m [Chuenpagdee, Liguori, Palomares, and Pauly, 2006]). Furthermore, SSF are viewed as being embedded within larger socio-ecological systems due to their inherent connection with the economic, social, and cultural aspects of local communities (Berkes et al., 2001; Jentoft, 2014). The majority of these fisheries are distributed throughout developing countries (90% [FAO, 2015]), however there are SSF in developed countries as well (Berkes, 2003). Finally, the people involved in SSF are often recognized for their high degree of poverty, not only in the economic sense, but also in the civil, political, social, and cultural sense (Bene, 2003).

There have historically been two contrasting opinions on the origins of poverty in SSF, both of which have influenced the understanding of and management strategies for SSF (Bene, 2003). The conventional opinion is based on an endogenous origin of poverty, where the open-access nature of the resource leads to overexploitation through a “tragedy of the commons” (i.e. when the net profit of an open-access resource is eliminated due to the collective action of individual self-interest working contrary to the common good [Gordon, 1954; Hardin, 1968]). This opinion describes that the tragedy of the commons leads to overfishing, and therefore forces the low income nature of fishing. In contrast, a more recent opinion is based on an exogenous
origin of poverty, where a lack of alternative livelihood options outside of the fishery forces the low income nature of fishers, rather than poverty being necessarily the result of the overexploitation of the fisheries resource itself (Cunningham, 1994). The combination of these two explanations for the origins of poverty in SSF have led past research and management to focus on the conservation of fish stocks, while also attempting to produce more economically efficient fisheries (Allison and Ellis, 2001). However, neither of these approaches have performed well in developing countries for a variety of reasons (Berkes, 2003). One of the main reasons being that the conservation of fish populations often requires an understanding of the dynamics of the harvested populations (Hilborn and Walters, 1992), and SSF catches are rarely monitored, due to the spread of fishing along the entire coastline of many countries (i.e. catches are not landed at specific ports [Lunn and Dearden, 2006]). Furthermore, the financial resources required to improve the economic efficiency of these fisheries is often not promoted by the government because the contribution of SSF to the Gross Domestic Product is perceived to be small (Zeller, Booth, and Pauly, 2006). This perceived lack of economic importance has resulted in further marginalization of SSF (Pauly, 1990) and in turn further poverty and a lack of effective management (Jacquet and Pauly, 2008). Overall, although the biological limits and economic efficiency of SSF are considered to play a potentially large role in driving poverty, researchers have begun to recognize that the institutional mechanisms which control the management of fisheries resources may in fact be the largest drivers of poverty in these systems (Bene, 2006).

1.2. Fisheries Co-Management

Fisheries co-management has become increasingly common throughout the globe in recent years (Berkes, 2007; Evans, Cherrett, and Pemsl, 2011; Hara and Nielsen, 2003; Pomeroy, Katon, and Harkes, 2001). Fisheries co-management can be defined as, “a partnership in which
government, the community of local resource users (fishers), external agents (non-governmental organizations, academic, and research institutions), and other fisheries and coastal resource stakeholders (boat owners, fish traders, money lenders, tourism establishments, etc.) share the responsibility and authority for making decisions about the management of a fishery” (Berkes et al., 2001). The recent adoption of the concept of co-management was borne out of the “Question of the Commons” (Wilson, 2003b), where the current answer of co-management has been proposed because it allows for a greater emphasis to be placed on local stakeholders (Dietz, Ostrom, and Stern, 2003). The emphasis on local stakeholders is inherently more transparent than conventional management, is more cost-effective, incorporates local knowledge, is adaptive to current local issues, and may promote a feeling of involvement and ownership in local communities, all of which are hypothesized to improve management development, implementation, and compliance (Berkes et al., 2001).

Co-management has been implemented most often in developing countries (Evans et al., 2011), however, there are examples of co-management in developed countries as well (Sen and Nielsen, 1996). Furthermore, there are accounts of management frameworks based upon a similar framework to co-management dating back to the late 1800’s (Jentoft and Kristoffersen, 1989), despite the fact that co-management has mostly appeared within the last 30 years. The majority of these co-management frameworks have been implemented in response to a perceived failure of conventional fisheries management (i.e. the population dynamics approach) due to its inability to account for the socio-ecological nature of SSF (Berkes et al., 2001; Cinner et al., 2012; Kittinger et al., 2013). However, one of the main challenges to the success of addressing the socio-ecological nature of fisheries in co-management involves the development of effective relationships between institutions and stakeholders (Jentoft, Mccay, and Wilson, 1998; Wilson, 1998).
2003a). These relationships allow for the exchange of information, a feeling of involvement by communities, and the establishment of trust, all of which are necessary for co-management to effectively address poverty in fishing communities in the context of sustainable fisheries management.

1.3. Small-Scale Fishery Monitoring

Investigations into the amount of fishing and number of fish caught by fisheries have served as the backbone of quantitative fisheries science since the mid-late 1800’s (Fulton, 1896; Garstang, 1900). Understanding the impact of fishing on fish populations is required to assess the sustainability of a fishery and in turn, develop sustainable management strategies (Shepard, 1988). Despite the well-known importance of monitoring for fisheries management, the high costs of collecting data and often complex nature of SSF have contributed to the lack of data collection for many systems (Gillett and Lightfoot, 2001; Jacquet et al., 2010; Mills et al., 2011). Partnerships between researchers and communities can allow for a cost-effective means of increasing monitoring in SSF, while simultaneously promoting the relevance of monitoring locally (Almany et al., 2010; Danielsen et al., 2008; Saunders and Xuereb, 2016). These forms of partnerships can vary in their level of researcher involvement from significant to almost none. Additionally, the type of monitoring can range from underwater visual census (Obura et al., 2002; Uychiaoco, Arceo, Green, and Cruz, 2005), to interviews with and/or by locals (Jones et al., 2008; Lunn and Dearden, 2006). Although the accuracy of local monitoring data can be questionable, there have been instances in which locally collected data have been of equal quality to researcher collected data (Danielsen, Burgess, and Balmford, 2005). If implemented appropriately, local fishery monitoring may serve as a direct means of promoting community engagement and knowledge sharing in co-management frameworks.
1.4. Tanzanian Fisheries

Tanzania is a developing nation in Eastern Africa in which much of the economy and consumed protein is generated by SSF (Jiddawi and Ohman, 2002). There are believed to be around 4,000,000 Tanzanians involved in fisheries related activities, in which 98% of the total landings are accounted for by the SSF (Hamidu, 2012). In addition, 30% of the protein consumed by Tanzanian’s is derived from fish (Sobo, 2004). The marine fisheries are concentrated in inshore, shallow waters because much of the fishing occurs on foot or in traditional canoe-type vessels. Catches are chronically under-reported, with estimates nearing 100,000 metric tons/year (~1.7 times higher than reported [Jacquet and Zeller, 2007]), and there are obvious signs of overexploitation (e.g. declining catch rates despite increased effort [Mapunda, 1983], frequent capture of juvenile fishes [Bush et al., 2017; Richmond, Wilson, Mgaya, and Le Vay, 2002]). Furthermore, destructive fishing methods (dynamite and drag nets) have plagued the country for decades, which has led to the destruction of important habitats (Jiddawi and Ohman, 2002).

In 2003, the Tanzanian government established a co-management framework centered around Beach Management Units (BMUs); a form of participatory resource management that involves local fishing communities (Sobo, 2012). The BMUs were established as a result of fisheries in Tanzania showing declining catch rates despite increasing numbers of fisherman, due in part to poor management by the national government. There are currently around 204 BMUs along the coast of Tanzania (Kanyange et al., 2014) and these BMUs are responsible for fisheries data collection, development of management plans, enforcement of management decisions, and fishing-related laws, as well as financing their own activities. BMU data collection involves data enumerators who survey returning fishermen for information about their fishing trip (e.g. number of people involved, gear used, species caught, number and weight of landings). This data can be
of questionable quality for various reasons, including instances of BMU’s using untrained community members as data-enumenators (Sobo, 2012). However, BMU data collection is an improvement over the alternative of no data collection.

1.5. Thesis Goals and Objectives

The present thesis aimed to identify the forms of data and information that local fishery monitoring can record about small-scale marine fisheries in Tanzania, and how that local monitoring data may be related to the spatial socio-ecological context of those fisheries. In chapter 2, my goal was to determine if BMU catch-assessment surveys can provide information on the behavior of small-scale fishing communities in Tanzania. To address that goal, I collected, translated, and analyzed BMU catch assessment surveys from 14 villages across two coastal districts of Tanzania. In chapter 3, I developed a modeling approach that used trends in fishery characteristics based on BMU catch assessment survey data to identify the spatial characteristics of SSF. These models required the combination of taxa landings data from BMUs with data on fishing effort, hydrology, and seascape habitat cover. Using the context of the small-scale coastal fishery in Tanzania, I generated regional models to identify areas with coral-reef associated and estuary-associated fishery characteristics. Overall, the research conducted in this thesis has identified the data and information that small-scale fishing communities in Tanzania are recording, and how that data can be used to improve our understanding of these fisheries.

1.6. References


CHAPTER 2. FISHERY CHARACTERISTICS IN TWO DISTRICTS OF COASTAL TANZANIA

2.1. Introduction

Management of multi-species, multi-gear, small-scale fisheries in tropical latitudes has historically posed significant challenges to scientists and resource managers throughout the globe (Mahon, 1997; Pauly, 1997; Berkes et al., 2001; McClanahan, 2011). These fisheries account for a small proportion of the total global fisheries landings, yet serve as the main protein source and income generating activity for millions of impoverished people living in developing nations (Donner and Potere, 2007; FAO, 2016; Newton et al., 2007). The implementation of traditional fisheries management—which has tended to focus on single species stock assessments—to these small-scale fisheries has proven problematic (Berkes, 2003; Berkes et al., 2001; Cinner et al., 2012). Management measures for small-scale fisheries likely need to account for the socio-economic conditions of fishing communities (McClanahan et al., 2009; Pauly, 1990) while simultaneously developing strategies to collect and analyze data in ecologically complex systems (Matsuda and Abrams, 2006; McClanahan and Mangi, 2004; Pauly et al., 1998).

Small-scale fishers are driven by social, economic, and environmental variability (Kittinger et al., 2013; Leenhardt et al., 2015; Mace, 2014), and management institutions must address the causes of, and potential responses to, their system’s variability to maintain the capacity to adapt (Finkbeiner, 2015; Folke, 2006; Young et al., 2006). In small-scale fisheries, this adaptation capacity is often reliant on individual fisher behavior. Fisher behaviors are...
defined by the decisions that fishers make about when, how, and where they will fish, as well as for what species (Smith and McKelvey, 1986; Hilborn and Walters, 1992b; Kasperski and Holland, 2013). These behaviors are often dependent on which fishery (defined by fishing location, gear-use, vessel-use, and target species) they operate in. Furthermore, individual fisher behavior is aligned along a gradient of specialist (operating in one fishery) to generalist behavior (operating in multiple fisheries) (Smith and McKelvey, 1986; Smith and Hanna, 1993; Salas, Sumaila, and Pitcher, 2004; Finkbeiner, 2015). Specialization generally predominates in systems characterized by low temporal variability in catch, while generalization dominates in systems with high variability in catch. Specialists operate more efficiently in their fishery due to expertise in their use of vessel, gear, and capture of taxon, while generalists are less efficient due to their lack of specific expertise in these areas, but benefit from the ability to switch between fisheries should there be a need (Smith and McKelvey, 1986). Most small-scale fishers are considered generalists because switching between target species is often a common tactic (Salas and Gaertner, 2004). However, managing small-scale fisheries without accounting for local fisher behavior can lead to the formation of systems with limited adaptation capacity.

Marine fisheries in Tanzania are the main source of protein for the coastal communities of nearly 9 million people (Hamidu, 2012), yet these fisheries have shown signs of overexploitation for decades (Berachi, 2003; Hamidu, 2012; Jacquet and Zeller, 2007; Mapunda, 1983). For example, an increase in fishing effort by coastal fishers in Tanzania in the 1980’s had little effect on total catch (Mapunda, 1983), while declines in catches of various commercial species, specifically of reef fishes throughout the coast of Tanzania, were recorded nearly 20 years later (Jacquet and Zeller, 2007). Furthermore, landings of coastal species in Tanzania are chronically under-reported (at least 1.7 times higher than reported) and catch rates appear to only
be maintained by a continual increase in effort (Jacquet and Zeller, 2007) and gear modification, such as the practice of using mosquito nets to seine for small fishes (Bush et al., 2017). Tanzanian marine fisheries are 99% artisanal (Sobo, 2004) and catches are used mainly for subsistence, with only a few species caught intended for commercial sale (Hamidu, 2012).

The main objective of co-management programs is to share resource management responsibility between the government and stakeholder groups, with the goal of promoting and providing more equitable management and governance (Armitage, Berkes, and Doubleday, 2007). Thus in 2003, the Tanzanian government established a community-based co-management program (Beach Management Units—BMUs) for fisheries nationwide (Sobo, 2012). Since the inception of these BMUs, the government, in collaboration with the World Wildlife Fund, has established 204 BMUs along the coast (Kanyange et al., 2014). One of the major purposes of these BMUs is to use local fishers as data enumerators to be responsible for catch-assessment surveys. Catch assessment surveys are used to survey fishery landings throughout the coast (Sobo, 2016). These surveys were designed to estimate total fish production by weight and value, catch per unit effort, and to conduct stock assessments. It is expected that using local fishers at each BMU landing site (i.e. representing villages or within villages) to collect data and return it to centralized (statistics) offices for analysis would allow for more complete coverage of data collection for these fisheries that lack centralized landing ports.

Due to the decentralization of the government and transfer of management duties to local governments in the late 1990's, the local district councils and BMUs themselves are responsible for financing BMUs (Hamidu, 2012; Kanyange et al., 2014). As a result, over 90% of BMUs do not generate enough finances to perform their desired operations, and at least half of them have no strategy to improve this situation. Despite the lack of funds, an apparent dissatisfaction in data
recording, and a perceived decline in fisheries landings, the majority of BMUs have been perceived to be useful by local communities, likely due to local conflict resolution and a feeling of involvement (Kanyange et al., 2014). Current datasets collected by the BMUs have only been analyzed using data from a subset of BMUs in aggregated summary statistics (e.g. total number of fishers, total number of gears used, and total value landed). Furthermore, there are many BMU landing sites that are collecting data that are not being represented in the summary statistics. Without an analysis of the collected data at smaller spatial scales (i.e. district or village), these communities may have little reason to continue collecting data as it will not be seen as useful for the management of their fisheries (Cinner, Wamukota, Randriamahazo, and Rabearisoa, 2009).

The objective of the current study was to determine if BMU catch-assessment surveys can provide information on the behavior of small-scale fishing communities in Tanzania. We first identified what forms of catch-assessment survey data were consistently collected among 14 total villages, across two spatially, socially, economically, and ecologically distinct districts of Tanzania over a three-year period. Second, we compared these data to identify similarities and differences between village fisheries. Finally, we discussed the potential social, economic, and ecological factors which may be driving the observed fishery characteristics.

2.1.1. Study Site

This study focused on villages in two distinct coastal districts of Tanzania, henceforth described by their approximate administrative boundaries as Pangani and Rufiji (Note: villages are the smallest spatial scale, they are nested within districts, which are nested within regions in Tanzania [Figure 2.1]). Pangani is a northern district which covers approximately 1,800 km² and is characterized by an arid climate and many coral reef fringed islands (Samoilys and Kanyange, 2008). It is home to around 55,000 people (TZNBS, 2013), many of whom are highly dependent
on fishing for their livelihoods. Pangani is a district within Tanga region. Tanga region has been historically infamous for dynamite fishing, a practice that has demolished a large fraction of the region’s coral reefs, and in turn resulted in dramatic reductions in fish abundance (Samoilys and Kanyange, 2008; Turque and Casper, 2016). Rufiji is a southern district defined by its large river delta (the largest in East Africa [Caras, 2001]). The Rufiji River Basin covers approximately 177,000 km² and contains the largest mangrove wetland (~53,000 ha) in Eastern Africa (Turpie, 2000). Due to the discharge of freshwater, nutrients, and silt there are few coral reefs off of the delta. The Rufiji delta is the most important prawn producing area in Tanzania (Richmond, Wilson, Mgaya, and Le Vay, 2002). The population of 220,000 people in Rufiji (TZNBS, 2013) is larger than Pangani (55,000) but is also spread over a larger area, resulting in a lower population density (17 people km⁻² in Rufiji compared to 31 people km⁻² in Pangani). The decreased density of the Rufiji population is likely due to the difficulties in developing infrastructure in an area prone to flooding events (Richmond et al., 2002). Similar to Pangani, many of the people in this district are heavily reliant on marine fisheries for their food and livelihoods. The marine fisheries are over-exploited, and almost all fish that are caught appear to be immature or just reaching maturity (Richmond et al., 2002). The over-exploitation may be the result of increasing population size (including many temporary migrants), habitat destruction, and/or the expansion of destructive fishing methods (Richmond et al., 2002).

2.2. Methods

We obtained historical BMU catch-assessment survey records in 2016 and 2017. The records in Rufiji district encompassed the period between 2014–2016 while the records in Pangani district included data from 2016–2017. Villages within districts did not conduct catch-assessment surveys on a regular, continuous basis, and as a result, the dates in which surveys
were conducted varied between villages and districts. Due to the lack of continuous records within and between villages, we cannot determine if surveys from certain time periods are absent, or if they were simply not conducted. As the survey records themselves could not be transported out of country, digital copies were made (see Appendix Figure A.1 for an example) and the original records were returned to the BMU officers. Survey records were then translated from Swahili to English using a combination of online language references and discussions with local fishers and BMU officers (including co-author H. Tilya). All translations were maintained and recorded to assist in future analyses (Appendix Table A.1).

BMU catch-assessment surveys were used to collect data from individual fishing trips. 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 for all analyses is based on individual fishing trips, irrespective of the number of fishers involved. All catch-assessment surveys had approximately the same templates (see Appendix Figure A.1 for an example). Data entry was performed by BMU enumerators and 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). Data were recorded inconsistently, although certain data types were less likely to be recorded than others (e.g. vessel registration).

Although the fisheries described here are opportunistic, we examined fishery-dependent data, collected without the intent to characterize species diversity. Thus, we used the term “taxon” to define each grouping (e.g. Groupers, Prawns, Jacks, etc.) and “fishery richness” to describe the number of groupings, to emphasize the inherent folk taxonomic nature of the data (May, 2005). Local fishers are able to identify the most commonly landed species (Berkes et al.,
2001); however, consistent identification of less common species can be questionable (May, 2005). Additionally, certain Swahili words used to identify species were not able to be matched to any taxonomy; in some cases, species were binned into other taxa groupings as there was no readily apparent distinction between their definitions. The species most commonly landed

![Figure 2.1 Map of Tanzanian coastline (left), Pangani District (upper right), and Rufiji District (lower right). Circles define the location of the major villages in each district, with the color of the circle indicating the number of surveys used in this study. Dark green represents mangrove wetlands, while dark blue lines represent relative river position (not scaled to represent river width as that data was not available).](image-url)
differed between districts, but the majority of taxa identifications were regarded as accurate. Although the use of local groupings can lead to difficulties in drawing ecological conclusions, these taxonomic groups represent species of economic importance to fishers (Obura et al., 2002).

The catch location data, while entered occasionally, referred to a local name for a fishing ground; however, without interviewing fishers to a greater degree we were unable to identify all specific geographic locations. Therefore, location was largely unknown and not included in the analysis. In contrast, catch landed per village was included because given the small-scale nature of the fishers and the vessels that they used, the village was likely relatively close to the location of capture. The monetary value of each trip was entered either by weight or by the total catch per species, depending on the BMU enumerator who recorded the data. We attempted to adjust these values accordingly to set all data in the same format based on our knowledge of approximate prices per kilogram of each species. There is still uncertainty in the value data entry and any conclusion using this data is tentative until further data are obtained in the future.

The FAO guide to Marine and Brackish Species in Tanzania (Blanchi, 1985) contains information on each species in coastal waters. The information includes average and maximum sizes, fishing gears, and macro-habitats where each species is commonly found. These published data were digitized and compared to our BMU taxa groupings, and used here to examine species-habitat relationships. Taxa groupings were explicitly associated to coral reef or estuarine habitats when a larger number of species in each taxa group were reported to use that habitat.

We evaluated the fishery data by single variables first (e.g. location, season, vessel, gear, fishery richness, catch biomass, and catch). Then we paired data to determine associated patterns and trends. Since there is not an operational definition for the differentiation between specialist and generalist fisheries, we defined specialization to be when the majority of fishing trips
(>50%) within a village over the study period used a single vessel, gear, or landed a specific taxon. This definition was generated based on a visual examination of the trends in our data. We used descriptive statistics, *t*-tests, ANOVAs, and the Tukey Honest Significant Difference post-hoc test to analyze single variables and their interactions. All analyses were done in R (R Core Team, 2017).

2.3. Results

2.3.1. Single-Variable Analyses

2.3.1.1. Spatial and Seasonal Data

There were 720 recorded fishing trips across Pangani district representing 8 villages: Kipumbwi, Mkujuni, Msaraza, Pangani Mashariki, Pangani Magharibi, Stahabu, Ushongo, and Ushongo Mtoni. Pangani fishing trips occurred between 2016 and 2017. The total number of trips reported for Rufiji district (479) included 6 villages: Jaja, Kiechuru, Mbwera Mashariki, Mbwera Magharibi, Mbwera, and Pombwe, in the period 2014–2016. Because of the limited data in certain villages, we either pooled the data to increase sample size or the villages were excluded from the analysis. Data were limited and therefore excluded from the following villages in Pangani: Mkujuni, Kipumbwi, Ushongo Mtoni, and Msaraza. While for Rufiji, we excluded Mbwera and Mbwera Magharibi. Pangani Mashariki recorded the largest number of trips in Pangani (*n*=207, 28.8%), followed by Ushongo (*n*=172, 24%), Pangani Magharibi (*n*=164, 22.8%), and Stahabu (*n*=125, 17.4%). These villages recorded similar numbers of fishing trips to one another when compared to the villages in Rufiji. In Rufiji, Kiechuru collected the most data by far (*n*=330, 68.9%), followed by Pombwe (*n*=93, 19.4%) and Mbwera Mashariki (*n*=35, 7.3%).
We observed significant differences in the data collection schedule between districts and villages within districts. Data were collected during different years, seasons, and months between districts (Figure 2.2). There was almost no overlap in the dates of collection between districts. The majority of data in Pangani were collected during the long rain (March through May) and long dry (June through September) seasons, while the majority of data in Rufiji were collected in the long dry and short dry (January through February) seasons. Additionally, data collection showed different patterns in different locations. For example, the majority of data collected in Ushongo were in the long rain season in both 2016 and 2017. Pangani Magharibi fishing trips were evenly split between the long dry and the long rain seasons. Most data were collected in Kiechuru during the long dry season. The variability between months, seasons, and years, both between and within districts precludes the ability to examine temporal trends with any confidence. As a result, additional analyses will generally ignore the effects of time, despite its

**Figure 2.2.** The recorded fishing trips in the eight villages with the most data in Pangani (top 4 panels) and Rufiji (bottom 4 panels) by month, season, and year.
well documented importance on fisheries catch (Beddington and May, 1977; Fulanda et al., 2009; McClanahan, 1988; Winemiller and Jepsen, 1998).

Villages showed different numbers of fishing trips per day. In Pangani district, Pangani Mashariki, Stahabu, and Ushongo recorded one trip per day on most days (>74%), with a lower frequency of two to six trips recorded per day. Pangani Magharibi recorded two, three, and four trips per day more often (55%) than in the other three villages in Pangani district. The only village in Rufiji to record one trip per day most often was Kiechuru (82%). Jaja and Mbwera Mashariki generally recorded two trips per day (41% and 45% respectively), while Pombwe was relatively split between recording one and two trips per day (~45% each).

2.3.1.2. Vessels

Although vessels require registration by law (Sobo, 2004) few were registered (~6%), especially in the Rufiji district (~1%). Seven categories of vessels were described in the BMU survey records (Table 2.1). Vessel type varied by district: canoes were the dominant vessel type (90%) in Rufiji district, while in Pangani district ngalawas (63%) were also used in addition to canoes (18.7%). Although there were six other types of vessels used across the districts, legs was the only other vessel to account for a significant proportion of trips (Rufiji 5.5%; Pangani 8.3%).

Table 2.1. Vessel type and descriptions for all vessels included in the BMU data.

<table>
<thead>
<tr>
<th>Vessel Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Boat</strong></td>
<td>Wooden plank boat, powered by engine</td>
</tr>
<tr>
<td><strong>Canoe</strong></td>
<td>Hollowed out wooden vessel, powered by paddle</td>
</tr>
<tr>
<td><strong>Dhow</strong></td>
<td>Larger wooden boat with angled mast, powered by sail</td>
</tr>
<tr>
<td><strong>Legs</strong></td>
<td>No vessel, walked to fishing grounds</td>
</tr>
<tr>
<td><strong>Mashua</strong></td>
<td>Wooden plank boat, powered by sail or engine</td>
</tr>
<tr>
<td><strong>Ngalawa</strong></td>
<td>Hollowed out wooden vessel with outriggers, powered by sail</td>
</tr>
<tr>
<td><strong>Ngwanda</strong></td>
<td>Wooden plank boat, powered by engine (different keel from Boat)</td>
</tr>
</tbody>
</table>
Fishers specialized in the use of one vessel in both districts. Various types of vessels were used in the villages in Pangani, although Ngalawas made up the largest proportion of trips in every village except Pangani Magharibi. Pangani Mashariki and Ushongo had the highest number of vessel types (4 and 5 respectively), in contrast to Stahabu village where only ngalawas were used. Pangani Magharibi was the only village in Pangani district where canoes were used instead of ngalawas.

Unlike in Pangani district, fishers in Rufiji relied on canoes in all villages. Although Kiechuru and Pombwe used vessels in addition to canoes, canoes were still used in >75% of the trips. The next most common vessel type used was legs. This category included women/children collecting nearshore species or male fishers using nets or spears from the beach.

2.3.1.3. Fishing Gears

There were 16 types of gears included in the BMU survey records (see Appendix Table A.2 for descriptions). The percentage of use varied between district with trips in Rufiji district most frequently using seines, thrown handlines, and handlines (Figure 2.3). Fishers in Pangani district mostly used handlines, spears, and traps. Every village in Pangani was specialized in using one gear (Pangani Mashariki and Magharibi: handlines; Stahabu: traps; Ushongo: spears). In Rufiji district, Kiechuru and Pombwe showed a large diversity in gear types (10 and 5 respectively), without specializing in any one gear as was observed in Pangani district. However, Mbwera Mashariki used only nets and handlines, while Jaja specialized with gillnets.
Figure 2.3. The proportional use of the ten most frequently used gear types within Pangani and Rufiji, Tanzania, 2014–2017. The gears that were not included in this figure accounted for 9.4% of trips in Rufiji and 7.8% of trips in Pangani.

2.3.1.4. Fishery Richness

Fishers reported landing 95 different locally identified (Swahili) fish groups, based on appearance. Because Swahili fish groups are not based on scientific taxonomy, some groups needed to be binned into broad (English) taxonomic groups which resulted in a smaller fishery richness of 61 taxa. The remainder of the analysis will focus on these taxa for ease of interpretation. Pangani district had a greater fisheries richness (50 taxa) than Rufiji district (34 taxa). Within Pangani district, Pangani Mashariki, Pangani Magharibi, and Ushongo fishers landed the greatest number of unique taxa (29, 24, and 20 taxa, respectively). Fishery richness was not directly related to the number of recorded fishing trips, as Pangani Magharibi fishers caught a wider variety of taxa with fewer trips than Ushongo fishers (24 taxa in 164 trips and 20 taxa in 172 trips, respectively). Similarly, Stahabu fishers caught the same number of unique taxa (10) as Ushongo Mtoni fishers yet had far more recorded trips (125 and 17 trips, respectively). In Rufiji district, Kiechuru and Pombwe recorded the same number of taxa (20) despite large
differences in the number of recorded fishing trips (330 and 93, respectively). Prawns, groupers, and crabs were the most commonly caught taxa in Rufiji (Figure 2.4). In Pangani district, octopus, parrotfish, and crabs were the most common. Thus, both districts focused fishing efforts on invertebrates rather than finfish.

A number of villages specialized in landing specific taxa. For example, Msaraza reported mainly crab catches, Stahabu caught mainly parrotfish, and Ushongo and Ushongo Mtoni caught mainly octopus. Fishing efforts in Pangani Mashariki and Magharibi were generalist but caught mostly finfish taxa. Villages in Rufiji were also generalists and no village specialized in the landing of a specific taxon. Despite this, taxa composition varied between every village in Rufiji.

Figure 2.4. The ten most commonly caught taxa in Rufiji and Pangani, Tanzania, 2014–2017.
The primary habitat of landed taxa in Rufiji and Pangani differed (Figure 2.5). Rufiji fishers landed estuary-associated taxa (321 times) more often than coral-associated taxa (254 times). Pangani fishers landed coral-associated taxa (700 times) more often than estuary-associated taxa (218 times).

Figure 2.5. The total number of trips which landed each of the ten most frequently landed taxa in Rufiji and Pangani, Tanzania 2014–2017.
2.3.1.5. Catch Biomass

Villages with the highest number of recorded fishing trips did not always correspond with the largest biomass catch. For instance, Stahabu village had far more recorded trips than Msaraza (152 and 36, respectively) but landed a smaller biomass (1,260 kg landed in Stahabu and 1,803 kg landed in Msaraza). Similarly, in Rufiji district, Pombwe landed a larger biomass (2,151 kg) than Kiechuru (1,862 kg), yet there were fewer trips recorded in Pombwe. One clear case representing the decoupling between the number of trips and total catch (biomass) along the Tanzanian coast was the village of Kiechuru, where the total biomass was lower (1,862 kg) than in three of the villages in the Pangani district: 4,772, 4,4230, and 3,898 kg.

2.3.1.6. Total Catch Value

Similar to the biomass catch pattern, the villages with the largest total fish biomass caught did not necessarily correspond to the largest catch value (1 USD = 2,200 TSHs–2017 value). Pangani Mashariki caught a smaller biomass than both Pangani Magharibi and Ushongo (≤ 530 kg), yet this biomass accounted for a larger total value (≥$219 USD). Another example of this pattern existed between Kiechuru and Pombwe. While the differences between these villages were relatively small, the change in rank-order of villages based on biomass and value of landings showed that value of catch per kilogram resulted in different yield. Additionally, the number of recorded fishing trips in a village did not correspond to total value landed (Figure 2.6). The difference between number of fishing trips, biomass, and value landed describes how trips in certain villages were more valuable (e.g. Pombwe, Pangani Magharibi) than trips in others (e.g. Kiechuru, Pangani Mashariki, Stahabu).
Figure 2.6. The total value of landings by the number of recorded fishing trips in each village within Pangani and Rufiji, Tanzania, 2014–2017.

2.3.1.7. Value per Kilogram

An initial analysis using t-tests of the value per kilogram data showed non-normally distributed data and heteroscedastic residuals, thus, values above the 95% quantile and below the 5% quantile were removed. Because original BMU surveys were recorded by hand, some numbers were difficult to read and potentially had one too many or too few zeros; removal of these potential outliers based on quantile range allowed for the reduction of bias. Values below the 5% quantile were represented by rays and sharks, which generally had particularly low value per kg, while values above the 95% quantile included crabs and lobsters. Crabs and lobsters are valued differentially based on size. For example, a 2 kg crab is worth more than double a 1 kg crab, likely due to the change in the ratio of meat weight to carapace weight. This variability in the assignment of monetary value contributed to the non-normally distributed data, heteroscedastic residuals, and bias towards locations with larger crabs when examining the
relationship between district and villages within district. To account for this bias, invertebrates and finfish were analyzed separately.

The finfish value per kg was higher in Pangani district ($1.50 kg\(^{-1}\)) than in Rufiji district ($1.05 kg\(^{-1}\); see Table 2.2). Only four taxa were more valuable per kilogram in Rufiji than in Pangani: prawns, crabs, variegated emperors, and rays (see Appendix A.3 for value per kg for all taxa). The ANOVA for value per kg also found differences between the villages (Pangani Mashariki, Pangani Magharibi, Stahabu, and Ushongo) within Pangani District (Table 2.2). All village combinations were different from one another except for Pangani Magharibi and Ushongo (Tukey Honest Significant Differences Post-Hoc). Pangani Mashariki had the highest mean (+/- standard deviation) value per kg ($1.90 +/- 0.27 kg\(^{-1}\)), followed by Pangani Magharibi ($1.55 +/- 0.37 kg\(^{-1}\)), Ushongo ($1.43 +/- 0.38 kg\(^{-1}\)), and finally Stahabu ($1.21 +/- 0.16 kg\(^{-1}\)). A similar comparison between finfish in Rufiji could not be completed because landings within villages almost always had the exact same value per kg, therefore, any variability around that median value lead to residual heteroscedasticity. Due to this characteristic we will describe villages in Rufiji district by their median value per kg rather than with the mean. Kiechuru and Jaja median value per kilogram was $0.91 kg\(^{-1}\), while in Mbwera Mashariki and Pombwe the median value was $1.14 kg\(^{-1}\). Only one trip landed prawns in Pangani district (Pangani Magharibi), so comparisons between districts and within Pangani district were not possible. In the case of Rufiji district, only Kiechuru and Pombwe landed prawns on multiple trips and similar to the finfish landings, the prawn value was the exact same value on almost every trip within village (Kiechuru = $2.27 kg\(^{-1}\); Pombwe = $1.15 kg\(^{-1}\)).
2.3.2. Multivariable comparisons

2.3.2.1. Vessels and Taxa

Using the ngalawa, the most common vessel in Pangani, fishers landed 37 different taxa. The majority of trips landed finfish, except in Ushongo where octopus was the most common taxon (44% of trips). The highest proportion of trips using ngalawas in Pangani Mashariki landed emperors (28.5%) and tunas (18%), in Pangani Magharibi jacks (19.6%), and Stahabu mainly caught parrotfish (79%). Ngalawa-based landings in Pangani Mashariki and Magharibi were not dominated by any one particular taxon like in Stahabu or Ushongo.

Canoe use in Pangani Magharibi landed 19 taxa, and included crabs (28.8%) and catfish (24.7%). “Legs” fishers in Pangani Magharibi landed 9 taxa and most of the catch was crabs (42.9%). When using legs or ngwandas, fishers in Ushongo landed few taxa (5 and 3, respectively) and landed octopus on their trips more often than any other taxon (82.1% and 94.1% of trips respectively). Pangani Mashariki and Stahabu villages used ngalawas on most trips, thus landings with other vessels may simply be a function of few reported trips.

Canoe use in Rufiji landed the largest taxa richness of any vessel regardless of village origin. The highest proportion of trips in canoes in Kiechuru landed prawns (28.2%), crabs (22.9%), and groupers (20%). While in Mbwera Mashariki wolf herring (24%), in Pombwe mullets (23.2%), grunts (16.8%), and groupers (20%), and in Jaja rays (32.1%), crabs (21.4%), and queenfish (14.3%) were the dominant taxa. When fishers in Kiechuru used a dhow, their trips only landed 7 taxa, with jacks (28.6%) and sharks (28.6%) caught most often. While on legs they landed 4 unique taxa with most trips catching crabs (60%). The Pombwe village fishers who used boats landed five taxa, where rays were common (38.5% of trips), while on legs they only landed Acetes sp. Fishers in Mbwera Mashariki and Jaja only used canoes.
2.3.2.2. Gear Type and Taxa Composition

The most common gears in Pangani district villages landed a variety of taxa. Handlines used in both Pangani Mashariki and Pangani Magharibi caught different taxa (25 and 19 taxa, respectively), although in Pangani Mashariki the most common landings were tunas (18.4% of trips) and emperors (15.2%), while Pangani Magharibi landed mostly jacks (18.2%) and crabs (17.2%). The use of spears in Ushongo landed 10 taxa, although the dominant taxa was octopus (90.7%), while traps in the Stahabu village landed 9 taxa with parrotfish caught most often (86.5%). Longlines in Pangani Magharibi caught mainly the same species as handlines, although catfish was more common (9.6% to 30.8%). Ringnets in Pangani Mashariki caught 4 taxa, where landings were mostly sardines (76.9%). Shark nets in Ushongo generally landed rays (47.7% of trips) and sharks (16.7%).

Nets and handlines in Mbwera Mashariki landed nearly the same taxa composition (e.g. wolf herring, rays, jacks, and groupers). Divers in Pombwe landed 6 unique taxa; the most common were mullets (55%), grunts (20%), and groupers (20%). When handlines were used in Pombwe, the second most common gear, landings included grunts (19.5%), groupers (17.1%), and variegated emperors (14.6%). Handlines in Kiechuru village caught groupers (64.3%) more frequently than any other taxa, while seines only landed 3 taxa, with most trips landing prawns (96.6%). Longlines used in Kiechuru caught 14 taxa, with groupers caught most often (25.9%), followed by other pelagic and reef associated species, including the critically endangered and extremely rare coelacanth (5.2% of trips). Finally, gillnets in Jaja caught 9 taxa, landing rays and queenfish most often (41.2% and 23.5% of trips respectively).
2.3.2.3. Catch per Unit Effort

Catch per unit effort (CPUE) was defined as the weight landed per trip per fisher. Median CPUE was lower in Rufiji (2.5 kg trip\(^{-1}\)) than in Pangani (6.5 kg trip\(^{-1}\)). The CPUE data between districts was not normally distributed. Removing data above (95%) and below (5%) set quantiles did not contribute to data normalization as performed in the case of the value per kilogram analysis. Thus, CPUE values were logarithmically transformed and compared between districts. When CPUE between districts was compared using a \(t\)-test, a significant difference was identified, with higher CPUE in Pangani than Rufiji (Table 2.2).

Differences in CPUE were present even when examined at the village level within each district. In Pangani district, Pangani Magharibi had the highest median CPUE (9 kg trip\(^{-1}\)), followed by Stahabu (8 kg trip\(^{-1}\)), Ushongo (6.25 kg trip\(^{-1}\)), and Pangani Mashariki (3.75 kg trip\(^{-1}\)). Median CPUE between villages in Rufiji was similar. Jaja showed the highest median CPUE (12.5 kg trip\(^{-1}\)), followed by Pombwe (11.3 kg trip\(^{-1}\)), Mbweru Mashariki (11 kg trip\(^{-1}\)). Kiechuru CPUE was lower than in other villages in Rufiji (1.5 kg trip\(^{-1}\)).

Similar to the \(t\)-test results comparing district differences, the CPUE results within district had heteroscedastic residuals which were dealt with by log-transform. The villages in Pangani, and those in Rufiji were described to yield statistically significant differences from other villages within their respective districts (Table 2.2). All village combinations but Pangani Magharibi and Stahabu in Pangani district were significantly different from one another (adjusted \(p\)-values<0.05). In Rufiji, Kiechuru had a different CPUE than the three other villages (adjusted \(p\)-values<0.05), while all other village comparisons were not significantly different.
2.3.2.4. Taxon Weight

There were significant differences in mean weight for some taxa when compared between Pangani and Rufiji districts (Table 2.2). Because individual fish weight is not provided in BMU surveys, we divided the total weight by the number of fish landed per taxon and report this value as the average fish weight by taxon. Our analysis examined district weight differences for each taxon landed on at least 20 trips in both districts; the data were log-transformed for analysis, although actual mean values are described below. Sharks, rays, grunts, and jacks showed significant weight differences between districts (Table 2.2). While the species landed in each taxa group may differ between districts, sharks were 8.4 kg heavier in Rufiji, rays were 4.4 kg heavier in Pangani, grunts were 3.8 kg heavier in Pangani, and jacks were 2.9 kg heavier in Pangani.

Table 2.2. Model equations, test statistics, and p-values for all t-tests and ANOVAs used throughout the results. Subscripts for t and F statistics represent the degrees of freedom. Significant p-values are shown in bold typeface.

<table>
<thead>
<tr>
<th>Subsection</th>
<th>Model Type</th>
<th>Response</th>
<th>Predictor</th>
<th>Test Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1.7</td>
<td>t-test</td>
<td>Finfish value per kg</td>
<td>District</td>
<td>$t_{919.19} = -27.311$</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.1.7</td>
<td>ANOVA</td>
<td>Finfish value per kg</td>
<td>Pangani Villages</td>
<td>$F_{4,643} = 4343$</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.2.3</td>
<td>t-test</td>
<td>log(CPUE)</td>
<td>District</td>
<td>$t_{768.37} = -10.9$</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.2.3</td>
<td>ANOVA</td>
<td>log(CPUE)</td>
<td>Pangani Villages</td>
<td>$F_{4,604} = 699.8$</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.2.3</td>
<td>ANOVA</td>
<td>log(CPUE)</td>
<td>Rufiji Villages</td>
<td>$F_{4,451}=200.1$</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.2.4</td>
<td>t-test</td>
<td>log(Shark Weight)</td>
<td>District</td>
<td>$t_{35.37} = -2.92$</td>
<td>0.006</td>
</tr>
<tr>
<td>3.2.4</td>
<td>t-test</td>
<td>log(Ray Weight)</td>
<td>District</td>
<td>$t_{78.45} = 3.94$</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.2.4</td>
<td>t-test</td>
<td>log(Grunt Weight)</td>
<td>District</td>
<td>$t_{30.46} = 4.10$</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.2.4</td>
<td>t-test</td>
<td>log(Jack Weight)</td>
<td>District</td>
<td>$t_{71.46} = 5.46$</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.2.4</td>
<td>t-test</td>
<td>log(Grouper Weight)</td>
<td>District</td>
<td>$t_{45.99} = 0.36$</td>
<td>0.717</td>
</tr>
<tr>
<td>3.2.4</td>
<td>t-test</td>
<td>log(Big Barracuda Weight)</td>
<td>District</td>
<td>$t_{47.47} = 1.21$</td>
<td>0.231</td>
</tr>
</tbody>
</table>
2.4. Discussion

2.4.1. Fisher Behavior

This study sought to determine if BMU catch-assessment surveys can provide an understanding of the behavior of small-scale fishing communities in two distinct coastal districts in Tanzania. Village BMU volunteers recorded fishing trips during different time periods, and the village fisheries differed in their diversity of vessels, gears, and taxa landed during those trips. The selected villages ranged from generalist to specialist in vessel-use, gear-use, and taxa landed, but every village was specialized in some measure. Fishery specialization was operationally defined as the use of specific equipment or landing of a specific taxon on at least 50% of recorded fishing trips in a village fishery throughout the study period. The most obvious examples of specialization were observed in two of the villages studied, Ushongo and Stahabu, in the more densely populated Pangani district, in which fishers specialized in vessel-use, gear-use, and taxon landed.

The specialization of both the Ushongo fishery on octopus and the Stahabu fishery on parrotfish were potentially the result of trophic cascades. It has been well documented that fish communities shift towards low trophic levels in response to predation release in overfished environments (Campbell and Pardede, 2006; Clua and Legendre, 2008; Jennings and Polunin, 1996b; Pauly et al., 1998). For instance, overfishing on Kenyan reefs first resulted in declines in carnivorous fishes that were replaced by octopus, and when both were removed, reefs became dominated by herbivorous fishes (e.g. parrotfish [McClanahan et al., 2008]). It appears that Ushongo reefs, which are dominated by octopus, may be at an earlier stage of the trophic cascade when compared with the parrotfish dominated Stahabu reefs, however, since our results are based on fisheries dependent data, these observations are speculative. This shift towards
parrotfish dominance is often accompanied by an increase in coral reef bio-erosion and potential shift to algal dominance (Campbell and Pardede, 2006; Jennings and Polunin, 1996a). It is clear that trophic cascades play a negative role in coral reef health and fisheries landings and further studies should examine whether trophic cascades are truly affecting the reefs studied here.

Village fisheries, like Ushongo and Stahabu, had distinct gear-use and vessel-use patterns which helped define their respective fishers’ behavior. Village fisheries had similar behavior patterns within district. For instance, fishers in Pangani district were more specialized and used vessels able to travel further offshore (e.g. ngalawas and dhows) with a limited number of gears and generally caught larger, reef associated fishes (e.g. emperors, tunas, and jacks). While fishers in Rufiji were more generalized and used vessels which were limited to inshore habitats (e.g. canoes and legs) with a wide range of gears to catch smaller, estuarine associated taxa (e.g. prawns, crabs, and wolf herring). Although gear and vessel-use, as well as taxa-captured, were unique to villages, the similarities within districts describes the importance of the scale of inference for the analysis of these coastal fisheries.

Despite Pangani district fishers showing significant specialization, they landed a larger fishery richness than the generalist fishers in Rufiji. While there are many factors which influence fisheries biodiversity (Rochet, Collie, Jennings, and Hall, 2011; Connolly, Hughes, and Bellwood, 2017) one of the major factors driving the differences seen here is likely the environmental setting (i.e. habitat). Coral reefs, which were more commonly accessible in Pangani, generally have higher fish diversity than estuaries (Dorenbosch et al., 2005; Nagelkerken and Faunce, 2008; Unsworth, Bell, and Smith, 2007). The difference in habitat-based fish diversity along the Tanzanian coast likely causes some of the difference in the diversity of landed taxa between districts. Furthermore, while it is common for reef fishes to use
estuaries as nurseries (Beck et al., 2001; Gajdzik et al., 2014; Kimirei, 2012; Kimirei, Nagelkerken, Mgaya, and Huijbers, 2013) juvenile reef-associated fishes inhabiting estuaries would be small and therefore of less interest for the fishery. Additionally, smaller individuals may be more difficult for fishers to identify than reef-associated adults which could lead to fishers grouping species that are captured in estuaries when they would be uniquely identified at larger sizes.

The ability to travel offshore to reefs and pelagic habitats requires an investment in vessels capable of traveling long distances (e.g. motor boats, dhows, and ngalawas), these investments are often made by “middlemen” who hire poorer or less experienced fishers, or provide loans to purchase or rent vessels and/or gears (Richmond et al., 2002; Fulanda et al., 2009; Wanyonyi, Wamukota, Tuda, et al., 2016). These middlemen may themselves drive the specialization or generalization of fisheries if they impose specific decisions (i.e. for vessel or gear-use) on a majority of fishers who would be unable to fish without loaned equipment (Crona and Bodin, 2010).

Local infrastructure and the transport of resources can also influence fishing behavior. For example, Rufiji has a larger subsistence fishery partially due to the limited infrastructure, which influences price, as middlemen must be paid for export to distant markets (Richmond et al., 2002; Turpie, 2000). In Rufiji, only prawns, crabs, variegated emperors, and rays were of more value per kilogram than in Pangani. This likely drives the generalist behavior that was observed, as fishers will use any resources that they have available to catch any taxa that may feed their communities (McClanahan et al., 2009). In contrast, specialization was observed in Pangani, where increased access to roads and refrigeration (PDC, 2017) provide fishers greater access to vessels, gear, and markets that offer higher prices for targeted fisheries. Furthermore,
the ability of communities in Rufiji to import resources may be particularly diminished during the rainy season when roads are flooded, thereby further increasing the reliance on fisheries for subsistence (Richmond et al., 2002).

Seasonality plays a role in marine fisheries (Dilasser, 2009; McClanahan, 1988; Winemiller and Jepsen, 1998); however, due to the lack of overlap in the fishing trip dates of collection between districts we cannot make any direct inferences on this effect. The monsoon brings about wind velocity and rain patterns that makes travel offshore difficult (Crona, Nyström, Folke, and Jiddawi, 2010; Wanyonyi, Wamukota, Tuda, et al., 2016). For instance, the octopus fishery in Ushongo and parrotfish fishery in Stahabu, both in Pangani district, are known to be seasonal. They supposedly cannot be fished in the Short and Long Wet seasons due to the effects of increased wind and water turbidity on the divers and trap sets (H. Tillya, personal communication). However, due to the lack of balanced temporal data we cannot confirm nor refute this claim. In addition to seasonal trends in wind and turbidity, increased freshwater flow in the Rufiji delta can lead to finfishes being more available for capture (Richmond et al., 2002). Finally, this seasonal variability may also play a role in the difference in fishing effort and landings between the two districts.

2.4.2. Fisheries Management

The villages examined in this study are not included in the subsample of 32 (out of 202) village BMUs used for calculating aggregated national statistics (Sobo, 2016). Current statistical analysis of these villages aggregates the data by vessel, gear, taxa, biomass, and value of trips to describe nationwide fisheries trends. Yet, there are differences in each metric (time, vessel, gear, taxa, and value) by district and by village within district, specifically when comparing specialist and generalist village fisheries. The aggregated values describe fisheries at the national spatial
scale alone and provide the impression of all fisheries being generalist. This form of subsampling and aggregating data from local institutions has been described as having questionable value because it will inherently miss and average local social, economic, and ecological variability (Dietz, Ostrom, and Stern, 2003), and our study provides further evidence of this. Without accounting for regional and local scale analysis of fishery metrics, national statistics will not improve local or regional management strategies and may lead to incorrect conclusions about these small-scale fisheries, especially when such generalizations are drawn from a small, unrepresentative subsample.

Scientifically-based quantitatively driven management in Tanzania is, for the time being, unlikely, yet much of the goal of BMU data collection is to allow just that (McClanahan, Castilla, White, and Defeo, 2009). BMUs catch assessment surveys were created with the goal of conducting stock assessments (Sobo, 2016). One metric that is commonly used in stock assessments for evaluating fish abundance is catch per unit effort (CPUE [Harley et al., 2001; Hilborn and Walters, 1992b]). Despite the well-known issues with CPUE as a sole indicator of fish abundance (specifically over broad geographic scales and for mixed communities) it is a relatively simple first step that can be used for assessing populations (Harley et al., 2001; Maunder et al., 2006). Here, the fishers in the district which maintained a larger human population density and higher fishing pressure, Pangani, yielded a higher CPUE than fishers in Rufiji. This difference presumably describes a higher abundance of fish in Pangani than in Rufiji, which may be the result of specialization and/or habitat context. However, these values of CPUE will undoubtedly vary based on gear, vessel, crew size, time of year, and other factors. A more equal representation of each of these factors (especially season) would be required for meaningful conclusions to be drawn, and as a result, is not possible with the current data.
A second potential use for BMU data may be to monitor the average size of species landed over time or space to identify potential signs of overfishing (Froese, 2004; Graham, Dulvy, and Polunin, 2005; Rochet and Verena, 2003). There were six taxa in our study with enough weight data collected in both Pangani and Rufiji to allow a district comparison. There was a significant difference in mean weight of four taxa (sharks, rays, grunts, and jacks) between districts. This difference in size may simply be the result of a difference in the species that make up the taxa between districts, that the fish in different districts have different size at age (growth), or that unobserved gear differences result in size selectivity (McClanahan and Mangi, 2004). For example, if fishes between districts have the same size at age, but are captured at different ages, we would likely identify a difference in the size of landed taxa. However, these differences may also be driven by fishing pressure.

Sharks were larger in Rufiji, which may be the result of more intense, directed fishing pressure in Pangani (Marshall and Barnes, 1997) having captured the majority of old, large sharks. The intrinsic difficulty involved with exporting fish from Rufiji likely limits any form of targeted fishing for sharks (Richmond et al., 2002). Jacks and grunts were larger in Pangani, which may be the result of capture of adults on coral reefs rather than juveniles in nursery habitat (Nagelkerken et al., 2002; Smith and Parrish, 2002). This size difference may also describe healthier than expected reefs, as serially overfished reefs would presumably have reduced numbers of large, high trophic level species. However, as previously mentioned, these differences in size could be the result of various processes and could be false signals altogether. Similar to CPUE analysis, any effort to describe size differences within a taxon would require higher spatio-temporal resolution data collection to justify the creation of management measures. Finally, weights were examined here rather than lengths (the more common size metric; Froese,
as length was not recorded in catch-assessment surveys. If length could be recorded in addition to what is already recorded, assessments of length frequency may function as a potential indicator of species population/fish community health.

BMU catch assessment surveys have provided a glimpse into the behavior of fishers and the composition of their catch along coastal Tanzania. While the data collected are lacking in various respects, adapting to the limitations of community-based data collection will allow for the implementation of appropriate and achievable fisheries management (McClanahan, 2011). Working with BMU officers to support data collection on a more regular basis, along with a modification of the surveys to include information on fish length and information on whether or not the fish will be used for subsistence or for export, will greatly improve our understanding of the fishery. However, for any of the data collection to be valuable, a system where collected data can be analyzed at regional and/or local scales is necessary. While nationwide analysis can produce overarching shifts in regulations (e.g. banning seines and dynamite fishing) that can create positive change, there are many smaller changes that can be made at the region, district, and village level if fishing behaviors can be identified. Local people want to manage their own resources, and working with them to develop a system where their hard work can benefit their communities should be the ultimate goal.

2.4.3. Limitations

The village fishery specialization noted in this study may simply be an artifact of data-collection procedures. Data collection by BMU officers may result in over-representation of fishers who are more common, friendlier with the officer, or who fish near where the officer collects data. Information gathered through interviews with fishers have been described as unreliable in other systems (Lunn and Dearden, 2006) and as a result, the conclusions drawn here
should be accepted with caution. Additionally, it is possible that defined data-collection procedures are not always followed exactly. While BMU protocol states that BMU officers need to collect data from at least three fishing trips per day (H. Tillya, personal communication), we noted variability in number of trips recorded per day, with many surveys recording fewer than three trips per day. The variability in number of daily recorded trips may be the result of limited BMU funding, the number of BMU officers collecting data, or the local belief in the efficacy of collecting data.

Migrant fishers, both from Tanzania and neighboring countries, are known to follow the monsoon for fishing (Fulanda et al., 2009; Wanyonyi, Wamukota, Mesaki, et al., 2016; Wanyonyi, Wamukota, Tuda, et al., 2016), which may greatly affect seasonal fishing pressure in villages generally used by migrant fishers. In other African country’s fisheries, it has been noted that migrant fishers can make up the majority of fishers (Fulanda et al., 2009; Njock and Westlund, 2010). Migrant fishers differ in their use of vessels and gears from local fishers and may drive a more diverse or specialized fishery than locals as well (Crona et al., 2010; Fulanda et al., 2009; Wanyonyi, Wamukota, Mesaki, et al., 2016; Wanyonyi, Wamukota, Tuda, et al., 2016). Despite the potential influence of migrants on these small-scale fisheries, the BMU data alone does not provide information on which communities are influenced or even if migrant’s trips are recorded by BMU data enumerators. Understanding how these migrations influence fishery statistics is important, and should be accounted for in subsequent data collection.

2.4.4. Conclusions

Our results describe regional and local variation in the fishing behaviors of coastal Tanzanian communities. While we cannot reveal the ratio of specialist to generalist individual fishers within the fisheries, we do describe community fisheries where most fishers are
specialists. The observed generalist and specialist fishing behaviors are driven by the taxa landed, vessel-use, gear-use, population size, infrastructure, season, and local habitats which define the fishing communities. Furthermore, the complete specializations recorded in the Ushongo and Stahabu villages in Pangani district may be the result of trophic cascades and could therefore be ecologically forced rather than chosen strategically by the fishers. Understanding the drivers of local fisher behavior and how these behaviors affect the fishery as a whole is important for managing community economies and local environments over time.

The BMU data examined here have allowed for the first insight into the minutiae of these small-scale fisheries. This study demonstrates that aggregating data on fisheries throughout the coast of Tanzania results in a mischaracterization of the local fishing behavior and as a result, a potential mischaracterization of the necessary management processes needed to allow continued subsistence. Furthermore, our results may indicate ecological trends (e.g. trophic cascades) that have occurred in response to years of overexploitation. Future studies are required to understand the processes behind these trends and how they may be reversed. While community collected data are far from perfect, they have and may continue to allow, for a greater understanding of small-scale fisheries.

2.5. References


Dilasser, Q. (2009). *Is gear-based management of herbivorous fish a viable tool to prevent or*


Stock Assessment (pp. 104–155). London: Chapman and Hall.


CHAPTER 3. PREDICTING COASTAL FISHING COMMUNITY CHARACTERISTICS IN TANZANIA USING LOCAL MONITORING DATA

3.1. Introduction

Fisheries co-management has become increasingly common in recent decades 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, Wamukota, Randriamahazo, and Rabearisoa, 2009; Evans, Cherrett, and Pemsl, 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, Berkes, and Doubleday, 2007). One of the main strengths of co-management is its focus on integrating local and scientific knowledge (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 knowledge between institutions and stakeholders, which can ultimately disrupt the efficacy of management (Nunan, Hara, and Onyango, 2015; Robertson et al., 2018).

Small-scale fisheries are defined by subsistence based fishers who generally use traditional or simple gears, on foot or in small boats (Chuenpagdee, Liguori, Palomares, and Pauly, 2006), and these fisheries often lack 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 (Danielsen, Burgess, and Balmford, 2005). Various co-management programs have begun to use local volunteers to monitor their
fishery resources (Cohen and Steenbergen, 2015; Dobbs et al., 2016; Saunders and Xuereb, 2016) and when performed correctly, local monitoring can be a reliable, cost-effective solution for monitoring fishing activity (e.g. Tanzania and Kenya [Obura, Wells, Church, and Horrill, 2002], Madagascar [Jones, Andriamarovololona, Hockley, Gibbons, and Milner-Gulland, 2008], Philippines [Uychiaoco, Arceo, Green, and Cruz, 2005]). Furthermore, local monitoring can involve different levels of relative involvement of local stakeholders and researchers, depending on the intended goals and 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).

Fisher behavior—i.e. the decisions that fishers make about when, how, and where they will fish—can be monitored and used to inform co-management in small-scale fisheries (Naranjo-Madrigal, Putten, and Norman-lópez, 2015; Thiault et al., 2017). Previous research has established that fisher behavior is particularly important in defining the dynamics and distribution of fishing effort (Hilborn and Walters, 1992; Salas and Gaertner, 2004; Fulton, Smith, Smith, and Putten, 2011). Furthermore, these behaviors are known to be influenced by the geomorphic and socioeconomic settings of the region (Abernethy, Allison, Molloy, and Côté, 2007; Berkes, 2003; Salas and Gaertner, 2004; Salas, Sumaila, and Pitcher, 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, Agostinho, and Gomes, 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. However, tools that incorporate local monitoring data with ecological and socioeconomic data to identify the behavior of small-scale fisheries in developing countries have yet to be developed.

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 managed by a community-based co-management program (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). Using these 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 as a result of the socioeconomic and ecological context in which fishing was occurring. Specifically, 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, while a wide variety of vessels and gears were used to catch many taxa (i.e. generalization) in the Rufiji district, which has a less dense human population inhabiting the largest deltaic system in East Africa. The creation of a conceptual framework where fishery characteristics along the coast can be related to spatial
attributes and mapped will allow for management decisions to be targeted to the appropriate locations.

Here, I propose a flexible modeling approach that uses trends in local monitoring data (i.e. BMU 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), I 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. Overall, I hypothesized that locally recorded landings data of taxa that were associated with coral reef or estuary based fishing characteristics would be related to fisher density, hydrology, and/or seascape habitats.

3.2. Methods
3.2.1. Study Site Description

This study focused on nine villages—5 in the Pangani district and 4 in the Rufiji district of coastal Tanzania (Note: villages are the smallest spatial scale, they are nested within districts, which are nested within regions in Tanzania [Figure 3.1]). Pangani is a northern district that covers approximately 1,800 km² 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 km² and contains the largest mangrove wetland (~53,000 ha) area in Eastern Africa (Turpie, 2000). Due to high river discharge (mean~800 m³s⁻¹ [Duvail and Hamerlynck, 2007]), nutrients, and silt, the majority of
the shelf surrounding the Rufiji delta lacks coral reefs (Richmond, Wilson, Mgaya, and Le Vay, 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 fisheries for their food and livelihoods.

3.2.2. Model Extent

The modeling objective is to identify spatial trends in fish catch by trip based on additive characteristics of coastal attributes, described henceforth as spatial metrics. The models specifically examined the fishery characteristics in the Pangani and Rufiji districts. The extent of the models (Figure 3.1) was based on the location of villages where catch data were available. To include all possible spatial metrics that may affect fishery characteristics, the extent of the models for both regions was set to 50 km to the north, south, and east of the village representing the furthest location in each of those respective cardinal directions for each region. The western boundary in each region was inland and was set 10 km and 25 km west of the westernmost village in Pangani and Rufiji respectively. Rufiji had a larger western boundary since the Rufiji delta extended further inland than the Pangani estuaries. Due to this difference in regional geomorphology, marine dominated fisheries occur further inland in Rufiji than in Pangani. The model resolution (i.e. grain size) was set to 300 m x 300 m. This resolution is larger than the habitat data at 30 m resolution; higher resolutions were not computationally feasible. Because preliminary examinations of the habitat patch characteristics at higher resolutions described relatively small changes in patch size and density with increasing resolution, I am confident that the grain size did not significantly affect model output. To allow for computation in the metric scale, all GIS layers were projected to the EPSG:21037 coordinate system for Arc 1960/UTM
zone 37S, that includes the boundaries for Tanzania, Kenya, Burundi, and Uganda. All analyses were performed in R (R Core Team, 2017).

Figure 3.1. 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).

3.2.3. Landings Data

Species capture data for the villages in the Rufiji and Pangani districts came from BMU catch-assessment survey records (i.e. datasheets). The records in Rufiji district encompassed the
period between 2014–2016, while the Pangani district records were from 2016–2017 (Robertson et al., 2018). Each survey recorded a single fishing trip (n=1160), with the recorded information based on an interview of one of the fishers who took part in the fishing trip. As a result, the unit of inference was based on individual fishing trips. Data entry was performed by BMU enumerators and included a wide variety of information about each fishing trip. 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, Mahon, McConney, Pollnac, and Pomeroy, 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) that each species could be
found in. 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 (Figure 3.2) into groups that matched past research (Robertson et al., 2018) and can therefore be regarded as accurate for the purposes of this study.

3.2.4. Spatial Metrics

Measures of landscape/seascape connectivity are important to evaluate how habitat types and habitat patches are interlinked (Nagelkerken, 2009; Taylor, Fahrig, Henein, and Merriam, 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, I 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 (8 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 (Appendix B). The mangrove forest habitat data was derived from ground verified Landsat-7 ETM+ data created in 2002 for FAO Africover (Wang et al., 2003). While, the seagrass layer was generated by Landsat-8 OLI Sensor data at 30-meter 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-meter resolution (UNEP-WCMC, WorldFish-Centre, WRI, and TNC, 2010).

In addition to considering habitat connectivity, I examined habitat patch size and density. The three metrics for each habitat (distance, area, and density) were compared visually (see Appendix B) 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.

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, Hansen, Jones, and Vincent, 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 area that these buffers covered within each district was used in combination with the estimate of the number of fishers per 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 it may not be valid in all cases. When this variable is incorporated in the model, the fisher density values is 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 >200 m. The majority of fishing

![Graph showing the total number of captures for each taxon in Rufiji and Pangani, Tanzania. The numbers 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).

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.

3.2.5. Model Parameterization

Spatial metric values were extracted at the location of each of the 9 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 (Figure 3.3; Ferrari and Cribari-Neto, 2004). Beta distributions are naturally heteroskedastic, asymmetric (Cribari-Neto, 2009), and therefore flexible enough to accommodate proportional response data. Since, my data included zeros and ones, which are not within the interval associated with the beta distribution (0,1), we transformed the response data by

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

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 (Figure 3.3) was evaluated as the linear predictor for the beta-regressions. For both model types, the response was modeled as

\[ y = \text{Beta}(\alpha, \beta) \]  

(2)

\[ \alpha = \mu \cdot \phi \]  

(3)

\[ \beta = (1 - \mu) \cdot \phi \]  

(4)

where \( \alpha \) and \( \beta \) are the shape parameters that describe the beta distribution, \( \mu \) is the expected value of \( y \) (i.e. \( E(y) \)), and \( \phi \) is the dispersion parameter (Ferrari and Cribari-Neto, 2004). \( \mu \) and \( \phi \) 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 \( y \) (\( \mu \)) was described with a linear predictor

\[ \logit(\mu) = \delta_0 + \delta_1 \cdot x_i \]  

(5)

where \( \delta_0 \) is the intercept, \( \delta_1 \) is the slope, and \( x_i \) is the spatial metric of interest. For logistic-shape relationships, the logit expectation of \( y \) (\( \mu \)) was described with a logistic function

\[ \logit(\mu) = \frac{1}{1 + e^{-\gamma_0 \cdot (x_i - \gamma_1)}} \]  

(6)

where \( \gamma_0 \) is the steepness of the curve, \( \gamma_1 \) 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 $\delta_0$, $\delta_1$, $\gamma_0$, $\gamma_1$, and $\phi$ were all given non-informative normal priors. We ran three Markov chains with each chain beginning with randomly selected values. From a total of 20,000 iterations the first 5,000 iterations of each chain were discarded as burn-in and further thinned by retaining every third value for a total of 5,000 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 Rufiji 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 3.1]) to generate distinct suitability layers (Figure 3.3). 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 3.1) 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 (Figure 3.3), with values within the interval [0,1]. Finally, to ensure that fishing characteristics

Figure 3.3. 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, $\alpha$ and $\beta$, which are modeled with Eqn 3 and Eqn 4, respectively. Both equations rely on the $\mu$ and $\phi$ parameters; $\phi$ is based on the dispersion of the data and is therefore not modeled explicitly, while independent data is used to predict $\mu$. The prediction of $\mu$ 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—one 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.
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 3.2.4.

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).

3.2.6. 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, I 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 (Section 3.2.5). To compare the modeled catch per estuary and coral reef associated taxa to actual recorded catch we extracted all modeled index values within 5 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 3.2.5.

3.3. Results

The beta-regression models described different relationships between each spatial metric and the proportion of coral associated or estuary and mixed-habitat taxa based on 9 villages in the Pangani and Rufiji districts (Table 3.1). The slope and mid-point of all relationships were credibly (95%) different from zero (Table 3.1). Coral associated catch was highest under these criteria: a) mangrove patches within 10 km of the village had an area <3.076 log(km$^2$), b) coral reef patches within 15 km of the village had an area >22.515 km$^2$, c) there were >3 seagrass patches within 10 km of the village that were larger than 0.5 km$^2$, and d) when the hydrologic index values were <0.052. Estuary associated and mixed-habitat taxa catch were highest when: a) mangrove patches within 10 km of the village had an area >4.867 log(km$^2$), b) coral reef patches within 15 km of the village had an area <12.21 km$^2$, c) there were <2 seagrass patches
within 10 km of the village that were larger than 0.5 km², and d) the fisher density was >1.5
fishers km⁻².

The coral fishery model in the Pangani district was high with coral fishery index values
typically >0.6 through most of the coast (Figure 3.4a). However, the coastline near estuaries in
the Pangani district showed lower coral fishery index values (<0.6) than the rest of the coast.
Specifically, the estuary that surrounds Pangani Mashariki and Pangani Magharibi (the two
northernmost villages in Figure 3.4a) had some of the lowest coral index values (<0.2) within the
region. The coral model in Rufiji had low coral fishery index values (<0.4) along the delta region
(Figure 3.4b). To the south of the delta region and in offshore locations, there were areas with
high coral fishery index values (>0.6). The estuary fishery characteristic model in Pangani had
low values (<0.4) throughout the entire coast (Figure 3.4c), while in Rufiji the same model had
high values (>0.6) across the delta area, with the highest values (>0.8) appearing in the northern
half of the delta (Figure 3.4d).

The simplified model output for the Pangani district did not identify any locations along
the coastline with preferred estuary fishing characteristics (Figure 3.5a). Most of the Pangani
district and northern Zanzibar coastlines had coral fishing characteristics, although there are a
few regions lacking these attributes. Specifically, the area near Pangani Mashariki and Pangani
Magharibi (the two northernmost villages in Figure 3.5a) had uncertain fishing characteristics.
The simplified model output for Rufiji district shows areas with coral, estuary, and uncertain
fishery characteristics (Figure 3.5b). Estuary characteristics were present throughout the middle
and higher 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.
Table 3.1. 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 3.2.5).

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

66
Figure 3.4. 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.
Figure 3.5. 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 was used to parameterize the models.

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]). Most of the modeled fishery index values were lower than the actual catch values for the estuary associated taxa. 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 other habitat, the majority of the modeled fishery index values were higher than actual catch values for coral associated taxa.
3.4. Discussion

3.4.1. Spatial Metric Relationships

The modeling approach proposed here uses local monitoring data along with spatial metrics to predict the spatial characteristics of small-scale fisheries. My models show that the capture of coral and estuarine associated fishes was related to the proximity, number, and area of mangrove, coral reef, and seagrass habitat patches in coastal Tanzania. For example, when coral reef patches near villages were larger, and seagrass patches more numerous, fisher trips landed a high proportion of coral reef associated taxa. The relationship between species richness, abundance, and habitat area is a long-recognized ecological phenomenon (Drakare, Lennon, and Hillebrand, 2006) observed on coral reefs (Bohnsack, Harper, Mcclellan, and Hulsbeck, 1994; Chittaro, 2002). Furthermore, coral reef associated fishes have been described to be most abundant and diverse when in close proximity to coral reef and seagrass habitats (Dorenbosch, Grol, Nagelkerken, and Velde, 2005; Dorenbosch, Verberk, Nagelkerken, and Velde, 2007; Grober-Dunsmore, Frazer, Lindber, and Beets, 2007). The association between the two habitats occurs because many coral taxa travel to seagrass patches for feeding and refuge (Saenger, Gartside, and Funge-Smith, 2013), and juvenile coral-associated fishes, specifically, use seagrasses as nursery habitats (Verweij et al., 2008). Similarly, the spatial arrangement of seagrasses in relation to coral reefs can influence the migration between these habitats (Nagelkerken, Bothwell, Nemeth, Pitt, and Velde, 2008). Therefore, the number of seagrass patches may have influenced the capture of coral-associated fishes by increasing the connectivity between the two habitat types.

The model results showed that when mangrove patches near villages were large, fisher trips landed a greater number of estuary associated and mixed-habitat taxa. Mangrove wetlands
are globally recognized as an extensive and dominant vegetation in tropical estuaries (Twilley, Snedaker, Yañez-Arancibia, and Medina, 1996), and this is no different in Tanzania (Muhando and Rumisha, 2008; Wang et al., 2003). These wetlands are often associated with a high abundance of riverine and estuarine fishes and invertebrates (Sasekumar, Chong, Leh, and Cruz, 1992). Additionally, larger mangrove patches have been related to a higher level of primary productivity, which may influence the productivity of fish populations within and in close proximity to mangrove forests (Carrasquilla-Henao and Juanes, 2016). Furthermore, some mangrove habitats are not located within estuaries (Dorenbosch, Grol, Christianen, Nagelkerken, and Van Der Velde, 2005; Nagelkerken, 2007) and are commonly described to be a part of the nearshore habitat continuum along with coral reefs and seagrasses (Mumby, 2006; Unsworth et al., 2009). Mangroves can act as feeding ground, refuge, and nursery habitat for seagrass and coral associated fishes, and because of these ecosystem services, the connectivity between these habitats is likely important (Gajdzik et al., 2014; Igulu et al., 2014; Kimirei, Nagelkerken, Mgaya, and Huijbers, 2013; Laegdsgaard and Johnson, 2001). Therefore, the three habitats are likely interlinked by various species movement and feeding patterns despite the models identifying that estuary associated fishing occurred more frequently in areas near mangroves and far from reefs and seagrasses. The ecological and spatially explicit relationship between the three habitats may have been a driving factor behind fishers landing both mixed-habitat taxa and estuarine associated taxa on the same trip.

A low hydrologic index values resulted in fisher trips landing a greater number of coral associated fishes. Coral reef habitats are known to be strongly influenced by a variety of environmental factors, including temperature, salinity, and turbidity (Kleypas, McManus, and Menez, 1999; Szmant, 2002). Therefore, it is likely that coral reefs near villages in estuarine
areas (i.e. those with high hydrologic index values) would be negatively impacted by the low salinity and increased sediment resuspension, turbidity, and nutrient load, which are associated with estuarine dominated areas. I expected to see a positive relationship between the hydrologic index and the capture of estuarine associated fishes, since they are more likely to be captured in areas in close proximity to rivers, and generally will be affected by estuary size and river discharge (Gillson, 2011; Meynecke, Lee, Duke, and Warnken, 2007). Furthermore, the biotic and abiotic characteristics of estuaries have both been shown to influence fish production (Houde and Rutherford, 1993; Whitfield, 2016). Nonetheless, the models were not able to clearly fit the hydrologic index to estuarine catch data. Probably because the highest hydrologic index values occurred in the Pangani estuary (in Pangani district) due to the high cumulative annual rainfall (~1200 mm yr\(^{-1}\)) in that region. Although the Pangani Magharibi landing site, located within the Pangani estuary, captured a relatively high proportion of estuary associated fishes, the Pangani Mashariki landing site at the mouth of the estuary, did not report similar catch; the lack of estuarine fishes captured in this location, despite the high hydrologic index value, strongly influenced the estuary model output. The reduced capture of coral associated fishes in both Pangani Magharibi and Pangani Mashariki (specifically when compared to Ushongo and Stahabu) was likely what drove the significant effect of the hydrologic index on the coral model output. The future addition of more accurate data describing the influence of freshwater flow throughout the coastline, along with data from a higher number of estuarine associated villages, may allow for a better model fit between the estuarine associated landings and the hydrologic index.

Fisher density was the only socioeconomic metric available for the analysis of coastal Tanzanian fisheries. I found that estuarine associated fishes were caught more often when fisher
density was high. Fisher density can be the highest in areas that lack alternative livelihood options (Allison and Ellis, 2001) since communities with larger numbers of fishers often struggle with poverty, lack of equipment, and funding (Bene, 2003) to travel offshore and fish in pelagic and coral reef habitats without equipment loans from others (Fulanda et al., 2009; Wanyonyi et al., 2016). In addition, market access can influence fishing pressure further affecting fishery characteristics (Brewer et al., 2012; Hutchison et al., 2015). The fisher density metric did not explicitly test this relationship due to a lack of available data. Yet, because of the difference in market access between the Pangani and Rufiji districts in general, this metric may have indirectly tested for the effect of market access. Finally, I acknowledge that the relationship between fisher density and the capture of estuarine associated fishes might have simply been the result of my limited data on fisher density lacking the necessary resolution to enhance the differences between fish landing sites.

The methods used to test for spatial relationships are based on the multi-criteria evaluation (MCE) literature. Modeling with MCE is a common method used in land-use resource allocation (Geneletti, 2004; Malczewski, 2006) and is currently implemented to describe the spatial variability in marine systems in both developed (Borrelle, Buxton, Jones, and Towns, 2015; Wood and Dragicevic, 2007) and developing countries (Hutchison et al., 2015; Thiault et al., 2017). When MCE is evaluated using a Geographical Information System (GIS), spatial attributes (e.g. land cover maps) represent the relative value of different ecosystem patches (Geneletti, 2005). It is common for these models to incorporate fuzzy membership functions to describe the relationship between spatial attributes and the ecosystem or land-use decision making process (Eastman, 2003). Fuzzy membership functions are monotonic functions based on relationships, including uncertainty, that allow for spatial attributes to be normalized to a
common interval (e.g. \([0,1]\) or \([0,256]\)). Thus, we developed an explicit modeling framework (Bayesian beta-regression) for the generation of fuzzy membership-like functions, rather than relying on assumed relationships or expert knowledge (Ehrgott, Figueira, and Greco, 2010; Hutchison et al., 2015). This approach was possible because the models sought to describe trends in fishery characteristics, rather than describing a qualitative suitability or ecosystem service value, two of the most common uses of MCE (e.g. Koschke, Fürst, Frank, and Makeschin, 2012; Wood and Dragicevic, 2007). Once standardized via a fuzzy membership function, MCE methods usually rank the spatial attributes according to their perceived value, weight them based on that value, and aggregate those spatial metrics using one of various combination methods (e.g. Boolean overlay, weighted linear combination, ordered weighted average) to generate maps of the spatial suitability for the selected decision problem (Malczewski, 2000). I adopted the most common way of combining spatial indicators, weighted linear combination, where the summation of spatial indicators allows for compensatory responses between indicators (Jiang and Eastman, 2000; Malczewski, 2006). In effect, while a certain location may have a low value in one spatial indicator, high values in others will still allow for a patch to yield a high ecosystem patch score (Geneletti, 2005); in my case, the fishery index. My proposed method reduces the limitations that some researchers have posed about somewhat arbitrary decisions used in the standardization for weighted linear combination (Drobne and Lisec, 2009), since the fuzzy membership and standardization process used here is quantitative.

### 3.4.2. Model Performance

The models generated maps of the spatial variability of fishing characteristics throughout the Tanzanian coastline. The models for the Pangani district identified the majority of the Pangani coastline to be driven by coral fishing characteristics. 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 showing 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, Muthiga, Kamukuru, and Machano, 1999; Robertson et al., 2018; Samoilys and Kanyange, 2008; Turque and Casper, 2016; Wells, Samoilys, Makoloweka, and Kalombo, 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 (Figure 3.5), one was located around Pangani Mashariki and Pangani Magharibi; two villages located near the Pangani river (one of Tanzania’s nine drainage basins; Komakech, Koppen, Mahoo, and Zaag, 2011). 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 my models described 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. 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, Kuguru, Senkondo, and Ngatunga, 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. The
estuary and mixed-habitat taxa landings used to parametrize the estuary model were related to
estuarine areas. These estuarine areas may promote localized fisheries that are not 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) may have matched the landing sites examined here
(Sobo, 2016). Those 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.

3.4.3. Limitations

The models have several limitations. BMU data, like those used to parameterize the models, 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, and the potential bias of fishers when describing their catch (Robertson et al., 2018). As described in section 3.4.2, the national landings data that were compared to the models across all districts is also of limited accuracy. 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. Furthermore, since the BMU data contains taxa data, rather than species level catch data, the habitat associations are based on aggregated taxa habitat associations as opposed to species level habitat associations, which undoubtedly vary.

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). Other spatial models have incorporated specific habitat types and characteristics (e.g. rugosity, depth, coral type, seagrass species [Guillemot, Deas, and Andre, 2014; Rufener, Kinas, Nóbrega, and Lins Oliveira, 2017]). 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. Future analyses and models would likely benefit from more recent habitat data and further habitat classifications,
as more specific habitat types may significantly affect fish populations and fisher spatial allocation. 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). Finally, the hydrologic index used here was limited by the amount of information available for the coast of Tanzania. Future analyses would benefit from data on river width, depth, discharge, nutrient loading, frequency of flooding, among other geophysical descriptors.

Despite these limitations, my 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 it is therefore likely to exist in similar forms in other data-limited, small scale fisheries. 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.

3.4.4. Application

The models 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, Guillemot, Rocklin, and Chen, 2014; Moreno-Báez, Orr, Cudney-Bueno, and Shaw, 2010; Naranjo-Madrigal et al., 2015;
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). I feel that my 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.

Historically, fisheries management has focused on identifying what 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 developing countries, where access to consistent fishery monitoring data can be problematic (Gillett and Lightfoot, 2001; Jacquet,
Fox, Motta, Ngusaru, and Zeller, 2010; Mills et al., 2011) and enforcement of harvesting regulations can be difficult (Berachi, 2003; Fulton et al., 2011; Kanyange et al., 2014).

Top-down decision making is prevalent in certain co-management institutions, including many in Africa (Hara and Nielsen, 2003). In Tanzania, management decisions are generally made by district councils and by the Ministry of Livestock and Fisheries Development (National Fisheries Policy, 2015), however, the formal link between those two management institutions has been “broken” since 1995 (Sobo, 2016). 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, Hilborn, and Defeo, 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, Mccay, and Wilson, 1998; Wilson, 2003). As such, models like the one developed here, that use local monitoring data and promote an understanding of the local variability in fishery characteristics and how this variability can affect the fishery at larger scales. These observations 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. 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).

3.4.5. 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 such 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 and in turn, focus on explicitly managing what, how, and where fishers operate. Furthermore, the integration of local data into management plans would inherently invoke discussions between 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.

3.5. References


Richmond, M. D., Wilson, J. D. K., Mgaya, Y. D., and Le Vay, L. (2002). An analysis of


CHAPTER 4. GENERAL DISCUSSION

4.1. Summary and Synthesis

The present thesis aimed to identify the forms of data and information that local fishery monitoring can record about small-scale marine fisheries in Tanzania, and how that local monitoring data may be connected to the spatial socio-ecological context of those fisheries. In chapter 2, local monitoring data (BMU catch-assessment surveys) were analyzed to assess whether this form of data collection could provide information on the behavior of small-scale fishing communities in Tanzania. Prior research on the behavior of small-scale fishers has identified that generalist behavior tends to dominate in systems with high catch variability (e.g. tropical small-scale fisheries [Salas and Gaertner, 2004]). However, the BMU data analyzed here identified that village fisheries had unique patterns of vessel-use, gear-use, and taxa landed, and that every village was specialized in some measure. Furthermore, village fisheries had similar patterns of behavior within district, with specialist behavior dominating in Pangani district fisheries and generalist behavior dominating in Rufiji district fisheries; therefore, describing fishing behavior to vary at multiple spatial scales throughout the coast. This spatial variability in fisher behavior was hypothesized to be the result of spatial differences in sociology, economy, and ecology.

In chapter 3, a spatial modeling approach was developed to use trends in fishery characteristics from the BMU data to identify the spatial relationships between small-scale fisheries and their surrounding socio-ecological context. The models described that the capture of coral and estuarine associated fishes were related to the proximity, number, and area of mangrove, coral reef, and seagrass habitat patches, along with the local hydrologic influence and fisher density. Furthermore, the predicted spatial characteristics matched previously reported
fishery characteristics in both districts. The maps developed by our modeling process may also 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. Finally, the flexibility of the framework developed here may allow for it to be used as a tool by researchers who wish to understand the spatial allocation of fishery characteristics in other systems which collect local monitoring data.

Researchers have begun to advocate for the development of local monitoring regimes (Danielsen et al., 2008; Saunders and Xuereb, 2016), and of tools for understanding the spatial allocation of fishing effort (Kavadas et al., 2015; Thiault et al., 2017), however, these approaches are few and far between, especially in data-poor fisheries. The largest barriers to the application of local monitoring are based on concerns over the accuracy and quality of locally collected data (Burton, 2012; Nielsen and Lund, 2012), as well as concerns that monitoring will be too expensive for local communities (financially and/or logistically) to be completed at a scale that will meet scientific goals (Danielsen et al., 2005). These barriers then further drive the notion that more research will be needed before appropriate management can be put in place (Johannes, 1998). The results of this thesis directly address some of these common oppositions to local monitoring. Although BMU data could not be used to examine temporal trends or to specifically identify the population dynamics of harvested species, the data were able to be used to identify differences in how, where, and what types of fishing were occurring throughout the coast.

Historically, management regulations have required more detailed information about fisheries than simply understanding how, where, and what types of fishing are occurring (Hilborn and Walters, 1992; Shepard, 1988), however, a basic understanding of fishery harvest may be particularly useful in small-scale fisheries where the population dynamics approach to
management has proven to be generally ineffective (Berkes, 2003; Mahon, 1997). Furthermore, although the biological data collected by BMUs was limited, it may still provide a mechanism by which qualitative ecosystem shifts can be monitored and thus act as a tool for adaptive management in small-scale fisheries (McClanahan et al., 2011). For example, the potential trophic cascade that was identified in Ushongo and Stahabu in chapter 2, may now receive further research attention to understand the status of the ecosystem, and the particular specialization of these fisheries could be addressed by management to minimize further ecosystem decline.

The success of co-management has been linked to the match between the spatial scale of management and the scale of fishery harvest (Gutierrez et al., 2011; McClanahan et al., 2009). This thesis has described that BMU data is able to identify variability in fisher behavior and how that variability may be accounted for by differences in socio-ecological setting. The ability to match governance to the appropriate context requires a diagnosis of the interactions between the resource system, resource units, users, and the socio-ecological setting in which systems are embedded (Ostrom, 2007). Although past studies have identified that local monitoring may be able to inform management at various scales, the majority of these studies have been on wildlife management rather than fisheries (Danielsen et al., 2008). Our results are therefore one of the first studies to indicate that local monitoring data may be able to be used to understand fisher behavior at various spatial scales.

One of the most appealing aspects of co-management is that it is meant to provide a partnership between the government and stakeholders (Berkes et al., 2001), however, this goal is often not fully realized in developing countries (Nunan et al., 2015). Not only would the use of local monitoring data itself be a form of indirect communication between top-down government
institutions and stakeholders, but it may also lead top-down institutions to better understand why local stakeholder knowledge is important for management. Overall, the recognition of the embedded nature of small-scale fisheries and the promotion of greater local control of management decisions may affect change in the institutional drivers of poverty (Bene, 2003; McClanahan et al., 2009; Ostrom, 2007).

Overall, the research conducted in this thesis has identified the data and information that small-scale fishing communities in Tanzania are recording, and one potential way that the data may be used to improve the understanding of the spatial trends in these fisheries. Our analysis of trip level BMU data is, to our knowledge, the first of its’ kind in Tanzania, despite villages having collected this type of data for more than a decade. Furthermore, our modeling framework is unique in its use of spatial ecological and socio-economic variables to predict fisher behavior, and may be flexible enough to act as a tool for other small-scale fisheries. Although further studies are required to better understand the complex interactions within the Tanzanian marine fishery, this thesis may act as an initial step towards understanding the fisher behavior, landings, and the socio-ecologic setting in which these important fisheries are set.

4.2. References


APPENDIX A. CHAPTER 2 SUPPLEMENTARY MATERIAL

Figure A.1. An example of a BMU datasheet template from Rufiji District
Table A.1. Swahili to English translations of all words encountered in BMU datasheets.

<table>
<thead>
<tr>
<th>Description</th>
<th>Swahili</th>
<th>English</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gear</td>
<td>2x2</td>
<td>2x2 inch mesh net/trap</td>
</tr>
<tr>
<td>Gear</td>
<td>Dmangu</td>
<td>Spear</td>
</tr>
<tr>
<td>Gear</td>
<td>GN2&quot;</td>
<td>2 inch mesh gillnet</td>
</tr>
<tr>
<td>Gear</td>
<td>HL Ndoano</td>
<td>Handline</td>
</tr>
<tr>
<td>Gear</td>
<td>Jarife</td>
<td>Gillnet</td>
</tr>
<tr>
<td>Gear</td>
<td>Kaputi</td>
<td>Longline</td>
</tr>
<tr>
<td>Gear</td>
<td>Kuchimba</td>
<td>Dig</td>
</tr>
<tr>
<td>Gear</td>
<td>Kuchokoa</td>
<td>Hand Collecting</td>
</tr>
<tr>
<td>Gear</td>
<td>Kutanda</td>
<td>Seine</td>
</tr>
<tr>
<td>Gear</td>
<td>Kuzumia</td>
<td>Diving</td>
</tr>
<tr>
<td>Gear</td>
<td>Mangu</td>
<td>Spear</td>
</tr>
<tr>
<td>Gear</td>
<td>Mchokoo</td>
<td>Spear</td>
</tr>
<tr>
<td>Gear</td>
<td>Mshipi</td>
<td>Handline</td>
</tr>
<tr>
<td>Gear</td>
<td>Mshipi Kaputi</td>
<td>Longline</td>
</tr>
<tr>
<td>Gear</td>
<td>Mshipi wa kaa</td>
<td>Crabline</td>
</tr>
<tr>
<td>Gear</td>
<td>Mshipi wa kurusha</td>
<td>Thrown Handline</td>
</tr>
<tr>
<td>Gear</td>
<td>Mtando</td>
<td>Ringnet</td>
</tr>
<tr>
<td>Gear</td>
<td>Nchi 4 play 9</td>
<td>4 inch mesh net</td>
</tr>
<tr>
<td>Gear</td>
<td>Nyavu</td>
<td>Net</td>
</tr>
<tr>
<td>Gear</td>
<td>Nyavu chuchunge</td>
<td>Halfbeak net</td>
</tr>
<tr>
<td>Gear</td>
<td>Nyavu ya kukokota</td>
<td>Seine</td>
</tr>
<tr>
<td>Gear</td>
<td>Nyavu ya kutanda</td>
<td>Prawn Beach Seine</td>
</tr>
<tr>
<td>Gear</td>
<td>SH</td>
<td>Shark Net</td>
</tr>
<tr>
<td>Gear</td>
<td>Sinia Jarife</td>
<td>Shark Net</td>
</tr>
<tr>
<td>Gear</td>
<td>Traps</td>
<td>Madema</td>
</tr>
<tr>
<td>Gear</td>
<td>Umangu</td>
<td>Spear</td>
</tr>
<tr>
<td>Gear</td>
<td>Zurumati</td>
<td>Longline</td>
</tr>
<tr>
<td>Gear</td>
<td>Zurumati Mshipi</td>
<td>Handline and longline</td>
</tr>
<tr>
<td>General</td>
<td>Aina ya chombo</td>
<td>Type of vessel</td>
</tr>
<tr>
<td>General</td>
<td>Aina ya mitego</td>
<td>Type of traps</td>
</tr>
<tr>
<td>General</td>
<td>Aina ya samaki</td>
<td>Kind of fish</td>
</tr>
<tr>
<td>General</td>
<td>Asubuhi</td>
<td>Morning</td>
</tr>
<tr>
<td>General</td>
<td>Bandari</td>
<td>Port/Harbor</td>
</tr>
<tr>
<td>General</td>
<td>Idadi</td>
<td>Number</td>
</tr>
<tr>
<td>General</td>
<td>Idadi ya mitego</td>
<td>Number of traps</td>
</tr>
<tr>
<td>General</td>
<td>Idadi ya wavuvi</td>
<td>Number of fishermen</td>
</tr>
<tr>
<td>--------------------------</td>
<td>--------------------------------</td>
<td>---------------------</td>
</tr>
<tr>
<td>General</td>
<td>Jana</td>
<td>Yesterday</td>
</tr>
<tr>
<td>General</td>
<td>Jioni</td>
<td>Evening</td>
</tr>
<tr>
<td>General</td>
<td>Juzi</td>
<td>The day before yesterday</td>
</tr>
<tr>
<td>General</td>
<td>Kijiji</td>
<td>Village</td>
</tr>
<tr>
<td>General</td>
<td>Kijiji wanakotoka wavuvi</td>
<td>Fisherman village of origin</td>
</tr>
<tr>
<td>General</td>
<td>Kuondoka</td>
<td>Leave</td>
</tr>
<tr>
<td>General</td>
<td>Kurudi</td>
<td>Return</td>
</tr>
<tr>
<td>General</td>
<td>Majuzi</td>
<td>Recently</td>
</tr>
<tr>
<td>General</td>
<td>Mchana</td>
<td>Afternoon</td>
</tr>
<tr>
<td>General</td>
<td>Mitoni</td>
<td>Rivers</td>
</tr>
<tr>
<td>General</td>
<td>Muda wa uvuvi</td>
<td>Duration of fishing</td>
</tr>
<tr>
<td>General</td>
<td>Mwandishi</td>
<td>Writer/Author</td>
</tr>
<tr>
<td>General</td>
<td>Na ya usijili</td>
<td>Registration</td>
</tr>
<tr>
<td>General</td>
<td>Sehemu aliyovua</td>
<td>Fishing Ground</td>
</tr>
<tr>
<td>General</td>
<td>Tarehe</td>
<td>Date</td>
</tr>
<tr>
<td>General</td>
<td>Tathmini ya safari uvuvi</td>
<td>Fishing Trip Evaluation</td>
</tr>
<tr>
<td>General</td>
<td>Thamani</td>
<td>Value</td>
</tr>
<tr>
<td>General</td>
<td>Usiku</td>
<td>Night</td>
</tr>
<tr>
<td>General</td>
<td>Uzito</td>
<td>Weight</td>
</tr>
<tr>
<td>General</td>
<td>Wengineo</td>
<td>Others</td>
</tr>
<tr>
<td>Taxa</td>
<td>Bangra</td>
<td>Yellowtail scad</td>
</tr>
<tr>
<td>Taxa</td>
<td>Chaa</td>
<td>Gerridae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Changu Doa</td>
<td>Thumbprint emperor</td>
</tr>
<tr>
<td>Taxa</td>
<td>Changu njana</td>
<td>Yellow banded emperor</td>
</tr>
<tr>
<td>Taxa</td>
<td>Changu wengineo</td>
<td>Lethrinidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Chazanda</td>
<td>Black Lutjanidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Chewa</td>
<td>Serranidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Chuchunge</td>
<td>Hemiramphidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Dagaa</td>
<td>Sardines</td>
</tr>
<tr>
<td>Taxa</td>
<td>Dagaa Mchele</td>
<td>Commerson's anchovy</td>
</tr>
<tr>
<td>Taxa</td>
<td>Dagaa Saradi</td>
<td>Sardinella neglecta</td>
</tr>
<tr>
<td>Taxa</td>
<td>Dimbwara</td>
<td>Red Snapper</td>
</tr>
<tr>
<td>Taxa</td>
<td>Dome</td>
<td>Cuttlefish</td>
</tr>
<tr>
<td>Taxa</td>
<td>Fuatundu</td>
<td>Humphead/Emperor Red Snapper</td>
</tr>
<tr>
<td>Taxa</td>
<td>Fulusi</td>
<td>Mahi mahi</td>
</tr>
<tr>
<td>Taxa</td>
<td>Hongwe</td>
<td>Catfish</td>
</tr>
<tr>
<td>Taxa</td>
<td>Jodari</td>
<td>Scombridae</td>
</tr>
<tr>
<td>--------------</td>
<td>-----------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>Taxa</td>
<td>Jodari</td>
<td>Tuna</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kaa</td>
<td>Crabs</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kamba</td>
<td>Lobster</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kamba</td>
<td>Prawns</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kamba Dura</td>
<td>Hairy River Prawn</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kambamiti</td>
<td>Tiger Prawn</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kanda</td>
<td>Chirocentridae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kangaja</td>
<td>Acanthuridae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kapungu</td>
<td>Rays</td>
</tr>
<tr>
<td>Taxa</td>
<td>Karamamba</td>
<td>Haemulidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kelea</td>
<td>Bluestripe/Blackspot Snapper</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kipepeo</td>
<td>Platacidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kisukuku</td>
<td>Coelacanth</td>
</tr>
<tr>
<td>Taxa</td>
<td>Koana</td>
<td>Squirrelfish</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kolekole</td>
<td>Carangidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Kungu</td>
<td>Lutjanidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mahongwe</td>
<td>Catfish</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mbarata</td>
<td>Shad</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mbasi</td>
<td>Swordfish</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mbiliwili</td>
<td>Platyecephalidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mishe</td>
<td>Tylosurus crocodilis</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mkizi</td>
<td>Mullets</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mkundaji</td>
<td>Mulidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mnendele</td>
<td>Chirocentridae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Msusa</td>
<td>Small Barracuda</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mzia</td>
<td>Big Barracuda</td>
</tr>
<tr>
<td>Taxa</td>
<td>Mzia wengineo</td>
<td>Barracuda</td>
</tr>
<tr>
<td>Taxa</td>
<td>Ndadi</td>
<td>Chanidae</td>
</tr>
<tr>
<td>Taxa</td>
<td>Ndamachacho</td>
<td>Lutjanus gibbus</td>
</tr>
<tr>
<td>Taxa</td>
<td>Ndoro</td>
<td>Barracuda</td>
</tr>
<tr>
<td>Taxa</td>
<td>Ndwaro</td>
<td>Swordfish</td>
</tr>
<tr>
<td>Taxa</td>
<td>Ngisi</td>
<td>Uroteuthis duvauceli</td>
</tr>
<tr>
<td>Taxa</td>
<td>Ngisi</td>
<td>Squid</td>
</tr>
<tr>
<td>Taxa</td>
<td>Nguru</td>
<td>Wahoo</td>
</tr>
<tr>
<td>Taxa</td>
<td>Nguru Kanadi</td>
<td>Kanadi Kingfish</td>
</tr>
<tr>
<td>Taxa</td>
<td>Nyamvi</td>
<td>Variegated emperor</td>
</tr>
<tr>
<td>Taxa</td>
<td>Taxa</td>
<td>Taxa</td>
</tr>
<tr>
<td>--------------</td>
<td>--------------</td>
<td>--------------</td>
</tr>
<tr>
<td></td>
<td>Pandu</td>
<td>Queenfish</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vessels</td>
<td>Boti</td>
<td>Plank boat</td>
</tr>
<tr>
<td></td>
<td></td>
<td>with outboard</td>
</tr>
<tr>
<td></td>
<td></td>
<td>engine</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

102
Table A.2. Gear names and descriptions for all vessels recorded in the BMU data.

<table>
<thead>
<tr>
<th>Gear Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crabline</td>
<td>Handline but specifically for crab</td>
</tr>
<tr>
<td>Dig</td>
<td>Digging with hands or a toll, generally for crabs</td>
</tr>
<tr>
<td>Diving</td>
<td>Fishers dive and collect fish</td>
</tr>
<tr>
<td>Gillnet</td>
<td>Passive net that is left underwater</td>
</tr>
<tr>
<td>Halfbeak net</td>
<td>A form of gillnet with mesh for small taxa</td>
</tr>
<tr>
<td>Hand and Longline</td>
<td>Some combination of handlines and longlines</td>
</tr>
<tr>
<td>Handline</td>
<td>Fishing line with baited hook</td>
</tr>
<tr>
<td>Longline</td>
<td>Long fishing line which fishes passively underwater with baited hooks</td>
</tr>
<tr>
<td>Net</td>
<td>Similar to gillnet but is somehow different</td>
</tr>
<tr>
<td>Prawn seine</td>
<td>Seine with small mesh for prawns</td>
</tr>
<tr>
<td>Ringnet</td>
<td>Similar to a purse seine</td>
</tr>
<tr>
<td>Seine</td>
<td>Large net that requires active fishing</td>
</tr>
<tr>
<td>Shark net</td>
<td>Gillnet with large mesh for larger taxa</td>
</tr>
<tr>
<td>Spear</td>
<td>Wooden pole with pronged metal tip</td>
</tr>
<tr>
<td>Thrown handline</td>
<td>Similar to handline, perhaps similar to rod and reel. Unknown exactly</td>
</tr>
<tr>
<td>Traps</td>
<td>Basket baited traps</td>
</tr>
</tbody>
</table>
Table A.3. Mean +/- standard deviation of taxa value (USD) per kilogram in Pangani and Rufiji, Tanzania, 2014-2017. When no standard deviation is provided next to the mean, it denotes that all recorded values were equal.

<table>
<thead>
<tr>
<th>Species</th>
<th>Pangani Mean +/- SD</th>
<th>Rufiji Mean +/- SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acanthuridae</td>
<td>1.06 +/- 0.30</td>
<td>0.95 +/- 0.30</td>
</tr>
<tr>
<td>Acetes spp</td>
<td>NA</td>
<td>0.45</td>
</tr>
<tr>
<td>Barracuda</td>
<td>1.25 +/- 0.16</td>
<td>0.99 +/- 0.18</td>
</tr>
<tr>
<td>Big Barracudas</td>
<td>1.74 +/- 0.21</td>
<td>NA</td>
</tr>
<tr>
<td>Black Lutjanidae</td>
<td>1.79 +/- 0.11</td>
<td>NA</td>
</tr>
<tr>
<td>Bluestripe/Blackspot Snapper</td>
<td>NA</td>
<td>1.14</td>
</tr>
<tr>
<td>Carangidae</td>
<td>1.75 +/- 0.21</td>
<td>1.08 +/- 0.35</td>
</tr>
<tr>
<td>Catfish</td>
<td>0.90 +/- 0.11</td>
<td>0.45</td>
</tr>
<tr>
<td>Chije</td>
<td>1.48 +/- 0.48</td>
<td>NA</td>
</tr>
<tr>
<td>Chirocentridae</td>
<td>1.59</td>
<td>1.11 +/- 0.09</td>
</tr>
<tr>
<td>Coelacanth</td>
<td>NA</td>
<td>1.44 +/- 1.30</td>
</tr>
<tr>
<td>Crabs</td>
<td>1.61 +/- 0.41</td>
<td>2.47 +/- 1.09</td>
</tr>
<tr>
<td>Cuttlefish</td>
<td>1.52 +/- 0.13</td>
<td>NA</td>
</tr>
<tr>
<td>Gerridae</td>
<td>1.75 +/- 0.25</td>
<td>0.94 +/- 0.05</td>
</tr>
<tr>
<td>Haemulidae</td>
<td>1.66 +/- 0.19</td>
<td>1.14</td>
</tr>
<tr>
<td>Hemiramphidae</td>
<td>1.36</td>
<td>NA</td>
</tr>
<tr>
<td>Herija</td>
<td>1.82</td>
<td>NA</td>
</tr>
<tr>
<td>Humphead/Emperor Red Snapper</td>
<td>NA</td>
<td>1.14</td>
</tr>
<tr>
<td>Kanadi Kingfish</td>
<td>1.89 +/- 0.13</td>
<td>NA</td>
</tr>
<tr>
<td>Lethrinidae</td>
<td>1.89 +/- 0.14</td>
<td>1.14</td>
</tr>
<tr>
<td>Lobster</td>
<td>15.47 +/- 5.35</td>
<td>NA</td>
</tr>
<tr>
<td>Lutjanidae</td>
<td>NA</td>
<td>0.95 +/- 0.09</td>
</tr>
<tr>
<td>Mackerel</td>
<td>1.67 +/- 0.13</td>
<td>1.09 +/- 0.19</td>
</tr>
<tr>
<td>Mahi mahi</td>
<td>1.59</td>
<td>NA</td>
</tr>
<tr>
<td>Mulidae</td>
<td>1.46 +/- 0.29</td>
<td>NA</td>
</tr>
<tr>
<td>Mullets</td>
<td>1.82</td>
<td>1.13 +/- 0.04</td>
</tr>
<tr>
<td>Mwekupe</td>
<td>1.36</td>
<td>NA</td>
</tr>
<tr>
<td>Octopus</td>
<td>1.77 +/- 0.20</td>
<td>NA</td>
</tr>
<tr>
<td>Parata</td>
<td>1.82</td>
<td>NA</td>
</tr>
<tr>
<td>Platacidae</td>
<td>NA</td>
<td>1.14</td>
</tr>
<tr>
<td>Platypcephalidae</td>
<td>NA</td>
<td>0.45</td>
</tr>
<tr>
<td>Species</td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>------------------------------</td>
<td>------</td>
<td>--------------------</td>
</tr>
<tr>
<td>Prawns</td>
<td>2.16 +/- 1.59</td>
<td>2.29 +/- 0.40</td>
</tr>
<tr>
<td>Queenfish</td>
<td>1.14</td>
<td>0.89 +/- 0.26</td>
</tr>
<tr>
<td>Rays</td>
<td>0.74 +/- 0.38</td>
<td>0.91 +/- 0.35</td>
</tr>
<tr>
<td>Red Snapper</td>
<td>5.28 +/- 7.08</td>
<td>NA</td>
</tr>
<tr>
<td>Sardines</td>
<td>4.32 +/- 2.24</td>
<td>0.45</td>
</tr>
<tr>
<td>Scaridae</td>
<td>1.16 +/- 0.14</td>
<td>1.14</td>
</tr>
<tr>
<td>Scombridae</td>
<td>1.93 +/- 0.12</td>
<td>NA</td>
</tr>
<tr>
<td>Serranidae</td>
<td>1.55 +/- 0.23</td>
<td>1.05 +/- 0.21</td>
</tr>
<tr>
<td>Shad</td>
<td>NA</td>
<td>1.14</td>
</tr>
<tr>
<td>Sharks</td>
<td>1.48 +/- 0.63</td>
<td>0.84 +/- 0.37</td>
</tr>
<tr>
<td>Siganidae</td>
<td>1.62 +/- 0.40</td>
<td>NA</td>
</tr>
<tr>
<td>Small Barracuda</td>
<td>1.52 +/- 0.26</td>
<td>NA</td>
</tr>
<tr>
<td>Squids</td>
<td>1.59</td>
<td>NA</td>
</tr>
<tr>
<td>Squirrelfish</td>
<td>1.73 +/- 0.20</td>
<td>NA</td>
</tr>
<tr>
<td>Swordfish</td>
<td>1.82</td>
<td>1.14</td>
</tr>
<tr>
<td>Thumbprint Emperor</td>
<td>1.69 +/- 0.16</td>
<td>1.02 +/- 0.23</td>
</tr>
<tr>
<td>Tiger Prawn</td>
<td>NA</td>
<td>2.36 +/- 0.56</td>
</tr>
<tr>
<td>Tuna</td>
<td>2.21 +/- 0.23</td>
<td>NA</td>
</tr>
<tr>
<td>Tylosaurus crocodilis</td>
<td>1.36</td>
<td>NA</td>
</tr>
<tr>
<td>Uroteuthis duvauceli</td>
<td>3.19 +/- 4.96</td>
<td>NA</td>
</tr>
<tr>
<td>Variegated Emperor</td>
<td>1.59</td>
<td>1.75 +/- 1.63</td>
</tr>
<tr>
<td>Wahoo</td>
<td>1.79 +/- 0.41</td>
<td>1.09 +/- 0.19</td>
</tr>
<tr>
<td>Wayo</td>
<td>0.91</td>
<td>NA</td>
</tr>
<tr>
<td>Yellow Banded Emperor</td>
<td>1.71 +/- 0.18</td>
<td>1.14</td>
</tr>
<tr>
<td>Yellowtail Scad</td>
<td>1.82</td>
<td>NA</td>
</tr>
</tbody>
</table>
Figure B.1. The distance (km) and area (km\(^2\)) of every mangrove patch in Pangani district from the six villages with catch data.

Figure B.2. The distance (km) and area (km\(^2\)) of every mangrove patch in Rufiji district from the four villages with catch data.
Figure B.3. The distance (km) and area (km$^2$) of every coral reef patch in Pangani district from the six villages of with catch data.

Figure B.4. The distance (km) and area (km$^2$) of every coral reef patch in Rufiji district from the four villages with catch data.
Figure B.5. The distance (km) and area (km$^2$) of every seagrass patch in Pangani district from the six villages with catch data.

Figure B.6. The distance (km) and area (km$^2$) of every mangrove patch in Rufiji district from the four villages with catch data.
APPENDIX C. COPYRIGHT INFORMATION

Rights & Access

Elsevier Ltd

Article: Fishery characteristics in two districts of coastal Tanzania
Corresponding author: Mr M.D. Robertson
E-mail address: mrob122@lsu.edu
Journal: Ocean and Coastal Management
Our reference: OCMA4543
PII: S0964-5691(18)30234-5
DOI: 10.1016/j.ocecoaman.2018.06.015

Your Status

- I am one author signing on behalf of all co-authors of the manuscript

Assignment of Copyright

I hereby assign to Elsevier Ltd the copyright in the manuscript identified above (where Crown Copyright is asserted, authors agree to grant an exclusive publishing and distribution license) and any tables, illustrations or other material submitted for publication as part of the manuscript (the "Article"). This assignment of rights means that I have granted to Elsevier Ltd, the exclusive right to publish and reproduce the Article, or any part of the Article, in print, electronic and all other media (whether now known or later developed), in any form, in all languages, throughout the world, for the full term of copyright, and the right to license others to do the same, effective when the Article is accepted for publication. This includes the right to enforce the rights granted hereunder against third parties.

Supplemental Materials

"Supplemental Materials" shall mean materials published as a supplemental part of the Article, including but not limited to graphical, illustrative, video and audio material.

With respect to any Supplemental Materials that I submit, Elsevier Ltd shall have a perpetual worldwide, non-exclusive right and license to publish, extract, reformat, adapt, build upon, index, redistribute, link to and otherwise use all or any part of the Supplemental Materials in all forms and media (whether now known or later developed), and to permit others to do so.

Research Data

"Research Data" shall mean the result of observations or experimentation that validate research findings and that are published separate to the Article, which can include but are not limited to raw data, processed data, software, algorithms, protocols, and methods.

With respect to any Research Data that I wish to make accessible on a site or through a service of Elsevier Ltd, Elsevier Ltd shall have a perpetual worldwide, non-exclusive right and license to publish, extract, reformat, adapt, build upon, index, redistribute, link to and otherwise use all or any part of the Research Data in all forms and media (whether now known or later developed) and to permit others to do so. Where I have selected a specific end user license under which the Research Data is to be made available on a site or through a service, the publisher shall apply that end user license to the Research Data on that site or service.
Reversion of rights

Articles may sometimes be accepted for publication but later rejected in the publication process, even in some cases after public posting in "Articles in Press" form, in which case all rights will revert to the author (see

Revisions and Addenda

I understand that no revisions, additional terms or addenda to this Journal Publishing Agreement can be accepted without Elsevier Ltd’s express written consent. I understand that this Journal Publishing Agreement supersedes any previous agreements I have entered into with Elsevier Ltd in relation to the Article from the date hereof.

Author Rights for Scholarly Purposes

I understand that I retain or am hereby granted (without the need to obtain further permission) the Author Rights (see description below), and that no rights in patents, trademarks or other intellectual property rights are transferred to Elsevier Ltd.

The Author Rights include the right to use the Preprint, Accepted Manuscript and the Published Journal Article for Personal Use and Internal Institutional Use. They also include the right to use these different versions of the Article for Scholarly Sharing purposes, which include sharing:

- the Preprint on any website or repository at any time;
- the Accepted Manuscript on certain websites and usually after an embargo period;
- the Published Journal Article only privately on certain websites, unless otherwise agreed by Elsevier Ltd.

In the case of the Accepted Manuscript and the Published Journal Article the Author Rights exclude Commercial Use (unless expressly agreed in writing by Elsevier Ltd), other than use by the author in a subsequent compilation of the author’s works or to extend the Article to book length form or re-use by the author of portions or excerpts in other works (with full acknowledgment of the original publication of the Article).

Author Representations / Ethics and Disclosure / Sanctions

Author representations

- The Article I have submitted to the journal for review is original, has been written by the stated authors and has not been previously published.
- The Article was not submitted for review to another journal while under review by this journal and will not be submitted to any other journal.
- The Article and the Supplemental Materials do not infringe any copyright, violate any other intellectual property, privacy or other rights of any person or entity, or contain any libellous or other unlawful matter.
- I have obtained written permission from copyright owners for any excerpts from copyrighted works that are included and have credited the sources in the Article or the Supplemental Materials.
- Except as expressly set out in this Journal Publishing Agreement, the Article is not subject to any prior rights or licenses and, if my or any of my co-authors institution has a policy that might restrict my ability to grant the rights required by this Journal Publishing Agreement (taking into account the Author Rights permitted hereunder, including Internal Institutional Use), a written waiver of that policy has been obtained.
- If I and/or any of my co-authors reside in Iran, Cuba, Sudan, Burma, Syria, or Crimea, the Article has been prepared in a personal, academic or research capacity and not as an official representative or otherwise on behalf of the relevant government or institution.
- Any software contained in the Supplemental Materials is free from viruses, contaminants or worms.
• If the Article or any of the Supplemental Materials were prepared jointly with other authors, I have informed the co-author(s) of the terms of this Journal Publishing Agreement and that I am signing on their behalf as their agent, and I am authorized to do so.

**Governing Law and Jurisdiction**

This Agreement will be governed by and construed in accordance with the laws of the country or state of Elsevier Ltd ("the Governing State"), without regard to conflict of law principles, and the parties irrevocably consent to the exclusive jurisdiction of the courts of the Governing State.

For more information about the definitions relating to this agreement click here.

☑ I have read and agree to the terms of the Journal Publishing Agreement.

5th July 2018

T-copyright-v22/2017
Matthew David Robertson was born in Concord, New Hampshire in 1994. He grew up in Deerfield, New Hampshire and Brighton, Michigan, and graduated from Winnacunnet High School in Hampton, New Hampshire in 2012. He attended Dalhousie University in Halifax, Nova Scotia, and graduated with a Bachelor of Science with Honours in Marine Biology in 2016. He began his studies at Louisiana State University in 2016 in pursuit of a Master of Science degree in Oceanography and Coastal Sciences under the supervision of Dr. Stephen Midway. Upon completion of his master’s degree, he will begin his PhD in Fisheries Science at the Fisheries and Marine Institute of Memorial University in St. John’s, Newfoundland.