Identifying Spatial Distribution of Fishing Effort of Artisanal Fishers in Coastal Kenya

MSc. Social Ecological Resilience for Sustainable Development (SERSD)

Stockholm Resilience Centre
Stockholm University

Roweena Patel
ABSTRACT

Coastal ecosystems such as coral reefs are under threat from multiple stressors, which include overfishing, pollution, and climate change. These ecosystems provide services to society for example fisheries provide income and a source of food. The disruption of marine ecosystems has diminished the services available. Marine Spatial Planning is a strategy used to couple social, cultural, economic, and political aspects that overlay biophysical attributes of ecosystems, to help resolve potential stakeholder conflicts. Marine protected areas (MPAs) are used to prevent overexploitation and reduce degradation of the marine ecosystems and their services. However with inadequate information MPA placement can be wide of the mark, reducing the resilience and sustainability of the system. Designating MPAs is especially important for artisanal fishers who fish as a source of livelihood. This study develops a method to identify spatial distribution of fishing effort of artisanal fishers, by comparing métiers (gear and vessel combination) at five locations off the coast of Kenya. K-means clustering algorithm was used to segment GPS fishing tracks into different behaviours e.g. travelling and fishing, by using speed and turning angle (change in heading). Once clusters that indicate travelling were identified a heat map was created with the proportion of time spent in each cell. Subsequently Spearman’s rank correlation coefficient was undertaken between unfiltered and filtered data, and between métiers. The results indicated there was a difference, but all showed a positive correlation (0.47 to 0.93). Filtered inter-métier analyses produced negative correlations suggesting that all métiers are spatially segregated. This information is useful for many platforms and scales, and will provide a pathway to couple social and ecological systems together to ensure a resilient and sustainable future.

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1. INTRODUCTION

1.1 The Problem Statement

Coastal ecosystems, such as coral reefs, mangroves, sea grasses, and salt marshes are under threat from multiple stressors such as overfishing, pollution, and climate change (Halpern et al. 2012; Selim et al. 2014). This has led to changes in both bottom up and top down effects within marine ecosystems. From the collapses of fisheries to eutrophication, these stressors are affecting structures of marine food webs. Coastal ecosystems provide services, which are beneficial for society (ecosystem services), for example fisheries provide income and a source of food. These services are linked to ecosystem functioning and process (Solan et al. 2012), which means that different ecosystem services rely on different aspects of the ecosystem.

Disrupting marine ecosystems diminishes the services available (Levin & Lubchenco 2008). In order to sustain safe seafood, stable fisheries, and abundant wildlife, priority must be given to protecting and restoring marine social- ecological systems (Levin & Lubchenco 2008). Current marine management schemes are implemented by sector, which leads to mismatches in spatial and temporal governance (Crowder et al. 2006).

Marine Spatial Planning (MSP) is one of the strategies used to implement Ecosystem Based Management (EBM) by coupling the social, cultural, economic, and political aspects that overlay biophysical attributes of an ecosystem (Crowder & Norse, 2008). Looking at these sectors together can help resolve potential conflicts associated with zoning in coastal ecosystems. MSP is also a way of improving decision-making and delivering an ecosystem based approach to human activities in the marine environment. Mumby et al. (2004) found that mangrove habitats can enhance the biomass of coral reef fish as mangroves can provide an intermediate nursery habitat for the young fish. Therefore it is important that management schemes, EBM and MSP also protect the connectivity of habitats, biodiversity, and natural resource degradation. The focus of MSP is to balance the social, ecological and economic interests of the marine environment (Tuda et al. 2014). Designating marine protected
areas (MPAs) in optimal locations is key to the sustainability and resilience of the coral reef ecosystems (Mumby et al. 2004)

UNESCO produced a guide to MSP: ‘Marine Spatial Planning: A Step-by-Step Approach toward Ecosystem Based Management’ (Ehler & Douvere 2009). This guides aims to maintain the biodiversity whilst still allowing sustainable use of the oceans. Defining and Analysing Existing Conditions is step five in the guide to MSP. Step five states the importance of gathering information on the current state of coastal and marine environment. This section is split into three categories. One of the categories described for implementing MSP is the requirement of spatial information about human activities (pg. 55). MSP has the potential to become an important means to reduce the problems associated with single species management, decision-making and gaps between ecological and jurisdictional boundaries. A key to success in MSP is designing governance and management schemes that align stakeholders with the objective of the management scheme (Crowder & Norse 2008).

The advancement of technology such as global positioning systems (GPS) has provided visibility on what had previously been inaccessible or unknown. There is increasing documentation on marine habitats, environmental conditions, and species range and interaction aiding marine resource management. However, the scope of information collected falls short in mapping and understanding human spatial activities (Step five: category two of Ehler & Douvere, 2009) (Martin & Hall-Arber 2008).

1.2 Aim of Thesis

This project aims to contribute to category two of step five of Ehler & Douvere (2009) by providing information on the spatial distribution of fishing effort of artisanal on the coast of Kenya. This information will aid management and policy in the implementation of MPAs and help reduce stakeholder conflict. The project also aims to develop methods and analyse data from GPS tracks of artisanal fishers.
1.3 Research Questions

General Research Question

What are the estimated fishing locations of artisanal fishers of coastal Kenya?

Specified Research Questions

1. Can GPS data be partitioned into different behaviours?
   a. If so, can estimated fishing locations be identified?
2. What are the practical challenges involved in the use of this kind of data?
3. What is the relationship between the estimated fishing locations of different métiers?
2. THEORETICAL AND CONCEPTUAL FRAMEWORK

2.1 Fisheries as Complex Adaptive Social-Ecological Systems

Coastal ecosystems are of great importance as they provide ecosystem services such as food, tourism, and water quality. Large disturbances would affect both natural and socioeconomic systems. These systems combined are known as social-ecological systems (SES). Both these systems are complex, and have the potential to undergo slow and rapid changes by exogenous and endogenous influences, causing regime shifts (Levin & Lubchenco 2008). The entire system can then be thought of as a complex adaptive system (CAS), where microscopic changes can influence and shape macroscopic system dynamics to feedback and influence the microscopic scale (Levin 1998; Levin 2003; Levin & Lubchenco 2008). In the case of fisheries, there is a ‘fish chain’ which extends from the resource base to the supporting ecosystem, harvesting, distribution to the consumer, and the direct and indirect effects on the marketplace, whether this is local or global (Mahon et al. 2008). The focus will be on the complexity of a system rather than the adaptation.

Traditionally fisheries management has implemented a ‘top down’ approach by governmental bodies due to external pressures. The complexity of fisheries can be placed onto a continuum (Figure 1) with two major types of fishery systems: large-scale fisheries and small-scale fisheries. Small-scale fisheries are seen as more complex due to the variety of stakeholders involved and the multi-species resource base. Shared values and principles are required when regulating small-scale fisheries to avoid conflict; regulation may emerge by self-organisation of stakeholders. Due to the complexity of small-scale fisheries, management often lacks the resources required for providing a holistic approach of all environmental and ecological inputs, stakeholders, and spatial effort. The complexities of small-scale fisheries are not fully understood but are especially important for marine spatial planners. MSP provides a scope in which to incorporate all these different factors at local, regional and national level, to create an integrated coastline. The characteristics of a complex system as a whole cannot be predicted from understanding the individual components alone as these components interact (Crowder & Norse 2008).
An understanding of effort allocation and patterns of fishers can be used to aid designing spatially closed areas. Without incorporation of multiple components placement of can be MPAs can be suboptimal (Wilen & Smith 2002). Previously, management of fisheries relied heavily on biological target, but MPA implementation should be more accommodating to human uses (Teh & Teh 2011). MPAs may require to be gear or métier specific (Teh et al. 2007), particularly in a multi-gear fishery. Métiers are defined here as the combination of gear and vessel type. Therefore it is important not only to know the spatial effort allocation of the fishers but also assign them by gear or métier. Once the spatial effort of fishing per métier is identified, the information can be combined with ecological information including habitat heterogeneity and critical habitats such as spawning sites. As each gear has a different affect on the environment, overexploitation of one particular location has the ability to affect the ‘resilience’ of the whole system. Resilience is defined as “the capacity of a system to absorb disturbance, undergo change and still retain essentially the same function, structure, identity and feedbacks” (Walker et al. 2004). This information can also be coupled with the factors that influence fisher behaviour, to understand what factors have the potential to cause greater exploitation of a particular fishing location. The combination of all these factors can affect the overall health of the ecosystem, as well as reducing the sustainability and resilience required for fishers’ livelihoods.
2.2 Foraging Theory to Spatial Distribution of Fishing Effort

Vessel Monitoring Systems (VMS) are used worldwide on commercial vessels for monitoring, controlling and enforcement purposes (Mills et al. 2007). The data provided by VMS can be used to analyse spatial distribution of fishing effort. VMS provides regular information (2 hours or less) on the position and discrete time of the fishing vessel (Mills et al. 2007). Currently, VMS data alone does not provide information on whether a vessel is fishing or not. However, fishing activity and locations can be identified using VMS, studies include e.g. Vermard et al. (2010); Mills et al. (2007); Lee et al. (2010); Gloaguen et al. (2015). To determine fishing activity (where fishers actively harvesting fish) analyses have been taken from behavioural ecology. Analyses distinguish between foraging and movement towards a patch (travelling or transiting) of animal tracks by using spatial relationships between successive position records (Deng et al. 2005; Morales et al. 2004; Austin et al. 2004). The travelling behaviour has been described as high speed and low turning angles whereas foraging has been described as low speeds and large turning angles (Knell & Codling 2012). These patterns in behaviour can be applied to fishing, where travelling to the fishing location is described as high speeds and low turning angle, and fishing described as low speed and high turning angle (Figure 2) (Mills et al. 2007). As VMS only provides data from two hours or less, many studies have to infer activities that occur between two points e.g Vermard et al. (2010), therefore analyses are more complex than that of GPS tracking with a maximum of two minute intervals. Alvard et al. (2015) collected GPS tracks of artisanal fishers in the commonwealth of Dominica. To segment the tracks they used speed as the main variable in the K-means clustering algorithm, it was possible from speed alone to differentiate travelling behaviours from foraging behaviours (fishing). These data analyses are typically used with large commercial vessels with VMS on board, but very little analysis has been undertaken on artisanal fishers. Artisanal fisheries are seen as benign compared to commercial fishers due to their scale of operation, simple gear and vessels. They are generally overlooked as they their impact is underestimated compared to commercial fisheries (Hawkins and Roberts 2004). However, McClanahan (1994) demonstrated that artisanal fishers could have a serious effect on the coral ecosystems.
Figure 2: GPS track indicating different behaviours, searching or travelling, and foraging or fishing, using foraging theory.
3. CASE STUDY & BACKGROUND

3.1 Kenyan Background

The coast of Kenya contains many ecosystems including coral reef, sea grass, mangrove, and soft sediment. Its coastline is between 640-880km, located on the Western Indian Ocean, bordering Somalia to the north and Tanzania to the south. The coastline of Kenya has fringing reefs 0.1 to 1.0km parallel to the shore. These reefs are important fishing grounds for artisanal fishers (Aloo 2000). Artisanal fishers make up the majority of the marine fisheries sector (53.5%) (Aloo et al. 2014). There is a total of 115 landing sites for artisanal fishers across the coast, where a landing site is defined as 5 or more fishing crafts landing on a daily basis (Aloo et al. 2014). The main catches of fish by artisanal fishers are dermersal scavengers, rabbitfish, snappers, and parrotfish (Daw et al. 2011; Aloo et al. 2014). The artisanal fishers use simple or no boats at all, with multiple gear types including, gill nets, spear guns, and handline. There are two main fishing seasons in Kenya, the South East Monsoon (SEM) from March to October, and North East Monsoon (NEM) from November to March, these seasons: have a direct effect on fishing (Hoorweg et al. 2009, p.19). NEM season offers the best fishing as the SEM is characterised by high cloud cover, heavy rainfall cool waters and a deep thermocline (Hoorweg et al. 2009, p.19). The coastline of Kenya has fringing reefs 0.1 to 1.0km parallel to the shore. These reefs are important fishing grounds for artisanal fishers.

Kenyan reefs are considered to be the most exploited in East Africa, with some considered overfished, well above the maximum sustainable yield (Malleret-King et al. 2003; McClanahan et al. 1997; McClanahan & Obura 1995). Gear restrictions were enforced in 1990 banning beach seines and spearguns to regulate fisheries, but the use of these gears still persists, pressurising the reef and the ecosystem (Tuda et al. 2015). Each gear has a different impact on the environment. Speargun fishers spend the most amount of time searching and walking on live corals. Gill net fishers trample the reef when spreading their nets. The fish caught by these fishers are found in high coral covered areas, and the high rate of contact damages the live corals and causes reef degradation. The impacts of El Nino between 1987 and 1994 has caused significant damage to the reefs and invertebrates (McClanahan & Mangi 2000), and
may have aggravated the impacts on the reefs which were already under intense pressure.

The artisanal fishery of Kenya has undergone many changes over the past decades due to both environmental variability and changes in management regimes. More detailed stock assessments of different target resources alongside socioeconomic drivers are required to develop a sustainable ecosystem based management. This study will provide information on the main regions of exploitation and the spatial difference between different métiers (Tuda & Wolff 2015).

3.2 Current State of Kenyan Fisheries and Marine Protected Areas

Between 1968 and 1986 there were six marine reserves and four marine parks implemented on the coast of Kenya. The government, primarily due to pressure from the tourism sector, implemented them. When the government established these MPAs there was very little involvement from the stakeholders such as fishers, boat operators, and traders, which caused conflicts amongst the stakeholder (McClanahan et al. 2005). Due to the many conflicts the Kenyan government has incorporated greater participatory initiatives (for example, Beach Management Units) into the implementation of MPAs. Beach Management Units or (BMUs) are a mechanism which involve fishers in the co-management of the fisheries (Oluoch et al. 2008). An official of the Fisheries Department drafts a co-management plan with the stakeholders to ensure sustainable use of the resource.

Tuda et al. (2014) applied the MSP approach to the Mombasa coast, Kenya, with greater knowledge of existing human activities in the marine environment, implementing MSP in coastal Kenya. This study and similar studies have the potential to provide a greater scientific knowledge for MSP and policy implementation.

Understanding human activities in the marine system will provide information to management schemes and also has the potential to reduce stakeholder conflicts.
3.3 Ethical Considerations

Ethical considerations of the project were firstly conducted by the Fishers in Space Project by the University of East Anglia International Development Research Ethics Committee, and further considerations were undertaken regarding intellectual property rights. Fishers in Space Project has granted permission for the use of this data for this project.

Specific fishing locations are only to be presented in aggregate form i.e. grid cells and not points, as identified by the Fishers in Space Project. Fishing behaviour is a representation of the individual knowledge of the fisher and is a valuable asset. Individual trips will not be presented but rather as collection of trips. If the fishing locations are represented by points they must represented as group of trips that are not be projected onto satellite images or presented with any landmarks and the latitude and longitude removed. This study will not publish or discuss anything that may cause harm to anyone involved or surrounding the project without prior consent form all parties involved.

Fishers in Space Project granted permission for the use of this data for this project. For the intellectual property rights surrounding this project, early communication will be given regarding authorship rights, to all parties involved. Each party involved with this project or Fishers in Space has the possibility to contribute. This decision is only valid for a given period of time after which it is assumed that the party no longer does not want to contribute and authorship rights rescinded, and only acknowledgements given. Should any party want to obtain authorship rights this should done during this communication period.
4. MATERIAL AND METHODS

4.1 Fishers in Space Project

4.1.1 Brief Summary and Study Sites

Daw et al., (2011) hereafter referred as the Fishers in Space Project (FIS) is a project based in Kenya and the Seychelles undertaken from 2008-2011 from which five major objectives were accomplished:

“1. Review the extent to which the spatial behaviour has been evaluated.
2. Examine the distribution of fishing effort for artisanal fishers in Kenya.
3. Explore how fishers chose their fishing sites in Kenya and the Seychelles;
4. Examine displacement of fishing effort in Kenya and the Seychelles;
5. Examine evidence for spill over of catch from marine reserves.”

To answer the aims and research questions, this study used the data from FIS only from Kenya. This was due to data availability in Kenya, a greater number of landing sites and GPS tracking. This study aims to complement the fieldwork of the FIS project and answer one of their desired aims; to identify fishing activity from navigation (travelling) or searching activities.

The data gathered by FIS was from eight locations of the coast of Kenya. These sites were: (from North to South) Takaungu, Kuruwitu, Vipingo, Kinuni, Bureni, Bamburi, Tiwi and Tradewinds (Figure 3). For this study, Kuruwitu, Vipingo, Kinuni and Bureni will be shown together, consistent with FIS project. The data gathered at these locations, were both qualitative and quantitative and consisted of interviews, surveys and, GPS and logbook monitoring. The logbook recorded characteristics of each trip, for example gear type, boat type (vessel), catches and number of fishers.

Thirty-three fishers were given a hand held GPS unit (Garmin Geko 201) to take on fishing trips. 1134 trips were recorded: 819 were classed as complete and used for analysis of fishing effort distribution. The thirty-three fishers used a variety of gears and vessel types as shown in Table 1 with English translation.
Table 1: Translation and description of Vessel and Gear types of fishers used in the FIS Project.

<table>
<thead>
<tr>
<th>Vessel Type</th>
<th>Swahili</th>
<th>English</th>
<th>Description</th>
<th>Gear Type</th>
<th>Swahili</th>
<th>English</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dau</td>
<td>Small timber vessel</td>
<td>Small timber vessel, no sail, no engine, 4-5 people, ca. 5m.</td>
<td>Gill Net</td>
<td>Gill Net</td>
<td>Any netted fishing gear</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mashua</td>
<td>Engine boat</td>
<td>Dugout canoe, e.g. (10m) with engine</td>
<td>Handline</td>
<td>Handline</td>
<td>Handline</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Horu</td>
<td>Dugout canoe</td>
<td>Dugout canoe, 1-2 people.</td>
<td>Jarife</td>
<td>Large Gill Net</td>
<td>Wide mesh used to capture shark and larger fish</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ngalawa</td>
<td>Sailing boat</td>
<td>Sailboat with outriggers. Range of sizes.</td>
<td>Kimiya</td>
<td>Cast Net</td>
<td>ca. 5cm long mesh size</td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>None</td>
<td>No boat - swimming/walking.</td>
<td>Mkamo</td>
<td>Small Mesh Gill Net</td>
<td>Nylon net, made from the fishing line</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surfboard</td>
<td>Surfboard</td>
<td>Surfboard</td>
<td>Khaki</td>
<td>Small Mesh Gill Net</td>
<td>Multi-filament gill net set on a reef</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Speargun</td>
<td>Speargun</td>
<td>Speargun</td>
<td></td>
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</tr>
</tbody>
</table>

Figure 3: Map of study sites and community closures. Taken from the Fishers in Space Report (Daw et al. 2011).
4.2 Data Processing and Analyses:

The FIS team downloaded all GPS points to an Access Database and assigned each point with an ID number, which were then combined per trip and assigned a trip ID using logbook data, based on time. When assigning trip IDs it was important to take care when dealing with trips that occurred overnight. An intern (Matamoros, G.) exported the data and placed this into a PostGIS database (PostGIS 2.1.0), alongside shape files of landmask (coastline) and reef crest (the edge of the reef) created in QGIS. Each trip was manually checked using QGIS and was flagged by goodness of trip and by completeness (Table 2), as well as comments, to identify outliers and other occurrences found on the trip (e.g. no clear start/end point of trip). This study continued this work; outlier points were removed (land- based and oceanic outliers) using QGIS and R (R version 3.1.1 (2014-07-10) -- "Sock it to Me") (see Appendix). Oceanic outliers (points within the sea where there was an erratic GPS signal) were checked using QGIS and Google Earth and originally flagged point IDs were noted, validated and removed. The land-based outliers (where the GPS signal was also erratic and fishers turned on their device too early) were excluded by importing the landmask (coastline) shape file from the PostGIS database into R using the packages ‘maptools’ and all points found within the landmask polygon were removed. The database was then updated by eliminating the outliers identified above. Subsequently the trips were filtered by a flagged score of zero and a completeness of three to ensure that all further analyses were undertaken on full-cleaned trips.

<table>
<thead>
<tr>
<th>Flagged</th>
<th>Completeness</th>
</tr>
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<tbody>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
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<tr>
<td></td>
<td>2</td>
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<td>3</td>
</tr>
</tbody>
</table>

*Table 2: Definition of flagged and completeness scores given by Matamoros, G.*
4.3 Métier Identification and Landing Sites

The FIS collected logbook data, where gear and type of vessel were noted for each fishing trip. This data was also stored within the Access Database; these files were exported and subsequently imported into the PostGIS database for queries. From the cleaned trips the number and size of each métier was identified. Following this the landing sites per métier were identified; here the number of trips can per landing site and métier can be estimated.

4.4 Spatial Effort Distribution:

4.4.1 Variables

Time, displacement, speed, and turning angle were calculated (see Appendix A for calculations) between each point of the cleaned trips. These variables were chosen because they are used in movement analyses and in segmentation of fishing tracks (e.g. Knell & Codling 2012; Vermard et al. 2010; Lee et al. 2010)

Time difference between the GPS points was calculated by the subtraction of a GPS point to the previous. Displacement was calculated via the pythagorean theorem. Speed was calculated given the time and displacement calculated previously. Turning angle was calculated by calculating the heading from the North Pole (90.0000° N, 0.0000° W) for each point, then subtracting the subsequent heading from the previous. Distance from land was calculated by the use of the landmask polygon in Arc Map (10.2.2), using the package ‘Generate Near Table Analysis’. Due to the large computational required by the function ‘dist2line’, in the package ‘geosphere’ in R (20 seconds per point) this was not undertaken in R. This distance calculated in ArcMap was provided in the form of decimal degrees. Therefore the results were extracted into a text file and imported into R to convert to metres and combined with the other independent variables calculated above.
4.4.2 Filtering data

The tracks required further filtering as there were outliers that were not visible by manual detection. The filters are important, as the K-means partitioning is susceptible to bias from outliers. Since speed normalises any issues associated with time difference and displacement (erratic GPS behaviour) it was used as a main filter. If there was a high speed, for example greater than 2 m/s for a fisher with vessel type ‘none’, it can be assumed that the GPS was behaving erratically. The filter for maximum speed was identified according to the vessel type and validated by histogram and local experts from the Fishers in Space team. It is assumed (validated by local experts) that in Takaungu, fishers are not fishing does not occur within the creek; therefore points less than 200 m from land were removed. All further analyses were undertaken in R.

4.5 Behavioural State Segmentation

Behavioural states are different conducts adopted by fishing vessels during a fishing trip (e.g. transit towards fishing zone and fishing activity) (Gloaguen et al. 2015). Behavioural states are calculated using K-means, a hard (requires a known amount of clusters beforehand), unsupervised clustering algorithm using the calculated independent variables (speed and turning angle). It is assumed that low speed and large turning angles are characteristics of fishing (Vermard et al. 2010; Lee & South 2010). As K-Means requires a known amount of clusters a priori, therefore it is important to find the optimal amount of clusters in which to run the K-means algorithm. This will provide details on the optimal amount of clusters to remove transiting (travelling towards the fishing zone) to provide greater accuracy on the fishing locations of each métier at a given landing site. All further analyses were undertaken in R.

4.5.1 Optimal K – Means Cluster

The variables used for clustering are normalised using z-scores. In this case the variables used are speed and turning angle. As the scales of these of both these
variables vary greatly (e.g. turning angle, $0 - 180^\circ$; speed, $0 - 2$ m/s), producing $z$ scores will ensure that the K-means algorithm uses each variable equally.

To calculate the optimal K–means cluster; the sum of squared error (SSE) is used. This is the sum of the squared distance between each member of the cluster and its centroid. Once this value has been calculated it can be plotted against, $k$, the number of clusters.

As the number of clusters increases the error decreases; this is because if there is an increase in the number of clusters the size of each cluster size should be smaller, and so the distortion is smaller. After creating this figure the ‘elbow method’ identifies the optimal amount of clusters per métier, by the percentage variance explained as a function of the number of clusters. The percentage of variance explained by the clusters is plotted against $k$. The point of the ‘elbow’ is the where the marginal gain of information will drop dramatically, producing an angle in the graph, the ‘elbow’ (Figure 4). When the optimal cluster is identified the subsequent cluster will not give a better modelling of the data (Kodinariya & Makwana 2013; Bholowalia & Kumar 2014). This method was chosen due it simplicity and ease of computation, however it is heuristic and requires the ‘elbow’ to be identified manually. The ‘elbow’ method is one of the oldest methods used to identify optimal cluster number (Kodinariya & Makwana 2013). It has also been used by Alvard et al. (2015) when identifying optimal cluster number in GPS tracks of artisanal fishers.

![Figure 4: Example SSE plot of 'Sailing Boat x Handline', where optimal k=3, at the 'elbow'.](image-url)
Once the optimal cluster is identified via the SSE and elbow method, the K-means algorithm explained in the next step is undertaken with both the optimal cluster and when \( k = 2 \). This is because the tracks can be partitioned into two behaviours, travelling and fishing, which can potentially be done when \( k = 2 \); where one cluster could be ‘travelling’ and the other cluster ‘fishing/other behaviours’. These were then manually analysed to identify whether the majority of travelling points are highlighted within a particular cluster.

### 4.5.2 Partitioning of Tracks by K-means Clustering

Once the optimal cluster number had been identified. The normalised data was then used in the default K-means algorithm (Hartigan & Wong, 1979) and assigned the optimal cluster as identified in 4.5.1 Optimal K – Means Cluster, where the number of iterations were 10 (default). The clusters identified with the combination of highest turning and speed was filtered (includes fishing location). The cluster assignments were combined with the original data frame in addition to being filtered by the filtered cluster for further analyses.

### 4.6 Spatial Distribution of Fishing Effort

Heat maps were created per métier and landing site, using function ‘stat_summary2d’ in package ‘ggplot2’ for (a) unfiltered (all data) from a given métier, and (b) filtered points (clusters that contained travelling were identified and removed), where each cell was coloured by the proportion of time. Cell size and location across a landing site was required to be of equal size and placement in order to conduct a correlation analysis across ‘fishing’ heat maps per métier. Cell size and location was kept consistent by using a regular grid size for each landing site, and the production of equal breaks across the grid.

The correlation analysis was undertaken in two parts by Spearman’s rank correlation coefficient. Firstly the filtered heat maps were correlated against the unfiltered heat

map from a given métier. This provided information on the relationship between other behaviours e.g. unfiltered and filtered. Secondly, the filtered heat maps per métier at a particular landing site were correlated against each other to inform on the relationship of fishing grounds per métier.
5. RESULTS

5.1 Data Processing and Cleaning

Cleaning of the GPS points provided a total of 462 trips, (198,323 points) with completeness of three and flagged of zero (Table 3). From the PostGIS database there were 837 trips and 324,969 points, from which a total of 338 trips and 126,646 points were removed after cleaning. The 338 trips were removed from the completeness filter. 18,158 points were removed by eliminating oceanic outliers and 108,488 removed from land outliers.

5.2 Métier Identification

From the 462 cleaned trips 14 métiers were identified (Table 3). The métiers with count greater than 10 trips (eight métiers) were used in the analysis. There were four different types of gears used: Gill Net, Speargun, Handline, and Small Mesh Gill Net. Six different vessel types: Dugout Canoe, None, Small Timber Vessel, Surfboard, Sailing Boat, and Engine Boat. A total of 95.5% of the cleaned trips, and 38.9% of all trips (1,134) collected by the FIS project were used for analysis.

Table 3: Total trips for all métiers where completeness = 3 and flagged = 0, and where all métiers above the line are the trips used in this study.

<table>
<thead>
<tr>
<th>Métier (Swahili)</th>
<th>Métier</th>
<th>Count</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hori x Gill Net</td>
<td>Dugout Canoe x Gill Net</td>
<td>189</td>
<td>40.91</td>
<td>40.91</td>
</tr>
<tr>
<td>None x Gill Net</td>
<td>None x Gill Net</td>
<td>70</td>
<td>15.15</td>
<td>56.06</td>
</tr>
<tr>
<td>None x Spear gun</td>
<td>None x Spear gun</td>
<td>68</td>
<td>14.72</td>
<td>70.78</td>
</tr>
<tr>
<td>Hori x Mkano</td>
<td>Dugout Canoe x Small Mesh Gill Net</td>
<td>33</td>
<td>7.14</td>
<td>77.92</td>
</tr>
<tr>
<td>Surfboard x Handline</td>
<td>Surfboard x Handline</td>
<td>28</td>
<td>6.06</td>
<td>83.98</td>
</tr>
<tr>
<td>Dau x Gill Net</td>
<td>Small Timber Vessel x Gill Net</td>
<td>20</td>
<td>4.33</td>
<td>88.31</td>
</tr>
<tr>
<td>Ngalawa x Handline</td>
<td>Sailing Boat x Handline</td>
<td>20</td>
<td>4.33</td>
<td>92.64</td>
</tr>
<tr>
<td>Mashua x Gill Net</td>
<td>Engine Boat x Gill Net</td>
<td>13</td>
<td>2.81</td>
<td>95.45</td>
</tr>
<tr>
<td>Hori x Handline</td>
<td>Dugout Canoe x Handline</td>
<td>7</td>
<td>1.52</td>
<td>96.97</td>
</tr>
<tr>
<td>Hori x Kimiya</td>
<td>Dugout Canoe x Cast Net</td>
<td>5</td>
<td>1.08</td>
<td>98.05</td>
</tr>
<tr>
<td>None x Handline</td>
<td>None x Handline</td>
<td>5</td>
<td>1.08</td>
<td>99.13</td>
</tr>
<tr>
<td>Ngalawa x Gill Net</td>
<td>Sailing Boat x Gill Net</td>
<td>2</td>
<td>0.43</td>
<td>11.26</td>
</tr>
<tr>
<td>Mashua x Handline</td>
<td>Engine Boat x Handline</td>
<td>1</td>
<td>0.22</td>
<td>99.78</td>
</tr>
<tr>
<td>None x Small Mesh Gill Net</td>
<td>None x Small Mesh Gill Net</td>
<td>1</td>
<td>0.22</td>
<td>100.00</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>462</td>
<td>100.00</td>
<td></td>
</tr>
</tbody>
</table>
5.3 Variables

Distribution of speed and turning angle showed that there are large amount of points at the lower end of the scale (Figure 5). It was expected that the distribution should show one large peak at the lower end for speed indicating ‘fishing’ points and at the lower end of turning angle for ‘travelling’ points. The larger speeds are assumed to be ‘travelling’, and larger turning angles to be ‘fishing’. There are clear artefacts shown in the turning angle distribution (Figure 5 (a)) at 0, 45, 90, 135 and 180 degrees. However, there is a small second peak towards 135 degrees in the distribution of turning angle. The speed distribution shows a relatively small peak around 1 m/s (Figure 5(b)).

Figure 5: Distribution of Turning Angle and Speed for métier, ‘Dugout Canoe x Small Mesh Gill Net’. 
When speed and turning angle distributions are combined (Figure 6), there is a clear aggregation point below 45 degrees and the centre is just below 1m/s. There are artefacts at regular intervals in the turning angles as shown in distribution histogram (Figure 5 (a)).

![Dugout Canoe x Small Mesh Gill Net](image)

*Figure 6: Scatter plot of turning angle and speed of métier, ‘Dugout Canoe x Small Mesh Gill Net’*

### 5.4 Behavioural Segmentation

#### 5.4.1 Optimal Clustering

The results of the SSE showed that all of the métiers had an optimal cluster of three (Figure 7). Here the ‘elbow’ indicates that three should be the optimal cluster number in order to reduce distortion. ‘Dugout Canoe x Gill Net’ (Figure 7) is used as an example, all other SSE figures can be found in Appendix B.
Still using ‘Dugout Canoe x Gill Net’ as an example, the result of two clusters were compared with the results of three clusters (Figure 8). Here it showed that when $k = 2$, the partitioning for filtered includes many low speed and low turning angle points. Figure 8 illustrates the difference between these clusters when the cluster number is associated with their latitude and longitude points. When $k = 2$, it is clear that what would be classed as ‘fishing’ includes many travelling points which have been removed when $k = 3$, the optimal cluster. Therefore for the behavioural segmentation analysis, $k = 3$, the optimal cluster will be used for analysis for all métiers.
Figure 8: Comparison of $k=2$ and $k=3$ for scatter plot, unfiltered points and filtered points by combination of highest turning and low speed. Axes and métiers are removed for ethical reasons.
5.4.2 Spatial Distribution of Fishing Effort

Intra-métier analysis (unfiltered vs filtered) produced positive correlations, indicating there is overlap in the proportion of time spent between filtered and unfiltered. The removal of the travelling points provided a clearer picture for when the fishers are estimated to be fishing and where they spend the greatest proportion of their time. All métiers produced a relatively high correlation between unfiltered and filtered. However, there was a slight difference between the proportion of time spent for the whole trip and the proportion of time spent when ‘fishing’. There is a greater correlation difference in the métiers that cross the reef crest and those that remain with the reef crest. For example the ‘Sailing Boat x Handline’ in the Kuruwitu Area, show a vast majority of cells in the unfiltered map that cross the reef crest and further away from shore, and the majority of these points are removed in the filtered heatmap. This is exemplified in the results of the correlation analysis between unfiltered and filtered with 0.47. Conversely, ‘None x Gill Net’ in Tiwi, had a correlation of 0.93.

All inter-métier analyses indicated a negative correlation, suggesting the cells that are estimated to be fishing are different for each métier. It would be expected that similar gear or vessel types would have a greater correlation, as they might be expected to fish similar species or in similar localities. However, this is not the case, in Takaungu, ‘Dugout Canoe x Gill Net’ and ‘Engine Boat x Gill Net’ has a strong negative correlation (-0.69) indicating there is not an overlap between gear types. In Takaungu, ‘Dugout Canoe x Gill Net’ and ‘Dugout Canoe x Small Mesh Gill Net’ also have a negative correlation (-0.74), suggesting that there is no overlap in estimated fishing locations. The weakest correlation is located within Tradewinds, ‘None x Speargun’ and ‘Surfboard x Handline’ (-0.37), demonstrating that there is a negative correlation across all métiers.
5.4.2.1 Takanugu

In Takanugu there were four different métiers: ‘Dugout Canoe x Gill Net’, ‘Dugout Canoe x Small Mesh Gill Net’, ‘Engine Boat x Gill Net’ and ‘None x Speargun’.

All correlation results between unfiltered and filtered showed a positive correlation, indicating the proportion of time suggesting there is some overlap in the proportion of time spent in a particular cell (Figure 9: Unfiltered). However, the correlation for ‘Engine Boat x Gill Net’ was less than expected (0.71), implying there is a change in the proportion of time spent between unfiltered and filtered. Both ‘Dugout Canoe x Gill Net’ and ‘Engine Boat x Gill Net’ had a higher positive correlation (0.83); there is some change in the proportion of time spent, but still positively correlated (Table 4).

From Figure 9 (Filtered) there is a cell in both ‘Dugout Canoe x Gill Net’ and ‘Dugout Canoe x Small Mesh Gill Net’ where the proportion of time spent in coloured red, greater than 0.08. From all of the cells on the map, this is where the highest proportion of time is spent. However, all results showed a negative correlation (Table 4). Spearman’s rank between ‘Dugout Canoe x Gill Net’ and ‘Dugout Canoe x Small Mesh Gill Net’ is strong negative correlation (-0.74), suggesting there is a large spatial segregation between the métiers. The other métiers have a smaller negative correlation ‘Dugout Canoe x Small Mesh Gill Net’ and ‘Engine Boat x Gill Net’ with a correlation of -0.69 and ‘Dugout Canoe x Gill Net’ and ‘Engine Boat x Gill Net’ with -0.60. Correlations were attempted between ‘None x Speargun’ and the other métiers but produced non-results and issues in aligning cells. In this case ‘None x Speargun’ was excluded from analysis due to the small sample size (n=1), and was not validated when asked by a local expert if this was a potential fishing location.

Table 4: Spearman’s Rank Correlation between filtered data of métiers in Takanugu and between unfiltered and filtered within a métier.

<table>
<thead>
<tr>
<th>Takanugu</th>
<th>Dugout Canoe x Gill Net</th>
<th>Dugout Canoe x Small Mesh Gill Net</th>
<th>Engine Boat x Gill Net</th>
<th>Unfiltered vs Filtered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dugout Canoe x Gill Net</td>
<td>Black</td>
<td></td>
<td></td>
<td>0.83</td>
</tr>
<tr>
<td>Dugout Canoe x Small Mesh Gill Net</td>
<td>-0.74</td>
<td>Black</td>
<td></td>
<td>0.83</td>
</tr>
<tr>
<td>Engine Boat x Gill Net</td>
<td>-0.69</td>
<td>-0.60</td>
<td>Black</td>
<td>0.71</td>
</tr>
</tbody>
</table>
Figure 9: Heatmap of unfiltered and filtered mètiers at Takaungu, where ‘Dugout Canoe x Gill Net’: n=189, ‘Dugout Canoe x Small Mesh Gill Net’: n=33 and ‘Engine Boat x Gill Net’: n=13.
5.4.2.2 Kuruwitu Area

Within the Kuruwitu Area (Bureni, Kinuni, Kuruwitu and Vipingo), there were four different métiers: ‘None x Gill Net’, ‘None x Speargun’, ‘Small Timber Vessel x Gill Net’ and ‘Sailing Boat x Handline’.

Visual comparison between unfiltered and filtered heat maps indicated there is very little difference in the location of the highest proportion of time spent. As the highest proportion of time spent in a cell in both scenarios are consistent with each other. However, visually ‘None x Gill Net’ has a change in the location of the greatest proportion of time spent in the Kuruwitu Area but when correlated showed a high positive correlation (0.84). Spearman’s rank showed the highest within the Kuruwitu Area between unfiltered and filtered in ‘None x Speargun’ (0.89). ‘Sailing Boat x Handline’ had the smallest positive correlation of (0.47), suggesting there is a greater change in the cells of proportion of time spent. Small Timber Vessel x Small Mesh Gill Net also had a high positive correlation (0.74), indicated visually by the highest proportion of time spent in similar cells (Table 5; Figure 10: Unfiltered).

The difference in the location proportion of time spent per métier in filtered is all negatively correlated (Table 5), where there is very little cross over of high-density cells (Figure 10: Filtered). The highest negative correlation (-0.80) between ‘None x Speargun’ and Small Timber Vessel x Small Mesh Gill Net. The lowest negative correlation between Small Timber Vessel x Small Mesh x Gill Net and ‘None x Gill Net’ (-0.54). Followed by Small Timber Vessel x Small Mesh Gill Net and ‘Sailing Boat x Handline’ (-0.57), with the remaining over -0.60. Negative correlation indicates that where there is a high proportion of time spent in one cell by métier the other métier spends very little or no time.
Figure 10: Heat map of unfiltered and filtered métiers in the Kuruwitu Area, where ‘None x Speargun’: n=24, ‘None x Gill Net’: n=61, ‘Small Timber Vessel x Gill Net’: n=20 and ‘Sailing Boat x Handline’: n=18.
Table 5: Spearman's Rank Correlation between the filtered data of métiers in the Kuruwitu Area and within métiers of unfiltered and filtered data.

<table>
<thead>
<tr>
<th>Kuruwitu/Bureni/Kinuni/Vipingo</th>
<th>None x Gill Net</th>
<th>None x Speargun</th>
<th>Small Timber Vessel x Small Mesh Gill Net</th>
<th>Sailing Boat x Handline</th>
<th>Unfiltered vs Filtered</th>
</tr>
</thead>
<tbody>
<tr>
<td>None x Gill Net</td>
<td></td>
<td>-0.62</td>
<td></td>
<td></td>
<td>0.84</td>
</tr>
<tr>
<td>None x Speargun</td>
<td>-0.54</td>
<td>-0.80</td>
<td></td>
<td></td>
<td>0.75</td>
</tr>
<tr>
<td>Small Timber Vessel x Small Mesh Gill Net</td>
<td>-0.67</td>
<td>-0.73</td>
<td>-0.57</td>
<td></td>
<td>0.47</td>
</tr>
</tbody>
</table>

5.4.2.3 Tiwi

In Tiwi, there were three different métiers: ‘Sailing Boat x Handline’, ‘None x Speargun’ and ‘None x Gill Net’. ‘Sailing Boat x Handline’ was excluded from analyses, due to the low number of trips (n=2).

Between unfiltered and filtered there seems to be very little difference between the cells of highest proportion of time spent. This is indicated by ‘None x Gill Net’, which has a very strong positive correlation (0.93) (Figure 11) and ‘None x Speargun’ with a strong positive correlation (0.78) (Table 6). This suggests a large overlap in the proportion of time spent in a particular cell.

Correlation across métiers initially show there is very little overlap and so the correlation should reflect this with no or negative correlation between the métiers. Spearman’s rank showed ‘None x Gill Net’ and ‘None x Speargun’ to have a relatively strong negative correlation (-0.67) (Table 6).

Figure 11: Heat map of unfiltered and filtered métiers in Tiwi, where ‘None x Gill Net’: n=9, ‘None x Speargun’: n=29 and ‘Sailing Boat x Handline’: n =2.

Table 6: Spearman’s Rank Correlation between filtered data of métiers in Tiwi, and within métiers between filtered and unfiltered data.
5.4.2.4 Tradewinds

In Tradewinds there were two different métiers: ‘None x Speargun’ and ‘Surfboard x Handline’.

In the métier, ‘None x Speargun’, there is a difference in the location where the highest proportion of time is spent between unfiltered and filtered. The majority of cells with highest proportion of time spent in unfiltered are seen in filtered with a small proportion of time. The number of cells with the highest proportion of time has increased from unfiltered to filtered. This suggests there is a difference in effort between unfiltered and filtered. In comparison, ‘Surfboard x Handline’ has a very little difference between the two heat maps, where the highest proportion of time spent remains in the same cell, with a reduction in the number of cells present in filtered. These results are represented in the results of Spearman’s rank correlation, ‘Surfboard x Handline’ (0.79) and ‘None x Speargun’ (0.77) (Table 7).

Comparing filtered between métiers shows there is minimal overlap. The location of highest proportion of time spent in each métier is different. Therefore there should be no or negative correlation between the métiers. Correlation between ‘None x Speargun’ and ‘Surfboard x Handline’ confirms that there is a weak negative correlation (-0.37) between both métiers (Table 7).

Table 7: Spearman’s Rank Correlation between métiers of filtered data in Tradewinds and within métiers between unfiltered and filtered data.

<table>
<thead>
<tr>
<th>Tradewinds</th>
<th>Surfboard x Handline</th>
<th>None x Speargun</th>
<th>Unfiltered vs Filtered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surfboard x Handline</td>
<td>-0.37</td>
<td>0.77</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Figure 12: Heat map of unfiltered and filtered métiers, where ‘None x Speargun’: n=14 and ‘Surfboard x Handline’: n=25.

5.4.2.5 Bamburi

There is only one métier identified in Bamburi, this is ‘Surfboard x Handline’. There is a difference between the locations of highest proportion of time spent in the heat map unfiltered and filtered. Due to a low sample size (n=3) Spearman’s rank correlation was not undertaken on this location and métier. There are changes in the proportion of time spent in a particular cell between unfiltered and filtered. Here the filtering can removed the estimated ‘travelling’ cells and provided a clearer picture of where these fishers are potentially fishing.

Bamburi – ‘Surfboard x Handline’

![Heat map of unfiltered and filtered ‘Surfboard x Handline’ in Bamburi, where n=3.](image)

Figure 13: Heat map of unfiltered and filtered ‘Surfboard x Handline’ in Bamburi, where n=3.
6. DISCUSSION

6.1 Fishing Locations

6.1.1 Behavioural Segmentation

Foraging theory provided theoretical explanations regarding fishers’ movements in the sea (i.e. travelling and fishing). The method used in this study, indicates that behavioural segmentation can be done on GPS data of artisanal fishers. Alvard et al. (2015) implemented a similar method to segmenting GPS tracks, but used speed alone in the clustering algorithm, due to greater variation in speeds. This study has less variation in speed, as many of the fishers do not use a vessel. Therefore in situations where there is less variation in speed, a combination of turning angle and speed is more useful for segmentation and comparison. The results of this study indicate that when there is a low speed variation, turning angle is important in segmenting behaviours. The artefacts of turning angle shown in the Figure 5(a) & 6 could be due to the resolution of the data overlaid onto the grid. Knell and Codling (2012) discussed that when travel distances are small, it is harder to differentiate between fishing and travelling; this is seen in the intra-métier results, fishers without vessels have a higher positive correlation. For example ‘Sailing Boat x Handline’ in the Kuruwitu Area travels further from land, therefore more cells can be identified as travelling suggesting the correlation between unfiltered and filtered of 0.47. Conversely, ‘None x Gill Net’ in Tiwi, had a correlation of 0.93, as this métier did not cross the reef crest, less cells were filtered out. This indicates a higher correlation between unfiltered and filtered. Another possibility for these results is due to the size of the cells themselves. Smaller cells would produce a smaller correlation, as less data points would be within a given cell. The larger the cell the greater chance of increased number of data points, so when correlated this produces a more positive correlation.

The method and results show that it is possible to map human activities at finer scales. Locations of fishing effort can be useful in detecting potential regions of ecosystem degradation. Mangi & Roberts (2006) stated that specific gear types and their associated vessels could impact the live corals. When using spearguns there is more
contact with the live corals as the fisher stands on them, assuming the fisher has no boat. This study shows the location of the fishing ground for ‘None x Speargun’, and where the greatest proportion of time is spent. Habitat surveyors can use this information to analyse the state of the corals in proportion to time spent fishing.

6.1.2 Comparison of Fishing Locations between Métiers

It would be expected that some métiers would overlap due to vessel or gear type, or possibly another underlying factor. These results indicate that all métiers at a particular landing site do not overlap in estimated fishing grounds, even with a particular gear or vessel in common. Reasons of which could come down to original métier choice and knowledge of fishing.

Different gear types require less learned skill and others more. Spearguns for example require less, but as with any skill catches will improve with experience (Lincoln Smith et al. 1989). The cost of fishing gear, especially nets, is rising. Some nets may require vessels to reach particular fishing grounds causing a rise in initial investment of fishing. Poorer fishers may opt for fishing gears that do not require a vessel (‘None x Speargun’). The selling price of fish is dependent on the size and species of the fish caught (Mangi et al. 2007), therefore targeted species are dependent on métier choice due to spatial constraints. The initial cost of investment can influence targeted fish species. The investment for a speargun is low, but usually target species that fetch the lowest price. As speargun fishers do not require a crew, profit is higher than those that do. Speargun fishers however require a large energy expenditure and time to harvest fish (Mangi et al. 2007). Therefore, improper MPA placement will cause an increase in energy expenditure for the speargun fishers to harvest fish. Mangi et al. (2007) stated that young fishers are more likely to start with spearguns due to low costs and low skill level required. However, many fishers change their métier due to seasonality, many handline fishers switch to spearguns in the spring low tides (Mangi et al. 2007). Gill nets are some of the most expensive gear to purchase, but they are highly profitable due their catch (large rabbitfish and emperors), therefore only fishers with sufficient investment could purchase a gill net. Métier choice is therefore constrained by fishers’ initial investment, and the métier chosen can restrict the
fishers spatially, influencing the target species harvested. Daw et al. (2008) discussed importance of analysing spatial effort of fishers and that the operating costs can have an influence on spatial behaviour. Nevertheless, this does not explain why métiers are spatially segregated, for this factors deciding where fishers decide to fish must understood. Daw et al. (2011) investigated how fishers decide to fish. They found that the greatest deciding factor on fishing was weather followed by currents. This meant that a clear sky or not foggy conditions are required for ease of navigation in the outer reefs. Fishers may also visit the same fishing ground frequently after a good catch. Family members or mentors will often initially influence the gear and fishing grounds visited. Another major influence of fishing ground is knowledge of a particular location and the behaviour of the fish species. Age and therefore experience also plays a major role in fishing locations (Daw et al. 2011). One or all of these factors discussed may play a contributing factor to why métiers are spatially segregated. All these factors coupled together influence the spatial distribution of fishing effort in a particular métier and the potential uses of knowing the spatial distribution of fishing effort are shown in (Figure 14). For a better understanding, it would be interesting to see the number of fishers per metier, as different fishers may visit separate fishing grounds. To obtain a better understanding of the spatial distribution of fishing effort by particular métiers there should be an equal number of different fishers per métier. The complexity of understanding small-scale fisheries is high, as there are many different contributing factors in spatial distribution of fishing effort (Figure 14).

Cinner et al. (2012) found that poorer fishers were more likely to be displaced due to MPA placement, but more likely to receive positively from spill over from an MPA. However, at what cost are the fishers likely to receive positively from the spill overs, and how long would it take for the fishers to reorganise and adapt to the new management regime. A longer time is required for fishers without boats and experience to discover new fishing ground. This will impact catch rates and therefore their livelihood. Navigating around an MPA can require large energy expenditure, as these fishers are swimming with fins, and on their return carrying the harvested fish. For MPA placement, management must consider the winners and losers, such as that exemplified by Cinner et al. (2012). Here they showed that displacement, effect on
catch, and the effect on livelihood was significant for the fishers in Kenya. Displacement by MPA will cause an immediate loss to some fishers and therefore impact their livelihood. Some fishers however are more likely to adapt quicker than others. Silva & Lopes (2015) found that younger fishers were more pro-conservation and part time fishers were more flexible and adaptable to change compared to older or full time fishers.

MPAs designation should take into consideration the constraints in which métier choices are made. Those with greater constraints (e.g. speargun fishers - energy, time, and inexperience) may be at greater loss than those with fewer constraints. Also MPA placement should consider the spatial segregation of métiers, not gear and vessel alone, and consider other factors involved in spatial distribution of fishing effort. Daw et al. (2015) discussed the need for transparency and accounting for all the trade-offs consequences of decision making for all stakeholders, to prevent marginalized losers.

Figure 14: Flowchart of key factors influencing spatial distribution of fishing effort and potential uses of the information.
6.2 Methodological Shortcomings

K-means is a hard, unsupervised clustering algorithm and compared to other clustering algorithms is considered relatively simple. K-means is used for its time–efficiency (Bholowalia & Kumar 2014), whereas other methods such as agglomerative hierarchical is used for its quality. However, there are pros and cons for each of these methods. Hierarchical clustering requires a vast amount of computational power and time. For these reasons this method was not used in this study, instead the simplicity and time-efficient K-means clustering algorithm was used. Hierarchical clustering automatically assigns an optimal cluster; therefore different métiers will have different cluster numbers, which can complicate analyses. The analysis required would be visual, as each métier would have different cluster numbers, and a variety of clusters could include potential fishing locations. However, as hierarchical clustering already optimises cluster number and K-means does not this leaves identifying the optimal cluster number to other methods such as SSE (used in this study), silhouette method or more complex calculations such as Bayesian Information Criterion (BIC). SSE requires visual analysis for the ‘elbow’, whereas BIC does not. The use of SSE can allow the optimal cluster number to be automated, but is unclear how, other studies such as Alvard et al. (2015) have also used the visual technique. Some of the other issues associated with SSE and the ‘elbow’ method is that there can be multiple ‘elbows’, this makes it difficult to analyse visually the optimal number of clusters. When there are multiple ‘elbows’ there would be the need to use other methods i.e. silhouette or BIC. Another method that could have been possibly implemented is the silhouette method. This method assigns each cluster a silhouette based on the comparison of its tightness and separation (Rousseeuw 1987). However, Baarsch & Celebi (2012) found that SSE was more effective at predicting the number of clusters than the silhouette method, but the silhouette method was a good alternative. In this study the SSE validation indicated there were not multiple ‘elbows’. The number of clusters will have an effect on the estimated ‘fishing’ locations. It is a choice whether to include potential ‘fishing’ locations to ensure that all the potential ‘travelling’ points are removed (k=3) or whether to keep some ‘travelling’ points in (k=2) in order to keep all of the estimated ‘fishing’ locations. This study decided that it was more

valuable to firstly use the optimal cluster number (k=3) and remove all potential travelling points, even if this meant that a few estimated ‘fishing’ points were removed.

Unequal sample sizes between métiers at a given location may not truly reflect the estimated ‘fishing’ locations, i.e. in Takaungu comparing ‘None x Speargun’, where n=1 and ‘None x Gill Net’, where n=189. It would better to have equal sample sizes greater than 20 to obtain a true representation of fishing locations. Therefore any sample size less than 10 was treated with caution. Alongside this each of the tracks had different settings for time difference, some set to 30 seconds, and some had a setting between 0 – 180 seconds, this why it was important to have proportion of time as the colour of the cell and not count. One major shortcoming of this study is the issue with validation. Interviews with fishers, and or observers are required to validate where the fishers actually fish, to confirm if the patterns found truly represent fishing. To fully understand fishing effort a combination of interviews, observations and data analyses should be combined.

From the data collected by the FIS, less than 40% was used in this study, exemplifying the issues associated with GPS devices. 60% of the tracks were not used and/or have not been fully cleaned, therefore a great representation of the métiers and potential ‘fishing’ locations are lost. The loss of métiers in analysis shows how complex this system is, even with eight métiers present the majority of métiers demonstrated a negative correlation. GPS devices provide a useful tool in tracking fishing trips but this comes at a price. The processing and cleaning of the data is a very lengthy process, as even with cleaning from the FIS team and an intern there were still many outliers and computational errors. This data was originally collected between 2008-2010 and the report published in 2011, since then a further year of work has been completed in order to locate estimated ‘fishing locations’. However, this method shows that once the cleaning and processing is complete, there is simple way to estimate fishing grounds.
6.3 Future Analyses

To understand the spatial distribution of fishing effort in artisanal fisheries further analyses need to be undertaken. FIS stated that one of the major influencing factors of fishing location is season. Therefore, further analyses should compare the difference of season on fishing effort. Comparing percentage of effort per cell per métier and within métier will provide a greater understanding in spatial dynamics per métier. An underlying factor of why fishers fish where they fish is due to fish and the strategies in which they employ. Due to changes in habitat i.e. by degradation or coral bleaching target species are likely to change their distribution. This will result in changes in the spatial distribution of fishing effort of fishers. Therefore overlapping habitat and species caught at particular locations will indicate which métiers are targeting what species, the locations in which they are harvesting them and the understanding the strategies of the species will indicate where they are likely to change their locality. Combining all the information can be used to model spatial distribution of fishing effort and predict fishing behaviour.

7. CONCLUDING STATEMENT

This study shows that the method to identify spatial distribution of fishing effort by the use of K-means is achievable. Validation by observers and the fishers themselves would give this method greater value. This method can provide spatial information on human activities, required for effective implementation of MSP. Identifying locations of fishing effort is a pathway to coupling social and ecological need with that of governance and management, to ensure resilience for sustainable development. Further studies are required to fully understand the complexity of SES of artisanal fishers in order to aid management and policy and to prevent conflicts between stakeholders.
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10. APPENDIX

10.1 Appendix A: Calculations

Time between the GPS points were calculated

*Equation 1: Time difference (seconds)*

\[ T_t = (t + 1) - t \]

Where,

- \( T_t \) = Time in seconds at time, \( t \).
- \( t \) = Time of a given GPS point.

Displacement is calculated via the pythagorean theorem, here the great circle distance was not used as the difference between a 3D and 2D plane is negligible due to the short distance travelled by the fishers (REF).

*Equation 2: Displacement (metres)*

\[ d_t = \sqrt{(x_{t+1} - x_t) + (y_{t+1} - y_t)} \]

Where:

- \( d_t \) = Displacement in metres, at time, \( t \)
- \( x_t \) = Latitude at time, \( t \)
- \( y_t \) = Longitude at time, \( t \)

Speed was calculated (Equation 3) given the time and displacement calculated in Equation 1 & 2

*Equation 3: Speed (metres per second) given from Equations 1 and 2.*

\[ v_t = \frac{d_t}{T_t} \]

Turning angle was calculated by calculating the heading from the North Pole (90.0000° N, 0.0000° W) for each point, then subtracting the subsequent heading from the previous (Equation 4).

Basic Turning Angle Equation:

$$\Delta \theta_t = |\theta_{t+1} - \theta_t|$$

The steps required:
1. Calculate true course/heading (the course of a ship or aeroplane measured with respect to true north)
   a. True north - North Pole
2. Calculate the difference between two true course points.
10.2 Appendix B: SSE plots

![SSE plots for Dugout Canoe x Gill Net](image1)

![SSE plots for None x Gill Net](image2)

![SSE plots for None x Spear Gun](image3)