Top fishing nations and fishing hotspots globally and in Palau

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1. Abstract

By using the dataset compiled by Global Fishing Watch and using exploratory data analysis and spatial statistics, this project was able to identify the top fishing countries in 2016 by fishing hours and by the number of vessels, the fishing patterns around the world for these countries, and the fishing hotspots around Palau and the spatial patterns of fishing efforts also for the top fishing countries. In 2016, China was the top fishing country by far globally in terms of number of fishing hours and number of fishing vessels. The top six fishing countries in 2016 are China, Taiwan, Spain, France, Italy and Japan, in that order, with China, Taiwan, Spain and Japan fishing more in the high seas while France in the northern Atlantic and Italy in the Mediterranean sea. Around Palau, Taiwan is the country with the top fishing effort, and hotspots were identified for the overall fishing effort within the Palau EEZ. The fishing effort around Palau has a clustered pattern with positive spatial correlation.

2. Introduction

2.1 Background

A decade ago fishing activity around the world has been a bit of a black box, as it was difficult to track individual vessels and identify where they are fishing. In recent years, with the advent in satellite technology, cloud computing and machine learning, the NPO Global Fishing Watch (https://globalfishingwatch.org) has compiled a global dataset of fishing activity. One of their studies (McCauley et al. 2019) identified that wealthy nations dominate industrial fishing. Vessels flagged to higher-income nations, for example, are responsible for 97% of the trackable industrial fishing on the high seas. The study also identified the top fishing countries: China, Taiwan, Japan, South Korea and

Spain. Inspired by this study, it would be interesting to investigate the top fishing countries in the year 2016 and where around the world they fish.

Moreover, apart from understanding global fishing patterns of top fishing countries, the fishing patterns around Palau would also be investigated. Palau serves as an interesting case study regarding fishing as it focuses a lot of efforts on conservation as a big part of its economy relies on ecotourism. It is a small country with 21,000 residents scattered across 250 islands, and its exclusive economic zone, which is the waters where it maintains fishing and mineral rights, extends 200 nautical miles from its coasts, which is a big area relatively to the land area. Conservation measures taken by Palau include banning bottom trawling, prohibiting commercial shark fishing by creating the world's first shark sanctuary, creating a ''no take'' reserve where all export fishing is prohibited (Urbina 2016).

2.2 Research Questions

This project will focus on the year 2016 and identify the 1) top fishing countries, 2) the fishing hotspots visually among these countries worldwide, 3) the fishing hotspots among these countries in a focused area that is within the Palau EEZ.

1) What are the top fishing countries of 2016 based on total fishing hours? And what are the top countries based on the number of fishing vessels? Are the results similar?

2) What are the fishing patterns around the world for the top fishing countries in 2016 visually?

3) What are the fishing hotspots around Palau for the top fishing countries in 2016 visually as well as based on results from a hotspot analysis? And how would the spatial pattern be quantified?

3. Methods

3.1 Data

The data being used in this analysis is the fishing efforts dataset compiled by Global Fishing Watch (https://globalfishingwatch.org/datasets-and-code/fishing-effort/). The data includes the following fields: date, lat_bin, lon_bin, geartype, vessel_hours, fishing_hours, mmsi_present and flag.

The "fishing_efforts" table was obtained using bigQuery in R, and the data was rebinned with lat_bin and lon_bin binned to a 0.1 degree resolution, then regrouped based on these two fields with the fishing hours summed in order to get the total fishing hours at a particular lat-lon bin combination throughout the whole year for 2016 (See **Code Snippet 1**).

3.2 Data Analysis

3.2.1 Top fishing nations in 2016

The "fishing_efforts" table was queried to produce the top 20 fishing countries based on the number of fishing hours in 2016 (See **Code Snippet 2 & 3**, **Table 1**, **Figure 1**).

The "fishing_efforts" table was also queried to produce the top 20 fishing countries based on the number of fishing hours in 2016 (See **Code Snippet 2 & 4**, **Table 2**, **Figure 2**).

3.2.2 Visualizing global fishing efforts of the top six fishing countries in 2016

Individual maps were produced for each of the top six fishing countries in 2016 based on fishing hours (China, Taiwan, Spain, Italy, France, Japan) visualizing global fishing efforts, in order to be able to see the pattern of where these top countries fish (See **Code Snippet 5** & **Figures 3-9**).

3.2.3 Top overall fishing countries in the context of Palau

Individual maps were produced for each of the top six fishing countries in 2016 based on fishing hours (China, Taiwan, Spain, Italy, France, Japan) visualizing fishing efforts within Palau EEZ, in order to be able to see the pattern of where these top countries fish (See **Code Snippet 6** & **Figures 10-13**).

3.2.4 Spatial Statistics

In preparation for spatial analysis, a neighborhood structure should first be defined. The K nearest neighbor method was used on the latitude and longitude bins within the Palau EEZ to create a matrix with indices of points belonging to the set of the k nearest neighbours of each other, where k is set to 4. A neighborhood structure was then created based on this matrix and a set of spatial weights was also defined using binary spatial weights.

Moran's I was used on the fishing hours dataset to quantify spatial patterns to investigate if the fishing pattern around Palau is random, regular or clustered (See **Code Snippet 7**).

Geray's C was used on the fishing hours dataset to investigate if the fishing efforts around Palau has a positive spatial correlation, negative spatial correlation, or no evidence of spatial correlation among the neighbors (See **Code Snippet 8**).

A hotspot analysis was conducted on the fishing hours dataset to identify the fishing hotspots around Palau by calculating the Getis-Ord Gi* statistic for each feature in a dataset (See **Code Snippet 9** & **Figure 14**).

4. Discussion

4.1 Top fishing countries in 2016

The top six fishing nations in 2016 based on fishing hours are the following: 1. China (CHN, at 16849182.9 hours), 2. Taiwan (TWN, at 2221199.7 hours), 3. Spain (ESP, at 2132107.8 hours), 4. Italy (ITA, at 2103236.1 hours), 5. France (FRA, at 1524341.3 hours), and 6. Japan (JPN, at 1400893.8 hours) (See **Figure 1**).

Among the top fishing countries, China takes the lead by a lot as there is a 14 million hours difference between China and Taiwan, the number two fishing nation. And while China is in the order of tens of millions with close to 17 million fishing hours, all the other top fishing nations are in the order of millions, ranging from around 1.4 million to 2.2 million hours spent fishing in 2016.

The top six fishing nations in 2016 based on number of fishing vessels are the following: 1. China (CHN, 264 vessels), 2. France (FRA, 62 vessels), 3. Norway (NOR, 62 vessels), 4. TUR (Turkey, 60 vessels), 5. Italy (ITA, 58 vessels), and The Netherlands (NLD, 53 vessels) (See **Figure 2**).

Again, China takes the lead in terms of the number of fishing vessels present in 2016, and again it leads by a lot as there are 202 vessel differences between China and France, the next country in line with the top number of fishing vessels. And while China is in the order of hundreds with 264 vessels, the rest of the countries on the list ranged from 53 to 62 fishing vessels used in 2016.

And though China is on the top of the list for both number of fishing hours and number of vessels, the rest of the list varies with Norway, Turkey, and the Netherlands making the list, while Taiwan only having 35 vessels, Spain 41 vessels and Japan not making the top 20 list (See **Table 2**).

4.2 Fishing patterns around the world

From the images produced for each of the top six fishing countries visualizing their fishing effort pattern (**Figures 3-9**), we are able to see where each country fish the most. For example, the European countries including France, Italy and Spain fish mainly in the Atlantic ocean or the Mediterranean sea, while China, Taiwan and Japan fish globally.

China fishes across the Pacific, along the west coast of South America, and near within the China EEZ. It seems that a big part of its fishing efforts are in the high seas, which is the the open ocean with areas that do not belong to any country. Taiwan similarly fishes in the Pacific ocean a lot, as well as in the Indian ocean and the Atlantic ocean and it also seems fish frequently in the high seas. Japan also has a similar fishing effort as Taiwan, as it fishes a lot in the Pacific, Atlantic and Indian oceans, and it also seems to fish frequently in the high seas.

Spain has the broadest fishing range among the European countries, and it fishes mainly in the Atlantic and the Mediterranean, and sometimes in the Pacific and Indian oceans. It also seems fish frequently in the high seas. Italy seems to focus their fishing efforts in the Mediterranean sea, and France focuses their efforts mainly in the Northern Atlantic, neither country seem as prominent in the high seas.

4.3 Fishing efforts and hotspots around Palau

From the images produced for each of the top six fishing countries visualizing their fishing effort pattern around Palau (**Figures 10-13**), we are able to see where each country fish the most and which of these countries fish the most around Palau. Taiwan seems to be Palau's major fisher by a lot, followed by China then Japan while the European nations doesn't seem to fish near Palau. This could be due partly to Palau being one of 17 countries with diplomatic relations with Taiwan (Lyons 2018).

Moran's I is a test for spatial correlation, if it is closer to -1 then the pattern would be regular, if it is closer to 1 then the pattern would be more clustered, and if it is closer to 0 then it would be random. For the two-sided Moran's I test using K-nearest neighbors, for fishing hours the observed Moran's I statistic is 0.6167442560. The p-value is $< 2.2e-16$. We reject the null hypothesis at the 5% level. There is strong evidence against the null hypothesis of CSR in the fishing hours around Palau. The results indicate that there is a clustered pattern (See **Table 4**).

Geary's C is a measure of dissimilarity and it ranges between 0 and 2. A value around 1 yields no evidence of spatial correlation, less than 1 indicates positive spatial correlation, and a value greater than 1 indicates negative spatial correlation. For the two-sided Geary's C test using K-nearest neighbors, for fishing hours the observed Geary's C statistic is 0.0.3872991141. The p-value is $< 2.2e-16$. We reject the null hypothesis at the 5% level. There is strong evidence against the null hypothesis of CSR in the fishing hours around Palau. The results indicate that there is a positive spatial correlation (See **Table 5**).

The hotspot analysis results in a z-value for each lat bin and lon bin combination. The resultant z-values indicates where features with either high or low values cluster spatially. High positive values indicate the possibility of a local cluster of fishing efforts, low values indicate a similar cluster of low fishing efforts. The maximum z-value is 12.09136, minimum z-value is -1.61692, and the mean z-value is 0.03924. There are many fishing hotspots within the Palau EEZ (See **Figure 14**), the top 50 of which are listed in table 3.

5. Conclusions

By using the dataset compiled by Global Fishing Watch and using exploratory data analysis and spatial statistics, this project was able to identify the top fishing countries in 2016 by fishing hours and by the number of vessels, the fishing patterns around the world for these countries, and the fishing hotspots around Palau and the spatial patterns of fishing efforts also for the top fishing countries.

In 2016, China is the top fishing country by far globally in terms of number of fishing hours and number of fishing vessels. The top six fishing countries in 2016 are China, Taiwan, Spain, France, Italy and Japan, in that order, with China, Taiwan, Spain and Japan fishing more in the high seas while France in the northern Atlantic and Italy in the Mediterranean sea. Around Palau, Taiwan is the country with the top fishing effort, and hotspots were identified for the overall fishing effort within the Palau EEZ. The fishing effort around Palau has a clustered pattern with positive spatial correlation.

Limitations include computational power, as this has limited further analyses being done on the global dataset. In the future, it may be interesting to use linear regression with fishing hours as a response and country or geartype as a predictor to see if a specific country or geartype spend more time fishing.

6. Citation

Lyons, K. 2018. 'Palau against China!': the tiny island standing up to a giant. *The Guardian*: 2018 Sept 8.

McCauley et al. 2019. Wealthy countries dominate industrial fishing. *Science Advances* 2018; 4 : eaau2161

Urbina, I. 2016. Palau vs The Poachers. *The New York Times*: 2016 Feb 17.

7. Figures

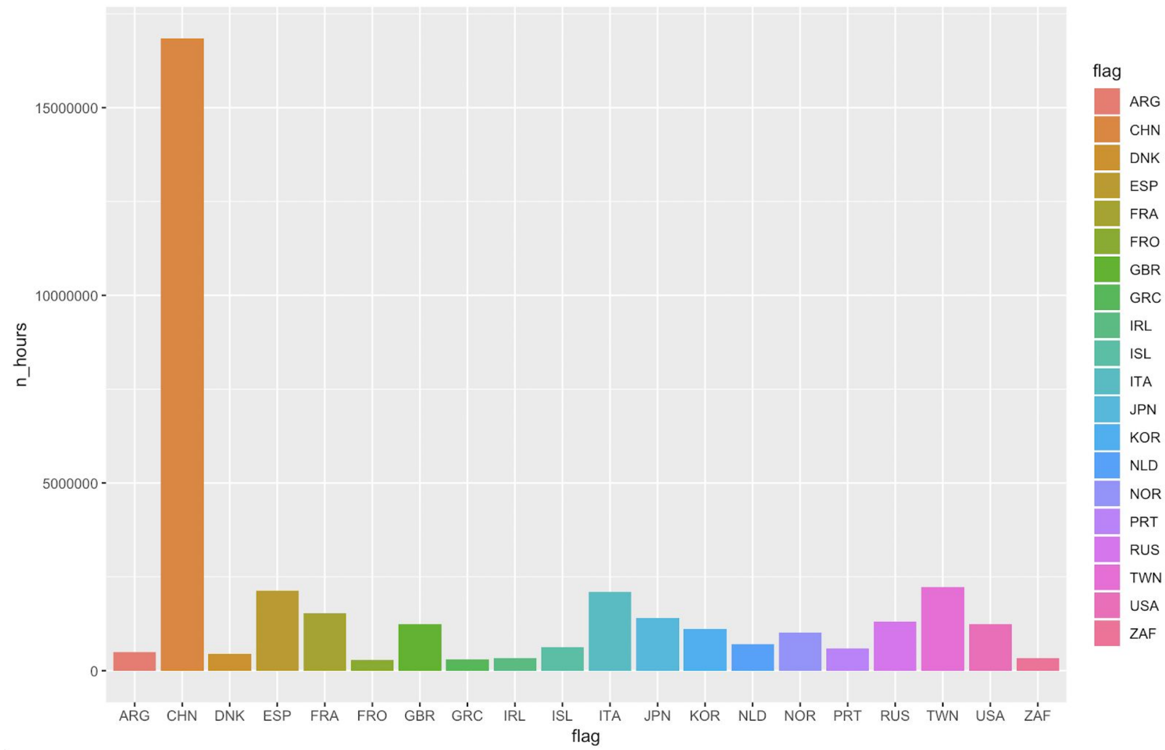

Figure 1. Fishing hours by country

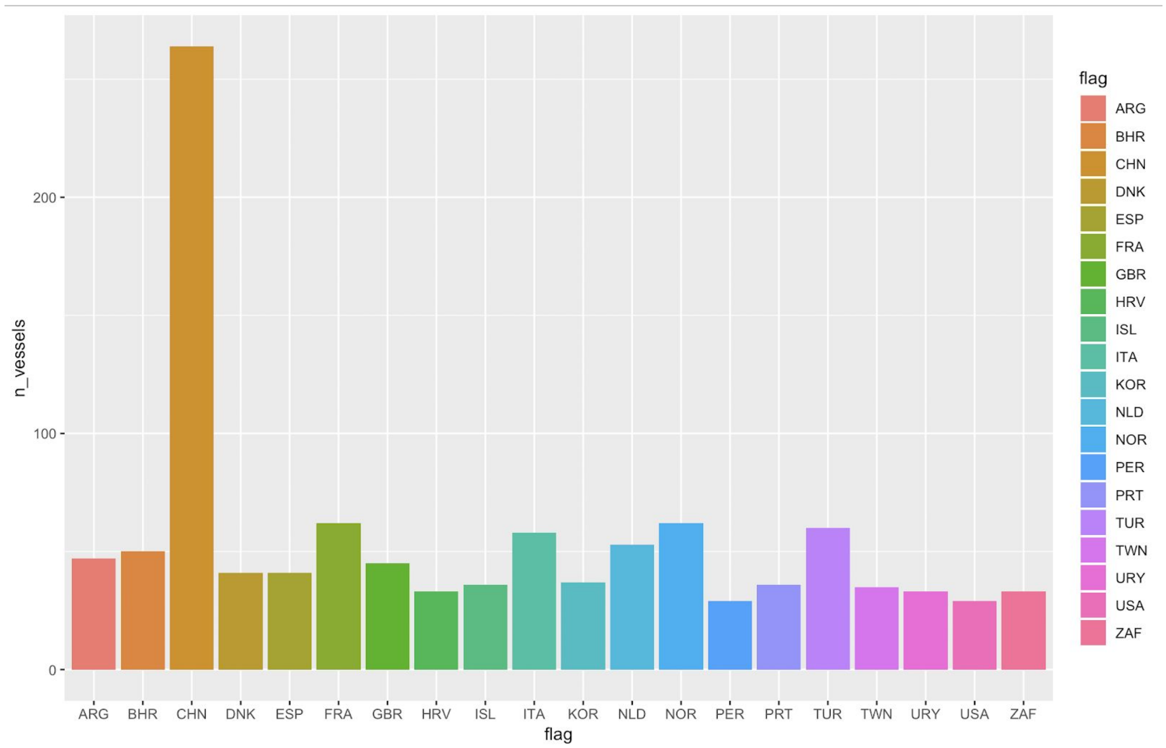

Figure 2. Number of fishing vessels by country

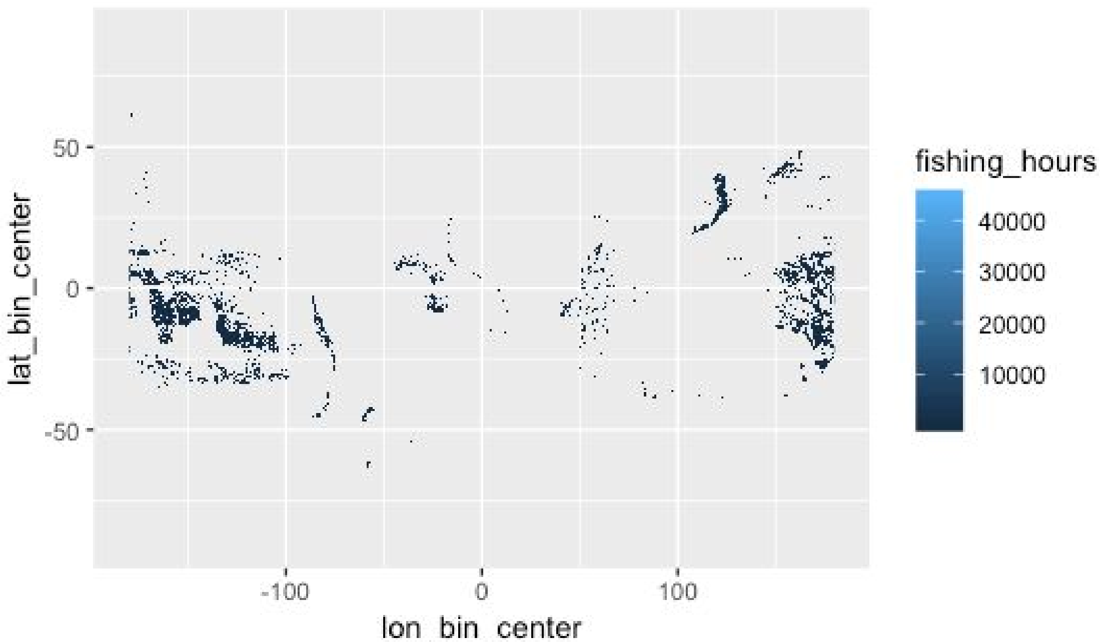

Figure 3. 2016 global fishing efforts for China

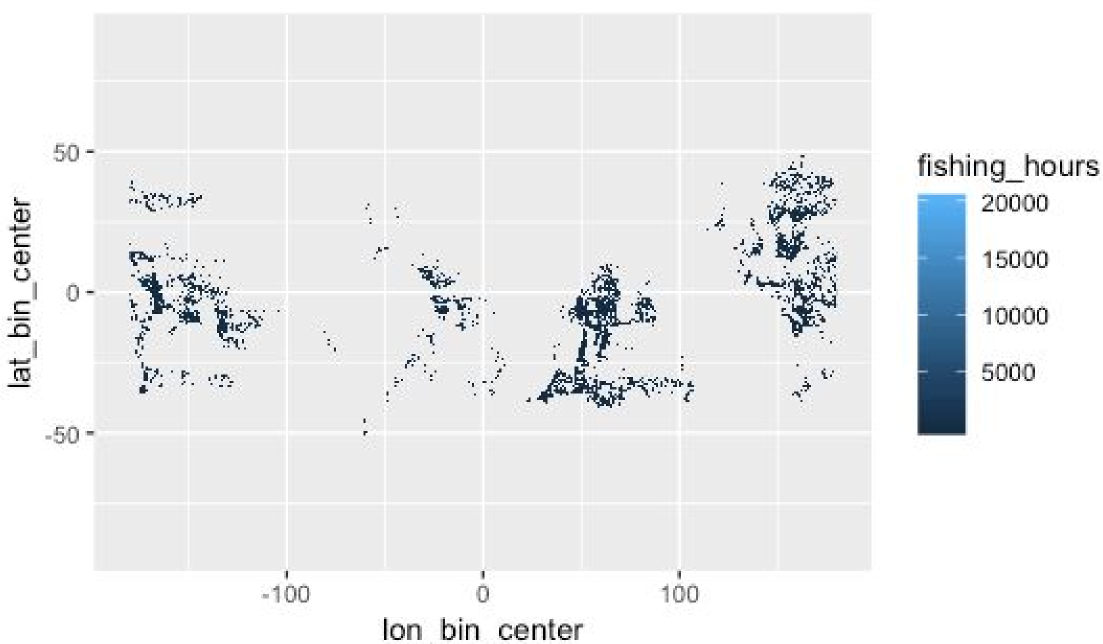

Figure 4. 2016 global fishing efforts for Taiwan

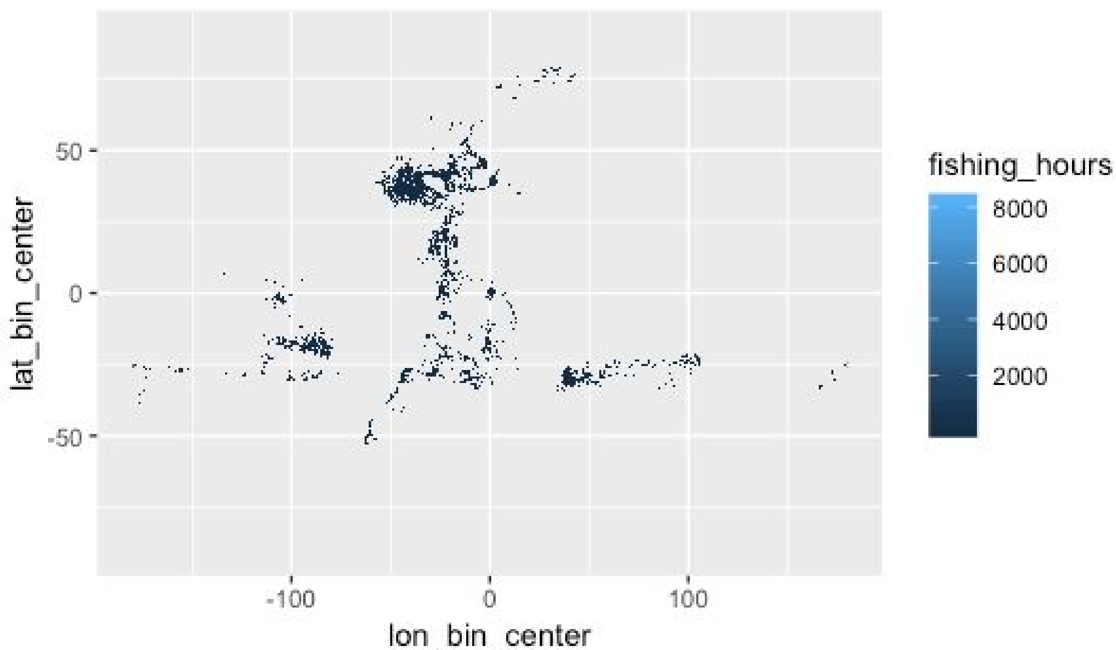

Figure 5. 2016 global fishing efforts for Spain

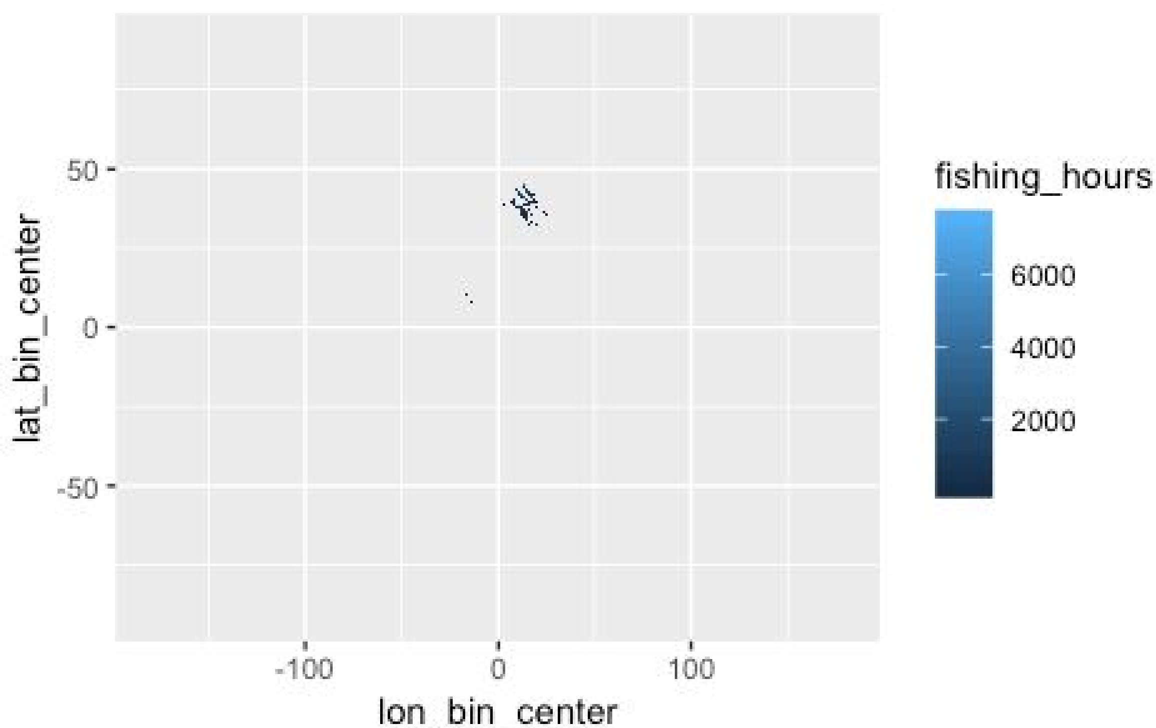

Figure 6. 2016 global fishing efforts for Italy

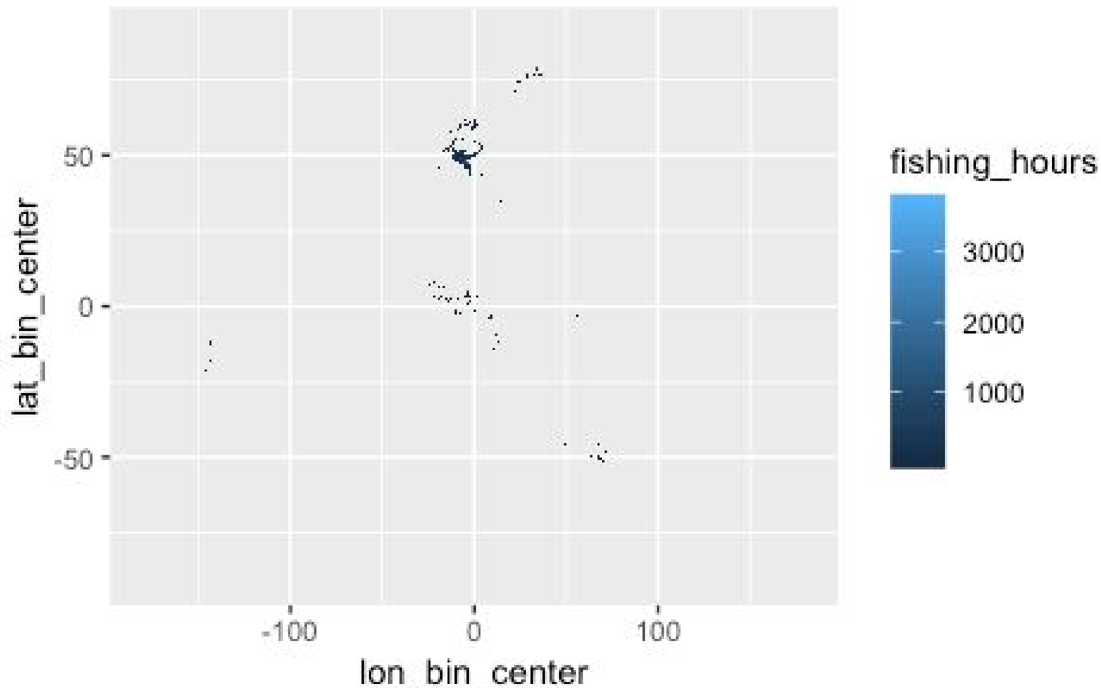

Figure 7. 2016 global fishing efforts for France

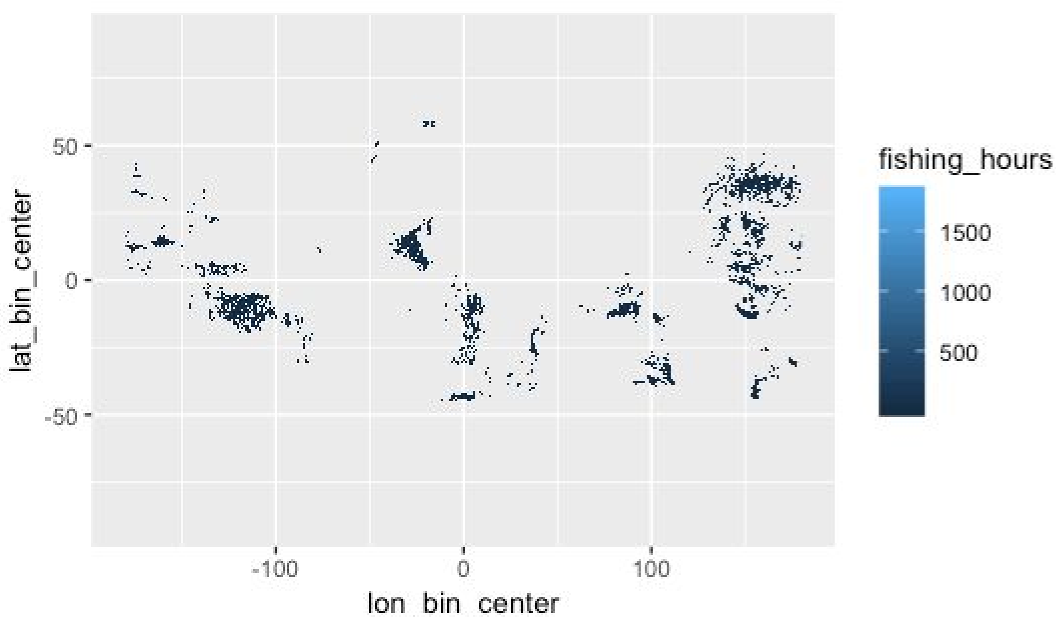

Figure 8. 2016 global fishing efforts for Japan

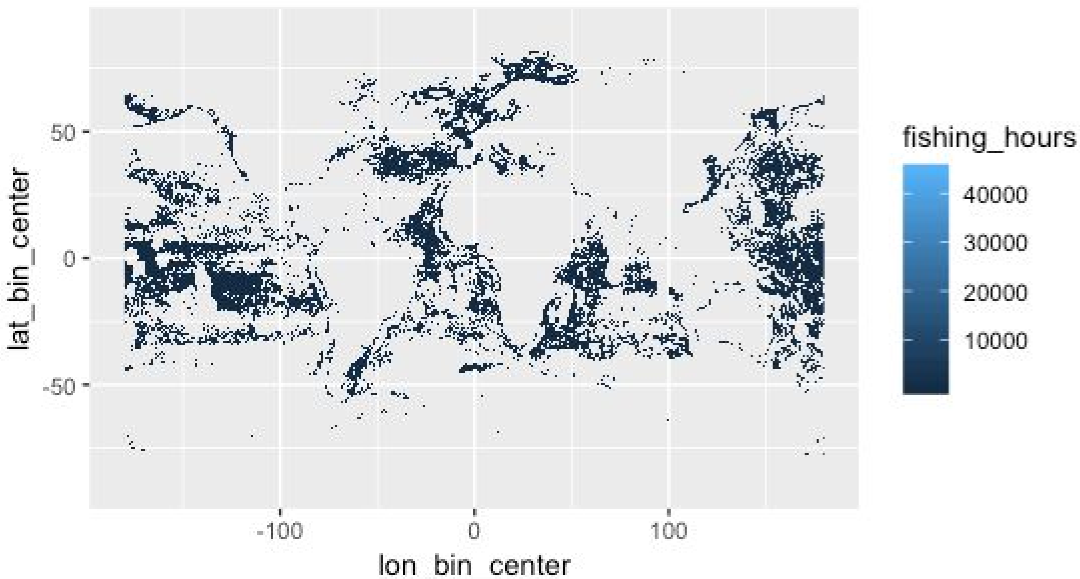

Figure 9. 2016 overall global fishing efforts

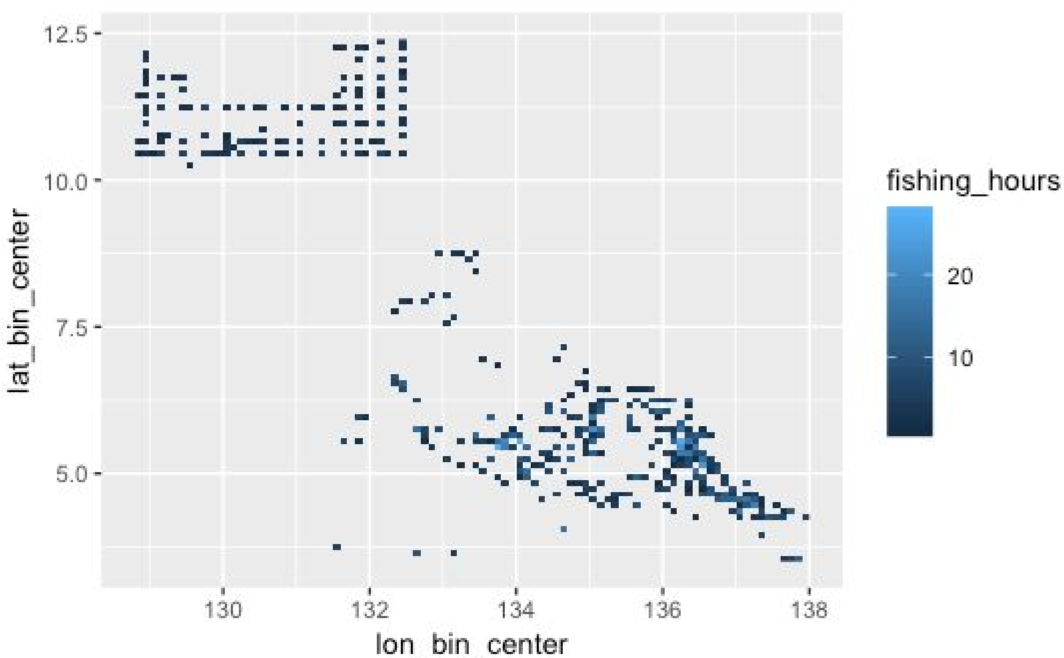

Figure 10. 2016 fishing efforts for China within Palau EEZ

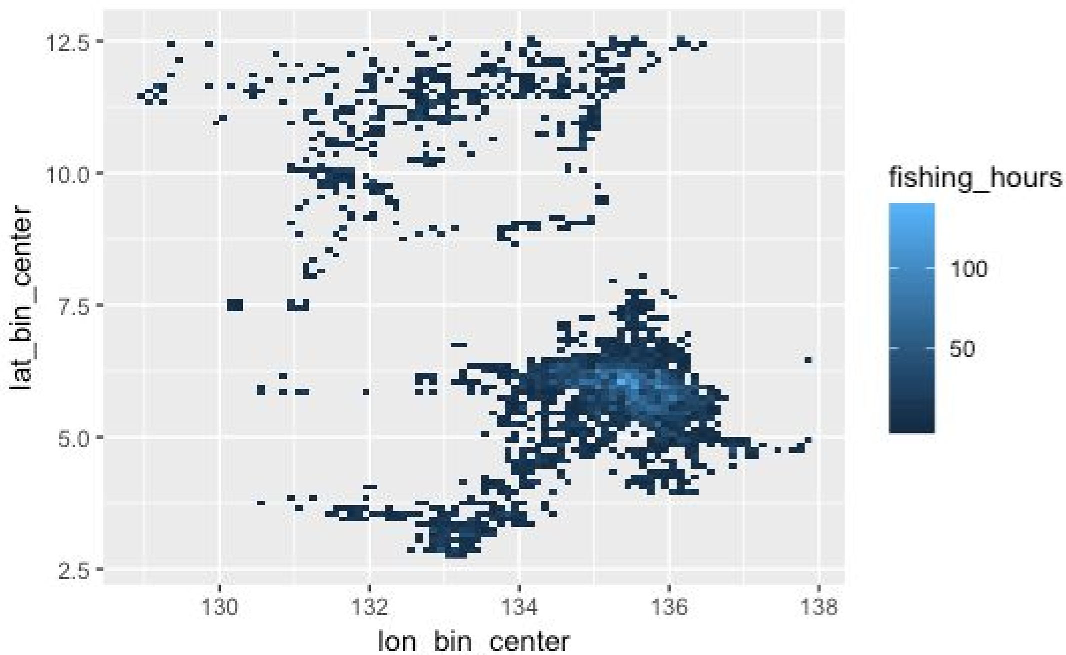

Figure 11. 2016 fishing efforts for Taiwan within Palau EEZ

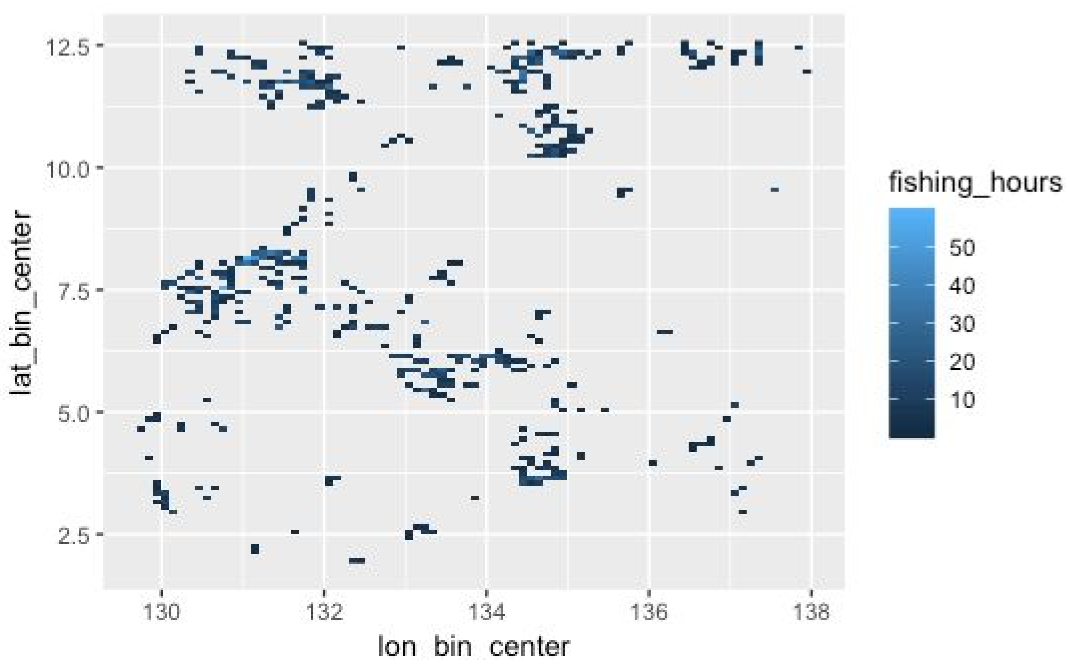

Figure 12. 2016 fishing efforts for Japan within Palau EEZ

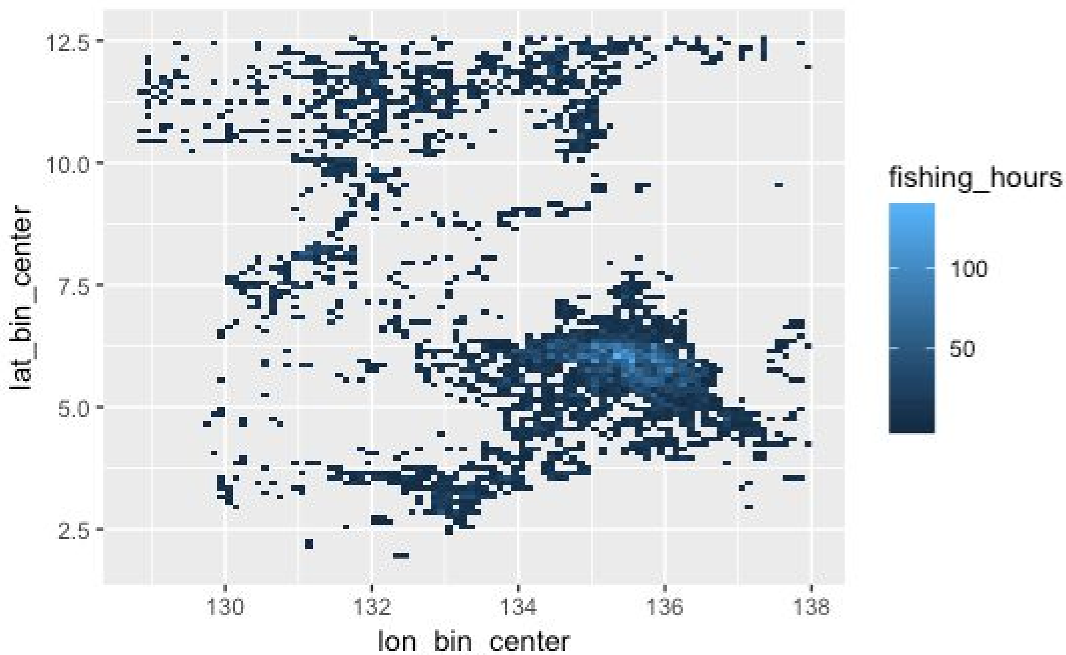

Figure 13. 2016 overall fishing efforts within Palau EEZ

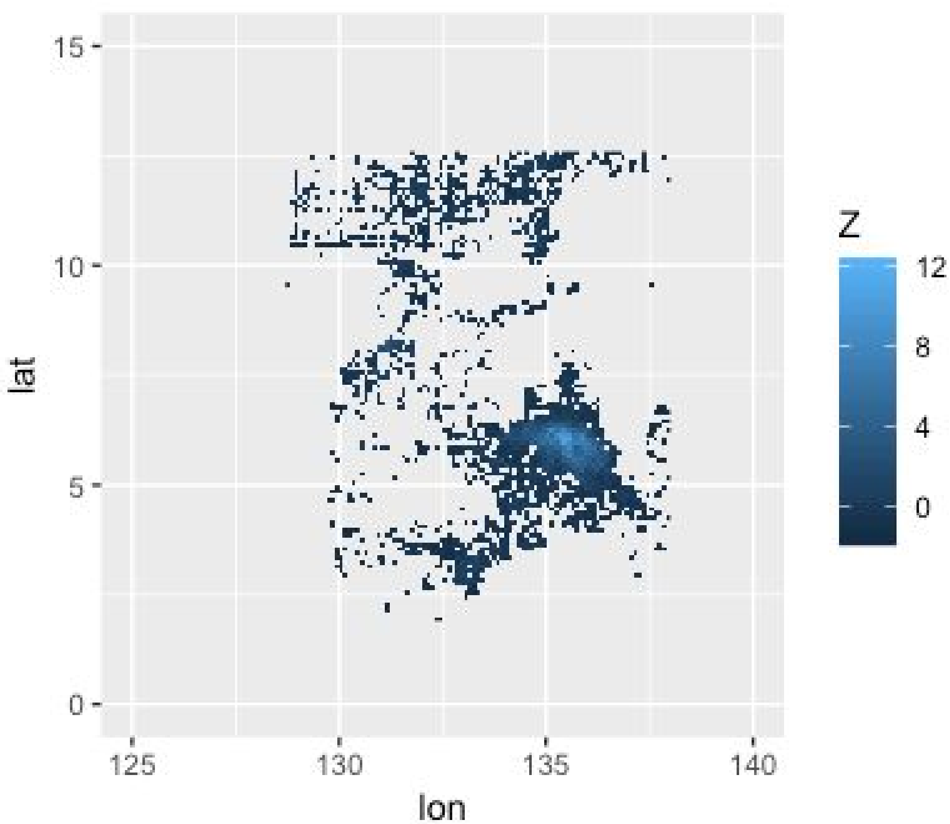

Figure 14. Fishing hotspots within Palau EEZ

8. Tables

Table 1. Top 20 fishing countries in 2016 by fishing hours

id	flag	n_hours
1	ARG	497158
2	CHN	16849183
3	DNK	450251
4	ESP	2132108
5	FRA	1524341
6	FRO	285730
7	GBR	1246703
8	GRC	302416
9	IRL	327132
10	ISL	622084
11	ITA	2103236
12	JPN	1400894
13	KOR	1105190
14	NLD	703764
15	NOR	1016998
16	PRT	599876
17	RUS	1311164
18	TWN	2221200
19	USA	1233422
20	ZAF	338927

Table 2. Top 20 fishing countries in 2016 by number of fishing vessels

id	flag	n_vessels
1	CHN	264
2	FRA	62
3	NOR	62
4	TUR	60
5	ITA	58
6	NLD	53
7	BHR	50
8	ARG	47
9	GBR	45
10	DNK	41
11	ESP	41
12	KOR	37
13	ISL	36
14	PRT	36
15	TWN	35
16	HRV	33
17	URY	33
18	ZAF	33
19	PER	29
20	USA	29

Table 3. Top 50 rows in descending order of z-values for Palau fishing effort based on hotspot analysis

id	lat	lon	Z
1	6.05	135.45	12.0913644
2	6.15	135.35	10.2738243
3	6.05	135.55	9.97406601
4	5.95	135.45	9.68634142
5	6.15	135.55	9.60583911
6	6.15	135.45	8.89394709
7	5.95	135.35	8.85027678
8	5.95	135.55	8.55554426
9	6.05	135.85	8.4841138
10	5.85	135.55	8.41682925
11	6.15	135.25	8.32434547
12	6.25	135.15	8.26930306
13	6.05	135.65	7.98906139
14	6.25	135.45	7.98607313
15	6.05	135.35	7.96596704
16	5.65	135.55	7.8737185
17	6.05	135.25	7.76232759
18	5.95	135.95	7.5923354
19	6.15	135.05	7.51618484
20	6.05	135.05	7.3566939
21	5.95	135.75	7.33993575

22	6.05	135.95	7.30788254
23	6.25	135.35	7.17573362
24	6.15	135.85	7.11475451
25	5.95	135.15	6.8449141
26	5.95	135.85	6.72680228
27	5.75	135.45	6.66088128
28	6.05	134.75	6.61093656
29	5.75	135.55	6.51221236
30	5.95	135.65	6.3965749
31	6.05	135.15	6.38067045
32	5.85	135.65	6.3629781
33	5.85	135.95	6.35873722
34	6.15	135.75	6.28186373
35	5.85	135.45	6.25263262
36	5.85	136.05	6.24815037
37	5.95	136.05	6.19089678
38	5.95	134.95	5.84548889
39	5.75	135.65	5.81359693
40	5.85	135.85	5.77896335
41	5.75	135.95	5.6440867
42	6.25	135.05	5.49824266
43	5.55	135.75	5.48726839
44	5.75	136.05	5.4791619

45	5.65	135.75	5.46404153
46	5.55	135.85	5.4374367
47	6.25	135.25	5.41035919
48	5.85	136.15	5.40129144
49	5.55	135.65	5.36444212
50	6.15	134.95	5.32841695

9. Code

Code Snippet 1

Purpose: For connecting to database

```
BQ_connection <- dbConnect(bigquery(),
                    project = 'global-fishing-watch',
                    dataset = 'global_footprint_of_fisheries',
                    billing = 'fishinghotspots',
                    use_legacy_sql=FALSE)
DBI::dbListTables(BQ_connection)
#"fishing_effort"      "fishing_effort_byvessel" "fishing_vessels"      "vessels"
```

Code Snippet 2

Purpose: For querying database to fetch flag, total fishing hours, total fishing vessels from the fishing effort table

```
top_fishing_data <- glue::glue_sql('SELECT flag,SUM(fishing_hours) AS n_hours,
COUNT(DISTINCT mmsi_present) AS n_vessels FROM
`global-fishing-watch.global_footprint_of_fisheries.fishing_effort` WHERE
_PARTITIONTIME >= "2016-01-01 00:00:00" AND _PARTITIONTIME <"2016-12-31
00:00:00" GROUP BY flag ORDER BY n_hours DESC')
top_fishing_data_fetched <- dbGetQuery(BQ_connection, top_fishing_data)
```

Code Snippet 3

Purpose: For obtaining the top 20 fishing countries based on number of hours fished in 2016, then plotting it as a bar chart

```
top_20_fishing_hours <- top_fishing_fetched %>% group_by(flag) %>%
summarize(n_hours = sum(n_hours)) %>% top_n(20, n_hours)

top_20_fishing_hours_dataframe <-data.frame(flag = top_20_flags_hours$flag,
n_hours = top_20_flags_hours$n_hours)
p <-ggplot(top_20_fishing_hours_dataframe, aes(flag, n_hours))
p +geom_bar(stat = "identity", aes(fill = flag))
```

Code Snippet 4

Purpose: For obtaining the top 20 fishing countries based on number of fishing vessels in 2016, then plotting it as a bar chart

```
top_20_flags_vessels <- flag_data_fetched %>% group_by(flag) %>%
summarize(n_vessels = sum(n_vessels)) %>% top_n(20, n_vessels)

flag_vessels_data <-data.frame(flag = top_20_flags_vessels$flag, n_vessels =
top_20_flags_vessels$n_vessels)
p2 <-ggplot(top_20_flags_vessels, aes(flag, n_vessels))
p2 +geom_bar(stat = "identity", aes(fill = flag))
```

Code Snippet 5

Purpose: For binning lat, lon, summing fishing hotspots and plotting them for the top fishing countries and world, on a global scale

```
binned_effort_around_World_CHN <- glue::glue_sql('SELECT
floor(lat_bin/{resolution})*{resolution}+0.5*{resolution} lat_bin_center,
floor(lon_bin/{resolution})*{resolution}+0.5*{resolution} lon_bin_center,
SUM(fishing_hours) fishing_hours, COUNT(flag) flag FROM (SELECT lat_bin/100
lat_bin, lon_bin/100 lon_bin, fishing_hours, flag FROM
`global-fishing-watch.global_footprint_of_fisheries.fishing_effort` WHERE
_PARTITIONTIME >= "2016-01-01 00:00:00" AND _PARTITIONTIME <"2016-12-31
00:00:00" AND flag = "CHN") GROUP BY lat_bin_center, lon_bin_center HAVING
fishing_hours>0',.con=BQ_connection)
binned_effort_around_World_CHN_data <- dbGetQuery(BQ_connection,
binned_effort_around_World_CHN)

# get world data for China
```

```
plotCHN_world <-binned_effort_around_World_CHN_data %>% filter(fishing_hours > 1) %>% ungroup() %>% ggplot()+ xlim(-180,180)+ ylim(-90,90)+ geom_raster(aes(x = lon_bin_center, y = lat_bin_center, fill = fishing_hours))
```

Code Snippet 6

Purpose: For loading in Palau EEZ shapefile, and getting binned lat, lon and summed fishing hours data from the GFW database for the world and top 6 countries around Palau

```
palau_eez <- readOGR(dsn=".", layer="eez",verbose=FALSE)

# get the bounding box of the shapefile
palau_bbox <- sf::st_bbox(palau_eez)

# extend the bounding box 1 degree in every direction.
min_lon <- palau_bbox[["xmin"]] - 1
max_lon <- palau_bbox[["xmax"]] + 1
min_lat <- palau_bbox[["ymin"]] - 1
max_lat <- palau_bbox[["ymax"]] + 1

# define mapping resolution in degrees
resolution <- 0.1

# get Palau data for China
binned_effort_around_Palau_CHN <- glue::glue_sql('SELECT
floor(lat_bin/{resolution})*{resolution}+0.5*{resolution} lat_bin_center,
floor(lon_bin/{resolution})*{resolution}+0.5*{resolution} lon_bin_center,
SUM(fishing_hours) fishing_hours, COUNT(flag) flag FROM (SELECT lat_bin/100
lat_bin, lon_bin/100 lon_bin, fishing_hours, flag FROM
`global-fishing-watch.global_footprint_of_fisheries.fishing_effort` WHERE
_PARTITIONTIME >= "2016-01-01 00:00:00" AND _PARTITIONTIME <"2016-12-31
00:00:00" AND flag = "CHN") WHERE lat_bin>={min_lat} AND lat_bin <={max_lat} AND
lon_bin >={min_lon} AND lon_bin<={max_lon} GROUP BY lat_bin_center,
lon_bin_center HAVING fishing_hours>0',.con=BQ_connection)
binned_effort_around_Palau_CHN_data <- dbGetQuery(BQ_connection,
binned_effort_around_Palau_CHN)

plotCHN <-binned_effort_around_Palau_CHN_data %>% filter(fishing_hours > 1) %>% ungroup() %>% ggplot()+ geom_raster(aes(x = lon_bin_center, y = lat_bin_center, fill = fishing_hours))
```

Code Snippet 7:

Purpose: Moran's I test

```
lat_bin_c <- c(binned_effort_around_Palau_data$lat_bin_center)
lon_bin_c <- c(binned_effort_around_Palau_data$lon_bin_center)

latlon <- do.call(rbind, Map(data.frame, lat=lat_bin_c, lon=lon_bin_c))
coords <- coordinates(latlon)

knn <- knearneigh(coords, k=4)
Palau_nb <- knn2nb(knn)
Palau_B <- nb2listw(Palau_nb, style="B")

binned_effort_around_Palau <- glue::glue_sql('SELECT
floor(lat_bin/{resolution})*{resolution}+0.5*{resolution} lat_bin_center,
floor(lon_bin/{resolution})*{resolution}+0.5*{resolution} lon_bin_center,
SUM(fishing_hours) fishing_hours, COUNT(flag) flag FROM (SELECT lat_bin/100
lat_bin, lon_bin/100 lon_bin, fishing_hours, flag FROM
`global-fishing-watch.global_footprint_of_fisheries.fishing_effort` WHERE
_PARTITIONTIME >= "2016-01-01 00:00:00" AND _PARTITIONTIME <"2016-12-31
00:00:00")WHERE lat_bin>={min_lat} AND lat_bin <={max_lat} AND lon_bin
>={min_lon} AND lon_bin<={max_lon} GROUP BY lat_bin_center, lon_bin_center
HAVING fishing_hours>0',.con=BQ_connection)

binned_effort_around_Palau_data <- dbGetQuery(BQ_connection,
binned_effort_around_Palau)

set.seed(1)
moran.test(binned_effort_around_Palau_data$fishing_hours,Palau_B,
alternative="two.sided")
```

Code Snippet 8:

Purpose: Geary's C test

```
geary.test(binned_effort_around_Palau_data$fishing_hours,Palau_B, alternative
="two.sided")
```

Code Snippet 9:

Purpose: LocalG test

```
fishing_G <- localG(binned_effort_around_Palau_data$fishing_hours, Palau_B,
zero.policy=NULL, spChk=NULL, return_internals=FALSE, GeoDa=FALSE)

fishing_G_data <- do.call(rbind, Map(data.frame, lat=lat_bin_c, lon=lon_bin_c, Z =
fishing_G))

fishing_G_data %>% ggplot()+ xlim(127,139)+ ylim(1,13)+ geom_raster(aes(x = lon, y =
lat, fill = Z))
```