

Distribution of Six Aquatic Species in the Southern Gulf of Saint Lawrence, Canada

Statistics for Data Science

David Fishman¹

Email ids: ¹davjfish@gmail.com

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1 Objectives

Canada oceans provide an important source of livelihood to Canadians as well as fulfill important ecological services. The Canadian Government has a mandate to ensure the Oceans remain healthy and economically and ecologically viable. The Department of Fisheries and Oceans (DFO) is tasked with conducting regular stock assessment surveys. These surveys can be carried out on either Canadian Coast Guard Science vessels or contracted through privately owned fishing vessels. The stock assessment surveys conduct fishing and oceanographic activity as a means to monitor fish populations and produce population indices. Many of the data from stock assessment surveys have been made available via the Open Government Portal [?].

1.1 Goal of the analysis

The importance of having robust models for predicting the distribution of aquatic organisms cannot be overstated. From a resource extraction point of view, modelled distributions can help direct fishing efforts; resulting in more efficient fisheries. From an environmental conservation point of view, modelled distributions can help identify which geographic areas should be targets for conservation efforts. The goal of this analysis is to build models that can be used to predict the probability of occurrences of species of interest in the Southern Gulf of St. Lawrence (sGSL). Specifically, I employ a logistic regression approach, using latitude, longitude and water depth (i.e., elevation) to predict the probability of occurrence of the following six species:

- American plaice (*Hippoglossoides platessoides*)
- Atlantic cod (*Gadus morhua*)
- Atlantic herring (*Clupea harengus*)
- Redfish unidentified (*Sebastes sp.*)
- American lobster (*Homarus americanus*)
- Snow crab (*Chionoecetes opilio*)

1.2 Rationale behind the analysis

Spatial autocorrelation, i.e., when observations in space that are closer together are more correlated, is a common occurrence in the natural world [?].

Accordingly, I would expect that using geographic coordinates to predict the distribution of occurrences would be useful.

A basic tenet of ecology is that different species acquire different specializations and thus inhabit different ecological niches and strategies. In aquatic ecosystems, the physio-chemical and ecological environments change substantially with water depth. For example, certain species will be physiologically adapted to cope with the colder temperature, higher pressure and salinity levels that occur at low elevations. However, within the scope of a given ecosystem (e.g., within the sGSL) certain species will specialize more than others; i.e., specialist versus generalists. Accordingly, I would expect that, at least for certain species using a measure of water depth at a given location would be useful in predicting the likelihood of occurrence.

2 Data Preparation

2.1 What was your data source?

Three datasets were used in this analysis.

The first, as noted above, was the Government of Canada’s Open Government Portal [?]. The name of the dataset is NAFO Division 4T groundfish research vessel trawl survey (September Survey) dataset [?]. The dataset contained information ecological information (i.e., species caught, specimen counts and specimen weights), fishing information (i.e., gear type used, fishing vessel) and spatial information (i.e., latitude and longitude). For mapping purposes, I also used a geospatial file of the Canada Provincial Boundaries from the same catalogue [?].

The dataset did not contain an elevation data and therefore this had to be acquired elsewhere. Luckily, there is an excellent website and web app called the General bathymetric Chart of the Oceans (GEBCO), which is maintained by the international community [?]. The web app provides an interface for downloading world ocean’s bathymetric data.

2.2 How good was the data quality?

The quality of the fishing data was excellent. There were no missing values and the column data types were respected. For example, the columns that you would expect to be *float* type, e.g., lat/lon values, were indeed. The dataset was accompanied by a data dictionary, which contained clear explanation of the variables in both English and French. The only thing worth mentioning was that the coordinate reference system for the latitudes and longitudes were difficult to obtain. They are not displayed on the website but the metadata XML file did specify EPSG 4269.

2.3 What did you need to do to procure it?

The data from the Open Government Portal was downloaded using a web browser. The data was accessible via a static link. The format of the fishing data was a single comma separated values (CSV) document and the map was formatted as a GEOJSON file. The GEBCO elevation data was downloaded using their customizable web application. In this application, I was able to download the bathymetric data as a NetCDF file for only the area of interest. I was very impressed with this tool!

2.4 What tools or code did you need to use to prepare it for analysis?

2.4.1 Fishing Data

As noted above, the species / fishing data was very clean. I loaded the data from its original CSV into a pandas dataframe. I ensured all the data types made sense using the **DataFrame.info()** method. The dataset contained 166,694 rows of data; each one being a species observation at a particular place and time. When exploring the dataset, it became apparent that there for a given coordinate on a given date, there were many species observed. For the sake of efficiency, I parsed the original dataset into two separate dataframes: one containing the biological information (species observed, how many, total weight) and the other containing the site / fishing set details (time, date, lat/lon). The linkage between the two tables was made by a fishing set ID column named **site_id**. After this was done, I was dealing with a total of 7,257 fishing sets which are on display in Figure 1. Finally, I wanted there to be a boolean response column in the fishing set dataframe for each species of interest. To do this, I used the pandas *Series.apply* method on the *set_id* column. The apply function took the set ID and searched for a corresponding entry in the species dataframe. If one was found, the function return *True*, otherwise it returned *False*.

2.4.2 Mapping Data

The GEOJSON file was loaded using the geopandas python library into a geodataframe. The only data preparation needed for these data was to re-project the dataset to the same coordinate reference system as the fishing data. As noted above, the point data from fishing was presented in EPSG 4269. Without this step, the points and polygons cannot be represented on the same map.

2.4.3 Elevation Data

The elevation data was downloaded in NetCDF format and loaded directly into the python Xarray library [?]. When plotted using **Matplotlib**, you can clearly see the familiar contours of Atlantic Canada, the characteristic shallow waters of the sGSL and the deeper waters out in the channel of the St. Lawrence seaway (see Figure 2).

Using this two-dimensional array of elevation data, the next step was to extrapolate an elevation value for each fishing set in the fishing set dataframe. To do this, I followed an example from the **Xarray** docs. Specifically, I made

use of the Data Array *sel* method. This method has an argument called *method* which specifies how to deal with inexact matches, i.e., when trying to determine elevation for a set of coordinates that are not in the array. I decided to use the *nearest* method, which returns value from the nearest coordinate. To add an elevation column to the dataframe, I used the pandas Dataframe.apply method in combination with the above. I then looked at a histogram of elevation value to: a) ensure that no single elevation value was greater than 0m (i.e. above sea level) and b) to get a sense of the distribution of elevation across the dataset (see Figure 3)

A screenshot of the first five rows of the final fishing set dataframe that was used in the subsequent phase of the analysis is presented in Figure 4

2.5 What challenges did you face?

Since geographic information systems is not my area of expertise, I found it challenging figuring out how to reproject a geographical data to another coordinate reference system. In the end, this was not too difficult, but it took time to figure out.

Another major challenge was learning about the Xarray python package [?]. This is a very impressive package, albeit quite complex. It took me a long time to figure out how to extract the data from a data array, manipulate it and create a new data array.

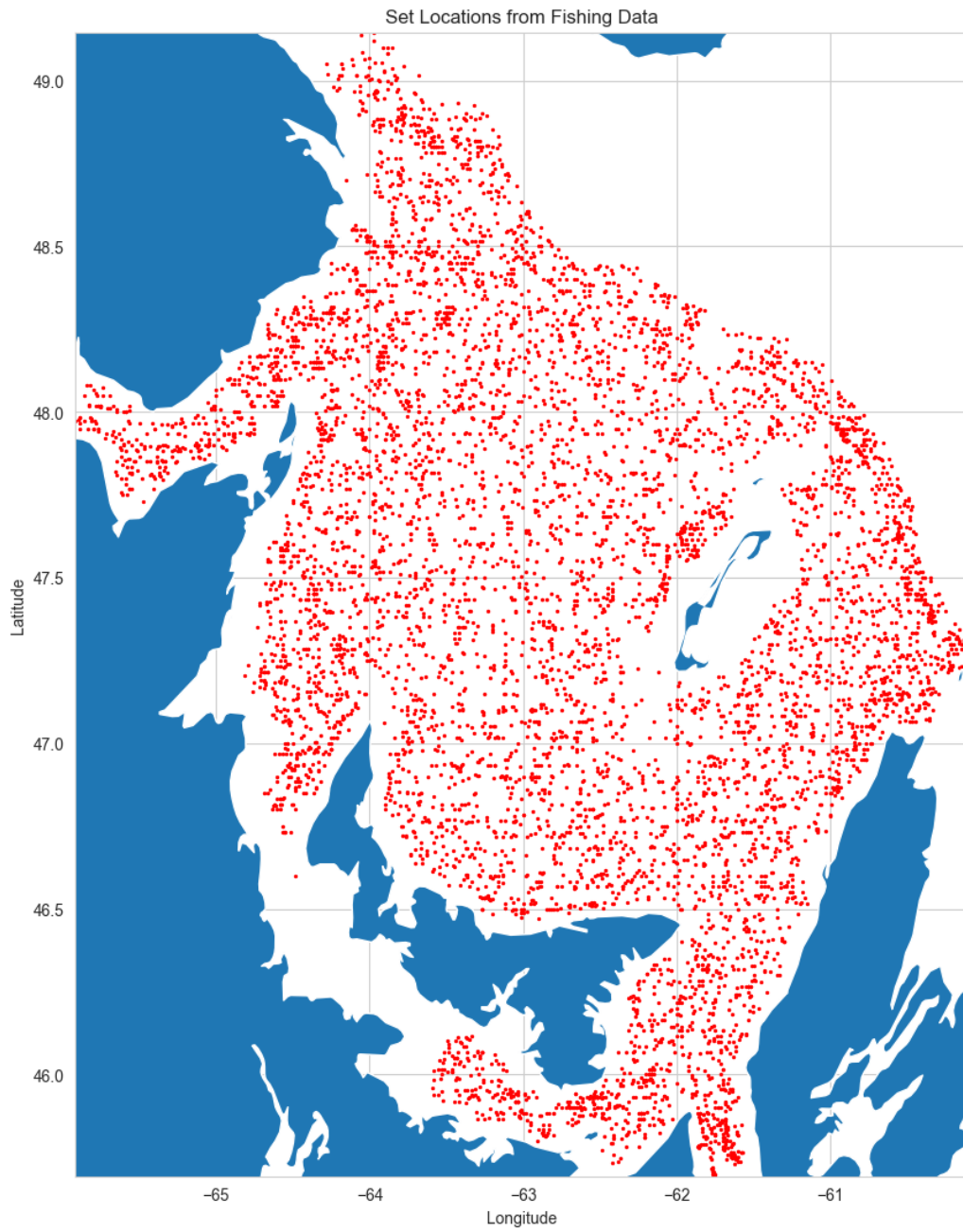


Figure 1: This figure displays the 7,257 fishing sets contained in this dataset. A fishing set is represented by a red point.

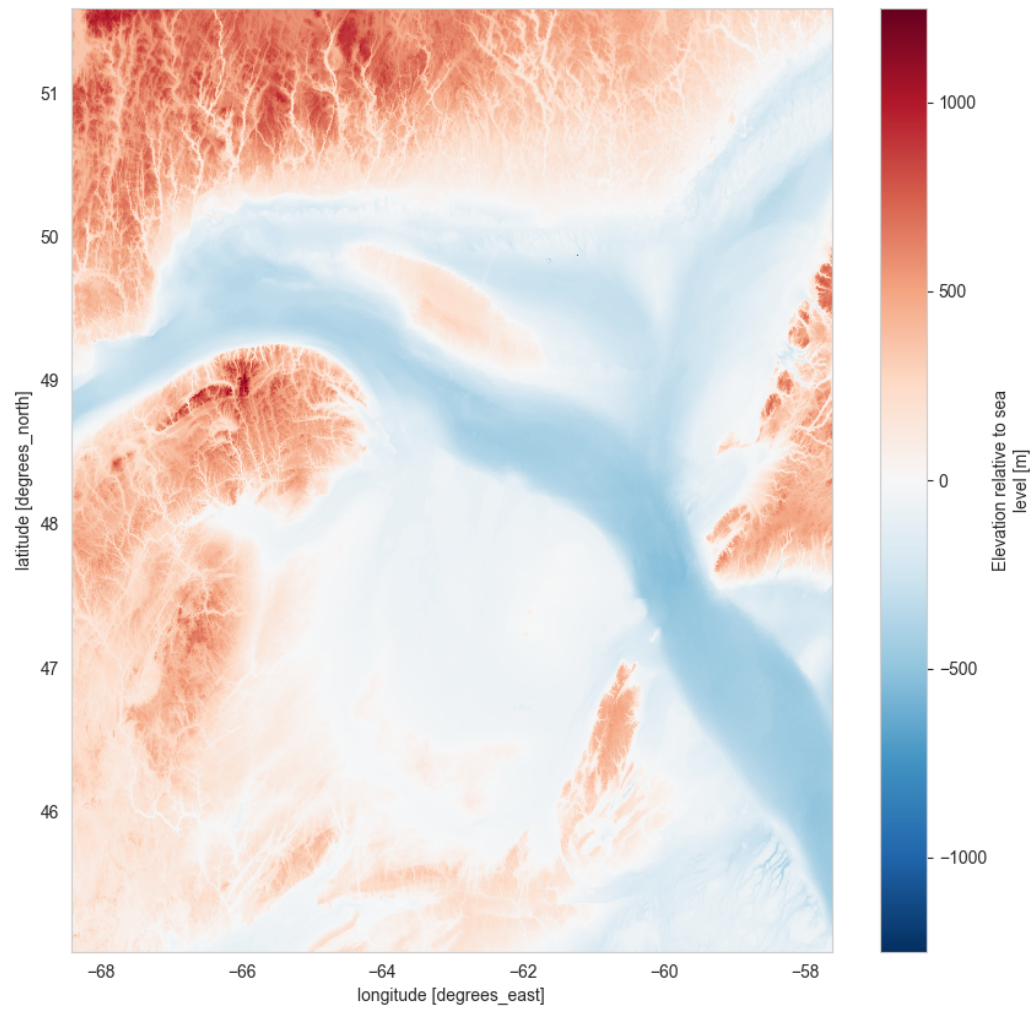


Figure 2: This figure shows the raw elevation data array. The values are color codes according to the elevation in meters

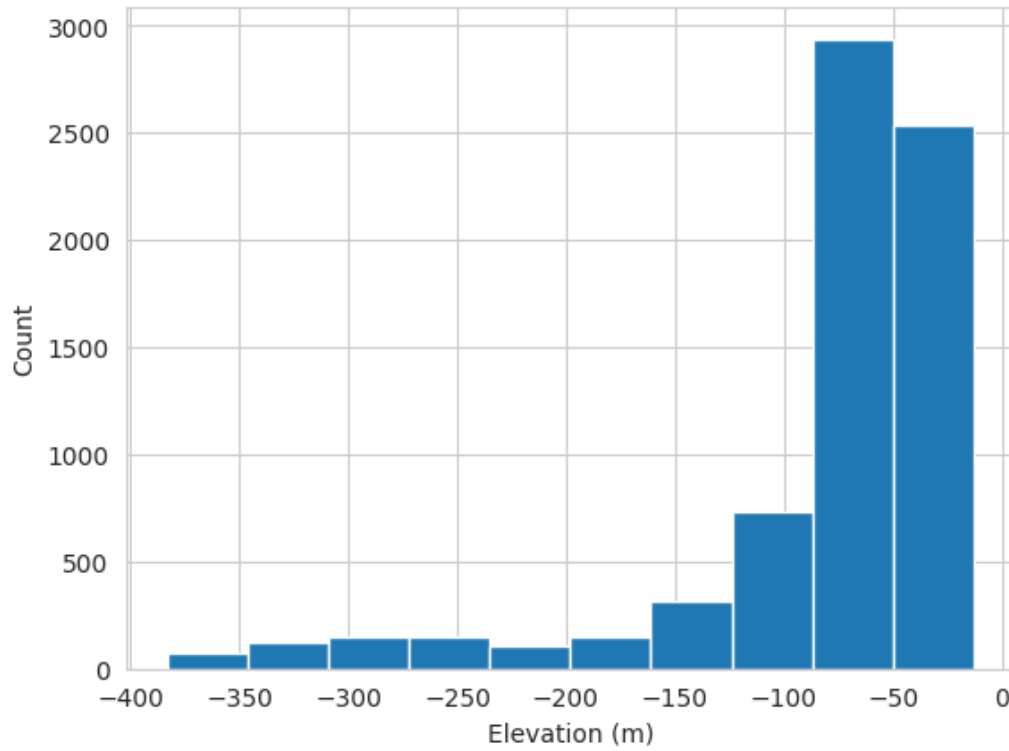


Figure 3: A frequency distribution of elevation in meters. Most of the sites have an elevation between -100m and 0m.

	set_id	latitude	longitude	dt	elevation	American plaice	Atlantic cod	Atlantic herring	Redfish unidentified	American lobster	Snow crab
11	1	47.966667	-65.116667	1971-09-07 11:15:00	-87	True	True	False	False	False	False
23	2	47.933333	-65.250000	1971-09-07 12:45:00	-73	True	True	False	False	False	False
24	3	47.916667	-65.516667	1971-09-07 15:05:00	-48	True	True	True	False	False	False
0	4	48.016667	-64.766667	1971-09-07 08:25:00	-80	True	True	True	False	False	False
35	5	48.216667	-64.483333	1971-09-08 10:25:00	-96	True	True	False	False	False	False

Figure 4: A screenshot of the first five rows of the fishing set dataframe, used in the subsequent phase of the analysis.

3 Analysis

3.1 Logistic Regression Models

The fishing dataset, as prepared in the previous section, was used to model the probability of observing each of the six species. A separate regression model was computed for each species, all taking on the following form:

- Where y is the number of chickens, measured in millions of individuals
- and x_1 is the price of chicken meat, in dollars per kilogram

4 Conclusions

4.1 Was the model useful?

Within the geographic scope of this dataset, certain species were found to be ubiquitous while others seemed to be more specialized and heterogeneous in their distributions. In the case of the former, American plaice being the best example, the models were of limited use. For species like Redfish and Lobster, which are known to respond strongly to water depth, the models were seemed to be very effective. In the heatmap for Lobster, it was interesting to note the areas which the model predicted the presence to be highest are very well-established lobster fishing areas (hence why no samples were collected there).

4.2 What did you learn about your data set?

Aquatic ecosystems face numerous challenges, from over-fishing to climate change to the introduction of invasive species. Distribution

Would be really interesting to look at the trends over time.