Problem Chosen	2020 MCM/ICM Summary Sheet	Team Control Number
A		**2013645**

Moving North: Fish For a Lifetime

Summary

Global climate change has aroused many issues worldwide. On account of absorbing excessive greenhouse gases, the average ocean temperature is continuously increasing year by year. This poses a potential threat to Scottish fishing companies to some extent. In this paper, we quantitatively introduce our prediction models of ocean subsurface temperature and spatial distribution of herring and mackerel to estimate how this trend would continue and how it would affect local fishing companies, especially smaller ones. Moreover, some decent advice examined by realistic background and a magazine article with two pages is also involved.

To begin with, we construct an Ocean Subsurface Temperature Prediction Model by multi-variable regression based on a database with 6,327,000 samples consisting of monthly average ocean temperature, time, depth, latitude and longitude. Because of its strong seasonal periodicity, our original model is improved by adding 12 binary time features. It is inevitable to meet some outliers in this immense database and we validate this model's feasibility under the scope of the UK's territory sea by presenting the distribution of R^2 by coordinates.

Then we estimate the spatial distribution of herring and mackerel based on our precious temperature model and two species' habits. Inspired by a study of other fish species' population, we assume that the possible density of herring and mackerel model satisfies a Gaussian function of temperature and verify its applicability by comparing our results with reliable research on the capture distribution of mackerel conducted in 2015. Thus, it follows a detailed analysis of how two species will migrate in the next fifty years.

Based on this macroscopical change, we propose three feasible approaches to helping small fishing companies in Scotland decrease their benefit loss as far as possible after determining their specific locations. First, we use the Analytic Hierarchy Process (AHP) model to confirm the necessity for these southern companies to relocate their assets to the northern port. Second, by applying the dynamic programming algorithm with vessels' detailed parameters, we obtain the most profitable fishing strategy by reallocating the ratio of small vessels. Third, enlightened by the application of trawling in pelagic fishing, we recommend adjusting the fishing nets in vessels over time according to a visualized depth-oriented distribution of mackerel. Finally, we put our suggestions under the realistic background, like consideration of territorial sea, and Brexit, to examine their credibility.

Keywords: Ocean temperature, Fish migration, Multi-variable linear regression, Gaussian distribution, Analytic Hierarchy Process model.

Contents

1 Introduction

1.1 Background

According to the Scottish Government's 'Ambition 2030' [1] strategy to strengthen Scottish food and drink as the most crucial industry in Scotland, mackerel and herring are perceived as the most crucial species to stabilize a valuable, and hopefully growing, market for Scottish seafood processors. They are precious natural resources from Scotland's shores and in high demand worldwide because of its tasty and rich nutrition. Therefore, the sale of mackerel and herring is the predominant source of the Scottish economy. However, confronted with the increasing climate change these years, the average global ocean temperatures are rising year by year, and it will be bound to influence the distribution of certain plankton species. Anxiety has spread to some small Scottish fishing companies and they are seeking help from a consulting company for some reasonable suggestions, in order to make plans according to the possible changes to achieve the maximized benefits stably. If the company does not properly deal with it, a conceivable crisis may cause great damage only to those fishing companies but also to the economic development of Scotland.

1.2 Restatement of the Problem

Our team is asked to predict how Atlantic herring and mackerel would migrate based on their habitus and optimum living temperature. This prediction model will enable the Scottish North Atlantic fishery management consortium to gain a better knowledge of the potential changes in the future and help them adopt the most reasonable and practical measure to deal with this unavoidable but predictable situation. In order to solve these problems, we will proceed as follows:

- Give a reasonable prediction of ocean temperature in the surrounding areas of Scotland by virtue of the ocean water change in previous years, and thus predict the spatial distribution of two fish species.
- Put forward the corresponding solutions to manage the potential danger to the smaller fishing companies in Scotland based on our prediction model
- Evaluate the feasibility of our proposals under the realistic situation, especially regarding the territorial waters of other countries.

1.3 Previous Research

Global climate change has been in a heated discussion these years, and lots of research indicates that the ocean absorbs most of the excess heat from green gas emissions. Thus, it leads to increasingly rising ocean temperatures. Data from the US National Oceanic and Atmospheric Administration (NOAA) [2] shows that the average global sea surface temperature – the temperature of the upper few meters of the ocean – has increased by approximately 0.13°C per decade over the past 100 years. A paper published in 2012 in the journal Geophysical Research Letters [3] revealed that the deep ocean is also affected, with one-third of the excess heat absorbed 700 m below the sea surface. Since the trend of global warming is inevitable, it sets alarm for fishing companies worldwide and some smaller fishing industries are bound to be influenced by this trend. Therefore, it is urgent for those companies to be aware of the potential effects that water temperature change would bring by predicting any small variation of the fishery in the next 50 more years.

2 Assumptions and Justifications

To simplify our problems, the first aspect that we took into major consideration was to make the following basic assumptions, all of which are properly justified.

- **Scottish herring and mackerel are sensitive enough to the change of water temperature and tend to move to their optimal habitat.** Owing to the small optimal temperature intervals of these two species, it is suggested that the two fish species are sensitive to the tiny change of water temperature. Other water properties including pH, dissolved oxygen, salinity are out of consideration.
- **The capture range of a vessel is a circle centered on a port, and all fish in that circle is possible to be captured**. In the course of the sailing, the vessels will not encounter a congestion.
- **Freshness of the catches is seen as the only factor that limit capture range of small vessels**. Because of the variety of vessel types, we will not consider fuel capacity as the main factor that limit capture range.

3 Notations

Symbol	Description
T	Temperature of the pixel
Y	Year
Lat	Latitude of the pixel
Lon	Longitude of the pixel
Dep	Depth of the pixel beneath ocean surface
$M_1, M_2, \ldots, M_{12}$	$1 \longrightarrow$ True; $0 \longrightarrow$ False for 12 months
$\mu_{H/M}$	Mean living temperature of Herring/Mackerel
$\sigma_{H/M}$	Living temperature's standard deviation of Herring/Mackerel
$D_{H/M}$	Probability density of Herring/Mackerel

4 Prediction of Ocean Subsurface Temperature in 50 Years

4.1 Case Study and Data

In order to predict the migration of Scottish herring and mackerel, it is important to predict temperature changes on the ocean surface, which dramatically impacts their motion. Our study area consists of the northeastern portion of Atlantic, the Norwegian Sea and the North Sea ($45°N - 80°N$ latitude and $20°W - 15°E$ longitude). We derive the ocean surface data from Ocean Data Assimilation Experiment [4], which is generated by incorporating multiple near real-time data with a resolution of $1°$. Our data consists of monthly average ocean surface temperature T of different time (year Y, month M), coordinates (latitude Lat and longitude Lon), and depth Dep. Since the moving ranges of both fish are within 200m beneath the ocean surface [5, 6], we will focus on water up to a depth of 200 meters. The time variable is the period from 1961-1 to 2010-12. Depth of water is from 0 - 200m, with the gap of 10m.

In total, we have the dataset consisting of 6,327,000 samples. We cut the samples according to the time variable. The training set is from 1961 to 1995, and the validation set is from 1996 to 2010.

4.2 Methodology

Based on the dataset, we are going to construct a multi-variable regression model between ocean surface temperature and relevant factors. First of all, we assume that there is a multiple linear regression model $T_{Lat,Lon,Dep}(Y, M)$ between time and temperature for every latitude, longitude and depth.

$$T_{Lat,Lon,Dep}(Y, M) = \beta_0 Y + \beta_1 M \tag{1}$$

We use $sklearn$ regression package in $Python$ to solve the model (all data was normalized before fitting into the model), and get average coefficient of determination $R^2 = 0.312$ and $RSME = 1.632$, which is not a satisfactory outcome.

To improve our model, by observing the difference between the prediction and the real in some sample points, we find there are strong seasonal periodicity. (Figure 1) Therefore, we highlight the season's impact on ocean temperature by adding 12 binary time features $M_1, M_2, \ldots M_{12}$.

Figure 1: Original Regression Figure

Therefore, we get the improved model below:

$$T_{Lat,Lon,Dep}(Y, M_1, M_2, \ldots, M_{12}) = \beta_0 Y + \beta_1 M_1 + \beta_2 M_2 + \cdots + \beta_{12} M_{12} \tag{2}$$

After solving the model, the improved overall R^2 is 0.735. After validating the model, the $RMSE$ is 0.7665. Compared to the first regression, the improved regression is Figure 2.

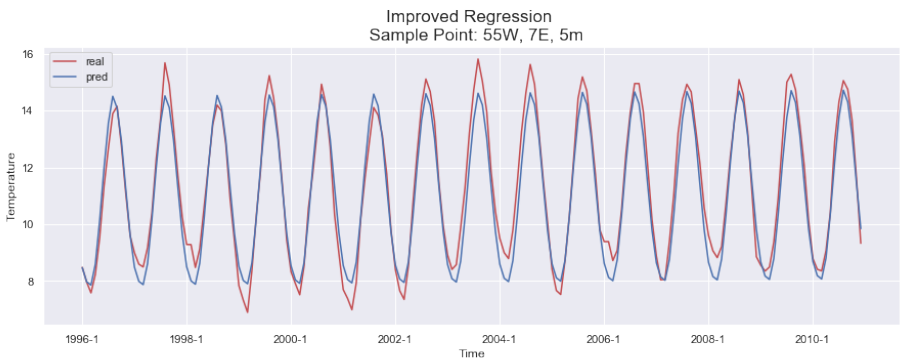

Figure 2: Improved Regression Figure

According to the distribution of R^2 by latitude and longitude (Figure 3), and find out that the R^2 is small in the high latitude area, which has small impacts on the following model.

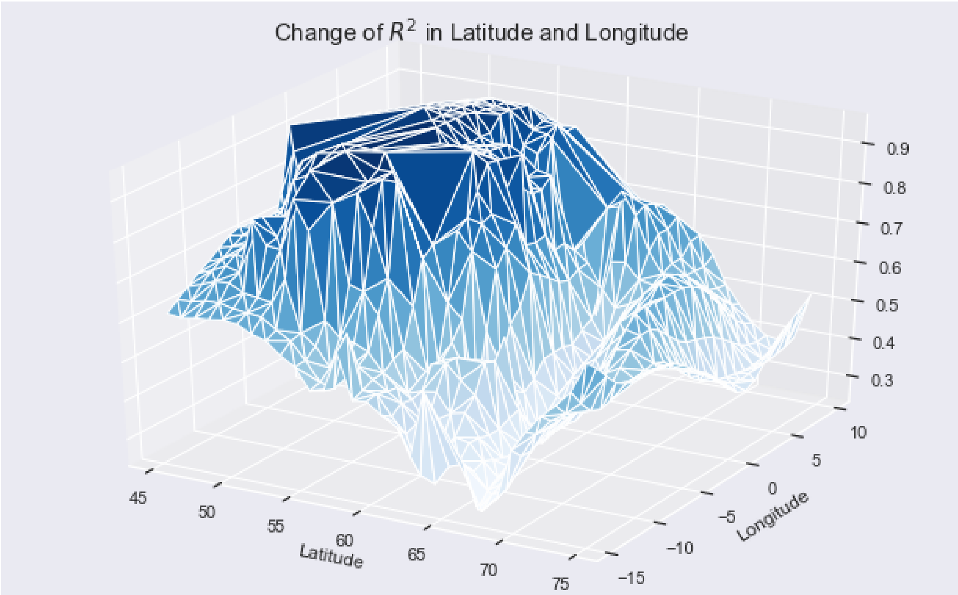

Figure 3: Change of R^2 in Latitude and Longitude

5 Estimate the Spatial Distribution of the Fish

5.1 Gaussian-distribution Assumption

According to our assumption, we will consider temperature as the only factor that influences the migration of fish. Scottish herring and mackerel are observed widely in the North Atlantic in a broad range of temperatures. However, the majority of mackerel (95%) are found in a much narrower temperature range of $5-15°C$ and most herring (95%) are found in $7-13°C$ [7, 8]. In a study of lumpfish population, Eriksen [9] shows that there is a linear relationship between the predicted log-density of lumpfish and mean temperature of the location. Without loss of generality, we assume that the possible density of Scottish herring and mackerel satisfies a Gaussian function of temperature.

5.2 Methodology

Based on our assumption of Gaussian-distribution, we are able to estimate the probability density of the appearance of fish by

$$p_{H/M}(T) = \frac{1}{\sqrt{2\pi\sigma_{H/M}^2}} e^{-\frac{(T-\mu_{H/M})^2}{2\sigma_{H/M}^2}} \tag{3}$$

where $\mu_M = 12°C$, $\sigma_M = 1.5°C$ for mackerel, and $\mu_H = 10°C$, $\sigma_H = 1.5°C$ for herring. With the ocean temperature model mentioned above, we can construct:

$$P_{H/M}(Y, M, lat, lon, dep) = p_{H/M}(T(Y, M, lat, lon, dep)) \tag{4}$$

To check this model, we search for the capture distribution of Mackerel 2015 [10]. Since the typical fishing season of Mackerel is May to November [11] and the typical depth of fishing is 0-20m for small vessels, we took the average density of and drawn the figure below. (Figure 4)

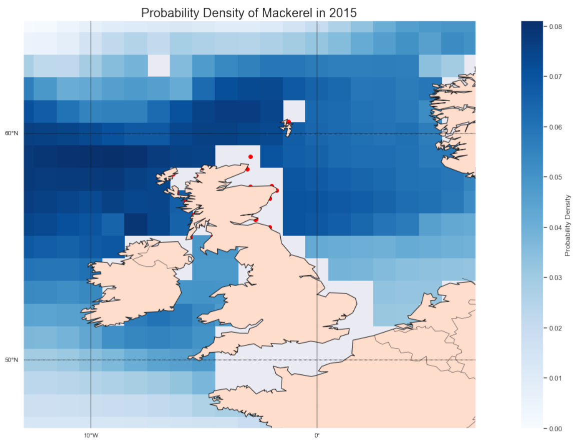

Figure 4: Predicted Distribution of Mackerel in 2015

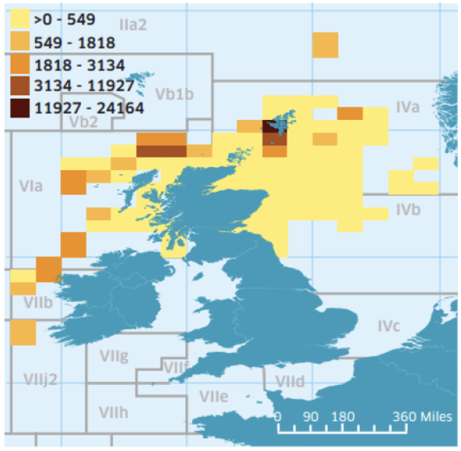

Figure 5: Real Distribution of Mackerel Catches [10]

5.3 The Estimated Fish Density in Next 50 Years

After computing the probability density of all $1^\circ \times 1^\circ$ pixels, we are able to analyze the trend of fish's migration. The result come from the average density from May to November (the fishing season in Scotland [11]) and the average density from 0m to 20m in depth, which is the typical fishing range of the small vessels.

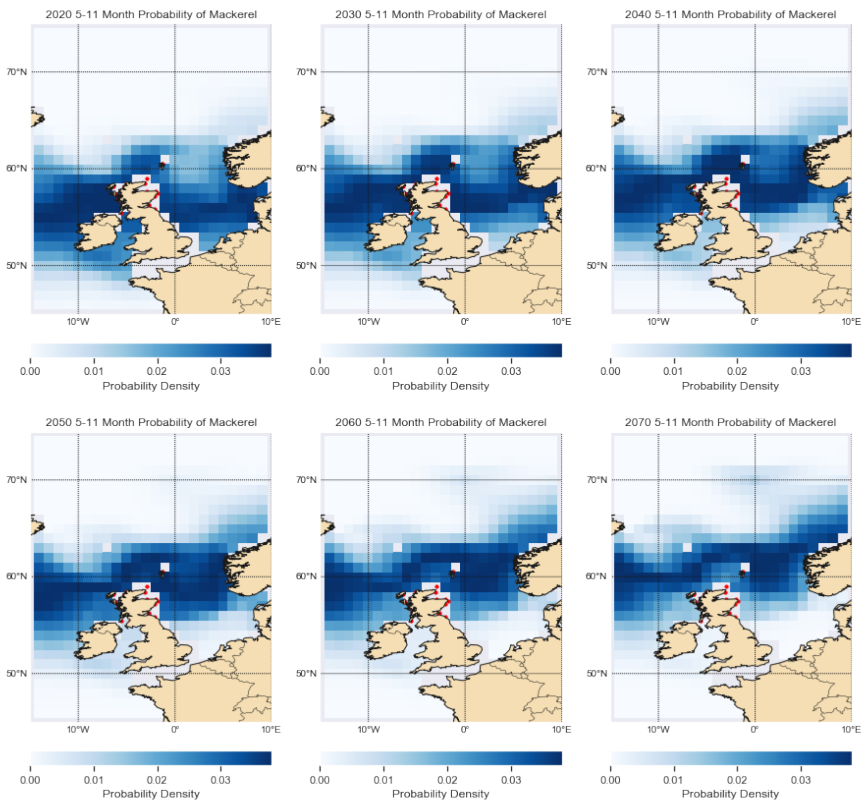

Figure 6: Spatial Distribution of Mackerel in 50 Years

In the case of mackerel, its high-density areas mainly locate in the western coast of Ireland, the northern and western coast of Scotland and all over the North Sea. Due to the water's temperature change, mackerel will migrate roughly in the direction of the northeast up to 2070. The high-density areas will mainly situate in the northeast of the Atlantic, including the Faroe Island's surrounding waters, the southeastern corner of Iceland northwest of Norway.

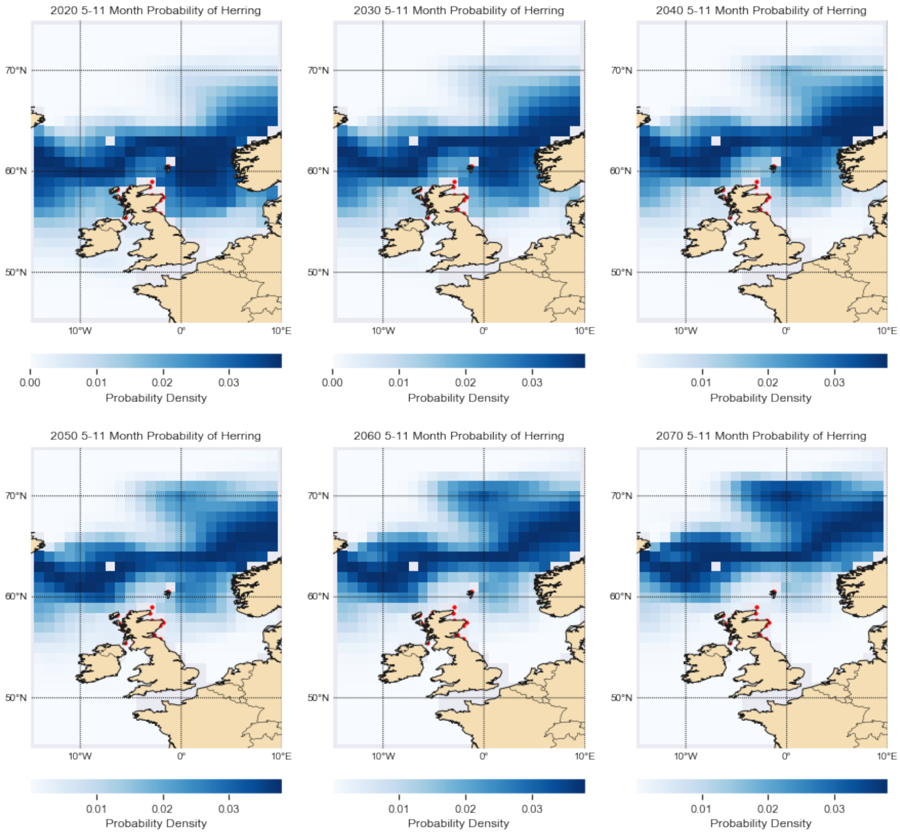

Figure 7: Spatial Distribution of Herring in 50 Years

In the case of herring, the high-density areas mostly locate in the southern coast of Iceland, north of Scotland, south of Faroe Island, the northwestern coast of Norway, and the northern part of North Sea. Because of the water's temperature change, herring will migrate roughly in the direction of north up to 2070. The high-density area will mainly situate in the northeast of Atlantic, including south of Iceland, the western and northern coast of the Faroe Island, and northeast of Norway.

In general, these two species both tend to migrate northward roughly in a relatively fast speed on account of the rapid change of water's temperature. However, the movement speed of herring is remarkably faster than mackerel, extending to over $4°$ by 2070 intuitively.

6 Prediction of Company Operating Situation

6.1 Case Study and Data

By calculating the vessels' speed, we estimate the capture radius of the small fishing company is $2°$. We have acquired the total capture of mackerel (tons) in some of the Scotland Ports [12,13]. We draw the name and the capture range of the ports in the following figure 8:

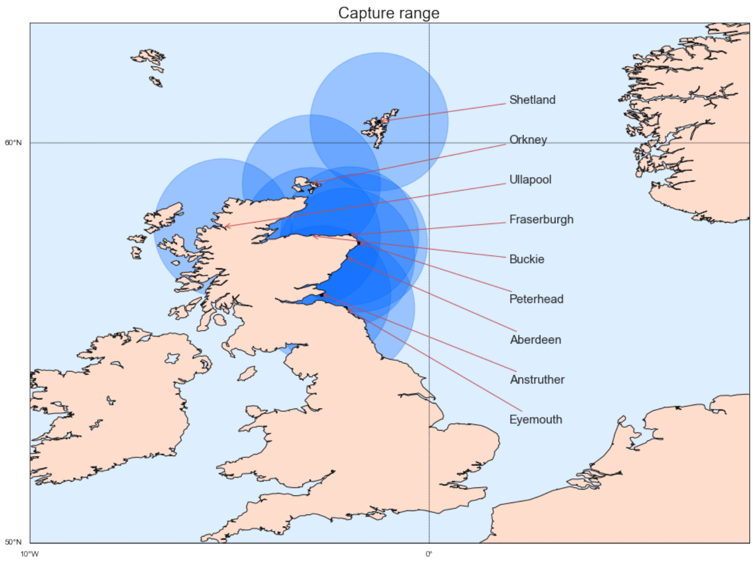

Figure 8: Capture Range of the Ports

6.2 Methodology

We can calculate the average mackerel or herring density for all the ports:

$$D_{H/M}(Lat_0, Lon_0) = \frac{1}{\pi r^2} \sum_{lat} \sum_{lon}^{dis<r} S(Lat_0, Lon_0, lat, lon, r) P_{H/M}(lat, lon, <dep>) \quad (5)$$

In (5), the $S(Lat, Lon, lat, lon, r)$ computes coverage area of the $1° \times 1°$ pixel at (lat, lon) as left down corner and port at (Lon, Lat) with the fishing range r. The diagram can be found in Figure 9.

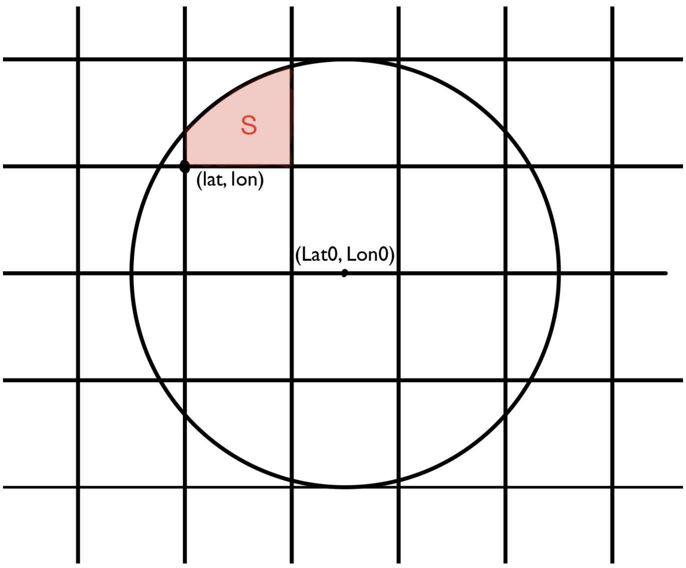

Figure 9: Diagram of S function

6.3 Results and Analysis

With the total capture of mackerel's and the mackerel's probability density of each port, we can get an average coefficient $k = \frac{Capture}{Density}$. Then, we can predict the capture of mackerel in each port with our previous model (Figure 10, 11, 12).

Through the analysis of Scottish Sea Fisheries Statistics in 2018 [13], we estimate that the fishing company will go out of business with its capture decreasing 20%. We use the 90% prediction interval to predicate the best case and worst case. We can see that those ports at the south, such as Eyemouth and Anstruther, tend to decrease faster, which the port at the north will hold longer, such as Shetland.

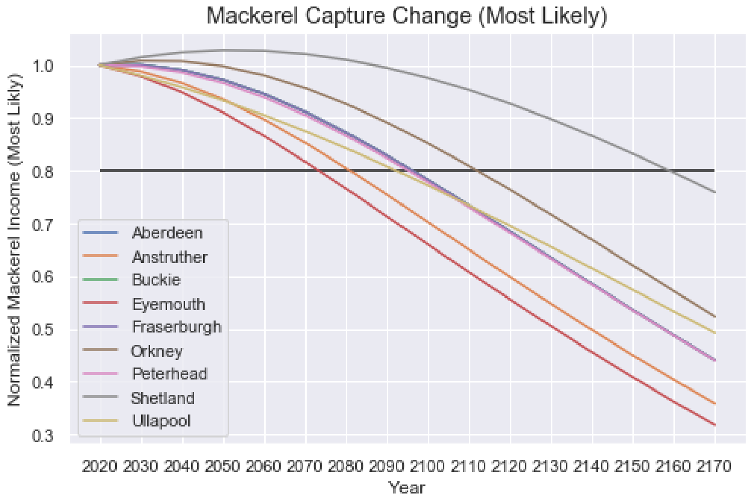

Figure 10: Mackerel Income Change (Most Likely)

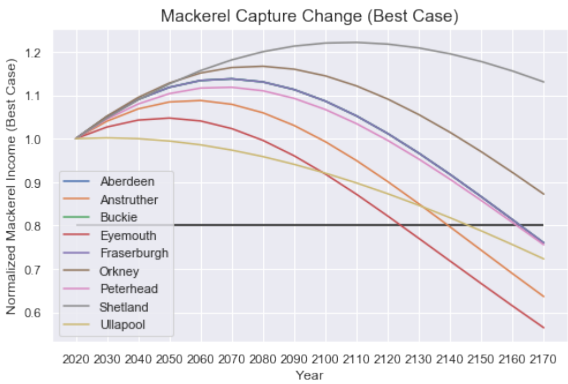

Figure 11: Mackerel Income Change (Best Case)

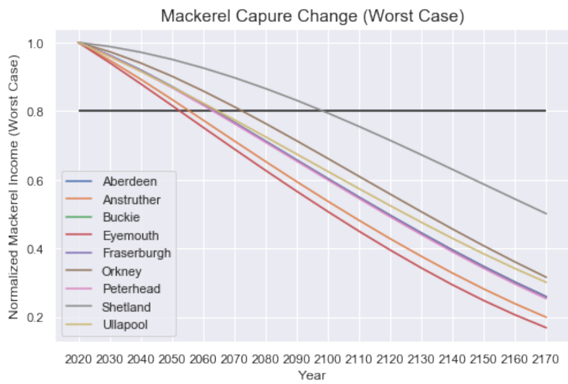

Figure 12: Mackerel Income Change (Worst Case)

As is vividly shown in those charts, for the best case, most companies will not go out of business until around 2140 to 2160 based on the previous premise. If so, those companies are not necessarily too worried about the species' potential migration. However, if we consider the worst case, those danger may arrive earlier, that is, between 2050 to 2080. Normally, it is more likely that the difficult time for most fishing companies is around 2090 to 2110.

7 Advice for Scottish Small Fishing companies

In view of the reasonably predictive analysis of the potential changes in water temperatures and possible migration of herring and mackerel, our team is considering making some recommendations for some small Scottish fishing companies to make some adjustments to maximize their benefits. As we can conclude from the previous analysis, these two species would likely move north in the future to seek for a better habitat with more appropriate temperature and ample fish baits, therefore, we came up with three different types of improvement measures and managed to verify their feasibility respectively.

7.1 Relocating Assets

The geographic position of the main assets is of great significance to a fishing company. In response to the migration of the fish, transferring some of the company's assets to Northern Scotland can reduce the distance between fishing companies and the port, which will, to some extent, decrease the cost. However, a much fiercer competition could happen in this industry and also this transferring could lead to environmental problems. Considering these potential influences, We adopt the AHP Model to examine whether it is worth relocating a company's assets using the three most influential criteria to grade different relocation options.

7.1.1 Establish a Hierarchical Model

There have been a few studies carried out on considering the most crucial factors in managing the fishery industry. For example, Zeraatkish [14] concluded that economic, political and biological factors are three dominant parts in this industry and Partovi [15] claimed that the quality and efficiency for a fishing company are both inevitable elements and became more vital when the species are in higher demand in the market segment. Besides those which have been mentioned in previous research, we also referred to some other practical factors related to this realistic problem based on the complex local situation. By combining and classifying these factors in an organized way, there is a detailed and visualized diagram demonstrated below:

Economic Index: Access to fish, Transferring cost, Employment, Labor condition

Political Index: Maintain fishing industry at present level

Environmental Index: MSY (Maximum Sustainable Yield), Efficiency

Through the analysis of the three main criteria above, which affect the evaluation significantly, hierarchy figure is portrayed below:

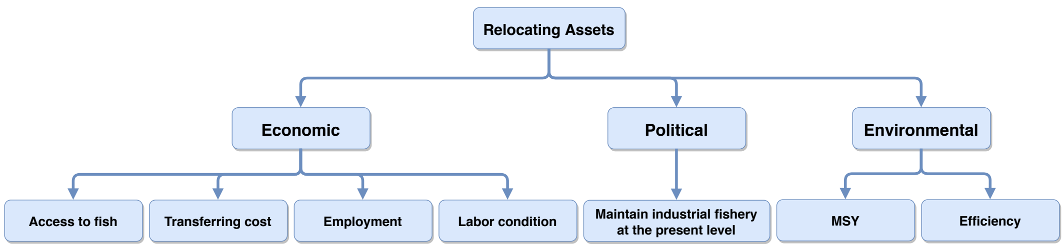

Figure 13: Hierarchy Figure

7.1.2 Analysis and Result

Integrating the previous studies mentioned above and both the current and predicted condition in Scotland, we obtained a comparison matrix dealing with the three indexes and got the weights of each one using AHP Model: (Complete matrix of hierarchy can be seen in the Appendix A)

As we can conclude from the data above and the ones in Appendix A, economic factors account for the largest proportion, and among them, two indexes from economic hierarchy *Access to fish*, *Transferring cost* and *MSY* are given the highest weight on the third hierarchy, to be more precise, their weights are all more than 0.2000. In other words, these three variables account for the maximum proportion when analyzing the decision of relocating assets in this

Table 1: Pairwise comparison matrix of hierarchy I-II (consistency ratio: 0.0068)

Comprehensive impact	Economic	Political	Environmental	Weight
Economic	1	7	3	0.6694
Political	1/7	1	1/3	0.0879
Environmental	1/3	3	1	0.2426

case. Back to the dilemma that these smaller Scottish fishing companies will encounter in the future, it is absolutely necessary for those who are now located in Southern part to consider moving their companies somewhere near the ports located in the north of Scotland so that the index *Access to fish* would be satisfied firstly even though transferring cost cannot be ignored. Besides, MSY does count in this measurement (0.2022), and this concept is, on one hand, based on the ecological concept of sigmoid population growth toward the carrying capacity of the ecosystem for the respective species. On the other hand, it reflects the optimal fishing amounts indeed. That is to say, the importance of MSY reveals the necessity of both avoiding overfishing, and maintaining the optimal economic benefits over the years. In conclusion, our team recommends relocating total assets for those Southern Scottish fishing companies based on the previous assumption.

7.2 Optimize Small-vessel Fishing without Land-based Support

Small fishing companies mainly use small vessels ($\leq 10m$) to conduct pelagic fishing. Their sizes limit their abilities to access areas far from shore, which may have higher fish population density. Therefore, to make a balance between reducing traveling expenses and getting close to high-density areas is of great importance to maximize profit. In the previous analysis, if a small vessel keeps fishing along the trip, it can approach a circular area with a radius of $2°$. But if we let the fishing vessels go to further waters, it must steam in the close distance, which will make the fishing area a ring-like shape. For example, the famous port, Peterhead, have the fishing radius in Figure 14.

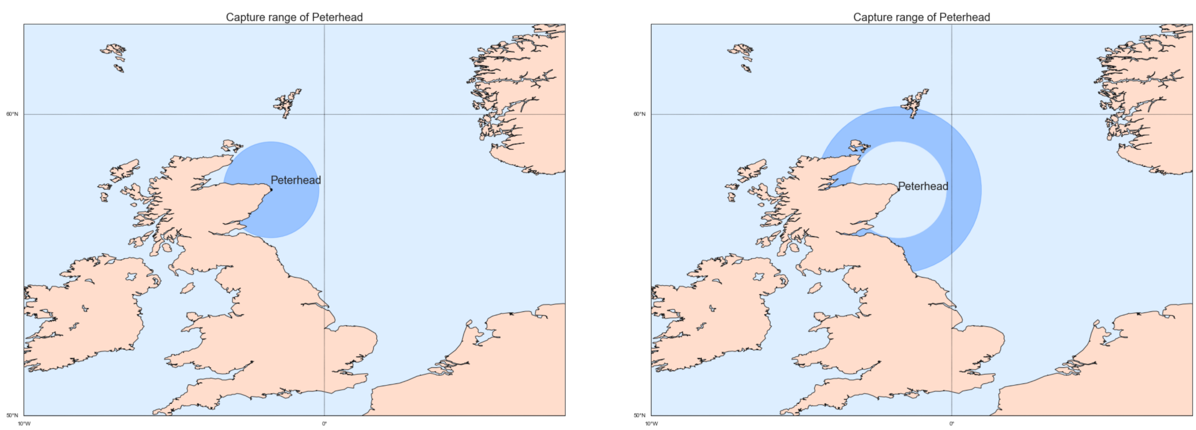

Figure 14: Capture Areas of Peterhead

By applying the dynamic programming algorithm, we find the most profitable fishing areas for each port. The improved profit percentage is drawn in the Figure 15.

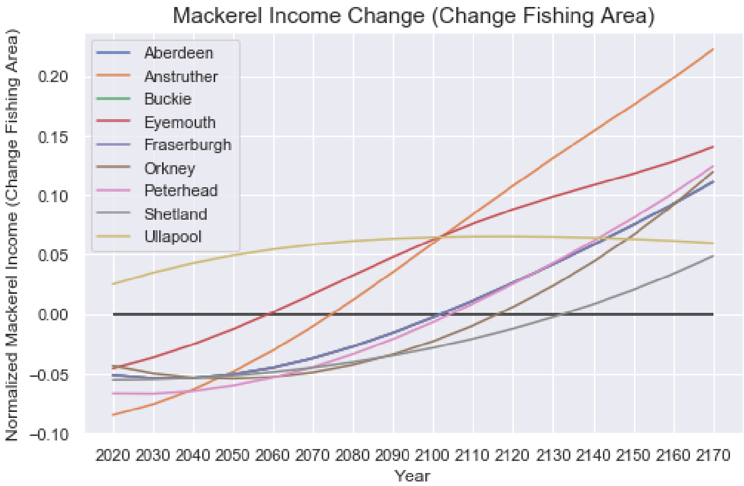

Figure 15: Mackerel Income Change (Changing Fishing Area)

Since we have the restriction that the steaming radius must be larger than $1°$ to see the difference with the original strategy, the percentage is negative for some ports. We can see that this strategy works better for the ports in the south. The reason might be the fish is going north.

7.3 Determine the Optimal Depth of a Fishing Net

In pelagic fishing, one of the most common fishing methods is trawling, where the depth of fishing nets plays an important role in capturing fish. According to our computation, the depth of the suitable temperature of both fish species will keep increasing due to global warming. It means that the high-density area of fish may keep becoming deeper as well. Therefore, we have developed a model to determine the best depth of fishing nets in different time series and thus offer advice for different ports.

7.3.1 Change of High-density Area's Depth

After computing the depth of high-density areas from 2020-2070 by choosing a sample point (62°N, $4.5°$W), we find that there exists a significant difference about the distribution of mackerel's density in the depth: (Figure 16)

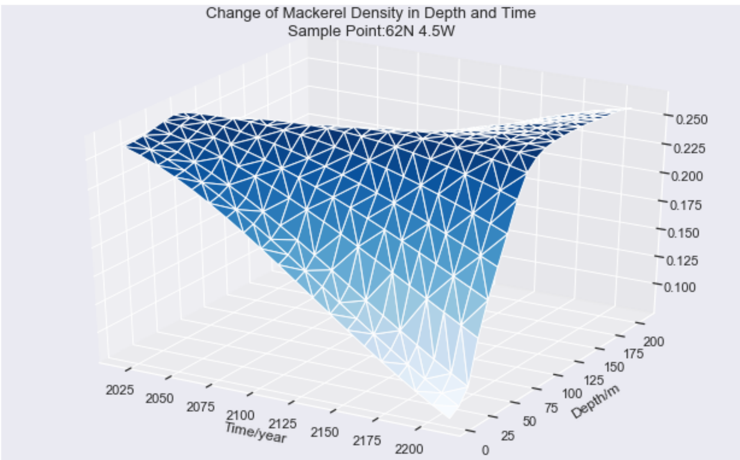

Figure 16: Changing of Probability in Depth and Time

7.3.2 Change of Optimal Depth with Respect to Time

After trying different depths (deeper than 20m for comparison), the improvement of optimal depths for each port is drawn in the Figure 17. We can see that this strategy begins to make profit in about 2050, and continue to raise in the following year. It also works better for the ports at the southern areas.

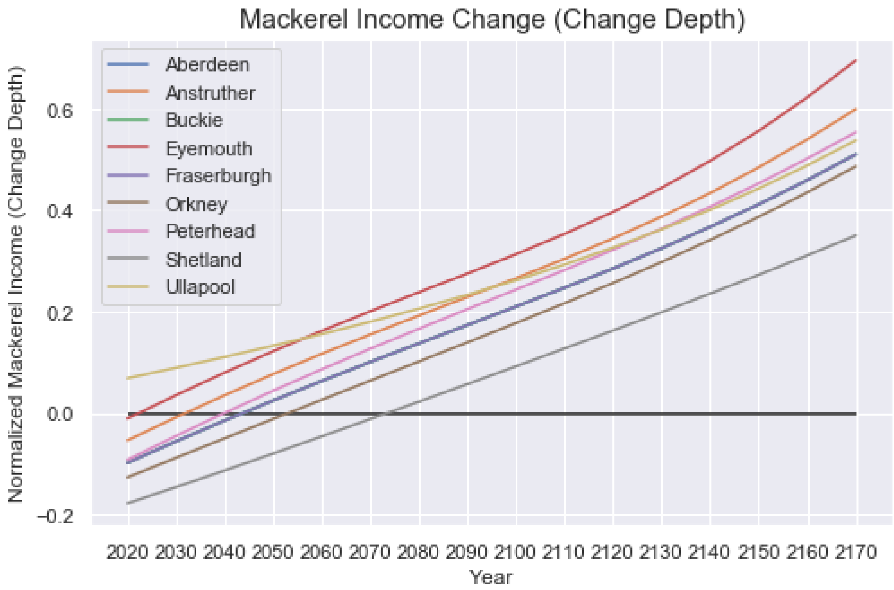

Figure 17: Mackerel Income Change (Change Depth)

8 Cross-border Fishing

According to the predictive analysis we have presented above, both herring and mackerel will probably move northward significantly. As a result, there exists a high possibility that Scottish fishing vessels cannot catch these two species due to the limitation of territory sea stipulated by each country and the EU. Therefore, it is necessary to test our model in a more realistic background. In other words, the feasibility of recommendations that we provided above is supposed to be examined under the regulation of the division of the territorial sea and other related agreements which have reached a comprehensive consensus. From the predictive distribution of the two fish species and the exclusive economic zones of the UK and neighboring coastal states [16], we find that those species tend to move to the territorial waters of Iceland, the Faroe Islands, and Norway, which are not part of the EU.

Since Brexit has taken effect from January 31, 2020, the UK has entered a transition period in terms of the relationship between this nation and the EU. In the following part, we will only consider the potential influence which will happen after the year 2021 when the UK has completely left the UK. Up till now, Faroe Island has signed up the free trade agreement with the UK and it will take effect after the first day of 2021. Thus, it is eligible for Scottish vessels to fish in those areas and export herring and mackerel to maintain a stable revenue. Although both Norway and Iceland have not been in agreement with the UK till now [17], we may as well assume that the policy between those three countries would at most make a tiny change after 2021 from one negotiation conducted in April 2019 [18].

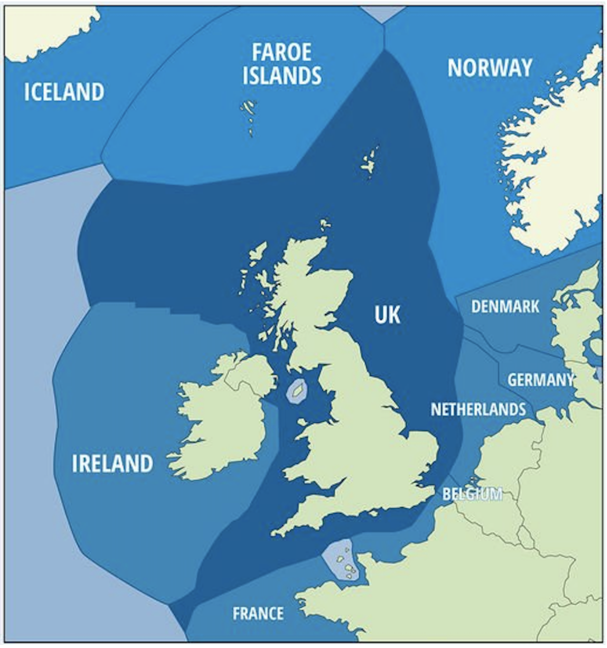

Figure 18: Exclusive Economic Zones of UK and Neighbouring Coastal States [16]

8.1 Changes in Proposal I

According to the analysis above, these changes will only influence some extra fixed tariffs if those fish are caught in the waters of Iceland and Norway. Thus, we decided to make some adjustments on the relative weight between economic and political factors, or add more on the Political hierarchy II-III, such as taxes and tariffs, to make it more reliable and practical in the AHP model that we constructed above. It will increase the cost by lowing the access to fish and adding other tariffs if Scottish fishing companies have no alternative but to fish in other territory waters. But the reality is that it will not let those companies go bankrupt, instead, it will maintain the level of profit. In conclusion, the change in the fish distribution will not extremely influence the feasibility of relocating assets.

8.2 Changes in Proposal II

In Proposal II, we have shown that without land-based supply, small vessels will only be able to travel about $4°$ from shore to ensure freshness of the catch. If the small fishing companies want to maximize their profit and fish in other countries' territorial waters (if permitted), the trip will probably beyond their reach (over $6°$). As a result, land-based support from nearby countries will be essential for small fishing companies. We suggest that the small fishing companies ask nearby countries for supply or sell their catch on those countries. From the map, we can see that Iceland, Faroe Islands and Norway are all within the reach if small vessels can get supply from them.

8.3 Changes in Proposal III

In Proposal III, we offer optimal fishing depth for small fishing companies. This proposal will not be significantly affected by the location of fishery, as long as the predicted spacial distribution is accurate enough.

9 Sensitivity Analysis

9.1 Impact of Global Warming Rate β_0 on Fish Density

The coefficient of Y (year), β_0, in our regression function is aimed to describe the global warming rate, which is rather important in the model. We analyze the change of global warming coefficient on the total capture of mackerel in two ports, Shetland and Ullapool, which are the most northern and southern port, respectively. (Table 2, 3)

Table 2: The Sensitivity of the Global Warming Rate in Shetland

β_0	Temperature					
	2020	2030	2040	2050	2060	2070
-15%	1.25%	1.45%	1.63%	1.82%	1.99%	2.16%
-10%	0.84%	0.96%	1.09%	1.21%	1.33%	1.44%
-5%	0.42%	0.48%	0.54%	0.61%	0.66%	0.72%
0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5%	-0.42%	-0.48%	-0.54%	-0.61%	-0.66%	-0.72%
10%	-0.84%	-0.96%	-1.09%	-1.21%	-1.33%	-1.44%
15%	-1.25%	-1.45%	-1.63%	-1.82%	-1.99%	-2.16%

Table 3: The Sensitivity of the Global Warming Rate in Ullapool

β_0	Temperature					
	2020	2030	2040	2050	2060	2070
-15%	1.04%	1.20%	1.36%	1.51%	1.66%	1.81%
-10%	0.69%	0.80%	0.91%	1.01%	1.11%	1.21%
-5%	0.35%	0.40%	0.45%	0.50%	0.55%	0.60%
0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5%	-0.35%	-0.40%	-0.45%	-0.50%	-0.55%	-0.60%
10%	-0.69%	-0.80%	-0.91%	-1.01%	-1.11%	-1.21%
15%	-1.04%	-1.20%	-1.36%	-1.51%	-1.66%	-1.81%

We could see that global warming coefficient β_0 change about $\pm 15\%$ would bring the capture change for about only $\pm 3\%$. Therefore, we come to the conclusion that the results are not sensitive to different values of β_0.

10 Model Evaluation and Further Discussion

10.1 Strengths

- We use multiple linear regression to predict ocean temperature in next 50 years based on a comprehensive dataset. Using our model, the monthly mean temperatures of a certain year can be predicted with a relatively high accuracy ($RMSE = 0.7665$).
- We use Gaussian Distribution to model the temperature's impact on the special distribution

of two fish species, and our predicted distribution shows high consistency with the real-catches distribution in Scotland.

- We develop an AHP model to help small fishing companies make better decision on relocating assets, which takes economic, political and environmental effect of relocation into consideration.

- Considering the lack of on-board refrigeration and land-based support, we build the Capture Range Model to help small fishing companies find their optimal fishing areas.

- We innovatively analyze the optimal trawling depth based on the Ocean Temperature Prediction Model we have developed. Our model is able to determine the optimal fishing depth at a certain location in a certain month, which will improve the fishing companies' efficiency and profit to a large extent.

- Throughout our modeling, we have set reasonable assumptions to provide convenience to build and solve models. We also take the sensitivity analysis which verified the stability of our models.

10.2 Weaknesses

- Many properties of water are ignored in our model, including transparency, pH, dissolved oxygen, salinity and so on. In reality, those factors may influence the migration of herring and mackerel comprehensively.

- Our training data only consist of 50 years, so the prediction in a long-time scale may lack confidence.

10.3 Further discussion

In our Ocean Surface Temperature Prediction Model, we apply multiple linear regression algorithm due to its low computational expense and high accuracy. It would be even more accurate if we can use more advanced prediction models like Recurrent Neural Networks(RNN) because ocean systems are generally nonlinear systems, and RNN has an inherent ability to learn sequentiality.

If given enough data about the operation cost of small fishing vessels, we can build up Fishing Cost Model and combine it with our optimizing catches model to quantitatively analyze and predict the revenue of small fishing companies.

Our model incorporates natural laws, logical mathematical principles and proposal for practical issues. It can be also adapted to study the spatial distribution of other fish species and fishing migration problems in other oceans.

11 Article for *Hook Line and Sinker* Magazine

Have you heard about greenhouse gas emissions and climate change? Perhaps you are familiar with these terms since you may overhear this news from social media but not clear about its seriousness towards the Scottish fishing industry in the next 50 years. But don't worry! The following prediction model will help you gain insight of how ocean temperature change would affect your future business prospects.

Our team has finished the model including three aspects: prediction of ocean subsurface temperature in 50 years, estimation of the spatial distribution of herring and mackerel, recommendations for fishing company operation.

We derived the ocean surface data from Ocean Data Assimilation Experiment [4], and shaped our database with over **6,327,000** samples, including time, coordinates, and depth, in order to better describe any average month ocean temperature near Scotland in the next 50 years. Based on these data, we firstly construct a multivariable regression model to identify the relationship between ocean temperature and other factors, like year, month, depth, longitude and latitude. Then this model is polished up by adjusting the related parameters when our team notices that there exist a strong seasonal periodicity and the effect of global warming.

On the basis of this temperature prediction model, our team successfully obtains a spatial distribution model by combining the habitat of herring and mackerel. Inspired by a study of the lumpfish population conducted by another scholar Eriksen [9],our team assumes that the density of Scottish herring and mackerel satisfies a Gaussian-distribution while temperature varies, which is commonly existed in our daily life. For example, the value of height and weight of fifth-grade primary school students in a certain area satisfy this normal distribution. Fortunately, this model fully corresponds to a statistical study in 2015, and it indicates that both fish tend to migrate to the north for over 4° in the next 50 years. For Scottish fishing companies, it is still not too late to take action to settle this problem.

But how? Perhaps some of you are still puzzled by this scientific analysis. Therefore, our team managed to adopt the AHP (Analytical Hierarchy Process) to identify whether it is worth relocating companies' assets or assigning some proportions of small vessels to pelagic areas in order to maximize their profits. The result is that the index *Access of fish* counts over several factors, whose weight accounts for **0.3608**. In other words, if the port where the vessels locate is too far from the fishery, it will strikingly decrease your company's profit, and even lead to a bankrupt. That's not joking. Certainly, maybe someone may argue that if those species migrate to other nation's territorial sea, how can their company deal with that situation? The answer is *Stay Calm*! Since we have noticed a free trade agreement between the UK and the Faroe Islands taking effect from 2021, and a positive trend that the UK, together with Norway and Iceland is likely to maintain their relationship of mutual benefit on the vessel permission and fixed tariffs after negotiating on the conference in 2020, a transition Brexit period. As a result, for your fishing company, the related policy and Brexit would not make a huge difference to the following adjustments.

We hope our proposals about the adjustments based on our prediction models helpful to you and wish your company survive in this unavoidable change!

References

[1] Ambition 2030 National Food and Drink Industry strategy. 2017. https://www.gov.scot/publications/foi-17-02823/

[2] NOAA. Climate at a Glance. https://www.ncdc.noaa.gov/cag/global/time-series/globe/ocean/ytd/12/1880-2017

[3] Levitus, S. et al. World ocean heat content and thermosteric sea level change (0-2000 m), 1955-2010. Geophysical Research Letters, 2012, 39(10). doi:10.1029/2012gl051106

[4] Whit, Anderson. Ocean Data Assimilation Experiment: An improved ocean state product. https://www.gfdl.noaa.gov/ocean-data-assimilation/

[5] New World Encyclopedia. Mackerel. https://www.newworldencyclopedia.org/entry/Mackerel

[6] Bigelow, Henry B. and William C. Schroeder. Fishery Bulletion of the Fish and Wildlife Service. http://www.gma.org/fogm/Clupea_harengus.htm#d0e10928

[7] Atlantic Mackerel Can't Stand Heat in Our Waters. https://vineyardgazette.com/news/2011/09/15/atlantic-mackerel-cant-stand-heat-our-waters

[8] Rockmann, Christine et al. Realized habitats of early-stage North Sea herring: Looking for signals of environmental change. ICES Journal of Marine Science, 2011. doi: 10.1093/icesjms/fsq171.

[9] Eriksen, Elena, Caroline M. F. Durif, and Dmitry Prozorkevich. Lumpfish (Cyclopterus lumpus) in the Barents Sea: development of biomass and abundance indices, and spatial distribution. ICES Journal of Marine Science, 2014.

[10] Davies, Damon. Mackerel. SPICe Briefing, 2018, SB: 18-30.

[11] ReelandRod. What are the Sea Fishing Seans in the UK. http://reelandrod.co.uk/what-are-the-sea-fishing-seasons-in-the-uk/

[12] Scottish Sea Fisheries Statistics 2012. https://www.gov.scot/publications/scottish-sea-fisheries-statistics-2012/

[13] Scottish Sea Fisheries Statistics 2018. https://www.gov.scot/publications/scottish-sea-fisheries-statistics-2018/

[14] Zeraatkish, S.Y. Utilization of analytic hierarchy process (AHP) to meet management objectives in fishery industry of the Sea of Oman. Iranian Journal of Fisheries Sciences, 2016, 15(4): 1379-1387.

[15] Partovi, Fariborz Y. An analytic model for locating facilities strategically. Science Direct, 2004.

[16] Exclusive Economic Zones around the United Kingdom. Oxford Analytica. https://dailybrief.oxan.com/Analysis/GI242020/

[17] https://norwaytoday.info/finance/the-eu-and-norway-are-not-in-line-with-the-2020-fisheries-agreement/

[18] https://www.gov.uk/government/news/uk-norway-and-iceland-signtrade-continuity-agreement

Appendices

Appendix A AHP model

Comparison Matrix of Criterion Hierarchy

Results in the form of comparison matrix of the following layers in detail:

Table 4: Pairwise comparison matrix of Economic hierarchy II-III (Consistency ratio: 0.0623)

Comprehensive impact	Access to fish	Transferring cost	Employment	Labor Condition	weight
Access to fish	1	2	9	7	0.3608
Transferring cost	1/2	1	7	5	0.2200
Employment	1/9	1/7	1	1/3	0.0294
Labor Condition	1/7	1/5	3	1	0.0592

Table 5: Pairwise comparison matrix of Environmental hierarchy II-III

Comprehensive impact	MSY	Efficiency	weight
MSY	1	5	0.2022
Efficiency	1/5	1	0.0404

MATLAB codes for AHP model

```
disp('Please print judgment matrix A')
A = input('A=');
[n, n] = size(A);

%Calculate the consistency index
[V, D] = eig(A);
Max_eig = max(max(D));
CI = (Max_eig - n) / (n - 1);
RI = [0 0.0001 0.52 0.89 1.12 1.26 1.36 1.41...
    1.46 1.49 1.52 1.54 1.56 1.58 1.59];
CR = CI / RI(n);
fprintf('Consistency ratio is %f\n', CR);
```

```
if CR < 0.10
    disp('This matrix is applicable.');
    %Use eigenvalue to determine the weight of different factors
[r,c] = find(D == Max_eig , 1);
disp('The weight of those factors are:');
disp( V(:, c) ./ sum(V(:, c)) )
else
    disp('This matrix is not applicable and needs revision');
end
```

Appendix B Codes

Python codes for Regression

```
from sklearn import datasets, linear_model
import pandas as pd
import numpy as np
from netCDF4 import Dataset
import time

Yea_max = 2170
Yea_min = 1961

# Class for linear regression and pridection interval
class LRPI:
    def __init__(self, normalize=False, n_jobs=1, t_value = 1.645):
        self.normalize = normalize
        self.n_jobs = n_jobs
        self.LR = linear_model.LinearRegression(normalize=self.normalize, n_jobs= self.n_jobs)
        self.t_value = t_value

    def fit(self, X_train, y_train):
        self.X_train = pd.DataFrame(X_train.values)
        self.y_train = pd.DataFrame(y_train.values)

        self.LR.fit(self.X_train, self.y_train)
        X_train_fit = self.LR.predict(self.X_train)
        self.MSE = np.power(self.y_train.subtract(X_train_fit), 2).sum(axis=0) / (self.X_train.shape[0] - self.X_train.shape[1] - 1)
        self.X_train.loc[:, 'const_one'] = 1
        self.XTX_inv = np.linalg.inv(np.dot(np.transpose(self.X_train.values) , self.X_train.values))

    def predict(self, X_test):
        self.X_test = pd.DataFrame(X_test.values)
        self.pred = self.LR.predict(self.X_test)
        self.X_test.loc[: , 'const_one'] =1
        SE = [np.dot(np.transpose(self.X_test.values[i]) , np.dot(self.XTX_inv, self.X_test.values[i]) ) for i in range(len(self.X_test)) ]
        results = pd.DataFrame(self.pred , columns=['Pred'])
```

```
        results.loc[:,"lower"] = results['Pred'].subtract((self.t_value)* (np.sqrt(self.MSE.values + np.multiply(SE,self.MSE.values) )),  axis=0)
        results.loc[:,"upper"] = results['Pred'].add((self.t_value)* (np.sqrt(self.MSE.values + np.multiply(SE,self.MSE.values) )),  axis=0)
        return results

# Normalization
def MaxMinNormalization(x, Max, Min):
    x = (x - Min) / (Max - Min);
    return x

# Get Year and Month from ISO time stamp
def Timestamp_datetime(value):
    value = time.localtime(value)
    return (int(time.strftime('%Y', value)), int(time.strftime('%m', value)))

#Regression
def Regression():
    dat = Dataset("hawaii5.nc")
    temps = dat.variables['temp'][:, :, :30, 35:60]
    lats = dat.variables['latitude'][:30]
    lons = dat.variables['longitude'][35:60]
    deps = dat.variables['depth'][:]
    tims = dat.variables['time'][:]
    Lmodels = {}
    for j in range(len(lats)):
        Lmodels[lats[j]] = {}
        for k in range(len(lons)):
            Lmodels[lats[j]][lons[k]] = {}
            for l in range(len(deps)):
                X_now = []
                Y_now = []
                for i in range(len(tims)):
                    if lats[j] is np.ma.masked or lons[k] is np.ma.masked or deps[l] is np.ma.masked or temps[i][l][j][k] is np.ma.masked: # Is land
                        break
                    year, month = Timestamp_datetime(tims[i])
                    tmp = [MaxMinNormalization(year, Yea_max, Yea_min)] # Year
                    for t in range(1, 13):
                        tmp.append(1 if month == t else 0) # Month
                    X_now.append(np.asarray(tmp))
                    Y_now.append(temps[i][l][j][k])
                if len(X_now) == 0:
                    continue
                Lmodels[lats[j]][lons[k]][deps[l]] = LRPI()
                Lmodels[lats[j]][lons[k]][deps[l]].fit(pd.DataFrame(X_now), pd.DataFrame(Y_now))
    return Lmodels

# Get prediction interval
def Pred_int(Lmodels, year, month, lat, lon, dep):
    X = [MaxMinNormalization(year, Yea_max, Yea_min)]
```

```
    for t in range(1, 13):
        X.append(1 if month == t else 0)
    return Lmodels[lat][lon][dep].predict(pd.DataFrame(np.asarray(X).reshape(1, -1)))
```

Python codes for Calculating Density

```
from scipy.stats import norm
from sklearn import datasets, linear_model
import pandas as pd
import numpy as np
from netCDF4 import Dataset
import time

# Get Density from temputure
High_Mackerel = 15
Low_Mackerel = 9
High_Herring = 13
Low_Herring = 7
def get_density_Herring(deg):
    return norm.pdf(x = deg, loc = (High_Herring + Low_Herring) / 2, scale = (High_Herring - Low_Herring) / 4)
def get_density_Mackerel(deg):
    return norm.pdf(x = deg, loc = (High_Mackerel + Low_Mackerel) / 2, scale = (High_Mackerel - Low_Mackerel) / 4)

# S function
def get_area(x0, y0, x1, y1, r):
    poi = 0
    di = [(0, 0), (0, 1), (1, 0), (1, 1)]
    for (p1, p2) in di:
        x2 = x1 + p1
        y2 = y1 + p2
        if np.sqrt((x2 - x0)**2 + (y2 - y0)**2) <= r:
            poi += 1
    if poi == 4:
        return 1
    if poi == 3:
        for (p1, p2) in di:
            x2 = x1 + p1
            y2 = y1 + p2
            if np.sqrt((x2 - x0)**2 + (y2 - y0)**2) > r:
                y3 = np.sqrt(r**2 - (x2 - x0)**2)
                x3 = np.sqrt(r**2 - (y2 - y0)**2)
                if x2 > x0:
                    x3 = x0 + x3
                else:
                    x3 = x0 - x3
                if y2 > y0:
                    y3 = y0 + y3
                else:
                    y3 = y0 - y3
                d = np.sqrt((x3 - x2)**2 + (y3 - y2)**2)
                p = np.arcsin(d / 2 / r) * r**2 - (np.sqrt(r**2 - (d/2)**2) * (d/2))
```

```
                return 1 - (np.abs(x3 - x2) * np.abs(y3 - y2) / 2) - p
    if poi == 2:
        for (p1, p2) in di:
            x2 = x1 + p1
            y2 = y1 + p2
            if np.sqrt((x2 - x0)**2 + (y2 - y0)**2) <= r:
                if np.abs(x2 - x0) < 1:
                    y3 = np.sqrt(r**2 - (x2 - x0)**2)
                    y3 = y3 - np.abs(y0 - y2)
                    d = y3
                    p = np.arcsin(d / 2 / r) * r**2 - (np.sqrt(r**2 - (d/2)**2) * (d/2))
                    return y3 + p
                if np.abs(y2 - y0) < 1:
                    x3 = np.sqrt(r**2 - (y2 - y0)**2)
                    x3 = x3 - np.abs(x0 - x2)
                    d = x3
                    p = np.arcsin(d / 2 / r) * r**2 - (np.sqrt(r**2 - (d/2)**2) * (d/2))
                    return x3 + p
    if poi == 1:
        for (p1, p2) in di:
            x2 = x1 + p1
            y2 = y1 + p2
            if np.sqrt((x2 - x0)**2 + (y2 - y0)**2) <= r:
                y3 = np.sqrt(r**2 - (x2 - x0)**2)
                x3 = np.sqrt(r**2 - (y2 - y0)**2)
                if x2 > x0:
                    x3 = x0 + x3
                else:
                    x3 = x0 - x3
                if y2 > y0:
                    y3 = y0 + y3
                else:
                    y3 = y0 - y3
                d = np.sqrt((x3 - x2)**2 + (y3 - y2)**2)
                p = np.arcsin(d / 2 / r) * r**2 - (np.sqrt(r**2 - (d/2)**2) * (d/2))
                return (np.abs(x3 - x2) * np.abs(y3 - y2) / 2) + p
    if poi == 0:
        return 0

# Is (lat, lon, dep) a land
def Is_land(lat, lon, dep):
    dat = Dataset("hawaii5.nc")
    All_t = dat.variables['temp'][:]
    lon = int(lon)
    lat = int(lat)
    lon += 50
    lat -= 45
    dep = int((dep - 5) / 10)
    return All_t[599][dep][lat][lon] is np.ma.masked

# Get mackerel density of port
def Get_Port_Density(Lmodels, Port_lat, Port_lon):
    dat = Dataset("hawaii5.nc")
    TEMP = dat.variables['temp'][599, :, :35, 35:60]
```

```python
    Port_avg = []
    Port_low = []
    Port_upp = []
    for i in range(len(Port_lat)):
        Port_avg.append([])
        Port_low.append([])
        Port_upp.append([])
        for Year in range(2020, 2171, 10):
            ans = 0
            lo = 0
            up =0
            count = 0
            for Month in range(5, 12): # Fishing seasons
                for dep in range(5, 26, 10): # Fishing depths
                    areas = 0
                    t1 = t2 = t3 = 0
                    for j in range(-3, 4):
                        for k in range(-3, 4):
                            if not Is_land(int(Port_lat[i]) + j, int(Port_lon[i]) + k, dep):
                                t_ar = get_area(Port_lat[i], Port_lon[i], Port_lat[i] + j, Port_lon[i] + k, 2) # 2 degree radius
                                if t_ar > 0:
                                    areas += t_ar
                                    df = Pred_int(Lmodels, Year, Month, int(Port_lat[i]) + j + 0.5, int(Port_lon[i]) + k + 0.5, dep)
                                    t1 = t1 + get_density_Mackerel(df['lower'][0]) * t_ar
                                    t2 = t2 + get_density_Mackerel(df['upper'][0]) * t_ar
                                    t3 = t3 + get_density_Mackerel(df['Pred'][0]) * t_ar
                    lo += t1 / areas
                    up += t2 / areas
                    ans += t3 / areas
                    count += 1
            Port_avg[i].append(ans / count)
            Port_low[i].append(lo / count)
            Port_upp[i].append(up / count)
    return Port_avg, Port_low, Port_upp
```