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A Migration Model to Predict the Distribution of Scottish Herring and Mackerel

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Abstract. To identify climate-related habitat changes and variations in abundance and distribution of herring and mackerel around the waters of Scotland, a new habitat suitability index (HSI) model and Markov Model were developed in this study. The study only used the distribution of annual catch and fishing efforts. The suitability index (SI) was constructed by newly defined estimate-catch-per-unit-effort (ECPUE). Through the voting method and data of sea surface temperature (SST), the habitat suitability index model (HSI) was established. Based on the HSI, Markov Model was established to predict the movement of shoals. Using the predicted data of future SST, this model can simulate the changes of fish distribution.

1. Introduction

Global ocean temperature change can affect some habitat range and location of Marine organisms. However, it is difficult to monitor the migration of Marine life because of the cost and time required to conduct the survey. Tagging with satellite transmitters is one way to observe the migration of Marine life [1]. Tag-recapture data from voluntary recreational fisheries programmes were used to build the species distribution models (SDMs) [2]. Fisheries catch records represent a common source of data for many targeted and non-targeted marine animals. Catch records can be obtained much easier from commercial fisheries, where formal catch and effort reporting process are required.

To investigate distribution shifts in marine organisms, some used Hidden Markov Model [1] and some constructed Habitat suitability model (HSI) [3]. This study combines HSI and Markov Model and provides a way to predict the distribution of fish in the future.

2. Methods

2.1. Data sets

This study used the sea surface temperature (SST) data which were based on month-by-month files of images of the world's oceans from the national oceanic and atmospheric administration (NOAA) website (https://www.climate.gov/). The horizontal resolution of the images is $1 \times 1°$. The temperature data were extracted by ArcGIS.

Fishery production data are derived from the annual *Scottish sea fisheries statistics* in the official website of the Government of Scotland (gov.soct) from 2014 to 2018. These data include longitude and latitude, year of operation, number of vessels released annually, total annual fishing in each sea area and other factors. Among them, the total annual fishing volume, the latitude and longitude range of each sea area in 2018 are shown in Figure 1 and Figure 2. According to the ICES Rectangle data of vessels in *Scottish sea fisheries statistics 2018*, which was provided by the official website of the Government of Scotland, the longitude range of fishing near Scotland is 19 °W-8 °E and the latitude range is 52 °-63 °N.

After considering the accuracy and calculation amounts of subsequent models, the grid horizontal space scale was selected as 1×1 °, and the time scale was year, combined with data.
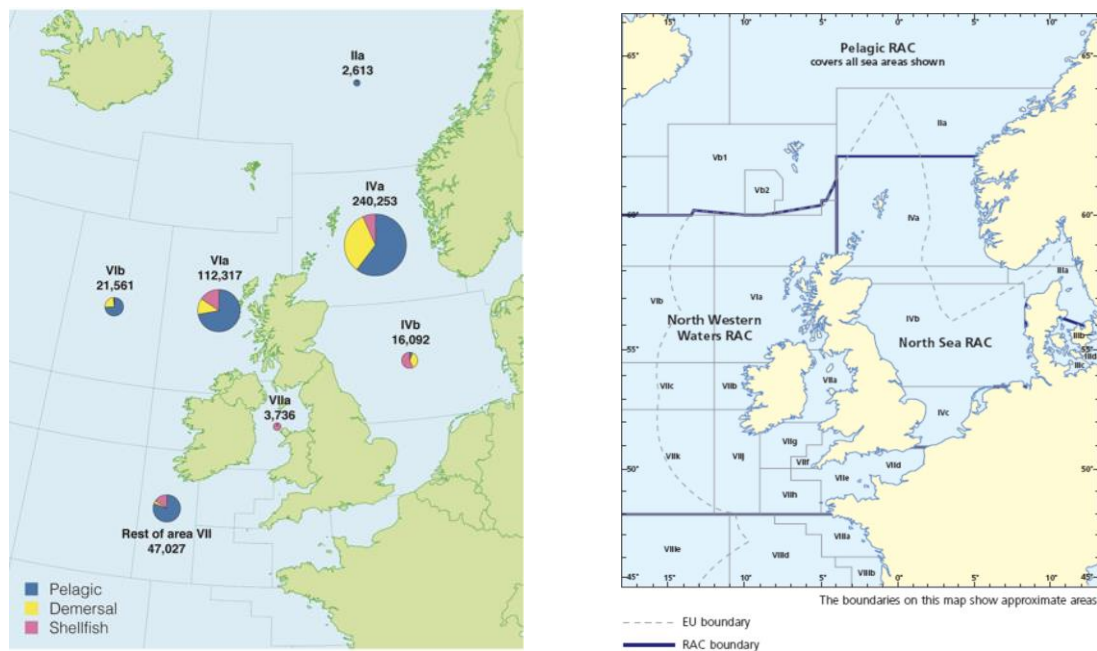

Figure 1. Total annual catch by region, 2018. [4]   **Figure 2.** Map of ICES subareas and divisions. [5]

Table 1. Total annual fishing volume of herring and mackerel in each ICES subarea.

Species	ICES area Year	Quantity (tonnes)							
		North Sea		Faroes	West Scotland		Irish Sea	Other	Total
		IVa	IVb	Vb	VIa	VIb	VIIa		
Herring	2018	59,885	948	0	1,207	0	0	0	62,040
Mackerel	2018	85,495	79	0	67,403	3	0	3	152,983
Herring	2017	49,012	502	0	2,550	0	0	0	52,064
Mackerel	2017	79,513	166	0	98,945	0	0	0	178,626
Herring	2016	58,537	683	0	2,423	0	0	0	61,644
Mackerel	2016	90,110	179	0	96,316	1	0	0	186,606
Herring	2015	48,291	32	0	10,404	0	0	0	58,726
Mackerel	2015	110,801	412	0	68,352	0	0	0	179,565
Herring	2014	41,826	3,151	0	12,155	0	0	0	57,133
Mackerel	2014	124,330	230	0	92,837	0	1	0	217,397

2.2. Establish the Habitat Suitability Index

The annual fishing volume of each grid was calculated by the total annual fishing volume of these subareas (Table 1) and the number of vessels released in the grid yearly belonging to the subarea. After

the quality control of the two spatial scale data of the data set, we defined estimate-catch-per-unit-effort (ECPUE) as a new and potential index of fish abundance in the grid. In this study, the annual ECPUE within a $1 \times 1\,°$ fishing grid was calculated by the following equation:

$$ECPUE_i = TAF_{zone} \times \frac{vessel_i}{\sum_i^{zone} vessel_i} \tag{1}$$

Where $ECPUE_i$ is the ECPUE of the grid i. TAF_{zone} is the total annual fishing volume of the sea subarea *zone*. And $vessel_i$ is the number of vessels released in the grid i yearly.

HSI modelling, incorporated with one or more key environmental variables, can be used to create probability maps for identifying the availability of fish species [6]. In this study, another HSI model combined with only one input variable, SST, was developed. To predict the habitat suitability of herring and mackerel, ECPUE was taken into account in relation to the biophysical environmental variables. ECPUE was considered as an index of fish abundance.

The first step was to compute the probability of fish availability, which was also defined as a suitability index (SI) based on ECPUE and SST. Using ECPUE of each grid from 2014 to 2018, the ECPUE-based SI value was defined as the ECPUE of each grid divided by the maximum ECPUE of the given grid in a specific year. The equation was established as follows:

$$SI = \frac{ECPUE_i}{ECPUE_{max}} \tag{2}$$

When the ECPUE of one grid is the maximum of ECPUE, the environment of this grid is optimal for fish habitat. And its SI value is determined to be 1. When the ECPUE of a grid is 0, its environment is the most inappropriate for fish habitat, whose SI value is 0.

Since there were many remote grids without vessels or fishing yield, we cannot conclude that the grids are not suitable for fish habitat. Therefore, this paper adopted the voting method to study the relationship between SST and SI. First, the SST interval was divided into appropriate number of cells. Obviously, the higher the SI, the more suitable the SST is for this kind of fish. Therefore, we determined that when $SI \leq 0.1$, the number of votes of the sample was 0. When $0.1 < SI \leq 0.3$, the number of votes was 1. When $0.3 < SI \leq 0.5$, the number of votes was 2. When $0.5 < SI \leq 0.7$, the number of votes was 3. When $0.7 < SI \leq 0.9$, the number of votes was 4. When sample's $SI > 0.9$, the number of votes was 5. Taking the midpoint of each interval as the abscissa and the total number of votes of the interval as the ordinate, the sample points to be fitted were obtained.

Then, the monthly SST was averaged to get the annual average SST. The calculated votes for annual SST were used as the input data to fit the votes models with each interval value. The votes model of annual SST for herring and mackerel was fitted by the following equations:

$$Votes = ae^{-((SST-b)/c)^2} \tag{3}$$

Where *Votes* is the number of votes. *SST* is the annual mean SST of each grid. a, b and c are estimated parameters. Matlab was used to solve the parameters of unitary nonlinear regression equation. The goodness of fit are as follows:
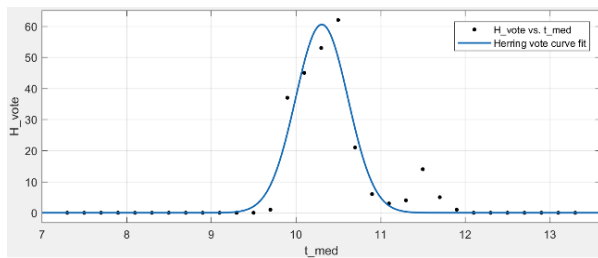
Figure 3. Votes fitting curve diagram of herring.
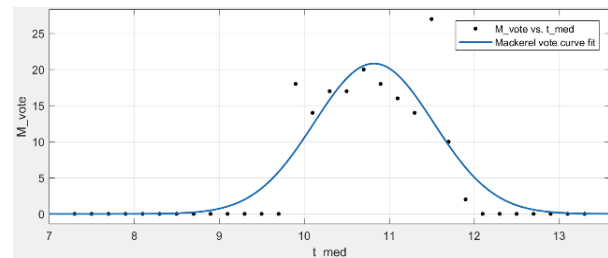
Figure 4. Votes fitting curve diagram of mackerel.

Table 2. Goodness of fit.

Species	SSE	R-square	Adjusted R-square	RMSE
Herring	698.6	0.9199	0.9142	4.995
Mackerel	404.9	0.8109	0.7974	3.803

Therefore, the goodness of fit seems good.

Finally, the fitted function in (3) was normalized to obtain the relationship between habitat suitability index (HSI) and SST:

$$H_{SI} = e^{-((SST-b)/c)^2} \tag{4}$$

The closer it is to 1, the more suitable it is for habitat. Conversely, the closer it gets to 0, the less suitable it is for habitat. And in this study, when $H_{SI} = 0$, the grid represents land.

2.3. Establish Markov Chain for habitat transfer

Markov Chain (MC) is a stochastic process with Markov property existing in discrete index set and state space in probability theory and mathematical statistics.

Suppose that the random sequence $\{N(t), t \in T\}$ represents the grid in which the shoal is located at moment t, and the state space is $E=\{1, 2, ..., D\}$. Considering that shoal movement has "no aftereffect", the process of shoal movement is a Markov process with countable set of state space, namely Markov Chain. In other words, the grid a shoal will be on next year depends only on the grid it was on this year, not on the grid it was on before this year. Therefore, Markov Model was used to predict the distribution of fish.

Suppose the study area was divided into m rows and n columns. The region can be characterized by matrixes of m rows and n columns.

According to the SST of moment t, the habitat suitability index matrix of the year was obtained as follows:

$$H(t) = \begin{pmatrix} h_{1,1} & h_{1,2} & \cdots & h_{1,n} \\ h_{2,1} & h_{2,2} & \cdots & h_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ h_{m,1} & h_{m,2} & \cdots & h_{m,n} \end{pmatrix} \tag{5}$$

Where $h_{i,j}$ is the suitability index of the ith row and the jth column.

Because fish move in random directions, it can move north, south, west, east, northwest, southwest, northeast, southeast, and stay where it was. Therefore, the fish in each grid may appear at nine locations at the next time. The one-step transition probability matrix is as follows:

$$P = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,m \times n} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,m \times n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m \times n,1} & p_{m \times n,2} & \cdots & p_{m \times n,m \times n} \end{pmatrix} \tag{6}$$

$$p_{i,i} = \begin{cases} p_{stay} + (1 - p_{stay}) \times \dfrac{h_{i \bmod m,[i/m]+1}}{sum_i} & h_{i \bmod m,[i/m]+1} > 0 \\[2mm] 1 & h_{i \bmod m,[i/m]+1} = 0 \end{cases} \tag{7}$$

$$p_{i,j} = \begin{cases} (1 - p_{stay}) \times \dfrac{h_{j \bmod m,[j/m]+1}}{sum_i} & j = i \pm 1, i \pm m, i \pm (m+1), i \pm (m-1) \\[2mm] 0 & otherwise \end{cases} \quad (i \neq j) \tag{8}$$

Where p_{stay} is the probability that the fish will stay where they are. By the definition of one-step transfer probability, $p_{i,j}$ represents the probability of moving from position i to position j when one step can be moved.

Since the time unit of the study is one year, the shoal's range of activity does not change much. Let's say a shoal of fish can only move one grid a year at most. First, set up the initial population ($p(0)$) according to the distribution of the fish in that year:

$$p(0) = (p_1(0), p_2(0), ..., p_s(0), ..., p_{m \times n}(0)) \tag{9}$$

Where $p_s(0)$ represents the size of the fish in grid s. Then, the next year's SST prediction data was used to obtain the one-step transition probability matrix. Finally, the predicted distribution of fish stocks for the next year ($p(1)$) can be obtained according to the following formula:

$$p(1) = p(0)P \tag{10}$$

2.4. Simulation for habitat migration of herring and mackerel
This study selected herring and mackerel as examples to check the goodness of the model. Root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE) and Theil inequality coefficient (TIC) were selected as measures of predictive accuracy (Table 2). Since the distribution of fish stocks varies little year by year, the distribution data of herring and mackerel in the previous year were used into the next year for testing as a reference (Table 3).

Table 3. Goodness of prediction.

Species	Year	RMSE	MSE	MAE	TIC
Herring	2018	3.1745	0.1780	0.9053	0.1203
Herring	2017	3.1224	0.1751	0.6784	0.1304
Herring	2016	5.4748	0.3070	1.3655	0.2222
Herring	2015	3.8730	0.2172	1.1479	0.1500
Mackerel	2018	2.3523	0.1319	0.7054	0.1285
Mackerel	2017	0.8431	0.0473	0.2604	0.0492
Mackerel	2016	2.5377	0.1423	0.6886	0.1389
Mackerel	2015	1.9004	0.1066	0.5498	0.1013

Table 4. Using data of the previous year for testing.

Species	Year	RMSE	MSE	MAE	TIC
Herring	2018	3.2096	0.1800	0.8928	0.1210
Herring	2017	3.1292	0.1755	0.6664	0.1301
Herring	2016	5.6024	0.3142	1.3618	0.2259
Herring	2015	3.8742	0.2173	1.1642	0.1510
Mackerel	2018	2.3805	0.1335	0.7216	0.1310
Mackerel	2017	0.8541	0.0479	0.2772	0.0503
Mackerel	2016	2.5838	0.1449	0.6719	0.1403
Mackerel	2015	1.8623	0.1044	0.5258	0.0986

As the two tables show, the model can predict the distribution of fish in the next year to some extent. Therefore, the movement of a shoal can be simulated with the distribution of shoals today and the predicted value of SST in the future.

3. Conclusion

The study defined and calculated the estimate-catch-per-unit-effort (ECPUE) from the distribution of annual catch and number of vessels, and then constructed the suitability index (SI). Through the voting method, the number of votes and SST data were fitted to establish the habitat suitability index model (HSI). Based on the HSI, Markov Model was established to predict the movement of shoals. This method has been tested to predict the future distribution of shoals to some extent. Using the predicted data of future SST, the model can simulate the changes of fish distribution. Under the circumstances of global warming, it can assist fishing companies in making future plans and governments in enacting policies.

Data for the ECPUE are easy to come by, but it can only predict the distribution of shoals roughly, not as accurately as the CPUE. PAR, SSHA and other factors also affect the distribution of fish stocks, so if more environmental factors are integrated into the prediction, the accuracy will be improved.

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