Data-driven habitat suitability modelling to support decision making in sustainable pelagic fisheries

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Introduction

Due to the withdrawal of the United Kingdom from the European Union, the Belgian fishing fleet lost access to part of their fishing waters and experienced diminished catches. The Belgian fishing fleet currently targets demersal fish [Landbouw en Visserij, 2021]. One of the initiatives to overcome the loss of fishing grounds is to provide information about alternative fishing grounds and niche fisheries. This study aims to contribute to the question of where and when pelagic fishing by the Belgian fishing fleet could be reintroduced by looking at the seasonal distribution of Atlantic herring (*Clupea harengus*), an economically important pelagic fish species in the Northeast Atlantic.

Habitat suitability models have been widely used to derive species-environment relationships and predict the geographical distribution of species [Thorson et al., 2016]. We developed a habitat suitability model for adult Atlantic herring (*Clupea harengus*) in the Northeast Atlantic. To take herring's spawning distribution into account, we also built a model for herring larvae.

Materials & methods: data

Occurrence data of Atlantic herring were retrieved from the International Council for the Exploration of the Sea (ICES) Database of Trawl Surveys (DATRAS, 13 294 adult records) and the International Herring Larvae Surveys (IHLS, 7 902 larvae records) in the Northeast Atlantic, restricted to 48°N – 62°N and 12°W – 10°E and from 2000 to 2020.

Sampling bias was considered by filtering occurrences in geographical space [Vollering J. et al., 2019]. A minimal distance of 10 nautical miles (NM) was taken as it is the recommended distance between valid hauls in the trawl surveys [Andersens, 2010]. Initial results showed spatial autocorrelation in the model residuals which was minimised by an additional filtering technique in environmental space, using the Malahanobis distance. [5]. A total of 400 adult and 400 larval occurrences were maintained to fit the two habitat suitability models.

Environmental variables were retrieved from the European Marine Observation and Data Network (EMODnet) and Copernicus Marine Service, including depth (https://emodnet.ec.europa.eu/en/bathymetry), Sea Surface Temperature (SST, https://doi.org/10.48670/moi-00021), Sea Surface Salinity (SSS, https://doi.org/10.48670/moi-00021), zooplankton (https://doi.org/10.48670/moi-00020) and phytoplankton concentration (https://doi.org/10.48670/moi-00058), nearby windfarm presence (https://emodnet.ec.europa.eu/en/human-activities) and seabed characteristics (https://emodnet.ec.europa.eu/en/seabed-habitats).

Preprocessing of these environmental variables involved aggregation to a 10NM-by-10NM grid per month to match the spatiotemporal resolution of the occurrence data [de Oliveira et al., 2014]. To account for multi-collinearity in the predictors, the least ecologically relevant variable of variables pairs with a Variance Inflation Factor (VIF) larger than 10 was discarded from analysis [Sillero et al., 2021].

Materials & methods: model

A machine-learning method, called maximum entropy (MaxEnt) model, was used to develop species-environmental relationships (using R-package *dismo* [Hijmans et al., 2023; Phillips et al., 2006]. Background points were sampled randomly and restricted to the ICES areas of the occurrences. The number of background points was set at 10 times the number of presences [Hysen et al., 2022]. Applying the appropriate model settings can enhance model interpretability and avoid overfitting [Merow et al., 2013]. Therefore, different MaxEnt model settings (feature class and regularisation multiplier) were evaluated using the corrected Akaike's Information Criterion (AICc) as a selection criterion (R-package *ENMeval*, Kass et al. [2021]). Model performance was evaluated using the Area Under the Curve (AUC) of the Receiver Operating Characteristic plot and the True Skill Statistic (TSS) using a 5-fold cross-validation [Báez et al., 2020; Liu et al., 2013].

Results

The larval model performed best (AUC of 0.9 and TSS of 0.7 compared to AUC of 0.7 and TSS of 0.3 for adults). Depth was the most important variable in both models (63 and 37% of total variable importance for adults and larvae respectively), followed by SST (13%) and SSS (11%) for adults and SST (15%), seabed substrate (14%), zoo- (13%) and phytoplankton (13%) concentration for larvae. For both life stages, habitat was most suitable in shallower waters compared to deep waters and at low sea surface water temperatures. If pelagic fishing by the Belgian Fishing fleet were reintroduced, fishing in the Belgian Part of the North Sea would involve the least shipping costs. In this area, habitat was found most suitable during winter months for both adults and larvae. Due to this overlap and to protect spawning stock, fisheries should be effectively managed. During other seasons, the Belgian fishing fleet would have to travel further, to the greater North Sea, to find Atlantic herring.

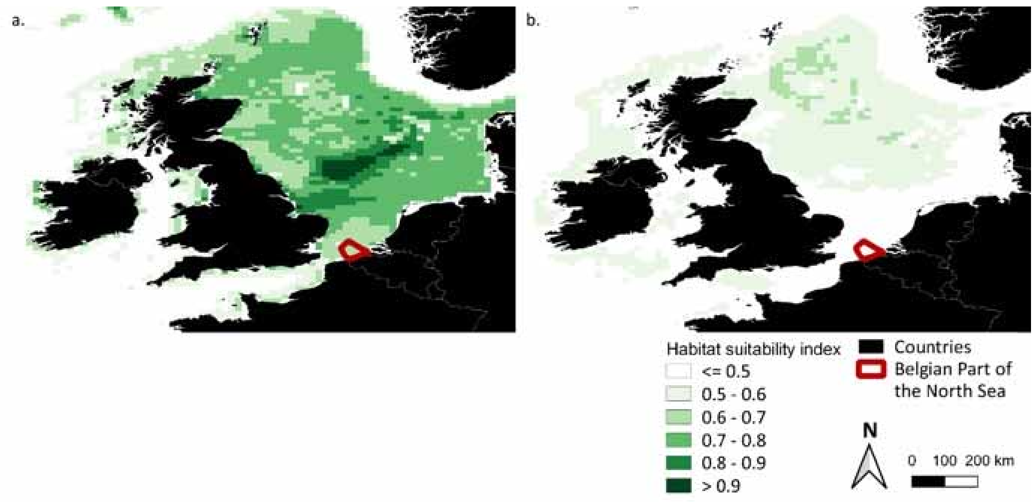

Figure 1 Predicted habitat suitability for Atlantic herring in the Northeast Atlantic in (a) January and (b) July averaged over 2000 - 2020. Darker shades of green depict areas that are more suitable during that month.

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