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Socio-ecological drivers of demersal fishing activity in the North Sea: The case of three German fleets

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A B S T R A C T

Worldwide, fisheries face the consequences of climate change and compete with expanding human activities at sea, which may trigger unforeseen reactions of fishers. Hence, knowledge on drivers of fishing behavior is crucial for management and needs to be integrated in resource management policies. In this study, we identify factors influencing fishing activity of North Sea demersal fleets. First, we explore drivers of the North Sea demersal fisheries in scientific literature. Subsequently, we study the effects of identified drivers on the spatio-temporal dynamics of German demersal fisheries using boosted regression trees (BRT), a supervised machine learning technique. An exploratory literature review revealed a lack of studies incorporating biophysical, economic and socio-cultural fishing drivers in a single quantitative analysis. Our BRT analysis contributed to filling this research gap and highlighted the importance of biophysical drivers such as temperature, salinity, and bathymetry for fishing behavior. Contrary to findings of previous studies, our empirical analysis identified quotas and market prices to be irrelevant, except for low brown shrimp prices, which counter-intuitively increased fishing effort. Moreover, economic and socio-cultural variables influencing brown shrimp fishing effort differed from the other fleets, especially determined by increased effort on workdays and reduced effort when fuel prices were high. Our findings provide key information for marine spatial planning and supports the integration of fishing fleet behavior into policies.

1. Introduction

Human use of the oceans has been increasing globally, leaving few untouched areas and leading to local competition for space (Halpern et al., 2015, 2019; Kannen, 2014). Fishing is the largest human activity in terms of spatial scale and intensity and therefore must be considered in marine spatial planning (MSP; (Halpern et al., 2008; Stelzenmüller et al., 2022, 2021, 2008). To enable sustainable management, scientists and policy makers must understand fishers' behavior and integrate it in new management directives (Hilborn, 2007; Salas and Gaertner, 2004). Ignorance of the human dimension in fisheries may cause fishers to respond unexpectedly to new regulations, which often exacerbates the state of the managed resource prior to these regulations (Fulton et al., 2011). Examples of such negative outcomes are spatial or temporal closures encouraging a 'race for fish' among the fishers (Gordon, 1954; Sys et al., 2017), or displacing fishing effort to areas with more vulnerable habitats or species (Dinmore et al., 2003; Liu et al., 2016; Rijnsdorp et al., 2001).

Individual fishing fleets often operate in different ranges of biophysical parameters (Crespo et al., 2018; Hintzen et al., 2021; van der Reijden et al., 2018). Knowing the exact parameter ranges affecting fleets would promote the development of regulations that not only consider the status of fish stocks, but also the behavior of fishers. Such an integration would help policy makers to support effective management, but also fishers to reduce their ecological footprint, e.g. by avoiding bycatch species (Soykan et al., 2014) or optimizing their fuel consumption (Bastardie et al., 2010a) . Although the concept of perceiving fisheries as a socio-ecological system is increasingly embraced (Partelow, 2018), empirical approaches integrating the analysis of biophysical, economic, and socio-cultural drivers of fishing are still rare (Andrews et al., 2020; Castrejón and Charles, 2020; Rijnsdorp et al., 2008).

North Sea fishers face many challenges, such as increased competition for space with renewable energy development (i.e. offshore wind farms) and marine conservation measures like marine protected areas (OECD, 2016; Stelzenmüller et al., 2022). Moreover, climate change is

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likely to alter fishing opportunities spatially (Baudron et al., 2020), adding to the potential for conflicts between fisheries and other users of ocean space (Link et al., 2017; Mendenhall et al., 2020). Therefore, the North Sea requires proactive MSP that integrates fishers' potential reactions to these changes.

In this study, we first conducted an exploratory literature review focusing on factors influencing fishing activity in the North Sea. We restricted our search to demersal fisheries, which account for the majority of fishing in the North Sea (STECF, 2020). Second, we modelled spatio-temporal fishing effort (in hours) of German demersal fisheries in the southern North Sea and identified their main drivers using boosted regression trees (BRT).

2. Material & methods

2.1. Exploratory literature review for factors influencing demersal north sea fishing activity

We performed an exploratory Web of Science literature review for studies investigating drivers of demersal North Sea fisheries (see Appendix I for details). This search retrieved 104 articles of which we only retained those that focused on the North Sea and specifically identified factors influencing demersal fishing activity. In our screening for relevant articles, we defined fishing activity as any parameter related to fishing, i.e. fishing effort, catches, landings, choices about fishing location, target species and gear, as well as the decision whether to go fishing or not. Eventually, we found eight relevant studies that specifically analyzed factors influencing demersal North Sea fishing activity. We complemented those with additional eight articles that were deemed relevant and did not show during our Web of Science search. Of the complementary articles, six were known to the authors or found by following references within the original eight relevant studies and two were suggested by one anonymous reviewer. From the resulting 16 relevant studies (see Supplementary Material for details), we identified factors influencing fishing activity and classified them into biophysical, economic, regulations, and socio-cultural. We grouped vessel characteristics to economic variables, because they are linked to investments. With our exploratory review, we do not claim to have exhausted all available relevant literature, but received a sufficiently large sample for this study.

2.2. Empirical modelling of factors influencing German demersal fleets

2.2.1. Preparation of fisheries data

We used several data sets comprising information of spatio-temporal fisheries dynamics and vessel characteristics. Commercial fishing logbooks contain information about fishing trips including start and end date, used gear, mesh sizes, as well as catch composition and weights. Spatial fishing dynamics were inferred from the vessel monitoring system (VMS), which is obligatory for all European fishing vessels larger than 12m. VMS data contain geo-coordinates (so-called 'pings'), timestamps, and vessel speed. Broadcasting frequencies differ among flag states and are set to 2 h for the German fishing fleet. Finally, we derived vessel characteristics, such as length and additional gear information, from the German Fishing Vessel Register and the European Fleet Register.

We selected all vessels that were active in the North Sea area (EU fishing regions 27.4A-C) and used fishing gear, mesh size, and catch composition to group them into three fleets, representing the major part of the German commercial fisheries in the southern North Sea (Appendix II). The three fleets were: (i) the coastal brown shrimp (BS) fleet using smaller vessels (median 18m) and beam trawls, targeting exclusively brown shrimp (*Crangon crangon*), and primarily run by family-businesses; (ii) the flatfish (FF) fleet comprising large vessels (median 36m), using beam and pulse trawls, mainly targeting plaice (*Pleuronectes platessa*) and sole (*Solea solea*), and affiliated to larger companies; (iii) and the mixed demersal (MDS) fleet composed of medium sized vessels (median 24m), using otter boards, mainly targeting plaice and Norway lobster (*Nephrops norwegicus*; Nephrops hereafter) and mostly affiliated to small businesses.

We obtained VMS data for each fleet for the period 2012–2018 and improved data quality by removing duplicates and pings in harbors or on land. Subsequently, we identified continuous fishing trips based on spatial and temporal information from the VMS data and merged them with data on fishing trips from logbooks (similar to Bastardie et al. (2010b)). We complemented missing vessel characteristics with data from the German Fishing Vessel Register and the European Fleet Register. Finally, we used the VMS tools package (Hintzen et al., 2012) to separate steaming from fishing pings and calculated fishing effort in hours per data point. We then aggregated fishing effort per day in a 0.25° Longitude × 0.25° Latitude grid. For each fleet, we used monthly frames, consisting of all cells with fishing effort in a month, to set the spatial frame for our daily-resolved fishing effort in the respective month. Since fishing effort data was available at a daily resolution, each monthly data set contained cells without fishing at certain days. To also represent cells where no fishing effort took place during a month, we created a 30 km buffer around each monthly frame. Adding negative samples enabled the model to not only learn which variables are affiliated to fishing effort, but also those that are affiliated to no fishing effort. The resulting data sets of the three fleets differed with respect to spatial extent, size, and fishing effort intensity (Fig. 1). With regard to quantities of data points (spatial grid cells at daily resolution), the MDS fleet represented the largest data set (n = 114703), followed by the FF (n = 90726) and BS fleet (n = 46974). In terms of mean fishing effort per day and grid cell, the order was reversed, as the BS fleet had the highest mean (3.67 h), followed by the FF (0.42 h) and MDS (0.35 h) fleets. We used the R programming language for all data processing (R Core Team, 2019), of which a detailed description can be found in the supplementary material (Appendix III).

2.2.2. Explanatory variables

We gathered publicly available data sets on potential drivers of fisheries, i.e. bottom temperature, salinity, bathymetry, sea surface height, mixed layer depth, significant wave height, wind speeds, sediment types, resource prices, resource quotas, crude oil price, spatial fishing restrictions, weekends, and holidays (see Appendix IV for sources). The only regulation considered in this study was the plaice box, prohibiting the activity of beam trawlers with engine powers above 221kw in coastal waters of the Netherlands, Germany, and Denmark (Beare et al., 2013). Explanatory variables were either spatially, temporally, or spatio-temporally resolved. In case the data presented a spatial component, we clipped them to the study area. Most spatial data sets were gridded at a finer resolution and thus adjusted to our grid size (0.25° Longitude × 0.25° Latitude) by taking the mean value. Wave height was the only variable with a coarser spatial resolution and thus was disaggregated. In case spatial data were in a polygon format, we calculated the percentage coverage of each grid cell with the respective polygon. Finally, we cropped temporal data to the study period (2012–2018) and adjusted them to a daily resolution.

Fishing quotas were extracted from monthly fishery reports of the German Federal Office for Agriculture and Food (German: BLE). There were several months with missing quotas, which we either reconstructed by using linear interpolation or, in case it was the beginning of the year, choosing the first available information of the year. The reason for this was that the EU distributes annual quotas at the beginning of January, however, the individual quotas for German fishers are only distributed earliest in February. In order to enable fishers to start their business, the BLE estimates quotas for the previous months of the year. We calculated available monthly quotas by subtracting catches from quotas for plaice, sole, and Nephrops. The brown shrimp fishery is self-managed by fishers and not restricted by quotas.

We used fishing effort in hours as response variable and the following

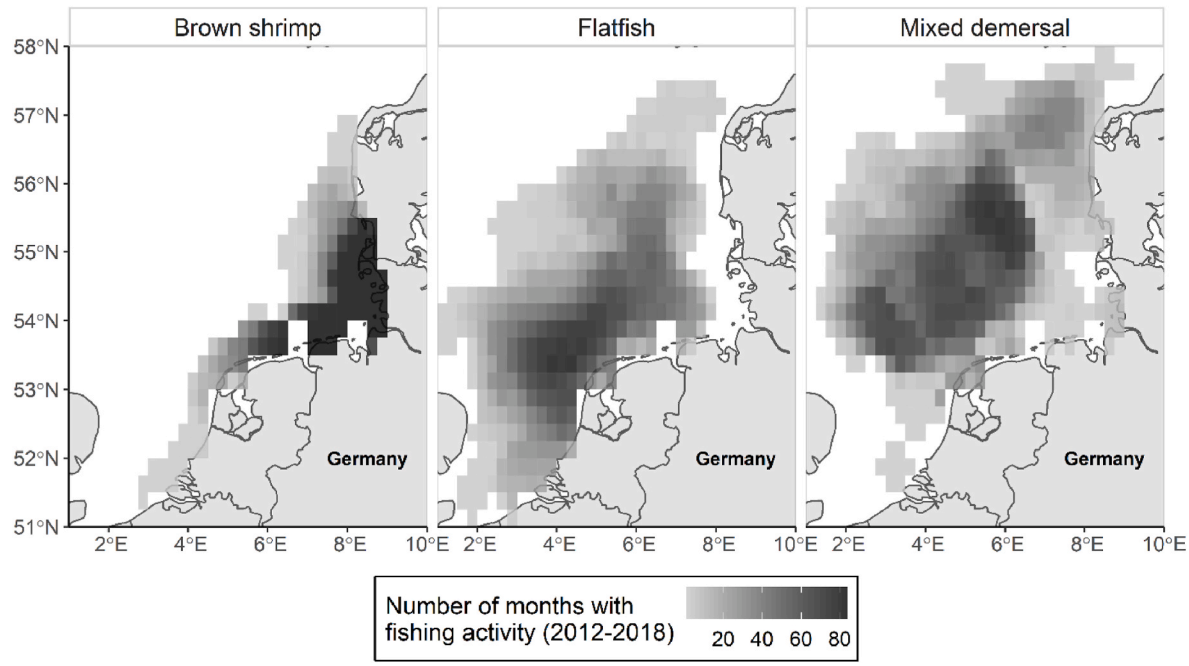

Fig. 1. Spatial extent and density of fishing activity of the three fleets in the study area, based on the number of months a fleet was active in a grid cell from 2012 to 2018.

explaining variables: (i) spatio-temporal features: u- and v-component of wind, wind gusts, wave height, sea floor temperature, sea surface height, salinity, and mixed layer depth; (ii) spatial features: distance to port, bathymetry, substrate type, and fishing restrictions; and (iii) temporal features: crude oil price, resource market prices, available fishing quota, holidays, weekends, and work days. The u-component represents wind speeds from the west (positive values) and east (negative values), and the v-component from the south (positive values) and north (negative values). We included fish prices and quotas only if they were considered important for the respective fleet, e.g. for the FF fleet we included prices and quotas for plaice and sole, but not for brown shrimp or Nephrops, because they are barely caught by the FF fleet (Appendix II). We included the following holidays in our analysis: Easter (Good Friday to Easter Sunday), Ascension Day, Pentecost, Christmas & New Year (22nd December to 4th January). For the BS fleet we also included Eid al-Fitr, the end of Ramadan and Muslim holiday, since brown shrimps are usually peeled in Morocco and then reimported to Europe (Aviat et al., 2011).

2.2.3. Boosted regression trees

We identified the importance of fisheries drivers by using boosted regression trees (BRT), a supervised machine learning technique that combines the advantages of tree-based models with boosting (Fig. 2; Friedman 2001). We used the *xgboost* package in R for BRT tuning and implementation (Chen et al., 2019; R Core Team, 2019). Contrary to other BRT approaches, the *XGboost* technique has a more sophisticated boosting algorithm, additional tuning parameters, an internal mechanism for imputing missing values, and scalability, i.e. parallel computation to reduce run-time (Chen and Guestrin, 2016; see Appendix V for more details).

For each fleet we randomly assigned 30% of the data to a test and 70% to a training data set. We tuned the BRTs in an iterative procedure using 10-fold cross validation and root mean square error (RMSE) to determine the best combination of tuning parameters in each step. To reduce run time and avoid overfitting, we set early stopping to 10 rounds, limited the maximum number of trees to 2000, and selected a learning rate between 0.01 and 0.2. Subsequently, we tried different combinations of the maximum tree level and the minimum leave weight

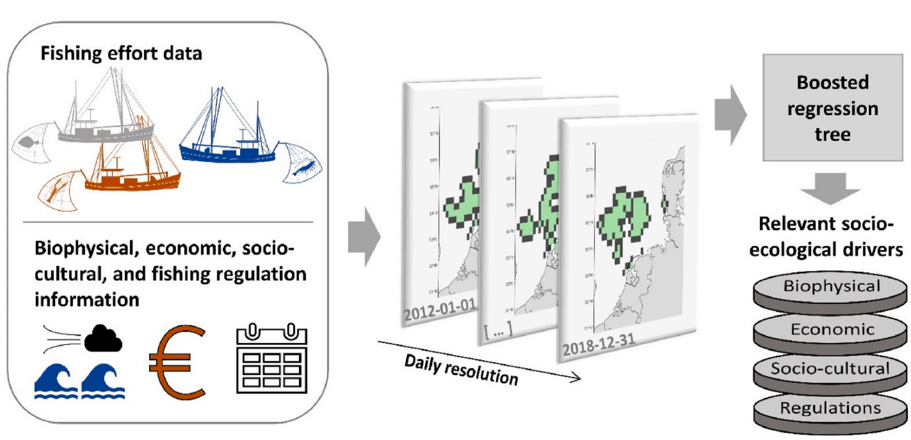

Fig. 2. The empirical work flow of this study starting with the preparation of input data and ending with the identified socio-ecological factors influencing fishing effort.

in steps from 2 to 10 and 1 to 5. Next, we tried values for the bag fraction and feature sampling between 0.5 and 0.9, respectively. Finally, we increased the number of trees to 10^3 and tuned the learning rate by trying the values 0.01, 0.05, and 0.1. Due to stochastic components in the model, i.e. bag fraction and feature sampling, the optimal number of trees varied in each model run. Therefore, we ran the model 10 times, recorded the optimal number of trees, and, in the final model, set maximum number of trees to the average of these recorded values.

We applied the final model with all tuned parameters – and without cross validation – to the training data set another 10 times to counteract stochasticity and to perform external model validation. We identified the most accurate of the 10 final models and assessed model quality by calculating the deviance explained (r^2) and four error measures, i.e. mean absolute error (MAE) and RMSE, as well as standardized versions of both. We used the *caret* package in R to calculate MAE, RMSE, and r^2 (Kuhn, 2019) and created standardized metrics by dividing them through the standard deviation of the response variable (Bennett et al., 2013). Standardized metrics have the advantage of being scale- and variance-independent and therefore may be used to make cross model comparisons (Li, 2016).

We determined the relevance of features by using variable importance (VI) rankings, a measure based on how often features were selected for performing a split in the BRT models (Friedman, 2001). The resulting VI values indicate relative importance and are scaled, so that they sum up to 100. To distinguish between relevant and irrelevant fishing drivers, we added a random feature to the model consisting of random numbers between 1 and 100, prior to constructing the final model (Soykan et al., 2014). We calculated VI scores for all of the 10 final models and defined features as *relevant*, if their minimum VI score was above the maximum VI score of the random number. Due to the large number of explanatory variables, we only provided results about relevant parameters. To show the importance by variable type, we calculated sum and mean VIs for parameter groups: (i) biophysical which may be further split into oceanographic and weather (wind speeds and wave height); (ii) economic (resource and oil prices, quotas, and distance to port); (iii) socio-cultural (work day, weekend, holidays); and (iv) regulations (plaice box).

We visualized the effect of relevant features on fishing effort through accumulated local effects (ALE) plots of the most accurate final model, which perform well even if explanatory variables are correlated (Apley and Zhu, 2016). ALE plots show the change of the modelled average response variable at a certain interval of the respective explanatory variable. We set the number of intervals to 30. In general, reliability of BRT models increases with more available data. We hence presented ALEs only in the ranges of the 10- to the 90-percentile of each relevant feature.

3. Results

3.1. Drivers identified by the exploratory literature review

Among the 16 relevant studies, methodological approaches varied between statistical modelling (7), the use of random utility models (RUM) or complex simulation approaches (7), and stakeholder elicitation methods such as in-depth interviews and surveys (4). Most studies included economic factors in their analysis (13), followed by socio-cultural (9), and biophysical (8) parameters, as well as regulations (4). While many studies investigated variables from more than one sector, only four combined biophysical, economic, and socio-cultural factors. Two of these studies used fisher surveys (Bastardie et al., 2013; Christensen and Raakjær, 2006), one applied a RUM (Andersen et al., 2012), and one used statistics (Rijnsdorp et al., 2008). Fig. 3 shows an overview of the identified factors influencing fishing activity and a summarizing table can be found in Appendix I.

Biophysical parameters influencing fishing activity may be grouped into weather and oceanographic variables, the former directly influencing fisher decisions, e.g. high waves restrict smaller vessels to go fishing (Bastardie et al., 2013; Christensen and Raakjær, 2006), and the latter affecting marine species, which in turn influences fisher behavior (van der Reijden et al., 2018). Oceanographic factors comprise bathymetry, bottom temperature, shear stress, and sediment compositions (Hintzen et al., 2019; van der Reijden et al., 2018). Most of these variables are subject to temporal dynamics causing seasonality in fishing activities in the North Sea (Rijnsdorp et al., 2006, 2008; van Oostenbrugge et al., 2008). Conventional economic factors are linked to revenue and are used to assess the profitability of a fishing trip. Therefore, higher fish prices are incentives to go fishing (Bastardie et al., 2013; Christensen and Raakjær, 2006), whereas higher fuel prices are an incentive to restrict fishing (Poos et al., 2013). Vessel characteristics, i.e. engine power or fishing gears, determine the efficiency of fishing vessels and state-of-the-art equipment is related to higher catches and landings per unit effort (Sys et al., 2016; Rijnsdorp et al., 2006). The decision-making of fishers differs among business structures, as owner-operators include more personal matters in their decisions, as opposed to larger companies (Schadeberg et al., 2021). Temporal or spatial restrictions trigger a displacement of fishing effort (Andersen et al., 2012; Poos and Rijnsdorp, 2007), whereas quota restrictions may inhibit an entire fishery (Ulrich et al., 2011). Especially in mixed

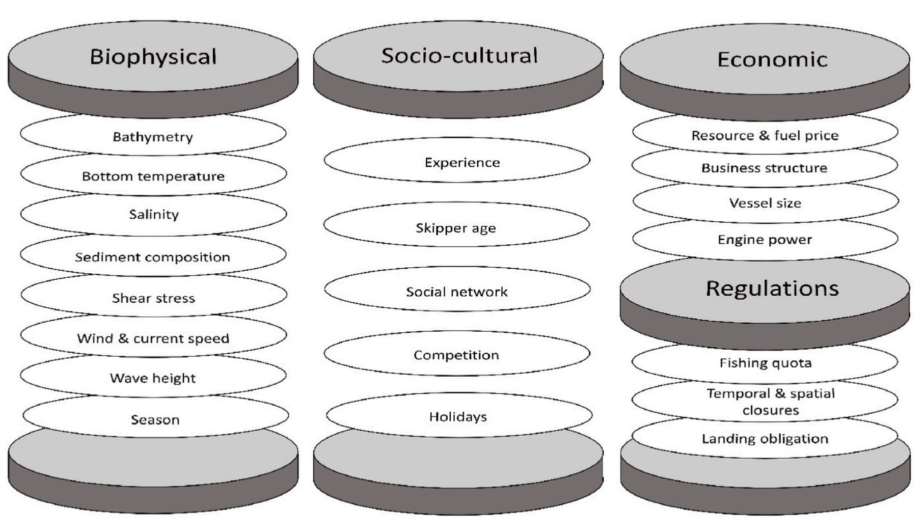

Fig. 3. Infographic displaying factors influencing North Sea demersal fishing activity based on the exploratory literature review.

fisheries, such as unselective demersal trawls, quotas may lead to an early fishing stop, if abundant bycatch species are subject to low quotas (Ulrich et al., 2011). This so-called 'choke species' effect is enhanced by landing obligations, prohibiting the discarding of undersized catches (Batsleer et al., 2016). Stakeholder elicitation methods with Danish fishers revealed that older skippers are more likely to abide regulations (Christensen and Raakjær, 2006). Socio-cultural factors are mostly linked to attributes of the fishers, i.e. age, experience, social network, or cultural norms. For this review we defined experience as information from past fishing trips used as a baseline for future decisions. Multiple studies revealed that fishers prefer previously known fishing locations (Andersen et al., 2012; Bastardie et al., 2013; Hutton et al., 2004; Poos and Rijnsdorp, 2007; Tidd et al., 2012). Memories of economic variables also influence the location choice, as high previous revenues function as an incentive for visiting that same fishing ground (Bastardie et al., 2013; Tidd et al., 2012), whereas high previous costs have the opposite effect (Tidd et al., 2012). In addition, information about profitable or unprofitable fishing events may also be acquired by information exchange among fishers (Christensen and Raakjær, 2006). As opposed to cooperative behavior on land, Poos and Rijnsdorp (2007) found that interactions at sea are more competitive and fishers generate less value per unit effort in areas with a high abundance of fishing vessels. Finally, low fishing effort during the bidweek (Rijnsdorp et al., 2008), a holiday for the Protestantism, and a preference for being at home during the weekend (Schadeberg et al., 2021) show that religious orientation may influence temporal fishing patterns as well.

3.2. Drivers identified by the empirical modelling

We found the best model fit for the brown shrimp (BS) fleet explaining a large part of the deviance in the response variable (fishing effort; $r^2 = 0.67$), followed by the models for fleets targeting mixed demersal (MDS; $r^2 = 0.21$) and flatfishes (FF; $r^2 = 0.18$). Accordingly, standardized RMSE values showed that least erroneous predictions of fishing effort (in hours) were made by the BS model (0.58), followed by MDS (0.89) and FF (0.91) models (see Appendix VI for all model metrics).

In all three models, spatio-temporal features achieved the highest variable importance (VI) scores (Appendix VI). In the BS model, spatial features were second and temporal features third most important, whereas the order was reversed for the FF and MDS models. Across feature types, biophysical parameters achieved the highest VI scores, followed by economic, and socio-cultural variables. Only in the BS model economic parameters were, on average, more important than biophysical features (Appendix VI). Fishing activities were not constrained by the plaice box, the only regulation used in the model.

We identified the highest number of relevant variables for the BS (13) followed by the MDS (10), and FF fleet (9) (Fig. 4). The biophysical variables bathymetry, salinity, and bottom temperature were most important, together amounting to 45% (BS), 27% (MDS), and 26% (FF) of total VI. In contrast to the other fleets, BS fishing effort was also strongly influenced by distance to port (11%).

Accumulated local effects (ALE) showed that fishing effort increased with decreasing depth for the BS and FF fleet, whereas the opposite trend was observed for the MDS fleet (Fig. 5A). The effects were highest at -3m (BS), −28m (FF), and −47m (MDS), reflecting the preferred depths at which the fleets operate. Warmer and less saline waters affected fishing effort of all fleets positively. However, the BS model was the only one with positive ALEs below 11 °C and 33 salinity, indicating that this fleet is active in colder and less saline waters compared to the other two. Sea surface height was relevant for the BS and MDS fleets with fluctuating effects and local maxima around −0.35m for both fleets.

Weather parameters influenced all fleets similarly, as ALEs decreased with rising values of wind gusts, meaning that fleets prefer to fish with less stormy weather (Fig. 5B). Likewise, fishing effort decreased with growing wave heights, except for the FF fleet showing a stronger resistance to high waves. The effects of south-north and west-east winds were negative around low wind speeds and increased with stronger winds in either direction. This pattern was most pronounced for the MDS and less for the FF fleet, the latter showing a strong positive effect at calm south-north winds and therefore a higher preference for windless days.

Distance to port was the only relevant economic variable for the FF and MDS fleets, whereas resource and fuel price were additional relevant parameters in the BS model (Figs. 4 & 5C). Positive ALEs of distance to port represented a gradient among fleets starting with the BS (20 km), and followed by the FF (139 km), and MDS fleet (175 km). This suggests less spatial flexibility for the BS in comparison to the other fleets. Moreover, the ALE of the BS model depicted a clear threshold with values being positive and constant above 18 km. Resource price

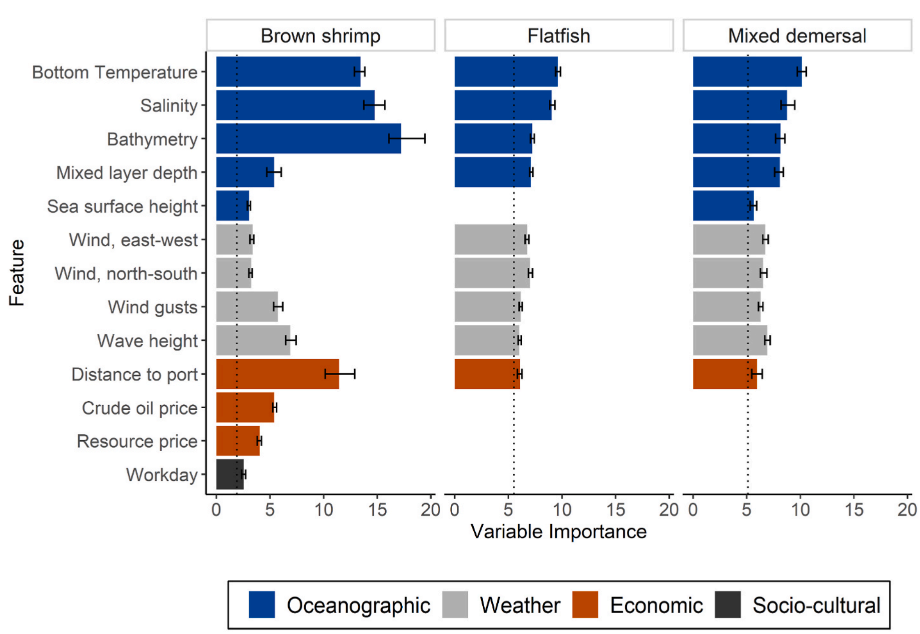

Fig. 4. Variable Importance (VI) scores for relevant explanatory variables computed by averaging VI scores of all 10 models with error bars indicating minimum and maximum values. The dotted line shows the VI score of the random variable, which was used to identify relevant parameters.

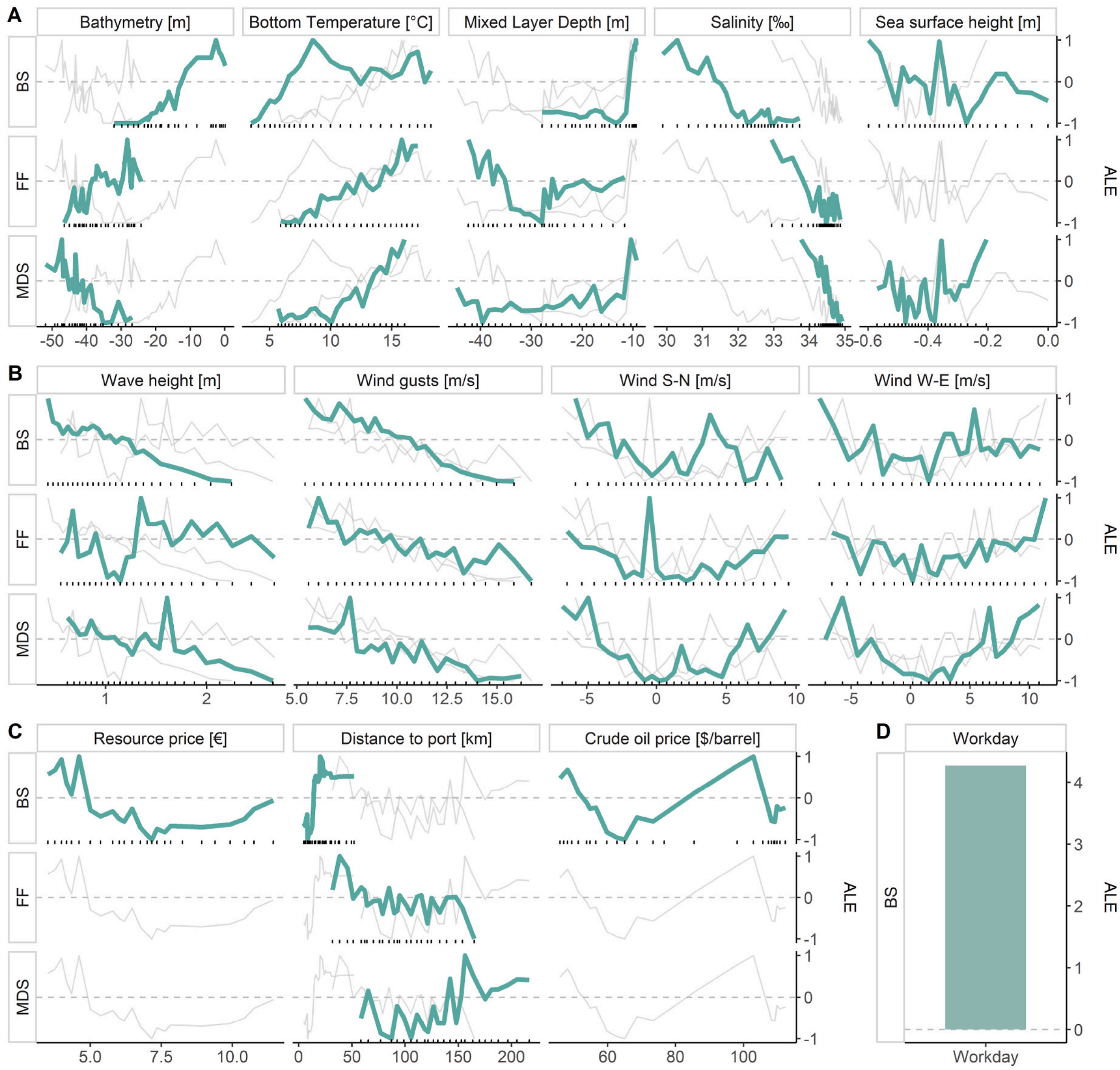

Fig. 5. Accumulated local effects (ALE) of relevant explanatory variables of the Brown Shrimp (BS), Flatfish (FF), and Mixed Demersal (MDS) fleet. Panels are grouped into oceanographic (A), weather (B), economic (C), and socio-cultural (D) variables. ALE of numeric variables (A–C) are standardized. Dark grey lines represent ALE of the respective fleets, light grey lines relevant ALE of other fleets, and rug plots the distribution of intervals used to calculate the ALE.

influenced BS fishing effort positively at lower prices. With regard to crude oil price, the distribution of underlying data was skewed towards the extremes, suggesting that ALE between $70 and $100 per barrel are unreliable. In ranges with more data, the effect of crude oil price on BS fishing effort was greater when fuel was less expensive, indicating that BS fishers favor lower fuel prices.

The only relevant socio-cultural parameter was workdays for the BS fleet, showing that fishers prefer to leave the port on workdays as opposed to weekends and holidays (Fig. 5D).

4. Discussion

We identified socio-ecological drivers influencing North Sea demersal fishing activity and modelled spatio-temporal fishing effort dynamics of German demersal fishing fleets in the North Sea using boosted regression trees (BRT). The exploratory literature review revealed that studies combining biophysical, economic, socio-cultural and fishing regulation factors in one single quantitative analysis are rare. As such, our empirical analysis contributed to filling this research gap. Advancing from previous BRT studies analyzing fishing effort (Castrejón and Charles, 2020; Cimino et al., 2019; Crespo et al., 2018; Soykan et al., 2014), our analysis considered a higher model resolution (i.e. daily fishing hours per grid cell). Biophysical variables were the most relevant for effort dynamics, although their effects varied among fleets. Quotas were not relevant for the German demersal North Sea fisheries and market prices only for the brown shrimp (BS) fleet, although our exploratory literature review revealed both parameters to be important influencing fishing activity. Contrary to the flatfish (FF) and mixed demersal (MDS) fleets, the BS fleet generally showed a stronger dependency on socio-economic drivers.

4.1. Biophysical drivers influencing fishing effort

The observed effects of bathymetry among fleets resemble the habitats of the respective fleet's target species, since brown shrimp is caught in shallow waters (Schulte et al., 2020) whereas plaice, sole and Nephrops occur in deeper areas (Hunter et al., 2003; Johnson et al., 2013; van Hal et al., 2016). Our results hence support earlier findings suggesting that biophysical drivers of fishing fleets reflect the ecological niches of their target species (Crespo et al., 2018; Hintzen et al., 2021;

van der Reijden et al., 2018). Furthermore, we found bottom temperature and salinity to be positively and negatively related to fishing effort, respectively. Assuming that effort distribution is steered by the dynamics of target species, this result contradicts ecological studies reflecting a negative influence of higher temperatures on the recruitment and occurrence of plaice (Akimova et al., 2016; Engelhard et al., 2011; Teal et al., 2012; van Hal et al., 2016) and weak effects of salinity on plaice and sole (Akimova et al., 2016; Fonds, 1979; Lauria et al., 2011), Nephrops (Johnson et al., 2013), and brown shrimp (Kerambrun et al., 2001). Biophysical variables are subject to seasonal variability (Appendix VII), which is also reflected in the fleets' target species. Seasonal catch variations of the main target species brown shrimp (Schulte et al., 2020; Temming and Damm, 2002), plaice (Hunter et al., 2003), sole (Rijnsdorp et al., 1992), and Nephrops (Redant, 1987), occur due to migrations or life cycles and peak in the warmer months from spring to autumn.

Our results are in line with the assumption that stormy weather limits the operationality of vessels (Bastardie et al., 2013; Boonstra and Hentati-Sundberg, 2016; Christensen and Raakjær, 2006). Differences in vessels' seaworthiness can be explained by technical dissimilarities, such as vessel sizes (Bastardie et al., 2013; Salas and Gaertner, 2004). In our case, the FF fleet is composed of the largest vessels (Appendix II) and thus resisted higher waves as compared to the other two fleets.

4.2. Economic and socio-cultural drivers influencing fishing effort

Our findings revealed that economic and socio-cultural drivers differ among fleets, despite operating in similar spatial areas and belonging to the same flag state. The only socio-economic variable influencing both the MDS and FF fleet was distance to port. In contrast, BS fishers have a higher dependency on market price dynamics and prefer fishing on workdays. An important difference between the BS and the other fleets is that BS fishers usually run family-owned businesses operating a single vessel, whereas several vessels in the FF fleet are managed by larger companies (STECF, 2020). Boonstra and Hentati-Sundberg (2016) demonstrated that Swedish small-scale fishers are motivated by personal norms, such as the need to spend time at home and Schadeberg et al. (2021) found that decisions of fishers owning small businesses are more influenced by personal matters as opposed to those made in larger fishing companies. This is in line with our results, as the BS fleet was the only one driven by workdays and hence preferred to stay home on weekends and holidays. Moreover, BS fishers operate closer to the coast and fishing trips usually last no longer than one day (Aviat et al., 2011), whereas the other two fleets operate for several days, limiting their flexibility to stay in port during the weekend (Poos et al., 2013).

Another difference between the BS and the other two fleets is that BS is not subject to any quota, despite being the largest fishery in the German Bight (STECF, 2020). Some BS fishers follow self-imposed regulations, such as weekend bans to prevent an excess supply and thus gain certain control on the resource price (Aviat et al., 2011; Döring et al., 2020). Resource price was only relevant for BS fishers and, contrary to previous findings (Bastardie et al., 2013; Christensen and Raakjær, 2006; Girardin et al., 2017; STECF, 2020), our results show that higher resource prices were affiliated with less fishing effort. One possible explanation could be a well-functioning offer and demand dynamic where retailers lower their prices if catches increase and vice versa. Another explanation could be that BS fishers reduce their fishing effort when the resource price is high – be it due to self-imposed regulations to prevent a glut of brown shrimp landings and preserve stable prices or because of achieving personal objectives, i.e. generating a certain weekly profit. Moreover, the BS fleet was most dependent on nearby ports, perhaps because, contrary to the other two fleets, its target species occurs in coastal areas. On the other hand, distance to port is a proxy for steaming time and thus the amount of fuel used per fishing trip, suggesting that the BS fleet is more restricted by fuel costs than the other two fleets. This finding is supported by the fact that the BS fleet is the only one for which we identified fuel price as a relevant driver.

Surprisingly, our results revealed that quotas were irrelevant for the German demersal fleets, despite low annual German quotas for Nephrops of less than 20t. To enable a Nephrops fishery, Germany has swapped Nephrops quotas with other EU member states (STECF, 2020). Since the data we used encompasses the amount of available quota after inter-country swaps, our results suggest that Germany always found partner countries for quota swaps, so that the MDS fleet was able to catch Nephrops without restrictions. However, the consequences of the Brexit will lower Germany's swapping capacities due to reduced cod quota, which was mostly used to swap for Nephrops quota from the United Kingdom (Letschert et al., 2021).

4.3. Implications for management

Our study supports the call for approaching fisheries as a socio-ecological system in management, which has been suggested by many authors (Hare, 2020; Hilborn, 2007; Salas and Gaertner, 2004). Furthermore, results on the three German fishing fleets highlight the importance of recognizing different biophysical and socio-cultural requirements among fleets in fisheries management (Christensen and Raakjær, 2006). This information is key for the advancement of integrative management approaches, such as marine spatial planning (MSP), and promotes the spatial representation of fishers in management plans (Trouillet et al., 2019). In this study, the BS fleet was the most distinctive in terms of influencing socio-economic factors suggesting a dependency on fuel and resource prices. Because of these dependencies, the BS fleet is also the most vulnerable to economic changes, especially since it suffered from the COVID-19 pandemic and a general old age of vessels (Goti-Aralucea et al., 2021). In practice, these factors limit the BS fleet's ability to switch to alternative fishing practices or catch grounds in response to area closures or displacement of its target species because of climate change (Pecl et al., 2017).

Another pressing issue for fisheries is the overlap with other marine industries. Equivalent to the massively growing ocean economy expected in the next decade (OECD, 2016), MSP needs to adapt and especially focus on underrepresented stakeholder groups, such as small-scale fisheries (Flannery et al., 2016). Especially in the North Sea, expanding offshore windfarms will constrain the available space for fishing and force fishers to displace their effort (Letschert et al., 2021; Stelzenmüller et al., 2022). However, alternative fishing grounds might not always provide the same biophysical conditions and therefore potentially reduce the safety, efficiency, or profitability of fishing operations. Examples are stormier or further offshore located displacement areas leading to less days when fishing is possible or increased trip lengths and fuel costs. As a consequence of longer trips, fishing could become less attractive to fishers who prefer to return to the port before the weekend. Furthermore, the reallocation of demersal fishing effort could lead to a higher overall benthic disturbance (Stelzenmüller et al., 2015). Socio-ecological drivers identified by this study can be used to find alternative fishing opportunities and thus aid to reduce the uncertainty linked to reactions following changes in the socio-ecological system of fisheries.

4.4. Methodological considerations

We acknowledge that our empirical model is static and based on aggregated fleet data. In our exploratory literature review, we identified vessel- and fisher-specific variables influencing fishing activity, i.e. vessel size, engine power, as well as skipper age and experience. Disaggregated and more dynamic models, such as agent-based models, would allow to include these variables and enable the analysis of individual fishing behavior and strategies. These models allow incorporating differences among individual fishers and combining empirical data with social science theories about human-decision making (Müller et al., 2013; Schlüter et al., 2019; Smajgl et al., 2011; Wijermans et al., 2020).

The performances of our models measured as deviance explained was similar to previous studies using BRTs to analyze fishing effort, even while applying a higher spatial and temporal resolution. However, BRTs of fleets with large spatial fishing grounds (FF and MDS) performed worse than those of fleets with a smaller spatial flexibility (BS). This is likely because of the larger variety in the spatial data. Additional explanatory factors might improve the model performance.

5. Conclusions

We identified potential drivers of demersal North Sea fishing fleets and showed that boosted regression trees (BRT) are a suitable tool to empirically analyze socio-ecological factors influencing fishing effort. Model performances were satisfying, although BRTs for fleets with large spatial variety might benefit from including additional explanatory factors. Our results revealed that individual fishing fleets might be influenced by distinct socio-ecological factors, even though they operate in similar geographical areas and target similar species assemblages. With our fleet-based results we set a possible frame for dynamic and vessel- or fisher-based models (i.e. agent-based models), which can be used to combine empirical data and human-decision making theories. Especially in the North Sea, fishers will be confronted with many socio-ecological changes leading to yet unpredictable adaptations in the coming decades. In this context, our study represents a strong contribution helping to unravel fishers' behavior and thereby reducing the uncertainty in fisheries management and integrated marine spatial planning.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Fishery related data is confidential and cannot be shared. Links to all other data sources are included in the supplementary material.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ocecoaman.2023.106543.

References

Akimova, A., Núñez-Riboni, I., Kempf, A., Taylor, M.H., 2016. Spatially-resolved influence of temperature and salinity on stock and recruitment variability of commercially important fishes in the North Sea. PLoS One 11, e0161917. https://doi.org/10.1371/journal.pone.0161917.

Andersen, B.S., Ulrich, C., Eigaard, O.R., Christensen, A., 2012. Short-term choice behaviour in a mixed fishery: investigating métier selection in the Danish gillnet fishery. ICES J. Mar. Sci. 69, 131–143. https://doi.org/10.1093/icesjms/fsr181.

Andrews, E.J., Pittman, J., Armitage, D.R., 2020. Fisher behaviour in coastal and marine fisheries. Fish Fish. 1–14 https://doi.org/10.1111/faf.12529.

Apley, D.W., Zhu, J., 2016. Visualizing the Effects of Predictor Variables in Black Box Supervised Learning Models.

Aviat, D., Neudecker, T., Berkenhagen, J., Müller, M., 2011. The North Sea Brown Shrimp Fisheries (Brussels, Belgium).

Bastardie, F., Nielsen, J.R., Andersen, B.S., Eigaard, O.R., 2013. Integrating individual trip planning in energy efficiency - building decision tree models for Danish fisheries. Fish. Res. 143, 119–130. https://doi.org/10.1016/j.fishres.2013.01.018.

Bastardie, F., Nielsen, J.R., Andersen, B.S., Eigaard, O.R., 2010a. Effects of fishing effort allocation scenarios on energy efficiency and profitability: an individual-based model applied to Danish fisheries. Fish. Res. 106, 501–516. https://doi.org/10.1016/j.fishres.2010.06.016.

Bastardie, F., Nielsen, J.R., Ulrich, C., Egekvist, J., Degel, H., 2010b. Detailed mapping of fishing effort and landings by coupling fishing logbooks with satellite-recorded vessel geo-location. Fish. Res. 106, 41–53. https://doi.org/10.1016/j.fishres.2010.06.016.

Batsleer, J., Rijnsdorp, A.D., Hamon, K.G., van Overzee, H.M.J., Poos, J.J., 2016. Mixed fisheries management: is the ban on discarding likely to promote more selective and fuel efficient fishing in the Dutch flatfish fishery? Fish. Res. 174, 118–128. https://doi.org/10.1016/j.fishres.2015.09.006.

Baudron, A.R., Brunel, T., Blanchet, M., Hidalgo, M., Chust, G., Brown, E.J., Kleisner, K. M., Millar, C., MacKenzie, B.R., Nikolioudakis, N., Fernandes, J.A., Fernandes, P.G., 2020. Changing fish distributions challenge the effective management of European fisheries. Ecography 43, 494–505. https://doi.org/10.1111/ecog.04864.

Beare, D., Rijnsdorp, A.D., Blaesberg, M., Damm, U., Egekvist, J., Fock, H., Kloppmann, M., Röckmann, C., Schroeder, A., Schulze, T., Tulp, I., Ulrich, C., van Hal, R., van Kooten, T., Verweij, M., 2013. Evaluating the effect of fishery closures: lessons learnt from the Plaice Box. J. Sea Res. 84, 49–60. https://doi.org/10.1016/j.seares.2013.04.002.

Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., Marsili-Libelli, S., Newham, L.T.H., Norton, J.P., Perrin, C., Pierce, S. A., Robson, B., Seppelt, R., Voinov, A.A., Fath, B.D., Andreassian, V., 2013. Characterising performance of environmental models. Environ. Model. Software 40, 1–20. https://doi.org/10.1016/j.envsoft.2012.09.011.

Boonstra, W.J., Hentati-Sundberg, J., 2016. Classifying Fishers' behaviour. An invitation to fishing styles. Fish Fish. 17, 78–100. https://doi.org/10.1111/faf.12092.

Castrejón, M., Charles, A., 2020. Human and climatic drivers affect spatial fishing patterns in a multiple-use marine protected area: the Galapagos Marine Reserve, PloS one. https://doi.org/10.1371/journal.pone.0228094.

Chen, T., Guestrin, C., 2016. XGBoost: A Scalable Tree Boosting System. Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min, pp. 785–794. https://doi.org/10.1145/2939672.2939785, 13-17-Augu.

Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., Cho, H., Chen, K., Mitchell, R., Cano, I., Zhou, T., Li, M., Xie, J., Lin, M., Geng, Y., Li, Y., 2019. Extreme Gradient Boosting.

Christensen, A.S., Raakjær, J., 2006. Fishermen's tactical and strategic decisions. A case study of Danish demersal fisheries. Fish. Res. 81, 258–267. https://doi.org/10.1016/j.fishres.2006.06.018.

Cimino, M.A., Anderson, M., Schramek, T., Merrifield, S., Terrill, E.J., 2019. Towards a fishing pressure prediction system for a western pacific EEZ. Sci. Rep. 9, 461. https://doi.org/10.1038/s41598-018-36915-x.

Crespo, G.O., Dunn, D.C., Reygondeau, G., Boerder, K., Worm, B., Cheung, W., Tittensor, D.P., Halpin, P.N., 2018. The environmental niche of the global high seas pelagic longline fleet. Sci. Adv. 4, eaat3681. https://doi.org/10.1126/sciadv.aat3681.

Dinmore, T.A., Duplisea, D.E., Rackham, B.D., Maxwell, D.L., Jennings, S., 2003. Impact of a large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. ICES J. Mar. Sci. 60, 371–380. https://doi.org/10.1016/S1054-3139(03)00010-9.

Döring, R., Berkenhagen, J., Hentsch, S., Kraus, G., 2020. Small-scale fisheries in Germany: a disappearing profession?, 483–502. https://doi.org/10.1007/978-3-030-37371-9_23.

Engelhard, G.H., Pinnegar, J.K., Kell, L.T., Rijnsdorp, A.D., 2011. Nine decades of North Sea sole and plaice distribution. ICES J. Mar. Sci. 68, 1090–1104. https://doi.org/10.1093/icesjms/fsr031.

Flannery, W., Ellis, G., Ellis, G., Flannery, W., Nursey-Bray, M., van Tatenhove, J.P.M., Kelly, C., Coffen-Smout, S., Fairgrieve, R., Knol, M., Jentoft, S., Bacon, D., O'Hagan, A.M., 2016. Exploring the winners and losers of marine environmental governance/Marine spatial planning: cui bono ?/"More than fishy business": epistemology, integration and conflict in marine spatial planning/Marine spatial planning: power and scaping/Surely not all. Plann. Theor. Pract. 17, 121–151. https://doi.org/10.1080/14649357.2015.1131482.

Fonds, M., 1979. Laboratory observations on the influence of temperature and salinity on development of the eggs and growth of the larvae of Solea solea. Mar. Ecol. Prog. Ser. 1, 91–99. https://doi.org/10.3354/meps001091.

Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. Ann. Stat. 1189–1232.

Fulton, E.A., Smith, A.D.M., Smith, D.C., Van Putten, I.E., 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish Fish. 12, 2–17. https://doi.org/10.1111/j.1467-2979.2010.00371.x.

Girardin, R., Hamon, K.G., Pinnegar, J., Poos, J.J., Thébaud, O., Tidd, A., Vermard, Y., Marchal, P., 2017. Thirty years of fleet dynamics modelling using discrete-choice models: what have we learned? Fish Fish. 18, 638–655. https://doi.org/10.1111/faf.12194.

Gordon, H.S., 1954. The economic theory of a common-property resource: the fishery. J. Polit. Econ. 62, 124–142.

Goti-Aralucea, L., Berkenhagen, J., Sulanke, E., Döring, R., 2021. Efficiency vs resilience: the rise and fall of the German brown shrimp fishery in times of COVID 19. Mar. Pol. 133, 104675 https://doi.org/10.1016/j.marpol.2021.104675.

Halpern, B.S., Frazier, M., Afflerbach, J., Lowndes, J.S., Micheli, F., O'Hara, C., Scarborough, C., Selkoe, K.A., 2019. Recent pace of change in human impact on the world's ocean. Sci. Rep. 9, 1–8. https://doi.org/10.1038/s41598-019-47201-9.

Halpern, B.S., Frazier, M., Potapenko, J., Casey, K.S., Koenig, K., Longo, C., Lowndes, J. S., Rockwood, R.C., Selig, E.R., Selkoe, K.A., Walbridge, S., 2015. Spatial and temporal changes in cumulative human impacts on the world's ocean. Nat. Commun. 6, 7615. https://doi.org/10.1038/ncomms8615.

Halpern, B.S., McLeod, K.L., Rosenberg, A.A., Crowder, L.B., 2008. Managing for cumulative impacts in ecosystem-based management through ocean zoning. Ocean Coast Manag. 51, 203–211. https://doi.org/10.1016/j.ocecoaman.2007.08.002.

Hare, J.A., 2020. Ten lessons from the frontlines of science in support of fisheries management. ICES J. Mar. Sci. 77, 870–877. https://doi.org/10.1093/icesjms/fsaa025.

Hilborn, R., 2007. Managing fisheries is managing people: what has been learned? Fish Fish. 8, 285–296. https://doi.org/10.1111/j.1467-2979.2007.00263_2.x.

Hintzen, N.T., Aarts, G., Poos, J.J., Van der Reijden, K.J., Rijnsdorp, A.D., 2021. Quantifying habitat preference of bottom trawling gear. ICES J. Mar. Sci. 78, 172–184. https://doi.org/10.1093/icesjms/fsaa207.

Hintzen, N.T., Aarts, G., Rijnsdorp, A.D., 2019. Persistence in the fine-scale distribution and spatial aggregation of fishing. ICES J. Mar. Sci. 76, 1072–1082. https://doi.org/10.1093/icesjms/fsy144.

Hintzen, N.T., Bastardie, F., Beare, D., Piet, G.J., Ulrich, C., Deporte, N., Egekvist, J., Degel, H., 2012. VMStools: open-source software for the processing, analysis and visualisation of fisheries logbook and VMS data. Fish. Res. 115–116, 31–43. https://doi.org/10.1016/j.fishres.2011.11.007.

Hunter, E., Metcalfe, J.D., Reynolds, J.D., 2003. Migration route and spawning area fidelity by North Sea plaice, 2097–2103. https://doi.org/10.1098/rspb.2003.

Hutton, T., Mardle, S., Pascoe, S., Clark, R.A., 2004. Modelling fishing location choice within mixed fisheries: English North Sea beam trawlers in 2000 and 2001. ICES J. Mar. Sci. 61, 1443–1452. https://doi.org/10.1016/j.icesjms.2004.08.016.

Johnson, M.P., Lordan, C., Power, A.M., 2013. Habitat and ecology of Nephrops norvegicus. In: Advances in Marine Biology. Elsevier Ltd., pp. 27–63. https://doi.org/10.1016/B978-0-12-410466-2.00002-9

Kannen, A., 2014. Challenges for marine spatial planning in the context of multiple sea uses, policy arenas and actors based on experiences from the German North Sea. Reg. Environ. Change 14, 2139–2150. https://doi.org/10.1007/s10113-012-0349-7.

Kerambrun, P., Rosecchi, E., Crivelli, A.J., Gelin, A., 2001. Can salinity changes affect reproductive success in the Brown shrimp Crangon Crangon. J. Crustac Biol. 21, 905–911. https://doi.org/10.1163/20021975-99990182.

Kuhn, M., 2019. Caret: Classification and Regression Training.

Lauria, V., Vaz, S., Martin, C.S., Mackinson, S., Carpentier, A., 2011. What influences European plaice (Pleuronectes platessa) distribution in the eastern English Channel? Using habitat modelling and GIS to predict habitat utilization. ICES J. Mar. Sci. 68, 1500–1510. https://doi.org/10.1093/icesjms/fsr081.

Letschert, J., Stollberg, N., Rambo, H., Kempf, A., Berkenhagen, J., Stelzenmüller, V., 2021. The uncertain future of the Norway lobster fisheries in the North Sea calls for new management strategies. ICES J. Mar. Sci. https://doi.org/10.1093/icesjms/fsab204.

Li, J., 2016. Assessing spatial predictive models in the environmental sciences: accuracy measures, data variation and variance explained. Environ. Model. Software 80, 1–8. https://doi.org/10.1016/j.envsoft.2016.02.004 1364-8152/.

Link, J.S., Thébaud, O., Smith, D.C., Smith, A.D.M., Schmidt, J., Rice, J., Poos, J.J., Pita, C., Lipton, D., Kraan, M., Frusher, S., Doyen, L., Cudennec, A., Criddle, K., Bailly, D., 2017. Keeping humans in the ecosystem. ICES J. Mar. Sci. 74, 1947. https://doi.org/10.1093/icesjms/fsx130. –1956.

Liu, O.R., Thomas, L.R., Clemence, M., Fujita, R., Kritzer, J.P., McDonald, G., Szuwalski, C., 2016. An evaluation of harvest control methods for fishery management. Rev. Fish. Sci. Aquac. 24, 244–263. https://doi.org/10.1080/23308249.2016.1161002.

Mendenhall, E., Hendrix, C., Nyman, E., Roberts, P.M., Hoopes, J.R., Watson, J.R., Lam, V.W.Y., Sumaila, U.R., 2020. Climate change increases the risk of fisheries conflict. Mar. Pol. 117, 103954 https://doi.org/10.1016/j.marpol.2020.103954.

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., Schwarz, N., 2013. Describing human decisions in agent-based models - ODD+D, an extension of the ODD protocol. Environ. Model. Software 48, 37–48. https://doi.org/10.1016/j.envsoft.2013.06.003.

OECD, 2016. The Ocean Economy in 2030, Water Intelligence Online. OECD Publishing, Paris. https://doi.org/10.2166/9781780408927.

Partelow, S., 2018. A review of the social-ecological systems framework: applications, methods, modifications, and challenges. Ecol. Soc. 23 https://doi.org/10.5751/ES-10594-230436.

Pecl, G.T., Araújo, M.B., Bell, J.D., Blanchard, J., Bonebrake, T.C., Chen, I.C., Clark, T.D., Colwell, R.K., Danielsen, F., Evengård, B., Falconi, L., Ferrier, S., Frusher, S., Garcia, R.A., Griffis, R.B., Hobday, A.J., Janion-Scheepers, C., Jarzyna, M.A., Jennings, S., Lenoir, J., Linnetved, H.I., Martin, V.Y., McCormack, P.C., McDonald, J., Mitchell, N.J., Mustonen, T., Pandolfi, J.M., Pettorelli, N., Popova, E., Robinson, S.A., Scheffers, B.R., Shaw, J.D., Sorte, C.J.B., Strugnell, J.M., Sunday, J. M., Tuanmu, M.N., Vergés, A., Villanueva, C., Wernberg, T., Wapstra, E., Williams, S. E., 2017. Biodiversity redistribution under climate change: impacts on ecosystems and human well-being. Science 80, 355. https://doi.org/10.1126/science.aai9214.

Poos, J.-J., Rijnsdorp, A.D., 2007. An "experiment" on effort allocation of fishing vessels: the role of interference competition and area specialization. Can. J. Fish. Aquat. Sci. 64, 304–313. https://doi.org/10.1139/f06-177.

Poos, J.J., Turenhout, M.N.J., van Oostenbrugge, H.A.E., Rijnsdorp, A.D., 2013. Adaptive response of beam trawl Fishers to rising fuel cost. ICES J. Mar. Sci. 70, 675–684. https://doi.org/10.1093/icesjms/fss196.

R Core Team, 2019. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing.

Redant, F., 1987. Reproduction and seasonal behaviour of the Norway lobster, Nephrops norvegicus. In: The Central North Sea. C. Doc. K.

Rijnsdorp, A.D., Daan, N., Dekker, W., 2006. Partial fishing mortality per fishing trip: a useful indicator of effective fishing effort in mixed demersal fisheries. ICES J. Mar. Sci. 63, 556–566. https://doi.org/10.1016/j.icesjms.2005.10.003.

Rijnsdorp, A.D., Piet, G.J., Poos, J.J., 2001. Effort allocation of the Dutch beam trawl fleet in response to a temporarily closed area in the North Sea. Ice C, 2001/N01 1–17.

Rijnsdorp, A.D., Poos, J.J., Quirijns, F.J., HilleRisLambers, R., De Wilde, J.W., Den Heijer, W.M., 2008. The arms race between Fishers. J. Sea Res. 60, 126–138. https://doi.org/10.1016/j.seares.2008.03.003.

Rijnsdorp, A.D., Van Beek, F.A., Flatman, S., Millner, R.M., Riley, J.D., Giret, M., De Clerck, R., 1992. Recruitment of sole stocks, Solea solea (L.), in the northeast atlantic. NJSR (Neth. J. Sea Res.) 29, 173–192. https://doi.org/10.1016/0077-7579(92)90018-A.

Salas, S., Gaertner, D., 2004. The behavioural dynamics of Fishers: management implications. Fish Fish. 5, 153–167. https://doi.org/10.1111/j.1467-2979.2004.00146.x.

Schadeberg, A., Kraan, M., Hamon, K.G., 2021. Beyond métiers: social factors influence Fisher behaviour. ICES J. Mar. Sci. https://doi.org/10.1093/icesjms/fsab050.

Schlüter, M., Müller, B., Frank, K., Müller, B., Frank, K., 2019. The potential of models and modeling for social-ecological systems research: the reference frame ModSES. Ecol. Soc. https://doi.org/10.5751/ES-10716-240131.

Schulte, K.F., Siegel, V., Hufnagl, M., Schulze, T., Temming, A., 2020. Spatial and temporal distribution patterns of brown shrimp (Crangon crangon) derived from commercial logbook, landings, and vessel monitoring data. ICES J. Mar. Sci. 77, 1017–1032. https://doi.org/10.1093/icesjms/fsaa021.

Smajgl, A., Brown, D.G., Valbuena, D., Huigen, M.G.A., 2011. Empirical characterisation of agent behaviours in socio-ecological systems. Environ. Model. Software 26, 837–844. https://doi.org/10.1016/j.envsoft.2011.02.011.

Soykan, C.U., Eguchi, T., Kohin, S., Dewar, H., 2014. Prediction of fishing effort distributions using boosted regression trees. Ecol. Appl. 24, 71–83. https://doi.org/10.1890/12-0826.1.

STECF, 2020. The 2020 Annual Economic Report on the EU Fishing Fleet (STECF 20-06). Publications Office of the European Union, Luxembourg. https://doi.org/10.2760/50052.

Stelzenmüller, V., Fock, H.O., Gimpel, A., Rambo, H., Diekmann, R., Probst, W.N., Callies, U., Bockelmann, F., Neumann, H., Kröncke, I., 2015. Quantitative environmental risk assessments in the context of marine spatial management: current approaches and some perspectives. ICES J. Mar. Sci. 72, 1022–1042. https://doi.org/10.1093/icesjms/fsu206.

Stelzenmüller, V., Gimpel, A., Haslob, H., Letschert, J., Berkenhagen, J., Brüning, S., 2021. Sustainable co-location solutions for offshore wind farms and fisheries need to account for socio-ecological trade-offs. Sci. Total Environ. 776, 145918 https://doi.org/10.1016/j.scitotenv.2021.145918.

Stelzenmüller, V., Letschert, J., Gimpel, A., Kraan, C., Probst, W.N., Degraer, S., Döring, R., 2022. From plate to plug: the impact of offshore renewables on European fisheries and the role of marine spatial planning. Renew. Sustain. Energy Rev. 158, 112108 https://doi.org/10.1016/j.rser.2022.112108.

Stelzenmüller, V., Rogers, S.I., Mills, C.M., 2008. Spatio-temporal patterns of fishing pressure on UK marine landscapes, and their implications for spatial planning and management. ICES J. Mar. Sci. 65, 1081–1091. https://doi.org/10.1093/icesjms/fsn073.

Sys K, ., Poos, J.J., Van Meensel, J., Polet, H., Buysse, J., 2016. Competitive interactions between two fishing fleets in the North Sea. ICES J. Mar. Sci. 73, 1485–1493.

Sys, K., Van Meensel, J., Polet, H., Buysse, J., 2017. A temporal race-for-fish: the interplay between local hotspots of flatfish and exploitation competition between beam trawlers after a seasonal spawning closure. Fish. Res. 193, 21–32. https://doi.org/10.1016/j.fishres.2017.03.018.

Teal, L.R., van Hal, R., van Kooten, T., Ruardij, P., Rijnsdorp, A.D., 2012. Bio-energetics underpins the spatial response of North Sea plaice (Pleuronectes platessa L.) and sole (Solea solea L.) to climate change. Global Change Biol. 18, 3291–3305. https://doi.org/10.1111/j.1365-2486.2012.02795.x.

Temming, A., Damm, U., 2002. Life cycle of Crangon crangon in the North sea: a simulation of the timing of recruitment as a function of the seasonal temperature signal. Fish. Oceanogr. 11, 45–58. https://doi.org/10.1046/j.1365-2419.2002.00184.x.

Tidd, A.N., Hutton, T., Kell, L.T., Blanchard, J.L., 2012. Dynamic prediction of effort reallocation in mixed fisheries. Fish. Res. 125, 243–253. https://doi.org/10.1016/j.fishres.2012.03.004.

Trouillet, B., Bellanger-Husi, L., El Ghaziri, A., Lamberts, C., Plissonneau, E., Rollo, N., 2019. More than maps: providing an alternative for fisheries and Fishers in marine spatial planning. Ocean Coast Manag. 173, 90–103. https://doi.org/10.1016/j.ocecoaman.2019.02.016.

Ulrich, C., Reeves, S.A., Vermard, Y., Holmes, S.J., Vanhee, W., 2011. Reconciling single-species TACs in the North Sea demersal fisheries using the Fcube mixed-fisheries advice framework. ICES J. Mar. Sci. 68, 1535–1547. https://doi.org/10.1093/icesjms/fsr060.

van der Reijden, K.J., Hintzen, N.T., Govers, L.L., Rijnsdorp, A.D., Olff, H., 2018. North Sea demersal fisheries prefer specific benthic habitats. PLoS One 13, 1–21. https://doi.org/10.1371/journal.pone.0208338.

van Hal, R., van Kooten, T., Rijnsdorp, A.D., 2016. Temperature induced changes in size dependent distributions of two boreal and three Lusitanian flatfish species: a

comparative study. J. Sea Res. 107, 14–22. https://doi.org/10.1016/j.seares.2015.06.020.
van Oostenbrugge, H.J.A.E., Powell, J.P., Smit, J.P.G., Poos, J.-J., Kraak, S.B.M., Buisman, E.F.C., 2008. Linking catchability and Fisher behaviour under effort management. Aquat. Living Resour. 21, 265–273. https://doi.org/10.1051/alr:2008035.
Wijermans, N., Boonstra, W.J., Orach, K., Hentati-Sundberg, J., Schlüter, M., 2020. Behavioural diversity in fishing—towards a next generation of fishery models. Fish Fish. 21, 872–890. https://doi.org/10.1111/faf.12466.