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Identifying fishing behavior groups from vessel movement data: Application to the German brown shrimp fleet

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ABSTRACT

The German brown shrimp (*Crangon crangon*) fleet in the North Sea is declining due to rising fuel costs and unpredictable shrimp prices. Furthermore, this fishery is adapting their area use to new EU Natura 2000 regulations. We analyze thirteen years of Vessel Monitoring System (VMS) data spatially and temporally to investigate fisher behavior for this specific métier. A total of 1938408 VMS pings from 211 vessels are clustered into four behavioral groups differing in vessel length, engine power, total brown shrimp catch, and landing per unit effort (LPUE). We evaluated the potential effect of recently implemented and future marine protected area (MPA) closures linked to the EU Action Plan 2023. The former have negligible overlap with areas exploited by shrimp fishers, but the latter cover grounds from which 70 % of brown shrimp landings originated during 2009–2021. The most affected behavioral group includes 119 vessels, characterized by smaller sizes (vessel length ~ 16 m), with potential landings decreasing by up to 80 % without effort relocation or behavioral adaptation. Our results show that vessels targeting the same species differ in fishing behavior and spatial footprints. More generally, our approach assesses diversity in fishing behavior and highlights varying adaptability to changing economic and management conditions.

1. Introduction

The brown shrimp (*Crangon crangon*) fishery is the largest part of the German fishing fleet in the North Sea (ICES et al., 2021). The fleet is rather old with an average vessel age of approximately 40 years. Vessels are mostly family-owned and operated by one skipper and one crew member (Döring et al., 2020). The German brown shrimp industry used to have a high economic value, with annual landings peaking in 2018 (ICES, 2023; STECF, 2020, 2019). However, since 2018, profits have declined owing to two factors. Firstly, the COVID-19 pandemic affected the supply chain, causing difficulties in sustaining the outsourcing of the peeling to Morocco, where personnel costs are lower (Goti-Aralucea et al., 2021). Secondly, the shrimp market price remained low while fuel costs continued to increase (ICES et al., 2021). Substituting the demand for brown shrimp products with other seafood products in Germany is not straightforward since the fishery has an important cultural and touristic value in coastal communities (Döring et al., 2020).

The North Sea brown shrimp stock is neither consistently monitored nor managed by any legislative authority and there is no species-specific regulation or Total Allowable Catch (TAC)(STECF, 2020). The major spatial restriction is the so-called plaice box, which excludes fishing vessels with an engine power above 221 kW from fishing (Amelot and Hintzen, 2022; Beare et al., 2013; European Parliament, Council of the European Union, 2019a) (Fig. 5). Bycatch regulation is planned but not yet implemented at the time of writing this article. Catch prices are mainly decided by the retailer. However, in 2011 shrimp prices were so low that almost all the regional (German, Dutch and Danish) fleets went on strike for 3 weeks and completely stopped fishing (STECF, 2020). This resulted in an increase in price and a 50 % increase in the average annual income of the fleet in the following years. In Germany, a harvest control rule (HCR) started to be applied in 2011 based on monitoring of the weekly total landings as a self-management strategy (Steenbergen et al., 2017). In 2014, following the demand from retailers, the shrimp fishery started an application for the Marine Stewardship Council (MSC) label ("Certificates North Sea Brown Shrimp - MSC Fisheries," n.d.). This requires having an effective management system in place to ensure a

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long-term sustainable yield and minimal ecosystem impacts. In order to meet these requirements, the fishery set up national producer organizations and started self-management. There were a few temporary management strategies applied by the producer organizations such as weekend closures. However, these regulations are not well documented and reported in the scientific literature.

The global expansion of marine protected areas (MPAs) reflects increasing recognition of the need to safeguard biodiversity, with Europe aligning to international targets like the EU Biodiversity Strategy aiming to protect 30 % of marine waters by 2030 (European Parliament, Council of the European Union, 2020; Rechberger et al., 2024). On the other hand, assessments indicate that 86 % of marine protected areas in the European Union exhibit low levels of protection or incompatibility with conservation targets (Aminian-Biquet et al., 2024, p. 80). MPAs and other access restrictions can profoundly impact fishing fleets by redistributing effort, altering catch composition, and potentially increase fuel use, as evidenced by varied international case studies (Grip and Blomqvist, 2020; Hogg et al., 2024; McDonald et al., 2024; Rufener et al., 2023; Scherrer et al., 2024).

The vessels that target North Sea brown shrimp use beam trawls and nets with 16 mm to 22 mm mesh size. They can be identified by so-called fleet segmentation using vessel-specific information such as vessel length, target species, gear type and net mesh size (Bastardie et al., 2022; Sulanke et al., 2025). Metier is another category commonly used by the EU to define and characterize fishing activities (European Parliament, Council of the European Union, 2009). It refers to fishing operations that target similar species with similar gear, and operate during the same period of the year and/or in the same geographic area. This type of fleet segmentation is useful for aggregating and quantifying fisheries in a standardized manner across countries or regions. However, spatial aspects are usually not considered. Vessels within the same fleet segment might conduct fishing trips with different fishing strategies and behaviors according to changing conditions (weather, holidays, etc.) (Kroodsma et al., 2018). This may result in a variety of spatial and temporal efforts within one fleet segment.

The availability of high-resolution spatial data enables new perspectives for monitoring and managing fisheries. For several decades EU fishing vessels have been using logbooks to report fishing trips, gear used and catch per species. In this case, the catch is mostly reported at the level of ICES (International Council for the Exploration of the Sea) squares, that is cells of 1° longitude and 0.5° latitude. Since 2005 vessels larger than 15 m and since 2012 vessels above 12 m are obliged to use a vessel monitoring system (VMS), which records the position (latitude, longitude), direction, and speed of vessels at least every two hours (European Parliament, Council of the European Union, 2015, 2011). With increasing VMS coverage of the EU fleets, we now have more than a 10-year-long time series of detailed data on individual vessel movement. For practical reasons, this spatial and temporal information is often summarized at the fleet level in fishing effort maps. However, these maps mask the variety of core fishing areas of individual vessels. Using spatial and temporal information would thus improve fleet segmentation and allows to manage the fleet at appropriate scales. In addition, it would contribute to a clearer understanding of how spatial regulations or closures impact fishing dynamics.

Incorporating human behavior into fisheries models is essential for accurately simulating fleet dynamics and predicting responses to external factors such as regulatory changes, market fluctuations, and environmental shifts (Andrews et al., 2021; van Putten et al., 2012). Agent-based models (ABMs) are particularly effective in capturing the complexity of fisher decision-making processes, offering more realistic representations of these dynamics (Christensen and Raakjær, 2006). Other models, such as discrete choice random utility models (DCM) (Wang et al., 2024), generalized linear mixed effects models (Riekkola et al., 2024) or bioeconomic models (Carr and Heyman, 2014; Nielsen et al., 2018) can account for human behavior and provide insights into the relationship of fishing activities and management strategies.

The aim of this paper is to investigate the behavioral patterns of the German brown shrimp fishing fleet. For this we calculated vessel-specific spatial and temporal parameters from VMS data over the past 13 years and clustered vessels into groups with similar fishing strategies. We were interested in the extent to which the clusters identified reflect differences in the economic performance of individual vessels and vessel characteristics, and the extent to which they are affected by current and future area closures.

2. Methods

2.1. Data sources and preparation

The spatial and temporal distribution of vessel-specific fishing effort of the German brown shrimp fishing fleet in the North Sea was estimated from VMS data for the years 2009–2021. Earlier years are not representative as VMS technology was not widely available in the fleet. The data were aggregated monthly and used to identify behavioral clusters.

The VMS data used to identify and describe fishing style groups (clusters) were matched with three additional data sources: the EU Fleet Register ("Fleet Register," n.d.), commercial fishing logbooks, and sale slips (landing data). All the data were collected under the EU data collection framework for the European fishing fleet and processed primarily by the German Federal Office for Agriculture and Food (BLE) (European Parliament, Council of the European Union, 2019a).

VMS data (pings broadcasted per vessel) consist of geo-coordinates (latitude and longitude), timestamp, vessel speed, and vessel direction. The frequency of reported VMS pings varies between flag states and use of a regulated marine spatial planning area, but is at least once every 2 h. For VMS data, we followed the cleaning steps suggested by (Bastardie et al., 2010b; Hintzen et al., 2012; ICES, 2022): we discarded vessel positions on land, implausibly high speeds, headings outside compass range, duplicated records, pseudo-duplicated records at less than 5 min intervals, and vessel positions lying either in harbors or very close to harbors.

In Germany, we prepare logbook data and sale slip information (for revenues) to fit the ICES Working Group on Spatial Fisheries Data (WGSFD) format: spurious mesh sizes, vessel length, total catch, duplicated or overlapping records, and trips with an arrival date before departure date are removed (ICES, 2022). After the ICES recommended cleaning steps, the VMS and logbook data were merged for each year at the fishing trip level using the R package VMStools version 0.75 (Hintzen et al., 2012). We used vessel speed to distinguish fishing pings from steaming pings and matched fishing pings to the corresponding trip landings. After cleaning the VMS data and matching the trip information from the logbooks to the pings, a total of 192302 individual trips and 4722311 pings remained for the investigated time period. The number of vessels ranged from 226 to 286 and thus represent the entire German fleet. We then processed the data with four additional filtering steps to narrow down the data to the brown shrimp fleet specifically. 1. We limited our study area to fishing trips that took place in the North Sea (ICES Statistical Fishing Areas 27.4.b and 27.4.c). 2. We discarded trips with unrealistically high catch values over 40000 Euros per trip. 3. We focused on vessels that mostly catch brown shrimp. For this we followed a "once a shrimper always a shrimper" rule whereby vessels that have derived at least 90 % of their total income from shrimp catch in any given month are categorized as shrimpers. 4. We only considered months with at least five fishing pings per month to calculate the monthly home range of a vessel. The final data set included 211 vessels, 1938408 pings and 142839 fishing trips for the 2009–2021 period. We used the R programming language for all data processing and statistical analysis (R Core Team, 2021).

2.2. Spatial and temporal attributes

We used 10 monthly estimated attributes to describe the temporal and spatial fishing behavior of vessels and for each attribute, we calculated the interannual mean and the interannual standard deviation to take temporal variability into account. The 10 attributes are listed in (Table 1).

Fishing vessels operate differently in terms of the length of their fishing trips, how far they go offshore and how variable their fishing areas are. In order to investigate this variability we analyzed the size of the so-called *home range* of a vessel. In animal ecology, home range defines the area individuals often visit for hunting or resting (Burt, 1943). Fishing vessels are operated by captains who also have site fidelity for areas they regularly visit (Powell and Mitchell, 2012). We applied the kernel density utilization (KUD) method to estimate the home range of each vessel for each month (Worton, 1989). Since we aggregated our data monthly, we refer to this attribute as the "core area index" to clarify that we are only using it to compare vessels and months as opposed to describing the size of the fishing grounds. We used R-package, *adehabitatHR* for our analysis (Calenge, 2006). As suggested by previous studies(Boyle, 2021), we investigated various *smoothing parameter (h-value)* options and decided to use the best suitable algorithm, *reference bandwidth (href)* method, in the R function kernelUD that uses the *Epanechnikov kernel method (epa)* (Laver and Kelly, 2008; Silverman, 1986). To make it consistent between the vessels, we used the same grid (with 0.01 degree by 0.01 degree resolution) for all vessels and months. By combining a consistent grid with tailored bandwidths, we achieve both comparability across datasets and improved precision in our individual estimations. We reported the settings for our analysis in a R script. We were able to estimate home range values for 21803 vessel/months over the 13 years study period.

The area-use pattern of one vessel for one month is presented in Fig. 1. The 50 % kernel utilisation distribution (KUD) is defined as the core area index. The relative area flexibility is calculated by dividing the 90 % KUD by 50 % KUD. The 100 % home range includes all recorded locations. The 50 % KUD focuses on the most revisited portion of the monthly fishing activity. The maximum distance to departure port is calculated per trip and then the monthly maximum is taken. Monthly mean of trip length and monthly sum of fishing hours are also calculated. The definition of each attribute used for clustering is provided in Table 1.

2.3. Statistical analyses

Our statistical analyses comprised three steps. In the first step, we used the spatial and temporal attributes described in Section 2.2 to identify behavioral groups by clustering. In the second part, we investigated the differences between clusters using vessel characteristics and catch. We then used multinomial regression models to select which variables explain the differences among clusters best. In the last step, we analyzed each attribute and predictor separately to determine their significance within the clusters.

In the first step the 10 attributes described in Table 1 were analyzed with hierarchical clustering using Ward's method and Euclidean

Table 1
Attributes used in the multivariate analysis: each value is calculated per vessel.

No.	Interannual Statistic	Attribute	Definition
1	Mean	Core area index	Home range calculated by
2	SD		kernel utility distribution 50 % (km^2)
3	Mean	Relative area	Home range 50 %
4	SD	flexibility	Home range 90 %
5	Mean	Trip length	Total time per fishing trip,
6	SD		steaming excluded (h)
7	Sum	Total fishing hours	Cumulative total fishing time,
8	SD		steaming excluded (h)
9	Mean	Distance to	The trips' maximum distance to the
10	SD	departure port	departure port (km)

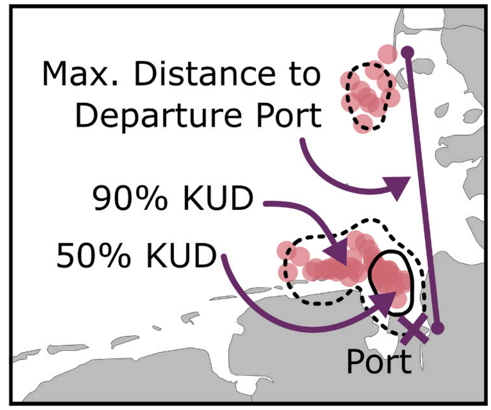


Fig. 1. Illustration of the spatial parameters used to quantify fishing behavior. Pink dots represent monthly fishing pings of one vessel (derived from vessel monitoring systems data). Dashed lines are the 90 % kernel utilization density (KUD) areas and the inner polygon with solid line is the 50 % KUD area. The maximum distance to departure port is calculated per trip and the monthly maximum is taken. We used the 50 % KUD to define the core area index and the ratio between 90 % and 50 % KUD to define monthly area flexibility.

distance (Ward Jr, 1963). To identify the optimal number of clusters, we used both the average silhouette score (Rousseeuw, 1987) and visual inspection of the dendrogram. Four clusters were found to be the most coherent and distinct. Furthermore, we performed a Principal Component Analysis (PCA) using the same Euclidian distance measure. We used the R-package *factoextra* for all the steps mentioned in this section and plotting the related figures(Kassambara, 2016).

In the second step, we explored additional vessel-specific attributes that could explain the differences among the identified clusters. These predictors were not included in the clustering analysis and have been used by other studies for fleet segmentation (Boonstra and Hentati-Sundberg, 2015; Letschert et al., 2023; Meyer and Krumme, 2021; Parsa et al., 2020; Schadeberg et al., 2021). We started with 12 predictors (Supplementary Table 3), aiming to include at least one predictor for landing, fishing effort and vessel characteristic. The pairwise Pearson correlation coefficient (Supplementary Figure 9) was used to identify pairs of predictors that were highly correlated with each other and thus potentially describe roughly the same feature. In this case, only one of the two predictors was used in subsequent analyses, prioritizing predictors derived from publicly available data when possible to improve reproducibility. The final set of predictors comprised two variables that commonly define vessel properties (vessel length (m) and vessel engine power (KW) recorded in logbooks in 2021) and three predictors related to catch and catch efficiency (total brown shrimp catch (kg), landing per unit effort (LPUE), and total species catch that are not brown shrimp (kg)). LPUE represented the efficiency of fishing trips that resulted in successful catches of North Sea brown shrimp. This measure was obtained by dividing the brown shrimp landing in kg by the fishing hours excluding steaming.

To investigate the relationship between the clusters and the vessel-specific variables, we employed multinomial logistic regression. This approach is well-suited for modeling discrete outcome variables, aligning with the clusters in our study. To determine the most appropriate model, we employed a simple to complex model selection approach, which identifies the significant predictors influencing the variation between the four fisher groups that we identified. We fitted a total of 26 models (from a simple one-predictor model to a full model with all five predictors and all possible two-way interactions) and compared their performance with the Akaike Information Criterion (AIC) and likelihood ratio test for significance.

Finally, we examined each attribute and predictor independently for the significance among the clusters. We used non-parametric Dunn's pairwise test and reported significant differences above 0.05 in Holmadjusted p values.

2.4. Regulations and conservation initiatives in the German North Sea

The consolidated version of the EU 2017/118 Regulation was updated on March 8, 2023 with the implementation of Delegated Regulation (EU) 2023/340(European Commission, 2023, 2017), which has significantly changed the spatial area and fisheries management in the German North Sea exclusive economic zone (EEZ). This regulation includes several fisheries measures within the designated Natura 2000 areas. Since May 1st 2023 all fishing activities in the Natura 2000 area of the Amrum Bank which was previously an intensively fished ground of the international brown shrimp fishery were banned. Furthermore, mobile bottom-contacting gears are excluded in the middle part of the Sylt outer reef and Borkum reef grounds. As part of the measures, although not relevant for the vessels using beam trawls, a year-round ban on fishing with gill and entangling nets has been introduced in the German nature reserve Doggerbank. Furthermore, in February 2023, the EU Commission released an "Action Plan to protect and restore marine ecosystems for sustainable and resilient fisheries". The plan suggests different steps to reduce the accidental catching of endangered animals, many of which are already under the protection of European Union regulations. Given the urgent need to protect and revive Marine Protected Areas (MPAs), which are crucial hubs of biodiversity, the Commission urges Member States to gradually stop bottom fishing in both current and future MPAs by 2030 (European Commission, Directorate-General for Maritime Affairs and Fisheries, 2023). As the shrimp fishery takes place mainly in the National Park area and beam trawling has an impact on the seabed, it will be affected by the forthcoming regulations of the Action Plan.

2.5. MPA scenarios

We investigated two scenarios for the brown shrimp fishing fleet: 1st the impact of the gear-specific regulations implemented in 2023 (current state (European Commission, 2023, 2017)), and 2nd the proposed regulations by the action plan. For the scenario of the EU Action Plan, all areas in accordance with the Habitats Directives (In German: FFH-Gebiete) were taken into account that are in German EEZ and coastal waters (territorial sea) (European Commission, Directorate-General for Maritime Affairs and Fisheries, 2023). The percentage of landings in potential closed areas was calculated in relation to the total landings in each cluster. The interannual average landings of North Sea brown shrimp (Supplementary Figure 7) in the whole of the German EEZ and coastal waters were used as the basis for calculating the percentage change.

3. Results

3.1. Fishing behaviour

A clustering analysis was conducted to categorize fishing vessels based on a set of spatial and temporal attributes derived from individual vessel movement data (Table 1). Four distinct clusters were revealed (Fig. 2, a): Clusters 1 and 2 exhibited the lowest dissimilarity. In contrast, clusters 3 and 4 were separated at a higher dissimilarity level, as evident from their separation at higher branch heights in the dendrogram (Fig. 2, a). The largest group was cluster 3, comprising 119 vessels, followed by cluster 1 with 63 vessels. Cluster 2 (N = 17) and cluster 4 (N = 12) have formed smaller groups despite the clustering method favoring even distribution. In the PCA biplot, clusters 3 and 4 show the largest differences along the first axis, whereas clusters 1 and 2 are located in between. (Fig. 2, b). The first axis explains 55.7 % of the variance, while the second dimension explains 13.7 %. Mean trip length and mean distance to the port explained a large proportion of the variation along the first dimension, each contributing more than 15 % to the variation of this axis (Supplementary Figure 8). Area flexibility (both standard deviation SD and mean) captured 55 % of the variation in the second dimension (Supplementary Figure 8), but this axis did not contribute to differentiate the four clusters (although the spread of this attribute along the second axis varied between the clusters, Fig. 2, b).

All attributes underwent a Shapiro-Wilk normality test which indicated non-normal distribution. The values of the key attributes used in the clustering analysis are shown for each cluster in Fig. 3b-f. Cluster 3

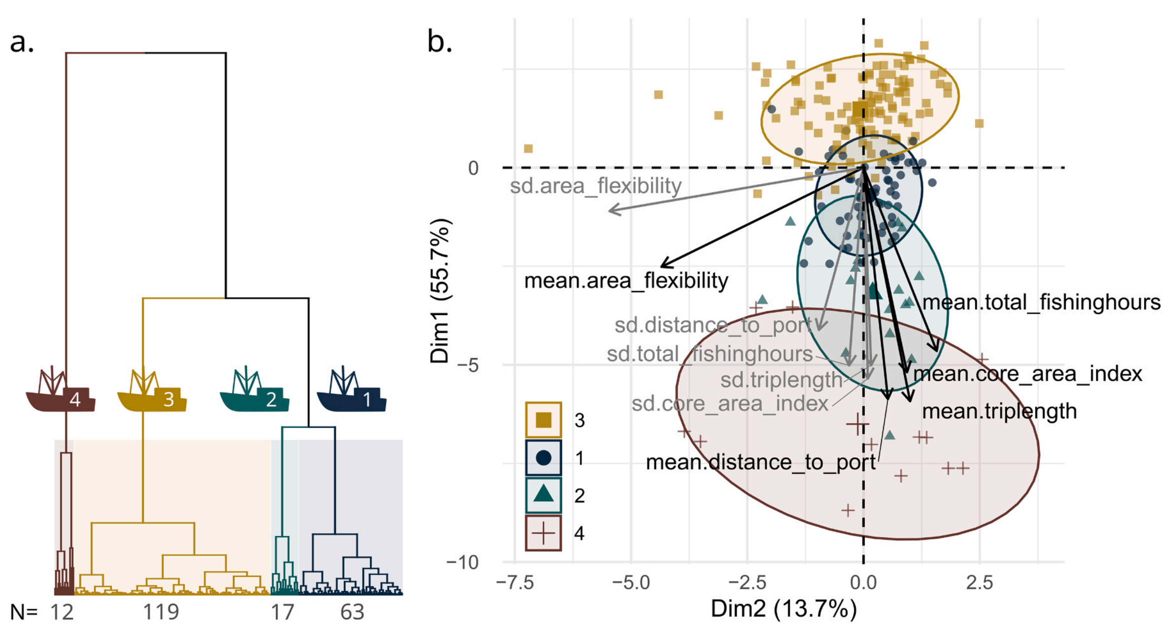


Fig. 2. Identification of fishing strategy clusters. The clustering analysis identified four different fishing strategies, which are color-coded (a). Branch length represents the dissimilarity between clusters and individual vessels. Leaves are the vessels included in the study and total number per cluster is stated at the bottom of the tree. Clusters are also visualized in the PCA biplot (b). The variable vectors represent the direction and strength of the attributes in reduced space, showing their contribution to each axis. The description of the attributes is provided in Table 2. The four clusters are color-coded and 90 % confidence interval ellipses are shown for each cluster.

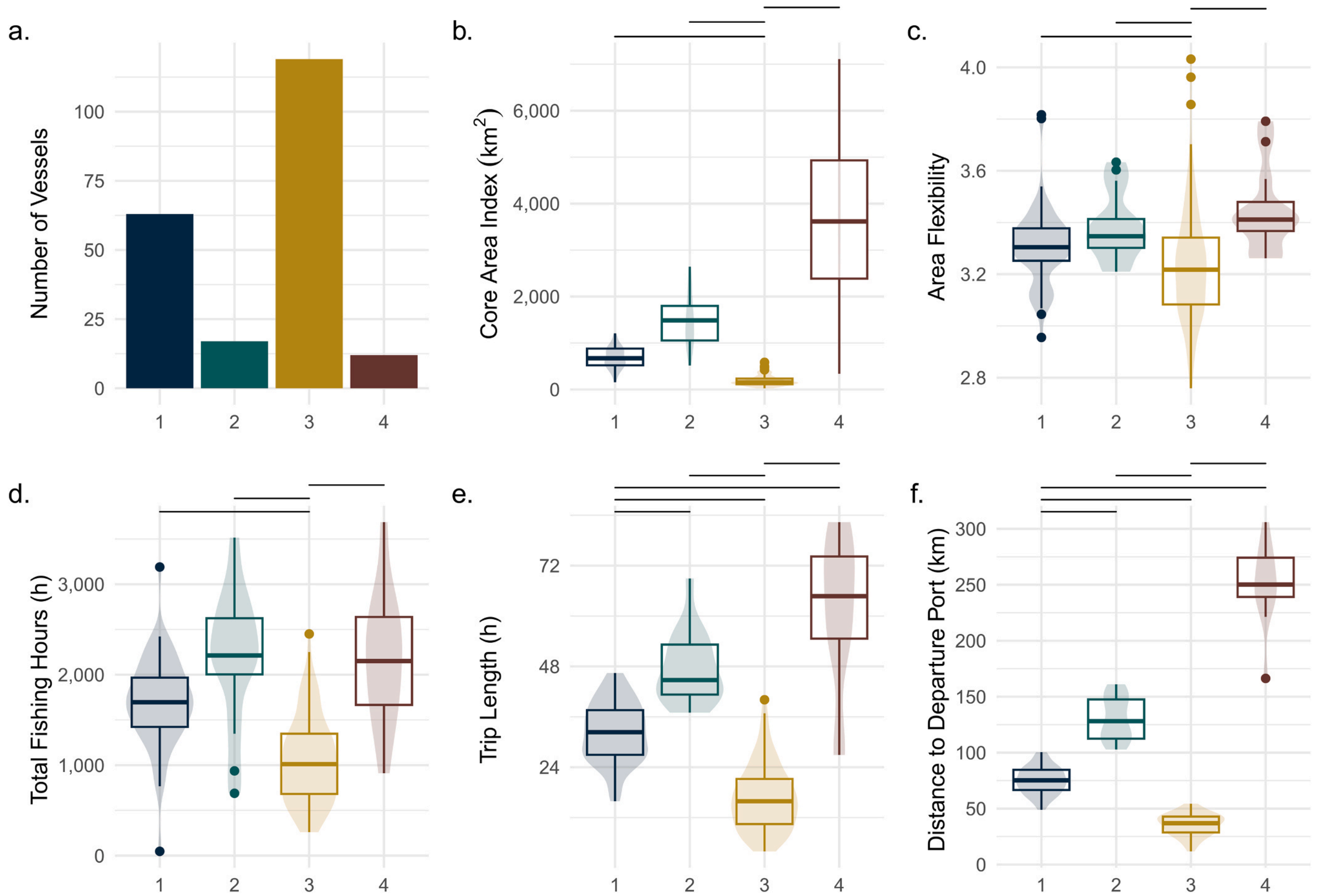
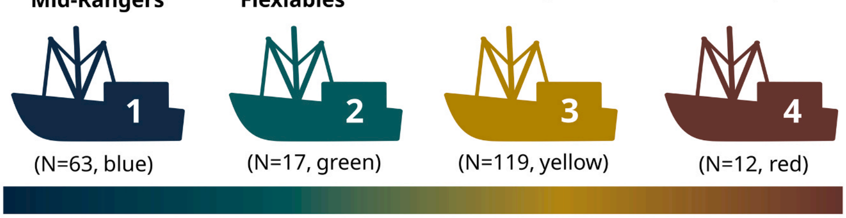


Fig. 3. Key attributes used in the clustering analysis. The total number of vessels per cluster is shown in (a), followed by key attributes used in the clustering process, which capture the spatial and temporal fishing characteristics of the vessels. These attributes include the core area index (b), area flexibility (c), total fishing hours (d), trip length (e), and distance to departure port (f). Significant differences below 0.05 are shown above each attribute. For detailed descriptions of these attributes, please refer to Table 1.

had the lowest median in all attributes. It had the smallest core area index (155 km^2), covering a median distance of less than 50 km from the departure ports. In three of the five attributes, core area index, area flexibility and total fishing hours, cluster 3 was the only group that was significantly lower than the others. Median annual fishing time was 1012 h and trip length was less than one day(median:16 h). In cluster 1, the fishing areas were the second smallest, with trips extending a maximum of 100 km from the port and typically lasting 1.5 days (median:32 h). Cluster 2 conducts fishing trips up to 170 km from the port, typically lasting two days(median: 45 h). Cluster 4 exhibited a significantly higher core area index compared to the other clusters; maintaining high total fishing hours (2150 h), with mean trip length of

Table 2
Behavioral clusters in the German North Sea Brown shrimp fishery are labelled to aid the interpretation of results.



	Nearshore Mid-Rangers	**Long Distance Flexiables**	**Local Regulars**	**Offshore Explorers**
	(N=63, blue)	(N=17, green)	(N=119, yellow)	(N=12, red)
Spatial	Small to medium area, Short distance (100 km)	Medium to large area, Long Distance (170 km)	Small area, Shortest distance (50 km)	Large area, Offshore distance (250 km)
Temporal	1-2 day long trips (32h), Moderate fishing hours	2 day trips (45 h), High fishing hours	Short trips (16 h), Low fishing hours	Long trips (65 h), High fishing hours

approximately 65 h, i.e. about three days. Dividing total fishing hours by average trip length provided the following average annual trip counts (in descending order): 64 (cluster 3), 52 (cluster 1), 49 (cluster 2) and 33 (cluster 4). To capture the dominant spatial and temporal patterns while acknowledging vessel variability and flexibility between groups we labelled them (Table 2). Nearshore mid-rangers (cluster 1) and local regulars (cluster 1) comprise the majority of the fleet.

3.2. Vessel and catch properties

We then explored whether identified clusters could be also described by vessel characteristics and landing data.The most parsimonious model with the lowest AIC value (AIC = 225.9) had four predictors: vessel length, vessel engine power (KW), total brown shrimp catch (kg), and landing per unit effort (LPUE) - and no interactions among predictors (Fig. 4). Since there was no interaction among predictors, we independently tested all five predictors separately.

The landing of species other than the brown shrimp did not significantly improve the most parsimonious model (Fig. 4-f). Nevertheless, cluster 4 had the highest median, and differed significantly from clusters 3 and 1. Cluster 1 also differed significantly from both cluster 2 and cluster 4. Interannual and cluster median landing of species other than the brown shrimp were, in descending order: 123050 kg (cluster 4), 1216 kg (cluster 2), 10 kg (cluster 1) and 1 kg (cluster 3). We present the clusters in order of their group size, from largest to smallest.

Cluster 3 (N = 119) showed significant differences in all five predictors compared to all other clusters. It was also the group with the highest number of vessels. This cluster exhibited the highest LPUE (52 kg/h) despite having the lowest annual brown shrimp landings (52 tons), indicating high efficiency. The vessels in this group were characterized by the smallest ships and the lowest engine power (15 m, 191 kW). All other clusters had a median vessel engine power of 221 kW.

In cluster 1 (N = 63), vessels had significantly different median vessel length (19 m) compared to all other clusters. This cluster also showed the second-highest annual brown shrimp landings (76 tons) which was still significantly lower than cluster 2. However, clusters 1 and 2 presented similar LPUE values, 41 and 45 kg/h respectively.

Cluster 2 (N = 17), had the highest annual brown shrimp landings (104 tons) and the second-highest median vessel length (22 m).

In cluster 4 (N = 12), the main target species during the study period was not the North Sea brown shrimp and brown shrimp landings (10 tons) differed significantly from clusters 1 and 2. Vessels were characterized by the largest median length (24 m) and only in this group there were vessels whose engine power exceeded 221 kW (N = 3).

In both cluster 3 (typical shrimpers) and cluster 4 (occasional-shrimpers), the total number of vessels declined over the years (Supplementary Figure 7-a.). Cluster 4 showed increasing landings of species other than brown shrimp from 2009 to 2016 and decreasing landings from 2016 to 2021. Additionally, the years 2014–2016 showed a negative trend in brown shrimp landings in all clusters (Supplementary Figure 7b. and c.).

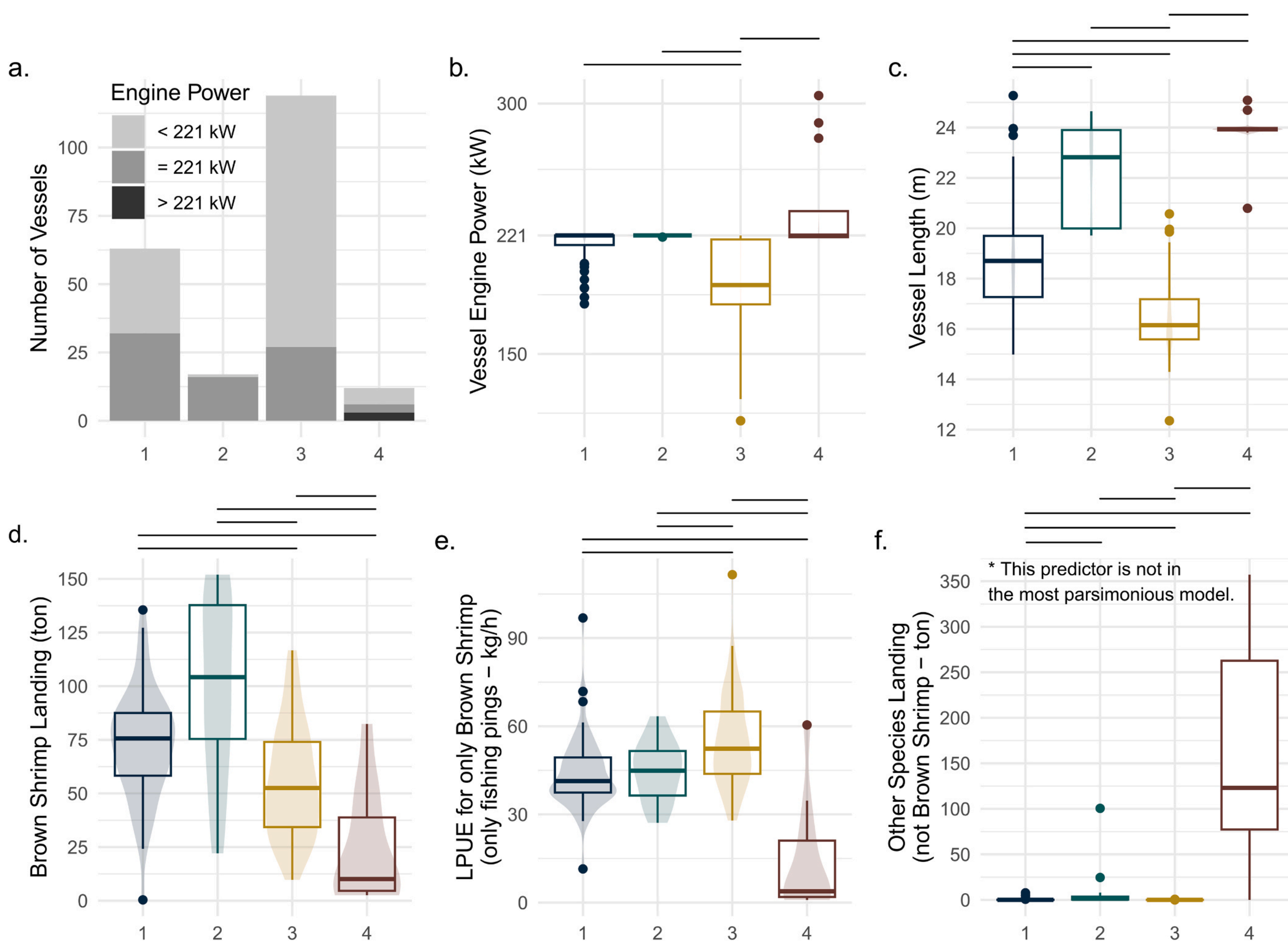


Fig. 4. Vessel-specific predictors influencing fishing behavior: (a,b) Vessel engine power (kW), (c) vessel length (m), (d) annual mean brown shrimp landings per vessel (kg), (e) LPUE (Landing Per Unit Effort) for brown shrimp only, and (f) landings of species other than North Sea brown shrimp. Significant differences ($p < 0.05$) are shown above each predictor.

3.3. Spatial distribution of fishing effort

The four clusters differed in terms of geographic effort distribution (Fig. 5). Clusters 1 and 3 showed extremely high fishing effort (h) close to the coast, locally exceeding 200 h/year and 0.025° x 0.025° grid cell (~4.42 km^2). In contrast, vessels of cluster 2 and cluster 4 did not fish in areas close to the coast. Cluster 2 had fishing activity at the border of plaice box in Dutch EEZ. Cluster 4, which represented the group of vessels fishing mainly for species other than brown shrimp, showed a completely different spatial distribution of fishing effort within three main offshore fishing areas.

3.4. Overlap of spatial measures and brown shrimp landings across clusters

Finally, we calculated the potential impact of spatial management measures on the catches of the four groups of vessels for the "current management" and "EU action plan" scenarios (Fig. 6). The first one reflects the current regulations that were initiated in 2023 (European Commission, 2023, 2017) and the second one includes all areas mentioned for possible mobile contact gear closure in the EU action plan for 2024. The aim of this analysis was to assess the spatial overlap between MPAs and brown shrimp landings for the different clusters. This overlap analysis provides insight into how much of these current and planned areas cover the fishing grounds for brown shrimp from the

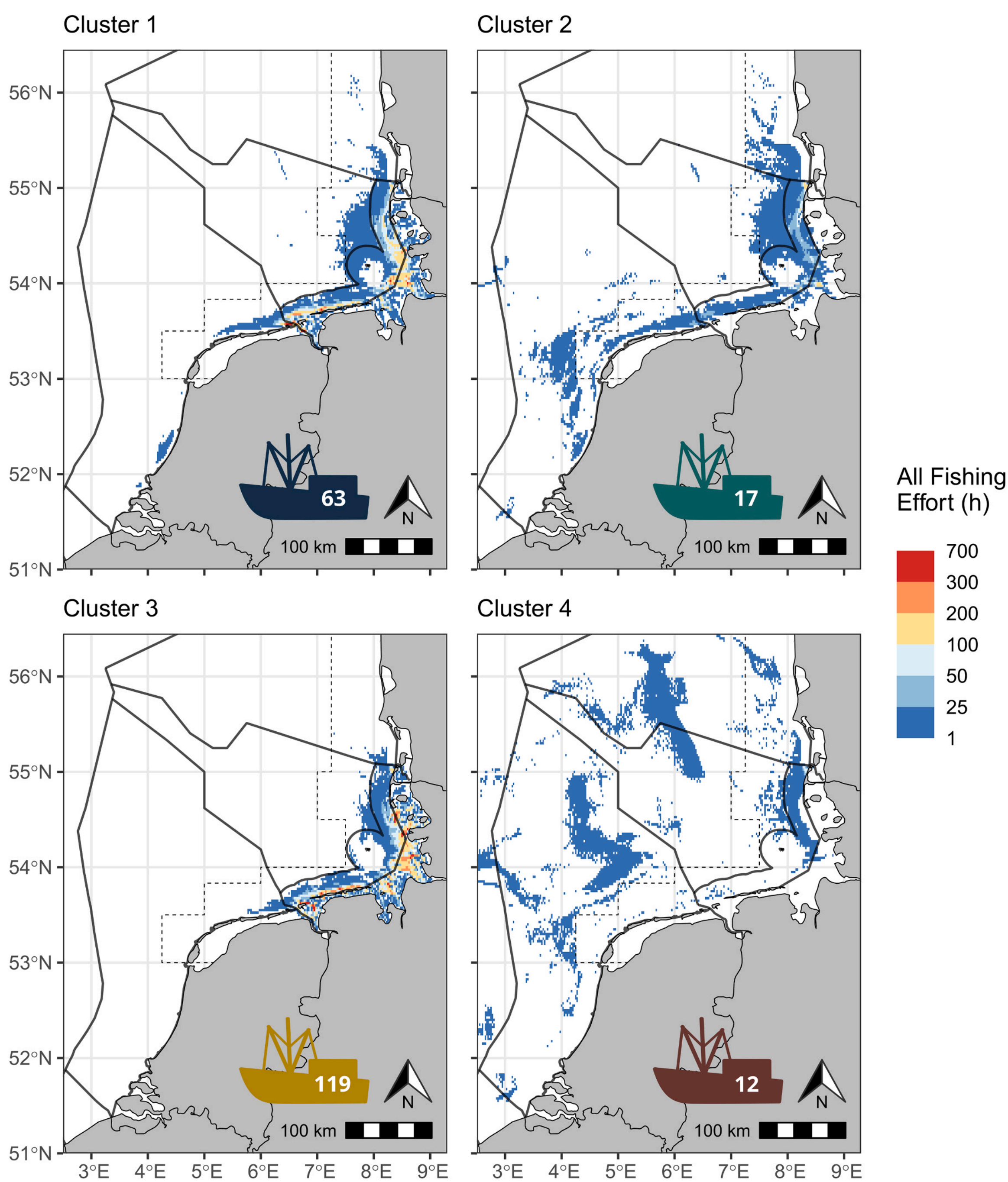


Fig. 5. Spatial distribution of average fishing effort (in hours) per cluster over the entire study period (2009–2021). Dashed lines mark the plaice box borders, solid lines outline national Exclusive Economic Zone (EEZ) borders and for Germany the 12 nm border. Grid cells below 1 h are removed. Grid cell size is 0.025° x 0.025°.

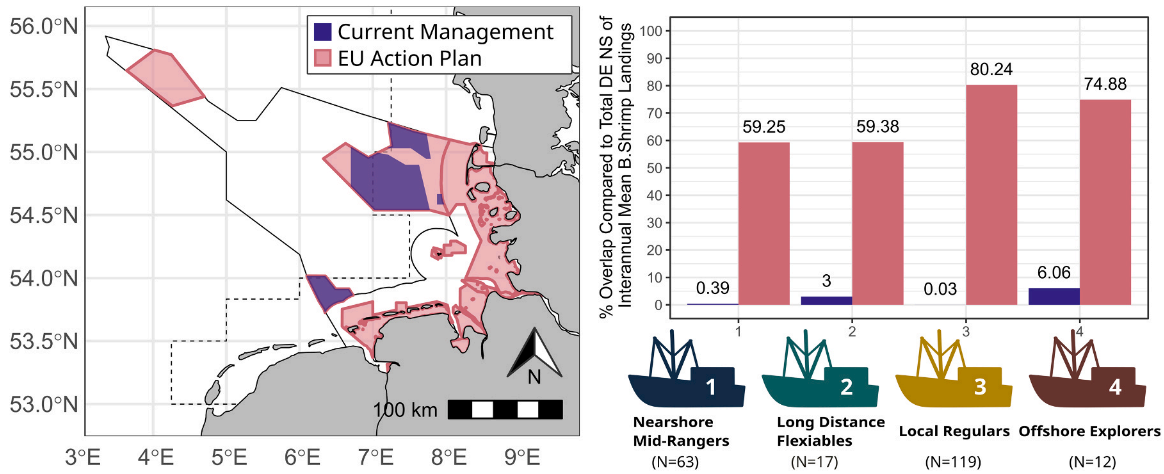


Fig. 6. Overlap between MPAs and brown shrimp landings for two scenarios “current management” (purple) and “EU action plan” (pink). The "current management" scenario depicts areas closed to shrimp fishing since May 2023. The "EU action plan" scenario illustrates MPAs potentially subject to regulations on mobile contacting gears starting from 2024, as outlined in the 2023 action plan. Right: Percentage overlap in brown shrimp landings in comparison to the total average landings from the entire study period (2009–2021) and both German EEZ and territorial sea, assuming that no compensation is possible. Dashed lines mark the plaice box borders, and solid lines outline national Exclusive Economic Zones (EEZs).

study period (2009–2021). Baseline brown shrimp landings were the interannual mean for the German EEZ and territorial waters. The exact values and spatial distribution of landing can be found in supplementary material (Table 4 and Figure 10). The current management scenario affected cluster 4 the most but only represented a 6 % potential decrease in catch. On the other hand, the EU action plan scenario covered the areas from which more than 70 % of all the brown shrimp landings come from and thus affected cluster 3 with a 80 % potential decrease compared to the baseline catch. The current management scenario did not affect areas with high landings, but the largest portion of the fleet (cluster 3) showed the highest overlap with the EU action plan scenario. The impact of the current management scenario is primarily observed in areas with lower landings.

4. Discussion

Spatial and temporal limitation regulations of fishing areas and fishing gears play an important role for fisheries management, complementing the common tool of setting annual quotas (European Commission, 2023, 2017). Fishing activities can be described and managed by economic segments or by the use of métiers (defined as fleet segments based on specific fishing practices, gear types, and target species) (European Parliament, Council of the European Union, 2009). In the EU, economic segmentation and métier level six are two distinct methods employed for clustering. At métier level six, fleet segments are defined with greater specificity, incorporating not only the gear type but also details like mesh size and target species. Economic segmentation, on the other hand, relies on broader classifications such as vessel size and fishing gear. However, the fleet segments are not static and in the North Sea, individual vessels, switch between segments or métiers. More importantly, vessels can show strong spatial and temporal differences in their fishing behaviour resulting in variable responses to area regulations. In this study, we therefore have introduced a segmentation that accounts for the spatial and temporal diversity of individual vessels and evaluated the implications of current and potential future management actions on the fleet.

Different terminologies are used to define behavioural subgroups in a fleet: fishing strategy (Abernethy, 2010; Allen and McGlade, 1986; Christensen and Raakjær, 2006), fishing style (Boonstra and Hentati-Sundberg, 2015) or behavioral types (O’Farrell et al., 2019; Pollnac et al., 2001). Here, we focus on the data derived from vessel movement and use the term fishing behaviour to interpret the patterns derived from vessel movement data. We use the term "cluster" to refer to groups of boats that have a similar fishing behaviour. By doing so we acknowledge that vessels are operated by captains who ultimately take the final decision for the fishing trip itinerary (Barz et al., 2020).

We describe the characteristics of the German North Sea brown shrimp fleet and show that this single-target fishery is not a homogeneous unit. 86 % of the vessels are typical shrimpers, with cluster 1, nearshore mid-rangers and 3, local regulars, exclusively targeting brown shrimp. They use beam trawls with mesh sizes of 16–31 mm. Cluster 2, long-distance flexiables, have the highest annual brown shrimp landings per vessel but also target a small amount of plaice and sole. For cluster 4, offshore explorers, brown shrimp is a by-catch or have been the primary target species in earlier years of the study period. Main target species are rather Norway lobster, plaice or sole, and the primary gears are beam trawls with mesh size larger than 80 mm (Letschert et al., 2021).

Our results show that vessel movement data enables to identify groups with different vessel properties and fishing success. Whereas bigger vessels can move further due to higher catch capacity and fuel storage, smaller vessels fish in more coastal areas and are more efficient and successful in catching brown shrimp, indicated by a particularly high LPUE. Geomorphology of the North Sea tidal flats can also explain the correlation of bigger vessels preferring seaward regions despite low LPUE. Tidal basins behind the islands are submerged for almost half of the day for two separate periods making them only available to vessels that can navigate dynamic depths between 1 and 5 m, for a limited 6 h and fuel consuming tidal currents. Previous studies on the same fleet also pointed out that extended vessel length tends to correlate with reduced LPUE (Schulte, 2015). Our findings also align well with a series of interviews on the Dutch brown shrimp fishery that revealed significant differences in trip length among groups, with smaller and more experienced vessels exhibiting higher LPUE (Schadeberg et al., 2021).

Although cluster 4 only targets brown shrimp as by-catch, their inclusion in the study is justified as the majority of their earnings were derived from brown shrimps for at least one month within the study period. Cluster 4 showed a positive trend in landings of species other than brown shrimp from 2009 to 2016 and a decrease in brown shrimp landings from 2014 to 2016 (Supplementary Figure 7). These contrasting trends in landings of brown shrimp compared to other species from 2014 to 2016 may reflect a buffer scenario where other species provide an alternative for vessels when the availability of brown shrimps has been low.

Given the heterogeneity in the behaviour of the brown shrimp fleet, not all vessels are equally affected by the spatial management in the North Sea. The Plaice box has been active since 1995, and the regulation has a strong effect on the fleet's engine power as fishing is prohibited for vessels with engine power exceeding 221 kW within the box. Our study group has 130 vessels with engines below 221 kW and 78 vessels with engines of 221 kW. There are only 3 vessels with more than 221 kW engine power and they all belong to cluster 4, i.e. brown shrimp is not their primary target species. In cluster 2 we have vessels bigger than 20 m, that could accommodate higher engine power, yet no vessel exceeds the limit: 16 of these large vessels have exactly 221 kw and one has an engine power below 221 kw. In this way they keep their access to areas inside the plaice box while maximising their engine power. These findings align with previous evaluations of plaice box regulation (Beare et al., 2013). However, there are indications of under-reporting of engine power in the EU fleet register. An EU report from 2019 revealed that nearly half of the inspected Dutch and German beam trawlers in the North Sea could potentially increase their engine power to 300 kW (European Parliament, Council of the European Union, 2019b). However, the clustering was independent from engine power, thus avoiding the problem of misreporting.

Our overlap analysis with the Natura 2000 no-take areas enforced in 2023 suggest little overlap with the brown shrimp fishing areas and thus little impact on the landings. However, the possible restrictions suggested in the EU action plan would affect all clusters significantly. More than 50 percent of the brown shrimp current landings come from areas considered for marine protection. The local regulars that fish close to the coast and have a low core area index and little area flexibility (cluster 3) would be the most affected, as the entire Wadden Sea National Park is being considered for closure to fishing. These shrimpers also make up the majority (60 percent) of the German brown shrimp fleet. This emphasizes the importance of considering the heterogeneity within fishing communities when formulating management strategies.

The cluster that only occasionally targets brown shrimp (Cluster 4), provides valuable information on the potential range of adaptation, such as changing target species or gear. Although reaching the fishing grounds for e.g. Norway lobster requires more steaming, switching to this species could still be profitable due to its high market price (Letschert et al., 2021). However, Norway lobster is managed by TACs and therefore requires a quota in addition to a larger vessel, all of which makes the fleet adaptation costly. The spatial overlap between fishing grounds and future area closures provide insights on how much of the landings are at risk. The ability to adapt to new regulations and measures will then certainly be an advantage for the fishery.

Given the spatial overlap between fishing activity and marine protected areas, our findings suggest that sustainability certifications like the MSC may benefit from incorporating more rigorous spatial conservation considerations into their assessment criteria (Lester et al., 2013). This could help future-proof the fishery and ensure its long-term sustainability. Additionally, the existing self-management strategies employed by the fishery could enable them to address these spatial challenges rapidly and proactively. This has the potential to enhance their reputation as stewards of sustainable practices, ultimately driving demand within the sustainable seafood market (Farmery et al., 2022).

4.1. Limitations

We deliberately selected a limited number of attributes for clustering to maintain simplicity and focused exclusively on movement-related information. While latitude and longitude might initially seem critical, we decided against their inclusion. The first researchers applying clustering methods on spatial data for a fleet with one target species included geographical parameters of the vessels (latitude-longitude) to segment the fleet (Joo et al., 2015). This approach was effective in Peru, where a long, north-south coastline allowed clear distinctions between fishing areas. However, in the German Bight, the compact and irregular shape of the region limits the utility of such geographical attributes for distinguishing spatial behavior. Other fisheries studies, such as O'Farrell et al. (O'Farrell et al., 2019) included total home range area size along with other trip and vessel specifications to define fishing strategies and analyze the variation in fleet response to environmental impacts. While we adopted a comparable approach by customizing the attributes for our fleet, we intentionally excluded technical vessel features. In our study we only used logbook data to select our study group and to statistically analyse the differences between the clusters. Clustering was based solely on attributes derived from satellite-based vessel tracking data. This allows for our method to be applied in regions where satellite tracking is available but logbook data are limited due to national data protection regulations.

Intra- and interannual variability of the brown shrimp and the fleet has been recorded previously where the proportion of ovigerous brown shrimp females rises from October, peaks in May, and declines until October (Hünerlage et al., 2019; Saborowski and Hünerlage, 2022). Fisheries also show consistent seasonal pattern (Respondek et al., 2014). Studies also show that locations with high LPUE for the fleet fluctuate significantly from year to year (Schulte et al., 2020). We account for interannual variability in fishing behaviour by including the interannual standard deviation of our clustering attributes. However, interannual differences can represent a trend but also discrete changes e.g. due to a change of the owner or sale to another company or country. We did not particularly investigate the change of ownership or vessels that left the fleet during the study period. However, we note that in both the local regulars (Cluster 3) and offshore explorers (Cluster 4), the total number of vessels decreased over the years, indicating that some vessels left the German fleet and were not replaced (Supplementary Figure 7). 2030 future scenarios developed during an expert based foresight workshop to investigate cumulative effects in the German North Sea also suggests a smaller fishing fleet in next decade (Stelzenmüller et al., 2024). Previous research reports an increasing number of vessels targeting Norway lobster and brown crab in the German fleet (Letschert et al., 2021).

Fisheries data from VMS or electronic logbooks can contain errors as well as biases in collection and processing methods. The processing of VMS data has been optimized in previous studies (Bastardie et al., 2010a; Gerritsen and Lordan, 2011; Katara and Silva, 2017; Watson and Haynie, 2016). However, VMS data has been shown to provide more accurate effort estimations for long fishing activities as the vessels send out pings usually every two hours (Gerritsen, 2023; Skaar et al., 2011). Yet in German brown shrimp vessels one haul is often shorter than 2 h, so fishing activity might go undetected, hence underestimating the effort as reported in Portuguese fisheries (Katara and Silva, 2017). We also note that using monthly home ranges (kernel utilization distributions) tends to overestimate the size of fishing areas in months when the number of pings is low (Calenge, 2006). However, as we only use the size of the fishing area (core area index) to compare vessels, any overestimation would affect all vessels equally, keeping them comparable. Merging VMS data with logbook and landing data can improve the accuracy of the spatial distribution of fishing effort (Russo et al., 2018).

4.2. Perspectives and conclusions

We show that vessel movement data can be used to cluster fishing strategies and provide an alternative to segmenting the fleet. Our analysis can be useful for other fisheries to identify groups that are differently affected by spatial management measures.

We did not engage with fishers to enhance the clustering process. However, such stakeholder involvement would be advantageous for future investigations as interviews found to be useful to build decision trees and understand the mechanisms behind fishing activity (Christensen and Raakjær, 2006; Schadeberg et al., 2021). Building trust between the community and scientists is crucial for obtaining quality interview data, and having data to discuss with fishers can facilitate this trust, although this process can be time-consuming (Holm and Soma, 2016). Additionally, our findings align with the behavioral groups in the

Dutch fleet without incurring the additional economic and time costs associated with interview-based methods (Schadeberg et al., 2021).

The clusters and patterns of behaviour identified in this study can be used in the parameterization of models aimed at simulating the behaviour of fisheries, such as agent-based models and can support the results from questionnaires. Such models can improve our understanding of the response of fishers and fleets to area closures, increased fuel costs, fluctuating shrimp prices, and regulatory changes (Bailey et al., 2019; Bastardie et al., 2014; Lemmen et al., 2024; Wijermans et al., 2020). Future studies could adopt methodologies similar to those developed by Cimino et. al. (Cimino et al., 2019), who used a comprehensive approach integrating oceanic variables, climate indices, and vessel flag data to predict fishing activity. Such integration allows for a better understanding of the implications of climate change on the fishing behavior of smaller vessels. This is particularly important given their vulnerability to extreme weather events which limits their active days at sea and lead to subsequent reductions in profitability (Pfeiffer, 2020; Sainsbury et al., 2021; Schadeberg et al., 2021).This analysis could inform management strategies, such as spatial management measures and adaptive policies, to mitigate the impact of changing environmental conditions on fisheries dynamics.

The obvious overlaps of area closures with existing fishing grounds indicate the need to develop new management strategies for the coexistence of different users of marine areas. The findings of this study indicate that the implementation of new area closures will inevitably overlap with existing fishing grounds, creating challenges for the fishing industry. Fisheries experts working in the German North Sea have noted that this overlap is likely to accelerate the reduction in fleet size (Stelzenmüller et al., 2024). This concern is partially issued in a recent press release by the German government announcing a fleet capacity reduction funding initiative ("Nachhaltige Fischerei stärken," 2024). Alternatively, there is potential to adopt fuel-efficient gear and engine technologies, develop regional processing facilities, and explore tourism as an additional income source for the region (Steins et al., 2021; Weiss et al., 2018). The results of this study show that the analysis of vessel movements by cluster analysis can help to identify fleet segments and is therefore also transferable to fisheries analyses in other regions.

CRediT authorship contribution statement

Diekmann Rabea: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition. **Puebla Oscar:** Writing – review & editing, Supervision. **Schulze Torsten:** Writing – review & editing, Supervision, Resources, Methodology, Formal analysis, Data curation. **Rehren Jennifer:** Writing – review & editing, Supervision. **Örey Serra:** Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used OpenAI's ChatGPT in order to enhance text clarity and, grammar; as well as to improve code efficiency. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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.

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This work is a satellite based data driven attempt to quantify the spatial behaviour of the fishers. Human behaviour is complex and this work focuses on just vessel movement for describing groups. Fishers are the only ones that can truly explain the motives behind the patterns we observe. We would like to acknowledge and appreciate the knowledge they produce and challenges they endure every day out at sea. S.Ö and J. R. were funded by the MuSSeL project (03F0862C and 03F0862D; BMBF - German Federal Ministry of Education and Research). J.R. also acknowledges funding from the GES4SEAS project funded by the European Union under the Horizon Europe program (grant agreement no. 101059877). We would also like to thank the two anonymous reviewers for their helpful comments on an earlier version of the manuscript.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fishres.2025.107285.

Data availability

Individual-level spatial and economic data are not possible to be shared publicly due to data privacy of vessel owners. However, for adapting the analysis to your needs and using similar methodology, two crucial steps are reported as R scripts and can be found in Supplementary Material.

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