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SITE CHOICE IN RECREATIONAL FISHERIES - TOWARDS AN AGENT-BASED APPROACH

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ABSTRACT

The site choice decisions of recreational fishers (anglers) have important implications for fish stocks, fisheries management, and coastal economies by influencing catch rates and determining where economic values are created. However, the mechanisms of site choice are poorly understood. In this paper, we make the first steps toward applying agent-based modeling to improve the understanding of site choice decisions. Using an exploratory approach, we identified travel distance dependent on angler origin as a key element in site choice to rebuild travel patterns and distances. The 5-year average catches had a subdominant role for the travel patterns but could recreate the angler's distribution among the fishing locations realistically. Utility functions combined both factors, but further model development and more realistic angler agents and catch rates are required to understand anglers' site choices in more detail.

1 INTRODUCTION

A high number of recreational fishers (anglers) target many different species with a broad range of fishing methods (Hyder et al. 2018), and recreational catches can even exceed commercial catches for certain fish stocks (Lloret et al. 2008; Herfaut et al. 2013). Further, recreational fishing creates significant economic values (Hyder et al. 2018). Especially for mixed commercial-recreational fisheries with a high proportion of anglers, the waiving of the recreational catches in the stock assessment produces inaccurate estimates of stock biomass, which can jeopardize management objectives (Griffiths and Fay 2015; Van Beveren et al. 2017; Hyder et al. 2018). Hence, understanding angler behavior is essential for management (Fulton et al. 2011; Hunt et al. 2013) not only to predict recreational catches but also for making management decisions.

In this study, we focus on the site choice of anglers, which influences catch and determines where economic values are created. Thus, site choices are important for fisheries management, coastal planning, and destination branding. The site choice is directly and indirectly influenced by various factors like management regulations and travel costs (Hunt et al. 2019).

Agent-based models (ABMs) are a promising tool to further understand human behavior in fisheries. They facilitate the explicit representation of individual decisions and interactions. Various ABMs already exist for commercial fisheries (Lindkvist et al. 2020). However, commercial and recreational fishers differ significantly in their goals, and consequently their decision processes. While the former decide predominantly on economic factors, the motivations of the latter are more complicated, including factors such as relaxation, satisfaction, natural beauty or personal preferences (e.g., for or against infrastructure). Hence, but more complex decision models are needed for recreational fisheries, that include these factors. Some ABMs with the focus on recreational fisheries already exist (Gao and Hailu 2011; Gao 2012; Tink 2015; Gao and Hailu 2018; Alós et al. 2019; Innes-Gold et al. 2021). Gao and Hailu (2011), Gao (2012), and Gao and Hailu (2018), for example, investigated the impacts of different site closures on the fishery with the goal to advise fisheries management by using a random utility approach to model the angler agents' decisions. Although site choices are included in some of these models, these studies have not examined the mechanisms behind anglers' site choices and have been developed in other fisheries contexts. For example, site choices in Tink (2015) and Alós et al. (2019) refer exclusively to boat anglers while they are already on the water.

In the following, we make the first steps towards an ABM of individual anglers to better understand how catches at a fishing site and travel distances from the home location to a fishing site determine anglers' site choice. Thus, the site choice describes the decision to which coastal location an angler travels from home to go fishing. The German western Baltic recreational cod fishery will serve as a case study since a comprehensive data set including angler characteristics, effort, and catches exists for different fishing methods. We adopt an exploratory modeling approach, whereby the model design is driven by the question being asked rather than by details of the system being studied (Bankes 1992). Model variants are presented in a provenance graph (Ruscheinski and Uhrmacher 2017) highlighting the different data sources and the models' developments. While we do not yet exploit the full potential of ABMs or present a final model, we explore different possibilities and illustrate the modeling process to facilitate future model development.

2 CASE STUDY

The Baltic Sea is a semi-enclosed brackish sea located in Northern Europe. The coasts of the two German federal states Schleswig-Holstein (SH) and Mecklenburg-Western Pomerania (MV) extend for 2631 km and attract anglers from all over Germany (Lewin et al. 2021).

Atlantic cod (Gadus morhua) is an ecological key species (Lindegren et al. 2009) divided into a western and an eastern stock and the main recreational target species in Germany (Strehlow et al. 2012; Weltersbach et al. 2021). The western Baltic cod stock collapsed in the recent past (ICES 2021).

In this fishery, anglers from all over Germany (163000 participants in 2013/14) spend approximately 1.3 million fishing days per year at the coast (Hyder et al. 2018). Figure 1 shows the travel patterns of these anglers. The dominant fishing with rod and line takes place from shores and piers (land-based), charter vessels, and rental or private boats (sea-based). The fishing days are evenly spent between land- and sea-based fishing methods but sea-based angling accounts for the majority of recreational cod catches (Strehlow et al. 2012; Eero et al. 2015). For a long time, a minimum landing size (MLS) and fishing license requirements were the only regulation of the recreational cod fishery, while the total allowed catches for the commercial fisheries were drastically reduced over the years. In order to rebuild the western Baltic cod stock and share the burden of stock rebuilding between the commercial and the recreational fishing sector, policymakers introduced a bag limit to the recreational fishing sector (see Haase et al. (2022b) for a detailed description of the introduction process). After the introduction of the bag limit, travel distances of certain angler groups and overall participation rates decreased (Lewin et al. 2021; Haase et al. 2022b). However, the mechanisms behind these changes are so far unclear.

2.1 Data Basis

We use data from 2012 up to 2016 because after 2016 the data were impacted by a 2017 implemented bag limit. The data for model building and comparison originate from two independent surveys. One is a representative nationwide random digit dialing telephone survey followed by a one-year diary survey, which was conducted in 2015, delivering angler characteristics and the fishing effort per year. In 2015 50,200 telephone interviews were carried out and 930 anglers participated in the one-year diary study. The other is an on-site access point intercept survey that is annually carried out since 2005 along the German Baltic coastline delivering anglers' catch rates and origins. Between 2012 and 2016 1027 samples were carried out and thereby 8805 anglers were intercepted. A detailed explanation of the on-site survey can be found in the supplementary materials of Haase et al. (2022b) and of the telephone-diary survey in Weltersbach et al. (2021). The data used for this study can be found in a Git repository (Haase et al. 2022a).

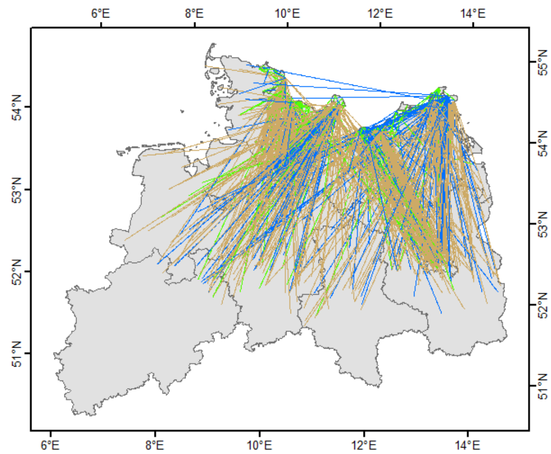


Figure 1: Travel pattern of German recreational cod angler. The map shows northern Germany with the complete Baltic Sea coast. The colors of the lines identify the different fishing methods of the angler (blue = private/rental boat, tan = charter boat, green = land).

3 MODEL DESCRIPTION AND DEVELOPMENT

We implemented the model in the Modeling Language for Linked Lives (ML3), a domain-specific modeling language designed for agent-based models in the social sciences (Reinhardt et al. 2022). Hence, we follow ML3's approach based on stochastic rules in continuous time, with unambiguously defined Markovian semantics. The implementation of the model and all experiments presented here, including the precise parameterization, are available in the same Git repository as the data (Haase et al. 2022a).

The model consists of two different agent types. First, angler agents, which are characterized by their home location (origin) and a fishing method. The home location is set as a German zip code area, which is identified by a unique number consisting of five digits. Whereby, only zip codes are included in the models that are within a three-hour travel range to the coast, as we intend to model only one-day trip decisions, assuming that angler's decision-making differs between one-day and multi-day trips. The fishing method can be one of the following and does not change within a simulation run: charter boats, private/rental boats including kayaks (further named boat), or land-based fishing including surfcasting and wading (further named land). The angler agents have origin zip codes and preferred fishing methods to represent the on-site data described above. We run all simulation experiments with a population of 10,000 anglers. The second agent type are fishing locations, which are characterized by a specific average catch and also a fishing method. The model includes all 73 fishing locations (33 boat locations, 13 charter boat locations, and 55 land locations) along the German coast that were visited between 2012 and 2016. It should be noted that some fishing locations only allow single fishing methods (e.g. charter boat harbors), whereas at other fishing locations, several methods are possible. We represent locations with multiple possible methods as multiple agents (for a total of 101 location agents), as we want to distinguish different methods in the site choice. An average catch at each fishing location is calculated separately for each fishing method as the 5 years average from the on-site data. The home locations of the angler agents and the fishing locations are connected through a distance map, whereby, the distances are calculated as geodetic distances from the centroids of the zip codes to the coordinates of the fishing locations based on the projected coordinate system for Europe (ED50/UTM 33). This serves to approximate of the actual travel distances or driving times, which are difficult to calculate, but should correlate with linear distance.

Anglers going fishing is modeled as a stochastic process, implemented in the ML3-Rule shown in Figure 2. Ml3-rules are *guard-rate-effect*-triplets. The guard defines a condition that agents must fulfill for the rule to be applied to them. In this case, the condition is set to true, applying to all anglers. The

```
1  Angler
2  | true              // guard
3  @ trip_rate         // rate
4  -> ego.fishing()    // effect
5
6  Angler.fishing() ->
7     ?location := ego.decide_site_location()
8     ego.n_fishingdays += 1
9     ego.last_fishing_location := ?location.name
10    ?location.trips += 1
```

Figure 2: Central parts of the ML3 implementation of the model: the rule describing the process of anglers going fishing (lines 1-4). When an angler goes fishing, the `fishing` procedure (lines 6-10) is called, of which size choice is a part (line 7). The different model versions change mostly `decide_site_location`, where the actual site choice is made.

rate defines the parameter of the exponential distribution governing the waiting time between firings of the rule. We set the rate so that on average each angler performs nine fishing trips per year, which is in accordance with the off-site data. The effect is executed when the rule is executed. The actual site choice is part of the `fishing()` procedure.

Simplest possible model (M.R): To develop an understanding of anglers' site choices, the exploitative model building process started with the **simplest possible decision model (M.R)**, in which anglers select a site completely at random from all fishing locations matching their preferred fishing method. This model serves as a baseline in the further exploratory model building process to better assess the generated effects of the other models.

Since Lewin et al. (2021) identify the spatial distribution of target species and local infrastructure as the main reasons for the clustering of angler effort in the western Baltic Sea, and Hunt (2005) has also generally identified travel cost and fishing quality as key points for a choice of location, we further developed two different models. One model focuses on the **catch rates (M.C1a)** and the other on the **travel distances (M.D1)**. We chose these two factors as a starting point, as we expect them to be of high impact, relatively easy to model, and because data on them is readily available. Both models were then iteratively extended, verified, and checked if they are able to reasonably represent the real world (Figure 3). The process will be described in the following. For each model, we compared the simulation results of a simulated prototypical year to real world data: fishing locations visited (Table 1), average differences in the travel distances (Table 2), the travel patterns via a map visualization (Figure 5), and key metrics (median, standard deviation (SD) from the mean and min, max values; Table 3) and the average percentage deviation of the angler distribution among the fishing locations. The code for the analysis of the model output can be found in the Git repository (Haase et al. 2022a).

Simple catch model (M.C1): In the catch model **M.C1a** (Figure 3), fishing locations are selected with a probability proportional to the expected catch:

$$P(\hat{l} = l) \propto l.average\_catch$$

Where l^* is the chosen fishing location and L is the set of all fishing locations. This mechanism, not completely rational in terms of catch, assumes anglers value also other things next to the pure catches (which are not yet modeled), or have imperfect knowledge of expected catch while better locations still have a higher probability to be identified as productive ones. With this model configuration, angler agents do not visit all locations (Table 1) but the key metrics of the angler distribution are close to the reality for boat fishing (Table 3). However, the travel distances are generally too high (Table 2) and no clear travel patterns can be identified on the map (Figure 5a).

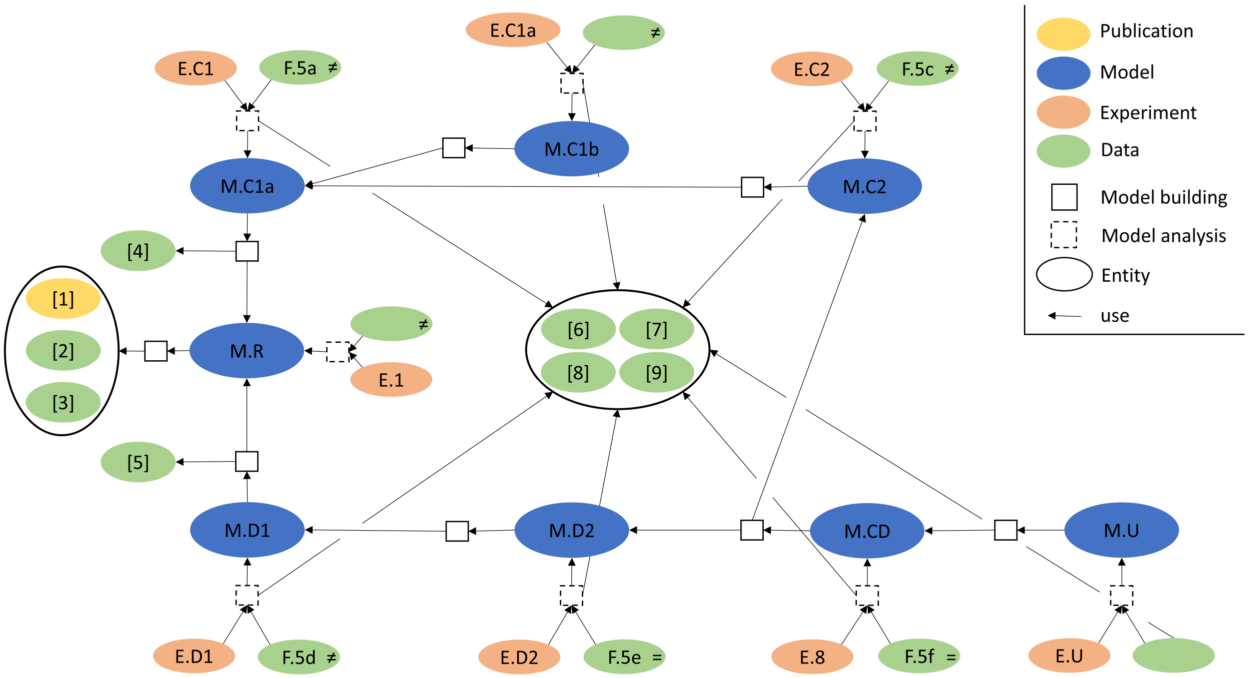


Figure 3: Provenance graph of the model building process including the data/literature basis, models, and experiments. M.R identifies the random model, M.C the models focusing on the catch rates, M.D the models focusing on the distances, M.CD the combined model, and M.U the utility models. The data entities with numbers in brackets refer to: [1] Lewin et al. (2021), [2] On-site data, [3] Off-site data, [4] average catch/harvest data, and [5] distance data to set up the models, and [6] locations visited, [7] angler's distributions (key metrics such as median, standard deviations and average difference), [8] distances traveled and [9] travel patterns to compare the model outputs with the real world. The other data entities refer to the data produced by the simulation. The symbols $=/\neq$ indicate whether the corresponding model corresponds to reality or not and the numbers in the data entities (e.g., F.5a) refer to the corresponding travel pattern figures in this publication.

The average catch is the total number of caught fish including fish that has been released voluntarily or due to regulations. Therefore, it is possible that the number of fish harvested is more important to anglers than the total number of caught fish, and thus fishing locations are more likely to be selected that promise a higher chance of success in catching fish that can be harvested. In the model **M.C1b** (Figure 3), fishing locations are selected using the same principle as in M.C1a, but with the 5 years average harvest instead of the average catch. Even though evidence exists that the number of harvested fish is important for anglers (Hunt et al. 2019), the use of the average harvest in the model did not deliver an improvement compared to M.C1a as the number of visited locations decreased (Table 1) and the average percentage deviation in the angler distribution increased for all fishing methods (boat 2.89% $\rightarrow$ 3%, charter 4.54% $\rightarrow$ 4.68%, and land 1.68% $\rightarrow$ 1.92%) and travel distances increased for charter and land fishing (Table 2).

Catch model with limited knowledge (M.C2): To restrict the agent's knowledge in the next model (**M.C2**; Figure 3) further, the agents only know the average catches of 10 random locations with the same fishing method as the agent. Between these locations, the agents decide in the same way as in M.C1a. This model configuration takes into account that it is reasonable to assume that constraints and cognitive abilities constrain the angler knowledge (Hunt 2005). Additional parameter of M.C2: N known locations = 10. Since this model improves the number of visited locations (Table 1), the average percentage deviation in the angler distribution (boat = 2.37%, charter = 4.10%, and land = 1.56%), the key metric for land fishing (Table 3), and the travel distances (Table 2) compared to M.C1a and M.C1b, it can be assumed that the angler's knowledge is limited in a certain way and thus also influences the choice of location. However, the travel patterns do not fit visually the reality (Figure 5b) and the random model generates some patterns that appear more realistic. Future work may include a parameter scan to find the ideal number of known locations. However, it already becomes apparent that a restriction of the agent knowledge leads to an improvement of the model outputs. Distance to the fishing location and the associated cost of higher distances may provide a possible explanation to realistically restrict the knowledge of the agents.

Simple distance model (M.D1): In the first model with the focus on the distance (**M.D1**; Figure 3), agents go to the fishing location with the shortest distance from the home location:

$$\hat{l}.distance = \min_{l \in L, l.method = a.method} l.distance$$

This implies the agents behave rational to keep the cost low, without other factors playing a role. With this model configuration, the travel distances of the agents are generally too short and therefore, the average differences are high (Table 2). Especially, agents living further away from the coast cluster at specific fishing locations (Figure 5c) which does not correspond to reality. The model demonstrates that something drives the angler to travel further.

Distance as restricting factor (M.D2): In the next model (**M.D2**; Figure 3) the distance to the fishing location is not implemented as an attracting factor, but as a restricting factor as higher costs are associated with higher distance. Therefore, for each zip code, a maximum travel distance is calculated from the on-site data. This max distance set up a range within which angler agents choose a random spot. This mechanism generates a model output where all locations are visited (Table 1) and the average percentage deviation in the angler distribution is the lowest of all models for boat (2.24%) and land (0.9%) fishing. In addition, the average difference in the travel distance is the lowest for land fishing (Table 2) and the travel patterns are realistic (Figure 5d). However, the driving distance is still shorter than in the real world, which indicates something must be driving the anglers to drive further.

Combining catch and distance (M.CD): Higher catch rates can be a possible reason to drive further as they may outweigh the higher cost. Therefore, the model **M.CD** (Figure 3) combines both distances (M.D2) and catches (M.C2). Whereby, the agent's knowledge is not randomly generated as in M.C2, instead, the max distance restricts the agent's knowledge and sets a range within which angler agents choose locations with higher average catch rates with a higher probability. This model on the one hand improves the modeled travel distance further for sea-based fishing (Table 2) and produces travel patterns close to the reality (Figure 5e), even though the average distances are still slightly too short. Additionally, the model improves most of the key metrics compared to M.D2 (Table 3). But on the other hand, the number of visited fishing locations is lower (Table 1) and the average angler distribution differences across the fishing methods increases (boat = 2.54%, charter = 4.25%, land = 1.46%). This indicates, that the site choice within the travel range is not necessarily better represented with the weighted average catch than a random choice, and another mechanism drives the anglers to travel further.

Utility of catch and distance (M.U): Since there must be a mechanism behind the maximum distances calculated so far from the on-site data, and since the interaction of distance and catch rates seems to play a role for the different fishing methods, we developed yet another model (**M.U**) that incorporates both aspects within a utility function. The utility u of a fishing location l is calculated as a weighted sum of the catch utility u_c, which increases with increasing average catches, and the distance utility u_d, which decreases with increasing distance. Both are linear functions, which are chosen such that they vary between 0 and 1. Catch utility is 0 if the expected catch is 0 and 1 for the maximum expected catch. Distance utility is 0 for the maximum possible travel distance, and 1 if the travel distance is 0. Linear functions are chosen as they present the simplest form of a utility function.

$$u(l) = a \cdot u_c(l) + (1 - a) \cdot u_d(l)$$

$$u_c(l) = \frac{1}{9} \cdot l.average\_catch$$

$$u_d(l) = 1 - \frac{1}{511} \cdot l.distance$$

The agents then chose a site $\hat{l}$ with a probability proportional to its utility:

$$P(\hat{l} = l) \propto u(l)$$

We then executed a parameter scan of a, varying a from $0 \rightarrow 1$ in steps of 0.05. While for land fishing the average percentage deviation in the distribution among fishing locations is lowest at a = 0.05 (1.03%), for charter fishing the best value is obtained at a = 0.25 (4.11%) and for boat fishing at a = 0.85 (2.47%; Figure 4a). For all fishing methods, key metric (median, min/max) fit reality better at higher values of a (Figure 4b-4d). For charter fishing the mean difference in the travel distance to the reality increase with increasing values of a (smallest average difference = 20.53 km), while for land and boat fishing the smallest differences are generated with a = 0.25 (22.12 km and 22.84 km, respectively; Figure 4e).

Table 1: The table shows the number of visited fishing locations in the real world from 2012 to 2016 and in the different models for the different fishing methods. Best value for each column is **bold**. Only in some models (M.R, M.D2, and M.U(a=0.0-0.95)) do the agents visit all fishing locations.

Model	Boat fishing	Charter fishing	Land fishing
real world	33	13	55
M.R	**33**	**13**	**55**
M.C1a	30	13	52
M.C1b	30	13	44
M.C2	33	13	52
M.D1	24	12	34
M.D2	**33**	**13**	**55**
M.CD	30	13	53
M.U(a=0.0-0.95)	**33**	**13**	**55**
M.U(a=1.0)	30	13	52

Table 2: Differences in the mean travel distance between the real world and the models. Mean travel distance differences are calculated per zip code and then the average overall locations are calculated. This calculation is done for boat, charter, and land anglers. Values are shown in km and the best value for each column is **bold**. The models M.D2 and M.CD improve significantly for all fishing methods compared to the other model. M.C2 improves compared to the random model (M.R) for boat fishing.

Model	Boat fishing	Charter fishing	Land fishing
M.R	27.27	27.67	27.03
M.C1a	28.23	36.35	25.28
M.C1b	27.71	36.40	28.74
M.C2	24.26	31.78	30.91
M.D1	40.01	34.12	33.26
M.D2	18.46	11.87	**13.90**
M.CD	**14.44**	**10.42**	14.55

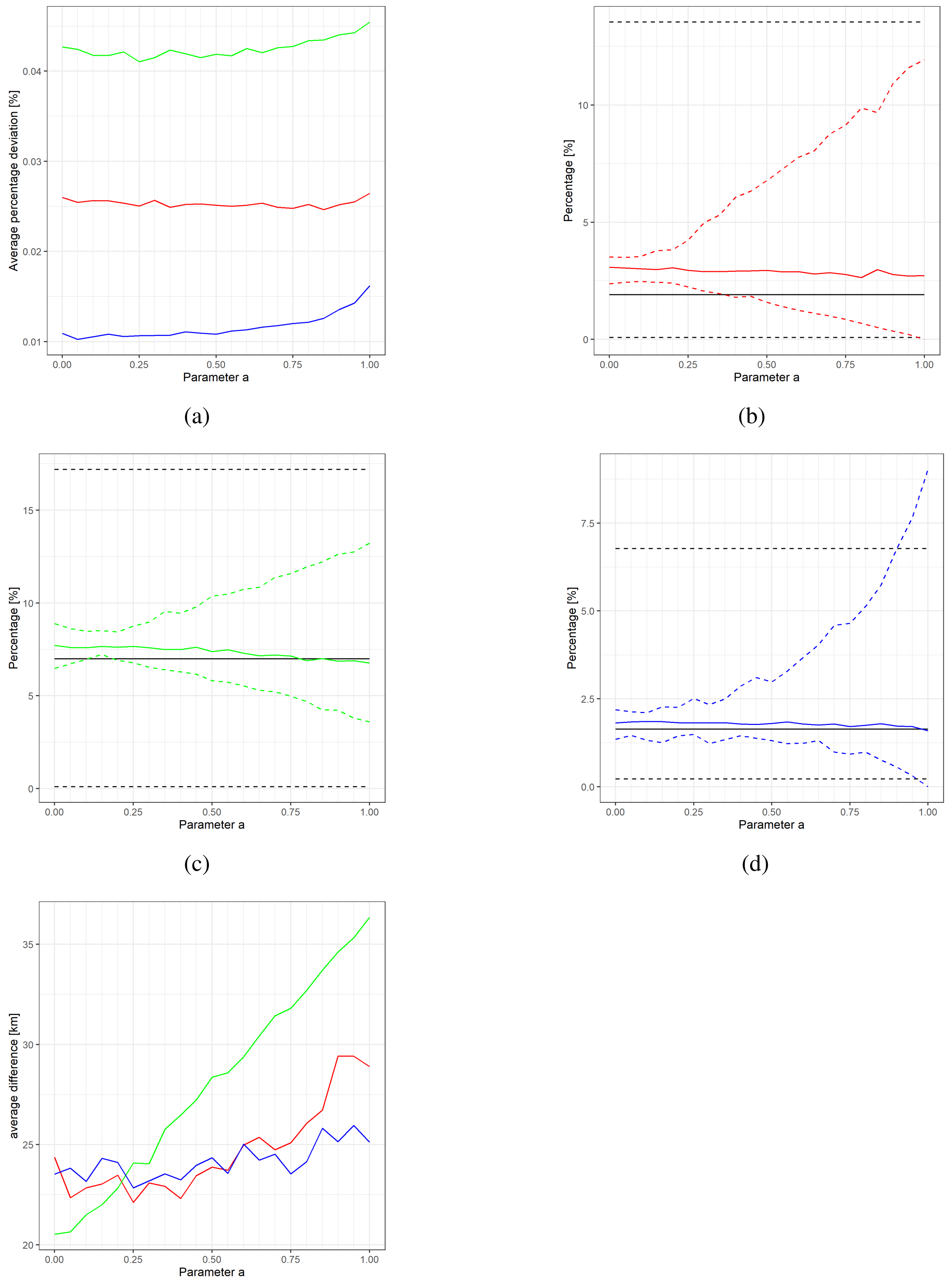
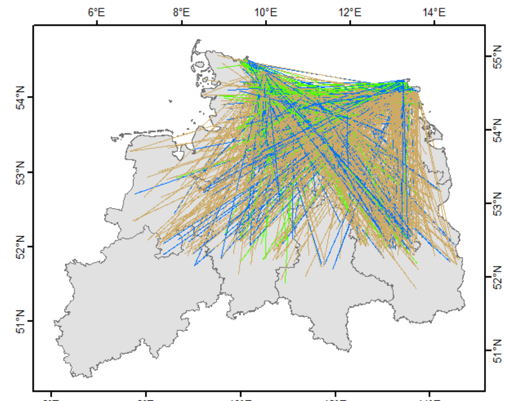
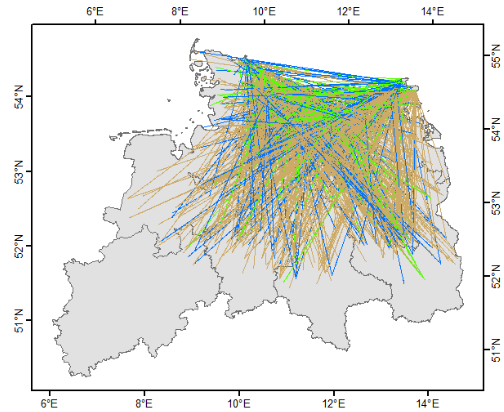


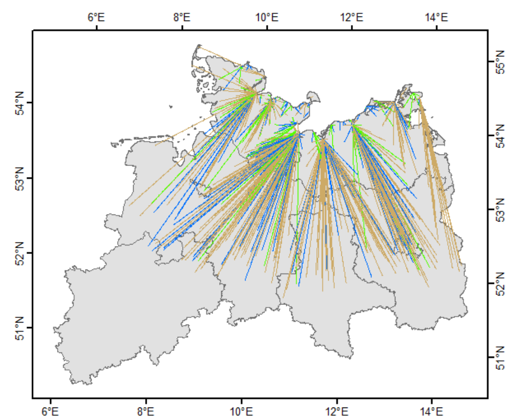
Figure 4: Plot a shows the average percentage deviation from the parameter scan of a from the utility model M.U to the real world for the different fishing methods. Plots b, c, and d show the median (full line) and the min/max (dotted lines) percentage of the angler distribution between the fishing locations for the different fishing methods. Plot e shows the average difference of the travel distance between the real world and the parameter scan of a from the utility model M.U. The colors identify the fishing method (real world = black, boot = red, charter = green, land = blue).



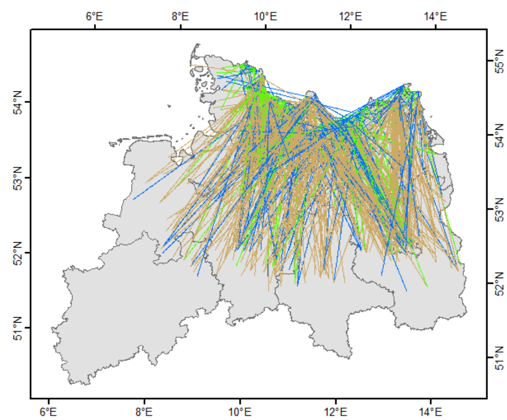
(a) Catch Model M.C1a



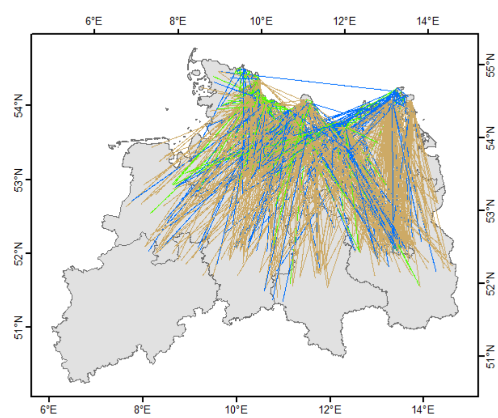
(b) Catch Model M.C2



(c) Distance Model M.D1



(d) Distance Model M.D2



(e) Combined Model M.CD

Figure 5: Travel pattern of selected models. The map shows northern Germany with the completed Baltic Sea coast. The colors of the lines identify the different fishing methods of the angler agents (blue = private/rental boat, tan = charter boat, green = land).

Table 3: Key metrics of the angler distribution for the real world and the different models. For each model, the percentage distribution of anglers among fishing locations was calculated separately for the different fishing methods. Which then allowed calculating the median, standard deviation (SD) from the mean (boat = 3.03, charter = 7.69, and land =1.82) and the min, max values for each fishing method. Values are shown in % and the best value for each column is **bold**. Especially, the catch models generate key metrics close to the real world.

Model	Boat fishing				Charter fishing				Land fishing			
	Med.	SD	Min	Max	Med.	SD	Min	Max	Med.	SD	Min	Max
real world	1.91	3.48	0.08	13.54	6.99	5.34	0.10	17.19	1.64	1.43	0.22	6.77
M.R	3.03	0.15	2.78	3.37	7.65	0.10	7.54	7.85	1.84	0.13	1.52	2.06
M.C1a	**2.59**	**2.51**	**0.00**	**12.42**	**6.85**	2.77	3.62	13.03	1.56	**1.51**	0.00	9.41
M.C1b	2.90	2.36	**0.00**	10.57	6.16	**3.52**	3.53	**14.17**	1.74	1.65	0.00	8.52
M.C2	3.07	1.43	0.14	6.81	7.68	1.27	5.91	10.08	**1.72**	1.12	0.00	5.87
M.D1	0.64	6.46	**0.00**	32.97	4.58	10.20	**0.00**	33.69	0.20	4.03	0.00	19.41
M.D2	2.91	1.54	1.14	7.25	7.25	2.66	3.36	12.61	1.93	1.05	**0.18**	4.46
M.CD	2.90	1.95	**0.00**	6.89	7.21	2.87	3.89	12.81	1.33	1.63	0.00	**7.23**

4 CONCLUSION

In this paper, we successively developed a series of simple models to capture the angler behavior in terms of travel patterns and site choice as observed in the empirical data from the German recreational cod fishery in the Baltic Sea between 2012-2016. In our experiments, we analyzed the potential influence of knowledge about catches at a site and distances to be traveled on the anglers' site choice. As outputs, we observed and compared the locations visited, key metrics (such as median, and standard deviations) and average differences of angler's distributions across fishing locations, distances traveled, and travel patterns (the latter visually). We identified maximum travel distance as a central element to rebuild the travel patterns and distances of anglers. The catch is particularly important to realistically recreate the key metric of angler distribution among fishing locations.

However, a closer look reveals significant deviations, e.g, not all sites are visited in models with the focus on catches, and even the most realistic distance models underestimate the travel distance. The latter could partly be explained by the fact that we do not distinguish between one-day and multi-day trips. Multi-day trips follow a different logic than daily trips (Hunt et al. 2019). In addition, our simplistic models have been based on average catches. However, catches vary over the year due to the different spatial distribution of cod (Strehlow et al. 2012). Consequently, the average catches over several years may not be a relevant predictor for site choice at a specific time of the year. Furthermore, anglers may not know the average catches. Catches have a high spatial, inter-annual, and daily variability that do not necessarily match their own catch experiences. It can therefore be assumed that long-term knowledge of the average catches does not build up or does not determine the site choice. A short-term knowledge of recent catches at a fishing location could be more important. Additionally, the models do not take into account the heterogeneity of anglers, even if this heterogeneity influences the site choice (Hunt 2005). Especially skill level and avidity (number of fishing days per angler and year) can be driving factors because highly-skilled and avid anglers can predict catches more accurately (Tink 2015).

Therefore, future models should allow the agents to make their own experiences, communicate and build their long-term knowledge concerning catches and expected catches. Additionally, short-term catch experiences should be included, generated by own recent experience or communication. To build realistic knowledge, the catches at a fishing location should differ between days, seasons, and years. The angler agents should include angler heterogeneity in terms of skill and avidity. Utility functions other than the linear function used so far should be tried to see which relationship gives the most realistic results. Finally, the angler effort, i.e., how often to fish, has been calculated from the data set so far. However, there has to be a mechanism behind this decision and future models should try to understand this mechanism.

While we do not yet exploit the full potential of ABM, e.g., regarding interactions and feedback (the results presented in this paper might even be gained analytically), we make important first steps towards establishing an exploratory modeling workflow, in which we test different models with different behavioral assumptions against each other and against real data. With a better understanding of anglers' decision-making processes, future ABMs may be able to replicate changes following the introduction of new regulations (such as the bag limits introduction in the western Baltic Sea in 2017 and the associated reduced travel distance of charter boat anglers (Lewin et al. 2021)) and thus enable the evaluation of future management regulations prior to their introduction.

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