Model documentation

for

FISHCODE- **FI**sheries **S**imulation with **H**uman **CO**mplex **DE**cision-making

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Abbreviations

Fishing gears / techniques

DTS – Demersal trawls and seiners

OTB – Bottom otter trawl

OTM – Midwater otter trawl

OTT – Twin bottom otter trawl

PUL – Pulse bottom trawl

SDN – Danish Seine (anchored)

SSC - Danish Seine (without anchor)

TBB – Beam trawl

Species

BLL – Brill (*Scophthalmus rhombus*)

CRE – Edible Crab (*Cancer pagurus*)

CSH – Common shrimp / brown shrimp (*Crangon crangon*)

HER – Hering (*Clupea harengus*)

LBE – Lobster (*Homarus Gammarus*)

NEP – Norway lobster (*Nephrops norvegicus*)

SAN – Sandeels nei (*Ammodytidae*)

SOL – Common sole (*Solea solea*)

SPR – Sprat (*Sprattus sprattus*)

TUR – Turbot (*Psetta maxima*)

PLE – European plaice (*Pleuronectes platessa*)

POK – Saithe (*Pollachius virens*)

Consumat

ESAT – existence satisfaction

EUNC – existence uncertainty

PSAT – personal satisfaction

SSAT – social satisfaction

SUNC – social uncertainty

WESAT – weighting of existence satisfaction

WEUNC – weighting of existence uncertainty

WPSAT – weighting of personal satisfaction

WSSAT – weighting of social satisfaction

WSUNC – weighting of social uncertainty

Other

ABM – Agent based model

DAS – days at sea

EE – Elementary effects

IQR – Inter quartile range

LPUE – Catch per unit effort

MPA – Marine protected area

OAT – One at a time

OWF – Offshore windfarm

POM – Pattern-oriented modelling

RMSE – root mean squared error

VL – Vessel length

VMS – Vessel monitoring system

VPUE – Value per unit effort

WOY – week of the year

Appendix A - TRACE

TRAnsparent and Comprehensive model Evaludation (TRACE)

This appendix contains most chapters of the TRACE protocol proposed by Ayllón et al. (2021).

1. Problem foundation & Model description

1.1 ODD Protocol

This section is represented by the ODD + D (Overview, Design concepts, Details, and human Decision making) protocol for agent-based-modelling (Grimm et al., 2006, 2010, 2020; Müller et al., 2013).

I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	FISHCODE is an agent-based model (ABM) simulating the spatio-temporal dynamics of German fishers in the southern North Sea by applying high temporal and spatial resolution and a complex human decision-making methodology that goes beyond pure profit maximization. The aim of FISHCODE is to test how different **scenarios** affect the spatio-temporal behavior and adaptive capacity of the fishers. Scenarios will encompass changes in resource availability (e.g. plaice migrates further offshore), closed fishing area (e.g. more OWFs or MPAs), market prices, and quotas (also with regard to Brexit). We also aim to provide policy advice by the development of **management recommendations** for federal agencies to support conservation efforts and a long-term perspective for a sustainable fisheries sector. Moreover, the model will assess the applicability of the Consumat approach for **fishers' behavior** beyond rational decision-making.
		I.i.b For whom is the model designed?	Researchers interested in the southern North Sea fisheries, adaptive capacity of fishers, behavior of fishers, or formalizations of human behavioral theories from social and psychological sciences. Stakeholders from federal agencies dealing with marine topics and the fishing sector.
	I.ii Entities, state variables and scales	I.ii.a What kinds of entities are in the model	**Agents** representing fishing vessels To the authors' state of knowledge addressed fisheries are composed of male fishers, which is why we refer to agents with "he" and "his". We acknowledge that our approach integrates the simulation of agents as fishing vessels rather than fishers, while the decision-making represents the behavior of skippers, which we assume to be constant for every vessel. **Ports** where agents start their fishing trips and land catches

			Fishing grounds where agents extract resources **Grid cells** (or patches)
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterised?	**Agents:** Satisfactions (existence, social, and personal) Uncertainties (existence and social) Weightings of satisfactions and uncertainties Overall Satisfaction Overall Uncertainty Status (fishing or in port) Social network (peers, extended peers) Vessel characteristics (fishing gears, size, engine power, fish hold capacity) Current landing port Affiliation (Fishing organization or independent) Probability to fish on the weekend Probabilities for certain trip length Probability for being an active fishing week Memory of past fishing trips (location, costs, catch, income, and vessel characteristics) Savings (€) Daily fixed costs (€) Target (aspired) savings (€) Perceived temperature Perceived market prices (fish & fuel) Common main target species Common fishing gears Available gears Fishing licenses (required to fish certain species) Vessel quota shares **Ports** Geographic position **Fishing grounds:** Geographic polygon Main target species (e.g. Plaice, Sole, Norway lobster, Brown shrimp) Affiliated fishing gear Weather parameters **Grid cells** (patches) Number of international fishing vessels Number of German fishing vessels Affiliation to fishing grounds Spatial fishing restrictions (for all vessels) Specific spatial fishing restrictions (specific for certain types of vessels) Passable grid cell (suited for navigation?) Local depletion coefficient Oceanographic parameters
		I.ii.c What are the exogenous	Oceanographic parameters: bottom temperature, mixed layer depth, and salinity (daily)

		factors/drivers of the model?	Weather parameters: wave height Market price per species (monthly) Market price of fuel (monthly) Fishing quotas per species (yearly for Nephrops; quarterly for sole) International fishing effort (weekly)
		I.ii.d If applicable, how is space included in the model?	The spatial model environment is a grid, in which agents operate. Each grid cell (patch) is affiliated to one or several fishing grounds, composed of gear and target species (these combinations are called metiers). Weekly oceanographic information is implemented on patch and weather information on fishing ground resolution. Agents move along the grid by choosing the shortest route between two grid cells, while avoiding non-passable cells (e.g. land).
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	The **temporal** resolution is daily and the data used for the model ranges from 2012 to 2018. The **spatial** model environment encompasses the southern North Sea up to 1.6°E and 57.4°N at a resolution of 0.045° lon × 0.045° lat (ca. 3km × 5km).
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	Beginning of every year: Refresh global plaice, Nephrops and sole quotas and aggregated species catches Agents update Nephrops quota Beginning of yearly quarter: Agents update sole quota Beginning of every month: Update market prices (species and fuel) Agents update lists of common species and gears Agents forget memory that is older than 12 months Beginning of every week: Agents update social network Update distribution of international vessels (per grid cell) Every day: Update bottom temperature Agents perceive temperature and market prices Agents update satisfactions and uncertainties Agents select action (if in port: stay in port or go fishing; including the Consumat approach) Agents act

II) Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	We assume that fishers will abide quota limits and fishing restrictions. Moreover, we assume that there are no unexplored fishing grounds in the study area and, on average, fishing fleets target the same spots (Hintzen et al., 2019; van der Reijden et al., 2018). Therefore, instead of using a biological sub-model, catch returns at fishing grounds are modelled by matching oceanographic parameters of the current model environment with those of a data base of observed fishing trips restricted by season. Catch efficiencies are equal within fishing grounds, but increase with larger engine sizes. Since the 2000s, the number of German vessels targeting sole and plaice decreased substantially, whereas some vessels started catching Norway lobster and others common shrimp. Therefore, agents are able to switch among metiers. Fishers are part of social networks comprised of peers that are in the same producer organization or land their catch in the same port. Information exchange among peers is stronger, however while being at sea fishers do not cooperate with each other. In case of spatial fishing closures (e.g. MPAs or OWFs) fishers displace their activity to other areas. The redistribution of German fishing effort and the socio-economic consequences are an emergent property of FISHCODE International fishing effort in closed areas are redistributed to the remaining area open to fisheries. We assume that fishing (i.e. extraction of resources and disturbing habitat) has an effect on the local abundance of resources. Simulated fishing activity (both German and international) reduces the LPUE in the affected grid cells by a fixed percentage. Every week, we simulated the recovery of resources and habitats by the growth of LPUE, also by a fixed percentage.
		II.i.b On what assumptions is/are the agents' decision model(s) based?	The decision for metier options is based on an established framework called the **Consumat** approach (Jager et al., 2000; Jager & Janssen, 2012). The Consumat approach is based on agent satisfactions and uncertainties that may each represent a facet of behavior. As such, it is an ideal framework to combine several behavioral theories. In our model we integrate aspects of **habitual behavior, bounded rationality, descriptive norms, and income optimization** (see *Satisfactions & Uncertainties*). Depending on the state of satisfaction and uncertainty the agents decide to use one of four actions: (1)

			repetition, (2) imitation, (3) deliberation, or (4) social comparison / inquiring. Agents have incomplete knowledge of the model environment, as they only perceive bottom temperature, but not any other oceanographic variable. Moreover, they perceive bottom temperature and market prices with a random error (see *Perceived values*). Fishers estimate catches for their perceived metier options based on their own memory or that of their social peers, as well as on current perceived market prices. They decide to go fishing if there is one metier option with the following criteria: (i) good weather enabling a sufficient trip length, (ii) right fishing season, (iii) owning necessary gear, (iv) owning necessary license for target species, (v) growth of the summed value of increase in satisfaction and decrease in uncertainty, (vi) available quota, (vii) available path to go to the fishing ground. Fishers targeting brown shrimp are not restricted by quotas, as the fishery is self-managed. Plaice is technically a quota-regulated species, but quotas are usually far from being exhausted, which is why we did not include individual plaice quotas per vessel.
		II.i.c Why is/are certain decision model(s) chosen?	The **Consumat** approach is suited for the envisioned model, since one of the aims is to model the decision-making of German fishers active in the southern North Sea with respect to their adaptive capacity and alternative business strategies, e.g. switching to another metier. The Consumat approach provides agents with sufficient flexibility by enabling them to choose between different metiers according to their states of satisfaction and uncertainty. The complex socio-ecological system of fisheries bears a large extent of uncertainty, which is explicitly incorporated by the Consumat approach. The Consumat approach dictates habitual behavior as long as agents are satisfied and certain about their actions. This behavior has been observed for small-scale fisheries, which are often run by family-owned businesses.
		II.i.d If the model/submodel (e.g. the decision model) is based on empirical data, where do the data come from?	Commercial fishing data are not publicly available and have to be requested from the German Federal Office for Agriculture and Food. However, data may be published on aggregated format (spatially or temporally). Environmental and economic data are publicly available and gathered from various data sources (Table A3).

		II.i.e At which level of aggregation were the data available?	See Table A3.
	II.ii Individual Decision-Making	II.ii.a What are the subjects and objects of the decision-making? On which level of aggregation is decision-making modelled? Are multiple levels of decision making included?	Agents that are currently in ports, decide daily whether they go out on a fishing trip or not. First, agents perceive metier options (combinations of target species and gear) and, in a second step, filter for viable options with regard to their state variables and the current model environment. Third, the agent will use an optimization procedure to select among the remaining metier options. See II.ii.c for details.
		II.ii.b What is the basic rationality behind agent decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	In general, agents choose actions that increase their overall satisfaction and decrease their overall uncertainty, which, in turn, consist out of three individual satisfactions and two uncertainties (see *Satisfactions & Uncertainties*). Moreover, agents avoid harsh weather, do not exceed global or individual quotas, and have a likelihood determining whether they want to be home on weekends and every evening. Potentially, these decision-making rules allow agents to engage in an unprofitable fishing option, since satisfactions and uncertainties are not purely related to profit. However, in case an agents' savings drop below half of the negative value of their target savings, they change their decision-making to pure profit maximization.
		II.ii.c How do agents make their decisions?	Agents' decision-making whether to go fishing comprises three steps. **Consumat approach** (Perceiving metier options)**:** Agents are satisfied and certain if their overall satisfaction and overall uncertainty are above 0.5. Below that value agents are unsatisfied and uncertain. Depending on these statuses, they perceive different sets of behavioral options. In any case, the option of staying in port, is always part of their pool of options. **Repetition – satisfied & certain**: Agent perceives metier from previous trip as the only option. If it is not possible to perform the repeated action for certain reasons (e.g. no quota or not right season), the agent will switch to deliberation. **Imitation – satisfied & uncertain**: Agent perceives the metier from his previous trip and the last trips of his close social network. If there is no possible action

			among the perceived options (e.g. no quota or not right season), the agent will switch to inquiring. **Deliberation – unsatisfied & certain**: Agent perceives all available metiers of the model including those that have not been used by any other agent yet. Deliberation is important for the flexibility of the agents, because it enables them to discover new metiers. **Inquiring – unsatisfied & uncertain**: Agent perceives the metier of the last trips from his entire social network (close and extended) and all metiers from his memory. Second, agents determine whether they can leave the port or not. They estimate the trip length for each of the perceived metier options by considering the weather in the respective fishing ground, weekends, and multi-day trip limitations. The agent filters for metiers with trip lengths larger than 0, those that are available in the current season, and that comply with available fishing licenses and gears. Also, agents will not consider any options and stay in the port, if they want to be back on the weekend, engage in a multi-day trip, and it is already Thursday. Next, agents predict profits, main catch species, and affiliated changes in satisfactions and uncertainties. Based on these values, they filter for metier options that promise a positive change in the sum of the gain of satisfaction and loss of uncertainty. Subsequently, the remaining options are checked for available quotas of their main catch species, a path to the fishing ground, and sufficient fishing time. The latter refers to the case that the steaming time is too long in relation to the trip length. If the option of staying in port is the only feasible option, the agent will do nothing. If there are feasible fishing options, agents choose the one with the highest sum of gain of satisfaction and loss of uncertainty. However, it might be that the option of staying in port is the best option even though fishing options are feasible. In the special case that an agent's savings are below half of the negative value of their target savings, they instead prioritize the most profitable option.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Yes, agents adapt **endogenously** by interaction with their social network. Moreover, agents adapt to **exogenous** variables, such as environmental parameters (oceanographic for modelling and predicting catches; weather for determining the possibility of fishing) and market prices (fish and fuel for predicting profits of fishing trips).
		II.ii.e Do social norms or cultural values play a role in the	The cultural value of preserving tradition is represented by the agents' tendency to act **habitual.** The Consumat approach makes them repeating their actions as long as

		decision-making process?	they are satisfied and certain. Specifically, the personal satisfaction represents the motivation to act habitual. Social norms are represented by the social satisfaction and the social uncertainty. The former increases agents' tendency to earn more than their colleagues and the latter to engage in similar fishing activities than their colleagues.
		II.ii.f Do spatial aspects play a role in the decision process?	Yes, fishing grounds are spatial polygons that may overlap. The further the fishing ground is offshore, the longer the steaming time and the higher the fuel costs. Also, oceanographic and weather parameter are different among fishing grounds. Therefore, it might happen that fishing ground A cannot be headed to due to stormy weather, whereas fishing ground B is navigable, because of lower waves. Ports are also spatial entities and the distance between port and fishing ground determines steaming times and fuel use. In addition, spatial fishing restrictions limit fishing space and obstacles prohibit navigation and might lead to longer steaming times.
		II.ii.g Do temporal aspects play a role in the decision process?	Some fishers prefer to go fishing on weekdays and avoid weekends or even prefer to be home every evening, avoiding multi-day trips. Furthermore, modelled landings of target species depend on oceanographic parameters which change daily and are characterized by seasonal fluctuations.
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	See *Satisfactions & Uncertainties*.
		II.ii.i To which extent and how is satisfaction included in the agents' decision rules?	See *Satisfactions & Uncertainties*.
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of	Agents' decisions are influenced by state variables and the current model environment, but the rules for decision making remain the same. Therefore, our model includes adaptation, but not learning, as defined by Dibble et al. (2006).

		their experience?	
		II.iii.b Is collective learning implemented in the model?	No.
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	The agents' **memory** includes fishing trip details of the last 12 months (landed value and catches, costs, perceived temperature at the time of the trip, landing port, starting and end date, fishing locatiojn). Agents also know their quota shares and foresee the exact weather for the time of the planned fishing trip. Agents don't have full knowledge about the oceanographic parameters, but only know their perceived temperature, which varies up to 3°C from the real value (see *Perceived values*). Moreover, agents perceive resource and fuel prices with an error of up to 5%. Perceived temperatures and market prices are used to predict landings and profits of fishing trips (see *Predicting fishing outcomes*).
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	Fishers have good, but not precise knowledge of actions of their close **social network** and vague knowledge of actions of fishers in their extended social network (see *Social network*). The exact variables they know from other agents are: fishing grounds, target species, fishing gear, engine power, and landing port. Perceived landings, revenues, and fuel use are obscured by 5% (close network) or 10% (extended network). During a fishing trip, agents sense the number of other fishing vessels and decide whether to search for a site with less vessels.
		II.iv.c What is the spatial scale of sensing?	The sensing of other fishing vessels during fishing trips occurs in a radius around the chosen center patch of the fishing trip. The radius is larger, the longer trip lasts (see *Spatial fishing model*)
		II.iv.d Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?	Variables are simply updated.
		II.iv.e Are the costs for	No.

		cognition and the costs for gathering information explicitly included in the model?	
	II.v Individual Prediction	II.v.a Which data do the agents use to predict future conditions?	Target species, gear, perceived temperature, engine power, perceived resource and fuel prices, and past profit of fishing trips (either their own or from peers). For a full description see *Predicting fishing outcomes*.
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	Agents use their perceived temperature and anticipated target metier (target species and gear) to find the most similar fishing trip in their own or their peers' memory. The landings and fuel use of this trip are then multiplied by the perceived market prices to predict profits. In case the information is derived from other vessels (i.e. peers), the catches and fuel use are standardized by the vessels' engine powers (see *Modelling catches*).
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	Predictions might be erroneous, as agents perceive temperature, market prices, and information from peers with an error (see II.iv.a & II.iv.b). Moreover, when agents predict the outcome of an envisioned fishing trip, they find the most similar fishing trip purely based on temperatures, whereas, in the underlying model, also salinity, oxygen, and primary production influence trip outcomes. Moreover, the local depletion of resources in grid cells may lead to temporally decreased LPUEs. Therefore, it might happen that an agent predicts a good outcome for a fishing trip, because this time the resources are in a worse condition (higher local depletion) than in the agent's memory.
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Agents do not interact with each other directly, but form social networks. Within social networks, agents may perceive information from each other leading to possible imitation of behaviors. Agents interact with ports as start and end points of their fishing trips. Agents using the same port are part of the same extended social network. In case they would also share a common producer organization, they would share a close social network. Agents extract resources from fishing grounds and deplete resources in all fished patches. Agents indirectly interact with each other, as they avoid crowded fishing grounds.

		II.vi.b On what do the interactions depend?	Agents will choose a fishing ground, which is specific to their target species and gear (metier). Similarly, landing ports might vary, as agents might transfer to another port that is closer to their fishing ground.
		II.vi.c If the interactions involve communication, how are such communications represented?	N/A
		II.vi.d If a coordination network exists, how does it affect the agent behavior? Is the structure of the network imposed or emergent?	The **social network** is emergent depending on the agent's affiliations (producer organization) and current landing ports. The current landing port is dynamic and might change due to vessel transfers, which is why the social network is also dynamic. Both variables are used to create a distance matrix using the Gower distance, a measure suited for categorical variables. A separation of fishers into closer and extended networks, as well as beyond an agent's social network is done based on the Gower distance between two agents (see *Social network*).
	II.vii Collectives	I.vii.a Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	Agents belong to one of three **fleets** (imposed and static), which are based on historic vessel catch compositions and used gears (see *Fishing metiers & fleets*). We calibrated model parameters per fleet, meaning that agents within fleets share the same calibrated values. Although fishers might adapt to new behaviors by engaging in different metiers - thus changing their catch compositions and used gears - the fleet affiliations remain static. In addition, agents are either independent or affiliated to a **producer organization** (imposed and static). See also the section about *Producer organizations*.
		I.vii.b How are collectives represented?	Affiliations in producer organizations are represented by state variable of the agents. Fleets are only important for the calibration of the model and not explicitly present. Beyond the calibration (fleets) and social networks (producer organizations), the aggregation in these collectives have no effect.
	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ	See Table A1.

		between the agents?	
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	Larger vessels may tolerate higher waves and have faster steaming speeds, meaning that they have more chances to go fishing and require less steaming time while consuming more fuel (Bastardie et al., 2013). All these factors may influence the decision of agents either directly (e.g. by being able to fish during stormier weather) or indirectly (e.g. by memorizing higher costs affiliated to a metier). Weightings of satisfactions and uncertainties are heterogeneous among fleets due to the calibration of model parameters by fleet. The weightings determine to what extent the individual satisfactions and uncertainties contribute to the overall satisfaction and overall uncertainty. As such, they regulate which motivations or behavioral theories influence the agents' decision-making in the Consumat framework.
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modelled by assuming they are random or partly random?	Modelled catches are multiplied by a random factor, which is larger the greater the Euclidean distance between current and matched fishing trip (from the trip data base; see *Modelling catches*). Perceived variables (see II.iv.a & II.iv.b) Probability for fishing on the weekend Anticipated fishing trip length Probability for an active fishing week Probability for vessel maintenance after a trip Distribution of daily international vessels Movement while fishing (see *Spatial fishing model*)
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding and analyzing it, and how and when are they collected?	Trip related state variables of agents (i.e. trip lengths, landings, revenues, fuel use, landing ports, spatial centroids, fished patches) Daily state variables of agents (i.e. perceived values, satisfactions, uncertainties, and decision outcome) Weekly state variables, i.e. peers and extended peers.
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	The information we extract from the model provides insights into the fishers' dynamic engagement in different metiers (combination of target species and gears), spatial fishing effort distribution over time (including displacement effects by e.g. OWFs and MPAs), and the motivations of the decision-making. The output data on fishing trip resolution can be used to analyze micro patterns or be aggregated to derive emerging macro patterns.

III) Details	III.i Implementation Details	III.i.a How has the model been implemented?	NetLogo 6.1.1
		III.i.b Is the model accessible, and if so where?	Upon publication, we will upload the model on https://www.comses.net/.
	III.ii Initialisation	III.ii.a What is the initial state of the model world, i.e. at time t = 0 of a simulation run?	Global parameters (environmental and economic) are filled by using historic data sets. Memories of agents are filled by using their most recent fishing trips before the model start date (from the trip data base; see *Initial memory*).
		III.ii.b Is the initialisation always the same, or is it allowed to vary among simulations?	We created a base year scenario using mean values of all economic and environmental data sets. We used the base year scenario to calibrate and validate the model, as well as testing the effect of other scenarios (e.g. Future expanse of OWF and MPAs). In the base year, agents' initial memories are the state of empirical data from 2015 (trip data base).
		III.ii.c Are the initial values chosen arbitrarily or based on data?	Initial parameters and state variables are chosen based on historical data (trip data base).
	III.iii Input Data	II.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	Yes, the model uses time series of oceanographic, weather, prices, and quota data of past years (Table A3).
	III.iv Submodels	II.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?	See the *Submodels* section.
		III.iv.b What are the model parameters, their dimensions and reference values?	See Table A2 and Table A3

		III.iv.c How were the submodels designed or chosen, and how were they parameterised and then tested?	See the *Submodels* section.

Table A1. State variables of agents (fishing vessels) and patches (grid cells).

Model dimension	**State variable (Netlogo)**	**Description**
Agents (fishing vessels)	current_port	The port in which the agent is currently landing catches. Agents can change their initial current port.
	list_ext_peers	Vessel reference numbers of the extended social network
	list_peers	Vessel reference numbers of the close social network
	list_perc_bottomT	Perceived values of current bottom temperature
	list_X (X = memory variables)	Agent's memory constituted by a number of lists. Some are saved daily (e.g. perceived values), whereas others are saved whenever agents go on a fishing trip (e.g. catches, profits)
	overall_sat	The summed value of the existence, personal, and social satisfactions
	overall_unc	The summed value of the existence and social uncertainties
	perc_price_X (X = species and fuel)	Perceived values for species and fuel prices
	quota_quarter_sol	Individual quarterly quota for Sole (available to vessels with a license for sole)
	quota_year_nep	Individual yearly quota for Nephrops (available to vessels with a license for Nephrops)
	X_sat (X = existence, personal, and social)	Individual satisfactions
	X_unc (X = existence and social)	Individual uncertainties
Patches	depletion_coeff	Coefficient about local depletion reducing LPUEs
	ger_ves_num	Number of the German fishing vessels that are currently fishing in the respective patch
	int_ves_num_daily	Number of the international vessels that are currently fishing in the respective patch
	spat_restr	Whether the patch is restricts fishing. May change with time as more offshore wind parks are constructed.
	NWS_X (X = oceanographic variable)	Weekly resolution of the oceanographic variables bottom temperature (bottomT), mixed layer depth (MLD), and salinity (SAL).
	elevation	Water depth.

Table A2. Most important global, agent, and patch parameters.

Model dimension	Parameter name (Netlogo)	Description	Reference
Global	LPUE_coefficient	Relative change in LPUE when converting to another engine power group	Trip data base
	Daily_int_ves_distr_mean	Mean value for normal random distribution (sd = 0.25) from which randomly drawn values are used to simulate the distribution of international vessels	International VMS data
	LPUE_uncertainty_multiplier	Multiplier affecting the Euclidian distance environmental conditions in the model and trip data base during modelling new LPUEs. The result is used as maximum error rate to obscure LPUEs from the matched trip.	Expert guess
	fish_depletion	Relative amount fish resources become depleted in a patch after a fishing event	Model calibration
	fish_recovery	Relative amount of fish resources recovering in every patch every day	Model calibration
	inBetween_steam	Per metier, the number of steaming hours added per trip day to simulate the steaming between fishing events in a single trip	Trip data base
	monthly_expanses	Monthly amount of money spent by agents (subtracted from savings in daily rates)	https://de.statista.com
	perceiving_error	Maximum error rate to perceive exogeneous (environmental and economic) variables, as well as information from social networks. For the extended social network, the error is doubled.	Expert guess
	probability_need_repair	The probability of vessels needing a two days repair after a fishing trip	Expert knowledge from fishery observers
	spatial_fishing_expansion	Per metier, the number of patches (spatial grid cells) required per trip day	Trip data base & VMS
	target_savings	The aspired savings used to calculate the existence satisfaction (set to 440 786€).	(BMEL, 2020)
	vesDens_thresholds	Per metier, thresholds for the maximum number of vessels tolerated in the proximity during fishing	Trip data base & VMS
Agent (Vessels)	avail_gears	Available gears determining the possible metier options	Initial memory
	chance_trip_length	Probabilities for certain trip lengths (0.5 – 8 days)	Trip data base
	chance_weekend	Probability for extending fishing trips during weekends	Trip data base
	chance_weekly	Monthly probabilities for going fishing during a week of the month	Trip data base
	engine_kw_step	The engine power group	See Table A3
	fish_licence	Licenses for quota-regulated species (Nephrops and Sole) determining possible metier options	Initial memory & endogenous
	fixed_costs	Daily rate of fixed costs that is subtracted from the agents' savings.	STECF
	max_catch	Maximum transport capacity for catches	Trip data base
	max_trip_days	Maximum number of trip days	Trip data base
	producer_organisation	The producer organization the agent is member of (or none)	See Table A3
	swh_thresh	Wave height threshold restricting fishing activity at stormy weather	Trip data base

	W_X_sat (X = existence, personal, and social)	Weights of the three satisfactions (existence, social, and personal) adding up to 1	Model calibration
	W_X_unc (X = existence and social)	Weights of the two uncertainties (existence and social) adding up to 1	Model calibration
Patch	FishGro	Affiliation to fishing grounds	Trip data base & VMS
	passable?	Whether the patch is passable for navigation	See Table A3

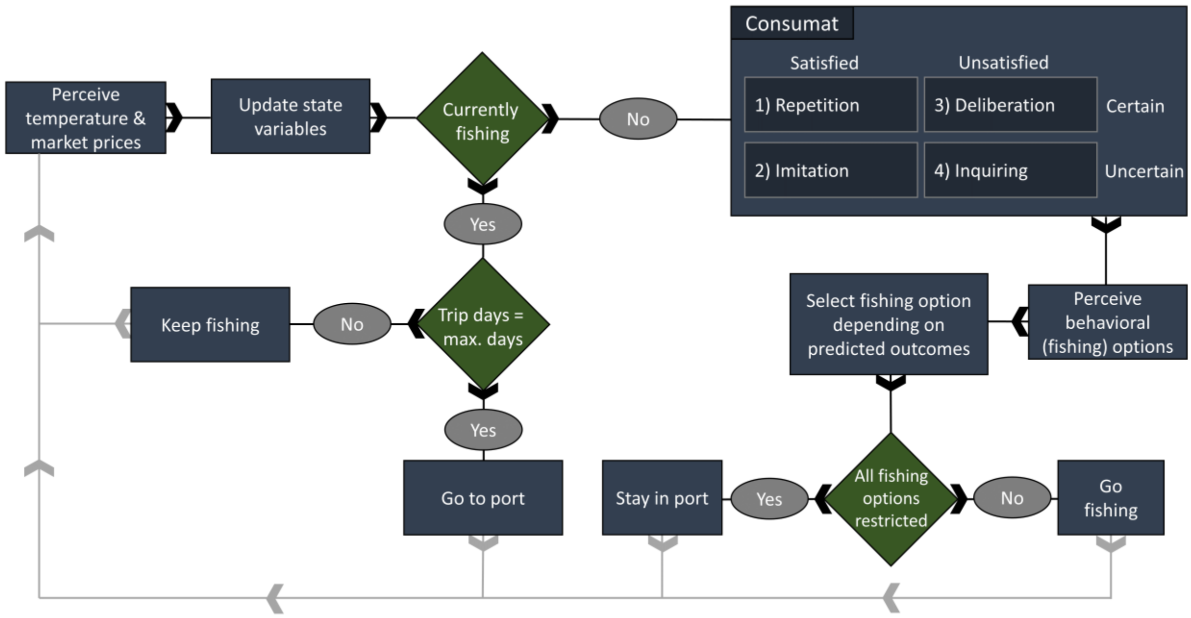

Figure A1. Infographic of the daily cycle each agent passes through in every model step.

1.2 Submodels

1.2.1 Perceived values

NetLogo

Corresponding code files:

- *perceive_and_SocNet.nls*

In the beginning of each time step, agents perceive values for current bottom temperature and prices of species and fuel. We assume that fishers have bounded knowledge about the environmental and economic system, which is why these values might differ from the actual values in the model environment. Bottom temperature may vary up to 3°C from the real value and species and fuel prices may vary up to 5%. These variations are random (floating) within their limits.

1.2.2 Predicting fishing outcomes

NetLogo

Corresponding code files:

- *behavioral_options.nls*

When agents consider choosing between metier options, they make predictions for each of them. Predictions consist of profits per trip day, most abundant species in the catch, spatial center patch of the fishing activity, and the potential change in Consumat variables (sum of gain in overall satisfaction and loss of overall uncertainty). The latter depends on several factors, such as the potential profit, main caught species, and fishing gear (see *Satisfactions & Uncertainties*).

The prediction starts with the agents comparing their perceived bottom temperature with all temperatures from trips in their memory and choose the trip with the most similar temperature. Catches and trip length of this trip serve as basis to calculate profits per trip day by using the agent's perceived species prices. The species potentially caught are split into abundant and bycatch species using bycatch thresholds (see *Fishing licenses*). Based on the predicted variables, the agent also calculates potential changes in four Consumat variables, i.e. existence, personal, and social satisfaction, as well as social uncertainty. The existence uncertainty is not predicted, because it compares predicted to actual profits and thus cannot be calculated during a prediction.

Agents first try to predict the outcome of a metier option with their own memory and then, if the option is not in their memory, use memories of their close social network (peers) and, if the option is also not available there, the memory of their extended social network. If agents used their peer memory predictions (profits, and catches) will be randomly altered by up to 5% and, if they use their extended peer memory, up to 10%.

If the option is unavailable in the agent's own and social network's memory, fishers assume the profit to be the average of all trips in their memory, and only consider target species as abundant, e. g. for *TBB – PLE&SOL* this would be plaice and sole. In this case predicted Consumat variables will be equal to the current ones.

1.2.3 Transfer to a new port

After choosing a perceived option, fishers check, whether it is worth to transfer their vessel to a new port before starting the trip. The new port must be part of the past fishing trip, agents used to predict their fishing outcome, which might be rooted in their own memory or the memory of their social network (see *Predicting fishing outcomes*). In case the new port is closer to the fishing ground than their current port, agents perform the transfer. This will delay their fishing trip for the time it takes them to steam from the old to the new port.

NetLogo

Corresponding code files:

- *fishing.nls*

Predictions of fishing outcomes are only made by using trips of the same metier. Therefore, the ports an agent might transfer to are not arbitrary, but restricted to ports used by agents engaged in the same metier. Apart from affecting the distance and steaming times to fishing grounds, this change in ports also affects their social network (see section *social network*).

1.2.4 Spatial fishing model

NetLogo

Corresponding code files:

- *fishing.nls*

The spatial environment of the model is a grid with a resolution of 0.045° longitude × 0.045° latitude. When agents go fishing they will choose the shortest path between their starting port and their target fishing patch, the latter being derived from either their own or peers' memories (see *Predicting fishing outcomes*). The path is determined by calculating the minimum number of steps an agent needs in horizontal, vertical, and diagonal direction to reach its destination. The number steps are then multiplied with the average distance in the study area for one step in the vertical (5.009 km), horizontal (2.914 km), and diagonal (5.796 km) direction. The center patch, might change depending on the vessel density in the area and the number of suitable fishing patches. First, the spatial scale required for the fishing trip is determined as the number of necessary fishing patches, which are increasing with the trip length (see *Fished patches*). The agent perceives all patches around the center patch in a radius, which is increasing with more necessary fishing patches. Patches in this radius are restricted to those, which meet the requirement for fishing, meaning that they are part of the specific metier fishing ground and do not violate any spatial restrictions (e.g. OWFs or MPAs). Then, agents will perceive the vessel density being the average value of vessel numbers (international and German) in patches suitable for fishing. In case the vessel density in the suitable patches exceeds the tolerance threshold or the number of suitable patches is below the required amount, the agent will move to another center patch, which is randomly selected from the suitable patches. Agents may repeat this search routine a maximum of 20 times, however, their steaming distance increases by 9 km (roughly two grid cells) for each search trial and thus with each search trial they lose fishing time and spend more fuel. Therefore, the more vessels are present and the lower their vessel tolerance threshold is, the shorter is the time left for fishing.

Once the agent found a suitable overall fishing area, the exact fishing path is simulated using Lévy flights, a specific version of random walks, in which agents randomly decide for a direction, as well as the number of cells moving in this direction. Among many other applications, this method is also used to simulate the forage movement patterns of marine predators (Sims et al., 2008). The number of cells moving in one direction (D) is a result of a random distribution, which is heavily tailed towards a minimum of 1,

$$D = r^{-0.5} \qquad \textit{(Eq. 1)}$$

where r is a random floating-point number between 0 and 1. In case the agent would enter a grid cell that doesn't meet the requirements for fishing, they choose a new random direction. Agents are allowed to enter a grid cell twice during Lévy flights, if there is no other possible direction. Since this may results in less unique fished patches than the required amount, if the shortage is five or larger, the fishing time is reduced relatively to the shortage of fished unique patches.

Using Lévy flights, the simulated tracks resemble fishing movement with some longer straight lines and several clumped patches. We visually compared modelled and observed fishing tracks of gears included in FISHCODE (Figure A2). Note that we do not claim to model matching tracks, but simply aim to simulate similar patterns.

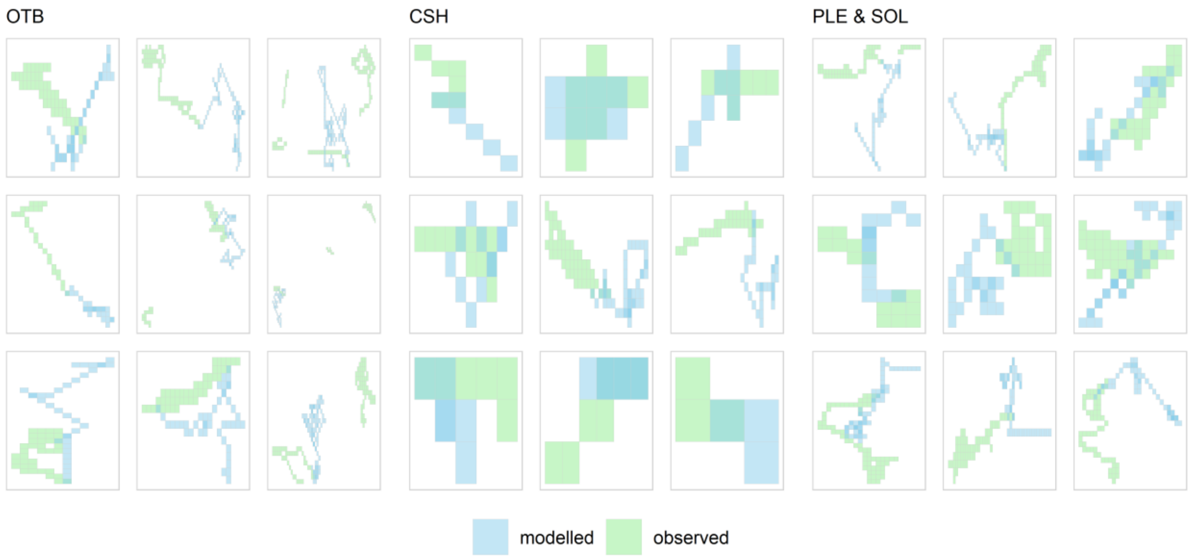

Figure A2. Observed (green) and modelled (blue) fsishing tracks as consecutive grid cells using Lévy flights. The four panels correspond to different types of gears: bottom otter boards (OTB), shrimp beam and pulse trawls (CSH), and flatfish beam and pulse trawls (PLE & SOL).

1.2.5 Modelling landings

> NetLogo
> Corresponding code files:
> ➢ *fishing.nls*

We model catches per fishing trip by using landings per unit effort (LPUEs) and landing compositions of the most similar fishing trip in the trip data base. To find the closest fishing trip, we match ambient oceanographic variables (bottom temperature, bottom salinity, mixed layer depth and bathymetry) of the patches that shall be fished with values from trips in the trip data base with the metier that shall be fished and the current season in the model. We find the best match by selecting the smallest Euclidean distance to the current model variables. Subsequently, we calculate the LPUE (kg / day) of the matched trip and adjust them according to the engine power groups by. For every engine power step difference, we increased or decreased LPUEs by 13% (see section *Relative changes of LPUEs*). In addition, local resource exhaustion influenced catches, meaning that patches that recently became fished extensively, yield less resources (lower LPUEs). We simulated the local resource exhaustion by multiplying LPUEs of all species with the depletion coefficient (see *Local depletion* for details). We also included some stochasticity in the determining LPUEs by obscuring them with an error of up to half of the Euclidean distance. Finally, we multiplied the LPUEs of each species with the fishing time of the respective fishing trip to simulate catches for every caught species. In case the newly calculated catches exceed the agent's fish hold capacity, we subtract catches in steps corresponding to 1 hour until aggregated trip catches are below the fish hold capacity and adjust the trip duration and trip end date.

We calculate revenues by multiplying the weight of all caught species with their current prices (see *Market prices*). Fishing costs in the model are comprised of fuel costs, as well as a number of other variable and fixed costs. We calculate fuel costs based on the agent's activity profile during a trip (i.e. steaming and fishing), whereas all other variable costs are based on the pure trip length (see *Fishing costs*). Finally, we subtract costs from revenues to calculate profits per fishing trip.

1.2.6 Local depletion

We simulated the local exhaustion of fished resources by proportionally lowering the LPUEs for all species in a patch for every time a vessel fished in that patch. Every patch has a depletion coefficient (DC) which is multiplied with the *fish_depletion* parameter ($FishD$) for every time a patch became fished (n).

NetLogo

Corresponding code files:

- *Main file*
- *fishing.nls*

$$DC_{patch} = DC_{patch} \times FishD^{n} \qquad (Eq.\ 2)$$

When modelling catches for a fishing trip, the LPUEs for all species are then multiplied with the average of all depletion coefficients of patches that are fished during the trip. At the end of every day, we simulated the recovery of fish resources by multiplying the depletion coefficient with the *fish_recovery* parameter ($FishR$).

$$DC_{patch} = DC_{patch} \times FishR \qquad (Eq.\ 3)$$

We parameterized both *fish_depletion* and *fish_recovery* resulting in 0.995 and 1.05 respectively (*6. Model output verification*).

1.2.7 Social network

Social networks are important for fishers, because they enable the sharing of information about yield of past fishing trips and alternative fishing strategies, which increases their chance for good catches (Barnes et al., 2017; Wilson, 1990). Social ties between fishers are more likely to form within homogeneous groups with regard to target species and landing port (Alexander et al., 2018; Gillis et al., 2021). In FISHCODE, we used the fisher state variables current port (dynamic) and producer organization (static) to define their close and extended social network. To quantify the similarity among agents, we create a matrix with current port and producer

NetLogo

Corresponding code files:

- *Perceive_and_SocNet.nls*

organization for each agent and apply the Gower distance, which is suited for categorical variables (Gower, 1971). We group fishers' peers in two categories, the extended social network (Gower distance of less than 0.5) and the close social networks (Gower distance of less than 0.25). Since the current port of agent may change (see *Transfer to a new port*), the social network may also change and is therefore updated every week.

1.2.8 Satisfactions & Uncertainties

NetLogo

Corresponding code files:

- *consumat.nls*

The **existence satisfaction** grows, the closer the agents' savings are to their aspired savings and therefore represents an aspect of **bounded rational behavior**. It is represented as the relative share of the savings compared to the target savings. If values are below 0, they are set to 0 and if values are above 1 they are set to 1. This ensures that only the downside risk is considered, meaning that as soon savings grow above the target savings the existence satisfaction does not grow disregarding from how much more profit is generated. Vice versa negative profits result in 0 existence satisfaction disregarding from how negative profits are. However, if savings are below target savings, the agents change their selection process of metier options to profit maximization.

$$S_e = \begin{cases} 1 \; if \text{ Savings} > \; Target\ savings \\ \dfrac{Savings}{Target\ savings} \\ 0 \; if \; Savings < 0 \end{cases} \qquad \textit{(Eq. 4)}$$

The **social satisfaction** grows if the agents earn more than their colleagues and therefore represent a **descriptive norm**. It is formalized as the proportion of agents' trip profits that are above the average profit of their peers at the moment of the trip. If the agent has no peers, S_s is removed and the weightings of the other satisfaction are equally increased so that they sum up to 1.

$$S_s = \frac{FT_{Higher}}{FT} \qquad \textit{(Eq. 5)}$$

- FT_{Higher} = Number of fishing trips with profits higher than mean profits of peers
- FT = Number of Fishing trips

The **personal satisfaction** grows if the agent performs similar actions, representing the **habitual** aspect of the agents' decision-making. It is formalized as the proportion of chosen options from the agents' memories with the main target species and fishing gears being part of the common target species and gear lists. These lists represent the target species and gears of an agent's memory with a frequency of at least 20% and new entries are added monthly.

$$S_p = \frac{1}{2} \times \frac{FT_{ComSpec}}{FT} + \frac{1}{2} \times \frac{FT_{ComGear}}{FT} \qquad \textit{(Eq. 6)}$$

- $FT_{ComSpec}$ = Number of fishing trips with primary species part of the common species list
- $FT_{ComGear}$ = Number of fishing trips with gear part of the common gear list

The **existence uncertainty** expresses a planning insecurity with regard to profits. It grows the lower realized profits are in comparison to predicted profits per trip, as well as the smaller the standard deviation across all profits in the memory. The larger the standard deviation, the smaller the existence uncertainty, because fishers are more used to fluctuating profits. In case the profits are higher than the prediction, the existence uncertainty for that specific trip is set to 0, meaning that only downside-risks are evaluated.

$$U_e = \begin{cases} 1 \; if \; PredDay_i < \; ProfDay_i \\ \frac{1}{FT} \times \sum_{i=1}^{FT} (PredDay_i - \; ProfDay_i) \; / \; ProfSD) \\ 0 \; if \; (PredDay_i - \; ProfDay_i) > \; ProfSD \end{cases} \qquad \textit{(Eq. 7)}$$

- $ProfDay_i$ = Profits per trip day at trip i
- $PredDay_i$ = Predicted profits per trip day at trip i
- $ProfSD$ = Standard deviation of profits in memory

The **social uncertainty** (U_s) decreases, the more similar used gears and primary target species are of an agent's memorized trips in comparison to his peers. Therefore, the social uncertainty represents the tendency to conformism and a **descriptive norm**. U_s is formalized as the portion of trip characteristics (used gears and primary target species) in an agent's memory that does not match trip characteristics of his peers' memories. While making the comparisons, past trip characteristics are matched with characteristics of the social network of that time. Since the behavior of peers and even the social network itself may change, so might the used gears and primary target species of an agent's social network. If the agent has no peers, U_s is removed and the weighting of U_e is set to 1.

$$U_s = \frac{1}{2} \times \frac{C_{gears}}{N} + \frac{1}{2} \times \frac{C_{species}}{N} \qquad \textit{(Eq. 8)}$$

- N= Number of trips in memory
- C_{gears} = Used gears that differ from those used by peers
- $C_{species}$ = Primary target species that differ from those caught by peers

Satisfactions and uncertainties are multiplied with their individual weightings and then summed to the **overall satisfaction** (S) and **overall uncertainty** (U)

$$S = WS_e \times \; S_e + \; WS_s \; \times S_s + \; WS_p \times S_p \qquad \textit{(Eq. 9)}$$

$$U = WU_e \times U_e + \; WU_s \times U_s \qquad \textit{(Eq. 10)}$$

- WS_e = Existence satisfaction weight
- WS_s = Social satisfaction weight
- WS_p = Personal satisfaction weight
- WU_e = Existence uncertainty weight
- WU_s = Social uncertainty weight

2. Data evaluation

Table A3. Characteristics and sources of used data sets.

Data set	Application in model	Range & Resolution	Variables	Source
Trip data base	Modelling landing composition, LPUE, and catch location per trip. Predicting catches, fuel costs, and profits.	- 2012-2019 - Fishing trip	Landing weights & values (per species), used gear, start and landing port	Fishing logbooks[1]
			fishing location, trip duration, time spent fishing and steaming	Vessel monitoring system (VMS)[1]
			metier	Cluster approach[2]
			Engine power and tonnage	European fleet register[3]
			Producer organization	German Fishing Vessel Register[1]
Fishing quotas	Restricts the total catch of a species	- 2009-2021 - Yearly	German fishing quotas	Monthly quota reports of the Federal Office for Agriculture and Food[4]
Resource prices	Calculation and prediction of trip revenues	- 2012 – 2019 - Monthly mean € / kg	Prices for commercially important species	Fishing logbooks[1]
Fuel price	Calculation and prediction of trip revenues	- 2002-2020 - Daily mean value	Marine gasoil prices in German ports	EUMOFA[5]
Environmental data	Modelling catches by matching the closest fishing trip using model environmental data and those from the trip data base	- 1995-2018 - Daily means - 0.111° lon x 0.067° lat	Bottom temperature, mixed layer depth, and bottom salinity.	Copernicus: NORTHWESTSHELF_REANALYSIS_ PHY_004_009[6]
Weather data	Restricting the ability of vessels to go out for fishing	- 1979 to present - 0.5°lon × 0.5° lat	Significant wave height [m]	Copernicus: ERA5 (HRES)[7]
International fishing effort	Determining whether vessel is	- 2012-2019	Occurrence of international vessels	VMS[1]

	searching for another catch location	- 0.045° lon × 0.045° lat - Weekly number of international fishing vessels		
Fishing costs	Used to calculate costs and profits per fishing trip.	- Per fishing metier and vessel length class	Cost structure per fleet segment and day at sea	STECF[8]
Offshore wind parks	Scenarios about spatial fishing restricitons	- Past and future OWFs - Worldwide	Spatial polygons of OWFs, start date, status	4COffshore[1, 9]
Natura2000 areas	Scenarios about spatial fishing restricitons	- Dedicated Natura2000 sites - North Sea	- Spatial polygons	Emodnet[10]

[1] Not publicly accessible
[2] Created by this study
[3] https://webgate.ec.europa.eu/fleet-europa/index_en;jsessionid=SZ3jDx6RabslAikFHIcPUhXdkiAH7OdGk_WKCtRzkVHLyQsvW4CF!-2104109509
[4] https://www.ble.de/DE/Themen/Fischerei/Fischwirtschaft/fischwirtschaft_node.html
[5] https://www.eumofa.eu/macroeconomic
[6] https://marine.copernicus.eu/
[7] https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=overview
[8] https://stecf.jrc.ec.europa.eu/data-dissemination
[9] https://www.4coffshore.com/
[10] https://emodnet.ec.europa.eu/en

2.1 Fishing metiers & fleets

Our aim was to classify fishing trips into distinct fishing practices (i.e. metiers) based on gear and landing composition information. FISHCODE metiers represent the fundamental pool of options agents can engage with when going fishing, although restricted by their state variables and the current model environment.

We merged logbook and VMS data from the years 2012 - 2019 according to Letschert et al. (2021) and selected fishing trips occurring in the North Sea (ICES fishing area 4). We excluded fishing trips with dredges (< 0.01%), gears flagged as miscellaneous (0.08%), and those targeting blue mussels (1.7%) representing vessels that transport blue mussels from aquaculture facilities (STECF, 2020). Per gear, we identified the 10 most caught species and removed all others. Per fishing trip, we converted total to relative catches proportional to the overall weight caught during the respective fishing trip. Based on the resulting proportional catches, we created a distance matrix applying the Euclidean distance using the *vegan* package for the R statistical software (Oksanen et al., 2019; R Core Team, 2023). Then, we clustered similar fishing trips by using the partitioning clustering method CLARA (Clustering LaRge Applications), implemented in the *cluster* package for R (Maechler et al., 2019), which is suited for large data sets (Kaufman & Rousseeuw, 2009). The CLARA algorithm is based on the portioning around medoids (PAM) technique, meaning that it defines clusters based on their medoids, which is more resilient towards outliers than methods using means of clusters, such as k-means (Gupta & Panda, 2018). CLARA is effective for large applications, because it forms clusters based on a sample data sets and then allocates remaining data points to the nearest clusters. The number of clusters needs to be defined a priori for CLARA. Based on the number of described German fisheries in the southern North Sea, we decided that 15 is a sufficiently conservative number of clusters to capture all different fishing practices (STECF, 2020). Therefore, for each gear, we defined 15 initial clusters and then merged clusters of the same gear if they had similar landing compositions, spatial distributions, used mesh sizes, and seasonal activities. We termed the resulting groups metiers, a term that is used in literature to describe a fishing practice based on target assemblage and technical vessel information on trip resolution (Ulrich et al., 2012). We removed the three metiers *OTB – POK*, *SSC – COD & mixed demersal*, and *OTM – HER* metiers from our data set, since the first two take place in the Norwegian trench and the last in front of the northern UK and thus outside of our study area, the southern North Sea. Furthermore, we removed the metiers with less than 10 trips (*GN – COD, GN – SOL*, *OTM – PLE*, and *OTB – SPR*) and those with less than three participating vessels (*FPO – CRE&LBE*, *OTM – SAN*, *OTT – NEP&PLE*, *OTT – PLE*, *SDN – PLE*, *GNS – SOL*, and *GNS – COD*). We compiled information on fishing trips from the resulting eight metiers (Table A4), which, from here on, we refer to as trip data base.

The created metiers differ in used gears and targeted species, however, some vessels might exercise multiple metiers, because they switch between gears and target species. Because certain vessel features, such as gear handling or steaming speeds, mainly depend on characteristics unique to vessels or gears and not to metiers, we also merged metiers into fleets (Table A4).

Table A4. Metiers and fleets defined for the agent-based model.

Metier	**Details**	**Fleet**
OTB - PLE	Otter board trawler catching mainly plaice.	OTB – PLE/NEP
OTB – NEP&PLE	Otter board trawler catching mainly plaice and Nephrops.	
TBB – PLE&SOL	Beam trawlers catching mainly plaice.	TBB/PUL – PLE/SOL
TBB – SOL&PLE	Beam trawlers making most profit from sole.	
PUL – PLE&SOL	Pulse trawlers catching mainly plaice	
PUL – SOL&PLE	Pulse trawlers making most profit from sole.	

TBB - CSH PUL - CSH	Beam trawlers catching common shrimp Pulse trawlers catching common shrimp	TBB/PUL – CSH

2.2 Fishing locations

We selected fishing pings (geographic vessel positions sent regularly via VMS) of previously defined metiers and removed fishing trips with only one ping. German fishing vessels broadcast their position every two hours leading to large gaps in their spatial tracks. To enable a more accurate representation of spatial fishing grounds, we linearly interpolated fishing pings in two steps. First, we split pings of each fishing trip into segments whenever the spatial distance was larger than 30 nm or the time difference was larger than 4 hours between two consecutive pings. This prevented false interpolation between two hauling events in one trip. Second, we linearly interpolated pings, so that the time difference between each ping was no larger than 20 min. We gridded fishing pings of each metier to a resolution of 0.045° longitude × 0.045° latitude (approximately 15 km² per cell at 54° latitude north) and aggregated catches per cell and day. We calculated mean values per grid cell and omitted all data points with catches lower than the 10th percentile to represent core fishing grounds of metiers spatially (Figure A3). Finally, we removed grids cells by hand for falsely identified fishing pings representing steaming lines from harbours to catch grounds.

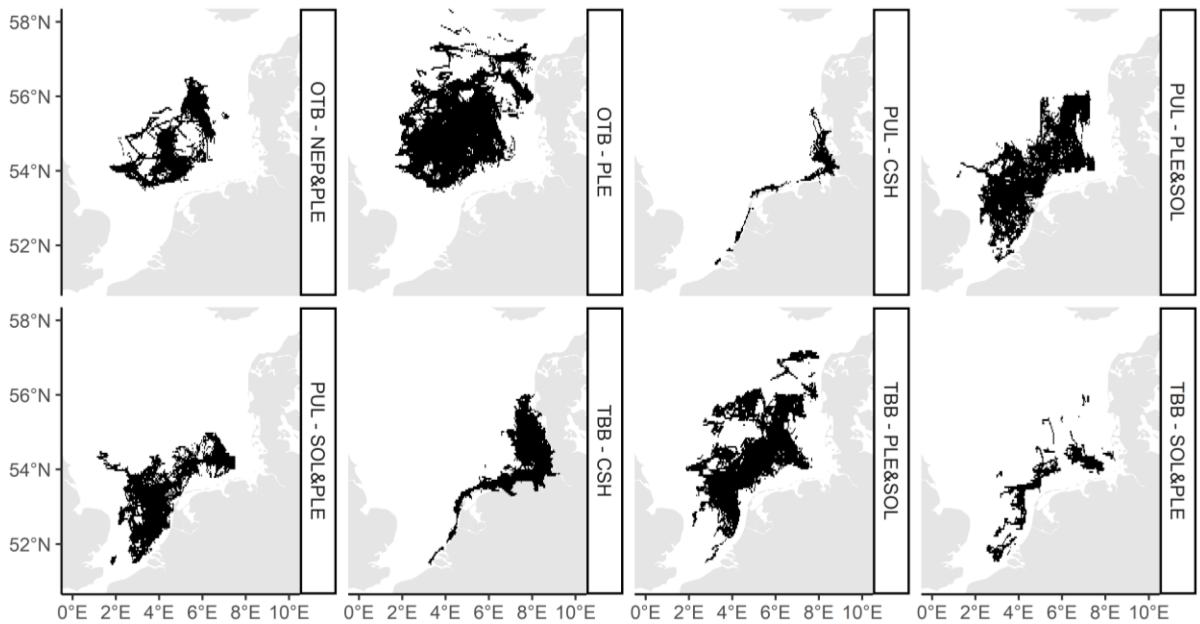

Figure A3. Fishing grounds of metiers derived from VMS data and used as spatial extend for simulated spatial fishing behaviour in FISHCODE.

2.3 Variables derived from trip data base

Our trip data base combines information on fishing trips, i.e. catches, revenues, start and landing ports, departing and landing dates, used gear, and centroids of fishing trips, with vessel characteristics, such as engine power and vessels lengths. It is a product of commercial logbook data and spatial vessel monitoring system's (VMS) data and an encompassing source of information, which we used frequently to obtain parameters for FISHCODE.

2.3.1 Validating trip data base

We identified and removed erroneous entries by filtering for unrealistic values by using percentile filters (2.5th to 97.5th percentile), which is a common method for outlier detection. We applied percentile filters to trip durations, relative fishing times, LPUEs, and VPUEs. In addition, we removed trips with a length shorter than 3 hours, a relative fishing time of less than 0.3 or more than 0.9, and a LPUE of more than 400 kg / h. Finally, we selected only metiers with sufficient data by removing those with less than 10 trips and less than 3 vessels. Figure A4 shows the number of trips per metier in the trip data base, as well as the relative amount of removed trips per metier. Detailed graphs for each percentile filter can found in *Appendix B*.

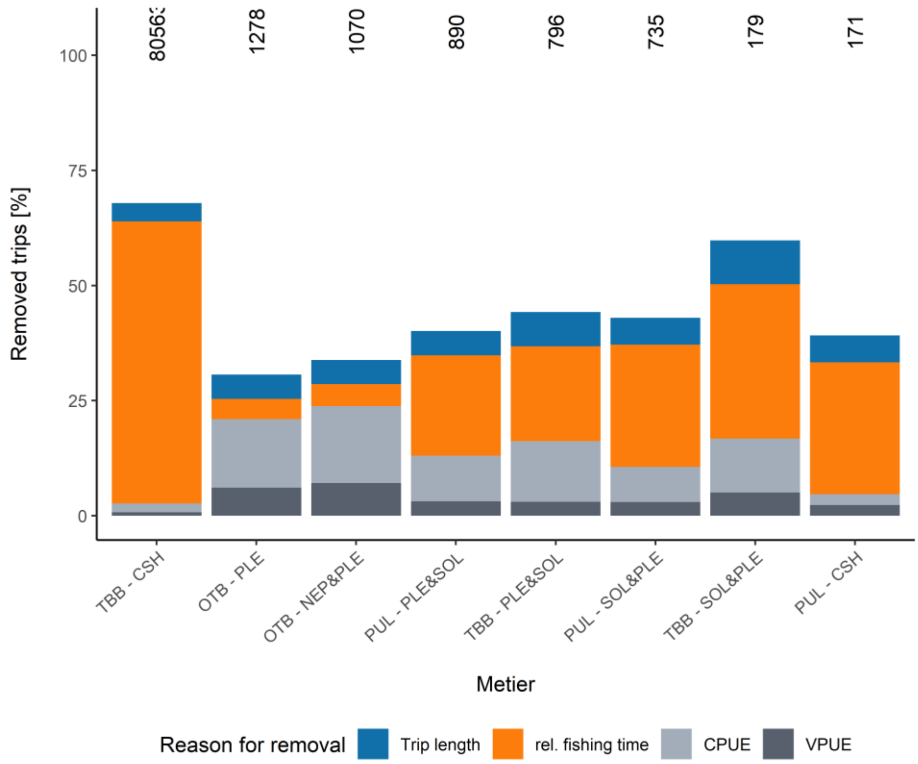

Figure A4. Bars show the percentage of removed trips per metier and per filter (color coded). The numbers on top of the bars show the total number of trips before applying any filters.

2.3.2 Fish hold capacity

We calculated fish hold capacities of vessels, meaning their maximum fish transport capacity, in several steps. First, we selected all vessels with more or equal than 100 trips from the trip to create a solid fundament for the next steps. Second, we aggregated catches of all species per fishing trip and derived the maximum amount of catch per vessel. Third, we calculated the fish hold efficiency by dividing aggregated trip catches by vessel tonnages. Most vessels have a fish hold efficiency of around 0.1, meaning that 10% of their tonnage may be used as storage for catches. We used the 75th percentile of vessels' fish hold efficiencies (0.134; Figure A5) to calculate fish hold capacities by multiplying it with vessel tonnages. We decided for the 75th percentile, since the fish hold capacity should represent the maximum amount vessels may transport, given that not all vessel might fish until their storages are full. We did not choose the maximum vessel fish hold efficiency, to remove outliers.

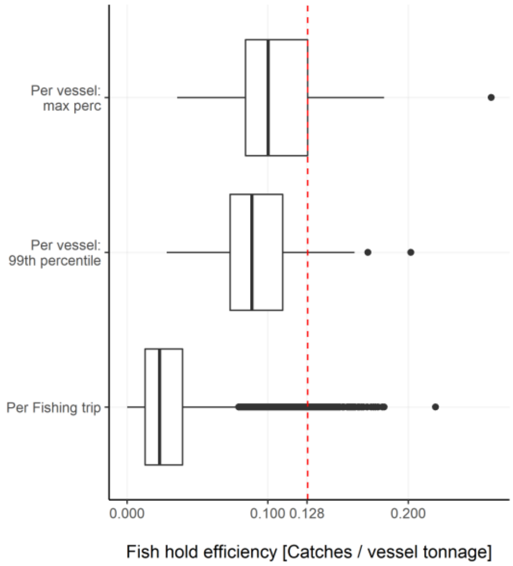

Figure A5. Fish hold efficiencies calculated for the maximum catch per vessels (*max perc*), the 99th percentiles of catches per vessel (*99th percentile*), as wells as per each fishing trip.

2.3.3 Engine power groups

Engine powers of vessels in the trip data base are ranging from 110 to 2030 kW. Most vessels' engine powers are concentrated in the lower end of the distribution and sparsely distributed across the whole range (Figure A6). We sorted vessels into five categories of engine power: 0 - 221, 222 - 499, 500 - 999, 1000 - 1499, larger or equal to 1500 (all in kW). We decided to restrain the first group to a maximum of 221kw, because the plaice box, a large coastal fishing closure, prohibits vessels with larger engine powers than 221kw and certain gears to fish (Beare et al., 2013). Thus, many vessels try to stay below this threshold to be able to fish within the plaice box.

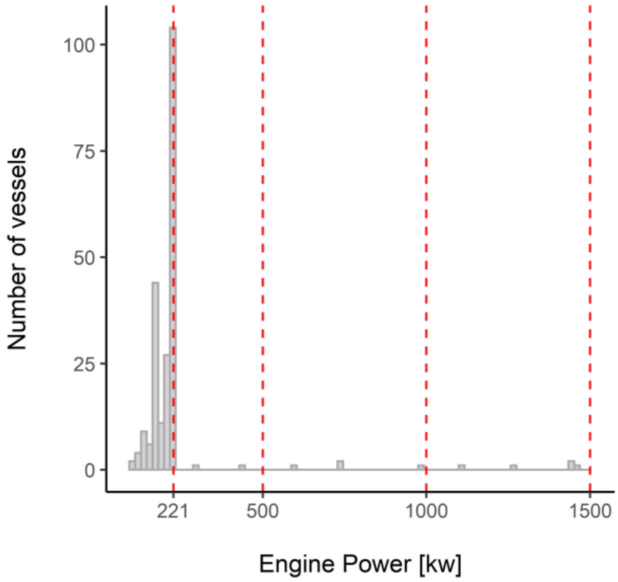

Figure A6. Distribution of engine powers (in kW) of vessels from the trip data base. Red dashed lines mark the edges of the five engine power groups.

2.3.4 Trip durations and active weeks

Trip duration is limited by technical constraints, such as the vessel size, as well as personal norms, such as the willingness to go out on the weekend. We extracted information about fishing trip durations from the trip data base.

Maximum trip duration

We derived the 90th percentile of all trip length per vessel from the trip data base to represent the vessel's maximum trip duration.

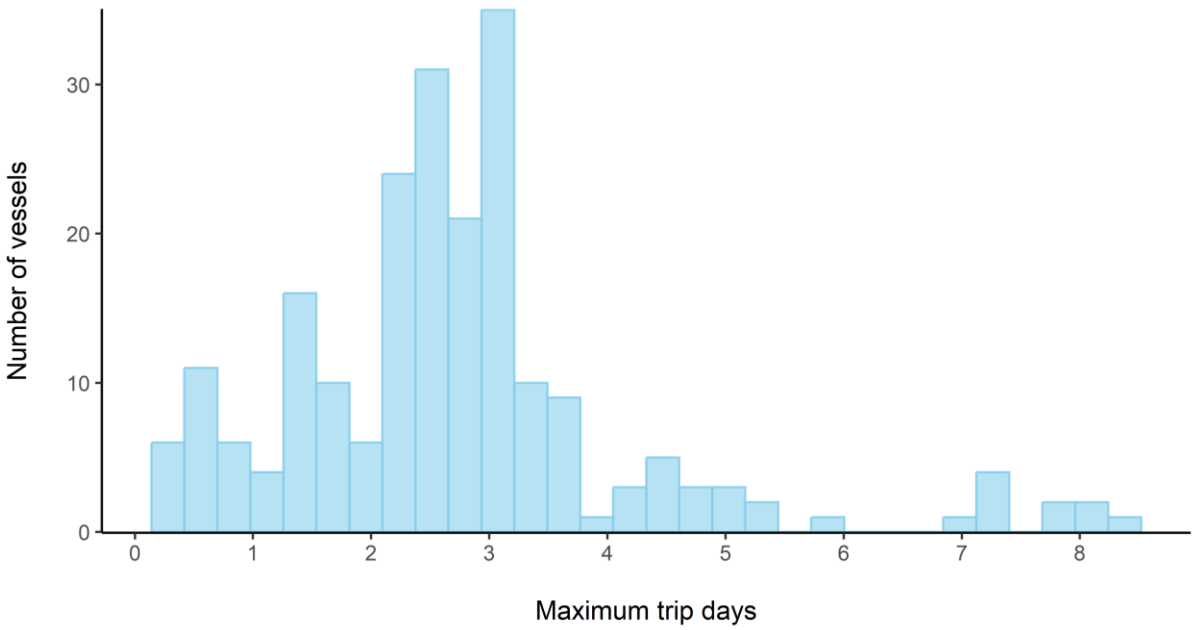

Figure A7. The distribution of maximum trip days per vessel derived from the trip data base as the 90th percentile of trip lengths per vessel.

Personal norms: Multi-day trips and weekends

Fishers might plan their fishing trips depending on their motivation to be home in the evening or on the weekend (Letschert et al., 2023; Schadeberg et al., 2021). To get an estimate about these motivations, we extracted the relative number of trips per vessel that intersect with weekend days (Saturday and Sunday). Additionally, we extracted proportions of trips per vessels longer than time periods ranging from 0.5 to 7.5 in steps of 0.5 (Figure A8). In FISHCODE, we used these relative numbers as probabilities to determine how long the agents' fishing trips last and whether they are active on the weekend. For example, if a vessel spent 20% of its trips intersecting with weekends and 60% of its trips were longer than two days, then the probability that this vessel will go out at weekends would be 20% and the probability that trips can be longer than two day would be 60%.

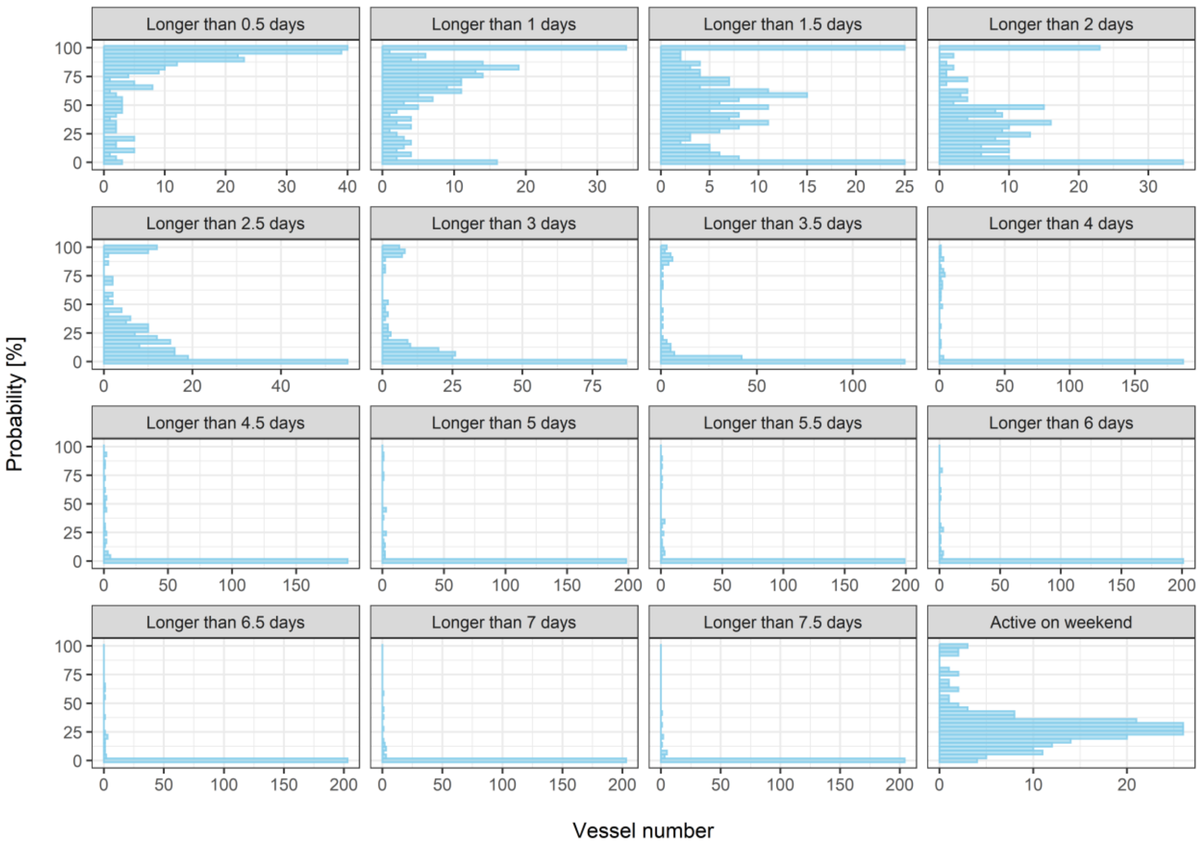

Figure A8. The probabilities agents undertaking fishing trips of certain lengths and on the weekend.

Active fishing weeks

In the model we included several reasons for agents to stay in port instead of leaving for a fishing trip, such as high waves, ship maintenance, and exacerbating satisfactions and/or uncertainties. Additional reasons for not going fishing might be vacation or pursuing side businesses like restaurants or hotels. To include these reasons in our model, we used the trip data base and determined probabilities of vessels to be inactive during an entire week. We calculated monthly averages and used these as probabilities in the model for agents to have an active or inactive fishing week.

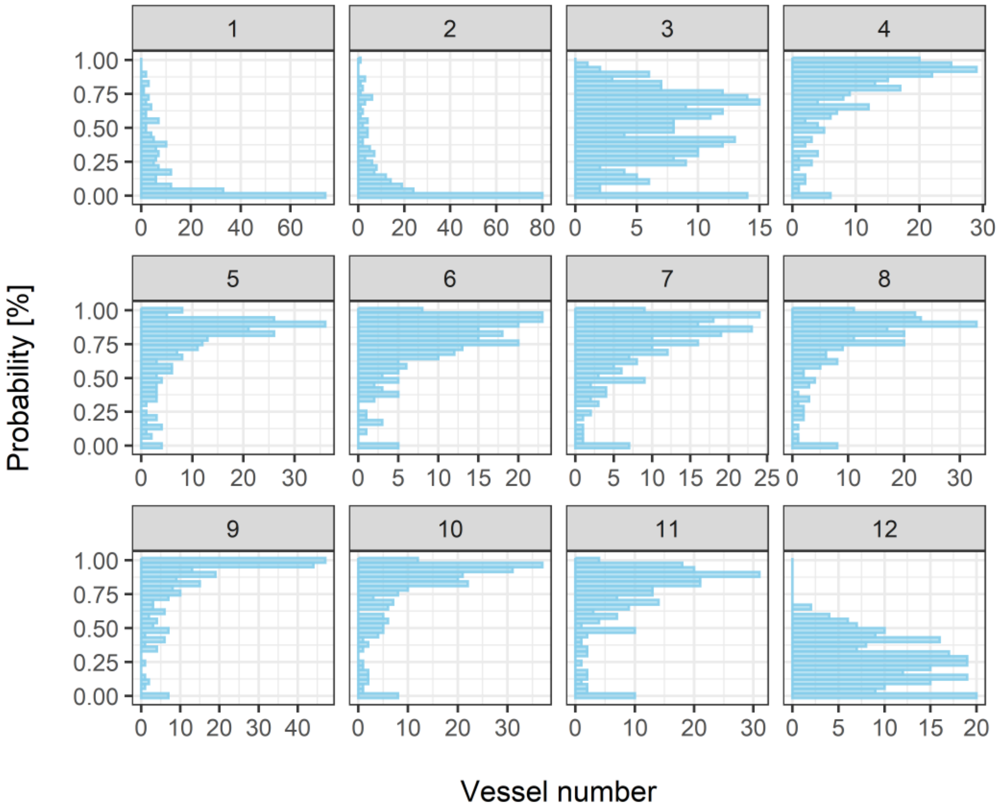

Figure A9. The probabilities agents undertaking fishing trips of certain lengths and on the weekend.

2.3.5 Relative changes of LPUEs

In the *Modelling catches* submodel, we calculate the LPUE (kg / day) of the matched trip and standardize them according to the engine power group. To achieve this standardization, we beforehand determined the relative increase or decrease of LPUE per engine power step for each metier. First, we grouped the trip data base into categories by metier, engine power group, and caught species and removed categories with less than 50 data points. Second, for each category, we calculate means of LPUEs and determined the relative change in average LPUE from every of the four engine power groups to another. In case the engine step was just from one engine power group to the next higher, we simply divided the LPUE of the higher engine group by the LPUE of the smaller. In case the step was from the 1st to 3rd or 4th engine group (or from the 2nd to 4th), we standardized the relative change by the number of steps using the following formula,

$$L\Delta = ((L_i - L_{i+n}) \,/\, n + L_i) \,/\, L_i \qquad \textit{(Eq. 11)}$$

where $C\Delta$ is the relative change in LPUE, C_i the LPUE at step i, and n the number of steps. Then, we formed median across all values (1.13) and used to standardize catches from vessels with different engine size groups (see *Modelling catches*).

2.3.6 Producer organization & current landing port

Producer organization is a fixed agent state variable derived from real world data. We obtained information on the memberships in fishing organization from the German Fishing Vessel Register. To determine initiative current landing ports per vessel, we used the most abundant landing ports, which is part of the electronic logbook data. In FISHCODE, *current landing port* is a dynamic state variable, as fishers might switch to another landing port, if the new port is closer to their fishing ground. However, they cannot choose arbitrary among ports, as decisions are limited to ports used for equal metiers by colleagues. Both, the German Fishing Vessel Register and logbook data are not publicly available, since they contain commercially sensitive information of fishers.

2.3.7 Market prices

We used all available logbook data to calculate monthly prices for species by dividing gained euros by catch amounts (Figure A10). Since not all species are caught every month, we linear interpolated prices for missing months. We obtained fuel prices from a publicly available data set of marine gasoil prices in German ports (www.eumofa.eu; Figure A11)

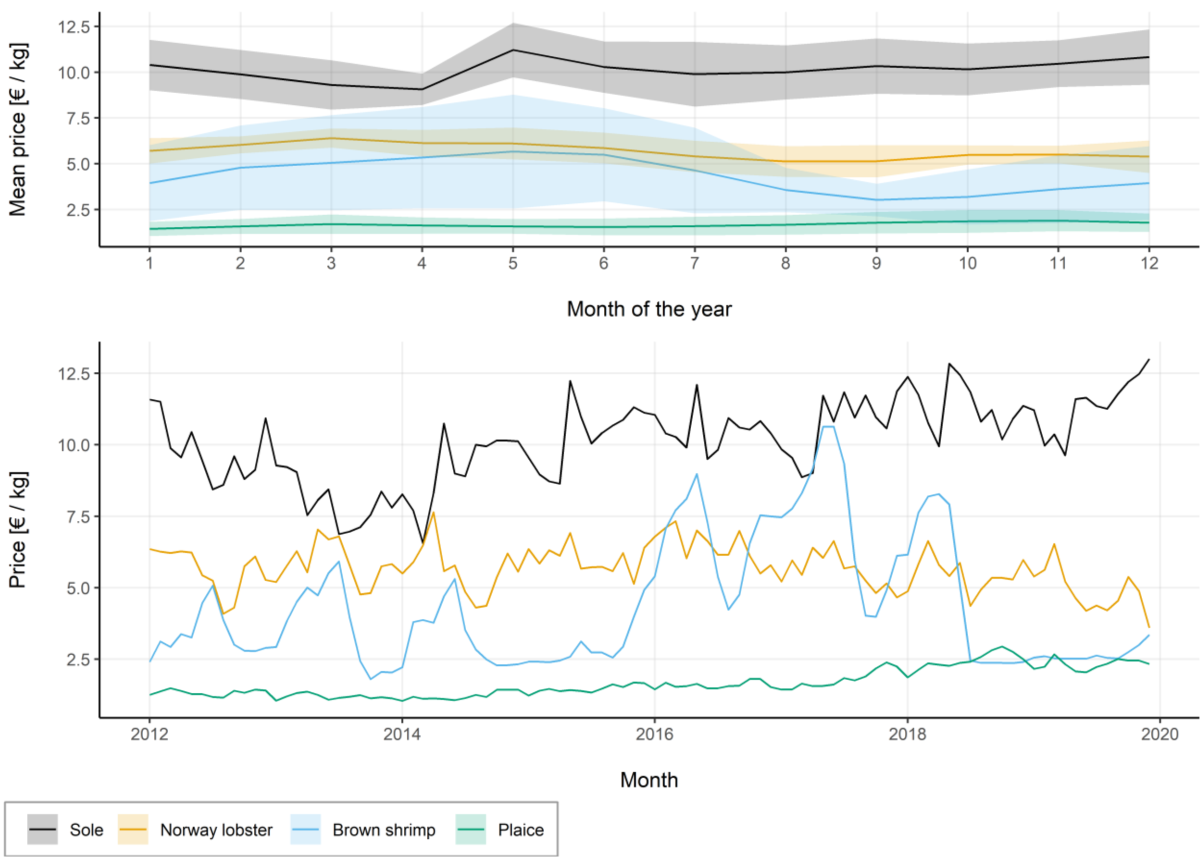

Figure A10. Resource prices of the most important caught species. The upper graph displays the mean and standard variation of prices per month of the year, whereas the lower graph shows prices for each month across the whole temporal range of the trip data base.

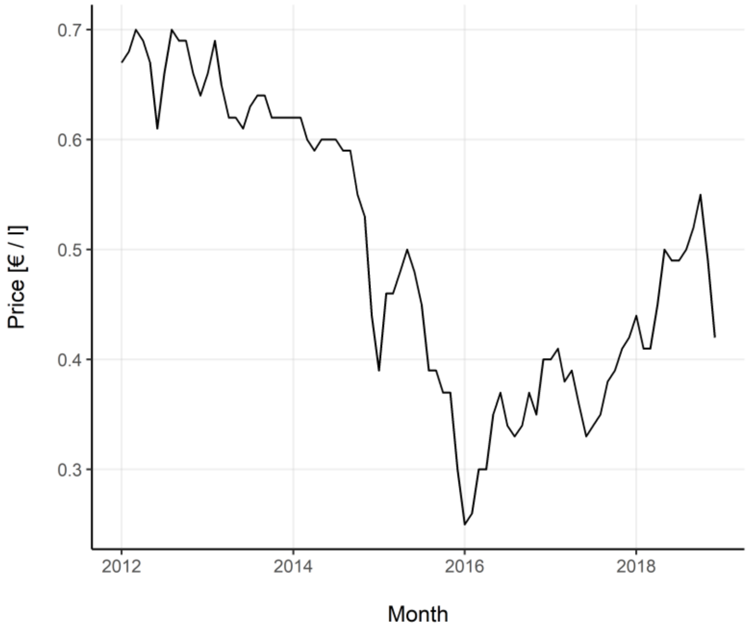

Figure A11. Monthly marine gasoil prices.

2.3.8 Steaming speed and time

We derived steaming speeds from the trip data base by calculating mean steaming speeds per fishing trip, gear and engine power group. First, we calculated distances travelled by fishing trip like we would in FISHCODE (see *Spatial fishing model*) rather than taking the steaming distances from the trip data base. Although the steaming distance from the trip data base is more precise since it is directly calculated from VMS positions, the newly calculated distances were a better choice, because any bias introduced will be the same for these distances and those in FISHCODE. We removed trips with speeds lower than 3 km/h assuming that they refer to fishing or inactive times rather than steaming. We determined steaming speeds by using mean values per fishing gear and engine power group (Figure A12).

Only in one out of the three fishing gears (PUL), there were examples of fishing trips from every engine power group. However, in FISHCODE, agents should theoretically be able to choose any metier, if vessel characteristics allow it. Therefore, we needed steaming speed values for all combinations of engine powers and fishing gears. For missing values, we linearly interpolated steaming speeds within fishing gears.

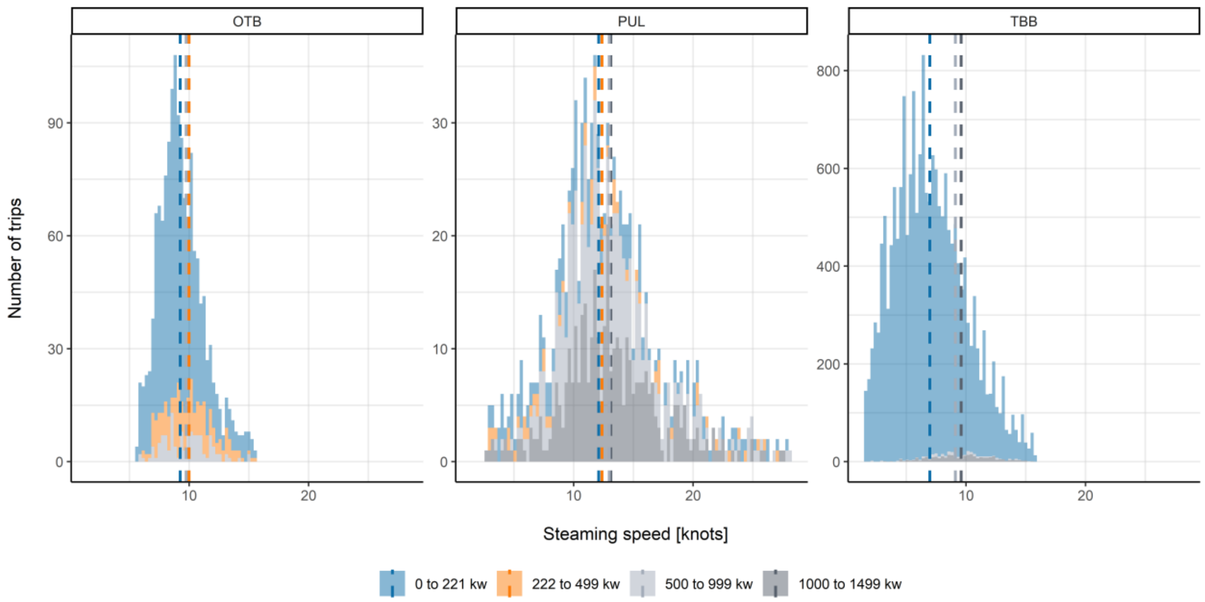

Figure A12. Histograms of steaming speeds per fishing gear and engine power group.

Table A5. Steaming speed values in knots (nautical miles/h) used in FISHCODE. Underlined values are determined from mean values within fishing gear and engine power groups. Non-underlined numbers are linearly interpolated.

Gear	0 to 221 kw	222 to 499 kw	500 to 999 kw	1000 to 1499 kw
OTB	<u>9.24</u>	<u>9.99</u>	<u>9.74</u>	9.99
TBB	<u>6.97</u>	7.87	<u>9.1</u>	<u>9.58</u>
PUL	<u>12.09</u>	<u>12.37</u>	<u>12.98</u>	<u>13.1</u>

If embarked on a multi-day trip, a fisher likely does not stay at one location throughout the trip, but changes fishing spots to increase their yield (Rijnsdorp et al., 2011). We model this by increasing the steaming time by a fixed number of hours per trip day, meaning that the fishing time decreases by the same amount. We extracted these fixed steaming hours from the trip data base for each metier. Following the methods of Letschert et al. (2021), we determined steaming and fishing times for each fishing trip based on speed values of geo-located pings of fishing vessels derived from the vessel monitoring system (VMS). This enabled us to differentiate between the steaming intervals in the beginning and end of fishing trips, representing navigation from and towards the port, and all other steaming times. We summed up all other steaming times and standardized them by trip days. Per metier, we then used a percentile filter (2.5th and 97.25th) to remove outliers and determined input values for FISHCODE by calculating medians (Figure A13).

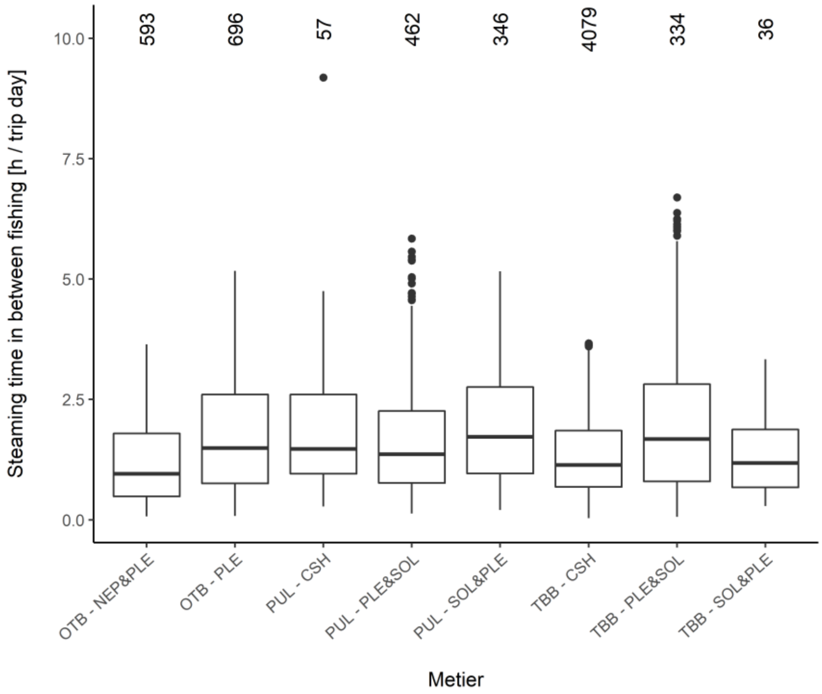

Figure A13. Boxplot of steaming times in between fishing events per fishing trip and metier. Trip numbers (after applied percentile filters) are indicated above each box and black horizontal lines represent medians.

2.3.9 Initial memory

The initial memory (memory at the point of model initiation) is based on the trip data base limited to the year before the model start. The minimum number of trips among all considered vessels, i.e. those that should be part of the model, decides for the number of trips among all vessels, since the model requires an equal length of values among agents. The minimum number of trips for the initial memory per vessel is 10. If a vessel has less trips than 10 in the year previous, to the model start it is not added to model.

2.3.10 Available gears

In general, all gears that the agent has ever used are available to this agent. During model initiation, the agents' memories are filled with information from the trip data base. Thus, the initial available gears, depend on the decision, which trips will be added to the initial memory.

2.3.11 Fishing licenses and individual (vessel) quotas

Quota-managed species in t FISHCODE are plaice, sole and Norway lobster, which are distributed to vessels with the fitting license. Turbot and brill are valuable species that are only managed by a bycatch quota, meaning that a targeted fishery is not allowed, but fishers are allowed to catch them as bycatch, as long as the national quota is not surpassed. Agents own licenses for all species that they targeted in their initial memory. Agents gain individual quota for a species in the beginning of a year, if they have the necessary license. The amount of quota is equal for every agent owning the fitting license and calculated by dividing 90% of the national quota by the number of agents owning a license. We only use 90%, because in reality the BLE keeps a certain buffer of quotas to cover bycatches in other fisheries. Sole poses an exception, since it is managed quarterly and thus individual quota for sole is set every three months by dividing 90% of the national quota by four and then by the number of fishers owning a license.

Agents can only engage in a metier, if they own the necessary license and still have quota available. For example, if they want to engage in the fishing metier *OTB – PLE* they need to own a license and available quota for plaice (PLE). Moreover, during the predictions of a metier option outcome, the most abundant species are determined. If any quota-regulated species surpasses a catch share of 10% it cannot be registered under bycatch quota anymore, meaning that the fisher needs the specific license and available individual quota to pursue this metier option.

2.3.12 Fished patches

We used linear interpolation to calculate the number of fished patches (grid cells) a vessel visits during a fishing trip for each metier. Slopes are based on linear models derived from the trip data base (Figure A14). In general, the number of patches is increasing with time a vessel spent fishing during a trip.

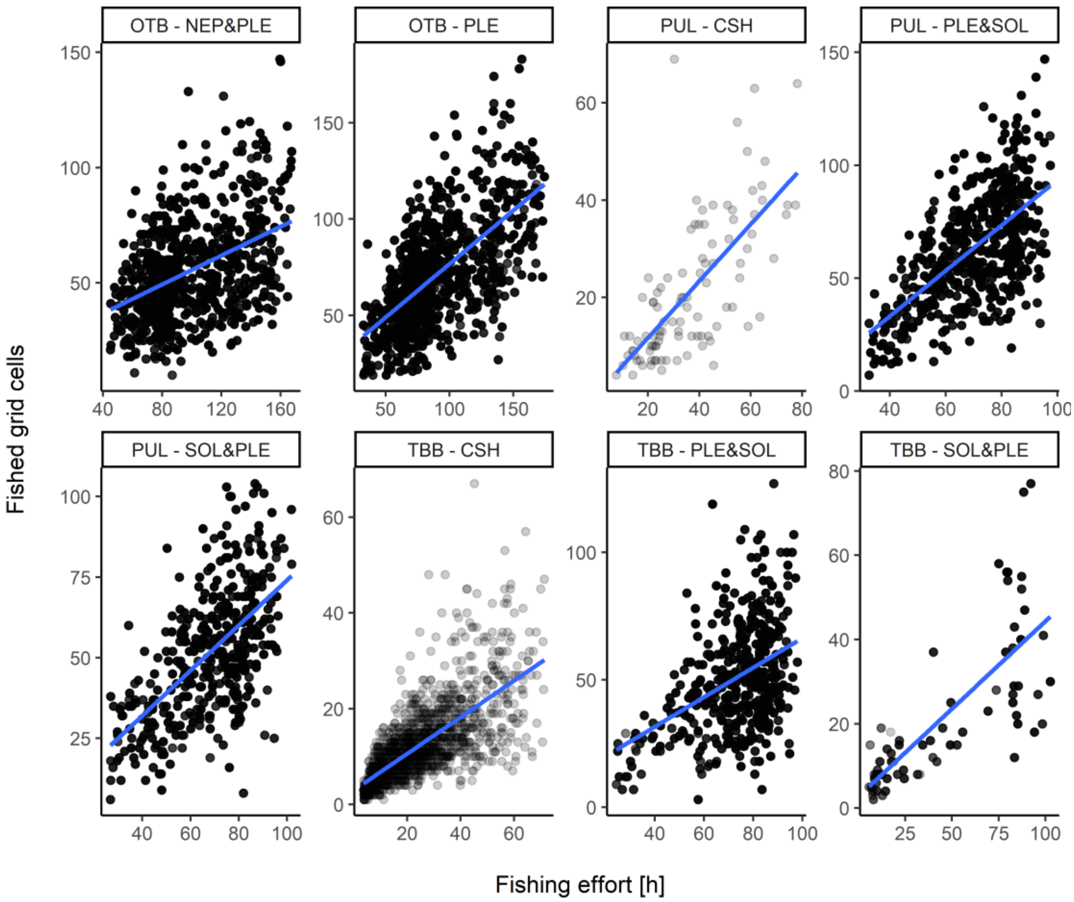

Figure A14. The number of fished patches (grid cells) depending on the fishing time length per metier. Based on the trip data base.

2.3.13 Vessel resistance to harsh weather

In general, larger vessels are more tolerant to harsh weather conditions such as strong winds and high waves. We used the trip data base to derive thresholds of significant wave heights (SWH) determining when a vessel can go fishing and when not. First, we combined fishing trips with a tempo-spatial data set of wave heights (SWH) and extracted the 97.5th SWH percentiles per vessel representing extreme weather conditions. Second, we visually inspected a scatter plot of the 97.5th SWH percentiles and identified three vessel length groups characterized by subsequent steep slopes (Figure A15A). Since overestimated SWH thresholds would have strong effects on the ABM, we determined SWH thresholds by deriving the upper value of the 1.5 inter quartile range (IQR), a common method to remove outliers (Figure A15B).

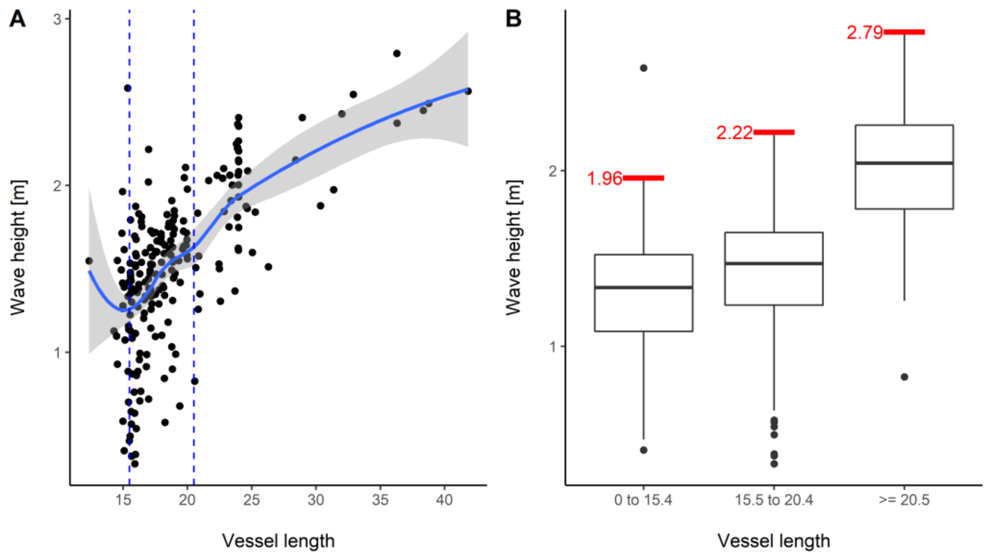

Figure A15. **A** displays a scatter plot of 97.5th quantiles of significant wave height (SWH) values per vessel with blue dashed lines signaling vessel length categories determined by subsequent steep slopes. **B** shows boxplots of 97.5th SWH quantiles per vessel length category with upper 1.5 × inter quartile ranges (IQR) in red.

2.3.14 Tolerance to vessel densities

The threshold of fishing vessels to tolerate a certain density of vessels around them might depend on personal norms and characteristics of fishing gears and locations. Examples for personal norms are fishers who don't care if other vessels are around, whereas others might be very sensitive, because they want to protect their secret fishing location. Gear and fishing location effects might comprise various spacings fishing gears require, as well as temporal exhaustions of resources after previous fishing activities in a specific location. Since we assume that there are no new fishing grounds to explore and no secret locations to protect, we excluding personal norms and based vessel density thresholds on metiers rather than individual agents.

We derived thresholds for vessel densities from the trip data base. For each fishing trip, we determined the number of required grid cells (or patches) by using the same approach as in FISHCODE (see section on *Fished patches*). Equivalent to the spatial submodel in the ABM, we chose the required number of fished patches randomly distributed around the center of each fishing trip (see section on *Spatial fishing model*). From all the selected patches we extracted the average of other active fishing vessels (German and international) per cell and day. Finally, we derived vessel density thresholds for each metier by using the upper boundary of the 1.5 × IQR interval (Figure A16). For those with zero values of IQR intervals, we used the next higher value from the other metiers.

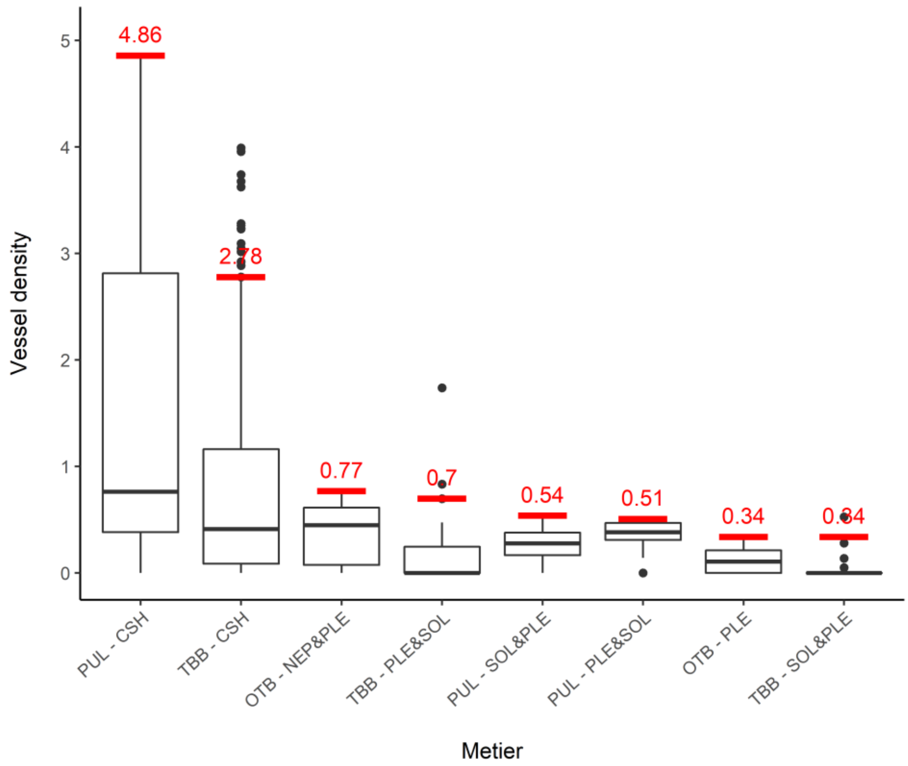

Figure A16. Boxplot of tolerated vessel densities during fishing trips by metier with 1.5 × inter quartile ranges (IQR) in red.

2.4 Fishing costs

We used information from the annual economic report of the Scientific, Technical, and Economic Committee for Fisheries (STECF) to model fishing costs except for fuel consumption which was calculated based on steaming and fishing times per trip. STECF information is available per year and fleet, the latter defined by fishing techniques (i.e. groups of fishing gears) and length classes. The STECF provides a wealth of economic variables, of which we will only mention the ones we used for our work (see https://stecf.jrc.ec.europa.eu/dd/fleet for all variables). All economic variables provided by the STECF are standardized for inflation by using the consumer price index of the year 2015 as a baseline. We extracted the following variables: *personnel costs, repair & maintenance costs, other variable costs, other non-variable costs, mean vessel length*, and *days at sea* (DAS). We restricted variables to the years 2008-2018, fishing techniques *demersal trawlers and seiners* (DTS), and *beam trawlers* (TBB), and the length classes to 12-18, 18-24, and 24-40 (all in m). Per year and fleet, we standardized all variable costs by dividing them through the DAS and created linear models by using mean lengths as explanatory and standardized costs as response variable (Figure A17A). Note that there was one data point per year resulting in 22 to 33 data points per length class and cost variable. Fixed costs (*other non-variable costs*) were not standardized by DAS and averaged across gears since they do not scale with effort or depend what gear is used gears. In the model, agents pay fixed costs every day depending on vessel size (Figure A17B).

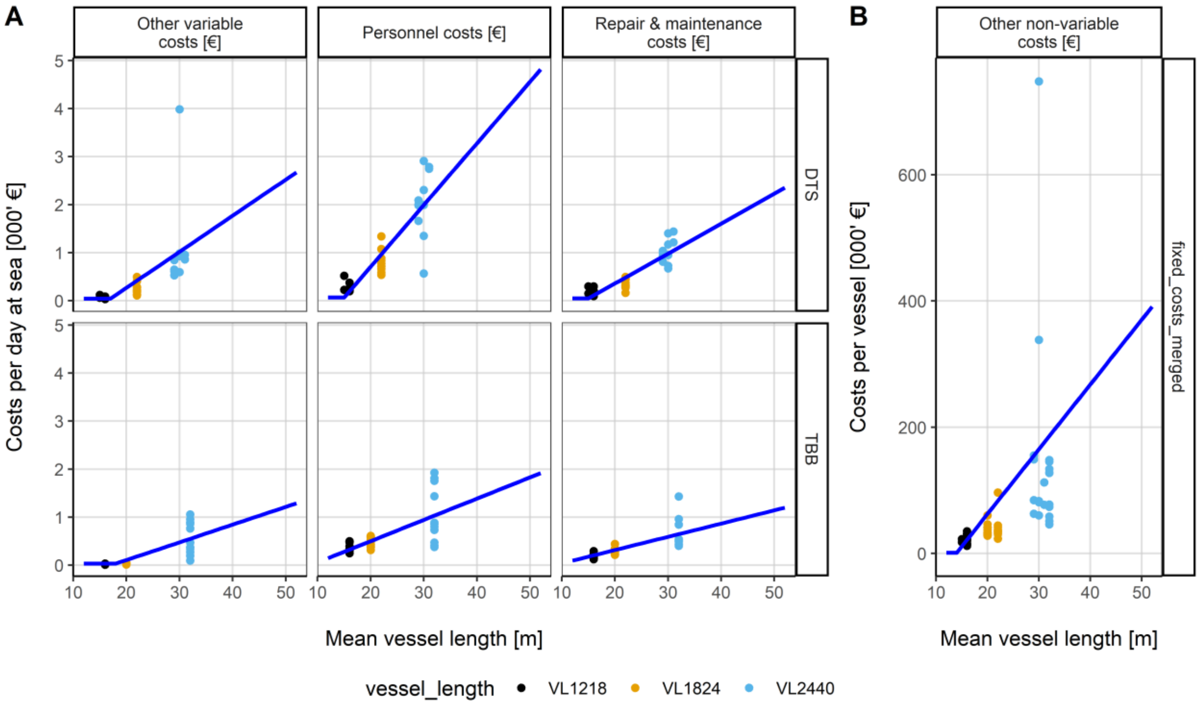

Figure A17. Yearly fishing costs per day at sea for each fishing technique present in FISHCODE. Blue lines represent linear models, ribbons 95% confidence intervals, and colors of points vessel length (VL) intervals in meters. A = variable costs; B = fixed costs. DTS: demersal trawlers and seiners, TBB: beam trawlers.

We calculated fuel costs per fishing trip based on vessels' engine power (kW), applying a formula developed by Bastardie et al. (2013),

$$C = (3.976 + 0.236 \times kW) \times A \qquad \textit{(Eq. 12)}$$

resulting in a proxy for fuel consumption per hour (C). A is a coefficient differentiating vessel activities, which is largest for when the vessel is fishing (1), smaller for steaming times (0.8), and smallest for inactive times (0.1). Inactive times were defined as those with speeds below 1 km/h. Pulse trawls are lighter than equivalent trawl gears, i.e. beam trawls, and have less contact with the sea floor resulting in a reduced fuel consumption of around 50% during trawling (Turenhout et al., 2016). Therefore, we changed A to 0.5 during fishing activity of pulse trawlers.

2.5 International fishing effort

Fishing effort in the North Sea is characterized by temporal variations induced by seasonal fisheries. To depict this distribution, we modeled weekly international vessel numbers per grid cell. We used available VMS data for the whole model area (North Sea) from 2015-2018 to derive weekly sums of international vessel occurrences per grid cell (0.045 lon × 0.045 lat). Subsequently, we calculated mean values per week of the year (WOY) for each cell and means and standard deviations for the whole area (entire grid). Then, we computed relative mean values per grid cell standardized by the mean area values during the respective WOY.

In FISHCODE, we update international vessel occurrences every week in two steps. First, we simulated the overall number of international vessel occurrences for the whole area. To do this, we create a standard distribution using the mean value and standard deviation of international vessel occurrences of the respective WOY and drawing one random number from it. Second, we read a raster file containing relative international vessel occurrences per grid cell for the respective WOY. Finally, we multiply relative grid cell values with the simulated overall value from step one.

In reality, some vessels might leave very early in the morning or they stayed overnight at sea, meaning that they are present before other vessels arrive, while others might leave the port later. For FISHCODE, this means that the distribution of international vessels should not always be at maximum, since the German fishers might be there before international vessels arrive. To simulate this variation in FISHCODE, we multiply international vessel numbers per grid cell with a number drawn from a random distribution (mean = 0.5, sd = 0.25) every day. This variation simulates that at some days international vessels are present before German vessels act and on other days they are already present.

2.6 Parameterization

We calibrated parameters that could not be derived from empirical data by using pattern-oriented modelling (POM), an established method for ABM parametrizations, which compares model simulations with varying input parameters to observed real-world patterns (Wiegand et al., 2003, 2004). In total, we parameterized seven model parameters (Table A6) using three categories of real-world patterns, i.e. spatial distribution of fishing effort, monthly number of trip days and monthly catch compositions. Each pattern category was split into sub-patterns: the catch composition into species (i.e. plaice, sole, brown shrimp, and Nephrops) and fishing effort and trip days into metiers with pulse and beam trawls grouped together (i.e. OTB – PLE, OTB – PLE&NEP, TBB/PUL – CSH, TBB/PUL – PLE&SOL, and TBB/PUL – SOL&PLE). With regard to the distribution of spatial fishing effort, we wanted to reproduce spatial fishing hotspots. Because the model operates on a high spatial resolution, we used a coarser grid resolution for the parameterization (0.5° × 0.5°) and relative fishing effort per grid cell instead of total hours. We created a base year scenario using averages of all economic and environmental data sets across the entire data range (2012-2018) and the initial agent memory of the year 2015. We compared model outputs to monthly averages (in case of trip number and catches) or monthly sums (in case of spatial fishing effort) of historical data (2012-2018). For every parameter constellation we performed 10 model runs and used averages to counteract the effect of stochasticity.

We used a step-wise procedure for the calibration of the seven model parameters to avoid extensive computation times due to large parameter spaces. In every step, we compared model results to sub-patterns by range-transforming (0 to 1) root mean square errors (RMSE). The transformed RMSEs had to fall below a threshold to pass the filter, which varied depending on the number of sub-patterns. A parameter constellation passed, if transformed RMSEs fell below the threshold in all tested sub-patterns. The number of sub-patterns varied in every step depending on the fleet that was parameterized and thus we adjusted the threshold to be more conservative when there were less sub-patterns and vice versa (details below).

First, we calibrated the two global parameters *fish depletion* and *fish recovery* by matching model outcomes of all fleets to nine sub-patterns with a threshold of 0.55. In this first step, we set the weightings of satisfactions and uncertainties equal meaning $0.\overline{33}$ and 0.5, respectively. *Fish depletion* and *fish recovery* influenced the patch-specific depletion coefficient and thus primarily affected catches, which is why we compared model outcomes to monthly catch compositions and spatial fishing effort. In addition, we removed all parameter constellations resulting in an averaged depletion coefficient of all patches <= 0.05 to avoid unrealistic high degrees of local depletion. Three parameter constellations passed all sub-patterns of which we used the median values for the following calibration steps and model validations. In the next three steps, we calibrated the five vessel specific weightings for the three satisfactions (i.e. existence, personal, and social) and two uncertainties (i.e. existence and social) individually for every fleet (CSH, OTB, and PLE&SOL). Depending on the fleet the number of sub-patterns varied and accordingly the transformed RMSEs had to fall below 0.35 (CSH), 0.4 (PLE&SOL), and 0.55 (OTB). When calibrating one fleet, we set the weightings of the other fleets equal. Weightings of satisfactions and uncertainties determined the agents' metier choices, which is why we used the two real-world pattern categories spatial fishing effort and monthly trip days. Note, that we only used sub-patterns of relevant metiers for each fleet, e.g. when parametrizing the OTB fleet, we used sub-patterns for the metiers OTB – PLE and OTB – NEP&PLE. In a final step, we used all constellations of weightings that passed the filters in the individual fleet calibrations and parameterized weightings for all fleets simultaneously. In this last round we set the threshold to 0.6 which resulted in one final parameter constellation (Table A6). Results of the final round can be found in *Appendix D*.

Table A6. Model parameter ranges used for the pattern-oriented modelling (POM) and results. CSH = brown shrimp, OTB = Otter bottom trawl (plaice & Nephrops), and SOL & PLE = flatfishes (sole and plaice). Bold values represent calibrated values used for the validation.

<table>
<tr><th>Parameter</th><th>Details</th><th>Tested values</th><th>Fleet</th><th colspan="2">Results</th></tr>
<tr><td>Fish depletion</td><td>The relative reduction in LPUE after a patch was fished</td><td>0.965 – 0.995 (0.05 steps) & 0.999</td><td>All</td><td colspan="2">.965|.97|.995</td></tr>
<tr><td>Fish recovery</td><td>The relative share of daily LPUE recovery</td><td>1.01 & 1.05 – 1.3 (0.05 steps)</td><td>All</td><td colspan="2">1.3|1.2|1.05</td></tr>
<tr><td></td><td></td><td></td><td></td><td>First</td><td>Final</td></tr>
<tr><td rowspan="3">Existence satisfaction</td><td rowspan="3">Increases the closer current savings are to target savings</td><td rowspan="3">0.1, 0.2, $0.\overline{33}$, 0.6, 0.8</td><td>OTB</td><td>$.2|.\overline{33}|.\overline{33}|.\overline{33}$</td><td>$.\overline{33}$</td></tr>
<tr><td>PLE&SOL</td><td>.1|.2|.2|.2</td><td>.2</td></tr>
<tr><td>CSH</td><td>$.\overline{33}|.6|.8$</td><td>.8</td></tr>
<tr><td rowspan="3">Personal satisfaction</td><td rowspan="3">Increases the more uniform own fishing actions are</td><td rowspan="3">0.1, 0.2, $0.\overline{33}$, 0.6, 0.8</td><td>OTB</td><td>$.2|.\overline{33}|.\overline{33}|.\overline{33}$</td><td>$.\overline{33}$</td></tr>
<tr><td>PLE&SOL</td><td>.1|.2|.2|.6</td><td>.2</td></tr>
<tr><td>CSH</td><td>$.\overline{33}|.2|.1$</td><td>.1</td></tr>
<tr><td rowspan="3">Social satisfaction</td><td rowspan="3">Increases the more often profits of trips are above those of peers</td><td rowspan="3">0.1, 0.2, $0.\overline{33}$, 0.6, 0.8</td><td>OTB</td><td>$.6|.\overline{33}|.\overline{33}|.\overline{33}$</td><td>$.\overline{33}$</td></tr>
<tr><td>PLE&SOL</td><td>.8|.6|.6|.2</td><td>.6</td></tr>
<tr><td>CSH</td><td>$.\overline{33}|.2|.1$</td><td>.1</td></tr>
<tr><td rowspan="3">Existence uncertainty</td><td rowspan="3">Decreases the more often profit predictions are higher than profits</td><td rowspan="3">0.1, 0.3, 0.5, 0.7, 0.9</td><td>OTB</td><td>.9|.5|.7|.9</td><td>.9</td></tr>
<tr><td>PLE&SOL</td><td>.3|.3|.9|.3</td><td>.3</td></tr>
<tr><td>CSH</td><td>.7|.7|.5</td><td>.5</td></tr>
<tr><td rowspan="3">Social uncertainty</td><td rowspan="3">Decreases the more similar fishing actions are to those of peers</td><td rowspan="3">0.1, 0.3, 0.5, 0.7, 0.9</td><td>OTB</td><td>.1|.5|.3|.1</td><td>.1</td></tr>
<tr><td>PLE&SOL</td><td>.7|.7|.1|.7</td><td>.7</td></tr>
<tr><td>CSH</td><td>.3|.3|.5</td><td>.5</td></tr>
</table>

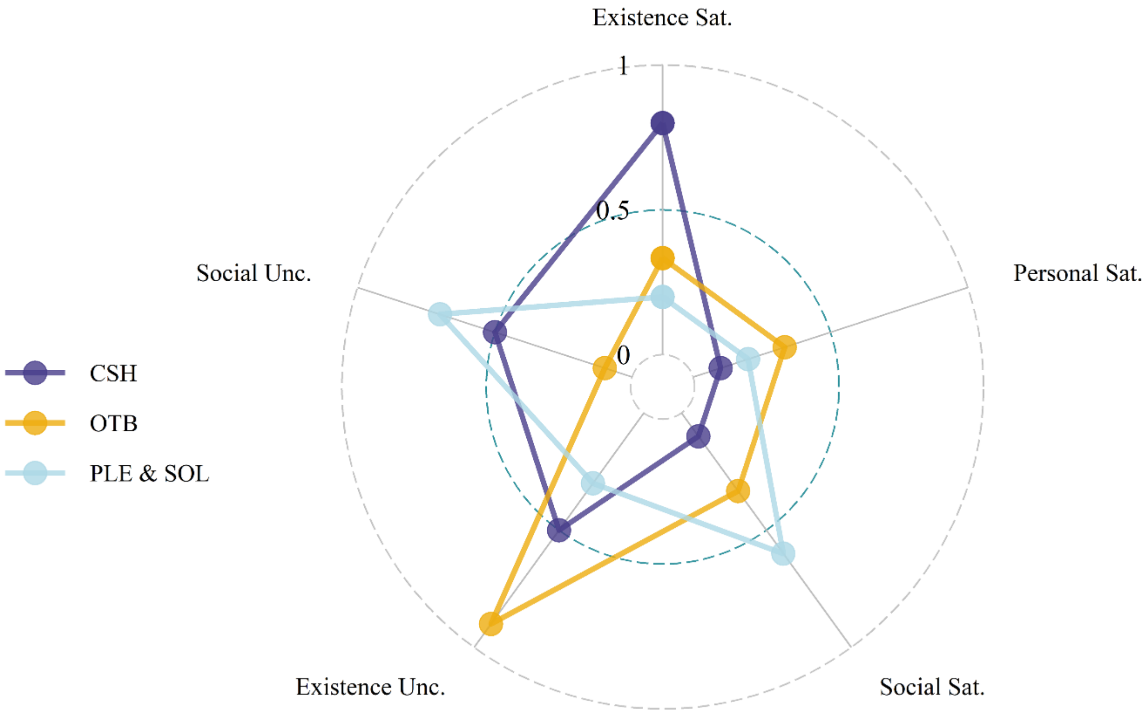

Figure A18. Parameterized weightings of satisfactions (Sat.), uncertainties (Unc.) after the final step of the pattern-oriented modeling for the three fleets: CSH = common (brown) shrimp, OTB = Otter bottom trawl (plaice & Nephrops), and SOL & PLE = flatfishes (sole and plaice).

3. Conceptual model evaluation

3.1 Description of the study system

FISHCODE is set in the southern North Sea, a shelf sea that is heavily fished since centuries and belongs to the most anthropogenically used areas in the world (Halpern et al., 2008, 2015). The southern North Sea is characterized by different habitats shaped by various sediment types (from fine sand to rocky reefs), geographical settings, such as trenches and low slopes between the coast and the barrier islands forming the Wadden Sea, and human-made spatial settings, i.e. offshore wind farms (OWFs) and fishing restrictions. German fisheries in the study area consist of the near-shore Brown Shrimp fleet and offshore demersal trawlers targeting either flatfishes (plaice and sole) or Nephrops. The Brown Shrimp fleet represents the largest German North Sea fishery in both economic relevance and vessel number, encompassing more than 200 vessels equipped with beam trawls. The flatfish and plaice offshore fleet is composed by about several medium sized “cutters”. For most vessels, plaice represents a lower incentive, because of the low market prices in comparison to sole and Nephrops. Nonetheless, there are some vessels that predominantly target plaice. All fisheries previously described use bottom trawls, which are very unselective and result in high bycatches. Fishing businesses are either small and mostly ran by families, or belong to large Dutch companies, although they are still registered as German-flagged vessels. Moreover, a large portion of the German catches are landed in the Netherlands where most of the processing industry is located. Most fishers are part of fishing organizations, which are organized by region and main target species.

3.2 Model assumptions

Due to the intense fishing activity in the southern North Sea, we assume that there are no unexplored fishing locations, meaning fishers do not need to invest time in exploring new catch grounds. In our model, this is reflected by a simplistic resource extraction sub-model. Both extensions of overall catch grounds and specific fishing locations are based on seven years of observed fishing effort. Similarly, the modelled catch amounts depend on standardized values of observed fishing trips of the same metier, which makes a biological submodel for fish stocks redundant.

Fishers are in contact with colleagues while being on land and in the port facilitating information exchange. Social ties are formed by geographical and institutional closeness, in our model, represented by social networks based on equal landing ports and/or being member of the same producer organization.

Human decision-making processes are complex and often involve motivations beyond pure profit maximization (Burgess et al., 2020; Groeneveld et al., 2017; van Duinen et al., 2016). Therefore, the individual decision-making of agents is the most complex part of FISHCODE involving economic motivations, habitual behavior, and social comparison. The Consumat approach allows the combination of different behavioral theories, making it is well-suited to model the decision-making of fishers in our study system (Jager et al., 2000; Jager & Janssen, 2012). Filatova et al. (2016) conclude that certain complexity in ABMs is required, so that the model can be restructured by its endogenous dynamics. In our model this necessary complexity is provided by the Consumat approach enabling agents to engage in different behavior strategies of varying complexity. Along with the heterogeneity of the agent's state variables, this ensures that agents can adapt to new situations, such as changing market prices or altered resource availabilities.

Especially small-scale and family-owned fishing businesses are often marked by habitual behavior, meaning that they want to continue fishing for the sake of fishing. For many fishing is a way of life rather than a profession (unpublished data from interviews with fishers), which is represented by the personal satisfaction of the Consumat approach. Being in contact with colleagues also facilitates rivalry for having the best catch, which is covered by the social satisfaction. Finally, fishers still need to survive from what they catch, which is why we included the existence satisfaction in the Consumat approach. Despite years of fishing experience, catches remain only partly predictable and together with new environmental settings due to climate change and policy reforms they impose high uncertainties for fishers. Fishers might feel uncertain if the majority of their colleagues engages in other fishing types. The social uncertainty increases, the more the past metiér choices of an agent differ from those of its colleagues. The existence uncertainty is related to the unpredictability of profits and increases if an agent's predictions for fishing trip revenues differs from what the agent earned after the trip. A detailed description of the Consumat approach can be found in the ODD+D protocol (*1. Problem foundation & 2. Model description*).

4. Implementation verification

4.1 Verification of behavioral drivers

We tested the functionality of the Consumat approach by setting the respective weightings of satisfactions and uncertainties to the extremes (1 and 0) for one vessel. Setting a weighting of a satisfaction to one automatically sets weightings of the other satisfactions to zero and thereby excludes them entirely. The same holds true for the two uncertainties. In total, we tested six parameter constellations comprised of extreme values (weighting = 1) for each of the five weightings of satisfactions and uncertainties and one constellation with equal weightings, i.e. $0.\overline{3}$ for satisfactions and 0.5 for uncertainties. The equal values were also chosen for the non-tested vessels, as well as for weightings of uncertainties when setting the weighting of a satisfaction to 1 and vice versa. We created an artificial testing environment consisting of three vessels from each metier and initialized their memory with random fishing trips from 2012 to 2015. All exogenous variables, i.e. market prices and environmental factors were set to monthly averages equal to the base year scenario. We ran 15 simulations for each scenario, averaged across these repetitions, and extracted results for the tested vessel. We repeated this exercise once for every metier.

Each of the satisfactions and uncertainties stands for a specific aspect of human behavior and increasing its weighting, enhances the respective behavioral aspect and allows analyzing the consequences. This enabled us to test whether the behavioral aspects influence the agents in the envisioned ways. Satisfactions and uncertainty influence agents' decisions on two stages. The first stage is the Consumat approach in which agents select different strategies to perceive a pool of metier options according to their current status of being satisfied or unsatisfied and certain or uncertain. Generally, the more successful an agent is in maximizing his satisfactions and minimizing his uncertainty, the more often will the agent choose repetition as his behavioral strategy leading to similar metier choices and vice versa. If the agent becomes unsatisfied or uncertain, he starts to perceive more than one possible metier choice and needs to decide which metier to engage into. In this second stage, agents predict fishing outcomes and the affiliated changes in satisfactions and uncertainties for all metier options they would technically be able to perform. They then choose the option that promises the highest sum of gains of overall satisfaction and loss of overall uncertainty. Therefore, setting the weighting for a satisfaction or uncertainty to one, should influence the agents' decision processes to prioritize options that lead to higher satisfactions or lower uncertainties. Here, we describe the results for two metiers (OTB – NEP&PLE and PUL – SOL&PLE) in detail while results for the others are in the *Appendix C*. Table A7 summarizes the expected effects of setting the weighting of certain satisfaction or uncertainty to one.

Table A7. Expected effects of increasing a certain weighting of a satisfaction or uncertainty to 1.

Weighting of	Expected effect
Existence satisfaction (WESAT)	Increased revenues
Personal satisfaction (WPSAT)	Metier continuity (habitual behavior)
Social satisfaction (WSSAT)	Increasing revenues to earn more than peers
Existence uncertainty (WEUNC)	No direct effect, but indirectly by setting WSUNC to 0
Social uncertainty (WSUNC)	Engage in similar metiers than peers

To test the functionality of our defined behavioral motivations, we experimented with setting the weightings of satisfactions and uncertainties to the extremes while observing one agent of a specific default metier. Observing an OTB – NEP&PLE agent, high WESAT and WSSAT led to the expected outcome of higher savings and a faster increase of the respective satisfactions as in comparison to the equal scenario (Figure A19B&C). Savings were much higher in the WSSAT scenario, because SSAT was mostly below the 0.5 threshold triggering deliberation as Consumat strategy, which increased the agent's flexibility in metier choices. The low savings in the WPSAT scenario clearly demonstrated the priority of choosing the same metier (OTB – NEP&PLE) over improving profit (Figure A19A&B). The only available gear to this agent was OTB, because the only metiers in his artificial initial memory were OTB – NEP&PLE and OTB – PLE. A high WSUNC triggers the alignment of an agent's metiers choices with his peers, however, this effect was limited, because of the constrained metier choices. This might differ when agents' initial memories are based on real-world trip histories, because some OTB fishers do occasionally switch to flatfishes giving them more options to choose from. In the WEUNC scenario, the agent accumulated high savings resulting in a high ESAT. The reasons were twofold, first, WSUNC was set to zero in this scenario meaning that the agent had no tendency of choosing similar metiers than his peers. Second, the usually lower SUNC was not present leading occasionally to the overall uncertainty being above 0.5, which in turn triggered a more complex consumat strategy (imitation) with multiple metier options to choose from. Both reasons increased flexibility in the agent's metier choices and therefore resulted in a higher economic efficiency.

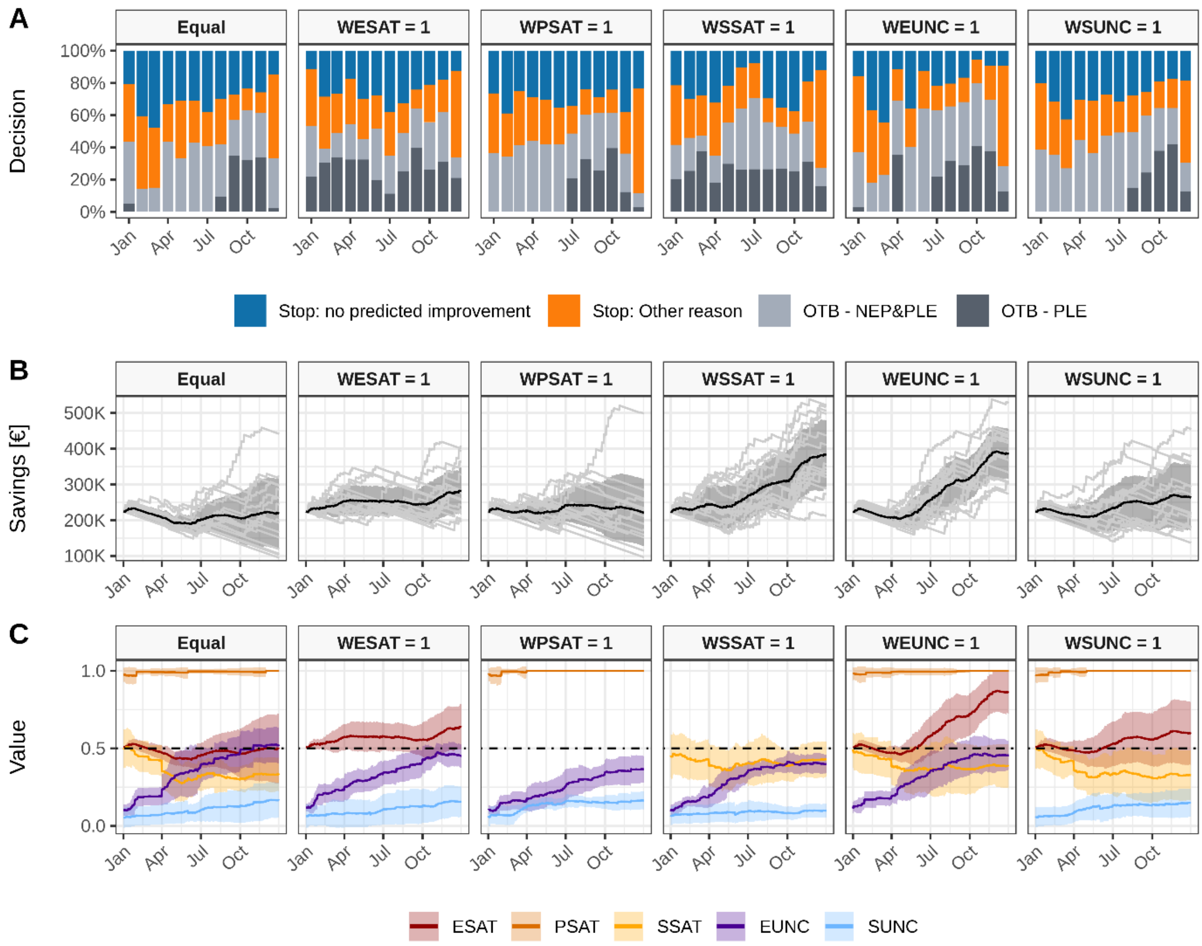

Figure A19. Outcome of the consumat testing for one vessel from the OTB – NEP&PLE metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean daily satisfactions and uncertainties with the dotted line displaying the threshold for being satisfied and uncertain. The ribbons in B and C represent standard deviations.

Testing an agent from the PUL – SOL&PLE metier, savings and ESAT grew most consistently across model runs in the WESAT scenario (Figure A20A&B). Except for setting WPSAT to one, all other scenarios led to similar high savings, although the variation across model runs was large with some resulting in not going fishing throughout most of the year leading to continuously decreasing savings. The reason for that was that most satisfactions and uncertainties require either a threshold to be surpassed or choosing a certain metier in order to increase. If the metier options available are not predicted to surpass profits from peers (for SSAT) or the right metier is not among them (for PSAT and SUNC), the agent will predict no improvements for the sum of gain in satisfaction and loss in uncertainty, meaning the agent would stay in the port. Setting WPSAT to one restricted the flexibility of choosing different metiers, because the agent’s only way to increase his overall satisfaction was to choose the same metier (PUL – SOL&PLE) again. With having WSUNC above zero, the agent engaged in similar metiers than his peers, i.e. PUL – PLE&SOL, and TBB – SOL&PLE. The effect of setting the WEUNC to one negated that effect, because WSUNC is zero in that scenario, meaning that the agent had more consistent metier choices. In some occasions, the agent's satisfaction was below or the uncertainty above 0.5 meaning that the agent switched his consumat strategy. This gave the agent more metier options to choose from leading to a more diverse metier engagement (e.g. in November and December of the Equal, WSSAT, or the WEUNC scenario).

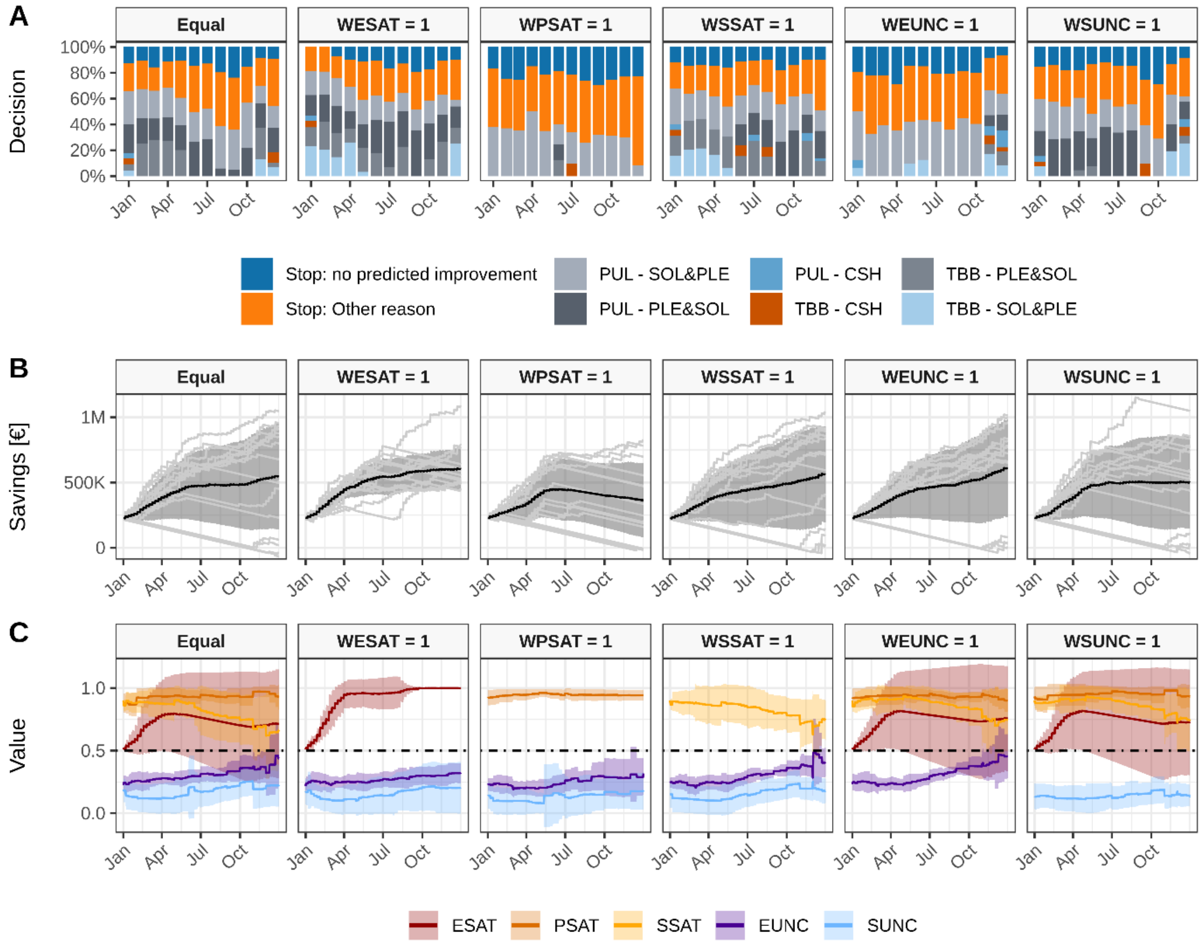

Figure A20. Outcome of the consumat testing for one vessel from the PUL – SOL&PLE metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean daily satisfactions and uncertainties with the dotted line displaying the threshold for being satisfied and uncertain. The ribbons in B and C represent standard deviations.

Generally, setting the weighting of a parameter to one led to maximizing the respective satisfaction confirming our general expectations (Table A7), although the effects were often blurred due to the complexity of the Consumat approach. Increasing a weighting did not only raise the incentive for maximizing the respective satisfaction (or reducing the respective uncertainty), but also led to the choice of different Consumat strategy. Those strategies offer varying numbers of metiers to choose from and therefore determine the agent's flexibility to engage into different. The effect of varying flexibility had a strong influence on economic efficiency.

Metier engagements were mostly influenced for agents with more available choices of metiers, such as those catching primarily the flatfish plaice and sole. In our model agents catching flatfish may choose either electric pulse (PUL) or beam trawls (TBB) and have sufficient quotas to switch between catching predominantly plaice (PLE&SOL) or sole (SOL&PLE) or even to common shrimp (CSH), which does not require any quota but uses the same fishing gears. Therefore, metier choices were most varied with agents engaged in flatfish metiers such as PUL – SOL&PLE. In addition, metier choices were most varied when WPSAT was high or WSUNC was low.

5. Model output verification

To validate our model, we performed 50 simulations of German southern North Sea fisheries using the base year scenario (see *Parameterization*). We then compared the 1.5 inter-quartile range (IQR) of model outputs on different aggregations, i.e. total, monthly, per vessel, per trip (x-axes in Figure A21A) and per grid cells (x-axes in Figure A21B), to observed values from 2012 to 2018. In case of the model results, each simulation (n = 50) and in case of the observed every year (n = 7) served as sample point. Some model outputs were recorded on a trip basis (i.e. *Trip days*, *Fishing time*, *Steaming time* in Figure A21A), whereas others were resolved on species level (i.e. *Landing weight* and *Revenue* in Figure A21B). In general, we calculated sums for the aggregation levels with the exception of *Trip length* and *Steaming time* per grid cell for which we calculated medians. When comparing landing weights and revenues per species, we selected only relevant species for the respective metier, e.g. plaice and sole for TBB – PLE&SOL. We considered a simulation output as a good fit, if the 1.5 IQRs of the modelled and observed values overlapped and calculated the percentage of data points with overlapping intervals. In case outputs were aggregated for the entire model run (i.e. as on the total aggregation), this percentage was either 0 or 100, meaning the interval either overlapped or it didn't, whereas it was more varied for all other aggregations.

On average, our model produced outcomes for *fishing time*, s*teaming time*, and t*rip length* that matched their historical counterparts best on the micro pattern of individual trips and the macro pattern of total aggregates (Figure A21A). The quality improved from vessel to monthly and was best for the total aggregation showing that simulations of individual agents reflected only marginally the reality of these vessels but results on higher aggregations were reliable. In the model, the three trip variables are closely interlinked, because f*ishing time* is the difference between *trip length* and *steaming time*. On single trip level, all variables had an excellent match for all metiers, confirming sensible estimations of steaming times and correlation between steaming and fishing time. The good match of *trip length* on trip level was expected, because they are derived from the trip data base and are not an emergent property of the simulation, but confirms the code functionality.

Modeled *steaming time* for TBB – CSH did not match well with observed values (Figure A21A), because steaming times per fishing trip were slightly overestimated for TBB metiers (Figure E3). In case of TBB – CSH this error adds up leading to a mismatch of total aggregated steaming times, because it is also the metier with the most fishing trips. We derived steaming speeds from the trip data base per fishing gear resulting in low speeds for the TBB gear in comparison to the PUL gear (*Steaming speed and time*). Interestingly these two gears can interchangeably be used by the same vessels and target assemblages and therefore should result in similar steaming speeds. Therefore, TBB steaming speeds are likely underestimated in FISHCODE.

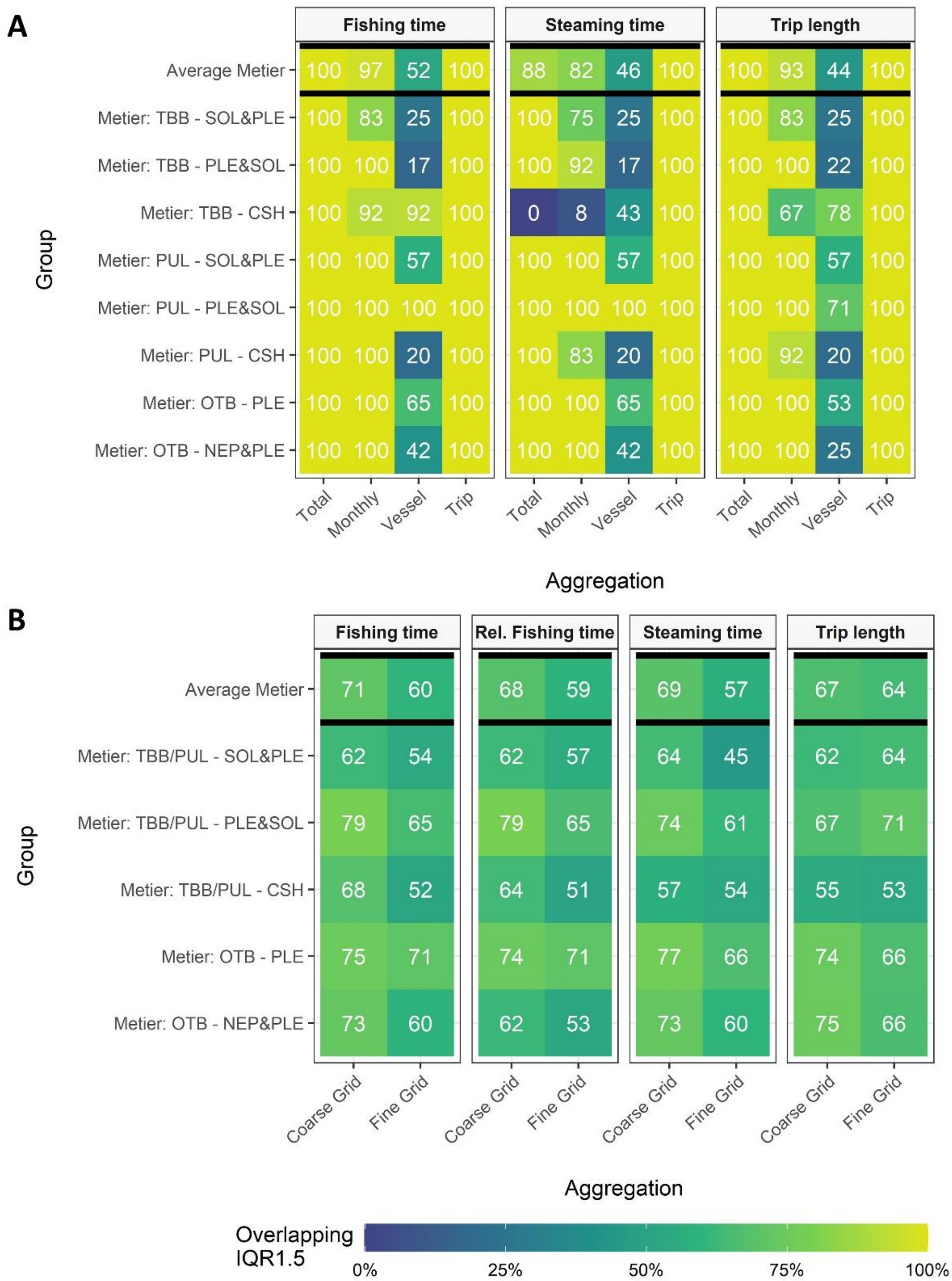

Figure A21. The percentage of data points with overlapping 1.5 times inter-quartile ranges (IQR1.5) between modelled and observed non-spatial (A) and spatial (B) variables. Colors and numbers correspond to the percentage of overlaps across different aggregations (columns) and metiers (rows).

With regard to spatial results, matches on coarse were better than on fine grid resolutions, meaning that the precision of simulated spatial fishing effort was more reliable if aggregated to coarse grid cells (Figure A21B). On average, percentages of matching coarse grid cells were in an acceptable range (above 60%), whereas fine grid cells matched about 10% worse. The total distribution of *fishing time* matched slightly better than the relative distribution of fishing effort, despite the fact that we used the latter for the model parameterization. This validates that in addition to spatial fishing hotspots, the model simulated fishing effort in a reasonable range. The good matching of median *steaming time* per grid cell validated assumptions for calculating steaming times and distances from ports to fishing grounds. Both the simulated and observed distribution of spatial fishing effort followed a decreasing trend from coast to offshore with some hotspots in the offshore areas (Figure A22A&C). These hotspots show a more refined pattern in the observed distribution, because the simulated fine-scale movements per fishing trips are the result of random paths (levy flights). A comparison of standard deviations (SD) shows that SDs scale with total fishing effort, but were larger in coastal grid cells among historical years than they were among model runs (Figure A22B&D).

Addition graphs for of validation can be found in *Appendix E*.

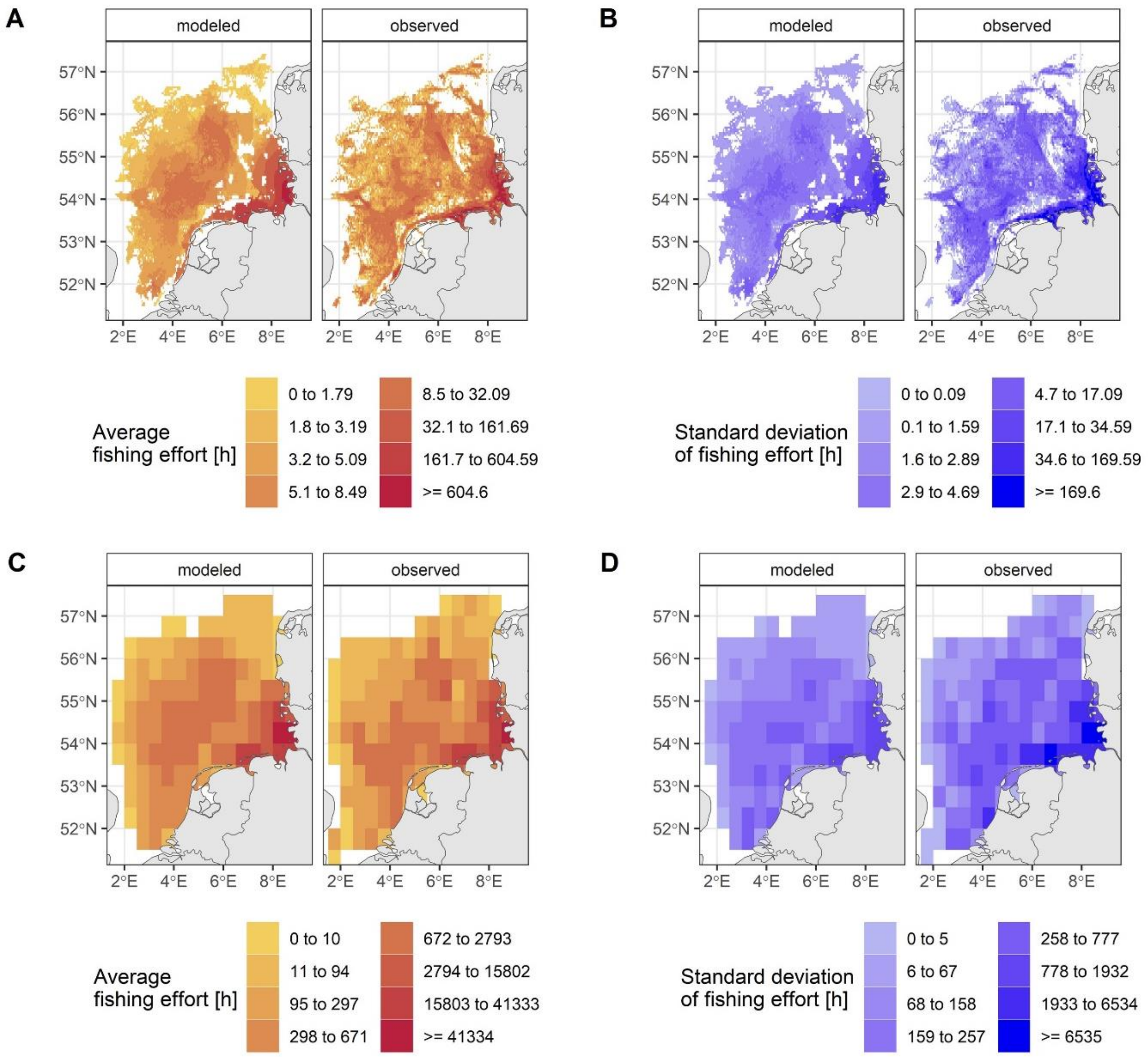

Figure A22. The averaged fine (A) and course (C) distribution, as well as fine (B) and course (D) standard deviation of fishing effort across validation model runs (modeled) and seven years of data (observed).

6. Sensitivity Analysis

6.1 Morris screening

To test the sensitivity of model parameters we used a Morris screening, which is an efficient way to test the sensitivity of large parameter spaces (Morris, 1991). Morris screening is based on the much simpler method of changing parameters one at a time (OAT) and involves many OAT procedures on different levels. For each tested parameter, the number of starting points, the total levels of changing each parameter and the number of levels changed (called grid jump) need to be defined. From the results, elementary effects (EE) can be calculated for each change and subsequently the parameters σ and μ^* derived, the former informing about the type of effect of the tested parameter and the latter about the strength of its influence (Campolongo et al., 2007). Furthermore, the ratio of σ and μ^* informs about whether parameter effects were almost linear (< 0.1), monotinic (< 0.5), almost monotonic (< 1) and non-linear and/or non-monotonic or interactions with other parameters (> 1) (Garcia Sanchez et al., 2014). In total, we tested the sensitivity of 13 model parameters on eight model outcomes (Figure A24). We set the starting points to 30, the levels to 11, and the grid jump value to five. We simulated the base year (see *Parameterization*) and included two vessels per metier. In order to test sensitivity on landing compositions, fishing effort, and spatial dynamics, we recorded the accumulated landings of plaice, sole, Nephrops, and common shrimp, the number of trip days, the total number of trips, as well as the mean longitudes and latitudes of fishing trips at the end of each simulation. All analyses were made in R with the nlrx package (R Core Team, 2023; Salecker et al., 2019).

The sensitivity analysis showed that almost all tested model parameters affected model outcomes in a complex way, meaning that the effects were non-linear and/or non-monotonic (Figure A23). The only factor with a less complex and almost monotonic effect on fishing trips and CSH catches was *probability needing repair*, which was expected because it represents a probability for vessels to be incapable of fishing for two days after an they returned from a fishing trip. It affected CSH catches stronger than other catches (Figure A24), because CSH fishers have the shortest and most fishing trips and therefore have a higher chance for vessels needing maintenance. The parameter *fish recovery* and *international vessel multiplicator* had a strong effect on catches of all species, the first regulating the recovery of marine resources and the latter the number of international fishing vessels. Of the weightings (W) for satisfactions and uncertainties, personal satisfaction (PSAT) and social satisfaction (SSAT) had the strongest impact, followed by social uncertainty (SUNC), existence uncertainty (EUNC), and existence satisfactions (ESAT). Economic parameters, i.e. *aspired savings* and *monthly expanses*, and those adding stochasticity to the model, i.e. *perceiving error* and *CPUE uncertainty*, had the weakest effects.

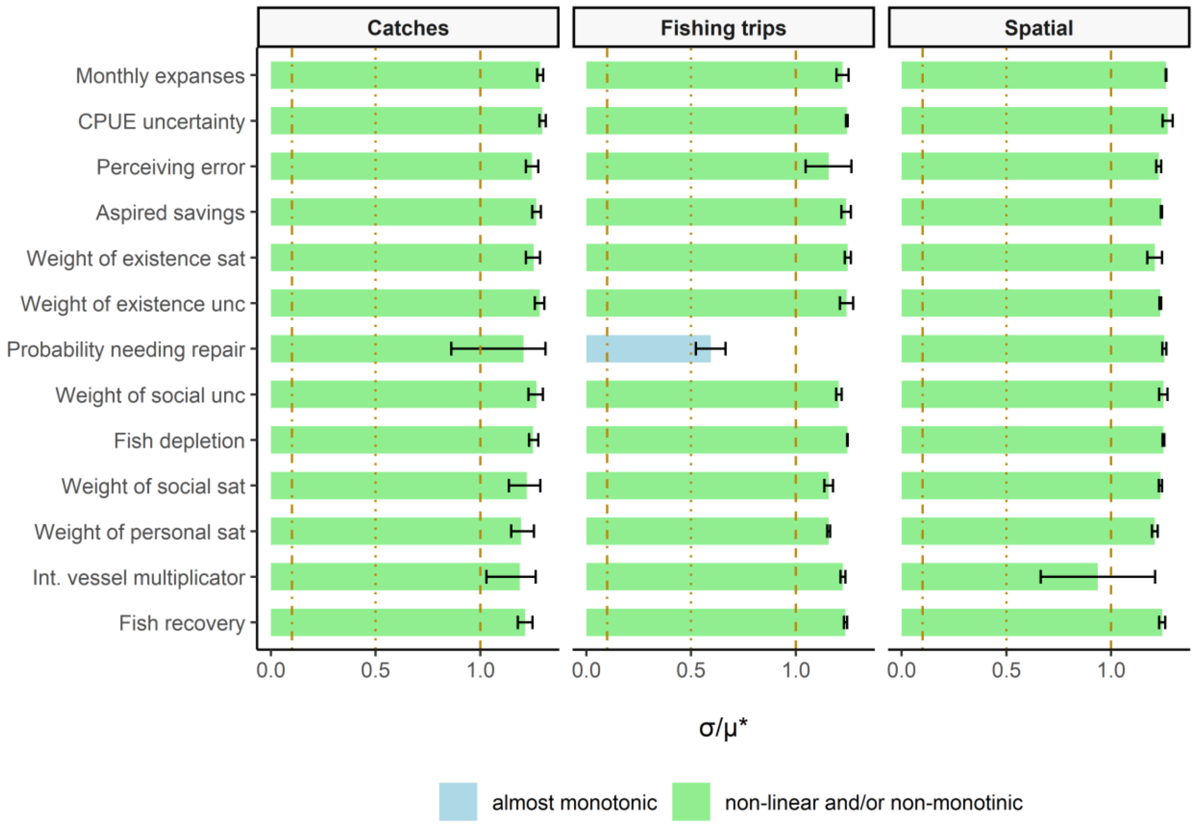

Figure A23. Results of the morris screening showing the type of effect from model parameters on groups of model outcomes. Panels represent groups of the model outcomes used to test sensitivies. Error bars represent minimum and maximum values in the respective group. Red dashed lines represent areas for almost linear (< 0.1), monotinic (< 0.5), almost monotonic (< 1) and non-linear and/or non-monotonic or interactions with other parameters (> 1) (Garcia Sanchez et al., 2014).

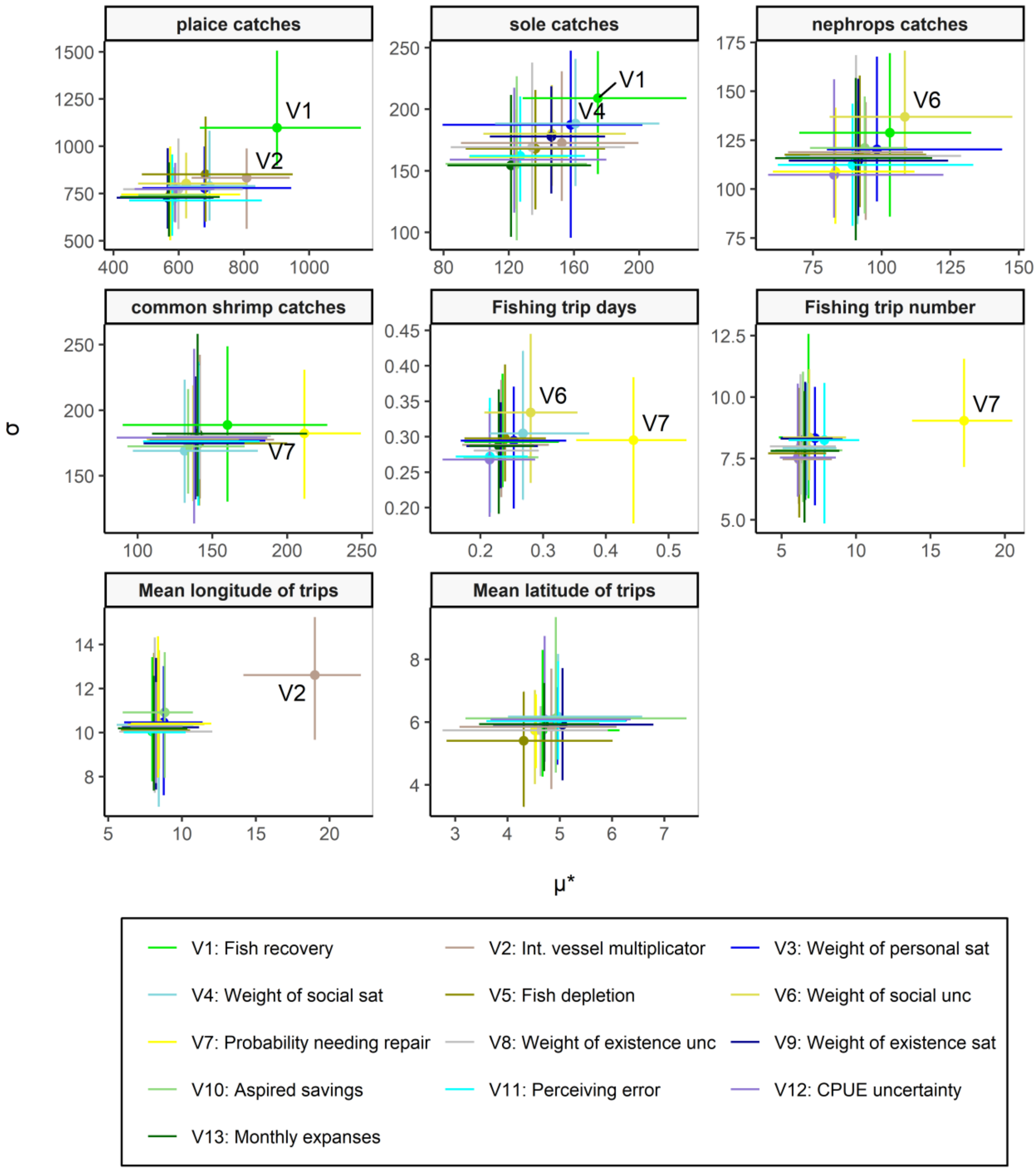

Figure A24. Results of the morris screening. Colors refer to the model parameters and panels the to the model outcomes. Y-axis show the absolute mean effect of a model parameter, while the x-axis shows the type effect.

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Appendix B - Details trip data base

Details on Percentile Filters Applied to the Trip Data Base

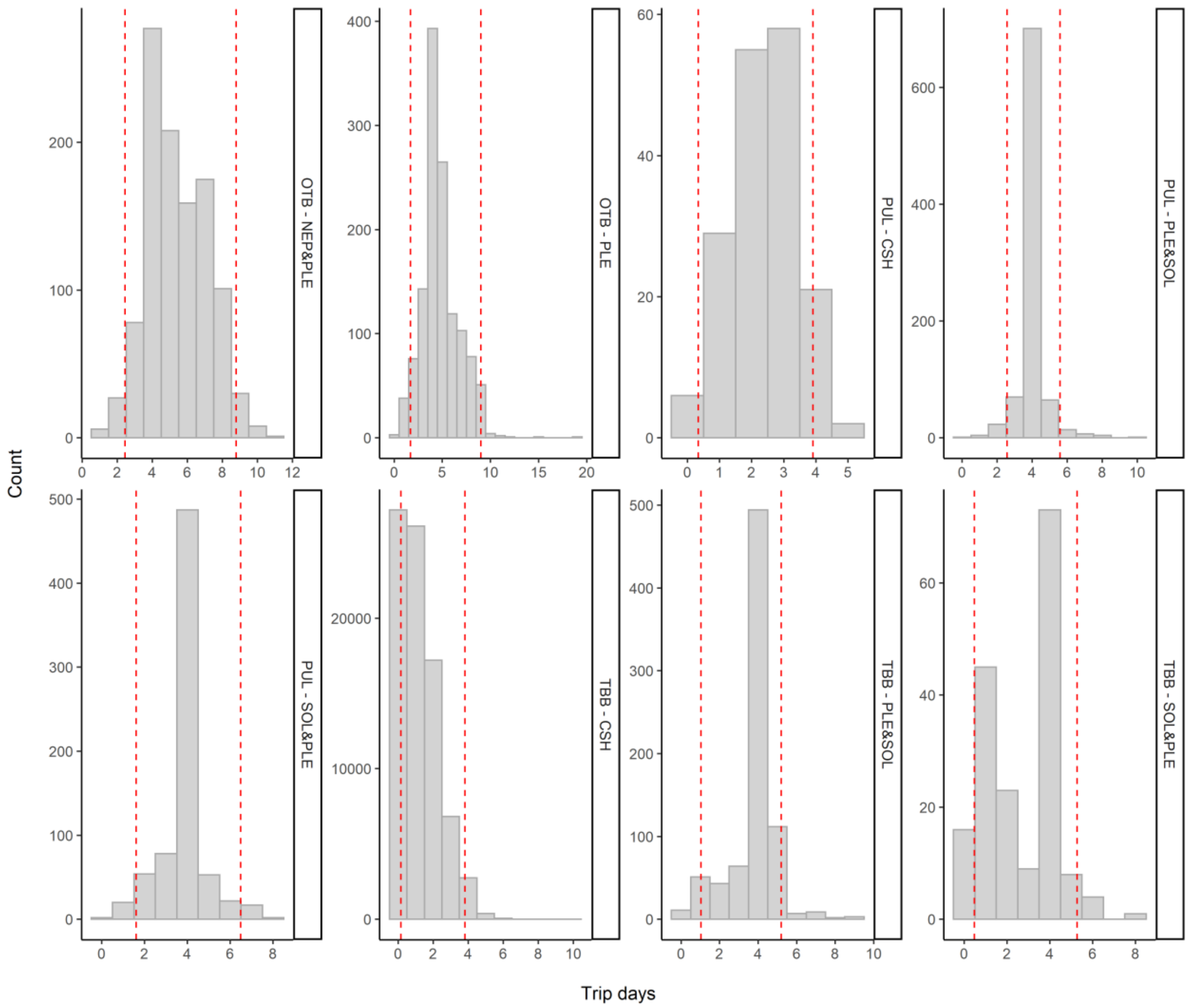

Figure B1. Fishing trip durations per metier. Red dotted lines show the 1st and 99th percentiles. Trips outside of this interval were considered erroneous and removed.

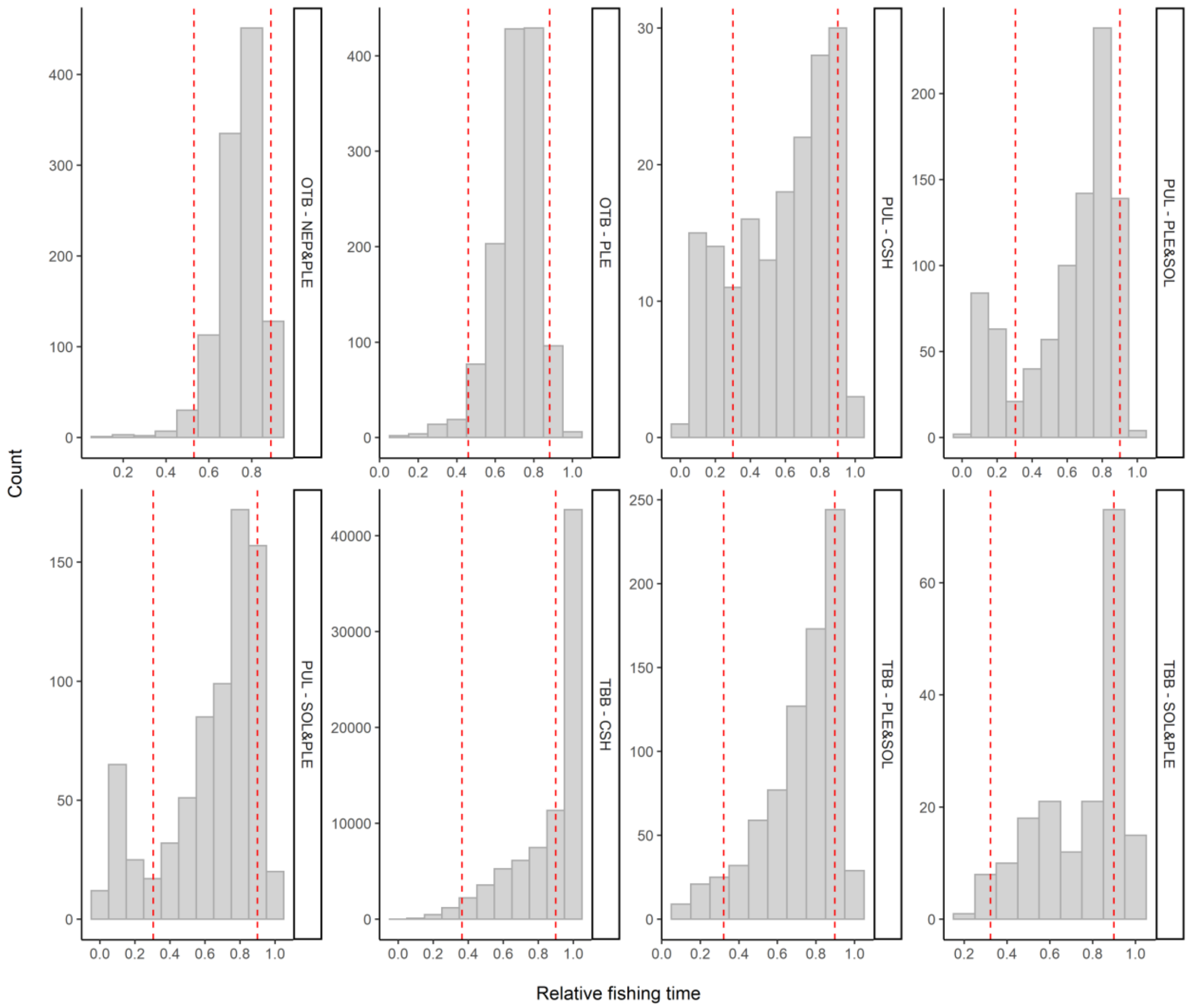

Figure B2. Relative shares of fishing time per trip and per metier. The red dotted line represents threshold (0.2), below which we removed fishing trips from the trip data base.

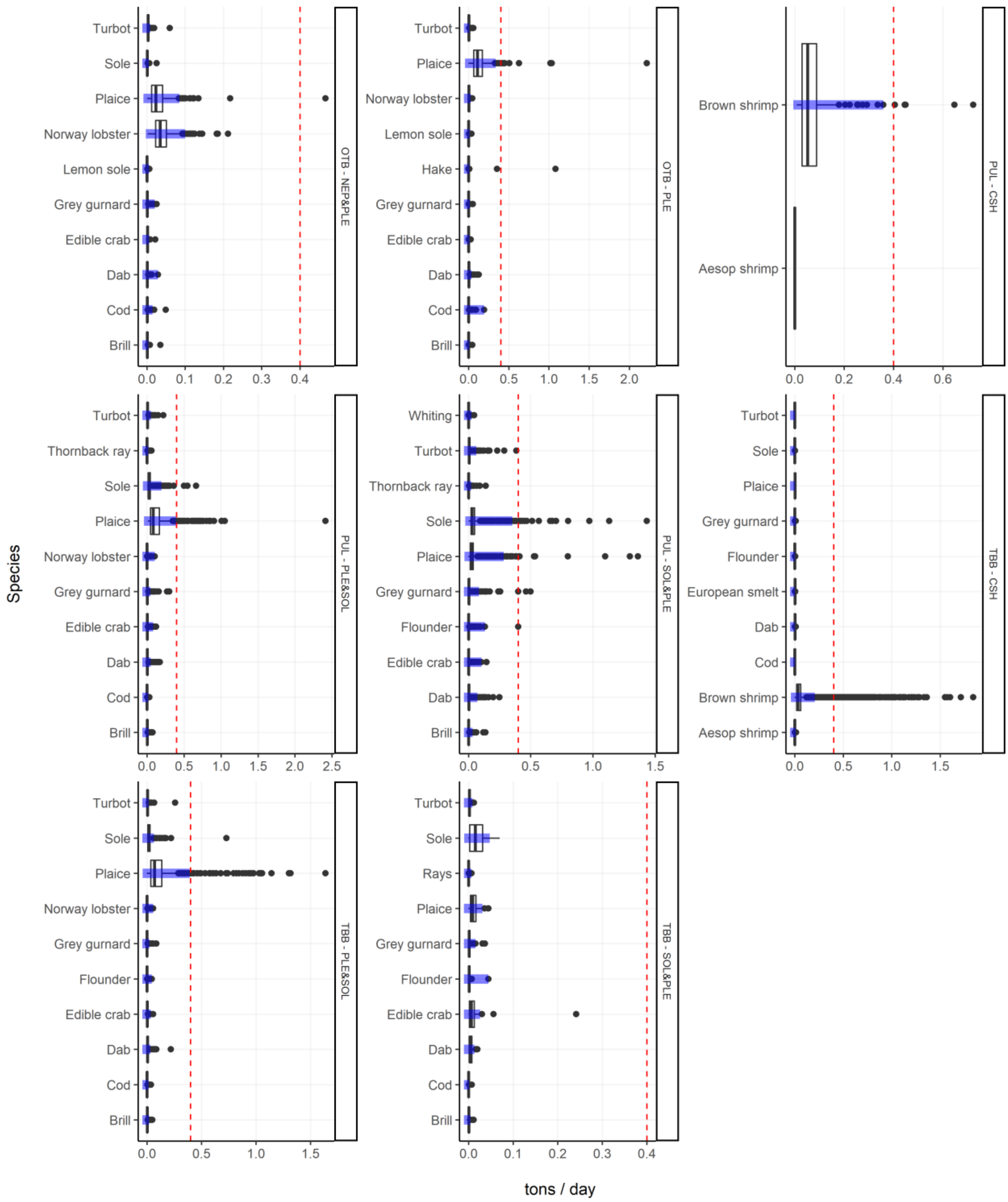

Figure B3. Catches per unit effort (LPUE; tons per trip day) per metiér of the 10 most abundant species caught species. Data points outside of the blue bars were removed either because of the 2.5th to the 97.5th percentile filters or being above 400 kg/h (red dashed lines).

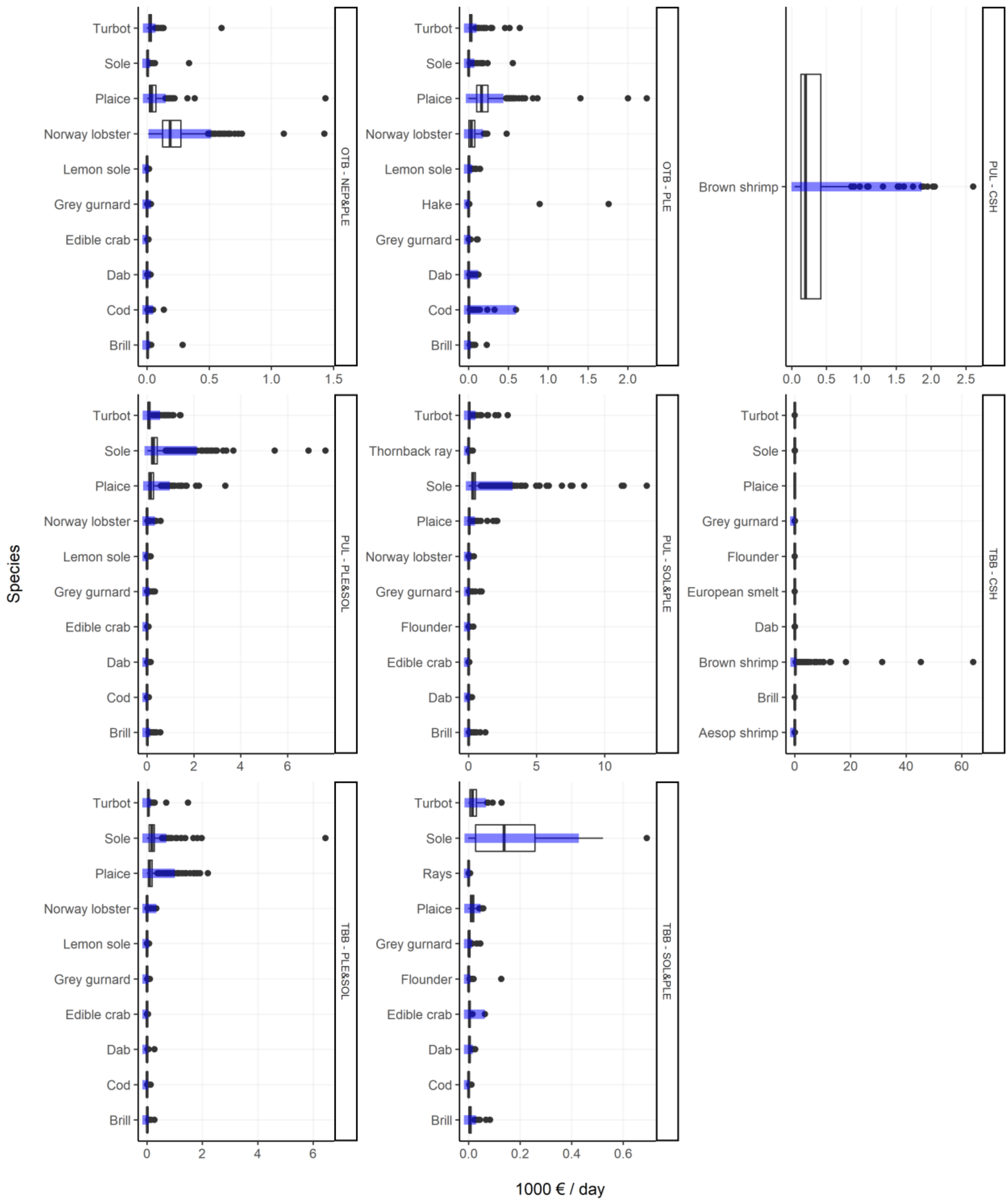

Figure B4. Values per unit effort (VPUE; 1000€ per trip day) per metier of the most abundant caught species. Data points outside of the blue bars were removed because of the 2.5th to the 97.5th percentile filters.

Appendix C – Details verification of behavioral drivers

Additional Implementation Verification Results

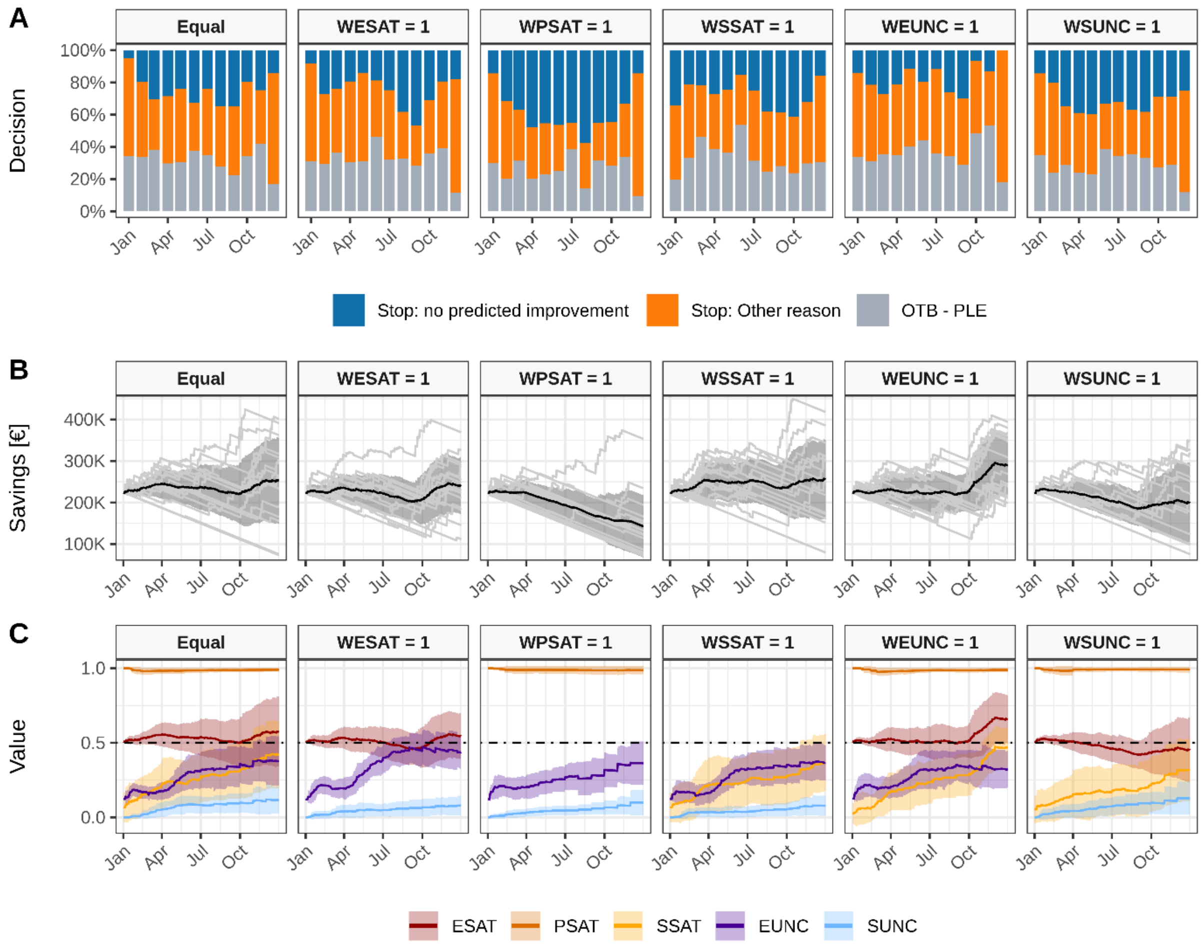

Figure C1. Outcome of the Consumat testing for one vessel from the OTB – PLE metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean daily satisfactions and uncertainties with the dotted line displaying the threshold for being satisfied and uncertain. The ribbons in B and C represent standard deviations.

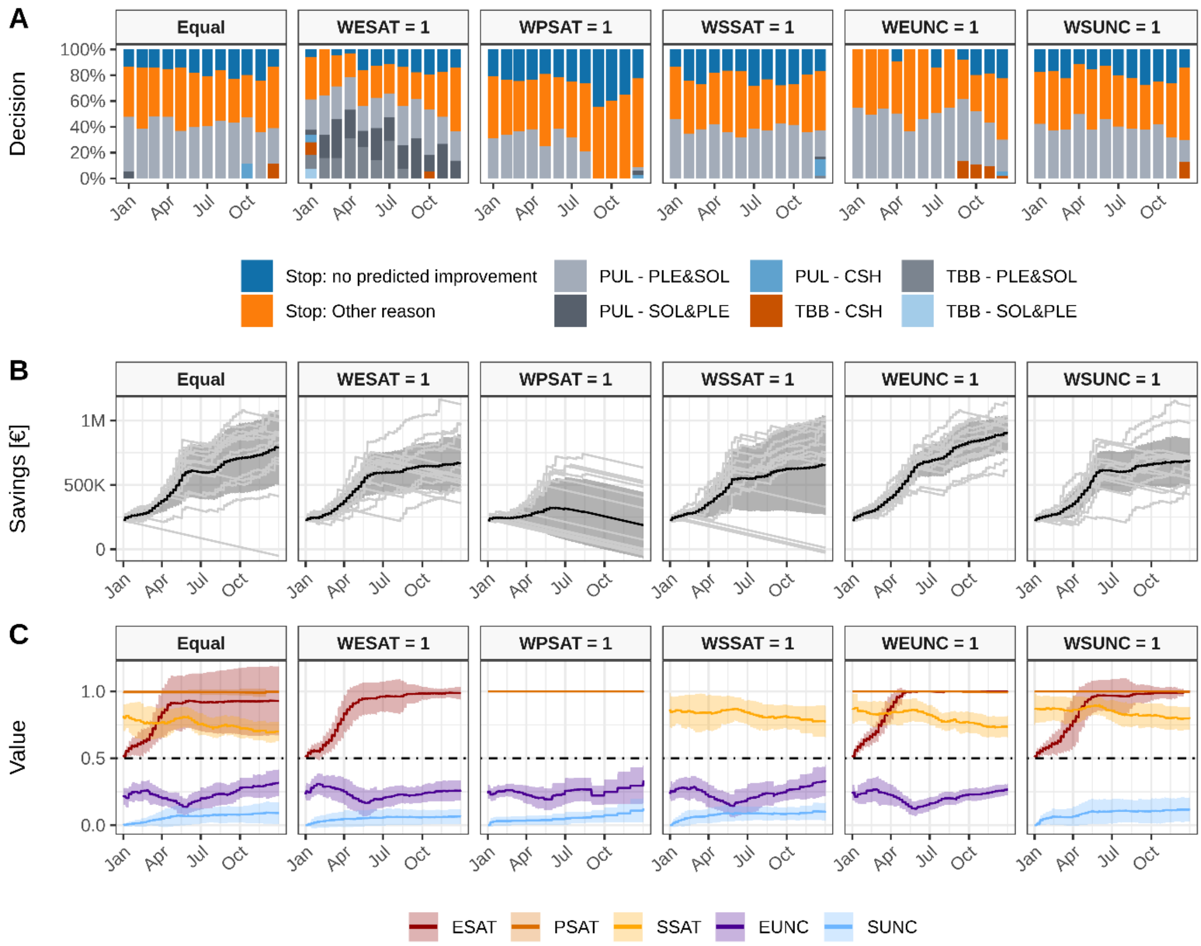

Figure C2. Outcome of the Consumat testing for one vessel from the PUL – PLE&SOL metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean daily satisfactions and uncertainties with the dotted line displaying the threshold for being satisfied and uncertain. The ribbons in B and C represent standard deviations.

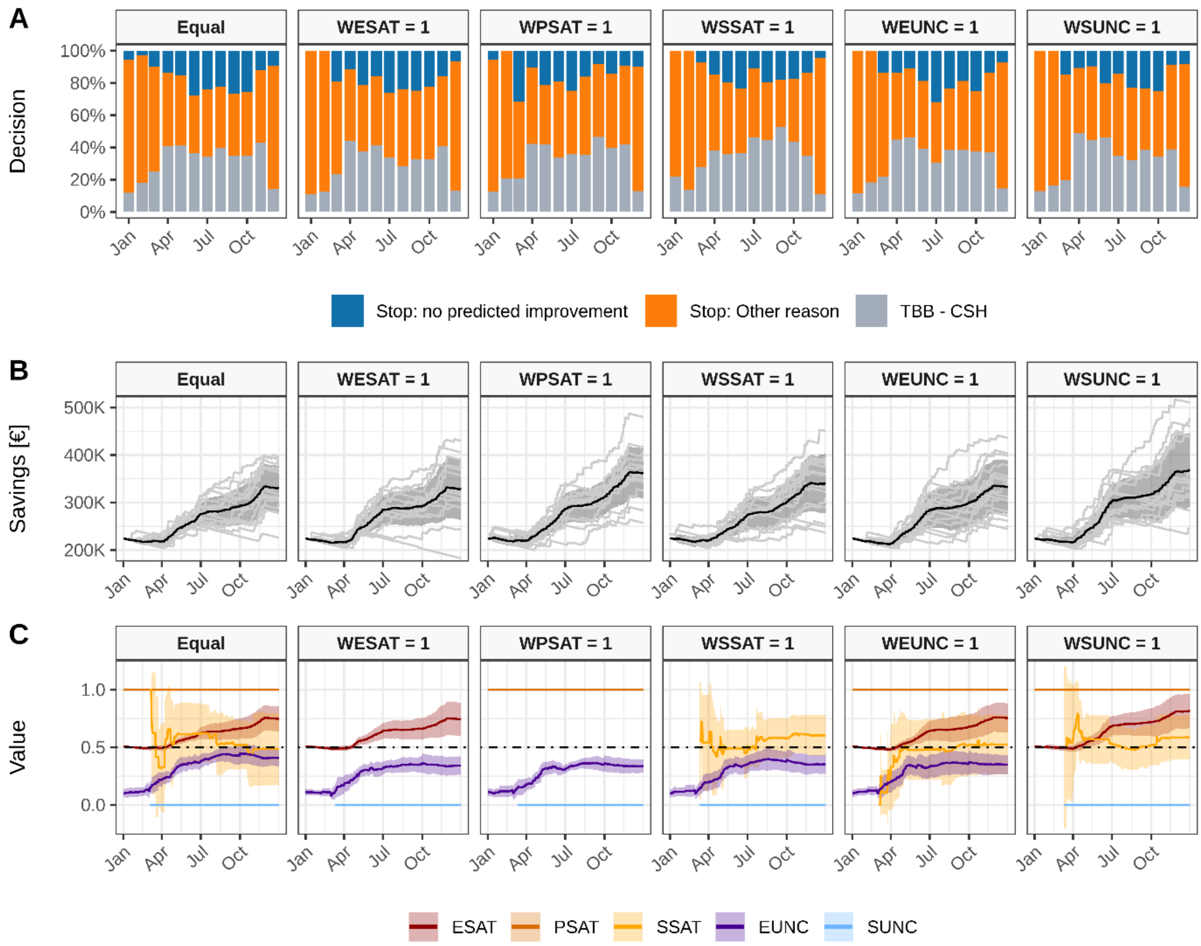

Figure C3. Outcome of the Consumat testing for one vessel from the TBB – CSH metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean daily satisfactions and uncertainties with the dotted line displaying the threshold for being satisfied and uncertain. The ribbons in B and C represent standard deviations.

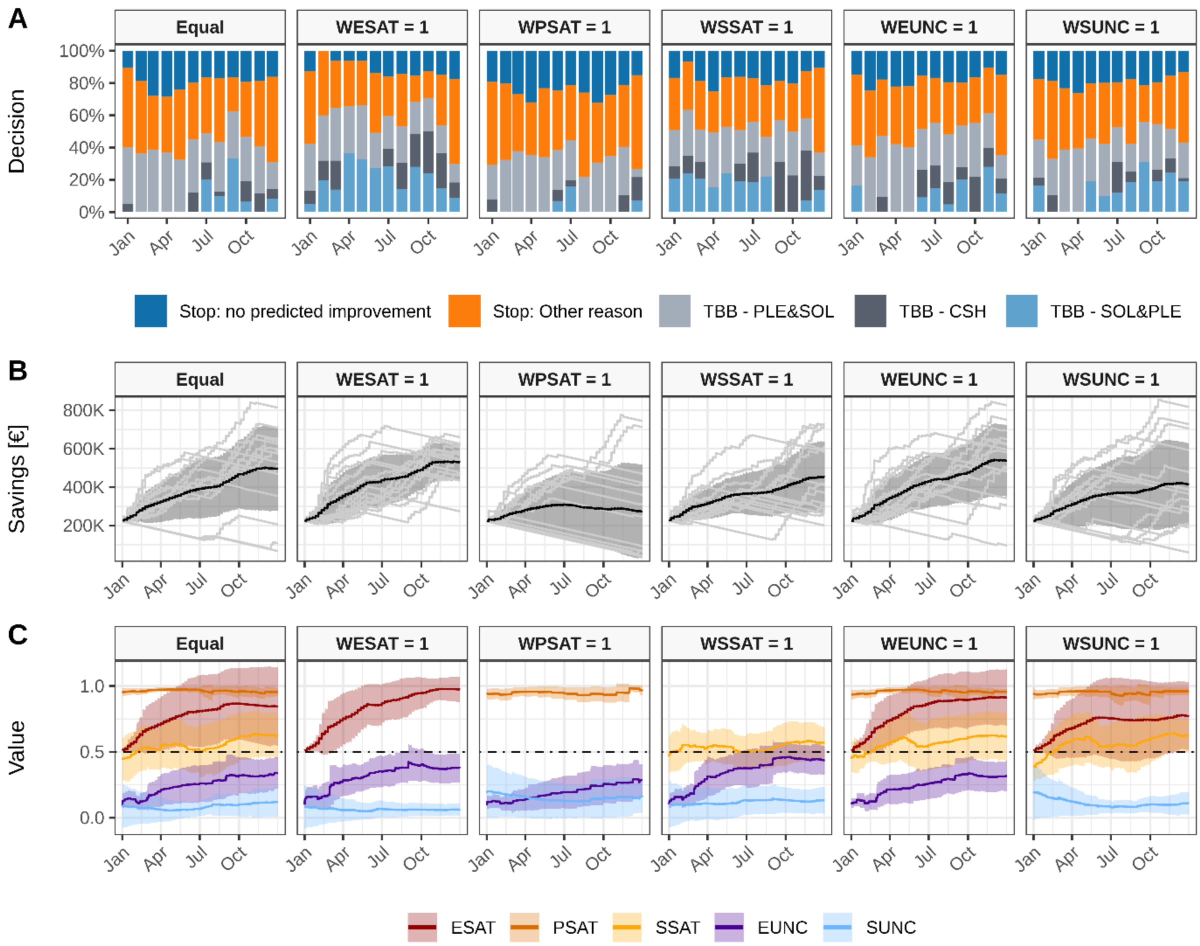

Figure C4. Outcome of the Consumat testing for one vessel from the TBB – PLE&SOL metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean daily satisfactions and uncertainties with the dotted line displaying the threshold for being satisfied and uncertain. The ribbons in B and C represent standard deviations.

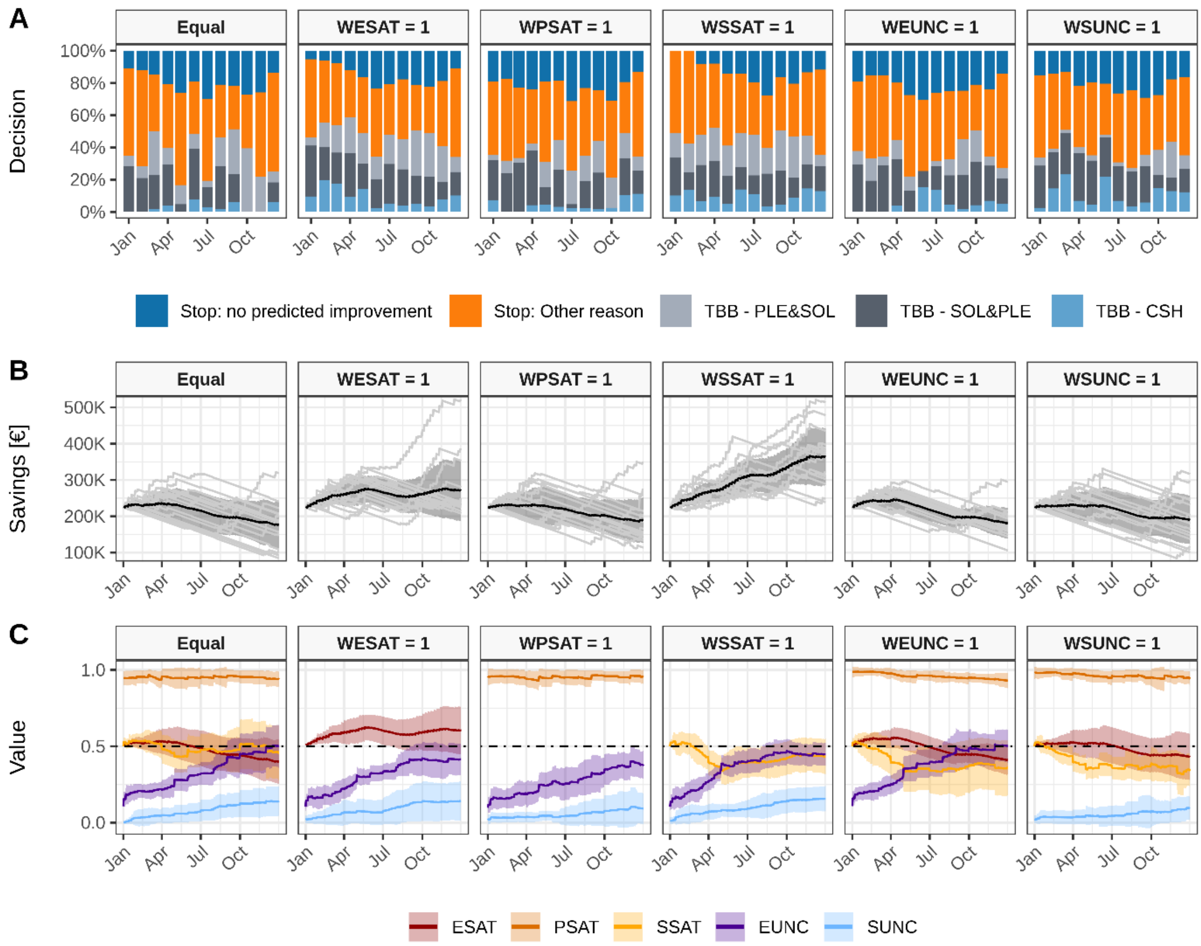

Figure C5. Outcome of the Consumat testing for one vessel from the TBB – SOL&PLE metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean daily satisfactions and uncertainties with the dotted line displaying the threshold for being satisfied and uncertain. The ribbons in B and C represent standard deviations.

Appendix D – Details POM

Pattern-Oriented Modelling Results

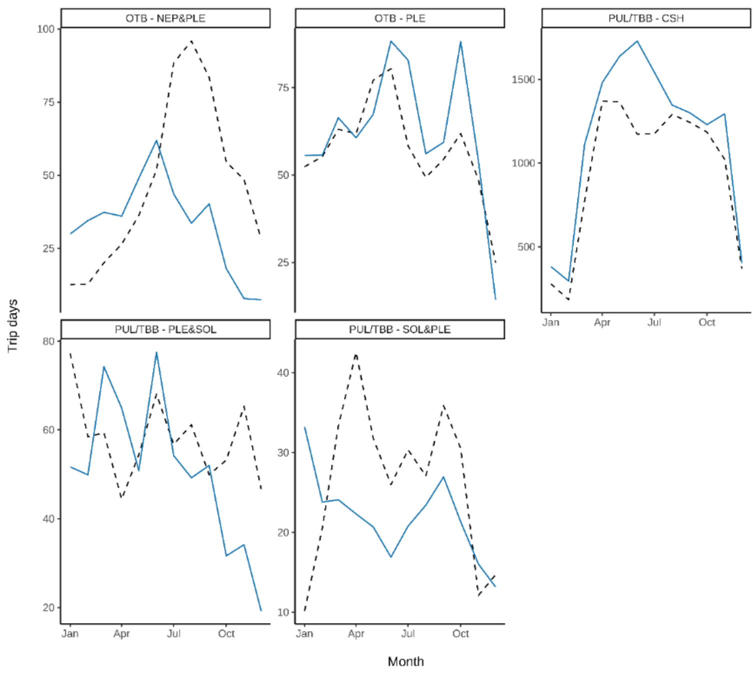

Figure D1. Outcome from the final step of the pattern-oriented modelling comparing modelled monthly trip days (blue) to observed ones (dashed black) per metier. Both lines represent monthly means across model runs (n = 10) and observed years (n = 7).

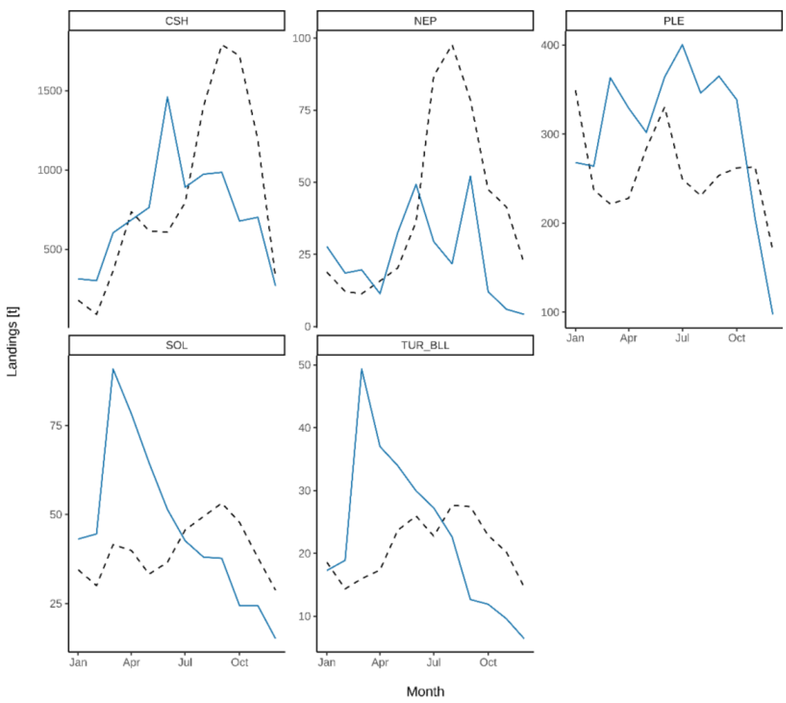

Figure D2. Outcome from the final step of the pattern-oriented modelling comparing modelled catches (blue) to observed ones (dashed black) per metier. Both lines represent monthly means across model runs (n = 10) and observed years (n = 7).

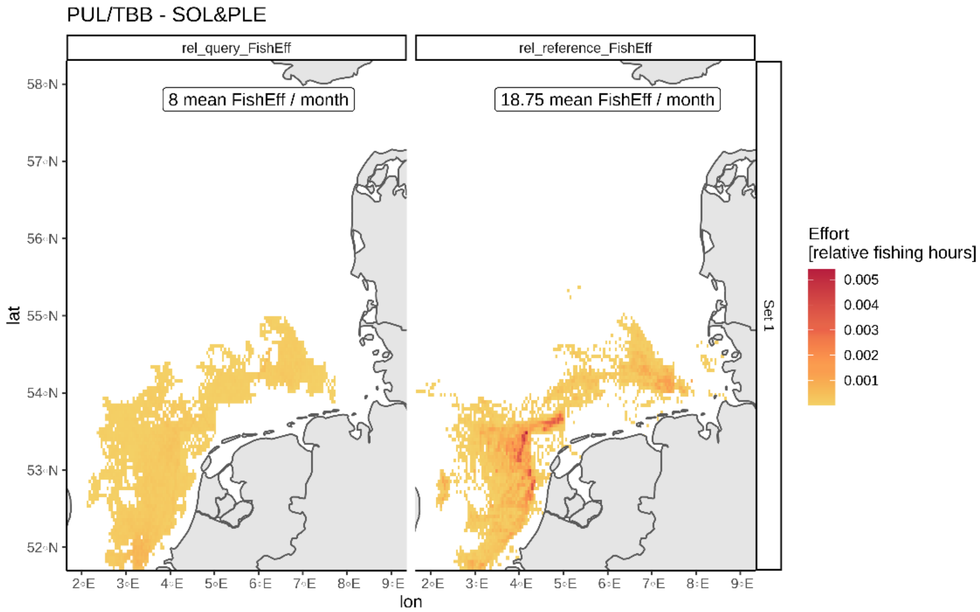

Figure D3. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the PUL/TBB – SOL&PLE metier group. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

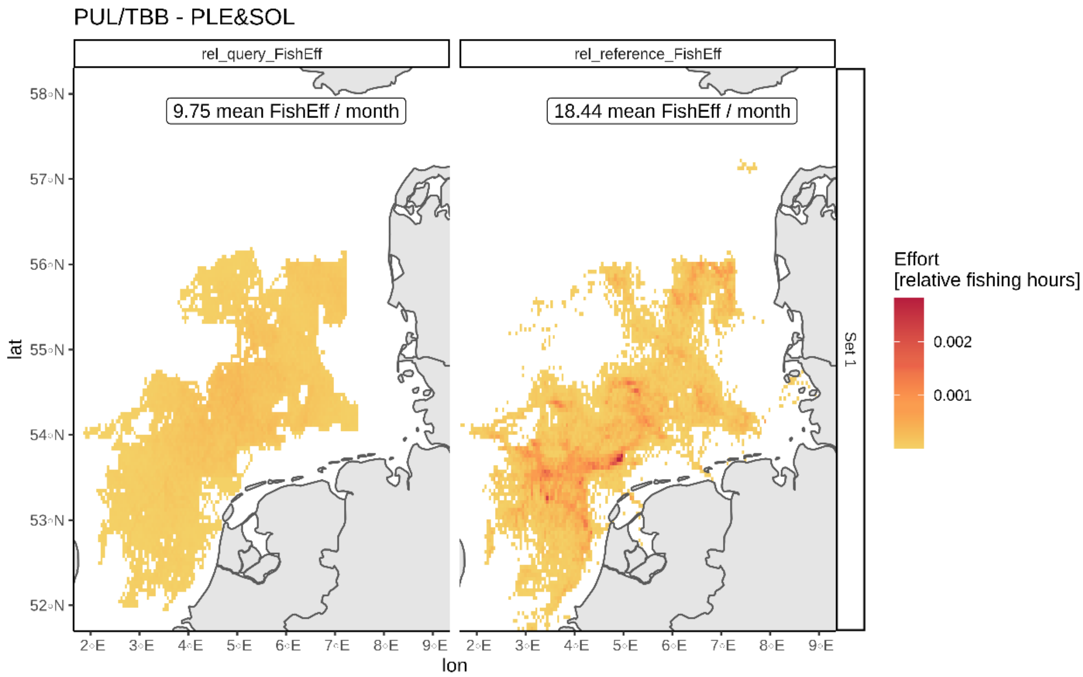

Figure D4. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the PUL/TBB – PLE&SOL metier group. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

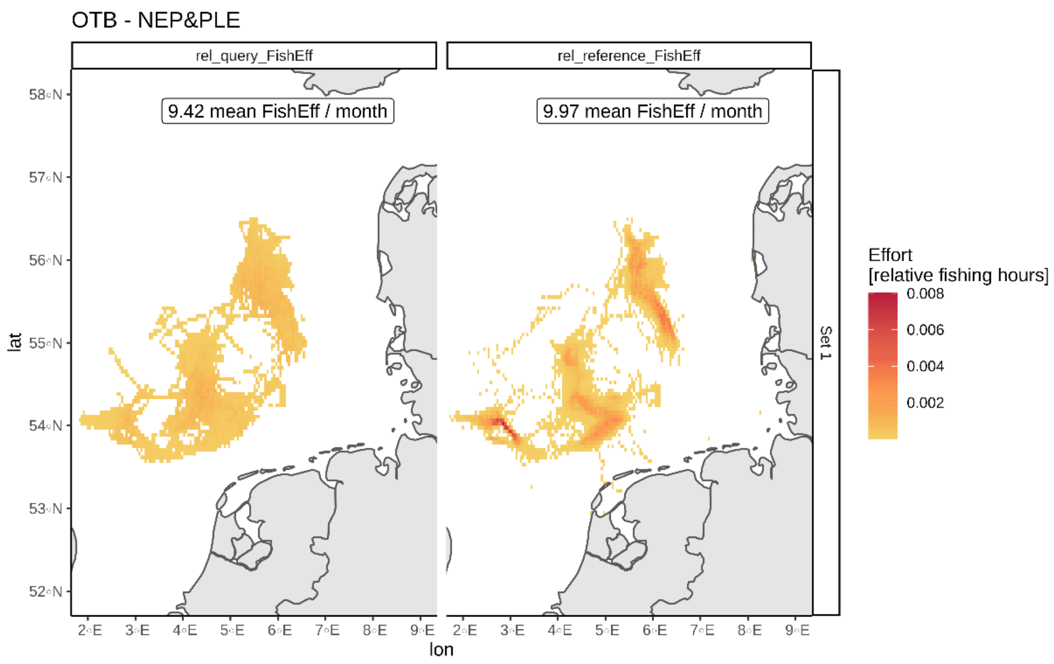

Figure D5. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the OTB – NEP&PLE metier. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

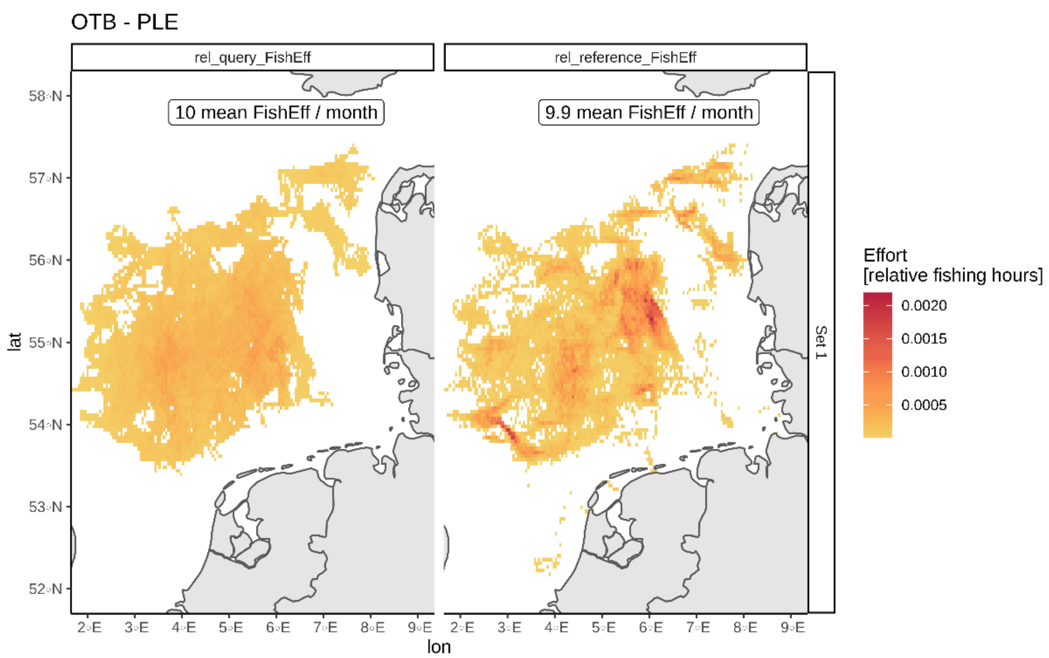

Figure D6. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the OTB – PLE metier. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

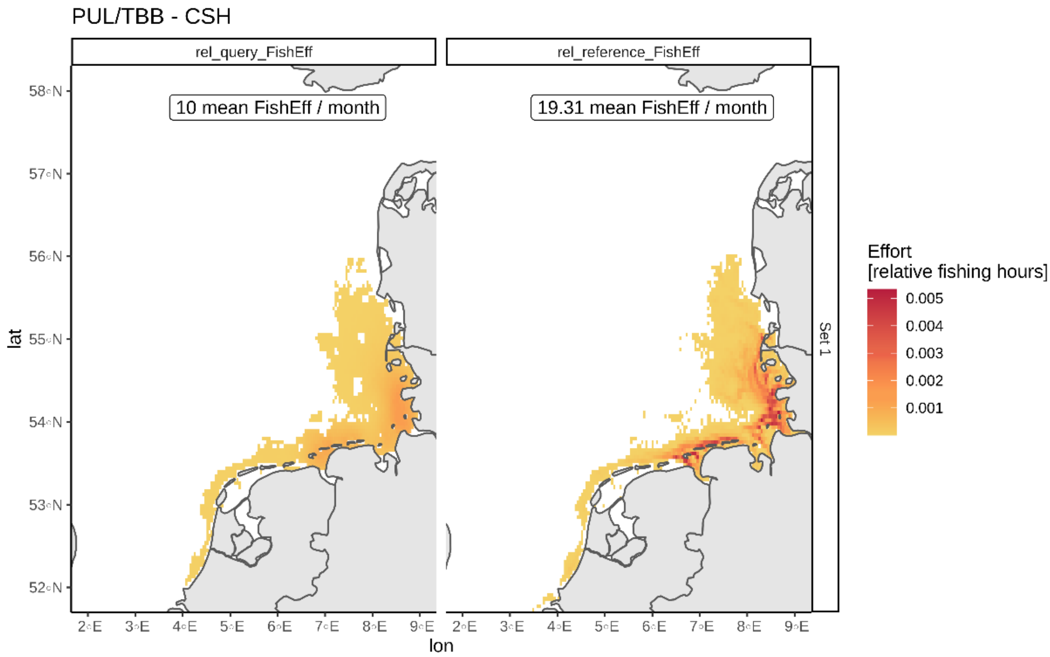

Figure D7. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the PUL/TBB metier group. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

Appendix E – Details output verification

Additional Validation Plots

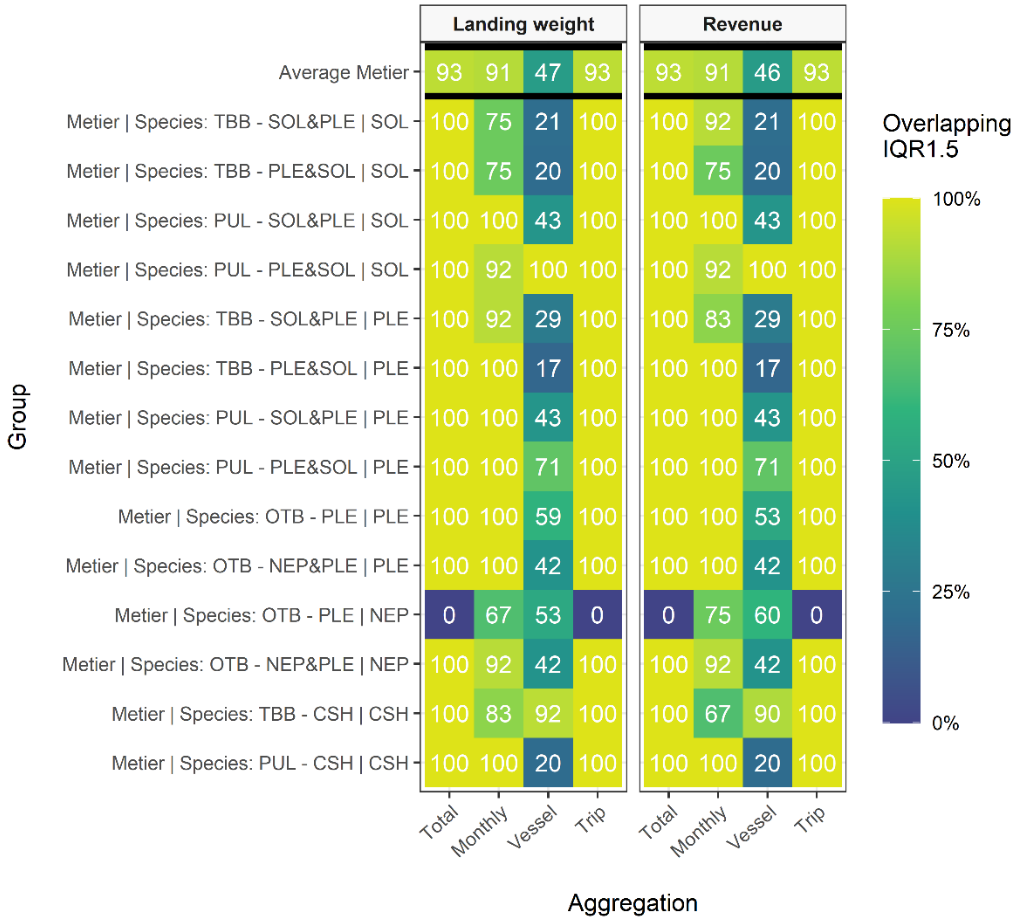

Figure E1. The percentage of data points with overlapping 1.5 times inter-quartile ranges (IQR1.5) between modelled and observed non-spatial variables resolved by metier and species. Colors and numbers correspond to the percentage of overlaps across different aggregations (columns), and metiers and species (rows).

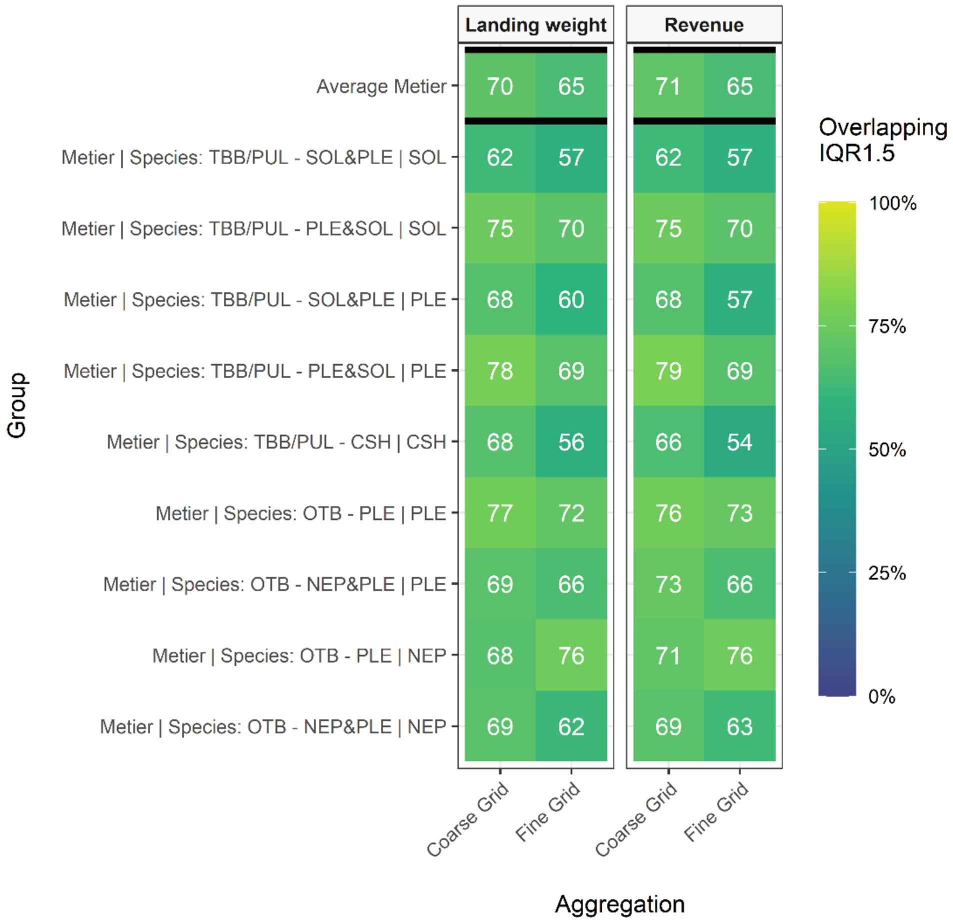

Figure E2. The percentage of data points with overlapping 1.5 times inter-quartile ranges (IQR1.5) between modelled and observed spatial variables resolved by metier and species. Colors and numbers correspond to the percentage of overlaps across different aggregations (columns), and metiers and species (rows).

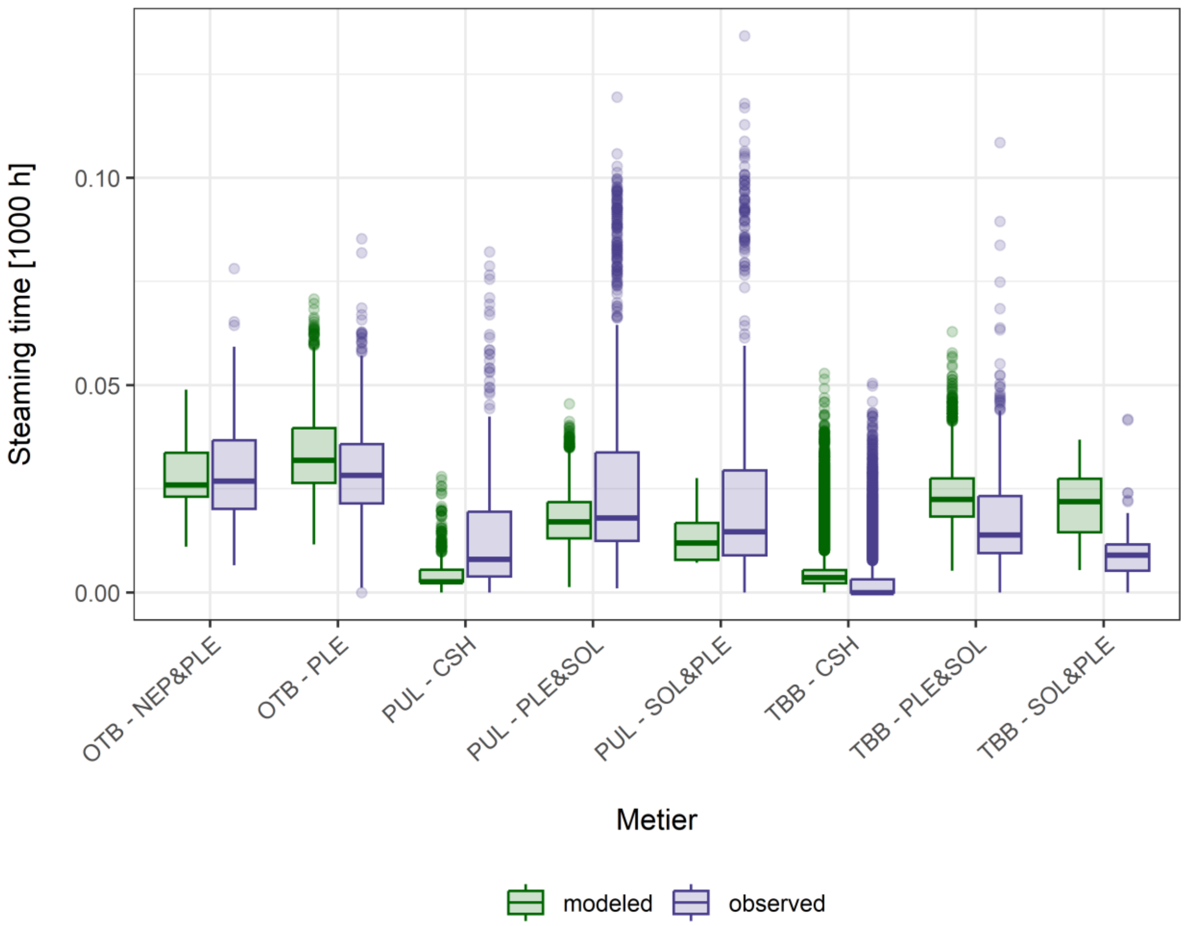

Figure E3. Steaming time per trip. Boxplots represent both distributions across trips and sample points (modelled n = 50 model runs; observed n = 7 observed years)

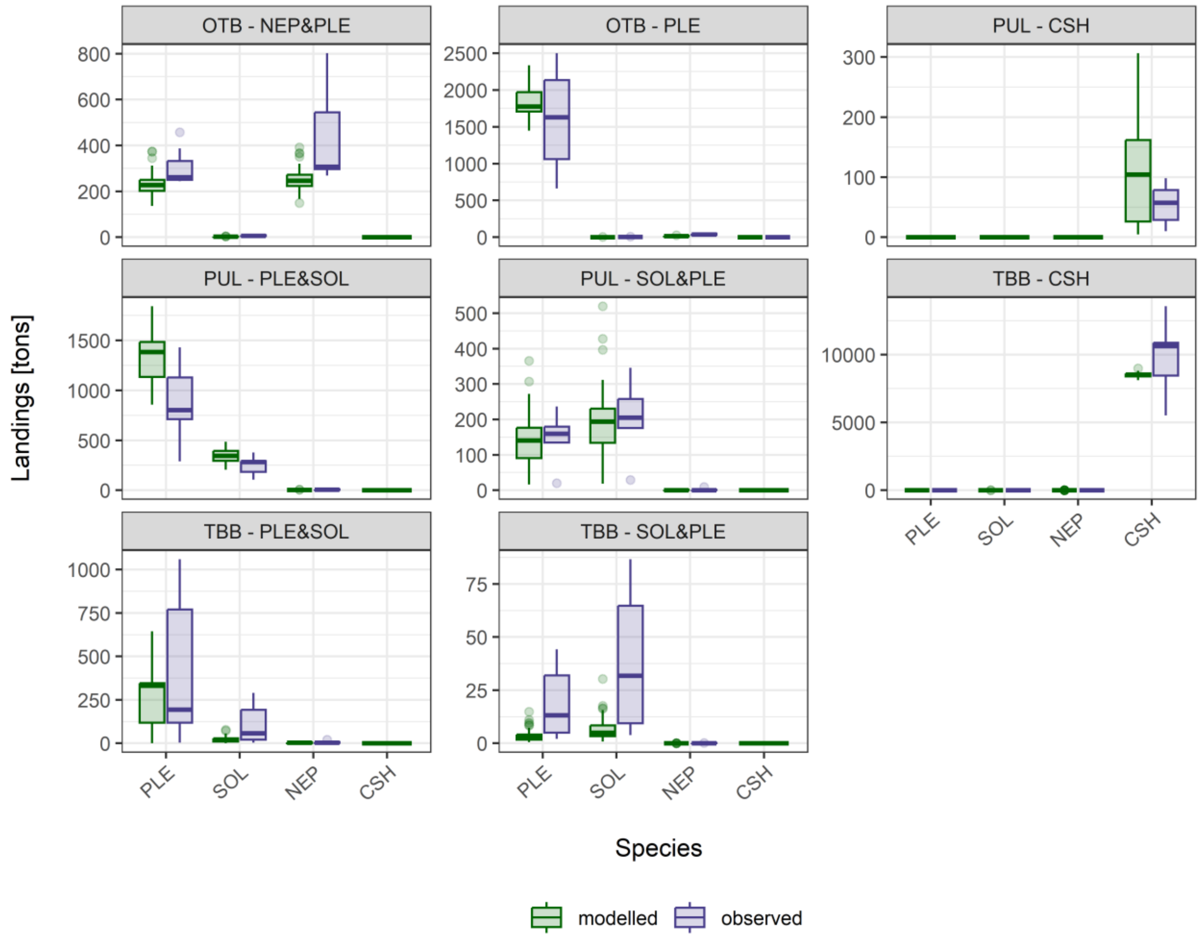

Figure E4. Landing composition per trip, species, and metier (panels). Boxplots represent both distributions across trips and sample points (modelled n = 50 model runs; observed n = 7 observed years)

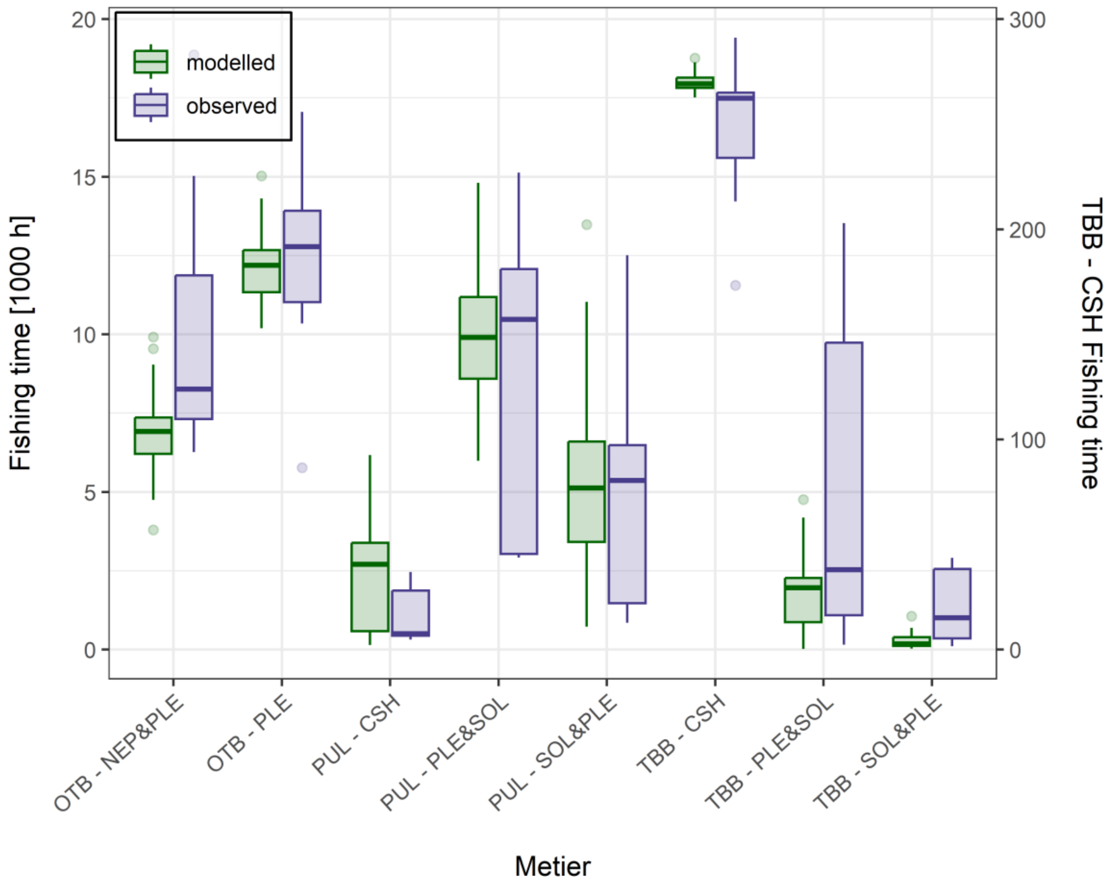

Figure E5. Fishing time per model run, species, and metier. Boxplots represent distribution across sample points (modelled n = 50 model runs; observed n = 7 observed years)

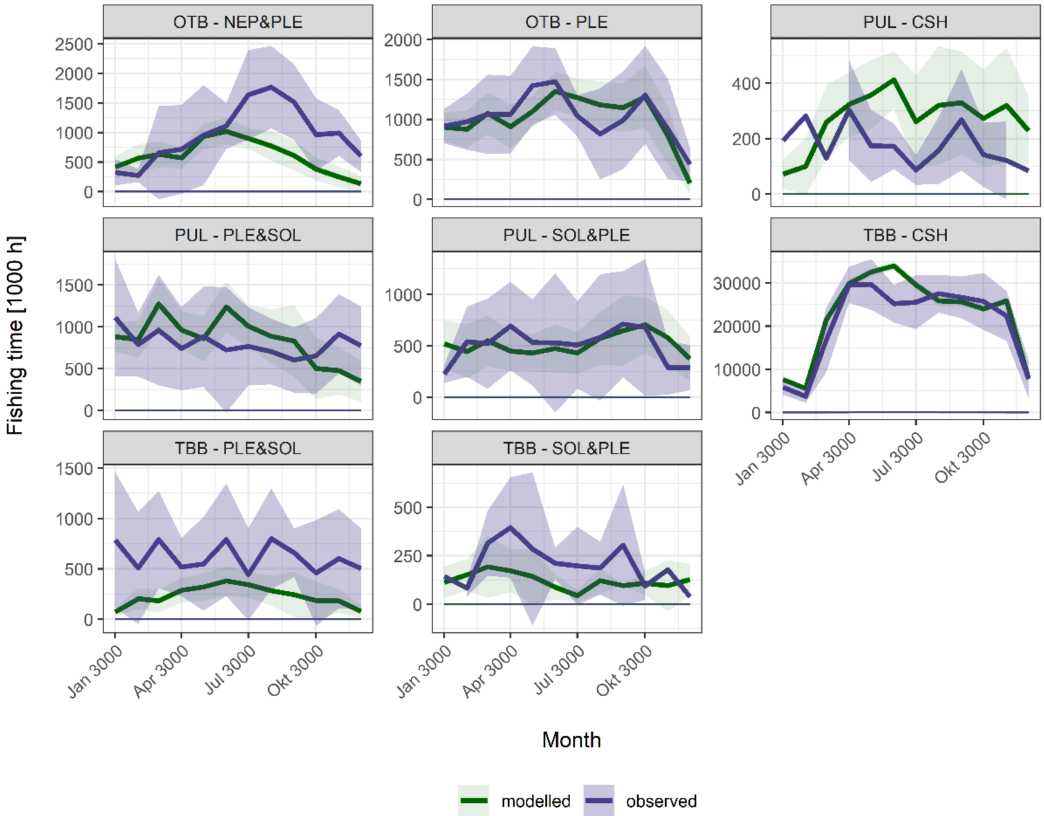

Figure E6. Fishing time per model run, species, and metier, and month. Ribbons represent standard deviations and lines means across model runs (green) and observed years (blue).

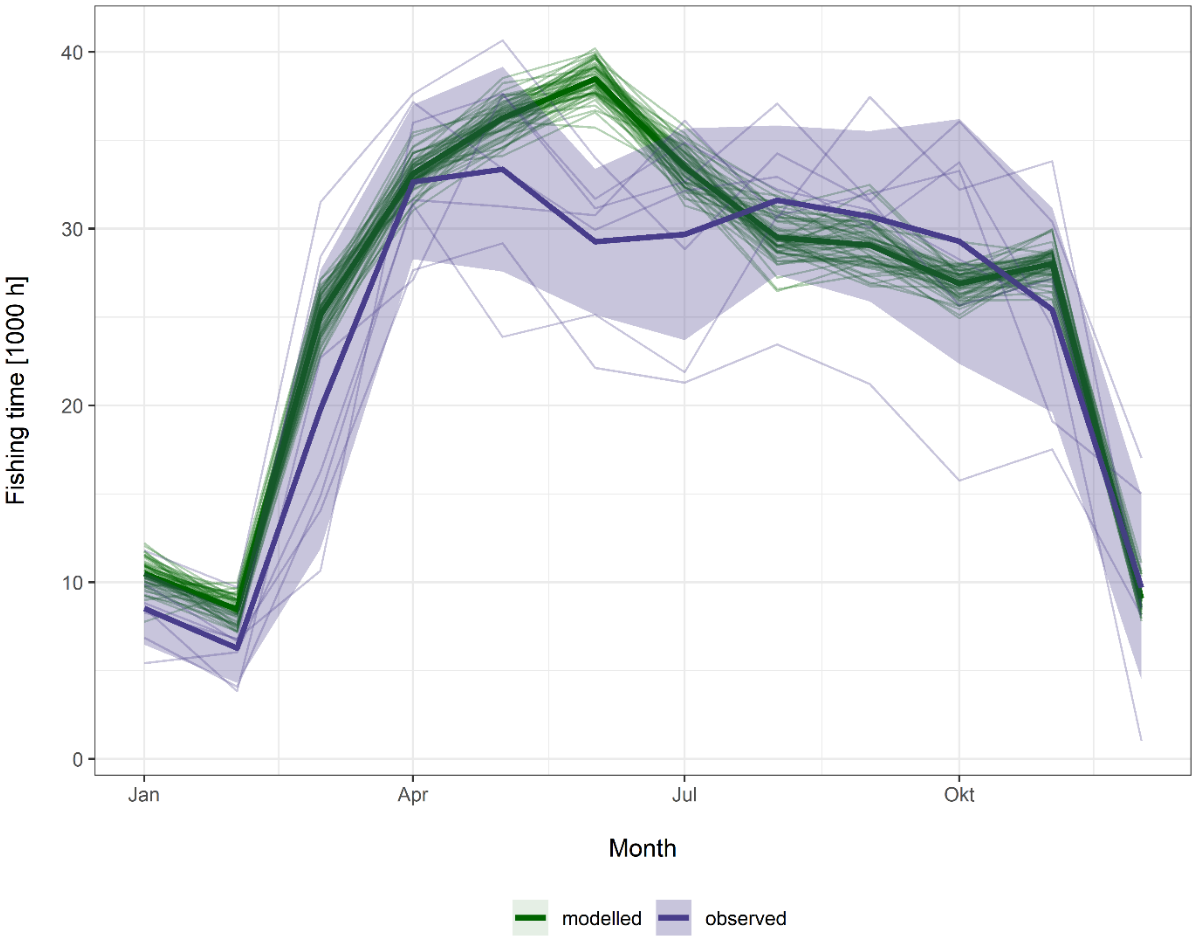

Figure E7. Fishing time per model run and month. Thin lines represent individual model runs (green) and observed years (blue), thick lines averages, and ribbons standard deviations.