Dynamics and pressures in German North Sea fisheries: from identification to simulation

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List of publications

Chapter I – published

This publication was conceptualized by Dr. Vanessa Stelzenmüller, Dr. Antje Gimpel and myself. My main contribution was collating the fishing effort data sets and performing the spatial overlap analysis including developing the necessary algorithm. Dr. Vanessa Stelzenmüller created the original draft and all author contributed by writing and editing the manuscript. This study is published in Renewable and Sustainable Energy Reviews.

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Chapter II – published

Nicole Stollberg and I developed the concept for this study and collected the various data sources, while Dr. Henrike Rambo supported the conceptualization and spatial analysis. I led the data analysis and visualization, as well as the writing of the original draft. All authors helped writing and editing the manuscript. The study is published in the ICES Journal of Marine Science.

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Chapter III – published

The concept of this study was designed by Dr. Vanessa Stelzenmüller, Dr. Antje Gimpel, and Dr. Holger Haslob. I contributed by designing and performing the analysis of fishing effort data, discussing results of the experimental fishing, writing the methodology, as well as editing the manuscript. The study is published Science of the Total Environment.

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

Chapter IV – published

The work was conceptualized by myself with support from Dr. Vanessa Stelzenmüller. I collected and combined data, performed the analysis, and wrote the original draft. Dr. Casper Kraan and Prof. Dr. Christian Möllmann gave advice for the interpretation and visualization of results. All authors edited the manuscript. The study is published in Ocean and Coastal Management.

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Chapter V – in preparation

The model presented in this manuscript was conceptualized by myself with contributions from Prof. Dr. Birgit Müller, and Dr. Gunnar Dressler, as well as advices from Dr. Vanessa Stelzenmüller and Prof. Dr. Christian Möllmann. I developed the model code and performed the sensitivity analysis and validation with support from Prof. Dr. Birgit Müller, and Dr. Gunnar Dressler. Furthermore, I wrote the original draft and all authors helped writing and editing. By the submission of this dissertation, the manuscript is in preparation for publication in Ecological Modeling. The model code and documentation is published www.comses.net (Letschert et al., 2024).

Chapter VI – in preparation

I conceptualized this study, performed the scenario analysis, and wrote the original draft. Dr. Vanessa Stelzenmüller contributed to the interpretation of results and edited the manuscript. The manuscript is currently in preparation for publication.

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Preface

Fishing is an ancient practice that has accompanied humanity for millennia. The ability to extract protein from the ocean has influenced the trajectory of human history and even facilitated the rise of kingdoms. Vikings discovered that dried Atlantic cod was a durable provision for sea journeys, enabling them to venture as far as modern Spain and Portugal, and the Hanseatic League would not have been as prosperous without rich Herring stocks. At the same time, the history of fisheries is tightly interwoven with unsustainable resource exploitation and devastating environmental consequences. Today, we may start witnessing a transformation of industrial fisheries in the southern North Sea. Marine space is increasingly used for green energy production and nature conservation, while fishing costs grow due to higher fuel prices, and questions arise concerning what the next 20 years will hold for fishers and their activities. This thesis presents insights into the current dynamics of German fisheries and tools to assess the effects of upcoming changes. I thereby provide information that may support management regimes integrating fisheries and other marine sectors such as nature conservation and offshore renewable energy.

Table of contents

Abstract

For centuries, the North Sea has been a global hotspot for anthropogenic activities, including fisheries. Fishers have adapted to fluctuating fish stocks, new marine management regimes, and increasing fishing costs, but the competition for space with offshore wind farms (OWF) and area-based conservation measures is a relatively new pressure. Within this doctoral thesis, I apply quantitative methods to reveal the extent of pressures for the southern North Sea fisheries with emphasis on German fleets. Moreover, I present possible mitigation strategies, and insights into fishing behavior necessary for effective management.

My co-authors and I quantified the race for space triggered by expanding OWFs and no-take zones by overlapping them with spatial fishing effort data. According to current plans, 60,000 km^2 of North Sea waters will be covered with OWFs by 2040, representing a 5-fold increase of conflict potential between fisheries and OWFs (Chapter I). A study on German vessels targeting Nephrops (Norway lobster; *Nephrops norvegicus*), revealed a coverage of German fishing grounds of up to 45% when OWFs and no-take zones are considered. Moreover, we highlighted other stressors such as potential difficulties for obtaining Nephrops quota due to Brexit and the risk for overfishing individual Nephrops populations (Chapter II).

Another perspective on OWFs is offered in Chapter III, in which we analyzed international fishing effort and experimental catches for brown crab in and around OWFs. Our results show increased levels of international fishing effort with passive gears in the vicinity of some OWFs, suggesting potential benefits for fisheries. Together with findings from the experimental catches, an economic break-even analysis demonstrates the feasibility of co-use fishing for brown crab with passive gears.

Foreseeing the reaction of fishers to changes is challenging and introduces a large source of uncertainty to fisheries management. Only by knowing the fisher's key behavioral motivations can management be drafted in a sustainable way. Therefore, I combined environmental, economic, and cultural information, and applied machine learning techniques to find factors that were substantially driving spatio-temporal fishing effort for three German fleets (Chapter IV). The results show a high importance of environmental factors for all fleets, while economic and cultural drivers only affected one fleet. This difference highlights the need for considering fishers' heterogeneity in scientific fisheries models and management.

Based on results and data products of the first four chapters, I developed an agent-based model (FISHCODE) simulating German southern North Sea fisheries involving complex human-decision making (Chapter V). After testing for model functionality and validation, I applied FISHCODE by testing scenarios of raised fuel prices, expanding OWFs and no-take zones, and the ban of electric pulse gear (Chapter VI). Results indicate lower profits in all scenarios, although fuel prices had by far the strongest effect. Additionally, fishing effort becomes displaced towards smaller areas, with the resulting increase in fishing pressure potentially having negative effects for marine ecosystems.

Together with recent political developments such as Brexit, the risk of overfishing, and rising fuel prices, spatial competition will be a major challenge for North Sea fisheries. Findings of this thesis help to uncover uncertainty about the future state of the fishing sector and identify knowledge gaps such as the impact of OWFs on the environment and the need for publicly available fisheries data on high spatial resolution. Management should be drafted in a participatory process to ensure the profitability of the fishing sector in co-existence with other marine spatial actors, i.e. nature conservation. Factoring in the heterogeneity of fishers is key for efficient management and marine spatial planning.

Zusammenfassung

Die Nordsee ist seit Jahrhunderten ein globaler Hotspot für anthropogene Aktivitäten, wie z.B. der Fischerei. Seit jeher haben sich Fischer an fluktuierende Fischbestände, neue Fischereibestimmungen und steigende Fischereikosten angepasst. Der Wettbewerb um Raum mit Offshore-Windparks (OWPs) und gebietsbezogenen Naturschutzmaßnahmen stellt einen relativ neuen Stressfaktor für die Fischerei dar. In dieser Dissertation wende ich quantitative Methoden an, um das Ausmaß des Drucks auf die Fischerei in der südlichen Nordsee mit Schwerpunkt auf den deutschen Flotten aufzuzeigen. Darüber hinaus präsentiere ich mögliche Strategien für eine Milderung negativer Konsequenzen sowie Einblicke in das Fischereiverhalten, die für ein effektives Management notwendig sind.

Die Überlagerung räumlicher Polygone von OWPs und Naturschutzmaßnahmen mit Fischereiaufwandsdaten, beleuchtet und quantifiziert den schrumpfenden freien marinen Raum. Nach derzeitigen Plänen werden bis 2040 60.000 km^2 der Nordsee mit OWPs bedeckt sein, was eine fünffache Zunahme des Konfliktpotenzials für die Fischerei bedeutet (Kapitel I). Weitere Stressfaktoren werden in einer Studie über die deutsche Kaisergranat-Fischerei (*Nephrops norvegicus*) deutlich. Zum einen erschwert der Brexit die Bedingungen für Deutschland Kaisergranat-Quoten zu erlangen und zum anderen besteht das Risiko einer Erschöpfung einzelner Kaisergranat-Populationen durch Überfischung (Kapitel II). Darüber hinaus könnten durch die Kombination von Fangverbotszonen und geplanten OWPs bis 2040 45 % der deutschen Fanggebiete für Kaisergranat nicht mehr für die Fischerei zur Verfügung stehen.

Eine andere Perspektive auf OWPs zeigen wir in Kapitel III, in dem meine Ko-Autoren und ich internationalen Fischereiaufwand und Versuchsfänge von Taschenkrebsen in und um OWPs analysiert haben. Unsere Ergebnisse zeigen einen erhöhten internationalen Fischereiaufwand mit passivem Fanggerät in der Nähe einiger OWPs, was auf mögliche Vorteile für die Fischerei hindeutet. Zusammen mit den Erkenntnissen aus den Versuchsfängen zeigt eine wirtschaftliche Break-Even-Analyse die Durchführbarkeit von Co-Use Strategien für die Fischerei mit passivem Fanggerät in OWPs.

Die Reaktion von Fischern auf o.g. Veränderungen vorherzusehen ist schwierig und stellt eine große Unsicherheitsquelle für das Fischereimanagement dar. Nur wenn die wichtigsten Verhaltensmotivationen von Fischern bekannt sind, kann Management nachhaltig gestaltet werden. Durch die Kombination von ökologischen, ökonomischen und kulturellen Informationen und der Anwendung von maschinellem Lernen, habe ich Faktoren identifiziert, die den räumlichen und zeitlichen Fischereiaufwand für drei deutsche Flotten wesentlich beeinflussen (Kapitel IV). Die Ergebnisse zeigen, dass Umweltfaktoren bei allen Flotten eine große Rolle spielen, während wirtschaftliche und kulturelle Faktoren nur für einer Flotte relevant sind. Dieser Unterschied verdeutlicht die Notwendigkeit, die Heterogenität der Fischer in wissenschaftlichen Modellen und im Fischereimanagement zu berücksichtigen.

Auf der Grundlage von Ergebnissen und Datenprodukten der ersten vier Kapitel habe ich ein agentenbasiertes Modell (FISHCODE) entwickelt, das die deutsche Fischerei in der südlichen Nordsee, unter Betracht von komplexem menschlichen Entscheidungsprozessen, simuliert (Kapitel V). Nach dem Test der Modellfunktionalität und der Validierung habe ich FISHCODE angewandt, um Szenarien zu erhöhten Treibstoffpreisen, der Ausweitung von OWPs und Naturschutzgebieten sowie dem Verbot von elektrischem Impulsfanggerät zu testen (Kapitel VI). Die Ergebnisse zeigen geringere Fischereigewinne in allen Szenarien, wobei die Treibstoffpreise bei weitem die stärksten Auswirkungen haben. Ein weiteres Ergebnis ist die Verlagerung von Fischereiaufwand in kleinere Gebiete, wobei der daraus resultierende höhere Fischereidruck negative Auswirkungen auf die Meeresökosysteme haben könnte.

Zusammen mit den jüngsten politischen Entwicklungen wie dem Brexit, dem Risiko von Überfischung und den steigenden Treibstoffpreisen wird der Wettbewerb um verfügbaren marinen Raum eine große Herausforderung für die Nordseefischerei darstellen. Die Ergebnisse dieser Arbeit tragen dazu bei, die Ungewissheit über den künftigen Zustand des Fischereisektors aufzudecken. Des Weiteren zeige ich Wissenslücken auf, wie z.B. die Auswirkungen von OWPs auf die Umwelt sowie den Bedarf an öffentlich zugänglichen Fischereidaten mit hoher räumlicher Auflösung. Fischereimanagement sollte in einem partizipativen Prozess gestaltet werden, um die Rentabilität des Fischereisektors in Koexistenz mit anderen marinen Raumakteuren, z. B. dem Naturschutz, zu gewährleisten. Die Berücksichtigung der Heterogenität von Fischern ist der Schlüssel zu effektivem Management und mariner Raumplanung.

General Introduction

Industrial fishing occurs on a global scale reaching even remote waters from the tropics to the poles (Kroodsma et al., 2018). Fisheries are an important provider for protein and their demand will likely increase during the 21st century due to a continuously growing world population (FAO, 2022). The fishing sector and its auxiliary industries employ 294,000 people in Europe alone, highlighting its socio-economic importance (FAO, 2022), whereas in terms of environmental impacts, fisheries have been affiliated with negative effects, reducing the abundance of fish populations, and destroying marine habitats (Jennings and Kaiser, 1998). Globally, most fish stocks are exploited at their sustainable limits, while 35.4 % are overfished (FAO, 2022). In particular, bottom trawling is known for its devastating effects on benthic habitats and species communities (Hiddink et al., 2020).

This thesis focuses mostly on the southern North Sea, a global hotspot for overall fishing activity, and specifically for bottom trawling (Amoroso et al., 2018; Halpern et al., 2019, 2008b). Here, I define the southern North Sea as the extent of fishing grounds used by the most important German fleets in the area catching brown shrimp (or common shrimp; *Crangon crangon*), common sole (*Solea solea*), European plaice (*Pleuronectes platessa*), and Nephrops (or Norway lobster; *Nephrops norvegicus;* Figure 1A). The following section provides important background information on the southern North Sea including physical characteristics, fisheries dynamics, as well as fisheries management. The second part of this introduction narrows the focus to the performed research by describing the relevance and important cornerstones of fisher behavior for management, as well as agent-based modelling. The final section outlines the chapters of this thesis and how they address knowledge gaps and states overall research objectives.

1. The southern North Sea

1.1 Physical characteristics

The North Sea is located on the European continental shelf and is characterized by different habitats shaped by various sediment types, ranging from fine sand to rocky reefs (Bockelmann et al., 2018). The Norwegian trench represents the only deep-sea habitat of the North Sea, while the rest is relatively shallow with decreasing depth towards the southern part where the deepest point is about 50m (Figure 1B). Vast tidal flats between barrier islands and the coasts of the Netherlands, Germany and Denmark form the Wadden Sea. The heavy tidal influence and river inputs in the southern North Sea result in yearly mixed water columns (ICES, 2022a). These biophysical features shape habitats that determine the occurrence and composition of species communities (Kraan et al., 2024; Neumann et al., 2013). For example, flatfish prefer sandy bottoms, but also occur in finer sediment (i.e. muddy areas), whereas burrowing megafauna such as Nephrops strictly prefers muddy habitat (Gutow et al., 2020; Lauria et al., 2011).

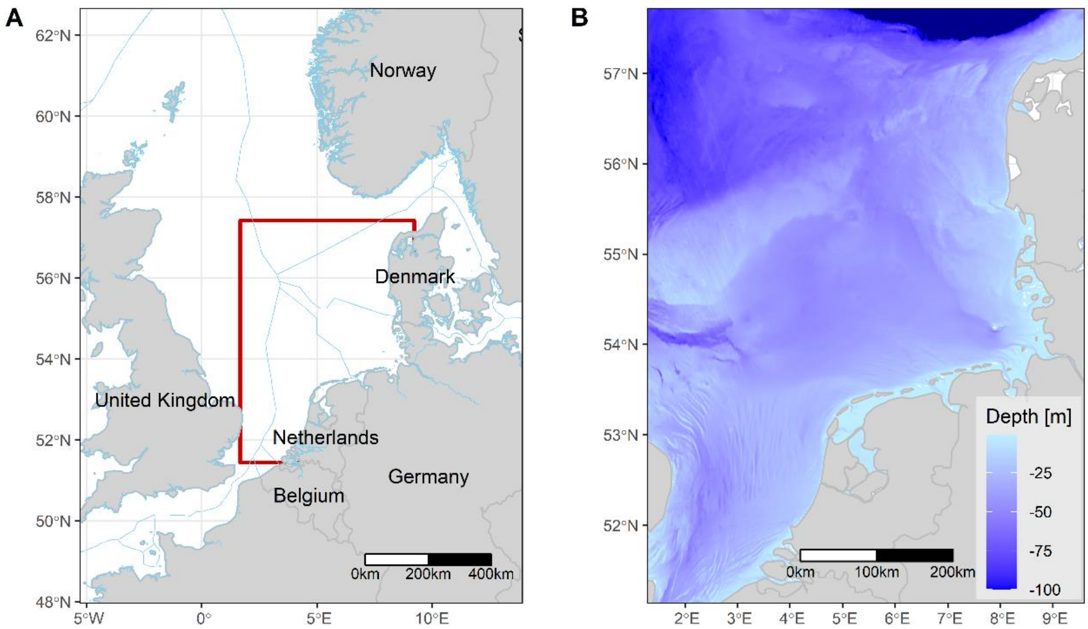


Figure 1. A: Greater North Sea region with maritime boundaries (blue; i.e. combined exclusive economic zone and territorial waters), as well as southern North Sea as defined in this thesis (red). B: Bathymetry of the southern North Sea (*www.gebco.net*).

1.2 Historical and current fisheries

North Sea fisheries have undergone many technological transitions during their centuries of history, starting with hunting marine mammals and gleaning shellfish in the Wadden Sea about 7500 years ago (Lotze, 2007). From medieval to modern times, fishing vessels have developed from sailing over steam- to diesel-powered vessels (Döring et al., 2020). This technological progress allowed to target fishing grounds that are located further offshore and drag heavy bottom-contacting nets across the sea bed. Gear modifications have increased catch efficiencies, such as the introduction of beam trawls (TBB; Figure 2) in the 1960s that largely replaced otter bottom trawls (OTB) (Rijnsdorp et al., 2008). TBB are efficient at catching flatfish buried deeper in the sea floor such as sole, because they are equipped with tickler chains digging into the sediment and startle the flatfish. Due to this change in fishing gear and increases in engine power and vessel size, the catch efficiency for sole more than doubled in 12 years (Rijnsdorp et al., 2008). The increasing fishing capacity took its toll on the environment, and the collapse of one fish population was often followed by a shift in exploitation to another species, e.g. the collapse of the herring stocks in the 1950s was followed by heavy exploitation of Atlantic cod (*Gadus morhua*) (Cushing, 1980). North Sea catches peaked in 1970 (4 million tons) and have since been declining due to dwindling fish populations down to 2 million tons nowadays (ICES, 2022b). As a consequence, fishing regulations were released in the 20th century by individual countries and regional management units ranging from fishing quotas to fishing effort restrictions with the aim of rebuilding fish stocks (van Hoof et al., 2020). In the early 2000s, TBB began to be replaced by electric pulse gear (PUL), first in the Dutch and later also in other fleets targeting the flatfish plaice and sole (van Hoof et al., 2020). In comparison to TBBs, PULs have a better catchability for the high-value flatfish sole, catch lower amounts of unwanted bycatches, and require less fuel due to the reduced drag in the water column (Suuronen et al., 2012). However, PUL are controversial because of potential negative effects on benthic communities, and have been banned by the EU in 2021 (Kraan et al., 2020; Le Manach et al., 2019).

Figure 2. Fishing vessels equipped with beam trawls.

Until today, the North Sea remains a hotspot for bottom trawling with OTB, TBB, and, until its ban in 2021, also PUL (Amoroso et al., 2018; ICES, 2022b). The catch composition of these gears depends on the area they are active in. In the southern North Sea, OTBs catch a mix of crustaceans and fish, e.g. plaice and Edible crab (or brown crab; *Cancer pagurus*), as well as Nephrops in muddy areas, TBBs and PULs target plaice and sole, while TBBs also target brown shrimp in coastal waters (ICES, 2022b). In terms of landed value, the United Kingdom (UK), Denmark, the Netherlands, and Germany (in decreasing order) are the most important actors (STECF, 2020). The fishing sector in the Greater North Sea region employs almost 8000 full time equivalents (STECF, 2020) and is of socio-economic relevance, especially for coastal communities where fishery is an important profession (Urquhart et al., 2011).

1.3 State of German fisheries in the southern North Sea

The German fisheries in particular face many challenges, such as a lack of successors for fishing businesses and overaged vessels lacking the necessary financial capital to invest in new ships (Döring et al., 2020). The German North Sea fisheries mostly consists of vessels smaller than 24m catching brown shrimp, with a few vessels targeting Nephrops, as well as several larger vessels catching sole and plaice. Many German fishers land in or export their catches to the Netherlands, where the main processing companies for fish and brown shrimp are located (STECF, 2020). Brown shrimp is further shipped to Morocco, where shrimps are pooled and then reimported (Aviat et al., 2011). Thus, German North Sea fisheries are very specialized and dependent on international cooperation, which compromises their resilience to crisis such as the COVID-19 pandemic (Goti-Aralucea et al., 2021). The continuing downward trend of German fishing capacity (STECF, 2020), reduces the socio-economic relevance of remaining fishers, which in turn lowers their gained political attention and power to negotiate with retailers (Döring et al., 2020).

1.4 Anthropogenic impacts on the environment

Apart from fisheries, the North Sea is also a hotspot for other anthropogenic uses, which can have harmful consequences for the environment (Halpern et al., 2019, 2008b). Among others, the threats to North Sea ecosystems are: non-indigenous species, pollution including eutrophication, overfishing, bottom trawling, man-made marine structures, and climate change (Emeis et al., 2015).

In the southern North Sea, most fish populations are exploited within sustainable boundaries, except for some Nephrops populations (ICES, 2022b). However, the large amount of bottom trawling poses a threat to benthic ecosystems through habitat destruction and unselective catches, with high amounts of bycatches (Hiddink et al., 2020; Reiss et al., 2009). For example, Nephrops are caught by a mixed fisheries with OTBs, resulting in high amounts of bycatch, although new gear features have been proposed to increase selectivity by sorting catches in the net (Catchpole and Revill, 2008; Cosgrove et al., 2019).

Additionally, the North Sea is warming up faster than other areas due to climate change, which has consequences for the food web and ecological communities (Dulvy et al., 2008; Lynam et al., 2017; Rijnsdorp et al., 2009). During the last century, North Sea cod, plaice, and sole have shifted their distribution northwards due to global warming, followed by a shift in the respective fisheries (Engelhard et al., 2014, 2011). Concurrently, species usually living in warmer waters, e.g. sardines and anchovies, have increased in abundance in their northern distribution boundaries and appeared in North Sea fisheries catches (Baudron et al., 2020). This change in species occurrences, abundances and distributions may increase the potential for conflicts between fisheries and other users of ocean space (Link et al., 2017; Mendenhall et al., 2020). Moreover, in combination with intensive fishing pressure, climate change can trigger ecological regime shifts from ecological communities dominated by gadoids (e.g. cod) and copepods to flatfish (e.g. plaice) and diatoms (Sguotti et al., 2022). These regime shifts imply discontinuous and non-linear dynamics, which may hinder the recovery of fish stocks despite reducing fishing pressure (Blöcker et al., 2023a).

However clear the effects of fishing pressure and climate change may be, initiatives towards sustainability and renewable energy use are not always straightforward. The effects of man-made structures such as offshore wind farms (OWFs) have both positive and negative effects on their surrounding environment that differ by taxonomic group and OWF development stage, i.e. construction and operation (Galparsoro et al., 2022; Watson et al., 2024). For examples, the pile driving during OWF construction may displace harbor porpoises, and operative OWFs can reduce bird abundances through a collision and displacement, while the abundance of fish species may increase (Galparsoro et al., 2022). OWFs monopiles and scour protection (sand-filled bags or rocks at the bottom of the monopile) act as artificial reef for sessile invertebrates, macrobenthos, and demersal fishes (Li et al., 2023; Stelzenmüller et al., 2016; Thatcher et al., 2023). The accumulation of species on this artificial hard substrate can increase biomass and abundance of fish and benthic species interesting for fisheries, and offer the potential for spill-over effects (Dannheim et al., 2020; Methratta and Dardick, 2019; Reubens et al., 2013). Among the attracted species, brown crab and lobster have high economic value for fisheries and could therefore be exploited directly in and around OWFs as part of a co-use strategy between OWF and fishery (Stelzenmüller et al., 2016). At the same time, artificial hard structures increase the potential for the introduction and spread of marine non-indigenous species, which may have severe ecological and economic consequences (De Mesel et al., 2015; reviewed by Laeseke et al., 2020). The closely spaced and high number of OWF monopiles may act as stepping stones for non-indigenous species with limited dispersal radius or habitat range (Molen et al., 2018).

1.5 Fisheries management

At first, fisheries were only managed in coastal waters up to 12 nm representing a nation's territorial water. Since the establishment of the United Nations Convention of the Law of the Sea (UNCLOS) in 1982, countries were able to claim fishing rights in their exclusive economic zones (EEZ) covering waters up to 200 nm offshore (Figure 1B). Shortly after, the EU common fisheries policy (CFP) entered into force, regulating marine living resources on an EU scale and introduced total allowable catches (TACs) to limit marine resource exploitation to sustainable boundaries (EU, 2013). In order to target specific fisheries or vessels with management, EU fisheries were grouped into metiers and fleets. Metiers cluster fishing trips based on the targeted species assemblage and used gear, while fleets are grouped per year based on technical characteristics such as vessel length and predominant gear (Ulrich et al., 2012). Every year, the International Council for the Exploration of the Sea (ICES) uses data collected by fleet and metier and provides advice for catch limits of individual species to the European Commission. Subsequently the Commission suggests catch limits to the European Council, which then distributes TACs to EU member states based on fixed percentage (so called relative stability) that is rooted in every countries' historic catch amounts. Fishing quotas can be swapped among EU member states at the beginning of every year to optimize the fishing opportunities of their fleets. In 2020, the long-established distribution and swapping of fishing quotas became challenged by Brexit. Starting in 2021, EU quotas are transferred to the UK in a step-wise procedure for fish stocks located in UK waters (EU, 2021). During this adjustment period, EU fishers have access to UK waters, but this agreement will be renegotiated in 2026 (Stewart et al., 2022).

Several management measures aim to reduce discards in EU fisheries. The plaice box is one of them and was established in 1995 to reduce discards of undersized plaice by prohibiting fishing activity for vessels equipped with TBB or PUL and engines >221 kw (Beare et al., 2013). It covers Dutch, German, and Danish coastal waters (Figure 3). Another EU measure to reduce unwanted bycatch is the landing obligation prohibiting fishers to discard any quota-regulated species. However, many exemptions apply for target species in fisheries that would otherwise be halted due to quick exhaustion of bycatch quota (so called "choke species") or for species with high post-discard survivability (European Commission, 2020a). Examples for exemptions are the two flatfish dab (*Limanda limanda*) and plaice caught by the North Sea TBB fleet (van Hoof et al., 2020).

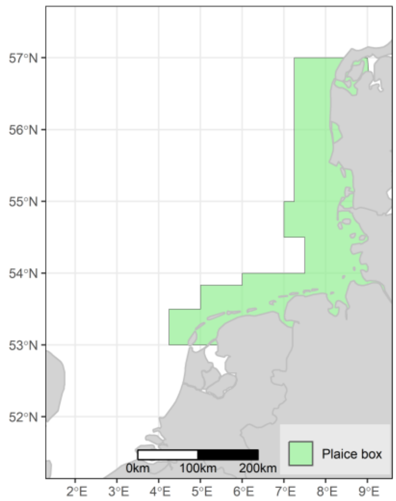


Figure 3. Southern North Sea with plaice box (green).

1.6 Marine spatial planning

Marine spatial planning (MSP) has its origins in the planning and spacing of marine protected areas (MPAs), and has since become a management approach to mitigate spatial conflicts and implement zoning for the use of all marine stakeholders (Frazao Santos et al., 2020; Jay et al., 2012). As such, MSP comprises a multitude of methods and objectives, but is generally determined to enable the co-existence of spatial anthropogenic uses in marine areas, while ensuring environmental protection (Stelzenmüller et al., 2021a).

Area-based marine conservation measures such as MPAs are effective in protecting and recovering marine habitats and ecological communities (Davies et al., 2021; Juffe-Bignoli et al., 2014; Püts et al., 2023; Sala and Giakoumi, 2018). Global and regional nature conservation strategies set targets to protect a certain percentage of marine areas. The Global Biodiversity Framework adopted during the COP15 in Montreal, Canada, aims to protect 30% of all marine areas until 2030 (UN, 2022). On a European level, the EU Birds and Habitat Directives requires member states to designate MPAs in their territorial waters and EEZs, resulting in the Nature2000 network. In the greater North Sea, 20 % of the total area is covered by MPAs (Werner et al., 2022). The management plans of MPAs are multi-facetted and can be composed of multi-use zones that allow for certain human uses, restrictions for specific fisheries or gears, and no-take zones prohibiting all fishing activity. Some Natura2000 are still lacking management plans, making them effectively “paper parks” (i.e. MPAs that only exist on paper), which is a phenomenon that occurs globally (Mazaris et al., 2018; Relano and Pauly, 2023). In 2023, the EU released an action plan suggesting to tighten management in MPAs and phase out all fishing activity with bottom-contacting gears in MPAs (EU, 2023). However, to date, the EU action plan has not resulted in any binding legislation.

Offshore renewable energy plants such as tidal and wave energy sites or OWFs are essential for meeting international objectives like the Paris Agreement aiming at reducing greenhouse gas emissions by 55 % until 2030 as compared to 1990 (GWEC, 2019). Europe is an important player in the transition to green energy, and financially promotes OWF development (European commission, 2012). In the North Sea, the first OWF was implemented in 2002, and since then OWFs have expanded, surpassing oil & gas infrastructures in 2021 (Martins et al., 2023; Paolo et al., 2024). Nowadays, European waters contain 52 % of global OWF structures and are one of the areas with the fastest OWF development rates (Paolo et al., 2024). Fishing activity is either prohibited in OWFs or does not take place, because of risks to damage cables and other infrastructure (Bonsu et al., 2024). Therefore, if placed in traditional fishing grounds, OWFs reduce the area available to fishers, displacing their activity (Gimpel et al., 2015; Stelzenmüller et al., 2015a). In the Norht Sea, particularly fishing grounds for plaice and sole overlap with current and planned OWF sites, which could result in economic losses for the flatfish fishery (Berkenhagen et al., 2010; Stelzenmüller et al., 2016). To mitigate the effect of OWFs on fisheries, North Sea ripparian states are developing legislation for co-use strategies that allow fishing in specific zones or with certain gears. However, these leglislation differ across country, e.g. Germany allows the fishing with passive gears such as pots and traps in a buffer zone from 150 m to 500 m around OWFs, while the Netherlands established multi-use zones for fishers within OWFs (Bonsu et al., 2024). Despite the existing co-use legislation, little is known about the feasability of these plans with regard to both profitability and ecological conditions, i.e. whether marine resources in OWFs will be sufficient to sustain this fishery.

In contrast to stakeholder groups with a fixed spatial claim (e.g. OWFs and marine conservation through MPAs), fisheries are a free-ranging human activity, which is why there are few examples of explicit consideration of fisheries in MSP despite their large spatial footprint (Trouillet et al., 2019). The German marine spatial plan introduced in 2021 poses an exception, as it includes a priority area for Nephrops fisheries (*www.bsh.de*).

2. Simulating fisheries

2.1 Fisher behavior matters

Fisheries are part of dynamic, complex systems that interact with ecological, economic, and social factors referred to as socio-ecological systems (Fuller et al., 2017; Partelow, 2018). In these systems, fishers play a central role, and therefore should be considered when researching fisheries dynamics or developing management (Hilborn, 2007; Kannen, 2014). The history of North Sea fisheries shows that change is an all-time companion of fishers who adapt to fluctuating fish populations, new fishing regulations, and rising fuel costs (Stelzenmüller et al., 2024a; van Hoof et al., 2020). The type and extent of these adaptations are difficult to foresee and may result in negative consequences for the ecosystem (Fulton et al., 2011). The displacement of fishing activity could have negative ecological effects if the new fishing grounds comprise threatened species or sensitive habitats (Dinmore et al., 2003; Liu et al., 2016; Rijnsdorp et al., 2001). Moreover, fishing closures can provide an incentive for fishers to increase their effort resulting in unsustainable levels of exploitation (Gordon, 1954; Sys et al., 2017) and mesh size regulations may lead to higher amounts of bycatches (Graham et al., 2007). Therefore, an essential part of sustainable management should be to anticipate fishers' reaction to changes and new regulations. This requires knowledge on drivers of fishing behavior and simulation tools considering fishers' decision-making to assess the adaptation of fishers to future changes.

2.2 Fisheries and agent-based models

Agent-based models (ABM) are computational tools for the simulation of heterogeneous individuals, i.e. agents, that act according to a set of rules in a digital environment (Bonabeau, 2002). They have been applied in many different disciplines, e.g. ecology, social science, and economy (Bruch and Atwell, 2015; Filatova et al., 2013; Grimm et al., 2006; Haase et al., 2023; Huber et al., 2018). Due to their great flexibility and capability to combine quantitative and qualitative data, ABMs are also increasingly used to model human decision-making in socio-ecological systems (An, 2012; Rounsevell et al., 2012; Schwarz et al., 2020).

Applications of ABMs in fisheries have simulated individual fishing vessels or skippers with distinct technical characteristics (e.g. vessel size, engine power, fish hold capacity), fishing gears, or personal preferences (Bailey et al., 2019; Bastardie et al., 2016; Wijermans et al., 2020). Hence, in comparison to the widely used bioeconomic models for fishing fleets (Blanz, 2018; Garcia et al., 2017; Salz et al., 2011), ABMs offer the opportunity to consider heterogeneity among agents. The suitability of ABMs for fisheries became reflected in the increasing number of application in fisheries for more than 20 years (Haase et al., 2023). However, most of these ABMs simplify human behavior by assuming rational choice and profit maximization (Andrews et al., 2020; Haase et al., 2023; Van Putten et al., 2012; Wijermans et al., 2020). Pollnac and Poggie (2008) noted that fishers can have a surprisingly strong attachment to their profession despite the many affiliated dangers that come with working on vessels and high uncertainties about profits. Therefore, fishers decision-making entails more complexities than generating profits, i.e. risk-averse behavior (Holland, 2008), tradition or habitual behavior (Stelzenmüller et al., 2024a), and avoiding bycatches of marine mammals (Barz et al., 2020). Implementing more realistic human behavior in ABMs is challenging, because usually data about the motives of human decisions are rare (Elsawah et al., 2020; Lindkvist et al., 2020; Schwarz et al., 2020). Conceptualizing human behavior based on theories is a common method and workaround if no empirical data is available (Schlüter et al., 2017; Schwarz et al., 2020). Many of these theories suggest behavior beyond profit maximization and rational choice, e.g. habitual behavior or descriptive norms (the observed behavior of others influences your own behavior) (Schlüter et al., 2017). The integration of theories or empirical knowledge on human behavior in fisheries ABMs, was recently termed as the “next generation of fishery models” highlighting the need to move beyond the simulation of pure profit maximization behavior (Wijermans et al., 2020).

3. Research gaps and objectives

In this thesis, I identify the effects and extent of current and future pressures for North Sea fisheries focusing mostly (but not exclusively) on German fleets in the southern North Sea. Furthermore, I develop an ABM to simulate spatio-temporal fishing dynamics.

The vast expansion of OWFs and other offshore renewable energy sites will compromise fishing opportunities by claiming areas in traditional fishing grounds. Prior the publication of Chapter I (Stelzenmüller et al., 2022), no scientific study had quantified the extent of this conflict potential. Therefore, in Chapter I, my co-authors and I integrate several sources of fishing effort data and perform a European-wide overlap analysis with present and future offshore renewable energy site polygons. As such, it is the only chapter with a geographical focus beyond the North Sea. However, results identify the North Sea as a hotspot for conflict potential especially between OWFs and bottom trawlers catching flatfish and Nephrops.

Designated MPAs in the North Sea often lack management plans or consist of a mixture of multi-use zones only partially restricting fisheries. However, regional and global nature conservation targets aim at an increasing number of no-take zones (i.e. restricting all fisheries), which could lead to a reduction of fishing grounds adding to those lost due to OWF expansions. Moreover, the balance of swapping quotas and access of the UK EEZ became challenged by Brexit, intensifying the uncertainty for fisheries already introduced due to spatial fishing restrictions. In Chapter II, my colleagues and I assess these uncertainties on the basis of the North Sea Nephrops fishery. The collation of many different data sources revealed that a combination of OWF and MPAs may reduce German fishing grounds by 45%, while high fishing activity risks local resource depletion, and Brexit worsens Germany's position to swap quotas.

Chapters I & II contribute to uncover the conflict potential of future spatial fishing restrictions and fisheries. Species aggregations around OWF infrastructure could offer the potential for co-locating OWF and fisheries and thereby mitigate the economic loss of fisheries. However, the knowledge base for the feasibility of these co-use strategies and the ecological conditions is thin. In Chapter III, I isolated vessels equipped with pots and traps (a common gear to catch brown crab and lobster) from international fishing effort data. Findings show several vessels prefering to fish around OWFs, supporting the hypothesis that OWFs could be of benefit for fisheries. Moreover, experimental fishing with pots and traps in and around OWFs revealed an increased abundance of brown crab. Based on these results, Chapter III provides an economic break-even analysis demonstrating the economic feasibility of co-use fisheries.

Within the coming decades, North Sea fishers will face many challenges possibly leading to a transformation of the entire sector (Chapters I & II). Anticipating fishers' reactions to these changes is one the largest sources of uncertainty in fisheries management. Therefore, in Chapter IV, my co-authors and I reviewed relevant scientific literature on factors influencing demersal fisheries in the North Sea, and performed a boosted regression tree analysis to identify environmental, economic, and cultural drivers for German fishing fleets. Results comprise a ranking of drivers influencing fishing effort, as well as their type of effect in specific parameter ranges. Our findings differed across fleets, which is why one of the main conclusions is to consider heterogeneity of fishers when releasing new fisheries regulations.

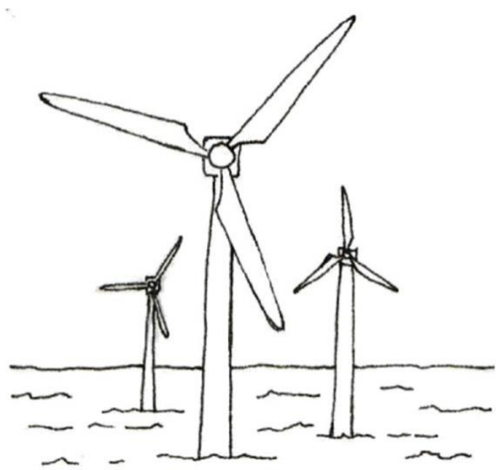
The majority of fisheries ABMs assume simplified human behavior based on a single economic objective. Fishers' behavior is more complex and often based on personal norms (being home during weekends), cultural values (fishing as way of life), and social interactions (what are other fishers doing). In Chapter V, I present FISHCODE, a spatio-temporal ABM for German fleets in the southern North Sea with emphasis on complex human behavior. Data products and developed methodologies from Chapter II help to prepare a comprehensive data base fundamental to FISHCODE, while insights from Chapter IV support conceptualizing the decision-making submodel. A comparison between observed data and model outcomes validate FISHCODE's structural realism and endorse the model as virtual laboratory and its application for scenario testing.

To unravel the effects of future changes on German North Sea fisheries, I created five scenarios based on potential spatial fishing restrictions (Chapters I & II), economic consequences of recent crises (i.e. rising fuel price), and a change in fishing regulations exemplified as the EU ban of PUL gears in 2021. Chapter VI describes these scenarios and applies FISHCODE to assess their effect on German fishing fleets in the southern North Sea. Model outcomes demonstrate a reduction of profits and fishing effort, a shift of metier engagement, as well as a spatial intensification of fishing effort. These findings are useful to reduce the uncertainty around future pressures for fisheries and develop MSP integrating the requirements of fishers and other stakeholders.

The above described chapters aim to fulfill the overall research objectives:

(1) identifying current and future pressures for North Sea fisheries with emphasis on spatial fishing restrictions (Chapter I & II)
(2) exploring co-use as a mitigation strategy for constrained fishing grounds due to offshore wind parks (Chapter III),
(3) identifying drivers of North Sea spatio-temporal fishing dynamics (Chapter IV), and
(4) constructing an agent-based model (ABM) to evaluate the effect of socio-economic scenarios on the German fishing sector (Chapter V & VI).

Chapter I



From plate to plug: the impact of offshore renewables on European fisheries and the role of marine spatial planning

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Abstract

Offshore renewables (OR), such as offshore wind farms, are a key pillar to address increasing energy demands and the global transition to a carbon-free power sector. The transition to ever more occupied marine spaces, often facilitated by marine spatial planning (MSP), increases the conflict potential with free ranging marine sectors such as fisheries. Here, we quantified for the first time the direct impact of current and future OR development on fisheries across European seas. We defined direct impact as the average annual fishing effort (h) overlapping with OR planning sites and applied an ensemble approach by deploying and harmonising various fisheries data to optimise spatial coverage for the European seas. The North Sea region will remain the centre of OR development for a long time, but a substantial increase of conflict potential between these sectors will also occur in other European sea basins after 2025. Across all sea basins, fishing fleets deploying bottom contacting gears targeting flatfish and crustaceans are and will be affected the most by the already constructed and planned OR. Our results provide a solid basis towards an understanding of the socio-economic effects of OR development on European fisheries. We argue that European MSP processes need to adopt common strategies to produce standardised and harmonised socio-economic data to understand implications of OR on free-ranging marine activities such as fisheries.

Keywords: Adaptive capacity, fishing effort displacement, fishing métiers, spatial overlap, offshore renewables, offshore wind farms

1. Introduction

The advancement of offshore renewables (OR), such as offshore wind farms (OWF) or wave and tidal energy devices, is a response to increasing energy demands and a key pillar in the global transition to a carbon-free power sector (GWEC, 2019). In 2018, the worldwide installed capacity of OWF summed up to 23.1 GW with a European contribution of roughly 79%. Europe in particular pushes the OR development further to progress towards the global Paris Agreement targeting a reduction of greenhouse gas emissions by 55 % by 2030 compared to 1990 (European commission, 2012; Gimpel, 2015; Leonhard et al., 2013; Lindeboom et al., 2015; Methratta, 2020; Pezy et al., 2020; Raoux et al., 2017). The global expansion of offshore marine structures also known as ocean sprawl is regarded as one of the most extreme man-made modifications to the marine environment with, as yet, uncharted cumulative environmental effects (Bugnot et al., 2021). Aside of its impact onto the marine environment (Lindeboom et al., 2015), the OR proliferation will also speed up the race for space in the already heavily used coastal and offshore waters (Halpern et al., 2019). The increase of blue growth and economic development bears numerous risks including those of loss of livelihoods for local fishers, lost access to marine resources, inequitable distribution of economic benefits and, social and cultural impacts (Bennett et al., 2021). OR license areas almost always reduce access to traditional fishing grounds forcing a subsequent displacement of fishing activities to other areas (Gimpel et al., 2015; Stelzenmüller et al., 2015a). The spatial designation of OR is often part of integrated spatial management approaches such as marine spatial planning (MSP). In contrast to the allocation of OR development areas, traditional free ranging human activities such as fisheries, which are strongly linked to spatio-temporal dynamics of fisheries resources, are barely considered in planning processes (Janssen et al., 2018; Said and Trouillet, 2020; Trouillet et al., 2019)

MSP has become the most widely used place-based management approach aiming to mitigate spatial use conflicts at sea, to create legal foundations for maritime investments, and to implement an ecosystem-based approach to marine governance (Frazao Santos et al., 2020). Hence, global MSP initiatives comprise diverse goals and objectives, but often address the growth of marine sectors and the safeguarding of biodiversity loss (Stelzenmüller et al., 2021a; Trouillet et al., 2019). Particularly Europe was at the forefront of putting MSP into practice (Ehler and Douvere, 2009). Triggered by Blue Growth initiatives, the first spatial plans were implemented in the southern North Sea (Belgium and Germany) in the early 2000s (European commission, 2012).

The socio-ecological effects of MSP, comprising OR development, are progressively being debated in the wake of the rapid MSP implementation. In Europe, a strategic environmental assessment is the mandatory key instrument to address the wider impact of spatial planning (Stelzenmüller et al., 2021a). As yet, little is known on the socio-economic impacts of planning and current research focused rather on qualitative analysis of spatial use conflicts among sectors, such as OR, shipping and fisheries (Haggett et al., 2020; Schupp et al., 2021). A comprehensive understanding of socio-economic impacts of the OR development on fisheries requires not only a profound knowledge of "lost" catches of target species due to the displacement of fishing activities from OR development areas, but also distinguished data on associated costs (e.g. energy, labour, investments, etc.) for the fisheries sector. While the current knowledge enables an estimation of spatially resolved revenues, it allows only for a limited analysis of displacement effects (Pascual et al., 2013; Stelzenmüller et al., 2011). Tools such as bio-economic modelling allow to link total costs of fishing activities with population dynamics of the respective resources, hence enabling tailored predictions on future catches at the local or regional seas scale (Nielsen et al., 2018). However, the direct use of such models to assess the socio-economic impacts of planning is constrained by the parameterisation with regard to ecological and socio-economic effects at such fine scale resolutions as OR planning sites (Bastardie et al., 2020).

For the first time, we quantify the spatio-temporal overlap of fishing activities with current and future OR locations within European coastal and offshore waters, and provide a first pan-European review on the implications of present and future OR development on fisheries. We assessed spatio-temporal trends in the development of conflict potential between OR and fisheries by comparing the present, mid-term and future overlap at various spatial scales. This allowed identifying the type of fisheries that will be affected the most by effort displacement. Finally, we discuss the capacity of MSP to plan with fisheries and OR, and identify data and knowledge needed for a comprehensive assessment of the socio-economic impacts of OR on fisheries.

2. Methods

2.1 Resolving spatio-temporal patterns of fishing activities in European seas

For this study, we distinguished six European seas i.e. the Black Sea, Baltic Sea, North Sea, Celtic Sea, Atlantic and Mediterranean (Figure I-1). As a starting point, we used the boundaries of the marine sub-regions as they have been defined for the Marine Strategy Framework Directive (MSFD) (Jensen et al., 2017). We merged the western and central Mediterranean, Ionian and Aegean Sea as well as the Adriatic Sea to one category representing the Mediterranean. The Bay of Biscay and the Iberian coast were categorised as Atlantic. Further, our definition of the greater North Sea comprised the Kattegat and English Channel. Since no OR development takes place in the Black Sea, we excluded this sea basin from the subsequent analysis. Interactions of fishing activities and OR sites occur at scales of a few hundred meters. Yet, there are no aggregated and standardised data on fishing effort covering all European sea basins at such high spatial resolution. To assess the conflict potentials between OR and European fisheries, we therefore integrated four fishing effort data sources with varying spatial and temporal resolutions (Table I-1, Appendix A).

Table I-1. Spatial and temporal coverage of data on fisheries activities used to analyse the conflict and impact potential of marine energy development

Data source	Type of data	Grouping variables	Temporal scale	Spatial scale	Resolution
Global Fishing Watch (GFW)	Fishing effort [h]	Fishing gear	2012-18	Global	Daily; 0.01° × 0.01°
OSPAR	Fishing effort of mobile bottom contacting gears [h]	Fishing métier level 5 (DCF)	2009-17	OSPAR region	Yearly; 0.05° × 0.05°
HELCOM	Fishing effort of mobile bottom contacting gears [h]	Fishing métier level 5 (DCF)	2009-16	HELCOM region	Yearly; 0.05° × 0.05°
Vessel monitoring system (VMS)	Fishing effort of German vessels [h]	Fishing métier level 5 (DCF)	2012- 19	German exclusive economic zone (EEZ) of the North Sea and Baltic Sea	Pings; 2 hrs frequency

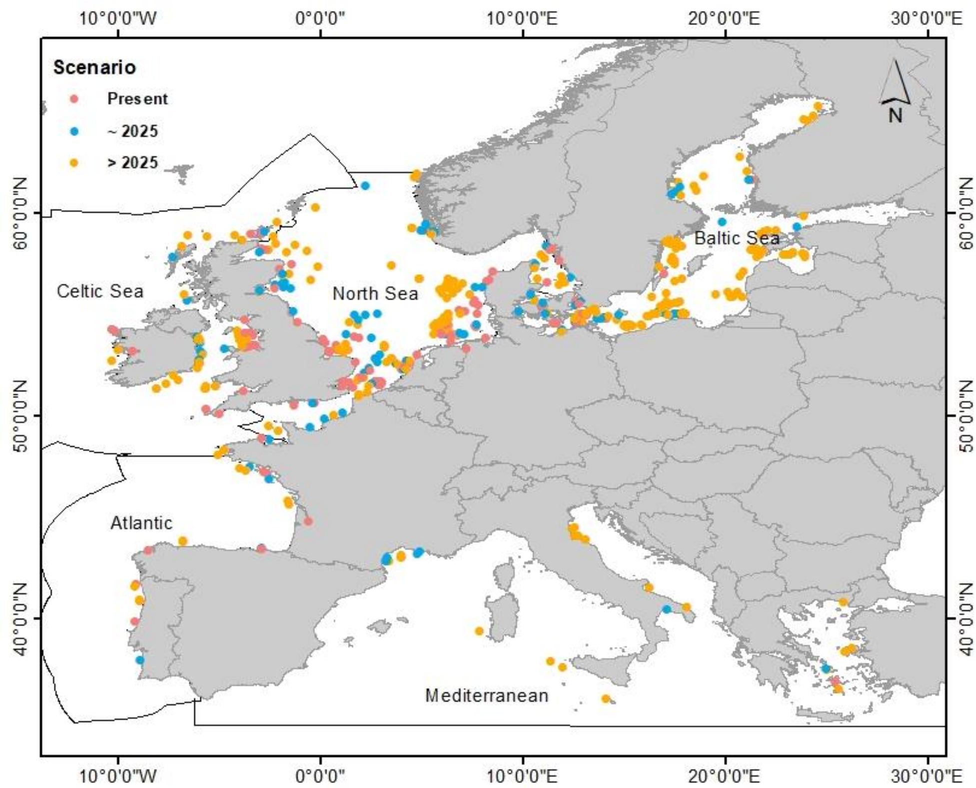

Figure I-1. European marine regions considered in this study, consisting of the Baltic Sea, North Sea, Celtic Sea, Atlantic and Mediterranean together with the spatial location of all 535 offshore renewable installations (status August 2020) that have been implemented (or constructed) before 2021 (red), until the end of 2025 (blue), and after 2025 (orange) (see data sources in Appendix A).

We extracted publicly available Global Fishing Watch (GFW) data to cover the entire study area (accessed 26.05.2020). These data comprise fishing effort by gear group but lack information on target assemblages or catch volumes. Further, we derived fishing effort data for the OSPAR (the Convention for the Protection of the Marine Environment of the North-East Atlantic) and HELCOM (Helsinki Commission for the protection of the Baltic Sea) regions, which are publicly available (0.05° longitude x 0.05° latitude). These fishing effort data are Vessel Monitoring System (VMS)-based and include catches by métier (fishing gear and target assemblage) of all bottom-contacting gears. The geographic scope of the OSPAR data encompasses the North Sea and Celtic Sea, while HELCOM data cover the Baltic Sea. VMS data frequency varies across member states but is often set at a time interval up to two hours from fishing vessels > 12 metres and include a number of attributes such as unique vessel ID, date, time, geographical position or speed. Finally, as an example of the use of high-resolution data to explore the conflict potential, we performed an analysis focussing on the German Exclusive Economic Zone (EEZ) of the North Sea. For the fine-scale German VMS data, we deleted duplicates of vessel reference numbers and time stamps and identified points within a three kilometres radius of harbours using the *pointInHarbour* function of the 'VMS tools'-package (Hintzen et al., 2012) for the R programming language (R Core Team, 2019). To distinguish between fishing trips and idle harbour time, we removed all points except for the last and first point of each harbour period indicating the beginning and end of a fishing trip. For each vessel, we calculated time steps and geographical distances between subsequent pings by summing up half of the times and distances from the previous to the current, and current to the next ping, respectively (Kroodsma et al., 2018). Based on the resulting distances and time steps, we calculated the speed in knots (nautical miles per hour) for each ping and removed those above 25 knots, representing unrealistic speeds and thus erroneous information. We merged each fishing trip with the corresponding logbook data containing information about landings, revenues, and métier (Letschert et al., 2021). We split the VMS data into groups with regard to gear and year and used the *activityTacsat* function of the VMS tool package (Hintzen et al., 2012) to classify pings into steaming, hauling, and fishing. We removed all steaming and hauling pings, so that the time step values of the remaining pings represented fishing effort. To enable a comparison between OSPAR and HELCOM VMS data, and German VMS data, we adapted métier names resulting in 14 common fishing métiers (level 5, (Decision)) based on the used gear and target assemblage (Table I-2).

2.2 Exploring the expansion of marine renewables in European seas

We derived spatial data on wave, tidal and, combined wind and wave energy plants from the EMODnet Human Activities portal (accessed 20.07.2020, Appendix A). These data also include information about the construction starting and, if applicable, ending date. However, only the EMODnet data of pilot sites included the necessary polygon information needed for this study. Since data on current and future OWF were not publicly available, we obtained a global data set on OWF development, from 4C Offshore Ltd (accessed 16.03.2021, Appendix A). We filtered the 4C Offshore data to OWF with available information about the starting date (i.e. the date at which the OWF is actively being developed on site) and status of the project. For those OWF with a valid status, but without start information, we reconstructed the starting year based on OWF of the same status with starting information (Figure I-1, Appendix A).

Table I-2. Overview of the métiers distinguished in the subsequent analysis of the OSPAR/HELCOM and German EEZ fishing effort data.

Gear type	Target assemblage/species	Métier (level 5)
Beam trawl	Crustaceans, mainly common shrimp (*Crangon crangon*)	TBB_CRU
Beam trawl	Demersal fish	TBB_DEF
Beam trawl	Molluscs	TBB_MOL
Danish seine	Demersal fish, mainly European plaice (*Pleuronectes platessa*) and Atlantic cod (*Gadus morhua*)	SDN_DEF
Dredge	Scallops and mussels	DRB_MOL
Midwater otter trawl	Small pelagic fish	OTM_SPF
Otter trawl	Crustaceans, mainly Norway lobster (*Nephrops norvegicus*) and common shrimp (*Crangon crangon*)	OTB_CRU
Otter trawl	Demersal fish	OTB_DEF
Otter trawl	Crustaceans, mainly Norway lobster (*Nephrops norvegicus*) and demersal fish	OTB_MIX_CRU_DEF
Otter trawl	Small pelagic fish, mainly European sprat (*Sprattus sprattus*) or sandeel (*Ammodytes*)	OTB_SPF
Pair trawl	Demersal fish	PTB_DEF
Pelagic pair trawl	Small pelagic fish	PTM_SPF
Scottish seine	Demersal fisheries, mainly Atlantic cod (*Gadus morhua*), Haddock (*Melanogrammus aeglefinus*) and flatfish species	SSC_DEF
Set gillnet	Demersal fish	GNS_DEF

EMODnet pilot sites and 4C Offshore data sets provided spatial polygons of OR sites and thus allowed for a spatial overlap analysis of present and future OR (OWF, wave, tidal and, combined wind and wave energy plants) with fishing effort data. Here we did not consider additional spatial overlap of fishing effort with associated infrastructure such as cables. We distinguished different periods (referred to as scenarios): (i) ≤ 2020 (“present”), (ii) ≤ 2025 (“mid-term”), and (iii) > 2025 (“long-term“). Further, we defined present OR as those with a starting date (i.e. start of construction) or status matching the temporal coverage of the respective fisheries data (Appendix A). Since the temporal coverage differed among the fishing effort data sets (Table I-1), the definition of present OR varies depending on the associated fishing effort data set.

2.3 Spatio-temporal overlap analysis on marine renewables and European fisheries

We conducted a spatial overlap analysis of European fishing activities (h) with present, mid-term and long-term OR installations by identifying the grid cells of the GFW, OSPAR and HELCOM fishing effort data, as well as the VMS pings for the German EEZ intersecting with the polygons of OR sites. To represent the conflict potential per OR location, we averaged the intersecting annual fishing effort (h). Thereby we considered only the years previous to the construction date of the respective OR project. A key obstacle when assessing the spatial overlap of fishing activities and areas designated for OR installations is the differing spatial resolution of fishing effort data. The examples of the overlap analysis between OR sites and the three fishing effort data sets indicated that the spatial overlap between OR and GFW and OSPAR/HELCOM fishing effort data are rather conservative and might lead to a general overestimation of the actual fishing effort associated with a given OR polygon (Appendix C).

3. Results

3.1 European expansion of offshore renewables

Present OR installations show the greatest spatial expansion in the North Sea and Baltic Sea, with the UK having allocated the largest surface area of approx. 1480 km^2 to marine energy sectors followed by Germany and Denmark (Figure I-2). In the Mediterranean Sea, a single OWF currently exists in Italy, several more OWF are planned in Italy and Greece (Figure I-2). The existing OR in the Baltic Sea are exclusively OWF clustered near Finland and between Sweden, Denmark, and Germany. In the North Sea, OWF are also the most important and common OR. Only a few tidal and wave energy installations exist as test and prototypes in Belgium, the Netherlands, Denmark, Sweden, Norway, and Scotland. In the Atlantic region, most installations target wave energy (Spain, France, UK), whereas tidal energy installations occur in France and UK. The majority of the mixed wave/wind energy pilot sites are located in Portugal and Spain. In the mid-term, the main OR installations comprise OWF in the North Sea and Baltic Sea, whereby UK defined the largest area for the OR development (~10,000 km^2). Furthermore, the installation of OWF will advance in the Atlantic region (Spain and Portugal), and in the Mediterranean (France, Italy and Greece). All planned OR after 2025 are OWF installations. The centre of these developments remains in the North Sea, with fewer new installations in the Baltic and Celtic Sea as well as along the French Atlantic coast. Across the three planning scenarios, the largest spatial expansion of the sector is planned for UK waters followed by Danish, Norwegian, Swedish, Irish and German waters.

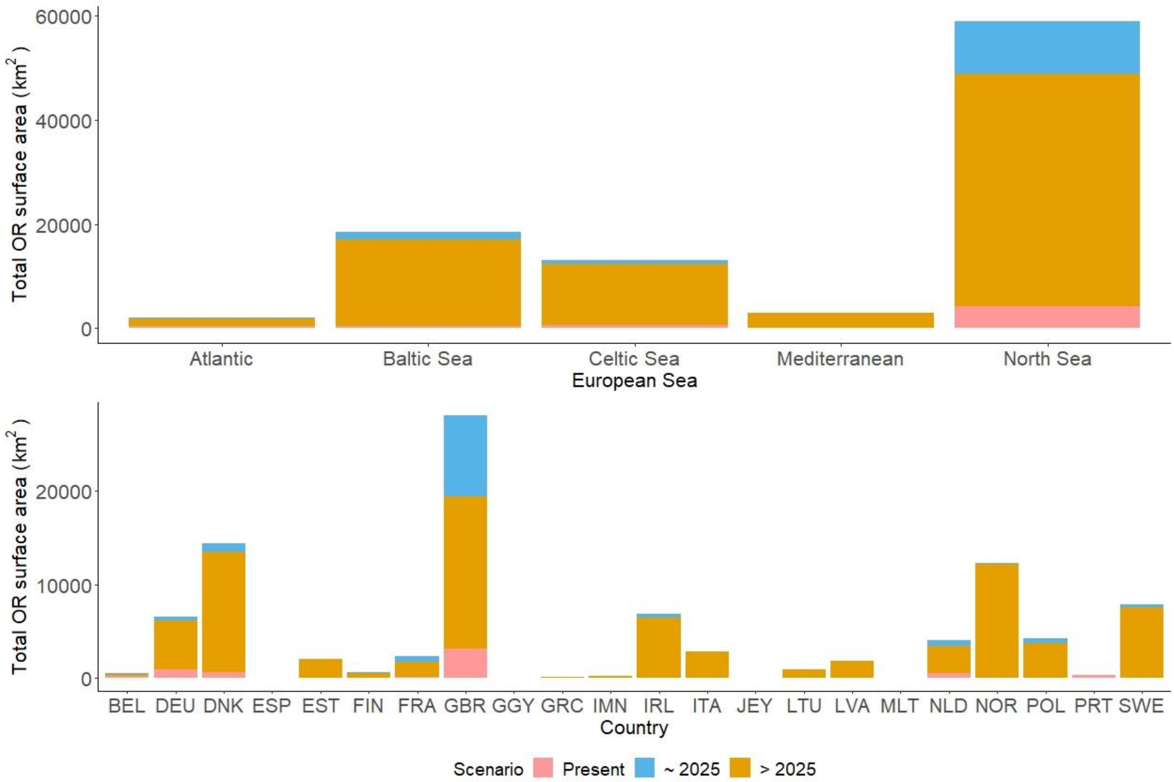

Figure I-2. Comparison of the total surface area (km2) designated for offshore renewable installations ("OR surface area") across European seas (top) and countries (bottom) for the present (red), mid-term (~ 2025; blue), and long-term (> 2025; orange) development scenarios.

3.2 Impact of offshore renewables on European fisheries

The spatial coverage of GFW data spanned across all European regions, hence allowing for a relative comparison of the total overlapping fishing effort across the European Seas by OR development scenario and course gear group (Figure I-3; see also Appendices C, D). Despite the uncertainties with regard to the accuracy of the actual spatial overlap at respective OR sites (Appendix C), we found the relative highest overlap of total fishing effort with OR sites in the North Sea and Celtic Sea (Figure I-3). Our analysis showed a substantial increase of conflict potential between the present state and the OR development from 2026 onwards for all European seas (Figure I-3; Appendix D). In the Baltic Sea, after 2025, the conflict potential (overlapping fishing effort) will increase 300-fold. For the long-term scenario we calculated for the Celtic Sea a 48-fold, for the Atlantic 8-fold and for the North Sea a 5-fold increase of conflict potential compared to the present spatial overlap of fishing effort. Across all European seas and for all scenarios, trawlers (demersal and pelagic; GFW data) will be affected the most by the expansion of OR (Figure I-3).

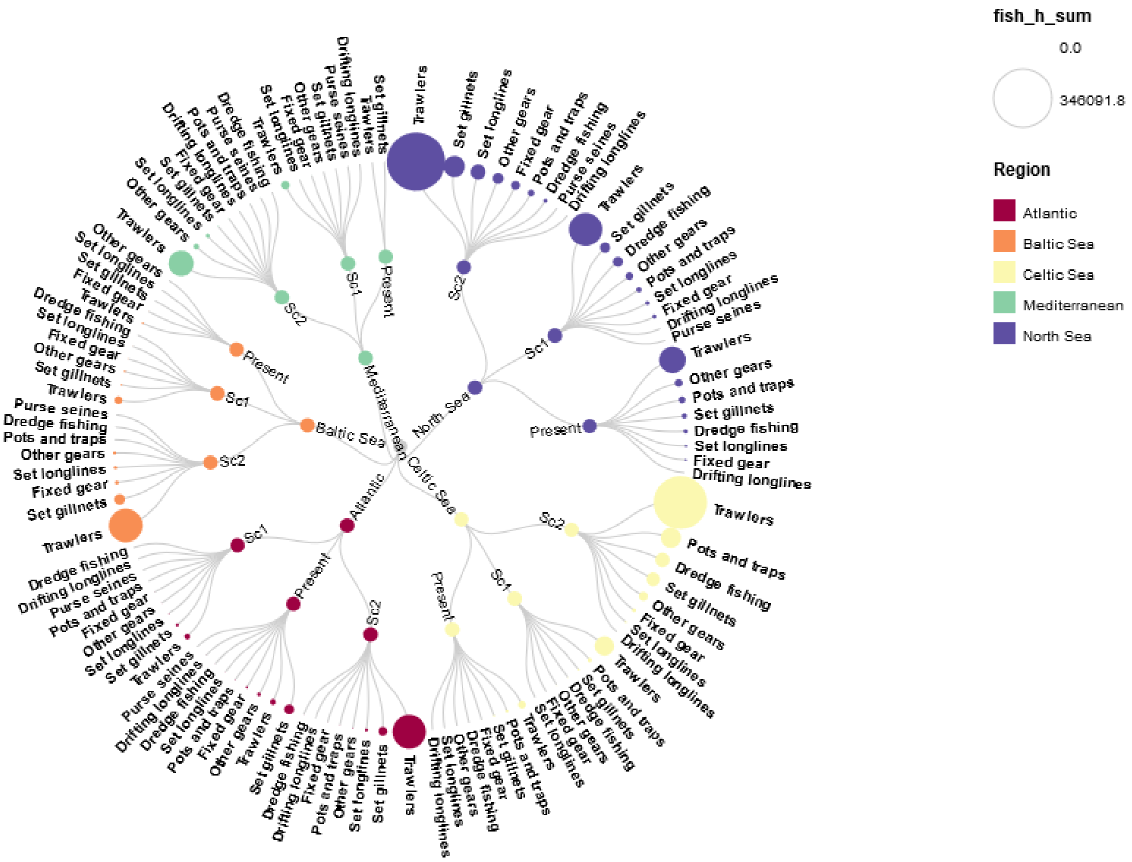

Figure I-3. Cyclic dendrogram showing the summed fishing effort (hours) being displaced by region, OR development scenario (present; sc1 = 2025; sc2 > 2025) and fishing gear type based on GFW data (see data sources in Appendix A); bubble sizes are relative to the maximum value of 346092 h (produced with RawGraphs; www.rawgraphs.io).

We mapped the average total fishing effort (log h) together with the location of the here considered 535 OR sites for the three different development scenarios (present, mid-term and long-term) for the North Sea, Celtic Sea Baltic Sea, and Atlantic, and Mediterranean (Figure I-4; A - E). The relative comparison of fishing effort across regions confirms the greatest spatial expansion and intensities of fishing activities in the North Sea and Celtic Sea. Hence, the spatial overlap with OR development sites in offshore waters points to the increasing conflict between these sectors in those two regions.

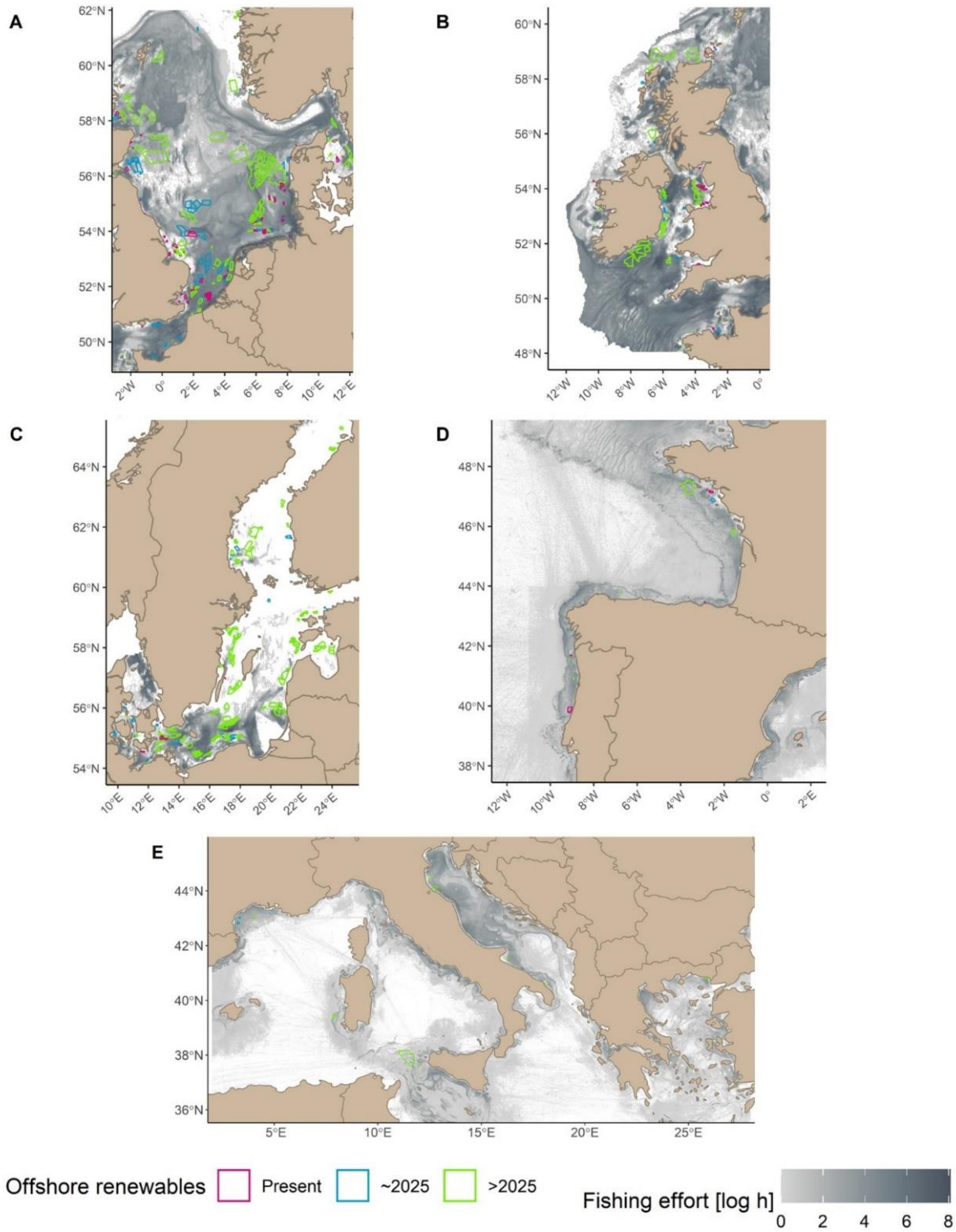

Figure I-4. Spatial distribution of the average annual fishing effort (log h) in the A) North Sea (2009-2017; OSPAR data), B) Celtic Sea (2009-2017; OSPAR data), C) Baltic Sea (2009-2016; HELCOM data), D) Atlantic (2012-2018; GFW data), and D) Mediterranean (2012-2018; GFW data) region together with the location and size of the OR development sites for the present (red), short-term (blue) and long-term (green) scenarios.

The types of fisheries that will be displaced due to the OR development varied greatly across the regions and development scenarios (Figure I-5). The use of the OSPAR and HELCOM fishing effort data in combination with our standardized métier definition enabled a better insight into the types of fisheries being affected in the Baltic Sea (HELCOM), Celtic Sea (OSPAR) and North Sea (OSPAR) (Figure I-5 A). In the Baltic Sea, the otter board fleet targeting demersal fish will be affected the most (> 80 %; HELCOM data). For instance, for the present state of OR development in the Celtic Sea roughly 30 % of the overlapping fishing effort can be associated to beam trawlers targeting demersal fish (TBB_DEF) and otter trawls targeting crustaceans (OTB_CRU), respectively. In contrast, for the next development phase the largest overlap of fishing effort will be mostly (~ 80%) with otter trawls targeting crustaceans (OTB_CRU). For the North Sea, such variations are less pronounced and beam trawlers targeting demersal fish remain to be the most affected. For the long-term scenario, 10 % of the North Sea fishing effort being displaced will be associated to otter boards targeting crustaceans and demersal fish. Comparing the type of fisheries to be displaced by the OR development for the Atlantic and Mediterranean Sea (GFW data; Figure I-5 B; Appendix D) showed that in the Atlantic region (Bay of Biscay and Portuguese coast), trawlers and set gillnets were the most affected gear group in terms of total effort for current future OR scenarios. In the Mediterranean Sea, the areas with the highest number of OR sites were the Gulf of Lions, the Ionian Sea (Gulf of Tarento) and the Aegean Sea for which we calculated a spatial overlap with mainly trawling fleets. Gill net and longline fleets will be affected only marginally by future OR expansions. Figure I-6 A reveals that the cumulative effect of OR installations across the Baltic Sea, Celtic Sea and North Sea will be most pronounced for otter boards targeting demersal fish and crustaceans, followed by beam trawlers targeting demersal fish. In the North Sea six fishing métiers will face a more or less equal amount of fishing effort displacement by the OR expansion.

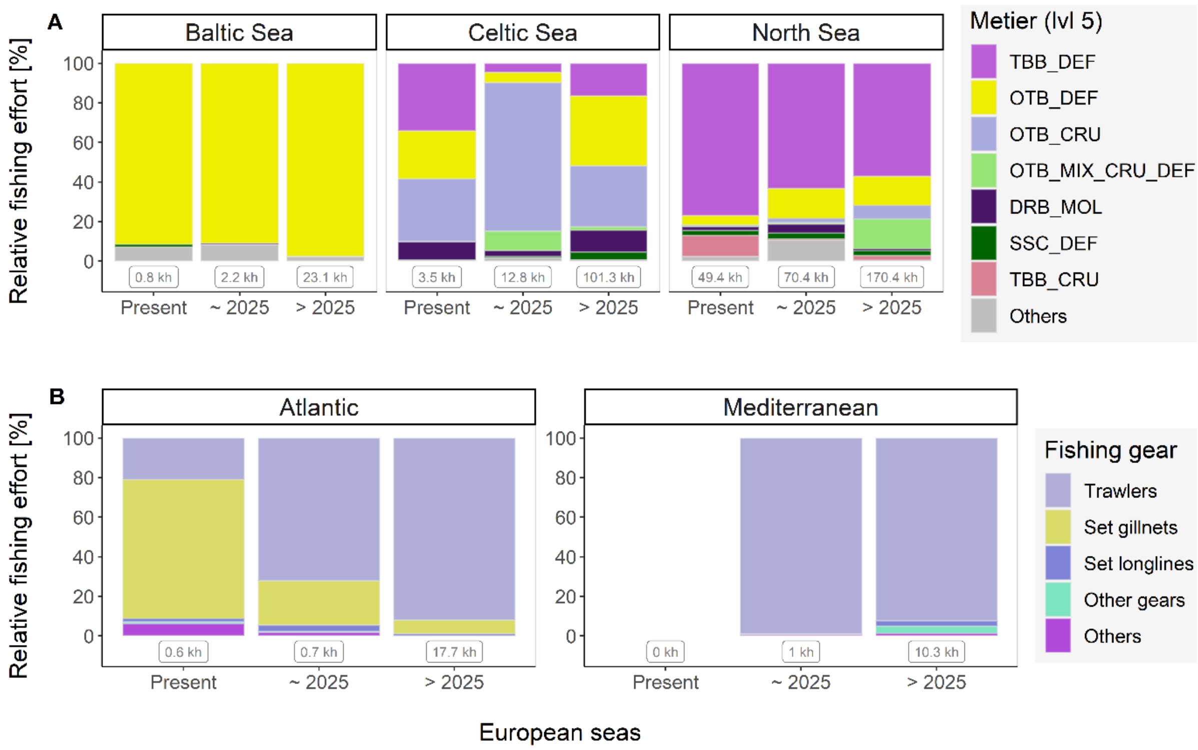

Figure I-5. Relative proportion of the total fishing effort of the main fishing fleets overlapping with the areas of the present, mid-term (until 2025), and long-term (> 2025) scenarios of offshore renewable installations in the Baltic Sea (HELCOM data), Celtic Sea and North Sea (OSPAR data) (top; see Table I-1 for the métier definitions) and Atlantic and Mediterranean Sea (bottom; based on GFW data). Numbers below bars indicate regional sums of annual mean fishing hours (conflict potentials; kh = 1000 hours) per OR for each development scenario.

The use of the high-resolution VMS and logbook data for the German EEZ of the Baltic Sea and North Sea allowed for a detailed assessment of the total hours fished by fishing métier being displaced across the OR scenarios (see comparison of scales in Appendix C). In the German Baltic Sea EEZ, pair trawls targeting demersal and small pelagic fish are affected by future OR expansions (Figure I-6B). The cumulative effect of the OR development in the German EEZ of the North Sea will displace substantial fishing effort of at least four different fleets targeting demersal resources. While in the entire North Sea the effort displacements were similar among development scenarios (Figure I-6A), the high-resolution VMS data revealed that the overall fishing effort displacement for German vessels within the German EEZ will be most substantial after 2025 (Figure I-6B).

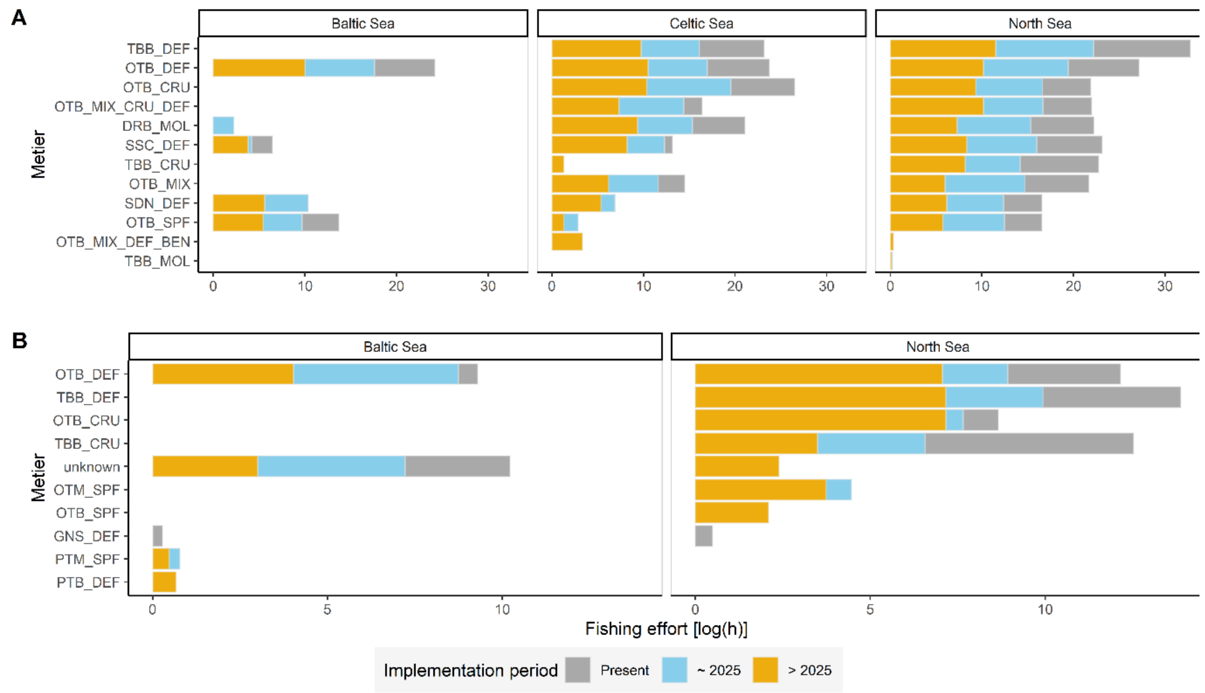

Figure I-6. Mean annual effort (log h) by métier affected by the present, mid-term (~ 2025), and long-term (> 2025) OR expansion in the Baltic Sea (HECLOM data), Celtic Sea (OSPAR data), and North Sea (OSPAR data) (A) and the German EEZs of the North Sea and Baltic Sea (VMS data) (B). To enable a better comparison, we added 1 to all values and then took the logarithm.

A relative comparison of fishing effort(h) and revenues (€) across the different data sets is shown in Figure I-7. GFW and OSPAR or HELCOM data represent international fishing effort, while the VMS data contain only German vessels. While this explains the large variation in absolute numbers of fishing effort and revenues, it also reflects the variability in precision of the respective overlap analysis due to mismatching spatial resolutions of data layers (see Appendix C).

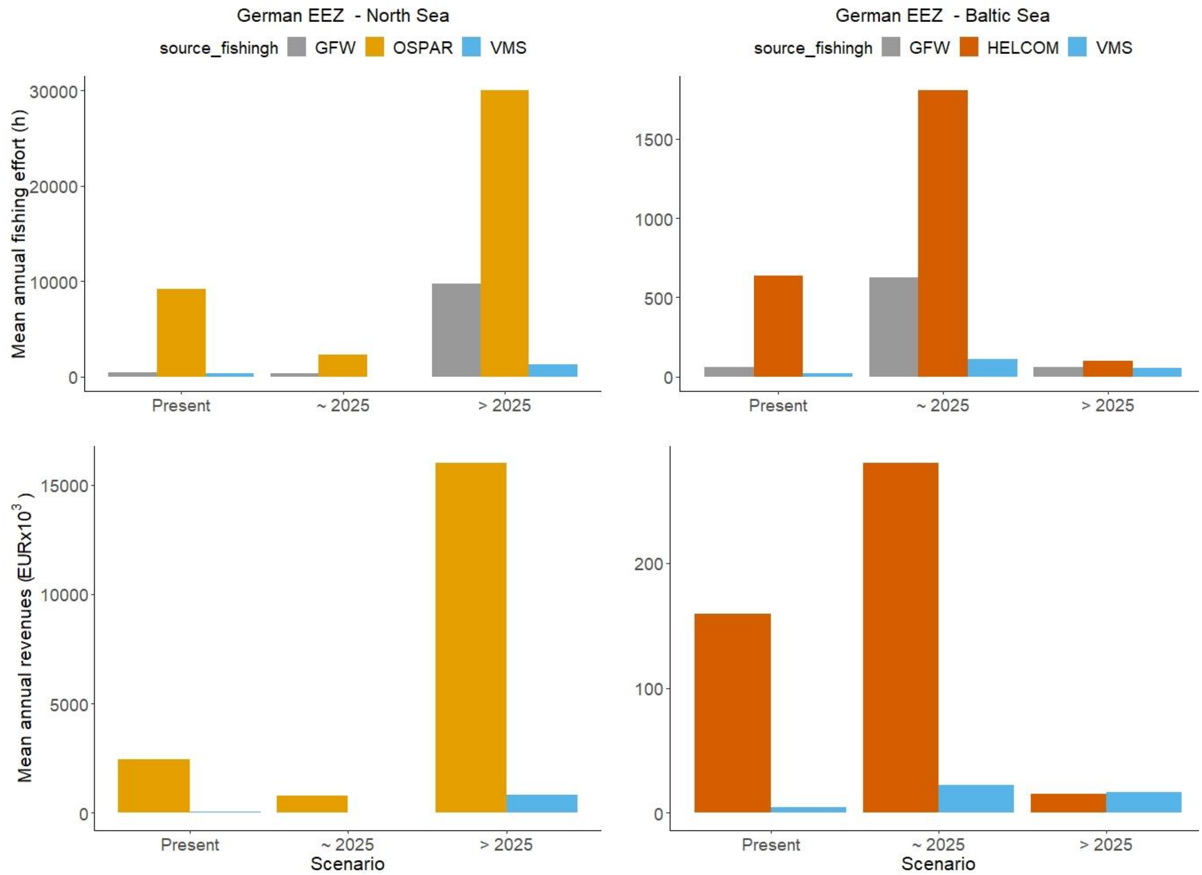

Figure I-7. Comparison of the mean annual fishing effort (h) (top) and mean annual revenues (€) (bottom) overlapping with present, mid-term (~ 2025), and long term (> 2025) OR planning sites in the German EEZs of the North Sea (left panel) and Baltic Sea (right panel) calculated with the three different fishing effort data (GFW, OSPAR/HECLOM, VMS).

4. Discussion

4.1 Analyzing conflict potential between offshore renewables and European fisheries

Our study provides for the first time a pan-European assessment of the potential socio-economic implications of OR development for European fisheries. We have shown that the North Sea region will remain the European center of OR development, but a substantial increase of conflict potential between this sector and fisheries can be expected in other European seas after 2025. Fishing fleets deploying bottom contacting gears targeting flatfish and crustaceans will be affected the most by the planned sprawl of OR in European seas. Here we applied for the first time an ensemble approach to analyze the exact spatial overlap of past European fishing activities with OR development sites. We deployed various fisheries data to optimize spatial coverage for the European seas and acknowledged the quantitative and qualitative differences between these fisheries data sources (Thoya et al., 2021). Detailed data on fishing activities and OR throughout Europe are not freely available, limiting high-resolution studies to areas where we had access to these data (German EEZ).

For the North Sea, Celtic Sea and Baltic Sea standardized data (OSPAR & HELCOM) on fishing activities using bottom-contacting gears were available including also information about target assemblages and generated values. Such aggregated data is still missing for other European seas. However, the spatial resolution of the OSPAR and HELCOM data is rather coarse given that some OR sites are as small as a few km². In contrast, GFW data has a finer spatial resolution enabling a sound overlap analysis with OR sites, but it is missing information about target assemblages and generated values. In addition, the gear classification of GFW data are rather coarse, i.e. there is no differentiation between pelagic and demersal trawls. For this reason, we used the standardized OSPAR and HELCOM data for a more detailed evaluation of European fishing effort displacements by fishing métier. Our analysis highlighted that the usage of VMS pings allowed for the highest spatial accuracy, while low resolutions of gridded fishing effort data led to large overlaps with individual OR sites, thereby overestimating the spatial intersection between fishing and OR.

The used data sets for the Atlantic, North Sea, Baltic Sea, and Celtic Sea did not include pelagic gears, adding a strong bias to our analysis. Additional sources of uncertainty for such spatial computations lie also in the nature of the fisheries data (AIS or VMS based data) with respective gaps in spatial and temporal coverages (Russo et al., 2019). For instance, two hours ping-intervals of VMS data result in large differences between real and estimated fishing tracks, stressing the need for high-resolution data (Katara and Silva, 2017). In addition, the lack of effort data for small-vessel fleets (vessels < 12 m length) such as e.g. gill-netters in the Baltic Sea or Mediterranean makes an evaluation of OR impacts on these fishing métiers particularly cumbersome. Potential cumulative effects of effort displacement could be substantial due to the large number of operating vessels, but this remains unknown as long as spatial highly resolved effort data for these vessels are not available. Particularly in areas with an intensive spatial expansion of OR, e.g. the German EEZ of the North Sea, local fishing effort displacements might have further knock-on effects on the *modus operandi* of the individual fishing fleets, hence leading to more fishing effort displacement, which we could not capture in our analyses. Accounting for these effects would require considering factors such as competition and subsequent local depletions of fishing resources (Hamon et al., 2014). Taken together, our ensemble analysis of conflict potential between OR development and European fisheries, using various fisheries data sources, highlights that care must be taken when interpreting and communicating absolute numbers of total fishing effort being displaced or associated revenues. With our approach we showed, that a sound quantification of conflict potential needs to start at the scale of individual planning sites and requires an ensemble approach together with a clear communication of the various sources of uncertainty (Stelzenmüller et al., 2015b).

4.2 Ways forward for sustainable marine spatial planning with fisheries

We illustrated that the progressing expansion of OR in European seas will lead to an increasing conflict potential between OR and European fisheries. Such sectoral conflicts should be mitigated by MSP since this management approach has the potential to align sectoral plans while contributing to ecosystem health (Abramic et al., 2020; Kirkfeldt, 2019; Manea et al., 2020). As yet, fisheries remain a spatially and legally unrecognized sector in many MSP processes (Said and Trouillet, 2020). Reasons for the notorious neglect of this sector are manifold and comprise spatial variations of fishing grounds which often are not spatially confined (Said and Trouillet, 2020), the lack of participatory planning approaches or political preferences of single sectors during the plan development (Aschenbrenner and Winder, 2019). Recent studies highlight the integrative capacities of MSP through frameworks (Vince and Day, 2020), participatory approaches (Quesada-Silva et al., 2019), or specific management measures (Reed et al., 2020). Management measures that can enhance the adaptive capacities of MSP also comprise the co-location of human activities in a given marine space (Jentoft and Knol, 2014; Kyvelou and Ierapetritis, 2019). The terms "co-location", "co-use" or "multi-use" are often used synonymously, but require a careful consideration of the spatial, temporal, provisional, and functional dimensions of the connectivity of uses (Schupp et al., 2019). As to date, most debated co-locations are the ones of OWF and aquaculture systems (Buck and Langan, 2017), and OWF and fisheries (Stelzenmüller et al., 2016). Co-location solutions with aquaculture would require technical modifications for foundations (Buck et al., 2004), while co-use with fisheries could only be restricted to passive gear fisheries such as pots and traps (Stelzenmüller et al., 2021c). However, sustainable co-use regulations of OR and fisheries requires the contemplation of socio-ecological trade-offs (Stelzenmüller et al., 2021c).

Fisher cannot claim a right to fish within a certain spatial location for instance within an OR site, but are usually managed by quotas for certain species or by a license system. Therefore, the OR development leads to a reduction of the available space for fishing, and fishing effort has to be relocated to other areas possibly resulting in increasing costs. From a methodological point of view fishing effort relocations due to OR development sites can be analyzed following the same methodologies as evaluating fisheries management measures (Malvarosa et al., 2019). For example, bio-economic models could be utilized to assess the socio-economic impacts of areas closed for fisheries (Nielsen et al., 2018; Simons et al., 2014). However, for MSP to consider only immediate or direct economic impacts for the fishing sector is cutting corners. Fishers are part of coastal communities, catches are directly sold or processed locally, hence adding value to the local economy. Banning fishing activities from multiple OR planning sites might lead to the necessity of fishers to search for alternative fishing grounds or move to another harbour. These are often traditional fishing communities that rely on fishing or tourism. Hence, most direct or indirect economic impacts of OR development on local fishing communities are barely understood and often not considered by planning authorities. We argue that MSP needs to embrace the socio-ecological complexity of fisheries, hence fisheries are socio-ecological systems with ecological, economic and social interdependencies (Lauerburg et al., 2019). This means that for integrative MSP processes it is key to better account for fisheries adaption strategies, which are a result of individual behavior (Schadeberg et al., 2021) and choices of fishing operators. Over the past years, agent-based models (ABM) have demonstrated to be useful means to understand the socio-ecological implications of human behavior (Cabral et al., 2010; Little et al., 2009; Wijermans et al., 2020). Exemplary categories and inputs to such models to better understand human behavior and choices comprise cultural heritages, traditions and beliefs, local attachment to space, identity of fishing communities, or degree of participation in various fisheries (Said and Trouillet, 2020). Such detailed socio-cultural knowledge is essential to understand the adaptive capacities of the fishing sectors and ultimately to evaluate the planning scenarios in terms of their capacity to mitigate socio-economic impacts. Our results point at the risk of unforeseen long-term socio-economic impacts for other sectors such as fisheries, depending on the advancement of OR and respective MSP regulations. However, common for European MSP processes is the need to conduct a strategic environmental assessment (SEA). A SEA is carried out at the planning or plan revision stage, as it contains a comparison between the current plan, the

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newly proposed plan and an alternative scenario (Stelzenmüller et al., 2021a). In theory, SEA should address environmental as well as socio-economic impacts of the proposed plan. Yet, in-depth socio-economic impacts of a marine spatial plan for spatially dynamic sectors such as fisheries are pending in current MSP practice (Stelzenmüller et al., 2021a). Hence, cumulative effects of existing and proposed OR development sites for fisheries (Berkenhagen et al., 2010) need to be urgently addressed in future SEAs.

5. Conclusions

The progressing transition from open seas to occupied spaces will lead to increasing conflict potential between stationary and free-ranging marine sectors such as offshore renewables and fisheries. Despite data collection and availability being key pillars of marine spatial planning, the access to socio-economic data related to fishing fleets and auxiliary businesses is still fragmented. Here, we accounted for trade-offs in spatial and temporal coverage of available fisheries data by using an ensemble analysis of fishing effort overlapping with individual planning sites. Hence, we exemplified that a sound quantification of such conflict potential starts at the scale of individual planning sites. The future increasing displacement of European fishing activities from offshore renewables planning sites has wider socio-economic implications than the immediate loss of fishing opportunities and revenues at those planning sites. We did not conduct a comprehensive socio-economic impact assessment; nevertheless, we believe that our results provide a solid basis to inform a participatory planning process. Marine spatial planning processes need to include fisheries and embrace the socio-ecological linkages in fisheries systems. This process will likely challenge the adaptive capacities of governance systems and processes. However, we argue that tools and approaches are readily available to improve the integrative marine spatial planning processes. These tools comprise e.g. participatory approaches or the consideration of co-location measures to mitigate economic impacts of fishing effort displacements. Standardised and harmonised socio-economic data on fisheries, namely spatially resolved data on fishing effort and landings as well as more details of affiliated companies, are needed for all European sea basins to foster such integrative MSP processes. In addition, more research is required to understand possible effects of investments in OR, on the fishing sector, coastal communities and economic activities onshore. Such an improved knowledge base would enable the integration of economic and socio-cultural data and the assessment of direct and indirect socio-economic impacts of planning options, as required legitimately by a strategic environmental assessment.

We argue that sustainable integrative planning with fisheries must be build bottom-up with knowledge on socio-economic trade-offs of planning options, comprising all existing and future spatial usage restrictions.

Supplementary material

Supplementary material of this chapter can be found in the *end of this thesis*.

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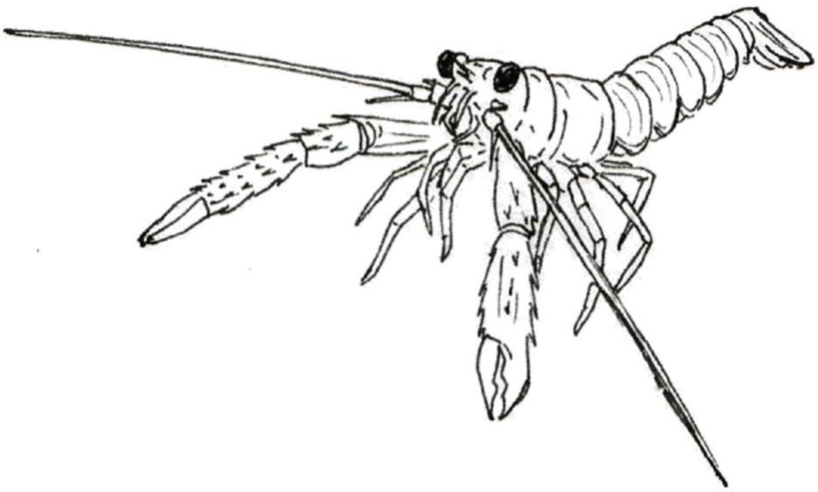
Author credit statements

VS: Conceptualization, Methodology, Resources, Formal analysis, Data curation, Funding acquisition, Writing - Original Draft; **JL**: Conceptualization, Methodology, Resources, Data curation, Writing - review & editing **AG**: Conceptualization, Methodology, Resources, Data curation, Project administration, Writing - review & editing; **CK**: Methodology, Resources, Formal analysis, Writing - review & editing; **WNP, SD, RD:** Methodology, Writing - review & editing.

Chapter II



The uncertain future of the Norway lobster fisheries in the North Sea calls for new management strategies

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Abstract

Nephrops (*Nephrops norvegicus*) is an economically valuable target species in the North Sea. Although individual Nephrops populations are scattered, the crustacean is managed regionally by the European Union (EU). The spatial competition for fisheries in the North Sea is growing especially due to expanding offshore wind farms (OWF) and newly implemented marine protected areas (MPA). Moreover, the Brexit affects the availability of EU fishing quotas and adds to overall uncertainty EU fishers face. We compare landings and catches to scientifically advised quantities and perform an overlap analysis of fishing grounds with current and future OWFs and MPAs. Furthermore, we explore the German Nephrops fleet using high-resolution spatial fishing effort and catch data. Our results confirm earlier studies showing that Nephrops stocks have been fished above scientific advice. Present OWFs and MPAs marginally overlap with Nephrops fishing grounds, whereas German fishing grounds are covered up to 45% in future scenarios. Co-use strategies with OWFs could mitigate the loss of fishing opportunities. Decreased cod quotas due to Brexit and worse stock conditions, lowers Germany's capability to swap Nephrops quotas with the UK. We support the call for a new management strategy of individual Nephrops populations and the promotion of selective fishing gears.

Keywords: German fishery, demersal fishery, resource management, offshore wind parks, Brexit, marine spatial planning

1. Introduction

The Norway lobster (*Nephrops norvegicus,* hereafter referred to as Nephrops) constitutes an important pillar of European fisheries generating a value of 107 M€, making it the 2nd most valuable landed shellfish species in the North Sea and Eastern Arctic region in 2018 (STECF, 2020). Since the start of commercial exploitation of Nephrops in the 1950s, the fishery grew substantially in the Celtic and North Sea, which are still the main Nephrops catch areas (Ungfors et al., 2013). The main fishing nations are the United Kingdom (UK), Denmark, Ireland, and the Netherlands (EUMOFA, 2019a). Several other nations, including Germany, represent minor actors in the international Nephrops fishery. The German Nephrops fishery presents an interesting case study, as it emerged relatively recently.

In waters of the European Union (EU), Nephrops is managed through the EU Common Fisheries Policy, and is one of only two crustacean fisheries in the EU that is subject to output controls (quota or catch limits), so called total allowable catches (TAC). Nephrops TACs are set annually and based on scientific advice provided by the International Council for the Exploration of the Sea (ICES). The EU Council Regulation allocates annual fishing quotas for each fishing area to EU member states according to the relative stability, a fixed proportional share for each country and fish stock. The relative stability is based on historical catch amounts and does not necessarily reflect present catches of EU member states. Therefore, EU member states may exchange quotas among each other (quota swaps). Although the Nephrops TAC applies on a regional scale, e.g. the entire North Sea, patchy suitable habitats for Nephrops (particular silt and clay contents) result in separate populations, which are referred to as Functional Units (FUs; Aguzzi and Sardà, 2008; Phillips and Bruce, 2008).

Despite the high economic value of this fishery several issues emerge that may jeopardise its future ecological and economic viability and call for closer examination. First, the mismatch between management at a regional (i.e. North Sea) scale and much smaller scale at which discrete stocks occur has been criticised for not ensuring sustainable exploitation rates and thus risking local depletion (ICES, 2019a; Williams and Carpenter, 2016). In fact, the Nephrops stock size has been considered too low in relation to biomass reference points in one FU and stock status is unknown for three of the nine North Sea Nephrops populations (ICES, 2020a). However, the EU management approach remains regional, although ICES releases annual scientific advices including Nephrops catch or landing recommendations for each individual FUs. Moreover, most Nephrops are caught by mixed fisheries using non-selective bottom trawls resulting in high amounts of bycatch (Briggs, 1986; Catchpole and Revill, 2008; Cosgrove et al., 2019; Evans et al., 1994). In fact, this diverse catch composition complicates the classification and distinction of a Nephrops fleet, since information on catch compositions, revenues, and vessel characteristics is used to group EU fisheries into so called fishing metiers (Ulrich et al., 2012). Despite all these issues concerning the Nephrops fishery, peer-reviewed scientific studies with a broad geographical focus, i.e. beyond single Nephrops FUs, are scarce (Ungfors et al., 2013).

The departure of the UK from the EU (Brexit) has been posing considerable uncertainty for EU Nephrops fisheries, given that the UK is allocated the largest share of the Nephrops TAC, and the main fishing grounds and FUs are located within the UK's exclusive economic zone (EEZ). In December 2020, a post-Brexit agreement was reached, which provided regulations for the joint management of over 100 shared fish stocks (European Commission, 2020b). Over a period of five and a half years (2021 to 2026), 25% of European fishing rights in UK territorial waters will be transferred to the UK fishing fleet. Although this does not affect the North Sea Nephrops quota allocation directly, it might influence quotas of species that are either caught in a mixed fishery with Nephrops or used to swap quotas with other EU member states. After the transition period there will be annual consultations held by the two parties on fishing opportunities with a focus on sustainable fishery management (European Commission, 2020b). Moreover, an agreement was achieved enabling quota swaps between individual EU member states and the UK (European Commission, 2021).

Like most fisheries in the North Sea, the Nephrops fishery competes for space with a large number of different stakeholder groups, such as shipping, offshore renewable energies, and nature protection (Halpern et al., 2015). The growth of the offshore wind farm (OWF) sector in particular is supported by the ambitious EU strategy of reducing greenhouse gas emissions, which could lead to an extensive overlap between fishing activities and OWFs (Stelzenmüller et al., 2020). Together with the future fisheries management measures of the Natura 2000 network of marine protected areas (MPAs), implemented under the Habitat and Birds Directive (Probst et al., 2021), a loss of spatial fishing opportunities is likely.

Here we describe the development of the Nephrops fishery in the North Sea since 2000 with emphasis on management, conflicts of spatial use, and implications of the Brexit. Our approach combines ecological, spatial, fisheries, and management information of the last two decades on Nephrops populations, i.e. FUs. We compare real and scientifically advised fishing opportunities for each Nephrops FU and perform a spatial analysis to assess the overlap of Nephrops fishing areas with current and future spatial fishing restrictions, such as OWFs and MPAs. In addition, we use logbook and spatially resolved effort data of German fisheries, as a case study for current and future challenges of the Nephrops fisheries in the German Bight. We apply a clustering approach to define German fishing practices distinguished by catch compositions.

2. Material and methods

2.1 International Nephrops fishing data

The study area encompasses the North Sea (FAO fishing area 27 subarea IV) and includes nine distinct Nephrops populations referred to as functional units (FU) (Figure II-1). We obtained Nephrops landings and discards data for each FU from ICES advices for Nephrops (downloaded from www.ices.dk). In addition, ICES advice is provided for Nephrops outside of the FUs. Landing data were unavailable in ICES advices for FU34 before 2009 and the outside area before 2010. For these areas, we obtained Nephrops landings data from the Scientific, Technical and Economic Committee for Fisheries (STECF) for the North Sea from 2002 to 2018 (Gibin and Zanzi, 2020), which are compiled quarterly and by statistical rectangle (1° Longitude × 0.5° Latitude), species, and EU member state. We aggregated annual Nephrops landings by FU to complement landings from ICES advices. Furthermore, we compiled STECF landings per country and FU in the German Bight to identify fishing nations active in FUs relevant for the German fleet. STECF data only include landings from EU fleets and therefore excludes Norway, which lands considerable amounts of Nephrops in FU32. A comparison of information from ICES advices and STECF can be found in Appendix C.

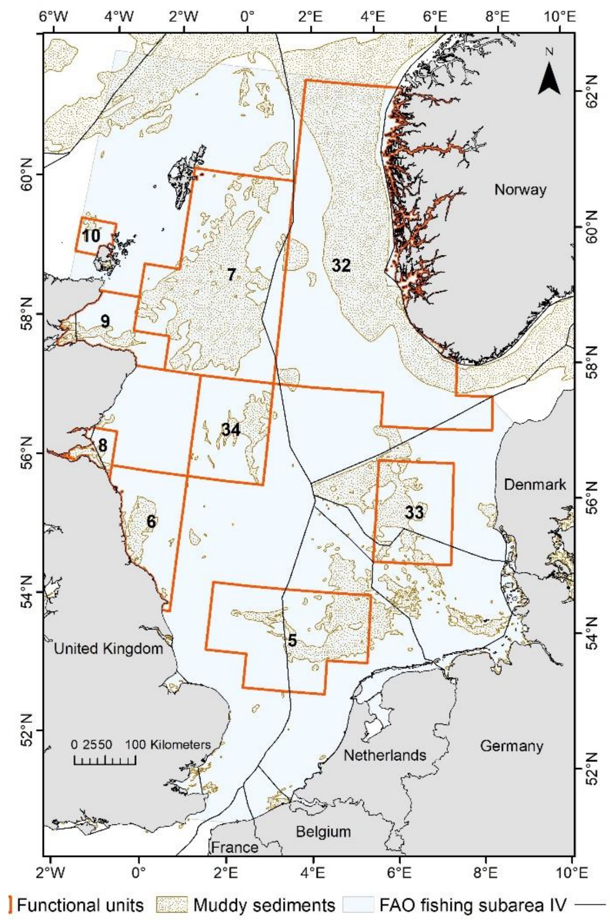

Figure II-1. Map of the study area (North Sea; FAO fishing area 27 IV) featuring the nine functional units for Nephrops management, the exclusive economic zones (EEZ) of adjacent countries, and the distribution of suitable (muddy) sediments for Nephrops.

If discards were available, we calculated catches by adding up landings and discards. Discard information were absent in ICES advices for the FUs 10, 33, and 34 and lacking for several years in advices of the other North Sea FUs. We gathered recommended total Nephrops catches and landings per FU from ICES advices between 2003 and 2021. Subsequently, we combined them with international Nephrops landings and catches to analyse the uptake and overshoot of advised fishing opportunities. Whenever information on discard was available, we compared catches to advised catches and in case either discards or catch advises were unavailable, we compared landings to advised landings.

Nephrops TACs are jointly set for the fishing areas 27 IV (North Sea) and EU (UK after Brexit) waters of 27 IIa (Norwegian Sea). For this area, we extracted Nephrops total allowable catches (TAC) per EU member state from annual Council Regulations of the EU (2003-2020). To assess the potential impacts of Brexit on North Sea Nephrops fisheries, we subtracted UK quotas from EU TACs and compared the results with landings (STECF) of EU member states catching Nephrops, i.e. Belgium, the Netherlands, Denmark, France, Germany. This was done for the years 2003 to 2016, as complete STECF landings by country for recent years were unavailable due to confidentiality issues.

2.2 German Nephrops fishery

To identify and analyse the German Nephrops fishery, we combined two types of vessel-specific data, i.e. commercial logbooks and vessel positions based on vessel monitoring system (VMS). Logbook data are resolved by fishing trip and comprise information about weight and composition of catches, revenues, and the statistical ICES rectangle (1° longitude × 0.5° latitude) where catches were recorded. VMS data contain geographical positions of vessels, which are broadcasted roughly every two hours (so called 'pings') by German vessels. Logbook data was available from 2000 to 2019, whereas reliable VMS data were available only from 2012 to 2019. All data-processing steps were done using the R programming language (R Core Team, 2019).

2.2.1 Fishing logbooks

We preselected vessels that targeted Nephrops within the last 20 years by choosing all vessels with a track record of more than 10% annual Nephrops catches in at least one year in the logbook data. Moreover, we excluded vessels that primarily fished in the Baltic Sea by choosing only those vessels that spent at least 50% of their annual fishing trips in the North Sea. Subsequently, we compiled all catch information of these vessels, selected only catch records of the 10 most caught species and, per fishing trip, converted total to proportional catches. Based on the resulting data set, we created a distance matrix (Euclidean distance) using the vegan package for R (Oksanen et al., 2019). We performed hierarchical agglomerative clustering using the average linkage method (Legendre and Legendre, 2012) and increased the number of clusters until a cluster emerged that mainly caught Nephrops. We ended up with seven fishery clusters, which we named after their main target species (Appendix A).

We visually explored the temporal distribution of the resulting fishery clusters and identified the year 2006 to be the first with fishing trips in the cluster targeting Nephrops. To analyse the development of the emerging German Nephrops fishery, we calculated changes of relative fishing activity before and after 2006 for each fishery cluster. First, we calculated the proportional fishing activity vessels spent in fishing clusters for both time periods, meaning 2000 to 2005 and 2006 to 2019, by dividing the number of fishing trips per cluster by the total number of fishing trips of the respective vessel. We removed vessels with fishing activity in only one time period and clusters with less than 30 trips across the entire study period, which made up less than 1% of all data. Second, we calculated the difference of proportional fishing activity before and after 2006 per cluster and vessel. Third, we summed up all proportional changes in fishing activity for each pair of fishing cluster. Finally, we visualized the shifts from one fishery cluster to another as a chord diagram using the circlize package for R (Gu, 2014).

2.2.2 Vessel monitoring system (VMS)

In a following step, we obtained VMS data for previously identified fishery clusters targeting Nephrops to analyse their spatial distribution. We removed duplicates and data points in ports from the VMS data and identified fishing pings, which are affiliated to slower speeds than when the vessel was steaming. We identified fishing pings by applying the *activityTacsat* function from the VMStools package for R (Hintzen et al., 2012). Subsequently, we selected only pings affiliated with fishing activity. Through merging logbook with VMS data (Appendix B for details), VMS data could be grouped according to the previously identified fishery clusters. Then, we generated their utility distribution, that is a function describing the probability of occurrence in a spatial area, using the least-square cross validation method with the adehabitatHR package for R (Calenge, 2006). We visualized core fishing areas by extracting 90% contours, referring to the minimum area in which vessels of a respective cluster have a 90% chance of occurrence.

2.2.3 Quotas

We received information on request about German Nephrops quotas (2003 – 2019) from the German Federal Office for Agriculture and Food (BLE; www.ble.de). Annual Nephrops quotas are assigned to EU member states and may then be swapped among countries. We received information on individual quota swaps from the BLE, which enabled us to quantify the amount of Nephrops quota Germany received from other EU member states and for what quota species it was swapped for.

2.3 Spatial overlap analysis

To assess current and future spatial competition of the Nephrops fishery with other human uses in the North Sea, we obtained a data set on offshore wind farm (OWF) development from *4C Offshore Ltd* (status March 2021) and marine Natura 2000 sites from the European Environmental Agency (status Dec 2020). Like all trawl fisheries, Nephrops trawler activity is prohibited in and around OWFs due to the risk of damaging OWF structures and submarine cables. We grouped OWFs in the North Sea according to three categories: (a) existing OWFs (sites that generate power or were under construction in 2020), (b) planned OWFs (all other sites with a construction start date between 2020 and 2033) and (c) potential sites (all sites without a construction start date minus those projects that have been cancelled or with failed proposals).

Furthermore, given that Nephrops FUs are based on statistical rectangles (1° Longitude × 0.5° Latitude) and do not represent fine-scale fishing grounds, we determined the suitable habitat for Nephrops within FUs using muddy sediment occurrence. We obtained substrate data from Emodnet (status Dec 2020) and used the classification 'mud to sandy mud' to characterize suitable Nephrops habitats. Subsequently, we determined relative spatial overlaps between present and future spatial restrictions, i.e. the three OWF groups and Natura 2000 sites, and all FUs in the North Sea, Nephrops habitats, and core fishing areas of the German fleet. All spatial analyses were done using ArcGIS 10.3.

3. Results

3.1 International Nephrops landings

Total international landings of Nephrops in the North Sea generally decreased from 2003 to 2018 peaking in 2007 with 24 kt (Appendix C). Across the entire time range, landings were highest in FU7 (7.3 kt), FU8 (2.1 kt) and FU6 (2 kt), all located in the UK exclusive economic zone (EEZ).

In only two out of nine North Sea Nephrops FUs, catches or landings have not been exceeding the advised amounts in any year (Figure II-2). From the years with available catches or landings and advised quantities, catches or landings exceed advised quantities in most years in the FUs 6 (77%) and 8 (85%). Landings or catches from the FUs 5, 9, 33, 34, and the outside region (North Sea area outside of FUs) exceeded advised quantities only after 2011, whereas FU 7 exceeded advised fishing opportunities only slightly from 2007 to 2009. On average, proportional excesses were highest in the outside area (216%) and lowest in FU7 (113%). For the years 2019 to 2021, no EU landing or catch data was available at the time we performed this analysis, but scientific advices remained on a similar level compared to previous years, except for FUs 7 and 8, with the former showing a decrease and the latter an increase.

A comparison of annual averages of landings and TACs by country (Figure II-3) revealed that the Netherlands and Germany have been fishing Nephrops above their quotas and therefore acquired additional catch capacities from other EU member states (Figure II-6; Appendix D). Germany required the highest additional quota on average (356 t) followed by the Netherlands (320 t). The UK, France, and Belgium fished below their quotas and therefore had capacities to swap their Nephrops quota with other EU member states. The UK had by far the highest average quota swap capacity (3400 t) followed by Belgium (770 t) and France (31 t).

Denmark's average Nephrops landings were only slightly lower than its TAC. Due to unavailable international catch and discards data, we compared landings to national quotas. This is a conservative comparison, because landings do not include discarded Nephrops at sea.

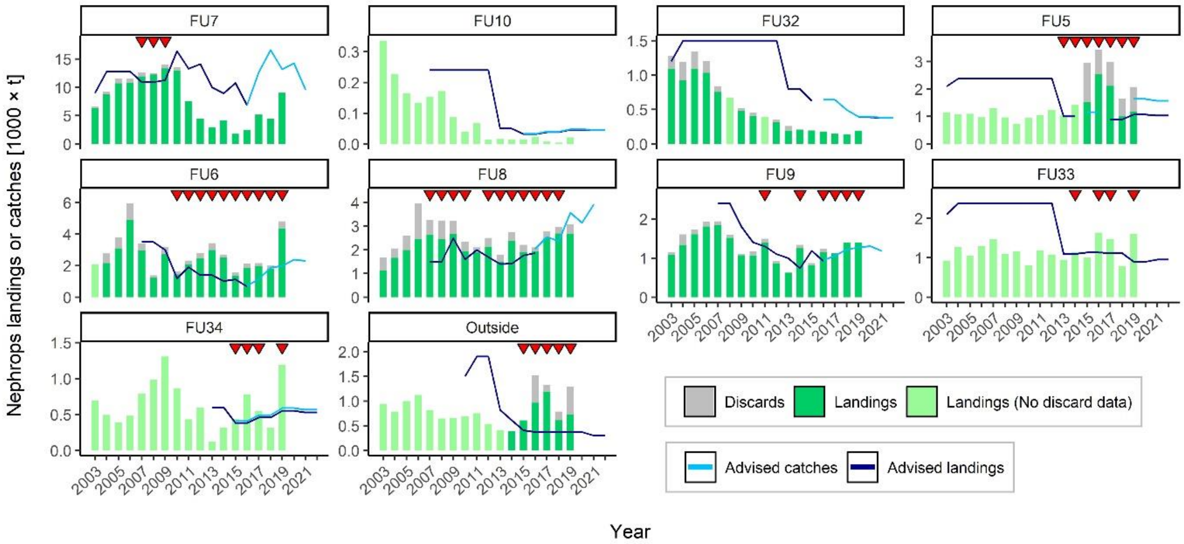

Figure II-2. International Nephrops landings and catches, as well as advised total catches (light blue) or landings (dark blue) from ICES per functional unit (FU). Catches are composed of landings (greens) and discards (grey). Years for which there were available discard information are coloured in dark green. The red arrows above bars indicate years with surpassed catch or landings recommendations.

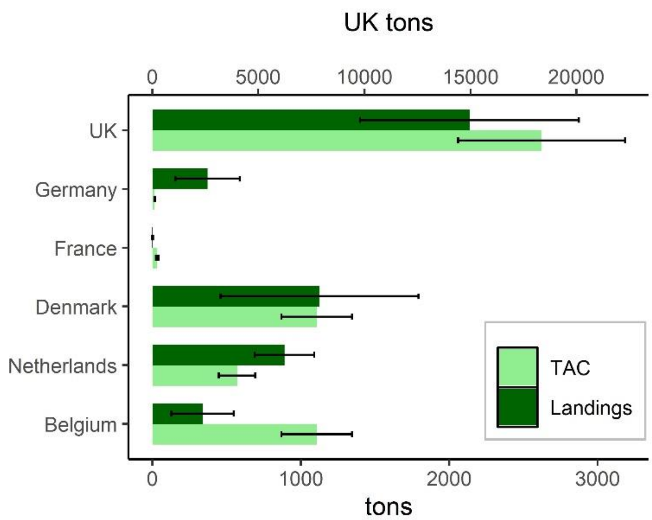

Figure II-3. Yearly averages (2003-2016) of Nephrops landings and total allowable catches (TAC) in North Sea per country. Displayed are all countries with a Nephrops TAC in the fishing area 27 IV and IIa. Error bars indicate standard deviation.

3.2 German Nephrops fisheries

3.2.1 Emergence of the German Nephrops fleet

We identified 22 vessels that targeted Nephrops in at least one year between 2000 and 2019 in the North Sea. Our cluster analysis revealed a distinct variation in fishing activities across these vessels over the past twenty years. We identified seven fishery clusters, which could be characterised by their main target assemblage: (I) *plaice*, (II) *whiting*, (III) *cod*, (IV) *sole*, (V) *brown shrimp*, (VI) *Nephrops & plaice*, and (VII) *brown crab.* Most fishery clusters target spatially different areas underlining that they are distinct fishing practices (see Appendix A for details). The only clusters catching substantial amounts of Nephrops (among the 10 most caught species) were *Nephrops & plaice* and *plaice*, the former primarily targeting Nephrops, whereas the latter primarily caught plaice and other demersal species with minor Nephrops amounts. The temporal composition of fishery clusters per year showed that the *Nephrops & plaice* group was merely present before 2006 and then remained stable with about 100 to 200 trips per year (Appendix A). The *brown shrimp* fishery cluster was another fishing practice that emerged in 2006 within the defined fleet. The other fishery clusters became less abundant over the time period and the *whiting* and *brown crab* groups disappeared in most years after 2012. Moreover, the clusters *brown crab* and *sole* were relatively small clusters with less than 30 trips (< 1% of all trips) and thus removed from the analysis.

As shown in Figure II-4, German vessels that switched to *Nephrops & plaice* after 2006 were previously engaging in the following fishery clusters (percentages represent proportional fishing activity of all vessels in the *Nephrops & plaice* cluster): *plaice* (82 %), *cod* (11%), *whiting* (4%), and *brown shrimp* (< 1%). Furthermore, a large amount of fishing activity became allocated to the *brown shrimp* cluster, emerging from the *plaice*, *cod*, and *whiting* clusters.

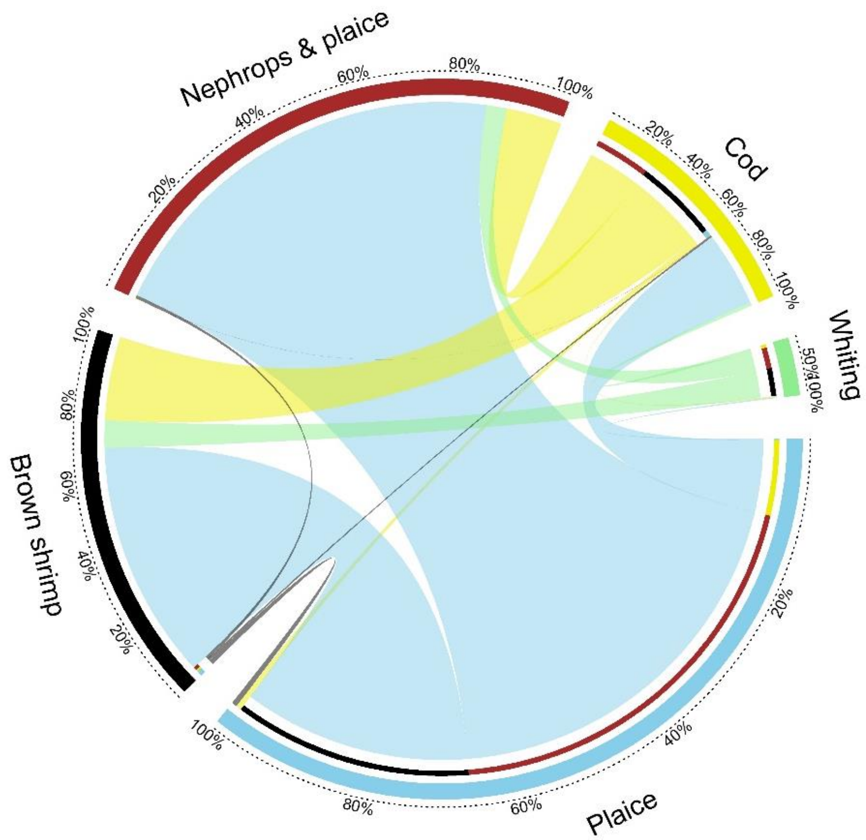

Figure II-4. The chord diagram shows the relative shift of fishing hours of all German vessels that ever participated in the Nephrops fishery (2000-2019). The connections represent flows from before to after 2006 between source clusters (outer wide circle) and target clusters (inner thin circle).

3.2.2 Spatial distribution, infrastructure, and quotas

The German Nephrops fleet targets FU5 and FU33 (Figure II-5), both located in the German Bight and, among all FUs, closest to German harbours (Figure II-1). The former is located in the EEZs of the Netherlands and UK, whereas the latter is located in the German and Danish EEZs. Several other nations are participating in the Nephrops fishery in the German Bight. Ranked in terms of landed Nephrops, from highest to lowest these are: the UK, the Netherlands, Belgium, Germany, Ireland and France (Figure II-5). Denmark predominantly fishes in FU33 and the UK in FU5, which represents the FUs closest to their coastlines. Moreover, there is a considerable amount of Nephrops landed from outside of the FUs suggesting some mismatch of FUs and catch areas. This also supported by the large areas of suitable Nephrops habitat adjacent to the FUs 5 and 33 (Figure II-1). Note that these results are based on STECF data excluding non-EU countries, such as Norway.

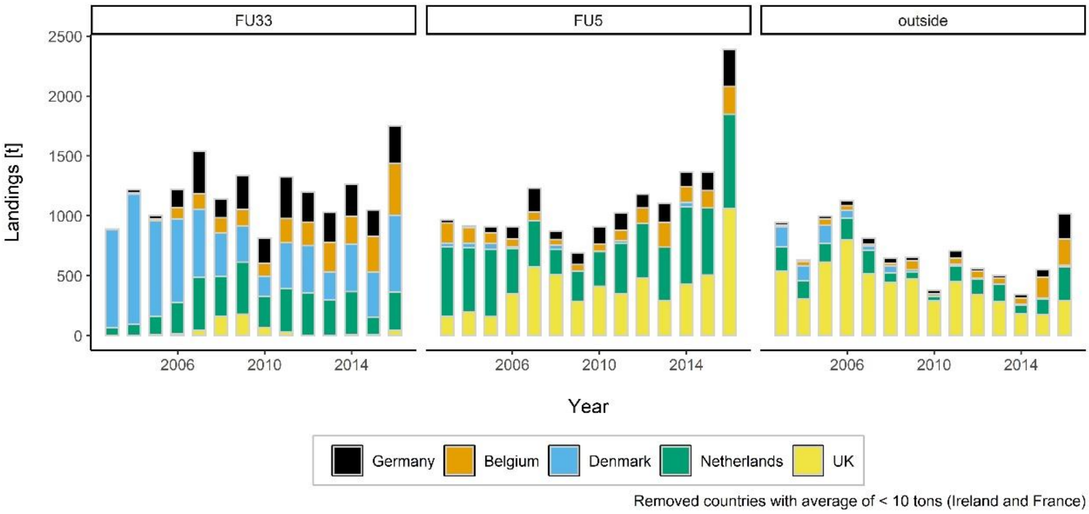

Figure II-5. Annual international Nephrops landings in the German Bight split into catches inside and outside of functional units (FU).

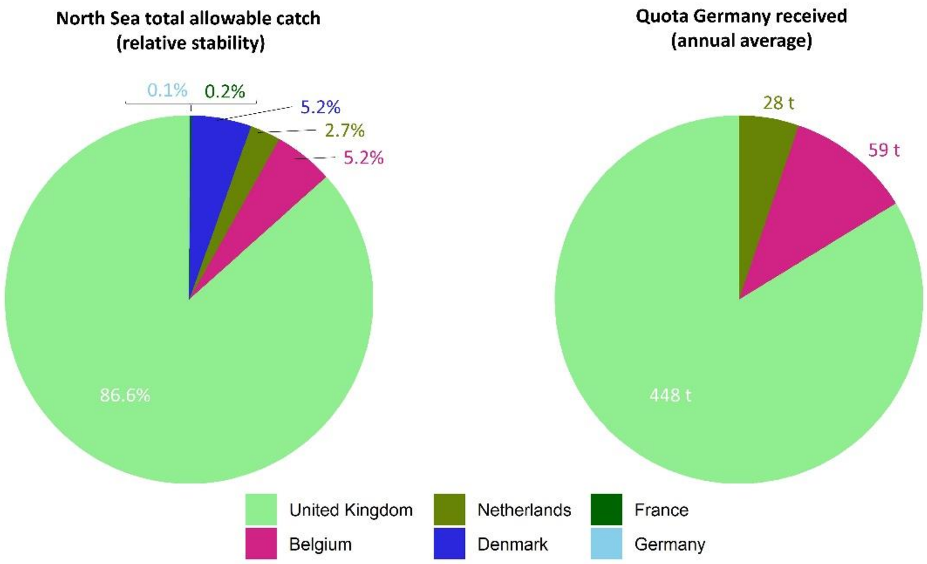

Figure II-6. Nephrops total allowable catch (TAC) in the North Sea as percentage per country (pre-Brexit), which is also referred to as relative stability (left) and annual averages of Nephrops quota (2003-2019) Germany received from other countries (right).

Based on an annual average, German vessels mainly landed Nephrops in Dutch (450 t) followed by German (31 t) and Danish ports (11 t), clearly highlighting the strong dependency of the German Nephrops fishery on international infrastructure (Appendix D).

The UK receives by far the largest share of North Sea Nephrops quota, followed by Belgium, Denmark, the Netherlands, France, and Germany (Figure II-6). The German share of the North Sea Nephrops TAC is extremely low (0.08%), which resulted in an annual average of just 17 t (2003-2020). To increase fishing opportunities, Germany swapped quota with other member states, mainly the UK, followed by Belgium and the Netherlands (Figure II-6). From 2003 to 2019, Germany performed 190 swaps gaining a total of 9100 t of Nephrops quota (Appendix D). With regard to the number of transfers, most species quotas used as exchange currency were cod (42), whiting (27), ling (24), anglerfish (21), haddock (17), hake (14), and sole (14). Despite the known received quantities of Nephrops quota, the data resolution did not allow to quantify the quotas given by Germany.

3.3 Current and future spatial constraints for the Nephrops fishery

3.3.1 North Sea

Currently only a minor fraction of FUs overlaps with OWFs and until 2033, on average, not even 1% of FUs will overlap with planned OWFs (Table II-1; Figure II-7a). However, if we consider potential OWF areas (those without starting date), we found an overlap of on average 8% per FU. An area of similar size (8%) could be closed to fishing under Natura 2000 regulations. While the majority of FUs face none or little spatial constraints from both OWF developments and Natura 2000 (0% to 6% when only suitable mud areas are considered), the FUs 5, 9, and 33 may face substantial losses of up to 28% of the fishing area.

3.3.2 German Nephrops fishery

There was almost no overlap (1%) of planned OWFs (until 2033) and the two German fishery clusters catching Nephrops (*plaice* and *Nephrops & plaice*; Table II-1; Figure II-7b). However, this is a conservative estimate including only OWFs for which a construction date was set. In fact, the overlap of both fishery clusters with potential OWF developmental areas and Natura 2000 sites was considerably larger. The relative overlap area was 45% for the *Nephrops & plaice* and 31% for the *plaice* cluster.

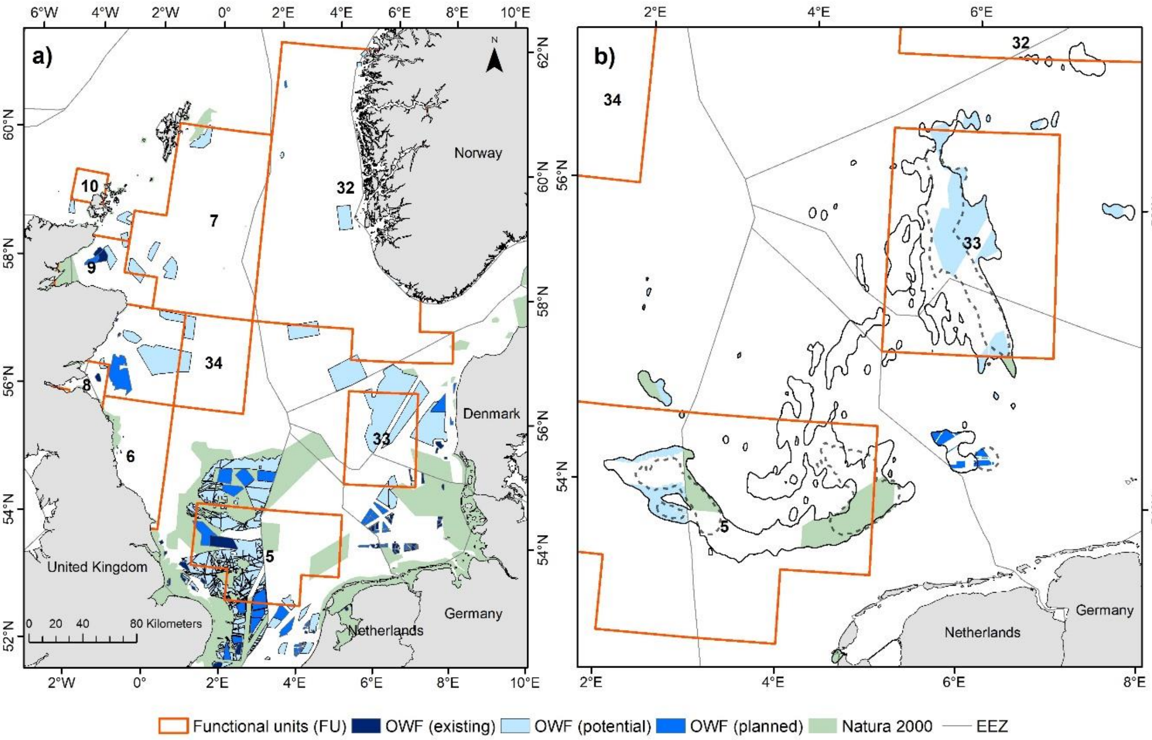

Figure II-7. (a) The North Sea with Nephrops functional units (FU), designated Natura 2000 conservation sites (in green), and offshore wind farms (OWF) at different developmental stages: existing (black; before 2020), planned (dark blue; 2020–2033), and potential (light blue; without starting date); (b) The German Bight with the core fishing areas of the German fishery clusters Nephrops & plaice (dashed line) and plaice (solid line) and their overlap with different stages of OWF development and Natura 2000 conservation sites.

Table II-1. Relative spatial overlap as percentage of functional units (FU) for Nephrops management and suitable Nephrops habitat (mud) per FU with Natura 2000 sites and offshore wind farms (OWF) at three different developmental stages: existing (before 2020), planned (2020 – 2033), and potential (without starting date). The bottom part displays the overlap of fishing core areas of German Nephrops fishery clusters with OWF developmental stages and Natura 2000 sites.

	Mud content	**OWF existing**	**OWF existing (mud)**	**OWF planned**	**OWF planned (mud)**	**OWF potential**	**OWF potential (mud)**	**N2000**	**N2000 (mud)**	**N2000 & all OWFs**	**N2000 & all OWFs (mud)**
FU											
10	12.9	0.0	0.0	0.0	0.0	0.6	0.0	2.4	0.0	3.1	0.0
32	42.7	0.0	0.0	1.0	2.1	1.3	2.1	0.0	0.0	1.4	2.2
33	37.6	0.2	0.0	0.0	0.0	30.2	27.5	1.3	0.2	31.8	27.7
34	20.0	0.0	0.0	0.0	0.0	6.8	0.9	0.0	0.0	6.8	0.9
5	27.7	2.4	0.0	3.5	0.0	22.0	1.5	39.8	22.1	52.7	23.5
6	19.0	0.0	0.0	0.0	0.0	0.1	0.2	6.1	2.9	6.3	3.3
7	49.8	0.0	0.0	0.0	0.0	3.6	1.2	0.7	0.1	4.2	1.3
8	23.6	3.0	2.0	0.7	0.0	2.7	0.8	9.8	2.7	16.2	5.6
9	18.5	3.6	0.0	1.9	0.0	6.1	0.0	13.0	27.6	24.8	27.6
Mean	28.0	1.0	0.2	0.8	0.2	8.2	3.8	8.1	6.2	16.4	10.2
Nephrops & plaice	-	0	-	1.2	-	22.6	-	21.3	-	45.1	-
Plaice-	-	0	-	0.9	-	17.5	-	13.5	-	30.7	-

4. Discussion

Our analysis revealed a heterogenous distribution of international Nephrops fishing activities in the North Sea. Some FUs were exploited above the advice, yet the overall quota was not exceeded. To date, Nephrops functional units (FUs) are not affected by spatial restrictions due to other sectoral plans, i.e. offshore wind farms (OWF) or marine protected areas (MPA). However, this will change with expanding OWFs and future MPAs being implemented in the EU Natura 2000 network. In particular FUs in the German Bight and core fishing areas of the German Nephrops fleet could experience spatial constraints of up to 45% due to the expansion of OWFs and newly implemented MPAs.

4.1 The North Sea Nephrops fishery

4.1.1 Fisheries management and ecological considerations

Although the overall total allowable catch (TAC) for Nephrops in the North Sea has not been exceeded in the past two decades, several annual landings and catches from individual Nephrops populations (FUs) were higher than advised by ICES. Out of the nine FUs in the North Sea, Nephrops landings or catches exceeded recommended fishing opportunities in seven FUs in at least one year. This is problematic from a marine conservation point of view, not only because the fishery threatens the health of the stock itself, but also because Nephrops is mainly caught in a mixed fishery with high bycatches using bottom trawls (Catchpole and Revill, 2008; Revill et al., 2006; Ungfors et al., 2013). Therefore, the concentration of fishing effort of Nephrops trawlers on several FUs might have negative effects for the whole benthic ecosystem. Bycatch species which are of an economic value may pose an important additional source of income for Nephrops fishers (Bailey et al., 2012). However, the proportion of undersized finfish and other non-marketable species is high and the Nephrops fishery has been identified as one of the main contributors to European unwanted bycatches (Catchpole et al., 2006; Catchpole and Revill, 2008). The reduction of unwanted bycatch could be achieved by using alternative fishing gears (Catchpole and Revill, 2008; Cosgrove et al., 2019; Santos, 2016). One example would be passive gears, such as creels, which have a higher selectivity and a lower impact on the sea floor (Hornborg et al., 2017). The usage of more selective trawls like "Sepnet" or trawls with selection grids are further examples how unwanted bycatch may be reduced (Catchpole and Revill, 2008). The promotion of selective and sustainable gears is also stated in the EU common fisheries policy article 17: "*[…] member states shall use transparent and objective criteria including those of environmental, social and economic nature. The criteria to be used may include, inter alia, the impact of fishing on the environment, the history of compliance, the contribution to the local economy […]*" (EU, 2013). It further states that "*[…] member states shall endeavour to provide incentives to fishing vessels deploying selective fishing gear […]*". As creels are more selective and may result in higher economic return (Hornborg et al., 2017; Leocádio et al., 2012; Williams and Carpenter, 2016), EU member states should create incentives to switch from Nephrops trawls to creels. However, in highly mixed Nephrops fisheries, which gain value by catching many different species, selective gears might be less economically viable.

Given that Nephrops is a rather sedentary species with specific habitat requirements (Johnson et al., 2013), populations are unable to shift to other areas. A major task in conserving Nephrops populations is thus to safeguard their habitats by managing the fisheries on each FU individually, rather than the entire North Sea (ICES, 2019a; Williams and Carpenter, 2016). Individual fisheries management should be based on sufficient knowledge about stock status in each FU. As there is still insufficient scientific information to estimate stock sizes for the FUs 5, 32, and 34 (ICES, 2020b), further ecological surveys in these FUs would be necessary. Climate change may pose another stressor for Nephrops, as ocean acidification has been observed to negatively affect Nephrops' physiology (Hernroth et al., 2012; Johnson et al., 2013). Moreover, Nephrops is habitat-bound and thus unable to mitigate unfavourable conditions by northward shifts of populations, as it has been observed for plaice, cod, and seabass (Colman et al., 2008; Engelhard et al., 2011; Neat et al., 2014).

4.1.2 Spatial competition in the North Sea

Our spatial analysis suggests that OWFs and Natura 2000 sites overlap only marginally with the North Sea Nephrops fisheries, especially if suitable Nephrops habitats rather than FUs are considered. Furthermore, the most productive FUs in terms of total landings, all located in UK waters, are among the least affected. However, there are vast differences among FUs ranging from hardly overlapping with OWFs and Natura 2000 sites to more than half of the area covered. This could indeed pose challenges, in particular for those fleets operating in FUs with large losses of fishing areas, as bottom trawling is prohibited in OWFs and largely restricted in Nature 2000 sites (Probst et al., 2021; Stelzenmüller et al., 2021c). Displacement options for the fisheries are limited, due to strong habitat requirements of Nephrops. In addition, OWFs may function as an obstacle for fishing vessels if they do not provide navigation corridors, potentially increasing time and fuel used by fishers to drive to fishing grounds. Underwater cables connecting OWFs to the main grid may further restrict bottom trawl activity if they are not burrowed deep enough (Rességuier et al., 2009).

One opportunity to reduce the impact of OWFs on fisheries is the introduction of co-location options and hence enable fishers to continue catching Nephrops in OWFs using passive gears, such as creels (Leocádio et al., 2012; Stelzenmüller et al., 2021c).

4.2 The German Nephrops fleet – a recent adaptation with an uncertain future

Our findings show that the German Nephrops fishery emerged in 2006 and originated from other fisheries targeting demersal species. The reason for this shift might be an adaptation to ecological and economic boundary conditions. Some fishers who originally targeted cod were likely forced to switch to another fishery, since cod catches have been declining in the southern and central North Sea as a result of a combination of overfishing, climate change, and falling recruitment (Beaugrand et al., 2003; Cook et al., 1997; Fock et al., 2014). By the end of 2019, there were almost no fishers left targeting cod in the considered fleet. Another reason might be low market prices for flatfish in the years before 2006. As a consequence, the demersal fishery targeting flatfish had become less profitable, making the option of switching to a Nephrops fishery economically more attractive.

4.2.1 Spatial competition in the German Bight

Core areas of the German Nephrops fishery will be spatially constrained by Natura 2000 sites. Although a ban of most bottom trawling in Natura 2000 sites is likely, fishing restrictions have not yet been finalised and therefore the real impact cannot be assessed at this point. When considering all potential OWFs and Natura 2000 sites, almost half of the Nephrops core fishing area would be covered and therefore likely unavailable for bottom trawling. Although this is the extreme scenario in terms of OWF expansion, ambitious national and EU climate targets (European Commission, 2020c) support the renewable offshore energy sector in the North Sea and indicate that it is indeed realistic.

4.2.2 The impact of Brexit

We have shown that the German and Dutch Nephrops fleets are dependent on additional Nephrops quotas acquired from other countries and thus might be most affected by the Brexit. Although both countries will still be able to swap quotas with the UK, decreased quotas of other species may affect their swapping capabilities. Germany used mainly cod quotas in exchange for UK Nephrops quotas, however, German North Sea cod TACs have been decreasing in the last decades due to the poor status of the southern North Sea cod stock (ICES, 2019b). Moreover, the EU-UK trade and cooperation agreement determines a decrease of 19% cod TAC for each EU member state from 2020 to 2025 (EU, 2021; European Commission, 2020d), meaning that Germany might lack sufficient quota swapping currency to sustain its Nephrops fishery.

4.2.3 The future of the German Nephrops fishery

Currently, Nephrops represents a commercially important species in the German fisheries. Whether this fishery can be maintained or even expanded depends on several aspects. Activities of the German Nephrops fishery almost completely coincided spatially over time (Appendix D), underpinning the strong habitat requirements of Nephrops (Johnson et al., 2013; Lolas and Vafidis, 2021). On the other hand, this highlights the vulnerability of the fishery, since, as it is the case for the target species itself, the fishery cannot move to alternative fishing grounds. In combination with the newly implemented OWFs and Natura 2000 sites, this will lead to substantial constraints of the German Nephrops fishery in the next few decades. The Brexit poses a more immediate threat for the German Nephrops fishery due to reduced Cod quota until 2025 and thus fewer swapping capacities for Nephrops quotas. However, the most general and uncertain effect will be due to climate change and affiliated changes, i.e. warming North Sea waters and ocean acidification. Moreover, past landings and catches from FUs in the German Bight surpassed ICES advices indicating unsustainable fishing and risking local depletions, that is despite ICES advices for FUs 5 and 33 recommending a decrease in catches since 2013. Therefore, from a conservation perspective, Nephrops fisheries in the German Bight should decrease in comparison to previous years, rather than expand.

Overall, our results point to reduced future opportunities for the German fishers targeting Nephrops in the German Bight. Therefore, possible adaptations would be either to switch to alternative fisheries or market lower catch amounts at a higher price. Switching to more selective gears, e.g. creels, might offer the chance to advertise the landed Nephrops as being caught more sustainably, thus justifying a higher price.

Our analysis focused on the evaluation of importance of distinct spatial areas for the German Nephrops fishery, hence not providing a measure of uncertainty for various future spatial use scenarios. However, our results provide an important baseline for subsequent studies of the spatio-temporal dynamics of this fishery and the effects of spatial use restrictions, as well as climate change.

Conclusions

Our results point to an exhaustion of the North Sea Nephrops fishing capacities, supporting the call for a precautionary and well-defined management for Nephrops, including individual regulations for stocks. Further ecological and fisheries research is needed to develop accurate stock assessments and explore the consequences of climate change on North Sea Nephrops. While the current and future spatial restrictions in most Nephrops fishing grounds in the North Sea are marginal overall, those in the German Bight will face a loss of up to almost 45% due to OWF expansion and fisheries regulations related to Natura 2000 sites. Co-location of OWF and fisheries including a switch to passive and more selective fishing gears could mitigate the loss of fishing opportunities and sustain fishers' livelihoods. Although the Brexit will not influence Nephrops quota distribution in the North Sea, cutbacks of other species TACs might reduce the swapping capacities of countries to acquire Nephrops quota from the UK. In the case of Germany, decreased cod quotas, will lower the ability to obtain Nephrops quota. Furthermore, our findings indicate that German fishers switched to Nephrops because of its high economic value and the declining availability of other former target species in the German Bight. Overall, in this study we analysed the various influences on international and German Nephrops fisheries from different angles. Our study highlights the need for cumulative impact assessments to understand historic developments in fisheries and to judge on upcoming risks. Only with this knowledge target-oriented mitigation measures may be recommended.

Supplementary Material

The following supplementary material is available at *ICESJMS* online and at the *end of this thesis*: Details about the cluster analysis of German Nephrops fishery (Appendix A), a description of how VMS and logbook data were merged (Appendix B), the international catch and TAC of the North Sea Nephrops fishery (Appendix C), and details on the German Nephrops fishery clusters (Appendix D).

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Authors contribution

NS, JL, HR, and VS were responsible for the conceptualization and design, JL and NS collected the data; JL analysed the German case study data; HR performed the spatial overlap analysis; AK and JB helped to interpret the results; JL lead the writing process; all authors revised and improved the manuscript.

Data availability statement

The majority of the data underlying this article is accessible in public repositories or the supplementary material. Details on the German fishing data cannot be shared due to commercial sensitive information. Spatial polygons of offshore windfarms cannot be made publicly available, because a license was purchased.

Chapter III

Sustainable co-location solutions for offshore wind farms and fisheries need to account for socio-ecological trade-offs

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Abstract

The spatial expansion of offshore wind farms (OWFs) is key for the transition to a carbon free energy sector. In the North Sea, the sprawl of OWFs is regulated by marine spatial planning (MSP) and results in an increasing loss of space for other sectors such as fisheries. Understanding fisheries benefits of OWF and mitigating the loss of fishing grounds is key for co-location solutions in MSP. For the German exclusive economic zone (EEZ) of the North Sea we conducted a novel socio-ecological assessment of fisheries benefits which combines exploring potential spill-over from an OWF with an experimental brown crab (*Cancer pagurus*) pot fishery and an economic viability analysis of such a fishery. We arrayed a total of 205 baited pots along transects from an OWF located near the island of Helgoland. After a soaking time of 24 h we retrieved the pots and measured the carapace width (mm), weight (g), and sex of each individual crab. To conclude on cumulative spill-over potentials from all OWFs in the German EEZ and drivers of passive gear fisheries we analysed vessel monitoring system (VMS)-data and computed random forest regressions. Local spill-over mechanisms occurred up to distances of 300 to 500 m to the nearest turbines and revealed an increasing attraction of pot fishing activities to particular OWFs. This corresponds to the observation of constantly increasing fishing effort targeting brown crab likely due to both a growing international demand and stable resource populations at suitable habitats, including OWFs. Our break-even scenarios showed that beam trawlers have the capacities to conduct during summer an opportunistic but economically viable pot fishery. We argue that particularly in the North Sea, where space becomes limited, integrated assessments of the wider environmental and socio-economic effects of planning are crucial for a sustainable co-location of OWFs and fisheries.

Key words: break-even analysis, brown crab, marine spatial planning, socio-ecological assessment, spill-over

1. Introduction

The advancement of offshore wind farms (OWFs) is a response to increasing energy demands and a key pillar in the global transition to a carbon-free power sector (GWEC, 2019). In a European comparison, the North Sea region is designating the largest total surface area (20 000 km^2) to the current and future development of offshore renewables (Stelzenmüller et al., 2020). Hence, the North Sea ecosystem is exposed to progressing human pressures (Halpern et al., 2019), while facing drastic effects of climate change (Holt et al., 2012) on food web structure and functioning (Lynam et al., 2017), and the composition of fish communities (Dulvy et al., 2008; Engelhard et al., 2014; Frelat et al., 2017). This highlights the urgent need for an integrated marine management approach accounting for complex interlinkages and feedbacks in coupled human and natural systems (Visbeck, 2018). The spatial expansion of offshore renewables increasingly steers a debate regarding local and cumulative environmental and socio-economic effects for other human activities. Thus, within a given area OWF and fisheries are often mutual exclusive evolving in a reallocation of fishing activities to other areas (Stelzenmüller et al., 2015a). Depending on the adaptive capacities of the affected fishing fleets, this could result in economic losses or even socio-cultural impacts for fishing communities (Stelzenmüller et al., 2020). Marine spatial planning (MSP) is an integrated management process that allocates human uses at sea according to planning activities (Zaucha and Gee, 2019). MSP should promote Blue Growth while maintaining ecosystem health, mitigate spatial use conflicts (Frazao Santos et al., 2020), and create synergies between sectors through the promotion of co-location solutions (Jentoft and Knol, 2014; Kyvelou and Ierapetritis, 2019). The terms “co-location”, “co-use” or “multi-use” are often used synonymously, but require a careful consideration of the spatial, temporal, provisional, and functional dimensions of the connectivity of uses (Schupp et al., 2019). In the North Sea region, national MSP processes foresee divergent measures regarding the co-location of fisheries and OWFs. While in the UK fishing with bottom contacting gear in OWFs is permitted, fishing activities are currently prohibited in OWFs and the respective buffer zones in the German exclusive economic zone (EEZ) (Stelzenmüller et al., 2016). The marine spatial plan of the German EEZ of the North Sea, implemented in 2009, was one of the first legally binding plans regulating primarily the allocation of marine transport, development of offshore renewables or aggregate extraction by the means of priority areas. At present, the plan is being revised and the evaluation process needed to account for both changing political priorities and progress towards the achievement of planning goals (Stelzenmüller et al., 2021b). In particular, the fishing sector calls for potential new regulations regarding a co-location of passive gear fisheries e.g. targeting brown crab (*Cancer pagurus*) in the proximity of OWFs. The revised draft plan comprises adaptations of shipping routes, an increase in priority areas for offshore renewables, the adoption of marine conservation areas, and a priority area for Norway lobster (*Nephrops norvegicus*) fisheries (www.bsh.de). Further the draft plan mentions the potential for passive gear fisheries within the safety zone up to a distance of 300 m to the OWF. Developing measures to mitigate economic losses for fisheries remains a key challenge for most MSP processes (Kularathna et al., 2019).

Empirical knowledge on ecological and socio-economic implications of co-location solutions for OWF and fisheries is still sparse. The construction of OWFs comprising activities such as piledriving or removal of soft bottom habitats has caused a decrease of abundance of pelagic fish by 50 % and effected the behaviour and physiology of fish (Lüdeke, 2015; Methratta, 2020). Over time the introduction of hard substrates leads to changes in species compositions (Stenberg et al., 2015), food web structures and complexity (Mavraki et al., 2020). Fisheries benefits of OWFs could result from small and meso-scaled ecological effects such as an increase of biomass, abundance and size of fisheries resources around piles and turbine scour protections (Dannheim et al., 2020; Methratta and Dardick, 2019; Reubens et al., 2013) and a subsequent spill-over into the surrounding waters. While the spill-over of biomass and related fisheries benefits have been extensively studied for many marine protected areas (MPA) (Edgar et al., 2014; Vandeperre et al., 2011), the spill-over effects in the context of OWFs remain largely uncharted. In the southern North Sea, a spill-over of biomass might be expected for target species such as European edible crab or brown crab, brown shrimp (*Crangon crangon*), and European lobster (*Homarus gammarus*) due to enlarged opportunities for shelter and increased food availability (Ashley et al., 2014; Krone et al., 2017, 2013). Hence, artificial reef structures such as monopiles with a scour protection led to local increases of brown crab biomass with an estimated increase of 320 % in the German Bight (Krone et al., 2017). Passive gear fisheries targeting decapods seem to be most feasible to be combined with OWFs (Hooper and Austen, 2014). In the southern North Sea, a growing interest in a brown crab pot fishery with distinct and persistent fishing grounds over time has been observed (Stelzenmüller et al., 2016). Between 2008 and 2016, overall yearly catches of brown shrimp of the EU fleet have increased from about 34 thousand tons to almost 50 thousand tons, with the value of landings increasing even more (STECF, 2018). These figures suggest that the demand for brown crab is growing, thus justifying also a closer view on this type of fisheries.

Yet, a quantification of potential fisheries benefits of OWFs due to emerging resources such as brown crab is pending. Quantifying fisheries benefits entails both a sound knowledge of local ecological processes and functions and an assessment of socio-economic constraints of the fishing vessels engaging in such a fishery.

Taking the German EEZ of the North Sea as an example, we contribute to the urgently needed empirical evidence of potential fisheries benefits of OWFs and reflect on sustainable co-location solutions of OWFs and pot fisheries. Our integrated approach combines for the first time an experimental brown crab fishery in the vicinity of an OWF with a supply balance and economic viability analysis for fishing vessels targeting brown crab. Further we explored the cumulative brown crab spill-over potential by analysing spatio-temporal trends in passive gear fisheries in the proximity of OWFs in the German EEZ with the help of vessel monitoring system (VMS) data and random forest regression.

2. Methods

To answer our research question if fisheries can benefit from man-made structures such as OWF and to understand the potential implications for co-locating OWFs and fisheries we structured our methodological approach along the following themes: i) empirical evidence of brown crab spill-over from OWFs; ii) attraction of international pot fishing vessels to OWFs indicating spill-over potential; iii) European supply and demand of brown crab from the North Sea; and iv) break-even scenarios for fishing vessels deploying occasionally pots to target brown crabs.

2.1 Experimental brown crab fishery around an offshore wind farm

Brown crabs are nocturnal animals and opportunistic feeders preying on bivalves, gastropods, barnacles, echinoderms, bristle worms, and other crustaceans (Klaoudatos et al., 2013). They reproduce in winter with planktonic larvae (1 mm) and live on habitats with coarse sediment, mud or sand preferably at depth varying from 6 to 40 m. The size (carapace width) at first sexual maturity (around 3 to 5 years of age) differs for males (~110 mm) and females (~127 mm) and varies regionally (Klaoudatos et al., 2013; Tonk and Rozemeijer, 2019). Regional stock assessments for the southern North Sea revealed stable population sizes in consecutive years and regional exploitation rates are lying within recommended boundaries to maintain maximum sustainable yields (MSY level proxy is 35 % of virgin spawner per recruit (SpR) (CEFAS, 2017). The minimum landing size (MLS) for crabs in the North Sea south of 56°N is 130 mm (CEFAS, 2017).

The German EEZ covers a significant surface area that is known for an increased brown crab density in the southern North Sea (CEFAS, 2017). Estimates for the Dutch North Sea (which borders the German EEZ to the west) indicated a potential of 100 brown crabs per km^2 (Tonk and Rozemeijer, 2019). The international fishing activities in the German EEZ targeting brown crab with baited pots remain of marginal economic relevance and have been persistently limited to distinct areas between April and November (Klaoudatos et al., 2013; Stelzenmüller et al., 2016). Considering the characteristics of this fishery, we conducted experimental fisheries with baited pots targeting brown crabs along transects near the OWF Meerwind Süd/Ost. The OWF is in operation since 2015 and is located approximately 20 km off the island of Helgoland (Figure III-1). The site encloses 80 turbines (monopiles with scour protection) at depths varying between 22 m and 27 m on sandy bottoms (see Figure III-1). In 2019 (June and August) we positioned a total number of 205 pots baited with fresh mackerel (*Scombrus scombrus*) along transects at distances of approximately 50 m, 500 m, 1000 m and 1500 m to the nearest wind turbine on the eastern border of the wind farm. In total, we arrayed 41 pot fleets (five pots per fleet) with a tow length of 30 m between individual pots and 15 kg of ground weight at both sides. The actual mid-points of the respective fleet positions are shown in Figure III-1. After a soaking time of approximately 24 h we retrieved the pots and measured the carapace width (mm), weight (g), and sex of each individual crab. We marked each animal with a bio-marker to enable a recognition of recaptures and released it in the direct proximity of the sampling stations. Further, we recorded at the 41 stations the water depth (m), sea surface temperature, bottom temperature, wind and weather conditions. For the subsequent statistical analysis, we standardised for each station the total biomass (kg), total number (N), sex ratio (male/female), and total biomass for brown crabs of the size classes < 130 mm and ≥ 130 mm for a soaking time of 24 h. For each of the 41 pot fleets we calculated size-based indices such as the minimum, maximum, and mean carapace width (mm) and its respective standard deviation. We computed linear regressions with distance to the nearest wind turbine

(m) as explanatory variable to determine significant spatial trends in size, sex ratio and biomass.

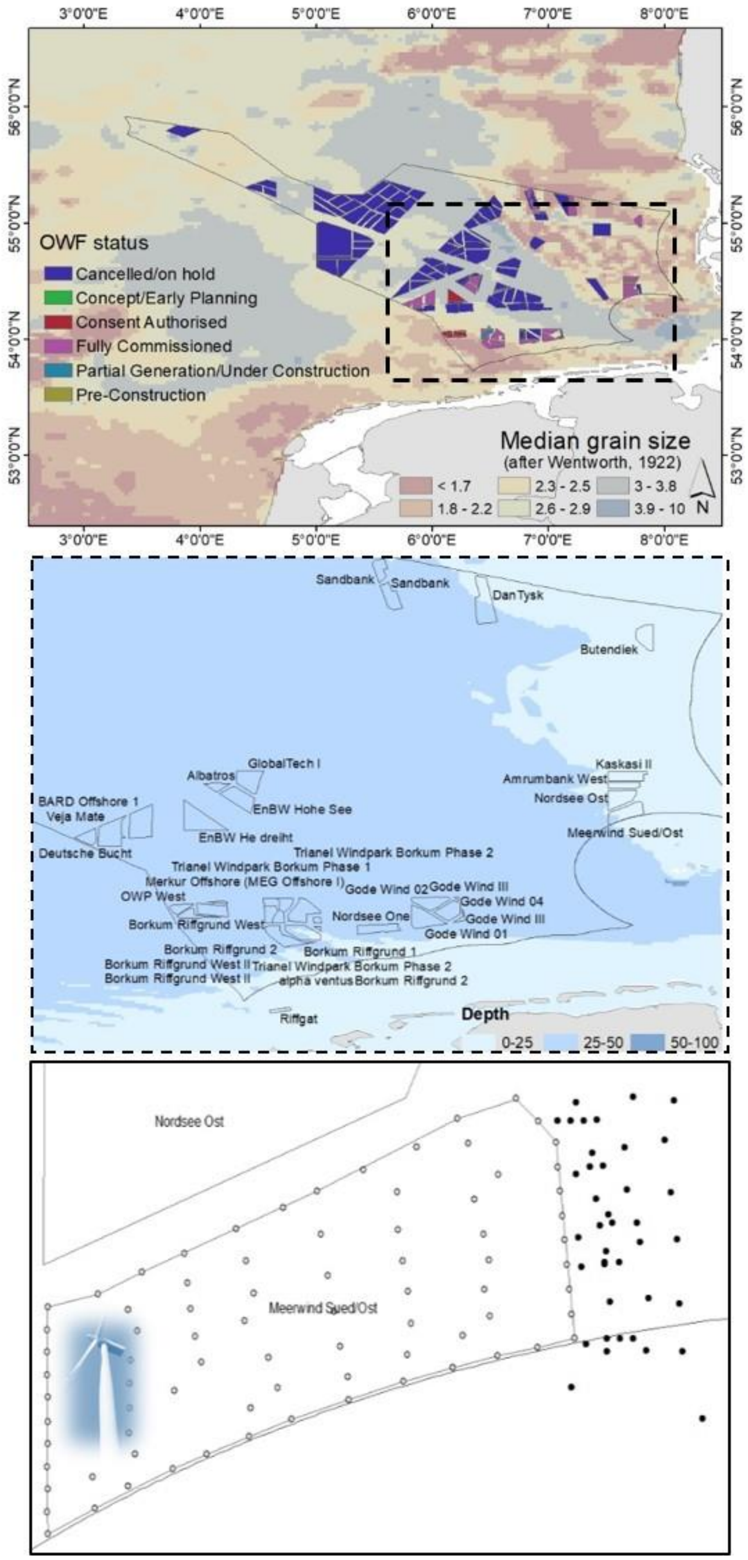


Figure III-1. Top panel: Median grain size distribution in the southern North Sea together with the location and status of offshore wind farms within the German EEZ and adjacent coastal waters (4COffshore.com, last update 2018). Note that the grain size distribution is shown in the Wentworth scale where the grain diameter (d) is calculated as $\log_2(d)$. The greater the values the smaller the actual grain diameter (e.g. sand < 4 > silt) (www.coastmap.hzg.de). The OWF areas are located at depth ranging from 10 to 50 m; mid panel: water depth (m) and OWFs being in operation, under construction or licensed; bottom panel: Location of turbines (grey dots) within the offshore wind farm Meerwind Süd/Ost and sampling stations (black dots).

2.2 Cumulative spill-over potential from offshore wind farms

We analysed spatio-temporal patterns of international pot fisheries to explore changes of patterns in fishing effort in the proximity of OWFs, suggesting a local spill-over mechanism of brown crab. Further, we evaluated the cumulative spill-over potential for the currently existing OWFs in the German EEZ. For this we compiled international VMS data from 2012 to 2019 comprising the vessel registration number, vessel position, and speed of fishing vessels with lengths greater than 12 m for the German North Sea. We first removed duplicated pings, pings with assigned speed values > 25 kn, and harbour pings except the last one using the VMStools package (Hintzen et al., 2012) for the software R 3.6.3 for statistical computing (R Core Team, 2019). Next, we matched vessel registration numbers of VMS data with the European fleet registry and filtered for vessels reporting pots as their primary or secondary fishing gear. We adopted the approach by (Kroodsma et al., 2018) to identify continuous vessel tracks and exclude fragmented vessel tracks. Hence, we calculated geographical and temporal distances for each consecutive VMS ping of the same vessel and summed up half of the time from the previous to the current and the current to the following ping, respectively. We neglected pings with temporal intervals < 120 min, because it represents the longest interval for transmitting VMS signals among included flag nations. Next, we identified continuous data segments among vessel data pieces by assigning a new segment number when the geographical or temporal distance between consecutive pings was > 50 nm or 24 h. We kept only segments with a total number of pings ≥ 4. From the remaining pings assigned to fishing segments, which reflected individual fishing trips, we filtered in a last step only pings indicating fishing. We separated fishing from steaming pings with the *activityTacsat* function from the VMStools package. Note that we determined peaks for steaming and fishing speeds manually by inspecting speed histograms of each vessel and year before running the *activityTacsat* algorithm. To enable analyses of spatio-temporal fishing patterns, we calculated for each VMS ping the distance to the nearest boundary of an OWF with the sf package (Pebesma, 2018) for R. With the help of Arc Map (10.5.1) we associated the name of the nearest OWF, depth (m), and median grain size to each retained VMS ping. This enabled us to calculate total hours fished by summing up the time steps for different aggregation levels, such as month, year, distance range to the nearest OWF (km), depth range (m), vessel, or nearest OWF.

In a next step, we selected OWFs to which fishing effort could be associated in four successional years and grouped those by the year they went in operation (2012 and 2015). This allowed us to explore the spatial patterns and intensity of pot fishing activities in the vicinity of those OWFs. To further explore the relationship between the fishing intensity (annual total hours fished) by the respective vessels and the explanatory variables (year, proximate OWF, distance to turbine, depth and median grain size) we applied random forest (RF) regressions (Breiman, 2001) with the R package randomForest (Liaw and Wiener, 2002) for fishing activities at distances < 15 km to the nearest OWF. RF is a supervised machine learning technique based on regression tree methodology. It predicts a response variable from a number of explanatory variables by recursively subdividing a dataset into subgroups (Hastie et al., 2009). Partitions are achieved by two means: (1) a random selection of explanatory variables to grow each tree and (2) each tree is based on a different random data subset, created by bootstrapping. We divided the data in a training subset (70 %; in-bag data) to develop the tree and prediction rules, whereas the out-of-bag data (30 %) provided estimates of the generalization error. The rank importance of each explanatory variable was measured as the change in mean square error estimated by leaving a variable out of the model. We further computed partial dependence plots to explore the relationships between individual explanatory variables and annual fishing effort.

2.3 European supply and demand of brown crab from the North Sea

To gain an overview of the European supply and demand of brown crab from the North Sea we calculated supply balances by accounting for the domestic supply (catches + import) and the amount of apparent consumption (available raw material of brown crab). Hence, we adopted the approach of the European Market Observatory for Fisheries and Aquaculture Products and calculated the apparent consumption of brown crab as national catches + import – export (t) (EUMOFA, 2019b). For catches we included all brown crabs caught by a country's fleet, independently from the area of landing and we extracted respective catch data as net weight (t) from Eurostat (https://ec.europa.eu/eurostat/web/main/data/database; fish_ca_main). To balance the data we converted net weights into live weight equivalents using the conversion factors provided by EUMOFA (EUMOFA, 2019c). We defined international trade as imports and exports (Eurostat, 2016). However, differences in concepts and definitions of the countries, as well as dissimilar reference periods due to transport times led to asymmetries between data the importer of one country and the exporter of another country. Therefore, we used only data on import to show the interactions between the major actors within Europe. Since the international trade of brown crab comprised mainly the UK, Ireland, France and Spain, we focused on those countries and we defined the remaining countries as “others”. In addition, we considered export data to China. We further simplified the trade between the main countries by offsetting when a trade was < 5 t, and when the trade volume between major actors and “others” was < 100 t.

2.4 Economic viability of an occasional brown crab fishery

An increasing stock of brown crab might provide fishing opportunities also for vessels which regularly target on other species. We identified German beam trawlers with a length of about 24 m targeting mainly brown shrimp as being capable to conduct a brown crab fishery. Entering a pot fishery would require only modification of on-board equipment, but no quota acquisition. Here we assessed the economic viability of this option based on the assumption that a brown crab fishery would take place only at times when a brown shrimp fishery is regarded inefficient, thus when the only alternative option would be to stay in the port. To assess the specific contribution margin we disregarded fixed costs and considered only fishing costs directly linked to a brown crab fishery. We derived the cost structure of German beam trawlers (18 and 24 m) targeting brown shrimp from the annual economic report on the EU fishing fleet, AER (STECF, 2019a) (Appendix D). In a subsequent step, we modified the cost and effort data in case the fleet segment is deploying pots targeting brown crab (Appendix D). Further, we anticipated a total investment of 65,000 € for pots, winch, containers and vessel modification (pers. comm. Christian Janhsen). The useful life of these assets is set to five years, resulting in an annual depreciation of 13,000 €. Variable costs (excluding personnel costs) were estimated at 330 € per day. Personnel costs were estimated at 22 % of the revenue (crew share).

Based on these figures, we computed the daily break-even revenue (BER). When assuming that neither fixed costs nor opportunity costs apply and interest rates are disregarded due to their low level, only variable costs and annual depreciation (DEP) for the investment in equipment for crab fishing has to be considered for the break-even analysis. Then the BER is the sum of DEP and the variable costs. The sum of depreciation and variable costs (excluding personnel costs) was increased by the crew share to account for personnel costs in the break-even case.

Garrett et al. (2015) reported prices of up to 4 € per kg brown crab landed in Spain and France with catches of specialized vivier vessels varying between 13 to 14 tons a week (in 2013). However, vivier vessels are highly specialized and retrofitted beam trawlers are unlikely to achieve comparably high catch rates. The 2018 STECF AER revealed that average prices (2008 - 2017) for brown crab landings varied significantly between countries (STECF, 2018). The prices were highest in Denmark (3.31 €/kg), followed by the UK (1.60 €/kg) and Ireland (1.23 €/kg). In contrast, German vessels sold only at 0.66 €/kg. Therefore, we calculated break-even scenarios for prices ranging from 0.66 to 3 € per kg landed brown crab.

3. Results

3.1 Spatial pattern of experimental brown crab catches

We sampled a total number of 792 brown crabs (males: 655; females: 137) with carapace width ranging from 69 to 225 mm and an overall mean width of 152 mm (+/-26.4 mm) (Appendix A). The frequency distribution of the respective carapace width (mm) for male and female with the corresponding mean width (females: 135 mm (+/- 21.92 mm); males: 156 mm (+/- 25.87 mm) is shown in Appendix A. We observed an overall sex ratio of 4.8 in favour of males. Out of the 137 females a total number of 39 (29 %) were below the size of first sexual maturity (127 mm; (Tonk and Rozemeijer, 2019)). In contrast, only a total number of 22 (3.4 %) of the 655 males were below the respective size of first sexual maturity (110 mm; (Tonk and Rozemeijer, 2019). The frequency distribution indicates a normal distribution of carapace width of female, but a slightly skewed distribution for females. In addition, the frequency distribution shown in the Appendix A shows that the majority of the caught brown crabs were above the MLS of 130 mm. Our experimental set up led to a mean catch per unit effort (cpue) of 9 $kg \cdot 24h^{-1}$ (+/- 3 $kg \cdot 24h^{-1}$) at distances between 213 and 2650 m to the wind turbines. The prevailing conditions in terms of sampling depth, surface and bottom temperature were relatively constant with a mean depth of 23 m and bottom temperatures of approximate 14 °C in June and 18 °C in August. Overall, we found a significant decrease of catches in biomass, numbers, males and individuals ≥ 130 mm with increasing distance to the turbines (Table III-1 and Figure III-2). Although the trend was statistically not significant (p-value of 0.13, see Table III-1), we found the highest cpue of brown crabs < 130 mm up to a distance of 300 m to the turbines, pointing to the functioning of turbines with scour protection as potential nursery areas of brown crab. Our results revealed clear differences in spatial patterns of female cpues and maximum carapace width between the stations sampled in June and August (Figure III-2). Hence, in August cpues of females almost doubled at distances ranging from 600 to 1100 m. This was on a par with increases of both minimum width and cpues of brown crabs < 130 mm at corresponding distances. Hence, these results indicate a clear shift in carapace width fractions of females within only a couple of weeks during summer time.

Table III-1. Results of the linear regression models as intercept, coefficient (b), degrees of freedom (df), R square (R^2), adjusted R square (R^2 adj), value of the F statistic (F), and p-value for the different response variables and time periods (June & August = 41 stations; June = 21 stations) with distance to the nearest turbine (m) as explanatory variable. Significant models (p-value < 0.05) are indicted in bold. Note that the sampling positions in August comprised only stations with a minimum distance to the nearest turbine > 500 m.

Response variable	**Period**	**Intercept**	**b**	**df**	**R^2**	**R^2adj**	**F**	**p-value**
Cpue ($kg \cdot 24h^{-1}$)	June &August	13.16	-0.01	31	0.26	0.24	11.13	**0.00**
Cpue ($N \cdot 24h^{-1}$)	June &August	18.96	-0.01	31	0.16	0.14	6.09	**0.02**
min width (mm)	June &August	101.77	0.02	31	0.06	0.03	1.85	0.18
max width (mm)	June &August	215.31	-0.04	31	0.38	0.36	18.75	**0.00**
$Cpue_F$ ($kg \cdot 24h^{-1}$)	June &August	0.83	0.00	31	0.01	-0.03	0.16	0.69
$Cpue_M$ ($kg \cdot 24h^{-1}$)	June &August	12.85	-0.01	31	0.41	0.39	21.33	**0.00**
$Cpue_{\geq 130\ mm}$ ($kg \cdot 24h^{-1}$)	June &August	13.32	-0.01	31	0.39	0.37	20.13	**0.00**
$Cpue_{< 130\ mm}$ ($kg \cdot 24h^{-1}$)	June &August	0.72	0.00	31	0.00	-0.03	0.00	0.96
Cpue ($kg \cdot 24h^{-1}$)	June	12.28	0.00	19	0.11	0.06	2.36	0.14
Cpue ($N \cdot 24h^{-1}$)	June	19.39	-0.01	19	0.19	0.15	4.54	**0.05**
min width (mm)	June	106.77	0.00	19	0.01	-0.04	0.21	0.65
max width (mm)	June	199.39	0.00	19	0.01	-0.04	0.15	0.70
$Cpue_F$ ($kg \cdot 24h^{-1}$)	June	0.78	0.00	19	0.00	-0.05	0.04	0.85
$Cpue_M$ ($kg \cdot 24h^{-1}$)	June	12.54	-0.01	19	0.26	0.23	6.84	**0.02**
$Cpue_{\geq 130\ mm}$ ($kg \cdot 24h^{-1}$)	June	12.75	-0.01	19	0.25	0.21	6.35	**0.02**
$Cpue_{< 130\ mm}$ ($kg \cdot 24h^{-1}$)	June	1.11	0.00	19	0.11	0.07	2.44	0.13

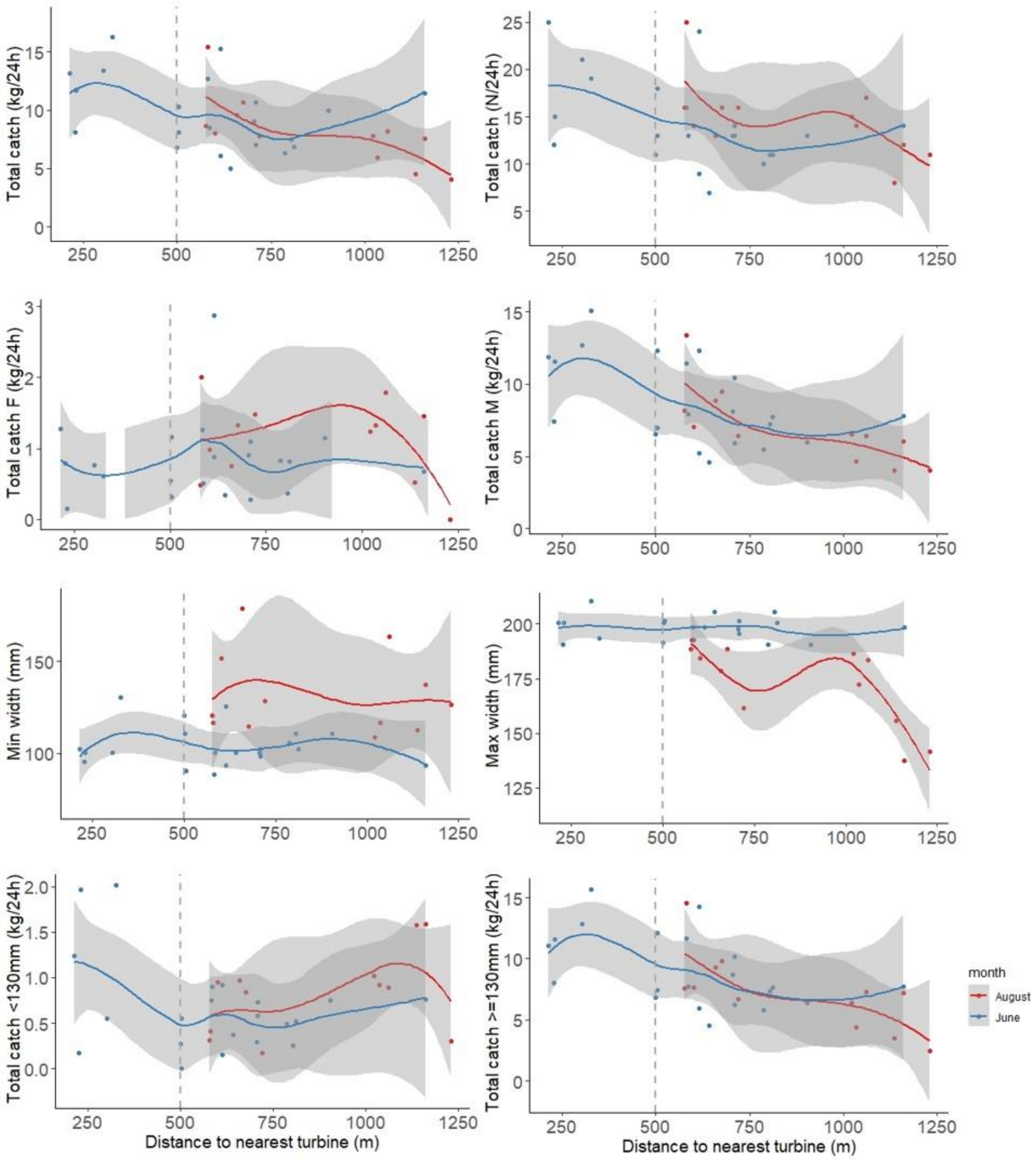


Figure III-2. Results of the non-linear regression of total catch of brown crab standardised by 24 h soaking time as biomass (top left), numbers (top right), biomass of females (second from top left), biomass of males (second from top right), minimum (second from bottom left) and maximum (second from top right) carapace width (mm) sampled at a station, and biomass of brown crab with a carapace with < 130 mm (bottom left) and ≥ 130 mm (bottom right) as a function of distance to the nearest wind turbine (m; maximum distance ≤ 1500 m); the dashed line indicates the 500 m buffer zone around the sampled offshore wind farm and the shaded area designates the 95 % confidence level.

3.2 Cumulative spill-over potential from offshore wind farms

We identified a total number of 32 993 VMS pings affiliated to pot fishing within the German EEZ and adjacent coastal waters (2012 to 2019). From those pings, 91 % were connected to UK vessels, 5 % to Irish vessels, 2 % to German vessels, and the remaining 2 % showed an equal share of fishing between Polish and Danish vessels. Only six vessels (5 UK vessels, 1 Irish vessel) made up for 97 % of the overall detected pot fishing activities. Effort peaked during the summer months across all years and increased by 400 % from 2012 to 2019 (Appendix B). Comparing the annual fishing effort at various distance classes (< 5 km, 5-10 km, 10-20 km, 20-30 km, and > 30 km) to the nearest OWF (km) revealed that annual fishing effort increased across all distances to the OWF (Figure III-3). Further, over time most effort was allocated at distances > 30 km to the nearest OWF, while at distances < 5 km the effort increased from 2017 onwards to levels which were comparable to other distance classes. Figure III-3 revealed that the annual fishing effort was general highest at depths ranging from 30 to 40 m. The retained OWFs being in operation since 2012 comprise DanTysk, Global Tech I, Meerwind Süd/Ost, Nordsee Ost, Riffgat and Trianel Borkum (Figure III-4, top). The fishing activities associated to Dan Tysk and Gobal Tech I took constantly place at distances beyond 30 km reflecting rather the increased suitability of the naturally prevailing habitats. Interestingly, the fishing effort associated to Meerwind Süd/Ost increased over time and converged towards the OWF, where we conducted our experimental brown crab fishery. The same observation holds for Nordsee Ost and Riffgat. The OWFs being in operation since 2015 encompassed Amrumbank West, Borkum Riffgrund 1, Gode Wind 01 and 02, Nordsee One and Sandbank. The observed fishing patterns around Gode Wind 01 and Gode Wind 02 could indicate a displaced pot fishery which now benefits from fishing in the closer proximity of an OWF (Figure III-4, bottom). One striking observation was that the fishing activities around Borkum Riffgrund 1 occurred after the OWF has been constructed, indicating a potential fishery benefit through spill-over of brown crab.

Based on the observed patterns of the pot fishing activities in the proximity of the OWF and the results of our experimental pot fisheries, we defined four archetypes of spatial patterns of pot fishing activities in the vicinity of an OWF (Figure III-5). Figure III-5 shows that a potential spill-over effect of brown crab could manifest in increased catches up to a distance of 5 km from OWFs (dark green zone). Thus, recurrent pot fishing activities taking place at such distances might indicate spill-over effects. On the contrary, we assumed that spill-over effects

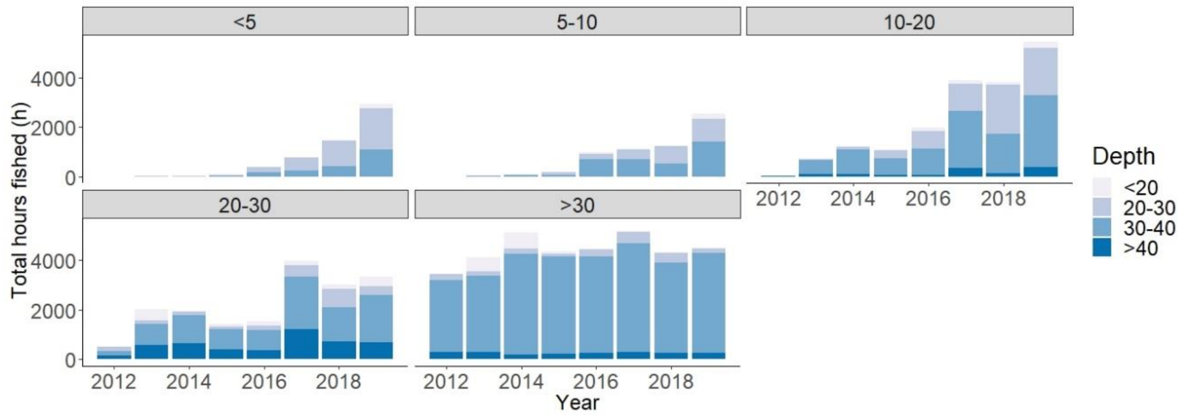


Figure III-3. Time series of total annual fishing effort (h) per distance to nearest offshore wind farm class (< 5 km, 5-10 km, 10-20 km, 20-30 km, > 30 km) and depth range (m).

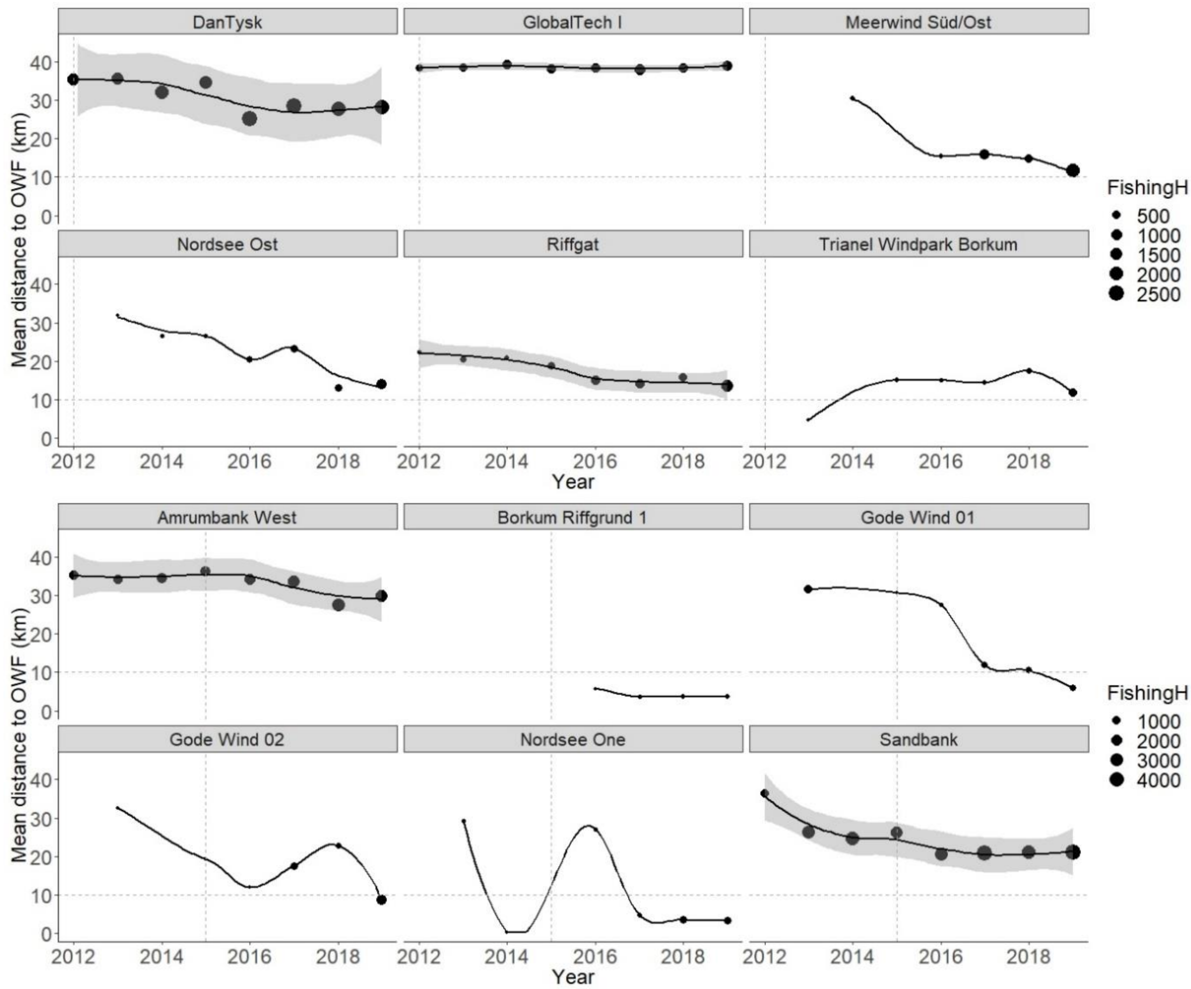


Figure III-4. Time series of annual mean distance (km) of the total fishing effort (black dots) allocated to the respective OWF. The vertical lines indicate the fishing restrictions due to the presence of the OWF since 2012 (top) and 2015 (bottom) and the horizontal line indicates that at distances > 10 km fisheries benefits due to the spill-over of brown crab is not very likely (see Figure III-6).

would not manifest at distances greater than 10 km to an OWF. The archetypes distinguish cases where e.g. previous pot fisheries have been displaced from an OWF area and recurred within a distance of 5 km, hence indicating rather suitable habitats for brown crabs. We described also a model where pot fisheries took place in the OWF proximity only after the OWF has been constructed, pointing to potential spill-over mechanisms.

The random forest models of fishing effort around the two groups of OWFs (OWFs in operation since 2012 and 2015) explained 24 % (OWF2012) and 19 % (OWF2015) of the variance and revealed a rank importance of the variables potentially driving the allocation of fishing effort (Appendix C). The rank importance (% IncMSE), representing the increase of the mean squared error when a given variable is randomly permuted, showed that the fishing effort around the OWF being constructed until 2012 was mainly determined by the explanatory variables year, location (associated OWF), and depth. Hence, the allocation of fishing effort has not been triggered by the proximity of these OWFs. In contrast, the fishing effort around OWFs being in operation since 2015 showed a deviating rank importance with median grain size, distance to the OWF, and location (associated OWF) being the most important variables. This points to the fact, that fishing effort could have been attracted by those respective OWFs due to increased brown crab abundances.

3.3 European supply balances and economic viability analysis

Total brown crab catches from the North Sea ranged from 40 000 to 47 100 t between 2010 and 2017. The supply balance analysis showed that in 2017 brown crab catches of UK, Ireland, France and Spain summed up to 43 373 t, whereby the UK alone contributed the largest share of 32 410 t (Figure III-6). The UK exported nearly one third of the catches and, considering small amounts of imports, the national apparent consumption was 22 326 t. By far, Spain had the smallest share of catches (61 t), these are usually by-catches. Due to an import of 3 945 t of brown crabs the Spanish apparent consumption was 3 688 t. In contrast, in France the apparent consumption was nearly three times higher, based on domestic catches of 4324 t, and imports of 7481 t received in equal parts from the UK and Ireland. Export markets to Asia, especially to China, Hong Kong, Taiwan and Vietnam are constantly growing. In 2017 the UK exported 2722 t and Ireland 909 t brown crab to China.

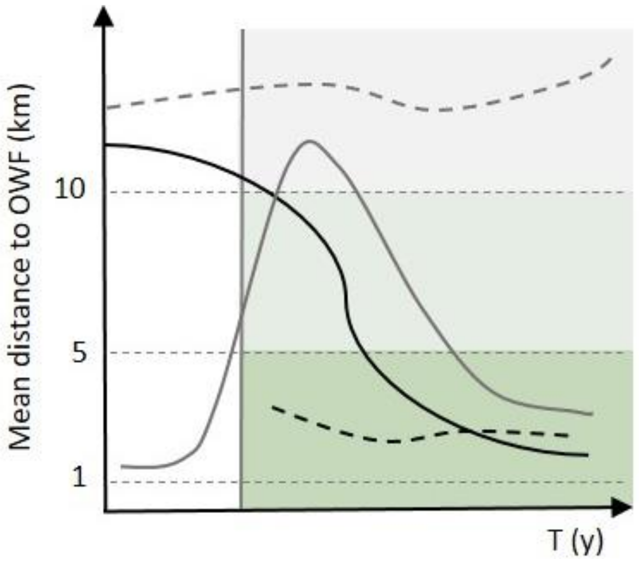


Figure III-5. Four archetypes of potential fishing patterns of passive gear fisheries targeting brown crab in the vicinity of an offshore wind farm (OWF). The vertical grey line indicates the beginning of fishing restrictions due to the construction of an OWF. The distance of 5 km to the OWF indicates the potential area (dark green) where a spill-over of brown crabs might results in increased catches. The grey dashed line indicates a fishing patterns at distances > 10 km which cannot be related to potential fisheries benefits of OWF (grey zone).The black line reflects an attraction of fishing effort by an OWF after its implementation; the grey line represents recurrent fishing activities after displacement, indicating rather a suitable habitat than a potential spill-over mechanism; the black dashed line designates attracted fishing effort due to expected fisheries benefits (spill-over); the grey dashed lines represent fishing activities which cannot be related to the presence of an OWF.

Figure III-7 illustrates the daily BER and corresponding catch for different price (€·kg^{-1}) scenarios for landed brown crab. The variable costs per day of a beam trawler (61 gross tonnes) targeting brown crab add up to 330 €·d^{-1} (61 × 5.4 €·d^{-1}; see Appendix D), excluding crew costs. With an annual depreciation of 13 000 € and crew costs as a 22 % share of the revenue the estimated crew costs result in 73 €·d^{-1} ((13.000 € × 0.22) + (330 €·d^{-1}× 0.22)) for the break-even case (Appendix D).

The annual BER is 403 € per day plus 16 667 €. Our break-even scenarios suggest that even in the case of high prices (3 € kg^{-1}) and a fishing period of 30 days per year the daily break-even catch is about 300 kg. If the price is about 1 € kg^{-1} and only ten fishing days can be assigned to brown crab fishing, then a daily catch of about 2.000 kg is necessary to cover variable costs and depreciation on crab fishing investment (Figure III-7).

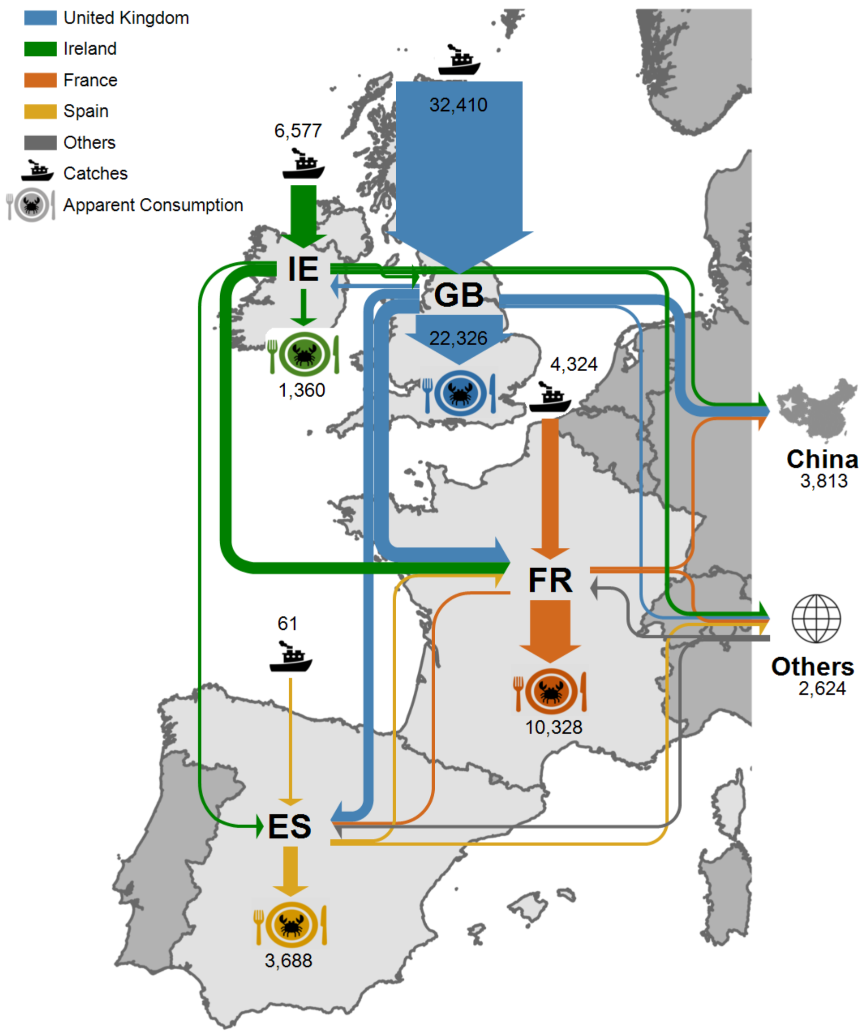


Figure III-6. Illustration of relative catches and apparent consumption of brown crab in UK, Ireland, Spain and France and trade between these, "others" and to China in tonnes live weight equivalent.

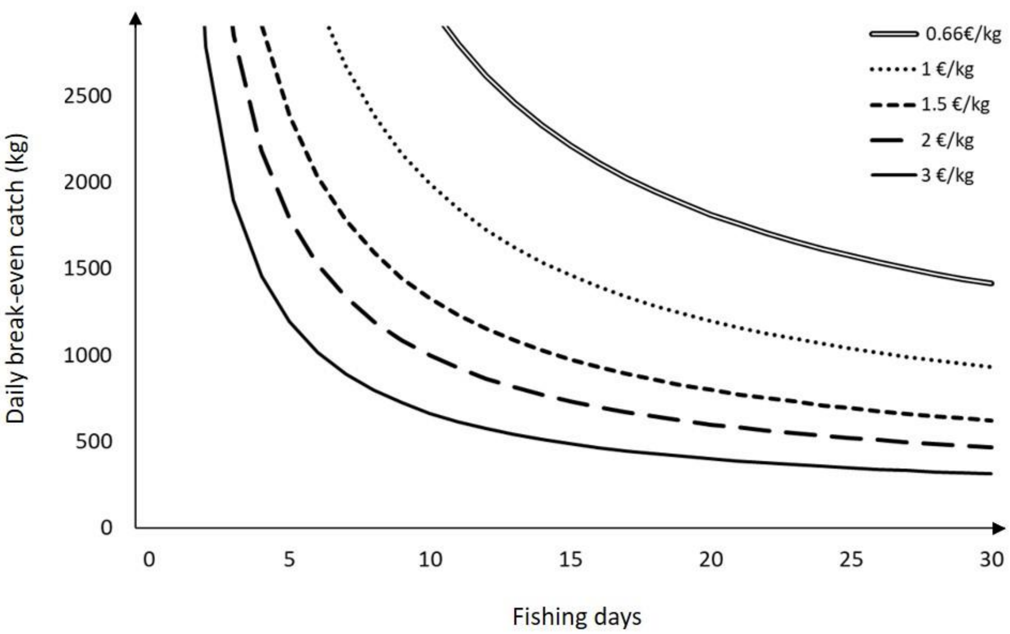


Figure III-7. Simulated daily break-even catches for different price scenarios for brown crab.

4. Discussion

We observed local spill-over mechanisms of brown crab from an OWF in the southern North Sea and demonstrated a patchy, but increasing attraction of pot fishing activities to OWFs. At the same time, we showed that the international fishing effort targeting brown crab enlarged gradually over the past years due to an increasing demand and stable resource populations at suitable habitats, including OWFs. Hence, we illustrate that under these conditions brown crab fisheries benefit from the rapid expansion of OWFs. The German fishing sector has not yet embraced these new fishing opportunities, but would have the capacities to conduct economically viable pot fisheries. We highlight that a comprehensive understanding of fisheries benefits due to the presence of OWFs requires combing knowledge about ecological effects on fisheries resources with socio-economic effects on the fishing fleets. Our study provides an urgently needed integrated assessment of socio-economic and ecological implications of MSP with offshore renewables and fisheries and sheds light on key requirements for an ecosystem-based planning approach.

4.1 Spill-over and implications for co-locating fisheries and OWF

The environmental conditions across the experimental fishing sites around an OWF were fairly stable, however, they were not directly located on known suitable habitats for brown crabs. Therefore, we assume that the observed spatial patterns of enlarged catches and sizes of brown crabs closer to the monopiles with a scour protection reflect both the increased availability of suitable artificial habitats and a spill-over mechanism. Since we performed our sampling during summer time, it is however important to note that the catchability between male and female differed since egg carrying females are burying in soft sediments (Tonk and Rozemeijer, 2019). In close proximity (~ 300 m) to the foundations our catches of brown crab with a carapace width < 130 mm were highest, pointing to the potential functioning scour protections as nursery area. This agrees well with existing observations (Krone et al., 2017, 2013), describing OWFs as nursery areas for brown crab and the importance of OWFs to enhance local populations. Our results emphasised also the importance of the increased water temperature, hence the timing of sampling. The measured minimum carapace widths at distances > 500 m to the turbines increased clearly from June to August, as well as the relative biomass of female crabs. In contrast, the maximum carapace widths sampled at such distances decreased from June to August. Thus, larger carapace widths could reflect individual growth.

In addition, migration and therefore the mobility increases with increasing water temperatures which could explain the enhanced catches of females in August (Woll and Ålesund, 2006). The decreased catches of larger individuals in August could point to an increased fishing mortality. The latter is supported by our analysis showing increased fishing effort in the third quarter of a year with August as one of the months of highest pot fishing intensities. The observed spatial patterns and trends in catches and sizes are relevant when advising MSP processes on how to regulate a sustainable co-location of fisheries and OWF. Pot fisheries are well suited for co-location solutions since pots do not disturb the seabed (Kopp et al., 2020) and therefore the risk to damage cables or other OWF infrastructure is low. Co-location solutions could also comprise temporal regulations where for instance pot fisheries is permitted up to 200 - 300 m to the foundations during summer or regulations for gear setting to avoid ghost fishing in the case of lost gear. For an OWF this would give planning security in the sense that e.g. maintenance involving increased ship traffic could be scheduled to minimise collision risk due to increased shipping activities. To keep local brown crab populations stable in the long term, fishing activities might be restricted in the OWF buffer zone during the first and second quarter of a year, while in July and August fisheries is permitted. The implementation of co-location solutions could also address regulations for OWF regarding the type foundations and scour protections to maximise the potential ecological benefits (Dannheim et al., 2020). The joint engagement of sectors in developing co-location solutions in MSP is to some extent an analogy to co-designing adaptive management and marine conservation measures (Christie et al., 2016).

4.2 Understanding trends of fishing activities in the vicinity of OWF

We showed that OWFs, being in operation since 2015, attracted pot fishing activities. These might be caused by general increasing brown crab abundance together with the newly established local populations as a result of the suitable artificial habitats. On the other hand, an increased fishing effort could also be linked to an overall upsurge of demand. The particular OWF sites (since 2015) represent rather new habitats for brown crabs since they are not located close to the persistent pot fishery hot spots (Stelzenmüller et al., 2016). But these OWFs are located in closer proximity to the coast and important fishing ports, hence being more attractive fishing grounds from an economic cost-benefit perspective. Based on our results we defined archetypes of fishing patterns indicating both new fishing activities and recurrent pot fisheries, which has been displaced due to construction activities. Overall, our analysis illustrated cumulative effects of biomass spill-over and confirms rising fishing opportunities and fisheries benefits. Still, we demonstrate also that spill-over effects cannot be generally assumed for a given OWF. Future studies focussing on cumulative spill-over potential of OWFs should put more attention on additional factors, i.e. habitat and foundation types, and prevailing fishing effort of both passive and trawled gears. We assessed the cumulative spill-over potential with the help of VMS data. Separating fishing from steaming pings encompasses a remaining uncertainty with regards to the correct categorisation.

4.3 Trends of demand and supply for brown crab from the North Sea

The demand and supply of brown crab from the North Sea showed striking differences in the apparent consumption between countries. Results should be treated with care and be used in relative terms instead of absolute terms (EUMOFA, 2019c). But, these differences are likewise reflected by country specific processing chains of brown crab. Basic and advanced processing takes place in UK and Ireland, e.g. white, brown or mixed meat, fresh, frozen or canned and produced pates, paste or crab cakes. As opposed to France and Spain, where only little or even no substantive processing (e.g. cooked as whole, preparing of claws) is taking place. This mirrors apparent differences in the consumption behaviour. In the UK and Ireland processed products are being preferred, while in Spain and France fresh and unprocessed, even alive crabs are favoured. Hence, in France live crabs are an indicator for quality and freshness of crabs (Garrett et al., 2015). In Spain, consuming brown crab is often combined with social events or special occasions such as Christmas or weddings. Overall the increasing export to China suggests that brown crab remains a profitable fisheries resource. This is also confirmed by current research focusing on the optimisation of long-distance transports of living crabs, hence allowing those products to enter the Chinese market (Ben-Asher et al., 2020).

4.4 Economic trade-offs of brown crab fisheries

A break-even analysis based on assumed catches and revenues allows for a first assessment of economic opportunities for pot fisheries. German beam trawlers with a length of about 18 - 24 m usually targeting brown shrimp could take advantage of brown crab fishing opportunities. These vessels almost exclusively target brown shrimp. This fishery is characterized by substantially fluctuating catches and prices and, as a consequence, shows highly volatile profitability (EUMOFA, 2019c). Our break-even scenarios for German beam trawlers indicated that fishing on brown crab can be a promising alternative to staying in the port in times when brown shrimp fishery is unprofitable. Going one step further and combining our results from the experimental pot fishery with the break-even analysis suggests that a catch of at least 300 kg·d^{-1} could be achieved when approx. 150 pots are deployed, assuming an average catch of 10 kg per fleet of 5 pots. Such a catch seems feasible and to be profitable it would require at least 15 days of fishing. On average in summer the brown shrimp fishery is unprofitable since the main fishing seasons is between March and July (Schulte et al., 2020). Therefore, German beam trawlers would have the adaptive capacity to target brown crab for a limited time in summer to compensate socio-economic losses or even generate additional revenues. Comparing roughly the value of the international landings of other species from the wider experimental fisheries study area (STECF, 2018; ICES rectangles 37F7 and 38F7) revealed that brown crab ranked third (~2.6 Mio €) after brown shrimp (~8.2 Mio €) and sprat (*Sprattus sprattus*; ~6.4 Mio €). Hence, the value of these brown crab landings were almost three times higher than the one of sole (*Solea solea*). This underlines the local potential for this fisheries resource.

Conclusions

The development of offshore renewables such as OWF in the North Sea is spurring the conflict potential with other sectors and in particular with fisheries. When space becomes limited, it is key for MSP to understand adaptive capacities of fishing fleets to offset the increasing loss of fishing grounds and accessibility of resources. Expected long term fisheries benefits of OWF as well as the fear of further losses of fishing resources due to e.g. climate change, Brexit, or further spatial constraints and regulations are the main reasons for the fishing sector to call for a more integrated regulation through MSP. For the German EEZ of the North Sea we illustrated that a brown crab fishery in the vicinity of OWF as a second pillar could be economically viable and could lower the susceptibility to risk by diversifying fishing activities. Our integrated assessment approach exemplifies that co-location solutions between these sectors should be built on a sound knowledge of ecological processes such as spill-over mechanisms as well as socio-economic constraints of respective fishing fleets. We argue that co-location solutions should follow the example of a cross-sectoral co-design of management options. Our results showed also that spill-over potentials of brown crabs differ according to the environmental setting of an OWF, therefore a bottom-up or micro-planning for co-location solutions would be most effective to establish sustainable co-location solutions. This could also entail measures for future OWFs regarding the design of foundations with scour protection to support e.g. settlement of benthic communities or the decommissioning of OWFs. Advising MSP processes on long-term adaptive capacities of fisheries requires more future research on the ecological effects of OWF including studies on local and regional shifts of food webs. Taken together we conclude that MSP processes with offshore renewables and fisheries require integrated and evidence-based assessments of the wider environmental and socio-economic effects of the plan and its measures.

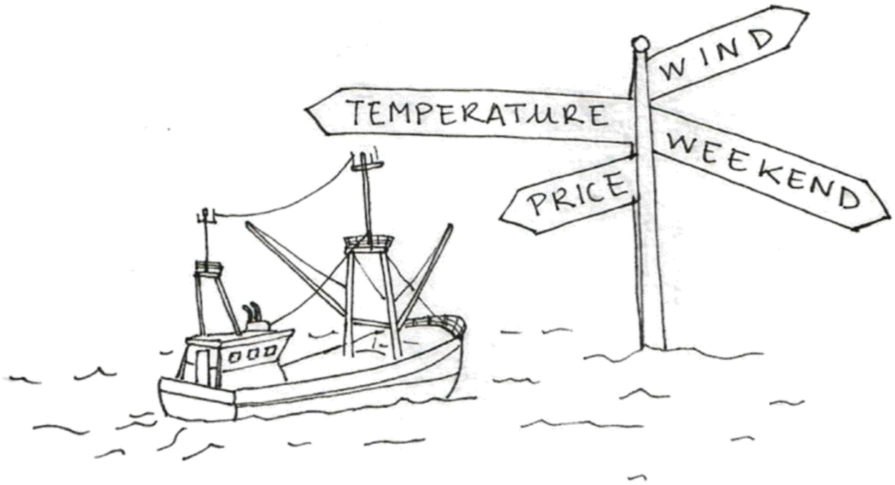
Supplementary material

Supplementary material of this chapter can be found in the *end of this thesis*.

Acknowledgements

We would like to thank WindMW for their collaboration and support during the experimental fishing around the OWF Meerwind Süd/Ost. Further we would like to thank the captain and crew of the FFS Solea for the great support and flexibility. A.G. was supported European EFRE funds granted by Bremerhavener Gesellschaft für Investitionsförderung und Stadtentwicklung mbH (BIS 989/AUF-FUE-V/2-1/2018 „Co-Nutzung von Offshore-Windparks als ökosystem-basiertes Raumplanungsmodell“). Many thanks to Nicole Stollberg for helping us with the graphical abstract.

Chapter IV



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

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Abstract

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

Key words: boosted regression tree, fishing drivers, fishing behavior, marine spatial planning, resource management

1. Introduction

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

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

North Sea fishers face many challenges, such as increased competition for space with renewable energy development (i.e. offshore wind farms) and marine conservation measures like marine protected areas (OECD, 2016; Stelzenmüller et al., 2022). Moreover, climate change is likely to alter fishing opportunities spatially (Baudron et al., 2020), adding to the potential for conflicts between fisheries and other users of ocean space (Link et al., 2017; Mendenhall et al., 2020). Therefore, the North Sea requires proactive MSP that integrates fishers' potential reactions to these changes.

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

2. Methods

2.1 Exploratory literature review for factors influencing demersal North Sea fishing activity

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

2.2 Empirical modelling of factors influencing German demersal fleets

2.2.1 Preparation of fisheries data

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

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

We obtained VMS data for each fleet for the period 2012-2018 and improved data quality by removing duplicates and pings in harbors or on land. Subsequently, we identified continuous fishing trips based on spatial and temporal information from the VMS data and merged them with data on fishing trips from logbooks (similar to Bastardie et al. (2010b)). We complemented missing vessel characteristics with data from the German Fishing Vessel Register and the European Fleet Register. Finally, we used the VMS tools package (Hintzen et al., 2012) to separate steaming from fishing pings and calculated fishing effort in hours per data point. We then aggregated fishing effort per day in a 0.25° Longitude × 0.25° Latitude grid. For each fleet, we used monthly frames, consisting of all cells with fishing effort in a month, to set the spatial frame for our daily-resolved fishing effort in the respective month. Since fishing effort data was available at a daily resolution, each monthly data set contained cells without fishing at certain days. To also represent cells where no fishing effort took place during a month, we created a 30km buffer around each monthly frame. Adding negative samples enabled the model to not only learn which variables are affiliated to fishing effort, but also those that are affiliated to no fishing effort. The resulting data sets of the three fleets differed with respect to spatial extent, size, and fishing effort intensity (Figure IV-1). With regard to quantities of data points (spatial grid cells at daily resolution), the MDS fleet represented the largest data set (n = 114703), followed by the FF (n = 90726) and BS fleet (n = 46974). In terms of mean fishing effort per day and grid cell, the order was reversed, as the BS fleet had the highest mean (3.67 h), followed by the FF (0.42 h) and MDS (0.35 h) fleets. We used the R programming language for all data processing (R Core Team, 2023), of which a detailed description can be found in the supplementary material (Appendix C).

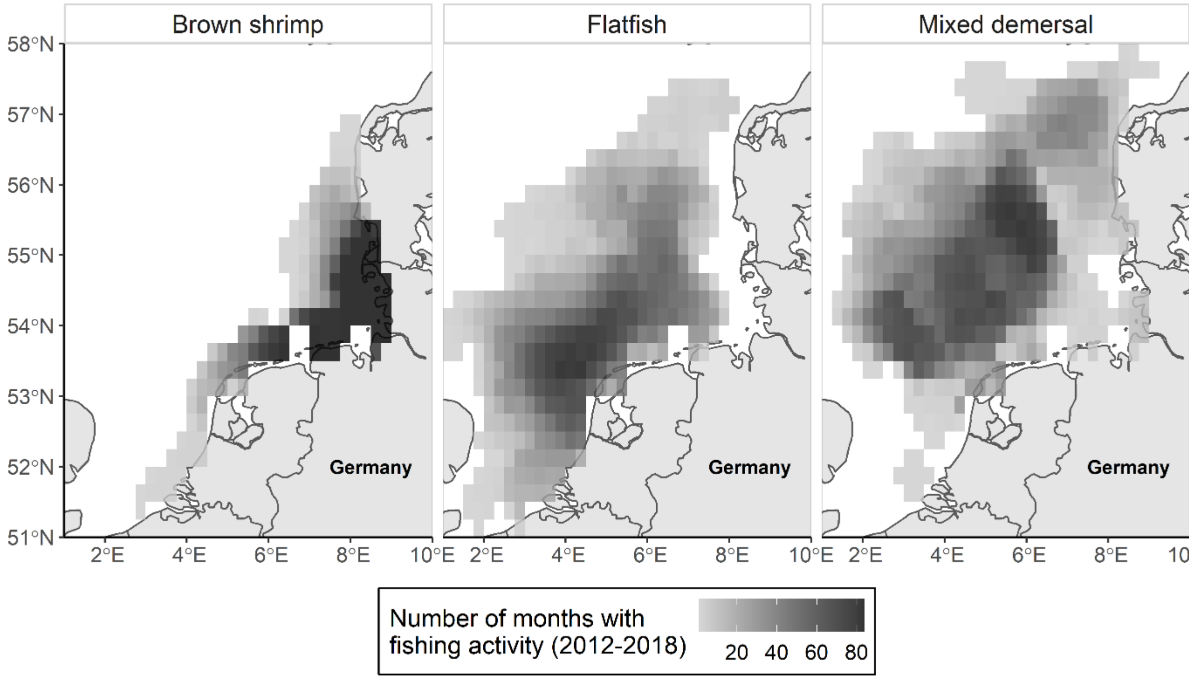

Figure IV-1: Spatial extent and density of fishing activity of the three fleets in the study area, based on the number of months a fleet was active in a grid cell from 2012 to 2018.

2.2.2 Explanatory variables

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

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

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

2.2.3 Boosted regression trees

We identified the importance of fisheries drivers by using boosted regression trees (BRT), a supervised machine learning technique that combines the advantages of tree-based models with boosting (Figure IV-2; Friedman 2001). We used the *xgboost* package in R for BRT tuning and implementation (Chen et al., 2019; R Core Team, 2023). Contrary to other BRT approaches, the *XGboost* technique has a more sophisticated boosting algorithm, additional tuning parameters, an internal mechanism for imputing missing values, and scalability, i.e. parallel computation to reduce run-time (Chen and Guestrin, 2016; see Appendix E for more details).

For each fleet we randomly assigned 30% of the data to a test and 70% to a training data set. We tuned the BRTs in an iterative procedure using 10-fold cross validation and root mean square error (RMSE) to determine the best combination of tuning parameters in each step. To reduce run time and avoid overfitting, we set early stopping to 10 rounds, limited the maximum number of trees to 2000, and selected a learning rate between 0.01 and 0.2. Subsequently, we tried different combinations of the maximum tree level and the minimum leave weight in steps from 2 to 10 and 1 to 5. Next, we tried values for the bag fraction and feature sampling between 0.5 and 0.9, respectively. Finally, we increased the number of trees to 10^3 and tuned the learning rate by trying the values 0.01, 0.05, and 0.1. Due to stochastic components in the model, i.e. bag fraction and feature sampling, the optimal number of trees varied in each model run. Therefore, we ran the model 10 times, recorded the optimal number of trees, and, in the final model, set maximum number of trees to the average of these recorded values.

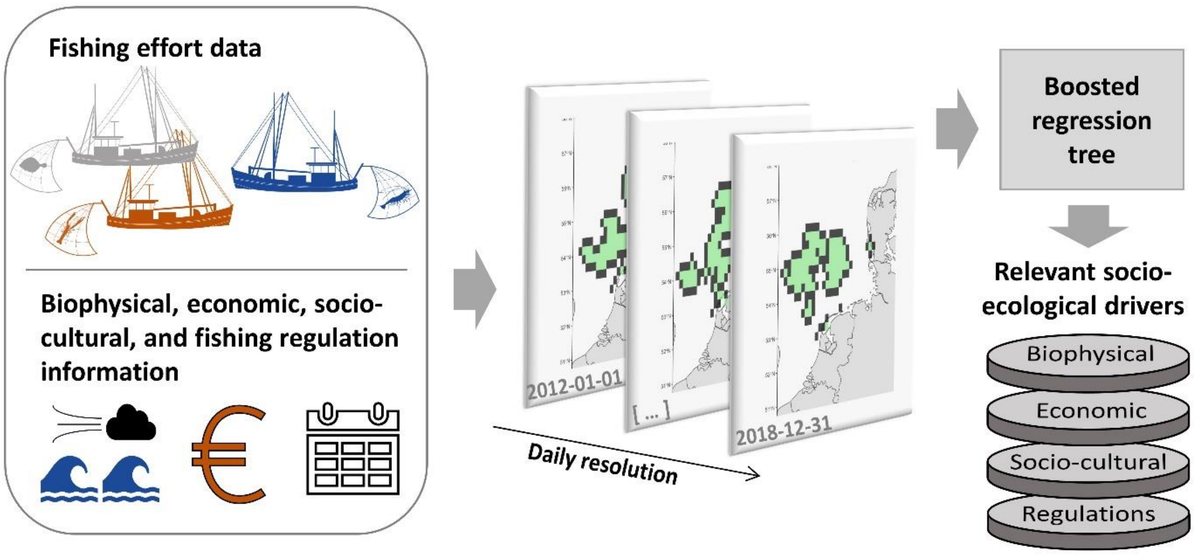

Figure IV-2: The empirical work flow of this study starting with the preparation of input data and ending with the identified socio-ecological factors influencing fishing effort.

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

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

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

3. Results

3.1 Drivers identified by the exploratory literature review

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

Biophysical parameters influencing fishing activity may be grouped into weather and oceanographic variables, the former directly influencing fisher decisions, e.g. high waves restrict smaller vessels to go fishing (Bastardie et al., 2013; Christensen and Raakjær, 2006), and the latter affecting marine species, which in turn influences fisher behavior (van der Reijden et al., 2018). Oceanographic factors comprise bathymetry, bottom temperature, shear stress, and sediment compositions (Hintzen et al., 2019; van der Reijden et al., 2018). Most of these variables are subject to temporal dynamics causing seasonality in fishing activities in the North Sea (Oostenbrugge et al., 2008; Rijnsdorp et al., 2008, 2006). Conventional economic factors are linked to revenue and are used to assess the profitability of a fishing trip. Therefore, higher fish prices are incentives to go fishing (Bastardie et al., 2013; Christensen and Raakjær, 2006), whereas higher fuel prices are an incentive to restrict fishing (Poos et al., 2013). Vessel characteristics, i.e. engine power or fishing gears, determine the efficiency of fishing vessels and state-of-the-art equipment is related to higher catches and landings per unit effort (Rijnsdorp et al., 2006; Sys et al., 2016). The decision-making of fishers differs among business structures, as owner-operators include more personal matters in their decisions, as opposed to larger companies (Schadeberg et al., 2021). Temporal or spatial restrictions trigger a displacement of fishing effort (Andersen et al., 2012; Poos and Rijnsdorp, 2007), whereas quota restrictions may inhibit an entire fishery (Ulrich et al., 2011). Especially in mixed fisheries, such as unselective demersal trawls, quotas may lead to an early fishing stop, if abundant bycatch species are subject to low quotas (Ulrich et al., 2011). This so-called ‘choke species’ effect is enhanced by landing obligations, prohibiting the discarding of undersized catches (Batsleer et al., 2016). Stakeholder elicitation methods with Danish fishers revealed that older skippers are more likely to abide regulations (Christensen and Raakjær, 2006). Socio-cultural factors are mostly linked to attributes of the fishers, i.e. age, experience, social network, or cultural norms. For this review we defined experience as information from past fishing trips used as a baseline for future decisions. Multiple studies revealed that fishers prefer previously known fishing locations (Andersen et al., 2012; Bastardie et al., 2013; Hutton et al., 2004; Poos and Rijnsdorp, 2007; Tidd et al., 2012). Memories of economic variables also influence the location choice, as high previous revenues function as an incentive for visiting that same fishing ground (Bastardie et al., 2013; Tidd et al., 2012), whereas high previous costs have the opposite effect (Tidd et al., 2012). In addition, information about profitable or unprofitable fishing events may also be acquired by information exchange among fishers (Christensen and Raakjær, 2006). As opposed to cooperative behavior on land, Poos & Rijnsdorp (2007) found that interactions at sea are more competitive and fishers generate less value per unit effort in areas with a high abundance of fishing vessels. Finally, low fishing effort during the bidweek (Rijnsdorp et al., 2008), a holiday for the Protestantism, and a preference for being at home during the weekend (Schadeberg et al., 2021) show that religious orientation may influence temporal fishing patterns as well.

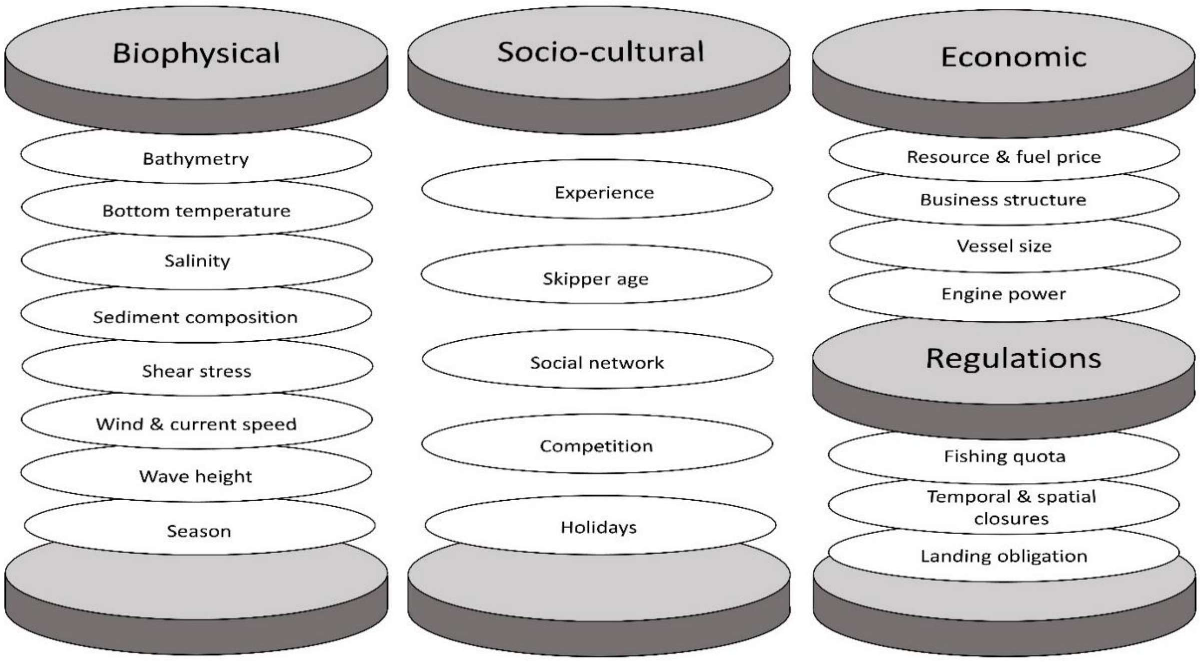

Figure IV-3: Infographic displaying factors influencing North Sea demersal fishing activity based on the exploratory literature review.

3.2 Drivers identified by the empirical modelling

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

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

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

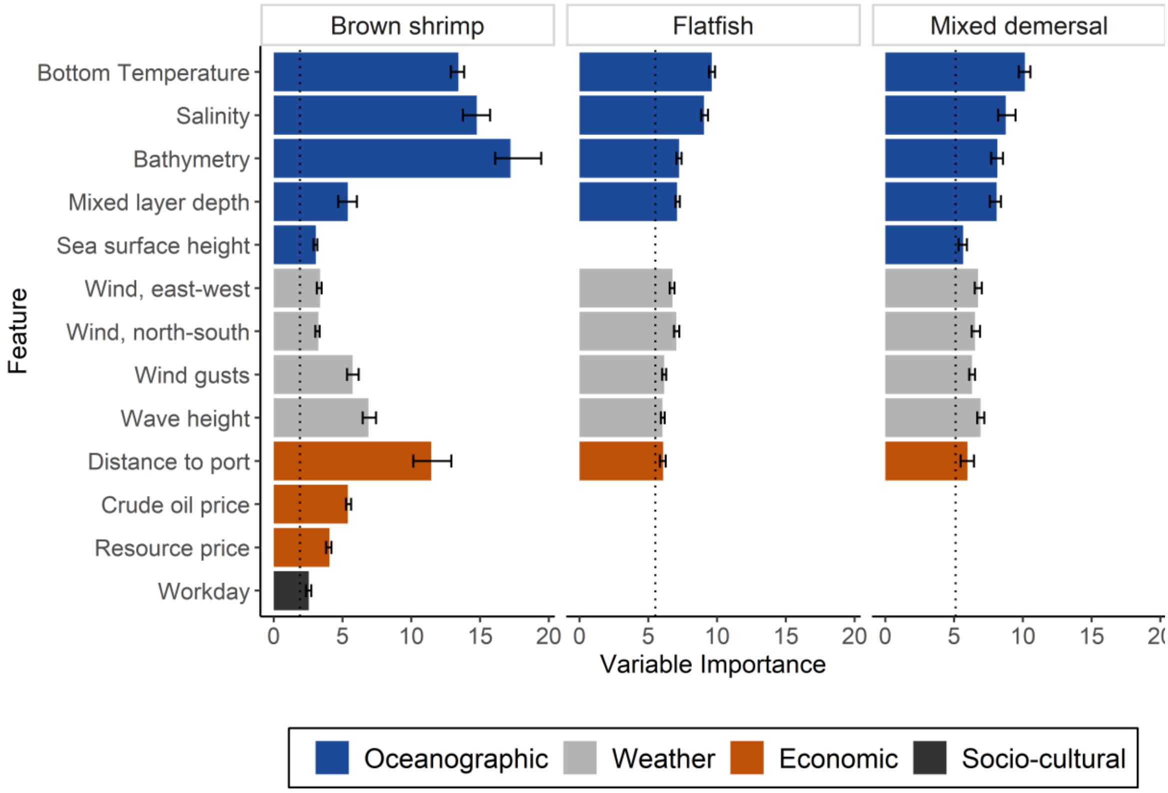

Figure IV-4: Variable Importance (VI) scores for relevant explanatory variables computed by averaging VI scores of all 10 models with error bars indicating minimum and maximum values. The dotted line shows the VI score of the random variable, which was used to identify relevant parameters.

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

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

Distance to port was the only relevant economic variable for the FF and MDS fleets, whereas resource and fuel price were additional relevant parameters in the BS model (Figure IV-4 & Figure IV-5C). Positive ALEs of distance to port represented a gradient among fleets starting with the BS (20km), and followed by the FF (139km), and MDS fleet (175km). This suggests less spatial flexibility for the BS in comparison to the other fleets. Moreover, the ALE of the BS model depicted a clear threshold with values being positive and constant above 18km. Resource price influenced BS fishing effort positively at lower prices. With regard to crude oil price, the distribution of underlying data was skewed towards the extremes, suggesting that ALE between $70 and $100 per barrel are unreliable. In ranges with more data, the effect of crude oil price on BS fishing effort was greater when fuel was less expensive, indicating that BS fishers favor lower fuel prices.

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

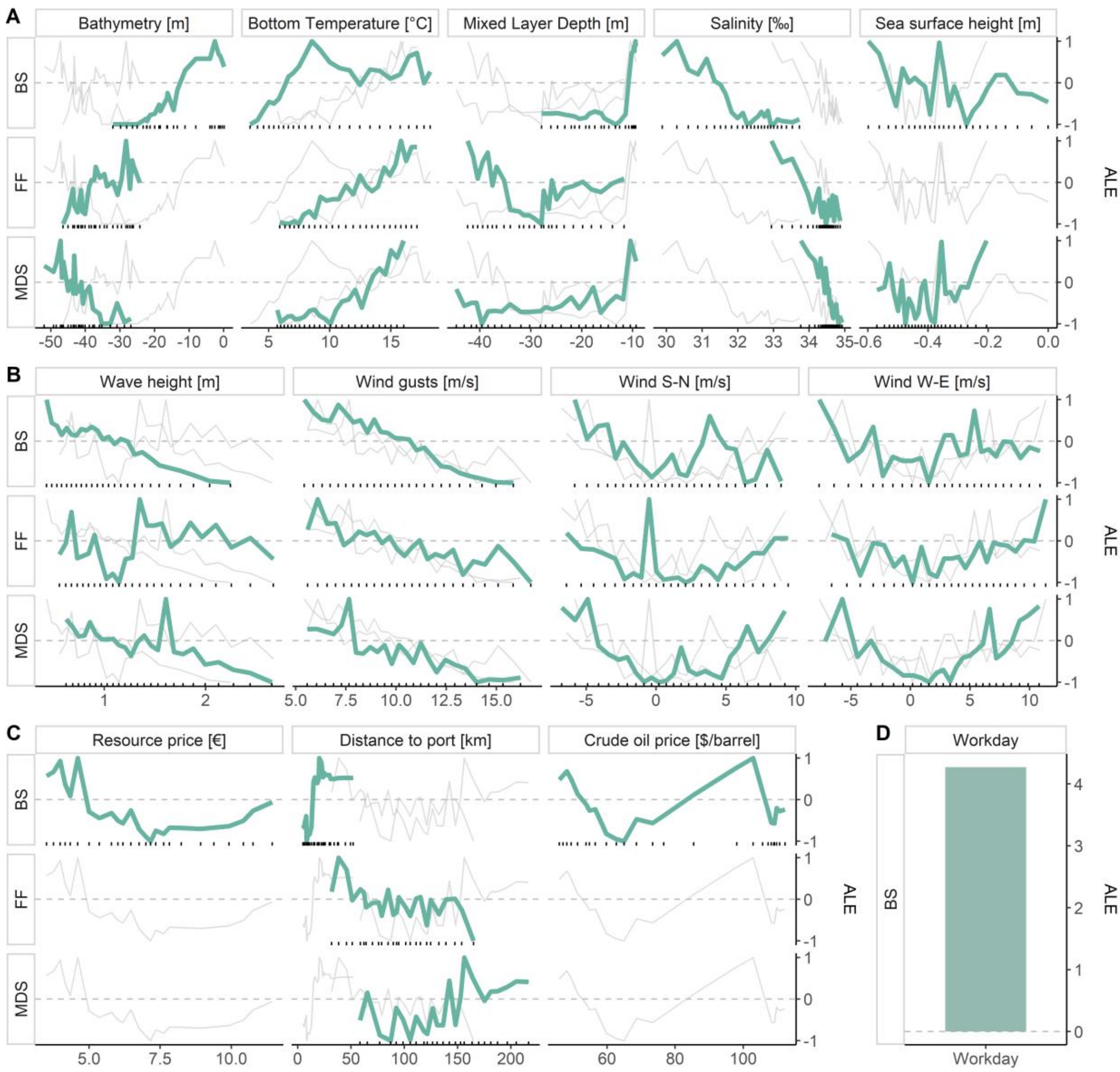

Figure IV-5: Accumulated local effects (ALE) of relevant explanatory variables of the Brown Shrimp (BS), Flatfish (FF), and Mixed Demersal (MDS) fleet. Panels are grouped into oceanographic (A), weather (B), economic (C), and socio-cultural (D) variables. ALE of numeric variables (A-C) are standardized.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

4. Discussion

We identified socio-ecological drivers influencing North Sea demersal fishing activity and modelled spatio-temporal fishing effort dynamics of German demersal fishing fleets in the North Sea using boosted regression trees (BRT). The exploratory literature review revealed that studies combining biophysical, economic, socio-cultural and fishing regulation factors in one single quantitative analysis are rare. As such, our empirical analysis contributed to filling this research gap. Advancing from previous BRT studies analyzing fishing effort (Castrejón and

Charles, 2020; Cimino et al., 2019; Crespo et al., 2018; Soykan et al., 2014), our analysis considered a higher model resolution (i.e. daily fishing hours per grid cell). Biophysical variables were the most relevant for effort dynamics, although their effects varied among fleets. Quotas were not relevant for the German demersal North Sea fisheries and market prices only for the brown shrimp (BS) fleet, although our exploratory literature review revealed both parameters to be important influencing fishing activity. Contrary to the flatfish (FF) and mixed demersal (MDS) fleets, the BS fleet generally showed a stronger dependency on socio-economic drivers.

4.1 Biophysical drivers influencing fishing effort

The observed effects of bathymetry among fleets resemble the habitats of the respective fleet's target species, since brown shrimp is caught in shallow waters (Schulte et al., 2020) whereas plaice, sole and Nephrops occur in deeper areas (Hunter et al., 2003; Johnson et al., 2013; van Hal et al., 2016). Our results hence support earlier findings suggesting that biophysical drivers of fishing fleets reflect the ecological niches of their target species (Crespo et al., 2018; Hintzen et al., 2021; van der Reijden et al., 2018). Furthermore, we found bottom temperature and salinity to be positively and negatively related to fishing effort, respectively. Assuming that effort distribution is steered by the dynamics of target species, this result contradicts ecological studies reflecting a negative influence of higher temperatures on the recruitment and occurrence of plaice (Akimova et al., 2016; Engelhard et al., 2011; Teal et al., 2012; van Hal et al., 2016) and weak effects of salinity on plaice and sole (Akimova et al., 2016; Fonds, 1979; Lauria et al., 2011), Nephrops (Johnson et al., 2013), and brown shrimp (Kerambrun et al., 2001). Biophysical variables are subject to seasonal variability (Appendix G), which is also reflected in the fleets' target species. Seasonal catch variations of the main target species brown shrimp (Schulte et al., 2020; Temming and Damm, 2002), plaice (Hunter et al., 2003), sole (Rijnsdorp et al., 1992), and Nephrops (Redant, 1987), occur due to migrations or life cycles and peak in the warmer months from spring to autumn.

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

4.2 Economic and socio-cultural drivers influencing fishing effort

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

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

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

4.3 Implications for management

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

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

4.4 Methodological considerations

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

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

Conclusions

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

Acknowledgements

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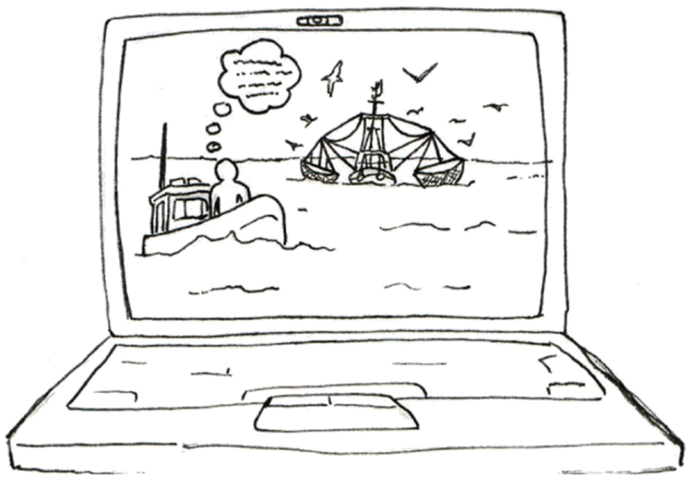
Data Availability Statement

Fisheries related data contain commercially sensitive information and can therefore not be made publicly available. Sources of other data sets used in this study can be found in the supplementary material at the *end of this thesis*.

Chapter V



Simulating Fishery Dynamics by Combining Empirical Data and Behavioral Theory

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Abstract

Understanding human decision-making in the context of complex fisheries socio-ecological systems remains one of the key challenges for ecosystem-based management. Agent-based models (ABM) are increasingly seen as one of the most promising methods to simulate human decision-making. In most fishery ABMs, human behavior is highly simplified and reduced to an economic motivation, although human behavior is more multi-facetted. Here, we present FISHCODE a spatio-temporal ABM for German fisheries in the southern North Sea. Our decision-making submodel combines different behavioral motivations, i.e. habitual behavior, profit maximization, competition, conformism, and planning insecurity. With the help of highly resolved information on fishing trips, we parameterized model parameters either straight from data or use pattern-oriented modelling. Model validation showed that aggregated model outputs were in realistic ranges when compared to observed data. FISHCODE hence represents a tool to assess the consequences of the ever-growing challenges to North Sea fisheries, e.g. expansions of offshore wind farms, gear restrictions, or increasing fuel prices.

Key words: Agent-based modeling, fisheries, human behavior, marine spatial planning, socio-ecological system

1. Introduction

Agent-based modelling (ABM) is an increasingly valued method to simulate human decision-making in socio-ecological systems (An, 2012; Rounsevell et al., 2012; Schwarz et al., 2020). Growing amounts of available empirical data offer the chance for more complex models and increase their structural realism (An et al., 2023; Elsawah et al., 2020). With a higher degree of realism, ABMs can be applied for simulation and scenario analysis and may represent virtual laboratories, in which the manipulation of model parameters allows estimating effects on real-world counterpart (Bruch and Atwell, 2015).

One facet where ABMs often come short is the representation of realistic human behavior. In a review of land-use ABMs, (Groeneveld et al., 2017) found that most models lack a theoretical foundation for human behavior and among those that used theories, economics was the dominant discipline. The same holds true for models of fisher behavior with rational choice being the most applied theory (Andrews et al., 2020; Haase et al., 2023; Van Putten et al., 2012), although a growing amount scientific literature suggests human behavior is more multifaceted (Barz et al., 2020; Schlüter et al., 2017; Wijermans et al., 2020). Selecting the right theory for human behavior is difficult due to incomplete knowledge (Elsawah et al., 2020; Schwarz et al., 2020) and has been identified as one of the main challenges in fisher behavior simulations (Lindkvist et al., 2020). One peculiarity among fishers is the often-observed strong attachment to their occupation. Despite fishing being hard work, very dangerous, and uncertain with regard to profits, fishers still continue their business, because to them it is more than a way of generating income (Pollnac and Poggie, 2008; Stelzenmüller et al., 2024a). Fishers decision-making can also be heavily influenced by risk-averse behavior especially if the fishers' wealth situation does not allow for experimenting (Holland, 2008). Humans in general rather play safe when they are exposed to uncertainty. In fisheries, there are many sources of uncertainty introduced by large variabilities in terms of environment, management, and market prices (Salas and Gaertner, 2004). New political settings (e.g. Brexit) can destabilize long established fisheries management systems, such as EU quota trade and distribution (Letschert et al., 2021). While assuming rational behavior with bioeconomic fleet models might be effective for modelling industrial fishing fleets on a large scale, they lack the necessary details to realistically depict decision-making of smaller case studies and more artisanal fisheries. Therefore, models on fisher behavior should consider the influence of uncertainty, risk-avoidance and social factors in addition to the traditionally applied economic theories (Van Putten et al., 2012).

In this study, we present FISHCODE, an empirically based ABM for German fisheries in the southern North Sea where planned offshore windfarms (OWF) and marine protected areas (MPA) might lead to unforeseen fishing displacement effects (Stelzenmüller et al., 2022). In order to achieve long-lasting and sustainable marine management, it is desirable to consider fisher's behavior when drafting new management plans (Fulton et al., 2011; Hilborn, 2007). Our study objectives were to develop a model that is able to (I) simulate fisher behavior beyond profit maximization and (II) reproduce spatio-temporal fishing dynamics with sufficient realism to assess scenarios. We modelled fisher decision-making by applying the Consumat approach (Jager et al., 2000; Jager and Janssen, 2012), in which agents choose different behavioral strategies based on their satisfaction and uncertainty levels. To achieve our objectives, we draw on theories of human behavior and combine these with heuristics rooted in quantitative historical data to enable the simulation of spatio-temporal fishing effort as an emergent property of individual agent decisions.

2. Methods

In our agent-based-model (ABM), termed FISHCODE (**FI**sheries **S**imulation with **H**uman **CO**mplex **DE**cision-making), agents technically represent fishing vessels, however, throughout this paper, we refer to agents as fishers, because with our decision-making submodel we focus on the human behavior of the deciding fisher on board, which we assume to be constant for every vessel. To the authors' state of knowledge, addressed fisheries are composed of male fishers, which is why we refer to agents with "he" and "his".

While we developed FISHCODE in Netlogo 6.1.1 (Wilensky, 1999), we used the R environment for data preparation and analysis of results (R Core Team, 2023), and performed the sensitivity analysis, parameterization, and model experiments by using the nlrx package for R (Salecker et al., 2019). The full model documentation and validation including an ODD+D protocol can be found in Appendix A in shape of a TRACE document to which we will refer throughout this study (Ayllón et al., 2021; Grimm et al., 2010, 2006; Müller et al., 2013).

2.1 Study system

The southern North Sea is a shelf sea that has been heavily fished for centuries and belongs to the most anthropogenically used areas in the world (Halpern et al., 2019, 2008b) with uncertain trajectories for human activities (Stelzenmüller et al., 2024b). The southern North Sea is characterized by different habitats shaped by various sediment types (from fine sand to rocky reefs), geographical features like trenches and low slopes between the coast and the barrier islands forming the Wadden Sea, and human-made spatial elements, i.e. offshore wind farms (OWF) and marine protected areas (MPA). The most important German fisheries in the study area consist of a near-shore brown shrimp (*Crangon crangon*) fleet and two fleets of demersal trawlers operating further offshore targeting either the flatfish plaice (*Pleuronectes platessa*) and sole (*Solea solea*) or Norway lobster (also called Nephrops; *Nephrops norvegicus*). The brown shrimp fleet represents the largest German North Sea fishery in both economic relevance and vessel number, encompassing more than 200 vessels with an average length of 18 m that are predominantly equipped with beam trawls (TBB) and sometimes electric pulse gears (PUL). Fishing businesses of this fleet are relatively small and family-owned. The sole and plaice fleets are composed of several "cutters" with an average length of 36 m and equipped with TBB or PUL. These vessels are affiliated to large Dutch companies, although they are still registered as German-flagged vessels. Fishers targeting plaice and Nephrops use vessels with an average length of 24 m and otter bottom trawls (OTB). They are owned by medium-sized German companies. For most vessels, plaice represents a lower incentive due to the low market prices in comparison to sole and Nephrops. Nonetheless, there are some OTB vessels that predominantly target plaice. All gears described above are bottom trawls, which are very unselective and result in relatively high bycatches. PUL has been introduced in the 2000s as a fuel-saving alternative for TBB due to its light weight and reduced seafloor contact, but was banned by the EU in 2021, because of its controversial effect on the ecosystem (Kraan et al., 2020; Le Manach et al., 2019). A large portion of the flatfish and Nephrops caught by the German fleets are landed in the Netherlands where most of the processing industry is located. The majority of German fishers are part of producer organizations that manage the distribution of fishing quotas and are organized by region and target species assemblage. Plaice, sole, and Nephrops are quota-regulated species, meaning fishers' catches are limited to the acquired quota. In the cases of Nephrops and sole the quotas could actually be a limiting factor, whereas the quota for plaice was never exhausted in the previous years.

2.2 Data processing

2.2.1 Data sources

We used a variety of data sources to inform FISHCODE at different stages. Most agent state variables were informed by vessel monitoring system (VMS) and logbook data containing geographical timestamps broadcasted every two hours (so called pings), landing weight and value compositions by species, as well as fishing gear, and landing ports. These were complemented by technical vessel details such as engine power and tonnage from the European fleet registry, and membership in producer organizations from the German vehicle registry. We combined all previously described information to a data base on fishing trip resolution to which from hereon we refer to as “trip data base”. We complemented the trip data base by calculating landings per unit of effort (LPUE) per species (kg / h), as well as fishing and steaming times. We cleaned the trip data base by checking for outliers in several variables, e.g. LPUE and trip length (days). Finally, the trip data base comprised 21828 fishing trips from 216 vessels over seven years (2012-2018). We informed environmental and economic variables with data sets from the Scientific, Technical, and Economic Committee for Fisheries (STECF), the European Market Observatory for Fisheries and Aquaculture (EUMOFA), and Copernicus. Monthly expenses and aspired savings of fishers were directly derived from webpages containing statistical information about German citizens. Details on all data processing steps can be found in Appendix A including a list of all data sources with links to online references (Table V-A3).

2.2.2 Defining metiers, fleets, and catch grounds

We grouped fishing trips into metiers, and vessels into fleets. Metier is a term that is used in fisheries literature to describe a fishing trip based on species assemblage and technical vessel information (e.g. gear or mesh size), whereas vessel characteristics such as size or main fishing gear are used to categorize fleets (Ulrich et al., 2012). Thus, a particular vessel is always associated to only one fleet, but can engage in fishing trips of different metiers throughout the year.

For FISHCODE, we defined eight metiers by clustering fishing trips with regard to catch compositions representing the major part of the German fisheries in the southern North Sea (Appendix A2.1). For simplicity reasons, we did not include net mesh size in our metier definitions. In FISHCODE, agents have one default metier, which is directly extracted from the trip data base and represents the metier they engaged most during the years before model initialization. While the default metier is fixed, agents dynamically choose metiers for every fishing trip according to certain state variables, (e.g. available gears and quotas for target species) and the current model environment (e.g. weather). Certain vessel features such as gear handling or steaming speeds depend on characteristics unique to vessels rather than metiers and therefore remain static. We used the fixed default metiers to group vessels into fleets (Table V-1). Every metier is linked to its own spatial catch ground with the exception of PUL metiers for which we merged catch grounds with the respective TBB metier, e.g. PUL – PLE&SOL and TBB – PLE&SOL, the reason being that these two gears can be used interchangeably by vessels (Appendix A2.2).

Table V-1. Default metiers and fleets defined for the agent-based model. Gear abbreviations stand for otter bottom trawl (OTB), beam trawl (TBB), and electric pulse trawl (PUL) and species for plaice (PLE), sole (SOL), Nephrops (NEP), and common shrimp (CSH).

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

2.3 Model Description

2.3.1 Model overview

Environmental, economic, and social factors play an important role in fisheries socio-ecological systems (Letschert et al., 2023; Stephenson et al., 2018). Environmental factors and habitats determine the occurrence and quantity of fish and other target species while market prices dictate their value and fuel, material, and personnel costs need to be paid. These dynamics are widely accepted and represent the core of bio-economic fishery models (Blanz, 2018; Garcia et al., 2017; Salz et al., 2011).

Humans are complex beings with different ages, educations, and life situations. Since fishers are a crucial element when describing fishery dynamics, it is evident that personal choices and norms of fishers should be considered in addition to environmental and economic factors (Andrews et al., 2020). Work rhythms and fishing trip lengths are affected by personal choices such as wanting to be home on the weekend or at the end of every day (Letschert et al., 2023; Schadeberg et al., 2021). Technical vessel characteristics are another source of heterogeneity. Vessel volume and size define the available space for storing catches (volume) and resisting storms (Bastardie et al., 2013; Letschert et al., 2023). Moreover, technical vessel characteristics limit fishing choices, because fishing gears have technical requirements, e.g. otter bottom trawls (OTB) require winches at the stern to pull nets on board, whereas beam trawls (TBB) and electric pulse trawls (PUL) are submerged from port- and starboard. A certain type of vessels, so called “eurocutter”, pose an exception, because they were built in a way to be able to use both OTB and TBB or PUL gears.

2.3.2 Agent decision-making

Before leaving for a fishing trip, agents in FISHCODE have to make three decisions that are influenced by exogenous or endogenous factors. Figure V-1 shows all factors directly influencing decisions and groups those into environmental, technical & regulation (exogenous), and cognitive (endogenous). We defined cognitive variables as those that involve the processing by agents.

Figure V-1. Infographic showing main agent decisions, factors directly influencing these decisions (arrows) grouped into Technical & Regulation, Environmental, and Cognitive factors (colors), and how the Consumat approach is embedded in the decision flow.

What to fish? refers to the decision of choosing a fishing metier. Agents can only engage in metiers with species for which they have available quotas and with gears that can be used by their vessels. The pool of metiers to choose from depends on the Consumat strategy (described below).

How long? refers to the determination of the trip length and is influenced by personal norms affecting the agents' work rhythms, such as wanting to be home on the weekend or restricting the overall trip length. Moreover, storms resulting in high waves limit trip lengths.

Go fishing? refers to the decision of actually going fishing or staying in port. Personal norms in the shape of probabilities for having an inactive week influence this decision and differ by season and month. Also, if the vessel needs maintenance, the agent will stay in the port. Derived from the decision *What to fish?*, agents have a pool of possible metiers and make forecasts about changes to their satisfactions and uncertainties (described below). If forecasts for all metiers yield a potential worsening of their situation, they will stay in the port.

The Consumat approach has recently been used to model farmers' decision on water irrigation (van Duinen et al., 2016), weed control in maize agriculture (Huber et al., 2021), and soil conservation (Van Oel et al., 2019). To the state of the authors' knowledge, there has not been an application of the Consumat approach in a fishery ABM except for the stylized fisher agents in the original publication (Jager et al., 2000).

Depending on whether agents are satisfied or unsatisfied and certain or uncertain, they decide to use one of four actions: (1) repetition, (2) imitation, (3) deliberation, or (4) inquiring (Table V-2). Each action involves a different behavioral strategy to perceive the potential options of metiers that agents may choose from. Independently of the chosen behavioral strategy, agents always have the option of staying in port, which they select if all other metier options would worsen the situation of the fisher. Agents evaluate their situation by calculating three satisfactions (existence, social, and personal) and two uncertainties (existence and social), each of them multiplied with a weighting factor. Formulas for the calculations of satisfaction and uncertainty can be found in Appendix A1.2.8. The advantages of using the Consumat are threefold on which we will elaborate in the next paragraphs.

Table V-2. Possible behavioral strategy from the Consumat approach that is chosen depending on the agents' satisfaction and uncertainty and determine the perceived behavioral options, i.e. metiers.

Behavioral strategy	**Satisfact-ion**	**Uncer-tainty**	**Perceived options**
Repetition	High	Low	Metier from previous trip as the only option. If it is not possible to perform the repeated action (e.g. no quota), the agent will switch to deliberation.
Imitation	High	High	Metiers from previous trip of agent's own memory and last trips of close social network. If there is no possible option among the perceived options (e.g. no quota), the agent will switch to inquiring.
Deliberation	Low	Low	All available metiers in FISHCODE including those that have not been used by any other agent yet.
Inquiring	Low	High	Metiers of the last trips from agent's extended social network and all metiers from his own memory.

First, the application of multiple satisfactions and uncertainties with different emphases allows to combine multiple behavioral theories. The existence satisfaction (ESAT) represents an aspect of bounded rational behavior as it reinforces profit maximization within the knowledge limitations of agents. It is calculated as the relative share of the savings compared to the aspired savings, meaning that as soon as the savings grow above the aspired savings, the ESAT does not grow disregarding how much more profit is generated. If savings fall below half the negative value of the aspired savings, the agents change their selection process for metier options to pure profit maximization. Attachment of German fishers to their occupation goes beyond a way of generating income (Stelzenmüller et al., 2024a). This aspect is covered by the personal satisfaction (PSAT), which grows the more similar the agent's previous metier choices are. The social satisfaction (SSAT) introduces an aspect of rivalry in the agents' behavior, as it grows, if they earn more than their colleagues. 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.

Another factor influencing decision-making is risk and uncertainty. One large source of uncertainty lies in the quality and quantity of catches. We represent this planning insecurity by the existence uncertainty (EUNC) that grows with profits per trip being lower than predicted profits and vice versa. The EUNC also decreases the larger the standard deviation of trip profits is representing that agents may get accustomed to varying profits. The second uncertainty, the social uncertainty (SUNC), covers the fact that fishers might feel uncertain if the majority of their colleagues engage in metiers different from their own. The SUNC decreases the more similar used gears and primary target species are of an agent's memorized trips in comparison to his peers. Therefore, the SUNC represents the tendency to conformism.

A second advantage of the Consumat approach is that by default it includes information exchange inherent to having a social network (Table V-2). In fisheries, social networks are decisive, because they enable the sharing of information about yields of past fishing trips and alternative fishing strategies increasing chances for good catches (Barnes et al., 2017; Wilson, 1990). Social ties between fishers are more likely to form within homogeneous groups marked by target species and landing port (Alexander et al., 2018; Gillis et al., 2021). In our ABM, we use the agents' current ports and their memberships in producer organizations to define their closeness and group them into social networks. Within a social network, agents are able to exchange information and perceive information of past fishing trips. This enables agents to adapt to fishing metiers used by their peers, given that technical vessel characteristics and quota availabilities meet the requirement.

Finally, the third reason why we chose the Consumat approach is the dynamic selection of behavioral strategies that equips agents with the flexibility to adapt their behavior. Agents evaluate whether it is worth it to go fishing at every time step, given they are currently in a port (Figure V-2). Once decided to leave on a fishing trip, they perceive a pool of options consisting of potential metiers they could engage in. The only exception is when they perceive a single metier option (repetition). In order to choose one metier, fishers must have some kind of selection process and choose the metier that is most appealing either due to economic, traditional, or some other values. We utilize the already defined satisfactions and uncertainties for this decision process. For every metier in the pool of options, agents predict the possible fishing outcomes including new satisfactions and uncertainties. Then, they select the metier that promises the highest sum of gain in satisfaction and loss of uncertainty.

2.4 Agent cycle and simulation of fishing trips

Every model step represents one day that agents start with perceiving ambient bottom temperature and market prices for species and fuel (Figure V-2). Agents perceive these variables with an error of up to 10% to simulate their imperfect knowledge (Appendix A1.2.1). Then, agents update their state variables, mainly involving satisfactions and uncertainties. If they are currently fishing, they continue unless the days already spent fishing equal the maximum days for that trip. In the latter case, they return to the port and land their catches. If the agents are currently in the port, they try to leave for a fishing trip by first perceiving a set of behavioral options representing potential metier choices. The number of metier options varies depending on their satisfaction and uncertainty statuses (Table V-2), but always include the option of not leaving on a fishing trip and staying in port. Metier options for which the agent does not own the right quota or fishing gear are removed from the pool. For each of the retained behavioral options, the agents assess the possible trip length, which is limited by weather conditions and personal norms such as maximum trip days and wanting to stay home on the weekend. Then, for each of the retained options, they predict fishing outcomes including the anticipated change in satisfactions and uncertainties (Appendix A1.2.2). The predictions are made using variables from past fishing trips of the same metier in the agents' memories. If a fishing trip of the metier doesn't exist in the agent's memory, they get information with an error from the memory of peers in their social network. Independent from which memory the information originates, the bottom temperatures of all trips in the selected memory are compared to the ambient one and the most similar trip is used for predictions. Landings, costs, profits, as well as changes in satisfactions and uncertainties are then predicted based on the landings per unit effort (LPUE) from the matched trip and the anticipated trip days. After predicting the outcomes, agents rank options according to the sum of the gain of satisfaction and loss of uncertainty. Starting with the option of the largest sum, agents will try to engage in a fishing trip of this option's metier and remove those with high quantities of bycatches potentially surpassing quotas.

Once an agent found a possible metier option, he chooses the shortest path between his starting port and the center patch of his fishing destination, the latter being derived from either his own or his peers' memory. 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 center patch might change depending on the vessel density in the area and the number of suitable fishing patches (Appendix A1.2.4). The fishing movements are simulated using Lévy flights, a specific version of random walks that has been used to simulate the forage movement patterns of marine predators (Sims et al., 2008). Using Lévy flights, agents randomly decide for a direction, while the number of steps in that direction is drawn from a tailed random distribution simulating fishing movement with some longer straight lines (trawling) and several clumped patches (searching). The longer the path from the landing port to the fishing ground and the lower the engine power of the agent's vessel, the longer the steaming time. Fishing time is calculated by subtracting the steaming time from the overall trip length. Additionally, we added a fixed number of steaming hours per trip day that varies depending on the metier based on empirical information from the trip data base (Appendix A2.3.8). To model landings for a certain metier, oceanographic variables from the trip data base (bottom temperature, bottom salinity, mixed layer depth and bathymetry) associated with fishing trips of the same metier and current season are compared to the ambient ones using Euclidean distances. The fishing trip with the best match is then used to derive species composition and LPUEs for the new trip. LPUEs are adjusted according to the engine powers of the matched trip and the current agent. Landings are calculated by multiplying the adjusted LPUEs with the fishing time and then multiplied with current market prices to calculate revenues (Appendix A1.2.5). Local depletion of resources is simulated by the patch-specific local depletion factor that becomes reduced for every vessel fishing in that patch and recovers a certain amount every day (Appendix A1.2.6). Whenever landings are simulated for a certain patch, the LPUEs are multiplied with the depletion factor. Fuel costs are directly calculated from steaming and fishing times, the latter having a slightly higher fuel consumption due to the additional drag of the fishing net. Other costs are derived from the annual STECF report and standardized by day at sea to simulate the costs of personnel, repair & maintenance, other variable costs per day at sea, while fixed costs are subtracted in daily rates independent of the agent's actions (Appendix A2.4).

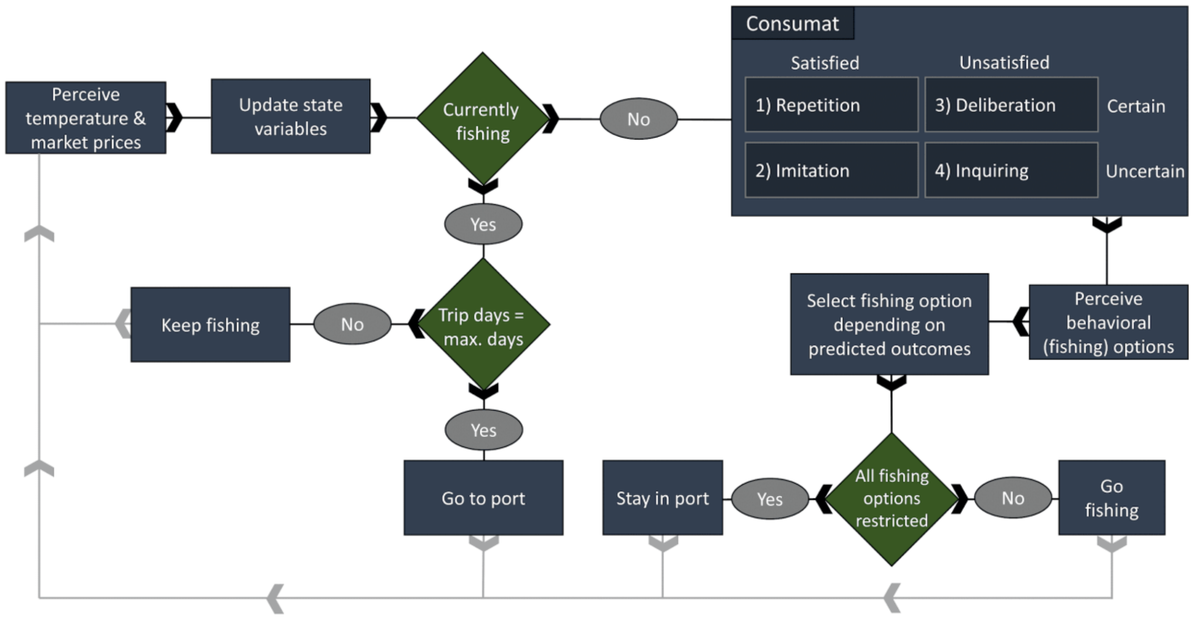

Figure V-2. Infographic of the daily cycle each agent passes through in every model step.

2.5 Sensitivity analysis

We used a Morris screening to test the sensitivity of model parameters, which performs efficiently for 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. From the results, indicators can be derived per parameter informing about the type of effect (i.e. monotonic, non-linear, interaction), as well as their strength (Campolongo et al., 2007; Garcia Sanchez et al., 2014). In total, we tested the sensitivity of 13 model parameters on eight model outcomes, i.e. catches of different species, fishing trip days, number of trips, as well as mean longitudes and latitudes of trips (see Annex A6.1 for details).

2.6 Model 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). In total, we parameterized seven model parameters (Table V-3) 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 FISHCODE 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.

Table V-3. 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>

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 V-3).

2.7 Model verification and validation

2.7.1 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. $0.\overline{33}$ 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 uncertainties 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 associated 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.

2.7.2 Validation of simulation results

To validate our model, we performed 50 simulations of German southern North Sea fisheries using the base year scenario. We then compared the 1.5 inter-quartile range (IQR) of model outputs to observed values from 2012 to 2018 on different aggregations involving a temporal or spatial component (per month or grid cell) or not (total, per vessel and per trip). In case of the model results, each simulation (n = 50) and in case of the observed every year (n = 7) served as data point. Some model outputs were recorded on a trip basis (i.e. trip days, fishing time, steaming time), whereas others were resolved on species level (i.e. landing weight and revenue). 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 did or did not overlap, whereas it was more varied for all other aggregations.

3. Results

3.1 Model functionality

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 V-A22). 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 they returned from a fishing trip. It affected CSH catches stronger than other catches (Figure V-A23), because CSH fishers have the shortest and most fishing trips and therefore have a higher chance for vessels needing maintenance. *Fish recovery* and parameters regulating the number of international vessels had a strong effect on catches of all species. 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 and those adding stochasticity to FISHCODE had the weakest effects.

To test the functionality of our defined behavioral motivations, we set the weightings (W) of satisfactions and uncertainties to the extreme (=1) and assessed whether model outcomes changed according to expectations based on the conceptual design of the behavioral submodel (Table V-4).

Table V-4. Expected effects of increasing a certain weighting of a satisfaction or uncertainty to 1.

Weighting (W) of	Scenario shortcut	Expected effect
Existence satisfaction (ESAT)	WESAT=1	Increased savings
Personal satisfaction (PSAT)	WPSAT=1	Metier continuity (habitual behavior)
Social satisfaction (SSAT)	WSSAT=1	Increasing savings to earn more than peers
Existence uncertainty (EUNC)	WEUNC=1	No direct effect, but indirectly by setting WSUNC to 0
Social uncertainty (SUNC)	WSUNC=1	Engage in similar metiers than peers

Observing an OTB – NEP&PLE agent, WESAT=1 and WSSAT=1 led to the expected outcome of higher savings and a faster increase of the respective satisfactions as in comparison to the equal scenario (Figure V-3B&C; Table V-4). Savings were much higher in the WSSAT=1 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=1 scenario clearly demonstrated the priority of choosing the same metier (OTB – NEP&PLE) over improving profits (Figure V-3A&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. These constrained metier choices limited the effect of WSUNC=1, which should trigger an alignment of an agent's metiers choices with his peers. In the WEUNC=1 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; Table V-2) with multiple metier options to choose from. Both reasons increased the agent's flexibility for choosing metiers and therefore resulted in a higher economic efficiency.

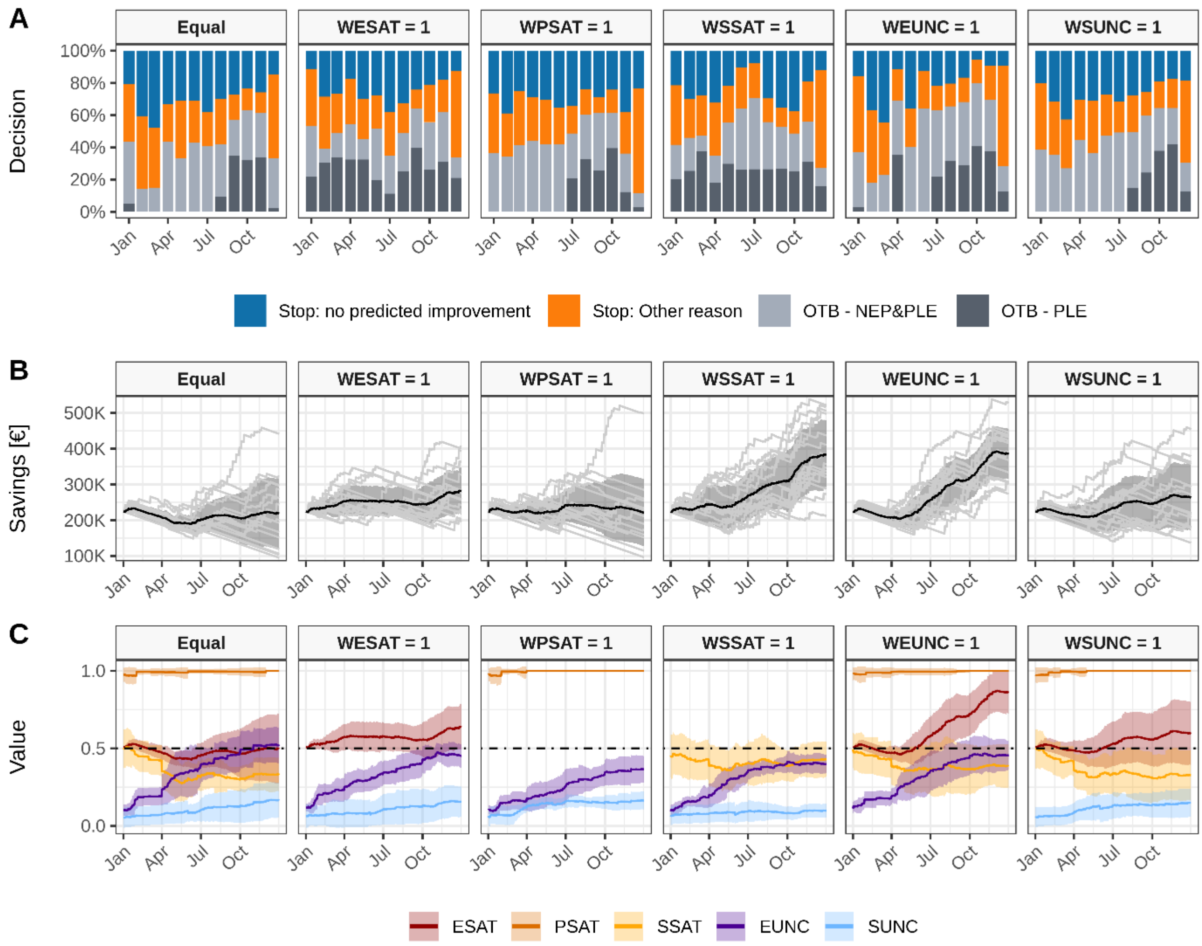

Figure V-3. Outcome of the Consumat testing for one vessel from the OTB – NEP&PLE metier for different scenarios, setting weightings for uncertainties and satisfactions to one (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their average (black), and C the mean daily satisfactions (ESAT, PSAT, SSAT) and uncertainties (EUNC, SUNC) 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=1 scenario (Figure V-4A&B). Except for WPSAT=1, 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. WPSAT=1 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 WEUNC=1 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=1, or the WEUNC=1 scenario).

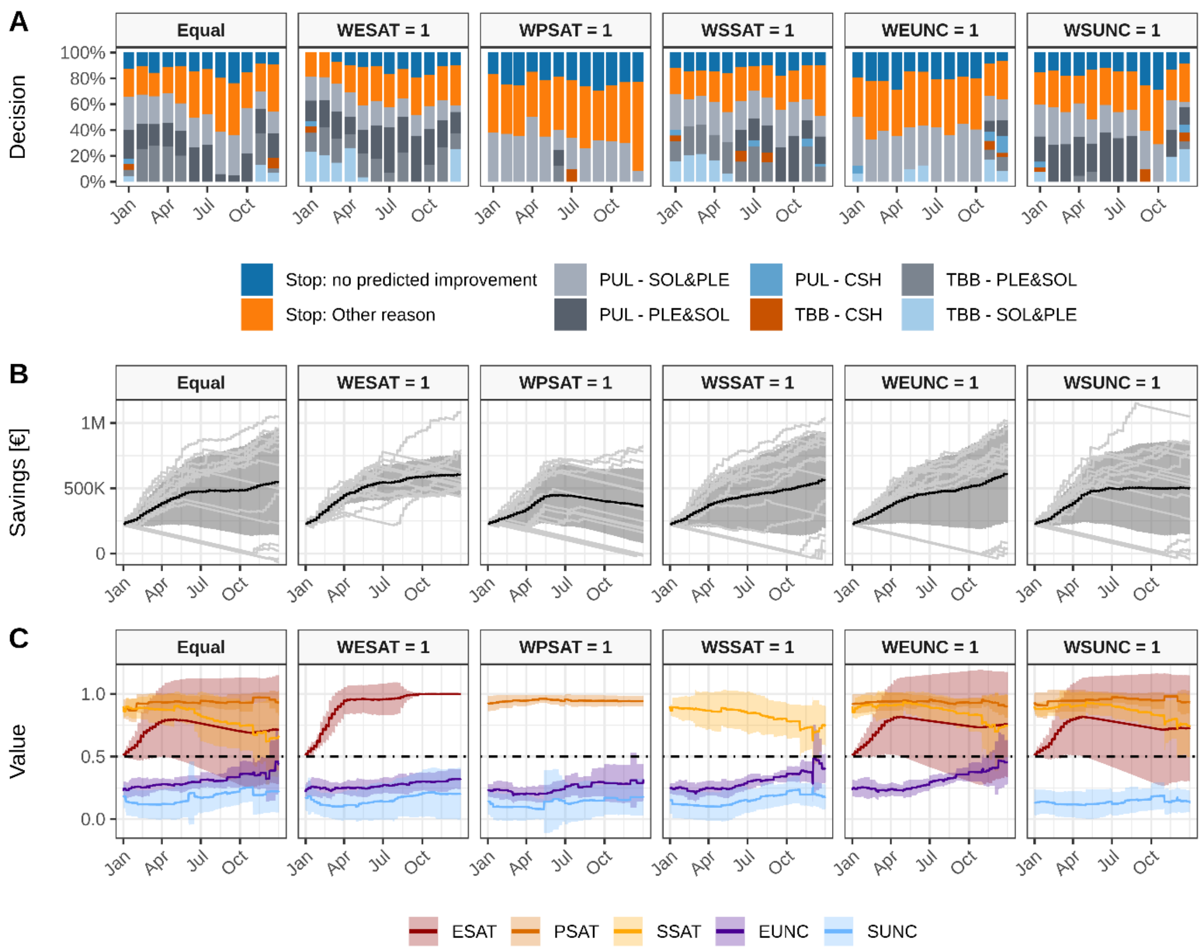

Figure V-4. Outcome of the Consumat testing for one vessel from the PUL – SOL&PLE metier for different scenarios, setting weightings for uncertainties and satisfactions to one (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their average (black), and C the mean daily satisfactions (ESAT, PSAT, SSAT) and uncertainties (EUNC, SUNC) with the dotted line displaying the threshold for being satisfied and uncertain. The ribbons in B and C represent standard deviations.

Setting the weighting of a parameter to one led to maximizing the respective satisfaction, confirming our general expectations (Table V-4), 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 choosing a different Consumat strategy. Those strategies offer varying numbers of metiers to choose from and therefore determine the agent's flexibility to engage into different metiers (Table V-2). The two exemplary metiers show that increasing flexibility positively influenced 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 FISHCODE, 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.

3.2 Model realism

On average, FISHCODE produced outcomes for *fishing time*, *steaming time*, and *trip length* that matched their historical counterparts best on the micro pattern of individual trips and the macro pattern of total aggregates (comparison of columns in Figure V-5A). The quality improved from vessel to monthly and was best for the total aggregation showing that simulations of individual agents only marginally reflected the reality of these vessels but results on higher aggregations were reliable. In the model, the three trip variables are closely interlinked, because *fishing 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 corresponded poorly with observed values (Figure V-5A), because steaming times per fishing trip were slightly overestimated for TBB metiers (Figure V-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 (Appendix A2.3.8). 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 our ABM.

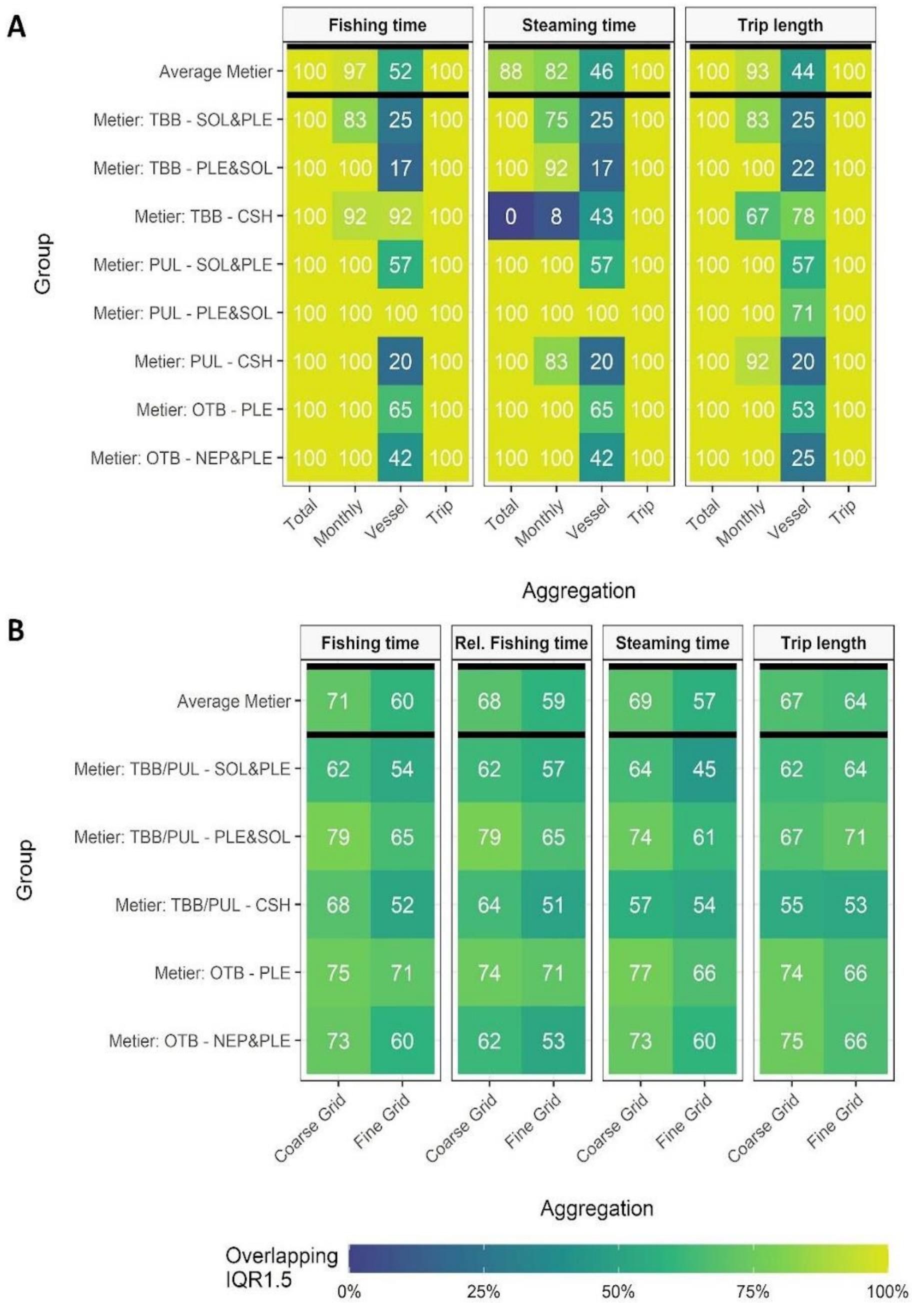

Figure V-5. The percentage of data points with overlapping 1.5 times inter-quartile ranges (IQR1.5) between modelled and observed non-spatial (A) and spatial (B) variables. Colors and numbers correspond to the percentage of overlaps across different aggregations (columns) and metiers (rows).

With regard to spatial results, matches on coarse were better than on fine grid resolutions, meaning that the accuracy of simulated spatial fishing effort was more reliable if aggregated to coarse grid cells (Figure V-5B). On average, percentages of matching coarse grid cells were in an acceptable range (above 60%), whereas fine grid cells matched about 10% lower. The total distribution of *fishing time* matched slightly better than *relative fishing time*. This validates that in addition to spatial fishing hotspots, FISHCODE 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 hotspots in the offshore areas (Figure V-6A&C). These hotspots show a more refined pattern in the observed distribution, because the simulated fine-scale fishing movements are the result of random paths (levy flights). A comparison of standard deviations shows that these scale with total fishing effort, but were larger in coastal grid cells among historical years than they were among model runs (Figure V-6B&D).

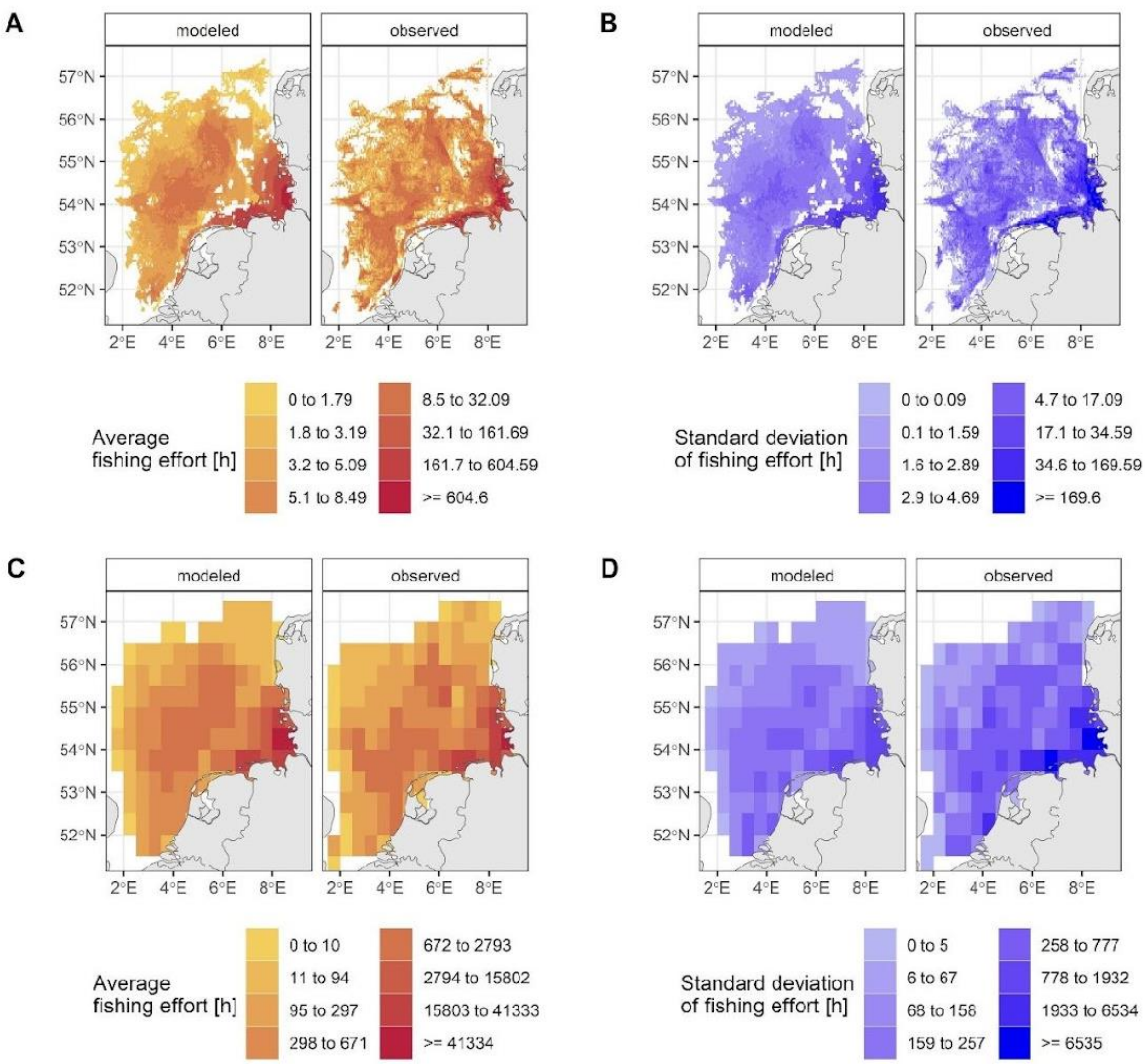

Figure V-6. The averaged fine (A) and coarse (C) distribution, as well as fine (B) and coarse (D) standard deviation of fishing effort across validation model runs (modeled) and seven years of data (observed).

4. Discussion

With FISHCODE, we developed a tool to simulate spatio-temporal fishing dynamics of three German fleets in the southern North Sea. Our model integrates several behavioral theories, which are combined by the Consumat approach in one decision-making framework (Jager et al., 2000; Jager and Janssen, 2012). In addition, we incorporated numerous partly highly resolved empirical data sources to inform technical, spatial, economic and environmental variables, and to specify heuristics for additional agent decision-making in the form of personal norms, e.g. work rhythm.

4.1 Emerging insights and model potential

FISHCODE presents a “virtual laboratory” for the German southern North Sea fisheries that can be used to make assumptions for the real-world system by manipulating model parameters. We validated our model by producing outputs in realistic ranges for most spatial and non-spatial variables on different aggregations despite its high complexity. Both model validation and structural realism are essential for models to be used for policy advice (Bruch and Atwell, 2015; Schulze et al., 2017; Will et al., 2021). Therefore, FISHCODE is suitable candidate to assess the impact of future changes to North Sea fisheries and could support future-oriented marine spatial planning (MSP). Especially, the quickly growing offshore wind parks (OWF) and newly implemented marine protected areas (MPAs) in the southern North Sea are a large source of uncertainty for fishing communities and will likely lead to a displacement of fishing effort (Letschert et al., 2021; Stelzenmüller et al., 2022). Other relevant themes for the North Sea which can be researched with FISHCODE are rising fuel prices, and new fishing regulations (i.e. banning electric pulse gears).

We implemented the Consumat, so that weighting factors of satisfactions and uncertainties incentivized agents towards the associated behavioral motivation, e.g. a high weighting in the personal satisfaction lead to more habitual metier choices. Due to the nature of the Consumat approach, changed satisfactions and uncertainties also affected the perceived behavioral options, i.e. choices of what to fish. Therefore, links from weighting factors to corresponding behavioral motivations are not entirely straightforward, however, we have shown that they still represent the envisioned effects. Increasing weightings for habitual behavior (personal satisfaction) and conformism (social uncertainty) primarily influenced metier choices leading to lower savings, because the agent’s priority was choosing certain metiers rather than earning money. Increasing weightings emphasizing on profits (existence satisfaction) and competition (social satisfaction) expectedly led to higher savings, which was amplified when Consumat strategies were chosen that involved multiple metier choices. These insights suggest that flexibility in the agents’ metier choices was an important driver for economic efficiency. Other studies have observed this phenomenon with coastal small-scale fishers that are described as generalists, i.e. engage in multiple fishing practices (Boonstra and Hentati-Sundberg, 2016; Salas and Gaertner, 2004).

The nature of the Consumat framework enabled agents to choose metiers that they previously had not been used and thus FISHCODE could also be applied for testing scenarios of introducing new metiers. Some fishers in the North Sea use passive gears such as gillnets to catch flatfishes and cod (*Gadus morhua*) or traps to catch brown crabs (*Cancer pagurus*) and European lobster (*Homarus gammarus*). We did not include these fishing options in our model, because the engagement of German fishers in these fisheries is low. However, with expanding OWFs, using passive gears like traps or fishing rods could offer an alternative for fishers to continue fishing inside or at least in buffer zones around OWFs (Bonsu et al., 2024; Stelzenmüller et al., 2021c). Analyzing these co-location scenarios with our ABM could create first insights on their feasibility not only with regard to technical and management requirements, but also considering the fishers' decision-making.

FISHCODE can also be used to answer more general questions such as testing theories about fisher behavior. By pairing the individual satisfactions and uncertainties with weighting factors, the Consumat represents a tool to assess the relevance of individual behavioral motivations. Our results have shown that manipulating those weighting factors affects the agent behavior and can give insight on the effect of prioritizing or neglecting certain motivations. Beyond manipulating the Consumat approach, performing a robustness analysis by simplifying fisher movements or deactivating social networks would generate insights on the importance of these model compartments in producing essential patterns (Grimm and Berger, 2016). Identified model compartments with weak impacts could then be simplified to reduce parameter uncertainty and computational cost (Ligmann-Zielinska et al., 2014).

4.2 Model uncertainty and way forward

The trade-off between model complicatedness and explainable outputs is a known dilemma leading to the decision of which system components should be simplified (Allison et al., 2018). In this paragraph we discuss uncertainties introduced by unknown values of parameters and model structure, suggest potential improvements, and identify shortcomings in available data.

Empirical information on the reasons for why humans act in a specific way is scarce, making it challenging to create empirical ABMs simulating human behavior (Bruch and Atwell, 2015). In our case study, we had a lot of information about fishing trips available that allowed us to derive rules and heuristics about certain behavioral decisions, e.g. how high the willingness is to go fishing during a weekend. However, we lacked information on cognitive behavioral drivers such as maximizing profits, habitual behavior, or competition. Interviews or surveys are suitable tools to investigate such questions (Smajgl et al., 2011). Examples from the Danish (Christensen and Raakjær, 2006), Swedish (Boonstra and Hentati-Sundberg, 2016), and Dutch fisheries (Schadeberg et al., 2021) contributed to framing our behavioral submodel, however, there is no such study focusing on the German North Sea fishery. Because fishers from different countries may have distinct cultures and habits and are subject to varying regulations (i.e. quota distribution), we calibrated our behavioral submodel by using pattern-oriented modelling. Additional information on the behavior of German North Sea fishers would greatly reduce the model's uncertainty.

We could derive many parameters directly from data, which allowed us to restrict our calibration to a sensible number of parameters. However, even with large amounts of available data on fishing trips, certain parameters introduced uncertainty. A mismatch of modelled and observed steaming times of TBB gears signal that more precise information on steaming speeds are necessary. Also, information for individual economic situations were scarce and only available in aggregated format, which is why we assumed uniform or linear interpolated values across agents. Furthermore, we simplified biological processes in FISHCODE by including uniform depletion and recovery factors and thus assumed that the effect of fishing on biological resources and their recovery is the same across gears, habitats, and species, which is an abstraction from real-world dynamics (Rijnsdorp et al., 2022). Our sensitivity analysis yielded that both fish recovery and depletion were among the five most impactful parameters. Having additional insight into individual economic and local depletion dynamics would greatly reduce the uncertainty of our model.

In the calibration, several parameter constellations passed the filters of the pattern-oriented modelling resulting in similar results, which is a phenomenon called equifinality and a common challenge for ABMs (An et al., 2023; Williams et al., 2020). This means that calibrated parameters do not necessarily reflect real-world behavioral drivers, which is highlighted by the weak effects of weighting factors on output variables of the CSH fleet. The reason is that the Consumat approach primarily influenced agents' metier choices, however, CSH fishers mainly engage in one metier (TBB – CSH).

While our human decision-making framework focuses mainly on choosing a metier and determining trip lengths, it only marginally addresses location choice. Agents in FISHCODE select catch locations that are either in their own or their peer's memory without considering any characteristics of this trip. Weighting location choice by memories of gained revenues or catch amount could enhance the realism of the agents' decisions as it has been shown that fishers prefer to return to catch locations with positive connotations (Bastardie et al., 2013; Tidd et al., 2012). Once decided for a catch location, the movements of vessels (or agents) during the trip are random and only restricted by the overall catch ground of the respective metier. This is the reason for spatial model outputs being about 10% more accurate for coarse than for fine spatial resolutions.

Market prices in FISHCODE were exogenous and based on observed monthly data. In reality, prices are dynamic and affected by landings and the availability of biological resources. This is especially exemplified for the CSH fishery, as the availability of shrimp varies across years leading to strong price fluctuations (Goti-Aralucea et al., 2021). Among German fishers, the CSH fleet is the largest and therefore likely has an effect on international market prices, however, all other fisheries in FISHCODE represent only fractions of the international North Sea fishing effort, likely limiting their effect on price dynamics.

Conclusion

ABMs simulating socio-ecological systems progressively incorporate more structural realism and their field of application has been expanding from testing theories towards prediction and scenario analysis. In FISHCODE, we propagated the use of empirical data and methods from model conceptualization to validation, and have shown that this may lead to a good degree of realism. Moreover, we included a multi-faceted human behavioral submodel integrating motivations beyond economic optimization (e.g. habitual behavior and social networks), as it suggested by an increasing amount of literature. Fisheries in the North Sea face a growing number of challenges, such as expanding other marine spatial uses (i.e. offshore wind farms), climate change, and high fuel costs. To reduce the uncertainty around fishers' reaction to future situations, it is important to incorporate realistic human behavior in models. FISHCODE bridges the gap between bio-economic fishery models that often assume profit-maximization and stylized fishery ABMs with more complex human behavior. As such, it provides a toolbox to test scenarios encompassing (but not limited to) economic changes, additional spatial fishing restrictions, new fisheries management such as banning gears or enforcing the landing obligation, or introducing alternative fishing practices.

Acknowledgements

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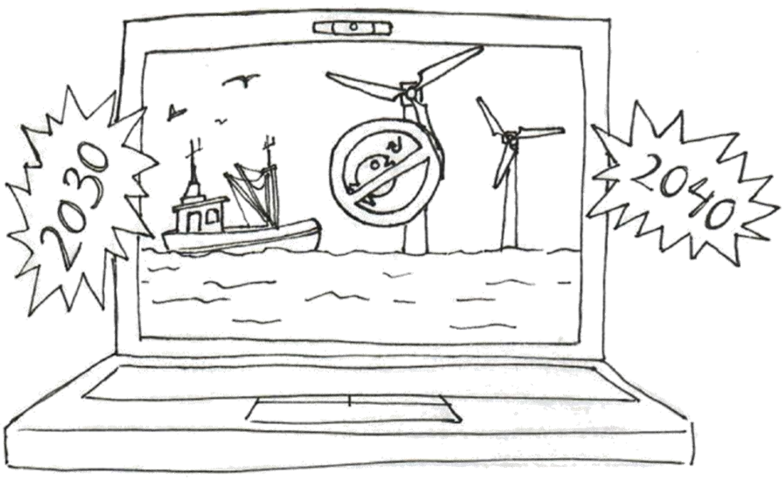
Data availability statement

All data source including available links can be found in the supplementary material at the *end of this thesis*. Ship positions and logbook data including those to run FISHCODE are confidential and can therefore not be shared. Model code and proxy input data can be found online on *www.comses.net* (Letschert et al., 2024).

Chapter VI



Testing the waters: explorative scenarios indicate lower fishing activity and profits for the North Sea

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Abstract

The North Sea is a global hotspot for cumulative human impacts including fisheries. The expansion of offshore wind farms (OWF) in the coming decades and increasing number of nature conservation measures, i.e. no-take zones (NTZ), reduce the space available for fishing activity. Moreover, fuel prices have been rising due to recent crisis and the EU banned the electric pulse gear (PUL) in 2021, a fuel-saving bottom-contacting gear. These changes pose challenges for North Sea fishers and introduce large uncertainties for their future existence. Here, we apply FISHCODE, an agent-based model (ABM) for German fisheries in the southern North Sea, to test scenarios of these pressures. FISHCODE simulates flatfish (sole and plaice), Nephrops, and brown shrimp fisheries on a high spatio-temporal resolution and has emphasis on flexible fisher behavior beyond profit maximization and is thus suited to simulate adaption. Results revealed a reduction of fishing effort and profits for all scenarios, i.e. more OWFs and NTZs, higher fuel prices, and the ban of PUL gears, however, only the extreme fuel scenario led to negative profits. Banning of PUL gears triggered a shift in fishing effort towards beam trawls, although resulting in lower levels of fishing effort, because beam trawls require more fuel than PUL and thus led to higher fishing costs. Spatial scenarios affected mostly flatfish and Nephrops fisheries, while brown shrimp fishing effort remained relatively equal. Moreover, fishing effort intensified in the remaining open areas, which could have negative effects for ecosystems. Our findings suggest that a combination of stressors would have an even stronger impact on German fisheries. Overall, we provide insights that are helpful to anticipate fishers' responses to change and therefore can support future-oriented spatial management (MSP).

Key words: North Sea, fisheries, scenario testing, agent-based modelling, marine spatial planning (MSP)

1. Introduction

The North Sea is a hotspot for anthropogenic cumulative impact (Halpern et al., 2019). Many different stakeholder groups share the shelf sea for offshore renewable and fossil fuel energy, sediment extraction, cargo shipping, conservation, and fishery. To maintain the sustainable co-existence of marine actors, riparian states employ marine spatial planning (MSP) involving the analyses and allocation of marine activities to zones (Jentoft and Knol, 2014). In the North Sea, the number of marine actors and the relatively small available area bear a large potential for conflict and thus challenge a balanced MSP (Kannen, 2014). North Sea fishery has been an important actor for centuries and nowadays represents an activity with a large spatial footprint (Döring et al., 2020; Rijnsdorp et al., 2008).

In the southern North Sea, fishery is mostly composed of bottom trawling targeting flatfishes and crustaceans. The benthic species European plaice (*Pleuronectes platessa*), sole (*Solea solea*), common shrimp (*Crangon crangon*), and Norway lobster (*Nephrops norvegicus*) are among the most important caught species in the southern North Sea. Demersal and benthic fishers target specific catch locations that are consistent across time and are comparable to the habitat preferences of their target species (van der Reijden et al., 2018). Despite this dependency, fishery has more spatial flexibility than other marine anthropogenic sectors, e.g. sediment extraction, oil rigs, or offshore wind farms (OWF), which is why fishery priority areas are underrepresented in marine spatial plans (Trouillet, 2019). Whenever crucial catch grounds overlap with other spatial marine uses that imply a closure to fishing, there is an opportunity for conflict (Letschert et al., 2021). Especially the vast plans for OWFs in the North Sea bear a large potential for conflict as they either prohibit fishing activity or fishers avoid OWFs due to security and insurance reasons (Bonsu et al., 2024; Stelzenmüller et al., 2022). The other large competitor for marine space is nature conservation. Marine protected areas (MPA) in the Greater North Sea have covered 20.2% in 2021 (Werner et al., 2022), while the Global Biodiversity Framework adopted during the COP15 in Montreal, Canada aims to protect 30% of all marine areas until 2030 (UN, 2022). Therefore, additional implementations of MPAs and no-take zones (NTZs) in the coming years can be expected to safeguard marine biodiversity.

Apart from spatial restrictions, rising fuel prices represent a serious stressor for fisheries and have been decreasing their profitability (Guillen et al., 2023). In times of frequent crisis, the development of fuel-saving fishing gears is important, an example being electric pulse gears (PUL) that have a lower drag than fishing with traditional beam trawls (Suuronen et al., 2012). The EU banned PUL in 2021, because of the gear's debated negative effects on the ecosystem (Kraan et al., 2020; Le Manach et al., 2019). In the North Sea, PUL has been mainly used by fishers targeting sole and plaice and the potential switch back to beam trawls after the PUL prohibition has not yet been researched.

The described changes and stressors will have strong effects on the fishing sector, which are challenging to foresee because fishers, as all humans, take decisions based on many different factors (Fulton et al., 2011; Hilborn, 2007). Agent-based models (ABM) simulate the behavior of agents in a digital environment and are thus a suitable tool to model human decision-making (Burgess et al., 2020). Our study objectives are to assess the effects of changes in OWF and NTZ coverage, fuel prices, as well as the PUL ban on the spatio-temporal dynamics of German fisheries in the southern North Sea. We use FISHCODE, a spatially-explicit fishery ABM with emphasis on complex human decision-making (Chapter V). Our results offer guidance for future-oriented MSP to ensure a sustainable future co-existence of fishery and other marine actors.

2. Methods

2.1 Brief description of FISHCODE

To analyze future scenarios, we used FISHCODE (**FI**sheries **S**imulation with **H**uman **CO**mplex **DE**cision-making), a model simulating German fisheries in the southern North Sea with human decision-making beyond profit maximization (Chapter V). In FISHCODE, agents represent skippers of fishing vessels who make daily decisions about whether, how long, and what to fish. After decided, fishing trips are simulated in a spatio-temporal model environment with daily time steps and spatial grid resolution of 0.045° × 0.045°. FISHCODE comprises eight fishing practices called metiers (Table VI-1).

FISHCODE uses data of historical fishing trips (2012-2018) to inform model parameters (e.g. working rhythms of fishers and maximum trip days), while steaming and fishing times are depended on the spatial distance from ports to fishing grounds. Landings are simulated with look-up tables of historical landings per unit of effort (LPUE) and vary depending on the environmental setting of the chosen spatial fishing ground. Environmental and economic variables are exogenous and updated weekly (environmental) and monthly (economic). Wave heights determine whether vessels can leave on a fishing trip or have to stay in port. The tolerance towards waves is higher for larger vessels. Personal, maintenance, and fixed costs are calculated per fishing trip and based on information from the annual economic report of the scientific, technical and economic committee for fisheries (STECF). Fuel use per fishing trip is estimated based on the steaming and fishing time, as well as the vessel's engine power. Fisher behavior is simulated by using the Consumat approach (Jager et al., 2000; Jager and Janssen, 2012). Agents have three satisfactions and two uncertainties representing the following behavioral motivations: habitual behavior, profit-maximization, competition, conformism, and planning insecurity. Depending on their levels of overall satisfaction and uncertainty, agents engage in one of four behavioral strategies offering varying numbers of metier options to choose from that may involve consulting their social network or not. For every possible metier options, agents make predictions about trip outcome and select the options with the highest sum of gain in satisfaction and loss of uncertainty. In case all options lead to a worsening of their situation, meaning that the before mentioned sum is negative, they will not leave for a fishing trip. Details about the model process, integrated data, parameterization, and validation of FISHCODE are in Chapter V and its supplementary material.

Table VI-1. Metiers defined for FISHCODE. Gear abbreviations stand for otter bottom trawl (OTB), beam trawl (TBB), and electric pulse trawl (PUL) and species for plaice (PLE), sole (SOL), Nephrops (NEP), and common shrimp (CSH).

Default metier	Details
OTB - PLE	Otter board trawler catching mainly plaice.
OTB – NEP&PLE	Otter board trawler catching mainly plaice and Nephrops.
TBB – PLE&SOL	Beam trawlers catching mainly plaice.
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	Beam trawlers catching common shrimp
PUL - CSH	Pulse trawlers catching common shrimp

2.1 Scenario descriptions

The current setup of FISHCODE only allows for the simulation of one year. Similar to the calibration and validation of FISHCODE, we compared model outcomes of a base run with scenarios. In the *Base-run*, spatial fishing restrictions (i.e. OWFs and NTZs) comply with the state of December 2018 and environmental and economic variables are set to weekly and monthly averages of 2012-2018.

We tested five different scenarios comprising two expansions of spatial fishing restrictions, two increased fuel prices, and one gear restriction (Table VI-2). We retrieved OWF polygons from 4COffshore (www.4coffshore.com, accessed April 2022), which are affiliated with construction dates or development status. We classified development statuses of OWFs to the 2030 or 2040 scenario according to Stelzenmüller et al. (2022) and assume fishing vessels having transit rights in all scenarios. In the 2030 and 2040 scenarios we added polygons of NTZs from marine spatial plans of the German Federal Maritime and Hydrographic Agency (German: BSH) and 30% of random grid cells in international designated marine protected areas representing about 10% of complete protection of the respective countries' exclusive economic zones (Figure VI-1).

We extracted monthly fuel prices from EUMOFA (*www.eumofa.eu*) and increased them to 300% and 600% for fuel price scenarios. On average between 2012 and 2018 monthly fuel prices per liter ranged between 0.45 and 0.48€, in the *Fuel-300%* between 1.35 and 1.43€ and in the *Fuel-600%* between 2.7 and 2.87€. For reference, monthly fuel prices from 2022 to 2023 ranged between 0.59 and 1.17€ and therefore our fuel scenarios assume even higher prices than those triggered by the Russo-Ukrainian war in the last two years. In *PUL-false*, we simulate the EU ban of the PUL gear in 2021, which occurred after the period of integrated observed data used for FISHCODE, i.e. 2012-2018.

Table VI-2. Summarizing the five scenarios according to changed model parameters: spatial settings, fuel price, and gear restrictions. OWF: offshore wind farms; NTZ: no-take zone; PUL: electric pulse trawl.

Scenario name	Spatial fishing restrictions	Fuel price [%]	PUL banned
Base-run	OWF status of 2018	100	No
OWF2030+NTZ	OWF status of 2030 and NTZs	100	No
OWF2040+NTZ	OWF status of 2040 and NTZs	100	No
Fuel-300%	OWF status of 2018, no NTZs	300	No
Fuel-600%	OWF status of 2018, no NTZs	600	No
PUL-false	OWF status of 2018, no NTZs	100	Yes

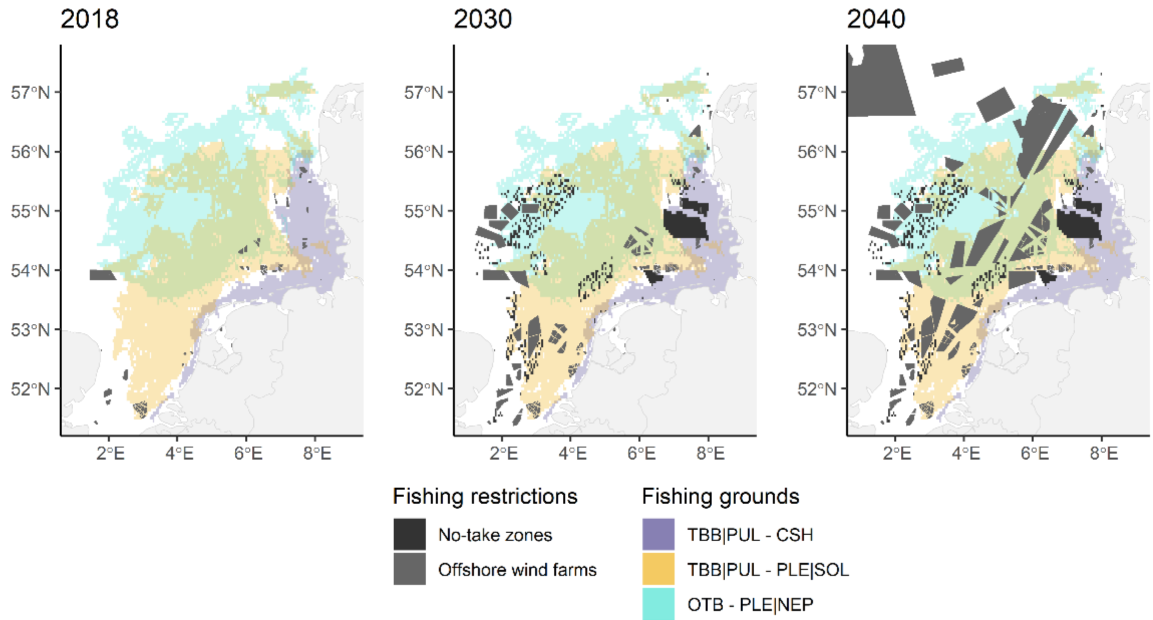


Figure VI-1. Fishing grounds of the three fleets in the model (colored polygons) and fishing restrictions in the *Base-run* (2018) and in two scenarios depicting the potential state of offshore wind farms and no-take zones at 2030 and 2040. TBB = beam trawl; PUL = electric pulse trawl; OTB = bottom otter trawl; CSH = common shrimp; PLE = plaice; SOL = sole; NEP = Nephrops.

2.2 Experimental design and analysis of results

Before analyzing scenarios, we identified the sensible number of model runs that was large enough to counteract stochasticity, while keeping computational cost low. We produced 50 model outcomes using the base scenario and calculated the cumulative standard error of fishing effort per metier across model for 50 permutations. Upon visual inspection, we decided that 25 is a suitable number of model runs, since additional runs did not substantially reduce standard errors (Figure VI-A1).

We ran the model 25 times for the *Base-run* and each of the five scenarios and summarized outcomes on different aggregations. Although FISHCODE produces results on daily and vessel resolution for a wide range of fisheries variables, we focused on the comparisons of total and relative change in fishing hours (hours and number of trips), steaming hours, profits, and number of fished cells, as well as the relative change in fishing hours per grid cell. To differentiate effects on individual metiers, we also compared fishing hours, steaming hours, and profits per metier and trip.

For the scenario of banned PUL, we tracked changes in metier switching behavior by quantifying daily agent activities, i.e. how many days an agent was fishing a certain metier or stay in the port, and averaged those across model runs. We converted metiers into sources and sinks for every agent and calculated flows, representing the change from the *Base-run* to the *PUL-false* scenario. If an agent had more than one sink (e.g. two metiers that increased in fishing days), we divided the fishing days of sources across all sinks. The sum of individual agent flows per metier represented the total shift of metier changes. Subsequently, we calculated changes as net fishing days (NDF), meaning that if there was a flow from A to B and B to A, those were subtracted from each other and the larger flow retained.

3. Results

All scenarios reduced the fishing effort and profits of agents (Figure VI-2 and Table VI-A1). Relative effects on fishing hours, steaming time, and number of trips were similar in all scenarios showing how interlinked these three are (Figure VI-2). The number of fished grid cells was almost 25% lower in both the *OWF2040+NTZ* and the *Fuel-600%* scenarios, however, the reasons differed across the two scenarios. In *OWF2040+NTZ* many grid cells were restricted to fishing also leading to more steaming hours, because distances from ports to fishing grounds increased. The reduction of fished cells in *Fuel-600* was due to the lower number of fishing trips (-72%). This result is also reflected in the mean relative change of increased fishing effort per grid cell, which increases in scenarios with more spatial fishing restrictions, i.e. *OWF2030+NTZ* (4.8%) and *OWF2030+NTZ* (30.9%), but decreases in fuel price scenarios, i.e. *Fuel-300%* (-15.1%) and *Fuel-600%* (-40.6%) (Figure VI-2). With regard to fishing effort (hours and trips), steaming time, and profits, fuel price scenarios had the strongest effect followed by the banning of PUL. *PUL-false* reduced profits by about 20% despite fishing effort levels being similar to *Base-run*, revealing that the relationship between the two variables is not necessarily linear – at least not when output variables are aggregated across all metiers (Figure VI-2). A comparison by metier shows fishers switched to TBB equivalents when PUL was banned and that PUL gears are more profitable than TBB gears (Figure VI-3). Therefore, in *PUL-false* profits decreased while fishing effort remained almost stable.

Fuel-300% reduced both fishing hours and profits substantially for all metiers and *Fuel-600%* even resulted in negative profits for all metiers except for those using PUL (Figure VI-3A). The same trend could be observed on the profit gained per fishing trip, while the fishing time per trip remained the same or even decreased (Figure VI-A2). This indicates that the reduction in aggregated fishing effort is the result of less fishing trips, because the incentive for going fishing was lower due to the reduced or negative profits. Fuel scenarios lead to higher LPUE for plaice of metiers using OTB and TBB-PLE&SOL, as well as for CSH for PUL-CSH and TBB-CSH (Figure VI-A3).

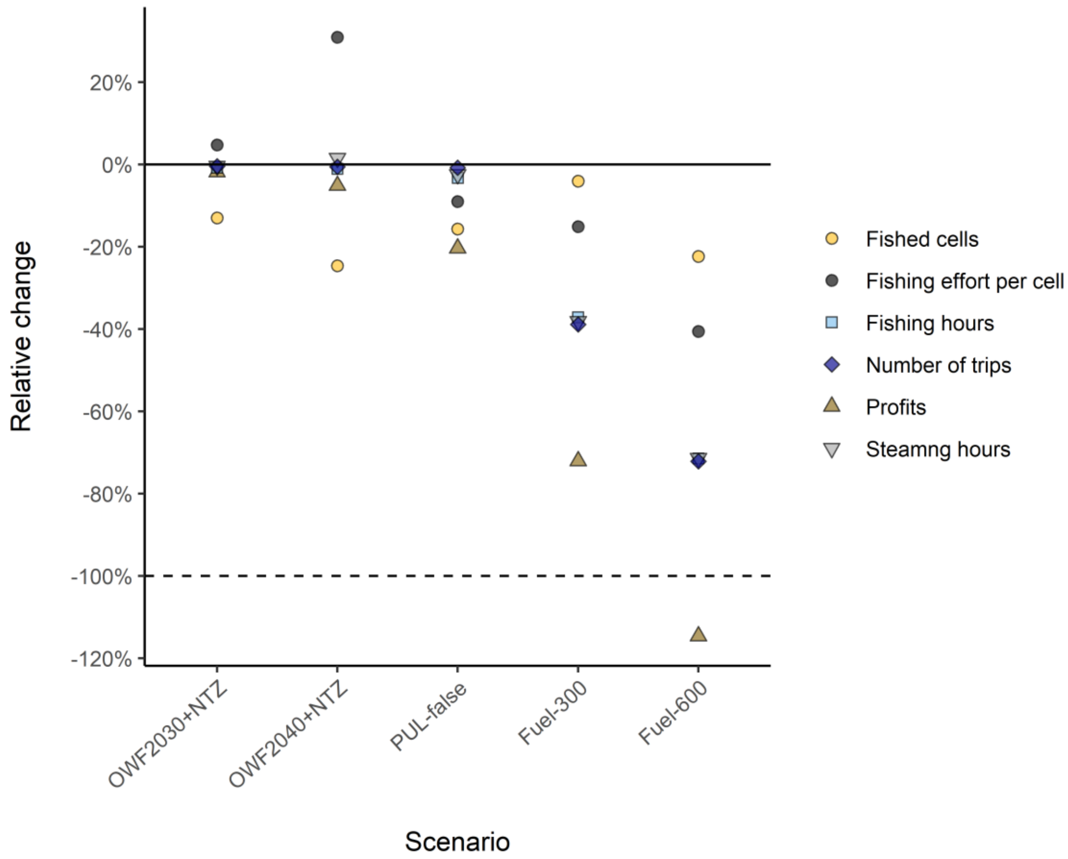


Figure VI-2. Relative effect of scenarios in comparison to the *Base-run*. The six output variables (color-coded) represent averaged relative changes across model runs.

Potential future spatial fishing restrictions lead to a reduction of fishing effort for all metiers except for those catching CSH (Figure VI-3B). This is because the coastal CSH fishing grounds are relatively unaffected by planned NTZs and OWFs. Other metiers had longer steaming times per fishing trip leaving less time for fishing (Figure VI-A2), because spatial fishing restrictions forced agents to target fishing grounds further offshore. For most metiers, *OWF2040+NTZ* reduced fishing effort stronger than *OWF2030+NTZ* with the exception of the PUL metiers catching the flatfishes PLE and SOL. PUL-PLE&SOL fishing effort increased in the 2030 and then decreased in the 2040 scenario, while the opposite was observed for PUL-SOL&PLE.

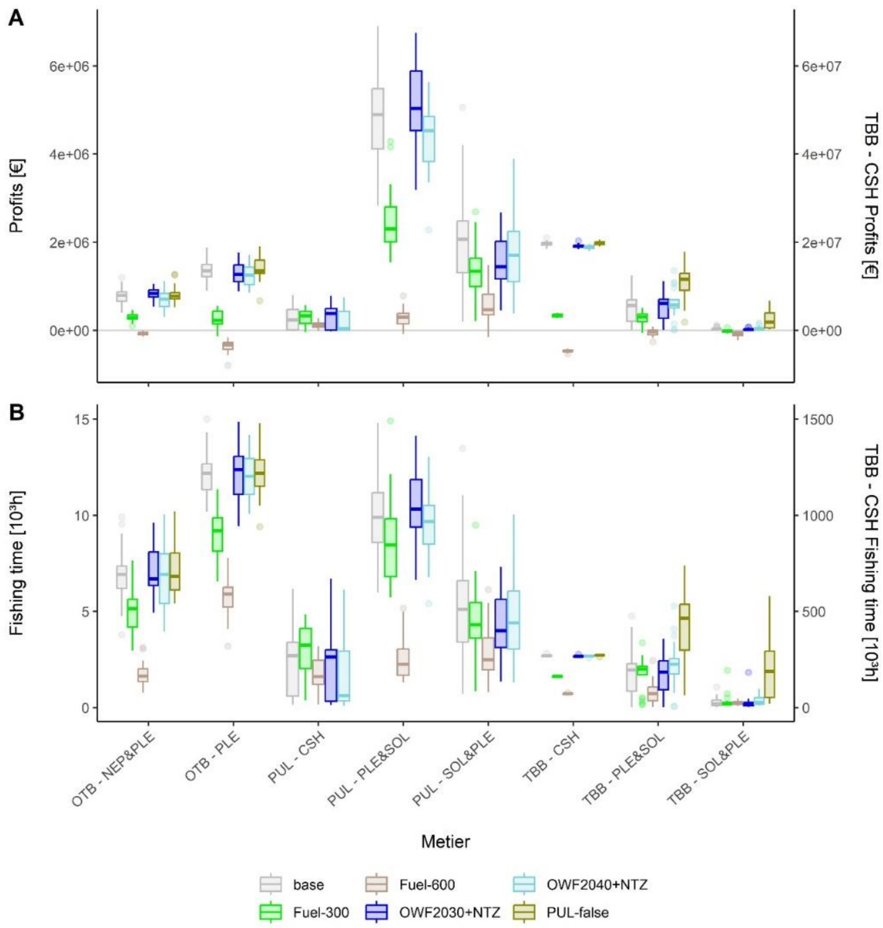


Figure VI-3. Total aggregates of profits (A) and fishing hours (B) per metier for *Base-run* and the five scenarios.

In *PUL-false* fishing effort of PUL metiers was not present, TBB fishing effort increased, and OTB metiers remained unaffected (Figure VI-3B). This scenario had no effect on variables resolved per fishing trip (Figure VI-A2), but lead to a shift of metier activity. In general, fishing effort of PUL metiers shifted to its TBB equivalents, i.e. 83.9 net fishing days (NFD; for a description see methods) from PUL-CSH to TBB-CSH (Figure VI-4). For PUL metiers targeting flatfish a large part of the effort became inactive, as fishers more frequently decided to stay in the port. From PUL-PLE&SOL 367 NFD became inactive and only 149 NFD shifted TBB equivalents. For PUL-SOL&PLE results are similar as 150 NFD became inactive and 101 NFD shifted to TBB equivalents.

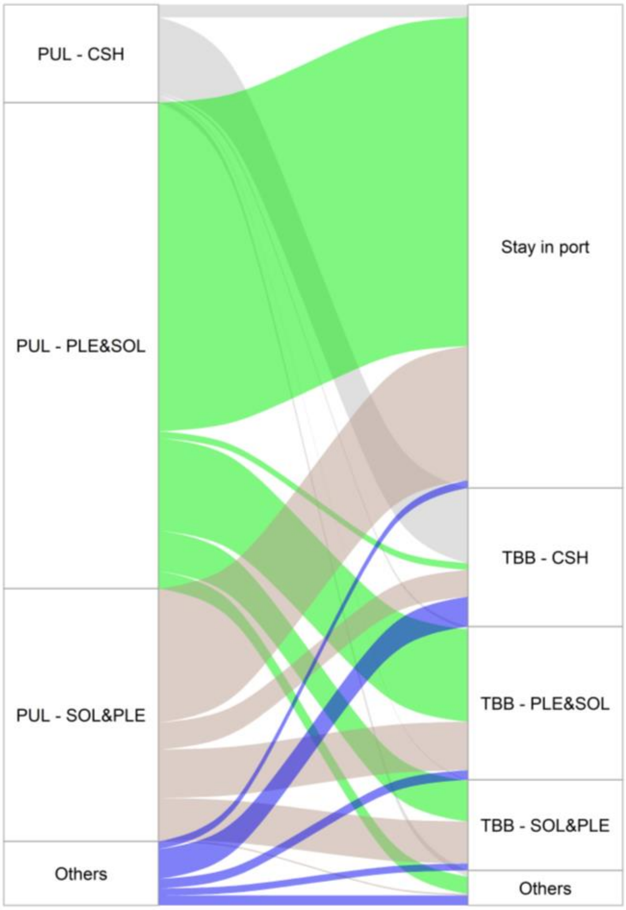


Figure VI-4. Shift of metier activity from the *Base-run* (left) to the *PUL-false* scenario (right). Sources (left) and sinks (right) with less than 10% of the total flows were grouped to “Others”.

With regard spatial output variables, fuel price scenarios decreased spatial fishing effort in the whole study area with regions of strong reduction in the coastal (shrimp) and offshore (Nephrops) fishing ground (Figure VI-5). *OWF2030+NTZ* and *OWF2040+NTZ* displaced fishing effort and led to an intensification of fishing hotspots further offshore. Fishing effort in coastal areas remained relatively constant due to few overlaps with fishing restrictions. *Pulse-false* lowered fishing effort in flatfish fishing grounds that are mostly caught by PUL gears, whereas coastal catch grounds remained relatively constant and fishing effort in offshore areas increased slightly.

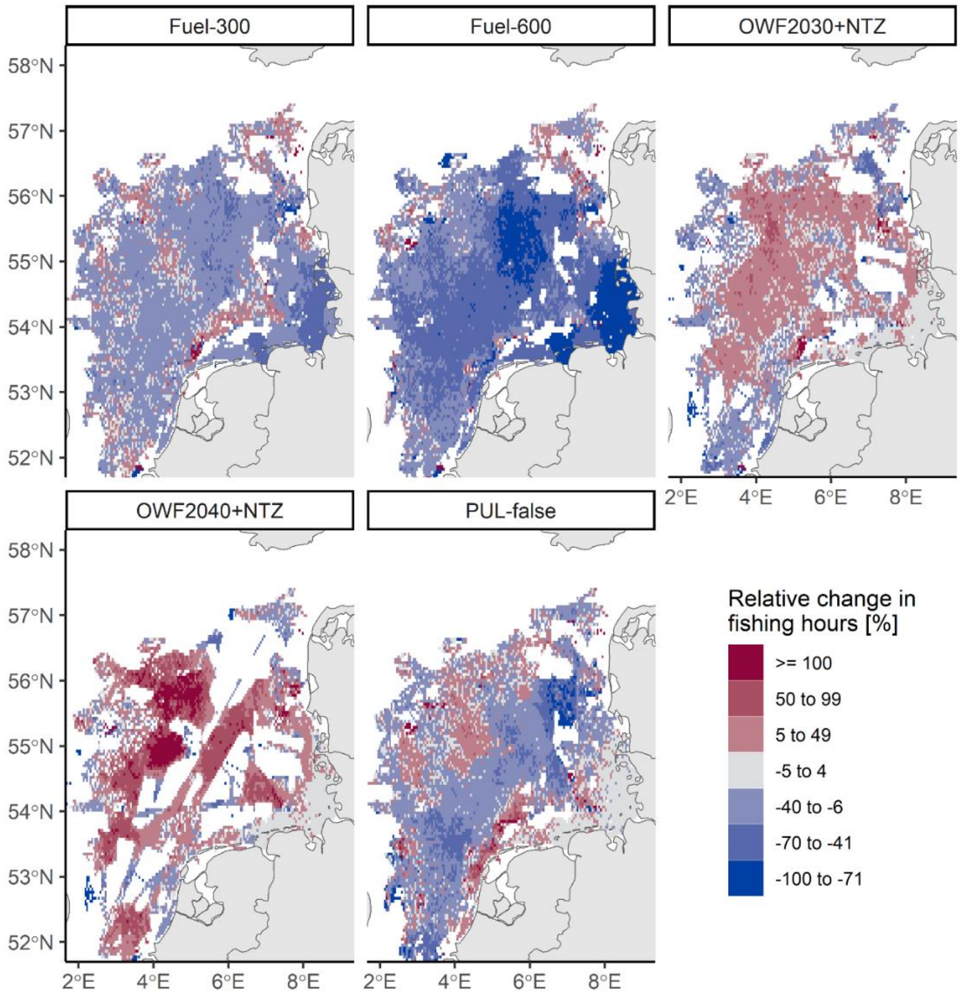


Figure VI-5. Relative change in spatial fishing effort of the five scenarios in comparison to the base run.

4. Discussion

4.1 Emergent pressure for North Sea fisheries

Scenarios of high fuel costs reduced the aggregated profits and fishing effort of all metiers, showing that high fuel prices are a systematic stressor for German North Sea fishers. The negative relationship of effort and fuel costs has also been observed for EU fleets in the years of 2002 to 2008 and most recently due to the increasing energy costs triggered by the Russo-Ukrainian war (Cheilari et al., 2013; Guillen et al., 2023). Guillen et al. (2023) identified 1.03€ per liter as average break-even point for EU fleets, describing the point at which gross profits become zero and the fishery unprofitable in the short-term. In our study, we did not calculate break-even points, however, profits of fishing trips were still positive when raising fuel costs by 300% resulting in higher costs than 1.03€ per liter. There could be several reasons for this discrepancy, first, the break-even point of German mixed-demersal North Sea fleets could be higher than the EU average. Second, our profits are naturally higher than gross profits, because we did not subtract depreciations (Chapter V). Third, Guillen et al. (2023) calculated new profits by increasing fuel costs with higher fuel prices, while all other values remain equal, e.g. fuel use and revenues. In FISHCODE, agents adapted to scenarios with higher fuel prices by changing their behavior leading to higher LPUE for plaice and common shrimps and slightly reduced steaming times for some metiers. This was the result of agents reducing the number of fishing trips to catch grounds further offshore or those with lower LPUE. Both reducing the steaming time and increasing catchability have been identified by previous studies as possible adaptation strategies to high fuel prices (Bastardie et al., 2013; Poos et al., 2013). All but PUL metiers became unprofitable when fuel prices were increased to 600% and although this represents an extreme scenario, it shows how resilient PUL are in comparison to more fuel-intensive gears and indicates a potential strong impact of banning PUL gears. Another effect of fuel scenarios was the reduction of averaged fishing effort per grid cell by up 40%, which could be a chance for marine conservation efforts.

Banning PUL in FISHCODE led to the expected shift to equivalent metiers using TBB, however, not all agents using PUL switched, but instead reduced their number of fishing trips. This shows the limits of the adaptive capacity of agents, because TBB metiers could only partially substitute former PUL metiers. The reason could be the lower profitability of TBB metiers or the habitual behavioral element introduced by the Consumat approach in FISHCODE. The latter incentivized agents to choose the same metier as long as they are satisfied while reducing their satisfaction when choosing a new metier (Chapter V). PUL gears have been effectively banned in the EU in 2021, which was after the core development of FISHCODE and its integrated data (2012-2018). By analyzing recent fishery data from 2022, the model outcome of the PUL scenario could be compared to the real-world effect of banning PUL. This approach would provide helpful insights into the realism of FISHCODE and its uncertainty when simulating scenarios.

Additional spatial fishing restrictions reduced fishing effort and profits underlining the conflict potential among future OWF expansions and fisheries (Letschert et al., 2021; Stelzenmüller et al., 2022). In the spatial fishing restrictions scenarios, fishing effort became displaced into the remaining open areas where it increased by more than 100% in some hotspots. The intensification of fishing effort did not decrease LPUE substantially, despite FISHCODE simulating local resource depletion as reduced catchability in patches that were previously fished. This indicates that the reduction of profits in future OWF and NTZ scenarios are triggered by longer steaming times rather than local resource depletion. The result is in line with Kraan et al. (2024) who found limited impact of bottom trawling on benthic communities, however, the authors argue that input data might be biased due to the long history of bottom trawling in the North Sea. In contrast, Reiss et al. (2009) detected a disturbance in benthic communities due to fishing in areas that were already fished at high intensities. In fact, repeated fishing events have been observed to impact catchability and the bathymetry of the seabed (Depestele et al., 2016; Rijnsdorp et al., 2022) and an ecosystem-based model found reduced fish biomass as a consequence of fishing effort displacement (Püts et al., 2023). The direct relationship between fishing activity and catchability is afflicted with some uncertainty. The biological assumptions of FISHCODE are strong simplifications that treat the effects of fishing on biological resources uniform independent of the used gear and target species. Once there is more scientific agreement on the relationship between fishing activity and biological resource availability, the biological submodel of FISHCODE should be improved.

4.2 Towards holistic scenarios

Our results hint that a combination of stressors might evoke a different outcome than testing them individually. PUL gears are most resilient against high fuel prices, which is why a combination of banning PUL and increasing fuel prices would have a stronger negative effect on overall fishing effort and profits. If all three pressure would be combined, the decrease of fishing effort in the PUL and fuel scenarios, could counteract the concentration of fishing effort in hotspots as a result of displacement and possibly lower the risk of local negative impacts on habitats.

Shared socio-economic pathways (SSP) combine potential future changes in several storylines offering a framework to represent complex scenarios without inflating the parameter space (Pinnegar et al., 2021). An operationalization of the SSP framework for EU fisheries suggests possible co-use of OWF and fisheries and alternative fishing gears that are less fuel-intensive and more selective (Hamon et al., 2021). One promising alternative are passive gears such as pots or creels, which avoid high unwanted bycatches (Hornborg et al., 2017) and are currently discussed to be permitted in or around OWFs of North Sea riparian states (Bonsu et al., 2024; Stelzenmüller et al., 2021c). The behavioral submodel of FISHCODE focuses on metier choice and thus is suited to test the effect of introducing new gears and target species. Analyzing these co-use scenarios would create first insights on their feasibility not only with regard to technical and management requirements, but also considering the fishers' decision-making.

Together with fishing pressure, climate change has been altering species communities in the North Sea and north-east Atlantic and thus should be considered when building complex future scenarios (Engelhard et al., 2014; Sguotti et al., 2022). Ecological processes are simplified in FISHCODE and thus analyzing climate change scenarios poses a challenge. We simulated landings by matching environmental variables in the model with look-up tables of observed fishing trips rather than having a biological submodel, which saved considerable complexity through bypassing mechanisms such as fish stock growth, species interactions, environmental impacts on species, and catchability of fishing gears. By deriving landings directly from observed data, we assume that the relation between environmental variables and catchability remains constant. One solution could be to alter simulated LPUE according to winner and loser species of climate change in the southern North Sea.

Using the US surfclam fishery as an example, Scheld et al. (2022) have shown, that the restriction of vessel traffic in OWF areas can reduce economic benefit of fishers even more. We assumed that fishing vessels have transit rights in OFWs in all scenarios reflecting the current regulations in the southern North Sea (Bonsu et al., 2024). However, regulations in the North Sea are made by several countries and are therefore prone to inconsistencies. Thus, varying regulations for transit rights in OWF areas would add to more holistic scenarios.

The Global Biodiversity Framework's goal of protecting 30% of all marine areas (UN, 2022) became reflected in an EU Action Plan suggesting to phase out all bottom trawling in MPAs by 2030 to protect the sea floor and ensure the conservation of marine biodiversity (EU, 2023). In scenarios of this study, only 5.5% of grid cells (approximately 17900 km²) were closed to fishing in no-take zones. To simulate international conservation targets, scenarios would need to entail much larger areas designated to no-take zones.

Conclusion

All tested scenarios reduced fishing effort and profits, but only extreme fuel price scenarios resulted in unprofitable fisheries. These results suggest that the current flexibility of fishers to switch metiers and adapt levels of fishing effort and spatial catch grounds is sufficient to cope with most stressors individually. However, this level of adaptation might be taxing especially for small fishing enterprises and even though the entire fishery remains profitable, every reduction of fishing activity may have eroding effects on port infrastructure and coastal communities. Additional spatial fishing restrictions led to an intensification of fishing effort, whereas the opposite trend was observed for higher fuel prices. Changed distribution of fishing effort should be considered in marine spatial management to achieve ideal outcomes for marine conservation. FISHCODE provides a suitable tool to perform scenario analysis and gain insight in potential future stressors for southern North Sea fisheries. The question about the effect of combined and more realistic future scenarios remains open and should be subjected to future research.

Supplementary material

Supplementary material of this chapter can be found in the *end of this thesis*.

General Discussion

The findings of this dissertation give insights into the extent of current and potential future stressors on the North Sea fisheries, i.e. spatial fishing restrictions, local depletion, Brexit, and fuel prices, while also demonstrating a feasible mitigation strategy, i.e. co-locating brown crab fishery with passive gears and offshore wind farms (Chapter I-III). My-coauthors and I disentangled the effects of a wide array of environmental, economic, and cultural drivers for fishery which varied across fleets, highlighting the need to consider differences of fisher behavior and vessel technicalities in models and management (Chapter IV). The agent-based model (ABM) FISHCODE, is rooted in results of the previous chapters and simulates spatio-temporal fishing effort while allowing fishers to decide individually if and what to fish. It represents a virtual laboratory for the German southern North Sea fisheries and is capable of analyzing consequences for socio-economic and spatial scenarios (Chapter V-VI). The following sections discuss the results of this thesis along the four research objectives presented in the general introduction, and embed the thesis' findings in the context of current management before drawing conclusions. The research objectives were:

(1) identifying current and future pressures for North Sea fisheries with emphasis on spatial fishing restrictions (discussed in *1.1*),
(2) exploring co-use as a mitigation strategy for constrained fishing grounds due to offshore wind parks (discussed in *1.2*),
(3) identifying drivers of North Sea spatio-temporal fishing dynamics (discussed in *2.1*), and
(4) constructing an agent-based model (ABM) to evaluate the effect of socio-economic scenarios on the German fishing sector (discussed in *2.2* and *2.3*).

1. The North Sea, high intensity – and high uncertainty

1.1 Pressures for North Sea fisheries

In the North Sea, the first offshore wind farm (OWF) entered service in 2002 and, since then, the sector has been ever-growing, while the number of fossil energy structures has been recently stagnating (Martins et al., 2023). More than 10 years ago, OWFs have been identified as an emergent actor in marine spatial planning (MSP) and potential competitor for North Sea fisheries (Berkenhagen et al., 2010; Kannen et al., 2008). Chapter I confirms these earlier results and is the first study to perform a detailed spatial overlay analysis on a larger scale taking into account all offshore renewable energy sites (including wave and tidal energy). OWFs constitute by far the majority of present and future offshore renewable sites, which is why, from now on, we will exclusively refer to OWFs when describing results of Chapter I. Compared to other EU waters, the North Sea is a hotspot for OWF expansions, which will cover up to 60,000 km² within the coming decades leading to a 5-fold increase of the overlapping area between fishing grounds and OWFs. Our results got confirmed even in a global context, as northern Europe scores second (after China) in OWF development rates, with the UK leading before Germany (Paolo et al., 2024).

In Chapter I, we integrated fishing effort data from four different sources with varying quality, because highly resolved data from the vessel monitoring system (VMS) for international fisheries was only available for the German exclusive economic zone (EEZ). Regional data published by OSPAR, HELCOM or global fishing watch comes at the cost of being aggregated on higher spatial and temporal levels or fishing gears (ICES, 2019c, 2019d; Kroodsma et al., 2018). OWF areas are often smaller than spatial units of these publicly available fishing effort data, meaning that intersections between OWFs and fishing effort may lead to overestimations of overlapping fishing effort (Chapter I). The same issues have been observed for studying the impact of MPAs on fisheries (Chollett et al., 2022). Moreover, fishing effort aggregated by year negates the detection of potential seasonal patterns (e.g. data for OSPAR and HELCOM regions) and gear aggregations can be problematic when they are on a high level such as the combination of pelagic and bottom trawls (e.g. global fishing watch data). Publicly available fishing effort data across EEZs and on higher spatio-temporal and metier resolution would improve impact assessments of spatial fishing restrictions. Finally, knowing the vessels' landing ports would also allow to estimate socio-economic effects on coastal communities.

In the North Sea, fishing grounds of beam trawlers catching flatfish (i.e. mostly sole and plaice) and otter bottom trawls targeting plaice and Nephrops, will be the most affected by OWF developments (Chapter I). If no-take zones in MPAs are added to OWFs, the loss of German Nephrops fishing grounds will be up to 45% (Chapter II). These calculations only consider fishing grounds important to the German fleet, but Nephrops fishing grounds are also located in the UK, Netherlands, and Denmark. Therefore, the picture is likely similar for other North Sea fleets, because all these countries are planning large-scale OWF expansions in their EEZs (Chapter I).

Apart from spatial fishing restrictions, Chapter II identified Brexit and overfishing as sources of uncertainty. Brexit had promised limited access of EU fishers to UK waters, which would increase UK quotas for many fish stocks, e.g. Nephrops, cod, and haddock. So far, reality differs from the original plans, as the Trade and Cooperation Agreement between the EU and UK regulates only a partial shift of quotas and does not include access limitations at least until June 2026 (EU, 2021). The shift of quota availability affects the capability of EU member states to swap quotas with the UK and may lead to complications, i.e. Germany's swaps for Nephrops quota (Chapter II). Brexit renegotiations in 2026 are a large source of uncertainty for North Sea fishers, because quota availabilities and access to UK waters are again on the table for discussion (Stewart et al., 2022). Constrained access to the UK EEZs would lead to an additional loss of fishing grounds for vessels targeting flatfish, Nephrops, herring, haddock, and many others. In the southern North Sea, fisheries might not be affected directly, but intensification of fishing activity is likely due to the displacement of vessels previously fishing in the UK increasing the local pressure on marine ecosystems.

The North Sea is a heavily fished area where bottom trawling has been raking most of the sea floor at high intensities for decades (reviewed by Emeis et al., 2015; Rijnsdorp et al., 2008). Nephrops in the southern North Sea is fished above the recommended limits most years, due to a mismatch of management units between individual population and total allowable catches (TAC) that are released for the entire region (Chapter II). Therefore, Nephrops, and many other species, would benefit from the combined protection of OWFs and no-take zones (Püts et al., 2023). Marine ecosystems have the potential to recover if fishing pressure by destructive gears such as bottom trawling or dredging is reduced, even if static gear fisheries continues (Davies et al., 2021). Thus, combining passive gear fisheries such as pots or traps and OWFs could enable both ecosystem recovery to certain extent and a continued source of livelihood for fishers. Passive gears are also more energy-efficient than bottom trawls (Suuronen et al., 2012), although the catch efficiency per used fuel is worse for passive than for active gears (Cheilari et al., 2013). This should be considered when making plans for sustainable future food production.

1.2 Will OWFs transform ecosystems and fisheries?

The hard substrate of wind farm monopiles act as artificial reefs that are first colonized by sessile species and later by mobile macrofauna such as brown crab (Chapter III), lobster, and cod (Gimpel et al., 2023; Stelzenmüller et al., 2021c; Thatcher et al., 2023). All these species have a rather high monetary value and are attractive for fisheries. In fact, there are incidences of commercial vessels preferably fishing in the proximity of wind farms with pots and traps (Chapter III). Although these results suggest that passive gear fisheries in the proximity of OWFs are feasible, fishers need to make investments in order to purchase equipment and perform technical modifications on their vessels. The few German vessels with passive gears in the North Sea use gillnets for catching cod, and pots and traps for European lobster. Experimental catches in the safety buffer of OWFs and economic analyses suggest that co-location with passive gears would be feasible for brown shrimp fishers in summer months when brown shrimp catches decrease and brown crabs are abundant (Chapter III). Scour protections of OWFs serving as a potential habitat for European lobster is a promising prospect, because it can be caught in the same fishery as brown crab and achieve a higher market price (Thatcher et al., 2023). The occurrence of species around scour protections is a result of many factors, e.g. surrounding habitat, OWF age, and scour protection material. With more results from experimental and field research, influences of these factors on species aggregations could be properly analyzed and subsequently the benefits for fisheries simulated.

Artificial hard substrate does not only attract species interesting for fisheries, but also unwanted colonizers such as non-indigenous fouling species (Laeseke et al., 2020). A study in Belgian waters found that OWF pillars and foundations act as stepping-stones for non-indigenous sessile invertebrates expanding their range from coastal to offshore zones (De Mesel et al., 2015). The same effect has been observed for blue mussels (*Mytilus spp.*) in the entire North Sea (Coolen et al., 2020). The impact of invertebrates introduced to a new habitat may seem small at first, but once established, non-indigenous marine species are nearly impossible to eradicate and can alter ecosystem functions (reviewed by Laeseke et al., 2020). Costs emerging from the consequences of biological invasions are not only paid by the ecosystem, but may also cause tremendous economic losses (Williams and Grosholz, 2008). This is why simulation studies assessing the connectivity introduced through planned OWFs are recommended as standard procedures to foresee and proactively manage the risk of marine non-indigenous species (Abramic et al., 2022). For the North Sea, Molen et al. (2018) performed a sensitivity study with existing wrecks, oil & gas, and OWF structures. However, man-made marine structure will increase with continued use of marine areas, especially due to the enormous planned OWF expansions in the coming decades. Therefore, connectivity studies should comprise future scenarios of OWFs in order to assess their impact on marine non-indigenous species.

Even though OWFs exclude fisheries due to the legislation or the fear of damaging cables and other infrastructure (Bonsu et al., 2024), they are not the same as no-take zones that are deliberately designed for nature conservation. Li et al. (2023) performed a statistical analysis for long-term effects of OWFs on the surrounding species community and could not find a significant effect for the absence of trawling. A review of scientific studies assessing impacts of OWFs on ecosystems revealed that more studies found negative than positive effects (Galparsoro et al., 2022). Birds were most consistently found to suffer from OWFs, whereas the findings about fish are not so clear, as the same numbers of studies found positive and negative effects, respectively. Elasmobranchs are possibly affected worse than other fish, because their electro-sensory organs can become disturbed by the electromagnetic OWF cables and transformers (reviewed by Bray et al., 2016). However, scientific findings are based on anecdotal evidence, likely case-specific due to differences in habitats and records of anthropogenic use, and biased towards fish and bird species while invertebrates are less researched (Galparsoro et al., 2022). More ecological time series need to be available and analyzed to achieve clarity about whether OWFs have harmful effects or can benefit nature conservation.

One way or the other, the extent of OWF implementation will lead to a transformation of the fishing sector and countries are already preparing legislation for co-use practices (Bonsu et al., 2024). Insights into the feasibility of co-location as mitigation strategy for lost fishing grounds, such as provided by Chapter III, are crucial for designing next steps in research and management. However, when it comes to assessing the impact of OWFs on fisheries, there are still many open questions: Can the remaining open areas sustain the current capacity of fishing activity? How will fishers react to the many pressures making their future so uncertain? To answer these questions, it is important to understand the drivers of fishing behavior (Fulton et al., 2011) and use more dynamic approaches such as ABMs to simulate fishing displacement (reviewed by Haase et al., 2023).

2. To fish or not to fish

2.1 Influencing drivers of fishing effort

Chapter IV includes a review of scientific literature on factors influencing behavior of demersal fishers in the North Sea. While the review shows that factors from the environmental, economic, and cultural dimensions, as well as fishing restrictions play a role, there are barely any studies combining them in one quantitative analysis. To bridge this gap, we combined data from all dimensions and performed boosted regression trees (BRT) to identify which factors are driving fishing effort dynamics of three German fleets, i.e. flatfish, mixed-demersal, and brown shrimp. Our results indicate that biophysical parameters had the strongest effect on brown shrimp and demersal fleets alike, whereas distance to port and fuel price only influenced brown shrimp fishing effort. The discrepancies across fleets may be related to varying socio-economic settings (e.g. business structure) and environmental parameters in fishing grounds. German brown shrimp fishers usually run smaller family-owned businesses, whereas fishers targeting flatfish are affiliated to larger international companies.

Conversely, Chapter IV revealed quotas to be unimportant for fishing behavior even though the German Nephrops total allowable catch comprise a fraction of actual catches. This is because Germany has been swapping quota with the UK, France, and Belgium to increase fishing opportunities for its Nephrops fishery (Chapter II). This reflects a methodological limitation of BRTs, since they can only make meaningful statements for historical data ranges and are not suited for scenario testing or extrapolation. The same holds true for tested fuel prices and environmental factors, which did not include previous political events (i.e. the Russo-Ukrainian war) or future changes due to climate change. Fuel price was only relevant for one fleet, while other studies identified it as an important factor in shaping fisher behavior such as reducing towing speed (Poos et al., 2013) and fishing effort (Cheilari et al., 2013). The socio-cultural dimension comprised a single parameter, i.e. differentiating days into workdays, weekends or holidays. Other cultural norms such as skipper age and experience can influence fishing behavior, but are more difficult to quantify (Christensen and Raakjær, 2006). Behavioral drivers may differ from fisher to fisher due to their varying background, but also because of different vessel characteristics, i.e. the vessel size and equipment determine a fisher's capability to visit certain fishing grounds (Stephenson et al., 2018). Other methods such as ABMs are suited to test parameter ranges beyond historical ranges and simulate the behavior of heterogeneous agents (Bonabeau, 2002).

2.2 Fishing agents – more than the sum of their profits

In current times, quantities of data are increasing, rapidly requiring more computational power while at the same time enabling more precise analyses. In this thesis, I used not only fishing effort data, but also landings, vessels registries, information from federal agencies (e.g. quotas), remote-sensed oceanographic and weather data, economic information on fishing businesses, and spatial polygons of MPAs and anthropogenic activities such as OWFs. Based on all this information, insights into factors driving fishing behavior (Chapter IV), and data products of Chapter I & II, I developed an ABM called FISHCODE: **FI**sheries **S**imulation with **H**uman **CO**mplex **DE**cision-making. FISHCODE simulates individual decisions of German fishers in the southern North Sea about if, what, and how long to fish, and produces output of fishing effort and economic variables on temporal (e.g. fishing trip or month) and spatial resolutions (Chapter V). Towards the end of the last millennia, scientific studies on fishery behavior grew in number (Van Putten et al., 2012) and the same has recently been observed for ABMs focusing on fishing behavior (Haase et al., 2023). FISHCODE stands out from other fisher ABMs and fleet models, because it takes into account fishers' behavior beyond profit maximization, e.g. habitual behavior and conformism. This is an important property as human behavior has been identified as a large source of uncertainty in fisheries management (Fulton et al., 2011). Human behavior research has roots in neoclassical economy, but during the last half of the 20th century became progressively mixed with discipline from psychology, sociology, political science, anthropology, and ecology (Constantino et al., 2021). The simulation of human behavior based on more than a single economic aim is progressively embraced by the scientific community (Constantino et al., 2021; Schlüter et al., 2017; Wijermans et al., 2020). As such, FISHCODE is a timely application for simulating humans' decision in the context of resource use and represents a virtual laboratory for testing scenarios in the southern North Sea.

Salas and Gaertner (2004) classified fishers' actions into tactical and strategic, the former being short-term, e.g. targeting a specific fishing ground, while the latter aim to achieve long-term objectives such as reducing costs per kg caught. Social factors influencing strategic decision-making is established in many fisher models (Van Putten et al., 2012), e.g. agents will keep fishing even though they do not make profit in the long term, because they simply want to be a fisher (Pollnac and Poggie, 2008; Stelzenmüller et al., 2024a). Applying this categorization on FISHCODE, the strategic long-term aims of agents are to maximize their satisfaction and reduce their uncertainty, which in turn stand for different behavioral motivations such as acting habitual or earning more than colleagues (Chapter V). However, most simulated decisions in FISHCODE are tactical, i.e. if, what, and how long to fish on a daily basis, a feature that is less common across fisher models. This makes FISHCODE especially suitable to simulate fishers who switch gears depending on the day or season, and can be used to virtually test the acceptance and feasibility of new fishing techniques and target species.

In Chapter IV, I showed that sensible clustering of fishers into groups is important, because they are affected differently by driving factors. In the data preparation for FISHCODE, I improved a cluster method developed for Chapter II to group fishing trips into metiers. I also define fleet affiliations for every vessel based on the metier used the most across all observed fishing trips. In comparison to metiers, fishing fleets are often used to create a temporally fixed classification that might involve technical characteristics (Ulrich et al., 2012). The grouping on metier and fleet level is useful to differentiate characteristics on fishing trip level (e.g. gear or catch composition) from annual parameters (e.g. personnel and fuel costs). At the same time, this dualism of vessel affiliation complicates the merging of data such as cost structures made publicly available by the Scientific Technological and Economic Committee for Fisheries on fleet level (e.g. in STECF, 2019a). The STECF publishes information for fishing fleets defined by the main metier and coarse intervals of vessel sizes (i.e. 0m – 12m, 12m - 24m, 24m - 40m, and >40m). This requires to match STECF data with fishing vessels based on a lot of assumptions, such as to linearly interpolate costs by meter of vessel length (Chapter V, Annex), which introduces additional uncertainty. The fleet definitions of STECF are long established and previous works suggested refining them, which would benefit many models and research methodologies (Sulanke, 2020; Sulanke et al., 2022).

Despite clustering fishing practices based on technical measures (e.g. metiers) being a common method, it remains an output criterium and does not describe what the fisher intended to do when planning the fishing trip (Schadeberg et al., 2021). Thus, a grouping based on fishing metiers alone can only have restricted significance in determining fishers' behavior. The quality of grouping typologies of fishers can be improved by including additional information such as the skipper's age, their fishing mobility, activity per year, scope of investments, and crew size (Christensen and Raakjær, 2006), as well as more qualitative characteristic, e.g. the fisher's culture and attitude towards change (Boonstra and Hentati-Sundberg, 2016). The decision-making submodel in FISHCODE assumes uniform behavioral motivations within fleets and thus could be improved if the clustering would be refined by using additional information. For example, Wijermans et al. (2020) presented an ABM in which they sorted fisher behaviors into three fishing styles that were identified by combining quantitative metier analysis with expert consultation and interviews of fishers (Boonstra and Hentati-Sundberg, 2016). In general, fisher interviews or focus groups have been proven helpful to gain insights into the motives of fishers, which can then be used to find behavioral groups (Barz et al., 2020; Schadeberg et al., 2021).

2.3 What does the future hold?

Scenarios of increased fuel prices, spatial fishing restrictions, and a ban of electric pulse gears (PUL) indicated decreasing fishing effort and profits for German fishers in the southern North Sea (Chapter VI). Overall, scenarios of raised fuel price had the strongest effect in reducing fishing effort and profits, while expansion of fishing restrictions led to an intensification of fishing activity, exceeding an increase of 100% in several hotspots. Despite banning pulse gears forcing agents to switch to alternative gears, a large part of previous PUL effort became inactive. These results not only gave important insights into future pressures on and responses of the fisheries socio-ecological system, but also confirmed FISHCODE's applicability for scenarios analysis.

In our analysis, fuel price scenarios had the strongest effect, as an increase of 300% heavily reduced both fishing effort (-37%) and profits (-72%). Both effects have also been observed on a large scale for the EU fleet in response to increased fuel prices. Comparing EU fleet performance before (2002) and after (2008) growing fuel prices of approximately 250%, an average vessel spent 40 days less at sea and its profitability was reduced by 33% (Cheilari et al., 2013). Thus, the effects on profits in FISHCODE scenarios was more twice as strong, which could have several reasons. First, the relationship of fuel prices and profits in FISHCODE are disproportional, because of adaptive fisher behavior. This is supported by the extreme FISHCODE scenario increasing fuel price by 600%, which did not lead to a doubling of reduced profits in comparison to the 300% scenario (Chapter VI). Second, Cheilari et al. (2013) calculated averages across EU fleets also including gears with lower fuel uses. The fleets represented in FISHCODE all use bottom trawls, which are among the most fuel-intensive gears and might therefore be more impacted than more energy-efficient gears, e.g. pots, traps, and gill nets (Suuronen et al., 2012). Another effect of increased fuel prices in the EU was that fishers passed on the higher costs to the consumers by raising fish prices, which could offset the increased energy costs by certain extent (Cheilari et al., 2013). These market dynamics are currently not included in FISHCODE and could add more realism to economic scenarios.

The nature of the Consumat framework in FISHCODE enabled agents to choose metiers that they previously had not been used and thus FISHCODE could also be applied for testing scenarios of introducing new metiers. Some fishers in the North Sea use passive gears such as gillnets to catch flatfishes and cod (*Gadus morhua*) or traps to catch brown crabs (*Cancer pagurus*) and European lobster (*Homarus gammarus*). We did not include these fishing options in our model, because of the low engagement of German fishers in these gears. However, with expanding OWFs, using passive gears like traps or fishing rods could offer an alternative for fishers to continue fishing inside or at least in buffer zones around OWFs (Bonsu et al., 2024; Stelzenmüller et al., 2021c). Analyzing these co-location scenarios with our ABM could create first insights on their feasibility not only with regard to technical and management requirements, but also considering the fishers' decision-making.

Just like any complex model, the outcomes of FISHCODE are affiliated with uncertainties due to its model structure, stochasticity, and assumptions made during the parameterization (discussed in Chapter V). The high complexity is one of the shortcomings of ABMs and the reason why they are rarely used for policy advice (Will et al., 2021). A possible way to circumvent this weakness would be ensemble modelling, meaning to draw conclusions based on the output of several similar models, as it has been suggested for fish stock assessments (Britten et al., 2021). Using ensembles instead of following a singular model output might prevent mistakes that have occurred in fisheries, such as the collapse of the Newfoundland cod stocks (Walters and Maguire, 1996). The two ABMs DISPLACE (Bastardie et al., 2016) and ViNoS (Lemmen et al., 2023) would be suitable candidates for an ensemble approach since both also simulate fishing effort in the North Sea. However, FISHCODE operates on higher spatio-temporal resolution and has stronger focus on decision-making beyond economic optimization, which would need to be considered when comparing model outputs. Applying FISHCODE to other areas or comparing its outputs to ABMs from other areas is challenging, since the North Sea is a very data rich area allowing for the development of complex fisheries models.

3. Management implications

3.1 The interplay of pressures, management, and adaptation

North Sea fish stocks are subject to many anthropogenic pressures, such as intense bottom trawling and warming waters (Emeis et al., 2015). These stressors affect marine ecosystems, leading to regime shifts of entire plankton and fish communities (Möllmann et al., 2021; Sguotti et al., 2022). North Atlantic cod (*Gadus morhua*) has been declining worldwide, prominently represented by the collapse of the seemingly endless Newfoundland populations in 1992. Cod in the North Sea has been on the losing end of a community-wide regime shift for decades, which can be tracked by abrupt changes lastly detected in the early 2000s (Blöcker et al., 2023b; Sguotti et al., 2022). The EU responded with a new regulation in 2002 restricting the days-at-sea for all vessels with mesh sizes >100 mm which were used by vessels targeting cod (EU Reg. 2341/2002). The Nephrops fleet was also affected by this new regulation, because they had previously moved to mesh sizes >100 mm in order to reduce bycatches. No differentiation was made between vessels targeting cod or Nephrops, which incentivized Nephrops fishers to move back to smaller nets, enabling them to retain their allowed days-at-sea, but also inevitably increased unwanted bycatches (Graham et al., 2007). Another side effect of both the decline of cod and its stricter management forced fishers to adapt and contributed to the emerging of the German Nephrops fleet in 2006 (Chapter II). Two conclusions can be drawn from the above described chain of events: First, management units (fleets) are crude definitions that make targeted management difficult. Thus, management should use groups of fishers on a finer resolution and consider how a new regulation tailored for one fleet will impact the others. This call for management on a finer resolution is also supported by results from Chapter II (i.e. defining metiers based on careful and detailed clustering) and Chapter IV (i.e. fleets differ in their response to fishing drivers), and has been discussed in the previous section (*2.2*). Second, effects of regime shifts or tipping points in fish stocks go beyond the ecological domain and may materialize as fishers adapting to new gears and target species. If management is not issued in a careful way, fishers' adaptions may be harmful for the ecosystem (i.e. switch to smaller mesh sizes increasing bycatches) essentially representing a negative feedback loop.

3.2 One plan to place them all

Spatial fishing restrictions represent another factor that force fishers to change their behavior, i.e. by targeting alternative fishing grounds. This displacement of fishing activity can have negative effects, if previously unfished areas or sensitive ecosystems are disturbed (Dinmore et al., 2003; Rijnsdorp et al., 2001; Stelzenmüller et al., 2015a). Therefore, future-oriented MSP is necessary to avert unwanted effects of growing spatial fishing restrictions, such as the potential expansions of OWFs and no-take zones demonstrated in Chapter I & II and the intensification of fishing effort resulting from simulated scenarios (Chapter VI). In contrast to OWFs, the future placement and regulations of MPAs is less certain. Currently, fishing is allowed in many MPAs or only restricted during a specific season or for individual gears, and many Natura2000 are still lacking any management regulations (Mazaris et al., 2018). However, ambitious global conservation targets such as the Global Biodiversity Framework aim to protect 30% of the earth's surface (UN, 2022). The recent EU Action Plan echoed the strive for more marine conservation areas by suggesting (among other objectives) to phase out all mobile bottom-contacting fishing activities in MPAs by 2030 (EU, 2023). This would have severe effects on the fisheries in the southern North Sea, which, to a large amount, take place in MPAs and exclusively use bottom-contacting gears (Figure 1).

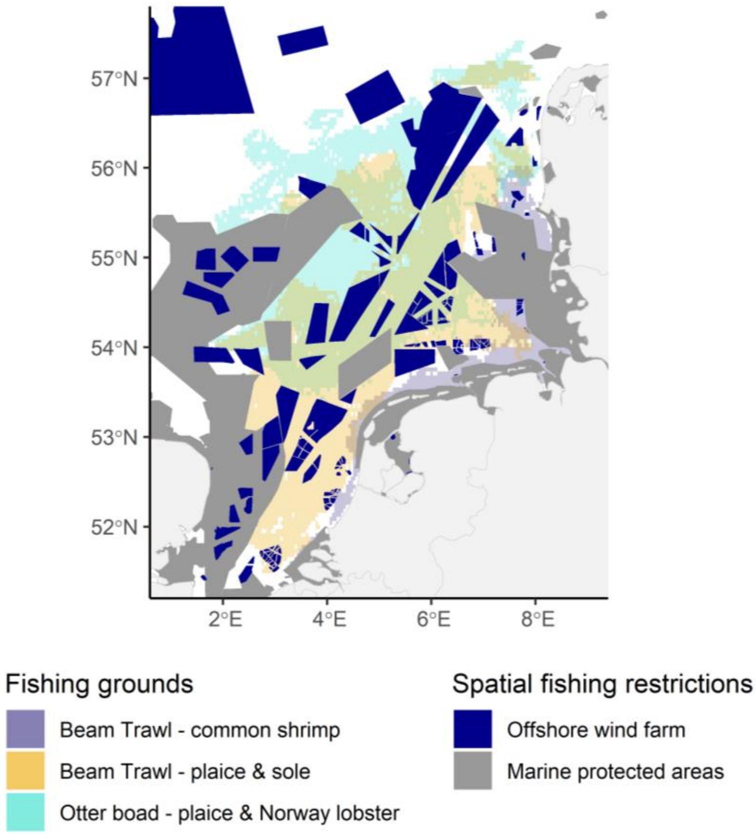


Figure 1. Fishing grounds of the most important German fleets in the southern North Sea (also represented in FISHCODE), as well as planned offshore windfarms (status 2040) and current marine protected areas (see Chapter V for data sources). Note, that many marine protected areas represent only partial or no restriction to fishing activity, which would change with the implementation of the EU action plan.

Even though the EU action plan did not find much fertile ground among EU member states and remains a suggestion until today, the trend of global and regional conservation targets has been developing in favor of more area-based measurements. Therefore, it is important for scientists to anticipate future no-take zone placements. A combination of several nature conservation objectives could be used to develop realistic scenarios. Implementing the EU action plan would effectively close off 39% of the German North Sea for fishing activity only due to MPAs and thus exceeds the aim of the Global Biodiversity Framework. More precise suggestions for no-take zones entailing exactly 30% of the German North EEZ could meet nature conservation targets, while still keeping areas open for fishing businesses to survive. Moreover, OWFs offer a certain degree of nature protection due to their exclusion of most fishing activity. Thus, they could be considered as Other Effective Area-based Conservation Measures (OECMs) to achieve nature conservation goals (IUCN, 2018). While even this idealized future-oriented MSP might not avoid all conflicts among marine stakeholders, it could still lay the foundation for an “as-good-as-possible” scenario.

Despite fishery being the most important marine actor historically, it is often not considered explicitly in MSP (Trouillet, 2019). One could argue that this is a gain for nature conservation, but in some cases important fishing grounds are not even considered for MPA placement, because the economic losses would be too great (Chollett et al., 2022). The placement of North Sea Natura2000 areas has recently been identified to be deficient in covering core areas of most demersal fish species (Probst et al., 2021), hinting that conservation targets have been compromised. In fact, the implementation of German Natura2000 sites in the North Sea has taken almost 20 years, because of changing governments and political aims in EU member states that hindered the process to find a balance between fisheries and nature protection (T. Schulze, personal communication, February 12, 2024). A review of the STECF on suggested Natura2000 areas in the North Sea concludes: "*[…] [spatial] restrictions proposed in the joint recommendation apply to areas where the fishing effort is already very low and will have very little economic impact.*" (STECF, 2019b, p. 135). This leads to the assumption that fisheries are actually considered in MSP despite not appearing in the actual marine spatial plan, which could potentially undermine area-based conservation efforts, because planned no-take zones are shifted to sustain the economic values of fisheries. If fishers would be respected in marine spatial plans with explicit fishing priority zones, it would not only ensure their claim to essential fishing grounds, but also invalidate the argument "fisheries are not explicitly considered in MSP" and therefore give leverage to other stakeholders such as marine conservation to place no-take zones in some areas with high fishing effort. Thus, putting fisheries zones on the map might benefit both fishers and marine conservation. Furthermore, these two actors are not necessary antagonists, as their general core interests are the same: protecting the ecosystem for conserving biodiversity and target species populations. Fishers might be in favor of multi-use MPAs with limited access of fishing, which might promise larger catches with less effort (Jentoft and Knol, 2014). Hence, this argument supports the conclusion of other studies that giving more power to fisheries organizations to speak and negotiate directly with marine conservation stakeholders could result in more effective solutions (Kannen, 2014; van Hoof et al., 2020).

4. Conclusion

In this thesis, I identified important stressors for the North Sea fisheries with special emphasis on spatial fishing restrictions, presented a mitigation strategy (i.e. co-use of offshore wind farms and fisheries), delved into the factors driving fishing behavior, and created and applied an agent-based fishery model for three German North Sea fleets. As such, I met all four research objectives stated in the general introduction.

Quantifying the overlap of offshore wind farms (OWFs) and fishing effort confirmed earlier studies anticipating the conflict between these two sectors and identified the North Sea as a hotspot OWF development. Along with marine protected areas (MPAs), expanding OWFs will spur a race for space in the heavily anthropogenically used North Sea. This will impact the fishing sector in general, but especially demersal trawlers catching flatfish and Nephrops. In addition, political developments of the recent years have affected North Sea fisheries. Brexit has been challenging the status quo of quota distribution and swaps among EU member states, while a partial exclusion of EU fishing activity from the UK EEZ could be the outcome of renegotiations of Brexit conditions in 2026. The COVID-19 pandemic as well as the Russo-Ukrainian war led to increasing fossil fuel prices, which reduced the profitability of fishing businesses.

The agent-based model (ABM) called FISHCODE represents a versatile tool for scenario testing and investigating essential drivers of fisher behavior. Model outcomes show a negative impact of future fishing restrictions and rising fuel prices on fishing effort and profits. This could be exacerbated through the EU ban of the electric pulse gear, which is more energy-efficient than conventional beam trawls, but was debated for negative impacts on the ecosystem. Moreover, spatial restrictions will reduce spatial fishing opportunities in the southern North Sea and could lead to an intensification of fishing effort in remaining open areas by more than 100% in hotspots. The potential limitation of the UK EEZ due to Brexit could even lead to more fishing effort displacement and further local intensification of fishing activity. Already now, Nephrops populations are fished above the recommended limit and thus any increase of fishing effort will raise the threat of local depletion. The development and application of selective and fuel-saving fishing gears and thus important for North Sea fisheries.

Co-use strategies could mitigate the effect on the fishing sector by offering an alternative fishing practice. Fishing with pots and traps for brown crab are a realistic option, because passive gears don't threaten OWF infrastructure and scour protections may serve as artificial habitat for demersal fish and macro-benthos. However, when thinking about upscaling co-use strategies, the lower catch efficiency per spent fuel of passive gears should be considered especially in the context of an increasing demand of protein and human-induced climate change. In general, so far, scientific evidence for the feasibility of co-use fishery is anecdotal and there is no consensus about OWFs affecting the surrounding ecosystems. Several extensive reviews found positive and negative effects depending on the taxonomic group, while it is proven that OWFs increase spreading capabilities of non-indigenous species. Further ecological knowledge is required to assess whether OWFs can be considered as additional nature protection measure, as well as to what extent they can sustain fisheries.

Researches deal with many uncertainties when it comes to data resolutions and availability. Pan-regional fisheries data on a high resolution would be necessary to precisely asses the effect of spatial fishing restrictions, move beyond current boundaries such as EEZs, and develop more realistic socio-ecological fisheries models.

Everything considered, fisheries in the North Sea will face many challenges within the coming decades triggered by a ceasing of fishing grounds, increasing fishing costs, political developments, as well as partly unknown effects on marine ecosystems as a result of a large-scale transformation. This would not be the first time North Sea fishers adapt to a new situation. The collapse of cod stocks and the emergence of the German Nephrops fleet pose an example for fishers switching to a new target species. However, the upcoming changes operate on a larger dimension especially with regard to how marine space is utilized. Careful management should be drafted to ensure the profitability of the fishing sector in co-existence with other marine spatial actors. Factoring in the heterogeneity of fishers is key for efficient regulations and marine spatial planning (MSP). Ideally, management units such as fishing fleets or metiers should include socio-economic or cultural variables to account for heterogeneous responses of fishers and policy drafts should be developed in a participatory approach with all actors.

Supplementary Material

of

Dynamics and pressures in German North Sea fisheries: from identification to simulation

Supplementary Material – Chapter I

From plate to plug: the impact of offshore renewables on European fisheries and the role of marine spatial planning

Appendix A

Table I-A1. Meta data of the spatially explicit data used in this study

Category	Grouping variable	Units of measure	Access rights	Portal & Title (data set name)	Effective	Temporal resolution	Spatial resolution	Data set	Source
Regions	NA	Maritime boundary (country borders)	free	Europe's seas	2016	NA	NA	MSFD-Regions[1]	European Environment Agency
Fisheries European-wide	Gear groups, flag state Gear groups, flag state, MMSI number (ship ID)	Fishing effort [h], vessel hours, number of vessels	free (2012 - 2016)	NA	2012 - 2018 (last 2 years preliminary)	Daily	0.01 * 0.01 degree	Fishing effort at 100th degree[2]	Global Fishing Watch
Fisheries OSPAR region	Métier groups [gear, target species assemblage	Fishing effort [h], fishing effort [kw h], value [€], catch weight [kg], surface swept area [km^2], surface swept	free	ODIM | ICES	2009 - 2017	Yearly	0.05 * 0.05 degree	Ospar_bottom_f_*[3]	OSPAR
Fisheries HELCOM region	Métier groups [gear, target species assemblage	Fishing effort [h], fishing effort [kw h], value [€], catch weight [kg], surface swept area [km^2], surface swept	free	NA	2009 - 2016	Yearly	0.05 * 0.05 degree	HELCOM fishing effort[4]	HELCOM

[1] https://www.eea.europa.eu/data-and-maps/data/europe-seas

[2] https://globalfishingwatch.org/datasets-and-code/

[3] http://www.ices.dk/sites/pub/Publication%20Reports/Forms/DispForm.aspx?ID=35169

[4] http://www.ices.dk/sites/pub/Publication%20Reports/Forms/DispForm.aspx?ID=35243

Category	German EEZ North Sea and Baltic Sea		Renewables	Category	Regions
Grouping variable	Métier groups [gear, target species assemblage	NA	NA	NA	NA
Units of measure	Fishing effort [h], value [€], catch weight [kg],	Country, name, status, start, end date etc.	amount, sea coverage (km²), size of turbines (m), capacity (GW), water depth (m), distance to shore (km)	Country, name, status, start, end date etc.	Country, name, status, start, end date etc.
Access rights	NA	free	licensed	free	free
Portal & Title (data set name)	NA	Human Activities: Finfish farming sites	Research & Intelligence: GIS Offshore Wind Farm Boundaries Data	Human Activities: Ocean Energy Projects	Human Activities: Ocean Energy Projects
Effective	2012 - 2019	2016	2020	2016	2016
Temporal resolution	Pings; 2 hrs frequency	NA	yearly, updated monthly	NA	NA
Spatial resolution	exact location	Polygon	Polygon	Point data	Point data
Data set	VMS (and Logbook) data	Existing farms Finfish[5]	Offshore Wind Farm Boundaries[6]	Wave energy[7]	Tidal energy[8]
Source	Federal office for Agriculture and Food.	**EMODnet (European Marine Observation and Data Network)**	**4C Offshore Ltd.**	**EMODnet (European Marine Observation and Data Network)**	**EMODnet (European Marine Observation and Data Network)**

[5] http://emodnet-humanactivities.eu/search-results.php?dataname=Finfish+Production

[6] https://www.4coffshore.com/offshorewind/

[7] http://emodnet-humanactivities.eu/search-results.php?dataname=Project+Locations

[8] http://emodnet-humanactivities.eu/search-results.php?dataname=Project+Locations

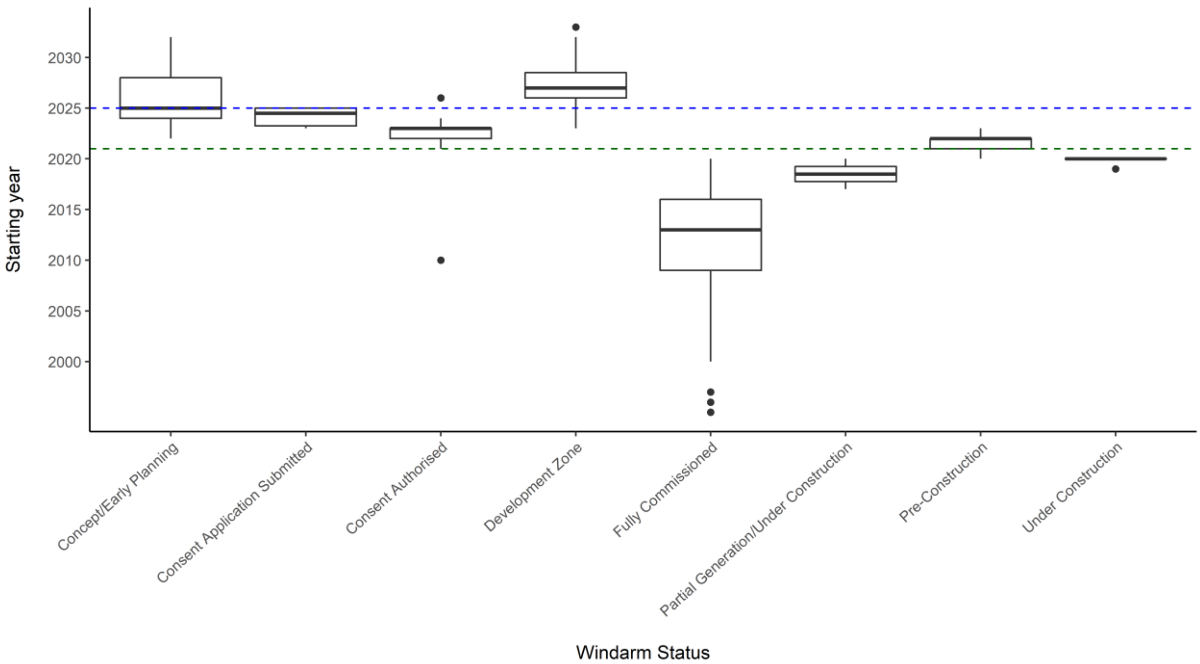


Figure I-A1. Starting years of offshore wind farms (source: 4COffshore) across different wind farm statuses. The green dashed line represents the start of the *present* (<= 2021) and the blue dashed line the start of the *mid-term* (<= 2026) scenario.

Table I-A2. Definitions of wind farm statuses (source 4COffshore) and the respective scenario where it was included. Note that, if there was a starting date available, the starting date instead of the scenario was used to classify the scenario of the respective wind farm.

Wind farm Status	Definition	Scenario
Development Zone	This refers to an area or zone that the government has identified as being suitable for development for offshore wind. Normally developers are then invited to submit project proposals falling within the area.	Long-term
Concept/Early Planning	The early stages of a wind farm. At this pre-application stage tasks are undertaken to establish the feasibility and design of the project.	Long-term
Consent Application Submitted	The formal application has been officially submitted and is awaiting a decision from the authorities.	Mid-term
Consent Authorised	Approval has been granted by the authorities and construction can begin assuming the developer wishes to invest.	Mid-term
Pre Construction	The project has reached financial close/made a final investment decision and is moving towards offshore construction	Mid-term
Under Construction	The offshore construction is in progress. No turbines are yet energised.	Present
Partial Generation/Under Construction	At least one turbine has been energised and is feeding power to the grid. Part of the project is still under construction.	Present
Fully Commissioned	All turbines energised and feeding power to the grid.	Present
Dormant	The planning process for a country is moving forward but the wind farm is not explicitly include in plans. However, the windfarm has not formally been declined by the authorities or cancelled by the developer.	Not included
Failed Proposal	The application has been declined by the authorities.	Not included
Cancelled	The developer/owner has decided that the project is not viable.	Not included
Decommissioned	The project has come to the end of its lifecycle. The turbines and foundations are removed.	Not included
Unknown	The project is known to exist but no information is yet available as to its current status.	Not included

Appendix B

Choosing between AIS and VMS data

An important decision prior to identifying interactions between fisheries and current and future marine OR is to choose between VMS or AIS data to analyse fleet movements and patch-choice detection. Note that the positional accuracy of VMS and AIS are similar (Russo et al., 2016). Importantly, neither system is perfect since 36% of the European vessels belong to 'hidden' length classes, meaning they have an overall length < 12 metres and therefore are not mandatorily equipped with AIS or VMS tracking devices (Russo et al., 2019). This leads to large regional differences in data coverage, depending on the composition of the fleet, as illustrated for Spanish (0% coverage), Italian (3.2% coverage), and Croatian (80% coverage) fleets trawling the Mediterranean (Russo et al., 2019). AIS data transmissions can be as frequent as a few seconds, allowing fine-scale assessments of fleet movements and patch-choice (de Souza et al., 2016; Vespe et al., 2016). Contrary to VMS data, global AIS point-data can be freely obtained from GFW (Taconet et al., 2019). But, caveats exist as reviewed by Taconet and colleagues (2019), such as lack of satellite coverage, not all vessels carrying AIS transponders, transponders and data can be altered or switched-off, multi-gear vessels cannot be identified or differentiate between their fishing activities (de Souza et al., 2016; Le Guyader et al., 2017; Shepperson et al., 2018). This results in, for example, underestimating the offshore fishing activities (Russo et al., 2016; Taconet et al., 2019). A direct comparison of concurrent AIS and VMS scallop fishing data in the southern UK revealed that AIS data only captured 26% of the time spent fishing compared to VMS data (Shepperson et al., 2018). Moreover, contrary to VMS data (Hintzen et al., 2012; Lee et al., 2010), for AIS data there is no standardised workflow. In practice this means that AIS requires more data handling, wrangling, even machine-learning methods to define fishing activities, although some of this can be achieved using the R-package VMS tools (Hintzen et al., 2012).

Appendix C

One key obstacle when assessing the spatial overlap of fishing activities and areas designated for OR installations is the differing spatial resolution. Below, we illustrate two examples (Wind 264 and Wind 296) of the overlap analysis with OR for the three fishing effort data sets differing in spatial resolutions. Fishing effort sources comprised GFW data, OSPAR/HELCOM and at the high-resolution German EEZ data. The panels highlight the effects of the variation in spatial scales on the aggregation of fishing effort per planning site. The GFW and OSPAR/HELCOM data are rather conservative and might overestimate the actual fishing effort related to a respective OR polygon.

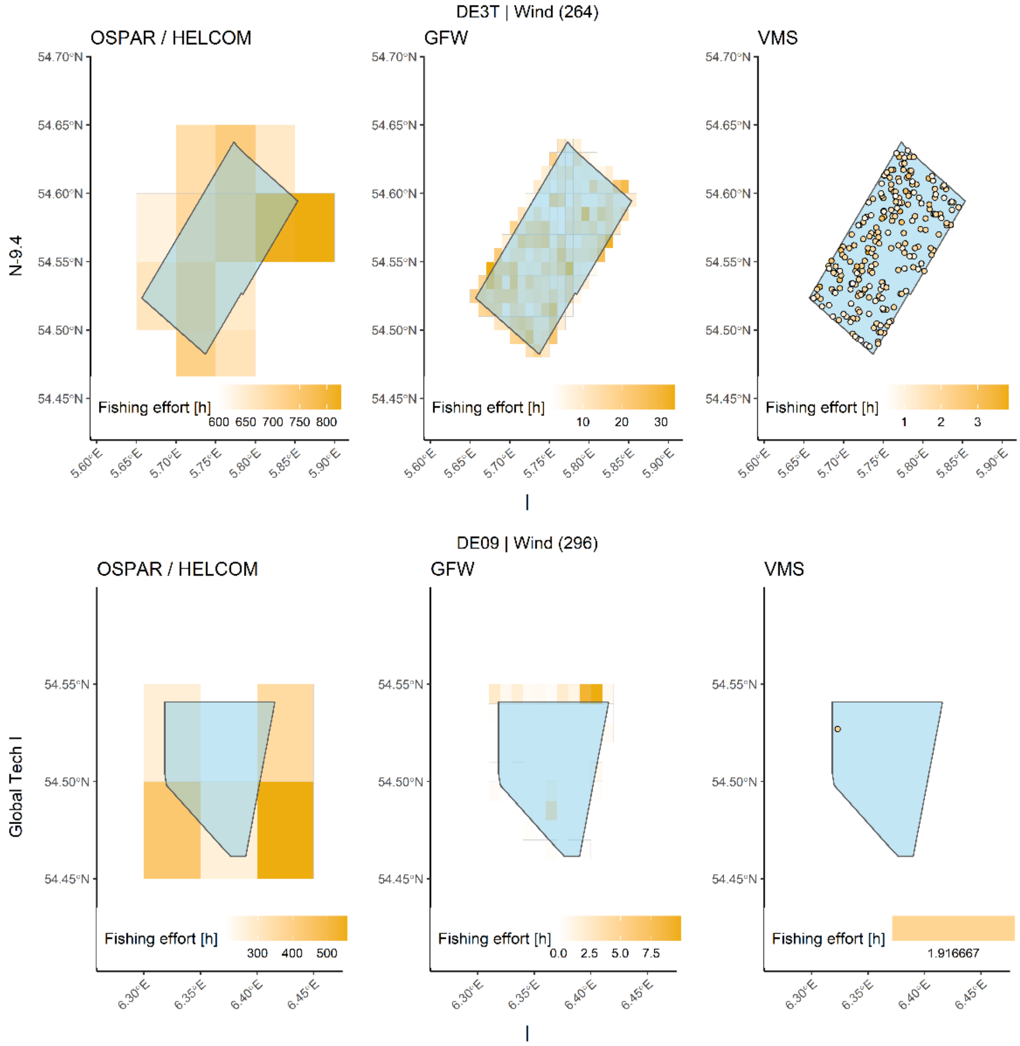


Figure I-C1. Comparison of total fishing effort estimated from three different data sources (GFW, OSPAR/HELCOM; VMS) overlapping with two different example OR sites.

Appendix D

Table I-D1. Total hours fished (GFW data) per gear group or métier overlapping with OR sites by regions and OR implementation scenario.

Region	Scenario	Total	Tuna purse seines	Trollers	Trawlers	Set long-lines	Set gill-	Purse seines	Pots and traps	Pole and line	Other seines	Other purse seines	Other gears	Fixed gear	Drifting long-lines	Dredge fishing
Atlantic	Present	16321	0		4040	68	9999	0	122	0	0	1442	67	562	7	14
	~ 2025	4934	0		3555	159	1111	0	2	1	18	48	20	20	0	0
	> 2025	123877	0	0	114121	1093	8385		96	14	5	110	14	30	7	2
Baltic Sea	Present	428		0	402	0	8					0	0	17		
	~ 2025	7199		0	6140	25	450					0	444	140		0
	> 2025	130007		10	114356	1345	11456	0	9	3		0	1089	1739		0
Celtic Sea	Present	7860		0	6306	0	389		1095		0	0	10	40	0	20
	~ 2025	42159			39122	2	443		2238		0	3	102	2		247
	> 2025	378018			286437	435	19147		41541	0	301	68	7737	1830	22	20500
Mediterranean	Present	0			0		0									

		North Sea			Total
~ 2025	> 2025	Present	~ 2025	> 2025	
7163	72259	89950	145932	442885	1468994
0	0	0	1	0	1
		0	1	139	150
7098	66778	72543	111000	346092	1177989
28	1820	657	2072	22959	30664
4	145	3003	11005	46904	112449
0	23		0	15	38
	27	4752	3193	4612	57687
		0	0	0	18
		209	1415	2245	4194
6	620	27	27	252	2602
0	2672	6292	4895	9760	33103
28	136	540	1774	7910	14768
0	38	0	0	0	75
	0	1926	10548	1997	35256

Table I-D2. Total hours fished (OSPAR data) per gear group or métier overlapping with OR sites by regions and OR implementation scenario.

Scenario	**Present**	**~ 2025**	**> 2025**	**Present**
Region	Celtic Sea			North Sea
Total	17811	115054	911685	436586
TBB_MOL				
TBB_DEF	6776	5228	150317	342209
TBB_CRU			24	41204
SSC_DEF	6	513	33915	9906
SDN_DEF	0	32	1950	753
OTB_SPF		33	24	569
OTB_MIX_DEF_BEN			237	
OTB_MIX_CRU_DEF	42	11042	13605	1590
OTB_MIX	230	2048	4284	9269
OTB_DEF	4573	6050	321340	20624
OTB_CRU	4547	86512	283534	1935
DRB_MOL	1638	3595	102455	8527

~ 2025	**> 2025**	
		Total
633438	1533857	3648430
0	2	2
401324	874961	1780816
3592	32444	77264
19462	37006	100808
4596	4135	11466
7500	2798	10925
	4	241
5687	234647	266613
55358	3500	74691
95848	227457	675893
12834	103134	492495
27234	13769	157217

Table I-D3. Total hours fished (HELCOM data) per gear group or métier overlapping with OR sites by regions and OR implementation scenario.

Region	**Scenario**	**DRB_MOL**	**OTB_DEF**	**OTB_SPF**	**SDN_DEF**	**SSC_DEF**	**Total**
Baltic Sea	Present		4965	69		64	5098
	~ 2025	66	16068	548	940	4	17625
	> 2025		180533	1869	2166	335	184904
Total		66	201566	2486	3106	404	207626

Table I-D4. Total hours fished (VMS data) per gear group or métier overlapping with OR sites by regions and OR implementation scenario.

Region	**Scenario**	**GNS_DEF**	**OTB_CRU**	**OTB_DEF**	**OTB_SPF**	**OTM_SPF**	**PTB_DEF**	**PTM_SPF**	**TBB_CRU**	**TBB_DEF**	**unknown**	**Total**
Baltic Sea	Present	1		3			2				79	85
	~ 2025			896				3			532	1430
	> 2025			439			8	5			155	607
North Sea	Present	2	7	112					1008	239		1368
	~ 2025		5	44		9			165	122		345
	> 2025		10303	9394	57	326			256	10266	80	30681
Total		3	10315	10888	57	334	10	8	1430	10626	845	34515

Supplementary Material – Chapter II

The uncertain future of the Norway lobster fisheries in the North Sea calls for new management strategies

Appendix A – German fishery clusters within the Nephrops fleet

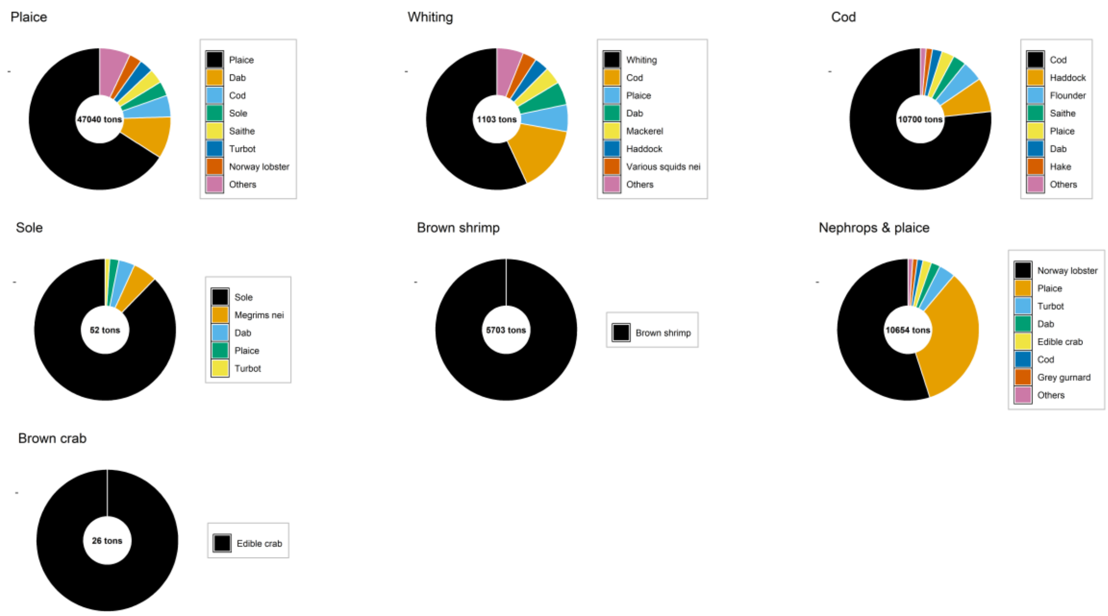


Figure II-A1. Catch composition per fishery cluster. The total aggregated catches per clusters are represented in the center of each pie diagram. Note that the clusters with less than 50 trips, i.e. *Whiting, Brown crab, and Sole*, were removed.

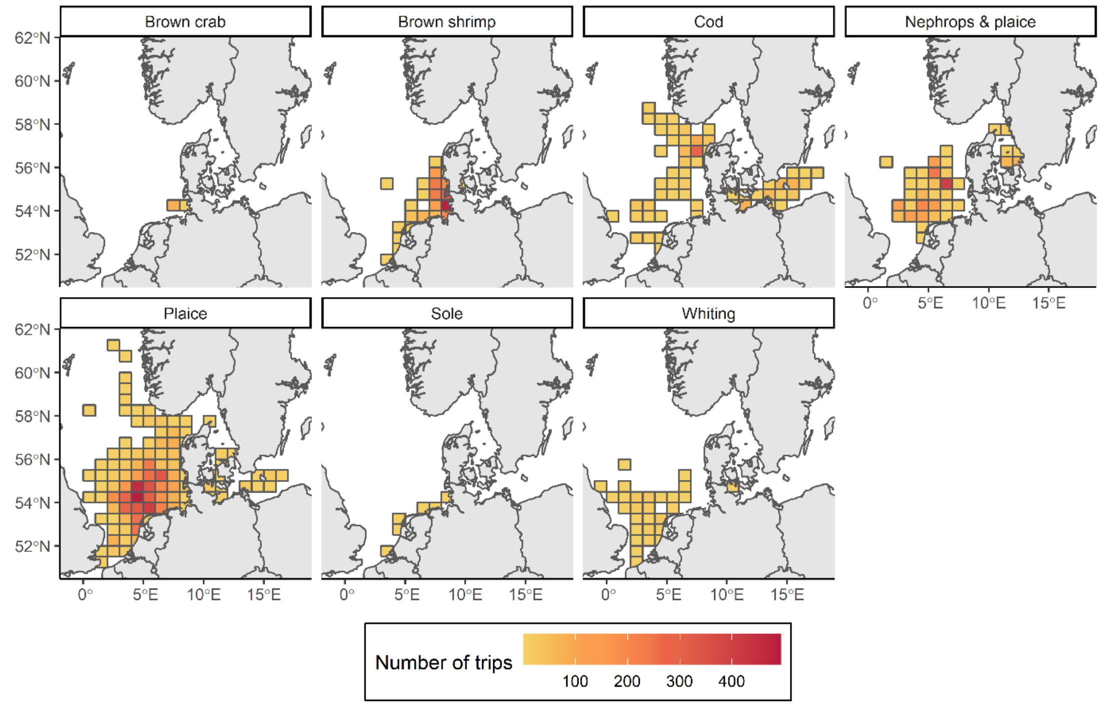


Figure I-A2. Spatial distribution of clustered fishing trips resolved by statistical ICES rectangle.

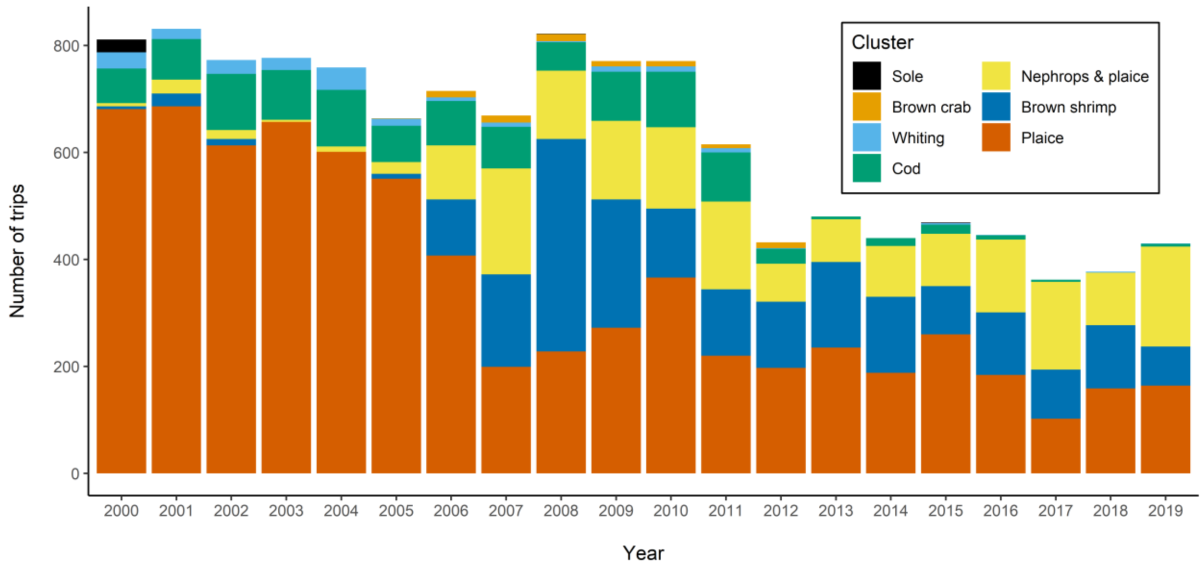


Figure II-A3. The number of trips per fishery cluster and year for all German vessels that ever participated in the Nephrops fishery.

Appendix B – Merging VMS and logbook data

In two steps we sorted VMS pings into fishing trips. First, pings of the same vessel between two points of ports were assigned as one fishing trip if the time spent in each harbour exceeded 200 minutes. Second, previously assigned fishing trip pings were split, if the time step or geographical distance between consecutive points exceeded 11 hours or 200 nautical miles. The thresholds used for the first step ensured that short harbour visits, e.g. created by passing vessels, were not used for the fishing trip classification, whereas the second step revealed undetected harbour stays indicated by temporal or geographical gaps in vessel tracks.

We determined the start and end times for each fishing trip in both logbook and processed VMS data. For each vessel, we identified temporal overlaps across logbook and VMS fishing trips and matched them whenever they overlapped. We solved multiple assignments of logbook trips to a single VMS trip depending on whether they were also assigned to other VMS trips or not. If they were, priority was given to the longest overlap and the other were removed, whereas, in the other case, all logbook trips remained assigned. The remaining unassigned logbook trips were merged with VMS points that were from the same ship, previously unassigned to any VMS fishing trip, and in between the starting and ending date of the logbook trip. In case there were still unmatched fishing trips we matched them based on the closest distance of mean times. Using this approach, we were able to assign on average 99% of all logbook fishing trips to 87% of the VMS data (Table II-B1).

Table II-B1. Merged logbook and VMS data as averages of yearly percentage and standard deviation (SD) at different steps of the merging procedure. The steps refer to the matching based on (I) temporal overlaps, (II) fishing trip start and end time from logbooks, (III) closest mean time among logbook and fishing trips. In general, the matching quality decreases with each step, and the first two steps are rooted in temporal intersections, whereas the third step merges fishing trips without temporal overlap.

Merging steps	**Assigned Logbook trips [%]**		**Assigned VMS data [%]**	
	mean	SD	mean	SD
(I) Temporal overlap	94.3	2.53	88.87	1.05
(II) Logbook times	97.0	2.28	88.88	1.05
(III) Mean time	99.25	0.47	89.08	1.11

Appendix C – International Nephrops fishery

Figure II-C1. Comparison and availability of international Nephrops landings and discards from sourced from STECF fisheries dependent information and ICES advices for Nephrops.

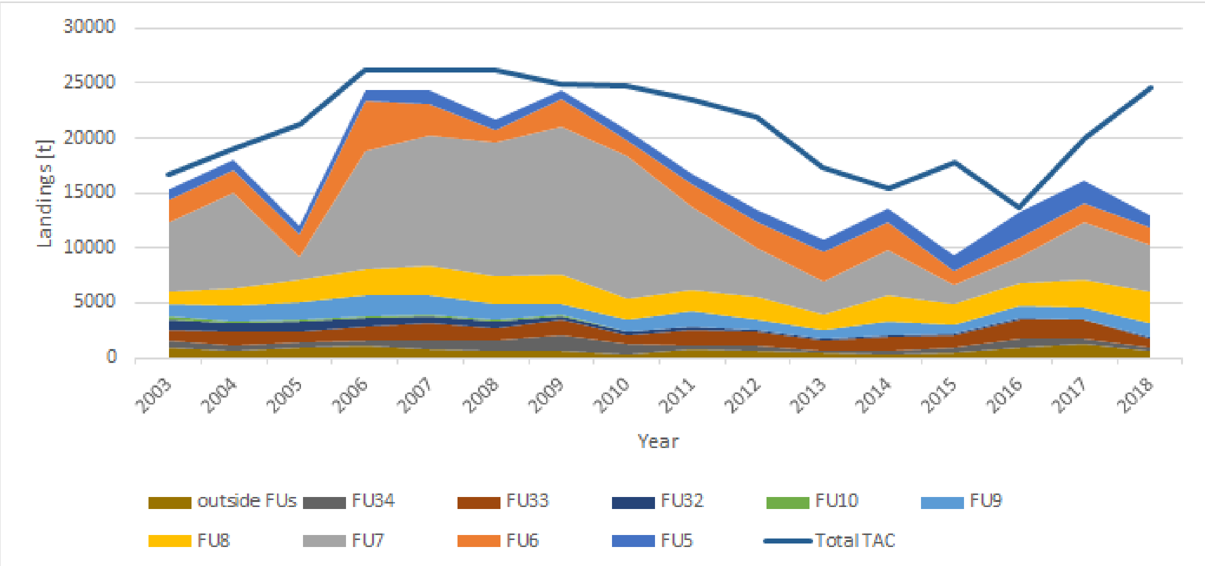


Figure II-C2. Total Nephrops landings of the functional units (FU) located in the North Sea between 2003 and 2018 in comparison to the total allowable catch (TAC). Note, that the TAC is provided for the EU fishing divisions IV (North Sea) and IIa (Norwegian Sea), but landing information are based on STECF data and thus exclude non-EU fleets, such as Norway.

Table II-C1. The total allowable catch (TAC) of Nephrops in the North Sea (fishing divisions 4 and 2a) for all European Union (EU) member states, the United Kingdom (UK), and the EU without the UK.

Year	TAC EU	TAC UK	TAC EU without UK
2003	16623	14399	2224
2004	18987	16446	2541
2005	21350	18492	2858
2006	26144	24380	1764
2007	26144	22644	3500
2008	26144	22644	3500
2009	24837	21513	3324
2010	24688	21384	3304
2011	23454	20315	3139
2012	21929	18994	2935
2013	17350	15027	2323
2014	15499	13424	2075
2015	17843	15456	2387
2016	13700	11865	1835
2017	20034	17353	2681
2018	24518	21237	3281
2019	22103	19145	2958
2020	23002	19924	3078

Appendix D – German Nephrops fishery

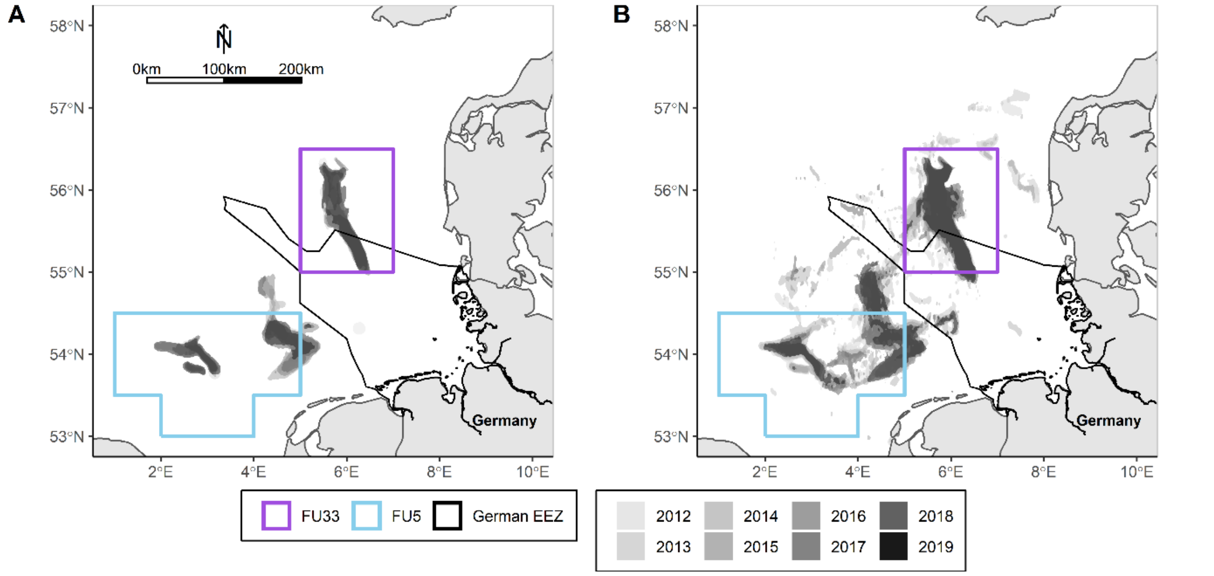


Figure II-D1. Annual fishing core areas of German fishery clusters catching Nephrops: *Nephrops & plaice* (A) and *plaice* (B). The gradient represents the different years, starting from 2012 (grey) to 2019 (dark). Relevant functional units (FU) and the German EEZ are colour-coded.

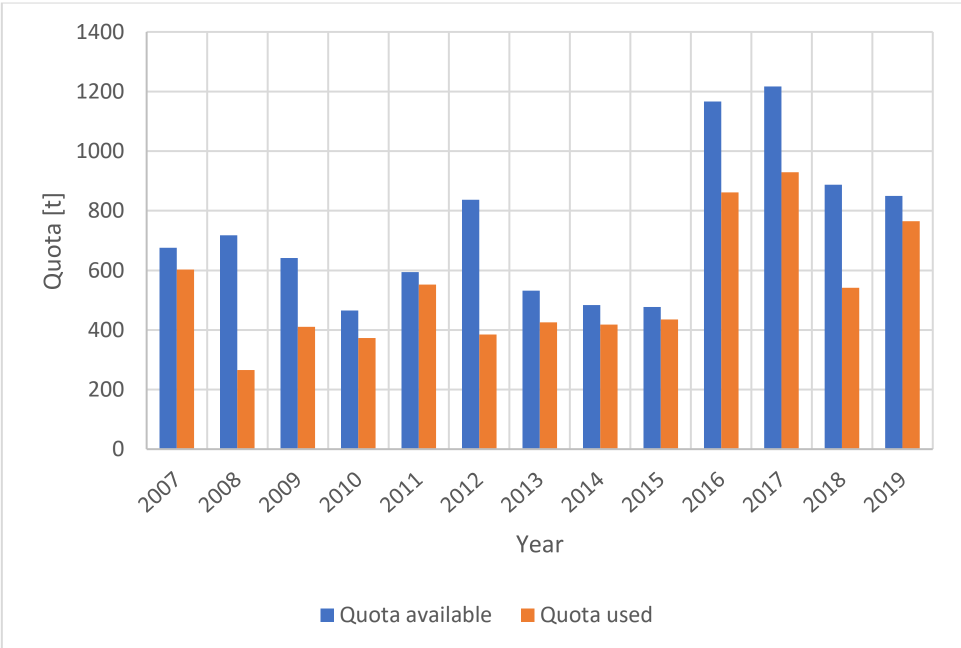


Figure II-D2. German Nephrops quota and catches per year.

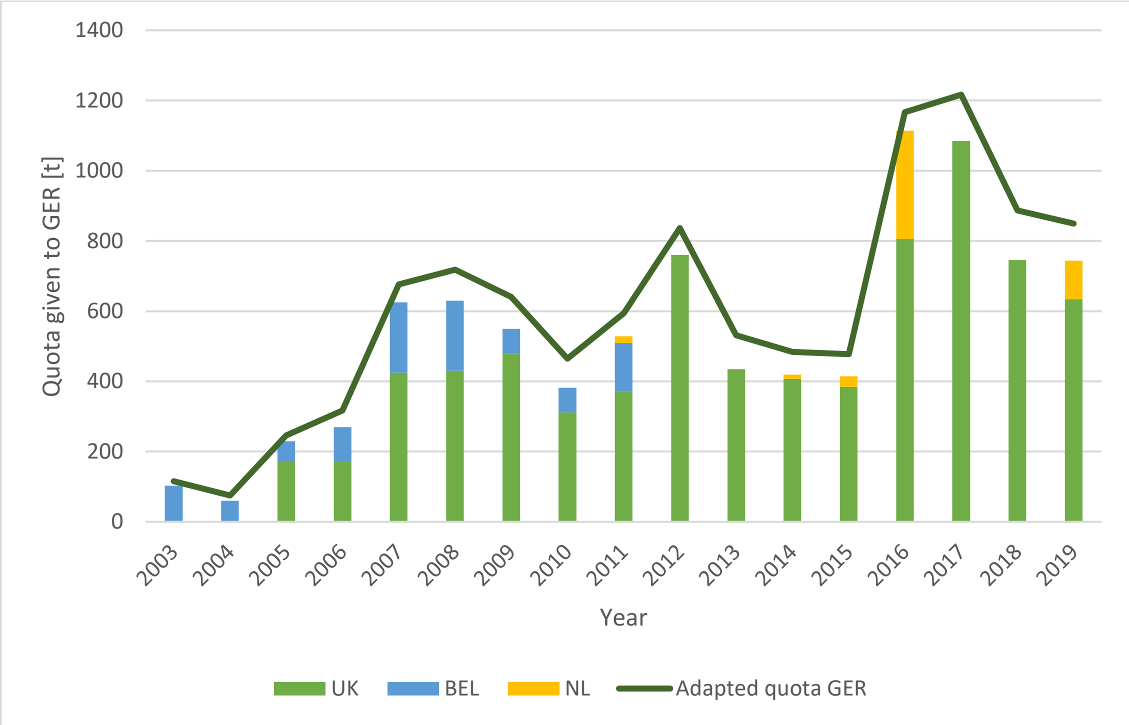


Figure II-D3. Nephrops quota given to Germany from the UK, Belgium and the Netherlands between 2003 and 2019. The adapted quota includes all swaps as well as Germany's original quota and quota transferred from the previous year (quota revisions).

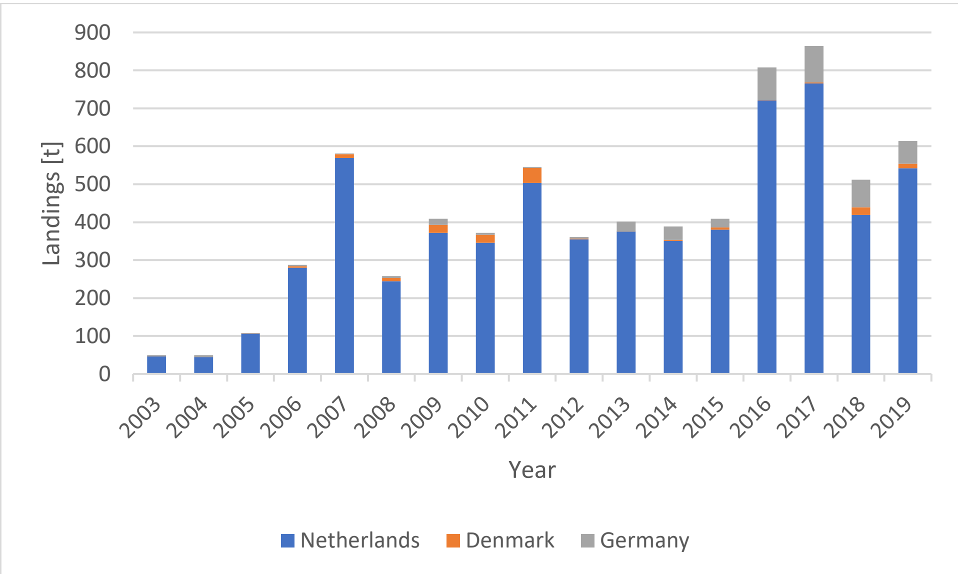


Figure II-D4. Yearly German Nephrops catches landed in German and international ports.

Table II-D1. Nephrops quota (in tons) received from the UK, Belgium and the Netherlands between 2003 and 2019

	UK	**Belgium**	**Netherlands**
2003	3	100	-
2004	-	60	-
2005	170	60	-
2006	170	100	-
2007	425	200	-
2008	430	200	-
2009	480	70	-
2010	312	70	-
2011	371	138	20
2012	760.5	-	-
2013	435	-	-
2014	407	-	12
2015	385	-	30
2016	806	-	308
2017	1085	-	-
2018	746	-	-
2019	634	-	110
Average [t]	476.2	110.9	95.9

Supplementary Material – Chapter III

Sustainable co-location solutions for offshore wind farms and fisheries need to account for socio-ecological trade-offs

Appendix A

Table III-A1: Summary statistics of the standardised total brown crab catches as biomass (kg) and numbers (Cpue; females = F; males = M; Carapace width < 130 mm; Carapace width ≥ 130 mm) from 41 sampling stations comprising the arithmetic mean (mean), standard deviation (sd), minimum value (min), maximum value (max), and range of values (max-min).

Measure	**mean**	**sd**	**min**	**max**	**range**
Soaking time (min)	1961	653	1406	2865	1459
Cupe (kg·24h^{-1})	8.9	3.0	4.0	16.3	12.3
Cupe (N·24h^{-1})	14.5	4.2	7.0	25.0	18.0
Distance to nearest turbine (m)	918	539	213	2650	2437
Depth (m)	23.0	0.8	22.0	24.8	2.8
Surface temperature (C°)	17.1	1.7	14.0	19.0	5.0
Bottom temperature (C°)	16.4	2.0	14.2	18.8	4.6
Cupe $_{F}$ (kg·24h^{-1})	0.9	0.6	0.0	2.9	2.9
Cupe $_{M}$ (kg·24h^{-1})	7.9	2.8	3.9	15.1	11.1
Cupe $_{\geq 130\ mm}$ (kg·24h^{-1})	8.1	3.0	2.5	15.7	13.2
Cupe $_{< 130\ mm}$ (kg·24h^{-1})	0.8	0.5	0.0	2.0	2.0

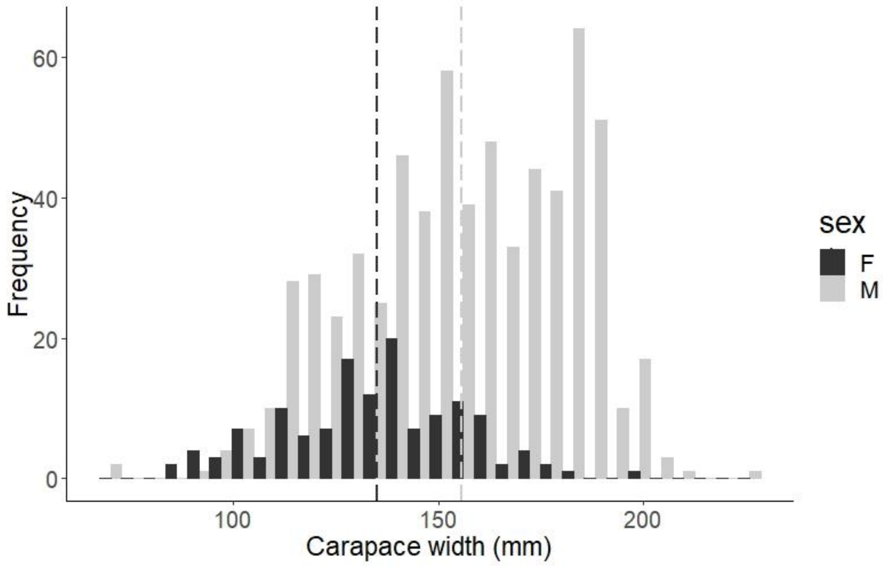


Figure III-A1: Frequency distribution of the carapace width (mm) of the sampled female (F, black) and male (M, grey) brown crabs, dashed lines indicate the respective mean width (F = 135 mm, M =156 mm).

Appendix B

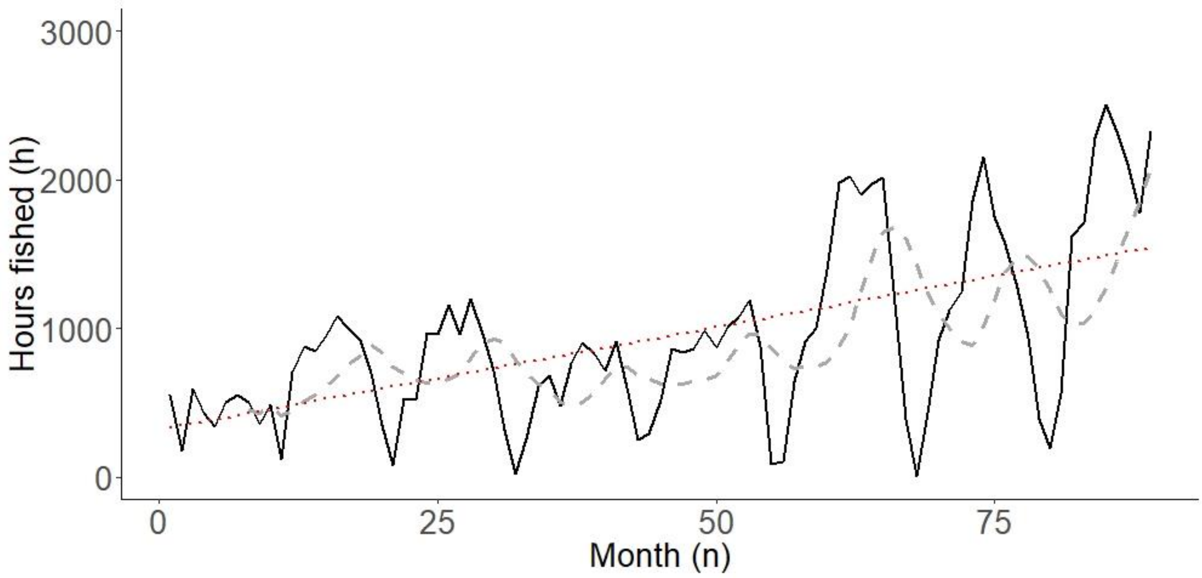
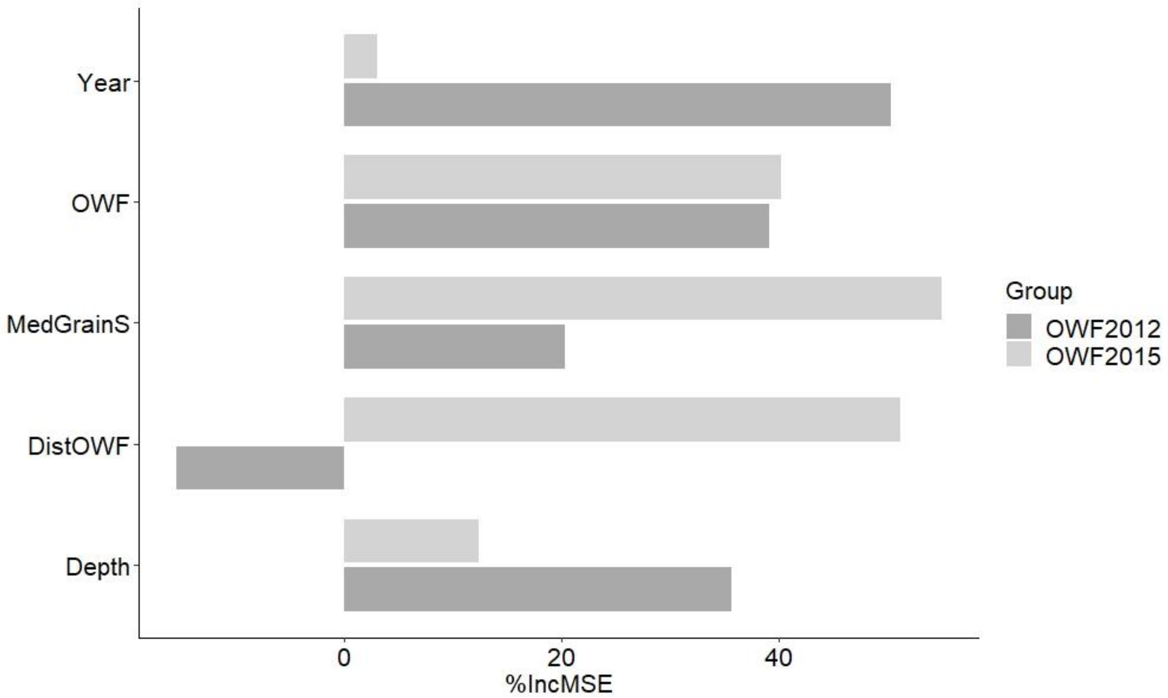


Figure III-B1: Within the German North Sea the temporal pattern of the total hours fished with pots (h) showed an increase of fishing effort during the summer month of each year (black solid line). Detrending the data with a moving average of 8 years (grey dashed line) confirmed the fitted linear increase of fishing effort over time (red line).

Appendix C

Figure III-C1: Calculated rank importance as increased mean square error (%; IncMSE) of the explanatory variables determining the allocation of the total annual fishing effort (h) around OWFs being in operation since 2012 (dark grey bar) and 2015 (light grey bar), respectively.



Appendix D

Table III-D1: Mean cost and effort data for German beam trawlers (18 - 24 m) targeting brown shrimp extracted from (EUMOFA, 2019c), estimated costs for beam trawlers deploying traps. We assumed a reduction of 50 % in fuel consumption and energy costs and repair and maintenance costs. When targeting brown crab with traps, towing resistance does not apply, and the auxiliary engine is not in use. Wear and tear of equipment is considerably lower compared to beam trawling. Other costs remain unchanged. All variable costs except for crew costs were estimated per GT-fishing day. Crew costs were estimated as share of the revenue.

	German beam trawler 18-24 m	**German beam trawler 18-24 m using traps**	**Assumption**
Energy costs / day (€)	280.6	140.3	-50%
Repair and maintenance costs / day (€)	329.4	164.7	-50%
Other variable costs / day (€)	24.4	24.4	Unchanged
Sum (energy, repair, other variable costs)/day	634.4	329.4	
Crew share on revenue	22%	22%	Unchanged

Table III-D2: Break even scenarios for different combinations of days of fishing and crab prices.

Fishing days	**Variable costs (€)**	**Depreciation per day (€)**	**Break even revenue per day ($€\cdot d^{-1}$)**	**Break even catch ($kg\cdot d^{-1}$) at 0.66€/kg**	**Break even catch ($kg\cdot d^{-1}$) at 1 €/kg**	**Break even catch ($kg\cdot d^{-1}$) at 1.5€/kg**	**Break even catch ($kg\cdot d^{-1}$) at 2€/kg**	**Break even catch ($kg\cdot d^{-1}$) at 3€/kg**
1	403	13000	16263	24641	16263	10842	8132	5421
5	2013	2600	3575	5417	3575	2383	1788	1192
10	4026	1300	1989	3014	1989	1326	995	663
15	6039	867	1460	2212	1460	973	730	487
20	8052	650	1196	1812	1196	797	598	399
25	10065	520	1037	1571	1037	691	519	346
30	12078	433	932	1412	932	621	466	311

Supplementary Material – Chapter IV

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

Appendix A – Exploratory review of drivers of demersal fishing activity in the North Sea

We performed an exploratory literature review in Web of Science on the 10.05.2021 using the following search string: TS = ((fisher* OR fleet) NEAR (*demersal OR benth* OR bottom OR beam)) AND TS = (motivation* OR behav* OR driver OR preferenc* OR choice OR strateg* OR tactic*) AND TS = ("North Sea") NOT TS = (freshwater OR lake). The first two terms filter for articles about demersal fisheries, whereas the third term specifies towards fishing behavior. The last two terms select studies focusing on the North Sea and exclude those about freshwater systems. This search retrieved 104 articles, which we reviewed for their relevance by retaining only those that focused on the North Sea and specifically analyzed factors influencing demersal fishing activity. We defined fishing activity as any parameter related to fishing, i.e. fishing effort, catches, landings, choices about fishing location, target species and gear, as well as the decision whether to go fishing or not. From those 104 articles, eight studies met our criteria. All the others did not analyze factors that influenced demersal North Sea fishing activity. We complemented those with eight additional articles that did not show during our Web of Science search, but met the criteria and were either known to the authors, found within references of the relevant articles from the literature review, or suggested by one anonymous reviewer.

Table IV-A1. Summarized results of the explorative literature search including the criteria that qualified the respective study as relevant.

	Factor	Effect on fishing activity	Reference
Biophysical	Weather	Smaller vessels are sensitive to wind and currents	(Bastardie et al., 2013; Christensen and Raakjær, 2006)
		Different fleet operate in areas with different wave heights	(van der Reijden et al., 2018)
	Season	Availability fish stocks influence the decision whether to go fishing	(Christensen and Raakjær, 2006)
		Varying catchability	(Rijnsdorp et al., 2006)
		Varying fishing effort	(Rijnsdorp et al., 2008)
		Varying value per unit effort	(Oostenbrugge et al., 2008)
	Oceanography	Bathymetry, bottom temperature, shear stress, and salinity affect the distribution of different fishing fleets.	(van der Reijden et al., 2018)
	Sediment type	Different sediments affect the distribution of different fishing fleets	(Hintzen et al., 2019; van der Reijden et al., 2018)
Economic	Business structure	Decisions in owner-operator business are more influence by personal matters than in larger companies.	(Schadeberg et al., 2021)
	Fish price	High prices have positive effect on decision to go fishing	(Bastardie et al., 2013; Christensen and Raakjær, 2006)
		Negative correlation with landing weights	(Rijnsdorp et al., 2008)
	Fuel price	Rising fuel prices have a negative effect on distance to shore, as well as vessel speed.	(Poos et al., 2013)
	Vessel size	The smaller the more likely to abide regulations	(Christensen and Raakjær, 2006)

	Engine power	Larger engine power lead to an increase of catchability	(Rijnsdorp et al., 2006; Sys et al., 2016)
Socio-cultural	Competition	The competition with Dutch beam trawlers from Mo – Thu leads to increased landing rates of sole for the Belgian fleet	(Sys et al., 2016)
		In areas with more vessels, the values per unit effort decreased	(Poos & Rijnsdorp, 2007)
	Experience	The more time fishers spent at a fishing ground, the more likely it is that the fisher chooses the same site	(Andersen et al., 2012; Bastardie et al., 2013; Hutton et al., 2004; Poos & Rijnsdorp, 2007; Tidd et al., 2012)
		Positive influence of past revenue at one fishing site to choose the same site	(Bastardie et al., 2013; Tidd et al., 2012)
		Negative influence of past costs at one fishing site to choose the same site	(Tidd et al., 2012)
	Skipper age	The older the more likely to abide regulations	(Christensen and Raakjær, 2006)
	Social network	Fishers with a small geographical mobility are more likely to consult colleagues	(Christensen and Raakjær, 2006)
	Religion & Holidays	Lower fishing effort during a holiday	(Rijnsdorp et al., 2008)
		Fishers prefer to be home during weekends	(Schadeberg et al., 2021)
Regulations	Fishing quota	Lowest quota in a mixed fishery determines the maximum fishing capacity (choke species)	(Ulrich et al., 2011)
	Area closure	Displacement to other fishing grounds	(Poos & Rijnsdorp, 2007)

	Temporal closures	Influencing the fisher's location choice	(Andersen et al., 2012)
	Landing obligation	Increased amount of undersized catches in a mixed fishery lead to an earlier stop of the entire fishery (choke species)	(Batsleer et al., 2016)

Appendix B – Fishing fleet information

Table IV-B1. Criteria used to group German fishing vessels into fleets. The catch criteria describe percentages relative to the total annual catch of the respective vessel. The gear abbreviations refer to otter trawls (OTB), otter twin trawl (OTT), electric pulse trawl (PUL), and beam trawl (TBB).

Fleet	**Relative yearly catch [%]**		**Gear**	**Mesh size [mm]**
	Plaice and sole	Brown shrimp		
Mixed demersal (MDS)	>= 50		OTB & OTT	>= 80
Flatfish (FF)	>= 50		TBB & PUL	80 to < 100
Brown shrimp (BS)		>= 50	TBB	0 to < 80

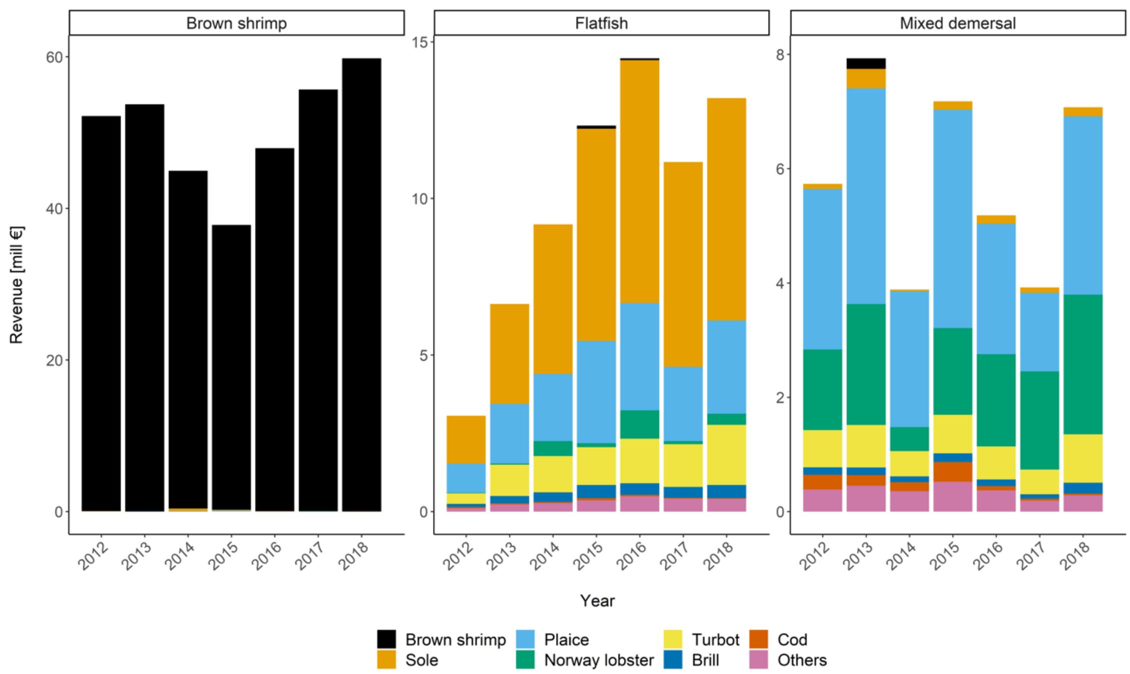


Figure IV-B1. Composition of revenue by species and fleet. Note that y-scales (revenue) differ among panels.

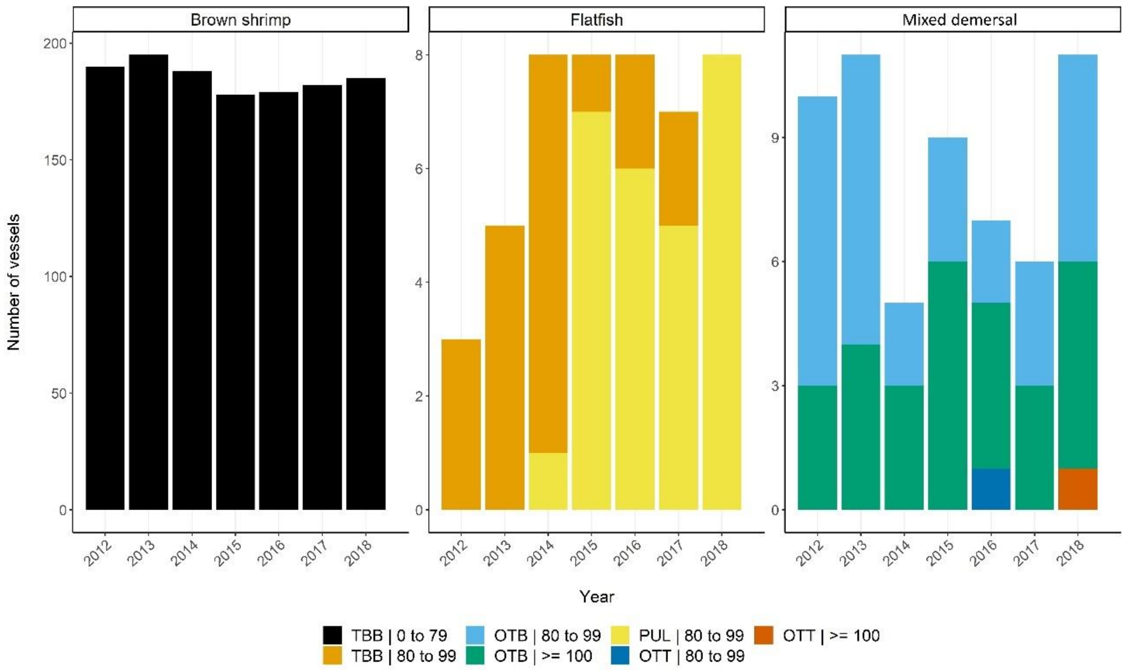


Figure IV-B2. The number of vessels per fleet (panel) and combination of gear and mesh size (color). The gear abbreviations refer to beam trawl (TBB), otter trawls (OTB), electric pulse trawl (PUL), and otter twin trawl (OTT).

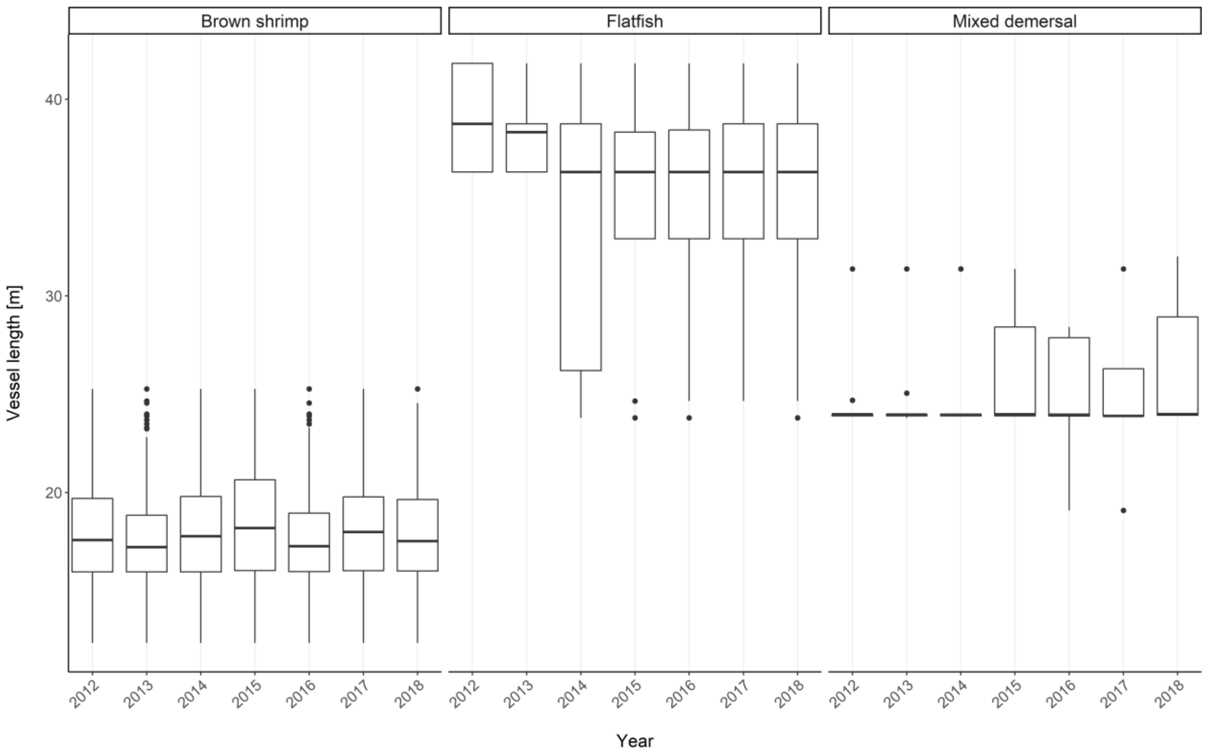


Figure IV-B3. Ranges of vessel sizes per year and fleet. Center bars represent median values.

Appendix C – VMS and logbook data processing

We obtained VMS data for each fleet and year by matching vessel reference numbers and deleted duplicates of time stamps and vessels. We identified points within a 3km radius of harbors using the *pointInHarbour* function of the VMS tools package (Hintzen et al., 2012) for the R programming language (R Core Team, 2023). We complemented the VMS tools harbor data base to capture all port areas in the study area. Subsequently, we removed all harbor points except the first and last of each period of consecutive harbor pings per vessel. Following a method proposed by Kroodsma et al. (Kroodsma et al., 2018), we calculated time steps and geographical distances between pings of each vessel by summing up half of the times and distances from the previous to the current, and current to the next ping, respectively. Based on the resulting distances and time steps, we calculated the speed in knots (nautical miles per hour) for each ping and removed those above 25 knots, representing unrealistic speeds and thus erroneous information. In two steps we sorted VMS pings into fishing trips. First, pings of the same vessel between two points of ports were assigned as one fishing trip if the time spent in each harbor exceeded 200 minutes. Second, previously assigned fishing trip pings were split, if the time step or geographical distance between consecutive points exceeded 11 hours or 200 nautical miles. The thresholds used for the first step ensured that short harbor visits, e.g. created by passing vessels, were not used for the fishing trip classification, whereas the second step revealed undetected harbor stays indicated by temporal or geographical gaps in vessel tracks.

We determined the start and end times for each fishing trip in both logbook and processed VMS data. For each vessel, we identified temporal overlaps across logbook and VMS fishing trips and matched them whenever they overlapped. We solved multiple assignments of logbook trips to a single VMS trip depending on whether they were also assigned to other VMS trips or not. If they were, priority was given to the longest overlap and the other were removed, whereas, in the other case, all logbook trips remained assigned. The remaining unassigned logbook trips were merged with VMS points that were from the same ship, previously unassigned to any VMS fishing trip, and in between the starting and ending date of the logbook trip. In case there were still unmatched fishing trips we matched them based on the closest distance of mean times (Bastardie et al., 2010b). Using this approach, we were able to assign on average 99% of all logbook fishing trips to 87% of the VMS data (Table IV-C1).

Table IV-C1. Merged logbook and VMS data as averages of yearly percentage and standard deviation (SD) at different steps of the merging procedure. The steps refer to the matching based on (I) temporal overlaps, (II) fishing trip start and end time from logbooks, (III) closest mean time among logbook and fishing trips. In general, the matching quality decreases with each step, and the first two steps are rooted in temporal intersections, whereas the third step merges fishing trips without temporal overlap.

Merging steps	**Assigned Logbook trips [%]**		**Assigned VMS data [%]**	
	mean	SD	mean	SD
(I) Temporal overlap	94.3	2.53	88.87	1.05
(II) Logbook times	97.0	2.28	88.88	1.05
(III) Mean time	99.25	0.47	89.08	1.11

Due to the merged fishing trips, we were able to join gear information from the logbooks with VMS pings. Missing gear information in logbooks were complemented with the German fishing vehicle register and, if also missing in there, with the European fleet registry. We split the VMS data into groups with regard to gear and year and used the *activityTacsat* function of the VMS tool package (Hintzen et al., 2012) to classify pings into steaming, hauling, and fishing. We removed all steaming and hauling pings, so that the time step values of the remaining pings represented fishing effort.

Appendix D – data sources

Table IV- D1. Characteristics and sources of data used for the boosted regression tree analysis.

Name	Significant wave height	10 metre wind gust	100 metre U wind	100 metre V wind	Bottom temperature	Mixed layer depth
Abbreviation	SWH	10fg	100u	100v	bottomT	MLD
Unit	[m]	[ms^{-1}]	[ms^{-1}]	[ms^{-1}]	[°C]	[m]
Spatial resolution	0.5° × 0.5°	0.25° × 0.25°	0.25° × 0.25°	0.25° × 0.25°	0.111° x 0.067°	0.111° x 0.067°
Temporal resolution	hourly	hourly	hourly	hourly	daily	daily
Description	Average height of the highest third of surface ocean/sea waves generated by wind and swell.	Maximum 3 second wind at 10 m height as defined by WMO	Horizontal speed of air moving towards the east, at a height of 100 metres above the	Horizontal speed of air moving towards the north, at a height of 100 meters above	Potential water temperature at sea floor	Depth where the density increase compared to density at 3m depth corresponds to
Data set	ERA5 (HRES)	ERA5 (HRES)	ERA5 (HRES)	ERA5 (HRES)	NORTHWESTSHELF_REANALYSIS_	NORTHWESTSHELF_REANALYSIS_
Source	https://cds.climate.copernicu	https://cds.climate.copernicu	https://cds.climate.copernicu	https://cds.climate.copernicu	https://marine.copernicus.eu/	https://marine.copernicus.eu/

Name	Salinity	Bathymetry / elevation	Substrate type	Fish market prices	Crude oil price	Fishing quota
Abbreviation	SAL	-	-	-	-	-
Unit	[‰]	[m]	Categorical	[€]	[US$ barrel^{-1}]	[t]
Spatial resolution	0.111° x 0.067°	0.0083° × 0.0083°	Polygon	-	-	-
Temporal resolution	daily	-	-	weekly	daily	monthly
Description	Seawater salinity	-	Distribution of substrate types based on monitoring and model data.	The European Market Observatory for Fisheries and Aquaculture products (EUMOFA).		Published in irregular intervals, but more or less monthly around the 15th (+/- 2
Data set	NORTHWESTSHELF_REANALYSIS_	GEBCO_2014	EUSM_2019_substrate	20191205_WEEKLY_FIRST_SA	crudeOilPricesBrent	-
Source	https://marine.copernicus.eu/	https://www.gebco.net/	https://www.emodnet.eu/	https://www.eumofa.eu/	https://fred.stlouisfed.org/	https://www.ble.de/

Appendix E – Boosted regression tree details

Boosted regression tree analysis (BRT) - sometimes called gradient tree boosting - is a supervised machine learning technique that combines the advantages of tree-based models with boosting. Starting with residuals of the null model, BRT constructs decision trees in an iterative process based on the prediction errors of the previous tree (Friedman, 2001). The outcome values of each tree, so called leaves, are summed up to form predictions depending on the features of the respective data point and thus the path in the tree. BRT will continue to construct new trees until there is no further improvement for model predictions or the maximum number of trees is reached. Each leave value is multiplied with a learning rate typically between 0.2 and 0.01 to shrink the contribution to the model improvement and leaving more space for additional trees. The maximum number of leaves in each tree is controlled by the maximum tree depth, determining the number of tree levels. For each new tree, the model considers a random subset of the data, the bag fraction, which prevents the model from overfitting.

We used the *xgboost* package in R for BRT tuning and implementation (Chen et al., 2019; R Core Team, 2023). In contrast to other common used BRT approaches, the *XGboost* technique has several advantages: it utilizes a more sophisticated boosting algorithm, including several additional tuning parameters; it applies an internal mechanism to find good replacements of missing values; and it is scalable, meaning that run-time may be reduced by parallel computation (Chen and Guestrin, 2016). *XGboost* finds the ideal data separation by considering all possible splits for the initial tree root and then selecting the best tree based on an internal ranking. Two tuning parameters regulate the size of trees in *XGboost*, restricting the maximum level of trees (*max_depth*) and the minimum weight of each new leave (*min_child_weight*). In general, larger trees capture more complex interactions and thus *max_depth* determines to which degree interactions are taken into account. On the other hand, setting a threshold to the weight of each new leave (*min_child_weight*) prevents the model from learning very specific cases, i.e. overfitting. Moreover, *XGboost* uses tree pruning, meaning that trees are always formed completely and then pruned backwards by cutting of branches if their gain of model prediction improvement is negative. In addition to the bag fraction and learning rate, *XGboost* includes two more mechanisms to avoid overfitting, namely feature sampling and regularization. The former means that each new tree selects a random subset of features, based on an input value between 0 and 1. Regularization refers to a method of panelizing complexity in a model and hence prevent it from overfitting (Hastie et al., 2009).

Appendix F – Additional BRT results

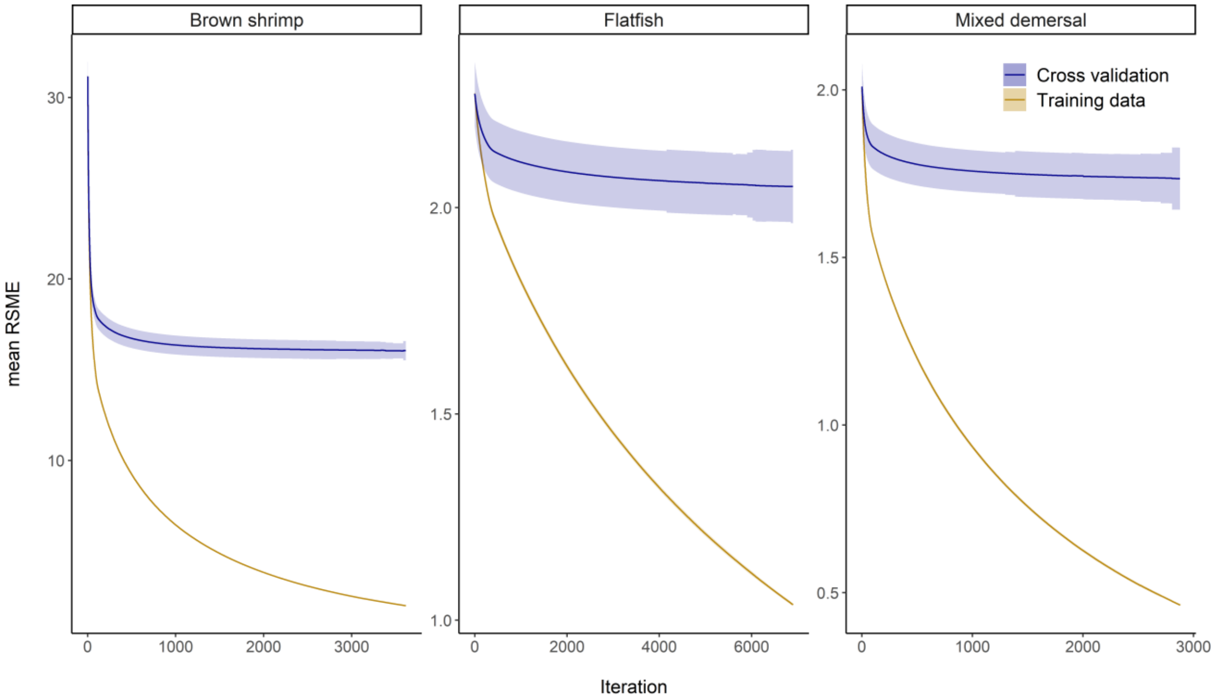


Figure IV- F1. Learning curves of the three boosted regression tree (BRT) models with iteration (tree) on the x-axis and root mean square error (RMSE) on the y-axis. The blue line represents the RMSE calculated by internal cross-validation and the red line through a test data set. Lines represent mean values and ribbons standard deviation computed by using all 10 models of the respective fishery.

Table IV- F1. Final boosted regression tree hyperparameter after tuning the three fleet models.

Fleet	Learning rate	max_depth	min_child_ weight	subsample	colsample_ bytree	n_tree
Brown shrimp	0.05	9	2	0.9	0.9	3048
Flatfish	0.01	10	4	0.9	0.6	5837
Mixed-demersal	0.05	10	4	0.8	0.7	2181

Table IV- F2. Model performance measured for the boosted regression tree models. Reported are the deviance explained (r^2) and four error measures, i.e. absolute error (MAE) and root mean square error (RMSE), as well as their standardized versions (SRMSE and SMAE).

Fleet	r^2	MAE	RMSE	SRMSE	SMAE
Brown shrimp	0.6679	7.5462	17.854	0.578	0.2443
Flatfish	0.1791	0.7213	2.0817	0.9104	0.3155
Mixed-demersal	0.214	0.6172	1.78	0.8904	0.3087

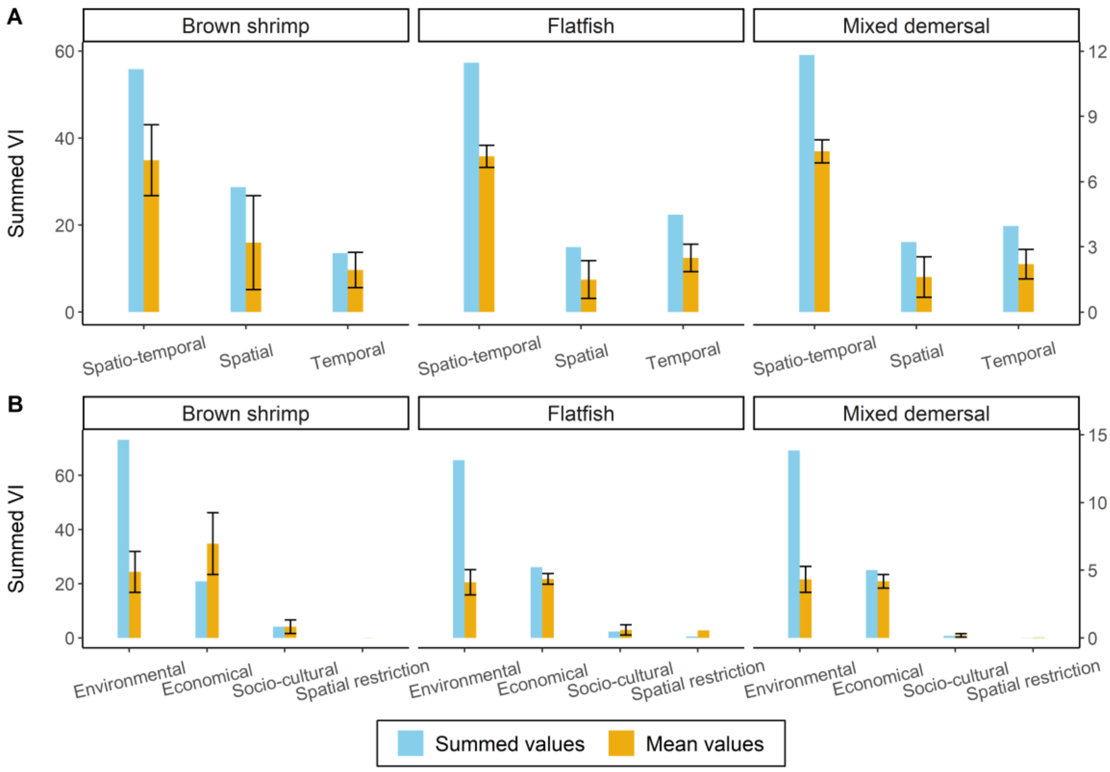


Figure IV- F2. Variable importance (VI) of the fleet-specific Boosted Regression Tree (BRT) models. Depicted are summed and averaged VI values of all features of the three fleet models grouped by their dimension (A), and according to their type (B). SE - Standard error of the mean.

Appendix G – Model data distribution

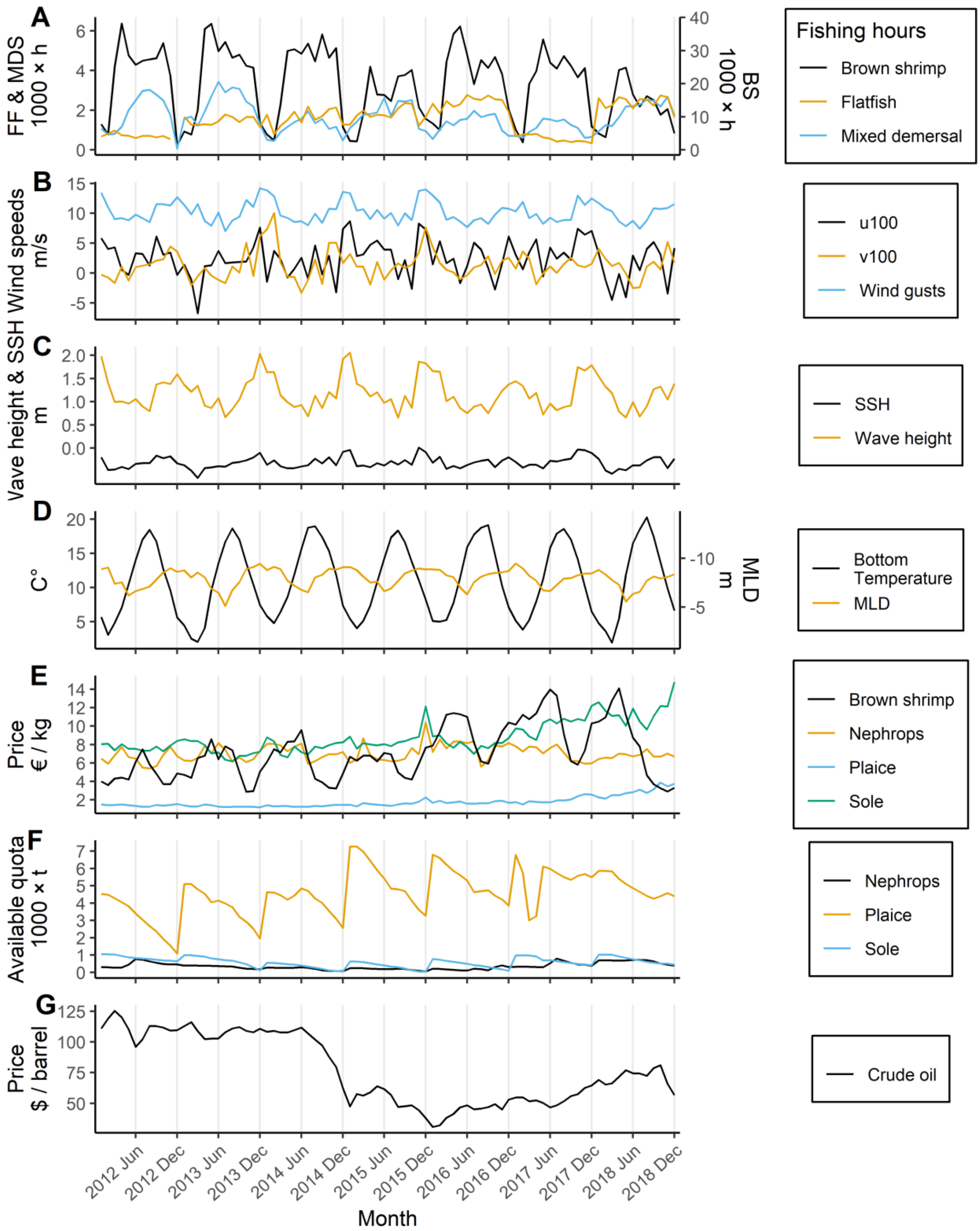


Figure IV- G1. Monthly aggregates fishing hours of each fleet (A), and monthly averages of numerical explanatory variables (B-G).

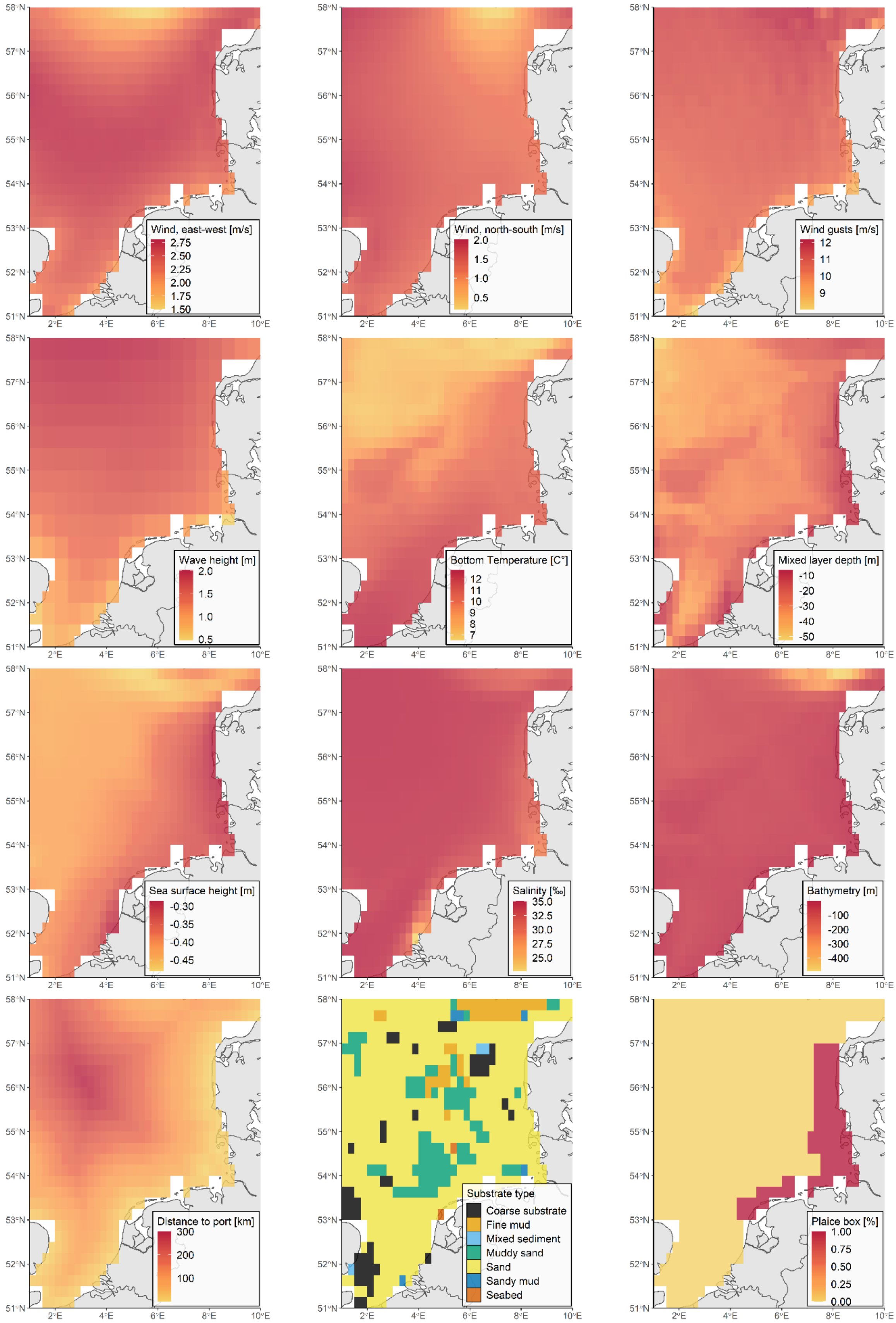


Figure IV- G2. Spatial parameters used for modelling. In case of temporally dynamic parameters, average values per grid cell (0.25° lon × 0.25° lat) are depicted.

Supplementary Material – Chapter V

Simulating Fishery Dynamics by Combining Empirical Data and Behavioral Theory

Model documentation

for

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

Table of contents

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., 2020, 2010, 2006; 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 factors/drivers of the model?	Oceanographic parameters: bottom temperature, mixed layer depth, and salinity (daily) 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 and 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 V-A3).
		II.i.e At which level of aggregation	See Table V-A3.

		were the data available?	
	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 decision-making process?	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 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	Agents' decisions are influenced by state variables and the current model environment, but the rules for decision

		in the decision process? How do individuals change their decision rules over time as consequence of their experience?	making remain the same. Therefore, our model includes adaptation, but not learning, as defined by Dibble et al. (2006).
		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 cognition and the costs for gathering information explicitly included in the model?	No.
	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	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

		of their decisions?	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 between the agents?	See Table V-A1.
		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	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)

		are random or partly random?	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?	https://www.comses.net/. (Letschert et al., 2024)
	III.ii Initialisation	III.ii.a What is the initial state of the model world, i.e. at time t = 0	Global parameters (environmental and economic) are filled by using historic data sets.

		of a simulation run?	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 V-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	See Table V-A2 and Table V-A3

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

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

Model dimensio	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 V-A2. Most important global, agent, and patch parameters.

Model dimensio	**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 V-A

	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 V-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
Patch	passable?	Whether the patch is passable for navigation	See Table V-A3

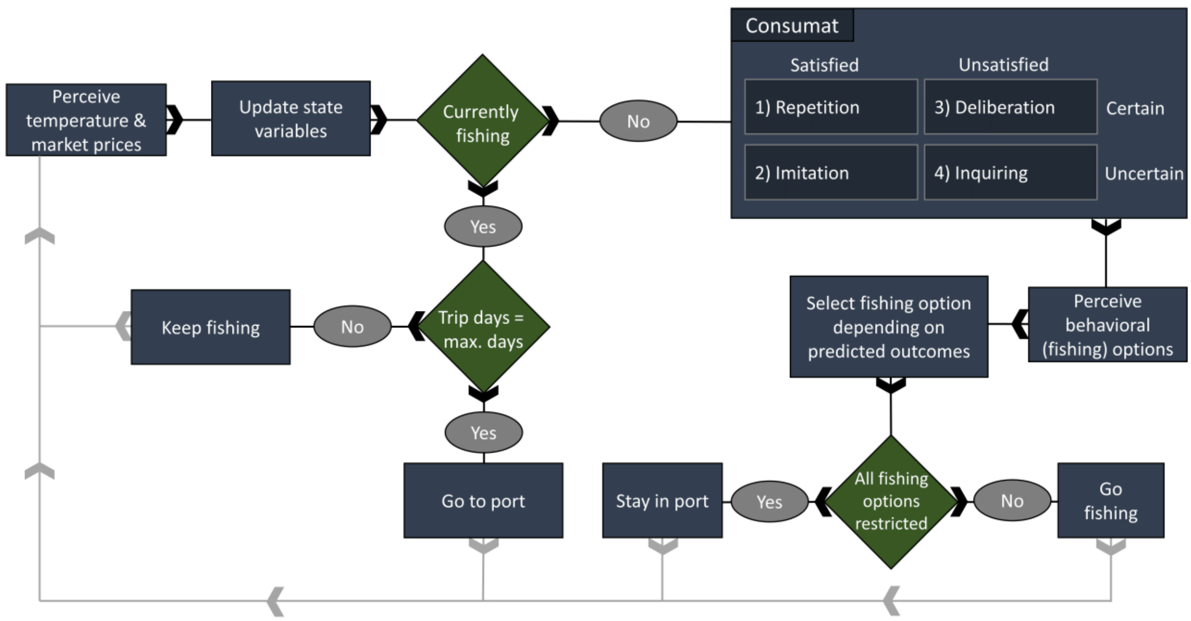


Figure V-A1. Infographic of the daily cycle each agent passes through in every model step.

1.2 Submodels

1.2.1 Perceived values

> 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

> 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

> Corresponding code files:
> - *fishing.nls*

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.

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 V-A2). Note that we do not claim to model matching tracks, but simply aim to simulate similar patterns.

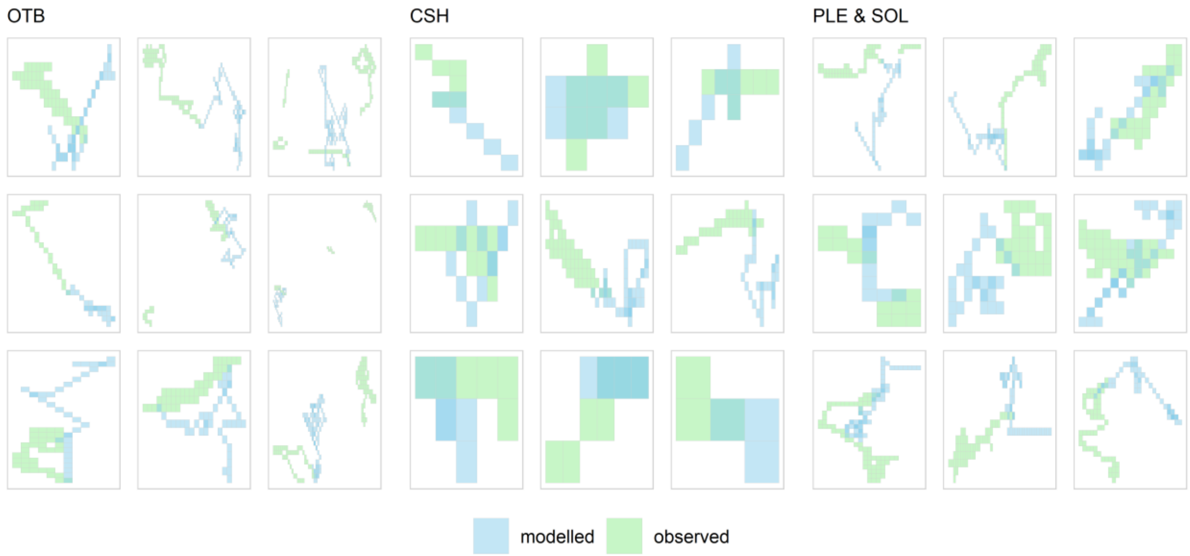


Figure V-A2. Observed (green) and modelled (blue) fsishing tracks as consecutive grid cells using Lévy flights. The four panels correspond to different types of gears: bottom otter boards (OTB), shrimp beam and pulse trawls (CSH), and flatfish beam and pulse trawls (PLE & SOL).

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

NetLogo
Corresponding code files:
- *Main file*
- *fishing.nls*

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).

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

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 ($FishR$).

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

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

NetLogo
Corresponding code files:
- *Perceive_and_SocNet.nls*

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 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.

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

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.

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

- 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.

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

- $FT_{ComSpec}$ = 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.

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

- $ProfDay_i$ = 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 V-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 searching for another catch location	- 2012-2019 - 0.045° lon × 0.045° lat - Weekly number of international fishing vessels	Occurrence of international vessels	VMS[1]
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 and 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 and 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 V-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 V-A4).

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

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 V-A3). Finally, we removed grids cells by hand for falsely identified fishing pings representing steaming lines from harbours to catch grounds.

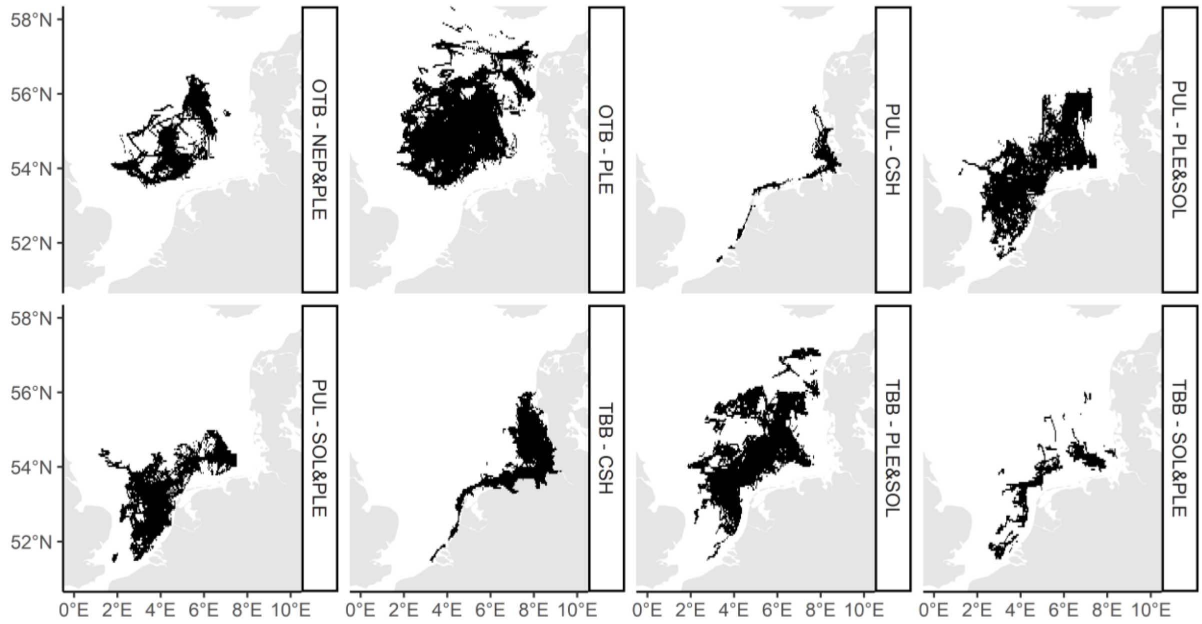


Figure V-A3. Fishing grounds of metiers derived from VMS data and used as spatial extend for simulated spatial fishing behaviour in FISHCODE.

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 V-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*.

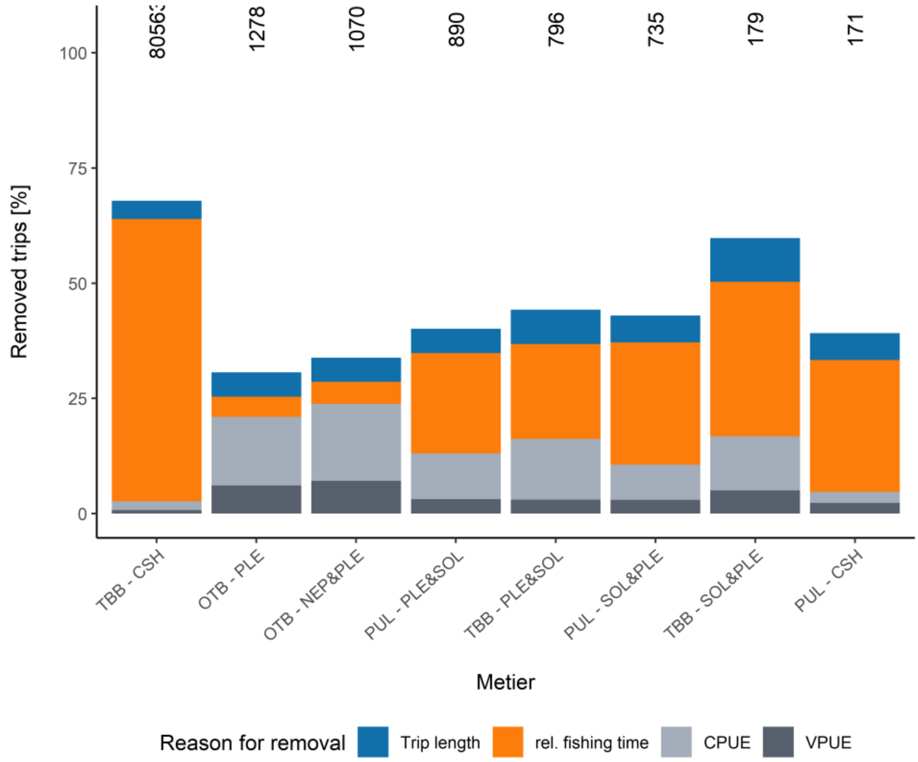


Figure V-A4. Bars show the percentage of removed trips per metier and per filter (color coded). The numbers on top of the bars show the total number of trips before applying any filters.

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 V-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.

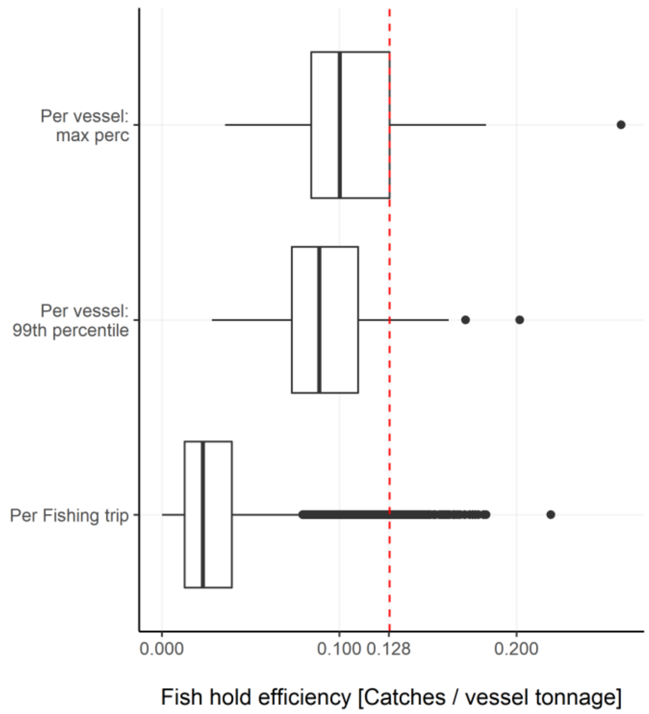


Figure V-A5. Fish hold efficiencies calculated for the maximum catch per vessels (*max perc*), the 99th percentiles of catches per vessel (*99th percentile*), as wells as per each fishing trip.

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. 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.

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.

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 V-A6).

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 V-A7). 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%.

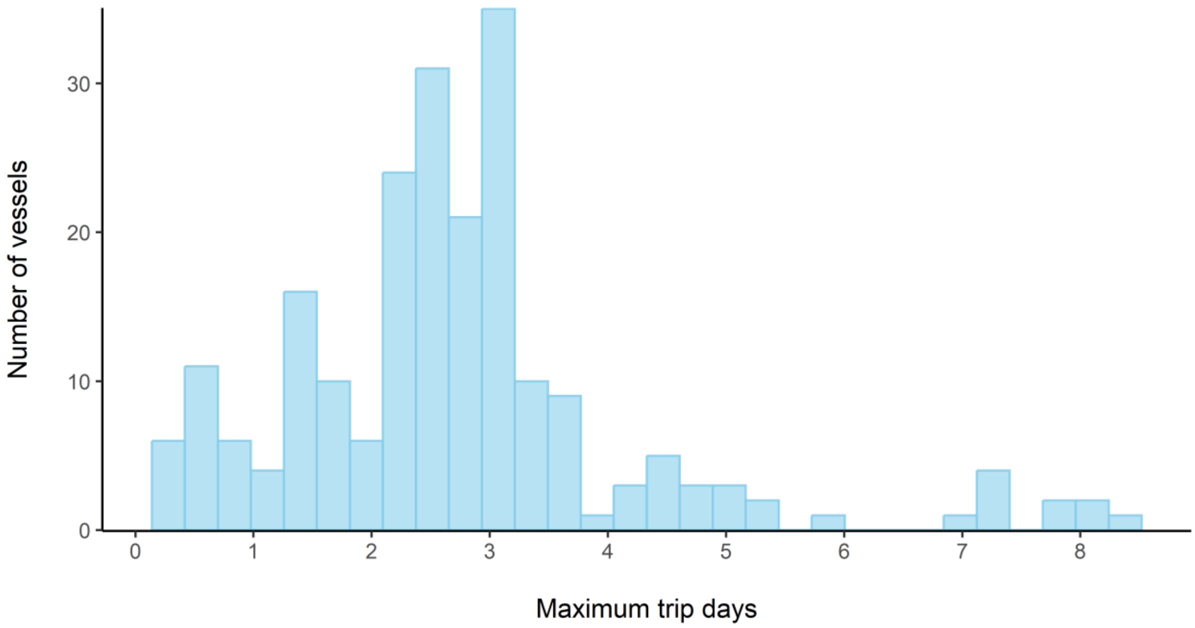


Figure V-A6. The distribution of maximum trip days per vessel derived from the trip data base as the 90th percentile of trip lengths per vessel.

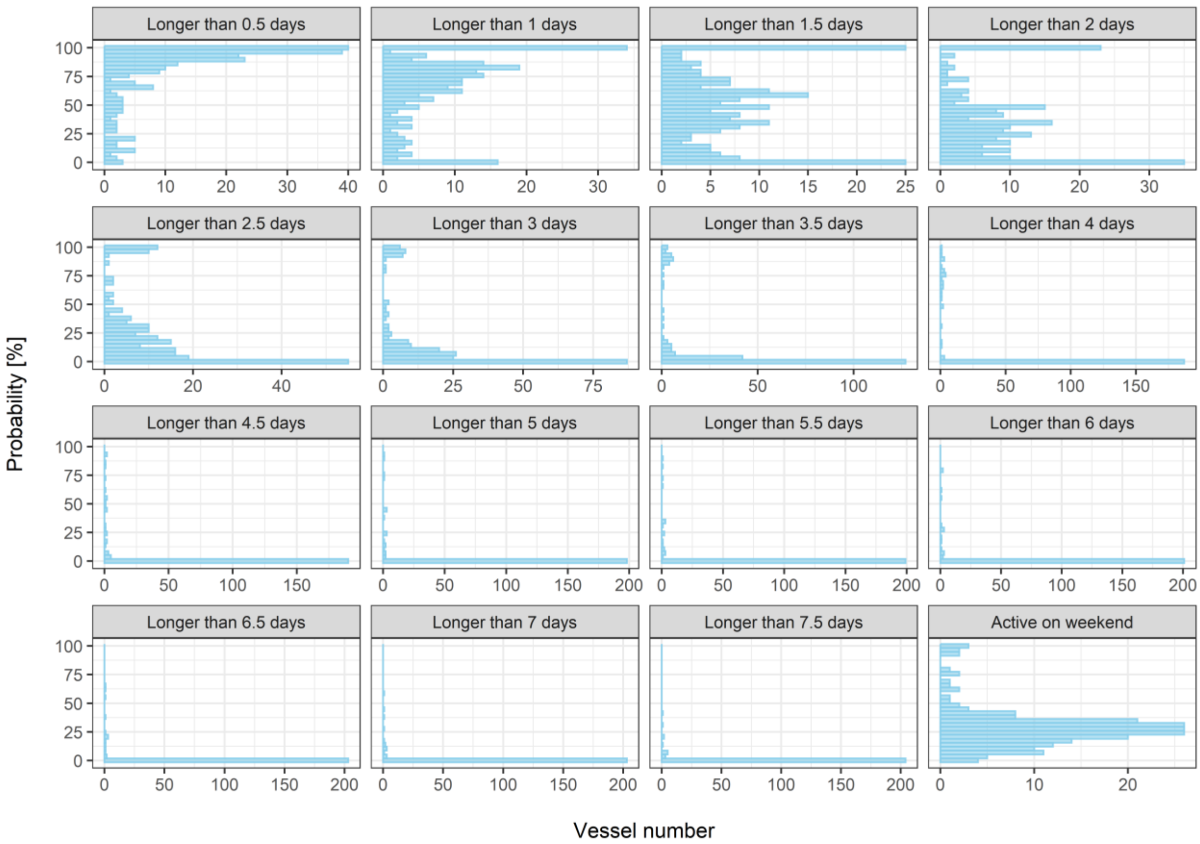


Figure V-A7. The probabilities agents undertaking fishing trips of certain lengths and on the weekend.

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 V-A8).

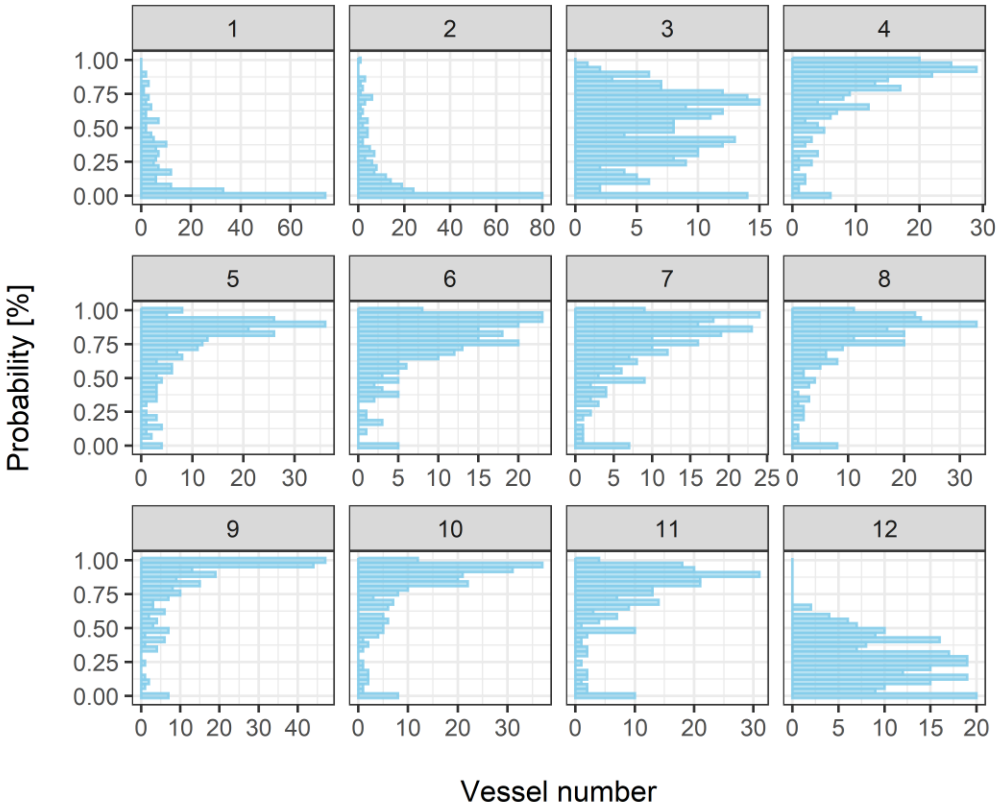


Figure V-A8. The probabilities agents undertaking fishing trips of certain lengths and on the weekend.

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 V-A9). 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 V-A10)

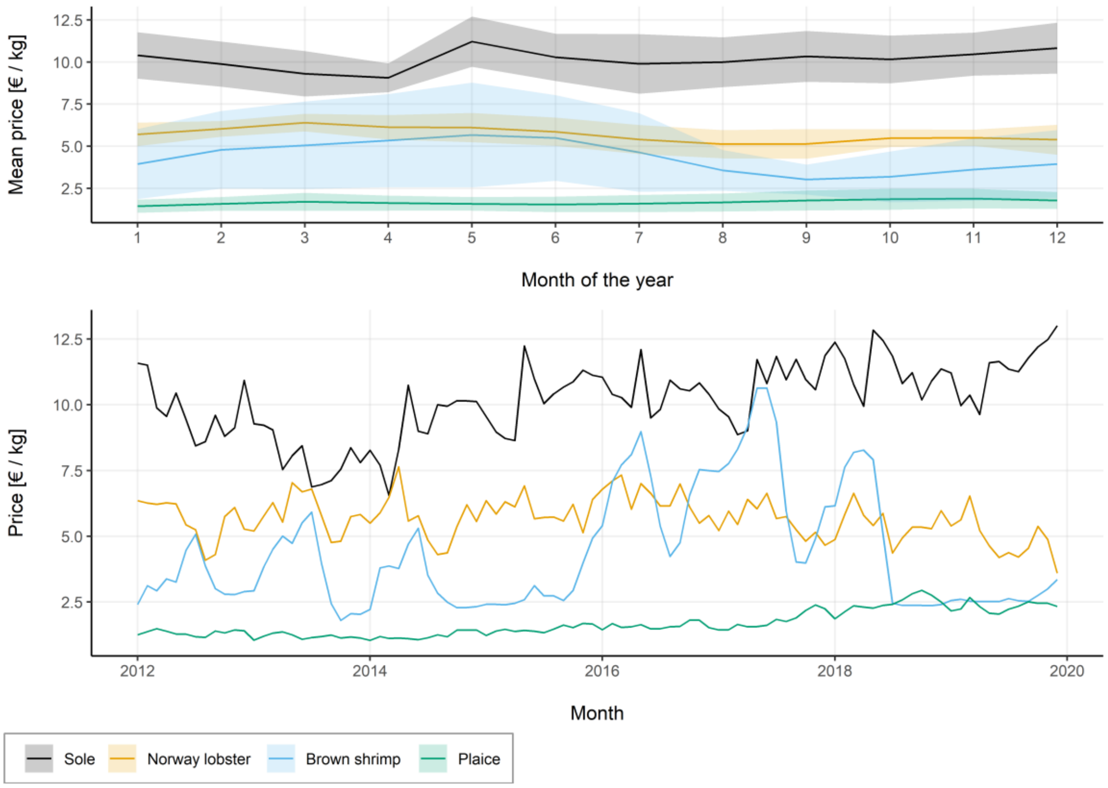


Figure V-A9. Resource prices of the most important caught species. The upper graph displays the mean and standard variation of prices per month of the year, whereas the lower graph shows prices for each month across the whole temporal range of the trip data base.

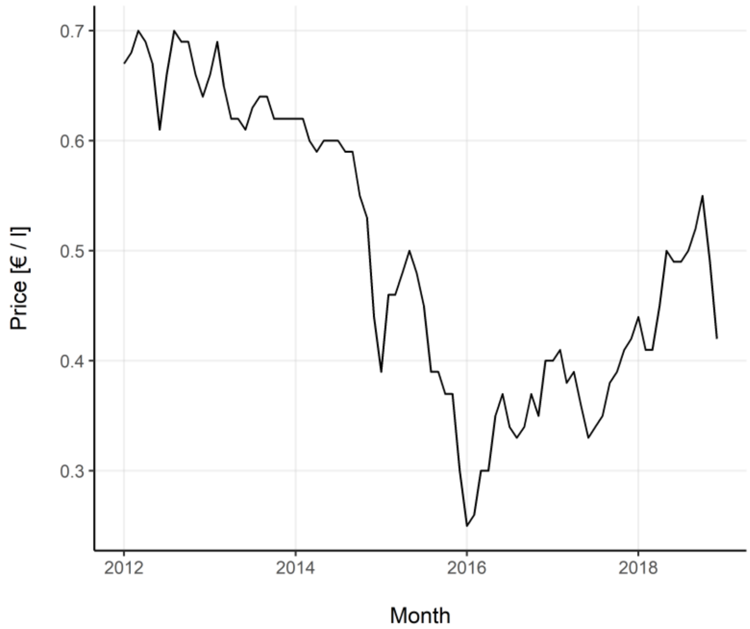


Figure V-A10. Monthly marine gasoil prices.

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 V-A11).

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.

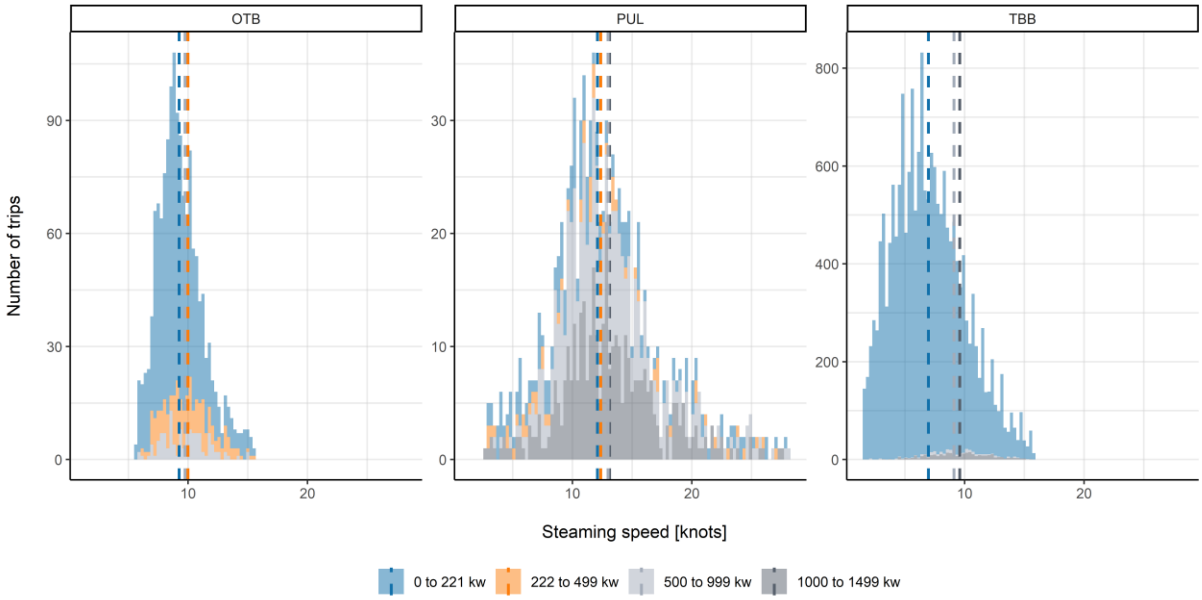


Figure V-A11. Histograms of steaming speeds per fishing gear and engine power group.

Table V-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	9.24	9.99	9.74	9.99
TBB	6.97	7.87	9.1	9.58
PUL	12.09	12.37	12.98	13.1

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 V-A12).

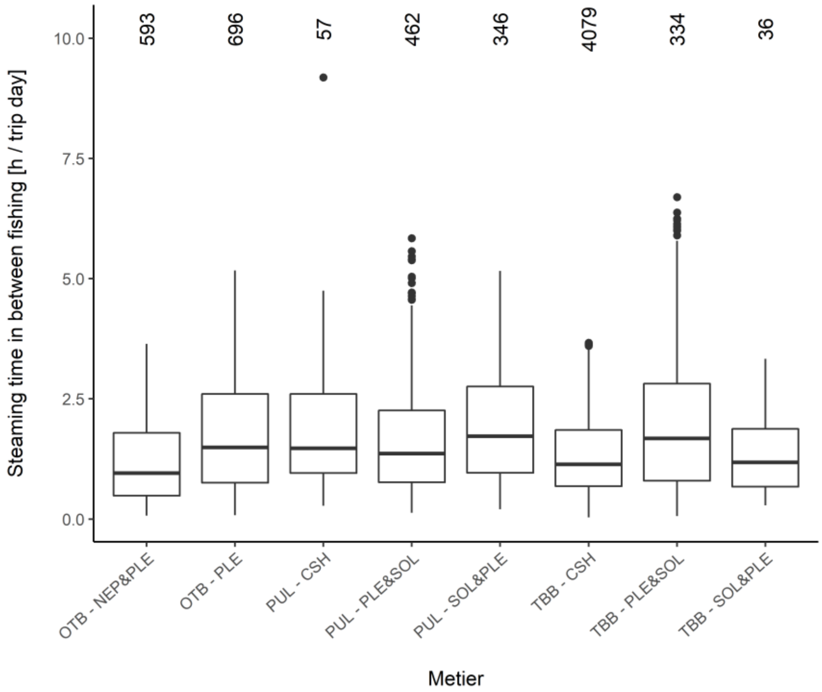


Figure V-A12. Boxplot of steaming times in between fishing events per fishing trip and metier. Trip numbers (after applied percentile filters) are indicated above each box and black horizontal lines represent medians.

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 V-A13). In general, the number of patches is increasing with time a vessel spent fishing during a trip.

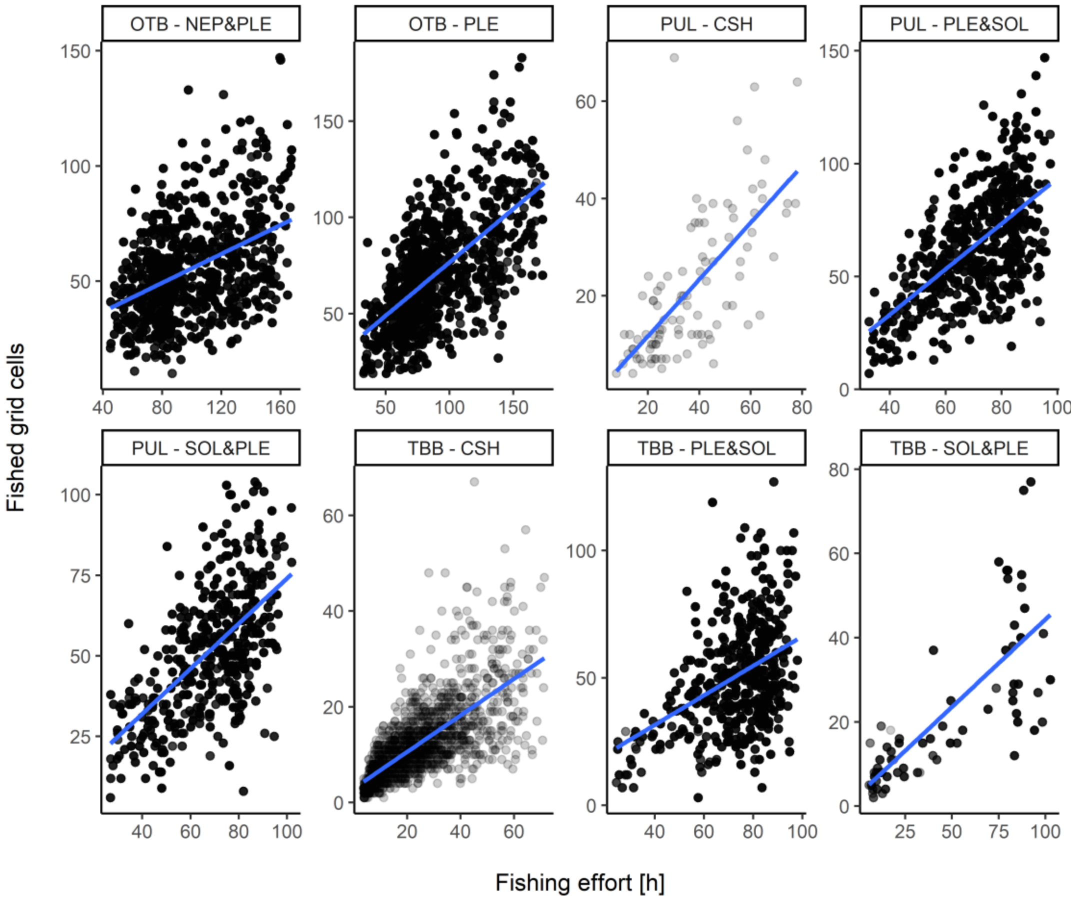


Figure V-A13. The number of fished patches (grid cells) depending on the fishing time length per metier. Based on the trip data base.

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 V-A14A). 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 V-A14B).

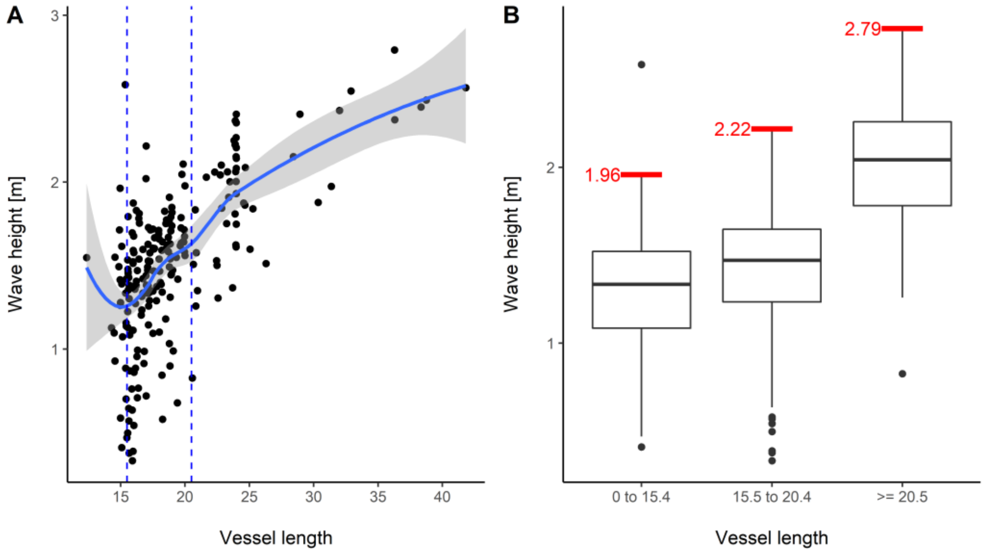


Figure V-A14. **A** displays a scatter plot of 97.5th quantiles of significant wave height (SWH) values per vessel with blue dashed lines signaling vessel length categories determined by subsequent steep slopes. **B** shows boxplots of 97.5th SWH quantiles per vessel length category with upper 1.5 × 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 V-A15). For those with zero values of IQR intervals, we used the next higher value from the other metiers.

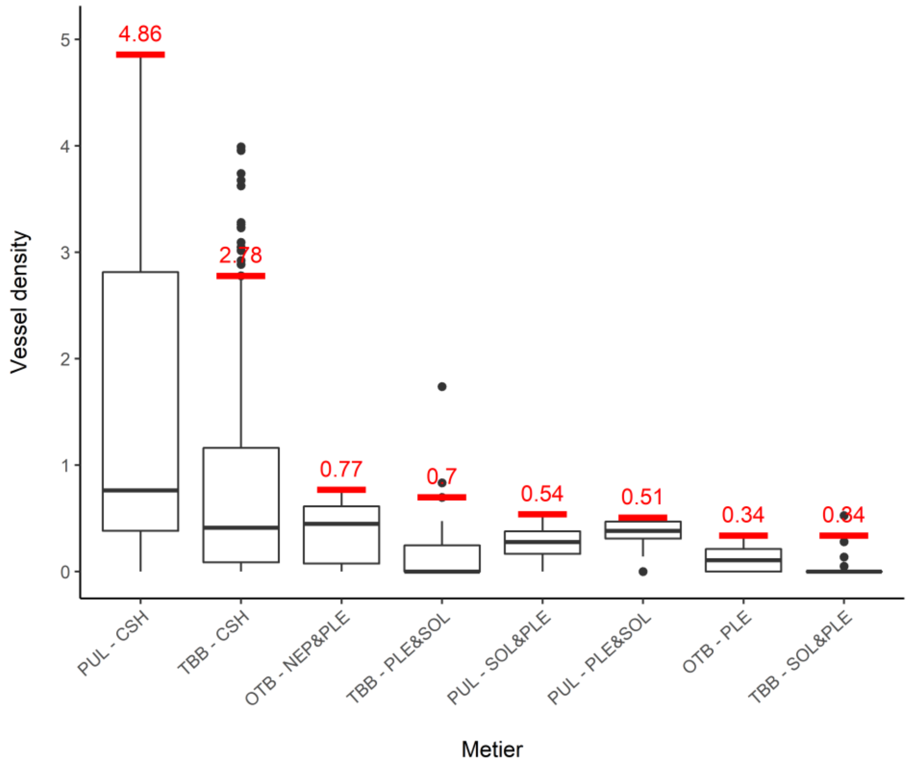


Figure V-A15. Boxplot of tolerated vessel densities during fishing trips by metier with 1.5 × inter quartile ranges (IQR) in red.

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 V-A16A). 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 V-A16B).

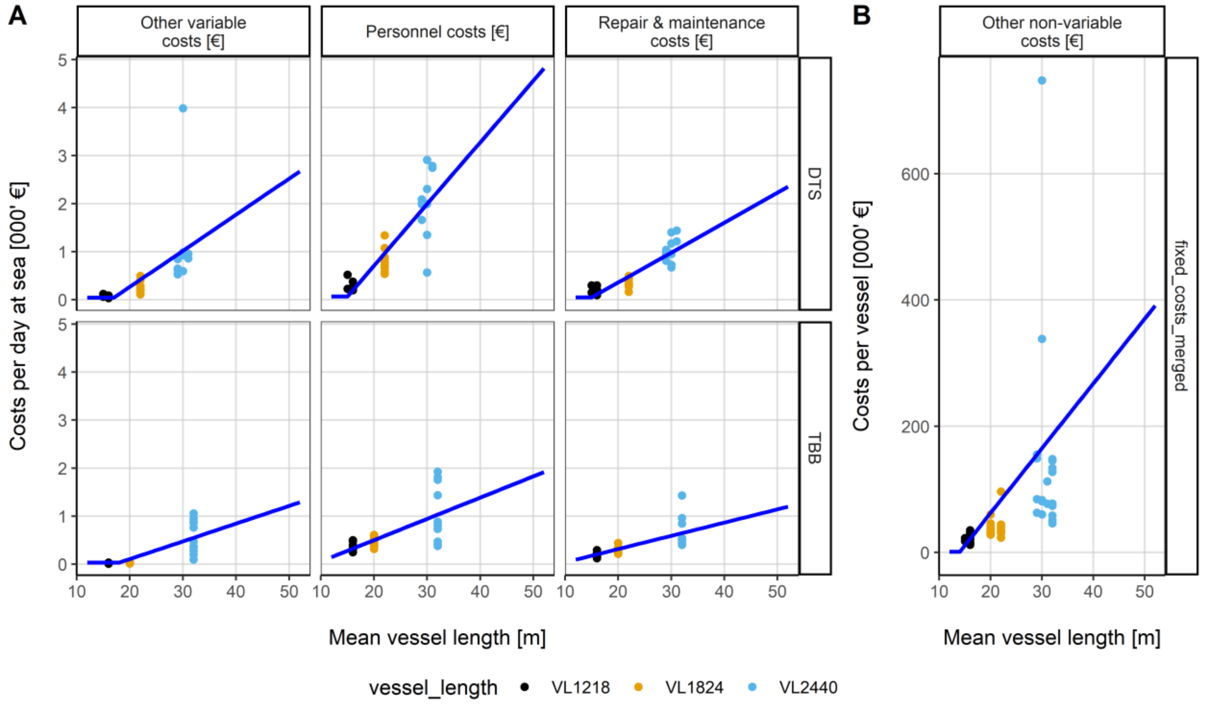


Figure V-A16. Yearly fishing costs per day at sea for each fishing technique present in FISHCODE. Blue lines represent linear models, ribbons 95% confidence intervals, and colors of points vessel length (VL) intervals in meters. A = variable costs; B = fixed costs. DTS: demersal trawlers and seiners, 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., 2004, 2003). In total, we parameterized seven model parameters (Table V-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 V-A6). Results of the final round can be found in *Appendix D*.

Table V-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.

Parameter	Details	Tested values	Fleet	Results	
Fish depletion	The relative reduction in LPUE after a patch was fished	0.965 – 0.995 (0.05 steps) & 0.999	All	$.965\vert\mathbf{.97}\vert.995$	
Fish recovery	The relative share of daily LPUE recovery	1.01 & 1.05 – 1.3 (0.05 steps)	All	$1.3\vert\mathbf{1.2}\vert1.05$	
				First	Final
Existence satisfaction	Increases the closer current savings are to target savings	0.1, 0.2, $0.\overline{33}$, 0.6, 0.8	OTB	$.2\vert.\overline{33}\vert.\overline{33}\vert.\overline{33}$	$.\overline{33}$
			PLE&SOL	$.1\vert.2\vert.2\vert.2$	.2
			CSH	$.\overline{33}\vert.6\vert.8$	.8
Personal satisfaction	Increases the more uniform own fishing actions are	0.1, 0.2, $0.\overline{33}$, 0.6, 0.8	OTB	$.2\vert.\overline{33}\vert.\overline{33}\vert.\overline{33}$	$.\overline{33}$
			PLE&SOL	$.1\vert.2\vert.2\vert.6$	.2
			CSH	$.\overline{33}\vert.2\vert.1$	.1
Social satisfaction	Increases the more often profits of trips are above those of peers	0.1, 0.2, $0.\overline{33}$, 0.6, 0.8	OTB	$.6\vert.\overline{33}\vert.\overline{33}\vert.\overline{33}$	$.\overline{33}$
			PLE&SOL	$.8\vert.6\vert.6\vert.2$	.6
			CSH	$.\overline{33}\vert.2\vert.1$	.1
Existence uncertainty	Decreases the more often profit predictions are higher than profits	0.1, 0.3, 0.5, 0.7, 0.9	OTB	$.9\vert.5\vert.7\vert.9$	.9
			PLE&SOL	$.3\vert.3\vert.9\vert.3$	.3
			CSH	$.7\vert.7\vert.5$	.5
			OTB	$.1\vert.5\vert.3\vert.1$	.1

Social uncertainty	Decreases the more similar fishing actions are to those of peers	0.1, 0.3, 0.5, 0.7, 0.9	PLE&SOL CSH	.7|.7|.1|.7 .3|.3|.5	.7 .5

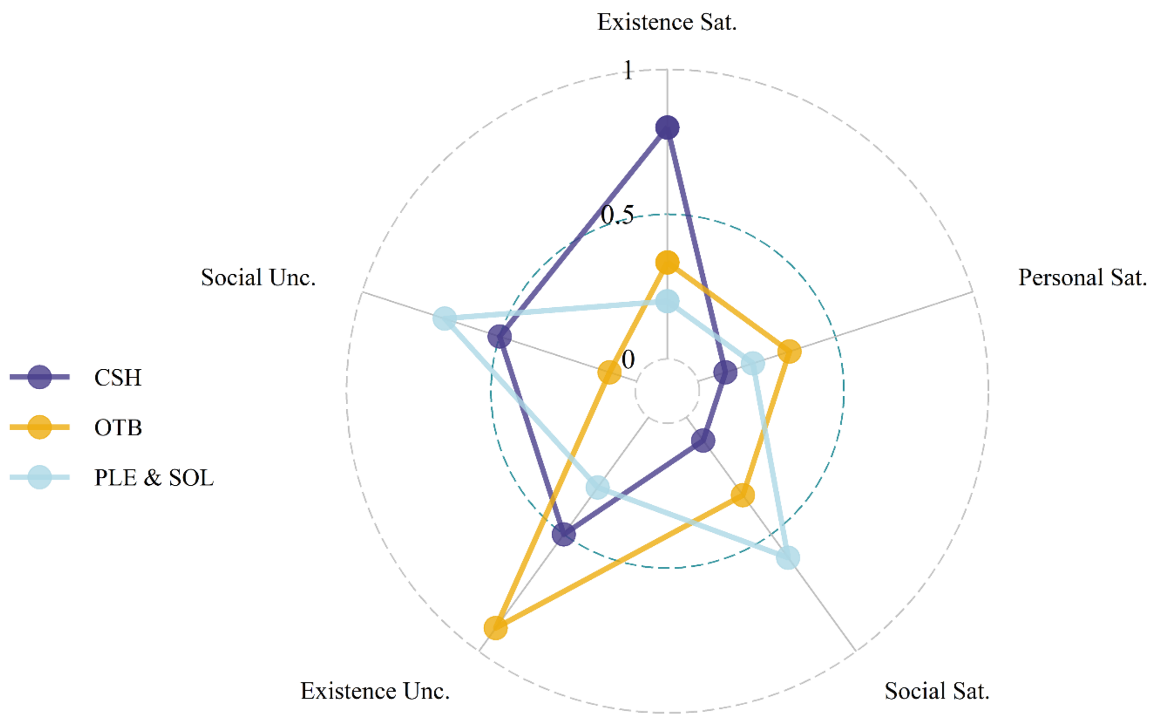


Figure V-A17. Parameterized weightings of satisfactions (Sat.), uncertainties (Unc.) after the final step of the pattern-oriented modeling for the three fleets: CSH = common (brown) shrimp, OTB = Otter bottom trawl (plaice & Nephrops), and SOL & PLE = flatfishes (sole and plaice).

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., 2015, 2008b). 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 and 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 V-A7 summarizes the expected effects of setting the weighting of certain satisfaction or uncertainty to one.

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

Weighting (W) of	Scenario shortcut	Expected effect
Existence satisfaction (ESAT)	WESAT=1	Increased savings
Personal satisfaction (PSAT)	WPSAT=1	Metier continuity (habitual behavior)
Social satisfaction (SSAT)	WSSAT=1	Increasing savings to earn more than peers
Existence uncertainty (EUNC)	WEUNC=1	No direct effect, but indirectly by setting WSUNC to 0
Social uncertainty (SUNC)	WSUNC=1	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 V-A18B&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 V-A18A&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.

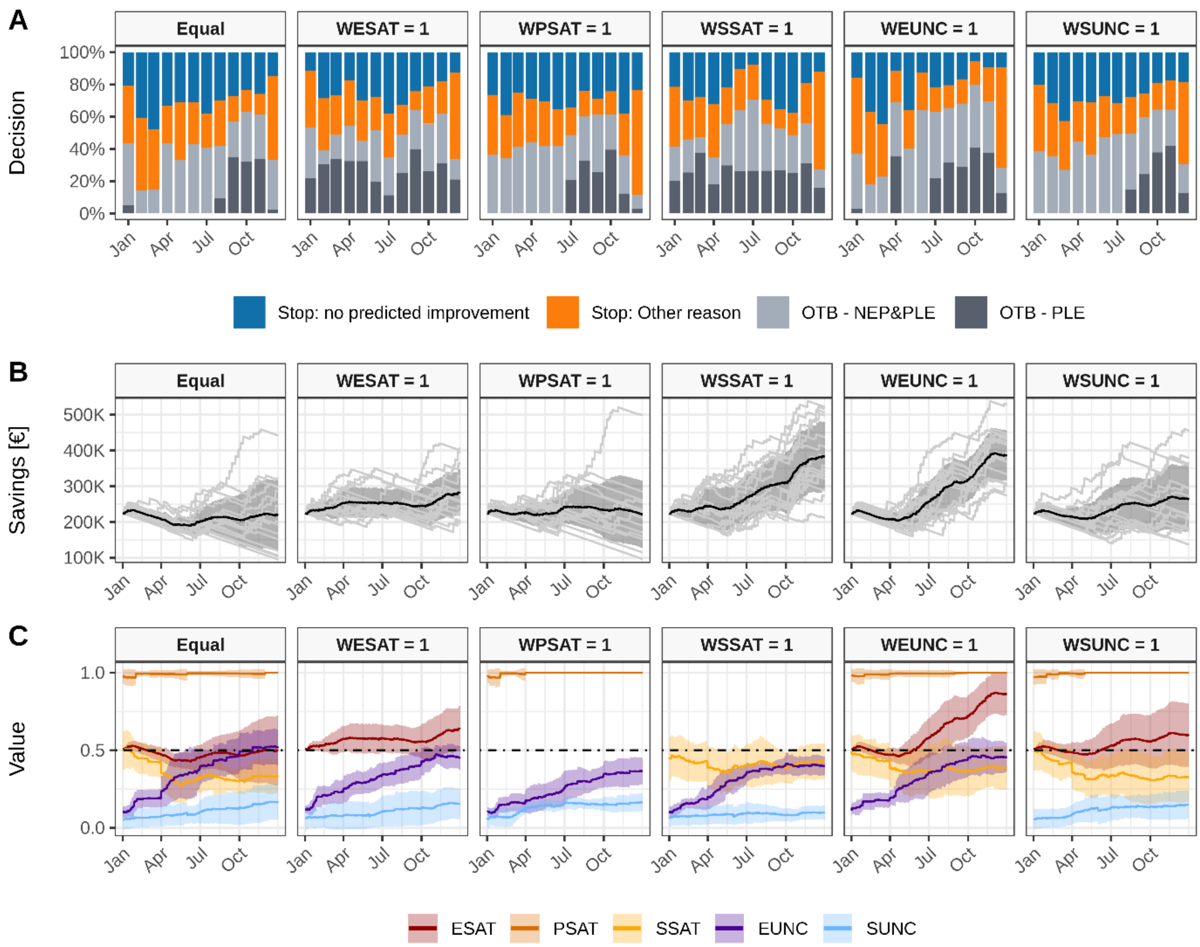


Figure V-A18. Outcome of the consumat testing for one vessel from the OTB – NEP&PLE metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the 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 V-A19A&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 V-A19. 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 V-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 V-A20A) and per grid cells (x-axes in Figure V-A20B), 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 V-A20A), whereas others were resolved on species level (i.e. *Landing weight* and *Revenue* in Figure V-A20B). 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 V-A20A). 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 V-A20A), because steaming times per fishing trip were slightly overestimated for TBB metiers (Figure V-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.

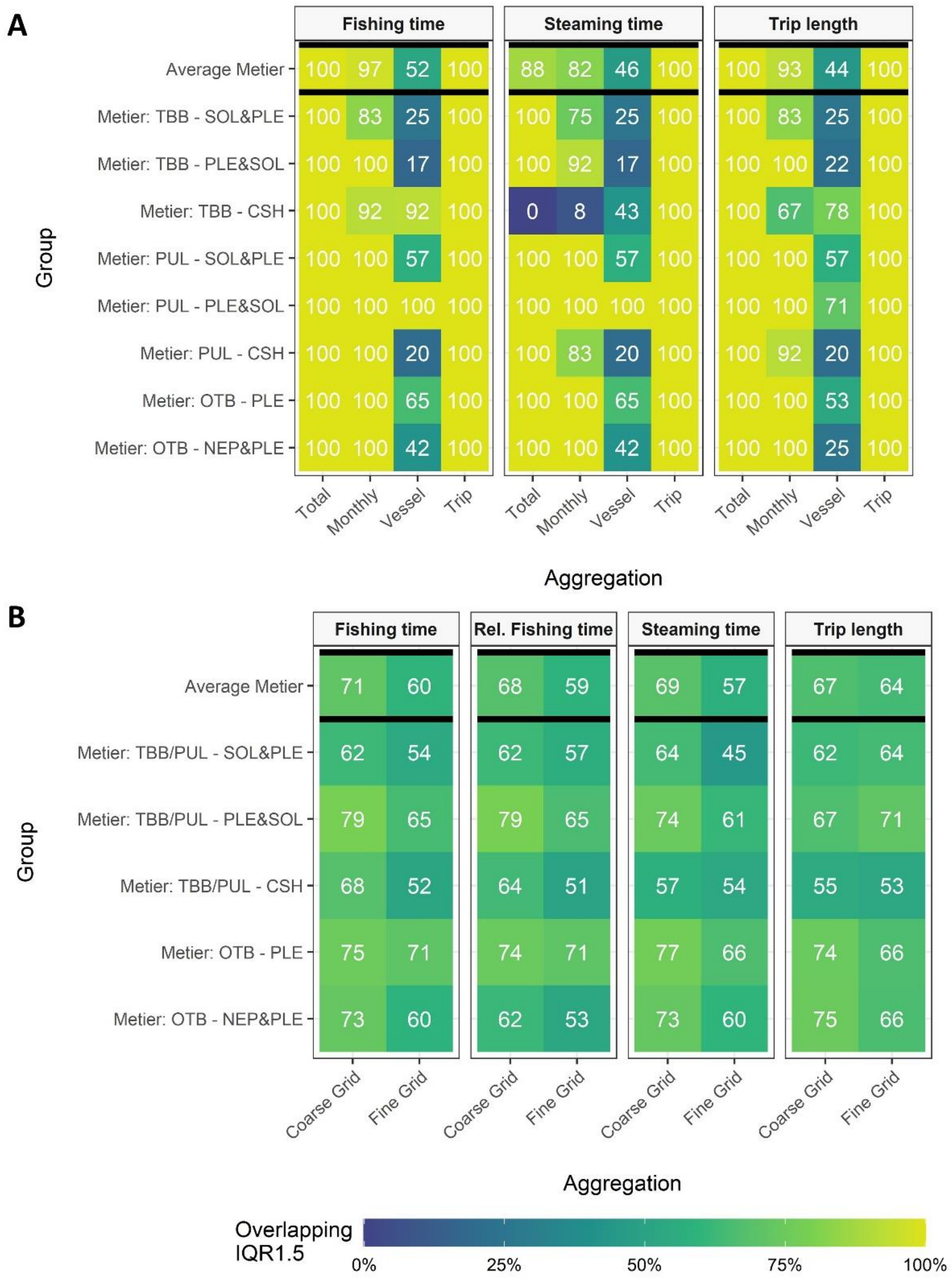


Figure V-A20. The percentage of data points with overlapping 1.5 times inter-quartile ranges (IQR1.5) between modelled and observed non-spatial (A) and spatial (B) variables. Colors and numbers correspond to the percentage of overlaps across different aggregations (columns) and metiers (rows).

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 V-A20B). 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 V-A21A&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 V-A21B&D).

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

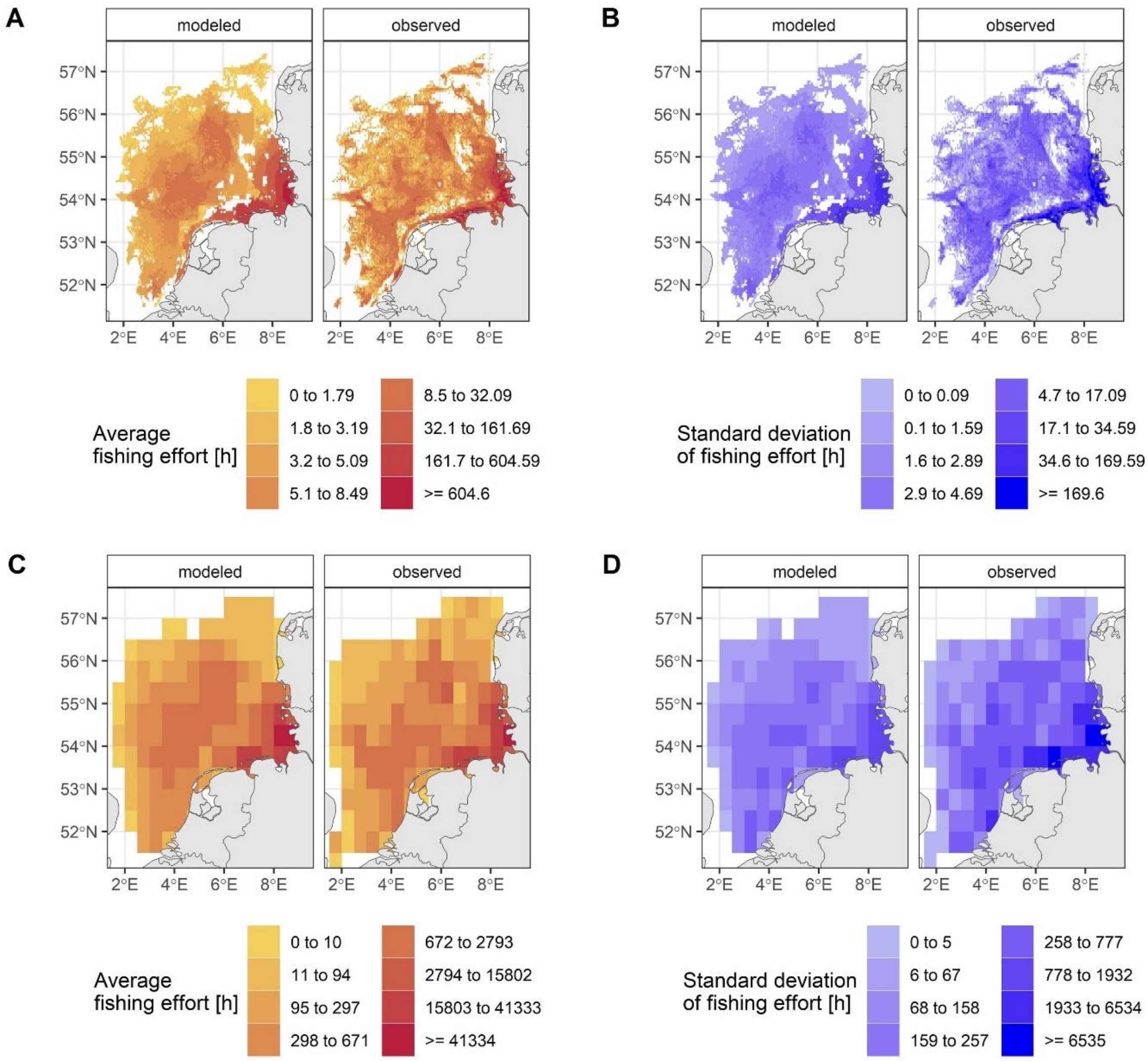


Figure V-A21. The averaged fine (A) and course (C) distribution, as well as fine (B) and course (D) standard deviation of fishing effort across validation model runs (modeled) and seven years of data (observed).

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 V-A22). 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 V-A22). 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 V-A23), 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.

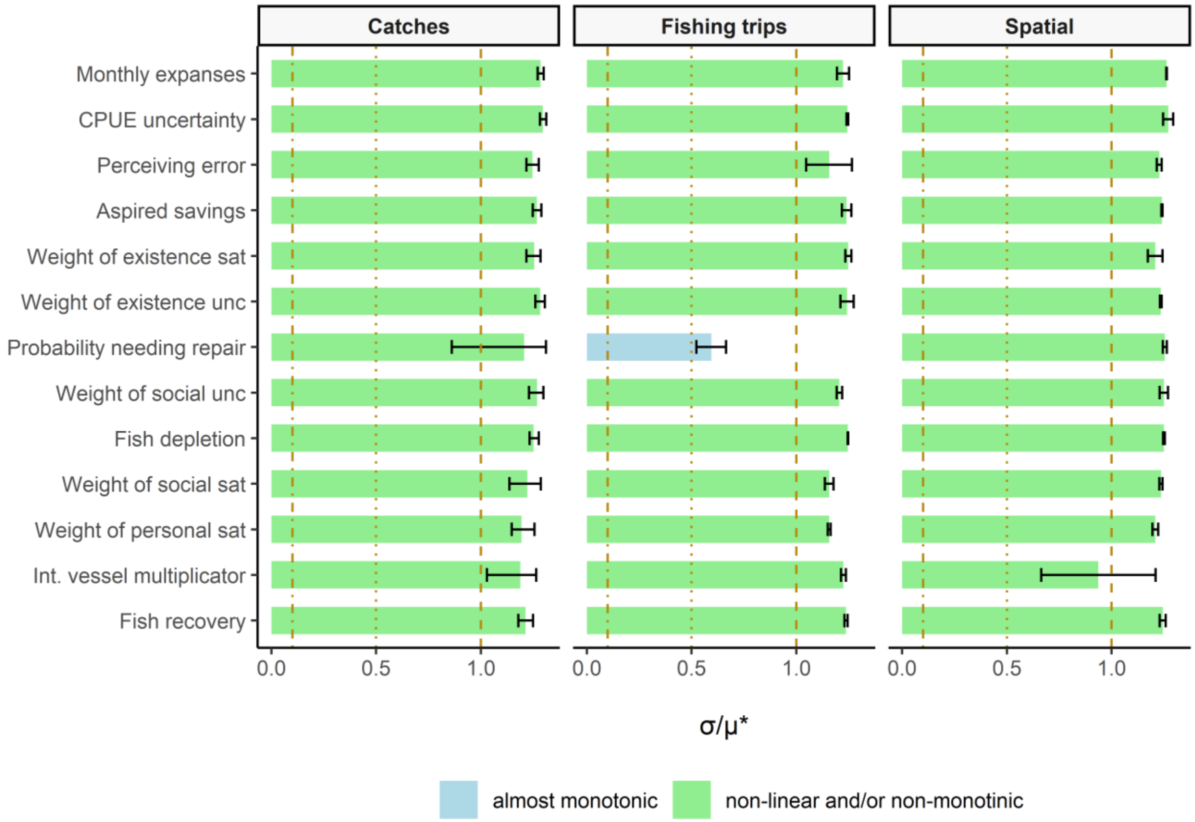


Figure V-A22. Results of the morris screening showing the type of effect from model parameters on groups of model outcomes. Panels represent groups of the model outcomes used to test sensitivies. Error bars represent minimum and maximum values in the respective group. Red dashed lines represent areas 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).

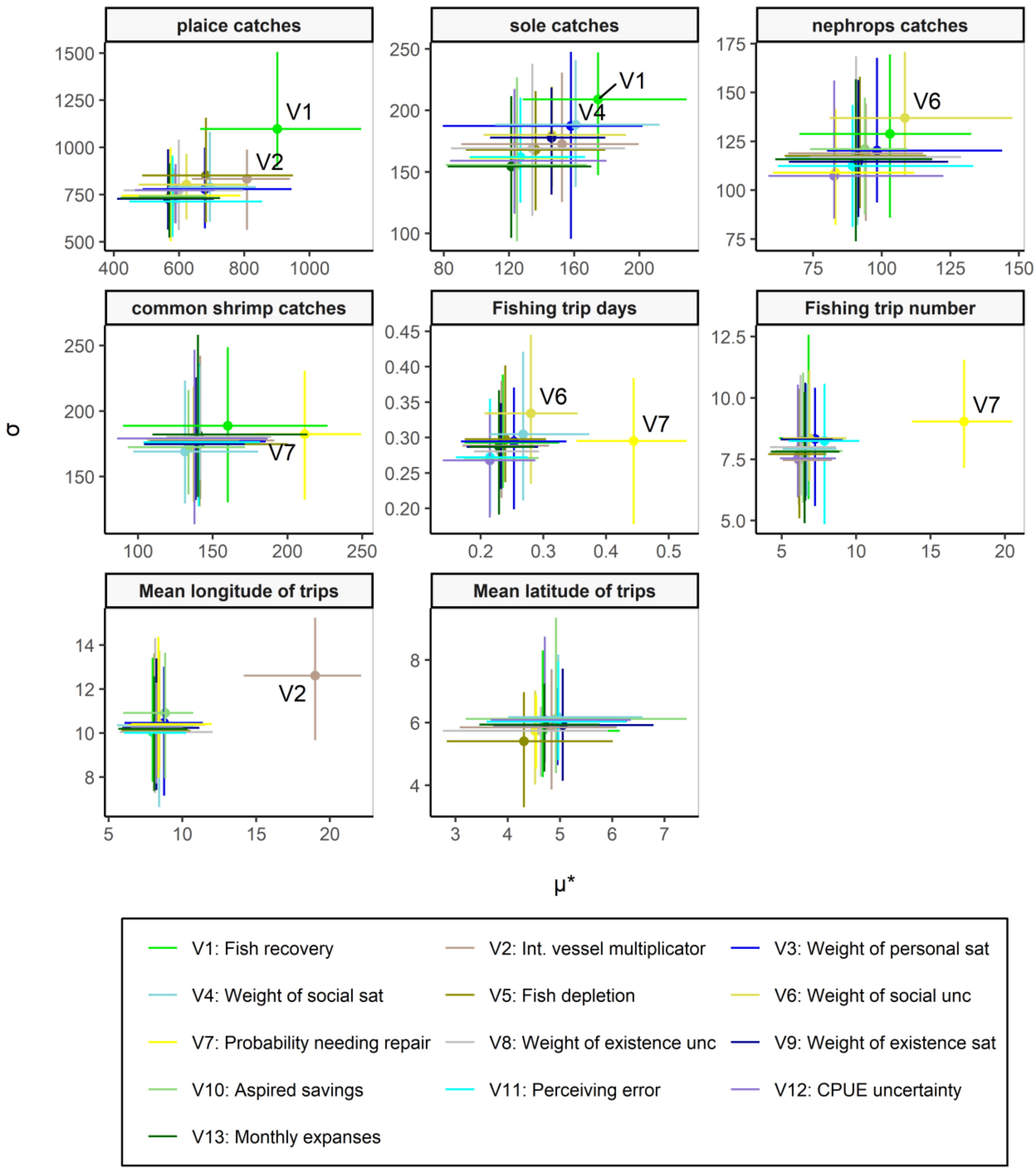


Figure V-A23. Results of the morris screening. Colors refer to the model parameters and panels the to the model outcomes. Y-axis show the absolute mean effect of a model parameter, while the x-axis shows the type effect.

Appendix B- Details trip data base

Details on Percentile Filters Applied to the Trip Data Base

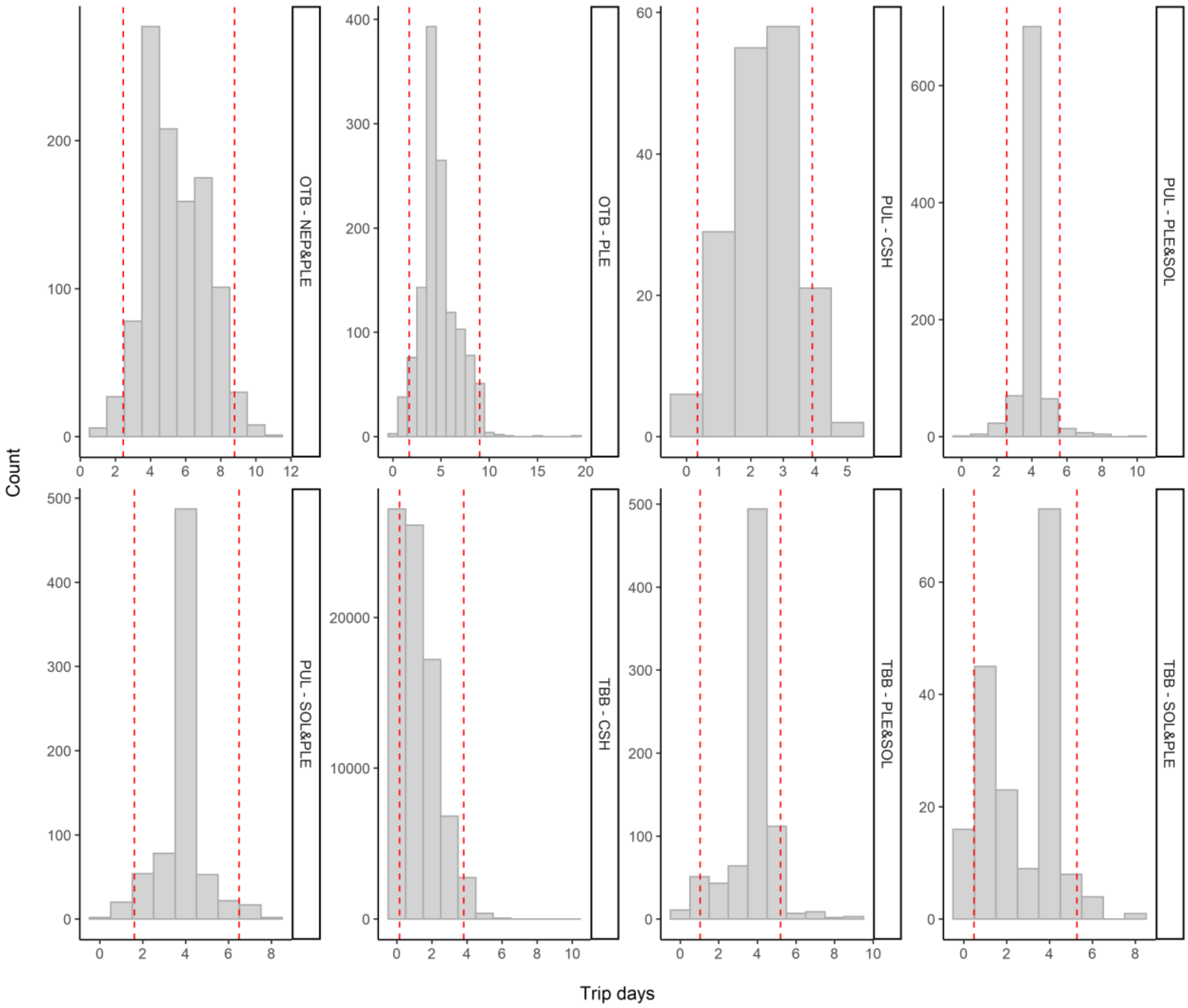


Figure V-B1. Fishing trip durations per metier. Red dotted lines show the 1st and 99th percentiles. Trips outside of this interval were considered erroneous and removed.

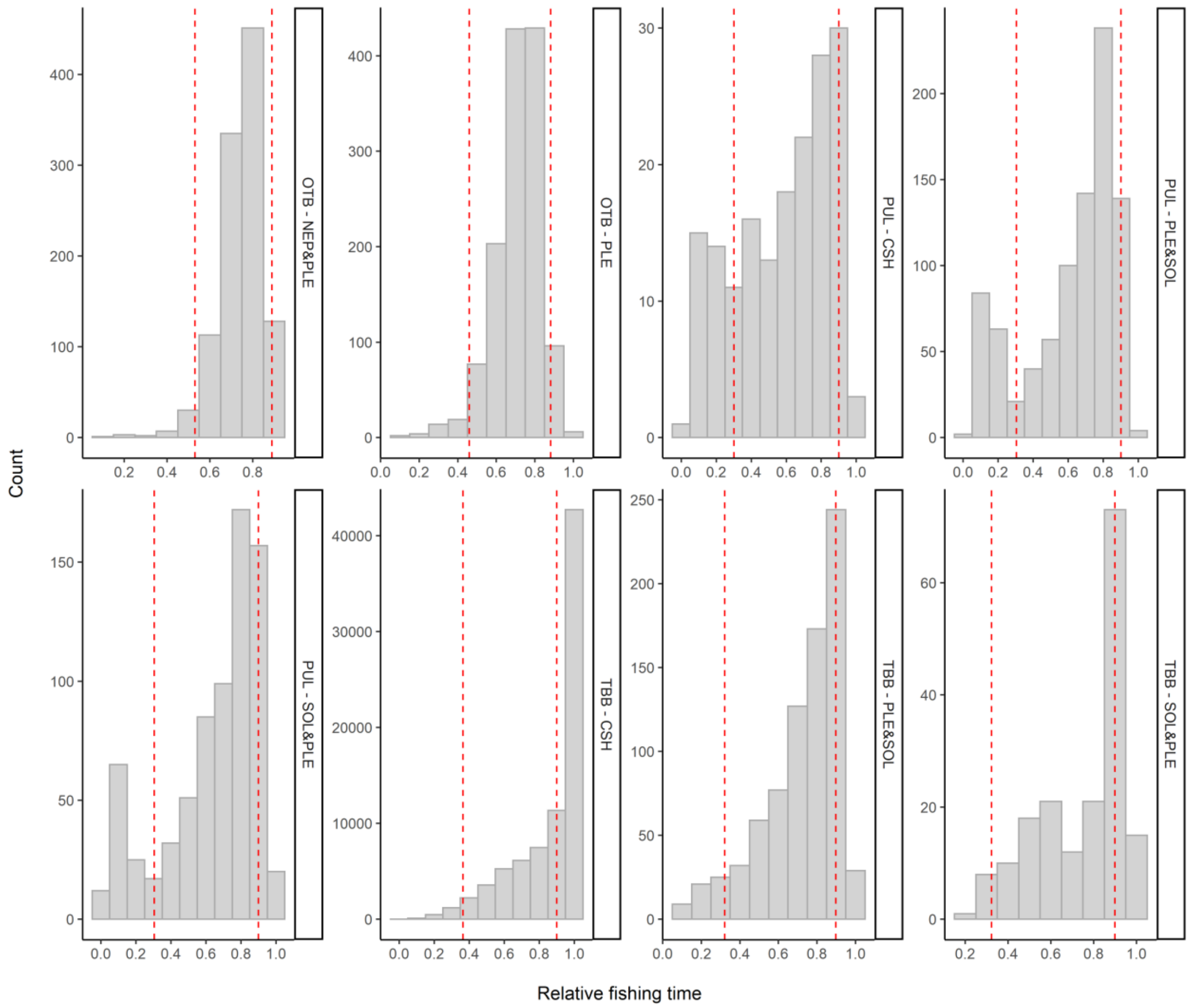


Figure V-B2. Relative shares of fishing time per trip and per metier. The red dotted line represents threshold (0.2), below which we removed fishing trips from the trip data base.

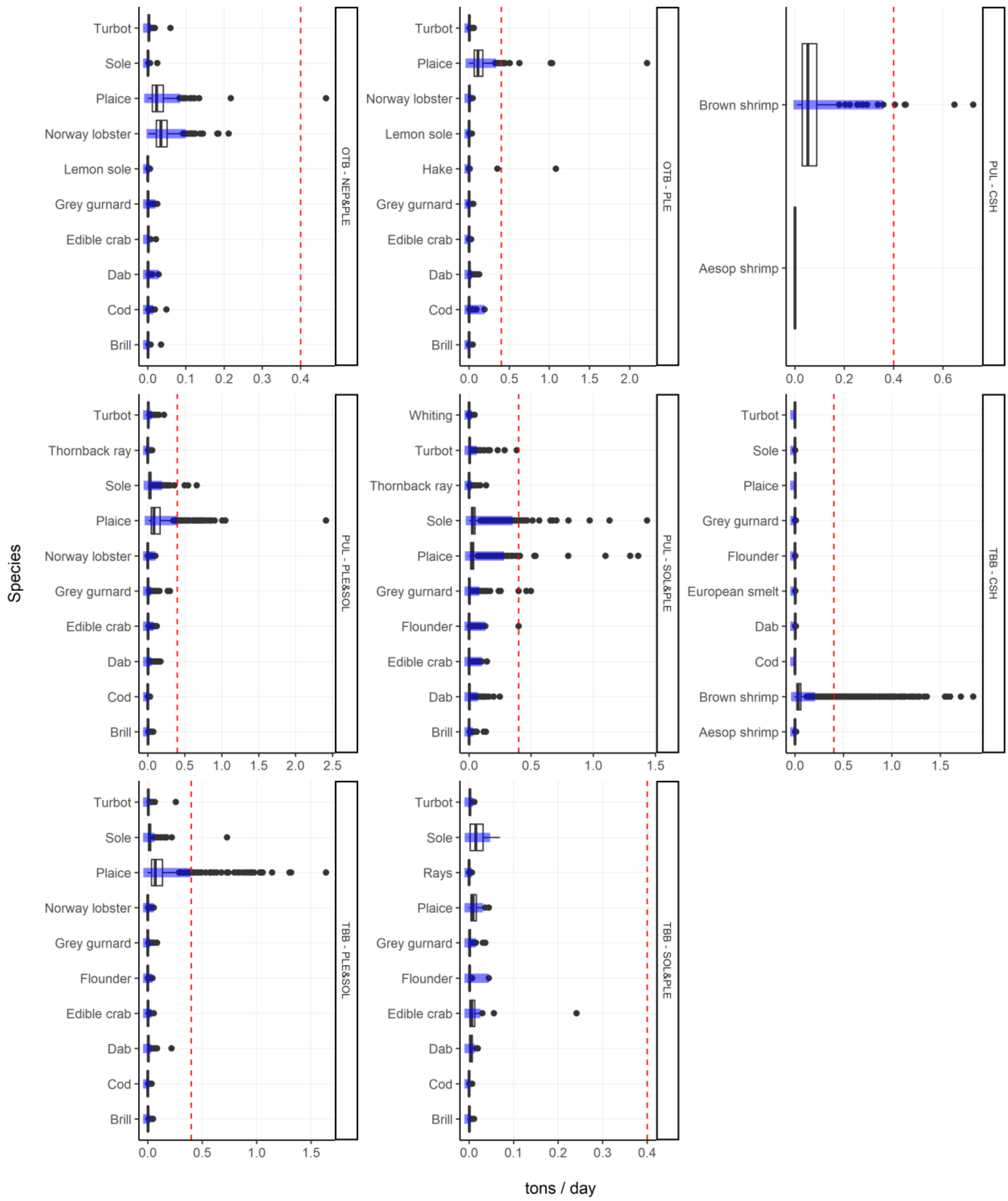


Figure V-B3. Catches per unit effort (LPUE; tons per trip day) per metiér of the 10 most abundant species caught species. Data points outside of the blue bars were removed either because of the 2.5th to the 97.5th percentile filters or being above 400 kg/h (red dashed lines).

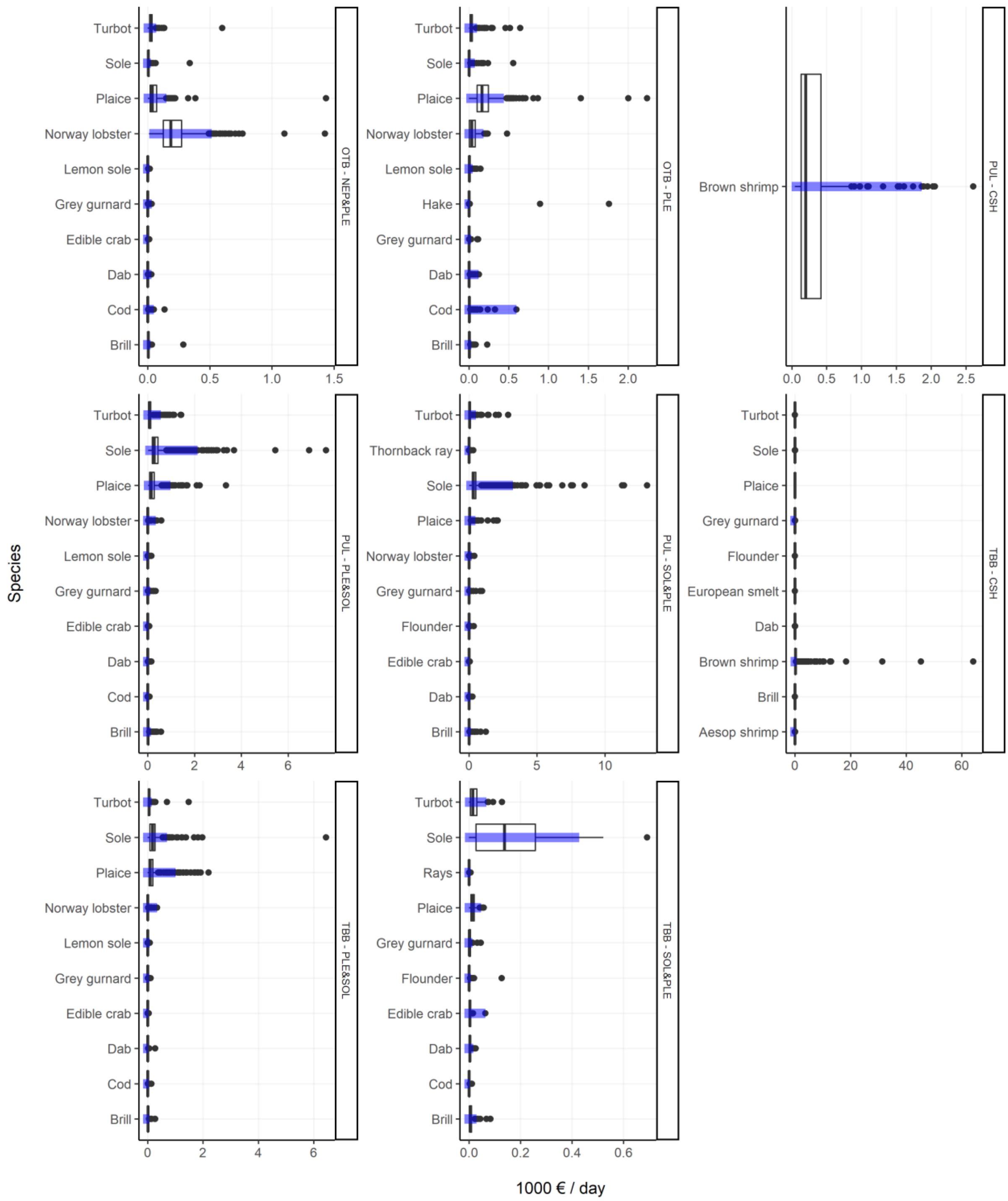


Figure V-B4. Values per unit effort (VPUE; 1000€ per trip day) per metier of the most abundant caught species. Data points outside of the blue bars were removed because of the 2.5th to the 97.5th percentile filters.

Appendix C – Details verification of behavioral drivers

Additional Implementation Verification Results

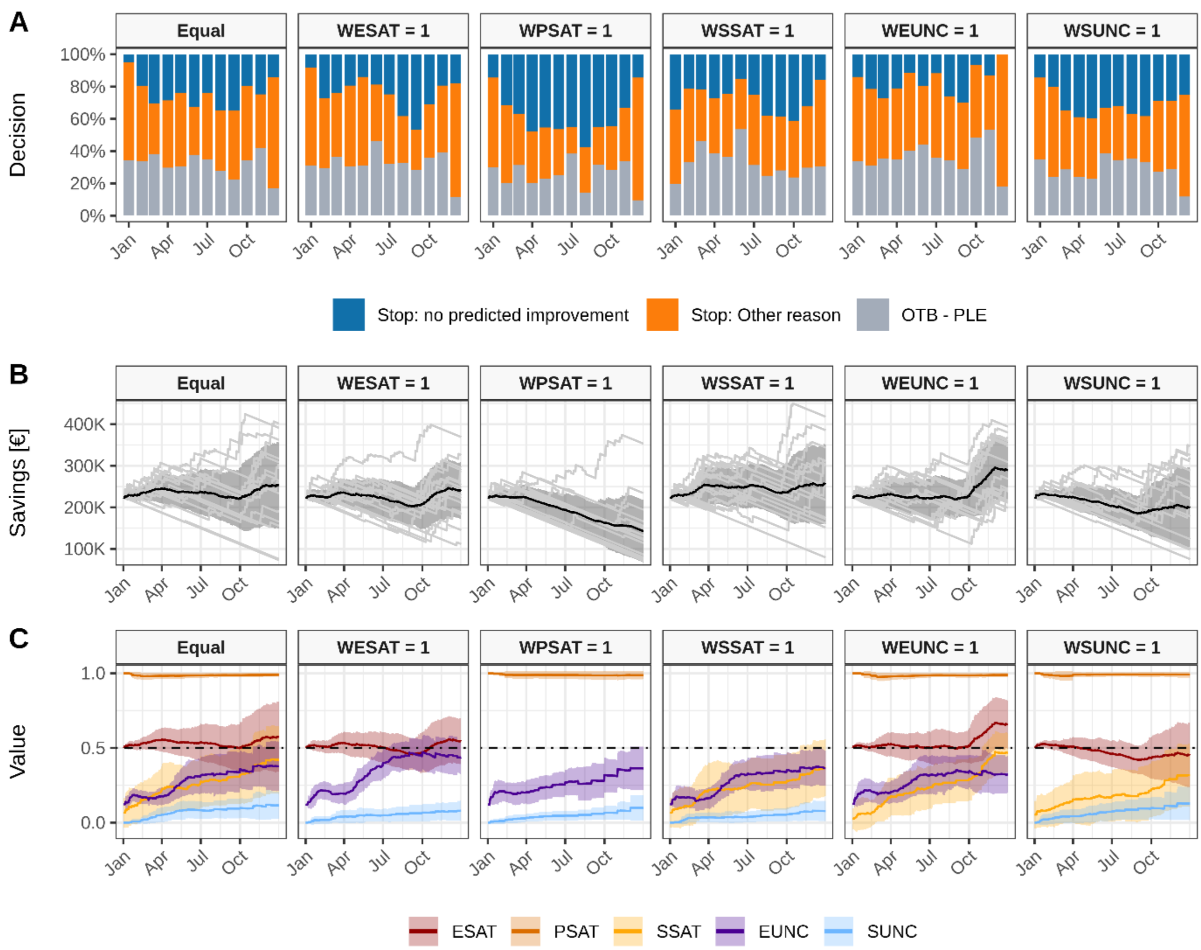


Figure V-C1. Outcome of the Consumat testing for one vessel from the OTB – PLE metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean 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.

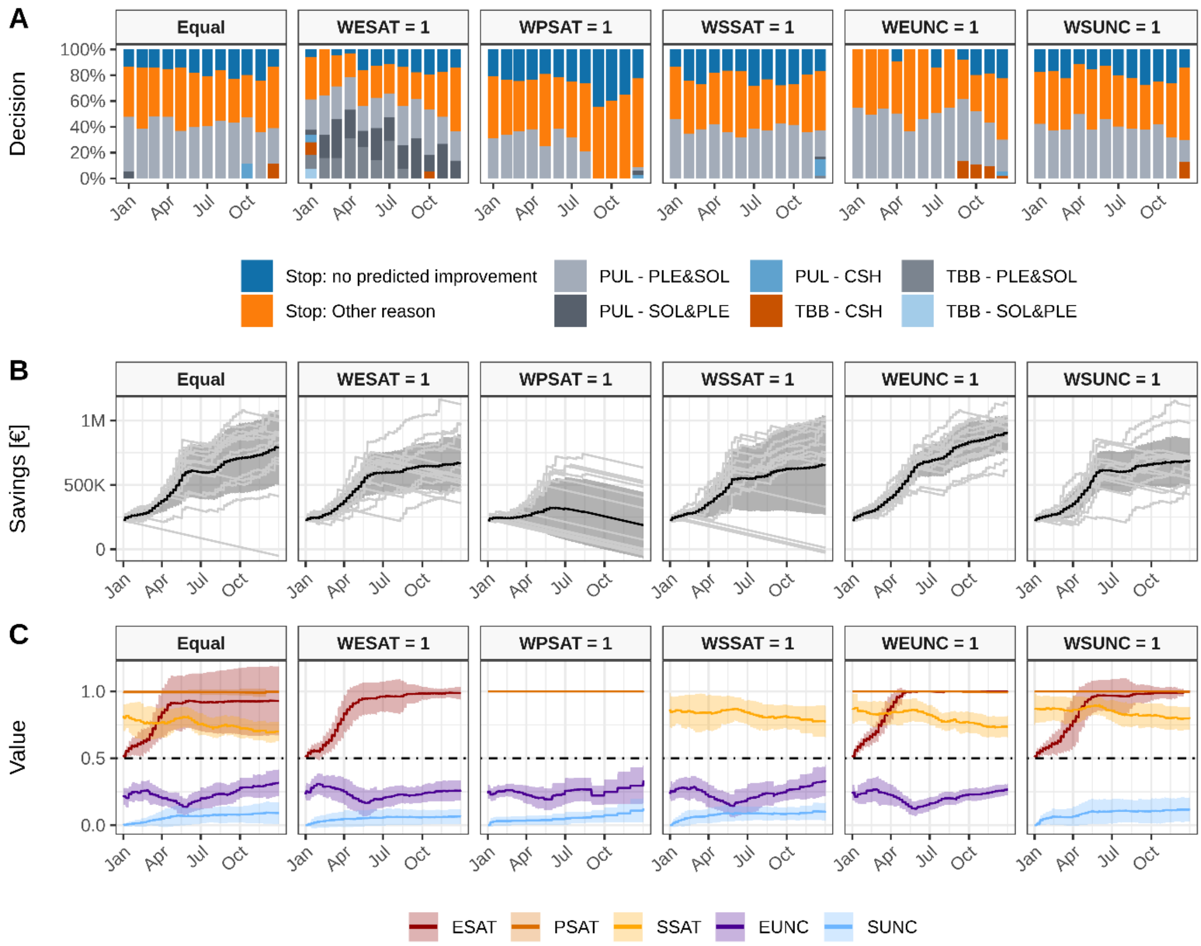


Figure V-C2. Outcome of the Consumat testing for one vessel from the PUL – PLE&SOL metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean 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.

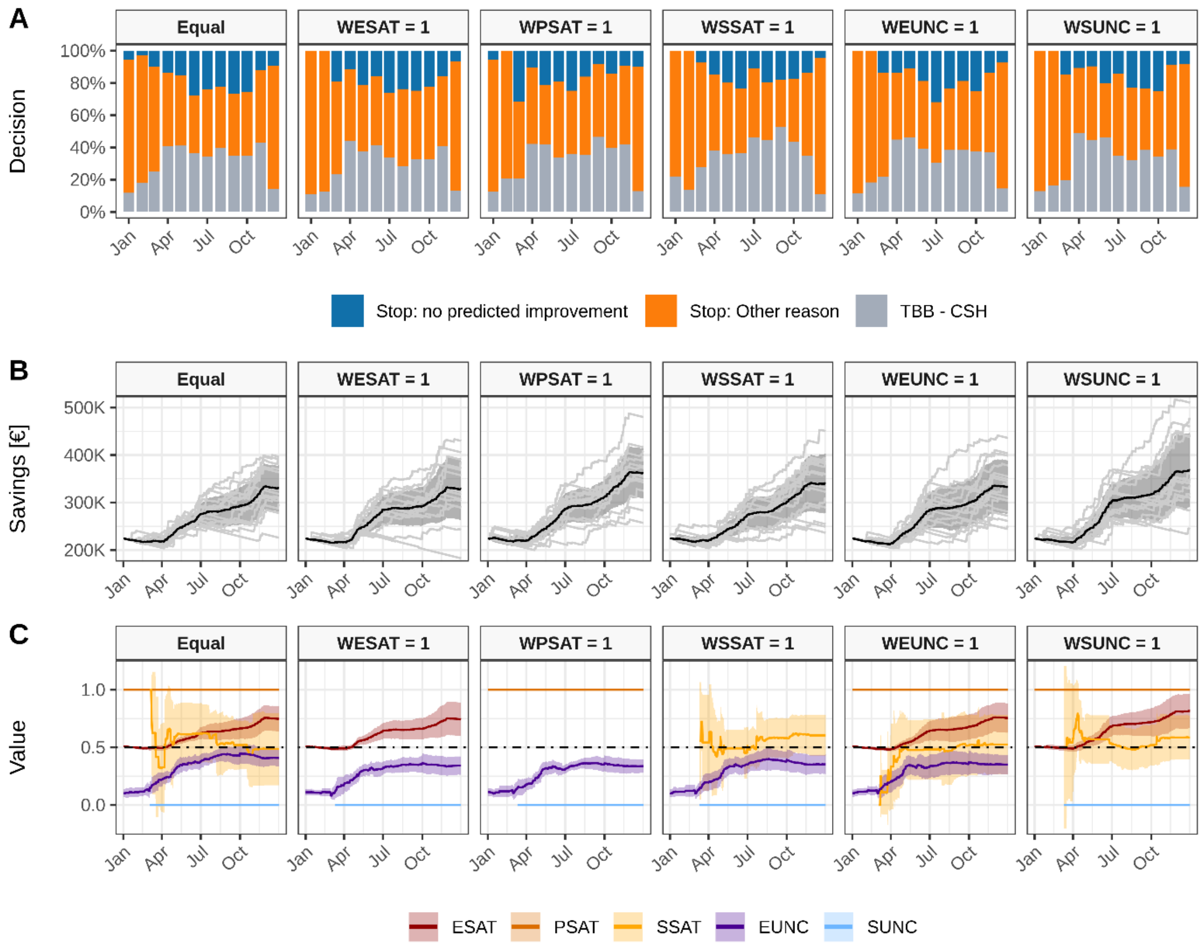


Figure V-C3. Outcome of the Consumat testing for one vessel from the TBB – CSH metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean 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.

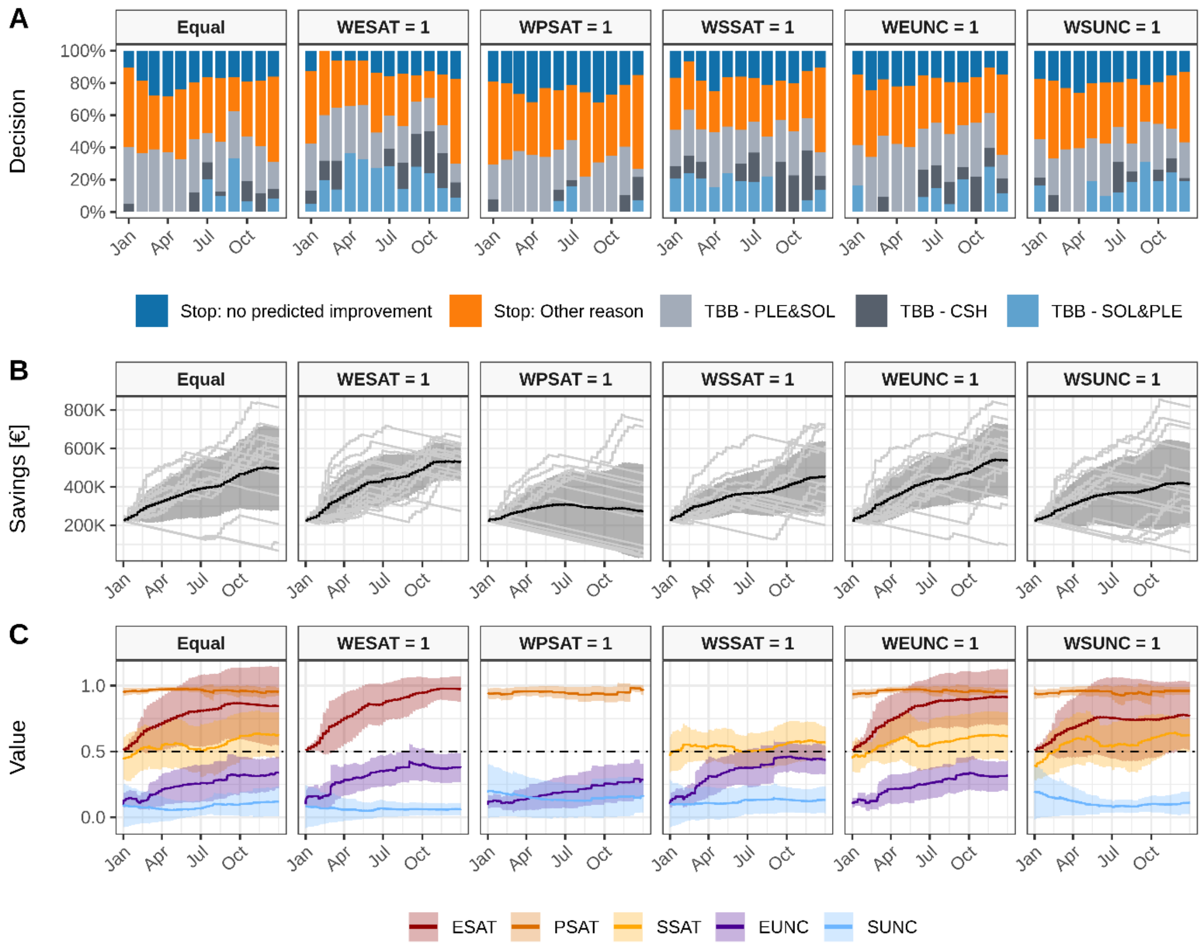


Figure V-C4. Outcome of the Consumat testing for one vessel from the TBB – PLE&SOL metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean 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.

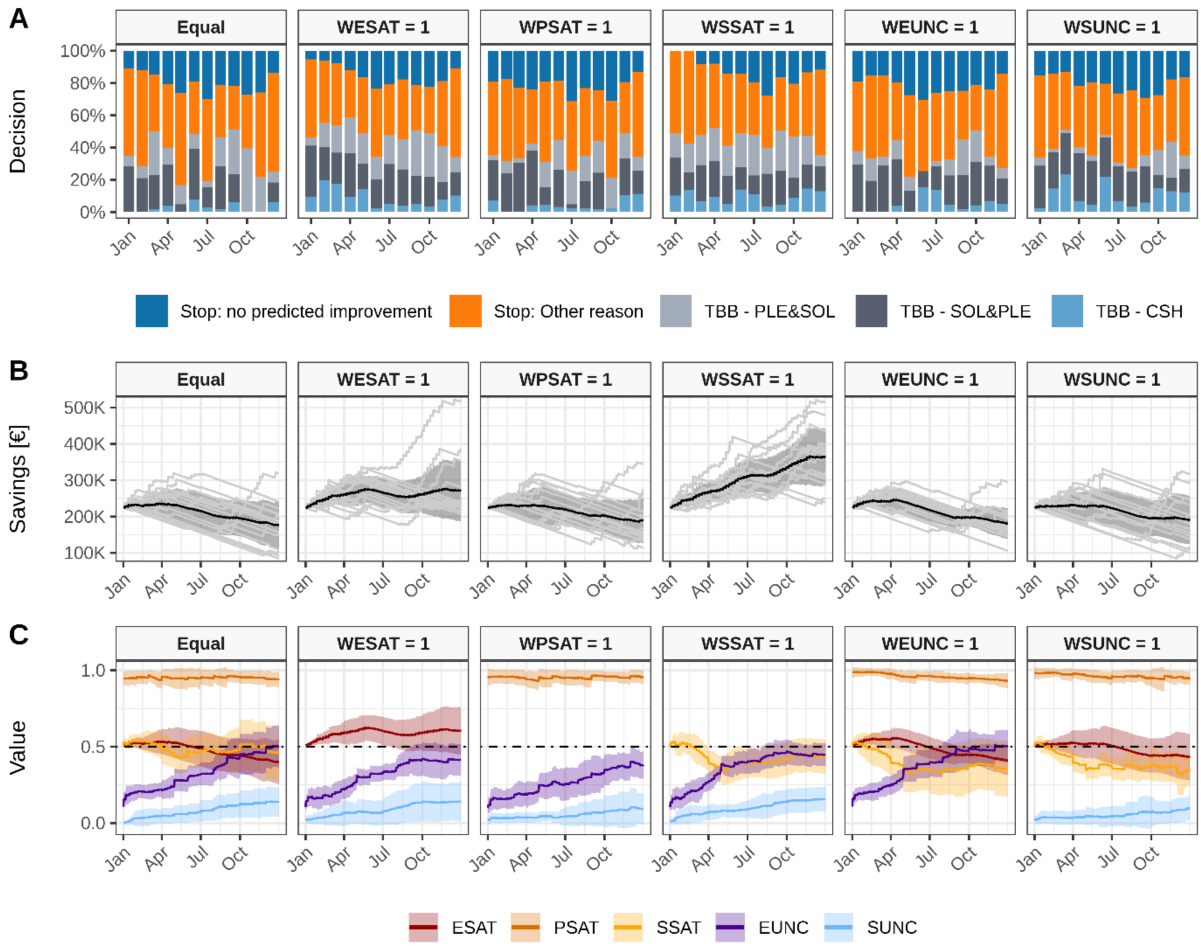


Figure V-C5. Outcome of the Consumat testing for one vessel from the TBB – SOL&PLE metier for different scenarios (panels). A shows the daily decision (going/being on a trip or staying in port) as percentage per month. B shows the savings per model run (light grey) and their mean (black), and C the mean 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

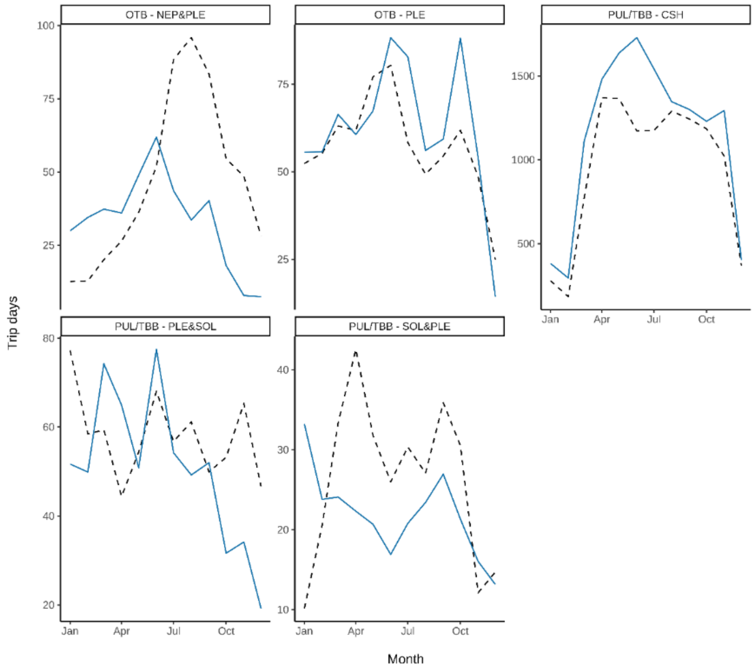


Figure V-D1. Outcome from the final step of the pattern-oriented modelling comparing modelled monthly trip days (blue) to observed ones (dashed black) per metier. Both lines represent monthly means across model runs (n = 10) and observed years (n = 7).

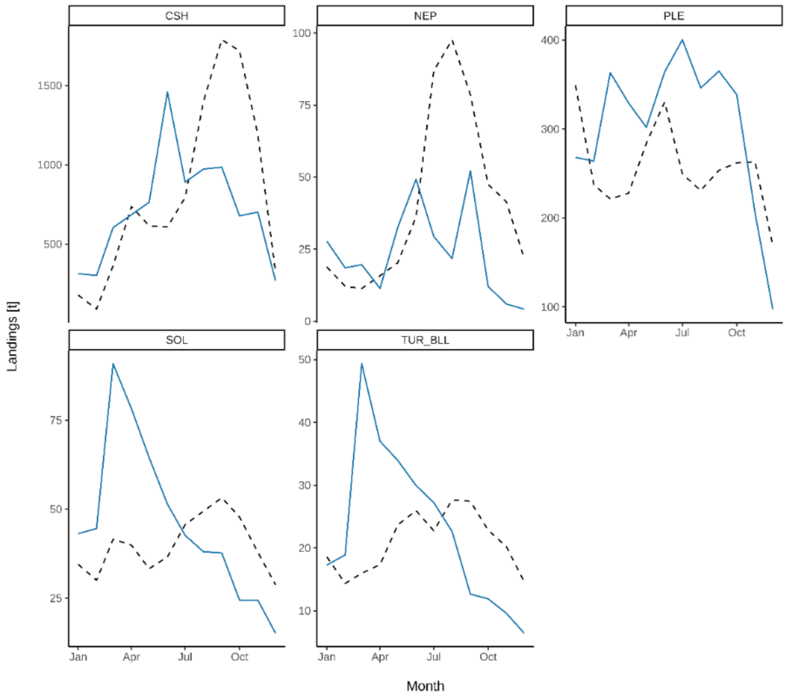


Figure V-D2. Outcome from the final step of the pattern-oriented modelling comparing modelled catches (blue) to observed ones (dashed black) per metier. Both lines represent monthly means across model runs (n = 10) and observed years (n = 7).

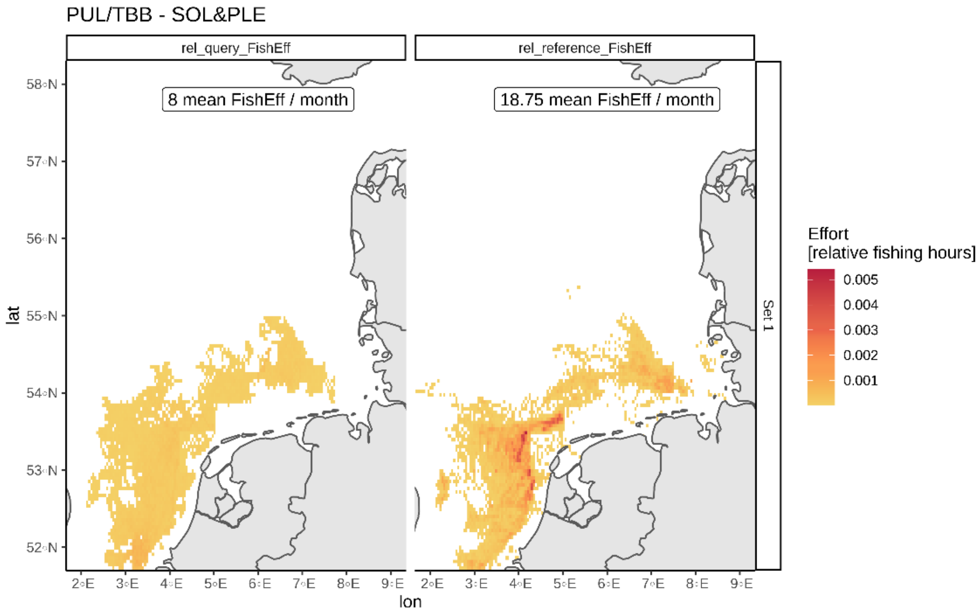


Figure V-D3. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the PUL/TBB – SOL&PLE metier group. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

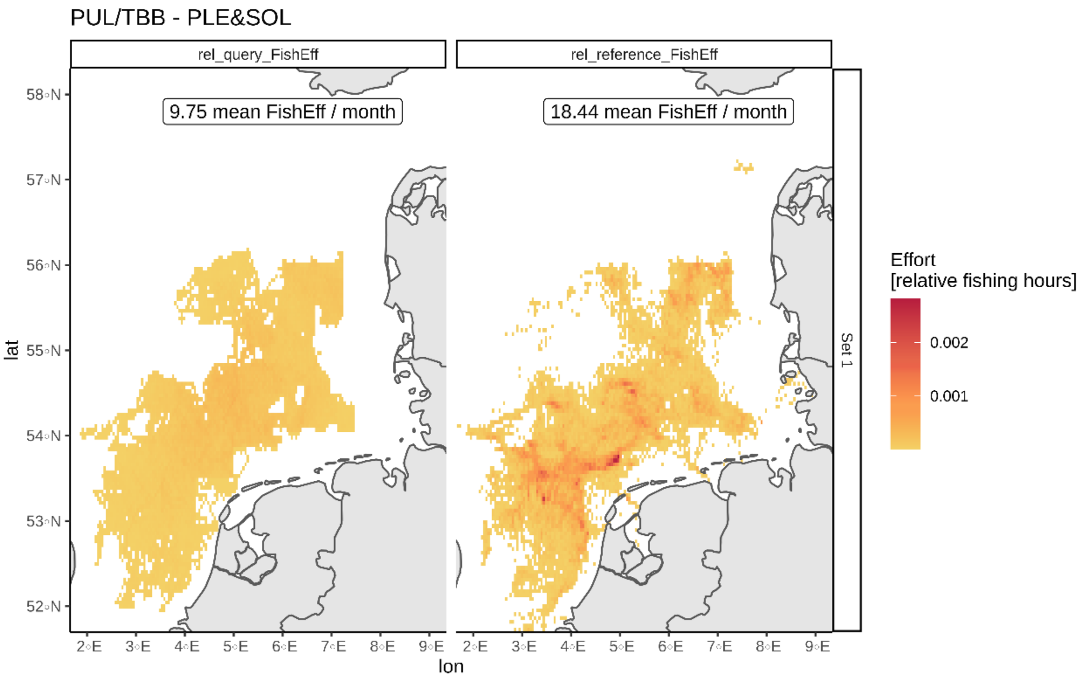


Figure V-D4. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the PUL/TBB – PLE&SOL metier group. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

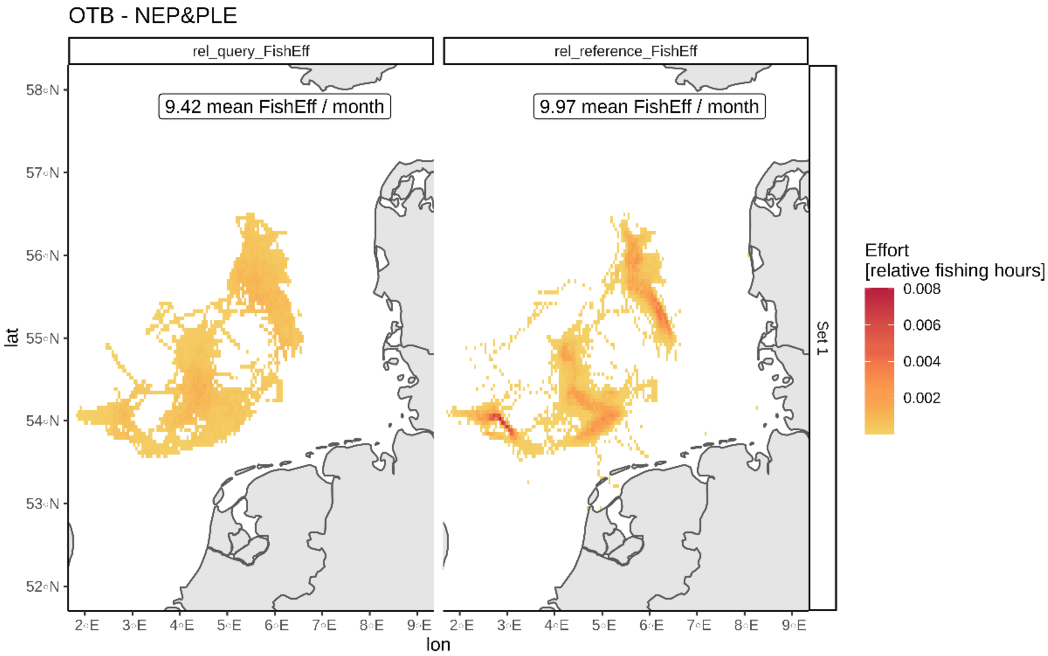


Figure V-D5. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the OTB – NEP&PLE metier. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

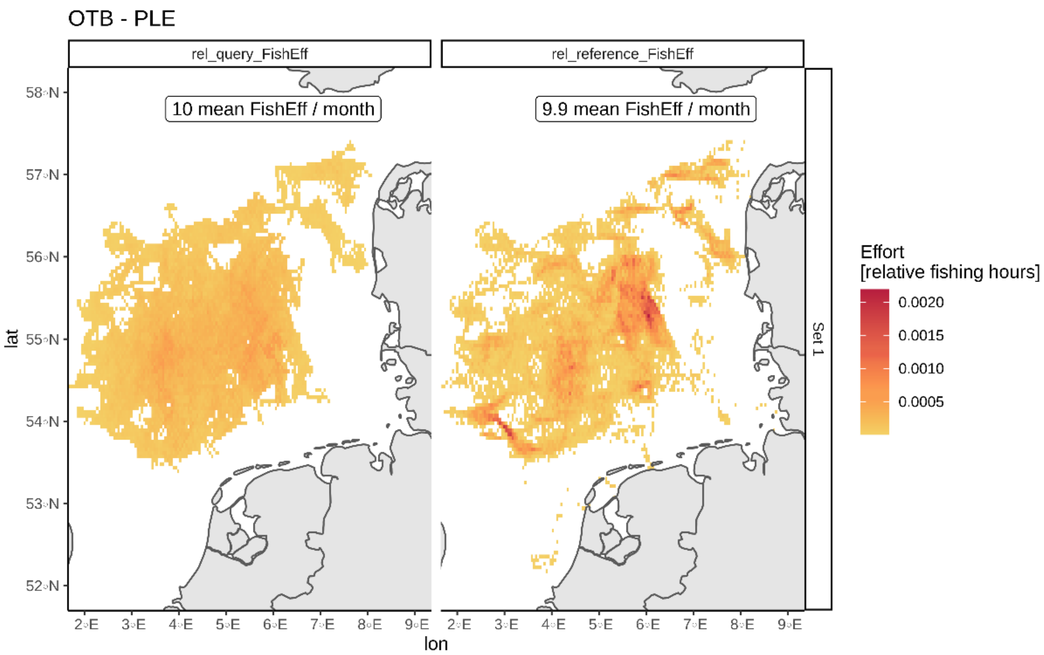


Figure V-D6. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the OTB – PLE metier. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

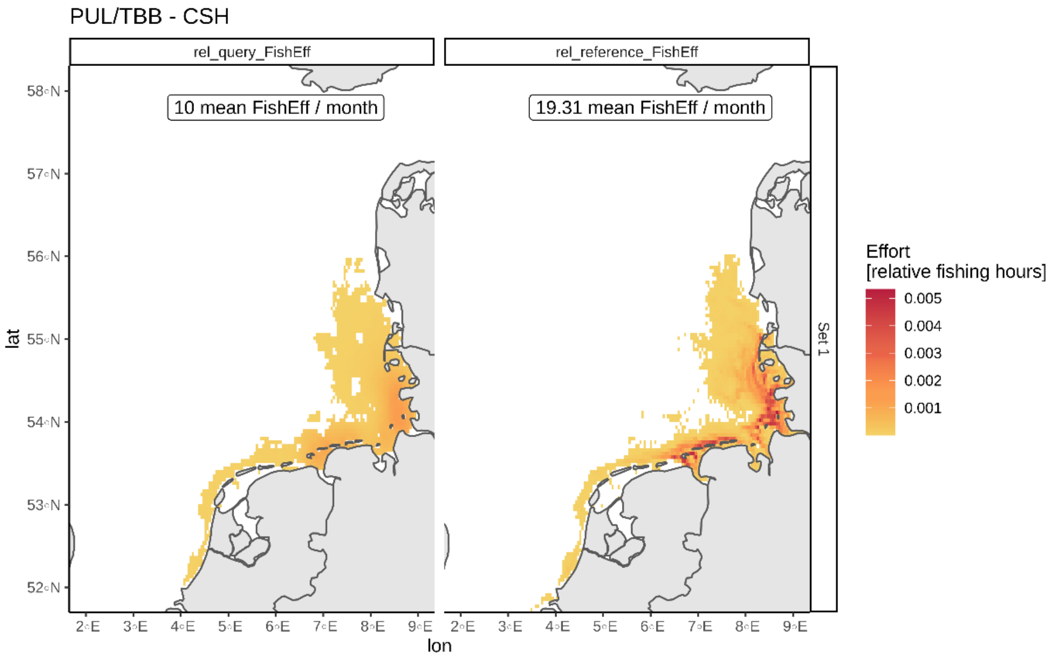


Figure V-D7. Outcome from the final step of the pattern-oriented modelling comparing modelled and observed relative fishing effort for the PUL/TBB metier group. Values per patch represent monthly means across model runs (n = 10) and observed years (n = 7).

Appendix E – Details output verification

Additional Validation Plots

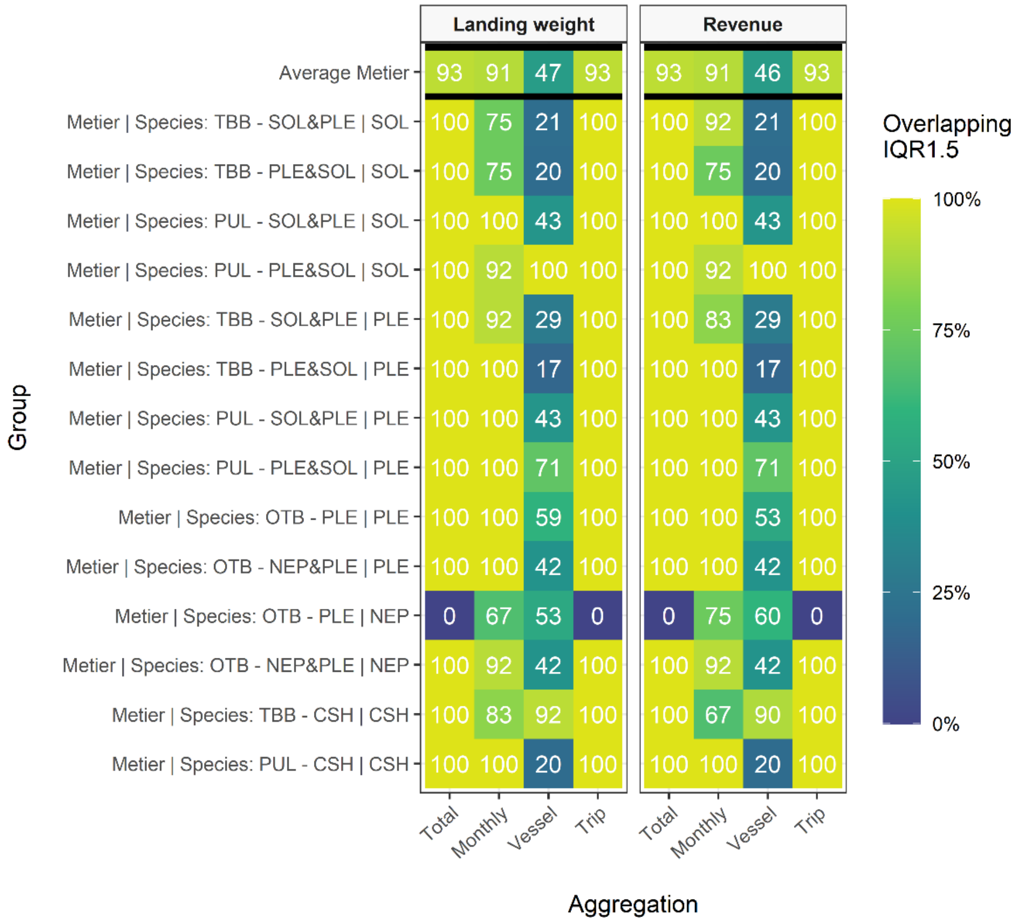


Figure V-E1. The percentage of data points with overlapping 1.5 times inter-quartile ranges (IQR1.5) between modelled and observed non-spatial variables resolved by metier and species. Colors and numbers correspond to the percentage of overlaps across different aggregations (columns), and metiers and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

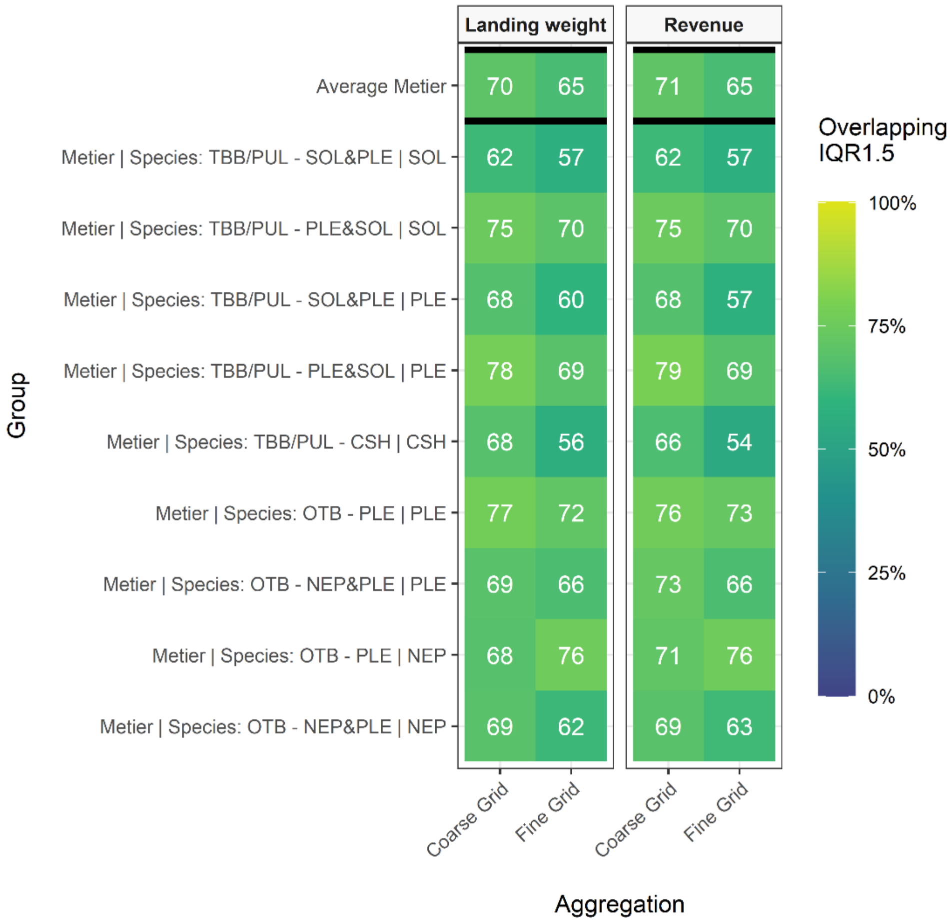


Figure V-E2. The percentage of data points with overlapping 1.5 times inter-quartile ranges (IQR1.5) between modelled and observed spatial variables resolved by metier and species. Colors and numbers correspond to the percentage of overlaps across different aggregations (columns), and metiers and species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

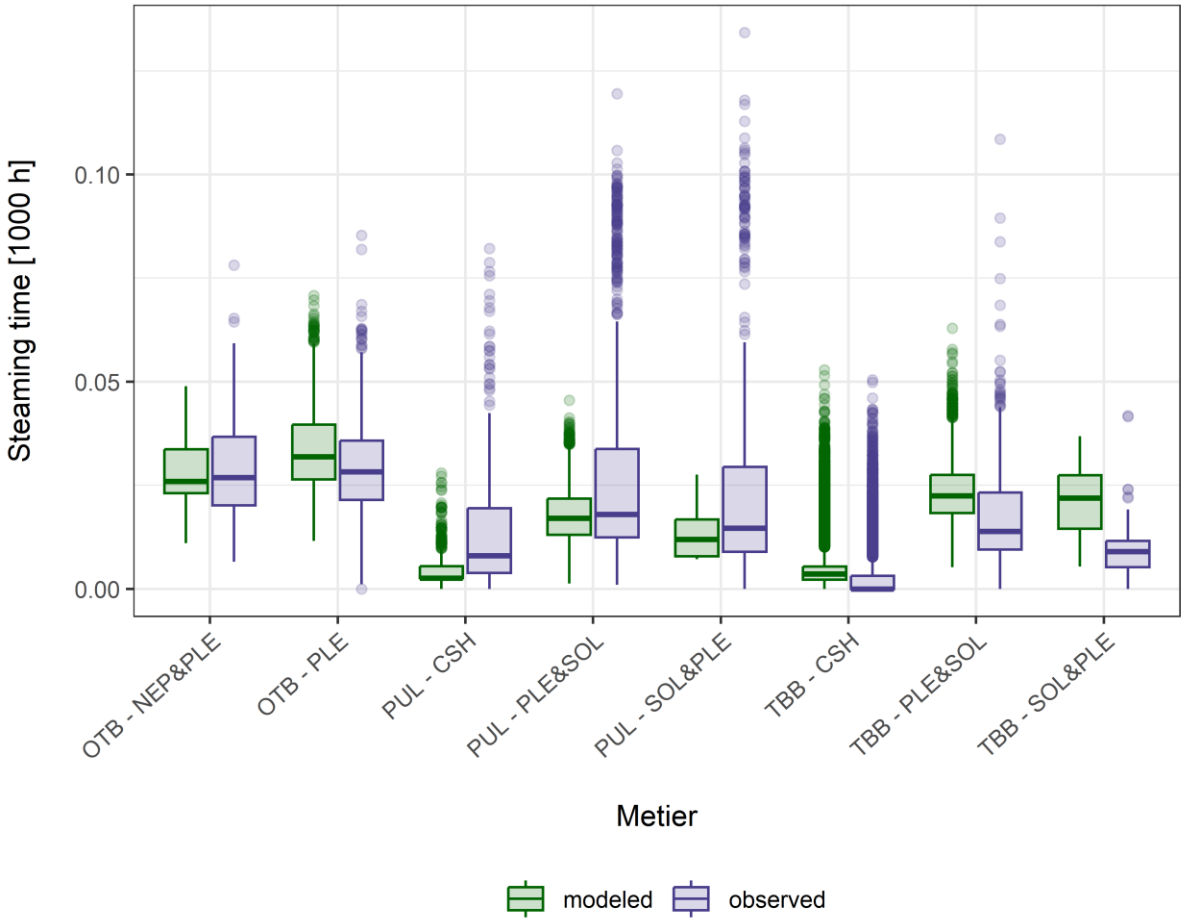


Figure V-E3. Steaming time per trip. Boxplots represent both distributions across trips and sample points (modelled n = 50 model runs; observed n = 7 observed years)

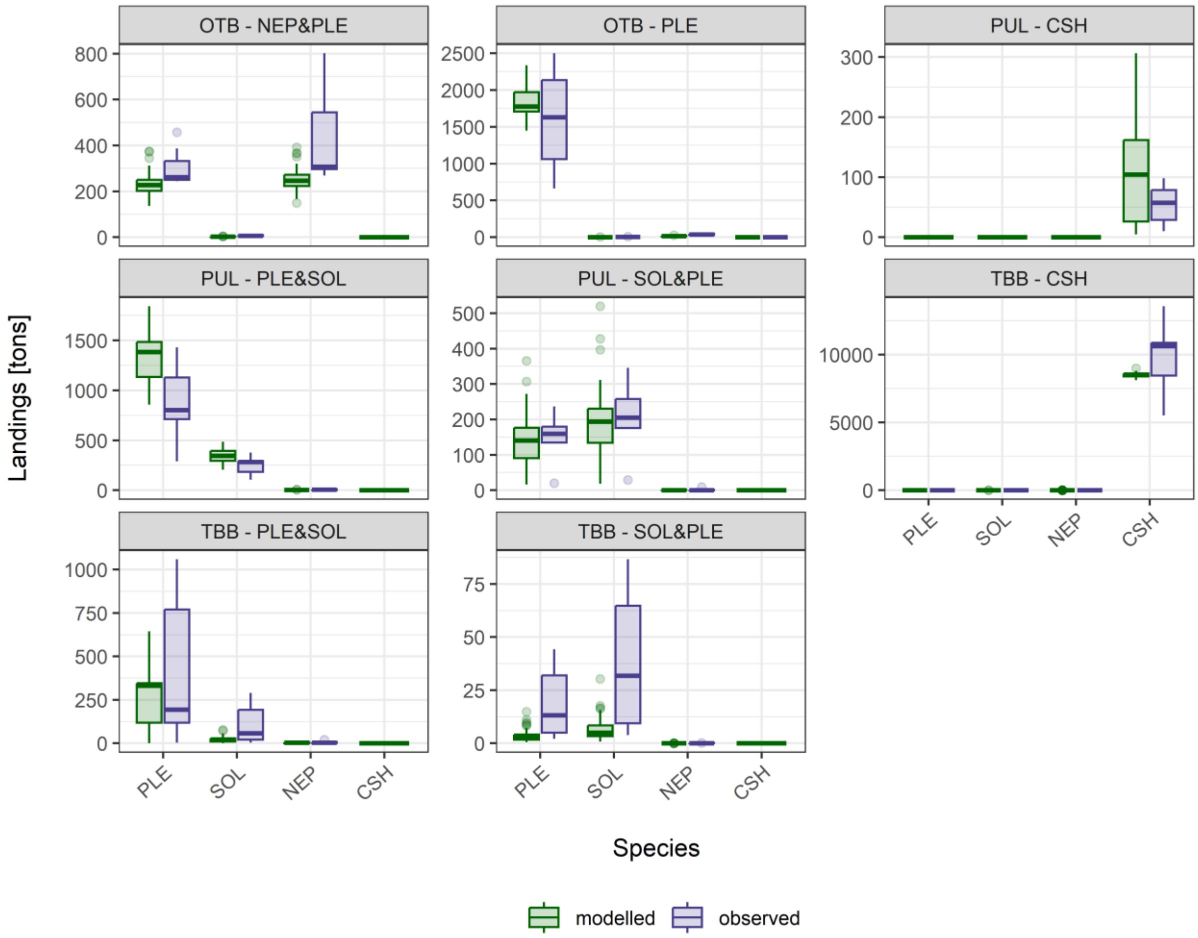


Figure V-E4. Landing composition per trip, species, and metier (panels). Boxplots represent both distributions across trips and sample points (modelled n = 50 model runs; observed n = 7 observed years)

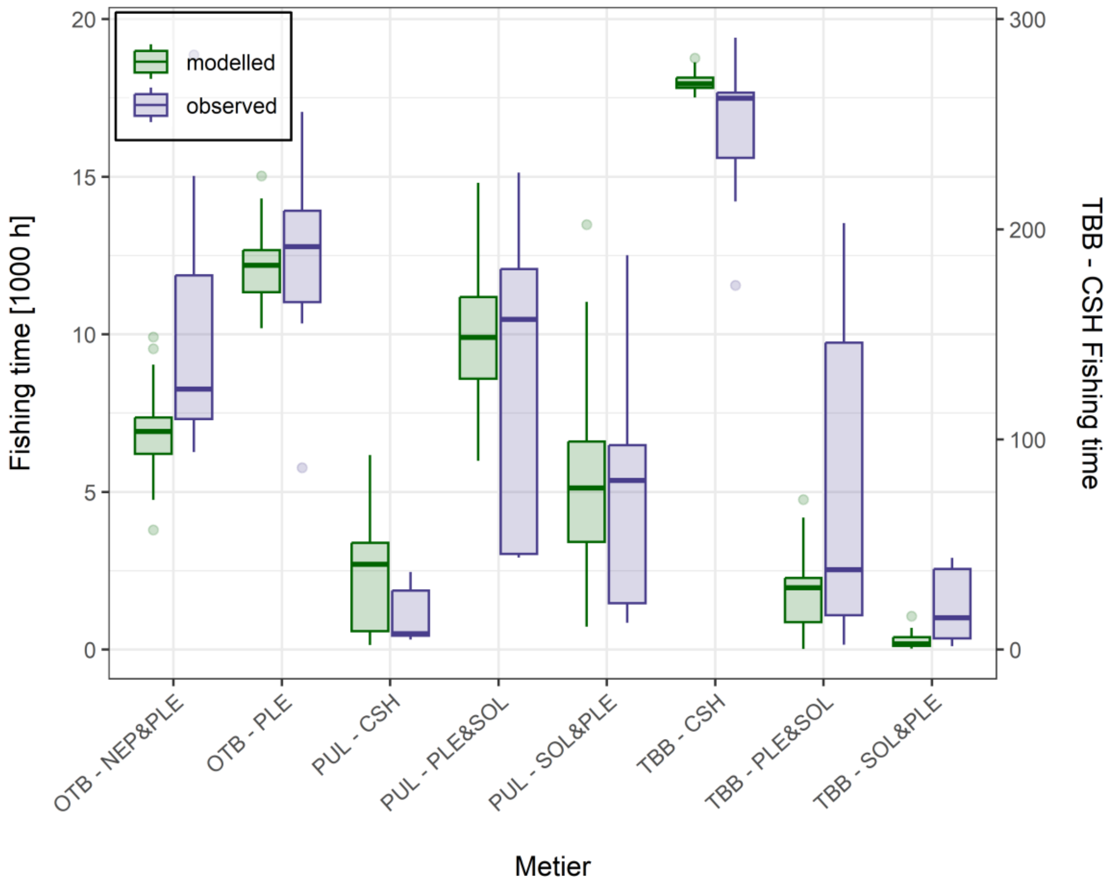


Figure V-E5. Fishing time per model run, species, and metier. Boxplots represent distribution across sample points (modelled n = 50 model runs; observed n = 7 observed years)

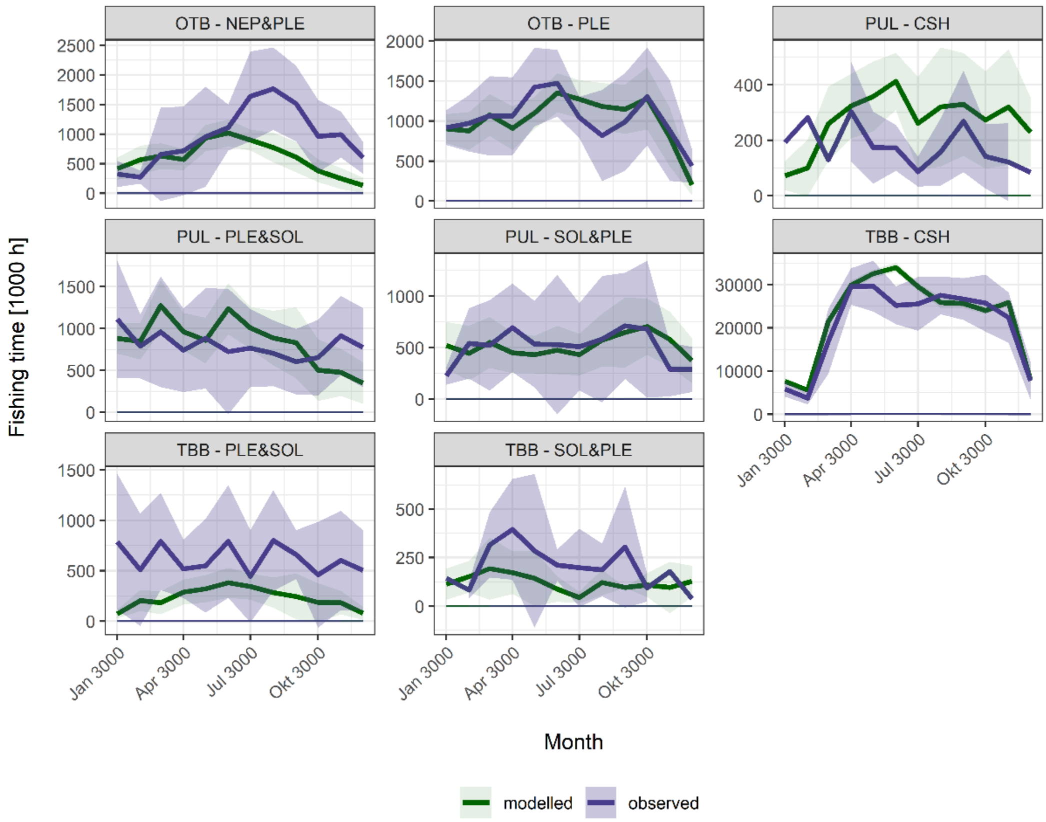


Figure V-E6. Fishing time per model run, species, metier, and month. Ribbons represent standard deviations and lines means across model runs (green) and observed years (blue).

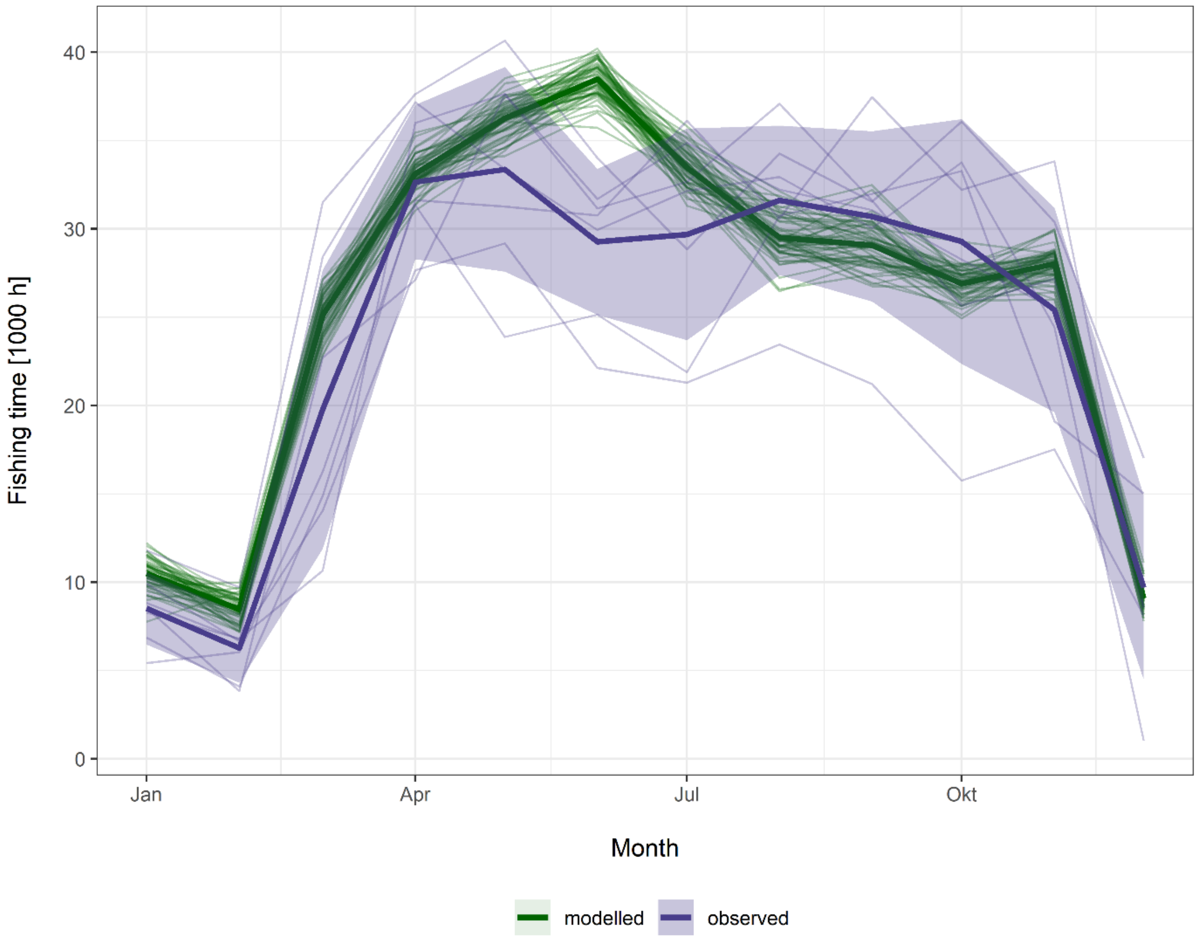


Figure V-E7. Fishing time per model run and month. Thin lines represent individual model runs (green) and observed years (blue), thick lines averages, and ribbons standard deviations.

Supplementary Material – Chapter VI

Testing the waters: explorative scenarios indicate lower fishing activity and profits for the North Sea

Appendix A

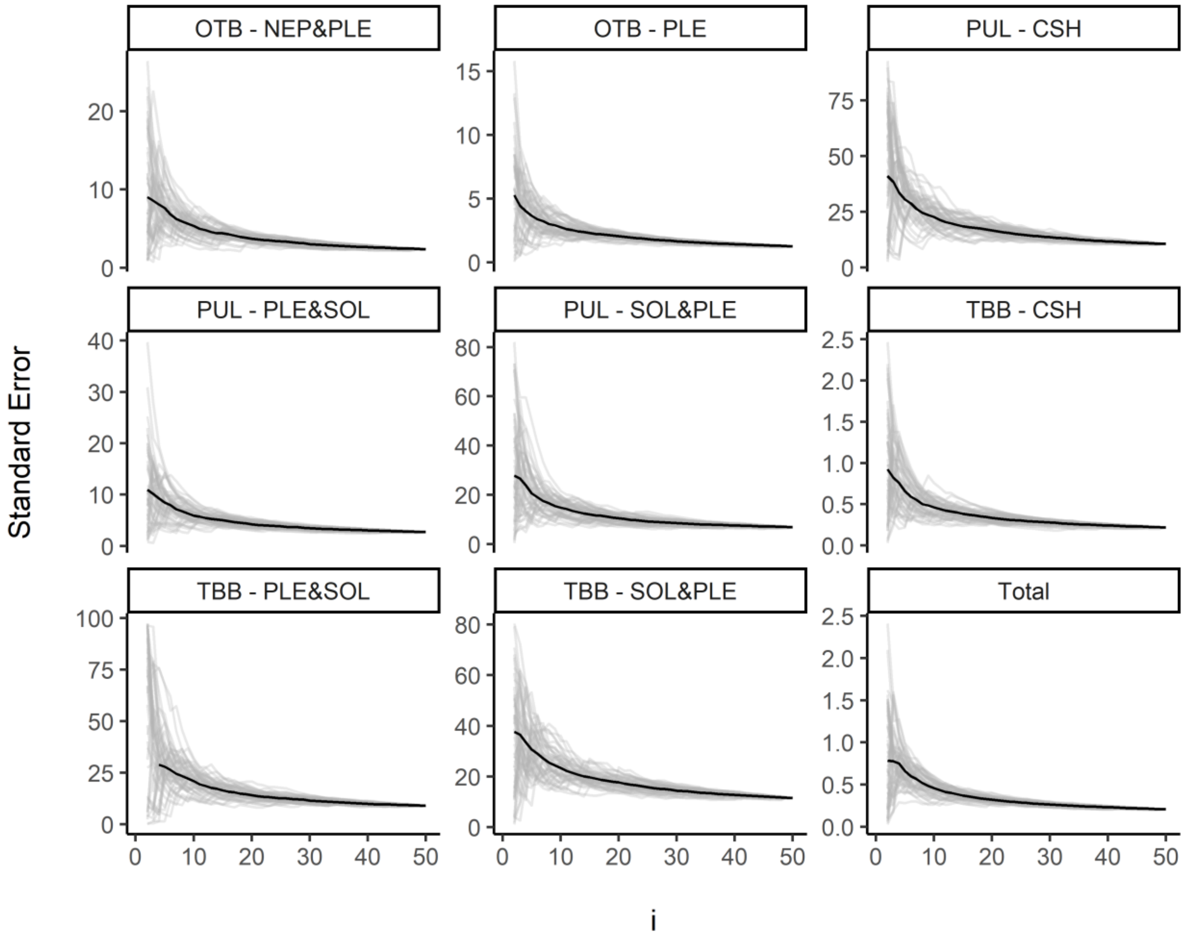


Figure VI-A1. Cumulative standard error across 50 model runs (on x-axis). Grey lines represent permutations of the order of model runs and the black line the average across all permutations.

Table VI-A1. Total changes in fishing hours, steaming hours, number of trips, profits, and fished cells of every scenario in comparison to *Base-run*. Numbers represent averages across all model runs.

	OWF2030+NTZ	**OWF2040+NTZ**	**PUL-false**	**Fuel-300%**	**Fuel-600%**
Fishing hours					
10^3 h	- 2.2	- 3.1	- 9.9	- 114.4	- 219.9
%	- 0.7	- 1	- 3.2	- 37.1	- 71.4
Steaming hours					
10^3 h	- 0.2	+ 1.1	- 1.7	- 26.8	- 50.2
%	- 0.3	+ 1.6	- 2.4	- 38.1	- 71.3
Number of trips					
#	- 46	- 55.9	- 80.2	- 4055.1	- 7523
%	- 0.4	- 0.5	- 0.8	- 38.9	- 72.1
Profits					
Mill €	- 0.5	- 1.5	- 5.9	- 21.1	- 33.5
%	- 1.8	- 5.1	- 20.3	- 72	- 114.6
Fished cells (average size: 14.56 km^2)					
#	- 1061.1	- 2010.4	- 1276.6	- 327.6	- 1821.7
%	- 13	- 24.6	- 15.6	- 4	- 22.3

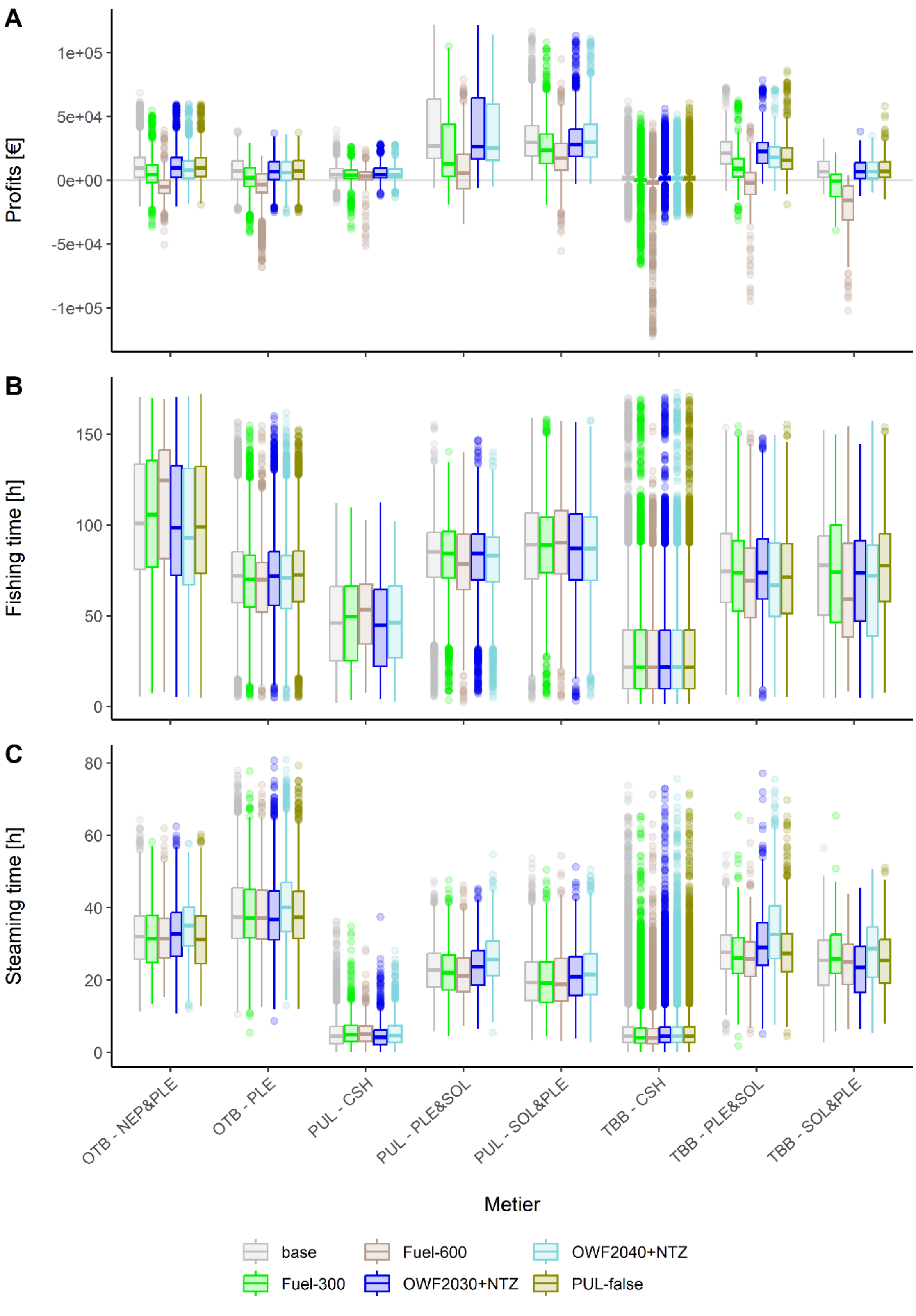


Figure VI-A2. Model outcomes per fishing trip and metier for the base run and the five scenarios (color coded). A = profits per trip; B = fishing hours per trip; C = steaming hours per trip.

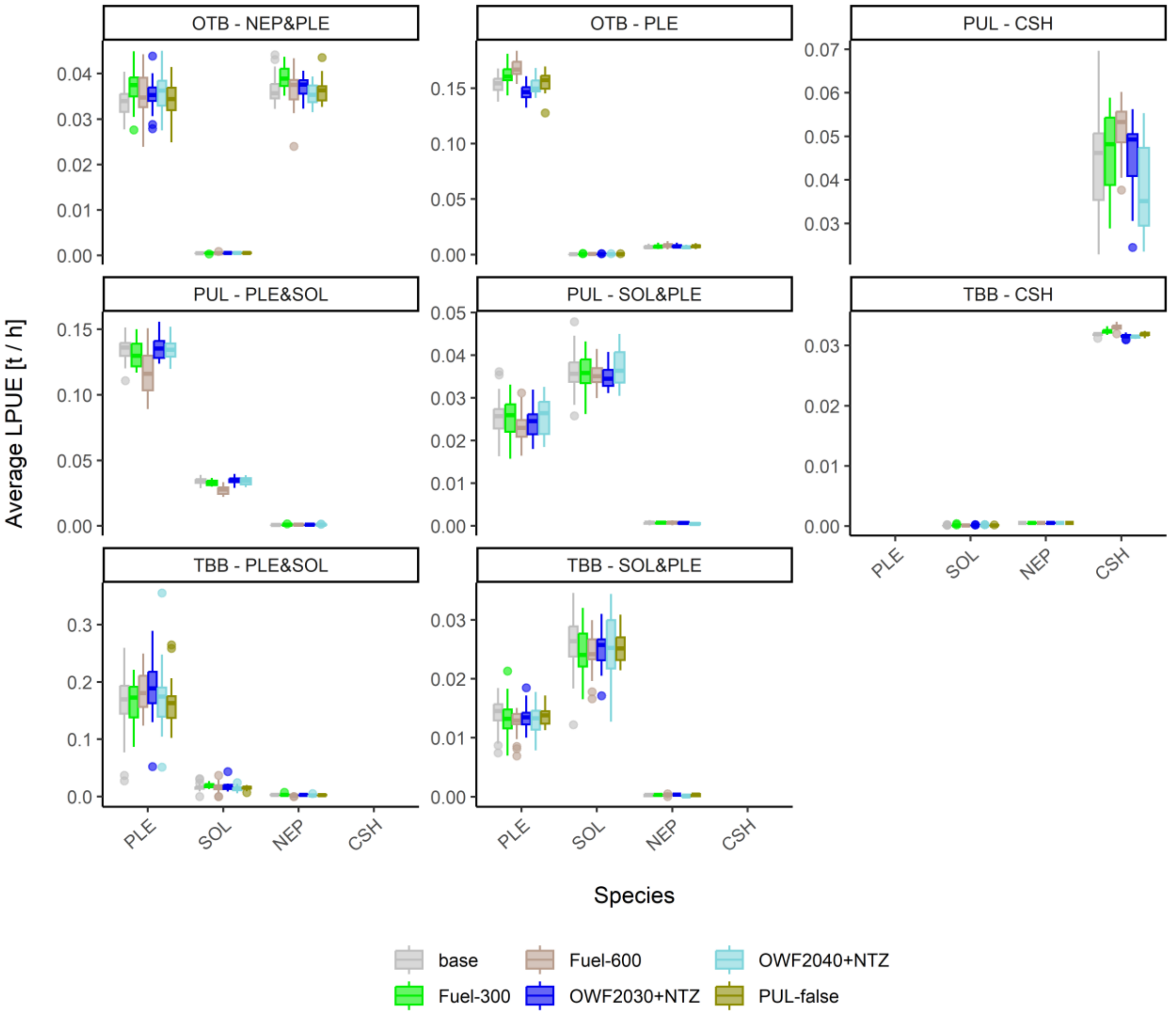


Figure VI-A3. Simulated landings per unit of effort (LPUE) per metier averaged across fishing trips and for the most relevant species, i.e. plaice (PLE), sole (SOL), Nephrops (NEP), and common shrimp (CSH).

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Eidesstattliche Versicherung - Declaration on oath

Hiermit erkläre ich an Eides statt, dass ich die vorliegende Dissertationsschrift selbst verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

I hereby declare, on oath, that I have written the present dissertation by my own and have not used other than the acknowledged resources and aids.

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