Geospatial Data and Fishery Management: Innovative Modelling Approaches

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Content

Abstract of the Dissertation iv
Acknowledgments vi
Introduction 1
Chapter I: Scale-dependency in discrete choice models: a fishery application 9
I.1. Introduction 10
I.2. Methods 15
I.2.1. Modelling framework 15
I.2.2. Tessellations 17
I.2.3. Monte Carlo experiments 17
I.2.4. Welfare impact of the implementation of a MPA 19
I.2.5. Bottom longline sector of the Gulf of Mexico Reef Fish fishery 21
I.3. Results 23
I.3.1. Goodness-of-fit and prediction capability 23
I.3.2. Parameter estimates 27
I.3.3. Evaluation of the welfare impact of a hypothetical MPA 30
I.3.4. Estimated losses for the hypothetical MPA in the GoMRF fishery 32
I.4. Conclusion 34
I.5. Appendix 39
I.5.1. Gulf of Mexico fishery Data 39
I.5.2. Spatial indexes used for the analysis 40
I.5.3. Maps of the partitions of space considered 43
I.5.4. Monte Carlo experiments 45
I.5.5. Complementary estimation assumptions for the applied case study 51
I.5.6. Complementary results 52
II.1. Introduction 61
II.2. Case study: French fleet operating in UK waters 66
II.3. Methods 68
II.3.1. Assessment of the economic dependency to UK waters 68
II.3.2. Discrete choice model of fishing relocation decisions 69
II.4. Results 73
II.4.1. Economic importance of UK waters for the French commercial fleet 73
II.4.2. Prediction of short-term reallocation of fishing effort 82

II.4.3. Discussion and Conclusion ... 89
II.5. Appendix ... 97
II.5.1. SACROIS Data ... 97
II.5.2. Dependency of the French fleet on UK waters ... 99
II.5.3. Discrete-Choice Model ... 115
II.5.4. Maps of the impact of spatial closures ... 122
II.5.5. References for Appendix II ... 132
Chapter III: Impact of IFQ on fishing strategies at sea: a Hidden-Markov Model approach 135
III.1. Introduction ... 136
III.2. Background on the impact of IFQs and on behavioral models ... 138
III.2.1. Evaluation of fishers' response to a shift in the regime of fishing rights ... 138
III.2.2. Modelling of fishing behavior at sea ... 140
III.2.3. Focus on State-Space Models and Hidden-Markov Models ... 142
III.3. Modelling framework ... 144
III.3.1. Data regularization with a SSM ... 144
III.3.2. HMM ... 146
III.3.3. Estimation strategy ... 146
III.4. Empirical Setting, model specification and validation approach ... 148
III.4.1. Background on fisheries in the Gulf of Mexico ... 148
III.4.2. Data ... 149
III.4.3. Bottom longline fishing sets ... 150
III.4.4. Model specification ... 151
III.4.5. Validation approach ... 155
III.5. Results ... 156
III.5.1. Model's validity ... 156
III.5.2. Behavioral impact of the GT-IFQ program ... 159
III.6. Discussion and conclusion ... 162
III.7. Appendix ... 171
III.7.1. Behavioral profile of longline fishing operations ... 171
III.7.2. Models' estimates ... 175
III.7.3. Mode decomposition of the speed and turning angle distribution ... 192
Conclusion ... 193

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Abstract of the Dissertation

This dissertation investigates how recent advances in the availability of geospatial data can be utilized to improve natural resources management. Taking Vessel Monitoring System (VMS) data and fisheries from the Gulf of Mexico and the North East Atlantic region as empirical settings, it develops novel approaches to better model commercial fishing behavior and to analyze policy interventions.

In Chapter I, I focus on discrete choice models and spatial aggregation issues. Combining simulated geospatial data from Monte Carlo experiments with real VMS data from fishing vessels in the Gulf of Mexico, I show how models' results depend on the choice of the spatial scale of analysis and on data spatial heterogeneity. I illustrate the implications for policy analysis exposing the potential biases when assessing the welfare impact of the implementation of a hypothetical marine protected area.

In Chapter II, I employ VMS data to explore a topical policy issue, examining the possible impacts of Brexit on the French commercial fishing fleet. I consider two spatial closure scenarios which could be implemented as a consequence of the United Kingdom leaving the European Union. Taking advantage of data high level of resolution, I draw a comprehensive picture of the dependency of French fisheries to UK waters. Focusing on five key fleet segments, I build on the methodological and modelling framework developed in Chapter I to anticipate fishing effort re-allocation patterns and to assess the welfare impact resulting from the closure of UK waters to French fishers.

In Chapter III, I develop an innovative framework based on Hidden-Markov Models to analyze the behavior of fishers at sea. I apply it using VMS data and I show how this approach can enhance our understanding of fishers' response to new management measures. Taking the example of the implementation of Individual Fishing Quotas in the Bottom Longline fishery in the Gulf of Mexico, I am able to uncover the heterogeneity of fishers' behavioral reaction to the new policy.

Overall, this dissertation takes a pluralistic approach to examine the value of geospatial data for resource management. Building upon a diversity of case studies and policy questions, it brings forward the scientific basis for decision-making in fisheries policy and more broadly for the sustainable management of natural resources.

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Introduction

In the context of the sustainable exploitation of natural resources, the understanding of the spatial and temporal dynamics of resource users is essential for the conception and the evaluation of management policies (Kritzer and Liu, 2014; Lewison et al., 2015).

In particular, a consensus has emerged that recognizes the fundamental role played by formal and informal institutions in shaping resource users' behavior (Bromley and Cernea, 1989; Leach et al., 1999). While the consensus originated from research on the management of common pool resources in general (Schlager and Ostrom, 1992; Van Laerhoven and Ostrom, 2007), commercial fishing is the archetypal example. It has provided some of the strongest evidence for the endogeneity between human behavior and institutional structure (Abbott and Wilen, 2011; Sanchirico and Wilen, 2007; Wilen et al., 2002).

The evidence also shows that failing to take into account this endogeneity can lead to unintended consequences from management interventions (Ludwig et al., 1993; Wilen et al., 2002; Degnbol and McCay, 2007; Hilborn, 2007; FAO, 2009; Fulton et al., 2011; Abbott and Haynie, 2012). Consequences that resulted in many important fish stocks around the world being overfished and experiencing overfishing (FAO, 2016). Thereby, understanding and anticipating fishers' response to policy interventions is a fundamental research area in fishery economics as well as in economics as a whole.

In this regard, fishery managers have now access to an unprecedented amount of micro-level data about fishing behavior, especially thanks to the advent of geolocation technologies and their large-scale deployment as monitoring tools since in 1990's. In particular, Vessel Monitoring

System (VMS) is becoming more and more widely used by regulatory agencies (McCauley et al., 2016). Fishery scientists have used them for various purposes such as delineating fishing grounds (Jennings and Lee, 2012; Lee et al., 2010), assessing the impact of fishing on the seabed (Harrington et al., 2007), validating self-reported data (Bastardie et al., 2010), and, most importantly, improving the estimation of fishing effort (Bastardie et al., 2010; Gerritsen and Lordan, 2011; Lee et al., 2010; Russo et al., 2013). More rarely, however, VMS data has been used to carry out analyses at the vessel level.

Yet, by allowing to observe directly individual fishing patterns at a very fine spatial and temporal resolution, VMS data opens up the possibility to improve spatially-explicit dynamic models of fishing behavior, which can allow managers to anticipate correctly fishers' response to new regulatory environments (Girardin, 2015; Gloaguen et al., 2015).

In the three chapters of this dissertation, I demonstrate how VMS data can be utilized to:

- improve the reliability of existing spatial economic models (Chapter I);
- better analyze and anticipate the consequences of policy shifts (Chapter II); and,
- implement innovative modelling tools for resource management and policy evaluation (Chapter III).

In the first chapter, I focus on discrete choice models (DCM), a modelling framework that dominates economic research on policy welfare analysis and on the prediction of the choices of fishing locations. Particularly suited for decisions in the extensive margin, DCMs fit also very well in the fishery setting, where the distribution of resources is often patchy (Sanchirico and Wilen, 1999). Although they provide a powerful framework for modelling spatial and temporal fishing

behavior (Smith, 2010), the reliability of DCM results hinges in part on the definition of the choice set, as analyses are often limited by data availability (Huang and Smith, 2014; Smith, 2005).

Issues associated with ill-defined choice sets are neither new nor unique to fisheries economics (Manski, 1977; McFadden, 1978). Most of research works, however, have focused on the issue of which choice alternatives to include in the consideration set and how to estimate it in a consistent manner (Hauser, 2014; Horowitz and Louviere, 1995; Prato, 2009). Much less attention has been given to the questions of how to aggregate information spatially and how this may shape DCM results. Chapter 1 contributes to fill this knowledge gap.

With the granular nature of VMS data permitting to control the discretization of space, I investigate the implications of spatial aggregation on the performance of DCMs. To do so, I use a novel empirical approach that relies on simulated and real data and estimates the same DCM at varying spatial resolutions. The simulated data is a series of Monte Carlo experiments where I control the data-generating process and vary the levels of spatial heterogeneity of the data. This allows me to disentangle and quantify the different biases due to spatial aggregation. Using a unique dataset on longline fishing activities in the Gulf of Mexico from 2007 to 2013, I then show the magnitude of those biases and the implication on welfare analysis.

Having addressed this methodological challenge and developed a robust analytical framework for using DCMs and VMS data in Chapter I, I implement it in a different context in Chapter II to investigate an utterly political issue.

I examine the possible impacts on the French commercial fishing fleet of two spatial closure scenarios which could be implemented as a consequence of Brexit. The first scenario consists in the closure of the territorial waters of the United Kingdom (UK) and the second scenario consists in the closure of its entire exclusive economic zone (EEZ).

The current discussions surrounding losing access to UK waters are missing quantitative assessments of the potential implications. To fill this gap, I take advantage of a unique dataset from the French Research Institute for Exploitation of the Sea (Ifremer) based on French VMS, logbooks and sales data ("SACROIS," 2017), to draw a comprehensive picture of the current dependency of French fisheries to UK waters. I exploit the high level of resolution of the dataset to successively break down the multidimensional aspects of the economic relationship at the levels of vessels, fleet segments, species and ports.

Narrowing down the focus on five key fleet segments deemed to be significantly impacted by a restriction of access to UK waters, I then use the same methodological and modelling framework developed in Chapter I to estimate a DCM of fishing locations in order to predict the re-allocation of fishing effort and welfare impact that would result from the closure of UK waters to French fishers. While highlighting important socio-economic implications for policy-makers, I point out some of the limitations of my results and provide suggestions to further investigate the full consequences on fisheries of the withdrawal of the UK from the European Union.

With the same focus on policy impact assessment as Chapter II but building on the empirical setting and VMS data exposed in Chapter I, Chapter III takes on a more innovative approach than DCMs for analyzing the consequences of institutional shifts.

In this last chapter, I focus on the impact on fishers' behavior at sea of the implementation in 2009 and 2010 of a set of new management measures – including Individual Fishing Quotas (IFQs) – in the Grouper-Tilefishes bottom longline (GT-BLL) fishery in the Gulf of Mexico. To do so, I develop a Hidden-Markov Model (HMM) of fishing behavior that I estimate with VMS data.

Despite commonly used in the animal ecology literature to study movement patterns (Bennison et al., 2018; Shamoun-Baranes et al., 2012), very few studies have employed HMMs in combination with VMS data to examine vessels' fishing strategies at sea (Vermard et al., 2010; Walker and Bez, 2010). None, to my knowledge, have used this powerful modelling framework to conduct policy impact assessment.

Chapter III fills this gap by taking the example of the 2009-10 policy shift in the GT-BLL fishery of the Gulf of Mexico and by estimating a HMM able to predict and characterize the behavioral states of fishers at sea. Focusing on three behavioral modes and validating model's results with observer data, I use a sub-sample of vessels that were fishing both before and after the policy shift to compare how behavioral modes have changed between the two periods.

The same theme underlies each chapter of this dissertation: how the revolution on spatial data can be put to work in practice for improving our management of natural resources users. Taking VMS data and fisheries as a case study, this dissertation tackles this challenging research question through both empirical and theoretical aspects and investigates it in various settings. By do so, I believe it provides a pluralistic view over the issue and helps bridging some significant knowledge gaps.

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Chapter I: Scale-dependency in discrete choice models: a fishery application[1]

Abstract

Modeling the spatial behavior of fishers is critical in assessing fishery management policies and has been dominated by discrete choice models (DCMs). This paper examines the complexity associated with the choice of the spatial scale in a DCM of fishing locations. We employ a novel empirical approach that relies on simulated and real data and estimates the same DCM at varying spatial resolutions. We assess model performance using goodness-of-fit, predictive capability, ability to recover parameter estimates, and the assessment of the fishery response to a hypothetical marine protected area. Results show that, even when the decision-making process is correctly specified, models can be structurally inconsistent because of the aggregation of data. Unfortunately, this inconsistency cannot be detected by a researcher conducting analysis at only one spatial scale. We conclude that best practice entails considering various spatial aggregation levels to assess the robustness of a model's results.

[1] This chapter is developed as a standalone paper with co-authors James N. Sanchirico, Olivier Thébaud, Shay O'Farrell, Alan C. Haynie, and Larry Perruso.

I.1. Introduction

Understanding and anticipating fishers' spatial behavior is a critical component in the design and the assessment of fishery management policies (Lewison et al., 2015; Valcic, 2009). Research on predicting the choice of fishing locations is dominated by discrete choice models (DCM), which are well-suited to the fishery setting where the resource distribution is often patchy (Sanchirico and Wilen, 1999). Although DCMs provide a powerful framework for modeling spatial and temporal fishing behavior (Smith, 2010), the reliability of DCM results hinges in part on the definition of the choice set, as analyses are often limited by data availability (Huang and Smith, 2014; Smith, 2005).

Issues associated with ill-defined choice sets are neither new nor unique to fisheries economics (Manski, 1977; McFadden, 1978). Most of the attention, however, has focused on the issue of what to include in the consideration set – the subset of the choice set which includes only the alternatives considered by the decision-maker – and how to estimate it in a consistent manner. For example, the marketing and transportation literature in particular has extensively investigated the heuristics of consideration sets since the 1970s (Hauser, 2014; Horowitz and Louviere, 1995; Prato, 2009). In the 1990s, a number of important papers in recreation demand and environmental economics demonstrated the impact of choice set specification on welfare outcomes – and thus on policy analyses – and showed that the sign and magnitude of welfare biases is not necessarily systematic and can be ambiguous (Parsons et al., 2000; Parsons and Hauber, 1998; Peters et al., 1995).

Over the last decade, the spatial resolution of data capturing fishing behavior has undergone a dramatic shift with the deployment of geolocation technologies, such as Vessel Monitoring Systems (VMS). The recent availability of vessel position data with high spatial resolution (better than 10 m accuracy) is a dramatic improvement over traditional data that were aggregated into

large statistical areas and opens up possibilities to refine the analyses of fisher behavior across space and time. VMS transponders are placed on each vessel and track vessel positions at certain intervals (e.g., each hour). With potentially millions of recorded locations for each vessel, VMS data allow researchers to relax some prior assumptions underlying many DCMs regarding the data-generating process and spatial scale of the analysis. That is, in prior studies constrained by coarse spatial data, there is the implicit assumption that the decision-making process generating the data operates at those scales.

VMS data allow a more refined discretization of space permitting us to investigate the implications of spatial aggregation on the performance of discrete choice models. Figure I.1 illustrates the effects of spatial resolution where the color value of each tile (the aggregated unit of analysis) results from a weighted average of the colors associated with each individual observation. Depending on the interplay between the spatial distribution of the data, its spatial heterogeneity and the partition of space that is considered, the outcome at the aggregated spatial level can differ dramatically. For instance, note the changes in the colors associated to the same area (e.g. purple in partition 1 but deep blue in partition 2) and in the share of areas with missing information (25% in partition 1 but 56% in partition 2). Those differences highlight the information (implicitly) integrated into a spatial analysis. With VMS, we are able to investigate how different partitions of space reveal the extent of the sensitivity of a spatial model to the aggregation process.

In this paper, we combine both simulated and real data to investigate the following questions. First, how do estimates of discrete choice models of spatial behavior change as the mismatch between the spatial scale of aggregation and spatial scale of the data generating process grows? Second, how does the consistency of estimates at a spatially-refined resolution depends on the spatial distribution and heterogeneity of the observations?

The spatial aggregation process is important in discrete choice models for several reasons. First, the aggregation determines where an observation is located in space. Second, it determines what and how many choices are available in the next decision-making period. Third, whether to change location in any period is a function of the opportunities available in the consideration set, which are modified by spatial aggregation. Finally, the opportunities in the different sites are assessed at the aggregation of the data (e.g., expected catches) and therefore the aggregation will affect the amount of information available to make those calculations. For example, expected fish catches for each site in the choice set are determined as the average of the observations for that site over some prior period of time.[2] What the impacts of these effects are individually and in aggregate, however, is not immediately clear and will likely depend on the underlying heterogeneity of the data across both space and time.

The simulations that we conduct in this analysis are a series of Monte Carlo experiments (600 in total) mimicking data from a commercial fishery. In addition to allowing us to control for the decision-making process of fishers – thus be free from misspecification issues – the simulations enable us to control for the level of spatial heterogeneity of data by considering different spatial concentrations of observations. Each experiment estimates the true decision-making process of three datasets of observations across different spatial distributions at increasingly aggregated resolutions. For each combination of dataset and spatial resolution, we assess whether the estimated model can recover the true decision-making process, how well the model fits the data, and the predictive ability of the model. We also use the model to evaluate the welfare impact of

[2] In particular, the expected productivity of fishing sites has been shown to be a major driver of fishers' decisions (Girardin et al., 2016). Yet, it is not clear which information fishers integrate to form their expectations, and how they combine information coming from different sources and of different spatial and temporal scales (Abbott and Wilen, 2011). The extent of information sharing among fishers is a rich research area (Evans and Weninger, 2014; Wilson, 1990).

the implementation of a hypothetical Marine Protected Area (MPA) because DCMs have been a popular tool to conduct the impact analysis of an MPA policy (Curtis and Hicks, 2000; Curtis and McConnell, 2004; Girardin et al., 2015; Hicks and Schnier, 2010; Hynes et al., 2016; van der Lee et al., 2014; Wilen et al., 2002). We then apply the same analytical framework to a real case study using a unique dataset on bottom longline fishing in the Gulf of Mexico reef fish (GoMRF) fishery that includes newly available geospatial data.

Our work contributes to the literature in two ways. First, our Monte Carlo experiments provide new insight into the effects of both spatial heterogeneity and spatial aggregation on DCMs. Monte Carlo experiments have been used to assess the effects of varying the choice set generation process (Bierlaire et al., 2010; Li et al., 2015; Pramono and Oppewal, 2012; Stafford, 2018; Torres et al., 2011) and to validate the prediction capabilities of DCMs (Haynie, 2005; Smith et al., 2014) but never to assess the sensitivity of the model to either the spatial heterogeneity of data or the partition of space. Second, we investigate the issue of the spatial scale of analysis in the context of VMS data utilization for DCM estimation. VMS data have been used in the context of discrete-choice modelling to refine the spatial identification of fishing sites or fishing operations (Hynes et al., 2016; Rijnsdorp et al., 2011; Russo et al., 2015) but never to explicitly address the relationship between the spatial scale of decisions and the spatial scale of analysis.

We find that even when the decision-making process is correctly specified, discrete choice models can be structurally inconsistent because of the aggregation of data, and that these effects are amplified as spatial heterogeneity increases. In contrast, we are not able to detect any effect of the spatial irregularity of data. Second, we demonstrate how VMS data can be used to possibly detect model inconsistency and to assess the robustness of discrete choice model results. Overall, our findings suggest caution in the use of discrete choice models for policy analysis, especially if

the researcher is unable to verify the robustness of their results across multiple spatial resolutions (e.g., due to data limitations).

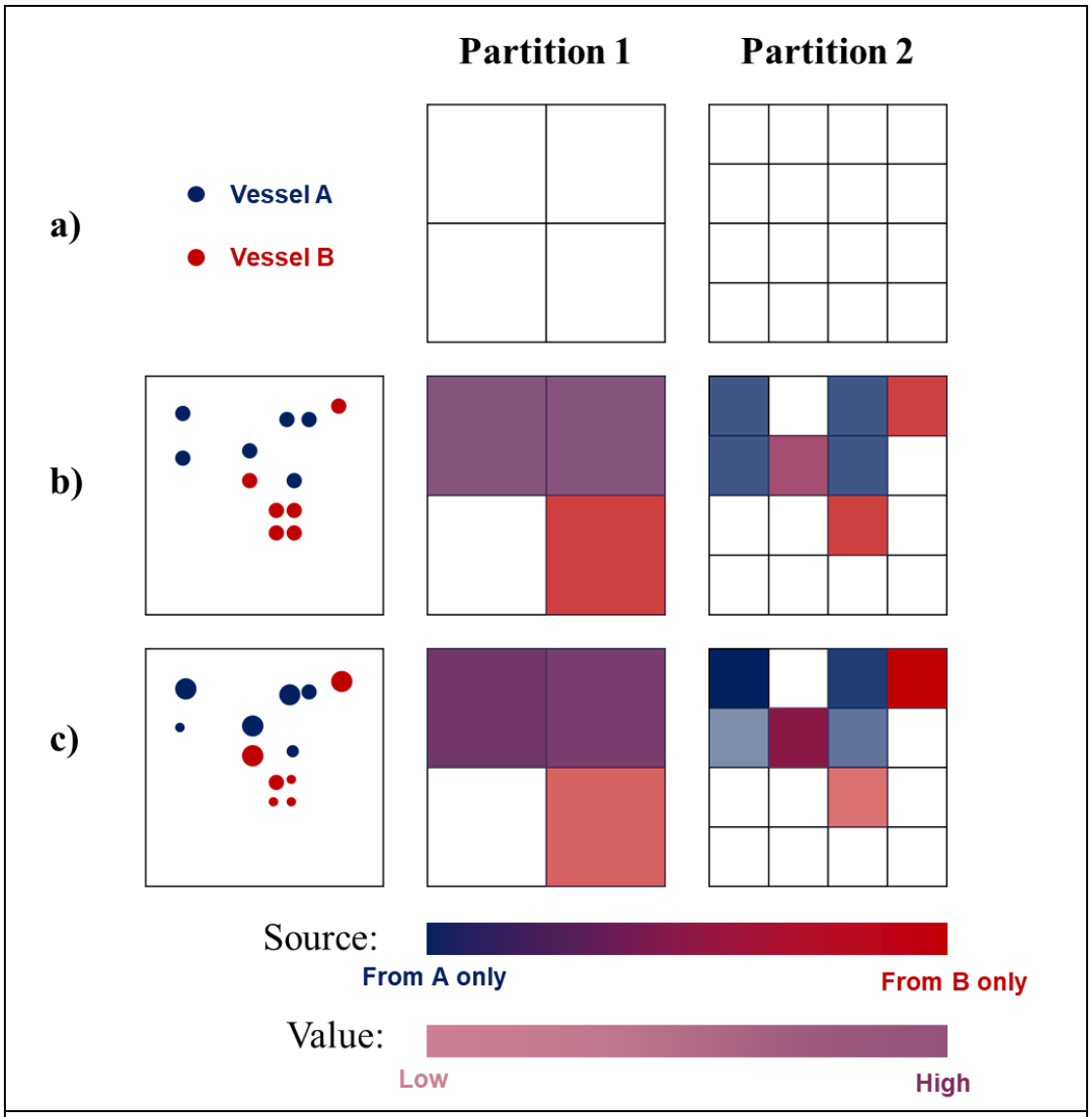

Figure I.1. Conceptual figure illustrating how the partition of space in a model intrinsically shapes how information is integrated and therefore the results the model. The panels are: a) identification of the two vessels and two alternative partitions of the fishing area; b) illustration of the case where observed values (e.g. catch rates) are homogeneous in all locations; c) illustration of the case where observed values are heterogeneous across locations (dots indicate scale).

In the remainder of the paper, we first describe our methods and data. We then show side-by-side the results with the simulated data and with observations from the bottom longline (BLL) sector of the GoMRF. Finally, we summarize our findings and we draw general conclusions about spatial models and the use of VMS data and we suggest possible future research in this area.

I.2. Methods

Identifying the effect of the spatial scale of estimation on a DCM's results is challenging because of the possible confounding effect of the misspecification of the decision-making process. For that reason, we apply the same random utility model (RUM) – a standard framework for researchers conducting welfare analyses – to both simulated data where the data-generating process is controlled and real empirical data where the decision-making process can only be assumed.

I.2.1. Modelling framework

We estimate the RUM where fishers, conditional on going on a fishing trip, make a unique daily decision on where to fish according to a simple utility criterion that weights travel costs and expected rewards in a linear way:

$$U_{ijt}=\beta_{dist}*Dist_{ijt}+\beta_{VPUE}*E\left[VPUE_{ijt}\right]+\varepsilon_{ijt} \text{ (Eq. I.1)}$$

where i=vessel, j=site, and t=day, β_{dist} and β_{VPUE} denote the marginal utilities of, respectively, the distance to a given location, $Dist_{ijt}$, and the associated expected value per unit of effort ($E[VPUE_{ijt}]$) , and ε_{ijt} is a random utility shock. The definition of what constitutes a site will vary across models.

Our specification is the standard workhorse model in the literature where travel costs and expected revenues are the main predictors of the choice of the fishing location (Girardin et al., 2016). A commonly used proxy for travel costs is the distance to the fishing sites, usually reduced to the centroids of the alternative and current location for computational purposes (Abbott and

Wilen, 2011; Haynie and Layton, 2010). Intuitively, this variable captures that more distant fishing sites incur higher fuel costs and more time to be reached.

With respect to fishers' expectations about revenues from a fishing site, we follow the literature that utilizes records of past performances for each site, aggregated at the fleet level (Girardin et al., 2015; Smith, 2005). Specifically, we assume that fishers combine both short and long-term information and weight information differently depending on what information is available (Abbott and Wilen, 2011; Hutniczak and Münch, 2018)[3].

In the analysis of the GoMRF grouper fishery, we include some additional controls to those in the Monte Carlo experiments, relating to the assumed but unobserved true decision-making process. Specifically, we control for the aggregate level of effort of other BLL fishers in a given alternative the day before (Eff.oth_{ijt-1}) so as to control for the possible influence of other fishers' activity. We also include fishers' own level of effort in a given site the day before (Eff.own_{ijt-1}), to control for the dynamic aspect of the daily choices of the fishing site when those choices are part of the same multiple day fishing trip:

$$U_{ijt}=\beta_{dist}*\text{Dist}_{ijt}+\beta_{VPUE}*E[\text{VPUE}_{ijt}]+\beta_{Eff.oth}*\text{Eff.oth}_{ijt-1}+\beta_{Eff.own}*\text{Eff.own}_{ijt-1}+\varepsilon_{ijt} \quad \text{(Eq. I.2)}$$

Indeed, the behaviors of other fishers along with fishers' past fishing patterns have been shown to influence fishers' decision-making (Girardin et al., 2016; Huang and Smith, 2014; Poos and Rijnsdorp, 2007).

[3] In the simulations we set the data-generating process is such that when VPUE averages are available over both short- and long-term period, fishers respond primarily to the more recent information signals and weight short-term VPUE average three times more than long-term average to form their revenues expectations. When one kind of information is missing fishers are assumed to put all the weight on the available information, and when no information is available fishers' revenues expectations for the given sites are assumed to be 0.
When we estimate the model – be it in with the simulated data or with the empirical data – we account for all the combinations of information available that are possible by using dummy variables (see Appendix Section I.5.4.5).

I.2.2. Tessellations

In both the simulated and GoMRF analysis, we estimate Eq.I.1 or Eq. I.2 with variables and alternatives defined at increasingly spatially-aggregated (i.e., coarser) spatial resolutions (see, for example, Figure I.2). For the simulations, we considered nine tessellations based on a grid, with cell sizes ranging from 1NM to 30NM. The data were generated on a 1NM scale.[4] For the analysis on the GoMRF fisheries, we consider gridded partitions of space and analyzed the results of the RUM across a set of tessellations, varying the length of the squared-shape alternatives from 0.25° ~ 15NM (1797 alternatives) to 3.5° ~ 210NM (15 alternatives). We use the 60NM-long statistical areas used by the U.S. National Marine Fisheries Service (NMFS) for logbook reporting since 2013 as a reference resolution, from which we consider both tessellations at finer and coarser scales. We also add a tessellation based on the statistical areas used by NMFS prior to 2013, which somewhat follows a longitudinal partitioning of space.

Across the tessellations and simulated and real data analyses, we measure (1) the goodness-of-fit and prediction capability of each model, (2) the normalized estimates of model parameters, and (3) the evaluation of the welfare impact of the implementation of a hypothetical Marine Protected Area[5] (MPA, shown in red in Figure I.2).

I.2.3. Monte Carlo experiments

The simulated setting we consider mimics either the case of a fishery targeting a species migrating seasonally across three different "hotspots" or the case of three non-migrating species each located in a different hotspot with seasonal variation in catch rates. The dynamics in fishing

[4] Here, we chose to focus on the issue of scale and therefore we consider only rectangle alternatives, by far the most common data collection framework.

[5] The choice of the location of the hypothetical MPA was arbitrary. Round latitudes and longitudes were chosen to define the north, south and east limits, and a round numbered bathymetric contour was used for the west limit

locations are driven by the seasonality and the stochasticity of the VPUEs that we generate. Specifically, fishers' experience independently and identically distributed random utility shocks when forming their decision and face different histories of VPUEs as the year progresses. Panel A of Figure I.2 shows a map of yearly average VPUEs for three levels of assumed spatial heterogeneity. The full details for the generation of the VPUEs distributions, the specification of fishers' expectations, and the data-generating process are available in the supplemental information.

Each experiment estimates Eq. I.1 across three datasets of observations with three different levels of spatial heterogeneity, with variables and choice alternatives defined at increasingly coarse spatial resolutions. We consider three different spatial distributions for the VPUE – and hence three datasets with varying level of spatial heterogeneity – to disentangle the effect of having observations with different spatial distributions from the structural effect of deviating from the spatial scale of the true DMP. To capture the latter effect, we display the results according to the level of spatial aggregation that we defined as the logarithm of the ratio of the area of the aggregated alternatives to the area of the "true" alternatives (Appendix Section I.5.2). In the Monte Carlo analysis, the index equals zero when the scale matches the DMP and as the index increases (non-linearly), the aggregation moves further away from the DMP (Appendix Figure I.5.3.a). In the GoMRF, zero represents the 60NM-long statistical areas used by the U.S. National Marine Fisheries Service (NMFS) for logbook reporting after 2013 and negative numbers correspond to finer spatial resolutions while positive numbers correspond to larger spatial resolutions (Appendix Figure I.5.3.b).

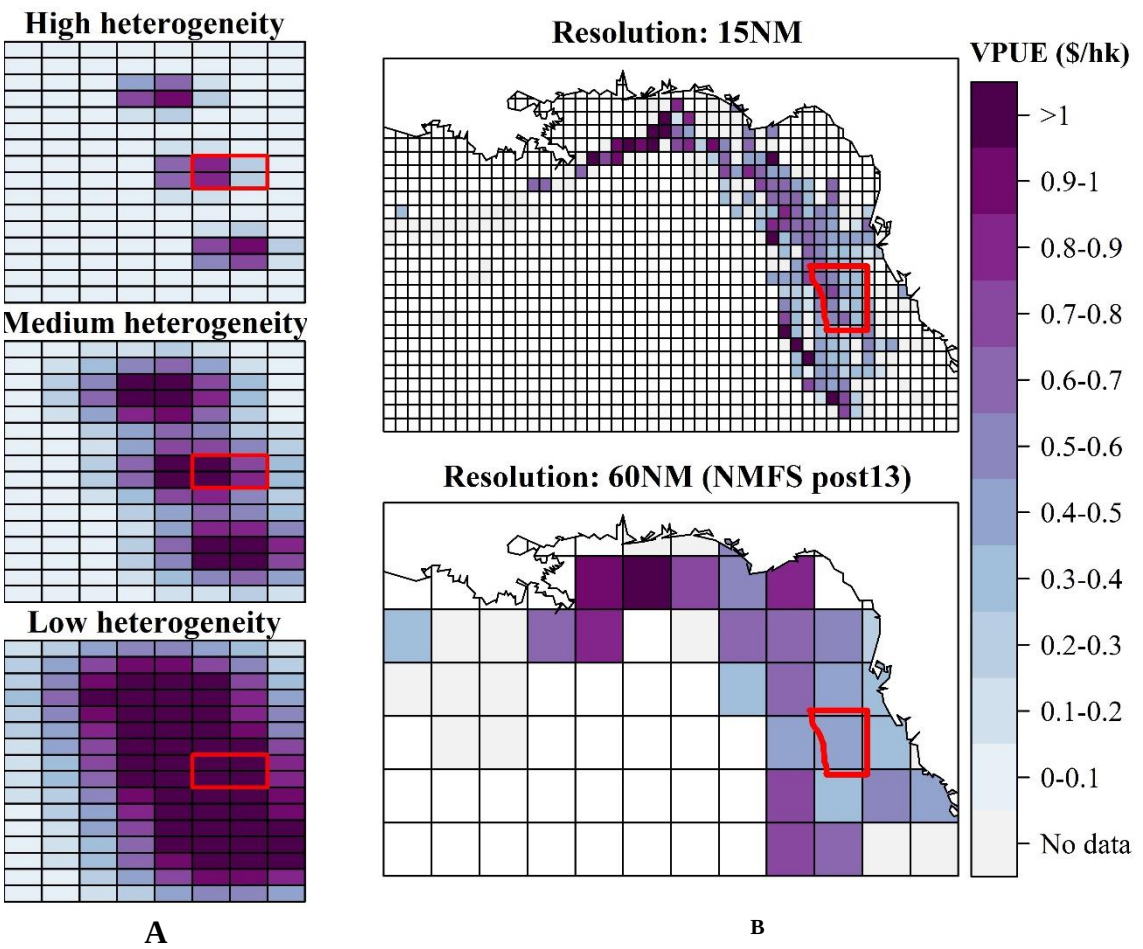

Figure I.2. Yearly average of value per unit of effort (VPUE, in $ per hook). Panel A shows the three spatial distributions of VPUE simulated for the Monte Carlo experiments, with a 30 NM grid. Panel B shows the observed VPUE for longline fishers in the Gulf of Mexico in 2008 for either a 15NM or 60NM grid. The hypothetical MPAs assumed for the welfare analyses are shown in red.

I.2.4. Welfare impact of the implementation of a MPA

Because measuring the impacts of scale and heterogeneity on parameters is not necessarily the same as having policy implications, we also simulate and measure the welfare impact of a hypothetical MPA across the different models and datasets. Specifically, we assess the distribution of welfare losses for the impacted choice occasions; that is, choice occasions where the chosen fishing location would have occurred in the MPA. The utility loss for an individual i facing a set of alternatives j was computed as the difference between the chosen alternative without the MPA

restriction and the chosen alternative restricting the choice set (CS) to alternatives that lie outside the MPA[6]:

$$\Delta U^{i} \equiv \max_{j \in \overline{CS}} U_j^i - \max_{j \in \overline{CS}\{MPA\}} U_j^i \text{ (Eq. I.3)}$$

In the case of the Monte Carlo experiments, the "true" utility loss corresponds to the case where the choice set is the "true" set of alternatives that were considered by fishers when seeking to maximize their utility (i.e., in our case all 115,200 1x1 NM rectangles):

$$\Delta U_{true}^{i} \equiv \max_{j \in \overline{CS}} U_j^i - \max_{j \in \overline{CS}\{MPA\}} U_j^i = \sum_k \beta_k \left(\bar{X}_k^{j^{max}} - \bar{X}_k^{j^{MPA}}\right) \text{ (Eq. I.4)}$$

where j^{max} is the alternative maximizing the utility over the true choice set ($\overline{CS}$) of alternatives, j^{MPA} is the alternative maximizing the utility over the true choice set of alternatives excluding alternatives in the MPA, and $\bar{X}_k^j$ is the value of the explanatory factor X_k evaluated on the true choice set for alternative j.

In the GoMRF analysis, the true choice set of alternatives considered by fishers when forming their decision is unknown by the researcher. In this case, a common approach is to assume that the choice set considered by fishers is the "observed" or "estimated" choice set; that is, the set of alternatives having been chosen at least once in the dataset:

$$\Delta U_{est}^{i} \equiv \max_{j \in \widehat{CS}} U_j^i - \max_{j \in \widehat{CS}\{MPA\}} U_j^i = \sum_k \widehat{\beta_k} \left(\hat{X}_k^{\widehat{j^{max}}} - \hat{X}_k^{\widehat{j^{MPA}}}\right) \text{ (Eq. I.5)}$$

where $\widehat{j^{max}}$ is the alternative maximizing the utility over the estimated choice set ($\widehat{CS}$) of alternatives, $\widehat{j^{MPA}}$ is the alternative maximizing the utility over the estimated choice set of

[6] Because the scale of the utility cannot be recovered, we normalize the utilities by the marginal utility of distance: $\widetilde{\Delta U}^{i} = \frac{\Delta U^{i}}{|\hat{\beta}_{dist}|}$.

alternatives excluding alternatives in the MPA, and $\hat{X}_k^j$ is the value of the explanatory factor X_k evaluated on the estimated choice set for alternative j.

The practical assumption regarding the choice set in empirical applications of DCMs however, is not benign. The choice set in such a setting may be ill-specified in two ways, which we label choice bias and aggregation bias:

(1) *Choice bias (C)*: Specified choice set may not include the same set of alternatives as the one considered by fishers (i.e., $\widehat{j^{max}} \neq j^{max}$ and/or $\widehat{j^{MPA}} \neq j^{MPA}$);

(2) *Aggregation bias (A)*: Specified choice set may not define the alternatives in the same way as they were considered by fishers, and so it may be the case that $\bar{X}_k^j \neq \hat{X}_k^j$

Utilizing our Monte Carlo experiments, we disentangle the effects of these two kinds of biases along with the effect of having biased estimates of the parameters, by decomposing the error in the estimation of the utility loss:

$$\Delta U^i \equiv \Delta U^i_{est} - \Delta U^i_{true} = \sum_k \underbrace{\widehat{\beta_k}\left(\left(\widehat{X}_k^{\widehat{j^{max}}} - \widehat{X}_k^{j^{max}}\right) - \left(\widehat{X}_k^{\widehat{j^{MPA}}} - \widehat{X}_k^{j^{MPA}}\right)\right)}_{\text{Choice bias}} +$$

$$\underbrace{\widehat{\beta_k}\left(\left(\widehat{X}_k^{j^{max}} - \bar{X}_k^{j^{max}}\right) - \left(\widehat{X}_k^{j^{MPA}} - \bar{X}_k^{j^{MPA}}\right)\right)}_{\text{Aggregation bias}} + \underbrace{\left(\widehat{\beta_k} - \beta_k\right)\left(\bar{X}_k^{j^{max}} - \bar{X}_k^{j^{MPA}}\right)}_{\text{Parameter bias}} \quad \text{(Eq. I.6)}$$

I.2.5. Bottom longline sector of the Gulf of Mexico Reef Fish fishery

We apply the same modelling and analytical framework in the Monte Carlo analysis to the bottom longline (BLL) sector of the Gulf of Mexico reef fish (GoMRF) fishery. The fleet primarily targets grouper and tilefish (GT) species but also lands other reef fish species such as snappers and jacks. In 2012, 65 vessels that held federal GoMRF permits reported 651 GT-BLL trips and 6135 days at sea to the Southeast Coastal Fisheries Logbook Program (Coastal Logbook). These numbers are down from 116 vessels reporting 1244 trips for 12075 days in 2008 and 155 vessels

reporting 1556 trips for 11669 days in 2005[7]. Although the GT-BLL fleet experienced considerable consolidation from 2005-2012, fleet efficiency increased during this period. Average days at sea per trip increased from 7.5 in 2005 to an annual average of 10.0 days per trip from (2008-2012) while pounds landed (inflation-adjusted revenues) increased from 3559 pounds ($10,803) in 2005 to 3779 pounds ($12,300) in 2008 and 6312 pounds ($21,911) in 2012. The GT-BLL fleet primarily operates off the west coast of Florida along a depth band of about 1° to 2° of latitude (Figure I.2 Panel B). This corresponds to the VPUE's distribution with the lowest spatial heterogeneity in the simulated data.

The GoMRF fishery offers a well-documented, data-rich research environment. Logbooks for coastal fishing have been collected since 1993, spatial fishing data have been collected since mid-2006 by onboard observers for a subset of the vessels and trips, and VMS data for all pelagic and reef fishing trips is available since 2006. Having data through 2013, we could estimate the RUM over the whole 2007-2013 period. However, the GT-BLL sector underwent several major disruptions in 2009 and 2010[8], including the BP Deepwater Horizon oil spill, that have likely changed the dynamics of fishing decisions. Consequently, we chose to estimate the RUM using two different datasets, one before and one after the 2009-10 period. Using one-year lagged predictors, we choose 2008 and 2012 as our two distinct training datasets, leaving 2013 observations to evaluate out-of-sample prediction performance.

[7] GT-BLL trips are defined as any trip reporting to the Coastal Logbook that landed at least one pound of GT species from one of five species categories (gag, red grouper, other shallow water groupers, deep water groupers, or tilefishes) covered by the GT-IFQ and used bottom longline as the primary gear on the trip. In cases of multi-gear trips, the primary gear type ("Topgear") is defined as the gear that produced a plurality of trip revenues.

[8] In 2009 a large part of the West coast of Florida were closed to longline fishing from May to October as an emergency action to reduce sea turtle bycatch, and starting 2010 an IFQ system was implemented for GT species.

I.3. Results

Overall, the results of the Monte Carlo (MC) experiments indicate a clear negative monotonic impact of the level of spatial aggregation on goodness-of-fit, prediction errors (out of sample), and parameter bias. Results of the GoMRF longline fishery analysis are more ambiguous but are qualitatively similar to the Monte Carlo results.

I.3.1. Goodness-of-fit and prediction capability

In the MC analysis, we observe a clear decrease of models' McFadden pseudo-R^2 and increase in prediction errors as the level of spatial aggregation increases[9] (Figure I.3 Panels A and B). Furthermore, the decrease in the pseudo-R^2 is more pronounced when the observations are spatially concentrated; that is, as the levels of VPUE are more heterogeneous within a given area – and tend asymptotically toward zero. The decrease in the pseudo-R^2 with the increase of the level of spatial aggregation means that the further from the resolution used for the DMP, there is a loss of information that is critical for explaining the choices. The sharper decrease observed when choices are more spatially concentrated suggests that it is the smoothing in the spatial heterogeneity of the explanatory factors that drives this loss of information. Indeed, if choices are more spatially concentrated, it is because the variations in the VPUE levels occur at a more spatially refined scale (or, similarly, because a given variation of VPUE occurs at a smaller spatial extent), which means that when averaging those levels at a given resolution, the set of values that are pooled together are more heterogeneous than if the variations of the VPUE were occurring at a larger spatial scale. The observation of a lower threshold in the goodness-of-fit is likely driven

[9] For the Monte Carlo experiments we evaluated the performance of the estimated models in terms of prediction capability by splitting each simulated dataset into a training dataset and a test dataset and we compute the rate of prediction errors of the models estimated with the training dataset on the test data.

by the explanatory power of distance, as it remains significant since increasing the spatial aggregation of site maintains – and even increases – the heterogeneity of the distance variable.

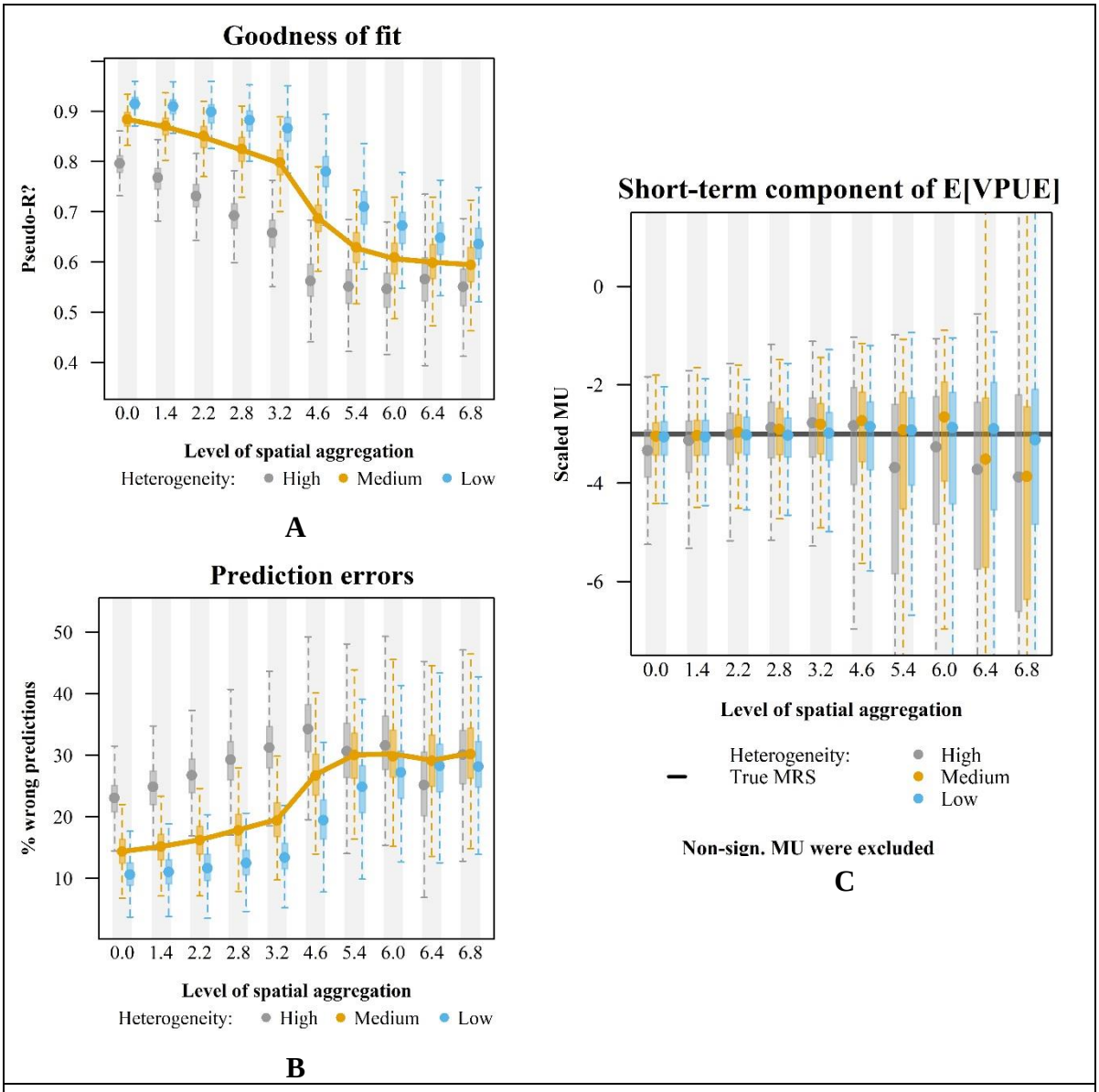

Figure I.3. Results of the Monte Carlo experiments for the three different levels of spatial heterogeneity (High, Medium and Low) in terms of fitting (Panel A) and predicting (Panel B) the data, and capacity to estimate the model's parameters (Panel C). Figures shows the median of: (A) model's Mc-Fadden pseudo-R^2; (B) model's rate of prediction errors; and, (C) the estimated marginal rate of substitution of the short-term component of the expected VPUE when no information is missing (results are similar for the other explanatory variables). Box edges are the 25th and 75th percentiles of the distribution of the losses and whiskers are located at +/- 1.5 times the interquartile ranges.

The fact that distance remains a meaningful predictor of spatial choices – as opposed to other predictors – probably helps to explain the results observed for the GoMRF data. In the GoMRF analysis, we do not find a clear correlation between models' goodness-of-fit and the level of spatial aggregation. Overall, pseudo-R^2 values range from 0.54 ($3° \times 3°$ Grid) to 0.76 ($2.5° \times 2.5°$ Grid) as shown in Figure I.4 Panel A. In this case, we assess the prediction capability using the observations from 2013 as test data. Contrary to the MC analysis, we find that higher predictions errors are observed for the most spatially-refined resolutions (Figure I.4 Panel B)[10].

This latter result is harder to interpret. However, if the spatial resolutions that we considered for the applied case correspond to the upper scale of the aggregations assessed in the simulations, then the seemingly downward trend actually may not be significant. It could simply reflect the decrease in the number of alternatives in the choice sets and the increase in the mean number of observations per alternative.

[10] To investigate, a possible effect of the spatial distribution of the observations in a more formal way than just comparing three levels of spatial heterogeneity in the Monte Carlo experiments, we looked also at possible correlations between the prediction error rates and spatial indexes capturing the distribution of the observations per alternative Namely, the first three moments as well as Shannon diversity and equitability indexes. We found no systematic correlations, be it within or across the simulated or real case studies.

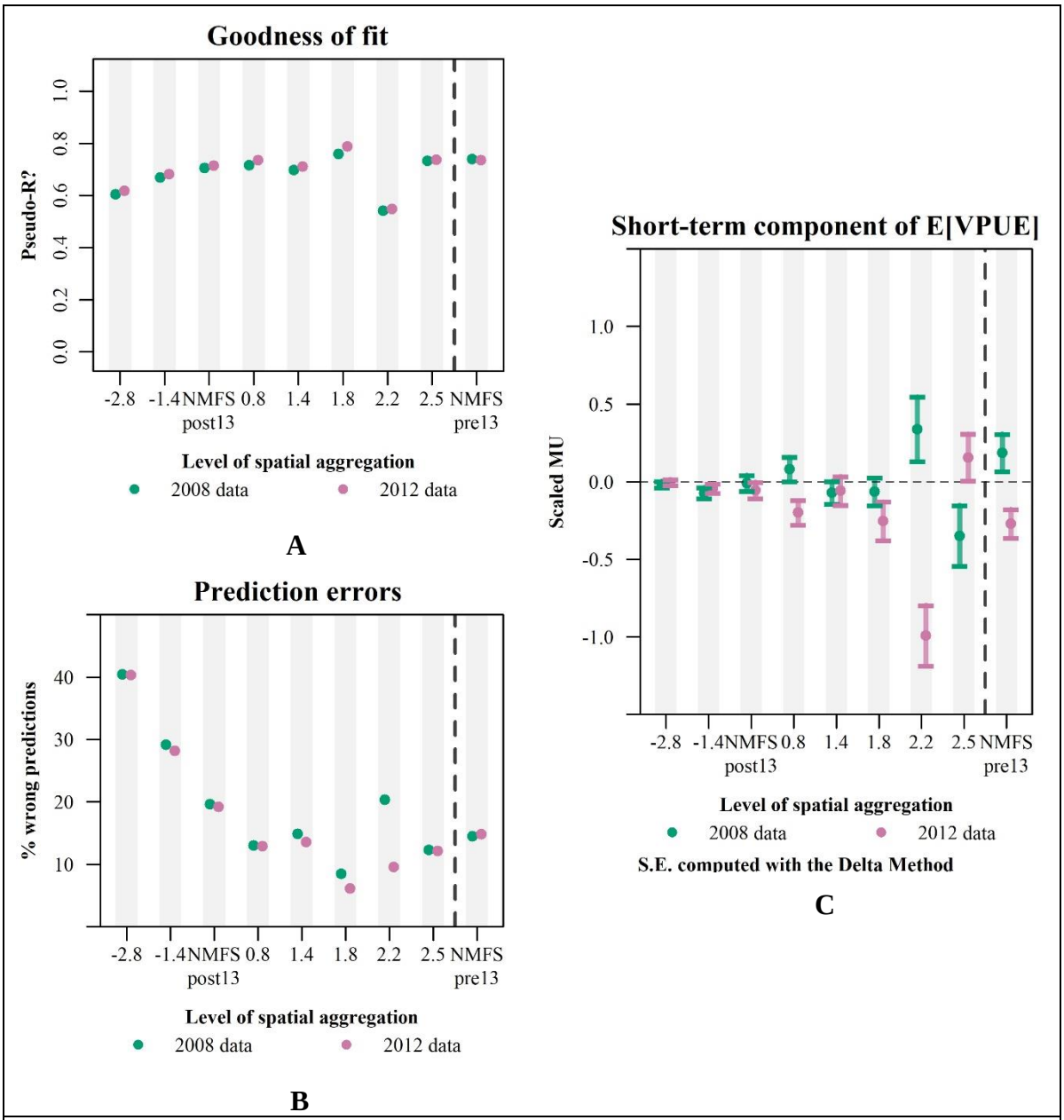

Figure I.4. Results of the GoMRF case study. Figures shows: (A) model's Mc-Fadden pseudo-R^2, (B) model's rate of prediction errors; and (C) point estimates and 95% confidence intervals of the marginal utility of the short-term component of the expected VPUE when no information is missing (results are similar for the other explanatory variables).

I.3.2. Parameter estimates

Given the logit specification, the scale of the utility levels cannot be recovered and the β parameters of Eq. I.1 or Eq. I.2 – or marginal utilities (MU) – are only estimated up to a multiplicative scale. To permit comparisons across estimated models, we normalized parameter estimates by β_{dist}, the MU of distance, which amounts to comparing estimated marginal rates of substitution (MRS) with distance.

Figure I.3 Panel C shows the distributions of the estimated scaled MU for the short-term component of the expected VPUE in the case where long-term information is also available (results for the other variables are similar)[11]. First, we note that when the models are estimated at the same spatial scale as the DMP (i.e., when the level of spatial aggregation is 0), the estimated MU is found to be not statistically different from the MU assumed in the DGP, which validates the consistency of our approach of analyzing biases that emerge as one departs from the true spatial scale of fishers' decisions. As the level of spatial aggregation increases, we observe that the distribution of the MU widens and, even though the MU may be close to the "true" value on average, it eventually becomes no longer statistically different from 0.

Figure I.4 Panel C shows the estimates for the same scaled MU with the GoMRF data, separately using either 2008 or 2012 data on each of the 9 different spatial choice sets. As mentioned previously the spatial aggregation affects the observations to be utilized in the calculation of expected catch (smaller areas, for example, might not have information available for the calculations in a given period). To investigate the robustness of our estimation results to

[11] MRS that were not significantly different from 0 were excluded from the analysis. These cases usually occurred because the MU of distance were not significantly different from 0. They represent no more than 13% of the draws at the coarser resolution and the number of cases decline rapidly toward 0 as the resolution increases (there are zero cases for the four more spatially refined resolutions).

the availability of information both in the short-term (one month prior) and long-term (one year prior), we estimated Eq. I.2 under a number of cases. In each analysis, we follow the literature on how it deals with missing information. Specifically, we took the same approach as Abbott and Wilen (Abbott and Wilen, 2011) interacting the different information signals with dummies for each case of type of information available and including a dummy for when no information is available. Results for the tessellation based on the pre-2013 NMFS statistical areas are shown separately at the right of each panel. The MU remains close to 0 for the three lowest levels of spatial aggregation before displaying more erratic patterns at higher levels of aggregation. Such a high variability is observed as well with the other explanatory factors (Table I.a). In particular, none of the variables forming the expected VPUE maintain consistent signs across the different tessellations.

Variable	% Significant (<0|>0)			
E[VPUE]			**Short-term information**	
			Not missing	Missing
	Long-term information	Not missing	*Short-term:* 22|33 *Long-term:* 11|67	0|56
		Missing	22|11	-
Eff.own	11|89			
Eff.oth	100|0			

Table I.a. Scaled marginal utilities (MU) of model variables estimated with the conditional logit model over the nine different tessellations with 2008 data. Numbers indicate the percentage of time the MU is significantly negative (left side) or positive (right side). Short-term information refers to the records of mean levels of VPUE across the fleet over the past 30 days. Long-term information refers to records of the mean levels of VPUE across the fleet over the 30 days prior the same date of year before.

The results of the MC experiments regarding the estimates of model parameters provide insight to the results of the case study. In both cases, we observe a dramatic increase in the variability of the estimated MU with the level of spatial aggregation. However, the Monte Carlo experiments reveal that even though MU may be statistically significant with a specific dataset

and at a given level of spatial aggregation, they are actually not significantly different from 0 when considering other possible datasets of observations generated according to the same decision-making process. This means that a researcher, who would be limited to a single set of observations and that would operate at a single level of spatial aggregation, may well find (or search for) statistically significant MU having the opposite signs than the true MU, *even though her model is properly specified*. Therefore, when operating at too high level of spatial aggregation, an estimated model may become structurally inconsistent just because of the effect of spatially aggregating choices and explanatory variables.

This higher variability of the estimated MU at high levels of spatial aggregation is reflected also in the GoMRF application through the inconsistency of the value of the estimates of model parameters and their increased invariance. The stability of the estimated MU for the three least aggregated tessellations suggests that the threshold for estimates' reliability seems to be 60NM by 60NM resolution or finer. When looking at the average marginal effects of each variable, we find the same pattern of increased variability at aggregated tessellations for the VPUE variables as we did in the simulations. In addition, for the distance variable, we also observe the same convergence toward 0 that we find in the simulations (Appendix Figures I.5.6.1.d and I.5.6.1.e).

One potential caveat to these findings is that they may be due to the temporal resolution of the information used to form fishers' daily expectations of returns in a given site. Indeed, information about catches and revenues were collected at the level of the fishing trip and scaled down by days and location proportionally to the fishing activity recorded based on processed VMS data (Appendix Section 5.1). Having had daily information about catches, for example, may have helped capture intra-fishing trip variability which would improve the explanatory power of our model.

I.3.3. Evaluation of the welfare impact of a hypothetical MPA

Given the past use of RUM models for policy analysis, specifically, the impacts of closing areas off to fishing, we investigate how the spatial resolution of the analysis interacts with welfare estimates associated with a hypothetical MPA.

In the Monte Carlo experiments, we decompose the error in the normalized utility losses into three components. Figure I.5 shows the distribution of the mean errors[12]. First, we find that even when estimated at the same spatial scale as the DMP, there is a consistent underestimation of the utility losses due to the restriction of the choice set to only the set of "observed" chosen alternatives (the combination of the aggregation and the choice biases). As the level of spatial aggregation increases, the underestimation of the losses due to the misspecification of the choice set is compensated and eventually dominated by the overestimation due to the bias in the estimated parameters. The magnitudes of the errors are widely distributed among the levels of spatial aggregation. When looking only at truly impacted choices (i.e., excluding false positive), the estimated utility losses are not different from the true utility losses on average but they can be as large as five times the true losses. As the level of spatial aggregation increases, the distribution of the relative errors widens even more and becomes skewed toward overestimation.

[12] The effect due to improper choice set specification ("Ch bias") has been computed as the difference between the full error and the other two components. Cases where the MU of distance were positive or non-significant were excluded. Positive and significant MU of distance represent no more than 10% of cases at the most aggregated spatial scale.

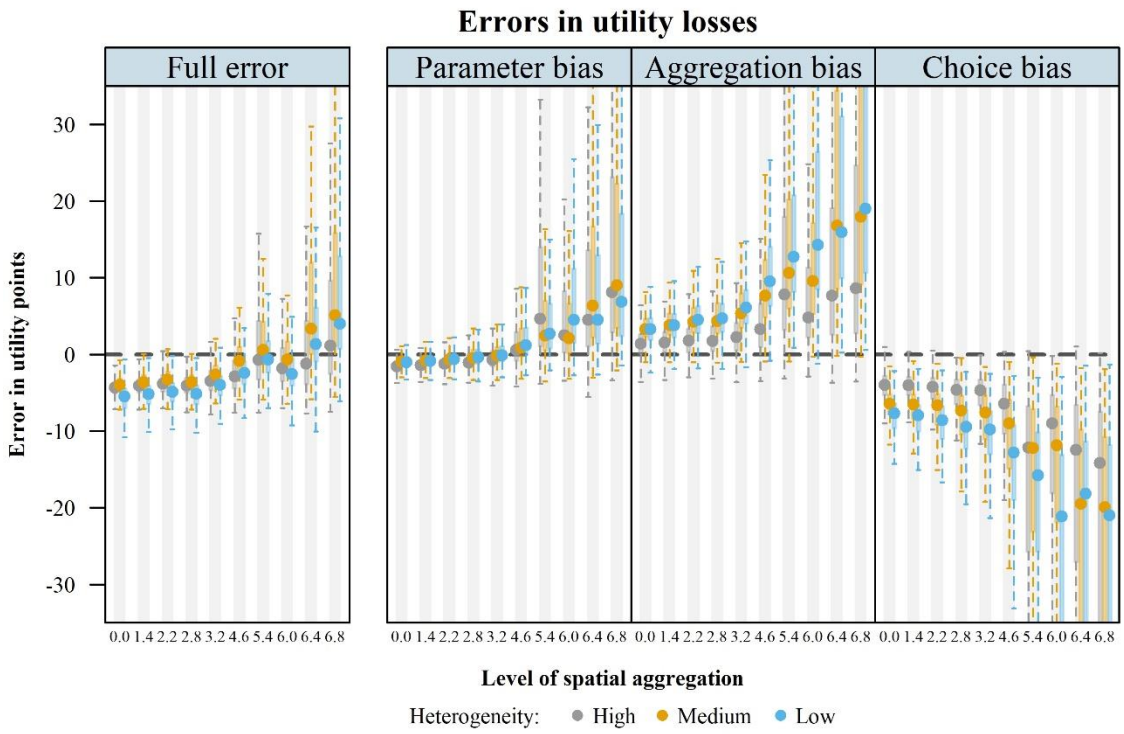

Figure I.5. Results of the Monte Carlo experiments in terms of capacity to evaluate the welfare impact of a MPA. The figure shows the distributions of the full error in the estimated mean utility loss of fishers (left panel), along with its decomposition into the part of the error due to the bias in the estimated parameters (right panel, 1st column), due to the spatial aggregation of the explanatory variables (right panel, 2nd column) and due to the utility maximization under the incomplete choice set (right panel, 3rd column). Cases where the marginal utility of $Dist$ were found to be positive or not significant were discarded. Utility levels were computed using only significant variables (the results do no change when not doing so). Box edges are the 25th and 75th percentiles of the distribution of the losses and whiskers are located at +/- 1.5 times the interquartile ranges.

I.3.4. Estimated losses for the hypothetical MPA in the GoMRF fishery

The hypothetical MPA that we considered for the GoMRF was delineated according to the bathymetry off the west coast of Florida to mimic how spatial regulations are actually designed in this part of the Gulf.[13] To examine the robustness of the impact evaluation to the input or training datasets, we considered the implementation of the MPA for both 2008 and 2012 and looked at results using models estimated with either 2008 or 2012 data. Figure I.6 shows the distribution of the normalized losses for each choice set configuration in each of the four combinations of training and input datasets. Results are robust to the choice of the input dataset and are consistent with the simulations: the mean and median of the estimated welfare losses increase with the level of spatial aggregation, as does the dispersion of the losses.

An implication of these findings is that prior policy analysis of MPAs (or any spatial policy for that matter) can be confounded by the underlying spatial scale of the analysis. The difficulty is that this confounding is not obvious and will not be apparent to a researcher only able to consider a single spatial scale (e.g. caused by data availability).

[13] Given that, depending on the spatial configuration of the fishing sites, the sites are not necessarily nested into the MPA, we slightly modified the tessellations by splitting in inside or outside fishing sites, fishing sites that were overlapping the MPA. We also estimated welfare impacts when merging together sites that were inside the MPA so that they would appear as a single alternative. In the end, we did not find large differences between the two approaches (the welfare losses with the MPA as a single alternative were just slightly lower in general).

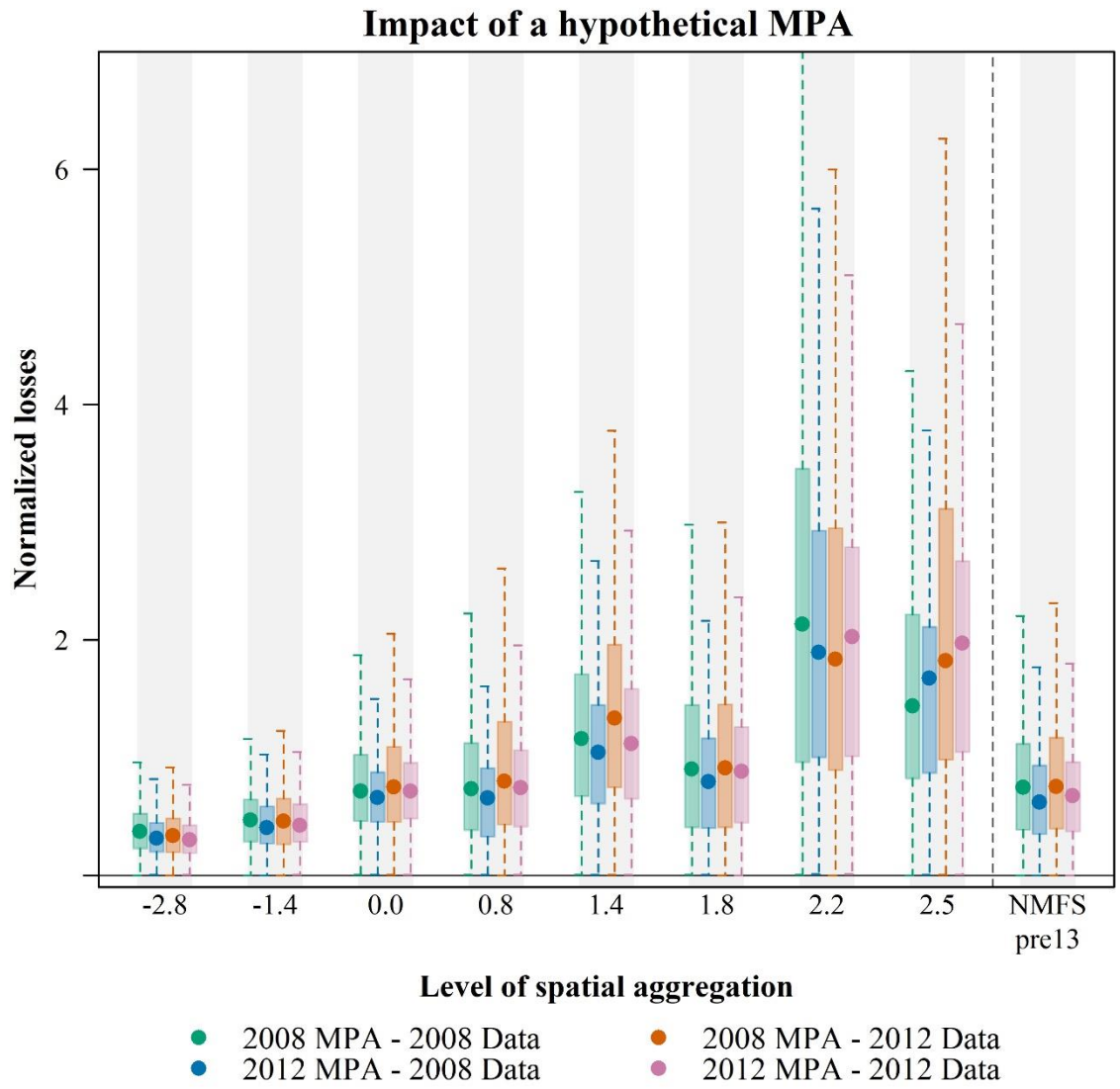

Figure I.6. The estimated welfare impact of the hypothetical MPA for longline fishers in the Gulf of Mexico as a function of the level of spatial aggregation. Filled dots indicate the mean utility losses. The box edges are the 25th and 75th percentiles of the distribution of the losses and whiskers are located at +/- 1.5 times the interquartile ranges.

I.4. Conclusion

In this paper, we developed an innovative empirical approach to examine the complex relationship between spatial decisions and the specification of the spatial unit of analysis in a discrete-choice model (DCM). We developed Monte Carlo simulations of fishing decisions that mimic the typical real conditions that researchers face when studying fisheries dynamics. The simulations highlighted the structural – and otherwise undetectable – biases induced by the spatial aggregation of observations. These observations raise questions on the robustness of the results of spatial models estimated only on a single partition of space.

We demonstrate the value of our approach by taking advantage of the availability of fine-scale geospatial data on the activity of commercial fishing vessels in the Gulf of Mexico to estimate a standard DCM of fishing locations over nine different spatial choice sets. We show that model outcomes can be highly sensitive to the scale of analysis, especially because of variation in the spatial heterogeneity of the values of some predictors – in particular the distance to fishing sites.

Moving forward, our work clearly demonstrates the value for spatial modelers to use more spatially-refined data, by allowing them to test the robustness of their results as a means to gain insights into potential structural biases due to spatial aggregation. Yet, whereas granular spatial data does indeed become more widely available, the possible increase in the reliability of results may be now limited by a lack of corresponding progress regarding the availability of temporally refined data. In the case of the modelling of fishery dynamics, the data revolution triggered by the increase availability of vessels' spatial activity data through VMS may now turn out to be limited by the access to temporally refined information about catch. Presently, data collection frameworks across countries remain inconsistent, with the reporting of catches that can be by haul, day or even fishing trip as in our case. The lack of robustness in parameters estimates also sheds light on the

need to ensure the consistency between data resolution and the scale of the decisions considered in terms of both spatial and temporal resolution.

In our analysis of the effects of varying the partitions of space considered in a spatial model, we restricted ourselves to only grid-based partitions of space and we did not consider alternative shapes for the fishing grounds. The few studies that have investigated non grid-based partitions in the DCM literature (Hynes et al., 2016; Valcic, 2009), however, did not carry out sensitivity analysis over the partition of space they considered. Yet, various approaches exist to define spatial zonings in relation to the spatial distribution of observations. For instance, it would be interesting to see how randomly-generated partitions of space, such as those generated using techniques developed in the geography literature (Openshaw, 1983, 1977; Wong, 2009), compare against homogeneous grids. Certainly, more advanced geo-statistical techniques (e.g., Páez and Scott, 2005) would be worth investigating as well in the context of spatial fishery models, in particular to better handle spatial heterogeneity of data availability. On that aspect, there might be gains to considering meteorological models and other methods specifically developed to deal with highly spatially and temporally heterogeneous observations, in order to improve the predictions of spatial fishery modelling. Data re-assimilation techniques (where predicted outcomes can be looped in as training data), or models averaging (ensemble approach) could be, in this regard, fruitful avenues to pursue.

Acknowledgments

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recommendations are those of the authors and do not necessarily reflect the views of the National Science Foundation or US NMFS.

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I.5. Appendix

The appendix gives further details on: 1) the sources and processing of the data used for the applied case study; 2) the alternative spatial indexes used for uncovering possible correlations between each model's results and the spatial heterogeneity of data availability; 3) the tessellations with varying levels of spatial aggregation that were considered for estimating the model; 4) the full methodology followed to carry out the Monte Carlo experiments; 5) the complementary estimation assumptions that have been made for estimating the model in the applied case study ; and, 6) complementary results for both the Monte Carlo experiments and the applied case study.

I.5.1. Gulf of Mexico fishery Data

Data used to study the BLL fleet was provided by the NMFS Southeast Fisheries Science Center (SEFSC). The SEFSC's Socioeconomic Panel (SEP) combines a variety of data sources to create a rich trip-level data set. The panel includes extensive information from the Coastal Logbook on landings disaggregated by species as well as effort data with reported variables depending on the primary gear used during the trip. In the case of BLL trips these variables include soaking time, number of hooks per line and the number of sets during the trip[14]. Effort data such as number of days at sea, number of crew, date of landing and dealer identifiers are also reported. The Logbook data is further supplemented with average price data from the Accumulated Landings Service to calculate trip revenues which are also disaggregated by species. Vessel technical characteristics (e.g. vessel length) from the NMFS Southeast Regional Office Permits Office are

[14] The information about soaking time was highly unreliable (fishers in some cases reported either the soaking time for the entire trip or the mean soaking time per set) and thus were discarded. Complementary analyses exploiting the observer data showed that soaking times were fairly similar across fishers – about an hour – and did not affect the level of catches of trips. Therefore, we defined and computed fishing effort for BLL as the total number of hooks having been soaked during the trip (i.e., number of hooks per line multiplied by the number of sets).

linked to the Logbook data at the trip level. VMS data were provided by the SEFSC's Social Science Research Group.

We identified the GT-BLL fleet using the "Topgear" variable provided in the SEP and linked these trips to VMS using vessel identifiers along with trip start and end dates (based on reported landing date and number of days at sea). After discarding a small number of logbook entries (38 out of 4054 for the years analyzed) that had trip dates that were overlapping other entries (e.g. because of reporting mistakes or because the entries referred to a same trip), and after further subsetting GT-BLL trips to trips deriving more than 75% of the revenue from GT species, we were left with, respectively for 2008 and 2012, 816 and 420 logbook entries matched to 99,027 and 42,008 VMS observations classified as fishing, covering 362 and 350 different days of the year and representing observations from 104 and 54 vessels.

VMS pings corresponding to fishing behavior were identified using a random forest model (O'Farrell et al., 2017), trained with observer data provided by the SEFSC's Galveston Laboratory. Specifically designed and tested for this dataset, this approach makes use of observer data to devise the best classification along factors such as vessel's speed, heading and previous behavior (the estimated accuracy rate in predicting fishing activity on the training dataset is 92 %).

I.5.2. Spatial indexes used for the analysis

I.5.2.1. Index of spatial aggregation

To analyze the results of the simulations relative to the level of spatial aggregation used during the estimation of the DCM, we associate each tessellation to an index of spatial aggregation defined as the logarithm of the ratio of the area of the aggregated alternatives to the area of the "true" alternatives (i.e., those considered for the decision-making process):

$$I_{tess} = \ln \frac{A_{tess}}{A_0} = 2 \ln \frac{L_{tess}^{alt}}{L_0^{alt}}$$

$I_{tess} = 0$ means that the DCM was estimated at the same spatial scale as the one used during the decision-making process. $I_{tess} = 2$ means that the DCM was estimated using alternatives that were $e^2 \approx 7.4$ times larger in terms of area, or $e^1 \approx 2.7$ times longer in terms of length, than the alternatives used during the decision-making process.

I.5.2.2. Indexes of spatial distribution

In addition of analyzing the effect of aggregating spatial choices made at a more refined scale, we are also interested in analyzing the effect of the spatial distribution of the observed choices. For that reason, we have considered different sizes of fishing hotspots which induced different spatial distributions of choices, with observations being more concentrated with small hotspots compared to large hotspots.

In addition of analyzing the results of the simulations individually for each of the spatial distributions, we also analyzed the results using indexes aiming at capturing the nature of the spatial distribution of choices relatively to the spatial resolution of the estimated models.

For that purpose, we computed for each pair of spatial distribution/hotspot's size and tessellation, the associated Shannon entropy and equitability indexes and the relative spatial resolution defined as the logarithm of the ratio of the size of the hotspot (defined as the area including the 95% highest VPUE levels) with the size of an alternative:

$$Res_{tess}^{hs} = \ln \frac{A_{hs}}{A_{tess}} = 2 \ln \frac{1.96\sigma_{hs}\sqrt{\pi}}{L_{tess}^{alt}}$$

$Res_{tess}^{hs} = 2$ means that a given hotspot is covered by $e^2 \approx 7.4$ alternatives.

The Shannon entropy index associated with a draw d is:

$$S_d = -\sum_{i \in A_d} \hat{p}_i * \ln \hat{p}_i$$

Where, $\hat{p}_i$ is the empirical frequency of choice for the alternative i (i.e. the number of simulated fishing locations falling in alternative i over the total number of simulated fishing locations); and A_d is the whole set of alternatives considered (i.e., having $\hat{p}_i > 0$).

The more skewed the distribution of choice frequency, the smaller the corresponding entropy. If almost all of the simulated fishing locations are concentrated in only one alternative, and the other alternatives are very "rare", the entropy approaches zero. Should the simulated fishing locations cover the alternatives in a perfectly balanced way, all the $\hat{p}_i$ would be equal, and the index would take the value $\ln N_d^A$, where N_d^A is the size of A_d (i.e., the number of alternatives considered). Therefore, a distribution of choices having a Shannon entropy index of S_d can be interpreted as "as diverse" as an even distribution of choices among $\exp(S_d)$ alternatives.

The Shannon entropy index is commonly used by ecologists as a diversity index (e.g., of species, phenotypes etc.) and as a measure of the predictability of type: the higher the index, the more diversity and the less predictable the type. This interpretation of the index can be somewhat misleading in our case since it assumes that predictions are based only on empirical frequencies and that there is not underlying model.

The Shannon equitability index is simply the Shannon entropy index normalized by its maximum value:

$$E_d = \frac{S_d}{\ln(N_d^A)}$$

I.5.3. Maps of the partitions of space considered

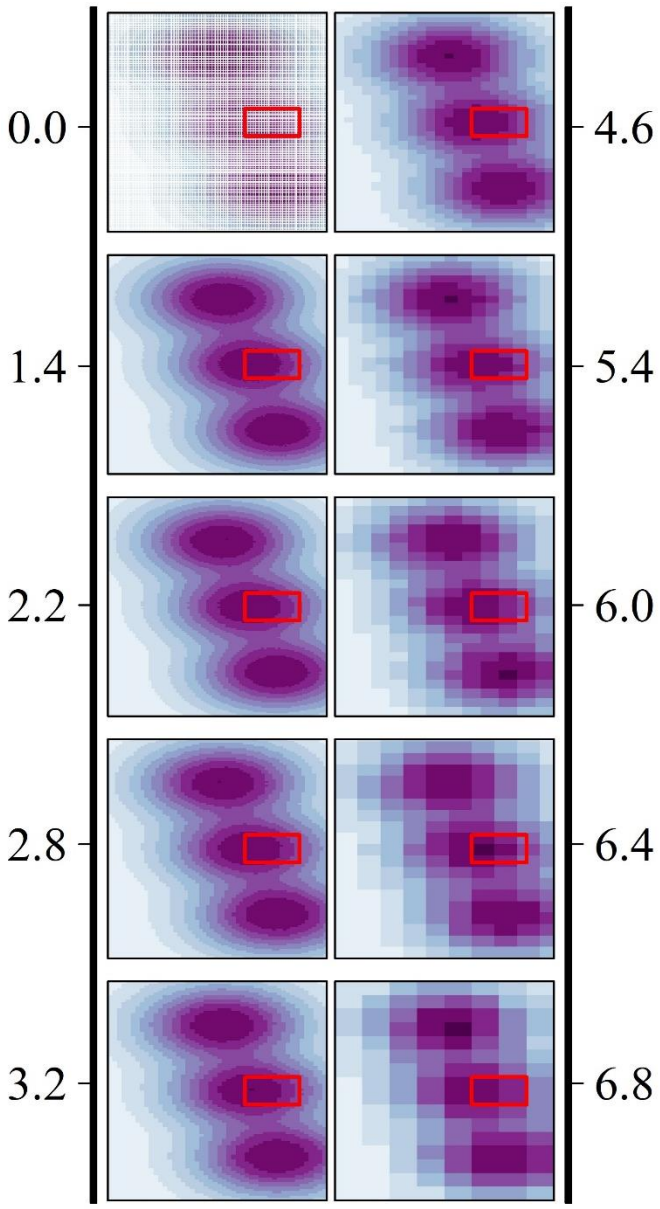


Figure I.5.3.a. Maps and indexes of spatial aggregation of the ten partitions of space considered in the Monte Carlo experiments for estimating the discrete-choice model of fishing locations. The index of spatial aggregation is computed as the logarithm of the ratio of the area of the aggregated alternatives to the area of the "true" alternatives.

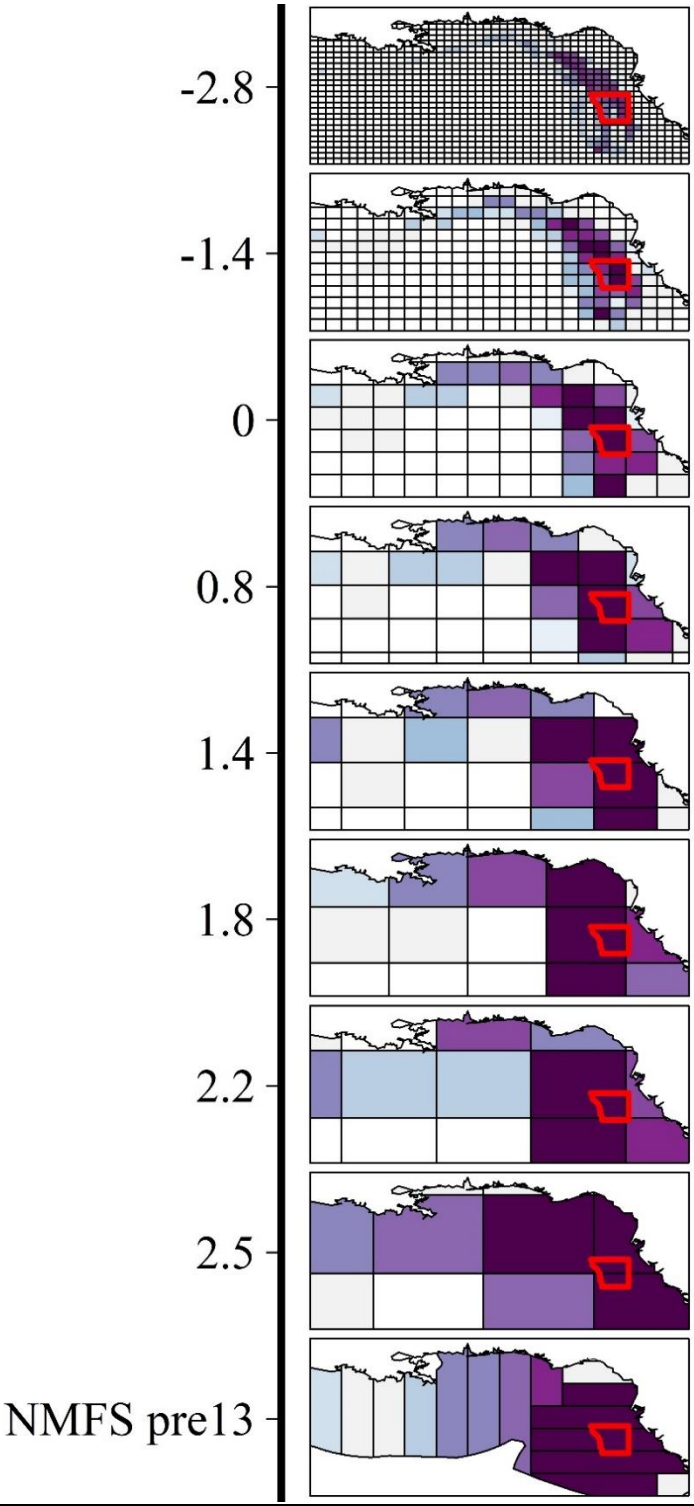


Figure I.5.3.b. Maps and indexes of spatial aggregation of the nine tessellations of the Gulf of Mexico considered for estimating the discrete-choice model of fishing locations. The index of spatial aggregation is computed as the logarithm of the ratio of the area of the aggregated alternatives to the area of the alternatives considered by the NMFS, starting 2013, for the reporting of fishing locations in logbooks.

I.5.4. Monte Carlo experiments

I.5.4.1. Utility function

We assume vessels' decide on their fishing location according to the following utility function:

$$\mathrm{U(lon, lat)} = \beta_{\mathrm{dist}} * \mathrm{Dist(lon, lat)} + \beta_{\mathrm{VPUE}} * \mathrm{VPUE(lon, lat, t)}$$

With:

- $\mathrm{Dist(lon, lat)} = \mathrm{C} + \sqrt{(\mathrm{lon})^2 + (\mathrm{lat})^2}$: We assume a "fixed-cost" of moving and that all vessels start their trip from the origin (0,0)
- $\mathrm{VPUE_h(lon, lat, t)} = \overline{\mathrm{VPUE_h}}(\mathrm{t})\mathrm{e}^{-\frac{(\mathrm{lon}-\mathrm{h_{lon}})^2}{\sigma_{\mathrm{lon}}^2}}\mathrm{e}^{-\frac{(\mathrm{lat}-\mathrm{h_{lat}})^2}{\sigma_{\mathrm{lat}}^2}}$: We assume that there is a hotspot in (h_{lon}, h_{lat}) with a Gaussian spatial distribution of fish abundance that depends on time.
    - We assume 3 hotspots located in the North (2.6,2.5), Center (3.1,0) or South (1.9,-2.4).
    - We consider 4 hotspot sizes taking $\sigma_{\mathrm{lon}} = \sigma_{\mathrm{lat}} \in \{0.4, 0.8, 1.2, 1.6\}$
- $\overline{\mathrm{VPUE_h}}(\mathrm{t}) = \overline{\mathrm{VPUE}}.\mathrm{base}\left(1 + \mathrm{A} * \cos\left(2\pi\frac{\mathrm{t}-\mathrm{t_h}}{\mathrm{T}}\right)\right)$:
    - The productivity of hotspots oscillates around $\overline{VPUE}.base$ with a period $T = 1$ and reaches their maxima at $\mathrm{t_h} \in \left\{\frac{2}{12}, \frac{5}{12}, \frac{8}{12}\right\}$.
    - We set $\overline{\mathrm{VPUE}}.\mathrm{base} = 4$.
- The productivity of a given point in space is the mean of the productivity of each hotspots at this given point with a stochastic error of +/- 100%:
    - $\mathrm{VPUE(lon, lat, t)} = \left(1 + \mathrm{u(lon, lat, t)}\right)\left(\frac{1}{\mathrm{n_h}}\sum_{\mathrm{h}}\mathrm{VPUE_h(lon, lat, t)}\right)$
    - $\mathrm{u(lon, lat, t)} \sim \mathrm{U}(-1,1)$

I.5.4.2. Expected VPUE

We assume the fishers can only form an expected VPUE at a given location based on the past observations of the fleet. Additional assumptions are required in this case:

a. Spatial extent of the expectations: we assume that fishers form their expectations on a refined grid of 1x1 NM (1NM = $\frac{1}{60}$°, 115,200 alternatives for a 4°lon x 8°lat space)

b. Temporal extent of the expectations: we assume that fishers use the VPUE records of:

   i. the past immediate 30 days

   ii. the past 30 days around the same day the year before

c. We assume the following expected VPUE (not distinguishing individual records from fleet records):

$$E\left[\mathrm{VPUE}_{\mathrm{ijt}}\right] = \left(\alpha_{\mathrm{ft,m-1}} + \alpha_{\mathrm{ft,ym-1}} * \mathrm{I}_{\mathrm{NA}}(\overline{\mathrm{VPUE}}^{\mathrm{ft}}_{\mathrm{j(ym-1)}})\right)\overline{\mathrm{VPUE}}^{\mathrm{ft}}_{\mathrm{j(m-1)}} + \left(\alpha_{\mathrm{ft,ym-1}} + \alpha_{\mathrm{ft,m-1}} * \mathrm{I}_{\mathrm{NA}}(\overline{\mathrm{VPUE}}^{\mathrm{ft}}_{\mathrm{j(m-1)}})\right)\overline{\mathrm{VPUE}}^{\mathrm{ft}}_{\mathrm{j(ym-1)}}$$

With: $\overline{\mathrm{VPUE}}^{\mathrm{ft}}_{\mathrm{j(m-1)}} = \sum_{i,t\prime\in[t-30,t[} \mathrm{VPUE}_{\mathrm{ijt'}}$,$\overline{\mathrm{VPUE}}^{\mathrm{ft}}_{\mathrm{j(ym-1)}} = \sum_{i,t\prime\in[t-370,t-350]} \mathrm{VPUE}_{\mathrm{ijt'}}$,

$\begin{cases} \alpha_{\mathrm{ft,m-1}} = 0.75 \\ \alpha_{\mathrm{ft,ym-1}} = 0.25 \end{cases}$, and I_{NA} being a dummy function valuing 1 when the argument (average of historical VPUE records) is not available.

d. To initiate the historical records we use the draws from one year of simulated positions under the assumption that fishers have a perfect knowledge of the VPUE maps and we discard the subsequent first year of simulated positions.

I.5.4.3. Vessels and fishing days

In the Monte Carlo analyses, we consider a fleet of identical vessels (with the same preferences) fishing during 3 periods (years) T. Vessels go out fishing all through the period but following a probability density function proportional to the mean VPUE through the space (Figure I.5.4.3). Since vessels are all identical we just make N_{draws} draws (with replacement) of vessels from a uniform distribution.

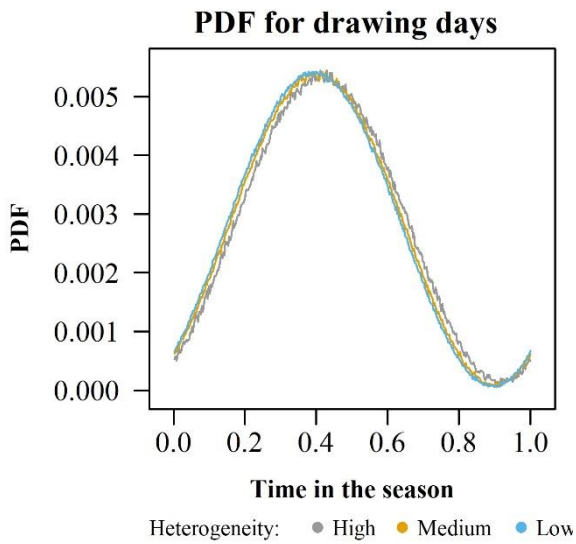


Figure I.5.4.3. Probability function for drawing the fishing days.

I.5.4.4. Fishing locations

Whereas a continuous approach could have been taken to generate draws of fishing locations (e.g., approximating the spatial probability distribution function using the Metropolis-Hastings algorithm), we chose to take a discrete approach consisting in discretizing space at a refine scale and generating a field of random errors. Thus, for each cell of the grid, a random error $\varepsilon(\mathrm{lon}, \mathrm{lat}, \mathrm{t})$ is drawn from a Gumbel distribution centered in 0 and with a scale of 1. We assume that errors are independent and identically distributed which implies that the difference of two different error

terms follows a logistic distribution with mean $\mu_{\Delta\varepsilon} = 0$ and a standard deviation $\sigma_{\Delta\varepsilon} = \frac{\pi}{\sqrt{3}}$. Since only differences in utilities matter, we scale the magnitude of the error terms relative to the distribution of the differences in the deterministic utilities across a whole season $\{\Delta V_{j,k}(t)\}_{j,k}$. Given the high skewness of the distributions of the utility differences (Figures I.5.4.4.a and I.5.4.4.b), we take the bottom 0.1% of the differences $P_{0.1}(\Delta V)$[15] – which is 116 alternatives in average per day – as the reference point.

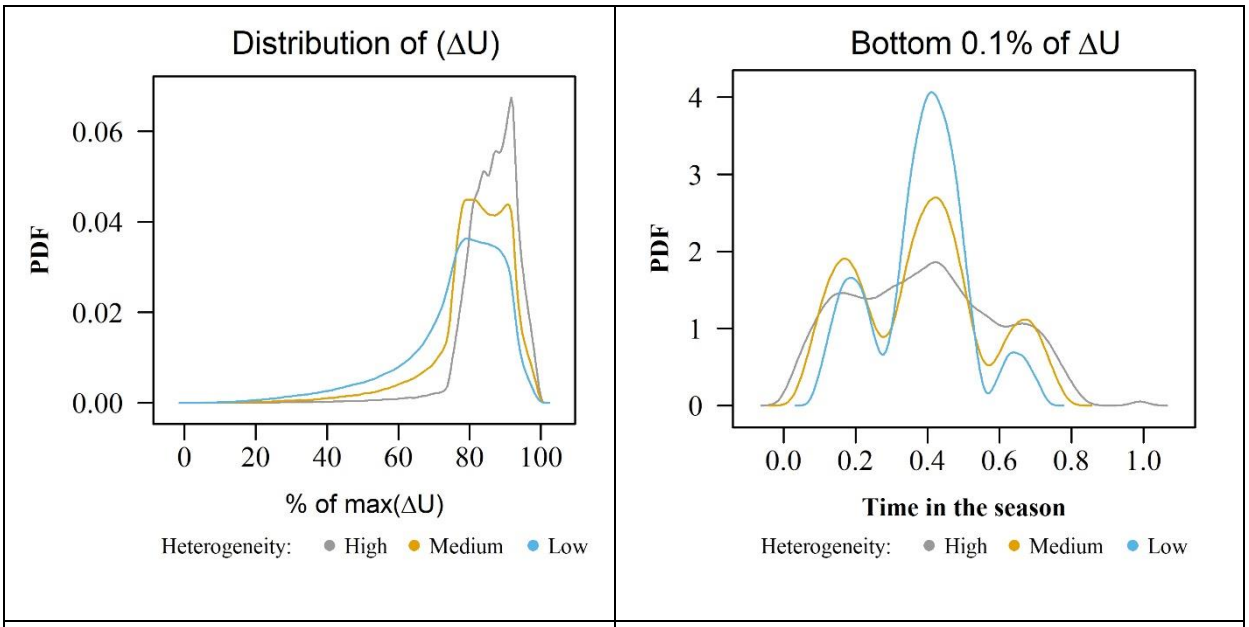


Figure I.5.4.4.a.: PDF of the differences in the deterministic utilities, for each level of spatial heterogeneity of the VPUE and over a whole season.

Figure I.5.4.4.b.: PDF of the temporal distribution of the bottom 0.1% of the differences in the deterministic utilities, for each level of spatial heterogeneity of the VPUE and over a whole season.

After having tested for differences of error terms ($\Delta\varepsilon$) having a standard deviation of 10%, 15%, 20%, and 25% of the bottom 0.1% of the differences in the deterministic utilities, we chose to scale the standard deviation of $\Delta\varepsilon$ as 15%, having found that starting at 15%[16]and increasing the

[15]i.e., the threshold for the 0.1% alternatives that are the closest to the alternative with the highest utility

[16] In practice, we multiply the errors terms ε by $0.15 * \frac{P_{0.1}(\Delta V)}{\frac{\pi}{\sqrt{3}}}$.

magnitude led to more and more random simulated fishing positions inducing significant drops in the capacity of the estimated DCM to fit the data and to recover the true parameters up to a scale factor (Figure I.5.4.4.c).

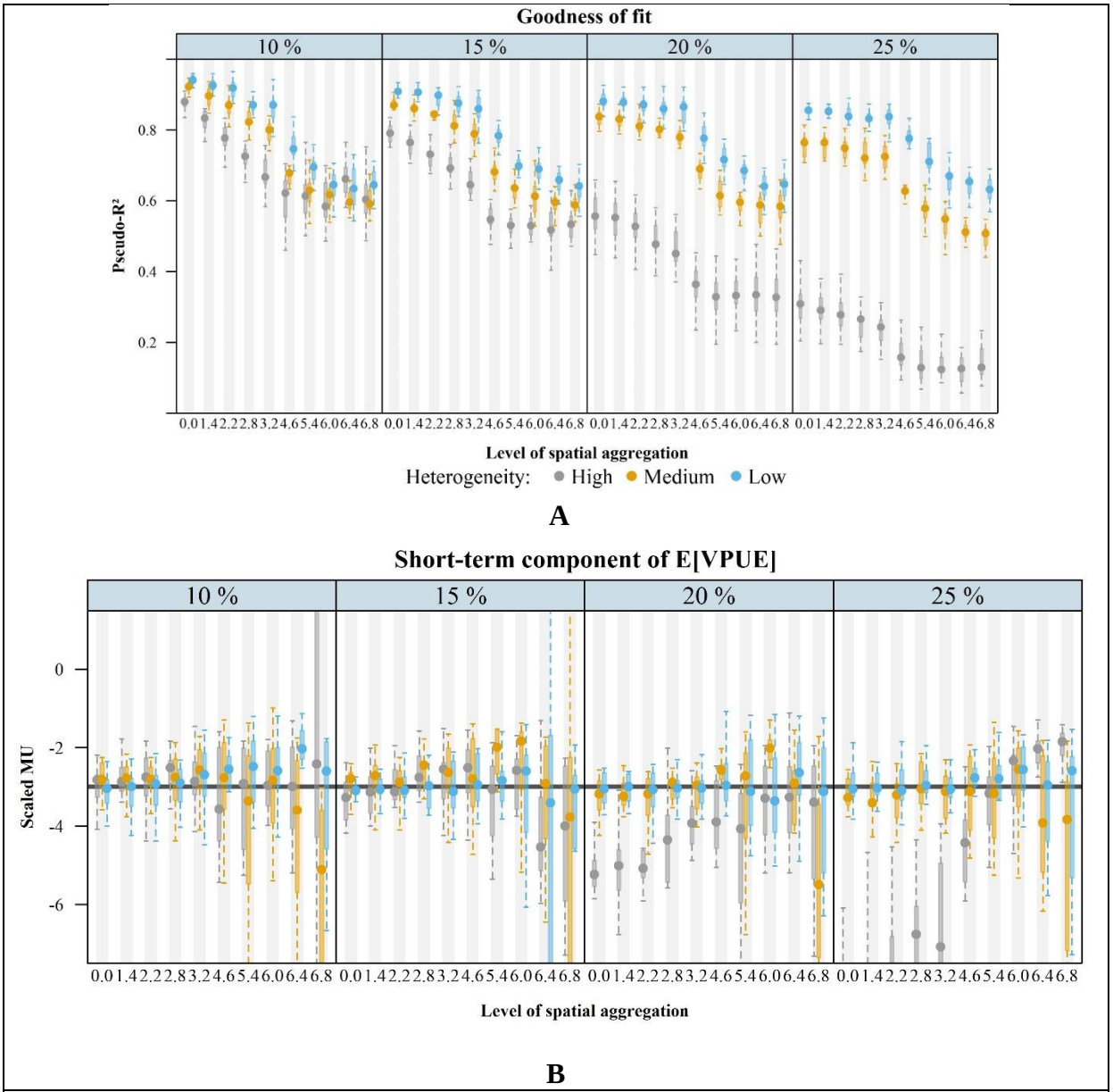


Figure I.5.4.4.c. Goodness-of-fit (Panel A) and estimated marginal utility of the short-term component of the expected VPUE (Panel B) of 15 Monte Carlo draws estimated for magnitudes of the stochastic part of the utilities varying from 10% to 25% (panels from left to right) of the bottom 0.1% of the distribution of differences in the deterministic part of the utility. Magnitudes of the errors term higher than 15% lead to a significant drop in the capacity of the RUMs to fit the data, included at the proper spatial scale (level of spatial aggregation = 0).

I.5.4.5. Model estimation

We estimate the simple conditional logit model corresponding to the data-generating process, assuming that the weights for forming fishers' expectations are unknown to the researcher, and distinguishing configurations of information availability using dummy variables:

$$U_{ijt}=\beta_{dist}*Dist_{ijt}+\beta_{VPUE}*E\left[VPUE_{ijt}\right]+\varepsilon_{ijt}$$

$$\beta_{VPUE}*E\left[VPUE_{ijt}\right]$$

$$=\begin{cases}\beta_{VPUE}^{Full\ info-short-term}*\overline{VPUE}_{m-1}^{ft}+\beta_{VPUE}^{Full\ info-long-term}*\overline{VPUE}_{ym-1}^{ft}\ if\ case\ 1\\ \beta_{VPUE}^{Short-term\ only}*\overline{VPUE}_{m-1}^{ft}if\ case\ 2\\ \beta_{VPUE}^{Long-term\ only}*\overline{VPUE}_{ym-1}^{ft}if\ case\ 3\\ \beta_{VPUE}^{No\ info}\ if\ case\ 4\end{cases}$$

With:

- case 1: both short-term **and** long-term historical VPUE are available
- case 2: **only** short-term historical VPUE are available
- case 3: **only** long-term historical VPUE are available
- case 4: **neither** short-term **or** long-term historical VPUE are available

The hypothesis is that we should be able to recover the weights as well as β_{VPUE}:

$$H:\begin{cases}\hat{\beta}_{VPUE}^{Full\ info-short-term}=\beta_{VPUE}*\alpha_{ft,m-1}\\ \hat{\beta}_{VPUE}^{Full\ info-long-term}=\beta_{VPUE}*\alpha_{ft,ym-1}\\ \hat{\beta}_{VPUE}^{Short-term\ only}=\hat{\beta}_{VPUE}^{Long-term\ only}=\beta_{VPUE}*\left(\alpha_{ft,m-1}+\alpha_{ft,y-1}\right)=\beta_{VPUE}\\ \hat{\beta}_{VPUE}^{No\ info}=0\end{cases}$$

I.5.5. Complementary estimation assumptions for the applied case study

A couple of assumptions were necessary to estimate the RUM. To begin with, we chose a daily time scale for choice occasions. This time scale is a compromise between the most refined time scale that would be based on fishing sets (but that would be much more data intensive and require a more refined analysis of the VMS pings) – and the coarser usual time scale used for similar studies in the literature, which is based on trips. Although this latter time scale may be very well suited for single-day trip fisheries (such as the urchin fishery studied extensively by Smith, e.g., Smith 2002, Smith, 2005), it is not appropriate here given the average duration of a fishing trip is approximately of one week. However, as the resolution of models becomes more spatially refined, the assumption of the uniqueness of choice becomes sometime violated (thereby emphasizing once more the trade-off between the spatial resolution of models and estimation issues). We followed a standard assumption in the literature (Girardin et al., 2015) of designating the "chosen" alternative as the one where most of the fishing effort was allocated[17]. Effort, catches and revenues were re-assigned accordingly. Depending on the tessellations, between 4% and 7% of effort was re-assigned according to that process. In total, we obtained 6,406 and 2,944 unique choice occasions (for 2008 and 2012 respectively), defined as a combination of a logbook trip with a day of the year.

We assume that the fishing effort remains constant over each fishing trip. Whereas the number of hooks per line is clearly fixed for a trip, the number of fishing sets[18] per day may vary from. However, we assumed it did not affect the decision of where to fish and, when allocating effort on

[17] When different sites had the same levels of effort, we randomly selected one of them.
[18] i.e., the number of times the longline is soaked and hauled back.

a daily basis, that the total number of fishing sets was homogenously distributed across the different days of the same trip.

Finally, we assume that the decision to go fishing and the decision on effort level fishing were independent from the decision of the fishing location. We tested those assumptions using 2008 logbooks and analyzed the correlation between fishing sites (reported for a given trip as the statistical area that yielded the highest revenue) and landing prices (a major driver for the decision to start a fishing trip or not) as well as the correlation between fishing sites and effort levels. In both cases, we found only a weak correlation[19].

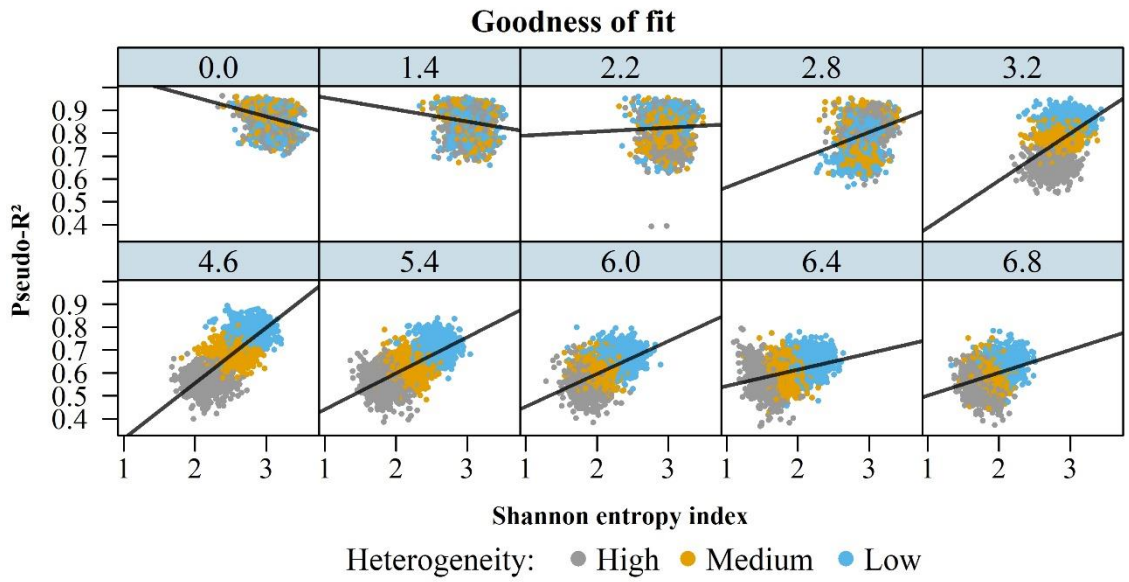
I.5.6. Complementary results

I.5.6.1. Monte Carlo experiments

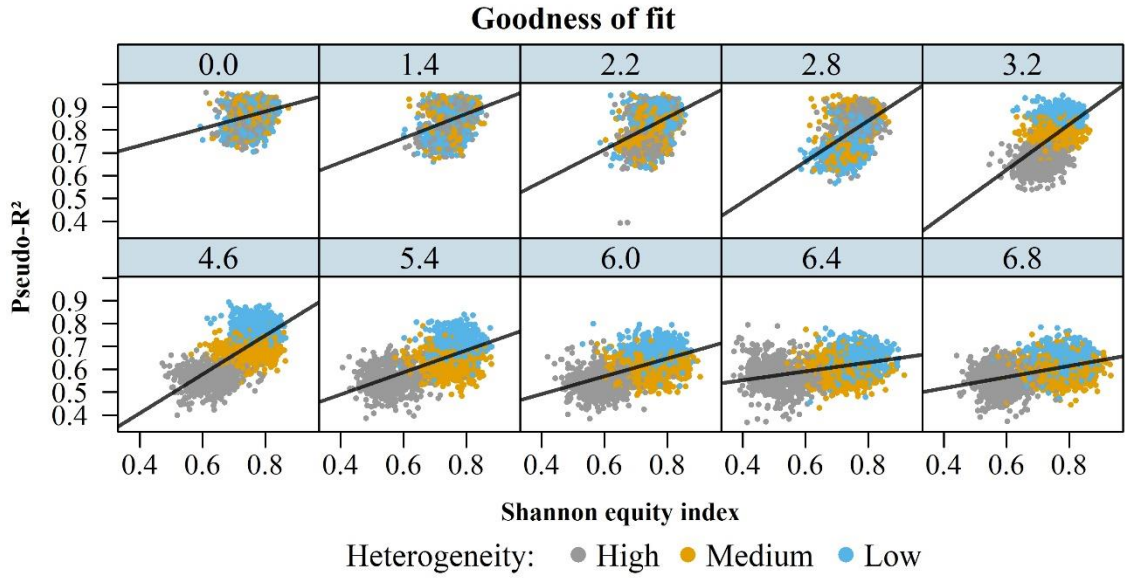
Absence of correlations between spatial indexes and model's performance

Figure I.5.6.1.a, I.5.6.1.b and I.5.6.1.c show the results of the correlation analyses that we carried out between the spatial indexes of data heterogeneity that we considered – Shannon entropy index and Shannon equity index (see Section I.5.2 of the Appendix) – and each model's performance in terms of goodness-of-fit (Figure I.5.6.1.a), prediction capability (Figure I.5.6.1.b) and capacity to recover the model's true parameters (Figure I.5.6.1.c).

[19] 3 out of 21 logbook statistical areas were associated with landing prices significantly different from the mean, and 5 out of 21 of the logbook statistical areas had effort levels significantly different from the mean.



A



B

Figure I.5.6.1.a. Goodness-of-fit of 600 Monte Carlo experiments in function of Shannon entropy (Panel A) and equity (Panel B) index. Panels reflect for the ten levels of spatial aggregation tested. The solid black lines show the results of a simple linear regression

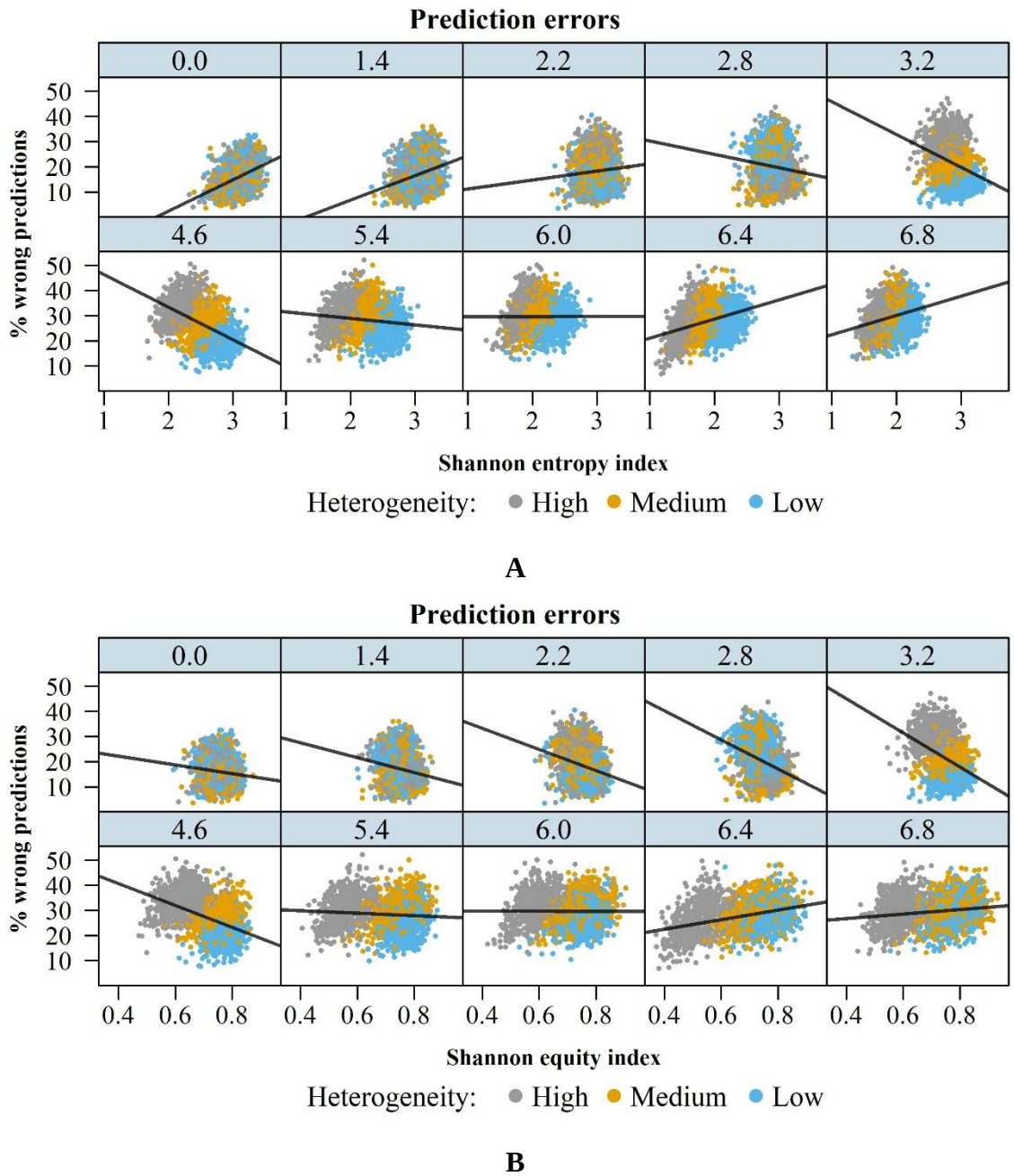
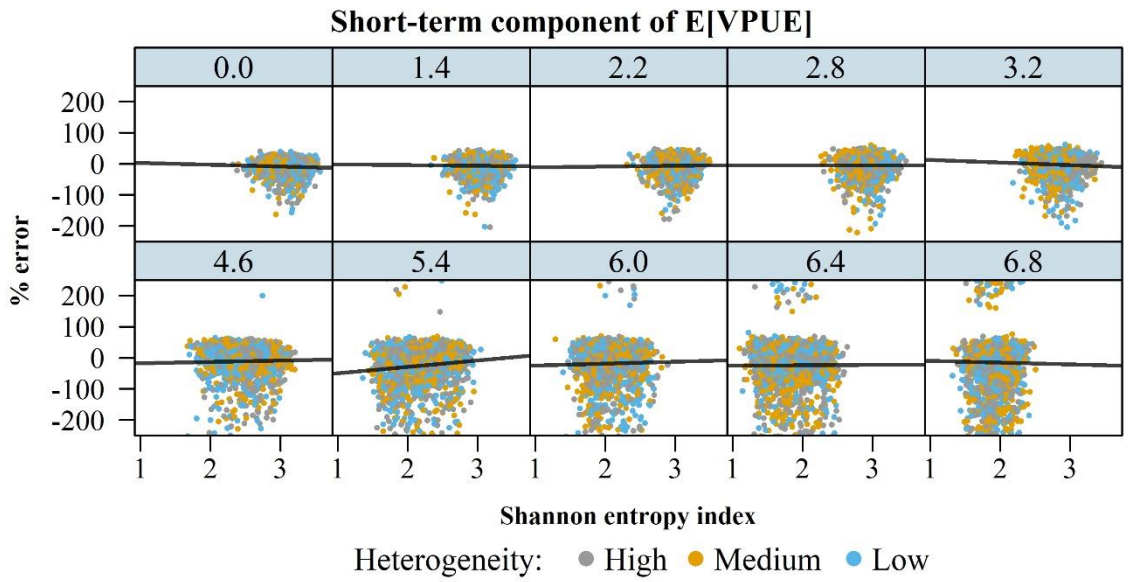
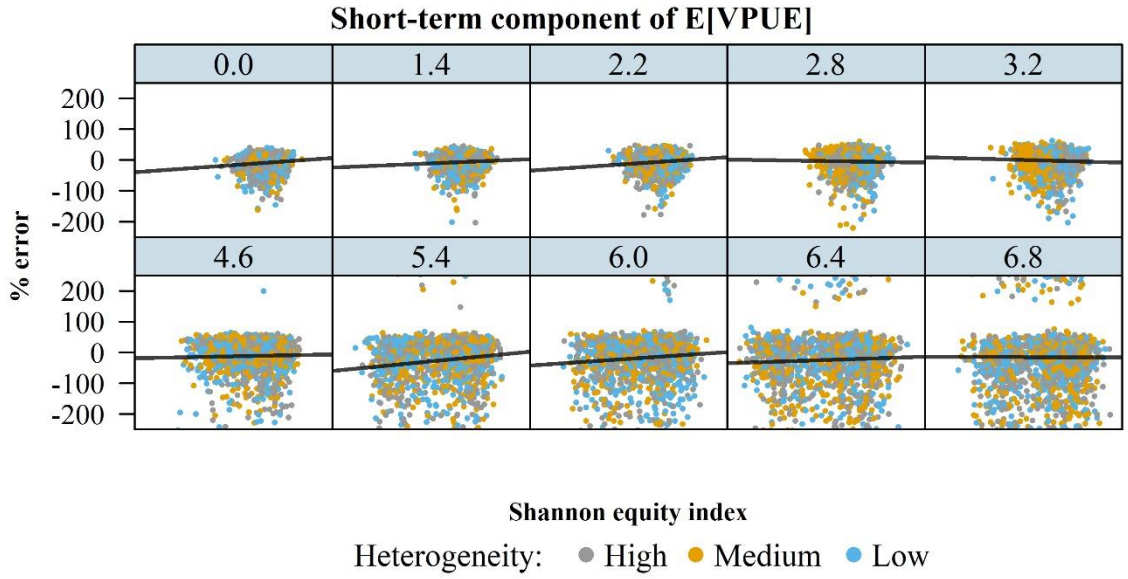


Figure I.5.6.1.b. Prediction errors of 600 Monte Carlo experiments in function of Shannon entropy (Panel A) and equity (Panel B) index. Panels reflect the ten levels of spatial aggregation tested. The solid black lines show the results of a simple linear regression



A



B

Figure I.5.6.1.c. % error in the estimation of the short-term component of the expected VPUE for each of 600 Monte Carlo experiments in function of Shannon entropy (Panel A) and equity (Panel B) index. Panels reflect the ten levels of spatial aggregation tested. The solid black lines show the results of a simple linear regression

Average Marginal Effects of explanatory variables

Here we show the average marginal effects of explanatory variables in estimating Eq I.1.

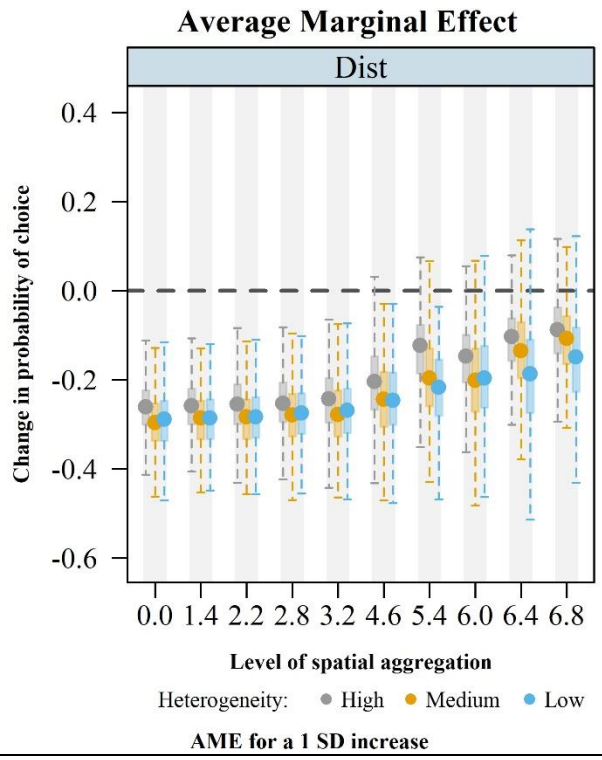


Figure I.5.6.1.d. Average marginal effects (AME) on choice probabilities of the distance variable estimated in the Monte Carlo experiments. Effects are computed for an increase of one standard deviation. The box edges are the 25th and 75th percentiles of the distribution of the AME and whiskers are located at +/- 1.5 times the interquartile ranges.

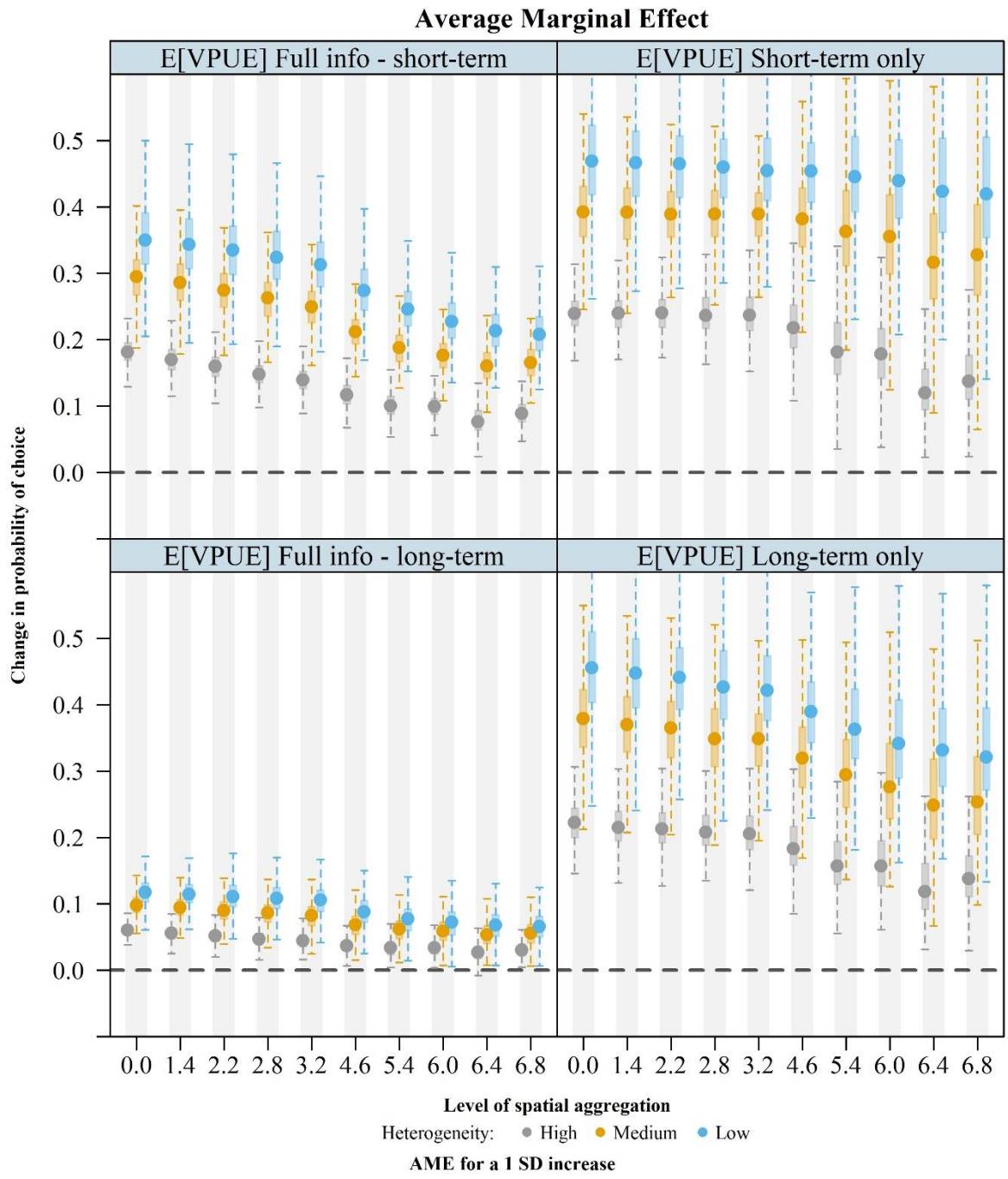


Figure I.5.6.1.e. Average marginal effects on choice probabilities of the four components of the expected VPUE estimated in the Monte Carlo experiments. Effects are computed for an increase of one standard deviation of the corresponding variable. The box edges are the 25th and 75th percentiles of the distribution of the AME and whiskers are located at +/- 1.5 times the interquartile ranges.

I.5.6.2. Applied case study

Here we show the average marginal effects of explanatory variables in estimating Eq I.2.

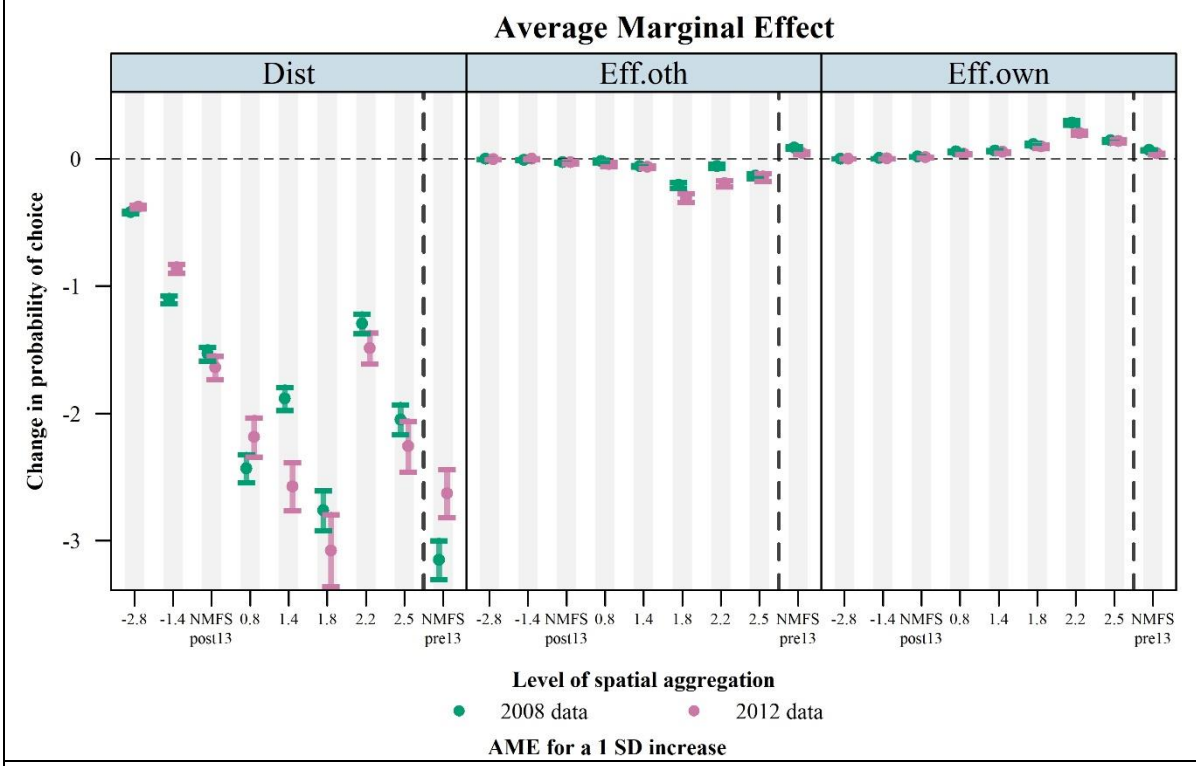


Figure I.5.6.2.a. Average marginal effects on choice probabilities of the distance to fishing grounds, of the fishing effort of other vessels and of vessel's own fishing effort the day before estimated with GoMRF data. Segments indicate the 95% confidence interval of the corresponding point estimate. Effects are computed for an increase of one standard deviation of the corresponding variable.

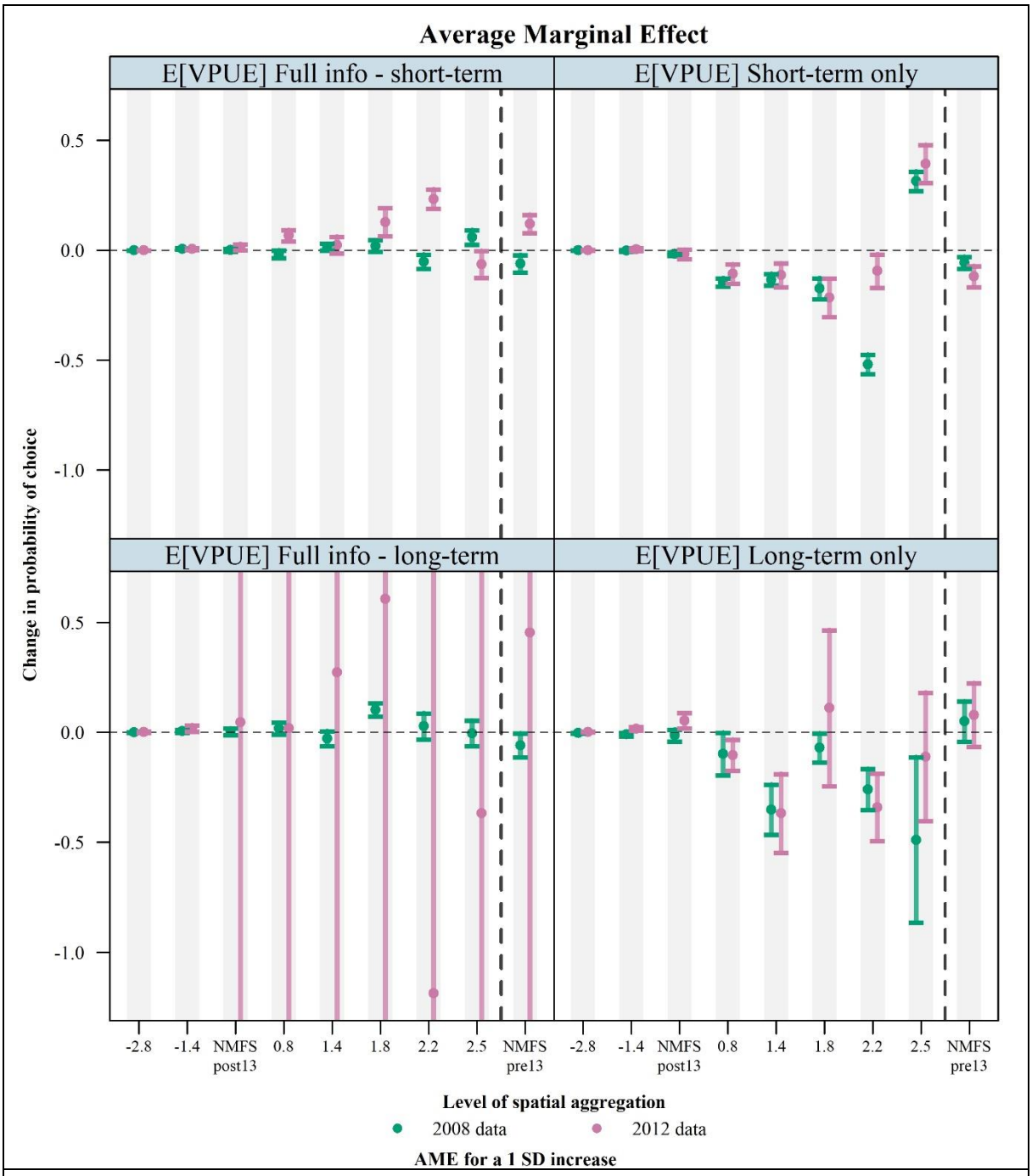


Figure I.5.6.2.b. Average marginal effects on choice probabilities of the four components of the expected VPUE estimated with GoMRF data. Segments indicate the 95% confidence interval of the corresponding point estimate. Effects are computed for an increase of one standard deviation of the corresponding variable.

Chapter II: An evaluation of the potential impacts of Brexit on the French commercial fishing fleet[1]

Abstract

We examine the possible impacts on the French commercial fishing fleet of two spatial closure scenarios which could be implemented as a consequence of Brexit: the closure of UK territorial waters and the closure of the entire UK EEZ. We focus on the subset of 724 French vessels operating in the North East Atlantic region (including the Channel) between 2012 and 2015. We provide estimates of the extent of possible displaced fishing effort, catches and revenues and we characterize the fisheries and vessels which would be the most impacted by the spatial closures. Using a discrete-choice model of fishing location, we provide estimates of the reallocation of fishing effort which could be expected for five key fleet segments.

We find that, based on 2012-15 data, the closure of the UK EEZ would significantly impact the fishing activity of 99 vessels – mostly bottom trawlers – that currently derive more than half of their revenues from UK waters. In the absence of fishers' adaptation, the potential loss for the entire fleet considered represents about 40,000 tons (20%) of catch and 100 M€ (18%) gross revenue per year. In addition, we anticipate the reallocation of fishing effort outside of the UK EEZ to trigger significant and complex chain reactions, which include an increased competition for the exploitation of sites located in the English Channel and in the Celtic Sea and potential user conflicts between large mobile vessels and smaller coastal fishers.

[11] This chapter is developed as a standalone paper with co-authors Olivier Thébaud and Jim Sanchirico.

II.1. Introduction

Prompted by the outcome of the "Brexit" referendum held on June 23rd 2016, the decision of the United Kingdom (UK) to leave the European Union (EU) triggered uncertainties in many domains, including fisheries policy. As promises to improve the economic conditions of UK fishers by "taking back the control of UK waters" fueled the Leave campaign (Smith, 2017)[2], the status of British fisheries has been one of the key element of the political debate about Brexit.

In 1983, the EU – and thereby the UK, who joined the Union in 1973 – adopted the Common Fishery Policy (CFP). The CFP sets total allowable catches for a set of species threatened by overfishing. The CFP also grants equal access for the EU Member States (MS) to the EU economic exclusive zone (EEZ) as a whole, subjected to the "relative stability" of the quotas allocation key. The CFP guarantees exclusive fishing rights to MS for their own territorial waters (0-12NM). However, in the case of the UK a specific provision based on the London Fisheries Convention (LFC) in 1964 was made to maintain fishing rights in its 6-12NM water belt for fishers from five other EU countries – Belgium, France, Germany, Ireland and the Netherlands – in return for reciprocal access to their inshore waters (Schatz, 2017).

On July 2nd 2017 the UK announced it will withdraw from the LFC, thereby starting to reshape its cooperation policy regarding fishery management with other MS, while it will still belong to the EU until March 2019. The decision to withdraw from the LFC raises the question of whether access to the 6-12NM water belt by foreign fleets will be maintained in the future. While catches from foreign vessels in this area only represent 1.3% of the total catches of UK

[2] Another pro-Brexit argument was achieving a fairer quota allocation. In reality, however, the quota allocation is not an EU decision (Steward and Carpenter, 2016).

fishers (Smith, 2017), the decision is deemed highly symbolic and could lead to additional moves in the future to restrict the access of foreign vessels to the entire EEZ of the UK.

Fishers of other MS have expressed concerns about the consequences of such decisions. For instance, Dutch fishers specialized in fishing for sole in UK waters fear they will go out of business (Bonnassieux and Zingaro, 2017). French fishers, especially from coastal regions bordering the Channel, have voiced similar concerns, pointing out that the relocation of large vessels currently operating in UK waters to French waters will increase competition, most likely to the detriment of small vessels (Smith, 2017). As a result of such a sensitive mix of social and economic issues, fisheries are deemed to be an important point of negotiation during the Brexit talks[3].

The current discussions surrounding losing access to UK waters are missing quantitative assessments of the potential implications. To fill this gap, we investigate the implications for the French fleet across a range of Brexit scenarios. Specifically, we investigate the effects for key segments of the French fleet of two potential policy options: 1) the closure of UK territorial waters, and 2) the closure of the entire UK EEZ (see Figure II.1).

There are several pathways the closure of UK waters may affect French fishers and the French fishery sector. Not surprisingly, the immediate impact is the loss of catches and revenue from UK waters. More subtly, it is not evident which of the fishing fleets, the catches of the

[3] As of August 2018, the latest negotiation document mentioning fisheries dated back to May 4th 2018 and merely listed "fishing opportunities" as a topic for further discussions. The latest released position paper tackling this subject is the 17th report of session of the House of the Lords published on June 8th 2018. It summarizes the positions of both parties: while affirming that the UK will leave the CFP, the UK government acknowledges the need to agree reciprocal access to fishing grounds, which the European Parliament states as a pre-condition for access to the EU domestic market.

different species, and the corresponding fish prices are going to be the most impacted. Regarding that latter aspect, catches of a same species may indeed not be comparable in terms of value, depending on the quality of the fish, the gear used or the catch area. Provided fishery data allows for such a level of disaggregation – and it does in our case – the assessment of this first-order effect is rather straightforward. One can simply look at each fleet's catch in UK waters and calculate the loss associated with losing that catch, valuing it at current landing prices. Such an estimate provides a quick and dirty approach to find what is likely an upper bound of the overall economic impact.

Intricate secondary and higher order effects also can be expected to come into play over time from such large-scale closures. The greatest of such effects is likely the simple fact that fishers will adapt to the new regulations in an attempt to mitigate their impact on the fishing enterprise (Branch et al., 2006; Fuller et al., 2017; Fulton et al., 2011). To account for this, we utilize a discrete-choice model of fishing locations – a powerful and popular framework among economists for modelling spatial and temporal fishing behavior (Sanchirico and Wilen, 1999; Smith, 2010). The discrete choice model permits us to identify the patterns of fishing effort reallocation that would be induced by the reductions of the accessible fishing area and to better measure the likely implications of the lost access.

Indeed, the reallocation of fishing effort can have consequences not only upstream, on fishing pressure and resource availability, but also downstream, across the fishery value chain from the ports of landing to the consumers. In this regard – and leaving aside issues related to market access –, how a new distribution of fishing effort and a new distribution of catches would translate into new landings' locations and new market dynamics is a central matter. Changes in fishers' level of activity in one place can have important impact on the local fishing communities, notably

in the processing sector that may be confronted to over- or under-capacity issues. Again, this may also impact fishers in turn, who may face changing landing prices and may have to establish new networks of wholesale fishmongers. Accounting for all of these dynamic effects is an utterly complex task which falls outside the scope of the current chapter. Nevertheless, we do set the first seeds of this work by providing some key elements of analysis to anticipate the variegated impact of Brexit scenarios on French fishers and on French coastal communities. In particular, we investigate the patterns of landing locations of vessels fishing into UK waters and we examine how catches from UK waters are distributed among French ports.

The chapter is organized as follows. First, we present the data and the methods we employ for our study. We then draw a comprehensive picture of the current dependency of French fisheries to UK waters by successively breaking down the multidimensional aspects of the economic relationship at the levels of vessels, fleet segments, species and ports. Narrowing down our focus on five key fleet segments deemed to be significantly impacted by a restriction of access to UK waters, we then show how our model predicts vessels would react to a closure of the UK territorial waters or of the entire UK EEZ. Finally, we discuss our results providing suggestions to further investigate the full consequences on fisheries of the withdrawal of the UK from the EU.

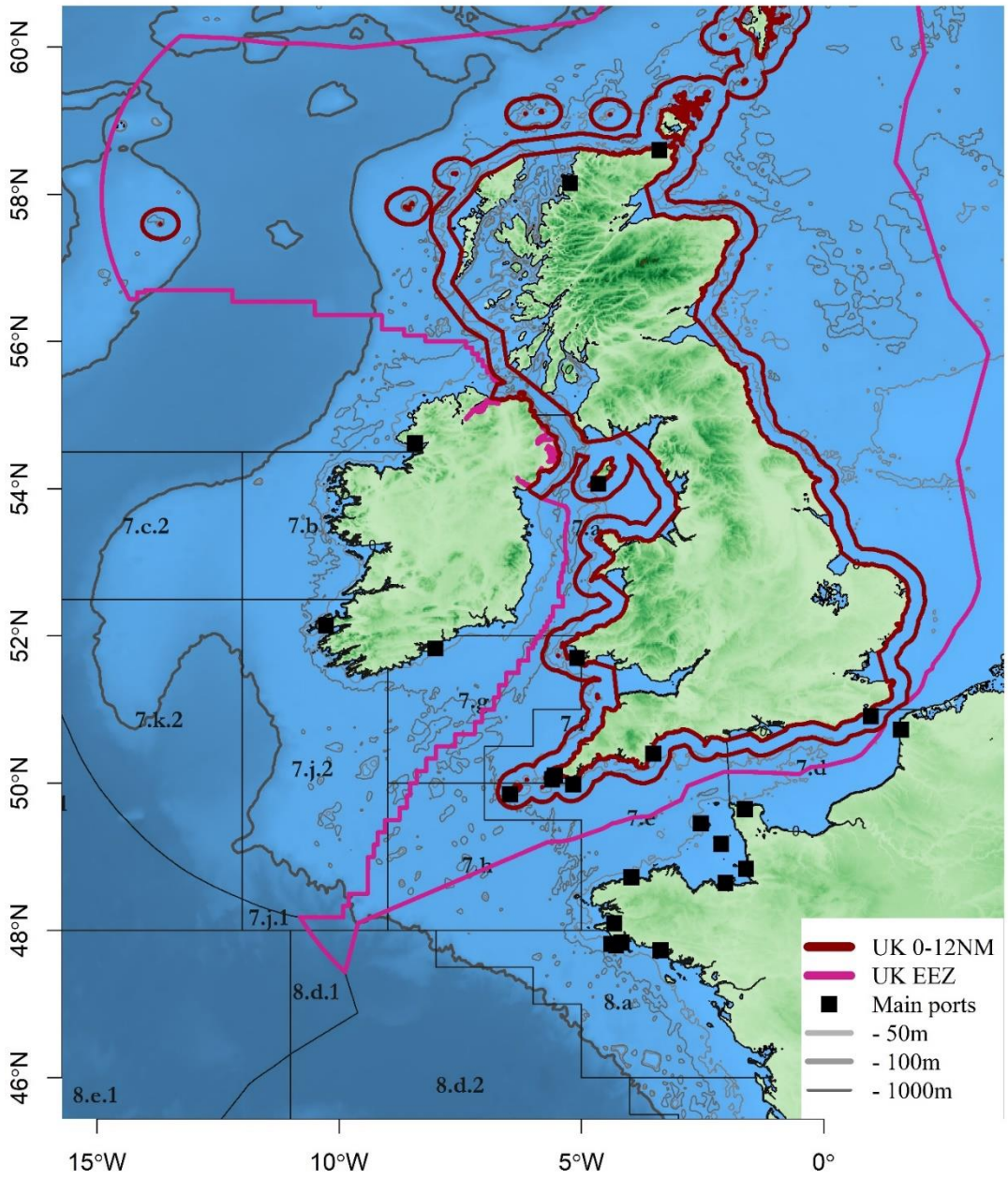


Figure II.1. Maritime boundaries and main fishing ports in the North East Atlantic regions. ICES areas VII and VIII's delineations are shown in light grey.

Source: authors production. Maritime boundaries are based on the Maritime Boundaries Geodatabase, version 10 from Flanders Marine Institute (2018) (available online at http://www.marineregions.org/).

II.2. Case study: French fleet operating in UK waters

Our analysis of the possible impact of Brexit on EU fisheries takes the French fishing fleet as a case study. Based on the EU Scientific, Technical and Economic Committee for Fisheries (STECF) data (2018), the French fishing fleet is one the main non-UK EU fleet to operate in UK waters, along with the Irish, Dutch, German and Danish fleets[4].

For this study, we exploit a subset of the SACROIS database developed by the French Research Institute for Exploitation of the Sea (Ifremer) under the supervision of the French Directorate for Marine Fisheries and Aquaculture (DPMA). The SACROIS database combines and reconciles French Vessel Monitoring System (VMS), logbooks and sales data from different sources ("SACROIS," 2017). The subset we accessed correspond to anonymized data for the VMS-equipped French fishers vessels operating in the fishing areas VII and VIII as defined by the International Council for the Exploration of the Sea (ICES), over the period from 2001 to 2015 (Figure II.1). In addition to information about vessels' technical characteristics (e.g., length, power) and vessels' type of fishing activity (categorization into "subfleets"), the data also includes trip-level information such as fishing time, catches, revenues, gear or métier, broken down by day and species and aggregated by $\frac{1}{20}° \times \frac{1}{20}°$ statistical squares (about $3\text{NM} \times 2\text{NM}$).

The database used contains only vessels equipped with a VMS device[5], which represents a fraction of the entire French fishing fleet. This fraction has been increasing over the years with

[4] Andersen et al. (2017) provide a similar study of the impact of Brexit on the Danish fishing sector (Andersen et al., 2017).

[5] The SACROIS dataset includes also some vessels for which VMS were not or is not yet compulsory (263 vessels in 2015, accounting for 39,000 tons of landings and 54 M€ of value), but the VMS coverage for those fleets remains very low. Vessels smaller than 12m that are in our dataset represent only 18% of vessels smaller than 12m registered in the Community Fishing Fleet Register for the Atlantic and Channel region in 2015. Moreover, no fleet segment achieves a VMS coverage higher than 50% (the highest being dredger trawlers with 48%).

VMS coverage expanding to the smaller vessels in the fleet. Implemented as part of the regulatory framework of the CFP, VMS began to apply to all vessels larger than 24m in 2000, then was extended to vessels larger than 18m in 2004, 15m in 2005 and 12m in 2012[6]. In 2015, among the 725 vessels larger than 12m registered as fishing in EU waters[7], 724 were included in the subset SACROIS dataset. Although those 725 vessels represented only 25% of French vessels operating in EU waters in 2015, they accounted for 73% (300,000 tons) and 75% (700 M€) of total French landings and landings value, respectively[8]. Focusing only on ICES areas VII and VIII, vessels larger than 12m accounted for 67% (221,000 tons) and 72% (597 M€) of French landings and landings value from these areas in 2015[9]. Thus, while we don't have a complete coverage of the French fleet, our subset is significant. In addition, it is also particularly relevant for the question we ask. Vessels larger than 12m being more mobile and having a larger capacity than smaller vessels, they are more likely to take longer fishing trips and to reach fishing grounds located beyond French waters and further away from their homeports. Therefore, even though our calculations of catches from UK waters will be underestimates, they will remain an excellent proxy for the whole fleet[10].

For these reasons we decided to focus only on vessels larger than 12m and only on the years starting from 2012.

[6] CE No 686/97; CE No 2244/2003.

[7] According to the EU Fleet Register (2018)

[8] Still according to EU Fleet Register.

[9] Those levels of catches and revenues reported by the EU Joint research Center[9] are consistent with levels computed with our dataset (221,000 tons and 592 M€).

[10] Based on our sample of vessels smaller than 12m equipped with VMS, catches from UK waters accounted only for 1.9% (730 tons) of total landings and 6.0% (3.3 M€) of total landings' value in 2015.

II.3. Methods

II.3.1. Assessment of the economic dependency to UK waters

In order to account for the heterogeneity of French fishing vessels that may induce differentiated patterns of dependency to UK waters, we consider groups of vessels that share similar fishing strategies rather than aggregating into one fleet. We categorize vessels into 28 different fleet segments, among which 15 have full VMS coverage. To define the fleet segments, we rely on Ifremer's identification of vessels' métiers and on the guidelines from the European Data Collection Framework to aggregate some sub-fleet segments (see section II.5.1 in the Appendix). We also aggregate the $\frac{1}{20}° \times \frac{1}{20}°$ statistical squares along UK territorial waters, the UK EEZ and the area outside of the UK EEZ. Based on these classifications, we compute – on a yearly basis – the share of fishing effort, value and catches from each area and at the fleet, vessel and species levels.

This enables us to rank vessels and species by their level of dependency on UK waters, in terms of the percentage of landed catches or landings' value. This way we can identify which kind of vessels or species will be the most exposed to our Brexit scenarios.

In the case of vessels, we further refined the typology of vessels that depend highly on UK waters by asking whether those latter exhibit specific patterns that would distinguish them from the rest of the fleet. Being able to identify potentially unique features of those vessels is essential to evaluate the impact that the closure of UK waters would have on them. Key questions are why vessels would target specifically UK waters and which capacity they would have to re-locate in other fishing grounds. By answering them, we can hope to better anticipate the nature and the extent of their response to the closure and, thereby, better evaluate its economic consequences.

Clustering the analysis at the fleet segment level, we investigate, therefore, potential correlations between a vessel's share of gross revenue from UK waters and its technical characteristics (power and length), trips characteristics (average landing, landing's value or effort), fishing efficiency (average catch or value per unit of effort, abbreviated as CPUE and VPUE), landing prices received, catch composition and landing port locations. For the first four sets of features we rely on statistical analysis to test the significance of potential differences, defining a dummy variable accounting for when a vessel derives more than half of its gross revenues from UK waters and performing two-sample t-tests and linear regressions. For the last two features – catch composition and landing ports locations – we map out species bundles and trips' schedules at the vessel level and rely on a systematic visual inspection of the correlation with the dependency to UK waters.

II.3.2. Discrete choice model of fishing relocation decisions

In order to predict the reallocation of fishing effort that would result from the closure of UK waters to French fishers, we estimate a discrete-choice model of fishing locations. We build on a random utility model framework where fishers are assumed to be able to assign utility values to each of the fishing alternatives they face and choose the alternative yielding the highest utility.

The model that we estimate assumes that – conditional on being actively fishing and conditional on a given level of fishing effort and on a given location – fishers make a unique daily decision on where to fish according to a simple utility criterion that weighs traveling costs and expected rewards from a fishing site *j*:

$$U_{ijt}=\beta_{dist}*Dist_{ijt}+\beta_{VPUE}*E\left[VPUE_{ijt}\right]+\beta_{Act.oth}*Act.oth_{ijt-1}+\beta_{Act.own}*Act.own_{ijt-1}+\varepsilon_{ijt} \quad \text{(Eq. II.1)}$$

where i is the vessel, j is the site, t is the day, and β_{dist}, β_{VPUE}, $\beta_{Act.oth}$ and $\beta_{Act.own}$ denote the marginal utilities of respectively, the distance to a given location, $Dist_{ijt}$, the associated expected value per unit of effort ($E[VPUE_{ijt}]$), the number of other vessels in site j at the same time; and vessel's own fishing effort in site j the day before, and ε_{ijt} is a random utility shock.

Our model specification is standard where travel costs and expected revenues are the main predictors of the choice of the fishing location (Girardin et al., 2016). A commonly used proxy for travel costs is the distance to the fishing sites, usually reduced for computational purposes to the centroids of the alternative and of the current location (Abbott and Wilen, 2011; Haynie and Layton, 2010). Intuitively, this variable captures that further fishing sites incur not only higher fuel costs, but also require more time to be reached[11].

With respect to fishers' expectations about revenues from a fishing site, we follow the literature that utilizes records of past performances for each site, aggregated at the fleet level (see, e.g., (Girardin et al., 2015; Smith, 2005)). Specifically, we assume that fishers combine both short and long-term information as well as both individual and fleet-level information, and weight information signals differently depending on which information is available or not (Abbott and Wilen, 2011; Hutniczak and Münch, 2018)[12].

The behaviors of other fishers along with fishers' past fishing patterns having been shown to influence fishers' decision-making (Girardin et al., 2016; Huang and Smith, 2014; Poos and

[11] To take into account the additional cost of visiting a site located further away from the port of return – as in Hutniczak and Münch (2018) – we also included the distance of sites to the observed landing port. However, we did not find the model to yield significantly different results in most of cases and thus decided not to present it here.

[12] Section II.5.3 of the Appendix gives the full details of model's specification as well as the procedure we followed for model selection.

Rijnsdorp, 2007), we account for those aspects by including the contemporaneous level of other fishers' activity – in terms of number of vessels – in a given alternative (Act.oth_{ijt}), as well as fishers' own level of fishing activity – in terms of number of fishing hours – in a given site the day before (Act.own_{ijt-1}),

The choice of the spatial scale of analysis must be carefully examined in the context of a discrete-choice framework. Numerous works have shown that an ill-specified spatial choice set may bias parameter estimates and substantially impair the reliability of model's results (Haab and Hicks, 1999; Jones et al., 2015; Manski, 1977; Parsons and Hauber, 1998).

Data permitting, the choice of model's spatial resolution (i.e., the size of the fishing sites in our case) must be considered in the context of the choice of the temporal framework for the decision, of the spatial extent of decision-makers' mobility patterns, and the underlying questions being investigated. In our case, being interested by the spatial reallocation of fishing effort, a finer spatial resolution would allow a more refined analysis of the reallocation patterns. However, we are also constrained in our choice of the temporal scale by the daily aggregation of the dataset. As a consequence, fishing sites must be defined with a spatial extent corresponding to the area that a vessel is likely to cover over a day of fishing. The specific spatial extent varies across vessels but tends to be more homogeneous within a fleet segment. For instance, in our dataset large bottom trawlers cover on average 20 (±8 s.d.) $\frac{1}{20}° \times \frac{1}{20}°$ statistical squares within a single day whereas the average for vessels using traps or pots is only 9 (±4 s.d.).

Narrowing down our analysis to the five key fleet segments – large exclusive bottom trawlers (BTR exc >=18m), large dominant bottom trawlers (BTR dom >=18m), vessels using traps (TRP >=12m), netters (DFN >=12m), and dredgers (DRD >=12m), we explore different

levels of spatial aggregation for each of them. The granularity of the VMS data permits us to investigate this issue. Specifically, we follow the methodology established in Chapter I to test the sensitivity of our model to different spatial scales. The size of the fishing sites that we assume, fishers consider to make their daily decisions is therefore either: (1) a $2° \times 2°$ square (1600 $\frac{1}{20}° \times \frac{1}{20}°$ squares); (2) a $1° \times$ ½° square (200 $\frac{1}{20}° \times \frac{1}{20}°$ squares) as defined by the ICES for its statistical analyses; or, (3) a ½° × ½° square (100 $\frac{1}{20}° \times \frac{1}{20}°$ squares).

Across the different spatial scales, we evaluate the reliability of the estimated models for predicting new choices of fishing locations by assessing the prediction capability of the model for each of the five fleet segments. For an additional robustness check, we train the model on 2013 and 2014 data and use 2015 data as a test dataset for out-of-sample predictions. We then compute the percentage of wrong predictions for each estimated model and use this information to select our preferred specification to predict the reallocation of fishing effort for each of the fleet segments.

By using a daily temporal framework for the fishing decisions, our model provides a snapshot of where fishers would go given the set of fishing sites available at a given time of the year. Holding fixed the distribution of choice occasions and of the associated levels of fishing effort, we are able to produce an estimate of the short-term reallocation of fishing effort for any given day of an observed fishing season. In order to have a representative picture of the new spatial distribution of fishing effort that would not be tailored to a specific day of the year, we choose to estimate effort reallocation for each choice occasion observed in 2014 and to average fishing efforts over this whole year.

II.4. Results

In this section we highlight key results of our economic assessment of the dependency of French fishers to UK waters, before showing the predictions of our model in terms of effort reallocation.

II.4.1. Economic importance of UK waters for the French commercial fleet

The extent of the economic dependency of the French fleet to UK waters can be investigated across several dimensions. A starting point is to look at the overall fishing activity of French vessels in UK waters in terms of landings and landings' value from catches from UK fishing grounds. Utilizing the unique level of disaggregation of our dataset, we undertake a much more refined analysis where we identify specific spatial patterns of fishing activity in UK waters (fishing "hotspots") and look at dependencies to UK waters at species and ports levels.

II.4.1.1. Vessels' landings and value from UK waters

Overall, more than 25% of the total fishing effort of all vessels larger than 12m was located in the UK EEZ in 2012-15, among which 3% was in UK territorial waters. This translates into 18% of all vessels' landings and landings' value originating from UK waters over the 2012-2015 period[13] (Table II.a). For 2015, this represented a total of 0.33 million fishing hours and 40,000 tons of landings worth close to 100 M€, derived from UK waters[14]. More than 325 vessels larger than 12m (about half of all vessels larger than 12m) were fishing regularly in the UK EEZ between

[13] Variations from one year to another remain small, and even though slight decreases can be observed at aggregated levels, they are not meaningful when accounting for variations at the vessel level.

[14] For UK territorial waters those numbers amount to 0.03 M (1.7%) fishing hours, and 5,000 tons (2.3%) of landings worth 10.5 M€ (1.8%).

2012 and 2015[15]. Among those, about half (172 in 2015, representing 24% of all vessels larger than 12m) were also fishing in the UK territorial waters (see section II.5.2.1 in the Appendix).

These aggregated figures hide the significant variability within the French fleet. Ranking segments by the share of landings originating from UK waters, the top three segments – bottom trawlers, exclusive or dominant, and vessels using traps – derived more than a third of their catches from UK waters. The levels of dependency drop to 15% and 10% for the next four segments and remain below 5% for the other segments[16]. Accounting for more than one fourth of all vessels larger than 12m and more than a third of all the landings, dominant and exclusive bottom trawlers comprise three quarters of all catches from UK waters. In contrast, vessels using pots and traps – even though highly dependent on UK waters – only account for about 3% of catches from this area.

Heterogeneity within the same fleet segment was also observed. Whereas for the two large bottom trawlers segments there is a rather evenly distributed continuum of levels of dependency with UK waters, for all the other segments there are only small subsets of vessels that rely heavily on UK waters (see Section II.5.2.3 of the Appendix). The vast majority of vessels do not derive more than half of their landings from this area. Three quarters of the 99 vessels that drew more than half of their revenues from UK waters over the 2012-2015 period were large bottom trawlers.

A natural question to ask is how the vessels depending highly on UK waters compare with the rest of the fleet. We do not find any significant differences[17] regarding either their technical characteristics (power and length), trips characteristics (average landing, landing's value or effort)

[15] They were 336 in 2015, representing 44% of all vessels larger than 12m.
[16] See Section II.5.2.2 of the Appendix for a break down by year and by segment
[17] Except in a few instances that turned out to be not consistent over time.

or fishing efficiency (average CPUE or VPUE). Regarding whether the exploitation of fishing grounds located in UK waters induces or reflects the exploitation of a specific bundle of species, we do not find so either: vessels from a same fleet segment are catching the same set of species in and outside the UK waters (see Section II.5.2.4 in the Appendix).

Similarly, we do no find specific patterns of landing locations related to exploiting UK waters. The vast majority of vessels fishing in UK waters leave and land their catches in France (see Section II.5.2.5 in the Appendix), and more generally the majority of vessels leave and land their catch in the same port. Focusing on the small subset of fishing trips involving ports in the UK, we find that almost all trips are from or to France. Furthermore, we find – surprisingly – that if bottom trawlers using UK ports also exploit UK waters (especially near shore), netters and dredgers stopping in UK facilities actually get most of their catch outside of the UK EEZ. Also, we find no vessels that appear to be based in UK ports or exhibiting a consistent pattern of visit to UK ports. Overall, this suggests that exploiting UK waters is largely uncoupled from utilizing ports in the UK. This may not be surprising when knowing that, not only gross fuel prices are higher in the UK, but French fishers also benefit from tax exemptions on fuel in France.

Finally, we investigate whether vessels fishing mainly in UK waters receive different landing prices. Differences could stem, for example, from a premium on catches from this region (e.g., because the quality or the size of the fishes would be different), a greater ability of fishers to target higher valued fishes, or from some specificities in fishers' network of fishmongers. To test this hypothesis, we estimate species-specific linear regression models for the top twelve main species with imputed landing prices between 2012 and 2015 at the fishing trip level, including a dummy for most dependent vessels and a series of controls (date of landing, port of landing, fleet, commercial category etc.). We find that vessels fishing mainly in UK waters had significantly

lower landing prices for the Atlantic cod, the Common sole, the Lemon sole, Monkfishes and the Whiting, while having significantly higher landing prices for the Haddock. Thus, we conclude that fishing in UK waters does not lead to fishers extracting higher landing prices. This finding implies, all things being equal – in particular catch rates and other market prices –, that the loss of access to UK waters will not result in lower prices for their catch.

	Landings				**Value**			
Fleet segment	%		tons		%		k€	
	UK EEZ	Terr. waters	UK EEZ	Terr. waters	UK EEZ	Terr. waters	UK EEZ	Terr. waters
Bottom Trawl exc. ≥18m	45	4	27,987	2,760	38	4	68,133	6,520
Pots & Traps ≥12m	35	2	1,244	62	36	2	3,139	180
Bottom Trawl dom. ≥18m	33	7	6,326	1,348	32	7	12,776	2,660
Bottom Seine ≥12m	15	2	606	87	9	1	1,267	176
Polyvalent Active ≥12m	13	2	645	119	12	2	1,425	277
Dredge ≥12m	12	1	1,863	231	13	2	4,959	706
Pelagic Trawl ≥12m	10	2	4,554	1,043	9	2	5,309	1,253
Drift & Fixed Nets ≥12m	4	0	1,303	34	5	0	5,134	162
Bottom Trawl dom. [12m-18m[	4	0	566	47	4	0	1,314	98
Polyvalent Passive ≥12m	4	1	26	4	3	1	57	11
Bottom Trawl exc. [12m-18m[	2	0	192	2	1	0	478	4
Lines & Hooks ≥12m	2	0	128	0	2	0	384	0
Beam Trawl ≥12m	1	0	3	0	1	0	10	0
Pelagic Seine ≥12m	0	0	0	0	0	0	0	0
Other ≥12m	0	0	0	0	0	0	0	0
Unknown	0	0	0	0	0	0	0	0

Table II.a. Average share of fishing effort, catches and landings' value located in the UK EEZ and in the UK territorial waters between 2012 and 2015.

II.4.1.2. Fishing hotspots in UK waters

The heterogeneity in the importance of UK waters between the fleet segments and between vessels can be better understood when looking at the location of the fishing in relation with the target species rather than through intrinsic vessel specificities.

Mapping out the spatial distributions of fishing effort and fishing productivity (VPUE) at the fleet segment level reveals four hotspots located in UK waters are critical for French fishers: (A) the south-west end of the UK EEZ; (B) the part of the Celtic sea west of the Bristol Channel; (C) the western part of the English Channel, south of Cornwall; and, (D) the eastern part of the English Channel between Southampton and Calais (between 2°W and 2°E) (Figure II.2 and section II.5.2.7 in the Appendix).

Area A is exploited by the two fleet segments of large bottom trawlers, pelagic trawlers, netters and vessels using hooks and lines. It overlaps the end of the continental shelf, which is a critical habitat for Monkfish – a key targeted species of large trawlers as it accounts for about 15% and 30% of total landings' of, respectively, the dominant and the exclusive bottom trawlers. Area A is also a productive site for European hake, the almost single target species of netters (50% of the landings' value) and longliners (80%), and a non-negligible species for pelagic trawlers (5%).

Area B is home to another bundle of species. Haddock and Atlantic cod, important species for large bottom trawlers, can be found there, as well as Norway lobster, a species that accounts for about 15% and 30% of the landings' value of mid-size dominant and exclusive trawlers respectively. At last, it is also a fishing ground for Edible crab which is the main target species of vessels using traps (80% of their total landings' value).

Similar species – and therefore similar fleet segments – can be found in areas C and D in the English Channel. These regions are also key fishing grounds for the Great Atlantic Scallop, a key species for active polyvalent vessels as well as dredgers and mid-size dominant bottom trawlers. Area D is a key fishing site for almost all the fleet segments we consider, being an

especially productive site as it concentrates catches of high-value species such as the Common sole, the Atlantic cod and Whiting.

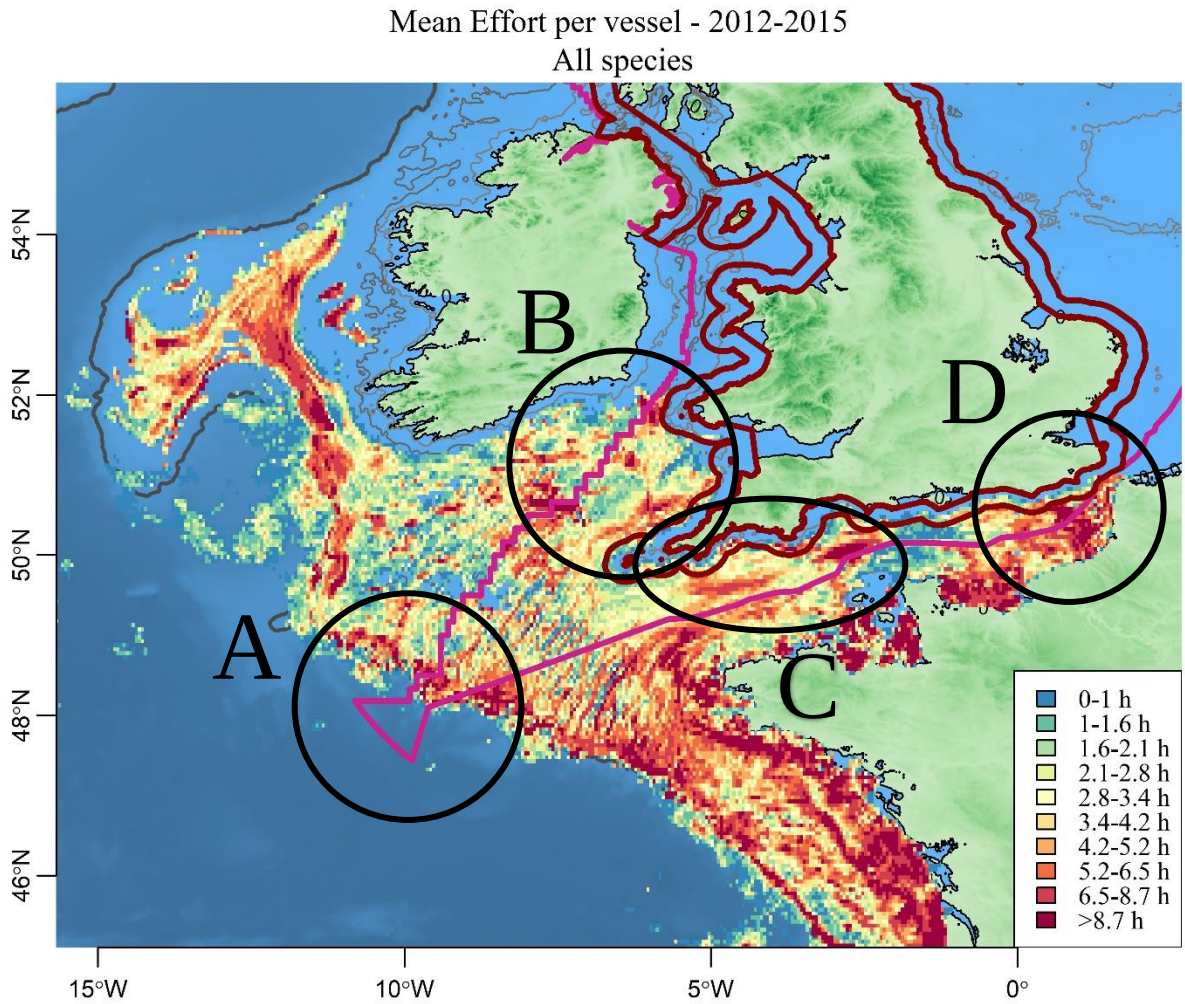


Figure II.2. Heat map of the average annual fishing effort per vessel between 2012 and 2015 with areas of interest A, B, C and D. The UK EEZ and territorial waters are delineated by the purple and dark red hard lines, respectively. Only vessels larger than 12m are represented.

Cells containing less than four vessels have been removed to protect anonymity of vessels.

II.4.1.3. Species exploited mainly in UK waters

While we find that vessels can be fishing the same bundle of species in or out UK waters, there are, however, species that are found to be exploited mainly in UK waters. Between 2012 and 2015, the top twelve main species[18] with the highest average share of landings from UK waters were Haddock (65%), Spotted ray (65%), Small-eyed ray (62%), Whiting (60%), Lemon sole (59%), Blonde ray (58%), Atlantic Cod (56%), Nursehound (48%), Witch flounder (46%), Variegated scallop (45%), Pouting (44%), and European flounder (42%)[19].

Focusing on the main species landed by French vessels, four species have more than half of their catches from UK waters between 2012 and 2015: Haddock (65% of the catches), Whiting (60%), Lemon sole (59%) and the Atlantic cod (57%). Figure II.3 shows the spatial distribution of the VPUE for those four species. About twenty main species have a share of catches from UK waters ranging from 12% to 37% (see Section II.5.2.6 in the Appendix). For those species individually, the average annual landings and landings' value from the UK EEZ amounts to about 1,400 tons and 3.5 M€ between 2012 and 2015. The highest value is reached by Monkfishes which, despite having only 20% of catches from UK waters, accounts for more than 15 M€ of landings' value from UK waters. Looking at catches from territorial waters only, the set of species whose catches are mostly taken in UK waters does not change very much. Dependency rates for the species of interest range from 4% (Mackerels) to 11% (Lemon soles).

[18] Species with an average annual catch greater than 10 tons.
[19] Églefin, Raie douce, Raie mêlée, Merlan, Limande sole, Raie lisse, Morue de l'Atlantique, Grande roussette, Plie cynoglosse, Pétoncle, Tacaud commun and Flet d'Europe in French.

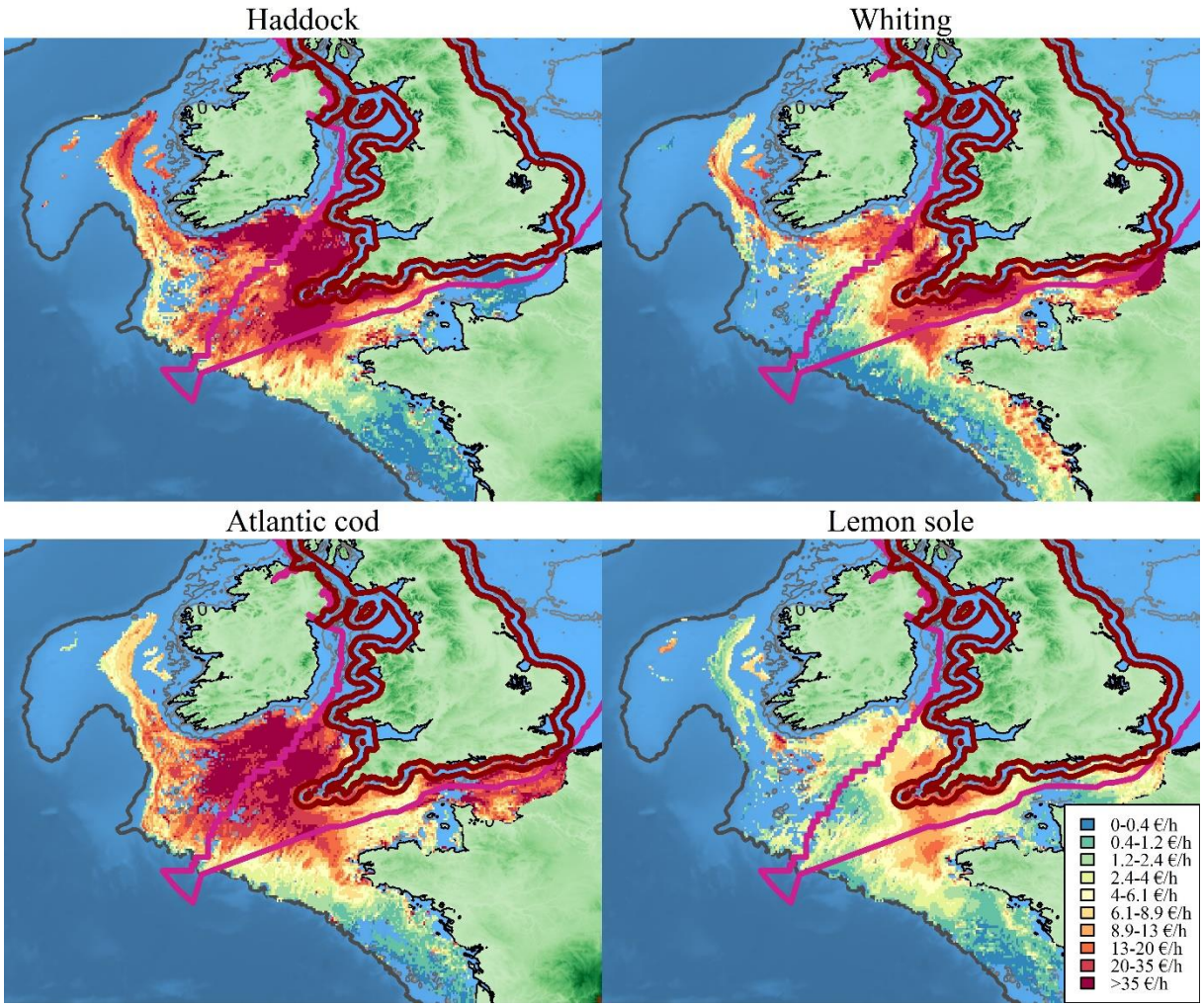


Figure II.3. Heat maps of the average VPUE between 2012 and 2015 for the four main species caught in UK waters by French vessels. The UK EEZ and territorial waters are delineated by the purple and dark red hard lines, respectively.

Cells containing less than four vessels have been removed to protect anonymity of vessels.

II.4.1.4. Ports' landings and value from UK waters

Turning to the question of where catches from UK waters are landed, we find that with 13,000 tons per year (34 M€) the first recipient port – by large and both in volume and in value – is the port of Bloscon-Roscoff, also the first landing port of the French Atlantic coast (Figure II.4). The next two largest receipients of catches from UK waters are also two major fishing ports on the

northern French coast: Cherbourg (9 M€), located midway in the English Channel, and Boulogne-Sur-Mer (10 M€), at the extreme East of the Channel. The majority of the other main recipients of catches from UK waters are located in the west of Brittany (see section II.5.2.8 in the Appendix).

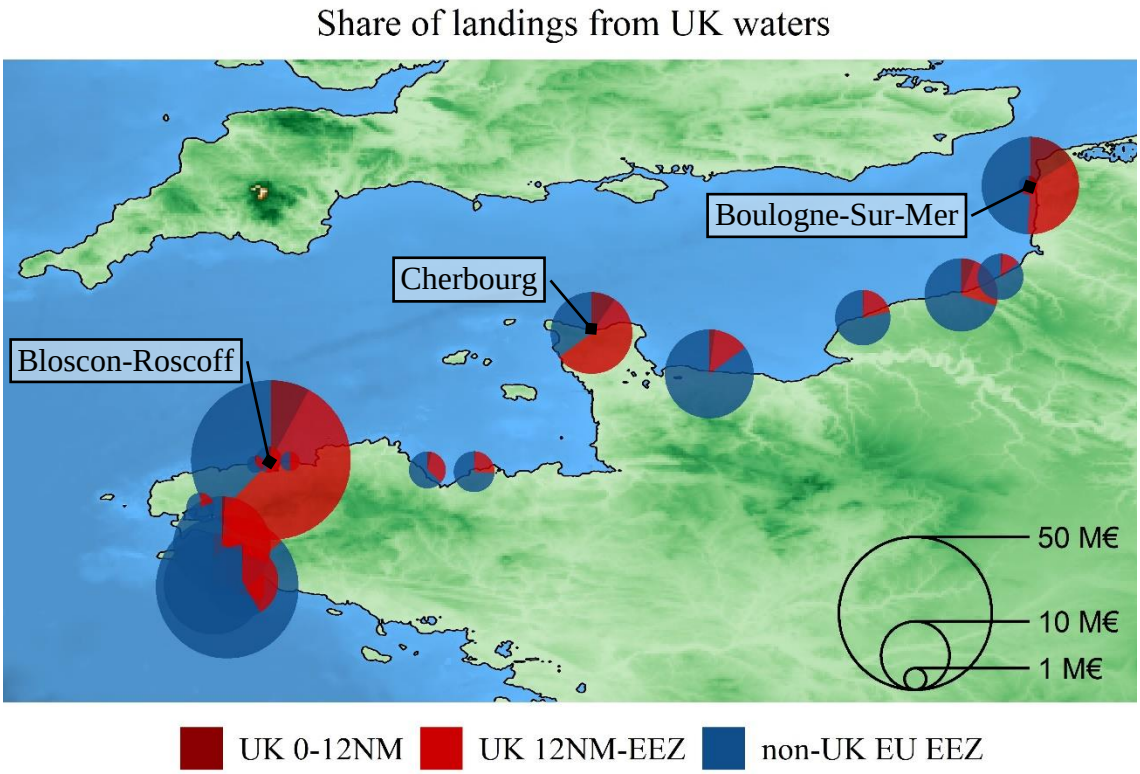


Figure II.4. Share of landings from UK waters by French vessels in French ports over the 2012-2015 period. Ports with less than 0.5 M€ of average yearly landings' value are not shown.

Strikingly, the vessels catching the most from UK waters in absolute terms are also the most dependent on UK waters in relative terms. We find that six ports have more than half of their landings' value from catches in UK waters between 2012 and 2015: Cherbourg (65 %), Nord-Boulogne (64 %), Bloscon-Roscoff (62 %), Roscoff (53 %), Boulogne-Sur-Mer (51 %) and

Plougasnou (50%). Overall, there are 18 main[20] French ports that had more than 10% of their total landings' value depending on UK waters (see Section II.5.2.8 in the Appendix). While the Finistère department in west Brittany receive the largest portion of catches from UK waters (23,000 tons worth 59 M€ in average per year), the départements of Manche and Pas-de-Calais are actually the most dependent on UK waters with respectively 65% and 51% of landings' value from UK fishing grounds, against 38% for Finistère.

II.4.2. Prediction of short-term reallocation of fishing effort

II.4.2.1. Model's estimates and choice of the scale of analysis

The examination of model's goodness of fit and prediction performance across the five fleet segments and the three spatial resolutions validates our approach in estimating segment-specific models at varying spatial scales. Indeed, as shown in Table II.b our model of daily decisions performs poorly at high spatial resolutions for the most mobile fleet segments – exclusive and dominant large bottom trawlers, whose daily fishing activities span areas of larger extents compared with the areas covered by the less mobile segments. Thus, reducing the choice of fishing location to a single 1° × ½° or ½° × ½° rectangle per day appears to be inappropriate for these former segments[21]. Yet, it is an assumption that is commonly made by researchers estimating spatial choice models in a similar setting, as they often tend to use ICES statistical grid as a

[20] i.e., with an average annual total landings' value larger than 0.1 M€

[21] It may seem surprising given that even a ½° × ½° rectangle encompasses 100 of our « base » $\frac{1}{20}° \times \frac{1}{20}°$ squares which is about twice the observed maximum of base squares covered by trawlers in our dataset. However, one as to remember that most of the time the observed disaggregated fishing locations of vessels are not confined to a single aggregated statistical rectangle and can span several ones, thereby inducing an approximation bias when reducing the number of visited rectangles to only one per day.

'default' and unique spatial scale of analysis (Batsleer et al., 2013; Poos and Rijnsdorp, 2007; Rijnsdorp et al., 2011; Simons et al., 2015).

		Goodness of fit (pseudo-R²)			Prediction errors (% wrong)		
Fleet segments	*N*	*2°x2°*	*ICES*	*½°x½°*	*2°x2°*	*ICES*	*½°x½°*
Bottom Trawl exc. ≥18m	28,475	0.69	0.61	0.58	28%	47%	56%
Bottom Trawl dom. ≥18m	7,330	0.69	0.58	0.54	27%	49%	53%
Pots & Traps ≥12m	1,725	0.76	0.71	0.67	9%	25%	26%
Drift & Fixed Nets ≥12m	20,569	0.84	0.78	0.74	11%	25%	28%
Dredge ≥12m	12,721	0.65	0.65	0.63	12%	25%	31%

Table II.b. Summary statistics of the estimated models of fishing locations.

In addition, even though the spatial extent of the English Channel could tempt researchers to use fine spatial resolutions, the levels of prediction errors for out-of-sample observations indicate that the spatial analysis should not be carried out at resolutions finer than 2° × 2° for the bottom trawlers and 1° × ½° for the netters, dredgers, and for the vessels using traps. Utilizing a unique spatial resolution for each fleet segment, our simple model is able to fit the data rather well, with pseudo-R^2 ranging from 0.67 to 0.78, and is able to predict out-of-sample observations with an error rate between 25% and 28%.

As shown in Table II.c, the distance variable is found to be significant and of the expected negative sign, while the variable accounting for the level of activity of other vessels in a site is found to be significant with a positive sign. Surprisingly, vessels' own activity the day before is not found to be significant across all of the models. As for the different components of the expected revenues from a site, a higher fleet-average productivity of a site the past 30 days is always found to be significant, but with a positive effect for exclusive bottom trawlers, vessels using traps and netters, and a negative effect for dominant bottom trawlers and dredgers. Conversely, a higher vessel-specific productivity in a site during the same time the past fishing season is always found

to have a negative effect but is only significant in exclusive bottom trawlers, netters and dredgers (see section II.5.3.2 in the Appendix for the estimated parameters at each spatial scale as well as for an interpretation of the estimates).

		Bottom Trawl exc. ≥18m	***Bottom Trawl dom. ≥18m***	***Pots & Traps ≥12m***	***Drift & Fixed Nets ≥12m***	***Dredge ≥12m***
Distance		-0.538***	-0.521***	-0.582***	-1.096***	-0.441***
Activity of other vessels		0.06***	0.047***	0.052***	0.032***	0.072***
Vessel's past fishing effort		-0.002.	0.002	-0.005	0.000	-0.001
Expected revenues	Short-term – fleet VPUE	0.034***	-0.038***	0.039**	0.027**	-0.047***
	Short-term – ind. VPUE	-0.014**	-0.001	-0.031*	0.001	0.000
	Long-term – fleet VPUE	-0.006	-0.01	-0.01	0.041*	-0.006
	Long-term – ind. VPUE	-0.024***	-0.01	-0.015	-0.026*	-0.027***

Table II.c. Average marginal effects of the explanatory variables of the discrete-choice model of fishing locations for an increase of 1 standard deviation. For each fleet segment the parameters shown are those obtained using the appropriate spatial scale for defining fishing site options, i.e. 2° × 2° squares for the two segments of bottom trawlers and ICES squares for the other. Significance levels: 0.1% ***, 1% **, 5% *, 10% ..

II.4.2.2. Effort reallocation predictions

Figure II.5 shows the increase – in absolute and relative terms – in the combined fishing pressure of the five key fleet segments studied in response of the closure of UK territorial waters or the UK EEZ (disaggregated results for each fleet segment are available in section II.5.4 of the Appendix). Not surprisingly the sites that are the closest to the current fishing grounds of French vessels in UK waters are those that are predicted to face the highest increases in fishing effort. For

the large exclusive bottom trawlers, this involves an increase in fishing effort in the western French part of the Channel north of Brittany, as well as in the northern part of the Celtic Sea south of the Irish shores. For the large dominant bottom trawlers, as well as for dredgers, the reallocation occurs in the same two areas, but in a more scattered manner, as well as in the eastern part of the Channel.

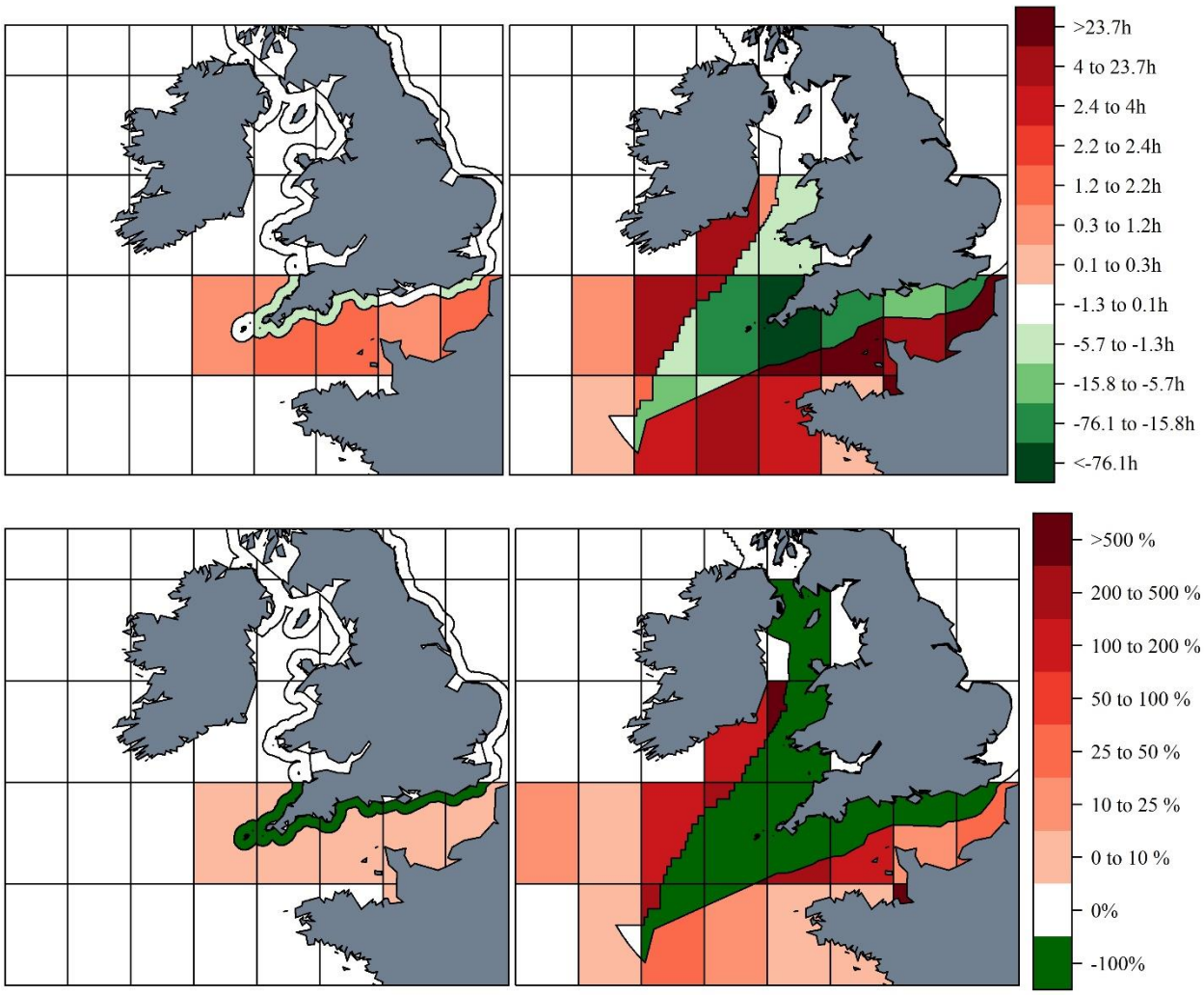


Figure II.5. Predicted absolute (upper panels) and relative (bottom panels) increase in the combined average daily fishing hours of the five key fleet segments considered (exclusive and dominant bottom trawlers, vessels using pots and traps, netters and dredgers) in response of the closure of UK territorial waters (left panel) or the UK EEZ (right panel). Vessels daily fishing effort and locations are based on 2014 observations.

For vessels using traps, there are only two clusters of increased fishing pressure, north of Brittany and in the western part of the Channel. Netters are also predicted to relocate their fishing effort in the two latter areas as well as in the area north of the west end of the UK EEZ. In terms of the magnitude of effort reallocation, should fishing efforts remain the same in the new sites as in the sites no-longer accessible, the increase would most of the time represents a doubling or tripling of the initial fishing pressure from the given fleet segments.

II.4.2.3. Welfare impacts of the loss of access to UK waters

A powerful feature of discrete-choice models based on a random utility framework is that, in addition to predicting new choices, they also permit to carry out welfare analysis. In our case, the closure of UK waters to French fishers amounts to a restriction of their choice set which may prevent them from selecting their most preferred fishing location[22], thereby incurring a welfare loss. Figure II.6 shows the cumulated welfare loss over a whole fishing season of the two Brexit scenarios for each fleet segment as well as the corresponding distribution of welfare losses at the vessel level[23]. Not surprisingly, the more fleet segments show occurences of vessels fishing in UK fishing grounds, the more they are impacted (panel A). But more interestingly, when looking at welfare losses at the vessel level a more nuanced pattern emerges (panel B).

[22] Preferred, not only in terms of higher expected profits, but also in terms of intrinsic preference for a particular site. However, in the specification of the model presented here we do not include vessel-specific site dummies that would capture this effect.

[23] Results are robust to the removing of observations related to sites at the spatial edges of our dataset (i.e., 18°W and 2°E).

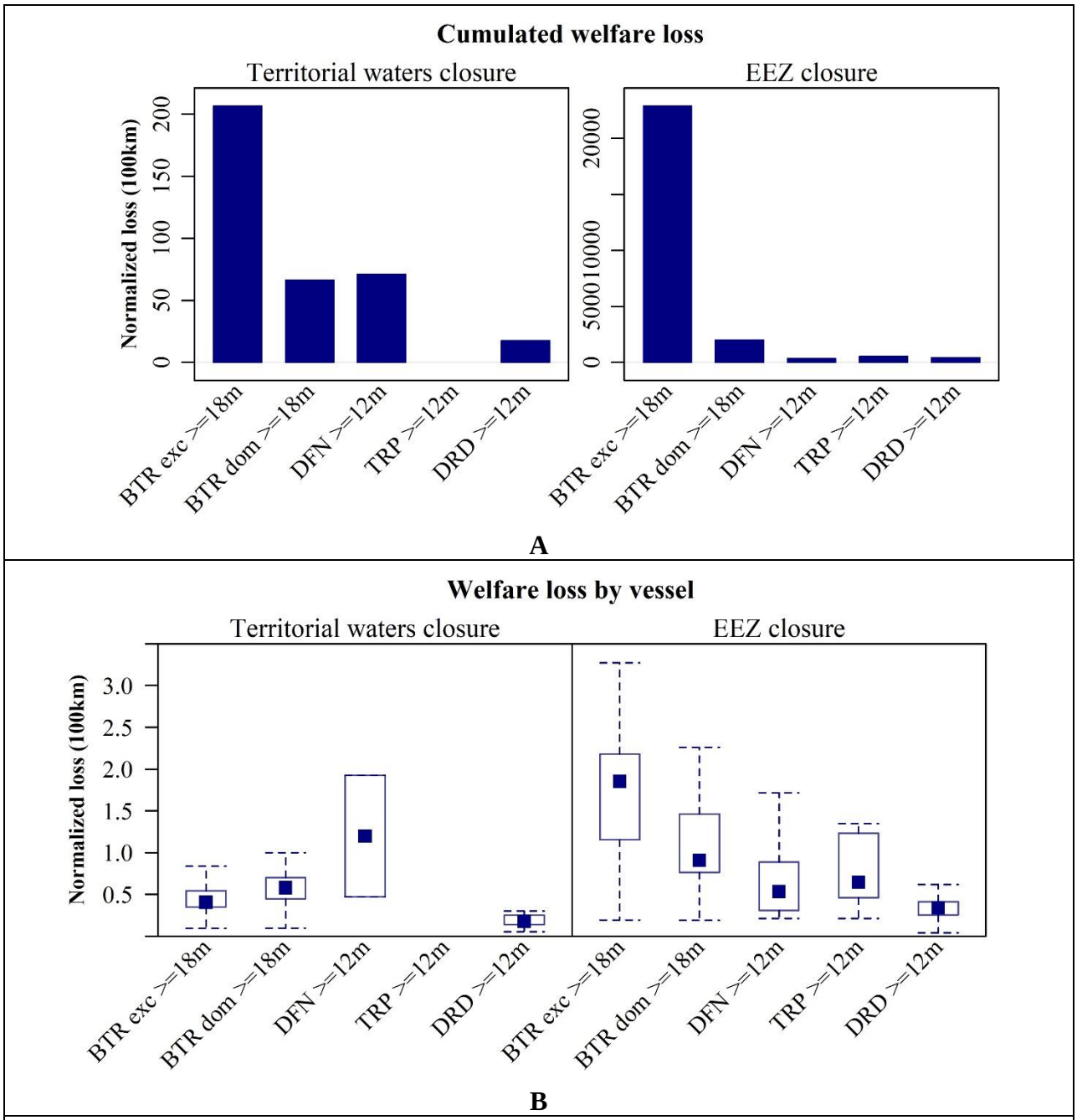


Figure II.6. Cumulated welfare loss (Panel A) and vessels' distribution of welfare losses (Panel B) for each fleet segment, in the case of a closure of UK territorial waters (left panels) or of the UK EEZ (right panels). Welfare loss is expressed in terms of normalized utility loss to allow comparison across separatedly estimated models.

In the case of a closure of UK territorial waters, it turns out that netters would suffer overall higher losses by choice occasion[24], while in the case of the closure of the entire EEZ of the UK, trawlers appear to be the most severely impacted overall. Given that we find that sites' probabilities of choice are mostly deternined by how far sites are from a vessel location (recall the larger estimates for the distance variable), these results could be driven by the spatial aggregation of fishing sites to statistical squares, which is determined in the model selection procedure and differs across the fleets.

In the case of trawlers, the level of spatial aggregation is larger than for the other fleet segments, which means that there is a greater heterogeneity in the distance to possible site options (that are proxied by the distance to the centroids of polygons). The effect of the spatial scale does not appear with the closure of territorial waters probably because of the computational artifice of splitting statistical squares intersecting the 0-12NM water band. The splitting of sites leads to sites located within territorial waters having a much smaller spatial extent – and thus centroids that are closer together – than sites located outside. Because of these computational choices, the differential in the distance between the best alternative located in the closed area and the next best available option located outside can appear to be smaller with (small-size) sites located in UK territorial waters than with (large-size) sites located in the UK EEZ.

In contrast, the impact of the spatial configuration of the sites and the closure areas is reversed for netters. Even though the spatial resolution that is used for netters is finer than for trawlers, the spatial scale is still rather coarse relatively to the eastern part of the Channel, the region where netters operate and would re-locate their fishing effort. Thus, the spatial

[24] This result should be viewed with some skepticism as there are only two vessels (for 61 choice occasions) impacted by the closure.

configuration of the statistical squares in the region may induce artificially large distance differentials between sites in UK territorial waters and sites located outside. Should the spatial resolution allow for a finer description of the area, distance differentials may be more homogeneously distributed between sites.

II.4.3. Discussion and Conclusion

Our approach to assess the potential consequences of Brexit on EU fisheries, taking the case of the French fleet, is a first step to start exploring and discussing the full ramifications of the UK decision to leave the EU.

Looking at the recent past, we find that about a fifth of French landings are caught in UK waters. This represents a sizeable – close to 100M€ per year – share of the gross revenue of French fishers. In addition, we find that the economic stakes were highly unevenly distributed in the French fishery sector. Large bottom trawlers are both the main fleet segments exploiting UK waters and among the most dependent to UK waters, along with vessels using pots or traps. Similarly, the three key ports of Bloscon-Roscoff, Cherbourg and Boulogne-Sur-Mer are both the main recipients of catches from the UK EEZ and exhibit some of the highest shares of landings from UK waters (more than half), among other smaller ports bordering the English Channel. Also, we find that tensions for the supply of some specific species, such as Haddock, Whiting, the Lemon sole or the Atlantic cod can be expected as they are currently caught mainly in UK waters. We believe this thorough analysis of the current economic dependencies to UK fishing grounds can be useful to decision-makers by helping them to frame the magnitude of the economic stakes and to identify where future points of friction could arise. Nevertheless, how these levels of dependency to UK waters translate *in effect* into vulnerability to possible Brexit scenarios disputing the access to UK fishing grounds is another question.

Primarily, there is the issue of species quotas. Ten out of the fourteen species with more than a fifth of the catches from UK waters are under a total allowable catch set by the EU. How quotas will be set and divided between countries after the UK will have left remains an open question. A failure to perpetuate the common management of fish stocks – which do not respect maritime boundaries – could very well result in an overall increase of the fishing pressure[25], thereby jeopardizing the health of the stocks and the sustainability of fisheries profits. Yet, regardless changes in the overall fishing pressure and in the allocation of catch between MS, there is also the question of how fishers would respond to a restriction of their fishing area. The second part of this study is an attempt to answer this question.

Focusing on the immediate reaction of fishers, we model the reallocation of fishing effort in the areas remaining accessible which would be the most obvious response in the short-term. Supported by our finding that the bundle of species of vessels exploiting fishing grounds in UK waters is not different from the bundle of species of other vessels, we make the underlying assumption that fishers would still be able to target the same set of species as in UK waters. Narrowing down the analysis to five main fleet segments, we are able to provide a snapchat of the average reallocation of fishing effort in the short-term. That enables us to identify three critical hotspots of increased fishing pressure: the western and eastern parts of the Channel close to the French coast, as well as the northern part of the Celtic Sea, south of the Irish shores. An intensification of the fishing activities in these areas is likely to increase the potential for conflicts of use of the maritime domain. We believe it should therefore catch the interest of decision-makers which may want to pay a closer attention to other activities in these regions.

[25] E.g., if the UK decides to set its own catch shares independently while the EU simply reallocates the UK quotas to MS without adjusting the overall catch limits.

This latter aspect of the consequences of having the same number of vessels fishing – in a competitive way or not – in a smaller area would probably be essential in the case of a closure of UK waters to non-UK fishers. Indeed, UK waters turn out to be already rather congested, especially in the Channel where the closure of the UK EEZ, but also of UK territorial waters, would represent is significant reduction of the accessible fishing areas. In addition, this specific zone is already hosting a stiff competition for space between different maritime activities (Girardin, 2015; Halpern et al., 2008). Moreover, even though our study focuses on the French fleet, it should not be forgotten, as mentioned earlier, that a certain number of other non-UK European vessels also exploit UK waters. For example, Belgian and Dutch vessels have been reported to fish side by side with French vessels in the eastern part of the English Channel (Girardin, 2015), while the Celtic Sea is known to be an economically important fishing site for Irish, Belgian and Spanish fishers (Mateo et al., 2016). Be it only in the case of the French fleet, our study fails to account also for smaller vessels. Not having reliable geospatial data on vessels smaller than 12m prevented us from accounting for three quarters of French vessels operating in the North Atlantic and Channel regions. Yet, the relocation that we predict of the large bottom trawlers closer to French coastal fishing grounds has the potential to trigger important dominos effects on the coastal fleet segments in the region, as well as on coastal ecosystems.

To have a full evaluation of the impacts of a closure of UK waters to EU fishers a more in-depth spatial bio-economic modelling of the all the fisheries in the North East Atlantic region would actually be needed to capture all the dynamic aspects of the issue. What would be the nature of the behavioral response of the impacted vessels and what would be the resulting effects on the whole dynamics of fisheries are indeed one of the biggest unknowns of the impact of Brexit on EU fisheries. Answering them in thorough details falls out of the scope of this chapter. The

predictions we make with our model should therefore be taken carefully as merely a rough overview of the very short-term reaction of fishers. If not as early as the first weeks following the closure, fishers would adjust their fishing strategies over the next fishing seasons through, for example, the search for new fishing grounds – potentially further away and costlier to reach – or the adoption of new fishing schedules over the season and potentially over a day.

A review of the literature on the response of fishers to spatial closures can provide us some hints about the types of adjustments that fishers may employ and the kind of domino effects that may be expected. As a matter of fact, the spillover economic effects of spatial closures have been the focus of a large part of the literature in fishery science. In particular, economists have been interested in the impact on catch and value per unit of effort. For example, Poos and Rijnsdorp (2007) (Poos and Rijnsdorp, 2007) documented a negative impact of a temporary area closure on fishing efficiency because of increased competition effects resulting from the displacement of effort to fishing grounds that remained accessible. Strategies consisting in "fishing the line" of a closed area have been also reported in the case where fishers would expect positive spillovers on fish abundance (e.g., such as in the case of marine sanctuaries or protected areas). However, this supposes an expectation of an increased biomass which, in our setting, means no fleet substitution of EU vessels by UK vessels. That seems very unlikely in the long term, but it may be the case during some transitory phase. A better stewardship of the resource because of a more "local" governance has been also largely hypothesized (Allison et al., 2012; Beddington et al., 2007), nevertheless historical examples in similar settings do not give a lot of credibility to such a scenario in the long term[26]. In essence, the effects of a spatial closure on fisheries productivity and

[26] E.g., the EEZ implementation in St Pierre et Miquelon with Canadian vessels quickly substituting French vessels and exhausting cod fish stock; or, similarly, the implementation of the EEZ in French Guyana and French vessels substituting US vessels for depleting fish resources.

efficiency depend for a large part on the modality of the closure (Marchal, 2002) and on the nature of interactions between fishers, with reportedly negative effects in non-cooperative contexts (van der Lee et al., 2013). As a result, the ramifications of the reallocation of effort in the longer-term are extremely complex and the full consequences of it remains uncertain.

We see several venues for extending this type of analysis. Without requiring an extensive bio-economic model of EU fisheries, a first improvement for the prediction of effort reallocation in a longer term could be rather easily obtained by refining the specification of our model (e.g., allowing for heterogeneous effects of vessels from other fleet segments) and by making it dynamic by updating the value of the explanatory variables with model's predictions. This would be especially important and helpful to explain possible deviations of our prediction to the observed behavior of vessels. Then, if our assessment of the current value of catches from UK waters is helpful to set some boundaries on the economic stakes, it falls short of taking into account any changes on the market side[27]. In addition of the uncertainty on future catch limits and catch shares, uncertainties on future trade agreements fundamentally questions the future dynamic of export and imports of fish products and thereby of fish supply. Therefore, a reliable monetary evaluation of the predicted economic impacts of Brexit on EU fisheries should also pay a close attention to changes in future market prices.

[27] We slightly hint on these issues comparing landing prices received by French vessels in UK and EU ports and found the French fishers received mainly lower prices in the UK. This suggests that their main motivation for landing in UK ports are likely lower costs to land in nearby UK ports instead of traveling back to their homeport. This explanation is supported by the analysis of flows between ports of departure and ports of landings, with the majority of trips leaving and going back to the same location.

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II.5. Appendix

II.5.1. SACROIS Data

Gear type	***Main gear***	***Exclusive gear***	***Vessels' Length***	***Fleet code***	***# vessels in 2015***
Active gear	Bottom Trawl	Yes	<12m	BTR exc <12m	5
			[12m-18m[	BTR exc [12m-18m[	110
			>=18m	BTR exc >=18m	154
		No	<12m	BTR dom<12m	58
			[12m-18m[	BTR dom [12m-18m[	43
			>=18m	BTR dom >=18m	36
	Pelagic Trawl		<12m	PTR <12m	1
			>=12m	PTR >=12m	45
	Beam Trawl		<12m	BMT <12m	1
			>=12m	BMT >=12m	4
	Bottom Seine		<12m	BSN <12m	0
			>=12m	BSN >=12m	13
	Pelagic Seine		<12m	PSN <12m	0
			>=12m	PSN >=12m	29
	Dredge		<12m	DRD <12m	52
			>=12m	DRD >=12m	99
	Polyvalent Active Gears		<12m	PLA <12m	21
			>=12m	PLA >=12m	28
Passive gear	Drift & Fixed Nets		<12m	DFN <12m	75
			>=12m	DFN >=12m	120
	Lines & Hooks		<12m	LGL <12m	2
			>=12m	LGL >=12m	19
	Pots & Traps		<12m	TRP <12m	26
			>=12m	TRP >=12m	15
	Polyvalent Passive Gears		<12m	PLP <12m	21
			>=12m	PLP >=12m	4
Other	Others		<12m	OTH <12m	8
			>=12m	OTH >=12m	4
Unknown					7
Total					994

Table II.5.1.a. Distribution of the number of vessels by fleet for 2015

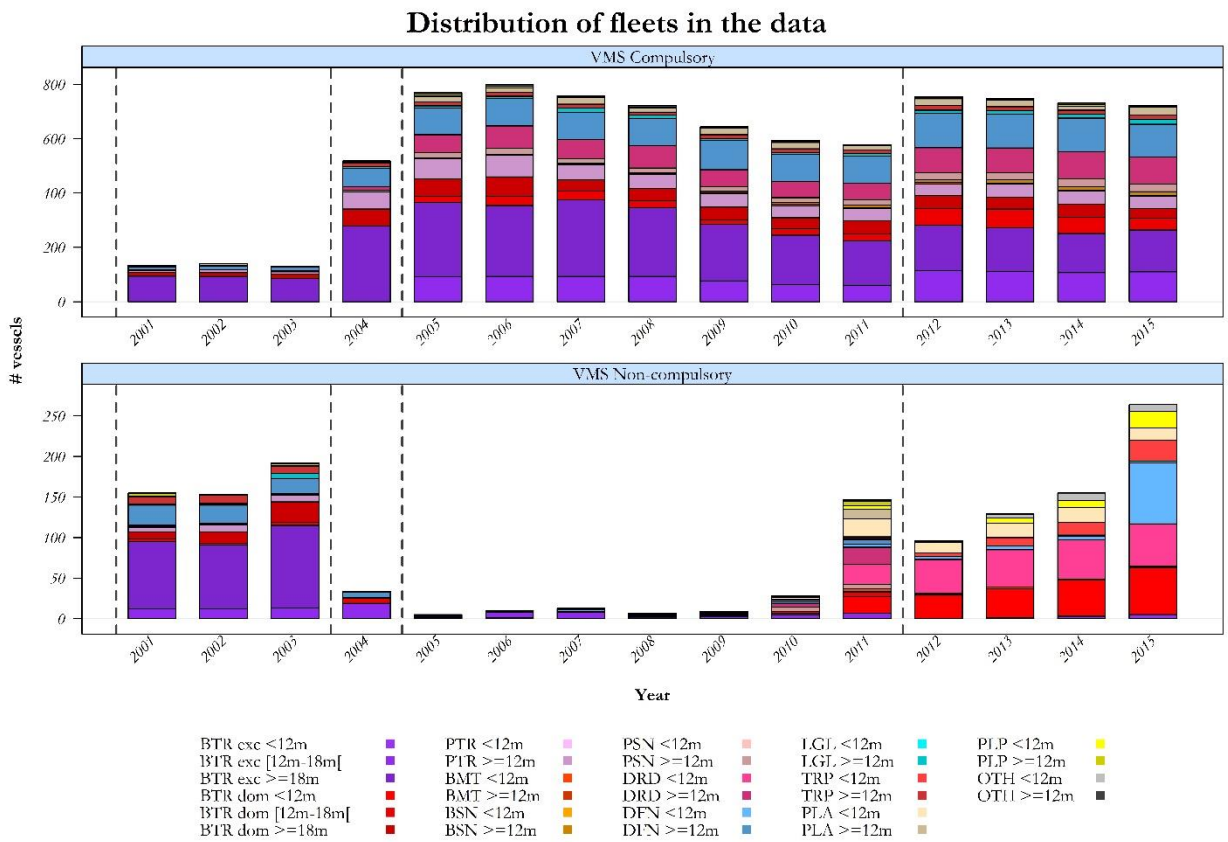

Figure II.5.1.1. Distribution of the number of vessels by fleet for each year in the SACROIS dataset. The upper panel shows only vessels for which VMS was compulsory for each given year. The three dotted lines indicate statutory changes for VMS, becoming compulsory for vessels >=18m in 2004, >=15m in 2005 and >=12m in 2012.

II.5.2. Dependency of the French fleet on UK waters

II.5.2.1. Number of vessels fishing in UK waters

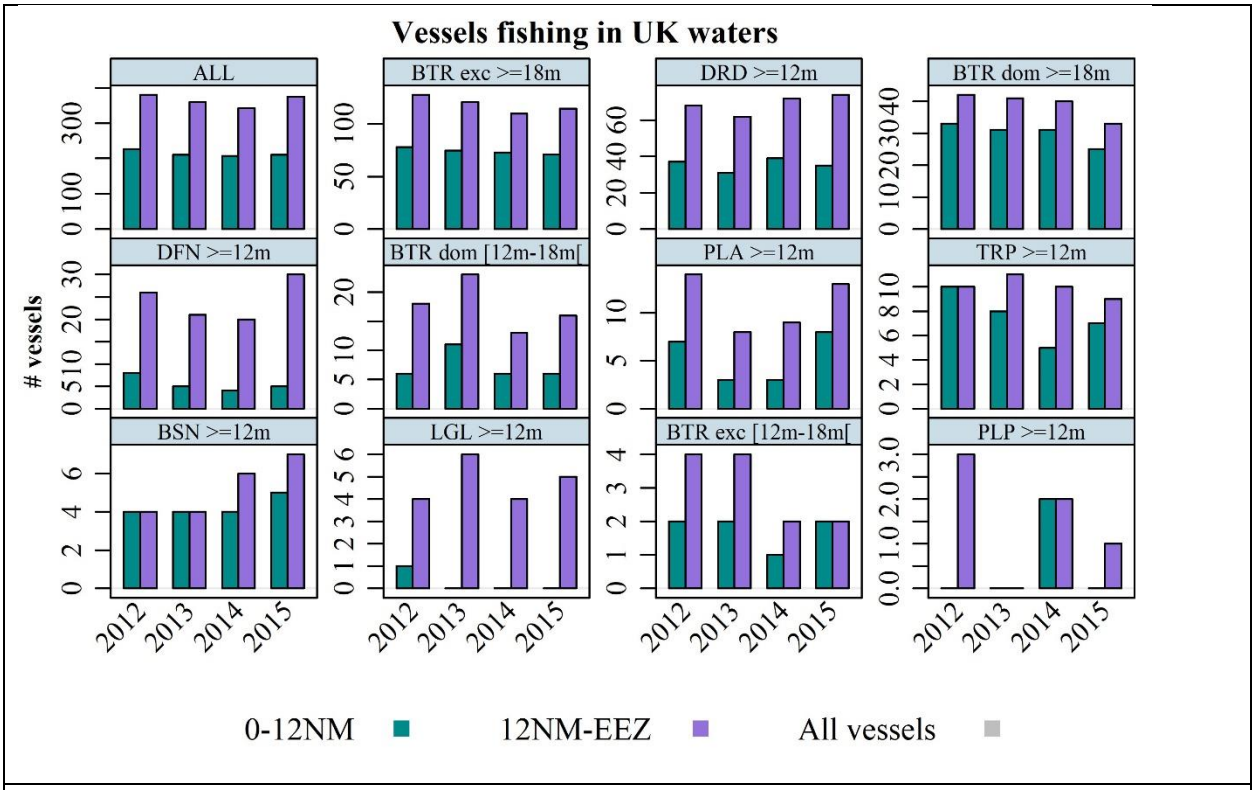

Figure II.5.2.1.1. Number of vessels fishing into UK waters by fleet, between 2012 and 2015.

II.5.2.2. Effort, catches and landing value from UK waters

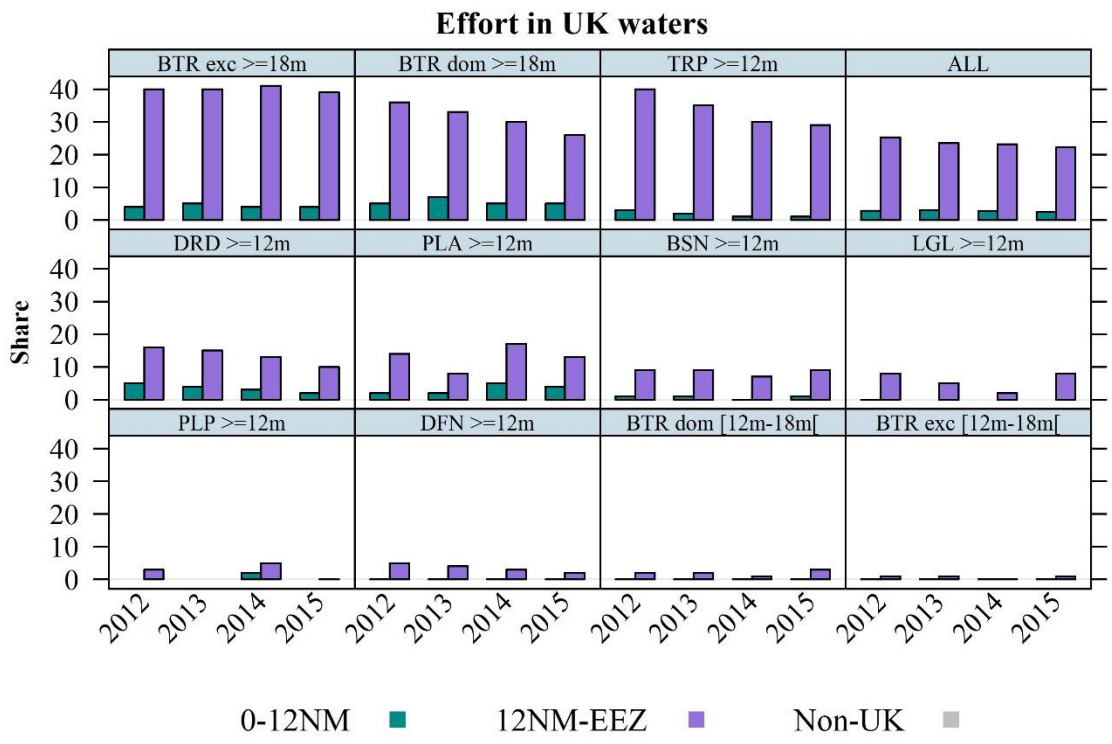

Figure II.5.2.2.1. Share of total fishing effort from UK waters by fleet, between 2012 and 2015.

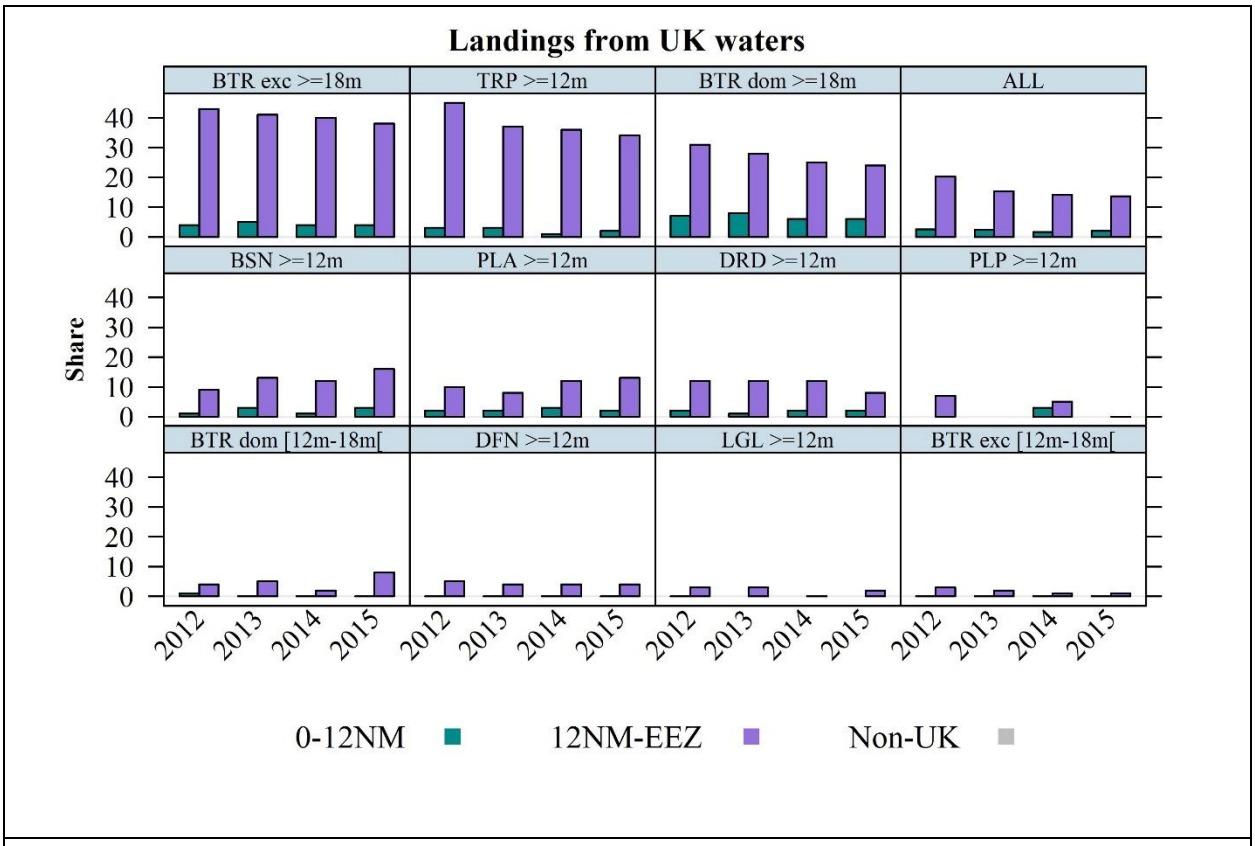

Figure II.5.2.2.2. Share of total landings from UK waters by fleet, between 2012 and 2015.

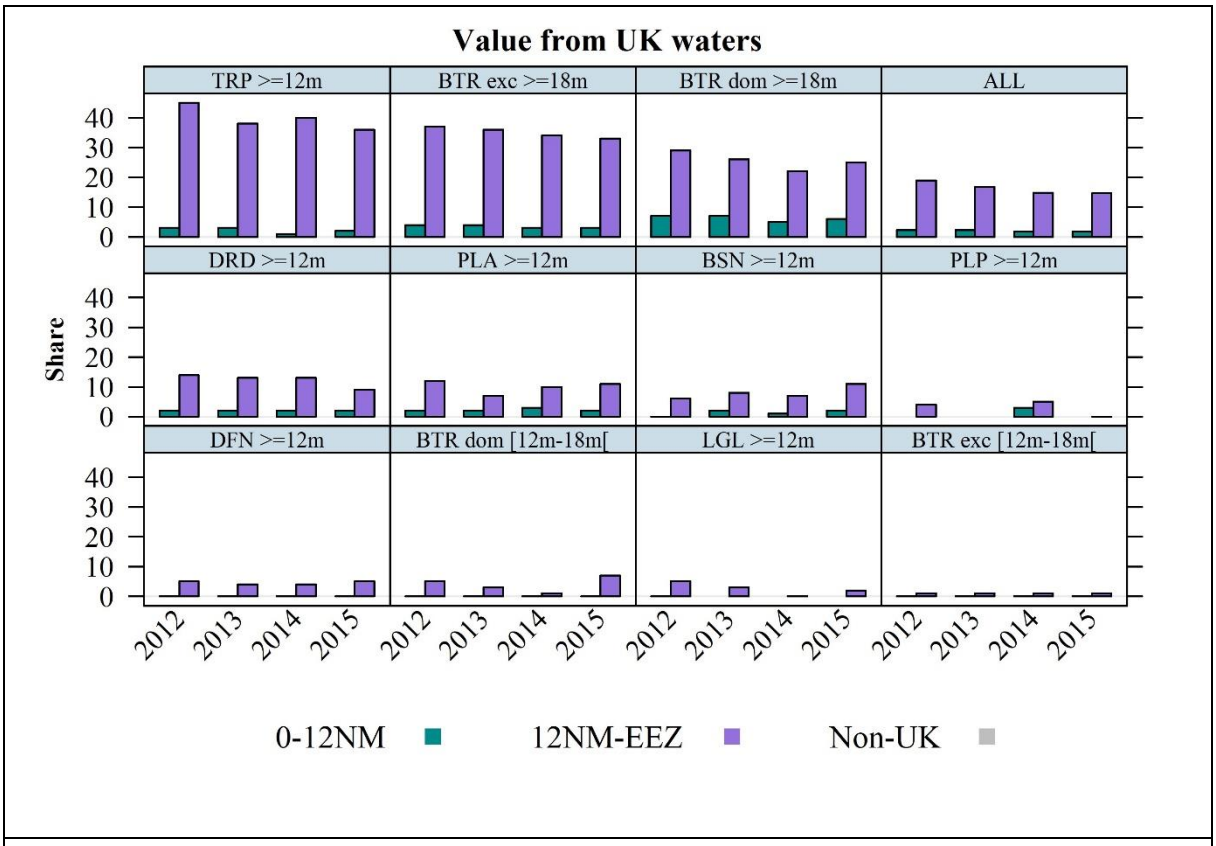

Figure II.5.2.2.3. Share of total value from UK waters by fleet, between 2012 and 2015.

II.5.2.3. Dependency to UK waters at the vessel level

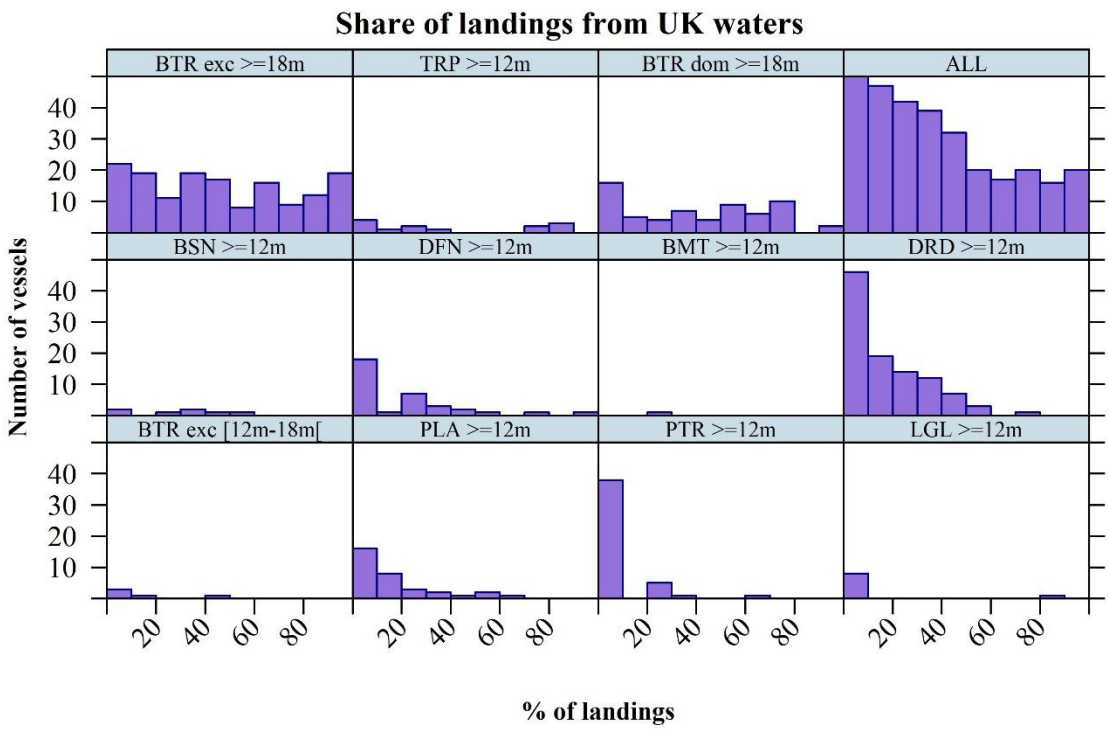

Figure II.5.2.3.1. Distributions of the average shares of landings from UK waters at the vessel level between 2012 and 2015.

II.5.2.4. Catch composition of vessels, by fleet

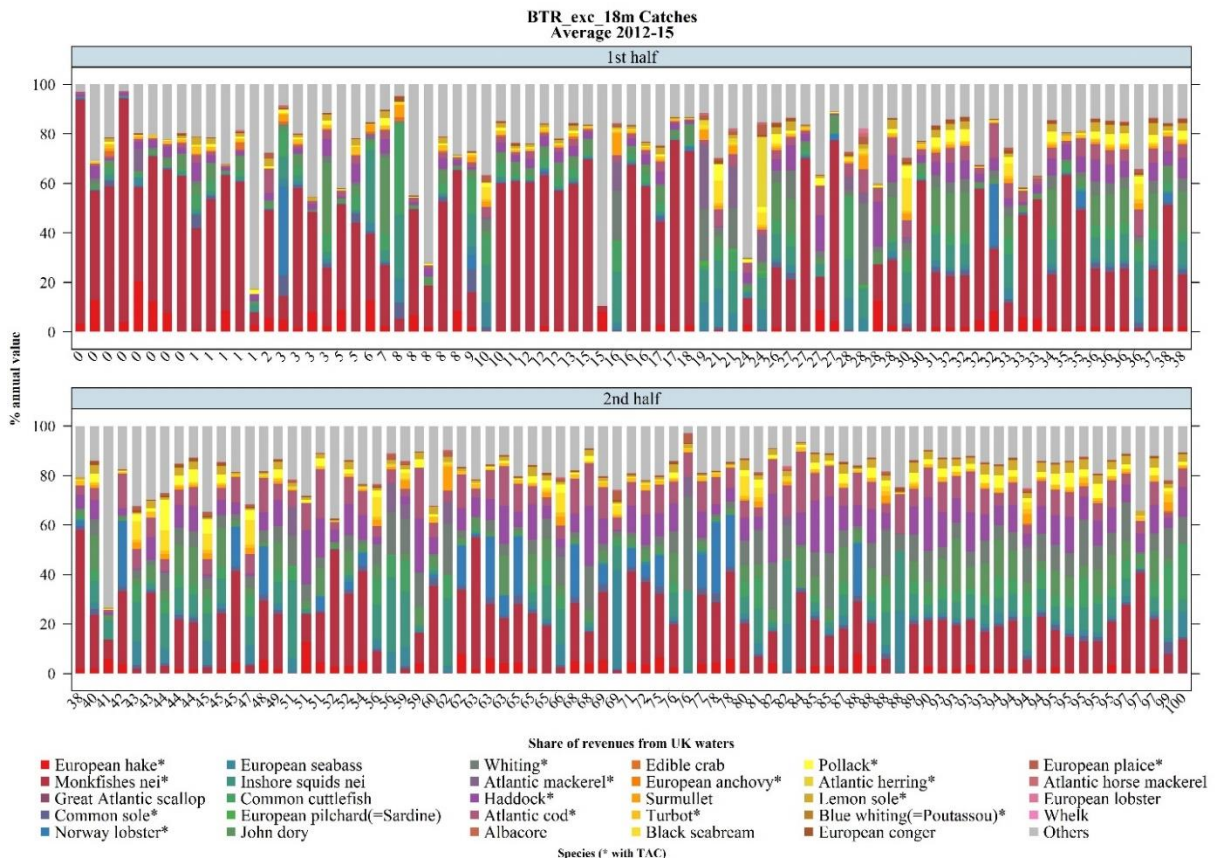

Figure II.5.2.4.1. Average catch composition of BTR exc >=18m vessels between 2012 and 2015. Vessels are ranked by their share of revenue from UK waters over the same period.

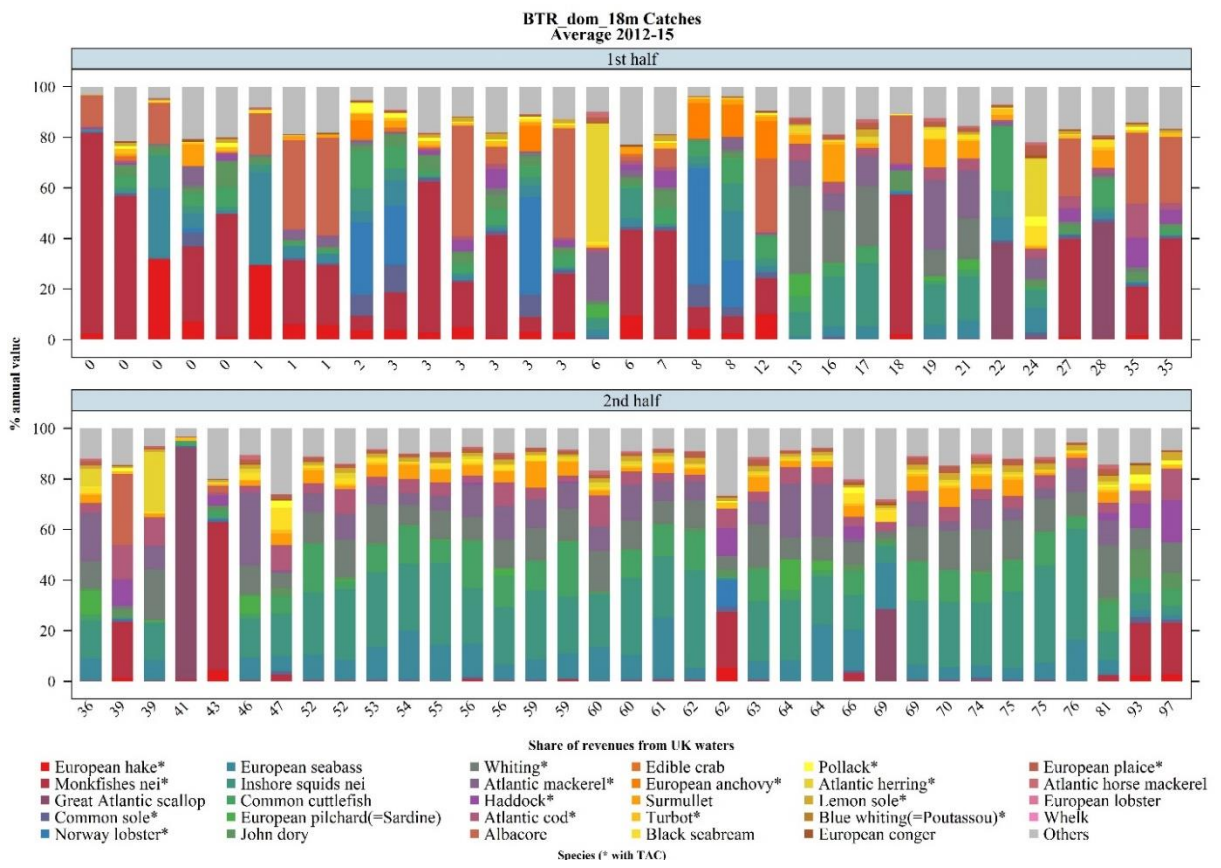

Figure II.5.2.4.2. Average catch composition of BTR dom >=18m vessels between 2012 and 2015. Vessels are ranked by their share of revenue from UK waters over the same period.

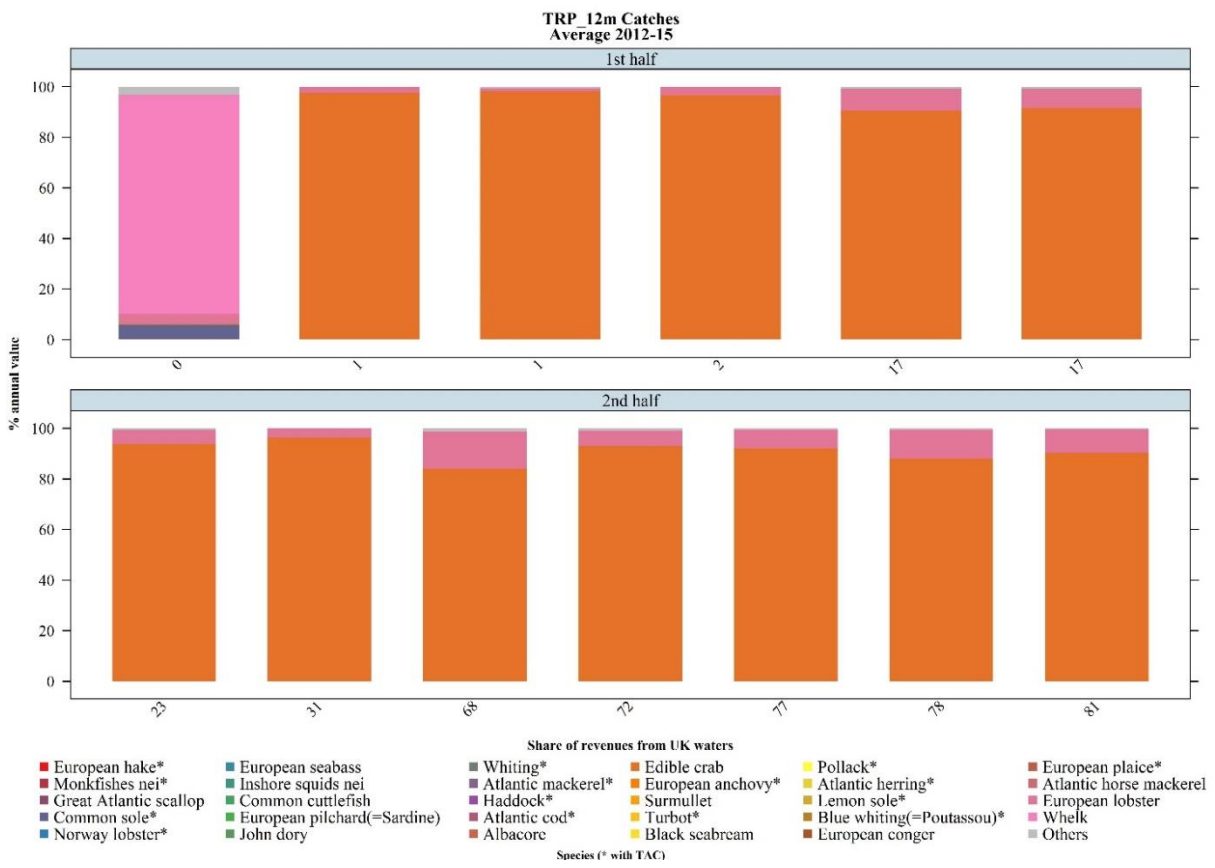

Figure II.5.2.4.3. Average catch composition of TRP >=12m vessels between 2012 and 2015. Vessels are ranked by their share of revenue from UK waters over the same period.

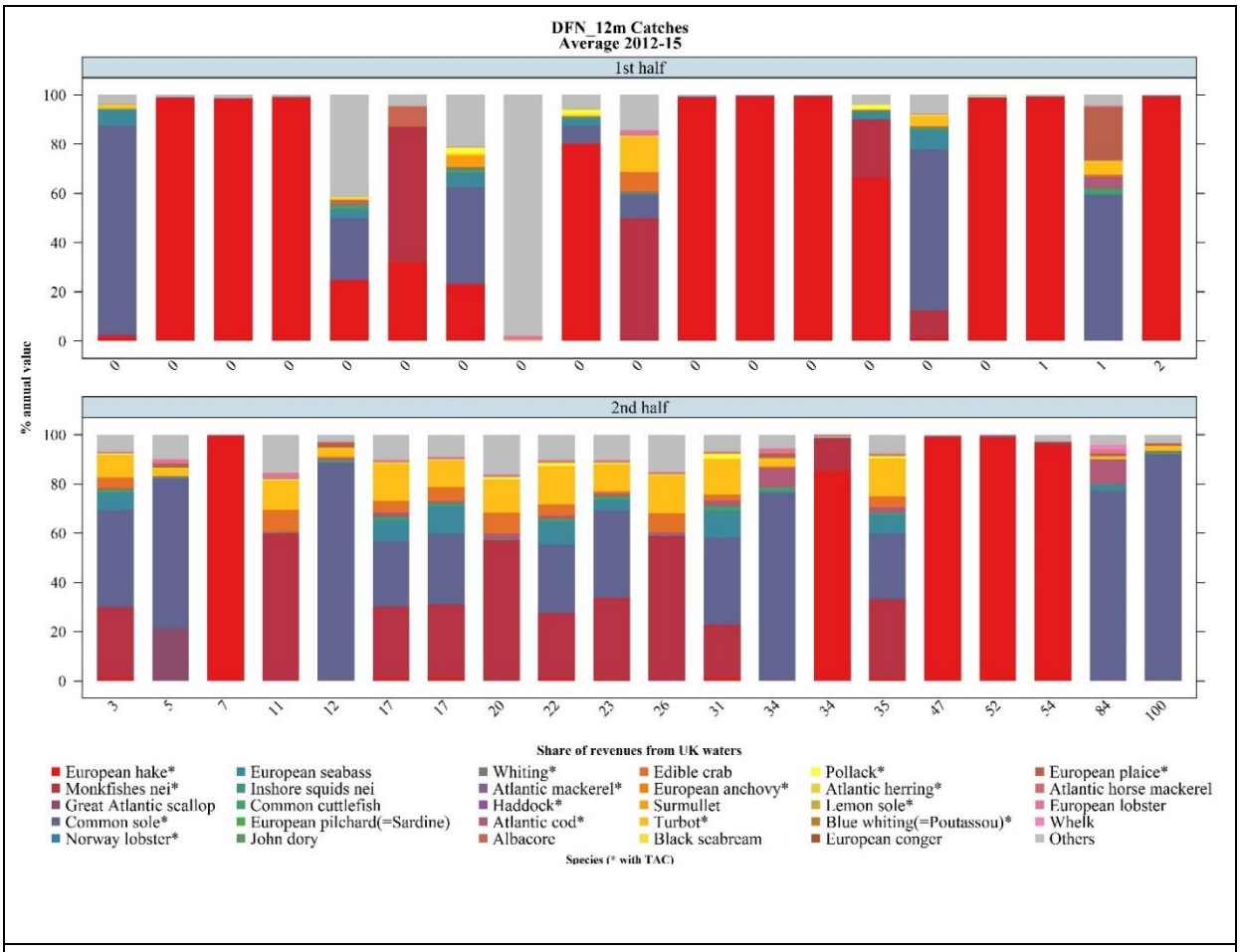

Figure II.5.2.4.4. Average catch composition of DFN >=12m vessels between 2012 and 2015. Vessels are ranked by their share of revenue from UK waters over the same period.

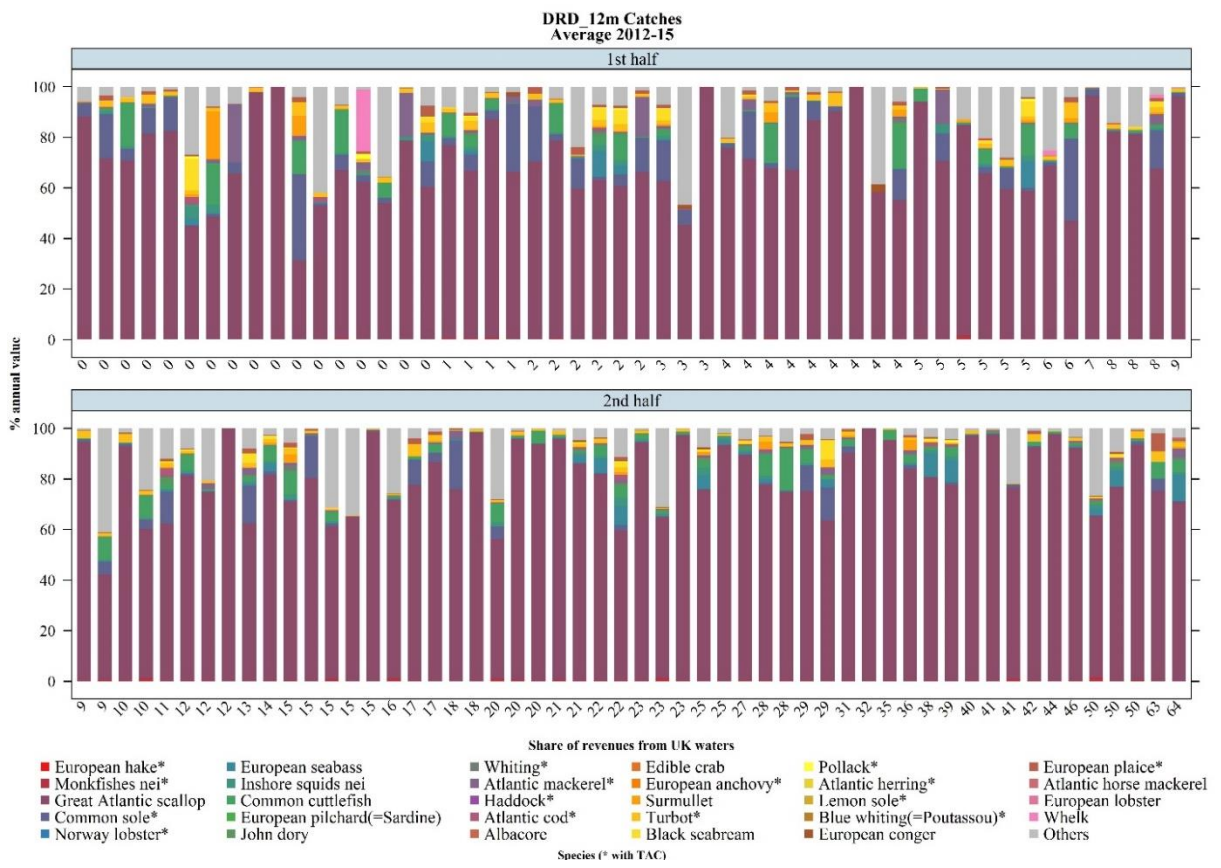

Figure II.5.2.4.5. Average catch composition of DRD >=12m vessels between 2012 and 2015. Vessels are ranked by their share of revenue from UK waters over the same period.

II.5.2.5. Patterns of landing locations

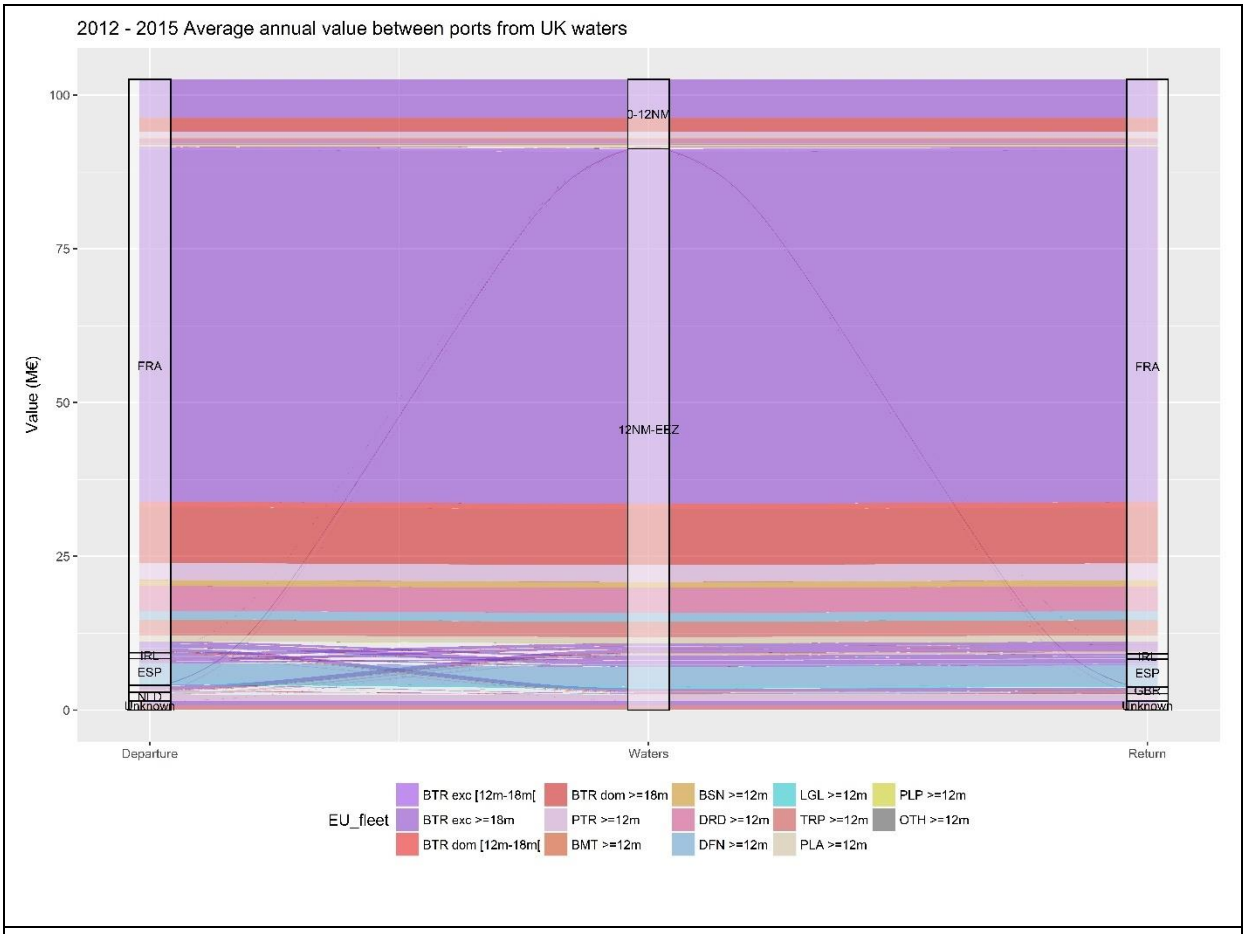

Figure II.5.2.5.1. Average annual value between 2012 and 2015 of catches from UK waters, broken down by vessels' country of departure (left axe), fishing area (middle axe) and vessels' country of landings. Flows are expressed in landings' value and colored by fleet segments. The vast majority of vessels fishing in UK waters leaves and lands their catches in France.

II.5.2.6. Dependency of single species to UK waters

Species	Landings				Value			
	%		tons		%		k€	
	UK EEZ	Terr. waters	UK EEZ	Terr. waters	UK EEZ	Terr. waters	UK EEZ	Terr. waters
*Haddock**	65	6	5,424	517	65	6	7,580	741
*Whiting**	60	10	4,659	770	59	10	7,015	1,135
*Atlantic cod**	57	5	2,377	215	56	5	6,539	594
*Lemon sole**	59	11	563	107	55	10	1,925	347
John dory	37	6	577	93	35	6	5,142	849
*Pollack**	34	4	530	56	31	3	1,655	188
Inshore squids	29	5	1,058	177	31	5	6,414	1,134
Edible crab	29	1	1,102	55	30	2	2,664	149
Seabass	31	7	784	165	28	6	6,130	1,413
*Herring**	28	7	2,688	620	27	6	1,001	230
*Plaice**	33	6	456	86	25	5	472	90
*Turbot**	26	2	115	8	24	2	1,442	111
Cuttlefish	22	1	1,442	70	20	1	3,665	172
*Monkfishes**	20	1	3,729	156	20	1	15,414	648
Surmullet	20	2	257	24	15	2	1,057	109
Conger	16	1	363	30	15	1	440	41
*Mackerel**	12	4	1,406	409	13	4	1,497	427
European lobster	15	2	12	2	13	2	171	22
*Horse mackerel**	15	4	542	158	13	4	230	66
Atlantic scallop	12	1	1,553	186	12	2	4,633	611
*Black seabream**	14	2	313	43	12	2	673	122
*Norway lobster**	12	0	352	0	7	0	2,122	0
*Hake**	6	0	1,771	24	6	0	4,916	47
*Common sole**	3	1	116	21	4	1	1,398	229

Table II.5.2.6.a. Shares of landings and landings' value of selected species that are from UK waters (annual average between 2012 and 2015). *Species under a total allowable catch.

II.5.2.7. Maps of value per unit of effort

All the fleets – All species

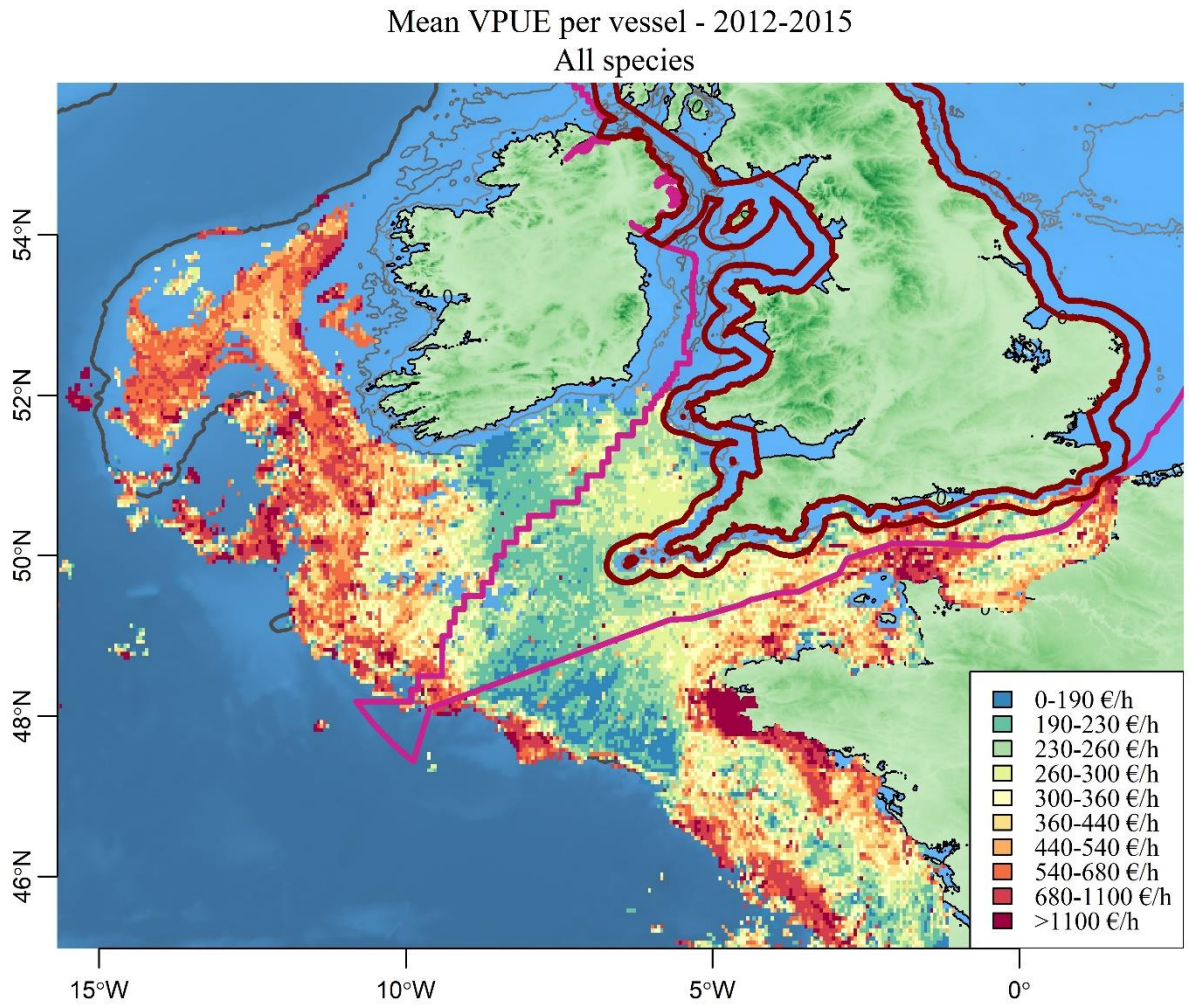

Figure II.5.2.7.1. Heat map of the mean VPUE per vessel (in €/h) between 2012 and 2015. The UK EEZ and territorial waters are delineated by the purple and dark red hard lines, respectively. Only vessels larger than 12m are represented.

Cells containing less than four vessels have been removed to protect anonymity of vessels.

II.5.2.8. Landings and landings' value from UK waters in French ports

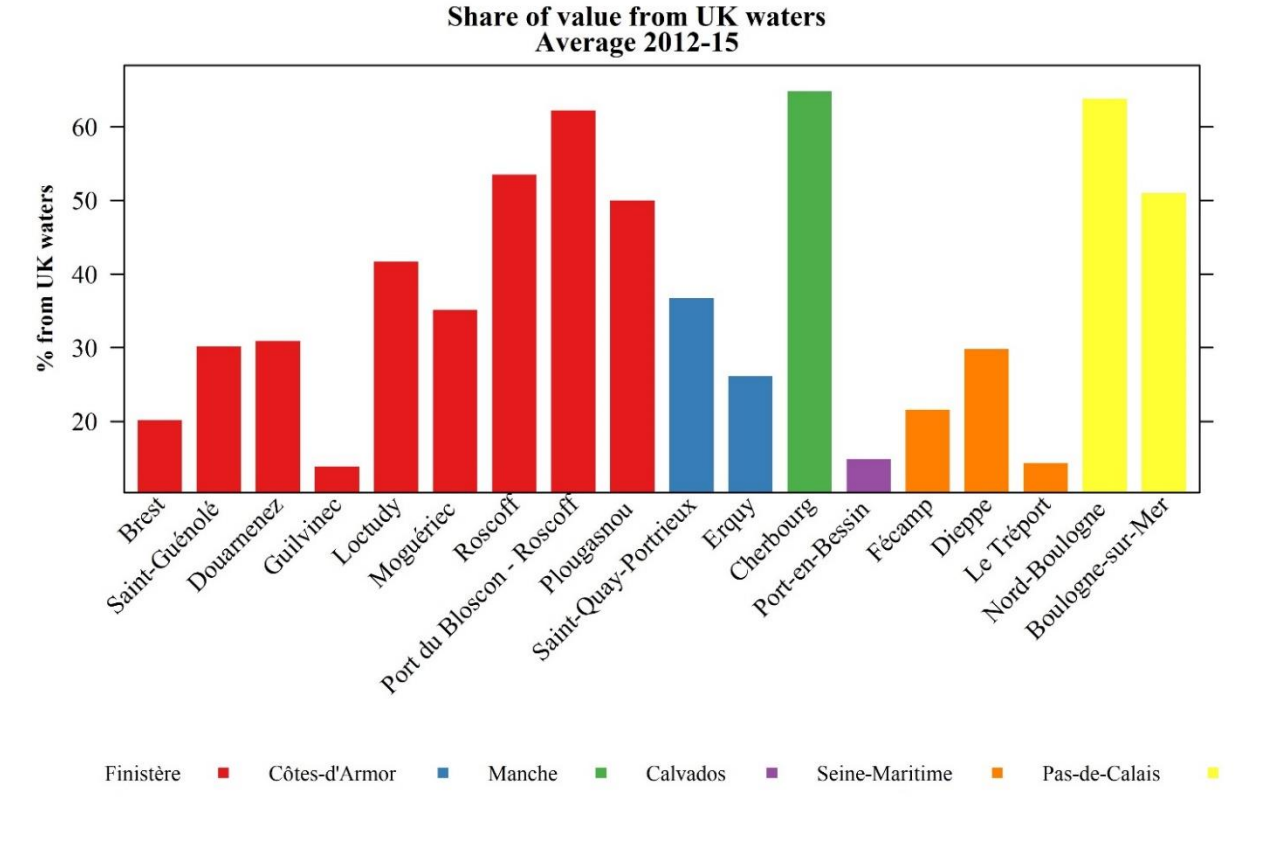

Figure II.5.2.8.1. Share of landings' value from catches in UK waters in French ports during the 2012-15 period. Ports with less than 0.5M€ of average yearly landings' value were excluded as well as ports with less than 10% of landings' value from UK waters.

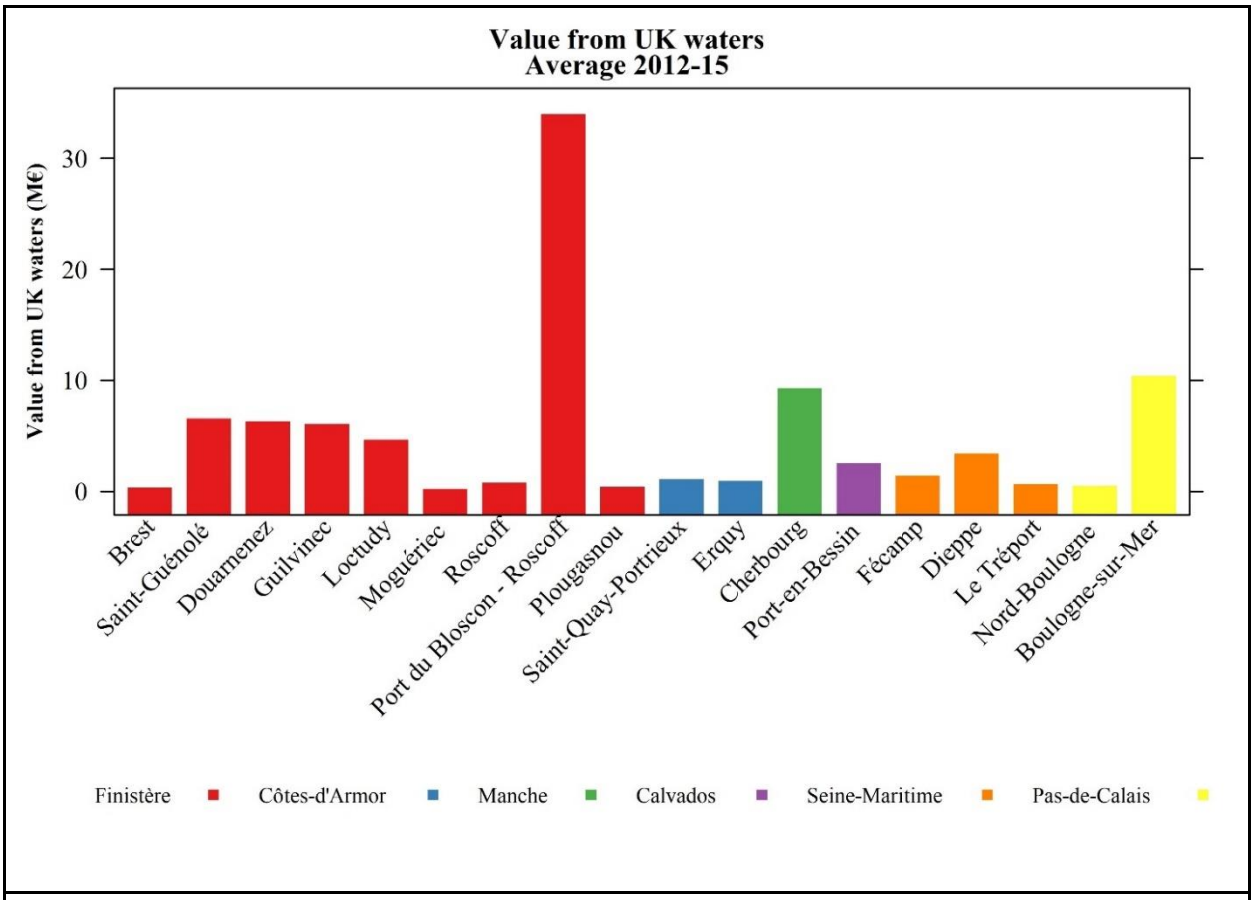

Figure II.5.2.8.2. Landings' value from catches in UK waters in French ports during the 2012-15 period. Ports with less than 0.5M€ of average yearly landings' value were excluded as well as ports with less than 10% of landings' value from UK waters.

Ports	Landings				Value			
	%		tons		%		k€	
	UK EEZ	Terr. waters	UK EEZ	Terr. waters	UK EEZ	Terr. waters	UK EEZ	Terr. waters
Cherbourg	72	11	4,432	677	65	10	9,283	1,383
Nord-Boulogne	59	17	218	65	64	21	499	165
Port du Bloscon - Roscoff	65	8	13,129	1,590	62	8	33,963	4,293
Roscoff	59	3	290	15	53	3	779	41
Boulogne-sur-Mer	43	15	5,208	1,774	51	16	10,394	3,280
Plougasnou	58	1	150	2	50	1	401	5
Loctudy	46	0	1,698	11	42	0	4,648	27
Saint-Quay-Portrieux	35	3	534	46	37	4	1,071	107
Moguériec	43	1	80	2	35	1	226	5
Douarnenez	21	1	2,467	89	31	1	6,307	219
Saint-Guénolé	20	0	2,503	13	30	0	6,560	34
Dieppe	28	6	1,324	277	30	6	3,420	731
Erquy	30	1	463	11	26	1	936	28
Fécamp	16	1	757	37	22	1	1,422	46
Brest	22	1	156	4	20	1	328	10
Port-en-Bessin	18	3	1,198	174	15	2	2,522	356
Le Tréport	16	2	336	48	14	2	649	83
Guilvinec	15	0	2,109	18	14	0	6,052	53

Table II.5.2.8.a. Shares of landings and landings' value of selected species that are from UK waters (annual average between 2012 and 2015).

II.5.3. Discrete-Choice Model

II.5.3.1. Model selection

Additional explanatory variables

We originally included in the model a couple of additional variables aimed at explicitly capturing sites' heterogeneity in terms of catch composition. Namely, we estimated Eq.II.1 for a sub-sample of the data and for five key species adding in a linear way:

$\mathrm{Sh}_{sdj}^{\exp}$: the expected share of species s in total catch from site j, proxy by a combination of the fleet historical records of share of landing value from species s over the past month and over the same 30 days period of the past year;

- $\mathrm{Diversity}^{\exp}{}_{dj}$: the expected species diversity for site j, proxy by a combination of the fleet historical records of species diversity over the past month and over the same 30 days period of the past year;

The species diversity of a given site is captured by the entropy index of species value shares: $\mathrm{Diversity}_{dj} = \sum_s -\mathrm{Sh}_{sdj} * \ln(\mathrm{Sh}_{sdj})$. It is inspired from the measures of services' diversity used in the transportation literature (Huang and Levinson, 2015).

However, those additional variables revealed to be not significant and we chose to drop them for further analysis.

VPUE expectations

In order to find a specification of the expected VPUE that would the most closely capture fishers' actual expectations, we estimated, separately for each fleet on which we focus in the

chapter, Eq. II.1 with 11 different combinations of information signals for the expected VPUE (Table II.5.3.1.a).

Model #	**Info. Source**	**Individual level**			**Fleet level**		
	Time span	*[t;t-30] (m1)*	*[t;t-365] (y1)*	*[t-350;t-370] (ym1)*	*[t;t-30] (m1)*	*[t;t-365] (y1)*	*[t-350;t-370] (ym1)*
1		N	N	N	Y	N	N
2		N	N	N	N	Y	N
3		N	N	N	N	N	Y
4		Y	N	N	Y	N	N
5		N	Y	N	N	Y	N
6		N	N	Y	N	N	Y
7		N	N	N	Y	Y	N
8		N	N	N	Y	N	Y
9		N	N	N	N	Y	Y
10		N	N	N	Y	Y	Y
11		Y	N	Y	Y	N	Y

Table II.5.3.1.a. Combinations of information signals considered for the specification of the expected VPUE

For each combination of information signals we allow the marginal utility of the expected VPUE to vary according to which combination of information is available. In practice, this means that for a given specification of the expected VPUE we interact dummies associated with a given case of information availability. For instance, for model 8 that accounts for both short-term and long-term information signals but only at the fleet-level, the specification for the expected VPUE is:

$$\beta_{\mathrm{VPUE}} * E\left[\mathrm{VPUE}_{ijt}\right] = \begin{cases} \beta_{\mathrm{VPUE}}^{Full\ info-short-term} * \overline{\mathrm{VPUE}}_{\mathrm{m-1}}^{\mathrm{ft}} + \beta_{\mathrm{VPUE}}^{Full\ info-long-term} * \overline{\mathrm{VPUE}}_{\mathrm{ym-1}}^{\mathrm{ft}}\ if\ case\ 1 \\ \beta_{\mathrm{VPUE}}^{Short-term\ only} * \overline{\mathrm{VPUE}}_{\mathrm{m-1}}^{\mathrm{ft}} if\ case\ 2 \\ \beta_{\mathrm{VPUE}}^{Long-term\ only} * \overline{\mathrm{VPUE}}_{\mathrm{ym-1}}^{\mathrm{ft}} if\ case\ 3 \\ \beta_{\mathrm{VPUE}}^{No\ info}\ if\ case\ 4 \end{cases}$$

With:

- case 1: both short-term **and** long-term historical VPUE are available
- case 2: **only** short-term historical VPUE are available
- case 3: **only** long-term historical VPUE are available
- case 4: **neither** short-term **or** long-term historical VPUE are available

Model selection

We then selected the best model for each fleet using the AIC. In the end the specifications showed very similar performances in terms of goodness of fit, even though Model 11 revealed to be systematically the best model for all the fleets (Table II.5.3.1.b).

		Spatial grid		
Fleet	Model	*2°x2°*	*ICES*	½° × ½°
BTR exc >=18m	1	10,732	13,522	15,733
	2	10,916	14,003	NA
	3	10,891	13,811	16,564
	4	1,666	2,263	2,823
	5	4,988	7,117	NA
	6	4,950	7,140	9,037
	7	10,728	13,507	NA
	8	10,695	13,415	15,484
	9	10,829	13,808	NA
	10	10,704	13,421	NA
	11	0	0	0
BTR dom >=18m	1	1,996	2,387	2,656
	2	2,295	3,079	NA
	3	2,015	2,839	3,143
	4	316	399	485
	5	1,021	1,530	NA
	6	1,390	2,011	2,255
	7	1,995	2,391	NA
	8	1,853	2,230	2,454
	9	1,969	2,704	NA
	10	1,858	2,234	NA
	11	0	0	0

TRP >=12m	1	213	431	625
	2	249	508	-3,732
	3	201	412	658
	4	103	127	139
	5	107	344	-3,732
	6	90	257	473
	7	215	426	-3,732
	8	190	365	530
	9	209	411	-3,732
	10	194	360	-3,732
	11	0	0	0
DFN >=12m	1	5,975	9,170	10,939
	2	6,753	10,643	NA
	3	6,297	10,203	12,085
	4	866	1,073	1,162
	5	2,356	4,474	NA
	6	3,411	6,704	8,534
	7	5,906	9,136	NA
	8	5,853	8,963	10,617
	9	NA	9,815	NA
	10	5,807	8,894	NA
	11	0	0	0
DRD >=12m	1	2,286	3,746	4,637
	2	2,369	4,062	NA
	3	2,293	3,879	4,825
	4	336	610	710
	5	897	1,723	NA
	6	1,455	2,514	3,228
	7	2,212	3,702	NA
	8	2,262	3,616	4,403
	9	2,213	3,829	NA
	10	2,191	3,598	NA
	11	0	0	0

Table II.5.3.1.b. ΔAIC with model 11 of the different model's specifications tried.

II.5.3.2. Model's estimates

			Spatial grid 2°x2°	ICES	½° × ½°
Dist.d1		*BTR exc >=18m*	-0.538***	-1.097***	-1.176***
		BTR dom >=18m	-0.521***	-1.263***	-1.42***
		TRP >=12m	-0.241***	-0.582***	-0.689***
		DFN >=12m	-0.279***	-1.096***	-1.547***
		DRD >=12m	-0.211***	-0.441***	-0.541***
Act.oth		*BTR exc >=18m*	0.06***	0.075***	0.07***
		BTR dom >=18m	0.047***	0.045***	0.041***
		TRP >=12m	0.039***	0.052***	0.069***
		DFN >=12m	0.009***	0.032***	0.036***
		DRD >=12m	0.053***	0.072***	0.069***
Act.own		*BTR exc >=18m*	-0.002.	0	0.001
		BTR dom >=18m	0.002	0.001	0
		TRP >=12m	-0.005	-0.005	-0.002
		DFN >=12m	0	0	0
		DRD >=12m	-0.001	-0.001	-0.001
E[VPUE]	Short-term – fleet info.	*BTR exc >=18m*	0.034***	0.022*	0.014.
		BTR dom >=18m	-0.038***	-0.051**	0
		TRP >=12m	0.021	0.039**	0.036**
		DFN >=12m	0.034***	0.027**	0.041***
		DRD >=12m	-0.008	-0.047***	-0.037***
	Short-term – ind. info.	*BTR exc >=18m*	-0.014**	0.003	0
		BTR dom >=18m	-0.001	-0.008	0
		TRP >=12m	0.013	-0.031*	-0.024
		DFN >=12m	-0.003	0.001	-0.003
		DRD >=12m	0.013	0	-0.017.
	Long-term – fleet info.	*BTR exc >=18m*	-0.006	-0.049***	-0.02*
		BTR dom >=18m	-0.01	-0.012	-0.038**
		TRP >=12m	0.009	-0.01	-0.028*
		DFN >=12m	-0.026	0.041*	0.044**
		DRD >=12m	-0.003	-0.006	0.007
	Long-term – ind. info.	*BTR exc >=18m*	-0.024***	-0.03*	-0.019*
		BTR dom >=18m	-0.01	-0.014*	-0.036**
		TRP >=12m	-0.015*	-0.015	-0.021.
		DFN >=12m	-0.025***	-0.026*	-0.035***
		DRD >=12m	-0.009	-0.027***	-0.021**

Table II.5.3.2.a. Average marginal effects of the explanatory variables of the discrete-choice model of fishing locations for an increase of 1 standard deviation. Significance levels: 0.1% ***, 1% **, 5% *, 10%..

Besides the expected significant negative effect of distance, we find a significant positive effect of the number of other vessels fishing on a site on the probability of visit for this same site. This suggests a herding behavior of fishers – presumably concentrating in the most productive sites – that is not undermined by a potential congestion effect. The discrete-choice literature has reported various effects in this regard (Girardin et al., 2016). Girardin (2015) for instance found that the presence of other French vessels in a given site in the English Channel often had a significant negative effect on the choice of a fishing location. However, they also found that the presence of English vessels had a positive effect, which they explain by the fact that some French and English fleet segments targets scallops, a lowly mobile species. Similarly, Russo et al. (2015) (2015) reported an attractive effect on the direction location choice of pair trawlers from fishing units but a repulsion effect from non-fishing units. At last, Abbott and Wilen (2011) reported in their Appendix, a positive effect of other vessels' presence in a site with a one-day lag but a negative effect with a two-day or three-day lag. In our definition of the activity of other vessels we pooled together vessels from all the fleet segments for which we had a full VMS coverage, i.e. all vessels with a length over all larger than 12m. It would be interesting for future works to see whether that herding effect persist when allowing for segment-specific effect and when including smaller vessels as well.

We find as well a consistent non-significative effect of vessels' own fishing effort on a given site the day before. This means that vessels are no more likely to move to exploit another fishing site than to stay fishing in the same ground. This findings goes somewhat against the general result in the literature which usually reports – though over sometimes different time-windows – a significant positive effect of past fishing patterns (Abbott and Wilen, 2011; Girardin et al., 2016, 2015; Hynes et al., 2016).

The most surprising results in terms of model's parameters estimates are perhaps those regarding the sign and the significance of the variables related to the expected productivity of the sites. First, we find highly differentiated effects across the five fleet segments which validates the approach of estimating segment-specific models for vessels having fundamentally different fishing strategies. Second, we find also differentiated effects depending on the type of information that is considered. This validates our approach of distinguishing between segment-level (public) and vessel-level (private) information, which is still rarely undertaken in the literature where most of modellers usually only consider fleet aggregate (Girardin et al., 2016). We find that in the short-term it is mainly segment-level information that matters, and when private information is found to be significant it tends to mitigate the effect of the former. This would mean that fishers would correct their expectation of site productivities based on fleet-segment aggregates when their own experience diverge from the segment average. In the long-term, we find the opposite pattern: public information tends not to have any effect while private information matters more. This may indicate that fishers consider public information to deprecate more in the long term (or to be less reliable) than their own private information. At last, a more puzzling result is the significant negative signs associated with historical productivity that we find for dominant bottom trawlers and dredgers in the short-term and using fleet segment-level information, and for exclusive bottom trawlers, netters and dredgers in the long-term and using vessel-specific information. To explain these counter-intuitive findings, we can follow some of the arguments of Girardin (2015) who reports a negative effect of past segment-level productivity in the short-term (one month lag) for mid-size demersal trawlers, and in the long term (12 months lag) for dredgers. They explain those negative estimates by a lack of capacity to respond to change in fisheries productivity in the short-term and by the result of specific seasonality changes in species abundance in the long-term.

II.5.4. Maps of the impact of spatial closures

II.5.4.1. Closure of the UK territorial waters

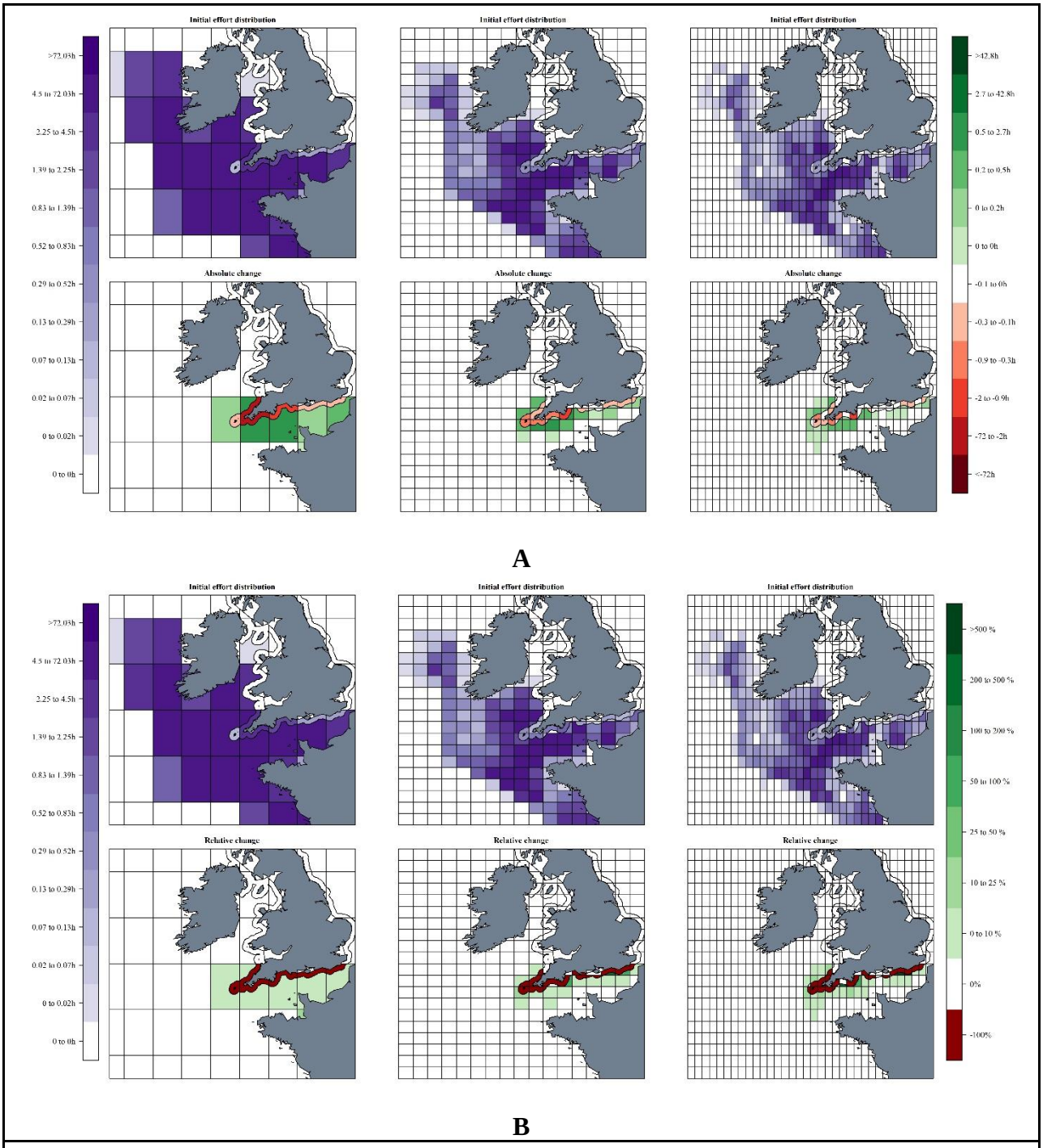

Figure II.5.4.1.1. Simulation of the reallocation of fishing effort due to the closure of the UK territorial waters for BTR exc >= 18m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

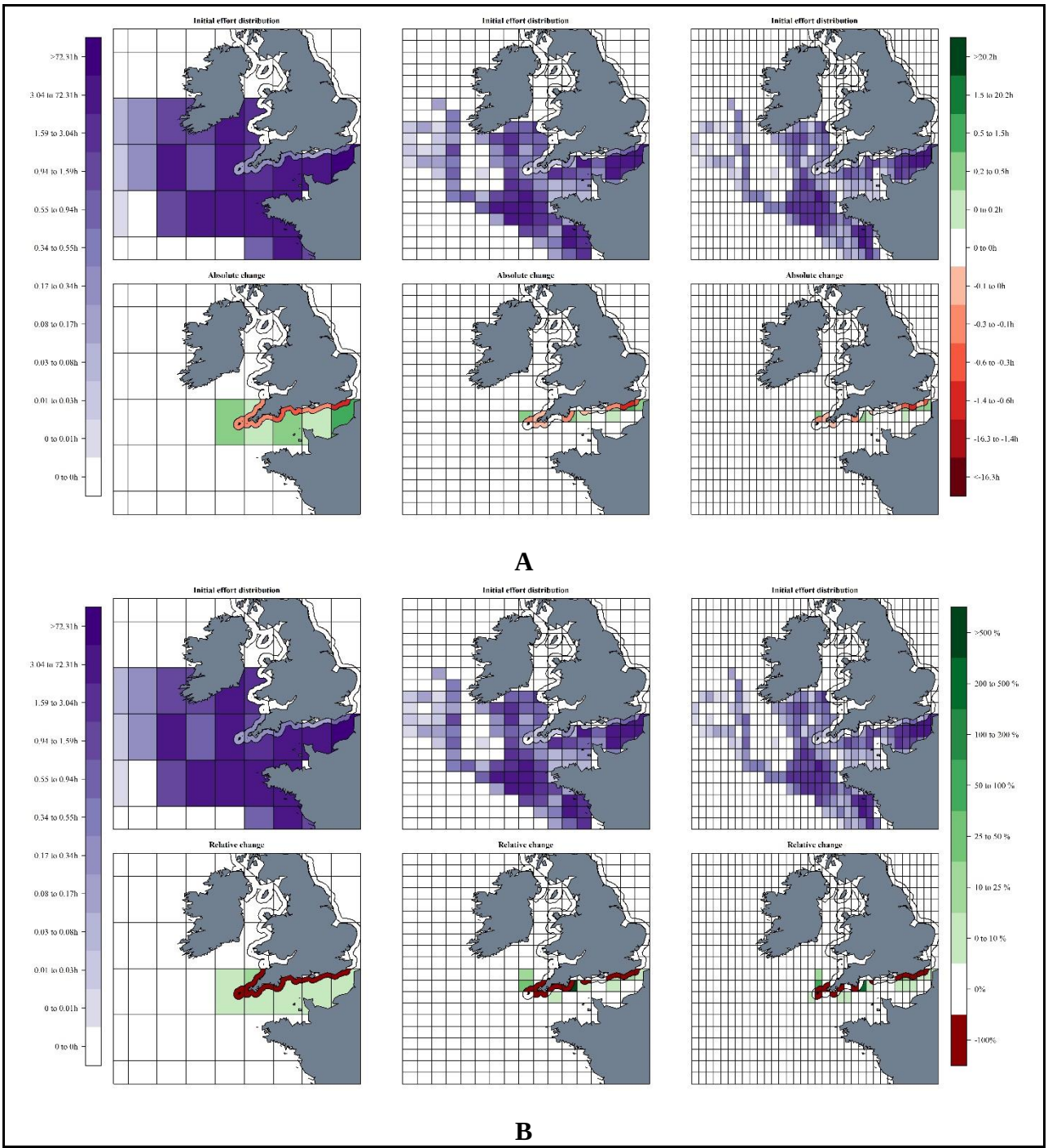

Figure II.5.4.1.2. Simulation of the reallocation of fishing effort due to the closure of the UK territorial waters for BTR dom >= 18m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

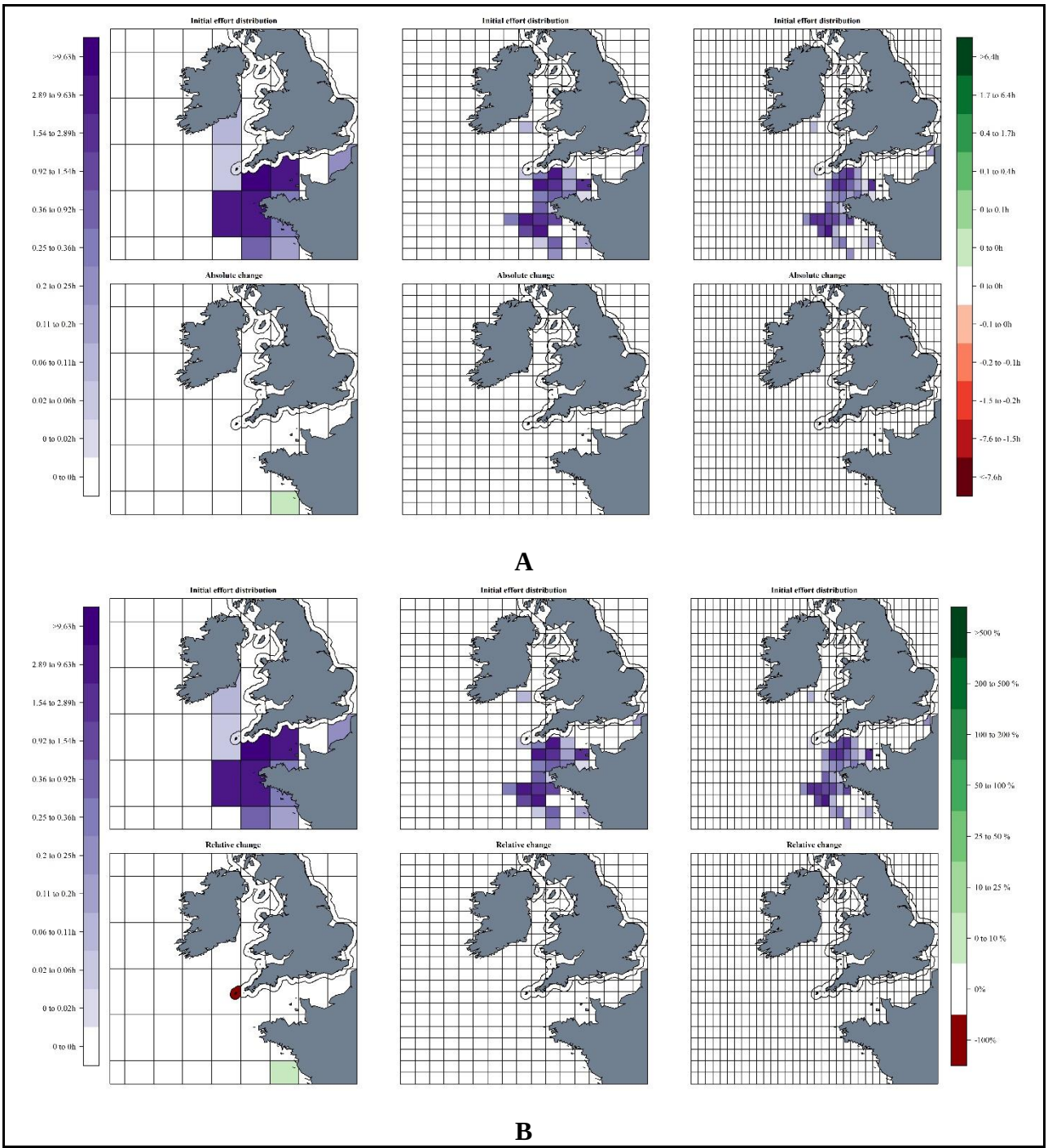

Figure II.5.4.1.3. Simulation of the reallocation of fishing effort due to the closure of the UK territorial waters for TRP >= 12m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

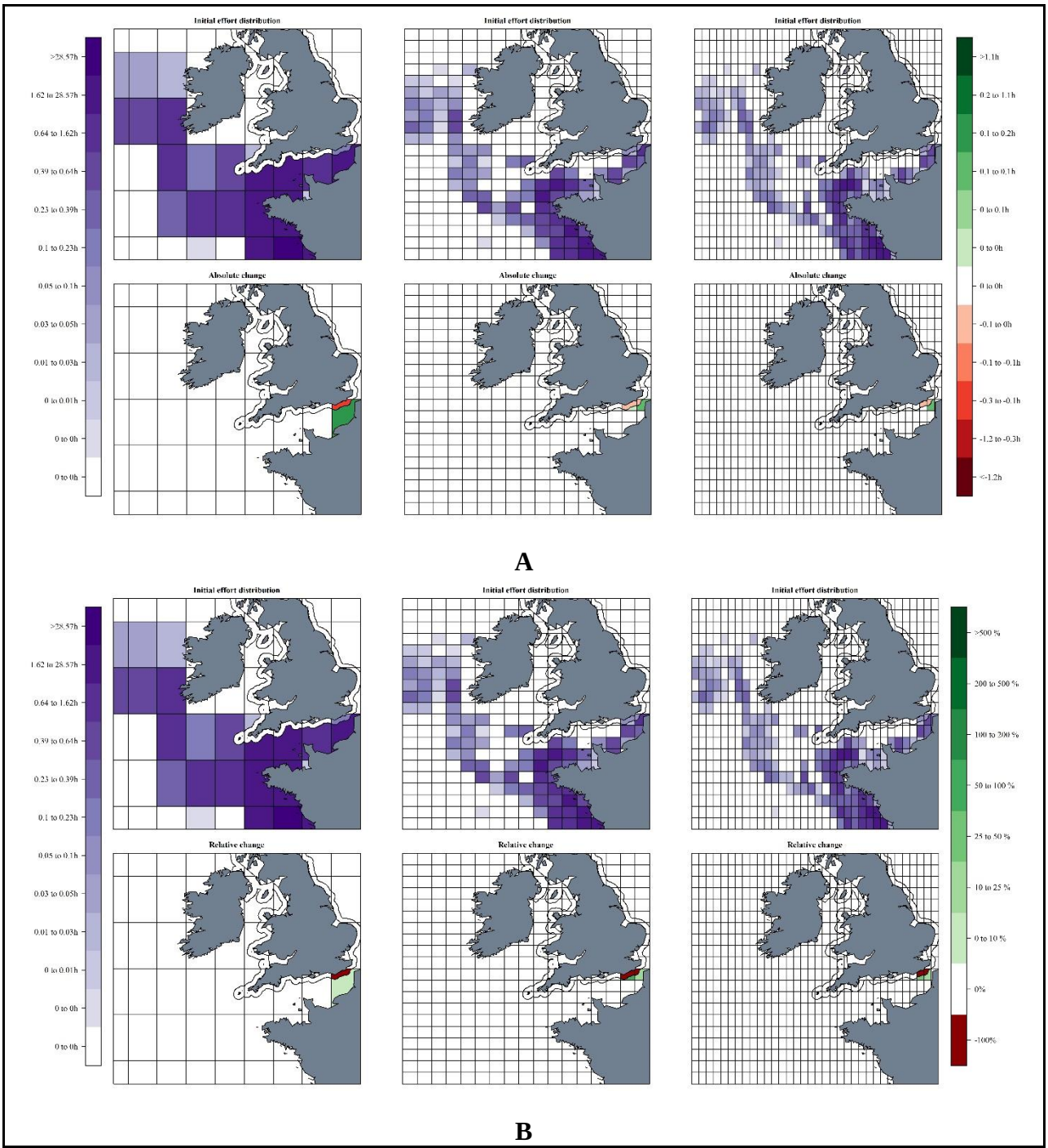

Figure II.5.4.1.4. Simulation of the reallocation of fishing effort due to the closure of the UK territorial waters for DFN >= 12m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

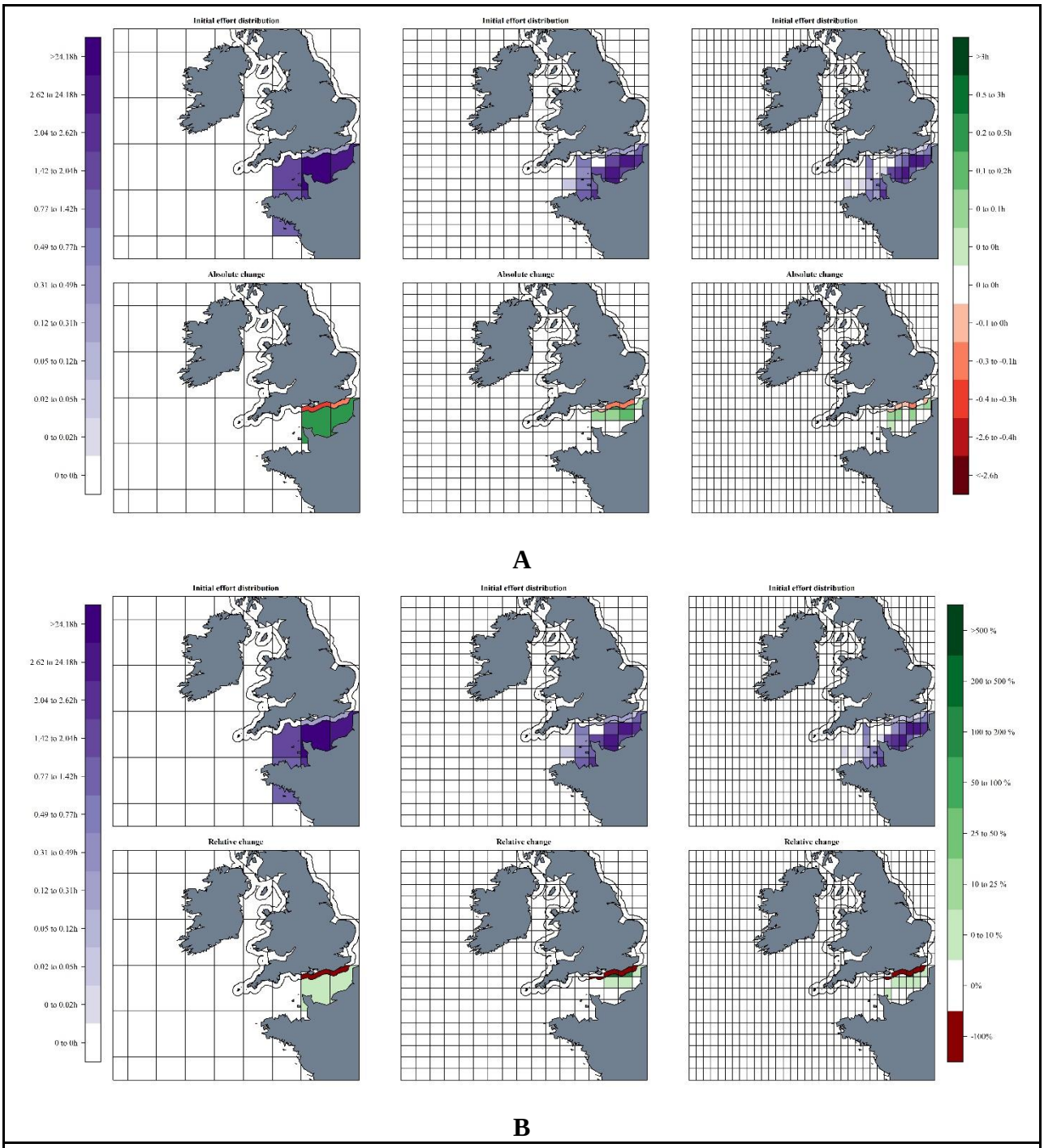

Figure II.5.4.1.5. Simulation of the reallocation of fishing effort due to the closure of the UK territorial waters for DRD >= 12m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

II.5.4.2. Closure of the UK EEZ

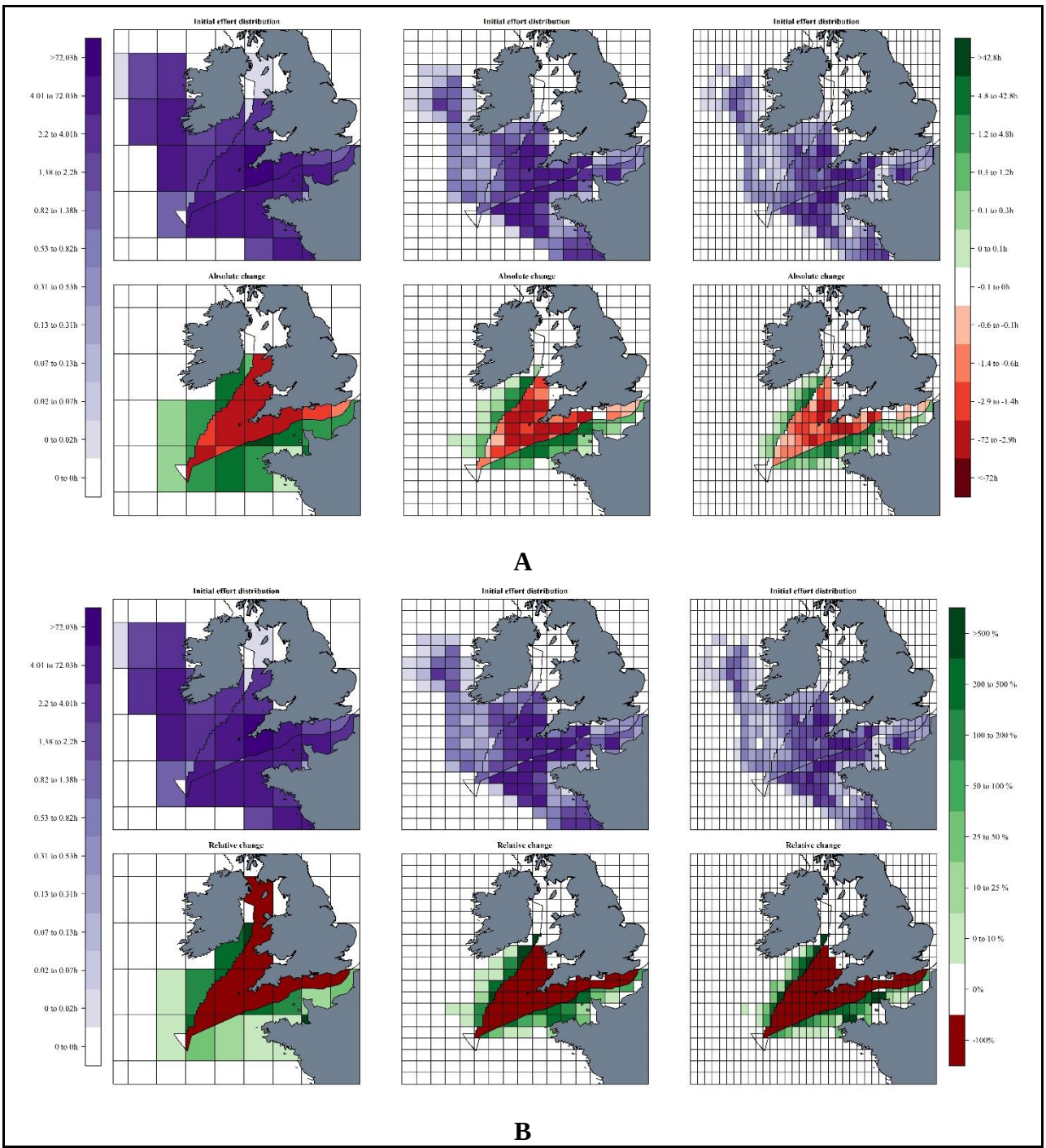

Figure II.5.4.2.1. Simulation of the reallocation of fishing effort due to the closure of the UKK EEZ for BTR exc >= 18m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

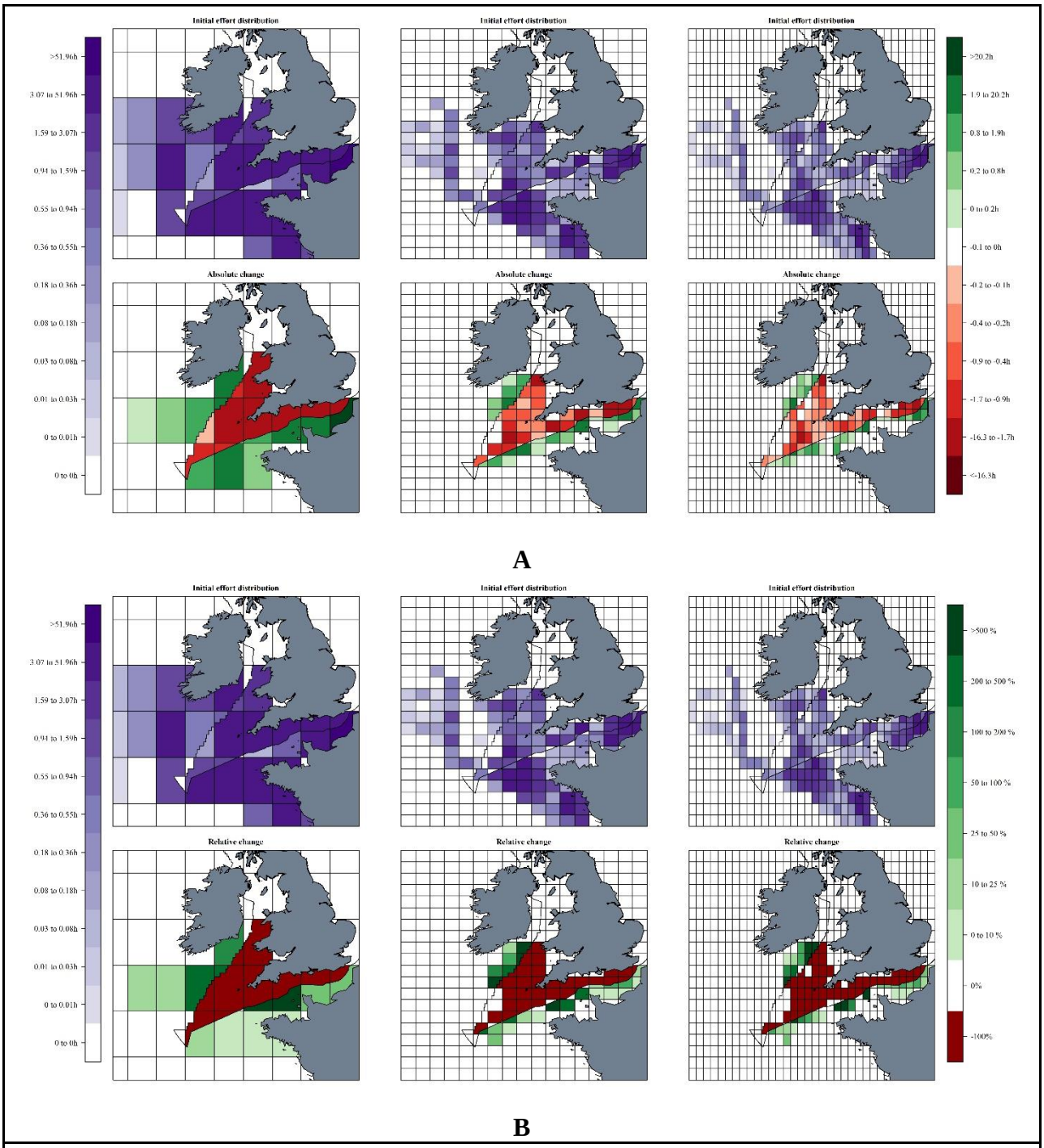

Figure II.5.4.2.2. Simulation of the reallocation of fishing effort due to the closure of the UK EEZ for BTR dom >= 18m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

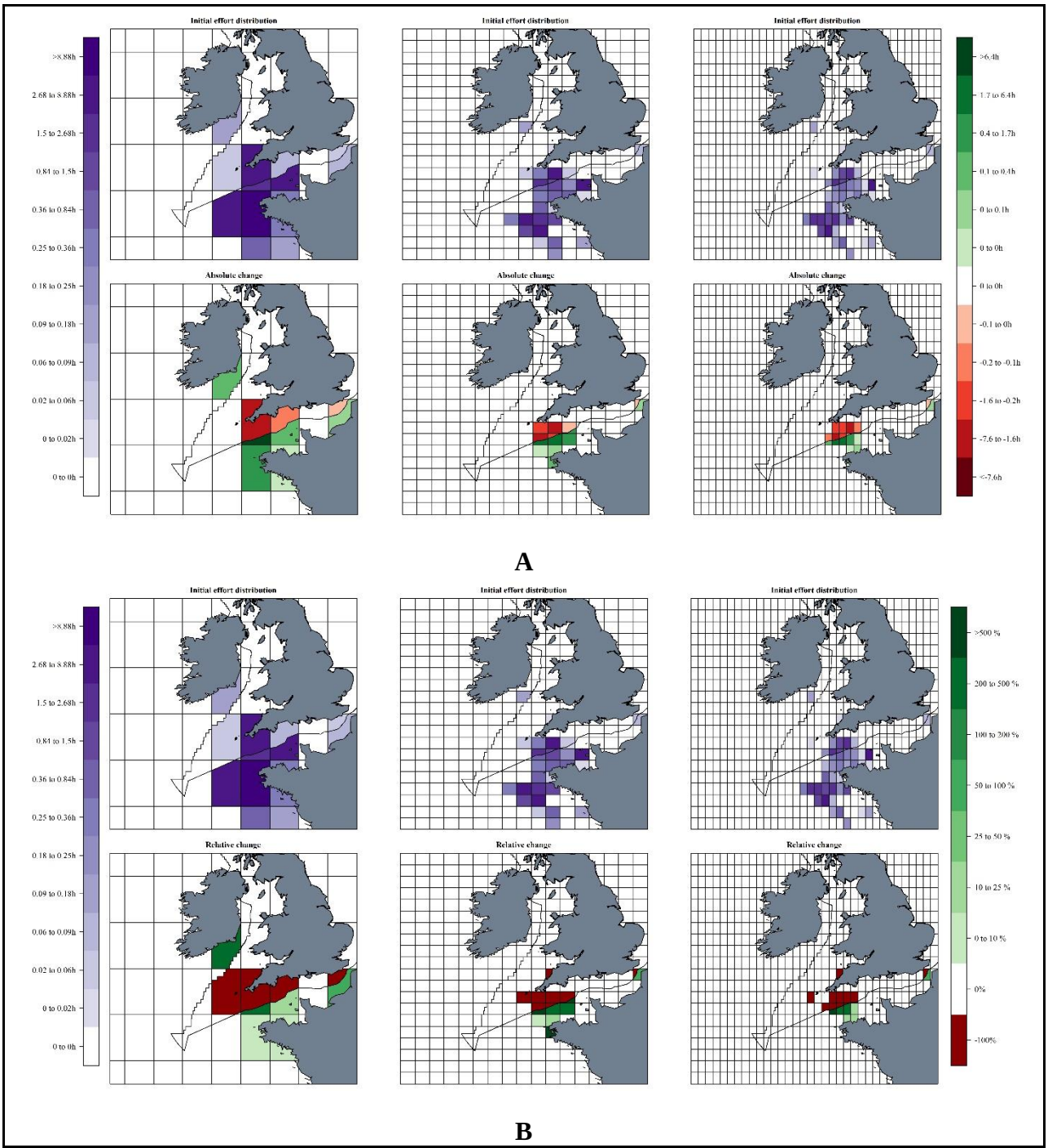

Figure II.5.4.2.3. Simulation of the reallocation of fishing effort due to the closure of the UK EEZ for TRP >= 12m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

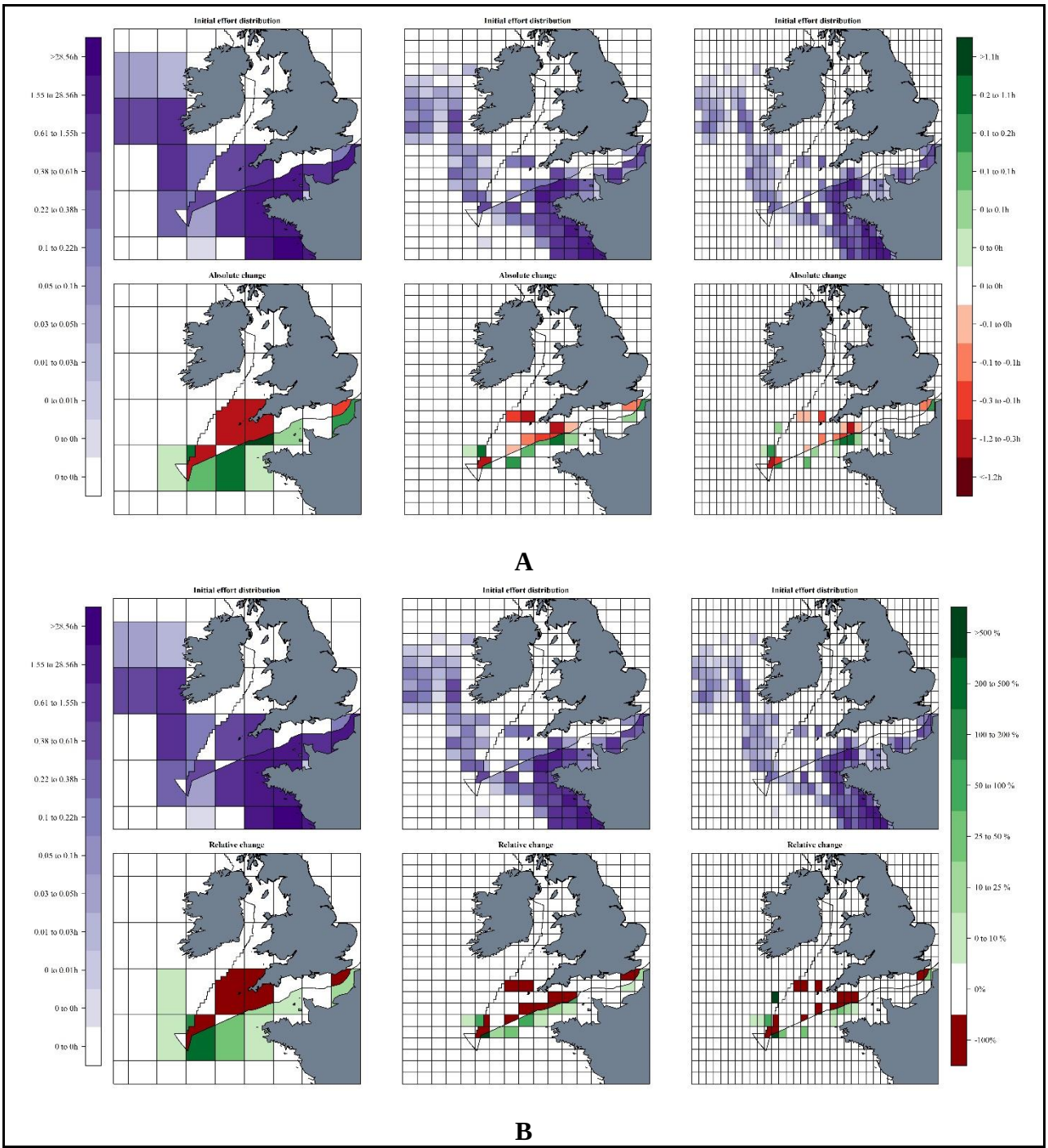

Figure II.5.4.2.4. Simulation of the reallocation of fishing effort due to the closure of the UK EEZ for DFN >= 12m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

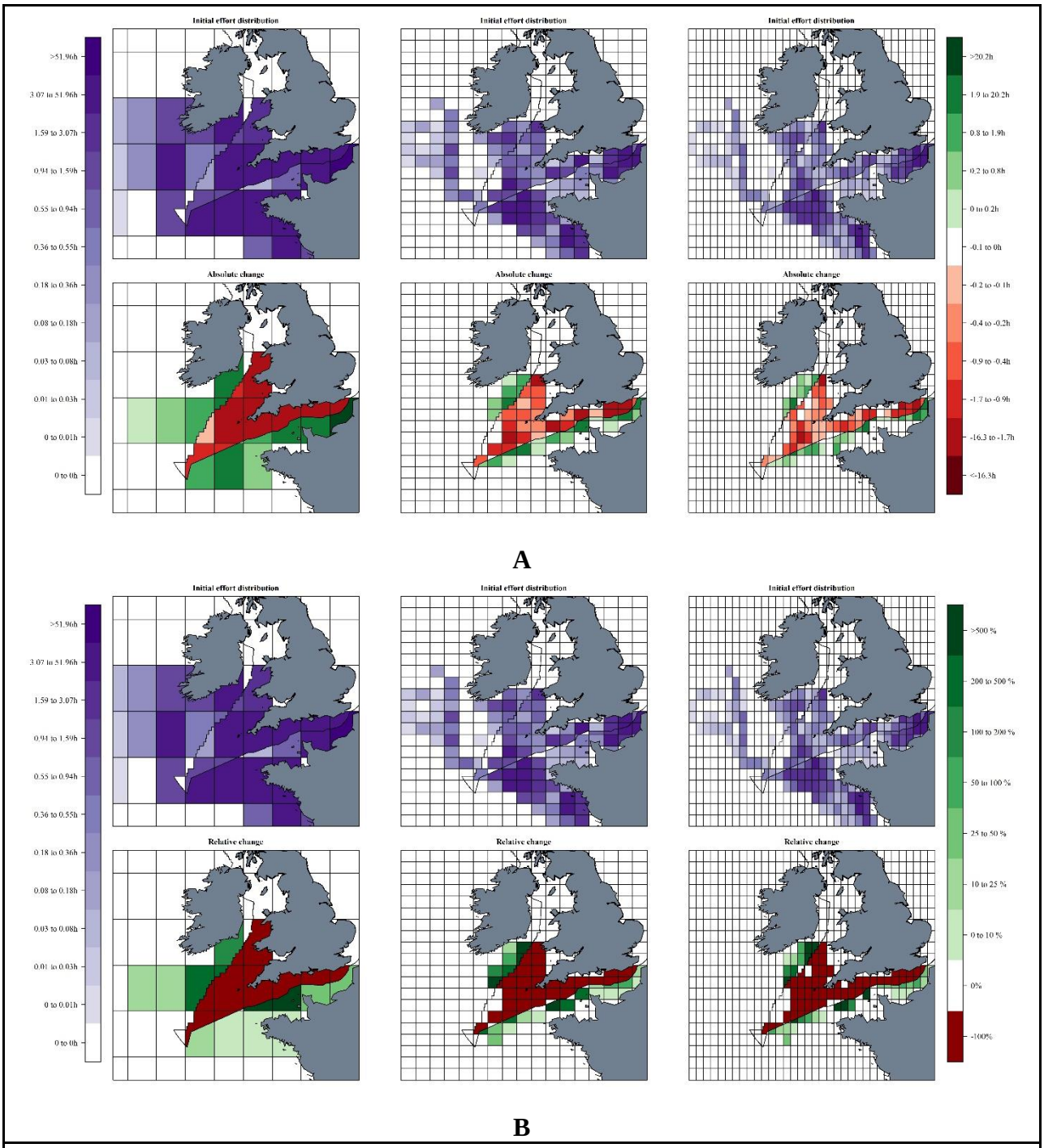

Figure II.5.4.2.5. Simulation of the reallocation of fishing effort due to the closure of the UK EEZ for DRD >= 12m vessels. The upper panels (purple color key) show the spatial distribution of effort for 2015 by deciles. The bottom panels (green and red color key) show (A) the absolute change in the mean daily fishing effort (in hours of fishing) and (B) the relative change in the average annual visit frequencies.

II.5.5. References for Appendix II

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Chapter III: Impact of IFQ on fishing strategies at sea: a Hidden-Markov Model approach

Abstract

In this chapter we look at the impact on fishing strategies at sea of the implementation in 2009 and 2010 of a set of new management measures – including Individual Fishing Quotas (IFQs) – in the Grouper-Tilefishes bottom longline (GT-BLL) fishery in the Gulf of Mexico. Using geospatial information about vessels from the fishery, we are capable of estimating a dynamic model of fishing decisions based on a Hidden-Markov modelling framework that is able to predict the behavioral states of fishers at sea. Focusing on three behavioral modes and validating model's results with observer data, we characterize the fishing strategies of a sub-sample of vessels that were fishing both before and after the implementation of the new fishing regulations and we compare how behavioral modes have change between the two periods. We show that, despite exhibiting no changes when looking at vessels as a homogenous fleet, the response of fishers was in fact extremely heterogenous. Beyond the implication of this finding in terms of resilience for the fishery and long-term impact of management measures, our work sets up a fruitful research avenue for policy-making and policy evaluation. By integrating increasingly available geospatial data on fishery activity in a robust and easy-to implement structural modelling framework, we provide resource managers with an innovative and powerful tool to analyze the spatial and behavioral effects of their policies.

III.1. Introduction

Commercial fishery management across the globe has been subjected to ongoing institutional transformations since the 1950's, shifting from open-access to rights-based regime while going through input-based regulations (Sanchirico and Wilen, 2007). The instability in management policies has been fueled mainly by inefficient approaches resulting from the lack of understanding and anticipation of fishers' behavior (Degnbol and McCay, 2007; FAO, 2009; Fulton et al., 2011; Wilen et al., 2002). Considerable progress has been made on in this regard and the need to favor an ecosystem-based management that accounts for the adaptive capacity of fishers is now well established (FAO, 2009; Pikitch, 2004). Yet, there is still much to be learnt about the nature of fishers' reactions to new institutional settings (Fuller et al., 2017; Fulton et al., 2011; Valcic, 2009).

Understanding the underlying mechanisms of fishers' behavior is essential to evaluate a policy. Reimer et al. (2017) have shown, for instance, that a misrepresentation of fishers' decision-making process can lead to overstate both the *ex-ante* and *ex-post* evaluation of the impact of a policy on fishers' production capabilities. Similarly, the same authors show that failing to account for fishers full set of behavioral responses can lead to a biased assessment of the effects of the new incentives set by a policy (Reimer et al., 2014). As a result, they argue that to properly evaluate the impacts of policy interventions, models of fishing behavior have to be *"sufficiently structural*", which implies an adequate knowledge of fishers' decisional mechanisms.

In this regard, fishery managers have now access to an unprecedented amount of micro data about fishing behavior, especially thanks to the advent of geolocation technologies and their large-scale deployment as monitoring tools since in 1990's. In particular, Vessel Monitoring System (VMS) is becoming more and more widely used by regulatory agencies (McCauley et al.,

2016). Fishery scientists have used them for various purposes such as delineating fishing grounds (Jennings and Lee, 2012; Lee et al., 2010), assessing the impact of fishing on the seabed (Harrington et al., 2007), validating self-reported data (Bastardie et al., 2010), and, most importantly, improving the estimation of fishing effort (Bastardie et al., 2010; Gerritsen and Lordan, 2011; Lee et al., 2010; Russo et al., 2013). More rarely, however, VMS data has been used to carry out analyses at the vessel level.

A few studies have taken advantage of VMS data to examine vessels' fishing strategies at sea. For example, Rijnsdorp et al. (2011) looked at patch exploitation dynamics and giving-up catch rate of Dutch beam trawlers, Hynes et al. (2016) focused on the choice of habitat-based fishing sites of Irish bottom trawlers, while Russo et al. (2015) looked at the strategical choices of within-trip locations of mid-water trawlers. One could add also Rijnsdorp's study (Rijnsdorp, 2000), which characterized the fishing behavior of beam trawlers by identifying searching and exploitation phases, and looked at changes in patch-specific catch rate in relation with the presence of other vessels nearby[1] .

Nevertheless, only one study – to our knowledge – has used VMS data in the context of policy impact assessment: Watson et al.'s (2018) analysis of the impact of the implementation in 2010 of Individual Fishing Quotas (IFQs) in the Grouper-Tilefishes bottom longline (GT-BLL) fishery in the Gulf of Mexico. Yet, they mainly use information from logbook data and utilize VMS data only to derive trip-specific metrics such as trip duration or trip length. Most importantly, they do not recover the underlying determinants of fishing choices and do not quantify the structural changes triggered by the new policy.

[1] They actually do not use data from VMS but from APR, which record the position of vessels at a 6-min frequency.

This is the gap we intend to fill in this chapter, using the same fishery context – GT-BLL fishers in the Gulf of Mexico –, and the same type of data – VMS recordings from before and after the implementation in 2009 and 2010 of a set of new management measures, which includes IFQs. We undertake an innovative approach that combines a data-regularizing technique borrowed from the animal behavior literature with a Hidden-Markov Model (HMM) framework. HMMs – and similar approaches such as artificial neural networks – have already been used in combination with VMS data, but mainly with the purpose of ping classification (Joo et al., 2011; Russo et al., 2011; Vermard et al., 2010a) or behavioral characterization (Walker and Bez, 2010), and never, to our knowledge, for policy evaluation.

In the following of the chapter, we begin by providing a brief literature review about the effects of institutional shifts on fishers. We focus in particular on the effects on fishers' behavior at sea and we look how that latter has been modelled by researchers so far. then. Considering HMMs as our modelling framework, we then expose their specific features and we show how they can be implemented. Next, we turn to the empirical setting of our study and give more information about the GT-BLL fishery in the Gulf of Mexico. Following, we succinctly detail the specification of the HMM we consider before showing the results of our estimation. Finally, we discuss them and we conclude, highlighting the implications of our work in terms of policy assessment and fishery management.

III.2. Background on the impact of IFQs and on behavioral models

III.2.1. Evaluation of fishers' response to a shift in the regime of fishing rights

The majority of empirical research that has investigated the effects of a switch to a rights-based regime has focused mainly on long-run economic outcomes and on resource use at the

aggregated level (Andersen et al., 2010; Bertolotti et al., 2016; Branch et al., 2005; Grafton et al., 2000; Grimm et al., 2012; Hermansen and Dreyer, 2010; Solís et al., 2014, 2015).

The question of how IFQs and right-based management policies affect fishers' behavior at sea has been, however, less thoroughly examined. Most of the work in that domain remains qualitative (Casey et al., 1995; Cullis-Suzuki et al., 2012; Dewees, 1998; Helmond et al., 2016; Knapp, 1997; McCay, et al., 1995), even though the collection of individual level data has allowed more quantitative studies in the recent years (Branch and Hilborn, 2008; Helmond et al., 2016; Pfeiffer and Gratz, 2016; Watson et al., 2018).

The primary rational for the implementation of IFQs – instead of fleet catch limits for instance – is that they would remove incentives for competitive behaviors and would provide fishers more flexibility in their decision of where, when and how to fish (Griffith, 2008). In effect, post-assessment surveys of IFQs programs did report fishers feeling less pressure from competition and enjoying better working conditions (Grafton et al., 2000; Knapp, 1997). These anecdotal testimonies have been further supported by quantitative evidence of behavioral changes of fishers at sea. In particular, researchers have documented changes in the temporal distribution of catches (McCay, et al., 1995), in the choice of fishing locations (Branch and Hilborn, 2008; Helmond et al., 2016; Watson et al., 2018), in trip duration and distance travelled (Watson et al., 2018); in crew working hours (Grafton et al., 2000), and in attitude toward risk exposure (Pfeiffer and Gratz, 2016). At the same time, heterogeneity in fishers' responsiveness have been acknowledged as well. Helmond et al. (2016) show, for example, that whereas large vessels would exhibit avoidance behavior of undersized fish after the introduction of a catch share program, smaller vessels participating in the same program would not change their fishing habits.

What are the underlying mechanisms driving those changes and what is the role played by the new institutional setting are intricate questions. As argued by Reimer et al. (2017), answering them properly requires a policy-invariant structural representation of fishers' behavior. Some quantitative works have modelled explicitly individual behavior under an IFQ regime (Batsleer et al., 2013; Branch and Hilborn, 2008; Reimer et al., 2014; Rijnsdorp et al., 2011; Simons et al., 2015), but none, to our knowledge, were able to identify and estimate quantitatively the effect of a shift in the rights regime on the behavior of fishers at sea. The most advanced endeavor in this direction is perhaps Reimer et al (2014), but, because of the complexity and the data intensity of their model of fishing decisions, their results are based on simulated experiments calibrated on observed aggregated outcomes.

III.2.2. Modelling of fishing behavior at sea

How fishers choose where to fish and how to model this process are ongoing research topics. It has been vastly investigated in the economic literature since the seminal work of Gordon (1954) and models now vary widely by modalities and level of complexity, with different choices in the selection of the determinants of fishers' decisions as well as different representations of the decision-making process (e.g., see Bjørndal et al.'s instructive 2004 review of operational research models for fisheries management).

Besides mere individual habits, the main drivers of fishers decisions that have been identified in the economic literature are travel costs, expected revenues and other fishers behavior (Girardin et al., 2016). However, the relevancy of those factors depends on the scale of decision that is being modelled. In the case of intra-day within trip (very short-term) decisions for example, a common assumption is that when fishers leave their homeport they have already decided on the duration or fishing effort of their trip as well as what will roughly be their itinerary (Hicks and

Schnier, 2008). The fishing strategies at sea are then highly fishery- and vessel-specific and can consist in a mixture of visits to familiar sites and exploration of new ones; with fishers' preferences, updated knowledge of resource distribution, environmental conditions and information about other vessels playing some role in the decision-making process (Abernethy et al., 2007; Eales and Wilen, 1986; Holland and Sutinen, 2000; Hutniczak and Münch, 2018; Larson et al., 1999; Salthaug and Aanes, 2003).

With the generalization of automated geolocation device and the ensuing increase in the availability of spatially-refined vessel data, studies of fishers' behavior at sea carried out at the level of fishing operations (e.g., trawls hauls or longline sets and hauls) are becoming more common. Yet, however extremely informative they can be, most of these studies remain descriptive (Bertrand et al., 2005; Rijnsdorp, 2000) and they seldom take the step further of modelling explicitly fishers' behavior.

As a matter of fact, the constraint on data availability is still strong. First, the geospatial datasets that are available usually only include information about vessels' trajectories and speed. Nothing is known about vessels' operations (e.g., fishing or steaming) or catches. Then, the temporal resolution of the data may be also too coarse relatively to the duration of fishing operations for certain gears. For example, VMS records are usually acquired every hours[2] whereas the typical set duration of a trap is about a few minutes, and longline soaking times are about one hour.

Only a few studies took advantage of high-resolution geospatial data to estimate models of fishing decisions at the operation level with an explicit focus on fishers' behavior. For instance,

[2] The minimum threshold set by the European Union in the context of the Common Fishery Policy is even of 2h.

Rijnsdorp et al.'s (2011) analyzes the giving-up catch rate of Dutch beam trawlers. The authors model fishers' behavior in a non-spatially explicit way – operating at the level of a fishing patch – , using a marginal value theorem that allows them to derive optimal patch residence times and catch rates, which they subsequently compare with actual observations. Another one is by Hicks and Schnier (2008), who took advantage of spatially-explicit on-board observer data on purse seiners in the Eastern Tropical Pacific Ocean to model the decision of set locations. They use a dynamic random-utility framework where fishers optimize the locations of the sequence of sets for each trip, making the strong assumption that fishers do not update their believes regarding the revenues they expect from each sites. Using a random-utility framework as well, Russo et al. (2015) estimate a discrete-choice model of fishing trajectories relying on VMS data from mid-water pair trawlers in the Adriatic Sea. Their model's specification is particularly parsimonious, consisting in only four explanatory variables that can be easily derived from VMS recordings. Finally, Vermard et al.'s (2010b) and Walker and Bez's (2010) studies take perhaps the most holistic and advanced approach by considering Hidden-Markov Models (HMMs) estimated in a Bayesian framework with VMS data from respectively, pelagic trawlers in the Bay of Biscay and tuna purse-seiners in the Indian Ocean.

III.2.3. Focus on State-Space Models and Hidden-Markov Models

HMMs are a promising approach for fishery modellers. While somewhat overlooked by economists, HMMs have been employed the animal ecology literature.

Indeed, like the spatial analysis of the fishing activity, the study of movement patterns has also dramatically benefited from advances in geospatial tracking technologies. With GPS, electronic tags or telemetry techniques making individual movement data more generally available, research has boomed in trying to find the adequate modelling frameworks to analyze

those datasets (Shamoun-Baranes et al., 2012). Facing geospatial datasets especially prone to measurement errors (e.g., Argos data) which have been shown to induce substantial biases in the analyses (Bradshaw et al., 2007), ecologists usually favor the use of state-space models (SSMs) to reconcile in a consistent way the underlying data-generating mechanism with the observations. SSMs consist in combining a stochastic movement model with an observational model which includes measurement errors (Patterson et al., 2008). The advantage of such an approach is that the uncertainties of the statistical inferences obtained from SSMs will embed as well the uncertainties in the raw data.

Correlated random walks are among the simplest movement models that can be assumed, but they lack the ability to distinguish between possible different behavioral modes (states). For that reason, HMMs have become remarkably popular recently (Bennison et al., 2018; Joo et al., 2013; Whoriskey et al., 2017; Woillez et al., 2016). In HMMs behavior is modelled as a set of different modes characterized by distinct profiles of behavioral characteristics, usually speeds and turning angles. Their specificity lies in the assumption that data is generated through an unobserved stochastic Markov process specified with a transition matrix which can be recovered by the modeller. As such, the estimation of a HMM allows to recover parameters characterizing both the distributions of the behavioral variables and the probabilities of switch between modes. Thus, it provides a more holistic approach to characterize behavior than a discrete-choice model – which only focus on the probability of adopting a given mode –, or than a mode decomposition – which only focus on the identification of the distinct distributions of the behavioral variables.

HMMs are not free of certain pitfalls. To begin with, their estimation as part of a SSM can be challenging. While Maximum-Likelihood Estimation have been used assuming no measurement errors in the data, more advanced techniques using Bayesian Monte-Carlo

Estimation have successfully released this assumption (Patterson et al., 2008). In addition, regardless of data accuracy in terms of location, some studies have shown that the reliability of HMMs can be highly sensitive to the time frequency of data acquisition, an issue that can be further exacerbated by data interpolation (Vermard et al., 2010). In this study we propose a modelling approach that allows to use HMMs to draw inferences about the change in the behavior of fishers after shifting to an IFQs regime, while circumventing both these issues.

III.3. Modelling framework

The modelling framework we implement is based on Michelot et al. (2017) and consists of two steps. First, we regularize the geospatial data by using a SSM that allows both the filtering of outliers and the interpolation of the observations at a higher time frequency. The SSM we implement models the movement process as a simple first-difference correlated random walk (DCRW) and assumes that observations are recorded with fixed measurement errors. In a second step, we use the regularized data to estimate a HMM of fishing behavior that assumes three distinct behavioral modes.

III.3.1. Data regularization with a SSM

In its most general form a SSM combines a data-generating process $\mathbf{x}_t = g(\mathbf{x}_{t-1}, \boldsymbol{\eta}_t)$ that includes a random component η_t, with a related data-acquisition model $\mathbf{y}_t = h(\mathbf{x}_t, \boldsymbol{\varepsilon_t})$ that bears some measurement errors ε_t. In this study, we follow Jonsen et al. (2005) and Michelot et al. (2017) and we assume that movements proceed from a DCRW such that:

$$\Delta\mathbf{x}_{t+1} \sim \boldsymbol{\mathcal{R}}(\theta_t)\Delta\mathbf{x}_t + \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}) \text{ (Eq. III.1)}$$

where $\mathbf{x}_t = \begin{bmatrix} lon_t \\ lat_t \end{bmatrix}$ denotes the location, θ_t the mean turning angle, $\boldsymbol{\mathcal{R}}(\theta_t) = \begin{bmatrix} \cos\theta_t & -\sin\theta_t \\ \sin\theta_t & \cos\theta_t \end{bmatrix}$ the rotational component of the movement and $\Delta\mathbf{x}_t = \mathbf{x}_t - \mathbf{x}_{t-1}$is the change between two

successive locations. θ_t follows a von Mises distribution[3] $\theta_{t+1} \sim \text{vonMises}(\theta_t, \kappa)$ and $\mathbf{\Sigma} = \begin{bmatrix} \sigma_{lon}^2 & \rho\sigma_{lon}\sigma_{lat} \\ \rho\sigma_{lon}\sigma_{lat} & \sigma_{lat}^2 \end{bmatrix}$ is the correlation matrix between longitude and latitude.

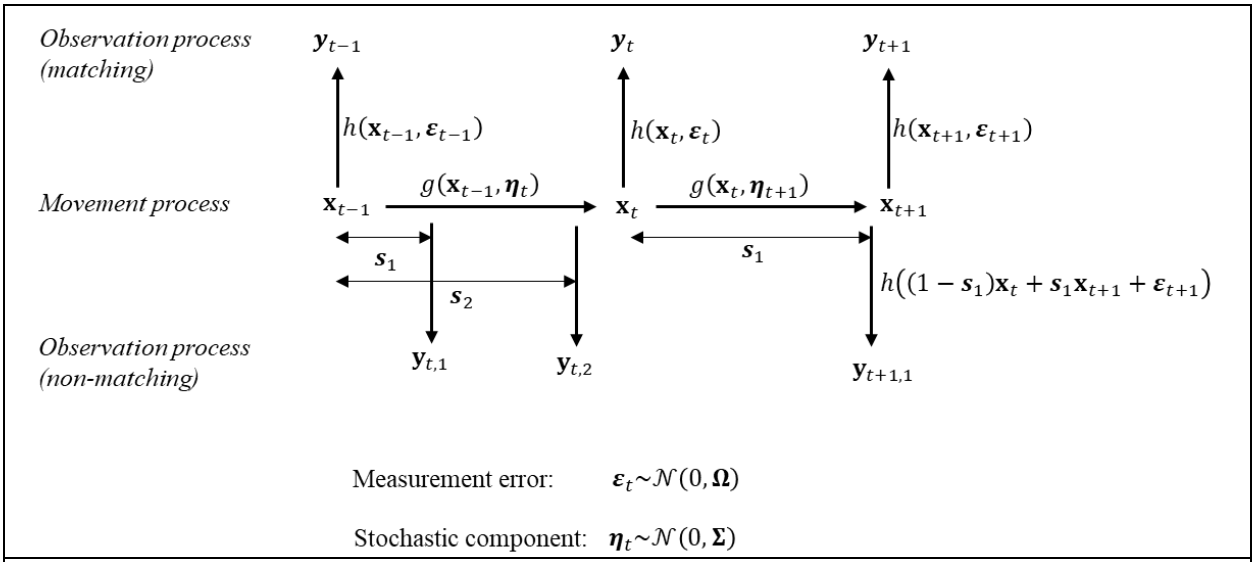

Figure III.1. Conceptual graph of a State-Space Model with an observational process that does not match the time support of the movement process.

In the observational model, we account for the irregularity in the frequency of data recordings by indexing with $i \in [\![1..n_t]\!]$ the observations – if any – between t and $t-1$. Assuming a straight line movement between t and $t-1$, the model writes:

$$\mathbf{y}_{t,i} = (1 - s_i)\mathbf{x}_{t-1} + s_i\mathbf{x}_t + \boldsymbol{\varepsilon}_t \text{ (Eq. III.2)}$$

With $\boldsymbol{s_i}$the share of the regular time interval between $\mathbf{x}_t$ and $\mathbf{x}_{t-1}$at which the observation $\mathbf{y}_{t,i}$is made, and $\boldsymbol{\varepsilon_t} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Omega})$the measurement error with zero mean and a time-invariant standard deviation[4] (see Figure III.1).

[3] A von Mises distribution is a continuous distribution on a circle that is a good approximation for a wrapped normal distribution (a normal distribution on a circle).
[4] That we set at 10m.

III.3.2. HMM

Generally speaking, HMMs are merely a particular case of SSMs which allows the movement process to follow different probability distributions – different modes or states. Decomposing movement data into step lengths (essentially speeds when the time interval is fixed) and turning angles such that $\mathbf{x}_t = d_t \boldsymbol{\mathcal{R}}(\theta_t)$, gives for instance with two modes:

$$d_t \sim \begin{cases} \Gamma(\mu_1, \sigma_1) \text{ if mode } 1 \\ \Gamma(\mu_2, \sigma_2) \text{ if mode } 2 \end{cases} \text{(Eq. III.3) and } \theta_t \sim \begin{cases} \text{vonMises}(\alpha_1, \kappa_1) \text{ if mode } 1 \\ \text{vonMises}(\alpha_2, \kappa_2) \text{ if mode } 2 \end{cases} \text{(Eq. III.4)}$$

In addition, in HMMs the succession of the different modes is assumed to follow a Markov chain, with the state of the system at time t depending of the state at $\mathrm{t} - 1$. Describing the state of the system with the probabilities of realization of each mode $\Pi_t = [\mathbb{P}_t(mode\ i)]$, and assuming a linear dependency, the state process can be modelled through a transition matrix $\mathbf{T}_{\boldsymbol{t}} = [\gamma_t^{ij}]$:

$$\boldsymbol{\Pi}_{\boldsymbol{t+1}} = \mathbf{T}_{\boldsymbol{t}} \boldsymbol{\Pi}_{\boldsymbol{t}} \text{ (Eq. III.5)}$$

with γ_t^{ij} being the probability of switching from mode *j* to mode *i*. Note that the transition probabilities can vary across time and may depend on covariates $\boldsymbol{z}_t$ such that $\mathbf{T}_{\boldsymbol{t}} \equiv \mathbf{T}(\boldsymbol{z}_{\boldsymbol{t}})$.

Besides facilitating the interpretation of model's parameters, the advantage of assuming a linear state process is that it makes the estimation stage less difficult by permitting the use of recursive algorithms that maximize the likelihood function to obtain the parameters.

III.3.3. Estimation strategy

As mentioned earlier, the main motivation for ecologists to use SSMs for modelling movement data is to integrate the uncertainty due to data unreliability with the estimation of the behavioral model so as to be able to draw inferences with appropriate confidence intervals.

However, this is not the approach we undertake for two reasons. First, the joint estimation of the observational model with a behavioral model, such as a HMM, increases dramatically the complexity of the estimation strategy along with the computational burden (e.g., see Box 2. in Patterson et al., 2008). Second, measurement errors in the data should not be a major concern in our case.

The time resolution we assume – 60 min –, and the typical distribution of speeds we observe – larger than one knot – imply that two observations are typically more than about 1,800 m apart. With the accuracy of our VMS data being about 15 m, measurement errors can therefore be reasonably assumed to be negligible. Instead we focus on resolving the time inconsistency of the data, which instead of following a regular 1h frequency can display a more erratic time support.

Given these challenges, we proceed to estimate the steps independently. First, we estimate SSMs with underlying DCRW movement models for each fishing trip. That allows us to obtain regularized data with a constant time interval between two positions. Then, using the regularized data, we estimate the HMMs for each vessel. In the first stage, we assume a non-linear stochastic process with the DCRW. As such, maximum likelihood estimation is not an option and we use Bayesian Monte-Carlo methods implemented using the *bsam* package in R (Jonsen et al., 2017). In the second stage, we focus on the estimation of the transition probabilities and since the switching process between the modes is linear, maximum likelihood estimation can be implemented. For this estimation, we make use of the *moveHMM* package in R (Michelot, 2018).

The main challenge for the estimation of the HMM is to be able to find the global maximum of the likelihood estimator and to prevent the optimizing algorithm to be attracted by a local maximum. Therefore, it is essential to provide the algorithm with a smart initial guess for the

vector of parameters to estimate, and to test the robustness of the estimation using various initial conditions.

III.4. Empirical Setting, model specification and validation approach

III.4.1. Background on fisheries in the Gulf of Mexico

For this study, we focus on the bottom longline (BLL) sector of the Gulf of Mexico reef fish (GoMRF) fishery. Undergoing a long-term scenario of resource depletion and partial recovery (GMFMC 2006; 2008), the GoM commercial reef fishery has experienced profound changes in management measures over the years, with the implementation of total catch limits, fishery closed areas, minimum size limits, and, most recently, IFQs, for Red Snappers in 2007 and for Groupers and Tilefishes in 2010. The BLL sector experienced further disruptions in 2009 as a large part of the West coast of Florida were closed to longline fishing from May to October and hook limits were implemented as emergency actions to reduce sea turtle by-catch. Therefore

The Grouper-Tilefish IFQ (GT-IFQ) program is a multi-species program that was established with the explicit objective of reducing the overcapitalization of the fisheries that had resulted in quota overages and early closures in the past. For example, in 2004 and 2005, the SWG fishing season was shortened by 6-10 weeks, and between 2003 and 2009, the DWG and TF seasons were shortened by more than 50%. The anticipated benefits of the program were notably: an increased market stability; the elimination of quota closures; a more cost-effective and enforceable management; an improved safety at sea; and an increased flexibility for fishing operations that would result in a greater balance of social, economic, and biological benefits.

So far the GT-IFQ program seems to have been successful in meeting its objectives in terms of fishing efficiency, quotas enforcement and increase in the revenue per active vessel. The number

of vessels landing GT-IFQ species went down from 630 in average between 2007-2009 to about 440 over the 2010-2014 period, while the total ex-vessel value increased from about $14 million in 2010 to more than $31 million in 2014 (NMFS, 2015). In terms of impact on the fishing operations at sea, Watson at al. (2018) documented seasonal changes in the locations of fishing grounds (e.g., exploitation of shallower waters during the first half of the fishing season) as well as small, but significant, reductions in the duration of trips and in the distance travelled during a trip (between -5% to 15% depending on when in the fishing season).

III.4.2. Data

The fisheries in the GoM offer an exceptionally well-documented, data-rich research environment: logbooks for coastal fishing have been collected since 1993, spatial fishing data have been collected since mid-2006 by onboard observers (OBO) for a subset of the vessels and trips; and VMS data for all pelagic and reef fishing trips is available since 2007. For this study, we do not make use of the available logbook data and we focus mainly on the VMS data.

We do make use of the OBO data, to help us in the design and calibration of the HMM first, and, most importantly, to evaluate the validity of our estimated HMM. In this regard, we are, to our knowledge, the only study along with Walker and Bez's (2010) to use such a validation approach. Indeed, the only other work that has applied a HMM framework to a fishery context is Vemard et al. (2010) and they relied on scenarios of data configurations to assess the reliability of the predictions of their model.

Interested by the impact of the series of management measures in 2009 and 2010 at the individual level, we restricted our analysis to vessels that were both active prior (i.e., in 2007 and 2009) and after the policy changes (i.e., from 2011), that were using a bottom longline as their

main fishing gear and that had at least one trip with full OBO information[5]. This left us with 39 vessels accounting for 1335 pre-IFQ identified fishing trips and 1165 post-IFQ identified fishing trips[6], among which 82[7] had also OBO data (there were no pre-IFQ trips with OBO data).

Our identification strategy to assess quantitatively the impact of the GT-IFQ program on behaviors at sea consists in estimating the HMM described above for each of the 39 vessels two times: using either pre- or post-IFQ data[8]. We then show the change in the estimated parameters and the associated shifts in: 1) the speeds and turning angles distributions in each behavioral mode; 2) in the influence of the covariates in the transition probabilities. We analyze the results both at the individual level by showing the distribution of the estimated parameters, and at the fleet level by aggregating for each parameter the estimates across vessels using the median.

III.4.3. Bottom longline fishing sets

A bottom longline fishing set consists of three phases. First, a longline of baited hooks is deployed along the seabed, then it is left soaking for a given time, and finally it is hauled back to remove the fish and to be rebaited before being redeployed again. The duration of the three phases vary from vessel to vessel and from trip to trip and will mostly depends on the length of the longline (which can reach several nautical miles), fish abundance, operational accidents (e.g., the line

[5] Among which 37 had no missing fishing sets. 8 vessels had a trip with OBO data but only with missing fishing sets, so we discarded these vessels.
[6] We used a series of filters to identify the sequence of fishing trips for each vessel. In particular, we began by identifying VMS positions corresponding with vessels being in port and then we flagged outbound and inbound movements using a series of rules on speeds and time between the observations.
[7] Note that in Walker & Bez's study (2010) they had even fewer observed trips with only 11 out of 120.
[8] The data that feed the HMM is not the raw VMS data but result from the regularization procedure that we detailed in the previous section, interpolating observations at a 15min frequency (as opposed to ~1h).

parting during the haul), and fisher's own judgment. However, typical durations are 30 to 60 min for the deployment phase, 15 to 75 min for the soaking time and 1 to 2 hours for the hauling phase[9]. During both the deployment and hauling phases, the vessel keeps moving, and given the lengths of the processes compared with typical hook saturation times (about an hour), a standard strategy is to cruise back to the beginning of the line as soon as it has been totally deployed (fishers have only one line). Therefore, a longline fishing set will often appear as one vessel doing a round-trip along the same segment of a few nautical miles.

The number of longline sets during a trip is also heterogeneous. In our dataset, we observed a median of 28 sets per fishing trips (for a minimum of 2 and a maximum of 67), translating into fishing trips lasting on average 9 days (for a minimum of 1 and a maximum of 16).

III.4.4. Model specification

III.4.4.1. Behavioral modes

Based on empirical evidence from our observer data, we consider a HMM that decomposes fishers' behavior at sea in three distinct behavioral modes: a *Steaming* mode, where fishers travel from or to their homeport or cruise between two fishing sites; a *Drifting* mode, where fishers are not actively cruising or fishing; and, a *Fishing* mode, where fishers proceed to fishing operations.

The *Steaming* mode is characterized by high travelling speeds and turning angles highly concentrated toward 0, while the *Drifing* mode is characterized by low and more dispersed travelling speeds, and by a lowly concentrated distribution of turning angles. The pre-analysis with the observer data suggests that the distribution of speeds for those modes could be model with

[9] Based on the durations we observed in the OBO data (see section III.5.1 of the Appendix).

gamma distributions (Figure III.2) while the distribution of turning angles could be parametrized as von Mises distributions $\theta_t \sim \begin{cases} \text{vonMises}(\mu_1, \kappa_1) \text{ if } Steaming \\ \text{vonMises}(\mu_3, \kappa_3) \text{ if } Drifting \end{cases}$.

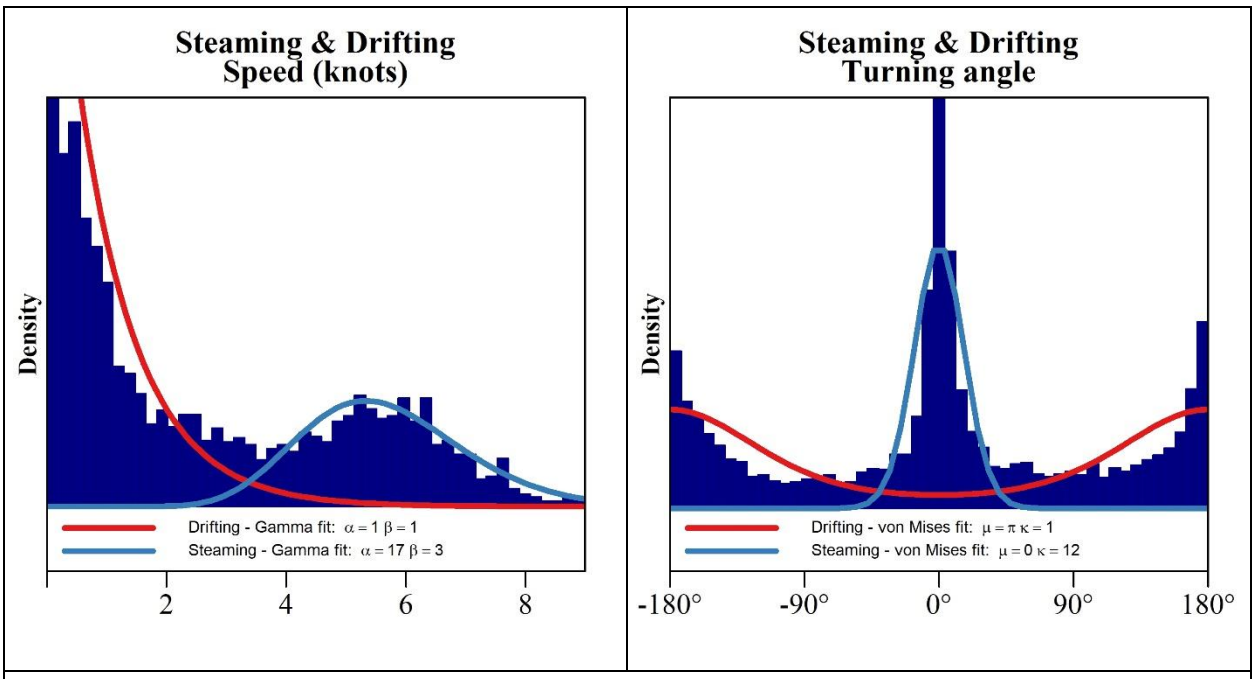

Figure III.2. Distributions of speeds and turning angle for observations not being identified as corresponding to fishing operations. Observations are from trips with complete on-board observer data, i.e. excluding trips with missing observed fishing sets. Examples of Gamma and von Mises fits for the *Drifting* and *Steaming* modes are presented in, respectively, red and blue lines.

At last, the *Fishing* mode is similar to the *Steaming* mode but with slightly lower and more dispersed speeds as well as less frequent direction changes with larger peaks at +/- 180 (Figure III.3). Note that here we include in the *Fishing* mode both the exploitation of targeted sites as well as the sampling of new ones. We keep exploiting and searching behaviors as one here, as our pre-analysis of speed, turning angles and soaking time distributions using observer data did not show evidence of distinct behavioral profiles in the case of longliners[10]. As well, fishing operations could

[10] In the case of vessels using a vertical line we only have very few observer data available (only five vessels) but the distribution of soaking times seems to result from the mixture of short setting

be further decomposed into a phase of setting of the gear, soaking and hauling of the gear. Again the pre-analysis with observer data did not display evidence of clear distinct behavioral modes between those three phases so we decided to keep them grouped together[11] (see section III.7.1 of the Appendix).

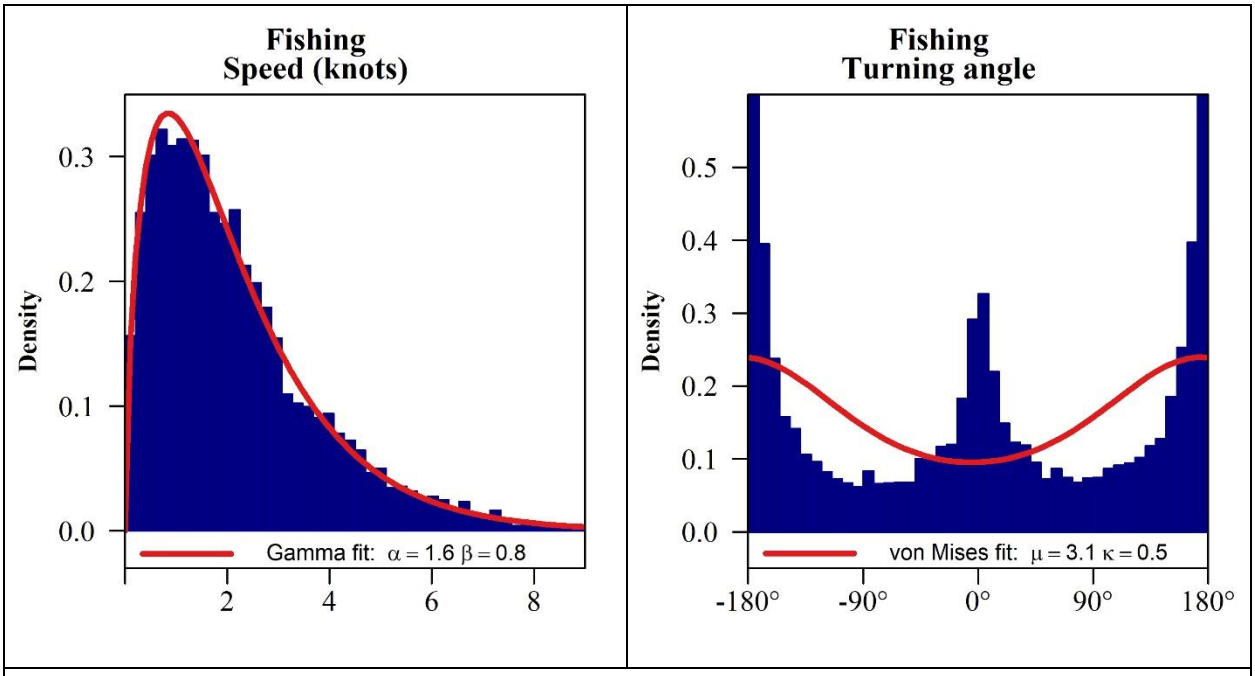

Figure III.3. Distributions of speeds and turning angle for observations identified as corresponding to fishing operations in the on-board observer data. Gamma and von Mises fits estimated by maximum likelihood are presented in red lines.

To summarize, we characterize the behavior of fishers at sea by a set of three behavioral modes, each described by a specific distribution of moving steps – equivalent to speeds – and a specific distribution of turning angles. We model the distribution of moving steps using Gamma

durations (sampling) with longer ones, which would allow for the identification of those two modes with the kind of simple HMM we present here.

[11] Note that even in the case of weak different behavior profiles, a way to help the identification of those modes would be to impose a specific structure to the transition matrix, forcing, for instance, the setting phase to be followed by the soaking phase which would be followed by the hauling phase.

distributions, while we model turning angles with von Mises distributions. All these distributions being defined by two parameters, the set of modes is described by $3 \times (2 + 2) = 12$ parameters.

III.4.4.2. Transition probabilities

The estimation procedure we employ allows flexibility in the parametrization of the transition probabilities in the sense that many covariates the modeller may have can be included. However, not only does this increases exponentially the computational burden and the numerical instability, but this makes more difficult the identification and the interpretation of the drivers of the switch between the modes. This is why the only two studies – to our knowledge – that have applied HMMs to fishers' behavior have assumed time-invariant transition probabilities (Vermard et al., 2010; Walker and Bez, 2010).

However, this is a strong assumption. In the context of BLL fishing, the probability that a fisher deploys its gear will likely depend on the bathymetry. From the subset of BLL trips that have OBO data, typical fishing depths lie in the range of 50 to 500 m deep. Moreover, fishers in the Gulf of Mexico are subjected to year-long and seasonal depth restrictions (e.g., any fishing below the 20 fathoms contour line is prohibited). We account for these restrictions by defining the dummy covariate $BLLrange_t$ that takes the value 1 when the fisher is located within the minimal authorized depth and 500m, and -1 when not. As well, even though some fishing operations such as hauling can be carried out at night, fishers mainly operate during the day and the crew is also likely to follow a schedule. For this reason, we define the dummy covariate Day_t that takes the value 1 between 6am and 10pm, and -1 the rest of the time[12].

[12] To avoid creating artificial abrupt changes and to allow for some tolerance around the boundaries we smooth the transition from 1 to -1 of the two dummy variables.

In order to keep a simple structure while ensuring that the states probabilities sum to 1 at each time, we include them linearly wrapped in logit function such that the probability of switching from mode j to mode i at time t is specified as:

$$\gamma_t^{ij} = logit\left(\beta_0^{ij} + \sum_k \beta_k^{ij} cov_k(t)\right) = \frac{e^{\beta_0^{ij} + \sum_k \beta_k^{ij} cov_k(t)}}{\sum_l e^{\beta_0^{lj} + \sum_k \beta_k^{lj} cov_k(t)}} \text{ (Eq. III.6)}$$

With a three modes structure, this implies to recover $3 \times (3 - 1) = 6$ transitions probabilities, each specified with $(1 + 2)$ parameters, meaning 18 parameters to be estimated.

$$\mathrm{T}_t = \begin{bmatrix} \gamma_t^{11} & \gamma_t^{12} & \gamma_t^{13} \\ \gamma_t^{21} & \gamma_t^{22} & \gamma_t^{23} \\ \gamma_t^{31} & \gamma_t^{32} & \gamma_t^{33} \end{bmatrix}$$

III.4.5. Validation approach

Having OBO data for a subset of vessels and a subset of trips, we are able to assess the prediction accuracy of a subset of estimated HMMs. Since OBO only record fishing operations (i.e., when and where fishing gears are set and hauled), we can only compute rates of prediction accuracy for the *Fishing* mode. We do so by simulating, for each observed fishing trips, the sequence of states obtained using the estimated parameters applied to the set of covariates associated to the trip.

To obtain predicted states for each observation, two methods are possible. One can either take a sequential approach and proceed to take random draws using the contemporaneous transition probabilities or one can consider the trip as a whole and recover the most probable sequence of states corresponding to the sequence of covariates. To avoid caring out computationally-intensive Monte Carlo simulations that would be required to estimate the prediction accuracy of the model using the first approach, we choose to keep the sequence of covariates fixed (i.e., not updating

with the states and movement realizations) and we take the second approach. We implement it using the Viterbi algorithm provided with the *moveHMM* R package.

III.5. Results

III.5.1. Model's validity

The HMM presented above was fitted for 39 vessels totaling 2500 trips – 1335 before 2010, 1165 after 2011 – representing 545,818 VMS observations.

Figure III.4 and Figure III.5 show the distributions, across vessels, of the estimated behavioral parameters for each of the modes in both pre- and post-IFQ periods. At both vessel and fleet levels estimates are consistent with the depiction of the modes from the observer data.

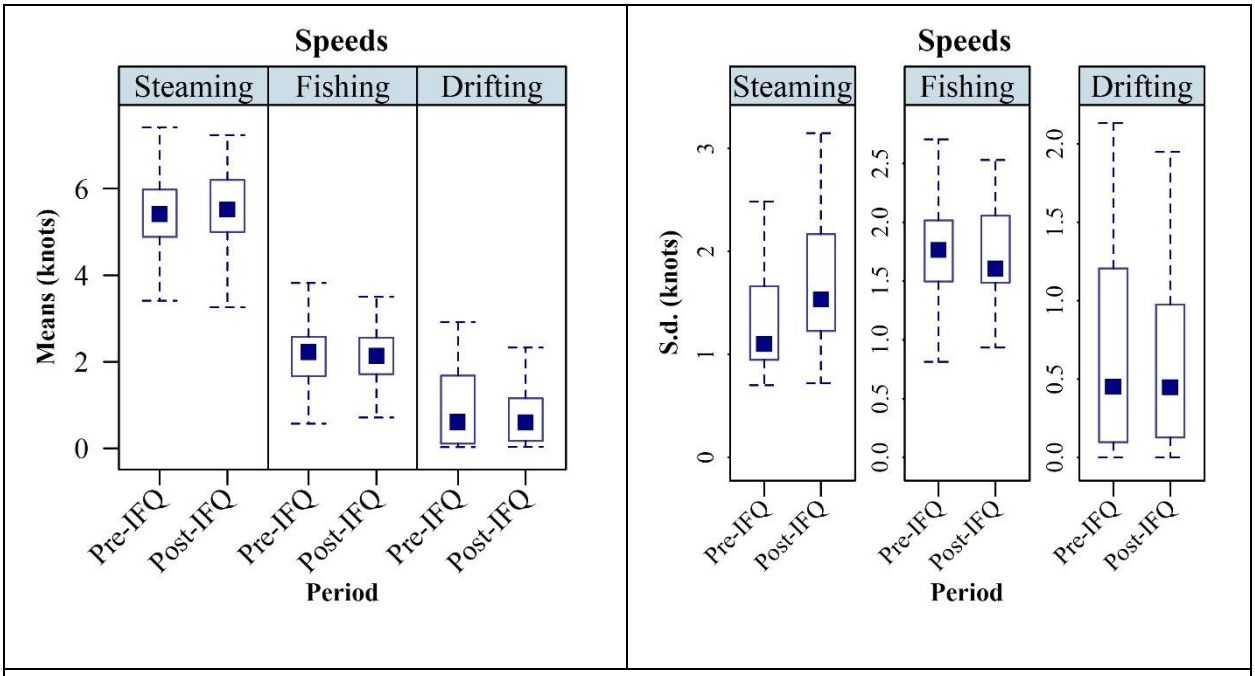

Figure III.4. Distribution of the estimated means (left panel) and standard deviations (right panel) of the speeds in each mode in the pre-IFQ and post-IFQ periods. The blue square dots denote the median value across vessels.

The *Steaming* mode is characterized by a distribution of speeds with a high mean (median: 5.4 and 5.5 knots for the pre- and post-IFQ period, respectively) and a large standard deviation

(median: 2.2 and 2.1 knots); and a distribution of turning angles centered at 0° with a high concentration (median κ: 67 and 31).

The distribution of speeds in the *Fishing* mode is found to have a lower mean than in the *Steaming* mode (median: 2.2 and 2.1 knots) but with a larger relative standard deviation (about the same as the mean: 1.8 and 1.6 knots). Strikingly, the distribution of turning angles is systematically found to be centered close to 180° with a relatively low concentration (median κ: 0.5 and 0.8). This is largely consistent with vessels going round-trip along the same segment when setting and hauling their longline.

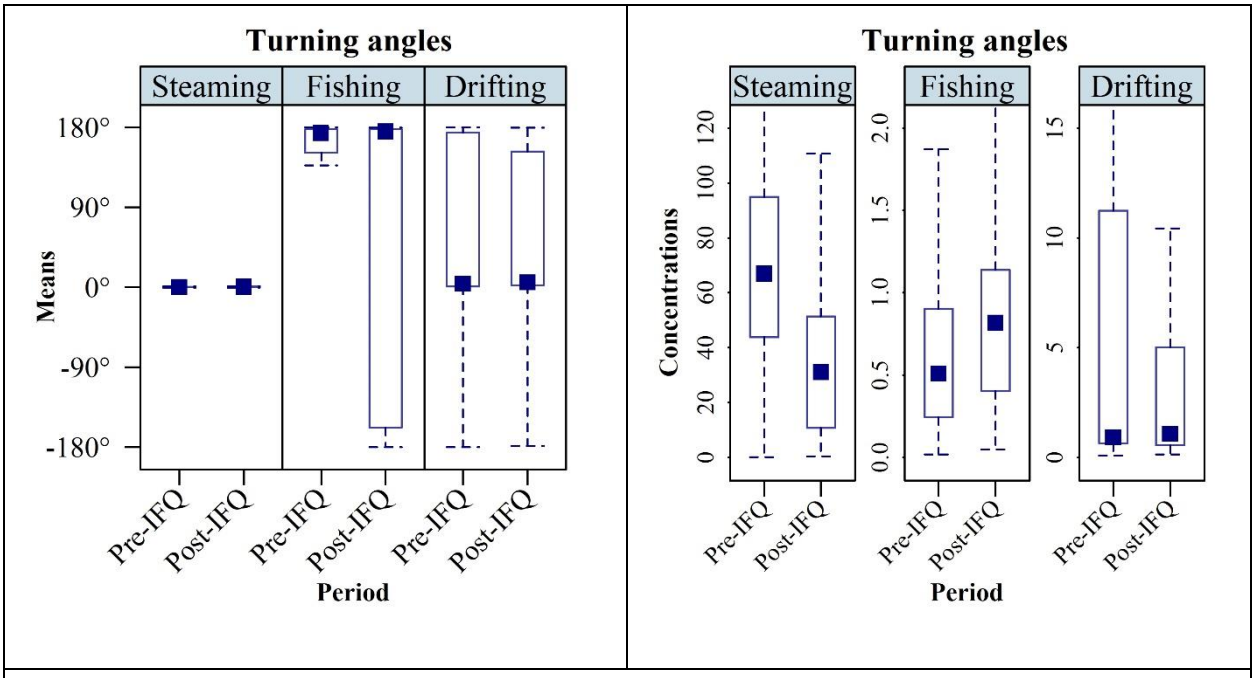

Figure III.5. Distribution of the estimated means (left panel) and concentrations (right panel) of the turning angles in each mode in the pre-IFQ and post-IFQ periods. The blue square dots denote the median value across vessels.

At last, also as we would expect, the distributions of speeds in the *Drifting* mode are found to be skewed toward 0 (medians: 0.6 knots for both periods). Contrary to the other two modes where the means and concentrations were extremely similar across vessels, the distributions of

turning angles present a broader variety of shapes with means varying from 0° to 180° (the median is close to 0 but the means are around 32° and 38°) and concentrations going from 0.1 to 149 (medians are 0.1 and 9). Highly concentrated distributions are surprising given that we would expect a vessel being drifting not follow any particular direction and being simply subjected to wind and local currents. Extremely high values of the concentration parameter likely result from a poor choice of convergence conditions in the optimization algorithm and would require a finer tuning, should time allows[13]. However, an explanation could be that the vessels which exhibit highly peaked turning angle distributions while drifting happened to have been systematically operating during the same strong wind and current conditions along all the trips we observe.

	Mean	*Min*	*Max*	*# obs*	*# trips*	*# vessels*
% FN	12	0	52	17,775	82	39
% FP	38	20	70	7,242	37	24
% P	56	12	93	17,775	82	39
# obs/trip	217	50	439			

Table III.a. Prediction accuracy for the *Fishing* mode of the HMM on the subset of observed trips. FN: False negatives; FP: False positives.

In line with those consistent characterization of the behavioral modes, the estimated HMMs for each of the vessels are found to perform relatively well in terms of prediction accuracy, even though they tend to over-predict fishing behavior (Table III.a). As illustrated by the example of decoded trip presented in Figure III.6 – and as we could have expected from our choice of covariates for the transition probabilities –, the model is good at capturing differences across day and night hours as well to changes in speeds, but it has more difficulties capturing switch of modes occurring during the day.

[13] As a point of comparison, Vermard et al. (2010) assumed concentration parameters from 0.2 to 0.9 in their simulations, and Michelot et al. (2017) estimates for elephant seals foraging trips range from 0.1 to 8.3.

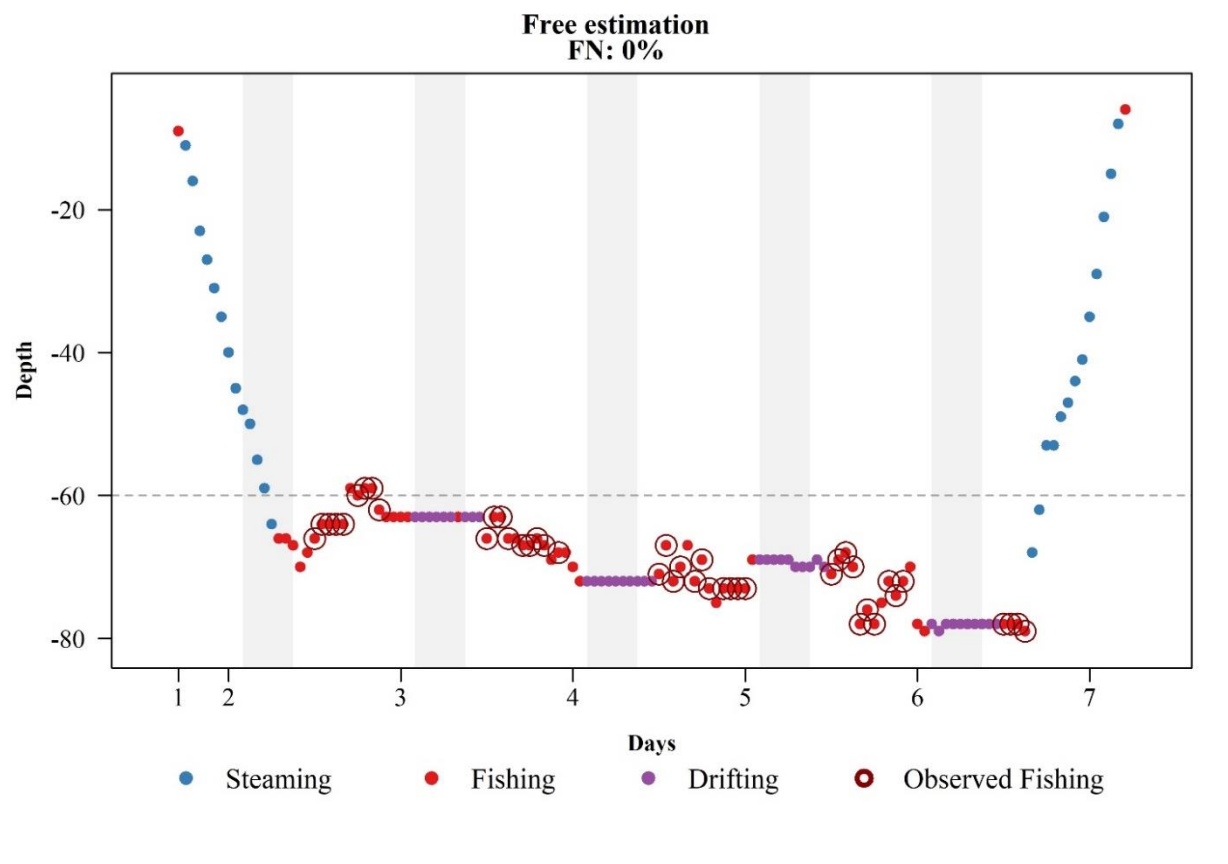

Figure III.6. Example of a fishing trip with OBO data and the decoded behavioral modes estimated with the HMM. Points corresponding to an observed fishing behavior are circled in red. In the example the are no false negative predictions, i.e., all the observations corresponding to fishing operations are correctly classified as such. Shaded areas indicate night hours and the grey dotted line indicates the minimal authorized fishing depth.

III.5.2. Behavioral impact of the GT-IFQ program

Collecting the set of behavioral parameters estimated for each vessel and for each pre- and post-IFQ period, we test for significant differences from one period to another, at both the vessel and fleet levels. At the vessel level, the two estimated values of the same parameter for both periods are considered significantly different if their 95% confidence intervals[14] do not intersect (all

[14] Confidence intervals are obtained through the Hessian of the maximum likelihood estimator which is approximated using forward simulations.

parameters' estimates with their 95% confidence intervals are reported in section III.7.2.1 of the Appendix). At the fleet level, significance in the differences is checked using boxplots and looking whether the medians of the estimates differed by more than their interquartile range.

As suggested by Figure III.4 and Figure III.5, looking only at the fleet level none of the behavioral parameters for the speed and turning angle distributions significantly differ from one period to the other. However, this result hides a strong heterogeneity between vessels. Whereas the means of the turning angle distributions indeed do not change from one period to the other for most of vessels, the pre- and post-IFQ comparison is much more contrasted for the other parameters (Figure III.6).

Regarding the means of the speed distributions, the directions of changes across vessels happen to be evenly distributed, with a third of the vessels exhibiting significantly lower mean speeds in the post-IFQ period, a third exhibiting no significant changes and the last third exhibiting significantly higher means. The same pattern more or less holds when looking at the standard deviations of the speeds, where significant increases or decreases in the dispersions of speeds are highly correlated with significant increases or decreases in the means of the speeds. For the concentration of the distributions of the turning angles, a majority of vessels show significantly less concentrated distributions in the post-IFQ period when *Steaming* while another majority of vessels show more concentrated ones when *Fishing*.

Looking, for the same behavioral parameter, how a significant change in one mode would correlate with a significant change in another mode, no consistent pattern emerges. For each combination of significant changes across two modes (e.g., an increase in the *Steaming* mode and a decrease in the *Fishing* mode, or an increase in the *Steaming* mode and a decrease in the *Drifting* mode), the most of vessels show no specific relationship between the changes. The same result

applies when looking at correlations between absences of significant changes. A vessel exhibiting no significant change in one mode is more – rather than less – likely to exhibit a significant change in another mode.

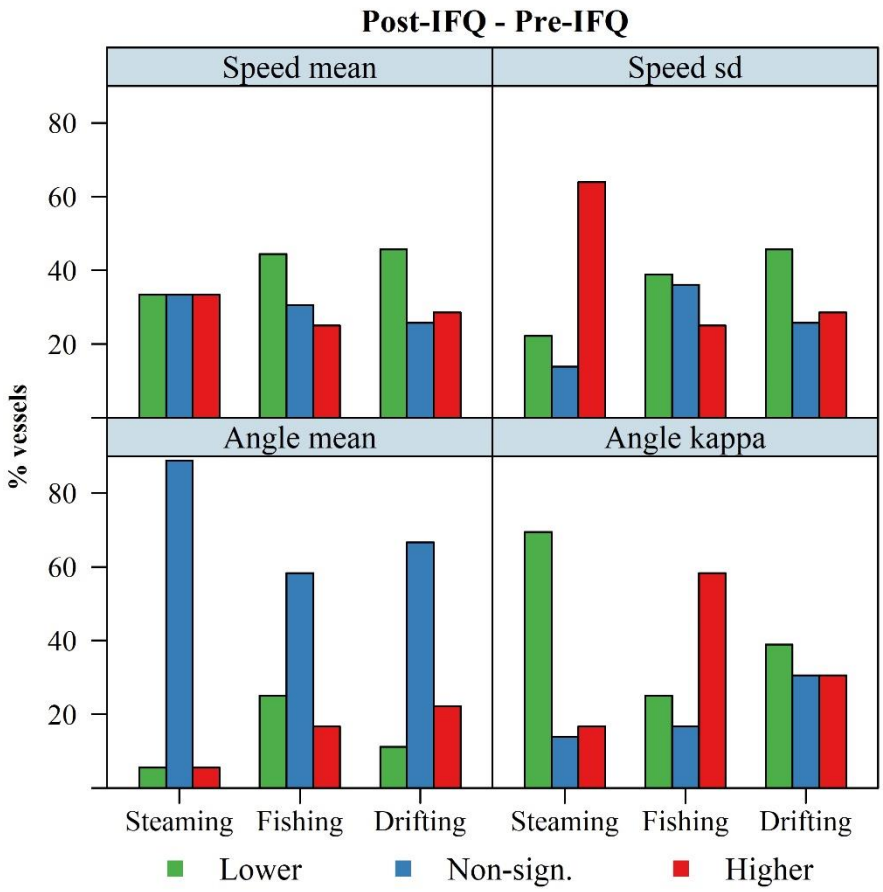

Figure III.6. Distribution of pre- and post-IFQ differences in the behavioral parameters for the speed and turning angle distributions. Differences are classified as: 1) "Lower" when estimates are significantly lower in the post-IFQ period (green bars on the left); 2) "Non-sign." when there is no significant difference between the estimates in both periods (blue bars in the middle); or 3) "Higher" when estimates are significantly higher in the post-IFQ period (red bars on the right).

At last, regarding the transition probabilities between modes vessels display a more homogeneous trend by showing most of the time no significant differences in the pre- and post-IFQ estimates (see section III.7.2.2 of the Appendix).

III.6. Discussion and conclusion

In this study we demonstrate how a structural model of fishing behavior can be successfully estimated relying on movement data collected for monitoring purpose, and how it can be used to identify and characterize behavioral changes following the implementation of a new policy. The model we consider is a Hidden-Markov Model (HMM) with three behavioral modes. We apply it to longline fishers in the Gulf of Mexico, focusing on changes subsequent new regulatory rules on gear specification along with the implementation of individual fishing quotas. The modelling framework as well as the kind of data we used is similar to two previous fishery studies by Vermard et al. (2011) and Walker et Bez (2011), and build substantially on estimation approaches developed in the ecology literature (Jonsen et al., 2005; Michelot et al., 2017). However, our work presents four major contributions.

First, we show how simple state-space models can be used to resolve possible temporal irregularities in the geospatial vessel data and how they can be employed to interpolate the data at finer resolutions in a way that is consistent with the level of spatial accuracy of the device recording the data. Not only this is important for computational purposes as it allows to provide regularized data to the optimizing algorithm, but it also gives researchers more flexibility in the choice of the temporal scale of analysis. As previous works have shown (e.g., Depalle et al., 2018; Patterson et al., 2008; Walker and Bez, 2010), this latter aspect is fundamental for the reliability and the coherence of the models, which have to be in line with the reality of the behavioral processes they aim to capture.

In addition to this novelty, our modelling framework is richer than Vermard et al.'s (2011) or Walker et Bez's (2011) in the sense we allow the transition probabilities to depend on exogenous covariates. This gives the model more flexibility to properly capture the switches between the

modes. In our case, it allows us to account for fishers' schedule during the day as well as habitat and regulatory constraints.

Another unique feature of our study that is shared only with Walker et Bez's (2011), is the use of on-board observer data to validate the consistency of model estimates and to evaluate its accuracy. Such an approach is essential to demonstrate the operationality of our modelling framework that would remain purely theoretical otherwise. In our case, we show that the models we estimate are excellent at detecting fishing behavior though it tends to over-predict it about a third of the time.

At last, our analysis distinguishes itself by its core purpose. We are the first one – to our knowledge – to use the powerful modelling framework that are HMMs to investigate behavioral changes in a fishery that may be triggered by a policy intervention. In this regard, our comparative analysis of the behavioral characteristics of 39 commercial fishing vessels that were active in the bottom longline Grouper-Tilefishes (BLL-GT) fishery in the Gulf of Mexico before and after the implementation of new gear restrictions and individual fishing quotas (IFQs) in 2009 and 2010 provides evidence of strongly heterogenous changes in vessels' behavior at sea.

In particular, we find that each of the vessels in our sample exhibits at least one significant change across one, if not many, dimension of their behavior at sea. More importantly, we find that those heterogenous changes *could not have been captured* should we had looked at *vessels as a homogenous fleet*. These results are strong findings. They imply that fishery managers cannot overlook individual specificities when carrying out *ex-ante* or *ex-post* policy evaluation, even within a seemingly homogenous set of vessels using *the same fishing gear* and targeting *the same species*.

Accounting for the heterogeneity of fishers' response is crucial for assessing the impact of a policy. Not only this is necessary to identify who would be the potential "losers" or "winners" of a policy intervention in the short-term, but this is also essential to anticipate the long-term impact of the intervention on the fishery as whole. In our case, the fact the 2009-10 set of management interventions in the BLL-GT fishery led to a diversity of behavioral responses while achieving their short-term objectives of fleet consolidation and higher profits for fishers can be seen as a positive outcome for the sustainability of fishing activities in the long-term. Indeed, the rationalization of the fishery, by consolidating around the most economically efficient vessels, could have led to a greater homogenization of the fleet in terms of fishing strategies. Our results suggest that it was not the case as the overall profile of fishing behaviors remained unchanged and did not converge toward a specific set of behaviors. Such a homogenization could be detrimental for the resiliency of the fishery in the future as it could question fishers' capability to adapt to changing environmental conditions.

At the same time, we do not find evidence of significant changes in the propensity of fishers to switch from one mode to another. Regarding that aspect, we do not find in particular that vessels are less likely to be fishing at night while previous studies could have suggested so, documenting better working conditions and less exposure to risk under an IFQ system (McCay, et al., 1995; Pfeiffer and Gratz, 2016).

As a first example of the quantitative assessment of the behavioral effects of the implementation of IFQs in a fishery using HMMs, we believe our work opens up exciting opportunities for improving our understanding of fishers' behavior and for anticipating their response to new policies. In this regard, a unique feature of our model that we do not exploit in this study is its capacity to perform simulations of realistic movement tracks for the vessels

(Michelot et al., 2017). Focusing on fishery management, this can prove to be both an appealing and powerful tool for managers. It can help them to directly visualize and assess the spatial effects of a new regulatory measure (e.g., a more stringent depth restriction in the case of the BLL-GT fishery) without being constrained to the set of spatial patterns observed in the past.

Further improvement of the model could focus on the inclusion of additional covariates that are susceptible to influence the probability of switching from one mode to another. In particular, the influence of the seabed habitat could be included explicitly instead of being proxied by depth. Also, the state of the sea and weather could be taken into account as harsher weather conditions are expected to impact the duration and the number of fishing operations for instance. At last, the interactions with other users of the sea could be also better accounted. For example, the proximity of other fishing vessels or the intensity of the nearby maritime traffic could be included.

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III.7. Appendix

III.7.1. Behavioral profile of longline fishing operations

The on-board observer (OBO) data we used contain information about the time of start and end of both the deployment and the hauling of the longline gear. Matching this data with the corresponding VMS records enables us to document the profiles of each of the different phases of a bottom longline fishing set in terms of duration, speed and turning angle distributions. Those profiles may change from vessel to vessel, but their shapes remain largely comparable. Here we give the distributions of durations (Figure III.7.1.1), speeds (Figure III.7.1.2) and turning angles (Figure III.7.1.3), of the deployment, soaking and hauling phases of 4860 sets from 163 observed trips of 39 vessels between February 2010 and March 2014. The similarities of the speeds and turning angles profiles led us not to distinguish these three phases in the model, and to consider them as a whole.

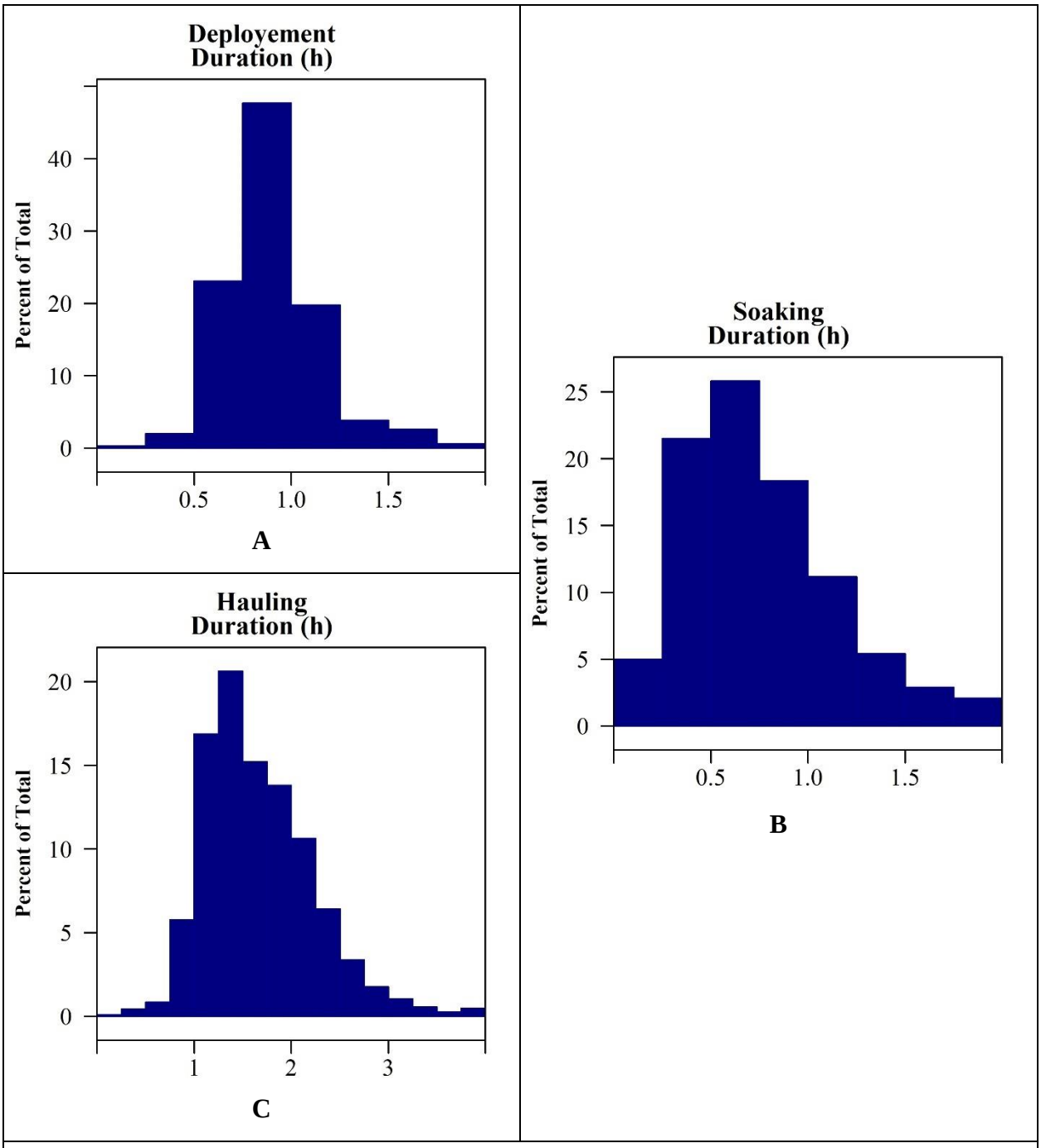

Figure III.7.1.1. Distributions of the duration of the deployement (A), Soaking (B) and Hauling (C) phases of the observed fishing sets in the OBO data.

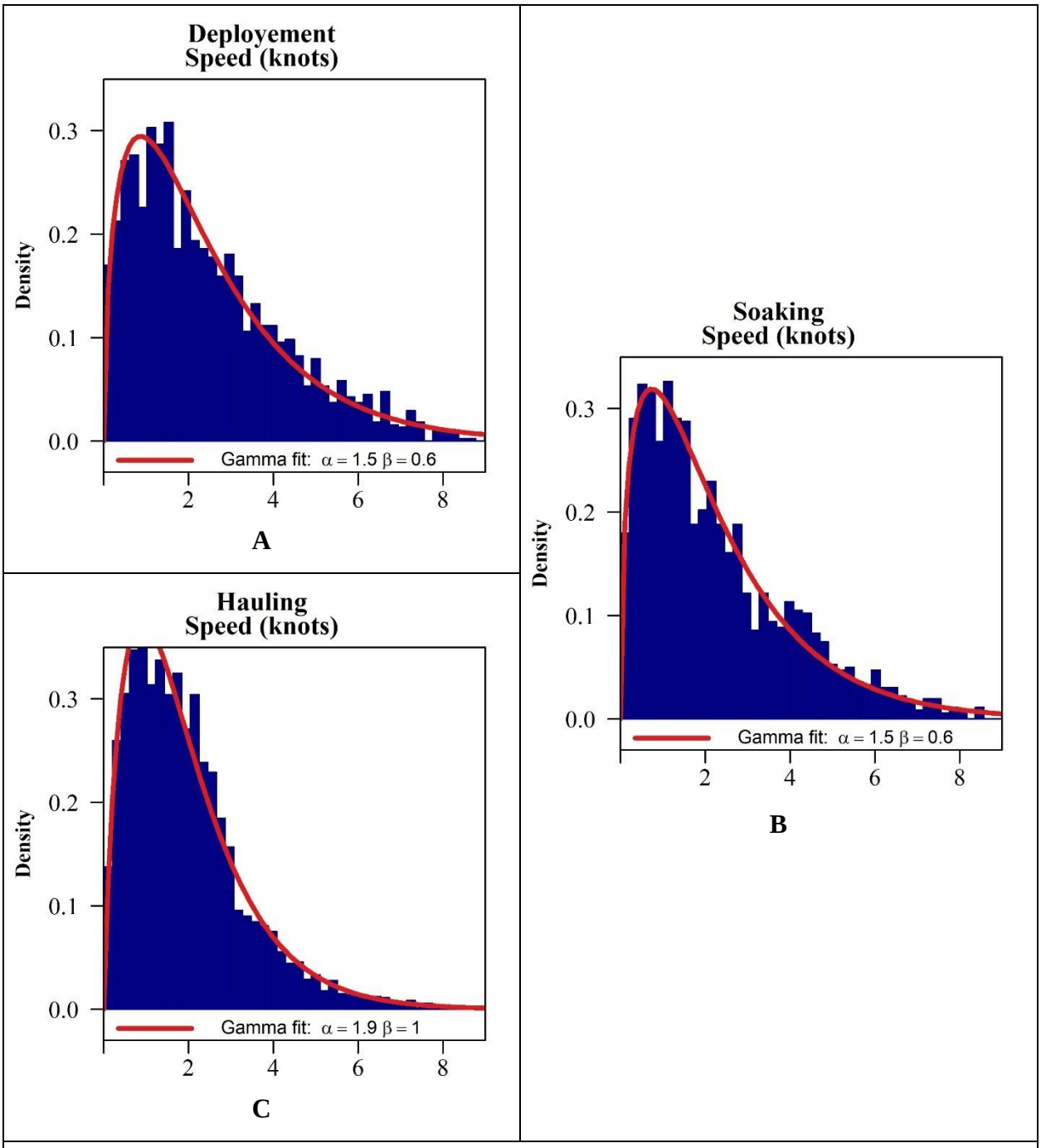

Figure III.7.1.2. Distributions of vessels' speeds during the deployement (A), Soaking (B) and Hauling (C) phases of the observed fishing sets in the OBO data. A gamma fit of the distributions is shown in red for each phase. The distributions are extremely similar.

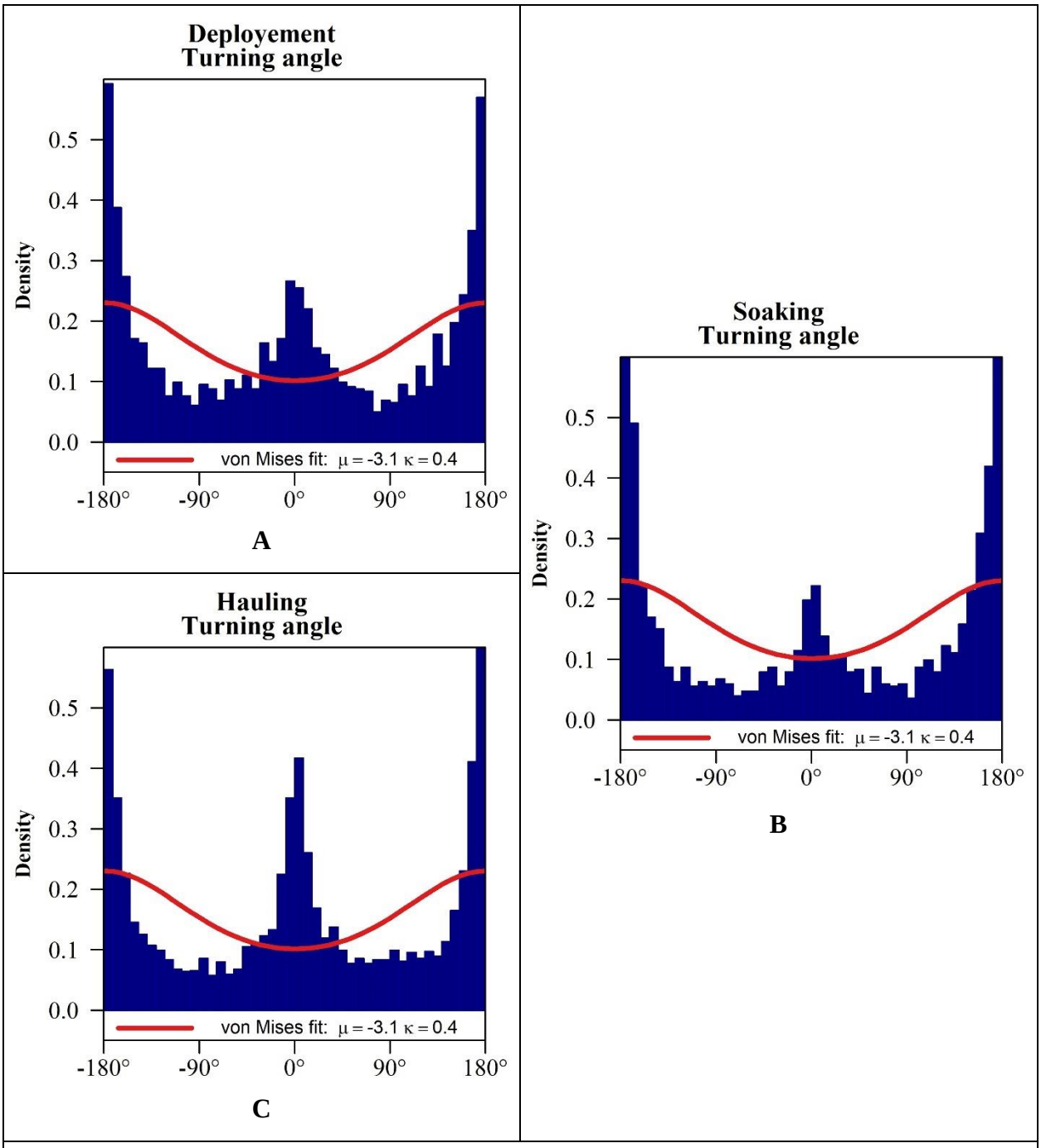

Figure III.7.1.3. Distributions of vessels' turning angles during the deployement (A), Soaking (B) and Hauling (C) phases of the observed fishing sets in the OBO data. A von Mises fit of the distributions is shown in red for each phase. The distributions are extremely similar.

III.7.2. Models' estimates

III.7.2.1. Estimates of speed and turning angle parameters for each vessel

Vessel #	*Modes*	*Para.*	*Pre-IFQ*	95% C.I.	*Post-IFQ*	95% C.I	Δ	*Sign.*
1	Steaming	Speed μ	3.2	[2.9;3.5]	4.2	[NA;NA]	1	NA
1	Steaming	Speed σ	2.8	[2.6;3]	4.4	[NA;NA]	1.6	NA
1	Steaming	Angle μ	0.00	[-0.13;0.13]	0.03	[NA;NA]	0.03	NA
1	Steaming	Angle κ	0.7	[0.54;0.87]	1.2	[NA;NA]	0.47	NA
1	Fishing	Speed μ	0.22	[0.2;0.25]	0.71	[NA;NA]	0.49	NA
1	Fishing	Speed σ	0.25	[0.22;0.28]	0.93	[NA;NA]	0.69	NA
1	Fishing	Angle μ	3.1	[3.1;3.2]	3.1	[NA;NA]	-0.04	NA
1	Fishing	Angle κ	0.84	[0.78;0.9]	0.92	[NA;NA]	0.08	NA
1	Drifting	Speed μ	2.3	[2.3;2.4]	1.6	[NA;NA]	-0.73	NA
1	Drifting	Speed σ	1.5	[1.4;1.5]	0.13	[NA;NA]	-1.3	NA
1	Drifting	Angle μ	3.1	[3.1;3.1]	-3.1	[NA;NA]	-6.2	NA
1	Drifting	Angle κ	78	[71;86]	150	[NA;NA]	71	NA
2	Steaming	Speed μ	5.7	[5.7;5.8]	5.7	[5.7;5.8]	0	No
2	Steaming	Speed σ	0.96	[0.91;1]	0.96	[0.91;1]	0	No
2	Steaming	Angle μ	0.01	[0;0.01]	0.01	[0;0.02]	0.01	No
2	Steaming	Angle κ	67	[60;73]	31	[28;35]	-36	Yes
2	Fishing	Speed μ	2	[2;2.1]	2.1	[2.1;2.2]	0.07	No
2	Fishing	Speed σ	1.6	[1.5;1.6]	1.6	[1.5;1.6]	0	No
2	Fishing	Angle μ	3	[2.7;3.3]	3.1	[3;3.2]	0.07	No
2	Fishing	Angle κ	0.1	[0.06;0.13]	0.35	[0.31;0.38]	0.25	Yes
2	Drifting	Speed μ	0.08	[0.06;0.1]	0.18	[0.16;0.2]	0.1	Yes
2	Drifting	Speed σ	0.07	[0.05;0.1]	0.21	[0.19;0.24]	0.14	Yes
2	Drifting	Angle μ	3	[2.9;3.2]	3.1	[3.1;3.2]	0.1	No
2	Drifting	Angle κ	0.64	[0.51;0.77]	1.1	[0.97;1.2]	0.44	Yes
3	Steaming	Speed μ	1.9	[1.9;2]	5.2	[5.1;5.3]	3.3	Yes
3	Steaming	Speed σ	1.7	[1.6;1.7]	1.1	[1;1.2]	-0.57	Yes
3	Steaming	Angle μ	3.1	[3.1;3.2]	0.02	[0;0.04]	-3.1	Yes
3	Steaming	Angle κ	0.73	[0.69;0.78]	15	[13;17]	14	Yes
3	Fishing	Speed μ	0.22	[0.2;0.24]	1.5	[1.5;1.6]	1.3	Yes
3	Fishing	Speed σ	0.27	[0.25;0.29]	1.7	[1.6;1.8]	1.5	Yes
3	Fishing	Angle μ	3.1	[3.1;3.2]	3.1	[3;3.1]	-0.07	No
3	Fishing	Angle κ	1	[0.91;1.1]	0.87	[0.81;0.94]	-0.13	No
3	Drifting	Speed μ	4.7	[4.6;4.8]	0.82	[0.78;0.86]	-3.9	Yes
3	Drifting	Speed σ	1.2	[1.1;1.2]	0.45	[0.42;0.49]	-0.71	Yes
3	Drifting	Angle μ	0	[-0.01;0.01]	0.07	[0.04;0.09]	0.07	Yes
3	Drifting	Angle κ	46	[40;53]	9.1	[7.8;10]	-37	Yes

4	Steaming	Speed μ	5.3	[5.2;5.3]	5.3	[5.2;5.4]	0.05	No
4	Steaming	Speed σ	1.1	[1;1.1]	1.7	[1.6;1.8]	0.62	Yes
4	Steaming	Angle μ	0.01	[0;0.02]	0.02	[0.01;0.02]	0.01	No
4	Steaming	Angle κ	60	[55;65]	70	[64;75]	10	No
4	Fishing	Speed μ	2.2	[2.2;2.3]	3	[2.9;3.2]	0.82	Yes
4	Fishing	Speed σ	1.9	[1.9;2]	2.4	[2.3;2.5]	0.48	Yes
4	Fishing	Angle μ	3	[2.9;3.1]	3.1	[3;3.1]	0.09	No
4	Fishing	Angle κ	0.46	[0.4;0.52]	2	[1.8;2.2]	1.5	Yes
4	Drifting	Speed μ	1.6	[1.6;1.7]	1.8	[1.8;1.9]	0.19	Yes
4	Drifting	Speed σ	1.2	[1.1;1.3]	1.4	[1.3;1.4]	0.18	Yes
4	Drifting	Angle μ	0.04	[0.03;0.05]	0.03	[-0.01;0.06]	-0.01	No
4	Drifting	Angle κ	13	[12;15]	1.5	[1.4;1.5]	-12	Yes
5	Steaming	Speed μ	2.3	[2.3;2.4]	4.7	[4.5;5]	2.4	Yes
5	Steaming	Speed σ	2.3	[2.2;2.4]	2.7	[2.5;3]	0.44	Yes
5	Steaming	Angle μ	3.1	[3;3.3]	0.04	[-0.02;0.09]	-3.1	Yes
5	Steaming	Angle κ	0.36	[0.31;0.41]	3.2	[2.8;3.5]	2.8	Yes
5	Fishing	Speed μ	0.57	[0.52;0.63]	0.91	[0.88;0.95]	0.34	Yes
5	Fishing	Speed σ	0.81	[0.74;0.9]	1.2	[1.2;1.3]	0.39	Yes
5	Fishing	Angle μ	3.1	[3;3.2]	3.1	[3.1;3.2]	0	No
5	Fishing	Angle κ	0.83	[0.75;0.91]	0.82	[0.77;0.87]	-0.01	No
5	Drifting	Speed μ	1.4	[NA;NA]	1.4	[NA;NA]	0	NA
5	Drifting	Speed σ	0.00	[NA;NA]	0.00	[0;0]	0.00	NA
5	Drifting	Angle μ	-0.62	[-3.2;-3.1]	-0.55	[-0.55;-0.55]	0.07	Yes
5	Drifting	Angle κ	18	[0.75;0.91]	19	[19;19]	0.81	Yes
6	Steaming	Speed μ	4.9	[4.8;5]	5	[4.9;5.1]	0.13	No
6	Steaming	Speed σ	0.92	[0.87;0.98]	1.5	[1.4;1.6]	0.6	Yes
6	Steaming	Angle μ	0.01	[0;0.01]	0	[-0.01;0.01]	0	No
6	Steaming	Angle κ	100	[91;110]	45	[40;50]	-56	Yes
6	Fishing	Speed μ	2	[2;2.1]	1.9	[1.8;1.9]	-0.2	Yes
6	Fishing	Speed σ	1.5	[1.4;1.5]	1.4	[1.4;1.4]	-0.09	Yes
6	Fishing	Angle μ	3	[2.9;3.1]	3.1	[3;3.2]	0.08	No
6	Fishing	Angle κ	0.42	[0.38;0.47]	0.58	[0.54;0.63]	0.16	Yes
6	Drifting	Speed μ	0.06	[0.06;0.07]	0.08	[0.08;0.08]	0.02	Yes
6	Drifting	Speed σ	0.06	[0.06;0.06]	0.07	[0.06;0.07]	0.01	No
6	Drifting	Angle μ	3.1	[3;3.2]	3.1	[3;3.2]	0.02	No
6	Drifting	Angle κ	0.77	[0.7;0.84]	0.79	[0.72;0.85]	0.02	No
7	Steaming	Speed μ	2.3	[2.2;2.4]	2.4	[2.3;2.6]	0.13	No
7	Steaming	Speed σ	2.2	[2.1;2.3]	2.6	[2.4;2.8]	0.41	Yes
7	Steaming	Angle μ	0.11	[-0.21;0.47]	0.17	[0.02;0.34]	0.06	No
7	Steaming	Angle κ	0.17	[0.09;0.26]	0.5	[0.37;0.63]	0.33	Yes
7	Fishing	Speed μ	1.7	[1.6;1.7]	1.3	[1.2;1.3]	-0.38	Yes

7	Fishing	Speed σ	1.4	[1.3;1.5]	1.1	[1;1.2]	-0.34	Yes
7	Fishing	Angle μ	3.1	[3.1;3.2]	3.1	[3.1;3.2]	0	No
7	Fishing	Angle κ	18	[15;21]	6.5	[5.6;7.5]	-12	Yes
7	Drifting	Speed μ	0.06	[0.06;0.07]	0.06	[0.06;0.06]	0	No
7	Drifting	Speed σ	0.05	[0.05;0.06]	0.05	[0.04;0.05]	0	No
7	Drifting	Angle μ	3.1	[3;3.1]	-3.1	[-3.2;-3]	-6.1	Yes
7	Drifting	Angle κ	0.88	[0.81;0.95]	0.85	[0.77;0.93]	-0.03	No
8	Steaming	Speed μ	5.4	[5.3;5.4]	5.2	[5.1;5.3]	-0.19	Yes
8	Steaming	Speed σ	0.99	[0.91;1.1]	1.4	[1.4;1.5]	0.43	Yes
8	Steaming	Angle μ	0.01	[-0.01;0.02]	0.01	[-0.01;0.03]	0.01	No
8	Steaming	Angle κ	24	[21;27]	10	[9.3;12]	-14	Yes
8	Fishing	Speed μ	2.5	[2.4;2.6]	1.3	[1.2;1.3]	-1.2	Yes
8	Fishing	Speed σ	1.4	[1.4;1.5]	1.5	[1.5;1.6]	0.12	Yes
8	Fishing	Angle μ	3.1	[3.1;3.1]	-3.1	[-3.2;-3.1]	-6.3	Yes
8	Fishing	Angle κ	37	[33;41]	1.5	[1.4;1.6]	-36	Yes
8	Drifting	Speed μ	1.3	[1.3;1.3]	1	[0.93;1.1]	-0.3	Yes
8	Drifting	Speed σ	1.6	[1.5;1.6]	0.88	[0.78;1]	-0.7	Yes
8	Drifting	Angle μ	2.4	[1.9;2.8]	0.03	[-0.01;0.08]	-2.3	Yes
8	Drifting	Angle κ	0.09	[0.05;0.13]	3.1	[2.6;3.6]	3	Yes
9	Steaming	Speed μ	5.3	[5.2;5.4]	5.1	[5;5.3]	-0.16	No
9	Steaming	Speed σ	1	[0.98;1.1]	1.6	[1.5;1.7]	0.53	Yes
9	Steaming	Angle μ	0	[-0.01;0.01]	0.01	[-0.01;0.03]	0.01	No
9	Steaming	Angle κ	79	[68;89]	16	[14;19]	-62	Yes
9	Fishing	Speed μ	1.5	[1.4;1.5]	2.5	[2.4;2.5]	0.97	Yes
9	Fishing	Speed σ	2	[1.9;2.1]	1.6	[1.5;1.7]	-0.41	Yes
9	Fishing	Angle μ	3.1	[3;3.1]	3.1	[3.1;3.1]	0.04	No
9	Fishing	Angle κ	1.4	[1.3;1.5]	9	[8.1;9.9]	7.6	Yes
9	Drifting	Speed μ	2	[1.9;2.1]	0.96	[0.91;1]	-1	Yes
9	Drifting	Speed σ	1.7	[1.6;1.8]	1.2	[1.2;1.3]	-0.48	Yes
9	Drifting	Angle μ	0.05	[0.02;0.08]	2.6	[2.1;3]	2.5	Yes
9	Drifting	Angle κ	3.7	[3.2;4.2]	0.14	[0.08;0.2]	-3.6	Yes
10	Steaming	Speed μ	5.9	[5.9;6]	6.2	[6.1;6.3]	0.26	Yes
10	Steaming	Speed σ	0.95	[0.9;1]	1.2	[1.1;1.3]	0.21	Yes
10	Steaming	Angle μ	0	[-0.01;0.01]	0	[-0.02;0.01]	0	No
10	Steaming	Angle κ	33	[28;39]	31	[27;35]	-2.3	No
10	Fishing	Speed μ	2.9	[2.8;3]	2.5	[2.4;2.6]	-0.4	Yes
10	Fishing	Speed σ	1.9	[1.9;2]	2	[1.9;2]	0.02	No
10	Fishing	Angle μ	3.1	[3;3.1]	3.1	[3.1;3.2]	0.05	No
10	Fishing	Angle κ	0.48	[0.44;0.52]	1	[0.96;1.1]	0.54	Yes
10	Drifting	Speed μ	0.46	[0.44;0.49]	0.43	[0.41;0.46]	-0.03	No
10	Drifting	Speed σ	0.45	[0.42;0.48]	0.45	[0.42;0.48]	0	No

10	Drifting	Angle μ	0.59	[0.19;1]	0.23	[0.02;0.45]	-0.35	No
10	Drifting	Angle κ	0.16	[0.1;0.22]	0.34	[0.26;0.42]	0.18	Yes
11	Steaming	Speed μ	5.4	[5.3;5.5]	5.5	[5.4;5.6]	0.11	No
11	Steaming	Speed σ	1.4	[1.3;1.4]	1.2	[1.1;1.2]	-0.19	Yes
11	Steaming	Angle μ	0	[-0.01;0.01]	-0.01	[-0.03;0.01]	-0.01	No
11	Steaming	Angle κ	45	[38;51]	15	[13;16]	-30	Yes
11	Fishing	Speed μ	2.5	[2.5;2.6]	2.6	[2.5;2.7]	0.07	No
11	Fishing	Speed σ	2	[1.9;2.1]	2.1	[2;2.1]	0.07	No
11	Fishing	Angle μ	3.1	[3;3.2]	3.1	[3;3.1]	-0.03	No
11	Fishing	Angle κ	0.44	[0.39;0.5]	0.84	[0.78;0.9]	0.4	Yes
11	Drifting	Speed μ	0.6	[0.58;0.62]	0.55	[0.53;0.57]	-0.05	Yes
11	Drifting	Speed σ	0.33	[0.31;0.35]	0.34	[0.33;0.36]	0.02	No
11	Drifting	Angle μ	0.06	[0.03;0.08]	0.1	[0.07;0.14]	0.05	No
11	Drifting	Angle κ	6.3	[5.4;7.1]	3.1	[2.6;3.6]	-3.1	Yes
12	Steaming	Speed μ	5.5	[5.4;5.6]	6.6	[6.4;6.7]	1.1	Yes
12	Steaming	Speed σ	1.5	[1.5;1.6]	2	[1.9;2.1]	0.44	Yes
12	Steaming	Angle μ	0	[0;0.01]	0	[-0.01;0.02]	0	No
12	Steaming	Angle κ	84	[75;93]	42	[37;47]	-42	Yes
12	Fishing	Speed μ	1.7	[1.6;1.7]	2.7	[2.6;2.8]	1	Yes
12	Fishing	Speed σ	2	[2;2.1]	1.9	[1.8;2]	-0.14	No
12	Fishing	Angle μ	-3.1	[-3.2;-3.1]	-3	[-3.2;-2.9]	0.12	No
12	Fishing	Angle κ	1.9	[1.7;2]	0.46	[0.39;0.54]	-1.4	Yes
12	Drifting	Speed μ	2.1	[2;2.1]	0.59	[0.55;0.64]	-1.5	Yes
12	Drifting	Speed σ	1.7	[1.6;1.8]	0.49	[0.45;0.53]	-1.2	Yes
12	Drifting	Angle μ	0.01	[-0.01;0.03]	0.15	[-0.03;0.33]	0.14	No
12	Drifting	Angle κ	4	[3.7;4.4]	0.53	[0.42;0.64]	-3.5	Yes
13	Steaming	Speed μ	5.1	[5.1;5.2]	5	[4.9;5.1]	-0.16	Yes
13	Steaming	Speed σ	0.94	[0.9;0.97]	1	[0.95;1.1]	0.07	No
13	Steaming	Angle μ	0	[-0.01;0.01]	0	[-0.02;0.02]	0	No
13	Steaming	Angle κ	43	[39;47]	24	[21;27]	-19	Yes
13	Fishing	Speed μ	2.5	[2.5;2.6]	2	[1.9;2.1]	-0.54	Yes
13	Fishing	Speed σ	1.7	[1.7;1.8]	1.8	[1.7;1.9]	0.1	No
13	Fishing	Angle μ	3.1	[2.9;3.2]	-3.1	[-3.3;-3]	-6.2	Yes
13	Fishing	Angle κ	0.22	[0.19;0.26]	0.73	[0.58;0.88]	0.5	Yes
13	Drifting	Speed μ	0.58	[0.53;0.63]	1.4	[1.3;1.5]	0.85	Yes
13	Drifting	Speed σ	0.58	[0.53;0.63]	1.1	[0.96;1.2]	0.49	Yes
13	Drifting	Angle μ	0.23	[0.04;0.43]	0.04	[0.02;0.07]	-0.19	No
13	Drifting	Angle κ	0.32	[0.25;0.39]	15	[11;19]	15	Yes
14	Steaming	Speed μ	2.3	[2.2;2.4]	2.8	[NA;NA]	0.47	NA
14	Steaming	Speed σ	1.8	[1.7;1.9]	2.4	[NA;NA]	0.62	NA
14	Steaming	Angle μ	0	[-0.03;0.04]	0.02	[NA;NA]	0.01	NA

14	Steaming	Angle κ	4.2	[2.5;5.9]	25	[NA;NA]	21	NA
14	Fishing	Speed μ	2.7	[2.6;2.9]	2.3	[NA;NA]	-0.37	NA
14	Fishing	Speed σ	2.8	[2.6;3]	2.2	[NA;NA]	-0.62	NA
14	Fishing	Angle μ	3.1	[3;3.2]	2.9	[NA;NA]	-0.16	NA
14	Fishing	Angle κ	1.2	[0.76;1.7]	0.29	[NA;NA]	-0.93	NA
14	Drifting	Speed μ	7.2	[7;7.4]	0.8	[NA;NA]	-6.4	NA
14	Drifting	Speed σ	1.7	[1.5;1.9]	0.48	[NA;NA]	-1.2	NA
14	Drifting	Angle μ	0.01	[0;0.02]	0.08	[NA;NA]	0.07	NA
14	Drifting	Angle κ	81	[62;100]	10	[NA;NA]	-70	NA
15	Steaming	Speed μ	4.5	[4.5;4.6]	5.8	[5.7;5.9]	1.3	Yes
15	Steaming	Speed σ	0.99	[0.95;1]	1.5	[1.5;1.6]	0.54	Yes
15	Steaming	Angle μ	0	[0;0]	0.01	[0;0.02]	0.01	No
15	Steaming	Angle κ	210	[190;230]	74	[67;81]	-140	Yes
15	Fishing	Speed μ	1.6	[1.6;1.6]	2.1	[2.1;2.2]	0.54	Yes
15	Fishing	Speed σ	1.3	[1.2;1.3]	1.5	[1.4;1.5]	0.19	Yes
15	Fishing	Angle μ	3	[2.6;3.5]	3	[3;3.1]	0.02	No
15	Fishing	Angle κ	0.07	[0.04;0.11]	0.52	[0.46;0.57]	0.44	Yes
15	Drifting	Speed μ	0.04	[0.04;0.05]	0.46	[0.42;0.49]	0.41	Yes
15	Drifting	Speed σ	0.04	[0.04;0.04]	0.51	[0.47;0.55]	0.47	Yes
15	Drifting	Angle μ	-3.1	[-3.2;-3.1]	0.13	[-0.01;0.26]	3.3	Yes
15	Drifting	Angle κ	0.8	[0.73;0.88]	0.47	[0.4;0.54]	-0.34	Yes
16	Steaming	Speed μ	5.7	[5.6;5.8]	5.2	[5.1;5.3]	-0.49	Yes
16	Steaming	Speed σ	1.3	[1.2;1.3]	1.8	[1.7;1.9]	0.52	Yes
16	Steaming	Angle μ	0	[0;0.01]	0.00	[-0.01;0.01]	0	No
16	Steaming	Angle κ	53	[45;60]	39	[35;43]	-14	Yes
16	Fishing	Speed μ	1.1	[1;1.2]	0.1	[0.1;0.11]	-1	Yes
16	Fishing	Speed σ	1.5	[1.4;1.6]	0.08	[0.08;0.09]	-1.4	Yes
16	Fishing	Angle μ	2.8	[2.4;3.2]	-3.1	[-3.2;-3]	-5.9	Yes
16	Fishing	Angle κ	0.11	[0.06;0.17]	0.73	[0.66;0.8]	0.62	Yes
16	Drifting	Speed μ	2.1	[2;2.2]	2.2	[2.1;2.3]	0.1	No
16	Drifting	Speed σ	2.1	[2;2.3]	1.9	[1.9;2]	-0.18	Yes
16	Drifting	Angle μ	3.1	[3.1;3.2]	3.1	[3;3.2]	-0.04	No
16	Drifting	Angle κ	30	[26;34]	0.36	[0.31;0.42]	-30	Yes
17	Steaming	Speed μ	5.9	[5.9;6]	6.3	[6.1;6.4]	0.31	Yes
17	Steaming	Speed σ	0.96	[0.9;1]	1.3	[1.2;1.4]	0.32	Yes
17	Steaming	Angle μ	0	[-0.01;0.01]	0	[-0.01;0.01]	0	No
17	Steaming	Angle κ	54	[47;61]	39	[33;44]	-15	Yes
17	Fishing	Speed μ	1.4	[1.3;1.4]	1.7	[1.6;1.8]	0.35	Yes
17	Fishing	Speed σ	1.7	[1.6;1.8]	2.1	[1.9;2.2]	0.34	Yes
17	Fishing	Angle μ	-3.1	[-3.2;-3.1]	3.1	[3;3.1]	6.2	Yes
17	Fishing	Angle κ	0.91	[0.84;0.98]	1.2	[1;1.4]	0.32	Yes

17	Drifting	Speed μ	1.4	[1.3;1.6]	1.3	[1.2;1.4]	-0.11	No
17	Drifting	Speed σ	1.2	[1;1.4]	1.1	[0.96;1.2]	-0.11	No
17	Drifting	Angle μ	0.06	[0.03;0.08]	0.04	[0;0.08]	-0.02	No
17	Drifting	Angle κ	12	[9.8;14]	7.8	[4.9;11]	-4.3	No
18	Steaming	Speed μ	5	[4.9;5]	3.3	[3.2;3.4]	-1.7	Yes
18	Steaming	Speed σ	0.86	[0.82;0.91]	2.4	[2.3;2.5]	1.5	Yes
18	Steaming	Angle μ	0	[0;0.01]	-0.01	[-0.03;0.01]	-0.01	No
18	Steaming	Angle κ	160	[150;180]	11	[9.8;13]	-150	Yes
18	Fishing	Speed μ	2.3	[2.3;2.4]	2	[2;2.1]	-0.29	Yes
18	Fishing	Speed σ	1.8	[1.8;1.9]	1.7	[1.6;1.8]	-0.15	Yes
18	Fishing	Angle μ	2.4	[0.51;5.5]	3.1	[3.1;3.2]	0.73	No
18	Fishing	Angle κ	0.02	[0.01;0.06]	1.6	[1.4;1.7]	1.5	Yes
18	Drifting	Speed μ	0.11	[0.1;0.12]	0.09	[0.08;0.1]	-0.02	Yes
18	Drifting	Speed σ	0.11	[0.1;0.12]	0.07	[0.07;0.08]	-0.04	Yes
18	Drifting	Angle μ	3.1	[3;3.1]	3	[3;3.1]	-0.03	No
18	Drifting	Angle κ	0.89	[0.82;0.96]	0.82	[0.75;0.9]	-0.06	No
19	Steaming	Speed μ	6.7	[6.7;6.8]	6.5	[6.3;6.6]	-0.26	Yes
19	Steaming	Speed σ	0.7	[0.67;0.74]	1.7	[1.6;1.8]	0.99	Yes
19	Steaming	Angle μ	0	[0;0.01]	0.01	[-0.01;0.02]	0	No
19	Steaming	Angle κ	150	[130;170]	15	[13;16]	-130	Yes
19	Fishing	Speed μ	2.2	[2.2;2.2]	1.8	[1.8;1.9]	-0.39	Yes
19	Fishing	Speed σ	1.8	[1.8;1.9]	1.6	[1.5;1.6]	-0.25	Yes
19	Fishing	Angle μ	3.1	[3;3.2]	3.1	[3;3.1]	-0.01	No
19	Fishing	Angle κ	0.38	[0.35;0.42]	0.73	[0.69;0.78]	0.35	Yes
19	Drifting	Speed μ	0.09	[0.09;0.1]	0.06	[0.06;0.06]	-0.03	Yes
19	Drifting	Speed σ	0.09	[0.08;0.09]	0.05	[0.04;0.05]	-0.04	Yes
19	Drifting	Angle μ	3.1	[3;3.1]	3.1	[3;3.2]	0.02	No
19	Drifting	Angle κ	0.92	[0.85;0.99]	0.85	[0.79;0.92]	-0.07	No
20	Steaming	Speed μ	6.1	[6.1;6.2]	5.1	[4.8;5.4]	-1.1	Yes
20	Steaming	Speed σ	0.87	[0.82;0.92]	2.5	[2.4;2.7]	1.7	Yes
20	Steaming	Angle μ	0.01	[0;0.01]	0.02	[-0.02;0.05]	0.01	No
20	Steaming	Angle κ	110	[96;130]	5.5	[4.9;6.1]	-110	Yes
20	Fishing	Speed μ	2.5	[2.5;2.6]	1.5	[1.5;1.6]	-1	Yes
20	Fishing	Speed σ	2.1	[2;2.1]	1.6	[1.5;1.7]	-0.48	Yes
20	Fishing	Angle μ	-3.1	[-3.2;-3]	-3.1	[-3.2;-3]	0.05	No
20	Fishing	Angle κ	0.48	[0.43;0.52]	0.55	[0.46;0.65]	0.08	No
20	Drifting	Speed μ	0.62	[0.59;0.64]	0.55	[0.52;0.57]	-0.07	Yes
20	Drifting	Speed σ	0.34	[0.32;0.36]	0.26	[0.24;0.29]	-0.07	Yes
20	Drifting	Angle μ	0.1	[0.07;0.13]	0.09	[0.05;0.13]	-0.02	No
20	Drifting	Angle κ	5.4	[4.7;6.2]	6.5	[5.4;7.6]	1	No
21	Steaming	Speed μ	4.9	[4.8;5]	5.1	[5;5.2]	0.26	Yes

21	Steaming	Speed σ	1.6	[1.5;1.7]	1.6	[1.6;1.7]	0.02	No
21	Steaming	Angle μ	0	[-0.01;0.01]	0	[0;0.01]	0	No
21	Steaming	Angle κ	79	[70;88]	81	[74;89]	2.2	No
21	Fishing	Speed μ	2.1	[2;2.1]	2.1	[2.1;2.2]	0.04	No
21	Fishing	Speed σ	1.7	[1.7;1.8]	1.7	[1.6;1.7]	-0.08	No
21	Fishing	Angle μ	-0.08	[-0.27;0.1]	-3.1	[-3.2;-3]	-3	Yes
21	Fishing	Angle κ	0.23	[0.18;0.27]	0.3	[0.27;0.34]	0.08	No
21	Drifting	Speed μ	0.17	[0.15;0.18]	0.15	[0.14;0.16]	-0.02	No
21	Drifting	Speed σ	0.14	[0.12;0.15]	0.13	[0.12;0.14]	-0.01	No
21	Drifting	Angle μ	-3.1	[-3.3;-3]	-3.1	[-3.2;-3.1]	-0.01	No
21	Drifting	Angle κ	0.71	[0.57;0.85]	1.1	[1;1.2]	0.38	Yes
22	Steaming	Speed μ	5.9	[5.8;6]	6.5	[6.5;6.6]	0.65	Yes
22	Steaming	Speed σ	0.74	[0.69;0.8]	0.97	[0.92;1]	0.22	Yes
22	Steaming	Angle μ	0	[-0.01;0.01]	0.01	[0;0.02]	0.01	No
22	Steaming	Angle κ	170	[150;190]	57	[52;63]	-110	Yes
22	Fishing	Speed μ	1.3	[1.3;1.4]	2.2	[2.1;2.2]	0.84	Yes
22	Fishing	Speed σ	1.1	[1.1;1.2]	1.6	[1.5;1.6]	0.44	Yes
22	Fishing	Angle μ	3.1	[3.1;3.2]	1.3	[0.61;2.1]	-1.8	Yes
22	Fishing	Angle κ	0.53	[0.49;0.57]	0.05	[0.02;0.09]	-0.48	Yes
22	Drifting	Speed μ	0.03	[0.03;0.03]	0.77	[0.72;0.83]	0.75	Yes
22	Drifting	Speed σ	0.02	[0.02;0.02]	0.75	[0.69;0.81]	0.73	Yes
22	Drifting	Angle μ	3.1	[3;3.2]	0.09	[0.03;0.15]	-3	Yes
22	Drifting	Angle κ	0.56	[0.5;0.61]	1.2	[1.1;1.3]	0.63	Yes
23	Steaming	Speed μ	3.4	[3.1;3.7]	3.3	[3.2;3.4]	-0.09	No
23	Steaming	Speed σ	2.5	[2.3;2.6]	2.2	[2.1;2.2]	-0.33	Yes
23	Steaming	Angle μ	0.01	[0;0.02]	0.01	[0;0.02]	0	No
23	Steaming	Angle κ	57	[37;77]	41	[36;46]	-16	No
23	Fishing	Speed μ	2.6	[2.4;2.8]	2.7	[2.6;2.9]	0.14	No
23	Fishing	Speed σ	2.2	[2;2.3]	2.1	[2;2.2]	-0.06	No
23	Fishing	Angle μ	3.1	[3;3.2]	3.1	[3;3.2]	-0.01	No
23	Fishing	Angle κ	0.62	[0.5;0.75]	0.91	[0.8;1]	0.28	Yes
23	Drifting	Speed μ	0.38	[0.3;0.49]	0.49	[0.45;0.53]	0.1	No
23	Drifting	Speed σ	0.37	[0.28;0.48]	0.42	[0.38;0.46]	0.05	No
23	Drifting	Angle μ	-0.2	[-0.85;0.25]	0.15	[0;0.3]	0.35	No
23	Drifting	Angle κ	0.23	[0.1;0.38]	0.49	[0.4;0.58]	0.26	Yes
24	Steaming	Speed μ	5.9	[5.8;5.9]	5.5	[5.5;5.6]	-0.32	Yes
24	Steaming	Speed σ	1.2	[1.1;1.2]	1.4	[1.3;1.5]	0.22	Yes
24	Steaming	Angle μ	0	[0;0.01]	0	[0;0.01]	0	No
24	Steaming	Angle κ	150	[130;170]	110	[100;120]	-37	Yes
24	Fishing	Speed μ	1.6	[1.6;1.7]	2.1	[2;2.2]	0.45	Yes
24	Fishing	Speed σ	1.4	[1.4;1.5]	1.7	[1.6;1.8]	0.26	Yes

24	Fishing	Angle μ	3.1	[3;3.1]	-3.1	[-3.2;-3.1]	-6.2	Yes
24	Fishing	Angle κ	0.63	[0.56;0.71]	2.1	[1.8;2.4]	1.4	Yes
24	Drifting	Speed μ	1.6	[1.6;1.7]	1.8	[1.8;1.9]	0.18	Yes
24	Drifting	Speed σ	1.2	[1.1;1.3]	1.3	[1.3;1.4]	0.15	Yes
24	Drifting	Angle μ	0.02	[0.01;0.04]	0.01	[-0.01;0.04]	-0.01	No
24	Drifting	Angle κ	12	[11;14]	4.1	[3.5;4.7]	-8.3	Yes
25	Steaming	Speed μ	5.3	[5.2;5.4]	6	[5.9;6]	0.65	Yes
25	Steaming	Speed σ	0.74	[0.69;0.78]	1.1	[1;1.2]	0.36	Yes
25	Steaming	Angle μ	0	[0;0.01]	0	[0;0.01]	0	No
25	Steaming	Angle κ	120	[100;140]	88	[79;97]	-33	Yes
25	Fishing	Speed μ	2.5	[2.5;2.6]	1.7	[1.7;1.8]	-0.77	Yes
25	Fishing	Speed σ	1.7	[1.6;1.7]	1.5	[1.5;1.5]	-0.18	Yes
25	Fishing	Angle μ	3.1	[3;3.2]	3	[2.9;3.1]	-0.05	No
25	Fishing	Angle κ	0.51	[0.47;0.55]	0.33	[0.3;0.36]	-0.18	Yes
25	Drifting	Speed μ	0.55	[0.53;0.58]	0.08	[0.07;0.08]	-0.48	Yes
25	Drifting	Speed σ	0.53	[0.5;0.56]	0.06	[0.06;0.07]	-0.46	Yes
25	Drifting	Angle μ	0.19	[0.09;0.29]	3	[2.9;3.1]	2.8	Yes
25	Drifting	Angle κ	0.63	[0.55;0.7]	0.91	[0.81;1]	0.28	Yes
26	Steaming	Speed μ	5.6	[5.5;5.7]	6.2	[NA;NA]	0.61	NA
26	Steaming	Speed σ	1.7	[1.6;1.7]	2.8	[NA;NA]	1.1	NA
26	Steaming	Angle μ	0	[0;0.01]	-0.01	[NA;NA]	-0.01	NA
26	Steaming	Angle κ	83	[73;93]	2.7	[NA;NA]	-80	NA
26	Fishing	Speed μ	2.4	[2.3;2.4]	2.6	[NA;NA]	0.19	NA
26	Fishing	Speed σ	1.8	[1.7;1.8]	1.7	[NA;NA]	-0.08	NA
26	Fishing	Angle μ	0.09	[0.03;0.16]	-2.9	[NA;NA]	-3	NA
26	Fishing	Angle κ	0.55	[0.51;0.59]	0.24	[NA;NA]	-0.31	NA
26	Drifting	Speed μ	0.33	[0.28;0.38]	0.51	[NA;NA]	0.18	NA
26	Drifting	Speed σ	0.34	[0.3;0.39]	0.41	[NA;NA]	0.07	NA
26	Drifting	Angle μ	-2.9	[-3.3;-2.3]	0.18	[NA;NA]	3	NA
26	Drifting	Angle κ	0.28	[0.12;0.45]	0.4	[NA;NA]	0.12	NA
27	Steaming	Speed μ	6.2	[6.1;6.3]	3.1	[2.9;3.3]	-3.1	Yes
27	Steaming	Speed σ	0.86	[0.81;0.91]	3.1	[2.9;3.4]	2.3	Yes
27	Steaming	Angle μ	0.01	[0;0.01]	0.05	[0.02;0.08]	0.04	Yes
27	Steaming	Angle κ	110	[100;130]	7.8	[6.8;8.9]	-110	Yes
27	Fishing	Speed μ	1.7	[1.6;1.7]	1.7	[1.7;1.8]	0.03	No
27	Fishing	Speed σ	1.5	[1.4;1.5]	1.4	[1.4;1.5]	-0.02	No
27	Fishing	Angle μ	3	[2.9;3.1]	3.1	[3;3.1]	0.06	No
27	Fishing	Angle κ	0.42	[0.38;0.46]	1.1	[0.94;1.2]	0.64	Yes
27	Drifting	Speed μ	0.05	[0.05;0.06]	0.05	[0.05;0.05]	0	No
27	Drifting	Speed σ	0.05	[0.04;0.05]	0.04	[0.04;0.04]	-0.01	No
27	Drifting	Angle μ	3	[3;3.1]	3.1	[3;3.2]	0.04	No

27	Drifting	Angle κ	0.84	[0.76;0.93]	0.93	[0.82;1]	0.09	No
28	Steaming	Speed μ	5.2	[5.1;5.3]	3.3	[3.1;3.4]	-1.9	Yes
28	Steaming	Speed σ	1.1	[1.1;1.2]	1.9	[1.8;2]	0.79	Yes
28	Steaming	Angle μ	0.01	[0;0.02]	0.01	[-0.01;0.04]	0.01	No
28	Steaming	Angle κ	56	[49;63]	9.9	[8.2;12]	-46	Yes
28	Fishing	Speed μ	2.7	[2.6;2.8]	2.6	[2.4;2.7]	-0.17	No
28	Fishing	Speed σ	1.8	[1.7;1.8]	2.2	[2;2.3]	0.41	Yes
28	Fishing	Angle μ	2.4	[1.6;3.2]	3	[2.9;3.1]	0.57	No
28	Fishing	Angle κ	0.08	[0.03;0.14]	0.94	[0.77;1.1]	0.86	Yes
28	Drifting	Speed μ	0.65	[0.59;0.71]	0.72	[0.65;0.8]	0.08	No
28	Drifting	Speed σ	0.61	[0.55;0.67]	0.43	[0.37;0.5]	-0.18	Yes
28	Drifting	Angle μ	0.12	[-0.04;0.29]	0.07	[0;0.12]	-0.06	No
28	Drifting	Angle κ	0.51	[0.41;0.62]	5.7	[3.9;7.6]	5.2	Yes
29	Steaming	Speed μ	5.3	[5.2;5.5]	6.4	[5.9;6.9]	1.1	Yes
29	Steaming	Speed σ	1.4	[1.3;1.5]	2.2	[1.8;2.6]	0.77	Yes
29	Steaming	Angle μ	0.01	[-0.01;0.02]	0.04	[-0.05;0.14]	0.04	No
29	Steaming	Angle κ	52	[43;61]	7.2	[4.8;9.6]	-45	Yes
29	Fishing	Speed μ	2.2	[2;2.3]	2.2	[2.1;2.4]	0.08	No
29	Fishing	Speed σ	1.7	[1.6;1.8]	1.5	[1.4;1.7]	-0.2	No
29	Fishing	Angle μ	3	[2.9;3.2]	-2.6	[-5.1;-0.75]	-5.6	Yes
29	Fishing	Angle κ	0.63	[0.54;0.73]	0.08	[0.02;0.23]	-0.55	Yes
29	Drifting	Speed μ	0.11	[0.1;0.13]	0.55	[0.44;0.7]	0.44	Yes
29	Drifting	Speed σ	0.12	[0.1;0.14]	0.56	[0.42;0.74]	0.44	Yes
29	Drifting	Angle μ	-3.1	[-3.3;-3]	0.76	[-2.5;2.7]	3.9	Yes
29	Drifting	Angle κ	1.1	[0.88;1.2]	0.14	[0.04;0.44]	-0.92	Yes
30	Steaming	Speed μ	6.2	[6.1;6.2]	5.9	[5.8;6]	-0.26	Yes
30	Steaming	Speed σ	1.1	[1.1;1.2]	1.5	[1.4;1.5]	0.36	Yes
30	Steaming	Angle μ	0.01	[0;0.01]	0.02	[0;0.03]	0.01	No
30	Steaming	Angle κ	71	[64;78]	23	[21;26]	-48	Yes
30	Fishing	Speed μ	2.8	[2.7;2.8]	2.2	[2.2;2.3]	-0.57	Yes
30	Fishing	Speed σ	2	[1.9;2]	1.5	[1.5;1.6]	-0.42	Yes
30	Fishing	Angle μ	2.9	[2.7;3.1]	3.1	[3.1;3.2]	0.24	Yes
30	Fishing	Angle κ	0.21	[0.17;0.25]	1	[0.97;1.1]	0.81	Yes
30	Drifting	Speed μ	0.08	[0.08;0.09]	0.15	[0.13;0.18]	0.07	Yes
30	Drifting	Speed σ	0.08	[0.08;0.09]	0.15	[0.12;0.18]	0.07	Yes
30	Drifting	Angle μ	-3.1	[-3.2;-3.1]	3.1	[3;3.2]	6.2	Yes
30	Drifting	Angle κ	0.72	[0.65;0.79]	0.81	[0.73;0.9]	0.09	No
31	Steaming	Speed μ	3.1	[2.9;3.3]	4.5	[4.4;4.6]	1.4	Yes
31	Steaming	Speed σ	2	[1.9;2.2]	1.4	[1.4;1.5]	-0.59	Yes
31	Steaming	Angle μ	0.03	[0.01;0.04]	0.01	[0;0.02]	-0.02	No
31	Steaming	Angle κ	27	[23;32]	70	[64;77]	43	Yes

31	Fishing	Speed μ	2.4	[2.2;2.6]	2.2	[2.1;2.3]	-0.16	No
31	Fishing	Speed σ	1.6	[1.5;1.7]	1.5	[1.4;1.5]	-0.11	No
31	Fishing	Angle μ	-3	[-3.4;-2.6]	2.9	[2.7;3]	5.9	Yes
31	Fishing	Angle κ	0.36	[0.16;0.58]	0.32	[0.26;0.38]	-0.05	No
31	Drifting	Speed μ	0.6	[0.49;0.74]	0.56	[0.53;0.6]	-0.04	No
31	Drifting	Speed σ	0.5	[0.4;0.62]	0.51	[0.48;0.55]	0.02	No
31	Drifting	Angle μ	0.22	[-0.04;0.52]	0.09	[-0.02;0.21]	-0.13	No
31	Drifting	Angle κ	0.51	[0.32;0.72]	0.59	[0.51;0.67]	0.07	No
32	Steaming	Speed μ	5.8	[5.7;5.9]	5.4	[5.3;5.6]	-0.36	Yes
32	Steaming	Speed σ	0.99	[0.93;1.1]	2.2	[2.1;2.4]	1.2	Yes
32	Steaming	Angle μ	0.01	[0;0.02]	0.02	[-0.01;0.05]	0.01	No
32	Steaming	Angle κ	59	[52;66]	8.6	[7.4;9.7]	-50	Yes
32	Fishing	Speed μ	2.2	[2.1;2.2]	1.7	[1.6;1.7]	-0.51	Yes
32	Fishing	Speed σ	2.2	[2.1;2.2]	1.4	[1.4;1.4]	-0.77	Yes
32	Fishing	Angle μ	3.1	[3.1;3.1]	3.1	[3.1;3.2]	0.02	No
32	Fishing	Angle κ	1.6	[1.4;1.8]	0.84	[0.79;0.89]	-0.74	Yes
32	Drifting	Speed μ	1.7	[1.6;1.8]	0.06	[0.06;0.07]	-1.7	Yes
32	Drifting	Speed σ	1.5	[1.4;1.6]	0.05	[0.05;0.06]	-1.5	Yes
32	Drifting	Angle μ	0.06	[0.03;0.09]	3.1	[3;3.2]	3.1	Yes
32	Drifting	Angle κ	4	[3.1;5]	0.83	[0.75;0.9]	-3.2	Yes
33	Steaming	Speed μ	7	[6.9;7]	7	[7;7.1]	0.06	No
33	Steaming	Speed σ	0.9	[0.86;0.93]	0.86	[0.81;0.91]	-0.04	No
33	Steaming	Angle μ	0	[0;0.01]	0	[0;0.01]	0.00	No
33	Steaming	Angle κ	180	[170;200]	60	[54;66]	-120	Yes
33	Fishing	Speed μ	2.7	[2.7;2.7]	2.8	[2.7;2.8]	0.07	No
33	Fishing	Speed σ	2.1	[2.1;2.1]	2.1	[2.1;2.2]	0.04	No
33	Fishing	Angle μ	0.13	[-0.14;0.41]	2.9	[2.7;3.1]	2.8	Yes
33	Fishing	Angle κ	0.1	[0.07;0.13]	0.19	[0.15;0.23]	0.1	Yes
33	Drifting	Speed μ	0.82	[0.8;0.84]	0.7	[0.68;0.73]	-0.11	Yes
33	Drifting	Speed σ	0.41	[0.39;0.43]	0.36	[0.34;0.38]	-0.05	Yes
33	Drifting	Angle μ	0.07	[0.06;0.08]	0.06	[0.04;0.08]	-0.01	No
33	Drifting	Angle κ	10	[9.4;11]	8.5	[7.5;9.6]	-1.9	No
34	Steaming	Speed μ	7	[6.9;7]	6.9	[6.8;6.9]	-0.1	No
34	Steaming	Speed σ	0.95	[0.88;1]	0.72	[0.68;0.76]	-0.22	Yes
34	Steaming	Angle μ	-0.01	[-0.02;0]	0	[-0.01;0.01]	0	No
34	Steaming	Angle κ	61	[53;70]	42	[38;46]	-19	Yes
34	Fishing	Speed μ	2.3	[2.2;2.4]	1.8	[1.8;1.9]	-0.47	Yes
34	Fishing	Speed σ	1.9	[1.8;2]	1.5	[1.4;1.5]	-0.39	Yes
34	Fishing	Angle μ	3.1	[2.7;3.6]	2.4	[1.9;2.9]	-0.76	No
34	Fishing	Angle κ	0.13	[0.07;0.19]	0.08	[0.04;0.12]	-0.05	No
34	Drifting	Speed μ	0.11	[0.1;0.12]	0.03	[0.03;0.04]	-0.08	Yes

34	Drifting	Speed σ	0.11	[0.1;0.13]	0.03	[0.02;0.03]	-0.09	Yes
34	Drifting	Angle μ	3	[2.9;3.2]	2.7	[2.4;3.1]	-0.29	No
34	Drifting	Angle κ	0.79	[0.67;0.92]	0.22	[0.15;0.3]	-0.58	Yes
35	Steaming	Speed μ	7.3	[7.2;7.4]	7.1	[7;7.2]	-0.19	No
35	Steaming	Speed σ	1.8	[1.7;1.9]	1.5	[1.4;1.6]	-0.31	Yes
35	Steaming	Angle μ	0.01	[0;0.02]	0.01	[0;0.02]	0	No
35	Steaming	Angle κ	76	[67;85]	45	[40;51]	-31	Yes
35	Fishing	Speed μ	3.3	[3.2;3.4]	2.8	[2.7;2.8]	-0.56	Yes
35	Fishing	Speed σ	2.6	[2.5;2.7]	2.1	[2;2.1]	-0.5	Yes
35	Fishing	Angle μ	-3.1	[-3.2;-3.1]	3.1	[3;3.2]	6.2	Yes
35	Fishing	Angle κ	0.9	[0.8;1]	0.64	[0.59;0.69]	-0.26	Yes
35	Drifting	Speed μ	1.3	[1.2;1.4]	0.88	[0.85;0.92]	-0.38	Yes
35	Drifting	Speed σ	0.88	[0.77;1]	0.47	[0.44;0.51]	-0.41	Yes
35	Drifting	Angle μ	0.04	[0.01;0.07]	0.05	[0.04;0.07]	0.02	No
35	Drifting	Angle κ	4.1	[3.5;4.8]	15	[13;18]	11	Yes
36	Steaming	Speed μ	6.2	[6.1;6.3]	6.2	[6.1;6.3]	0.02	No
36	Steaming	Speed σ	1.7	[1.6;1.8]	1.3	[1.2;1.4]	-0.4	Yes
36	Steaming	Angle μ	0	[0;0.01]	0	[-0.01;0.01]	0	No
36	Steaming	Angle κ	86	[74;99]	38	[35;42]	-48	Yes
36	Fishing	Speed μ	2.8	[2.7;2.9]	2.8	[2.7;3]	0.03	No
36	Fishing	Speed σ	2.7	[2.6;2.9]	2.3	[2.2;2.4]	-0.43	Yes
36	Fishing	Angle μ	3	[3;3.1]	-3.1	[-3.2;-3.1]	-6.2	Yes
36	Fishing	Angle κ	0.94	[0.81;1.1]	1.6	[1.3;1.8]	0.62	Yes
36	Drifting	Speed μ	2.7	[2.5;2.8]	2	[2;2.1]	-0.62	Yes
36	Drifting	Speed σ	1.8	[1.7;1.9]	1.5	[1.4;1.5]	-0.36	Yes
36	Drifting	Angle μ	0.02	[-0.01;0.04]	0	[-0.02;0.03]	-0.01	No
36	Drifting	Angle κ	7.7	[6.6;8.8]	4.3	[3.7;4.9]	-3.4	Yes
37	Steaming	Speed μ	2.9	[2.7;3.1]	6.2	[6;6.4]	3.3	Yes
37	Steaming	Speed σ	2.5	[2.3;2.7]	1.4	[1.2;1.6]	-1.1	Yes
37	Steaming	Angle μ	-0.22	[-0.37;-0.07]	0	[-0.04;0.04]	0.22	Yes
37	Steaming	Angle κ	0.69	[0.55;0.82]	11	[8.8;14]	11	Yes
37	Fishing	Speed μ	3.8	[3.5;4.2]	3.2	[3;3.3]	-0.65	Yes
37	Fishing	Speed σ	2.7	[2.4;3]	2.3	[2.2;2.5]	-0.35	No
37	Fishing	Angle μ	3.1	[3.1;3.1]	-3.1	[-3.2;-3.1]	-6.2	Yes
37	Fishing	Angle κ	12	[7.8;16]	2.2	[1.9;2.5]	-9.9	Yes
37	Drifting	Speed μ	2.9	[2.6;3.2]	2	[1.9;2.1]	-0.93	Yes
37	Drifting	Speed σ	1.9	[1.7;2.2]	1.4	[1.3;1.5]	-0.53	Yes
37	Drifting	Angle μ	0.04	[-0.01;0.08]	0.02	[-0.02;0.06]	-0.02	No
37	Drifting	Angle κ	12	[9.2;15]	3.2	[2.7;3.7]	-8.8	Yes
38	Steaming	Speed μ	6	[5.8;6.2]	5.7	[5.7;5.8]	-0.26	Yes
38	Steaming	Speed σ	1	[0.92;1.2]	1.1	[1;1.1]	0.02	No

38	Steaming	Angle μ	0.01	[0;0.03]	0	[-0.01;0.01]	-0.02	No
38	Steaming	Angle κ	88	[66;110]	120	[110;140]	36	No
38	Fishing	Speed μ	1.9	[1.8;2.1]	1.6	[1.5;1.6]	-0.35	Yes
38	Fishing	Speed σ	1.5	[1.4;1.6]	1.2	[1.2;1.3]	-0.27	Yes
38	Fishing	Angle μ	3	[2.6;3.5]	3.1	[3;3.2]	0.11	No
38	Fishing	Angle κ	0.26	[0.16;0.38]	0.61	[0.54;0.69]	0.35	Yes
38	Drifting	Speed μ	0.04	[0.03;0.04]	0.9	[0.84;0.97]	0.87	Yes
38	Drifting	Speed σ	0.03	[0.02;0.03]	1.1	[1.1;1.2]	1.1	Yes
38	Drifting	Angle μ	3.1	[2.9;3.3]	0.29	[0.15;0.43]	-2.8	Yes
38	Drifting	Angle κ	0.66	[0.51;0.83]	0.51	[0.43;0.59]	-0.16	No
39	Steaming	Speed μ	7.4	[7.3;7.5]	7.2	[7.1;7.4]	-0.17	No
39	Steaming	Speed σ	1.4	[1.3;1.5]	2.2	[2.1;2.3]	0.79	Yes
39	Steaming	Angle μ	0.01	[0;0.02]	0.00	[-0.01;0.01]	-0.01	No
39	Steaming	Angle κ	74	[62;86]	110	[97;120]	33	Yes
39	Fishing	Speed μ	3.4	[3.3;3.5]	3.5	[3.4;3.6]	0.06	No
39	Fishing	Speed σ	2.5	[2.5;2.6]	2.5	[2.5;2.6]	-0.02	No
39	Fishing	Angle μ	3	[2.9;3]	3.1	[3.1;3.1]	0.15	Yes
39	Fishing	Angle κ	0.63	[0.53;0.72]	2.2	[2.1;2.4]	1.6	Yes
39	Drifting	Speed μ	2.8	[2.7;2.9]	2.3	[2.3;2.4]	-0.5	Yes
39	Drifting	Speed σ	1	[0.89;1.1]	1.7	[1.7;1.8]	0.69	Yes
39	Drifting	Angle μ	0.01	[-0.01;0.04]	0.02	[0;0.04]	0.01	No
39	Drifting	Angle κ	14	[11;16]	3.3	[3.1;3.6]	-10	Yes

Table III.7.2.1.a. Estimates of parameters for the speed and turning angle distributions for each vessel in each mode and for both Pre- and Post-IFQ periods. The difference between the two periods is considered significant if the 95% confidence intervals of the estimates do not intersect.

III.7.2.2. Differences in the transition probabilities

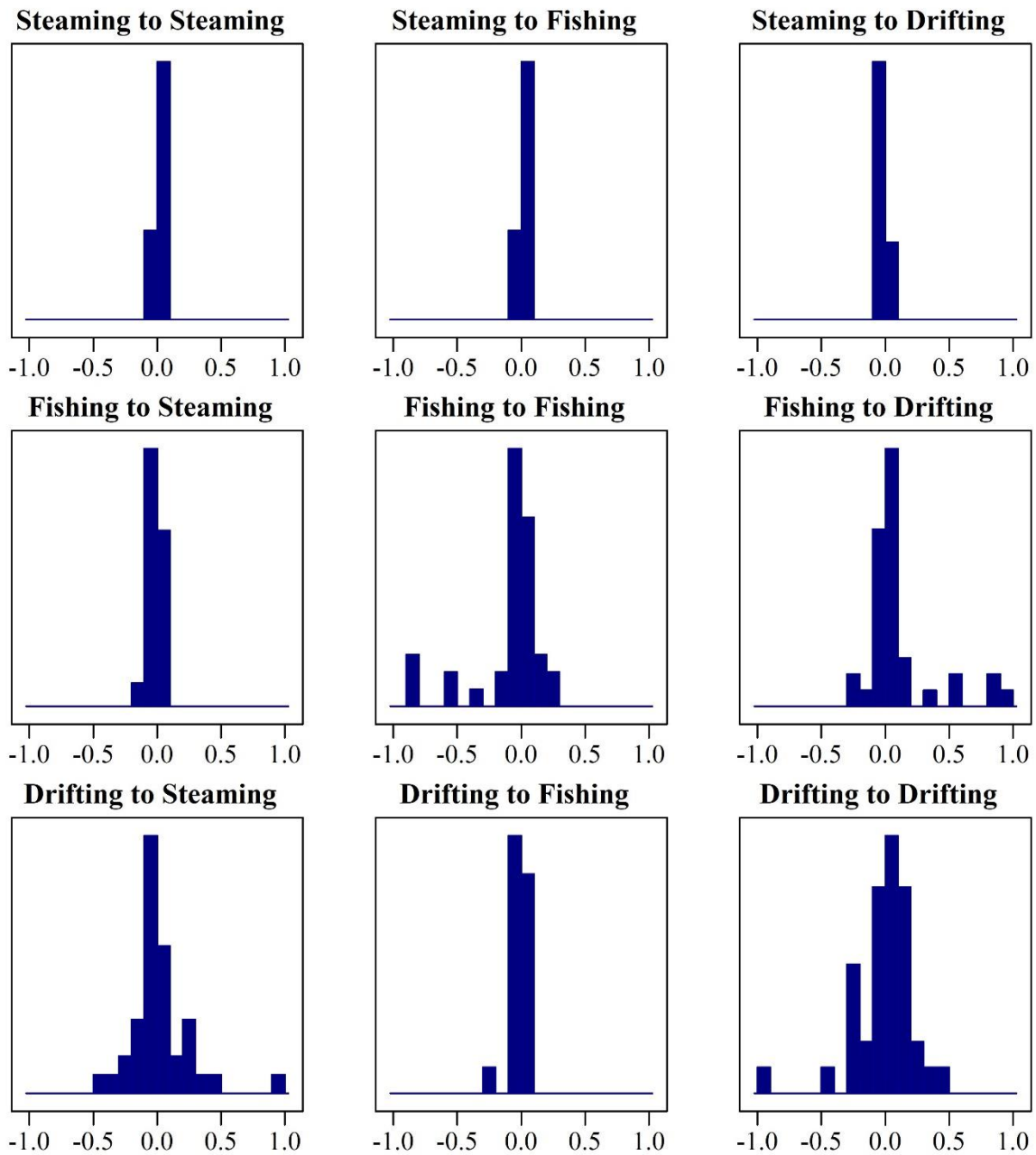

Figure III.7.2.2.1. Distribution of the differences Post-IFQ – Pre-IFQ in the transition probabilities. The probabilities are computed assuming $BLLrange_t = 0$ and $Day_t = 0$.

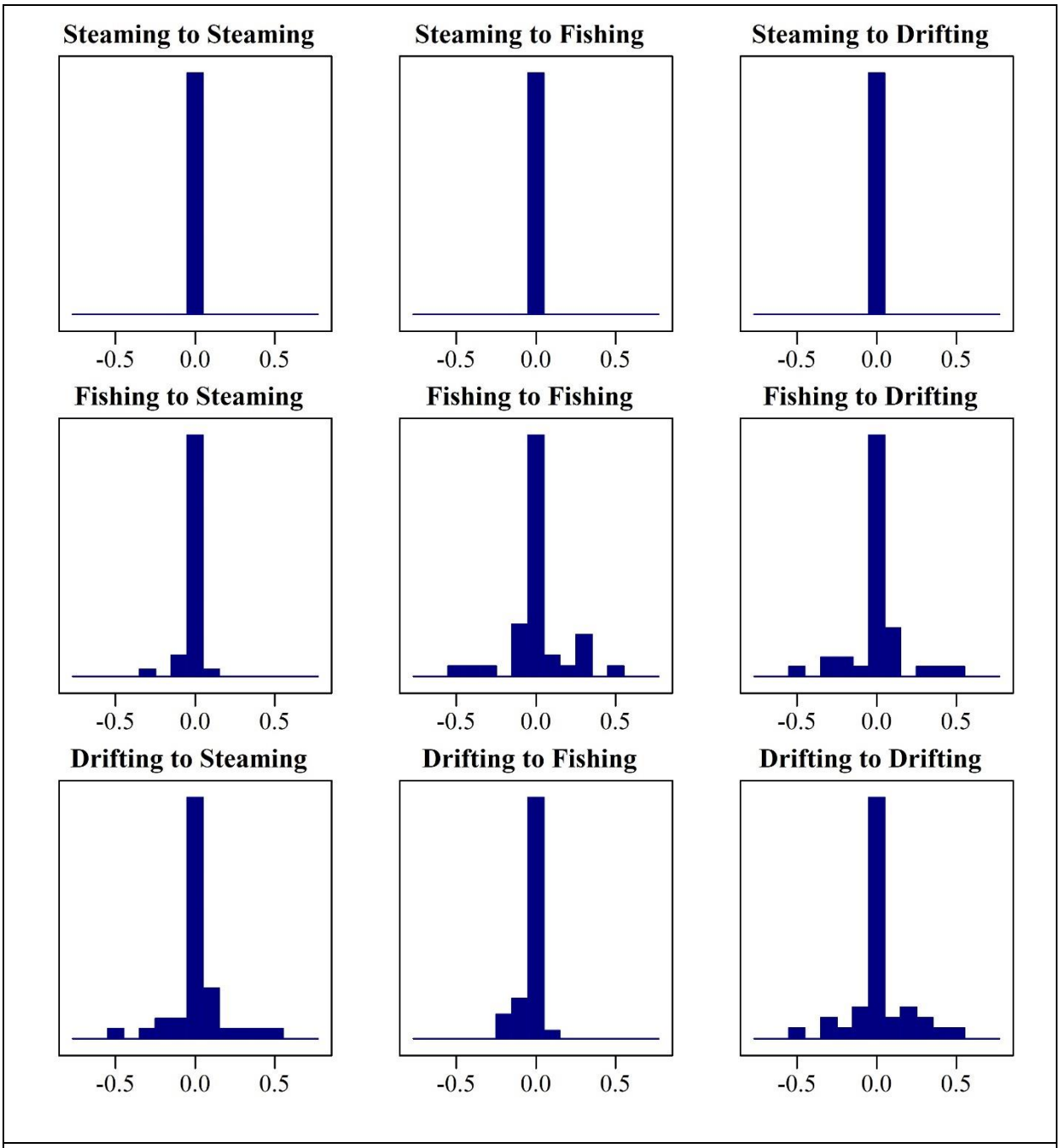

Figure III.7.2.2.2. Distribution of the differences Post-IFQ – Pre-IFQ in the transition probabilities. The probabilities are computed assuming $BLLrange_t = 1$ and $Day_t = 1$.

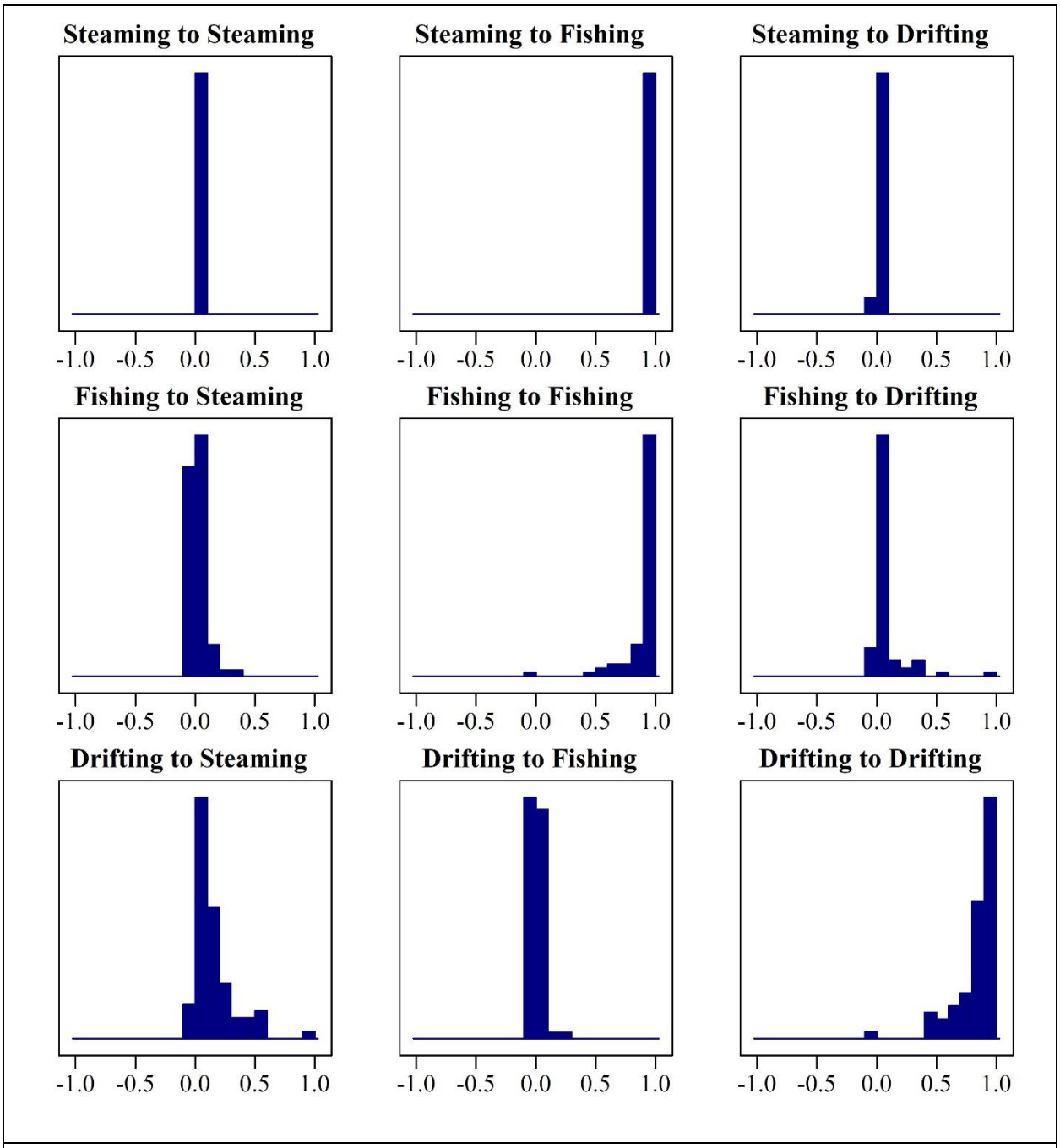

Figure III.7.2.2.3. Distribution of the differences Post-IFQ – Pre-IFQ in the transition probabilities. The probabilities are computed assuming $BLLrange_t = 1$ and $Day_t = 0$..

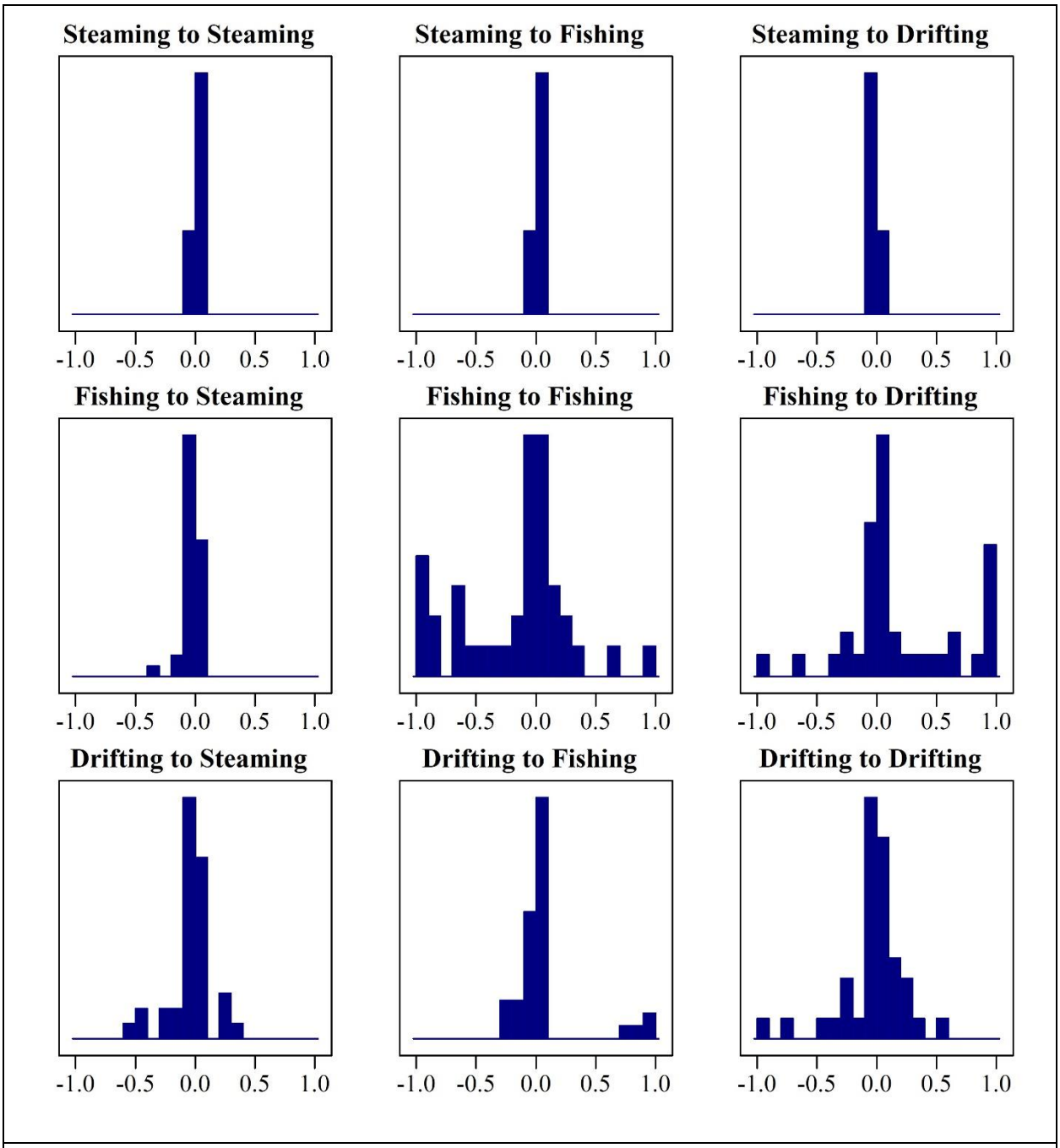

Figure III.7.2.2.4. Distribution of the differences Post-IFQ – Pre-IFQ in the transition probabilities. The probabilities are computed assuming $BLLrange_t = 0$ and $Day_t = 1$..

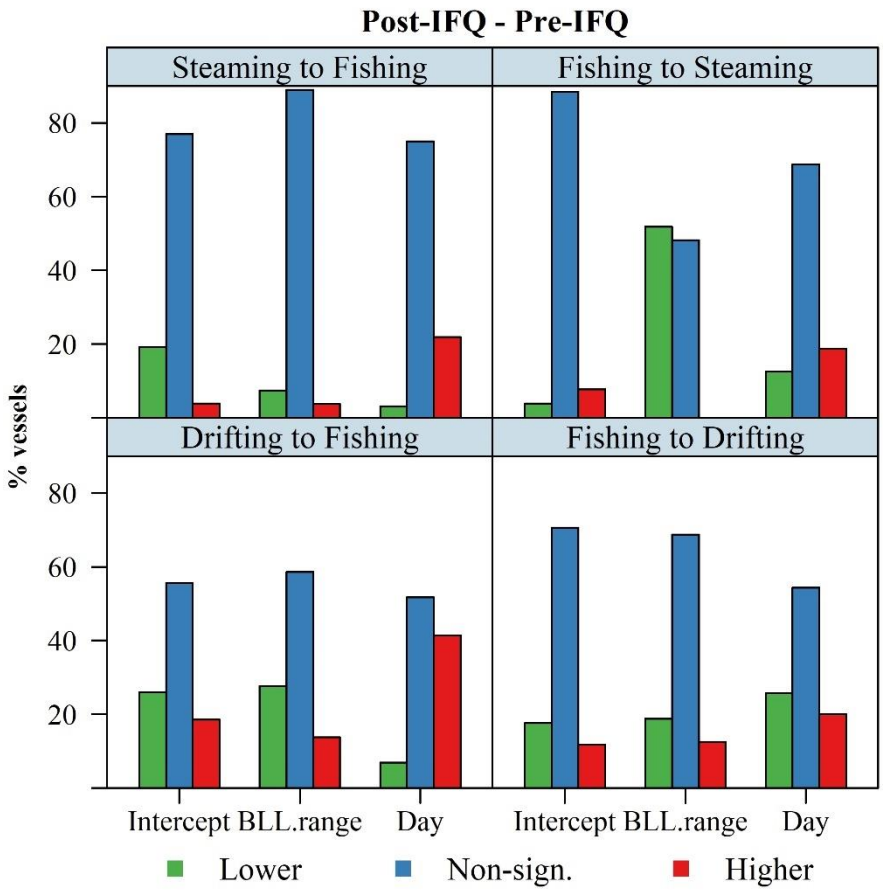

Figure III.7.2.2.5. Distribution of differences between pre- and post-IFQ periods in the covariate estimates for selected mode transitions Differences are classified as: 1) "Lower" when estimates are significantly lower in the post-IFQ period (green bars on the left); 2) "Non-sign." when there is no significant difference between the estimates in both periods (blue bars in the middle); or 3) "Higher" when estimates are significantly lower in the post-IFQ period (red bars on the right).

III.7.3. Mode decomposition of the speed and turning angle distribution

The absence of significant pre- and post-IFQ differences at the fleet level can be clearly observed when decomposing along the three behavioral modes the distribution of speeds and angles of all vessels in both periods (Figure III.C.1).

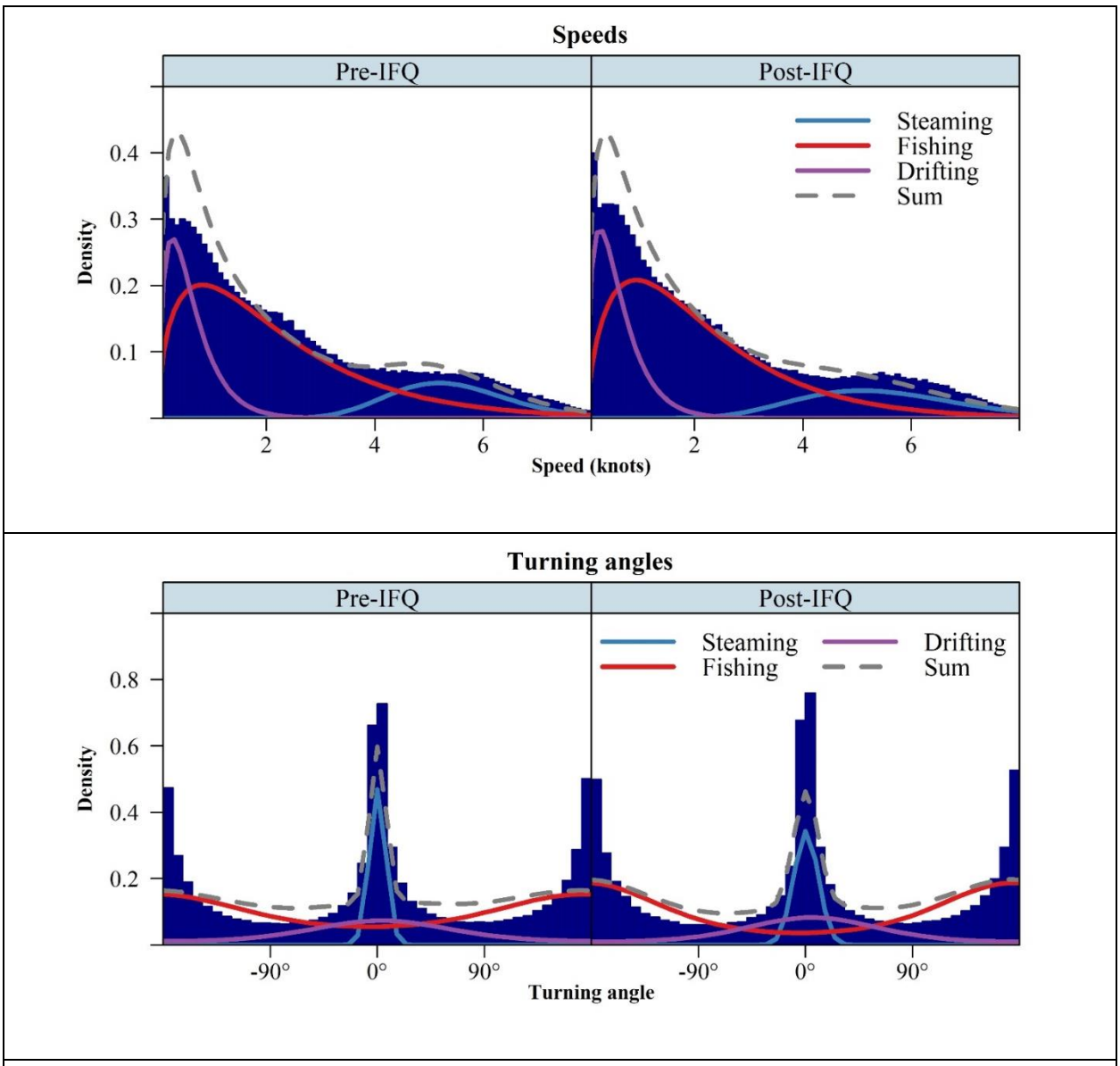

Figure III.7.3.1. Distribution of speeds and turning angles in the pre-IFQ (left panel) and post-IFQ (right panel) periods. The blue bars show the observed distribution of speeds and angles of all the vessels studied. The colored lines show the median across vessels of the estimated distributions for each mode.

Conclusion

The recent deployment of geolocation technologies, especially when used as monitoring tools, provides researchers and environmental managers with an unprecedented amount of high-resolution spatial data on resource users' activity. While enabling more refined analyses of users' dynamics, this data revolution allows to consider improving current management tools, notably through the development of behavioral models better able to capture the response of resource users to new constraints. In this dissertation, I put these principles into practice focusing on fishery management and geospatial data from Vessel Monitoring Systems (VMS). I explored both methodological and policy aspects, and considered two distinct case studies, one in the United States with the bottom longline fishery in the Gulf of Mexico, and one in Europe with the French commercial fishing fleet operating in the North East Atlantic region. While qualifying some of the expected benefits from accessing higher resolution spatial data, the results of my works clearly demonstrate the value of this new geospatial data and provide concrete avenues for incorporating it in policy design and policy evaluation.

In the first chapter I began by investigating a fundamental methodological issue in spatial modelling, that is data spatial aggregation. Using VMS data from fishers in the Gulf of Mexico I was able to go beyond the theoretical results and to exhibit empirical evidence of the scale-dependency of discrete-choice models. With high-resolution spatial data becoming more broadly available, I concluded that best practice for modelers should be to consider various spatial aggregation levels so as to assess the robustness of the results of their models. In addition, a key implication of this chapter's findings is that critical questions should be raised about the validity

of similar location choice analyses where data would not allow to consider different spatial scales of aggregation.

In Chapter II, I took advantage of VMS data to provide key elements of analysis to decision-makers, taking the example of a highly topical issue: the impact of Brexit on French fisheries. I exploited the high level of desegregation of data on commercial fishing vessels to disentangle and quantify some of the main potential effects of a large-scale closure of UK waters. In particular, I showed that 99 specific vessels, four specific species and three specific ports would significantly be impacted. Furthermore, I employed the same analytical framework developed in Chapter I to carry out some prospective and welfare analysis by predicting the new fishing location choices of the impacted vessels. Exposing the kind of complex chain reactions to expect from the re-allocation of a significant share of fishing effort outside of UK waters, the analysis of Chapter II highlights some important trade-offs that decision-makers may face in the near future.

In Chapter III I continued to focus on policy evaluation while exploring a novel modelling approach made possible by VMS data. As in Chapter I the bottom longline fishery of the Gulf of Mexico was the empirical setting, but this time I concentrated on the behavioral impact of the unique institutional shift that the fishery underwent in 2009-2010. Borrowing a modelling framework originating from ecology and developed for the study of animal movements, I successfully estimated a dynamic model of fishing behavior on a subset of longline fishers that were active in the fishery before and after the institutional shift. The characterization of fishers' behavioral states at sea in both periods suggests that the institutional shift triggered extremely heterogenous responses from fishers while leaving unchanged the overall behavioral profile of the fleet at sea. Beyond the possible implications in terms of policy assessment and long-term impact for the sustainability of the fishery, the analysis carried out in Chapter III demonstrates how VMS

data can be integrated to a flexible and structural modelling framework, thereby providing resource managers with a powerful tool to evaluate the spatial and behavioral effects of their policies.

Overall, this dissertation has built upon a broad diversity of case studies, based on distinct fisheries and focusing on different management and policy issues. In doing so, it demonstrates clearly the wide applicability of the approaches and methods that I have developed. No less important, it has also provided an opportunity to foster the dissemination of international research ideas and to contribute to the development of new research synergies between the United States and Europe. As such, this research work is a significant step forward to improve the scientific basis for decision-making in fisheries policy and more broadly in the sustainable management of marine and natural resources.