Accounting for Fleet Heterogeneity in Estimating the Impacts of Large-Scale Fishery Closures

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ABSTRACT

To date, the empirical literature on spatial closures has focused on specific fleets and/or areas, and relatively less attention has been paid to the evaluation of responses to large-scale spatial restrictions on ocean fishing. Where such restrictions occur, a broad range of fleets may be affected, with diverse response mechanisms determining the redistribution of fishing effort and the associated welfare impacts. We propose a methodological approach to address such situations. Using hypothetical scenarios regarding the closure of the UK exclusive economic zone (EEZ) to a diverse subset of French vessels as an example, we develop a spatial discrete choice model that incorporates the possibility to adjust the resolution of choice sets at the fleet level to account for heterogeneous behavioral patterns across fleets. We show how neglecting fleet diversity in the choice of the spatial resolution of analysis may bias the results of an impact study on large spatial closures.

Key words: Discrete choice model, spatial closures, spatial resolution, VMS, welfare analysis.
JEL codes: Q22, Q50.

INTRODUCTION

With the development of marine spatial planning and the growing enclosure of the maritime domain, spatial restrictions have become popular for allocating access to maritime areas and resources (Collie et al. 2013; Sanchirico et al. 2010). This includes restrictions on commercial fisheries for biodiversity conservation (with the implementation of marine protected areas), fisheries management measures (seasonal closures, territorial use rights for fisheries [TURFs]), or the access to other uses of the marine areas (e.g., aquaculture, maritime transport, renewable energy farms). The impacts of spatial restrictions on fisheries are complex and multidimensional,

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with consequences in the ecological, socioeconomic, and political realms (Eagle, Sanchirico, and Thompson 2008). While conservationists have widely praised ecosystem-based approaches (FAO 2009; Pikitch et al. 2004), they may be hard to implement in practice, because of a mismatch with the scale and scope of policies, or because of the lack of institutions able to resolve ocean-uses externalities (Sanchirico et al. 2010; Scott 1955; Sievanen et al. 2011). Many have called for a better and systematic identification and assessment of trade-offs in maritime activities as a prerequisite for the success of marine spatial plans (Collie et al. 2013; Jones 2016; Sanchirico et al. 2010).

Stakeholders involved in the development and implementation of large-scale spatial closures often focus primarily on the immediate economic consequences of such measures. Provided the data are available, what could be called "first-order" effects can be easily evaluated by identifying lost catch possibilities and valuing them at their current landing prices, taking into account price variations across species, gear, and areas from which the catches originate. However, the overall economic impacts of spatial closures are likely to be determined by intricate secondary and higher-order effects (see section A of the online appendix). The greatest of these effects is from fishers adapting to the new regulations in an attempt to mitigate impacts on their fishing enterprise (Branch et al. 2006; Fuller et al. 2017; Fulton et al. 2011).

With the increased availability of information on the spatial distribution of fishing activities, discrete choice models (DCMs) of fishing location choices have become established as a powerful and popular framework for modeling spatial and temporal fishing behavior (Eales and Wilen 1986; Smith 2010). DCMs can both identify the patterns of fishing effort reallocation induced by the changes in accessible fishing areas, and measure the likely welfare implications of the changes.[1]

However, the literature on the response of fishing fleets to spatial closures has largely focused on specific fleets and/or areas. Relatively less attention has been paid to the evaluation of responses to large-scale spatial restrictions on ocean fishing, where multiple fleets are simultaneously impacted. In most cases, spatial effort restrictions apply uniformly to all fishing activities, regardless of the diversity of fishing activities that often coexist in a fishery. The implication is that a broad range of fishing fleets may be affected, with diverse response mechanisms determining the potential redistribution of fishing effort and associated welfare impacts. Thébaud and Soulié (2007) have shown for instance that the costs of a fishing ban may be either exacerbated or mitigated depending on vessels' levels of mobility and polyvalence (i.e., ability to change métiers or targeted species) and the status of fishing opportunities in the areas surrounding the area closed to fishing. Therefore, neglecting fleet heterogeneity in the evaluation of the impacts of a fishing closure may strongly bias the evaluation.

We develop a methodological approach to integrate the diversity of fishing activities and associated behavioral patterns. Using potential access restrictions to the UK exclusive economic zone (EEZ) for foreign vessels following Brexit as a case study, and considering hypothetical scenarios regarding a large-scale closure to a subset of French vessels operating in the northeast Atlantic region between 2012 and 2015, we develop a spatial DCM that we estimate independently for each affected fleet segment. In doing so, we allow each segment to have its own spatial choice definition to account for the diversity of effort allocation patterns across fleets. Following Depalle et al. (n.d.)—who also estimate the same DCM using choice sets with a decreasing spatial resolution but focus only on a single specific fleet segment (longliners)—and using fine-resolution

1. DCMs can also be used to assess effort reallocation and ensuing distributional impacts of catch share policies (Kuriyama et al. 2019).

data on the allocation of fishing activity across a range of different fishing fleets, the model is used to estimate the potential reallocation of fishing effort under various assumptions regarding the definition of the choice sets at fleet level. We show how applying a one-size-fits-all choice of the spatial resolution of analysis across a diverse set of fleets may bias the results of a study on the welfare impacts from a large-scale closure.

The paper is organized as follows. First, we present our approach to assess the response of fleets with different fishing patterns to the same large-scale spatial closure. Next, the fleets considered for the analysis are described, using the available data for a subset of French fleets operating in the northeast Atlantic area. We then describe the model predictions on how vessels would react to the closure and how predictions may vary according to the assumptions regarding spatial resolution of the choice set for each fleet. Finally, we discuss our results, providing suggestions to further investigate the full consequences of large-scale spatial closures on multispecies, multifleet fisheries.

METHODS

The evaluation of the impacts of closure scenarios on the fleets is carried out in two stages: first, to elicit the expected first-order impacts on landings, we determine the level of dependency of the example fleet to the areas that could be closed, and characterize this dependency in terms of the existence of alternatives for the impacted vessels; second, we consider the higher-order consequences of likely adjustments in effort allocation of the fleet segments in the areas expected to remain accessible.

FIRST-ORDER IMPACTS

In order to identify potential heterogenous patterns of dependency to the fishing areas that are to be closed, we begin by clustering the impacted fishing fleet by groups of vessels—hereafter "fleet segments"—that share similar fishing métiers, defined as combinations of vessel sizes, gear types, and target species (Girardin et al. 2015). Using data at the highest level of spatial aggregation available ($\frac{1}{20}° \times \frac{1}{20}°$ statistical squares), we sum catches and revenues from areas inside or outside closed waters and we compute—on a yearly basis over a baseline period from 2012 to 2015—the share of fishing effort, catches, and catch value from each area at the levels of vessels and fleet segments.[2] This enables us to rank vessels by their level of dependency on the closed areas, in terms of the landed catches and landings' value, and to identify the vessels most exposed to the closure scenarios. We further refine the typology of vessels that depend highly on the fishing areas to be closed by considering whether they exhibit specific patterns of activity that would distinguish them from the rest of the fleet. Clustering the analysis at the fleet segment level, we investigate potential correlations between a vessel's share of gross revenue from the fishing grounds to be closed and its technical characteristics (power and length), trip characteristics (average landing, landing's value, and associated fishing effort), fishing efficiency (average catch and 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

2. We consider that as soon as a statistical square has some of its portion overlapping the closed area, all the catches and revenues allocated to this square belong to the closed area. Proceeding similarly using more spatially aggregated data (e.g., at the resolutions used for estimating the DCM) would have resulted in an increasing overestimation of the losses and smoothed out the levels of dependency to the closed area between the different fleet segments.

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 the closed waters and performing two-sample *t*-tests and linear regressions. For the last two features—catch composition and landing port locations—we map species bundles and trips' schedules at the vessel level.

SECOND-ORDER IMPACTS

Discrete choice model of fishing relocation decisions. In order to predict the reallocation of fishing effort that would result from the spatial closure, we estimate a DCM of fishing locations.[3] 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 (McFadden 1974; Smith 2010).

The model 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*:

$$\begin{aligned} U_{\mathrm{ijt}} = {} & \beta_{\mathrm{dist}} \times \mathrm{Dist}_{\mathrm{ijt}} + \beta_{\mathrm{VPUE}} \times \mathrm{E}\left[\mathrm{VPUE}_{\mathrm{ijt}}\right] + \beta_{\mathrm{Nb.vs.oth.ft}} \times \mathrm{Nb.vs.other.ft}_{\mathrm{ijt\text{-}1}} \\ & + \beta_{\mathrm{Nb.vs.same.ft}} \times \mathrm{Nb.vs.same.ft}_{\mathrm{ijt\text{-}1}} + \beta_{\mathrm{Act.own}} \times \mathrm{Act.own}_{\mathrm{ijt\text{-}1}} + \varepsilon_{\mathrm{ijt}}, \end{aligned} \tag{1}$$

where i is the vessel, j is the site, t is the day, and β_{dist}, β_{VPUE}, $\beta_{\mathrm{Nb.vs.oth.ft}}$, $\beta_{\mathrm{Nb.vs.same.ft}}$, and $\beta_{\mathrm{Act.own}}$ denote the marginal utilities of, respectively, the distance to a given location, $\mathrm{Dist}_{\mathrm{ijt}}$, the associated expected value per unit of effort ($\mathrm{E}[\mathrm{VPUE}_{\mathrm{ijt}}]$), the number of other vessels from the other fleet segments in site *j* the day before, the number of other vessels of the same fleet segment in site *j* the day before, and the vessel's own fishing effort in site *j* the day before; $\varepsilon_{\mathrm{ijt}}$ is a random utility shock.

Following the results in the prior literature on DCMs (Smith, Sanchirico, and Wilen 2009), our model specification assumes that 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 distance between the centroids of the alternative locations and the centroid of the current location (Abbott and Wilen 2011; Haynie and Layton 2010). Intuitively, this variable captures that further fishing sites not only incur higher fuel costs, but also require more time to be reached.[4]

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 consider both short- and long-term information as well as both individual- and fleet-level information, and weight information signals differently depending on what information is available (Abbott and Wilen

3. Note that instead of using the model to assess where fishers would go if a large-scale closure were implemented, the model could be also used to build the counterfactual of where fishers would have gone if a large-scale closure had not been implemented. The underlying assumption would be that the drivers of choices for individual vessels considered have not changed and are still being adequately captured by the data used (i.e., in the absence of serious observation biases), between the before and after situations. In particular, this implies that the model would remain relevant probably only for relatively short-term impact assessments, given the complexity of determinants of fishing behavior in a diverse fishery system such as the one considered here.

4. To take into account the additional cost of visiting a site located farther 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.

2011; Hutniczak and Münch 2018). Section C of the online appendix provides more details on how expected revenue is estimated, which model's specifications were considered, and how the model was selected.

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). We account for those aspects by including the lagged level of other fishers' activity—in terms of number of vessels—in a given alternative ($\text{Nb.vs.other.ft}_{ijt\text{-}1}$ and $\text{Nb.vs.same.ft}_{ijt\text{-}1}$), as well as fishers' own level of fishing activity—in terms of number of fishing hours—in a given site the day before ($\text{Act.own}_{ijt\text{-}1}$).[5]

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

For instance, Hicks and Schnier (2010) showed that welfare estimates are increased when accounting for endogenous consideration sets ("macro-regions") and using a two-stage decision-making framework. However, their study focused on only a single-species fishery, for Atka mackerel. In line with this, latent class models have been commonly used in the recreation literature to account for heterogeneous choice sets resulting from decision-makers considering different sets of options (Von Haefen 2008). Nevertheless, their application to spatial choices makes them prone to the dimensionality curse and leaves open the issue of defining the consideration sets. Explicitly accounting for observable heterogeneous characteristics of fishing vessels, Zhang and Smith (2011) investigated how a spatial closure—a marine reserve in this case—had different impacts across fishers. Yet, limited by the resolution of their dataset, they could not explore how such heterogeneity impacted the choice of the spatial definition of the choice set.

Data permitting, the choice of the model's spatial resolution (i.e., the size of the fishing sites in our case) must be considered alongside the temporal resolution at which decisions are made, the spatial extent of mobility patterns for the individual decision-maker, as well as the questions being investigated. In a study focusing on the spatial reallocation of fishing effort, a finer spatial resolution should allow a more refined analysis of potential reallocation patterns. However, we are also constrained in our choice of spatial resolution by the temporal scale of the dataset (daily aggregation). 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. Analysis of the dataset shows that the specific spatial extent varies across vessels but tends to be more homogeneous within a fleet segment (table 1).[6] It is thus likely that the resolution at which choices are defined for different fleet segments will vary, and that this should be accounted for in the estimation of the model.

We follow the methodology established by Depalle et al. (n.d.) to test the sensitivity of our model to different spatial resolutions of the alternatives, for the different fleet segments. Across the different spatial resolutions, we evaluate the reliability of the estimated models for predicting new choices of fishing locations, for each fleet segment. As an additional robustness check, we

5. Specifically, we account for the fishing activity across all of the other fleet segments in our dataset, rather just focusing on the activity of the other vessels among the five selected fleet segments.

6. For instance, in our dataset large bottom trawlers cover on average 20 (±8 SD) 1/20° × 1/20° statistical squares within a single day, whereas the average for vessels using traps or pots is only 9 (±4 SD).

Table 1. Spatial Extent of Fishing Activities for Each Fleet Segment (in numbers of 1/20° × 1/20° squares visited per day, 2012–15 period)

	Range (1/20° × 1/20° squares)			
Fleet Segments	Mean	SD	Min	Max
Bottom trawl exc. ≥ 18 m	20	8	1	52
Bottom trawl dom. ≥ 18 m	16	8	1	46
Pots and traps ≥ 12 m	9	4	1	26
Drift and fixed nets ≥ 12 m	6	3	1	45
Dredge ≥ 12 m	7	5	1	44

partition the data into a training dataset and a test dataset to perform 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. We also make predictions with the nonpreferred spatial specifications to show the extent of the bias that would arise by assuming a homogeneous fleet and considering only a single spatial resolution of analysis.

A powerful feature of discrete choice models based on a random utility framework is that, in addition to predicting new choices, they can be used to undertake a 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,[7] thereby incurring a welfare loss. We compute the welfare loss for a vessel facing a set of possible fishing sites as the utility difference (normalized by the marginal utility of distance) between the chosen site without the spatial restriction and the chosen site, restricting the choice set to sites that lie outside the exclusion area.[8]

Case study. We consider a hypothetical case study simulating the closure of the UK EEZ to a subset of the French commercial fishing fleet, as could occur following the exit of the UK from the European Union[9] (see figure 1). Data were extracted from 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), logbook, and sales data from different sources (SACROIS 2017; see section B of the online appendix for further details).

We estimated the DCM described above on five key fleet segments—large exclusive bottom trawlers (BTR exc. ≥ 18 m), large dominant bottom trawlers (BTR dom. ≥ 18 m), vessels using traps (TRP ≥ 12 m), netters (DFN ≥ 12 m), and dredgers (DRD ≥ 12 m), and we explore three levels of spatial aggregation for the size of the fishing sites. Table 2 summarizes the main characteristics of the fleet segments retained in the analysis. To make their daily decisions, we assumed fishers consider either (1) 2 ° × 2 ° squares; (2) 1 ° × ½ ° squares (as defined by the International

7. 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.

8. Statistics regarding the distribution of welfare losses within a fleet segment were computed at the level of the choice occasion. Clustering first by vessels did not significantly change the results.

9. Based on the EU Scientific, Technical, and Economic Committee for Fisheries (STECF) data (2018), the French fishing fleet is one of the main non-UK EU fleets to operate in UK waters, along with the Irish, Dutch, German, and Danish fleets (see Andersen et al., 2017, for a study of the possible impact of Brexit on the Danish fishing sector).

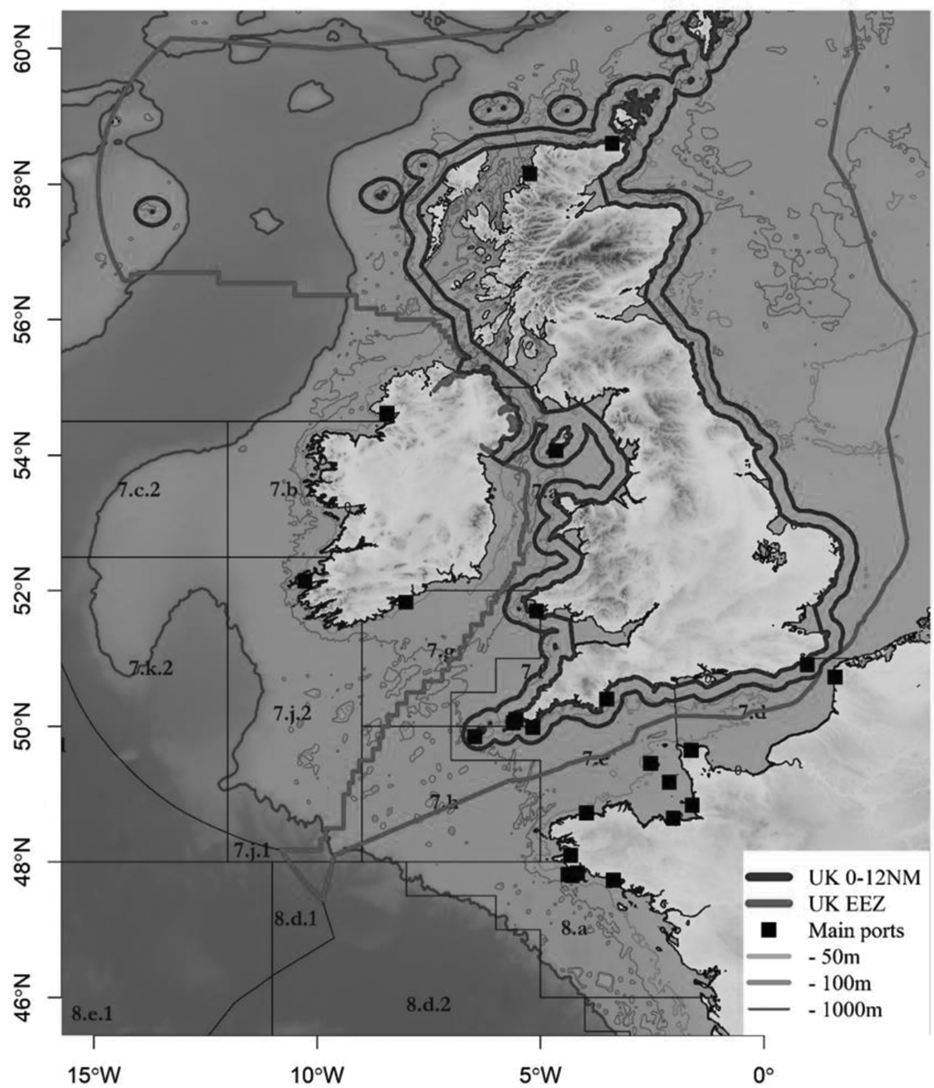

Figure 1. Maritime Boundaries and Main Fishing Ports in the Northeast Atlantic Regions. ICES areas VII and VIII's delineations are shown in light gray. Source: Authors' production. Maritime boundaries are based on the Maritime Boundaries Geodatabase, version 10, from Flanders Marine Institute, 2018 (available online at http://www.marineregions.org/).

Table 2. Main Characteristics of the Selected Fleet Segments (2012–15 period)

		Length (m)		Catch (kg/day)		Trip Duration (day)	
Fleet Segments	No. of vessels	Mean	SD	Mean	SD	Mean	SD
Bottom trawl exc. ≥ 18 m	189	25.6	8.2	1,688	1,638	6.4	3.6
Bottom trawl dom. ≥ 18 m	71	24.2	5.0	1,879	3,283	3.4	3.0
Pots and traps ≥ 12 m	19	19.7	4.5	1,307	2,013	2.4	3.2
Drift and fixed nets ≥ 12 m	135	19.4	6.6	1,118	1,870	1.8	2.5
Dredge ≥ 12 m	131	16.0	2.6	872	1,660	1.1	1.0

Council for the Exploration of the Sea [ICES] for its statistical analyses); or (3) ½ ° × ½ ° squares. We trained the model on 2013 and 2014 data, and we used 2015 data for the test dataset.

RESULTS

FIRST-ORDER IMPACTS: ECONOMIC IMPORTANCE OF UK WATERS FOR THE SELECTED FLEET SEGMENTS

Ranking fleet 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. Dominant and exclusive bottom trawlers accounted for more than one-fourth of vessels and one-third of landings from our subset of fleets. In contrast, vessels using pots and traps—even though highly dependent on UK waters—accounted for only about 3% of the landings from the same subset.

When assessing the extent to which vessels depending highly on UK waters compared with the rest of the fleet, we did not find any significant differences[10] regarding their technical characteristics (power and length), trip characteristics (average landing, landing's value, or fishing effort), and fishing efficiency (average CPUE or VPUE). We also did not find that the exploitation of fishing grounds located in UK waters focused on a specific bundle of species: vessels from a same fleet segment caught the same sets of species in and outside the UK waters. Similarly, we did not find specific patterns of landing locations related to exploiting UK waters. The vast majority of vessels from the segments under study that fished in UK waters left and landed their catches in France, and more generally the majority of vessels left and landed their catch in the same port.

Finally, we assessed whether vessels fishing mainly in UK waters received 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 fish would be different), from a greater ability of fishers to target higher-valued fish, or from some specificities in fishers' networks of fishmongers. A statistical analysis of the imputed landing prices of 12 main species between 2012 and 2015 revealed that fishing in UK waters did not lead to fishers extracting higher landing prices. This finding implies, all else equal—in particular catch rates and other market prices—that the loss of access to UK waters for the segments under study would likely not result in lower prices for their catch.

Given these results, our use of the same métier structure to examine fishing choices before and after a hypothetical closure to the selected fishing fleets seems an appropriate assumption.

SECOND-ORDER IMPACTS: FISHING EFFORT REALLOCATION AND WELFARE IMPACT

We first present the results regarding the model estimates given the choice of spatial resolution for the alternatives. We then look at the model predictions regarding effort reallocation and welfare impacts of the closure scenarios on the selected fleets. Finally, we present the extent of estimate biases when not accounting for fleet heterogeneity.

10. Except in a few instances such as the average landing per trip of large dominant bottom trawlers or the average CPUE of large exclusive bottom trawler, that turned out not to be consistent from one year to another.

Table 3. Summary Statistics of the Estimated Models of Fishing Locations

		Goodness of Fit (pseudo R^2)			Prediction Errors (% wrong)		
Fleet Segments	No.	2° × 2°	ICES	½° × ½°	2° × 2°	ICES	½° × ½°
Bottom trawl exc. ≥ 18 m	28,475	0.710	0.626	0.590	30	49	57
Bottom trawl dom. ≥ 18 m	7,330	0.705	0.590	0.549	31	53	61
Pots and traps ≥ 12 m	1,725	0.817	0.782	0.746	11	20	25
Drift and fixed nets ≥ 12 m	20,569	0.862	0.805	0.775	13	25	30
Dredge ≥ 12 m	12,721	0.661	0.630	0.613	15	30	36

Note: Prediction errors were computed by performing an out-of-sample prediction in 2015 from the trained model in 2013–14.

Model's estimates given the spatial resolution of the choice set. Examination of the 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 using varying spatial resolutions for the choice sets. Indeed, as shown in table 3 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 larger areas than those covered by the less mobile segments. Thus, reducing the choice of fishing location to a single 1 ° × ½ ° (ICES rectangle) or ½ ° × ½ ° rectangle per day appears to be inappropriate for these former segments.[11] Yet, it is an assumption that is commonly made by researchers estimating spatial choice models in a similar setting, who tend to use the ICES statistical grid as the default and unique spatial resolution of analysis (Batsleer et al. 2013; Poos and Rijnsdorp 2007; Rijnsdorp et al. 2011; Simons, Doring, and Temming 2015).

In addition, even though data might allow the use of 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 vessels using traps. Based on these results, we retain the following different spatial resolutions for each fleet segment: 2 ° × 2 ° squares for the two segments of bottom trawlers, and ICES squares for the other.

Considering only those selected resolutions, our simple model fits the data rather well, with pseudo R^2 ranging from 0.63 to 0.81, and it is able to predict out-of-sample observations with an error rate between 20% and 31%.[12]

Table 4 illustrates the parameter estimates. Consistent with the prior literature, we find that the distance variable is significant statistically and negative. We also find that the variables accounting for the level of past activity of other vessels in a site are significant and positive for vessels from other fleet segments but significant and negative for vessels of the same fleet segment. The latter effect is commonly attributed to congestion and competition, but the former

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

12. Unfortunately, we cannot offer a theoretical basis to support the choice of one metric over another, should there be conflicting conclusions regarding the adequate spatial resolution. However, as our welfare analysis is ex ante and based on the estimation of a counterfactual—where fishers would go in the case of a large-scale closure—it would make sense to favor a metric based on its ability to account for the prediction performance of the model rather than on its ability to fit the data well.

Table 4. Average Marginal Effects of the Explanatory Variables of the Discrete Choice Model of Fishing Locations for an Increase of 1 Standard Deviation

	Bottom Trawl exc. ≥ 18 m	Bottom Trawl dom. ≥ 18 m	Pots and Traps ≥ 12 m	Drift and Fixed Nets ≥ 12 m	Dredge ≥ 12 m
Distance	**–0.050*** **	**–0.166*** **	**–0.058*** **	**–0.091*** **	**–0.132*** **
N.vs.other.ft.d1	**0.012*** **	**0.031*** **	**0.022*** **	**0.009*** **	**0.019*** **
N.vs.same.ft.d1	**–0.993*** **	**–1.471*** **	**–1.272*** **	**–1.740*** **	**–2.854*** **
Vessel's past fishing effort	**0.006*** **	**0.011*** **	**0.029*** **	**0.004*** **	**0.002*** **
Expected revenues					
Short-term – fleet VPUE	**0.008*** **	–0.001	0.012	**0.008*** **	–0.001
Short-term – ind. VPUE	–0.003.	0.007	–0.018	–0.001	–0.001
Long-term – fleet VPUE	0.001	0.020*	–0.005	**0.024*** **	**0.013*** **
Long-term – ind. VPUE	**–0.006*** **	0.002	–0.005	**–0.007***	**–0.011***

Note: For each fleet segment, the parameters shown are those obtained using the appropriate spatial resolution 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%.

effect is often not addressed given the scope of prior studies. Interestingly, other activity appears to attract vessels; mechanisms for this could in part be due to "safety in numbers" and the oceanographic characteristics of the sites.

The discrete choice literature has reported various effects regarding the effect of other fishers (Girardin et al. 2016). Girardin (2015), for instance, found that the contemporaneous 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 target scallops, a relatively sedentary species. Similarly, Russo et al. (2015) reported an attractive effect on the location choice of pair trawlers from fishing units but a repulsion effect from vessels that are not fishing, which would signal the absence of resources.[13]

Vessels' own activity the day before is found to be positively significant across all of the models. This means that vessels are more likely to stay fishing in the same ground rather than to move to exploit another fishing site. This finding is in line with the general result in the literature that usually reports—though over sometimes different time windows—a significant positive effect of past fishing patterns (Abbott and Wilen 2011; Girardin et al. 2016; Girardin et al. 2015; Hynes et al. 2016).

As for the different components of the expected revenues from a site, a higher fleet-average productivity of a site in the past 30 days is found to be positively significant for exclusive bottom trawlers and netters, and not significant for other fleet segments.

When considering the impacts of past productivity on current location choices, the expectation is that fleet segments might weight past information in different ways because of the ephemeral characteristics of information in their respective fisheries. For example, we find that

13. In Russo et al. (2015), "units" designate pairs of vessels fishing by means of a pair trawl system. The distinction between fishing and nonfishing units is made by applying a speed filter: vessels having VMS points with a speed of between 3.5 $km \cdot h^{-1}$ and 4.5 $km \cdot h^{-1}$ are considered as units that are fishing.

productivity of a site at the same point in time in the last season is statistically significant for dominant bottom trawlers, netters, and dredgers with a positive effect when considering fleet-based historical average, whereas it is found to be statistically significant and negative for exclusive bottom trawlers, netters, and dredgers when considering vessel-specific historical average. We also find across all fleet segments that vessel-specific past short-term average productivity is not statistically significant. When considering fleet-based short-term historical average, a significant positive effect is found for exclusive bottom trawlers and netters only.

A combination of a positive effect of short-term public information with a negative or non-significant effect of long-term private information appears consistent for vessels targeting highly mobile species with changing seasonal spatial patterns. In these cases, the value of information likely deprecates quickly, implying that vessels are likely better off basing their expectations on a larger pool of information sources or on tracking technologies equipping the majority of vessels in the segment.

Overall, we find differentiated effects across the five fleet segments and across the four types of information. This supports our approach of estimating segment-specific models and considering different types of information for vessels having fundamentally different fishing strategies (see section C in the online appendix for the estimated parameters at each spatial resolution as well as for a more detailed interpretation of the estimates).

Effort reallocation and welfare impact predictions. 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 the distribution of choice occasions and of the associated levels of fishing effort fixed, we 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, we choose to estimate effort reallocation for each choice occasion observed in 2015 and to average fishing efforts over the year. Our approach is less susceptible to having a specific day of the year given undue weight in these calculations.

Figure 2 shows the predicted change—in terms of mean fishing hours per day—of the fishing pressure of each of the five key fleet segments in response to the hypothetical closure of the UK EEZ, using models estimated at the relevant spatial resolution for each fleet. Not surprisingly, the sites that are the closest to the initial fishing grounds of French vessels in UK waters are those that are predicted to face the highest increases in fishing effort. For bottom trawlers, this involves an increase in fishing effort in the west of Brittany and in the Channel, as well as in the northern part of the Celtic Sea, south of the Irish shores. For vessels using traps, there is mainly one cluster of increased fishing pressure, north of Brittany. Netters are also predicted to relocate their fishing effort in this area, as well as in the area north of the west end of the UK EEZ. Dredgers are predicted to increase their fishing pressure north of Normandy, in the eastern part of the Channel (see figures D.1 to D.5 in the online appendix).

According to our estimation, exclusive bottom trawlers and vessels using pots and traps are the most impacted, particularly because of the large welfare losses incurred by the loss of access to the fishing areas surrounding Cornwall (see figure 2, top right panel). When excluding those sites, the magnitude of the mean utility loss of those two fleet segments becomes similar to the magnitude of the losses of the other fleet segments. Overall, the level of welfare losses of each

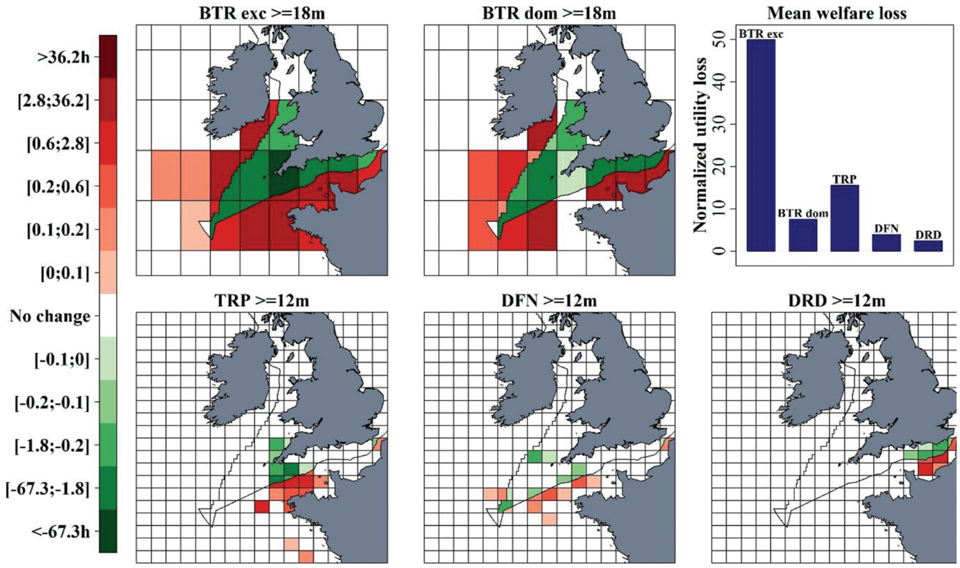

Figure 2. Predicted Absolute Changes in the Mean Daily Fishing Hours and in the Mean Welfare Loss of the Five Key Fleet Segments Considered in Response to the Closure of the UK EEZ. Welfare losses are computed at the choice occasion level and measured in terms of utility loss normalized with the marginal utility of distance.

fleet reflects their level of dependency to the closed areas. Dominant bottom trawlers show larger levels of impact than those for dredgers and netters (which derive less catches from the closed areas). Such a pattern of correllation is consistent with the assumption of utility maximization of our model: the more attractive a site, the more likely it is to be visited by vessels.

The magnitude of the welfare losses and changes in the fishing effort intensifications we predict, however, needs to be qualified. Indeed, choosing a simplistic model for the sake of clarity, the predictions we present here do not take into account the dynamic nature of the behavior of fishers, who are likely to smooth the reallocation of their fishing effort through space and time. We attempted to assess the implications of such dynamic behavior by updating the day-to-day predictions of the model.[14] Chaining predictions over the first 30 days of 2015 (the process is computationally demanding and the updating assumptions become weaker as the time span expands), we obtained welfare losses that are noticeably smaller for exclusive bottom trawlers and vessels using pots and traps (about 80% smaller), moderately smaller for dominant bottom trawlers and netters (about 20% smaller), and noticeably larger for dredgers (about 300% larger) than the welfare losses that would be estimated without chaining the predictions (cf. figure E.5 in the online appendix).

Similarly, we also do not model for the timing of the decisions to go on a fishing trip. Neither does our model account for the heterogeneity of choices within a fishing trip. As suggested in the literature by Sun, Hinton, and Webster (2016) and Kuriyama et al. (2019), for instance, fishers may be, for example, more likely to choose fishing sites farther away for the first day of a trip. We investigated the first day of trip effects and found, as in previous studies, that those effects are

14. To do so we needed to make an assumption regarding how the variables related to the productivity of vessels in each of the potentially selected sites were updated over time (see section E of the online appendix for further details).

significant (see section E of the online appendix for results). We leave this question as an interesting area for future research, as the quantitative exploration of the impacts of these effects on the analysis is beyond the scope of the present study.

Accounting for this nuance in the choice of the fishing location on the first days of trips can have mixed implications for the reallocation of effort that is predicted by the model. On one side, sites that are located close to the French shores may be predicted to be less likely chosen, thereby alleviating part of the fishing intensification in the Channel, for instance. However, on the other side it may also lead sites located near the southwest end of the UK EEZ to be predicted to be more likely chosen, thereby increasing the fishing pressure in this area.

A key consideration in the analysis of impacts of closures is calibrating the spatial choice set with the decision-making process and scale of the closures. Any potential bias in the impact measures is also likely specific to fleet heterogeneity. For example, considering the same spatial scale with a fleet that includes vessels forming their decisions over largely different spatial ranges can lead to overestimating the impact for some and underestimating the impact for others, with an uncertain aggregate effect. Figure 3 shows the deviation of the predicted relative change in the total fishing effort of the five fleet segments when the same spatial resolution is used for the choice sets of all segments (results are aggregated at the coarser spatial resolution considered to allow comparisons; disagregated results for each spatial resolution are available in section C of the online appendix).

Using only the coarsest resolution in model estimation leads to predicted relative changes that are relatively close to the predicted changes with specific choice set resolutions for each segment. The largest discrepancies in the predictions, neglecting marginally exploited areas, are the predicted increases in the fishing effort located at the edge of the UK EEZ, south of the Celtic Sea (+216% vs. +228% increased effort pressure), and north of Brittany (+171% vs. +161%). Carrying out the analysis using ICES spatial resolution (1 ° × ½ ° rectangles) produces results that differ more noticeably across the fleet segments. The increases in the fishing effort south of Ireland and north of Brittany are substantially overestimated with deviations of, respectively, +17% and +30%, and compensated by lower predicted increases in the Celtic Sea close to the UK EEZ

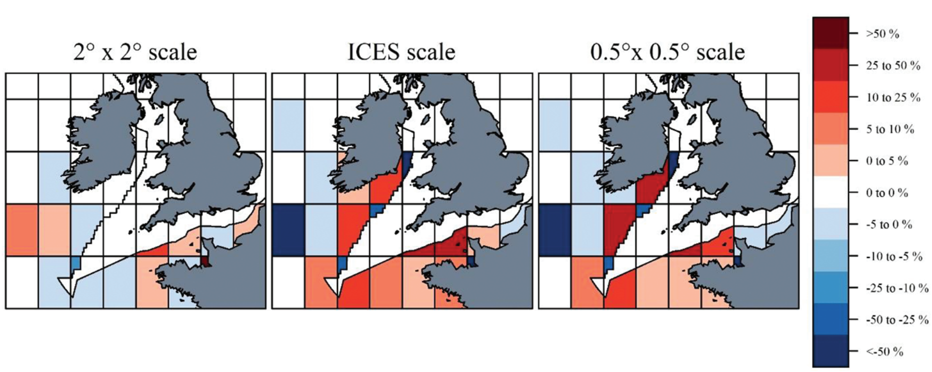

Figure 3. Deviation (in Percentage Points) with the Predicted Relative Changes in the Total Fishing Hours of the Five Fleet Segments When Using One Spatial Resolution for All the Segments. To allow comparisons, results are aggregated at the coarser spatial resolution considered (2° × 2°). An *x*% deviation shown in the figure means that if the model estimated at the relevant spatial resolutions predicted a *y*% change in the total fishing pressure of the five fleet segments, then using the same resolution for all the segments leads to an ($x + y$)% predicted change.

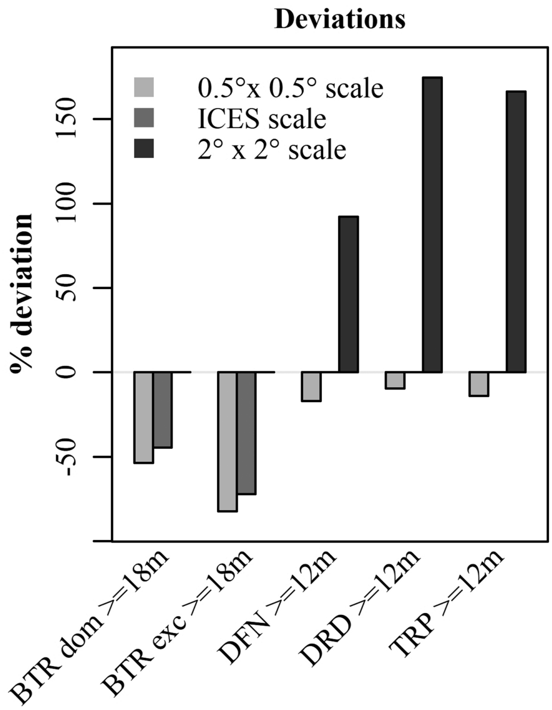

Figure 4. Deviation (Relative to the Estimates Presented in Figure 2) in the Normalized Mean Welfare Loss by Choice Occasion When Using the Same Spatial Resolution for All the Fleet Segments.

(–33%) and farther west (–50%). Figure 4 shows the estimated welfare losses when using the same spatial resolution for all fleet segments, expressed in terms of percentage deviation from the estimates presented in figure 2. Losses are generally estimated to be less important as the spatial resolution chosen gets finer. This is likely due to the large weight given to the distance factor relative to other factors in our model, combined with the mechanical reduction of the differences in distance characteristics between two options, when considering finer scales.

DISCUSSION AND CONCLUSION

Large-scale spatial closures are increasingly considered as part of the marine policy toolbox. At the same time, there have been growing efforts to develop approaches that help assess the impacts of such closures on marine fisheries, beyond the first-order consequences associated with the loss of access to certain areas, and including the cascading effects due to the reallocation of fishing effort. We propose a methodology to assess such impacts while accounting for the diversity of fishing strategies among fishing fleets. Using a hypothetical scenario regarding the exclusion of selected French fleet segments from the UK EEZ, we first provide a thorough analysis of the current economic dependencies of these fleet segments to UK fishing grounds. While this produces a first-order assessment of the magnitude of the economic stakes and of where future points of friction may arise, on which stakeholders are likely to focus when examining alternative spatial management scenarios, it does not provide an actual assessment of the total effects resulting from the reallocation of fishing effort because it misses the adaptation of the fleets.

We then model the immediate reallocation of fishing effort in the areas remaining accessible, which would be the most obvious response of fishers to an area closure in the short term. Supported by our finding that the bundle of species caught by vessels exploiting fishing grounds in UK waters is not different from the bundle of species of other vessels, we assume that fishers would still be able to target the same set of species as in UK waters. Focusing on five main fleet segments, we provide a snapshot of the average short-term reallocation of fishing effort. This points to three critical hotspots of potentially 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 fishing activities in these areas is likely to increase the potential for conflicts of use of resources and of the maritime domain.

Our results also show that the ability to account for this diversity increases the reliability and the accuracy of impact assessments. The approach illustrates the value of fine-resolution spatial data to analyze fishing activities and to assess the robustness of predictions regarding the response of fishers to changes in their fishing opportunities by testing different spatial scales. If we could not tailor the spatial resolution of choice sets to specific fleet segments, our results show that an impact assessment could be misleading. For example, we find that, provided our identification of more relevant resolution is correct, using the resolution of the ICES rectangles when modeling choices of all vessels would overpredict reallocation of effort towards regions close to the south shores of Ireland, and underpredict effort reallocation towards regions closer to the delineation line of the UK EEZ.

Regarding welfare impacts on the fleets, we find that using a finer resolution for the choice sets when coarser resolutions may be more relevant (as suggested by better prediction performances, for instance) leads to an under-estimate of the losses. At the same time, we also show that model predictions may be highly unreliable with such resolution. Given that we find that the probabilities of choosing a site are mostly determined by how far sites are from a vessel location (recall the larger estimated coefficients for the distance variable), this may not be surprising because the gap in the distance to alternative site options gets larger as the spatial resolution gets coarser. However, this result does not apply for dredgers and netters at the finest spatial resolution. This may be explained by the specific spatial configurations of the sites and of the closure area in the Channel. Indeed, all the spatial resolutions we considered in this region are still rather coarse relative to the eastern part of the Channel,[15] the region where netters and dredgers operate and would relocate their fishing effort. Thus, depending on the spatial configuration of the statistical squares in the region, the attractiveness of the sites located outside the closed area may be extremeley heterogenous. Should the spatial resolution allow for a finer description of the area, distance or productiviy differentials may be more homogeneously distributed between sites.

The relocation that we predict of the large bottom trawlers closer to French coastal fishing grounds would have the potential to trigger important domino effects on the coastal fleet segments in the region, as well as on coastal ecosystems. Examining the full consequences of the same number of vessels fishing in a smaller area would also require information on a number of other uses of marine space. Indeed, areas such as the Channel are already experiencing intense competition for space between maritime activities (Girardin 2015; Halpern et al. 2008). Moreover, even though our study focuses on French fleet segments, a number of other European

15. In the finest spatial scale the longitudinal size of the statistical squares is 30 nm, whereas the shortest distance between French and British shores is only 18 nm.

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, Pawlowski, and Rober 2016). Interactions with smaller vessels, not accounted for in our study, should also be considered.

The reallocation of fishing effort can also have consequences 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 impacts on the local fishing communities, notably in the processing sector that may be confronted with over- or undercapacity issues. This may in turn impact fishers, who may face changing landing prices and may have to establish new networks of wholesale fishmongers.

Finally, the impact of the spatial reallocation of fishing effort on the dynamics of the biological stocks should also be taken into account, as this would entail changes in the catch rates and revenues per unit of effort associated with different métiers applied to different areas. While the state and the dynamics of some of the most important fish stocks are now generally well understood and regularly monitored, the understanding of their spatial distribution at fine scales is not as strong, and many of the species contributing to the economic returns of the fleets remain poorly known. This makes the anticipation of the impact of changes in the intensity and spatial distribution of fishing pressure by the fleets even more uncertain.

Accounting for the full suite of these dynamic effects is a complex task that would require the development of a complete bioeconomic model of the different fleets and their interactions with the fish stocks, as well as the European fish supply chain.

REFERENCES

Abbott, J. K., and J. E. Wilen. 2011. "Dissecting the Tragedy: A Spatial Model of Behavior in the Commons." *Journal of Environmental Economics and Management* 62:386–401. https://doi.org/10.1016/j.jeem.2011.07.001.

Andersen, P., J. L. Andersen, A. Hoff, and L. Ståhl. 2017. "The Economic Consequences for the Danish Fishery Following the United Kingdom's Decision to Leave the European Union." IFRO Report No. 263, Department of Food and Resource Economics, University of Copenhagen.

Batsleer, J., J. Poos, P. Marchal, Y. Vermard, and A. Rijnsdorp. 2013. "Mixed Fisheries Management: Protecting the Weakest Link." *Marine Ecology Progress Series* 479:177–90. https://doi.org/10.3354/meps10203.

Branch, T. A., R. Hilborn, A. C. Haynie, G. Fay, L. Flynn, J. Griffiths, K. N. Marshall, et al. 2006. "Fleet Dynamics and Fishermen Behavior: Lessons for Fisheries Managers." *Canadian Journal of Fisheries and Aquatic Sciences* 63:1647–68. https://doi.org/10.1139/f06-072.

Collie, J. S., W. L. (Vic) Adamowicz, M. W. Beck, B. Craig, T. E. Essington, D. Fluharty, J. Rice, and J. N. Sanchirico. 2013. "Marine Spatial Planning in Practice." *Estuarine, Coastal and Shelf Science* 117:1–11. https://doi.org/10.1016/j.ecss.2012.11.010.

Depalle, M., J. N. Sanchirico, A. C. Haynie, O. Thébaud, S. O'Farrell, and L. Perruso. n.d. "Scale-Dependency in Discrete Choice Models: A Fishery Application." Working paper, University of California, Davis.

Eagle, J., J. N. Sanchirico, and B. H. Thompson Jr. 2008. "Ocean Zoning and Spatial Access Privileges." *New York University Environmental Law Journal* 17 (1): 646–68.

Eales, J., and J. E. Wilen. 1986. "An Examination of Fishing Location Choice in the Pink Shrimp Fishery." *Marine Resource Economics* 2 (4): 331–51. http://www.jstor.org/stable/42628909.

FAO. 2009. "Fisheries Management: 2. The Ecosystem Approach to Fisheries. 2.2. The Human Dimensions of the Ecosystem Approach to Fisheries." *FAO Technical Guidelines for Responsible Fisheries* 4 (Suppl. 2, Add. 2). Rome: FAO.

Fuller, E. C., J. F. Samhouri, J. S. Stoll, S. A. Levin, and J. R. Watson. 2017. "Characterizing Fisheries Connectivity in Marine Social–Ecological Systems." *ICES Journal of Marine Science* 74:2087–96. https://doi.org/10.1093/icesjms/fsx128.

Fulton, E. A., A. D. M. Smith, D. C. Smith, and I. E. van Putten. 2011. "Human Behaviour: The Key Source of Uncertainty in Fisheries Management." *Fish and Fisheries* 12:2–17. https://doi.org/10.1111/j.1467-2979.2010.00371.x.

Girardin, R. 2015. "Ecosystem and Fishers' Behaviour Modelling: Two Crucial and Interacting Approaches to Support Ecosystem Based Fisheries Management in the Eastern English Channel." PhD diss., Université Lille 1.

Girardin, R., K. G. Hamon, J. Pinnegar, J. J. Poos, O. Thébaud, A. Tidd, Y. Vermard, and P. Marchal. 2016. "Thirty Years of Fleet Dynamics Modelling Using Discrete-Choice Models: What Have We Learned?" *Fish and Fisheries.* https://doi.org/10.1111/faf.12194.

Girardin, R., Y. Vermard, O. Thébaud, A. Tidd, and P. Marchal. 2015. "Predicting Fisher Response to Competition for Space and Resources in a Mixed Demersal Fishery." *Ocean and Coastal Management* 106:124–35. https://doi.org/10.1016/j.ocecoaman.2015.01.017.

Haab, T. C., and R. L. Hicks. 1999. "Choice Set Considerations in Models of Recreation Demand: History and Current State of the Art." *Marine Resource Economics* 14:271–81.

Halpern, B. S., S. Walbridge, K. A. Selkoe, C. V. Kappel, F. Micheli, C. D'Agrosa, J. F. Bruno, et al. 2008. "A Global Map of Human Impact on Marine Ecosystems." *Science* 319:948–52. https://doi.org/10.1126/science.1149345.

Haynie, A. C., and F. D. Layton. 2010. "An Expected Profit Model for Monetizing Fishing Location Choices." *Journal of Environmental Economics and Management* 59:165–76. https://doi.org/10.1016/j.jeem.2009.11.001.

Hicks, R. L., and K. E. Schnier. 2010. "Spatial Regulations and Endogenous Consideration Sets in Fisheries." *Resource and Energy Economics* 32 (2): 117–34 https://doi.org/10.1016/j.reseneeco.2009.11.008.

Huang, L., and M. D. Smith. 2014. "The Dynamic Efficiency Costs of Common-Pool Resource Exploitation." *American Economic Review* 104:4071–103. https://doi.org/10.1257/aer.104.12.4071.

Hutniczak, B., and A. Münch, 2018. "Fishermen's Location Choice under Spatio-Temporal Update of Expectations." *Journal of Choice Modelling* 28:124–36. https://doi.org/10.1016/j.jocm.2018.05.002.

Hynes, S., H. Gerritsen, B. Breen, and M. Johnson. 2016. "Discrete Choice Modelling of Fisheries with Nuanced Spatial Information." *Marine Policy* 72:156–65. https://doi.org/10.1016/j.marpol.2016.07.004.

Jones, J., I. Thomas, and D. Peeters. 2015. "Forecasting Jobs Location Choices by Discrete Choice Models: A Sensitivity Analysis to Scale and Implications for LUTI Models." *Region* 2:67–93.

Jones, P. J. S. 2016. "Marine Spatial Planning in Reality: Introduction to Case Studies and Discussion of Findings." *Marine Policy* 9.

Kuriyama, P. T., D. S. Holland, L. A. K. Barnett, T. A. Branch, R. L. Hicks, and K. E. Schnier. 2019. "Catch Shares Drive Fleet Consolidation and Increased Targeting but Not Spatial Effort Concentration nor Changes in Location Choice in a Multispecies Trawl Fishery." *Canadian Journal of Fisheries and Aquatic Sciences*. https://doi.org/10.1139/cjfas-2019-0005.

Manski, C. F. 1977. "The Structure of Random Utility Models." *Theory and Decision* 8:229–54. https://doi.org/10.1007/BF00133443.

Mateo, M., L. Pawlowski, and M. Rober. 2016. "Highly Mixed Fisheries: Fine-Scale Spatial Patterns in Retained Catches of French Fisheries in the Celtic Sea." *ICES Journal of Marine Science* 74 (1): 91–101. fsw129. https://doi.org/10.1093/icesjms/fsw129.

McFadden, D. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics*, 105–42. New York: Academic Press.

Parsons, G. R., and A. B. Hauber. 1998. "Spatial Boundaries and Choice Set Definition in a Random Utility Model of Recreation Demand." *Land Economics* 74 (1): 32–48. https://doi.org/10.2307/3147211.

Pikitch, E., C. Santora, E. Babcock, A. Bakun, R. Bonfil, D. Conover, P. Dayton, et al. 2004. "Ecosystem-Based Fishery Management." *Science* 305 (5682): 346–47. https://doi.org/10.1126/science.1098222.

Poos, J.-J., and A. D. Rijnsdorp. 2007. "An 'Experiment' on Effort Allocation of Fishing Vessels: The Role of Interference Competition and Area Specialization." *Canadian Journal of Fisheries and Aquatic Sciences* 64:304–13. https://doi.org/10.1139/f06-177.

Rijnsdorp, A. D., J. J. Poos, F. J. Quirijns, and J. Grant. 2011. "Spatial Dimension and Exploitation Dynamics of Local Fishing Grounds by Fishers Targeting Several Flatfish Species." *Canadian Journal of Fisheries and Aquatic Sciences* 68:1064–76. https://doi.org/10.1139/f2011-032.

Russo, T., J. Pulcinella, A. Parisi, M. Martinelli, A. Belardinelli, A. Santojanni, S. Cataudella, S. Colella, and L. Anderlini. 2015. "Modelling the Strategy of Mid-Water Trawlers Targeting Small Pelagic Fish in the Adriatic Sea and Its Drivers." *Ecological Modelling* 300:102–13. https://doi.org/10.1016/j.ecolmodel.2014.12.001.

SACROIS. 2017. Système de Informations Halieutiques. https://wwz.ifremer.fr/peche/Le-role-de-l-Ifremer/Observation/Systeme-d-Informations-Halieutiques/Donnees-traitees.

Sanchirico, J. N., J. Eagle, S. Palumbi, and B. H. Thompson Jr. 2010. "Comprehensive Planning, Dominant-Use-Zones, and User Rights: A New Era in Ocean Governance." *Bulletin of Marine Science* 86.

Scott, A. 1955. "The Fishery: The Objectives of Sole Ownership." *Journal of Political Economy* 63 (2): 116–24.

Sievanen, L., H. M. Leslie, J. M. Wondolleck, S. L.Yaffee, K. L. McLeod, and L. M. Campbell. 2011. "Linking Top-Down and Bottom-Up Processes through the New US National Ocean Policy." *Conservation Letters* 4 (4): 298–303.

Simons, S. L., R. Doring, and A. Temming. 2015. "Modelling Fishers' Response to Discard Prevention Strategies: The Case of the North Sea Saithe Fishery." *ICES Journal of Marine Science* 72:1530–44. https://doi.org/10.1093/icesjms/fsu229.

Smith, M. D. 2005. "State Dependence and Heterogeneity in Fishing Location Choice." *Journal of Environmental Economics and Management* 50:319–40. https://doi.org/10.1016/j.jeem.2005.04.001.

———. 2010. "Toward an Econometric Foundation for Marine Ecosystem-Based Management." *Bulletin of Marine Science* 86:461–77.

Smith, M. D., J. N. Sanchirico, and J. E. Wilen. 2009. "The Economics of Spatial-Dynamic Processes: Applications to Renewable Resources." *Journal of Environmental Economics and Management* 57:104–21. https://doi.org/10.1016/j.jeem.2008.08.001.

Sun, J., M. G. Hinton, and D. G. Webster. 2016. "Modeling the Spatial Dynamics of International Tuna Fleets." *PLoS ONE* 11 (8): e0159626. https://doi.org/10.1371/journal.pone.0159626.

Thébaud, O., and Soulié, J.-C. 2007. "Fishing through Fish Communities: A Simple Bio-Economic Model." *Land, Water and Environmental Management: Integrated Systems for Sustainability, Proceedings.*

Von Haefen, R. H. 2008. "Latent Consideration Sets and Continuous Demand Systems." *Environmental and Resource Economics* 41:363–79. https://doi.org/10.1007/s10640-008-9196-x.

Zhang, J., and M. D. Smith. 2011. "Estimation of a Generalized Fishery Model: A Two-Stage Approach." *Review of Economics and Statistics* 93 (2): 690–99.