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Scale-dependency in discrete choice models: A fishery application

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ABSTRACT

Modeling the spatial behavior of fishers is critical in assessing fishery management policies and has been dominated by discrete choice models (DCM). Motivated by the widespread availability of micro-data on fishing vessel locations, this paper examines the complexity associated with the choice of the spatial scale in a DCM of fishing locations. Our empirical approach estimates the standard DCM at varying spatial resolutions using both simulated data and vessel monitoring system data from the Gulf of Mexico longline fishery. We assess model performance using goodness-of-fit, predictive capacity, parameter estimates, and the assessment of the fishery response to a hypothetical marine protected area. Results show that, even when the specification of the decision-making process is correct, models can be structurally biased because of the aggregation of spatial scale that neglects the value of many fishing locations. The extent of such biases can only be detected by considering various spatial aggregation levels.

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1. Introduction

Understanding and anticipating fishers' spatial behavior is a critical component in the design and assessment of fishery management (Lewison et al., 2015; Smith, 2010; Valcic, 2009). Research on predicting how management measures impact 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 DCM 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 research 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,

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the marketing and transportation literature has extensively investigated the heuristics of consideration sets since the 1970s (Hauser, 2014; Horowitz and Louviere, 1995; Narayana and Markin, 1975; 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 dramatically improved 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 remarkable advance over traditional data aggregated into large statistical areas. In many fisheries, VMS transponders placed on each vessel track vessel positions at certain specified time intervals (e.g., each hour). These new data open up possibilities to refine analyses of fisher behavior across space and time. With potentially millions of recorded locations for each vessel, VMS data allow researchers to relax some prior assumptions underlying many DCM regarding the data-generating process and spatial scale of the analysis. In particular, it allows relaxing the implicit assumption of studies constrained by coarse spatial data that the decision-making process generating the data operates at that coarse scale. VMS data allow a more refined discretization of space permitting us to investigate the implications for the performance of classical DCM of the aggregation process related to partitioning space in different manners.

Through a novel approach that combines both simulated and real data, this paper investigates the following questions. First, how do estimates of traditional DCM of spatial behavior change as the mismatch between the spatial scale of aggregation and the spatial scale of the data-generating process grows? Second, how do estimates at spatially-refined resolutions depend on the spatial distribution and heterogeneity of the observations?

Spatial aggregation impacts DCM's estimation through two main mechanisms. On the one hand, it affects the structure of the choice set. Aggregation determines what and how many choices are available in the decision-making sequence and it determines where an observed choice is located in space. Further, whether to change location in any period is a function of the opportunities available in the consideration set, which are modified by the level of spatial aggregation. On the other hand, aggregation affects the quantity and quality of the information used to estimate a DCM. Indeed, the opportunities in the different sites are assessed with the aggregated data (e.g., expected catches) and therefore the aggregation will affect the amount of information available to make those calculations, in particular by levelling out some data variability. For example, a fisher's expected catch for each site in the choice set is the result of a complex process that likely combines individual and fleet-level observations for that site over some prior period of time.¹ The impacts of spatial aggregation on the modeling of this process, however, is not immediately clear and will likely depend on the underlying heterogeneity of the data across both space and time. Fig. 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.

We conduct a series of Monte Carlo experiments (two sets of 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 consists in estimating, at varying resolutions, the true decision-making process of three datasets of observations having different spatial distributions. We consider spatial choice sets defined at both higher and lower resolutions than the resolution of the true decision-making process, and without necessarily a nested structure (see Figure C.a in the appendix). This enables us to identify more precisely the respective effects of the two aggregation mechanisms we described.

For each combination of dataset and spatial resolution, we assess how well the estimated model can recover the true parameters of the decision-making process, how well the model fits the data, and how well it can predict unobserved choices out-of-sample. We also use the model to evaluate the welfare impact of the implementation of a hypothetical Marine Protected Area (MPA) because DCM have been a popular tool to conduct the impact analysis of an MPA policy (Curtis and Hicks, 2000; Hicks and Schnier, 2010; Hynes et al., 2016; van der Lee et al., 2014). We then apply the same analytical framework to a real case study using a unique dataset on bottom longline (BLL) fishing in the Gulf of Mexico reef fish (GoMRF) fishery that includes recently 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 DCM. 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 DCM (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

¹ In particular, the expected productivity of fishing sites has been shown to be a major driver of fishers' decisions (Eales and Wilen, 1986; 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).

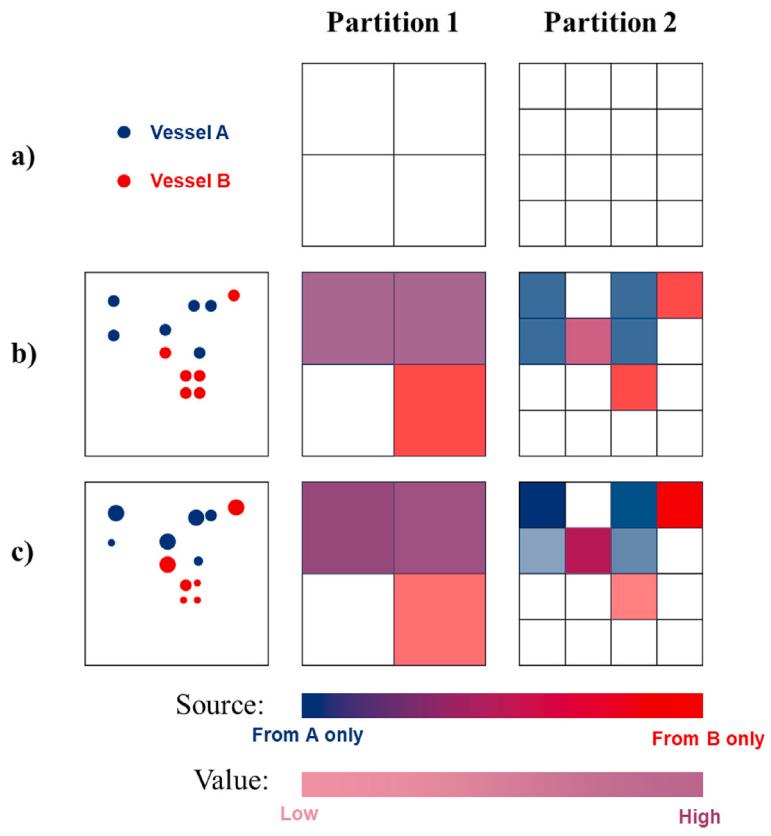


Fig. 1. Conceptual figure illustrating how the partition of space in a model intrinsically shapes how information is integrated and, therefore, model's results. The panels are: a) identification of two vessels and two alternative partitions of the fishing area; b) illustration of the case where observed values (e.g., catch rates) are homogeneous in all locations; c) illustration of the case where observed values are heterogeneous across locations (dots indicate the number of observations). 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. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

of discrete-choice modeling 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, DCM can be biased because of the aggregation of data, and that these effects are amplified as spatial heterogeneity of a site's quality increases. In contrast, we are not able to detect any effect of the spatial irregularity of the observation sample. Second, we demonstrate how VMS data can be used to detect model bias and to assess the robustness of DCM results. Our findings suggest caution in the use of DCM for policy analysis, when the researcher is unable to verify the robustness of their results across multiple spatial resolutions (e.g., due to data limitations).

In the remainder of the paper, we first describe our methodological approach, detailing the setting of the Monte Carlo experiments and the empirical data. We then show the results of the model estimations with the simulated data and with observations from the bottom long-line (BLL) sector of the Gulf of Mexico reef fish fisheries (GoMRF). Finally, we summarize our findings, draw general conclusions about spatial models and the use of VMS data, and suggest possible future research in this area.

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. This section presents the modeling approach applied in the simulation and empirical example.

Table 1

Different cases investigated with regard to the amount of information available to vessels in the formation of their expected value per unit effort (VPUE) for the different sites in the choice set. Short-term information refers to historical VPUE records averaged over the month prior to the fishing trip ("m-1" subscript) while long-term information refers to historical VPUE records averaged over the same month of the year prior to the fishing trip ("ym-1" subscript). The superscript "ft" indicates that VPUE have been averaged across all the active vessels of the fleet.

Case	Information available to form $E[VPUE]$	$\beta_{VPUE} * E[VPUE_{ijt}]$ is equal to
1	Both short-term and long-term historical VPUE are available	$\beta_{VPUE}^{\text{Full info - short-term}} * \bar{VPUE}_{m-1}^{\text{ft}} + \beta_{VPUE}^{\text{Full info - long-term}} * \bar{VPUE}_{ym-1}^{\text{ft}}$
2	Only short-term historical VPUE are available	$\beta_{VPUE}^{\text{Short-term only}} * \bar{VPUE}_{m-1}^{\text{ft}}$
3	Only long-term historical VPUE are available	$\beta_{VPUE}^{\text{Long-term only}} * \bar{VPUE}_{ym-1}^{\text{ft}}$
4	Neither short-term or long-term historical VPUE are available	$\beta_{VPUE}^{\text{No info}}$

2.1. Modeling framework

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

$$U_{ijt} = \beta_{\text{dist}} * \text{Dist}_{ijt} + \beta_{VPUE} * E[VPUE_{ijt}] + \varepsilon_{ijt} \quad (1)$$

where i is the vessel, j is the site, and t is the 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 effort ($E[VPUE_{ijt}]$) and ε_{ijt} is a random shock. The definition of what constitutes a site (i.e., the scale of space discretization) will vary across models.

Our specification is the standard workhorse model in the literature where expected revenues and travel costs 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 require more travel time.

With respect to fishers' expectations about revenues from a fishing site, we follow the literature that utilizes records of past performance 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; Hutzicak and Münch, 2018).² When we estimate the model we account for all possible combinations of information available by using dummy variables (Table 1).

In the empirical 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}) 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:

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

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). More details on the empirical specification and other possible representations are provided in Section E of the Appendix.

2.2. Tessellations

In the simulated and GoMRF analysis, we estimate Eq. (1) or Eq. (2) with variables and alternatives defined at increasingly spatially-aggregated (i.e., coarser) resolutions (see, for example, Fig. 2). For the simulations, we considered nine tessellations based on a grid, with cell sizes ranging from 1 Nautical Mile (NM – although distances are only relative in the simulations) to 30NM. We test two resolutions for the data-generating process, a 1NM scale and a 10NM scale.³ The 1NM scale allows us to focus only on the effect of data aggregation whereas the 10NM scale allows to see the effects of both non-nested and overly spatially-refined estimation choice sets. For the analysis on the GoMRF fisheries, we consider gridded partitions of space and analyze the results of the RUM across a set of tessellations, varying the length of the squared-shape alternatives from 0.25° 15NM (1797 sites) to 3.5° 210NM (15 sites). We use the 60NM-long statistical areas used by the U.S. National Marine Fisheries

² In the simulations we set the data-generating process 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 (see Appendix Section D.5).

³ 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.

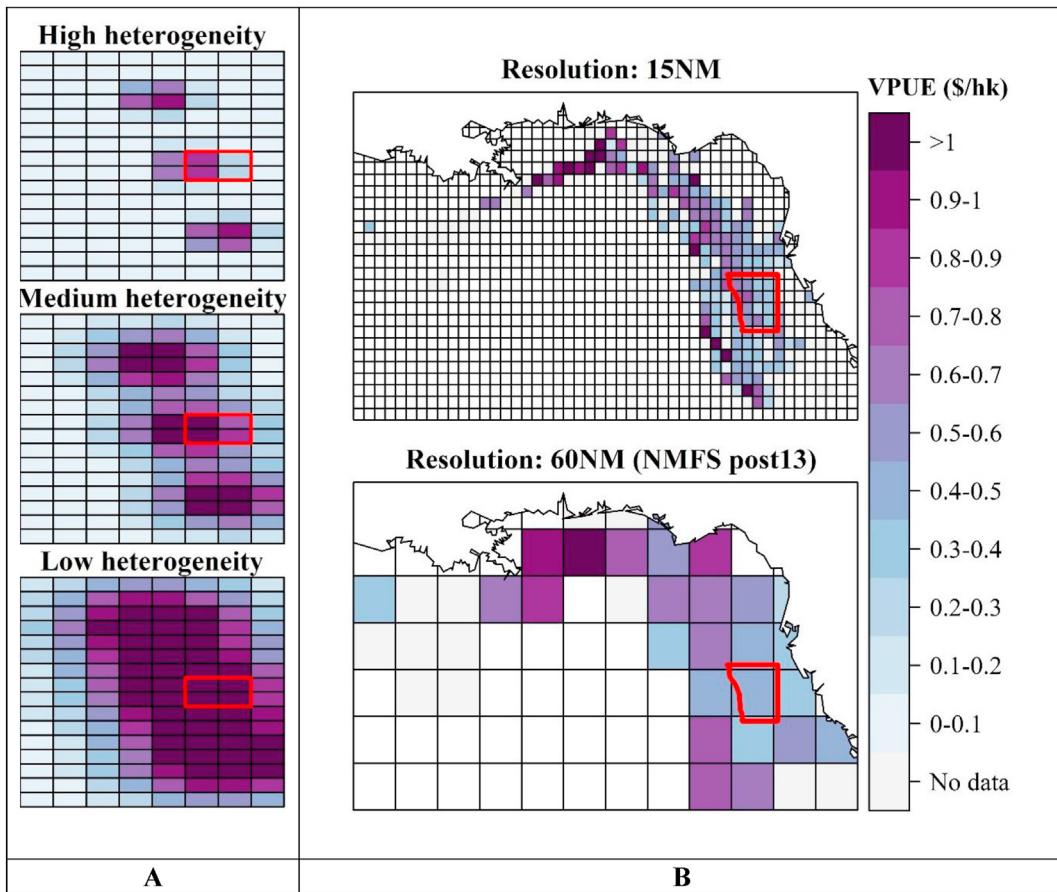


Fig. 2. Yearly average of value per unit effort (VPUE, in \$ per hook). Panel A shows the three spatial distributions of VPUE simulated in the Monte Carlo experiments with a 30 NM grid. Panel B shows the observed VPUE for longline fishers in the Gulf of Mexico in 2008 for 15NM or 60NM grids. The hypothetical MPAs assumed for the welfare analyses are shown in red. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

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 Area⁴ (MPA, shown in red in Fig. 2).

2.3. Monte Carlo experiments

The simulated setting we consider mimics the case of a fishery targeting a species migrating seasonally across three different “hotspots” or, similarly, the case of three non-migrating species each located in a different hotspot with seasonal variation in catch rates. We operationalize spatial and time-varying value per unit effort for each unit of space in each decision period (t) by assuming that the productivity of a given point in space (whose coordinates are x,y) is equal to the mean of the productivity of the hotspots (recall we assume there are three hotspots) with a stochastic error of $\pm 100\%$:

⁴ 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.

$$VPUE(x, y, t) = (1 + u(x, y, t)) \left(\frac{1}{3} \sum_h VPUE_h(x, y, t) \right) \quad (3)$$

with $u(x, y, t) \sim U(-1, 1)$, $VPUE_h(x, y, t) = \overline{VPUE}_h(t) e^{\left(\frac{-(x-h_x)^2}{\sigma_x^2} \right)} e^{\left(\frac{-(y-h_y)^2}{\sigma_y^2} \right)}$ and $\overline{VPUE}_h(t) = \overline{VPUE} \cdot \text{base} \left(1 + A \cdot \cos \left(2\pi \frac{t-t_h}{T} \right) \right)$, where h represents a hotspot. Therefore, we assume that there is a hotspot (h_x, h_y) ⁵ with a Gaussian spatial distribution of fish abundance that oscillates through time around a base value of $VPUE$ ($\overline{VPUE} \cdot \text{base}$) with a period T and reaches its maximum at t_h .

The dynamics in fishing locations are driven by the seasonality and the stochasticity of the $VPUE$ s that we generate. Specifically, fishers' experience independently and identically distributed random utility shocks when forming their decision and face different histories of $VPUE$ s as the year progresses.⁶ Fig. 2a shows a map of *yearly average* $VPUE$ s for three levels of assumed spatial heterogeneity (see Figure D2 in the Appendix for maps at different points in time during the year). The full details for the generation of the $VPUE$ s distributions, the specification of fishers' expectations, and the data-generating process are available in the supplemental information.

Each experiment estimates Eq. (1) across three datasets of observations with three different levels of spatial heterogeneity, with variables and choice alternatives defined at varying spatial resolutions. The three different levels of spatial heterogeneity we consider correspond to three different spatial distributions for the $VPUE$. This variation in the spatial regularity of the datasets enables us to disentangle the effect of having observations with different spatial distributions from the effect of deviating from the spatial scale of the true decision making process (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 B). In the Monte Carlo analysis, the index equals zero when the scale matches the DMP and as the index changes (non-linearly), the aggregation moves further away from the DMP (Appendix Figure C.a). In the GoMRF analysis, the index equals zero for 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.⁷

2.4. Welfare impact of the implementation of a MPA

In addition to measuring the impacts of scale and heterogeneity on model parameters, we examine the implications of these results for policy advice by simulating and measuring 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. For an individual i facing a set of alternatives j the utility loss was computed as the difference between the chosen alternative without the MPA restriction and the chosen alternative when restricting the choice set (CS) to alternatives that lie outside the MPA:⁸

$$\Delta U^i \equiv \max_{j \in \overline{CS}} U_j^i - \max_{j \in \overline{CS} \setminus \{MPA\}} U_j^i \quad (3)$$

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 1×1 NM rectangles):

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

⁵ We assume 3 hotspots located in the North (2.6,2.5), Center (3.1,0) or South (1.9,-2.4).

⁶ We assume fishers make a single choice of fishing location when they go on a trip and that they all start from the same "homeport" located at the origin (0,0). To initiate the historical records in the simulation, 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.

⁷ For example, a $2^\circ \times 2^\circ$ grid corresponds to an index of 1.4, whereas a $\frac{1}{6}^\circ \times \frac{1}{6}^\circ$ grid corresponds to an index of -1.4. Similarly, a $2.5^\circ \times 2.5^\circ$ grid corresponds to an index of 1.8, and a $\frac{1}{4}^\circ \times \frac{1}{4}^\circ$ grid corresponds to an index of -2.8 (see Figure C.b in the Appendix).

⁸ Because the scale of the utility cannot be recovered, we normalize the utilities by the marginal utility of distance: $\widetilde{\Delta U^i} = \frac{\Delta U^i}{|\beta_{\text{dist}}|}$.

where j^{\max} is the alternative maximizing the utility over the true choice set (\bar{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 decisions is unknown to 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:

$$\Delta U_{\text{est}}^i \equiv \max_{j \in \bar{CS}} U_j^i - \max_{j \in \bar{CS} \setminus \{\text{MPA}\}} U_j^i = \sum_k \widehat{\beta}_k \left(\widehat{X}_k^{j^{\max}} - \widehat{X}_k^{j^{\text{MPA}}} \right) \quad (5)$$

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

The practical assumptions made in defining the choice set in empirical applications of DCM, unfortunately, 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)*: the specified choice set may not include the same set of alternatives as the one considered by fishers (i.e., $j^{\max} \neq j^{\max}$ and/or $j^{\text{MPA}} \neq j^{\text{MPA}}$);
- (2) *Aggregation bias (A)*: the specified choice set may not account for the opportunities *within* each alternative in the same way as they were considered by fishers, and so it may be the case that $\bar{X}_k^j \neq \widehat{X}_k^j$

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:

$$\begin{aligned} \Delta U^i \equiv \Delta U_{\text{est}}^i - \Delta U_{\text{true}}^i &= \sum_k \widehat{\beta}_k \underbrace{\left(\left(\widehat{X}_k^{j^{\max}} - \widehat{X}_k^{j^{\max}} \right) - \left(\widehat{X}_k^{j^{\text{MPA}}} - \widehat{X}_k^{j^{\text{MPA}}} \right) \right)}_{\text{Choice bias}} + \widehat{\beta}_k \underbrace{\left(\left(\widehat{X}_k^{j^{\max}} - \widehat{X}_k^{j^{\max}} \right) - \left(\widehat{X}_k^{j^{\text{MPA}}} - \widehat{X}_k^{j^{\text{MPA}}} \right) \right)}_{\text{Aggregation bias}} \\ &\quad + \underbrace{(\widehat{\beta}_k - \beta_k) \left(\widehat{X}_k^{j^{\max}} - \widehat{X}_k^{j^{\text{MPA}}} \right)}_{\text{Parameter bias}} \end{aligned} \quad (6)$$

Application: Bottom longline sector of the Gulf of Mexico Reef Fish fishery.

We apply the same modeling and analytical framework in the Monte Carlo analysis to the BLL sector of the GoMRF fishery. The BLL fleet primarily targets grouper and tilefish (GT) species, with other minor 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 12,075 days in 2008.⁹ Fleet efficiency increased during the 2005–2012 period, which coincides with the GT-BLL fleet experiencing considerable consolidation. 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 3779 pounds (\$12,300) in 2008–6312 pounds (\$21,911) in 2012. The GT-BLL fleet primarily operates off the west coast of Florida along a depth band of about 1°–2° of latitude (Fig. 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 2010¹⁰, 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

⁹ 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.

¹⁰ In 2009 a large part of the West coast of Florida was 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. See Watson et al. (2018) for discussion of these management changes and their impacts on the fishery.

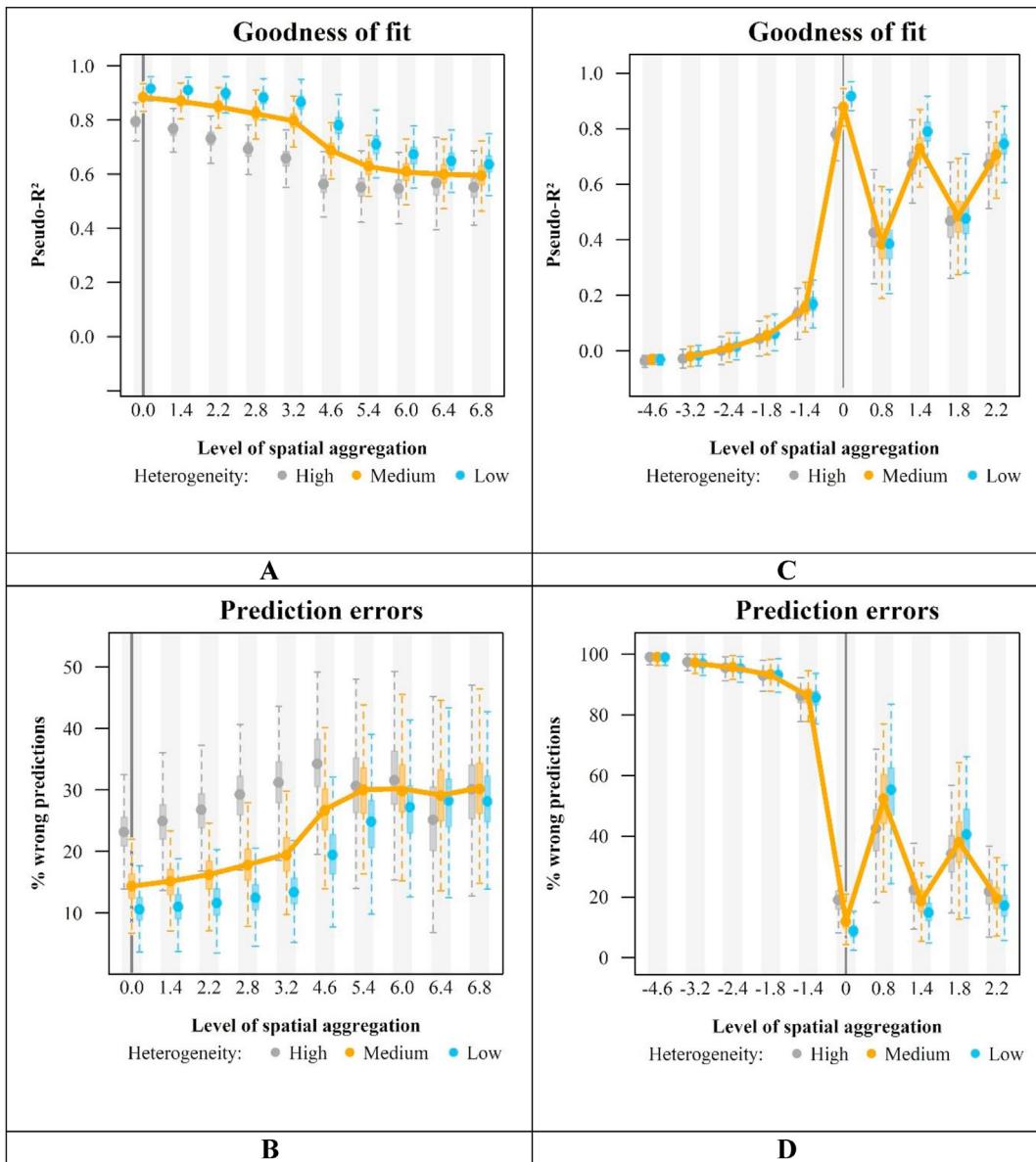


Fig. 3. Results of the Monte Carlo experiments for the three different levels of spatial heterogeneity (High, Medium and Low) in terms of fitting (upper panels) and predicting (lower panels) the data, with the DGP set at on a 1x1 (left panels) or 10x10 (right panels) grid. Figures shows the median of: (A and C) model's McFadden pseudo- R^2 ; and (B and D) model's rate of prediction errors. 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.

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.

3. Results

3.1. Monte Carlo experiments

Overall, the results of the Monte Carlo (MC) experiments confirm the intuition that goodness-of-fit, prediction errors (out of sample), and parameter bias increase as the spatial scale used for the estimation is further away from the spatial scale of the data-generating process. They also show that the effect of having a non-nested structure with the true spatial choice set is larger than the effect of averaging information, and that data aggregation impacts more datasets with an initially high level of heterogeneity. Perhaps less evidently, our results indicate as well asymmetric effects of estimating models at overly coarse or

refined resolutions: using a resolution which is twice smaller than the resolution of the DGP has a much bigger effect than using a resolution which is twice bigger. At last, they also show that, as the resolution used for estimation becomes coarser, goodness-of-fit and prediction errors tend to a threshold while the distributions of the estimated parameters become larger.

3.2. Goodness-of-fit and prediction capability

In the MC analysis, as the level of spatial aggregation increases, we observe an initial decrease of the models' McFadden pseudo- R^2 and increase in prediction errors¹¹ and then a leveling off (Fig. 3 Panels A and B). When using overly spatially-refined resolutions, models' goodness-of-fit and prediction accuracy also decrease, but to a much larger extent and with a sharper initial jump (Fig. 3 Panels C and D). Furthermore, the decrease in the pseudo- R^2 - or increase in prediction errors - is more pronounced and the leveling off starts at lower levels of spatial aggregation when the observations are spatially concentrated; that is, as the levels of VPUE are more heterogeneous within a given area. The decrease in the pseudo- R^2 with the increase of the level of spatial aggregation means that, as the modeled resolution moves away from the resolution of the DMP, a loss of information occurs that is critical for explaining the choices. The sharper and earlier 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.¹² The leveling off in both the goodness-of-fit and prediction errors with higher spatial aggregation is likely driven by the explanatory power of distance, which remains significant since increasing the spatial aggregation of sites maintains – and even increases – the heterogeneity of the distance variable. The same mechanisms, but in a reverse way, explain the trend observed when using overly refined resolutions. By assuming site options that have smaller spatial extents than the site options considered for decision-making, estimated models pick up more non-relevant data variations (noise). So much so that they may even end up performing worse than null models (models have negative pseudo- R^2). At last, clustering data in such a way that the spatial structure of the true choice set is not nested within the choice set used for the estimation also implies introducing non-relevant data variations which alters the capacity of DCM to properly explain the observed choices. Note, however, that these non-relevant data variations are levelled off as spatial aggregation increases, which explains why the performance of non-nested choice sets increases with the resolution (while performing less well than a nested choice set).

3.3. Parameter estimates

Given the conditional logit specification, the scale of the utility levels cannot be recovered and the $\beta\beta\beta$ parameters of Eq. (1) or Eq. (2) – or marginal utilities (MU) – are only estimated up to a multiplicative scale. To permit comparisons across estimated models, we normalized parameter estimates by $\beta_{\text{dist}}\beta_{\text{dist}}$, the MU of distance, which amounts to comparing estimated marginal rates of substitution (MRS) with distance.¹³

Fig. 4 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 and are presented in table F1 of the Appendix.¹⁴ As the level of spatial aggregation increases, we observe that the distribution of the MU widens and, even though the MU remain not statistically different from the "true" value on average (-3 in this case), the likelihood of obtaining an estimated *significant* parameter which is far off – and possibly of the opposite sign than - the true value dramatically increases. Not surprisingly, when using overly refined spatial scales, MU are found to be less and less significantly different from 0 (Fig. 4 Panel B). Regarding the effects of the spatial heterogeneity of datasets on the distribution of biases in parameter estimates, we cannot identify any particular trend.

3.4. 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. Fig. 5 Panel A shows the distribution of the mean errors for increasingly aggregated nested choice sets.¹⁵ First, we find that even

¹¹ 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.

¹² 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.

¹³ In the simulations, we set by β_{dist} at -5 and β_{VPUE} at +20.

¹⁴ 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).

¹⁵ 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.

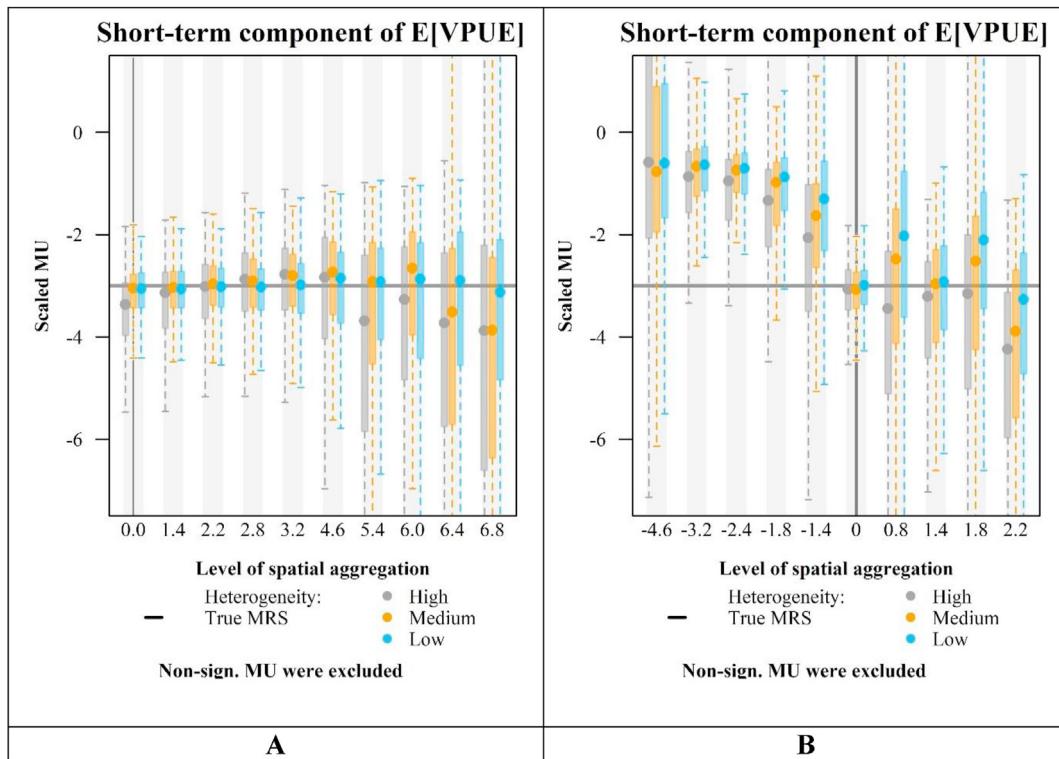


Fig. 4. Results of the Monte Carlo experiments for the three different levels of spatial heterogeneity (High, Medium and Low) in terms of capacity to estimate the model's parameters, with the DGP set at on a 1x1 (Panel A) or 10x10 (Panel B) grid. Figures shows the median of the estimated marginal rate 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.

when a model is estimated at the same spatial scale as the DMP, there is a systematic 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). For intermediate levels of aggregation, 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 positives), 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. On the contrary, when using more spatially-refined spatial scales we find an opposite trend, toward a reduction of the estimated welfare impact (Fig. 5 Panel B). This results from the lack of significance of the estimated parameters and from the poor explanatory power of the models, which tend toward null models where the difference in utility levels of choices are directly proportional to the observed empirical distribution of choices (with a uniform distribution all options have the same utility).

Overall, the MC analysis highlights the potentially large biases of models estimated at a different spatial scale than the spatial scale of the DMP. Our analysis also reveals the great difference in the results a researcher may encounter with a single dataset when comparing spatial scales. The analysis with the data from the GoMRF longline fishery offers a typical illustration of such a situation.

4. Application

Results with the GoMRF longline fishery data show the same patterns as the results of the MC analysis with overly spatially-refined and non-nested estimation choice sets. Results interpretation must, however, remain cautious as, first, the true DGP is unknown and confounding effects from misspecification issues cannot be excluded; and, then, as the metrics and parameters that are presented in this section correspond to only two samples of data (datasets from 2008 or from 2012), compared with 600 samples utilized in the MC section. Therefore, in this section the analysis of the effect of the spatial scale is carried out at the *point* level, without knowledge about the whole distribution of the observations.

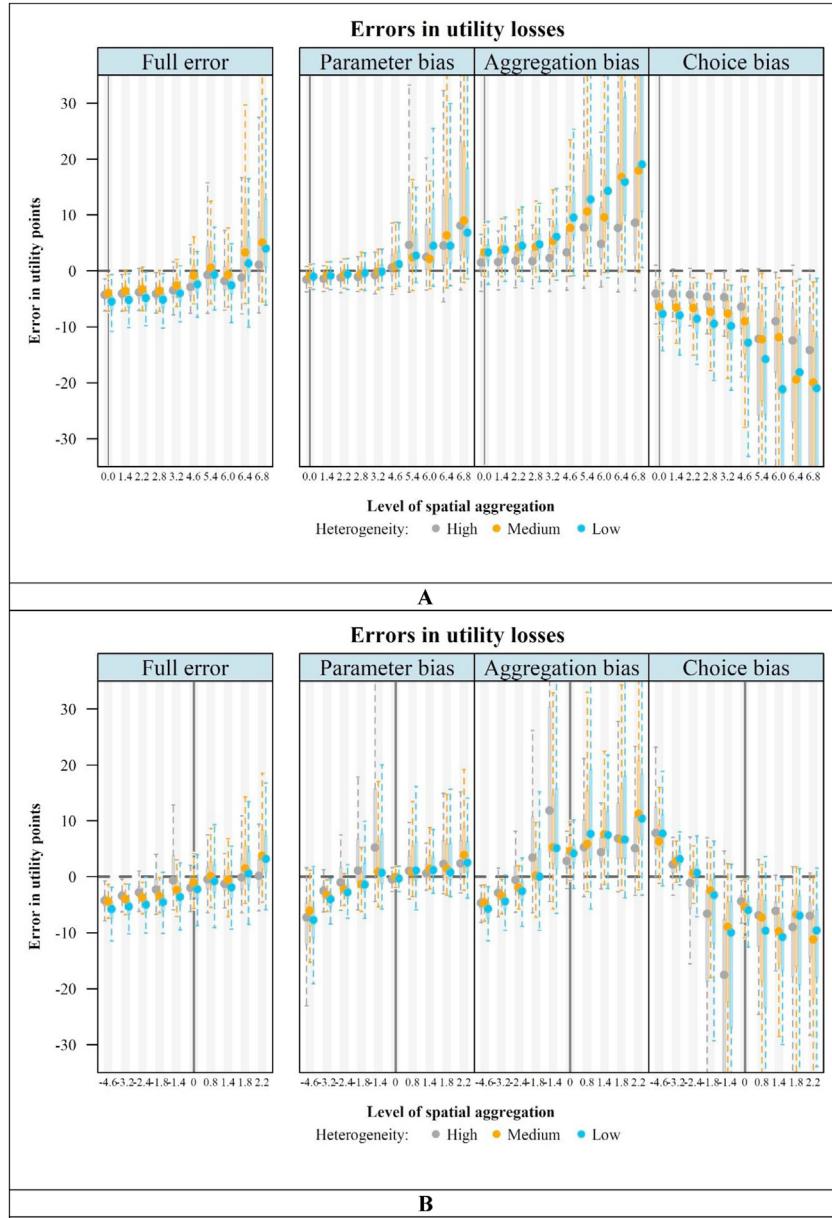


Fig. 5. Results of the Monte Carlo experiments in terms of capacity to evaluate the welfare impact of a MPA, with the DGP set at a 1x1 (Panel A) or 10x10 (Panel B) grid. The figure shows the distributions of the full error in the estimated mean utility loss of fishers (left panel), along with its decomposition 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 not 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.

4.1. Goodness-of-fit and prediction capability

We find model's goodness-of-fit to be maximal at 0.76 with the $2.5^\circ \times 2.5^\circ$ grid and to decrease monotonically for more refined or coarser resolutions, except for a jump at 0.54 for the $3^\circ \times 3^\circ$ grid (Fig. 6 Panel A.). A similar pattern can be observed with model's prediction performance, with the rate of prediction errors reaching a minimum below 10% for the $2.5^\circ \times 2.5^\circ$ grid and increasing as the resolution used for the estimation gets finer or coarser. A jump for the $3^\circ \times 3^\circ$ grid can also be

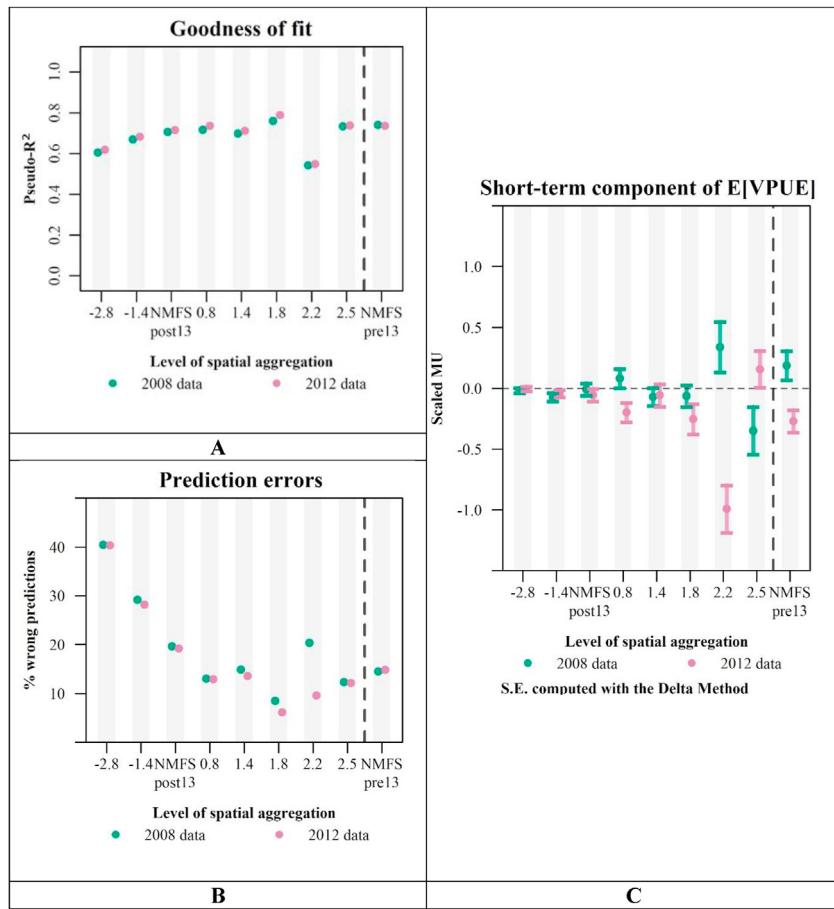


Fig. 6. Results of the GoMRF case study. Figures shows: (A) model's McFadden pseudo-R², (B) model's rate of prediction errors; and (C) point estimates and 95% confidence intervals of the marginal utility of the short-term component of the expected VPUE when no information is missing (results are similar for the other explanatory variables).

observed, but only for 2008 dataset (Fig. 6 Panel B).¹⁶ In this way, results for the GoMRF match those of the MC experiments where the $2.5^\circ \times 2.5^\circ$ grid would be close to the spatial scale used for the DMP and where the $3^\circ \times 3^\circ$ grid would have a spatial structure markedly mismatching the “true” choice set. Nonetheless, contrary to the results of MC experiments we do not observe a sharp decrease when halving the resolution of the supposedly “true” resolution. The fact that distance remains a meaningful predictor of spatial choices – as opposed to other predictors – even for the most refined or coarse spatial scales probably helps to explain this absence of sharp decrease of the goodness-of-fit. In addition, the large distributions of prediction accuracy we obtained in the MC experiments for the same spatial scale and the relatively limited shift in the centers of the distribution from one spatial scale to another should question the significance of the downward trends in our two empirical datasets. All the more so as the prediction scores obtained in the applied case also demonstrate some variability as the level of spatial aggregation increases (results are not monotonic).

4.2. Parameter estimates

As mentioned previously, the spatial aggregation impacts the observations that are utilized in the calculation of expected catch (e.g., smaller areas might not have information available for calculations in a given period). To investigate the robustness of our estimation results to the availability of information both in the short-term and long-term, we estimate Eq. (2) under a

¹⁶ 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.

Table 2

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 the year before.

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

number of cases, testing for different combinations of time windows and scope for the inclusion of information.¹⁷ In each analysis, we follow the literature on how to deal with missing information. Specifically, we take the same approach as [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. We also estimate each model considering a mixed specification with all the estimated parameters assumed to be random. Results being almost the same between the mixed and the multinomial specification; we present only results for the latter.

[Fig. 6](#) Panel C shows the estimates for the same scaled MU as in the MC experiments, using the two GoMRF datasets for each of the 9 different spatial choice sets. 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 also observed in the other explanatory factors ([Table 2](#)). In particular, none of the variables forming the expected VPUE maintain consistent signs across the different tessellations.

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 find that overly refined spatial scales lead to MU close to 0 (explanatory variables do not discriminate choices) and we observe a seemingly increase in the variability of the estimated MU with the level of spatial aggregation. However, the MC experiments reveal that even though a particular MU may be statistically significant with a specific dataset and at a given level of spatial aggregation, it may actually not be 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 of the true MU, *even though their model is properly specified*. Therefore, when operating at too high a level of spatial aggregation, an estimated model may become 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 also reflected in the GoMRF application through the inconsistency of the estimates of model parameters and their increased invariance. When looking at the average marginal effects of each variable, we also find the same pattern of increased variability at aggregated tessellations for the VPUE variables as we did in the simulations (Appendix [Figures F1.d](#) and [F1.e](#)). Nonetheless, for the applied case such instability could also result from a misspecification of our model, which cannot be excluded given its simplicity.

In addition, another important caveat to these findings is that they may be due to the temporal resolution of the information used to form 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 A). 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.

4.3. 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.¹⁸ 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. [Fig. 7](#) 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

¹⁷ We consider cases where the information taken into account could be only public, or public and private; and could span only the month prior to the beginning of a fishing trip, the month and the whole year prior, or only the same month of the year prior.

¹⁸ 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).

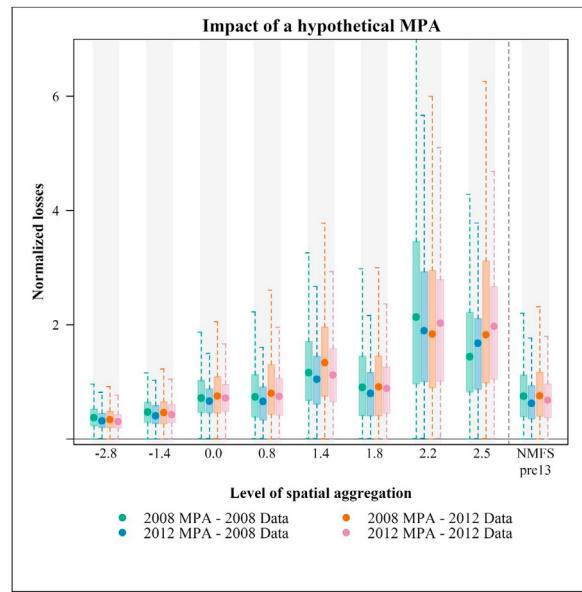


Fig. 7. The estimated welfare impact of the hypothetical MPA for longline fishers in the Gulf of Mexico as a function of the level of spatial aggregation. Filled dots indicate the mean utility losses. The box edges are the 25th and 75th percentiles of the distribution of the losses and whiskers are located at ± 1.5 times the interquartile ranges.

choice of the input dataset and are consistent with the simulations: the mean and median of the estimated welfare losses, as well as the dispersion of the losses, increase with the level of spatial aggregation, but with two jumps for the $2^\circ \times 2^\circ$ and the $3^\circ \times 3^\circ$ grids. Once again, this pattern is similar as in the MC experiments where the $2.5^\circ \times 2.5^\circ$ grid would be matching the true spatial choice set used for decision-making.

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., if data are reported by management area).

5. Conclusion

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 fleet dynamics. The simulations highlighted the - otherwise undetectable - biases induced by the spatial aggregation of observations. These results point to the importance for the robustness of the results of spatial models to be able to test for the consequences of alternative spatial partitioning of the choice sets.

We illustrate this using 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 -, or because the data heterogeneity captured by the model mismatches the level of heterogeneity which is actually considered by decision-makers. This may be the case when the attributes of choice options are computed at an overly refined resolution for instance. Therefore, the likelihood of obtaining biased results increases when using granular data to model the spatial decisions in fisheries where fishing sites cover large spatial extents.

Moving forward, our work clearly demonstrates the value for spatial modelers to use more spatially-refined data, which would allow testing the robustness of their results and gain insights into potential biases due to spatial aggregation. Whereas granular spatial data is indeed becoming 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 modeling 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) have not examined sensitivity to the partitioning of space 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, 1977, 1983; 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 modeling. Data re-assimilation techniques (where predicted outcomes can be looped in as training data), or model averaging (ensemble modeling) could be, in this regard, fruitful avenues to pursue.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jeem.2020.102388>.

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