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# Fishing site choice modelling using Vessel Monitoring System data

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**Abstract**

In this paper, EU Vessel Monitoring System (VMS) data is combined with other site and vessel information and used to model the fishing site choice decision of Irish demersal otter trawlers. Uniquely, the fishing ground options used in the analysis reflect the actual seabed contours trawled by the fleet. The fishing site choice model, based on this natural site definition is compared to an alternative destination choice model where the fleet decision is specified using a grid based site definition as employed in previous work. It is argued that the natural site specification is a more realistic specification of the fisher site choice decision. Using the preferred natural fishing site choice model, a policy option involving the hypothetical closure of one of the fishing ground options is then simulated to examine the possible redistribution of fishing effort.

**Keywords:** Discrete fisheries site choice model, ecosystem based fisheries management, random parameters logit, marine protected areas, fishing ground closure, demersal otter trawlers.

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## 1. Introduction

It is widely recognised that fisheries management focussing on a single species at a time is not sufficient and that a more inclusive 'ecosystem' approach is required (Schramm and Hubert, 1996, FAO, 2003). An extension to this ecosystem approach to management is ecosystem-based marine spatial management (EBMSM) which is seen as a way to deal with conflicts among various users of the seas and to ensure the sustainability of marine ecosystems and their services to humans (Katsanevakis *et al.*, 2011). According to Olsen et al. (2013) the goal of EBMSM is to maintain marine ecosystems in a healthy, productive and resilient condition by balancing the increasing diversity and intensity of human activities with the sea's ability to provide ecosystem services.

Closed areas are one of the tools proposed through the EBMSM approach for fisheries management. These may be temporary closures or more established and permanent Marine Protected Areas (MPAs). Management in MPAs is very diverse, with local restrictions ranging from 'no-take' to zoning or gear limitations. While there is consistent evidence for the positive effects of full and partial protection on the density and biomass of protected species (see for example Sciberras et al. 2013 and Potts et al. 2014), the indirect effects of closures on fishing patterns in the unprotected areas are less well characterized. Holland (2000) and Smith and Wilen (2003) were some of the earliest to highlight the possible impacts from the displacement of fishing effort following closures. More recently, Kahui and Alexander (2008) Hattamet al. (2014) and Haynie and Layton (2010) also examine the impacts from closures and effort displacement; the latter developing a model that implicitly monetizes location choices.

Potential displacement effects can also be assessed in an ecosystem context by analyses of spatially resolved catch data. For example, Gerritsen et al. (2012) modelled the impacts of a temporary closure in mixed fishing areas where the cod quota is generally the first to be exceeded, resulting in discarding of the cod catch. By closing areas with low effort and relatively high cod landings, the rate at which cod quota was met could be reduced, with relatively few displacement effects on the other components of the mixed fishery. Gerritsen et al. (2012) modelled three plausible scenarios for how the effort displaced from closed areas may be directed.

The choices made by displaced fishers can be analysed from revealed preference site choice models (Hynes et al, 2008) where location choice is modeled as a function of expected catch and travel distance to each area. Since its first use (Bockstael, 1983 and Eales and Wilen, 1986), this basic approach has been expanded on and applied to various fisheries (Holland and Sutinen, 2000, Valcic, 2008; Smith, 2005; Haynie and Layton, 2010). The alternative fishing site choices can be modelled using random utility theory to describe the perceived value of different fishing site characteristics to a fisher. It is assumed that fishers trade off visiting one fishing site versus another based on the fishing characteristics of the sites and the effort that needs to be invested to catch a particular quality of fish at each site.

In bottom otter trawling site choices, for example, the fisher typically chooses among a number of available bottom trawling sites, each characterized by distance, costs, expectation of catches in terms of species composition and abundance at that site (based on past experience and knowledge of seasonal and tidal effects), convenience and comfort. If a behavioral model for fishers site choice is estimated one can apply this model to assess the changes in the spatial distribution of fishers that follow from changing quotas or steaming costs (price of fuel) or by closing down a site option through its designation as a Marine Protected Area that prohibits bottom trawling.

A number of discrete choice models have previously been developed that examine the spatial choice of commercial fishers. Early research that employed this modelling approach examined the Californian pink shrimp trawl fishery (Eales and Wilen, 1986) and the British Columbian salmon fishery (Dupont, 1993). Holland and Sutinen (2000) and Smith (2005) have also used discrete choice models to consider the effect of past experiences on fishers' location choice. Mistiaen and Strand (2000) presented a model of location choice for short-run fishing behaviour that examined the potential for heterogeneous risk preferences amongst the U.S. East Coast and Gulf longline fleet. More recently, Ran et al. (2011) employed a mixed logit model to analyze both monetary and non-monetary factors that influence location choice behaviour of the U.S. Gulf of Mexico shrimpers. A number of previous papers have also used the discrete choice method to examine the spatial impact of a simulated closure of a fishing ground. Wilen et al. (2002) simulated a closure in the California sea urchin fishery; Valvic (2008) simulated a closure in the Oregon bottom trawl groundfish fishery and illustrated their modelling approach by considering the closing of the Steller seal lion conservation area in the United States Bering Sea to Pollock fishing.

This paper follows the discrete choice modelling approach used by the previous studies mentioned above and investigates the factors that determine the fishing site choice of Irish demersal otter trawlers in Irish waters by using Vessel Monitoring System (VMS) data combined with sales note and log book information. Fishing site choice is modelled as a function of the distance travelled to each fishing ground, the earnings potential of each ground, the main species to be caught at each ground, characteristics of the seabed and the likely variance of earnings per trip at each ground. Closures are simulated for an extensively used ground in the Irish Celtic Sea. The simulated redistribution of fishing effort after the implementation of the closures is then compared with the actual distribution of effort revealed from the VMS data.

The paper adds to the literature in this area by developing a model where the boundaries of the fishing ground options used in the analysis are defined by their species composition, seafloor characteristics and the natural contours and gullies followed by the sample fleet. The fishing site choice model, based on this nuanced, or 'natural', site definition is then compared to an alternative destination choice model where the fleet decision is specified using a grid based fishing site definition, i.e. using artificial boundaries, as employed in previous work. Following the comparison of the site choice models using the different underlying site definitions a more complex site choice model is presented for the preferred nuanced site data that accounts for preference heterogeneity across vessels. Using this model, a policy change involving the closure of a site is then simulated to examine fishing effort displacement following the closure. It is also the first study of its kind to examine the site choice preference of a European fishing fleet and to use the EU VMS data in this modelling approach.

In what follows section 2 briefly describes the Irish bottom otter trawl fleet, the sources of data used in the analysis and the site choice options. Some summary statistics are also presented. Section 3 then describes the discrete choice methodology used and in particular the random parameter logit model. The results are presented in section 4 and the final section includes a discussion related to the findings; the use of the modelling approach presented and potential avenues for future research.

## 2. Fleet and Data Sources

The Irish trawl fleet consists of between 250 and 300 vessels. This fleet utilizes a variety of different gear configurations and lands over 100 species from various species assemblages annually (Davie and Lordon, 2011). Annual landings by the fleet account for approximately 75% of annual Irish landings in value. For the analysis presented in this paper the data for "trawl gears" used by this fleet is restricted to Irish vessels greater than 15 meters in length that utilise bottom otter trawls. We estimate our model of fishing site choices on a trip basis using the 2010 data of Irish fishers that participated in bottom otter trawling[1]. Data were obtained on a total of 3,160 trips taken by the 101 vessels in the Irish bottom otter trawl fleet (that range in size from 30 tons to 400 tons) to any of thirty possible fishing locations in the Irish coastal waters of the Atlantic, the Celtic Sea, and the Irish Sea. It should be noted that this is an unbalanced panel as the vessels in the sample make different numbers of trips in the season. We therefore have a panel of observations that differ in their number of choice occasions.

- **Figure 1 here**

The natural fishing grounds used to describe the site choices were based on fishing sites in the waters around Ireland used by the bottom otter trawling fleet as described by Gerritsen et al. (2012)[2]. These are shown in figure 1. All trips made by our sample of vessels are to one or more of these sites. As shown in the summary statistics of table 1 over the course of 2010, vessels made an average of 41.6 trips. In order to compare the results of the site choice model based on the natural site definitions to a model that is based on the grid based site definitions more commonly used in the

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[1] In bottom otter trawling a large net is dragged along the bottom behind a towing vessel. The mouth of the net is held open by two large 'doors' (often referred to as otters) which are attached to either side of the net.

[2] Gerritsen et al. (2012) used hierarchical cluster analysis on the species composition of the Irish demersal otter trawl fleets. They identified 8 clusters with relatively homogenous species compositions. These 8 clustered formed 34 spatially distinct fishing sites. Each site is associated with a particular species cluster: haddock mixed; deep water species; monkfish; *Nephrops*; nephrops mixed; whiting; rays and general mixed (see Figure 1). In our sample only 30 sites are used as some sites were combined in to one (Slope1 and 2 were combined as were Stanton 1 and 2) and no trips were made to the Tory, Blackstone or Porcupine3 sites so they were excluded.

literature, the area surrounding the coast was also divided into 30 rectangles that account for 98.5% of the trawling effort of the fleet. The rectangles are based on an arbitrary grid of 1 degree latitude by 1 degree longitude which was chose so that the number of rectangles was equal to the number of natural fishing sites. Each rectangle represents an area that a vessel may choose to trawl at on any give choice occasion. As shown in Figure 2, rectangles adjacent to the coast are reduced in size due to the contour line of the landmass.

- **Figure 2 here**

In order to determine which sites (however they are defined) were visited and fished by each fisher on any given trip, vessel monitoring system (VMS) data were used. VMS is a satellite-based monitoring system which at regular intervals provides data to the relevant authorities on the location, course and speed of vessels. Since 2005, all European Community (EC) fishing vessels of ≥15 m in overall length have to be fitted with VMS transponders which transmit their position at least once every 2 hours whilst at sea (EC, 2003). The standard data report includes the VMS unit's unique identifier, date, time, speed, heading and position in latitude and longitude. The EU was one of the first fisheries regulators to introduce compulsory VMS tracking for all the larger boats in its fleet. The EU legislation also requires that all coastal EU countries should set up systems that are compatible with each other, so that countries can share data and the Commission can monitor that the rules are respected (EC, 2003). Using the VMS information and certain assumptions about the range of speeds at which the vessels steam and trawl at, the analyst knows which sites are visited on any given trip and also can distinguish between actual trawling and steaming to and from the fishing grounds.

- **Table 1 here**

In order to identify the species catch on any given trip and the price received for the associated landings, data from sales notes and vessel logbooks were used. EU logbooks are completed by the masters of fishing vessels when landing their catch. They contain information on the volume of catch per species landed. All vessels greater than 10m in length are required to fill out these log sheets and submit them to their local Port Office. The data is then entered to the Integrated Fisheries Information

System (IFIS) database by Sea Fisheries Protection Authority (SFPA) staff[3]. Sales notes data contain information on the price per kg per species landed by each vessel and are electronically submitted by the buyer at the first sale of the fish. Together the VMS, sales notes and logbook information provide enough information to calculate the earnings of a vessel in terms of the value of the landings per trip per grounds.

Following the methods employed by Gerritsen and Lordan (2011) a simple speed rule was applied to identify VMS records that correspond to fishing activity for each trip made by the sample of bottom otter trawlers. The VMS data were analysed for vessel speeds between 1.5 and 4.5 knots which indicated records corresponding to fishing activity. Gerritsen and Lordan (2011) have shown that vessel speed can distinguish fishing activity with an accuracy of 88%. The VMS data was then integrated with the catch data from the logbooks and the price data from the sales note information using date and the community fleet registration number for each vessel which acts as vessel identifier across all data sources. The Integrated Fisheries Information System (IFIS) database, provided by the Irish Department of Agriculture, Food and the Marine was the source of the logbook and sales note data for the analysis presented in this paper. VMS data were provided to the Marine Institute by the Irish Naval Service. The average earnings per site were determined by allocating the earnings per trip (calculated based on the sales note and log book information for each trip) across the sites based on the proportion of time spend trawling in each site per visit.

We also derived attributes for each of the sites that are believed to be important characteristics when the fisher forms his site choice decision. Information on the number of times a fishing site has been visited in the previous year by each vessel is used as a indicator of the fisher's experience and it is assumed that the more experience a vessel had of a fishing ground in the previous year, the more likely it will be fished again this year. The monetary variables included in this model are expected earnings per vessel per fishing ground as experienced in the previous year, the variance in expected earnings, and the distance from home port to the centroid of each fishing ground[4].

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[3] Since 2011 many vessels now have electronic logbooks, where data are entered by the skipper and go straight into IFIS.

[4] Distances were estimated using the R package 'gdistance' by creating a geographic grid containing cells that were either marked as land or sea. This was translated into a transition matrix that only

The variance in earnings variable is used to pick up on the risk preferences of the fishers. The average variance in the return from alternative sites is a factor that has been found previously to significantly influence the spatial decision of fishers (Valcic, 2008; Curtis and McConnell, 2004 and Eales and Wilen, 1986). The number of different species landed from each trip is also included in the model. It might be expected that sites where fish can be more selectively caught will be more attractive to fish at. The percentage of rocky ground on the seabed at each of the fishing sites was also included as a site attribute that may influence the fisher's site choice. The information on the construct of the seabed was taken from the EU funded Mapping European Seabed Habitats (MESH) project (http://www.searchmesh.net/) and linked to the fishing sites using geographical information system software. While most vessels now have sophisticated equipment that allows them to operate around rocks on the seabed it would still be expected that a fisher will prefer grounds that have a lower percentage of rock that could damage their expensive trawling gear. Finally, dummy variables for the Irish Sea and the Celtic Sea regions are also included in the model. It might be assumed that certain fishers will prefer to stay in one regional sea area when deciding on a site to visit.

Using the natural sites as our fishing ground definition we find that vessels fished at an average of 8.3 sites per year. Just over 55% of the fishing trips involved trawling at a single ground. A further 29% involved trawling at 2 grounds while the remaining 16% of trips in the sample involved visits to between 3 and 5 grounds on a single trip occasion. While the vessel trip characteristics are the same no matter how you specify the sites; specifying the sites using the grid system results in changes in the average number of sites visited per trip. For the grid based site definitions, vessels fished at an average of 10.6 sites per year. With this alternative site definition we find that the number of fishing trips involved trawling at a single site is reduced to 41% of trips. A further 32 % involved trawling at 2 grounds, 15% at 3 grounds, 8% at 4 grounds and the remaining trips in the sample involved visits to between 5 and 9 grounds on a single trip occasion. Therefore we see that by using the grid based site definitions we

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allowed a path to pass through connecting 'sea' cells. This matrix was used to establish the shortest sea-route between each possible combination of port and fishing site. Where multiple grounds were visited in a single trip we followed Valcic (2008) and assumed a distance of 5 miles for distance from one site to the next. A model was also estimated for single site trips alone and the estimated attributes displayed similarly signed preference parameters as in the extended model with all trips included.

end up dealing with a more complex site choice modelling situation with a higher frequency of trips visited per trip.

The fishing sites are used as the basis of the fishing choice decision in our discrete choice model. Further statistics related to the characteristics of the bottom otter trawl fleet in the sample such as average vessel age, engine power, earnings (value of catch per trip and annual), effort levels, etc are presented in table 1. Furthermore, the number of fishing trips to each natural site in 2010 is shown in figure 1b.

## 3. Methodology

The Random utility model (RUM) (McFadden, 1974) represent the standard theoretical framework used to estimate behavioural models of site choice (in our study, this is characterized by fishers' choice between several possible fishing grounds with varying attributes). The main idea of the RUM model is that the fisher chooses from a number of alternatives possible sites (to trawl at) and selects the one that yields the highest expected utility level on any given choice occasion. By observing and modelling how fishers change their preferred site option in response to the changes in the levels of the site attributes, it is possible to determine how fishers trade-off between the different fishing ground characteristics. In this application, it is assumed that fishers consider all 30 site alternatives on any given choice alternative and their choices are based on the alternatives that provide them with the highest utility.

Assume that a fisher, *n*, has J possible multi-attribute fishing sites from which to choose. The total utility perceived by fisher *n* from visiting a possible site *i* is assumed to be given by:

$$U_{in} = \beta X_{in} + \varepsilon_{in} \qquad (1)$$

Here, $\beta X_{in}$ is the indirect but observable part of utility function from visiting fishing site *i*, $X_{in}$ is a vector of explanatory variables including perceived site attributes and vessel specific characteristics and $\varepsilon_{in}$ is the stochastic element of utility. Whenever the utility from visiting fishing site $i$ is greater than the utility from visiting all other possible sites $j \in J$, site $i$ will be chosen. The probability that the fisher will choose this alternative can then be written as:

$$\Pr(i) = \Pr(\beta X_{in} + \varepsilon_{in} > \beta X_{jn} + \varepsilon_{jn}), \forall j \in J. \quad (2)$$

The RUM model can be specified in different ways depending on the distribution of the error term. If the error terms are independently and identically drawn from an extreme value distribution, the RUM model is specified as a standard Conditional Logit (CL) (McFadden, 1974). This implies that the probability of choosing site $j$ is the familiar logit with scale parameter $\mu$, or:

$$P_i = exp(\mu\beta X_{in}) \,/\, \Sigma_{k=1}^{J} exp(\mu\beta X_{jn}) \quad (3)$$

While the basic conditional logit model still remains a popular specification to analyse choice data amongst researchers, the standard conditional logit model has some noted limitations. These include the fact that it generally fails to meet the assumption implied by the independence from irrelevant alternatives property (IIA); it cannot handle situations where the unobserved part of the utility function is correlated over time and finally it represents only systematic taste variation rather than random taste variation across respondents (Train, 2003). Due to these restrictive assumptions, mixed logit models, such as the random parameter logit (RPL), have become more popular as they provide a more flexible econometric method for any discrete choice model derived from the random utility maximization framework (McFadden and Train, 2000).

The RPL model generalizes the CL by allowing the coefficients of observed variables to vary randomly over people rather than being fixed. Following Henscher and Greene (2001) the stochastic component is partitioned into two additive (i.e. uncorrelated) parts. One part is correlated over alternatives and heteroskedastic, and another part is independently, identically distributed over alternatives and individuals. Models of this form are often called *mixed logit* because the choice probability is a mixture of logits with $f$ as the mixing distribution (Hensher and Greene, 2001).

Conditional on individual tastes the choice probability is still logit, but the marginal probability across individuals requires integrating over a distribution of tastes which needs to be specified by the analyst.

Due to the integrals in the probability function, simulated maximum likelihood is used for estimation, which is discussed in detail in Train (2009). Note that in our estimation the integral is approximated by simulation based on 500 Halton draws. By specifying both a mean and a standard deviation for each ß associated with a particular attribute (treating it as a random parameter) the presence of (unobserved) preference heterogeneity in the sampled population is accommodated. It is also possible to re-parameterise the mean estimates of random parameters to establish heterogeneity associated with observable influences. For example we make the mean ß of distance a linear function of average number of days a vessel stays at sea assuming the latter picks up on some influences such as the size and power of the vessel and perhaps the ability of the crew. As pointed out by Hensher and Greene (2001) this is one way of 'removing' some of the unobserved heterogeneity from the parameter distribution by 'segmenting' the mean with continuous or discrete variation[5].

Following the estimation of the RPL[6] model the sample is reset such that one frequently fished site in the Celtic Sea (the Galley fishing ground) is made unavailable in the choice set; simulating the establishment of an MPA in that location. A model simulation is then produced to predict choice among this reduced set of site options where probabilities for the full choice set are reallocated amongst the remaining sites. The probabilities for each alternative fishing site based on the full model are then compared to those derived from the restricted choice set where the

[5] See Train (2009) and Hynes et al. (2008) for a comprehensive discussion of the RPL model.

[6] In this application we are assuming that fishers consider all site alternatives and their choices are based on the alternatives that provide them with the highest utility. We also considered the use of a Nested Logit model where the fishers might first decide to fish or not fish on any given day (Smith and Wilen, 2003) or perhaps where they first decide on which regional sea they fish in and then decide which site to trawl in the second stage. However, the nature of our data does not support the inclusion of the option of not fishing. The RPL model also allows for a much broader analysis of heterogeneity in preferences. Furthermore, the fishery under analysis here is unusual in the sense that there are no restrictions that prevent the bottom otter trawling vessels changing from fishing one species to another or from one gear type to another. Indeed, most vessels in the fleet routinely change gear, fishing grounds, etc. depending on the season, weather, catch rates, market price, etc. (Davie et al. 2015). Therefore we opted to use a modelling structure that assumes the consideration of all possible site alternatives.

predicted probabilities are the means of the sample predictions from the model absent the change specified in the closure scenario.

## 4. Results

For the purpose of modelling alternative fishing ground preferences, the indirect utility for any site option is assumed to depend on the levels of the attributes of that site. The same attributes are allowed to enter the utility function of all fishing site choice options with the levels varying in each. We also assume that the average number of days spent at sea per trip by a vessel in the previous season may influence fishers' preferences and therefore also include this variable in the model. Due to the fact that this variable does not vary between choice options for any given fisher, it is interacted with the distance variables. The average number of days that a vessel can stay at sea is expected to pick up on the size and power of the vessel and the skill level of the skipper and crew. It might be expected that these characteristics would also influence site choice and in particular the distance that a vessel will be willing to travel and the number of trips to undertake to any particular site.

In what follows we present the results of the conditional logit models (reported in table 2) using both the natural site definitions and the grid based site definitions. The RPL model is then reported; estimated based on the natural site definitions (reported in tables 3). All models are estimated from our (unbalanced) panel of vessels, providing a total of dataset of 171,510 fisher site choice observations for the natural site sample and 276, 840 for the grid based sample. In all models, the dependent variable (fishing site visit) takes a value of 1 if a fisher has trawled at fishing site *i* in each of the trip choice occasions taken in the previous 12 months and 0 otherwise. As explanatory variables for choice probabilities we used 9 site attributes; distance to fishing site, average earnings per site, variance in earnings, the percentage of rock at the site, number of species caught at each site in the previous season, experience as measured by number of trips to each ground in the previous season, dummies for a number of fish species and the area that the site covers in $km^2$. The other choice variables are constants for specific groupings of the fishing sites by the regional sea they are located in (Celtic and Irish Seas relative to the base case of the Atlantic).

- **Table 2 here**

Table 2 gives results from the conditional logit models. It may be seen that all site attributes coefficient estimates in the natural site choice CL model are statistically significant bar the Irish Sea and the Whiting species dummies. In general all attributes are also of the expected sign. As found by Smith and Wilen (2003), the greater the distance a site is from the home port the lower the probability that site will be visited. Also similar to previous findings in the literature, the higher the likely monetary return, as measured by the value of the average catch per hour per unit engine power in the previous season for each fishing ground, the higher the probability that site will be chosen. Interestingly, the negative sign on the variance of earnings variable indicates that the fishers are generally risk adverse and will have a higher probability of visiting a site when the expected return from that site is more predictable. This is in line with previous work by Ran et al. (2011) although elsewhere Eggert and Martinsson (2003) found that risk was not an important factor in fisher's fishing site choice decisions. As indicated by the negative sign on the number of species caught coefficient fishers also prefer sites where they can be more selective about the variety of fish caught. Given the current debate on discards this finding suggests that fishers as well as policy makers are also keen to target a smaller number of species.

The number of visits to a site in the previous season, as shown by the experience parameter, would appear to have a positive effect on the probability of that area being chosen on any given choice occasion. This is in line with previous evidence of repeat behaviour found by Holland and Sutinen (2000), Smith (2005) and Valcic (2008). The interaction of the average number of days at sea per trip with the distance variable was also found to be significant and indicate, as expected that the longer a vessel can stay at sea for any given trip the further the vessel will be willing to travel to a site. Overall, the model would appear to have a good explanatory power relative to other published choice experiments with a pseudo-$R^2$ of 0.38. Finally, the $\chi^2$ statistic of 14,101 shows that, taken jointly, the coefficients in the conditional logit model are significant at the 1% level.

There are a number of key differences between the parameter estimates in our natural site choice CL model and our grid based site choice CL model. The distance, area, experience and days at sea interaction term are significant and have the same sign as their counterparts in the natural site model. The dummies for Celtic Sea and Herring, the rock parameter and the variance of earnings parameter are however no longer significant. In the grid based site choice CL model (last column in table 2) the earnings variable also has an unexpected negative sign and the variance coefficient is insignificant. The dummy for Irish Sea is now also unexpectedly positive and significant. The significant prawn dummy has also flipped its sign. These strange findings are very much dependent on the size of the grids chosen to specify the sites. A closer look at the data helps explain for example why we get a counter intuitive positive earnings coefficient.

Based on the grid based definition, there are a number of sites adjacent to the shore where we see a high frequency of the trawls begin, based on the VMS data. The trawls then continue out of these boxes into one or more of a number of adjacent boxes. Based on the time spend trawling in each box a higher proportion of earnings from the trip will be spend in the outer boxes but a higher frequency of visits to the inner box (associated with a lower share of the earnings for the trip) is still recorded. Specifying a larger grid system could change this result. The fact that the rock parameter is now insignificant is also not surprising given that a rectangular area may have a high percentage of rock but it may not be in that part of the box where the trawls occur. The natural site definitions follow the contours used by the fishers in their trawls so the percentage of rock in those sites is expected to impact on site visitation decisions. The explanatory power of the model is less than that of the natural site choice model based on the value of the pseudo-$R^2$ and it also has a higher log-likelihood value (although given that the underlying site definitions are different the log-likelihoods are not directly comparable).

The data issues observed with the grid based model will also be present for the RPL specification. The extra complexity in the grid based data also meant that attempts to estimate a RPL model failed, with the optimum of the maximum likelihood function not being found. The difficulty in estimating mixed logit models with such data has been previously highlighted by Valcic (2008, p35). Given the proceeding discussion we proceed only with the preferred natural site specification when estimating the RPL model and carrying out the site closure simulation.

- **Table 3 here**

Table 3 presents the results from the RPL site choice model based on the natural site definitions. This model is specified to allow for random heterogeneity in the attribute parameters. For each random attribute parameter in the RPL, parameters for the mean and standard deviation are estimated. In order to aid estimation we specified the parameters for the individual species as fixed. We assume a normal distribution for the majority of the random parameters in the utility function so that negative as well as positive values for site attributes are permitted. However, a log-normal distribution is assumed for the size of grounds and expected earnings parameters as it is assumed fishers prefer strictly positive quantities of each[7]. An insignificant mean parameter in a RPL model implies that the center of the distribution is around zero but if the associated standard deviation estimate is significant then this suggests a considerable variation in taste-intensities across the sampled fishers. Together the two estimates allow an inference of what proportion of the bottom otter trawl fleet like or dislike a given site attribute. Under normality a negative mean implies that the majority of fishers dislike the attribute. This is the result in our preferred model for distance, the variance of earnings, the percentage rock at the grounds and the number of species caught per trip.

The majority of fishers also appear to have a positive preference for sites associated with higher per trip earnings, the size of the fishing grounds[8], the regional dummy for the Irish Sea and, based on the experience parameter estimate, are once again more likely to trawl a fishing ground that they have visited frequently in the past. These results are in line with the results of the CL model except for the fact that the Irish Sea parameter was insignificant in the CL model. The estimated mean values are all estimated as being significantly different from zero at the 1% level. Turning our attention to the estimated standard deviations for the fishing site attributes we find that they are all significant at the 1%. It may seem implausible to expect any fisher to favour a higher percentage of rock on the seabed at the grounds being trawled but

[7] We do not impose a log-normal distribution on distance that would force all probability mass to be negative since there is evidence within the VMS data that some vessels may prefer to travel greater distances to fishing grounds. There is also evidence that some fishers may be attracted to sites with a higher variance in potential earnings (Eggert and Martinsson, 2004) so once again the variance in earnings parameter is assumed to follow a normal distribution.

[8] While the estimated earnings and size of grounds parameters in the model appear negative it should be noted that these parameters represent the mean (b) and standard deviation (SD) of the natural logarithm of the coefficients. The mean and standard deviation of the coefficient themselves are given by $exp(b + SD^2/2)$ and $exp(b + SD^2/2) \times \sqrt{exp(SD^2) - 1}$, respectively (Train, 2003). Upon conversion the mean effect in each case is positive.

with modern equipment it is possible for fishers to trawl on rockier grounds and some may prefer to do so if they expect a good return from their fishing effort in that particular location. The significance of the remaining standard deviations parameters indicates that the preferences for all attributes also vary across the fleet.

The relative magnitudes of the standard deviations are quite high for the regional seas dummies, the number of species caught and the variance in earnings, suggesting a considerable variation in taste-intensities across the fleet in relation to these attributes - to the extent that all distributions have a high share in both the negative and positive domains. This supports our choice of using normal distributions to represent the random taste variation in these cases. The fact that the standard deviation parameter associated with the variance in earnings variable has approximately the same value as its mean would imply almost as high a proportion of risk loving as risk adverse fishers in the fleet. It is also worth noting in the model that the random taste variation remains for the distance parameter even after the inclusion of observed sources of preference heterogeneity (i.e., the number of days a vessel stays at sea per trip). This suggests that preferences vary considerably more than can be explained by this observed characteristic of the fishers. Except for the distance and earnings parameters, the standard deviation parameters are greater than the mean coefficient estimates indicating very large between vessel variability in preferences. As expected, those vessels that tend to take longer trips have a higher probability of trawling at sites further from their home.

The simulated log likelihood of -9811 compared to the standard log likelihood of -11,336 for the basic conditional logit specification suggests an improvement in the fit of the model. However, these models are non-nested. We therefore carried out a Vuong test (Vuong, 1989) to examine if the RPL is appropriate. The Vuong statistic has a limiting distribution that is normal with large positive values favouring the corrected model and with large negative values favouring the standard version of the model. Values close to zero in absolute terms favour neither model. The calculated Vuong statistic of 21.59 results in a clear rejection of the null hypothesis that the models are indistinguishable. To gauge the RPL model's ability to predict the actual behaviour of the fleet, the model's estimate of the probability of fishing at a particular site are compared to the actual fishing site choices revealed in the data. The predictions of the model are very close to the actual fishing site choice probabilities revealed in the data with differences ranging from just -0.003 to 0.038[9].

- **Table 4 here**

Over the past several years there has been a growing concern about the impact that intensive trawling and/or dredging activities have on the habitat on the sea bottom. With this in mind we used our RPL model to simulate a hypothetical grounds closure that restricts the fisher's choice set by excluding an area that has a high frequency of trawls in the Celtic Sea. This is the 'Galley' fishing ground south of Cork. Using the VMS data on fleet activity we also analysed which areas of seabed in the Celtic sea were trawled at least once in the season by the Irish bottom otter trawl fleet. This is accomplished by generating swept-area ratios which represent the area swept by the gear (distance covered by trawl multiplied by door spread) divided by the area of the grid cell (Gerritsen et al, 2013). It is the mean number of times a patch of ground is covered by demersal otter trawls. As is evident in figure 3, the vast majority of the Celtic sea seabed is swept at least once per year and the area representing the Galley fishing ground has one of the highest frequencies of trawling. This is also reflected in the estimated probability of site choices where the estimated probability of choosing that site to fish at was found to be 0.17.

- **Figure 3 here**

It should be noted that the simulation process assumes that the bottom otter trawl fleet comply with the ground closure. This is a fair assumption given that their activity is being monitored through the VMS system and non-compliance it is assumed would mean substantial fines. Also it is assumed the total fishing effort of the fleet remains unchanged which implies that the simulation will result in an increase in the effort in the remaining open areas. This assumption is more restrictive as one might expect that total fishing effort may fall as some fishers choose the option of employment outside the fishery following the closure. Conversations with boat operators would suggest though that it is unlikely that many fishers will give up fishing because of a closure.

[9] As well as demonstrating the ability of the model to predict the actual choices made by our sample of fishers we also uses a hold-out sample where we reserved the latter 15% of observations in our data, re-estimated the model, and predicted into the hold-out sample. Once again we find that the model does a good job in terms of predicting the fishing site choice probabilities revealed in the hold out sample; the max difference between actual and predicted probability for any site being just 0.05.

The results of the simulated closure suggest that the fishing grounds in close proximity to the closed site are the ones that will see the highest percentage change in probability of being fished by the fleet. As shown in table 4, the highest percentage change in probability are associated with Cork (+71%), Labadie2 (+54%), Labadie1 (+29%), Smalls (+23%), Mizen1 (+25%) and Nymphe (+22%). As can be seen from figure 1 these are all grounds that border or are in very close proximity to the closed site thus reflecting a spatial effect that Wilen et al. (2002) referred to as “a spatial autocorrelation ripple effect”.

## 5. Discussion and Conclusions

In this paper EU Vessel Monitoring System (VMS) data was combined with other site and vessel information and used to model the fishing site choice decision of Irish demersal otter trawlers. Uniquely, the fishing ground options used in the analysis reflect the actual seabed contours trawled by the fleet. The fishing site choice model, based on this natural site definition was then compared to an alternative destination choice model where the fleet decision is specified using a grid based site definition as employed in previous work. The preferred natural site choice model was then used to examine the spatial trade-offs involved in closing a high fishing effort area. We find that the chosen model does a good job in estimating the actual fishing site choices revealed in the data and also demonstrates that there is significant heterogeneity amongst the otter trawler population in terms of their preferences for the different attributes of the fishing site choices. The simulated redistribution of fishing effort after the implementation of the closure was also compared with the actual distribution of effort revealed from the VMS data and it was found that the fishing grounds in close proximity to the closed site are the ones that will see the highest percentage change in probability of being fished by the fleet.

From an ecosystem fisheries management perspective a key question is which species and habitats are likely to be most impacted from the spatial redistribution of effort. Looking at the clusters of species dominant at each site (see figure 1) that the simulation predict will see a significant increase in effort one can say something in this regard. The closed site is characterised by mixed cluster of haddock and other species. The sites likely to see the greatest displacement in effort; Cork, Labadie 1 & 2, Smalls and Mizen1 are dominated by the mixed nephrops clusters of species while the Nymphe site is characterised by whiting. It should be noted that these clusters were defined by Gerritsen et al. (2012) based on the composition of the landings of Irish demersal otter trawlers during the period 2006–2009. They will therefore also be influenced by quota restricting in place during that period. Analysing the habitats impacted at these sites would require further fieldwork to identify the composition of the seabed.

The changes in effort predicted around the closed area are also similar to those predicted from the phenomenon of 'fishing the line': a concentration of effort on the edges of a protected area thought to be a response to the availability of spill-over of stock migrating out of the protected area (Kellner et al. 2007). In this study however, the clustering of effort reflects the behavioural choices underlying choice of grounds rather than any choice to catch spill-over stock. Observations of fleet fishing the line around protected areas may therefore reflect additional behavioural choices, rather than a direct response to perceived spill-over.

Since ecosystem-based fisheries management requires a multispecies perspective, empirical methodologies that can fulfil this criterion are in demand. Typically, empirical multispecies analysis have followed one of two formats; a bio-economic model which determines the optimal harvest rate of more than one species using estimated predator-prey or competitor parameters, or structural ecosystem models that can be used to determine optimal Total Allowable Catches (TACs) across multiple species. The methodology used in this paper provided a third alternative to model the impact of management changes on multiple species by using realistic fishing site options within a discrete choice modelling framework. The use of such an approach can provide policy makers with an assessment of the ecological, economic and potentially social implications of different designation strategies in order to meet the requirements of policies such as the Marine Strategy Framework Directive (MSFD), the Habitats Directive and the reformed Common Fisheries Policy (CFP) and also in helping to decide on potential conflicts in the establishing of networks of MPAs in European waters.  As pointed out by Katsanevakis *et al.* (2011), many of these conflicts will only be resolved through the use of ecosystem-based marine spatial management, which is now seen as the most appropriate approach for the integrated management of the sea.

It should also be noted that the analysis conducted in this paper took place against the backdrop of a particular quota regime which may impact on the choices being made by fisherman as they work to fill their quota for the different species they are targeting. An area therefore for further research using the fisheries site choice model developed in this paper would be to investigate the impact of recommended quota changes for different species across different ICES areas on the spatial distribution of effort. It would also be interesting to expand the analysis out to the approximate 300 vessels in the wider Irish trawl fleet. Adding in cost data may also improve the fit of the model as would information relating to the attitudes of the skippers of each vessel to each of the sites specified. It would also be interesting to investigate the skipper viewpoint on what sites should be closed if closures are on the table as a management option.

When analysing the site choice data we assumed that respondents consider all offered alternatives and their choices are based on the alternatives that provides them with the highest utility. However, at least in principle, one may postulate the hypothesis that due to differences in locations and accessibility, as well as preferences, fishers may restrict their consideration set to a subset of all possible fishing grounds that do not exceed certain thresholds and cut-offs. The recently developed Independent Availability Logit (IAL) model (Habib et al., 2013) is a modelling approach that could test this hypothesis and is another interesting area for future research. Having said that, the model developed here does achieve its objective of giving us an insight into the factors driving the fishing site choice decision of an EU based bottom otter trawling fleet.

We would also argue that defining the fishing site alternative in a manner that is more in line with what the fishers perceive as being the shape and location of fishing grounds as was done in this paper should increase the predictive power of the site choice models and is in line with the ecosystem based fisheries management perspective. Using the natural sites as our fishing ground definition we find that we had to deal with a less complex site choice modelling situation with a lower frequency of trips visited per trip compared to the grid based site definitions (with the natural site definitions 55% of the fishing trips involved trawling at a single ground compared to 41% using the grid based definitions). We also saw how using an arbitrary grid system to define the sites can lead to misleading findings such as negative impact of earnings on site choice due to trawling starting in one box and proceeding into other boxes. With the natural definitions the trawl is generally started and completed within the site.

Finally, including information on the substrate or seabed habitats may be meaningless in models based on the grid based system since the percentage of any substrate type within a site may be in a location that the fishers never trawl. Since the natural site follows the contours generally followed by the fishers the percentage of rock on the ground or other habitat information should be much more relevant when modelling site choice decisions. From an ecosystem based fisheries management perspective the inclusion of this ecosystem information in our analysis of fisher behaviour is important and the availability of such data is getting much better all the time with seabed mapping projects such as INFOMAR and the requirements for such data under policies such as the EU Marine Strategy Framework Directive and EU Biodiversity Strategy.

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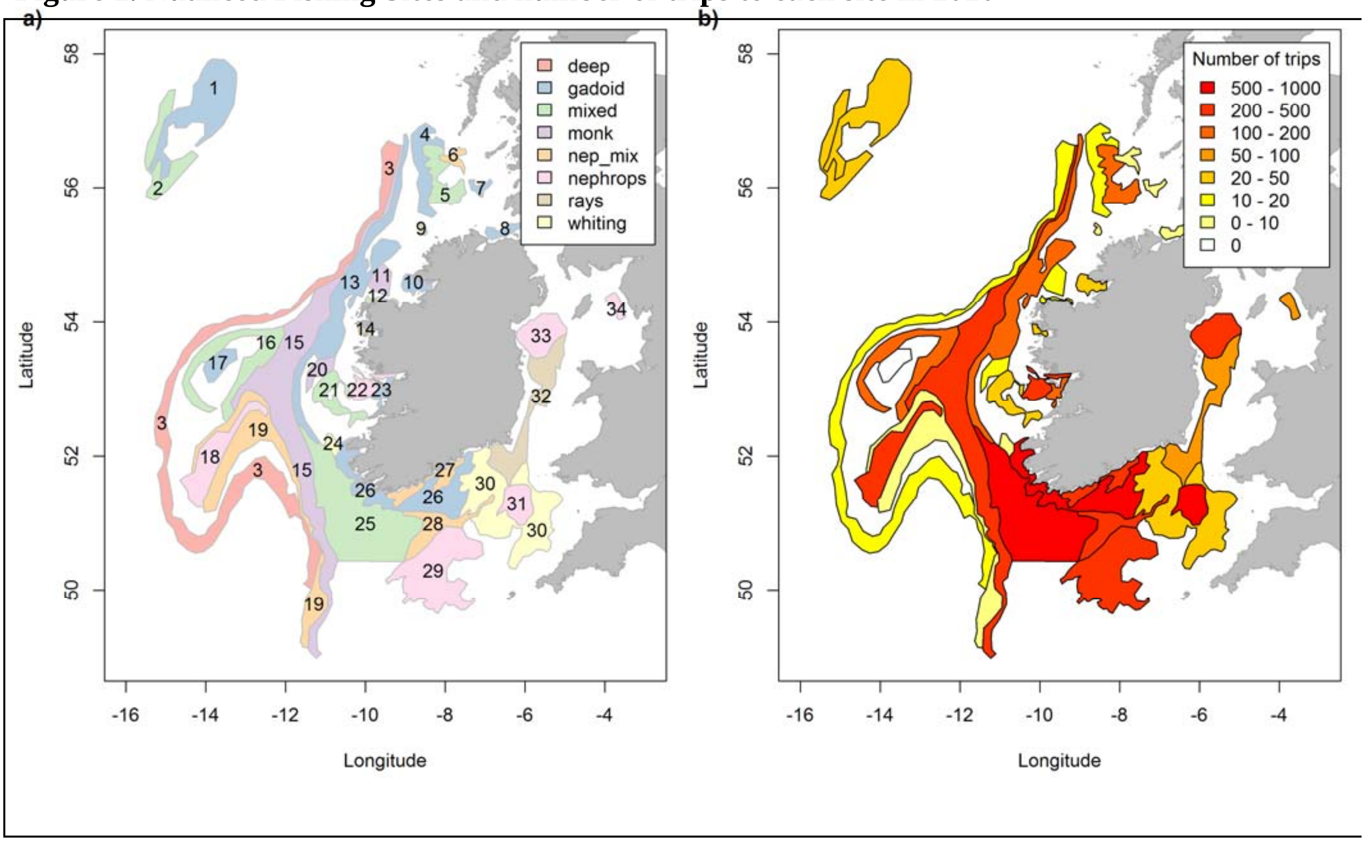
## Figures

**Figure 1. Nuanced Fishing Sites and number of trips to each site in 2010**




The map on the right (a) shows fishing sites and species clusters associated with each site. The numbers correspond to the names of the sites: 1)Rockall1; 2)Rockall2; 3)Deep; 4)Hebrides; 5)Stanton1; 6)Stanton2; 7)Blackstones; 8)Cape; 9)Tory; 10)Donegal; 11)Stags; 12)Mullet; 13)Erris; 14)Achill;

15)Slope; 16)Porcupine2; 17)Porcupine3; 18)Porcupine1; 19)Slope1; 20)Slyne; 21)LoopHead; 22)Aran; 23)Moher; 24)Blaskets; 25)Mizen 1 and 2; 26)Galley; 27)Cork; 28)Labadie2; 29)Labadie1; 30)Nymphe; 31)Smalls; 32)StGeorge; 33)IrishSea; 34)Morecambe. The map on the right (b) shows he number of trips to each site in 2010.

**Figure 2. Grid Based Fishing Sites**

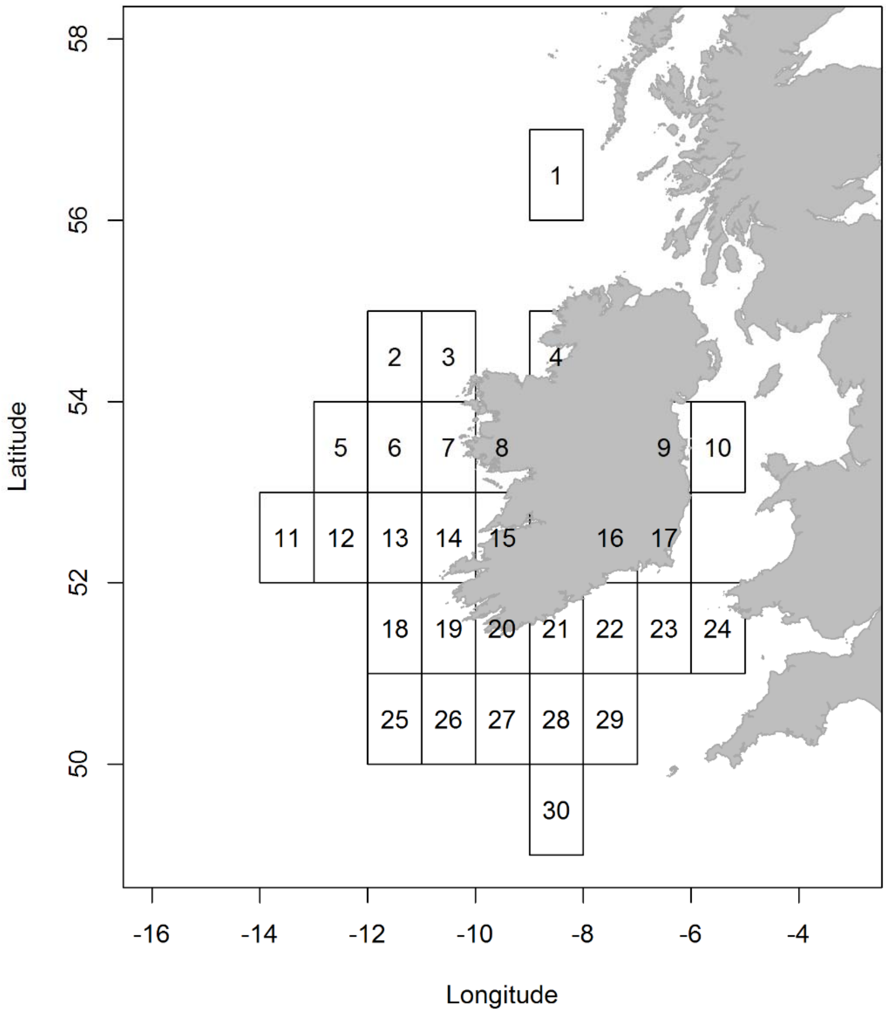
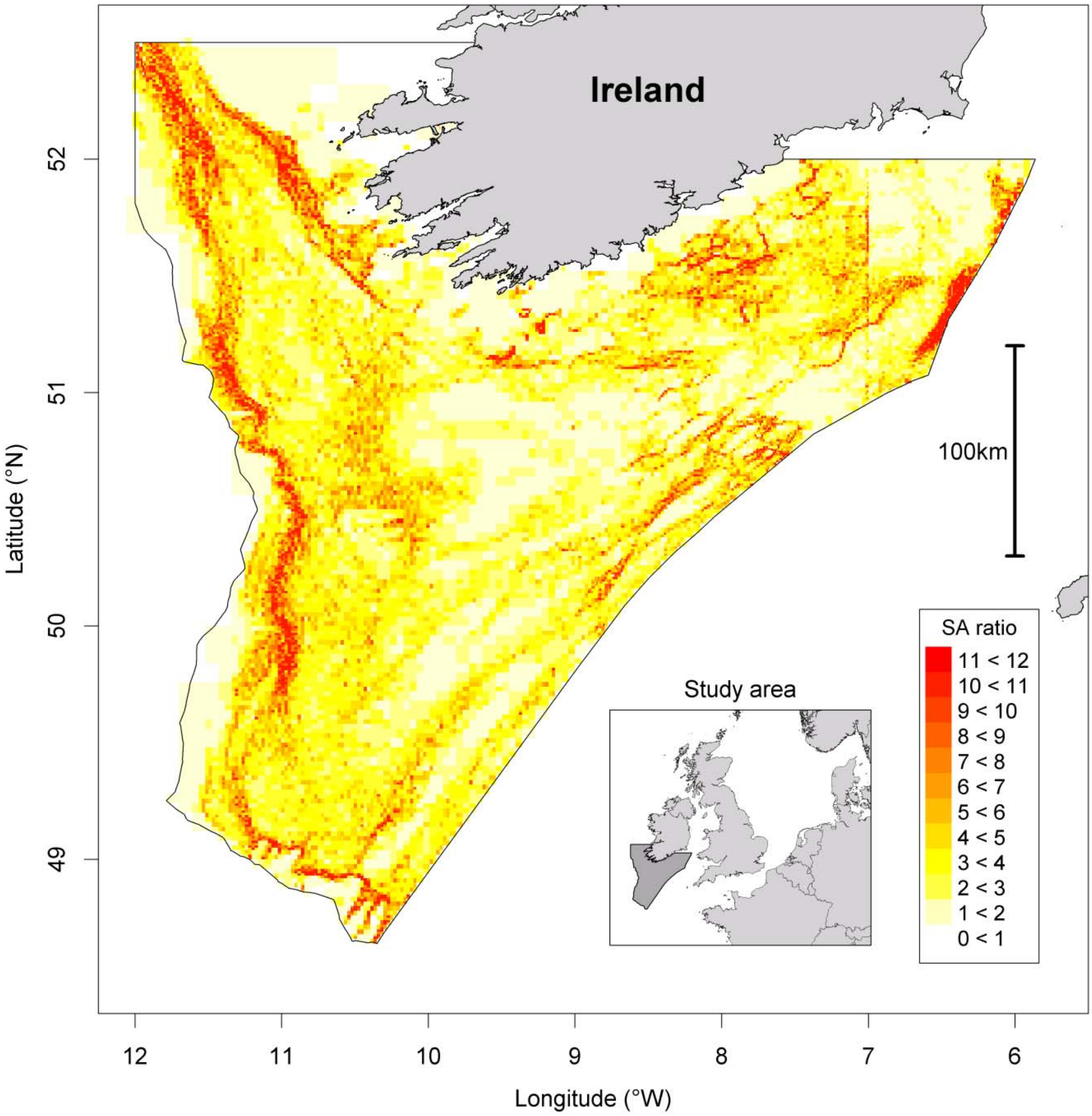


**Figure 3. Swept-Area ratios for bottom otter trawls in the Celtic Sea for 2010**




The swept-area ratio is the mean number of times a patch of ground is covered by demersal otter trawls.

**Tables**

**Table 1. Summary Statistics**

| Variable | Mean | Std. Dev. |
|---|---|---|
| Fishing Effort per Trip (hours based on VMS data) | 68.22 | 53.26 |
| Fishing Effort per Trip (KW hours based on VMS data) | 29,287 | 33,982 |
| Age of Vessel | 21.36 | 13.03 |
| Engine Power (KW) | 398.62 | 304.98 |
| Vessel Tonnage | 158.13 | 201.09 |
| Number of Days at Sea (per trip) | 4.86 | 3.40 |
| Number of Days Fishing (per trip) | 4.01 | 2.73 |
| Live weight of fish caught per trip (kg) | 5,169 | 7,884 |
| Earnings per Trip (€) | 11,508 | 13,110 |
| No. of Trips per Year | 41.59 | 18.13 |
| Total Earnings per Year (€) | 421,160 | 312,602 |

**Table 2. Conditional Logit Models**

| Variable | Fisher Natural Site Choice Model Coefficient | Rectangular Site Choice Model Coefficient |
|---|---|---|
| Distance from port to fishing ground return | -0.405 (0.015) *** | -0.136 (0.013) *** |
| Earnings per unit engine power (KW) | 0.033 (0.003) *** | -0.012 (0.002) *** |
| Average number of species caught at grounds | -0.013 (0.002) *** | 0.011 (0.001) *** |
| Celtic Sea | 0.819 (0.063) *** | -0.058 (0.041) |
| Irish Sea | -0.041 (0.082) | 0.127 (0.059) ** |
| Monkfish | -1.662 (0.173) *** | -0.249 (0.052) *** |
| Prawns | -0.491 (0.071) *** | 0.086 (0.042) ** |
| Whiting | -0.006 (0.084) | 0.322 (0.044) *** |
| Herring | -0.441 (0.074) *** | 0.065 (0.046) |
| Saithe | -0.752 (0.228) *** | -0.222 (0.111) ** |
| Experience | 0.078 (0.001) *** | 0.124 (0.001) *** |
| Variance in earnings per unit engine power | -0.0001 (0.00001) *** | 0.001 (0.001) |
| Percentage rock at grounds | -0.034 (0.004) *** | -0.00002 (0.00003) |
| Size of grounds (km2/1000) | 0.025 (0.003) *** | 0.035 (0.009) *** |
| Distance from port to fishing ground return: Days at Sea | 0.028 (0.002) *** | 0.011 (0.002) *** |
| | | |
| Log likelihood function | -11,336 | -20,502 |
| Pseudo R-squared | 0.383 | 0.347 |
| Likelihood Ratio Chi$^2$ Statistic [15 d.f.] | 14,101 | 21,768 |

Figures in parenthesis indicate the values of the standard errors. ***significant at 1%; **significant at 5%. Experience relates to the number of trips to each fishing grounds in 12 months prior to the current 12 month period in which the trips take place.

**Table 3. Random Parameter Logit Fisher Natural Site Choice Model**

| **Random Parameters in Utility Function** | **Mean of Coefficient** | **Standard Deviation of Coefficient** |
|---|---|---|
| Distance from port to fishing ground return | -0.552 (0.023)*** | 0.316 (0.011)*** |
| Average number of species caught at grounds | -0.013 (0.003)*** | 0.032 (0.002)*** |
| Celtic Sea | 0.547 (0.078)*** | 1.115 (0.049)*** |
| Irish Sea | 0.249 (0.098)** | 0.371 (0.106)*** |
| Experience | 0.078 (0.002)*** | 0.059 (0.002)*** |
| Variance in earnings per unit engine power | -0.00009 (0.00001)*** | 0.0002 (0.00002)*** |
| Percentage rock at grounds | -0.050 (0.005)*** | 0.049 (0.004)*** |
| Size of grounds (km2/1000) | -3.861 (0.180)*** | 0.484 (0.113)*** |
| Earnings per unit engine power (KW) | -3.310 (0.089)*** | 0.466 (0.035)*** |
| <u>Non Random Parameters in Utility Function</u> | | |
| Monkfish | -1.095 (0.180)*** | |
| Prawns | -0.265 (0.080)*** | |
| Whiting | 0.126 (0.096) | |
| Herring | 0.075 (0.085) | |
| Saithe | -1.053 (0.233)*** | |
| <u>Heterogeneity in mean, Parameter: Variable</u> | | |
| Distance: Days at Sea | 0.022 (0.003)*** | |
| Log likelihood function | -9,811 | |
| Likelihood Ratio $Chi^2$ Statistic [9 d.f.] | 3,049 | |
| Number of site visit observations | 5,406 | |

(i) Figures in parenthesis indicate the values of the standard errors. ***significant at 1%; **significant at 5%; *significant at 10%.Experience relates to the number of trips to each fishing grounds in previous 12 months.
(ii) Note: The estimated earnings and size of grounds parameters in the above model represent the mean and standard deviation of the natural logarithm of the coefficients. Also see footnote 7.

**Table 4. Predicted Percentage change in Probability of visiting site after Closure of Galley**

| Site | % change following Closure | Site | % change following Closure |
|---|---|---|---|
| Achill | 5.23 | Mizen2 | 17.95 |
| Aran | 4.70 | Moher | 8.44 |
| Blaskets | 14.20 | Morecambe | 7.93 |
| Cape | 3.42 | Mullet | 8.11 |
| Cork | 70.63 | Nymphe | 22.50 |
| Deep | 9.04 | Porcupine1 | 9.45 |
| Donegal | 3.34 | Porcupine2 | 8.33 |
| Erris | 3.35 | Rockall1 | 6.16 |
| Galley | -100 | Rockall2 | 6.04 |
| Hebrides | 5.51 | Slope 1& 2 | 8.30 |
| IrishSea | 2.79 | Slyne | 21.04 |
| Labadie1 | 29.12 | Smalls | 23.35 |
| Labadie2 | 54.15 | StGeorge | 12.20 |
| LoopHead | 9.89 | Stags | 3.16 |
| Mizen1 | 24.81 | Stanton1 | 3.80 |

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