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Dynamic prediction of effort reallocation in mixed fisheries

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ABSTRACT

A discrete choice model is applied to determine how fishing effort is allocated spatially and temporally by the English and Welsh North Sea beam trawl fleet. Individual vessels can fish in five distinct areas, and the utility of fishing in an area depends on expected revenue measured as previous success (value per unit effort) and experience (past fishing effort allocation), as well as perceived costs (measured as distance to landing port weighted by fuel price). The model predicts fisher location choice, and the predictions are evaluated using iterative partial cross validation by fitting the model over a series of separate time-periods (nine separate time-periods). Results show the relative importance of the different drivers that change over time. They indicate that there are three main drivers throughout the study, past annual effort, past monthly effort in the year of fishing, and fuel price, largely reflecting the fact that previous practices where success was gained are learned (i.e. experience) and become habitual, and that seasonal variations also dominate behaviour in terms of the strong monthly trends and variable costs. In order to provide an indication of the model's predictive capabilities, a simulated closure of one of the study areas was undertaken (an area that mapped reasonably well with the North Sea cod 2001 partial closure of the North Sea for 10 weeks of that year). The predicted reallocation of effort was compared against realized/observed reallocation of effort, and there was good correlation at the trip level, with a maximum 10% misallocation of predicted effort for that year.

1. Introduction

It is becoming increasingly evident that fisheries management is not solely a biological issue. Fisheries science is an interdisciplinary field, and combining social, economic, and ecological information has proven to be increasingly important in achieving sustainable fisheries management (Mumford et al., 2009). Of increasing importance to fisheries science and management is the ability to anticipate fisher behaviour in response to management regulation, in order to reduce implementation error, i.e. where the effects of management differ from that intended. An example of implementation error is where fishing effort is redistributed following a spatial closure to protect a stock (or cohort) in a way that was not anticipated by management.

Many factors influence a fisher's decision where and when to fish, including fish distribution, fuel price, regulations, their habits and experience, previous catch rates, market prices, and the proximity to landing ports. These factors can lead to differences in observed individual fisher behaviour and the way a group of fishers (a fleet) allocate their effort in time and space. Several studies have looked at behavioural aspects of the way fishers spatially allocate their effort (Rijnsdorp et al., 2000; Hilborn et al., 2005; Smith et al., 2009). An important element influencing fisher behaviour is stock density, because fishers tend to have prior knowledge (Begossi, 2001) of resource distribution and habitat (Hilborn and Ledbetter, 1979; Gillis et al., 1993; Pet-Soede et al., 2001). Catch rates are related to stock density and will have a large impact on fisher behaviour (Eales and Wilen, 1986; Marchal et al., 2006). This means that fishers will gravitate towards areas where catch rate is greatest, and gravity models have been specified and applied to model fishing vessel spatial distribution (e.g. Walters and Bonfil, 1999). Economic factors and management measures in the form of technical measures (size restrictions or gear restrictions; Bene and Tewfik, 2001), marine protected areas (MPAs), and spatial closures may also force fishers to search for new fishing grounds (Hutton et al., 2004).

Over the past few years, much attention has been paid to predicting fisher location choice by applying random utility methodology and discrete choice models (Andersen et al., 2010). Predicting fisher behaviour using discrete choice models has

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increased in popularity with the increasing availability of appropriate data (vessel-by-vessel trip data), because such models offer an opportunity to study individual behaviour at finer resolutions of time and space than other techniques (Coglan et al., 2004; Hutton et al., 2004). These models can be applied to theoretical policy scenarios, which can also be simulated. The key characteristics of discrete choice models or random utility models (RUMs) are that they model discrete decisions, and the assumption of homogeneity among individuals does not need to hold. As with other economics-based choice models, utility drives individual choice with a deterministic component and a stochastic error component (hence the name "random" utility model). Prior to implementation in fisheries behaviour models, discrete choice models were used in the travel industry to analyse the behaviour of consumers of transportation services and facilities (McFadden, 1974; Ben-Akiva and Lerman, 1985).

The behaviour of fishers can be studied in the short term (their tactics), for example on a trip-by-trip basis in terms of decisions where to fish and which species to target, or the long term (their strategies), i.e. choices made year by year where the availability of decommissioning grants, stock status, catch quotas, investment, and other key factors play a critical role in the decision of a fisher to invest in the fishing operation (Tidd et al., 2011). Models prior to the application of discrete choice models assumed the ocean to be a homogenous space in which fish are distributed uniformly and fishing locations are identical (e.g. Holland and Brazee, 1996; Smith and Wilen, 2003). Sanchirico and Wilen (1999) modelled behavioural dynamics, including both spatial and temporal aspects, under conditions of open access. The results of their analysis suggested that fishing effort across a system of interconnected spatial patches is driven by the bio-economic conditions in each patch, and the biological dispersal rates between patches. In patches where costs are high or the catchability and prices low (mix of low price species and/or cohorts), effort is driven away, and as it relocates, it affects the distribution and density of stocks (i.e. the local density and the potential for dispersal to nearest-neighbour patches) of other patches directly and indirectly. Incorporating economic variables (such as revenue and travel costs) into decision-maker behaviour is therefore important when analysing a resource that is distributed heterogeneously in space.

In this study, we investigate whether tactical behaviour by fishers is influenced by expected revenues, habitual seasonal fishing patterns, effort fluctuations, and changes in fuel costs, and whether there are dynamic changes in the relative importance of these drivers through time. Focus is on the English and Welsh North Sea beam trawl fleet, where there have been changes in both ownership and spatial management; as such, this study provides an opportunity to investigate the dynamics and drivers of fisher behaviour. Also of interest to this study is the fact that, during 2001, the European Commission implemented a temporary closure or MPA in the North Sea between mid-February and the end of April, to conserve spawning of North Sea cod (EC, 2001). As a regulatory management measure that impacted fishing effort, the 2001 closure of the North Sea covered most of Roundfish area 7, which beam trawlers frequent, and the remainder of which included a plaice box preventing trawlers >300 hp from entering (Fig. 1). This allowed us to evaluate the predictive power of the model and analysis, and among other factors the response of the fleet to a management measure.

An earlier study also applied a discrete choice model to the same fleet using individual fishing trip data over the years 1999–2000. Previous knowledge or experience of fishing grounds (in 1999) was found to have a bearing on the decision to fish in a given area in 2000, and this information was then used to construct a simple effort redistribution model to simulate the implications of the 2001 closure (Hutton et al., 2004). Although that study investigated detailed spatial location choice, there are limitations to such

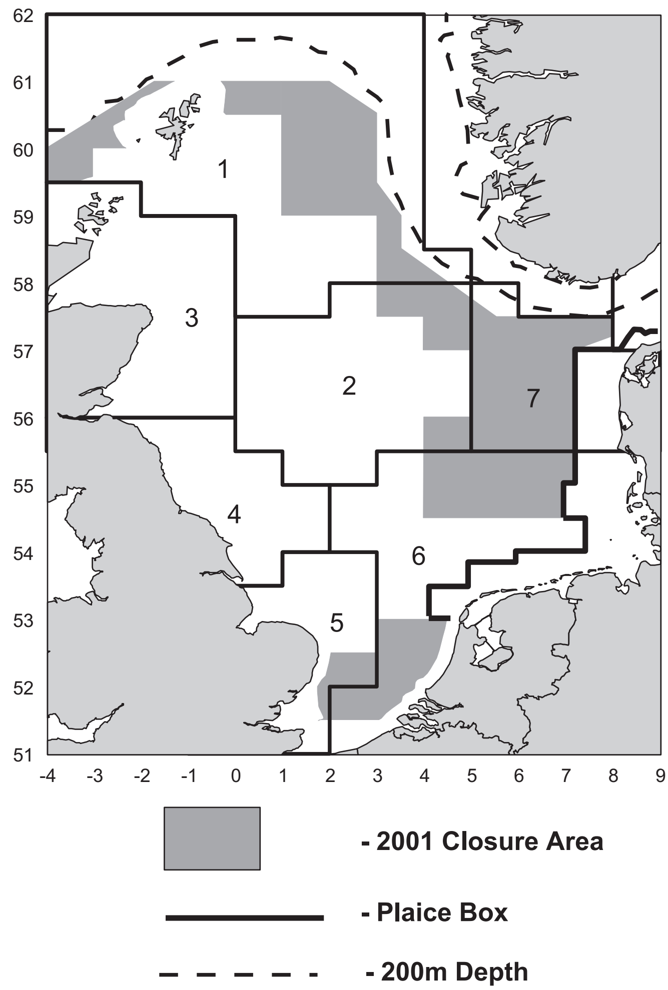

Fig. 1. The study area and Roundfish areas, including the 2001 closure areas and the plaice box.

work for considering temporal changes in fisher behaviour. This is because of the short time-period of data and the type of discrete choice model used. Hutton et al. (2004) used a conditional logit model, a model often criticized when used for spatial policy analysis because of the Independence of Irrelevant Alternatives (IIA) it imposes, i.e. choices are assumed to be independent, and a change in one choice would not affect the relative choice set, which could have serious implications if used for a spatial policy analysis (Wilen et al., 2002).

Here, focus is on the dynamic changes in tactical behaviour over a 12-year period. We introduce the use of a mixed model (relaxing the IIA assumption) and extend the set of explanatory variables investigated to a wider range of potential drivers (such as distance to landing port and separation of catch into their targeted components, plaice and sole). To understand better the drivers and dynamics of fisher location choice over space and time, we fit discrete choice models over different periods and investigate the effects of the various explanatory variables (which are proxies of expected revenue and costs perceived by fishers from past experience on monthly and annual time-scales). We then predict fisher location choice over separate periods to evaluate the model predictions, along with the versatility and robustness to potential changes in tactics. Finally, we develop a framework for investigating fisher location choice that can be used to reduce potential implementation error and scientific uncertainty and allow for the management system to be adjusted or adapted to what is learned.

2. Materials and methods

2.1. English North Sea beam trawl fleet

English beam trawl vessels in the North Sea have traditionally caught mostly plaice in a directed beam trawl fishery using 120 mm mesh north of 56°N, and a mixture of plaice and sole using 80 mm beam trawls in the southern North Sea. In 2003, international landings of North Sea plaice amounted to 66,502 t, compared with a peak of 170,000 t in 1989. Some 42% of the total plaice international landings were reported by vessels from the Netherlands, the UK accounted for 21%, Denmark for 21%, and Belgium, Germany, France, and other countries the balance of 16% (ICES, 2007). In the English fishery, the high value of sole makes it one of the most important species targeted by inshore vessels using trawls and fixed nets. The fishery is mainly conducted from March to October, but sole are also taken as a target species by offshore beam trawlers, otter trawlers, and gillnetters. The English North Sea beam trawl fleet operated mainly out of east coast English ports until 2003, typically spending an average of 250 days at sea in trips lasting about six days (Hutton et al., 2004).[i]

Towards the end of 2002, the main English east coast beam trawl company ceased fishing because it could not fish profitably. This was largely due to a fuel crisis from late 2000, with high and rising fuel prices over several years along with declining catch rates of large plaice. That company and other operators claimed that they could not catch the fish for which they had quota entitlement, that prices for fish were poor, and that the fuel costs incurred by vessels having to travel long distances to catch the fish were too high (Hansard, 2002). Subsequently, the fishing vessels were sold to operators in the Netherlands, but they still maintained the English flag and quota allocations. Some vessels were leased initially in 2001, with formal transfer of ownership depending on vessel taking place from 2002 to 2005. English beam trawl fishers generally choose to target both plaice and sole, but in recent years because of the shrinking fleet size and the transfer of ownership to fishers from the Netherlands, skippers generally targeted sole because of its high commercial value and short distance from port in the southern North Sea, generally in Roundfish area 6 (Fig. 1).

2.2. Data

The areas in the study were chosen based on the International Bottom Trawl Survey (IBTS) and in particular the Netherlands Beam Trawl Survey (BTS) which stratifies its sampling of sole and plaice to Roundfish areas (Fig. 1; ICES, 2009). The fishery-independent survey results are used in the ICES North Sea demersal working group (WGNSSK) for assessing sole and plaice. These Roundfish areas also represent the main fishing grounds at a large spatial scale, and are independent, i.e. they are discrete choice decision units.

Individual trip data for the commercial beam trawlers were collated for the years 1996–2007. Roundfish areas 1 and 3 (see Fig. 1) were excluded from the study because English beam trawlers generally do not fish there. The number of trips decreased annually during the study period (Fig. 2). The data collected for each vessel included species landed, hours fished, landed weight per ICES statistical rectangle (kg), month of fishing, year of fishing, and total value of the catch by species by vessel and trip. Within the EU, it is currently only a requirement for vessels >10 m long to submit logbooks, but the database also contains a subset of catch from <10 m vessels that historically reported their catches by means of logbooks.

[i] See Fig. A1 for effort distribution of the beam trawl fleet, 1997–2007.

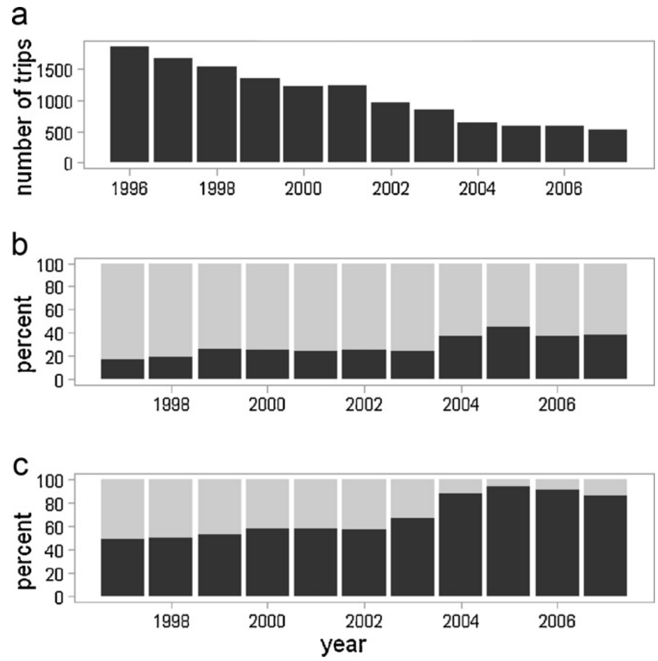

Fig. 2. (a) Number of trips by registered English and Welsh beam trawlers during the study period. (b) Approximate representation of the percentages of registered owned English and Welsh beam trawlers, black bars indicating foreign (excluding UK and Ireland) ownership. (c) Percentage of trips by English and Welsh beam trawlers to English or foreign (excluding UK and Ireland) landing ports, with black bars indicating foreign landing ports.

The methodology for the definition of fleets is based on the European Commission's data collection regulation (DCR; EC, 2000). We use a method developed independently (see EC, 2006), preceding the present data collection framework (DCF; EC, 2008), which defines the beam trawl fleet based on its use of a beam trawl for >50% of a fishing trip.

The fleet activity or métier is determined by the fisher's tactic at a trip level, which is defined on the basis of the mix of target species. In other words, métiers are characterized on the basis of the outcome of a trip defined by the composition of the landings. That composition is calculated as a proportion of the total value of the catch, removing the differences in catch rates attributable to vessel capacity. Moreover, the proportions of the catches are based on economic value rather than weight, reflecting the notion that fishers are profit maximizers, so valuable species being targeted receive more weight in the analysis. In this study, the beam trawl métier that primarily targeted crustaceans (brown shrimp) was omitted, and a single demersal métier was defined (beam trawl demersal) and used in the analysis. This fleet targets the main flatfish stocks (plaice and sole) in the North Sea.

We anticipate there would have been changes in tactics attributable to changes in the availability of fish, prices, fuel costs, and whether skippers were re-employed. Unfortunately, there is no information available on ownership or personal information about the owners (and/or skippers), but just limited information on vessels registered to the UK and whether they record their landings under the UK flag. However, we do have detailed information on port landed,[iii] where they fish, and traditional landings data such as species landed, effort, and price paid. Spatial location

[iii] Although the work is currently unpublished, the second author contributed to a series of surveys on technological change in this fleet, and witnessed first-hand the switch in port (from a UK port to a port in the Netherlands) that occurred over the period of this study. The switch in port nationality for the large beam trawl vessels was characterized by a change in vessel ownership from UK-owned and operated

choice is discrete instead of continuous because it can be represented as 0–1 decision in the context of a choice model. The choices are planned a priori and influenced by seasonality, tradition, habit, belief, demand, fish habitat, and the spatial distribution of the target stocks.

2.3. Model description

Fishers gain economic benefit, i.e. a utility μ, from fishing, and have to make a choice of fishing location each trip based upon the potential catch rates (i.e. revenue), the cost of travelling to a location, and other preferences for a particular location (knowledge of fishing ground and weather). These will differ between locations, so the total utility μ_{njt} of fisher n for site j in trip t is

$$\mu_{njt} = \beta_n x_{njt} + \varepsilon_{njt}, \tag{1}$$

where $\beta_n x_{njt}$ are the vectors of coefficients and explanatory variables providing information on the known or observed component, and ε_{njt} is the random or unobservable component of each vessel's utility and, for simplicity, β_n is assumed to be homogeneous among individual fishers (such that the vector β has the same length as the number of explanatory variables x). However, the conditional logit has often been criticized because it imposes an independence of irrelevant alternatives (IIA) property (Ben-Akiva and Lerman, 1985), especially for spatial models (Wilen et al., 2002). The IIA property assumes that the random error component ε_{njt} is independent across choices for each decision-maker, and the unmeasured attributes of choice are assumed to be uncorrelated. This implies that a change in the choice set would not affect the relative probabilities. The probability ratio of any two choices depends on the attribute vectors of the respective choices, despite any single probability depending on the attributes of all choices.

The RUM used in this study is a mixed logit model (also known as a random parameters logit) (Hensher and Greene, 2003; Train, 2003) which relaxes the IIA property because it assumes heterogeneity among alternatives at the population level. It differs from the conditional logit (McFadden, 1974) in that β_n varies in a population across individuals. Instead of estimating β_n for all individuals, the mean $\bar{\beta}$ plus its standard deviation σ_n are used to represent the preference distribution in the population of fishers (Train, 1998). The mixed logit choice model takes the form of Eq. (2) below, where $\bar{\beta} x_{njt}$ represents the observed utility and $\sigma_n x_{njt}$ represents the unobserved utility. One part of the error distribution (unobserved), therefore, is correlated over alternatives, and the other part, ε_{njt}, is independent and identically distributed (iid) over alternatives and individuals (McFadden, 1981; Maddala, 1983), and is written as

$$\mu_{njt} = \bar{\beta} x_{njt} + \sigma_n x_{njt} + \varepsilon_{njt}. \tag{2}$$

Within the mixed logit framework, β_n was assumed to follow a normal distribution, and for a given value of n (for simplicity disregarding t), the conditional probability of choice j across all other choices $k = 1$ to J is estimated by drawing random values β by simulation using

$$P_n(j) = \frac{\exp(\beta x_{nj})}{\sum_{k=1}^{j} \exp(\beta x_{nk})}, \tag{3}$$

where β is a vector of coefficients that varies across individuals, and x_{nj} is a vector of the attributes of each choice that was made. All covariates met the normality assumption following log-transformation. In keeping with economic theory, distance is a proxy for cost, so enters the model with a negative sign, and expected revenues enter with a positive sign (Train, 1998; Ran et al., 2011). The analysis was carried out in the SAS package PROC MDC (SAS, 1999) using quasi-Newton optimization and 100 Halton draws, and was re-run in the R mlogit package (R Development Core Team, 2008) to cross-validate results. The resulting lognormal coefficients of the mean, b, and standard deviation, s, for the log of β required back-transformation to provide correct interpretation (see Ran et al., 2011), e.g. for $\ln(\beta)$, the median, mean and standard deviation can be calculated as follows: $\exp(b)$, $\exp[b + (s^2/2)]$, and $\exp[b + (s^2/2)]\sqrt{\exp(s^2) - 1}$.

to Netherlands-owned and operated (with lease agreements at first), and a change in the nationality of the skipper and the crew.

Table 1
Definition of the variables used in the random utility model (RUM).

Variable	Definition
plelagyr	Average vpue of plaice from fishing in the same location in the same month in the previous year
sollagyr	Average vpue of sole from fishing in the same location in the same month in the previous year
timelagyr	Percentage effort spent in the location in the same month the previous year
plelagm	Average vpue of plaice from fishing in the same location the previous month in the actual year of fishing
sollagm	Average vpue of sole from fishing in the same location the previous month in the actual year of fishing
timelagm	Percentage effort spent in the location in the previous month in the actual year of fishing
distcost	Average distance to port of landing from the same location the previous month in the actual year of fishing weighted by the fuel price[a]

Source: DECC (UK Department of Energy and Climate Change).
[a] Average marine fuel prices (£ per litre, excluding VAT and duty).

2.4. Selection of explanatory variables

Fishing is a risky business, and predicting catches and revenues in advance is difficult, so experience and knowledge of fishing locations are important. Therefore, rather than using revenue and costs per trip as the utility (as measures of economic gross benefit or economic costs), we use value per unit effort (vpue). We assume that vpue is a proxy for net benefit (i.e. utility) and that targeting of a stock would be based on its vpue because fishers would attempt to target the most valuable species, and any reduction in vpue would indicate that a species had been depleted or the market and effort diverted to a less valuable species. The variable vpue can be computed from fishing in the same location in the same month of the previous year (i.e. lagged average vpue). The vpue had to be used because, although obtaining cost data for each decision unit is possible, we had no access to individual cost data. Moreover, accessing individual cost data is expensive in terms of research effort, and the economic data are anyway generally confidential in nature. In order to take account of strong spatial and temporal fluctuations and strong (or weak) year classes in the target species, a lagged average vpue was used on a monthly scale in the within-year of fishing as a proxy for the attractiveness of fishing in the same location as the previous month. This variable captures the within-year seasonal trends. Table 1 lists all the covariates estimated in the model. Not present in the skippers' logbooks was fuel consumption, so distances to the port of landing were weighted by marine monthly average diesel price per litre over the study years as a proxy for cost, because true trip costs were not available. The assumption is that before a skipper proceeds to the fishing grounds, he already has a good idea where he will land his fish in order to achieve the best return (Caddy and Carocci, 1999). Distant sites are expected to have better quality fish stocks, however, so the choice of how far to travel is a trade-off between higher travel costs to distant grounds and the expected better quality catch there.

Table 2
Mean values of the input variables for 1997 (as an example year) over all months.

Roundfish area	vpue sole (£/h)	vpue plaice (£/h)	Distance (km)	Trips (%)
2	3.2 (96)[a]	143.8 (24)	440.3 (4)	18.3 (36)
4	27.2 (107)	73.2 (29)	249.9 (22)	6.9 (41)
5	34.4 (58)	30.5 (75)	156.8 (37)	29.1 (24)
6	10.1 (77)	123.6 (13)	316.9 (11)	29.7 (23)
7	3.4 (105)	138.6 (34)	409.2 (8)	15.9 (36)

The coefficients of variation (*CV*) associated with the variables are given in parenthesis, showing variation for distance (as ports vary) and variation in the other variables attributable to individual differences for each decision unit and trip.
[a] Note the large variation, because sole catches are minimal in this area.

Distance was calculated using the Haversine formula (Sinnott, 1984), using the distance from the centre of the ICES statistical rectangle where a declared landing was taken to the port of landing for each trip in a particular month. A mean distance was then calculated by year, month and Roundfish area. The distances in our model are the average kilometres from fishing in the same location in the previous month of the same year, so they take account of the expected travel costs and the landing behaviour of the fleet. It was assumed that fishers would have received prior information of where to land, so reflecting better market prices for the distance travelled to land their catch (Mathiesen, 2003). Table 2 lists the average values for the chosen covariates for each spatial unit for 1997, to illustrate the scale of covariate values and differences from one area to another.

It is not unreasonable to assume that fishers are profit maximizers (Robinson and Pascoe, 1997), basing their decisions to fish in a certain location on catch rate, effort and essentially economic return. However, previous effort allocation (an average of the entire beam trawl fleet) also adds to experience and knowledge gained of a location and contributes to the utility of a choice. Fishers tend to choose the same areas, based on previous experience, and apply habitual behaviour, which in this case is referred to as a habit variable. Therefore, the utility of the location choice is modelled by the observed choice of location last year (% effort spent) in the same month (i.e. lagged location). The explanatory variables within the model were calculated as a mean by year, month and area (i.e. for each trip in a particular month and ICES rectangle, a mean was calculated by year, month and Roundfish area) for the fleet, the result of which made the choice set for year, month and area. This set was merged with individual trip data by year, month and area, such that for every trip, the decision-maker had a choice. If the choice was made, the values took a value of 1 if chosen, or 0 otherwise.

The analysis was carried out in two steps. First, the RUM was fitted to the fishing trip dataset in nine time-windows (each three years long), each with a monthly time-step. These nine time-periods were 1997–1999, 1998–2000, 1999–2001, 2000–2002, 2001–2003, 2002–2004, 2003–2005, 2004–2006, and 2005–2007. Note that because lagged variables were used as explanatory variables (as an example, vpue in the same month of the previous year), data from the previous year (starting from 1996) were used to predict choice in the current year.[iiiii] These nine time-windows were used to evaluate whether alternative explanatory variables were apparent because of differing circumstances (economic or habit), or through changes in management, the populations being fished, or other factors.

The second step involved using the selected best models (based on each time-window) to predict future choice by fishers. Therefore, monthly time-series of predicted fisher location choice were projected over the periods corresponding to each of the above models (different cumulative time periods depending on the original model time-period): 1999–2007, 2000–2007, 2000–2007, 2001–2007, 2002–2007, 2003–2007, 2004–2007, and 2005–2007. Here we were attempting to get an indication of each model's predictive capability, at least partially. We were also replicating a typical analysis that would have been performed by a researcher who would have cross-checked a model's predictive power by fitting over a time-period, predicting ahead one year, then later cross-checking predicted against observed values. Here, it is important to acknowledge that as tactics change over time, they result in differences in the significance of the explanatory variables, as noted above. This provides the rationale for the cross-validation as carried out. A likelihood ratio test was also conducted on the constrained model (log-likelihood under the null hypothesis) fits against an unconstrained model, to determine whether any model reduction was necessary (and to check the hypothesis that the random parameters are uncorrelated). This statistical test provides a comparison of the random effects model (null model) over its simpler form, a deterministic conditional logit model. The test describes how many more times likely one model is over the other. The resulting *p*-value indicates the significance (usually <0.05) of whether to reject the null model over the simpler model. The mixed logit was also tested for the IIA property using the Hausman test (Hausman, 1978). The assumption behind this test is to estimate the model with all the choice sets, then to reduce it to a small set of alternatives, and then to re-estimate. The resulting estimates should not change when the alternatives are removed, and the two models can be compared and tested for IIA. If IIA holds, the null model is said to be efficient, otherwise the model is said to be inconsistent and IIA does not hold.

3. Results

All statistical fits to the RUM were significantly better than null models (likelihood ratio test; Table 3), so the mixed model was considered the best model in terms of likelihood. The likelihood ratio tests suggested that all random coefficients were important additions to the model fits and clearly reject the hypothesis that the random parameters are uncorrelated. However, a direct comparison is not correct because of the degrees of freedom in the two models. Results from the Hausman test for IIA after Roundfish area 2 was removed from the data and re-estimated for all the fits showed that all models failed, giving a χ^2 value of between 0.006 and 0.02 and $p = 0.99$. As a test, the models were reduced to the simpler conditional model and the results indicated that it passed the IIA assumption, giving a χ^2 value of between 23.8 and 74.0 and $p < 0.05$, proving that the mixed model was the correct model to have used. The significant variables and their estimated coefficients for each of the models are listed in Table 4. Several variables had a significant influence on the utility and probability of location choice, including distance to landing port from fishing grounds, expected revenue of plaice and sole, and past habits on the same fishing grounds. In general, the coefficients of the estimated variables were consistent with expectations; a positive sign was observed for expected revenues and a negative one for expected costs (Table 4). The signs of the standard deviations in some instances are negative, but for estimation purposes they are free to take any sign, because the

[iiiii] Lagged vpue for a particular month in year $1 = -m$; lagged annual vpue in year $- 1 = m$.

Table 3
Results of the likelihood ratio test for each of the model fits, with d.f. representing the degrees of freedom for the constrained and unconstrained model, and d.f. Chisq the χ^2 value with the degrees of freedom equal to the difference in the number of degrees of freedom between the two models.

Model	1997–1999	1998–2000	1999–2001	2000–2002	2001–2003	2002–2004	2003–2005	2004–2006	2004–2007
d.f.									
Unconstrained	35	35	35	35	35	35	35	35	35
Constrained	14	14	14	14	14	14	14	14	14
Log-likelihood									
Unconstrained	−8881	−8063.3	−7307.1	−6481.5	−5766.5	−4659.6	−3921.9	−3336.8	−2871.7
Constrained	−8916.6	−8093.4	−7337.8	−6537.1	−5822.2	−4706.0	−3944.1	−3349.6	−2892.4
d.f. Chisq	−2169.9***	−2160.3***	−2161.3***	−2111.3***	−2111.5***	−2192.7***	−2144.3**	−2125.6**	−2141.4**

** Statistical significance at 5% level.
*** Statistical significance at 1% level.

normal distribution is symmetrical around its mean, and the absolute value can be taken to estimate the variance. The estimated standard deviation of the coefficients in Table 4 show highly significant estimates of some of the drivers for location choice, indicating that the parameters (timelagyr, timelagm, sollagm) vary in the population of fishers.

Fig. 3 provides a visual summary of the changing relative influences of different factors on fleet decisions, over the nine time-windows (representing short and long term). This represents a transition between changing tactics (in the short term) and changing strategies (in the long term). The results highlight the noteworthy pattern (shown by the cells shaded darker) that past monthly effort in the year of fishing (timelagm) and fishing in the same location as the same month the previous year (timelagyr) is common and dominant in every model fit, implying a positive tactic by the fishers to choose an area based on past effort. Another variable which has a positive influence over almost all nine time-periods fitted is the variable for past catch rates of plaice (plelagyr). Model fits for the period 1997–1999 were more prominent in colour and showed that the fishers' tactics appeared to be based on past expected revenue of plaice. There is also substantial variation in the influence of the different variables across the model fits (a lack of homogeneity in the shaded cells across columns). This implies that fisher tactics were changeable across the different time-windows. For example, for the 1998–2003 fit, the expected revenue of sole from fishing in the same location in the same month of the same year (sollagm) had a noticeable influence. Conversely, the plaice coefficient was insignificant other than in the 2000–2002 fit. This was not consistent throughout all fits, because it was not until the fits of 2005–2007 did they reappear as significant, displaying an obvious

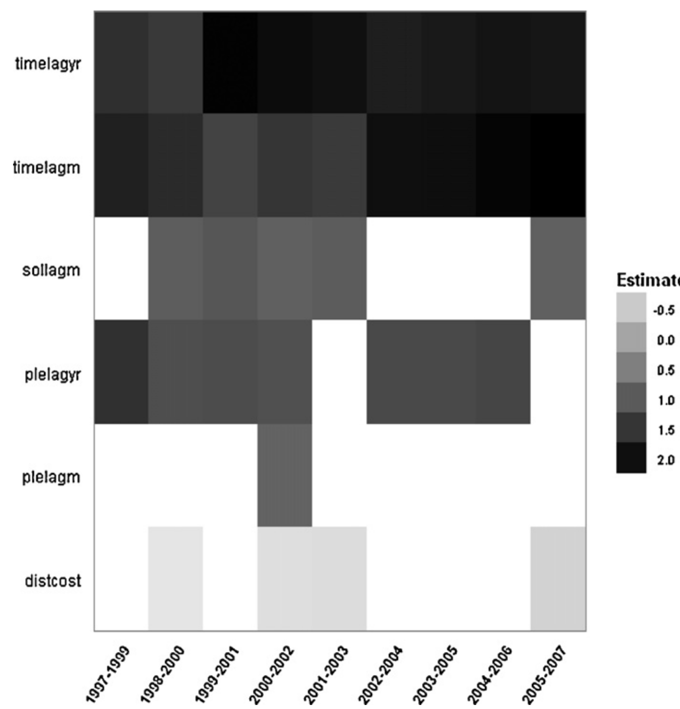

Fig. 3. Heatmap of the transformed mean parameter estimates for each significant variable, where $p < 0.05$ shows the relative importance of the different variables over time.

Table 4
Estimated lognormal parameter estimates for each of the models.

Parameter	1997–1999	1998–2000	1999–2001	2000–2002	2001–2003	2002–2004	2003–2005	2004–2006	2005–2007
sollagyr_M	0.0405	0.00548	0.0426	0.0167	0.0441	0.0242	0.0507	0.0209	0.0317
sollagyr_S	−0.1256	−0.1484	0.00509	0.0554	0.0737	−0.0498	0.0289	−0.00656	0.00482
plelagm_M	0.0714	0.0806	0.0304	0.1153*	0.0745	0.0156	0.0534	0.058	0.0813
plelagm_S	0.6663***	0.0205	0.00497	0.00025	0.00116	−0.0125	−0.00408	0.0179	−0.00267
sollagm_M	0.0302	0.0926***	0.1318***	0.1829***	0.1799***	0.0262	−0.0276	0.0519	0.118**
sollagm_S	0.2156*	−0.285***	−0.2213**	−0.2531***	−0.3071***	−0.0846	0.0054	−0.00556	0.00268
timelagm_M	0.5504***	0.4914***	0.2646***	0.3919***	0.3469***	0.5762***	0.5442***	0.5951***	0.6391***
timelagm_S	−0.2174	−0.0174	0.0204	0.1636	0.1585	−0.4889***	0.5556***	0.5686***	−0.5554***
plelagyr_M	0.1799**	0.1476***	0.17***	0.1222*	−0.00577	0.2069***	0.2064***	0.2413***	0.0879
plelagyr_S	0.7301***	−0.0249	−0.00247	0.00179	−0.00173	0.0144	0.00071	0.00017	−0.0149
timelagyr_M	0.323***	0.3629***	0.6843***	0.5788***	0.5621***	0.4618***	0.5575***	0.5267***	0.5222***
timelagyr_S	0.5094***	0.00322	−0.4376***	0.5267***	−0.4971***	−0.4991***	−0.3758***	−0.5151***	−0.499***
distcost_M	−0.1382	−0.1512*	−0.106	−0.2511v	−0.2859***	0.1174	0.1558	−0.151	−0.4989**
distcost_S	0.3732	0.0122	0.00987	−0.0122	−0.0016	−0.0326	−0.00415	0.0051	−0.00022

Parameters marked _M are the lognormal mean coefficients and _S are their between-population standard deviations.
* Statistical significance at 10% level.
** Statistical significance at 5% level.
*** Statistical significance at 1% level.

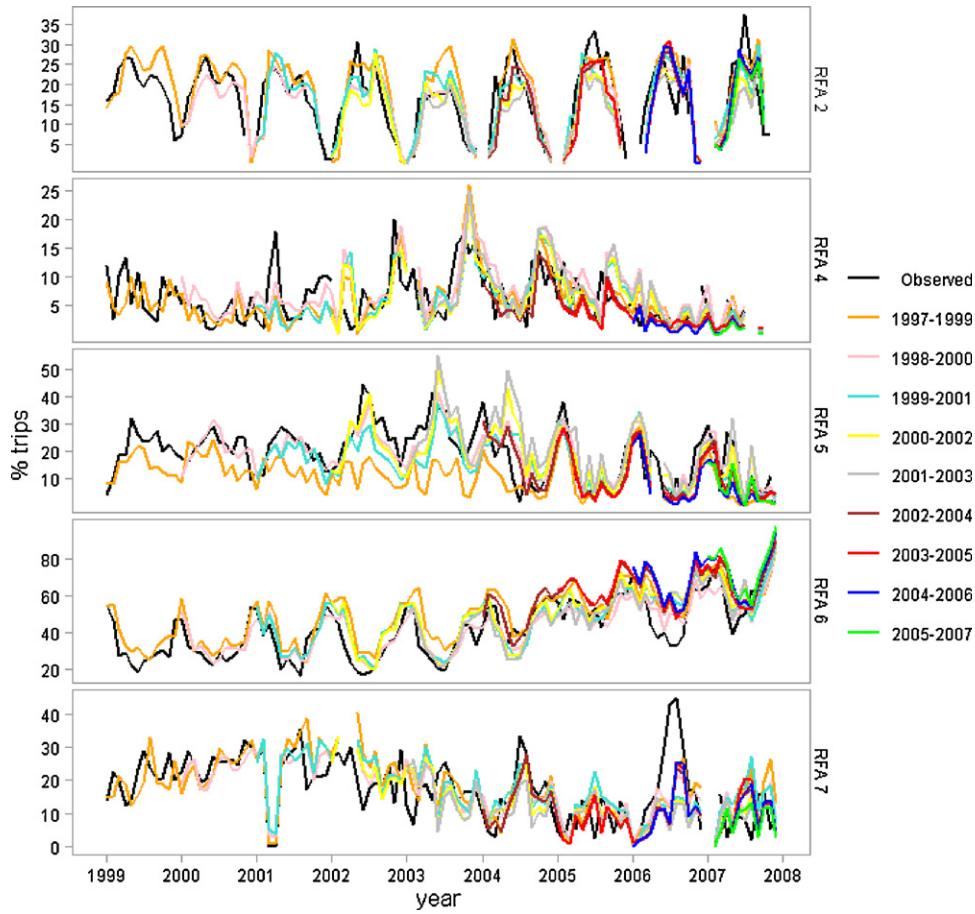

Fig. 4. Plots of eight of the model predictions based on fits to the data, showing the relationship between the percentages of predicted and observed fishing trips, the black line representing the "perfect" fit and RFA meaning Roundfish area.

change in tactics. The expected revenue of sole from fishing in the same location in the same month in the previous year (sollagyr) is a noticeable absentee from all fits, implying that it was not a significant factor in determining location choice. The distance proxy (distcost) displays significant negative coefficients in four of the year fits, suggesting that fishers were affected by changes in fuel prices. The lack of significance of the distcost coefficients in other years possibly suggests that distance travelled to fishing grounds is traded off against the value of the catch, such that the costs to reach the best fishing grounds are compensated for by better catch rates there. Interestingly, the observations of significance in fuel price, the gap in the significance of expected sole and plaice revenue (sollagm and plelagyr), and the different strengths of the habitual effort (timelagyr and timelagm), coincide with the change of ownership of the fishing vessels from the UK to the Netherlands (see Fig. 2). Over the longer term (1997–2007), past annual and monthly effort (timelagyr and timelagm) were the most persistent driving factors influencing fisher choice (Fig. 3).

Elasticities were calculated for plelagyr and distcost for model fit 2000–2002; this fit was chosen because it yielded the most significant contribution of the coefficients. The effect of a 50% increase/decrease in value/cost was explored with respect to a change in the probability of location choice relative to the model predictions. A 50% decrease (50% increase) in plelagyr had a negligible effect on the predicted location choices throughout the time-series except in July 2007, when there was an 8% increase (4.8% decrease) towards the probability of fishing in Roundfish area 5 and <0.02% reductions (0.01% increases) in the probabilities of fishing in other areas. In contrast, distcost had a much more persistent and greater effect throughout the predicted time-series. A 50% decrease in distcost resulted in a 19% increase in the probability of choosing Roundfish area 5, and small reductions of ∼0.04% for other areas. A 50% increase in distcost resulted in a 10% decrease in the probabilities of choosing Roundfish area 5, with small increases (∼0.02%) towards selecting Roundfish areas 2, 4, 6 and 7.

3.1. Predicting future choice

The predictions for all model fits through time are presented in Fig. 4 along with the observed percentage of trips in each Roundfish area (black line in the figure). Predictions were computed using the estimated significant parameter estimates and the mean values of these variables at a monthly scale (Eq. (3)). Overall, the models (shown as different colours of line) yielded good fits relative to the observed (black line) monthly time-series (Fig. 4). The models predict the effort allocation in Roundfish areas 2 and 6, possibly because these are the main fishing grounds for plaice, and have expected good catch rates (Fig. 4).

The model fit to data over the period 1998–2000 was used to predict effort reallocation during the closure in 2001. As Roundfish area 7 encompassed part of the study area, we simulated a closure by forcing all variables in the area to take a value of 0. Using the estimated model coefficients, the probabilities of different trip choices were predicted, then compared with actual trip choice to assess the degree of effort redistribution (Fig. 5). The percentage of trips to Roundfish area 7 predicted to reallocate effort during the closure to Roundfish area 2 for the months March and April 2001 were 23 and 25%, respectively, compared with the observed percentages of

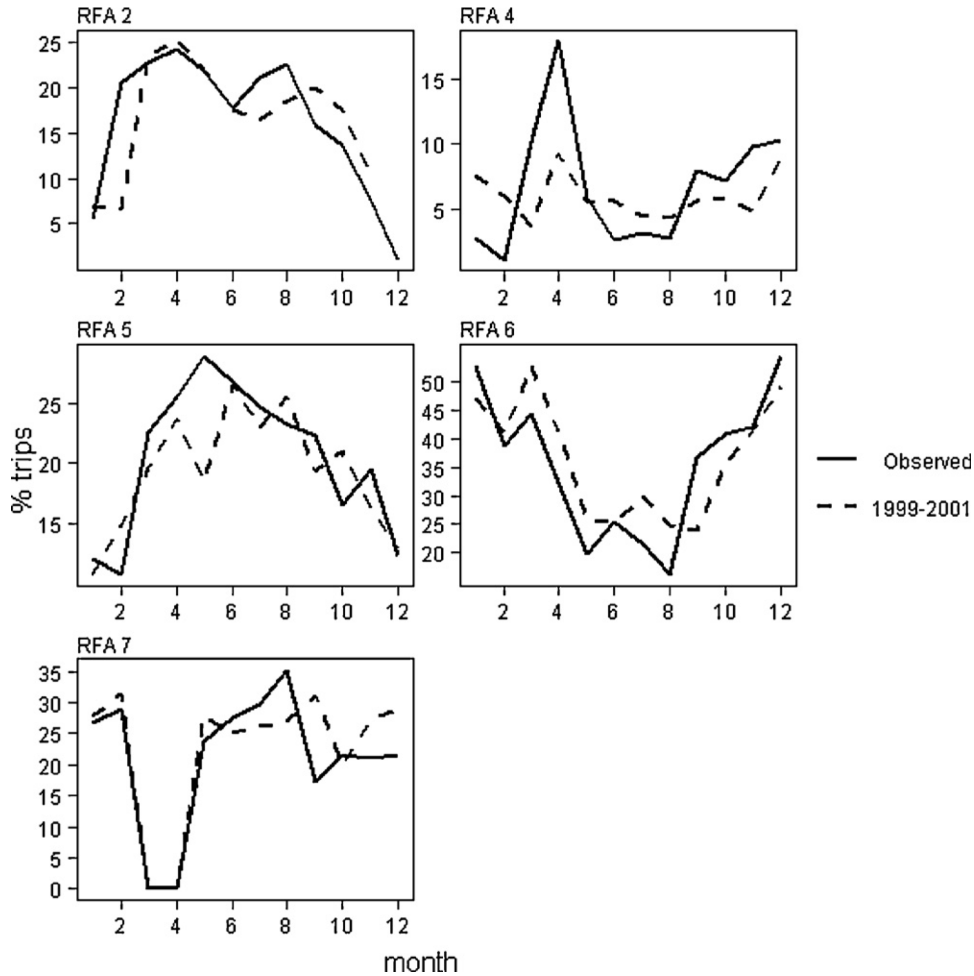

Fig. 5. Model predictions from the 2001 closure simulation, based on closing Roundfish area (RFA) 7.

23 and 24% of trips (20 and 24% in 2000). Roundfish area 4 showed predicted estimates of 4 and 9% compared with observation percentage allocations of effort of 10 and 18%[iiiiiiiv] (5 and 5% in 2000), Roundfish area 5 showed predicted estimates of 20 and 24% compared with observations of 23 and 26% for percentage reallocation of effort (21 and 23% in 2000), and Roundfish area 6 showed predicted estimates of 53 and 42% compared with observations of 45 and 32% for percentage reallocation of effort (30 and 39% in 2000). The notable differences were in Roundfish areas 4 and 6 in April, for which there were 9 and 10% over- and underestimates of predicted vs. observed, respectively. Most of the predictions are, however, reasonable for the choices made during the closure period (Fig. 5).

4. Discussion

The work documented here has described a novel method of predicting choice of fishing location for the English North Sea beam trawl fleet fishing in the southern North Sea, using a mixed model. The model showed good fits relative to the observed monthly time-series (Fig. 3) and predicted the general patterns of spatial change by fishers over time. Model variability in prediction is apparent in Roundfish areas 4, 5, and 7 compared with Roundfish areas 2 and 6, where the main plaice and sole grounds are respectively located. The model was also used to simulate part of the cod closure in 2001 (Figs. 1 and 5), and showed good agreement with actual observations on a monthly time-scale.

One of the key findings from this study is that although fishers' tactics are driven by persistent long-term habits, there are also shorter-term subtleties driven by additional issues that can vary in their relative importance over time. The utility of fishing in a location (a distinct fishing area) depends on previous success measured as good catch rates in terms of economic vpue, as well as previous experience, in this case a measure of past fishing practice monthly and annually (the effort allocation variable; Hutton et al., 2004). Therefore, the results of the RUM analysis here reveal some of the assumptions that could be expected a priori for location choice. Essentially, some previous knowledge or experience of a given area has the dominant bearing on the decision whether or not to fish there. In addition to past experience, we also found that cost (i.e. distance to port of landing and fuel prices) was an important driver of choice (see Abernethy et al., 2010). The results of the analyses also revealed that fishers made their decisions based on past habitual behaviour/previous experience in combination with targeting for plaice (i.e. one-year lagged vpue), fuel price, and past monthly catch rates of sole. The heterogeneity in the selection of fishing grounds by fishers is attributable to individual variations in decision along with other unexplained factors. The mixed model handles this type of heterogeneity and makes it a useful tool for fisher choice modelling approaches.

[iiiiiiiv] The EU flag vessel legislation requires member states to have some economic link with its national fisheries communities. During the closure period, the economic link rules applied, so because the western part of the North Sea was open rather than closed, they landed in Grimsby and met the rule as a so-called benefit.

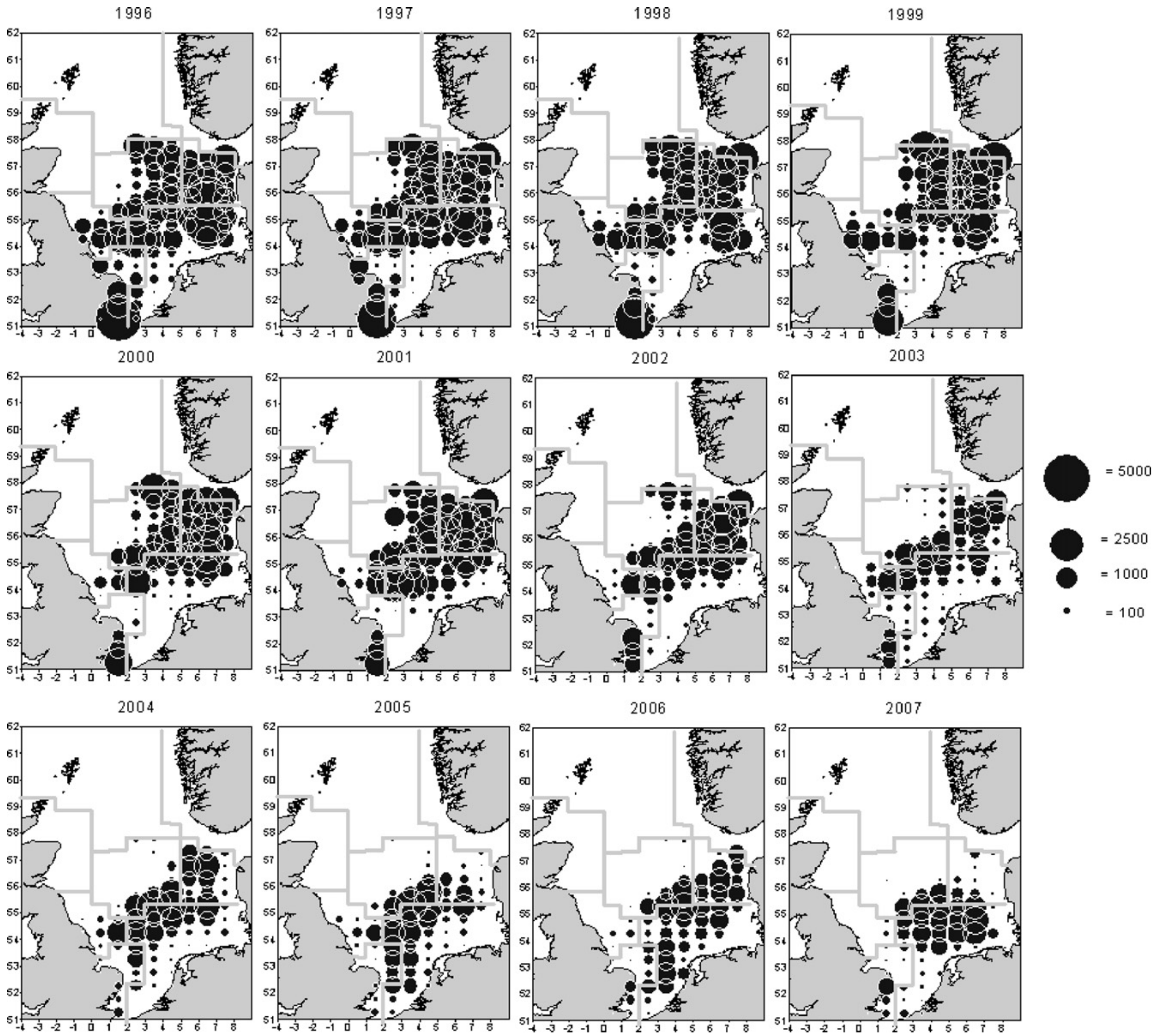

Fig. A1. Total hours fished by the ≥10 m English beam trawl fleet operating in the study area.

Past and current failings of fishery management relate partly to uncertainty in the stock assessments and the management. These range from different sources of model error, through biased input data or process error, to implementation error (Peterman, 2004). Fig. 4 is an example of the temporal and spatial variation or uncertainties of fishing patterns attributable to model error. To reduce these uncertainties, there is a need to improve understanding of the processes driving location choice, i.e. more-detailed economic (fuel, market prices), social (employment), biological (recruitment, spawning-stock biomass) and regulatory (quotas, technical measures) influences. Of course, many processes are complex and interrelated, and it is difficult to account for all the uncertainty, but each process needs to be understood better along with the sources of the uncertainty. This study progresses our understanding of the drivers of this fleet significantly in terms of the short-term choice of location both temporally and spatially, which appear to be largely driven by habit, but also by other subtle drivers. In an environment where change is the norm, fishers develop tactics and strategies to survive when faced with rising fuel costs, fluctuating stock levels, regulations, and market conditions (some of which can be observed in our study; see also Abernethy et al., 2010). In a management context, it is important to understand fisher behaviour in the face of a changing environment so as to manage the system better (Hilborn, 1985; Fulton et al., 2011). This is especially important when considering closed areas or marine protected areas, MPAs.

5. Conclusions and future work

To conclude, the implementation here of a discrete choice mixed model allowed us to explore and improve understanding of English and Welsh beam trawl fisher short-term tactical behaviour over a 12-year period. The results confirm the notion that expected revenues from target species, experience or habit, and fuel prices are significant factors in determining fisher decision-making. Some of the unobserved random components of the model causing heterogeneity in the selection of fishing grounds by fishers could be attributable to individual variations in decision-making along with other unexplained factors. For example, factors that we have not captured could include skipper skill, age, nationality and vessel attribute. Compiling data on these factors to investigate the influence fisher attributes would be a valuable aim of future work.

Nevertheless, even without these, model predictions were similar to observed choices during the study period, and the simulated closure we modelled resulted in discrepancies of location choice of just 9 and 10%.

Future application of the fleet behaviour model taking account of implementation error within a Management Strategy Evaluation (MSE) framework could help evaluate future stock levels and the profitability of this fleet (Pilling et al., 2008). The main factor that could contribute to this analysis would be the accuracy of predictions of location choice based on knowledge of the two main target species, bearing in mind the fact that fisheries have historically been managed on a stock-by-stock basis. Although several studies have been published on the North Sea sole and plaice fishery (Kell et al., 1999, 2005; Ulrich et al., 2007; Kraak et al., 2008; Andersen et al., 2010), the work reported here on the spatial dynamics of the fleet may complement future research effort, as it has in other MSE spatial studies (Pelletier and Mahévas, 2005; Bastardie et al., 2010; Lehuta et al., 2010). Such an analysis could provide an insight into mixed fishery management, because in the short term, an approach needs to be developed to resolve conflicting management advice for different species in the same fishery.

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Appendix A.

See Fig. A1.

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