Informing improved management of mixed fisheries through comparative modelling of fleet dynamics

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I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of PhD is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Abstract

Mixed fisheries, where several species are caught in the same fishing operation, are ubiquitous and a major challenge for fisheries management. Overexploitation occurs in mixed fisheries where fishers catch species for which they have no quota and then discard. Understanding how these 'technical interactions' lead to decisions by fishers about where to fish in response to management is key to addressing the sustainability of mixed fisheries.

The objectives of this thesis were to i) improve understanding of how fishers exploit different populations in space and time, and ii) develop a comparative framework for modelling location choice to better predict how fishing effort is allocated in response to population and fishery dynamics subject to management interventions.

Addressing exploitation in space and time, Chapter 2 developed a spatiotemporal dimension-reduction framework to understand how community and fishery dynamics interact to determine species composition. We identified where species can be effectively decoupled through changes in spatial fishing patterns. Chapter 3 developed a highly resolved discrete-event simulation model of mixed fisheries to understand how data source and resolution impact inference on mixed fisheries interactions.

To improve prediction of effort allocation, Chapter 4 compared process-based and statistical location choice models from theoretical and applied perspectives. We found theoretical equivalences among simplified models but important differences in application. By implementing alternative location choice models as operating models in mixed fishery management strategy evaluation (MSE, Chapter 5), we demonstrated significant impact on inferred sustainability of given management plans.

This thesis advances the scientific basis for mixed fisheries advice by a) providing a basis for understanding co-occurrence and separability of species, b) critiquing the utility of different sources of data to support management, c) providing a comparative understanding of location choice models in theory and application, and d) demonstrating how these can be used in an MSE framework capturing structural model uncertainty.

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Chapter 1

General Introduction

1.1 The importance of mixed fisheries

Globally, marine fisheries land over 84 million tonnes of fish, molluscs and crustacea annually (FAO, 2020). While landings from monospecies fisheries such as anchoveta (*Engraulis ringens*), walleye pollock (*Gadus chalcogrammus*) and skipjack tuna (*Katsuwonus pelamis*) dominate the top ten species landed, the majority of the worlds fisheries are mixed, catching a range of demersal fish in the same fishing operation. Such demersal fisheries are a major source of food and income producing >20 million tonnes of landings annually (FAO, 2019).

Typically demersal mixed fisheries use towed or static fishing gear to exploit an assemblage of species found on the seabed. In deploying the fishing gear, fishers cannot be certain about what species they have caught until the gear is hauled and the catch sorted. This unselective nature of "mixed fisheries" can result in catches of multiple stocks found in the same habitat but with conflicting conservation statuses (Murawski, 1991).

In Europe, mixed fisheries are widespread. Since the first study by Laurec et al. (1991) significant effort has gone into describing the 'technical interactions' that result in mixed demersal trawl fisheries in the English Channel (Ulrich et al., 2001), North Sea (Lewy and Vinther, 1994), Celtic Sea (Davie and Lordan, 2011; Mateo et al., 2017; Moore et al., 2019), Bay of Biscay (Poulard and Léauté, 2002), Iberian waters (Cardoso et al., 2015), deepwater fisheries (Marchal et al., 2013) and the implications for management.

In the Celtic Sea, mixed demersal trawl fisheries are prosecuted by a range of countries targeting different species groups (ICES, 2019b, see Figure 1.1). Belgian vessels fish for sole (*Solea solea*), rays (*Batodiea*), plaice (*Pleuronectes platessa*) and anglerfishes (*Lophius spp.*) using beam trawls and otter trawls; French vessels target the gadoids: cod (*Gadus morhua*), haddock (*Melanogrammus aeglefinus*) and whiting (*Merlangius merlangus*), *Nephrops*, anglerfishes, megrims (*Lepidorhombus*) and rays; Spanish vessels target hake (*Merluccius merluccius*) using longlines and megrims, anglerfishes and hake using otter trawls and gillnets; English vessels use otter trawls to target a mix of gadoids and rays with beam trawls fishing for sole and anglerfishes and gillnets for hake and anglerfishes. Irish vessels target *Nephrops*, gadoids and benthic species using trawls, gillnets for hake, pollack (*Pollachius pollachius*), anglerfishes and cod and beam trawls for megrims, anglerfishes, sole, plaice and rays. In particular, the poor state of gadoid species such as cod and haddock in the region has led to calls for a mixed fishery approach to managing fisheries in the Celtic Sea, and mixed fishery based management advice (ICES, 2019b).

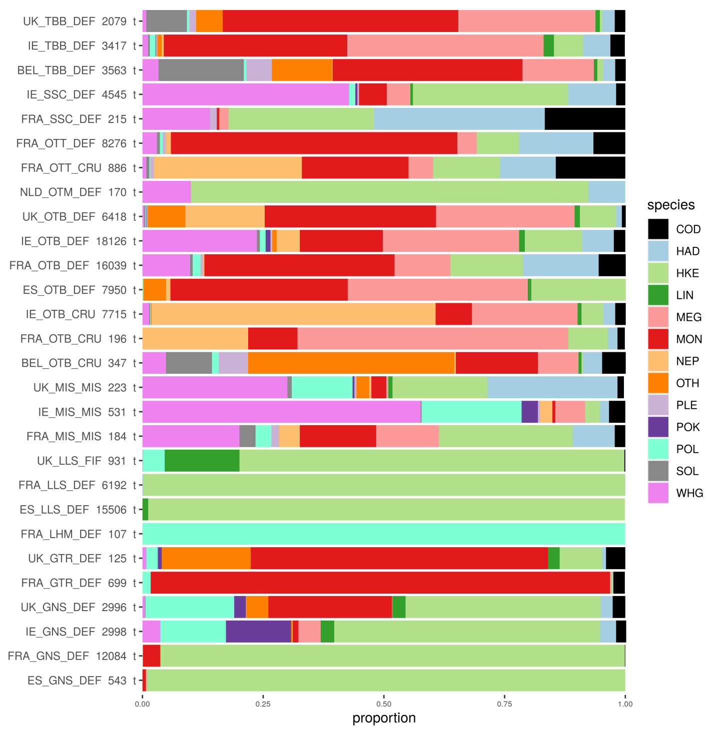

Figure 1.1: Métier used for demersal fisheries in the Celtic Sea and west of Ireland showing the species composition of the main demersal métiers (landings >100 tonnes) operating in the Celtic Sea and west of Ireland. The label incorporates the EU Member State, gear group, target assemblage, and mean annual (2016–2018) landings(tonnes). Reproduced from ICES (2019).

Taking a mixed fishery approach requires a detailed description of the fisheries and their characteristics. The sheer diversity of fisheries including gear used, location and target species has led researchers to classify fisheries for sampling and management purposes into different métier based on activity (Deporte et al., 2012). A métier is considered a group of fishing events that use a similar gear targeting a specific group of species at a particular time of year and/or in a particular area. In practice these métier often contain quite geographically diverse fisheries, are classified from landings data *a posteriori*, and reflect a broad spatial and temporal pattern of activity. In the EU's data collection framework this results in a six level classification, with the most detailed classification including gear group (level 4), target assemblage (level

5) and mesh size (level 6) (Dörner et al., 2018).

1.2 The challenge of managing mixed fisheries

The lack of full control over the species caught has made managing by total allowable catch (TAC) or quota limits particularly challenging in mixed fisheries (Ulrich et al., 2011). In some fisheries it may be impossible to sufficiently decouple exploitation of one species from another so as to meet the management goals for one or more species (Le Quesne and Jennings, 2012; Needle and Catarino, 2011). When a fisher catches a species for which they have no quota they either have to stop fishing and 'choke' off fishing opportunities for other species (Baudron and Fernandes, 2015; Kuriyama et al., 2016) or 'discard' the species for which they have no quota (Catchpole et al., 2005; Kelleher, 2005; Poos et al., 2010). Such decisions impact both on the sustainability of the fish stocks (Batsleer et al., 2015) and the economic viability of the fishery (Condie et al., 2014; Hoff et al., 2018).

To address discarding in mixed fisheries, the European Union introduced effort limitations in 2004 (European Commission, 2004), revised in 2008 (European Commission, 2008), based on métier definitions that were a combination of gear group (level 4) and mesh size range (level 6, as a proxy for target species). These effort limits were gradually reduced in line with the required reduction in exploitation on the most vulnerable species caught in the fisheries. The effectiveness of the measures was questioned based on the inability of fishing effort adjustments based on broad *a priori* métier definitions to control fishing mortality (García-Carreras et al., 2015). Issues included the range of fisheries that the definitions covered and the ability of fishers to switch between fisheries within a métier. Further, the measures were universally unpopular with fishers due to the limitations placed on fisheries with only small catches of the vulnerable species, and subsequent derogations from restrictions diluted the effectiveness of the measures (Kraak et al., 2013).

Such broad métier classification, while describing the main differences in capture characteristics for data collection, fail to sufficiently reflect the diversity of fisheries that result from fisher's use of spatial features to target particular species assemblages. This is particularly important for understanding mixed fishery dynamics as fishers can change the species composition of their catch by using knowledge of spatial and temporal heterogeneity in species distributions to target particular species or groups of species. This can be achieved by fishing particular habitat, depths and location (Branch et al., 2005; Gerritsen et al., 2012), times of year (Aguzzi et al., 2004) or environmental conditions (Ziegler et al., 2003; Mahévas et al., 2011) with the choice of where to fish depending on individual quota restrictions for the fishers.

Recent advances in technology have increased availability of more nuanced spatial information by linking logbook data to high resolution Vessel Monitoring System (VMS) data (Lee et al., 2010; Gerritsen and Lordan, 2011). This has been used to define spatial areas with contiguous patterns in fisheries landings (Bastardie et al., 2010; Gerritsen et al., 2012; Mateo et al., 2017) providing a detailed picture of how space is used to target different species mixes. At present, such spatial differences are not included in métier definitions used for management but provide a potential fisheries-dependent data driven way to define métier with spatial features for understanding location choice. However, a key question remains whether commercial landings information is sufficiently representative of the underlying population dynamics for use in modelling and management advice.

In 2013 the European Union Common Fisheries Policy was amended to include a landing obligation where all species that are caught count against their respective quotas (European Commission, 2013; Catchpole et al., 2017). The regulation came into force in January 2015, starting with pelagic fisheries with a phased approach such that all quota species would be covered by 2019. Excepting a limited number of derogations and exemptions, fishers are now limited by the first quota they reach. This has removed métier based effort limitations, but led to a renewed focus on understanding how spatiotemporal dynamics in particular métier can help to reduce the misalignment of quotas for species caught together (Reid et al., 2018; Robert et al., 2019; Calderwood et al., 2020) and an emphasis on managing fisheries, not fish stocks, to bring about sustainability. Progressing a mixed fishery management approach in Europe, alongside consideration of how biological interactions affect population dynamics, are key steps towards implementing ecosystem-based fisheries management (Bianchi and Skjoldal, 2008). Taking account of technical interactions and understanding of spatial dynamics in mixed fisheries could support future sustainability, allow fisheries to maximise yield and minimise the risk to vulnerable stocks (Thorpe et al., 2016, 2017).

1.3 Science to support mixed fisheries management in Europe

In Europe, provision of scientific advice for mixed fisheries was first developed for the North Sea to understand the impact of single stock TACs in a mixed fisheries context (Ulrich et al., 2007, 2011); with subsequent expansion to the Celtic Sea (ICES, 2019b) and Bay of Biscay (ICES, 2019a). The methodology used by the International Council for the Exploration of the Sea (ICES) is to apply a “Fleet and Fishery" approach by describing: a) the activity of fleets (groups of vessels with similar physical characteristics) and b) the allocation of fishing effort to different fisheries (métier), resulting in c) the impact of fleet activity on catches of the different species caught in the context of single stock management objectives (Figure 1.2). The method has further been extended to provide multi-stock TAC advice (Ulrich et al., 2017; Garcia et al., 2020; Briton et al., 2020) that is more consistent with a mixed fisheries approach and evaluated in a management strategy evaluation framework (MSE). MSEs take account of full feedback mechanisms in the advisory, management and assessment processes (Garcia et al., 2017, in a mixed fisheries context).

The approach taken to modelling short-term mixed fishery interactions relies on three key mechanisms (Figure 1.2):

1. The overall effort deployed by a fleet to catch the available quota given fixed economic costs and constraints on the fleet (point a, first tier of the tree);

2. an understanding of how fleets allocate fishing effort to different métier given the variable costs of fishing in the métier, the catch composition expected and available fishing opportunities (point b, second tier of the tree);

3. estimation of catchability for the species caught within a métier given gear characteristics and availability, and an understanding as to how it might develop over time through a quantifiable relationship between

fishing effort and fishing mortality, either as a linear function or otherwise (point c, third tier of the tree).

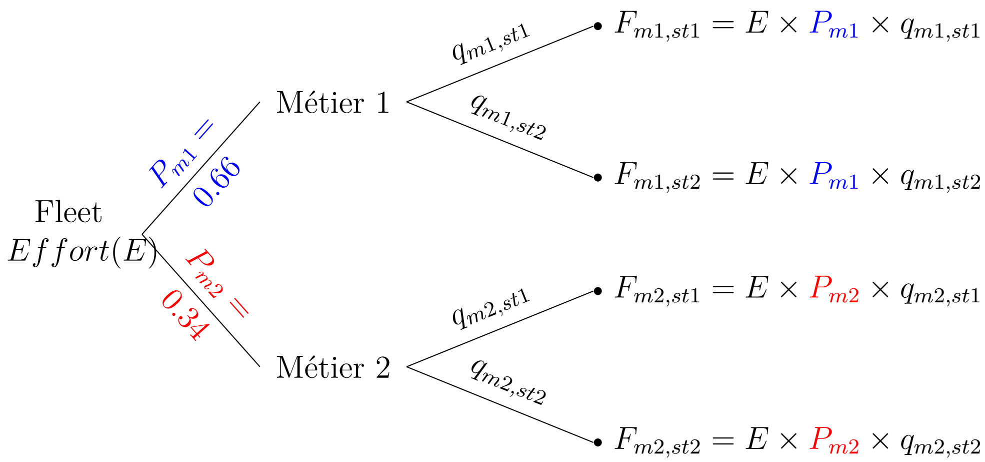

Figure 1.2: Relationship between fishing effort (E), the proportion of effort among métier (P) and partial fishing mortality (F) of three stocks dependent on their catchability (q). Colours show the dependence of fishing mortality on métier choice.

In principle the greater fidelity with which métier can be defined to reflect the differences between fisheries, the more likely that catchability (3) is constant over time and the relationship between fishing effort and fishing mortality is linear, though in reality there will always be some inter-annual variability in catchability through many seasonal (Liu and Heino, 2014), environmental (Ziegler et al., 2003), fishing technological (Marchal et al., 2006, 2007; Quirijns et al., 2008) and spatial population (Wilberg et al., 2010; Zhang et al., 2020) dynamics. The goal in defining métier should be to reduce this variability as far as practicably possible. The proportionality assumption between fishing effort and fishing mortality has been debated since early fishery models that rely on using catch rates as an index of abundance (Beverton and Holt, 1957; Harley et al., 2001; Fraser et al., 2007), and depends in part on how fishing effort is measured (Rijnsdorp et al., 2006). However, at some spatiotemporal scale the link between fishing effort and fishing mortality is predictable (Tidd, 2013), which emphasises the importance of understanding fisheries characteristics and effort allocation among métier (2).

Predicting how fishers allocate fishing effort among different métier is a major research goal (Berman, 2006). Due to the challenges that prediction of effort allocation presents, applications of mixed fisheries models generally assume that the share of fishing effort among métier is constant. However, fishers respond to changing fishing opportunities by exploiting different fishing grounds (Hilborn and Walters, 1987) and the lack of incorporation of short-term fleet dynamics in mixed fisheries models inhibits efforts to evaluate how different quota and management regulations might impact on fisheries and fish stocks in future. To address this shortcoming, in this thesis I consider two key dependencies in mixed fisheries:

1. To what extent can fishers decouple fishing mortalities of species caught together in mixed fisheries ?

2. How does location choice contribute to this decoupling ?

1.4 Influence of fleet dynamics on management outcome

It is widely recognised that successful fisheries management requires understanding of the human drivers that determine how fishers, individually and collectively, respond to changing fishing opportunities and regulation (Hilborn, 2007). Fishing behaviour can be classified as either short- or long-term. Short-term behaviour includes decisions about when and where to fish (Holland and Sutinen, 2000) and changes in practices such as discarding certain sizes or species (Gillis et al., 1995; Batsleer et al., 2016). Long-term behaviour includes investment and disinvestment in vessels, new fishing gear or technology (Hilborn and Walters, 1992; Nøstbakken et al., 2011; Eigaard et al., 2014) and exit and entry into fisheries (Tidd et al., 2011). Collectively, these behavioural responses have a fundamental impact on the level and pattern of exploitation of different fish stocks and on the economic success of fishers. While such 'fleet dynamics' are recognised of critical importance and elements are well studied (Salas and Gaertner, 2004; Pelletier and Mahévas, 2005; Fulton et al., 2011; Van Putten et al., 2013), there has been limited progress in integrating such considerations into operational management decision making tools. This is due to the challenge of predicting human behaviour and a lack of adequate available models at an appropriate scale (Andersen et al., 2010).

Short- and long-term fleet dynamics can be combined in a bioeconomic modelling framework (e.g., Prellezo et al., 2012). Application of such frameworks integrate the effect of profitability in fisheries on optimal fleet sizes (Thøgersen et al., 2015), technological development (Marchal et al., 2007; Eigaard et al., 2014) and price dynamics (Hanson and Ryan, 1998) given changing population dynamics and short-term location choice decisions. Bioeconomic models have historically often simplified the biological processes through surplus production type models (Gordon, 1954; Clark, 1974), differing from the age-structured models used for contemporary data-rich fisheries management advice. More recently, new approaches have sought to combine detailed simulation of cohort population dynamics with economic components. Fisheries Library for Bio Economic Impact Assessment (FLBEIA, Garcia et al., 2017) is one such approach, and provides a platform for the modular progression of fleet- and fishery-based models that evaluate the biological and economic impact of management measures within a full feedback approach, though the methods developed within this thesis are equally applicable in other similar frameworks (e.g. Mahévas and Pelletier, 2004; Salz et al., 2011).

1.5 Short-term dynamics and location choice models

While both short- and long-term components of fleet dynamics have been studied intensely to understand how they impact fisheries management, arguably the most direct impact is from fisher's short-term decisions. Decisions about when and where to fish determine the species, size and relative composition of catch. These have a fundamental impact on: in-year exploitation patterns (Liu and Heino, 2014), ability of fishers to meet catch limits, and by extension the success of the management measures. Fishers are driven by a range of motivations, which may include, *inter alia*: regulatory constraints (Hilborn, 2007; Rochet et al., 2012), economic opportunism (Marchal et al., 2013), profit maximisation (Hilborn and Walters, 1987), risk aversion or seeking (Holland and Sutinen, 1999; Dowling et al., 2015), tradition (Holland and Sutinen, 2000; Girardin et al., 2017) and information sharing (Dreyfus-Leon and Gaertner, 2006).

Several modelling approaches have been developed to predict fishers location choice decisions. These include process-based models that seek to mechanistically describe the relationship between individual parts of a system so that the calibrated dynamics are an emergent property of these relationships; such as gravity models (Caddy, 1975), Dynamic State Variable Models (DSVMs, Clark and Mangel, 2000), rule-based and individual-based approaches (Fulton et al., 2011; Bastardie et al., 2010) and those deriving from ecological theory such as Ideal Free Distribution (IFD, Gillis, 2003) and Central Place Foraging (CFP, Frid et al., 2016). They also include statistical models where location choice is a categorical distribution and parameters of the distribution of a function of covariates, estimated against data. By far the most widely applied statistical approach derives from micro-economic theory on the basis that fishers maximise utility among a set of discrete choices, applied as Random Utility Models (McFadden, 1973, RUMs, also known as conditional logit models). However, Markov Transition Models (MTMs) have also been applied and introduce the concept of state dependency in location choice, so that fishers probability of moving to a fishery depends on the fishery they are currently prosecuting (Venables et al., 2009).

Each location choice model inherently assumes there is some utility function to be maximised. Utility is a concept deriving from economics relating to the total benefit derived from a choice (Grant and Van Zandt, 2009). Gravity Models are explicit in that the utility is defined as a function of revenue, costs or other factor that represents attractiveness to a particular fishery as described in the model. A Gravity Model based on the relative catch rates in each fishery predicts fishing effort similarly to the IFD principle (Gillis, 2003) where foragers (in this case fishers) will allocate their effort proportionate to the density of prey available and over time catch rates across areas will equalise due to competition (Gillis et al., 1993). Additional factors can be incorporated and act as a weighting on predictions that may better reflect observed dynamics in the fishery (Hilborn and Walters, 1987; Allen and McGlade, 1986). While providing intuitively useful and logical predictions, little empirical evidence has been provided for the accuracy of the predictions from Gravity Models. Dynamic State Variable Models are a dynamic programming optimisation technique that can optimise utility incorporating both short-term and long-term decisions and constraints (Clark and Mangel, 2000). DSVMs have been applied in fisheries contexts to explore quota and discarding policies (Gillis et al., 1995; Babcock and Pikitch, 2000; Poos et al., 2010), but have not yet been tested within a full feedback bioeconomic management strategy evaluation approach. In the statistical models the effect of different variables on the underlying utility is estimated to understand drivers in the fishery. RUMs have been applied to several fisheries (see Girardin et al., 2017, for a review) and in bioeconomic simulations (Ulrich et al., 2007), while Markov Transition Models have received less attention but have been applied to the Northern Prawn fishery in Australia (Venables et al., 2009).

Location choice determines effort allocation to a given métier and hence has a fundamental impact on the dynamics of exploitation. To progress mixed fishery management, location choice needs to be considered explicitly within management tools, avoiding default assumptions. To include location choice models requires: i) an understanding of detailed spatiotemporal dynamics when fisheries exploit multiple stocks, including how fishers are able to decouple (or not) exploitation of species caught using fine-scale information, ii) understanding of how fisheries-dependent data can be used to infer spatiotemporal dynamics and iii) a formal comparison of the available approaches for modelling location choice. In this thesis, I address some of these factors that have previously impeded routine application of location choice models in mixed fishery MSE frameworks.

1.6 Overview and aims of thesis

The aim of this thesis was two-fold: i) to further understanding of spatiotemporal dynamics in mixed fisheries and how they relate to location choice, ii) to compare and contrast extant approaches to location choice modelling for application in mixed fishery management strategy evaluations. Research presented in Chapter 2 - 5 (manuscripts I - IV) addressed these objectives (Figure 1.3). I start by modelling haul-level data for key species in the Celtic Sea (Chapter II), developing a simulation framework to understand finescale fishery interactions (Chapter III), applying the knowledge gained to understand how these interactions affect predictions in location choice models (Chapter IV) and integrating these models within a wider mixed fishery management strategy framework for a Celtic Sea demersal fishery (Chapter V).

The thesis addresses a crucial knowledge-gap for a component of the Ecosystem Approach to Fisheries through providing greater understanding of how the biological (i.e. populations) and economic (i.e. fishery) dynamics of mixed fisheries interact. Incorporating location choice models into fleet operating models for mixed fishery management strategy evaluation provides a basis to integrate the feedback loop between management goals, populations and fishers' response to changing fishery and regulatory dynamics.

Specific objectives for this thesis were:

Chapter 1: Introduction

Provide an overview of mixed fisheries, recent management approaches and scientific advice for mixed fisheries management and the importance of considering location choice in fleet dynamics for mixed fishery management strategy evaluation.

Chapter 2: Spatial separation of catches in highly mixed fisheries.

To understand the spatial and temporal co-occurrence of key commercial demersal fish species in the Celtic Sea we applied advanced vector-based geostatistical mixed models to fisheries-independent data to understand time-varying co-occurrence of species that are commonly caught together and which can be separated through spatiotemporal management measures. This provides important insight into the extent to which fishers can change what they catch by moving to different fishing grounds.

Manuscript I is published as:

Dolder, P. J., Thorson, J. T., & Minto, C. (2018). Spatial separation of catches in highly mixed fisheries. *Scientific reports*, 8(1), 1-11.

Chapter 3: Highly resolved spatiotemporal simulations for exploring mixed fishery dynamics.

To explore the limitations of fisheries dependent data for modelling and management application. To do so we developed a mixed fishery simulation framework which combines heterogeneously distributed populations and full population dynamics with individual-based fishery dynamics at a high spatiotemporal resolution. By developing a simplified simulation model with realistic fishery dynamics we were able to investigate whether fisheries dependent data could be used to support management of mixed fisheries.

Manuscript II is published as:

Dolder, P. J., Minto, C., Guarini, J. M., & Poos, J. J. (2020). Highly resolved spatiotemporal simulations for exploring mixed fishery dynamics. *Ecological Modelling*, 424, 109000.

Further, the simulation provided a simulation framework as a basis for the analytical comparison of fleet dynamics models under Chapter IV.

Chapter 4: Comparing fleet dynamics models for predicting fishing location choice: what works well, when?

To compare and contrast different extant fishery modelling approaches that describe and predict effort allocation; including statistical econometric approaches such as Random Utility Models (RUMs) and Markov models; and mechanistic modelling approaches such as Dynamic State Variable Models and Gravity Models. A theoretical comparison highlights fundamental links and differences among the models. All models were applied to simulated fishery data (generated by the model developed in Chapter III) to gain insight into their structure and function and to compare accuracy in predicting year-ahead effort dynamics under different management scenarios. By comparing the different approaches we were able to better understand which approaches are more applicable for incorporation in a wider management strategy evaluation framework in Chapter V.

Manuscript III has been submitted to *Fish and Fisheries*:

Dolder, P. J., Minto, C., García, D., & Poos, J. J. (submitted). Comparing fleet dynamics models for predicting fishing location choice: what works well, when? *Fish and Fisheries.*

Chapter 5: Alternative hypotheses for location choice in mixed-fishery management strategy evaluations.

To integrate the methods for predicting location choice (a RUM, Markov Transition Model, Gravity Model) within a bio-economic modelling framework (Fisheries Library Bioeconomic Impact Assessment, FLBEIA) in a flexible generic way for application to any fishery. We present an example of how it can be used to improve evaluation of mixed fisheries management strategy by applying to a case study for a Celtic Sea demersal fishery. By doing so we demonstrate how incorporation of dynamic location choice as hypotheses can improve understanding of the impact of management measures in mixed fisheries.

Manuscript IV is *in prep* for submission to *ICES Journal of Marine Science*:

Dolder, P. J., Minto, C., García, D., & Poos, J. J. (in prep.). Alternative hypotheses for location choice in mixed-fishery management strategy evaluations. *ICES Journal of Marine Science*.

Chapter 6: Discussion

Here, I provide a synthesis of the findings within this thesis, place the work within the context of wider scientific literature and outline how the work contributes to improving science to support mixed fisheries management.

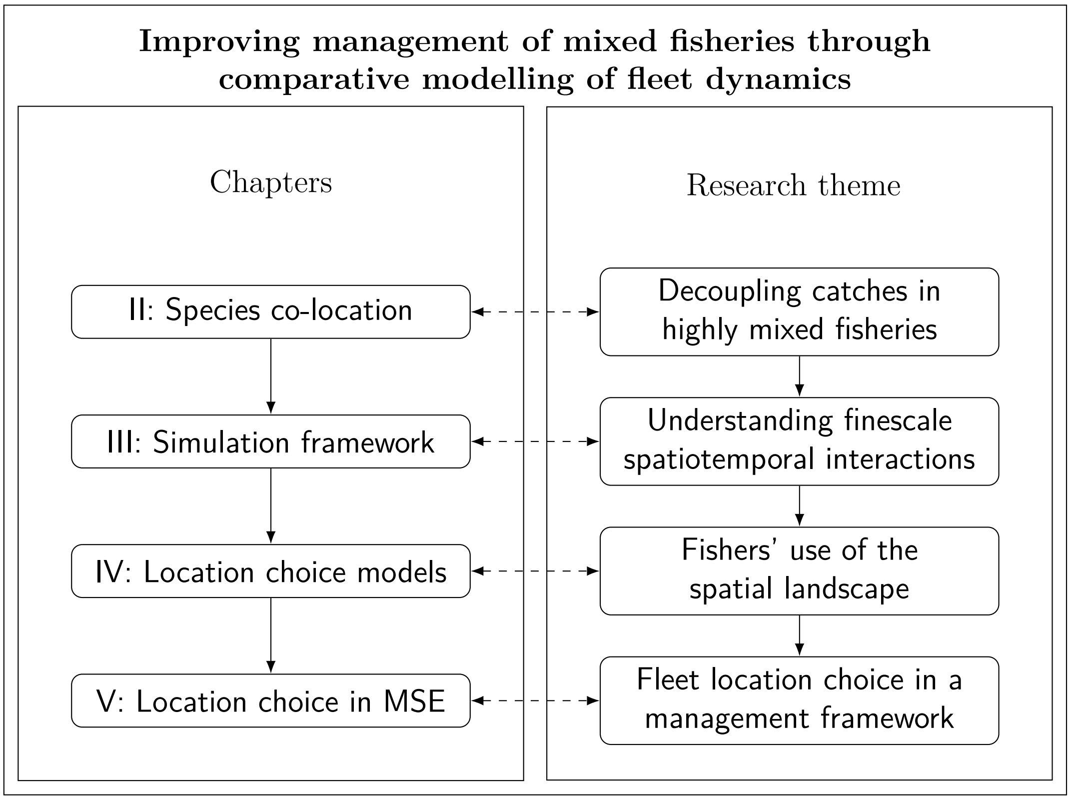

Figure 1.3: Thematic overview of the thesis outlining linkages among chapters and research themes.

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Chapter 2

Spatial separation of catches in highly mixed fisheries

This chapter is a verbatim reproduction from the following published paper. The published version is found in Appendix A, Supplementary Data analysis in Appendix B, and Tables and Figures in Appendix C.

Dolder, P. J., Thorson, J. T., & Minto, C. (2018). Spatial separation of catches in highly mixed fisheries. *Scientific reports*, 8(1), 1-11.

2.1 Abstract

Mixed fisheries are the dominant type of fishery worldwide. Overexploitation in mixed fisheries occurs when catches continue for available quota species while low quota species are discarded. As EU fisheries management moves to count all fish caught against quota (the "landing obligation"), the challenge is to catch available quota within new constraints, else lose productivity.

A mechanism for decoupling exploitation of species caught together is spatial targeting, which remains challenging due to complex fishery and population dynamics. How far spatial targeting can go to practically separate species is often unknown and anecdotal. We develop a dimension-reduction framework based on joint species distribution modelling to understand how spatial community and fishery dynamics interact to determine species and size composition.

In application to the highly mixed fisheries of the Celtic Sea, clear common spatial patterns emerge for three distinct assemblages. While distribution varies interannually, the same species are consistently found in higher densities together, with more subtle differences within assemblages, where spatial separation may not be practically possible.

We highlight the importance of dimension reduction techniques to focus management discussion on axes of maximal separation and identify spatiotemporal modelling as a scientific necessity to address the challenges of managing mixed fisheries.

2.2 Introduction

2.2.1 Mixed fisheries and the EU landing obligation

Recent efforts to reduce exploitation rates in commercial fisheries have begun the process of rebuilding depleted fish populations (Worm et al., 2009). Improved management of fisheries has the potential to increase population sizes and allow increased sustainable catches, yet fisheries catch globally remains stagnant (FAO, 2014). In light of a projected increase in demand for fish protein (Béné et al., 2016) there is an important role for well managed fisheries in supporting future food security (Mcclanahan et al., 2015) necessitating fisheries are managed efficiently to maximise productivity.

A particular challenge in realising increased catches from rebuilt populations is maximising yields from mixed fisheries (Branch and Hilborn, 2008; Kuriyama et al., 2016; Ulrich et al., 2017). In mixed fisheries, the predominant type of fishery worldwide, several fish species are caught together in the same net or fishing operation (known as a “technical interaction”). If managed by individual quotas, and catches do not match available stock quotas, either a vessel must stop fishing when the first quota is reached (the “choke” species) or overexploitation of the weaker species occurs while fishers continue to catch more healthy species and throw back (“discard”) the fish for which they have no quota (Batsleer et al., 2015). There is, therefore, a pressing need for scientific tools, which simplify the complexities of mixed fisheries to help avoid discarding.

Mixed fisheries require specific management approaches to avoid overfishing. Sustainability of European fisheries has been hampered by the “mixed fishery problem” for decades with large-scale discarding resulting (Borges, 2015; Uhlmann et al., 2014). A paradigm shift is being introduced under the EU Common Fisheries Policy (CFP) reform of 2012 through two significant management changes. First, by 2019 all fish that are caught are due to be counted against the respective stock quota even if they are discarded; second, by 2020 all fish stocks must be fished at an exploitation rate corresponding to their Maximum Sustainable Yield (MSY) (European Commission, 2013). The changes are expected to contribute to attainment of the goal of Good Environmental Status (GES) under the European Marine Strategy Framework Directive (MSFD; (European Parliament, 2009)) and move Europe towards an ecosystem based approach to fisheries management (Garcia et al., 2003).

Conflicts between overall management goals and drivers for individual actors must be overcome to achieve sustainability. Societal objectives for fisheries to achieve MSY across ecosystem components are paralleled by individual fishers’ goals to maximise utility; whether that be profit, income or the continuance of traditional practices (Holland, 2008). Under the new policy, unless fishers can avoid catch of unwanted species they will have to stop fishing when reaching their first restrictive quota. This introduces a potential significant cost to fishers of under-utilised quota (Hoff et al., 2010; Ulrich et al., 2017) and provides a strong incentive to mitigate such losses (Condie et al., 2014, 2013).

The ability to align catch with available quota depends on being able to exploit target species while avoiding unwanted catch. Methods by which fishers can alter their fishing patterns include by switching fishing method (e.g. trawling to netting), changing technical gear characteristics (e.g. introducing escapement panels in nets), or altering the timing and location of fishing activity (Fulton et al., 2011; Van Putten et al., 2012). For example, otter trawl gears are known to have higher catch rates of roundfish due to the higher headline and wider sweeps, which herd demersal fish into the net. Conversely, beam trawls employ chain mesh to "dig" benthic flatfish species, have higher catch rates for these species (Fraser et al., 2008). Fishing location choice also has a significant effect of catch (Gerritsen et al., 2012), something that fishers routinely consider in their decision making based on their own knowledge.

In the past, spatiotemporal management measures (such as time-limited fishery closures) have been applied to reduce unwanted catch with varying degrees of success (e.g. Needle and Catarino, 2011; Holmes et al., 2011; Beare et al., 2010; Dinmore et al., 2003) while move-on rules have also been proposed or implemented to influence catch rates of particular vulnerable species in order to reduce or eliminate discards (e.g. Gardner et al., 2008; Dunn et al., 2011, 2014). However, such measures have generally been targeted at individual species without considering associations and interactions among several species. Highly mixed fisheries are complex with spatial, technological and community interactions combining. The design of spatiotemporal management measures that aim to allow exploitation of high quota stocks while protecting low quota stocks requires understanding these interactions at a scale meaningful to managers and fishers. While fisheries surveys and commercial fishing routinely generate a large amount of geo-referenced information on numbers and weight of fish caught, integrating spatiotemporal information from across multiple sources of fisheries-dependent and independent survey data requires an effective framework to reduce and understand the complexities of the system.

Here, our goal is to develop a framework for understanding these complexities. We do so by 1) implementing a spatiotemporal dimension reduction method that estimates the likely correlation in catches for multiple species at each fishing location, 2) using the results to draw inference on the fishery-community dynamics, 3) creating a framework to identify trends common among species, and 4) describing the potential for and limitation of spatial measures to mitigate unwanted catches in highly mixed fisheries.

2.2.2 Framework for analysing spatiotemporal mixed fisheries interactions

We present a framework for analysing how far spatiotemporal avoidance can contribute towards mitigating imbalances in quota in mixed fisheries. Fisheries-independent survey data are used to characterise the spatiotemporal dynamics of key components of a fish community by employing a geostatistical Vector Autoregressive Spatiotemporal model (VAST). Therein, a factor analysis decomposition was used to describe trends in spatiotemporal dynamics of the different species as a function of latent variables (Thorson et al., 2015) representing spatial variation (9 factors; termed “average” spatial variation) and spatiotemporal variation (9 factors) for encounter probability and positive catch rates (termed “positive density”) separately (Thorson et al., 2015). Resultant factor analyses identify community dynamics and drivers common among 9 species, each analysed separately for juveniles and adult stages. We refer to each combination of species and size class as a “species", and present results for the 18 species through transformation of the loading matrices using PCA rotation. This PCA rotation is used to visualise a reduced number of orthogonal factors representing average spatial variation or spatiotemporal variation while explaining the majority of covariation among catch rates, as well as the association of each species with these maps. We refer to the association of each species with a given factor as its “association with this factor", and the value of each factor at a given location as its “coefficient" at that location". By describing the species dynamics through underlying spatiotemporal factors we can take account of how the factors contribute to affect catches of the species in mixed fisheries. Gaussian Markov Random Fields (GMRFs) capture spatial and temporal dependence within and among species for both encounter probability and positive density (Thorson and Ward, 2013). VAST is set in a mixed modelling framework which allows estimation of fixed effects to account for systematic differences driving encounter and catches, such as differences in sampling efficiency (catchability), while random effects capture the spatiotemporal dynamics of the fish community.

2.2.3 Dynamics of Celtic Sea fisheries

The highly mixed demersal fisheries of the Celtic Sea are used as a case study. The Celtic Sea is a temperate sea where fisheries are spatially and temporally complex; mixed fisheries are undertaken by several nations using different gear types (Ellis et al., 2000; Gerritsen et al., 2012). Close to 150 species have been identified in the commercial catches of the Celtic Sea, with approximately 30 species dominating the catch (Mateo et al., 2017).

Our spatiotemporal model is parametrised using catch data from seven fisheries-independent surveys undertaken in the Celtic Sea over the period 1990 - 2015 (Table S1) and include nine of the main commercial species: Atlantic cod (*Gadus morhua*), Atlantic haddock (*Melanogrammus aeglefinus*), Atlantic whiting (*Merlangius merlangus*), European hake (*Merluccius merluccius*), white-bellied anglerfish (*Lophius piscatorius*), black-bellied anglerfish (*Lophius budegassa*), megrim (*Lepidorhombus whiffiagonis*), European plaice (*Pleuronectes platessa*) and common sole (*Solea solea*). These species comprise over 60 % of landings by towed fishing gears for the area (average 2011 - 2015 (STECF, 2017)). Each species was separated into juvenile and adult size classes based on their legal minimum conservation reference size (Table S2).

The data were analysed to understand how the different associations among species (combination of species and size class) form distinct assemblages with common drivers of spatiotemporal distributions, and how these affect catch compositions for fishers operating in mixed fisheries. We consider how these have changed over time, and the implications for mixed fisheries in managing catches of quota species under the EU landing obligation.

2.3 Results

Using relatively few factors in a spatial dynamic factor analysis the Celtic Sea demersal fish community can be partitioned into three species assemblages (roundfish, flatfish and deeper water species). Within these assemblages there are common trends in spatiotemporal distributions in encounter probability and positive density, which can be partitioned into time invariant (“average effect") spatial trends and time variant (“spatiotemporal") trends. We show through presentation of factor coefficients that time invariant trends may be linked to physical characteristics of the system including depth and predominant substrate type, while species loadings on to time varying spatial trends show changes in distribution of species over time to be similar within an assemblage. We demonstrate how this information can be used to help inform spatial targeting and avoidance of the different assemblages. More nuanced differences in spatiotemporal distributions exist within an assemblage presenting a greater challenge to spatially separate catches, yet we show how this information may be utilised by managers and fishers to inform ways to better match catch to quota in highly mixed fisheries through changes in gear and location fished.

2.3.1 Spatial distributions indicate three species assemblages

A spatial dynamic factor analysis was used to decompose the dominant spatial patterns driving differences in average spatial variation. The first three factors (after PCA rotation) account for 83.7 % of the between species variance in the probability of encountering a species (the “average encounter probability") and 69 % of the explained variance in catch rates on encounter (“average positive density"). A clear spatial pattern can been seen both for average encounter probability and average positive density, with a positive coefficient value associated with the first factor in the inshore north easterly part of the Celtic Sea into the Bristol Channel and Western English Channel, moving to a negative coefficient value offshore in the south-westerly waters (Figure 2.1). The species loadings show plaice, sole and whiting to be positively associated with the first factor for average encounter probability while the other species are negatively associated. For average positive density, positive associations are also found for haddock and juvenile cod. This is indicative of a more inshore distribution for these species.

On the second spatial factor for average encounter probability a north / south split can be seen at approximately 49° N while positive density is more driven by a positive coefficient in the deeper westerly waters as well as some inshore areas. Species loadings for the second factor indicate there are positive asso-

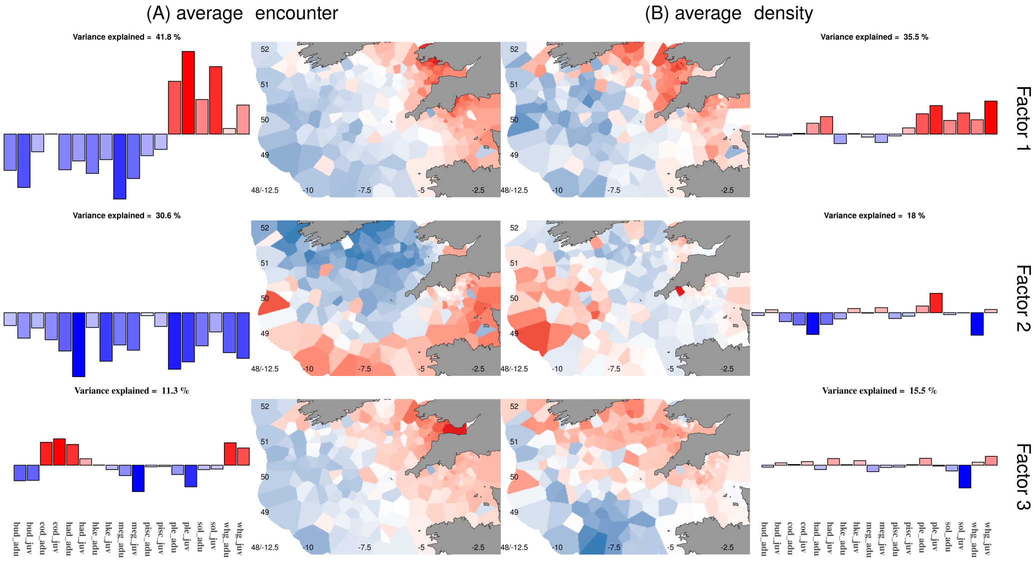

Figure 2.1: Factor values for the first three factors for (a) Average encounter probability and (b) Average positive density for the species (outer figures) and spatially (inner figures). Red: positive association to the factor, Blue: negative association.

ciations for juvenile monkfish (*L. piscatorius*), juvenile hake, juvenile megrim, plaice and juvenile whiting with average positive density, which may reflect two different spatial distributions in the more offshore and in the inshore areas (Figure 2.1).

On the third factor, there is a positive coefficient for the easterly waters for encounter probability and negative coefficient with the westerly waters. This splits the roundfish species (cod, haddock and whiting that all have a positive association with the third factor for average encounter probability) from the rest of the species (that have a negative association). Positive density is driven by a north / south split (Figure 2.1), with positive coefficient values in the northerly areas. Juvenile monkfish (*L. budgessa* and *L. piscatorius*), cod, juvenile haddock, hake, adult plaice and whiting are also positively associated with the third factor towards the north while adult monkfish (*L. budgessa* and *L. piscatorius*), adult haddock, megrim, juvenile plaice and sole have negative loadings reflecting their more southerly distribution (Figure 2.1).

While this exploratory factor analysis models unobserved drivers of distribution, we considered what might be driving the differences seen in the spatial factor coefficients and species loadings. The first factor was highly correlated with log(depth) for both average encounter probability coefficients (-0.85, CI = -0.88 to -0.81; Figure S1) and average positive density coefficients (-0.71, CI = -0.77 to -0.65; Figure S2). A random forest classification tree assigned 80 % of the variance in the first factor for average encounter probability to depth and predominant substrate type, with the majority (86 %) of the variance explained by depth. The variance explained by these variables dropped to 25 % on the second factor with a more even split between depth and substrate, while explaining 60 % of the variance on the third factor. For average positive density, the variables explained less of the variance with 62 %, 35 %, and 31 % for each of the factors, respectively.

It is clear that depth and to a lesser extent substrate are important variables for describing the main driver of similarities and differences in distributions and abundances for the different species. The first factor correlates strongly with these variables, despite them not explicitly being incorporated in the model. While depth and substrate were incorporated as covariates in an alternative model formulation (see Methods), they were found not to improve predictions as the random fields adequately captured the influence of these variables on spatial variation in abundance. The utility of these variables as predictors of species distributions has been identified in other marine species distribution models (Robinson et al., 2011). The advantage to the approach taken here is that, where such data is unavailable at appropriate spatial resolution, the spatial factor analysis has adequately characterised their influences on species spatial dynamics.

2.3.2 Species assemblages show similar spatiotemporal patterns

While there are clear spatial patterns in the factor coefficients describing differences in average encounter probability and positive density (Figure 2.1), the interannual differences in factor coefficients show less structure (Figures S5, S6). These interannual differences are important as they reflect the ability of fishers to predict where they can target or avoid species from one year to the next, without which it may be difficult to balance catches with available quota and avoid unwanted catch.

Spatiotemporal factor coefficients for encounter probability and positive density did not show the same spatial pattern driving species distributions from year to year but correlation among species showed clear relationships in species association with spatiotemporal factor coefficients resulting in the formation of three different assemblages (Figure 2.2). The same factors appear to drive spatiotemporal (interannual changes in) distributions of megrim, anglerfish species and hake (the deeper water species, forming an assemblage negatively associated with the second axes of Figure 2.2) and the roundfish and flatfish (two assemblages more positively associated with the second axes of Figure 2.2a). For spatiotemporal positive density (Figure 2.2b) cod, haddock and whiting (the roundfish species) are separated from plaice, sole (the flatfish) and deeper water assemblage. As such, it can be predicted that higher catches of a species within an assemblage (e.g. cod in roundfish) would be expected when catching another species within that assemblage (e.g. whiting in roundfish).

This suggests that one or more common environmental drivers are influencing the distributions of the assemblages, and that driver differentially affects the different assemblages. Temperature is often included as a covariate in species distribution models, but was found not to contribute to the variance in the first factor coefficients (Figure S6, no correlations found for either spatiotemporal encounter probability or positive density) and so was not included as a covariate in the final model.

2.3.3 Covariance in spatiotemporal abundance within species assemblages

In order to gain greater insight into the community dynamics we considered how species covary in space and time through correlations among species. Pearson correlation coefficients for the modelled average spatial encounter probability (Figure 2.3a) show clear strong associations between adult and juvenile size classes for all species (>0.75 for all species except hake, 0.56). Among species, hierarchical clustering identified the same three common species-groups as our visual inspection of factor loadings above, with roundfish (cod, haddock, whiting) closely grouped, with correlations for adult cod with adult haddock and adult whiting of 0.73 and 0.5 respectively, while adult haddock with adult whiting was 0.63 (Figure 2.3a). Flatfish (plaice and sole) are also strongly correlated with adult plaice and sole having a coefficient of 0.75.

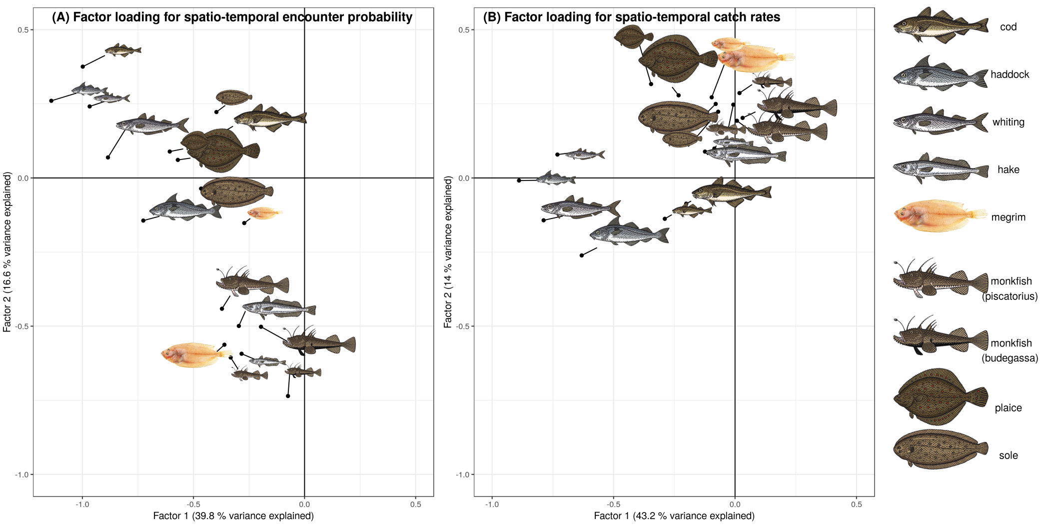

Figure 2.2: Position of each species on the first two axes from the factor analysis for (a) spatiotemporal encounter probability and (b) spatiotemporal positive density. Fish images from The Fisherman/Shutterstock.com and Richard Griffin/Shutterstock.com

The final group are principally the species found in the deeper waters (hake, megrim and both anglerfish species) with the megrim strongly associated with the budegassa anglerfish species (0.88). Negative relationships were found between plaice and sole, and the monkfish species (-0.27, -0.26 for the adult size class with budegassa adults respectively) and hake (-0.33, -0.37) (Figure 2.3a) indicating spatial separation in distributions , with the flatfish found more inshore. This underscores the correlations among species seen in associations of each species with factors, with three distinct assemblages being confirmed.

Correlation coefficients for the average positive density (Figure 2.3b) show fewer significant positive or negative relationships among species than for encounter probability, but still evident are the strong correlation among the roundfish with higher catches of cod correlated with higher catches of haddock (0.58) and whiting (0.47), as well as the two anglerfish species (0.71 for piscatorius and 0.44 for budegassa) and hake (0.73). Similarly, plaice and sole are closely correlated (0.31) and higher catches of one would expect to see higher catches of the other, but also higher catches of some juvenile size classes of roundfish (whiting and haddock) and anglerfish species. Negative correlation of juvenile megrim, anglerfish (budegassa) and hake with adult sole (-0.61, -0.61 and -0.47 respectively), plaice (-0.36 and -0.35 for megrim and hake only) indicate high catches of one can predict low catches of the

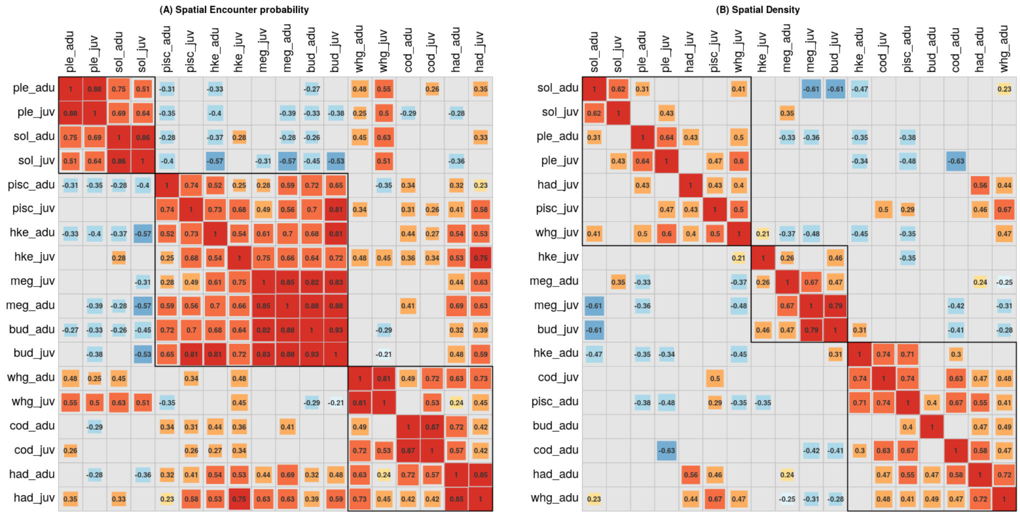

Figure 2.3: Inter-species correlations for (a) spatial encounter probability over all years and (b) spatial positive density. Species are clustered into three groups based on a hierarchical clustering method with non-significant correlations (the Confidence Interval [± 1.96 * SEs] spanned zero) left blank.

other successfully.

To understand how stable relationships between catches of pairs of species were from one year to the next, we regressed the correlation coefficients for the average spatial correlations between pairs for species x and species y across all years (Figure 2.3) with those of the spatiotemporal population correlations, representing how correlations between species x and species y change from year to year (Figure S9). The correlations were 0.60 (0.52 - 0.66) and 0.47 (0.38 - 0.55) for encounter probability and positive density respectively (Figures S9a and S9b). These indicate generally predictable relationships between species from one year to the next and suggests that a positive or negative correlation between two species is likely to persist from one year to the next, and that species are consistently correlated in hauls. However, the regressions between the spatial correlations and the spatiotemporal correlations shows high variance (R^2 = 0.36 and 0.22 respectively), indicating that the scale of these relationships do change from one year to the next. This unpredictability would have implications for the fishery if, for example, catches of an unwanted species increased when caught with a target species above a level expected in the fishery potentially leading to challenges for fishers when trying to balance catch with quotas in mixed fisheries. It can be seen in the spatial factor maps that there are subtle differences in patterns in spatial factor coefficients from one year to the next (Figures S4 and S5), indicating changes may be driven by temporally changing environmental factors and species behaviour.

2.3.4 Potential to separate catches within assemblages under the landing obligation

The analysis shows the interdependence within three assemblages of roundfish, flatfish and deeper water species, where catching one species within the group indicates a high probability of catching the other species. This has important implications for how spatial avoidance can be used to support implementation of the EU's landing obligation. If production from mixed fisheries is to be maximised, decoupling catches of species between and within the groups will be key. For example, asking where the maximal separation in the densities of two coupled species is likely to occur? To address this requirement, we map the difference in spatial distribution within a species-group for each pair of species for a single year (2015; Figure 2.4).

Cod had a more north-westerly distribution than haddock and a more westerly distributed than whiting roughly delineated by the 7° W line (Figure 4a). Whiting appeared particularly concentrated in an area between 51 and 52 ° N and 5 and 7 ° W, which can be seen by comparing the whiting distribution with both cod (Figure 2.4b) and haddock (Figure 2.4c). For the deeper water species, hake are more densely distributed in two locations around 10 W and 48 N and 12 W and 50 N compared to the anglerfish species (anglerfishes have been presented together as they are jointly managed under a single quota) and megrim which were more widely spatially distributed (Figures 2.4d, and 2.4e). Megrim has a fairly stable density across the modelled area as indicated by the large amount of white space in Figure 2.4e. For anglerfishes and megrim (Figure 2.4f), anglerfishes have a more easterly distribution than megrim. For the flatfish species plaice and sole (Figure 2.4g), plaice appear to be more densely distributed along the coastal areas of Ireland and Britain, while sole are more densely distributed in the Southern part of the English Channel along the coast of France.

Predicted catch distribution from a "typical" otter trawl gear and beam trawl fishing at three different locations highlights the differences fishing gear makes to catches (Figure 2.4h). As can be seen, both the gear selectivity and location

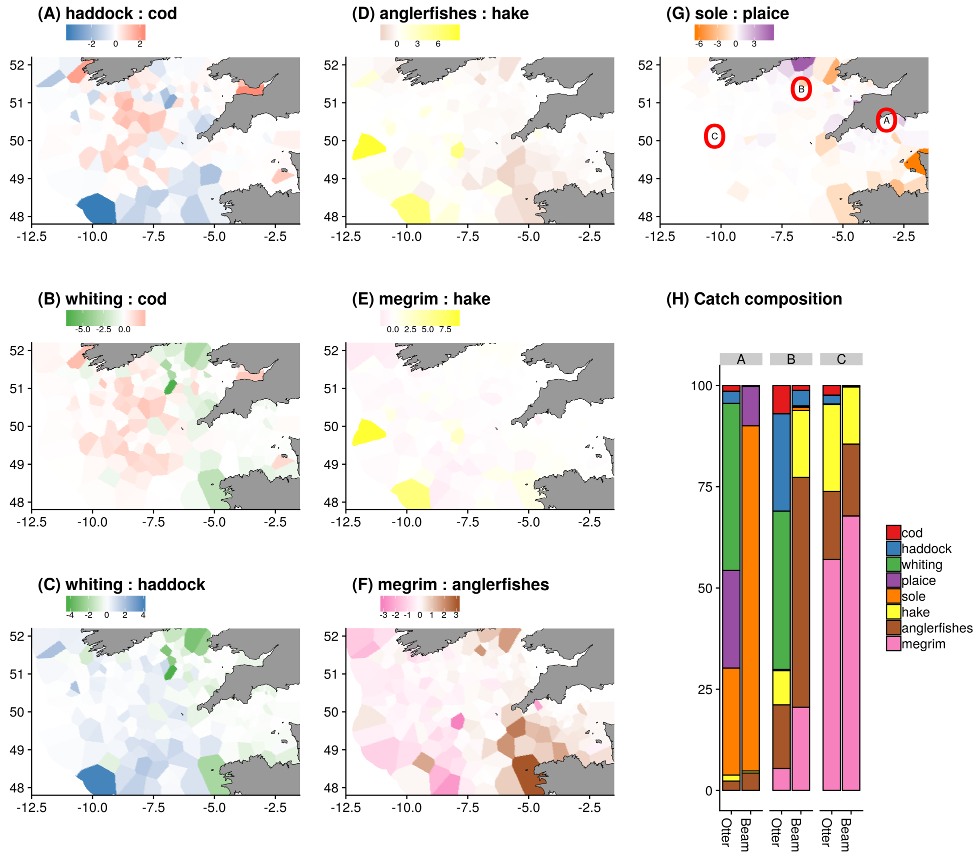

Figure 2.4: Differences in the standardised spatial density for pairs of species and expected catch rates for two different gears at three different locations in 2015.

fished play important contributions to the catch compositions; in the inshore area (location "A") plaice and sole are the two main species in the catch reflecting their distribution and abundance, though the otter trawl gear catches a greater proportion of plaice to sole than the beam trawl. The area between Britain and Ireland (location "B") has a greater contribution of whiting, haddock, cod, hake and anglerfishes in the catch with the otter trawl catching a greater proportion of the roundfish, haddock, whiting and cod while the beam trawl catches more anglerfishes and megrim. The offshore area has a higher contribution of megrim, anglerfishes and hake with the otter trawl catching a greater share of hake and the beam trawl a greater proportion of megrim. Megrim dominates the catch for both gears in location "C", reflecting its relative abundance in the area irrespective of the gear deployed.

2.4 Discussion

Our study is framed by the problem of addressing the scientific challenges of implementing the landing obligation for mixed fisheries. In application to the Celtic Sea, we have identified spatial separation of three distinct assemblages (roundfish, flatfish and deeper water species) while showing that only subtle differences exist in distributions within assemblages. The differences in catch compositions between gears at the same location (Figure 2.4h) show that changing fishing methods can go some way to affecting catch, yet that differences in catches between locations are likely to be more important. For example, beam trawls fishing at the inshore locations (e.g. location "A" in Figure 2.4) are likely to predominately catch plaice and sole, yet switching to the offshore locations (e.g. location "C") would likely yield greater catches of megrim and anglerfishes. Such changes in spatial fishing patterns are likely to play an important role in supporting implementation of the landing obligation.

More challenging is within-group spatial separation due to significant overlap in spatial distributions for the species, driven by common environmental factors. Subtle changes may yield some benefit in changing catch composition, yet the outcome is likely to be much more difficult to predict. For example, subtle differences in the distribution of cod, haddock and whiting can be seen in Figures 2.4a-c, showing spatial separation of catches is much more challenging and likely to need to be supported by other measures such as changes to the selectivity characteristics of gear (Santos et al., 2016). For example we identified a spatial overlap of flatfish with juvenile roundfish in our species correlations (Figure 2.3); reducing catches of incidental bycatch on the main target fishing grounds will likely require adaptations to fishing gear to address bycatch without significant economic impacts on the fishery.

A role that science can play in supporting effectiveness of spatiotemporal avoidance could be to provide probabilistic advice on hotspots for species occurrence and high species density, which can inform fishing decisions. Previous modelling studies have shown how spatiotemporal models could improve predictions of high ratios of bycatch species to target species (Ward et al., 2015; Cosandey-Godin et al., 2015; Breivik et al., 2016), and geostatistical models are well suited to this as they incorporate spatial dependency while providing for probabilities to be drawn from posterior distributions of the parameter estimates. We posit that such advice on "hot spots" as a supportive measure to incentivise avoidance of areas of high bycatch risk could be enhanced by integrating data obtained directly from commercial fishing vessels rapidly while modelling densities at small time scales (e.g., weekly). Short-term forecasts of distribution could inform fishing choices while also capturing seasonal differences in distributions, akin to weather forecasting. Advice informed by a model including a seasonal or real-time component could inform optimal policies for time-area closures, move-on rules or even as informal information to be utilised by fishers directly without the need for costly continuous data collection on environmental parameters, but by using the "vessels-as-laboratories" approach.

An important question for the implementation of the EU's landing obligation is how far spatial avoidance can go to achieving catch balancing in fisheries. Our model captures differences between location fished for two gear types and their broad scale effect on catch composition, information crucial for managers in implementing the landing obligation. It is likely, however, that this analysis reflects a lower bound on the utility of spatial avoidance as fine-scale behavioural decisions such as time-of-day, gear configuration and location choices can also be used to affect catch (Abbott et al., 2015; Thorson and Kristensen, 2016). Results of empirical studies undertaken elsewhere (Branch and Hilborn, 2008; Kuriyama et al., 2016) suggest limits to the effectiveness of spatial avoidance. Differences in ability to change catch composition have also been observed for different fleets; in the North Sea targeting ability was found to differ between otter and beam trawlers as well as between vessels of different sizes (Pascoe et al., 2007).

Further, under the landing obligation the balance of risk-reward for trip level fishing decisions about where to fish may change. For example, are fishers likely to fish in "safe" areas where its known there are lower catches of the target species but also decreased risk of encountering bycatch? How do decisions about level of risk affect the likelihood of overshooting available quota and potential profit and losses for individual trips? Set in this context, the parameter estimates could be used to simulate from a distribution of catches in the fishery at different locations and therefore inform on the possibility of extreme catch events and potential consequences for overshooting quotas. Alternatively, where fisheries data is available with factors such as weather, quota uptake and previous catches, these could be included as covariates in the model to help identify causes for high bycatch events. This information may be of interest in identifying optimum strategies, or used in future work to model closure risks for fisheries operating in different locations and conditions given quota constraints. Such analysis on risk and decision making is likely to hinge on micro-level decisions by fishers and such study would be an interesting compliment to broader scale considerations such as those detailed here.

Our framework allows for a quantitative understanding of the broad scale global production set available to fishers (Reimer et al., 2017) and thus the extent to which they can alter catch compositions while operating in a mixed fishery. Simulations of spatial effort allocation scenarios based on the production sets derived from the model estimates could be used as inputs to fisher behavioural models to allow for identification of the lower bounds of optimum spatial harvest strategies. Modelling of different spatial strategies at the individual or fishery level would provide managers with information useful for examining trade-offs in quota setting by integrating potential for spatial targeting in changing catch composition, thus providing a scientific contribution to assessing the ability of technical measures to meet the goal of maximising catches in mixed fisheries within single stock quota constraints (Ulrich et al., 2017). Further, the correlations among species could provide information on fisheries at risk of capturing protected, endangered or threatened species such as elasmobranches, and allow identification of areas where there are high ratios of protected to target species.

Complex environmental, fishery and community drivers of distribution for groups of species highlights the scale of the challenge in separating catches within the assemblages using spatial management measures. This has important implications for management of the mixed fisheries under the EU landing obligation. Our analysis identifies where it may be easier to separate catches of species (among groups) and where it is more challenging (within groups). We propose that the dimension-reduction framework presented in Figures 2.1-2.4 provides a viable route to reducing the complexity of highly mixed fisheries. This can allow informed management discussion over more traditional anecdotal knowledge of single-species distribution in space and time.

2.5 Methods

2.5.1 Model structure:

VAST (Software in the R statistical programming language can be found here: `www.github.com/james-thorson/VAST`) implements a delta-generalised linear mixed modelling (GLMM) framework that takes account of spatiotemporal correlations among species through implementation of a spatial dynamic factor analysis (SDFA). Spatial variation is captured through a Gaussian Markov Random Field, while we model random variation among species and years. Covariates affecting catchability (to account for differences between fishing surveys) and density (to account for environmental preferences) can be incorporated for predictions of presence and positive density. The following briefly summarises the key methods implemented in the VAST framework. For full details Thorson and Barnett (2017).

SDFA: A spatial dynamic factor analysis incorporates advances in joint dynamic species models (Thorson and Barnett, 2017) to take account of associations among species by modelling response variables as a multivariate process. This is achieved through implementing a factor analysis decomposition where common latent trends are estimated so that the number of common trends is less than the number of species modelled. The factor coefficients are then associated through loadings for each factor that return a positive or negative association of one or more species with any location. Log-density of any species can be described as a linear combination of factors and loadings:

$$\theta_c(s,t) = \sum_{j=1}^{n_j} L_{c,j}\psi_j(s,t) + \sum_{k=1}^{n_k} \gamma_{k,c}\chi_k(s,t) \tag{2.1}$$

Where $\theta_c(s,t)$ represents log-density for species c at site s at time t, ψ_j is the coefficient for factor j, $L_{c,j}$ the loading matrix representing association of species c with factor j and $\gamma_{k,c}\chi_k(s,t)$ the linear effect of covariates at each site and time (Thorson et al., 2016).

The factor analysis can summarize community dynamics and identify which species and life-stages have similar spatiotemporal patterns. This allows inference regarding species distributions and abundance of poorly sampled species through association with other species, and also provides estimates of spatiotemporal correlations among species (Thorson et al., 2016).

Estimation of abundances: Spatiotemporal encounter probability and positive catch rates are modelled separately with spatiotemporal encounter probability modelled using a logit-link linear predictor;

$$logit[p(s_i, c_i, t_i)] = \beta_p(c_i, t_i) + \sum_{f=1}^{n_\omega} L_\omega(c_i, f)\omega_p(s_i, f) + \sum_{f=1}^{n_\varepsilon} L_\varepsilon(c_i, f)\varepsilon_p(s_i, f, t_i) + \sum_{v=1}^{n_v} \delta_p(v) Q_p(c_i, v_i) \tag{2.2}$$

and positive catch rates modelling using a gamma- distribution (Thorson et al., 2015).

$$log[r(s_i, c_i, t_i)] = \beta_r(c_i, t_i) + \sum_{f=1}^{n_\omega} L_\omega(c_i, f)\omega_r(s_i, f) + \sum_{f=1}^{n_\varepsilon} L_\varepsilon(c_i, f)\varepsilon_r(s_i, f, t_i) + \sum_{v=1}^{n_v} \delta_r(v) Q_r(c_i, v_i) \tag{2.3}$$

where $p(s_i, c_i, t_i)$ is the predictor for encounter probability for observation i, at location s for species c and time t and $r(s_i, c_i, t_i)$ is similarly the predictor for the positive density. $\beta_*(c_i, t_i)$ is the intercept, $\omega_*(s_i, c_i)$ the spatial variation at location s for factor f, with $L_\omega(c_i, f)$ the loading matrix for spatial covariation among species. $\varepsilon_*(s_i, c_i, t_i)$ is the linear predictor for spatiotemporal variation, with $L_\varepsilon(c_i, f)$ the loading matrix for spatiotemporal covariance among species and $\delta_*(c_i, v_i)$ the contribution of catchability covariates for the linear predictor with Q_{c_i,v_i} the catchability covariates for species c and vessel v; $*$ can be either p for probability of encounter or r for positive density.

The Delta-Gamma formulation is then:

$$\begin{aligned} Pr(C = 0) &= 1 - p \\ Pr(C = c | c > 0) &= p \cdot \frac{\lambda^k c^{k-1} \cdot exp(-\lambda c)}{\Gamma_k} \end{aligned} \tag{2.4}$$

for the probability p of a non-zero catch C given a gamma distribution for for the positive catch with a rate parameter λ and shape parameter k.

Spatiotemporal variation: The spatiotemporal variation is modelled using Gaussian Markov Random Fields (GMRF) where observations are correlated in space through a Matérn covariance function with the parameters estimated within the model. Here, the correlation decays smoothly over space the further from the location and includes geometric anisotropy to reflect the fact that correlations may decline in one direction faster than another (e.g. moving offshore) (Thorson and Ward, 2013). The best fit estimated an anisotropic covariance where the correlations were stronger in a north-east - south-west direction, extending approximately 97 km and 140 km before correlations for encounter probability and positive density reduced to <10 %, respectively (Figure S10). Incorporating the spatiotemporal correlations among and species provides more efficient use of the data as inference can be made about poorly sampled locations from the covariance structure.

A probability distribution for spatiotemporal variation in both encounter probability and positive catch rate was specified, $\varepsilon_*(s,p,t)$, with a three-dimensional multivariate normal distribution so that:

$$vec[\mathbf{E}_*(t)] \sim MVN(0, \mathbf{R}_* \otimes \mathbf{V}_{\varepsilon *}) \tag{2.5}$$

Here, $vec[\mathbf{E}_*(t)]$ is the stacked columns of the matrices describing $\varepsilon *(s,p,t)$ at every location, species and time, $\mathbf{R}_*$ is a correlation matrix for encounter probability or positive catch rates among locations and $\mathbf{V}_*$ a covariance matrix for encounter probability or positive catch rate among species (modelled within the factor analysis). $\otimes$ represents the Kronecker product so that the correlation among any location and species can be computed (Thorson and Barnett, 2017).

Incorporating covariates Survey catchability (the relative efficiency of a gear catching a species) was estimated as a fixed effect in the model, $\delta_s(v)$, to account for differences in spatial fishing patterns and gear characteristics, which affect encounter and capture probability of the sampling gear (Thorson et al., 2015). Parameter estimates (Figure S11) showed clear differential effects of surveys using otter trawl gears (more effective for round fish species) and beam trawl gears (more effective for flatfish species).

No fixed covariates for habitat quality or other predictors of encounter probability or positive density were included. While incorporation may improve the spatial predictive performance (Thorson and Barnett, 2017), it was not found to be the case here based on model selection with Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Parameter estimation Parameter estimation was undertaken through Laplace approximation of the marginal likelihood for fixed effects while integrating the joint likelihood (which includes the probability of the random effects) with respect to random effects. This was implemented using Template Model Builder (Kristensen et al., 2016, TMB,) with computation through support by the Irish Centre for High End Computing (ICHEC; `https://www.ichec.ie`) facility.

2.5.2 Data

The model integrates data from seven fisheries-independent surveys taking account of correlations among species spatiotemporal distributions and abundances to predict spatial density estimates consistent with the resolution of the data.

The model was fitted to nine species separated into adult and juvenile size classes (Table S2) to seven survey series (Table S1) in the Celtic Sea bound by 48° N to 52 ° N latitude and 12 ° W to 2° W longitude (Figure S8) for the years 1990 - 2015 inclusive.

The following steps were undertaken for data processing: i) data for survey stations and catches were downloaded from ICES Datras (`www.ices.dk/marine-data/data-portals/Pages/DATRAS.aspx`) or obtained directly from the Cefas Fishing Survey System (FSS); ii) data were checked and any tows with missing or erroneously recorded station information (e.g. tow duration or distance infeasible) removed; iii) swept area for each of the survey tows was estimated based on fitting a GAM to gear variables so that Doorspread = s(Depth) + DoorWt + WarpLength + WarpDiameter + SweepLength and a gear specific correction factor taken from the literature (Piet et al., 2009); iii) fish lengths were converted to biomass (Kg) through estimating a von bertalanffy length weight relationship, $Wt = a \cdot L^b$, fit to sampled length and weight of fish obtained in the EVHOE survey and aggregated within size classes (adult and juvenile). Details on the downloading and processing of the data are available in Rmarkdown format (code and steps combined) as supplementary material.

The final dataset comprised of estimates of catches (including zeros) for each station and species and estimated swept area for the tow.

2.5.3 Data availability

Data used to fit the model is available via the ICES Datras data portal (`http://www.ices.dk/marine-data/data-portals/Pages/DATRAS.aspx`) for two surveys and on request to the author for the remaining five surveys.

2.5.4 Model setup

The spatial domain was set up to include 250 knots representing the Gaussian Random Fields. The model was configured to estimate nine factors each to describe the spatial and spatiotemporal encounter probability and positive density parameters, with a logit-link for the linear predictor for encounter probability and log-link for the linear predictor for positive density, with an assumed gamma distribution.

Three candidate models were identified, i) a base model where the vessel interaction was a random effect, ii) the base but where the vessel x species effect was estimated as a fixed covariate, iii) with vessel x species effect estimated, but with the addition of estimating fixed density covariates for both predominant habitat type at a knot and depth. AIC and BIC model selection favoured the second model (Table S3). The final model included estimating 1,674 fixed parameters and predicting 129,276 random effect values.

2.5.5 Model validation

Q-Q plots show good fit between the derived estimates and the data for positive catch rates and between the predicted and observed encounter probability (S12, S13). Further, model outputs are consistent with stock-level trends abundances over time from international assessments (S14), yet also provide detailed insight into species co-occurrence and the strength of associations in space and time.

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Chapter 3

Highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

This chapter is a verbatim reproduction from the following published paper. The published version is found in Appendix D, Supplementary Tables and Figures in Appendix E, *MixFishSim* R package help file in Appendix F and a *MixFishSim* vignette on how to use the package in Appendix G.

Dolder, P. J., Minto, C., Guarini, J. M., & Poos, J. J. (2020). Highly resolved spatiotemporal simulations for exploring mixed fishery dynamics. *Ecological Modelling*, 424, 109000.

3.1 Abstract

To understand how data resolution impacts inference on mixed fisheries interactions we developed a highly resolved spatiotemporal discrete-event simulation model *MixFishSim* incorporating: i) delay-difference population dynamics, ii) population movement using Gaussian Random Fields to simulate patchy, heterogeneously distributed and moving fish populations, and iii) fishery dynamics for multiple fleet characteristics based on population targeting under an explore-exploit strategy.

We applied *MixFishSim* to infer community structure when using data generated from: commercial catch, a fixed-site sampling survey design and the true (simulated) underlying populations. In doing so we thereby establish the potential limitations of fishery-dependent data in providing a robust characterisation of spatiotemporal distributions. Different spatial patterns were evident and the effectiveness of the spatial closure reduced when data were aggregated across larger spatial areas. A simulated area closure showed that aggregation across time periods has less of a negative impact on the closure success than aggregation over space. While not as effective as when based on on the true population, closures based on high catch rates observed in commercial data were still able to reduce fishing on a protected species.

Our framework allows users to explore the assumptions in modelling observational data and evaluate the underlying dynamics of such approaches at a fine spatial and temporal resolutions. From our application we conclude that commercial data, while containing bias, provide a useful tool for managing catches in mixed fisheries if applied at the correct spatiotemporal scale.

3.1.1 Keywords

spatiotemporal, mixed fisheries, individual based, spatial management, heterogeneity, bycatch avoidance

3.2 Introduction

Fishers exploit a variety of fish populations that are heterogeneously distributed in space and time. Fishers generally only have partial knowledge of species distributions and so limited control over what species they select when fishing in 'mixed fisheries'. This results in catches of vulnerable species and species with low-quota. These species may be thrown overboard in a process called discarding and discarding catches that are not recorded leads to biased perception of the effects of fisheries on ecosystems. Ultimately the unaccounted discards limit our ability to control fishing mortality (Alverson, 1997; Crowder et al., 1998; Rijnsdorp et al., 2007) and the ability to manage biological and economic sustainability of fisheries (Ulrich et al., 2011; Batsleer et al., 2015).

There is increasing interest in technical solutions such as gear adaptations and spatial closures as measures to reduce discarding of unwanted catches (Kennelly and Broadhurst, 2002; Catchpole and Revill, 2008; Bellido et al., 2011; Cosgrove et al., 2019). Adaptive spatial management strategies have been proposed as a way of reducing over-quota discards (Holmes et al., 2011; Little et al., 2015; Dunn et al., 2014). However, to reduce unwanted catch through spatial measures requires an in-depth understanding of the spatiotemporal dynamics of the fishery.

Effective spatial management requires implementation at appropriate spatial scales. These spatial scales shape the trade-offs between protection of populations and economic impacts on fisheries (Dunn et al., 2016). In mixed fisheries, the problem is to identify a scale that promotes species avoidance for vulnerable or low-quota species while allowing continuance of sustainable fisheries for available quota species. Identifying the appropriate spatial scale remains challenging because collecting data on fish distribution at high temporal and spatial resolutions is expensive and difficult. Proxies for the spatial distributions are usually inferred from fisheries-dependent data or from fisheries-independent data. Fisheries-dependent data includes all data on catch and effort from commercial fishing operations while fisheries-independent data includes data collected on board scientific research vessels.

Inferences on fish distributions are hampered where spatial and temporal information is coarse. Sampling designs for scientific research vessel surveys generally aim for unbiased estimates of local abundance. However, high costs of these surveys generally results in restrictions in terms the number of samples. As a result, sampling is usually restricted to a few weeks a year, and sampling stations are usually coarsely spaced. Moreover, the gear chosen for the survey determines the selectivity for certain species and size classes within fish communities. This selectivity determines the usefulness of relative occurrence in survey catches as proxies for abundances in the fish communities.

Proxies for spatial distribution derived from commercial fisheries in theory allow for much larger sample sizes. These commercial fisheries are often at sea throughout the year, making many fishing hauls. However, spatial information from fisheries is often limited because data on catch and effort is collected or aggregated across larger gridded areas (Branch et al., 2005). If spatially aggregated data does not allow identification of spatial features it may lead to poorly designed spatial management measures that are ineffectual or have unintended consequences (Costello et al., 2010; Dunn et al., 2016). For example, increased benthic impact on previously unexploited areas from the cod closure in the North Sea were observed without the intended effect of reducing cod exploitation (Rijnsdorp et al., 2001; Dinmore et al., 2003).

Even where high-resolution spatiotemporal information is available (see e.g. Lee et al., 2010; Bastardie et al., 2010; Gerritsen et al., 2012; Mateo et al., 2017) commercial catch per unit of effort may still be biased because of fisheries dynamics. Fishers establish favoured fishing grounds through an explore-exploit strategy (Rijnsdorp et al., 2011; Bailey et al., 2019) where they search for areas with high catches and then use experience to return to areas where they have experienced high catch in the past. This leads to inherently biased sampling where target species are over-represented in the catch because fishers exploit areas of high abundance. For effective adaptive spatial management the effects of spatiotemporal aggregation in data and fishery targeting need to be understood.

To understand the effect of spatiotemporal aggregation of data and fishery targeting on our perception of spatial abundance of different fish populations we ask two fundamental questions regarding inference derived from observational data:

1. Do different sources of sampling-derived fisheries data reflect the underlying community structure?
2. How do data aggregation and data source impact on the success of spatial fisheries management measures?

To answer these questions we i) develop a simulation model where population dynamics are highly-resolved in space and time, using a Gaussian spatial process to define suitable habitat for different populations. As the precise locations of the fish are known directly rather than inferred from sampling or commercial catch, we can use the population model to validate how inference from fisheries-dependent and fisheries-independent sampling relates to the real community structure in a way we could not with real data. We ii) compare, at different spatial and temporal aggregations, the real (simulated) population distributions to samples from fisheries-dependent and fisheries-independent catches to test if these are a true reflection of the relative density of the populations. We then iii) simulate a fishery closure to protect a species based on different spatial and temporal data aggregations.

We use these evaluations to draw inference on the utility of commercial data in supporting management decisions.

3.3 Materials and Methods

A Discrete-event simulation (DES) model of a hypothetical fishery was developed as a software package (*MixFishSim*). The modular approach enabled efficient computation by allowing for sub-modules implemented on time-scales appropriate to capture the characteristics of the different processes (Figure 3.1). Sub-modules to capture the full system comprised: 1) population dynamics, 2) recruitment dynamics, 3) population movement, 4) fishery dynamics.

Population dynamics for any number of species, as chosen by the user, operate on a daily time-step (with recruitment occurring only during defined seasons for each population), while population movement occurs on a weekly time-step, with the fishing module operating on a tow-by-tow basis (i.e., multiple events a day).

3.3.1 Population dynamics

The basic population level processes were simulated using a modified two-stage Deriso-Schnute delay difference model that models the fish populations in terms of aggregate biomass of recruits and mature components rather than

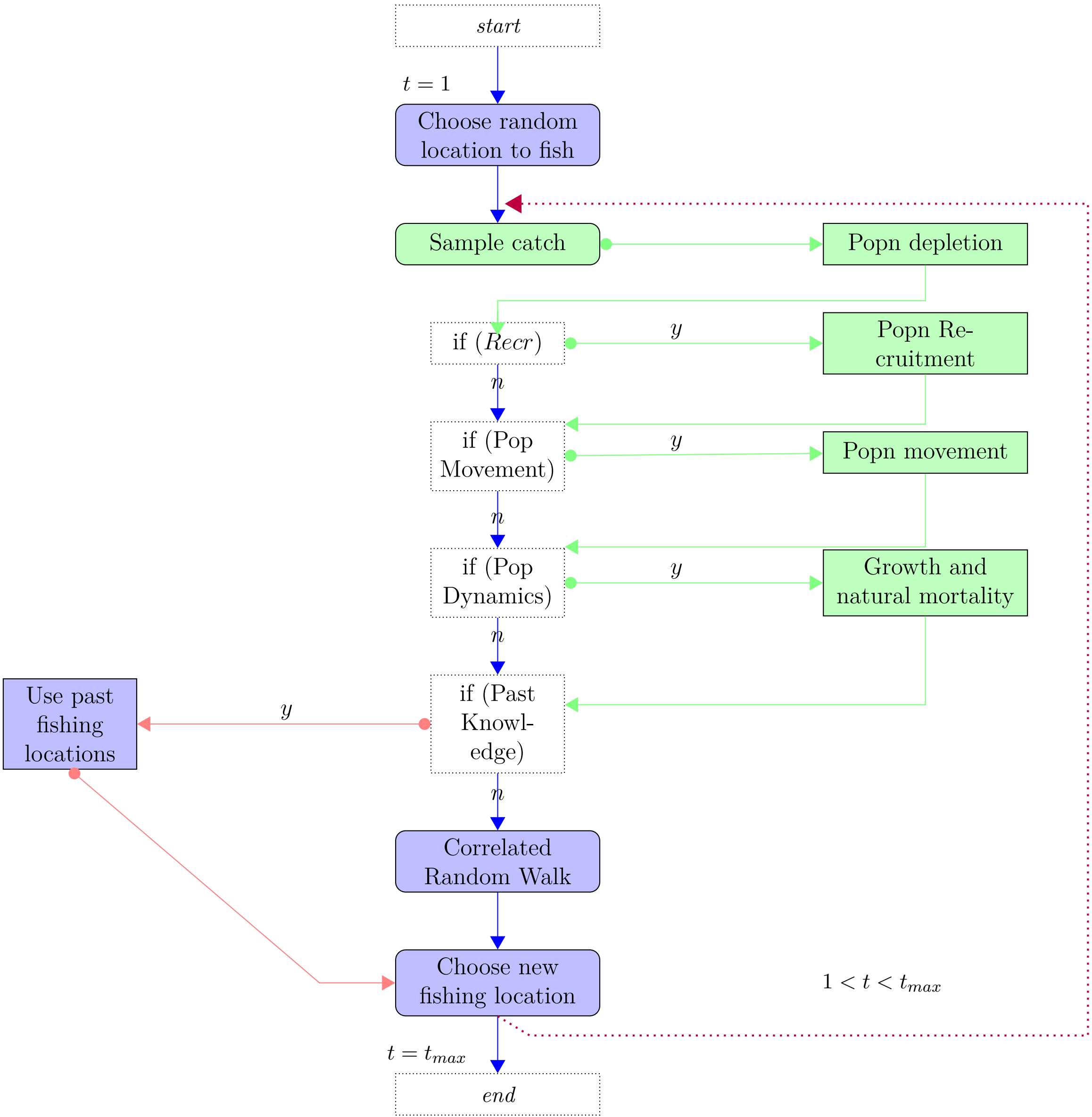

Figure 3.1: Schematic overview of the simulation model. Blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the time steps at which processes occur; t = tow, *tmax* is the total number of tows; (Recr), (Pop Movement), (Pop Dynamics) logic gates for recruitment periods, population movement and population dynamics for each of the populations, (Past Knowledge) a switch whether to use a random (exploratory) or past knowledge (exploitation) fishing strategy.

keeping track of individuals (Deriso, 1980; Schnute, 1985; Dichmont et al., 2003). A daily time-step was chosen to discretise continuous population processes on a biologically relevant and computationally tractable timescale. Population biomass growth was modelled as a function of previous recruited biomass, intrinsic population growth and recruitment functionally linked to the adult population size. Biomass for each cell c was incremented each day d as follows (see Table 3.1 for all parameter details):

$$B_{c,d+1} = \begin{aligned} &(1+\rho)\,B_{c,d} \cdot \mathrm{e}^{-Z_{c,d}} - \rho \cdot \mathrm{e}^{-Z_{c,d}} && \times \\ &\Big(B_{c,d-1} \cdot \mathrm{e}^{-Z_{c,d-1}} + W_{R-1} \cdot \Big(\alpha_{d-1} \cdot R_{\tilde{y}(c)}\Big)\Big) && + \\ &W_R \cdot \Big(\alpha_d \cdot R_{\tilde{y}(c)}\Big) \end{aligned} \tag{3.1}$$

where ρ is Ford's growth coefficient shown to be equal to e^{-K} when K is the Brody growth coefficient, the rate at which the asymptote is approached from a von Bertalanffy growth model (Schnute, 1985). W_{R-1} is the average weight of fish prior to recruitment, while W_R is the average recruited weight. α_d represents the proportion of fish recruited during that day for the year, while $R_{c,\tilde{y}(c)}$ is the annual recruits in year y for cell c.

Mortality $Z_{c,d}$ can be decomposed to natural mortality, $M_{c,d}$, and fishing mortality, $F_{c,d}$, where both $M_{c,d}$ and $F_{c,d}$ are instantaneous rates with $M_{c,d}$ fixed and $F_{c,d}$ calculated by solving the Baranov catch equation (Hilborn and Walters, 1992) for $F_{c,d}$:

$$C_{c,d} = \frac{F_{c,d}}{F_{c,d} + M_{c,d}} \cdot \Big(1 - \mathrm{e}^{-(F_{c,d}+M_{c,d})}\Big) \cdot B_{c,d} \tag{3.2}$$

where $C_{c,d}$ is the summed catch from the fishing model across all fleets and vessels in cell c for the population during the day d, and $B_{c,d}$ the daily biomass for the population in the cell. Here, catch is the sum of those across all fleets and vessels, $C_{c,d} = \sum_{fl=1}^{FL} \sum_{v=1}^{V_{fl}} E_{fl,v,c,d} \cdot Q_{fl} \cdot D_{c,d}$ with fl and FL the fleet and total number of fleets, v and V_{fl} the vessel and total number of vessels per fleet respectively and $E_{fl,v,c,d}$ and Q_{fl} fishing effort and catchability of the gear, and $D_{c,d}$ is the density of the population at the location fished.

3.3.2 Recruitment dynamics

Recruitment is modelled as a function of adult biomass. In *MixFishSim*, it can either take the form of a stochastic Beverton-Holt stock recruitment relationship, or a stochastic Ricker stock recruitment relationship. The Beverton-Holt

Table 3.1: Description of variables for population and recruitment dynamics sub-modules.

Variable	Meaning	Units
	Population dynamics	
Delay-difference model		
$B_{c,d}$	Biomass in cell c and day d	kg
$Z_{c,d}$	Total mortality in cell c for day d	-
$R_{c,\tilde{y}}$	Annualy recruited fish in cell	yr^{-1}
ρ	Ford's growth coefficient	yr^{-1}
Wt_R	Weight of a fully recruited fish	kg
Wt_{R-1}	Weight of a pre-recruit fish	kg
α_d	Proportion of annually recruited fish recruited during day d	-
Baranov catch equation		
$C_{c,d}$	Catch from cell c for day d	kg
$F_{c,d}$	Rate of fishing mortality in cell c on day d	d^{-1}
$M_{c,d}$	Rate of natural mortality in cell c on day d	d^{-1}
$B_{c,d}$	Biomass in cell c on day d	kg
	Recruitment dynamics	
$\bar{R}_{c,d}$	is the number of fish recruited in cell c for day d	d^{-1}
α	the maximum recruitment rate (Beverton Holt) or maximum productivity per spawner (Ricker)	number fish
β	the stock size required to produce half the maximum rate of recruitment (Beverton Holt) or density dependent reduction in productivity per capita of SSB	number fish

relationship is defined as(Beverton and Holt, 1957):

$$\begin{aligned} \bar{R}_{c,d} =& \frac{(\alpha S_{c,d})}{(\beta + S_{c,d})} \\ \ln(R_{c,d}) \sim& N[(\ln(\bar{R}_{c,d}), \sigma^2)] \end{aligned} \tag{3.3}$$

where α is the maximum recruitment rate, β the spawning stock biomass (SSB) required to produce half the maximum stock size, S current stock size and σ^2 the variability in the recruitment due to stochastic processes. The stochastic Ricker form (Ricker, 1954) is:

$$\begin{aligned} \bar{R}_{c,d} =& B_{c,d} \cdot \mathrm{e}^{(\alpha - \beta \cdot B_{c,d})} \\ \ln(R_{c,d}) \sim& N[(\ln(\bar{R}_{c,d}), \sigma^2)] \end{aligned} \tag{3.4}$$

Table 3.2: Description of variables for population movement sub-module.

Variable	Meaning	Units
Thermal tolerance		
$T_{c,wk}$	Temperature for cell c in week wk	°C
μ_p	Mean of the thermal tolerance for population p	°C
σ_p	Standard deviation of thermal tolerance for population p	°C
Population movement model		
λ	Decay rate for population movement	-
$Hab_{c,p}$	Habitat suitability for cell c and population p	-
$Tol_{c,wk,p}$	Thermal tolerance for in cell c at week wk for population p	-
$d_{I,J}$	Euclidean distance between cell I and cell J	-

Table 3.3: Description of variables for fleet dynamics sub-module.

Variable	Meaning	Units
Rev	Revenue from fishing tow	€
$RefRev$	Reference revenue for determining the step function	€
L_p	Landings of population p	kg
Pr_p	Average price of population p	€.kg^{-1}
Le	Step length for vessel	-
Br	Bearing	degrees
k	Concentration parameter for von mises distribution	-
β_1	shape parameter for step function	-
β_2	shape parameter for step function	-
β_3	shape parameter for step function	-

where α is the maximum productivity per spawner and β the density-dependent reduction in productivity as the SSB increases.

3.3.3 Population movement dynamics

Population movement is a combination of directed (advective) movement where at certain times of year the population moves towards spawning grounds by increasing the probabilities of moving into the spawning grounds from adjacent cells, and random (diffusive) movement, governed by a stochastic process where movement between adjacent cells is described by a set of probabilities. Stochastic probabilities are affected by the suitability of habitat, temperature

Table 3.4: Population dynamics and movement parameter settings.

Parameter	Pop 1	Pop 2	Pop 3	Pop 4
Habitat quality				
Matérn ν	1/0.015	1/0.05	1/0.01	1/0.005
Matérn κ	1	2	1	1
Anisotropy	1.5,3,-3,4	1,2,-1,2	2.5,1,-1,2	0.1,2,-1,0.2
Spawning areas (bound box)	40,50,40,50; 80,90,60,70	50,60,30,40; 80,90,90,90	30,34,10,20; 60,70,20,30	50,55,80,85; 30,40,30,40
Spawning multiplier = 10				
Movement $\lambda = 0.1$				
Population dynamics				
Starting Biomass	1e5	2e5	1e5	1e4
Beverton-Holt Recruit α	6	27	18	0.3
Beverton-Holt Recruit β	4	4	11	0.5
Beverton-Holt Recruit σ^2	0.7	0.6	0.7	0.6
Recruit week	13-16	12-16	14-16	16-20
Spawn week	16-18	16-19	16-18	18-20
$K = 0.3$				
$wt = 1$				
$wt_{d-1} = 0.1$				
M (annual)	0.2	0.1	0.2	0.1
Movement dynamics				
μ_p	12	15	17	14
σ_p^2	8	9	7	10

in a cell and the thermal tolerance of a population to that temperature.

The combined process results in a population structure and movement pattern unique to each population, with population movement occurring on a weekly basis. Modelling population movement on a weekly timescale reflects that fish tend to aggregate in species-specific locations that have been observed to last between one and two weeks (Poos and Rijnsdorp, 2007b). Therefore this process approximated the demographic shifts in fish populations throughout a year with seasonal spawning patterns (Figure S5).

To simulate fish population distribution in space and time a Gaussian spatial process was employed to model habitat suitability for each of the populations on a 2d grid. We first defined a Gaussian random field process,

Table 3.5: Fleet dynamics parameter settings.

Parameter	Fleet 1	Fleet 2	Fleet 3	Fleet 4	Fleet 5
Targeting preferences	pop 2/4	pop 1/3	-	pop 4	pop 2/3
Price $Pr_p1 = 100$					
Price $Pr_p2 = 200$					
Price $Pr_p3 = 350$					
Price $Pr_p4 = 600$					
Q_p	0.01	0.02	0.02	0.01	0.01
Q_p	0.02	0.01	0.02	0.01	0.03
Q_p	0.01	0.02	0.02	0.01	0.02
Q_p	0.02	0.01	0.02	0.05	0.01
Exploitation dynamics					
β_1	1	2	1	2	3
β_2	10	15	8	12	7
β_3, the landings value nth quantile	90	90	85	90	80
step function *rate*	20	30	25	35	20
Past Knowledge = TRUE					
Threshold	0.7	0.7	0.7	0.7	0.7
Fuel Cost	3	2	5	2	1

$\{S(c) : c \in \mathbb{R}^2\}$, where for any set of cells $c_1, \ldots, c_n$, the joint distribution of $S = \{S(c_1), \ldots S(c_n)\}$ is multivariate Gaussian with a *Matérn* covariance structure, where the correlation strength weakens with distance controlled by two parameters, with ν a scale parameter in the units of distance and κ a shape parameter which determines the smoothness of the process. We use the most commonly used Matérn covariance structure as it is a flexible form that contains the exponential and double exponential as special cases and it enables us to model the spatial autocorrelation observed in animal populations where density is more similar in nearby locations (Tobler, 1970; F. Dormann et al., 2007; Poos and Rijnsdorp, 2007b).

We change the parameters to implement different spatial structures for the different populations using the *RandomFields* R package (Schlather et al., 2015). We define a stationary habitat field with an anisotropic pattern (to simulate a depth gradient) and combine it with a temporally dynamic thermal tolerance field to imitate two key drivers of population dynamics without modelling the processes explicitly. Each population was initialised at a single location, and subsequently moved across the entire space according to a probabilistic distribution based on habitat suitability (represented by the normalised values from the GRFs), temperature tolerance and distance from current cell:

$$Pr(C_{wk+1} = J | C_{wk} = I) = \frac{\mathrm{e}^{-\lambda \cdot d_{I,J}} \cdot (Hab_{J,p}^2 \cdot Tol_{J,p,wk})}{\sum_{c=1}^{C} \mathrm{e}^{-\lambda \cdot d} \cdot (Hab_{c,p}^2 \cdot Tol_{c,p,wk})} \tag{3.5}$$

Where $d_{I,J}$ is the euclidean distance between cell I and cell J, λ is a given rate of decay, $Hab_{c,p}$ is the index of habitat suitability for cell c and population p, with $Tol_{c,p,wk}$ the temperature tolerance for cell c by population p in week wk (see below).

During pre-defined weeks of the year the habitat suitability is modified with user-defined spawning habitat locations, resulting in each population having concentrated areas where spawning takes place. The populations then move towards these cells in the weeks prior to spawning, resulting in directional movement towards the spawning grounds.

A time-varying temperature covariate changes the interaction between time and suitable habitat on a weekly time-step. Each population p was assigned a thermal tolerance with mean, μ_p and standard deviation, σ_p so that each cell and population temperature tolerance is defined as:

$$Tol_{c,p,wk} = \frac{1}{\sqrt{2\pi\sigma_p^2}} \exp\left(-\frac{(T_{c,wk} - \mu_p)^2}{2\sigma_p^2}\right) \tag{3.6}$$

Where $Tol_{c,p,wk}$ is the tolerance of population p for cell c in week wk, $T_{c,wk}$ is the temperature in the cell given the week and μ_p and σ_p the mean and standard deviation of the population temperature tolerance (see Table 3.2 for variable descriptions).

3.3.4 Fleet dynamics

Fleet dynamics were broadly categorised into three components. *Fleet targeting* determined the fleet catch efficiency and preference towards a particular population; *trip-level decisions* determined the initial location to be fished at the beginning of a trip; and *within-trip decisions* determined fishing locations within a trip. This results in an explore-exploit strategy for individual vessels to maximise their catch from an unknown resource distribution (Bailey et al., 2019). The decision to use an individual based model for fishing vessels was taken because fishers are heterogeneous in their location choice behaviour due to different objectives, risk preference and targeting preference (Van Putten et al., 2012; Boonstra and Hentati-Sundberg, 2016). Therefore fleet dynamics are emergent from individual dynamics rather than pre-defined group dynamics.

3.3.4.1 Fleet targeting

Each fleet of n_{fl} vessels was characterised by both a general efficiency, Q_{fl}, and a population specific efficiency, $Q_{fl,p}$ which are each bound by [0,1]. The product of these parameters $[Q_{fl} \cdot Q_{fl,p}]$ affects the overall catch rates for the fleet and the preferential targeting of one species over another. This, in combination with the parameter choice for the step-function defined below (as well as some randomness from the exploratory fishing process) determined the preference of fishing locations for the fleet.

3.3.4.2 Decision about where to fish at the start of a trip

Several studies (for a review see Girardin et al., 2017) have confirmed past activity and past catch rates are strong predictors of fishing location choice. For this reason, the fleet dynamics sub-model included a learning component, where a vessel's initial fishing location in a trip was based on selecting from previously successful fishing locations. This was achieved by calculating an expected revenue based on the catches from locations fished in the preceding trip as well as the same month periods in previous years and the travel costs from the port to the fishing grounds. Then a vessel chooses randomly from the top 70 % of fishing events (defined as the 'threshold') in terms of expected profit within that season.

3.3.4.3 Decision about where to fish within a trip

Fishing locations within a trip are initially determined by a modified random walk process. As the simulation progresses the within-trip decision become gradually more influenced by experience gained from past fishing locations (as per the initial trip-level location choice), moving location choice towards areas of higher perceived profit. A random walk was chosen for the exploratory fishing process as it is the simplest assumption commonly used in ecology to describe optimal animal search strategy for exploiting heterogeneously distributed prey about which there is uncertain knowledge (Viswanathan et al., 1999). In a random walk, movement is a stochastic process through a series of steps. These steps have a length, and a direction that can either be equal in length or take some other functional form. The direction of the random walk was also correlated (known as 'persistence') providing some overall directional movement (Codling et al., 2008).

For our implementation of a random walk, directional change is based on a negatively correlated circular distribution where a favourable fishing ground is likely to be "fished back over" by the vessel returning in the direction it came from. The step length (i.e. the distance travelled from the current to the next fishing location) is determined by relating recent fishing success, measured as the summed value of fish caught (revenue, *Rev*);

$$Rev_{c,d} = \sum_{p=1}^{P} L_{c,d,p} \cdot Pr_p \tag{3.7}$$

where $L_{c,d,p}$ is landings of a population p, and Pr_p price of a population. All population prices were kept the same across fleets and seasons. Here, when fishing is successful vessels remain in a similar location and continue to exploit the local fishing grounds. When unsuccessful, they move some distance away from the current fishing location. The movement distance retains some degree of stochasticity, that can be controlled separately, but is determined by the relationship:

$$Le = \mathrm{e}^{\ln(\beta_1)+\ln(\beta_2)-\left(\ln\left(\frac{\beta_1}{\beta_3}\right)\right)\cdot Rev} \tag{3.8}$$

Where β_1, β_2 and β_3 are parameters determining the shape of the step function in its relation to revenue, so that, a step from (x_t,y_t) to (x_{t+1}, y_{t+1}) is defined by:

$$\begin{aligned}
(x_{t+1}, y_{t+1}) = & x_t + Le \cdot \cos\left(\frac{\pi \cdot Br_{t+1}}{180}\right), \\
& y_t + Le \cdot \sin\left(\frac{\pi \cdot Br_{t+1}}{180}\right) \\
when \quad & Br_t < 180, Br_{t+1} = 180 + \sim vm[(0,360), k] \\
& Br_t > 180, Br_{t+1} = 180 - \sim vm[(0,360), k]
\end{aligned} \tag{3.9}$$

where Le is the step length, Br_t is the bearing at time t, k the concentration parameter from the von Mises distribution that we correlate with the revenue so that $k = (Rev + 1/RefRev) \cdot max_k$, where max_k is the maximum concentration value, k, and $RefRev$ is parametrised as for β_3 in the step length function. Details of the variables, meaning and units for fleet dynamics are provided in Table 3.3.

3.3.4.4 Local population depletion

Where several fishing vessels exploit the same fish population, competition is known to play an important role in local distribution of fishing effort (Gillis and Peterman, 1998). If several vessels are fishing on the same patch of fish, local depletion and interference competition will affect fishing location choice of the fleet as a whole (Rijnsdorp, 2000; Poos and Rijnsdorp, 2007a). To account for this behaviour, the fishing sub-model operates spatially on a daily time-step so that for future days the biomass available to the fishery is reduced in the areas fished. The cumulative effect is to make heavily fished areas less attractive as a future fishing location choice as reduced catch rates will be experienced.

3.3.5 Fisheries-independent survey

A fisheries-independent survey is simulated where fishing on a regular grid begins each year at the same time for a given number of stations (a fixed station survey design). Catches of the populations at each station are recorded but not removed from the population (catches are assumed to have negligible impact on population dynamics). This provides a fishery independent snapshot of the populations at a regular spatial intervals each year, similar to scientific surveys undertaken by fisheries research agencies.

3.3.6 Software: R-package development

The simulation framework is implemented in the statistical software package R (R Core Team, 2017) and available as an R package from the author's github site (`www.github.com/pdolder/MixFishSim`).

3.3.7 Model calibration

We calibrate *MixFishSim* to investigate the influence of data aggregation on spatial inference.

3.3.7.1 Population models

We calibrated the simulation model for four example populations with different demographics, growth rates, natural mortality and recruitment (Table 3.4). Habitat preference (Figure S7) and temperature (Figure S9), with temperature tolerance (Figure S10) defined to be unique to each population resulting in differently weekly distribution patterns (Figures S1-S4). In addition, each of the populations was assumed to have two defined spawning areas that result in the populations moving towards these areas in pre-defined weeks (Figure S8) with population-specific movement rates (Table 3.4). The population demographics were chosen to broadly represent three mobile low-medium value groundfish species and one high value species with low mobility. The dynamics were hypothetical but might be expected in a typical demersal fishery.

3.3.7.2 Fleet calibration

Fleets were calibrated to reflect five different characteristic fisheries with unique exploitation dynamics (Table 3.5). By setting different catchability coefficients ($Q_{fl,p}$) we create different targeting preferences between the fleets and hence different spatial dynamics. The learned random walk process implies that within a fleet different vessels have different spatial distributions based on individual experience. The step function was calibrated dynamically within the simulations as the maximum revenue obtainable was not known beforehand. This was implemented so that vessels take smaller steps when fishing at a location that yields landings value in the top 90th percentile of the value experienced in that year so far (as defined per fleet in Table 3.5).

Fishing locations were chosen based on random search and, with increasing proportion as time progressed, experience of profitable catches built up in the same month from previous years and from the previous trip. 'Profitable' in this context was defined as the locations where the top 70 % of expected profit would be found given revenue from previous trips and cost of movement to the new fishing location. This probability was based on a logistic sigmoid function with a lower asymptote of 0 and upper asymptote of 0.95, and a slope that ensures the upper asymptote (where decisions are mainly based on past knowledge) is reached approximately halfway through the simulation.

3.3.7.3 Survey settings

The survey simulation was set up with a fixed gridded station design with 100 stations fished each year, starting on day 92 and ending on day 112 (5 stations per day) with same catchability parameter ($Q_p = 1$) for all populations. This approximates a real world survey design with limited seasonal and spatial coverage.

3.3.7.4 Example research question

To illustrate the capabilities of *MixFishSim*, we investigate the influence of the temporal and spatial resolution of different data sources on the reduction in catches of a population given spatial closures. To do so, we set up a simulation to run for 50 years based on a 100 $\times$ 100 square grid (undetermined units), with five fleets of 20 vessels each and four fish populations. Fishing takes place four times a day per vessel and five days a week, while population movement is every week.

How does sampling-derived fisheries data reflect the underlying population structure?

To answer this question we compare different spatial and temporal aggregations of the true population distributions to:

a) **fisheries-independent data:** the inferred population density from a fixed-site sampling survey design as commonly used for fisheries monitoring purposes;

b) **fisheries-dependent data:** the inferred population density from our fleet model that includes fishery-induced sampling dynamics.

We allow the simulation to run unrestricted for 30 years, then implement spatial closed areas for the last 20 years of the simulation based on data (either derived from the commercial catches, fisheries-independent survey or the true population) used at different spatial and temporal scales.

The following steps are undertaken to determine closures:

1. Extract data source (true population, commercial or survey),
2. Aggregate according to desired spatial and temporal resolution,
3. Interpolate across entire area at desired resolution using simple bivariate interpolation using the *interp* function from the R package akima (Akima and Gebhardt, 2016). This is intended to represent a naive spatial model of catch rates, without knowledge of the spatial population dynamics.
4. Close area covering top 5 % of catch rates.

In total, 28 closure scenarios were run that represent combinations of:

- **data types:** commercial logbook data, survey data and true population,
- **temporal resolutions:** weekly, monthly and yearly closures,
- **spatial resolutions:** 1 x 1 grid, 5 x 5 grid, 10 x 10 grid and 20 x 20 grid,

We implemented a series of spatial closures targeted at reducing fishing mortality on population 3, given the different data sources and spatial and temporal resolutions above. We use the effectiveness of these closures in reducing fishing mortality as a way of evaluating the trade-offs in data sources and resolution. Survey closures were on an annual basis only, as this was the most temporally resolved survey data available. We evaluated the factors contributing to the success of the closures through a regression tree (using the R package REEMtree (Sela and Simonoff, 2011)) to identify the factor most contributing to differences in fishing mortality before and after the closure.

3.4 Results

3.4.1 Emergent simulation dynamics

Individual habitat preferences and thermal tolerances result in different spatial habitat use for each population (Figure S5) and consequently different seasonal exploitation patterns (Figure S6).

It can be seen from a single vessels' movements during a trip that the vessel exploits three different fishing grounds, each of them multiple times (Figure 3.2A), while across several trips, fishing grounds that are further apart are fished (Figure 3.2B). These different locations relate to areas where the highest revenue were experienced, as shown by Figure 3.2D, where several vessels' tracks are overlaid on the revenue field.

Vessels from the same fleet (and therefore targeting preference) may exploit some shared and some different fishing grounds depending on their own personal experience during the exploratory phase of the fishery (Figure 3.2 (C)). This results from the randomness in the correlated random walk step function, with distance moved during the exploitation phase and the direction stochastically related to the revenue experienced on the fishing ground (Figure 3.2 (D)).

3.4.2 How does sampling-derived fisheries data reflect the underlying population structure?

Catch composition aggregated at different spatial resolutions from each of the data sources (average seasonal patterns over a ten-year period) highlights different patterns in perceived community structure depending on the data source and aggregation level (Figure 3.3). The finer spatial grid for the true population (top left) and commercial data (top middle) show visually similar patterns, though there are large unsampled areas in the commercial data from a lack of fishing activity (particularly in the lower left part of the sampling domain). Survey data at this spatial resolution displays very sparse information about the spatial distributions of the populations. The slightly aggregated data on a 5 x 5 grid shows similar patterns and, while losing some of the spatial detail, there remains good consistency between the true population and the commercial data. Survey data starts to pick out some of the similar patterns as the other data sources, but lacks spatiotemporal coverage. The spatial catch information on a 10 x 10 and 20 x 20 grid lose a significant amount of information about the spatial resolutions for all data sources, and some differences between the survey, commercial and true population data emerge.

Different perceptions of the proportion of each stock in an area are seen when we aggregate the data at different timescales, with weekly (top), monthly

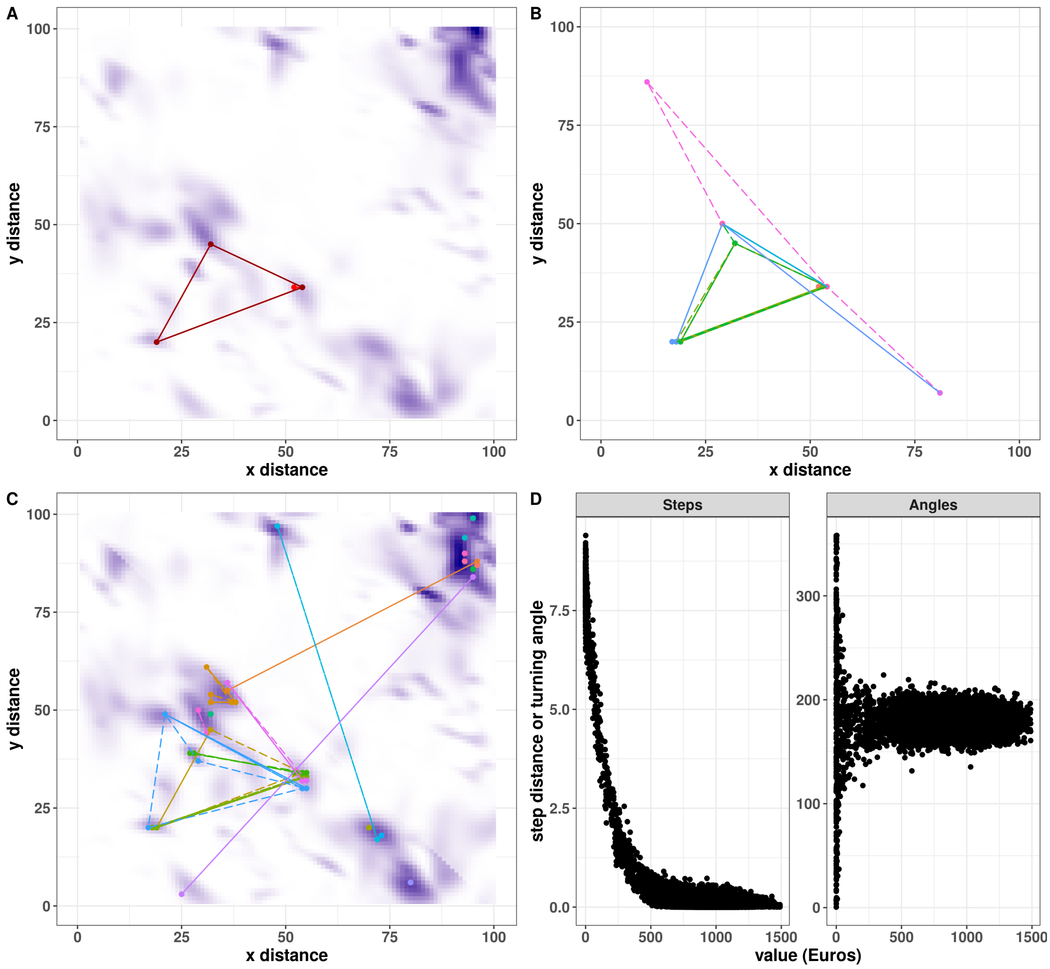

Figure 3.2: (A) The fishing locations (points) and movements (lines) of a single vessel during a trip overlaid on the revenue of a fishing site (landings x price; darker purple = higher revenue); (B) the fishing locations of the vessel over several trips (value field changes over the period so not shown). Note that movements are a mixture of correlated random walk (solid lines) and experience-based (dashed lines), and that the field is wrapped on a torus so that opposite sides of the spatial domain are considered spatially close; (C) the locations of multiple vessels from the same fleet overlaid on the value field, (D) the realised step distance and turning angles for a single vessel over the simulation.

(middle) and yearly (bottom) catch compositions from across an aggregated 20 x 20 area showing different patterns (Figure 3.4). In the true population, the monthly aggregation captures the major patterns of composition seen in the weekly data with the percentage of different populations in the catch having similar mean and standard deviations (Table 3.6). In the weekly and monthly data population 2 dominates. However, some of the variation was lost when aggregated to an annual level, as indicated from the lower standard deviations (Table 3.6).

Weekly commercial data shows some of the same patterns as the true population, though population 1 is less well represented and some weeks are missing catches from the area. Here, weekly and monthly compositions were nearly identical (Figure 3.4; Table 3.6). Yearly values had a similar mean but smaller standard deviation. The survey data was only available on an annual basis, and showed again a slightly different composition from the true population and the commercial data; in particular a greater proportion of population 4 (Figure 3.4).

Table 3.6: Mean and standard deviation of proportions of each species at different levels of temporal aggregation

Data type	Timescale	Population 1	Population 2	Population 3	Population 4
commercial	monthly	0.047(0.014)	94.435(1.47)	3.122(1.468)	2.396(0.444)
commercial	weekly	0.047(0.016)	94.426(1.514)	3.117(1.563)	2.411(0.498)
commercial	yearly	0.051(0.001)	94.388(0.205)	3.021(0.175)	2.539(0.046)
True Population	monthly	9.225(3.872)	83.287(5.522)	3.624(1.151)	3.864(1.519)
True Population	weekly	9.358(3.992)	83.165(5.596)	3.567(1.233)	3.91(1.592)
True Population	yearly	9.899(0.173)	82.25(0.308)	3.821(0.119)	4.031(0.05)
survey	yearly	0.372(0.005)	87.667(0.193)	0.729(0.02)	11.232(0.172)

3.4.3 How does data aggregation and source impact on spatial fisheries management measures?

In most cases the fishery closure was successful in reducing fishing mortality on the species of interest (population 3; Figure 3.5). Interestingly the largest reductions in fishing mortality happened immediately after the closures, following which the fisheries “adapted" to the closures by finding new areas of high abundance to fish. This led to fishing mortality increasing again, though not to past levels (Figure 3.5). The exception to the success was the closures implemented based on the coarsest spatial (20 x 20) and temporal resolution (yearly) that was ineffective (i.e. failed to reduce fishing mortality) with all data sources. As expected, closures based on the “known" population distribution were most effective, with differing degrees of success using the commercial data. Fishing mortality rates on the other species changed in different proportions, depending on whether the displaced fishing effort moved to areas where the populations were found in greater or lesser density.

Table 3.7: Fishing mortality effects of the closure scenarios on population 3 (ordered by most effective first). The fishing mortality rate before the closure was 1.08.

Scenario No	F after closure	% F change	data type	timescale	resolution
9	0.29	-73.47	true Population	weekly	1.00
10	0.29	-72.94	true Population	monthly	1.00
11	0.35	-68.04	true Population	yearly	1.00
45	0.58	-46.70	commercial	yearly	20.00
1	0.58	-46.21	commercial	weekly	1.00
23	0.59	-45.27	true Population	weekly	5.00
2	0.59	-45.06	commercial	monthly	1.00
7	0.60	-44.48	survey	yearly	1.00
24	0.61	-43.20	true Population	monthly	5.00
3	0.64	-40.82	commercial	yearly	1.00
25	0.65	-39.94	true Population	yearly	5.00
17	0.67	-38.11	commercial	yearly	5.00
15	0.71	-34.38	commercial	weekly	5.00
43	0.71	-34.31	commercial	weekly	20.00
16	0.73	-32.58	commercial	monthly	5.00
51	0.78	-27.92	true Population	weekly	20.00
37	0.78	-27.76	true Population	weekly	10.00
39	0.79	-26.98	true Population	yearly	10.00
38	0.81	-25.47	true Population	monthly	10.00
21	0.81	-25.21	survey	yearly	5.00
35	0.81	-25.05	survey	yearly	10.00
44	0.87	-19.91	commercial	monthly	20.00
52	0.88	-18.39	true Population	monthly	20.00
30	0.96	-11.06	commercial	monthly	10.00
29	0.98	-9.80	commercial	weekly	10.00
31	1.03	-4.36	commercial	yearly	10.00
53	1.06	-1.64	true Population	yearly	20.00
49	1.07	-1.01	survey	yearly	20.00

The factor most contributing to differences in fishing mortality before and after the closure was the population (72 % showing that the closures were effective for population 3), followed by spatial data resolution (21 %), data type (7 %) with the least important factor the timescale (< 1 %). In general the finer the spatial resolution of the data used the greater reduction in fishing mortality for population 3 after the closures (Figure 3.6). The notable outliers are the commercial data at the coarsest spatial resolution (20 x 20) at a yearly and weekly timescale, where closures were nearly as effective as the fine-scale resolution. In this case the closures were sufficiently large to protect a core area of the habitat for the population, but this was achieved in a fairly crude manner by closing a large area - including area where the species was not found (Figure 3.7) that may have consequences in terms of restricting the fishery in a much larger area than necessary. We found that these trade-offs existed, with high catches maintained with an effective closure when the highest resolution data was used, with the effect being linear when the true population distribution was known and also persisting for closures based on commercial information (Figure 3.8).

3.5 Discussion

Our study presents a new highly resolved fisheries simulation framework to evaluate the importance of data scaling and considers potential bias introduced through data aggregation when using fisheries data to infer spatiotemporal dynamics of fish populations. Understanding how fishers exploit multiple heterogeneously distributed fish populations with different catch limits or conservation status requires detailed understanding of the overlap of resources; this is difficult to achieve using conventional modelling approaches due to species targeting in fisheries resulting in preferential sampling (Martínez-Minaya et al., 2018). Often data are aggregated or extrapolated which requires assumptions about the spatial and temporal scale of processes. Our study explores the assumptions behind such aggregation and preferential sampling to identify potential impacts on management advice. With modern management approaches increasingly employing more nuanced spatiotemporal approaches to maximise productivity while taking account of both the biological and human processes operating on different time-frames (Dunn et al., 2016), understanding assumptions behind the data used - increasingly a combination of logbook and positional information from vessel monitoring systems - is vital to ensure measures are effective.

3.5.1 Simulation dynamics

We employ a simulation approach to model each of the population and fishery dynamics in a hypothetical 'mixed fishery', allowing us to i) evaluate the consequences of different aggregation assumptions on our understanding of the spatiotemporal distribution of the underlying fish populations, and ii) evaluate the effectiveness of a spatial closure given those assumptions.

Our approach is unique in that it captures fine scale population and fishery dynamics and their interaction in a way not usually possible with real data and thus not usually considered in fisheries simulations. While other simulation frameworks seek to model individual vessel dynamics based on inferred dynamics from VMS and logbook records (Bastardie et al., 2010), or as a system to identify measures to meet particular management goals (Bailey et al., 2019), our framework allows users to explore assumptions in modelling observational data and to evaluate the underlying dynamics of such approaches at fine spatial and temporal scales. This offers the advantage that larger scale fishery patterns are emergent properties of the system and results can be compared to those obtained under a statistical modelling framework.

Typically, simulation models that treat fish as individuals are focussed on exploring the inter- and intra- specific interactions among fish populations (e.g. OSMOSE; Shin et al. (2004)) in order to understand how they vary over space and time. Our focus was on understanding the strengths and limitations of inference from catch data obtained through commercial fishing activity with fleets exploiting multiple fish populations. This shows how realised catch distributions may differ from the underlying populations, as identified by Gillis et al. (2008). As such, we favoured a minimum realistic model of the fish populations (Plagányi et al., 2014) taking account of environmental but not demographic stochasticity, while incorporating detailed fishing dynamics that take account of different drivers in a mechanistic way.

Demographic stochasticity arises due to individual-level variability in time to reproduction and death. This form of stochasticity is often modelled by drawing random time intervals from a given distribution (Gillespie, 1977). The impact of demographic stochasticity depends on the population size, with the effects expected to decrease with increasing population size (Lande et al., 2010). This contrasts with environmental stochasticity, which affects all population sizes and is present at the population level in our model by variability in recruitment.

We take account of heterogeneity in fleet dynamics due to different preferences and drivers similarly to other approaches (Fulton et al., 2011), but at an individual vessel rather than fleet level. We do not explicitly define fleets as rational profit maximisers at the outset, but consider there are several stages to development of the fishery; information gathering through search where the resource location is not known, followed by individual learnt behaviour of profitable locations. This provides a realistic model of how fishing patterns are established and maintained to exploit an uncertain resource through an explore-exploit strategy (Mangel and Clark, 1983; Bailey et al., 2019).

3.5.2 How does sampling-derived fisheries data reflect the underlying population structure?

Our results demonstrate the importance of considering data scale and resolution when using observational data to support management measures. We find that understanding of the community composition dynamics will depend on the level of data aggregation and it is important to consider the scale of processes; including population movement rates, habitat uniformity and fishing targeting practices if potential biases in data are to be understood and taken into account (Figures 3.2 and S7).

Our simulation shows that, despite biases introduced through the fishing process, the commercially derived data could still inform on the key spatial patterns in the community structures where the fisheries occurred, which was spatially limited due to the “hotspots" of commercially valuable species being fished. Similarly, despite even spatial coverage, the survey captured some of the same spatial patterns as the true population, but missed others due to gaps between survey stations limiting spatial and temporal coverage (Figure 3.3). This provides a challenge when modelling unsampled areas in inferring species distribution maps, though these limitations may be overcome by understanding the relationship between the species and habitat covariates where these are known at unsampled locations (Robinson et al., 2011).

3.5.3 How does data aggregation and source impact on spatial fisheries management measures?

From our simulations, spatial disaggregation was more important than the temporal disaggregation of the commercial data. This reflects the fact that there was greater spatial heterogeneity over the spatial domain than experienced in given locations over the course of the year (Figure S5).

The yearly data assumes the same proportion of each population caught at any time of the year due to the data aggregation. This assumption introduces 'aggregation bias' as the data may only be representative of some point (or no point) in time. The monthly data shows some consistency between the real population and commercial data for population 2 - 4, though population 1 remains under-represented. On an annual basis, interestingly, the commercial data under represents the population 1 while the survey over represents population 4. This is likely due to the biases in commercial sampling, with the fisheries not targeting the areas where population 1 are present and the survey sampling areas where population 4 is more abundant than on average. This indicates that fixed closures, at the right resolution, when based on commercially derived data have the potential to reduce fishing mortality. The likely cost of poor spatial and temporal resolution is associated with reduced effectiveness and potentially closing fishing opportunities for other fisheries (Figure 3.8).

Two contrasting real world approaches in this respect were the spatial closures to protect cod in the North Sea. In one example, large scale spatial closures were implemented with little success due to effort displacement to previously unfished areas (Dinmore et al., 2003), while in another, small scale targeted spatiotemporal closures were considered to have some effect in reducing cod mortality without having to disrupt other fisheries substantially (Needle and Catarino, 2011). These examples emphasise the importance of considering the right scale and aggregation of data when identifying area closures and the need to consider changing dynamics in the fisheries in response to such closures.

Our study showed that fishing rates on other populations also changed (both up and down) as a side-effect of closures to protect one species. This indicates the importance of considering fishing effort reallocation following spatial closures, and our simulation allows us to consider the spatiotemporal reasons for these changes.

3.5.4 Model assumptions and caveats

We modelled the population and fleet dynamic processes to draw inference on the importance of data scale and aggregation in understanding and managing mixed fisheries and their impact on multiple fish populations. In doing so, we necessarily had to make a number of simplifying assumptions.

Fish populations in our simulations move in pre-defined timescales and according to fixed habitat preferences and temperature gradients (Figures S7, S9). Our assumptions in calibrating the model (movement rates, temperature tolerances) will have a direct impact on our conclusions on the relative importance of spatial and temporal processes. These assumptions could be explored in a future study by varying the parameters and assessing the robustness of our conclusions. For our example application we have chosen movement rates to reflect aggregation periods observed in past studies (Poos and Rijnsdorp, 2007b).

In addition, we have assumed that fishing vessels are not restricted by quota and therefore discarding of species for which vessels have no quota or that are unwanted is not taken into account. This is likely to be a significant source of bias in any inference using commercial data and should also be explored. For example, *MixFishSim* could be altered to allow for spatiotemporal appraisal of the impact of discarding on fisher behaviour and underlying populations via inclusion as discarding behaviour, or through move-on rules or cessation of fishing activity when quota is exhausted.

3.5.5 Future applications of *MixFishSim*

We consider that the increased availability of high resolution catch and locational information from commercial fisheries will make it a key source of data for ensuring management is implemented at the right scale in future. For example, identifying hot-spots for bycatch reduction or identifying spatial overlaps in mixed fisheries (Dolder et al., 2018; Gardner et al., 2008; Little et al., 2015; Dedman et al., 2015; Ward et al., 2015). Our simulation model has the potential to test some of the assumptions behind the modelling approaches in identifying such hotspots and indeed behind spatiotemporal modelling in general, e.g. comparing GAMs, GLMMs, Random Forests and geostatistical models under different data generation processes as exampled by Stock et al. (2020).

Other novel applications of our framework could be: testing different survey designs given multiple species and data generating assumptions (Xu et al., 2015); commercial index standardisation methods and approaches and understanding of appropriate scales and data aggregations and non-proportionality in catch rate and abundance (Harley et al., 2001; Maunder and Punt, 2004); exploring assumptions about the distribution of natural mortality and fishing mortality throughout the year and importance of capturing in-year dynamics in estimating stock status (Liu and Heino, 2014); at-sea sampling scheme designs to deliver unbiased estimates of population parameters (Cotter and Pilling, 2007; Kimura and Somerton, 2006); adaptive management (Walters, 2007; Dunn et al., 2016); testing the ability of commonly employed fleet dynamics models such as Random Utility Models to capture fine scale dynamics and understand their importance (Girardin et al., 2017); and as a detailed operating model in a management strategy evaluation (Mahévas and Pelletier, 2004).

3.6 Conclusions

MixFishSim provides a detailed simulation framework to explore the interaction of multiple fisheries exploiting different fish populations. The framework enables users to evaluate assumptions in modelling commercially derived data through comparison to the true underlying dynamics at a fine spatial and temporal scale. Understanding these dynamics, the limitations of the data and any potential biases that may be introduced when making inference on spatiotemporal interactions will enable users to identify weaknesses in modelling approaches and identity where data collection is needed to strengthen inference.

Our application shows that inference on community dynamics may change depending on the scale of data aggregation. There is an important balance in ensuring that the data are sufficiently spatially and temporally disaggregated that the main features of the data are captured, yet maintaining enough data coverage that the features can be distinguished. We found greater spatial than temporal heterogeneity. When using aggregated data to define spatial closures coarser temporal resolution (months instead of weeks) could still achieve the same results in reducing exploitation rates of a vulnerable species as the highest temporal resolution data. Conversely, reducing the spatial resolution had a negative effect on the effectiveness of the measures though, importantly, there was still some benefit even with coarse spatial resolution.

While case-specific, our findings emphasise the need to understand population demographics, habitat use and movement rates in designing any closure scenario based on observational sampling. This information can then be used to set the bounds on data aggregation used in modelling studies aimed at informing the management measures.

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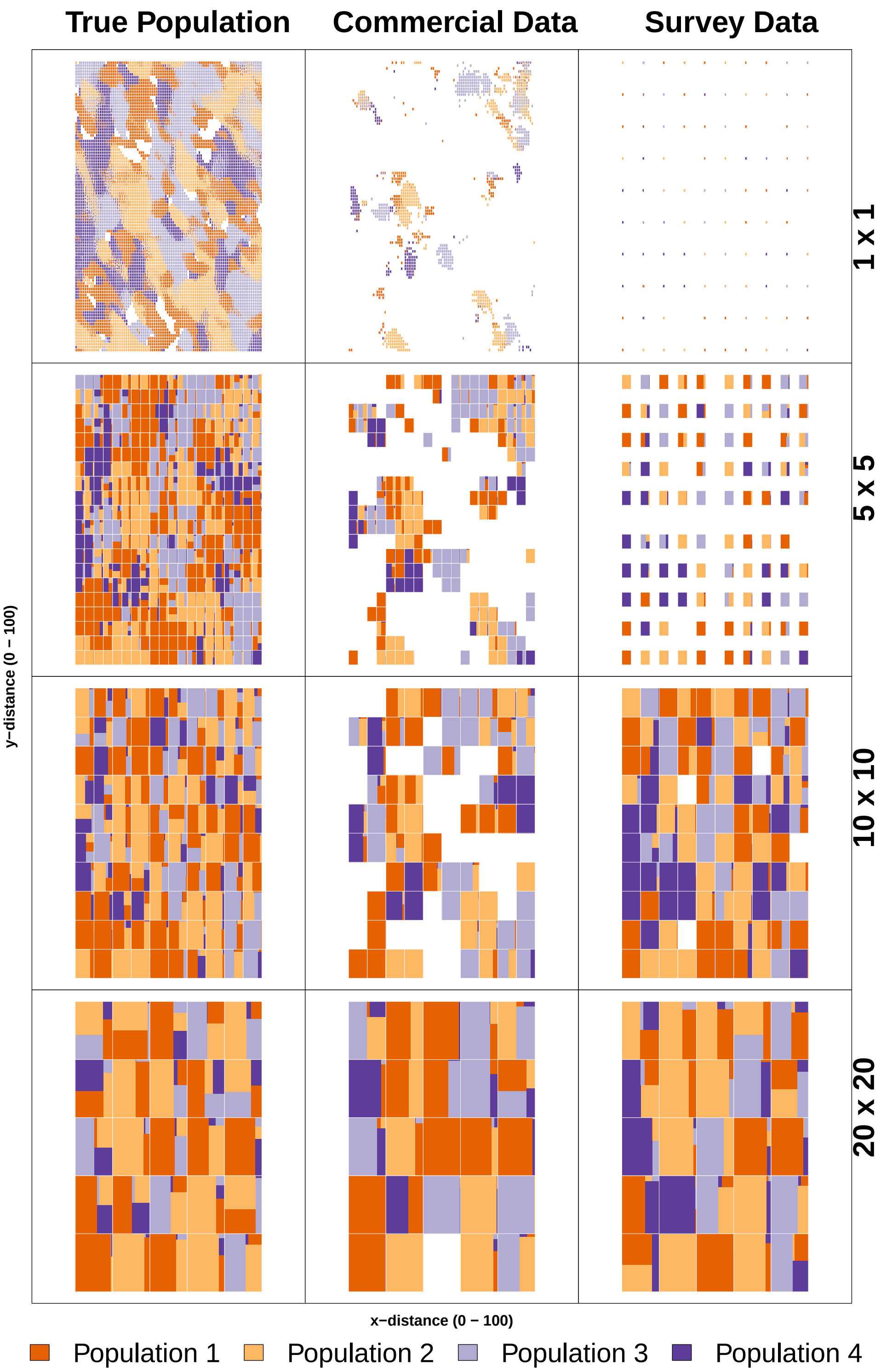

Figure 3.3: Data aggregation at different spatial resolutions over a ten year period. The figure shows catch composition at each spatial unit represented by a square pie chart of the four populations. The area of each colour is proportional to the weight of each population caught in that unit. Figure produced using the R package 'mapplots' (Gerritsen (2014).

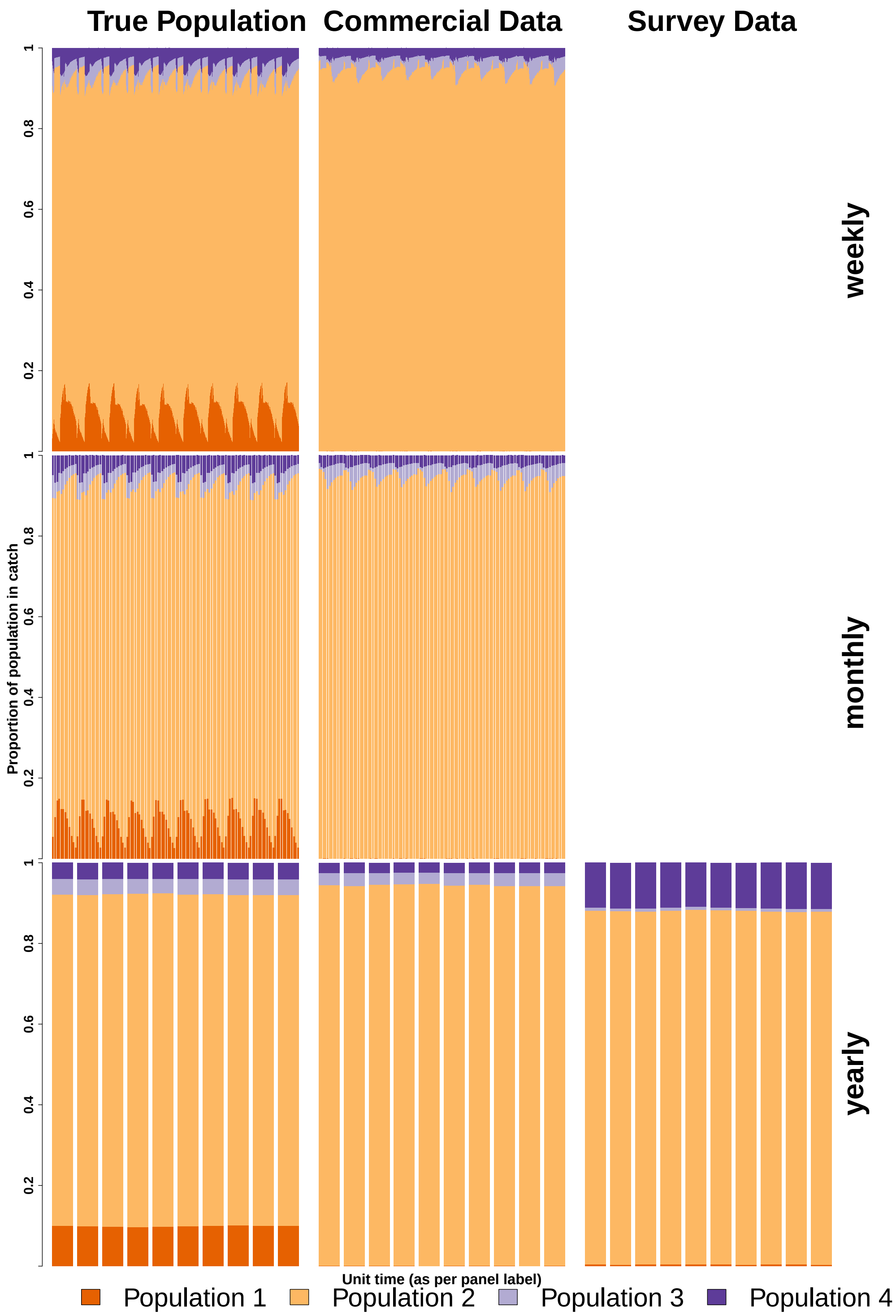

Figure 3.4: Proportion of each population (y axis) for data aggregated at different temporal resolutions. Data is aggregated over a ten-year period for an area 20 x 20. Each bar represents either a week, month or year respectively.

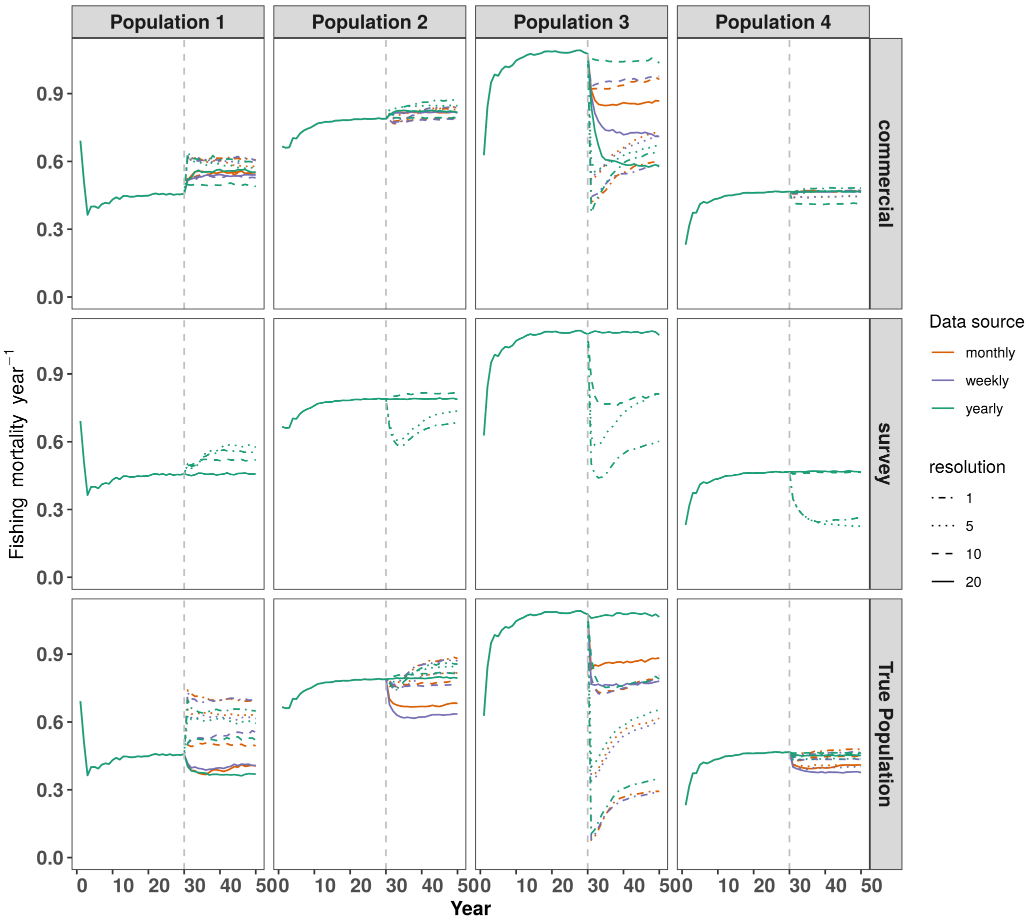

Figure 3.5: Comparison of closure scenarios effect on fishing mortality trends. Line colour denotes timescale, while linestyle denotes spatial resolution. The vertical dashed line indicates the onset of the spatial closures.

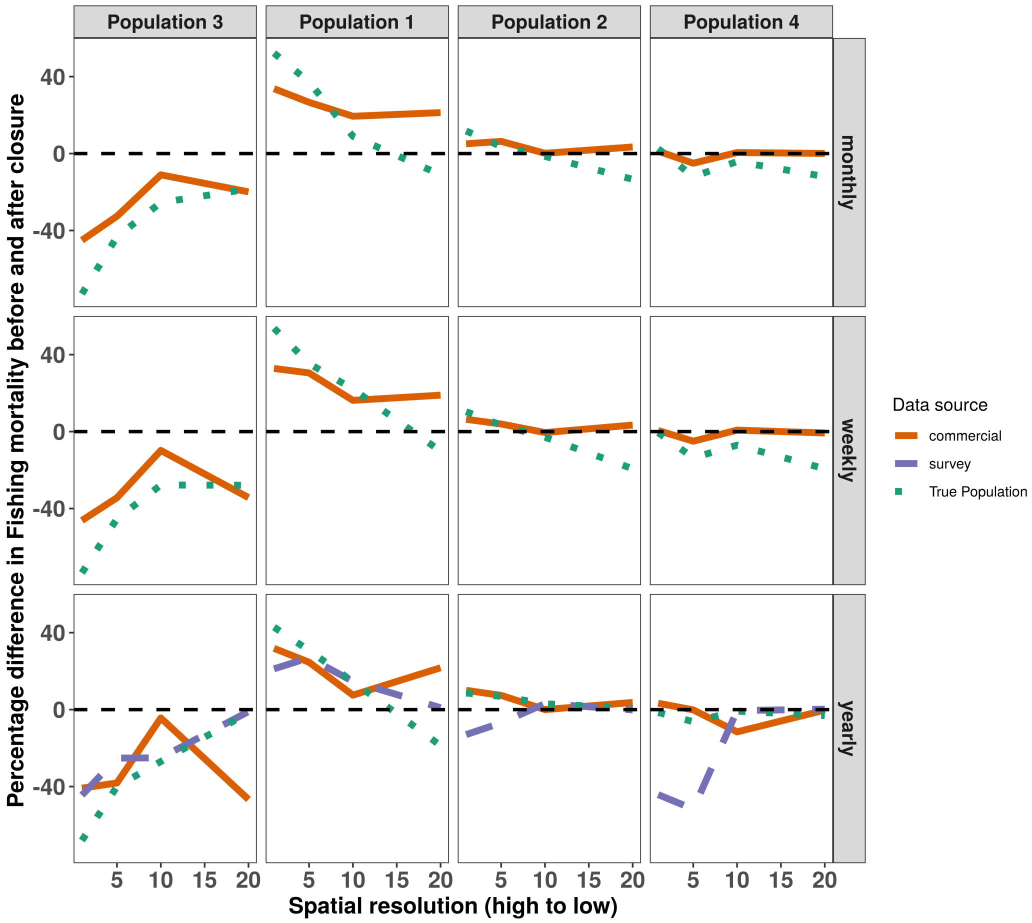

Figure 3.6: Comparison of closure scenario effectiveness based on different spatial and temporal resolutions.

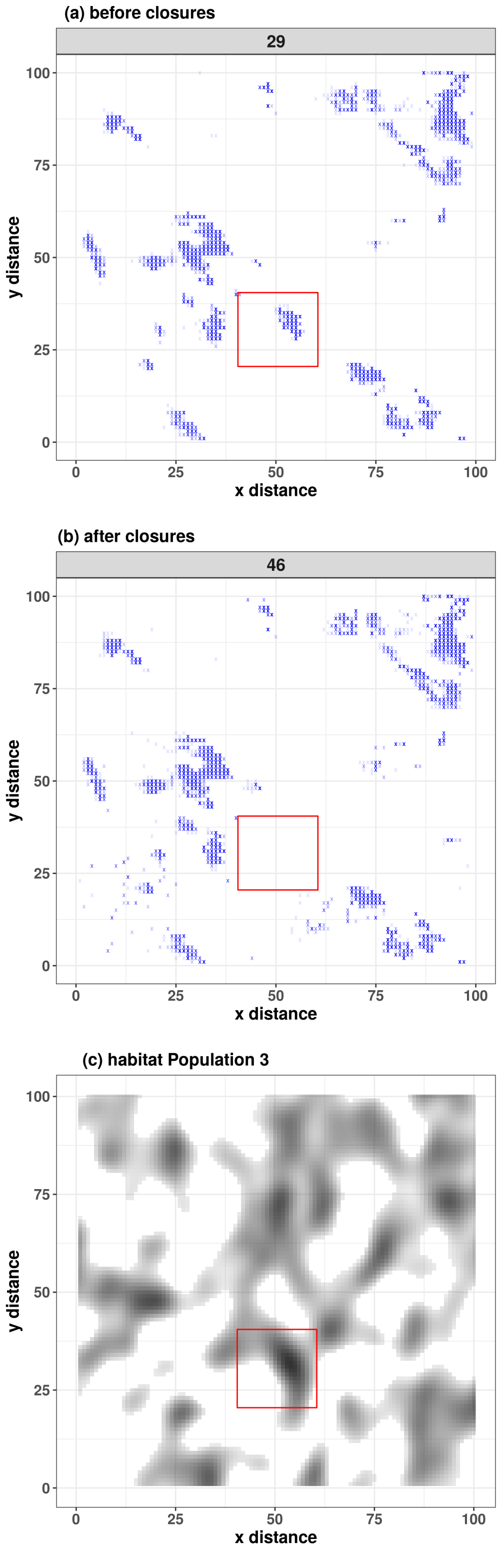

Figure 3.7: The location of fishing effort, (a) before the spatial closure and (b) after the spatial closure (years in panel), and (c) the suitable habitat for population 3. The site of the closure can be seen in the red box on all three panels.

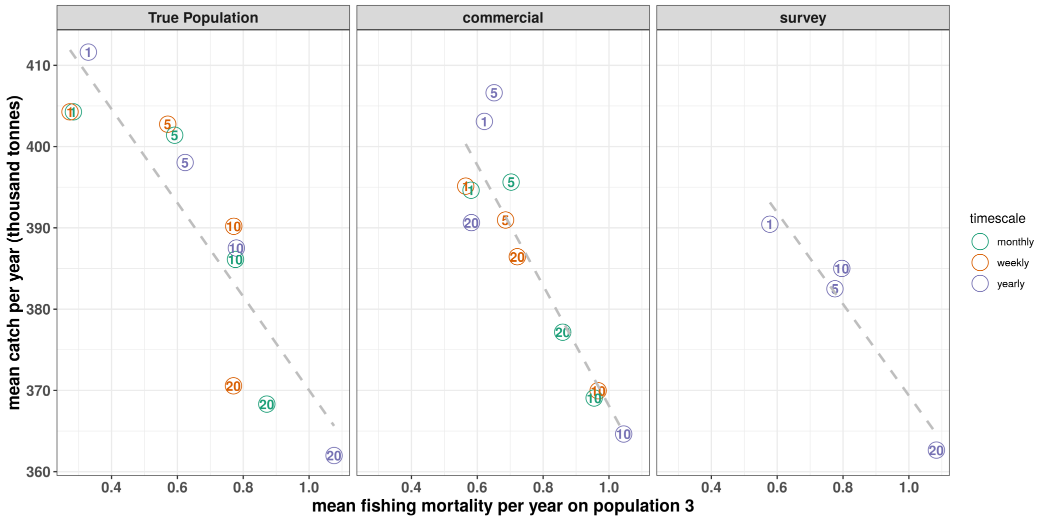

Figure 3.8: Effectiveness of closure with regards to reducing fishing mortality on the protected population (further left on x-axis is best) and maintaining high catches in the fishery (highest on y-axis is best). The numbers indicate the spatial resolution of the data, while grey lines indicate the direction of the trade-off between reducing fishing mortality and overall catches.

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Chapter 4

Comparing fleet dynamics models for predicting fishing location choice: what works well, when?

This chapter is a verbatim reproduction of a paper submitted to *Fish and Fisheries*. Supplementary material can be found in Appendix H.

Dolder, P. J., Minto, C., García, D., & Poos, J. J. (submitted). Comparing fleet dynamics models for predicting fishing location choice: what works well, when? *Fish and Fisheries*.

4.1 Abstract

Scientific advice for fisheries management rarely incorporates consideration of how fishers respond to regulation, often leading to poor implementation and negative stock sustainability and outcomes for fisheries. Fishers adapt to regulation in many ways and short-term decisions about when and where to fish are one of the greatest sources of uncertainty in predicting management outcomes.

Several different models have been developed to predict how fishers allocate effort in space and time under regulations, including: process-based gravity and dynamic state variable models; and statistical methods such as random utility and Markov Transition Models. These have been individually applied to predict effort allocation for various fisheries previously but no comparative synthesis of their structure and performance is available.

We demonstrate that in their simplest form there are strong theoretical links between Gravity, Random Utility and Markov Transition Models, as well as dynamic state variable models. Using an advanced event-based simulation framework, where vessels have business as usual behaviour until a spatial closure, we find that: process models bias effort allocation to certain areas due to strong assumptions about the drivers; and conversely, statistical models accurately predict the distribution of fishing effort under business as usual but predictive performance degrades with previously unobserved dynamics, such as a spatial closure. Process models were less suited to general application under business as usual, but provide a useful framework for testing hypotheses about a fishery system in response to policy change.

While based on simple model formulations, the comparison elicited some important insights into the nature of the models and how they might be applied to assess mixed-fishery sustainability.

4.1.1 Keywords

Keywords: Fishing behaviour, fisheries sustainability, mixed fisheries, short-term decision making, process-based modelling, utility.

4.2 Introduction

It is widely acknowledged that successful fisheries management requires understanding the human drivers that determine how fishers, individually and collectively, respond to changing fishing opportunities and regulation (Hilborn, 2007; Fulton et al., 2011; Van Putten et al., 2012). Fishers' behavioural responses can be broadly classified as short-term, including decisions about when and where to fish (Holland and Sutinen, 2000) or changes in fishing practices such as discarding certain sizes or species of fish (Gillis et al., 1995; Batsleer et al., 2016); or longer term, such as investment and disinvestment in vessels, new fishing gear or technology (Hilborn and Walters, 1992; Nøstbakken et al., 2011; Eigaard et al., 2014). Collectively these 'fleet dynamics' have a fundamental impact on the exploitation of fish stocks and on the economic success of fishers. While fleet dynamics are recognised as of critical importance and elements are well studied (e.g., Salas and Gaertner, 2004; Pelletier and Mahévas, 2005; Fulton et al., 2011; Van Putten et al., 2012), there has been limited progress in integrating such considerations into operational management decision support tools. This is due to the challenge of predicting human behaviour and the lack of adequate available models at an appropriate scale (Andersen et al., 2010).

4.2.1 Fleet dynamics in Management Strategy Evaluations

Management Strategy Evaluation (MSE), the evaluation of management strategies using simulation, has become the primary tool for supporting management decisions due to explicit recognition of uncertainty in outcomes when simulating complex fisheries-ecological systems (Butterworth and Punt, 1999; Kell et al., 2006; De Oliveira et al., 2009; Punt et al., 2016). MSEs strive to characterise a system and incorporate all sources of uncertainty in a full feedback loop, providing managers with a quantitative basis to make decisions among competing fisheries management options (Punt et al., 2016). Thus, the focus in MSE analytical development is not on predicting particular outcomes but on providing a simulation framework that can account for uncertainties in the biological and management systems. Results can then be summarised through probability based metrics against agreed indicators, allowing consideration of trade-offs between short-term and long-term ecological and economic goals.

Management Strategy Evaluations are now widely and routinely applied across the world to provide fisheries management advice (Goethel et al., 2019). However, they are still largely applied on a stock-by-stock basis without taking account of the interdependence among stocks through biological and technical interactions (e.g. Needle, 2008). There is a pressing requirement from managers and stakeholders for the extension of MSEs to consider the mixed nature of most fisheries (Ono et al., 2018). Further, more nuanced policy levers that go beyond setting fishing mortality levels and assuming that these will be achieved by quotas will need to be considered. These policy levers should include changes to fishing gear and spatio-temporal closures (known collectively as technical measures), because these are increasingly being considered (Dunn et al., 2016; Dolder et al., 2018). This requires MSEs to explicitly take account of how fisheries respond to setting quotas, interacting with multiple stocks simultaneously, thus necessitating fleet dynamics as a core dynamic in MSEs.

While recently MSE approaches have started to incorporate fleet dynamics (see Table 4.1) including *inter alia* through effort allocation among métier assuming economic optimisation (Hoff et al., 2010) or representation of fleet dynamics in the simulation frameworks with simplified biological representation (e.g. Salz et al., 2011), there has been limited take up for management advice. Full bio-economic coupling with dynamic harvesting models are rare but can improve understanding of trade-off among management options (Dichmont et al., 2008; Marchal et al., 2013; Ono et al., 2018) and help to avoid unintended management outcomes (Smith and Wilen, 2003; Salas and Gaertner, 2004). Such unintended management outcomes include changing catchability and selectivity for fish stocks that result from adaptive location choice by fishers, using spatial heterogeneity in marine ecosystems while adapting to fisheries regulations. Thus, to take account of location choice in response to changing fishing opportunities requires incorporating models of location choice in MSEs in a robust manner that allows uncertainty about inferred location choice to be incorporated in the MSE framework.

Table 4.1: Management Strategy Evaluations using location choice models

Geographical location	Fishery	Model	Reference
Baltic and Kattegat	Demersal fish	RUM	Ulrich et al. (2007)
North Sea	flatfish	"	Andersen et al. (2010)
Bay of Biscay	Anchovy	"	Vermard et al. (2012)
Australia	Prawn	Markov transition	Dichmont et al. (2008)
Australia	Prawn	"	Venables et al. (2009)
Torres Strait, Austriala	Sea cucumber	Gravity model	Plagányi et al. (2013)
Brunei	Demersal fish	"	Walters et al. (1999)
New Zealand	Hoki	"	Marchal et al. (2009)
Bay of Biscay	demersal	"	Briton et al. (2020)
Australia	Demersal fish	"	Fulton et al. (2011)
English Channel	Demersal fish	"	Lehuta et al. (2015)
Australia	Prawn	"	Ives et al. (2013)
Baltic Sea	Cod	Individual or rule based	Bastardie et al. (2010)
Bering Sea	groundfish	"	Ono et al. (2018)

4.2.2 Fishing location choice

Location choice is generally modelled as an extension of the discrete choice problem in economics, considering fishers as actors pursuing utility maximization through location choice (McFadden, 1973). Utility includes both monetary and non-monetary goals (Hess et al., 2018; Holland and Sutinen, 2000; Marchal et al., 2009; Girardin et al., 2017). Alternative models have been formulated to explain deviations of observed choice from utility maximization theory, including bounded rationality, which results in suboptimal decisions playing a key role in pursuit of what are termed 'satisficing' objectives for individuals, where goals are not optimality but meeting some minimum requirement for profit or other driver (Holland, 2008). Location choice models for fishers stemming from ecological literature hypothesise that fishers act as predators using optimal prey foraging strategies with the objective of maximising fitness (Gillis, 2003; Marchal et al., 2007; Bertrand et al., 2007). This fitness maximization is analogous to utility maximization in the sense that both represent a single currency against which choices can be evaluated. Models stemming from ecological literature include the Ideal Free Distribution (IFD) where predator density distributes according to density of prey (Fretwell and Lucas, 1969) and central place foraging (CPF) where predators search for prey from a central point where they return (e.g. to feed young or nest Frid et al., 2016). The choices are affected by uncertain knowledge about resource distribution (Abernethy et al., 2007), competition (Gillis et al., 1993; Poos et al., 2010), information sharing (Gaertner and Dreyfus-Leon, 2004) and risk sensitivity (Dowling et al., 2015). Understanding how these drivers contribute to behavioural response to management intervention remains an ongoing challenge in fisheries science. Given the enormous complexity of factors that influence utility and fitness, most modelling studies apply proxies to define them. When using utility, simple monetary proxies are often chosen, that include expected revenues and costs of visiting areas. However, more complex proxies are possible, e.g. those that include if locations have been visited previously.

4.2.3 Location choice modelling

We broadly divide location choice models into 'process' and 'statistical' approaches (see Table 4.2 for a summary). 'Process' models are those that seek to mechanistically describe the relationship between individual parts of a system so that the whole system is an emergent property of these relationships. Statistical models for location choice typically assume a categorical distribution (Agresti, 2006) where the parameters of the distribution are functions of covariates. Parameters are estimated against testing datasets using maximum likelihood or Bayesian inference.

Table 4.2: Model information table

	Gravity Model	Dynamic State Variable Model	Random Utility Model	Markov Model
Key method reference	Caddy (1975)	Romani et al. (2010)	McFadden (1973)	Howard (1971)
Key properties	Mechanistic. Effort allocated proportionately to cpue (or vpue in multispecies context).	Mechanistic. Optimises long term objective function based on a defined utility and constraints.	Statistical. Can incorporate choice specific covariates and individual specific covariates.	Statistical. Choices are dynamic series of events with transition probabilities dependent on covariates.
Data type	Aggregated (across months and areas) species catch-per-unit-effort or value-per-unit-effort	Aggregated (across months and areas) individual species catch-per-unit-effort and standard deviations; value of landings per species; cost of effort and effort use per area fished.	Individual (tow-level) choice of locations fished assigned to areas; estimated values of all the alternatives are at each time period.	Time-series of locations fished (tow-level) as a sequence of events, as assigned to areas.

Table 4.2: Model information table

	Gravity Model	Dynamic State Variable Model	Random Utility Model	Markov Model
Key assumptions and limitations	Catch rates are known perfectly; costs of travel among options are negligible; cpue/vpue reflects abundance/density in area; effort allocation reflects abundance perfectly. Does not take account of within trip decisions.	Catch rates (and standard deviations) are known perfectly; catch rates are normally distributed within an area; actors seek to optimise utility to some degree (though degree of optimality optional); vessels maximise long-term profits.	Independence of Irrelevant Alternatives (IIA) – removing an option does not affect the probabilities at other locations; alternative choice set assumed to be the average of all other locations at that time period; Complex to fit with a large number of areas and/or covariates. Does not take account of within trip decisions (though possible to include current state/area as a covariate).Does not take account of within trip decisions.	Markov property assumes that the current state observed contains all the required information to predict the next state transitioned to; Complex to fit with a large number of areas and/or covariates.

Table 4.2: Model information table

	Gravity Model	Dynamic State Variable Model	Random Utility Model	Markov Model
Basis of predictions (with/ without closures)	With closures: Estimated densities Without closures: Estimated densities excluding closure areas	With closures: Estimated densities Without closures: Estimated densities excluding closure areas	With closures: Predictions from RUM fit Without closures: Re-estimated parameters from RUM fit excluding the closed areas.	With closures: Transition probabilities as a time-series Without closures: Transition probabilities as a time-series excluding closure areas and standardised to 1.
Variations	Can be modified to take account of distance from port (e.g. Caddy and Carocci (1999))	Can incorporate quota limits, discarding rules and other management restrictions.	Can incorporate any conceivable covariates which may affect area choice. Alternative specification includes the mixed logit model, which relaxes IIA assumption and treats individual variation as a probability distribution.	Can incorporate any conceivable covariates which directly affect the log-odds of transitioning between pairs of areas.
Data resolution (spatial)	Aggregated to pre-defined spatial units mean values	Aggregated to pre-defined spatial units mean and standard deviation – assumed normally distributed	Data allocated to pre-defined spatial units	Data allocated to pre-defined spatial units

Table 4.2: Model information table

	Gravity Model	Dynamic State Variable Model	Random Utility Model	Markov Model
Data resolution (temporal)	Mean value across each month	Mean and standard deviation values across each month – assumed normally distributed	Individual tow level data, but fit to monthly model estimates of parameters	Individual tow level data, but fit to monthly model estimates of parameters
Estimation/ fitting approach	Base R	R library RDynState5NAsigmaseason6Age	R library *mlogit*	*multinom* function from R library *nnet*
Example MSE/ applications	Walters et al. (1993); Mahévas and Pelletier (2004)	Gillis et al. (1995); Poos et al. (2010)	Hutton et al. (2004); Tidd et al. (2012); Girardin et al. (2015)	Venables et al. (2009).

4.2.3.1 Process models

Process models are derived from first principles and generally conditioned or tuned so that parameter values describe the observed dynamics (Cuddington et al., 2013). In the fisheries literature, we identified Ideal Free Distribution, Central Place Foraging, Gravity Models and Dynamic State Variable Models (DSVMs) as process-driven approaches to predicting location choice. However, as gravity models can be formulated to resemble both IFD and CPF, we focus only on these two models for the comparison. Similarly we exclude models that required detailed case specific conditioning, such as the DISPLACE model from Bastardie et al. (2014) because they are less suited to general application in an MSE framework, and share similar features to the gravity model approach.

Ideal Free Distribution and Central Place Foraging: The concepts of ideal free distribution and central place foraging come from the tenet that individuals seek to maximize their fitness and do so by exploiting patches of food in the most efficient manner (Fretwell and Lucas, 1969). For IFD it is assumed that there is no cost associated with travelling to feeding sites and so predators distribute proportionally to the density of prey, equalising density across the area through predation pressure. Conversely CPF assumes that predators are based at a single point and repeatedly exploit the same patches that are optimum in terms of travel cost and reward. In fisheries literature IFD has received more attention that CPF; CPF is considered to be a suitable framework mainly for recreational or artisanal small scale fisheries that leave and return from the same place, lasting a single day (Frid et al., 2016). It may be less applicable to large-scale commercial fisheries exploiting numerous distant areas before returning to port (Frid et al., 2016).

Gravity Model: The basic principle of Gravity Models is that a flow of goods and services (Isard, 1954) or people (Duddy, 1932) may be described by some measure of attractiveness and inverse proportionality to distance. Commonly used in social sciences, a Gravity Model was first applied to fisheries by Caddy (1975) with attractiveness to a fishing ground modelled as proportional to the observed catch rates in the area where catch rates can be evaluated in terms of weight or value of catch.

Key assumptions in a basic fisheries Gravity Model include that catch rates are known perfectly and there are no travel costs to reach each fishing area, thus vessel density will equalise catch rates across areas by allocating higher fishing effort to areas of greater catch rates. Predictions of effort allocation reflect the expected catch at each spatial area and season, similar in concept to IFD Fretwell and Lucas (1969). Due to fisheries exhibiting deviations from IFD (Gillis, 2003) a Gravity Model is often reparameterised to incorporate wider considerations such as bias towards areas of high abundance (e.g., Walters et al., 1993), travel costs (Caddy and Carocci, 1999), differing species prices (Hilborn and Walters, 1987), information exchange among fishers (Allen and McGlade, 1986) or tradition (Marchal et al., 2013). Gravity Models have been implemented as part of MSE routines (e.g. Walters and Bonfil, 1999; Mahévas and Pelletier, 2004) though the accuracy of predictions is rarely evaluated.

Dynamic State Variable Model: Dynamic State Variable Models (Romani et al., 2010) specify that actors (here fishers) are maximisers of a defined utility. Choices between options are evaluated in terms of their contribution to the utility, and that choice with the highest marginal utility is chosen. These individual choices define effort allocation given both long-term and short-term constraints such as costs, quota, or any other constraints such as discarding penalties (Poos et al., 2010; Alzorriz et al., 2018). It is dynamic in the sense that it keeps track of the "state" of an individual, and that the optimal choice depends on this state. In fisheries, this state can be the total cumulative catch over time. Meanwhile, the results of choices in DSVM such as the catch in a time step can be random variables so that individuals will gradually differ in state, even when making the same choices. Hence, optimisation depends on the actions in previous time-steps. Optimisation is achieved recursively through backwards iteration, which may be computationally challenging if there are a large number of variables as the number of potential states increases exponentially – known as the 'curse of dimensionality', (Bellman, 1987). DSVM also generally have a forward step algorithm which simulates the trajectory of individuals using monte carlo simulation. In this forward simulation the choices are modelled for a set individuals. Errors in decision making can be introduced in this forward simulation so that a distribution of choices over options can be modelled given individual state, rather than only the optimal option (Dowling et al., 2012).

A unique advantage that the DSVM approach has is the ability to take account of short-term decisions about location choice (including staying in port) given long-term constraints (Babcock and Pikitch, 2000). For example, it has been used to predict location choice given quota limits and discarding practices in mixed-fisheries (Poos et al., 2010; Girardin et al., 2015; Batsleer et al., 2016) as well as response of fishers to a Marine Protected Area (Dowling et al., 2012) allowing the models to provide a detailed understanding of fishers' potential response to developing or new policies.

4.2.3.2 Statistical models

Commonly applied statistical models for location choice include: Random Utility and Markov Transition Models.

Random Utility Model: Random Utility Models (RUMs) are a discrete choice modelling approach that derive from micro-economic theory on individuals' decisions among competing options (McFadden, 1973). A central tenet is that an individual seeks to choose the option that maximises their utility with attractiveness defined by a combination of deterministic explanatory variables and a random component. RUMs can have both case-specific (variable constant across choices, e.g., time of the year) and choice-specific (variable differs across choices, e.g., expected catch rate) components (McFadden, 1973); RUMs have been variously applied to consumer choice and marketing (Boxall and Adamowicz, 2002), transport planning (De La Barra, 1989) and labour market analysis (Maier and Fischer, 1985) as well as fishing effort allocation (Hutton et al., 2004; Tidd et al., 2012; Hynes et al., 2016). They can take a number of different forms, with the key property that choice is conditional on all the choices available to the actor (hence, also being known as conditional logit models).

RUMs are the primary method by which location choice has been evaluated and predicted in the past with numerous examples (see Girardin et al., 2017, for a review). A potential limitation is the need to comply with assumption of Independence of Irrelevant Alternatives (IIA) where removing a choice or area should not affect the relative probabilities for the other choices. This is particularly relevant for spatial discrete choice models as two areas may be substitutable due to their similar catch compositions or other characteristics meaning removing one option increases the probability of choosing the other relative to the other options available. However, it is possible to relax this assumption by using a nested logit (Wilen et al., 2002; Campbell and Hand, 1999) which ensures independence between choices, or mixed logit model which treats variation among individuals as a probability distribution (Tidd et al., 2012).

Markov Model: A Markov or semi-Markov Model focusses on the transition probabilities between different states, with the probability of a transition between one state and another (including sojourns where actors stay in the same state) only dependent on the current state not on any previously observed states (Howard, 1971). The difference between a Markov and semi-Markov is the presence of holding times in the latter, with time spent in a state separately estimable (Kingman and Howard, 1972). Importantly, the dynamics can be described by the departing state transition, so there is explicit link between current and future activity.

There are a few examples of the use of Markov Transition Models within fisheries literature, but these have mainly been applied to understand vessel activity state to distinguish fishing from other activity (Vermard et al., 2010; Peel and Good, 2011; Joo et al., 2013), with the notable exception of Venables et al. (2009) and Dichmont et al. (2008) where location choice in the Australian northern prawn fishery was modelled.

4.2.4 A need for synthesis

Incorporating short-term fleet dynamics in MSEs remains a challenge, partly because by necessity any location choice model would need to be generalised in order to predict effort allocation of multiple fleets impacts on stocks in a mixed-fishery (Andersen et al., 2010) and because of limited data on the spatial distribution and movement of populations at appropriate spatiotemporal scales, important for understanding the impact of changing spatial distribution of fishing effort on a population (Goethel et al., 2011; Cadrin, 2020; Dolder et al., 2020). While several different approaches to location choice have been implemented, these have been specific applications for defined fisheries and there has not to date been a general comparison to understand the strengths and weaknesses of each approach.

Understanding the structure, characteristics and predictive capability of the different location choice models is necessary in order to understand the assumptions they may introduce in a management simulation framework (Punt et al., 2016). This understanding provides confidence in interpreting outputs of simulations to compare different management options when using one or more of the location choice models as an operating model in a full feedback MSE.

4.2.5 Study aims

The aim of the study is to review the different methods and approaches that have been used to describe and predict how fishers allocate fishing effort in space and time. We compare the mechanisms of the models used and their underlying structure and their characteristics in predicting future effort allocation in response to management change using a simulated example. We also identify strengths and weaknesses of the approaches to a given plausible management intervention that perturbs the *status quo*, namely a spatial closure. By doing so we provide guidance on the most promising approaches for incorporation into MSEs considering contemporary goals for the evaluation of different management tools.

The approach we take is to:

1. Evaluate the structure, formulation, implementation and predictive capacity of the different models for predicting spatial effort allocation in mixed fisheries,

2. Illustrate some theory demonstrating linkages and differences among the location choice models.

3. Use a simple simulated example to assess the differences, including strengths and weaknesses of each of the approaches and their potential for application within an MSE setting.

4. Formally evaluate predictive capacity of all models under a) business as usual scenario, and b) spatial closure scenario, for the ability of the models to predict future effort allocation.

5. Outline the potential application of the models in different circumstances and their potential for integration into MSEs.

4.3 Materials and Methods

We compare the formulation and structure of the models through i) theoretical comparison of the mathematical structure of the models, and ii) an applied comparison of the predictive performance on the emergent dynamics of an event-based simulation.
We set out by defining a general model that seeks to predict the proportion of effort in each area as a basis for comparing predictions from each of the model classes.

A general model gives that the effort $E_{a,t}$ in area a at time t is a portion of the total effort:

$$E_{a,t} = p_{a,t}E_t \tag{4.1}$$

All of the methods predict $p_{a,t}$ and a goal is to compare them theoretically and practically.

4.3.1 Theoretical comparison

We evaluate if each of the models can be formulated to produce identical predictions under certain conditions. The main results are demonstrations of equivalence presented in the Results section with full derivations provided in the Supplementary Information.

4.3.2 Applied comparison

To evaluate the characteristics of the four location choice modelling frameworks we fit each of the models to simulated data generated by an individual-vessel event-based mixed fishery simulation tool *MixFishSim* (Dolder et al., 2020, see below for simulation setup).

We fit two variants of Gravity Model, a Dynamic State Variable Model, two variants of Random Utility Models and a Markov Transition Model to simulated fishery data. As a null model we included predictions where effort share remained unchanged from previous years.

The formulation of each of these models (Table 4.3) is briefly summarised below and the notation collated in Table 4.4.

Table 4.3: Model name and description

Code	Description
Mechanistic models	
PastShare	Null model, effort share is the same as in the past.
Gravity	Gravity Model
GravityCombo	80% of PastShare and 20% Gravity model.
DSVM	Dynamic State Variable Model
Statistical models	
Markov	Markov transition Model
RUM	Random Utility Model
RUMRparam	Reparameterised Random Utility Model

Table 4.4: Model notation

Notation	Meaning	index	units
a	Area	a = 1...A=9	
y	Year	y = 1....Y=50	
t	Time	t = 1...T=12	
s	Species	s = 1...S=4	
L	Landings		
Px	Price	..	*euro*
Pr	Profit Per Unit Effort		$euro\ tow^{-1}$
D	Distance	..	
f	Fuel cost	..	*euro*
E	Effort	tow	
$\lambda_a(l_s, t)$	Probability of landings l tonnes of species s	[0,1]	
β_a	Coefficients for area a	1...∞	
X_t	Covariates at time t for β coefficients	1...∞	
γ	Coefficients for individual	1...∞	
$Z_{a,t}$	Covariates for γ coefficients	1...∞	
n	number of observations	1...N	tow
p	Proportion of effort	[0,1]	
z	Past state	z=1.....Z=9	
$\beta_{z,a}$	Coefficients for state z and area a	1...∞	
X_t	Covariates at time t	1...∞	

4.3.2.1 Model formulations

Past Effort

As a null model (superscript p) we include predictions where the proportion of effort in area a at time t is:

$$p^p_{a,t} = \overline{p}_a \tag{4.2}$$

where $\overline{p}_a$ is the average proportion of effort in the area previously, calculated as the sum of the effort in an area over three years divided by the sum of the total effort across all areas over the same period.

Gravity Model

We defined a Gravity Model (g) such that the proportion of effort in area a at time t is given by:

$$p^g_{a,t} = \frac{\overline{Pr_a}}{\sum\limits_{a=1}^{A} \overline{Pr_a}} \tag{4.3}$$

where $\overline{Pr_a}$ is the average profit per unit effort for the preceding three years over all areas S, where Pr for a given year is defined as:

$$Pr_{a,t} = \sum_{s=1}^{S} L_{a,t,s} P\mathrm{x}_s - D_{a,t} f \tag{4.4}$$

comprised of the sum of the landings L of each species s for area a at time t multiplied by the price $P\mathrm{x}_s$ minus fuel cost f per unit of effort, multiplied by distance travelled $D_{a,t}$.

Gravity and Past Share Combination

An alternative formulation of a Gravity Model was included, where 80% (denoted by α) of the effort allocation was determined by past effort (tradition, or inertia) and 20% by the Gravity Model (economic opportunism) after Marchal et al. (2013). The 80/20 split has been chosen for illustrative purposes, though the value could be tuned to best fit the data. This Gravity-Tradition combination model (superscripted c) is given by:

$$p^c_{a,t} = \alpha \cdot p^p_{a,t} + (1 - \alpha) \cdot p^g_{a,t} \tag{4.5}$$

where α controls the proportional weighting of either model.

Dynamic State Variable Model

Here, we define our utility function such that:

$$U(Pr, E) = E \cdot Pr \tag{4.6}$$

where Pr is the profit per unit effort, as defined in equation 5.4 given effort E. The value function links the maximum revenue between year t and end T where the expected net revenue is:

$$V(Pr_i, t) = \underset{a}{max}\left(Pr_i(a, t) + X_a[V(Pr_i, t + 1)]\right) \tag{4.7}$$

where the Pr now follows a probability distribution function, so that:

$$Pr_i(a, t) = \left(\sum_{s=1}^{S} \lambda_a(l_s, t) \cdot pr_s\right) - D_{a,t} \cdot f \tag{4.8}$$

where $\lambda_a(l_s, t)$ is the probability of landing l tonnes of species s defined as a discretized normal distribution with mean $\mu_{s,a,t}$ and standard deviation $\sigma_{s,a,t}$.

where Pr_i is the profit per unit effort for the individual i, $Pr_i(a, t)$ the Pr contribution from choice a at time t, and $X_a[V(Pr_i, t + 1)]$ the expected future utility over all possible states resulting from choice a. As with Alzorriz et al. (2018) choices were not assumed to be optimal, but proportional to the expected utility where a tuning parameter determines how optimally decisions are made by the actors. The tuning parameter was such that where $U*$ is the optimal choice, the actual choice was:

$$\Delta_a = U*_a - U_a, \tag{4.9}$$

and the distribution of choices determined by

$$P_{a=i} = \frac{e^{-\Delta_{a=i}/\sigma}}{\sum_{a=i}^{A} e^{-\Delta_a/\sigma}} \tag{4.10}$$

In this case, the tuning parameter σ was set by optimising the Root-Mean-Squared-Error fit to the observational data during the fitting period for each set of predictions. Estimation used the R implementation of a DSVM developed by Poos et al. (2010).

Random Utility Model

Here, we defined a case- and choice- specific multinomial logit RUM (superscript r) where:

$$p^r_{a,t} = \frac{e^{\beta_a \cdot X_t + \gamma \cdot Z_{a,t}}}{1 + e^{\beta_a \cdot X_t + \gamma \cdot Z_{a,t}}} \tag{4.11}$$

and the multinomial distribution at time t given by:

$$\frac{n_t!}{n_{1,t}! \cdots n_{A,t}!} p_{1,t}^{n_{1,t}} \cdots p_{A,t}^{n_{A,t}} \tag{4.12}$$

where $n_{a,t}$ is the number of vessels choosing area a at time t and n_t is the total number of vessels at time t. The r superscript has been dropped for simplicity.

The choice-specific covariates $Z_{a,t}$ comprised profit from fishing at that location during the corresponding period in the data years, while the case-specific covariates included month and a quadratic effect of month to capture cyclical seasonal in the choice probabilities.

Model fitting was undertaken in the R software library *mlogit* (Liao, 2011).

Reparameterised Random Utility Model

An alternative RUM was also included, where we reformulated the choice-specific covariate data as the log ratio of the revenue and costs relative to area A. This reparameterisation reflected theoretical results from the analytical analysis (see Results). Except covariates, the model formulation was the same as in Equation (5.6).

Markov Model

In the Markov Model the proportion of effort in area a at time t is the sum of the transitioned proportions of effort from areas z (departing area) at time $t-1$:

$$p^m_{a,t} = \sum_{z=1}^{A} p^m_{z,t-1} p^m_{z,a,t} \tag{4.13}$$

where the transition probabilities are given by the logit function:

$$p^m_{z,a,t} = \frac{e^{\beta_{z,a} X_t}}{1 + e^{\beta_{z,a} X_t}} \tag{4.14}$$

where we allowed seasonal changes in the model by including a quadratic effect of month in the vector X_t. We estimated transition matrices between each of the states of a Markov Model (m), which were time-inhomogeneous to capture seasonal dynamics. Additional covariates can be incorporated when estimating the Markov transition matrices (Davie, 2013), but we focussed on a simple formulation for comparison.

Markov Model fitting was undertaken in the R software library *nnet* (Venables and Ripley, 2002).

4.3.2.2 Simulation data generation

MixFishSim a mixed-fishery simulation tool was used to generate discrete event-based simulation data on a fishery exploiting multiple stocks that are heterogeneously distributed. The process is summarised in the following steps and described in detail in Dolder et al. (2020):

1. Spatiotemporal population dynamics of four populations with different characteristics were simulated with population demographics (recruitment, natural mortality) unique to each population and population movement (diffusive and directed) on a weekly time-step.

2. The fishing process was simulated at an individual-vessel level with an explore-exploit strategy, where fishing is characterised by a) a period of exploration through a correlated random walk to explore unknown fish distributions, and b) a period of established fishery dynamics where fishing location choice is based on expected revenue and costs of moving between fishing grounds known to the individual. It is important to highlight that vessel decisions are made individually in a microeconomic manner with location choice across all vessels being an emergent property.

   Fishing takes place on a tow-by-tow basis over week-long trips, with return to port at the end of each week.

Each fish population was calibrated to represent a species found in a typical mixed-fishery. The first population mimicked a widely but patchily distributed roundfish of lower value, such as whiting (*Merlangius merlangus*), while population two was a more densely and localised distributed roundfish of medium value but high abundance such as cod (*Gadus morhua*). Population three was setup as patchily distributed medium value species such as haddock (*Melanogrammus aeglefinus*), while population four was a high value densely populated species but a lower overall biomass (e.g. *Nephrops norvegicus*). The framework simulated the spatial distribution, fishing mortality and biomass dynamics for each of the four populations for 50-years (Figure 4.1).

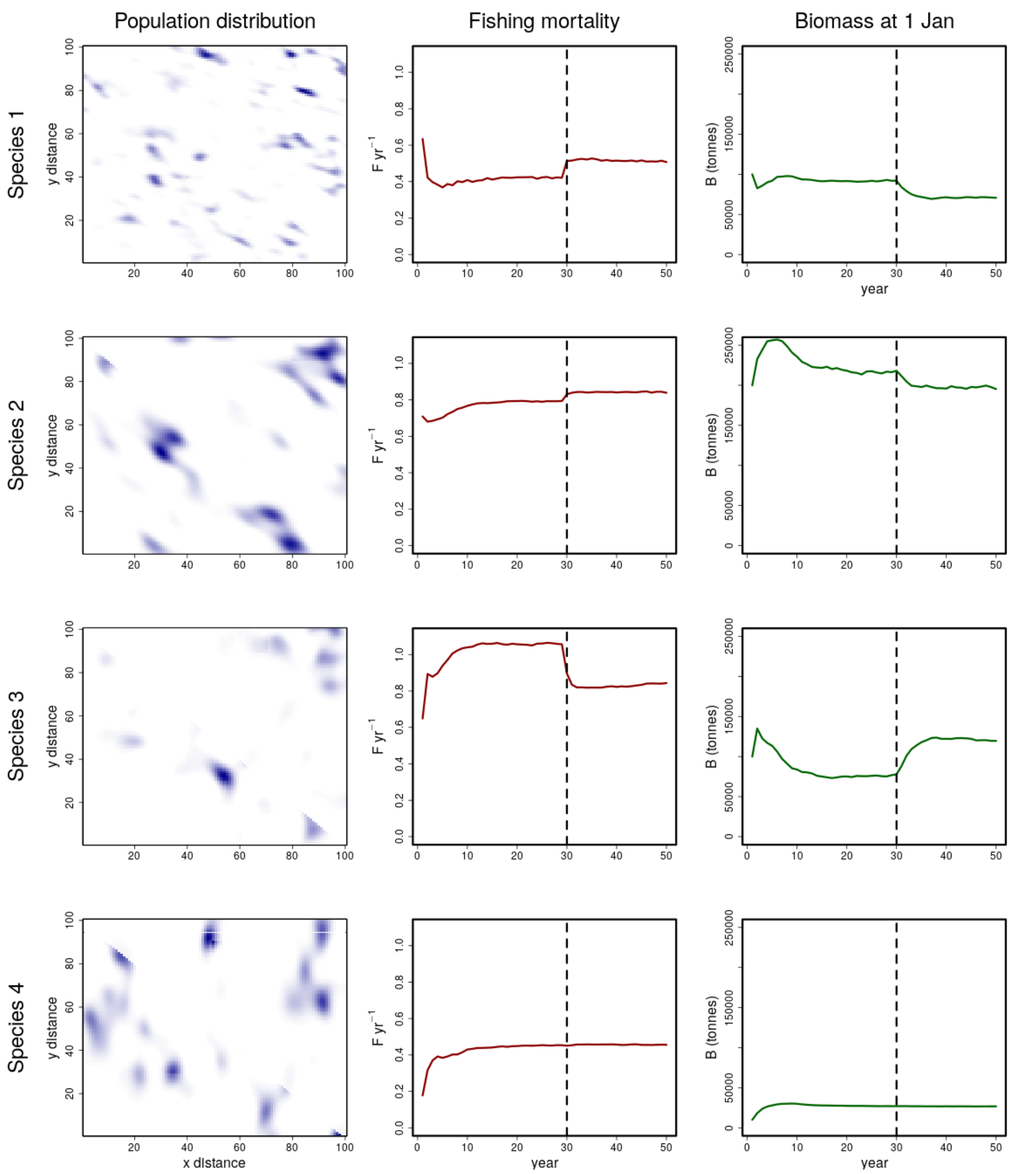

Figure 4.1: Average location of each population over a year, annualised fishing mortality rates and biomass a 1 January each year during the simulation. Spatial closure implementation indicated by the dashed line.

The fishing model operates so that each vessel generates their own established patterns based on their experience of exploring the revenue field in an emergent manner. For each vessel the simulation starts by fishing in a random location; they then explore the surrounding revenue field through a correlated random walk for twenty tows until returning to port. At the beginning of each trip, they again fish at a random location and continue exploration. Over time the location choice and random exploration is replaced by identifying previously profitable locations, calculating travel costs from the current position and expected revenue at new locations and drawing randomly from locations in the upper 70th percentile of expected profits. This transition between the exploratory phase of the fishery to the established phase is based on a logistic function, so that the probability of using the correlated random walk function starts at 1.0 at the beginning of the simulation and transitions to 0.05 by the end where location choice is primarily based on past experience.

The simulation was run for 29 years to establish the fishery before a closure was introduced at year 30 and then run for a further 20 years (50 years in total). No quotas or other restrictions are put in place but effort is fixed each year at the same level for each vessel. The spatial closures were designed to minimise fishing mortality on population 3 by closing the areas of highest catch rates for this species. It can be seen to reduce the fishing mortality rates on population 3, while fishing mortality goes up on populations 1 and 2 due to the spatial reallocation of fishing effort to areas where those populations are more abundant (Figure 4.1).

4.3.2.3 Location choice set and data processing

The simulated logbook data was processed to define spatially contiguous areas that constituted the location choices for fitting the models. The procedure was as follows:

1. The landings logs of all vessels for 10 years prior to the closure (year 20 - 29) were averaged at the spatial resolution of the data (1 unit x 1 unit),
2. On this processed dataset a clustering algorithm Partitioning Around Medoids (Maechler et al., 2005) was run on the proportion of each species in the landings at each location to assign each of the spatial points to one of four clusters,
3. Each of these clusters were assigned to unique spatially contiguous units. This was achieved by converting the rasterised locations of each cluster to separate non-overlapping spatial polygons (treating any space between similarly clustered areas as a break in the spatial unit) using the R package raster (van Etten, 2013). This approach ensured that areas with similar catch rates for the different species but different physical characteristics (i.e. distance from port (0,0) and from other areas) were separately treated in the analysis,

4. The areas used for the spatial closures were separately assigned as spatial units (C_1 and C_2) through the entire time-series so we can consider the effort reallocation from these areas following the closures,
5. Any small spatial units were removed and assigned to the “OTH" in order to reduce the choice set to 9 spatial units in total,
6. Each of the original catch records in the fishing logs were assigned to one of these spatial units from their coordinates.

The final location choice set shows different patches of fish exploited by the fishery, with differing catch compositions at the locations (Figure 4.2).

Alternative choice set for RUM

To fit a Random Utility Model to the data a further processing step was required to generate the “alternate" choice data set. For each fishing location choice all other possible alternative values were calculated, as follows:

1. The average cost of moving between each area was estimated based on the distance between the centroid of each area. This was multiplied by the fuel cost per unit effort for the fleet. While the actual cost in the simulation may depend on the relative locations within the fishing areas, distance from the centroids is used as an approximation for alternatives,
2. The expected landings-per-tow of fishing in an area and the overall value of fishing in an area was calculated as the mean of the observed values across the fleet,
3. Where possible, the expected landings were from the same month, else the average across the year was used.

4.3.2.4 Model fitting and predictions

Formulation of each of the models was kept deliberately simple to facilitate cross-model comparison with the same data and variables. Each model was provided with the same data and covariates for model fitting and predictions. The covariates chosen included a seasonal (monthly) effect and past profit at a location. Inference on location choice was based on previous observation, the profit when fishing during the observations and how the model fits the data only. However, while the statistical models (RUM, Markov) are fit

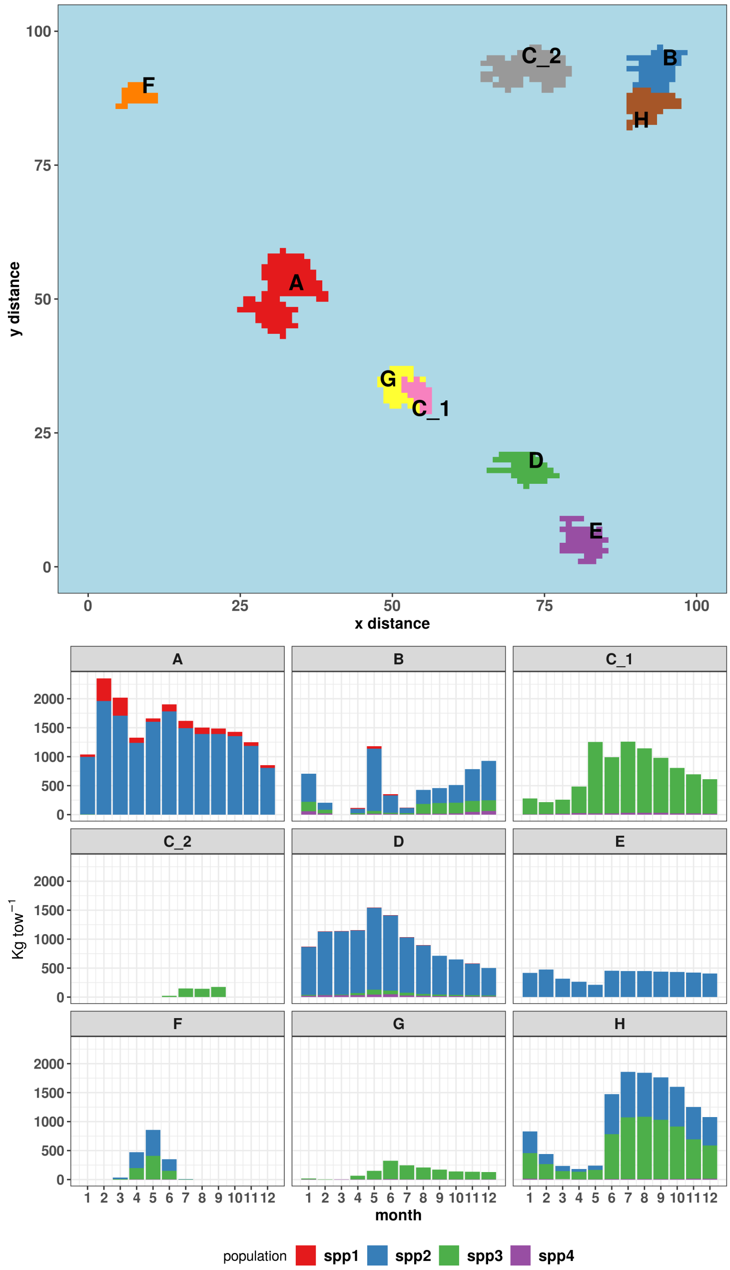

Figure 4.2: Top: Spatial units defined for the models based on clustering of catch data over a 10 year period (years 20 - 29, prior to the spatial closure). Colours indicate distinct areas and are not related to the species in the bottom panel. Bottom: The average monthly catch rate for each population in each spatial unit.

to the individual fishing event data it is necessary for the process models (Gravity, DSVM) to be calibrated with the monthly mean of the data; in the case of the DSVM, this also includes the standard deviation of the catch rates.

The characteristics of each of the models is summarised in Table 4.2. Full code for the fitting, predictions and model output is provided at `http://github/com/pdolder/Lit-Review/Comparative_modelling/funcs`.

4.3.2.5 Model performance evaluation

Each of the models was fit on a rolling basis to three years of data on observed fishing locations for a single fleet (fleet 3), with predictions made for the following two years. This approach was deliberately taken to mimic a short-term forecast procedure undertaken as part of an operating model in a management strategy evaluation. The predictions were made over 10 years spanning prior to the closure implementation through to several years after the closure implementation, with the first year predicted being year 23 (training on years 20 - 22) and the last year predicted being year 39 (training on years 36 - 38). We chose to compare proportion of effort in each area because the total effort required is subject to other factors such as quota availability and the management regime.

Model performance was assessed in three ways:

- Forecast residual diagnostics: Comparison of the pairwise difference between the observed and the predicted proportions in each area and month.
- Root Mean Squared Error Deviation of the predictions: $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2}$, where O_i is the observed proportion for an area in a given month and P_i the predicted proportion.
- Spearman's rank correlation coefficient of the proportions: $r_s = \rho_{rg_O,rg_P} = \frac{cov(rg_O,rg_P)}{\sigma_{rg_O},\sigma_{rg_P}}$ where ρ is spearmans's correlation coefficient, $cov(rg_O, rg_P)$ and $\sigma_{rg_O}, \sigma_{rg_P}$ the covariance and standard deviation of the ranked observed and predicted proportions, respectively.

4.4 Results

4.4.1 Theoretical comparison

4.4.1.1 Gravity Model

For $a \in \{1, \ldots, A\}$, the proportion of effort in area a from the Gravity Model is given by:

$$p_{a,t}^{(g)} = \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \tag{4.15}$$

where $Pr_{a,t-\tau}$ is the profit per unit effort in the previous time step.

4.4.1.2 Random Utility Model

A multinomial logit model, typically models the log-odds of a given category relative to a baseline category. Setting area one as the baseline category and equating with the Gravity Model proportions gives:

$$\theta_a = \ln\left(\frac{p_{a,t}^{(l)}}{p_{1,t}^{(l)}}\right) = \ln\left(\frac{\frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}}}{\frac{Pr_{1,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}}}\right) = \ln\left(\frac{Pr_{a,t-\tau}}{Pr_{1,t-\tau}}\right) \tag{4.16}$$

We can therefore state the equivalence of the Gravity and multinomial logit model when the log-odds of the multinomial are given by the log of the ratio of the value in a given fishery divided by the value in baseline fishery (Equation 4.16). This model is more formally a conditional logit model (McFadden, 1973) as the variables are choice specific. We can therefore write the Gravity Model as a conditional logit by specifying that the probability of choosing area a at time t

$$P(y_t = a|\mathbf{X}_{t-\tau}) = \frac{e^{\beta X_{a,t-\tau}}}{\sum_{j=1}^{A} e^{\beta X_{j,t-\tau}}} \tag{4.17}$$

where $\beta = 1$ and $X_{a,t-\tau} = \ln\left(\frac{Pr_{a,t-\tau}}{Pr_{1,t-\tau}}\right)$.

Departures from simple Gravity dynamics can be tested via hypotheses on the β parameter.

4.4.1.3 Markov Model

The Markov property states

$$P(Y_t = y_t|Y_{t-1} = y_{t-1}, \ldots, Y_0 = y_0) = P(Y_t = y_t|Y_{t-1} = y_{t-1}) \tag{4.18}$$

where Y_t is the state (area) at time t. So the probability is dependent only on the previous state and not those preceding the previous step. A transition probability matrix governs the probability of transitioning among the available states of a Markov Model. For A possible fisheries the transition matrix can be written

$$\mathcal{P}(t) = \begin{bmatrix} p_{1,1}(t) & p_{1,2}(t) & \dots & p_{1,A}(t) \\ p_{2,1}(t) & p_{2,2}(t) & \dots & p_{2,A}(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_{A,1}(t) & p_{A,2}(t) & \dots & p_{A,A}(t) \end{bmatrix} \tag{4.19}$$

where rows denote departing state and columns destination state (at time t) (probabilities sum to unity across rows). Note the transition probabilities are here assumed time t specific. A state probability (as distinct from a transition probability) gives the probability that a given state is occupied at a given time and is denoted $\pi_{f,t}$ where

$$\pi_{f,t} = \sum_{j=1}^{F} \pi_{j,t-1} p_{j,f}(t), \tag{4.20}$$

that is, the sum of the proportions moving into area a at time t from all areas j at time $t-1$.

Where the system is memoryless such that $p_{i,a} = p_{j,a} = p_a$:

$$\begin{aligned} \sum_{j=1}^{A} \frac{Pr_{j,t-1-\tau}}{\sum_{k=1}^{A} Pr_{k,t-1-\tau}} p_{j,a}(t) &= \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \\ p_a(t) \sum_{j=1}^{F} \frac{Pr_{j,t-1-\tau}}{\sum_{k=1}^{A} Pr_{k,t-1-\tau}} &= \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \\ p_a(t) &= \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \end{aligned} \tag{4.21}$$

That is, where the transition probabilities are the same irrespective of the departing state (memoryless) and given by the Gravity Model probabilities, the Markov and Gravity Models equate. The transition matrix would be written

$$\mathcal{P}(t) = \begin{bmatrix} p_1(t) & p_2(t) & \dots & p_A(t) \\ p_1(t) & p_2(t) & \dots & p_A(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_1(t) & p_2(t) & \dots & p_A(t) \end{bmatrix} \tag{4.22}$$

which removes the conditional probability of the Markov Model depending on the previous state (all rows are the same). Departures from the RUM assumptions could then be evaluated based on hypotheses regarding similarity or differences among the rows.

4.4.1.4 Dynamic state variable model

Dynamic state variable models (DSVMs) introduce a discretized utility state. For example, profit utility is discretized and movements between areas (patch) would result in increment or decrements of profit state. A fundamental difference with the statistical models that focus on area transitions (i.e. Markov Transition Models) is that DSVMs focus on utility transitions and optimal choice is emergent from the calculation procedure. A simple DSVM predicts the optimal policy (set of choices) is to go to the area with the highest profit.

That the optimal choice is to go to the area with the highest value means it cannot be simply equated with the other models. To have policies with the same proportions to the statistical models would require that the distribution of the vessels among utility states times the optimal transition matrix among utility states (Reimer et al., 2019) and summed by area would be equal that of the statistical model. The error-in-decision-making approach developed by (Dowling et al., 2012; Alzorriz et al., 2018) offers a solution to this under specific circumstances. Where the utility is time independent (i.e. without any long term constraints) the predictions can be equated to the Gravity Model where the Gravity is treated as a multinomial so that σ in equation 4.10 is

$$\sigma_a = \frac{Pr_a - max\left(Pr_{a=1 \ldots A}\right)}{\log\left(\frac{Pr_a}{Pr_{a=1}}\right)} \tag{4.23}$$

where Pr_a is profit from area a.

This requires a unique σ for each area, and in essence substitutes the short-term utility in the DSVM with a Gravity Model where the weight is the profit in an area relative to a reference area.

4.4.2 Applied comparison

4.4.2.1 Population and fishery dynamics

Prior to implementation of spatial closures, the fishery exploited different areas at different times of year (Figure 4.2). This is evident from monthly peaks in effort allocated to area A in months 2 and 3, coinciding with peaks in spawning migration where populations were found in higher density as they aggregated to spawn; the fishery exploited these aggregations due to higher catch rates (Figure 4.2). Activity is highest in B in months 5, 11 and 12, while area F is only fished in months 4 and 5 and the C_2 area was only fished in months 7 - 10 (Figure 4.3).

Following implementation of the closure, seasonal dynamics in the fishery remained largely similar, though there was increased activity in area G in later months of the year (Figure 4.3). It can be seen that the fleet redistributed effort away from the closure areas to alternative fisheries, with patterns of "fishing the line" evident where vessels move to fish around the area closed to fishing (in area A on the border of C_2) as well as increased effort in alternate fisheries (C, D and F) and new fishing grounds that were not part of the location choices (Figure 4.4).

4.4.2.2 Predictive performance

Predictions from each of the models captured the seasonal dynamics in location choice well, but there were notable differences in effort allocations to areas between the purely process models (Gravity, DSVM) and the statistical models (Markov, RUM). The Gravity, DSVM and RUM all predicted the peaks in effort in months 2 and 3 in areas A (Figure 4.3 top left panel) and in the peaks in month 5, 11 and 12 for area B (Figure 4.3 second down, left panel). The Markov Model did less well at capturing the monthly peaks, with the effort transitions between months having a smoother structure (e.g. for the effort allocations in Area B in the middle panel, second down in Figure 4.3).

The statistical models trialled predicted effort allocations that were closer to the observed values than the process models in most cases, though it is notable that for the Gravity-Tradition model, a process model which included both revenue and tradition as determinants of effort allocation, the predictions

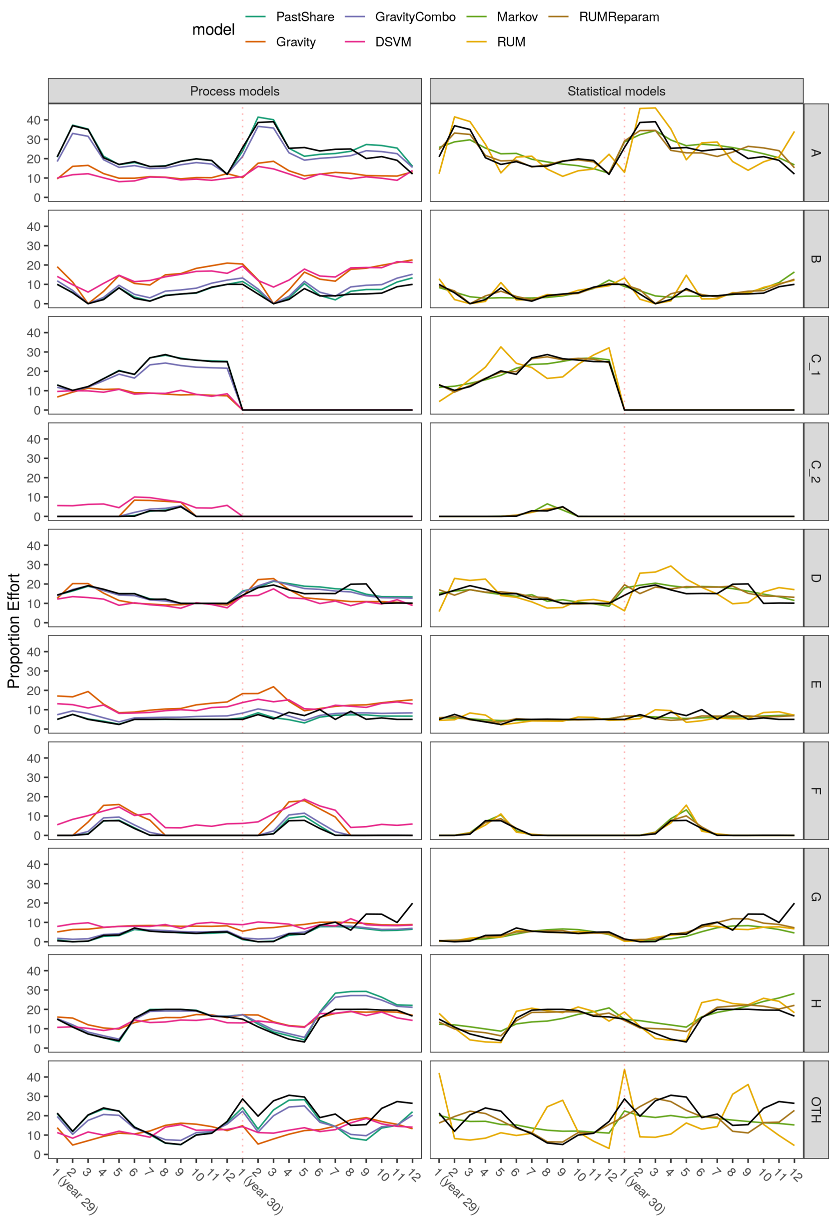

Figure 4.3: Predictions for the monthly proportion (shown as a percentage) of effort in each spatial unit before the closure implementation (year 29) and during the first year of the closure (year 30) for each of the models. Observations are shown as a black line, the red dashed line indicates the start of the spatial closure.

match well the observations prior to the closure (Figure 4.3). The reparameterised RUM (with the predictors being the log-odds of profit and value) also predicted effort allocations that were closer to the observed allocations than the RUM as originally formulated.

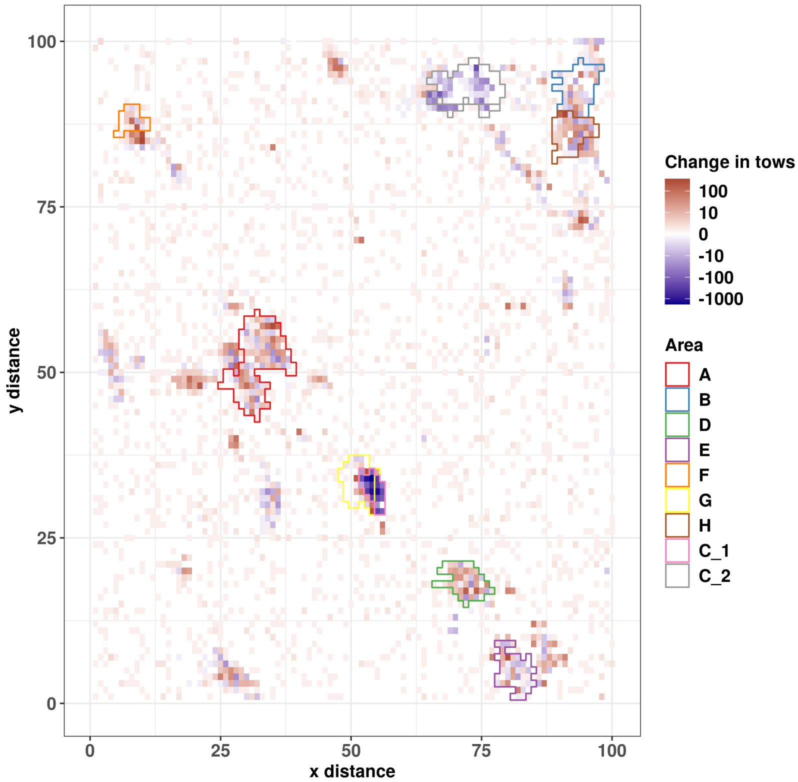

Figure 4.4: Difference in number of tows for each fishing location (finescale) choice between years 29 (before the closure) and 30 (first year of the closure). Grouped areas that made up the choice set are shown in coloured boundaries.

The statistical models generally showed less systematic bias in the forecast residuals than the process models (Figure 4.5). Forecast residuals showed no inter-monthly correlations before or after the closure for the Markov, RUM, or the reparameterised RUM, with the exception of the 'OTH' area (Figure 4.5). The Gravity and DSVM both consistently over-predict effort in areas B, E and F and under-predict effort allocated to areas A and C_1 (Figure 4.5).

Prior to the implementation of the spatial closure (< year 30) PastShare was the best predictor of future effort allocation (RMSE = 0.282 %), but this was not the case immediately following the closure (year = 30) where the re-parametrised RUM outperformed the other models (RMSE = 3.03 %, Figure 4.6, Table 4.5) including PastShare (RMSE = 3.66 %). Of the other models PastShare, Gravity-Tradition and Markov performed broadly similarly to each other, with the RUM, Gravity and DSVM performing the worst (Figure 4.6). Following a couple of years of the closure the prediction accuracy increased for most models except the Gravity and DSVM models, with a steadily decreas-

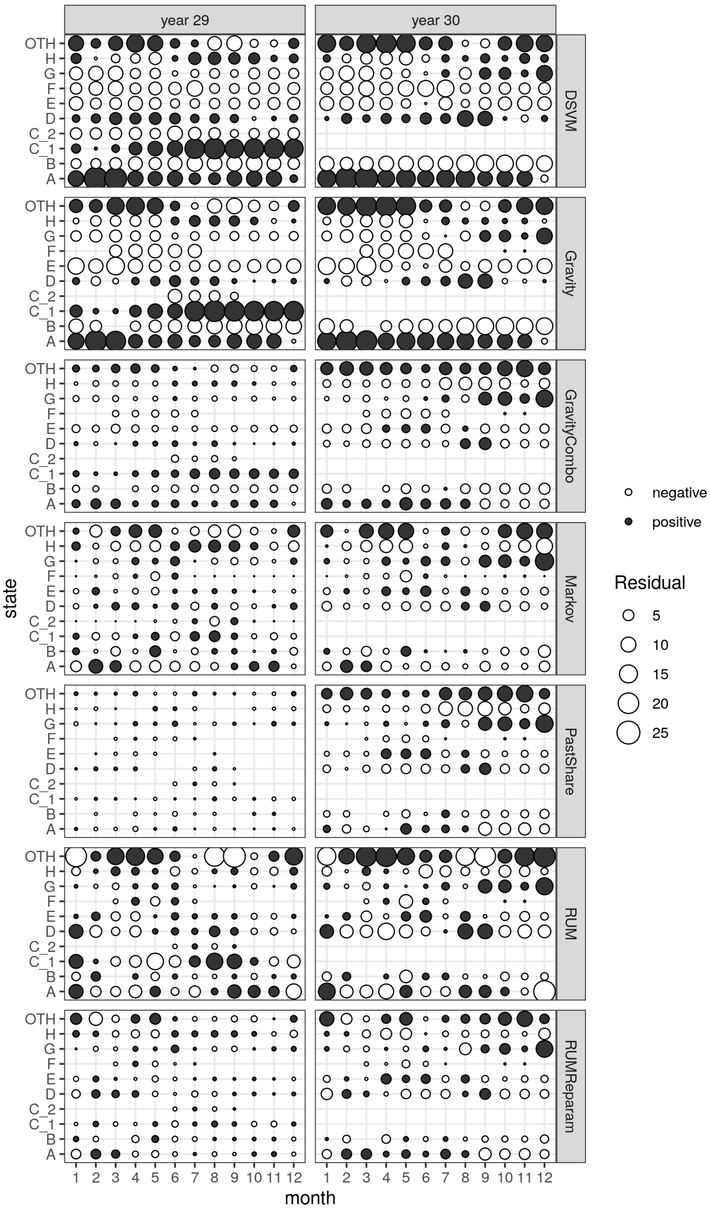

Figure 4.5: Forecast residuals for each of the models by month for years 29 and 30 when fitting to data on years 26-28.

ing accuracy after a few years (Figure 4.6). Over time the PastShare model gradually re-establishes itself as having the best predictive accuracy (Figure 4.6).

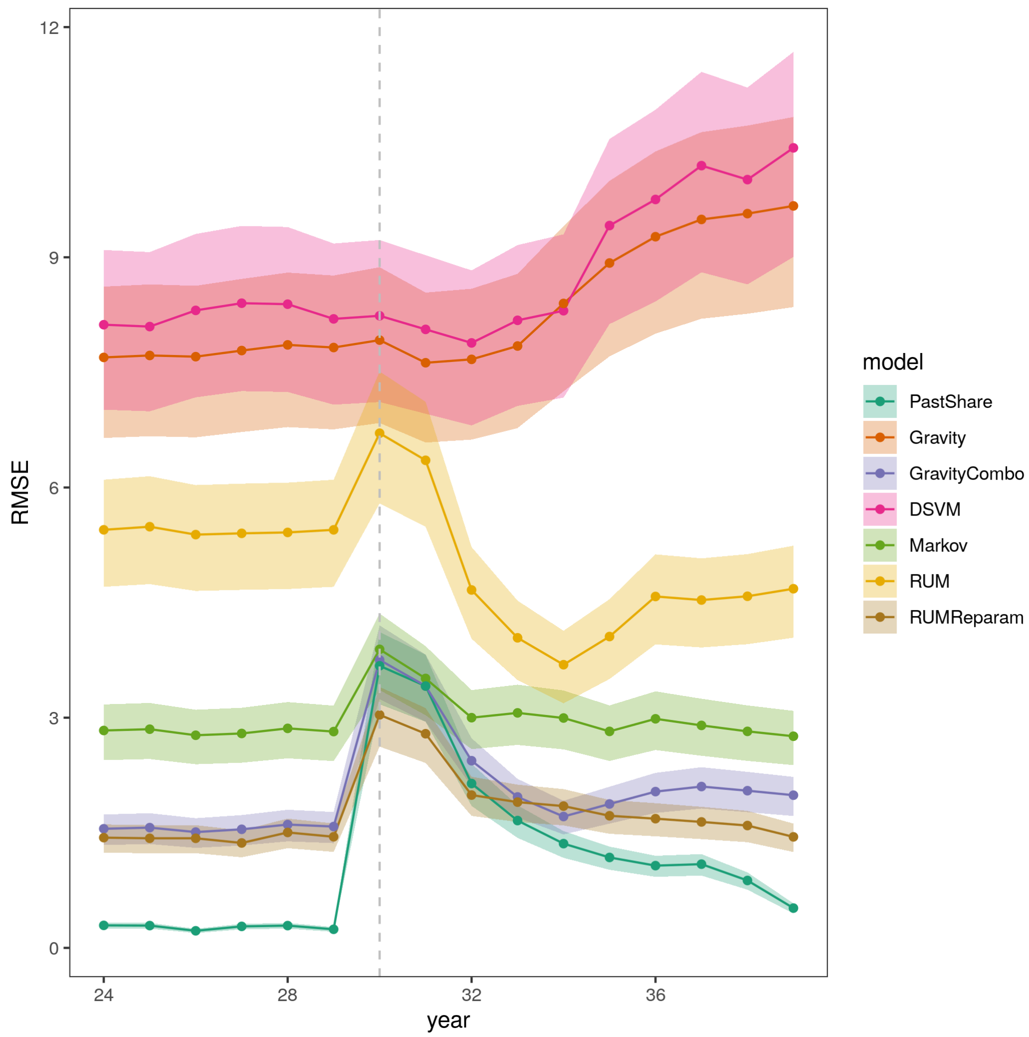

Figure 4.6: The Root Mean Squared Error (RMSE) for each of the models predictions, 95% confidence intervals are shown in the shaded areas.

Table 4.5: Summary of model comparison metrics

model_type	model	closure_period	RMSE	MAE	spearmans	spearmans_pvalue
Process model	DSVM	Before Closure	8.2136	6.7268	0.3910	< 2.22e-16
Process model	DSVM	During Closure	8.2274	6.1358	0.6150	< 2.22e-16
Process model	DSVM	After Closure	9.1587	6.5968	0.5450	< 2.22e-16
Process model	Gravity	Before Closure	7.7687	5.8964	0.5080	< 2.22e-16
Process model	Gravity	During Closure	7.9185	5.5525	0.6690	< 2.22e-16
Process model	Gravity	After Closure	8.8359	5.9956	0.5810	< 2.22e-16
Process model	GravityCombo	Before Closure	1.5663	1.1813	0.9930	< 2.22e-16
Process model	GravityCombo	During Closure	3.7406	2.6962	0.9410	< 2.22e-16
Process model	GravityCombo	After Closure	2.1224	1.4385	0.9830	< 2.22e-16
Statistical model	Markov	Before Closure	2.8262	1.9598	0.9510	< 2.22e-16
Statistical model	Markov	During Closure	3.8743	2.4650	0.9370	< 2.22e-16
Statistical model	Markov	After Closure	2.9307	1.9528	0.9550	< 2.22e-16
Process model	PastShare	Before Closure	0.2820	0.1788	0.9980	< 2.22e-16
Process model	PastShare	During Closure	3.6635	2.3555	0.9510	< 2.22e-16
Process model	PastShare	After Closure	1.4707	0.6883	0.9880	< 2.22e-16
Statistical model	RUM	Before Closure	5.4275	3.1780	0.8950	< 2.22e-16
Statistical model	RUM	During Closure	6.6967	4.1234	0.8960	< 2.22e-16
Statistical model	RUM	After Closure	4.4988	2.7606	0.9340	< 2.22e-16
Statistical model	RUMReparam	Before Closure	1.4485	0.8611	0.9840	< 2.22e-16

Statistical model	RUMReparam	During Closure	3.0317	1.9357		0.9630	$< 2.22e\text{-}16$
Statistical model	RUMReparam	After Closure	1.7751	1.0390		0.9850	$< 2.22e\text{-}16$

Spearman correlation coefficients (ρ) show the strength of relation of individual predictions with the models' observations for the same area and month (Figure 4.7). Before the closure, PastShare ($\rho = 0.998$) was the best predictor of future share of fishing effort, with the GravityCombo ($\rho = 0.993$) and reparameterised RUM ($\rho = 0.984$) the best performing models. The Markov ($\rho = 0.951$) and the RUM ($\rho = 0.895$) also performed well. This generally remains true during and after the closure, with the reparameterised RUM performing best both during ($\rho = 0.963$) and after the closure ($\rho = 0.985$).

It's notable that during the closure the process models performed no worse (and in cases better) than they did before the closure. The Gravity Model increased accuracy from before ($\rho = 0.508$) to during ($\rho = 0.669$) and then decreased slightly after the closure ($\rho = 0.581$). The DSVM showed a similar pattern ($\rho = 0.391$ before, 0.615 during and 0.545 after), though for these models there were a number of predictions that were very different from the observations, with over- or under-estimated values (Figure 4.7). All the statistical models performed worse during the closure than before and after, though still better than the process models in absolute terms for the model predictions. The Markov Model performance degraded the least during the closure ($\rho = 0.951$ compared to 0.937).

4.5 Discussion

We compared both the structure and predictive capability of four different types of location choice model: process models included Gravity and Dynamic State Variable models, and statistical models included Random Utility and Markov Transition Models. In addition, we fit models based on past share of fishing effort (as a null model). We sought not to find the "best predicting" model, but to develop a basis to understand the similarities and differences among the commonly applied models.

4.5.1 Theoretical comparison

We found that equivalent models could be derived for a Gravity Model and a Random Utility Model under the condition that the covariate used in the multinomial model used to fit the RUM was the log of the ratio of the profit per unit effort between two areas. This resulted in predictions generated in line with Ideal Free Distribution theory and is consistent with previous anal-

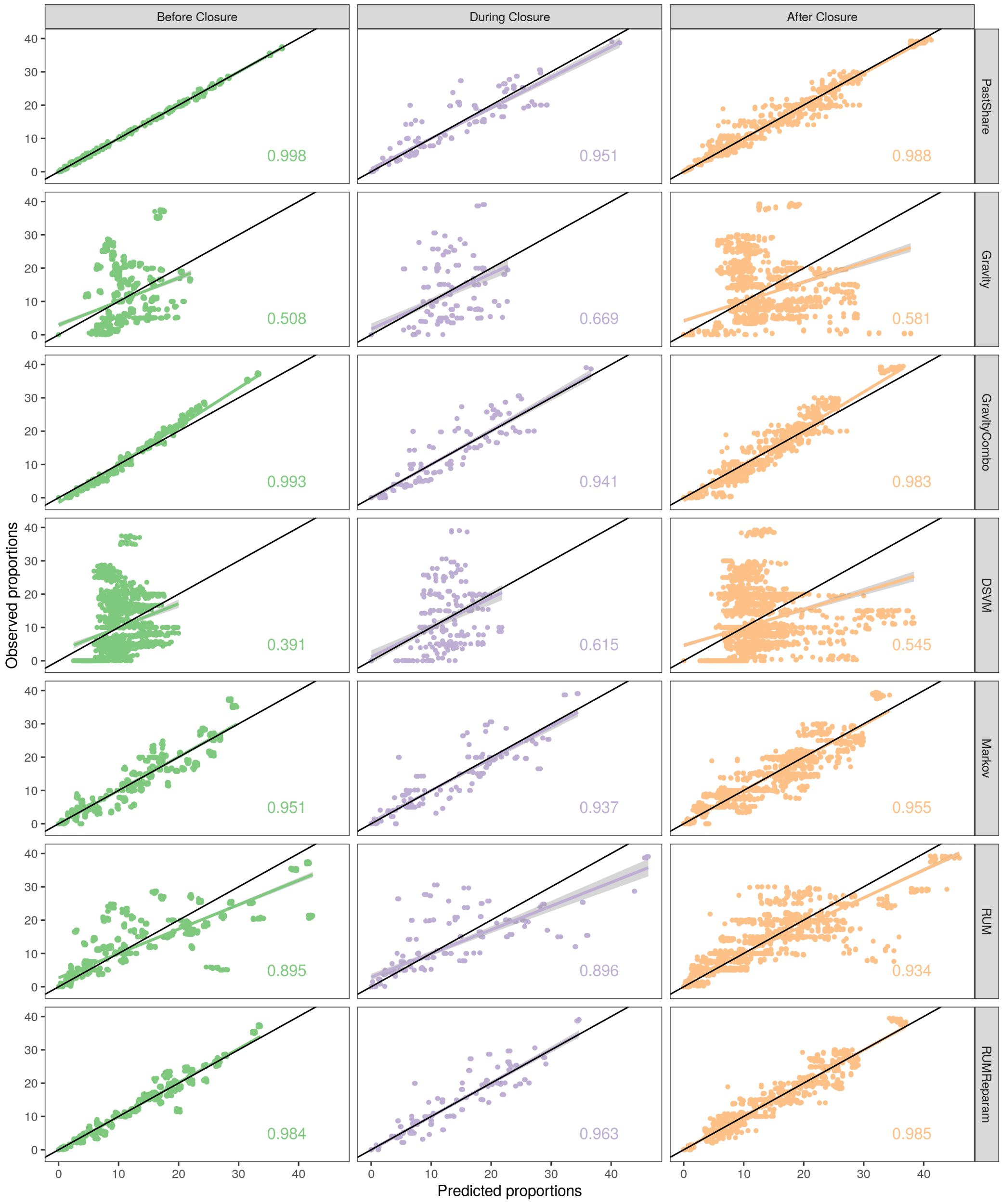

Figure 4.7: Spearman correlation coefficients for Predicted against Observed proportions for each of the model and periods. Before is year < 30, during is year 30 and after is year > 30.

ysis that showed the structural similarities between the two classes of models and that model specification determines the difference between the two (Anas, 1983; Sheppard, 1978). It's rarely the case that relative profit between areas fished is the only driver of effort allocation; tradition is one predictor that is often found to be significant when fitting a RUM to data (Girardin et al., 2017). Tradition, alongside a number of variables, can be incorporated in a Gravity Model as a weighting of the attractiveness component. If the weighting is estimated from past data either through calibration or estimation it provides a conceptually similar model to a RUM that can achieve similar predictions. The advantage in specifying a Gravity Model in this way is the model will better fit past observations of dynamics in the fishery. However, it limits flexibility with the model to respond to changing system dynamics, as tradition or 'inertia' is a concept that likely reflects many other past endogenous drivers rather than an explicitly stated dynamic. Therefore it would be better that these drivers could be explicitly included to provide the mechanistic representation required to improve future predictions.

Extending the theoretical comparison we found that the Gravity and Markov Model showed equivalence when the Markov transitions were the same irrespective of the starting area and the probabilities of transition were determined by the relative profit-per-unit-effort of the different areas. This provides the ability to use similarly configured models to test for the presence of a Markovian property or if the decisions are independent of the departing area, by demonstrating if the Markov Model outperforms a similarly configured Gravity Model.

We found the Dynamic State Variable model to be distinct from the other classes of models and that it could not be simply equated to a Gravity, RUM or Markov model except within a single time-step. The model seeks to find the optimal long-term solution; in doing so the model requires that the utility function is well defined and that relevant constraints are incorporated and then find the single best set of decisions to maximise this utility. Some vessels may pursue sub-optimal policies and Dowling et al. (2012) and Alzorriz et al. (2018) offer an interesting solution with error-in-decision-making which may be substitutable for a single time-step to match a Gravity Model, but not with long term constraints. Further, Reimer et al. (2019) provide a method for exploring sub-optimality in dynamic state programming approaches. Another approach may be to define constraints for individual vessels with heterogeneous conditions; this would lead to a spectrum of optimal solutions that may more closely match those found with models that deal with heterogeneity among individuals. In this way no single solution will exist for the fleet but a set of solutions which could be used as a probability set for the overall fleet.

4.5.2 Applied comparison

We fitted several different location choice models to simulated data to evaluate their predictive performance under different fishery management scenarios. The models were all implemented in a general way to allow cross-comparison and no attempt was made to define the best model. All the models could have been improved in their overall predictive capacity, but the simple formulation allowed us to elicit some important insights into the nature of the models and how they might be applied within a management strategy evaluation framework.

While both the process and statistical models captured the temporal dynamics in fishing location choice, the process models were generally biased where the statistical models were largely unbiased in their predictions (Figure 4.5). This is because the statistical models infer utility directly from the data, including unobserved drivers. The process models as specified here assume that profit-per-unit effort is the only driver of effort allocation among the areas and that the distribution of this value is known *a priori*. It would be expected that the statistical models performed better as their estimated parameters explicitly encompass utility in their parameterisation (McFadden, 1973) and an error component that captures the variance in the historical data, allowing for unexplained factors to contribute to the model fit. That the predictions are biased in the process models demonstrates that more than profit is determining effort allocation by fleets, which may be captured by the parameters in the statistical models. The importance of past and personal knowledge of fishing locations can be inferred from that fact that the GravityCombo model, where the effort allocation is a weighted average of predictions from the Gravity Model and the PastShare in the fisheries, much better reflects the observed allocations.

The accuracy of the process models was affected less than the statistical models following the spatial closure (Figure 4.7) suggesting they adapted better in relative terms, though in absolute terms the overall RMSE was still larger for the process models. This may reflect that the process model predictions are better at dealing with previously unobserved situations, where the statistical models struggle to predict changes to the system. Cuddington et al. (2013) demonstrate how good understanding of the process may be able to outperform a statistical model in previously unobserved situations. However, due to the potential for bias to be introduced from misspecification, particular care should be taken in model tuning and consideration of a error-correction factor [cite]. The reparameterised RUM provides a useful contrast in this example as it included both statistical and mechanistic properties derived from theoretical linkages between the models (Equation 4.16).

It's unsurprising that the predictions from all models were better before closure than during and after the closure. The effort patterns for the fishers were established by this point and decisions about where to fish were being based on past knowledge of profitable locations. That the process models were biased reflects the fact that the utility function for the Gravity and DSVM determining effort allocation did not include all of the factors determining effort allocation among areas, where the statistical models did not define the utility *a priori*. It's notable, however, that once the closure is introduced the accuracy of the process models does not immediately decrease as with all the statistical models and in fact increases (Figure 4.6). This illustrates the importance of understanding the drivers for allocation, and highlights that a correctly specified process model can perform better for predictions of unobserved states, where statistical model predictions are typically bounded by the observed drivers and dynamics.

The DSVM and Gravity Model performance degraded in the years after the closure. This is down to an overallocation of effort to particular areas where biomass increases for the species protected by the closure, thus as that stock increases more effort is allocated to these areas. The overallocation is likely down to the models predicting effort based on catch rates and relative value of each fish species, where increasingly the vessels allocate based on their own experience and traditional areas they exploit - leading to the differences in predictions and observations. In reality the simulated fishery did not allocate as much effort to these areas as predicted (C, B and E), but distributed it more evenly across the remaining locations and also to new locations not previously exploited. These new locations were in areas where population 2 and population 4 were more abundant, suggesting a move to targeting these species (Figure 4.4).

The area that received more effort than predicted by any of the models was area G. This was the open area adjacent to C_1 that also includes the "core" grounds for population 3, the protected population. In particular, it can be seen that the simulated fishery allocates more effort in months 9 - 12 than any of the models predict (Figure 4.5). This is an example of "fishing the line" where the effort was reallocated to a concentrated area surrounding the closure (Figure 4.4) where vessels were still able to get high catch rates close to boundary, not represented in the overall G catch rate before the closure and therefore not predicted for the area as a whole (Figure 4.8). This effect has been observed in response to spatial closures put in place for Scotian shelf haddock (van der Lee et al., 2013), the Trevose closure off the UK coast (Armstrong et al., 2007) and elsewhere (Kellner et al., 2007) and highlights the need to ensure that management measures and choice sets are at the appropriate spatiotemporal scale (Dolder et al., 2020; Hicks et al., 2020).

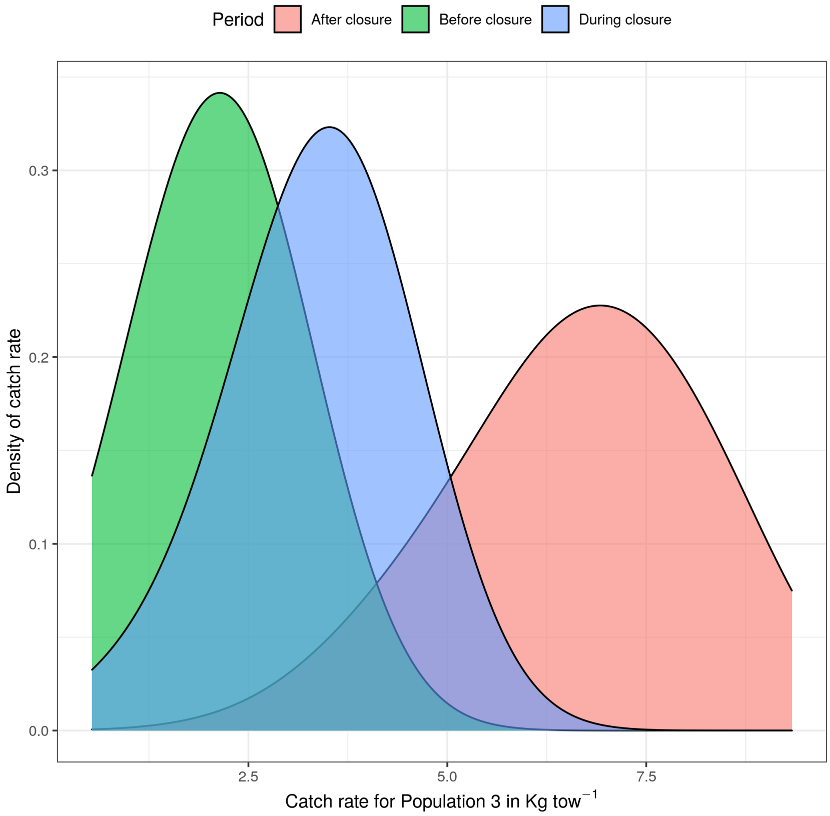

Figure 4.8: Differences in catch rates for Population 3 Before, During and After the closure. Bandwidth for kernel density is set to 1 standard deviation.

The Random Utility Model and Markov Model describe quantitatively the main drivers in location choice through a formal statistical framework, which provides inference on the importance of competing drivers for effort allocation. However, predicting from statistical models beyond the observed conditions must be done with care. For example, when a spatial closure is implemented or a quota for a species is significantly reduced the relationships between the predictor variables may change. This is because alternatives to the closure area may not be independent where, for example, the area closed can be substituted by another area which has similar characteristics (for example, similar species caught) but was less favourable than the area closed. This changes the utility for the new area area once the other opportunity is closed to an individual, violating the principle that variables are independent and identically distributed (IID). While there have been developments in RUM applications to address the IID problem (e.g. nested or mixed-logits) the alternative choices must be understood prior to implementation. The strong influence of past choice as an explanatory variable (Girardin et al., 2017) may mask understanding of these relationships.

In addition, there is a debate about whether fishers are maximisers of any utility, however defined, given the largely uncertain information with which they make decisions. Holland (2008) outlines how alternatives which take account potential non-linearities in risk-reward behaviour in decision making, such as prospect theory, may provide closer predictions for location choice. Such 'satisficing' objectives may be better defined with rule based decision making rather than expected utility maximisation.

Process based models require strong *a priori* assumptions about the drivers of dynamics in the fisheries, and if developed to characterise such satisficing and rule-based decisions the emergent dynamics may be better able to provide insight into previously unobserved system dynamics. This explicit statement of assumptions allows for unambiguous understanding of the mechanisms behind effort allocation but provides a challenge in describing all of the mechanisms that contribute to the dynamics and being able to distinguish among them in calibrating such models. Further, misspecified models run the risk of leading to biased predictions due to the over-influence of one or more variables.

The reparameterised RUM performed better than any of the other statistical or process based models. The model combines features of both in that it estimates the influence of profit from the fisheries relative to each other, similar to the Ideal Free Distribution principle in a Gravity Model that states effort allocates according to relative distribution of the resource. By estimating the influence of the relative value the reparameterised RUM does not assume a direct relationship, but estimates the strength of this relationship in making predictions. Linking theoretical and statistical models provides a basis for combining strengths from each of the modelling approaches and highlights bases for inference among models.

The Dynamic State Variable Model was applied here as a general location choice model, but our application did not include more detailed policy exploration that models have been developed for in the past. These applications include exploring the response of fisheries to different management measures on mixed fisheries including catch limits (Babcock and Pikitch, 2000) and catch limits in combination with discard bans (Poos et al., 2010; Batsleer et al., 2016; Alzorriz et al., 2018). DSVMs are arguably the only class of model that can evaluate such detailed policies due to their ability to incorporate both short-term and long-term constraints in decisions about when and where to fish. Though the effect of quota availability could be incorporated in RUMs and Markov Transition Models, to our knowledge this hasn't been considered to date (Girardin et al., 2017).

The predictions in our comparison are limited by the limited definition of the fisheries in the study; activity in the "elsewhere" category also show some spatial patterns likely to be differentiated fisheries, and as such all the models do a much poorer job of predicting effort allocation (including seasonal distribution) in the fisheries not specifically pre-defined. The exception to this is the PastShare model predictions that capture the dynamics and scale of the effort allocated to the "elsewhere" areas well (Figure 4.4). It may be that the other models could similarly improve their prediction accuracy if the fisheries in the rest of the spatial domain were better characterised and could therefore be described in part by their past profit or other covariates. As accuracy of the predictions is not the goal of this paper, we did not refine the location choices further but highlight the importance of accurate area definitions.

An interesting feature of the simulation data that the models were fit to was the ability to replicate the "fishing the line" around a spatial closure, observed in real world examples of spatial closures. This observed behaviour was more challenging to predict due to the discrete nature of the spatial areas defined for location choice, with locations being an aggregate across an area with similar catch patterns. Defining consistent spatial units from aggregated data is a challenge highlighted previously and new continuous space approaches (Hicks et al., 2020) offer a promising direction to capture the full spectrum of choices available to fishers.

4.6 Conclusions

We set out to establish the theoretical and applied basis for comparing location choice models commonly used in fisheries science. We derived the mathematical equivalence of some of the models under specific circumstances opening avenues for inference. We then used a simulation framework to compare and contrast predictions of fishing effort allocation following a spatial closure. To our knowledge this is the first cross-comparison of location choice models and provides a basis for continual development of these methods and inclusion of location choice models in an MSE setting.

We find that while several different models for location choice have been proposed from different foundations including micro-economic and ecological theory, the models were more similar structurally than anticipated. We could equate Gravity, Random Utility, Markov and Dynamic State Variable models under certain conditions and found the data, formulation and covariate parametrisation are some of the main determinants of different predictions from the models.

Our applied comparison demonstrated the different characteristics of the location choice models; before introduction of the spatial closure no model outperformed the null model (*status quo* effort allocation among areas) in predicting future share of fishing effort among the fisheries. However, the statistical models all performed significantly better than the process based models, which biased effort allocation towards particular fisheries. Following implementation of the closure the performance of the statistical models, while still providing more accurate predictions, degraded where the process models did not. The reparameterised version of a RUM, which included predictions based on the relative profit from each fishery, equivalent to a Gravity Model but where the influence of profit in each area was estimated rather than assumed to follow an Ideal Free Distribution, performed best. This model combined aspects of a statistical and process-based model in that it defined a mechanism but estimated the fit of the data to that mechanism.

There are advantages to both classes of models; the statistical models are able to 'let the data speak for itself' and deal with both explained variance, e.g. due to catch rates of different stocks and unexplained variance through an error term. However, when a major change is implemented, such as a spatial closure, then some of the assumptions in the model may be violated leading to extrapolation and degradation in performance. In this case the inclusion of a process model either in combination or supplementing the statistical model should be considered. This reflects that process models and statistical models have different properties: statistical models capture dynamics well when there are no significant management interventions ignored in the model matrices, but process models are able to reflect emergent properties of a system that allows them to better adapt predictions for unobserved states. We argue that these differences are complimentary and that both approaches should be considered and where possible features of each approach formally combined. This could be achieved either by formulating the model to include elements of both statistical and process-based dynamics (Cuddington et al., 2013) as with the reparameterised RUM, or through an ensemble framework as a statistical meta-model (Spence et al., 2018). Doing so provides a robust framework for consideration of location choice when implementing MSEs for mixed-fishery management plan evaluations.

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Chapter 5

Alternative hypotheses for location choice in mixed-fishery management strategy evaluations

This chapter is in preparation for submission to *ICES Journal of Marine Science*. Supplementary material can be found in Appendix I, and the new function to implement the location models in FLBEIA in Appendix J.

Dolder, P. J., Minto, C., García, D., & Poos, J. J. (in prep.). Alternative hypotheses for location choice in mixed-fishery management strategy evaluations. *ICES Journal of Marine Science*.

5.1 Abstract

Management strategy evaluations (MSEs) are generally undertaken on a stock by stock basis despite the fact that most fisheries exploit multiple stocks simultaneously. This lack of integration may result in over-quota catches and poor implementation of management measures, leading to suboptimal outcomes. While mixed fisheries models explicitly account for these technical interactions, they are yet to routinely incorporate fleet dynamics in simulations, including how fishers might change their spatial allocation of effort in response to changing fishing opportunities.

The choice of when and where to fish has a fundamental impact on the mix of species caught due to differences in density of fish at different fishing grounds, yet is challenging to predict due to the complex drivers of spatial dynamics. We argue this necessitates a hypothesis led approach to inclusion of location choice in mixed fisheries MSEs. This allows for consideration of alternative models and model formulations that describe location choice and explicit consideration of how location choice might affect management goals without reliance on a 'best' model.

We implement three different location choice models in the bioeconomic management strategy evaluation framework FLBEIA: a Gravity Model, a Random Utility Model and a Markov Transition Model. Each are integrated into FLBEIA in a flexible manner, updating predictions of effort share and allocation among métier dynamically in the simulation through integration with the biological and economic components of the model. We illustrate application of the models as part of the fleet operating model for Irish otter trawlers fishing in the mixed demersal fishery in the Celtic Sea.

Results show how different models provide for alternative realisations of future effort allocations among métier, and how this affects fisheries indicators and the potential outcomes of management measures within a mixed fishery. For example, while the gravity location choice model predicts low risk to fishing >Fmsy for haddock in the mixed fishery, the other models predict a risk >50%, qualitatively changing the conclusions of the MSE. We argue that explicitly modelling location choice dynamics in a mixed fishery MSE framework even when no 'best' model is available improves robustness of management advice.

5.1.1 Keywords

MSE, mixed fisheries, fleet dynamics, RUM, Markov

5.2 Introduction

Most of the world's fisheries are mixed with several different species being exploited together in the same fishing operation (Ulrich et al., 2012). When the species caught have varying quota limits and exploitation rates such technical interactions can result in discarding unwanted catch or "choking" of quota where the quota of the species whose catch is most easily obtained is reached. This can have a fundamental impact on management outcome as the intended restrictions on catches may not be achieved or the full quota may not be caught, having implications for both stock status and fisheries yield.

Evaluation of the performance of management rules is generally undertaken through management strategy evaluation (MSE, Punt et al., 2016), but while this method is considered the gold-standard in fisheries science it is largely still based on single-species models that do not take account of the interactions between stocks. These interactions, including predator-prey biological (Thorpe et al., 2016) and technical (mixed-fishery) interactions (Ulrich et al., 2001), are treated only as random noise around biological parameters or directed bias in catches in single stock MSEs when assessing harvest rates for sustainability (known in MSE frameworks as "implementation error", Sethi et al., 2005; Dichmont et al., 2006)

In order to progress evaluation of fishery-based management strategies it is crucial for MSEs to take account of multi-stock processes, to better understand the impact they have on management outcome. Failure to account for these processes may result in misleading conclusions when comparing different management approaches and suboptimal management.

To address this gap, mixed fishery methods have been developed and applied to numerous case studies (Ulrich et al., 2011, 2017; Iriondo et al., 2012; Garcia et al., 2020). The mixed-fishery approach used in Europe to provide management advice (ICES, 2019) models activity of fleets (vessels of similar physical characteristic) and how fishing effort is deployed in different métiers (activity defined by similar catch patterns) to predict catch of multiple stocks caught together. As each métier has a different catch pattern and catchability (the biomass-standardised catch per unit of effort) for each stock, the choice of which métiers to fish results in different catch outcomes for the fishery and exploitation rates for each of the stocks. Considered together, the sum of the different fleets activity (and their unique catchability patterns) provide an alternative way to forecast how the exploitation of stocks caught together in numerous different fisheries might develop by taking account of their technical interactions.

Location choice is one key decision that effects catch in mixed fisheries. This is rarely taken into account in simulations of management strategies. Different locations have different density of target and non-target species, therefore choice of where to fish determines how much of each species is caught. However, with the absence of an alternative, mixed fishery models often assume that the proportional share of fishing effort among different métier remains unchanged from one year to the next. This is despite the fact that fishers are known to change their behaviour in response to available fishing opportunities (Van Putten et al., 2012). A lack of operating model to account for how fisher behaviour affects catch of multiple stocks limits the ability to evaluate management strategies from a mixed fishery perspective. There are few examples (e.g. Dichmont et al., 2008; Fulton et al., 2014) where such an operating model has been incorporated in an MSE.

FLBEIA (Garcia et al., 2017) is a bioeconomic framework for simulating management strategies for multi-stock multi-fleet fisheries taking account of mixed-fishery (technical) interactions. It is based on the FLR library of fisheries management tools (Kell et al., 2007), and can be used to evaluate the effect of different harvest rules and model selectivity improvements and spatial closures to assess their impact on biological and economic components of the stocks and fisheries. FLBEIA takes a modular approach, with components for biological and fleet operating models and a management procedure taking account of the perceived state of the system and implementation of defined management rules, thus taking account of full feedback and uncertainty in management outcome (See Figure 5.1).

FLBEIA applications typically assume constant share of a fleets' fishing effort among different métier (Ulrich et al., 2017; Garcia et al., 2020), with ex-

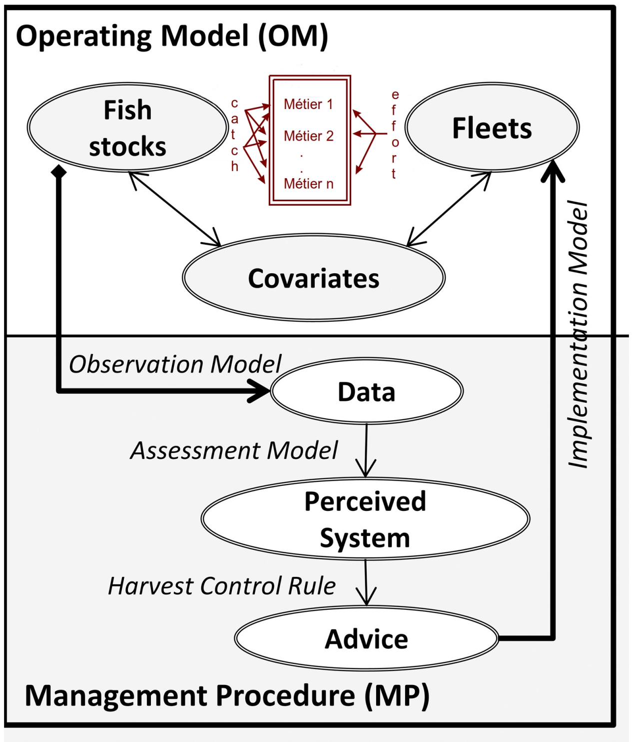

Figure 5.1: FLBEIA schematic, adapted from Garcia et al. (2017) to show the métier interaction (dark red) in the modelling framework.

ploitation per unit of effort for different fleets remaining static inter-annually. Therefore while the fleet and its activity among different métier are characterised and parameterised in the model, these interactions are not dynamic in the simulation. For example, no account is taken of how vessels might switch between a demersal fish fishery and a *Nephrops* fishery due to changing prices and fishing opportunities, though these dynamics are known to exist (Davie and Lordan, 2011). This limits understanding of the impact of fleet dynamics on outcomes for different fisheries strategies.

Here, we extend application of FLBEIA to include three commonly used fleet dynamics models for location choice. These are the Caddy Gravity Model (Caddy, 1975), the conditional logit Random Utility Model (McFadden, 1973) and a Markov Transition Model (Venables et al., 2009). We apply the models to the Celtic Sea demersal fisheries, with location choice for Irish otter trawlers among seven areas determined by each of the models and compared to a base case of constant effort share.

In applying the different location choice models to a case study in the Irish otter trawl fishery in the Celtic Sea we seek to establish if i) the models provide different predictions of fishing effort share among métier, ii) if those differences result in different exploitation patterns for the stocks exploited, and iii) if the differences would lead to qualitatively different conclusions on the sustainability of a management strategy given the different assumptions on location choice.

5.3 Methods

As an overview of the methods, we implemented five location choice models within the FLBEIA modelling framework; i) a base 'tradition' model where effort share among métier remains the same as in the past, ii) a Gravity Model where effort is predicted from attractiveness based on revenue per unit effort, iii) a hybrid gravity-tradition model, iv) a conditional logit Random Utility Model (RUM) and v) a Markov Transition Model, both of which include catch rates for a selection of stocks and season as predictors. Each of the models were fitted to real data and relevant coefficients used to forecast effort share among métier within the FLBEIA simulation. Effort allocations were thus updated dynamically based on changes in the fishery dynamics.

We implemented the models based on the Irish Otter trawl fleet with 9 different locations (defined as métier) within a management strategy evaluation framework for a mixed fishery exploiting 11 stocks in the Celtic Sea (ICES subdivisions 7bc,e-k). A closure of one of the métier was implemented part way through the simulations. We then compared the outcomes for the fisheries catch projections for the fleet and stock-based fishery indicators to assess the differences in outcome given the location choice model used. We now describe each component in detail.

5.3.1 FLBEIA

Here, we focus only on the methods implemented that control allocation of fishing effort among métier and how that affects catches, fishing mortality and biomass across the assemblage. Full details of the population, management and fleet capital dynamics as well as details on setting up an FLBEIA simulation and can be found in the technical manual (Garcia et al., 2017), with examples found here: (`https://flr-project.org/doc/FLBEIA_A_Simple_Example.html`). FLBEIA can be installed as a library in R from github (`www.github.com/flr/FLBEIA`).

To model seasonal and inter-annual fleet dynamics, FLBEIA explicitly defines the relationships between the fishing effort of each fleet and the catch of each stock using a Cobb-Douglas catch equation: determined by the overall effort by a fleet, allocation of that effort among different métier and catchability for each stock within the métier (Garcia et al., 2017):

$$C_{f,s} = q_{f,m,s} \cdot B_s^{\beta_{f,m,s}} \cdot (E_f \cdot \delta_{f,m})^{\alpha_{f,m,s}} \tag{5.1}$$

Where within a given timestep $C_{f,s}$ is the catch of fleet f for stock s, q is the catchability for métier m for the stock (which is a function of both selectivity and availability to capture) and B biomass for the stock, with $E_f \cdot \delta_{f,m}$ the Effort E and δ the métier effort share ($0 \leq \delta_{f,m} \leq 1$). α and β are Cobb-Douglas production coefficients, where when set to 1 gives a proportional relationship between fishing effort and catch for a given biomass. For simplicity, the time and age subscripts have been dropped, but Equation (5.1) also applies on an age-by-age basis for catch, catchability and biomass.

Our focus in implementing location choice models within FLBEIA is on determining how $\delta_{f,m}$ for $m = 1...M$ might respond to changing fishing opportunities and management regulation. By proposing alternative hypotheses on how effort share might change over time, we provide plausible alternative fleet operating models that can be used in evaluating multi-stock mixed fishery management strategies.

Once the division of effort among métier is decided, the overall effort deployed by the fleet determines the catch of each stock. However, a prediction must be made as to how much effort a fleet would deploy in response to the available fishing opportunities. Optional rules include stopping fishing when the first quota is reached ('min'), the last quota is reached ('max') or a spectrum in between: this approach is known within FLBEIA as 'Simple Mixed Fishery Behaviour' (SMFB).

5.3.2 Derivation of the location choice models

The five models implemented to provide alternative hypotheses of effort share among métier include:

(i) A **Base model** (b) where the proportion of effort in métier m at time t is:

$$p_{m,t}^{(b)} = \overline{p}_m \tag{5.2}$$

This ensures that future effort is simply determined by the past share of effort, as an average over the past years defined by the user.

(ii) A **Gravity Model** (g) where the proportion of effort in métier m at time t is given by:

$$p_{m,t}^{(g)} = \frac{\overline{R}_m}{\sum\limits_{m=1}^{M} \overline{R}_m} \tag{5.3}$$

where $\overline{R}_m$ is the expected revenue per unit effort in a given métier, where R for a given year is defined as:

$$R_{m,t} = \sum_{s=1}^{S} L_{m,t,s} P\mathrm{x}_s \tag{5.4}$$

comprised of the sum of the landings per unit effort L of each species s for métier m at time t multiplied by the price $P\mathrm{x}_s$. The expected landings per unit of effort are updated in simulations to reflect changes in biomass for the stocks, providing dynamic feedback to the predictions. It's also possible to implement this approach based on profit per unit effort, where the cost per unit of effort of fishing in a particular métier are subtracted from Equation (5.4).

(iii) A **Gravity and Tradition combination**, an alternative formulation of a Gravity Model was included, where 80% (denoted by ϕ) of the effort allocation was determined by past effort (tradition, or inertia) and 20% by the Gravity Model (economic opportunism). This Gravity-Tradition combination model (c) is given by:

$$p_{m,t}^{(c)} = \phi \cdot p_{m,t}^{(b)} + (1 - \phi) \cdot p_{m,t}^{(g)} \tag{5.5}$$

where ϕ controls the proportional weighting of either model.

(iv) A **Random Utility Model** where a case- and choice- specific multinomial logit RUM (r) is implemented so that:

$$p^{(r)}_{m,t} = \frac{e^{\beta_m \cdot X_t + \gamma \cdot Z_{m,t}}}{1 + e^{\beta_m \cdot X_t + \gamma \cdot Z_{m,t}}} \tag{5.6}$$

The choice-specific covariates $Z_{m,t}$ can comprise catch rates or revenue from stocks from fishing in the métier, while the case-specific covariates (X_t) included a seasonal effect.

(v) A **Markov Transition Model** where the proportion of effort in métier m at time t is the sum of the transitioned proportions of effort from métier z (the departing métier) at time $t-1$:

$$p^{(m)}_{m,t} = \sum_{z=1}^{M} p^{(m)}_{z,t-1} p_{z,m,t} \tag{5.7}$$

where the transition probabilities are given by the logit function:

$$p_{z,m,t} = \frac{e^{\beta_{z,m} X_t}}{1 + e^{\beta_{z,m} X_t}} \tag{5.8}$$

Seasonal changes can be included through the effect of month in the vector X_t.

5.3.3 Implementing location choice models in FLBEIA

We implemented each of the location choice models flexibly within FLBEIA so that the covariates are derived from one or more of the stock-specific catch rates or elements from an internal FLBEIA object. For example, by specifying a particular stock or slot from an FLMetierExt (e.g., effshare) it can be included in the model estimation and prediction of effort allocation among métier.

Here we describe the changes to a model setup required to implement the location choice models in FLBEIA; the general model setup is described in Garcia et al. (2017) and will be specific to case studies. For all models, the 'effort.model' should be set as 'SMFB_ES' (Simple Mixed Fishery Behaviour Effort Share) within the 'fleets_ctrl' object passed to the main 'FLBEIA' function. This accesses the location choice model settings:

```
fleets.ctrl[[fleet]][['effort.model']]   <- 'SMFB_ES'
```

Each of the location choice models can then be specified through the following changes.

(i) **Base model**

No changes to existing FLBEIA code are needed to implement this approach as it is the default.

(ii) **Gravity Model**

To implement the Gravity Model requires no model formula to be passed to FLBEIA, but you can set different options once the effort share model has been specified. The following implements a Gravity Model based only on the revenue from each métier:

```
fleets.ctrl[[fleet]][['effshare.model']] <- 'gravity.flbeia'
fleets.ctrl[[fleet]][['gravity.model']] <- 'revenue' ##
   alternative:profit
```

(iii) **Gravity tradition model**

To extend (i) to the gravity-tradition hybrid model requires an additional option to be passed to FLBEIA specifying the proportion of the métiers effort that should be determined by the past share (or tradition):

```
fleets.ctrl[[fleet]][["gravity.tradition"]] <- 0.8 ## 80 %
   from tradition
```

(iv) **Random Utility Model**

To implement a RUM, the model must first be estimated using the R package *mlogit* (Liao, 2011) and the function **mlogit**. This takes a specifically formatted data frame which includes values for both the choice and the alternatives (see the helpfile of *mlogit.data* for details) and a standard formula and returns a model object. For example, a model with 'cod' and 'had' catch rates as choice specific covariates and season as a case specific covariate is specified as:

```
model <- mlogit(choice ~ Cod + Had | season, data = data)
```

Following estimation, the model object can then be passed directly to FLBEIA as follows:

```
fleets.ctrl[[fleet]][['effshare.model']] <-  'mlogit.flbeia'
fleets.ctrl[[fleet]][['mlogit.model']]   <-  model
```

(v) **Markov Transition Model**

The Markov Model is estimated with the R package *nnet* and the function **multinom**. To enforce the Markov property and generate transition probabilities between states, the previous state should be included as a covariate, for example:

```
model <- multinom(choice ~ choice.tminus1*(Cod.tminus1 + Had.
   tminus1) + season.tminus1, data = data)
```

Following estimation, the model object should be passed to FLBEIA as follows:

```
fleets.ctrl[[fleet]][['effshare.model']] <-  'Markov.flbeia'
fleets.ctrl[[fleet]][['Markov.model']]   <-   model
```

5.3.4 Applied example

We demonstrate use of the location choice models as alternate hypotheses for short-term fleet dynamics through application to an MSE for the Celtic Sea demersal fisheries. We defined a multi-stock multi-fleet fishery and applied the same management measures with each of the location choice models, utilising the models as alternative fleet dynamics in a wider MSE setup. Focus is solely on the location choice models to demonstrate their use, rather than the wider MSE set up (Graham, 2016).

5.3.4.1 FLBEIA model for the Celtic Sea

To demonstrate the use of the location choice models we conditioned an FLBEIA model based on the Celtic Sea (ICES sub-divisions 7bc,e-k) demersal fisheries. It included 11 stocks; six with age-based population dynamics: European cod (*Gadus morhua*), haddock (*Melanogrammus aeglefinus*), anglerfishes (*Lophius spp.*), European hake (*Merluccius merluccius*), Megrims (*Lepidorhombus spp.*), European whiting (*Merlangius merlangus*) and five *Nephrops norvegicus* stocks (Functional Units 16, 17, 19, 20-21 and 22) with biomass-based population dynamics. The model was conditioned to be seasonal, with quarterly time-steps and included 12 fleets; the Irish Otter trawl fleet was explicitly modelled while the remaining catches were aggregated into a separate fleet ("COD_fleet", "HAD_fleet" etc..). This approach ensured that any differences observed between scenarios was down to the choice of location model for the Irish otter trawl fleet only.

We assumed that the Irish otter trawl fleet stops fishing when the effort corresponding to the effort required to catch the stock that effort was closest to in the previous year for all location choice models. While other choices are available (as outlined in Section 5.3.3), we considered this to be a reasonable representation of dynamics in the fishery.

5.3.4.2 Model conditioning

The data used to condition the model included the assessment outputs from the ICES single stock assessments undertaken in 2018 (ICES, 2018) which include the biological parameters such as numbers-at-age, weights-at-age, maturity and natural mortality as well as recent fishing mortality rates. As the data is annual we partitioned the data into quarterly estimates by fitting a Von Bertalanffy Growth curve to the mean weights and allocating the catch at age according to the quarterly weighted estimates of catches from the fleet data.

Fleet catch data was derived from the EU Fisheries Dependent Information (FDI) database (STECF, 2017) which included i) spatially-disaggregated landings (in tonnes), ii) spatial fishing effort (in hours fished), and iii) spatially-aggregated fishing effort (kilowatt-days) and iv) landings and discards (in tonnes). We used the spatial data as a relative reference as it did not include discards and disaggregated the non-spatial landings, discard and effort data according to this reference. We then disaggregated the catch across age-classes according to the relative catch at age in the ICES assessment data. While we would ideally want to make the age-structure of the catch data fleet and métier specific, the data were processed for illustrative purposes to demonstrate use of the location choice model rather than a detailed assessment of management-ready options.

Métier were defined by using the FDI spatial data set to aggregate ICES statistical rectangles into groups of spatial areas that were similar in catch profile, as defined by the ward clustering algorithm implemented in R 3.6.3 (RCoreTeam, 2020), which were subsequently adjusted based on expert knowledge to form contiguous fishing areas.

5.3.4.3 Location choice model fits

To fit the RUM and Markov Model we allocated the historical activity of the fleets to each of the métier. As the data were aggregated to quarterly information, which was unsuitable for fitting the conditional logit (for the RUM) and the multinomial (for the Markov Model) we generated pseudo-data at the trip level by i) sampling 1000 times with replacement from the observed proportions in each of the métier in each year, ii) sampling from the observed mean catch rates with a standard deviation of 0.2 x mean for each of the stocks, iii) using the generated data as individual observations for trips in a given season and year.

We then use the pseudo-dataset to fit all 8192 possible combinations of RUM covariates (11 stocks, plus past effort share and season = $11^2 \times 4$) using *mlogit* to find the best fitting model according to BIC (Schwarz, 1978). Due to computing limitations, rather than fit all combinations of the Markov Model we used the same covariates as identified for the RUM.

5.3.4.4 Simulations with location choice models

For each stock the harvest rate was set according to the ICES Fmsy strategy where fishing mortality is targeted at F_{MSY} unless the stock is below the biomass reference point $MSY_{Btrigger}$, in which case it is reduced linearly to zero (see Table 5.1 for reference points). Resultant seasonal catch was determined by the fishing opportunities, total fleet effort as predicted by the SFMB (taking account of mixed-fishery interactions) and effort share among métier according to the location choice model.

Simulations were run from 2018 - 2030 with a closure introduced in year 2021 for métier ‘F’. Population variability in the simulations was introduced by

Stock	Code	Fmsy	Blim	Bmsytrigger	r	K
Cod	COD	0.35	7,300	10,300	-	-
Haddock	HAD	0.4	6,700	10,000	-	-
Anglerfishes	ANF	0.28	16,032	22,278	-	-
European Hake	HKE	0.28	32,000	45,000	-	-
Megrims	LEZ	0.191	37,100	41,800	-	-
Whiting	WHG	0.52	25,000	35,000	-	-
Nephrops FU16	NEP16	0.062	19,880	49,700	0.25	71,000
Nephrops FU17	NEP17	0.085	4,637	11,593	0.6	16,000
Nephrops FU19	NEP19	0.093	4,032	10,080	0.6	24,000
Nephrops FU2021	NEP2021	0.06	33,040	82,600	0.6	118,000
Nephrops FU22	NEP22	0.128	7,585	18,963	0.6	29,000

Table 5.1: Biological Reference Points used in the Harvest Control Rules for each stock when setting the overall annual Total Allowable Catch. Biomass dynamic growth (r) and capacity (K) only shown for Biomass Dynamic stocks.

fitting a hockey-stock stock-recruit relationship for each of the stocks and lognormal variability around the estimated fit used to generate draws for 500 iterations. The *Nephrops* population growth was assumed to be deterministic with biomass dynamic growth rate (r) and capacity (K) parameters used to simulate stock development with a Pella-Tomlinson biomass dynamic model (Pella and Tomlinson, 1969).

In addition to stochasticity in recruitment for the age-structure stocks, we added variation in the catchability for each métier-stock combination for the Irish otter trawl fleet by sampling from the last three years' estimates, to generate variability in the within-métier catchabilities among species. These were sampled jointly to ensure the same relationship between stocks as observed variance may reflect some historic inter-annual differences in targeting for a métier. Recruitment and catchability variance were multiplicative and the same seed was used for each location choice model in order to ensure the stochasticity was identical for comparison across location choice models.

5.3.4.5 Comparison

Location choice models were implemented as plausible alternative fleet operating models in a management strategy evaluation for a multi-stock mixed-fishery. As such no "correct" approach is to be identified; instead we compare the impact different assumptions might have on i) realised fishing mortality given the mixed-fishery interactions, ii) catches for the Irish otter trawl fleet, iii) development of spawning stock biomass (SSB), iv) risk based stock indicators. These differences are discussed in the context of progressing towards a mixed-fishery MSE approach.

5.4 Results

5.4.1 Métier definitions

The spatial métier identified for the Irish otter trawl fleet (Figure 5.2) show seven distinct areas with different catch patterns. Métier A is a large area defined by a broad mix of stocks where there is relatively low fishing effort compared to the concentration of effort in the other areas. Métier B is defined by catches of *Nephrops FU16* (Porcupine bank) but also includes catch of anglerfishes, hake and megrim and a small proportion of haddock. Métier C is defined by catches of *Nephrops FU20-21* (Labadie, Jones and Cockburn grounds) but also includes a mix of megrims, hake, haddock, cod and anglerfishes. Métier D covers an area South-West of Ireland and is characterised by catches of whiting, haddock, megrims, hake, anglerfishes, *Nephrops FU19*, and a small proportion of cod. Métier E covers an area South-East of Ireland and includes a large proportion of whiting and haddock, and shares of megrims, *Nephrops FU19*, anglerfishes, cod, hake and *Nephrops FU22*. Métier F is a single ICES statistical rectangle on the Smalls grounds, with the majority of catch comprised of *Nephrops FU22* and whiting, but also with catches of haddock, cod and anglerfishes and smaller proportions of megrims and hake. Finally, métier G is an area off the West coast of Ireland (Aran grounds) which is predominately catches of *Nephrops FU17* with a mix of whiting, megrims, haddock and anglerfish and a small catch of hake.

5.4.2 Catch rate influence on Gravity, RUM and Markov predictions

For the Gravity Model the influence of a stock catch rate on effort allocation was determined directly by the relative abundance of a stock in a métier and the relative price (Equation 5.4). For example, an increase in abundance of hake results in an increase in allocation of effort to métier D while an increase in abundance of *Nephrops FU16* results in an increase in effort allocation to métier B (Figure S1). For most species the effect of an increase in catch rate is for an increase in one métier and decrease in others or occasionally an increase in allocation to two métier (haddock and megrims in Figure S1). *Nephrops*

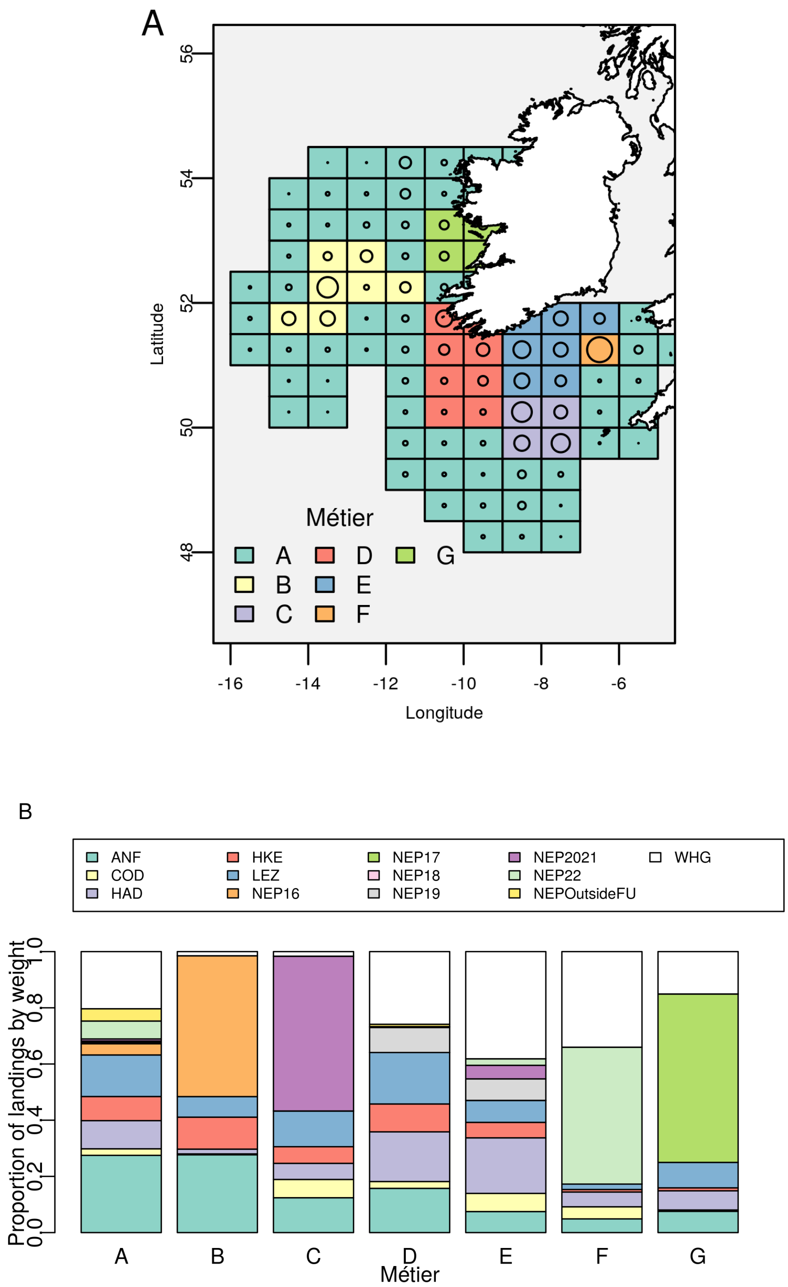

Figure 5.2: A: Métier defined through spatial clustering of similar landings composition for Irish otter trawlers modified by using knowledge of fishing grounds to make coherent spatial units. Circles represent relative fishing effort in each of the rectangles. B: Catch compositions for the métier indicating the dominant stocks in catches for each of the fishing grounds. Stock codes are presented in Table 5.1.

catch rates had relatively large magnitude effects on proportional allocation to main métier associated with given functional units (Figure S1).

For the RUM, the model including catch rates of anglerfishes, cod, hake, *Nephrops* FU19, *Nephrops* FU22 and whiting along with a seasonal affect (Figure S4) fit best (lowest BIC of models trialled). Unlike the Gravity Model, the sign on a parameter estimate for a species-specific covariate could be both positive and negative. As such, an increasing stock catch rate in an area could lead to less effort being allocated there; for example we found that increasing abundance of anglerfishes led to more fishing effort being allocated to métier F and less to métier A despite métier A having a higher proportion of its catch as anglerfish (Figure 5.2). This was because the effect of anglerfish on effort allocation was negative (a coefficient of -1.13), so increases in anglerfish resulted in more effort to areas where it was less abundant (Figure S2).

For the Markov Model (beyond the intercept) a seasonal effect (Figure S5) and increasing abundance of anglerfishes led to more effort allocated to métier C while increasing abundance of whiting led to more effort allocated to métier E (Figure S3). In general, increasing catch rates led to more fishing effort being allocated to métier C as nearly all stock effects were strongest towards this métier.

5.4.3 Effort allocations under different location choice assumptions

All of the models included seasonal differences in allocation of fishing effort to the different métier and (except for the base case) had differences reflecting recruitment and catchability variability (Figure 5.3). Changes in population dynamics influence catch rates and was present in all of the models except the base case where location was determined by past allocations alone. We found that prior to the closure of métier F, the Gravity model allocated more effort to métier B and G than the base case or the other models, while the RUM allocated more effort to métiers E and F (Figure 5.4). The Markov Model allocated more effort to métier D and A and less to and B than the rest of the models (Figure 5.4). The gravity-tradition model was a compromise between the base case and the pure Gravity Model and allocated effort as expected by their relative weighting in this model.

Before the spatial closure the effect of the models on effort allocation can be seen to be stronger in the process-based Gravity Model than the statistical models (Figure 5.5). There was a strong preference in the Gravity Model to allocate effort to métier C, and while this was also the case with the Markov

Model which was not nearly as pronounced, suggesting that fitted parameters from the RUM and Markov Model were explained by more than just revenue per unit effort.

Following the closure of métier F differences can be seen in how the location choice models allocated effort to other open areas (Figure 5.6). While the baseline run reallocated effort proportionally to the existing allocations, the Gravity Model reduced effort in métier B and allocated a greater proportion of the effort to métiers C, D and E. The RUM allocated a greater proportion of effort to métier E, C and G than the others, with increased amplitude of seasonal differences apparent (Figure 5.3). The Markov Model showed the greatest variation in allocating a greater proportion of the effort to métier C and B and decreasing allocation of effort to métier D and G (Figure 5.6).

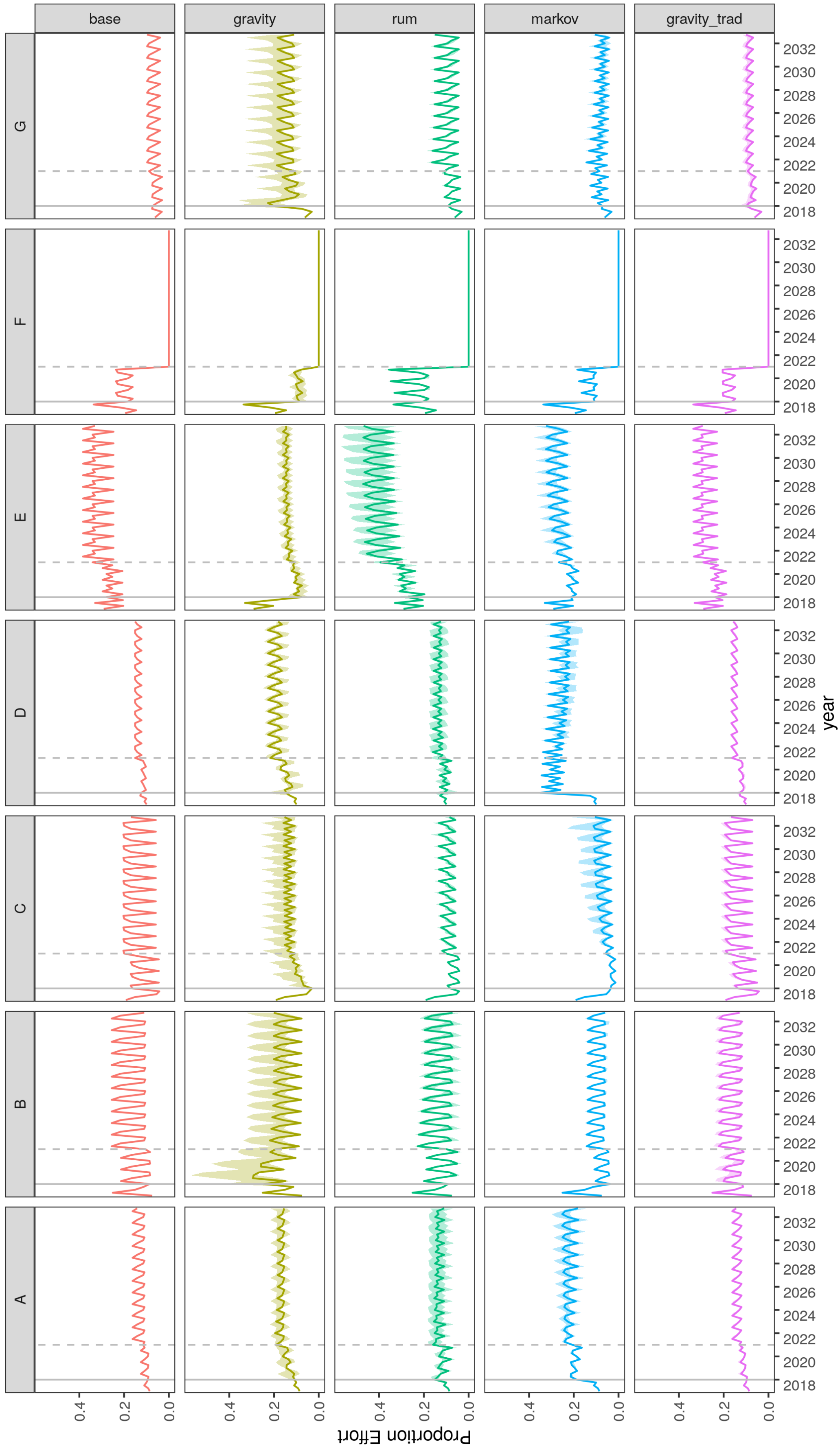

Figure 5.3: Quarterly fishing effort share (proportion) for each métier and location choice model in the Operating Model (2017 - 2032). Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure.

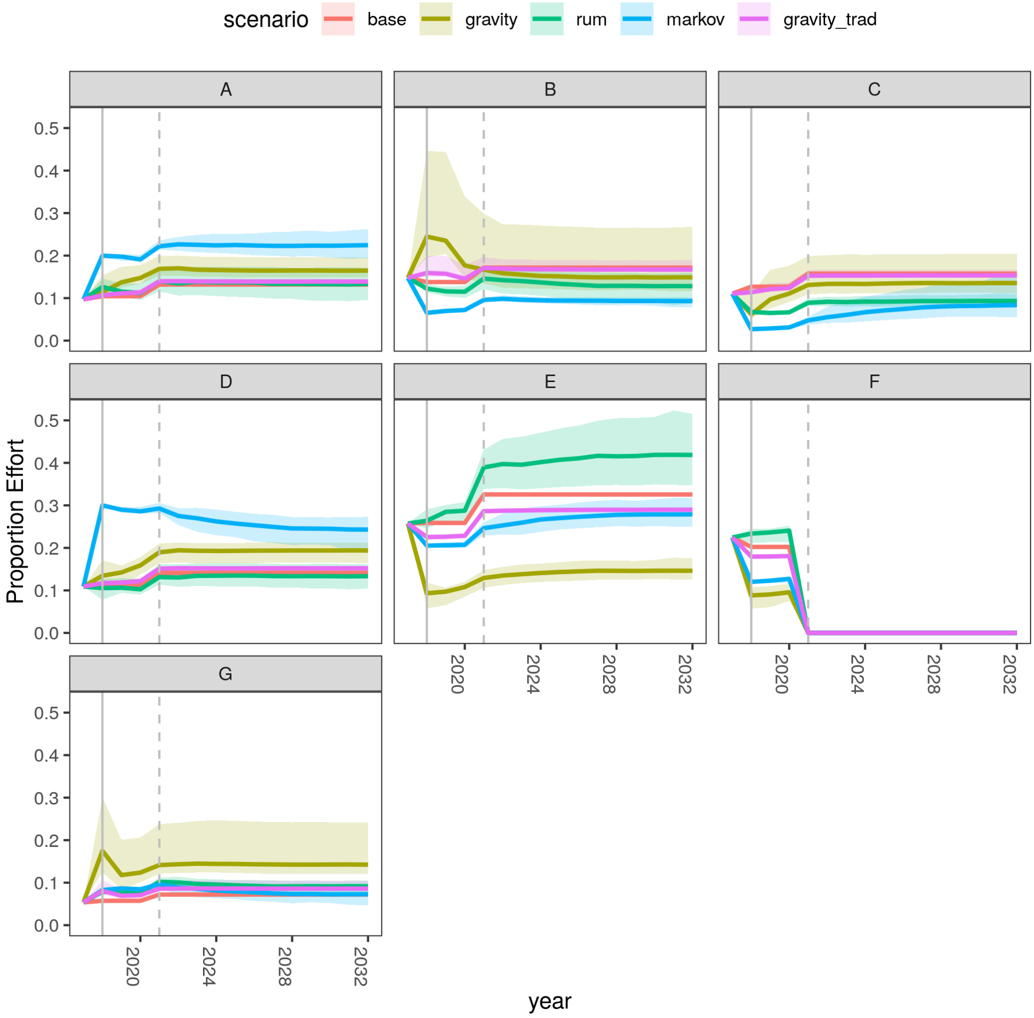

Figure 5.4: Annualised effort share (proportion) for each métier and location choice model (2017 - 2032). Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure.

5.4.4 Impact of location choice models on stock level indicators

The location choice model led to differences in median catches of all stocks (Figure 5.7), with lower catches of cod and haddock under the Gravity Model and higher catches of megrims under both the gravity and RUM choice models. Higher catches of hake were observed with the Markov Model, reflecting an initial increase in allocation to area D, Figure 5.3. In general, however, the scale of catches was more influenced by the recruitment and within métier catchability variability than the location choice model (the variability across iterations

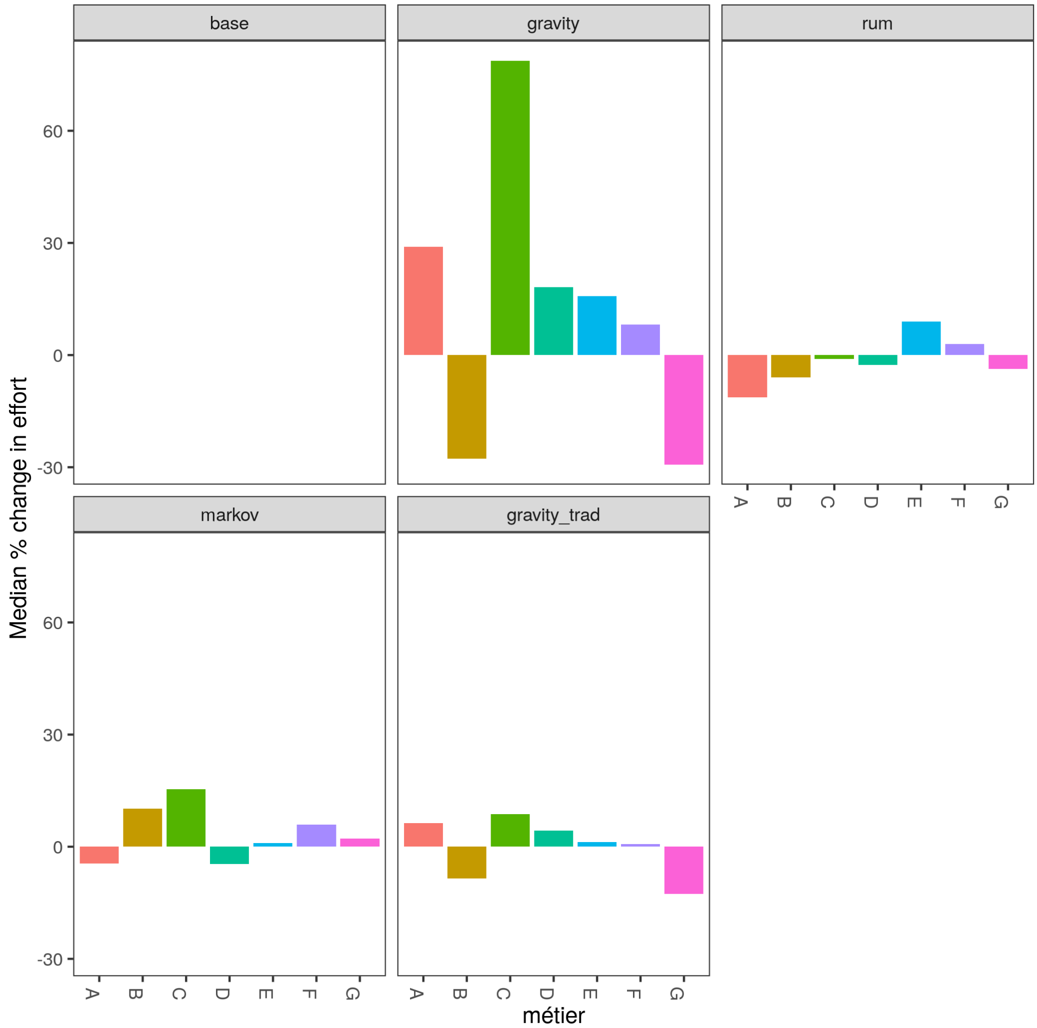

Figure 5.5: Percentage change in annualised effort share for each of the métier from before any closure (between years 2018 and 2020) .

was larger than the difference between medians of the location choice models).

At the stock level the difference in catches under the different choice models, while again influenced more by recruitment for the different stocks, led to a lower median fishing mortality on cod with the Gravity Model, while there was a higher fishing mortality on megrims with the markov and the Gravity Models and a lower fishing mortality with the RUM model. Conversely there was a higher fishing mortality on whiting with the RUM and Markov Transition Models (Figure 5.8). Importantly, for some species these differences comprise different inferences regarding whether the stock is above or below the F_{MSY} reference point (e.g., haddock and megrims in Figure 5.8). These difference led to some differences in spawning stock biomass develop-

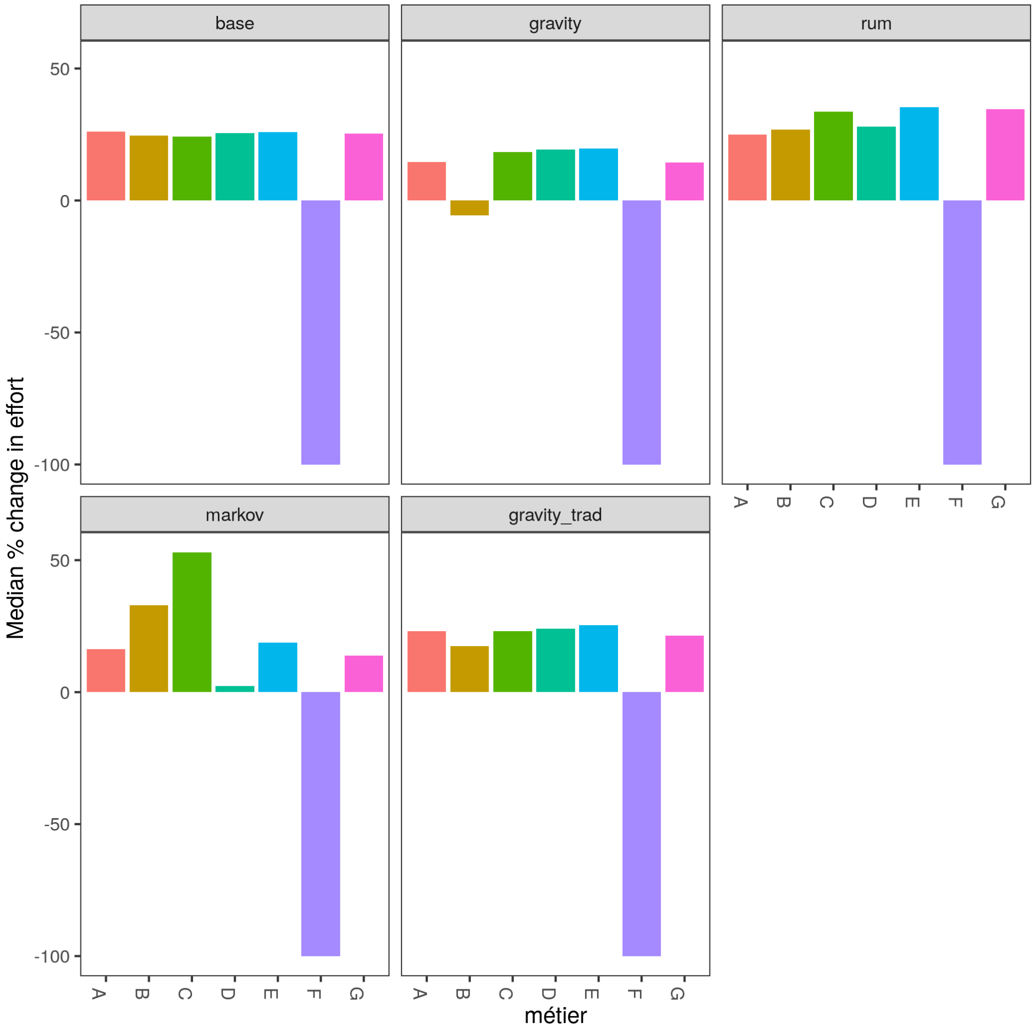

Figure 5.6: Percentage change in annualised effort share for each of the métier from before (2020) the closure of métier F and first year of the closure (2021).

ment (Figure 5.9) with cod rebuilding more quickly under the Gravity Model assumption and megrims SSB plateauing at a lower level under the gravity and Markov Transition Models.

While the differences among the location choice models for the main stock indicators was comparatively small, it did lead to appreciable differences in the risk based indicators (Figure 5.10). Risk to being above F_{MSY} objective was lower for cod and haddock under the Gravity Model than the other models. Whereas for megrims the risk was greater under the Gravity Model than the others (except the Markov Model). Interestingly the risk under the gravity-tradition model was less for megrims than either component (Figure 5.10). Relatively minor differences in risk to biomass-based indicators were observed under each model (Figure 5.10).

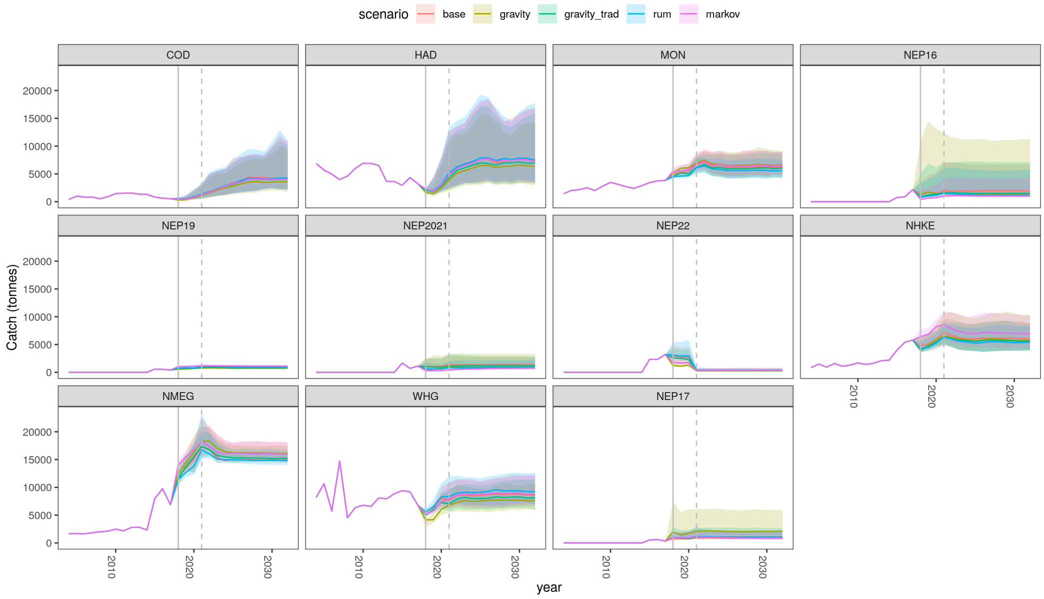

Figure 5.7: Catches of each stock by Irish Otter trawlers under the different location choice models. Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure.

5.5 Discussion

There is increasing interest in fishery-based management approaches to reduce incompatibilities between quotas for stocks caught as part of mixed fisheries (Ulrich et al., 2017; Garcia et al., 2020). To support the move away from single stock management towards a multi-stock approach requires scientific tools to evaluate how a management measure impacts all the stocks caught together in the fishery. Mixed-fishery based approaches require not only taking account of existing technical interactions (Ulrich et al., 2011; Garcia et al., 2017), but understanding how short- and long-term decisions made by fishers affect the development of those interactions over time to effectively evaluate management strategies and how fleet dynamics might affect management outcome (Marchal et al., 2013).

We generally implemented a range of location choice models in the FLBEIA framework; from a simple process-based Gravity Model to more complex statistical RUM and Markov Transition Models. All have been implemented in

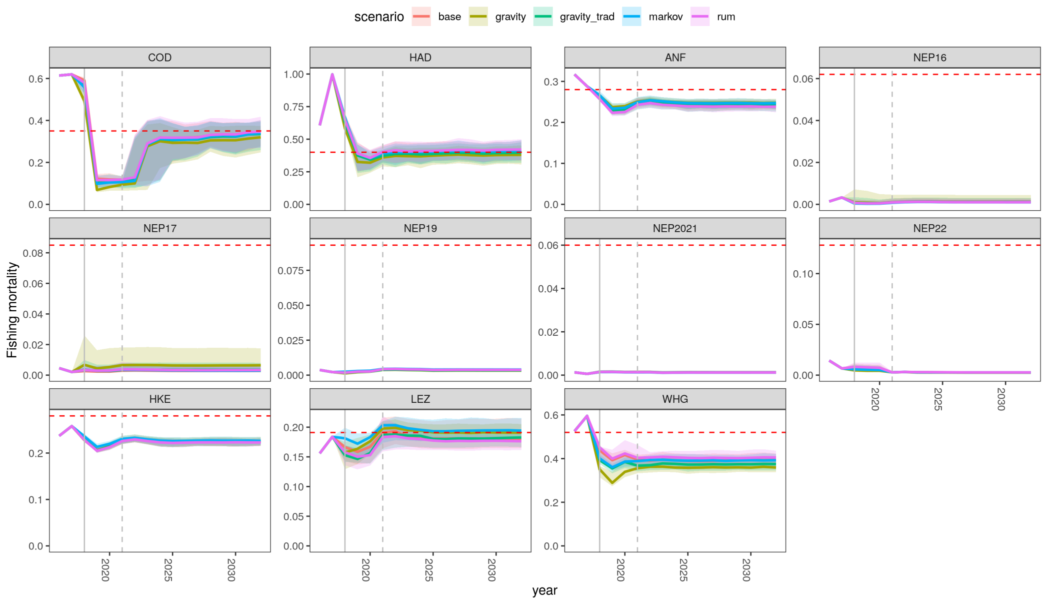

Figure 5.8: Fishing mortality for each stock under the different location choice models. Each stock was targeted to be fished at its Fmsy rate, using the ICES MSY Harvest Control Rule. Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure. Dashed red lines indicate the stock Fmsy reference point.

a flexible way, to provide the user with the ability to tailor the model to the specificities of the fishery. A key development was to identify effort share within a fleet as the most suitable entry point in which to embed these models. Transitions among fleets is not typically possible but how vessels within a fleet operate is replete with choices and hence naturally accommodates location choice models.

As implemented currently, possible covariates include stock-specific catch rates as well as costs, seasonal effects and past share spent in the métier. The framework is, however, easily extendable by using the “covariates” input to FLBEIA. Basing the model fitting and estimation on extant model implementations (e.g., mlogit, nnet::multinom) and processing those models internally, we enable flexibility to cover widely used methods in familiar modelling frameworks (Venables et al., 2009; Dichmont et al., 2006; Hynes et al., 2016). We also envisage compatability with other methods in the future, reflecting the modular structure. Importantly, we broaden the scope of previous applications to ask what their impact might be when used as operating model hypotheses to test management strategies, over their traditional use as standalone model fitting investigations.

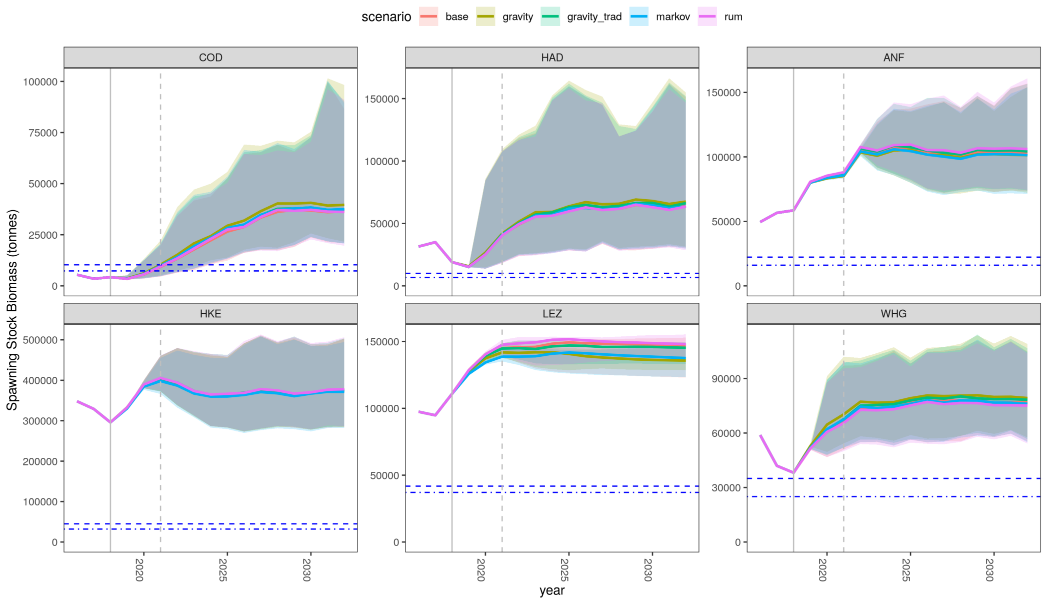

Figure 5.9: Spawning Stock Biomass for the fish stocks under each location model scenario. Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure. Dotdashed and dashed blue lines indicate the Blim reference and Bmsytrigger reference points respectively.

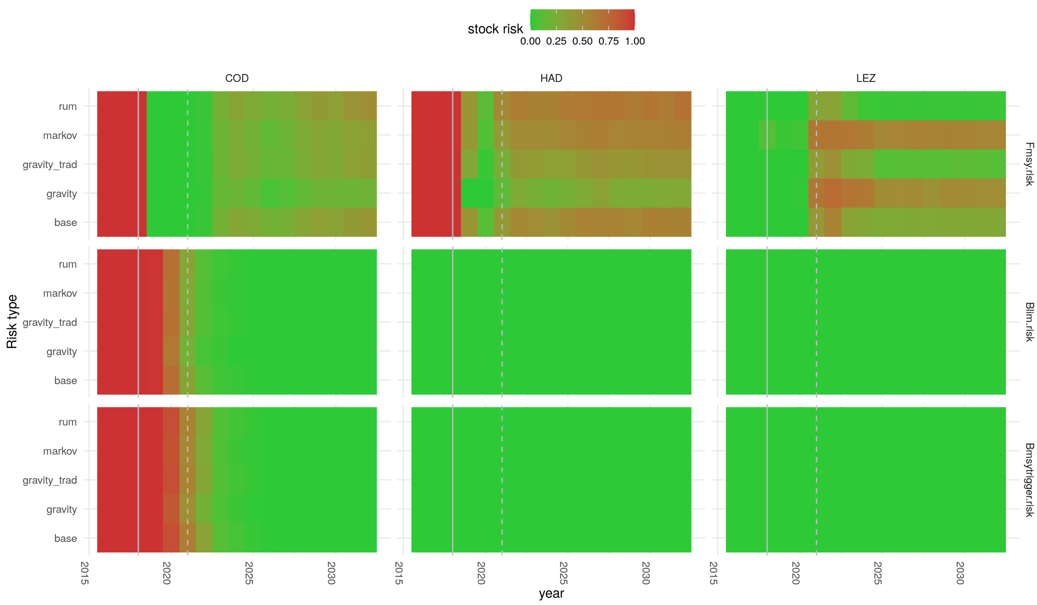

Figure 5.10: Stock risk indicators for each of the fish stock and location choice model scenarios. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure.

The approach is dependent on being able to characterise fishing grounds at the right spatial and temporal resolution to capture important spatiotemporal interactions (Dolder et al., 2020). While information on spatial dynamics generally needs to be inferred from fisheries-dependent information, the increasing availability of fine-scale data on fishing activity makes this possible (Gerritsen et al., 2012; Mateo et al., 2017) and has been applied to define choice sets in a location choice framework (Hynes et al., 2016). The modelling frameworks therefore synthesise highly-resolved decisions into formulations with parameters that reflect choice and variability of choice that can thus be brought into a strategy evaluation operating at a less resolved scale. It may also be possible to include stakeholder-informed formulations based on scenarios developed by stakeholders that could be formalised as discrete choice experiments (Johnson et al., 2013). Including stakeholder understanding opens interesting avenues for meaningful engagement and input into management strategy evaluation.

While predicting fisher response to management regulation continues to present challenges (Andersen et al., 2010) by using different models and model formulations it is possible to develop a range of hypotheses on the likely effect of location choice dynamics on fisheries management measures (Dolder et al., 2020, *submitted*). Including hypotheses on location choice in mixed-fishery MSEs thus provides a robust framework to potential formulation, similar to how uncertainty about the form of recruitment dynamics is included in single stock MSEs (e.g. ICES, 2020).

Through application to a case study for the Celtic Sea demersal fishery we demonstrate how the stock specific and seasonal covariates introduced might influence effort allocations across different métier (representing fishing grounds) in a gravity, RUM and Markov Model (Figures 5.3). Further, we show through simulation how this leads to different allocations of effort across métier and how this effects management outcome including catches, fishing mortality and SSB and risk-based indicators (Figures 5.7 – 5.10). While our MSE was only implemented as a demonstration, we show clearly that the decisions of fishers on where to fish can affect the conclusions about the sustainability of a particular approach - thus consideration of location choice is crucial when evaluating mixed fishery management measures. The impact at the stock level in our case study was limited by the fact that the fleet dynamics model was only implemented for the Irish otter trawl fleet, which only catches a proportion of the total catch for each of the stocks. The impact would expected to be larger with a model applied to all fleets within a mixed fishery.

We argue that inclusion of location choice models as part of a fleet operating model in a mixed-fishery MSE is essential to consider the potential impact on management outcome, and show how conclusions might be affected by these short-term fleet dynamics. Future MSE approaches for evaluations of mixed-fishery management measures should consider plausible location choice dynamics and include them alongside the biological and management operating models when conducting mixed-fishery MSEs. This will allow the framework to better quantitatively characterise the range of potential outcomes for fisheries and strengthen the scientific basis for assessing the robustness of management measures to implementation error and outcome uncertainty.

5.6 Conclusions

We demonstrate the importance of considering the short-term dynamics arising from location choice by implementing a range of plausible models for a multi-stock mixed fishery in the Celtic Sea. While predicting the location choice of fishers is challenging due to the complexity of factors involved there are a range of different approaches that once embedded in an MSE framework can characterise the influence on management outcome. As different models lead to different predictions we leave their choice to the user but show how they can be used as alternative hypotheses in an MSE setting. We recommend implementation of different fleet location choice operating models when undertaking mixed-fishery MSEs in order to incorporate this important dynamic alongside plausible biological dynamics to better characterise outcomes for fisheries indicators.

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Chapter 6

General Discussion

The aim of this thesis were two-fold: i) to further understanding of spatiotemporal dynamics in mixed fisheries and how they relate to location choice, ii) to compare and contrast extant approaches to location choice modelling for application in mixed fishery management strategy evaluations. Research presented in Chapter 2 - 5 (manuscripts I - IV) addressed these objectives. Here, I briefly summarise the main findings, which are placed in context thereafter.

Chapter 2 (manuscript I, Dolder et al., 2018) addressed the first objective by applying state-of-the-art geostatistical methods to haul level data from multiple fisheries-independent surveys in the Celtic Sea. Modelled densities and spatial and spatiotemporal factor loadings among species were estimated to understand how separable catches of species are when caught together in highly mixed fisheries. We found that while some species can be separated by changing gear and location fished, others are tightly coupled and consistently found together, therefore spatial decoupling for these species is much more challenging. Our methods provide a framework for managers to explore how far spatial and spatiotemporal separation can go to separating species. This work has subsequently been presented as a framework for understanding mixed fisheries interactions at the ICES working group on mixed fisheries methods (ICES WGMIXFISH-Methods).

Chapter 3 (manuscript II, Dolder et al., 2020) developed and applied an event-based simulation framework *MixFishSim* to understand whether fisheries-dependent data can be used to infer underlying population dynamics for multiple species caught in mixed fisheries. We concluded that commercial data, when aggregated at an appropriate spatial and temporal scale, can provide useful information for management of mixed fisheries and be used to define locations with different fishery characteristics. *MixFishSim* has numerous potential additional applications, including: survey design and at-sea sampling programmes, index standardisation, operating models, and testing of location choice models, among others.

Chapter 4 (manuscript III) reviewed and compared four main types of location choice models prevalent in fisheries literature: process-based Gravity and Dynamic State Variable Models, and the statistical Random Utility and Markov Transition Models. By comparing the modelling approaches from theoretical and applied perspectives we concluded that, while having different origins, many of the concepts and structures within the different models can be equated to provide identical predictions under certain conditions. The formulation of the models, treatment of covariates, constraints imposed and estimation of parameters are the components that lead to divergent model predictions. We demonstrated how statistical models and their fitting procedures are more suited to “business as usual" applications, while process-based models can elucidate potential unexpected responses to management change. This results from predicting fisher location choice through a more mechanistic first principle understanding of dynamics.

Chapter 5 (manuscript IV) implements three of these models: the Gravity Model, a conditional logit RUM and a Markov Transition Model in the mixed fishery management strategy evaluation framework FLBEIA. In application to a case study for Irish otter trawlers in the Celtic Sea we demonstrated how different hypotheses on location choice, given changing fishing opportunities for the fleet, can impact evaluation of management measures in mixed fisheries. In doing so, we recommend the routine definition of fisheries to include spatiotemporal catch characteristics and the use of models that consider location choice dynamics when comparing different management measures for mixed fisheries. We concluded by setting out the approaches that work best for different circumstances; assuming *status quo* effort shares in short-term forecasts, a range of hypotheses generated from statistical models in medium term simulations and inclusion of process-based dynamics under change (e.g. in response to a spatial closures) .

The following sections relate findings of this thesis to wider work on spatial dynamics, location choice and mixed fisheries models in a management advisory framework.

6.1 Spatiotemporal dynamics of location choice

Fishers make decisions about when and where to fish on an almost continual basis. They do this subject to regulatory constraints: including quotas (Poos et al., 2010), closed areas or fisheries (Dowling et al., 2012; Vermard et al., 2008) and discard policies (Batsleer et al., 2016); economic constraints: including cost of fuel (Tidd et al., 2012), potential landings value and fish prices (Dupont, 1993); environmental constraints such as weather (Smith,

2005) and personal preference including risk tolerance (Holland, 2008; Dowling et al., 2015) and their own experiences (Holland and Sutinen, 2000). They further make these decisions with uncertain, partial knowledge of the distribution of target species and the associated catch (Mangel and Clark, 1983). This inevitably leads to variation in both intended and realised outcomes, which makes fishers' decisions and the consequences difficult to predict.

Nevertheless, there are clear spatial patterns in the exploitation of species assemblages that lead to a certain degree of predictability about what will be caught when fishing at different locations at given times. These spatiotemporal patterns are complex, yet fisheries landings are generally reported to a spatial grid or statistical area meaning the resolution of reported catches are rarely sufficient to identify complex species associations (Branch et al., 2005; Hicks et al., 2020). However, the increased availability of high resolution data, brought about by use of automated vessel monitoring systems (VMS), electronic logbooks (elogs) and remote electronic monitoring (REM), is increasingly allowing us to identify these spatiotemporal patterns and build up a more detailed picture of mixed fishery dynamics (Gerritsen et al., 2012; Mateo et al., 2017; Plet-Hansen et al., 2020).

In Chapter 2 (manuscript I), this thesis explored predictability of the co-occurrence of different species caught together in the highly mixed fisheries of the Celtic Sea. To do so we applied state of the art geostatistical methods that used a Joint Species Distribution Model in a generalised linear mixed model (Thorson et al., 2015, 2016; Thorson, 2019). Using this we developed a novel framework for understanding how far spatiotemporal avoidance can contribute to mitigating quota imbalances in mixed fisheries (Dolder et al., 2018). In applying the framework to haul-level fisheries independent data from seven different surveys undertaken in the Celtic Sea we found there were three distinct target species groups caught by demersal fisheries that were consistently found together: the gadoids (cod, haddock and whiting), the benthic flatfish (sole and plaice) and the deeper water species anglerfishes, megrims and hake. While there was separation between the groups of species, within a group the spatiotemporal relationships were persistent with only subtle differences in spatial dynamics. This has important implications when trying to decouple exploitation within mixed fisheries, particularly as the EU grapples with implementing a landing obligation and scientific advice seeks to inform understanding how fishers can avoid unwanted catch (Reid et al., 2018; Robert et al., 2019; Calderwood et al., 2020).

Inability to separate vulnerable species in catch has occurred where strictly enforced catch limits have been implemented elsewhere (Kuriyama et al., 2016). Our work developed a data-driven mixed assemblage framework directly applicable to understand and inform contemporary management challenges. While there have been applications of spatial modelling to understand bycatch risk for particular vulnerable species (Gardner et al., 2008; Dedman et al., 2015; Cosandey-Godin et al., 2015; Ward et al., 2015) or discarded species in general (Paradinas et al., 2016), to our knowledge this is the first application in a multi-stock mixed fisheries context. There is an ongoing need for a framework to understand co-occurrence in mixed-fisheries at the haul-level to inform management on how much flexibility fishers have to adapt their spatial behaviour to available fishing opportunities in mixed fisheries, and this chapter makes a contribution to this effort.

While several studies have highlighted the use of fisheries-dependent data in understanding the dynamics of mixed fisheries (Gerritsen et al., 2012; Mateo et al., 2017; Hynes et al., 2016; Calderwood et al., 2020), it is hard to validate whether spatiotemporal patterns observed in fisheries landings represent the underlying fish populations because the data is collected from opportunistic sampling that is potentially biased by fishers targeting preferences (Thorson et al., 2016; Pennino et al., 2019). In Chapter 3 (manuscript II) we develop and apply an R package *MixFishSim* for event-based simulations of mixed fisheries dynamics at a high spatial and temporal resolution (Dolder et al., 2020). In the simulation framework fish populations are heterogeneously distributed using different parameterisation of Gaussian Random Fields (GRFs) for suitable habitat for each population, informed by Chapter 2. When combined with a moving temperature field and individual temperature tolerance for each population this resulted in realistic weekly directed and diffusive movement for fish populations (Dolder et al., 2020). Combined with delay-difference population dynamics, the simulation model provides a platform to simulate realistic population dynamics for any number of species (within computational practicalities of given machines).

The fishery component of *MixFishSim* was individual-based, with vessels' heuristic exploration of the populations dependent on their own targeting preference and experience built up from a correlated random walk process (Codling et al., 2008). The simulation model provides a simplified system in which the “true" population is known in order to test hypotheses about the effectiveness of management measures based on survey or commercial data. In applying the framework to analyse how well the catches from the fisheries represented the “true" populations we found that they were representative when catch data were not overly spatially aggregated. Further, we found that variability was higher between different spatial locations than over time, similar to Gerritsen et al. (2012) and Dolder et al. (2018). This finding strengthens the idea that spatial landings information from fisheries can be used to explore location choice decisions and support mixed fisheries management (Hicks et al., 2020), and appropriate spatial aggregation to reflect ecological-oceanographic features can be used to delineate differences in spatial use in mixed fisheries (Hynes et al., 2016).

Chapter 3 highlighted the importance of developing simulation frameworks for mixed fisheries to test hypotheses that could not otherwise be addressed due to data limitations (reporting and access). Simulation frameworks are commonly applied in fisheries research (Skagen et al., 2013), and provide researchers with a platform to capture the important dynamics in a simplified manner and hypothesis test different management implications and data generation processes. Such applications are not possible on real data due to the complexity and cost of generating data at such a high spatiotemporal distribution over large areas. By developing a simulation framework with realistic representation of population dynamics for species with different demographics and overlaying this with an individual-based fishery dynamics, Chapter 3 was able to ask fundamental questions about how observed catch from a biased sampling framework (i.e., a commercial fishery) might support development of management measures based on that data. Further, the framework has many potential future applications *inter alia* testing survey designs (Cotter and Pilling, 2007; Kimura and Somerton, 2006), methods for commercial catch per unit effort (CPUE) index standardisation (Harley et al., 2001; Maunder and Punt, 2004; Maunder et al., 2020; Thorson et al., 2020), in year dynamics of exploitation and its impact on stock assessments (Liu and Heino, 2014) and adaptive management measures (Walters, 2007; Dunn et al., 2016; Needle and Catarino, 2011) as well as providing a simulation framework for testing the performance of location choice models (Fulton et al., 2011, and Chapter 4, manuscript III). Extending the framework to age- or length- based population models would also allow consideration of differential use of habitat for different life-stages, and how spatial exploitation of different locations affects the population structure. A modular design should assist such future developments.

6.2 Developing location choice models for management application

The findings in Chapter 2 (manuscript I) and Chapter 3 (manuscript II) have important implications for developing location choice models that can be operationally used to evaluate mixed fishery management approaches. They identify that while there will always be uncertainty about catch in mixed fisheries, persistent spatiotemporal patterns and inter-species location relationships that can be taken into account when developing location choice models.

Incorporating a generally applicable location choice model in a framework for management advice has proved challenging (Andersen et al., 2010; Marchal et al., 2013) with a range of drivers of location choice identified depending on the circumstance of the fishery (Naranjo-Madrigal et al., 2015; Girardin et al., 2015), meaning most applications have been of relatively simple model formulations or rule-based approaches (Plagányi et al., 2014). However, location choice is fundamental to management outcome (Fulton et al., 2011) and thus an essential consideration if progress is to be made in moving beyond single stock management strategy evaluations (Punt et al., 2016) to more complex tactical advisory models that include consideration of technical interactions alongside population dynamics (Plagányi et al., 2014). Several different modelling approaches have been developed to predict location choice, including Gravity Models, Random Utility Models, Dynamic State Variable Models and Markov Transition Models, yet no formal comparison of the approaches had previously been made. Chapter 4 (manuscript III) reviews extant approaches to location choice modelling to compare and contrast them from both a theoretical and applied perspective. Chapter 5 (manuscript IV) implements the most suitable models in a generally applicable manner in a management strategy evaluation framework.

Chapter 4 (manuscript III) identified that from a theoretical perspective all the models could be equated to provide the same predictions under certain conditions. This result is important as while the models derive from different origins such as micro-economic theory and ecological theory, the difference between them is principally down to model formulation and parameterisation. Of particular importance is that by formulating Gravity Models as RUMs one could test the Gravity assumption via testing how the values of the coefficients differ from unity (Chapter 4). Allowing those parameters to differ from unity opens avenues to a wide range of possible models not yet formulated on the basis of a lack of theoretical equivalence demonstrated here.

One of the major differences in formulation for Markov Transition Models is the state dependence property, where the next location choice is dependent on the current location (Howard, 1971), where in the Random Utility Model the choice is conditional on the relative utility compared to all the other options available at the time (McFadden, 1973). Notwithstanding, there are links that could improve both models, either testing state independence in the RUM or by allowing for the transition probabilities of the Markov Transition Model to depend on case and choice-specific variables as in a RUM (McFadden, 1973). By demonstrating given equivalences we thus highlight where developments could occur in all methods.

A unique feature of Dynamic State Variable Models is that they can incorporate both short- and long-term constraints in identifying the optimal solution given the defined utility maximisation goal (Clark and Mangel, 2000). In principle, this utility goal could incorporate many different drivers and dynamics of location choice, as with the other models. A Gravity Model defines the utility objective through formulation of the mechanistic process that determines effort allocation. Similarly, such a formulation could include any number of drivers and weightings that would enable it to produce similar predictions to the other models. However, in practice the approach has generally been to make predictions based on profit maximisation and economic opportunism in both the process-based models (e.g. Caddy, 1975; Poos et al., 2010; Batsleer et al., 2016), though adaptations have included incorporation of other factors including properties of tradition or risk aversion to better match observed patterns (Marchal et al., 2013; Alzorriz et al., 2018; Dowling et al., 2015).

To further understand the differences between the models we applied simple formulation of each to three years of data and predicted fishing effort for the following two years (using *MixFishSim* of Chapter 3). This procedure was repeated over a 17 year period, which included the introduction of a spatial closure in one of the fishing locations part way through the simulations. In this applied comparison differences in model formulations lead to different predictions, elucidating some general properties about the models. Firstly, we found that no model produced better predictions in the short-term than a null model where effort share in the next year was the same as in the previous year, excepting immediately following the introduction of a spatial closure where a reparamtrised version of a RUM did outperform the null model. The fact that during a period of settled dynamics the null model was best may reflect that strong habitual patterns the fishers demonstrate (Holland and Sutinen, 2000), something that was built into the individual vessel based simulation model developed in Chapter 3 (manuscript II). Secondly, we found that in general the statistical methods (Random Utility Models and Markov Transition Models) outperformed the process-based models (Gravity and Dynamic State Variable Models), particularly before the introduction of a spatial closure and before there was significant change imposed on fishers. This may reflect the strong influence of tradition identified in the application of RUMs (Girardin et al., 2015) and its influence in the choice intercept, and in estimating transition probabilities within a Markov framework (Venables et al., 2009). Thirdly, we found that while the process-based models produced biased predictions towards fishing locations where fishing effort share was not found to proportionally reflect their relative profit, when change was imposed on fishers through the spatial closure the performance of these models degraded less than with the statistical models. This may reflect that they were less reliant on past behaviour in making future predictions, indicating the value of incorporating process-based approaches. The findings in this chapter are relevant not just to location choice in fisheries, but in all situations where model-based simulations are needed to consider response to change in a human-ecological system (Cuddington et al., 2013).

6.3 Improving advice for management of mixed fisheries

In Europe, management advice for mixed fisheries is provided by the International Council for the Exploration of the Seas (ICES) through characterising fishing fleets within a number of métier that broadly describe differences between fisheries (combinations of gear type and proxies for target species); and then estimating the effort required to meet the fleet's quotas to evaluate over- and under-quota catches from a mixed fishery perspective (Ulrich et al., 2011; Iriondo et al., 2012; Garcia et al., 2017). Under this 'Fleet and Fishery' approach the effort share among métier is generally assumed to remain constant in future years, and therefore technical interactions are fixed. While such an assumption may be reasonable in the short-term, in the medium-term fishers adapt to fishing opportunities and regulation to move among fisheries to better match their fishing patterns to available quota. Such considerations are not currently incorporated in models that provide management advice, in part due to a lack of suitable model to capture the potential dynamics (Andersen et al., 2010). Though there have been applications of each of the location-models described above to assess management implications of fishers response to management regulations, including RUMs (Ulrich et al., 2007), Markov Transition Models (Venables et al., 2009), Gravity Models (Marchal et al., 2013; Briton et al., 2020) and Dynamic State Variable Models (Alzorriz et al., 2018) these are still not routinely applied in mixed fishery MSE applications for management advice.

In Chapter V (manuscript IV), a conditional logit RUM, a Markov Transition Model and a Gravity Model were implemented in a general, accessible manner in the FLBEIA modelling framework (Garcia et al., 2017). The chapter demonstrates application of each of the location choice models by fitting the models and applying them within a management strategy evaluation routine for a simplified case study of the Irish otter trawl fleet in the Celtic Sea. In doing so the work shows how spatial information on catches can be used to define consistent fishing locations (as métier) for a fleet, and then a hypothesis testing approach can evaluate different management approaches while taking account of potential responses of fleets to the changing fishing opportunities. A hypothesis testing approach is taken as there may be no clear 'best' model of location choice, as identified in Chapter IV (manuscript III), so multiple potential location choice operating models are included in keeping with MSE best practice (Punt et al., 2016). This approach, similar to including different potential models of recruitment dynamics applied in a single species assessment context (ICES, 2020), allows consideration to be taken of different models and model formulations in evaluating the consistency of management approaches with sustainability and fishery indicators, while taking account of uncertainty in the process model. This is the first time location choice dynamics have been considered from such a multi-model approach.

Results of Chapter 5 showed how different realisations of effort distributions from the location choice models might affect assessment of outcomes for stocks, including risks of exceeding management thresholds. In the example application it was demonstrated how under a model with no location choice dynamics the mixed fishery management approach resulted in fishing rates $< F_{MSY}$ for megrims, but the Gravity and Markov Transition Model resulted in fishing $> F_{MSY}$ potentially leading to implementation error in the management rule (Dichmont et al., 2006; Sethi et al., 2005). Such considerations are increasingly important to progress multi-stock harvest control rules in mixed fisheries, where location choice dynamics can affect management outcome (Ulrich et al., 2017; Garcia et al., 2020).

To move beyond a single stock approach to management it is imperative that technical interactions are taken into account for management rules to reduce imbalances in quota caught together in mixed fisheries. The current approach to mixed fisheries advice within Europe promotes a fleet and métier based approach to characterisation of tensions in a single stock management system (Ulrich et al., 2011). This has been built on by developing multi-stock harvest control rule approaches to overcome these tensions (Ulrich et al., 2017; Garcia et al., 2020). Chapters 4 (manuscript III) and 5 (manuscript IV) further this approach by consideration of location choice dynamics and how it affects medium-term management outcomes in evaluating these management rules.

On the basis of these chapters, I make the following recommendations in this regard:

1. In short-term forecasts for management advice where no significant changes in fisheries are anticipated the current assumption that effort allocation among métier will be the same as in previous years is sufficient

to take account of dynamics, as used in Ulrich et al. (2011).

2. When evaluating management rules for mixed fisheries in the medium term, an MSE approach is required and the following should be considered as part of the process:

   (a) Characterising métier explicitly using high resolution information on landings derived from VMS or REM data that can be analysed to identify spatially consistent choice sets. These can be used for input to location choice models to capture sufficiently relationships and co-occurrence among species caught in mixed fisheries (Gerritsen et al., 2012; Mateo et al., 2017; Dolder et al., 2020).

   (b) Using the framework develop in Dolder et al. (2018) to identify where species are intractably spatially linked in catch through shared habitat use and thus where joint species management might need to be considered.

   (c) Develop a number of statistical models and model formulations when simulating location choice, with the different plausible representations of location choice incorporated in fleet operating models as hypotheses to improve robustness of mixed fisheries models to location choice dynamics.

3. Where a policy intervention is expected to incur major changes that are likely to perturb current dynamics in the fisheries (e.g., through a spatial closure), a operationally conditioned process based approach should also be incorporated into the potential location choice models to consider emergent dynamics that have not been observed in the past.

By implementing these procedures, we can improve how technical interactions are taken account of in scientific management advice for mixed fisheries.

6.4 Future research priorities

Research in this thesis has progressed understanding of spatial dynamics in mixed fisheries by i) providing a framework for considering how species exploitation may or may not be decoupled through changes in gear or location fished (Chapter 2, manuscript I); and by ii) demonstrating how fisheries dependent data can be used to identify consistent management units that define different species compositions in mixed fisheries landings (Chapter 3, manuscript II). It then iii) compares and contrasts methods for modelling location choice by fishers given these spatial dynamics (Chapter 4, manuscript III) and, iv) demonstrates how location choice models can be implemented in a mixed fishery management strategy evaluation taking account of uncertainty about location choice dynamics and model structure (Chapter 5, manuscript IV).

There are a number of areas of research where our understanding of location choice dynamics could be improved. Firstly, understanding of spatial dynamics in catch is restricted by limited knowledge of the spatial dynamics of fish populations. Application of geostatistical methods to both fisheries-independent and fisheries-dependent data can help support integration of information on species spatial dynamics in Models of Intermediate Complexity for Ecosystem assessments (MICE, Thorson et al., 2019; Plagányi et al., 2014). Such methodological developments alongside increased application of spatial stock assessment methods (Cadrin and Secor, 2009; Goethel et al., 2011; Punt, 2019; Cao et al., 2020) would further improve understanding of the interactions of fisheries with different life stages and allow consideration of how these affect management outcome. Relatedly, there is a need to improve our understanding of in-year dynamics (Liu and Heino, 2014), including how population demographic processes such as migrations, differential habitat use by different life stages and aggregations for spawning contribute to changing exploitation patterns for different stocks. Understanding these processes in high spatial and temporal resolution is an ongoing research challenge. Integrating detailed information from fisheries-dependent catch from REM sources (Plet-Hansen et al., 2020) may provide future avenues for incorporation of data that can help describe seasonal dynamics in fisheries and provide understanding of environmental drivers of processes linked with different catch compositions and relationships between species (Brodie et al., 2020).

Secondly, the findings in this thesis raise some interesting questions about the role of statistical and process-based models in simulating effort dynamics in fisheries. While statistical approaches can describe the relative weight of different components contributing to the utility that drives effort allocation, such weights may only hold true under current or past dynamics in the fisheries. Further, it's often the case that significant weight is attached to components such as previous effort allocation to an area lagged to a month or year, which may be broadly grouped as "tradition" (Girardin et al., 2015). It's unclear if tradition or habit is in itself a description of a behaviour or if it reflects some unknown component of the utility that could otherwise be explicitly defined (Holland and Sutinen, 2000) and so the question remains if the statistical models might be able to better predict response to unobserved dynamics if the components of tradition were better described. The role of information (and disinformation) sharing in location choice may also provide insight into why predicting location choice by fishers remains a challenge (Little et al., 2004; Curtis and McConnell, 2004; Gillis and Showell, 2002; Dreyfus-Leon and Gaertner, 2006), while there continues to be an outstanding question as to whether fishers are acting as utility maximisers or influenced by drivers that are more difficult to define such as "good enough" profits or other objectives that fall into the concept of "satisficing" (Holland, 2008).

Beyond process-based and statistical methods for predicting location choice, individual based approaches have also been applied (Bastardie et al., 2014). Integrating IBMs within a wider management framework is challenging due to the need for models operating on different timescales to traditional population dynamics models, but there are several avenues that could be explored in this regard. For example, pattern-oriented modelling (Grimm and Railsback, 2012) and machine learning techniques could also be employed to strike a balance between individual level information and wider patterns in drivers of effort allocation. Integrating statistical and process-based approaches as advocated by Cuddington et al. (2013) could also be approached by replacing hypothesis testing approaches with statistical ensemble models that use the strengths of each approach and down weight the weaknesses to provide a more robust model that effectively characterises uncertainty in a combined process models (Spence et al., 2018). Such approaches may also provide a framework for greater stakeholder input and incorporation of expert knowledge in the modelling framework (Haapasaari et al., 2013).

Finally, an outstanding question is how far fishers can adapt their spatial behaviour to avoid unwanted catch (Reid et al., 2018) and how far management systems need to adapt to take account of these interactions (Ulrich et al., 2017; Garcia et al., 2020). This may be informed by modelling the optimal effort allocation among different métier and seasons to understand how limitations such as cost of movement, weather and other factors result in suboptimal outcomes in fisheries. Such improved understanding of location choice decisions may enable better design of management measures in future that explicitly take account of mixed fisheries interactions including adaptive management approaches on several spatial and temporal scales (Dunn et al., 2016). It is hoped that the research in this thesis contributes to the body of literature supporting improved management of mixed fisheries as part of an Ecosystem Based Approach to Fisheries Management.

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Appendix A

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Spatial separation of catches in highly mixed fisheries

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Mixed fisheries are the dominant type of fishery worldwide. Overexploitation in mixed fisheries occurs when catches continue for available quota species while low quota species are discarded. As EU fisheries management moves to count all fish caught against quota (the "landing obligation"), the challenge is to catch available quota within new constraints, else lose productivity. A mechanism for decoupling exploitation of species caught together is spatial targeting, which remains challenging due to complex fishery and population dynamics. How far spatial targeting can go to practically separate species is often unknown and anecdotal. We develop a dimension-reduction framework based on joint dynamic species distribution modelling to understand how spatial community and fishery dynamics interact to determine species and size composition. In application to the highly mixed fisheries of the Celtic Sea, clear common spatial patterns emerge for three distinct assemblages. While distribution varies interannually, the same species are consistently found in higher densities together, with more subtle differences within assemblages, where spatial separation may not be practically possible. We highlight the importance of dimension reduction techniques to focus management discussion on axes of maximal separation and identify spatiotemporal modelling as a scientific necessity to address the challenges of managing mixed fisheries.

Mixed fisheries and the EU landing obligation

Recent efforts to reduce exploitation rates in commercial fisheries have begun the process of rebuilding depleted fish populations[1]. Improved management of fisheries has the potential to increase population sizes and allow increased sustainable catches, yet fisheries catch globally remains stagnant[2]. In light of a projected increase in demand for fish protein[3] there is an important role for well managed fisheries in supporting future food security[4] necessitating that fisheries are managed efficiently to maximise productivity.

A particular challenge in realising increased catches from rebuilt populations is maximising yields from mixed fisheries[5–7]. In mixed fisheries, the predominant type of fishery worldwide, several fish species are caught together in the same net or fishing operation (known as a "technical interaction"). If managed by individual quotas, and catches do not match available stock quotas, either a vessel must stop fishing when the first quota is reached (the "choke" species) or overexploitation of the weaker species occurs while fishers continue to catch more healthy species and throw back ("discard") the fish for which they have no quota[8]. There is, therefore, a pressing need for scientific tools to simplify the complexities of mixed fisheries and help avoid discarding.

Sustainability of European fisheries has been hampered by the "mixed fishery problem" for decades with large-scale discarding resulting[9,10]. Mixed fisheries require specific management approaches to avoid overfishing and a paradigm shift is being introduced under the EU Common Fisheries Policy (CFP) reform of 2012 through two significant management changes. First, by 2019 all fish that are caught are due to be counted against the respective stock quota even if they are discarded; second, by 2020 all fish stocks must be fished at an exploitation rate corresponding to their Maximum Sustainable Yield (MSY)[11]. These changes are expected to contribute to attainment of the goal of Good Environmental Status (GES) under the European Marine Strategy Framework Directive (MSFD[12]) and move Europe towards an ecosystem based approach to fisheries management[13].

Conflicts between overall management goals and drivers for individual actors must be overcome to achieve sustainability. Societal objectives for fisheries to achieve MSY across ecosystem components are paralleled by individual fishers goals to maximise utility; whether that be profit, income or the continuance of traditional practices[14]. Under the new policy, unless fishers can avoid catch of unwanted species they will have to stop fishing

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when reaching their first restrictive quota. This introduces a potential significant cost to fishers of under-utilised quota[7,15] and provides a strong incentive to mitigate such losses[16,17].

To align catch with available quota depends on the ability to exploit target species while avoiding unwanted catch. Methods by which fishers can alter their fishing patterns include switching fishing method (e.g. trawling to netting), changing technical gear characteristics (e.g. introducing escapement panels in nets), or altering the timing and location of fishing activity[18,19]. For example, otter trawl gears are known to have higher catch rates of roundfish due to the higher headline and wider sweeps, which herd demersal fish into the net; conversely, beam trawls that employ chain mesh to "dig" benthic flatfish species, have higher catch rates for these species[20]. Fishing location choice also has a significant effect on catch[21], something that fishers routinely consider in their decision making based on their own knowledge of good fishing locations.

In the past, spatiotemporal management measures (such as time-limited fishery closures) have been applied to reduce unwanted catch with varying degrees of success (e.g.[22–25]) while move-on rules have also been proposed or implemented to influence catch rates of particular vulnerable species to reduce or eliminate discards (e.g.[26–28]). However, such measures have generally been targeted at individual species without considering associations and interactions among several species. Highly mixed fisheries are complex with spatial, technological and community interactions combining. The design of spatiotemporal management measures that aim to allow exploitation of high quota stocks while protecting low quota stocks requires understanding these interactions at a scale meaningful to managers and fishers. While fisheries surveys and commercial fishing routinely generate a large amount of geo-referenced information on numbers and weight of fish caught, integrating spatiotemporal information from across multiple sources of fisheries-dependent and independent survey data requires an effective framework to reduce and understand the complexities of the system.

Here, our goal is to develop a framework for understanding these complexities. We do so by (1) implementing a spatiotemporal dimension reduction method that estimates the correlation in catches for multiple species at each fishing location, (2) using the results to draw inference on the fishery-community dynamics, (3) creating a framework to identify common trends among species, and (4) describing the potential for and limitation of spatial measures to mitigate unwanted catches in highly mixed fisheries.

Framework for analysing spatiotemporal mixed fisheries interactions

We present a framework for analysing how far spatiotemporal avoidance can contribute towards mitigating imbalances in quota in mixed fisheries. Fisheries-independent survey data are used to characterise the spatiotemporal dynamics of key components of a fish community by employing a geostatistical Vector Autoregressive Spatiotemporal model (VAST). Therein, a factor analysis decomposition was used to describe trends in spatiotemporal dynamics of the different species as a function of latent variables[29] representing spatial variation (9 factors; termed "average" spatial variation) and spatiotemporal variation (9 factors) for encounter probability and positive catch rates (termed "positive density") separately[30]. Resultant factor analyses identify community dynamics and drivers common among 9 species, each analysed separately for juvenile and adult stages. We refer to each combination of species and size class as a "species", and present results for the 18 species through transformation of the loading matrices using PCA rotation. This PCA rotation is used to visualise a reduced number of orthogonal factors representing average spatial variation or spatiotemporal variation while explaining the majority of covariation among catch rates, as well as the association of each species with these maps. We refer to the association of each species with a given factor as its "association with this factor", and the value of each factor at a given location as its " 'coefficient' at that location". By describing the species dynamics through underlying spatiotemporal factors we can take account of how the factors contribute to affect catches of the species in mixed fisheries. Gaussian Markov Random Fields (GMRFs) capture spatial and temporal dependence within and among species for both encounter probability and positive density[31]. VAST is set in a mixed modelling framework which allows estimation of fixed effects to account for systematic differences driving encounter and catches, such as differences in sampling efficiency (catchability), while random effects capture the spatiotemporal dynamics of the fish community.

Dynamics of Celtic Sea fisheries

The highly mixed demersal fisheries of the Celtic Sea are used as a case study. The Celtic Sea is a temperate sea where fisheries are spatially and temporally complex; mixed fisheries are undertaken by several nations using different gear types[21,32]. Close to 150 species have been identified in the commercial catches of the Celtic Sea, with approximately 30 species dominating the catch[33].

Our spatiotemporal model is parametrised using catch data from seven fisheries-independent surveys undertaken in the Celtic Sea over the period 1990–2015 (Table S1) and include nine of the main commercial species: Atlantic cod (*Gadus morhua*), Atlantic haddock (*Melanogrammus aeglefinus*), Atlantic whiting (*Merlangius merlangus*), European Hake (*Merluccius merluccius*), white-bellied anglerfish (*Lophius piscatorius*), black-bellied anglerfish (*Lophius budegassa*), megrim (*Lepidorhombus whiffiagonis*), European plaice (*Pleuronectes platessa*) and common sole (*Solea solea*). These species comprise over 60% of landings by towed fishing gears for the area (average 2011–2015[34]). Each species was separated into juvenile and adult size classes based on their legal minimum conservation reference size (Table S2).

The data were analysed to understand how the different associations among species (combination of species and size class) form distinct assemblages with common drivers of spatiotemporal distributions, and how these affect catch compositions for fishers operating in mixed fisheries. We consider how these have changed over time, and the implications for mixed fisheries in managing catches of quota species under the EU landing obligation.

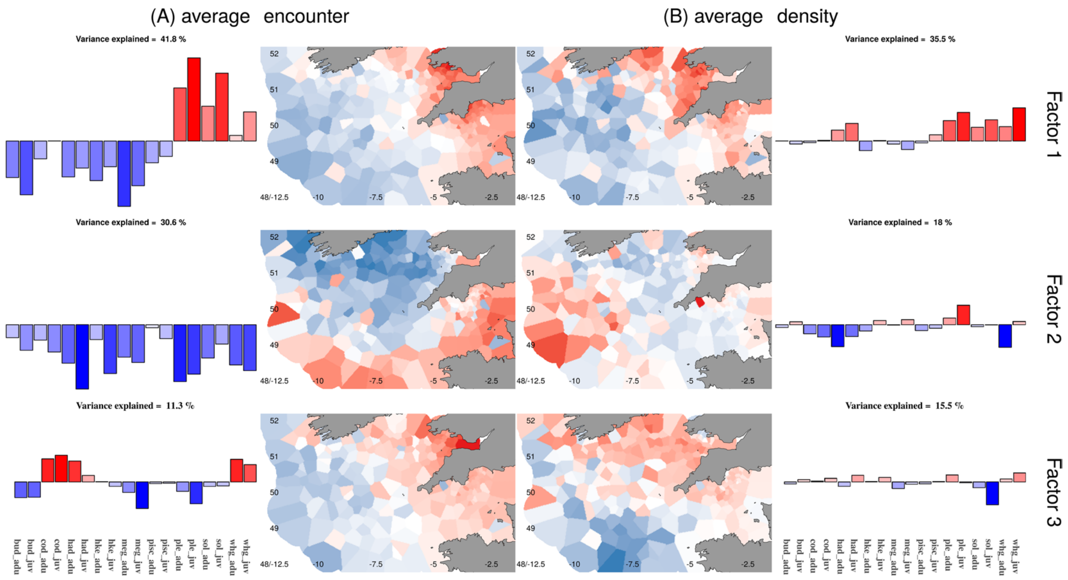

Figure 1. Factor values for the first three factors for (**A**) Average encounter probability and (**B**) Average positive density for the species (outer figures) and spatially (inner figures). Red: positive association to the factor, Blue: negative association.

Results

Using relatively few factors in a spatial dynamic factor analysis the Celtic Sea demersal fish community can be partitioned into three species assemblages (roundfish, flatfish and deeper water species). Within these assemblages there are common trends in spatiotemporal distributions in encounter probability and positive density, which can be partitioned into time invariant ("average effect") spatial trends and time variant ("spatiotemporal") trends. We show through presentation of factor coefficients that time invariant trends may be linked to physical characteristics of the system including depth and predominant substrate type, while species loadings on to time varying spatial trends show changes in distribution of species over time to be similar within an assemblage. We demonstrate how this information can be used to help inform spatial targeting and avoidance of the different assemblages. More nuanced differences in spatiotemporal distributions exist within an assemblage presenting a greater challenge to spatially separate catches. Yet we show how this information may be utilised by managers and fishers to better match catch to quota in highly mixed fisheries through changes in gear and locations fished.

Spatial distributions indicate three species assemblages. A spatial dynamic factor analysis was used to decompose the dominant spatial patterns driving differences in average spatial variation. The first three factors (after PCA rotation) account for 83.7% of the between species variance in the probability of encountering a species (the "average encounter probability") and 69% of the explained variance in catch rates on encounter ("average positive density"). A clear spatial pattern can been seen both for average encounter probability and average positive density, with a positive coefficient value associated with the first factor in the inshore north easterly part of the Celtic Sea into the Bristol Channel and Western English Channel, moving to a negative coefficient value offshore in the south-westerly waters (Fig. 1). The species loadings show plaice, sole and whiting to be positively associated with the first factor for average encounter probability while the other species are negatively associated. For average positive density, positive associations are also found for haddock and juvenile cod (weakly positive), indicative of a more inshore distribution for these species.

On the second spatial factor for average encounter probability a north/south split can be seen at approximately 49°N while positive density is more driven by a positive coefficient in the deeper westerly waters as well as some inshore areas. Species loadings for the second factor indicate there are positive associations for juvenile white-bellied anglerfish, juvenile hake, juvenile megrim, plaice and juvenile whiting with average positive density, which may reflect two different spatial distributions in the more offshore and in the inshore areas (Fig. 1).

On the third factor, there is a positive coefficient for the easterly waters for encounter probability and negative coefficient with the westerly waters. This splits the roundfish species (cod, haddock and whiting, that all have a positive association with the third factor for average encounter probability) from the rest of the species (that have a negative association). Positive density is driven by a north/south split (Fig. 1), with positive coefficient values in the northerly areas. Juvenile anglerfishes (white- and black- bellied), cod, juvenile haddock, hake, adult plaice and whiting are also positively associated with the third factor towards the north while adult anglerfishes, adult haddock, megrim, juvenile plaice and sole have negative loadings reflecting their more southerly distribution (Fig. 1).

While this exploratory factor analysis models unobserved drivers of distribution, we considered what might be driving the differences seen in the spatial factor coefficients and species loadings. The first factor was highly correlated with log(depth) for both average encounter probability coefficients (−0.85, CI = −0.88 to −0.81; Fig. S1) and average positive density coefficients (−0.71, CI = −0.77 to −0.65; Fig. S2). A random forest classification tree

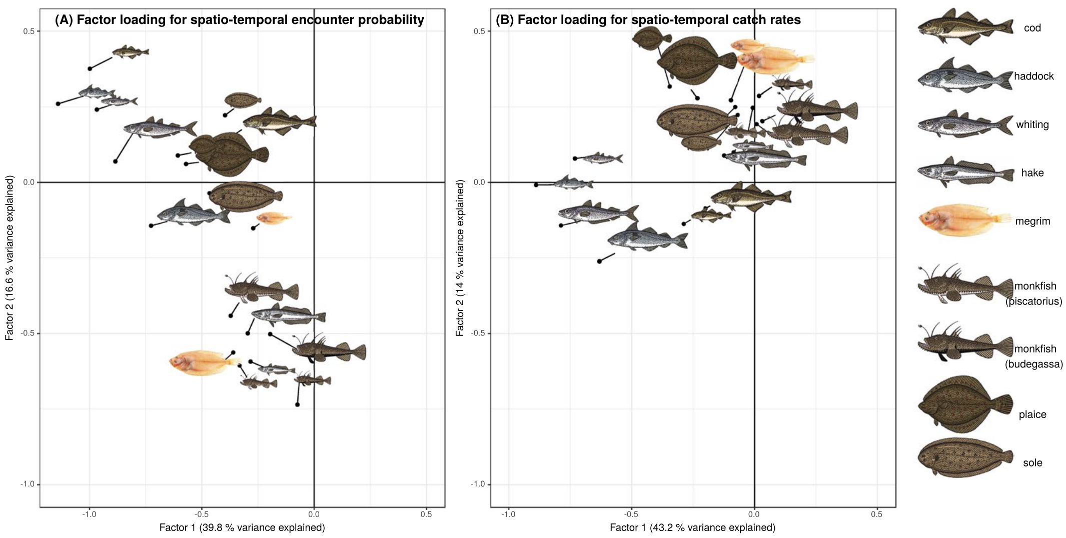

Figure 2. Position of each species on the first two axes from the factor analysis for (**A**) spatiotemporal encounter probability and (**B**) spatiotemporal positive density. Fish images from The Fisherman/Shutterstock.com and Richard Griffin/Shutterstock.com.

assigned 80% of the variance in the first factor for average encounter probability to depth and predominant substrate type, with the majority (86%) of the variance explained by depth. The variance explained by these variables dropped to 25% on the second factor with a more even split between depth and substrate, while explaining 60% of the variance on the third factor. For average positive density, the variables explained less of the variance with 62%, 35%, and 31% for each of the factors, respectively.

It is clear that depth and to a lesser extent substrate are important variables for describing the main driver of similarities and differences in distributions and abundances for the different species. The first factor correlates strongly with these variables, despite them not explicitly being incorporated in the model. While depth and substrate were incorporated as covariates in an alternative model formulation (see Methods), they were not found to improve predictions as the random fields adequately captured the influence of these variables on spatial variation in abundance. The utility of these variables as predictors of species distributions has been identified in other marine species distribution models[35]. The advantage to the approach taken here is that, where such data is unavailable at an appropriate spatial resolution, the spatial factor analysis can adequately characterised the species spatial dynamics.

Species assemblages show similar spatiotemporal patterns. While there are clear spatial patterns in the factor coefficients describing differences in average encounter probability and positive density (Fig. 1), the interannual differences in factor coefficients show less structure (Figs S5 and S6). These interannual differences are important as they reflect the ability of fishers to predict where they can target or avoid species from one year to the next, without which it may be difficult to balance catches with available quota and avoid unwanted catch.

Spatiotemporal factor coefficients for encounter probability and positive density did not show the same spatial pattern driving species distributions from year to year, but when the first two factor loadings are plotted clear relationships in species association with spatiotemporal factor coefficients identify the three different assemblages (Fig. 2). The same factors appear to drive spatiotemporal (interannual changes in) distributions of megrim, anglerfish species and hake (the deeper water species, forming an assemblage negatively associated with the second axes of Fig. 2) and the roundfish and flatfish (two assemblages more positively associated with the second axes of Fig. 2A). For spatiotemporal positive density (Fig. 2B) cod, haddock and whiting (the roundfish species) are separated from plaice, sole (the flatfish) and the deeper water assemblage. As such, it can be predicted that higher catches of a species within a assemblage (e.g. cod in roundfish) would be expected when catching another species within that assemblage (e.g. whiting in roundfish). This suggests that one or more common environmental drivers are influencing the distributions of the assemblages, and that driver differentially affects the different assemblages. Temperature is often included as a covariate in species distribution models, but was found not to contribute to the variance in the first factor coefficients (Fig. S6, no correlations found for either spatiotemporal encounter probability or positive density) and so was not included as a covariate in the final model.

Covariance in spatiotemporal abundance within species assemblages. To gain greater insight into the community dynamics we considered how species covary in space and time through correlations among species. Pearson correlation coefficients for the modelled average spatial encounter probability (Fig. 3A) show clear strong associations between adult and juvenile size classes for all species (>0.75 for all species except hake, 0.56). Among species, hierarchical clustering identified the same three common species-groups as our visual inspection of factor loadings above, with roundfish (cod, haddock, whiting) closely grouped, with correlations for adult cod with adult haddock and adult whiting of 0.73 and 0.5 respectively, while adult haddock with adult whiting was 0.63 (Fig. 3A). Flatfish (plaice and sole) are also strongly correlated with adult plaice and sole having

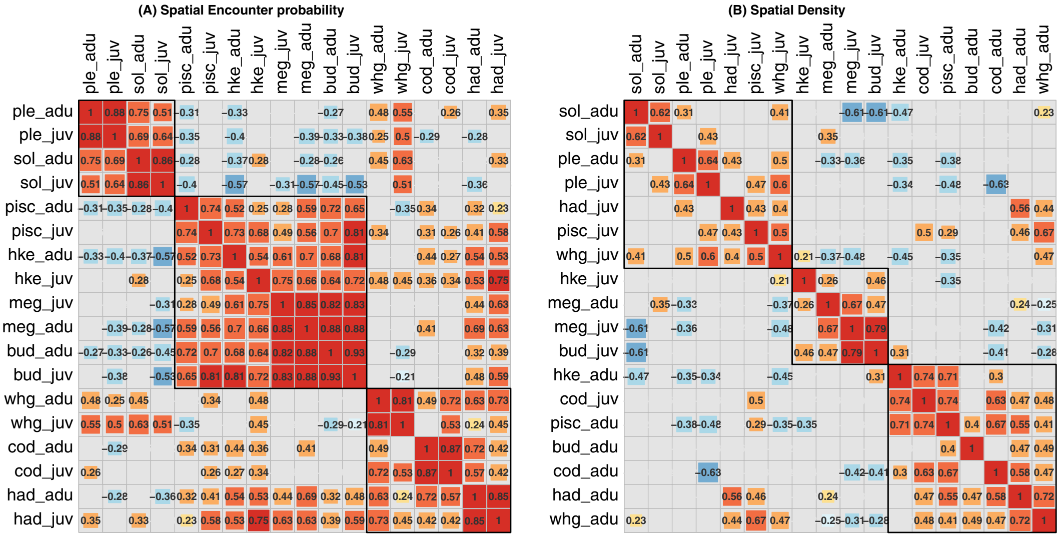

Figure 3. Inter-species correlations for (A) spatial encounter probability over all years and (B) spatial positive density. Species are clustered into three groups based on a hierarchical clustering method with non-significant correlations (the Confidence Interval [±1.96 * SEs] spanned zero) left blank.

a coefficient of 0.75. The final group are principally the species found in the deeper waters (hake, megrim and both anglerfish species) with megrim strongly associated with the black-bellied anglerfish species (0.88). Negative relationships were found between plaice and sole, and white-bellied anglerfish (−0.31 and −0.28 for the adult size class), black-bellied anglerfish (−0.27, −0.26 for the adult size class) and hake (−0.33, −0.37) (Fig. 3A) indicating spatial separation in distributions, with the flatfish found more inshore. This underscores the correlations among species seen in associations of each species with factors, with three distinct assemblages being confirmed.

Correlation coefficients for the average positive density (Fig. 3B) show fewer significant positive or negative relationships among species than for encounter probability, but still evident are the strong correlation among the roundfish with higher catches of cod correlated with higher catches of haddock (0.58) and whiting (0.47), as well as the two anglerfish species (0.71 for white-bellied and 0.44 for black-bellied) and hake (0.73). Similarly, plaice and sole are correlated (0.31) and higher catches of one would expect to see higher catches of the other, but also higher catches of some juvenile size classes of roundfish (whiting and haddock) and anglerfish species. Negative correlation of juvenile megrim, anglerfish (budegassa) and hake with adult sole (−0.61, −0.61 and −0.47 respectively), plaice (−0.36 and −0.35 for megrim and hake only) indicate high catches of one can predict low catches of the other successfully.

To understand how stable relationships between catches of pairs of species were from one year to the next, we regressed the correlation coefficients for the average spatial correlations between pairs for species x and species y across all years with those of the spatiotemporal population correlations, representing how correlations between species x and species y change from year to year (Fig. S9). The correlations were 0.60 (0.52–0.66) and 0.47 (0.38–0.55) for encounter probability and positive density respectively (Fig. S9a,b). These indicate generally predictable relationships between species from one year to the next and suggests that a positive or negative correlation between two species is likely to persist from one year to the next, and that species are consistently correlated in hauls. However, the regressions between the spatial correlations and the spatiotemporal correlations shows high variance ($R^2 = 0.36$ and 0.22 respectively), indicating that the scale of these relationships do change from one year to the next. This unpredictability would have implications for the fishery if, for example, catches of an unwanted species increased when caught with a target species above a level expected in the fishery potentially leading to challenges for fishers when trying to balance catch with quotas in mixed fisheries. It can be seen in the spatial factor maps that there are subtle differences in patterns in spatial factor coefficients from one year to the next (Figs S4 and S5), indicating changes may be driven by temporally changing environmental factors and species behaviour.

Potential to separate catches within assemblages under the landing obligation. The analysis shows the interdependence within three assemblages of roundfish, flatfish and deeper water species, where catching one species within the group indicates a high probability of catching the other species. This has important implications for how spatial avoidance can be used to support implementation of the EU's landing obligation. If production from mixed fisheries is to be maximised, decoupling catches of species between and within the groups will be key. For example, asking where the maximal separation in the densities of two coupled species is likely to occur? To address this requirement, we map the difference in spatial distribution within a species-group for each pair of species for a single year (2015; Fig. 4).

Cod had a more north-westerly distribution than haddock and a more westerly distributed than whiting roughly delineated by the 7°W line (Fig. 4A). Whiting appeared particularly concentrated in an area between 51 and 52°N and 5 and 7°W, which can be seen by comparing the whiting distribution with both cod (Fig. 4B) and haddock

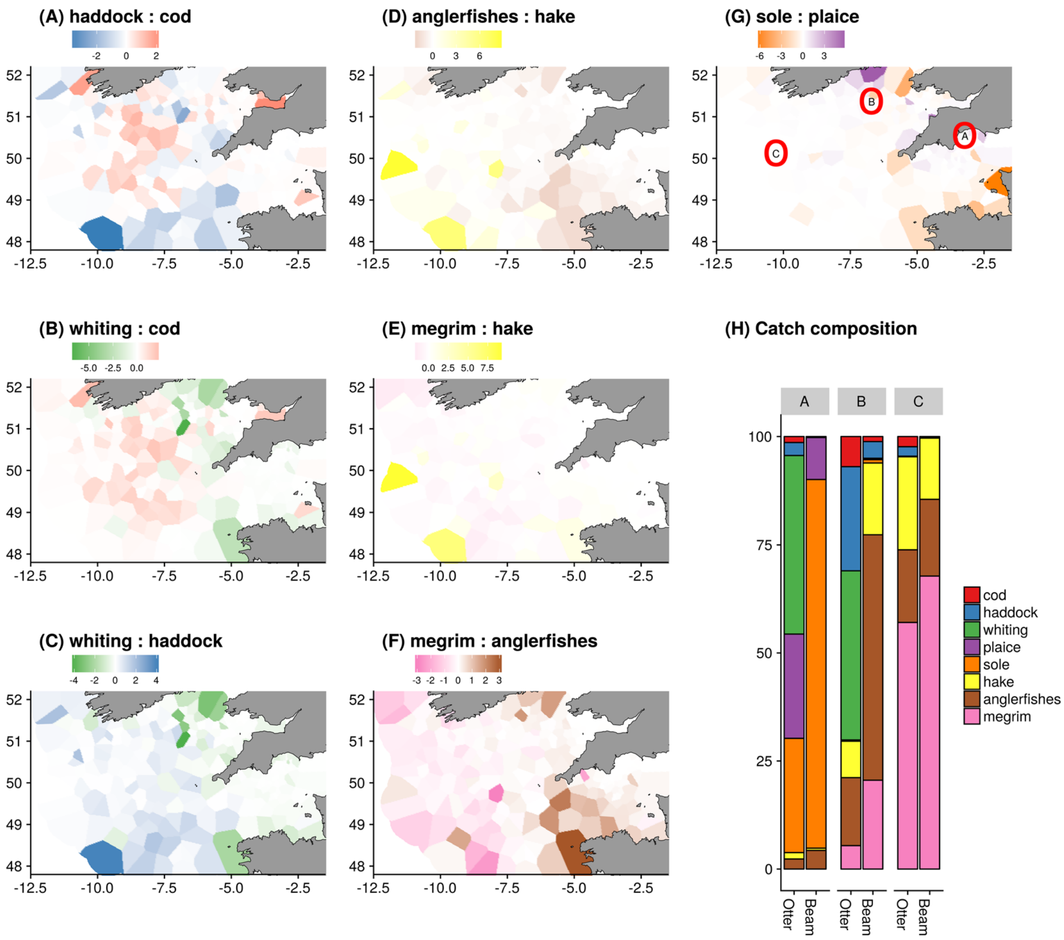

Figure 4. Differences in the standardised spatial density for pairs of species and expected catch rates for two different gears at three different locations in 2015. A, B and C in sub-figure (**H**) correspond to the spatial locations illustrated in sub-figure (**G**).

(Fig. 4C). For the deeper water species hake are more densely distributed in two locations around 10 W and 48 N and 12 W and 50 N compared to the anglerfish species (anglerfishes have been presented together as they are jointly managed under a single quota) and megrim, which were more widely spatially distributed (Fig. 4D,E). Megrim has a fairly even density across the modelled area as indicated by the large amount of white space in Fig. 4E. For anglerfishes and megrim (Fig. 4F), anglerfishes have a more easterly distribution than megrim. For the flatfish species plaice and sole (Fig. 4G), plaice appear to be more densely distributed along the coastal areas of Ireland and Britain, while sole are more densely distributed in the Southern part of the English Channel along the coast of France.

Predicted catch distribution from a "typical" otter trawl gear and beam trawl fishing at three different locations highlights the differences fishing gear makes on catches (Fig. 4H). Both gear selectivity and location fished have important effects on the catch composition; in the inshore area (location "A") plaice and sole are the two main species in the catch reflecting their distribution and abundance, though the otter trawl gear catches a greater proportion of plaice to sole than the beam trawl. The area between Britain and Ireland (location "B") has a greater contribution of whiting, haddock, cod, hake and anglerfishes in the catch with the otter trawl catching a greater proportion of the roundfish, haddock, whiting and cod while the beam trawl catches more anglerfishes and megrim. The offshore area has a higher contribution of megrim, anglerfishes and hake with the otter trawl catching a greater share of hake and the beam trawl a greater proportion of megrim. Megrim dominates the catch for both gears in location "C", reflecting its relative abundance in the area irrespective of the gear deployed.

Discussion

Our study is framed by the problem of addressing the scientific challenges of implementing the landing obligation for mixed fisheries. In application to the Celtic Sea, we have identified spatial separation of three distinct assemblages (roundfish, flatfish and deeper water species) while showing that only subtle differences exist in distributions within assemblages. The differences in catch compositions between gears at the same location (Fig. 4H) show that changing fishing methods affects catch, yet that differences in catches between locations are likely to be more important. For example, beam trawls fishing at the inshore locations (e.g. location "A" in Fig. 4) are likely to predominately catch plaice and sole, yet switching to the offshore locations (e.g. location "C") would likely yield greater catches of megrim and anglerfishes. Such changes in spatial fishing patterns are likely to play an important role in supporting implementation of the landing obligation.

More challenging is within-group spatial separation due to significant overlap in spatial distributions for the species, driven by common environmental factors. Subtle changes may yield some benefit in changing catch composition, yet the outcome is likely to be much more difficult to predict. For example, subtle differences in the distribution of cod, haddock and whiting can be seen in Fig. 4A–C, showing spatial separation of catches is much more challenging and likely to require support from other measures such as changes to the selectivity characteristics of gear[36]. For example we identified a spatial overlap of flatfish with juvenile roundfish in our species correlations (Fig. 3); reducing catches of incidental bycatch on the main target fishing grounds will likely require adaptations to fishing gear to address bycatch without significant economic impacts on the fishery.

A role that science could play in supporting effectiveness of spatiotemporal avoidance would be to provide probabilistic advice on hotspots for species occurrence and high species density, which can inform fishing decisions. Previous modelling studies have shown how spatiotemporal models could improve predictions of high ratios of bycatch to target species[37–39], and geostatistical models are well suited to this as they incorporate spatial dependency while providing for probabilities to be drawn from posterior distributions of the parameter estimates. We posit that such advice on "hot spots" as a supportive measure to incentivise avoidance of areas of high bycatch risk could be enhanced by integrating data obtained directly from commercial fishing vessels rapidly while modelling densities at small time scales (e.g., weekly). Short-term forecasts of distribution could inform fishing choices while also capturing seasonal differences in distributions, akin to weather forecasting. Advice informed by a model including a seasonal or real-time component could inform optimal policies for time-area closures, move-on rules or even as informal information to be utilised by fishers directly without the need for costly continuous data collection on environmental parameters, but by using the "vessels-as-laboratories" approach.

An important question for the implementation of the EU's landing obligation is how far spatial avoidance can go to achieving catch balancing in fisheries. Our model captures differences between location fished for two gear types and their broad scale effect on catch composition, information crucial for managers in implementing the landing obligation. It is likely, however, that this analysis reflects a lower bound on the utility of spatial avoidance as fine-scale behavioural decisions such as time-of-day, gear configuration and location choices can also be used to affect catch[40,41]. Results of empirical studies undertaken elsewhere[5,6] suggest limits to the effectiveness of spatial avoidance *in situ*. For example, differences in ability to change catch composition have been observed for different fleets; in the North Sea targeting ability was found to differ between otter and beam trawlers as well as between vessels of different sizes[42]. The particular socioeconomic circumstances for individual vessels is therefore important to take account when considering the effectiveness of spatial targetting and avoidance.

Under the landing obligation the balance of risk-reward for trip level fishing decisions about where to fish may change. For example, are fishers likely to fish in "safe" areas where its known there are lower catches of the target species but also decreased risk of encountering bycatch? How do decisions about level of risk affect the likelihood of overshooting available quota and potential profit and losses for individual trips? Set in this context, the parameter estimates could be used to simulate from a distribution of catches in the fishery at different locations and therefore inform on the possibility of extreme catch events and potential consequences for overshooting quotas. Alternatively, where fisheries data is available with factors such as weather, quota uptake and previous catches these could be included as covariates in the model to help identify causes for high bycatch events. This information may be of interest in identifying optimum strategies, or used in future work to model closure risks for fisheries operating in different locations and conditions given quota constraints. Such analyses on risk and decision making are likely to hinge on micro-level decisions by fishers and would be a useful compliment to broader scale considerations such as those detailed here.

Our framework allows for a quantitative understanding of the broad scale global production set available to fishers[43] and thus the extent to which they can alter catch compositions while operating in a mixed fishery. Simulations of spatial effort allocation scenarios based on the production sets derived from the model estimates could be used as inputs to fisher behavioural models to allow for the identification of lower bounds of optimum spatial harvest strategies. Modelling different spatial strategies at the individual or fishery level would provide managers with an information base to examine trade-offs in quota setting, thus providing a scientific basis to assessing the ability of technical measures to meet the goal of maximising catches in mixed fisheries within single stock quota constraints[7]. Additionally, the correlations among species could provide information on fisheries at risk of capturing protected, endangered or threatened species such as elasmobranchs, and allow identification of areas where there are high ratios of protected to target species.

Complex environmental, fishery and community drivers of distribution for groups of species highlights the scale of the challenge in separating catches within the assemblages using spatial management measures. This has important implications for management of mixed fisheries under the EU landing obligation. Our analysis identifies where it may be easier to separate catches of species (among groups) and where it is more challenging (within groups). We propose that the dimension-reduction framework presented in Figs 1–4 provides a viable route to reducing the complexity of highly mixed fisheries. This can allow informed management discussion over more traditional anecdotal knowledge of single-species distribution in space and time.

Methods

Model structure. VAST (software in the R statistical programming language can be found here: www.github.com/james-thorson/VAST) implements a delta-generalised linear mixed modelling (GLMM) framework that takes account of spatiotemporal correlations among species through implementation of a spatial dynamic factor analysis (SDFA). Spatial variation is captured through a Gaussian Markov Random Field, while we model random variation among species and years. Covariates affecting catchability (to account for differences between fishing surveys) and density (to account for environmental preferences) can be incorporated for predictions of presence and positive density. The following briefly summarises the key methods implemented in the VAST framework. For full details see Thorson *et al.*[44].

SDFA. A spatial dynamic factor analysis incorporates advances in joint dynamic species distribution models[44] to take account of associations among species by modelling response variables as a multivariate process. This is achieved through implementing a factor analysis decomposition where common latent trends are estimated so that the number of common trends is less than the number of species modelled. The factor coefficients are then associated through loadings for each factor that return a positive or negative association of one or more species with any location. Log-density of any species is then be described as a linear combination of factors and loadings:

$$\theta_c(s,\ t) = \sum_{j=1}^{n_j} L_{c,j}\psi_j(s,\ t) + \sum_{k=1}^{n_k} \gamma_{k,c}\chi_k(s,\ t) \tag{1}$$

where $\theta_c(s, t)$ represents log-density for species c at site s at time t, ψ_j is the coefficient for factor j, $L_{c,j}$ the loading matrix representing association of species c with factor j and $\gamma_{k,c}\chi_k(s, t)$ the linear effect of covariates at each site and time[45].

The factor analysis can summarize community dynamics and identify which species and life-stages have similar spatiotemporal patterns. This allows inference regarding species distributions and abundance of poorly sampled species through association with other species, and also provides estimates of spatiotemporal correlations among species[45].

Estimation of abundances. Spatiotemporal encounter probability and positive catch rates are modelled separately with spatiotemporal encounter probability modelled using a logit-link linear predictor;

$$\begin{aligned} logit[p(s_i,\ c_i,\ t_i)] \ &= \ \beta_p(c_i,\ t_i) + \sum_{f=1}^{n_\omega} L_\omega(c_i,\ f)\omega_p(s_i,\ f) + \sum_{f=1}^{n_\varepsilon} L_\varepsilon(c_i,\ f)\varepsilon_p(s_i,\ f,\ t_i) \\ &\quad + \sum_{v=1}^{n_v} \delta_p(v)Q_p(c_i,\ v_i) \end{aligned} \tag{2}$$

and positive catch rates modelling using a gamma- distribution[30].

$$\begin{aligned} log[r(s_i,\ c_i,\ t_i)] \ &= \ \beta_r(c_i,\ t_i) + \sum_{f=1}^{n_\omega} L_\omega(c_i,\ f)\omega_r(s_i,\ f) + \sum_{f=1}^{n_\varepsilon} L_\varepsilon(c_i,\ f)\varepsilon_r(s_i,\ f,\ t_i) \\ &\quad + \sum_{v=1}^{n_v} \delta_r(v)Q_r(c_i,\ v_i) \end{aligned} \tag{3}$$

where $p(s_i, c_i, t_i)$ is the predictor for encounter probability for observation i, at location s for species c and time t and $r(s_i, c_i, t_i)$ is similarly the predictor for the positive density. $\beta_*(c_i, t_i)$ is the intercept, $\omega_*(s_i, c_i)$ the spatial variation at location s for factor f, with $L_\omega(c_i, f)$ the loading matrix for spatial covariation among species. $\varepsilon_*(s_i, c_i, t_i)$ is the linear predictor for spatiotemporal variation, with $L_\varepsilon(c_i, f)$ the loading matrix for spatiotemporal covariance among species and $\delta_*(c_i, v_i)$ the contribution of catchability covariates for the linear predictor with Q_{c_i,v_i} the catchability covariates for species c and vessel v; * can be either p for probability of encounter or r for positive density.

The Delta-Gamma formulation is then:

$$\begin{aligned} Pr(C = 0) \ &= \ 1 - p \\ Pr(C = c|c > 0) \ &= \ p \cdot \frac{\lambda^k c^{k-1} \cdot exp(-\lambda c)}{\Gamma_k} \end{aligned} \tag{4}$$

for the probability p of a non-zero catch C given a gamma distribution for for the positive catch with a rate parameter λ and shape parameter k.

Spatiotemporal variation. The spatiotemporal variation is modelled using Gaussian Markov Random Fields (GMRF) where observations are correlated in space through a Matérn covariance function with the parameters estimated within the model. Here, the correlation decays smoothly over space the further from the location and includes geometric anisotropy to reflect that correlations may decline in one direction faster than another (e.g. moving offshore)[31]. The best fit estimated an anisotropic covariance where the correlations were stronger in a north-east - south-west direction, extending approximately 97 km and 140 km before correlations for encounter probability and positive density reduced to $<10\%$, respectively (Fig. S10). Incorporating the spatiotemporal correlations among species provides more efficient use of the data as inference can be made about poorly sampled locations from the covariance structure.

A probability distribution for spatiotemporal variation in both encounter probability and positive catch rate was specified, $\varepsilon_*(s, p, t)$, with a three-dimensional multivariate normal distribution so that:

$$vec[\mathbf{E}_*(t)] \sim MVN(0,\ \mathbf{R}_* \otimes \mathbf{V}_{\varepsilon*}) \tag{5}$$

Here, $vec[\mathbf{E}_*(t)]$ is the stacked columns of the matrices describing $\varepsilon_*(s,\ p,\ t)$ at every location, species and time, $\mathbf{R}_*$ is a correlation matrix for encounter probability or positive catch rates among locations and $\mathbf{V}_*$ a covariance matrix for encounter probability or positive catch rate among species (modelled within the factor analysis). $\otimes$ represents the Kronecker product so that the correlation among any location and species can be computed[44].

Incorporating covariates. Survey catchability (the relative efficiency of a gear catching a species) was estimated as a fixed effect in the model, $\delta_s(v)$, to account for differences in spatial fishing patterns and gear characteristics, which affect encounter and capture probability of the sampling gear[46]. Parameter estimates (Fig. S11) showed clear differential effects of surveys using otter trawl gears (more effective for round fish species) and beam trawl gears (more effective for flatfish species).

No fixed covariates for habitat quality or other predictors of encounter probability or positive density were included. While incorporation may improve the spatial predictive performance[44], it was not found to be the case here based on model selection with Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Parameter estimation. Parameter estimation was undertaken through Laplace approximation of the marginal likelihood for fixed effects while integrating the joint likelihood (which includes the probability of the random effects) with respect to random effects. This was implemented using Template Model Builder (TMB[47]) with computation supported by use of the Irish Centre for High End Computing (ICHEC; http://www.ichec.ie) facility.

Data. The model integrates data from seven fisheries-independent surveys taking account of correlations among species spatiotemporal distributions and abundances to predict spatial density estimates consistent with the resolution of the data.

The model was fitted to nine species separated into adult and juvenile size classes (Table S2) to seven survey series (Table S1) in the Celtic Sea bounded by 48°N to 52°N latitude and 12°W to 2°W longitude (Fig. S8) for the years 1990–2015 inclusive.

The following steps were undertaken for data processing: (i) data for survey stations and catches were downloaded from ICES Datras (www.ices.dk/marine-data/data-portals/Pages/DATRAS.aspx) or obtained directly from the Cefas Fishing Survey System (FSS); (ii) data were checked and any tows with missing or erroneously recorded station information (e.g. tow duration or distance infeasible) removed; (iii) swept area for each of the survey tows was estimated based on fitting a GAM to gear variables so that Doorspread = s(Depth) + DoorWt + WarpLength + WarpDiameter + SweepLength and a gear specific correction factor taken from the literature[48]; (iii) fish lengths were converted to biomass (Kg) through estimating a von bertalanffy length weight relationship, $Wt = a \cdot L^b$, fit to sampled length and weight of fish obtained in the EVHOE survey and aggregated within size classes (adult and juvenile). Details on the downloading and processing of the data are available in Rmarkdown format (code and steps combined) as supplementary material.

The final dataset comprised of estimates of catches (including zeros) for each station and species and estimated swept area for the tow.

Model setup. The spatial domain was set up to include 250 knots representing the Gaussian Random Fields. The model was configured to estimate nine factors each to describe the spatial and spatiotemporal encounter probability and positive density parameters, with a logit-link for the linear predictor for encounter probability and log-link for the linear predictor for positive density, with an assumed gamma distribution.

Three candidate models were identified, (i) a base model where the vessel interaction was a random effect, (ii) the base but where the vessel x species effect was estimated as a fixed covariate, (iii) with vessel × species effect estimated, but with the addition of estimating fixed density covariates for both predominant habitat type at a knot and depth. AIC and BIC model selection favoured the second model (Table S3). The final model included estimating 1,674 fixed parameters and predicting 129,276 random effect values.

Model validation. Q-Q plots show good fit between the derived estimates and the data for positive catch rates and between the predicted and observed encounter probability (S12, S13). Further, model outputs are consistent with stock-level trends abundances over time from international assessments (S14), yet also provide detailed insight into species co-occurrence and the strength of associations in space and time.

Data Availability

Data used to fit the model is available via the ICES Datras data portal (http://www.ices.dk/marine-data/data-portals/Pages/DATRAS.aspx) for two surveys and on request to the corresponding author for the remaining five surveys.

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Author Contributions
P.J.D., C.M. and J.T.T. designed the study. P.J.D. conducted the analysis. All authors contributed to writing the manuscript.

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Appendix B

Data processing for manuscript I

Processing and exploration for Celtic Sea fishery-independent trawl survey data

Paul J Dolder

May 4, 2017

This document is to detail the processing steps and workng up of data for fitting a geostatistical model (VAST; see https://github.com/james-thorson/VAST for detail) to trawl survey data covering the Celtic Sea.

The following data sources were used:

- ICES Datras (http://www.ices.dk/marine-data/data-portals/Pages/DATRAS.aspx exhchange data of Ifremer (France) EVHOE and Marine Institute (Ireland) IGFS fisheries-independent survey locations and catch records.
- Cefas (UK) collection of trawl survey locations and catch records.
- ICES Datras data product on estimated weights of fish at various lengths from the EVHOE survey series.

1 Length-weight conversion factors

As the survey records consist of count of fish at each length class and we are interested in working with biomass (weight) of fish, we first estimate a length-weight relationship for the different species from the Datras data product of weight at length estimates. The data is baseds on the EVHOE survey series only, due to availability within Datras.

A standard von bertalanffy length weight relationship was used, with two parameters to estimate:

$$Wt = a \cdot L^b \tag{1}$$

The raw data looks as follows for cod, megrim, anglerfishes, haddock, whiting, hake, plaice and sole:

```r
# Read data and remove records without corresponding weight
DF <- read.csv(file.path("DATRAS", "SMALK_EVHOE.csv"))  # read data
DF <- DF[!is.na(DF$IndWgt), ]

# Subset to species of interest sort(unique(DF$Species))
spp <- c("Gadus morhua", "Lepidorhombus whiffiagonis", "Lophius piscatorius",
    "Lophius budegassa", "Merlangius merlangus", "Melanogrammus aeglefinus",
    "Merluccius merluccius", "Pleuronectes platessa", "Solea solea")

## N.B. The length-weight relationship for anglerfishes
## doesn't hold, so we might need an alternative
## solution....'Pollachius pollachius' - no juveniles??

DF <- DF[DF$Species %in% spp, ]

# Plot
ggplot(DF, aes(x = LngtClass, y = IndWgt)) + geom_point(aes(colour = factor(Year))) +
    facet_wrap(~Species, scale = "free") + theme_bw()
```

To simplify the fitting procedure, the von bertalanffy relationship in equation 1 was rearranged to be linear on a log scale:

$$log(Wt) = log(a) + b \cdot log(L) + \varepsilon \tag{2}$$

```r
DF$lWt <- log(DF$IndWgt)
DF$lL <- log(DF$LngtClass)

ggplot(DF, aes(x = lL, y = lWt)) + geom_point(aes(colour = factor(Year))) +
    facet_wrap(~Species, scale = "free") + theme_bw()
```

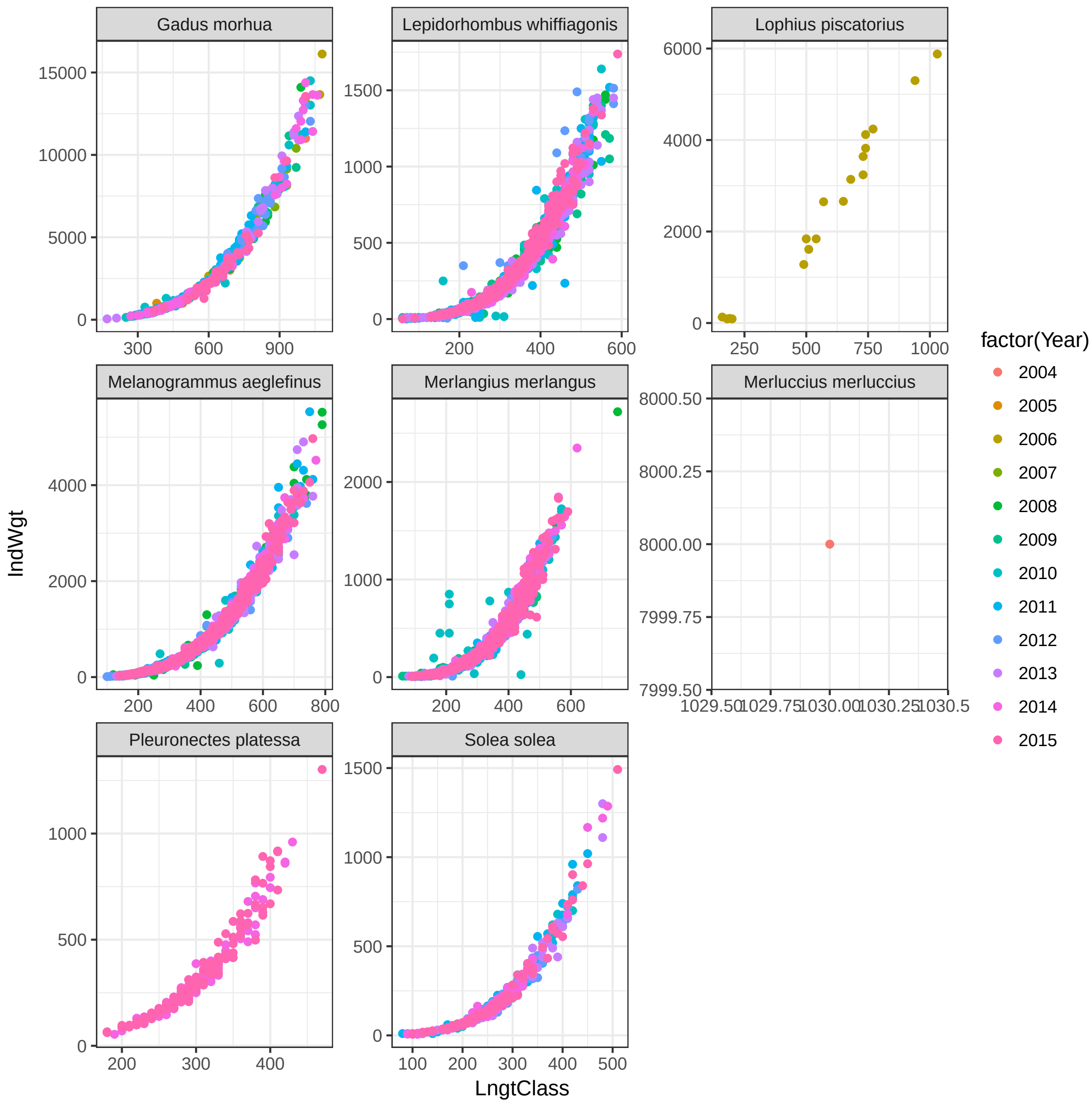
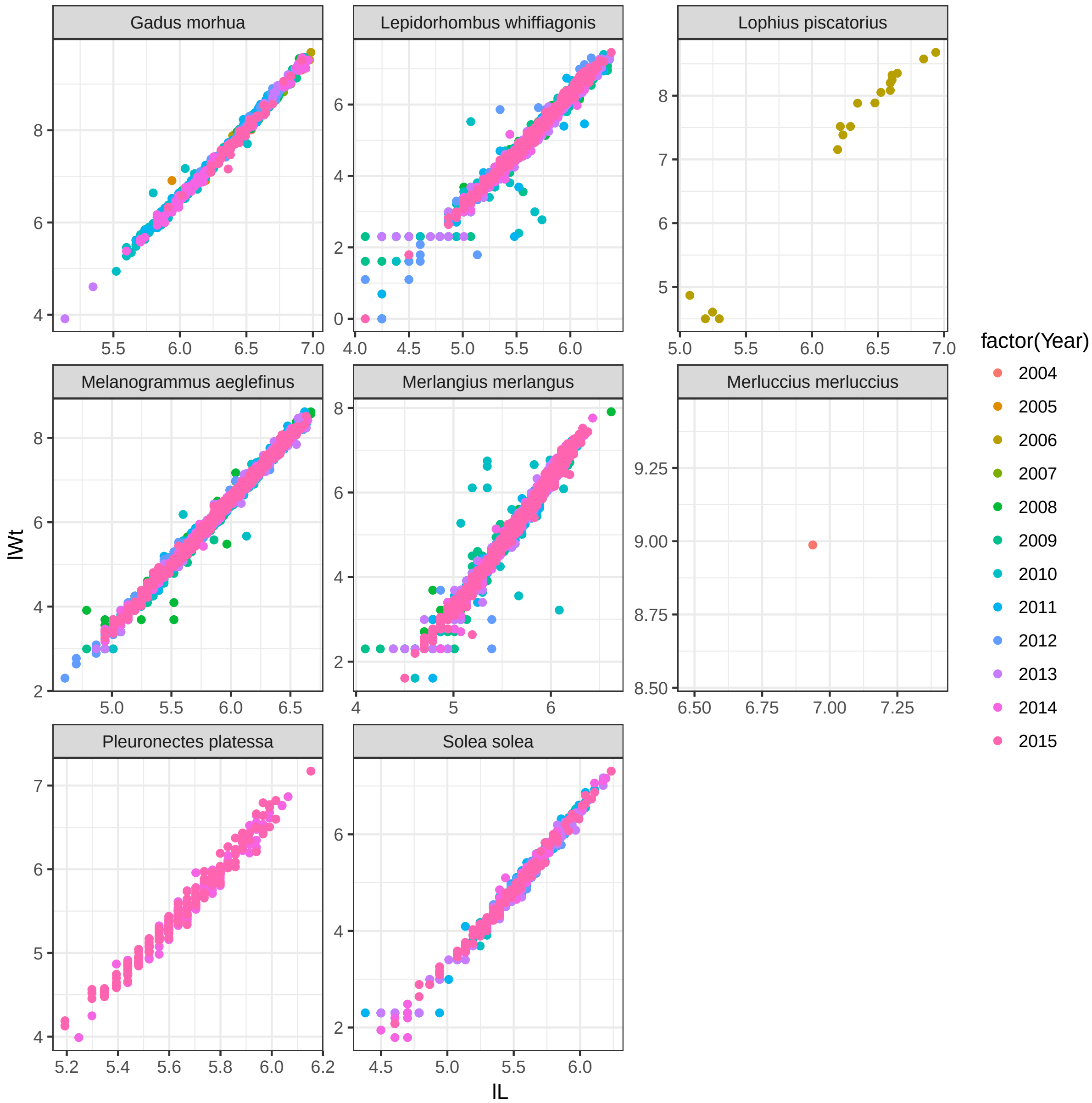


Figure 1: Estimates of individual weights at length for the gadoid species. Colours indicate individual years measurements



A linear model with species and year as factors was fit using the *glm* function in the base R package. We separate the roundfish and flatfish due to the different morphological forms affecting the length weight relationship:

```
gads <- c("Gadus morhua", "Melanogrammus aeglefinus", "Merluccius merlucciu
    "Merlangius merlangus")
flats <- c("Lepidorhombus whiffiagonis", "Solea solea", "Pleuronectes plates
lops <- c("Lophius piscatorius", "Lophius budegassa")

lm1.gad <- glm(lWt ~ lL + Species + Year, data = filter(DF, Species %in%
```

```r
    gads))
lm2.gad <- glm(lWt ~ lL + Species, data = filter(DF, Species %in%
    gads))

stargazer(lm1.gad, lm2.gad, font.size = "small", align = T, title = "glm out
    table.placement = "H")
```

Table 1: glm output from the two model fits to gadoids

	Dependent variable:	
	lWt	
	(1)	(2)
lL	3.085^{***}	3.085^{***}
	(0.005)	(0.005)
SpeciesMelanogrammus aeglefinus	-0.015^{**}	-0.015^{**}
	(0.007)	(0.007)
SpeciesMerlangius merlangus	-0.199^{***}	-0.199^{***}
	(0.008)	(0.008)
SpeciesMerluccius merluccius	-0.435^{***}	-0.436^{***}
	(0.149)	(0.149)
Year	0.0001	
	(0.001)	
Constant	-12.263^{***}	-11.977^{***}
	(1.607)	(0.034)
Observations	6,624	6,624
Log Likelihood	3,219.649	3,219.633
Akaike Inf. Crit.	-6,427.297	-6,429.266
Note:	*p<0.1; **p<0.05; ***p<0.01	

```r
lm1.flat <- glm(lWt ~ lL + Species + Year, data = filter(DF,
    Species %in% flats))
lm2.flat <- glm(lWt ~ lL + Species, data = filter(DF, Species %in%
    flats))

stargazer(lm1.flat, lm2.flat, font.size = "small", align = T,
```

```
    title = "glm output from the two model fits to flatfish",
    table.placement = "H")
```

Table 2: glm output from the two model fits to flatfish

	Dependent variable:	
	lWt	
	(1)	(2)
lL	3.106***	3.106***
	(0.010)	(0.010)
SpeciesPleuronectes platessa	0.361***	0.358***
	(0.013)	(0.012)
SpeciesSolea solea	0.190***	0.188***
	(0.009)	(0.009)
Year	−0.001	
	(0.002)	
Constant	−9.739***	−12.410***
	(3.147)	(0.056)
Observations	3,180	3,180
Log Likelihood	753.089	752.728
Akaike Inf. Crit.	-1,496.177	-1,497.456
Note:	*p<0.1; **p<0.05; ***p<0.01	

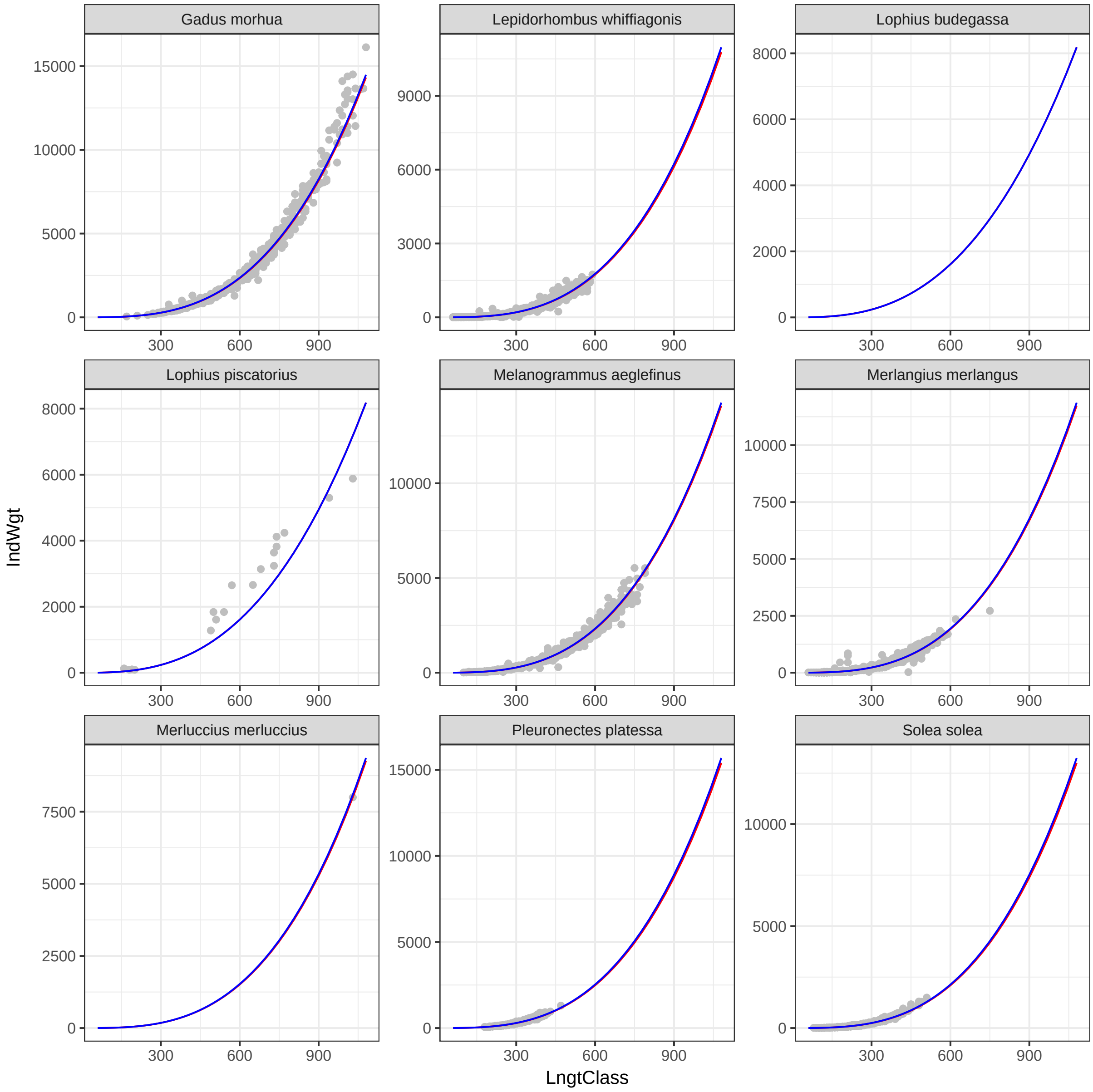
Year was initially also included as a factor, but found not to be significant and the second, across year, fit was chosen as the best models (Table 1, Table 2). These models were then used to predict over all lengths for each species. A bias correction was applied to adjust for the fact that the mean weights from the model fit on a log scale are geometric means on the normal scale (cf = $e^{\frac{\sigma^2}{2}}$).

For anglerfish, as there is insufficient data for a fit a model (few data points for piscatorius, no data points for budegassa), we use estimates from fishbase: $a = 0.03330$, $b = 2.766$.

```
lop <- c(a = 0.0333, b = 2.766)

predDF <- expand.grid(lL = seq(log(min(DF$LngtClass)), log(max(DF$LngtClass)),
    l = 80), Species = spp)

predDF$lWt[predDF$Species %in% gads] <- predict(lm2.gad, newdata = predDF[predDF$Species %
```

```
    gads, ])
predDF$lWt[predDF$Species %in% flats] <- predict(lm2.flat, newdata = predDF[predDF$Species
    flats, ])
predDF$Wt[predDF$Species %in% lops] <- lop[["a"]] * (exp(predDF$lL[predDF$Species %in%
    lops])^lop[["b"]])/1000
```

```
# Exponentiate the predictions
predDF$L <- exp(predDF$lL)
predDF$Wt[predDF$Species %in% c(gads, flats)] <- exp(predDF$lWt[predDF$Species %in%
    c(gads, flats)])

## Now we need to bias correct due to the fact that the mean
## on the logscale is the geometric mean...
corr.fact.gad <- exp(sigma(lm2.gad)^2/2)
corr.fact.flat <- exp(sigma(lm2.flat)^2/2)
print(paste("Correction factor for gadoids=", round(corr.fact.gad,
    3), "and flats = ", round(corr.fact.flat, 3)))


## [1] "Correction factor for gadoids= 1.011 and flats =  1.018"


predDF$WtCorr[predDF$Species %in% gads] <- predDF$Wt[predDF$Species %in%
    gads] * corr.fact.gad
predDF$WtCorr[predDF$Species %in% flats] <- predDF$Wt[predDF$Species %in%
    flats] * corr.fact.flat
predDF$WtCorr[predDF$Species %in% lops] <- predDF$Wt[predDF$Species %in%
    lops]

# Plot the von bertalanffy fits
ggplot(DF, aes(x = LngtClass, y = IndWgt)) + geom_point(colour = "grey") +
    facet_wrap(~Species, scale = "free") + geom_line(data = predDF,
    aes(x = L, y = Wt), col = "red") + geom_line(data = predDF,
    aes(x = L, y = WtCorr), col = "blue") + theme_bw()
```




```r
lm2 <- list(lm2.gad, lm2.flat)
corr.fact <- list(corr.fact.gad, corr.fact.flat)

## Save the fit and the correction factor
save(lm2, corr.fact, lop, file = file.path("DATRAS", "LengthWeightPredictCelticSea.RData"))
```

2 DATRAS data processing

Next the ICES Datras database was queried for all survey data from the Celtic Sea, extracting the haul data with the function *getHHdata* and the catch data using the function *getHLdata* from the package *icesDatras*.

The objective was to check, clean and format the data into suitable input data for the VAST model. For the Datras data this involved:

- Only retain valid hauls (excluding those at night, where there were problems with the gear etc..)
- As we want point data, calculate the midpoint of each tow based on the geodesic distance (also estimating any missing data on distance towed).
- In order to calculate swept area, obtain model estimates for any missing data points on door spread through modelling the relationship between depth and door spread.
- Calculate swept area for each tow in the surveys.
- Estimate weight at length using the length weight relationship predictions obtained from equation 1 above.
- Raise the data to weight, partioned between adult and juvenile fish.
- Merge station and catch data ensuring there is one record per species for each of the stations fished (including where there were zero catches).

2.1 Midpoint of tows

To calculate the tow midpoints, we assume tows are in a straight line and use the haversine formula (based on location in radians) to calculate the total distance.

$$Loc(R) = Loc(D) \cdot \frac{\pi}{180} \tag{3}$$

Where R and D are radians and decimal degrees respectively.

To calculate the distance:

$$fD(km) =$$
$$R \cdot \left[2 \cdot \arcsin\left(\min\left(1, \sqrt{\sin(\frac{Lat_{y1} - Lat_{y2}}{2})^2 + \cos(Lat_{x1}) \cdot \cos(Lat_{x2}) \cdot \sin(\frac{Lon_{x1} - Lon_{x2}}{2})^2}\right)\right)\right] \tag{4}$$

Where R is the mean Radius of the Earth, 6 341 km.

Total records were:

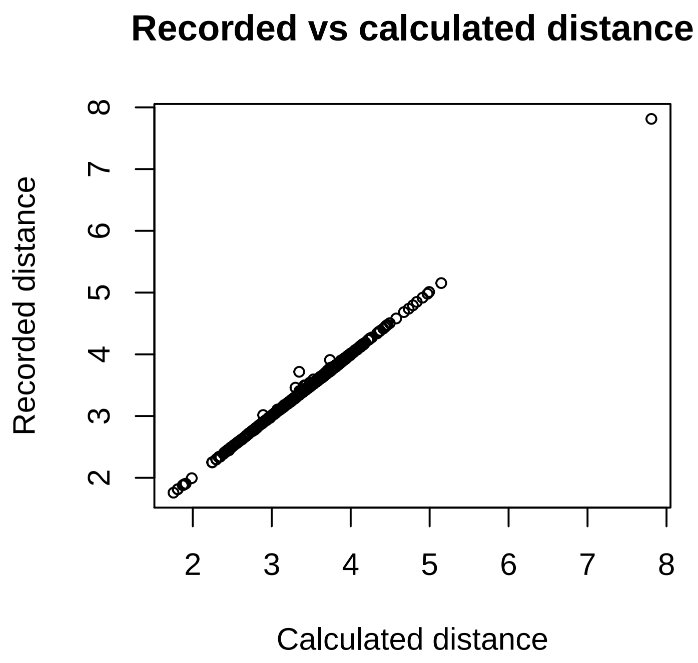
```
load(file.path("DATRAS", "CelticSurveyData.RData"))  # pre-downloaded data, HH is station,

kable(group_by(HH, Survey, HaulVal) %>% summarise(n = n()))
```

Survey	HaulVal	n
EVHOE	I	2
EVHOE	V	2643
IE-IGFS	V	2118

```
## Some initial cleaning
HH <- filter(HH, HaulVal == "V")  # only valid hauls

# Convert degrees to radians
deg2rad <- function(deg) return(deg * pi/180)

# Calculates the geodesic distance between two points
# specified by radian latitude/longitude using the Haversine
# formula (hf)
gcd.hf <- function(long1, lat1, long2, lat2) {
    R <- 6371  # Earth mean radius [km]
    delta.long <- (long2 - long1)
    delta.lat <- (lat2 - lat1)
    a <- sin(delta.lat/2)^2 + cos(lat1) * cos(lat2) * sin(delta.long/2)^2
    c <- 2 * asin(min(1, sqrt(a)))
    d = R * c
    return(d)  # Distance in km
}
############################
an <- as.numeric
```

```
HH$Dist <- mapply(gcd.hf, long1 = deg2rad(an(HH$ShootLong)),
    lat1 = deg2rad(an(HH$ShootLat)), long2 = deg2rad(an(HH$HaulLong)),
    lat2 = deg2rad(an(HH$HaulLat)))
```

```
plot(an(HH$Distance[(HH$Distance != -9)])/1000 ~ HH$Dist[(HH$Distance !=
    -9)], main = "Recorded vs calculated distance", ylab = "Recorded distance",
    xlab = "Calculated distance", cex = 0.7)
```



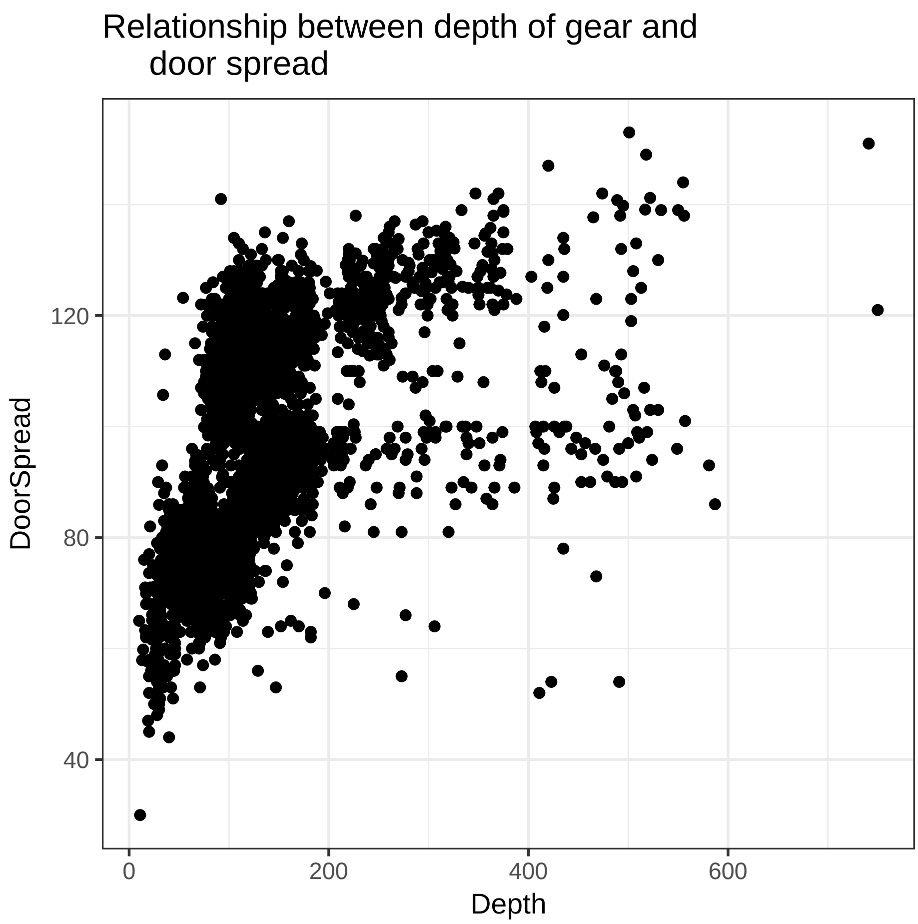

```
## Looks good - use the calculated estimates ##
```

2.2 Swept area

To calculate the swept area, we first have to estimate the door spread for any records where it's missing. There were only 5 records with missing door spread, but use the predicted door spread for all records.

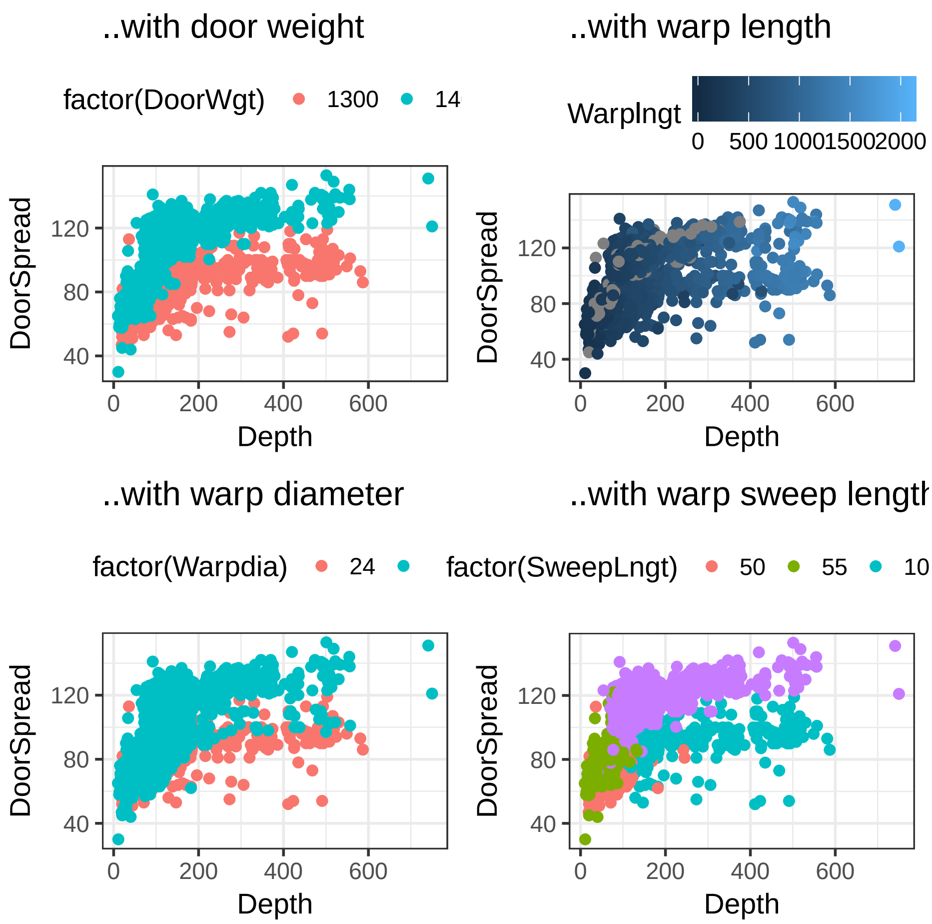
```
# Covert numeric variables so we can explore the covariates
HH$SweepLngt <- as.numeric(HH$SweepLngt)
HH$HaulDur <- as.numeric(HH$HaulDur)
HH$DoorSpread <- as.numeric(HH$DoorSpread)
HH$Depth <- as.numeric(HH$Depth)
HH$Netopening <- as.numeric(HH$Netopening)
HH$Warplngt <- as.numeric(HH$Warplngt)
HH$Warpdia <- as.numeric(HH$Warpdia)
```

```
HH$DoorSurface <- as.numeric(HH$DoorSurface)
HH$DoorWgt <- as.numeric(HH$DoorWgt)
HH$WingSpread <- as.numeric(HH$WingSpread)
HH$KiteDim <- as.numeric(HH$KiteDim)
HH$TowDir <- as.numeric(HH$TowDir)
HH$GroundSpeed <- as.numeric(HH$GroundSpeed)
HH$SpeedWater <- as.numeric(HH$SpeedWater)
HH$SurCurDir <- as.numeric(HH$SurCurDir)
HH$SurCurSpeed <- as.numeric(HH$SurCurSpeed)
HH$BotCurDir <- as.numeric(HH$BotCurDir)
HH$BotCurSpeed <- as.numeric(HH$BotCurSpeed)
HH$WindDir <- as.numeric(HH$WindDir)
HH$WindSpeed <- as.numeric(HH$WindSpeed)
HH$SwellDir <- as.numeric(HH$SwellDir)
HH$SwellHeight <- as.numeric(HH$SwellHeight)
HH$SurTemp <- as.numeric(HH$SurTemp)
HH$BotTemp <- as.numeric(HH$BotTemp)
HH$SurSal <- as.numeric(HH$SurSal)
HH$BotSal <- as.numeric(HH$BotSal)

HH[HH == -9] <- NA

ggplot(HH, aes(x = Depth, y = DoorSpread)) + geom_point() + theme_bw() +
    ggtitle("Relationship between depth of gear and
     door spread")
```



There may be another covariate affecting doorspread, indicated by the clustering of some of the data...lets look at some of them.

```
p1 <- ggplot(HH, aes(x = Depth, y = DoorSpread)) + geom_point(aes(colour = factor(DoorWgt)
    theme_bw() + ggtitle("..with door weight") + theme(legend.position = "top")

p2 <- ggplot(HH, aes(x = Depth, y = DoorSpread)) + geom_point(aes(colour = Warplngt)) +
    theme_bw() + ggtitle("..with warp length") + theme(legend.position = "top")

p3 <- ggplot(HH, aes(x = Depth, y = DoorSpread)) + geom_point(aes(colour = factor(Warpdia)
    theme_bw() + ggtitle("..with warp diameter") + theme(legend.position = "top")

p4 <- ggplot(HH, aes(x = Depth, y = DoorSpread)) + geom_point(aes(colour = factor(SweepLngt
    theme_bw() + ggtitle("..with warp sweep length") + theme(legend.position = "top")

grid.arrange(p1, p2, p3, p4, ncol = 2)
```



There looks to be a relationship between depth and doorspread where it increases to around 200 m and then flattens out, but with a covariate effect. We will model this relationship with a gam.

```
# Without covariate
m1 <- gam(DoorSpread ~ s(Depth), data = HH)
# summary(m1)

# With all covariate, no interactions
m2 <- gam(DoorSpread ~ s(Depth) + factor(DoorWgt) + Warplngt +
    factor(Warpdia) + factor(SweepLngt), data = HH)
# summary(m2)

### full interactions
m3 <- gam(DoorSpread ~ s(Depth) + factor(DoorWgt) * Warplngt *
    factor(Warpdia) * factor(SweepLngt), data = HH)
# summary(m3)
```

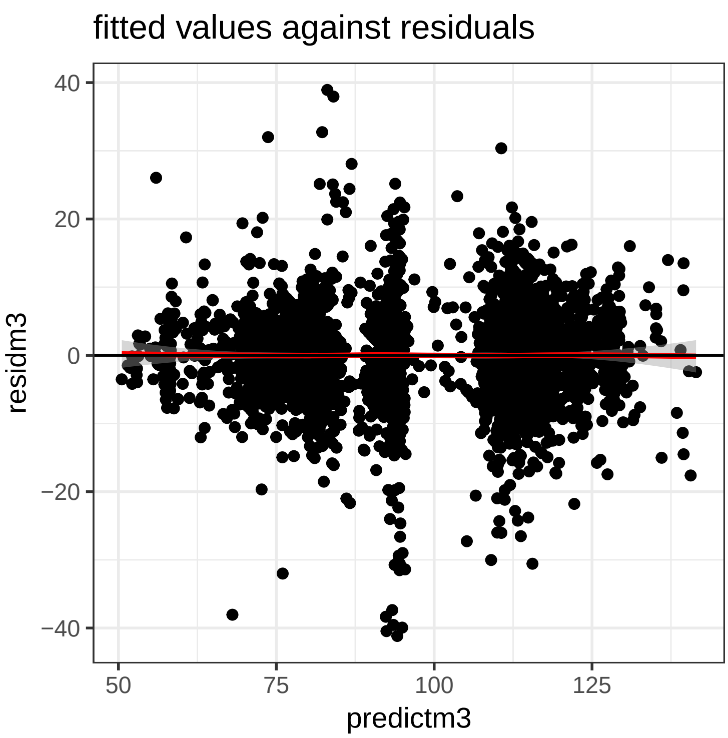
```r
kable(AIC(m1, m2, m3))
```

	df	AIC
m1	10.37315	31310.46
m2	14.90415	24524.39
m3	20.57980	24261.34

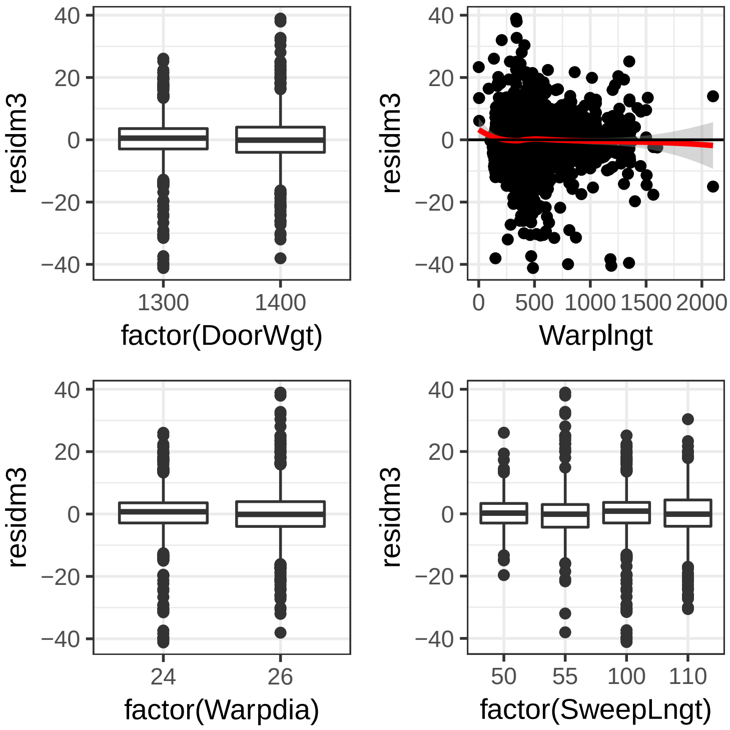
```r
# stargazer(m1,m2,m3, font.size = 'small', align = T, title =
# 'gam output from model with and without covariates',
# table.placement = 'H', single.row = T)
```

Full model looks best, but let's check the residuals against the covariates

```r
HHresid <- filter(HH, !is.na(DoorWgt), !is.na(Warplngt), !is.na(Warpdia),
    !is.na(SweepLngt), !is.na(Depth), !is.na(DoorSpread))

HHresid$residm3 <- resid(m3)
HHresid$predictm3 <- fitted(m3)

## Plot resids
ggplot(HHresid, aes(x = predictm3, y = residm3)) + geom_point() +
    geom_smooth(method = "loess", col = "red") + theme_bw() +
    ggtitle("fitted values against residuals") + geom_hline(yintercept = 0)
```

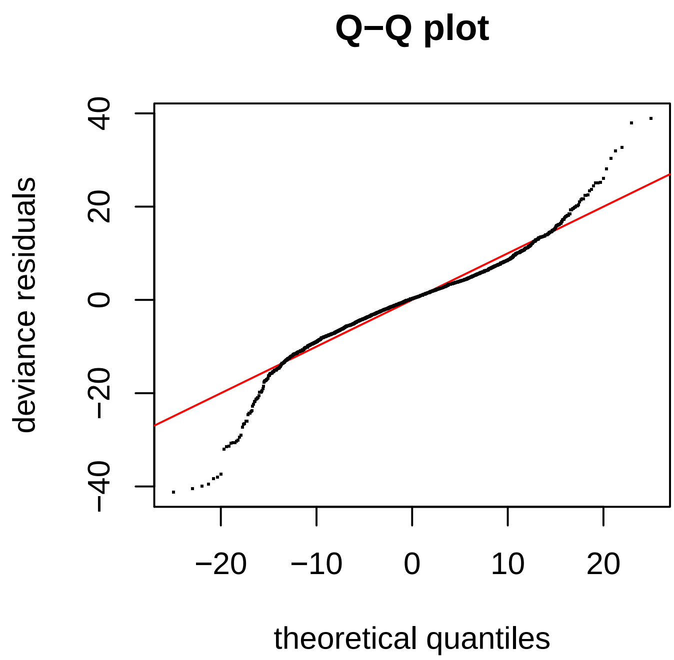


```r
p1 <- ggplot(HHresid, aes(x = factor(DoorWgt), y = residm3)) +
    geom_boxplot() + theme_bw()

p2 <- ggplot(HHresid, aes(x = Warplngt, y = residm3)) + geom_point() +
    geom_smooth(method = "loess", colour = "red") + theme_bw() +
    geom_hline(yintercept = 0)

p3 <- ggplot(HHresid, aes(x = factor(Warpdia), y = residm3)) +
    geom_boxplot() + theme_bw()

p4 <- ggplot(HHresid, aes(x = factor(SweepLngt), y = residm3)) +
    geom_boxplot() + theme_bw()

grid.arrange(p1, p2, p3, p4, ncol = 2)
```

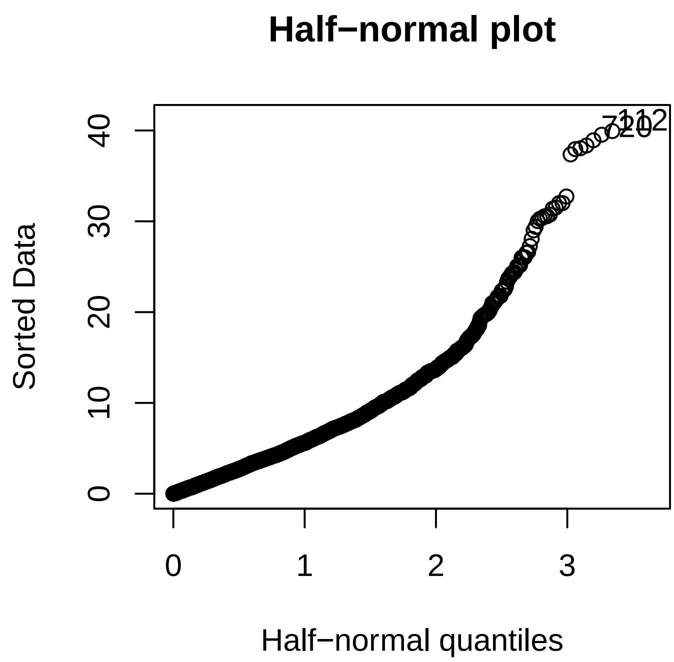


Residuals look OK, so let's look at a Q-Q plot, half-normal plot and check the predictions against the measurements...

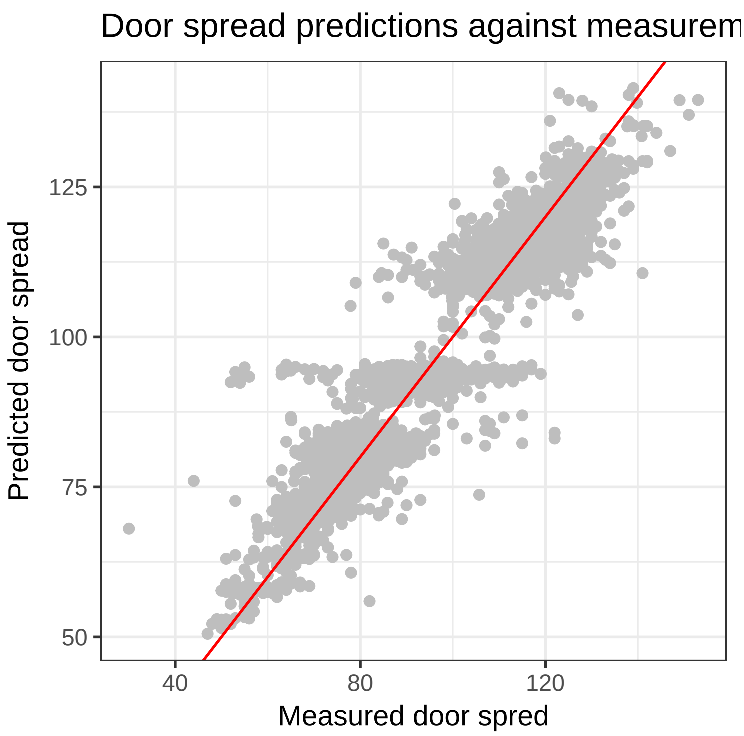
```r
qq.gam(m3, main = "Q-Q plot")
```




```r
faraway::halfnorm(resid(m3), main = "Half-normal plot")
```



```r
HH$PredSpread <- predict(m3, newdata = HH)

ggplot(HH, aes(x = DoorSpread, y = PredSpread)) + geom_point(colour = "grey") +
    geom_abline(slope = 1, intercept = 0, col = "red") + theme_bw() +
    ylab("Predicted door spread") + xlab("Measured door spred") +
    ggtitle("Door spread predictions against measurements")
```



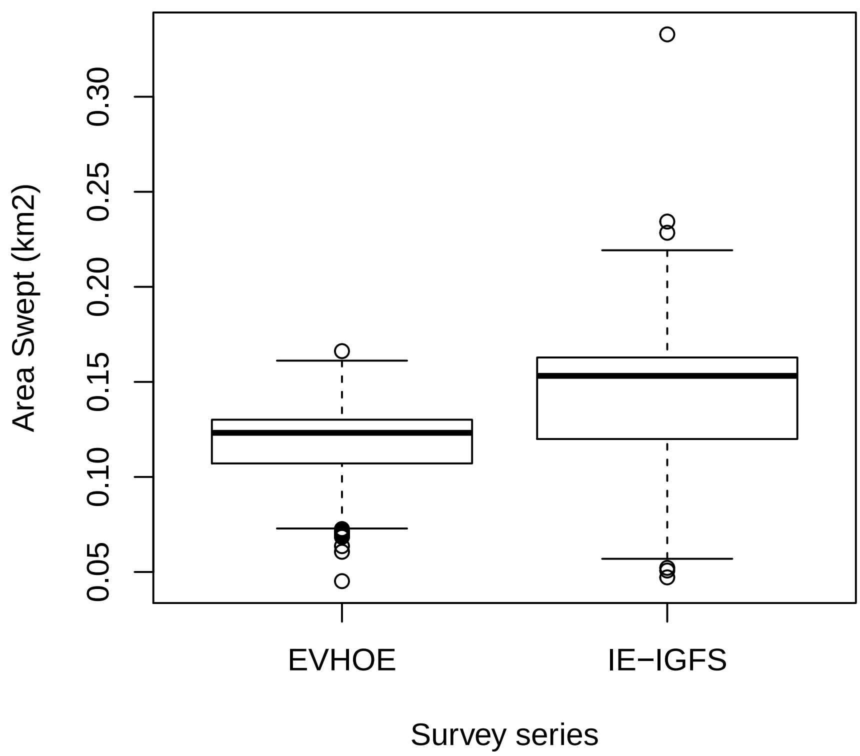

```r
nrow(HH[is.na(HH$PredSpread), ])

## [1] 209

HH$PredSpread[is.na(HH$PredSpread) & !is.na(HH$DoorSpread)] <- HH$DoorSpread[is.na(HH$PredS
    !is.na(HH$DoorSpread)]

nrow(HH[is.na(HH$PredSpread), ])  # leaves 17 values

## [1] 17

# Use simple depth relationship (m1) where possible
HH$PredSpread[is.na(HH$PredSpread) & !is.na(HH$Depth)] <- predict(m1,
    newdata = HH[is.na(HH$PredSpread) & !is.na(HH$Depth), ])

# For the remainder, use the standard 87 estimate
HH$PredSpread[is.na(HH$PredSpread)] <- 87
```

Looks OK. We use this to predict the door spread for the tows (filling some NAs without available covariates). Then, we calculate swept area based on:

$$SweptArea(km^2) = Distance(km) \cdot \frac{Doorspread(m)}{1000} \cdot CF \quad (5)$$

Where CF is a correction factor for the efficiency of the gear, taken from Piet et al as 0.38 for otter trawl gears. ADD REF

```
HH$SweptArea <- HH$Dist * HH$PredSpread/1000

HH$SweptAreaAdjFac <- 0.38
HH$SweptAreaAdj <- HH$SweptArea * HH$SweptAreaAdjFac

boxplot(HH$SweptAreaAdj ~ HH$Survey, ylab = "Area Swept (km2)",
    xlab = "Survey series")
```



2.3 Converting to weight

The length data were converted to weight through the following process:

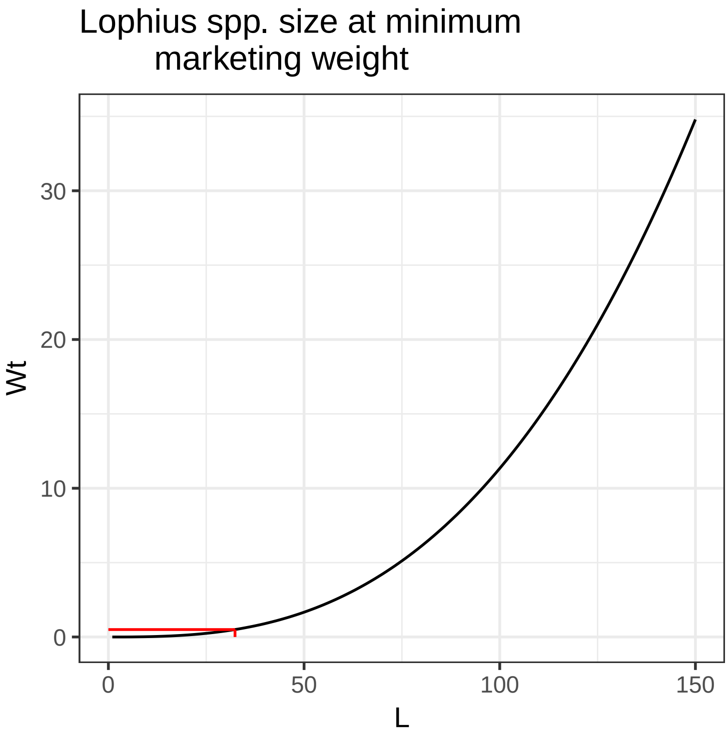
- Standardise unit of measurement to cm
- Add .5cm to each length group to reflect the fact that lengths are rounded down on measurement.
- Adjusting one outlier (a single whiting of 2.5 m, an order greater than actual length)
- Predict weights from the length weight relationships obtained above using equation 1.
- Multiply the number caught at length by the subfactor (fraction measured at length from the haul) and by the predicted weight at length, converting to KG.
- Relabel the species to reflect if they are juvenile or adult length. The lengths to define this split were based on the EU technical regulation defining the minimum conservation reference size (MCRS); for cod = 35 cm, haddock = 30 cm, whiting = 27 cm, hake = 27 cm, plaice = 27 cm, sole = 24 cm, megrim = 20 cm. For anglerfishes (piscatorius and budegassa) at value of 32 cm was used, equivalent to the 500 g minimum marketing weight.
- Aggregate across length classes by species.
- Merge the station information with the catch records, retaining zero entries for each species at each station, where appropriate.
- Retaining all stations within 12 W - 2 W & 48 N - 52 N (the Celtic Sea area).

The output from an estimation of the length at minimum marketing size for anglerfishes was as follows:

```
## Add species names
load(file.path("DATRAS", "DatrasSpeciesCodes.RData"))
HL$SpeciesName <- DatrasSpeciesCodes$scientific.name[match(HL$SpecCode,
    DatrasSpeciesCodes$code_number)]

# need as numeric
an <- as.numeric
HL$LngtClass <- an(HL$LngtClass)
HL$HLNoAtLngt <- an(HL$HLNoAtLngt)
HL$SubFactor <- an(HL$SubFactor)

# Deal with different length codes - standarise to cm
HL$LngtClass[(HL$LngtClass == 2460 & HL$SpeciesName == "Merlangius merlangus")] <- HL$Lngt
    2460 & HL$SpeciesName == "Merlangius merlangus")]/10  ## Dodgy datapoint!
HL$LngtClass[HL$LngtCode == ". "] <- HL$LngtClass[HL$LngtCode ==
    ". "]/10
```

```
HL$LngtClass[HL$LngtCode == 0] <- HL$LngtClass[HL$LngtCode ==
    0]/10

# Round down length classes & add 0.5
HL$LngtClass[HL$LngtCode != "5"] <- round(HL$LngtClass[HL$LngtCode !=
    "5"])
HL$LngtClass[HL$LngtCode != "5"] <- HL$LngtClass[HL$LngtCode !=
    "5"] + 0.5

## Now raise with the Model predictions
load(file = file.path("DATRAS", "LengthWeightPredictCelticSea.RData"))

# Filter to the species of interest
HL$Species <- HL$SpeciesName
HL <- filter(HL, Species %in% spp)  ## spp from above

# Add log(length)
HL$lL <- log(HL$LngtClass * 10)

# Predict log weight gadoids
HL$LogWtLength[HL$Species %in% gads] <- predict(lm2[[1]], newdata = HL[HL$Species %in%
    gads, ])
# flats
HL$LogWtLength[HL$Species %in% flats] <- predict(lm2[[2]], newdata = HL[HL$Species %in%
    flats, ])
# anglerfishes
HL$WtLength[HL$Species %in% lops] <- (lop[["a"]] * HL$LngtClass[HL$Species %in%
    lops]^lop[["b"]])/1000

HL$WtLength[HL$Species %in% c(gads, flats)] <- exp(HL$LogWtLength[HL$Species %in%
    c(gads, flats)])  # convert back to weight in grams

HL$Wt <- HL$WtLength * HL$HLNoAtLngt * HL$SubFactor  # Total weight in g
HL$Wt <- HL$Wt/1000  # Weight in Kg
# bias correct
HL$Wt[HL$Species %in% gads] <- HL$Wt[HL$Species %in% gads] *
    corr.fact[[1]]
HL$Wt[HL$Species %in% flats] <- HL$Wt[HL$Species %in% flats] *
    corr.fact[[2]]

## And aggregate across lengths split into Ju and Ad

## For anglerfish, there is no minimum size but a minimum
## landing weight of 500g for marketing...let's find the
## equivalent length from the data

# Find the length equivalent of the 500 g
fn_opt <- function(a, b, L) {
    res <- (a * (L^b))/1000
    return(res - 0.5)
}
```

```
# optimise
print(uniroot(f = fn_opt, a = lop[["a"]], b = lop[["b"]], interval = c(0,
    150)))

## $root
## [1] 32.35575
##
## $f.root
## [1] 1.712325e-07
##
## $iter
## [1] 10
##
## $init.it
## [1] NA
##
## $estim.prec
## [1] 6.103516e-05

size <- uniroot(f = fn_opt, a = lop[["a"]], b = lop[["b"]], interval = c(0,
    150))$root
## Anglerfish minimum size is equivalent to 32.35 cm

lop[["a"]] * (size^lop[["b"]])/1000

## [1] 0.5000002

lop.df <- data.frame(L = 1:150, Wt = (lop[["a"]] * (c(1:150)^lop[["b"]]))/1000)

ggplot(lop.df, aes(x = L, y = Wt)) + geom_line() + geom_segment(data = data.frame(x = size,
    x1 = size, y = 0, y1 = 0.5), aes(x = x, xend = x1, y = y,
    yend = y1), colour = "red") + geom_segment(data = data.frame(x = 0,
    x1 = size, y = 0.5, y1 = 0.5), aes(x = x, xend = x1, y = y,
    yend = y1), colour = "red") + theme_bw() + ggtitle("Lophius spp. size at minimum
\t\t\t\t\t\t  marketing weight")
```




```
## Assign to length groups
HL$SpeciesName <- ifelse(HL$SpeciesName == "Gadus morhua" & HL$LngtClass <
    34.5, paste(HL$SpeciesName, "Juv", sep = "_"), ifelse(HL$SpeciesName ==
    "Gadus morhua" & HL$LngtClass >= 34.5, paste(HL$SpeciesName,
    "Adu", sep = "_"), ifelse(HL$SpeciesName == "Melanogrammus aeglefinus" &
    HL$LngtClass < 29.5, paste(HL$SpeciesName, "Juv", sep = "_"),
    ifelse(HL$SpeciesName == "Melanogrammus aeglefinus" & HL$LngtClass >=
        29.5, paste(HL$SpeciesName, "Adu", sep = "_"), ifelse(HL$SpeciesName ==
        "Merlangius merlangus" & HL$LngtClass < 26.5, paste(HL$SpeciesName,
        "Juv", sep = "_"), ifelse(HL$SpeciesName == "Merlangius merlangus" &
        HL$LngtClass >= 26.5, paste(HL$SpeciesName, "Adu", sep = "_"),
        ifelse(HL$SpeciesName == "Merluccius merluccius" & HL$LngtClass <
            26.5, paste(HL$SpeciesName, "Juv", sep = "_"), ifelse(HL$SpeciesName ==
            "Merluccius merluccius" & HL$LngtClass >= 26.5, paste(HL$SpeciesName,
            "Adu", sep = "_"), ifelse(HL$SpeciesName == "Pleuronectes platessa" &
            HL$LngtClass < 26.5, paste(HL$SpeciesName, "Juv",
            sep = "_"), ifelse(HL$SpeciesName == "Pleuronectes platessa" &
            HL$LngtClass >= 26.5, paste(HL$SpeciesName, "Adu",
            sep = "_"), ifelse(HL$SpeciesName == "Solea solea" &
            HL$LngtClass < 23.5, paste(HL$SpeciesName, "Juv",
            sep = "_"), ifelse(HL$SpeciesName == "Solea solea" &
            HL$LngtClass >= 23.5, paste(HL$SpeciesName, "Adu",
            sep = "_"), ifelse(HL$SpeciesName == "Lepidorhombus whiffiagonis" &
            HL$LngtClass >= 19.5, paste(HL$SpeciesName, "Adu",
            sep = "_"), ifelse(HL$SpeciesName == "Lepidorhombus whiffiagonis" &
            HL$LngtClass < 19.5, paste(HL$SpeciesName, "Juv",
            sep = "_"), ifelse(HL$SpeciesName == "Lophius piscatorius" &
```

```
              HL$LngtClass >= 32.5, paste(HL$SpeciesName, "Adu",
              sep = "_"), ifelse(HL$SpeciesName == "Lophius piscatorius" &
              HL$LngtClass < 32.5, paste(HL$SpeciesName, "Juv",
              sep = "_"), ifelse(HL$SpeciesName == "Lophius budegassa" &
              HL$LngtClass >= 32.5, paste(HL$SpeciesName, "Adu",
              sep = "_"), ifelse(HL$SpeciesName == "Lophius budegassa" &
              HL$LngtClass < 32.5, paste(HL$SpeciesName, "Juv",
              sep = "_"), paste(HL$SpeciesName, "All", sep = "_"))))))))))))))))))

DF <- HL[!is.na(HL$Wt), ]
DF <- DF %>% group_by(Survey, Quarter, Country, Ship, Gear, StNo,
    HaulNo, Year, SpeciesName) %>% summarise(Kg = sum(Wt)) %>%
    as.data.frame()

# Now merge in the station details: lat, lon etc..  midpoint
# of haul locations - small enough distances to not worry
# about spherical distances
HH$HaulLatMid <- (an(HH$ShootLat) + an(HH$HaulLat))/2
HH$HaulLonMid <- (an(HH$ShootLon) + an(HH$HaulLon))/2

# Fix blank spaces in variables...
DF$Survey <- gsub(" ", "", DF$Survey)
DF$Gear <- gsub(" ", "", DF$Gear)
DF$Ship <- gsub(" ", "", DF$Ship)
DF$StNo <- gsub(" ", "", DF$StNo)

## Create a haul record for each species
HH <- merge(x = HH, y = data.frame(SpeciesName = unique(DF$SpeciesName)))

# Join on the catch data
DF2 <- full_join(x = HH, y = DF)
DF2$Kg[is.na(DF2$Kg)] <- 0  #NAs are zero catches of the species

# Subset to variables of interest
DF <- DF2[c("Survey", "Ship", "StNo", "HaulNo", "Year", "Month",
    "SpeciesName", "HaulLatMid", "HaulLonMid", "HaulDur", "SweptArea",
    "SweptAreaAdj", "Kg")]

# Remove marginal areas
DF <- filter(DF, HaulLonMid < -2 & HaulLonMid > -12)
DF <- filter(DF, HaulLatMid > 48 & HaulLatMid < 52)

# Save
save(DF, file = file.path("Cleaned", "CelticSurveyFormattedSize.RData"))
```

3 Cefas survey data

The same process was undergone for the Cefas survey data. The only differences were:

- 12 040 tows were recorded as valid, with 677 either recorded invalid, abnormal or otherwise classified as irregular.
- Due to some abnormally large tow distances, a standardised tow distance (per 60 m) was calculated, and a Median Absolute Deviation (MAD) per survey series, with only standardised tow distances +- 5 times the value kept. This removed 578 outlier tows (keeping 9022).
- Swept Area sometimes reflected the use of a single or double beam trawl.
- The correction factor used was either an otter trawl value of 0.38 (as above) or a beam trawl value of 0.19, as appropriate.

```
FSS <- read.csv(file = file.path("CEFAS", "WesternSurveys_V20160905.dat"))

###################################### Process station data
Stations <- group_by(FSS, fldSeriesName, fldCruiseName, fldGearDescription,
    Year, Month, Day, Time, fldCruiseStationNumber, fldValidityCode,
    fldTowDuration) %>% summarise(ShootLat = mean(fldShotLatDecimalDegrees),
    ShootLon = mean(fldShotLonDecimalDegrees), HaulLat = mean(fldHaulLatDecimalDegrees),
    HaulLon = mean(fldHaulLonDecimalDegrees)) %>% as.data.frame()
######################################

# Keep only valid hauls
table(Stations$fldValidityCode)
Stations <- filter(Stations, fldValidityCode == "V")

################################################################## There are some tows whi
################################################################## distance...  so to clea
################################################################## varies greatly over tim

############################ 3
Stations$Dist <- mapply(gcd.hf, long1 = deg2rad(Stations$ShootLon),
    lat1 = deg2rad(Stations$ShootLat), long2 = deg2rad(Stations$HaulLon),
    lat2 = deg2rad(Stations$HaulLat))

summary(Stations$Dist)

Stations$DistStand <- (Stations$Dist/Stations$fldTowDuration) *
    60

# Remove any over or under the SE of median distance for the
# survey (robust detection of outliers
# https://www.r-bloggers.com/absolute-deviation-around-the-median/)

StationsClean <- group_by(Stations, fldSeriesName) %>% summarise(median = median(DistStand)
    mean = mean(DistStand), MAD = mad(DistStand, center = median(DistStand))) %>%
    as.data.frame()

StationsClean$Up <- StationsClean$median + 5 * StationsClean$MAD
StationsClean$Lo <- StationsClean$median - 5 * StationsClean$MAD
```

```r
## Now add the upper and lower thresholds to the stations
Stations$LoThres <- StationsClean$Lo[match(Stations$fldSeriesName,
    StationsClean$fldSeriesName)]
Stations$UpThres <- StationsClean$Up[match(Stations$fldSeriesName,
    StationsClean$fldSeriesName)]

Stations$InTol <- ifelse(Stations$DistStand >= Stations$LoThres &
    Stations$DistStand <= Stations$UpThres, "KEEP", "LOSE")

table(Stations$InTol)

###################################################################### midpoint of haul
###################################################################### worry about spher
an <- as.numeric
Stations$HaulLatMid <- (an(Stations$ShootLat) + an(Stations$HaulLat))/2
Stations$HaulLonMid <- (an(Stations$ShootLon) + an(Stations$HaulLon))/2

## Calculate the swept area per gear for beam trawls its easy,
## for otter trawls need to include the doorspread for
## effective swept area

Surveys <- sort(unique(Stations$fldGearDescription))

Surveys <- Surveys[c(1:9, 23, 31:46, 48, 49)]
# Only keep the trawl fish surveys
print(Surveys)
Stations <- filter(Stations, fldGearDescription %in% Surveys)

## No details for otter trawl deployment, so use the standard
## 87m doorspread
Stations$GearWidth <- ifelse(Stations$fldGearDescription %in%
    Surveys[1], 2, ifelse(Stations$fldGearDescription %in% Surveys[2:5],
    3, ifelse(Stations$fldGearDescription %in% Surveys[6:9],
        4, ifelse(Stations$fldGearDescription %in% Surveys[10],
            87, ifelse(Stations$fldGearDescription %in% Surveys[11:12],
                4, ifelse(Stations$fldGearDescription %in% Surveys[13:25],
                  87, ifelse(Stations$fldGearDescription %in%
                    Surveys[26:27], 4, ifelse(Stations$fldGearDescription %in%
                    Surveys[28], 87, NA))))))))

Stations$SweptArea <- Stations$Dist * (Stations$GearWidth/1000)

## Adjust swept area for gear efficiencies, after Piet et al
## for roundfish:

# BT: 0.19 OT: 0.22 - 0.54 (Juv, ad). 0.38

Stations <- Stations[!is.na(Stations$GearWidth), ]

Stations$SweptAreaAdjFac <- sapply(Stations$GearWidth, function(x) {
    if (x %in% c(2.5, 3, 4))
```

```
        return(0.19)
    if (x == 87)
        return(0.38) else return(NA)
})

Stations$SweptAreaAdj <- Stations$SweptArea * Stations$SweptAreaAdjFac

# Only keep stations in tolerance
Stations <- filter(Stations, InTol == "KEEP")

by(data = Stations$SweptAreaAdj, INDICES = Stations$fldSeriesName,
    FUN = mean, na.rm = T)

############################### Process the catches ####

# Convert all lengths to cm and round to 5cm size class
FSS$fldLengthGroup <- (FSS$fldLengthGroup/10) + 0.5

# load a/b parameters Add a and b parameters for
# length-weight Load the modelled length weight
# relationships....
load(file.path("DATRAS", "LengthWeightPredictCelticSea.RData"))

# Only species of interest
FSS <- filter(FSS, fldScientificName %in% toupper(spp))  # species list from above

# Add log length
FSS$lL <- log(FSS$fldLengthGroup * 10)

# Scientific names to small case except first letter
FSS$Species <- paste(toupper(substring(FSS$fldScientificName,
    1, 1)), tolower(substring(FSS$fldScientificName, 2, 1000)),
    sep = "")

# Predict log weight gads
FSS$LogWtLength[FSS$Species %in% gads] <- predict(lm2[[1]], newdata = FSS[FSS$Species %in%
    gads, ])
# flats
FSS$LogWtLength[FSS$Species %in% flats] <- predict(lm2[[2]],
    newdata = FSS[FSS$Species %in% flats, ])
# anglers
FSS$WtLength <- NA
FSS$WtLength[FSS$Species %in% lops] <- (lop[["a"]] * FSS$fldLengthGroup[FSS$Species %in%
    lops]^lop[["b"]])/1000

FSS$WtLength[FSS$Species %in% c(gads, flats)] <- exp(FSS$LogWtLength[FSS$Species %in%
    c(gads, flats)])  # convert back to weight in grams

FSS$Wt <- FSS$WtLength * FSS$Numbers  # Total weight in g
FSS$Wt <- FSS$Wt/1000  # Weight in Kg
```

```r
# bias correct
FSS$Wt[FSS$Species %in% gads] <- FSS$Wt[FSS$Species %in% gads] *
    corr.fact[[1]]
FSS$Wt[FSS$Species %in% flats] <- FSS$Wt[FSS$Species %in% flats] *
    corr.fact[[2]]

FSS <- FSS[!is.na(FSS$Wt), ]  ## Lack length measurements

# Aggregate split into Ju and Ad

FSS$Species <- ifelse(FSS$Species == "Gadus morhua" & FSS$fldLengthGroup <
    34.5, paste(FSS$Species, "Juv", sep = "_"), ifelse(FSS$Species ==
    "Gadus morhua" & FSS$fldLengthGroup >= 34.5, paste(FSS$Species,
    "Adu", sep = "_"), ifelse(FSS$Species == "Melanogrammus aeglefinus" &
    FSS$fldLengthGroup < 29.5, paste(FSS$Species, "Juv", sep = "_"),
    ifelse(FSS$Species == "Melanogrammus aeglefinus" & FSS$fldLengthGroup >=
        29.5, paste(FSS$Species, "Adu", sep = "_"), ifelse(FSS$Species ==
        "Merlangius merlangus" & FSS$fldLengthGroup < 26.5, paste(FSS$Species,
        "Juv", sep = "_"), ifelse(FSS$Species == "Merlangius merlangus" &
        FSS$fldLengthGroup >= 26.5, paste(FSS$Species, "Adu",
        sep = "_"), ifelse(FSS$Species == "Merluccius merluccius" &
        FSS$fldLengthGroup < 26.5, paste(FSS$Species, "Juv",
        sep = "_"), ifelse(FSS$Species == "Merluccius merluccius" &
        FSS$fldLengthGroup >= 26.5, paste(FSS$Species, "Adu",
        sep = "_"), ifelse(FSS$Species == "Pleuronectes platessa" &
        FSS$fldLengthGroup < 26.5, paste(FSS$Species, "Juv",
        sep = "_"), ifelse(FSS$Species == "Pleuronectes platessa" &
        FSS$fldLengthGroup >= 26.5, paste(FSS$Species, "Adu",
        sep = "_"), ifelse(FSS$Species == "Pollachius pollachius" &
        FSS$fldLengthGroup < 29.5, paste(FSS$Species, "Juv",
        sep = "_"), ifelse(FSS$Species == "Pollachius pollachius" &
        FSS$fldLengthGroup >= 29.5, paste(FSS$Species, "Adu",
        sep = "_"), ifelse(FSS$Species == "Solea solea" & FSS$fldLengthGroup <
        23.5, paste(FSS$Species, "Juv", sep = "_"), ifelse(FSS$Species ==
        "Solea solea" & FSS$fldLengthGroup >= 23.5, paste(FSS$Species,
        "Adu", sep = "_"), ifelse(FSS$Species == "Lepidorhombus whiffiagonis" &
        FSS$fldLengthGroup >= 19.5, paste(FSS$Species, "Adu",
        sep = "_"), ifelse(FSS$Species == "Lepidorhombus whiffiagonis" &
        FSS$fldLengthGroup < 19.5, paste(FSS$Species, "Juv",
        sep = "_"), ifelse(FSS$Species == "Lophius piscatorius" &
        FSS$fldLengthGroup >= 32.5, paste(FSS$Species, "Adu",
        sep = "_"), ifelse(FSS$Species == "Lophius piscatorius" &
        FSS$fldLengthGroup < 32.5, paste(FSS$Species, "Juv",
        sep = "_"), ifelse(FSS$Species == "Lophius budegassa" &
        FSS$fldLengthGroup >= 32.5, paste(FSS$Species, "Adu",
        sep = "_"), ifelse(FSS$Species == "Lophius budegassa" &
        FSS$fldLengthGroup < 32.5, paste(FSS$Species, "Juv",
        sep = "_"), paste(FSS$Species, "All", sep = "_"))))))))))))))))))))))

# Summarise as weight
FSS <- group_by(FSS, fldSeriesName, fldGearDescription, Year,
```

```
    Month, fldCruiseStationNumber, Species) %>% summarise(Kg = sum(Wt)) %>%
    as.data.frame()

## Some stations have multiple gear deployments, we want to
## have one location per station - to do so, sum the tow
## durations and swept area so we get an accurate swept area

Stations <- group_by(Stations, fldSeriesName, Year, Month, Day,
    Time, fldCruiseStationNumber, fldValidityCode, ShootLat,
    ShootLon, HaulLat, HaulLon, HaulLatMid, HaulLonMid) %>% summarise(fldTowDuration = mean
    Dist = sum(Dist), DistStand = sum(DistStand), SweptArea = sum(SweptArea),
    SweptAreaAdj = sum(SweptAreaAdj)) %>% as.data.frame()

## Also need to sum the biological data
FSS <- group_by(FSS, fldSeriesName, Year, Month, fldCruiseStationNumber,
    Species) %>% summarise(Kg = sum(Kg)) %>% as.data.frame()

## Now match the positional and catch data
Stations <- merge(x = Stations, y = data.frame(Species = unique(FSS$Species)))

FSS <- FSS[c("fldSeriesName", "Year", "Month", "fldCruiseStationNumber",
    "Species", "Kg")]

FSS <- full_join(x = Stations, y = FSS)
# Add zeros
FSS$Kg[is.na(FSS$Kg)] <- 0

by(FSS$Kg, INDICES = FSS$Species, summary)

FSS <- FSS[c("fldSeriesName", "Year", "Month", "fldCruiseStationNumber",
    "HaulLatMid", "HaulLonMid", "fldTowDuration", "SweptArea",
    "SweptAreaAdj", "Species", "Kg")]

## Trim to only keep data within core Celtic Sea
FSS <- filter(FSS, HaulLonMid > -12 & HaulLonMid < -2)  # remove extreme Lons
FSS <- filter(FSS, HaulLatMid > 48 & HaulLatMid < 52)  # remove extreme Lats

# plot(FSS$SweptAreaAdj ~ FSS$fldSeriesName)
# boxplot(FSS$SweptAreaAdj ~ FSS$Year)

table(FSS$Month, FSS$Year, FSS$fldSeriesName)

save(FSS, file = file.path(getwd(), "Cleaned", "CelticSurvey2FormattedSize.RData"))
```

4 Exploratory plots

The following section details some exploratory plots from the cleaned data. This guides the final dataset used to fit the VAST model.

```
###################################################

# Load in data
load(file.path(getwd(), "Cleaned", "CelticSurveyFormattedSize.RData"))  # Datras data by we
load(file.path(getwd(), "Cleaned", "CelticSurvey2FormattedSize.RData"))  # Cefas data by we

DWt <- DF
CWt <- FSS
rm(DF, FSS)  # Rename to avoid confusion

################################################### Combine the datasets
Wt <- data.frame(Survey = c(DWt$Survey, as.character(CWt$fldSeriesName)),
    Year = c(DWt$Year, CWt$Year), Month = c(DWt$Month, CWt$Month),
    HaulNo = c(DWt$HaulNo, CWt$fldCruiseStationNumber), Lon = c(DWt$HaulLonMid,
        CWt$HaulLonMid), Lat = c(DWt$HaulLatMid, CWt$HaulLatMid),
    HaulDur = c(DWt$HaulDur, CWt$fldTowDuration), SweptArea = c(DWt$SweptAreaAdj,
        CWt$SweptAreaAdj), Species = c(DWt$Species, CWt$Species),
    Kg = c(DWt$Kg, CWt$Kg))
rm(DWt, CWt)
```

4.1 Survey locations

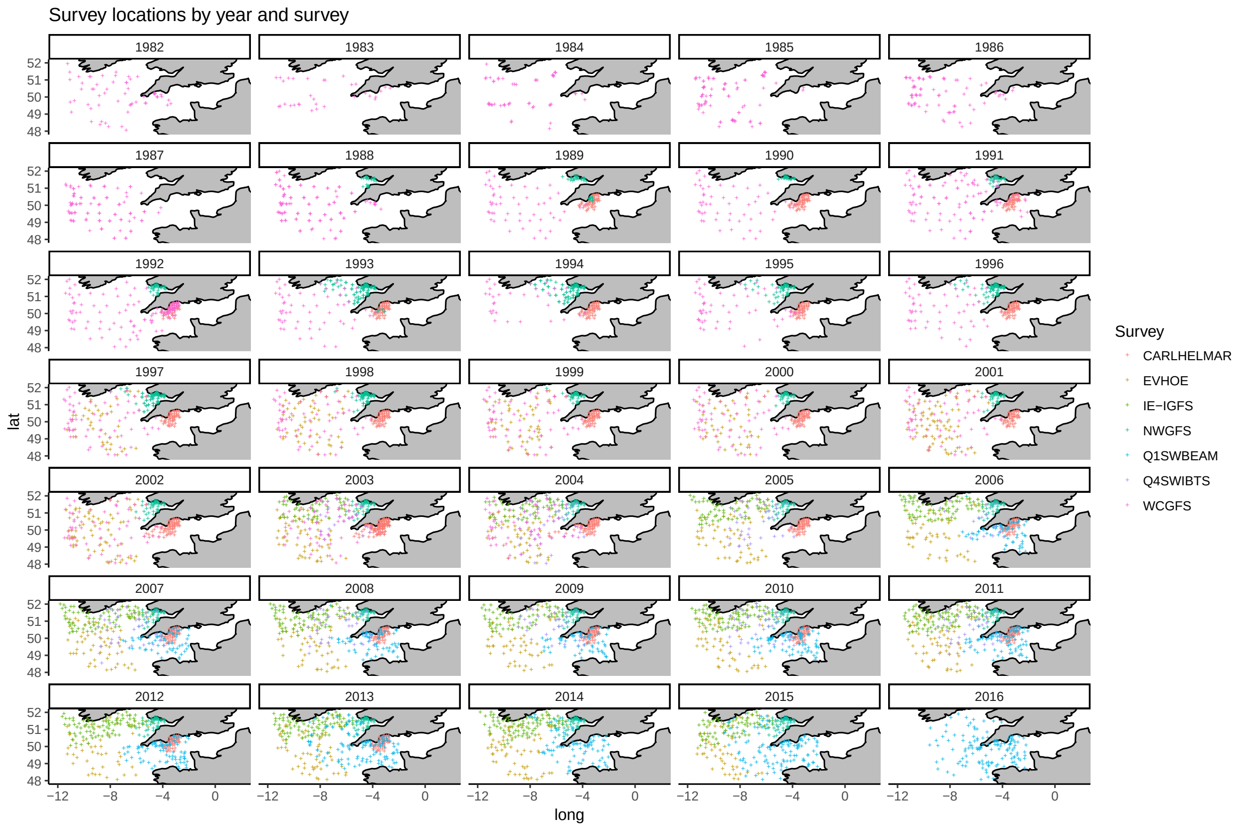
The following figure shows the surveys locations each year, with each survey coloured differently.

As can be seen, initially (1982 - 1985) survey coverage was sparse and irregular, only covered by the Cefas WCGFS. From 1986 this survey becomes more regular and established, but is discontinued in 2003. The NWGFS beam trawl survey was added in 1988 and the CARLHELMAR beam trawl survey covered the western channel from 1989 until 2013.

The next significant change is the addition of the EVHOE survey in 1997, followed by the IE-IGFS survey and the Q1SWIBTS in 2003 (with the latter discontinuing in 2010). Finally, the Q1SWBEAM is added around 2006.

It is worth noting that the ICES cod and whiting assessments use a truncated survey series from the WCGFS, only using 1992 - 2004 due to changes in survey area and concerns about its impact on selectivity.

```
Stations <- Wt[!duplicated(paste(Wt$Survey, Wt$Year, Wt$Lon,
    Wt$Lat)), ]

yrs <- sort(unique(Stations$Year))
n.yrs <- length(yrs)

map <- map_data("world", region = c("UK", "Ireland", "France"))

print(ggplot() + geom_polygon(data = map, aes(x = long, y = lat,
    group = group), colour = "black", fill = "grey") + coord_fixed(xlim = c(-12,
    2), ylim = c(48, 52), ratio = 1.3) + geom_point(data = Stations,
    aes(x = Lon, y = Lat, colour = Survey), shape = "+") + facet_wrap(~Year,
    ncol = 5) + theme_classic() + ggtitle("Survey locations by year and survey"))
```


Survey locations by year and survey
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
long
Survey
CARLHELMAR
EVHOE
IE−IGFS
NWGFS
Q1SWBEAM
Q4SWIBTS
WCGFS

4.2 Survey temporal coverage

The following table and plots detail the temporal coverage of the surveys. As can be seen, the number of stations was initially low (¡ 100) but increased to ¿ 200 by 1997.

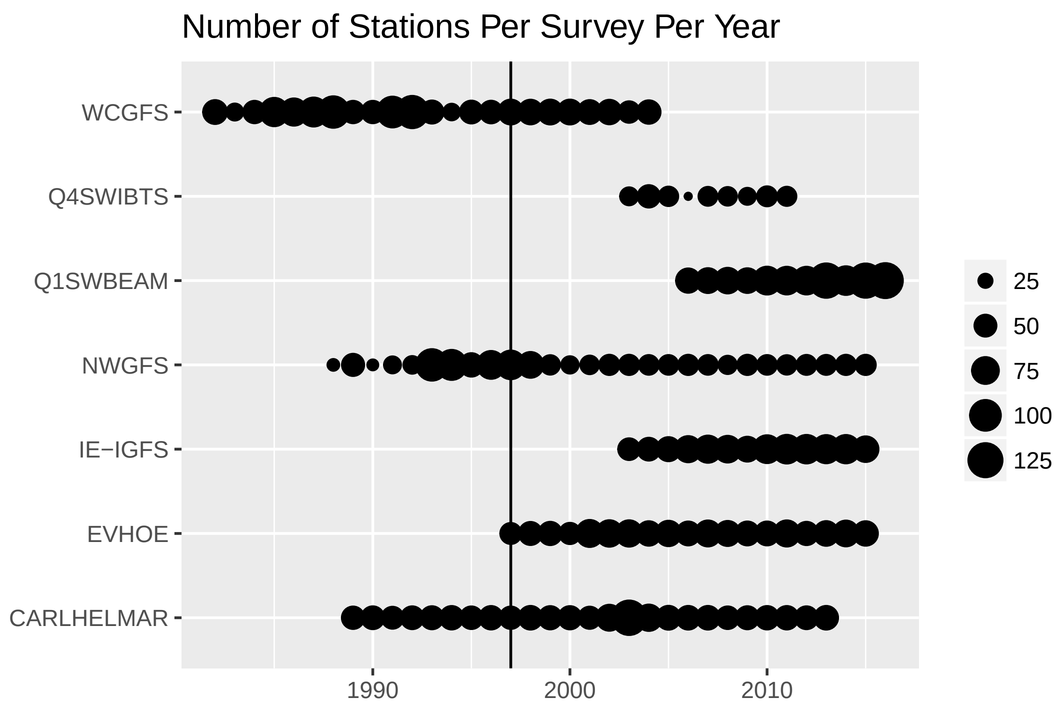
The majority of survey effort is in the fourth quarter, though some survey effort is also undertaken in the first quarter

The majority of survey effort is in the fourth quarter, though some survey effort is also undertaken in the first quarter.

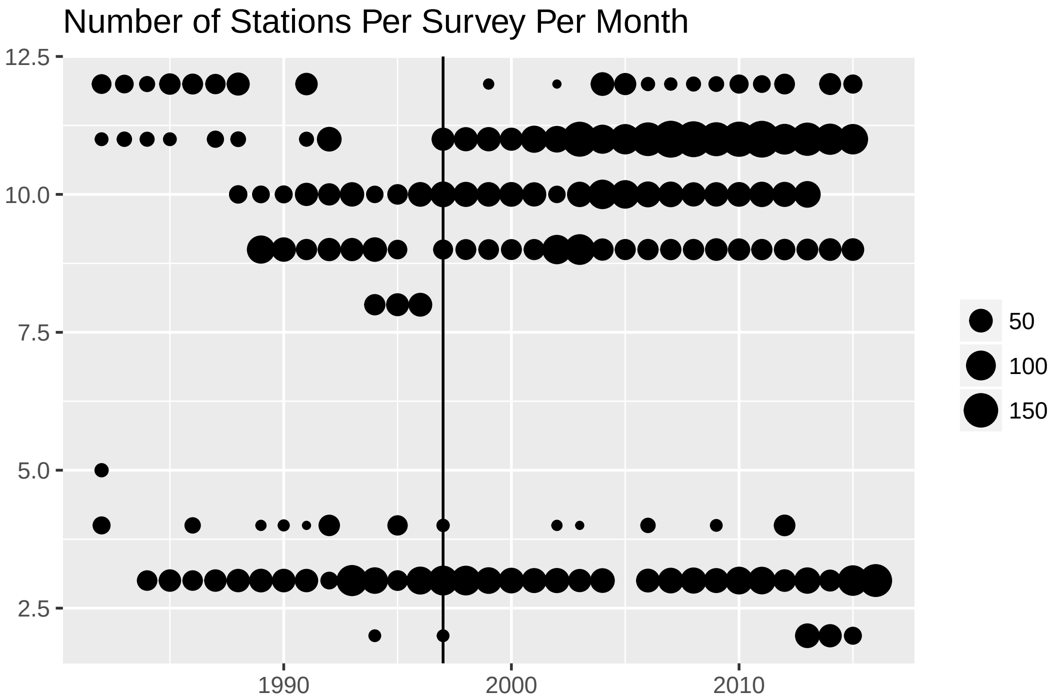
```r
kable(table(Stations$Year, Stations$Survey))
```

	CARLHELMAR	EVHOE	IE-IGFS	NWGFS	Q1SWBEAM	Q4SWIBTS	WCGFS
1982	0	0	0	0	0	0	59
1983	0	0	0	0	0	0	32
1984	0	0	0	0	0	0	52
1985	0	0	0	0	0	0	84
1986	0	0	0	0	0	0	77
1987	0	0	0	0	0	0	88
1988	0	0	0	21	0	0	105
1989	52	0	0	51	0	0	52
1990	54	0	0	20	0	0	52
1991	50	0	0	32	0	0	100
1992	54	0	0	34	0	0	111
1993	55	0	0	105	0	0	55
1994	57	0	0	95	0	0	31
1995	53	0	0	57	0	0	54
1996	57	0	0	81	0	0	53
1997	52	46	0	86	0	0	64
1998	58	55	0	69	0	0	63
1999	56	56	0	40	0	0	64
2000	56	47	0	33	0	0	64
2001	51	76	0	37	0	0	59
2002	70	73	0	43	0	0	62
2003	128	72	49	43	0	35	48
2004	72	62	54	41	0	52	57
2005	59	67	60	41	0	40	0
2006	58	59	71	43	61	18	0
2007	58	70	77	41	64	38	0
2008	53	65	74	36	68	37	0
2009	55	59	64	43	63	32	0
2010	57	59	81	41	81	42	0
2011	57	71	86	40	80	39	0
2012	54	56	85	42	80	0	0
2013	58	63	83	42	127	0	0
2014	0	69	84	43	86	0	0
2015	0	62	68	43	126	0	0
2016	0	0	0	0	132	0	0

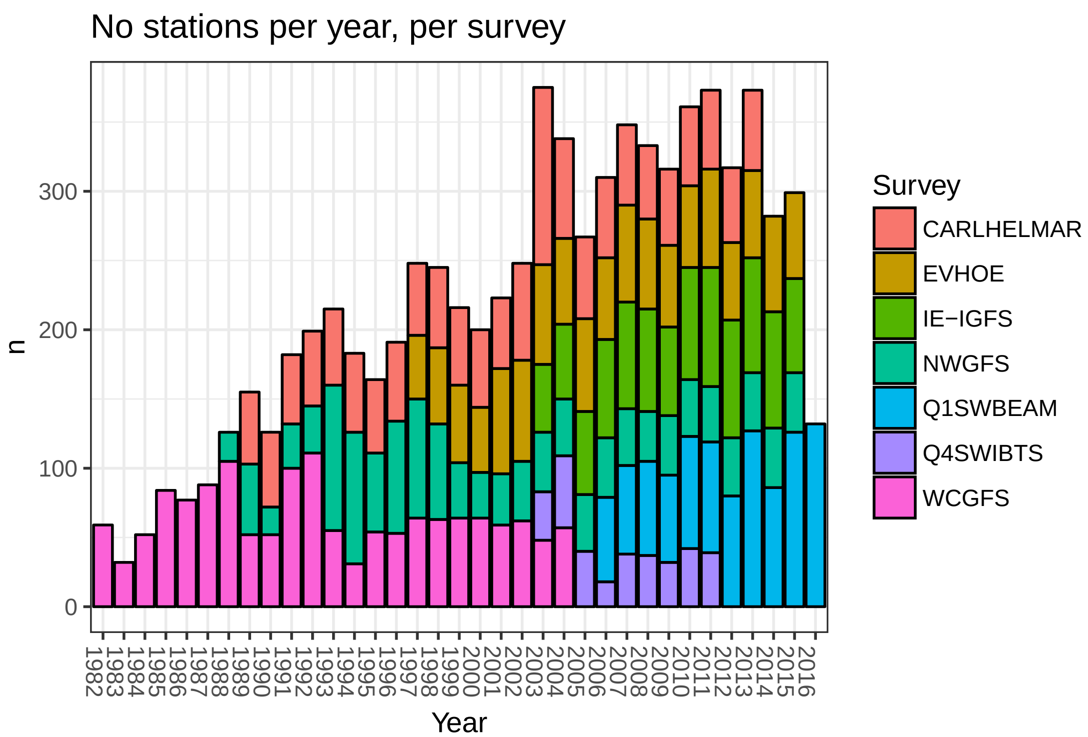
```
surveyyrs <- reshape2::melt(table(Stations$Survey, Stations$Year))

print(ggplot(surveyyrs[surveyyrs$value != 0, ], aes(x = Var2,
    y = Var1)) + geom_point(aes(size = value)) + xlab("") + ylab("") +
    theme(legend.title = element_blank()) + geom_vline(xintercept = 1997) +
    ggtitle("Number of Stations Per Survey Per Year"))
```




```r
surveymo <- reshape2::melt(table(Stations$Month, Stations$Year))

print(ggplot(surveymo[surveymo$value != 0, ], aes(x = Var2, y = Var1)) +
    geom_point(aes(size = value)) + xlab("") + ylab("") + theme(legend.title = element_blan
    geom_vline(xintercept = 1997) + ggtitle("Number of Stations Per Survey Per Month"))
```

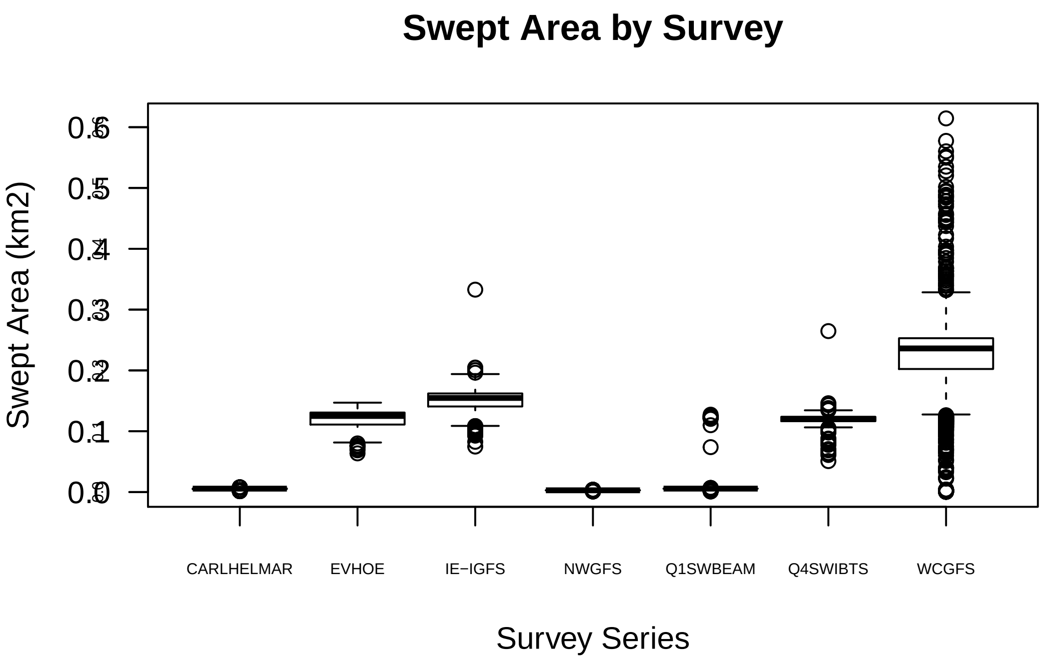



```r
surveyno <- group_by(Stations, Survey, Year) %>% summarise(n = n())

print(ggplot(surveyno, aes(x = Year, y = n)) + geom_bar(stat = "identity",
    aes(fill = Survey), colour = "black") + theme_bw() + theme(axis.text.x = element_text(a
    ggtitle("No stations per year, per survey"))
```

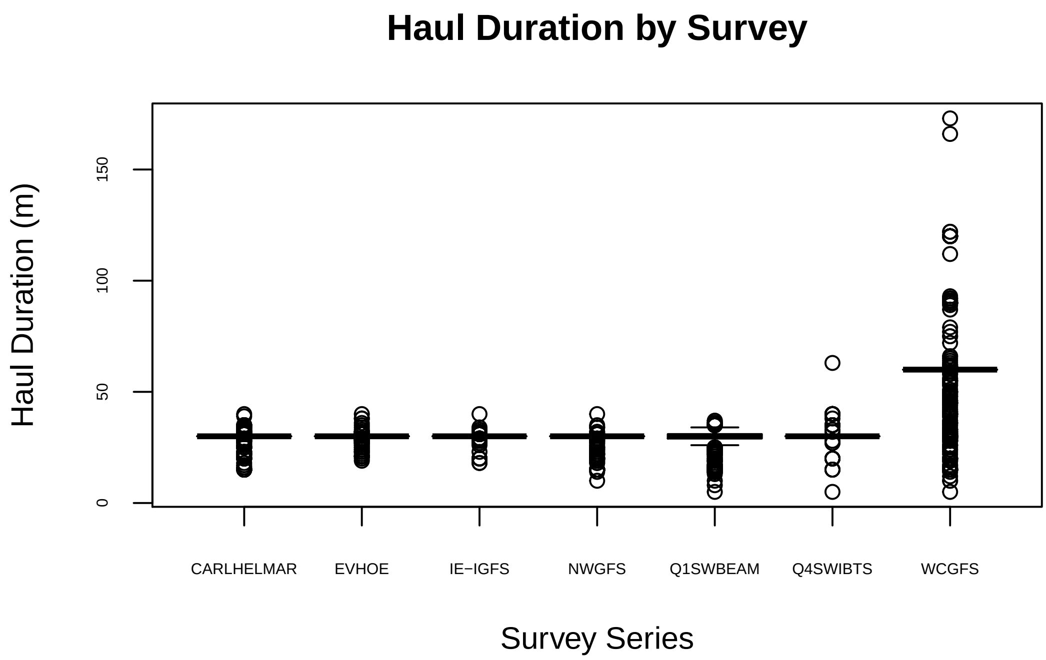


The surveys are using different gears. The main difference being that the WCGFS, IE-IGFS, EVHOE and WCGFS use otter trawl gears, while the CARLHELMAR, NWGFS, Q1SWBEAM use beam trawl gears. The WCGFS initially used hour long tows, but changes to 30 min tows consistent with other surveys later in the series.

```
boxplot(Stations$SweptArea ~ Stations$Survey, xlab = "Survey Series",
    ylab = "Swept Area (km2)", main = "Swept Area by Survey",
    cex.axis = 0.5)
axis(2, las = 1)
```




```
boxplot(as.numeric(as.character(Stations$HaulDur)) ~ Stations$Survey,
    xlab = "Survey Series", ylab = "Haul Duration (m)", main = "Haul Duration by Survey",
    cex.axis = 0.5)
```

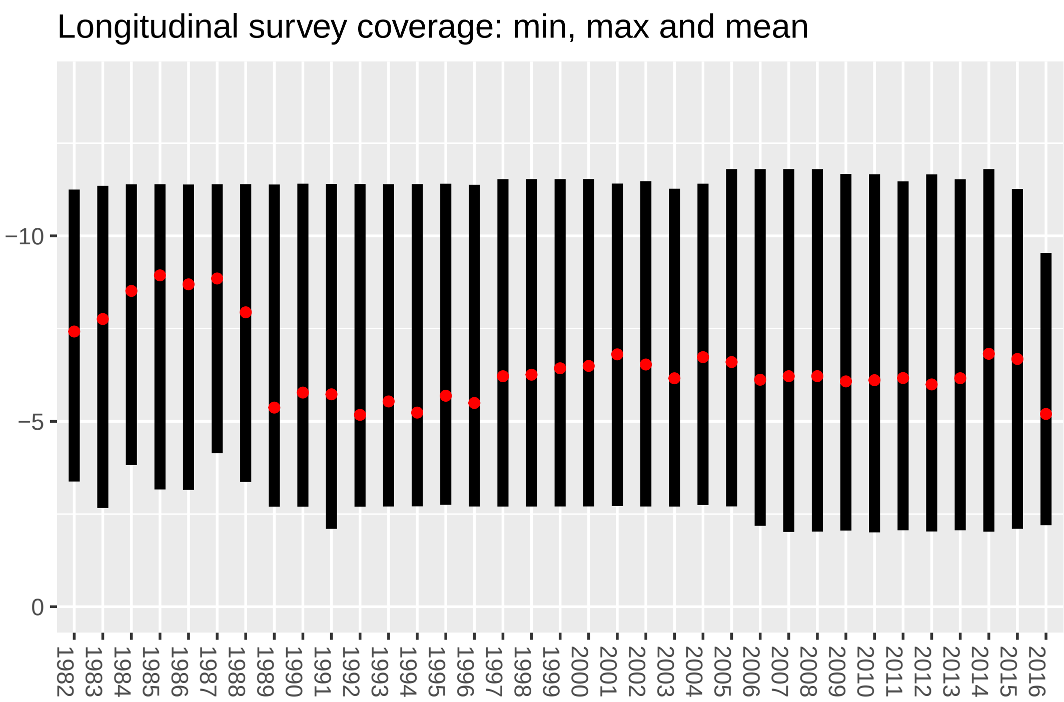


The following plots show the minimum, maximum and mean (red points) survey latitude and longitude per year, to explore changes in survey coverage.

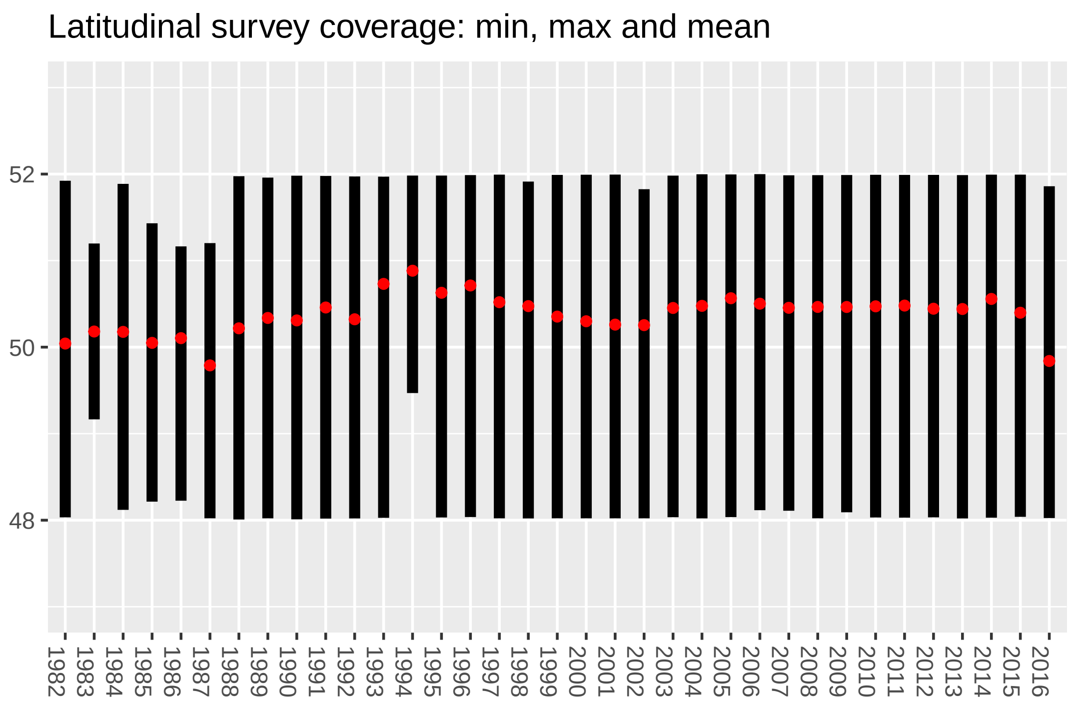
The longitude max and min has broadly been at -2.5 to -12 for the time series, though has been more consistent since 1990. The addition of the CARLHELMAR survey in 1988 shifted the mean survey location eastwards, from around -8 to -5 degrees.

The latitudinal max and min has also generally been from 48 to 52 degrees over the time series, though this has been more consistent since 1996. The mean has generally been around 51 degrees.

```
Lats_Lons <- group_by(Stations, Year) %>% summarise(minLon = min(Lon),
    maxLon = max(Lon), meanLon = mean(Lon), minLat = min(Lat),
    maxLat = max(Lat), meanLat = mean(Lat))
print(ggplot(Lats_Lons, aes(x = Year, y = minLon)) + geom_segment(aes(xend = Year,
    yend = maxLon), lwd = 2) + geom_point(aes(y = meanLon), colour = "red") +
    theme(axis.text.x = element_text(angle = -90)) + ylim(0,
    -14) + ylab("") + xlab("") + ggtitle("Longitudinal survey coverage: min, max and mean")
```

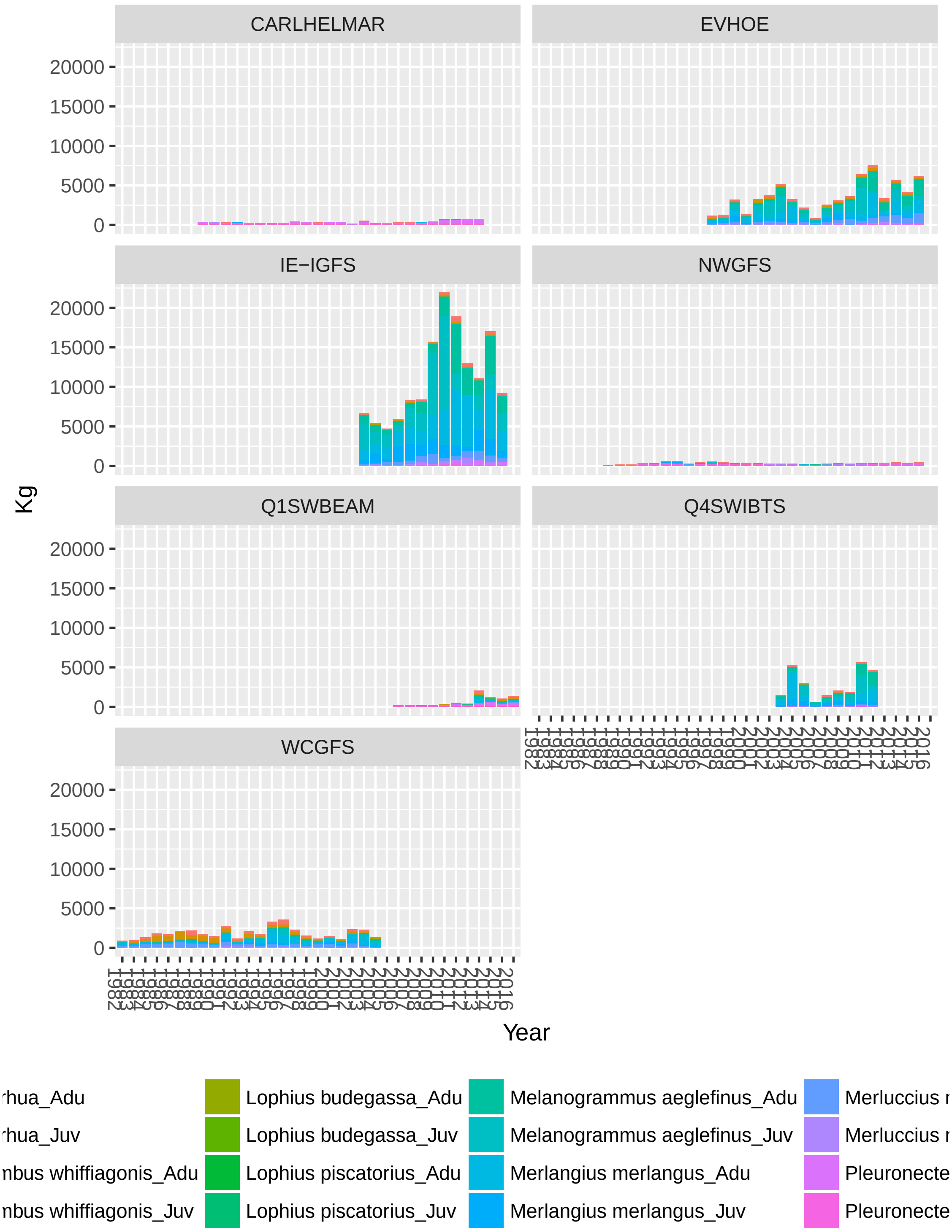



```
print(ggplot(Lats_Lons, aes(x = Year, y = minLat)) + geom_segment(aes(xend = Year,
    yend = maxLat), lwd = 2) + geom_point(aes(y = meanLat), colour = "red") +
    theme(axis.text.x = element_text(angle = -90)) + ylim(47,
    53) + ylab("") + xlab("") + ggtitle("Latitudinal survey coverage: min, max and mean"))
```



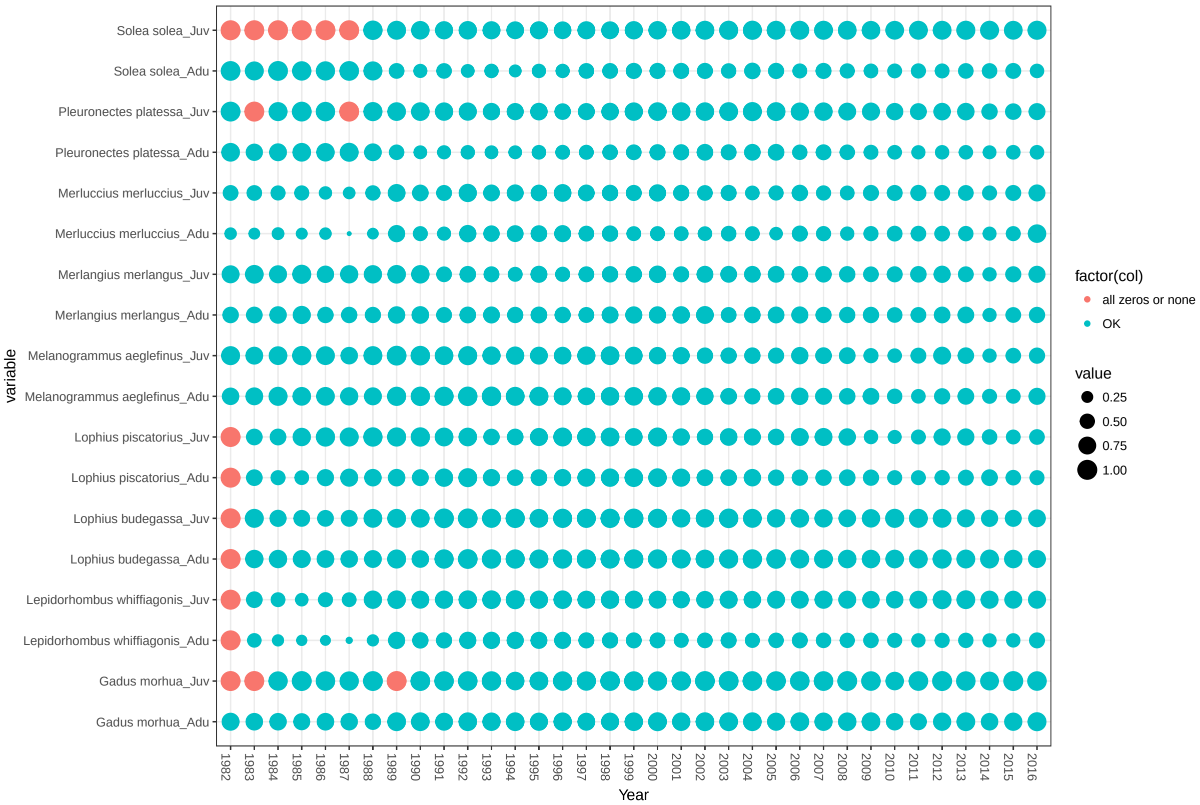
The following details the total catch by year, by survey. As can be seen, the IE-IGFS, EVHOE, WCGFS, Q4SWIBTS and Q1SWBEAM catch reasonable quantities of gadoids, while the CARL-HELMAR and NWGFS catch very little.

```
tot <- group_by(Wt, Survey, Species, Year) %>% summarise(Kg = sum(Kg))

print(ggplot(tot, aes(x = Year, y = Kg)) + geom_bar(stat = "identity",
    aes(fill = Species)) + facet_wrap(~Survey, ncol = 2) + theme(legend.position = "bottom"
    axis.text.x = element_text(angle = -90)))
```



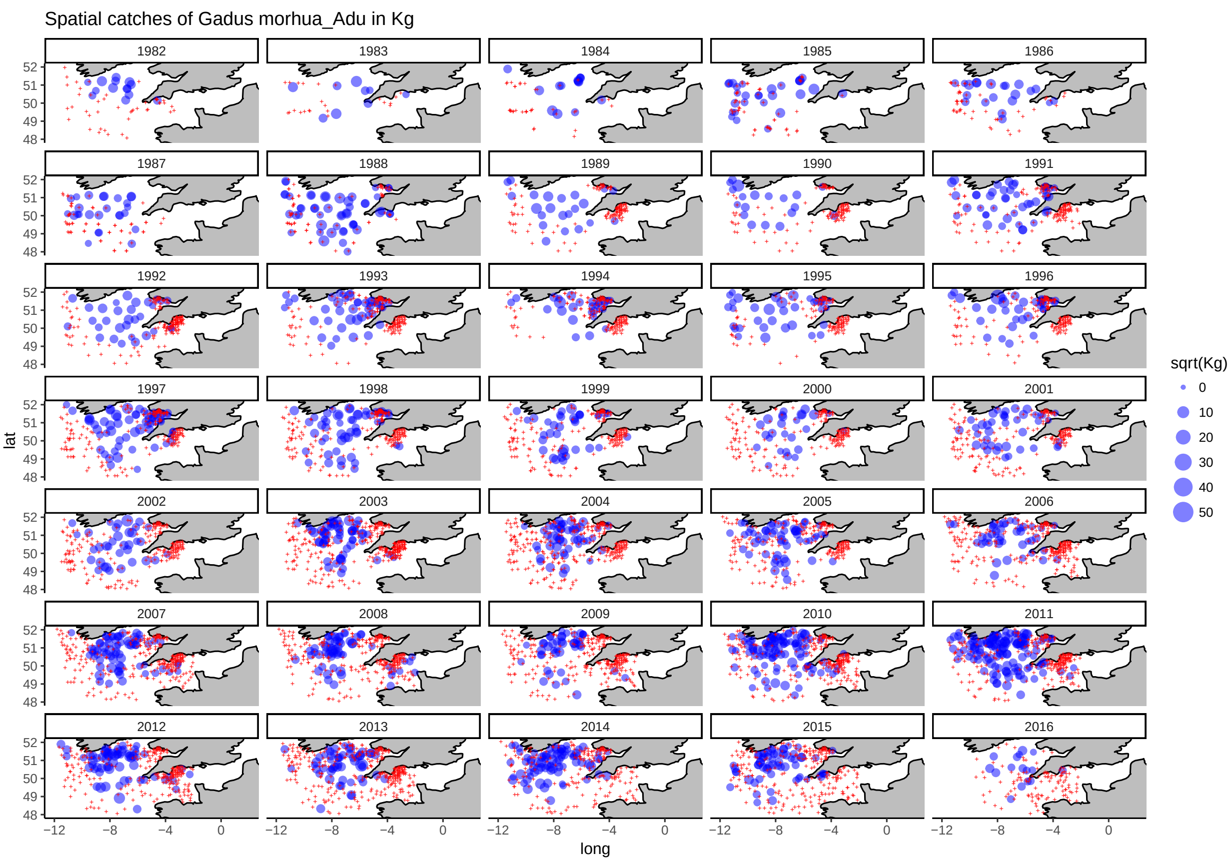
We need to check on the proportion of zeros in the data (for the delta model)...

```r
## Proportion of zeros for each species/year
yrs <- sort(unique(Wt$Year))
spp <- sort(unique(Wt$Species))

PropZeros <- matrix(NA, nrow = length(yrs), ncol = length(spp))

for (y in 1:length(yrs)) {
    for (s in 1:length(spp)) {
        tmp <- filter(Wt, Year == yrs[y], Species == spp[s])
        PropZeros[y, s] <- nrow(tmp[tmp$Kg == 0, ])/length(tmp$Kg)
    }
}

PropZeros <- as.data.frame(PropZeros)
colnames(PropZeros) <- spp
PropZeros$Year <- yrs

x <- reshape2::melt(PropZeros, id = "Year")
x$col <- ifelse(x$value == 0 | x$value == 1, "all zeros or none",
    "OK")

ggplot(x, aes(x = Year, y = variable)) + geom_point(aes(size = value,
    col = factor(col))) + theme_bw() + theme(axis.text.x = element_text(angle = -90))
```



The next pages detail the spatial catch distribution of the different species, followed by the catch per unit effort for the different survey series for each species.

```r
spp <- sort(unique(Wt$Species))

for (s in 1:length(spp)) {

    plotDF <- Wt[Wt$Species == spp[s], ]

    print(ggplot() + geom_polygon(data = map, aes(x = long, y = lat,
        group = group), colour = "black", fill = "grey") + coord_fixed(xlim = c(-12,
        2), ylim = c(48, 52), ratio = 1.3) + geom_point(data = plotDF[plotDF$Kg !=
        0, ], aes(x = Lon, y = Lat, size = sqrt(Kg)), colour = "blue",
        alpha = 0.5) + scale_size_continuous(limits = range(sqrt(Wt$Kg))) +
        geom_point(data = plotDF[plotDF$Kg == 0, ], aes(x = Lon,
            y = Lat), colour = "red", shape = "+") + facet_wrap(~Year,
        ncol = 5) + theme_classic() + ggtitle(paste("Spatial catches of",
        spp[s], "in Kg", sep = " ")))
}
```


Spatial catches of Gadus morhua_Adu in Kg
1982
1983
1984
1985
1986
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1988
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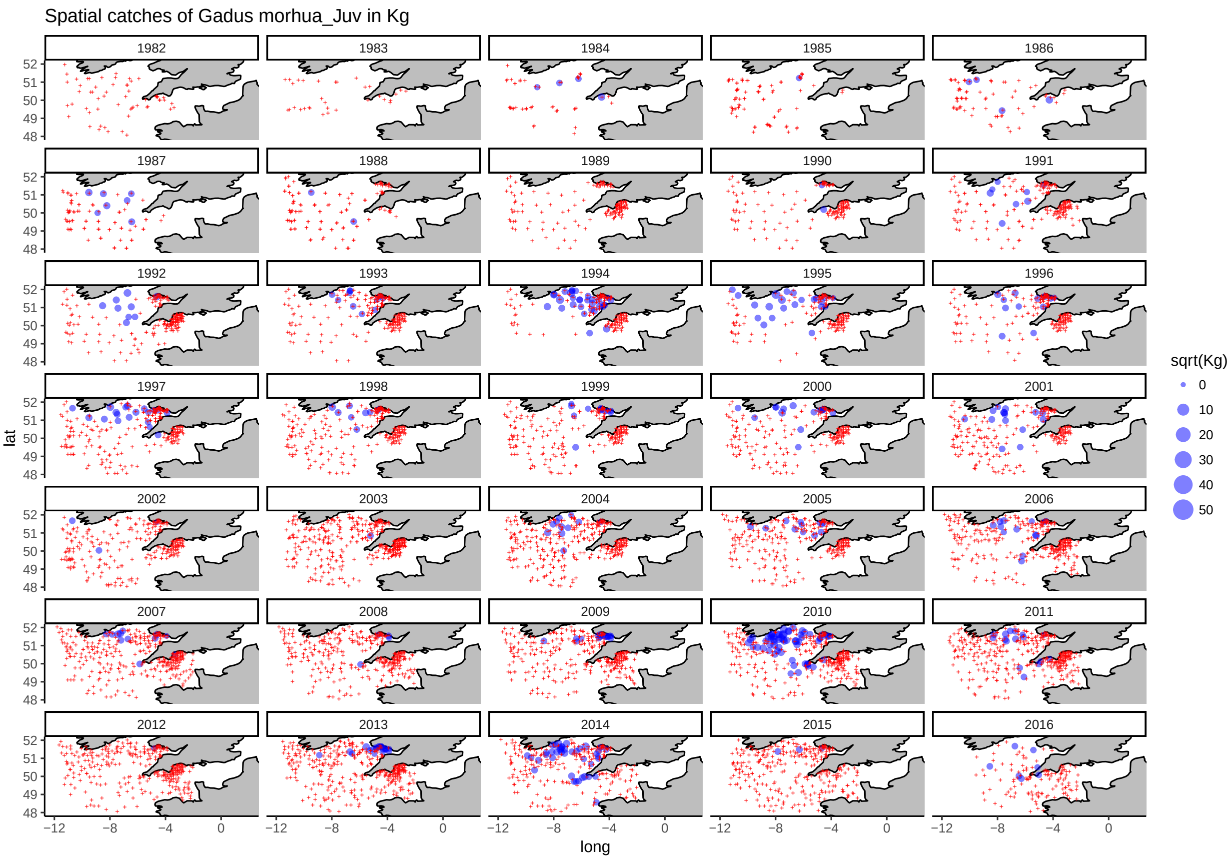
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
52
51
50
49
48
long
−12
−8
−4
0
sqrt(Kg)
0
10
20
30
40
50


Spatial catches of Gadus morhua_Juv in Kg
1982
1983
1984
1985
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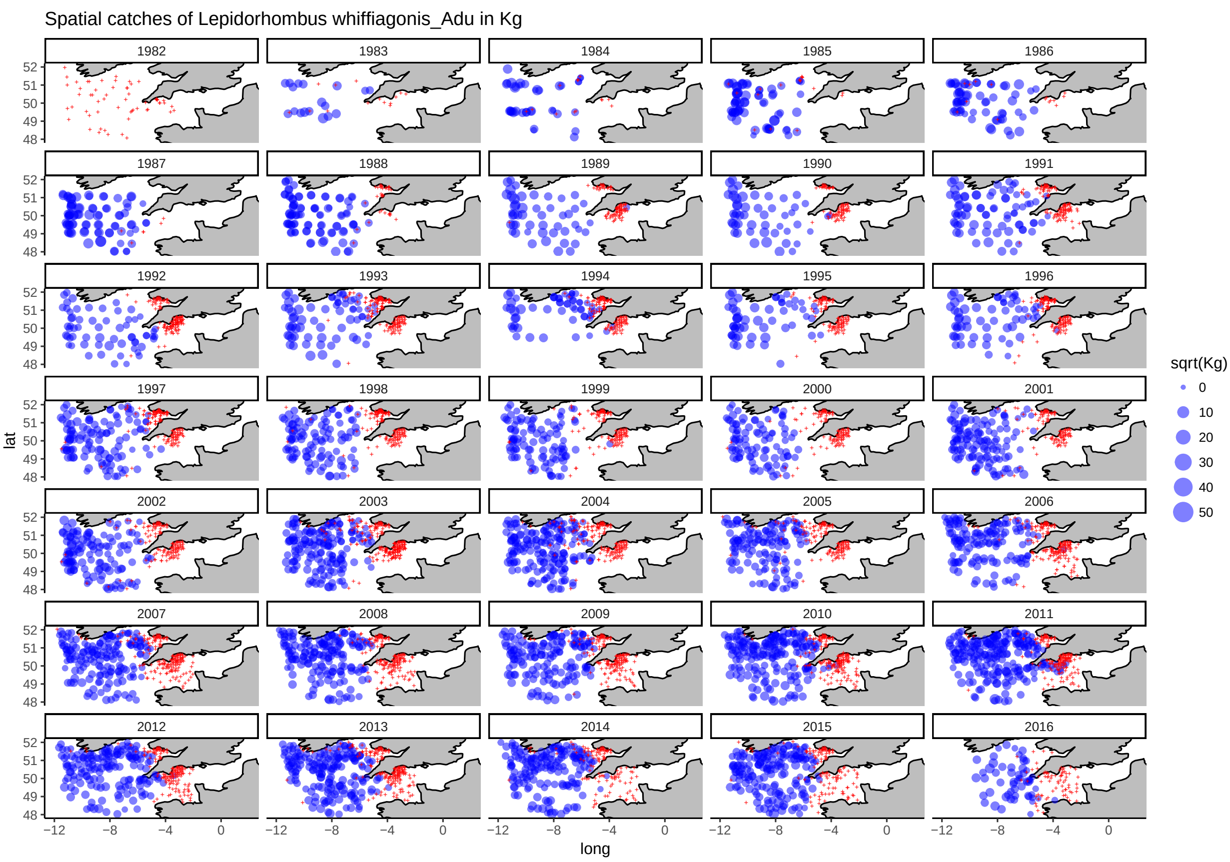
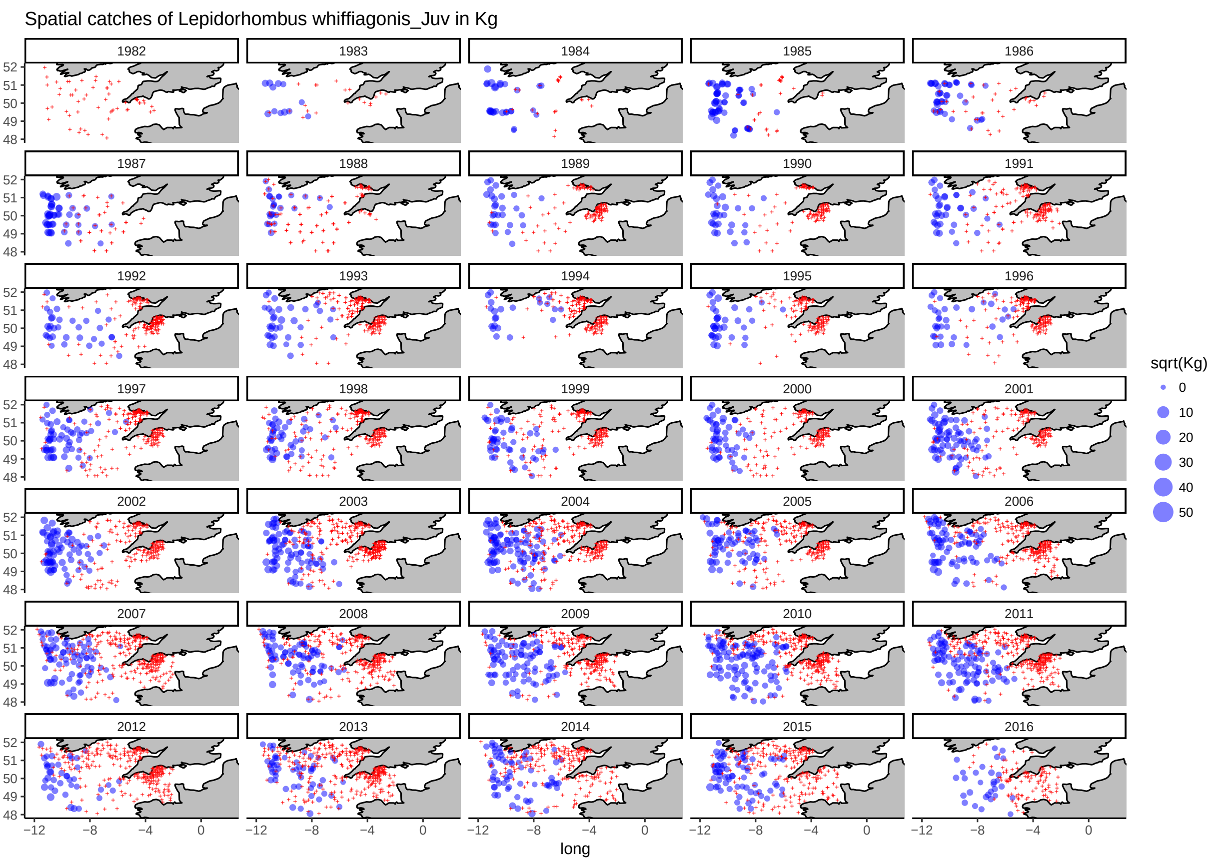
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
long
sqrt(Kg)
0
10
20
30
40
50


Spatial catches of Lepidorhombus whiffiagonis_Adu in Kg
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
long
sqrt(Kg)
0
10
20
30
40
50


Spatial catches of Lepidorhombus whiffiagonis_Juv in Kg
1982
1983
1984
1985
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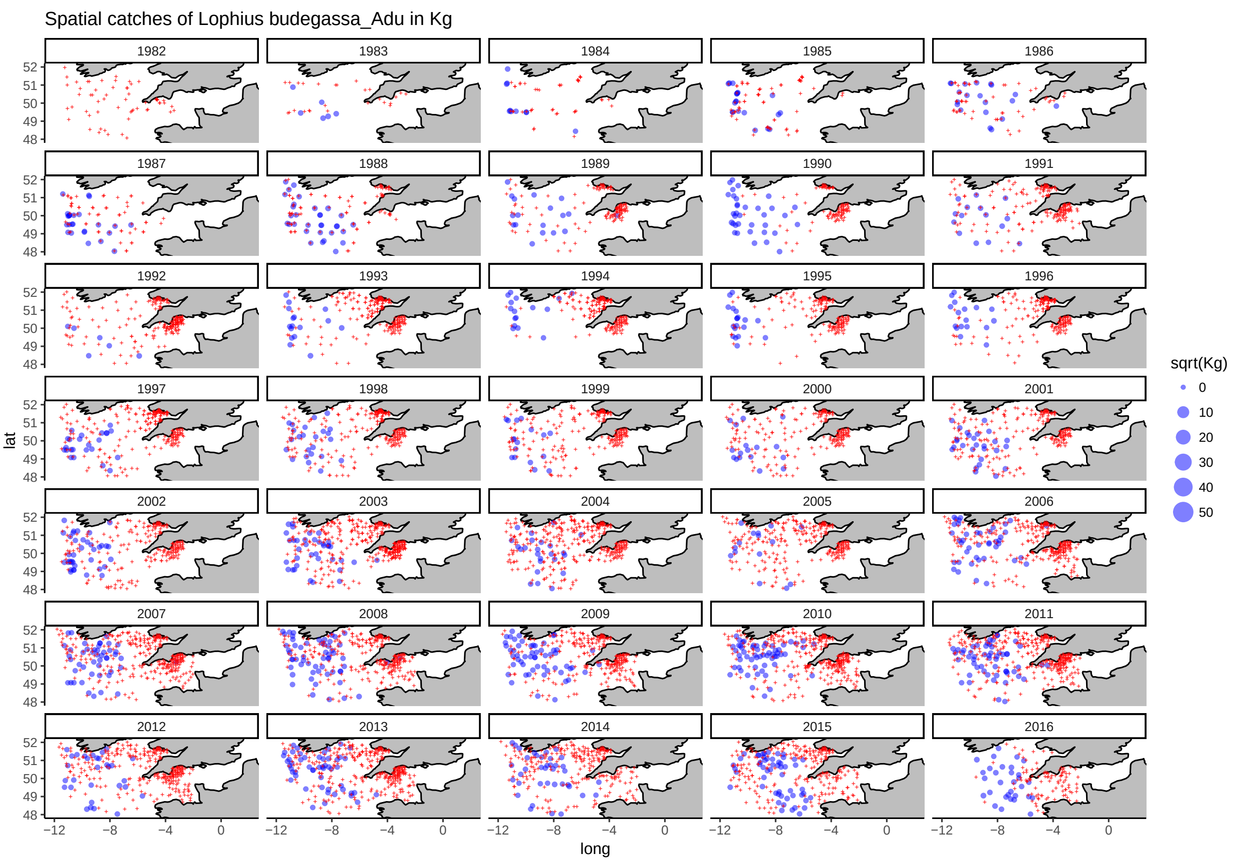
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
long
sqrt(Kg)
0
10
20
30
40
50


Spatial catches of Lophius budegassa_Adu in Kg
1982
1983
1984
1985
1986
1987
1988
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1990
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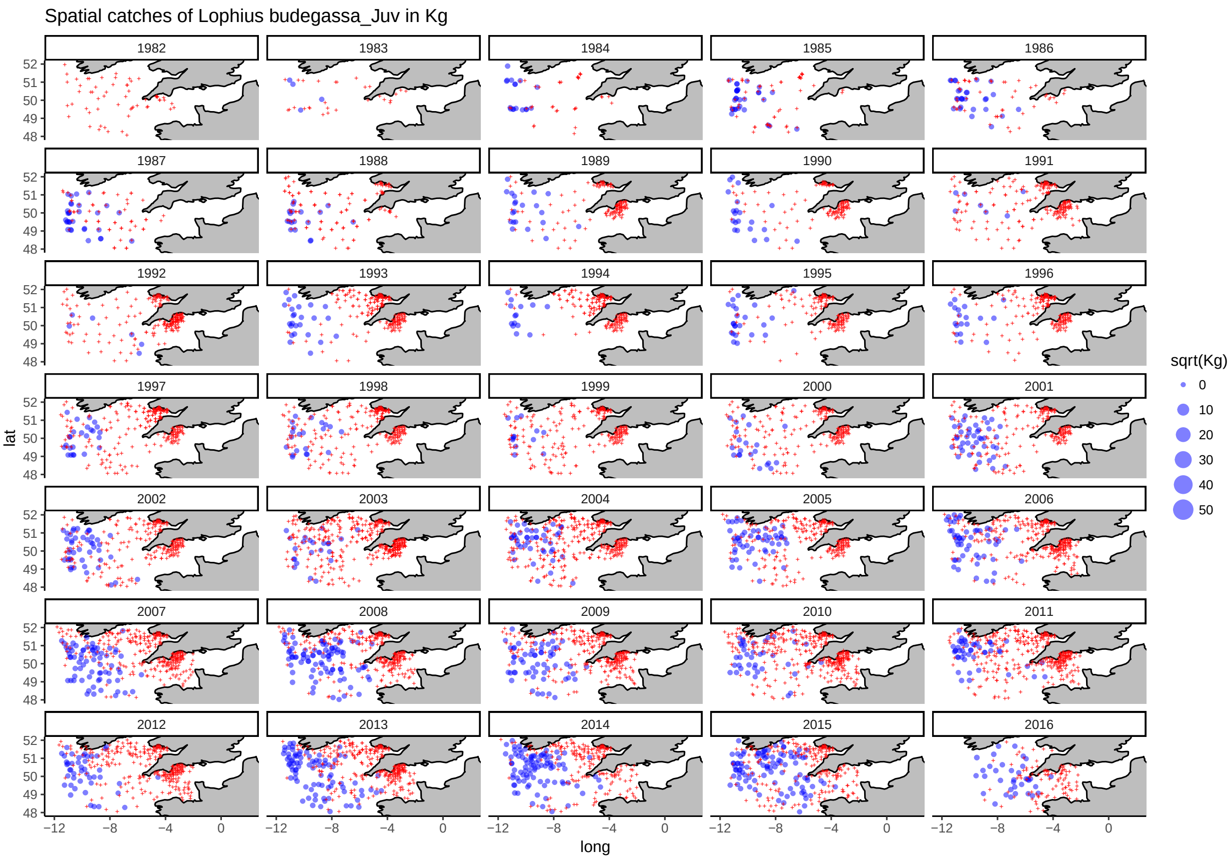
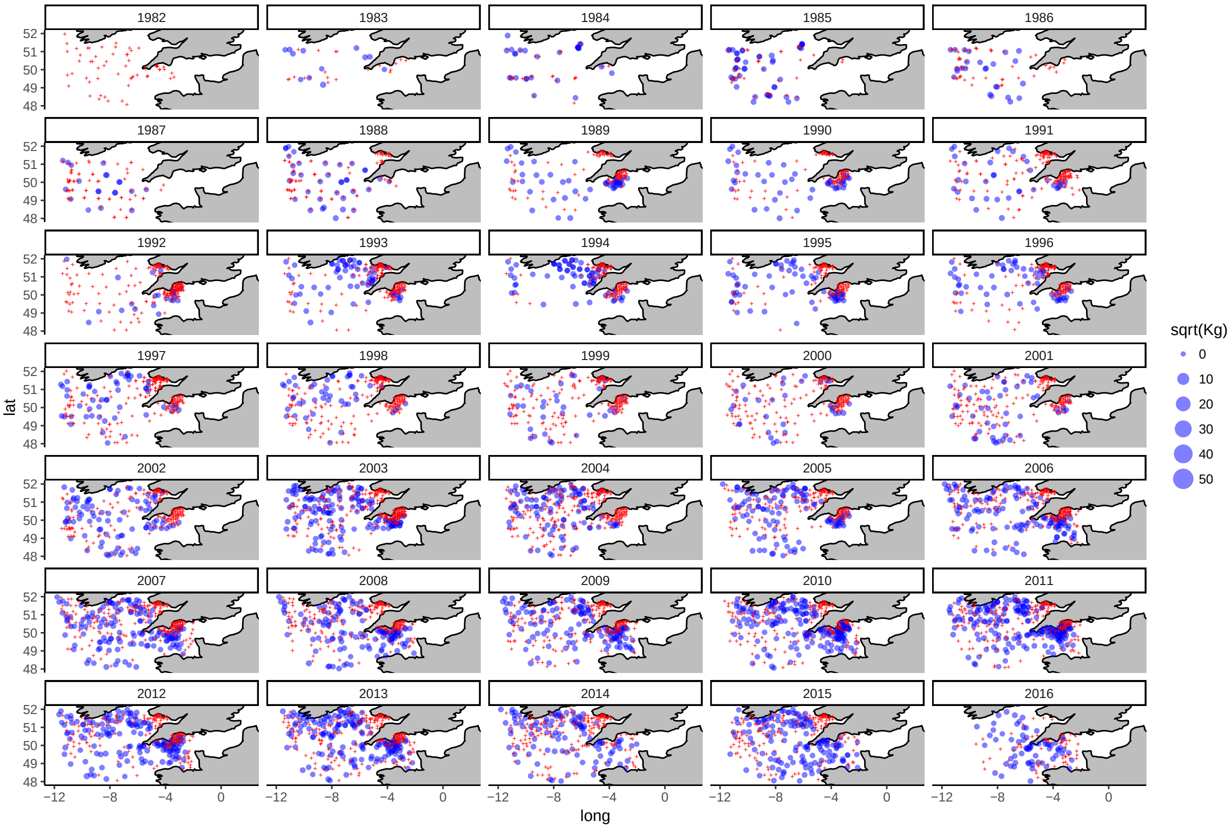
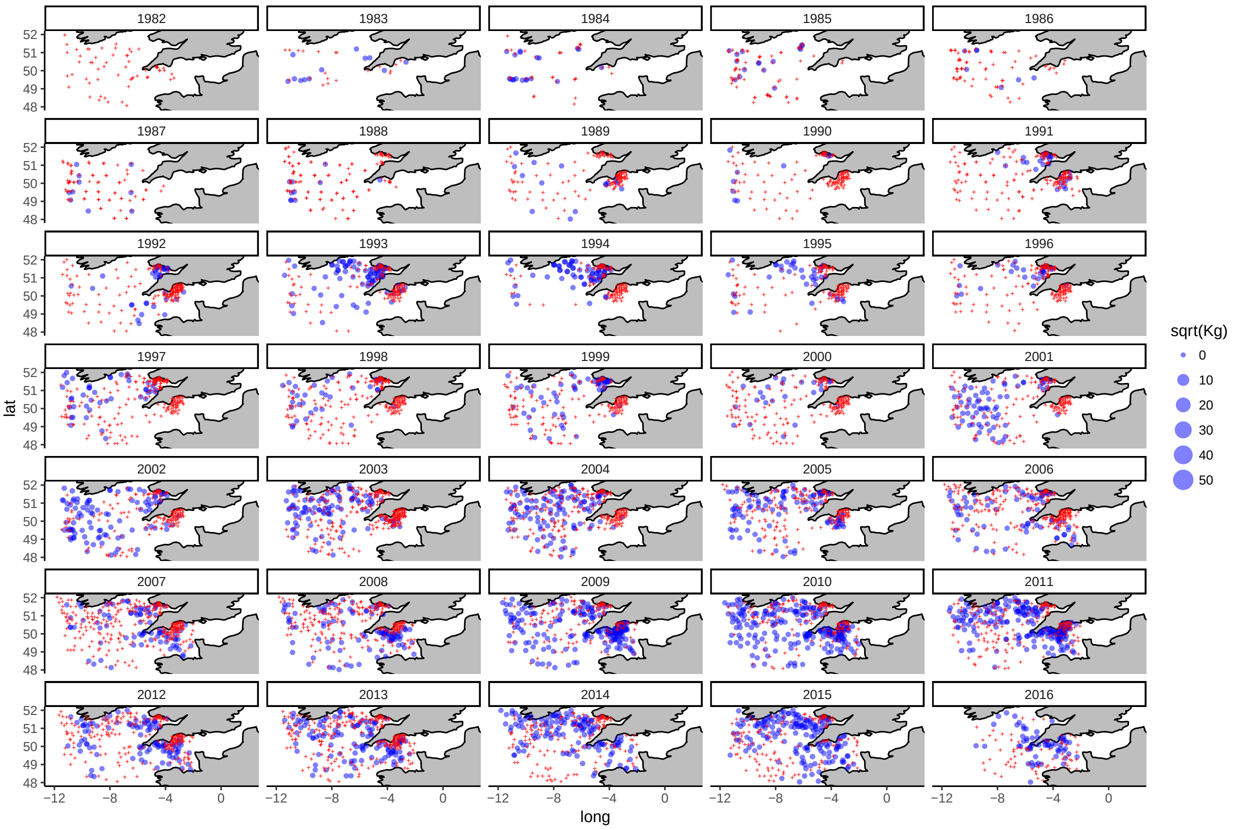
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
52
51
50
49
48
long
−12
−8
−4
0
sqrt(Kg)
0
10
20
30
40
50

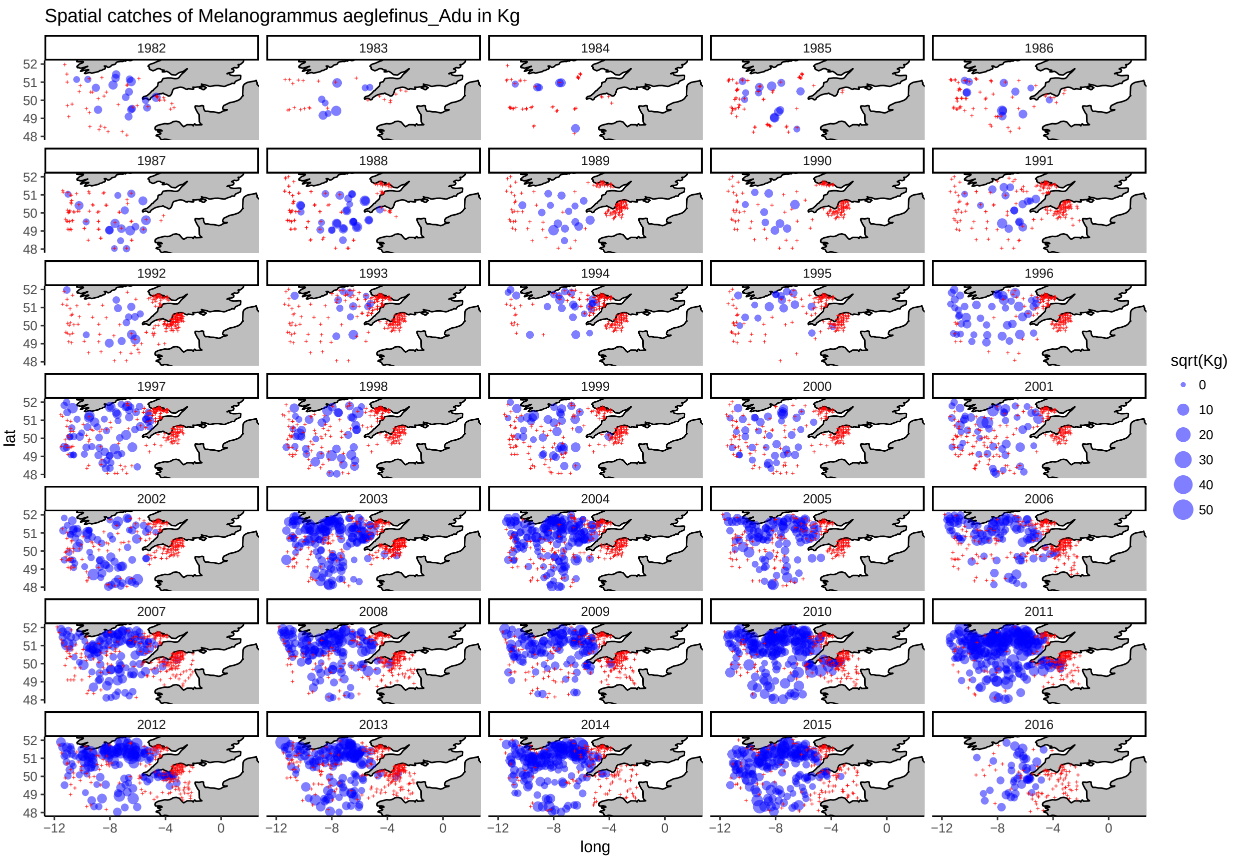

Spatial catches of Lophius budegassa_Juv in Kg
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
52
51
50
49
48
long
−12
−8
−4
0
sqrt(Kg)
0
10
20
30
40
50

Spatial catches of Lophius piscatorius_Adu in Kg

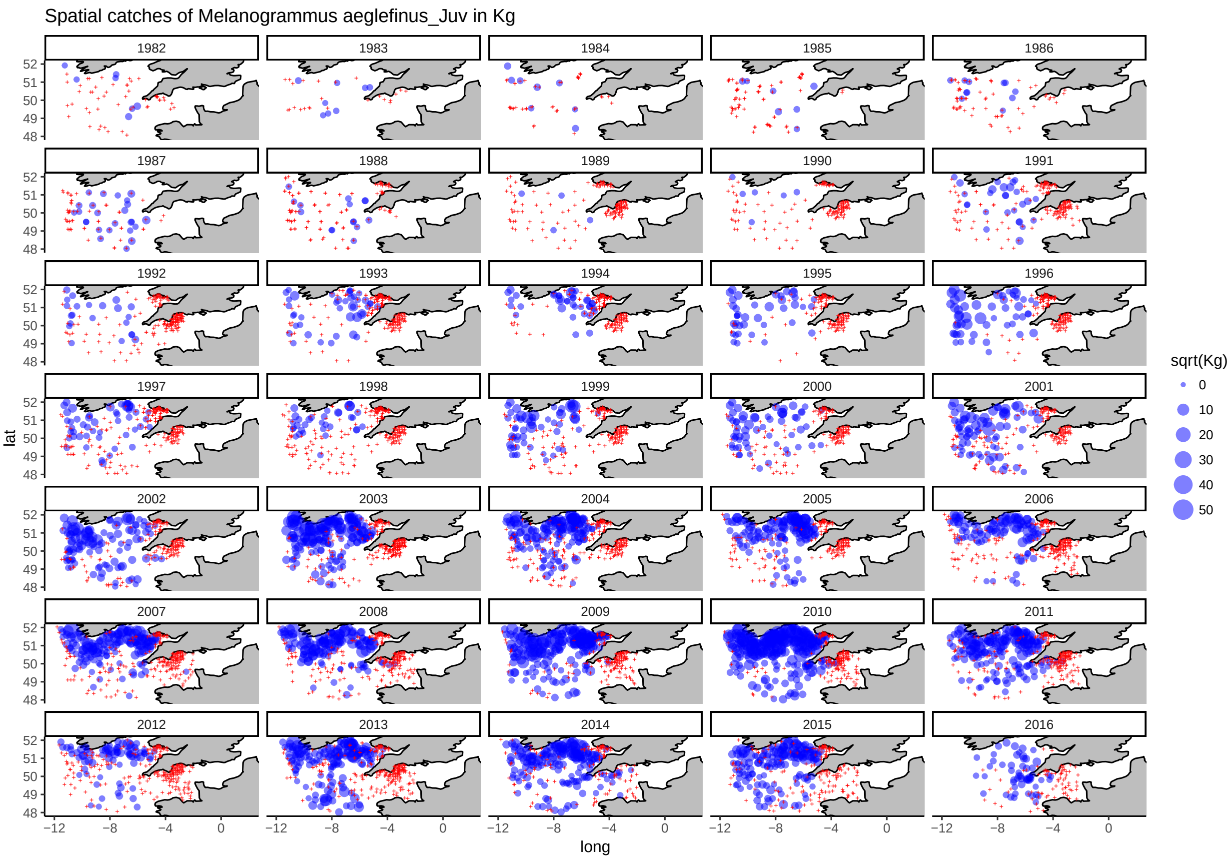


Spatial catches of Lophius piscatorius_Juv in Kg

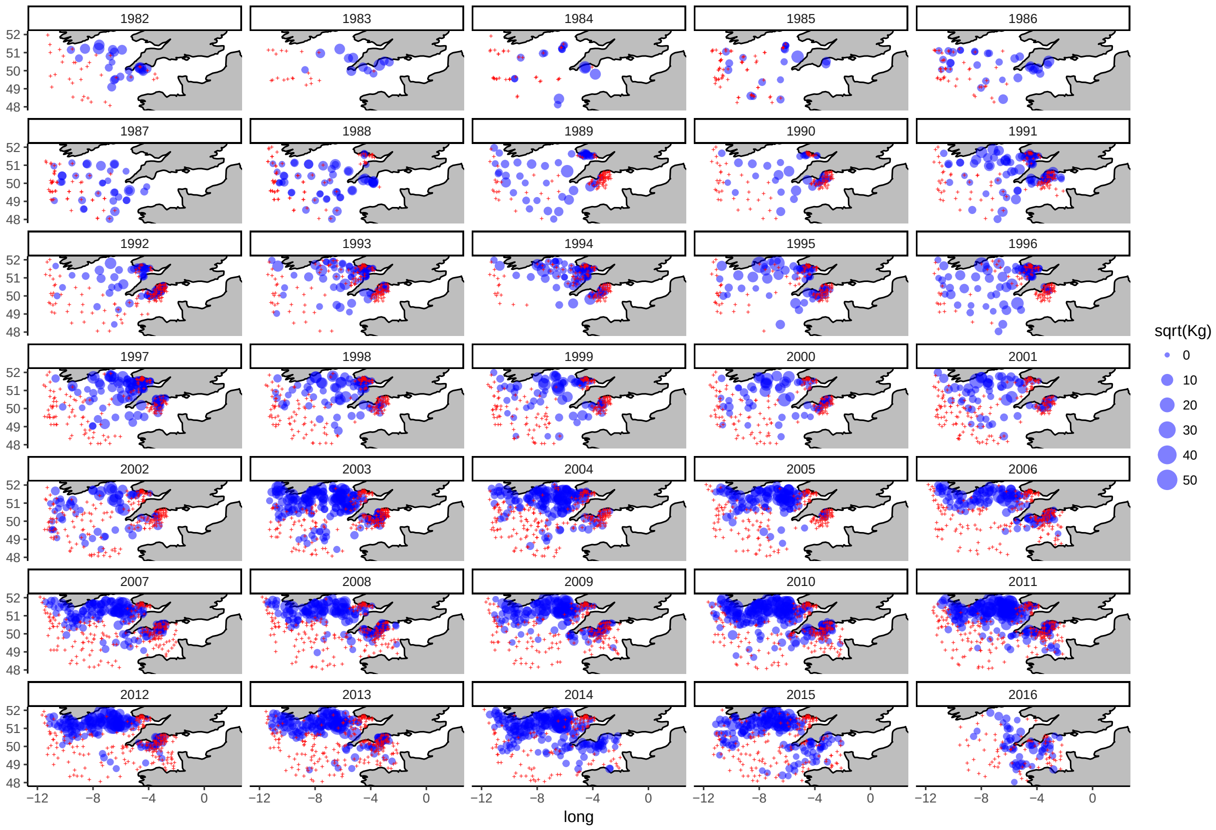


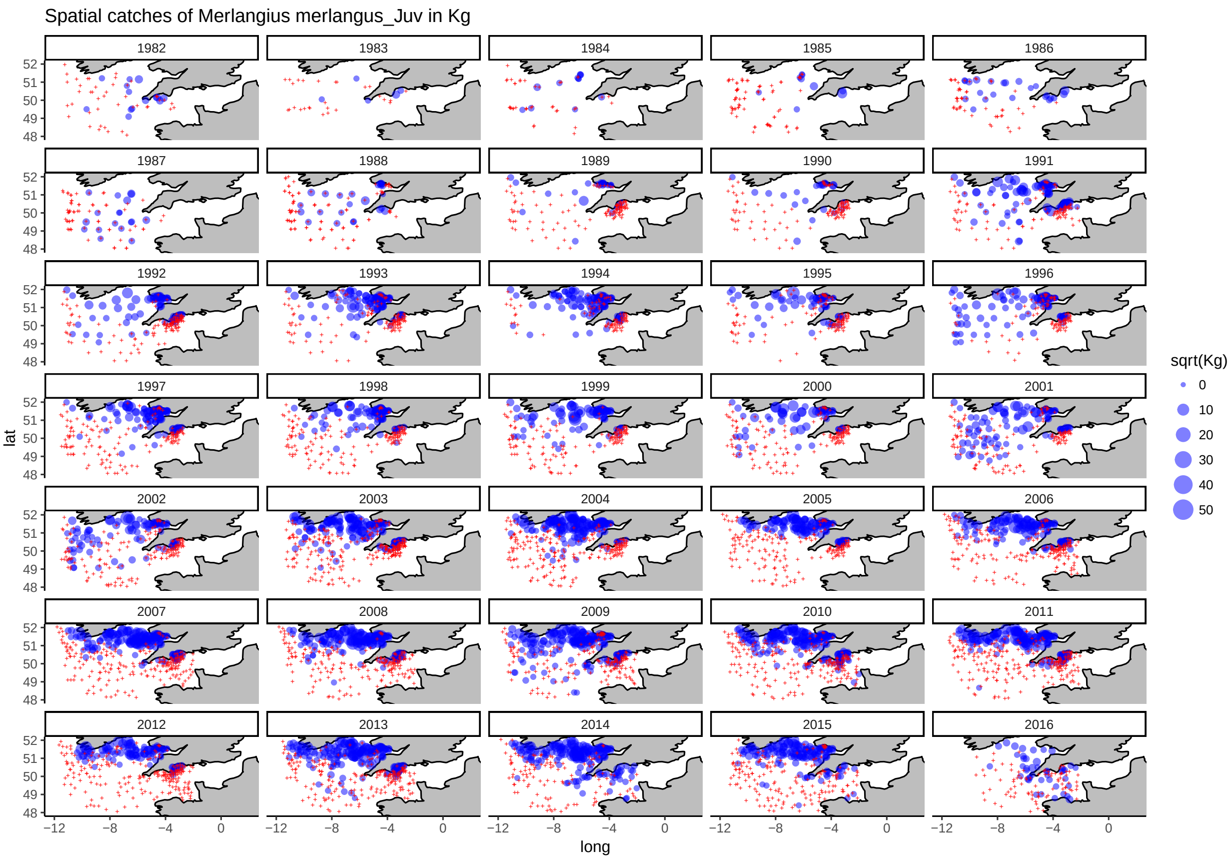


Spatial catches of Melanogrammus aeglefinus_Adu in Kg
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
52
51
50
49
48
long
−12
−8
−4
0
sqrt(Kg)
0
10
20
30
40
50


Spatial catches of Melanogrammus aeglefinus_Juv in Kg
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
52
51
50
49
48
long
−12
−8
−4
0
sqrt(Kg)
0
10
20
30
40
50

Spatial catches of Merlangius merlangus_Adu in Kg




Spatial catches of Merlangius merlangus_Juv in Kg
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
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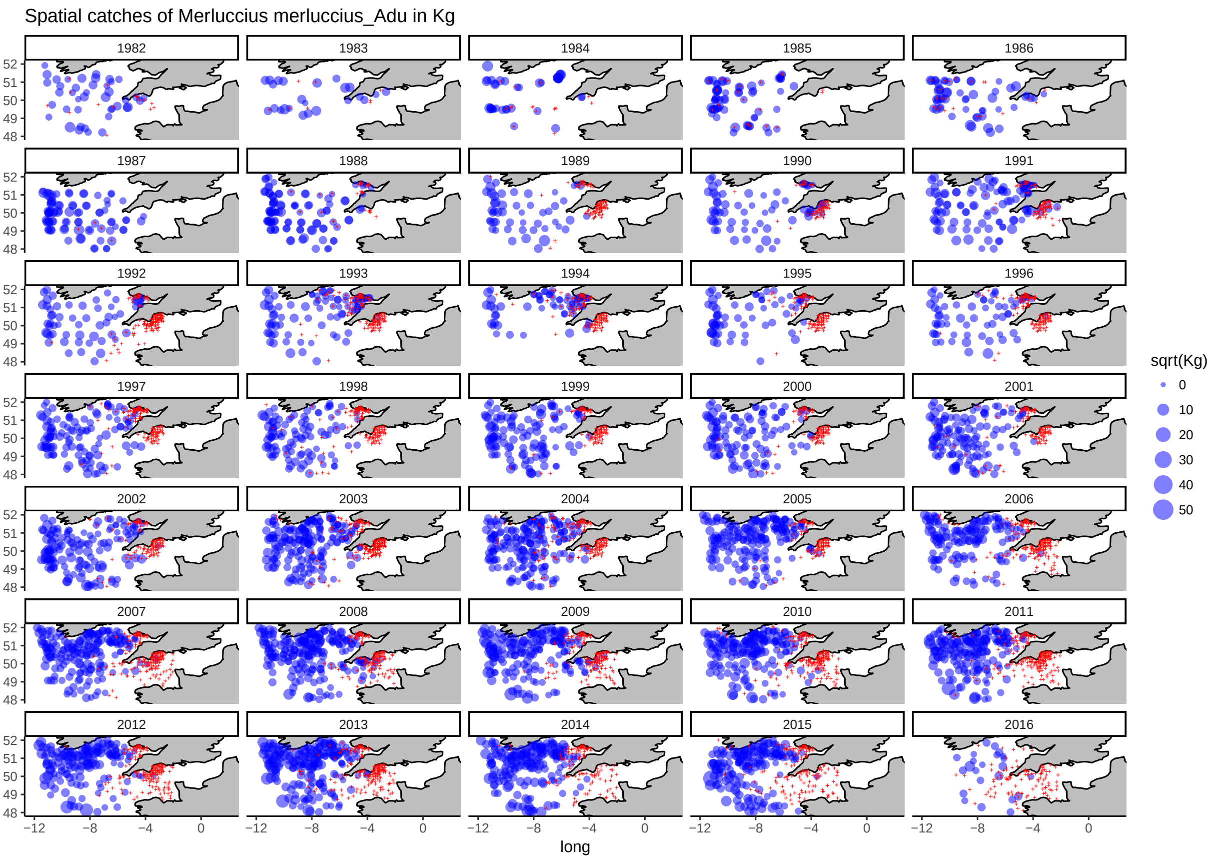
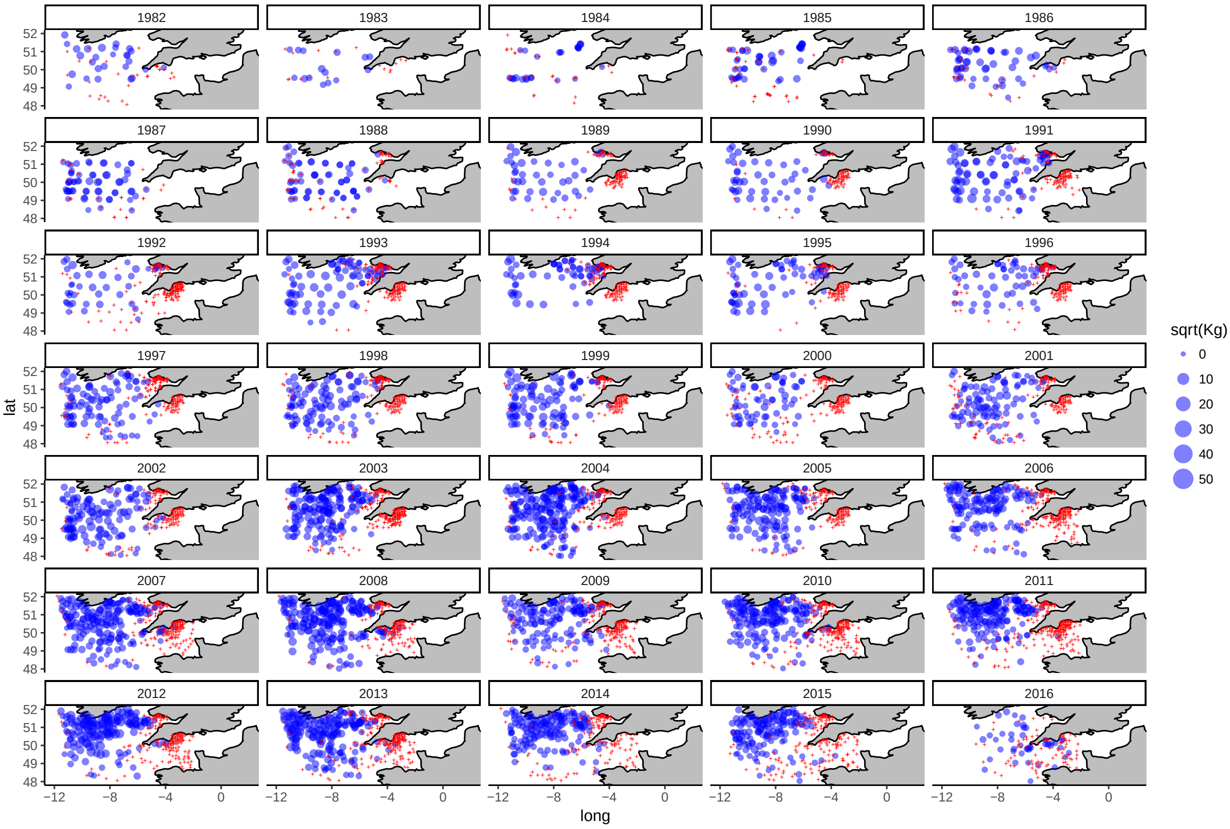
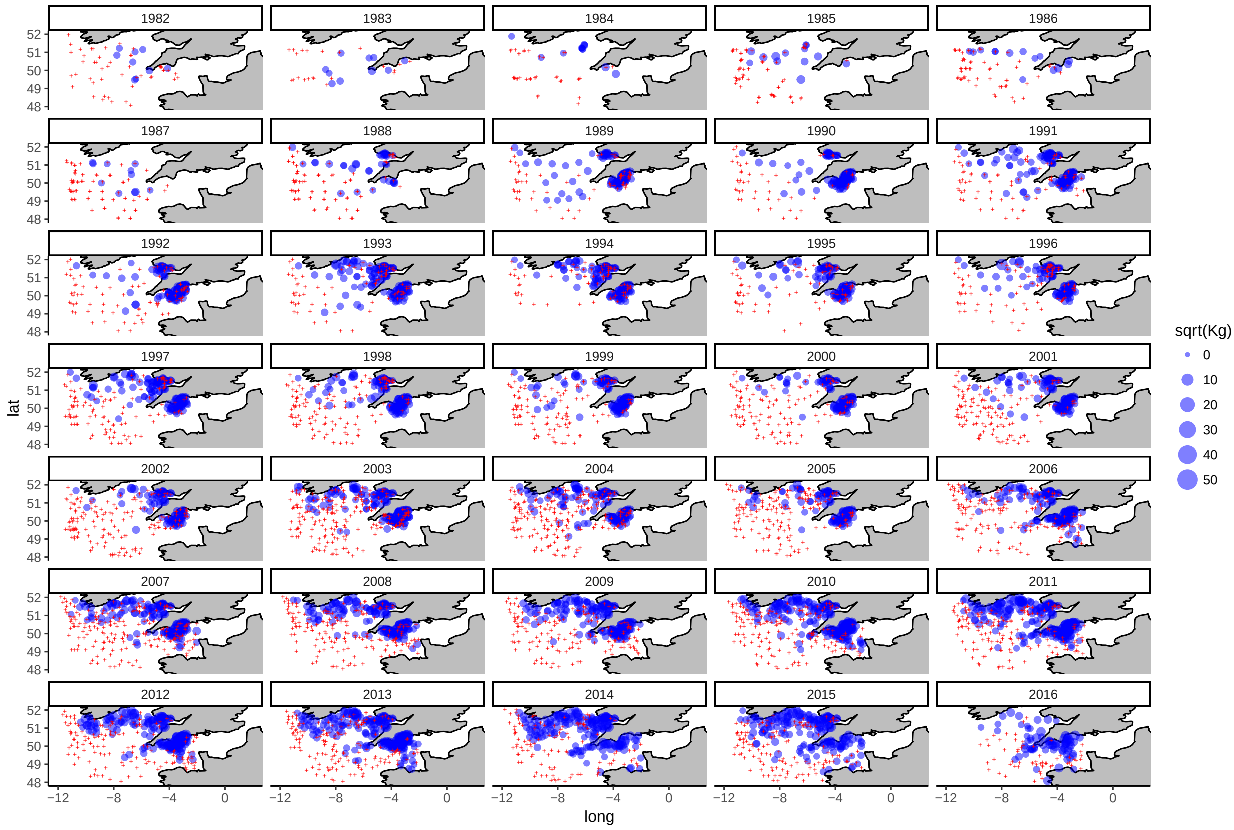
2009
2010
2011
2012
2013
2014
2015
2016
lat
52
51
50
49
48
long
−12
−8
−4
0
sqrt(Kg)
0
10
20
30
40
50

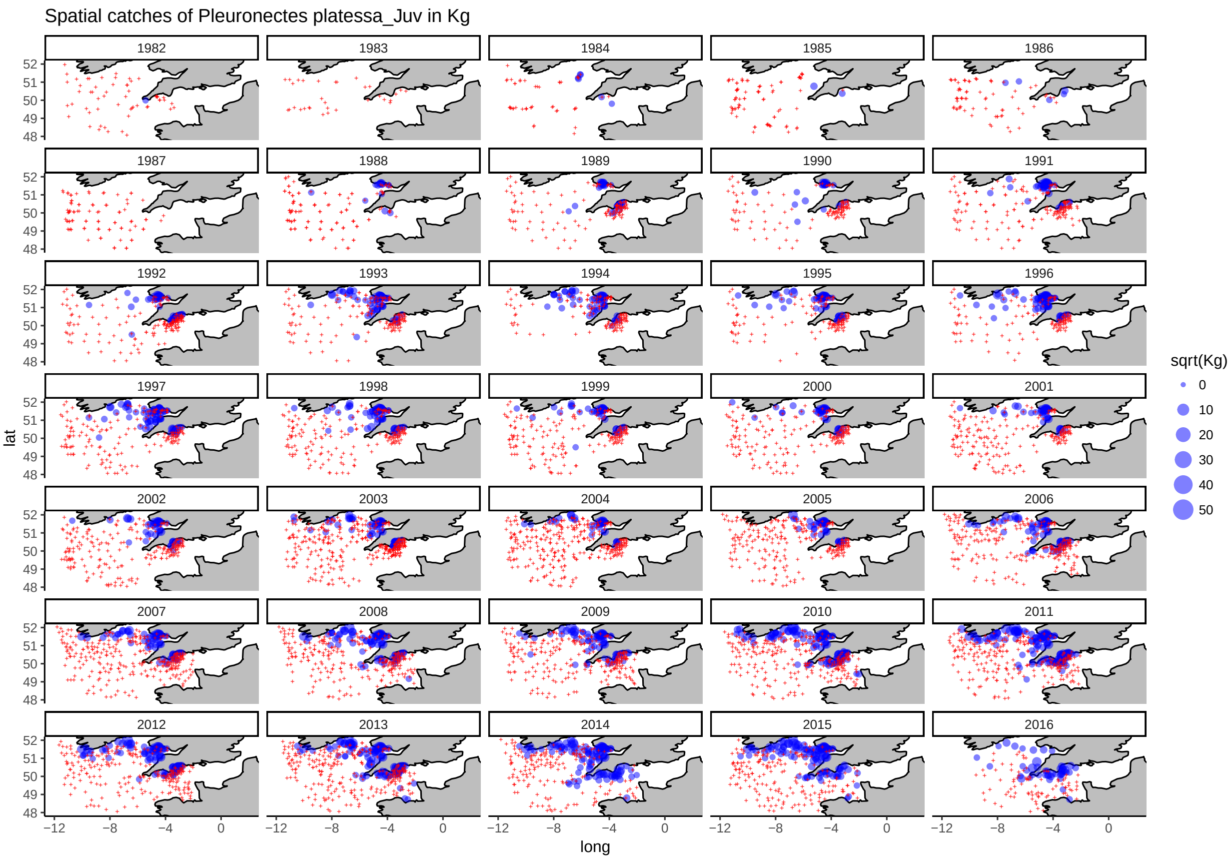

Spatial catches of Merluccius merluccius_Adu in Kg
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
52
51
50
49
48
long
−12
−8
−4
0
sqrt(Kg)
0
10
20
30
40
50

Spatial catches of Merluccius merluccius_Juv in Kg



Spatial catches of Pleuronectes platessa_Adu in Kg





Spatial catches of Pleuronectes platessa_Juv in Kg
1982
1983
1984
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1988
1989
1990
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1992
1993
1994
1995
1996
1997
1998
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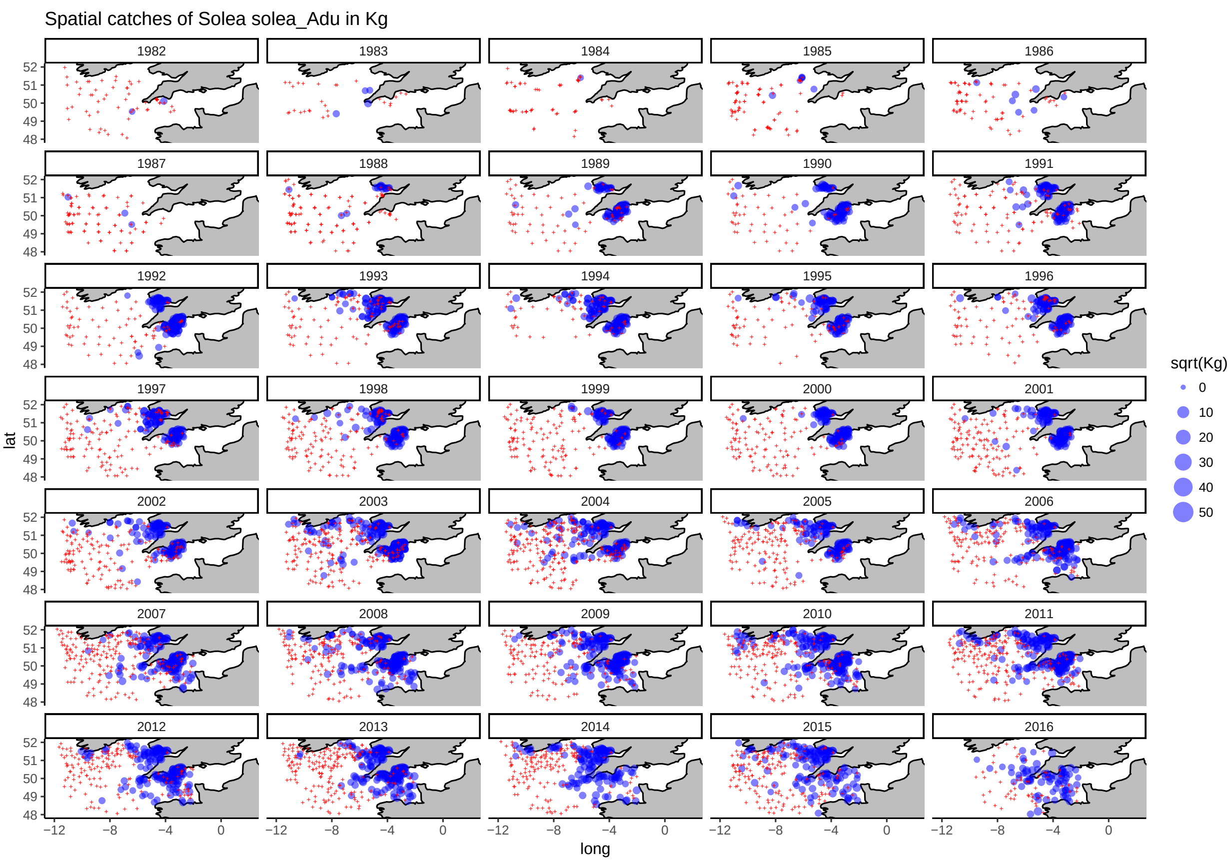
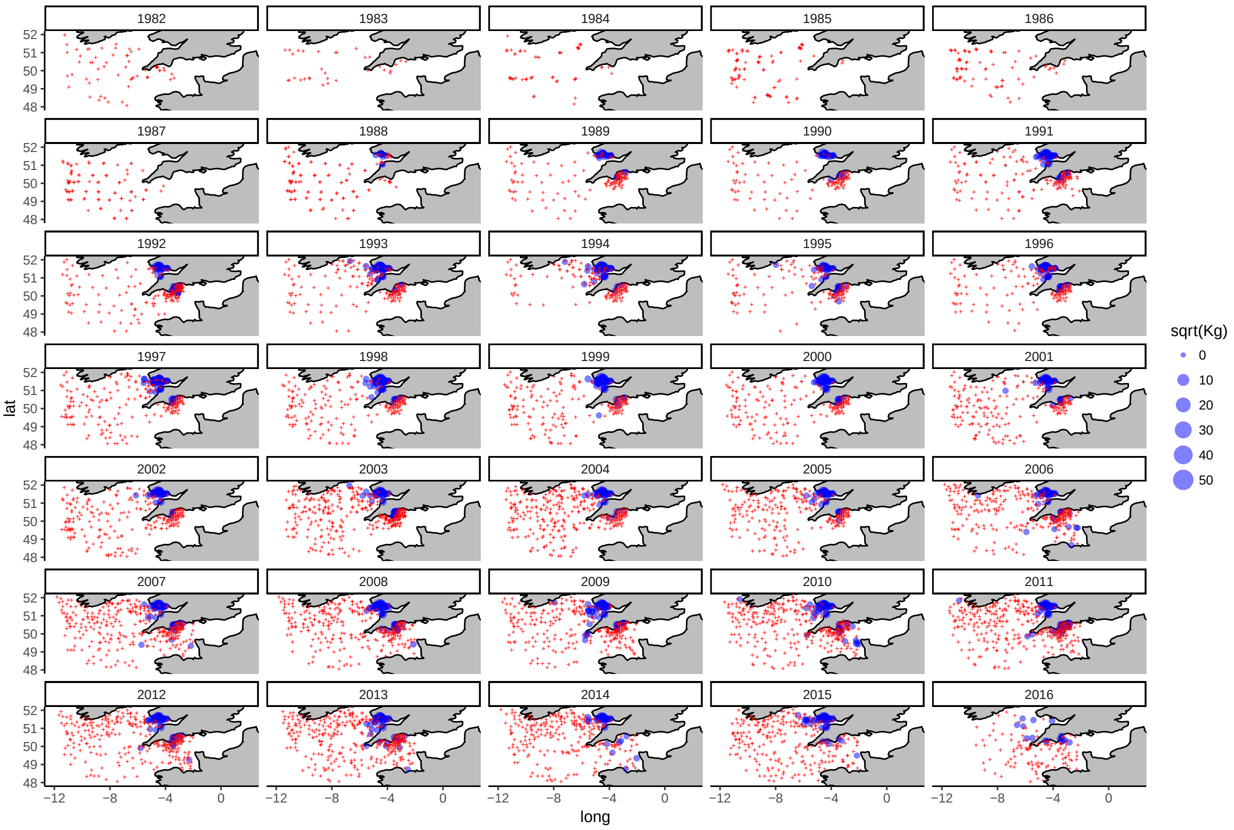
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
52
51
50
49
48
long
−12
−8
−4
0
sqrt(Kg)
0
10
20
30
40
50


Spatial catches of Solea solea_Adu in Kg
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
lat
long
sqrt(Kg)
0
10
20
30
40
50

Spatial catches of Solea solea_Juv in Kg



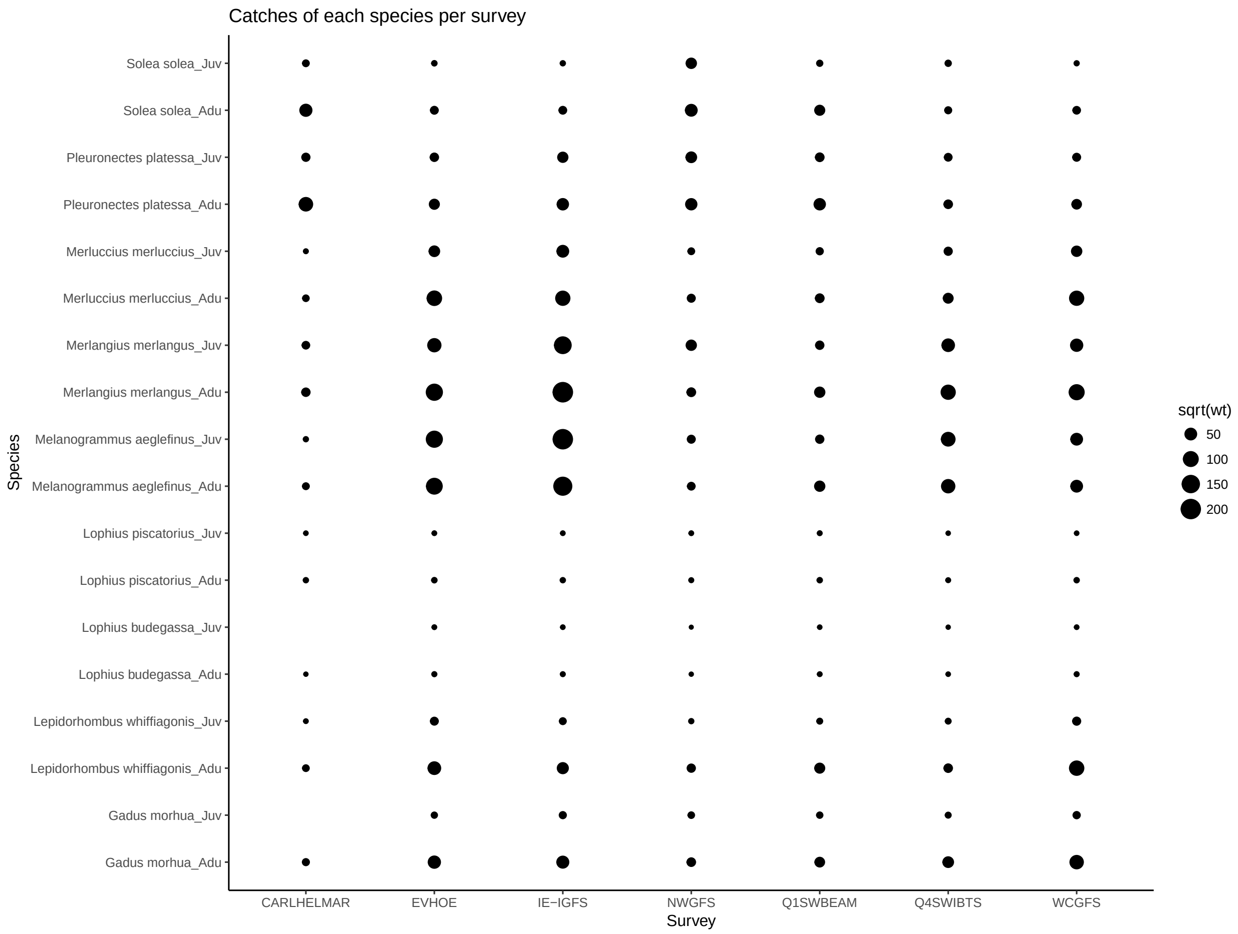
```
Wt$HaulDur <- as.numeric(as.character(Wt$HaulDur))

cpue <- group_by(Wt, Survey, Year, Species) %>% summarise(q05 = quantile(Kg/HaulDur *
    60, prob = 0.05, na.rm = T), q50 = quantile(Kg/HaulDur *
    60, prob = 0.5, na.rm = T), mean = mean(Kg/HaulDur * 60,
    na.rm = T), q95 = quantile(Kg/HaulDur * 60, prob = 0.95,
    na.rm = T))

print(ggplot(cpue, aes(x = Year, y = mean)) + geom_line(aes(group = Survey,
    colour = Survey)) + facet_wrap(~Species, ncol = 2, scale = "free_y") +
    theme(axis.text.x = element_text(angle = -90)) + ylab("Kg per hour tow") +
    xlab("") + ggtitle("CPUE (Kg per hour tow)"))
```


CPUE (Kg per hour tow)
Kg per hour tow
Gadus morhua_Adu
Gadus morhua_Juv
Lepidorhombus whiffiagonis_Adu
Lepidorhombus whiffiagonis_Juv
Lophius budegassa_Adu
Lophius budegassa_Juv
Lophius piscatorius_Adu
Lophius piscatorius_Juv
Melanogrammus aeglefinus_Adu
Melanogrammus aeglefinus_Juv
Merlangius merlangus_Adu
Merlangius merlangus_Juv
Merluccius merluccius_Adu
Merluccius merluccius_Juv
Pleuronectes platessa_Adu
Pleuronectes platessa_Juv
Solea solea_Adu
Solea solea_Juv
Survey
CARLHELMAR
EVHOE
IE−IGFS
NWGFS
Q1SWBEAM
Q4SWIBTS
WCGFS

```r
cpsa <- group_by(Wt, Survey, Year, Species) %>% summarise(q05 = quantile(Kg/SweptArea,
    prob = 0.05, na.rm = T), q50 = quantile(Kg/SweptArea, prob = 0.5,
    na.rm = T), mean = mean(Kg/SweptArea, na.rm = T), q95 = quantile(Kg/SweptArea,
    prob = 0.95, na.rm = T))

print(ggplot(cpsa, aes(x = Year, y = mean)) + geom_line(aes(group = Survey,
    colour = Survey)) + facet_wrap(~Species, ncol = 2, scale = "free_y") +
    theme(axis.text.x = element_text(angle = -90)) + ylab("Density (catch per km2 swept)") +
    xlab("") + ggtitle("CPUE (Catch per km2 swept area)"))
```


CPUE (Catch per km2 swept area)
Density (catch per km2 swept)
Gadus morhua_Adu
Gadus morhua_Juv
Lepidorhombus whiffiagonis_Adu
Lepidorhombus whiffiagonis_Juv
Lophius budegassa_Adu
Lophius budegassa_Juv
Lophius piscatorius_Adu
Lophius piscatorius_Juv
Melanogrammus aeglefinus_Adu
Melanogrammus aeglefinus_Juv
Merlangius merlangus_Adu
Merlangius merlangus_Juv
Merluccius merluccius_Adu
Merluccius merluccius_Juv
Pleuronectes platessa_Adu
Pleuronectes platessa_Juv
Solea solea_Adu
Solea solea_Juv
Survey
CARLHELMAR
EVHOE
IE−IGFS
NWGFS
Q1SWBEAM
Q4SWIBTS
WCGFS

```r
## Catchs per survey, per year

Wt_Sur <- group_by(Wt, Survey, Species) %>% summarise(wt = sum(Kg))

Wt_Sur[Wt_Sur$wt == 0, ]


## Source: local data frame [2 x 3]
## Groups: Survey [1]
##
##        Survey               Species    wt
##        <fctr>                <fctr> <dbl>
## 1 CARLHELMAR      Gadus morhua_Juv     0
## 2 CARLHELMAR Lophius budegassa_Juv     0


Wt_Sur$wt[Wt_Sur$wt == 0] <- NA

print(ggplot(Wt_Sur, aes(x = Survey, y = Species)) + geom_point(aes(size = sqrt(wt))) +
    theme_classic() + ggtitle("Catches of each species per survey"))
```


Catches of each species per survey
Species
Solea solea_Juv
Solea solea_Adu
Pleuronectes platessa_Juv
Pleuronectes platessa_Adu
Merluccius merluccius_Juv
Merluccius merluccius_Adu
Merlangius merlangus_Juv
Merlangius merlangus_Adu
Melanogrammus aeglefinus_Juv
Melanogrammus aeglefinus_Adu
Lophius piscatorius_Juv
Lophius piscatorius_Adu
Lophius budegassa_Juv
Lophius budegassa_Adu
Lepidorhombus whiffiagonis_Juv
Lepidorhombus whiffiagonis_Adu
Gadus morhua_Juv
Gadus morhua_Adu
CARLHELMAR
EVHOE
IE−IGFS
NWGFS
Q1SWBEAM
Q4SWIBTS
WCGFS
Survey
sqrt(wt)
50
100
150
200

It's apparent from the information that the CARLHELMAR survey area in the Western Channel sees little catch of the gadoid species. This is perhaps unsurprising given its designed as a flatfish survey.

The WCGFS, EVHOE, IE-IGFS and Q4SWIBTS show reasonable consistency with each other in terms of CPUE trends for cod, though the WCGFS caught less haddock and whiting.

4.3 Conclusion on survey availability

Having reviewed the available survey data, coverage prior to 1992 was patchy and incomplete and the CARLHELMAR and NWGFS surveys are focused on flatfish catches, with little information on gadoid species. Therefore it will be important to check model diagnostics to entire the characteristics are being treated appropriately. However, all the data will be kept for the first runs.

5 Habitat covariates

There is also the possibility to include habitat covariates in the model. In order to explore this, two datasets were downloaded:

- EU Sea Map Atlantic Habitat Classifications (from http://www.emodnet-seabedhabitats.eu/) which provides a substrate classification (e.g. rocky, sandy etc..) for the Celtic Sea area.
- Bathymetry data (from http://www.emodnet-hydrography.eu/ which provides water depth.

The following function is used to assign the correct habitat location to the knot locations generated by the VAST model.

```
HabAssignFunc <- function(Kmeans = NULL, zone = 29, locationHabMap = NULL,
    nameHabMap = NULL) {
    library(rgdal)
    library(VAST)
    # Create a dataframe of the knots
    DF <- data.frame(X = Kmeans$centers[, "E_km"], Y = Kmeans$centers[,
        "N_km"])
    attr(DF, "projection") = "UTM"
    attr(DF, "zone") <- zone
```

```
    LLs <- PBSmapping::convUL(DF)

    HabMap <- readOGR(dsn = file.path(locationHabMap), layer = nameHabMap)

    # joint the spatial points..
    LLs <- SpatialPoints(LLs)
    proj4string(LLs) <- CRS("+proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,

    join <- over(x = LLs, y = HabMap)

    LLs <- SpatialPointsDataFrame(LLs, join)
    KmeanHab <- data.frame(Habitat = LLs$substrate)

    return(KmeanHab)

}
```

Appendix C

Supplementary material for manuscript I

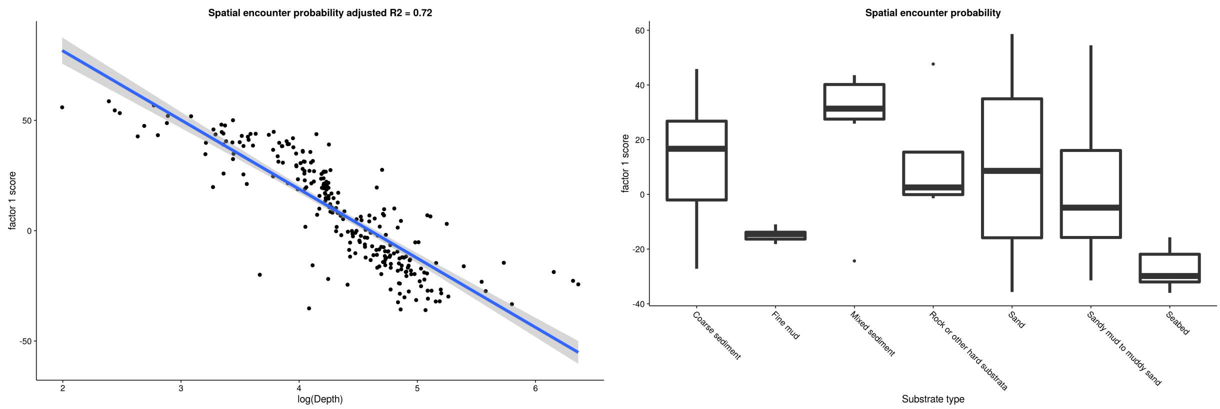


Figure S1: Left: Average spatial encounter probability factor 1 values correlated against; Left - Depth, Right - substrate type.

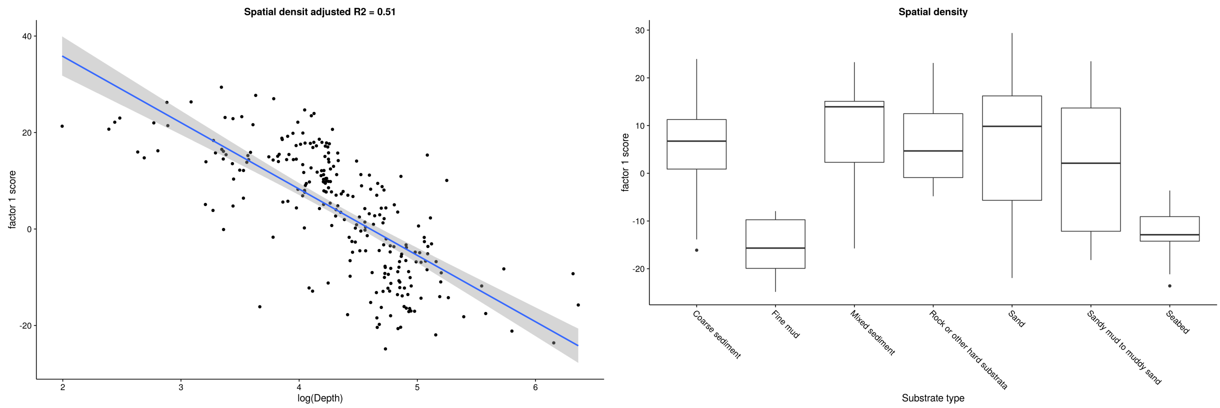


Figure S2: Left: Average spatial positive density factor 1 values correlated against; Left- Depth, Right- substrate type.

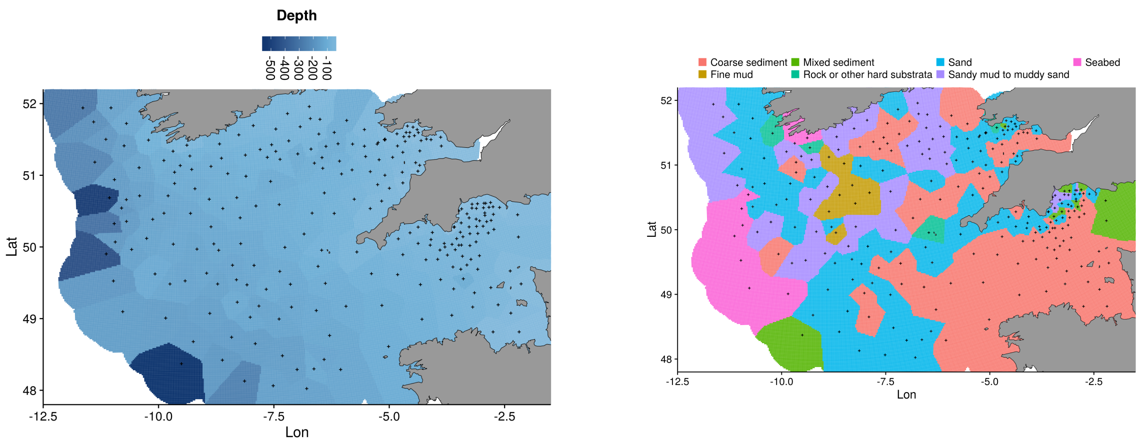


Figure S3: Left: Depth, Right: Substrate assigned to each spatial knot.

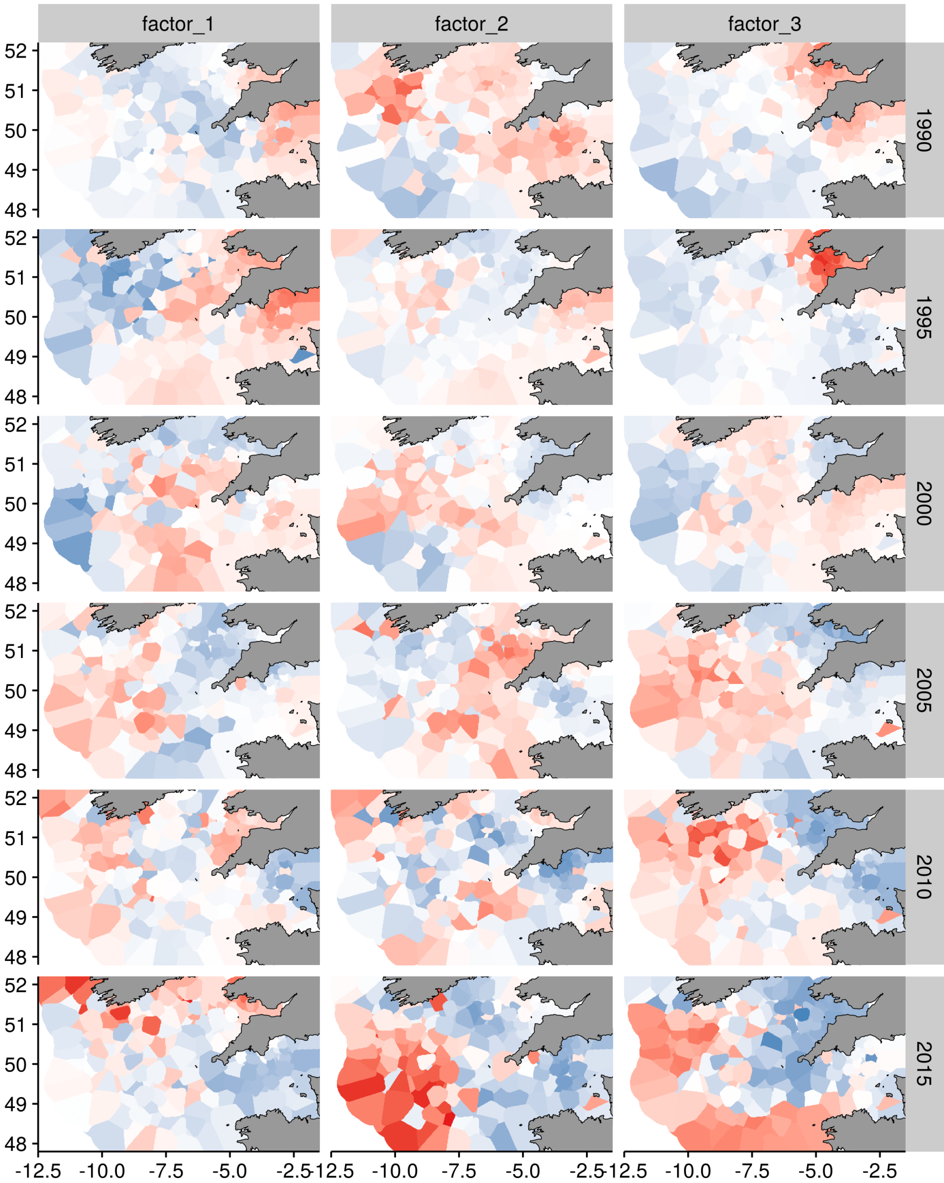


Figure S4: Spatial Loadings for first three factors every five years for spatio-temporal encounter probability.

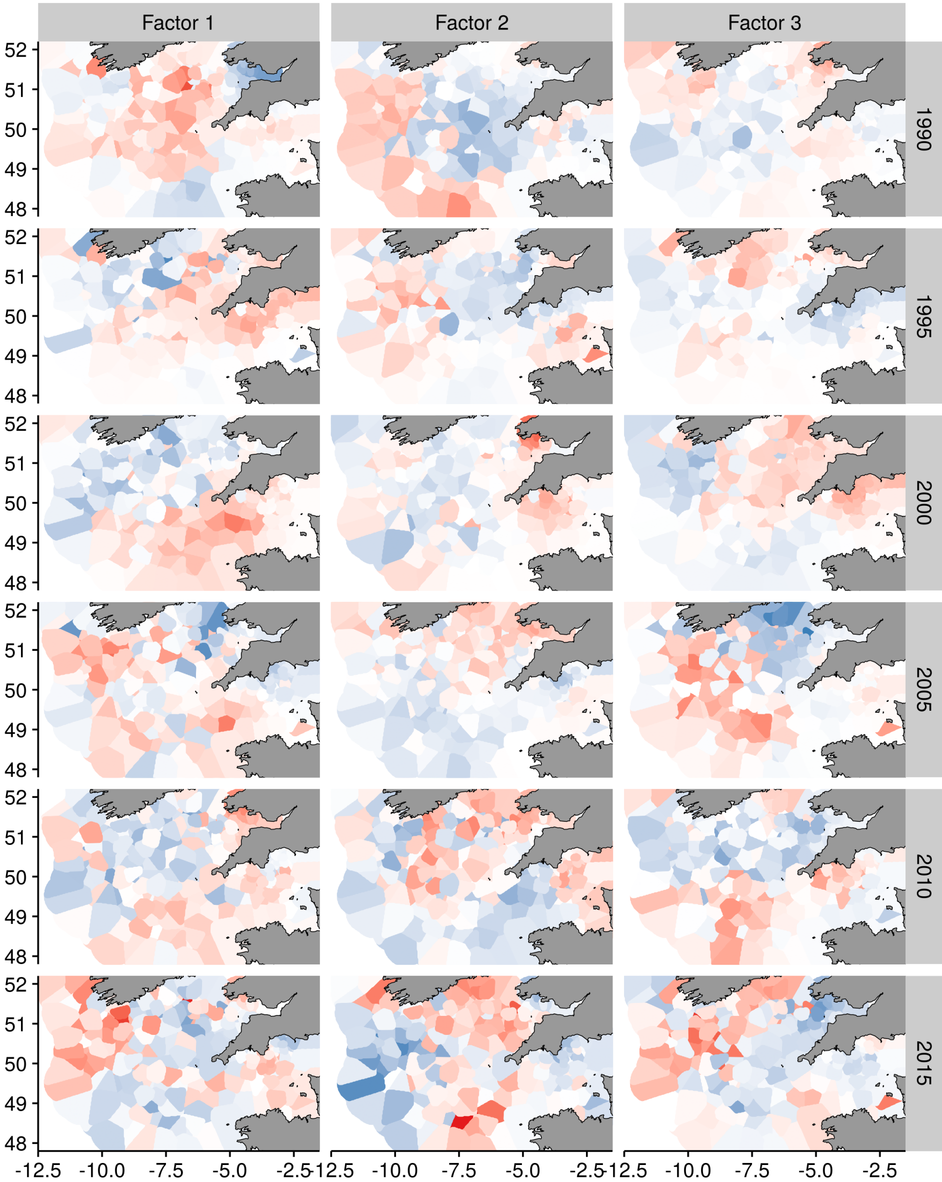


Figure S5: Spatial Loadings for first three factors every five years for spatio-temporal density.

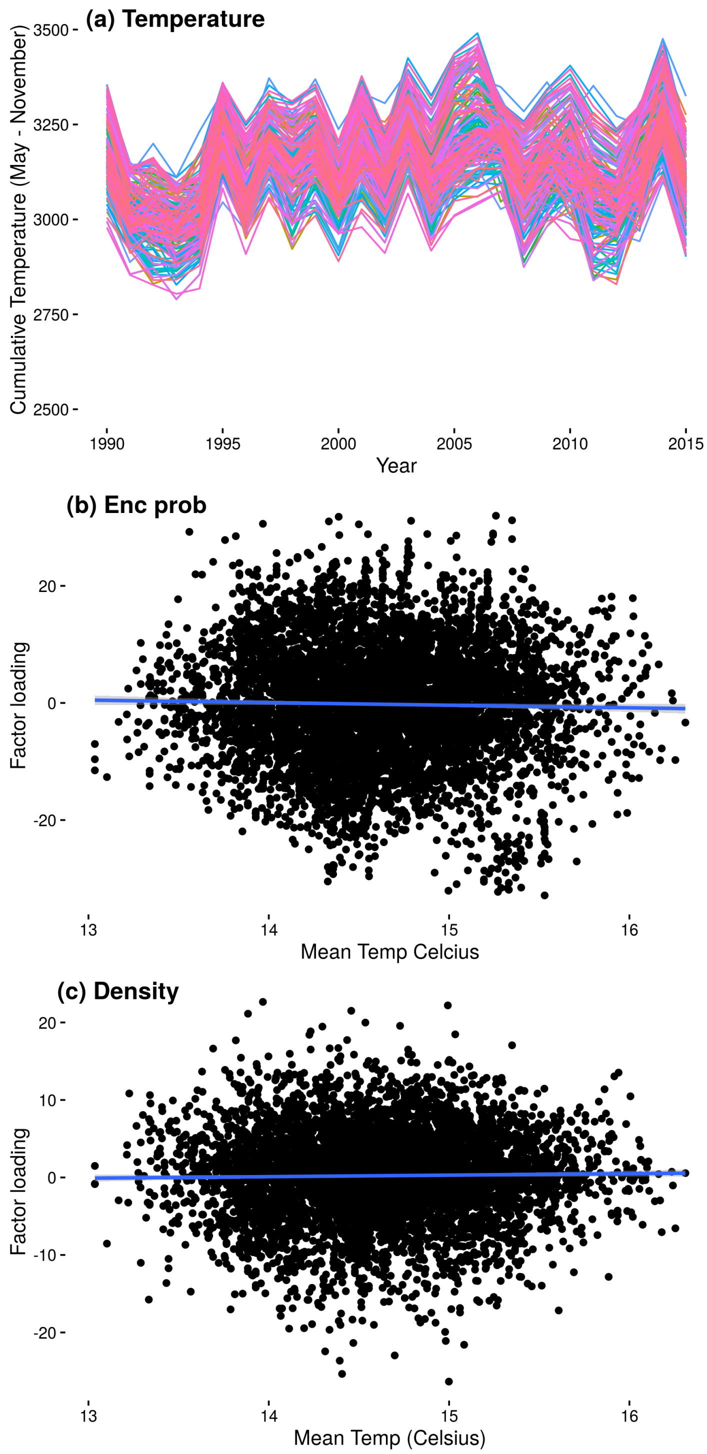


Figure S6: Association of temperature and knots (individual lines; top) with Spatio-temporal factor loadings for encounter probability (middle) and density (bottom).

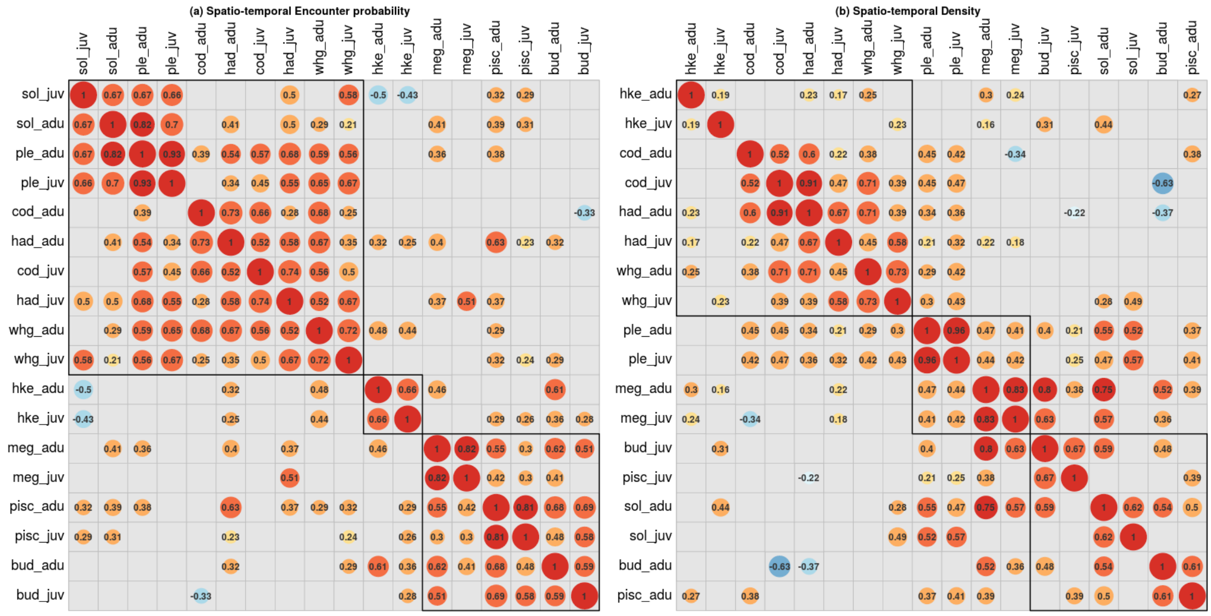


Figure S7: Inter-species correlations for (a) spatio-temporal encounter probability and b) spatio-temporal density. Species are clustered into three groups based on a hierarchical clustering method with non-significant correlations (the Confidence Interval [± 1.96 * SEs] spanned zero) left blank.

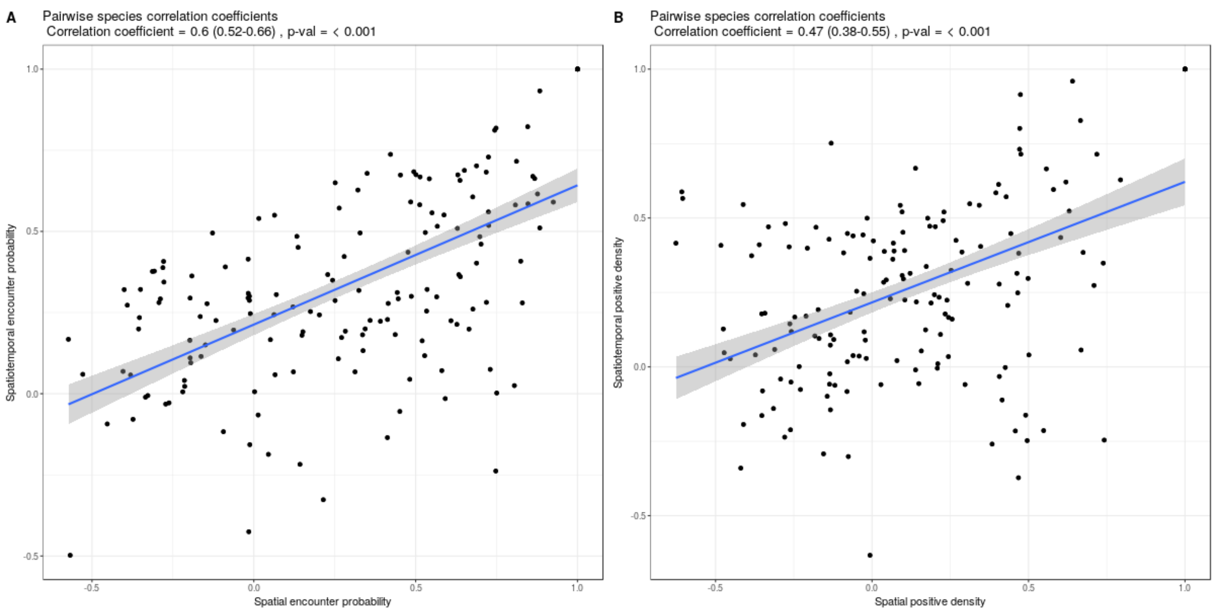


Figure S8: Pairwise species correlation coefficients for a) spatial encounter probability and spatiotemporal encounter probability, and b) spatial positive densitiy and spatiotemporal positive density

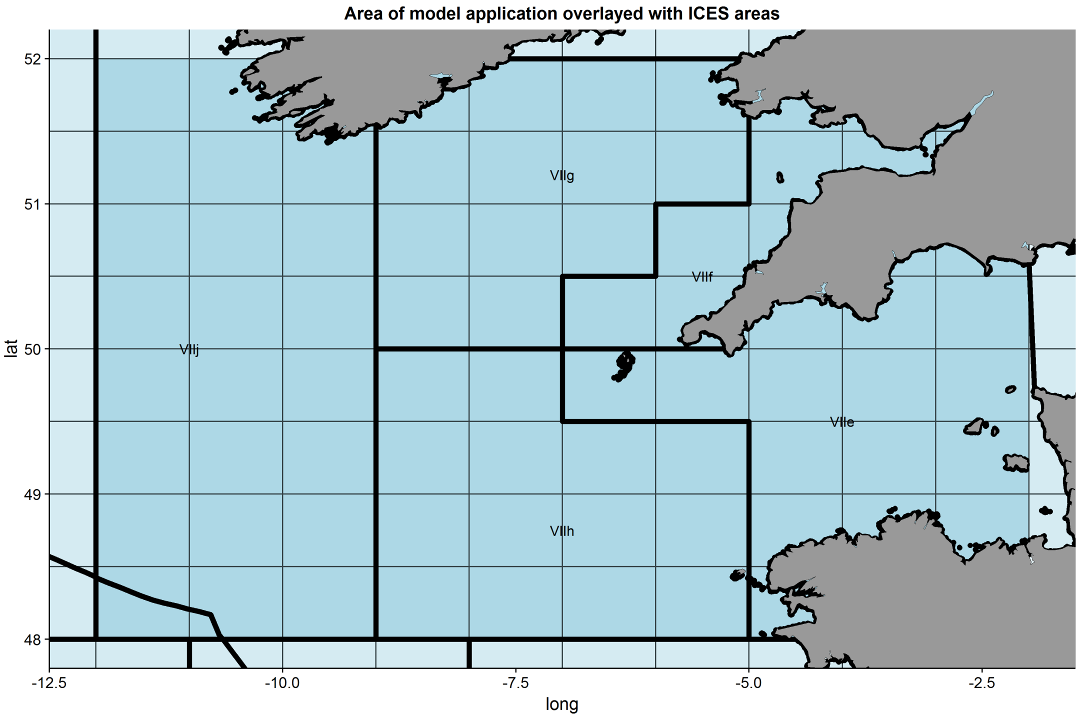


Figure S9: Spatial bounds of case study area.

Table S1: List of survey codes, names and brief description.

Survey code	Name	Gear	Temporal extent
CEXP	Celtic Explorer (IE)	Otter trawl	2003 - 2015
CARLHELMAR	Carlhelmar (UK)	Commercial beam trawl	1989 - 2013
NWGFS	North West groundfish survey (UK)	Beam trawl	1988 - 2015
Q1SWBEAM	Quarter 1 south-west beam trawl survey (UK)	beam trawl	2006 - 2015
Q4SWIBTS	Quarter 4 south-west international bottom trawl survey (UK)	Otter trawl	2003 - 2010
THA2	EVHOE survey on Thalasa (FR)	Otter trawl	1997 - 2015
WCGFS	Western channel groundfish survey (UK)	Otter trawl (Portugese high headline)	1982 - 2004

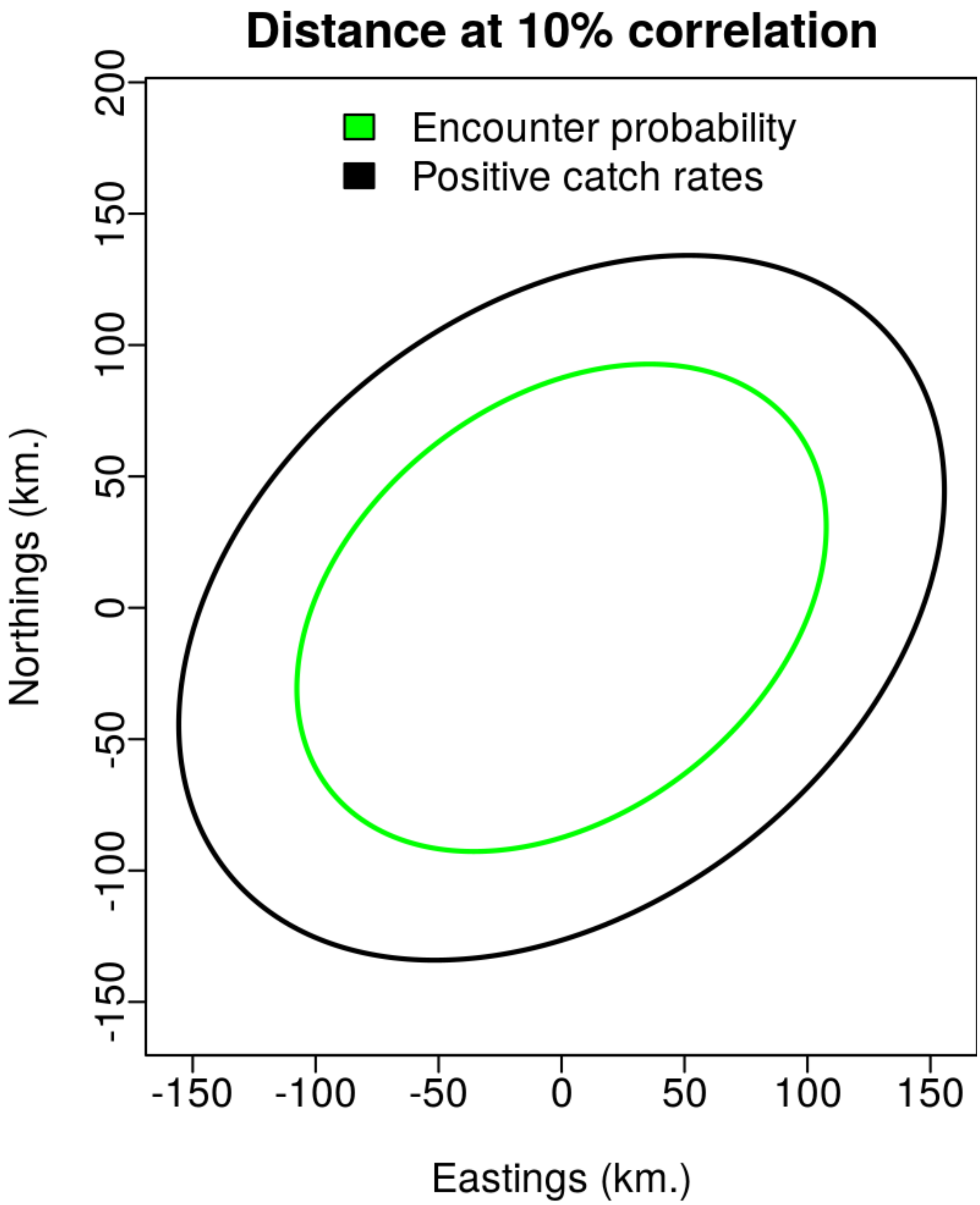


Figure S10: Estimates of distances at 10 % correlation from the Matérn covariance function for encounter probability and positive catch rates.

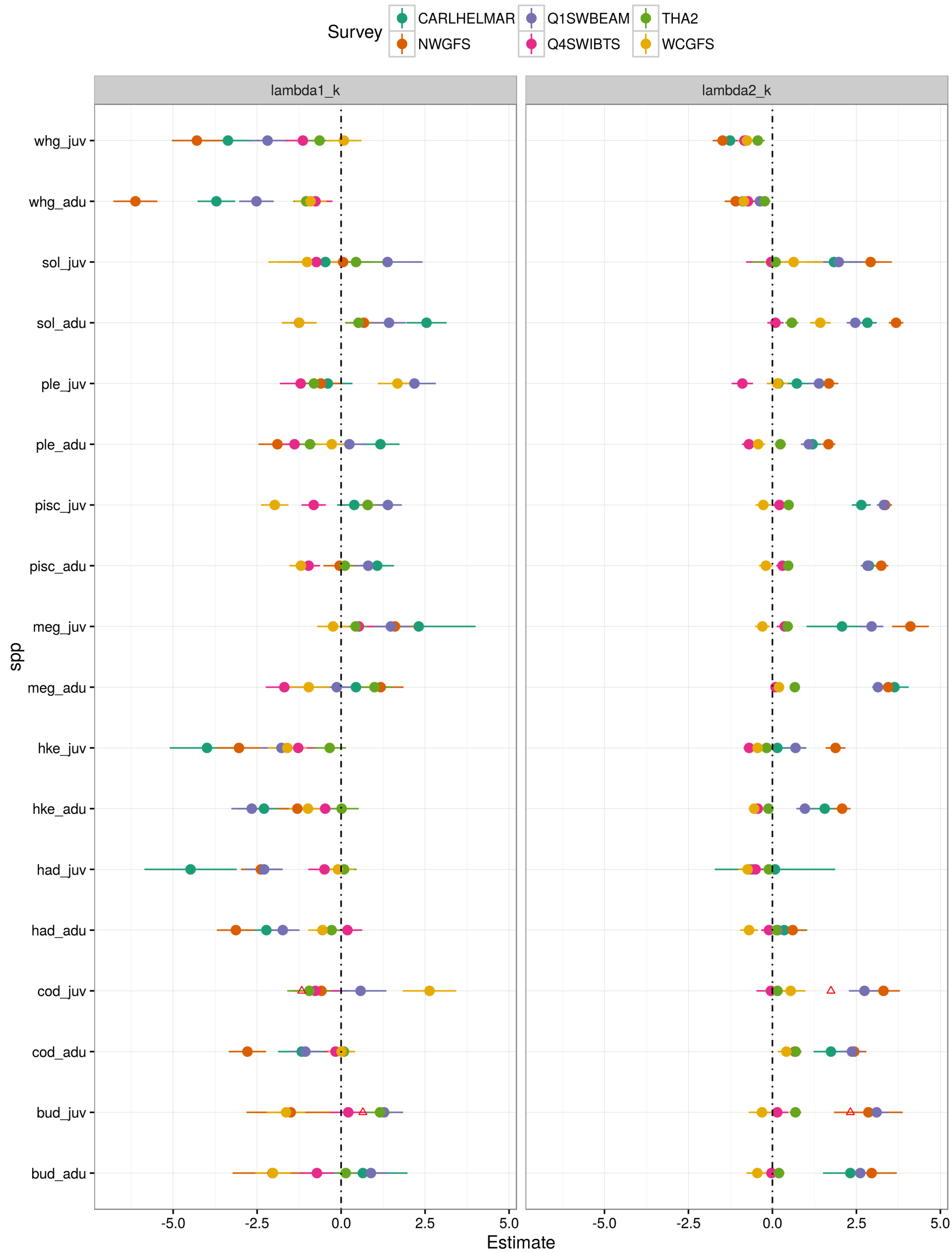


Figure S11: Fixed effect estimates for surveys for each species-group. Point estimate as a circle with ±1.96 x SE shown as a line. Note all values within a species-group are relative to the CEXP survey.

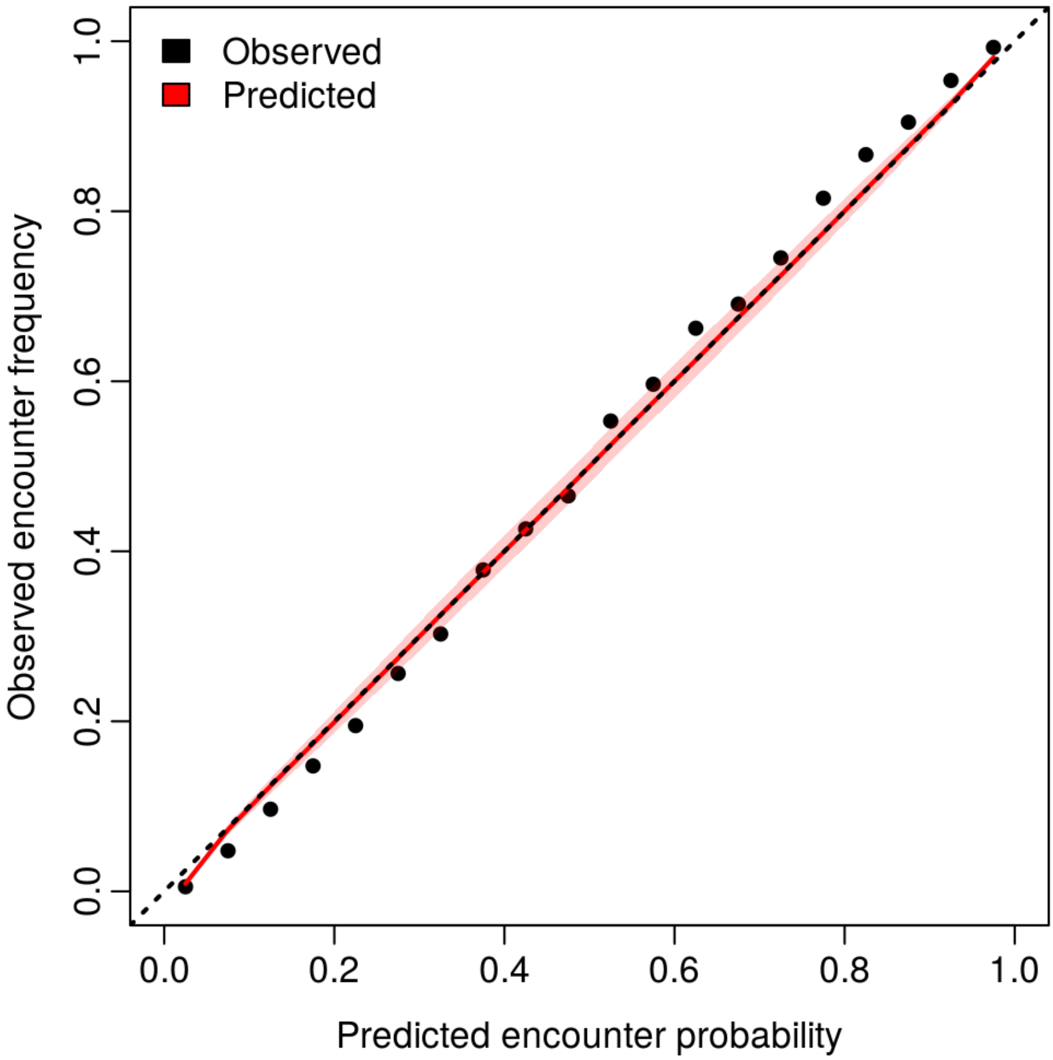


Figure S12: Model diagnostics output showing correlation between the predicted encounter probability and the data.

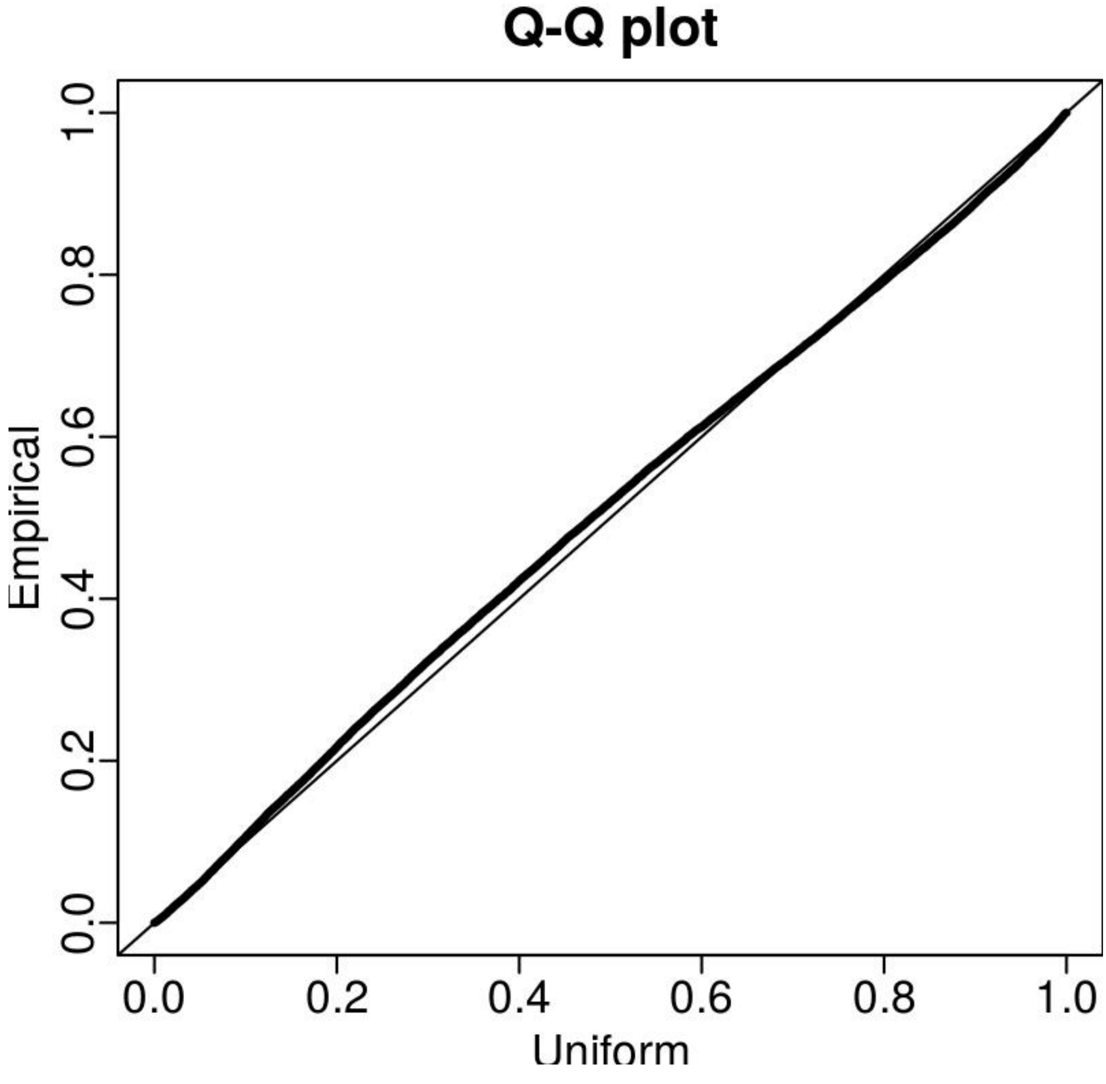


Figure S13: Model diagnostics output showing the Q-Q plot for the positive catch rates.

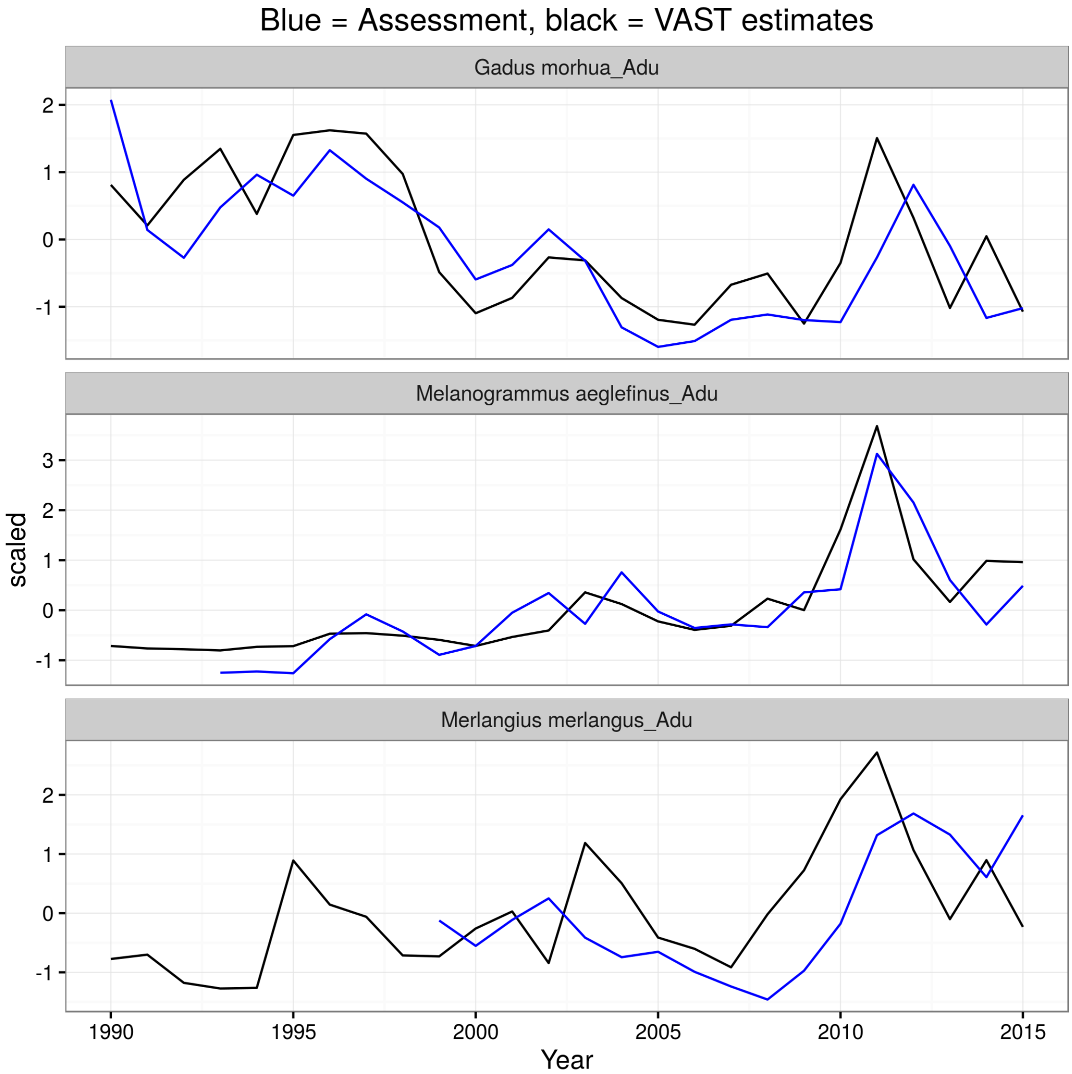


Figure S14: Comparison between the standardised index from the VAST output and the standardised spawning stock biomass (SSB) from the assessments for cod, haddock and whiting.

Table S2: List of species codes, names and minimum conservation reference size used to separate juvenile and adult fish.

Species code	Common name	Species	MCRS (cm)
juv	Juvenile		
adu	Adult		
bud	Black bellied anglerfish	*Lophius budgessa*	32*
cod	Atlantic cod	*Gadus morhua*	35
had	Atlatic haddock	*Melanogrammus aeglefinus*	30
hke	Atlantic hake	*Merluccius merluccius*	27
meg	Megrim	*Lepidorhombus whiffiagonis*	20
pisc	White bellied anglerfish	*Lophius piscatorius*	32*
ple	European Plaice	*Pleuronectes platessa*	27
sol	Common sole	*Solea solea*	24
whg	Atlantic whiting	*Merlangius merlangus*	27

*Anglerfish species estimated based on a 500g minimum marketing weight

Table S3: Description of model variants and AIC / BIC.

Model	Description	No fixed parameters	No random parameters	AIC	BIC
H0	Vessel random effects, no covariates	1462	129276	125954	140187
H1	With fixed gear effect, no density covariates	1674	129276	116012	132309
H2	With fixed gear effect, substrate and depth density covariates	1688	129276	116013	132446

Appendix D

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Highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

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ABSTRACT

To understand how data resolution impacts inference on mixed fisheries interactions we developed a highly resolved spatiotemporal discrete-event simulation model *MixFishSim* incorporating: i) delay-difference population dynamics, ii) population movement using Gaussian Random Fields to simulate patchy, heterogeneously distributed and moving fish populations, and iii) fishery dynamics for multiple fleet characteristics based on population targeting under an explore-exploit strategy. We applied *MixFishSim* to infer community structure when using data generated from: commercial catch, a fixed-site sampling survey design and the true (simulated) underlying populations. In doing so we thereby establish the potential limitations of fishery-dependent data in providing a robust characterisation of spatiotemporal distributions. Different spatial patterns were evident and the effectiveness of a simulated spatial closure was reduced when data were aggregated across larger spatial areas. The simulated area closure showed that aggregation across time periods has less of a negative impact on the closure success than aggregation over space. While not as effective as when based on the true population, closures based on high catch rates observed in commercial data were still able to reduce fishing on a protected species. Our framework allows users to explore the assumptions in modelling observational data and evaluate the underlying dynamics of such approaches at fine spatial and temporal resolutions. From our application we conclude that commercial data, while containing bias, provides a useful tool for managing catches in mixed fisheries if applied at the correct spatiotemporal scale.

1. Introduction

Fishers exploit a variety of fish populations that are heterogeneously distributed in space and time. Fishers generally only have partial knowledge of species distributions and so limited control over what species they select when fishing in ‘mixed fisheries’. This results in catches of vulnerable species and species with low-quota. These species may be thrown overboard in a process called discarding and discarding catches that are not recorded leads to biased perception of the effects of fisheries on ecosystems. Ultimately the unaccounted discards limit our ability to control fishing mortality (Alverson et al., 1994; Crowder et al., 1998; Rijnsdorp et al., 2007) and the ability to manage biological and economic sustainability of fisheries (Batsleer et al., 2015; Ulrich et al., 2011).

There is increasing interest in technical solutions such as gear adaptations and spatial closures as measures to reduce discarding of unwanted catches (Bellido et al., 2011; Catchpole and Revill, 2008; Cosgrove et al., 2019; Kennelly and Broadhurst, 2002). Adaptive spatial management strategies have been proposed as a way of reducing over-quota discards (Dunn et al., 2014; Holmes et al., 2011; Little et al., 2015). However, to reduce unwanted catch through spatial measures requires an in-depth understanding of the spatiotemporal dynamics of the fishery.

Effective spatial management requires implementation at appropriate spatial scales. These spatial scales shape the trade-offs between protection of populations and economic impacts on fisheries (Dunn et al., 2016). In mixed fisheries, the problem is to identify a scale that promotes species avoidance for vulnerable or low-quota species while allowing continuance of sustainable fisheries for available quota species. Identifying the appropriate spatial scale remains challenging

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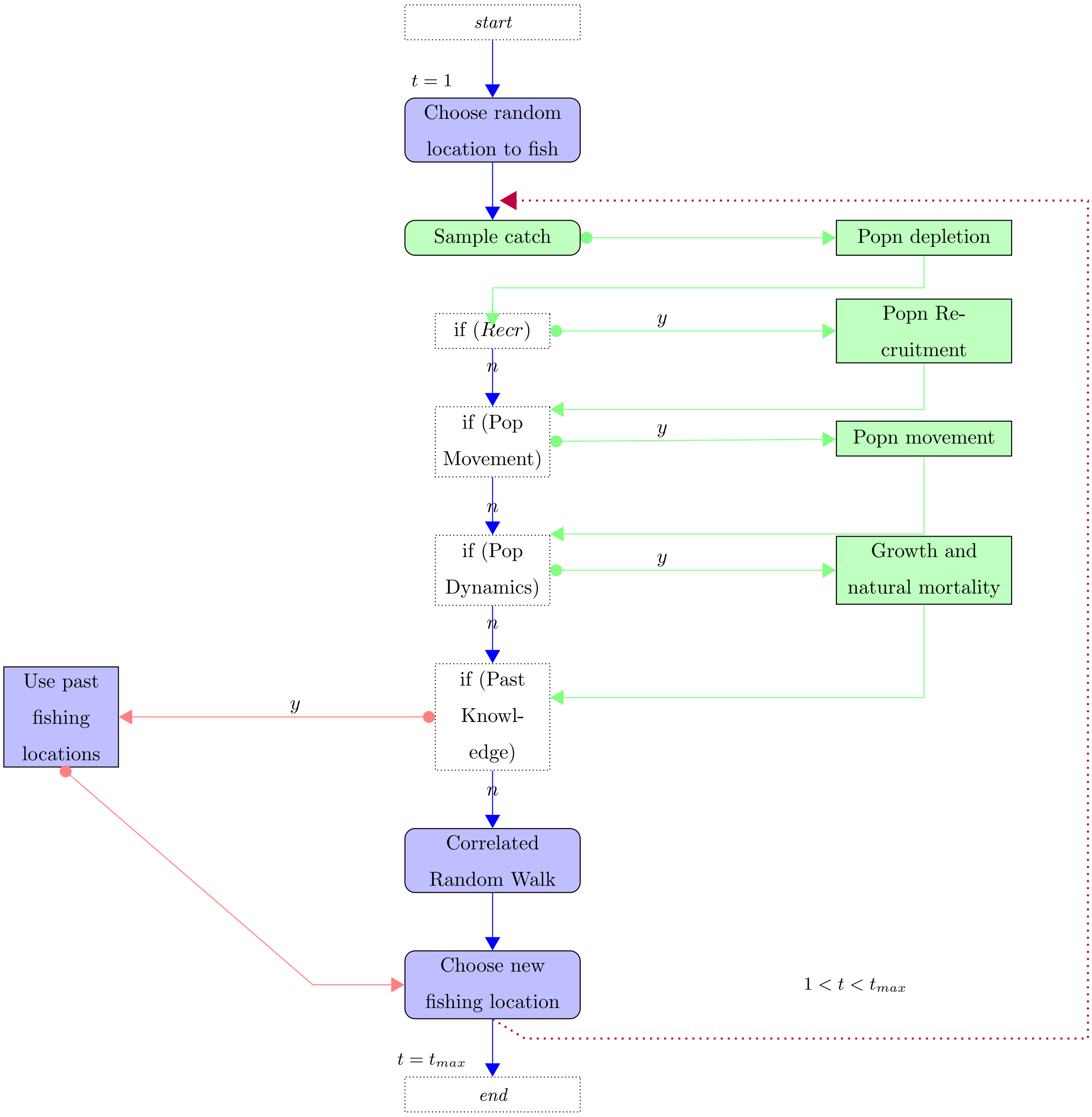

Fig. 1. Schematic overview of the simulation model. Blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the time steps at which processes occur; t = tow, *tmax* is the total number of tows; (Recr), (Pop Movement), (Pop Dynamics) logic gates for recruitment periods, population movement and population dynamics for each of the populations, (Past Knowledge) a switch whether to use a random (exploratory) or past knowledge (exploitation) fishing strategy.

because collecting data on fish distribution at high temporal and spatial resolutions is expensive and difficult. Proxies for the spatial distributions are usually inferred from fisheries-dependent data or from fisheries-independent data. Fisheries-dependent data includes all data on catch and effort from commercial fishing operations while fisheries-independent data includes data collected on board scientific research vessels.

Inferences on fish distributions are hampered where spatial and temporal information is coarse. Sampling designs for scientific research vessel surveys generally aim for unbiased estimates of local abundance. However, high costs of these surveys generally results in restrictions in terms the number of samples. As a result, sampling is usually restricted to a few weeks a year, and sampling stations are usually coarsely spaced. Moreover, the gear chosen for the survey determines the selectivity for certain species and size classes within fish communities. This selectivity determines the usefulness of relative occurrence in survey catches as proxies for abundances in the fish communities.

Proxies for spatial distribution derived from commercial fisheries in theory allow for much larger sample sizes. These commercial fisheries are often at sea throughout the year, making may fishing hauls. However, spatial information from fisheries is often limited because data on catch and effort is collected or aggregated across larger gridded areas (Branch et al., 2005). If spatially aggregated data does not allow identification of spatial features it may lead to poorly designed spatial management measures that are ineffectual or have unintended consequences (Costello et al., 2010; Dunn et al., 2016). For example, increased benthic impact on previously unexploited areas from the cod closure in the North Sea were observed without the intended effect of reducing cod exploitation (Dinmore et al., 2003; Rijnsdorp et al., 2001).

Even where high-resolution spatiotemporal information is available (see e.g. Bastardie et al., 2010; Gerritsen et al., 2012; Lee et al., 2010; Mateo et al., 2017) commercial catch per unit of effort may still be biased because of fisheries dynamics. Fishers establish favoured fishing grounds through an explore-exploit strategy (Bailey et al., 2019; Rijnsdorp et al., 2011) where they search for areas with high catches and then use experience to return to areas where they have experienced high catch in the past. This leads to inherently biased sampling where target species are over-represented in the catch because fishers exploit areas of high abundance. For effective adaptive spatial management the effects of spatiotemporal aggregation in data and fishery targeting need to be understood.

To understand the effect of spatiotemporal aggregation of data and fishery targeting on our perception of spatial abundance of different fish populations we ask two fundamental questions regarding inference derived from observational data:

1. Do different sources of sampling-derived fisheries data reflect the underlying community structure?
2. How do data aggregation and data source impact on the success of spatial fisheries management measures?

To answer these questions we i) develop a simulation model where population dynamics are highly-resolved in space and time, using a Gaussian spatial process to define suitable habitat for different populations. As the precise locations of the fish are known directly rather than inferred from sampling or commercial catch, we can use the population model to validate how inference from fisheries-dependent and fisheries-independent sampling relates to the real community structure in a way we could not with real data. We ii) compare, at different spatial and temporal aggregations, the real (simulated) population distributions to samples from fisheries-dependent and fisheries-independent catches to test if these are a true reflection of the relative density of the populations. We then iii) simulate a fishery closure to protect a species based on different spatial and temporal data aggregations.

We use these evaluations to draw inference on the utility of commercial data in supporting management decisions.

2. Materials and Methods

A discrete-event simulation (DES) model of a hypothetical fishery was developed as a software package (*MixFishSim*). The modular approach enabled efficient computation by allowing for sub-modules implemented on time-scales appropriate to capture the characteristics of the different processes (Fig. 1). Sub-modules to capture the full system comprised: 1) population dynamics, 2) recruitment dynamics, 3) population movement, 4) fishery dynamics.

Population dynamics for any number of species, as chosen by the user, operate on a daily time-step (with recruitment occurring only during defined seasons for each population), while population movement occurs on a weekly time-step, with the fishing module operating on a tow-by-tow basis (i.e., multiple events a day).

2.1. Population dynamics

The basic population level processes were simulated using a modified two-stage Deriso–Schnute delay difference model that models the fish populations in terms of aggregate biomass of recruits and mature components rather than keeping track of individuals (Deriso, 1980; Dichmont et al., 2003; Schnute, 1985). A daily time-step was chosen to discretise continuous population processes on a biologically relevant and computationally tractable timescale. Population biomass growth was modelled as a function of previous recruited biomass, intrinsic population growth and recruitment functionally linked to the adult population size. Biomass for each cell c was incremented each day d as follows (see Table 1 for all parameter details):

$$B_{c,d+1} = (1+\rho)B_{c,d}\cdot e^{-Z_{c,d}} - \rho\cdot e^{-Z_{c,d}} \times \left(B_{c,d-1}\cdot e^{-Z_{c,d-1}} + W_{R-1}\cdot\left(\alpha_{d-1}\cdot R_{\tilde{y}(c)}\right)\right) + W_R\cdot\left(\alpha_d\cdot R_{\tilde{y}(c)}\right) \quad (1)$$

Table 1
Description of variables for population and recruitment dynamics sub-modules.

Variable	Meaning	Units
	Population dynamics	
Delay-difference model		
$B_{c,d}$	Biomass in cell c and day d	kg
$Z_{c,d}$	Rate of total mortality in cell c for day d	d^{-1}
$R_{c,\tilde{y}}$	Annualy recruited fish in cell	yr^{-1}
ρ	Ford's growth coefficient	yr^{-1}
Wt_R	Weight of a fully recruited fish	kg
Wt_{R-1}	Weight of a pre-recruit fish	kg
α_d	Proportion of annually recruited fish recruited during day d	-
Baranov catch equation		
$C_{c,d}$	Catch from cell c for day d	kg
$F_{c,d}$	Rate of fishing mortality in cell c on day d	d^{-1}
$M_{c,d}$	Rate of natural mortality in cell c on day d	d^{-1}
$B_{c,d}$	Biomass in cell c on day d	kg
	Recruitment dynamics	
$\tilde{R}_{c,d}$	is the number of fish recruited in cell c for day d	d^{-1}
α	the maximum recruitment rate (Beverton Holt) or maximum productivity per spawner (Ricker)	number fish
β	the stock size required to produce half the maximum rate of recruitment (Beverton Holt) or density dependent reduction in productivity per capita of SSB	number fish

where ρ is Ford's growth coefficient shown to be equal to e^{-K} when K is the Brody growth coefficient, the rate at which the asymptote is approached from a von Bertalanffy growth model (Schnute, 1985). W_{R-1} is the average weight of fish prior to recruitment, while W_R is the average recruited weight. α_d represents the proportion of fish recruited during that day for the year, while $R_{c,\tilde{y}(c)}$ is the annual recruits in year y for cell c.

Mortality $Z_{c,d}$ can be decomposed to natural mortality, $M_{c,d}$, and fishing mortality, $F_{c,d}$, where both $M_{c,d}$ and $F_{c,d}$ are instantaneous rates with $M_{c,d}$ fixed and $F_{c,d}$ calculated by solving the Baranov catch equation (Hilborn and Walters, 1992) for $F_{c,d}$:

$$C_{c,d} = \frac{F_{c,d}}{F_{c,d} + M_{c,d}}\cdot\left(1 - e^{-(F_{c,d}+M_{c,d})}\right)\cdot B_{c,d} \quad (2)$$

where $C_{c,d}$ is the summed catch from the fishing model across all fleets and vessels in cell c for the population during the day d, and $B_{c,d}$ the daily biomass for the population in the cell. Here, catch is the sum of those across all fleets and vessels, $C_{c,d} = \sum_{fl=1}^{FL}\sum_{v=1}^{V_{fl}} E_{fl,v,c,d}\cdot Q_{fl}\cdot D_{c,d}$ with fl and FL the fleet and total number of fleets, v and V_{fl} the vessel and total number of vessels per fleet respectively and $E_{fl,\,v,\,c,\,d}$ and Q_{fl} fishing effort and catchability of the gear, and $D_{c,d}$ is the density of the population at the location fished.

2.2. Recruitment dynamics

Recruitment is modelled as a function of adult biomass. In *MixFishSim*, it can either take the form of a stochastic Beverton–Holt stock recruitment relationship, or a stochastic Ricker stock recruitment relationship. The Beverton–Holt relationship is defined as(Beverton and Holt, 1957):

$$\bar{R}_{c,d} = \frac{(\alpha S_{c,d})}{(\beta + S_{c,d})}$$
$$\ln(R_{c,d}) \sim N\left[(\ln(\bar{R}_{c,d}), \sigma^2)\right] \quad (3)$$

where α is the maximum recruitment rate, β the spawning stock biomass (SSB) required to produce half the maximum stock size, S current spawning stock size and σ^2 the variability in the recruitment due to stochastic processes. The stochastic Ricker form (Ricker, 1954) is:

$$\overline{R}_{c,d} = S_{c,d}\cdot e^{(\alpha-\beta\cdot S_{c,d})}$$
$$\ln(R_{c,d}) \sim N\left[(\ln(\overline{R}_{c,d}), \sigma^2)\right] \quad (4)$$

where α is the maximum productivity per spawner and β the density-dependent reduction in productivity as the SSB increases.

2.3. Population movement dynamics

Population movement is a combination of directed (advective) movement where at certain times of year the population moves towards spawning grounds by increasing the probabilities of moving into the spawning grounds from adjacent cells, and random (diffusive) movement, governed by a stochastic process where movement between adjacent cells is described by a set of probabilities. Stochastic probabilities are affected by the suitability of habitat, temperature in a cell and the thermal tolerance of a population to that temperature.

The combined process results in a population structure and movement pattern unique to each population, with population movement occurring on a weekly basis. Modelling population movement on a weekly timescale reflects that fish tend to aggregate in species-specific locations that have been observed to last between one and two weeks (Poos and Rijnsdorp, 2007b). Therefore this process approximated the demographic shifts in fish populations throughout a year with seasonal spawning patterns (Figure S1).

To simulate fish population distribution in space and time a Gaussian spatial process was employed to model habitat suitability for each of the populations on a 2d grid. We first defined a Gaussian random field process, $\{S(c): c \in \mathbb{R}^2\}$, where for any set of cells $c_1, \cdots, c_n$, the joint distribution of $S = \{S(c_1), \cdots S(c_n)\}$ is multivariate Gaussian with a *Matérn* covariance structure, where the correlation strength weakens with distance controlled by two parameters, with ν a scale parameter in the units of distance and κ a shape parameter which determines the smoothness of the process. We use the most commonly used Matérn covariance structure as it is a flexible form that contains the exponential and double exponential as special cases and it enables us to model the spatial autocorrelation observed in animal populations where density is more similar in nearby locations (F. Dormann et al., 2007; Poos and Rijnsdorp, 2007b; Tobler, 1970).

We change the parameters to implement different spatial structures for the different populations using the *RandomFields* R package (Schlather et al., 2015). We define a stationary habitat field with an anisotropic pattern (to simulate a depth gradient) and combine it with a temporally dynamic thermal tolerance field to imitate two key drivers of population dynamics without modelling the processes explicitly. Each population was initialised at a single location, and subsequently moved across the entire space according to a probabilistic distribution based on habitat suitability (represented by the normalised values from the GRFs), temperature tolerance and distance from current cell:

$$Pr(C_{wk+1} = J | C_{wk} = I) = \frac{e^{-\lambda \cdot d_{I,J}} \cdot (Hab_{J,p}^2 \cdot Tol_{J,p,wk})}{\sum_{c=1}^{C} e^{-\lambda \cdot d} \cdot (Hab_{c,p}^2 \cdot Tol_{c,p,wk})} \tag{5}$$

Where $d_{I,J}$ is the euclidean distance between cell I and cell J, λ is a given rate of decay, $Hab_{c,p}$ is the index of habitat suitability for cell c and population p, with $Tol_{c,\ p,\ wk}$ the temperature tolerance for cell c by population p in week wk (see below).

During pre-defined weeks of the year the habitat suitability is modified with user-defined spawning habitat locations, resulting in each population having concentrated areas where spawning takes place. The populations then move towards these cells in the weeks prior to spawning, resulting in directional movement towards the spawning grounds.

A time-varying temperature covariate changes the interaction between time and suitable habitat on a weekly time-step. Each population p was assigned a thermal tolerance with mean, μ_p and standard deviation, σ_p so that each cell and population temperature tolerance is defined as:

Table 2
Description of variables for population movement sub-module.

Variable	Meaning	Units
Thermal tolerance		
$T_{c,\ wk}$	Temperature for cell c in week wk	°C
μ_p	Mean of the thermal tolerance for population p	°C
σ_p	Standard deviation of thermal tolerance for population p	°C
Population movement model		
λ	Decay rate for population movement	-
$Hab_{c,p}$	Habitat suitability for cell c and population p	-
$Tol_{c,\ wk,\ p}$	Thermal tolerance for in cell c at week wk for population p	-
$d_{I,J}$	Euclidean distance between cell I and cell J	-

$$Tol_{c,p,wk} = \frac{1}{\sqrt{2\pi\sigma_p^2}} \exp\left(-\frac{(T_{c,wk} - \mu_p)^2}{2\sigma_p^2}\right) \tag{6}$$

Where $Tol_{c,\ p,\ wk}$ is the tolerance of population p for cell c in week wk, $T_{c,\ wk}$ is the temperature in the cell given the week and μ_p and σ_p the mean and standard deviation of the population temperature tolerance (see Table 2 for variable descriptions).

2.4. Fleet dynamics

Fleet dynamics were broadly categorised into three components. *Fleet targeting* determined the fleet catch efficiency and preference towards a particular population; *trip-level decisions* determined the initial location to be fished at the beginning of a trip; and *within-trip decisions* determined fishing locations within a trip. This results in an explore-exploit strategy for individual vessels to maximise their catch from an unknown resource distribution (Bailey et al., 2019). The decision to use an individual based model for fishing vessels was taken because fishers are heterogeneous in their location choice behaviour due to different objectives, risk preference and targeting preference (Boonstra and Hentati-Sundberg, 2016; Van Putten et al., 2012). Therefore fleet dynamics are emergent from individual dynamics rather than pre-defined group dynamics.

2.4.1. Fleet targeting

Each fleet of n_{fl} vessels was characterised by both a general efficiency, Q_{fl}, and a population specific efficiency, $Q_{fl,p}$ which are each bound by [0,1]. The product of these parameters $[Q_{fl} \cdot Q_{fl,p}]$ affects the overall catch rates for the fleet and the preferential targeting of one species over another. This, in combination with the parameter choice for the step-function defined below (as well as some randomness from the exploratory fishing process) determined the preference of fishing locations for the fleet.

2.4.2. Decision about where to fish at the start of a trip

Several studies (for a review see Girardin et al., 2017) have confirmed past activity and past catch rates are strong predictors of fishing location choice. For this reason, the fleet dynamics sub-model included a learning component, where a vessel's initial fishing location in a trip was based on selecting from previously successful fishing locations. This was achieved by calculating an expected revenue based on the catches from locations fished in the preceding trip as well as the same month periods in previous years and the travel costs from the port to the fishing grounds. Then a vessel chooses randomly from the top 70 % of fishing events (defined as the 'threshold') in terms of expected profit within that season.

2.4.3. Decision about where to fish within a trip

Fishing locations within a trip are initially determined by a modified random walk process. As the simulation progresses the within-trip decision become gradually more influenced by experience gained from past fishing locations (as per the initial trip-level location choice), moving location choice towards areas of higher perceived profit. A random walk was chosen for the exploratory fishing process as it is the simplest assumption commonly used in ecology to describe optimal animal search strategy for exploiting heterogeneously distributed prey about which there is uncertain knowledge (Viswanathan et al., 1999). In a random walk, movement is a stochastic process through a series of steps. These steps have a length, and a direction that can either be equal in length or take some other functional form. The direction of the random walk was also correlated (known as 'persistence') providing some overall directional movement (Codling et al., 2008).

For our implementation of a random walk directional change is based on a negatively correlated circular distribution where a favourable fishing ground is likely to be "fished back over" by the vessel returning in the direction it came from. The step length (i.e. the distance travelled from the current to the next fishing location) is determined by relating recent fishing success, measured as the summed value of fish caught (revenue, *Rev*);

$$Rev_{c,d} = \sum_{p=1}^{P} L_{c,d,p} \cdot Pr_p \tag{7}$$

where $L_{c,d,p}$ is landings of a population p, and Pr_p price of a population. All population prices were kept the same across fleets and seasons. Here, when fishing is successful vessels remain in a similar location and continue to exploit the local fishing grounds. When unsuccessful, they move some distance away from the current fishing location. The movement distance retains some degree of stochasticity, that can be controlled separately, but is determined by the relationship:

$$Le = e^{\ln(\beta_1)+\ln(\beta_2)-\left(\ln\left(\frac{\beta_1}{\beta_3}\right)\right)\cdot Rev} \tag{8}$$

where Le is the step length, β_1, β_2 and β_3 are parameters determining the shape of the step function in its relation to revenue, so that, a step from (x_t, y_t) to (x_{t+1}, y_{t+1}) is defined by:

$$\begin{aligned}(x_{t+1}, y_{t+1}) = \; & x_t + Le \cdot \cos\left(\frac{\pi \cdot Br_{t+1}}{180}\right), \\ & y_t + Le \cdot \sin\left(\frac{\pi \cdot Br_{t+1}}{180}\right) \\ \textit{when} \quad & Br_t < 180,\ Br_{t+1} = 180 + \sim vm[(0, 360), k] \\ & Br_t > 180,\ Br_{t+1} = 180 - \sim vm[(0, 360), k]\end{aligned} \tag{9}$$

where Br_t is the bearing at time *t*, k the concentration parameter from the von Mises distribution that we correlate with the revenue so that $k = (Rev + 1/RefRev) \cdot max_k$, where max_k is the maximum concentration value, k, and $RefRev$ is parametrised as for β_3 in the step length function. Details of the variables, meaning and units for fleet dynamics are provided in Table 3.

2.4.4. Local population depletion

Where several fishing vessels exploit the same fish population competition is known to play an important role in local distribution of fishing effort (Gillis and Peterman, 1998). If several vessels are fishing on the same patch of fish, local depletion and interference competition will affect fishing location choice of the fleet as a whole (Poos and Rijnsdorp, 2007a; Rijnsdorp, 2000). To account for this behaviour, the fishing sub-model operates spatially on a daily time-step so that for future days the biomass available to the fishery is reduced in the areas fished. The cumulative effect is to make heavily fished areas less attractive as a future fishing location choice as reduced catch rates will be experienced.

Table 3
Description of variables for fleet dynamics sub-module.

Variable	Meaning	Units
Rev	Revenue from fishing tow	€
RefRev	Reference revenue for determining the step function	€
L_p	Landings of population *p*	kg
Pr_p	Average price of population *p*	€.kg^{-1}
Le	Step length for vessel	-
Br	Bearing	degrees
k	Concentration parameter for von mises distribution	-
β_1	shape parameter for step function	-
β_2	shape parameter for step function	-
β_3	shape parameter for step function	-

2.5. Fisheries-independent survey

A fisheries-independent survey is simulated where fishing on a regular grid begins each year at the same time for a given number of stations (a fixed station survey design). Catches of the populations at each station are recorded but not removed from the population (catches are assumed to have negligible impact on population dynamics). This provides a fishery independent snapshot of the populations at a regular spatial intervals each year, similar to scientific surveys undertaken by fisheries research agencies.

2.6. Software: R-package development

The simulation framework is implemented in the statistical software package R (R Core Team, 2017) and available as an R package from the author's github site (www.github.com/pdolder/MixFishSim).

3. Model calibration

We calibrate *MixFishSim* to investigate the influence of data aggregation on spatial inference.

3.1. Population models

We calibrated the simulation model for four example populations with different demographics, growth rates, natural mortality and recruitment (Table 4). Habitat preference (Figure S7) and (temperature (Figures S9, with temperature tolerance S10) defined to be unique to each population resulting in differently weekly distribution patterns (Figures S1-S3). In addition, each of the populations was assumed to have two defined spawning areas that result in the populations moving towards these areas in pre-defined weeks (Figure S8) with population-specific movement rates (Table 4). The population demographics were chosen to broadly represent three mobile low-medium value groundfish species and one high value species with low mobility, with the dynamics hypothetical but might be expected in a typical demersal fishery.

3.2. Fleet calibration

Fleets were calibrated to reflect five different characteristic fisheries with unique exploitation dynamics (Table 5). By setting different catchability coefficients ($Q_{fl,p}$) we create different targeting preferences between the fleets and hence different spatial dynamics. The learned random walk process implies that within a fleet different vessels have different spatial distributions based on individual experience. The step function was calibrated dynamically within the simulations as the maximum revenue obtainable was not known beforehand. This was implemented so that vessels take smaller steps when fishing at a location that yields landings value in the top 90th percentile of the value experienced in that year so far (as defined per fleet in Table 5).

Fishing locations were chosen based on random search and, with increasing proportion as time progressed, experience of profitable catches built up in the same month from previous years and from the previous trip. 'Profitable' in this context was defined as the locations where the top 70 % of expected profit would be found given revenue from previous trips and cost of movement to the new fishing location. This probability was based on a logistic sigmoid function with a lower

Table 4
Population dynamics and movement parameter settings.

Parameter Habitat quality	Pop 1	Pop 2	Pop 3	Pop 4
Matérn ν	1/0.015	1/0.05	1/0.01	1/0.005
Matérn κ	1	2	1	1
Anisotropy	1.5,3,-3,4	1,2,-1,2	2.5,1,-1,2	0.1,2,-1,0.2
Spawning areas (bound box)	40,50,40,50; 80,90,60,70	50,60,30,40; 80,90,90,90	30,34,10,20; 60,70,20,30	50,55,80,85; 30,40,30,40
Spawning multiplier = 10				
Movement λ = 0.1				
Population dynamics				
Starting Biomass	1e5	2e5	1e5	1e4
Beverton-Holt Recruit α	6	27	18	0.3
Beverton-Holt Recruit β	4	4	11	0.5
Beverton-Holt Recruit σ^2	0.7	0.6	0.7	0.6
Recruit week	13-16	12-16	14-16	16-20
Spawn week	16-18	16-19	16-18	18-20
K = 0.3				
wt = 1				
wt_{d-1} = 0.1				
M (annual)	0.2	0.1	0.2	0.1
Movement dynamics				
μ_p	12	15	17	14
σ_p^2	8	9	7	10

Table 5
Fleet dynamics parameter setting.

Parameter Targeting preferences	Fleet 1 pop 2/4	Fleet 2 pop 1/3	Fleet 3 -	Fleet 4 pop 4	Fleet 5 pop 2/3
Price Pr_p1 = 100					
Price Pr_p2 = 200					
Price Pr_p3 = 350					
Price Pr_p4 = 600					
Q_p	0.01	0.02	0.02	0.01	0.01
Q_p	0.02	0.01	0.02	0.01	0.03
Q_p	0.01	0.02	0.02	0.01	0.02
Q_p	0.02	0.01	0.02	0.05	0.01
Exploitation dynamics					
β_1	1	2	1	2	3
β_2	10	15	8	12	7
β_3, the landings value *nth* quantile	90	90	85	90	80
step function *rate*	20	30	25	35	20
Past Knowledge = TRUE					
Threshold	0.7	0.7	0.7	0.7	0.7
Fuel Cost	3	2	5	2	1

asymptote of 0 and upper asymptote of 0.95, and a slope that ensures the upper asymptote (where decisions are mainly based on past knowledge) is reached approximately halfway through the simulation.

3.3. Survey settings

The survey simulation was set up with a fixed gridded station design with 100 stations fished each year, starting on day 92 and ending on day 112 (5 stations per day) with same catchability parameter (Q_p = 1) for all populations. This approximates a real world survey design with limited seasonal and spatial coverage.

3.4. Example research question

To illustrate the capabilities of *MixFishSim*, we investigate the influence of the temporal and spatial resolution of different data sources on the reduction in catches of a population given spatial closures. To do so, we set up a simulation to run for 50 years based on a 100 × 100 square grid (undetermined units), with five fleets of 20 vessels each and four fish populations. Fishing takes place four times a day per vessel and five days a week, while population movement is every week.

How does sampling-derived fisheries data reflect the underlying population structure?

To answer this question we compare different spatial and temporal aggregations of the true population distributions to:

a) **Fisheries-independent data:** The inferred population density from a fixed-site sampling survey design as commonly used for fisheries monitoring purposes;
b) **Fisheries-dependent data:** The inferred population density from our fleet model that includes fishery-induced sampling dynamics.

We allow the simulation to run unrestricted for 30 years, then implement spatial closed areas for the last 20 years of the simulation based on data (either derived from the commercial catches, fisheries-independent survey or the true population) used at different spatial and temporal scales.

The following steps are undertaken to determine closures:

1. Extract data source (true population, commercial or survey),
2. Aggregate according to desired spatial and temporal resolution,
3. Interpolate across entire area at desired resolution using simple bivariate interpolation using the *interp* function from the R package akima (Akima and Gebhardt, 2016). This is intended to represent a naive spatial model of catch rates, without knowledge of the spatial population dynamics.
4. Close area covering top 5 % of catch rates.

In total 28 closure scenarios were run that represent combinations of:

- **Data types:** Commercial logbook data, survey data and true population,
- **Temporal resolutions:** Weekly, monthly and yearly closures,
- **Spatial resolutions:** 1 x 1 grid, 5 x 5 grid, 10 x 10 grid and 20 x 20 grid,

We implemented a series of spatial closures targeted at reducing fishing mortality on population 3, given the different data sources and spatial and temporal resolutions above. We use the effectiveness of these closures in reducing fishing mortality as a way of evaluating the trade-offs in data sources and resolution. Survey closures were on an annual basis only, as this was the most temporally resolved survey data available. We evaluated the factors contributing to the success of the

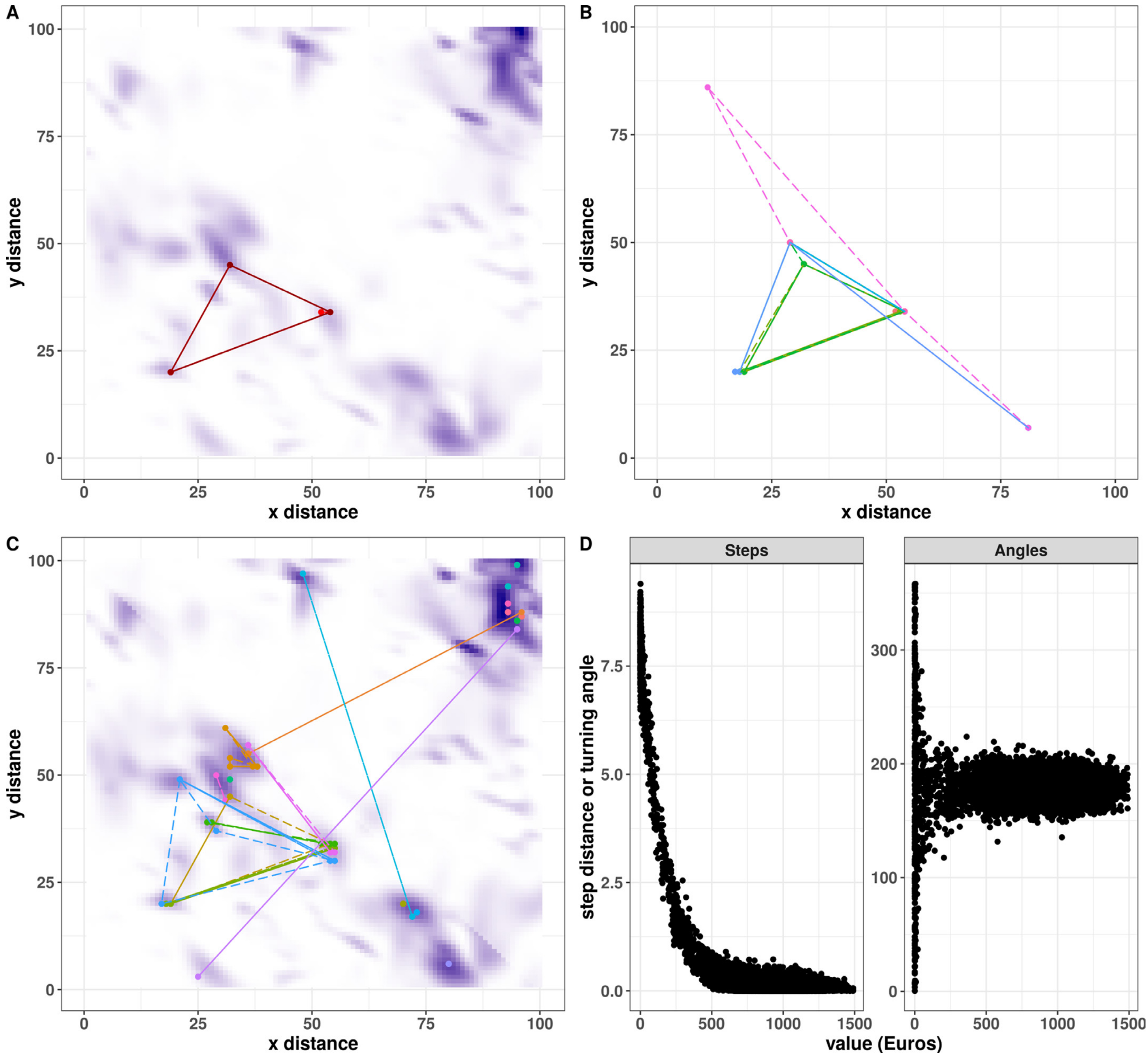

Fig. 2. (A) The fishing locations (points) and movements (lines) of a single vessel during a trip overlaid on the revenue of a fishing site (landings x price; darker purple = higher revenue); (B) the fishing locations of the vessel over several trips (value field changes over the period so not shown). Note that movements are a mixture of correlated random walk (solid lines) and experience-based (dashed lines), and that the field is wrapped on a torus so that opposite sides of the spatial domain are considered spatially close; (C) the locations of multiple vessels from the same fleet overlaid on the value field, (D) the realised step distance and turning angles for a single vessel over the simulation.

closures through a regression tree (using the R package REEMtree (Sela and Simonoff, 2011)) to identify the factor most contributing to differences in fishing mortality before and after the closure.

4. Results

4.1. Emergent simulation dynamics

Individual habitat preferences and thermal tolerances result in different spatial habitat use for each population (Figure S5) and consequently different seasonal exploitation patterns (Figure S6).

It can be seen from a single vessels movements during a trip that the vessel exploits three different fishing grounds, each of them multiple times (Fig. 2A), while across several trips fishing grounds that are further apart are fished (Fig. 2B). These different locations relate to areas where the highest revenue were experienced, as shown by Fig. 2C, where several vessels tracks are overlaid on the revenue field.

Vessels from the same fleet (and therefore targeting preference) may exploit some shared and some different fishing grounds depending on their own personal experience during the exploratory phase of the fishery (Fig. 2C). This results from the randomness in the correlated random walk step function, with distance moved during the exploitation phase and the direction stochastically related to the revenue experienced on the fishing ground (Fig. 2D).

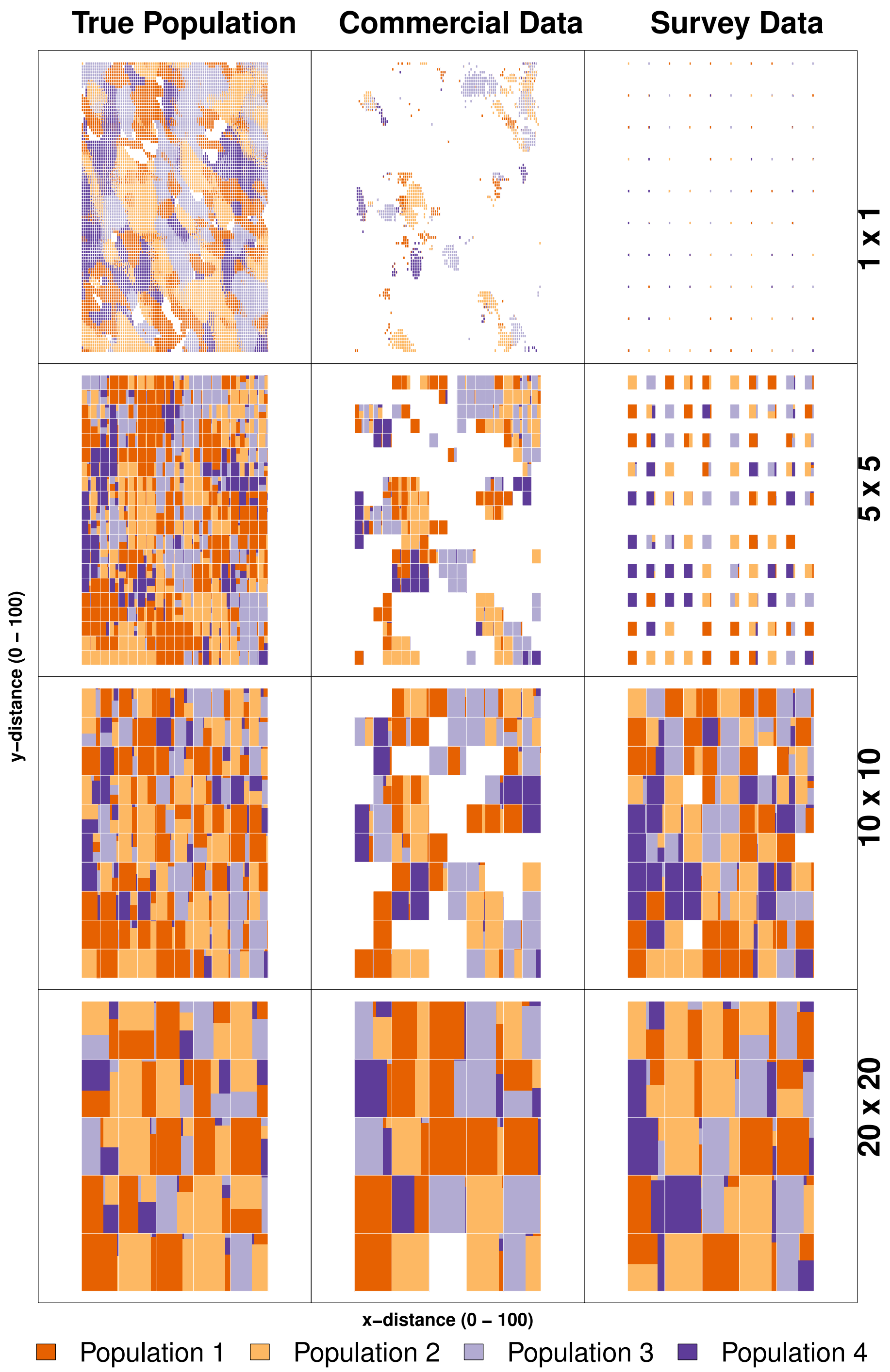

Fig. 3. Data aggregation at different spatial resolutions over a ten year period. The figure shows catch composition at each spatial unit represented by a square pie chart of the four populations. The area of each colour is proportional to the weight of each population caught in that unit. Figure produced using the R package 'mapplots' (Gerritsen (2014)).

4.2. How does sampling-derived fisheries data reflect the underlying population structure?

Catch composition aggregated at different spatial resolutions from each of the data sources (average seasonal patterns over a ten-year period) highlights different patterns in perceived community structure depending on the data source and aggregation level (Fig. 3). The finer spatial grid for the true population (top left) and commercial data (top middle) show visually similar patterns, though there are large unsampled areas in the commercial data from a lack of fishing activity (particularly in the lower left part of the sampling domain). Survey data at this spatial resolution displays very sparse information about the spatial distributions of the populations. The slightly aggregated data on a 5 x 5 grid shows similar patterns and, while losing some of the spatial detail, there remains good consistency between the true population and the commercial data. Survey data starts to pick out some of the similar patterns as the other data sources, but lacks spatiotemporal coverage. The spatial catch information on a 10 x 10 and 20 x 20 grid lose a significant amount of information about the spatial resolutions for all data sources, and some differences between the survey, commercial and true population data emerge.

Different perceptions of the proportion of each stock in an area are

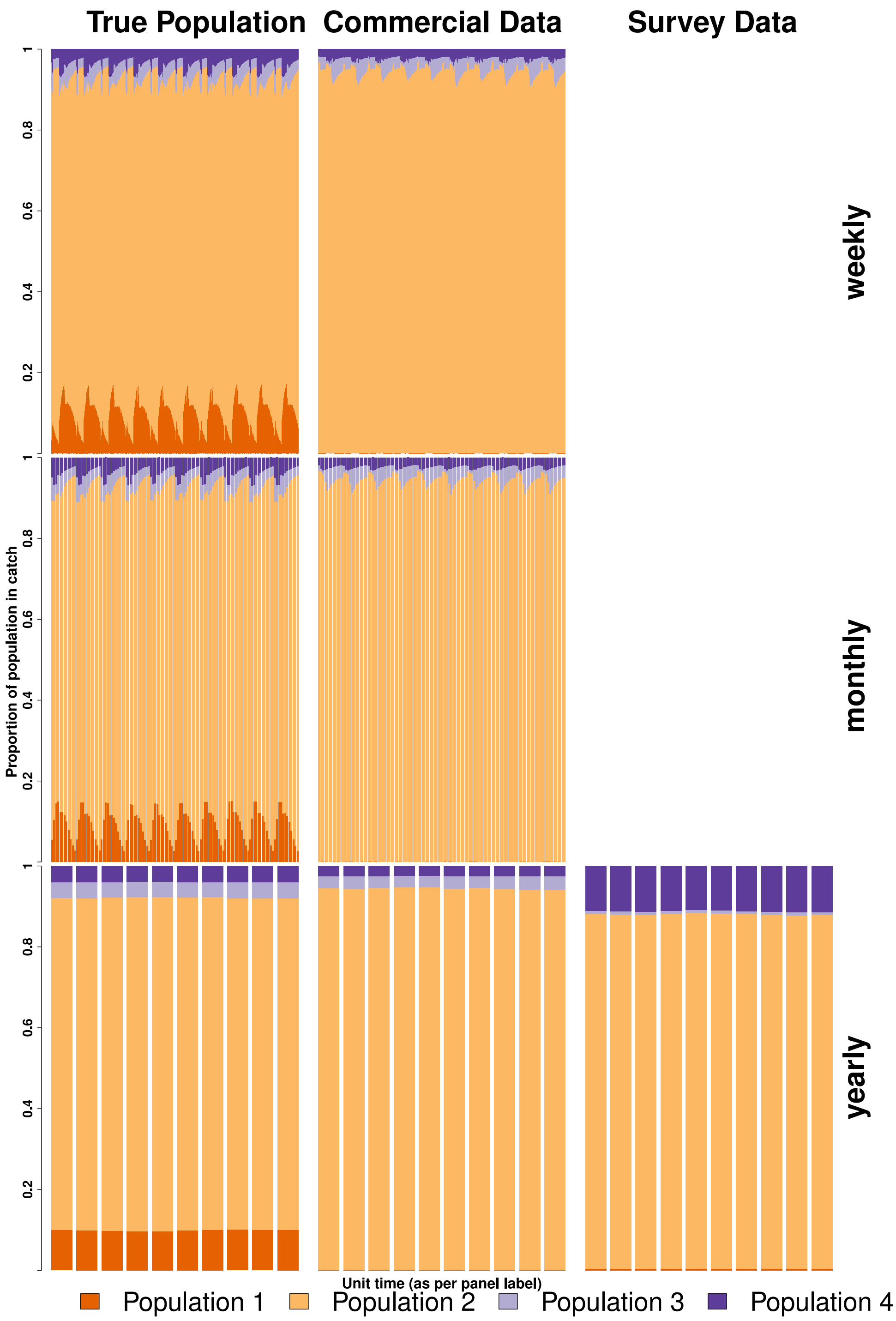

Fig. 4. Proportion of each population (y axis) for data aggregated at different temporal resolutions. Data is aggregated over a ten-year period for an area 20 x 20. Each bar represents either a week, month or year respectively.

seen when we aggregate the data at different timescales, with weekly (top), monthly (middle) and yearly (bottom) catch compositions from across an aggregated 20 x 20 area showing different patterns (Fig. 4). In the true population, the monthly aggregation captures the major patterns of composition seen in the weekly data with the percentage of different populations in the catch having similar mean and standard deviations (Table 7). In the weekly and monthly data population 2 dominates. However, some of the variation was lost when aggregated to an annual level, as indicated from the lower standard deviations (Table 7).

Weekly commercial data shows some of the same patterns as the true population, though population 1 is less well represented and some weeks are missing catches from the area. Here, weekly and monthly compositions were nearly identical (Fig. 4; Table 7). Yearly values had a similar mean but smaller standard deviation. The survey data was only available on an annual basis, and showed again a slightly different composition from the true population and the commercial data; in particular a greater proportion of population 4 (Fig. 4).

Table 6
Fishing mortality effects of the closure scenarios on population 3 (ordered by most effective first). The fishing mortality rate before the closure was 1.08.

Scenario No	F after closure	% F change	data type	timescale	resolution
9	0.29	-73.47	True Population	Weekly	1.00
10	0.29	-72.94	True Population	Monthly	1.00
11	0.35	-68.04	True Population	Yearly	1.00
45	0.58	-46.70	Commercial	Yearly	20.00
1	0.58	-46.21	Commercial	Weekly	1.00
23	0.59	-45.27	True Population	Weekly	5.00
2	0.59	-45.06	Commercial	Monthly	1.00
7	0.60	-44.48	Survey	Yearly	1.00
24	0.61	-43.20	True Population	Monthly	5.00
3	0.64	-40.82	Commercial	Yearly	1.00
25	0.65	-39.94	True Population	Yearly	5.00
17	0.67	-38.11	Commercial	Yearly	5.00
15	0.71	-34.38	Commercial	Weekly	5.00
43	0.71	-34.31	Commercial	Weekly	20.00
16	0.73	-32.58	Commercial	Monthly	5.00
51	0.78	-27.92	True Population	Weekly	20.00
37	0.78	-27.76	True Population	Weekly	10.00
39	0.79	-26.98	True Population	Yearly	10.00
38	0.81	-25.47	True Population	Monthly	10.00
21	0.81	-25.21	Survey	Yearly	5.00
35	0.81	-25.05	Survey	Yearly	10.00
44	0.87	-19.91	Commercial	Monthly	20.00
52	0.88	-18.39	True Population	Monthly	20.00
30	0.96	-11.06	Commercial	Monthly	10.00
29	0.98	-9.80	Commercial	Weekly	10.00
31	1.03	-4.36	Commercial	Yearly	10.00
53	1.06	-1.64	True Population	Yearly	20.00
49	1.07	-1.01	Survey	Yearly	20.00

4.3. How does data aggregation and source impact on spatial fisheries management measures?

In most cases the fishery closure was successful in reducing fishing mortality on the species of interest (population 3; Fig. 5; Table 6). Interestingly the largest reductions in fishing mortality happened immediately after the closures, following which the fisheries "adapted" to the closures by finding new areas of high abundance to fish. This led to fishing mortality increasing again, though not to past levels (Fig. 5). The exception to the success was the closures implemented based on the coarsest spatial (20 x 20) and temporal resolution (yearly) that was ineffective (i.e. failed to reduce fishing mortality) with all data sources. As expected, closures based on the simulated population distribution were most effective, with differing degrees of success using the commercial data. Fishing mortality rates on the other species changed in different proportions, depending on whether the displaced fishing effort moved to areas where the populations were found in greater or lesser density.

The factor most contributing to differences in fishing mortality before and after the closure was the population (72 % showing that the closures were effective for population 3), followed by spatial data resolution (21 %), data type (7 %) with the least important factor the timescale ($<$ 1 %). In general the finer the spatial resolution of the data used the greater reduction in fishing mortality for population 3 after the closures (Fig. 6). The notable outliers are the commercial data at the coarsest spatial resolution (20 x 20) at a yearly and weekly timescale, where closures were nearly as effective as the fine-scale resolution. In this case the closures were sufficiently large to protect a core area of the habitat for the population, but this was achieved in a fairly crude manner by closing a large area - including area where the species was not found (Figure 7) that may have consequences in terms of restricting the fishery in a much larger area than necessary. We found that these trade-offs existed, with high catches maintained with an effective closure when the highest resolution data was used, with the effect being linear when the true population distribution was known and also persisting for closures based on commercial information (Figure 8).

5. Discussion

Our study presents a new highly resolved fisheries simulation framework to evaluate the importance of data scaling and considers potential bias introduced through data aggregation when using fisheries data to infer spatiotemporal dynamics of fish populations. Understanding how fishers exploit multiple heterogeneously distributed fish populations with different catch limits or conservation status requires detailed understanding of the overlap of resources; this is difficult to achieve using conventional modelling approaches due to species targeting in fisheries resulting in preferential sampling (Martínez-Minaya et al., 2018). Often data are aggregated or extrapolated which requires assumptions about the spatial and temporal scale of processes. Our study explores the assumptions behind such aggregation and preferential sampling to identify potential impacts on management advice. With modern management approaches increasingly employing more nuanced spatiotemporal approaches to maximise productivity while taking account of both the biological and human processes operating on different time-frames (Dunn et al., 2016), understanding assumptions behind the data used - increasingly a combination of logbook and positional information from vessel monitoring systems - is vital to ensure measures are effective.

5.1. Simulation dynamics

We employ a simulation approach to model each of the population and fishery dynamics in a hypothetical 'mixed fishery', allowing us to i) evaluate the consequences of different aggregation assumptions on our understanding of the spatiotemporal distribution of the underlying fish populations, and ii) evaluate the effectiveness of a spatial closure given those assumptions.

Our approach is unique in that it captures fine scale population and fishery dynamics and their interaction in a way not usually possible with real data and thus not usually considered in fisheries simulations. While other simulation frameworks seek to model individual vessel dynamics based on inferred dynamics from VMS and logbook records (Bastardie et al., 2010), or as a system to identify measures to meet particular management goals (Bailey et al., 2019), our framework allows users to explore assumptions in modelling observational data and

Table 7
Mean and standard deviation of proportions of each species at different levels of temporal aggregation.

Data type	Timescale	Population 1	Population 2	Population 3	Population 4
Commercial	Monthly	0.047(0.014)	94.435(1.47)	3.122(1.468)	2.396(0.444)
Commercial	Weekly	0.047(0.016)	94.426(1.514)	3.117(1.563)	2.411(0.498)
Commercial	Yearly	0.051(0.001)	94.388(0.205)	3.021(0.175)	2.539(0.046)
True Population	Monthly	9.225(3.872)	83.287(5.522)	3.624(1.151)	3.864(1.519)
True Population	Weekly	9.358(3.992)	83.165(5.596)	3.567(1.233)	3.91(1.592)
True Population	Yearly	9.899(0.173)	82.25(0.308)	3.821(0.119)	4.031(0.05)
Survey	Yearly	0.372(0.005)	87.667(0.193)	0.729(0.02)	11.232(0.172)

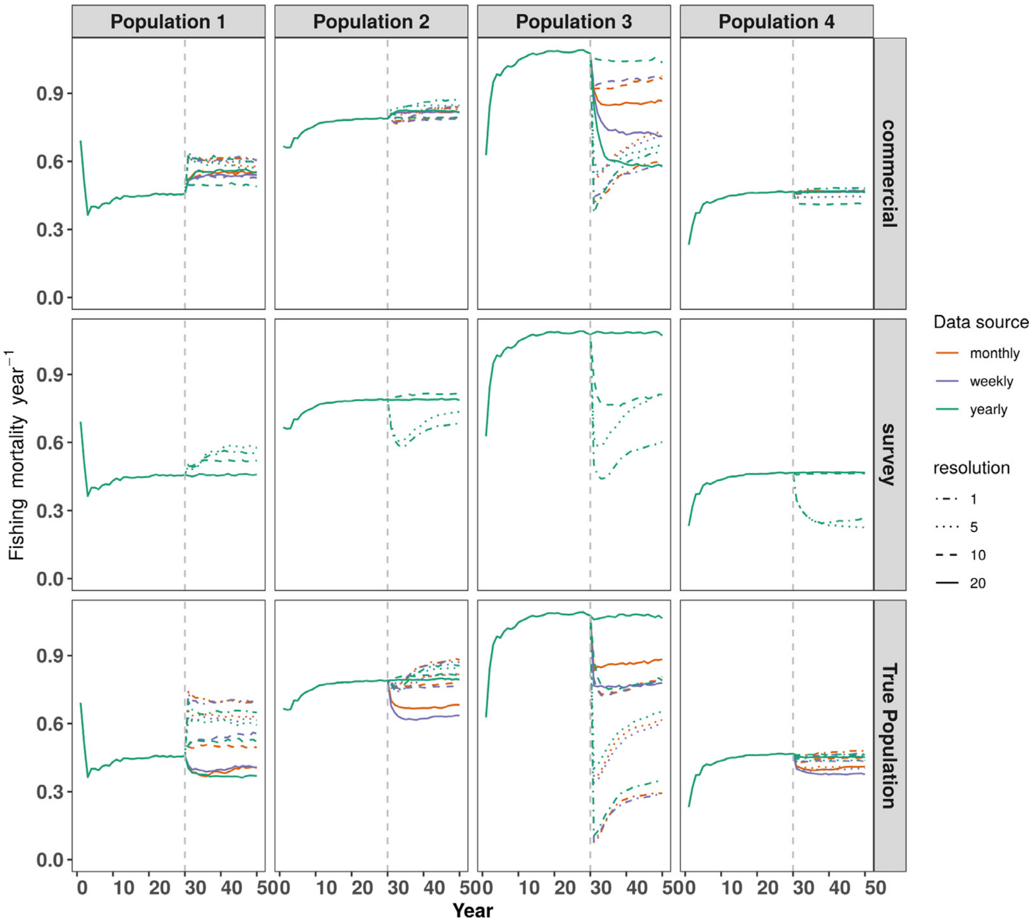

Fig. 5. Comparison of closure scenarios effect on fishing mortality trends. Line colour denotes timescale, while linestyle denotes spatial resolution. The vertical dashed line indicates the onset of the spatial closures.

to evaluate the underlying dynamics of such approaches at fine spatial and temporal scales. This offers the advantage that larger scale fishery patterns are emergent properties of the system and results can be compared to those obtained under a statistical modelling framework.

Typically, simulation models that treat fish as individuals are focussed on exploring the inter- and intra- specific interactions among fish populations (e.g. OSMOSE; Shin et al. (2004)) in order to understand how they vary over space and time. Our focus was on understanding the strengths and limitations of inference from catch data obtained through commercial fishing activity with fleets exploiting multiple fish populations. This shows how realised catch distributions may differ from the underlying populations, as identified by Gillis et al. (2008). As such, we favoured a minimum realistic model of the fish populations (Plagányi et al., 2014) taking account of environmental but not demographic stochasticity, while incorporating detailed fishing dynamics that take account of different drivers in a mechanistic way.

Demographic stochasticity arises due to individual-level variability in time to reproduction and death. This form of stochasticity is often modelled by drawing random time intervals from a given distribution (Gillespie, 1977). The impact of demographic stochasticity depends on the population size, with the effects expected to decrease with increasing population size (Lande et al., 2010). This contrasts with environmental stochasticity, which affects all population sizes and is present at the population level in our model by variability in recruitment.

We take account of heterogeneity in fleet dynamics due to different preferences and drivers similarly to other approaches (Fulton et al., 2011), but at an individual vessel rather than fleet level. We do not explicitly define fleets as rational profit maximisers at the outset, but consider there are several stages to development of the fishery; information gathering through search where the resource location is not known, followed by individual learnt behaviour of profitable locations. This provides a realistic model of how fishing patterns are established and maintained to exploit an uncertain resource through an explore-exploit strategy (Bailey et al., 2019; Mangel and Clark, 1983).

5.2. How does sampling-derived fisheries data reflect the underlying population structure?

Our results demonstrate the importance of considering data scale and resolution when using observational data to support management measures. We find that understanding of the community composition dynamics will depend on the level of data aggregation and its important to consider the scale of processes; including population movement rates, habitat uniformity and fishing targeting practices if potential biases in data are to be understood and taken into account (Fig. 2 and S5).

Our simulation shows that, despite biases introduced through the fishing process, the commercially derived data could still inform on the key spatial patterns in the community structures where the fisheries occurred, which was spatially limited due to the “hotspots” of commercially valuable species being fished. Similarly, despite even spatial coverage the survey captured some of the same spatial patterns as the true population, but missed others due to gaps between survey stations limiting spatial and temporal coverage (Fig. 3). This provides a challenge when modelling unsampled areas in inferring species distribution maps, though these limitations may be overcome by understanding the

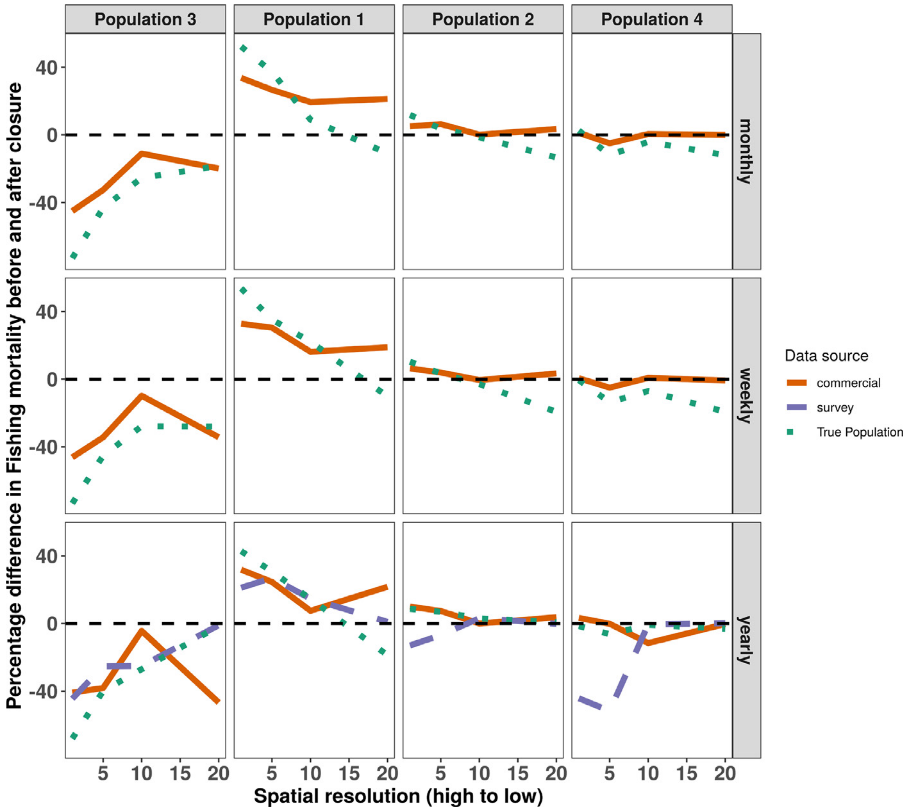

Fig. 6. Comparison of closure scenario effectiveness based on different spatial and temporal resolutions.

relationship between the species and habitat covariates where these are known at unsampled locations (Robinson et al., 2011).

5.3. How does data aggregation and source impact on spatial fisheries management measures?

From our simulations spatial disaggregation was more important than the temporal disaggregation of the commercial data. This reflects the fact that there was greater spatial heterogeneity over the spatial domain than experienced in given locations over the course of the year (Figure S5).

The yearly data assumes the same proportion of each population caught at any time of the year due to the data aggregation. This assumption introduces 'aggregation bias' as the data may only be representative of some point (or no point) in time. The monthly data shows some consistency between the real population and commercial data for population 2 - 4, though population 1 remains under-represented. On an annual basis, interestingly the commercial data under represents the first species while the survey over represents species 1. This is likely due to the biases in commercial sampling, with the fisheries not targeting the areas where population 1 are present and the survey sampling areas where population 1 is more abundant than on average. This indicates that fixed closures, at the right resolution, when based on commercially derived data have the potential to reduce fishing mortality. The likely cost of poor spatial and temporal resolution is associated with reduced effectiveness and potentially closing fishing opportunities for other fisheries (Figure 8).

Two contrasting real world approaches in this respect were the spatial closures to protect cod in the North Sea. In one example, large scale spatial closures were implemented with little success due to effort displacement to previously unfished areas (Dinmore et al., 2003), while in another small scale targeted spatiotemporal closures were considered to have some effect in reducing cod mortality without having to disrupt other fisheries substantially (Needle and Catarino, 2011). These examples emphasise the importance of considering the right scale and aggregation of data when identifying area closures and the need to consider changing dynamics in the fisheries in response to such closures.

Our study showed that fishing rates on other populations also changed (both up and down) as a side-effect of closures to protect one species. This indicates the importance of considering fishing effort reallocation following spatial closures, and our simulation allows us to consider the spatiotemporal reasons for these changes.

5.4. Model assumptions and caveats

We modelled the population and fleet dynamic processes to draw inference on the importance of data scale and aggregation in understanding and managing mixed fisheries and their impact on multiple fish populations. In doing so, we necessarily had to make a number of simplifying assumptions.

Fish populations in our simulations move in pre-defined timescales and according to fixed habitat preferences and temperature gradients (Figures S7, S9). Our assumptions in calibrating the model (movement rates, temperature tolerances) will have a direct impact on our conclusions on the relative importance of spatial and temporal processes. These assumptions could be explored in a future study by varying the parameters and assessing the robustness of our conclusions. For our example application we have chosen movement rates to reflect aggregation periods observed in past studies (Poos and Rijnsdorp, 2007b).

In addition, we have assumed that fishing vessels are not restricted by quota and therefore discarding of species for which vessels have no quota or that are unwanted is not taken into account. This is likely to be a significant source of bias in any inference using commercial data and should also be explored. For example, *MixFishSim* could be altered to allow for spatiotemporal appraisal of the impact of discarding on fisher behaviour and underlying populations via inclusion as discarding behaviour, or through move-on rules or cessation of fishing activity when

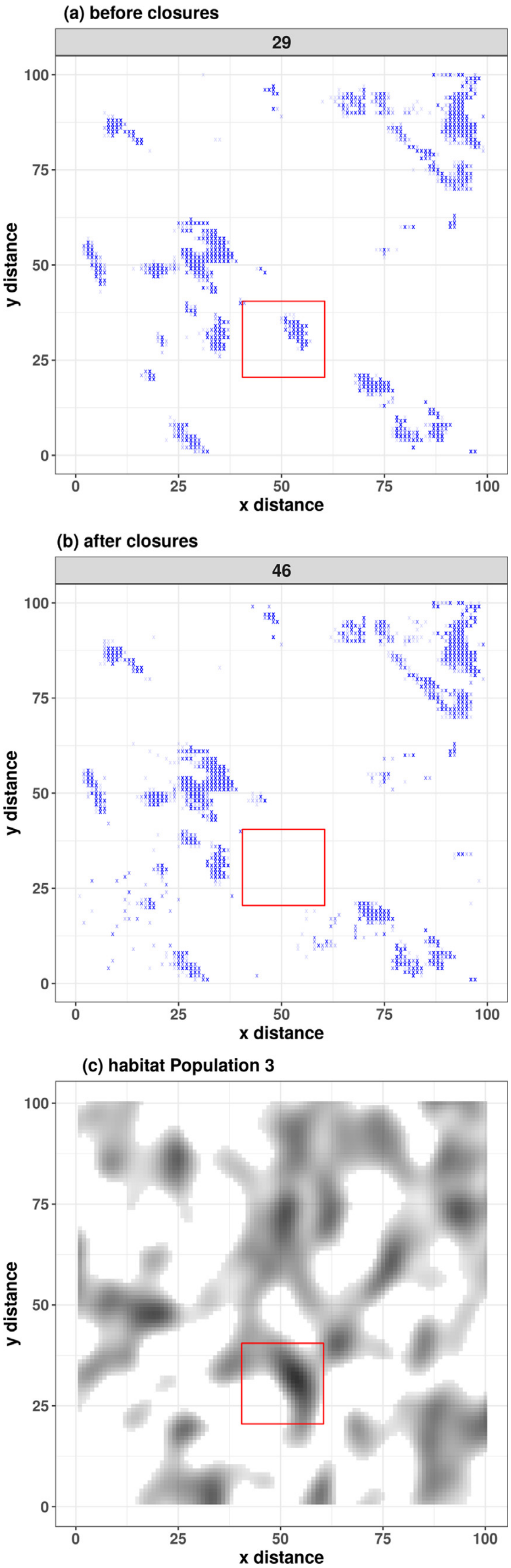

Fig. 7. The location of fishing effort, (a) before the spatial closure and (b) after the spatial closure (years in panel), and (c) the suitable habitat for population 3. The site of the closure can be seen in the red box on all three panels.

quota is exhausted.

5.5. *Future applications of MixFishSim*

We consider that the increased availability of high resolution catch and locational information from commercial fisheries will make it a key source of data for ensuring management is implemented at the right scale in future. For example, identifying hot-spots for bycatch reduction or identifying spatial overlaps in mixed fisheries (Dedman et al., 2015; Dolder et al., 2018; Gardner et al., 2008; Little et al., 2015; Ward et al., 2015). Our simulation model has the potential to test some of the assumptions behind the modelling approaches in identifying such hot-spots and indeed behind spatiotemporal modelling in general, e.g. comparing GAMs, GLMMs, Random Forests and geostatistical models under different data generation processes as exampled by Stock et al. (2019).

Other novel applications of our framework could be: testing different survey designs given multiple species and data generating assumptions (Xu et al., 2015); commercial index standardisation methods and approaches and understanding of appropriate scales and data aggregations and non-proportionality in catch rate and abundance (Harley et al., 2001; Maunder and Punt, 2004); exploring assumptions about the distribution of natural mortality and fishing mortality throughout the year and importance of capturing in-year dynamics in estimating stock status (Liu and Heino, 2014); at-sea sampling scheme designs to deliver unbiased estimates of population parameters (Cotter and Pilling, 2007; Kimura and Somerton, 2006); adaptive management (Dunn et al., 2016; Walters, 2007); testing the ability of commonly employed fleet dynamics models such as Random Utility Models to capture fine scale dynamics and understand their importance (Girardin et al., 2017); and as a detailed operating model in a management strategy evaluation (Mahévas and Pelletier, 2004).

6. Conclusions

MixFishSim provides a detailed simulation framework to explore the interaction of multiple fisheries exploiting different fish populations. The framework enables users to evaluate assumptions in modelling commercially derived data through comparison to the true underlying dynamics at a fine spatial and temporal scale. Understanding these dynamics, the limitations of the data and any potential biases that may be introduced when making inference on spatiotemporal interactions will enable users to identify weaknesses in modelling approaches and identity where data collection is needed to strengthen inference.

Our application shows that inference on community dynamics may change depending on the scale of data aggregation. There is an important balance in ensuring that the data are sufficiently spatially and temporally disaggregated that the main features of the data are captured, yet maintaining enough data coverage that the features can be distinguished. We found greater spatial than temporal heterogeneity. When using aggregated data to define spatial closures coarser temporal resolution (months instead of weeks) could still achieve the same results in reducing exploitation rates of a vulnerable species at the highest temporal resolution data. Conversely, reducing the spatial resolution had a negative effect on the effectiveness of the measures though, importantly, there was still some benefit even with coarse spatial resolution.

While case-specific, our findings emphasise the need to understand population demographics, habitat use and movement rates in designing any closure scenario based on observational sampling. This information can then be used to set the bounds on data aggregation used in modelling studies aimed at informing the management measures.

Declaration of Competing Interest

The authors declare that they have no known competing financial

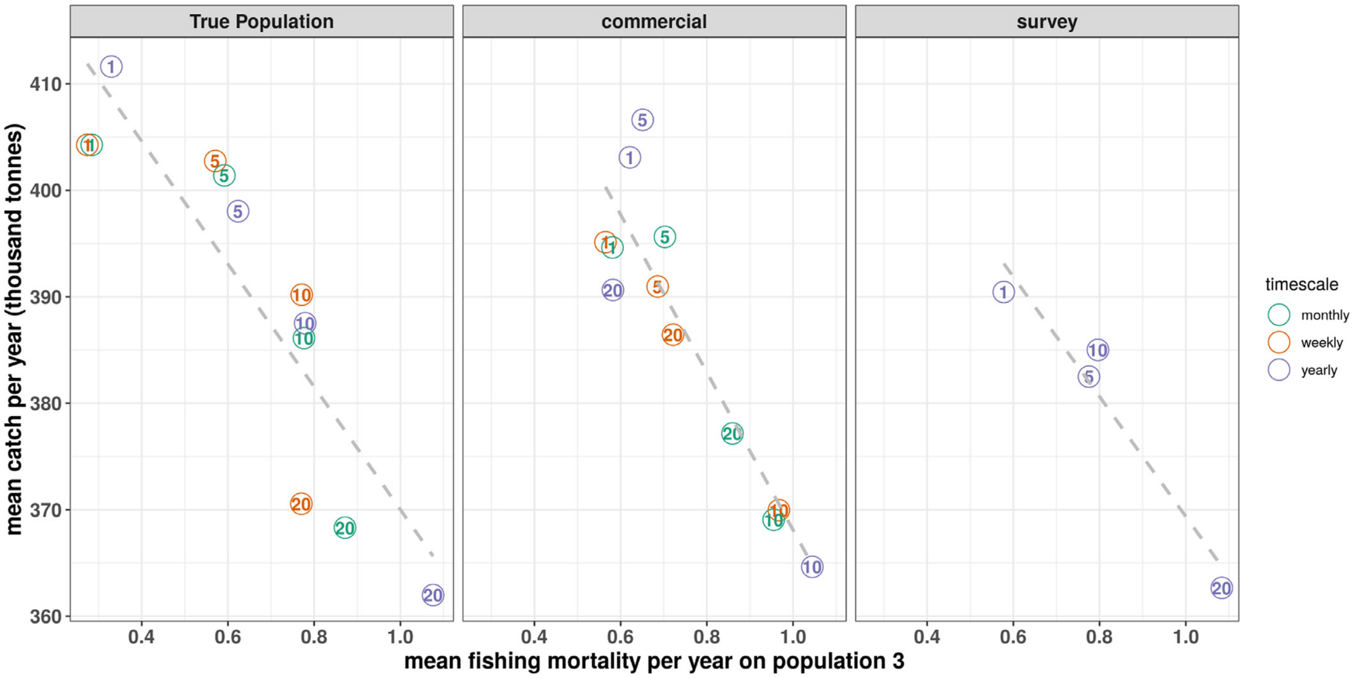

Fig. 8. Effectiveness of closure with regards to reducing fishing mortality on protected population (further left on x-axis is best) and maintaining high catches in the fishery (highest on y-axis is best). The numbers indicate the spatial resolution of the data, while grey lines indicate the direction of the trade-off between reducing fishing mortality and overall catches.

interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Paul J. Dolder: Conceptualization, Methodology, Software, Writing - original draft. **Cóilín Minto:** Conceptualization, Methodology, Writing - review & editing, Funding acquisition. **Jean-Marc Guarini:** Methodology, Writing - review & editing, Funding acquisition. **Jan Jaap Poos:** Methodology, Writing - review & editing.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.ecolmodel.2020.109000 .

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Appendix E

Supplementary material for manuscript II

MixFishSim: Supplementary Figures

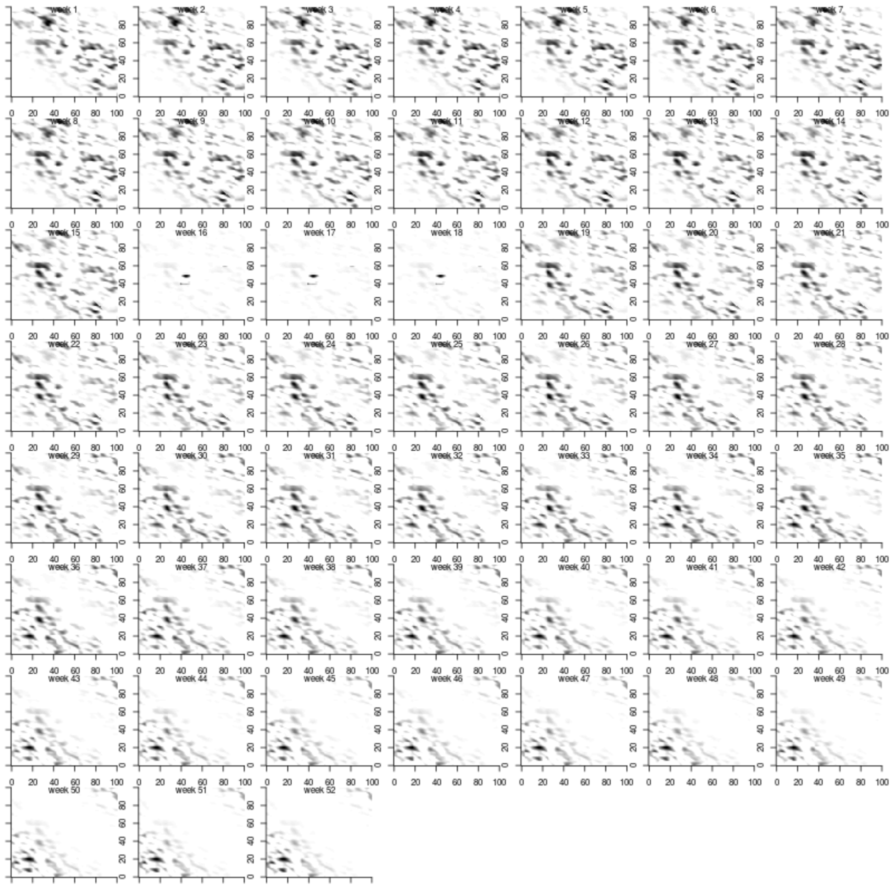

Figure S1: Spatiotemporal habitat suitability - the suitability habitat (for Population 1) for 52 separate weeks. The darker the colour, the more suitable the habitat for the population given the habitat and temperature tolerance.

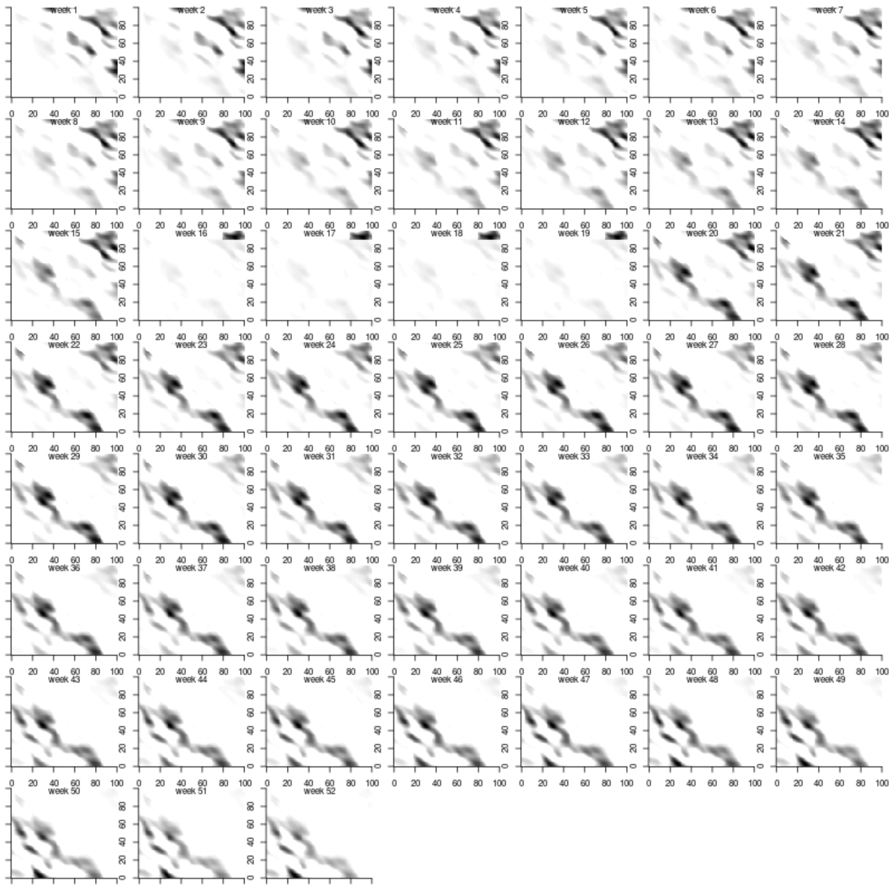

Figure S2: Spatiotemporal habitat suitability - the suitability habitat (for Population 2) for 52 separate weeks. The darker the colour, the more suitable the habitat for the population given the habitat and temperature tolerance.

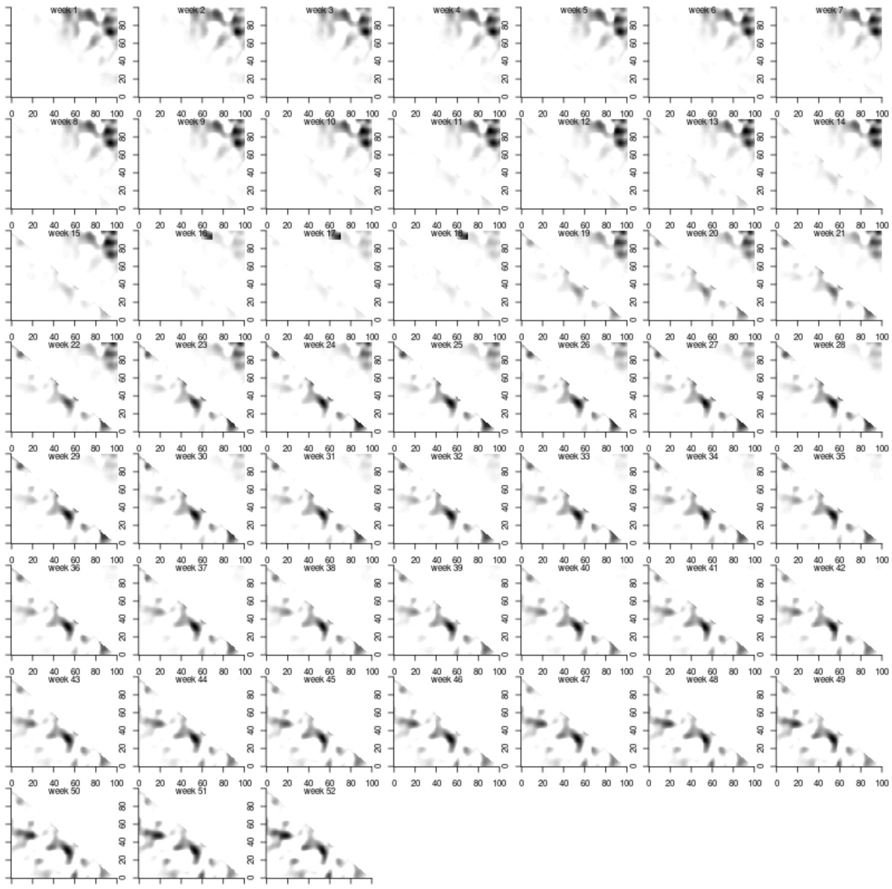

Figure S3: Spatiotemporal habitat suitability - the suitability habitat (for Population 3) for 52 separate weeks. The darker the colour, the more suitable the habitat for the population given the habitat and temperature tolerance.

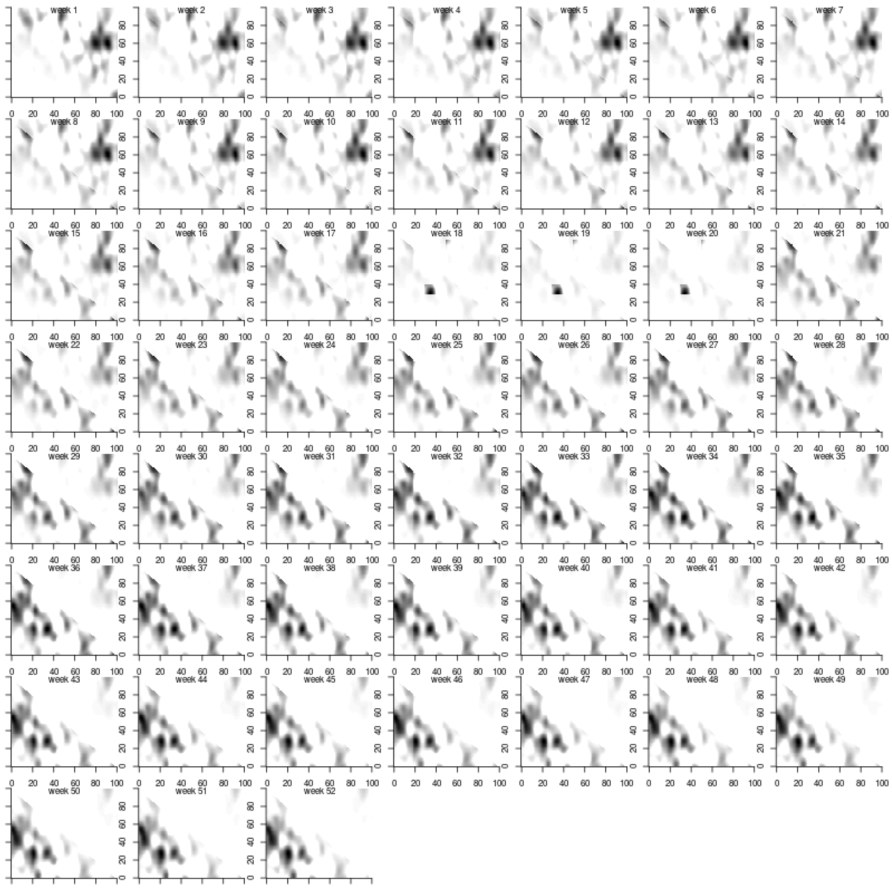

Figure S4: Spatiotemporal habitat suitability - the suitability habitat (for Population 4) for 52 separate weeks. The darker the colour, the more suitable the habitat for the population given the habitat and temperature tolerance.

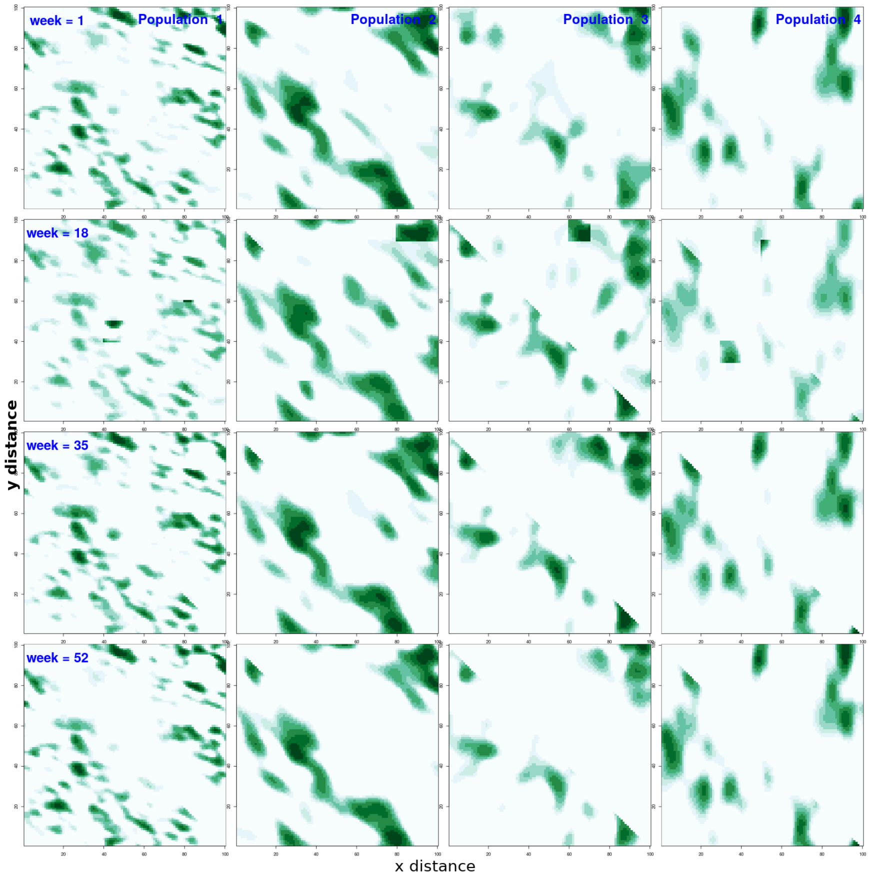

Figure S5: Spatial density (log abundance) for each of the four populations at four time steps. The darker the colour the greater the density of the population. Note that a diagonal anisotropic pattern (mimicking a depth gradient) can be clearly seen in populations 2 and 3. The concentrated spawning areas are also visible in the second row of the panels (t=18).

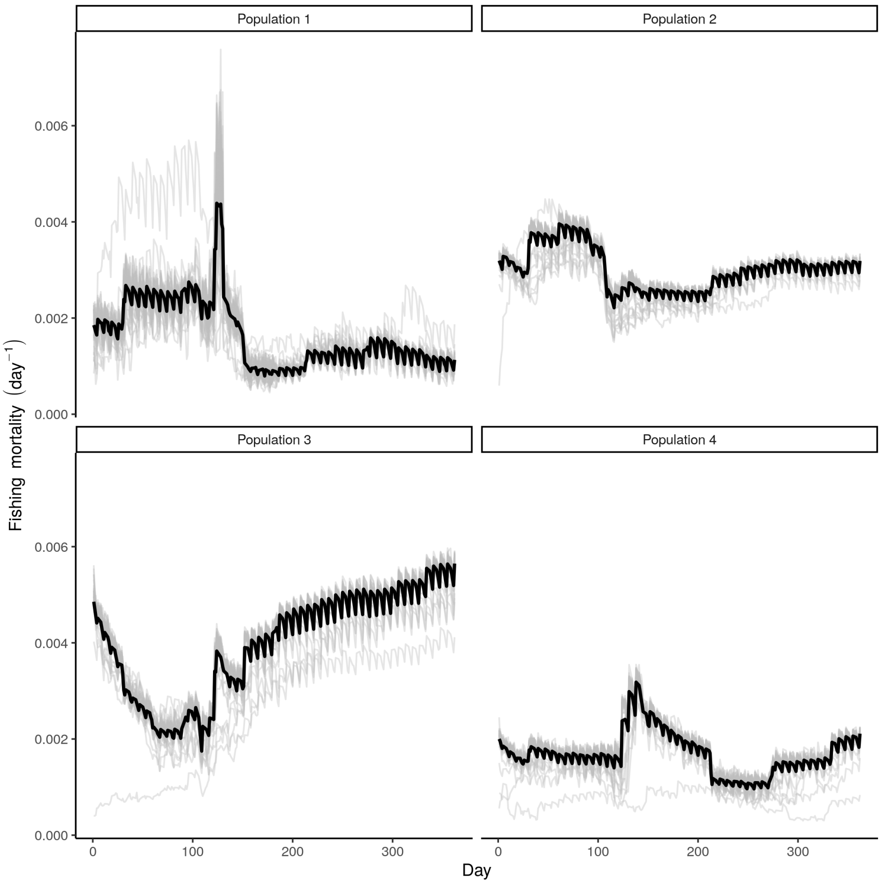

Figure S6: Fishing mortality dynamics - the daily fishing mortalities aggregated across the entire spatial domain showing weekly and seasonal patterns in exploitation. Individual years are the light grey lines, the mean of all years the thick black line.

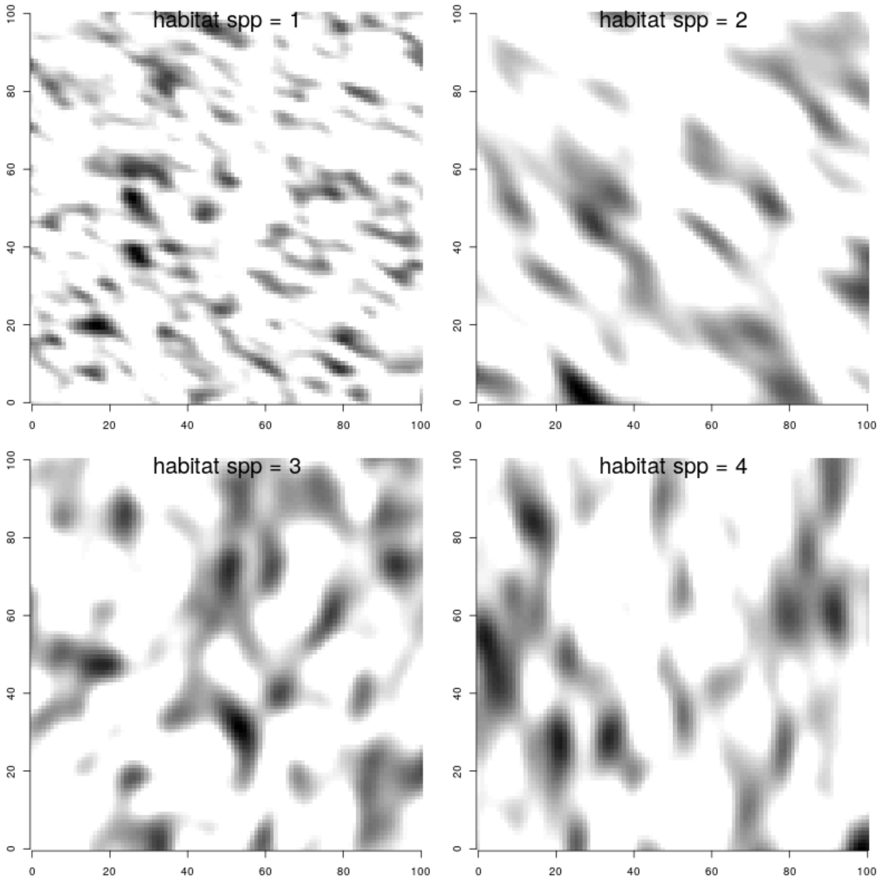

Figure S7: Habitat preference: the distribution of suitable habitat for each population, with the darker colour showing greater habitat suitability.

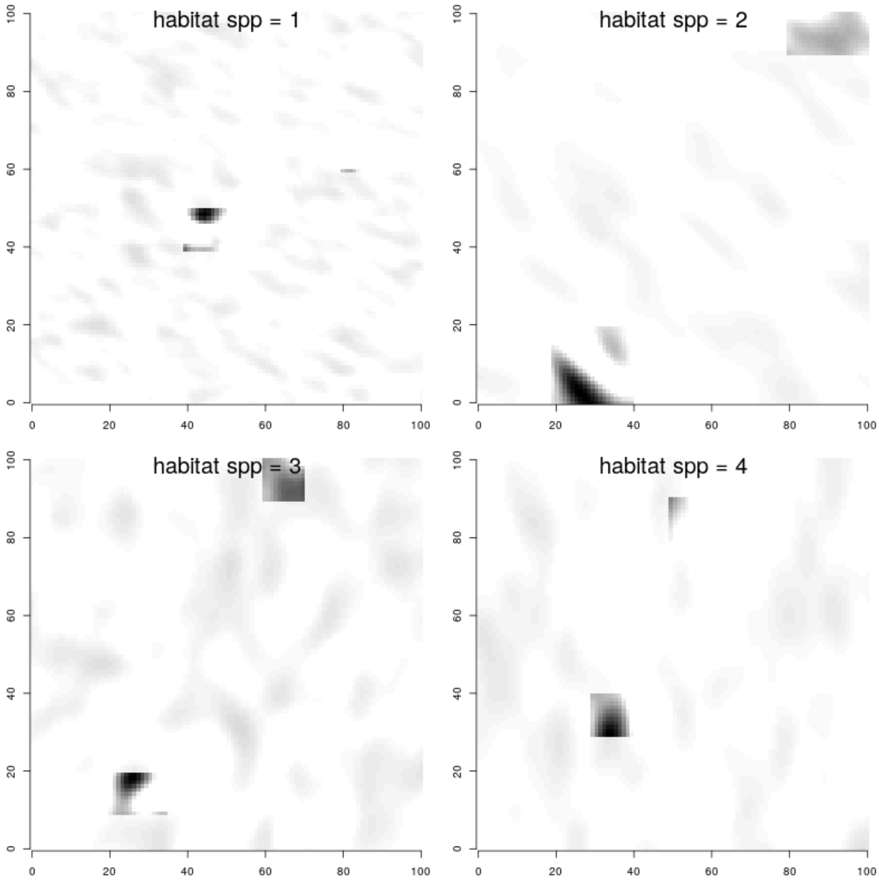

Figure S8: Spawning habitat preference: the habitat suitability during spawning periods for each population. The darker the colour, the more suitable the habitat. The location of the spawning habitat is highlighted by the squares in each panel.

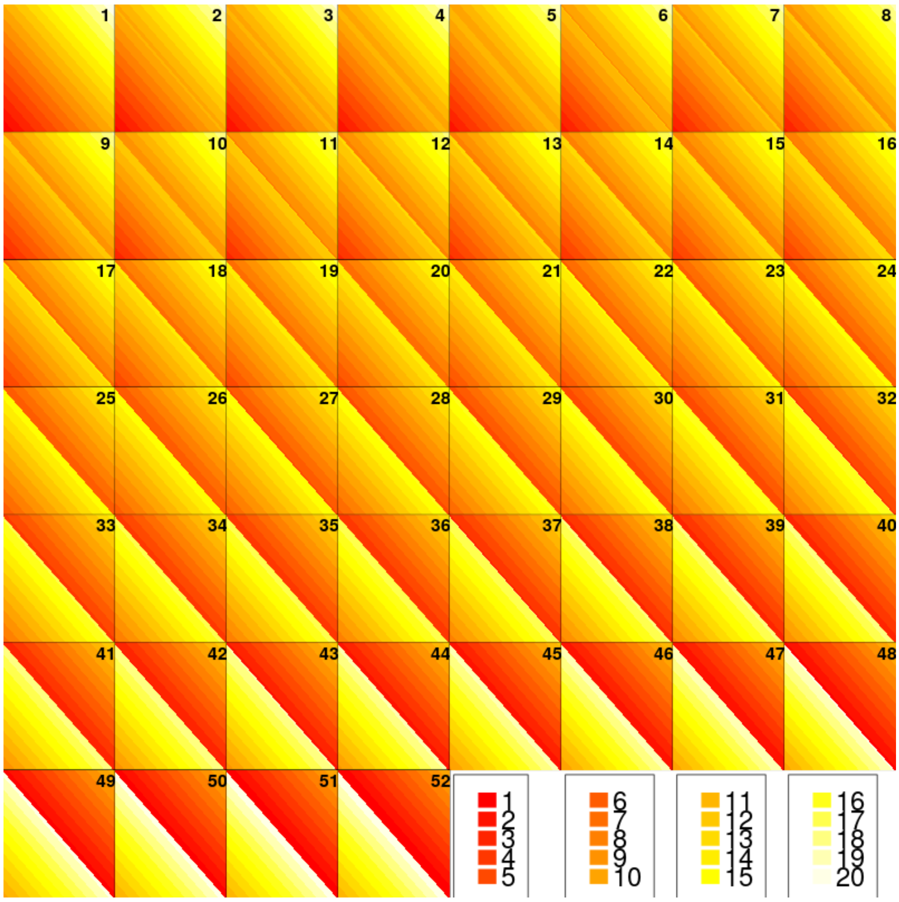

Figure S9: Spatiotemporal temperature gradient: The temperature gradient for each time step (weeks, shown in top right corner of each panel.)

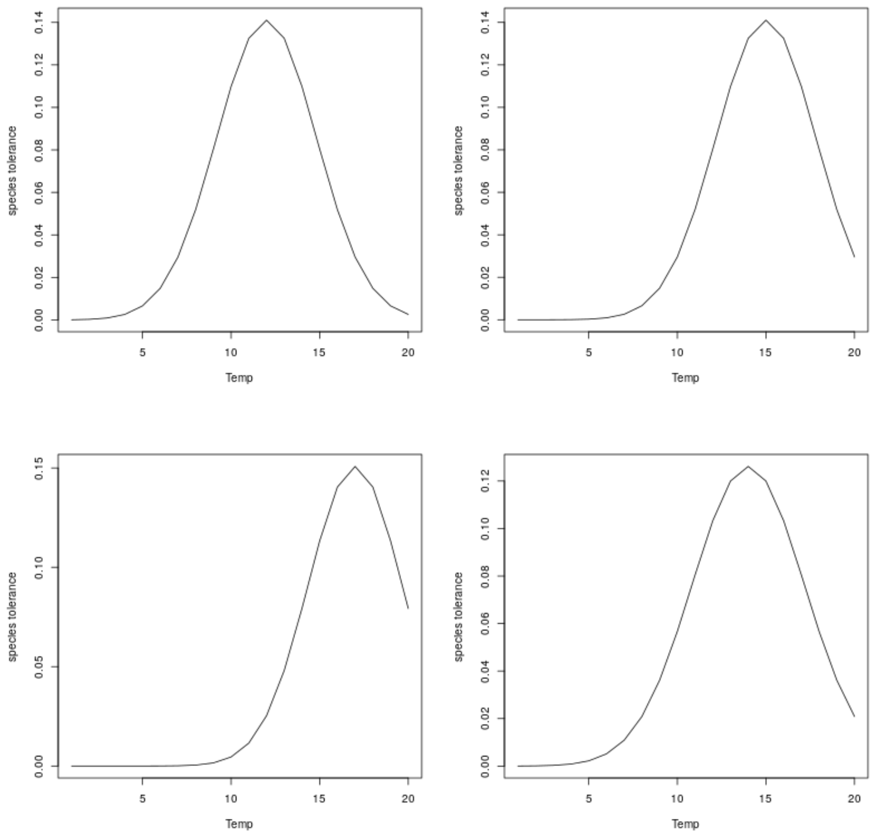

Figure S10: Species thermal tolerances: The tolerance of each population to different temperatures (x-axis) shown as a probability density function.

Appendix F

MixFishSim R package help file associated with manuscript II

Package 'MixFishSim'

June 12, 2018

Title Mixed Fishery fleet dynamics simulation tool

Version 0.0.0.9000

Description A simulation framework for evaluating fleet dynamics in mixed fisheries.

Depends R (>= 3.3.1),

Imports CircStats,
doParallel,
dplyr,
parallel,
RandomFields,
Rcpp

License What license is it under?

Encoding UTF-8

LazyData true

RoxygenNote 6.0.1

Suggests testthat,
ggplot2,
dplyr,
akima

LinkingTo Rcpp

R topics documented:

`baranov_f` *Baranov F*

Description

`baranov_f` provides the function to solve in `find_f` for estimating weekly fishing mortality from catch (C), biomass (B) and natural mortality (M). It's based on the standard Baranov catch equation.

Usage

```
baranov_f(F, C, B, M)
```

Arguments

`F`	is the fishing mortality rate to solve.
`C`	is a Numeric vector detailing the catch at wk_t
`B`	is a Numeric vector of the biomass at wk_t
`M`	is a Numeric vector of the natural mortality rate at wk_t

Value

returns nothing, is objective to be solved by `find_f`

Examples

```
## No examples
```

`close_areas` *Close areas*

Description

The `close_areas` function implements the closures according to the settings from init_closure and passes the areas to go_fish. Its an internal function, requiring no user input.

Usage

```
close_areas(sim_init = sim_init, closure_init = NULL,
  commercial_logs = NULL, survey_logs = NULL, real_pop = NULL, t = t)
```

Arguments

`closure_init`	is the output from init_clousre.
`commercial_logs`	is the commercial landings data, the output from combine_logs. Only needed if closure 'basis' = 'commercial'.
`survey_logs`	is the survey data, the survey[["log.mat"]]. Only needed if closure 'basis' is 'survey'.
`real_pop`	is the popualtions as recorded. Only needed if closure 'basis' is 'real_pop'.

Value

is a list of closed cells, to pass to go_fish

Examples

```
None
```

combine_logs *Combine logs*

Description

combine_logs is a helper function to convert the list of fleet and vessels catch logs into a single dataframe.

Usage

```
combine_logs(fleets_catches)
```

Arguments

fleets_catches is the list output of fleets_catches from run_sim

Value

is a dataframe of the fleet and vessel catches in logbook format

Examples

```
logs <- combine_logs(fleets_catches)
## Not run
```

create_fields *Create species distribution fields*

Description

create_fields parametrises and returns the spatio-temporal fields used for the spatial distribution of fish populations and movement in space and time for the simulations.

The spatio-temporal fields are generated using spate.sim function from the *spate* package using an advective-diffusion Stochastic Partial Differential Equation (SPDE). See *Lindgren 2011 and Sigrist 2015* for further detail.

Usage

```
create_fields(npt = 1000, t = 1, seed = 123, n.spp = NULL,
  spp.ctrl = NULL, plot.dist = FALSE, plot.file = getwd())
```

Arguments

- `npt` — Numeric integer with the dimensions of the field in *npt * npt*
- `t` — Numeric integer with the number of time-steps in the simulation
- `seed` — (Optional) Numeric integer with the seed for the simulation
- `n.spp` — Numeric integer with the number of species to be simulated. Each species must have an individual control list as detailed below.
- `spp.ctrl` — List of controls to generate each species spatio-temporal distribution. Must be of the form spp.ctrl = list(spp.1 = c(rho0 = 0.001, ...), spp.2 = c(rho0 = 0.001, ..),..) and contain the following:
  - **rho0** (>=*0*) Controls the range in a matern covariance structure.
  - **sigma2** (>=*0*) Controls the marginal variance (i.e. process error) in the matern (>=*0*) covariance structure.
  - **zeta** (>=*0*) Damping parameter; regulates the temporal correlation.
  - **rho1** (>=*0*) Range parameter for the diffusion process
  - **gamma** (>=*0*) Controls the level of anisotropy
  - **alpha** (*[0,* $\pi/2$*]*) Controls the direction of anisotropy
  - **muX** (*[-0.5, 0.5]*) x component of drift effect
  - **muY** (*[-0.5, 0.5]*) y component of drift effect
  - **tau2** (>=*0*) Nugget effect (measurement error)
  - **nu** Smoothness parameter for the matern covariance function
- `plot.dist` — Boolean, whether to plot the distributions to file
- `plot.file` — path to save the plots of the species distributions

Value

Silently returns a list of spatial distributions with first level of the list being the population (1 -> n.spp) and the second being time (1 -> t). If `plot.dist = TRUE` it produces an image of the spatial distributions at each time step for each of the populations saved to the working directory (unless specified otherwise in `plot.file`)

Examples

```
fields <- create_fields(n.spp = 1, t = 2,
      spp.ctrl = list(
      'spp.1' = c('rho0' = 0.1, 'sigma2' = 1, 'zeta' = 0.1,
  'rho1' = 0.01, 'gamma' = 0.3, 'alpha' = pi/4,
  'muX' = -0.05, 'muY' = -0.05, 'tau2' = 0, 'nu' = 1.5)),
plot.dist = TRUE, plot.file = getwd())
```

`create_hab` *Create habitat distribution fields*

Description

`create_hab` parametrises and returns the spatial fields used for the distribution of suitable habitat for the populations in the simulation.

The spatial fields are generated using `RFsimulate` function from the *RandomFields* package.

Usage

```
create_hab(sim_init = sim, seed = 123, spp.ctrl = NULL,
  spawn_areas = NULL, spwn_mult = 10, plot.dist = FALSE,
  plot.file = getwd(), cores = 3)
```

Arguments

`spp.ctrl`	List of controls to generate suitable habitat for each species. Must be of the form spp.ctrl = list(spp.1 = c(var = 20, ...), spp.2 = c(var = 10, ..),..) and contain the following: • **nu** (>=*0*) • **var** (>=*0*) Controls the range in a matern covariance • **scale** (>=*0*) • **Aniso** (*matrix, dim = c(2,2)*)
`plot.dist`	Boolean, whether to plot the distributions to file
`plot.file`	path to save the plots of the species distributions
`sim`	is the parameter settings for the simulation, made by `init_sim` function.

Value

Silently returns a list of spatial distributions of suitable habitat with first level of the list being the population (1 -> n.spp). If `plot.dist = TRUE` it produces an image of the spatial distributions at each time step for each of the populations saved to the working directory (unless specified otherwise in `plot.file`)

Examples

```
hab <- create_hab(sim.init = sim.init, spp.ctrl = list(
      'spp.1' = list('nu' = 1/0.15, var = 1, scale = 10, Aniso =
      matrix(nc=2, c(1.5, 3, -3, 4)))), spawn_areas = list("spp1" =
      list("area1" = c(2,4,6,8))), list("spp2" = list("area1" =
      c(0,10,23,35))), spwn_mult = 10, plot.dist = TRUE, plot.file =   getwd())
```

`create_spawn_hab` *create spawning habitat*

Description

`create_spawn_hab` modifies the habitat preference maps created by `create_hab` to account for spawning habitat preference - can be used as a substitute during spawning periods.

Usage

```
create_spawn_hab(hab = hab, spwnareas = NULL, mult = 10)
```

Arguments

`hab`	is the habitat preference for the population
`spwnareas`	is a list of Numeric vectors with the West, East, South and North dimensions of the spawning areas, in the form list(spwn1 = c(x1, x2, y1, y2)
`mult`	is a Numeric with the attractiveness of the spawning area (a multiplier)

Value

is the new habitat preference, taking account of the spawning area

Examples

```
create_spawn_hab(hab = matrix(nc = 100, runif(100 *
100)), spwnareas = list(spwn1 = c(20, 30, 50, 60)), mult = 10)
```

`define_spawn` *define spawning areas*

Description

`define_spawn` is an auxiliary function called by `create_spawn_hab` to create the spawning habitat preferences.

Usage

```
define_spawn(coord = NULL, spwn = NULL, mult = 10)
```

Arguments

`coord`	is a List of Numeric vectors of the boundaries of the spawning areas, i.e. list(spwn1 = c(x1, x2, y1, y2), spwn2 = ...)
`spwn`	is a Numeric matrix of 1s fed in by `create_spawn_hab`
`mult`	is a Numeric of the attractiveness of the spawning areas

Value

a matrix of spawning preference

Examples

```
define_spawn(coord = list(spwn1 = c(2,4,2,4)), spwn = matrix(nc = 3, runif(9)), mult = 10)
```

---

deg2rad *Degrees to radians*

Description

deg2rad is a helper function to covert decimal degrees to radians

Usage

```
deg2rad(d)
```

Arguments

r	is the bearing in radians

Value

is the bearing in degrees

Examples

```
deg2rad(90)
```

---

delay_diff *Delay-difference (weekly)*

Description

delay_diff implements a two-stage delay-difference model with a weekly time-step after *Dichmont 2003*. Given the starting biomass, overall mortality and recruitment it returns the biomass in wk+1.

Usage

```
delay_diff(K = 0.3, F = NULL, M = 0.2, wt = 1, wtm1 = 0.1, R = NULL,
  B = NULL, Bm1 = NULL, al = NULL, alm1 = NULL)
```

Arguments

K	is a Numeric vector describing growth. Note: K is transformed to rho with $\rho = exp{-K}$ for the model. estimate of instantaneous fishing mortality (obtained elsewhere, via find_f and baranov_f functions.
F	is the weekly fishing mortality rate.
M	is a Numeric vector of the instantaneous rate of natural mortality for the population
wt	is a Numeric vector of the weight of a fish when fully recruited
wtm1	is a Numeric vector of the weight of a fish before its recruited
R	is a Numeric vector of the annual recruitment for the population in numbers
B	is the biomass of the population during wk_t
Bm1	is a Numeric vector of the biomass of the population in the previous week wk_{t-1}
al	is a Numeric vector of the proportion of recruits to the fishery in wk_t
alm1	is a Numeric vector of the proportion of recruits to the fishery in wk_{t-1}

Value

Returns the biomass at the beginning of the following week, wk_{t+1}

Examples

```
delay_diff(K = 0.3, F = 0.2, M = 0.2, wt = 1, wtm1 = 0.1, R = 1e6, B = 1e5,
Bm1 = 1e4, al = 0.5, alm1 = 0.1)
```

---

distance_calc *distance calculation*

Description

distance_calc calculates the euclidean distance between two cell references.

Usage

```
distance_calc(x1, y1, x2, y2)
```

Arguments

x1	is an integar for the starting x position
y1	is an integar for the starting y position
x2	is an integar for the end x position
y2	is an integar for the end y position

Value

is a distance between the two cells

Examples

```
distance_calc(2, 3, 5, 7)
```

---

find_f — *find F (fishing mortality)*

Description

`find_f` uses `uniroot` to find the fishing mortality rate given the catch, biomass and natural mortality using the `baranov_f` objective function.

Usage

```
find_f(C = C, B = B, M = M, FUN = baronov_f)
```

Arguments

C	is a Numeric vector detailing the catch at wk_t
B	is a Numeric vector of the biomass at wk_t
M	is a Numeic vector of the natural mortality rate at wk_t
FUN	is the objective function, here the Baranov equation baranov_f

Value

Gives the fishing mortality estimate *F*

Examples

```
find_f(C = 3000, B = 12000, M = 0.2, FUN = baranov_f)
```

---

find_spat_f — *find spatial Fs (fishing mortality rates)*

Description

`find_spat_f` uses `uniroot` to find the fishing mortality rate for a population given the catch, biomass and natural mortality using the `baranov_f` objective function.

Usage

```
find_spat_f(sim_init = NULL, C = C, B = B, M = M, FUN = baranov_f)
```

Arguments

sim_init	is the parameterised sim settings, made by init_sim
C	is a Numeric vector detailing the catch at wk_t
B	is a Numeric vector of the biomass at wk_t
M	is a Numeic vector of the natural mortality rate at wk_t
FUN	is the objective function, here the Baranov equation baranov_f

Value

Gives a matrix the spatial fishing mortality estimate *F*

Examples

```
find_spat_f(sim_init = sim, C = matrix(1000,3000, nc =2), B =
matrix(12000,10000, ncol = 2), M = 0.2, FUN = baranov_f)
```

---

find_spat_f_pops   *find spatial f pops*

Description

find_spat_f_pops applies the find_spat_f function to all the populations, returning the spatial fishing mortality rates for each of the populations.

Usage

```
find_spat_f_pops(FUN = find_spat_f, sim_init = sim, C = C, B = B,
  dem_params = NULL, ...)
```

Arguments

FUN	is the find_spat_f function
sim_init	is the simulation settings initialised by init_sim
C	is the spatial catch matrices for all populations
B	is the spatial biomass for all populations
dem_params	are the demographic parameters for all populations (containing the natural mortality rate, M.

Examples

```
None as yet
```

get_bearing *Get bearing function*

Description

`get_bearing` is a function to calculate a new bearing for a vessel. The new bearing is determined from the Von Mises circular distribution, with a concentration parameter, *k* which is linked to the value of the recent tow. Thus, if a vessel has a good tow, its more likely to turn round and fish again in the same area.

Usage

```
get_bearing(b = NULL, k = NULL)
```

Arguments

b	is a Numeric based on decimal degrees (0 - 360) of the current bearing for the vessel
k	is a Numeric [0-100] for the concentration parameter determining the likely new direction for the vessel.

Value

bearing - is the new bearing for the vessel

Examples

```
get_bearing(b = 270, k = 100)
```

go_fish *Go fish*

Description

`go_fish` is a function used to apply the fishing simulation model

Usage

```
go_fish(sim_init = NULL, fleet_params = NULL, fleet_catches = NULL,
  sp_fleet_catches = NULL, pops = NULL, closed_areas = NULL, t = t)
```

Arguments

`sim_init`	is the initialised object from `init_sim`.
`fleet_params`	is the parameter settings initialised from `_init_fleets`
`fleet_catches`	is the DF initialised from `_init_fleets`
`sp_fleet_catches`	is a list of spatial catches (as a Numeric matrix) for the fleet of each population @param closed_areas is a dataframe with the x,y coordinates are any closed areas, provided internally by close_areas

Value

is a list containing i) the fleet catch dataframes , ii) the spatial catches of each population

---

`go_fish_fleet` *Go fish fleet*

Description

`go_fish_fleet` applies the function `go_fish` to the entire fleet with an lapply.

Usage

```
go_fish_fleet(FUN = go_fish, sim_init = NULL, fleets_params = NULL,
  fleets_catches = NULL, sp_fleets_catches = NULL, pops = NULL,
  closed_areas = NULL, t = t, ...)
```

Arguments

`fleets_params`	is the parameter settings initialised from `_init_fleets`
`fleets_catches`	is the DF initialised from `_init_fleets`
`closed_areas`	is a dataframe with the x,y coordinates are any closed
`Pop`	is the population matrix for all populations
`sp_fleet_catches`	is a list of spatial catches (as a Numeric matrix) for the fleet of each population

Value

is a list with the objects catch detailing the fleet catches and catch_matrices detailing the spatial catches, to input to the delay difference model

Examples

```
None as yet
```

init_closure *Initialise spatial closure(s)*

Description

`init_closure` sets up the parameters for spatial closure(s) in the simulation.

Usage

```
init_closure(input_coords = NULL, basis = "commercial",
  rationale = "high_pop", spp1 = "spp1", spp2, year_start = 1,
  year_basis = NULL, closure_thresh = 0.95, sc = 1, temp_dyn = "annual")
```

Arguments

`input_coords`	is a dataframe of x,y coordinates defining the closure(s). If the temp_dyn are not static, the list should be multilayered with the [[week/month]][x, y]
`basis`	is a character string detailing the data used to define a closure 'on the fly'. Can be *survey* to be based on survey data, *commercial* to be based on commercial data, *real_pop* to be based on the simulated population. Not needed if coordinates defined.
`rationale`	is the basis for any 'on the fly' closure. Can be *high_pop* for the areas of a highest population or *high_ratio* for the areas of the highest ratio of population 1: population 2. Not needed if coordinates defined.
`spp1`	is the first population as basis for the closure. If rationale = high_pop then that should go here If rationale = high_ratio, its the target (high quota) population. Not needed if coordinates are defined.
`spp2`	is the second population when rationale = high_ratio, the lowest quota population. Not needed if coordinates provided or rationale = high_pop.
`year_start`	is a Numeric indicating the first year the spatial closure(s) shoud be implemented.
`year_basis`	is a vector indicating the years of data the closure is based on...Must be before `year_start`. If `NULL` then closure will be calculated dynamically each year.
`closure_thresh`	is the quantile of catches or high catch ratio which determines closed cells
`sc`	is a Numeric indicating the scale of data to use for the closure, e.g. if the data is aggregated to 2 x 2 cells, is 2.
`temp_dyn`	is a character string detailing whether closures should be temporally 'annual', or change 'monthly' or 'weekly'.

Value

is a list of parameter settings for the spatial closures which serves as an input to run_sim.

Examples

```
Not as yet
```

init_fleet *Initialise fleet*

Description

init_fleet sets up the parameters and results data frame to record the catches from the simulation.

Usage

```
init_fleet(sim_init = NULL, VPT = NULL, Qs = NULL, fuelC = 0,
  step_params = NULL, past_knowledge = FALSE, past_year_month = FALSE,
  past_trip = FALSE, threshold = NULL)
```

Arguments

sim_init	is the output (a list) from the sim_init function with the indexing for the simulation.
VPT	is a named vector of numerics detailing the value-per-tonne for catches from each of the species (same for all fleets)
Qs	is a list (an element for each fleet) with each element containing a named vector with the catchability parameters for each species the vessels in the fleet
fuelC	is the fuel cost per unit of distance moved in euro
step_params	is a list (an element for each fleet) with each element containing a named vector with the step parameters used in step_length. This must include the named elements **rate**, **B1**, **B2**, **B3**.
past_knowledge	is a Boolean (TRUE / FALSE) whether past knowledge should determine fishing location (only after the first year)
past_year_month	is a Boolean (TRUE / FALSE) that indicates whether the same month in previous years should be included in the past knowledge decision
past_trip	is a Boolean (TRUE / FALSE) that indicates whether the past trip undertaken should be included in the past knowledge decision
knowledge_threshold	is a numeric (0 - 1) detailing the threshold at which a fishing tow should be considered "good" and included in the selection of possible choices of starting fishing locations in future tows.

Value

is a list with three elements containing i) the fleet parameters, a named list **fleet_params**, ii) the fleet catches, **catches_list**, which is a list of a list. For the**catches_list** the first element denotes the fleet number, the second element is the vessel number with a dataframe for recording the vessels catches. Finally, iii) is the spatial catches for the fleets, which is a list (fleet) containing a list (vessels) containing a list (population) - which is to be passed to the delay difference model.

Examples

```
None yet, to add
```

`init_moveCov` *Initialise movement covariates*

Description

This function creates a list of covariates, to be used

Usage

```
init_moveCov(sim_init = NULL, steps = 52, spp_tol = NULL)
```

Arguments

`sim_init`	is the output from the function init_sim.
`steps`	is a Numeric with the number of timesteps over which the covariate changes
`spp_tol`	is a named list (each species) with a list of mean (mu) and variance (va) for the normal distribution for thermal tolerance.

Examples

```
None
```

`init_pop` *Initialise populations*

Description

`init_pop` sets up the populations spatial distribution based on the habitat preference, starting cell and 'n' numbers of movements for all populations in the simulation.

Usage

```
init_pop(sim_init = sim_init, Bio = NULL, hab = NULL, start_cell = NULL,
  lambda = NULL, init_move_steps = 10, rec_params = NULL, rec_wk = NULL,
  spwn_wk = NULL, M = NULL, K = NULL, cores = 3)
```

Arguments

`Bio`	is a named Numeric vector of the starting (total) biomass for each of the populations.
`hab`	is the list of Matrices with the habitat preferences created by `create_hab`
`start_cell`	is a list of Numeric vectors with the starting cells for the populations
`lambda`	is the strength that the movement distance decays at in the `move_prob` function
`init_move_steps`	is a Numeric indicating the number of movements to initialise for the population distributions
`rec_params`	is a list with an element for each population, containing a vector of the stock recruit parameters which must contain **model**, **a**, **b** and **cv**. See `Recr` for details.
`rec_wk`	is a list with an element for each population, containing a vector of the weeks in which recruitment takes place for the population
`spwn_wk`	is a list with an element for each population, containing a vector of the weeks in which spawning takes place for the population
`M`	is a named vector, with the annual natural mortality rate for each population
`K`	is a named vector, with the annual growth rate for each population
`spawn_areas`	is a list of lists, with the first level the population ("spp1" etc..) and the second the boundary coordinates (x1, x2, y1, y2) for the `create_spawn_hab` function

Value

The function returns the recording vectors at the population level, the spatial matrices for the starting population densities and the demographic parameters for each population

Examples

```
init_pop(sim_init = sim_init, Bio = c("spp1" = 1e6, "spp2" = 2e5), hab = list(spp1 = matrix(nc = 10,
runif(10*10)), spp2 = matrix(nc = 10, runif(10*10)), lambda = c("spp1" =
0.2, "spp2" = 0.3), init_move_steps = 10), rec_params = list("spp1" =
c("model" = "BH", "a" = 10, "b" = 50, "cv" = 0.2), "spp2" = c("model" = "BH",
"a" = 1, "b" = 8, "cv" = 0.2)), rec_wk = list("spp1" = 13:16, "spp2" =
13:18), spwn_wk = list("spp1" = 15:18, "spp2" = 18:20),M = c("spp1" = 0.2,
"spp2" = 0.1), K = c("spp1" = 0.3, "spp2" = 0.2))
Note, example will not have the right biomass
```

`init_sim` *Initialise simulation*

Description

`init_sim` sets up the general simulation parameters such as number of tows in a day, number of days fished in a week, how often species movement occurs and number of years for the simulation. It also creates some vector and matrix structures which are used in the `init_pop` and `init_fleet` functions.

Usage

```
init_sim(n_years = 1, n_tows_day = 4, n_days_wk_fished = 5,
  n_fleets = 1, n_vessels = 1, n_species = 1, nrows = nrows,
  ncols = ncols, move_freq = 2)
```

Arguments

`n_years`	is an integar defining the number of years for the simulation
`n_days_wk_fished`	is an integar defining the number of days in a calendar week that are fished (e.g. 5 (out of 7))
`n_fleets`	is an integar defining the number of fleets in the simulation
`n_vessels`	is an integar defining the number of vessels in each fleet
`n_species`	is an integar defining the number of species in the simulation
`nrows`	Numeric integer with the y dimension of the field in *nrow * ncol*
`ncols`	Numeric integer with the x dimension of the field in *nrow * ncol*
`move_freq`	is an integar defining the duration (in weeks) between spatial movements for the populations
`n_tow_day`	is an integar defining the number of tows in a days fishing

Value

is a list of lists, detailing the indexs and data formats necessary for the simulation.

Examples

```
init_sim(n_years = 1, n_tows_day = 4, n_days_wk_fished = 5,
n_fleets = 1, n_vessels = 1, n_species = 1, move_freq = 2)
```

`init_survey` *Initialise survey settings*

Description

`init_survey` is a function to mimic a fisheries-independent survey to sample catches from the populations.

Usage

```
init_survey(sim_init = NULL, design = "fixed_station", n_stations = 50,
  start_day = 90, stations_per_day = 5, Qs = NULL)
```

Arguments

`sim_init`	is the general simualtion settings from sim_init
`design`	is the survey design used, at the moment only *fixed_station*
`n_stations`	is a Numeric for the number of stations to be fished each. Note: If using 'fixed_station' design this will be rounded down to maintain a grid shape if not divisble.
`start_day`	is a Numeric for the first day of the survey each year
`stations_per_day`	is a Numeric for the number of stations surveyed per day
`Qs`	is a named Numeric Vector containing any survey catchabilities, assumed to be time invariant.

Value

is a list consisting of the survey setting and a a matrix for storing the log of catches from the survey, to be used as an input to run_sim.

Examples

```
init_survey(design = 'fixed_station', n_stations = 50, start_day = 90, stations_per_days = 5, Qs = c("spp1" = 0.1, "
```

`logistic` *Logistic probability*

Description

`logistic` is a helper function to generate a logistic curve to transition through the fishery stages (exploratory > transition > established). Where ~0 is exploratory fishing and ~1 is established on past knowledge. Only Q (can be set at tmax/100) and t (current tow) need to be supplied.

Usage

```
logistic(A = 0, K = 0.95, C = 1, Q = 200, B = NULL, v = 1,
  t = NULL)
```

Arguments

`A`	is the lower asymptote, set at 0
`K`	is the upper asymptote, set at 0.95 (to keep some few exploratory tows, even when established)
`C`	= 1
`Q`	defines the lower curve, related to Y at 0, usefully set at tmax/100
`B`	is the growth rate, e.g· 0.001
`v`	affects bear where asymptote maximum growth occurs, set at 1

Examples

```
NOT RUN
```

---

make_step *make step function*

Description

`make_step` determines the new position of the vessel following a move, using the step distance and bearing inputs.

Usage

```
make_step(stepD, Bear, start.x, start.y)
```

Arguments

`stepD`	is a Numeric vector of the distance to move
`Bear`	is a Numeric vector of the bearing to move (in degrees)
`start.x`	is the starting point on the x-axis
`start.y`	is the starting point on the y-axis

Value

returns a new coordinate position through a vector (x, y)

Examples

```
make_step(stepD = 20, Bear = 90, start.x = 20, start.y = 5)
```

---

move_population *population movement function*

Description

`move_population` redistributes the population based on the movement probabilities

Usage

```
move_population(moveProp, StartPop)
```

Arguments

`moveProp`	is a list of the proportion of the population from each cell to reallocated to each of the other cells
`StartPop`	is a Numeric Matrix of the current populations distribution

Value

is a list of the new position for the population from each of the cells.

NOTE: This is not aggregated and requires calling the R function *Reduce('+', Lst)* to reaggregate. Would be better if done in function but Reduce is currently faster...but much more memory intensive to get out the lists...using the standard c++ accumulate function may work for this but untested

Examples

```
None at the moment
```

`move_prob` *movement probability function*

Description

`move_prob` calculates the movement probability between a cell and all other cells based on the distance and *lambda*.

Usage

```
move_prob(start, lambda, hab)
```

Arguments

`start`	is a Numeric vector of dim 2 for the starting position c(x,y)
`lambda`	is an integar for the value for the exponential decay in probability of movement, i.e. $Pr(B\|A) = \exp -\lambda * dist_{a,b}/Sum(c = 1 : c = n) \exp -\lambda * dist$
`hab`	is a matrix of the habitat suitability

Value

is a matrix of the movement probabilities from a cell

Examples

```
move_prob(c(2, 5), 0.3, matrix(nc = 3, runif(9)))
```

`move_prob_Lst` *movement probability function as a list*

Description

`move_prob_list` applies `move_prob` from all cells to all other cells and returns as a list.

Usage

```
move_prob_Lst(lambda, hab)
```

Arguments

`lambda`	is the decay value as in `move_prob`
`hab`	is a matrix of the habitat suitability for the population

Value

is a list of the movement probabilities form each cell to all other cells

Examples

```
None at the moment
```

`norm_fun` *Normal distribution*

Description

Helper function used for returning the PDF of a normal distribution from the supplied temperature tolerances in init_moveCov

Usage

```
norm_fun(x, mu, va)
```

Arguments

`move_init`	is the output from init_moveCov

Examples

```
sapply(seq(2,20,0.1), mu = 10, va = 6)
```

`plot_catch_comp` *Plot the spatial catch composition from the commercial catches as 'square pie charts' using mapplots.*

Description

Plotting of spatial catch compositions at different levels of aggregation

Usage

```
plot_catch_comp(gran = c(20, 10, 5), logs = logs, fleets = 1:2,
  vessels = 1:5, trips = 1:20, years = 18:20, cluster_plot = FALSE,
  cluster_k = 5, scale_data = NULL)
```

Arguments

`gran`	is a Numeric Vector of granularities required
`logs`	is the fleet logs from combine_logs
`fleets`	is a Numeric Vector of the fleets to include in the catch composition plot
`vessels`	is a Numeric Vector of the vessels to include in the plot
`trips`	is a Numeric Vector of the trips to include
`years`	is a Numeric Vector of the years
`cluster_plot`	is a logical, determines whether also to run PAM cluserting on the catch compositions and plot the clusters spatially
`scale_data`	is a logical, whether to normalise the data before the clustering
`clusters_k`	is the number of clusters to search for in the PAM clustering algorithm

Examples

```
plot_catch_comp(gran = c(20,10,5,2), logs = logs, fleets = 1:2, vessels =
1:5. trips = 1:20, years = 18:20, cluster_plot = FALSE, cluster_k = 5,
scale_data = TRUE)
```

`plot_daily_fdyn` *Plot daily fishing mortality dynamics*

Description

`plot_daily_fdyn` plots the daily fishing mortality dynamics by year.

Usage

```
plot_daily_fdyn(results)
```

Arguments

`results`	is output from the function run_sim.

Value

is a matplot of the daily fishing mortality dynamics

Examples

```
plot_daily_fdyn(results = results)
```

`plot_fleet_trip` *Plot an entire fleet for a trip*

Description

`plot_fleet_trip` is a plot of a whole fleets vessels movement during one trip. It's intended for diagnostics.

Usage

```
plot_fleet_trip(logs = logs, fleet_no = 1, year_trip = 1, trip_no = 1)
```

Arguments

`logs`	is the combined log file, from combine_logs.
`fleet_no`	is a Numeric, the fleet from which to plot
`year_trip`	is a Numeric, the year in which the trip took place
`trip_no`	is a Numeric for the trip you wish to plot

Examples

```
plot_fleet_trip(logs = logs, fleet_no = 1, year_trip = 1, trip_no = 1)
```

plot_pop_summary *Plot population summary*

Description

`plot_pop_summary` plots the four population dynamic metrics: catches, biomass, fishing mortality and recruitment. It can either operate at a daily timestep or an annual timestep

Usage

```
plot_pop_summary(results = res, timestep = "daily", save = FALSE,
  save.location = ".")
```

Arguments

`results`	is an output from the function run_sim.
`timestep`	is a character string determining whether the plot is 'daily' or 'annual'
`save`	is a logical whether to save the plot
`save.location`	is a location (defaults to current directory)

Value

is a ggplot of all the species and metrics as a faceted plot examples plot_pop_summary(results = res, timestep = 'daily', save = TRUE, location = '.') ## Not run

plot_realised_stepF *Plot realised step function*

Description

`plot_realised_stepF` diagnostics plot of the step function shape realised in the simulation

Usage

```
plot_realised_stepF(logs = logs, fleet_no = 1, vessel_no = 1)
```

Arguments

`logs`	is the log file from combine_logs
`fleet_no`	is a Numeric of the fleet to plot
`vessel_no`	is a Numeric of the vessel to plot

Examples

```
plot_realised_stepF(logs = logs, fleet_no = 1, vessel_no = 1)
```

plot_spatiotemp_hab *Plot spatiotemporal habitat suitability*

Description

Function to plot out the habitat suitability, as adjusted by the spatiotemporal move covariates

Usage

```
plot_spatiotemp_hab(hab = NULL, moveCov = NULL, plot.file = getwd(),
  spwn_wk = NULL)
```

Arguments

hab	is the output from create_hab
moveCov	is the output from init_moveCov
plot.file	path to save the plots of the spatiotemporal habitats
spwn_wk	is a named list of the spawning week for each population

Examples

```
None
```

plot_survey *Plot the fisheries independent survey results*

Description

plot_survey plots the spatial abundances and an index from the fisheries independent survey, for each population.

Usage

```
plot_survey(survey = NULL, type = "spatial")
```

Arguments

survey	is the survey results from the run_sim function.
type	is a character indicating if *spatial* or *index*

Value

is a plot of the spatial distribution of survey catches and an inter-annual abundance index

Examples

```
plot_survey(survey = survey, type = "spatial")
```

`plot_vessel_move` *Plot vessel move*

Description

`plot_vessel_move` is a plot of a single vessel movement during one trip. It's intended for diagnostics.

Usage

```
plot_vessel_move(sim_init = NULL, logs = logs, fleet_no = 1,
  vessel_no = 1, year_trip = 1, trip_no = 1, fleets_init = NULL,
  pop_bios = NULL)
```

Arguments

`logs`	is the combined log file, from combine_logs.
`fleet_no`	is a Numeric, the fleet from which to plot
`vessel_no`	is a Numeric, the vessel to plot from the chosen fleet
`year_trip`	is a Numeric, the year in which the trip took place
`trip_no`	is a Numeric for the trip you wish to plot
`fleets_init`	is the output from init_fleet
`pop_bios`	is the output from run_sim when option save_pops_bios = TRUE

Examples

```
plot_vessel_move(sim_init = NULL, logs = logs, fleet_no = 1, vessel_no = 1, year_trip = 1,
trip_no = 1, fleets_init = NULL, pop_bios = NULL)
```

`rad2deg` *Radians to degrees*

Description

`rad2deg` is a helper function to covert radians to decimal degrees

Usage

```
rad2deg(r)
```

Arguments

`r`	is the bearing in radians
`d`	is the bearing in degrees

Examples

```
rad2deg(pi)
```

Recr *Recruitment function*

Description

Recr returns a biomass of recruited fish to the population based on a stock-recruit relationship and some measure of variation.

Usage

```
Recr(model, params, B, cv, ..)
```

Arguments

model	is a character detailing the recruitment function to use (currently 'BH' for Beverton and Holt or 'Ricker' for a Ricker stock-recruit relationship.
params	is a Numeric vector of length 2, containing labelled *a* and *b* parameters for the stock-recruit function. For Beverton and Holt *a* refers to the maximum recruitment rate in biomass, *b* refers to the Spawning Stock Biomass (SSB) required to produce half the maximum. For Ricker *a* refers to the maximum productivity per spawner and *b* the density dependent reduction in productivity as the stock increases.
B	is a Numeric vector containing the SSB of the adult population from which the recruitment derives.
cv	is a Numeric vector containing the coefficient of variation in the recruitment function.

Value

returns the recruitment to the population in biomass.

Examples

```
Recr(model = 'BH', params = c("a" = 2000, "b" = 200), B = 1000, cv = 0.1)
```

`Recr_mat` *Recruitment function applied to matrix*

Description

`Recr_mat` returns a matrix of spatially referenced biomass of recruited fish to the population based on a stock-recruit relationship and some measure of variation.

Usage

```
Recr_mat(model, params, B, cv, ..)
```

Arguments

`model`	is a character detailing the recruitment function to use (currently 'BH' for Beverton and Holt or 'Ricker' for a Ricker stock-recruit relationship.
`params`	is a Numeric vector of length 2, containing labelled *a* and *b* parameters for the stock-recruit function. For Beverton and Holt *a* refers to the maximum recruitment rate in biomass, *b* refers to the Spawning Stock Biomass (SSB) required to produce half the maximum. For Ricker *a* refers to the maximum productivity per spawner and *b* the density dependent reduction in productivity as the stock increases.
`B`	is a Numeric matrix containing the SSB of the adult population from which the recruitment derives.
`cv`	is a Numeric vector containing the coefficient of variation in the recruitment function.

Value

returns the recruitment to the population in biomass.

Examples

```
Recr(model = 'BH', params = c("a" = 2000/4, "b" = 200/4), B =
matrix(c(1000,2000,500,750), nc = 2), cv = 0.1)
```

`run_sim` *Run sim*

Description

`run_sim` is the overarching simulation function, taking all the parameterised inputs and returning the results.

Usage

```
run_sim(sim_init = NULL, pop_init = NULL, move_cov = NULL,
  fleets_init = NULL, hab_init = NULL, InParallel = TRUE, cores = 1,
  save_pop_bio = FALSE, survey = NULL, closure = NULL, ...)
```

Arguments

`sim_init`	is the parameterised simulation settings from `init_sim`
`pop_init`	is the parameterised populations from `init_pop`
`move_cov`	is a parameterised movement covariate object, from `init_moveCov`
`fleets_init`	is the parameterised fleets from `init_fleets`
`hab_init`	is the parameterised habitat maps from `create_hab`
`InParallel`	is a BOLEEN indicating whether calculations should be done using parallel processing from `parallel`, default is TRUE
`save_pop_bio`	is a logical flag to indicate if you want to record #' true spatial population at each time step (day)
`survey`	is the survey settings from init_survey, else NULL if no survey is due to be simulated
`closure`	is the spatial closure settings from init_closurem else NULL if no closures are to be implemented

Value

is the results...

Examples

```
Not yet
```

`step_length` *Step length function*

Description

`step_length` is a function to calculate the step length a vessel takes based on the step parameters provided for a gamma function and the revenue from the most recent fishing activity.

Usage

```
step_length(step_params = params[["step_params"]], revenue = revenue)
```

Arguments

`step_params`	is a list of parameters which determine the relationship between revenue gained from the recent fishing activity and the next move step length, based on a gamma function. The list contains the following: • **rate** Determines the rate .... • **B1** Determines... • **B2** Determines ... • **B3** Determines ..
`revenue`	is the last observed fishing revenue for the vessel

Value

step - the size of the next step

Examples

```
step_length(step_params = list(B1 = 1, B2 = 50, B3 = 2000, rate = 1),
revenue = 300)
```

`sum_fleets_catches` *Sum fleets catches*

Description

`sum_fleets_catches` is a helper function to apply `sum_fleet_catches` to all fleets, returning a single list of matrices with the catches of each population across all fleets and vessels.

Usage

```
sum_fleets_catches(FUN = sum_fleet_catches, fleets_log = NULL,
  sim_init = sim, ...)
```

Arguments

`FUN`	is the function, i.e. `sum_fleet_catches`
`fleets_log`	is the log of all the catches for all fleets, coming from application of go_fish_fleet to all fleets
`n_spp`	is the number of populations in the simulation (NOTE: can remove this and take from the overall sim settings)

Value

is a list of matrices (one for each population) with all fleets catches of each population. This is then used as an input to the baranov calcs

Examples

```
spp_catches <- sum_fleets_catches(FUN = sum_fleet_catches,
fleets_log = applied_to_fleets, n_spp = 2)
```

---

sum_fleet_catches *Sum fleet catches*

Description

sum_fleet_catches is a helper function to take the spatial catches for an entire fleet and sum them as a matrix of catches for the fleet for each population

Usage

```
sum_fleet_catches(sim_init = sim, fleet_log = NULL)
```

Arguments

sim_init	is the initialised simulation settings, from init_sim
fleet_log	is the output of go_fish_fleet, i.e. the catch log information for a single fleet

Value

is a list of matrices (one for each population) with the entire fleets catches of the population

Examples

```
test <- sum_fleet_catches(fleet_log = applied_to_fleets[[1]])
```

---

test_step *test step length function*

Description

test_step is a function to test and review parameters for the step_length function. This is primarily to help with identifying the right parameters for the desired relationship between revenue and step length.

Usage

```
test_step(step_params = step_params, rev.max = 2000)
```

Arguments

`step_params` is a list of parameters which determine the relationship between revenue gained from the recent fishing activity and the next move step length, based on a gamma function. The list contains the following:

- **rate** Determines the rate ....
- **B1** Determines...
- **B2** Determines ...
- **B3** Determines ..

`rev.max` is the maximum revenue at which to test the step length function.

Value

is a plot of the relationship between revenue and step length

Examples

```
test_step(step_params = list(B1 = 1, B2 = 50, B3 = 2000, rate = 1), rev.max
= 2000)
```

`use_past_knowledge` *Use past knowledge*

Description

`use_past_knowledge` is a helper function to make a random draw whether to do exploratory fishing or go to known fishing grounds

Usage

```
use_past_knowledge(p = NULL)
```

Arguments

`p` is the probability of using past knowledge, drawn from logistic

Examples

```
None
```

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Appendix G

MixFishSim vignette for R package associated with manuscript II

Simple MixFishSim Example

This is a simple example of how to use **'MixFishSim'** to generate simulations of the dynamics in a mixed fishery. We describe how to calibrate the habitat fields, the population models, the fishery model and implement a simple fixed spatial closure. \

First, load the packages and set a seed for reproducibility.

Load MixFishSim

```
library(MixFishSim)
library(knitr)
opts_chunk$set(tidy = TRUE)

set.seed(123)
```

Initialise the simulation

This vignette is a paired down example of how to construct a simulation using MixFishSim. We include only a basic example and encourage users to explore the other features of the package. \

Base parameters

First we specify the basic parameters of the simulation. This includes the dimensions of the spatial domain, the number of years to simulate, the number of fleets and vessels per fleet and the number of species and how often (in weeks) the fish move.

The object returned is used internally by MixFishSim a list with two levels:

- sim$idx : The different units of different processes
- sim$brk.idx: breaks for each of the key processes in units of a timestep

```
sim <- init_sim(nrows = 10, ncols = 10, n_years = 10, n_tows_day = 4, n_days_wk_fished = 5,
    n_fleets = 2, n_vessels = 20, n_species = 2, move_freq = 2)

class(sim)
```

```
## [1] "list"
```

```
sim$idx
```

```
##          ntd          ndf           nw          nwm           nt           nm
##     4.000000     5.000000    52.000000     4.333333    26.000000    12.000000
##           ny         ntow      ntow.py        n.spp        ncols        nrows
##    10.000000 10400.000000  1040.000000     2.000000    10.000000    10.000000
##           nf           nv
##     2.000000    20.000000
```

```r
names(sim$brk.idx)
```

```
## [1] "tow.breaks"   "day.seq"      "day.breaks"   "trip.breaks"  "week.breaks"
## [6] "month.breaks" "year.breaks"
```

Habitat setup

This function creates the spatial fields which support the fish populations and determine their spatial distributions. You define the parameters for the matern covariance function for each population and optionally the location of any spawning closure areas.

It returns a list of suitable habitat for each species (hab), the habitat as adjusted during the spawning period (spwn_hab) and the binary location of spawning areas (spwn_loc). It also returns the locations as x1,x2,y1,y2 and the multiplier of attractiveness to the spawning area during spawning periods (spwn_mult).

If plot.dist = TRUE, it returns the plots to a file.

```r
hab <- create_hab(sim_init = sim, spp.ctrl = list(spp.1 = list(nu = 1/0.015, var = 1,
    scale = 1, Aniso = matrix(nc = 2, c(1.5, 3, -3, 4))), spp.2 = list(nu = 1/0.05,
    var = 2, scale = 12, Aniso = matrix(nc = 2, c(1, 2, -1, 2)))), spawn_areas = list(spp1 = list(area1
    5, 2, 5), area2 = c(6, 8, 6, 8)), spp2 = list(area1 = c(5, 6, 6, 6)), spwn_mult = 10,
    plot.dist = FALSE))

print(hab)
```

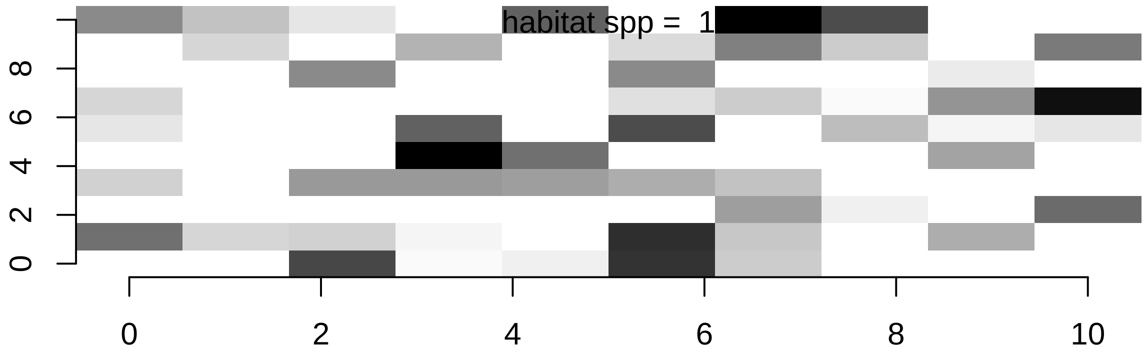
```
## $hab
## $hab$spp1
##              [,1]        [,2]        [,3]       [,4]       [,5]        [,6]
##  [1,] 0.000000000 0.029825902 0.000000000 0.01039088 0.00000000 0.006172062
##  [2,] 0.000000000 0.008892648 0.000000000 0.00000000 0.00000000 0.000000000
##  [3,] 0.037956246 0.009801995 0.000000000 0.02177983 0.00000000 0.000000000
##  [4,] 0.001875668 0.002737579 0.000000000 0.02148636 0.05272189 0.033344790
##  [5,] 0.003157360 0.000000000 0.000000000 0.02010557 0.02965351 0.000000000
##  [6,] 0.041802396 0.043484595 0.000000000 0.01686307 0.00000000 0.036926873
##  [7,] 0.011404170 0.012310136 0.020240954 0.01356676 0.00000000 0.000000000
##  [8,] 0.000000000 0.000000000 0.003822176 0.00000000 0.00000000 0.014088794
##  [9,] 0.000000000 0.016889727 0.000000000 0.00000000 0.01895698 0.003077039
## [10,] 0.000000000 0.000000000 0.030435272 0.00000000 0.00000000 0.005274148
##              [,7]        [,8]         [,9]      [,10]
##  [1,] 0.009250407 0.000000000 0.0001379017 0.02420836
##  [2,] 0.000000000 0.000000000 0.0093889316 0.01346243
##  [3,] 0.000000000 0.024271144 0.0000000000 0.00587302
##  [4,] 0.000000000 0.000000000 0.0156625272 0.00000000
##  [5,] 0.000000000 0.000000000 0.0000000000 0.03309048
##  [6,] 0.007286046 0.024920046 0.0080618195 0.00000000
##  [7,] 0.010952094 0.000000000 0.0267578154 0.05323659
##  [8,] 0.001337087 0.000000000 0.0107145287 0.03756461
##  [9,] 0.022477609 0.004296533 0.0000000000 0.00000000
## [10,] 0.050045746 0.000000000 0.0279588814 0.00000000
##
## $hab$spp2
##       [,1] [,2] [,3] [,4]       [,5]       [,6]       [,7]       [,8]
##  [1,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
##  [2,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
##  [3,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
```

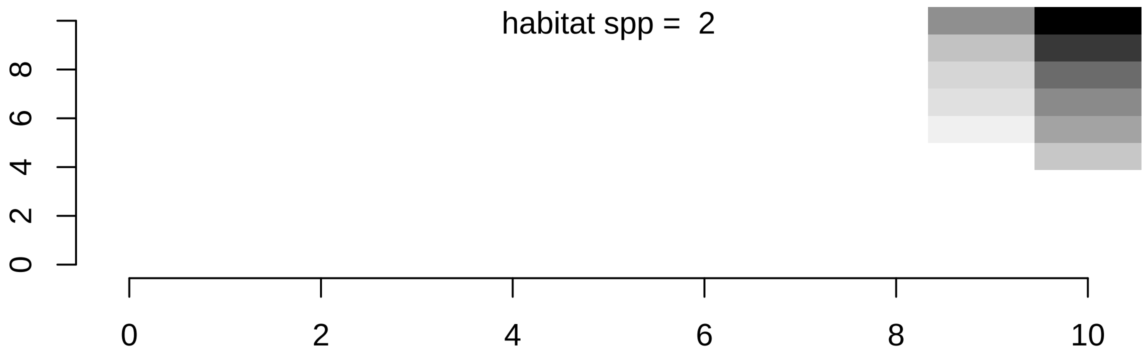
```
## [4,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [5,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [6,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [7,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [8,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [9,]    0    0    0    0 0.00000000 0.01503961 0.02789571 0.03571187
## [10,]   0    0    0    0 0.05190594 0.08078570 0.10187944 0.13122104
##            [,9]      [,10]
## [1,] 0.00000000 0.0000000
## [2,] 0.00000000 0.0000000
## [3,] 0.00000000 0.0000000
## [4,] 0.00000000 0.0000000
## [5,] 0.00000000 0.0000000
## [6,] 0.00000000 0.0000000
## [7,] 0.00000000 0.0000000
## [8,] 0.00000000 0.0000000
## [9,] 0.05709544 0.0988671
## [10,] 0.17483444 0.2247637
##
##
## $spwn_hab
## $spwn_hab$spp1
##               [,1]        [,2]        [,3]        [,4]        [,5]         [,6]
## [1,] 0.0000000000 0.008865640 0.000000000 0.003088652 0.000000000 0.0018346228
## [2,] 0.0000000000 0.026433070 0.000000000 0.000000000 0.000000000 0.0000000000
## [3,] 0.0112823555 0.029136071 0.000000000 0.064739751 0.000000000 0.0000000000
## [4,] 0.0005575354 0.008137354 0.000000000 0.063867416 0.156713904 0.0099116170
## [5,] 0.0009385138 0.000000000 0.000000000 0.059763071 0.088143981 0.0000000000
## [6,] 0.0124256094 0.012925637 0.000000000 0.005012486 0.000000000 0.1097637792
## [7,] 0.0033898479 0.003659143 0.006016549 0.004032671 0.000000000 0.0000000000
## [8,] 0.0000000000 0.000000000 0.001136128 0.000000000 0.000000000 0.0418784240
## [9,] 0.0000000000 0.005020410 0.000000000 0.000000000 0.005634894 0.0009146385
## [10,] 0.0000000000 0.000000000 0.009046773 0.000000000 0.000000000 0.0015677214
##             [,7]        [,8]         [,9]       [,10]
## [1,] 0.002749650 0.000000000 4.099077e-05 0.007195847
## [2,] 0.000000000 0.000000000 2.790826e-03 0.004001657
## [3,] 0.000000000 0.007214509 0.000000e+00 0.001745734
## [4,] 0.000000000 0.000000000 4.655629e-03 0.000000000
## [5,] 0.000000000 0.000000000 0.000000e+00 0.009836026
## [6,] 0.021657505 0.074073925 2.396346e-03 0.000000000
## [7,] 0.032554700 0.000000000 7.953663e-03 0.015824380
## [8,] 0.003974443 0.000000000 3.184855e-03 0.011165944
## [9,] 0.006681387 0.001277129 0.000000e+00 0.000000000
## [10,] 0.014875915 0.000000000 8.310675e-03 0.000000000
##
## $spwn_hab$spp2
##      [,1] [,2] [,3] [,4]       [,5]       [,6]       [,7]       [,8]
## [1,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [2,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [3,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [4,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [5,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [6,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
## [7,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
```

```
##  [8,]    0    0    0    0 0.00000000 0.00000000 0.00000000 0.00000000
##  [9,]    0    0    0    0 0.00000000 0.01503961 0.02789571 0.03571187
## [10,]    0    0    0    0 0.05190594 0.08078570 0.10187944 0.13122104
##             [,9]      [,10]
##  [1,] 0.00000000 0.0000000
##  [2,] 0.00000000 0.0000000
##  [3,] 0.00000000 0.0000000
##  [4,] 0.00000000 0.0000000
##  [5,] 0.00000000 0.0000000
##  [6,] 0.00000000 0.0000000
##  [7,] 0.00000000 0.0000000
##  [8,] 0.00000000 0.0000000
##  [9,] 0.05709544 0.0988671
## [10,] 0.17483444 0.2247637
##
##
## $spwn_loc
## $spwn_loc$spp1
##       [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
##  [1,]    0    0    0    0    0    0    0    0    0     0
##  [2,]    0    1    1    1    1    0    0    0    0     0
##  [3,]    0    1    1    1    1    0    0    0    0     0
##  [4,]    0    1    1    1    1    0    0    0    0     0
##  [5,]    0    1    1    1    1    0    0    0    0     0
##  [6,]    0    0    0    0    0    1    1    1    0     0
##  [7,]    0    0    0    0    0    1    1    1    0     0
##  [8,]    0    0    0    0    0    1    1    1    0     0
##  [9,]    0    0    0    0    0    0    0    0    0     0
## [10,]    0    0    0    0    0    0    0    0    0     0
##
## $spwn_loc$spp2
##       [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
##  [1,]    0    0    0    0    0    0    0    0    0     0
##  [2,]    0    0    0    0    0    0    0    0    0     0
##  [3,]    0    0    0    0    0    0    0    0    0     0
##  [4,]    0    0    0    0    0    0    0    0    0     0
##  [5,]    0    0    0    0    0    1    0    0    0     0
##  [6,]    0    0    0    0    0    1    0    0    0     0
##  [7,]    0    0    0    0    0    0    0    0    0     0
##  [8,]    0    0    0    0    0    0    0    0    0     0
##  [9,]    0    0    0    0    0    0    0    0    0     0
## [10,]    0    0    0    0    0    0    0    0    0     0
##
##
## $spawn_areas
## $spawn_areas$spp1
## $spawn_areas$spp1$area1
## [1] 2 5 2 5
##
## $spawn_areas$spp1$area2
## [1] 6 8 6 8
##
##
## $spawn_areas$spp2
```

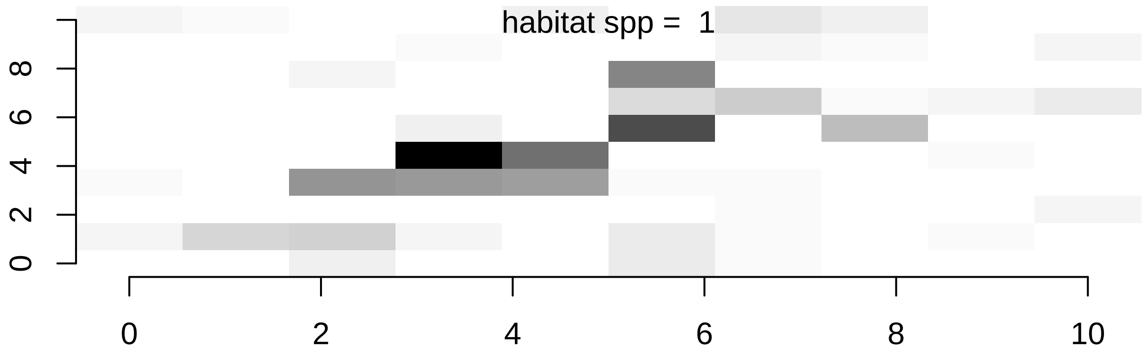
```
## $spawn_areas$spp2$area1
## [1] 5 6 6 6
##
##
## $spawn_areas$spwn_mult
## [1] 10
##
## $spawn_areas$plot.dist
## [1] FALSE
```

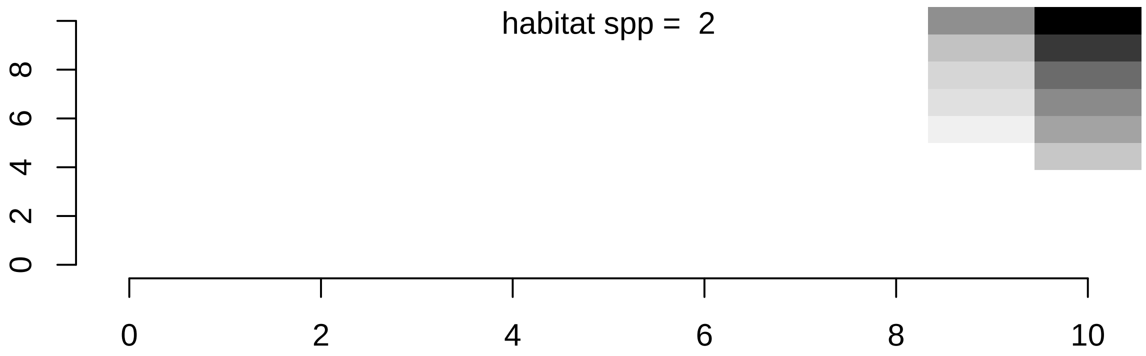
```r
## Plot the unadjusted habitat fields
plot_habitat(hab$hab)
```






```r
## Plot the adjusted habitat fields
plot_habitat(hab$spwn_hab)
```





Population models

Now we need to set up the population models for the simulations. We do this with the init_pop function. We set the initial population biomasses, movement rates, recruitment parameter and growth and natural mortality rates.

The object created stores all the starting conditions and containers for recording the changes in the populations during the simulations.

We can plot the starting distributions for each population as a check.

```
Pop <- init_pop(sim_init = sim, Bio = c(spp1 = 1e+05, spp2 = 1e+05), hab = hab[["hab"]],
    start_cell = c(5, 5), lambda = c(spp1 = 0.1, spp2 = 0.1), init_move_steps = 20,
    rec_params = list(spp1 = c(model = "BH", a = 54, b = 2, cv = 0.7), spp2 = c(model = "BH",
        a = 27, b = 4, cv = 0.3)), rec_wk = list(spp1 = 3:6, spp2 = 4:8), spwn_wk = list(spp1 = 4:8,
        spp2 = 4:8), M = c(spp1 = 0.2, spp2 = 0.2), K = c(spp1 = 0.3, spp2 = 0.3))

names(Pop)
```

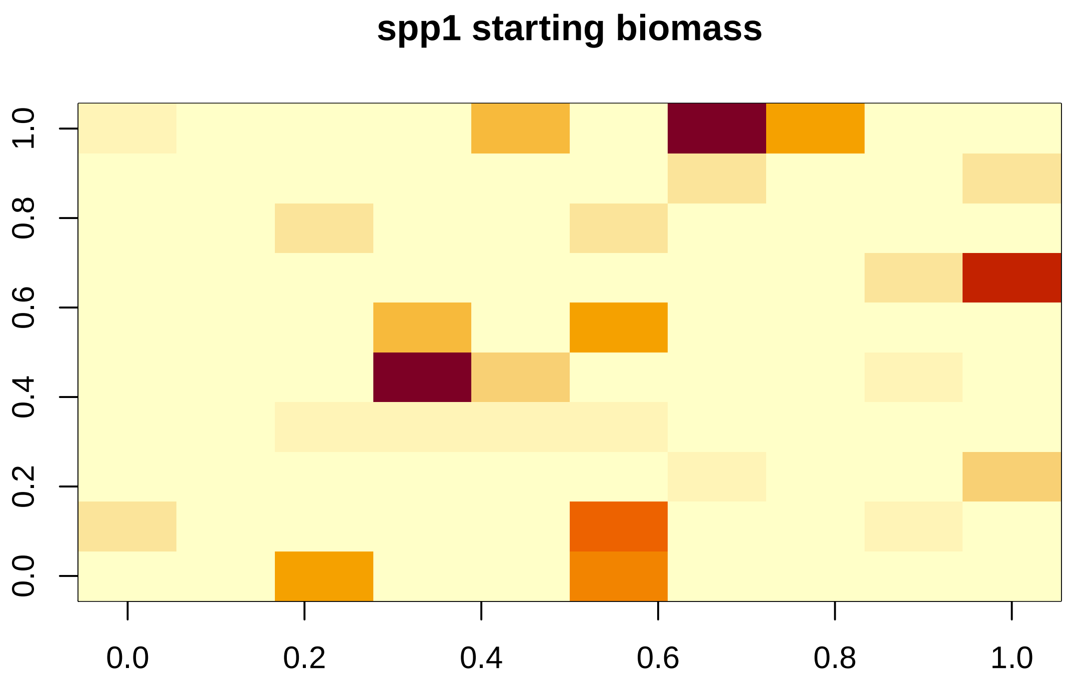
```
## [1] "Pop_record" "Start_pop"  "dem_params"
```

```
Pop$dem_params
```

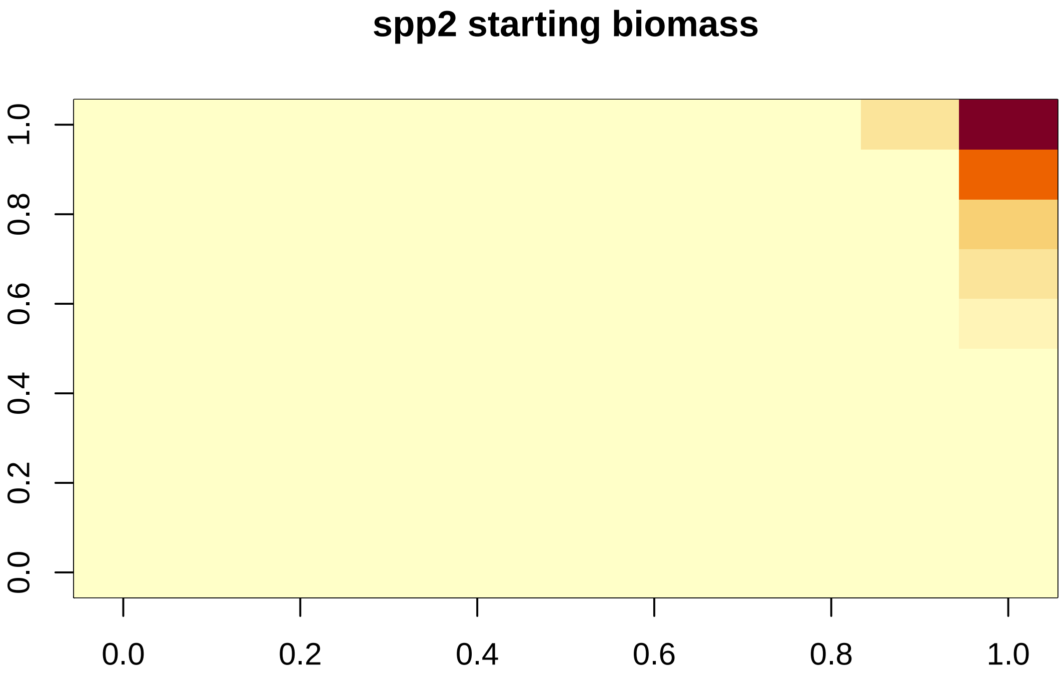
```
## $spp1
## $spp1$rec_params
## model     a     b    cv
##  "BH"  "54"   "2" "0.7"
##
## $spp1$rec_wk
## [1] 3 4 5 6
```

```
##
## $spp1$spwn_wk
## [1] 4 5 6 7 8
##
## $spp1$M
## [1] 0.2
##
## $spp1$K
## [1] 0.3
##
##
## $spp2
## $spp2$rec_params
## model      a      b     cv
##  "BH"   "27"    "4"  "0.3"
##
## $spp2$rec_wk
## [1] 4 5 6 7 8
##
## $spp2$spwn_wk
## [1] 4 5 6 7 8
##
## $spp2$M
## [1] 0.2
##
## $spp2$K
## [1] 0.3
```

```r
image(Pop$Start_pop[[1]], main = "spp1 starting biomass")
```



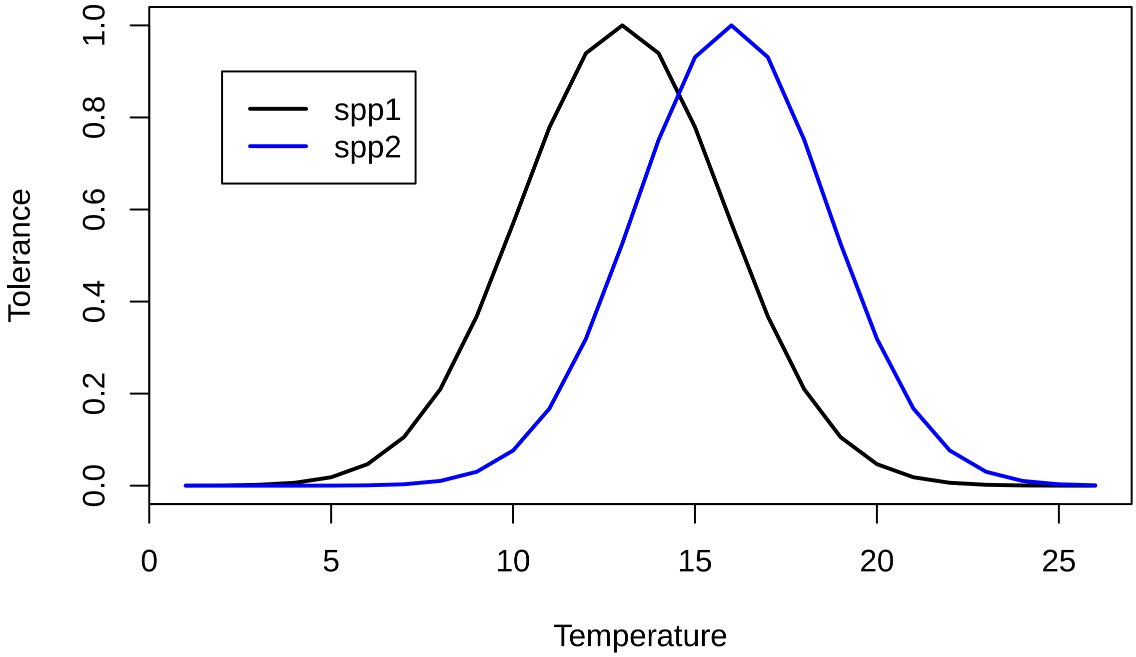

```r
image(Pop$Start_pop[[2]], main = "spp2 starting biomass")
```



Population movement

Now we set up the population tolerance to different temperatures which determines how the populations move during the course of a year. We can then plot the combined spatiotemporal suitable habitat to examine how these interact.

```
moveCov <- init_moveCov(sim_init = sim, steps = 52, spp_tol = list(spp1 = list(mu = 12,
    va = 8), spp2 = list(mu = 15, va = 7)))

plot(norm_fun(x = 0:25, mu = 12, va = 8)/max(norm_fun(0:25, 12, 8)), type = "l",
    xlab = "Temperature", ylab = "Tolerance", lwd = 2)
lines(norm_fun(x = 0:25, mu = 15, va = 7)/max(norm_fun(0:25, 15, 7)), type = "l",
    col = "blue", lwd = 2)
legend(x = 2, y = 0.9, legend = c("spp1", "spp2"), lwd = 2, col = c("black", "blue"))
```



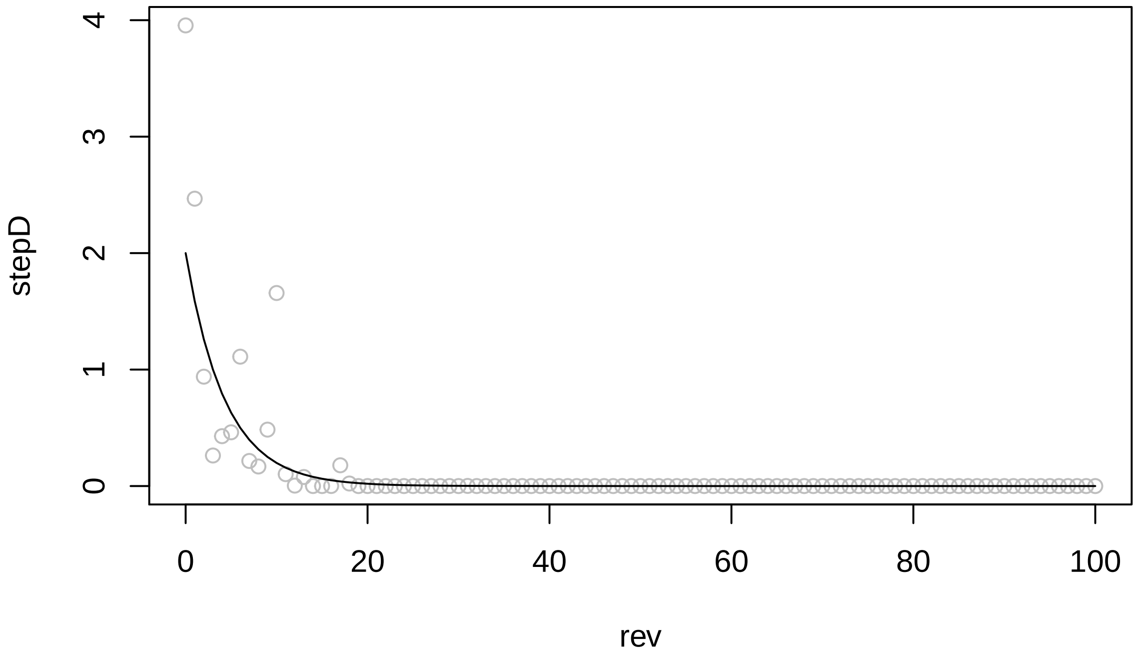

```
plot_spatiotemp_hab(hab = hab, moveCov = moveCov, spwn_wk = list(spp1 = 4:8, spp2 = 4:8))
```

Fleet models

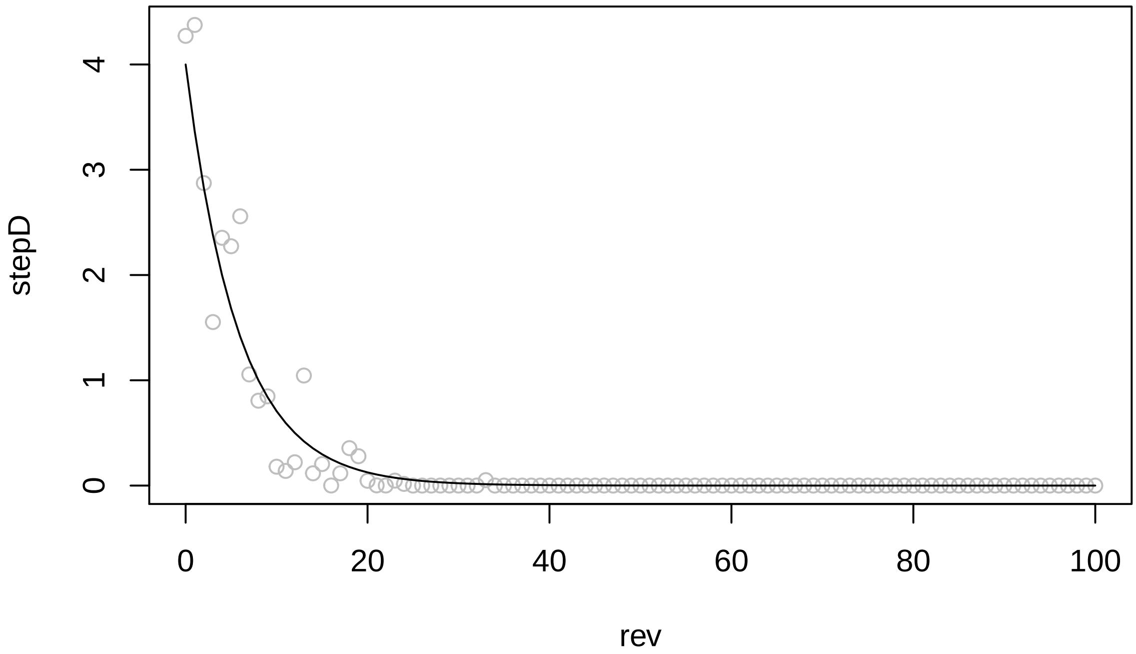
Here we initialise the fleet with fish landings price per tonne, catchability coefficients per population, fuel cost, the coefficients for the step function and fleet behaviour.

We can plot the behaviour of the step function to check its suitable for our simulations. This determines the relationship between the monetary value gained from a fishing tow and the next move by the vessel when using the correlated random walk function.

```
fleets <- init_fleet(sim_init = sim, VPT = list(spp1 = 4, spp2 = 3), Qs = list(`fleet 1` = c(spp1 = 1e-0
    spp2 = 3e-05), `fleet 2` = c(spp1 = 5e-05, spp2 = 1e-05)), fuelC = list(fleet1 = 3,
    `fleet 2` = 8), step_params = list(`fleet 1` = c(rate = 3, B1 = 1, B2 = 2, B3 = 3),
    `fleet 2` = c(rate = 3, B1 = 2, B2 = 4, B3 = 4)), past_knowledge = TRUE, past_year_month = TRUE,
    past_trip = TRUE, threshold = 0.7)

test_step(step_params = fleets$fleet_params[[1]]$step_params, rev.max = 100)
```




```
test_step(step_params = fleets$fleet_params[[2]]$step_params, rev.max = 100)
```



Spatial closure

We set up a spatial closure. There are multiple options in defining this, but we simply define a static fixed site closure for demonstration purposes.

```
closure <- init_closure(input_coords = data.frame(x = c(9, 10), y = c(6, 10)), spp1 = "spp1",
    year_start = 5)
```

Survey

Its also possible to define a survey design using the init_survey function, but we do not do so for this demonstration. Please refer to the function help file if this is required.

Run simulation

Finally we run the simulation. The output is a list of objects containing all the information on fisheries catches, the population dynamics and population distributions. These can be examined with some inbuilt plotting functions.

```r
res <- run_sim(sim_init = sim, pop_init = Pop, move_cov = moveCov, fleets_init = fleets,
    hab_init = hab, save_pop_bio = TRUE, survey = NULL, closure = closure)
```

```
## [1] "Calculating movement probabilities"
## [1] "You are implementing spatial closures...."
## [1] "----------year 1 -----------"
## [1] "tow == 1 ---- 0 %"
## [1] "tow == 101 ---- 1 %"
## [1] "tow == 201 ---- 2 %"
## [1] "tow == 301 ---- 3 %"
## [1] "tow == 401 ---- 4 %"
## [1] "tow == 501 ---- 5 %"
## [1] "tow == 601 ---- 6 %"
## [1] "tow == 701 ---- 7 %"
## [1] "tow == 801 ---- 8 %"
## [1] "tow == 901 ---- 9 %"
## [1] "tow == 1001 ---- 10 %"
## [1] "----------year 2 -----------"
## [1] "tow == 1101 ---- 11 %"
## [1] "tow == 1201 ---- 12 %"
## [1] "tow == 1301 ---- 13 %"
## [1] "tow == 1401 ---- 13 %"
## [1] "tow == 1501 ---- 14 %"
## [1] "tow == 1601 ---- 15 %"
## [1] "tow == 1701 ---- 16 %"
## [1] "tow == 1801 ---- 17 %"
## [1] "tow == 1901 ---- 18 %"
## [1] "tow == 2001 ---- 19 %"
## [1] "----------year 3 -----------"
## [1] "tow == 2101 ---- 20 %"
## [1] "tow == 2201 ---- 21 %"
## [1] "tow == 2301 ---- 22 %"
## [1] "tow == 2401 ---- 23 %"
## [1] "tow == 2501 ---- 24 %"
## [1] "tow == 2601 ---- 25 %"
## [1] "tow == 2701 ---- 26 %"
## [1] "tow == 2801 ---- 27 %"
## [1] "tow == 2901 ---- 28 %"
## [1] "tow == 3001 ---- 29 %"
## [1] "tow == 3101 ---- 30 %"
## [1] "----------year 4 -----------"
## [1] "tow == 3201 ---- 31 %"
## [1] "tow == 3301 ---- 32 %"
```

```
## [1] "tow == 3401 ---- 33 %"
## [1] "tow == 3501 ---- 34 %"
## [1] "tow == 3601 ---- 35 %"
## [1] "tow == 3701 ---- 36 %"
## [1] "tow == 3801 ---- 37 %"
## [1] "tow == 3901 ---- 38 %"
## [1] "tow == 4001 ---- 38 %"
## [1] "tow == 4101 ---- 39 %"
## [1] "----------year 5 -----------"
## [1] "Setting manually defined closures"
## [1] "Closures are yearly"
## [1] "tow == 4201 ---- 40 %"
## [1] "tow == 4301 ---- 41 %"
## [1] "tow == 4401 ---- 42 %"
## [1] "tow == 4501 ---- 43 %"
## [1] "tow == 4601 ---- 44 %"
## [1] "tow == 4701 ---- 45 %"
## [1] "tow == 4801 ---- 46 %"
## [1] "tow == 4901 ---- 47 %"
## [1] "tow == 5001 ---- 48 %"
## [1] "tow == 5101 ---- 49 %"
## [1] "----------year 6 -----------"
## [1] "tow == 5201 ---- 50 %"
## [1] "Setting manually defined closures"
## [1] "Closures are yearly"
## [1] "tow == 5301 ---- 51 %"
## [1] "tow == 5401 ---- 52 %"
## [1] "tow == 5501 ---- 53 %"
## [1] "tow == 5601 ---- 54 %"
## [1] "tow == 5701 ---- 55 %"
## [1] "tow == 5801 ---- 56 %"
## [1] "tow == 5901 ---- 57 %"
## [1] "tow == 6001 ---- 58 %"
## [1] "tow == 6101 ---- 59 %"
## [1] "tow == 6201 ---- 60 %"
## [1] "----------year 7 -----------"
## [1] "Setting manually defined closures"
## [1] "Closures are yearly"
## [1] "tow == 6301 ---- 61 %"
## [1] "tow == 6401 ---- 62 %"
## [1] "tow == 6501 ---- 63 %"
## [1] "tow == 6601 ---- 63 %"
## [1] "tow == 6701 ---- 64 %"
## [1] "tow == 6801 ---- 65 %"
## [1] "tow == 6901 ---- 66 %"
## [1] "tow == 7001 ---- 67 %"
## [1] "tow == 7101 ---- 68 %"
## [1] "tow == 7201 ---- 69 %"
## [1] "----------year 8 -----------"
## [1] "Setting manually defined closures"
## [1] "Closures are yearly"
## [1] "tow == 7301 ---- 70 %"
## [1] "tow == 7401 ---- 71 %"
## [1] "tow == 7501 ---- 72 %"
```

```
## [1] "tow == 7601 ---- 73 %"
## [1] "tow == 7701 ---- 74 %"
## [1] "tow == 7801 ---- 75 %"
## [1] "tow == 7901 ---- 76 %"
## [1] "tow == 8001 ---- 77 %"
## [1] "tow == 8101 ---- 78 %"
## [1] "tow == 8201 ---- 79 %"
## [1] "tow == 8301 ---- 80 %"
## [1] "----------year 9 -----------"
## [1] "Setting manually defined closures"
## [1] "Closures are yearly"
## [1] "tow == 8401 ---- 81 %"
## [1] "tow == 8501 ---- 82 %"
## [1] "tow == 8601 ---- 83 %"
## [1] "tow == 8701 ---- 84 %"
## [1] "tow == 8801 ---- 85 %"
## [1] "tow == 8901 ---- 86 %"
## [1] "tow == 9001 ---- 87 %"
## [1] "tow == 9101 ---- 88 %"
## [1] "tow == 9201 ---- 88 %"
## [1] "tow == 9301 ---- 89 %"
## [1] "----------year 10 -----------"
## [1] "Setting manually defined closures"
## [1] "Closures are yearly"
## [1] "tow == 9401 ---- 90 %"
## [1] "tow == 9501 ---- 91 %"
## [1] "tow == 9601 ---- 92 %"
## [1] "tow == 9701 ---- 93 %"
## [1] "tow == 9801 ---- 94 %"
## [1] "tow == 9901 ---- 95 %"
## [1] "tow == 10001 ---- 96 %"
## [1] "tow == 10101 ---- 97 %"
## [1] "tow == 10201 ---- 98 %"
## [1] "tow == 10301 ---- 99 %"
## [1] "time taken is : 17.89409 mins"
```

Summary plots

There are a series of input plotting functions to visualise the results of the simulation. For example, we can explore:

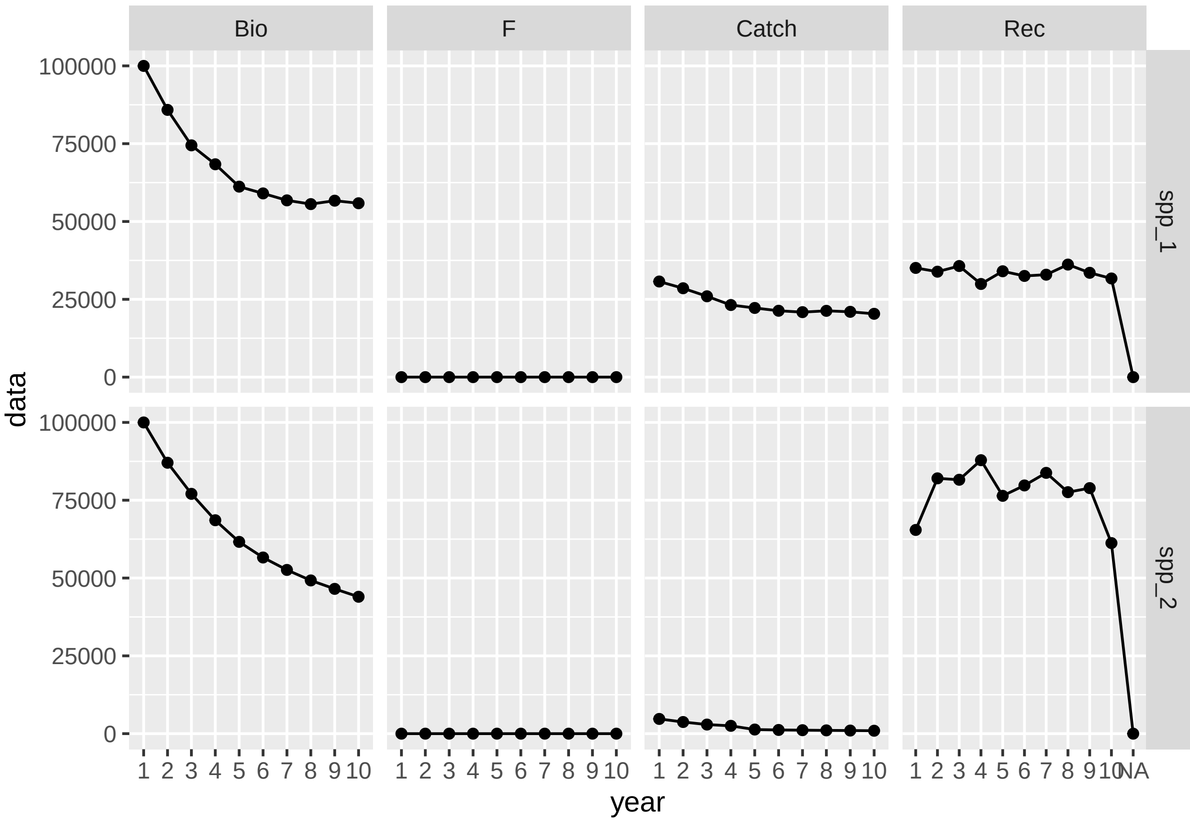
- the population dynamics for each species
- Seasonal patterns in exploitation
- the location choice of a vessel
- the realised step function for a vessel

Users will wish to define their own plots, depending on the issues of interest and all the results are saved in the output from the run_sim function.

```
## Biological
p1 <- plot_pop_summary(results = res, timestep = "annual", save = FALSE)
```

```
## Warning in `[<-.factor`(`*tmp*`, ri, value = 1:11): invalid factor level, NA
## generated
```

```
## Warning in `[<-.factor`(`*tmp*`, ri, value = 1:11): invalid factor level, NA
## generated

## Loading required package: ggplot2

## Loading required package: dplyr

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

## Warning: Factor `year` contains implicit NA, consider using
## `forcats::fct_explicit_na`
```

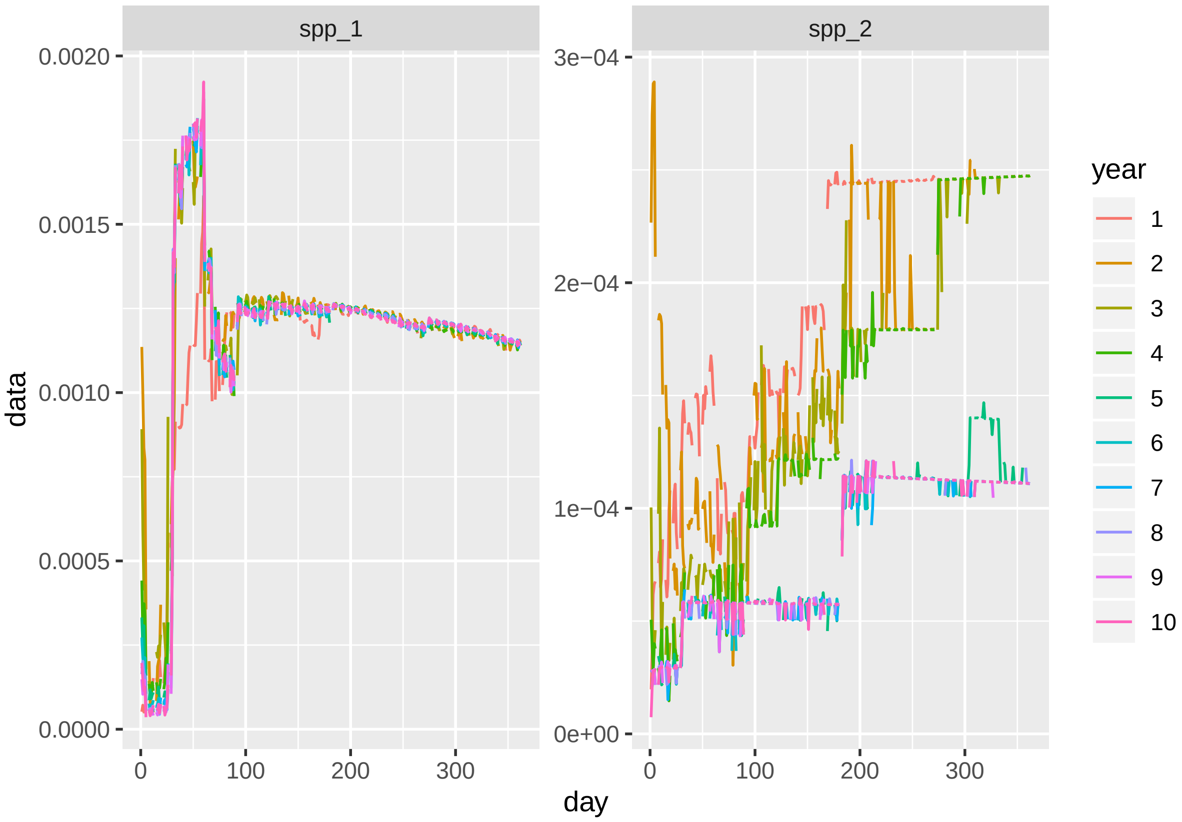



```
p1
```

```
## NULL
```

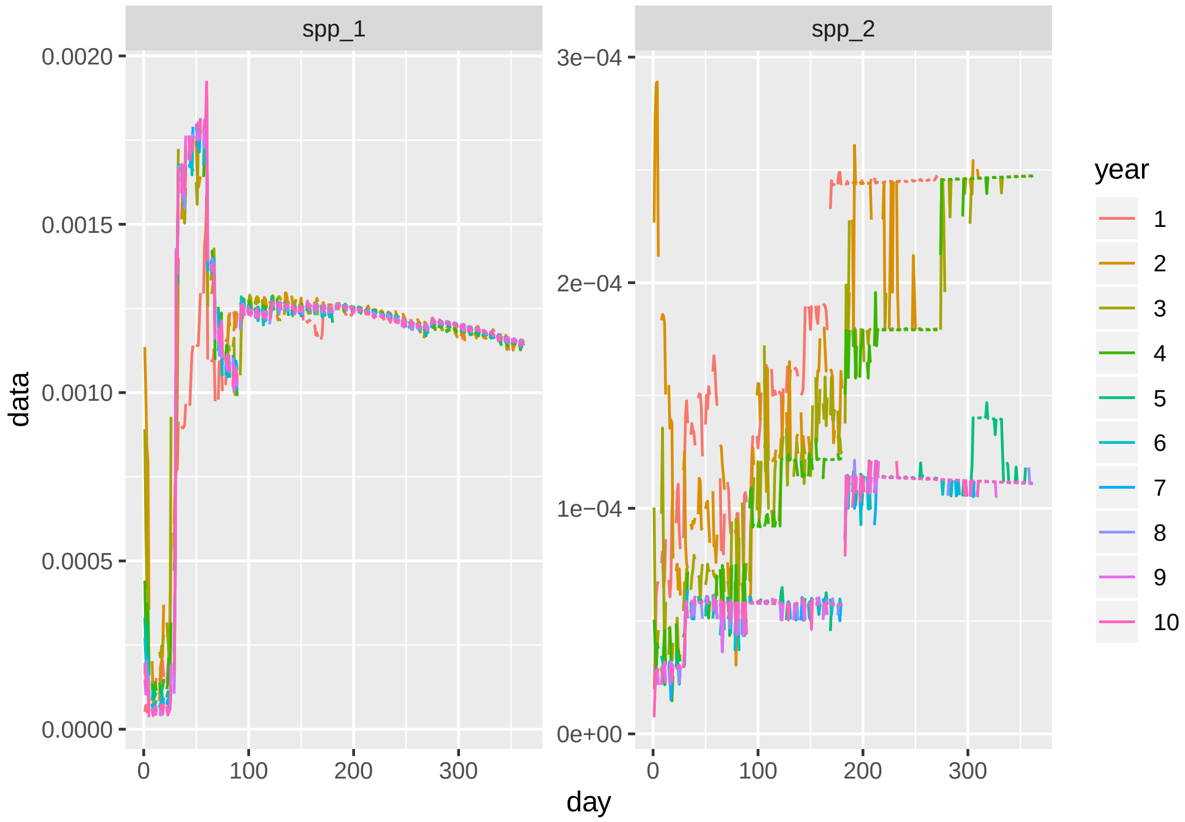
```
p2 <- plot_daily_fdyn(res)
```

```
## Warning: Removed 1 rows containing missing values (geom_path).
```

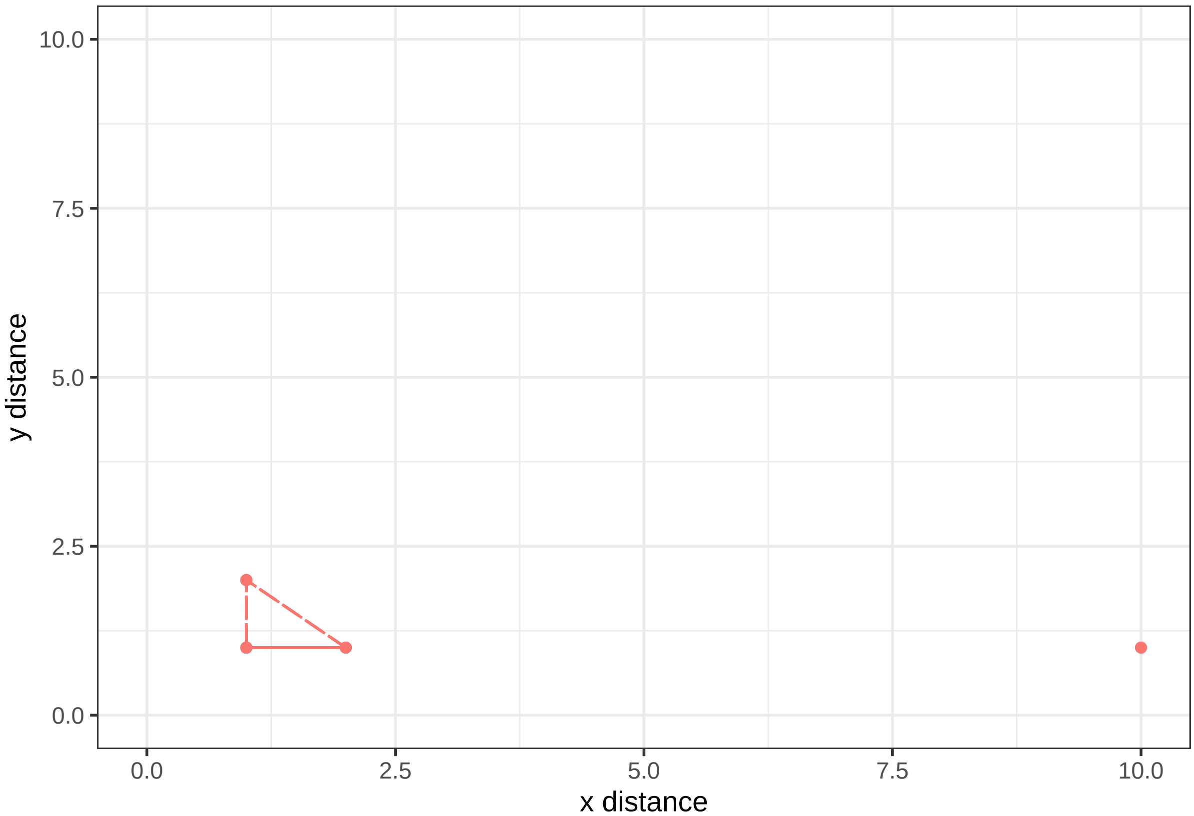



```
p2
```

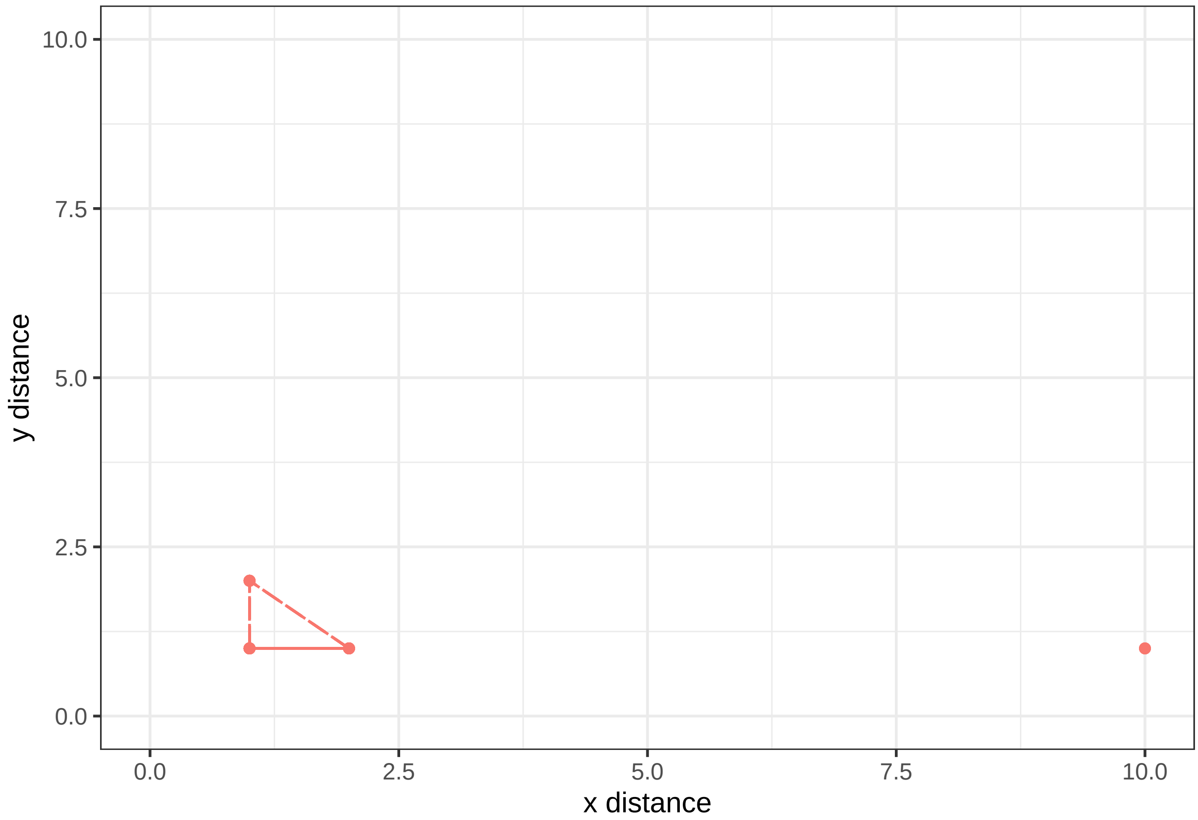
```
## Warning: Removed 1 rows containing missing values (geom_path).
```



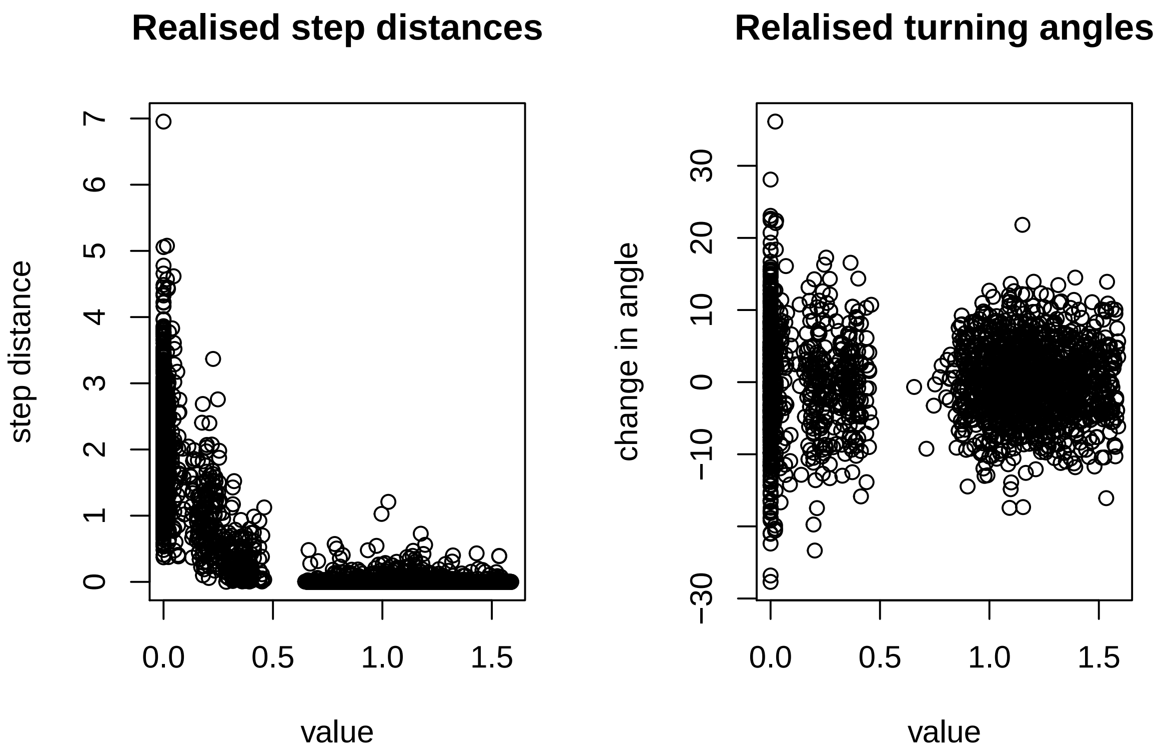

```
## Fishery

logs <- combine_logs(res[["fleets_catches"]])

p3 <- plot_vessel_move(sim_init = sim, logs = logs, fleet_no = 1, vessel_no = 5,
    year_trip = 5, trip_no = 10)
```




```
p3
```




```r
p4 <- plot_realised_stepF(logs = logs, fleet_no = 1, vessel_no = 1)
```




```
## NULL
```

```
p4
```

```
## NULL
```

Note in our example how the fishing mortality rate for species 2 changes following the spatial closure, which was set to cover some of the core distribution of the population.

Appendix H

Supplementary material for manuscript III

A general model gives that the effort $E_{a,t}$ in area a at time t is a portion of the total effort:

$$E_{a,t} = p_{a,t} E_t \tag{H.1}$$

All of the methods predict $p_{a,t}$ and a goal is to compare them theoretically and practically.

Gravity model

A basic gravity model assumes

$$p_{a,t}^{(g)} = \frac{Pr_{a,t-\tau}}{\sum_a Pr_{a,t-\tau}} \tag{H.2}$$

where (g) denotes the gravity model, Pr is the profit-per-unit-effort τ time units prior.
Working with two fisheries for initial simplicity $a \in \{1, 2\}$, the proportion of effort in area one from the gravity model is given by:

$$p_{1,t}^{(g)} = \frac{Pr_{1,t-\tau}}{Pr_{1,t-\tau} + Pr_{2,t-\tau}} \tag{H.3}$$

RUM model

A multinomial logit model for the counts in either of the two states (i.e., binomial) would model the counts per area and estimate:

$$p_{1,t}^{(l)} = \frac{1}{1+e^{-\theta_1}} \tag{H.4}$$

where the superscript (l) denotes the multinomial logit model, and θ_1 the log-odds of the proportion in area 1 to area 2. To obtain the same effort allocation between the gravity and multinomial model requires:

$$\begin{aligned}
p_{1,t}^{(g)} &= p_{1,t}^{(l)} \qquad\qquad (H.5)\\
\frac{Pr_{1,t-\tau}}{Pr_{1,t-\tau}+Pr_{2,t-\tau}} &= \frac{1}{1+e^{-\theta_1}}\\
1+e^{-\theta_1} &= \frac{Pr_{1,t-\tau}+Pr_{2,t-\tau}}{Pr_{1,t-\tau}}\\
e^{-\theta_1} &= \frac{Pr_{1,t-\tau}+Pr_{2,t-\tau}}{Pr_{1,t-\tau}} - 1\\
e^{-\theta_1} &= \frac{Pr_{2,t-\tau}}{Pr_{1,t-\tau}}\\
-\theta_1 &= \ln\left(\frac{Pr_{2,t-\tau}}{Pr_{1,t-\tau}}\right)\\
\theta_1 &= \ln\left(\frac{Pr_{1,t-\tau}}{Pr_{2,t-\tau}}\right) \qquad\qquad (H.6)
\end{aligned}$$

Equation (H.6) shows that the gravity and binomial logit model are equivalent when the log-odds for the logit model is given by the log of the ratio of the value-per-unit-effort in area 1 to area 2. With real data, one could fit an intercept-only binomial model, estimate the log-odds as a free parameter and compare with that predicted by the gravity model treated as a null hypothesis, for example. Or one could add in an intercept and slope over $Pr_{1,t}$ in the binomial to see which assumption differs from the gravity model.

More areas

Now $a \in \{1,\dots,A\}$, the proportion of effort in area a from the gravity model is given by:

$$p_{a,t}^{(g)} = \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \tag{H.7}$$

A multinomial logit model, typically models the log-odds of a given category relative to a baseline category. Setting area one as the baseline category and equating with the gravity model proportions gives:

$$\theta_a = \ln\left(\frac{p_{a,t}^{(l)}}{p_{1,t}^{(l)}}\right) = \ln\left(\frac{\frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}}}{\frac{Pr_{1,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}}}\right) = \ln\left(\frac{Pr_{a,t-\tau}}{Pr_{1,t-\tau}}\right) \tag{H.8}$$

with the probabilities given by

$$p_{a,t}^{(l)} = \frac{e^{\theta_a}}{\sum_{j=1}^{A} e^{\theta_j}} \tag{H.9}$$

One can demonstrate the equivalence for an example, say area 1 in a three area system:

$$\begin{aligned}
p_{1,t}^{(l)} &= \frac{e^{\theta_1}}{\sum_{j=1}^{3} e^{\theta_j}} \\
&= \frac{e^{\ln\left(\frac{Pr_{1,t-\tau}}{Pr_{1,t-\tau}}\right)}}{\sum_{j=1}^{3} e^{\ln\left(\frac{Pr_{j,t-\tau}}{Pr_{1,t-\tau}}\right)}} \\
&= \frac{\frac{Pr_{1,t-\tau}}{Pr_{1,t-\tau}}}{\sum_{j=1}^{3} \frac{Pr_{j,t-\tau}}{Pr_{1,t-\tau}}} \\
&= \frac{\frac{Pr_{1,t-\tau}}{Pr_{1,t-\tau}}}{\frac{Pr_{1,t-\tau}+Pr_{2,t-\tau}+Pr_{3,t-\tau}}{Pr_{1,t-\tau}}} \\
&= \frac{Pr_{1,t-\tau}}{Pr_{1,t-\tau} + Pr_{2,t-\tau} + Pr_{3,t-\tau}},
\end{aligned}$$

as in the gravity model (Equation H.7).

We can therefore state the equivalence of the gravity and multinomial logit model when the log-odds of the multinomial are given by the log of the ratio of the value in a given area divided by the value in baseline area (Equation H.8). This model is more formally a conditional logit model (McFadden) as the variables are choice specific. We can write the gravity model as a conditional logit by specifying that the probability of choosing area a at time t

$$P(y_t = a|\mathbf{X}_{t-\tau}) = \frac{e^{\beta X_{a,t-\tau}}}{\sum_{j=1}^{A} e^{\beta X_{j,t-\tau}}} \tag{H.10}$$

where $\beta = 1$ and $X_{a,t-\tau} = \ln\left(\frac{Pr_{a,t-\tau}}{Pr_{1,t-\tau}}\right)$.

Markov model

The Markov property states

$$P(Y_t = y_t|Y_{t-1} = y_{t-1}, \dots, Y_0 = y_0) = P(Y_t = y_t|Y_{t-1} = y_{t-1}) \tag{H.11}$$

where Y_t is the state (area) at time t. So the probability is dependent only on the previous state and not those preceding the previous step. A transition probability matrix governs the probability of transitioning among the available states of a Markov model. For A possible areas the transition matrix can be written

$$\mathcal{P}(t) = \begin{bmatrix} p_{1,1}(t) & p_{1,2}(t) & \dots & p_{1,A}(t) \\ p_{2,1}(t) & p_{2,2}(t) & \dots & p_{2,A}(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_{A,1}(t) & p_{A,2}(t) & \dots & p_{A,A}(t) \end{bmatrix} \tag{H.12}$$

where rows denote departing state and columns destination state (at time t) (probabilities sum to unity across rows). Note the transition probabilities are here assumed time t specific. A state probability (as distinct from a transition probability) gives the probability that a given state is occupied at a given time and is denoted $\pi_{a,t}$ where

$$\pi_{a,t} = \sum_{j=1}^{A} \pi_{j,t-1} p_{j,a}(t), \tag{H.13}$$

that is, the sum of the proportions moving into area a at time t from all fisheries j at time $t-1$.
To equate the Markov and gravity model requires:

$$\begin{aligned} \pi_{a,t} &= p_{a,t}^{(g)} \\ \sum_{j=1}^{A} \pi_{j,t-1} p_{j,a}(t) &= \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \\ \sum_{j=1}^{A} \frac{Pr_{j,t-1-\tau}}{\sum_{k=1}^{A} Pr_{k,t-1-\tau}} p_{j,a}(t) &= \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \end{aligned} \tag{H.14}$$

which has no unique solution. While the system is undetermined with an infinite number of solutions, a particularly relevant solution is that where the system is memoryless such that $p_{i,a} = p_{j,a} = p_a$:

$$\begin{aligned} \sum_{j=1}^{A} \frac{Pr_{j,t-1-\tau}}{\sum_{k=1}^{A} Pr_{k,t-1-\tau}} p_{j,a}(t) &= \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \\ p_a(t) \sum_{j=1}^{A} \frac{Pr_{j,t-1-\tau}}{\sum_{k=1}^{A} Pr_{k,t-1-\tau}} &= \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \\ p_a(t) &= \frac{Pr_{a,t-\tau}}{\sum_{j=1}^{A} Pr_{j,t-\tau}} \end{aligned} \tag{H.15}$$

That is, where the transition probabilities are the same irrespective of the departing state (memoryless) and given by the gravity model probabilities, the Markov and gravity models equate. The transition matrix would be written

$$\mathcal{P}(t) = \begin{bmatrix} p_1(t) & p_2(t) & \dots & p_A(t) \\ p_1(t) & p_2(t) & \dots & p_A(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_1(t) & p_2(t) & \dots & p_A(t) \end{bmatrix} \tag{H.16}$$

which removes the conditional probability of the Markov model depending on the previous state. As such the model is no longer Markovian but may be useful for testing between Markov and RUM assumptions. An example three state system is illustrated in the footnote[1]

Dynamic state variable model

DSVMs introduce a discretized utility state, which is explicitly/implicitly represented in a Gravity, Markov and RUM so there they are similar in that underlying concept. However, due to the long-run optimisation in a DSVM in their simplest implementations they are fundamentally different.

Setting up a simplified setting with three areas and different values (integer) in each. Value utility is discretized and if you go in a area you increment that number of value states, each day fishing costs one unit value.

---

[1]

$$\begin{bmatrix} \pi_1 & \pi_2 & \pi_3 \end{bmatrix} \begin{bmatrix} p_1 & p_2 & p_3 \\ p_1 & p_2 & p_3 \\ p_1 & p_2 & p_3 \end{bmatrix} = \begin{bmatrix} \pi_1 p_1 + \pi_2 p_1 + \pi_3 p_1 \\ \pi_1 p_2 + \pi_2 p_2 + \pi_3 p_2 \\ \pi_1 p_3 + \pi_2 p_3 + \pi_3 p_3 \end{bmatrix}^T = \begin{bmatrix} p_1(\pi_1 + \pi_2 + \pi_3) \\ p_2(\pi_1 + \pi_2 + \pi_3) \\ p_3(\pi_1 + \pi_2 + \pi_3) \end{bmatrix}^T = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}^T$$

As $\pi_1 + \pi_2 + \pi_3 = 1$.

If you go with simply that set up, the model predicts the optimal policy is to go to the patch with the highest value in each time step. If there are patches with the same value they have equal optimality. That the optimal choice is to go to the patch with the highest value makes sense in the absence of any other information but it therefore cannot be equated with the other models.

Dynamic state variable models (DSVMs) introduce a discretized utility state. For example, profit utility is discretized and movements between areas (patch) would result in increment or decrements of profit state. A fundamental difference with the statistical models that focus on area transitions (i.e. Markov models) is that DSVMs focus on utility transitions and optimal choice is emergent from the calculation procedure. A simple DSVM predicts the optimal policy (set of choices) is to go to the area with the highest profit.

That the optimal choice is to go to the area with the highest value means it cannot be simply equated with the other models. To have policies with the same proportions to the statistical models would require that the distribution of the vessels among utility states times the optimal transition matrix among utility states (Reimer et al., 2019) and summed by area would be equal that of the statistical model. The error-in-decision-making approach developed by (Dowling et al., 2012; Alzorriz et al., 2018) offers a solution to this under specific circumstances. Where the utility is time independent (i.e. without any long term constraints) the predictions can be equated to the gravity model where treaty the gravity as a multinomial so that σ in equation 4.10 is

$$\sigma_a = \frac{Pr_a - max\left(Pr_{a=1\ldots A}\right)}{\log\left(\frac{Pr_a}{Pr_{a=1}}\right)} \tag{H.17}$$

where Pr_a is profit from area a.

This requires a unique σ for each area, and in essence substitutes the short-term utility in the DSVM with a gravity model where the weight is the profit in an area relative to a reference area. Under these conditions, the models can be equated up until the point there are long-term constraints in the DSVM.

Appendix I

Supplementary material for manuscript IV

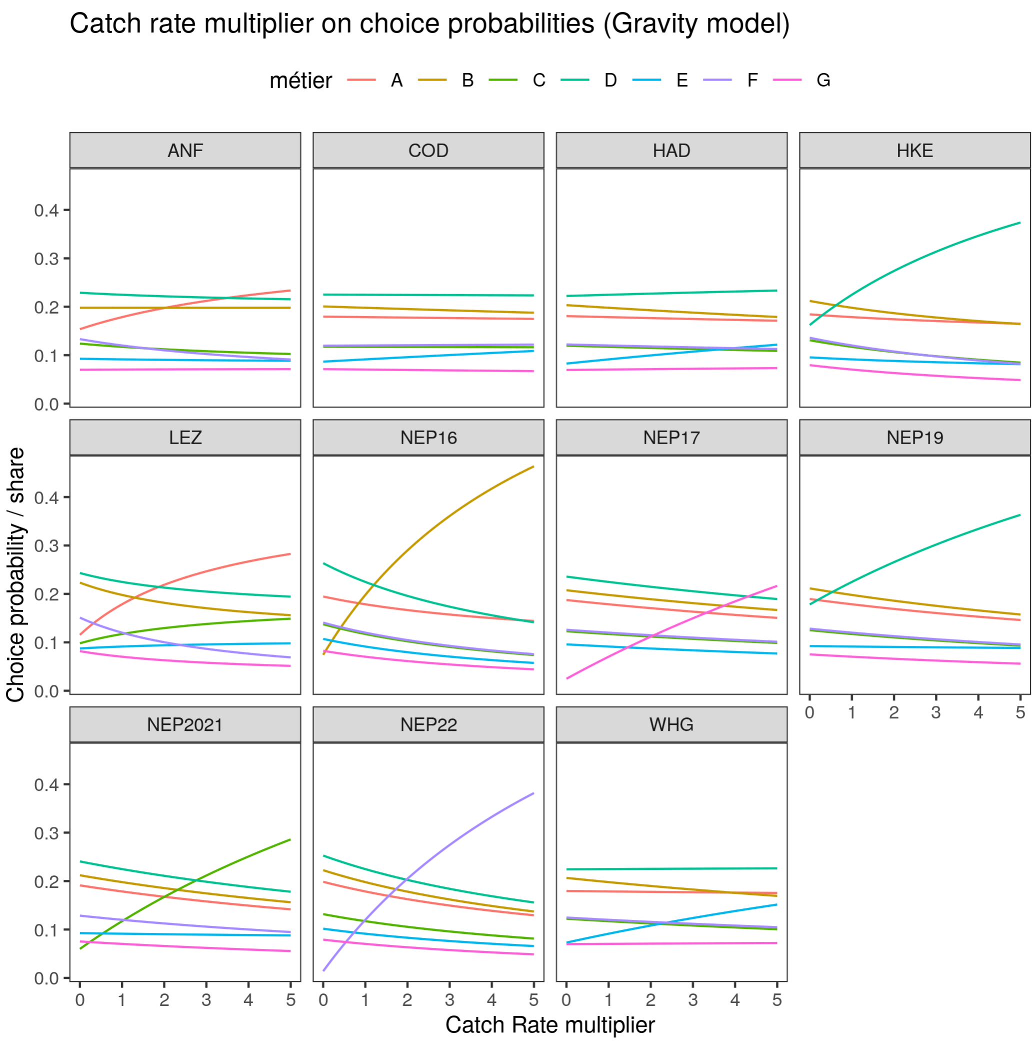


Figure S1: The influence of changes in catch rates of different stocks on effort allocation among métier from the Gravity model.

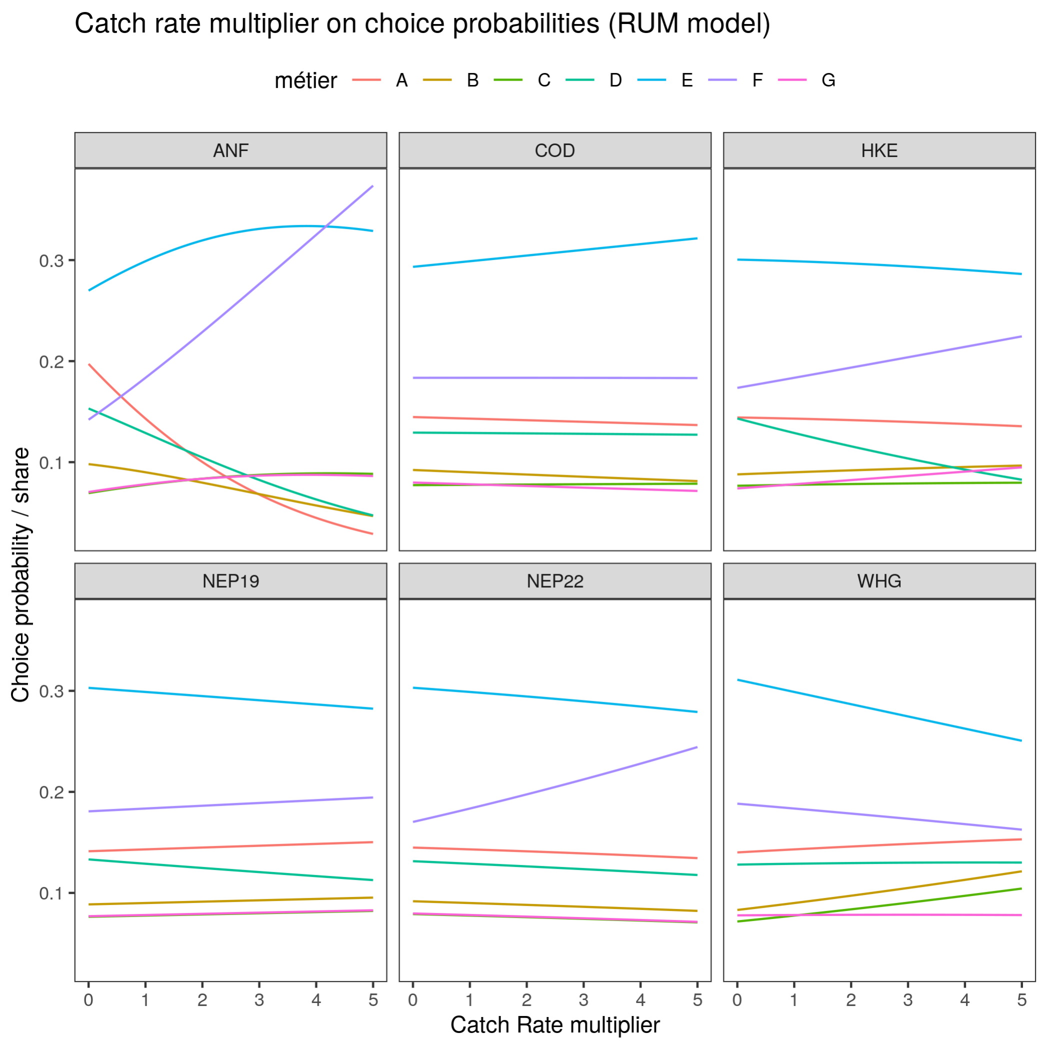


Figure S2: The influence of changes in catch rates of different stocks on effort allocation among métier from the RUM.

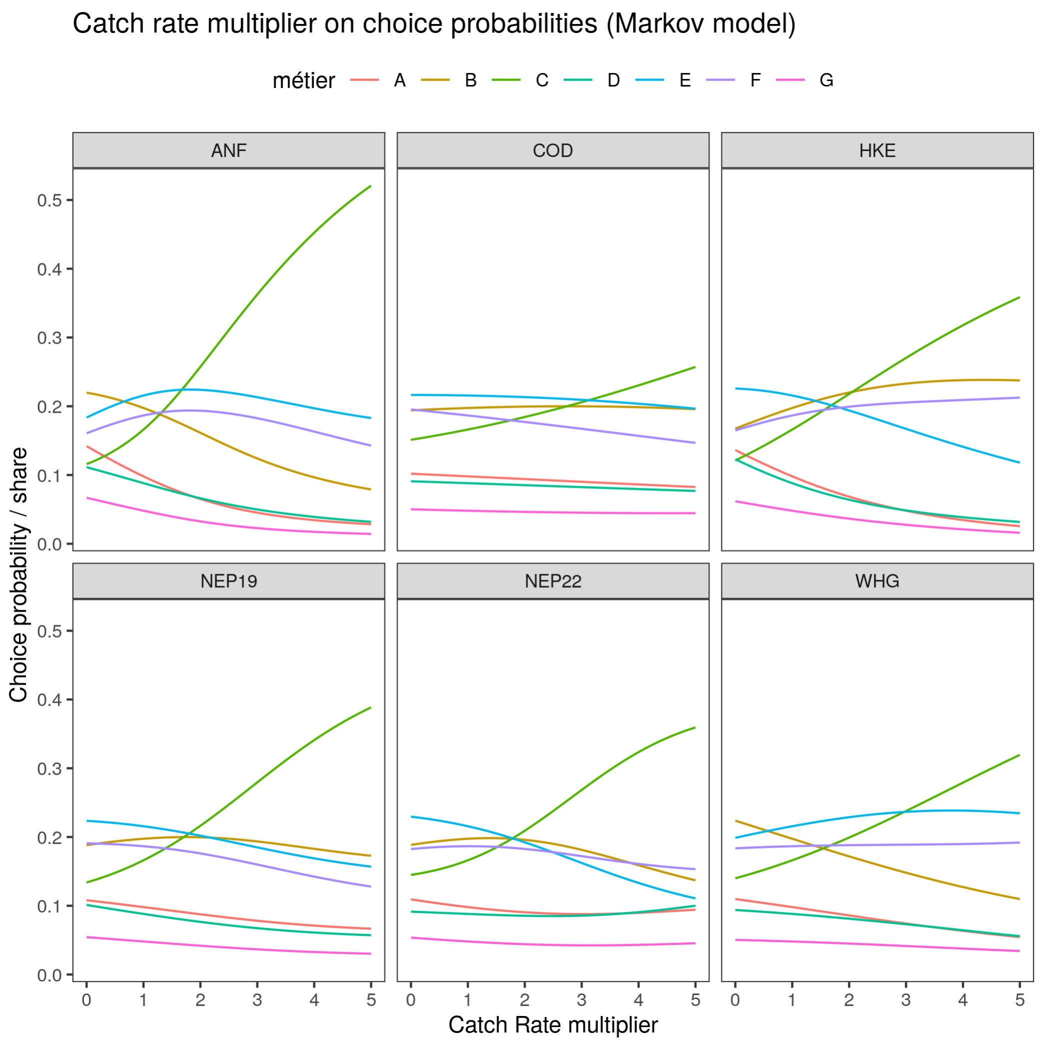


Figure S3: The influence of changes in catch rates of different stocks on effort allocation among métier from the Markov model.

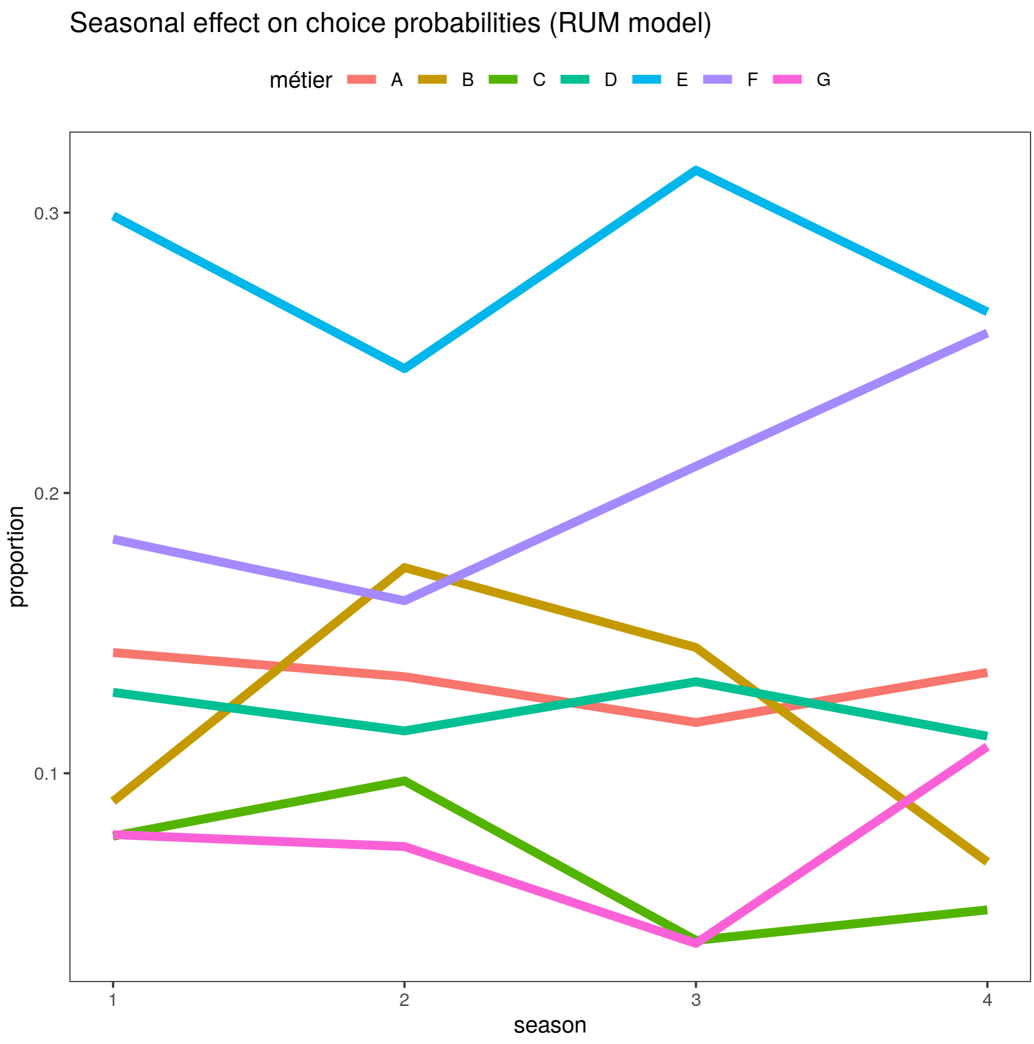


Figure S4: Seasonal effect in the RUM model.

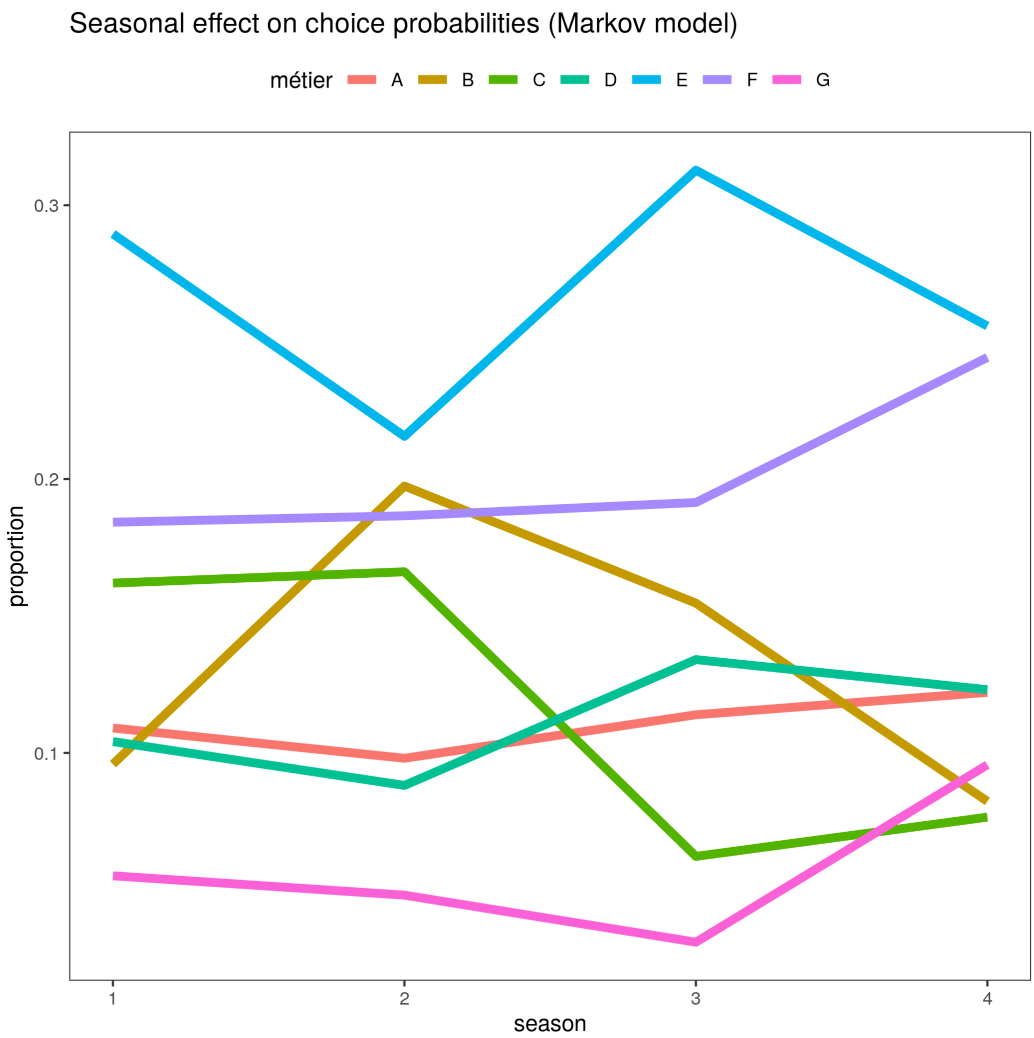


Figure S5: Seasonal effect in the Markov model.

Appendix J

FLBEIA functions to implement location choice models

Code located at:
`https://github.com/flr/FLBEIA/blob/master/R/OM_2a_Effort_Dynamics_SMFB_VarEffortShare.R`

```
# 
  ----------------------------------------------------------------------------
# 	  ORIGINAL SMFB function with extra functionalities to 
  reproduce the
#	 landing obligation policy with the following 
  exemptions:
#	   o Minimise
#	   o Quota transfers between years.
#	   o Quota swap btw stocks.
#
# New arguments in fleets.ctrl[[flnm]] object to control the 
  landing obligation implementation:
#   o LandObl: Logical TRUE/FALSE, Is the landing obligation 
  in place?
#   o LandObl_minimis: logical[nyr], is minimis exemption 
  applied? one element per year with ALL the years, including
   historical ones.
#   o LandObl_yearTransfer: logical[nyr], is quota transfer 
  between years exemption applied? one element per year with 
  ALL the years, including historical ones.
#   o LandObl_minimis_p: matrix[st,ny], if minimis applied 
  declare the proportion for each year.
#   o LandObl_yearTransfer_p: matrix[st,ny], if minimis 
  applied declare the proportion for each year.
#   o LandObl_discount_yrtransfer: If yearTransfer == TRUE, 
  the discount to be applied in the first year.
#   o LO_stk_grp: The groups to swap quotas.
#
# 'SMFB' - (Simple mixed fisheries behaviour). - Everything 
  constant  except effort
#	 that is updated based on landings or catch share.
#	 (multiple TACs so min, max Effort options are applied)
#
# Dorleta GarcYYYa
# Created: 23/10/2014 12:33:04
# Changed: 13/01/2015
# Changed: 01/04/2015 Itsaso Carmona
# Changed: 29/04/2015 Itsaso carmona (LO in some years)
# Added Effort share models: 20/03/2019 Dorleta
# 
  ----------------------------------------------------------------------------
```

```
#
  ------------------------------------------------------------------------
# SMFB_LO(fleets, biols, covars, fleets.ctrl, year = 1, season
   = 1)
#
  ------------------------------------------------------------------------

SMFB_ES <- function(fleets, biols, BDs, covars, advice, biols.
   ctrl, fleets.ctrl, advice.ctrl, flnm, year = 1, season =
   1,...){

    if(length(year) > 1 | length(season) > 1)
        stop('Only one year and season is allowed' )

    # If year/season/iter numerics => indicate position
    # else names => get positions.
    if(length(year) > 1 | length(season) > 1)
        stop('Only one year and season is allowed' )

    # 'year' dimension.
    # Dimnsions and fl
    fl     <- fleets[[flnm]]

    # The effort is restricted only by the stocks in 'stocks.
       restr'
    # If the restrictors are missing => all the stocks
       restrict.
    #
       ---------------------------------------------------------------------

    if(is.null(fleets.ctrl[[flnm]][['stocks.restr']]) |
       length(fleets.ctrl[[flnm]][['stocks.restr']]) == 0) {
      fleets.ctrl[[flnm]][['stocks.restr']] <- catchNames(
         fleets[[flnm]])
    }
    sts    <- intersect(fleets.ctrl[[flnm]][['stocks.restr']],
       catchNames(fl))

    stnms  <- names(biols)
    mtnms  <- names(fl@metiers)
    nmt    <- length(mtnms)
    nst    <- length(biols)
    ns     <- dim(biols[[1]]@n)[4]
    dimnms  <- dimnames(biols[[1]]@n)
```

```
nit <- dim(biols[[1]]@n)[6]

yr <- year
if(is.character(year)) yr <- which(dimnms[[2]] %in% year)
if(length(yr) == 0) stop('The␣year␣is␣outside␣object␣time␣
   range')

# 'season' dimension.
ss <- season
if(is.character(season)) ss <- which(dimnms[[4]] %in%
   season)
if(length(ss) == 0) stop('The␣season␣is␣outside␣object␣
   season␣range')

# Check fleets.ctrl elements.
restriction <- ifelse(length(fleets.ctrl[[flnm]]$
   restriction) == 1, fleets.ctrl[[flnm]]$restriction,
   fleets.ctrl[[flnm]]$restriction[year])
if(!(restriction %in% c('catch', 'landings')))
    stop("fleets.ctrl[[f]]$restriction␣must␣be␣equal␣to␣'
       catch'␣or␣'landings'")


# Advice season for each stock
adv.ss <- setNames( rep(NA,nst), stnms)
for (st in stnms) adv.ss[st] <- ifelse(is.null(advice.ctrl
   [[st]][["adv.season"]]), ns, advice.ctrl[[st]][["adv.
   season"]]) # [nst]


# Transform the FLR objects into list of arrays in order
   to be able to work with non-FLR
list2env(FLObjs2S3_fleetSTD(biols = biols, fleets = fleets
   , advice = advice, covars = covars,
                           biols.ctrl = biols.ctrl,
                              fleets.ctrl = fleets.ctrl,
                              BDs=BDs,
                           flnm = flnm, yr = yr, ss = ss,
                               iters = 1:nit, adv.ss),
                              environment())

## Update the effort-share using the defined model
effortShare.fun <- fleets.ctrl[[flnm]][['effshare.model']]
efs.m <- eval(call(effortShare.fun, Cr = Cr.f,  N = N, B =
    B, q.m = q.m, rho = rho, efs.m = efs.m, alpha.m,
```

```
                       beta.m = beta.m, ret.m = ret.m, wl.m =
                          wl.m, wd.m = wd.m, pr.m = pr.m, vc.m
                           = vc.m,
                       season = ss, year = yr, fleet = fl,
                          fleet.ctrl = fleets.ctrl[[flnm]],
                          restriction = restriction, covars=
                          covars))

    cat('Effort␣share:␣', efs.m, ',␣sum:', apply(efs.m,2,sum),
        '\n')
    # Update the fleets object with the new effort share
    for(mt in names(fl@metiers))  fl@metiers[[mt]]@effshare[,
       yr,,ss] <-  efs.m[mt,]


     for(st in sts){      # q.m, alpha.m.... by metier but
        stock specific

        effort.fun <- paste(fleets.ctrl[[flnm]][[st]][['catch.
           model']], 'effort', sep = '.')
        for(i in 1:nit){

           if(!is.null(dim(rho))) rhoi <- rho[,i,drop=F]
           else rhoi <- matrix(rho, length(stnms), 1, dimnames
               = list(stnms, 1))

           # Extract the i-th element from the lists.
            Ni         <- lapply(setNames(sts, sts), function(x)
                array(N[[x]][,,i,drop=T], dim = c(dim(N[[x]])[
               c(1,2)],1)))
            q.mi       <- lapply(setNames(sts, sts),   function(
               x) q.m[[x]][,,,i,drop=F])
            beta.mi    <- lapply(setNames(sts, sts),   function(
               x) beta.m[[x]][,,,i,drop=F])
            alpha.mi <- lapply(setNames(sts, sts),   function(
               x) alpha.m[[x]][,,,i,drop=F])
            ret.mi     <- lapply(setNames(sts, sts),   function(
               x) ret.m[[x]][,,,i,drop=F])
            wl.mi      <- lapply(setNames(sts, sts),   function(
               x) wl.m[[x]][,,,i,drop=F])
            wd.mi      <- lapply(setNames(sts, sts),   function(
               x) wd.m[[x]][,,,i,drop=F])

            Nyri_1     <- lapply(setNames(sts, sts), function(x)
                array(Nyr_1[[x]][,,i,drop=T], dim = c(dim(Nyr_
```

```
            1[[x]])[c(1,2)],1)))
        Cyri_1   <- lapply(setNames(sts, sts), function(x)
             array(Cyr_1[[x]][,,i,drop=T], dim = c(dim(Cyr_
            1[[x]])[c(1,2)],1)))
        Cfyri_1  <- lapply(setNames(sts, sts), function(x)
             array(Cfyr_1[[x]][,,i,drop=T], dim = c(dim(
            Cfyr_1[[x]])[c(1,2)],1)))
        Myri_1   <- lapply(setNames(sts, sts), function(x)
             array(Myr_1[[x]][,,i,drop=T], dim = c(dim(Myr_
            1[[x]])[c(1,2)],1)))
        Mi       <- lapply(setNames(sts, sts), function(x)
             array(M[[x]][,,i,drop=T], dim = c(dim(M[[x]])[
            c(1,2)],1)))

        effs[st, i] <-  eval(call(effort.fun, Cr = Cr.f[,i
            , drop=F],  N = Ni, q.m = q.mi, rho = rhoi, efs
            .m = efs.m[,i,drop=F],
                              alpha.m = alpha.mi, beta.m =
                                 beta.mi, ret.m = ret.mi, wl
                                 .m = wl.mi, wd.m = wd.mi,
                                 stknm=st,
                              restriction = restriction,  QS
                                 .groups = fleets.ctrl[[flnm
                                 ]][['QS.groups']],
                              tac=TAC[,i,drop=F], Cyr_1 =
                                 Cyri_1, Nyr_1 = Nyri_1, Myr
                                 _1 = Myri_1,  M = Mi, Cfyr_
                                 1 = Cfyri_1))
    }
}

if(LO == FALSE){
    # Choose the effort.
    if(length(fleets.ctrl[[flnm]]$effort.restr)==1){
      rule=fleets.ctrl[[flnm]]$effort.restr
    }else{
      rule=fleets.ctrl[[flnm]]$effort.restr[yr]
    }
    eff <- effRule.SMFB(effs = effs, prev.eff = matrix(
       fl@effort[,yr-1,,ss,drop=T],1,nit), rule = rule)
    # Capacity restrictions.
    eff <- capacityRest.SMFB(eff, c(fl@capacity[,yr,,ss,
       drop=T]))
    fl@effort[,yr,,ss] <- eff
}
```

```
  else{ # landObl == TRUE
    eff <- numeric(nit)
    discount_yrtransfer <- matrix(0,nst,nit, dimnames = list
        (sts,1:nit))
    ret.m.new <- ret.m # retention may change derived from
        minimis exemption.
    min_ctrl <- rep(FALSE, length(sts))
    names(min_ctrl) <- sts

    # Identify the stocks that are unable to 'receive' any
        extra TAC from others due to overfishing.
    stks_OF <- overfishing(biols, fleets, advice.ctrl, yr) #
         matrix[nst,nit]


    # Identify the minimum effort and compare with capactity
        , if > capacity => eff = capacity and the algorithm
        finish.
      for(i in 1:nit){
          Emin <- min(effs[,i])
          if(Emin > c(fl@capacity[,yr,,ss,,i,drop=T])){
            fl@effort[,yr,,ss,,i] <- fl@capacity[,yr,,ss,,i,
                drop=T]
              next
          }
          else{ # Minimis, Quota transfer btw years and
              QuotaSwap.

            minimis <- fleets.ctrl[[flnm]]$LandObl_minimis #
                logical(ny)
            yrtrans <- fleets.ctrl[[flnm]]$LandObl_
                yearTransfer # logical(ny)


            if(!is.null(dim(rho))) rhoi <- rho[,i,drop=F]
            else rhoi <- matrix(rho, length(stnms), 1,
                dimnames = list(stnms, 1))

            # Extract the i-th element form the lists.
            Ni        <- lapply(setNames(stnms, stnms),
                function(x) array(N[[x]][,,i,drop=T], dim = c
                (dim(N[[x]])[c(1,3)],1)))
            q.mi      <- lapply(setNames(sts, sts),
                function(x) q.m[[x]][,,,i,drop=F])
```

```
              beta.mi  <- lapply(setNames(sts, sts),
                 function(x) beta.m[[x]][,,,i,drop=F])
              alpha.mi <- lapply(setNames(sts, sts),
                 function(x) alpha.m[[x]][,,,i,drop=F])
              ret.mi   <- lapply(setNames(sts, sts),
                 function(x) ret.m[[x]][,,,i,drop=F])
              wl.mi    <- lapply(setNames(sts, sts),
                 function(x) wl.m[[x]][,,,i,drop=F])
              wd.mi    <- lapply(setNames(sts, sts),
                 function(x) wd.m[[x]][,,,i,drop=F])

              K <- c(fl@capacity[,yr,,ss,,i,drop=T])

              Cr.f_min_qt <- Cr.f
              eff_min_qt <- effs[, i]
              # Minimis and Quota transfer.
              if(minimis[yr] == TRUE | yrtrans[yr] == TRUE){

                eff_min_qt <- numeric(length(Ni))
                names(eff_min_qt) <- stnms

                Cr.f_min_qt <- Cr.f

                for(st in sts){

                  if(!is.null(dim(rho))) rhoi <- rho[,i,drop=F
                     ]
                  else rhoi <- matrix(rho, length(stnms), 1,
                     dimnames = list(stnms, 1))

                  # Extract the i-th element form the lists.
                  Ni        <- lapply(setNames(stnms, stnms),
                     function(x) array(N[[x]][,,i,drop=T], dim
                      = c(dim(N[[x]])[c(1,3)],1)))
                  q.mi      <- lapply(setNames(sts, sts),
                     function(x) q.m[[x]][,,,i,drop=F])
                  beta.mi   <- lapply(setNames(sts, sts),
                     function(x) beta.m[[x]][,,,i,drop=F])
                  alpha.mi  <- lapply(setNames(sts, sts),
                     function(x) alpha.m[[x]][,,,i,drop=F])
                  ret.mi    <- lapply(setNames(sts, sts),
                     function(x) ret.m[[x]][,,,i,drop=F])
                  wl.mi     <- lapply(setNames(sts, sts),
                     function(x) wl.m[[x]][,,,i,drop=F])
```

```
wd.mi    <- lapply(setNames(sts, sts),
   function(x) wd.m[[x]][,,,i,drop=F])

Nyri_1   <- lapply(setNames(stnms, stnms),
   function(x) array(Nyr_1[[x]][,,i,drop=T],
    dim = c(dim(Nyr_1[[x]])[c(1,2)],1)))
Cyri_1   <- lapply(setNames(stnms, stnms),
   function(x) array(Cyr_1[[x]][,,i,drop=T],
    dim = c(dim(Cyr_1[[x]])[c(1,2)],1)))
Cfyri_1  <- lapply(setNames(stnms, stnms),
   function(x) array(Cfyr_1[[x]][,,i,drop=T
   ], dim = c(dim(Cfyr_1[[x]])[c(1,2)],1)))
Myri_1   <- lapply(setNames(stnms, stnms),
   function(x) array(Myr_1[[x]][,,i,drop=T],
    dim = c(dim(Myr_1[[x]])[c(1,2)],1)))
Mi       <- lapply(setNames(stnms, stnms),
   function(x) array(M[[x]][,,i,drop=T], dim
    = c(dim(M[[x]])[c(1,2)],1)))

effort.fun <- paste(fleets.ctrl[[flnm]][[st
   ]][['catch.model']], 'effort', sep = '.')
# To calculate the final quota, the year
   transfer % needs to be applied to the
   original quota before
# discounting the quota used the pevious
   year and then discount this quota.
min_p <- fleets.ctrl[[flnm]]$LandObl_minimis
   _p[st,yr] # matrix(st,ny)
yrt_p <- fleets.ctrl[[flnm]]$LandObl_
   yearTransfer_p[st,yr] # matrix(st,ny)


Cr.f_min_qt[st,i] <- (Cr.f[st,i] + fleets.
   ctrl[[flnm]]$LandObl_discount_yrtransfer[
   st,yr-1,i])*(1+min_p+yrt_p) - # The quota
    restriction is enhanced in the
   proportion allowed by minimis and year
   transfer.
                     fleets.ctrl[[flnm]]$
                        LandObl_discount_
                        yrtransfer[st,yr-1,
                        i]

eff_min_qt[st] <-  eval(call(effort.fun, Cr
   = Cr.f[,i, drop=F],  N = Ni, q.m = q.mi,
```

```
                    rho = rhoi, efs.m = efs.m[,i,drop=F],
                                                 alpha.m = alpha
                                                       .mi, beta.m
                                                       = beta.mi,
                                                       ret.m = ret.
                                                       mi, wl.m =
                                                       wl.mi, wd.m
                                                       = wd.mi,
                                                       stknm=st,
                                                 restriction =
                                                       restriction,
                                                         QS.groups
                                                       = fleets.
                                                       ctrl[[flnm
                                                       ]][['QS.
                                                       groups']],
                                                 tac=TAC[,i,drop
                                                       =F], Cyr_1 =
                                                        Cyri_1, Nyr
                                                       _1 = Nyri_1,
                                                        Myr_1 =
                                                       Myri_1,  M =
                                                        Mi, Cfyr_1
                                                       = Cfyri_1))


          }
        }
        E1 <- min(eff_min_qt) # The effort resulting
              from minimis and year quota transfer
              examptions.
                                     # We will use this
                                           effort later to
                                           divide the extra
                                           catch, in discards (
                                           from minimis), year
                                           quota transfer
                                     # to discount in the
                                           following year and
                                           quota swap (in this
                                           order)


        # Quota Swap
        if(!is.null(dim(rho))) rhoi <- rho[,i,drop=F]
```

```
          else rhoi <- matrix(rho, length(stnms), 1,
             dimnames = list(stnms, 1))

          fcube_lo <- QuotaSwap(stknms = sts, E1, Cr.f =
             Cr.f[,i], Cr.f_exemp = Cr.f_min_qt[,i], N =
             Ni, B = B[,i,drop=F], efs.m = efs.m[,i,drop=F
             ], q.m = q.mi, alpha.m = alpha.mi, beta.m =
             beta.mi,
                                  wl.m = wl.mi, wd.m = wd.
                                     mi, ret.m = ret.mi, K
                                      = K, rho = rhoi,
                                     flnm = flnm, fleets.
                                     ctrl = fleets.ctrl,
                                     stks_OF = stks_OF[,i
                                     ],approach = 'fcube')

          eff[i] <- fcube_lo$E
          fl@effort[,yr,,ss,,i] <- fcube_lo$E
               cat('Effort after Landing Obligation
                  Exemptions: ',fcube_lo$E, '\n')

          # Divide the extra catch, in discards (from
             minimis, only those derived from MLS), year
             quota transfer
          # to discount in the following year and quota
             swap (in this order)
          # discount_yrtransfer must be discounted from
             the quota next year.

          catch_Elo <- fcube_lo$catch
          diff      <- catch_Elo[sts]/Cr.f[sts,i] #[nst]
          diff <- ifelse(Cr.f[sts,i]  == 0 & catch_Elo[sts
             ] == 0, 0, diff)
          discount_yrtransfer[,i] <- ifelse(diff < 1 +
             fleets.ctrl[[flnm]]$LandObl_minimis_p[,yr],
             0,
                                    ifelse((diff - fleets.
                                       ctrl[[flnm]]$
                                       LandObl_minimis_p[,
                                       yr] - 1) < fleets.
                                       ctrl[[flnm]]$
                                       LandObl_
                                       yearTransfer_p[,yr
                                       ],
```

```
                                                   (diff - fleets.
                                                      ctrl[[flnm]]
                                                      $LandObl_
                                                      minimis_p[,
                                                      yr] - 1),
                                                    fleets.ctrl[[
                                                       flnm]]$
                                                       LandObl_
                                                       yearTransfer
                                                       _p[,yr]))*
                                                       Cr.f[,i]

            # update ret.m to account for the discards due
               to minimise exemption.
            for(st in sts){
            # if discards due to size are higher than
               discards allowed by minimise, ret.m.i is not
               changed,
            # otherwise nit is increased so that the total
               discards equal to min_p*Cr.f

              Cr.f[st,i] <- ifelse(Cr.f[st,i] == 0, 1e-6, Cr
                 .f[st,i])
              min_p <- fleets.ctrl[[flnm]]$LandObl_minimis_p
                 [st,yr] # matrix(st,ny)
              yrt_p <- fleets.ctrl[[flnm]]$LandObl_
                 yearTransfer_p[st,yr] # matrix(st,ny)
              Ca <- fcube_lo$Ca[[st]] # catch at age in
                 weight
              Da <- fcube_lo$Da[[st]]
              Ds <- sum(Da)
              ret.m.new[[st]][,,,i] <- ret.m[[st]][,,,i] -
                 ifelse(Ds/Cr.f[st,i] > min_p, 0, min_p- Ds/
                 Cr.f[st,i])
              min_ctrl[st] <- ifelse(Ds/Cr.f[st,i]  > min_p,
                  FALSE, TRUE)
            }

          }
      }

     # Update the retention curve according to minimis.
     if(any(min_ctrl)){
         sts_min <- names(which(min_ctrl))
    #      browser()
```

```
          for(mt in names(fl@metiers)){
           if(any(sts_min %in% catchNames(fl@metiers[[mt]]))){
             for(st in sts_min[which(sts_min %in% catchNames(
                fl@metiers[[mt]]))]){


               fl@metiers[[mt]]@catches[[st]]@landings.sel[,yr
                  ,] <- ret.m.new[[st]][mt,,,]
               fl@metiers[[mt]]@catches[[st]]@discards.sel[,yr
                  ,] <- 1-ret.m.new[[st]][mt,,,]

             }
           }
          }

          fleets.ctrl[[flnm]]$LandObl_discount_yrtransfer[,yr
             ,] <- discount_yrtransfer
      }
    }


   # Update the quota share of this step and the next one if
      the
   # quota share does not coincide with the actual catch. (
      update next one only if s < ns).
   for(st in sts){

        if (adv.ss[st] == ns) {
          yr.share <- advice$quota.share[[st]][flnm,yr,, drop=
             T]       # [nit]
          ss.share <- t(matrix(fleets.ctrl$seasonal.share[[st
             ]][flnm,yr,,, drop=T], ns, nit)) # [nit,ns]
        } else {
          ss1 <- (adv.ss[st]+1):ns
          ss2 <- 1:adv.ss[st]

          if (ss <= adv.ss[st]) {
            yr.share <- advice$quota.share[[st]][flnm,yr-1,,
               drop=T]       # [nit]
            ss.share <- cbind( t(matrix(fleets.ctrl$seasonal.
               share[[st]][flnm,yr,,ss2, drop=T], length(ss2),
                nit)),
                                 t(matrix(fleets.ctrl$seasonal.
                                    share[[st]][flnm,yr-1,,ss1,
                                    drop=T], length(ss1), nit)))
```

```
                                  # [nit,ns]
          } else {
            yr.share <- advice$quota.share[[st]][flnm,yr,,
               drop=T]       # [nit]
            ss.share <- cbind( t(matrix(fleets.ctrl$seasonal.
               share[[st]][flnm,yr+1,,ss2, drop=T], length(ss2
               ), nit)),
                              t(matrix(fleets.ctrl$seasonal.
                                 share[[st]][flnm,yr,,ss1,
                                 drop=T], length(ss1), nit)))
                                  # [nit,ns]
          }
        }

        quota.share.OR <- matrix(t(yr.share*ss.share), ns, nit
           )

        # The catch.
        catchFun <- fleets.ctrl[[flnm]][[st]][['catch.model']]

        catchD <- array(NA, dim=dim(q.m[[st]]))

        for(i in 1:nit){

          if(is.null(dim(rho)))    rhoi <- rho
          if(length(dim(rho))==2) rho <- rho[st,i]
          Nyri_1    <- lapply(setNames(sts, sts), function(x)
             array(Nyr_1[[x]][,,i,drop=T], dim = c(dim(Nyr_1[[
             x]])[c(1,2)],1)))
          Cyri_1    <- lapply(setNames(sts, sts), function(x)
             array(Cyr_1[[x]][,,i,drop=T], dim = c(dim(Cyr_1[[
             x]])[c(1,2)],1)))
          Cfyri_1   <- lapply(setNames(sts, sts), function(x)
             array(Cfyr_1[[x]][,,i,drop=T], dim = c(dim(Cfyr_
             1[[x]])[c(1,2)],1)))
          Myri_1    <- lapply(setNames(sts, sts), function(x)
             array(Myr_1[[x]][,,i,drop=T], dim = c(dim(Myr_1[[
             x]])[c(1,2)],1)))
          Mi        <- lapply(setNames(sts, sts), function(x)
             array(M[[x]][,,i,drop=T], dim = c(dim(M[[x]])[c
             (1,2)],1)))

          #browser()
```

```
      catchD[,,,i] <- eval(call(catchFun, Cr=Cr.f[st,i],N
          = Ni[[st]],  E = eff[i], efs.m = efs.m[,i,drop=
        FALSE], q.m = q.m[[st]][,,,i,drop=FALSE],
                          alpha.m = alpha.m[[st]][,,,i,drop=
                              FALSE], beta.m = beta.m[[st
                              ]][,,,i,drop=FALSE], wd.m = wd.
                              m[[st]][,,,i,drop=FALSE],
                          wl.m = wl.m[[st]][,,,i,drop=FALSE
                              ], ret.m = ret.m[[st]][,,,i,
                              drop=FALSE], rho = rho,
                          tac=TAC[st,i], Cyr_1 = Cyri_1[[st
                              ]], Nyr_1 = Nyri_1[[st]], Myr_1
                               = Myri_1[[st]],  M = Mi[[st]],
                          Cfyr_1 = Cfyri_1[[st]]))
   }
  itD <- ifelse(is.null(dim(catchD)), 1, length(dim(
      catchD)))
  catch <- apply(catchD, itD, sum)  # sum catch along
      all dimensions except iterations.

  quota.share     <- updateQS.SMFB(QS = quota.share.OR,
      TAC = TAC.yr[st,], catch = catch, season = ss, adv.
      season = adv.ss[st]) # [ns,nit]

  quota.share.NEW <- t(t(quota.share)/apply(quota.share,
       2,sum)) #[ns,nit] double 't' to perform correctly
      the division between matrix and vector.

  if (adv.ss[st] == ns) {
    fleets.ctrl$seasonal.share[[st]][flnm,yr,,] <- quota
        .share.NEW
  } else {
    if (ss <= adv.ss[st]) {
      fleets.ctrl$seasonal.share[[st]][flnm,yr-1,,ss1,]
          <- quota.share.NEW[ss1,]
      fleets.ctrl$seasonal.share[[st]][flnm,yr,,ss2,]
          <- quota.share.NEW[ss2,]
    } else {
      fleets.ctrl$seasonal.share[[st]][flnm,yr,,ss1,]
          <- quota.share.NEW[ss1,]
      fleets.ctrl$seasonal.share[[st]][flnm,yr+1,,ss2,]
          <- quota.share.NEW[ss2,]
    }
  }
```

```
    }

  fleets[[flnm]] <- fl

    return(list(fleets = fleets, fleets.ctrl = fleets.ctrl))
}

#-------------------------------------------------
## GRAVITY MODEL TO UPDATE THE EFFORT SHARE
#-------------------------------------------------

gravity.flbeia <- function(Cr,  N, B, q.m, rho, efs.m, alpha.m
    , beta.m,
                    ret.m, wl.m, wd.m, pr.m, vc.m, season,
                       year, fleet, fleet.ctrl, restriction =
                       restriction,...){

  NO <- N

  if(fleet.ctrl$gravity.model == 'revenue'){
    V.m  <- Reduce('+', lapply(names(q.m), function(x)
                             apply(q.m[[x]]*(sweep(wl.m[[x]],
                                 2:4, NO[[x]], "*")^beta.m[[x
                                ]])*ret.m[[x]]*pr.m[[x]],c
                                (1,4),sum)))
    TotV <- apply(V.m,2,sum)
    res <- sweep(V.m, 2, TotV, "/")
  }else{
    if(fleet.ctrl$gravity.model == 'profit'){
        V.m  <- Reduce('+', lapply(names(q.m), function(x)
            apply(q.m[[x]]*(sweep(wl.m[[x]], 2:4, NO[[x]], "*"
               )^beta.m[[x]])*ret.m[[x]]*pr.m[[x]],c(1,4),sum)
               ))
        TotV <- apply(V.m - vc.m,2,sum)

        res <- sweep(V.m, 2, TotV, "/")

    }
    else stop('gravity.model argument must be equal to "profit
       " or "revenue')
  }

  trad <- ifelse(is.null(fleet.ctrl$gravity.tradition), 0,
     fleet.ctrl$gravity.tradition)
```

```
  res <- efs.m*trad+ res*(1-trad)



  return(res)
}




#-------------------------------------------------
## mlogit MODEL TO UPDATE THE EFFORT SHARE
#-------------------------------------------------
mlogit.flbeia <- function(Cr, N, B, q.m, rho, efs.m, alpha.m,
                          beta.m, ret.m, wl.m, wd.m, pr.m, vc.
                             m,
                          season, year, fleet, fleet.ctrl,
                             restriction,...){

  ## step 1
  predict.df <- make_RUM_predict_df(model = fleet.ctrl[['
     mlogit.model']], fleet = fleet, season = season)

  res <- efs.m
  res[] <- NA

  for(i in 1:dim(N[[1]])[3]){
  ## step 2

    Ni          <- lapply(N, function(x) x[,,i, drop=F])
    q.m.i       <- lapply(q.m, function(x) x[,,,i,drop=F])
    alpha.m.i   <- lapply(alpha.m, function(x) x[,,,i,drop=F])
    beta.m.i    <- lapply(beta.m, function(x) x[,,,i,drop=F])
    wl.m.i      <- lapply(wl.m, function(x) x[,,,i,drop=F])
    wd.m.i      <- lapply(wd.m, function(x) x[,,,i,drop=F])
    ret.m.i     <- lapply(ret.m, function(x) x[,,,i,drop=F])
    pr.m.i      <- lapply(pr.m, function(x) x[,,,i,drop=F])

    updated.df <- update_RUM_params(model = fleet.ctrl[['
       mlogit.model']], predict.df = predict.df,
                                   fleet = fleet, covars =
                                      covars, season = season,
                                      year = year,
                                   N = Ni, q.m = q.m.i, wl.m =
                                      wl.m.i, beta.m = beta.m.i
                                      , ret.m = ret.m.i, pr.m =
```

```
                                        pr.m.i,
                                   iter = i)
   ## step 3

       # If all of the catch.q for a given metier are zero,
          that metier is closed.
       # so to work out which metier are closed
       met.close <- apply(do.call(rbind, lapply(q.m.i,
          function(x) apply(x==0,1,all))),2,all)
       met.close <- ifelse(identical(names(which(met.close ==
           TRUE)), character(0)), NA,
                  names(which(met.close == TRUE)))

    res[,i] <- predict_RUM(model = fleet.ctrl[['mlogit.model'
       ]], updated.df = updated.df, season, close = met.close
       )
  }


  return(res)
}



# ** make_RUM_predict_df **:  this makes the correctly
   formated dataframe over which to predict
#     the effort shares. It requires the mlogit model, fleet
   object and season as input.
make_RUM_predict_df <- function(model = NULL, fleet = NULL,
   season) {

  ## Pass mlogit model object
  ## Pass fleet object

  mod.coefs <- names(coef(model)) ## Model coefficients

  ## 1. season - note, just return the season for which we're
     predicting
  seas <- if(any(grepl("season", mod.coefs))) { season } else
     { NA }
  ## Determine if a factor or numeric
    if(!is.na(seas)) {

    if(any(class(model.frame(model)$season) == "numeric")) {
       seas <- as.numeric(seas) } else {
       seas <- as.factor(seas)
```

```
      }

    ## If season is a factor, we need to include the other
       seasons for contrast
    if(class(seas) == "factor") {
    seas <- as.factor(1:max(as.numeric(as.character(model.
       frame(model)$season)), na.rm = T))
    }
      }


  ## 2. catch or catch rates
  C <- if(any(sapply(catchNames(fleet), grepl, mod.coefs))) {

    ## Return the catchnames that are in the coefficients
    catchNames(fleet)[unlist(sapply(catchNames(fleet),
       function(n) { any(grepl(n, mod.coefs))}))]

  } else { NA }

  ## 3. vcost
  v    <- if(any(grepl("vcost", mod.coefs))) { -1 } else { NA
     }

  ## 4. effshare
  e    <- if(any(grepl("effshare", mod.coefs))) { -1 } else {
     NA }

  ## Construct the dataframe
  predict.df <- expand.grid(metier = fleet@metiers@names,
                            choice = c(TRUE,FALSE),
                            season = seas,
                            vcost = v,
                            effshare = e,
                            stringsAsFactors = FALSE)
  ## Remove any columns with NAs, indicating variable not used
  predict.df <- predict.df[,which(sapply(predict.df, function(
     x) all(!is.na(x))))]

  ## Combine with the catch rate columns
  if(!all(is.na(C))) {
    C.df <- as.data.frame(matrix(-1, ncol = length(C), nrow =
       nrow(predict.df)))
    colnames(C.df) <- C
```

```
    predict.df <- cbind(predict.df, C.df)
  }

  predict.df$index <- seq_len(nrow(predict.df))
  ## Use mFormula to define model form
  LD.predict <- mlogit::mlogit.data(predict.df, choice = "
     choice", shape = "long",
                              alt.var = "metier", chid.var = "
                                 index")

  return(LD.predict)
}

# ** update_RUM_params **: For this I have tried to keep the
   inputs the same as for the gravity model.
#                 Here, we update the data in the predict_df (
   from 1) with the values to predict over.
update_RUM_params <- function(model = NULL, predict.df, fleet,
    covars, season, year,
                              N, q.m, wl.m, beta.m, ret.m, pr.
                                 m, iter) {

  ## Update the values in the predict.df

  ## 2. catch / catch rates - on same scale.
  ## Note, these should be updated based on the biomass
     increases, so we do a
  ## similar calculation as for the gravity model
  ## Here have to be careful as not all metiers may catch all
     stocks...

  if(any(sapply(catchNames(fleet), grepl, names(coef(model))))
     ) {

    N0 <- N

    ## catch rate per stock per metier
    CR.m    <- lapply(names(q.m), function(x)
      cbind(stock = x,
            as.data.frame(
              apply(q.m[[x]]*(sweep(wl.m[[x]], 2:4, N0[[x]], "
                 *")^beta.m[[x]])*ret.m[[x]],c(1,4),sum)
            )
      )
    )
```

```
    CR <- do.call(rbind, CR.m)

    for(st in unique(CR$stock)) {
      predict.df[,st] <- CR[CR$stock == st,2]
    }
    predict.df[is.na(predict.df),] <- 0

  }

  # 3. vcost
  if("vcost" %in% colnames(predict.df)) {
    v <- do.call(rbind, lapply(fleet@metiers, function(x)
       cbind(metier = x@name,as.data.frame(x@vcost[,year,,
       season,,iter]))))
    predict.df$vcost <- v$data
  }

  # 4. effort share - past effort share, y-1
  if("effshare" %in% colnames(predict.df)) {
    e <- do.call(rbind, lapply(fleet@metiers, function(x)
       cbind(metier = x@name,as.data.frame(x@effshare[,year
       -1,,season,,iter]))))
    predict.df$effshare <- e$data
  }

  return(predict.df)

}


# ** predict_RUM ** : this function does the predictions and
   returns the effort shares.
predict_RUM <- function(model, updated.df, season, close) {


  ## Just the predictions we're interested in...
  updated.df <- updated.df[updated.df$choice == TRUE &
                              updated.df$season == season,]

  ## Extract the model matrix and parameter coefficients
  mod.mat <- model.matrix(mlogit::mFormula(model$formula),
     data = updated.df)
  beta <- as.matrix(coef(model))
```

```
## Check the model matrix and coefficients are ordered correctly
if(any(!colnames(mod.mat) == rownames(beta))) {
  stop("Model matrix and coefficients are not the same")
}

## If season is a factor, we want to exclude these options and just get the
## predictions for the relevant season. Note if season is a numeric, the model
## matrix already only includes the right season

if(any(grepl("season", colnames(mod.mat)))) {

if(any(class(model.frame(model)$season) == "factor")) {
    seas <- 1:max(as.numeric(as.character(model.frame(model)$season)),na.rm=T)
    toRemove <- paste0("season", seas[!seas %in% season])

    # remove from mod.mat
    mod.mat <- mod.mat[,!colnames(mod.mat) %in% grep(paste(toRemove, collapse = "|"), colnames(mod.mat), value = T)]
    # remove from beta
    beta <- beta[!rownames(beta) %in% grep(paste(toRemove, collapse = "|"), rownames(beta), value = T),]
}

}

## linear predictor long
eta_long <- mod.mat %*% beta

## linear predictor wide
eta_wide <- matrix(eta_long, ncol = length(unique(updated.df$metier)), byrow = TRUE)
names(eta_wide) <- updated.df$metier

## Implement spatial closures
eta_wide[names(eta_wide) %in% close] <- -Inf

## convert to a probability
p_hat <- exp(eta_wide) / rowSums(exp(eta_wide))
colnames(p_hat) <- unique(updated.df$metier)
p_hat <- as.data.frame(t(p_hat))
```

```
  return(p_hat[,1])

}



#-------------------------------------------------
## MARKOV MODEL TO UPDATE THE EFFORT SHARE
#-------------------------------------------------

Markov.flbeia <- function(Cr, N, B, q.m, rho, efs.m, alpha.m,
                          beta.m, ret.m, wl.m, wd.m, pr.m, vc.
                             m,
                          season, year, fleet, fleet.ctrl,
                             restriction,...){

  args   <- list(...)
  covars <- args$covars

  ## step 1
  predict.df <- make_Markov_predict_df(model = fleet.ctrl[['
     Markov.model']], fleet = fleet, season = season)

  res <- efs.m
  res[] <- NA

  for(i in 1:dim(N[[1]])[3]){
    ## step 2
    Ni          <- lapply(N, function(x) x[,,i, drop=F])
    q.m.i       <- lapply(q.m, function(x) x[,,,i,drop=F])
    alpha.m.i   <- lapply(alpha.m, function(x) x[,,,i,drop=F])
    beta.m.i    <- lapply(beta.m, function(x) x[,,,i,drop=F])
    wl.m.i      <- lapply(wl.m, function(x) x[,,,i,drop=F])
    wd.m.i      <- lapply(wd.m, function(x) x[,,,i,drop=F])
    ret.m.i     <- lapply(ret.m, function(x) x[,,,i,drop=F])
    pr.m.i      <- lapply(pr.m, function(x) x[,,,i,drop=F])


    updated.df <- update_Markov_params(model = fleet.ctrl[['
       Markov.model']], predict.df = predict.df,
                                       fleet = fleet, covars =
                                          covars, season = season
                                          , year = year,
```

```
                                    N = Ni, q.m = q.m.i, wl.m
                                        = wl.m.i, beta.m = beta
                                        .m.i, ret.m = ret.m.i,
                                        pr.m = pr.m.i, iter = i
                                        )
    ## step 3

    # If all of the catch.q for a given metier are zero, that
       metier is closed.
    # so to work out which metier are closed
    met.close <- apply(do.call(rbind, lapply(q.m.i, function(x
       ) apply(x==0,1,all))),2,all)
    met.close <- ifelse(identical(names(which(met.close ==
       TRUE)), character(0)), NA,
                   names(which(met.close == TRUE)))

    res[,i] <- predict_Markov(model = fleet.ctrl[['Markov.
       model']], updated.df = updated.df, fleet = fleet,
       season = season, year = year, close = met.close, iter =
        i)
  }


  return(res)
}


make_Markov_predict_df <- function(model = NULL, fleet = NULL,
    season) {

  ## Pass multinom model object
  ## Pass fleet object

  mod.coefs <- model$coefnames ## Model coefficients

  ## 1. season - note, just return the season for which we're
     predicting
  seas <- if(any(grepl("season", mod.coefs))) { season } else
     { NA }

  ## 2. catch or catch rates
  C <- if(any(sapply(catchNames(fleet), grepl, mod.coefs))) {

    ## Return the catchnames that are in the coefficients
```

```
    catchNames(fleet)[unlist(sapply(catchNames(fleet),
      function(n) { any(grepl(n, mod.coefs))}))]

  } else { NA }

  ## 3. vcost
  v    <- if(any(grepl("vcost", mod.coefs))) { -1 } else { NA
    }

  ## 4. effshare
  e    <- if(any(grepl("effshare", mod.coefs))) { -1 } else {
    NA }

  ## Construct the dataframe
  ## Note, we need the state from which vessels are coming
  predict.df <- expand.grid(state.tminus1 =
    fleet@metiers@names,
                           season = seas,
                           vcost = v,
                           effshare = e,
                           stringsAsFactors = FALSE)
  ## Remove any columns with NAs, indicating variable not used
  predict.df <- predict.df[,which(sapply(predict.df, function(
    x) all(!is.na(x))))]

  ## Correct attributes for prediction data
  if(!is.na(seas)) {
    if(attr(model$terms, "dataClasses")[["season"]] == "factor
      ") {
      predict.df$season <- as.factor(predict.df$season)
    }
  }

  ## Combine with the catch rate columns
  if(!all(is.na(C))) {
    C.df <- as.data.frame(matrix(-1, ncol = length(C), nrow =
      nrow(predict.df)))
    colnames(C.df) <- C

    predict.df <- cbind(predict.df, C.df)
  }

  return(predict.df)
}
```

```
update_Markov_params <- function(model = NULL, predict.df,
   fleet, covars, season, year,
                                N, q.m, wl.m, beta.m, ret.m,
                                   pr.m, iter) {

  ## Update the values in the predict.df

  ## 2. catch / catch rates - on same scale.
  ## Note, these should NOT be updated based on the biomass
     increases,
  ## we take these from the previous season (as it should of
     been fitted)

  if(any(sapply(catchNames(fleet), grepl, model$coefnames))) {

## old method
#     N0 <- N
    ## This should be the catch rate per stock per metier ??
#     CR.m   <- lapply(names(q.m), function(x)
#       cbind(stock = x,
#             as.data.frame(
 #              apply(q.m[[x]]*(sweep(wl.m[[x]], 2:4, N0[[x]],
    "*")^beta.m[[x]])*ret.m[[x]],c(1,4),sum)
  #          )
  #     )
  #   )

 #    CR <- do.call(rbind, CR.m)

 ## New method with lagged data
# if first season, last season previous year
  year_lag <- ifelse(season == 1, year-1, year)
  seas_lag <- ifelse(season == 1, dim(fleet@effort)[4], season
     -1)

## Get the landings in last season
land <- do.call(rbind, lapply(fleet@metiers, function(m) {
do.call(rbind, lapply(m@catches, function(x) cbind(metier =
   m@name, stock= x@name,as.data.frame(x@landings[,year_lag,,
   seas_lag, , iter]))))
}))

## Get the metier effort last season
```

```
 eff <- do.call(rbind, lapply(fleet@metiers, function(x) {
 cbind(metier = x@name,as.data.frame(x@effshare[,year_lag,,
    seas_lag, , iter]))}))

eff$data <- as.data.frame(fleet@effort[,year_lag,,seas_lag,,
   iter])$data * eff$data

# combine the effort and landings and calculate the lpue
land$effort <- eff$data[match(land$metier, eff$metier)]
land$lpue   <- land$data / land$effort


  for(st in colnames(predict.df)) {

     predict.df[predict.df$state.tminus1 %in% land[land$stock
        == st, "metier"],st] <- land[land$stock == st, "lpue"]
     #predict.df[,st] <- land[land$stock == st, "lpue"]
     # CR[CR$stock == st,2]  ## This will repeat, to ensure we
         get for each metier combinations
    }
    predict.df[is.na(predict.df)] <- 0
  }

  # 3. vcost
  if("vcost" %in% colnames(predict.df)) {
    v <- do.call(rbind, lapply(fleet@metiers, function(x)
       cbind(metier = x@name,as.data.frame(x@vcost[,year_lag,,
       seas_lag, , iter]))))
    predict.df$vcost <- v$data
  }

  # 4. effort share - past effort share, y-1
  if("effshare" %in% colnames(predict.df)) {
    e <- do.call(rbind, lapply(fleet@metiers, function(x)
       cbind(metier = x@name,as.data.frame(x@effshare[,year_
       lag,,seas_lag, , iter]))))
    predict.df$effshare <- e$data
  }

  return(predict.df)

}
```

```
predict_Markov <- function(model, updated.df, fleet, season,
   year, close, iter = i) {

  # Transition probs
  p_hat <- cbind(updated.df[c("state.tminus1")], nnet:::
     predict.multinom(model, updated.df, type = "probs"))
  p_hat_mat <- as.matrix(p_hat[,2:ncol(p_hat)])

  ## Implement spatial closures
  p_hat_mat[,colnames(p_hat_mat) %in% close] <- 0
  p_hat_mat <- p_hat_mat / rowSums(p_hat_mat, na.rm = TRUE)

  # past effort

  # New year
  if(season == 1) {
    last.season <- dims(fleet)[["season"]]
    cur.eff <- as.matrix(sapply(fleet@metiers, function(x)
       x@effshare[,year-1, , last.season,, iter]))
  }

  # Same year
  if(season > 1) {
    cur.eff <- as.matrix(sapply(fleet@metiers, function(x)
       x@effshare[, year, , season-1,, iter]))
  }

  new.share <- apply(p_hat_mat, 2, function(x) x %*% cur.eff)

  if(round(sum(new.share),6) != 1) {stop("Error - effort share
     does not sum to 1")}

  return(new.share)

}
```

Appendix K

List of other relevant peer reviewed manuscripts published during the period of this thesis:

The following six manuscripts were also contributed to during the period of this thesis and have direct relation to the work undertaken:

Thorpe, R. B., **Dolder, P. J.**, Reeves, S., Robinson, P., & Jennings, S. (2016). Assessing fishery and ecological consequences of alternate management options for multispecies fisheries. ICES Journal of Marine Science, 73(6), 1503-1512.

Ulrich, C., Vermard, Y., **Dolder, P.J.**, Brunel, T., Jardim, E., Holmes, S.J., Kempf, A., Mortensen, L.O., Poos, J.J. and Rindorf, A., 2017. Achieving maximum sustainable yield in mixed fisheries: a management approach for the North Sea demersal fisheries. ICES Journal of Marine Science, 74(2), pp.566-575.

Thorpe, R. B., Jennings, S., & **Dolder, P. J.** (2017). Risks and benefits of catching pretty good yield in multispecies mixed fisheries. ICES Journal of Marine Science, 74(8), 2097-2106.

Moore, C., Davie, S., Robert, M., Pawlowski, L., **Dolder, P.**, & Lordan, C. (2019). Defining métier for the Celtic Sea mixed fisheries: A multiannual international study of typology. Fisheries Research, 219, 105310.

Spence, M. A., Bannister, H. J., Ball, J. E., **Dolder, P. J.**, Griffiths, C. A., & Thorpe, R. B. (2020). LeMaRns: A Length-based Multi-species analysis by numerical simulation in R. PloS one, 15(2), e0227767.

Garcia, D., **Dolder, P. J.**, Iriondo, A., Moore, C., Prellezo, R., & Urtizberea, A. (2020). A multi-stock harvest control rule based on "pretty good yield" ranges to support mixed-fisheries management. ICES Journal of Marine Science, 77(1), 119-135.