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

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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.

Keywords: MSE, mixed fisheries, fleet dynamics, RUM, Markov

1 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.

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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's 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 the deployment of fishing effort 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 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., 2017b) 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 1).

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

2 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.

2.1 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., 2017a), 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., 2017a):

$$C_{f,s} = q_{f,m,s} \cdot B_s^{\beta_{f,m,s}} \cdot (E_f \cdot \delta_{f,m})^{\alpha_{f,m,s}} \tag{1}$$

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 (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).

2.2 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:

$$p^{(b)}_{m,t} = \overline{p}_m \tag{2}$$

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:

$$p^{(g)}_{m,t} = \frac{\overline{R}_m}{\sum\limits_{m=1}^{M} \overline{R}_m} \tag{3}$$

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

$$R_{m,t} = \sum_{s=1}^{S} L_{m,t,s} P\mathrm{x}_s \tag{4}$$

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 (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:

$$p_{m,t}^{(c)} = \phi \cdot p_{m,t}^{(b)} + (1 - \phi) \cdot p_{m,t}^{(g)} \tag{5}$$

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:

$$p_{m,t}^{(r)} = \frac{e^{\beta_m \cdot X_t + \gamma \cdot Z_{m,t}}}{1 + e^{\beta_m \cdot X_t + \gamma \cdot Z_{m,t}}} \tag{6}$$

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 $t - 1$:

$$p_{m,t}^{(m)} = \sum_{z=1}^{M} p_{z,t-1}^{(m)} p_{z,m,t} \tag{7}$$

where the transition probabilities are given by the logit function:

$$p_{z,m,t} = \frac{e^{\beta_{z,m} X_t}}{1 + e^{\beta_{z,m} X_t}} \tag{8}$$

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

2.3 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. (2017a) 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
```

2.4 Applied example

We demonstrate use of the location choice models as alternate hypotheses for short-term fleet dynamics though 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).

2.4.1 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 2.3), we considered this to be a reasonable representation of dynamics in the fishery.

2.4.2 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.

2.4.3 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.

2.4.4 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 6 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 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.

2.4.5 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.

3 Results

3.1 Métier definitions

The spatial métier identified for the Irish Otter trawl fleet (Figure 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.

3.2 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 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* 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 both 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 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.

3.3 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 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 4). The Markov model allocated more effort to métier D and A and less to and B than the rest of the models (Figure 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). 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 is 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 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 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 6).

3.4 Impact of location choice models on stock level indicators

The location choice model led to differences in median catches of all stocks (Figure 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 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 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 models (Figure 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 8). These difference led to some differences in spawning stock biomass development (Figure 9) with cod rebuilding more quickly under the gravity model assumption and megrims SSB plateauing at a lower level under the gravity and markov 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 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 10). Relatively minor differences in risk to biomass-based indicators were observed under each model (Figure 10).

4 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., 2017b), 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 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 stand-alone model fitting investigations.

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., 2020b). 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., 2020a, *in prep*). 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 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 7 – 10). While our MSE was only implemented as a demonstration, we show clearly that the decisions of fishers on where to fish can effect 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 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.

Acknowledgements

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6 Tables

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 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 BD stocks.

7 Figures

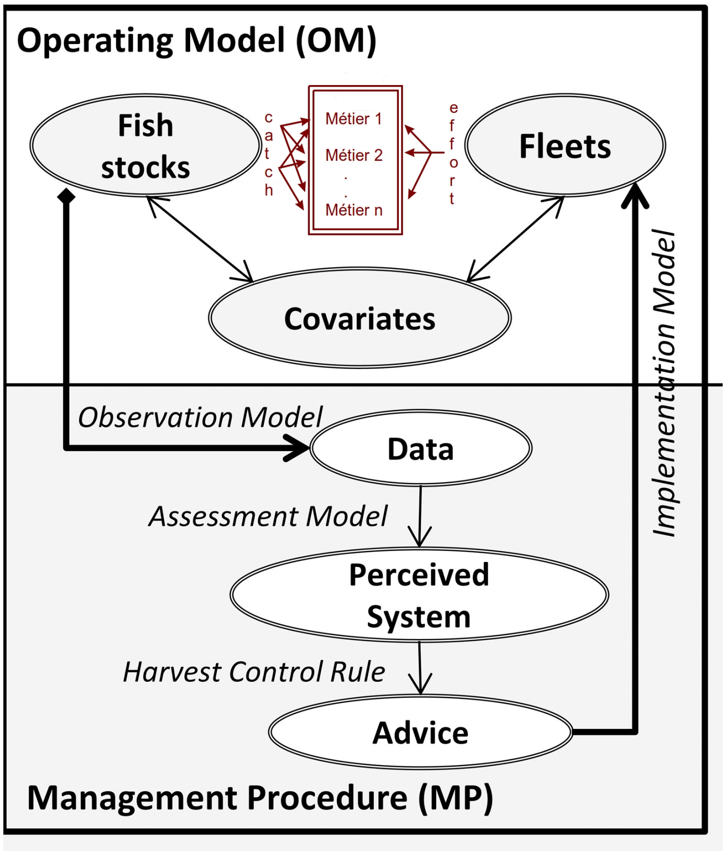

Figure 1: FLBEIA schematic, adapted from Garcia et al. (2017b) to show the métier interaction (dark red) in the modelling framework.

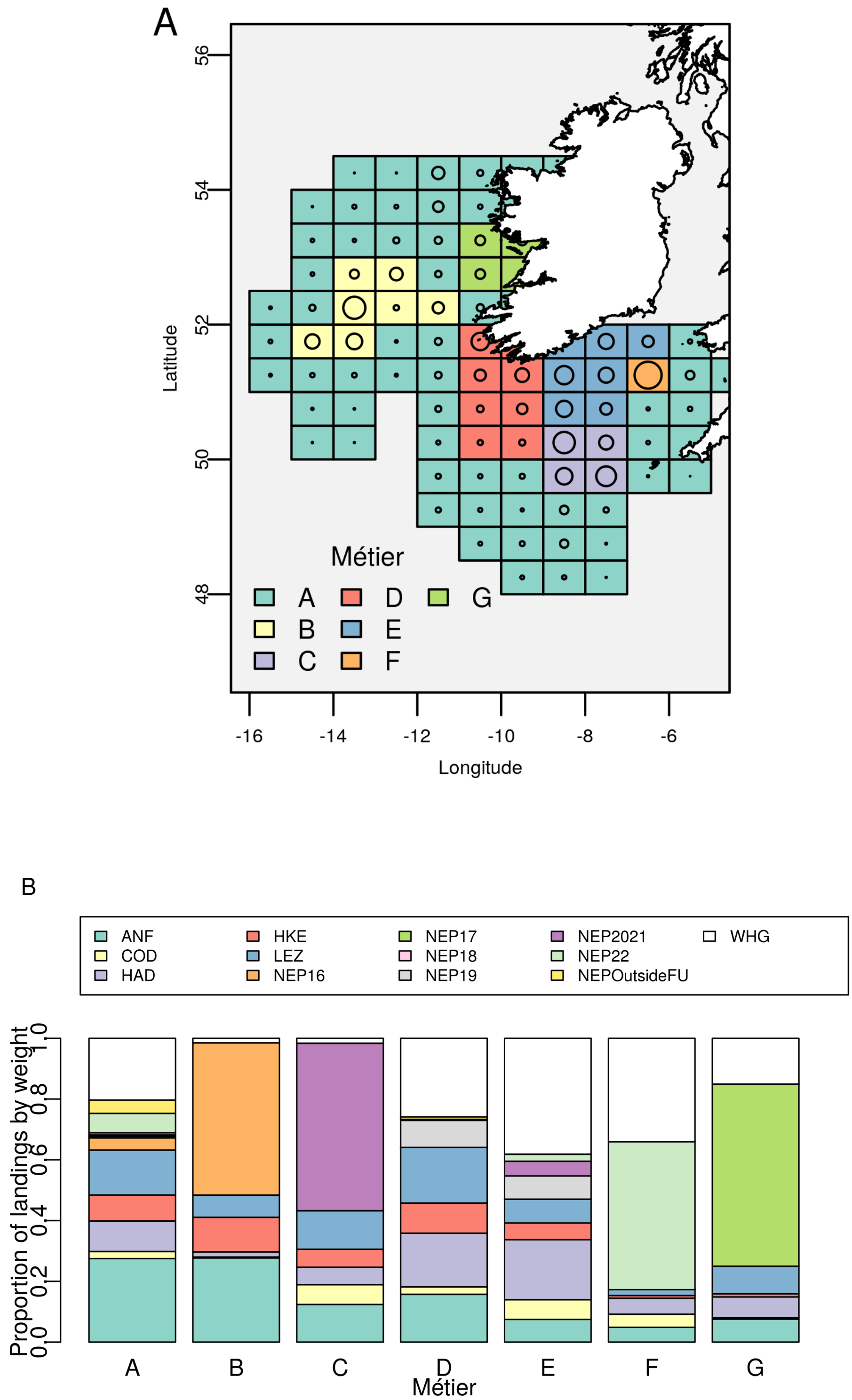

Figure 2: A: Métier defined through spatial clustering of similar catch composition for Irish Otter trawlers modified by using knowledge of fishing grounds to make coherent spatial units. Circles represent relative fishing effort in each of the rectangles. B: Catch compositions for the métier indicating the dominant stocks in catches for each of the fishing grounds. Stock codes are presented in Table 6.

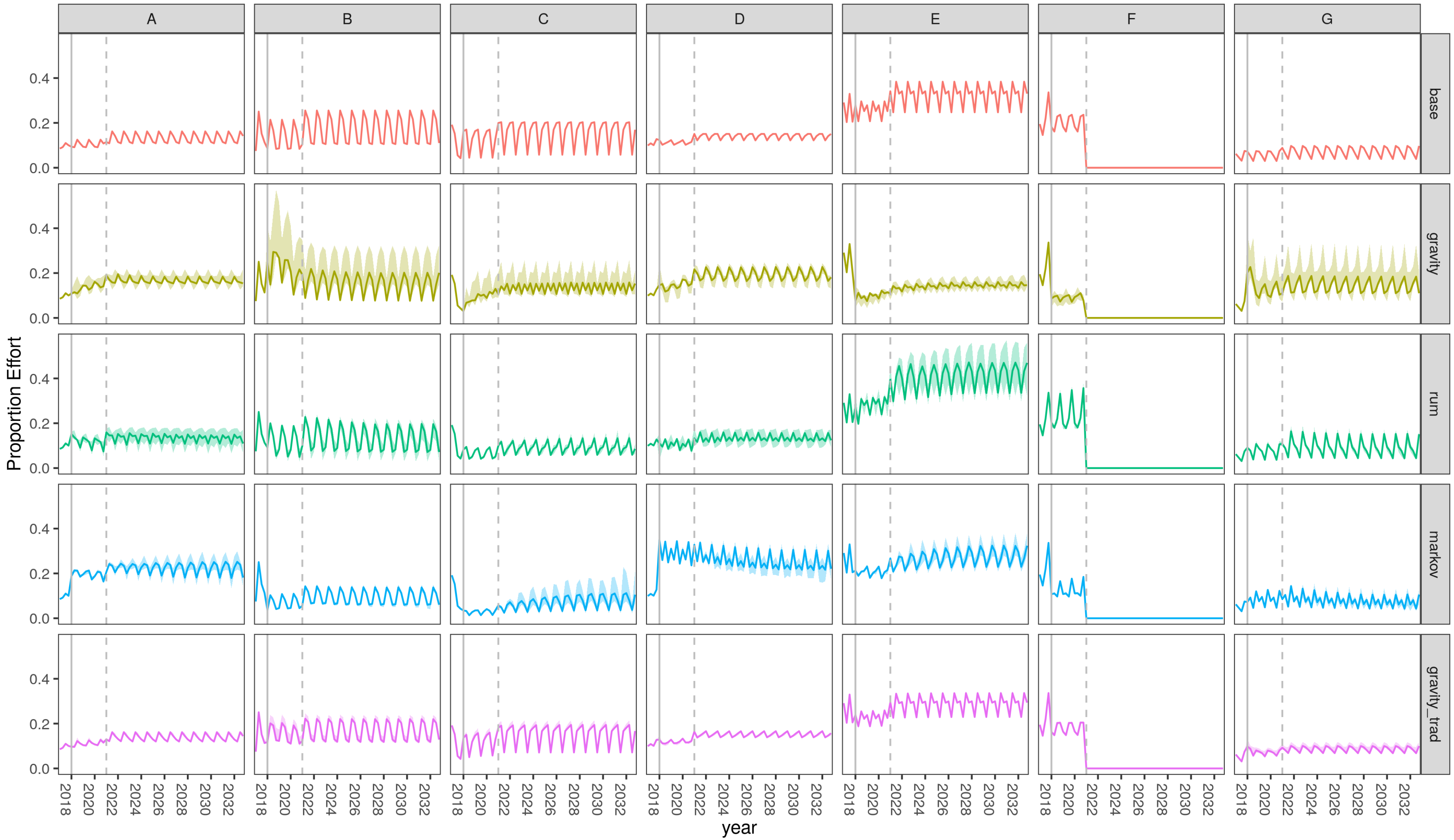

Figure 3: Quarterly fishing effort share (proportion) for each métier and location choice model in the Operating Model (2017 - 2032). Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure.

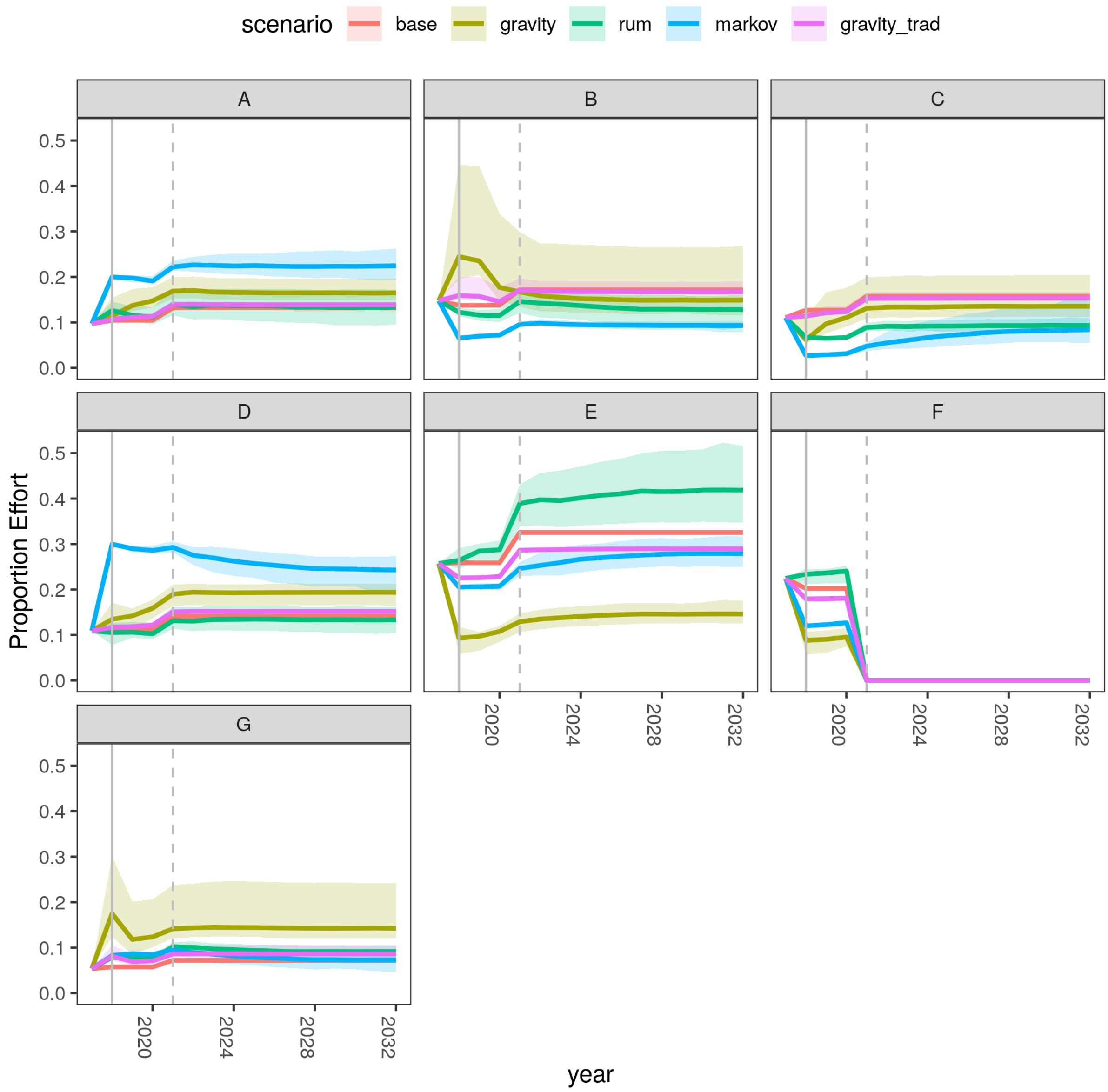

Figure 4: Annualised effort share (proportion) for each métier and location choice model (2017 - 2032). Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure.

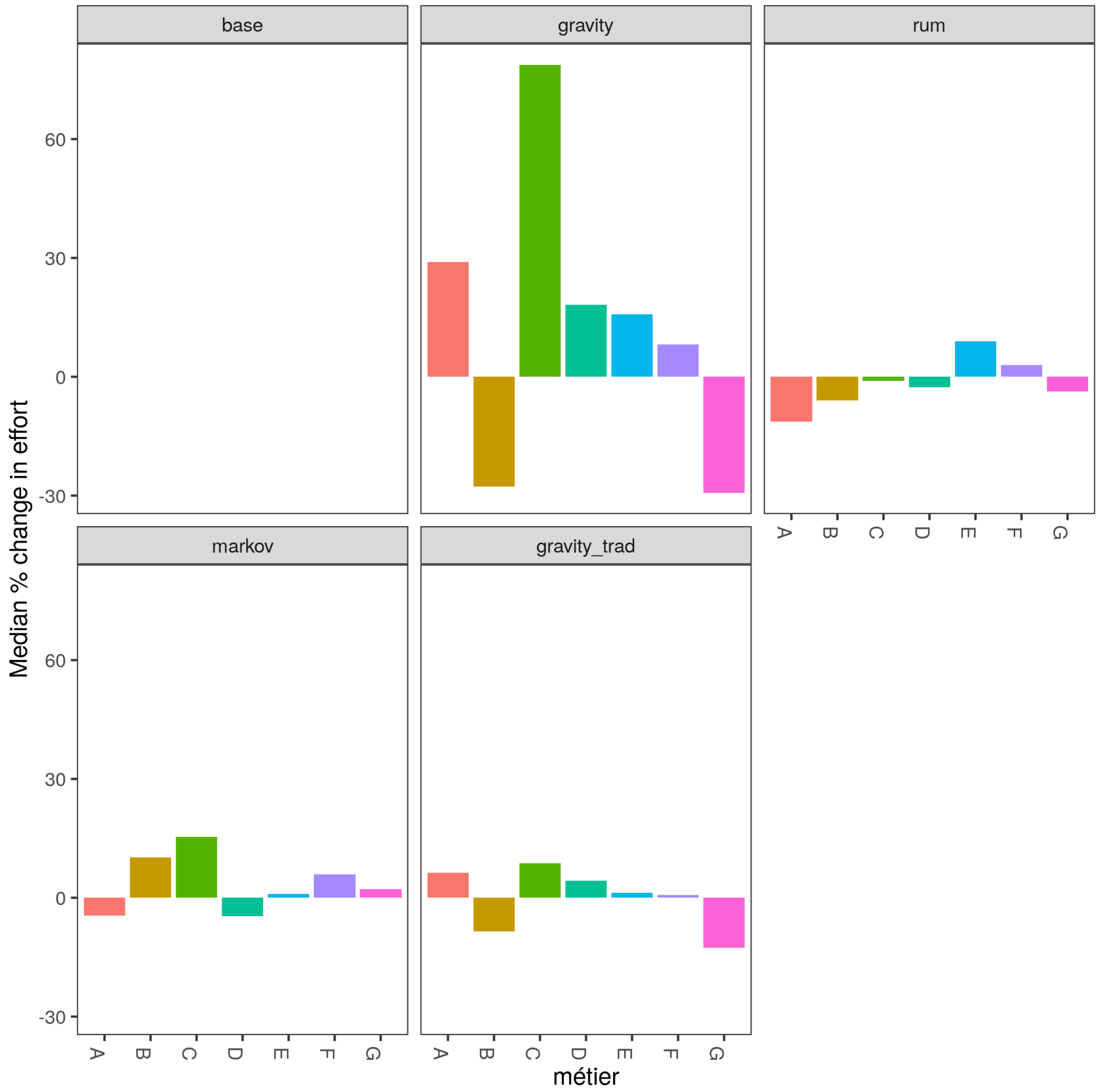

Figure 5: Percentage change in annualised effort share for each of the métier from before any closure (between years 2018 and 2020) .

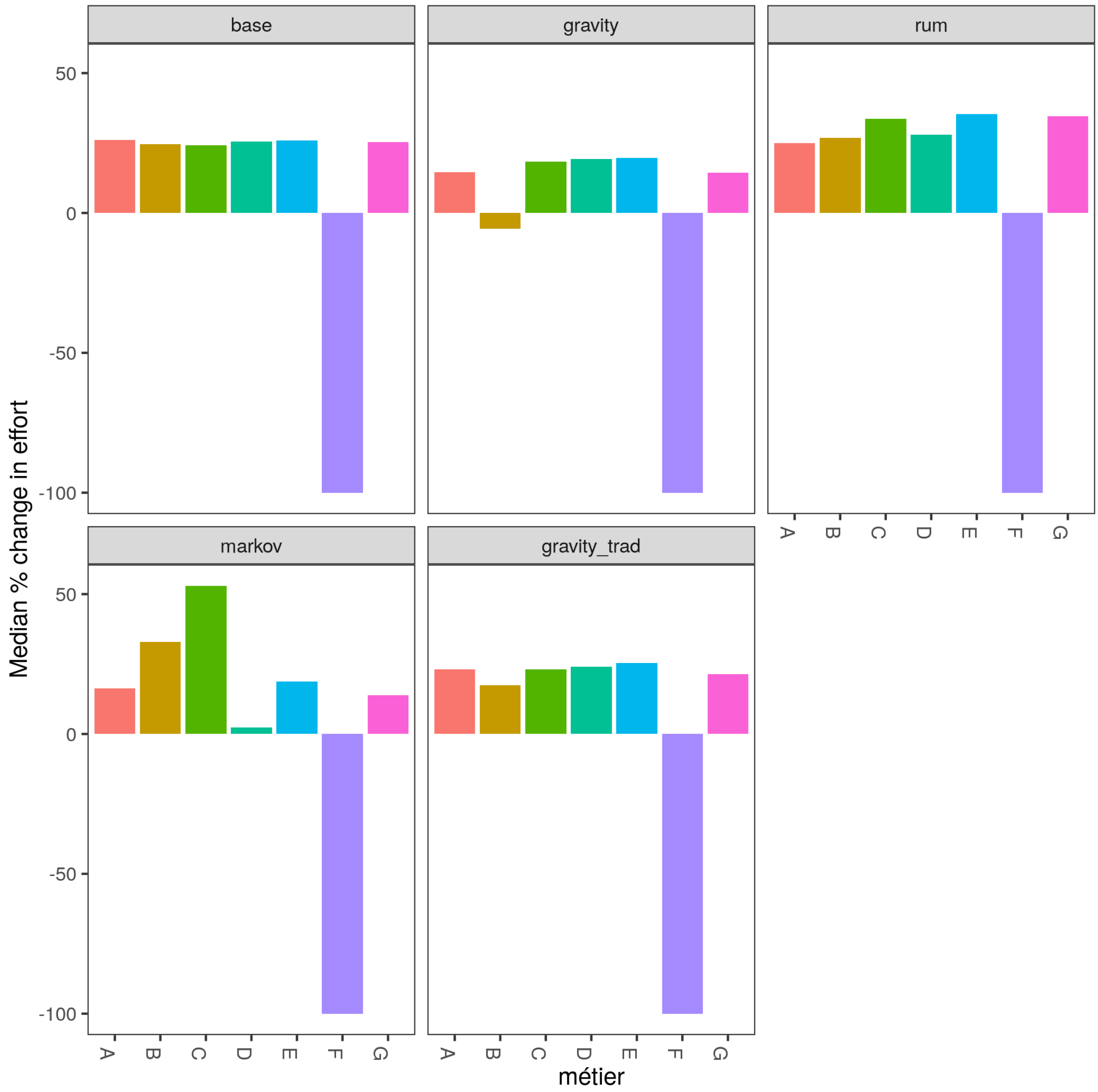

Figure 6: Percentage change in annualised effort share for each of the métier from before (2020) the closure of métier F and first year of the closure (2021).

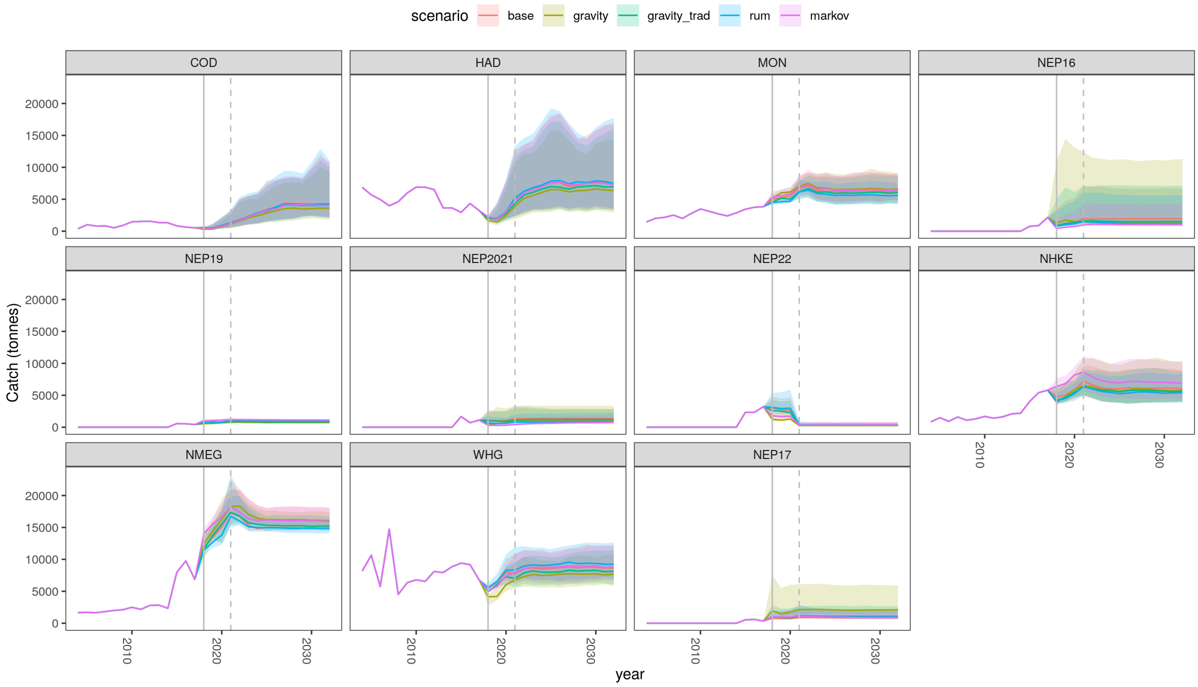

Figure 7: Catches of each stock by Irish Otter trawlers under the different location choice models. Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure.

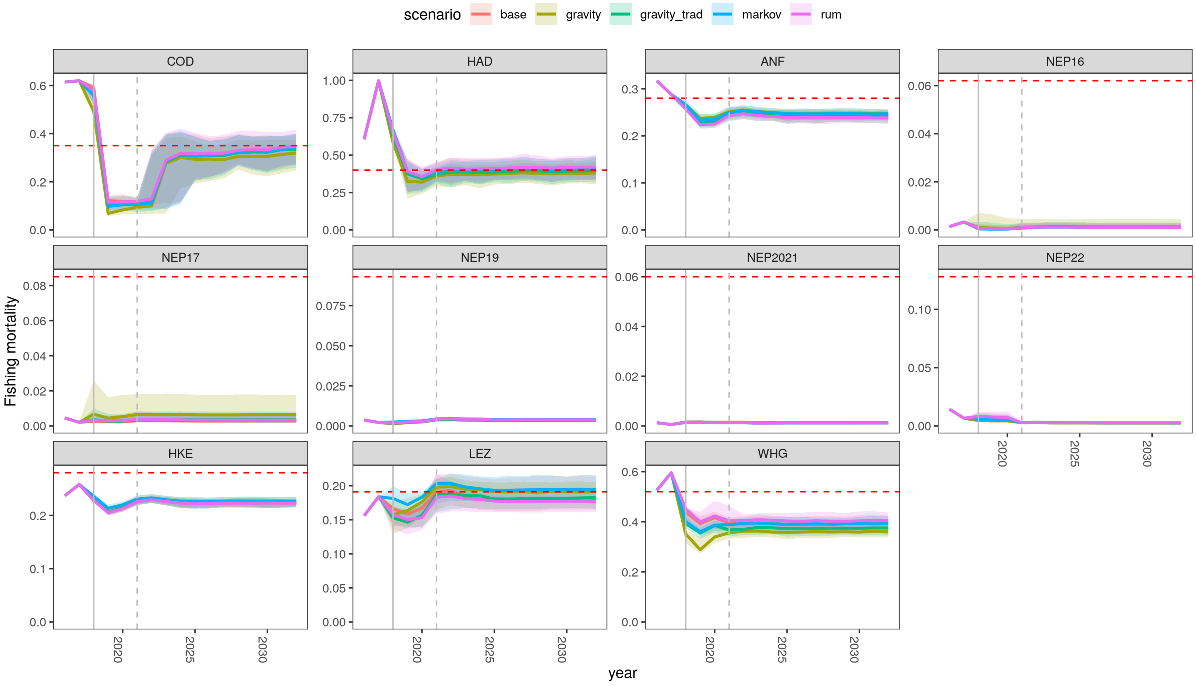

Figure 8: Fishing mortality for each stock under the different location choice models. Each stock was targeted to be fished at its Fmsy rate, using the ICES MSY Harvest Control Rule. Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure. Dashed red lines indicate the stock Fmsy reference point.

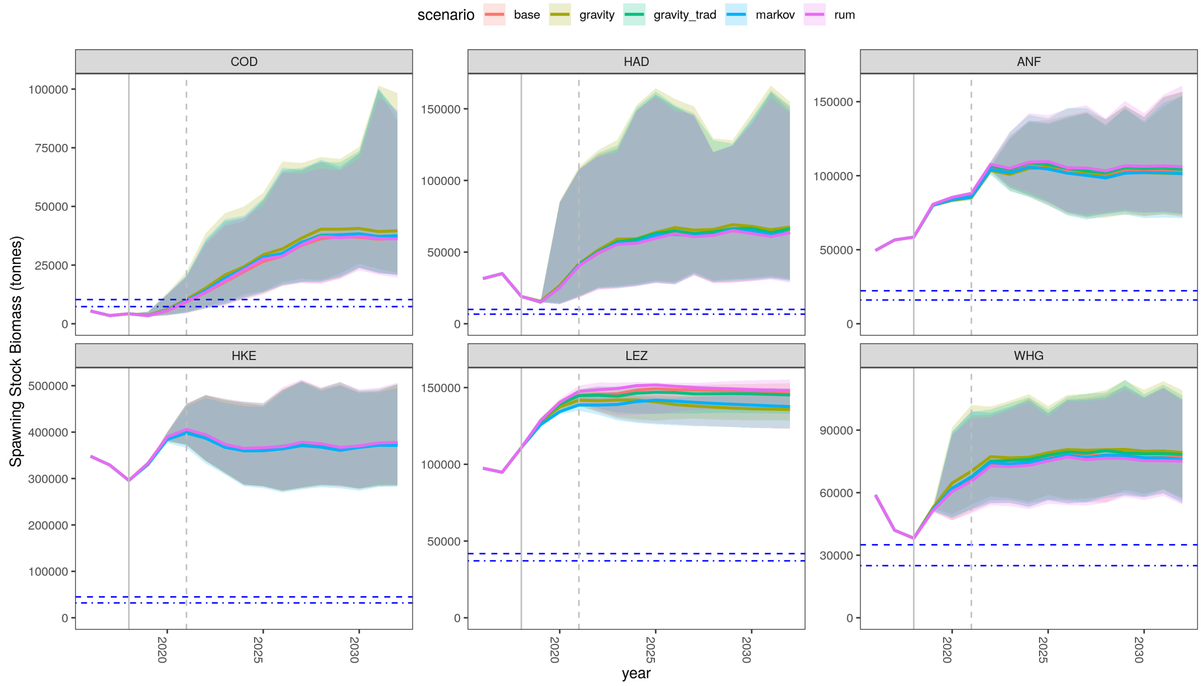

Figure 9: Spawning Stock Biomass for the fish stocks under each location model scenario. Light shading represents 5% and 95% variability due to recruitment and catchability. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure. Dotdashed and dashed blue lines indicate the Blim reference and Bmsytrigger reference points respectively.

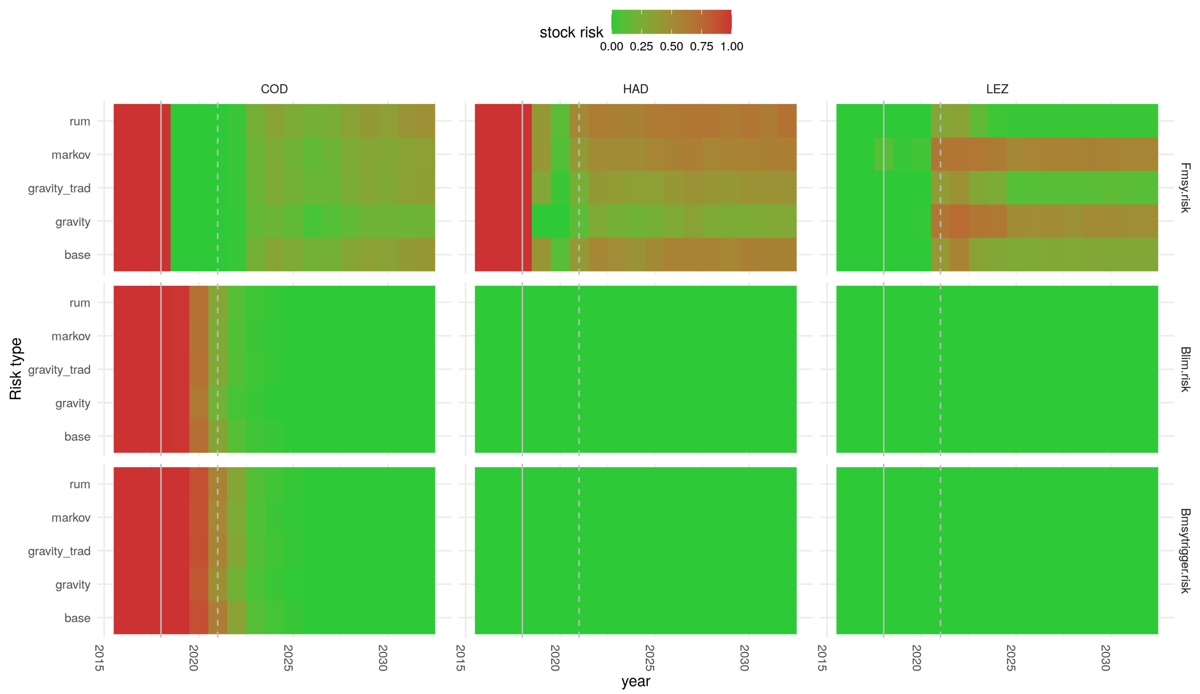

Figure 10: Stock risk indicators for each of the fish stock and location choice model scenarios. Solid line indicates end of the data/start of simulations and the dashed line the implementation of the spatial closure.

8 Supplementary material

Appendix A

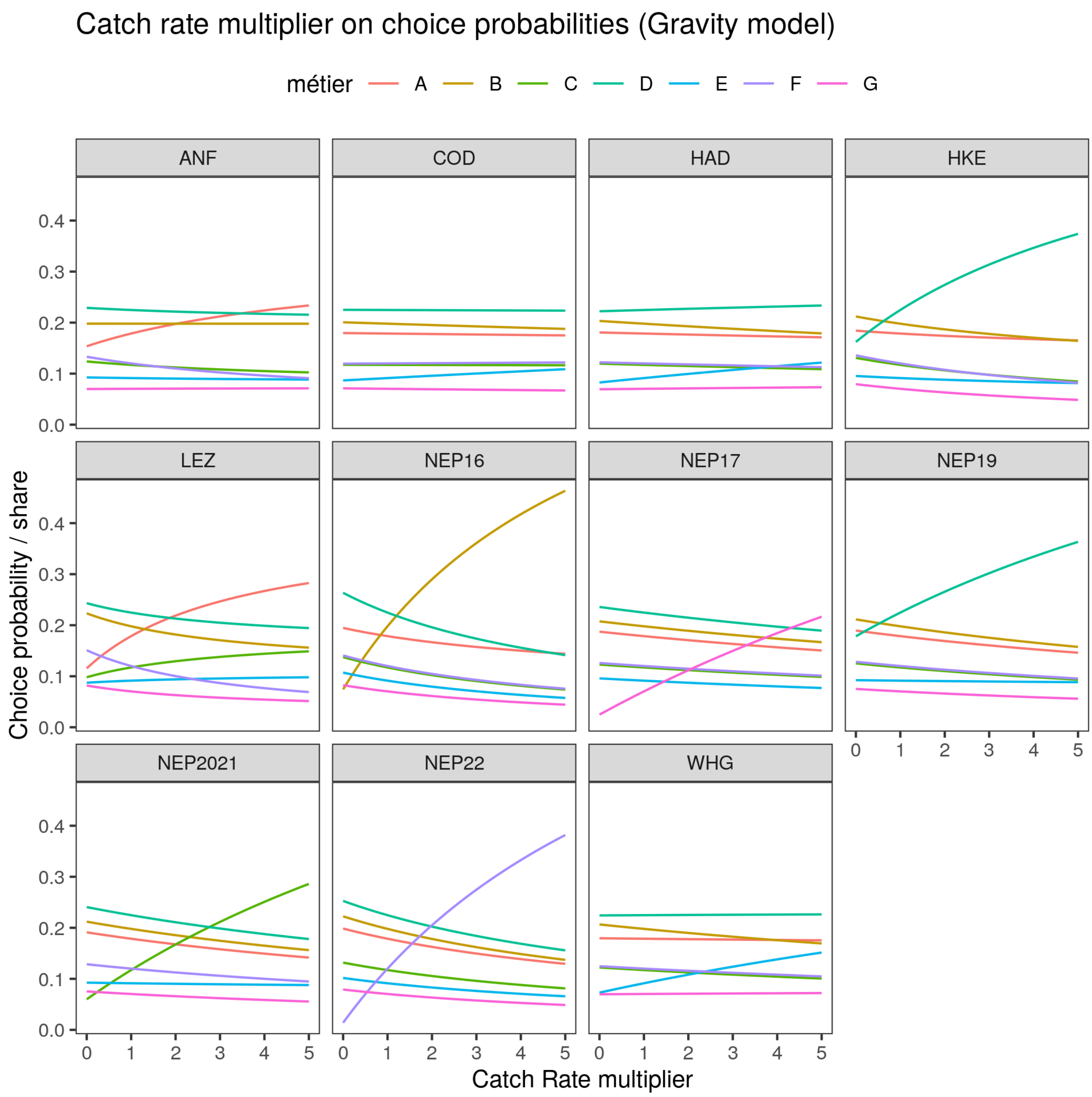

Figure S1: The influence of changes in catch rates of different stocks on effort allocation among métier from the Gravity model.

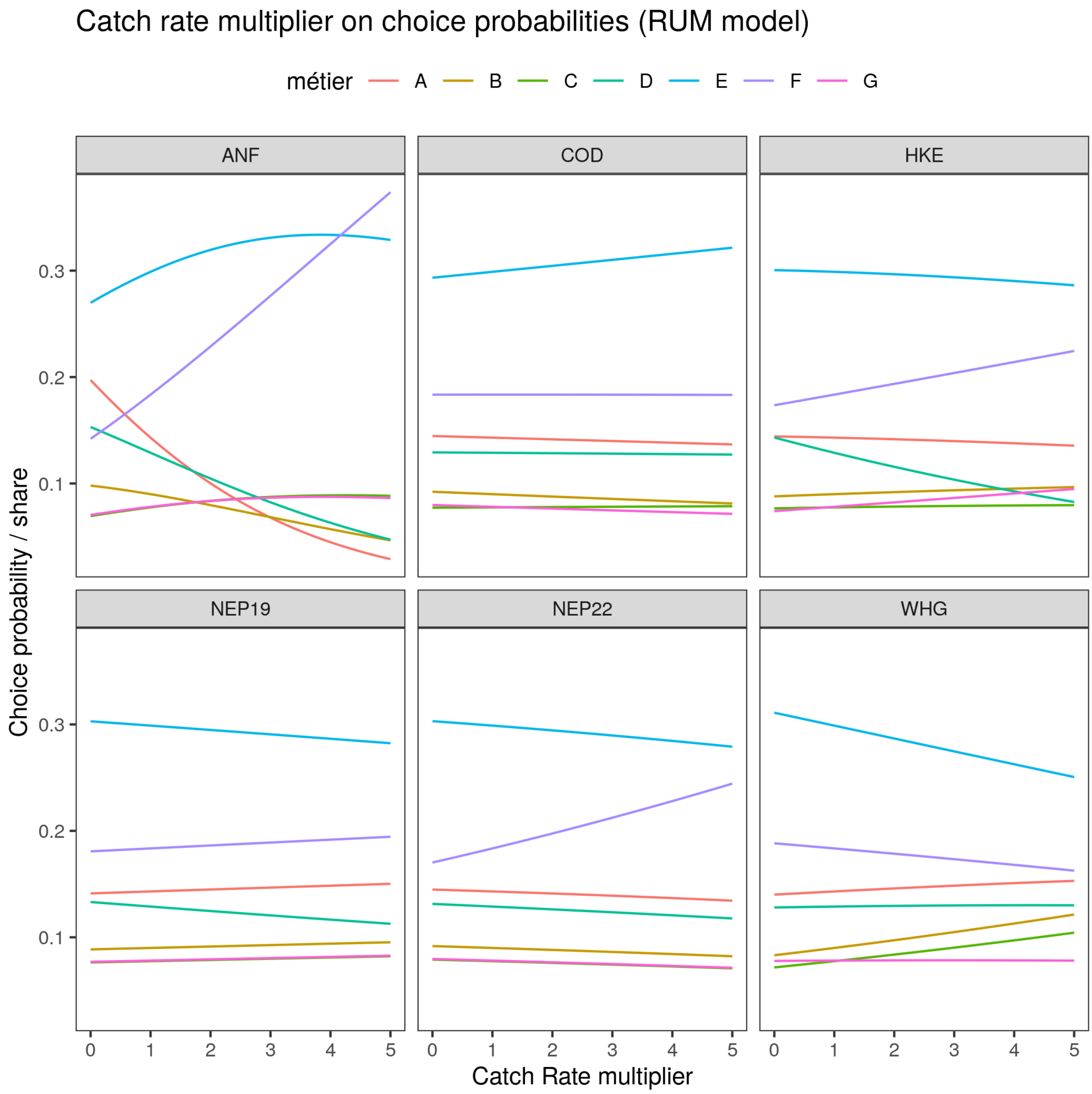

Figure S2: The influence of changes in catch rates of different stocks on effort allocation among métier from the RUM.

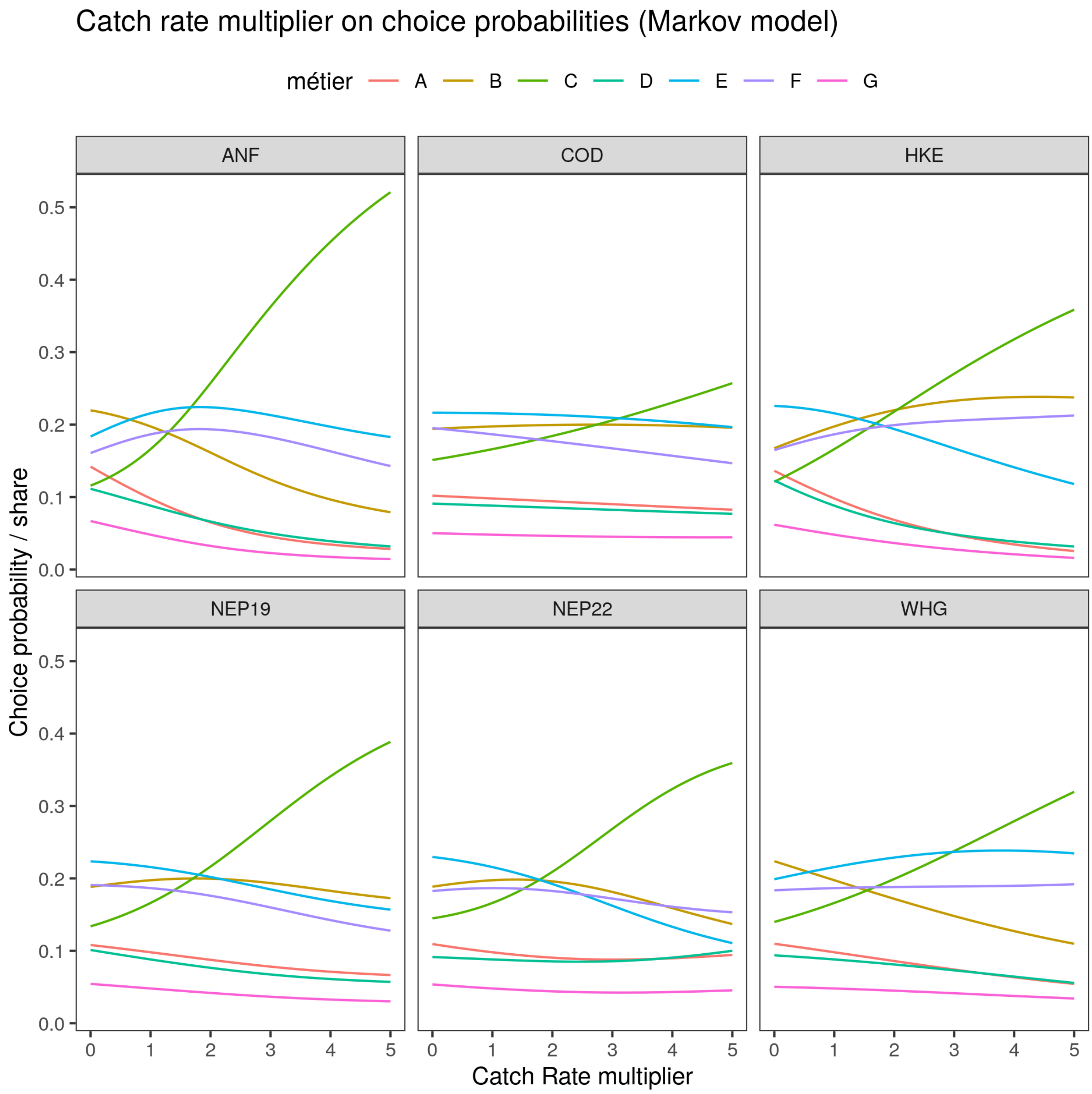

Figure S3: The influence of changes in catch rates of different stocks on effort allocation among métier from the Markov model.

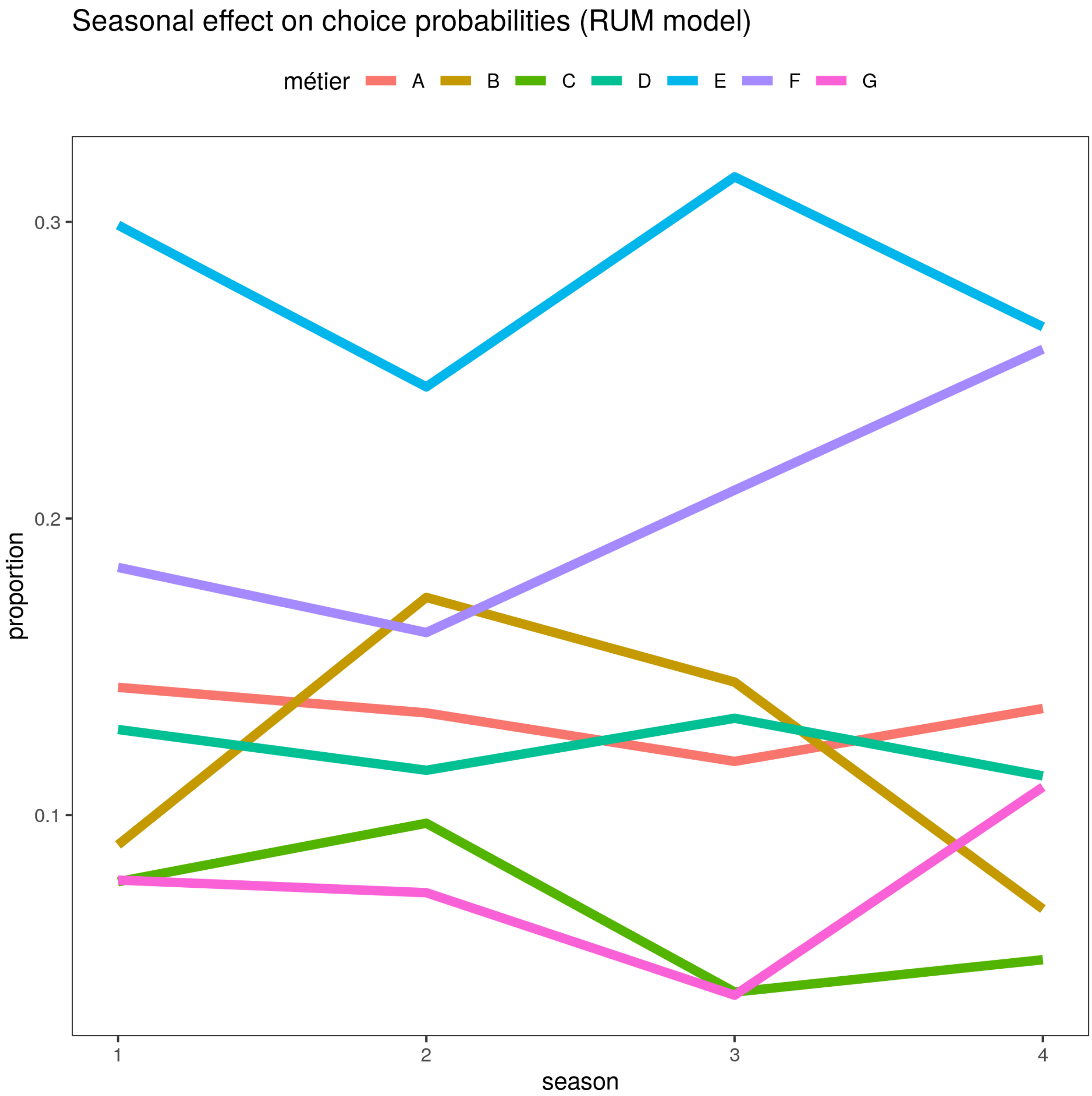

Figure S4: Seasonal effect in the RUM model.

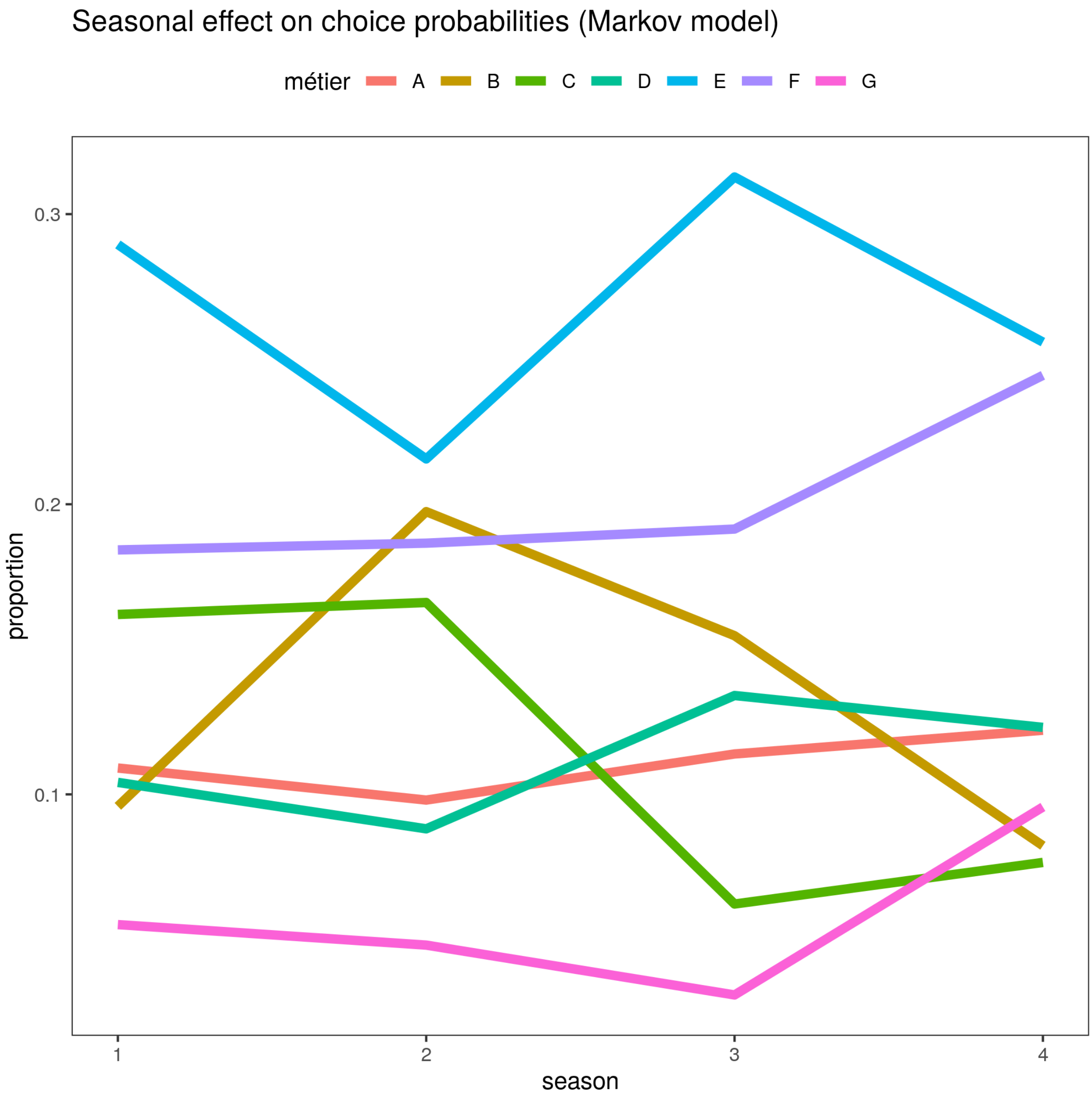

Figure S5: Seasonal effect in the Markov model.