

MixFishSim: highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

Paul J. Dolder^{a,b,*}, C  il  n Minto^a, Jean-Marc Guarini^c, Jan Jaap Poos^d

^a*Galway-Mayo Institute of Technology (GMIT), Dublin Road, Galway, Ireland*

^b*Centre for Environment, Fisheries and Aquaculture Science (Cefas), Pakefield Road, Lowestoft, UK*

^c*Sorbonne Universit  , Faculty of Sciences, 4 Place Jussieu, 75005 Paris, France*

^d*Wageningen Marine Research, Haringkade 1 1976 CP IJmuiden, Netherlands*

Abstract

Most fisheries exploit a variety of spatially and temporally heterogeneous fish populations, using species-unselective gear that can result in unintended, unwanted catch of low quota or protected species. Reducing these unwanted catches is crucial for biological and economic sustainability of ‘mixed fisheries’ and implementation of an ecosystem approach to fishing.

If fisheries are to avoid unwanted catch a good understanding of spatiotemporal fishery dynamics is required. However, traditional scientific advice is limited by a lack of highly resolved knowledge of population distributions, population movement and how fishers interact with different fish populations. This reflects the fact that data on fish location at high temporal and spatial resolutions is expensive and difficult to collect. Proxies inferred from either scientific surveys or commercial catch data are often used to model distributions, often with sparse data at limited spatial and temporal resolution.

To understand how data resolution impacts inference on mixed fisheries interactions, we develop a highly resolved spatiotemporal simulation model incorporating: i) delay-difference population dynamics, ii) population movement

*Corresponding author

Email address: paul.dolder@gmit.ie (Paul J. Dolder)

using Gaussian Random Fields to simulate patchy, heterogeneously distributed populations, and iii) fishery dynamics for multiple fleet characteristics based on species targeting via a mix of correlated random walk movement (for exploration) and learned behaviour (for exploitation) phases of the fisheries.

We simulate 50 years of fishing and use the results from the fisheries catch to draw inference on the underlying population structures. We compare this inference to i) a simulated fixed-site sampling design commonly used for fisheries monitoring purposes, and ii) the true underlying population structures input to the simulation. We use the results to establish the potential and limitations of fishery-dependent data - an inherently biased sampling method due to fisher's targeting- to provide a robust picture of spatiotemporal distributions. Finally, we simulate an area closure based on areas defined from the known ("real-population") distribution, commercial catch data and survey data at different temporal and spatial resolutions and assess their effectiveness on reducing catches of a fish population.

We conclude from our simulations that commercial data, while not unbiased, provides a useful tool for managing catches in mixed fisheries if applied at the correct spatiotemporal scale.

[333 words]

Keywords: Some, keywords, here. Max 6

2010 MSC: 00-01, 99-00

1. Introduction

Fishers exploit a variety of fish populations that are heterogeneously distributed in space and time with varying knowledge of species distributions using species-unselective fishing gear. In doing so fisheries catch an assemblage of species and may discard overquota catch when managed by single species quo-

6 tas, leading to overexploitation of fish populations (Ulrich et al., 2011; Batsleer
7 et al., 2015). This discarding of fish in excess of quota hampers the ability
8 to limit fishing mortality to within sustainable limits (Alverson et al., 1994;
9 Crowder and Murawski, 1998; Rijnsdorp et al., 2007) and ensure biological and
10 economic sustainability of fisheries. As such, there is increasing interest in tech-
11 nical solutions such as gear and spatial closures as ways of reducing unwanted
12 catch (Kennelly and Broadhurst, 2002; Catchpole and Reville, 2008; Bellido et al.,
13 2011).

14
15 Changes to spatial fishing patterns have been proposed as a method to reduce
16 discards (Holmes et al., 2011; Little et al., 2014; Dunn et al., 2014). However,
17 implementation is hampered by lack of knowledge of fish and fishery spatiotem-
18 poral dynamics and understanding of the scale at which processes are impor-
19 tant for management. Understanding the correct scale for spatial management
20 is crucial in order to implement measures at a resolution that ensures effective
21 management (Dunn et al., 2016) while minimising economic impact. For exam-
22 ple, a scale that promotes species avoidance for vulnerable or low quota species
23 while allowing continuance of sustainable fisheries for available quota species.

24
25 Identifying an appropriate scale has been a challenge in the past that has
26 led to ineffectual measures with unintended consequences such as limited impact
27 towards the management objective or increased benthic impact on previously
28 unexploited areas (e.g. the cod closure in the North Sea (Rijnsdorp et al., 2001;
29 Dinmore et al., 2003)). More refined spatial information has since become avail-
30 able through the combination of logbook and Vessel Monitoring System (VMS)
31 data (Lee et al., 2010; Bastardie et al., 2010; Gerritsen et al., 2012; Mateo et al.,
32 2016) and more real-time spatial management has been possible (e.g. Holmes
33 et al., 2011). Such information is, however, patchy and derived from an inher-
34 ently biased sampling programme (i.e. targeted fishing).

35
36 In order to understand the consequences of using VMS-linked landings to

draw inference on the underlying population structure we develop a simulation model where population dynamics are highly-resolved in space and time. Being known directly rather than inferred from sampling or commercial catch, we can use the population model to evaluate how inference from fisheries-dependent and fisheries independent sampling relates to the real population structure. In our model system population movement is driven by random (diffusive) and directed (advective) processes and we incorporate characterisation of a number of different fishing fleet dynamics exploiting four fish populations with different spatial and population demographics.

Using our model we simulate 50 years of exploitation of the fish populations. We use the results

1. to understand how sampling-derived data reflects the underlying population structures. We compare at different spatial and temporal aggregations of data the real population to:
 - (a) the inferred population from a stratified fixed-site sampling survey design commonly used for fisheries monitoring purposes, otherwise known as a fisheries-independent survey,
 - (b) the inferred population from our fishery-dependent model which includes fishery-induced sampling dynamics.
2. to understand the impact of data aggregation and source on spatial fisheries management measures we simulate a fishery closure to protect a species based on different spatial and temporal data aggregations:
 - (a) as if the real spatial population structure were known,
 - (b) the fishery-independent inferred population structure
 - (c) the fishery-dependent inferred population structure

We evaluate the theoretical "benefit" to the population of the closure(s), the effect on the other three populations and fishery catch.

67 2. Materials and Methods

68 A modular event-based simulation model was developed with sub-modules
 69 implemented on independent time-scales appropriate to capture the character-
 70 istic of the different processes (Figure 1). The following sub-modules were in-
 71 cluded to capture the full system: 1) Population dynamics, 2) Recruitment
 72 dynamics, 3) Population movement, 4) fishery dynamics.

73
 74 Population dynamics (fishing and natural mortality, growth) operate on a
 75 daily time-step, while population movement occurs on a weekly time-step. Re-
 76 cruitment takes place periodically each year for a set time duration specified for
 77 each population, while the fishing module operates on a tow-by-tow basis (i.e.
 78 multiple events a day). The simulation framework is implemented in the sta-
 79 tistical software package R (R Core Team, 2017) and available as an R package
 80 from the authors github site (www.github.com/pdolder/MixFishSim).

82 2.1. Population dynamics

The basic population level processes are simulated using a modified two-
 stage Deriso-Schnute delay difference model (Deriso, 1980; Schnute, 1985; Dich-
 mont et al., 2003) occurring at a daily time-step. A daily time-step was chosen
 as to discretise continuous population processes on a biologically relevant and
 computationally tractable timescale. Under the population dynamics module
 population biomass growth and depletion for pre-recruits and recruited fish
 are modelled separately as a function of previous recruited biomass, intrinsic
 population growth and recruitment. Biomass for each cell is incremented each
 day as follows (the full parameter list is detailed in Table 1):

$$\begin{aligned}
 B_{c,d+1} = & \\
 & (1 + \rho)B_{c,d} \cdot e^{-Z_{c,d}} - \rho \cdot e^{-Z_{c,d}} \quad \times \\
 & (B_{c,d-1} \cdot e^{-Z_{c,d-1}} + Wt_{R-1} \cdot \alpha_{d-1} \cdot R_{\tilde{y}(c,y,d-1)}) \quad + \\
 & Wt_R \cdot \alpha_d \cdot R_{\tilde{y}(c,y,d)}
 \end{aligned}$$

83 where ρ is Brody's coefficient, shown to be approximately equal to e^{-K} when
 84 K is the growth rate from a von Bertalanffy logistic growth model (Schnute,
 85 1985). Wt_{R-1} is the weight of fish prior to recruitment, while Wt_R is the re-
 86 cruited weight. α_d represents the proportion of fish recruited during that day
 87 for the year, while $R_{c,\tilde{y}}$ is the annual recruits in cell c for year y .

88

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 $F_{c,d}$:

$$C_{c,d} = \frac{F_{c,d}}{F_{c,d} + M_{c,d}} * (1 - e^{-(F_{c,d} + M_{c,d})}) * B_{c,d}$$

89 where $C_{c,d}$ is the summed catch from the fishing model across all fleets and
 90 vessels in cell c for the population during the day d , and $B_{c,d}$ the daily biomass
 91 for the population in the cell.

92

93 2.2. Recruitment dynamics

Recruitment is modelled through a function relating the mature biomass to
 recruits at time of recruitment. In *MixFishSim*, it can be modelled either either
 as a stochastic Beverton-Holt stock-recruit form (Beverton and Holt, 1957):

$$\bar{R}_{c,d} = \frac{(\alpha * B_{c,d})}{(\beta + B_{c,d})}$$

$$R_{c,d} \sim \log N[(\log(\bar{R}_{c,d}), \log(\sigma^2))]$$

Where α is the maximum recruitment rate, β the spawning stock biomass (SSB)
 required to produce half the maximum, B current SSB and σ^2 the variability in
 the recruitment due to stochastic processes, or a stochastic Ricker form (Ricker,
 1954):

$$\bar{R}_{c,d} = B_{c,d} * e^{(\alpha - \beta * B_{c,d})}$$

$$R_{c,d} \sim \log N[(\log(\bar{R}_{c,d}), \log(\sigma^2))]$$

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

To simulate fish population distribution in space and time a Gaussian spatial process was employed to model habitat suitability for each of the populations. An advection-diffusion process controlled population movement over time with a moving temperature covariate to capture temporal dependencies.

For habitat we defined a Gaussian random field process, $\{S(c) : c \in \mathbb{R}^2\}$, where for any set of cells c_1, \dots, c_n , the joint distribution of $S = \{S(c_1), \dots, S(c_n)\}$ is multivariate Gaussian. The distribution is specified by its mean function, $\mu(c) = E[S(c)]$ and its covariance function, $\gamma(c, c') = Cov\{S(c), S(c')\}$ (Diggle and Ribeiro, 2007).

The covariance structure affects the smoothness of the surfaces which the process generates; we used the *Matérn* covariance structure, as the correlation strength weakens the further the distance apart. The Matérn covariance structure models the spatial autocorrelation, where animal densities are observed to be more similar in nearby locations (Tobler, 1970; F. Dormann et al., 2007). It is a two-parameter family where:

$$\rho(u) = \{2^{\kappa-1}\Gamma\kappa\}^{-1}(u/\phi)^{\kappa}K_{\kappa}(u/\phi)$$

$K_{\kappa}(\cdot)$ is a modified Bessel function of order κ , $\phi > 0$ is a scale parameter with the dimensions of distance, and $\kappa > 0$, called the order, is a shape parameter which determines the smoothness of the underlying process.

The habitat for each of the populations was generated with the *RFSimulate* function of the *RandomFields* R package (Schlatter et al., 2015), implementing different parameter settings to affect the patchiness of the populations. Each

population was initialised at a single location, and subsequently moved according to a probabilistic distribution based on habitat suitability, temperature and distance from current cell:

$$Pr(J|I) = \frac{e^{-\lambda * d_{IJ}} \cdot (Hab_{J,p}^2 \cdot Tol_{J,p,wk})}{\sum_{c=1}^C e^{-\lambda * d} \cdot (Hab_{c,p}^2 \cdot Tol_{c,p,wk})} \quad (1)$$

Where d_{IJ} is the euclidean distance between cell I and cell J , λ is a given rate of decay, $Hab_{J,p}^2$ is the squared index of habitat suitability for cell J and population p , with $Tol_{J,p,wk}$ the temperature tolerance for cell J by population p in week wk .

During specified weeks of the year, the habitat quality was modified for user-defined spawning habitat, resulting in each population having a concentrated area where spawning takes place and the population moved towards these cells in the weeks prior to spawning.

The temperature field was simulated to be on a gradient from a South-Westerly to North-Easterly direction, with temperature in each cell changing gradually on a week-by-week basis so that initially high temperature areas cycled to lower temperatures and low temperature areas vice versa. Each population p was assigned a thermal tolerance with mean, μ_p and variance, σ_p^2 so that each cell and population temperature suitability is defined that:

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

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^2 the mean and standard deviation of the population temperature tolerance.

The final process resulted in independent populations structure and movement patterns, with population movement occurring on a weekly basis. This process approximated the demographic shifts in fish populations throughout a year with seasonal spawning patterns.

137 2.4. Fleet dynamics

138 The fleet dynamics can be broadly categorised into three components; fleet
139 targeting - which determined the fleet catch efficiency and preference towards
140 a particular species; trip-level decisions, which determined the initial location
141 to be fished at the beginning of a trip; and within-trip decisions, determining
142 movement from one fishing spot to another within a trip.

143 2.4.1. Fleet targeting

144 Each fleet of n vessels was characterised by both a general efficiency, Q ,
145 and a population specific efficiency, Q_p . Thus, the product of these parameters
146 affects the overall catch rates for the fleet and the preferential targeting of one
147 population over another. This, in combination with the parameter choice for the
148 step-function defined below (as well as some randomness from the exploratory
149 fishing process) determined the preference of fishing locations for the fleet. All
150 species prices were kept the same across fleets and seasons.

151 2.4.2. Trip-level decisions

152 NOTE: THIS IS EXPLORE-EXPLOIT STRATEGY VIZ. BAILEY ET AL
153 POSEIDON MODEL.

154 Several studies (e.g. Hutton et al., 2004; Tidd et al., 2012; Girardin et al.,
155 2015) have confirmed past activity and past catch rates are strong predictors of
156 fishing location choice. For this reason, the fleet dynamics sub-model included a
157 learning component, where a vessel's initial fishing location in a trip was based
158 on selecting from previously successful fishing locations. This was achieved by
159 calculating an expected profit based on the profit from locations previously
160 fished in the preceding trip as well as the same month periods in preceding
161 years, and choosing randomly from the top 75 % of fishing events as defined by
162 the expected profit. Expected profit was estimated from the revenue achieved
163 in previous fishing events at a location minus the fuel cost of travelling from the
164 currently location to the new location. Simulation testing indicated that this
165 learning increased the mean value of catches for the vessels, over just relying on

166 the correlated random walk function as described for the 'within trip' decisions
167 below (MIGHT NEED TO INCLUDE IN SUPPLEMENTARY).

168 2.4.3. *Within-trip decisions*

169 Fishing locations within a trip are initially determined by a modified ran-
170 dom walk process. As the simulation progresses, the within-trip decision become
171 gradually more influenced by past locations fished, based on the same process as
172 the initial trip-level location, influenced by expected profit at a fishing location.
173 A random walk was chosen for the exploratory fishing process as it is the sim-
174 plest assumption commonly used in ecology to describe optimal animal search
175 strategy for exploiting homogeneously distributed prey about which there is un-
176 certain knowledge (Viswanathan et al., 1999). In a random walk, movement is
177 a stochastic process through a series of steps. These steps have a length, and a
178 direction that can either be equal in length or take some other functional form.
179 The direction of the random walk can be correlated, (known as 'persistence'),
180 providing some overall directional movement (Codling et al., 2008) .

181

182 A *Lévy flight* is a particular form of random walk characterised by a heavy-
183 tailed distribution of step-length . The Lévy flight has received a lot of at-
184 tention in ecological theory in recent years as having shown to have very sim-
185 ilar characteristics as those observed by animals in nature, and being a near
186 optimum searching strategy for predators pursuing patchily distributed prey
187 (Viswanathan et al., 1999; Bartumeus et al., 2005; Sims et al., 2008). Bertrand
188 et al. (2007) showed that Peruvian anchovy fishermen have a stochastic search
189 pattern similar to that observed with a lévy flight. However, it remains a subject
190 of debate (e.g. see Edwards, 2011; Reynolds, 2015), with the contention that
191 search patterns may be more simply characterised as random walks (Sakiyama
192 and Gunji, 2013) with specific patterns related to the characteristics of the prey
193 field (Sims et al., 2012).

194

We use a modified random walk where directional change is based on a

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 and step length (i.e. the distance travelled from the current to the next fishing location) is determined by recent fishing success, measured as the summed value of fish caught (revenue, Rev),

$$Rev = \sum_{p=1}^P L_p \cdot Pr_p \quad (3)$$

where L_p is landings of a population p , and Pr_p price of a population. 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, which can be controlled separately, but is determined by the relationship:

$$StepL = e^{\log(\beta_1) + \log(\beta_2) - (\log(\frac{\beta_1}{\beta_3}))} * Rev$$

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 $(x1, y1)$ to $(x2, y2)$ is defined by:

$$(x2, y2) = x1 + StepL \cdot \cos(\frac{\pi \cdot Br}{180}),$$

$$y1 + StepL \cdot \sin(\frac{\pi \cdot Br}{180})$$

$$with \quad Br_{t-1} < 180, Br_t = 180 + \sim vm[(0, 360), k]$$

$$Br_{t-1} > 180, Br_t = 180 - \sim vm[(0, 360), k]$$

195 where k the concentration parameter from the von Mises distribution which we
 196 correlate with the revenue so that $k = (Rev + 1 / RefRev) * max_k$, where max_k
 197 is the maximum concentration value, k , and $RefRev$ is parametrised as for β_3
 198 in the step length function.

199 2.4.4. Local population depletion

200 Where several fishing vessels are exploiting the same fish population compe-
 201 tition is known to play an important role in local distribution of fishing effort
 202 (Gillis and Peterman, 1998). If several vessels are fishing on the same patch

203 of fish, local depletion and interference competition will affect fishing location
 204 choice of the fleet as a whole (Rijnsdorp, 2000; Poos and Rijnsdorp, 2007). In
 205 order to account for this behaviour, the fishing sub-model operates spatially on
 206 a daily time-step so that for future days the biomass available to the fishery
 207 is reduced in the areas fished. The cumulative effect is to make heavily fished
 208 areas less attractive as future fishing opportunities.

209 *2.5. Fisheries independent survey*

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

216 **3. Calculation**

217 *3.1. Population parametrisation*

218 We parametrised the simulation model for four populations with differing
 219 habitat preference, temperature tolerances (Figures S1, S3, S4, S5, S6, S7),
 220 population demographic and recruitment functions. In addition, each of the
 221 populations has two defined spawning areas which result in the populations
 222 moving towards these areas in given weeks (Figure S2) and population-specific
 223 movement rates (Table 4). The realised movement of the populations for a
 224 number of weeks is shown in Figure S9 while the realised daily fishing mortality
 225 are shown in Figure S10.

226 *3.2. Fleet parametrisation*

227 The fleets were parametrised to reflect five different characteristics based
 228 on targeting preference and exploitation dynamics (Table 5). Setting a target-
 229 ing parameter (Q) that differed across fleets ensured different spatial dynamics,

230 due to preferential targeting of populations that differ in their spatial distri-
231 butions. The stochasticity in the random walk process ensures that different
232 vessels within a fleet have slightly different spatial distributions based on indi-
233 vidual experience, while the step function was parametrised dynamically so that
234 vessels take smaller steps where the fishing location yields in a top quartile of
235 the value available in that year (as defined per fleet in Table 5).

236
237 Each fleet was parametrised so that, after the first year, fishing locations
238 were chosen based on experience built up in the same month from previous
239 years and from past trip fishing success. 'Success' in this context was defined
240 as the locations where the top 75 % of expected profit would be found given
241 previous trips revenue and cost of movement to the new fishing location.

242
243 An example of the realised fleet movements for a single vessel during a single
244 trip are given in Figure S11, while Figure S12 shows multiple trips for a single
245 vessel, Figure S13 the vessel movements for some trips overlaid on the value
246 field, Figure S14 shows fishing locations for an entire fleet of 20 vessels for a
247 single trip, and Figure S15 shows an example of the step function realisation
248 and turning angles from the correlated random walk.

249 3.3. Survey settings

250 The survey simulation was set up with follow a fixed gridded station design
251 with 100 stations fished each year, starting on day 92 and ending on day 112 (5
252 stations per day) with same catchability parameters for all populations ($Q_p =$
253 1).

254 3.4. Simulation settings

255 To illustrate the capabilities on *MixFishSim*, we investigate the influence of
256 the temporal and spatial resolution of different data sources on the reduction in
257 catches of a population given spatial closures. To do so, we set up a simulation
258 to run for 50 years based on a 100 X 100 square grid, 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.

We allow the simulation to run unrestricted for 30 years, and subsequently close areas for the last 20 years of the simulation based on data (either derived from the commercial catches, fisheries-independent survey or the 'real population' - the underlying populations assumed to be known perfectly) used at different spatial and temporal scales.

The following steps are undertaken to determine closures:

1. Extract data source
2. Aggregate according to resolution
3. Interpolate across entire area at desired resolution
4. Close area covering top 5 % of catch

In total 56 closure scenarios were run which represent combinations of

- **data types:** commercial logbook data, survey data and 'real 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,
- **closure basis:** high catch rates of protected species, or high ratio of protected species v secondary species.

Survey closures were on an annual basis only, as this was the most temporally resolved survey data available.

4. Results

The consequences of different spatial aggregations of the data are shown in Figure 2, which represents the aggregation of catch from each of the data sources over a year at different spatial resolutions.

286 The finer spatial grid for the the real population (top left) and commercial
 287 data (top middle) show similar patterns, though there are unsampled gaps in
 288 the commercial data from a lack of fishing activity (particularly in the lower left
 289 part of the sampling domain). The survey data at this spatial resolution shows
 290 very sparse and uninformative information about the spatial distributions of the
 291 populations. The slightly aggregated data on a 5 x 5 grid shows similar patterns,
 292 and while losing some of the spatial detail there remains good consistency be-
 293 tween the 'real population' and the commercial data. Survey data starts to pick
 294 out some of the similar patterns as the other data sources, but lacks coverage.
 295 The spatial catch information on a 10 x 10 and 20 x 20 grid loses a signifi-
 296 cant amount of information about the spatial resolutions for all data sources,
 297 and some differences between the commercial and 'real population' data emerge.

298
 299 Figure 3 shows the consequences of different temporal aggregations of the
 300 data, with 156 weekly (top), 36 monthly (middle) and 3 yearly (bottom) catch
 301 compositions across a 20 x 20 area.

302
 303 As can be seen from the 'real population', the monthly aggregation captures
 304 the major patterns seen in the weekly data, albeit missing more subtle differ-
 305 ences. The yearly data results in a constant catch pattern due to the aggregation
 306 process (sometimes known as an aggregation bias). The commercial data on a
 307 weekly basis shows some of the same patterns as the 'real population', though
 308 the first species (in red) is less well represented and some weeks are missing
 309 catches from the area. The monthly data. The monthly data shows some con-
 310 sistency between the 'real population' and commercial data for species 2 - 4,
 311 though species 1 remains underrepresented. On an annual basis, interestingly
 312 the commercial data underrepresents the first species (in red) while the survey
 313 overrepresents species 1. This is likely due to the biases in commercial sampling,
 314 with the fisheries not targeting the areas where species 1 are present, and the
 315 biases in the survey sampling from overrepresentation of the spatial distribution.

316

317 We implemented a spatial closure using the different data sources and spatial
 318 and temporal aggregations as outlined in the protocol in Section 3.4. We used
 319 this to assess the efficacy of a closure in reducing fishing mortality on species 1,
 320 given availability of data and its use at different resolutions in order to evaluate
 321 the trade-offs in data sources. Figure 4 shows the trend in fishing mortality
 322 for each species simulated (columns) given the data sources (rows), temporal
 323 aggregations (colour lines) and spatial aggregations (linestyles), while Figure 5
 324 shows the change in fishing mortality from before the closure (average F years
 325 2 - 4) to after the closure (average F years 8 - 10).

326
 327 For the closures based on 'real population' (bottom row), the most disag-
 328 gregated data (a weekly timescale and 1 x 1 resolution) was most effective,
 329 reducing fishing mortality on species 1 (left) by $\sim 60\%$. Next was the monthly
 330 closures ($< \sim 30\%$). The least effective were the yearly closures (blue lines)
 331 at all spatial resolutions, which resulted in increased fishing mortalities (> 30
 332 $\%$ - N.B. Note though, this is consistent with the increasing trends in F, which
 333 is probably more related to the fact that Fs hadn't stabilised in the simulation
 334 from the fishing vessels "learning" the best locations - I will rerun the sims for
 335 a longer time (20 - 30 years).

336
 337 For the survey data, which can only be implemented on a yearly timescale,
 338 the closures had no effect at any data resolution. The results are identical for
 339 the different data resolutions except 20 x 20, which is why you can't see more
 340 than 2 points. This is because of the sparsity of the sampling locations.

341
 342 For the commercial data, the most effective closure scenario was based on 1
 343 x 1 data at a monthly temporal resolution. This results in $\sim 10\%$ reduction
 344 in F for species 1. This was the only closure scenario to have positive effect
 345 according to Figure 5, though looking at the trend in Figure 4 this looks more
 346 related to the continued increased in F trend, as other scenarios had an initial
 347 effect. Interestingly the monthly data scenario was more effective than weekly

348 data, which I'd posit is due to the increase amount of data available from the
349 commercial sampling across a month compared to a week.i Commercial data
350 used at an annual timestep was ineffective in bringing fishing mortality down
351 for species 1.

352

353 Given the scenarios above, it seems clear that spatial disaggregation is more
354 important than the temporal disaggregation of the commercial data, except
355 when its used at an annual timeframe, which is the scenario that gave the worst
356 results.

357 For the other species in the simulation (population 2 - 4) there was little
358 difference in fishing mortalities across scenarios.

359 Note: The monthly commercial data scenario is the most effective of the
360 realistic scenarios, as the 'real population' can only be seen as a baseline com-
361 parison.

362 5. Discussion

363 6. Conclusions

364 Appendices

365 Abbreviations

366 Detail any unusual ones used.

367 Acknowledgements

368 those providing help during the research..

369 Funding

370 This work was supported by the MARES doctoral training program; and the
371 Centre for Environment, Fisheries and Aquaculture Science seedcorn program.

Table 1: Description of variables for population dynamics sub-module

Variable	Meaning	Units
Population dynamics		
<i>Delay-difference model</i>		
$B_{c,d}$	Biomass in cell c and day d	kg
$Z_{c,d}$	Total mortality in cell c for day d	-
$R_{c,\bar{y}}$	Annually recruited fish in cell	yr ⁻¹
ρ	Brody'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	-
<i>Baranov catch equation</i>		
$C_{c,d}$	Catch from cell c for day d	kg
$F_{c,d}$	Instantaneous rate of fishing mortality in cell c on day d	-
$M_{c,d}$	Instantaneous rate of natural mortality in cell c on day d	-
$B_{c,d}$	Biomass in cell c on day d	kg
Recruitment dynamics		
$\tilde{R}_{c,d}$	is the recruitment in cell c for day d	d^{-1}
$B_{c,d}$	is the Biomass in cell c for day d	d^{-1}
α	the maximum recruitment rate	kg
β	the biomass required to produce half the maximum rate of recruitment	kg

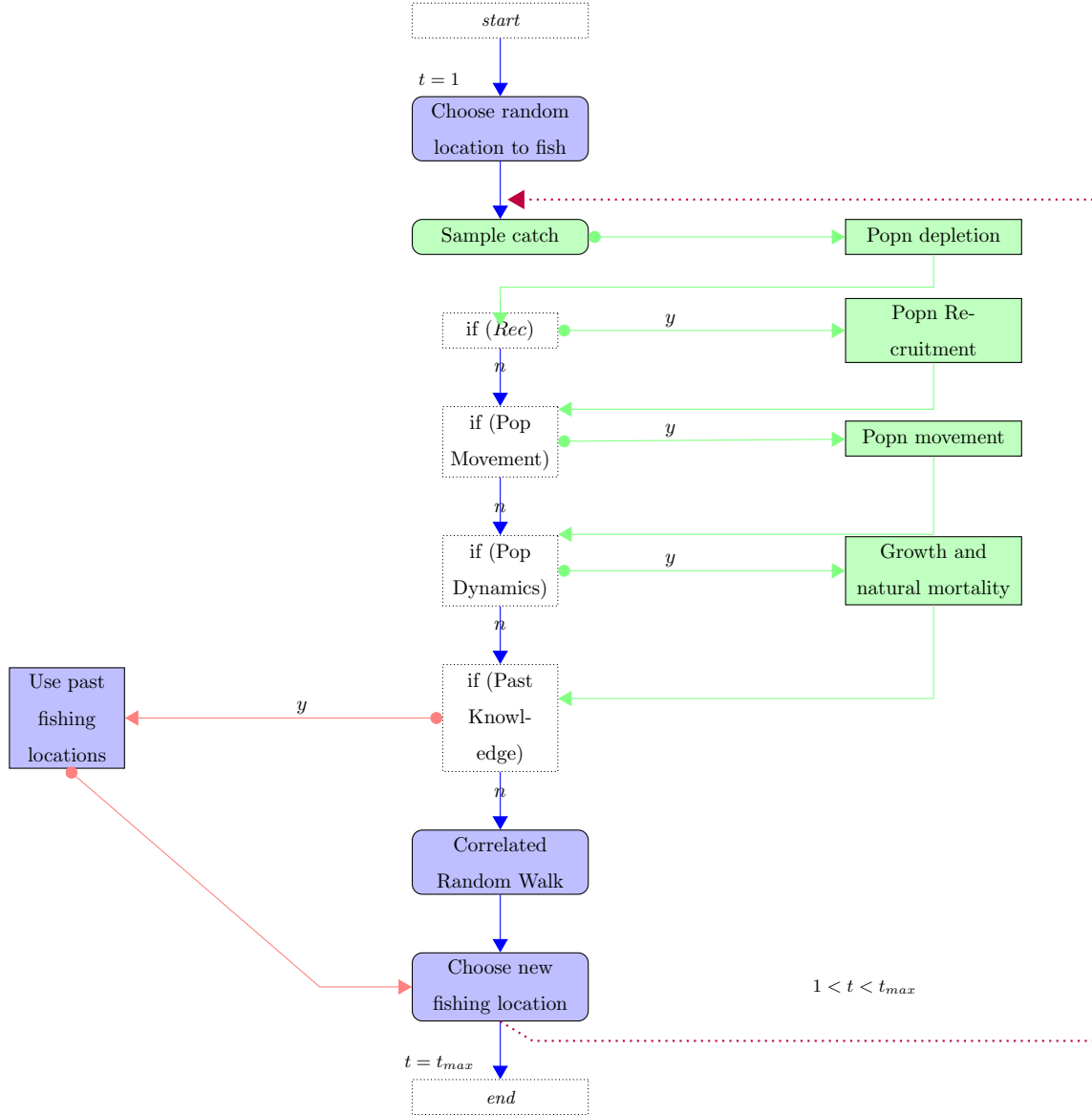


Figure 1: Overview Schematic of simulation model. The blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the time steps at which processes occur; $t = t_{ow}$, t_{max} is the total number of tows; (Rec), (Pop Movement), (Pop Dynamics) 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.

Table 2: Description of variables for population movement sub-module

Variable	Meaning	Units
Population movement dynamics		
<i>Habitat model</i>		
a	b	c
<i>Thermal tolerance</i>		
$T_{c,wk}$	Temperature for cell in week	°C
μ_p	Mean of the thermal tolerance for population	°C
σ_p^2	Standard deviation of thermal tolerance for the population	°C
<i>Population movement model</i>		
λ	decay rate for population movement	-
$Hab_{c,p}^2$	Square of habitat suitability for cell c and population p	-
$Tol_{c,p,wk}$	Thermal tolerance for population p in cell c at week wk	-
d_{IJ}	euclidean distance between cell I and cell J	-

Table 3: Description of variables for fleet dynamics sub-module

Variable	Meaning	Units
Short-term fleet dynamics		
Rev	Revenue from fishing tow	€
L_p	Landings of population p	kg
Pr_p	Average price of population p	€ kg ⁻¹
StepL	Step length for vessel	euclidean distance
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	-

Table 4: Population dynamics and movement parameter setting

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	10	10	10
Movement λ	0.1	0.1	0.1	0.1
Population dynamics				
Starting Biomass	1e5	2e5	1e5	1e4
Beverton-Holt Recruit 'a'	6	27	18	0.3
Beverton-Holt Recruit 'b'	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	0.3	0.3	0.3
wt	1	1	1	1
wt_{d-1}	0.1	0.1	0.1	0.1
M (annual)	0.2	0.1	0.2	0.1
Movement dynamics				
μ	12	15	17	14
σ^2	8	9	7	10

Table 5: Fleet dynamics parameter setting

Parameter	Fleet	Fleet	Fleet	Fleet	Fleet
	1	2	3	4	5
Targeting preferences					
Price Pop1	100	100	100	100	100
Price Pop2	200	200	200	200	200
Price Pop3	350	350	350	350	350
Price Pop4	600	600	600	600	600
Q Pop1	0.01	0.02	0.02	0.01	0.01
Q Pop2	0.02	0.01	0.02	0.01	0.03
Q Pop3	0.01	0.02	0.02	0.01	0.02
Q Pop4	0.02	0.01	0.02	0.05	0.01
Exploitation dynamics					
step function β_1	1	2	1	2	3
step function β_2	10	15	8	12	7
step function β_3	Q90	Q90	Q85	Q90	Q80
step function $rate$	20	30	25	35	20
Past Knowledge	T	T	T	T	T
Past Year & Month	T	T	T	T	T
Past Trip	T	T	T	T	T
Threshold	0.7	0.7	0.7	0.7	0.7
Fuel Cost	3	2	5	2	1

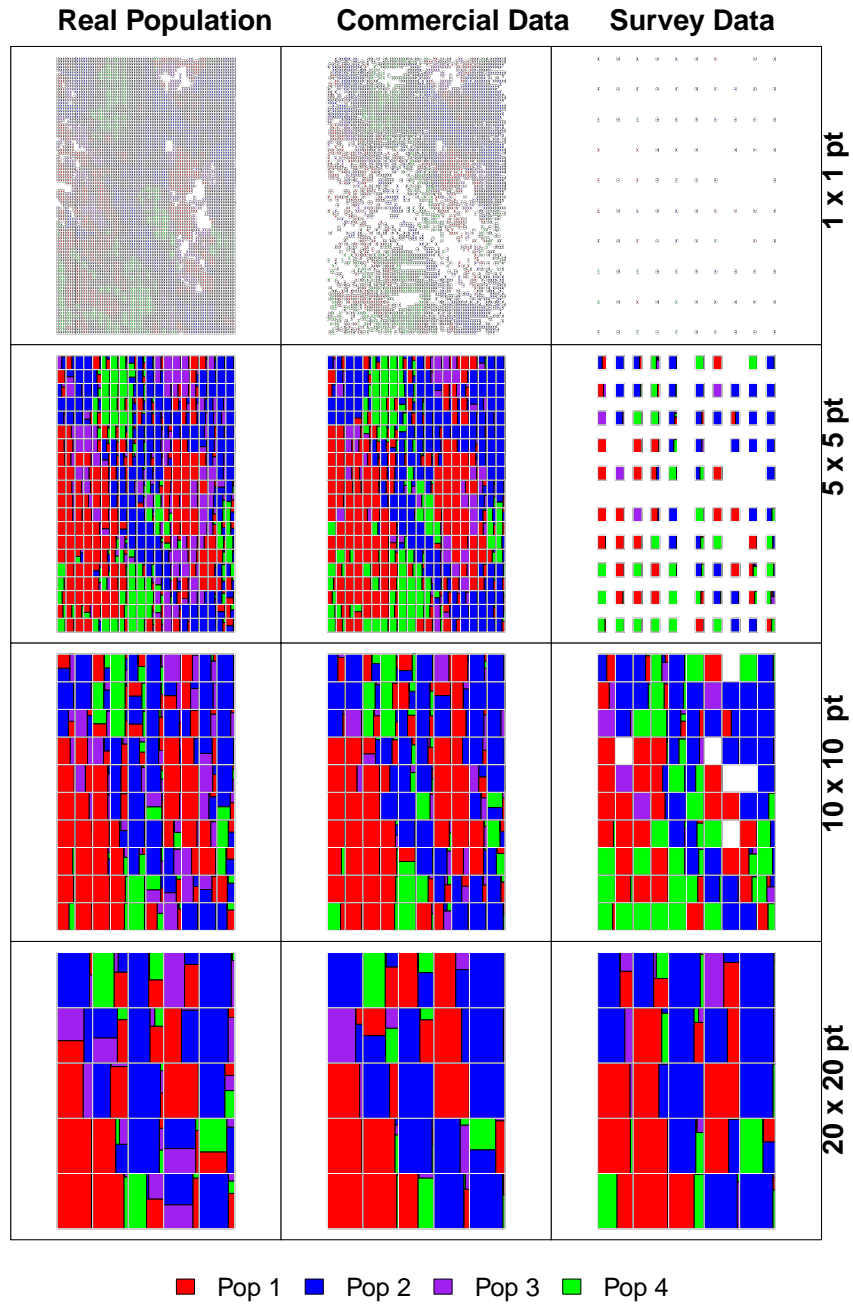


Figure 2: Data aggregation at different spatial resolutions

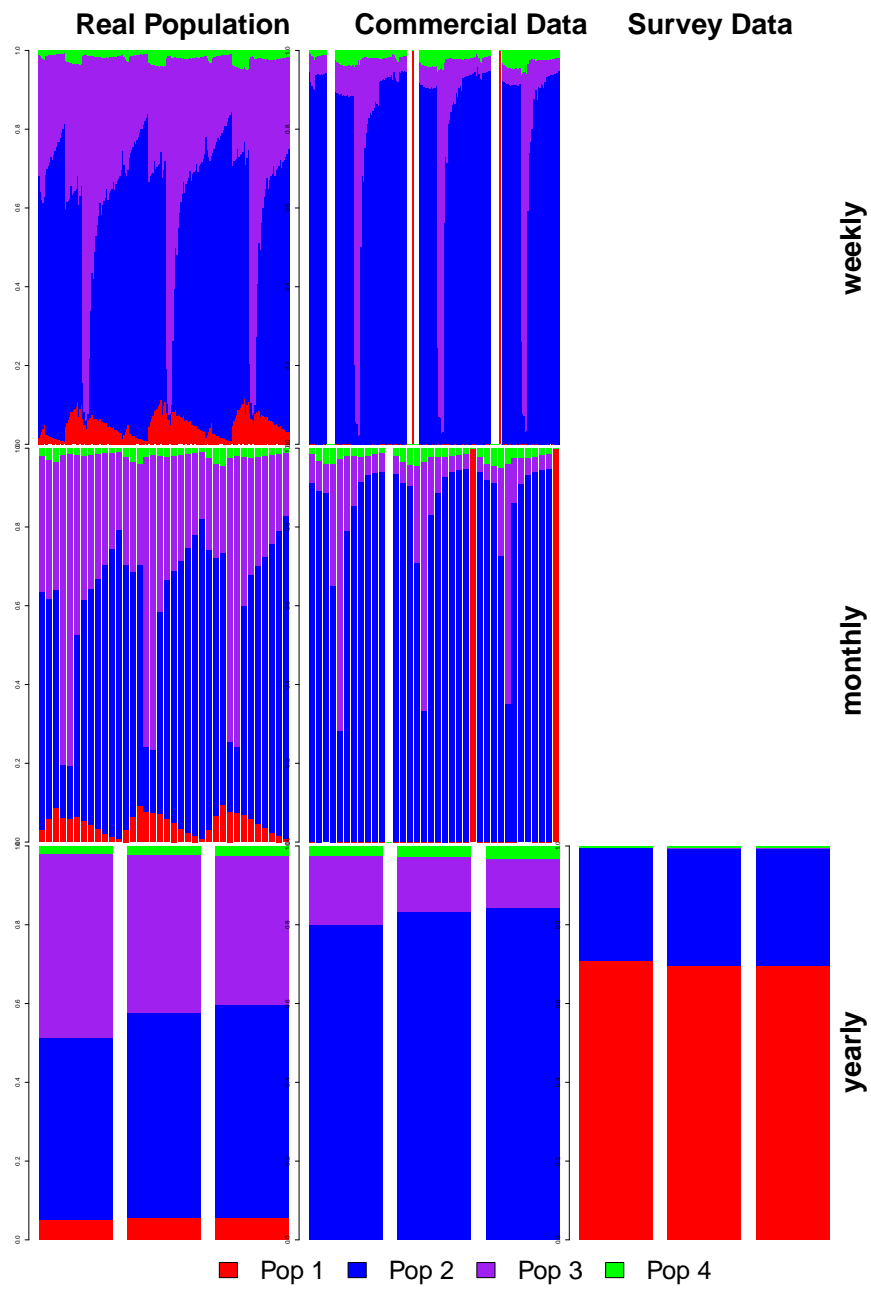


Figure 3: Data aggregation at different temporal resolutions

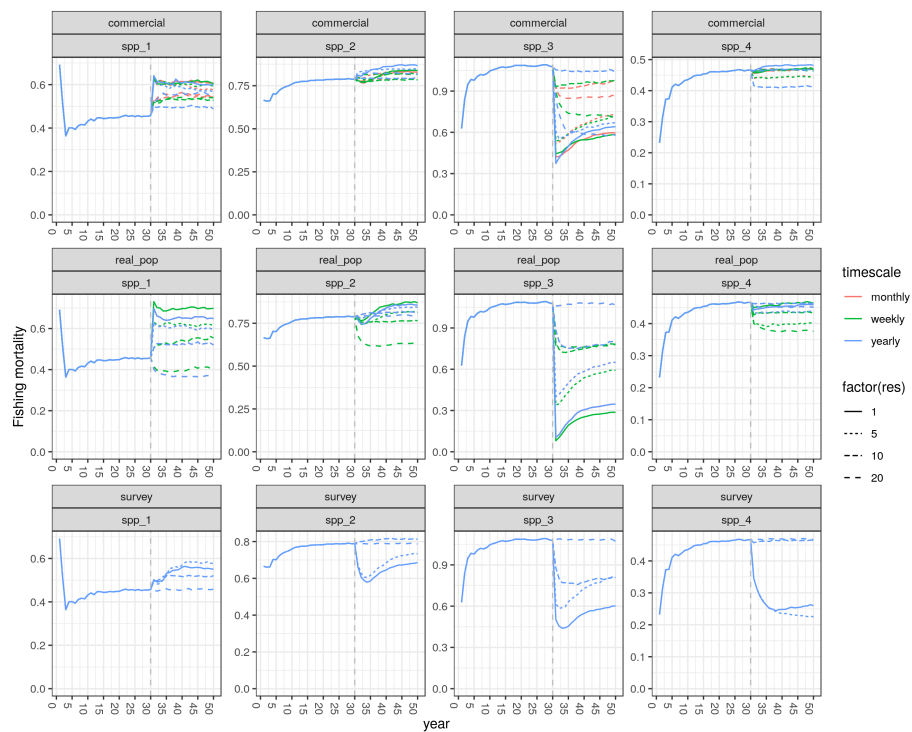


Figure 4: Comparison of closure scenarios - F trends

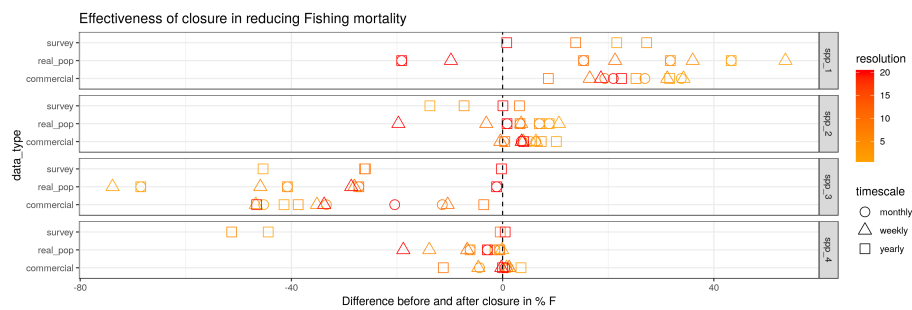


Figure 5: Comparison of closure scenarios

372 **References**

- 373 Alverson, D.L., Freeberg, M.H., Murawski, S.A., Pope, J., 1994. A global as-
374 sessment of fisheries bycatch and discards.
- 375 Bartumeus, F., Da Luz, M.G.E., Viswanatham, G.M., Catalan, J., 2005. Animal
376 Search Strategies: A Quantitative Random Walk Analysis. *Ecological Society*
377 *of America* 86, 3078–3087.
- 378 Bastardie, F., Nielsen, J.R., Ulrich, C., Egekvist, J., Degel, H., 2010. De-
379 tailed mapping of fishing effort and landings by coupling fishing logbooks
380 with satellite-recorded vessel geo-location. *Fisheries Research* 106, 41–53.
- 381 Batsleer, J., Hamon, K.G., Overzee, H.M.J., Rijnsdorp, A.D., Poos, J.J., 2015.
382 High-grading and over-quota discarding in mixed fisheries. *Reviews in Fish*
383 *Biology and Fisheries* 25, 715–736.
- 384 Bellido, J.M., Santos, M.B., Pennino, M.G., Valeiras, X., Pierce, G.J., 2011.
385 Fishery discards and bycatch: Solutions for an ecosystem approach to fisheries
386 management?
- 387 Bertrand, S., Bertrand, A., Guevara-Carrasco, R., Gerlotto, F., 2007. Scale-
388 invariant movements of fishermen: The same foraging strategy as natural
389 predators. *Ecological Applications* 17, 331–337.
- 390 Beverton, R.J., Holt, S.J., 1957. On the Dynamics of Exploited Fish Populations
391 , 533.
- 392 Catchpole, T.L., Revill, A.S., 2008. Gear technology in Nephrops trawl fisheries.
393 *Reviews in Fish Biology and Fisheries* 18, 17–31.
- 394 Codling, E.A., Plank, M.J., Benhamou, S., Interface, J.R.S., 2008. Random
395 walk models in biology. *Journal of the Royal Society, Interface / the Royal*
396 *Society* 5, 813–34.
- 397 Crowder, L.B., Murawski, S.A., 1998. Fisheries Bycatch: Implications for Man-
398 agement. *Fisheries* 23, 8–17.

399 Deriso, R.B., 1980. Harvesting Strategies and Parameter Estimation for an Age-
400 Structured Model. *Canadian Journal of Fisheries and Aquatic Sciences* 37,
401 268–282. [arXiv:1410.7455v3](#).

402 Dichmont, C.M., Punt, A.E., Deng, A., Dell, Q., Venables, W., 2003. Applica-
403 tion of a weekly delay-difference model to commercial catch and effort data
404 for tiger prawns in Australia ’ s Northern Prawn Fishery. *Fisheries Research*
405 65, 335–350.

406 Diggle, P.J., Ribeiro, P.J., 2007. *Model-based Geostatistics* (Springer Series in
407 Statistics). volume 1.

408 Dinmore, T.A., Duplisea, D.E., Rackham, B.D., Maxwell, D.L., Jennings, S.,
409 2003. Impact of a large-scale area closure on patterns of fishing disturbance
410 and the consequences for benthic communities. *ICES Journal of Marine Sci-*
411 *ence* 60, 371–380.

412 Dunn, D.C., Boustany, A.M., Roberts, J.J., Brazer, E., Sanderson, M., Gardner,
413 B., Halpin, P.N., 2014. Empirical move-on rules to inform fishing strategies:
414 A New England case study. *Fish and Fisheries* 15, 359–375.

415 Dunn, D.C., Maxwell, S.M., Boustany, A.M., Halpin, P.N., 2016. Dynamic
416 ocean management increases the efficiency and efficacy of fisheries manage-
417 ment. *Proceedings of the National Academy of Sciences* , 201513626.

418 Edwards, A.M., 2011. Overturning conclusions of Lévy flight movement patterns
419 by fishing boats and foraging animals. *Ecology* 92, 1247–1257.

420 F. Dormann, C., M. McPherson, J., B. Araújo, M., Bivand, R., Bolliger, J.,
421 Carl, G., G. Davies, R., Hirzel, A., Jetz, W., Daniel Kissling, W., Kühn, I.,
422 Ohlemüller, R., R. Peres-Neto, P., Reineking, B., Schröder, B., M. Schurr,
423 F., Wilson, R., 2007. Methods to account for spatial autocorrelation in the
424 analysis of species distributional data: A review. *Ecography* 30, 609–628.

425 Gerritsen, H.D., Lordan, C., Minto, C., Kraak, S.B.M., 2012. Spatial patterns
426 in the retained catch composition of Irish demersal otter trawlers: High-

427 resolution fisheries data as a management tool. *Fisheries Research* 129-130,
428 127–136.

429 Gillis, D.M., Peterman, R.M., 1998. Implications of interference among fishing
430 vessels and the ideal free distribution to the interpretation of CPUE. *Canadian*
431 *Journal of Fisheries and Aquatic Sciences* 55, 37–46.

432 Girardin, R., Vermard, Y., Thébaud, O., Tidd, A., Marchal, P., 2015. Predicting
433 fisher response to competition for space and resources in a mixed demersal
434 fishery. *Ocean & Coastal Management* 106, 124–135.

435 Hilborn, R., Walters, C., 1992. Quantitative fisheries stock assessment: Choice,
436 dynamics and uncertainty. volume 2. [arXiv:1011.1669v3](#).

437 Holmes, S.J., Bailey, N., Campbell, N., Catarino, R., Barratt, K., Gibb, A., Fer-
438 nandes, P.G., 2011. Using fishery-dependent data to inform the development
439 and operation of a co-management initiative to reduce cod mortality and cut
440 discards. *ICES Journal of Marine Science* 68, 1679–1688.

441 Hutton, T., Mardle, S., Pascoe, S., Clark, R.a., 2004. Modelling fishing location
442 choice within mixed fisheries: English North Sea beam trawlers in 2000 and
443 2001. *ICES Journal of Marine Science* 61, 1443–1452.

444 Kennelly, S.J., Broadhurst, M.K., 2002. By-catch begone: Changes in the phi-
445 losophy of fishing technology. *Fish and Fisheries* 3, 340–355.

446 Lee, J., South, A.B., Jennings, S., 2010. Developing reliable, repeatable, and
447 accessible methods to provide high-resolution estimates of fishing-effort distri-
448 butions from vessel monitoring system (VMS) data. *ICES Journal of Marine*
449 *Science* 67, 1260–1271.

450 Little, A.S., Needle, C.L., Hilborn, R., Holland, D.S., Marshall, C.T., 2014.
451 Real-time spatial management approaches to reduce bycatch and discards:
452 experiences from Europe and the United States. *Fish and Fisheries* , n/a–
453 n/a.

454 Mateo, M., Pawlowski, L., Robert, M., 2016. Highly mixed fisheries: fine-scale
455 spatial patterns in retained catches of French fisheries in the Celtic Sea. ICES
456 Journal of Marine Science: Journal du Conseil , fsw129.

457 Poos, J.J., Rijnsdorp, A.D., 2007. An "experiment" on effort allocation of fishing
458 vessels: the role of interference competition and area specialization. Canadian
459 Journal of Fisheries and Aquatic Sciences 64, 304–313.

460 R Core Team, 2017. R Core Team (2017). R: A language and environment for
461 statistical computing. R Foundation for Statistical Computing, Vienna, Aus-
462 tria. URL <http://www.R-project.org/> , R Foundation for Statistical Com-
463 puting.

464 Reynolds, A., 2015. Liberating Lévy walk research from the shackles of optimal
465 foraging.

466 Ricker, W.E., 1954. Stock and recruitment. Journal of the Fisheries Research
467 Board of Canada 11, 559 – 623.

468 Rijnsdorp, A., 2000. Competitive interactions among beam trawlers exploiting
469 local patches of flatfish in the North Sea. ICES Journal of Marine Science 57,
470 894–902.

471 Rijnsdorp, a.D., Daan, N., Dekker, W., Poos, J.J., Van Densen, W.L.T., 2007.
472 Sustainable use of flatfish resources: Addressing the credibility crisis in mixed
473 fisheries management. Journal of Sea Research 57, 114–125.

474 Rijnsdorp, A.D., Piet, G.J., Poos, J.J., 2001. Effort allocation of the Dutch
475 beam trawl fleet in response to a temporarily closed area in the North Sea.
476 Ices Cm 2001/N: 01 , 1–17.

477 Sakiyama, T., Gunji, Y.P., 2013. Emergence of an optimal search strategy from
478 a simple random walk. Journal of the Royal Society, Interface 10, 20130486.

479 Schlater, M., Malinowski, A., Menck, P.J., 2015. Analysis, Simulation and Pre-
480 diction of Multivariate Random Fields with Package RandomFields. Journal
481 of Statistical Software 63, 1–25. [arXiv:1501.0228](https://arxiv.org/abs/1501.0228).

482 Schnute, J., 1985. A general theory for analysis of catch and effort data. Canadian
483 Journal of Fisheries and Aquatic Sciences 42, 414–429.

484 Sims, D.W., Humphries, N.E., Bradford, R.W., Bruce, B.D., 2012. Lévy flight
485 and Brownian search patterns of a free-ranging predator reflect different prey
486 field characteristics. Journal of Animal Ecology 81, 432–442.

487 Sims, D.W., Southall, E.J., Humphries, N.E., Hays, G.C., Bradshaw, C.J.A.,
488 Pitchford, J.W., James, A., Ahmed, M.Z., Brierley, A.S., Hindell, M.A., Mor-
489 ritt, D., Musyl, M.K., Righton, D., Shepard, E.L.C., Wearmouth, V.J., Wil-
490 son, R.P., Witt, M.J., Metcalfe, J.D., 2008. Scaling laws of marine predator
491 search behaviour. Nature 451, 1098–U5.

492 Tidd, A.N., Hutton, T., Kell, L.T., Blanchard, J.L., 2012. Dynamic prediction
493 of effort reallocation in mixed fisheries. Fisheries Research 125–126, 243–253.

494 Tobler, W.R., 1970. A Computer Movie Simulating Urban Growth in the Detroit
495 Region. Economic Geography 46, 234. [arXiv:1011.1669v3](#).

496 Ulrich, C., Reeves, S.a., Vermard, Y., Holmes, S.J., Vanhee, W., 2011. Re-
497 conciling single-species TACs in the North Sea demersal fisheries using the
498 Fcube mixed-fisheries advice framework. ICES Journal of Marine Science 68,
499 1535–1547.

500 Viswanathan, G.M., Buldyrev, S.V., Havlin, S., Da Luz, M.G.E., Raposo, E.P.,
501 Stanley, H.E., 1999. Optimizing the success of random searches. Nature 401,
502 911–914.