

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 ~~Universit   Pierre-et-Marie-Curie~~^{JM}, 4 Place Jussieu, 75005 Paris, France*

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

Abstract

Most fisheries ~~Fishing~~^{JJ} exploits^{JJ} spatially and temporally heterogenous 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.

To implement effective spatial measures to reduce discards a good understanding of spatiotemporal fishery dynamics is required. However, traditional scientific advice is limited by a lack of highly resolved knowledge of population distribution, movement and how fishers interact with different fish populations. This reflects that data on fish location at high temporal and spatial resolutions is expensive and difficult to collect and therefore proxies inferred from either scientific surveys or commercial catch data are often used to model distributions, often with limited spatial and temporal resolution.

To understand how resolution impacts mixed fisheries inference, we develop a highly resolved spatiotemporal simulation model incorporating: i) delay-

*Corresponding author

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

difference population dynamics, ii) population movement using Gaussian Random Fields to simulate patchy, heterogenously distributed populations, and iii) fishery dynamics for multiple fleet characteristics based on targetting via correlated random walk movement and learned behaviour.

We simulate 20 years of exploitation of the fish populations and use the results from the fishing model 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, 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 commercial 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 fish populations that are heterogenously distributed in space and time with varying knowledge of species distributions using species-unselective fishing gear. Fisheries that catch an assemblage of species, known as mixed fisheries may, ~~when managed by single species quotas can end up~~^{JJ} discarding^{JJ}

overquota catch when managed by single species quotas,^{JJ} leading to overex-
 ploitation of fish populations (Ulrich et al., 2011; Batsleer et al., 2015)^{JJ}. This
 discarding of fish in excess of quota hampers the ability to limit fishing mortal-
 ity to within sustainable limits (Alverson et al., 1994; Crowder and Murawski,
 1998; Rijnsdorp et al., 2007).^{JJ} Reducing discarding is crucial to ensure biological
 and economic sustainability of fisheries ~~and implementation of an ecosystem~~
~~approach to fisheries~~^{JJ} and. As such^{PD} there is increasing interest in technical
 solutions such as gear and spatial closures as ways of avoiding discarding of
 fish (Kennelly and Broadhurst, 2002; Catchpole and Revill, 2008; Bellido et al.,
 2011)^{sJJ}.

Use of spatial management as a tool has been proposed as a method to reduce
 discards (Holmes et al., 2011; Little et al., 2014; Dunn et al., 2014)^{PD}. How-
 ever, its implementation is hampered by lack of knowledge of fish and fishery
 spatiotemporal dynamics and understanding of the scale at which processes are
 important for management. Understanding the correct scale for spatial man-
 agement is crucial in order to implement measures at a resolution that ensures
 effective management (Dunn et al., 2016) while minimising economic impact.
 For example, a scale that promotes species avoidance for vulnerable or low
 quota species while allowing continuance of sustainable fisheries for available
 quota species.

Ensuring measures are implemented at an appropriate scale has been a chal-
 lenge in the past that has led to ineffectual measures with unintended conse-
 quences such as limited impact towards the management objective or increased
 benthic impact on previously unexploited areas (e.g. the cod closure in the
 North Sea (Rijnsdorp et al., 2001; Dinmore et al., 2003)). Since then more
 refined spatial information has become available through the combination of
 logbook and Vessel Monitoring System (VMS) data (Lee et al., 2010; Bastardie
 et al., 2010; Gerritsen et al., 2012; Mateo et al., 2016) and more real-time spatial
 management has been possible (e.g. Holmes et al., 2011). Such information is,

37 however, patchy and derived from an inherently biased sampling programme
38 (i.e. targeted fishing). Further, fishers generally only recorded landings (not
39 catch) on a daily basis. This leads to questions about the validity of inference
40 that can be drawn from landings data assigned to VMS activity pings.

Its not clear what the problem is: landed collected on daily basis or landings recorded rather than catch^{JJ}

41
42 In order to understand challenges that face VMS-linked landings to draw
43 inference on the underlying population structure we develop a simulation model
44 where population dynamics are highly-resolved in space and time and are known
45 rather than inferred from sampling or commercial catches. Population move-
46 ment is driven by a random (diffusive) and directed (advective) process and we
47 incorporate characterisation of a number of different fisheries exploiting four
48 fish populations with different spatial and population demographics.

This comes as a surprise: I thought this was going to be about discards^{JJ}

49
50 Using our model we simulate 20 years of exploitation of the fish populations
51 and use the results from the fishing model to draw inference on the underlying
52 population structures. We compare this inference to: i) a stratified fixed-site
53 sampling survey design commonly used for fisheries monitoring purposes, other-
54 wise know as a fisheries-independent survey, and ii) the underlying population
55 structures input to the simulation.

56
57 We simulate a fishery closure to protect one species based on the fishery-
58 dependent inferred distributions at a spatial and temporal scale typical in fish-
59 eries management, and assess a theoretical "benefit" to the population, and
60 effect on the other three populations. Further, we extend our analysis to a
61 range of spatial and temporal scales to assess the impact of these processes on
62 the success of the management measure.

If the paper has two goals this should be clear from the start, but may be better over 2 MSs^{JJ}

64 2. Materials and Methods

65 ~~A We developed and implemented a simulation model with a~~^{PD} modular

event-based simulation model was developed with approach, where sub-^{PD} modules
^{are}^{PD} implemented on independent time-scales appropriate to capture the char-
acteristic of the different processes~~process modelled~~^{PD} (Figure 1). The following
sub-modules were included to capture the full system: 1) Population dynamics,
2) Recruitment dynamics, 3) Population movement, 4) fishery dynamics.^{PD}

The fishing model operated on a tow-by-tow basis, while ^{PD} P^{PD} population
dynamics (fishing and natural mortality, growth) operate on a daily time-step,
while p.^{PD} population movement occurs on a weekly time-step. R,^{PD} while
^r^{PD} recruitment takes place~~occurs~~^{PD} periodically each year for a set time duration~~period~~^{PD}
(e.g. 3 weeks)^{PD} at a specified point individual to a species.^{PD}, while the fish-
ing module operates on a tow-by-tow basis (multiple events a day)^{PD}. The
simulation framework is implemented in the statistical software package R (R
Core Team, 2017) and^{PD} available as an R package from the authors github
(www.github.com/pdolder/MixFishSim).

Here we describe each of the model components; 1) Population dynamics, 2)
Recruitment dynamics, 3) Population movement dynamics, 4) fishery dynamics.^{PD}

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 cho-
sen as to discretise continuous population processes on a biologically relevant
and computationally tractable timescale.^{PD} Under the population dynamics
module~~Here,~~^{PD} population biomass growth and depletion for pre-recruits and
fish^{PD} recruited fish^{PD} to the fishery^{PD} are modelled separately as a function
of previous recruited biomass, intrinsic population growth and recruitment:

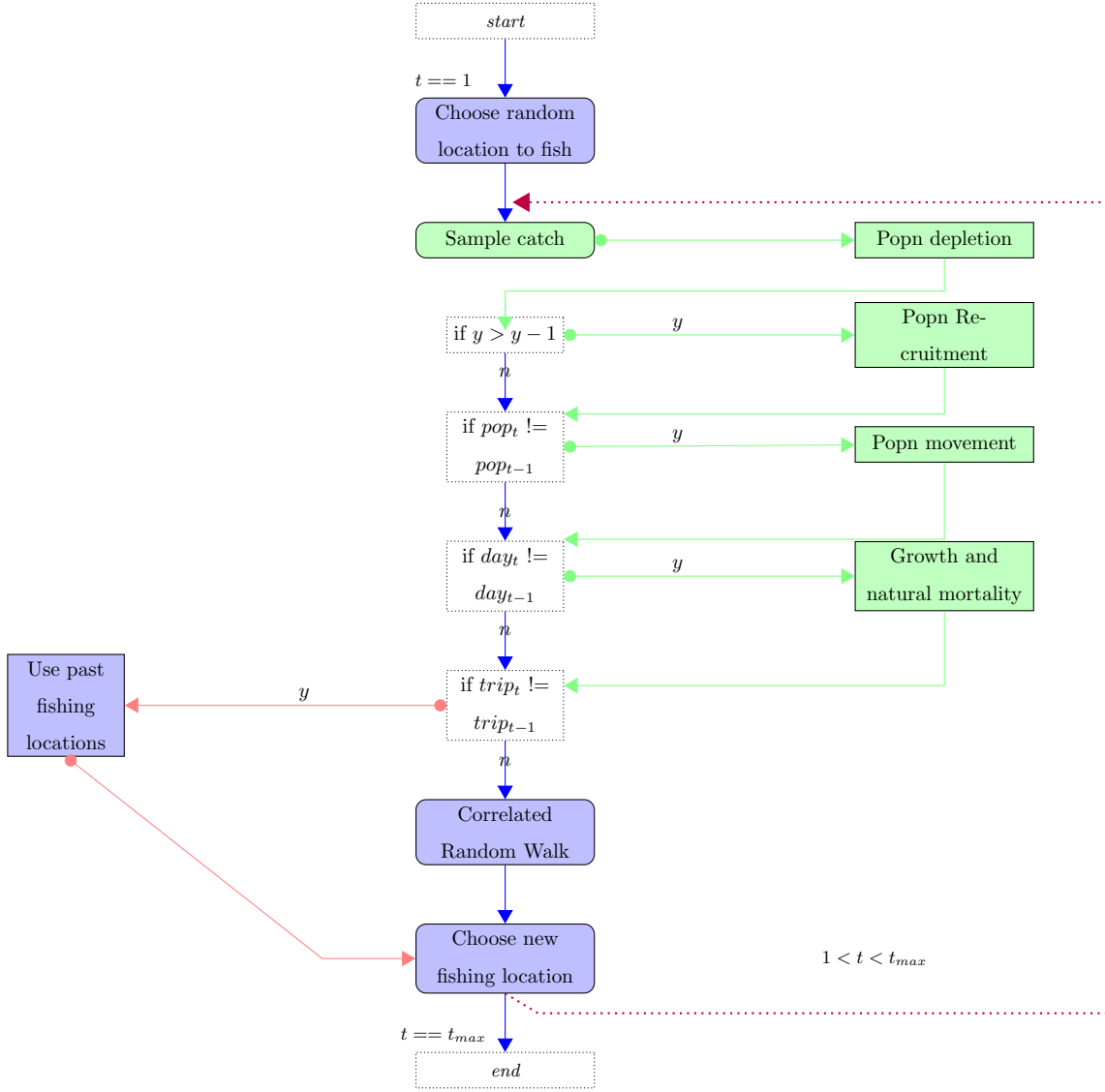


Figure 1: Overview Schematic of simulation model. The blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the timesteps at which processes occur; $t = \text{tow}$, t_{max} is the total number of tows, $y = \text{year}$, pop_t is time of population movement, day is a day timestep, $trip$ is a trip time step.

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

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

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 $F_{c,d}$:

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

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

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):

[link F to effort and catchability - as I think we have F as an emergent property of the fleets rather than something we solve for (I could be wrong though!) - catch for a vessel is a product of catchability and biomass, i.e. $C = qB$, but this catch is summed to solve for F . So its both really]^{CM}

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

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

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 ~~how~~^{JJ} fish populations ~~might be~~^{JJ} distributioned^{JJ} in space and time, ~~we employed~~^{JJ} a Gaussian spatial process ~~was employed~~^{JJ} to model habitat suitability for each of the populations. ~~An, with an~~^{JJ} advection-diffusion process ~~to~~^{JJ} controlled^{JJ} ~~how the~~^{JJ} populations^{JJ} movement^{JJ} over time with a moving temperature covariate to capture temporal dependencies. ~~This was intended to balance realism in population movement, capturing the main directed and random processes, and practicality of modelling the population rather than individual fish.~~^{JJ}

For ~~the~~^{PD} habitat we defined^{PD} a Gaussian random field process, $\{S(c) : c \in \mathbb{R}^2\}$, ~~that is a stochastic process~~^{PD} where ~~for~~^{PD} any set of cells c_1, \dots, c_n ~~where for each $c_i \in \mathbb{R}^{2PD}$~~ , 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; ~~and~~^{PD} we used the *Matérn family of*^{PD} covariance structures^{PD}, ~~as one where~~^{PD} the correlation strength weakens the further the distance apart ~~(i.e. the correlation between $S(x)$ and $S(x')$ decreases as the distance $u = ||x - x'||$ increases)~~^{PD}. The Matérn covariance structure models the spatial autocorrelation observed with animal distributions (Tobler, 1970; F. Dormann et al., 2007)^{PD} and ~~The Matérn correlation~~^{PD} is a two-parameter family where:

What have a temperature covariate? Could just use time^{JJ} Was intended as some biological meaning - species thermal tolerances load onto the temperature effect^{PD}

Not clear how habitat/GRF affect local abundances, only have $B_{y,d}$ ^{JJ} Have included cell reference, c to make spatial link explicit^{PD}

Introduce the gamma function, and why this covariance structure? Why correlate values in the random field?^{JM} to allow populations to have different aggregation densities: have tried to clarify^{PD}

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

$K_{\kappa}(\cdot)$ 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.

In the simulation model, the habitat for each of the populations was generated through 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.

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

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 habitats, 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 was assigned a thermal tolerance with mean, μ_p and variance,

What does it mean concisely? Areas are assigned?^{JM}
Yes, the areas are pre-defined - I have amended to reflect and tried to clarify.^{PD}

170 σ_p^2 ^{PD} so that each cell and population temperature suitability is defined that:

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

171 Where $Tol_{c,p}$ is the tolerance of population p in cell c , T_c is the temperature
 172 in the cell and μ_p ^{PD} and σ_p^2 ^{PD} the mean and standard deviation of the popu-
 173 lation temperature tolerance.

174

175 The final process resulted in independent populations structure and move-
 176 ment patterns, with population movement occurring on a weekly basis. This
 177 process approximated the demographic shifts in fish populations throughout a
 178 year while maintaining seasonal patterns for spawning.^{PD}

179 2.4. Fleet dynamics

180 The fleet dynamics can be broadly categorised into three components; fleet
 181 targeting - which determines the fleet catch efficiency and preference towards
 182 a particular species; trip-level decisions, which determine the initial location
 183 to be fished at the beginning of a trip; and within-trip decisions, determining
 184 movement from one fishing spot to another within a trip.

185 2.4.1. Fleet targeting

186 Each fleet of n vessels is characterised by both a general efficiency, Q , and
 187 a population specific efficiency, Q_p . Thus, the product of these parameters
 188 affects the overall catch rates for the fleet and the preferential targeting of one
 189 population over another. This, in combination with the parameter choice for the
 190 step-function (as well as some randomness from the exploratory fishing process)
 191 determines the preference of fishing locations for the fleet. All species prices are
 192 kept the same, across fleets, though can be made to vary seasonally.

193 2.4.2. Trip-level decisions

194 Several studies (e.g. Hutton et al., 2004; Tidd et al., 2012; Girardin et al.,
 195 2015) have confirmed past activity and past catch rates are strong predictors of

196 fishing location choice. For this reason, the fleet dynamics sub-model includes
 197 a learning component, where a vessel’s initial fishing location in a trip is based
 198 on selecting from previously successful fishing locations. This is achieved by
 199 sorting all previous fishing events in the previous trip as well as the previous
 200 time periods in past years, and choosing randomly from the top x % of fishing
 201 events in value. Simulation testing indicated that this learning increased the
 202 mean value of catches for the vessels, over just relying on the correlated random
 203 walk function.

204 2.4.3. *Within-trip decisions*

205 Fishing locations within a trip are determined by a modified random walk
 206 process. A random walk type was chosen as it is the simplest assumption com-
 207 monly used in ecology to describe animal movement which searching for ho-
 208 mogeneously distributed prey about which there is uncertain knowledge. In a
 209 random walk, movement is a stochastic process through a series of steps that
 210 can either be equal in length or take some other functional form. The direction
 211 of the random walk can be correlated, a characteristic known as ‘persistence’,
 212 providing some overall location of directional movement (Codling et al., 2008)
 213 or uncorrelated.

214
 215 A *lévy walk* is a particular form of random walk characterised by a heavy-
 216 tailed distribution of step-length and has received a lot of attention in ecological
 217 theory in recent years as having shown to have very similar characteristics as
 218 those observed by animals in nature, and being a near optimum searching strat-
 219 egy for predators pursuing patchily distributed prey (Bartumeus et al., 2005;
 220 Sims et al., 2008). Bertrand et al. (2007) showed that Peruvian anchovy fish-
 221 ermen have a stochastic search pattern similar to that observed with a lévy
 222 walk. However, it remains a subject of debate, with the contention that search
 223 patterns may be more simply characterised as random walks (Sakiyama and
 224 Gunji, 2013) with specific patterns related to the characteristics of the prey field
 225 (Sims et al., 2012).

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 relating recent fishing success, measured as the summed value of fish caught,

$$Rev = \sum_{s=1}^{\infty} C_s \cdot Pr_s$$

where C_s is catch of a species, and Pr_s price of a species, to step distance. 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.

The step function takes the form:

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

So that, a step from (x1,y1) to (x2, y2) is defined by:

$$\begin{aligned} (x2, y2) = & x1 + StepL \cdot \cos\left(\frac{\pi \cdot Br}{180}\right), \\ & y1 + StepL \cdot \sin\left(\frac{\pi \cdot Br}{180}\right) \end{aligned}$$

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

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

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

238 2.4.4. *Local population depletion*

239 Where several fishing vessels are exploiting the same fish population compe-
240 tition is known to play an important role in local distribution of fishing effort
241 (Gillis and Peterman, 1998). If several vessels are fishing on the same patch of
242 fish, local depletion and interference will affect fishing location choice of the fleet
243 as a whole (Rijnsdorp, 2000; Poos and Rijnsdorp, 2007). In order to account for
244 this behaviour, the fishing sub-model operates spatially on a daily time-step so
245 that for future days the biomass available to the fishery is reduced in the areas
246 fished. The cumulative effect is to make heavily fished areas less attractive as
247 future fishing opportunities.

248 2.5. *Fisheries independent survey*

249 A fisheries-independent survey is simulated where fishing on a regular grid
250 begins each year at the same time for a given number of stations (a fixed sta-
251 tion survey design). Catches of the populations present are recorded but not
252 removed from the population. This provides a fishery independent snapshot of
253 the populations at a regular spatial distribution each year, similar to scientific
254 surveys undertaken by fisheries research agencies.

255 3. **Calculation**

256 3.1. *Population parameterisation*

257 We parameterised the simulation model for four populations with differing
258 habitat preference and temperature tolerances (Figures S1, S3, S4, S5, S6, S7),
259 population demographic and recruitment functions. In addition, each of the
260 populations has two defined spawning areas which result in the populations
261 moving towards these areas in given weeks (Figure S2) and population-specific
262 movement rates (Table 2). The realised movement of the populations for a num-
263 ber of weeks is shown in Figure S9 while the realised daily fishing mortality are
264 shown in Figure S10.

265

266 3.2. Fleet parameterisation

267 The fleets were parameterised to reflect five different characteristics based
268 on targeting preference and exploitation dynamics (Table 3). This ensures that
269 different fleets have different spatial dynamics, preferentially targeted different
270 fish populations. The stochasticity in the random walk process ensures that dif-
271 ferent vessels within a fleet have slightly different spatial distributions based on
272 individual experience, while the step function was parameterised dynamically so
273 that vessels take smaller steps where the fishing location yields in a top quartile
274 of the value available in that year (as defined per fleet in Table 3).

275
276 Each fleet was set so that, after the first year, fishing locations were chosen
277 based on experience built up in the same month from previous years and from
278 past trip fishing success. 'Success' in this context was defined as the locations
279 where the top 75 % of revenue from was found in previous trips.

280 An example of the realised fleet movements for a single vessel during a single
281 trip are given in Figure S11, while Figure S12 shows multiple trips for a single
282 vessel, S13 the vessel movements for some trips overlaid on the value field, S14
283 shows fishing locations for an entire fleet of 20 vessels for a single trip, while
284 S15 shows an example of the step function realisation and turning angles from
285 the correlated random walk.

286 3.3. Survey settings

287 The survey simulation was set up with follow a fixed gridded station design
288 with 100 stations fished each year, starting on day 92 with same catchability
289 parameters for all populations ($Q = 1$).

290 3.4. Simulation settings

291 To illustrate the capabilities on *MixFishSim*, we investigate the influence
292 of the temporal and spatial resolution of different data sources on the reduc-
293 tion in catches of a population given spatial closures. To do so, we first set up
294 with simulation to run for 10 years based on a 100 X 100 square grid, with five

295 fleets of 20 vessels each and four fish populations. Fishing takes place four times
296 a day per vessel and five days a week, while population movement is every week.

297

298 We allow the simulation to run unrestricted for 5 years, and subsequently
299 close areas for the last 5 years of the simulation based on data (either derived
300 from the commercial catches, fisheries-independent survey or the 'real popu-
301 lation' - the underlying populations assumed to be known perfectly) used at
302 different spatial and temporal scales.

303

304 The following steps are undertaken to determine closures:

- 305 1. Extract data source
- 306 2. Aggregate according to resolution
- 307 3. Interpolate across entire area at desired resolution
- 308 4. Close top 5 % of areas

309 In total 56 closure scenarios were run which represent combinations of

- 310 • **data types:** commercial logbook data, survey data and 'real population',
- 311 • **temporal resolutions:** weekly, monthly and yearly closures,
- 312 • **spatial resolutions:** 1 x 1 grid, 5 x 5 grid, 10 x 10 grid and 20 x 20 grid.

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

315 4. Results

316 The species distribution themselves

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

320

321 The finer spatial grid for the the real population (top left) and commercial
 322 data (top middle) show similar patterns, though there are unsampled gaps in
 323 the commercial data from a lack of fishing activity (particularly in the lower left
 324 part of the sampling domain). The survey data at this spatial resolution shows
 325 very sparse and uninformative information about the spatial distributions of the
 326 populations. The slightly aggregated data on a 5 x 5 grid shows similar patterns,
 327 and while losing some of the spatial detail there remains good consistency be-
 328 tween the 'real population' and the commercial data. Survey data starts to pick
 329 out some of the similar patterns as the other data sources, but lacks coverage.
 330 The spatial catch information on a 10 x 10 and 20 x 20 grid loses a signifi-
 331 cant amount of information about the spatial resolutions for all data sources,
 332 and some differences between the commercial and 'real population' data emerge.

333
 334 Figure 3 shows the consequences of different temporal aggregations of the
 335 data, with 156 weekly (top), 36 monthly (middle) and 3 yearly (bottom) catch
 336 compositions across a 20 x 20 area.

337
 338 As can be seen from the 'real population', the monthly aggregation captures
 339 the major patterns seen in the weekly data, albeit missing more subtle differ-
 340 ences. The yearly data results in a constant catch pattern due to the aggregation
 341 process (sometimes known as an aggregation bias). The commercial data on a
 342 weekly basis shows some of the same patterns as the 'real population', though
 343 the first species (in red) is less well represented and some weeks are missing
 344 catches from the area. The monthly data. The monthly data shows some con-
 345 sistency between the 'real population' and commercial data for species 2 - 4,
 346 though species 1 remains underrepresented. On an annual basis, interestingly
 347 the commercial data underrepresents the first species (in red) while the survey
 348 overrepresents species 1. This is likely due to the biases in commercial sampling,
 349 with the fisheries not targeting the areas where species 1 are present, and the
 350 biases in the survey sampling from overrepresentation of the spatial distribution.

351

352 We implemented a spatial closure using the different data sources and spatial
 353 and temporal aggregations as outlined in the protocol in Section 3.4. We used
 354 this to assess the efficacy of a closure in reducing fishing mortality on species 1,
 355 given availability of data and its use at different resolutions in order to evaluate
 356 the trade-offs in data sources. Figure 4 shows the trend in fishing mortality
 357 for each species simulated (columns) given the data sources (rows), temporal
 358 aggregations (colour lines) and spatial aggregations (linestyles), while Figure 5
 359 shows the change in fishing mortality from before the closure (average F years
 360 2 - 4) to after the closure (average F years 8 - 10).

361
 362 For the closures based on 'real population' (bottom row), the most disag-
 363 gregated data (a weekly timescale and 1 x 1 resolution) was most effective,
 364 reducing fishing mortality on species 1 (left) by $\sim 60\%$. Next was the monthly
 365 closures ($< \sim 30\%$). The least effective were the yearly closures (blue lines)
 366 at all spatial resolutions, which resulted in increased fishing mortalities (> 30
 367 $\%$ - N.B. Note though, this is consistent with the increasing trends in F, which
 368 is probably more related to the fact that Fs hadn't stabilised in the simulation
 369 from the fishing vessels "learning" the best locations - I will rerun the sims for
 370 a longer time (20 - 30 years).

371
 372 For the survey data, which can only be implemented on a yearly timescale,
 373 the closures had no effect at any data resolution. The results are identical for
 374 the different data resolutions except 20 x 20, which is why you can't see more
 375 than 2 points. This is because of the sparsity of the sampling locations.

376
 377 For the commercial data, the most effective closure scenario was based on 1
 378 x 1 data at a monthly temporal resolution. This results in $\sim 10\%$ reduction
 379 in F for species 1. This was the only closure scenario to have positive effect
 380 according to Figure 5, though looking at the trend in Figure 4 this looks more
 381 related to the continued increased in F trend, as other scenarios had an initial
 382 effect. Interestingly the monthly data scenario was more effective than weekly

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

387

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

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

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

397 **5. Discussion**

398 **6. Conclusions**

399 **Appendices**

400 **Abbreviations**

401 Detail any unusual ones used.

402 **Acknowledgements**

403 those providing help during the research..

404 **Funding**

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

Table 1: Description of variables for sub-modules

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
Population movement dynamics		
a	b	c
a	b	c
Fleet dynamics		
a	b	c
a	b	c

Table 2: Population dynamics and movement parameter setting

Parameter	Pop 1	Pop 2	Pop 3	Pop 4
Habitat quality				
Matérn ν	1/0.15	1/0.05	1/0.55	1/0.05
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	0.3	0.3	0.3	0.3
Population dynamics				
Starting Biomass	1e5	2e5	1e5	1e4
Beverton-Holt Recruit 'a'	60	100	80	2
Beverton-Holt Recruit 'b'	250	250	200	50
Beverton-Holt Recruit σ^2	0.4	0.3	0.4	0.3
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	0.2	0.2	0.1

Table 3: Fleet dynamics parameter setting

Parameter	Fleet 1	Fleet 2	Fleet 3	Fleet 4	Fleet 5
Targeting preferences					
Price Pop1	100	100	100	100	100
Price Pop2	200	200	200	200	200
Price Pop3	600	600	600	600	600
Price Pop4	1600	1600	1600	1600	1600
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	10	8	12	7
step function β_3	Q90	Q90	Q85	Q90	Q80
step function $rate$	10	20	15	25	10
Past Knowledge	T	T	T	T	T
Past Year & Month	T	T	T	T	T
Past Trip	T	T	T	T	T
Threshold	0.75	0.75	0.75	0.75	0.75

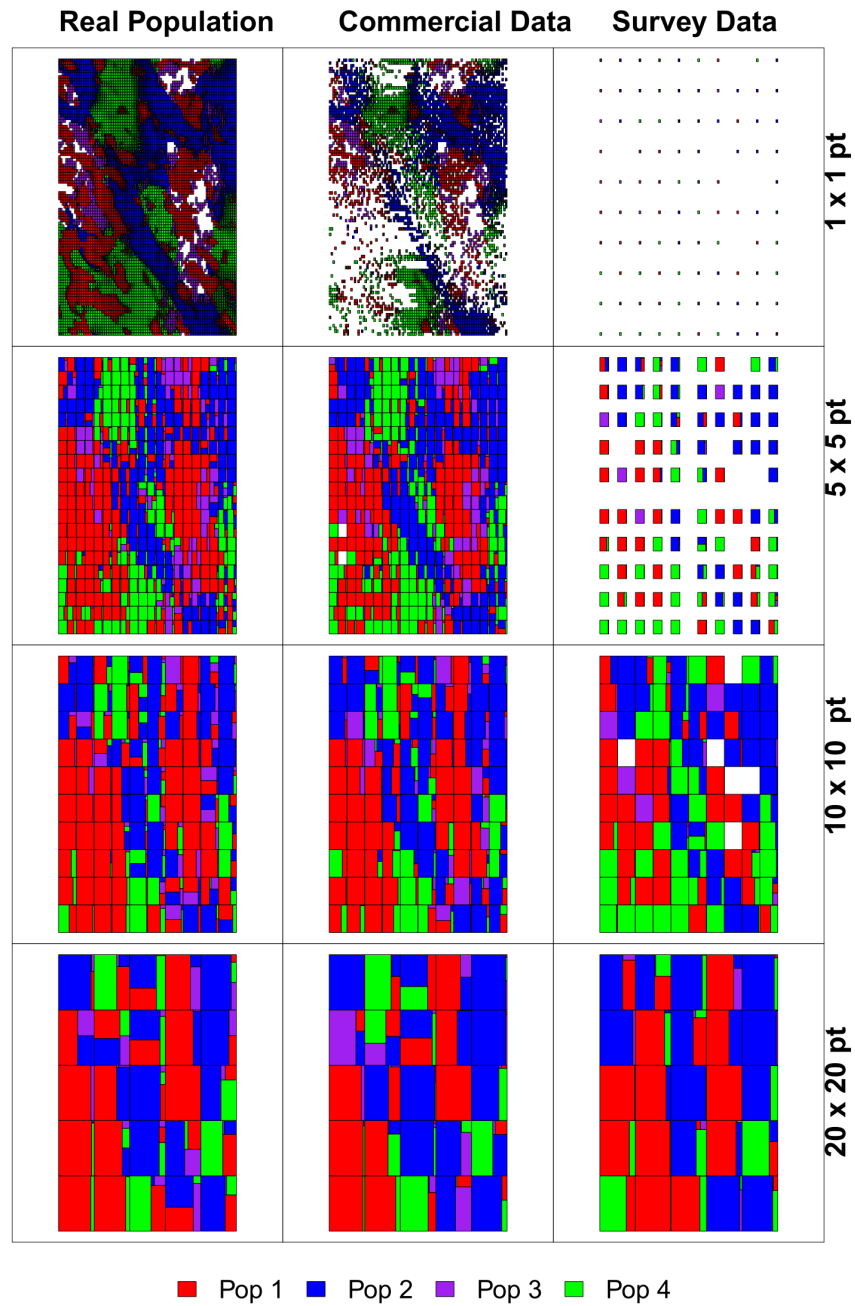


Figure 2: Data aggregation at different spatial resolutions

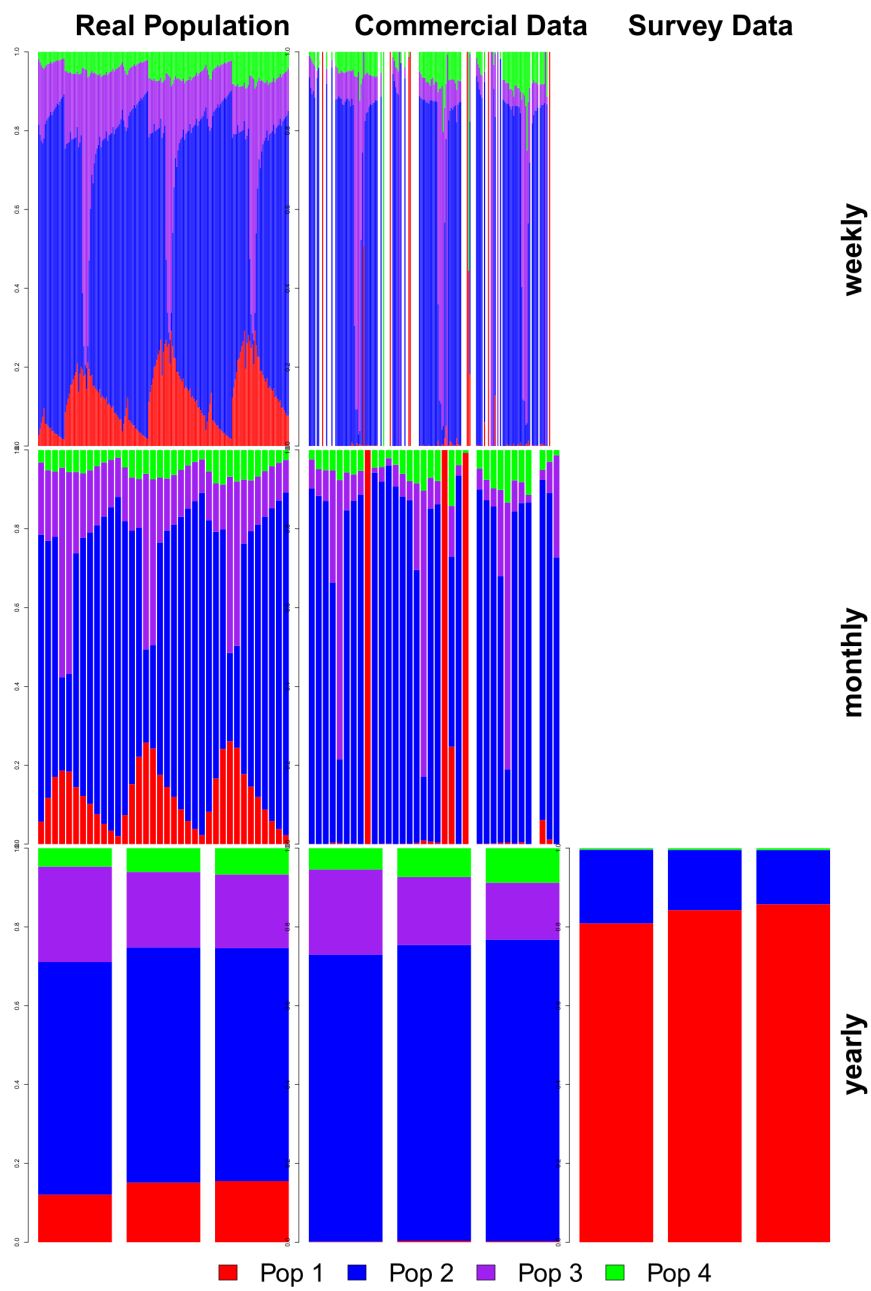


Figure 3: Data aggregation at different temporal resolutions

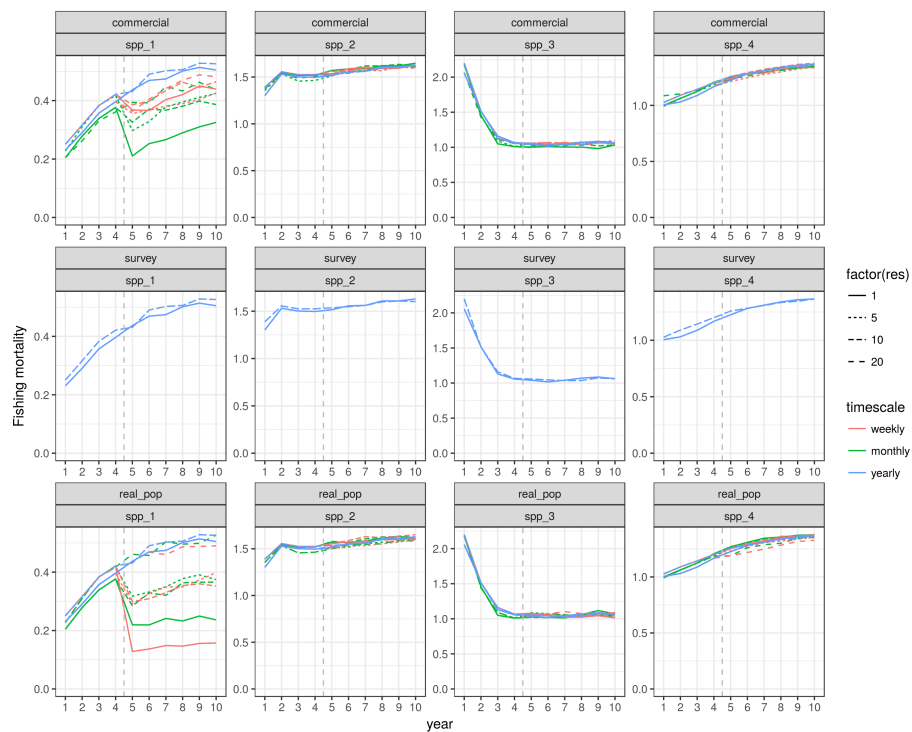


Figure 4: Comparison of closure scenarios - F trends

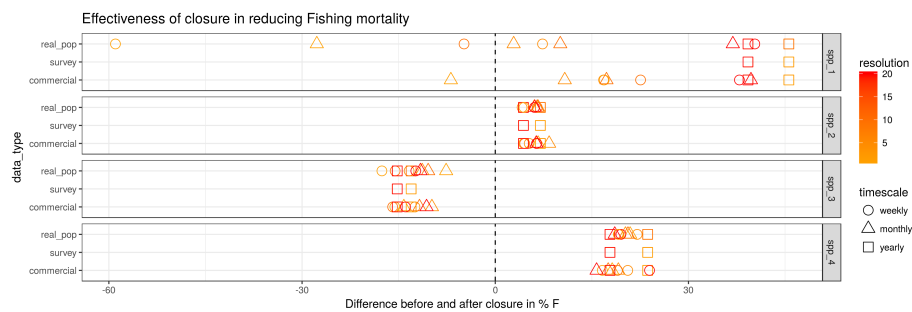


Figure 5: Comparison of closure scenarios

References

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

434 Deriso, R.B., 1980. Harvesting Strategies and Parameter Estimation for an Age-
435 Structured Model. *Canadian Journal of Fisheries and Aquatic Sciences* 37,
436 268–282. [arXiv:1410.7455v3](#).

437 Dichmont, C.M., Punt, A.E., Deng, A., Dell, Q., Venables, W., 2003. Applica-
438 tion of a weekly delay-difference model to commercial catch and effort data
439 for tiger prawns in Australia ’ s Northern Prawn Fishery. *Fisheries Research*
440 65, 335–350.

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

443 Dinmore, T.A., Duplisea, D.E., Rackham, B.D., Maxwell, D.L., Jennings, S.,
444 2003. Impact of a large-scale area closure on patterns of fishing disturbance
445 and the consequences for benthic communities. *ICES Journal of Marine Sci-*
446 *ence* 60, 371–380.

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

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

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

458 Gerritsen, H.D., Lordan, C., Minto, C., Kraak, S.B.M., 2012. Spatial patterns
459 in the retained catch composition of Irish demersal otter trawlers: High-
460 resolution fisheries data as a management tool. *Fisheries Research* 129-130,
461 127–136.

- 462 Gillis, D.M., Peterman, R.M., 1998. Implications of interference among fishing
463 vessels and the ideal free distribution to the interpretation of CPUE. Canadian
464 Journal of Fisheries and Aquatic Sciences 55, 37–46.
- 465 Girardin, R., Vermard, Y., Thébaud, O., Tidd, A., Marchal, P., 2015. Predicting
466 fisher response to competition for space and resources in a mixed demersal
467 fishery. Ocean & Coastal Management 106, 124–135.
- 468 Hilborn, R., Walters, C., 1992. Quantitative fisheries stock assessment: Choice,
469 dynamics and uncertainty. volume 2. [arXiv:1011.1669v3](#).
- 470 Holmes, S.J., Bailey, N., Campbell, N., Catarino, R., Barratt, K., Gibb, A., Fer-
471 nandes, P.G., 2011. Using fishery-dependent data to inform the development
472 and operation of a co-management initiative to reduce cod mortality and cut
473 discards. ICES Journal of Marine Science 68, 1679–1688.
- 474 Hutton, T., Mardle, S., Pascoe, S., Clark, R.a., 2004. Modelling fishing location
475 choice within mixed fisheries: English North Sea beam trawlers in 2000 and
476 2001. ICES Journal of Marine Science 61, 1443–1452.
- 477 Kennelly, S.J., Broadhurst, M.K., 2002. By-catch begone: Changes in the phi-
478 losophy of fishing technology. Fish and Fisheries 3, 340–355.
- 479 Lee, J., South, A.B., Jennings, S., 2010. Developing reliable, repeatable, and
480 accessible methods to provide high-resolution estimates of fishing-effort distri-
481 butions from vessel monitoring system (VMS) data. ICES Journal of Marine
482 Science 67, 1260–1271.
- 483 Little, A.S., Needle, C.L., Hilborn, R., Holland, D.S., Marshall, C.T., 2014.
484 Real-time spatial management approaches to reduce bycatch and discards:
485 experiences from Europe and the United States. Fish and Fisheries , n/a–
486 n/a.
- 487 Mateo, M., Pawlowski, L., Robert, M., 2016. Highly mixed fisheries: fine-scale
488 spatial patterns in retained catches of French fisheries in the Celtic Sea. ICES
489 Journal of Marine Science: Journal du Conseil , fsw129.

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

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

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

499 Rijnsdorp, A., 2000. Competitive interactions among beam trawlers exploiting
500 local patches of flatfish in the North Sea. *ICES Journal of Marine Science* 57,
501 894–902.

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

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

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

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

513 Schnute, J., 1985. A genera theory for analysis of catch and effort data. *Cana-*
514 *dian Journal of Fisheries and Aquatic Sciences* 42, 414–429.

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

- 518 Sims, D.W., Southall, E.J., Humphries, N.E., Hays, G.C., Bradshaw, C.J.A.,
519 Pitchford, J.W., James, A., Ahmed, M.Z., Brierley, A.S., Hindell, M.A., Mor-
520 ritt, D., Musyl, M.K., Righton, D., Shepard, E.L.C., Wearmouth, V.J., Wil-
521 son, R.P., Witt, M.J., Metcalfe, J.D., 2008. Scaling laws of marine predator
522 search behaviour. *Nature* 451, 1098–U5.
- 523 Tidd, A.N., Hutton, T., Kell, L.T., Blanchard, J.L., 2012. Dynamic prediction
524 of effort reallocation in mixed fisheries. *Fisheries Research* 125-126, 243–253.
- 525 Tobler, W.R., 1970. A Computer Movie Simulating Urban Growth in the Detroit
526 Region. *Economic Geography* 46, 234. [arXiv:1011.1669v3](#).
- 527 Ulrich, C., Reeves, S.a., Vermard, Y., Holmes, S.J., Vanhee, W., 2011. Rec-
528 onciling single-species TACs in the North Sea demersal fisheries using the
529 Fcube mixed-fisheries advice framework. *ICES Journal of Marine Science* 68,
530 1535–1547.