

MixFishSim: highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

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Abstract

Fishing exploits 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.

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-difference population dynamics, ii) population movement using Gaussian Ran-

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dom 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.

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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, when managed by single-species quotas can end up discarding overquota catch leading to overexploitation of fish populations. Reducing discarding is

7 crucial to ensure biological and economic sustainability of fisheries and imple-
8 mentation of an ecosystem approach to fisheries. As such there is increasing
9 interest in technical solutions such as gear and spatial closures as ways of avoid-
10 ing discards.

11

12 Use of spatial management as a tool has been proposed as a method to reduce
13 discards. However, its implementation is hampered by lack of knowledge of fish
14 and fishery spatiotemporal dynamics and understanding of the scale at which
15 processes are important for management. Understanding the correct scale for
16 spatial management is crucial in order to implement measures at a resolution
17 that ensures effective management[1] while minimising economic impact. For
18 example, a scale that promotes species avoidance for vulnerable or low quota
19 species while allowing continuance of sustainable fisheries for available quota
20 species.

21

22 Ensuring measures are implemented at an appropriate scale has been a chal-
23 lenge in the past that has led to ineffectual measures with unintended conse-
24 quences such as limited impact towards the management objective or increased
25 benthic impact on previously unexploited areas (e.g. the cod closure in the
26 North Sea[2, 3]). Since then more refined spatial information has become avail-
27 able through the combination of logbook and Vessel Monitoring System (VMS)
28 data[4, 5, 6, 7] and more real-time spatial management has been possible (e.g.
29 [8]). Such information is, however, patchy and derived from an inherently bi-
30 ased sampling programme (i.e. targeted fishing). Further, fishers generally only
31 recorded landings (not catch) on a daily basis. This leads to questions about
32 the validity of inference that can be drawn from landings data assigned to VMS
33 activity pings.

34

35 In order to understand challenges that face VMS-linked landings to draw
36 inference on the underlying population structure we develop a simulation model
37 where population dynamics are highly-resolved in space and time and are known

rather than inferred from sampling or commercial catches. Population movement is driven by a random (diffusive) and directed (advective) process and we incorporate characterisation of a number of different fisheries exploiting four fish populations with different spatial and population demographics.

Using our model 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 stratified fixed-site sampling survey design commonly used for fisheries monitoring purposes, otherwise known as a fisheries-independent survey, and ii) the underlying population structures input to the simulation.

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

2. Materials and Methods

We develop a simulation model with a modular event-based approach, where modules are implemented on independent time-scales appropriate to capture the characteristic of the process modelled (Figure 1). The fishing model operated on a tow-by-tow basis, while population dynamics (fishing and natural mortality, growth) operate on a daily time-step. Population movement occurs on a weekly time-step, while recruitment occurs periodically each year for a set time period (e.g. 3 weeks) at a specified point individual to a species. The simulation framework is implemented in the statistical software package R [9]; available as an R package from the authors github (www.github.com/pdolder/MixFishSim).

67

68 Here we describe each of the model components; 1) Population dynamics, 2)
69 Recruitment dynamics, 3) Population movement, 4) fishery dynamics.

70 2.1. Population dynamics

71 The basic population level processes are simulated using a modified two-
72 stage Deriso-Schnute delay difference model [10, 11, 12] occurring at a daily
73 time-step. Here, population biomass growth and depletion for pre-recruits and
74 fish recruited to the fishery are modelled separately as a function of previous
75 recruited biomass, intrinsic population growth and recruitment:

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

76 where ρ is Brody's coefficient, shown to be approximately equal to $\exp(-K)$,
77 where K is the growth rate from a von bertalanffy logistic growth model [11].
78 Wt_{R-1} is the weight of fish prior to recruitment, while Wt_R is the recruited
79 weight. α_d represents the proportion of fish recruited during that day for the
80 year, while $R_{\tilde{y}}$ is the annual recruits.

81

82 Mortality Z can be decomposed to natural mortality, M , and fishing mor-
83 tality, F , where both M and F are instantaneous rates with M fixed and F
84 calculated by solving the Baranov catch equation [13] for F :

$$C_d = \frac{F_d}{F_d + M_d} * (1 - e^{-(F_d + M_d)}) * B$$

85 where C is the summed catch from the fishing model across all fleets and ves-
86 sels for the population during the day, and B the daily biomass for the species.
87 [link F to effort and catchability - as I think we have F as an emergent property
88 of the fleets rather than something we solve for (I could be wrong though!) -

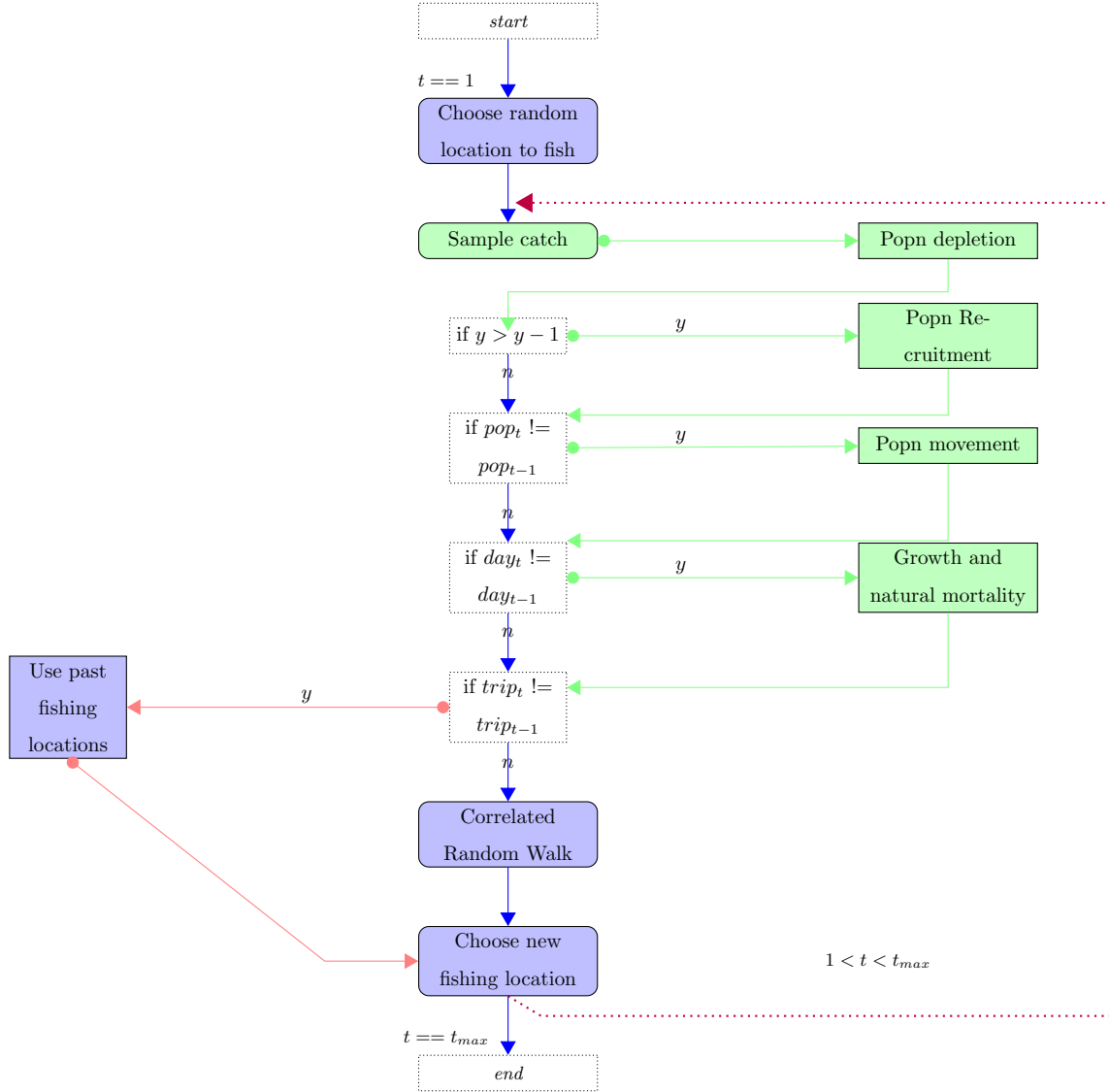


Figure 1: Overview Schematic of simulation model. The blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the timesteps at which processes occur; $t = \text{tow}$, t_{\max} is the total number of tows, $y = \text{year}$, pop_t is time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

89 catch for a vessel is a product of catchability and biomass, i.e. $C = qB$, but this
 90 catch is summed to solve for F . So its both really]

91

92 2.2. Recruitment dynamics

93 Recruitment is modelled through a function relating the mature biomass to
 94 recruits at time of recruitment. In *mixfishsim*, it can be modelled either either
 95 as a stochastic Beverton-Holt stock-recruit form ([14]):

$$\bar{R} = \frac{(\alpha * B)}{(\beta + B)}$$

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

96 Where α is the maximum recruitment rate, β the spawning stock biomass (SSB)
 97 required to produce half the maximum, B current SSB and σ^2 the variability
 98 in the recruitment due to stochastic processes.

99

100 or a stochastic Ricker form [15]

$$\bar{R} = B * e^{(\alpha - \beta * B)}$$

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

101 where α is the maximum productivity per spawner and β the density depen-
 102 dent reduction in productivity as the SSB increases.

103 2.3. Population movement

104 To simulate how fish populations might be distributed in space and time,
 105 we employed a Gaussian spatial process to model habitat suitability for each of
 106 the populations, with an advection-diffusion process to control how the popula-
 107 tions moved over time with a moving temperature covariate to capture temporal
 108 dependencies. This was intended to balance realism in population movement,
 109 capturing the main directed and random processes, and practicality of mod-
 110 elling the population rather than individual fish.

111

112 For the habitat we define a Gaussian random field process, $\{S(x) : x \in \mathbb{R}^2\}$,
 113 that is a stochastic process where any collection of locations x_1, \dots, x_n where
 114 for each $x_i \in \mathbb{R}^2$, the joint distribution of $S = \{S(x_1), \dots, S(x_n)\}$ is multivariate
 115 Gaussian. The distribution is specified by its *mean function*, $\mu(x) = E[S(x)]$
 116 and its *covariance function*, $\gamma(x, x') = Cov\{S(x), S(x')\}$ [16].

117
 118 The covariance structure affects the smoothness of the surfaces which the
 119 process generates, and we used the *Matérn* family of covariance structures, one
 120 where the correlation strength weakens the further the distance apart (i.e. the
 121 correlation between $S(x)$ and $S(x')$ decreases as the distance $u = \|x - x'\|$ in-
 122 creases). The *Matérn* correlation is a two-parameter family where:

$$123 \quad \rho(u) = \{2^{\kappa-1} \Gamma \kappa\}^{-1} (u/\phi)^\kappa K_\kappa(u/\phi)$$

124
 125 $K_\kappa(\cdot)$ is a modified Bessel function of order κ , $\phi > 0$ is a scale parameter
 126 with the dimensions of distance, and $\kappa > 0$, called the order, is a shape param-
 127 eter which determines the smoothness of the underlying process.

128
 129 The temperature field is simulated to be on a gradient from a South-Westerly
 130 to North-Easterly direction, with temperature in each cell changing gradually
 131 on a week-by-week basis so that initially high temperature areas cycle to lower
 132 temperatures and low temperature areas vice versa. Each population is as-
 133 signed a thermal tolerance with mean, μ and variance, σ^2 so that each cell and
 134 population temperature suitability is defined that:

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

135 Where $Tol_{c,p}$ is the tolerance of population p in cell c , T_c is the temperature
 136 in the cell and μ and σ^2 the mean and standard deviation of the population
 137 temperature tolerance.

138

139 In the simulation model, the habitat for each of the populations is generated
 140 through the *RFSimulate* function of the *RandomFields* R package [17], imple-
 141 menting different parameter settings to affect the patchiness of the populations.
 142 Each population is initialised at a single location, and subsequently moves ac-
 143 cording to a probabilistic distribution based on habitat suitability, temperature
 144 and distance from current cell.

$$Pr(B|A) = \frac{e^{-\lambda * d_{AB}} \cdot (Hab_B^2 \cdot Tol_{B,wk})}{\sum_{c=1}^C e^{-\lambda * d} \cdot (Hab_B^2 \cdot Tol_{B,wk})} \quad (2)$$

145 Where d_{AB} is the euclidean distance between cell A and cell B , λ is a given
 146 rate of decay, Hab_B^2 is the squared index of habitat suitability for cell B and
 147 $Tol_{B,wk}$ the temperature tolerance for the cell in week wk ; population index, p
 148 has been dropped for simplicity.

149

150 During specified weeks of the year, the habitat quality is modified for spawn-
 151 ing habitats, meaning each population has a concentrated area where spawning
 152 takes place and the population moves towards this in the weeks prior to spawn-
 153 ing.

154

155 2.4. Fleet dynamics

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

161 2.4.1. Fleet targeting

162 Each fleet of n vessels is characterised by both a general efficiency, Q , and
 163 a population specific efficiency, Q_p . Thus, the product of these parameters
 164 affects the overall catch rates for the fleet and the preferential targeting of one

165 population over another. This, in combination with the parameter choice for the
 166 step-function (as well as some randomness from the exploratory fishing process)
 167 determines the preference of fishing locations for the fleet. All species prices are
 168 kept the same, across fleets, though can be made to vary seasonally.

169 2.4.2. *Trip-level decisions*

170 Several studies (e.g.[18, 19, 20]) have confirmed past activity and past catch
 171 rates are strong predictors of fishing location choice. For this reason, the fleet
 172 dynamics sub-model includes a learning component, where a vessel’s initial fish-
 173 ing location in a trip is based on selecting from previously successful fishing
 174 locations. This is achieved by sorting all previous fishing events in the previous
 175 trip as well as the previous time periods in past years, and choosing randomly
 176 from the top x % of fishing events in value. Simulation testing indicated that
 177 this learning increased the mean value of catches for the vessels, over just relying
 178 on the correlated random walk function.

179 2.4.3. *Within-trip decisions*

180 Fishing locations within a trip are determined by a modified random walk
 181 process. A random walk type was chosen as it is the simplest assumption com-
 182 monly used in ecology to describe animal movement which searching for ho-
 183 mogeneously distributed prey about which there is uncertain knowledge. In a
 184 random walk, movement is a stochastic process through a series of steps that
 185 can either be equal in length or take some other functional form. The direction
 186 of the random walk can be correlated, a characteristic known as ‘persistence’,
 187 providing some overall location of directional movement [21] or uncorrelated.

188
 189 A *lévy walk* is a particular form of random walk characterised by a heavy-
 190 tailed distribution of step-length and has received a lot of attention in ecological
 191 theory in recent years as having shown to have very similar characteristics as
 192 those observed by animals in nature, and being a near optimum searching strat-
 193 egy for predators pursuing patchily distributed prey [22, 23]. [24] showed that

194 Peruvian anchovy fishermen have a stochastic search pattern similar to that
 195 observed with a lévy walk. However, it remains a subject of debate, with the
 196 contention that search patterns may be more simply characterised as random
 197 walks [25] with specific patterns related to the characteristics of the prey field
 198 [26].

199

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,

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

200 where C_s is catch of a species, and Pr_s price of a species, to step distance. Here,
 201 when fishing is successful vessels remain in a similar location and continue to
 202 exploit the local fishing grounds. When unsuccessful, they move some distance
 203 away from the current fishing location. The movement distance retains some
 204 degree of stochasticity, which can be controlled separately.

205 The step function takes the form:

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

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

$$\begin{aligned} (x2, y2) &= x1 + StepL \cdot \cos(\frac{\pi \cdot Br}{180}), \\ & y1 + StepL \cdot \sin(\frac{\pi \cdot Br}{180}) \\ \text{with } Br_{t-1} &< 180, Br_t = 180 + \sim vm[(0, 360), k] \\ Br_{t-1} &> 180, Br_t = 180 - \sim vm[(0, 360), k] \end{aligned}$$

207 with k the concentration parameter from the von mises distribution which
 208 we correlate with the revenue so that $k = (Rev + 1/RefRev) * max_k$, where

209 max_k is the maximum concentration value, k , and RefRev is parameterised as
210 for β_3 in the step length function.

211 2.4.4. Local population depletion

212 Where several fishing vessels are exploiting the same fish population compe-
213 tition is known to play an important role in local distribution of fishing effort
214 [27]. If several vessels are fishing on the same patch of fish, local depletion and
215 interference will affect fishing location choice of the fleet as a whole [28, 29]. In
216 order to account for this behaviour, the fishing sub-model operates spatially on
217 a daily time-step so that for future days the biomass available to the fishery
218 is reduced in the areas fished. The cumulative effect is to make heavily fished
219 areas less attractive as future fishing opportunities.

220 2.5. Fisheries independent survey

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

227 3. Calculation

228 3.1. Population parameterisation

229 We parameterised the simulation model for four populations with differing
230 habitat preference and temperature tolerances (Figures S1, S3, S4, S5, S6, S7),
231 population demographic and recruitment functions. In addition, each of the
232 populations has two defined spawning areas which result in the populations
233 moving towards these areas in given weeks (Figure S2) and population-specific
234 movement rates (Table 1). The realised movement of the populations for a num-
235 ber of weeks is shown in Figure S9 while the realised daily fishing mortality are

236 shown in Figure S10.

237

238 3.2. Fleet parameterisation

239 The fleets were parameterised to reflect five different characteristics based
240 on targeting preference and exploitation dynamics (Table 2). This ensures that
241 different fleets have different spatial dynamics, preferentially targeted different
242 fish populations. The stochasticity in the random walk process ensures that dif-
243 ferent vessels within a fleet have slightly different spatial distributions based on
244 individual experience, while the step function was parameterised dynamically so
245 that vessels take smaller steps where the fishing location yields in a top quartile
246 of the value available in that year (as defined per fleet in Table 2).

247

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

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

258 3.3. Survey settings

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

262 3.4. Simulation settings

263 To illustrate the capabilities on *MixFishSim*, we investigate the influence
264 of the temporal and spatial resolution of different data sources on the reduc-

tion in catches of a population given spatial closures. To do so, we first set up with simulation to run for 10 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 5 years, and subsequently close areas for the last 5 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 top 5 % of areas

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.

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

4. Results

The species distribution themselves

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

291 over a year at different spatial resolutions.

292

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

305

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

309

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

322 biases in the survey sampling from overrepresentation of the spatial distribution.

323

324 We implemented a spatial closure using the different data sources and spatial
325 and temporal aggregations as outlined in the protocol in Section 3.4. We used
326 this to assess the efficacy of a closure in reducing fishing mortality on species 1,
327 given availability of data and its use at different resolutions in order to evaluate
328 the trade-offs in data sources. Figure 4 shows the trend in fishing mortality
329 for each species simulated (columns) given the data sources (rows), temporal
330 aggregations (colour lines) and spatial aggregations (linestyles), while Figure 5
331 shows the change in fishing mortality from before the closure (average F years
332 2 - 4) to after the closure (average F years 8 - 10).

333

334 For the closures based on 'real population' (bottom row), the most disag-
335 gregated data (a weekly timescale and 1 x 1 resolution) was most effective,
336 reducing fishing mortality on species 1 (left) by $\sim 60\%$. Next was the monthly
337 closures ($< \sim 30\%$). The least effective were the yearly closures (blue lines)
338 at all spatial resolutions, which resulted in increased fishing mortalities (> 30
339 $\%$ - N.B. Note though, this is consistent with the increasing trends in F, which
340 is probably more related to the fact that Fs hadn't stabilised in the simulation
341 from the fishing vessels "learning" the best locations - I will rerun the sims for
342 a longer time (20 - 30 years).

343

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

348

349 For the commercial data, the most effective closure scenario was based on 1
350 x 1 data at a monthly temporal resolution. This results in $\sim 10\%$ reduction
351 in F for species 1. This was the only closure scenario to have positive effect
352 according to Figure 5, though looking at the trend in Figure 4 this looks more

353 related to the continued increased in F trend, as other scenarios had an initial
354 effect. Interestingly the monthly data scenario was more effective than weekly
355 data, which I'd posit is due to the increase amount of data available from the
356 commercial sampling across a month compared to a week.i Commercial data
357 used at an annual timestep was ineffective in bringing fishing mortality down
358 for species 1.

359

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

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

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

369 5. Discussion

370 6. Conclusions

371 Appendices

372 Abbreviations

373 Detail any unusual ones used.

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Table 1: 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 2: 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

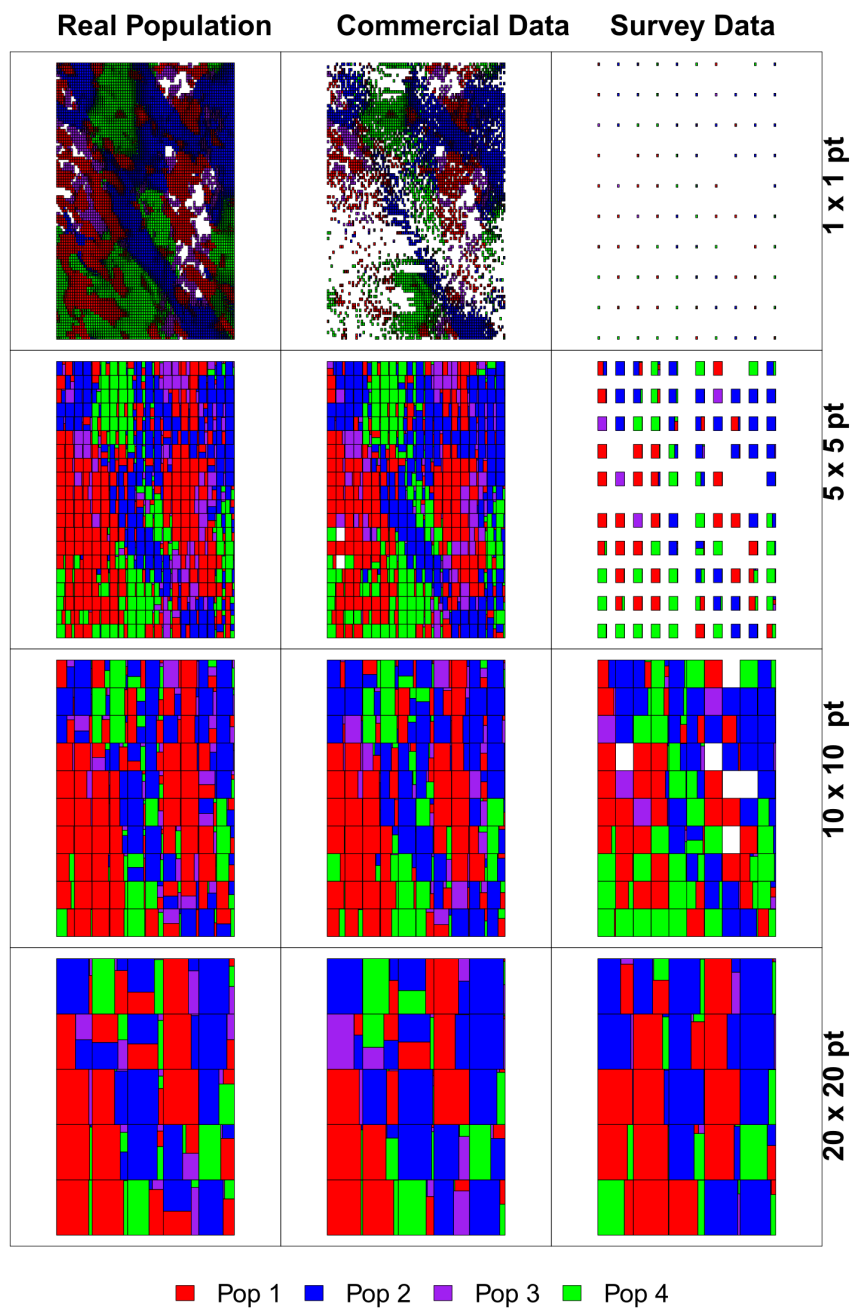


Figure 2: Data aggregation at different spatial resolutions

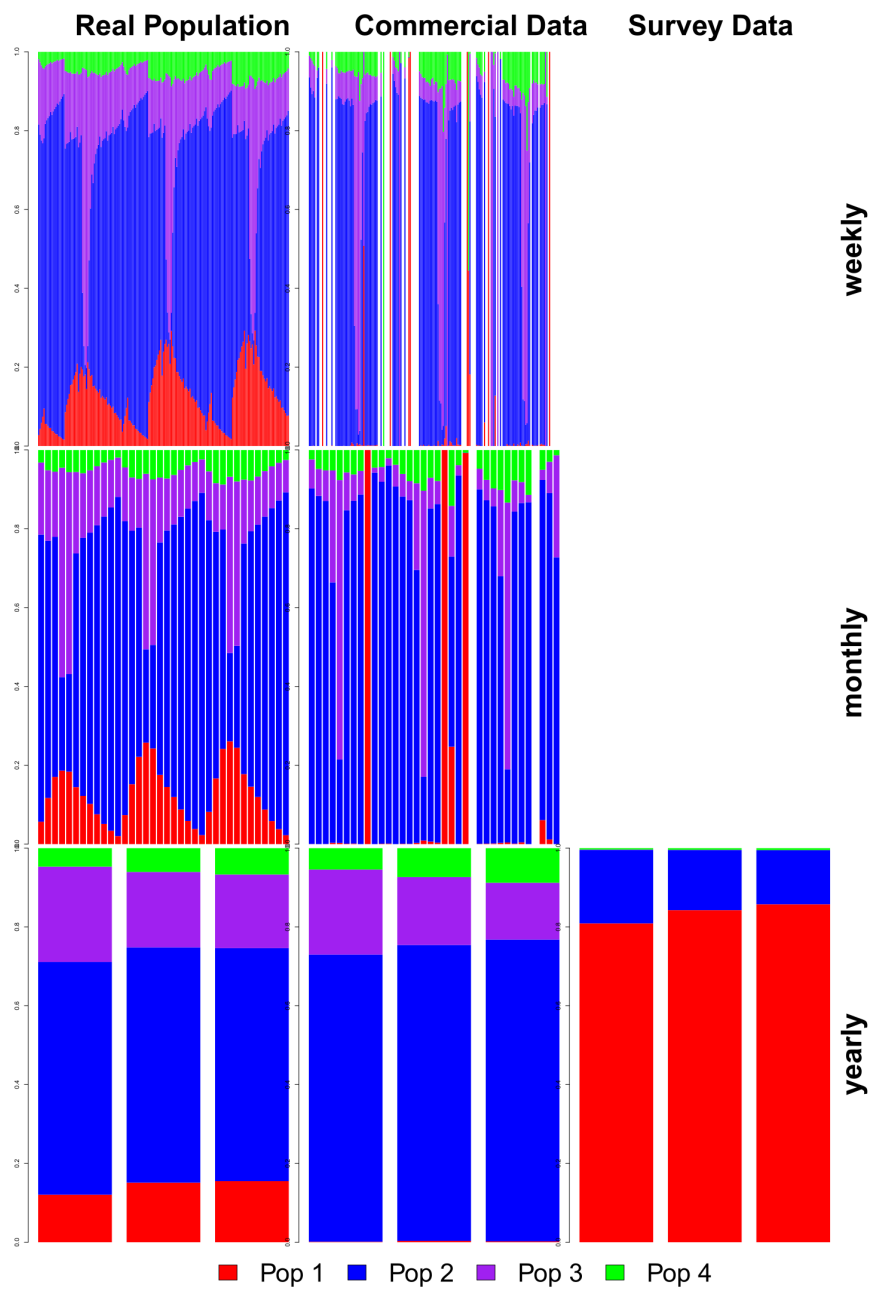


Figure 3: Data aggregation at different temporal resolutions

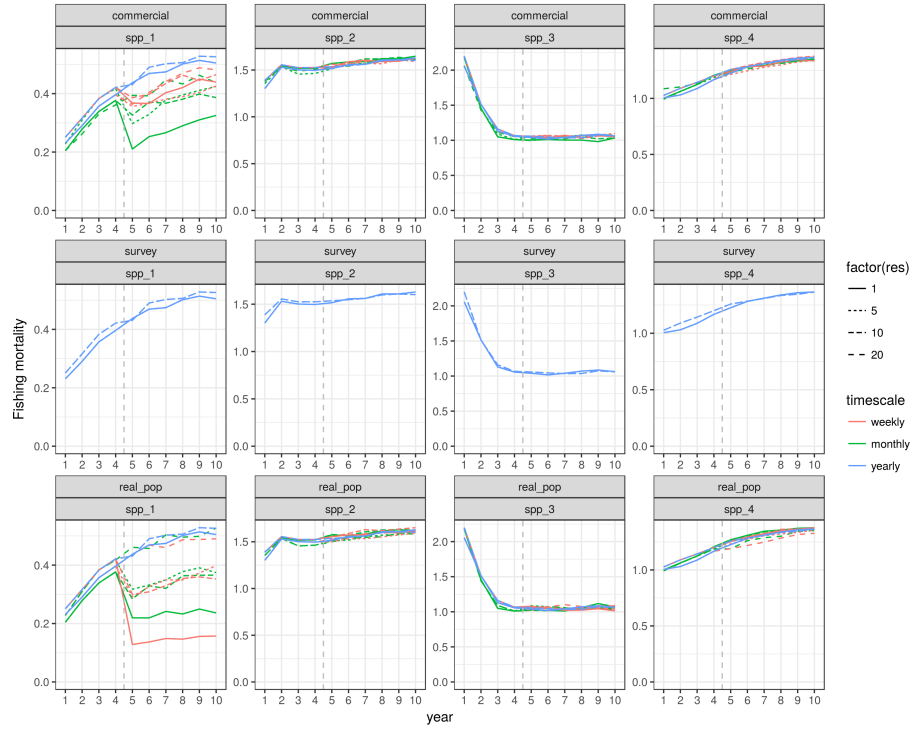


Figure 4: Comparison of closure scenarios - F trends

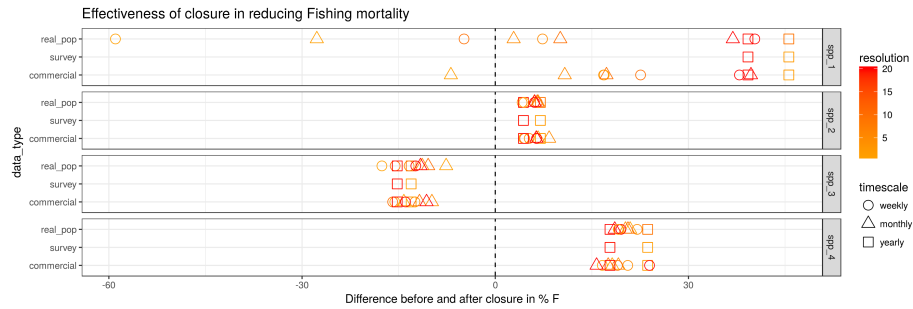


Figure 5: Comparison of closure scenarios

379 References

- 380 [1] D. C. Dunn, S. M. Maxwell, A. M. Boustany, P. N. Halpin, Dynamic ocean
381 management increases the efficiency and efficacy of fisheries management,
382 Proceedings of the National Academy of Sciences (2016) 201513626doi:
383 10.1073/pnas.1513626113.
384 URL [http://www.pnas.org/content/early/2016/01/02/1513626113.](http://www.pnas.org/content/early/2016/01/02/1513626113.abstract)
385 abstract
- 386 [2] A. D. Rijnsdorp, G. J. Piet, J. J. Poos, Effort allocation of the Dutch beam
387 trawl fleet in response to a temporarily closed area in the North Sea, *Ices*
388 *Cm* 2001/N: 01 (2001) 1–17.
- 389 [3] T. A. Dinmore, D. E. Duplisea, B. D. Rackham, D. L. Maxwell, S. Jennings,
390 Impact of a large-scale area closure on patterns of fishing disturbance and
391 the consequences for benthic communities, *ICES Journal of Marine Science*
392 60 (2) (2003) 371–380. doi:10.1016/S1054-3139(03)00010-9.
- 393 [4] J. Lee, A. B. South, S. Jennings, Developing reliable, repeatable, and acces-
394 sible methods to provide high-resolution estimates of fishing-effort distribu-
395 tions from vessel monitoring system (VMS) data, *ICES Journal of Marine*
396 *Science* 67 (6) (2010) 1260–1271. doi:10.1093/icesjms/fsq010.
- 397 [5] F. Bastardie, J. R. Nielsen, C. Ulrich, J. Egekvist, H. Degel, Detailed
398 mapping of fishing effort and landings by coupling fishing logbooks with
399 satellite-recorded vessel geo-location, *Fisheries Research* 106 (1) (2010) 41–
400 53. doi:10.1016/j.fishres.2010.06.016.
401 URL <http://dx.doi.org/10.1016/j.fishres.2010.06.016>
- 402 [6] H. D. Gerritsen, C. Lordan, C. Minto, S. B. M. Kraak, Spatial patterns
403 in the retained catch composition of Irish demersal otter trawlers: High-
404 resolution fisheries data as a management tool, *Fisheries Research* 129-130
405 (2012) 127–136. doi:10.1016/j.fishres.2012.06.019.
406 URL <http://dx.doi.org/10.1016/j.fishres.2012.06.019>

- 407 [7] M. Mateo, L. Pawlowski, M. Robert, Highly mixed fisheries: fine-scale
 408 spatial patterns in retained catches of French fisheries in the Celtic
 409 Sea, *ICES Journal of Marine Science: Journal du Conseil* (2016)
 410 fsw129doi:10.1093/icesjms/fsw129.
 411 URL [http://icesjms.oxfordjournals.org/lookup/doi/10.1093/](http://icesjms.oxfordjournals.org/lookup/doi/10.1093/icesjms/fsw129)
 412 [icesjms/fsw129](http://icesjms.oxfordjournals.org/lookup/doi/10.1093/icesjms/fsw129)
- 413 [8] S. J. Holmes, N. Bailey, N. Campbell, R. Catarino, K. Barratt, A. Gibb,
 414 P. G. Fernandes, Using fishery-dependent data to inform the development
 415 and operation of a co-management initiative to reduce cod mortality and
 416 cut discards, *ICES Journal of Marine Science* 68 (8) (2011) 1679–1688.
 417 doi:10.1093/icesjms/fsr101.
 418 URL [http://icesjms.oxfordjournals.org/cgi/doi/10.1093/](http://icesjms.oxfordjournals.org/cgi/doi/10.1093/icesjms/fsr101)
 419 [icesjms/fsr101](http://icesjms.oxfordjournals.org/cgi/doi/10.1093/icesjms/fsr101)
- 420 [9] R Core Team, R Core Team (2017). R: A language and environment for
 421 statistical computing., R Foundation for Statistical Computing, Vienna,
 422 Austria. URL <http://www.R-project.org/>. (2017) R Foundation for Statis-
 423 tical Computing.
- 424 [10] R. B. Deriso, Harvesting Strategies and Parameter Estimation for an
 425 Age-Structured Model, *Canadian Journal of Fisheries and Aquatic Sci-*
 426 *ences* 37 (2) (1980) 268–282. arXiv:arXiv:1410.7455v3, doi:10.1139/
 427 f80-034.
- 428 [11] J. Schnute, A genera theory for analysis of catch and effort data, *Canadian*
 429 *Journal of Fisheries and Aquatic Sciences* 42 (1970) (1985) 414–429. doi:
 430 10.1139/f85-057.
- 431 [12] C. M. Dichmont, A. E. Punt, A. Deng, Q. Dell, W. Venables, Application
 432 of a weekly delay-difference model to commercial catch and effort data for
 433 tiger prawns in Australia ’ s Northern Prawn Fishery, *Fisheries Research*
 434 65 (2003) 335–350. doi:10.1016/j.fishres.2003.09.024.

- [13] R. Hilborn, C. Walters, Quantitative fisheries stock assessment: Choice, dynamics and uncertainty, Vol. 2, 1992. `arXiv:arXiv:1011.1669v3`, doi: 10.1007/BF00042883.
- [14] R. J. Beverton, S. J. Holt, On the Dynamics of Exploited Fish Populations (1957) 533doi:10.1007/978-94-011-2106-4.
- [15] W. E. Ricker, Stock and recruitment, Journal of the Fisheries Research Board of Canada 11 (5) (1954) 559 – 623.
- [16] P. J. Diggle, P. J. Ribeiro, Model-based Geostatistics (Springer Series in Statistics), Vol. 1, 2007.
URL <http://www.amazon.es/Model-based-Geostatistics-Springer-Series-Statistics/dp/0387329072>
- [17] M. Schlater, A. Malinowski, P. J. Menck, Analysis, Simulation and Prediction of Multivariate Random Fields with Package RandomFields, Journal of Statistical Software 63 (2015) 1–25. `arXiv:arXiv:1501.0228`, doi:<http://dx.doi.org/10.18637/jss.v063.i08>.
- [18] T. Hutton, S. Mardle, S. Pascoe, R. a. Clark, Modelling fishing location choice within mixed fisheries: English North Sea beam trawlers in 2000 and 2001, ICES Journal of Marine Science 61 (8) (2004) 1443–1452. doi: 10.1016/j.icesjms.2004.08.016.
- [19] A. N. Tidd, T. Hutton, L. T. Kell, J. L. Blanchard, Dynamic prediction of effort reallocation in mixed fisheries, Fisheries Research 125-126 (2012) 243–253. doi:10.1016/j.fishres.2012.03.004.
URL <http://dx.doi.org/10.1016/j.fishres.2012.03.004>
- [20] R. Girardin, Y. Vermard, O. Thébaud, A. Tidd, P. Marchal, Predicting fisher response to competition for space and resources in a mixed demersal fishery, Ocean & Coastal Management 106 (2015) 124–135. doi:10.1016/j.ocecoaman.2015.01.017.

- 462 URL [http://linkinghub.elsevier.com/retrieve/pii/](http://linkinghub.elsevier.com/retrieve/pii/S0964569115000265)
463 S0964569115000265
- 464 [21] E. A. Codling, M. J. Plank, S. Benhamou, J. R. S. Interface, Random walk
465 models in biology., *Journal of the Royal Society, Interface / the Royal*
466 *Society* 5 (25) (2008) 813–34. doi:10.1098/rsif.2008.0014.
467 URL [http://www.pubmedcentral.nih.gov/articlerender.fcgi?](http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2504494&tool=pmcentrez&rendertype=abstract)
468 [artid=2504494&tool=pmcentrez&rendertype=abstract](http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=2504494&tool=pmcentrez&rendertype=abstract)
- 469 [22] F. Bartumeus, M. G. E. Da Luz, G. M. Viswanatham, J. Catalan, Ani-
470 mal Search Strategies: A Quantitative Random Walk Analysis, *Ecological*
471 *Society of America* 86 (11) (2005) 3078–3087. doi:10.1890/04-1806.
- 472 [23] D. W. Sims, E. J. Southall, N. E. Humphries, G. C. Hays, C. J. A. Brad-
473 shaw, J. W. Pitchford, A. James, M. Z. Ahmed, A. S. Brierley, M. A.
474 Hindell, D. Morritt, M. K. Musyl, D. Righton, E. L. C. Shepard, V. J.
475 Wearmouth, R. P. Wilson, M. J. Witt, J. D. Metcalfe, Scaling laws of
476 marine predator search behaviour, *Nature* 451 (7182) (2008) 1098–U5.
477 doi:10.1038/nature06518.
- 478 [24] S. Bertrand, A. Bertrand, R. Guevara-Carrasco, F. Gerlotto, Scale-
479 invariant movements of fishermen: The same foraging strategy as nat-
480 ural predators, *Ecological Applications* 17 (2) (2007) 331–337. doi:
481 10.1890/06-0303.
482 URL <http://www.ncbi.nlm.nih.gov/pubmed/17489242>
- 483 [25] T. Sakiyama, Y.-P. Gunji, Emergence of an optimal search strategy from a
484 simple random walk., *Journal of the Royal Society, Interface* 10 (86) (2013)
485 20130486. doi:10.1098/rsif.2013.0486.
486 URL <http://www.ncbi.nlm.nih.gov/pubmed/23804445>
- 487 [26] D. W. Sims, N. E. Humphries, R. W. Bradford, B. D. Bruce, Lévy flight
488 and Brownian search patterns of a free-ranging predator reflect different
489 prey field characteristics, *Journal of Animal Ecology* 81 (2) (2012) 432–
490 442. doi:10.1111/j.1365-2656.2011.01914.x.

- 491 [27] D. M. Gillis, R. M. Peterman, Implications of interference among fish-
492 ing vessels and the ideal free distribution to the interpretation of CPUE,
493 Canadian Journal of Fisheries and Aquatic Sciences 55 (1) (1998) 37–46.
494 doi:10.1139/f97-206.
- 495 [28] A. Rijnsdorp, Competitive interactions among beam trawlers exploiting
496 local patches of flatfish in the North Sea, ICES Journal of Marine Science
497 57 (4) (2000) 894–902. doi:10.1006/jmsc.2000.0576.
498 URL [http://icesjms.oxfordjournals.org/cgi/doi/10.1006/jmsc.](http://icesjms.oxfordjournals.org/cgi/doi/10.1006/jmsc.2000.0576)
499 2000.0576
- 500 [29] J.-J. Poos, A. D. Rijnsdorp, An "experiment" on effort allocation of fish-
501 ing vessels: the role of interference competition and area specialization,
502 Canadian Journal of Fisheries and Aquatic Sciences 64 (2) (2007) 304–313.
503 doi:10.1139/f06-177.