

# *MixFishSim*: highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

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## Abstract

[Guidance: A concise and factual abstract is required. The abstract should state briefly the purpose of the research, the principal results and major conclusions. An abstract is often presented separately from the article, so it must be able to stand alone. For this reason, References should be avoided, but if essential, then cite the author(s) and year(s). Also, non-standard or uncommon abbreviations should be avoided, but if essential they must be defined at their first mention in the abstract itself. Graphical abstract: Although a graphical abstract is optional, its use is encouraged as it draws more attention to the online article. The graphical abstract should summarize the contents of the article in a concise, pictorial form designed to capture the attention of a wide readership. Graphical abstracts should be submitted as a separate file in the online submission system. Image size: Please provide an image with a minimum of 531 X 1328 pixels (h X w) or proportionally more. The image should be readable at a size of 5 x 13 cm using a regular screen resolution of 96 dpi. Preferred file types: TIFF, EPS, PDF or MS Office files.]

Fishing exploits spatially and temporally heterogeneous fish populations, using species-unselective gear that can result in unintended, unwanted catch of

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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 Random Fields to simulate patchy, heterogeneously 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

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## 1. Introduction

[Guidance:: State the objectives of the work and provide an adequate background, avoiding a detailed literature survey or a summary of the results.]

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 crucial to ensure biological and economic sustainability of fisheries and implementation of an ecosystem approach to fisheries. As such there is increasing interest in technical solutions such as gear and spatial closures as ways of avoiding discards.

Use of spatial management as a tool has been proposed as a method to reduce discards. However, 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 management is crucial in order to implement measures at a resolution that ensures effective management[1] while minimising economic impact. For example, a scale that promotes species avoidance for vulnerable or low quota

22 species while allowing continuance of sustainable fisheries for available quota  
23 species.

24

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

37

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

45

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

52

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

59

## 60 2. Materials and Methods

61 [Guidance: Provide sufficient details to allow the work to be reproduced  
62 by an independent researcher. Methods that are already published should be  
63 summarized, and indicated by a reference. If quoting directly from a previously  
64 published method, use quotation marks and also cite the source. Any modifi-  
65 cations to existing methods should also be described.]

66

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

76

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

### 79 2.1. Population dynamics

80 The basic population level processes are simulated using a modified two-  
81 stage Deriso-Schnute delay difference model [10, 11, 12] occurring at a daily

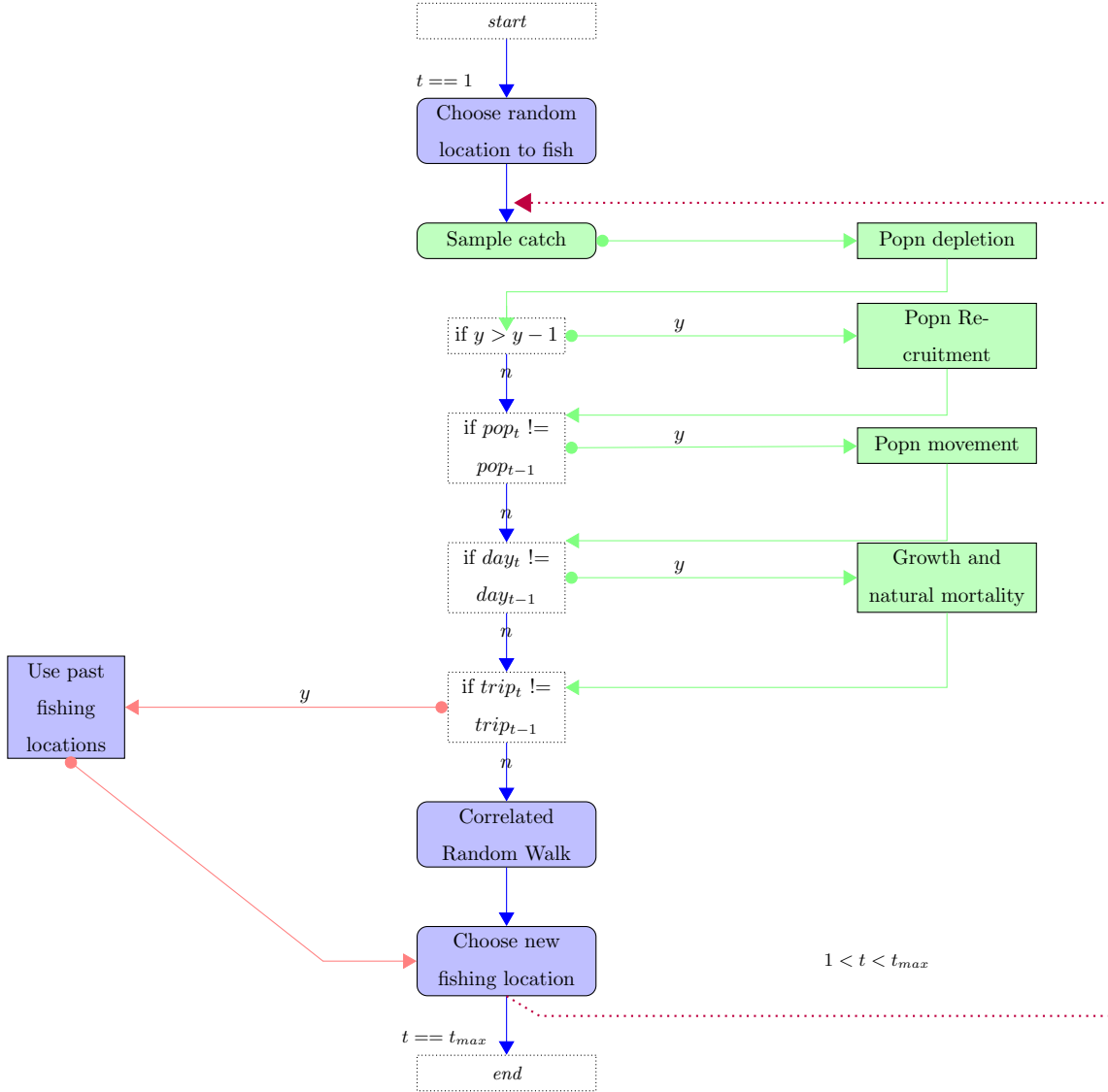


Figure 1: Overview Schematic of simulation model. The blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the timesteps at which processes occur;  $t = tow$ ,  $t_{max}$  is the total number of tows,  $y = year$ ,  $pop_t$  is time of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

82 time-step. Here, population biomass growth and depletion for pre-recruits and  
 83 fish recruited to the fishery are modelled separately as a function of previous

84 recruited biomass, intrinsic population growth and recruitment:

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

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

90

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

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

94 where  $C$  is the summed catch from the fishing model across all fleets and ves-  
95 sels for the population during the day, and  $B$  the daily biomass for the species.  
96 [link  $F$  to effort and catchability - as I think we have  $F$  as an emergent property  
97 of the fleets rather than something we solve for (I could be wrong though!) -  
98 catch for a vessel is a product of catchability and biomass, i.e.  $C = qB$ , but this  
99 catch is summed to solve for  $F$ . So its both really]

100

## 101 2.2. Recruitment dynamics

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

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

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

Where  $\alpha$  is the maximum recruitment rate,  $\beta$  the spawning stock biomass (SSB) required to produce half the maximum,  $B$  current SSB and  $\sigma^2$  the variability in the recruitment due to stochastic processes.

or a stochastic Ricker form [15]

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

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

where  $\alpha$  is the maximum productivity per spawner and  $\beta$  the density dependent reduction in productivity as the SSB increases.

### 2.3. Population movement

To simulate how fish populations might be distributed in space and time, we employed a Gaussian spatial process to model habitat suitability for each of the populations, with an advection-diffusion process to control how the populations moved 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.

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



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

$$132 \quad \rho(u) = \{2^{\kappa-1}\Gamma\kappa\}^{-1}(u/\phi)^{\kappa}K_{\kappa}(u/\phi)$$

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

137  
 138 The temperature field is simulated to be on a gradient from a South-Westerly  
 139 to North-Easterly direction, with temperature in each cell changing gradually  
 140 on a week-by-week basis so that initially high temperature areas cycle to lower  
 141 temperatures and low temperature areas vice versa. Each population is as-  
 142 signed a thermal tolerance with mean,  $\mu$  and variance,  $\sigma^2$  so that each cell and  
 143 population temperature suitability is defined that:

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

144 Where  $Tol_{c,p}$  is the tolerance of population  $p$  in cell  $c$ ,  $T_c$  is the temperature  
 145 in the cell and  $\mu$  and  $\sigma^2$  the mean and standard deviation of the population  
 146 temperature tolerance.

147  
 148 In the simulation model, the habitat for each of the populations is generated  
 149 through the *RFSimulate* function of the *RandomFields* R package [17], imple-  
 150 menting different parameter settings to affect the patchiness of the populations.  
 151 Each population is initialised at a single location, and subsequently moves ac-  
 152 cording to a probabilistic distribution based on habitat suitability, temperature

153 and distance from current cell.

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

154 Where  $d_{AB}$  is the euclidean distance between cell  $A$  and cell  $B$ ,  $\lambda$  is a given  
 155 rate of decay,  $Hab_B^2$  is the squared index of habitat suitability for cell  $B$  and  
 156  $Tol_{B,wk}$  the temperature tolerance for the cell in week  $wk$ ; population index,  $p$   
 157 has been dropped for simplicity.

158

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

163

#### 164 2.4. Fleet dynamics

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

##### 170 2.4.1. Fleet targeting

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

#### 178 2.4.2. Trip-level decisions

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

#### 188 2.4.3. Within-trip decisions

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

197  
198 A *lévy walk* is a particular form of random walk characterised by a heavy-  
199 tailed distribution of step-length and has received a lot of attention in ecological  
200 theory in recent years as having shown to have very similar characteristics as  
201 those observed by animals in nature, and being a near optimum searching strat-  
202 egy for predators pursuing patchily distributed prey [22, 23]. [24] showed that  
203 Peruvian anchovy fishermen have a stochastic search pattern similar to that  
204 observed with a *lévy walk*. However, it remains a subject of debate, with the  
205 contention that search patterns may be more simply characterised as random  
206 walks [25] with specific patterns related to the characteristics of the prey field  
207 [26].

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  $\beta_3$  in the step length function.

#### 220 2.4.4. *Local population depletion*

221 Where several fishing vessels are exploiting the same fish population compe-  
222 tition is known to play an important role in local distribution of fishing effort  
223 [27]. If several vessels are fishing on the same patch of fish, local depletion and  
224 interference will affect fishing location choice of the fleet as a whole [28, 29]. In  
225 order to account for this behaviour, the fishing sub-model operates spatially on  
226 a daily time-step so that for future days the biomass available to the fishery  
227 is reduced in the areas fished. The cumulative effect is to make heavily fished  
228 areas less attractive as future fishing opportunities.

#### 229 2.5. *Fisheries independent survey*

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

### 236 3. Calculation

237 [Guidance: A Theory section should extend, not repeat, the background to  
238 the article already dealt with in the Introduction and lay the foundation for fur-  
239 ther work. In contrast, a Calculation section represents a practical development  
240 from a theoretical basis.]

#### 242 3.1. *Population parameterisation*

243 We parameterised the simulation model for four populations with differing  
244 habitat preference and temperature tolerances (Figures S1, S3, S4, S5, S6, S7),  
245 population demographic and recruitment functions. In addition, each of the  
246 populations has two defined spawning areas which result in the populations  
247 moving towards these areas in given weeks (Figure S2) and population-specific

248 movement rates (Table 1). The realised movement of the populations for a num-  
249 ber of weeks is shown in Figure S9 while the realised daily fishing mortality are  
250 shown in Figure S10.

251

### 252 3.2. Fleet parameterisation

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

261

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

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

### 272 3.3. Survey settings

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

### 276 3.4. Simulation settings

277 To illustrate the capabilities on *MixFishSim*, we investigate the influence  
278 of the temporal and spatial resolution of different data sources on the reduc-  
279 tion in catches of a population given spatial closures. To do so, we first set up  
280 with simulation to run for 10 years based on a 100 X 100 square grid, with five  
281 fleets of 20 vessels each and four fish populations. Fishing takes place four times  
282 a day per vessel and five days a week, while population movement is every week.

283  
284 We allow the simulation to run unrestricted for 5 years, and subsequently  
285 close areas for the last 5 years of the simulation based on data (either derived  
286 from the commercial catches, fisheries-independent survey or the 'real popu-  
287 lation' - the underlying populations assumed to be known perfectly) used at  
288 different spatial and temporal scales.

289  
290 The following steps are undertaken to determine closures:

- 291 1. Extract data source
- 292 2. Aggregate according to resolution
- 293 3. Interpolate across entire area at desired resolution
- 294 4. Close top 5 % of areas

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

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

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

## 301 4. Results

302 The species distribution themselves

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

306  
307 The finer spatial grid for the the real population (top left) and commercial  
308 data (top middle) show similar patterns, though there are unsampled gaps in  
309 the commercial data from a lack of fishing activity (particularly in the lower left  
310 part of the sampling domain). The survey data at this spatial resolution shows  
311 very sparse and uninformative information about the spatial distributions of the  
312 populations. The slightly aggregated data on a 5 x 5 grid shows similar patterns,  
313 and while losing some of the spatial detail there remains good consistency be-  
314 tween the 'real population' and the commercial data. Survey data starts to pick  
315 out some of the similar patterns as the other data sources, but lacks coverage.  
316 The spatial catch information on a 10 x 10 and 20 x 20 grid loses a signifi-  
317 cant amount of information about the spatial resolutions for all data sources,  
318 and some differences between the commercial and 'real population' data emerge.

319  
320 Figure 3 shows the consequences of different temporal aggregations of the  
321 data, with 156 weekly (top), 36 monthly (middle) and 3 yearly (bottom) catch  
322 compositions across a 20 x 20 area.

323  
324 As can be seen from the 'real population', the monthly aggregation captures  
325 the major patterns seen in the weekly data, albeit missing more subtle differ-  
326 ences. The yearly data results in a constant catch pattern due to the aggregation  
327 process (sometimes known as an aggregation bias). The commercial data on a  
328 weekly basis shows some of the same patterns as the 'real population', though  
329 the first species (in red) is less well represented and some weeks are missing  
330 catches from the area. The monthly data. The monthly data shows some con-



331 sistency between the 'real population' and commercial data for species 2 - 4,  
 332 though species 1 remains underrepresented. On an annual basis, interestingly  
 333 the commercial data underrepresents the first species (in red) while the survey  
 334 overrepresents species 1. This is likely due to the biases in commercial sampling,  
 335 with the fisheries not targeting the areas where species 1 are present, and the  
 336 biases in the survey sampling from overrepresentation of the spatial distribution.

337  
 338 We implemented a spatial closure using the different data sources and spatial  
 339 and temporal aggregations as outlined in the protocol in Section 3.4. We used  
 340 this to assess the efficacy of a closure in reducing fishing mortality on species 1,  
 341 given availability of data and its use at different resolutions in order to evaluate  
 342 the trade-offs in data sources. Figure 4 shows the trend in fishing mortality  
 343 for each species simulated (columns) given the data sources (rows), temporal  
 344 aggregations (colour lines) and spatial aggregations (linestyles), while Figure 5  
 345 shows the change in fishing mortality from before the closure (average F years  
 346 2 - 4) to after the closure (average F years 8 - 10).

347  
 348 For the closures based on 'real population' (bottom row), the most disag-  
 349 gregated data (a weekly timescale and 1 x 1 resolution) was most effective,  
 350 reducing fishing mortality on species 1 (left) by  $\sim 60\%$ . Next was the monthly  
 351 closures ( $< \sim 30\%$ ). The least effective were the yearly closures (blue lines)  
 352 at all spatial resolutions, which resulted in increased fishing mortalities ( $> 30$   
 353  $\%$  - N.B. Note though, this is consistent with the increasing trends in F, which  
 354 is probably more related to the fact that Fs hadn't stabilised in the simulation  
 355 from the fishing vessels "learning" the best locations - I will rerun the sims for  
 356 a longer time (20 - 30 years).

357  
 358 For the survey data, which can only be implemented on a yearly timescale,  
 359 the closures had no effect at any data resolution. The results are identical for  
 360 the different data resolutions except 20 x 20, which is why you can't see more  
 361 than 2 points. This is because of the sparsity of the sampling locations.

362

363 For the commercial data, the most effective closure scenario was based on 1  
364 x 1 data at a monthly temporal resolution. This results in  $\sim 10\%$  reduction  
365 in  $F$  for species 1. This was the only closure scenario to have positive effect  
366 according to Figure 5, though looking at the trend in Figure 4 this looks more  
367 related to the continued increased in  $F$  trend, as other scenarios had an initial  
368 effect. Interestingly the monthly data scenario was more effective than weekly  
369 data, which I'd posit is due to the increase amount of data available from the  
370 commercial sampling across a month compared to a week. Commercial data  
371 used at an annual timestep was ineffective in bringing fishing mortality down  
372 for species 1.

373

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

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

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

383 [Guidance: Results should be clear and concise.]

## 384 5. Discussion

385 [Guidance: This should explore the significance of the results of the work, not  
386 repeat them. A combined Results and Discussion section is often appropriate.  
387 Avoid extensive citations and discussion of published literature.]

## 388 **6. Conclusions**

389 [Guidance: The main conclusions of the study may be presented in a short  
390 Conclusions section, which may stand alone or form a subsection of a Discussion  
391 or Results and Discussion section.]

## 392 **Appendices**

393 [Guidance: If there is more than one appendix, they should be identified  
394 as A, B, etc. Formulae and equations in appendices should be given separate  
395 numbering: Eq. (A.1), Eq. (A.2), etc.; in a subsequent appendix, Eq. (B.1)  
396 and so on. Similarly for tables and figures: Table A.1; Fig. A.1, etc.]

## 397 **Abbreviations**

398 Detail any unusual ones used.

## 399 **Acknowledgements**

400 those providing help during the research..

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403 Centre for Environment, Fisheries and Aquaculture Science seedcorn program.

Table 1: Population dynamics and movement parameter setting

Parameter	Pop 1	Pop 2	Pop 3	Pop 4
Habitat quality				
Matérn $\nu$	1/0.15	1/0.05	1/0.55	1/0.05
Matérn $\kappa$	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 $\lambda$	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 $\sigma^2$	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 $\beta_1$	1	2	1	2	3
step function $\beta_2$	10	10	8	12	7
step function $\beta_3$	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

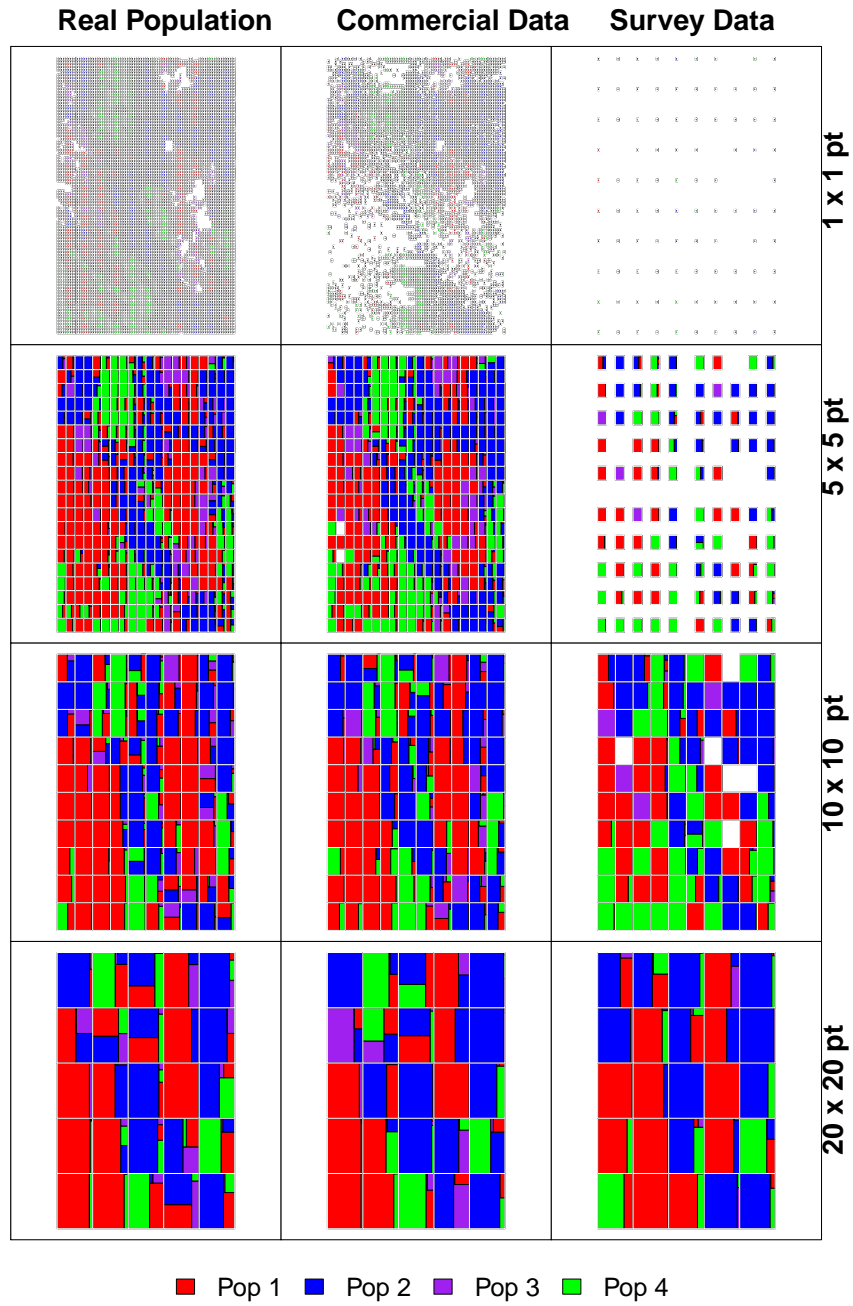


Figure 2: Data aggregation at different spatial resolutions

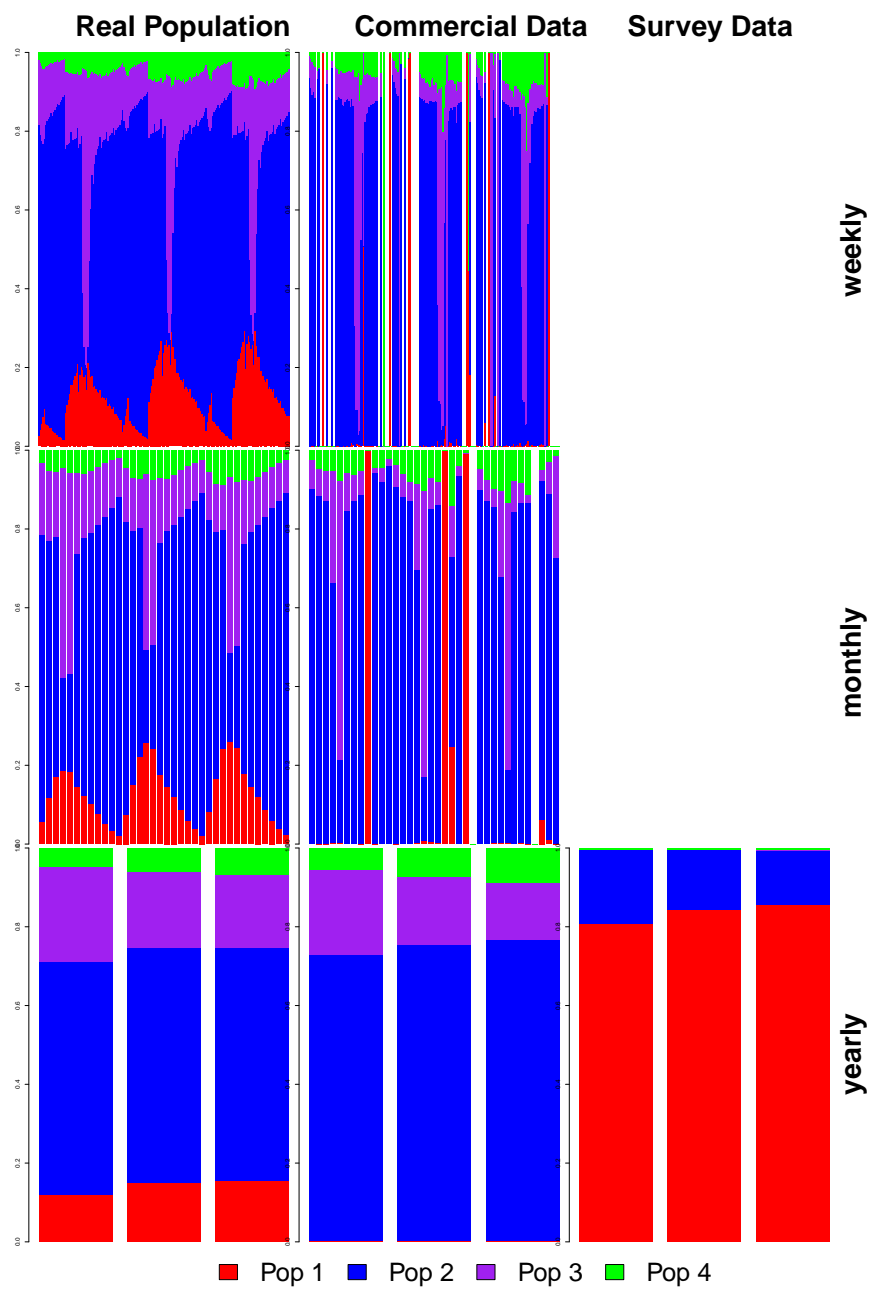


Figure 3: Data aggregation at different temporal resolutions

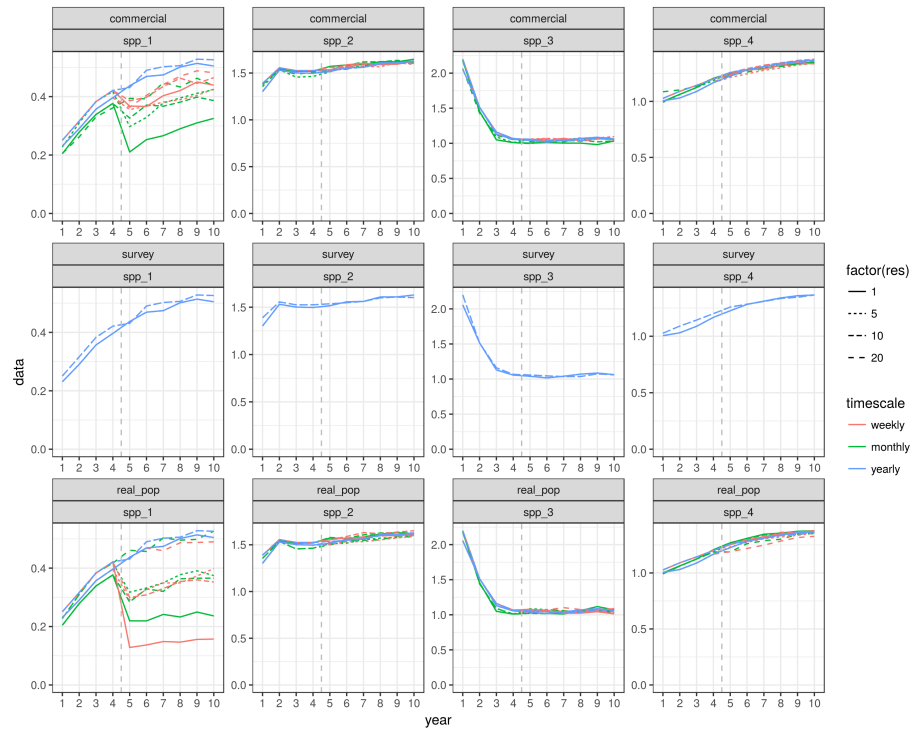


Figure 4: Comparison of closure scenarios - F trends

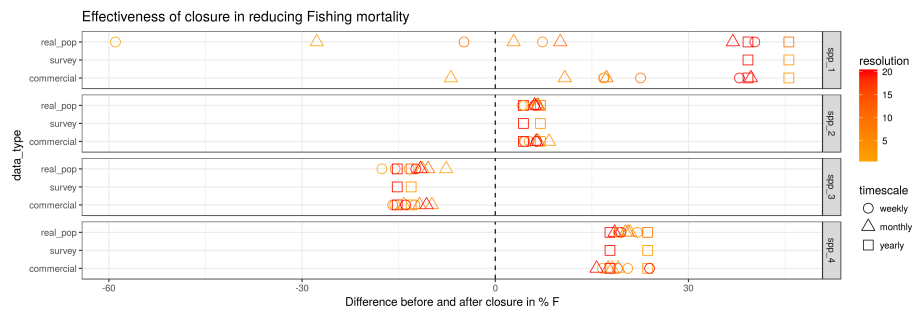


Figure 5: Comparison of closure scenarios



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