

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

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## Abstract

Most fisheries ~~Fishing~~<sup>JJ</sup> exploits<sup>JJ</sup> 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-

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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]

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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 may, ~~when managed by single species quotas can end up~~<sup>JJ</sup> discarding<sup>JJ</sup>

overquota catch when managed by single species quotas,<sup>JJ</sup> leading to overex-  
 ploitation of fish populations (Ulrich et al., 2011; Batsleer et al., 2015)<sup>JJ</sup>. 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).<sup>JJ</sup> Reducing discarding is crucial to ensure biological  
 and economic sustainability of fisheries ~~and implementation of an ecosystem~~  
~~approach to fisheries~~<sup>JJ</sup> and. As such<sup>PD</sup> 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)s<sup>JJ</sup>.

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)<sup>PD</sup>. 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<sup>JJ</sup>

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<sup>JJ</sup>

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<sup>JJ</sup>

## 64 2. Materials and Methods

65 ~~A We developed and implemented a simulation model with a~~<sup>PD</sup> modular

event-based simulation model was developed with approach, where sub-<sup>PD</sup> modules  
<sup>are</sup><sup>PD</sup> implemented on independent time-scales appropriate to capture the char-  
acteristic of the different processes~~process modelled~~<sup>PD</sup> (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.<sup>PD</sup>

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

## 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.<sup>PD</sup> Under the population dynamics  
module~~Here,~~<sup>PD</sup> population biomass growth and depletion for pre-recruits and  
fish<sup>PD</sup> recruited fish<sup>PD</sup> to the fishery<sup>PD</sup> are modelled separately as a function  
of previous recruited biomass, intrinsic population growth and recruitment:



where  $\rho$  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.  $\alpha_d$  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  $\alpha$  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 (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]<sup>CM</sup>

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

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

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

### 2.3. Population movement dynamics

To simulate ~~how~~<sup>JJ</sup> fish populations ~~might be~~<sup>JJ</sup> distributioned<sup>JJ</sup> in space and time, ~~we employed~~<sup>JJ</sup> a Gaussian spatial process ~~was employed~~<sup>JJ</sup> to model habitat suitability for each of the populations. ~~An, with an~~<sup>JJ</sup> advection-diffusion process ~~to~~<sup>JJ</sup> controlled<sup>JJ</sup> ~~how the~~<sup>JJ</sup> populations<sup>JJ</sup> movement<sup>JJ</sup> 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.~~<sup>JJ</sup>

For ~~the~~<sup>PD</sup> habitat we defined<sup>PD</sup> a Gaussian random field process,  $\{S(c) : c \in \mathbb{R}^2\}$ , ~~that is a stochastic process~~<sup>PD</sup> where ~~for~~<sup>PD</sup> 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~~<sup>PD</sup> we used the *Matérn family of*<sup>PD</sup> covariance structures<sup>PD</sup>, ~~as one where~~<sup>PD</sup> 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)~~<sup>PD</sup>. The Matérn covariance structure models the spatial autocorrelation observed with animal distributions (Tobler, 1970; F. Dormann et al., 2007)<sup>PD</sup> and ~~The Matérn correlation~~<sup>PD</sup> is a two-parameter family where:

What have a temperature covariate? Could just use time<sup>JJ</sup> Was intended as some biological meaning - species thermal tolerances load onto the temperature effect<sup>PD</sup>

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

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



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

$K_{\kappa}(\cdot)$  is a modified Bessel function of order  $\kappa$ ,  $\phi > 0$  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  $J$ ,  $\lambda$  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,  $\mu_p$  and variance,

What does it mean concisely? Areas are assigned?<sup>JM</sup>  
Yes, the areas are pre-defined - I have amended to reflect and tried to clarify.<sup>PD</sup>

170  $\sigma_p^2$ <sup>PD</sup> 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  $\mu_p$ <sup>PD</sup> and  $\sigma_p^2$ <sup>PD</sup> 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.<sup>PD</sup>

#### 179 2.4. Fleet dynamics

180 The fleet dynamics can be broadly categorised into three components; fleet  
181 targeting - which determined<sup>PD</sup> the fleet catch efficiency and preference towards  
182 a particular species; trip-level decisions, which determined<sup>PD</sup> 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 <sup>was</sup><sup>PD</sup> characterised by both a general efficiency,  $Q$ ,  
187 and a population specific efficiency,  $Q_p$ . Thus, the product of these parameters  
188 affected<sup>PD</sup> the overall catch rates for the fleet and the preferential targeting of  
189 one population over another. This, in combination with the parameter choice  
190 for the step-function <sup>defined below</sup><sup>PD</sup> (as well as some randomness from the  
191 exploratory fishing process) determined<sup>PD</sup> the preference of fishing locations for  
192 the fleet. All species prices <sup>were</sup><sup>PD</sup> kept the same, across fleets<sup>and seasons</sup>;  
193 ~~though can be made to vary seasonally~~<sup>PD</sup>.

##### 194 2.4.2. Trip-level decisions

195 Several studies (e.g. Hutton et al., 2004; Tidd et al., 2012; Girardin et al.,  
196 2015) have confirmed past activity and past catch rates are strong predictors

of fishing location choice. For this reason, the fleet dynamics sub-model included<sup>PD</sup> a learning component, where a vessel's initial fishing location in a trip ~~wai~~<sup>PD</sup>s based on selecting from previously successful fishing locations. This ~~wai~~<sup>PD</sup>s achieved by sorting all previous fishing events in the previous trip as well as the previous time periods in past years, and choosing randomly from the top 75 % of fishing events ~~as defined by the revenue gained in value~~<sup>PD</sup>. Simulation testing indicated that this learning increased the mean value of catches for the vessels, over just relying on the correlated random walk ~~function as described~~ for the 'within trip' decisions below<sup>PD</sup>.

Correlated random walk of what<sup>JJ</sup>

#### 2.4.3. Within-trip decisions

Fishing locations within a trip are determined by a modified random walk process. A random walk type was chosen as it is the simplest assumption commonly used in ecology to describe ~~optimal~~<sup>PD</sup> animal ~~movement which~~<sup>PD</sup> search ~~strategizing~~<sup>PD</sup> for ~~exploiting~~<sup>PD</sup> homogeneously distributed prey about which there is uncertain knowledge (Viswanathan et al., 1999). In a random walk, movement is a stochastic process through a series of steps. ~~These steps have a length, and a direction~~<sup>JJ</sup> that can either be equal in length or take some other functional form. The direction of the random walk can be correlated, a characteristic known as 'persistence', providing some overall ~~location of~~<sup>PD</sup> directional movement (Codling et al., 2008) ~~or uncorrelated~~<sup>PD</sup>.

A *Lévy flight*~~lévy-walk~~<sup>JJ</sup> is a particular form of random walk characterised by a heavy-tailed distribution of step-length . ~~The Lévy flight and~~<sup>JJ</sup> has received a lot of attention in ecological theory in recent years as having shown to have very similar characteristics as those observed by animals in nature, and being a near optimum searching strategy for predators pursuing patchily distributed prey (Viswanathan et al., 1999; Bartumeus et al., 2005; Sims et al., 2008). Bertrand et al. (2007) showed that Peruvian anchovy fishermen have a stochastic search pattern similar to that observed with a lévy walk. However, it remains a subject of debate (e.g. see Edwards, 2011; Reynolds, 2015)<sup>PD</sup>, with the contention that

search patterns may be more simply characterised as random walks (Sakiyama and Gunji, 2013) with specific patterns related to the characteristics of the prey field (Sims et al., 2012).

230

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<sup>JJ</sup> recent fishing success, measured as the summed value of fish caught (revenue,  $Rev$ ),

$$Rev = \sum_{p=1}^P \underline{LC}^{PD}_p \cdot Pr_p$$

where  $\underline{LC}^{PD}_p$  is landingseatch<sup>PD</sup> of a population  $p$ , and  $Pr_p$  price of a population, 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:

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

237

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

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

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

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

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

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

239

So step length increases with increasingly gross revenue?<sup>JJ</sup> No, the opposite<sup>PD</sup>

241 where  $max_k$  is the maximum concentration value,  $k$ , and RefRev is parame-  
242 terised as for  $\beta_3$  in the step length function.

#### 243 2.4.4. Local population depletion

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

#### 253 2.5. Fisheries independent survey

254 A fisheries-independent survey is simulated where fishing on a regular grid  
255 begins each year at the same time for a given number of stations (a fixed station  
256 survey design). Catches of the populations ~~at each station~~<sup>present</sup>~~present~~<sup>JJ</sup> are recorded  
257 but not removed from the population. This provides a fishery independent  
258 snapshot of the populations at a regular spatial ~~intervals~~<sup>distribution</sup>~~distribution~~<sup>JJ</sup> each  
259 year, similar to scientific surveys undertaken by fisheries research agencies.

### 260 3. Calculation

#### 261 3.1. Population parameterisation

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

269 shown in Figure S10.

270

### 271 3.2. Fleet parameterisation

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

280

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

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

### 291 3.3. Survey settings

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

### 295 3.4. Simulation settings

296 To illustrate the capabilities on *MixFishSim*, we investigate the influence  
297 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

324 over a year at different spatial resolutions.

325

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

338

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

342

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



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

356

357 We implemented a spatial closure using the different data sources and spatial  
358 and temporal aggregations as outlined in the protocol in Section 3.4. We used  
359 this to assess the efficacy of a closure in reducing fishing mortality on species 1,  
360 given availability of data and its use at different resolutions in order to evaluate  
361 the trade-offs in data sources. Figure 4 shows the trend in fishing mortality  
362 for each species simulated (columns) given the data sources (rows), temporal  
363 aggregations (colour lines) and spatial aggregations (linestyles), while Figure 5  
364 shows the change in fishing mortality from before the closure (average F years  
365 2 - 4) to after the closure (average F years 8 - 10).

366

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

376

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

381

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

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

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

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

Note: The monthly commercial data scenario is the most effective of the realistic scenarios, as the 'real population' can only be seen as a baseline comparison.

## 5. Discussion

## 6. Conclusions

## Appendices

## Abbreviations

Detail any unusual ones used.

## Acknowledgements

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Table 1: Description of variables for sub-modules

Variable	Meaning	Units
<b>Population dynamics</b>		
<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 <sup>-1</sup>
$\rho$	Brody's growth coefficient	yr <sup>-1</sup>
$Wt_R$	Weight of a fully recruited fish	kg
$Wt_{R-1}$	Weight of a pre-recruit fish	kg
$\alpha_d$	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
<b>Recruitment dynamics</b>		
$\tilde{R}_{c,d}$	is the recruitment in cell $c$ for day $d$	$d^{-1}$
$B_{c,d}$	is the Biomass in cell $c$ for day $d$	$d^{-1}$
$\alpha$	the maximum recruitment rate	kg
$\beta$	the biomass required to produce half the maximum rate of recruitment	kg
<b>Population movement dynamics</b>		
a	b	c
a	b	c
<b>Fleet dynamics</b>		
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 $\nu$	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 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 $\beta_1$	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

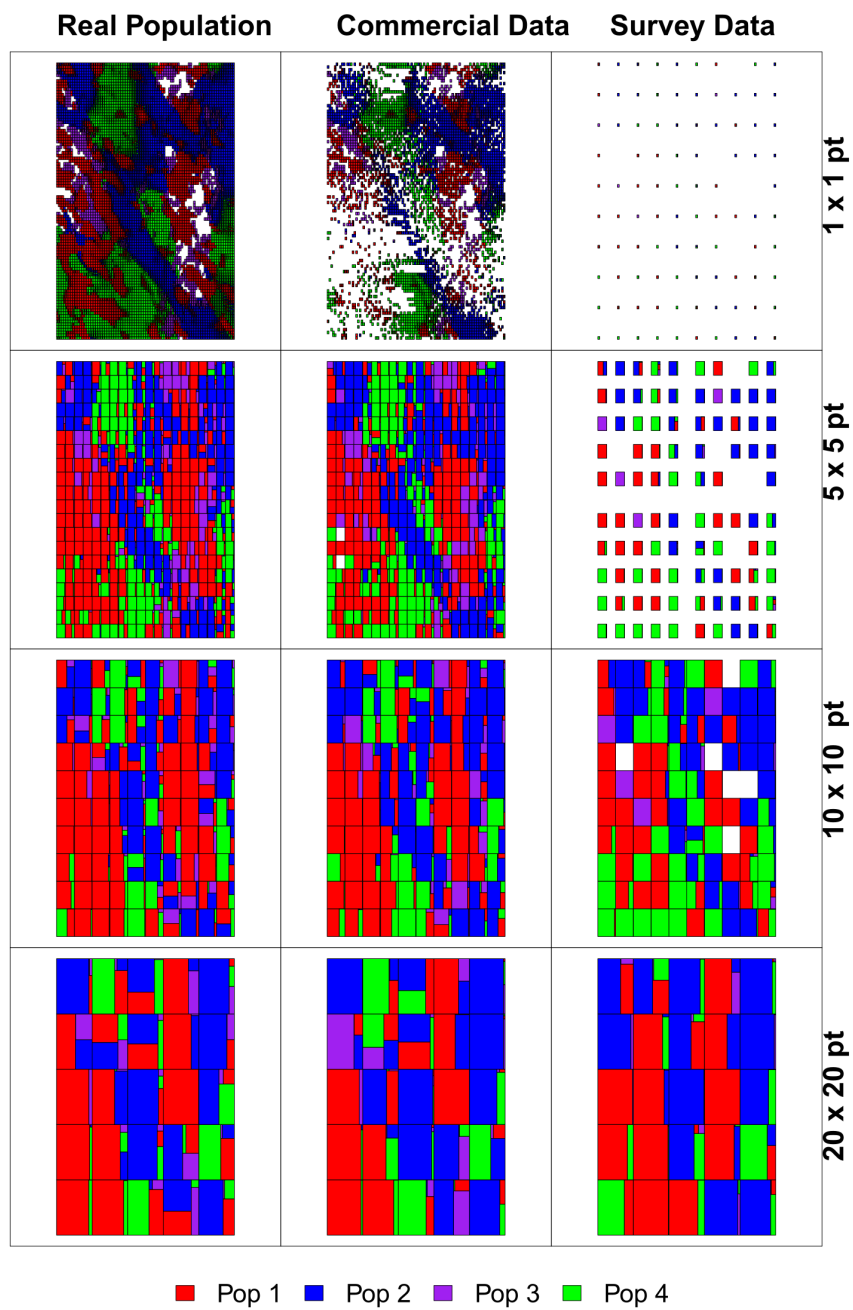


Figure 2: Data aggregation at different spatial resolutions

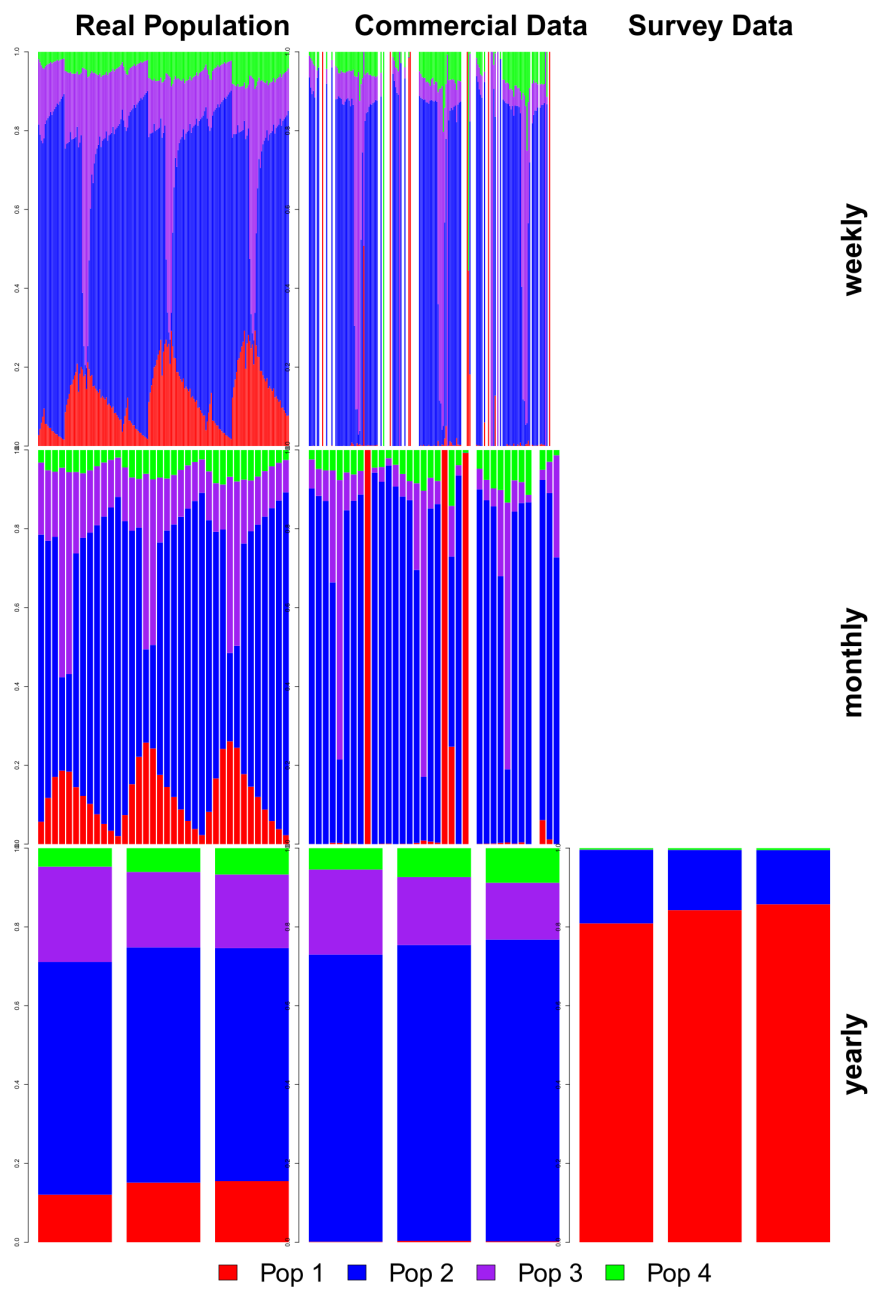


Figure 3: Data aggregation at different temporal resolutions

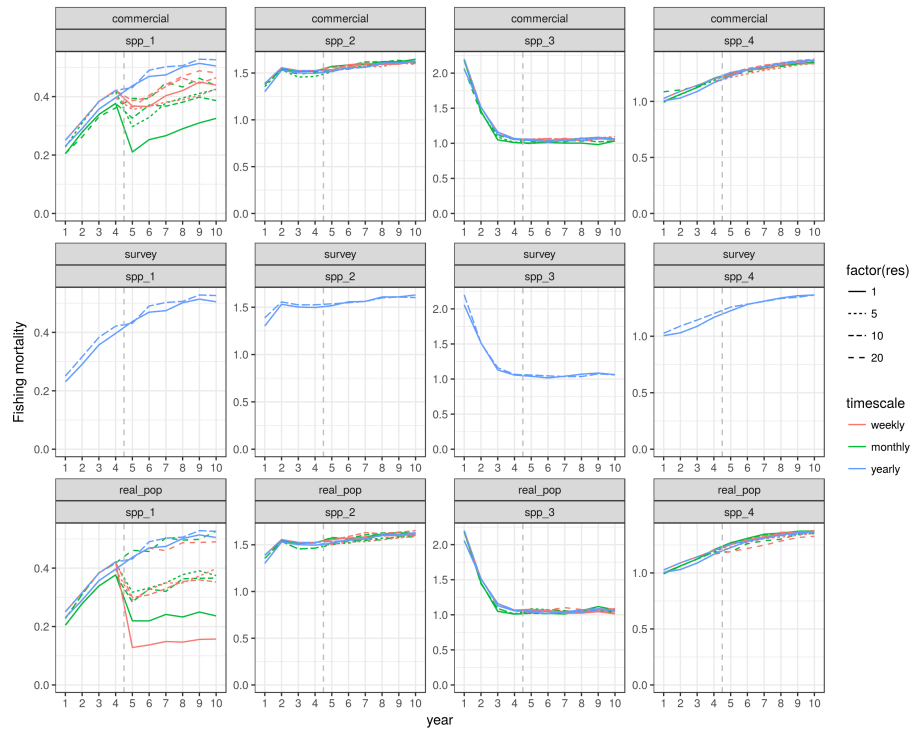


Figure 4: Comparison of closure scenarios - F trends

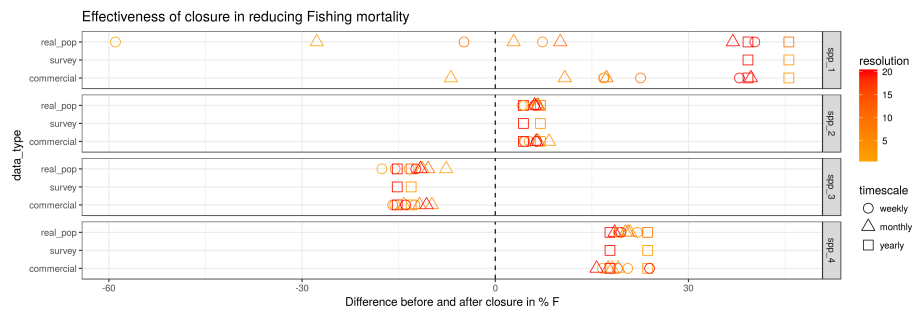


Figure 5: Comparison of closure scenarios



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