

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. [We simulate a closure based on areas defined from commercial catch data and assess its effectiveness on reducing catches of a fish population.]

We conclude that...

[233 words]

Keywords: Some, keywords, here. Max 6

2010 MSC: 00-01, 99-00

¹ **1. Introduction**

² [Guidance:: State the objectives of the work and provide an adequate back-
³ ground, avoiding a detailed literature survey or a summary of the results.]

⁴

⁵ Fishers exploit fish populations that are heterogenously distributed in space
⁶ and time with verying knowledge of species distributions using species-unselective
⁷ fishing gear. Fisheries that catch an assemblage of species, known as mixed fish-
⁸ eries, when managed by single-species quotas can end up discarding overquota
⁹ catch leading to overexploitation of fish populations. Reducing discarding is
¹⁰ crucial to ensure biological and economic sustainability of fisheries and imple-
¹¹ mentation of an ecosystem approach to fisheries. As such there is increasing
¹² interest in technical solutions such as gear and spatial closures as ways of avoid-
¹³ ing discards.

¹⁴

¹⁵ Use of spatial management as a tool has been proposed as a method to reduce
¹⁶ discards. However, its implementation is hampered by lack of knowledge of fish
¹⁷ and fishery spatiotemporal dynamics and understanding of the scale at which
¹⁸ processes are important for management. Understanding the correct scale for
¹⁹ spatial management is crucial in order to implement measures at a resolution
²⁰ that ensures effective management[1] while minimising economic impact. For
²¹ 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 (advection) 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 known as a fisheries-independent survey, and ii) the underlying population
51 structures input to the simulation.

52

53 [Could fit a geostatistical model (e.g. VAST) to the fisheries-dependent and
54 fisheries-independent data, though may be overkill...]

55

56 We simulate a fishery closure to protect one species based on the fishery-

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

62

63 2. Materials and Methods

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

69

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

79

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

82 2.1. Population dynamics

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

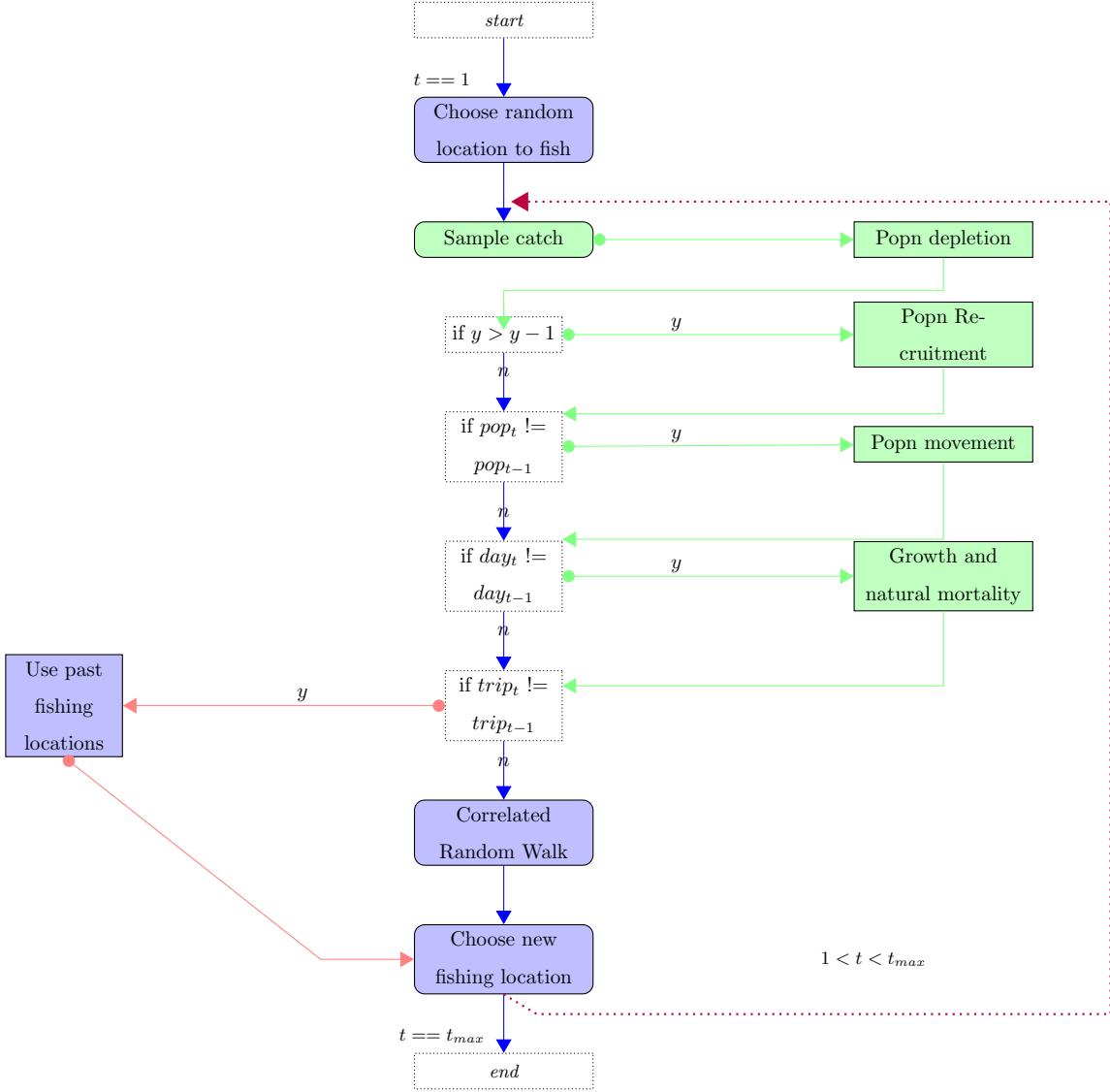


Figure 1: Overview Schematic of simulation model. The blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the timesteps at which processes occur; $t = \text{tow}$, t_{\max} is the total number of tows, $y = \text{year}$, pop_t is time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

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

87 recruited biomass, intrinsic population growth and recruitment:

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

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

93

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

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

97 where C is the summed catch from the fishing model across all fleets and ves-
98 sels for the population during the day, and B the daily biomass for the species.

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

103

104 2.2. Recruitment dynamics

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

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

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

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

111

112 or a stochastic Ricker form [15]

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

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

113 where α is the maximum productivity per spawner and β the density dependent reduction in productivity as the SSB increases.

115 *2.3. Population movement*

116 To simulate how fish populations might be distributed in space and time,
117 we employed a Gaussian spatial process to model habitat suitability for each of
118 the populations, with an advection-diffusion process to control how the populations
119 moved over time with a moving temperature covariate to capture temporal
120 dependencies. This was intended to balance realism in population movement,
121 capturing the main directed and random processes, and practicality of modelling
122 the population rather than individual fish.

123

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

129

130 The covariance structure affects the smoothness of the surfaces which the
 131 process generates, and we used the *Matérn* family of covariance structures, one
 132 where the correlation strength weakens the further the distance apart (i.e. the
 133 correlation between $S(x)$ and $S(x')$ decreases as the distance $u = ||x - x'||$ in-
 134 creases). The *Matérn* correlation is a two-parameter family where:
 135

$$136 \quad \rho(u) = \{2^{\kappa-1}\Gamma\kappa\}^{-1}(u/\phi)^\kappa K_\kappa(u/\phi)$$

137 $K_\kappa(\cdot)$ is a modified Bessel function of order κ , $\phi > 0$ is a scale parameter
 138 with the dimensions of distance, and $\kappa > 0$, called the order, is a shape param-
 139 eter which determines the smoothness of the underlying process.
 140

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

$$147 \quad Tol_{c,p} = \frac{1}{\sqrt{(2\pi \cdot \sigma_p^2)}} \cdot \exp\left(-\frac{(T_c - \mu_p)^2}{2 \cdot \sigma_p^2}\right) \quad (1)$$

147 Where $Tol_{c,p}$ is the tolerance of population p in cell c , T_c is the temperature
 148 in the cell and μ and σ^2 the mean and standard deviation of the population
 149 temperature tolerance.
 150

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

156 and distance from current cell.

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

157 Where d_{AB} is the euclidean distance between cell A and cell B , λ is a given
158 rate of decay, Hab_B^2 is the squared index of habitat suitability for cell B and
159 $Tol_{B,wk}$ the temperature tolerance for the cell in week wk ; population index, p
160 has been dropped for simplicity.

161

162 During specified weeks of the year, the habitat quality is modified for spawning
163 habitats, meaning each population has a concentrated area where spawning
164 takes place and the population moves towards this in the weeks prior to spawning.
165

166

167 *2.4. Fleet dynamics*

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

173 *2.4.1. Fleet targeting*

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

181 2.4.2. *Trip-level decisions*

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

191 2.4.3. *Within-trip decisions*

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

200

201 A *lévy walk* is a particular form of random walk characterised by a heavy-
202 tailed distribution of step-length and has received a lot of attention in ecological
203 theory in recent years as having shown to have very similar characteristics as
204 those observed by animals in nature, and being a near optimum searching strat-
205 egy for predators pursuing patchily distributed prey [22, 23]. [24] showed that
206 Peruvian anchovy fishermen have a stochastic search pattern similar to that
207 observed with a lévy walk. However, it remains a subject of debate, with the
208 contention that search patterns may be more simply characteristed as random
209 walks [25] with specific patterns related to the characteristics of the prey field
210 [26].

211

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,

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

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

217 The step function takes the form:

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

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

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

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

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

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

223 *2.4.4. Local population depletion*

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

232 *2.5. Fisheries independent survey*

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

239 **3. Calculation**

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

244

245 *3.1. Population parameterisation*

246 We parameterised the simulation model for four populations with differing
247 habitat preference (Figure 5), population demographic and recruitment func-
248 tions; each of the populations also has two defined spawning areas and move-
249 ment rates (Table 2).

250

251 *3.2. Fleet parameterisation*

252 The fleets were parameterised to reflect five different characteristics based
253 on targeting preference and exploitation dynamics (Table 3). This ensures that
254 different fleets have different spatial dynamics, preferentially targeted different
255 fish populations. The stochasticity in the random walk process ensures that dif-
256 ferent vessels within a fleet have slightly different spatial distributions based on
257 individual experience, while the step function was parameterised dynamically
258 so that vessels take smaller steps where the fishing location yields in the top
259 X [??]quartile of the value available in that year (as defined per fleet in Table 3).

260

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

265 *3.3. Survey settings*

266 The survey simulation was set up with follow a fixed gridded station design
267 with 49 stations fished each year, starting on day 92 with same catchability
268 parameters for all populations ($Q = 1$).

269 *3.4. Simulation settings*

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

276

277 We allow the simulation to run unrestricted for 5 years, and subsequently
278 close areas for the last 5 years of the simulation based on data (either derived

²⁷⁹ from the commercial catches, fisheries-independent survey or the 'real popula-
²⁸⁰ tion') used at different spatial and temporal scales.

²⁸¹ The following steps are undertaken to determine closures:

²⁸² i. Extract data source ii. Aggregate according to resolution iii. Interpolate
²⁸³ across entire area at desired resolution iv. Close top 5 % of areas

Table 1: Closure scenarios

| Data type | Temporal resolution | Spatial resolution |
|---|------------------------|--------------------|
| Commercial logs, survey data, real population | weekly, monthly, years | 1, 2, 5, 10 |

²⁸⁴ ABOVE WOULD BE BETTER AS SOME SORT OF GRAPHICAL ILLUS-
²⁸⁵ TRATION OF AGGREGATION CONSEQUENCES, E.G. COMMERCIAL
²⁸⁶ DATA SPARSITY, SURVEY DATA CONSISTENCY, REAL POPULATION
²⁸⁷ IS ALL.

²⁸⁸ TEMPORALLY VARYING PROPORTIONS DIVIDED BY WEEK, MONTH,
²⁸⁹ YEAR

²⁹⁰ CELLS AGGREGATED ACCORDING TO SIMULATION EXAMPLES !!!

²⁹¹ Total 56 scenarios.

²⁹² 4. Results

²⁹³ Need to consider what best to present here as 4 / 5 figures:

- ²⁹⁴ • Spatial dynamics: e.g. Figure 14. showing the population movement
²⁹⁵ across weeks, including a spawning period.
- ²⁹⁶ • Overall population trends: e.g. Figure 3, showing the population dynamics
²⁹⁷ at play.
- ²⁹⁸ • Realised step function: e.g. Figure 13, showing how the movement and
²⁹⁹ turning angle responds. This could be combined with Figure 7 for a more
³⁰⁰ complete visualisation.

- 301 • Catch composition and spatial clustering: e.g. Figure 10, showing the
302 importance of spatial resolution.
- 303 • Some measure of temporal trends/changes in spatial composition - could
304 pick a certain cell and show how the proportions change over time ? An
305 example is Figure 15, though there is little variation here. I think this is
306 because the static habitat with population movement is far more stable
307 than the previous directly affected population distributions (where there
308 was an advective-diffusive process from the SPDE). Might need to consider
309 how to change this? Could include a spatiotemporally changing habitat
310 suitability covariate, e.g. temperature ?? [temperature would be very
311 interesting and cover varying spatial fields]
- 312 • Comparison of population structure from i) commercial sampling, ii) fish-
313 eries independent survey, iii) real population. This should be some statis-
314 tical measure...not sure best approach here.

ether this is also a seasonal closure.

316 Present simulated closures in terms of % change in population biomass and
317 fishery.

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

319 **5. Discussion**

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

323 **6. Conclusions**

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

³²⁷ **Appendices**

³²⁸ [Guidance: If there is more than one appendix, they should be identified
³²⁹ as A, B, etc. Formulae and equations in appendices should be given separate
³³⁰ numbering: Eq. (A.1), Eq. (A.2), etc.; in a subsequent appendix, Eq. (B.1)
³³¹ and so on. Similarly for tables and figures: Table A.1; Fig. A.1, etc.]

Table 2: Population dynamics and movement parameter setting

| Parameter | Pop 1 | Pop 2 | Pop 3 | Pop 4 |
|----------------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Habitat quality | | | | |
| Matérn ν | 1/0.15 | 1/0.05 | 1/0.55 | 1/0.05 |
| Matérn κ | 1 | 2 | 1 | 1 |
| Anisotropy | 1.5,3,-3,4 | 1,2,-1,2 | 2.5,1,-1,2 | 0.1,2,-1,0.2 |
| Spawning areas (bound box) | 40,50,40,50; 80,90,60,70 | 50,60,30,40; 80,90,90,90 | 30,34,10,20; 60,70,20,30 | 50,55,80,85; 30,40,30,40 |
| Spawning multiplier | 10 | 10 | 10 | 10 |
| Movement λ | 0.3 | 0.3 | 0.3 | 0.3 |
| Population dynamics | | | | |
| Starting Biomass | 1e5 | 2e5 | 1e5 | 1e4 |
| Beverton-Holt Recruit 'a' | 60 | 100 | 80 | 2 |
| Beverton-Holt Recruit 'b' | 250 | 250 | 200 | 50 |
| Beverton-Holt Recruit σ^2 | 0.4 | 0.3 | 0.4 | 0.3 |
| Recruit week | 13-16 | 12-16 | 14-16 | 16-20 |
| Spawn week | 16-18 | 16-19 | 16-18 | 18-20 |
| K | 0.3 | 0.3 | 0.3 | 0.3 |
| wt | 1 | 1 | 1 | 1 |
| wt_{d-1} | 0.1 | 0.1 | 0.1 | 0.1 |
| M (annual) | 0.2 | 0.2 | 0.2 | 0.1 |

³³² // //Supplementary //

Table 3: Fleet dynamics parameter setting

| Parameter | Fleet | Fleet | Fleet | Fleet | Fleet |
|---------------------------|-------|-------|-------|-------|-------|
| | 1 | 2 | 3 | 4 | 5 |
| Targeting preferences | | | | | |
| Price Pop1 | 100 | 100 | 100 | 100 | 100 |
| Price Pop2 | 200 | 200 | 200 | 200 | 200 |
| Price Pop3 | 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 <i>rate</i> | 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 |

³³³ **Abbreviations**

³³⁴ Detail any unusual ones used.

³³⁵ **Acknowledgements**

³³⁶ those providing help during the research..

³³⁷ **Funding**

³³⁸ This work was supported by the MARES doctoral training program; and the
³³⁹ Centre for Environment, Fisheries and Aquaculture Science seedcorn program.

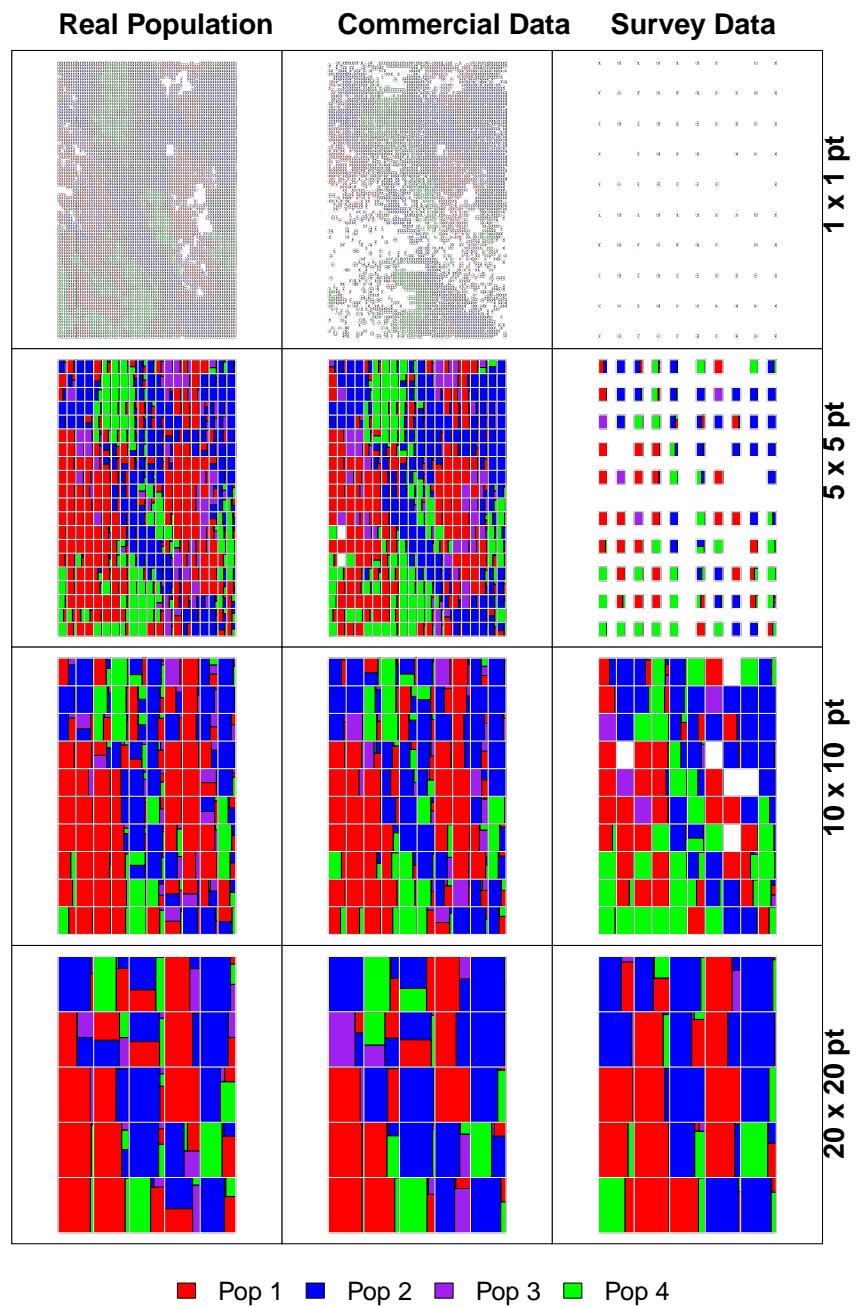


Figure 2: Data aggregation at different spatial resolutions

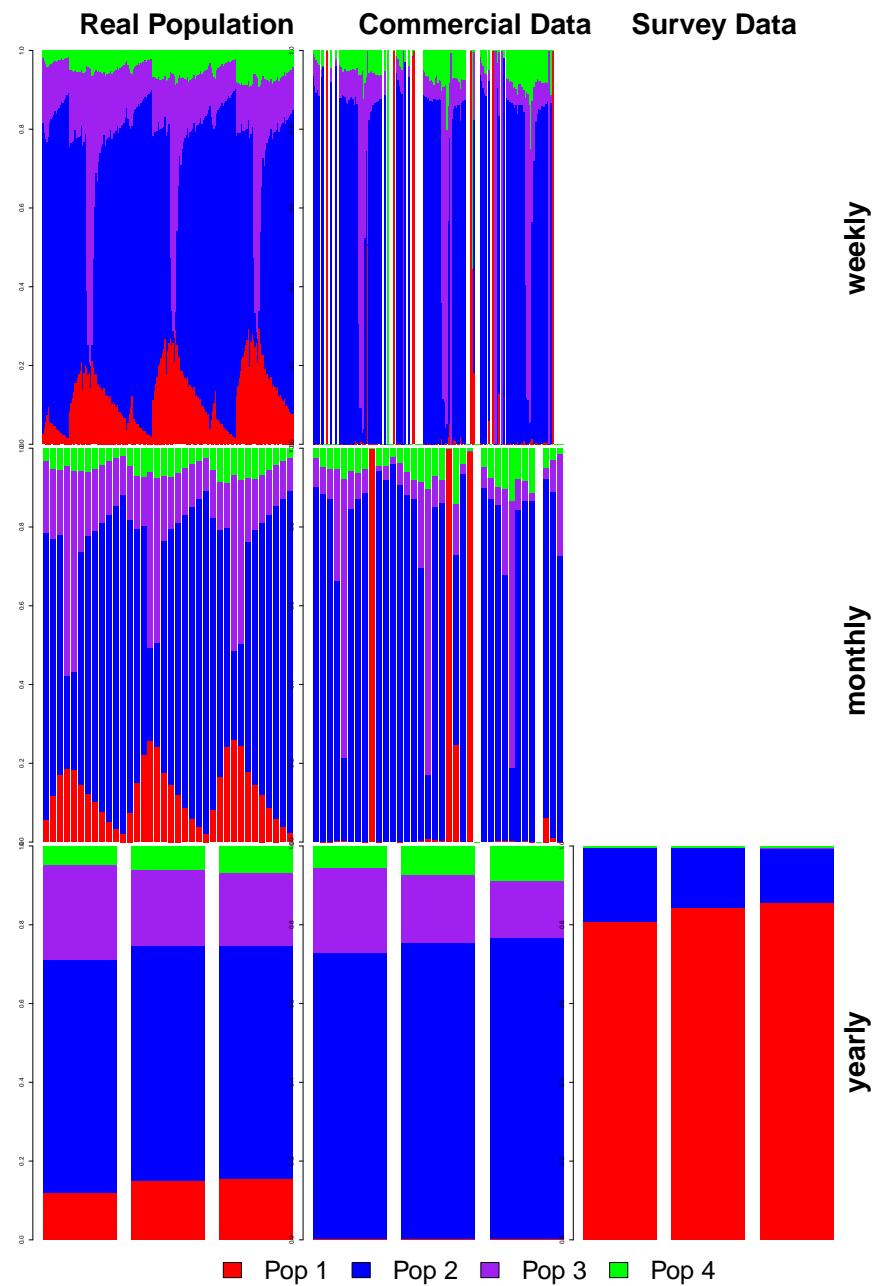


Figure 3: Data aggregation at different temporal resolutions

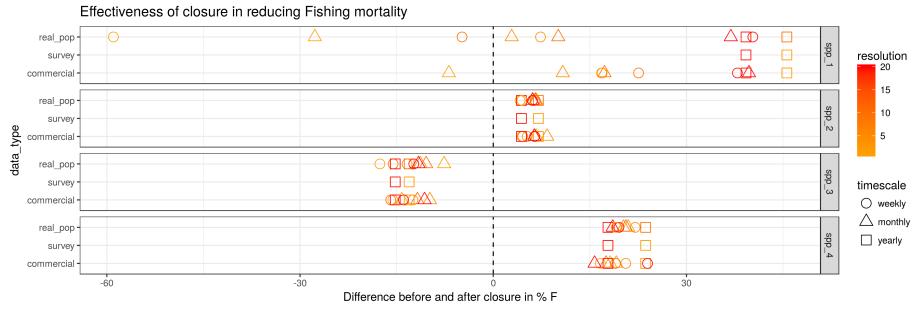


Figure 4: Comparison of closure scenarios

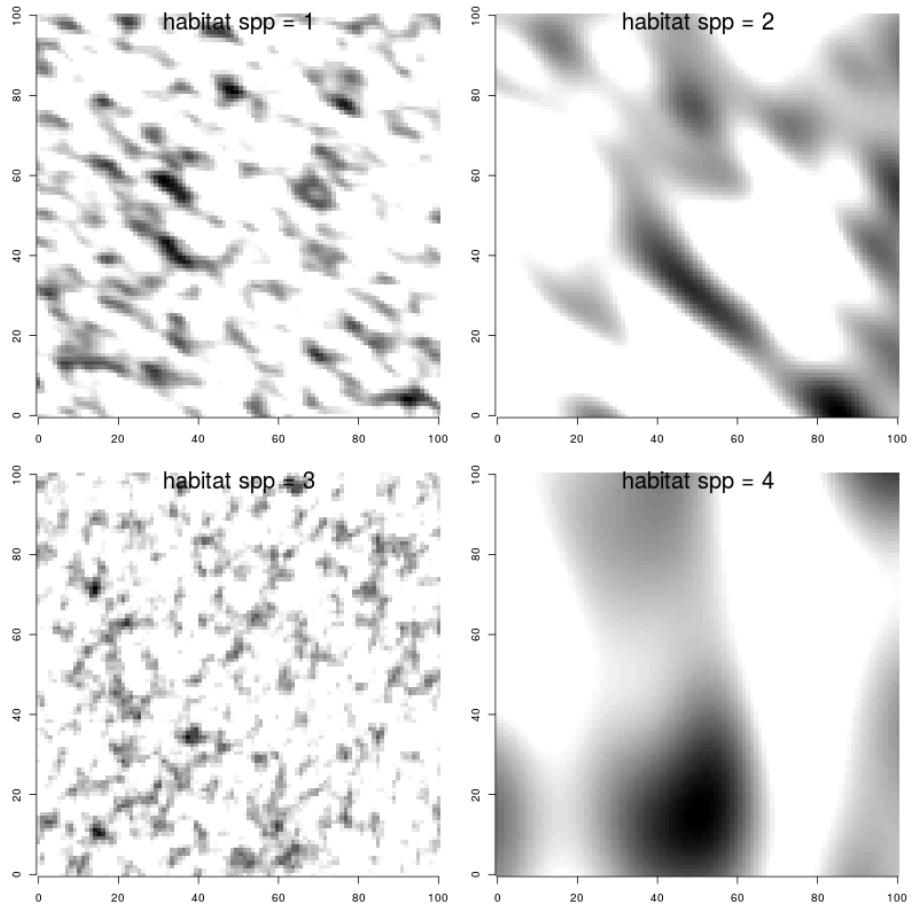


Figure 5: habitat preference

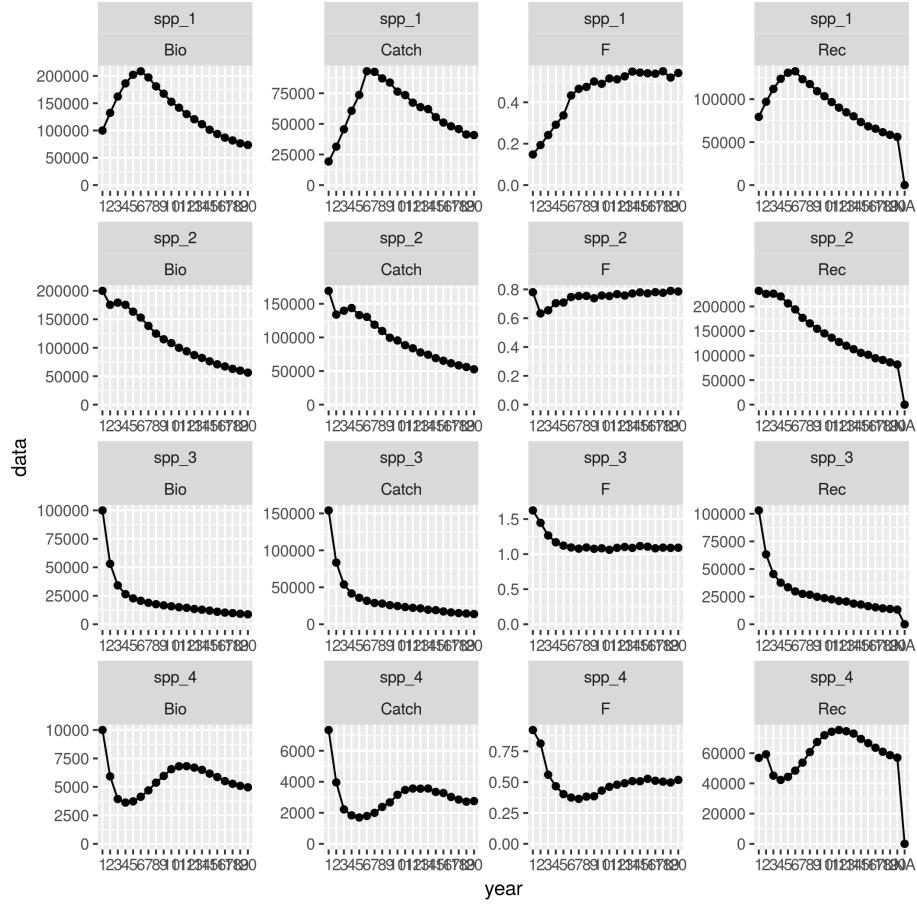


Figure 6: Summary of annualised metrics: biomass, catch, fishing mortality and recruitment. x-axis is the year, y the value

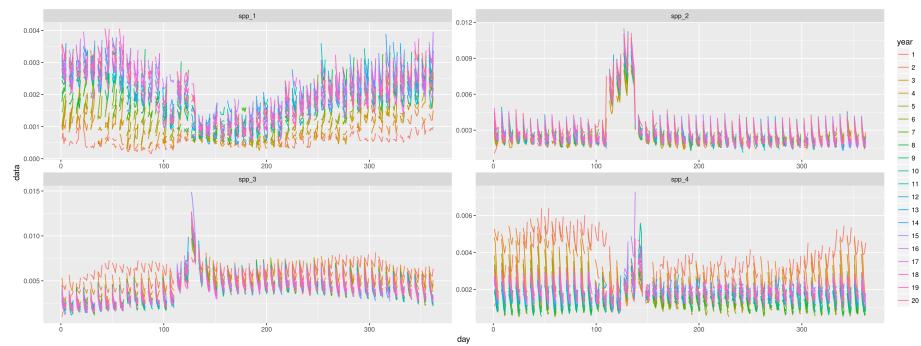


Figure 7: f dynamics - the daily fishing mortalities, each year is a different colour

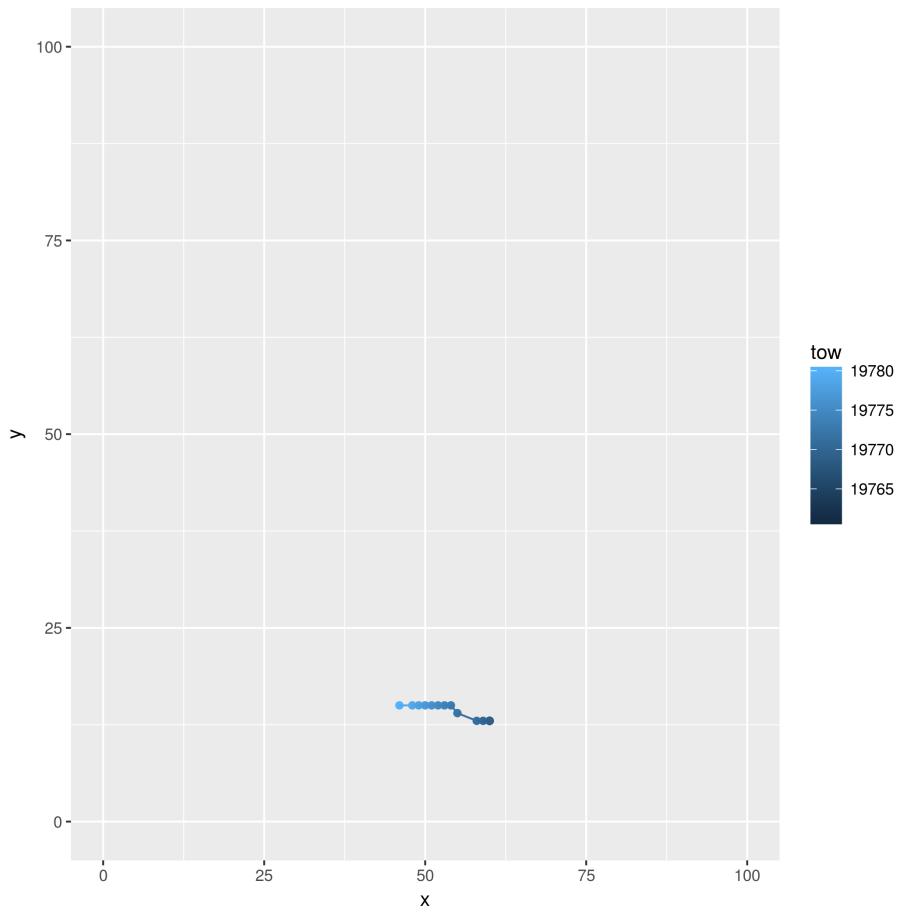


Figure 8: vessel movement - a single trip movement for one vessel

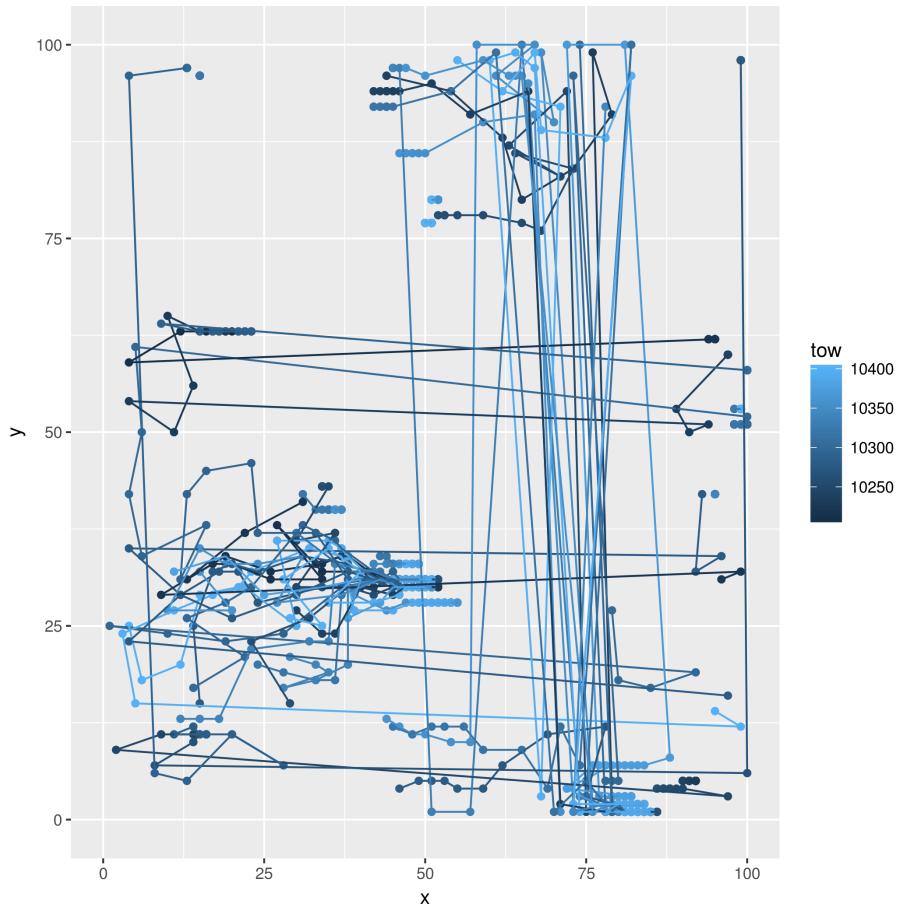


Figure 9: vessel movement for multiple trips from a single vessel. Note the movement off the side pops up the other side, but is joined by a line across the grid. This is from the torus approach rather than the edges being barriers

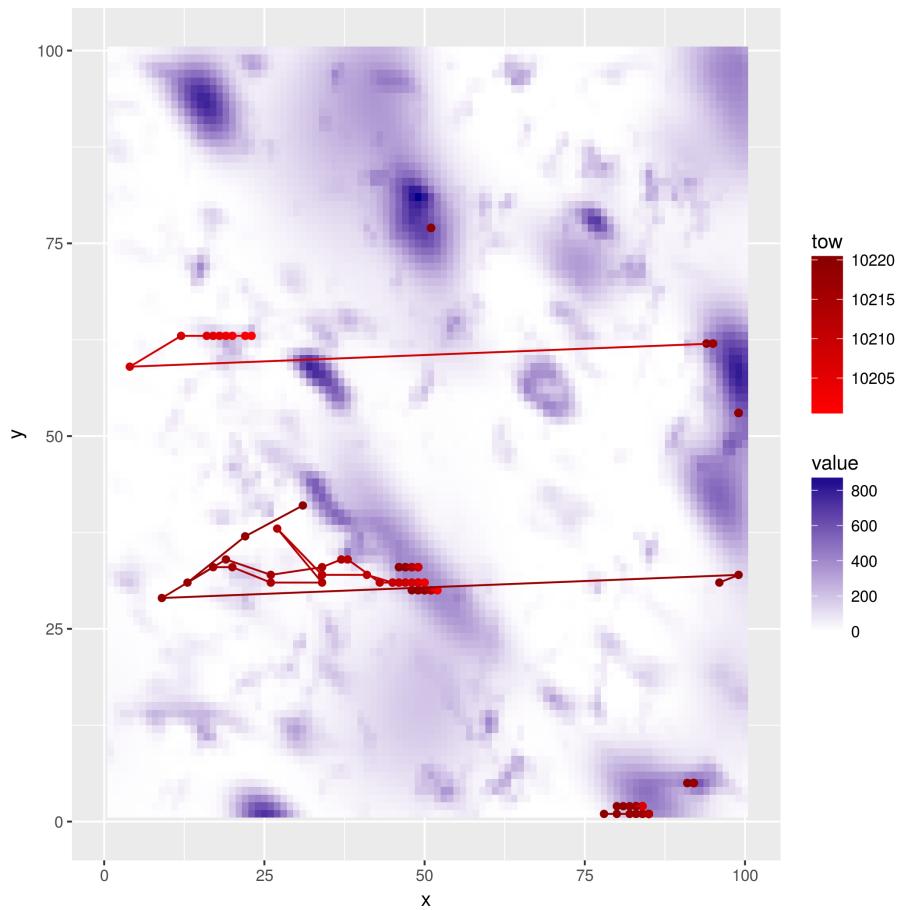


Figure 10: movement of a single vessel over a few trips overlaid on the value field (i.e. sum of the population abundance x catchability x value)

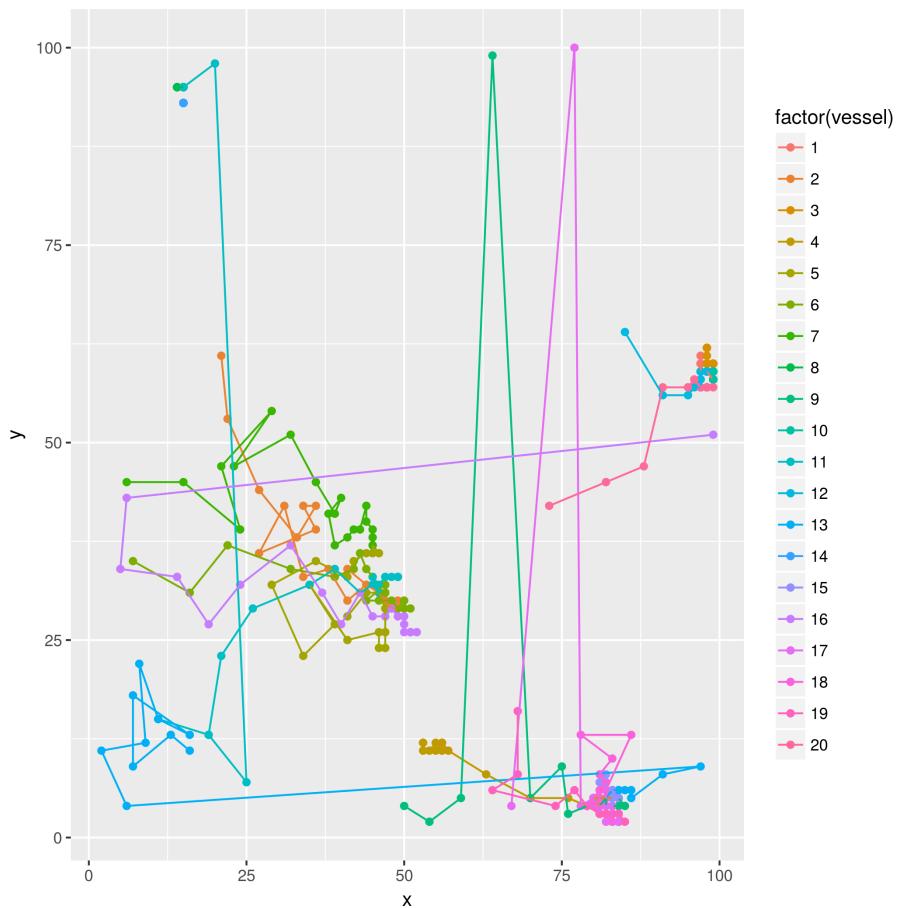


Figure 11: An entire fleets (20 vessels) movement for a single trip

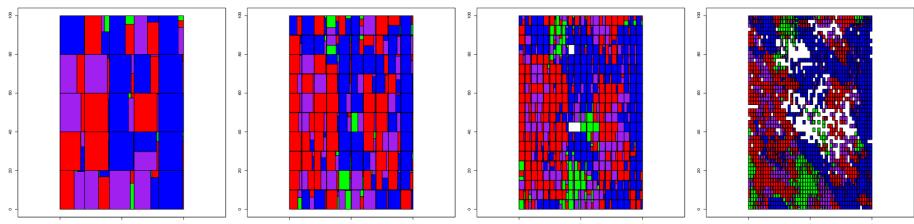


Figure 12: spatial catch composition - the raw catches per cell at 4 different spatial resolutions.
Sorry, its a bit small at the moment!

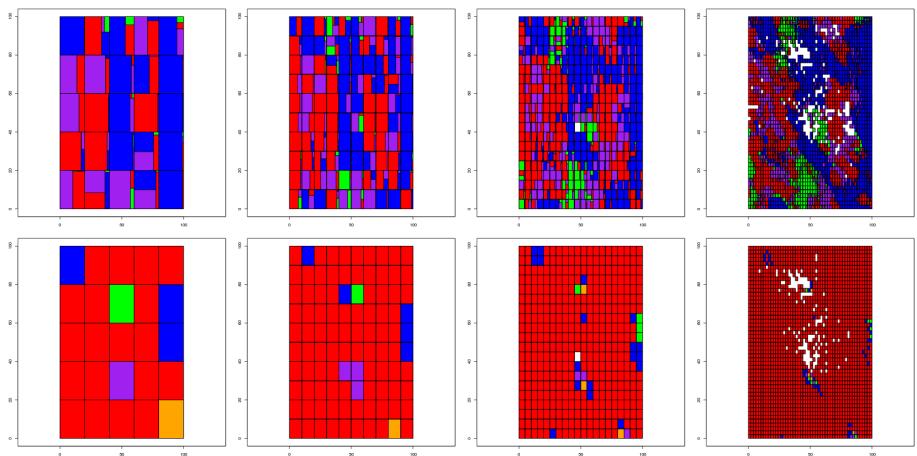


Figure 13: spatial catch composition (as above) but with clustering of cells performs on the bottom row. I'm confused as to why some entirely blue cells in the raw catch composition get allocated to the same cluster as some entirely red cells - needs investigating, it may be the clustering is not optimal

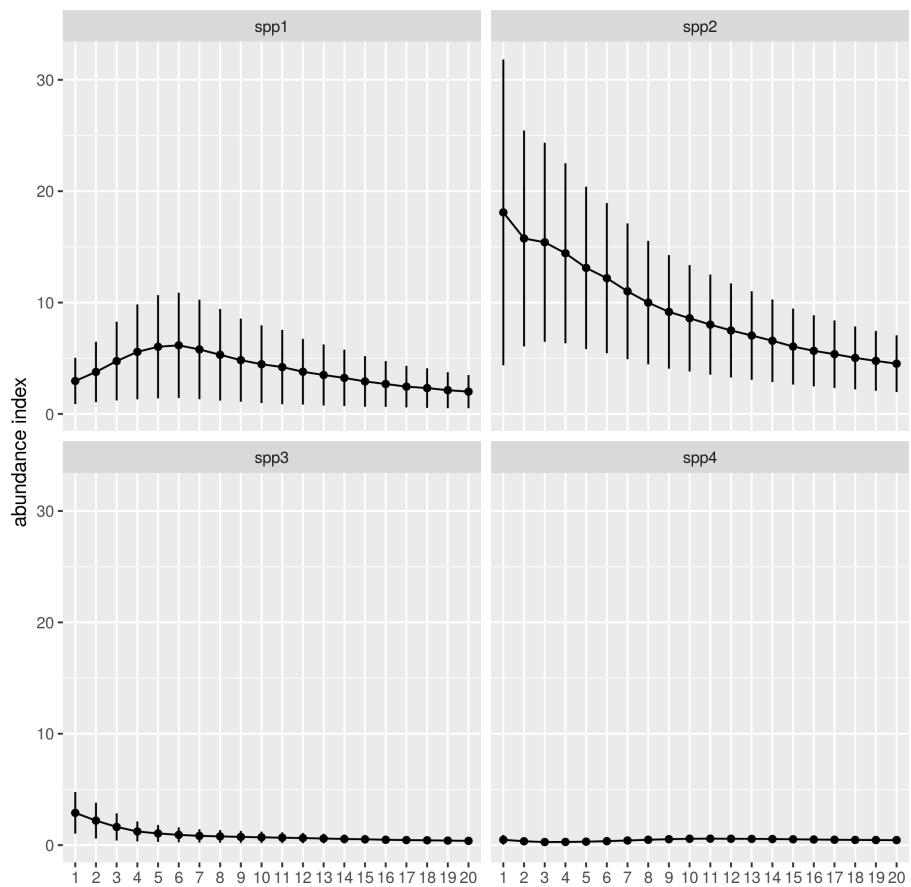


Figure 14: survey index - a non-spatial index generated from the fishery independent survey

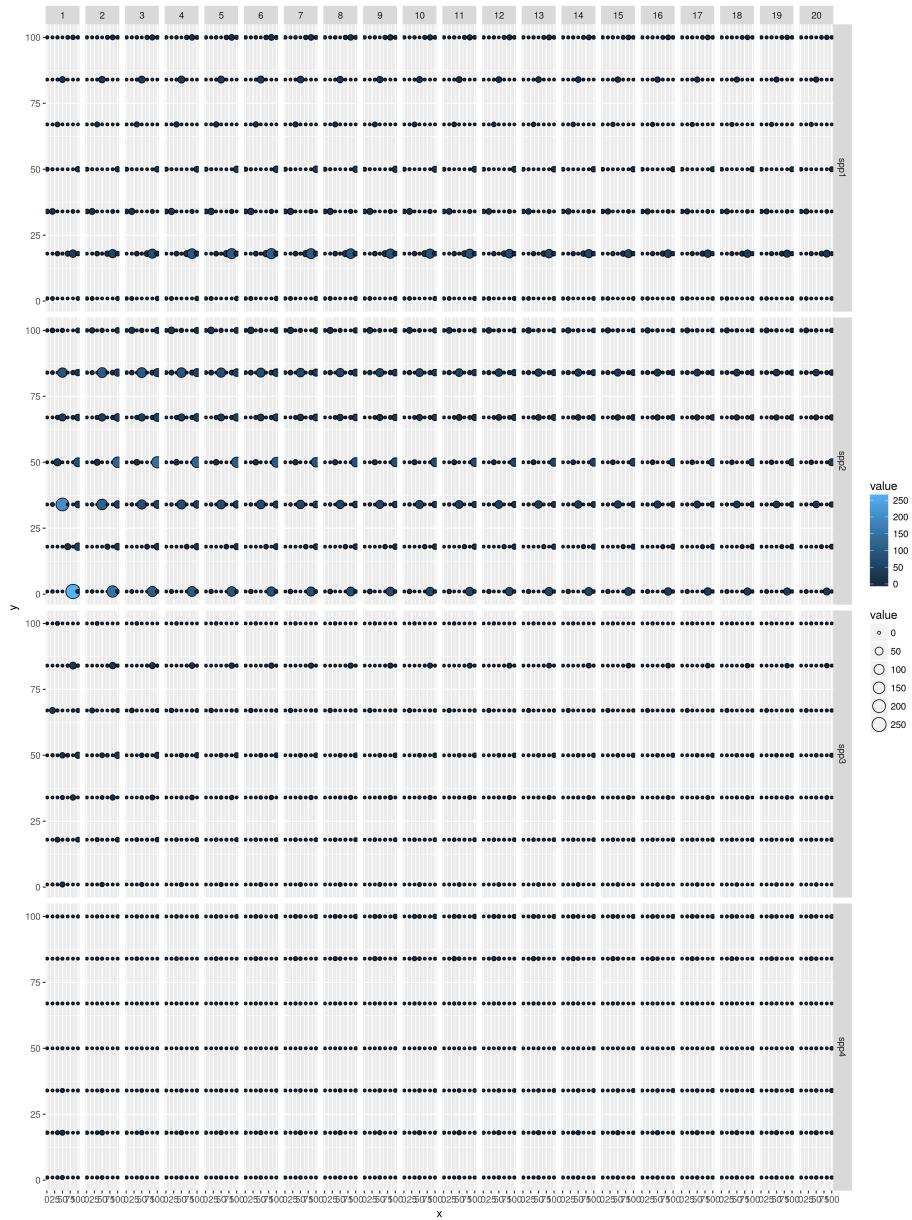


Figure 15: survey spatial abundance - a bubble plot of the survey abundances, not really useful for the paper

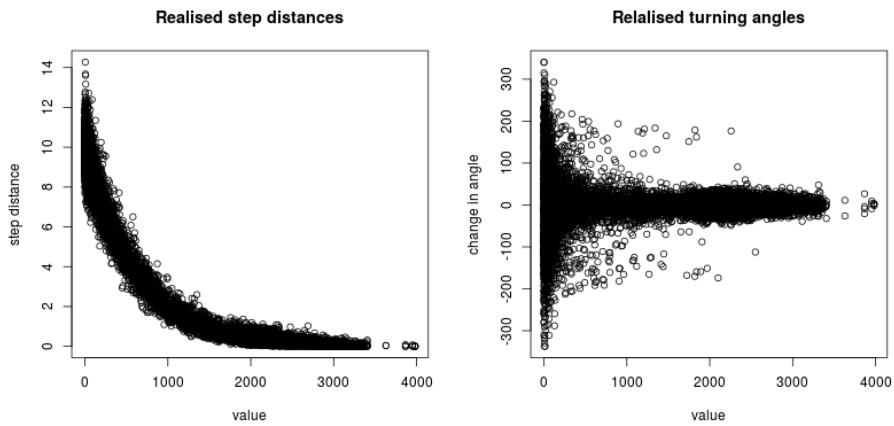


Figure 16: Realised step function - the step function as realised for a single fleet. For turning angles, it can be seen that at higher values, the turning range is less

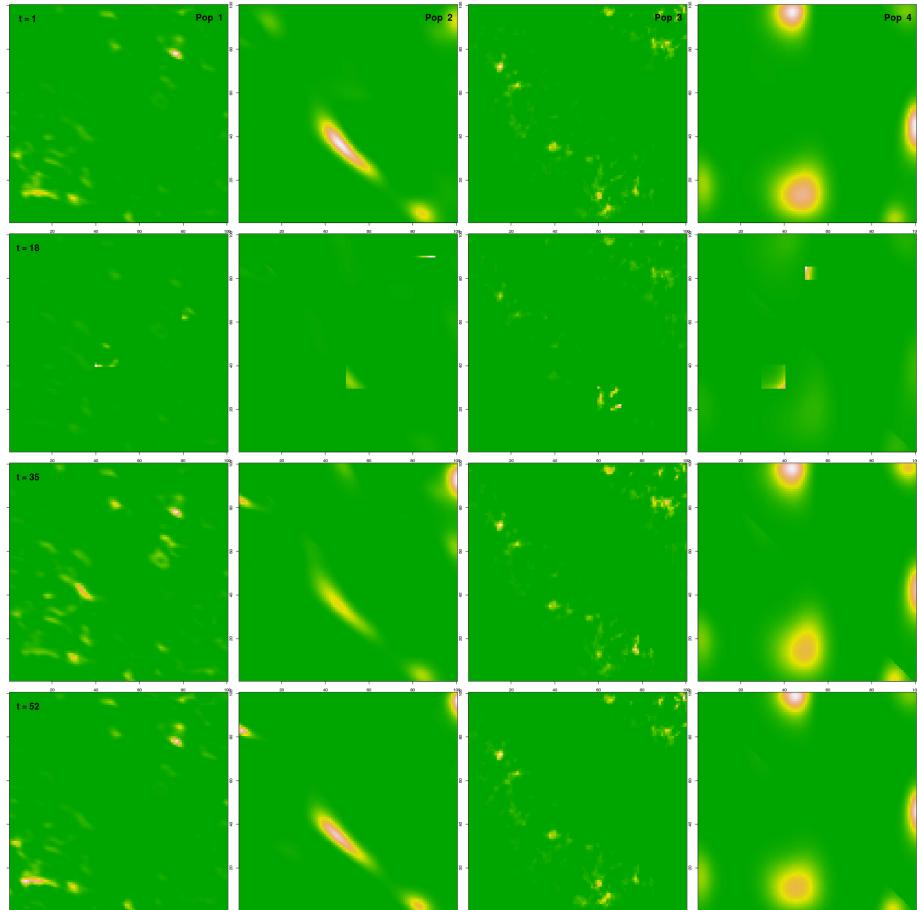


Figure 17: Spatial dynamics - the four populations at four time steps. Not really happy about the lack of dynamics here - mainly down to the static habitat leading to the populations settle in same cells over most time steps (exception: during the spawning period). Could include a temperature covariate or something to force some more temporal changes?

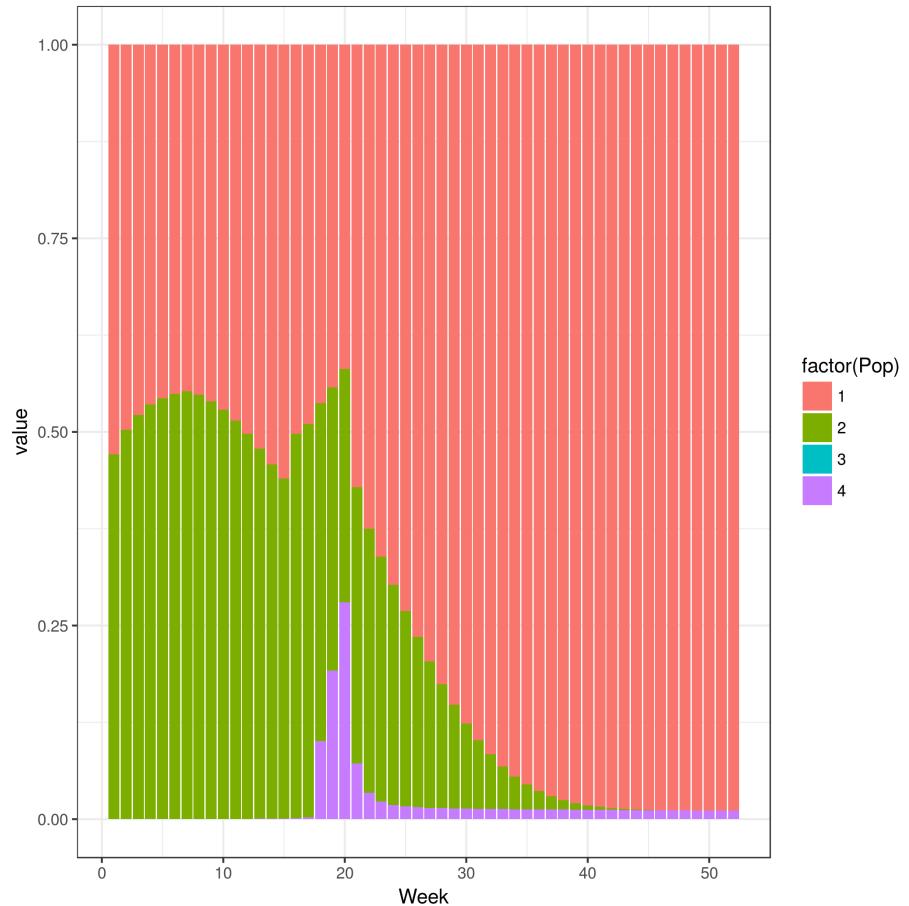


Figure 18: Temporal dynamics - the proportion of each population in a randomly chosen cell.
Similar criticism as above

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