

MixFishSim: highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

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Abstract

Fishing exploits spatially and temporally heterogeneous fish populations, using species-unselective gear that can result in unintended, unwanted catch of low quota or protected species. Reducing these unwanted catches is crucial for biological and economic sustainability of ‘mixed fisheries’ and implementation of an ecosystem approach to fishing.

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

To understand how resolution impacts mixed fisheries inference, we develop a highly resolved spatiotemporal simulation model incorporating: i) delay-difference population dynamics, ii) population movement using Gaussian Ran-

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

We simulate 20 years of exploitation of the fish populations and use the results from the fishing model to draw inference on the underlying population structures. We compare this inference to i) a simulated fixed-site sampling design commonly used for fisheries monitoring purposes, and ii) the true underlying population structures input to the simulation, to establish the potential and limitations of fishery-dependent data - an inherently biased sampling method due to fisher's targeting- to provide a robust picture of spatiotemporal distributions. Finally, we simulate an area closure based on areas defined from commercial the known ("real-population") distribution, commercial catch data and survey data at different temporal and spatial resolutions and assess their effectiveness on reducing catches of a fish population.

We conclude from our simulations that commercial data, while not unbiased, provides a useful tool for managing catches in mixed fisheries if applied at the correct spatiotemporal scale.

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1. Introduction

Fishers exploit fish populations that are heterogenously distributed in space and time with varying knowledge of species distributions using species-unselective fishing gear. Fisheries that catch an assemblage of species, known as mixed fisheries, when managed by single-species quotas can end up discarding overquota catch leading to overexploitation of fish populations. Reducing discarding is

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

11
12 Use of spatial management as a tool has been proposed as a method to re-
13 duce discards. However, its implementation is hampered by lack of knowledge
14 of fish and fishery spatiotemporal dynamics and understanding of the scale at
15 which processes are important for management. Understanding the correct scale
16 for spatial management is crucial in order to implement measures at a resolu-
17 tion that ensures effective management (Dunn et al., 2016) while minimising
18 economic impact. For example, a scale that promotes species avoidance for vul-
19 nerable or low quota species while allowing continuance of sustainable fisheries
20 for available quota species.

21
22 Ensuring measures are implemented at an appropriate scale has been a chal-
23 lenge in the past that has led to ineffectual measures with unintended conse-
24 quences such as limited impact towards the management objective or increased
25 benthic impact on previously unexploited areas (e.g. the cod closure in the
26 North Sea (Rijnsdorp et al., 2001; Dinmore et al., 2003)). Since then more
27 refined spatial information has become available through the combination of
28 logbook and Vessel Monitoring System (VMS) data (Lee et al., 2010; Bastardie
29 et al., 2010; Gerritsen et al., 2012; Mateo et al., 2016) and more real-time spatial
30 management has been possible (e.g. Holmes et al., 2011). Such information is,
31 however, patchy and derived from an inherently biased sampling programme
32 (i.e. targeted fishing). Further, fishers generally only recorded landings (not
33 catch) on a daily basis. This leads to questions about the validity of inference
34 that can be drawn from landings data assigned to VMS activity pings.

35
36 In order to understand challenges that face VMS-linked landings to draw
37 inference on the underlying population structure we develop a simulation model

38 where population dynamics are highly-resolved in space and time and are known
 39 rather than inferred from sampling or commercial catches. Population move-
 40 ment is driven by a random (diffusive) and directed (advective) process and we
 41 incorporate characterisation of a number of different fisheries exploiting four
 42 fish populations with different spatial and population demographics.

43

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

50

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

57

58 **2. Materials and Methods**

59 We develop a simulation model with a modular event-based approach, where
 60 modules are implemented on independent time-scales appropriate to capture
 61 the characteristic of the process modelled (Figure 1). The fishing model op-
 62 erated on a tow-by-tow basis, while population dynamics (fishing and natural
 63 mortality, growth) operate on a daily time-step. Population movement occurs
 64 on a weekly time-step, while recruitment occurs periodically each year for a
 65 set time period (e.g. 3 weeks) at a specified point individual to a species.
 66 The simulation framework is implemented in the statistical software package

67 R (R Core Team, 2017); available as an R package from the authors github
 68 (www.github.com/pdolder/MixFishSim).

69

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

72 2.1. Population dynamics

73 The basic population level processes are simulated using a modified two-stage
 74 Deriso-Schnute delay difference model (Deriso, 1980; Schnute, 1985; Dichmont
 75 et al., 2003) occurring at a daily time-step. Here, population biomass growth and
 76 depletion for pre-recruits and fish recruited to the fishery are modelled separately
 77 as a function of previous recruited biomass, intrinsic population growth and
 78 recruitment:

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

79 where ρ is Brody's coefficient, shown to be approximately equal to $\exp(-K)$,
 80 where K is the growth rate from a von bertalanffy logistic growth model (Schnute,
 81 1985). Wt_{R-1} is the weight of fish prior to recruitment, while Wt_R is the re-
 82 cruited weight. α_d represents the proportion of fish recruited during that day
 83 for the year, while $R_{\bar{y}}$ is the annual recruits.

84

85 Mortality Z can be decomposed to natural mortality, M , and fishing mor-
 86 tality, F , where both M and F are instantaneous rates with M fixed and F
 87 calculated by solving the Baranov catch equation (Hilborn and Walters, 1992)
 88 for F :

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

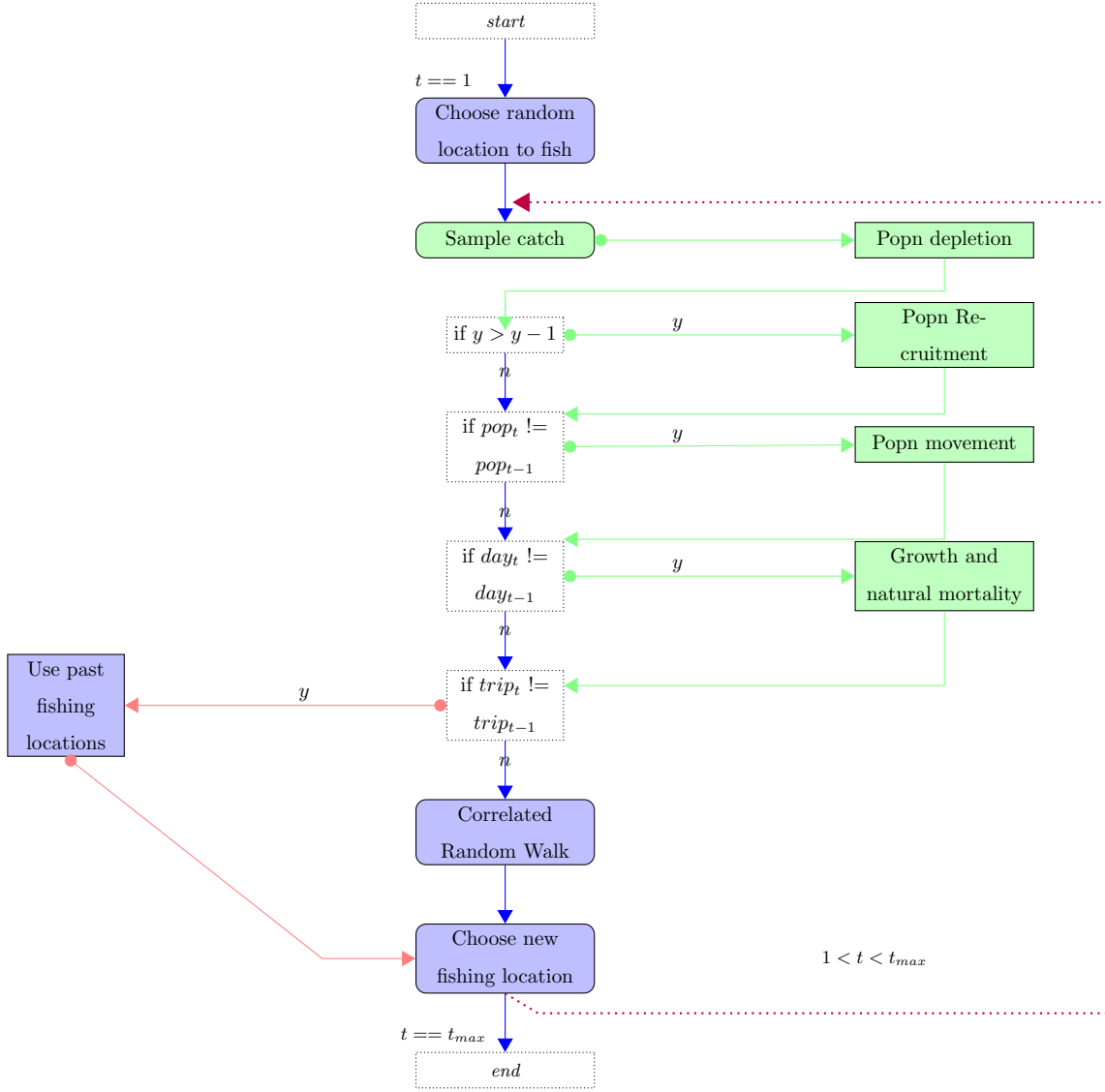


Figure 1: Overview Schematic of simulation model. The blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the timesteps at which processes occur; $t = \text{tow}$, t_{max} is the total number of tows, $y = \text{year}$, pop_t is time of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

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

[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]

95

96 2.2. Recruitment dynamics

97 Recruitment is modelled through a function relating the mature biomass to
98 recruits at time of recruitment. In *mixfishsim*, it can be modelled either either
99 as a stochastic Beverton-Holt stock-recruit form (Beverton and Holt, 1957):

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

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

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

103

104 or a stochastic Ricker form (Ricker, 1954):

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

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

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

107 2.3. Population movement

108 To simulate how fish populations might be distributed in space and time,
109 we employed a Gaussian spatial process to model habitat suitability for each of
110 the populations, with an advection-diffusion process to control how the popula-
111 tions 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*, $\gamma(x, x') = Cov\{S(x), S(x')\}$ (Diggle and Ribeiro, 2007).

The covariance structure affects the smoothness of the surfaces which the process generates, and we used the *Matérn* family of covariance structures, one where 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). The *Matérn* correlation is a two-parameter family where:

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

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

The temperature field is 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 cycle to lower temperatures and low temperature areas vice versa. Each population is assigned a thermal tolerance with mean, μ and variance, σ^2 so that each cell and population temperature suitability is defined that:

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

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

In the simulation model, the habitat for each of the populations is 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 is initialised at a single location, and subsequently moves according to a probabilistic distribution based on habitat suitability, temperature and distance from current cell.

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

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

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

2.4. Fleet dynamics

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

166 2.4.1. *Fleet targeting*

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

174 2.4.2. *Trip-level decisions*

175 Several studies (e.g. Hutton et al., 2004; Tidd et al., 2012; Girardin et al.,
176 2015) have confirmed past activity and past catch rates are strong predictors of
177 fishing location choice. For this reason, the fleet dynamics sub-model includes
178 a learning component, where a vessel's initial fishing location in a trip is based
179 on selecting from previously successful fishing locations. This is achieved by
180 sorting all previous fishing events in the previous trip as well as the previous
181 time periods in past years, and choosing randomly from the top x % of fishing
182 events in value. Simulation testing indicated that this learning increased the
183 mean value of catches for the vessels, over just relying on the correlated random
184 walk function.

185 2.4.3. *Within-trip decisions*

186 Fishing locations within a trip are determined by a modified random walk
187 process. A random walk type was chosen as it is the simplest assumption com-
188 monly used in ecology to describe animal movement which searching for ho-
189 mogeneously distributed prey about which there is uncertain knowledge. In a
190 random walk, movement is a stochastic process through a series of steps that
191 can either be equal in length or take some other functional form. The direction
192 of the random walk can be correlated, a characteristic known as 'persistence',
193 providing some overall location of directional movement (Codling et al., 2008)
194 or uncorrelated.

195

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

207

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,

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

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

213 The step function takes the form:

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

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

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

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

219 *2.4.4. Local population depletion*

220 Where several fishing vessels are exploiting the same fish population compe-
 221 tition is known to play an important role in local distribution of fishing effort
 222 (Gillis and Peterman, 1998). If several vessels are fishing on the same patch of
 223 fish, local depletion and interference will affect fishing location choice of the fleet
 224 as a whole (Rijnsdorp, 2000; Poos and Rijnsdorp, 2007). In order to account for
 225 this behaviour, the fishing sub-model operates spatially on a daily time-step so
 226 that for future days the biomass available to the fishery is reduced in the areas
 227 fished. The cumulative effect is to make heavily fished areas less attractive as
 228 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 3.1. Population parameterisation

238 We parameterised the simulation model for four populations with differing
239 habitat preference and temperature tolerances (Figures S1, S3, S4, S5, S6, S7),
240 population demographic and recruitment functions. In addition, each of the
241 populations has two defined spawning areas which result in the populations
242 moving towards these areas in given weeks (Figure S2) and population-specific
243 movement rates (Table 1). The realised movement of the populations for a num-
244 ber of weeks is shown in Figure S9 while the realised daily fishing mortality are
245 shown in Figure S10.

247 3.2. Fleet parameterisation

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

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

261 An example of the realised fleet movements for a single vessel during a single
262 trip are given in Figure S11, while Figure S12 shows multiple trips for a single
263 vessel, S13 the vessel movements for some trips overlaid on the value field, S14
264 shows fishing locations for an entire fleet of 20 vessels for a single trip, while

265 S15 shows an example of the step function realisation and turning angles from
266 the correlated random walk.

267 3.3. Survey settings

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

271 3.4. Simulation settings

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

278
279 We allow the simulation to run unrestricted for 5 years, and subsequently
280 close areas for the last 5 years of the simulation based on data (either derived
281 from the commercial catches, fisheries-independent survey or the 'real popu-
282 lation' - the underlying populations assumed to be known perfectly) used at
283 different spatial and temporal scales.

284
285 The following steps are undertaken to determine closures:

- 286 1. Extract data source
- 287 2. Aggregate according to resolution
- 288 3. Interpolate across entire area at desired resolution
- 289 4. Close top 5 % of areas

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

- 291 • **data types:** commercial logbook data, survey data and 'real population',

- 292 • **temporal resolutions:** weekly, monthly and yearly closures,
- 293 • **spatial resolutions:** 1 x 1 grid, 5 x 5 grid, 10 x 10 grid and 20 x 20 grid.

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

296 4. Results

297 The species distribution themselves

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

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

314
 315 Figure 3 shows the consequences of different temporal aggregations of the
 316 data, with 156 weekly (top), 36 monthly (middle) and 3 yearly (bottom) catch
 317 compositions across a 20 x 20 area.

318

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

332
 333 We implemented a spatial closure using the different data sources and spatial
 334 and temporal aggregations as outlined in the protocol in Section 3.4. We used
 335 this to assess the efficacy of a closure in reducing fishing mortality on species 1,
 336 given availability of data and its use at different resolutions in order to evaluate
 337 the trade-offs in data sources. Figure 4 shows the trend in fishing mortality
 338 for each species simulated (columns) given the data sources (rows), temporal
 339 aggregations (colour lines) and spatial aggregations (linestyles), while Figure 5
 340 shows the change in fishing mortality from before the closure (average F years
 341 2 - 4) to after the closure (average F years 8 - 10).

342
 343 For the closures based on 'real population' (bottom row), the most disag-
 344 gregated data (a weekly timescale and 1 x 1 resolution) was most effective,
 345 reducing fishing mortality on species 1 (left) by $\sim 60\%$. Next was the monthly
 346 closures ($< \sim 30\%$). The least effective were the yearly closures (blue lines)
 347 at all spatial resolutions, which resulted in increased fishing mortalities (> 30
 348 $\%$ - N.B. Note though, this is consistent with the increasing trends in F, which
 349 is probably more related to the fact that Fs hadn't stabilised in the simulation

350 from the fishing vessels "learning" the best locations - I will rerun the sims for
351 a longer time (20 - 30 years).

352

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

357

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

368

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

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

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

378 **5. Discussion**

379 **6. Conclusions**

380 **Appendices**

Table 1: Population dynamics and movement parameter setting

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

381 **Abbreviations**

382 Detail any unusual ones used.

Table 2: 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 $rate$	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

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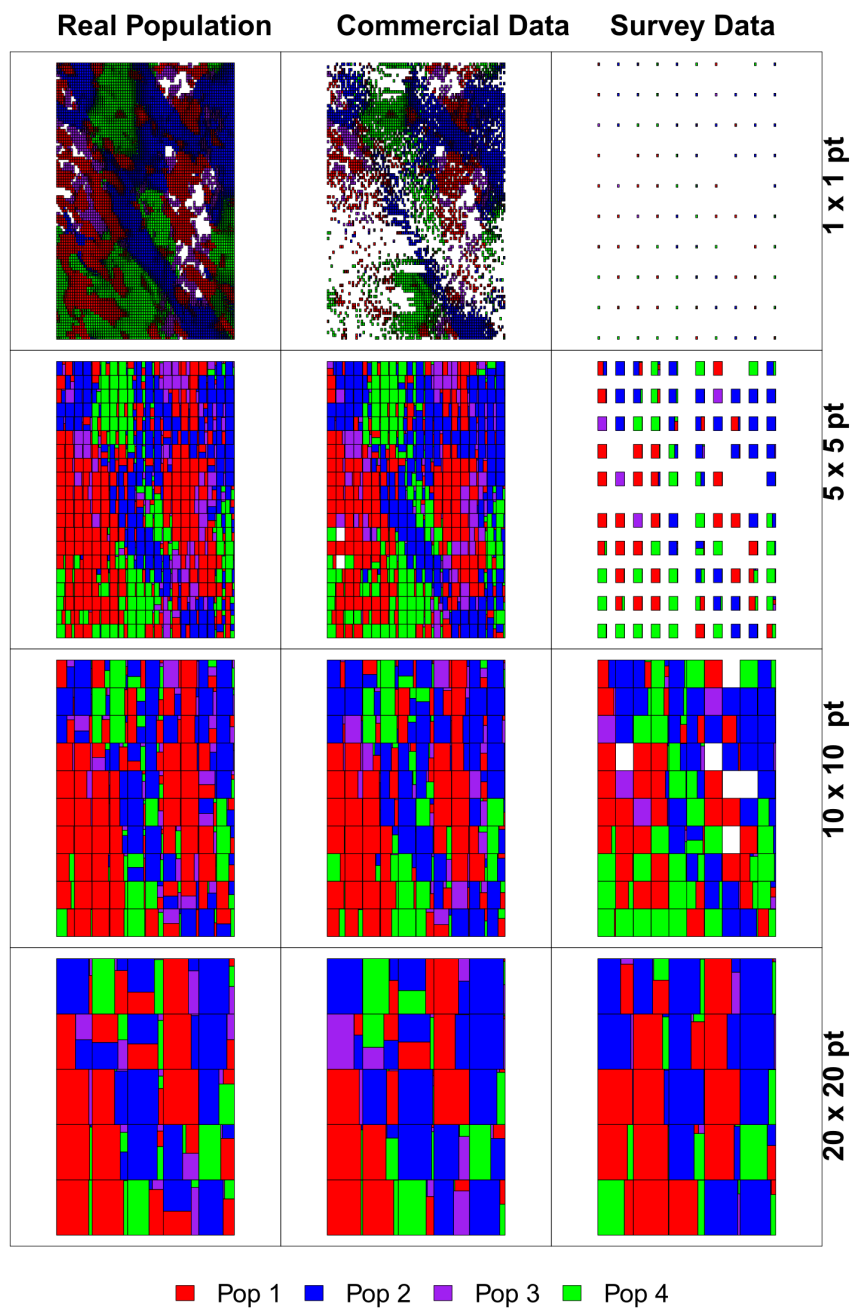


Figure 2: Data aggregation at different spatial resolutions

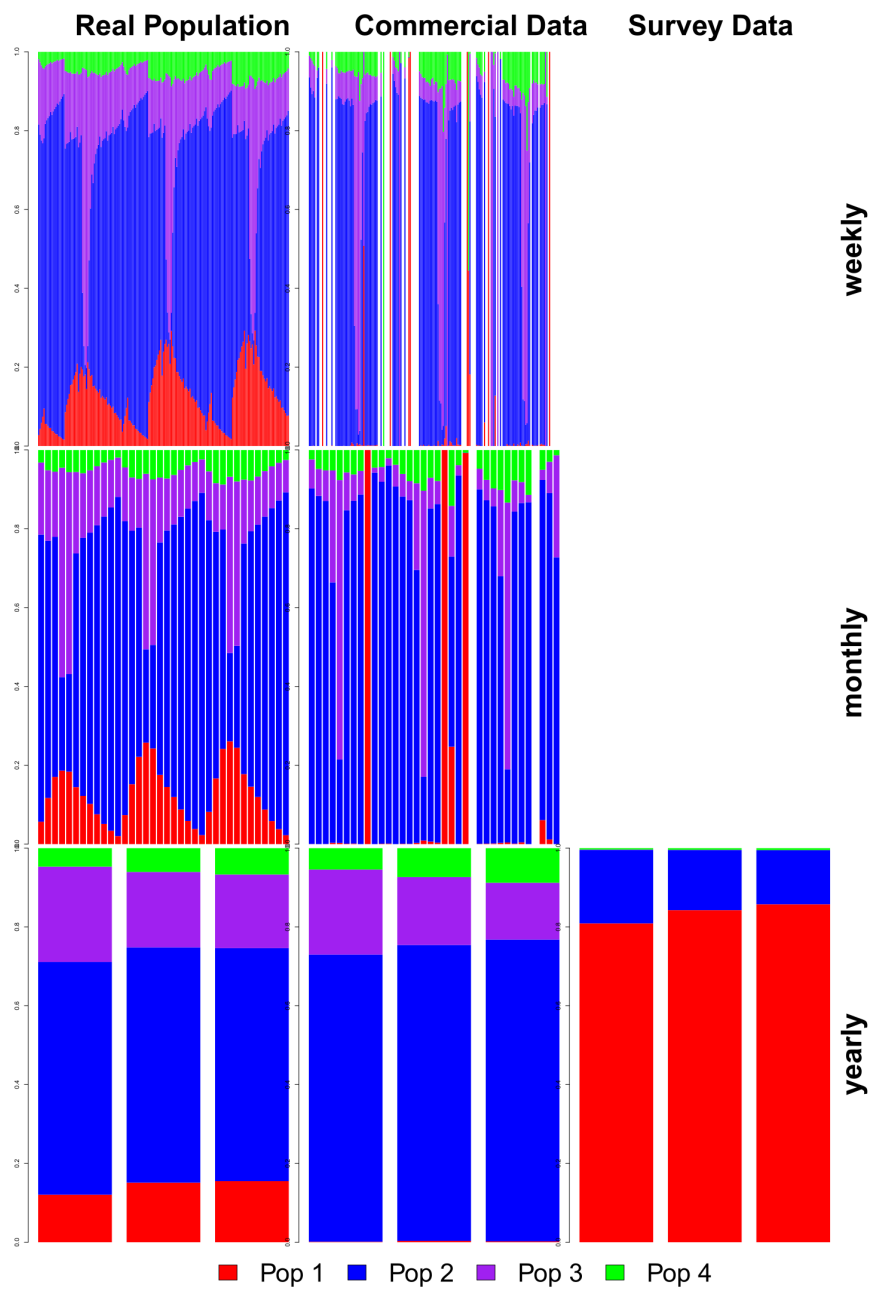


Figure 3: Data aggregation at different temporal resolutions

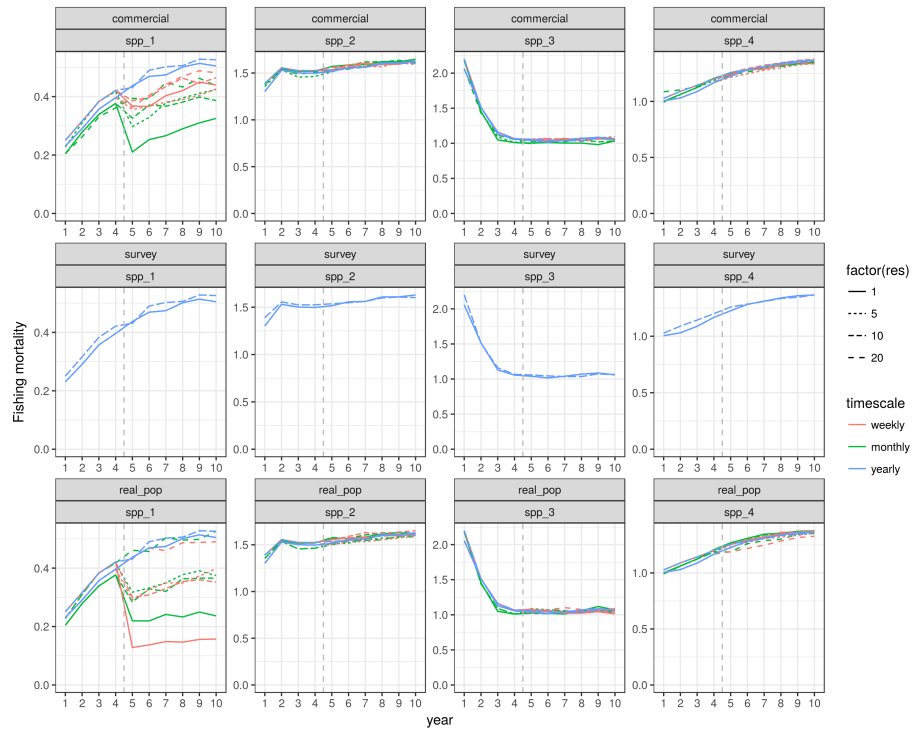


Figure 4: Comparison of closure scenarios - F trends

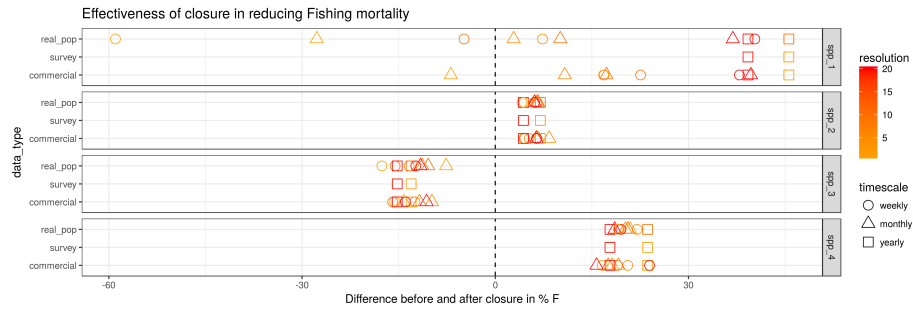


Figure 5: Comparison of closure scenarios

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