

MixFishSim: highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

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Abstract

Most fisheriesFishing^{JJ} exploits^{JJ} 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.

If fisheries are to avoid unwanted catchTo implement effective spatial measures to reduce discards^{PD} 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

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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 targeting via correlated random walk movement and learned behaviour.

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

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

[333 words]

Keywords: Some, keywords, here. Max 6

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1. Introduction

Fishers exploit fish populations that are heterogeneously distributed in space and time with varying knowledge of species distributions using species-unselective fishing gear. In doing so^{PD} fisheries ~~that~~^{PD} catch an assemblage of species

~~and~~^{PD}, ~~known as mixed fisheries~~ may, ~~when managed by single-species quotas~~
~~can end up~~^{JJ} ~~discarding~~^{JJ} overquota catch when managed by single species
 quotas,^{JJ} leading to overexploitation of fish populations (Ulrich et al., 2011; Bat-
 sleer et al., 2015)^{JJ}. This discarding of fish in excess of quota hampers the abil-
 ity to limit fishing mortality to within sustainable limits (Alverson et al., 1994;
 Crowder and Murawski, 1998; Rijnsdorp et al., 2007)^{JJ} ~~;~~ ~~reducing discarding~~
~~is crucial~~^{PD} to ensure biological and economic sustainability of fisheries ~~and~~
~~implementation of an ecosystem approach to fisheries~~^{JJ} ~~and.~~ ~~As such~~^{PD} there
 is increasing interest in technical solutions such as gear and spatial closures as
 ways of ~~reducing unwanted catch~~ ~~avoiding discarding of fish~~^{JJPD} (Kennelly and
 Broadhurst, 2002; Catchpole and Revill, 2008; Bellido et al., 2011).

Changes to spatial fishing patterns ~~have~~ ~~Use of spatial management as a~~
~~tools~~^{PD} been proposed as a method to reduce discards (Holmes et al., 2011;
 Little et al., 2014; Dunn et al., 2014)^{PD}. However, ~~its~~^{PD} implementation is
 hampered by lack of knowledge of fish and fishery spatiotemporal dynamics and
 understanding of the scale at which processes are important for management.
 Understanding the correct scale for spatial management is crucial in order to
 implement measures at a resolution that ensures effective management (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.

~~Identifying~~ ~~Ensuring measures are implemented at~~^{PD} an appropriate scale
 has been a challenge in the past that has led to ineffectual measures with unin-
 tended consequences such as limited impact towards the management objective
 or increased benthic impact on previously unexploited areas (e.g. the cod clo-
 sure in the North Sea (Rijnsdorp et al., 2001; Dinmore et al., 2003)). ~~MSince~~
~~then in~~^{PD} more refined spatial information has ~~since~~^{PD} 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)

36 and more real-time spatial management has been possible (e.g. Holmes et al.,
 37 2011). Such information is, however, patchy and derived from an inherently
 38 biased sampling programme (i.e. targeted fishing). ~~Further, fishers generally~~
 39 ~~only recorded landings (not catch) on a daily basis. This leads to questions~~
 40 ~~about the validity of inference that can be drawn from landings data assigned~~
 41 ~~to VMS activity pings.~~^{PD}

42
 43 In order to understand ~~the consequences of using~~challenges that face^{PD}
 44 VMS-linked landings to draw inference on the underlying population structure
 45 we develop a simulation model where population dynamics are highly-resolved
 46 in space and time. ~~Being and are~~^{PD} known ~~directly~~^{PD} rather than inferred from
 47 sampling or commercial catches, we can use the population model to evaluate
 48 how inference from fisheries-dependent and fisheries independent sampling re-
 49 lates to the real population structure^{PD}. In our model system ~~p~~^{PD}opulation
 50 movement is driven by random (diffusive) and directed (advective) processes and
 51 we incorporate characterisation of a number of different fisheries ~~dynamics~~^{PD}
 52 exploiting four fish populations with different spatial and population demo-
 53 graphics.

54
 55 Using our model we simulate ~~2040~~^{PD} years of exploitation of the fish popu-
 56 lations. ~~We and~~^{PD} use the results ~~from the fishing model:~~^{PD}

- 57 1. to understand how sampling-derived data reflects the underlying popula-
 58 tion structures. We compare at different spatial and temporal aggregations
 59 of data the real population to:
 - 60 (a) the inferred population from a stratified fixed-site sampling survey
 61 design commonly used for fisheries monitoring purposes, otherwise
 62 know as a fisheries-independent survey,
 - 63 (b) the inferred population from our fishery-dependent model which in-
 64 cludes fishery-induced sampling dynamics.

This comes as a surprise: I thought this was going to be about discards^{JJ} Agree, have removed this to avoid confusion^{PD}

2. to understand the impact of data aggregation and source on spatial fisheries management measures we simulate a fishery closure to protect a species based on different spatial and temporal data aggregations:

- (a) as if the real spatial population structure were known,
- (b) the fishery-independent inferred population structure
- (c) the fishery-dependent inferred population structure

We evaluate the theoretical "benefit" to the population of the closure(s), and effect on the other three populations. ~~Further, we extend our analysis to a range of spatial and temporal scales to assess the impact of these processes on the success of the management measure.~~^{PD}

2. Materials and Methods

~~A~~We developed and implemented a simulation model with a^{PD} modular event-based simulation model was developed with~~approach, where sub-~~^{PD}modules ~~are~~^{PD} implemented on independent time-scales appropriate to capture the characteristic of the ~~different processes~~^{PD} (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.^{PD}

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

If the paper has two goals this should be clear from the start, but may be better over 2 MSs^{JJ} I would like to keep both parts, but have made clearer in how its set out. The closure scenarios form validation of the data aggregation, rather than effectiveness of the closures themselves - so its a continuation of the same question in my eyes^{PD}

95 Here we describe each of the model components; 1) Population dynamics, 2)
 96 Recruitment dynamics, 3) Population movement dynamics, 4) fishery dynamics.^{PD}

97 2.1. Population dynamics

98 The basic population level processes are simulated using a modified two-
 99 stage Deriso-Schnute delay difference model (Deriso, 1980; Schnute, 1985; Dich-
 100 mont et al., 2003) occurring at a daily time-step. A daily time-step was cho-
 101 sen as to discretise continuous population processes on a biologically relevant
 102 and computationally tractable timescale.^{PD} Under the population dynamics
 103 module^{PD} Here,^{PD} population biomass growth and depletion for pre-recruits and
 104 fish^{PD} recruited fish^{PD} to the fishery^{PD} are modelled separately as a function
 105 of previous recruited biomass, intrinsic population growth and recruitment:

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

106 where ρ is Brody's coefficient, shown to be approximately equal to $\exp(-K)$,
 107 where K is the growth rate from a von bertalanffy logistic growth model (Schnute,
 108 1985). Wt_{R-1} is the weight of fish prior to recruitment, while Wt_R is the re-
 109 cruited weight. α_d represents the proportion of fish recruited during that day
 110 for the year, while $R_{c,\tilde{y}}$ is the annual recruits in cell c for year y .

111

112 Mortality $Z_{c,d}$ can be decomposed to natural mortality, $M_{c,d}$, and fishing
 113 mortality, $F_{c,d}$, where both $M_{c,d}$ and $F_{c,d}$ are instantaneous rates with $M_{c,d}$
 114 fixed and $F_{c,d}$ calculated by solving the Baranov catch equation (Hilborn and
 115 Walters, 1992) for $F_{c,d}$:

$$C_{c,d} = \frac{F_{c,d}}{F_{c,d} + M_{c,d}} * (1 - e^{-(F_{c,d} + M_{c,d})}) * B_{c,d}$$

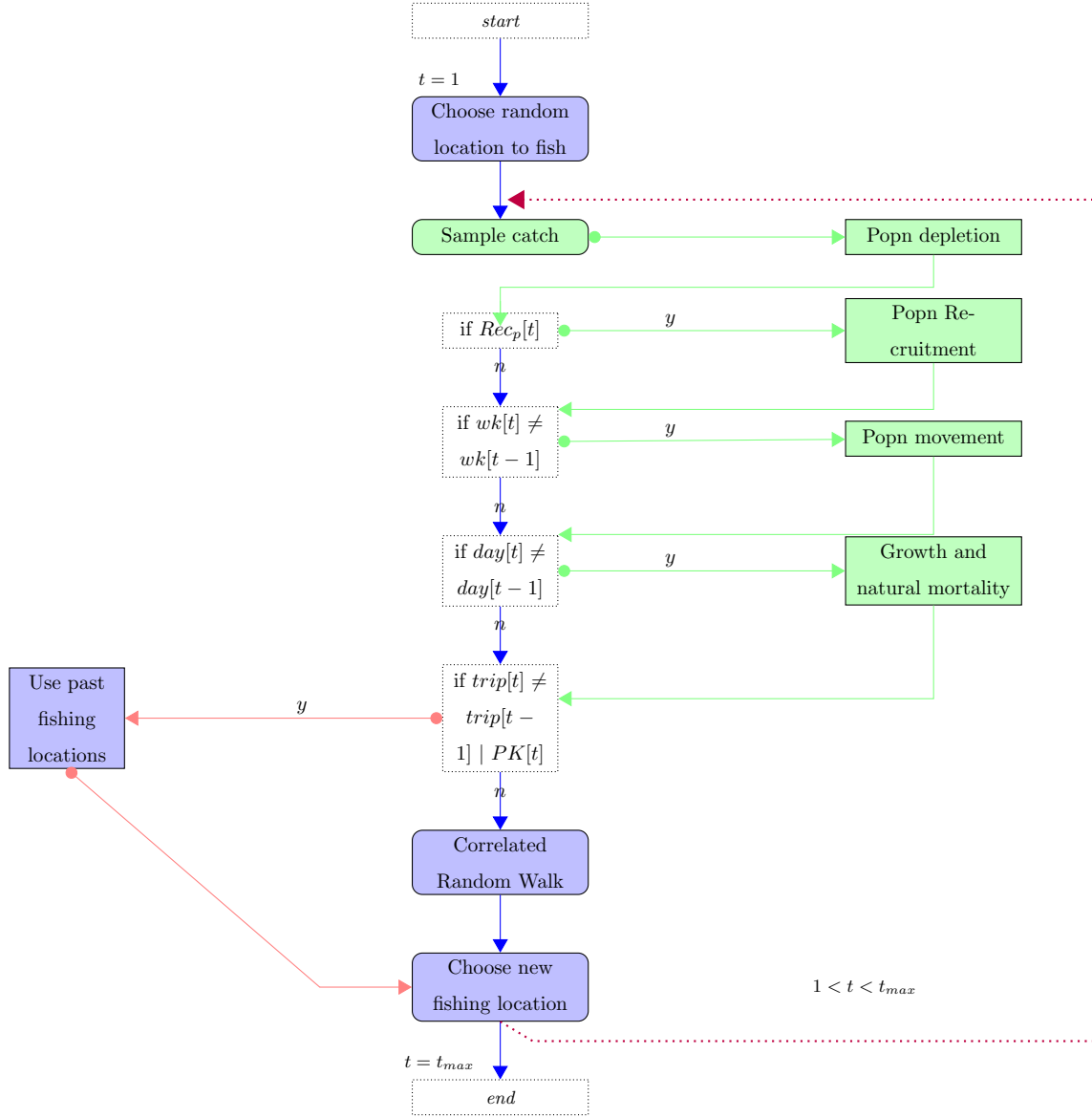


Figure 1: Overview Schematic of simulation model. The blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the timesteps at which processes occur; Rec is a recruitment period for population p , $t = tow$, $tmax$ is the total number of tows, wk is a weekly timestep, day is a day timestep, $trip$ is a trip time step.

116 where $C_{c,d}$ is the summed catch from the fishing model across all fleets and
 117 vessels in cell c for the population during the day d , and $B_{c,d}$ the daily biomass
 118 for the population in the cell.

120 2.2. Recruitment dynamics

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

$$\bar{R}_{c,d} = \frac{(\alpha * B_{c,d})}{(\beta + B_{c,d})}$$

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

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

127
 128 or a stochastic Ricker form (Ricker, 1954):

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

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

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

131 2.3. Population movement dynamics

132 To simulate ~~how~~^{JJ} fish populations ~~might be~~^{JJ} distributioned^{JJ} in space and
 133 time, ~~we employed~~^{JJ} a Gaussian spatial process ~~was employed~~^{JJ} to model habi-
 134 tat suitability for each of the populations. ~~An, with an~~^{JJ} advection-diffusion
 135 process ~~to~~^{JJ} controlled^{JJ} ~~how the~~^{JJ} populations^{JJ} movement^{JJ} over time with
 136 a moving temperature covariate to capture temporal dependencies. ~~This was~~

[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]CM

What have a temperature covariate? Could just use time^{JJ} Was intended as some biological meaning - species thermal tolerances load onto the temperature

intended to balance realism in population movement, capturing the main directed and random processes, and practicality of modelling the population rather than individual fish.^{JJ}

For the^{PD} habitat we defined^{PD} a Gaussian random field process, $\{S(c) : c \in \mathbb{R}^2\}$, that is a stochastic process^{PD} where for^{PD} 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).

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

The covariance structure affects the smoothness of the surfaces which the process generates; and^{PD} we used the Matérn family of^{PD} covariance structures^{PD}, as one where^{PD} 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)^{PD}. The Matérn covariance structure models the spatial autocorrelation observed with animal distributions (Tobler, 1970; F. Dormann et al., 2007)^{PD} and The Matérn correlation^{PD} is a two-parameter family where:

Introduce the gamma function, and why this covariance structure? Why correlate values in the random field?^{JM} to allow populations to have different aggregation densities; have tried to clarify^{PD}

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

$K_\kappa(\cdot)$ 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.

In the simulation model, the habitat for each of the populations was^{PD} generated with^{PD} 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^{PD} initialised at a single location, and subsequently moved^{PD} according to a probabilistic distribution based on habitat suitability, temperature and distance from current

167 cell:^{PD}

$$Pr(J|I) = \frac{e^{-\lambda * d_{IJ}} \cdot (Hab_{J,p}^2 \cdot Tol_{J,p,wk})}{\sum_{c=1}^C e^{-\lambda * d} \cdot (Hab_{c,p}^2 \cdot Tol_{c,p,wk})} \quad (1)$$

168 Where d_{IJ} is the euclidean distance between cell I and cell J , λ is a given
 169 rate of decay, $Hab_{J,p}^2$ is the squared index of habitat suitability for cell J and
 170 population p , with $Tol_{J,p,wk}$ the temperature tolerance for cell J by population
 171 p in week wk .

172

173 During specified weeks of the year, the habitat quality ^{was}is^{PD} modified for
 174 user-defined^{PD} spawning habitats^{PD}, resulting in ~~meaning~~^{PD} each population
 175 ~~had~~has^{PD} a concentrated area where spawning takes place and the population
 176 moved^{PD} towards these cell~~s~~his^{PD} in the weeks prior to spawning.

177

178 The temperature field ^{was}is^{PD} simulated to be on a gradient from a South-
 179 Westerly to North-Easterly direction, with temperature in each cell changing
 180 gradually on a week-by-week basis so that initially high temperature areas cy-
 181 cled^{PD} to lower temperatures and low temperature areas vice versa. Each pop-
 182 ulation p ~~wa~~i^{PD}s assigned a thermal tolerance with mean, μ_p^{PD} and variance,
 183 $\sigma_p^2^{\text{PD}}$ so that each cell and population temperature suitability is defined that:

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

184 Where $Tol_{c,p,wk}^{\text{PD}}$ is the tolerance of population p in cell c in week wk^{PD} ,
 185 $T_{c,wk}^{\text{PD}}$ is the temperature in the cell given the week^{PD} and μ_p^{PD} and $\sigma_p^2^{\text{PD}}$
 186 the mean and standard deviation of the population temperature tolerance.

187

188 The final process resulted in independent populations structure and move-
 189 ment patterns, with population movement occuring on a weekly basis. This
 190 process approximated the demographic shifts in fish populations throughout a
 191 year while maintaining seasonal patterns for spawning.^{PD}

What does
it mean con-
cisely? Areas
are assigned?^{JM}
Yes, the ar-
eas are pre-
defined - I have
amended to re-
flect and tried
to clarify.^{PD}

192 2.4. Fleet dynamics

193 The fleet dynamics can be broadly categorised into three components; fleet
194 targeting - which determined^{PD} the fleet catch efficiency and preference towards
195 a particular species; trip-level decisions, which determined^{PD} the initial location
196 to be fished at the beginning of a trip; and within-trip decisions, determining
197 movement from one fishing spot to another within a trip.

198 2.4.1. Fleet targeting

199 Each fleet of n vessels was^{PD} characterised by both a general efficiency, Q ,
200 and a population specific efficiency, Q_p . Thus, the product of these parameters
201 affected^{PD} the overall catch rates for the fleet and the preferential targeting of
202 one population over another. This, in combination with the parameter choice
203 for the step-function defined below^{PD} (as well as some randomness from the
204 exploratory fishing process) determined^{PD} the preference of fishing locations for
205 the fleet. All species prices were^{PD} kept the same, across fleets and seasons;
206 ~~though can be made to vary seasonally^{PD}.~~

207 2.4.2. Trip-level decisions

208 Several studies (e.g. Hutton et al., 2004; Tidd et al., 2012; Girardin et al.,
209 2015) have confirmed past activity and past catch rates are strong predictors
210 of fishing location choice. For this reason, the fleet dynamics sub-model in-
211 cluded^{PD} a learning component, where a vessel's initial fishing location in a
212 trip was^{PD} based on selecting from previously successful fishing locations. This
213 was^{PD} achieved by calculating expected profit from locations fished during^{PD}
214 previous fishing events in the previous trip as well as the previous time periods
215 in past years, and choosing randomly from the top 75 % of fishing events as de-
216 fined by the expected profit in value^{PD}. Expected profit was estimated from the
217 revenue from previous times fished at a location minus the fuel cost of travelling
218 to the location.^{PD} Simulation testing indicated that this learning increased the
219 mean value of catches for the vessels, over just relying on the correlated random
220 walk function as described for the 'within trip' decisions below^{PD}.

Correlated ran-
dom walk of
what^{JJ}

221 2.4.3. Within-trip decisions

222 Fishing locations within a trip are initially^{PD} determined by a modified ran-
 223 dom walk process. As the simulation progresses, the within-trip decision become
 224 gradually more influenced by past locations fished, based on the same process
 225 as the initial location, influenced by expected profit at a fishing location.^{PD} A
 226 random walk was chosen for the exploratory fishing process as it is the simplest
 227 assumption commonly used in ecology to describe optimal^{PD} animal movement
 228 which^{PD} search strategizing^{PD} for exploiting^{PD} homogeneously distributed prey
 229 about which there is uncertain knowledge (Viswanathan et al., 1999). In a ran-
 230 dom walk, movement is a stochastic process through a series of steps. These
 231 steps have a length, and a direction^{JJ} that can either be equal in length or take
 232 some other functional form. The direction of the random walk can be corre-
 233 lated, (known as ‘persistence’), providing some overall location-of^{PD} directional
 234 movement (Codling et al., 2008) or-uncorrelated^{PD}.

235
 236 A Lévy flight~~lévy-walk~~^{JJ} is a particular form of random walk characterised by
 237 a heavy-tailed distribution of step-length . The Lévy flight~~and~~^{JJ} has received a
 238 lot of attention in ecological theory in recent years as having shown to have very
 239 similar characteristics as those observed by animals in nature, and being a near
 240 optimum searching strategy for predators pursuing patchily distributed prey
 241 (Viswanathan et al., 1999; Bartumeus et al., 2005; Sims et al., 2008). Bertrand
 242 et al. (2007) showed that Peruvian anchovy fishermen have a stochastic search
 243 pattern similar to that observed with a lévy walk. However, it remains a subject
 244 of debate (e.g. see Edwards, 2011; Reynolds, 2015)^{PD}, with the contention that
 245 search patterns may be more simply characterised as random walks (Sakiyama
 246 and Gunji, 2013) with specific patterns related to the characteristics of the prey
 247 field (Sims et al., 2012).

248

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^{JJ} recent fishing success, measured as the summed value of fish caught (revenue, Rev),

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

249 where \underline{LC}^{PD}_p is landingseatch^{PD} of a population p , and Pr_p price of a popula-
 250 tion, to step distance. Here, when fishing is successful vessels remain in a similar
 251 location and continue to exploit the local fishing grounds. When unsuccessful,
 252 they move some distance away from the current fishing location. The movement
 253 distance retains some degree of stochasticity, which can be controlled separately.

254 The step function takes the form:

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

255
 256 So that, a step from (x1,y1) to (x2, y2) is defined by:

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

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

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

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

257 with k the concentration parameter from the von Mm^{JJ} ises distribution
 258 which we correlate with the revenue so that $k = (Rev + 1/RefRev) * max_k$,
 259 where max_k is the maximum concentration value, k , and RefRev is parame-
 260 terised as for β_3 in the step length function.

261 2.4.4. Local population depletion

262 Where several fishing vessels are exploiting the same fish population compe-
 263 tition is known to play an important role in local distribution of fishing effort

So step length increases with increasingly gross revenue?^{JJ} No, the opposite^{PD}

(Gillis and Peterman, 1998). If several vessels are fishing on the same patch of fish, local depletion and interference ~~competition~~^{JJ} will affect fishing location choice of the fleet as a whole (Rijnsdorp, 2000; Poos and Rijnsdorp, 2007). In order to account for this behaviour, the fishing sub-model operates spatially on a daily time-step so that for future days the biomass available to the fishery is reduced in the areas fished. The cumulative effect is to make heavily fished areas less attractive as future fishing opportunities.

2.5. Fisheries independent survey

A fisheries-independent survey is simulated where fishing on a regular grid begins each year at the same time for a given number of stations (a fixed station survey design). Catches of the populations ~~at each station~~^{JJ} are recorded but not removed from the population. This provides a fishery independent snapshot of the populations at a regular spatial ~~intervals~~^{JJ} each year, similar to scientific surveys undertaken by fisheries research agencies.

3. Calculation

3.1. Population parameterisation

We parameterised the simulation model for four populations with differing habitat preference, ~~and~~ temperature tolerances (Figures S1, S3, S4, S5, S6, S7), population demographic, ~~and~~ recruitment functions. In addition, each of the populations has two defined spawning areas which result in the populations moving towards these areas in given weeks (Figure S2) and population-specific movement rates (Table 4). The realised movement of the populations for a number of weeks is shown in Figure S9 while the realised daily fishing mortality are shown in Figure S10.

3.2. Fleet parameterisation

The fleets were parameterised to reflect five different characteristics based on targeting preference and exploitation dynamics (Table 5). ~~Setting a tar-~~

292 getting parameter (Q) that differed across fleets ensured different spatial dy-
 293 namics, due to preferential targeting of populations that differ in their spatial
 294 distributions. ~~This ensures that different fleets have different spatial dynamics,~~
 295 ~~preferentially targeted different fish populations~~^{PD}. The stochasticity in the
 296 random walk process ensures that different vessels within a fleet have slightly
 297 different spatial distributions based on individual experience, while the step
 298 function was parameterised dynamically so that vessels take smaller steps where
 299 the fishing location yields in a top quartile of the value available in that year
 300 (as defined per fleet in Table 5).

301

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

306 An example of the realised fleet movements for a single vessel during a single
 307 trip are given in Figure S11, while Figure S12 shows multiple trips for a single
 308 vessel, [Figure](#)^{PD} S13 the vessel movements for some trips overlaid on the value
 309 field, [Figure](#)^{PD} S14 shows fishing locations for an entire fleet of 20 vessels for
 310 a single trip, ~~and Figure~~^{PD} S15 shows an example of the step function
 311 realisation and turning angles from the correlated random walk.

312 3.3. Survey settings

313 The survey simulation was set up with follow a fixed gridded station design
 314 with 100 stations fished each year, starting on day 92 ~~and ending on day 112~~
 315 ~~(5 stations per day)~~^{PD} with same catchability parameters for all populations
 316 ($Q_p = 1$).

317 3.4. Simulation settings

318 To illustrate the capabilities on *MixFishSim*, we investigate the influence
 319 of the temporal and spatial resolution of different data sources on the reduc-
 320 tion in catches of a population given spatial closures. To do so, we first set up

Move some of
 the supple-
 mentary fig-
 ures to the
 manuscript^{JJ}

321 with simulation to run for 10 years based on a 100 X 100 square grid, with five
 322 fleets of 20 vessels each and four fish populations. Fishing takes place four times
 323 a day per vessel and five days a week, while population movement is every week.

324
 325 We allow the simulation to run unrestricted for 5 years, and subsequently
 326 close areas for the last 5 years of the simulation based on data (either derived
 327 from the commercial catches, fisheries-independent survey or the 'real popu-
 328 lation' - the underlying populations assumed to be known perfectly) used at
 329 different spatial and temporal scales.

330
 331 The following steps are undertaken to determine closures:

- 332 1. Extract data source
- 333 2. Aggregate according to resolution
- 334 3. Interpolate across entire area at desired resolution
- 335 4. Close top 5 % of areas

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

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

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

342 4. Results

343 The species distribution themselves

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

347

move to start
of methods
section^{JJ}I think
ecological mod-
elling wants
the 'calcu-
lations' sec-
tion here..will
check^{PD}

Is there equi-
librium after
5 years or still
some trend in
B^{JJ}Not at equi-
librium yet...I
need to rerun
until steady
state, looks
20 years. Will
update^{PD}

Procedure un-
clear. Refer
to symbols in
methods sec-
tion or switch
order starting
with description
of data type
etc..^{JJ}Yes, will
redo^{PD}

348 The finer spatial grid for the the real population (top left) and commercial
 349 data (top middle) show similar patterns, though there are unsampled gaps in
 350 the commercial data from a lack of fishing activity (particularly in the lower left
 351 part of the sampling domain). The survey data at this spatial resolution shows
 352 very sparse and uninformative information about the spatial distributions of the
 353 populations. The slightly aggregated data on a 5 x 5 grid shows similar patterns,
 354 and while losing some of the spatial detail there remains good consistency be-
 355 tween the 'real population' and the commercial data. Survey data starts to pick
 356 out some of the similar patterns as the other data sources, but lacks coverage.
 357 The spatial catch information on a 10 x 10 and 20 x 20 grid loses a signifi-
 358 cant amount of information about the spatial resolutions for all data sources,
 359 and some differences between the commercial and 'real population' data emerge.

360
 361 Figure 3 shows the consequences of different temporal aggregations of the
 362 data, with 156 weekly (top), 36 monthly (middle) and 3 yearly (bottom) catch
 363 compositions across a 20 x 20 area.

364
 365 As can be seen from the 'real population', the monthly aggregation captures
 366 the major patterns seen in the weekly data, albeit missing more subtle differ-
 367 ences. The yearly data results in a constant catch pattern due to the aggregation
 368 process (sometimes known as an aggregation bias). The commercial data on a
 369 weekly basis shows some of the same patterns as the 'real population', though
 370 the first species (in red) is less well represented and some weeks are missing
 371 catches from the area. The monthly data. The monthly data shows some con-
 372 sistency between the 'real population' and commercial data for species 2 - 4,
 373 though species 1 remains underrepresented. On an annual basis, interestingly
 374 the commercial data underrepresents the first species (in red) while the survey
 375 overrepresents species 1. This is likely due to the biases in commercial sampling,
 376 with the fisheries not targeting the areas where species 1 are present, and the
 377 biases in the survey sampling from overrepresentation of the spatial distribution.

378

379 We implemented a spatial closure using the different data sources and spatial
380 and temporal aggregations as outlined in the protocol in Section 3.4. We used
381 this to assess the efficacy of a closure in reducing fishing mortality on species 1,
382 given availability of data and its use at different resolutions in order to evaluate
383 the trade-offs in data sources. Figure 4 shows the trend in fishing mortality
384 for each species simulated (columns) given the data sources (rows), temporal
385 aggregations (colour lines) and spatial aggregations (linestyles), while Figure 5
386 shows the change in fishing mortality from before the closure (average F years
387 2 - 4) to after the closure (average F years 8 - 10).

388
389 For the closures based on 'real population' (bottom row), the most disag-
390 gregated data (a weekly timescale and 1 x 1 resolution) was most effective,
391 reducing fishing mortality on species 1 (left) by $\sim 60\%$. Next was the monthly
392 closures ($< \sim 30\%$). The least effective were the yearly closures (blue lines)
393 at all spatial resolutions, which resulted in increased fishing mortalities (> 30
394 $\%$ - N.B. Note though, this is consistent with the increasing trends in F, which
395 is probably more related to the fact that Fs hadn't stabilised in the simulation
396 from the fishing vessels "learning" the best locations - I will rerun the sims for
397 a longer time (20 - 30 years).

398
399 For the survey data, which can only be implemented on a yearly timescale,
400 the closures had no effect at any data resolution. The results are identical for
401 the different data resolutions except 20 x 20, which is why you can't see more
402 than 2 points. This is because of the sparsity of the sampling locations.

403
404 For the commercial data, the most effective closure scenario was based on 1
405 x 1 data at a monthly temporal resolution. This results in $\sim 10\%$ reduction
406 in F for species 1. This was the only closure scenario to have positive effect
407 according to Figure 5, though looking at the trend in Figure 4 this looks more
408 related to the continued increased in F trend, as other scenarios had an initial
409 effect. Interestingly the monthly data scenario was more effective than weekly

410 data, which I'd posit is due to the increase amount of data available from the
411 commercial sampling across a month compared to a week.i Commercial data
412 used at an annual timestep was ineffective in bringing fishing mortality down
413 for species 1.

414

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

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

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

424 **5. Discussion**

425 **6. Conclusions**

426 **Appendices**

427 **Abbreviations**

428 Detail any unusual ones used.

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Table 1: Description of variables for population dynamics sub-module

Variable	Meaning	Units
Population dynamics		
<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 ⁻¹
ρ	Brody's growth coefficient	yr ⁻¹
Wt_R	Weight of a fully recruited fish	kg
Wt_{R-1}	Weight of a pre-recruit fish	kg
α_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
Recruitment dynamics		
$\tilde{R}_{c,d}$	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}
α	the maximum recruitment rate	kg
β	the biomass required to produce half the maximum rate of recruitment	kg

Table 2: Description of variables for population movement sub-module

Variable	Meaning	Units
Population movement dynamics		
<i>Habitat model</i>		
a	b	c
<i>Thermal tolerance</i>		
$T_{c, wk}$	Temperature for cell in week	°C
μ_p	Mean of the thermal tolerance for population	°C
σ_p^2	Standard deviation of thermal tolerance for the population	°C
<i>Population movement model</i>		
λ	decay rate for population movement	-
$Hab_{c,p}^2$	Square of habitat suitability for cell c and population p	-
$Tol_{c,p, wk}$	Thermal tolerance for population p in cell c at week wk	-
d_{IJ}	euclidean distance between cell I and cell J	-

Table 3: Description of variables for fleet dynamics sub-module

Variable	Meaning	Units
Short-term fleet dynamics		
Rev	Revenue from fishing tow	€
L_p	Landings of population p	kg
Pr_p	Average price of population p	€ kg ⁻¹
StepL	Step length for vessel	euclidean distance
Br	Bearing	degrees
k	Concentration parameter for Von mises distribution	-
β_1	shape parameter for step function	-
β_2	shape parameter for step function	-
β_3	shape parameter for step function	-

Table 4: Population dynamics and movement parameter setting

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

Table 5: Fleet dynamics parameter setting

Parameter	Fleet 1	Fleet 2	Fleet 3	Fleet 4	Fleet 5
Targeting preferences					
Price Pop1	100	100	100	100	100
Price Pop2	200	200	200	200	200
Price Pop3	600	600	600	600	600
Price Pop4	1600	1600	1600	1600	1600
Q Pop1	0.01	0.02	0.02	0.01	0.01
Q Pop2	0.02	0.01	0.02	0.01	0.03
Q Pop3	0.01	0.02	0.02	0.01	0.02
Q Pop4	0.02	0.01	0.02	0.05	0.01
Exploitation dynamics					
step function β_1	1	2	1	2	3
step function β_2	10	10	8	12	7
step function β_3	Q90	Q90	Q85	Q90	Q80
step function $rate$	10	20	15	25	10
Past Knowledge	T	T	T	T	T
Past Year & Month	T	T	T	T	T
Past Trip	T	T	T	T	T
Threshold	0.75	0.75	0.75	0.75	0.75

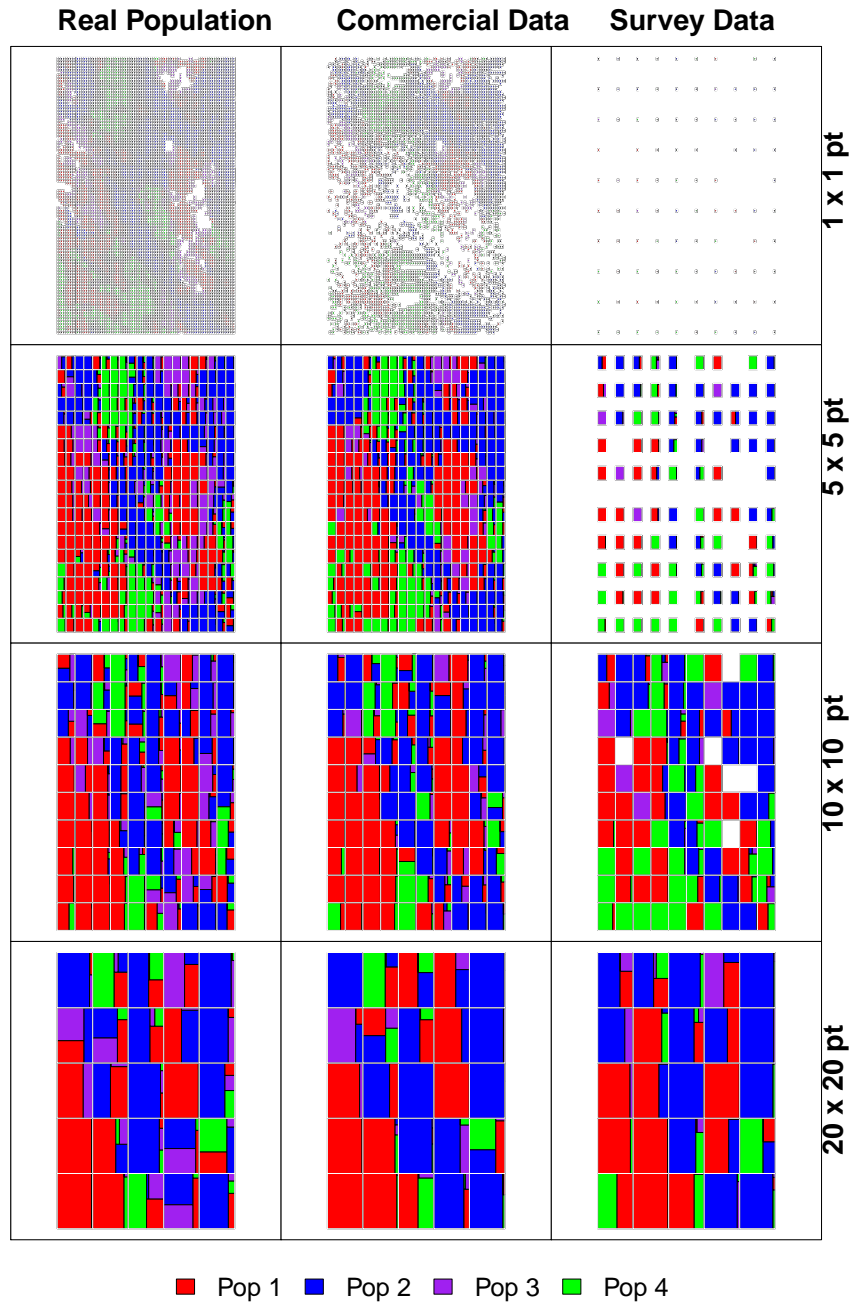


Figure 2: Data aggregation at different spatial resolutions

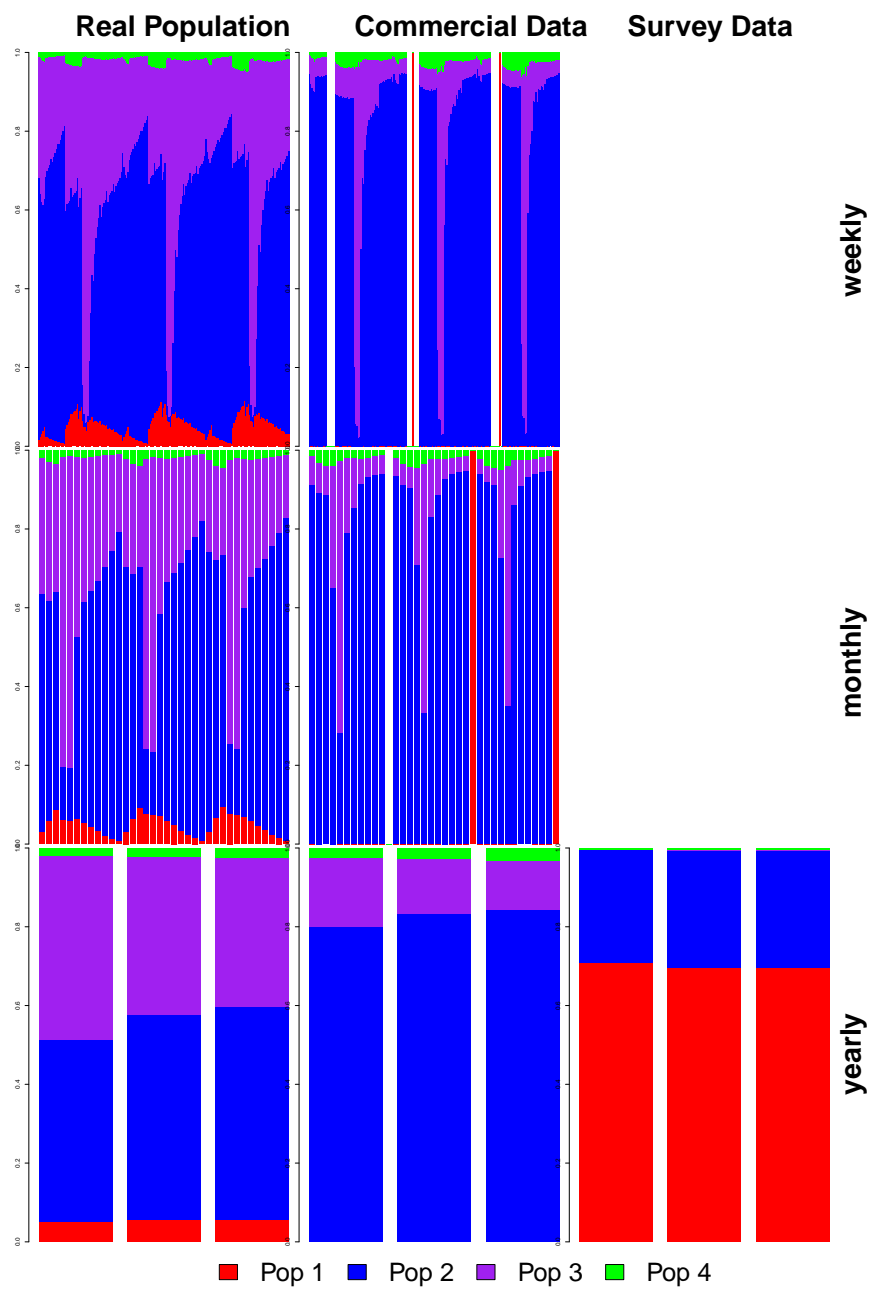


Figure 3: Data aggregation at different temporal resolutions

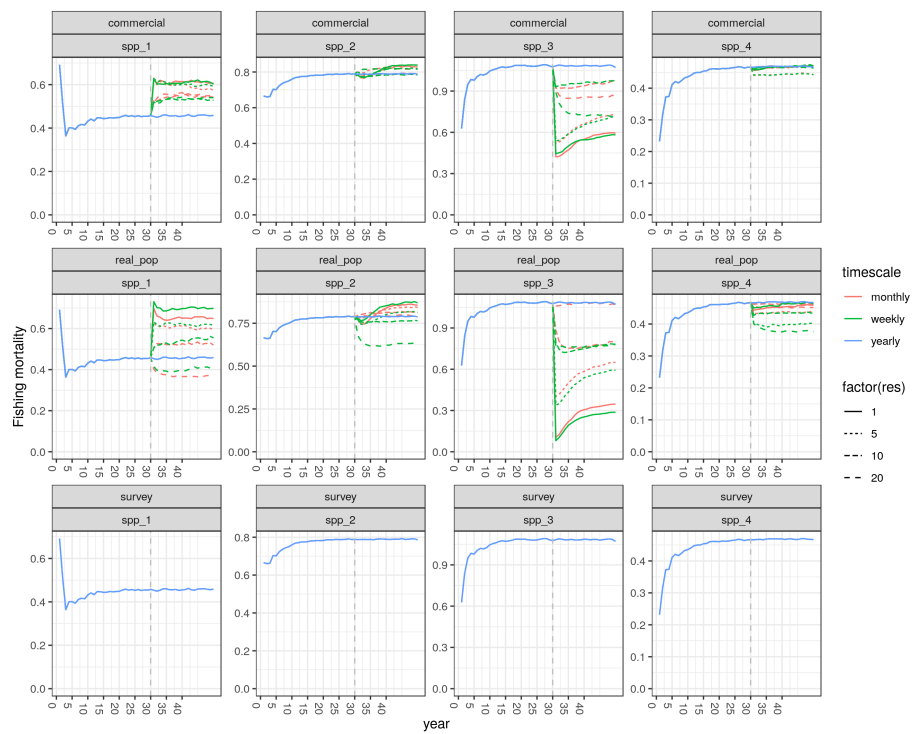


Figure 4: Comparison of closure scenarios - F trends

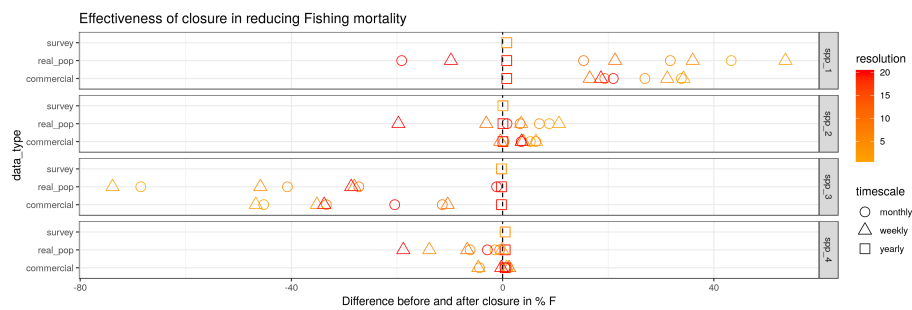


Figure 5: Comparison of closure scenarios

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