MixFishSim: highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

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Abstract

Most fisheries~~Fishing~~[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 catch~~To 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]

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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]~~ discard~~ing~~[JJ] overquota catch when managed by single species quotas,[JJ] leading to overexploitation of fish populations (Ulrich et al., 2011; Batsleer et al., 2015)[JJ]. This discarding of fish in excess of quota hampers the ability 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~~[JJ][PD](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 unintended consequences such as limited impact towards the management objective or increased benthic impact on previously unexploited areas (e.g. the cod closure in the North Sea (Rijnsdorp et al., 2001; Dinmore et al., 2003)). M~~Since then m~~[PD]ore 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)

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

In order to understand the consequences of using~~challenges that face~~[PD] VMS-linked landings to draw inference on the underlying population structure we develop a simulation model where population dynamics are highly-resolved in space and time. Being ~~and are~~[PD] known directly[PD] rather than inferred from sampling or commercial catches , we can use the population model to evaluate how inference from fisheries-dependent and fisheries independent sampling relates to the real population structure[PD]. In our model system p~~P~~[PD]opulation movement is driven by random (diffusive) and directed (advective) processes and we incorporate characterisation of a number of different fisheries dynamics[PD] exploiting four fish populations with different spatial and population demographics.

Using our model we simulate 20~~40~~[PD] years of exploitation of the fish populations. We ~~and~~[PD] use the results ~~from the fishing model:~~[PD]

1. to understand how sampling-derived data reflects the underlying population structures. We compare at different spatial and temporal aggregations of data the real population to:
   (a) the inferred population from a stratified fixed-site sampling survey design commonly used for fisheries monitoring purposes, otherwise know as a fisheries-independent survey,
   (b) the inferred population from our fishery-dependent model which includes 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]

66   2. to understand the impact of data aggregation and source on spatial fish-
67   eries management measures we simulate a fishery closure to protect a
68   species based on different spatial and temporal data aggregations:

69   (a) as if the real spatial population structure were known,

70   (b) the fishery-independent inferred population structure

71   (c) the fishery-dependent inferred population structure

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

76

2. Materials and Methods

78   ~~A~~We developed and implemented a simulation model with a[PD] modular
79   event-based simulation model was developed with~~approach, where~~ sub-[PD]modules
80   ~~are~~[PD] implemented on independent time-scales appropriate to capture the char-
81   acteristic of the different processes~~process modelled~~[PD] (Figure 1). The following
82   sub-modules were included to capture the full system: 1) Population dynamics,
83   2) Recruitment dynamics, 3) Population movement, 4) fishery dynamics.[PD]

84

85   ~~The fishing model operated on a tow-by-tow basis, while~~[PD] P~~p~~[PD]opulation
86   dynamics (fishing and natural mortality, growth) operate on a daily time-step,
87   while p~~. P~~[PD]opulation movement occurs on a weekly time-step. R~~, while~~
88   r~~[PD]~~ecruitment takes place~~occurs~~[PD] periodcally each year for a set time duration~~period~~
89   ~~(e.g. 3 weeks)~~[PD] at at specified point individual to a species~~.~~[PD], while the fish-
90   ing module operates on a tow-by-tow basis (i.e. multiple events a day)[PD]. The
91   simulation framework is implemented in the statistical software package R (R
92   Core Team, 2017) and~~;~~[PD] available as an R package from the authors github
93   (www.github.com/pdolder/MixFishSim).

94

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]

5

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 relevent
102 and computationally tractable timescale.[PD] Under the popualation dynamics
103 module~~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 $R_{c,y}$ 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.

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

2.2. Recruitment dynamics

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

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

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

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

or a stochastic Ricker form (Ricker, 1954):

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

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

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

2.3. Population movement dynamics

To simulate how[JJ] fish populations might be[JJ] distributioned[JJ] in space and time, we employed[JJ] a Gaussian spatial process was employed[JJ] to model habitat suitability for each of the populations. An, with an[JJ] advection-diffusion process to[JJ] controlled[JJ] how the[JJ] populations[JJ] movementd[JJ] over time with a moving temperature covariate to capture temporal dependencies. This was

8

137 ~~intended to balance realism in population movement, capturing the main directed~~
138 ~~and random processes, and practicality of modelling the population rather than~~
139 ~~individual fish.~~[JJ]

140

141 For ~~the~~[PD] habitat we defined[PD] a Gaussian random field process, $\{S(c) : c \in$
142 $\mathbb{R}^2\}$, ~~that is a stochastic process~~[PD] where for[PD] any set of cells $c_1, \ldots, c_n$ ~~where~~
143 ~~for each $c_i \in \mathbb{R}^2$~~[PD], the joint distribution of $S = \{S(c1), \ldots S(c_n)\}$ is multivari-
144 ate Gaussian. The distribution is specified by its *mean function,* $\mu(c) = E[S(c)]$
145 and its *covariance function,* $\gamma(c, c') = Cov\{S(c), S(c')\}$ (Diggle and Ribeiro,
146 2007).

147

148 The covariance structure affects the smoothness of the surfaces which the
149 process generates~~;, and~~[PD] we used the *Matérn* ~~family of~~[PD] covariance struc-
150 tures[PD], as~~one where~~[PD] the correlation strength weakens the further the dis-
151 tance apart ~~(i.e. the correlation between $S(x)$ and $S(x')$ decreases as the~~
152 ~~distance $u = \|x - x'\|$ increases)~~[PD]. The Matérn covariance structure models
153 the spatial autocorrelation observed with animal distributions (Tobler, 1970;
154 F. Dormann et al., 2007)[PD] and~~The *Matérn* correlation~~[PD] is a two-parameter
155 family where:

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

157 $K_{\kappa}(.)$ is a modified Bessel function of order κ, $\phi > 0$ is a scale parameter
158 with the dimensions of distance, and $\kappa > 0$, called the order, is a shape param-
159 eter which determines the smoothness of the underlying process.

160

161 ~~T~~~~In the simulation model, t~~[PD]he habitat for each of the populations wa~~s~~is[PD]
162 generated with~~through~~[PD] the *RFSimulate* function of the *RandomFields* R
163 package (Schlater et al., 2015), implementing different parameter settings to
164 affect the patchiness of the populations. Each population wa~~s~~is[PD] initialised at
165 a single location, and subsequently move~~ed~~s[PD] according to a probabilistic dis-
166 tribu[PD]tion based on habitat suitability, temperature and distance from current

167 cell:.[PD]

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

168 Where d_{IJ} is the euclidean distance between cell I and cell J, λ is a given
169 rate of decay, $Hab^2_{J,p}$ 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 habitat~~s~~[PD], resulting in~~meaning~~[PD] each population
175 had~~has~~[PD] a concentrated area where spawning takes place and the population
176 move~~ds~~[PD] towards these cells~~this~~[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 σ^2_p[PD] so that each cell and population temperature suitability is defined that:

$$Tol_{c,p,wk}\text{[PD]} = \frac{1}{\sqrt{(2\pi \cdot \sigma^2_p)}} \cdot \exp(-\frac{(T_{c,wk}\text{[PD]} - \mu_p)^2}{2 \cdot \sigma^2_p}) \quad (2)$$

184 Where $Tol_{c,p,wk}$[PD] is the tolerance of population p in cell c in week wk[PD],
185 $T_{c,wk}$[PD] is the temperature in the cell given the week[PD] and μ_p[PD] and σ^2_p[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]

2.4. Fleet dynamics

The fleet dynamics can be broadly categorised into three components; fleet targeting - which determineds[PD] the fleet catch efficiency and preference towards a particular species; trip-level decisions, which determined[PD] 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.

2.4.1. Fleet targeting

Each fleet of n vessels wasis[PD] characterised by both a general efficiency, Q, and a population specific efficiency, Q_p. Thus, the product of these parameters affectsed[PD] the overall catch rates for the fleet and the preferential targeting of one population over another. This, in combination with the parameter choice for the step-function defined below[PD] (as well as some randomness from the exploratory fishing process) determineds[PD] the preference of fishing locations for the fleet. All species prices wereare[PD] kept the same, across fleetsand seasons, though can be made to vary seasonally[PD].

2.4.2. Trip-level decisions

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

> Correlated random walk of what[JJ]

11

2.4.3. Within-trip decisions

Fishing locations within a trip are initially[PD] determined by a modified random walk process. As the simulation progresses, the within-trip decision become gradually more influenced by past locations fished, based on the same process as the initial location, influenced by expected profit at a fishing location.[PD] A random walk was chosen for the exploratory fishing process as it is the simplest assumption commonly used in ecology to describe optimal[PD] animal ~~movement which~~[PD] search ~~strategying~~[PD] for exploiting[PD] homogeneously distributed prey about which there is uncertain knowledge (Viswanathan et al., 1999). In a random walk, movement is a stochastic process through a series of steps. These steps have a length, and a direction[JJ] that can either be equal in length or take some other functional form. The direction of the random walk can be correlated, (known as 'persistence'), providing some overall ~~location of~~[PD] directional movement (Codling et al., 2008) ~~or uncorrelated~~[PD].

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

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),

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

249 where $L\underline{C}^{\text{PD}}{}_p$ is landings~~catch~~[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:

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

So step length increases with increasingly gross revenue?[JJ] No, the opposite[PD]

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

₂₆₄ (Gillis and Peterman, 1998). If several vessels are fishing on the same patch of
₂₆₅ fish, local depletion and interference competition[JJ] will affect fishing location
₂₆₆ choice of the fleet as a whole (Rijnsdorp, 2000; Poos and Rijnsdorp, 2007). In
₂₆₇ order to account for this behaviour, the fishing sub-model operates spatially on
₂₆₈ a daily time-step so that for future days the biomass available to the fishery
₂₆₉ is reduced in the areas fished. The cumulative effect is to make heavily fished
₂₇₀ areas less attractive as future fishing opportunities.

₂₇₁ *2.5. Fisheries independent survey*

₂₇₂ A fisheries-independent survey is simulated where fishing on a regular grid
₂₇₃ begins each year at the same time for a given number of stations (a fixed station
₂₇₄ survey design). Catches of the populations at each station~~present~~[JJ] are recorded
₂₇₅ but not removed from the population. This provides a fishery independent
₂₇₆ snapshot of the populations at a regular spatial intervals~~distribution~~[JJ] each
₂₇₇ year, similar to scientific surveys undertaken by fisheries research agencies.

₂₇₈ **3. Calculation**

₂₇₉ *3.1. Population parameterisation*

₂₈₀ We parameterised the simulation model for four populations with differing
₂₈₁ habitat preference,~~and~~ temperature tolerances (Figures S1, S3, S4, S5, S6, S7),
₂₈₂ population demographic,~~and~~ recruitment functions. In addition, each of the
₂₈₃ populations has two defined spawning areas which result in the populations
₂₈₄ moving towards these areas in given weeks (Figure S2) and population-specific
₂₈₅ movement rates (Table 4). The realised movement of the populations for a num-
₂₈₆ ber of weeks is shown in Figure S9 while the realised daily fishing mortality are
₂₈₇ shown in Figure S10.

₂₈₈

₂₈₉ *3.2. Fleet parameterisation*

₂₉₀ The fleets were parameterised to reflect five different characteristics based
₂₉₁ on targeting preference and exploitation dynamics (Table 5). Setting a tar-

14

geting parameter (Q) that differed across fleets ensured different spatial dynamics, due to preferential targeting of populations that differ in their spatial distributions~~This ensures that different fleets have different spatial dynamics, preferentially targeted different fish populations~~[PD]. The stochasticity in the random walk process ensures that different vessels within a fleet have slightly different spatial distributions based on individual experience, while the step function was parameterised dynamically so that vessels take smaller steps where the fishing location yields in a top quartile of the value available in that year (as defined per fleet in Table 5).

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

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

Move some of the supplementary figures to the manuscript[JJ]

3.3. Survey settings

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

3.4. Simulation settings

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

with simulation to run for 10 years based on a 100 X 100 square grid, with five

fleets of 20 vessels each and four fish populations. Fishing takes place four times

a day per vessel and five days a week, while population movement is every week.

We allow the simulation to run unrestricted for 5 years, and subsequently

close areas for the last 5 years of the simulation based on data (either derived

from the commercial catches, fisheries-independent survey or the 'real popu-

lation' - the underlying populations assumed to be known perfectly) used at

different spatial and temporal scales.

The following steps are undertaken to determine closures:

1. Extract data source

2. Aggregate according to resolution

3. Interpolate across entire area at desired resoltion

4. Close top 5 % of areas

In total 56 closure scenarios were run which represent combinations of

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

- **temporal resolutions:** weekly, monthly and yearly closures,

- **spatial resolutions:** 1 x 1 grid, 5 x 5 grid, 10 x 10 grid and 20 x 20 grid.

Survey closures were on an annual basis only, as this was the most temporally

resolved survey data available.

4. Results

The species distribution themselves

The consequences of different spatial aggregations of the data are shown in

Figure 2, which represents the aggregation of catch from each of the data sources

over a year at different spatial resolutions.

move to start of methods section[JJ]I think ecological modelling wants the 'calculations' section here..will check[PD]

Is there equilibrium after 5 years or still some trend in B[JJ]Not at equilibrium yet...I need to rerun until steady state, looks 20 years. Will update[PD]

Procedure unclear. Refer to symbols in methods section or switch order starting with description of data type etc..[JJ]Yes, will redo[PD]

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

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

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

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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).

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 ~ 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).

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.

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 ~ 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

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

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

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

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

5. Discussion

6. Conclusions

Appendices

Abbreviations

Detail any unusual ones used.

Acknowledgements

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

Variable	Meaning	Units
Population dynamics		
Delay-difference model		
$B_{c,d}$	Biomass in cell c and day d	kg
$Z_{c,d}$	Total mortality in cell c for day d	-
$R_{c,\tilde{y}}$	Annualy 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	-
Baranov catch equation		
$C_{c,d}$	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		
Habitat model		
a	b	c
Thermal tolerance		
$T_{c,wk}$	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
Population movement model		
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
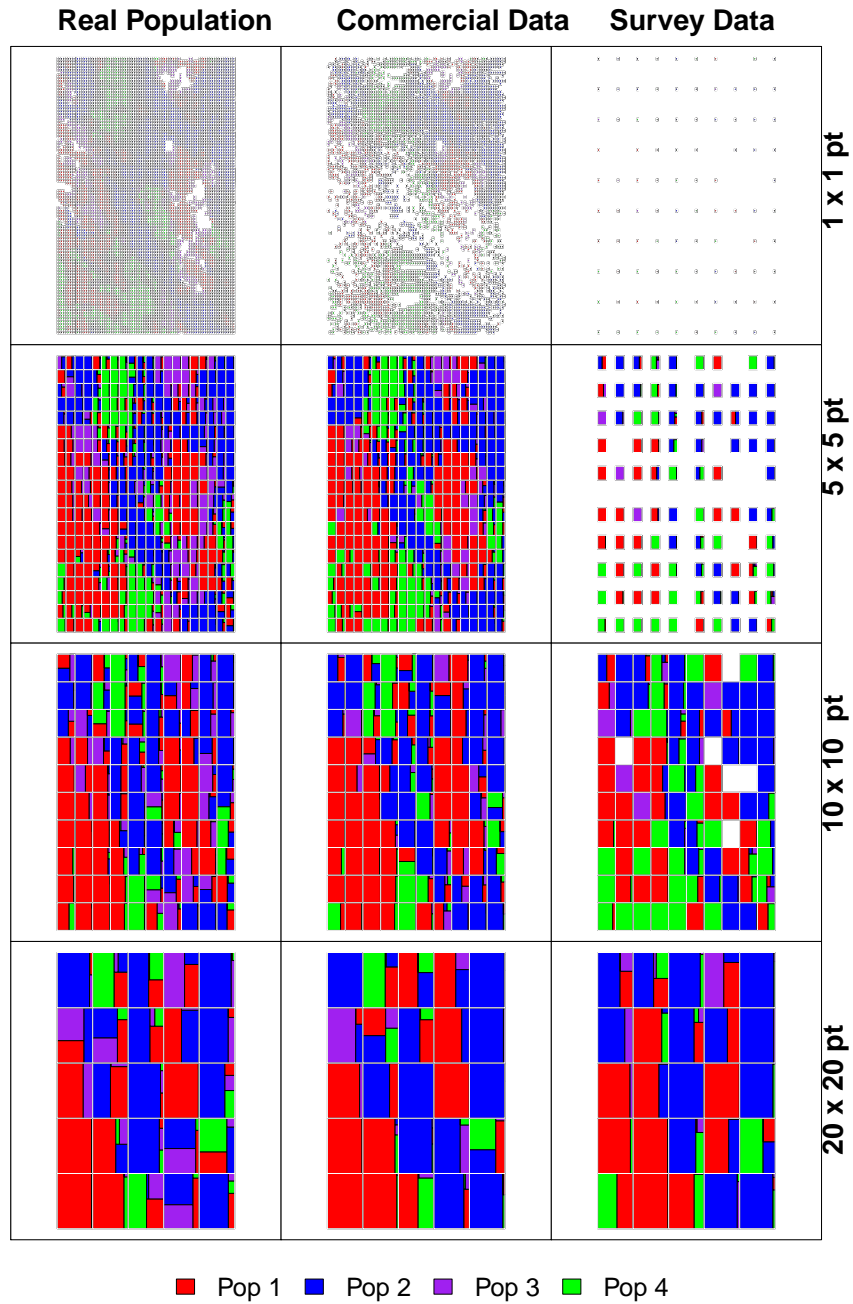
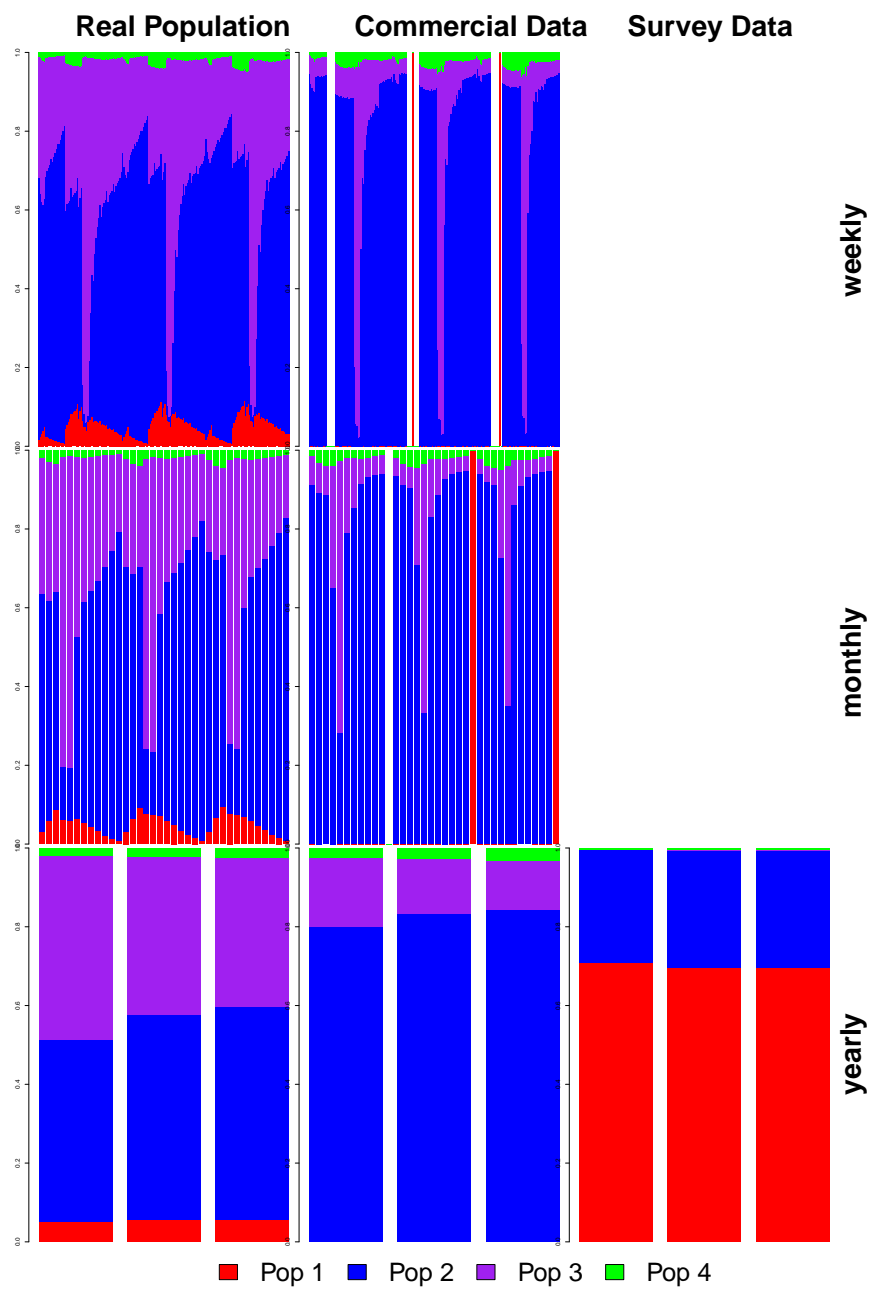Figure 2: Data aggregation at different spatial resolutions

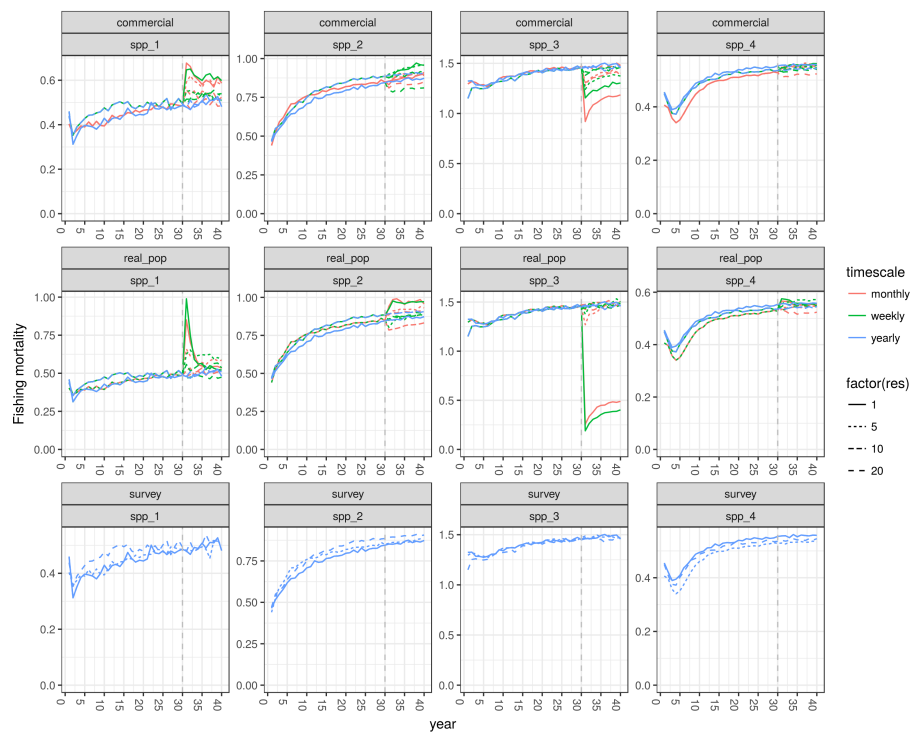Figure 3: Data aggregation at different temporal resolutions
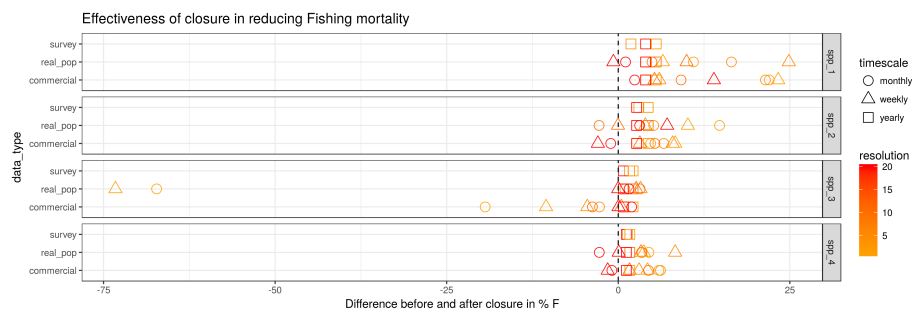
Figure 4: Comparison of closure scenarios - F trends

Figure 5: Comparison of closure scenarios

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