

Working title: Highly resolved spatiotemporal simulations for exploring mixed fishery dynamics

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Abstract

Most fisheries exploit a variety of spatially and temporally heterogeneous fish populations using species-unselective gear. This can result in unintended, unwanted catch of low quota or protected species and reducing these catches is crucial for biological and economic sustainability of ‘mixed fisheries’.

If fisheries are to avoid unwanted catch, an in-depth understanding of spatiotemporal fishery dynamics is required. However, traditional scientific advice is limited by a lack of highly resolved knowledge of population distributions and movement, and how fishers interact with different fish populations. Because data on fish location at high temporal and spatial resolutions is expensive and difficult to collect proxies are usually inferred from scientific surveys or commercial catches with limited spatial and temporal resolution.

To understand how data resolution impacts inference on mixed fisheries interactions, we developed a highly resolved spatiotemporal event-based 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 species targeting under an explore-exploit strategy. This is implemented via a mix of correlated random walk movement (for exploration) and

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learned behaviour (for exploitation) phases of the fisheries.

Fifty years of sub-daily fishing was simulated and used to draw inference on the underlying community structures. We compared inferences based on: commercial catch, a simulated fixed-site sampling survey design and the true underlying community. We i) establish the potential limitations of fishery-dependent data in providing a robust picture of spatiotemporal distributions; and then ii) simulated an area closure based on areas defined from the different data sources at a range of temporal and spatial resolutions.

Our framework allows users to explore the assumptions in modelling observational data and evaluate the underlying dynamics of such approaches at a fine spatial and temporal scale. We conclude from our example framework application that commercial data, while containing bias, provide a useful tool for managing catches in mixed fisheries if applied at the correct spatiotemporal scale. [NEED A LITTLE MORE DETAIL OF THE RESULTS HERE - 2 MORE SENTENCES ON KEY TAKE-HOME RESULTS]

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1. Introduction

Fishers exploit a variety of fish populations that are heterogeneously distributed in space and time, with varying knowledge of species distributions. In doing so fisheries catch an assemblage of species and may discard over-quota catch when managed by single species quotas and fishers exhaust one or more quota. This may lead to overexploitation of fish populations (Ulrich et al., 2011; Batsleer et al., 2015). Discarding of fish in excess of quota limits the ability to maintain fishing mortality within sustainable limits (Alverson et al., 1994; Crowder et al., 1998; Rijnsdorp et al., 2007) and the ability to manage for the biological and economic sustainability of fisheries. As such, there is increasing interest in technical solutions such as gear and spatial closures as measures to

12 reduce unwanted catch (Kennelly and Broadhurst, 2002; Catchpole and Reville,
13 2008; Bellido et al., 2011; Cosgrove et al., 2019).

14
15 Adaptive spatial management strategies have been proposed as a way of re-
16 ducing over-quota discards (Holmes et al., 2011; Little et al., 2014; Dunn et al.,
17 2014). However, implementation is restricted by lack of knowledge of fish and
18 fishery spatiotemporal dynamics and understanding of the scale at which pro-
19 cesses become important for management. Understanding the correct scale for
20 spatial measures is crucial for implementing effective solutions which minimising
21 economic impact (Dunn et al., 2016). For example, the problem can be to iden-
22 tify a scale that promotes species avoidance for vulnerable or low quota species
23 while allowing continuance of sustainable fisheries for available quota species.

24
25 Identifying appropriate spatial scales for fisheries closures has been a chal-
26 lenge in the past but is crucial to their success (Costello et al., 2010; Dunn
27 et al., 2016). Inference is hampered where spatial information is coarse due to
28 low resolution reporting of fisheries catch which is aggregated across larger grid-
29 ded areas (Branch et al., 2005). Further, if data does not allow identification of
30 spatial features it may lead to poorly sited closures which are ineffectual or have
31 unintended consequences. For example, increased benthic impact on previously
32 unexploited areas from the cod closure in the North Sea were observed without
33 the intended effect of reducing cod exploitation (Rijnsdorp et al., 2001; Dinmore
34 et al., 2003)). More refined spatiotemporal information has since become avail-
35 able through the combination of logbook and Vessel Monitoring System (VMS)
36 data (Lee et al., 2010; Bastardie et al., 2010; Gerritsen et al., 2012; Mateo et al.,
37 2016) and more real-time spatial management has been possible (e.g. Holmes
38 et al., 2011). However, fishers establish favoured fishing grounds through an
39 explore-exploit strategy (Bailey et al., 2018) where they search for areas with
40 high catches and then use experience to return to areas where they’ve experi-
41 enced high catch in the past. This leads to an inherently biased sampling where
42 target species are over-represented in the catch as fishers exploit areas of high

43 abundance.

44

45 To understand the effect of spatiotemporal aggregation of data and fishery
46 targeting we ask two fundamental questions regarding inference derived from
47 observational data:

- 48 1. How does sampling-derived fisheries data reflects the underlying commu-
49 nity structure?
- 50 2. How does data aggregation and source impact on spatial fisheries man-
51 agement measures?

52 To answer these questions we i) develop a simulation model where popula-
53 tion dynamics are highly-resolved in space and time by use of a Gaussian spatial
54 process to define suitable habitat for different populations. Precise locations of
55 the fish being known directly rather than inferred from sampling or commercial
56 catch, we can use the population model to validate how inference from fisheries-
57 dependent and fisheries independent sampling relates to the real community
58 structure in a way we could not with real data. We ii) compare, at different
59 spatial and temporal aggregations, the real (simulated) population distributions
60 to samples from fisheries-dependent and fisheries independent catches to test if
61 these are a true reflection of the relative density of the populations. We then
62 iii) simulate a fishery closure to protect a species based on different spatial and
63 temporal data aggregations.

64

65 We use these evaluations to draw inference on the utility of commercial data
66 in supporting management decisions.

67 2. Materials and Methods

68 An event-based simulation model of a hypothetical fishery was developed as
69 a software package (*MixFishSim*). The modular approach enabled efficient com-
70 putation by allowing for sub-modules implemented on time-scales appropriate

71 to capture the characteristic of the different processes (Figure 1). The following
 72 sub-modules were included to capture the full system: 1) Population dynamics,
 73 2) Recruitment dynamics, 3) Population movement, 4) fishery dynamics.

74

75 Population dynamics operate on a daily time-step, while population move-
 76 ment occurs on a weekly time-step, with the fishing module operating on a
 77 tow-by-tow basis (i.e. multiple events a day).

78 2.1. Population dynamics

79 The basic population level processes were simulated using a modified two-
 80 stage Deriso-Schnute delay difference model which models the fish populations in
 81 terms of aggregate biomass of recruits and mature components rather than keep-
 82 ing track of individuals (Deriso, 1980; Schnute, 1985; Dichmont et al., 2003). A
 83 daily time-step was chosen to discretise continuous population processes on a bi-
 84 ologically relevant and computationally tractable timescale. Population biomass
 85 growth was modelled as a function of previous recruited biomass, intrinsic pop-
 86 ulation growth and recruitment functionally linked to the adult population size.
 87 Biomass for each cell c was incremented each day d as follows (the full parameter
 88 list is detailed in Table 1):

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

89 where ρ is Brody's coefficient, shown to be equal to e^{-K} when K is the growth
 90 rate from a von Bertalanffy logistic growth model (Schnute, 1985). Wt_{R-1} is
 91 the average weight of fish prior to recruitment, while Wt_R is the average re-
 92 cruited weight. α_d represents the proportion of fish recruited during that day
 93 for the year, while $R_{c,\tilde{y}}$ is the annual recruits in cell c for year y .

94

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

$$C_{c,d} = \frac{F_{c,d}}{F_{c,d} + M_{c,d}} \cdot \left(1 - e^{-(F_{c,d} + M_{c,d})}\right) \cdot B_{c,d} \quad (2)$$

99 where $C_{c,d}$ is the summed catch from the fishing model across all fleets and
 100 vessels in cell c for the population during the day d , and $B_{c,d}$ the daily biomass
 101 for the population in the cell. Here, catch and fishing mortality are the sum of
 102 those across all fleets and vessels, where $F_{fl,v,c,d,p} = E_{fl,v,c,d} \cdot Q_{fl,p} \cdot D_{c,d,p}$ with
 103 fl , v and p the fleet, vessel and population respectively and E and Q fishing
 104 effort and catchability of the gear, and D is the density of the population at the
 105 location fished.

106

107 2.2. Recruitment dynamics

108 Recruitment is modelled through a function relating to adult biomass. In
 109 *MixFishSim*, it can be either as a stochastic Beverton-Holt stock-recruit form
 110 (Beverton and Holt, 1957):

$$\begin{aligned} \bar{R}_{c,d} &= \frac{(\alpha \cdot S_{c,d})}{(\beta + S_{c,d})} \\ R_{c,d} &\sim \log N[(\log(\bar{R}_{c,d}), \sigma^2)] \end{aligned} \quad (3)$$

111 Where α is the maximum recruitment rate, β the spawning stock biomass (SSB)
 112 required to produce half the maximum stock size, S current stock size and σ^2
 113 the variability in the recruitment due to stochastic processes, or a stochastic
 114 Ricker form (Ricker, 1954):

$$\begin{aligned} \bar{R}_{c,d} &= B_{c,d} \cdot e^{(\alpha - \beta \cdot B_{c,d})} \\ R_{c,d} &\sim \log N[(\log(\bar{R}_{c,d}), \log(\sigma^2))] \end{aligned} \quad (4)$$

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

117 2.3. Population movement dynamics

118 Population movement is a combination of random (diffusive) movement,
 119 governed by a stochastic process where movement between adjacent cells is
 120 described by a set of probabilities, and directed (advective) movement where
 121 at certain times of year the population moves towards spawning grounds by
 122 increasing the probabilities of moving into the spawning grounds from adjacent
 123 cells. We characterise a set of different fishing fleet dynamics exploiting four
 124 fish populations with different spatial and population demographics.

125
 126 To simulate fish population distribution in space and time a Gaussian spa-
 127 tial process was employed to model habitat suitability for each of the popula-
 128 tions on a 2d grid. We first defined a Gaussian random field process, $\{S(c) :$
 129 $c \in \mathbb{R}^2\}$, where for any set of cells c_1, \dots, c_n , the joint distribution of $S =$
 130 $\{S(c_1), \dots, S(c_n)\}$ is multivariate Gaussian with a *Matérn* covariance structure,
 131 where the correlation strength weakens with distance. This enables us to model
 132 the spatial autocorrelation observed in animal populations where density is more
 133 similar in nearby locations (Tobler, 1970; F. Dormann et al., 2007) and we
 134 change the parameters to implement different spatial structures for the differ-
 135 ent populations using the *RandomFields* R package (Schlatter et al., 2015). We
 136 define a stationary habitat field and combine with a temporally dynamic ther-
 137 mal tolerance field to imitate two key drivers of population dynamics. Each
 138 population was initialised at a single location, and subsequently moved accord-
 139 ing to a probabilistic distribution based on habitat suitability (represented by
 140 the normalised values from the GRFs), temperature and distance from current
 141 cell:

$$Pr(C_{wk+1} = J | C_{wk} = I) = \frac{e^{-\lambda * d_{IJ}} \cdot (Hab_{J,p}^2 \cdot Tol_{J,p,wk})}{\sum_{c=1}^C e^{-\lambda * d} \cdot (Hab_{c,p}^2 \cdot Tol_{c,p,wk})} \quad (5)$$

142 Where d_{IJ} is the euclidean distance between cell I and cell J , λ is a given rate
 143 of decay, $Hab_{J,p}^2$ is the squared index of habitat suitability for cell J and popu-
 144 lation p , with $Tol_{J,p,wk}$ the temperature tolerance for cell J by population p in

145 week wk (see below).

146

147 During pre-defined weeks of the year the habitat suitability is modified with
148 user-defined spawning habitat locations, resulting in each population having
149 concentrated areas where spawning takes place. In the simulations the popu-
150 lations move towards these cells in the weeks prior to spawning, resulting in
151 directional movement towards the spawning grounds.

152

153 An advection-diffusion process controls population movement, with a time-
154 varying temperature covariate used to change the interaction between time and
155 suitable habitat on a weekly time-step. Each population p was assigned a ther-
156 mal tolerance with mean, μ_p and variance, σ_p^2 so that each cell and population
157 temperature suitability is defined that:

$$Tol_{c,p,wk} = \frac{1}{\sqrt{(2\pi \cdot \sigma_p^2)}} \cdot \exp\left(-\frac{(T_{c,wk} - \mu_p)^2}{2 \cdot \sigma_p^2}\right) \quad (6)$$

158 Where $Tol_{c,p,wk}$ is the tolerance of population p for cell c in week wk , $T_{c,wk}$ is
159 the temperature in the cell given the week and μ_p and σ_p^2 the mean and standard
160 deviation of the population temperature tolerance.

161

162 The final combined process results in a population structure and movement
163 pattern unique to each species, with population movement occurring on a weekly
164 basis. The decision to model population movement on a weekly timescale was
165 to reflect that fish tend to aggregate in species specific locations that have
166 been observed to last around one to two weeks (Poos and Rijnsdorp, 2007b).
167 Therefore this process approximated the demographic shifts in fish populations
168 throughout a year with seasonal spawning patterns (Figure S5).

169 2.4. Fleet dynamics

170 Fleet dynamics can be broadly categorised into three components: fleet tar-
171 geting - that determined the fleet catch efficiency and preference towards a
172 particular species; trip-level decisions, that determines the initial location to

173 be fished at the beginning of a trip; and within-trip decisions, that determines
 174 movement from one fishing spot to another within a trip. Together, these ele-
 175 ments implement an explore-exploit type strategy for individual vessels to max-
 176 imise their catch from an unknown resource distribution (Bailey et al., 2018).
 177 The decision to use an individual based model for fishing vessels was taken
 178 because fishers are heterogeneous in their location choice behaviour due to dif-
 179 ferent objectives, risk preference and targeting preference (Van Putten et al.,
 180 2012). Therefore in the simulations fleet dynamics reflect individual experiences
 181 rather than pre-defined group dynamics.

182 *2.4.1. Fleet targeting*

183 Each fleet of n vessels was characterised by both a general efficiency, Q_{fl} ,
 184 and a population specific efficiency, $Q_{fl,p}$. Thus, the product of these param-
 185 eters $[Q_{fl} \cdot Q_{fl,p}]$ affects the overall catch rates for the fleet and the preferential
 186 targeting of one population over another. This, in combination with the param-
 187 eter choice for the step-function defined below (as well as some randomness from
 188 the exploratory fishing process) determined the preference of fishing locations
 189 for the fleet.

190 *2.4.2. Trip-level decisions*

191 Several studies (e.g. Hutton et al., 2004; Tidd et al., 2012; Girardin et al.,
 192 2015) have confirmed past activity and past catch rates are strong predictors of
 193 fishing location choice. For this reason, the fleet dynamics sub-model included a
 194 learning component, where a vessel's initial fishing location in a trip was based
 195 on selecting from previously successful fishing locations. This was achieved by
 196 calculating an expected revenue based on the catches from locations fished in
 197 the preceding trip as well as the same month periods in previous years and the
 198 travel costs from the port to the fishing grounds, and choosing randomly from
 199 the top 75 % of fishing events as defined by the expected profit, that has a
 200 seasonal component.

201 2.4.3. *Within-trip decisions*

202 Fishing locations within a trip are initially determined by a modified ran-
 203 dom walk process. As the simulation progresses the within-trip decision become
 204 gradually more influenced by experience gained from past fishing locations (as
 205 per the initial trip-level location choice), moving location choice towards areas
 206 of higher perceived profit. A random walk was chosen for the exploratory fishing
 207 process as it is the simplest assumption commonly used in ecology to describe
 208 optimal animal search strategy for exploiting heterogeneously distributed prey
 209 about which there is uncertain knowledge (Viswanathan et al., 1999). In a ran-
 210 dom walk, movement is a stochastic process through a series of steps. These
 211 steps have a length, and a direction that can either be equal in length or take
 212 some other functional form. The direction of the random walk was also cor-
 213 related (known as ‘persistence’) providing some overall directional movement
 214 (Codling et al., 2008).

215
 216 For our implementation of a random walk directional change is based on a
 217 negatively correlated circular distribution where a favourable fishing ground is
 218 likely to be “fished back over” by the vessel returning in the direction it came
 219 from. The step length (i.e. the distance travelled from the current to the next
 220 fishing location) is determined by relating recent fishing success, measured as
 221 the summed value of fish caught (revenue, Rev);

$$Rev = \sum_{p=1}^P L_p \cdot Pr_p \quad (7)$$

222 where L_p is landings of a population p , and Pr_p price of a population. All
 223 species prices were kept the same across fleets and seasons. Here, when fishing
 224 is successful vessels remain in a similar location and continue to exploit the local
 225 fishing grounds. When unsuccessful, they move some distance away from the
 226 current fishing location. The movement distance retains some degree of stochas-
 227 ticity, that can be controlled separately, but is determined by the relationship:

228

$$StepL = e^{\log(\beta_1) + \log(\beta_2) - \left(\log\left(\frac{\beta_1}{\beta_3}\right)\right)} \cdot Rev \quad (8)$$

229 Where β_1 , β_2 and β_3 are parameters determining the shape of the step function
 230 in its relation to revenue, so that, a step from (x1,y1) to (x2, y2) is defined by:

$$\begin{aligned} (x2, y2) = & x1 + L \cdot \cos\left(\frac{\pi \cdot Br}{180}\right), \\ & y1 + L \cdot \sin\left(\frac{\pi \cdot Br}{180}\right) \end{aligned} \quad (9)$$

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

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

231 where L is the step length, k the concentration parameter from the von Mises
 232 distribution that we correlate with the revenue so that $k = (Rev + 1/RefRev) *$
 233 max_k , where max_k is the maximum concentration value, k , and $RefRev$ is
 234 parametrised as for β_3 in the step length function. A realised example of the
 235 step length and turning angle relationships to revenue can be seen at Figure
 236 S12.

237 2.4.4. Local population depletion

238 Where several fishing vessels exploit the same fish population competition is
 239 known to play an important role in local distribution of fishing effort (Gillis and
 240 Peterman, 1998). If several vessels are fishing on the same patch of fish, local
 241 depletion and interference competition will affect fishing location choice of the
 242 fleet as a whole (Rijnsdorp, 2000; Poos and Rijnsdorp, 2007a). To account for
 243 this behaviour, the fishing sub-model operates spatially on a daily time-step so
 244 that for future days the biomass available to the fishery is reduced in the areas
 245 fished. The cumulative effect is to make heavily fished areas less attractive as a
 246 future fishing location choice as reduced catch rates will be experienced.

247 2.5. Fisheries independent survey

248 A fisheries-independent survey is simulated where fishing on a regular grid
 249 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 are recorded but not removed from the population (catches are assumed to have negligible impact on population dynamics). This provides a fishery independent snapshot of the populations at a regular spatial intervals each year, similar to scientific surveys undertaken by fisheries research agencies.

2.6. Software: R-package development

The simulation framework is implemented in the statistical software package R (R Core Team, 2017) and available as an R package from the author's github site (www.github.com/pdolder/MixFishSim).

3. Parameterisation

We parameterise *MixFishSim* to investigate the influence of data aggregation on spatial inference.

3.1. Population models

We parametrised the simulation model for four example populations with different demographics, growth rates, natural mortality and recruitment parameters (Table 4). Habitat preference (Figure S1) and temperature tolerances (Figures S3, S4) were defined to be unique to each population resulting in differently weekly distribution patterns (Figures S5-S7). In addition, each of the populations was assumed to have two defined spawning areas that result in the populations moving towards these areas in pre-defined weeks (Figure S2) with population-specific movement rates (Table 4). In such a configuration, the individual habitat preferences and thermal tolerances result in different spatial habitat use for each population (Figure 2) and consequently different seasonal exploitation patterns (Fishing mortality in Figure 3).

276 3.2. Fleet parametrisation

277 The fleets were parametrised to reflect five different characteristic fisheries
278 with unique exploitation dynamics (Table 5). By setting different catchability
279 parameters ($Q_{fl,p}$) we create different targeting preferences between the fleets
280 and hence spatial dynamics. The learned random walk process implies that
281 within a fleet different vessels have different spatial distributions based on indi-
282 vidual experience. The step function was parametrised dynamically within the
283 simulations as the maximum revenue obtainable was not known beforehand.
284 This was implemented so that vessels take smaller steps when fishing at a loca-
285 tion that yields landings value in the top 90th percentile of the value experienced
286 in that year so far (as defined per fleet in Table 5).

287

288 With increasing probability throughout the simulation, fishing locations were
289 chosen based on experience of profitable catches built up in the same month from
290 previous years and from the previous trip. 'Profitable' in this context was de-
291 fined as the locations where the top 70 % of expected profit would be found
292 given revenue from previous trips and cost of movement to the new fishing lo-
293 cation. This probability was based on a logistic sigmoid function with a lower
294 asymptote of 0 and upper asymptote of 0.95, and a growth rate that ensures
295 the upper asymptote (where decisions are mainly based on past knowledge) is
296 reached approximately halfway through the simulation.

297

298 3.3. Survey settings

299 The survey simulation was set up with a fixed gridded station design with
300 100 stations fished each year, starting on day 92 and ending on day 112 (5
301 stations per day) with same catchability parameters for all populations ($Q_p =$
302 1). This approximates a real world survey design with limited seasonal and
303 spatial coverage.

3.4. Example research question

To illustrate the capabilities of *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 set up a simulation to run for 50 years based on a 100×100 square grid (undetermined units), 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.

How does sampling-derived fisheries data reflect the underlying population structure?

To answer this question we compare different spatial and temporal aggregations of the real population distributions to:

- a) **fisheries-independent data:** the inferred population from a fixed-site sampling survey design as commonly used for fisheries monitoring purposes;
- b) **fisheries-dependent data:** the inferred population from our fleet model that includes fishery-induced sampling dynamics.

We allow the simulation to run unrestricted for 30 years, then implement spatial closed areas for the last 20 years of the simulation based on data (either derived from the commercial catches, fisheries-independent survey or the real population used at different spatial and temporal scales.

The following steps are undertaken to determine closures:

1. Extract data source (real population, commercial or survey),
2. Aggregate according to desired spatial and temporal resolution,

331 3. Interpolate across entire area at desired resolution using simple bivariate
 332 interpolation using the *interp* function from the R package akima (Akima,
 333 2006). This is intended to represent a naive spatial model of catch rates,
 334 without knowledge of the spatial population dynamics.

335 4. Close area covering top 5 % of catch rates

336 In total 28 closure scenarios were run that 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 • **closure basis:** highest 5 % of catch rates for the protected species

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

343 4. Results

344 4.1. Emergent simulation dynamics

It can be seen from a single vessels movements during a trip that the vessel exploits four different fishing grounds, three of them multiple times (Figure S9), while across several trips fishing grounds that are further apart are fished (Figure S10). These different locations relate to areas where the highest revenue were experienced, as shown by Figure 4, where several trips for the vessel overlaid on the revenue field, i.e.

$$\sum_{c=1}^c \sum_{s=1}^s B_{s,c} \cdot Q_{s,c}$$

345 Vessels from the same fleet (and therefore targeting preference) may exploit
 346 some shared and some different fishing grounds depending on their own personal
 347 experience during the exploratory phase of the fishery (Figure S11). This results
 348 from the randomness in the correlated random walk step function, with distance
 349 moved during the exploitation phase and the direction stochastically related to
 350 the revenue experienced on the fishing ground (Figure S12).

351 *4.2. How does sampling-derived fisheries data reflect the underlying population*
 352 *structure?*

353 Figure 5 shows the aggregated catch composition from each of the data
 354 sources over a ten-year period (to average seasonal patterns) at different spa-
 355 tial resolutions. The finer spatial grid for the real population (top left) and
 356 commercial data (top middle) show visually similar patterns, though there are
 357 large unsampled areas in the commercial data from a lack of fishing activity
 358 (particularly in the lower left part of the sampling domain). The survey data at
 359 this spatial resolution displays very sparse information about the spatial distri-
 360 butions of the populations. The slightly aggregated data on a 5 x 5 grid shows
 361 similar patterns and, while losing some of the spatial detail, there remains good
 362 consistency between the real population and the commercial data. Survey data
 363 starts to pick out some of the similar patterns as the other data sources, but
 364 lacks spatiotemporal coverage. The spatial catch information on a 10 x 10 and
 365 20 x 20 grid lose a significant amount of information about the spatial resolu-
 366 tions for all data sources, and some differences between the survey, commercial
 367 and real population data emerge.

368
 369 Figure 6 shows the consequences of different temporal aggregations of the
 370 data over a ten-year period, with weekly (top), monthly (middle) and yearly
 371 (bottom) catch compositions from across an aggregated 20 x 20 area. In the
 372 real population, the monthly aggregation captures the major patterns of com-
 373 position seen in the weekly data with the percentage of different species in the
 374 catch having similar mean and standard deviations. In the weekly data species
 375 1 = 9.36 (3.99), species 2 = 83.2 (5.60), species 3 = 3.57 (1.23), species 4 =
 376 3.91 (1.59); in the monthly data species 1 = 9.23 (3.87), species 2 = 83.3 (5.52),
 377 species 3 = 3.62 (1.15), species 4 = 3.86 (1.52). While means were similar some
 378 of the variation was lost when aggregated to an annual level; species 1 = 9.90
 379 (0.173), species 2 = 82.2 (0.308), species 3 = 3.82 (0.119), species 4 = 4.03
 380 (0.0502).

381

382 The commercial data on a weekly basis shows some of the same patterns
 383 as the real population, though the species 1 (in red) is less well represented
 384 and some weeks are missing catches from the area. Here, weekly and monthly
 385 compositions were nearly identical, with monthly composition of species 1 =
 386 0.0472 (0.0139), species 2 = 94.4 (1.47), species 3 = 3.12 (1.47), species 4 =
 387 2.40 (0.444). Again, yearly values head a similar mean but smaller standard
 388 deviation.

389
 390 The survey data was only available on an annual basis, and showed again
 391 a slightly different composition; species 1 = 0.372 (0.00473), species 2 = 87.7
 392 (0.193), species 3 = 0.729 (0.0200), species 4 = 11.2 (0.172).

393 *4.3. How does data aggregation and source impact on spatial fisheries manage-* 394 *ment measures?*

395 We implemented a spatial closure using the different data sources and spatial
 396 and temporal aggregations as outlined in the protocol in Section 3.4. We used
 397 this to assess the efficacy of a closure in reducing fishing mortality on species 3,
 398 given availability of data and its use at different resolutions in order to evaluate
 399 the trade-offs in data sources.

400 The trend in fishing mortality for each species show that in most cases the
 401 fishery closure was successful in reducing fishing mortality on the species of in-
 402 terest (species 3; Figure 7), though interestingly the largest reductions in fishing
 403 mortality happened immediately after the closures, following which the fisheries
 404 “adapted” to the closures and fishing mortality increased again somewhat. The
 405 exception to the success was the closures implemented based on the coarsest
 406 spatial (20 x 20) and temporal resolution (yearly) that was ineffective with all
 407 data sources. As expected, closures based on the “known” population distribu-
 408 tion were most effective, with differing degrees of success using the commercial
 409 data. Fishing mortality rates on the other species changed in different propor-
 410 tions, depending on whether the displaced fishing effort moved to areas where
 411 the populations were found in greater or lesser density.

412

413 A regression tree (using the R package REEMtree (Sela and Simonoff, 2012))
 414 highlights that the factor most contributing to differences in fishing mortality
 415 before and after the closure was the population (72 % showing that the closures
 416 were effective for population 3), followed by data resolution (21 %), data type
 417 (7 %) with the least important factor the timescale (< 1 %). In general the finer
 418 the spatial resolution of the data used the greater reduction in fishing mortality
 419 for population 3 after the closures (Figure 8). The notable outliers are the com-
 420 mercial data at the coarsest spatial resolution (20 x 20) at a yearly and weekly
 421 timescale, where closures were nearly as effective as the fine-scale resolution. In
 422 this case the closures were sufficiently large to protect a core area of the habitat
 423 for the population, but this was achieved in a fairly crude manner by closing a
 424 large area - including area where the species was not found (Figure 9) that may
 425 have consequences in terms of restricting the fishery in a much larger area than
 426 necessary.

427

428 5. Discussion

429 Our study presents a new highly resolved fisheries simulation framework,
 430 evaluates the importance of data scaling and considers potential bias introduced
 431 through data aggregation when using fisheries data to infer spatiotemporal dy-
 432 namics of fish populations. Understanding how fishers exploit multiple hetero-
 433 geneously distributed fish populations with different catch limits or conservation
 434 status requires detailed understanding of the overlap of resources; this is difficult
 435 to achieve using conventional modelling approaches due to species targeting in
 436 fisheries resulting in preferential sampling (Martínez-Minaya et al., 2018). Of-
 437 ten data are aggregated or extrapolated which requires assumptions about the
 438 spatial and temporal scale of processes. Our study explores the assumptions
 439 behind such aggregation and preferential sampling to identify potential impacts
 440 on management advice. With modern management approaches increasingly

employing more nuanced spatiotemporal approaches to maximise productivity while taking account of both the biological and human processes operating on different time-frames (Dunn et al., 2016), understanding assumptions behind the data used - increasingly a combination of logbook and positional information from vessel monitoring systems - is vital to ensure measures are effective.

5.1. *Simulation dynamics*

We employ a simulation approach to model each of the population and fishery dynamics in a hypothetical ‘mixed fishery’, allowing us to i) evaluate the consequences of different aggregation assumptions on our understanding of the spatiotemporal distribution of the underlying fish populations, and ii) evaluate the effectiveness of a spatial closure given those assumptions.

Our approach is unique in that it captures fine scale population and fishery dynamics and their interaction in a way not usually possible with real data and thus not usually considered in fisheries simulations. While other simulation frameworks seek to model individual vessel dynamics based on inferred dynamics from VMS and logbook records (Bastardie et al., 2010), or as a system to identify measures to meet particular management goals (Bailey et al., 2018), our framework allows users to explore the assumptions in modelling observational data and evaluate the underlying dynamics of such approaches at a fine spatial and temporal scale. This offers the advantage that larger scale fishery patterns are emergent properties of the system and results can be compared to those obtained under a statistical modelling framework.

Typically, simulation models that treat fish as individuals are focussed on exploring the inter- and intra- specific interactions among fish populations (e.g. OSMOSE Shin et al. (2004)) in order to understand how they vary over space and time. Our focus was on understanding the strengths and limitations of inference from catch data obtained through commercial fishing activity with

471 fleets exploiting multiple fish populations and realising catch distributions that
 472 may differ from the underlying populations. As such, we favoured a minimum
 473 realistic model of the fish populations (Plagányi et al., 2014) taking account of
 474 environmental but not demographic stochasticity, while incorporating detailed
 475 fishing dynamics that take account of different drivers in a mechanistic way.

476

477 Demographic stochasticity arises due to individual-level variability in time to
 478 reproduction and death. This form of stochasticity is often modelled by drawing
 479 random time intervals from a given distribution (Gillespie, 1977). The impact
 480 of demographic stochasticity depends on the population size, with the effects
 481 expected to decrease with increasing population size (Lande et al., 2010). This
 482 contrasts with environmental stochasticity, which affects all population sizes
 483 and is present at the population level in our model by variability in recruitment.

484

485 We take account of heterogeneity in fleet dynamics due to different prefer-
 486 ences and drivers similarly to other approaches (Fulton et al., 2011), but at an
 487 individual vessel rather than fleet level. We do not explicitly define fleets as
 488 rational profit maximisers at the outset, but consider there are several stages
 489 to development of the fishery; information gathering through search where the
 490 resource location is not known, followed by individual learnt behaviour of prof-
 491 itable locations. This provides a realistic model of how fishing patterns are
 492 established and maintained to exploit an uncertain resource through an explore-
 493 exploit strategy (Mangel and Clark, 1983; Bailey et al., 2018).

494 *5.2. How does sampling-derived fisheries data reflect the underlying population* 495 *structure?*

496 Our results demonstrate the importance of considering data scale and resolu-
 497 tion when using observational data to support management measures. We find
 498 that understanding of the community composition dynamics will depend on the
 499 level of data aggregation and its important to consider the scale of processes;
 500 including population movement rates, habitat uniformity and fishing targeting

501 practices if potential biases in data are to be understood and taken into account
502 (Figures X,Y,Z).

503

504 Our simulation shows that, despite biases introduced through the fishing
505 process, the commercially derived data could still inform on the key spatial
506 patterns in the community structures where the fisheries occurred, which was
507 spatially limited due to the “hotspots” of commercially valuable species being
508 fished. Similarly, despite the even spatial coverage the survey was able to cap-
509 ture some of the same spatial patterns as the real population, but missed others
510 due to gaps between survey stations limiting spatial and temporal coverage
511 (Figures X,Y,Z). This provides a challenge when modelling unsampled areas in
512 inferring species distribution maps, though these limitations may be overcome
513 by understanding the relationship between the species and habitat covariates
514 where these are known at unsampled locations (Robinson et al., 2011).

515

516 *5.3. How does data aggregation and source impact on spatial fisheries manage-* 517 *ment measures?*

518 From our simulations spatial disaggregation was more important than the
519 temporal disaggregation of the commercial data. This reflects the fact that there
520 was greater spatial heterogeneity over the spatial domain than experienced in
521 individual locations over the course of the year (Figure 2).

522

523 The yearly data assumes the same proportion of each population caught at
524 any time of the year due to the data aggregation. This assumption introduces
525 ‘aggregation bias’ as the data may only be representative of some point (or no
526 point) in time. The monthly data shows some consistency between the real
527 population and commercial data for species 2 - 4, though species 1 remains
528 under-represented. On an annual basis, interestingly the commercial data un-
529 der represents the first species (in red) while the survey over represents species
530 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 survey sampling areas where species 1 is more abundant than on average. This indicates that fixed closures, at the right resolution, when based on commercially derived data have the potential to reduced fishing mortality. The likely cost of poor spatial and temporal resolution is associated with reduced effectiveness and potentially closing fishing opportunities for other fisheries.

Two contrasting real world approaches in this respect were the spatial closures to protect cod in the North Sea. In one example, large scale spatial closures were implemented with little success due to effort displacement to previously unfished areas (Dinmore et al., 2003), while in another small scale targeted spatiotemporal closures were considered to have some effect in reducing cod mortality without having to disrupt other fisheries significantly (Needle and Catarino, 2011). These examples emphasise the importance of considering the right scale and aggregation of data when identifying area closures and the need to consider changing dynamics in the fisheries in response to such closures.

Our study showed that fishing rates on other populations also changed (both up and down) as a side-effect of closures to protect one species. This indicates the importance in considering fishing effort reallocation following spatial closures, and our simulation allows us to consider the spatiotemporal reasons for these changes.

5.4. Model assumptions and caveats

We model the population and fleet dynamic processes to draw inference on the importance of data scale and aggregation in understanding and managing mixed fisheries and their impact on multiple fish populations. In doing so, we have necessarily had to make a number of simplifying assumptions.

Fish populations in our simulations move in pre-defined timescales and according to fixed habitat preferences and temperature gradients (Figures S1, S3).

Our assumptions in parameterising the model (movement rates, temperature tolerances) will have a direct impact on our conclusions on the relative importance of spatial and temporal processes. These assumptions could be explored in a future study by varying the parameters and assessing the robustness of our conclusions. For our example application we have chosen movement rates to reflect aggregation periods observed in past studies (Poos and Rijnsdorp, 2007b).

In addition, we have assumed that fishing vessels are not restricted by quota and therefore discarding of species for which vessels have no quota or that are unwanted is not taken into account. This is likely to be a significant source of bias in any inference using commercial data and should also be explored. For example, *MixFishSim* could be altered to allow for spatiotemporal appraisal of the impact of discarding on fisher behaviour and underlying populations via inclusion as discarding behaviour, or through move-on rules or cessation of fishing activity when quota is exhausted.

5.5. Future applications of *MixFishSim*

We consider that the increased availability of high resolution catch and locational information from commercial fisheries will require it to be a key source of data for ensuring management is implemented at the right scale in future. For example, identifying hot-spots for bycatch reduction or identifying spatial overlaps in mixed fisheries (Dolder et al., 2018; Gardner et al., 2008; Little et al., 2014; Dedman et al., 2015; Ward et al., 2015). Our simulation model has the potential to test some of the assumptions behind the modelling approaches in identifying such hotspots and indeed behind spatiotemporal modelling in general (e.g. comparing GAMs, GLMMs, Random Forests and geostatistical models under different data generation processes as exemplified by Stock et al. (2019)).

Other novel applications of our framework could be: testing different survey designs given multiple species and data generating assumptions (Xu et al.,

2015); commercial index standardisation methods and approaches and understanding of appropriate scales and data aggregations and non-proportionality in catch rate and abundance (Harley et al., 2001; Maunder and Punt, 2004); exploring assumptions about the distribution of natural mortality and fishing mortality throughout the year and importance of capturing in-year dynamics in estimating stock status (Liu and Heino, 2013); at sea sampling scheme designs to deliver unbiased estimates of population parameters (Cotter and Pilling, 2007; Kimura and Somerton, 2006); adaptive management (Walters, 2007; Dunn et al., 2016); testing the ability of commonly employed fleet dynamics models such as Random Utility Models to capture fine scale dynamics and understand their importance (Girardin et al., 2016); and as a detailed operating model in a management strategy evaluation (Mahévas and Pelletier, 2004).

6. Conclusions

MixFishSim provides a detailed simulation framework to explore the interaction of multiple fisheries exploiting different fish populations. The framework enables users to evaluate assumptions in modelling commercially derived data through comparison to the true underlying dynamics at a fine spatial and temporal scale. Understanding these dynamics, the limitations of the data and any potential biases that may be introduced when making inference on spatiotemporal interactions will enable users to identify weaknesses in modelling approaches and identify where data collection is needed to strengthen inference.

Our application shows that inference on community dynamics may change depending on the scale of data aggregation. There is an important balance in ensuring that the data are sufficiently spatially and temporally disaggregated that the main features of the data are captured, yet maintaining enough data coverage that the features can be distinguished. We found in our application that there was greater spatial heterogeneity than temporal heterogeneity and

620 that when using aggregated data to define spatial closures coarser temporal reso-
621 lution (months instead of weeks) could still achieve the same results in reducing
622 exploitation rates of a vulnerable species at the highest temporal resolution
623 data. Conversely, reducing the spatial resolution had a negative effect on the
624 effectiveness of the measures (though importantly, there was still some benefit
625 even with coarse spatial resolution).

626

627 While any findings are likely to be case specific, our findings emphasise the
628 need to understand population demographics, habitat use and movement rates
629 in designing any closure scenario based on observational sampling. This infor-
630 mation can then be used to set the bounds on data aggregation used in modelling
631 studies aimed at informing the management measures.

632

633 *MixFishSim* has numerous potential additional applications as it enables
634 the user to apply methods to a fisheries system where there is detailed under-
635 standing of underlying spatiotemporal dynamics. This enables identification of
636 weaknesses or limitations which would not be possible otherwise. In future, we
637 recommend use of the framework to test hypothesis that are otherwise unable
638 to be analysed using real world data due to limitations of data collection. That
639 way the knowledge gained through simulation can inform the future design of
640 management measures.

641 **Abbreviations**

642 Detail any unusual ones used.

643 **Acknowledgements**

644 those providing help during the research..

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Appendices

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}
$S_{c,d}$	is the stock size in cell c for day d	d^{-1}
α	the maximum recruitment rate	kg
β	the stock size 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	1/0.015	1/0.05	1/0.01	1/0.005
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	0.1	0.1	0.1	0.1
Population dynamics				
Starting Biomass	1e5	2e5	1e5	1e4
Beverton-Holt Recruit 'a'	6	27	18	0.3
Beverton-Holt Recruit 'b'	4	4	11	0.5
Beverton-Holt Recruit σ^2	0.7	0.6	0.7	0.6
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	0.1	0.2	0.1
Movement dynamics				
μ	12	15	17	14
σ^2	8	9	7	10

Table 5: Fleet dynamics parameter setting

Parameter	Fleet	Fleet	Fleet	Fleet	Fleet
	1	2	3	4	5
Targeting preferences	pop	pop	-	pop 4	pop
	2/4	1/3			2/3
Price Pop1	100	100	100	100	100
Price Pop2	200	200	200	200	200
Price Pop3	350	350	350	350	350
Price Pop4	600	600	600	600	600
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	15	8	12	7
step function β_3	Q90	Q90	Q85	Q90	Q80
step function $rate$	20	30	25	35	20
Past Knowledge	T	T	T	T	T
Past Year & Month	T	T	T	T	T
Past Trip	T	T	T	T	T
Threshold	0.7	0.7	0.7	0.7	0.7
Fuel Cost	3	2	5	2	1

Table 6: Fishing mortality effects of the closure scenarios. Results show the fishing mortality before the closure (f.before) and after the closure (f.after) and the percentage change in f (f.change). The results are ordered by most effective scenario first, least effective last.)

scenario	metric	pop	f.before	f.after	f.change	timescale	basis	data_type	resolution
9	F	spp_3	1.08	0.29	-73.47	weekly	high_pop	real_pop	1.00
10	F	spp_3	1.08	0.29	-72.94	monthly	high_pop	real_pop	1.00
11	F	spp_3	1.08	0.35	-68.04	yearly	high_pop	real_pop	1.00
45	F	spp_3	1.08	0.58	-46.70	yearly	high_pop	commercial	20.00
1	F	spp_3	1.08	0.58	-46.21	weekly	high_pop	commercial	1.00
23	F	spp_3	1.08	0.59	-45.27	weekly	high_pop	real_pop	5.00
2	F	spp_3	1.08	0.59	-45.06	monthly	high_pop	commercial	1.00
7	F	spp_3	1.08	0.60	-44.48	yearly	high_pop	survey	1.00
24	F	spp_3	1.08	0.61	-43.20	monthly	high_pop	real_pop	5.00
3	F	spp_3	1.08	0.64	-40.82	yearly	high_pop	commercial	1.00
25	F	spp_3	1.08	0.65	-39.94	yearly	high_pop	real_pop	5.00
17	F	spp_3	1.08	0.67	-38.11	yearly	high_pop	commercial	5.00
15	F	spp_3	1.08	0.71	-34.38	weekly	high_pop	commercial	5.00
43	F	spp_3	1.08	0.71	-34.31	weekly	high_pop	commercial	20.00
16	F	spp_3	1.08	0.73	-32.58	monthly	high_pop	commercial	5.00
51	F	spp_3	1.08	0.78	-27.92	weekly	high_pop	real_pop	20.00
37	F	spp_3	1.08	0.78	-27.76	weekly	high_pop	real_pop	10.00
39	F	spp_3	1.08	0.79	-26.98	yearly	high_pop	real_pop	10.00
38	F	spp_3	1.08	0.81	-25.47	monthly	high_pop	real_pop	10.00
21	F	spp_3	1.08	0.81	-25.21	yearly	high_pop	survey	5.00
35	F	spp_3	1.08	0.81	-25.05	yearly	high_pop	survey	10.00
44	F	spp_3	1.08	0.87	-19.91	monthly	high_pop	commercial	20.00
52	F	spp_3	1.08	0.88	-18.39	monthly	high_pop	real_pop	20.00
30	F	spp_3	1.08	0.96	-11.06	monthly	high_pop	commercial	10.00
29	F	spp_3	1.08	0.98	-9.80	weekly	high_pop	commercial	10.00
31	F	spp_3	1.08	1.03	-4.36	yearly	high_pop	commercial	10.00
53	F	spp_3	1.08	1.06	-1.64	yearly	high_pop	real_pop	20.00
49	F	spp_3	1.08	1.07	-1.01	yearly	high_pop	survey	20.00

Table 7: Proportions of each species at different levels of temporal aggregation

data_type	timescale	spp1	sd_spp1	spp2	sd_spp2	spp3	sd_spp3	spp4	sd_spp4
commercial	monthly	0.047	0.014	94.435	1.470	3.122	1.468	2.396	0.444
commercial	weekly	0.047	0.016	94.426	1.514	3.117	1.563	2.411	0.498
commercial	yearly	0.051	0.001	94.388	0.205	3.021	0.175	2.539	0.046
real_pop	monthly	9.225	3.872	83.287	5.522	3.624	1.151	3.864	1.519
real_pop	weekly	9.358	3.992	83.165	5.596	3.567	1.233	3.910	1.592
real_pop	yearly	9.899	0.173	82.250	0.308	3.821	0.119	4.031	0.050
survey	yearly	0.372	0.005	87.667	0.193	0.729	0.020	11.232	0.172



Figure 1: Schematic overview of the simulation model. Blue boxes indicate fleet dynamics processes, the green boxes population dynamics processes while the white boxes are the time steps at which processes occur; $t = \text{tow}$, t_{max} is the total number of tows; (Rec), (Pop Movement), (Pop Dynamics) logic gates for recruitment periods, population movement and population dynamics for each of the populations, (Past Knowledge) a switch whether to use a random (exploratory) or past knowledge (exploitation) fishing strategy.

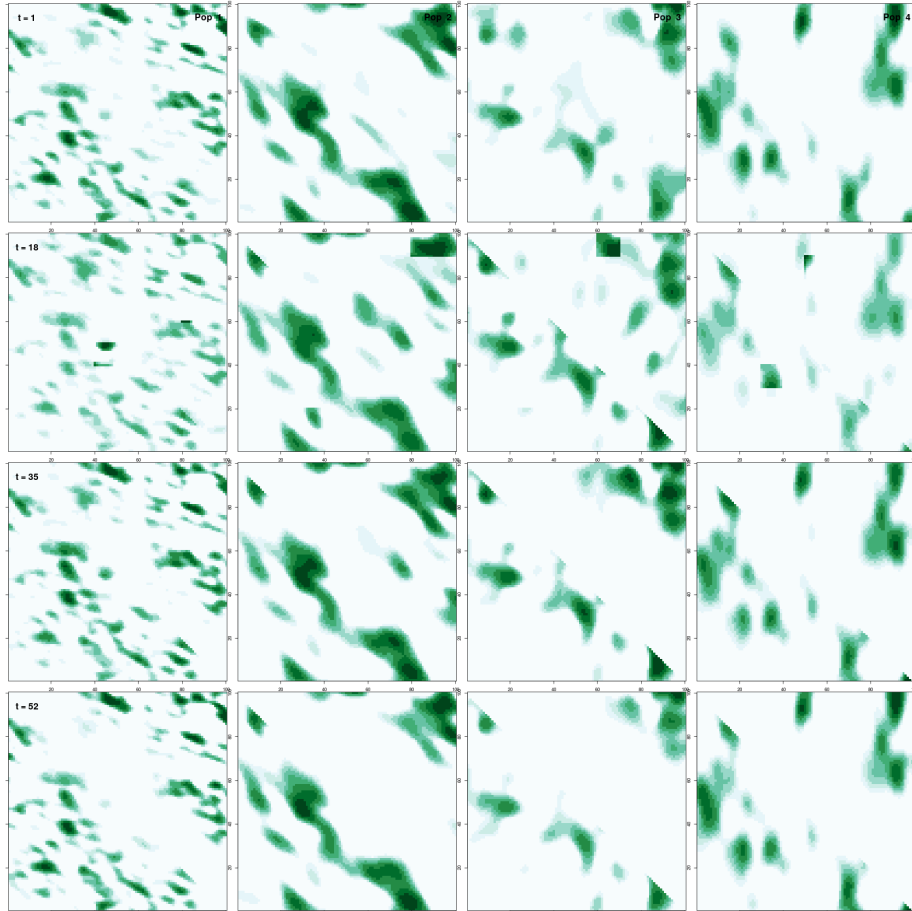


Figure 2: Simulated spatial dynamics - the four populations abundance ($\log+1$) at four time steps.

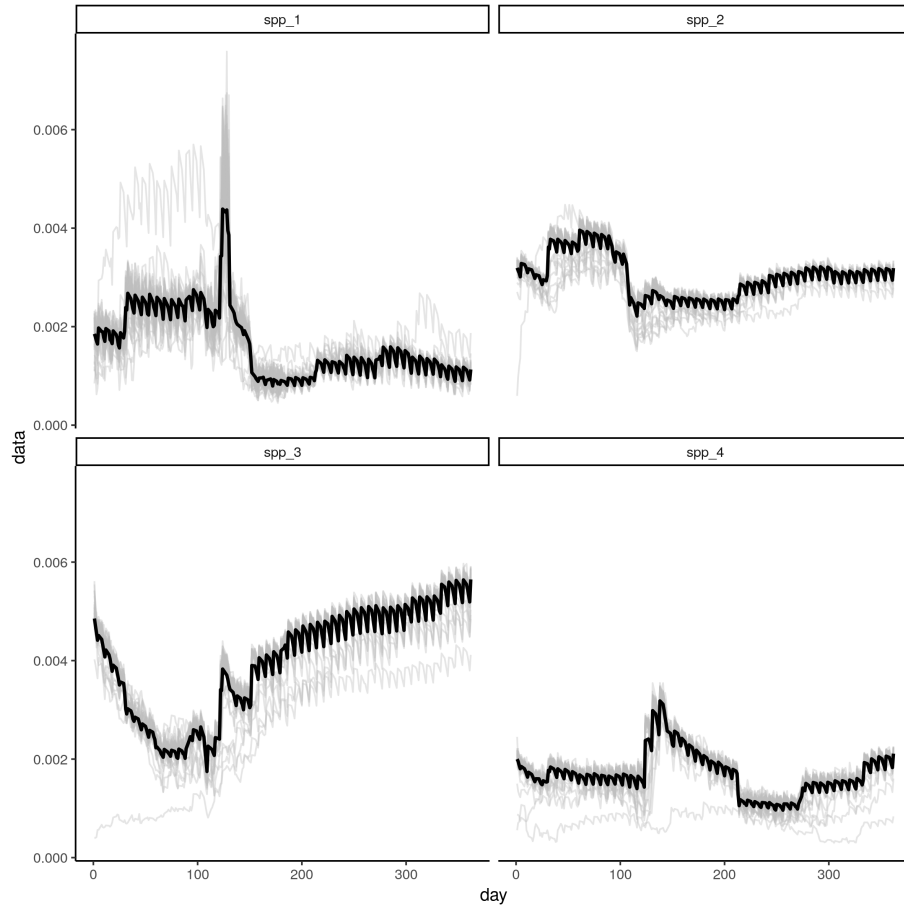


Figure 3: Fishing mortality dynamics - the daily fishing mortalities showing weekly and seasonal patterns in exploitation. Individual years and the light grey lines, the mean of all years the thick black line

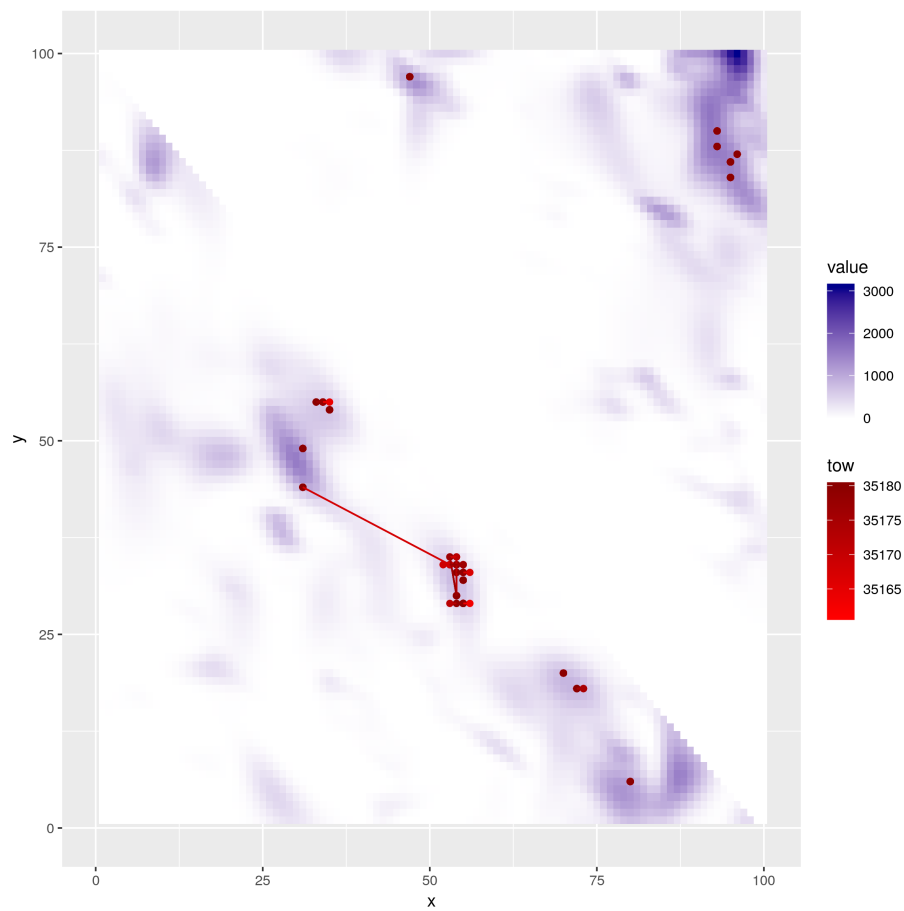


Figure 4: movement of a fleet over a single trip reference overlaid on the value field (i.e. sum of the population abundance x catchability x value

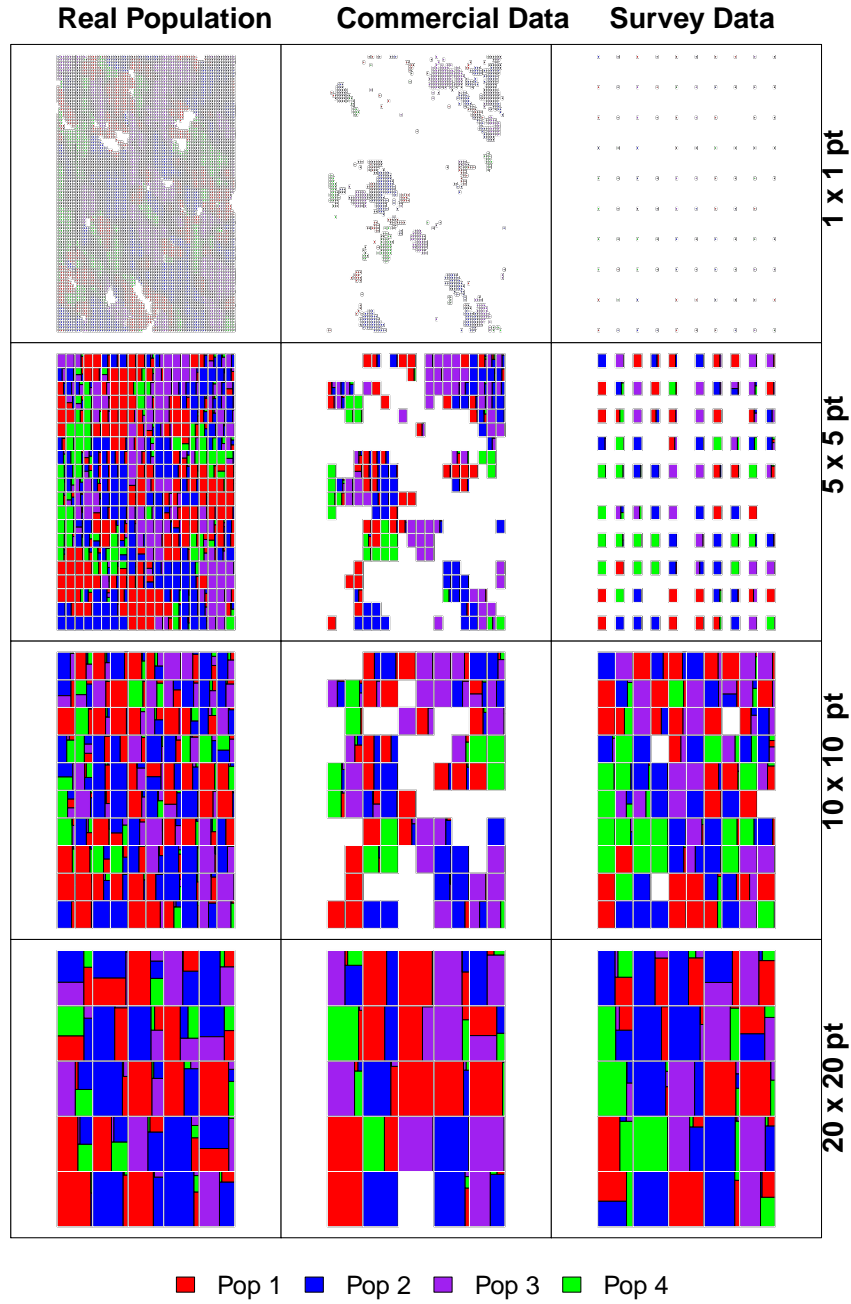


Figure 5: Data aggregation at different spatial resolutions over a ten year period

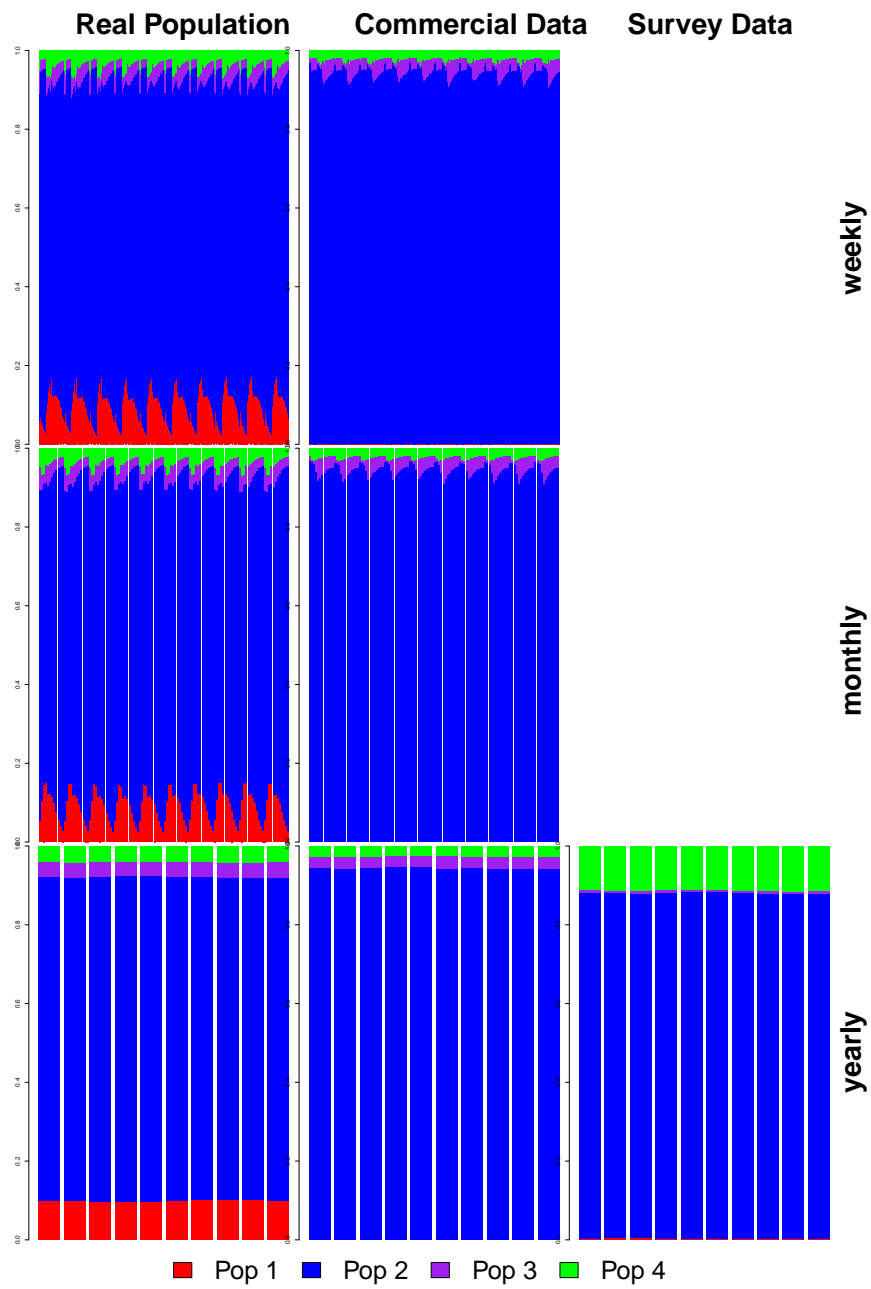


Figure 6: Data aggregation at different temporal resolutions over a ten-year period

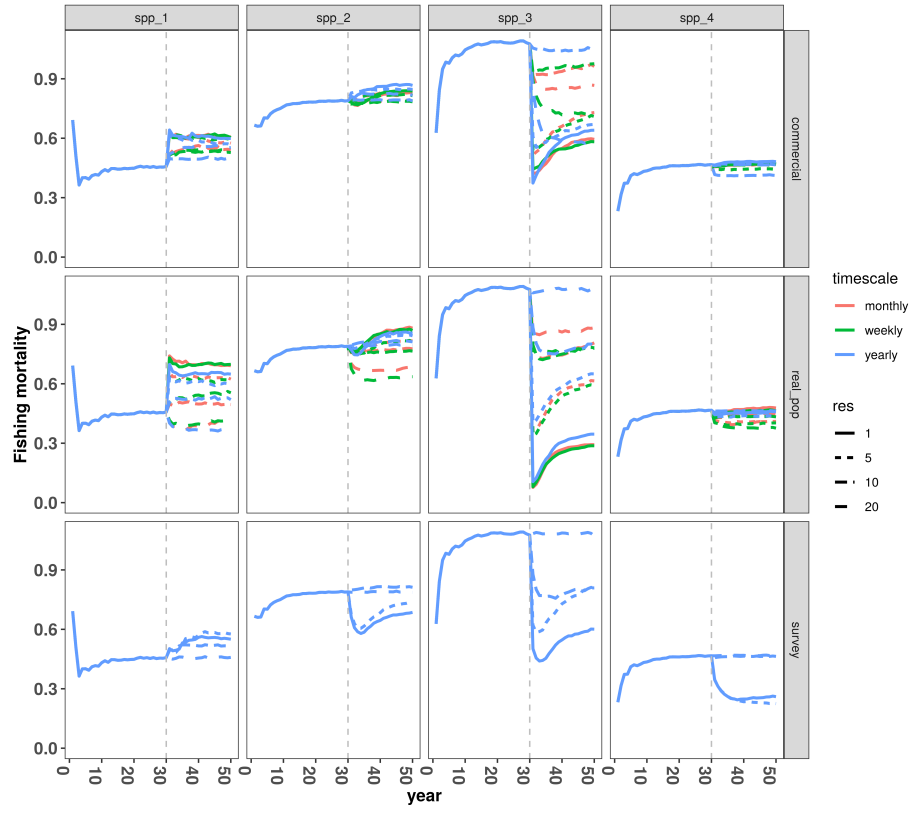


Figure 7: Comparison of closure scenarios effect on fishing mortality trends. Line colour denotes the timescale, while linestyle denotes the spatial resolution.

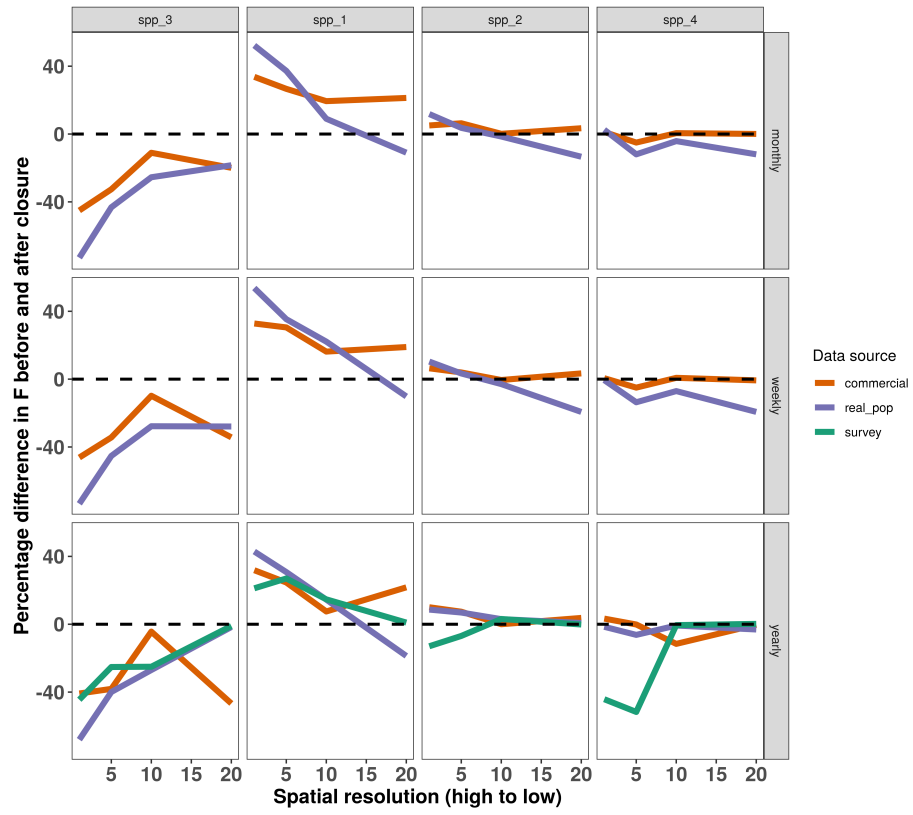


Figure 8: Comparison of closure scenario effectiveness based on different spatial and temporal resolutions.



Figure 9: Closure fishing locations based on annual closures with a coarse spatial resolution. Closure location can be seen in red in relation to a) before the closure fishing locations, b) after the closure fishing locations, c) species 3 habitat distribution

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