

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. 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 reduce unwanted catch (Kennelly and Broadhurst, 2002; Catchpole and Revill, 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
18 and fishery spatiotemporal dynamics and understanding of the scale at which
19 processes become important for management. Understanding the correct scale
20 for spatial measures is crucial for implementing effective solutions which min-
21 imising economic impact (Dunn et al., 2016). For example, the problem can be
22 to identify a scale that promotes species avoidance for vulnerable or low quota
23 species while allowing continuance of sustainable fisheries for available quota
24 species.

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

45

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

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

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

65

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

68 2. Materials and Methods

69 An event-based simulation model of a hypothetical fishery was developed
70 as a software package (‘MixFishSim’). The modular approach enabled efficient
71 computation by allowing for sub-modules implemented on time-scales appro-
72 priate to capture the characteristic of the different processes (Figure 1). The
73 following sub-modules were included to capture the full system: 1) Population

74 dynamics, 2) Recruitment dynamics, 3) Population movement, 4) fishery dy-
 75 namics.

76

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

80 2.1. Population dynamics

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

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

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

96

97 Mortality $Z_{c,d}$ can be decomposed to natural mortality, $M_{c,d}$, and fishing
 98 mortality, $F_{c,d}$, where both $M_{c,d}$ and $F_{c,d}$ are instantaneous rates with $M_{c,d}$

fixed and $F_{c,d}$ calculated by solving the Baranov catch equation (Hilborn and Walters, 1992) for $F_{c,d}$:

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

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. Here, catch and fishing mortality are the sum of 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 fl , v and p the fleet, vessel and population respectively and E and Q fishing effort and catchability of the gear, and D is the density of the population at the location fished.

2.2. Recruitment dynamics

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

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

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

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

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

119 2.3. Population movement dynamics

120 Population movement is a combination of random (diffusive) movement,
 121 governed by a stochastic process where movement between adjacent cells is
 122 described by a set of probabilities, and directed (advective) movement where
 123 at certain times of year the population moves towards spawning grounds by
 124 increasing the probabilities of moving into the spawning grounds from adjacent
 125 cells. We incorporate characterisation of a number of different fishing fleet dy-
 126 namics exploiting four fish populations with different spatial and population
 127 demographics. The following describes the implementation of each of the sub-
 128 modules.

129 To simulate fish population distribution in space and time a Gaussian spatial
 130 process was employed to model habitat suitability for each of the populations
 131 on a 2d grid.

132

133 We first defined a Gaussian random field process, $\{S(c) : c \in \mathbb{R}^2\}$, where
 134 for any set of cells c_1, \dots, c_n , the joint distribution of $S = \{S(c_1), \dots, S(c_n)\}$ is
 135 multivariate Gaussian with a *Matérn* covariance structure, where the correlation
 136 strength weakens with distance. This enables us to model the spatial autocor-
 137 relation observed in animal populations where density is more similar in nearby
 138 locations (Tobler, 1970; F. Dormann et al., 2007) and we change the parameters
 139 to implement different spatial structures for the different populations using the
 140 *RandomFields* R package (Schlatter et al., 2015). We define a stationary habitat
 141 field and combine with a temporally dynamic thermal tolerance field to imitate
 142 two key drivers of population dynamics. Each population was initialised at a
 143 single location, and subsequently moved according to a probabilistic distribu-
 144 tion based on habitat suitability (represented by the normalised values from the
 145 GRFs), temperature and distance from current cell:

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

146 Where d_{IJ} is the euclidean distance between cell I and cell J , λ is a given rate

of decay, $Hab_{J,p}^2$ is the squared index of habitat suitability for cell J and population p , with $Tol_{J,p,wk}$ the temperature tolerance for cell J by population p in week wk (see below).

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

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

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

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

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

173 2.4. Fleet dynamics

174 The fleet dynamics can be broadly categorised into three components; fleet
175 targeting - that determined the fleet catch efficiency and preference towards
176 a particular species; trip-level decisions, that determined the initial location
177 to be fished at the beginning of a trip; and within-trip decisions, that deter-
178 mined movement from one fishing spot to another within a trip. Together,
179 these elements implemented an explore-exploit type strategy for individual ves-
180 sels to maximise their catch from an unknown resource distribution (Bailey
181 et al., 2018). The decision to use an individual based model for fishing vessels
182 was taken because fishers are heterogeneous in their location choice behaviour
183 due to different objectives, risk preference and targeting preference (Van Putten
184 et al., 2012). Therefore in the simulations fleet dynamics are the productive of
185 individual experiences rather than pre-defined group dynamics.

186 2.4.1. Fleet targeting

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

194 2.4.2. Trip-level decisions

195 Several studies (e.g. Hutton et al., 2004; Tidd et al., 2012; Girardin et al.,
196 2015) have confirmed past activity and past catch rates are strong predictors of
197 fishing location choice. For this reason, the fleet dynamics sub-model included a
198 learning component, where a vessel's initial fishing location in a trip was based
199 on selecting from previously successful fishing locations. This was achieved by
200 calculating an expected revenue based on the catches from locations fished in
201 the preceding trip as well as the same month periods in previous years and the

202 travel costs from the port to the fishing grounds, and choosing randomly from
203 the top 75 % of fishing events as defined by the expected profit, that has a
204 seasonal component.

205 2.4.3. *Within-trip decisions*

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

219
220 We use a *Lévy flight* which is a particular form of random walk charac-
221 terised by a heavy-tailed distribution of step-length. The Lévy flight has re-
222 ceived a lot of attention in ecological theory in recent years as having shown to
223 have very similar characteristics as those observed by animals in nature, and
224 being a near optimum searching strategy for predators pursuing patchily dis-
225 tributed prey (Viswanathan et al., 1999; Bartumeus et al., 2005; Sims et al.,
226 2008). Bertrand et al. (2007) showed that Peruvian anchovy fishermen have a
227 stochastic search pattern similar to that observed with a lévy flight. However,
228 it remains a subject of debate (e.g. see Edwards et al., 2011; Reynolds, 2015),
229 with the contention that search patterns may be more simply characterised as
230 random walks (Sakiyama and Gunji, 2013) with specific patterns related to the
231 characteristics of the prey field (Sims et al., 2012).

232

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

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

239 where L_p is landings of a population p , and Pr_p price of a population. All
 240 species prices were kept the same across fleets and seasons. Here, when fishing
 241 is successful vessels remain in a similar location and continue to exploit the local
 242 fishing grounds. When unsuccessful, they move some distance away from the
 243 current fishing location. The movement distance retains some degree of stochasticity,
 244 that can be controlled separately, but is determined by the relationship:

245

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

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

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

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

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

248 where k the concentration parameter from the von Mises distribution that we
 249 correlate with the revenue so that $k = (Rev + 1/RefRev) * max_k$, where max_k
 250 is the maximum concentration value, k , and $RefRev$ is parametrised as for β_3
 251 in the step length function. A realised example of the step length and turning
 252 angle relationships to revenue can be seen at Figure ??.

253 2.4.4. *Local population depletion*

254 Where several fishing vessels exploit the same fish population competition
255 is known to play an important role in local distribution of fishing effort (Gillis
256 and Peterman, 1998). If several vessels are fishing on the same patch of fish,
257 local depletion and interference competition will affect fishing location choice
258 of the fleet as a whole (Rijnsdorp, 2000; Poos and Rijnsdorp, 2007a). In order
259 to account for this behaviour, the fishing sub-model operates spatially on a
260 daily time-step so that for future days the biomass available to the fishery is
261 reduced in the areas fished. The cumulative effect is to make heavily fished
262 areas less attractive as a future fishing location choice as reduced catch rates
263 will be experienced.

264 2.5. *Fisheries independent survey*

265 A fisheries-independent survey is simulated where fishing on a regular grid
266 begins each year at the same time for a given number of stations (a fixed station
267 survey design). Catches of the populations at each station are recorded but not
268 removed from the population (catches are assumed to have negligible impact
269 on population dynamics). This provides a fishery independent snapshot of the
270 populations at a regular spatial intervals each year, similar to scientific surveys
271 undertaken by fisheries research agencies.

272

273 2.6. *Software: R-package development*

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

277

278 3. Parameterisation

279 3.1. Population models

280 We parametrised the simulation model for four populations with different de-
281 mographics; growth rates, natural mortality and recruitment parameters (Table
282 4). Habitat preference (Figure ??) and temperature tolerances (Figures ??, ??)
283 were defined to be unique to each population resulting in differently weekly
284 distribution patterns (Figures ??-??). In addition, each of the populations was
285 assumed to have two defined spawning areas that result in the populations mov-
286 ing towards these areas in pre-defined weeks (Figure ??) with population-specific
287 movement rates (Table 4). In such a configuration, the individual habitat pref-
288 erences and thermal tolerances result in different spatial habitat use for each
289 population (Figure ??) and consequently different seasonal exploitation patterns
290 (Fishing mortality in Figure ??).

291 3.2. Fleet parametrisation

292 The fleets were parametrised to reflect five different characteristic fisheries
293 with unique exploitation dynamics (Table 5). By setting different catchability
294 parameters ($Q_{fl,p}$) we create different targeting preferences between the fleets
295 and hence spatial dynamics. The random walk process implies that within a
296 fleet different vessels have different spatial distributions based on individual
297 experience. The step function was parametrised dynamically within the simu-
298 lations as the maximum revenue obtainable was not known beforehand. This
299 was implemented so that vessels take smaller steps when fishing at a location
300 that yields landings value in the top 90th percentile of the value experienced in
301 that year so far (as defined per fleet in Table 5).

302
303 With increasing probability throughout the simulation, fishing locations were
304 chosen based on experience of profitable catches built up in the same month from
305 previous years and from the previous trip. 'Profitable' in this context was de-
306 fined as the locations where the top 70 % of expected profit would be found

307 given revenue from previous trips and cost of movement to the new fishing lo-
308 cation. This probability was based on a logistic sigmoid function with a lower
309 asymptote of 0 and upper asymptote of 0.95, and a growth rate that ensures
310 the upper asymptote (where decisions are mainly based on past knowledge) is
311 reached approximately halfway through the simulation.

312

313 3.3. Survey settings

314 The survey simulation was set up with a fixed gridded station design with
315 100 stations fished each year, starting on day 92 and ending on day 112 (5
316 stations per day) with same catchability parameters for all populations ($Q_p =$
317 1). This approximates a real world survey design with limited seasonal and
318 spatial coverage.

319 3.4. Example research question

320 To illustrate the capabilities of *MixFishSim*, we investigate the influence of
321 the temporal and spatial resolution of different data sources on the reduction in
322 catches of a population given spatial closures. To do so, we set up a simulation
323 to run for 50 years based on a 100×100 square grid (undetermined units), with
324 five fleets of 20 vessels each and four fish populations. Fishing takes place four
325 times a day per vessel and five days a week, while population movement is every
326 week.

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

331

332 The following steps are undertaken to determine closures:

- 333 1. Extract data source
- 334 2. Aggregate according to desired spatial and temporal resolution

335 3. Interpolate across entire area at desired resolution using simple bivariate
 336 interpolation using the *interp* function from the R package akima (Akima,
 337 2006). This is intended to represent a naive spatial model of catch rates,
 338 without knowledge of the spatial population dynamics.

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

340 In total 28 closure scenarios were run that represent combinations of:

- 341 • **data types:** commercial logbook data, survey data and ‘real population’,
- 342 • **temporal resolutions:** weekly, monthly and yearly closures,
- 343 • **spatial resolutions:** 1 x 1 grid, 5 x 5 grid, 10 x 10 grid and 20 x 20 grid,
- 344 • **closure basis:** highest 5 % of catch rates for the protected species

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

347 4. Results

348 4.1. 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 ??), while across several trips fishing grounds that are further apart are fished (Figure ??). These different locations relate to areas where the highest revenue were experienced, as shown by Figure ??, where several trips for the vessel overlaid on the revenue field, i.e.

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

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

355 *4.2. How does sampling-derived fisheries data reflect the underlying population*
356 *structure?*

357 In order to answer this question we compare different spatial and temporal
358 aggregations of the 'real population' distributions to:

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

364 Figure ?? shows the aggregated catch composition from each of the data
365 sources over a ten-year period (to average seasonal patterns) at different spa-
366 tial resolutions. The finer spatial grid for the real population (top left) and
367 commercial data (top middle) show visually similar patterns, though there are
368 large unsampled areas in the commercial data from a lack of fishing activity
369 (particularly in the lower left part of the sampling domain). The survey data at
370 this spatial resolution displays very sparse information about the spatial distri-
371 butions of the populations. The slightly aggregated data on a 5 x 5 grid shows
372 similar patterns and, while losing some of the spatial detail, there remains good
373 consistency between the 'real population' and the commercial data. Survey data
374 starts to pick out some of the similar patterns as the other data sources, but
375 lacks spatiotemporal coverage. The spatial catch information on a 10 x 10 and
376 20 x 20 grid lose a significant amount of information about the spatial resolu-
377 tions for all data sources, and some differences between the survey, commercial
378 and 'real population' data emerge.

379

380 Figure ?? shows the consequences of different temporal aggregations of the
381 data over a ten-year period, with weekly (top), monthly (middle) and yearly
382 (bottom) catch compositions from across an aggregated 20 x 20 area. In the
383 'real population', the monthly aggregation captures the major patterns of com-
384 position seen in the weekly data with similar mean and standard deviations. In

the weekly data species 1 = 9.36 (3.99), species 2 = 83.2 (5.60), species 3 = 3.57 (1.23), species 4 = 3.91 (1.59); in the monthly data species 1 = 9.23 (3.87), species 2 = 83.3 (5.52), species 3 = 3.62 (1.15), species 4 = 3.86 (1.52). While means were similar some of the variation was lost when aggregated to an annual level; species 1 = 9.90 (0.173), species 2 = 82.2 (0.308), species 3 = 3.82 (0.119), species 4 = 4.03 (0.0502).

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

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

4.3. How does data aggregation and source impact on spatial fisheries management measures?

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

The trend in fishing mortality for each species show that in most cases the fishery closure was successful in reducing fishing mortality on the species of interest (species 3; Figure ??), though interestingly the largest reductions in fishing mortality happened immediately after the closures, following which the fisheries "adapted" to the closures and fishing mortality increased again some-

415 what. The exception to the success was the closures implemented based on the
 416 coarsest spatial (20 x 20) and temporal resolution (yearly) that was ineffective
 417 with all data sources. As expected, closures based on the "known" population
 418 distribution were most effective, with differing degrees of success using the com-
 419 mercial data. Fishing mortality rates on the other species changed in different
 420 proportions, depending on whether the displaced fishing effort moved to areas
 421 where the populations were found in greater or lesser density.

422

423 A regression tree (using the R package REEMtree (Sela and Simonoff, 2012))
 424 highlights that the factor most contributing to differences in fishing mortality
 425 before and after the closure was the population (72 % showing that the clo-
 426 sures were effective for population 3), followed by data resolution (21 %), data
 427 type (7 %) with the least important factor the timescale (< 1 %). In general
 428 the finer the spatial resolution of the data used the greater reduction in fishing
 429 mortality for population 3 after the closures (Figure ??). The notable outliers
 430 are the commercial data at the coarsest spatial resolution (20 x 20) at a yearly
 431 and weekly timescale, where closures were nearly as effective as the fine-scale
 432 resolution. In this case the closures were sufficiently large to protect a core
 433 of the habitat for the population, but this was achieved in a fairly crude manner
 434 by closing a large area - including area where the species was not found (Figure
 435 ??) that may have consequences in terms of restricting the fishery in a much
 436 larger area than necessary.

437

438 5. Discussion

439 Our study evaluates the importance of data scaling and considers poten-
 440 tial bias introduced through data aggregation when using fisheries data to infer
 441 spatiotemporal dynamics of fish populations. Understanding how fishers ex-
 442 ploit multiple heterogeneously distributed fish populations with different catch
 443 limits or conservation status requires detailed understanding of the overlap of

resources; this is difficult to achieve using conventional modelling approaches due to species targeting in fisheries resulting in preferential sampling (Martínez-Minaya et al., 2018). Often data are aggregated or extrapolated which requires assumptions about the spatial and temporal scale of processes. Our study explores the assumptions behind such aggregation and preferential sampling to identify potential impacts on management advice. With modern management approaches increasingly employing more nuanced spatiotemporal approaches in order 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

474 obtained under a statistical modelling framework.

475

476 Typically, simulation models that treat fish as individuals are focussed on
477 exploring the inter- and intra- specific interactions among fish populations (e.g.
478 OSMOSE Shin et al. (2004)) in order to understand how they vary over space
479 and time. Our focus was on understanding the strengths and limitations of
480 inference from catch data obtained through commercial fishing activity with
481 fleets exploiting multiple fish populations and realising catch distributions that
482 may differ from the underlying populations. As such, we favoured a minimum
483 realistic model of the fish populations (Plagányi et al., 2014) taking account of
484 environmental but not demographic stochasticity, while incorporating detailed
485 fishing dynamics that take account of different drivers in a mechanistic way.

486

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

494

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

504 *5.2. How does sampling-derived fisheries data reflect the underlying population*
505 *structure?*

506 Our results demonstrate the importance of considering data scale and resolu-
507 tion when using observational data to support management measures. We find
508 that understanding of the community composition dynamics will depend on the
509 level of data aggregation and its important to consider the scale of processes;
510 including population movement rates, habitat uniformity and fishing targeting
511 practices if potential biases in data are to be understood and taken into account.

512
513 Our simulation shows that, despite biases introduced through the fishing
514 process, the commercially derived data could still inform on the key spatial
515 patterns in the community structures where the fisheries occurred, which was
516 spatially limited due to the “hotspots” of commercially valuable species be-
517 ing fished. Similarly, despite the even spatial coverage the survey was able to
518 capture some of the same spatial patterns as the ‘real population’, but missed
519 others due to gaps between survey stations limiting spatial and temporal cov-
520 erage. This provides a challenge when modelling unsampled areas in inferring
521 species distribution maps, though these limitations may be overcome by un-
522 derstanding the relationship between the species and habitat covariates where
523 these are known at unsampled locations (Robinson et al., 2011).

524
525 *5.3. How does data aggregation and source impact on spatial fisheries manage-*
526 *ment measures?*

527 From our simulations spatial disaggregation was more important than the
528 temporal disaggregation of the commercial data. This reflects the fact that there
529 was greater spatial heterogeneity over the spatial domain than experienced in
530 individual locations over the course of the year (Figure ??).

531
532 The yearly data assumes the same proportion of each population caught at
533 any time of the year due to the data aggregation. This assumption introduces

534 ‘aggregation bias’ as the data may only be representative of some point (or no
535 point) in time. The monthly data shows some consistency between the ‘real
536 population’ and commercial data for species 2 - 4, though species 1 remains
537 under-represented. On an annual basis, interestingly the commercial data un-
538 der represents the first species (in red) while the survey over represents species
539 1. This is likely due to the biases in commercial sampling, with the fisheries not
540 targeting the areas where species 1 are present and the survey sampling areas
541 where species 1 is more abundant than on average.

542

543 This indicates that fixed closures, at the right resolution, when based on
544 commercially derived data have the potential to reduced fishing mortality. The
545 likely cost of poor spatial and temporal resolution is associated with reduced
546 effectiveness and potentially closing fishing opportunities for other fisheries.

547

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

557

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

563 5.4. *Model assumptions and caveats*

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

568
569 Fish populations in our simulations move in pre-defined timescales and ac-
570 cording to fixed habitat preferences and temperature gradients (Figures ??, ??).
571 Our assumptions in parametrising the model (movement rates, temperature tol-
572 erances) will have a direct impact on our conclusions on the relative importance
573 of spatial and temporal processes. These assumptions could be explored in a
574 future study by varying the parameters and assessing the robustness of our con-
575 clusions. For our example application we have chosen movement rates to reflect
576 aggregation periods observed in past studies (Poos and Rijnsdorp, 2007b).

577
578 In addition, we have assumed that fishing vessels are not restricted by quota
579 and therefore discarding of species for which vessels have no quota or that are
580 unwanted is not taken into account. This is likely to be a significant source of
581 bias in any inference using commercial data and should also be explored. For
582 example, MixFishSim could be altered to allow for spatiotemporal appraisal of
583 the impact of discarding on fisher behaviour and underlying populations via in-
584 clusion as discarding behaviour, or through move-on rules or cessation of fishing
585 activity when quota is exhausted.

587 5.5. *Future applications of MixFishSim*

588 We consider that the increased availability of high resolution catch and lo-
589 cational information from commercial fisheries will require it to be a key source
590 of data for ensuring management is implemented at the right scale in future.
591 For example, identifying hot-spots for bycatch reduction or identifying spatial
592 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

622 and identity where data collection is needed to strengthen inference.

623

624 Our application shows that inference on community dynamics may change
625 depending on the scale of data aggregation. There is an important balance in
626 ensuring that the data are sufficiently spatially and temporally disaggregated
627 that the main features of the data are captured, yet maintaining enough data
628 coverage that the features can be distinguished. We found in our application
629 that there was greater spatial heterogeneity than temporal heterogeneity and
630 that when using aggregated data to define spatial closures coarser temporal reso-
631 lution (months instead of weeks) could still achieve the same results in reducing
632 exploitation rates of a vulnerable species at the highest temporal resolution
633 data. Conversely, reducing the spatial resolution had a negative effect on the
634 effectiveness of the measures (though importantly, there was still some benefit
635 even with coarse spatial resolution).

636

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

642

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

651 **Abbreviations**

652 Detail any unusual ones used.

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659 **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.

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