

A simulation framework for exploring spatio-temporal dynamics in mixed fisheries

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Abstract

[Guidance: A concise and factual abstract is required. The abstract should state briefly the purpose of the research, the principal results and major conclusions. An abstract is often presented separately from the article, so it must be able to stand alone. For this reason, References should be avoided, but if essential, then cite the author(s) and year(s). Also, non-standard or uncommon abbreviations should be avoided, but if essential they must be defined at their first mention in the abstract itself. Graphical abstract: Although a graphical abstract is optional, its use is encouraged as it draws more attention to the online article. The graphical abstract should summarize the contents of the article in a concise, pictorial form designed to capture the attention of a wide readership. Graphical abstracts should be submitted as a separate file in the online submission system. Image size: Please provide an image with a minimum of 531 X 1328 pixels (h X w) or proportionally more. The image should be readable at a size of 5 x 13 cm using a regular screen resolution of 96 dpi. Preferred file types: TIFF, EPS, PDF or MS Office files.]

Fishing exploits spatio-temporally heterogeneous fish populations without fully selective gear which can result in unintended, unwanted catch of low quota or

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protected species. Reducing these unwanted catches is crucial for biological and economic sustainability of 'mixed fisheries'.

Understanding of spatio-temporal fishery dynamics is limited by a lack of full understanding of population distribution and how fishers interact with the different populations. We develop a spatio-temporal simulation model that incorporate i) delay-difference population dynamics, ii) population movement dynamics using Gaussian Random Fields, iii) fishery dynamics for multiple fleet characteristics based on a correlated random walk and learned behaviour.

Using our model we simulation 20 years of exploitation of the fish populations and use the results from the fishing model to draw inference on the underlying population structures. We compare this inference to i) a simulated fixed-site sampling design commonly used for fisheries monitoring purposes, ii) the underlying population structures input to the simulation.

We find that...

Keywords: Some, keywords, here. Max 6

2010 MSC: 00-01, 99-00

1. Introduction

[Guidance:: State the objectives of the work and provide an adequate background, avoiding a detailed literature survey or a summary of the results.]

5 Fishers exploit fish populations that are heterogenously distributed in space and time without prior knowledge of species distributions and non-selective fishing gear. Fisheries managed by single-species quotas catch an assemblage of species, known as mixed fisheries, leading to discarding of overquota catch. Reducing discarding is crucial to ensure biological and economic sustainability

10 of fisheries. As such there is increasing interest in technical solutions such as gear, spatial closures as a way of avoiding discarding unwanted catch.

Use of spatial management as a tool is hampered by lack of knowledge of fish and fishery spatiotemporal dynamics and understanding of the scale at which processes are important for management. Understanding of the correct
15 scale for spatial management is crucial in order to implement measures at a resolution that ensures effective management[1] while minimising economic impact; for example a scale which promote species avoidance for vulnerable or low quota species while allowing continuance of sustainable fisheries for available
20 quota species.

Ensuring measures are implemented at an appropriate scale has been a challenge in the a past that has led to ineffectual measures with unintended consequences such as limited impact towards the management objective or increased
25 benthic impact on previously unexploited areas (e.g. the cod closure in the North Sea[2, 3]). Since then more refined spatial information has become available through the combination of logbook and Vessel Monitoring System (VMS) data[4, 5, 6, 7], though such information is patchy and derived from an inherently biased sampling programme (i.e. targeted fishing). Further, generally fishers
30 only recorded landings (not catch) on a daily basis. This leads to questions about the validity of inferences that can be drawn from landings data assigned to VMS activity pings.

In order to test the assumption that VMS associated landings data can be
35 used to draw inference on the underlying population structures we develop a simulation model where population dynamics are known rather than inferred from sampling or commercial catches. Population movement is driven by a random (diffusive) and directed (advective) process and we incorporate characterisation of a number of different fisheries exploiting four fish populations with
40 different spatial and population demographics.

Using our model we simulation 20 years of exploitation of the fish populations and use the results from the fishing model to draw inference on the underlying population structures. We compare this inference to i) a simulated [stratified] fixed-site sampling design commonly used for fisheries monitoring purposes, ii) the underlying population structures input to the simulation.

[Could fit a geostatistical model (e.g. VAST) to the fisheries-dependent and fisheries-independent data, though may be overkill...]

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

2. Materials and Methods

[Guidance: Provide sufficient details to allow the work to be reproduced by an independent researcher. Methods that are already published should be summarized, and indicated by a reference. If quoting directly from a previously published method, use quotation marks and also cite the source. Any modifications to existing methods should also be described.]

We develop a simulation model with a modular event-based approach, where modules occur on independent time-scales appropriate to capture the characteristic of the process modelled. The fishing model operated on a tow-by-tow basis, while population dynamics (fishing and natural mortality, growth) operate on a daily time-step. Population movement occurs on a two-weekly time-step, while

70 recruitment occurs periodically each year for a set time period (e.g. 3 weeks) at
 at specified point individual to a species. The model structure is summarised in
 Figure 1.

In the following section, we describe each of the model components; 1) Popu-
 75 lation dynamics, 2) Recruitment dynamics, 3) Population movement, 4) fishery
 dynamics.

2.1. Population dynamics

The basic population level processes are simulated using a modified two-
 80 stage Deriso-Schnute delay difference model [8, 9, 10] occurring at a daily time-
 step. Here, population biomass growth and depletion for pre-recruits and fish
 recruited to the fishery are modelled separately as a function of previous re-
 cruited biomass, intrinsic population growth and recruitment:

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

where ρ is Brody's coefficient, shown to be approximately equal to $\exp(-K)$,
 85 where K is the growth rate from a von bertalanffy logistic growth model [9].
 Wt_{R-1} is the weight of fish prior to recruitment, while Wt_R is the recruited
 weight. α_w represents the proportion of fish recruited during the week, while
 $R_{\tilde{y}}$ is the annual recruits.

90 Mortality Z can be decomposed to natural mortality, M , and fishing mor-
 tality, F , where both M and F are instantaneous rates with M fixed and F
 calculated by solving the Baranov catch equation [11] for F :

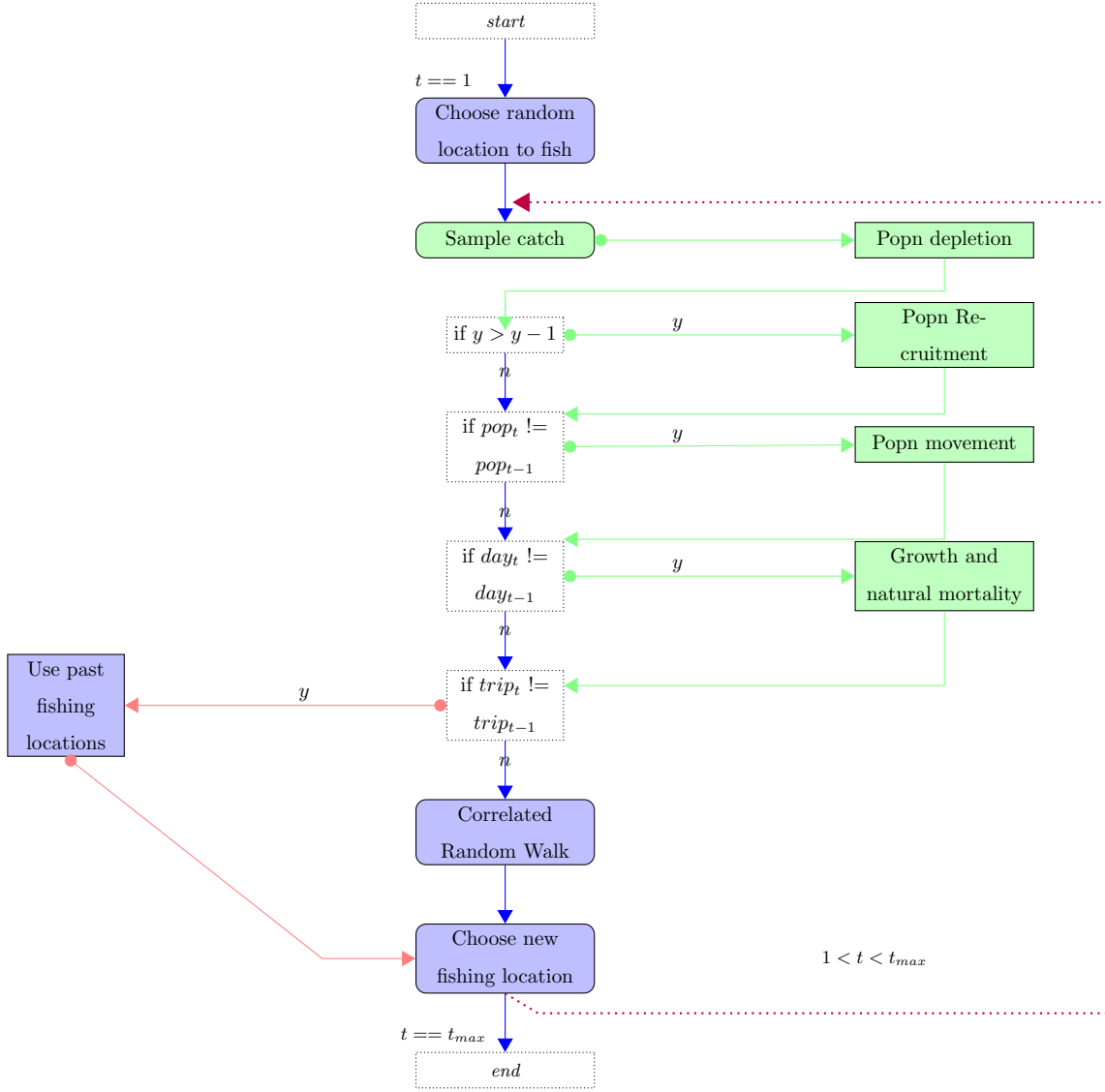


Figure 1: Overview Schematic of simulation model

$$C_w = \frac{F_w}{F_w + M_w} * (1 - e^{-(F_w + M_w)}) * B$$

where C is the summed catch from the fishing model across all fleets and vessels for the population during the day, and B the daily biomass for the species.

2.2. Recruitment dynamics

Recruitment is modelled through a function relating the biomass at time of recruitment to recruits, either as a stochastic Beverton-Holt stock-recruit form ([12]):

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

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

100 Where α is the maximum recruitment rate, β the spawning stock biomass (SSB) required to produce half the maximum, and B current SSB;

or a stochastic Ricker form [13]

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

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

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

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2.3. Population movement

In order to simulate how fish populations might be distributed in space and time, we employed a Gaussian spatial process to model habitat suitability for each of the populations, with an advection-diffusion process to control how the

110

populations moved in time.

For the habitat we define a Gaussian random field process, $\{S(x) : x \in \mathbb{R}^2\}$, that is a stochastic process where any collection of locations x_1, \dots, x_n where for each $x_i \in \mathbb{R}^2$, the joint distribution of $S = \{S(x_1), \dots, S(x_n)\}$ is multivariate

115

Gaussian. The distribution is specified by its *mean function*, $\mu(x) = E[S(x)]$

and its *covariance function*, $\gamma(x, x') = Cov\{S(x), S(x')\}$ [14].

The specification of the covariance structure directly affects the smoothness of the surfaces which the process generates. We used the *Matérn* family of covariance structures, one where the correlation strength weakens the further the distance apart (i.e. the correlation between $S(x)$ and $S(x')$ decreases as the distance $u = \|x - x'\|$ increases). The *Matérn* correlation is a two-parameter family where:

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

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

The population is initialised at a single location, and subsequently moves according to a probabilistic distribution based on habitat suitability and distance from current cell.

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

Where d_{AB} is the euclidean distance between cell A and cell B , and λ is some rate of decay.

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

2.4. Fleet dynamics

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

2.4.1. Fleet targeting

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

2.4.2. Trip-level decisions

Several studies (e.g.[15, 16, 17]) have confirmed past activity and past catch rates are strong predictors of fishing location choice. For this reason, the fleet dynamics sub-model includes a learning component, where a vessels initial fish-
160 ing location in a trip is based on selecting from previously successful fishing locations. This is achieved by sorting all previous fishing events in the previous trip as well as the previous time periods in past years, and choosing randomly from the top x % of fishing events in value. Simulation testing indicating this increased the mean value of catches for the vessels, over just relying on the
165 correlated random walk function.

2.4.3. Within-trip decisions

Fishing locations within a trip are determined by a Random Walk process. A Random walk was chosen as it is commonly used in ecology to describe animal movement which searching for homogeneously distributed prey about which

170 there is uncertain knowledge. In a random walk, movement is a stochastic process through a series of steps that can either be equal in length or take some other functional form. The direction of the random walk can be correlated, a characteristic known as 'persistence', providing some overall location directional movement [18] or uncorrelated.

175

A *lévy walk* is a particular form of random walk characterised by a heavy-tailed distribution of step-length and has received a lot of attention in ecological theory in recent years as having shown to have very similar characteristics as those observed by animals in nature, and being a near optimum searching strategy for predators pursuing patchily distributed prey [19, 20]. [21] showed that 180 Peruvian anchovy fishermen have a stochastic search pattern similar to that observed with a lévy walk. However, it remains a subject of debate, with the contention that search patterns may be more simply characterised as random walks [22] with specific patterns related to the characteristics of the prey field 185 [23].

We use a modified random walk where directional change is based on a correlated circular distribution where a favourable fishing ground is likely to be "fished back over" by the vessel returning in the direction it came from and step length (i.e. the distance travelled from the current to the next fishing location) is determined by relating recent fishing success, measured as the summed value of fish caught,

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

where C_s is catch of a species, and Pr_s price of a species, to step distance. Here, when fishing is successful vessels remain in a similar location and continue to exploit the local fishing grounds. When unsuccessful, they move some distance 190 away from the current fishing location. The movement distance retains some degree of stochasticity, which can be controlled separately.

The step function takes the form:

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

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

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

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

200 2.4.4. Local population depletion

Where several fishing vessels are exploiting the same fish population competition is known to play an important role in local distribution of fishing effort [24]. If several vessels are fishing on the same patch of fish, local depletion and interference will affect fishing location choice of the fleet as a whole [25, 26]. In
205 order to account for this behaviour, the fishing sub-model operates spatially on a daily time-step so that for future days the biomass available to the fishery is reduced in the areas fished. The cumulative effect is to make heavily fished areas less attractive as future fishing opportunities.

210 2.5. Fisheries independent survey

A fisheries-independent survey is simulated where fishing on a regular grid begins each year at the same time for a given number of stations (a fixed station survey design). Catches of the populations present are recorded but not

removed from the population. This provides a fishery independent snap shot of
215 the populations at a regular spatial distribution each year, similar to scientific
surveys undertaken by fisheries research agencies.

3. Theory/calculation

[Guidance: A Theory section should extend, not repeat, the background to
220 the article already dealt with in the Introduction and lay the foundation for fur-
ther work. In contrast, a Calculation section represents a practical development
from a theoretical basis.]

3.1. Simulation settings

225 We set up with simulation to run for 20 years based on a 100 X 100 square
grid, with five fleets of 20 vessels each and four fish populations. Fishing takes
place four times a day per vessel and five days a week, while population move-
ment is every two weeks.

230 3.2. Population parameterisation

We parameterised the simulation model for four populations with differing
habitat preference (Figure 2) and defined two spawning areas for each of the
populations (Table 1).

235 3.3. Fleet parameterisation

The fleets were parameterised to reflect five different characteristics based
on targeting preference and exploitation dynamics (Table 2). This ensures that
different fleets have different spatial dynamics, preferentially targeted different
fish populations. The stochasticity in the random walk process ensures that
240 different vessels within a fleet have slightly different spatial distributions based

Table 1: Population dynamics and movement parameter setting

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

on individual experience.

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

Table 2: Fleet dynamics parameter setting

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

3.4. Survey settings

The survey simulation was set up with follow a fixed gridded station design with 49 stations fished each year, starting on day 92 with same catchability parameters for all populations ($Q = 1$).

4. Results

Present simulated closures in terms of % change in population biomass and
255 fishery.

[Guidance: Results should be clear and concise.]

5. Discussion

[Guidance: This should explore the significance of the results of the work, not
repeat them. A combined Results and Discussion section is often appropriate.
260 Avoid extensive citations and discussion of published literature.]

6. Conclusions

textcolorgray[Guidance: The main conclusions of the study may be pre-
sented in a short Conclusions section, which may stand alone or form a subsec-
tion of a Discussion or Results and Discussion section.]

265 Appendices

[Guidance: If there is more than one appendix, they should be identified
as A, B, etc. Formulae and equations in appendices should be given separate
numbering: Eq. (A.1), Eq. (A.2), etc.; in a subsequent appendix, Eq. (B.1)
and so on. Similarly for tables and figures: Table A.1; Fig. A.1, etc.]

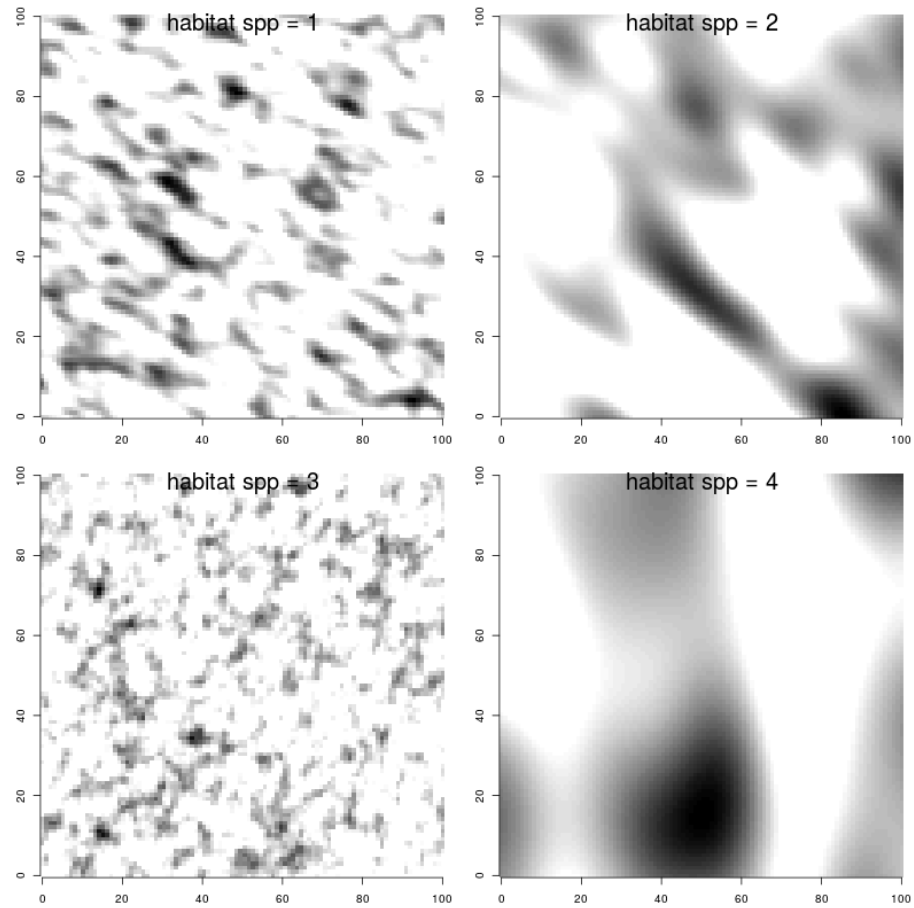


Figure 2: habitat preference

270 Abbreviations

Detail any unusual ones used.

Acknowledgements

those providing help during the research..

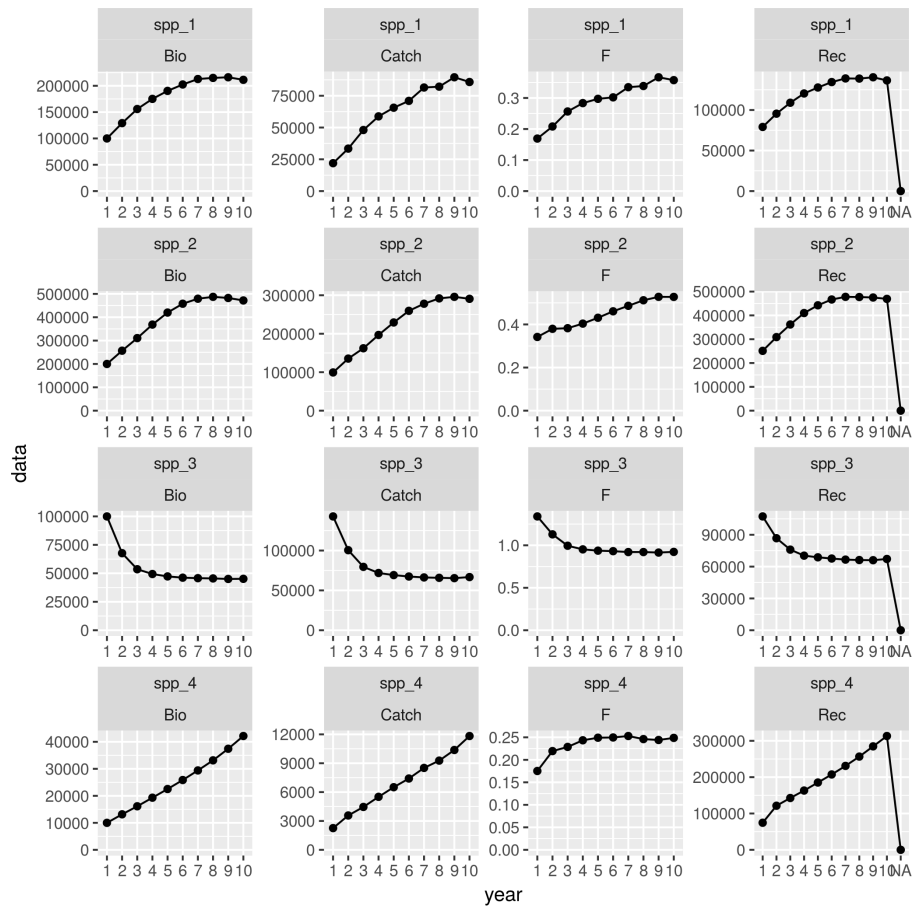


Figure 3: Annual Summary

Funding

275 This work was supported by the MARES doctoral training program; and the Centre for Environment, Fisheries and Aquaculture Science seedcorn program.

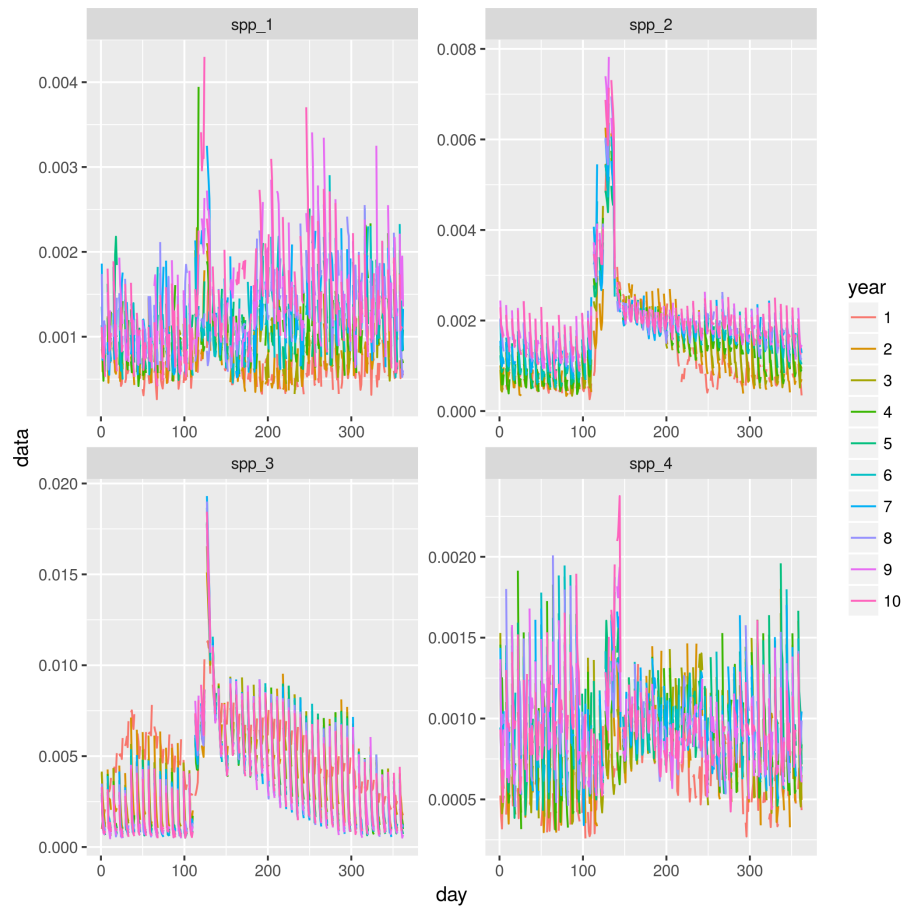


Figure 4: f dynamics

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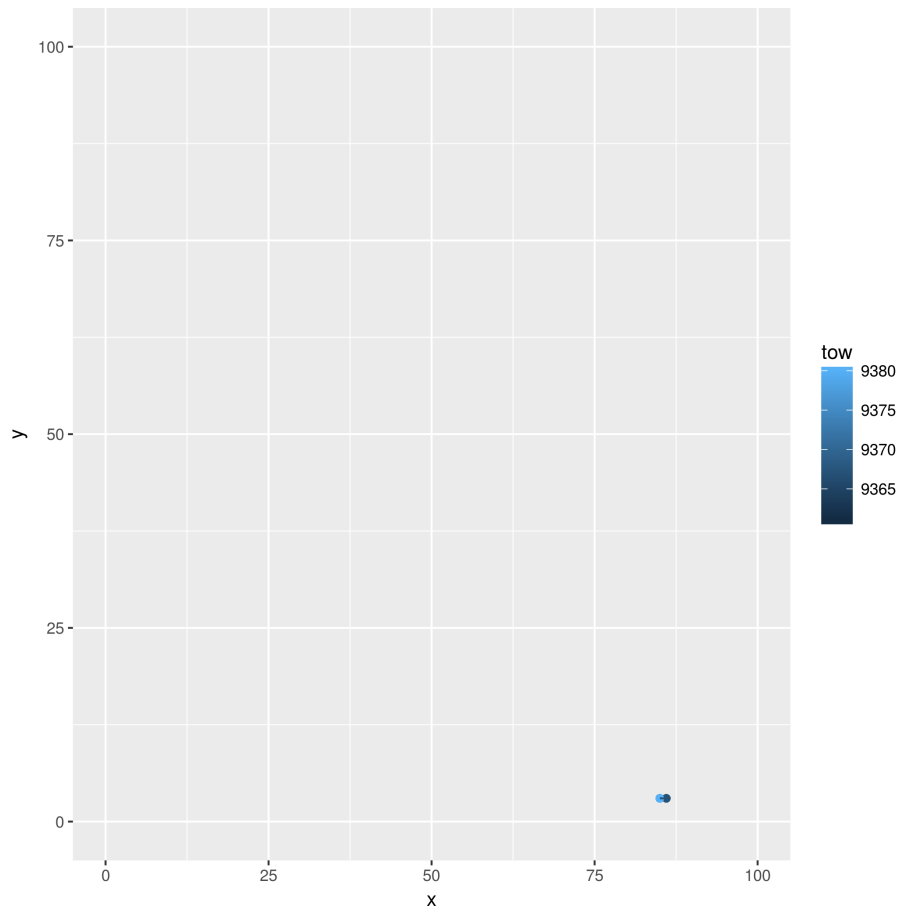


Figure 5: vessel movement

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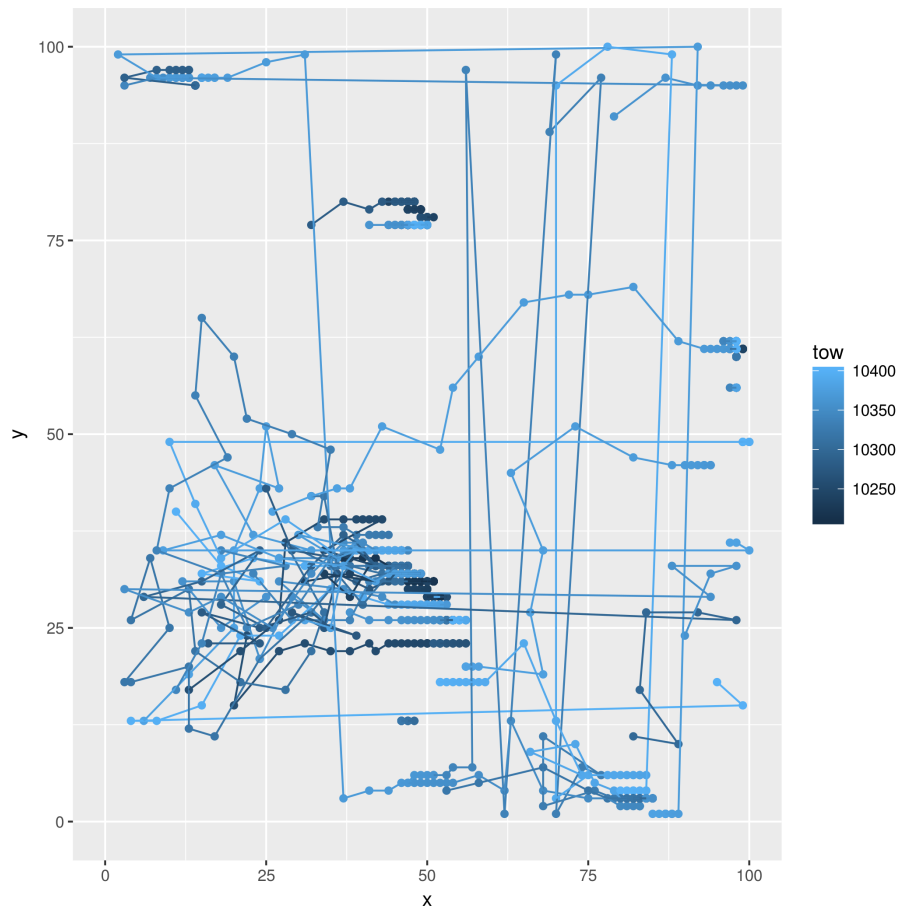


Figure 6: vessel movement multi

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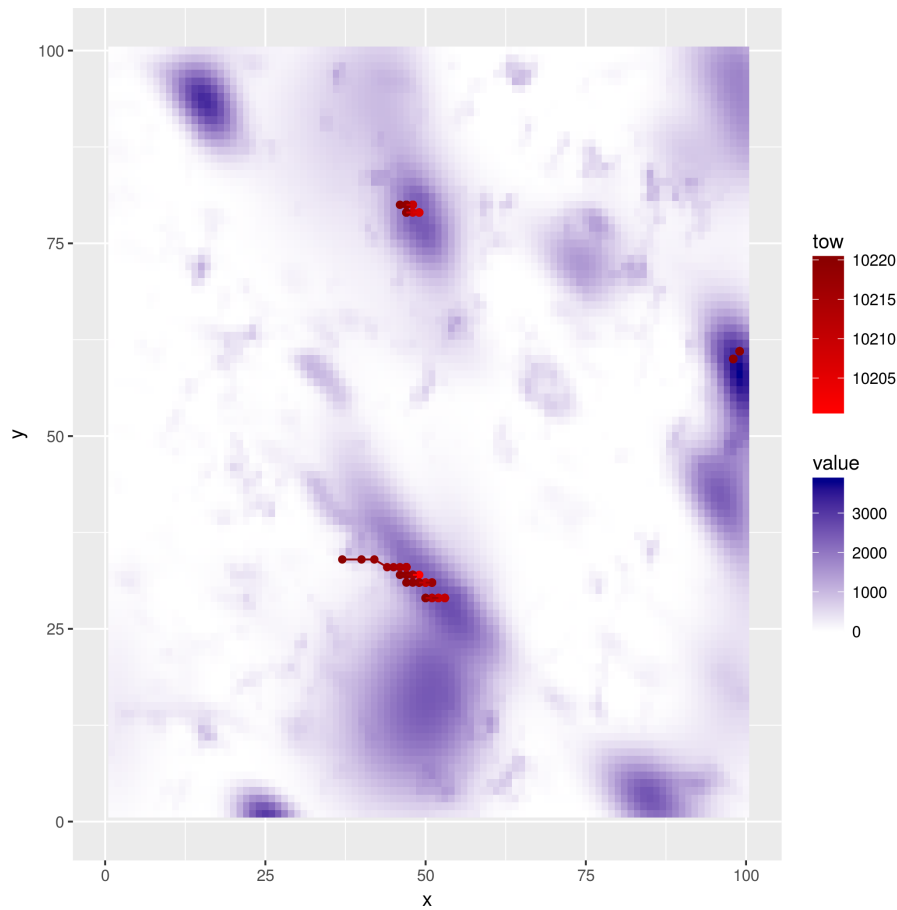


Figure 7: vessel movement value

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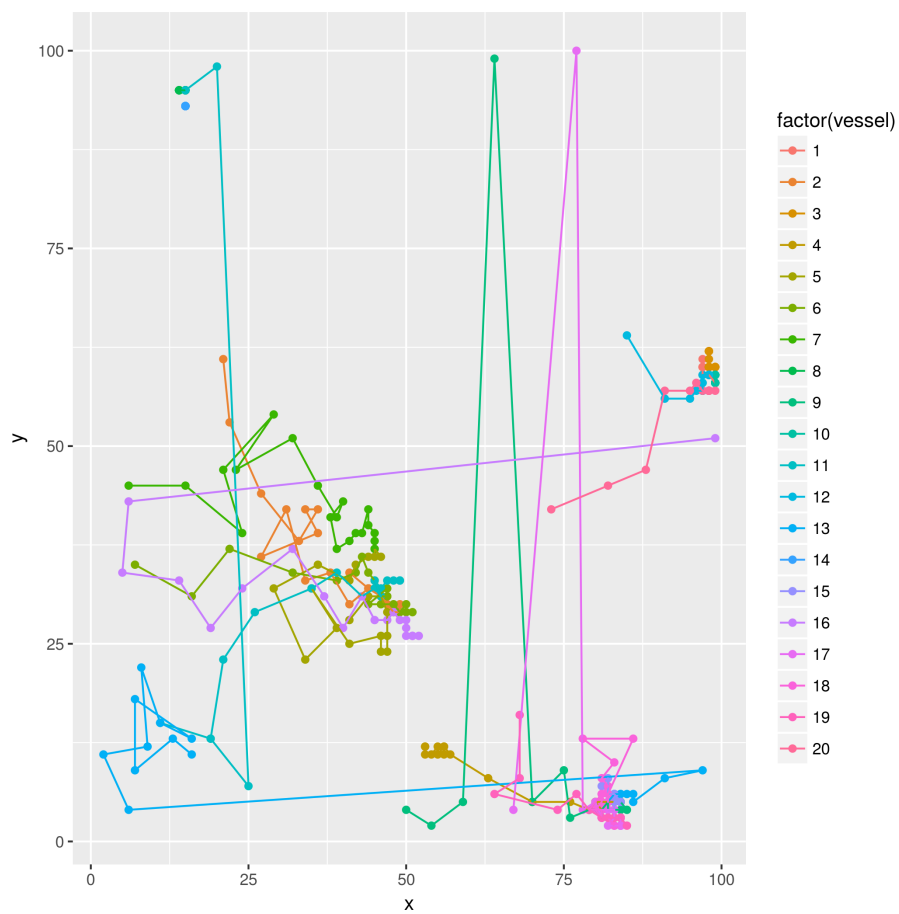


Figure 8: fleet movement

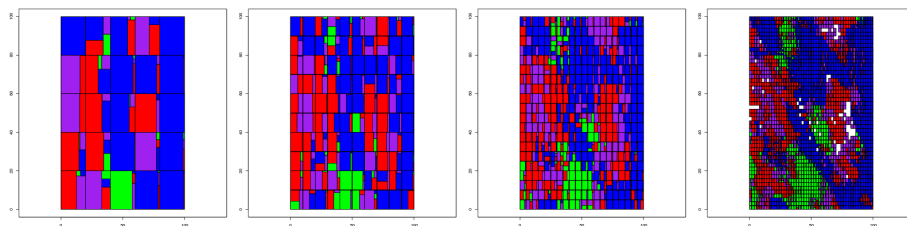


Figure 9: spatial catch composition

URL <http://icesjms.oxfordjournals.org/lookup/doi/10.1093/icesjms/fsw129>

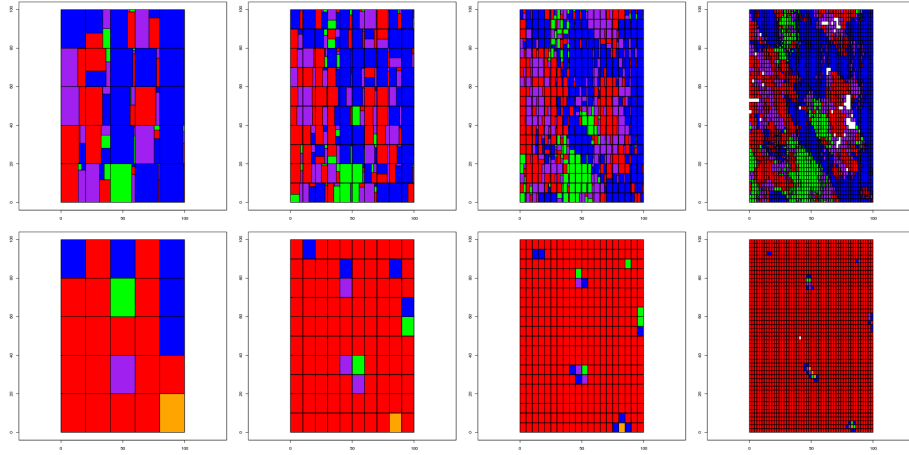


Figure 10: spatial catch composition with clustering

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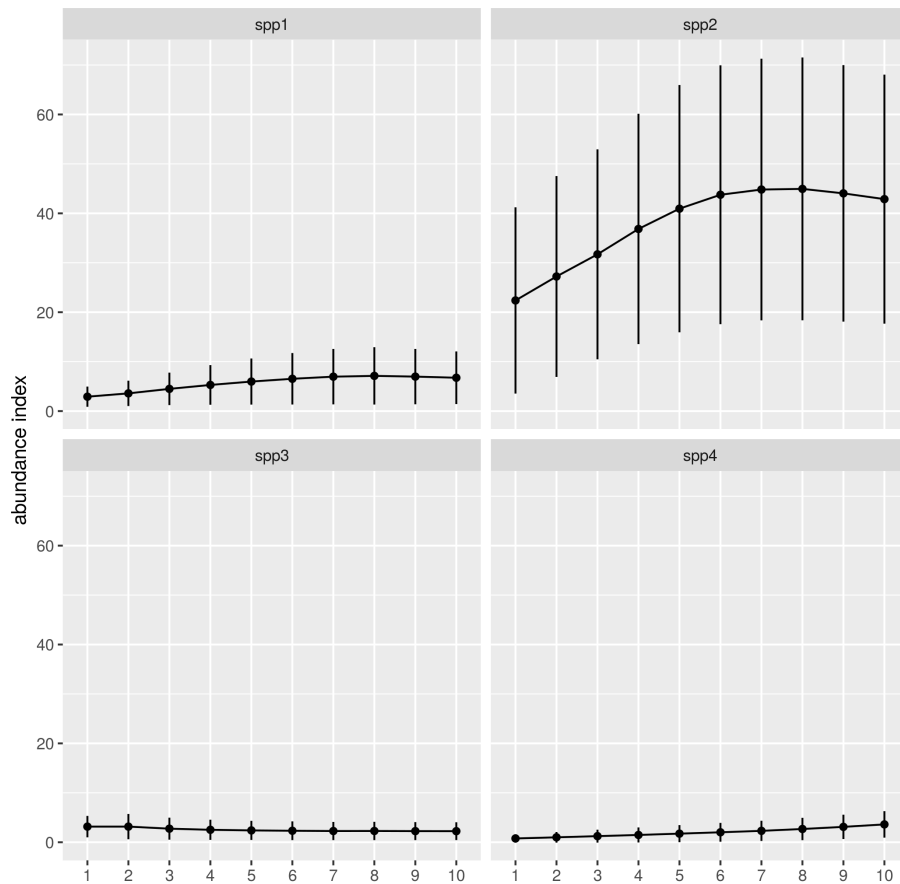


Figure 11: survey index

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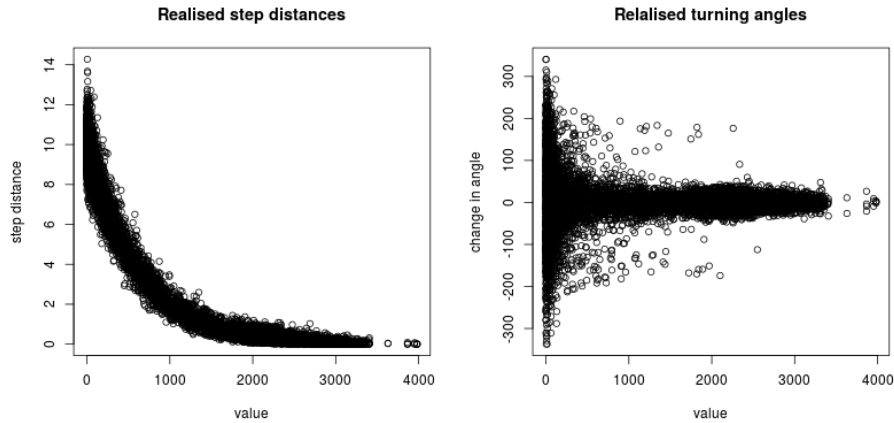


Figure 13: Realised step function

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