Simulating Space Use from fitted iSSFs

Johannes Signer

March 2023

Outline

- Why – Reasons for simulations
- How – Approaches to do simulations
- Case Study

Think-pair-share: Can we use a HSF/RSF to predict a possible path of an animal.

Why – Reasons for simulations

H/RSFs vs iSSFs

- RSFs:
  - There is no movement model built-in that we can take advantage of when simulating space use.
  - It is common practice to just multiply coefficients with resources to obtain, exponentiate and normalize to obtain a utilization distribution.

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- iSSF:
  - We have a simple movement model built-in, that allows integration of the movement process.
  - We can no longer simply multiply selection coefficients with resources.

For iSSFs this is a bit more complicated

If we take the same approach for iSSFs, we introduce a **bias** because we are neglecting conditional formulation of iSSFs when creating maps.

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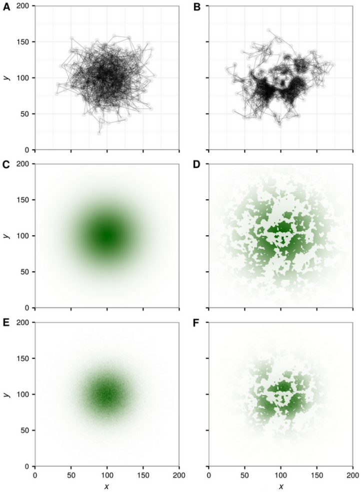
Estimating utilization distributions from fitted step-selection functions

Johannes Signer, John Fieberg, Tal Avgar

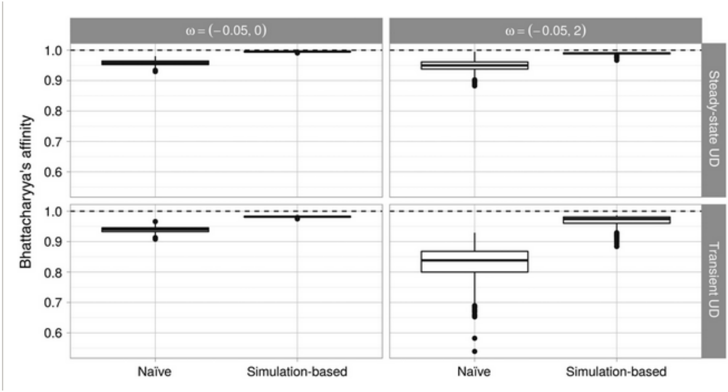
First published: 11 April 2017 | https://doi.org/10.1002/ecs2.1771 | Citations: 24

Corresponding Editor: Lucas N. Joppa.

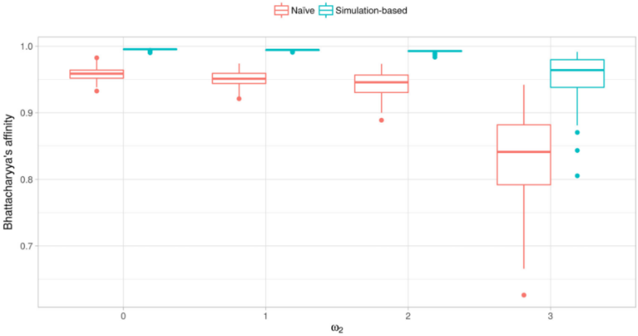
- We used simulations to compare the two approaches:
    - naive
    - simulation-based



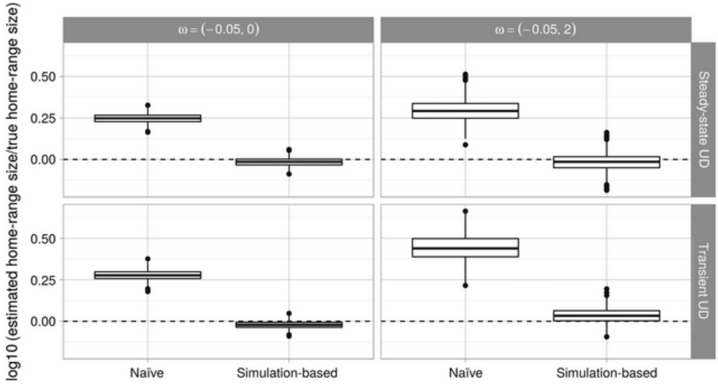
- Comparison between *true* space use and simulated space use:



- The bias becomes even larger if selection is stronger:



- This bi as also propagates through derived quantities (e.g., home-range size)



Analytical solutions

Under certain conditions there are analytical solutions to the long term space use ($=$ range distribution or steady state distribution).

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Methods in Ecology and Evolution | BRITISH ECOLOGICAL SOCIETY

RESEARCH ARTICLE

Parametrizing diffusion-taxis equations from animal movement trajectories using step selection analysis

Jonathan R. Potts, Ulrike E. Schlägel

First published: 17 May 2020 | https://doi.org/10.1111/2041-210X.13406 | Citations: 8

Analytical solutions

Under certain conditions there are analytical solutions to the long term space use (= range distribution or steady state distribution).

Received: 19 July 2022 | Accepted: 16 October 2022
DOI: 10.1111/1365-2656.13832
Journal of Animal Ecology BRITISH ECOLOGICAL SOCIETY

RESEARCH METHODS GUIDE

How to scale up from animal movement decisions to spatiotemporal patterns: An approach via step selection

Jonathan R. Potts[1] | Luca Börger[2,3]

Motivation to simulate: Understanding the model

The model specification can be abstract, e.g., what does the interaction between a covariate at the start of a step and the cosine of the turn angle mean?

What how does the redistribution kernel for $\sim \beta_1 \cos(\text{ta}) x_{\text{start}}$ look, if $\beta_1 = -4$?

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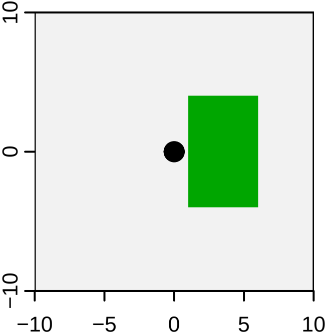
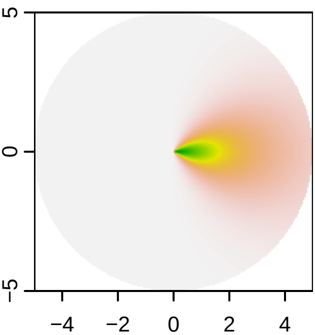
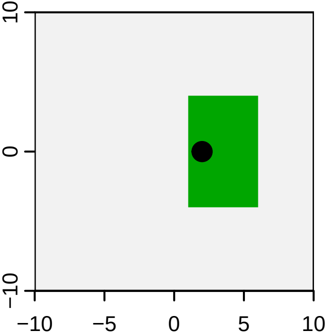
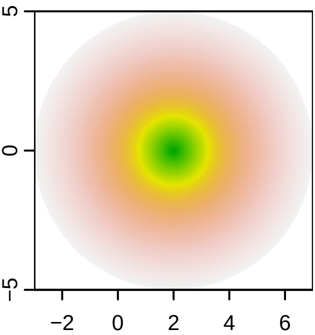




Same model, but different position in geographic space.





What if the animal shows a preference for x? E.g., $\sim \beta_1 \cos(\text{ta}) x_{\text{start}} + \beta_2 x_{\text{end}}$ and $\beta_2 = 2$.

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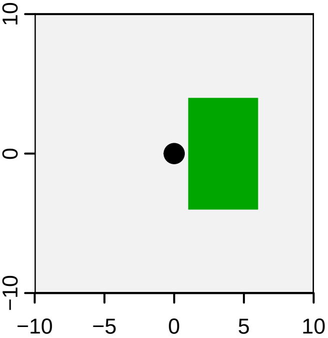
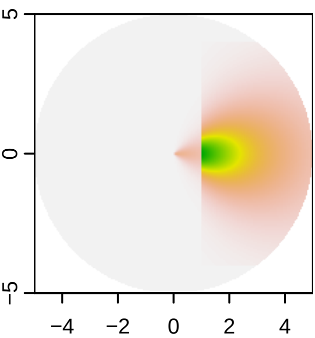
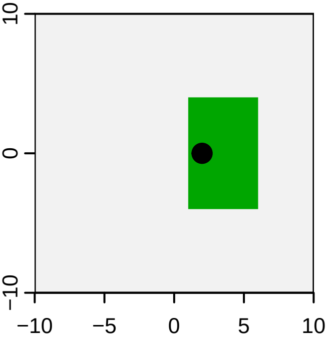




Same model, but different starting position.



Obtain space use of animals from fitted iSSFs

Different simulation targets:

1. An individual path of the animal.
2. Where is the animal next?

Often we are aiming for the **Utilization Distribution** (UD).
The UD is defined as:

> *The two-dimensional relative frequency distribution of space use of an animal (Van Winkle 1975)*

We can distinguish between two different types of UDs:

1. Transient UD (TUD) is the expected space-use distribution over a short time period and is thus sensitive to the initial conditions (e.g., the starting point).
2. Steady state UD (SSUD) is the long-term (asymptotically infinite) expectation of the space-use distribution across the landscape.

Asses model fit, does it reflect the biology of the animal?

- We can compare the observed track with simulated tracks and visually check if the model captures mechanisms of the observed track.

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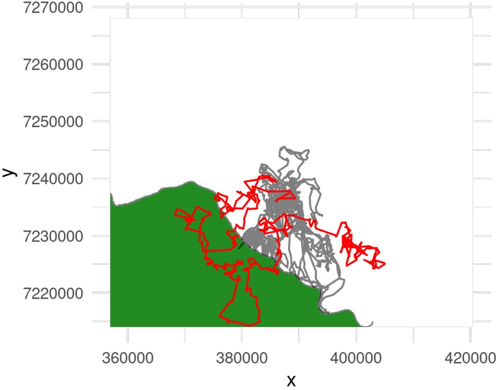

How – Approaches to do simulations

The redistribution kernel

$$(\mathbf{s}, t + \Delta t)$$

We want to model the probability that the animals moves to position $\mathbf{s}$ at time $t + \Delta t$

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- The movement-free habitat-selection function $w(\mathbf{X}(\mathbf{s}); \beta(\Delta t))$

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$$(\mathbf{s}, t + \Delta t) | u(\mathbf{s}', t) = \frac{w(\mathbf{X}(\mathbf{s}); \beta(\Delta t))\phi(\theta(\mathbf{s}, \mathbf{s}'), \gamma(\Delta t))}{}$$

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The redistribution kernel

$$(\mathbf{s}, t + \Delta t) | u(\mathbf{s}', t) = \underbrace{\frac{w(\mathbf{X}(\mathbf{s}); \beta(\Delta t))\phi(\theta(\mathbf{s}, \mathbf{s}'), \gamma(\Delta t))}{\int_{\tilde{\mathbf{s}} \in G} w(\mathbf{X}(\tilde{\mathbf{s}}); \beta(\Delta t))\phi(\theta(\tilde{\mathbf{s}}, \mathbf{s}'); \gamma(\Delta t)) d\tilde{\mathbf{s}}}}_{\text{Normalizing constant}}$$

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Argumentes to the redistribution kernel

In **amt** there is the function `redistribution_kernel()`, with several arguments (some are discussed here):

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- `model`: This can be the result of an iSSF fitted to data with the function `fit_issf()` or a model built from scratch with the function `make_issf_model()`.

```
library(amt)
m1 <- make_issf_model(
  # the selection coefficients
  coefs = c("x_end" = 1),
  # sl distribution
  sl = make_gamma_distr(shape = 2, scale = 2),
  ta = make_unif_distr() # uniform turn angles
)
```

- `map`: This is the landscape (with the resources). This needs to be one or more `SpatRasts` from the **terra** package.

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```
r1 <- terra::rast(xmin = -20, xmax = 20,
                  ymin = -20, ymax = 20, res = 1)
r1[] <- 1
r1[ , 1:20] <- 0
names(r1) <- "x"
```

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r1[ , 1:20] <- 0
names(r1) <- "x"
```

- `function`: This a function that is executed at each time step. Often the default (`function(xy, map) { extract_covariates(xy, map, where = "both")}`) is sufficient and no modifications are needed.

- `max.dist`: This is the distance at which redistribution kernel is truncated. By default this is the 0.99 quantile of the step length distribution.

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- `start`: The start position and start direction.

```
start <- make_start(c(0, 0), ta_ = 0)
```

Representation of space

We implemented two ways to represent space:

1. **Discrete space:** each pixel in the redistribution kernel up to the truncation distance is potentially available. Correction for the tentative movement parameter estimates of the movement kernel and the transformation from polar to Euclidean coordinates are needed.

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1. **Discrete space:** each pixel in the redistribution kernel up to the truncation distance is potentially available. Correction for the tentative movement parameter estimates of the movement kernel and the transformation from polar to Euclidean coordinates are needed.

2. **Continuous space:** a large number of points are sampled under the tentative movement kernel.

```r
library(amt)
rdk1 <- redistribution_kernel(
  m1, map = r1,
  start = start, as.rast = TRUE)
```

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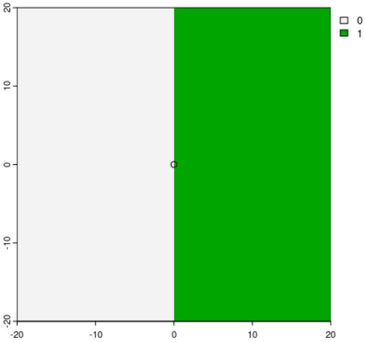

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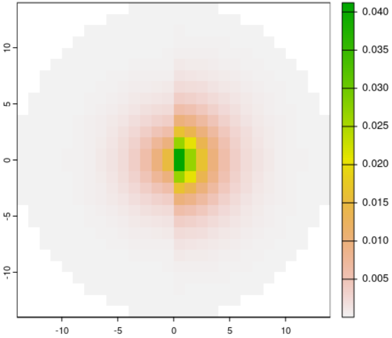

```r
rdk2 <- redistribution_kernel(
  m1, map = r1,
  start = make_start(c(10, 0)), as.rast = TRUE)
```

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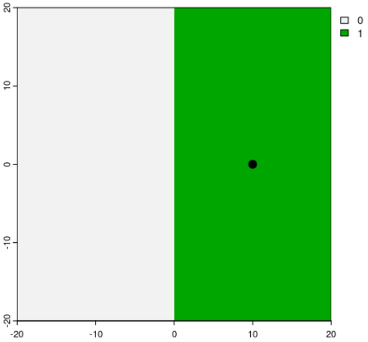
```



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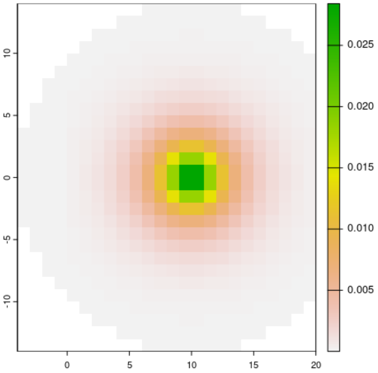

From the redistribution kernel to a path

First we need to create a slightly bigger landscape.

```
r <- terra::rast(xmin = -100, xmax = 100,
                 ymin = -100, ymax = 100, res = 1)
r[] <- 0
r[50:100, ] <- 1
names(r) <- "x"
```

Then we have to specify the redistribution kernel again

```r
# Start
start <- make_start(c(0, 0), ta_ = pi/2)

# Model
m <- make_issf_model(
  coefs = c(x_end = 2),
  sl = make_gamma_distr(shape = 2, scale = 2),
  ta = make_vonmises_distr(kappa = 1))

# Redistribution kernel
rdk.1a <- redistribution_kernel(
  m, start = start, map = r,
  stochastic = TRUE, max.dist = 5,
  n.control = 1e4)
```

And now we simulate 15 steps from this redistribution kernel:

```
p1 <- simulate_path(rdk.1a, n.steps = 20, start = start)
```

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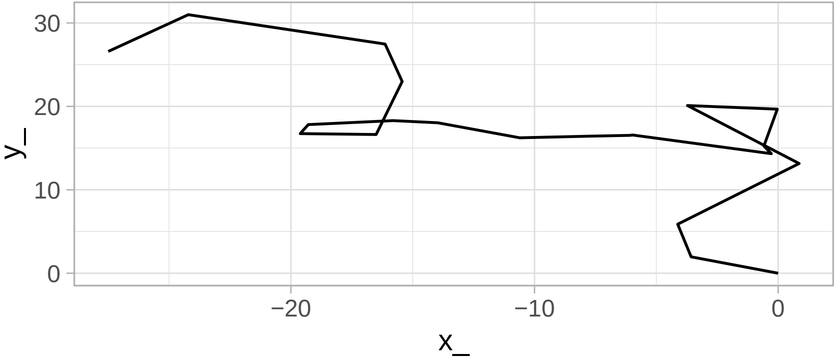
```

```
ggplot(p1, aes(x_, y_)) + geom_path()
```

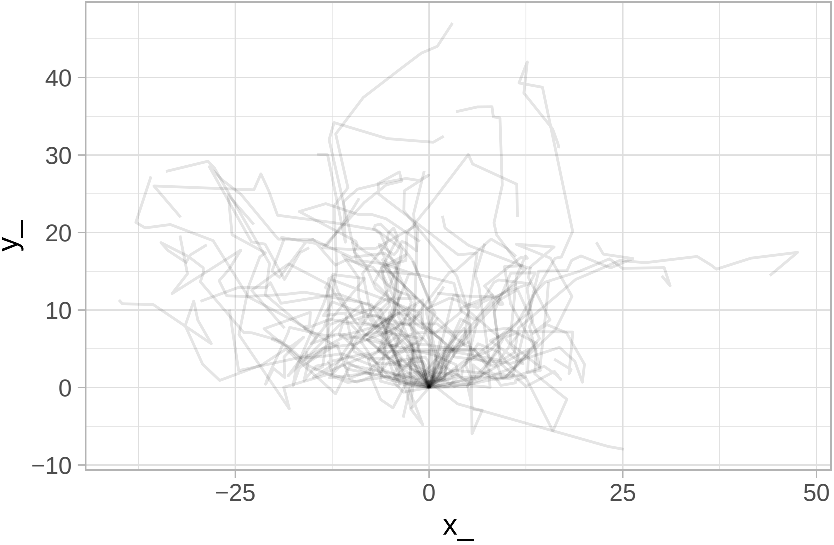


But this is just one realization, lets repeat this for $n = 50$ animals:

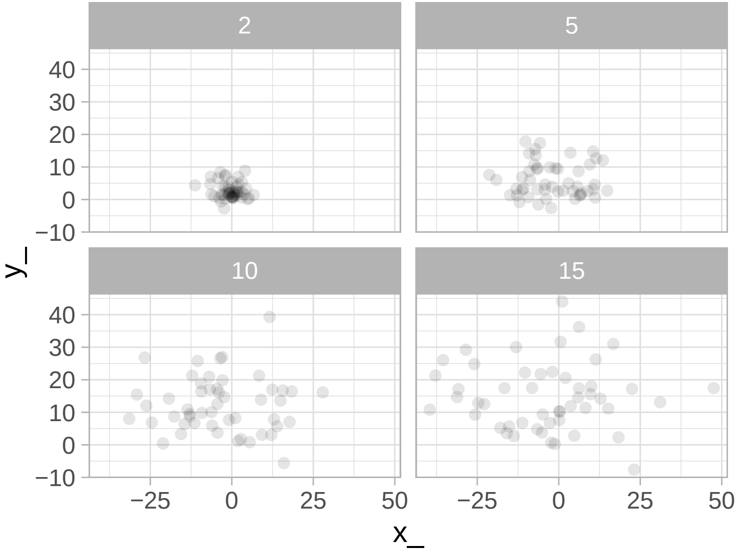
```
n <- 50
system.time(p1 <- replicate(
  n, simulate_path(rdk.1a, n = 15,
                   start = start),
  simplify = FALSE))
```

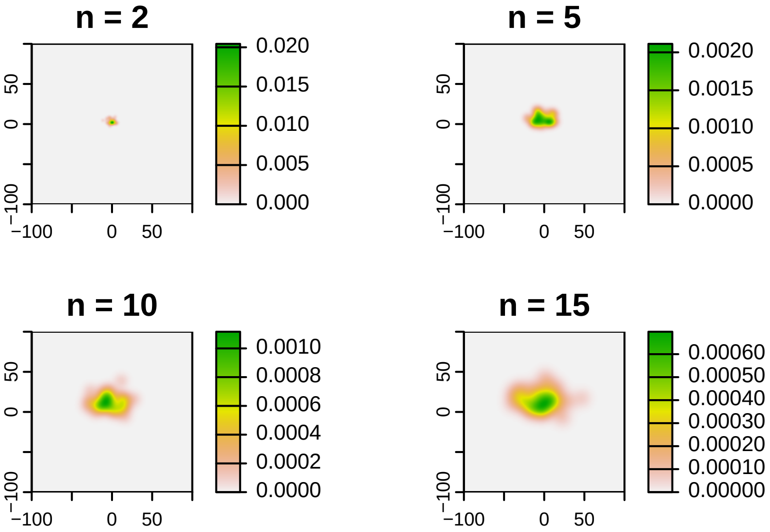
```
   user  system elapsed
 56.826   0.044  57.174
```

Individual paths of 50 simulated animals



From a redistribution kernel to a map




n = 2
n = 5
n = 10
n = 15
−100
0
50
0.020
0.015
0.010
0.005
0.000
0.0020
0.0015
0.0010
0.0005
0.0000
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0.00060
0.00050
0.00040
0.00030
0.00020
0.00010
0.00000

Case Study

African Buffalo

To illustrate the use of simulation, we fitted an iSSF to tracking data of a single African buffalo[1,2].

[1] For details of the data see: Getz et al. 2007 LoCoH: Nonparameteric kernel methods for constructing home ranges and utilization distributions. PLoS ONE

[2] Cross et al. 2016. Data from: Nonparameteric kernel methods for constructing home ranges and utilization distributions. Movebank Data Repository. DOI:10.5441/001/1.j900f88t.

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2. **Home-range model**: `case_ ~ cos(ta_) + sl_ + log(sl_) + water_dist_end + x2_ + y2_ + I(x2_^2 + y2_^2)`

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3. **River model**: `case_ ~ cos(ta_) + sl_ + log(sl_) + water_dist_end + x2_ + y2_ + I(x2_^2 + y2_^2) + I(water_crossed_end != water_crossed_start)`

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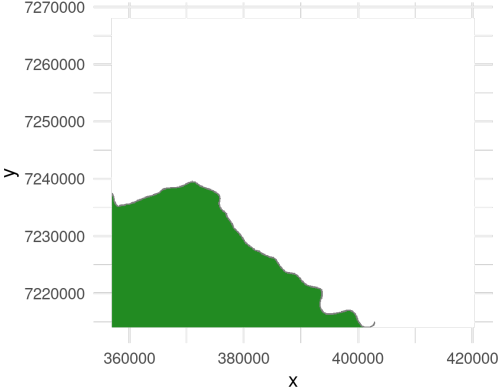
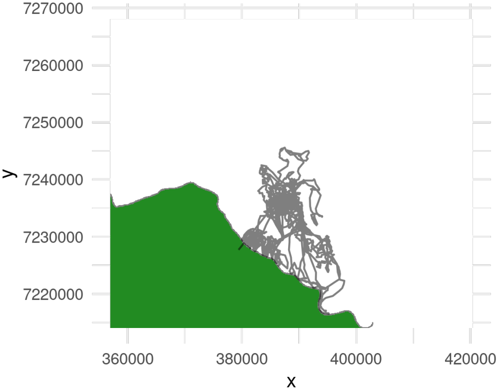
The setting

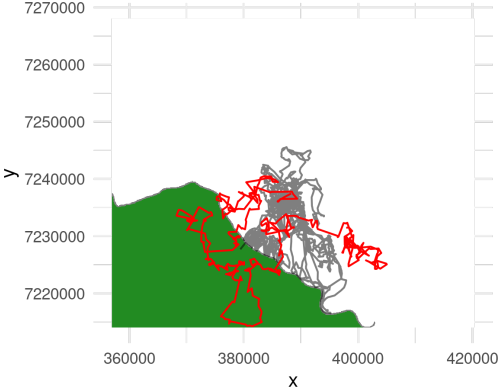


7270000
7260000
7250000
7240000
7230000
7220000
y
360000
380000
400000
420000
x

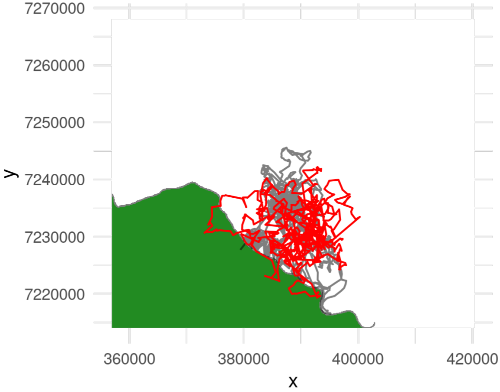
The observed track



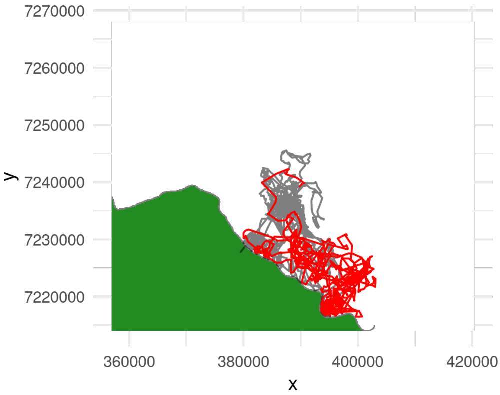
Base model: `case_ ~ cos(ta_) + sl_ + log(sl_) + water_dist_end`



Home-range model: `case_ ~ cos(ta_) + sl_ + log(sl_) + water_dist_end + x2_ + y2_ + I(x2_^2 + y2_^2)`



River model: `case_ ~ cos(ta_) + sl_ + log(sl_) + water_dist_end + x2_ + y2_ + I(x2_^2 + y2_^2) + I(water_crossed_end != water_crossed_start)`



More applications

Research Article | Open Access | Published: 17 February 2023

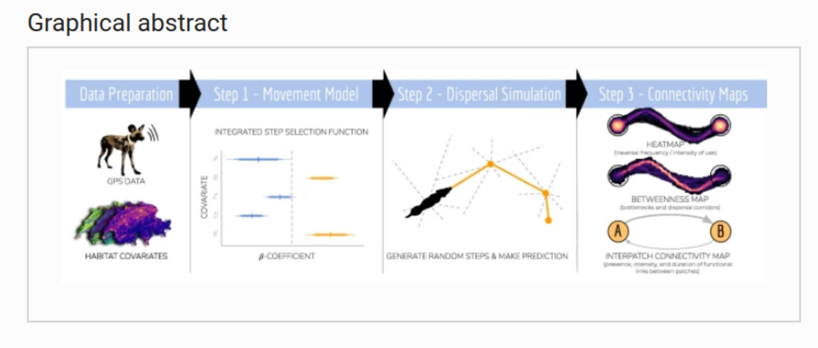
A three-step approach for assessing landscape connectivity via simulated dispersal: African wild dog case study

David D. Hofmann, Gabriele Cozzi, John W. McNutt, Arpat Ozgul & Dominik M. Behr

Landscape Ecology (2023) | Cite this article

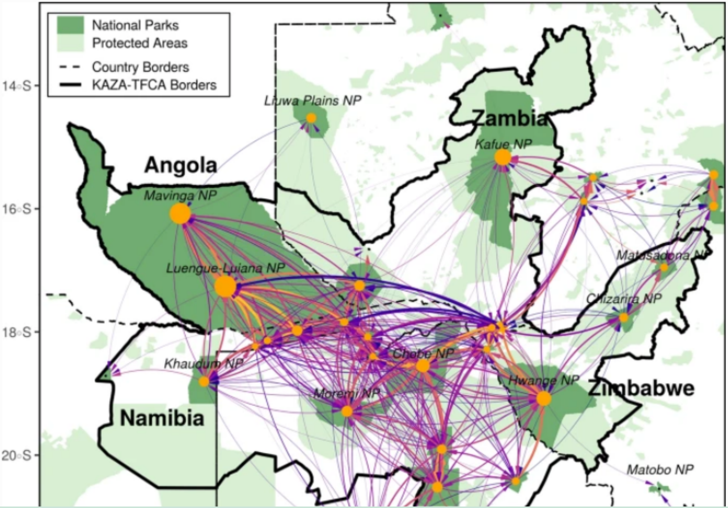
875 Accesses | **6** Altmetric | Metrics

More applications



More applications

Fig. 6



More applications

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A utilization distribution for the global population of Cape Vultures (*Gyps coprotheres*) to guide wind energy development

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Movement models and simulation reveal highway impacts and mitigation opportunities for a metapopulation-distributed species

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