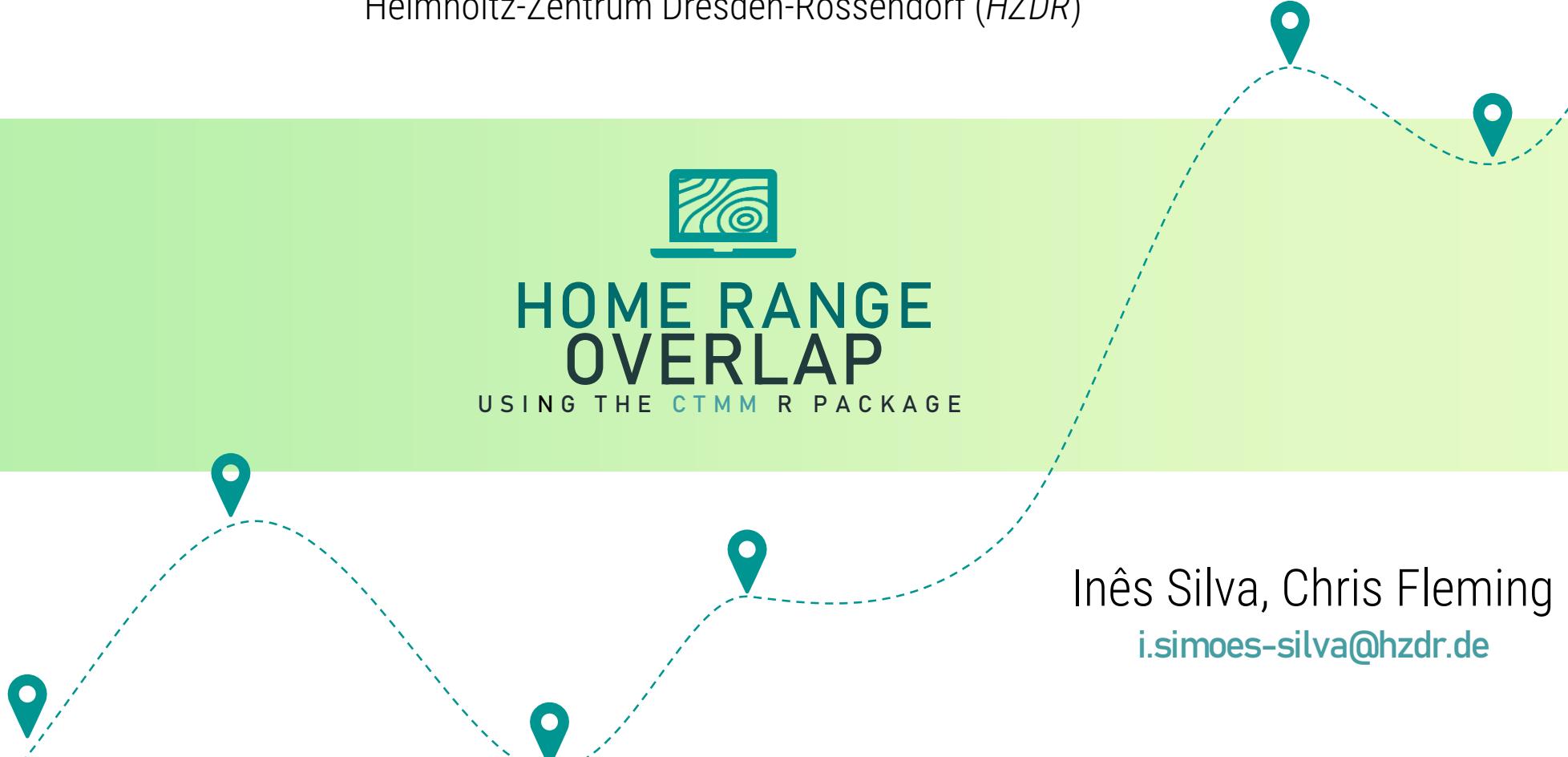


Center for Advanced Systems Understanding (CASUS)
Helmholtz-Zentrum Dresden-Rossendorf (HZDR)



HOME RANGE OVERLAP

USING THE `CTMM R PACKAGE`



Inês Silva, Chris Fleming
i.simoes-silva@hzdr.de

@ Jenny van Twillert

Quantifying overlap can provide an informative metric for:
interspecific competition,
territoriality,
mating systems,
social network structure,
and **contact rates (disease transmission),**
many more.

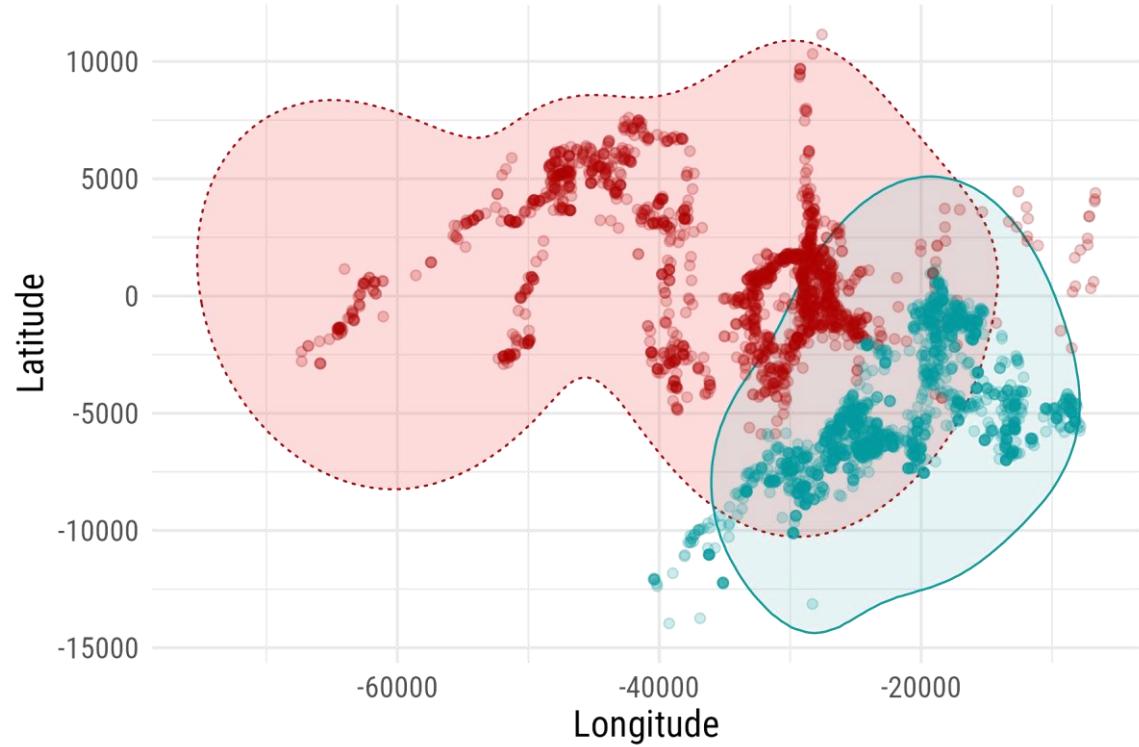


@ Debbie Stewart

Home range overlap captures potential for interactions.

Numerous overlap indices available, many are *ad-hoc*,
and none have confidence intervals.

Fieberg & Kochanny (2005)
DOI: 10.2193/0022-541X(2005)69



What do you need:

1. Comparable home range estimates.



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1. Comparable home range estimates.



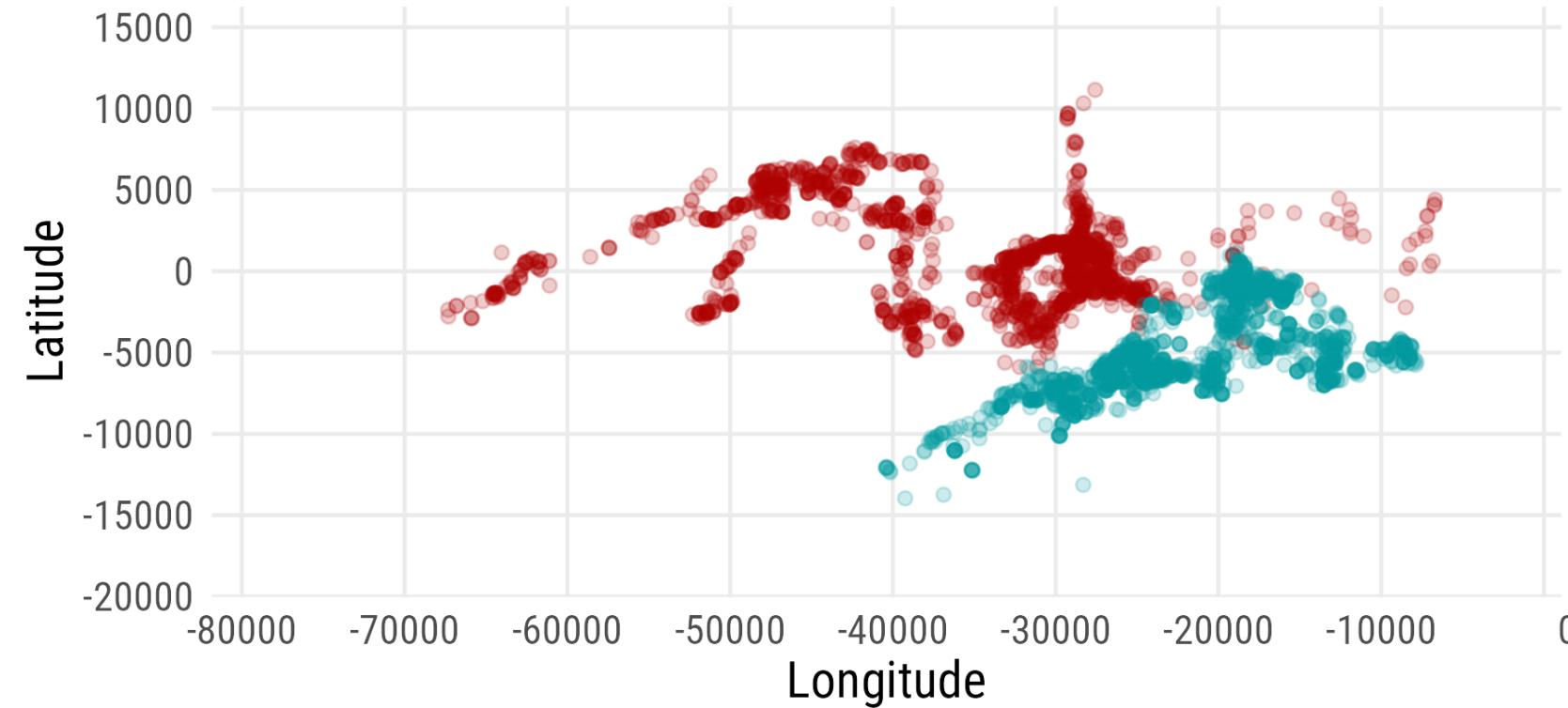
e.g. dealing with unmodelled autocorrelation,
small effective sample size,
temporally-biased sampling.

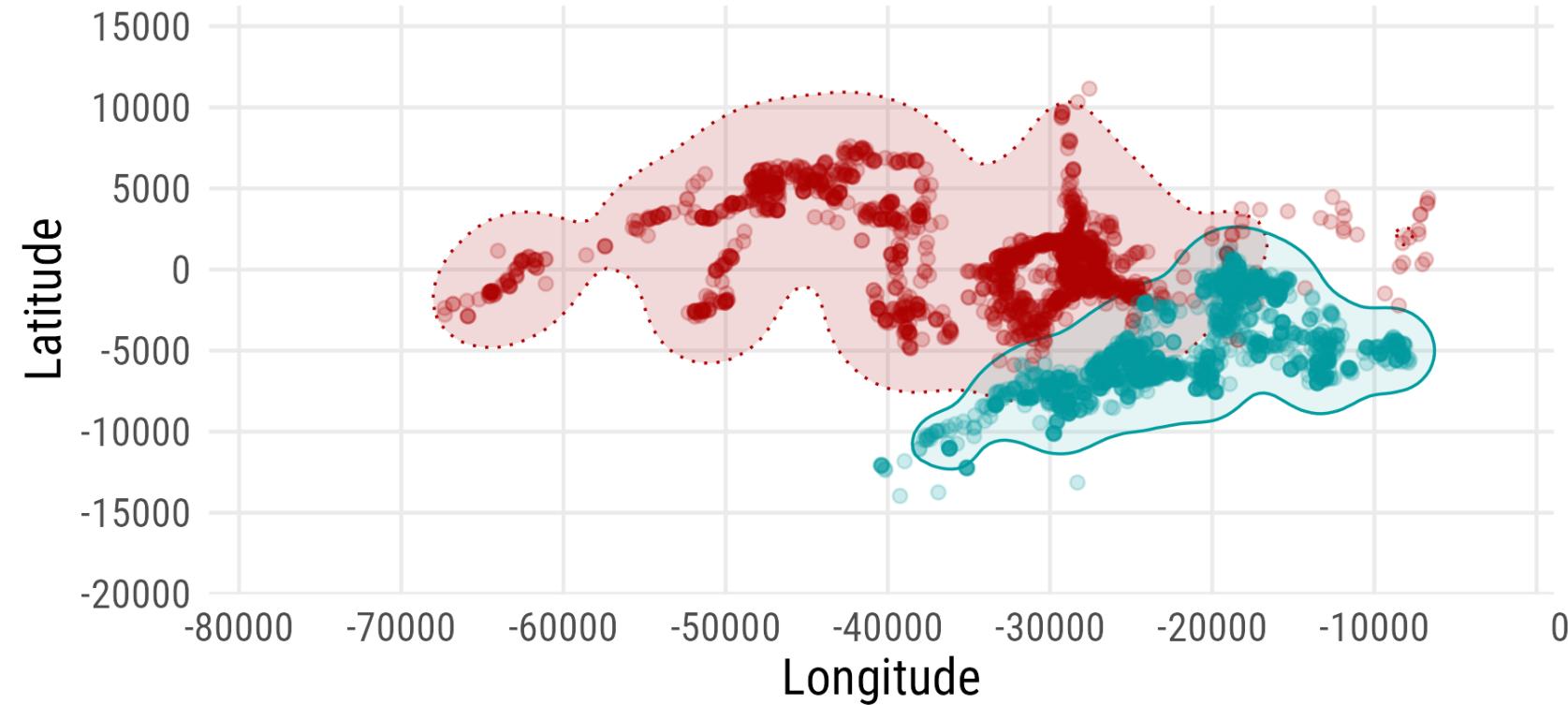
What do you need:

1. Comparable home range estimates. 
2. An interpretable, relatively unbiased overlap index.

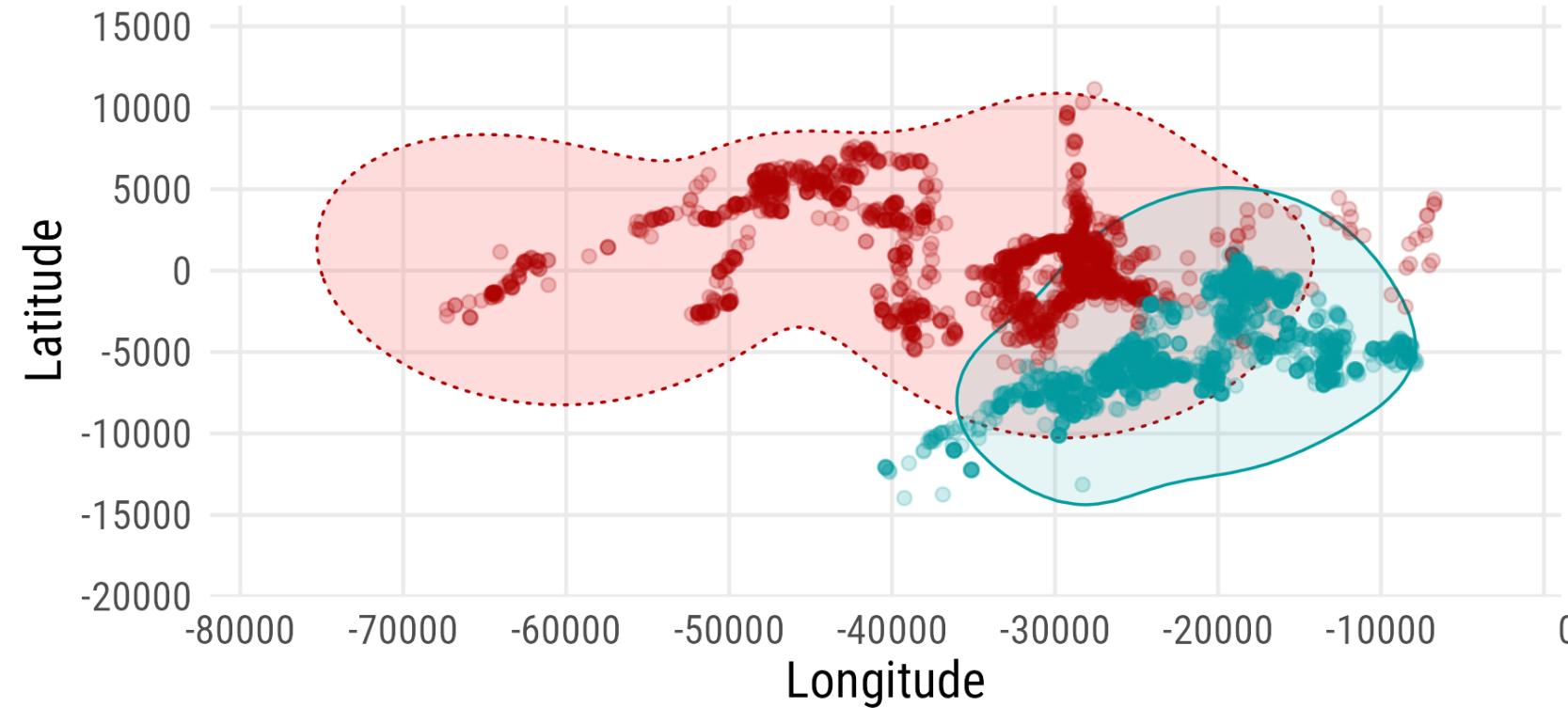
What do you need:

1. Comparable home range estimates. 
2. An interpretable, relatively unbiased overlap index.
3. A way to propagate uncertainty in home range estimates into overlap estimates.

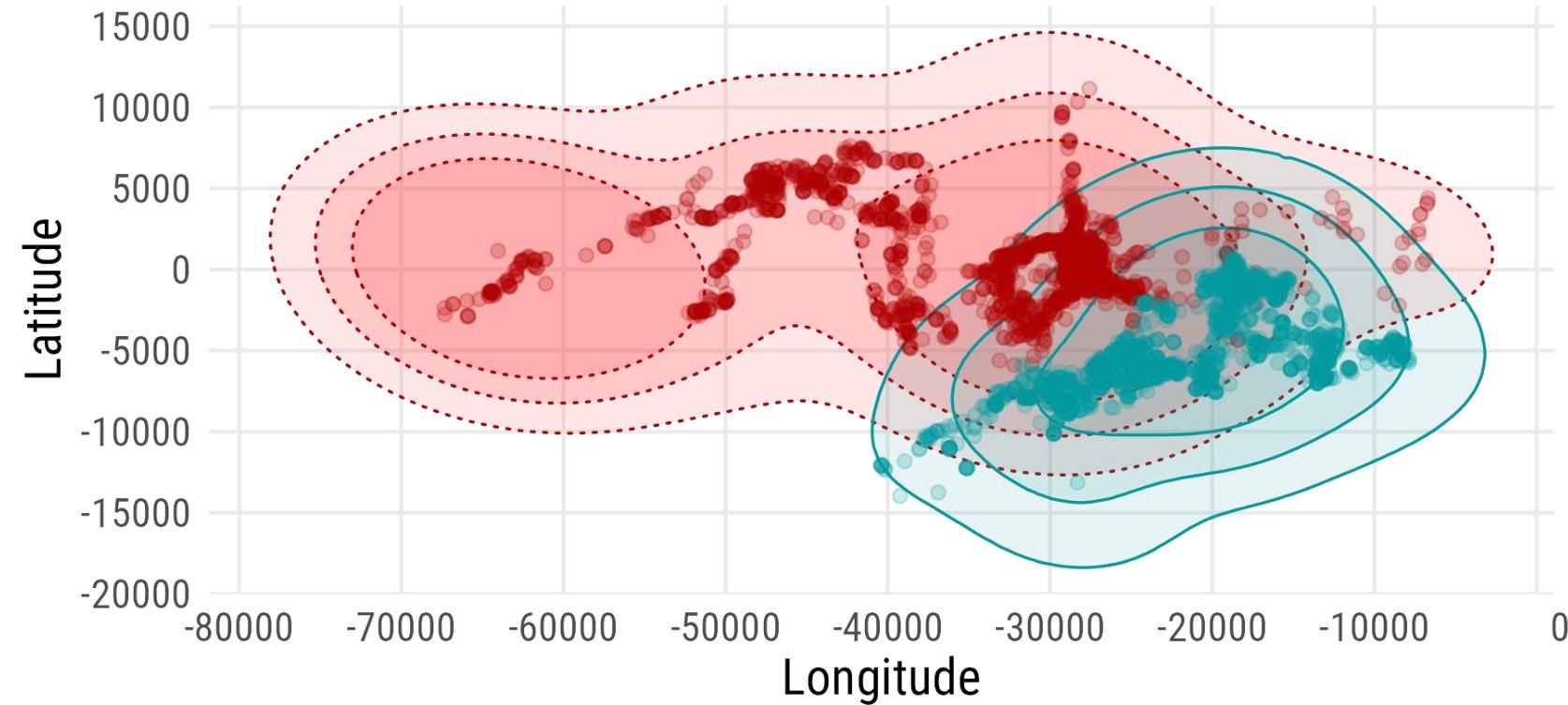




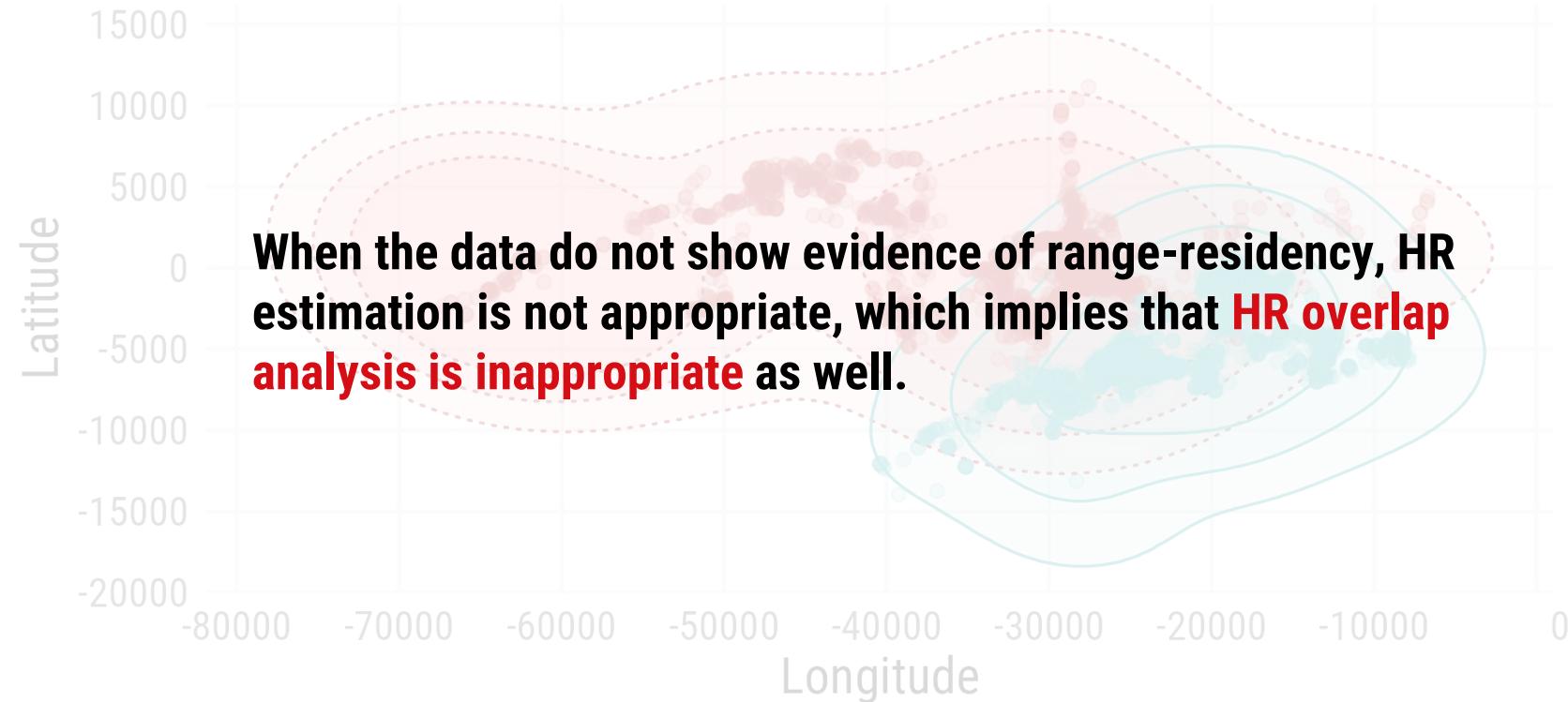
Kernel density estimator (KDE)



Autocorrelated Kernel density estimator (AKDE)



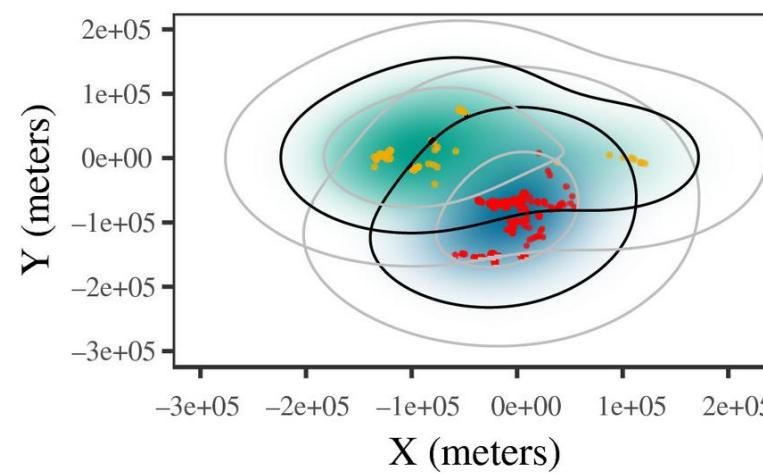
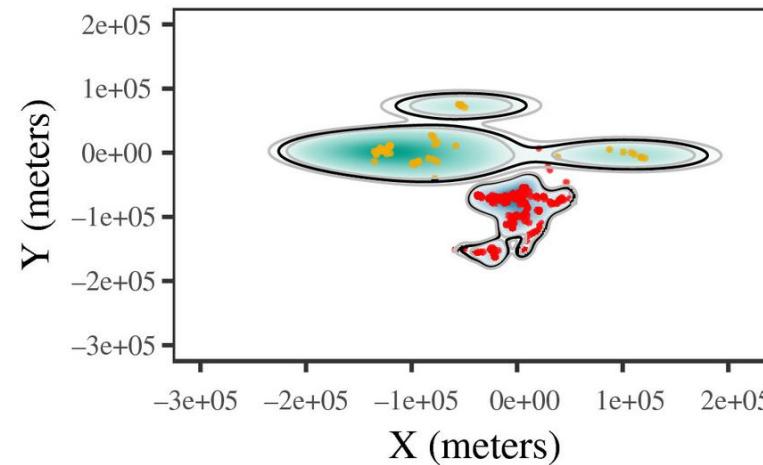
Autocorrelated Kernel density estimator (AKDE)



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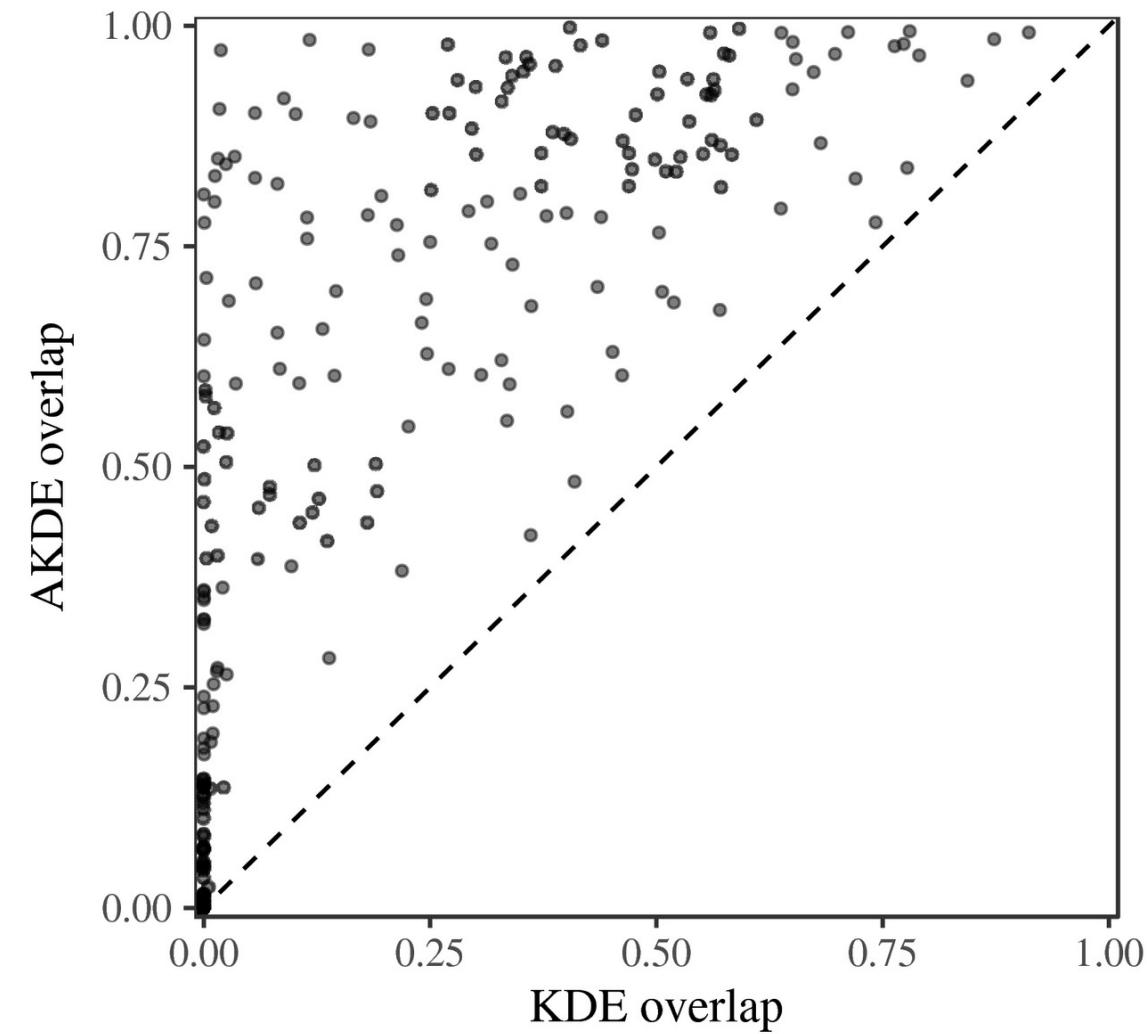
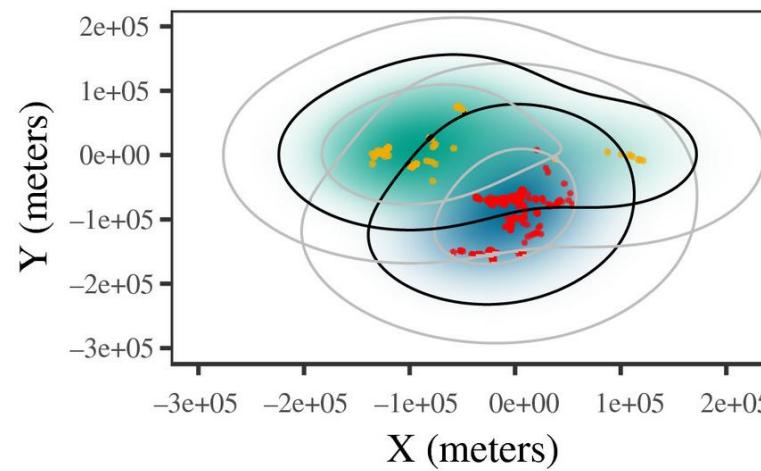
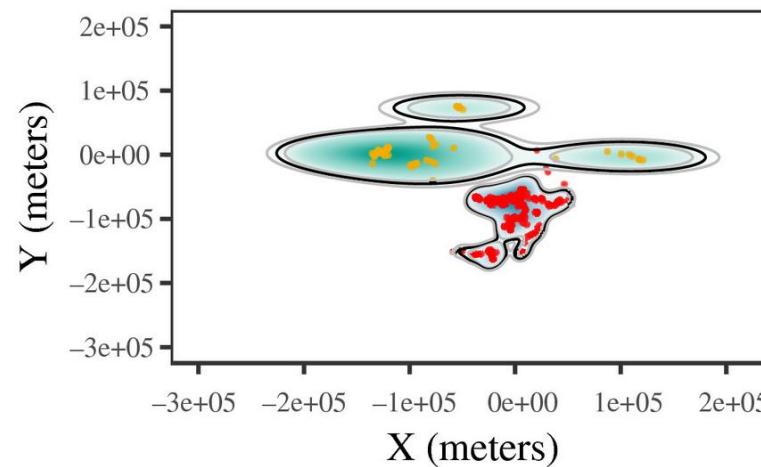
ESTIMATION OVERLAP

ANIMOVE 2022



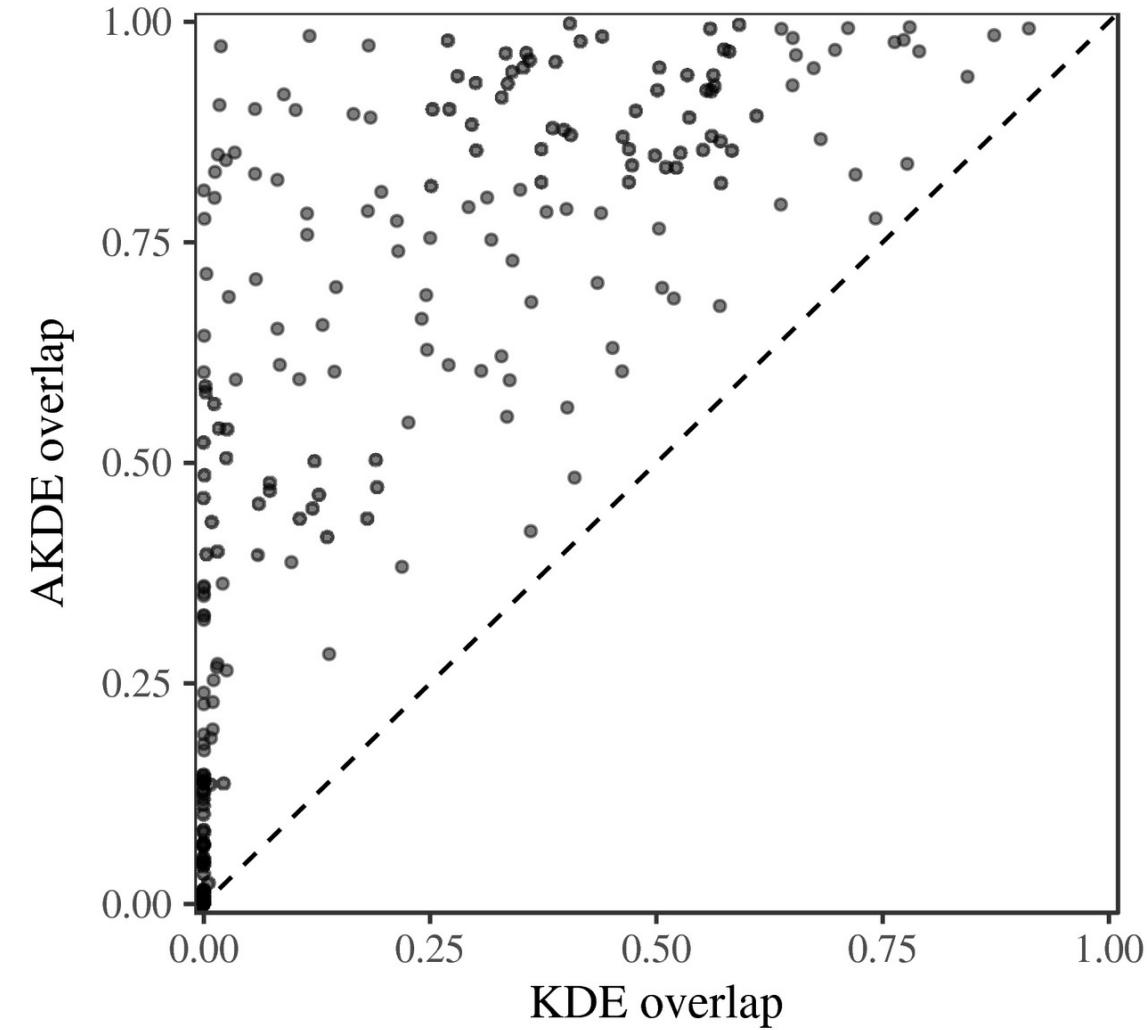
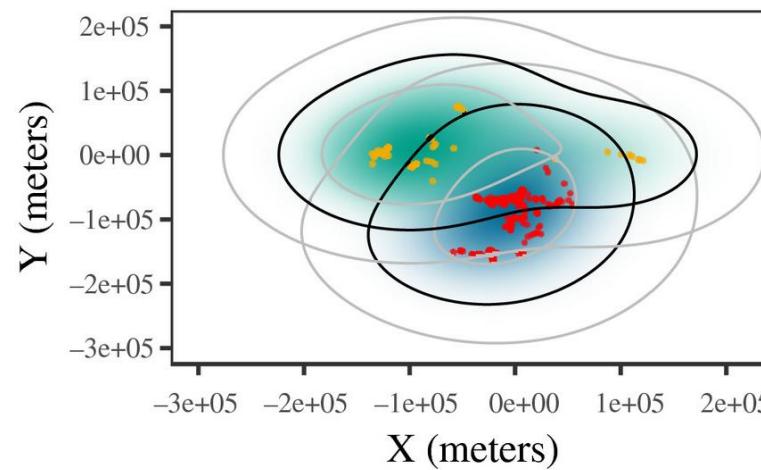
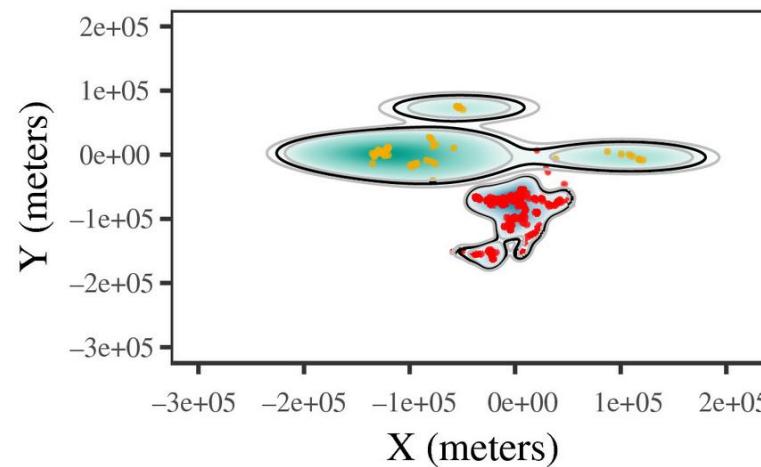
ESTIMATION OVERLAP

ANIMOVE 2022



ESTIMATION OVERLAP

ANIMOVE 2022



Important when considering **biologically meaningful conclusions** from these analyses.

What do you need:

1. Comparable home range estimates. 
 2. An interpretable, relatively unbiased overlap index.
 3. A way to propagate uncertainty in home range estimates *into* overlap estimates.
- 

Bhattacharyya coefficient (BC)

measure of similarity between two probability distributions



BC ranges from **zero** (no overlap) to **1** (identical distributions).

Fieberg & Kochanny (2005)

DOI: 10.2193/0022-541X(2005)69

Bhattacharyya coefficient (BC)

measure of similarity between two probability distributions



BC ranges from **zero** (no overlap) to **1** (identical distributions).

- = Bias-corrected AKDE HR estimates
- = Bias-corrected BC estimator.
- = Approximate CIs for the BC point estimate.

Winner *et al.* (2018)
DOI: 10.1111/2041-210X.13027

Bhattacharyya coefficient (BC)

measure of similarity between two probability distributions



BC ranges from **zero** (no overlap) to **1** (identical distributions).



Utilization Distribution Overlap Index (UDOI)

measure of space sharing (quantifies HR similarity while incorporating information about shared space use)



UDOI equals **1** between identical distributions (space use is uniform), but may **exceed 1** for highly concentrated distributions with a high overlap.

Tilberg & Dixon (2022)
DOI: 10.1111/2041-210X.13813

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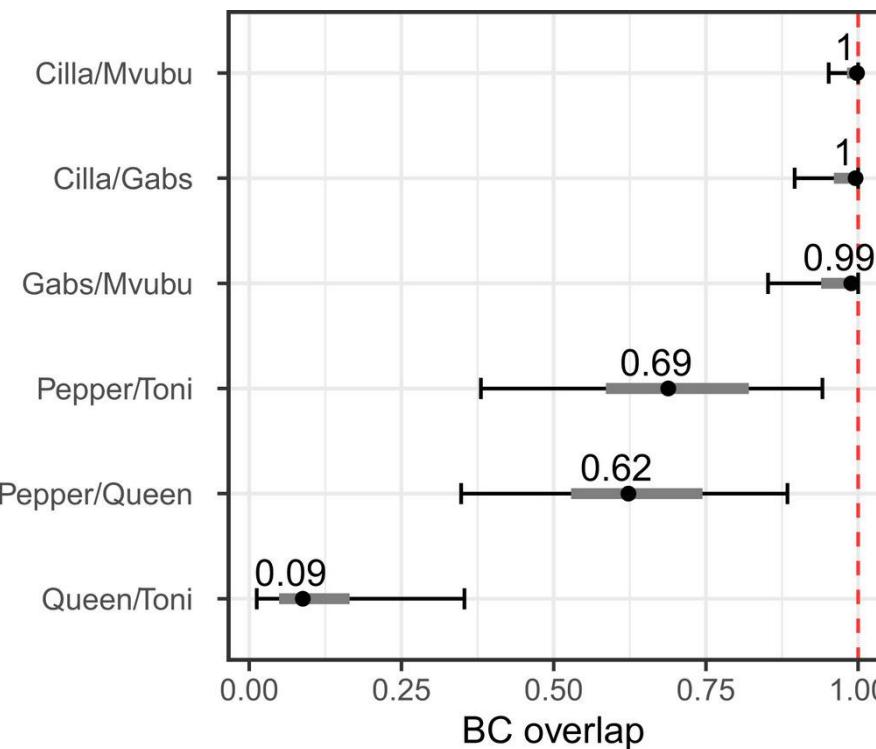
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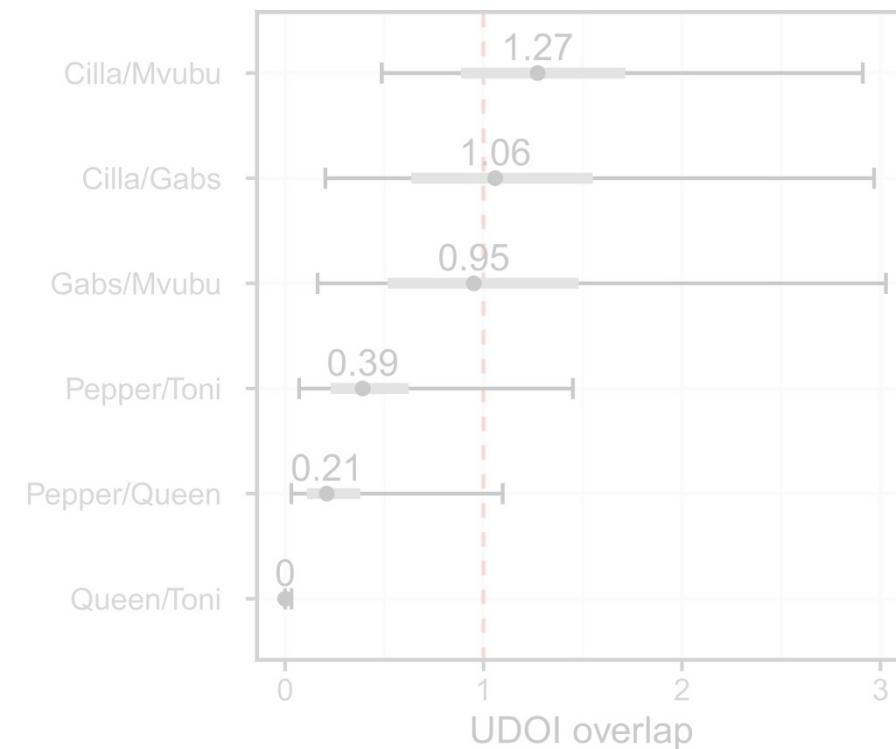
INFERENCES OVERLAP

ANIMOVE 2022

Bhattacharyya coefficient (BC)

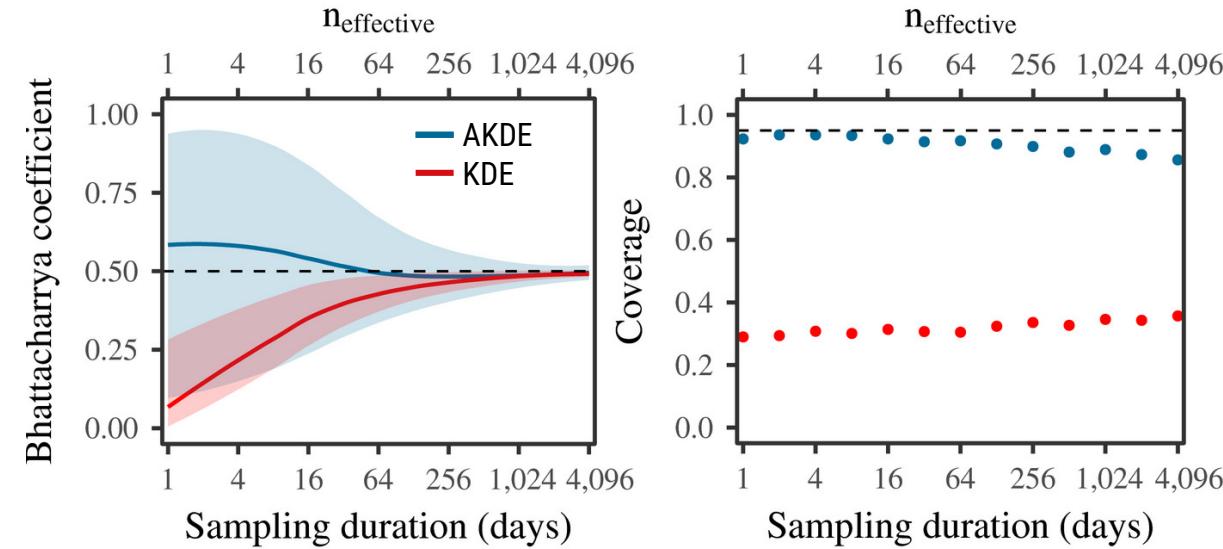


Utilization Distribution Overlap Index (UDOI)

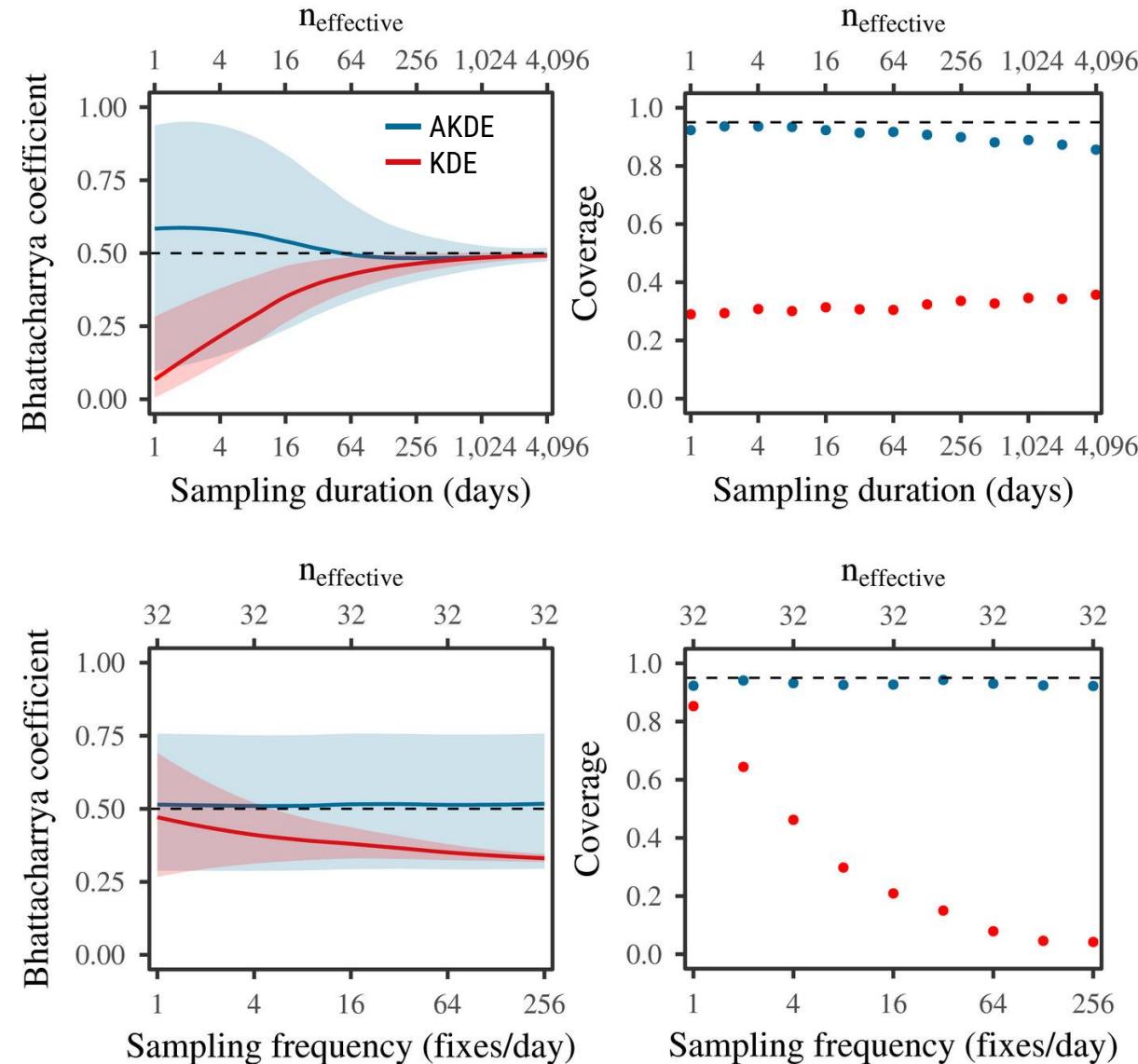


Tilberg & Dixon (2022)

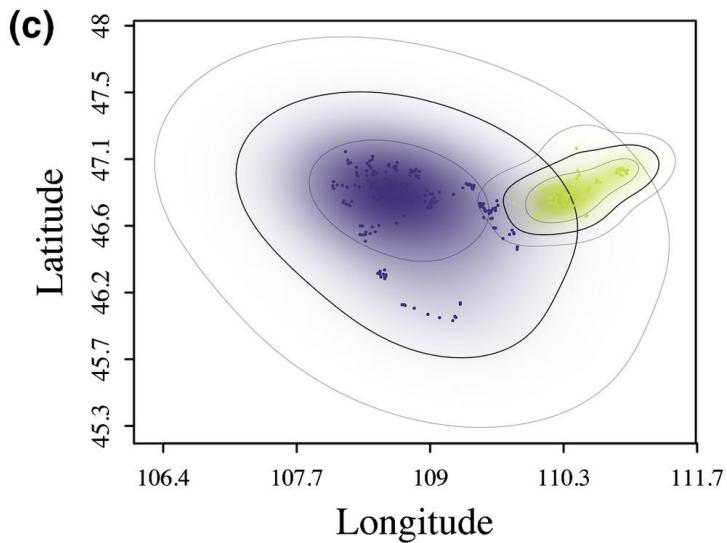
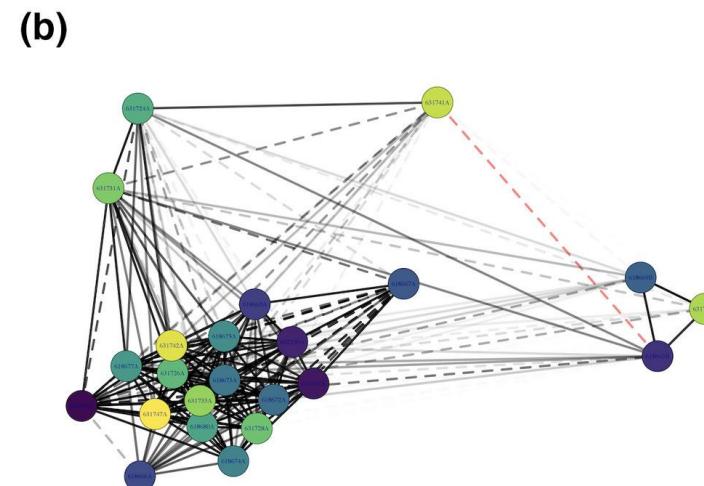
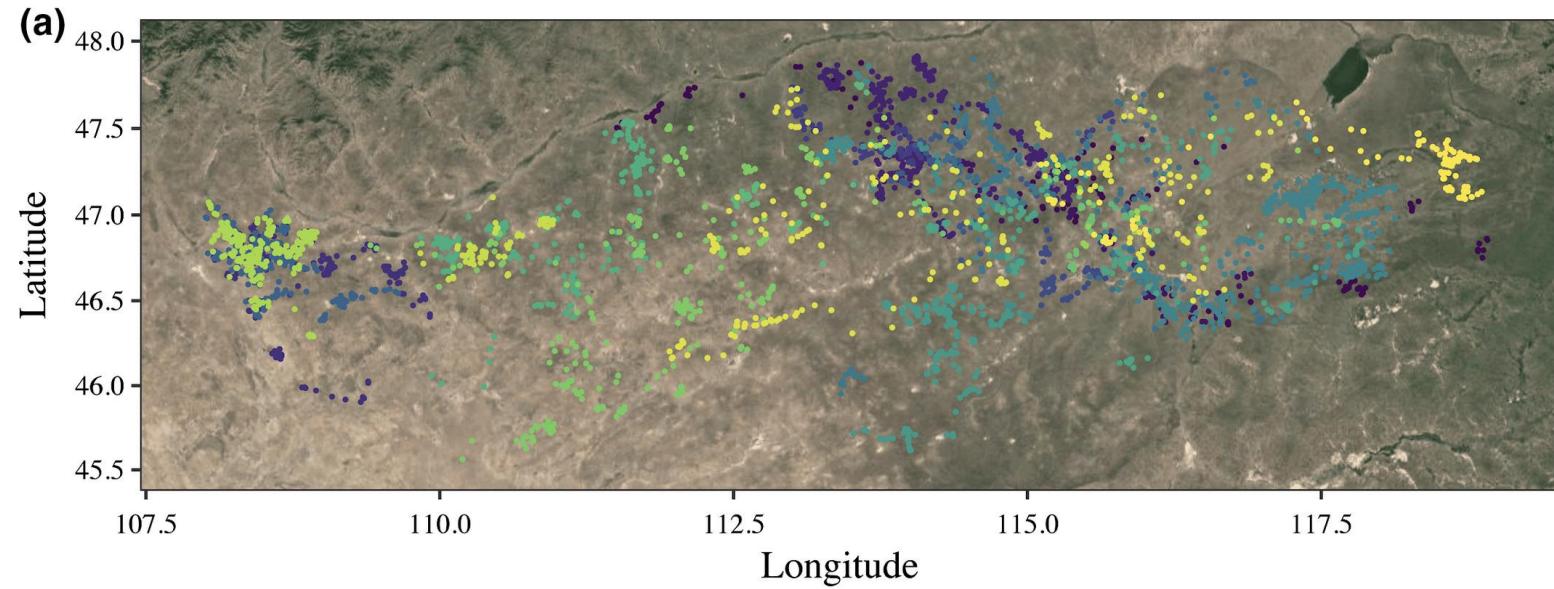
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 OVERLAP ESTIMATION

📍 OVERLAP ESTIMATION



OVERLAP ESTIMATION



 OVERLAP ESTIMATION

- ▶ The first inferential framework for overlap.
- ▶ Meaningful comparisons (e.g. different sampling regimes and/or movement behaviors).
= can be validly be compared across studies
- ▶ Stepping stone to higher level processes.

Winner et al. (2018)
DOI: 10.1111/2041-210X.13027

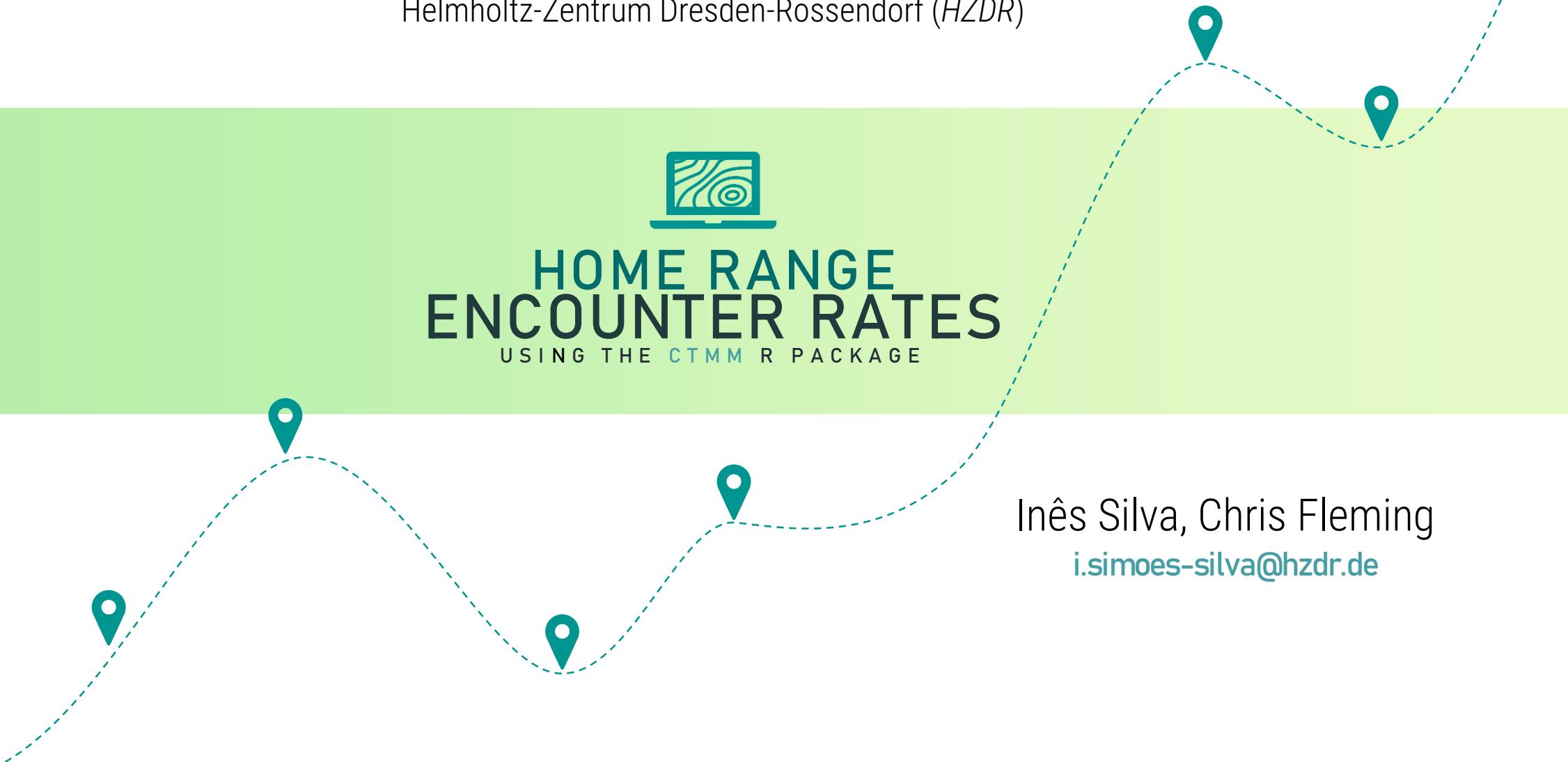


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HOME RANGE ENCOUNTER RATES

USING THE `CTMM` R PACKAGE



Inês Silva, Chris Fleming
i.silva@hzdr.de

Encounters as **keystone events** Understanding large-scale ecological processes

predator–prey dynamics



@ Amy Long



@ Antero Topp

Intraspecific interactions



@ Ryan Dorgan

human–wildlife conflict

Encounters as **keystone events** Understanding large-scale ecological processes



↑
MAXIMIZE
POSITIVE ENCOUNTERS



predator-prey dynamics

↓
MINIMIZE
NEGATIVE ENCOUNTERS



@ Antero Topp

Intraspecific interactions

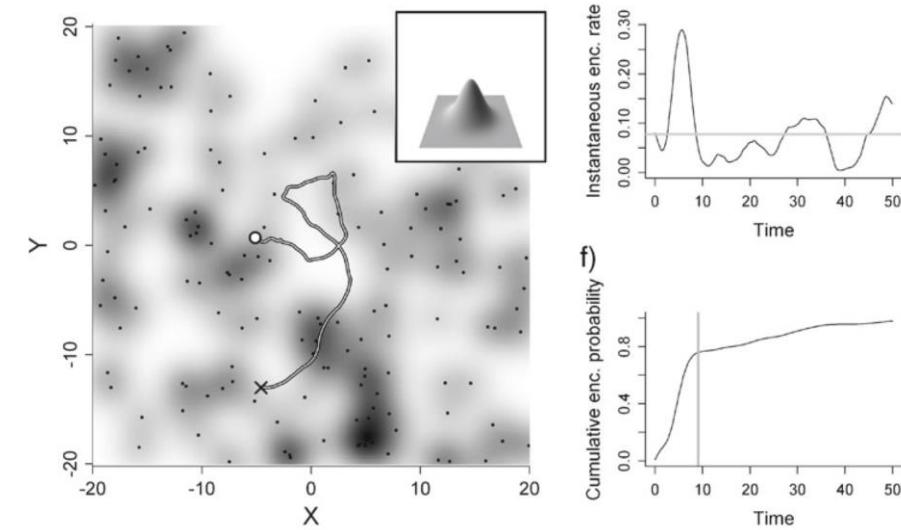
human-wildlife conflict

ESTIMATION ENCOUNTERS

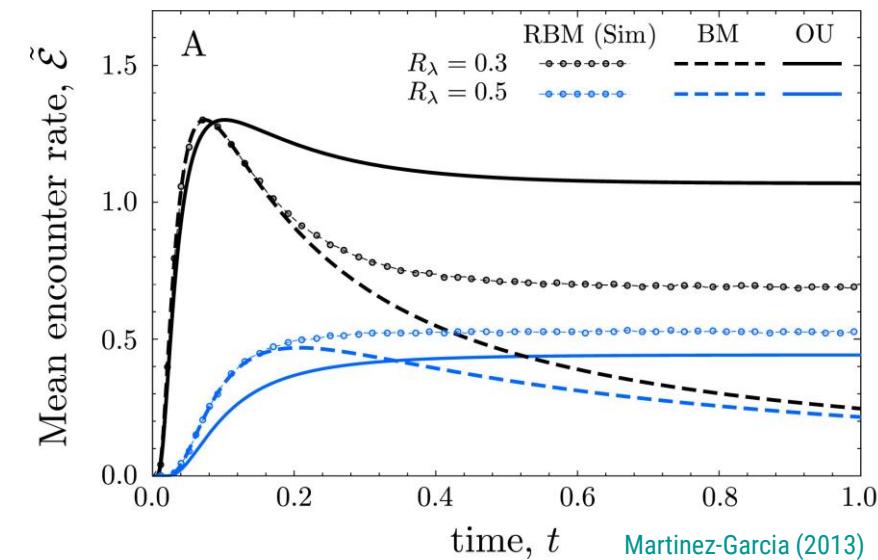
ANIMOVE 2022

Encounter theory has not kept pace with the developments in animal tracking or movement modelling.

- ▶ Mainly focused on *estimating encounter rates*.



Gurarie & Ovaskainen (2013)



Martinez-Garcia (2013)

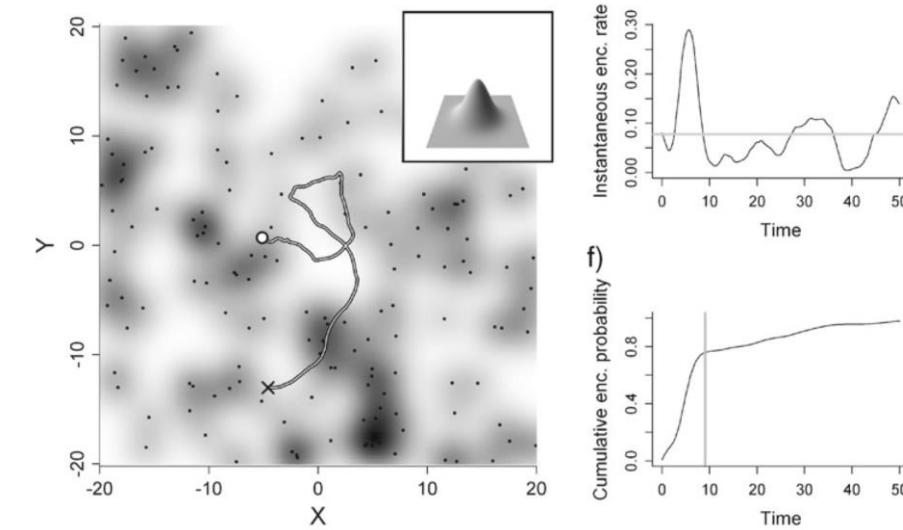
ESTIMATION ENCOUNTERS

ANIMOVE 2022

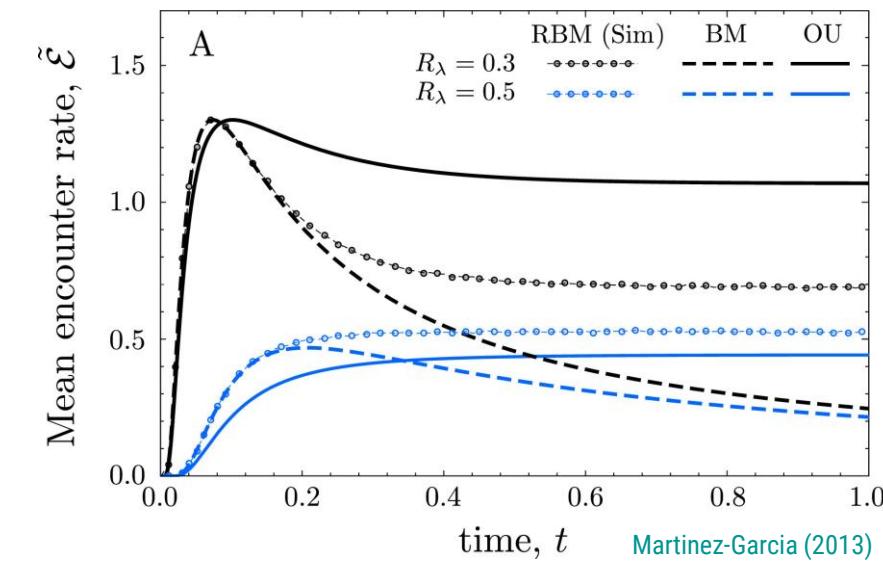
Encounter theory has not kept pace with the developments in animal tracking or movement modelling.

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Relating *individual movement* with the *spatial locations* of encounter events



Gurarie & Ovaskainen (2013)

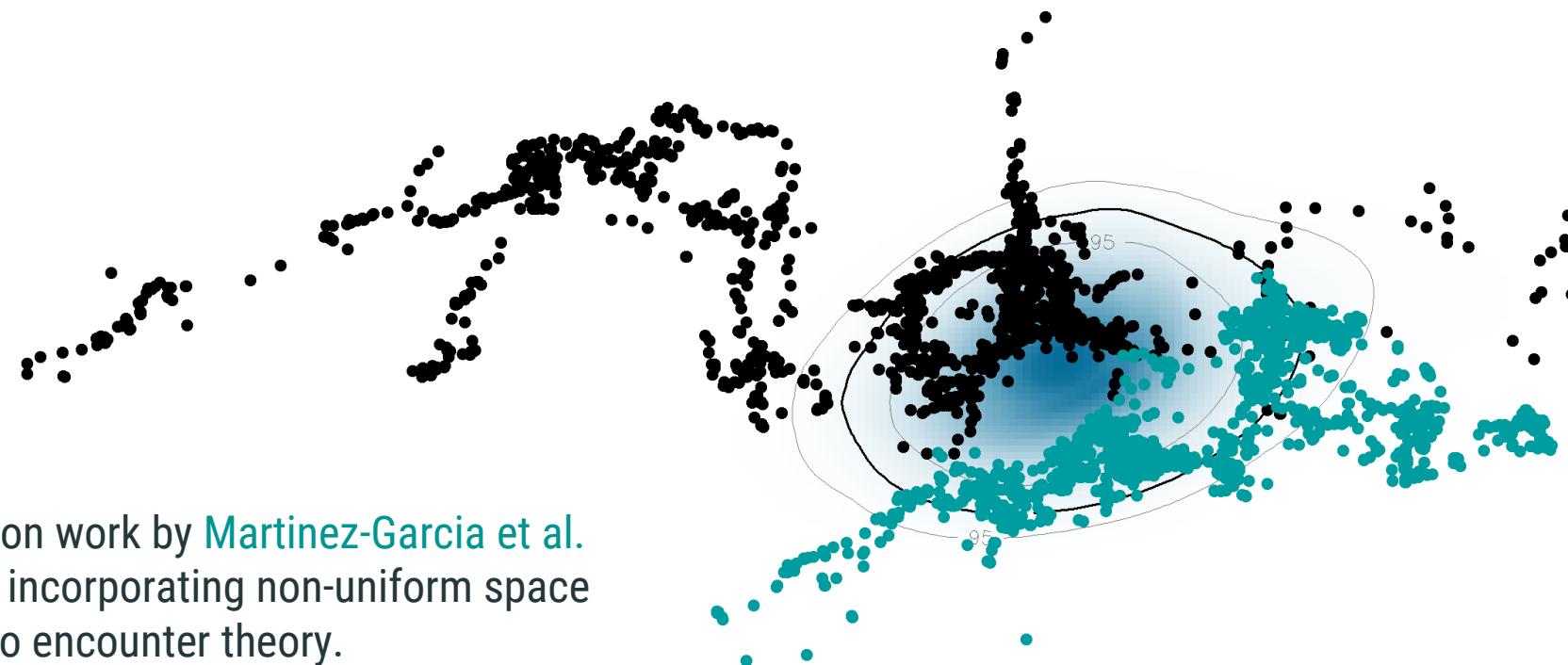


Martinez-Garcia (2013)

Conditional Distribution of Encounter events (CDE)

Described in [Noonan et al. \(2021\)](#)

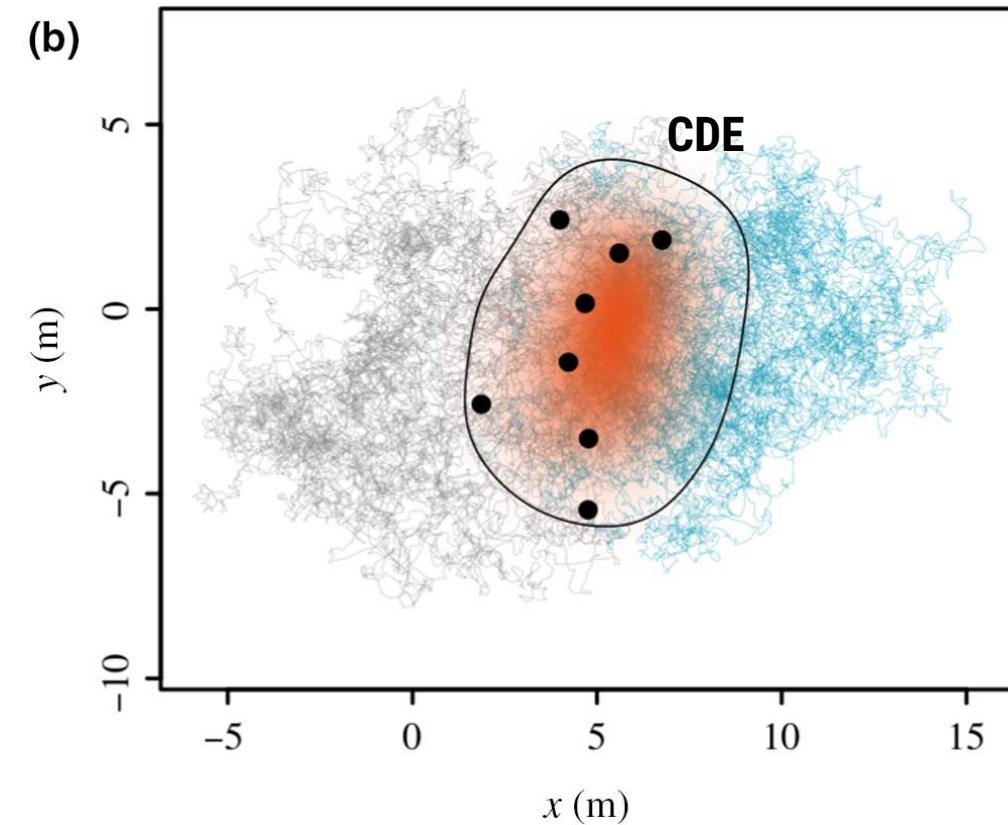
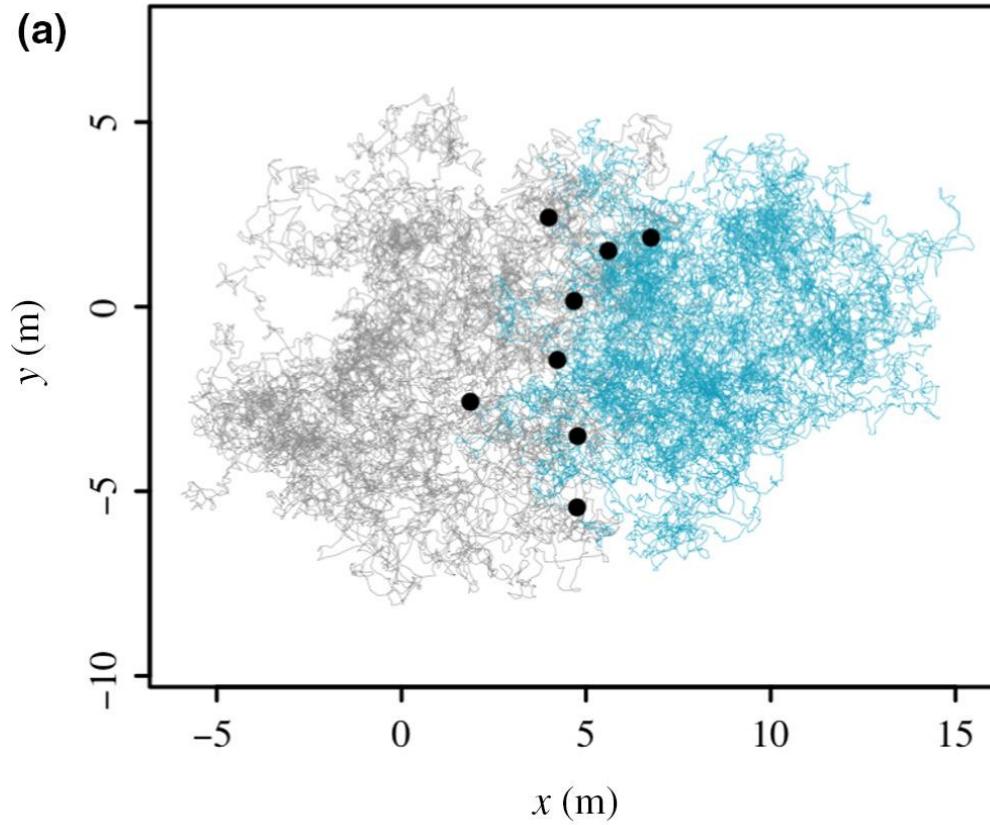
[10.1111/2041-210X.13597](https://doi.org/10.1111/2041-210X.13597)



Based on work by [Martinez-Garcia et al. \(2020\)](#) incorporating non-uniform space use into encounter theory.

ESTIMATION ENCOUNTERS

ANIMOVE 2022



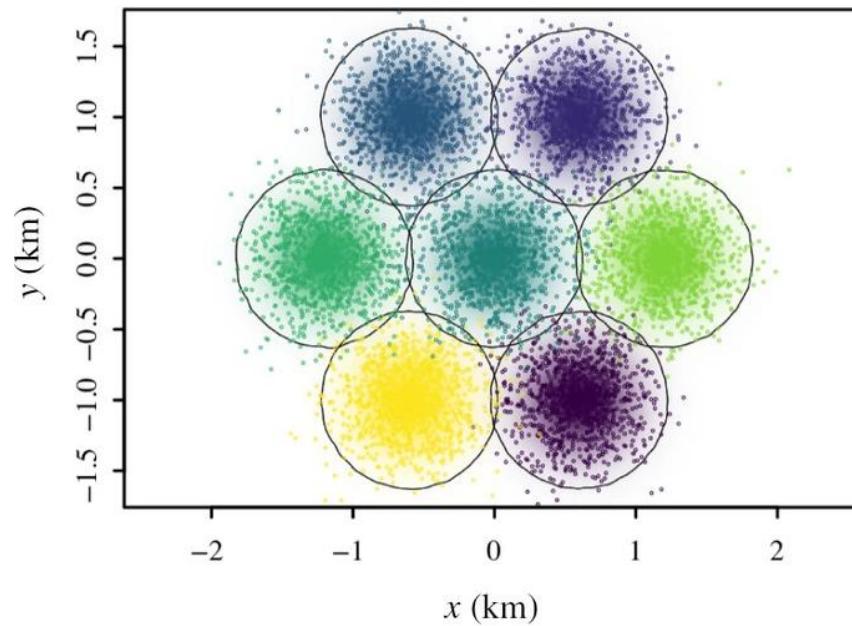
The CDE between individuals i and j is given by:

$$\text{CDE}_{ij}(r) = \frac{p_i(r) p_j(r)}{\iint d^2 r' p_i(r') p_j(r')}$$

All you need is information on the different home ranges!

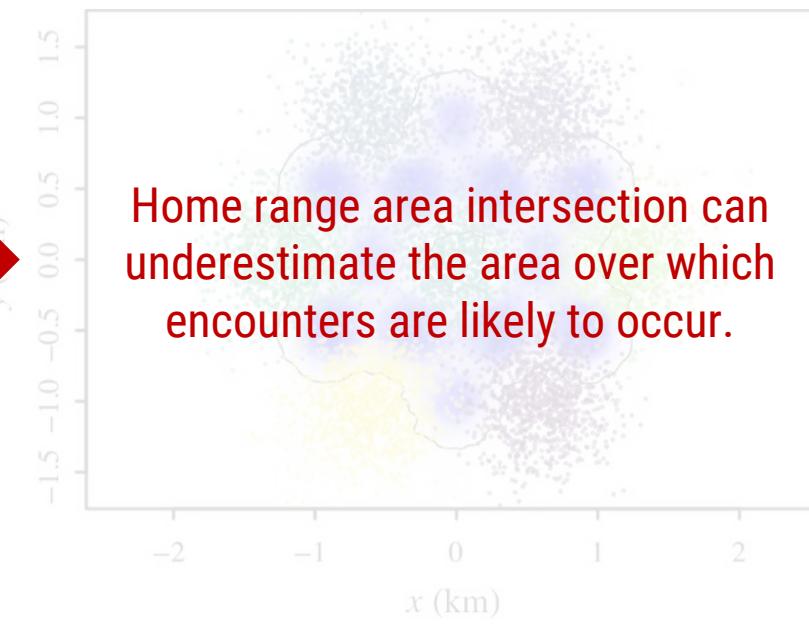
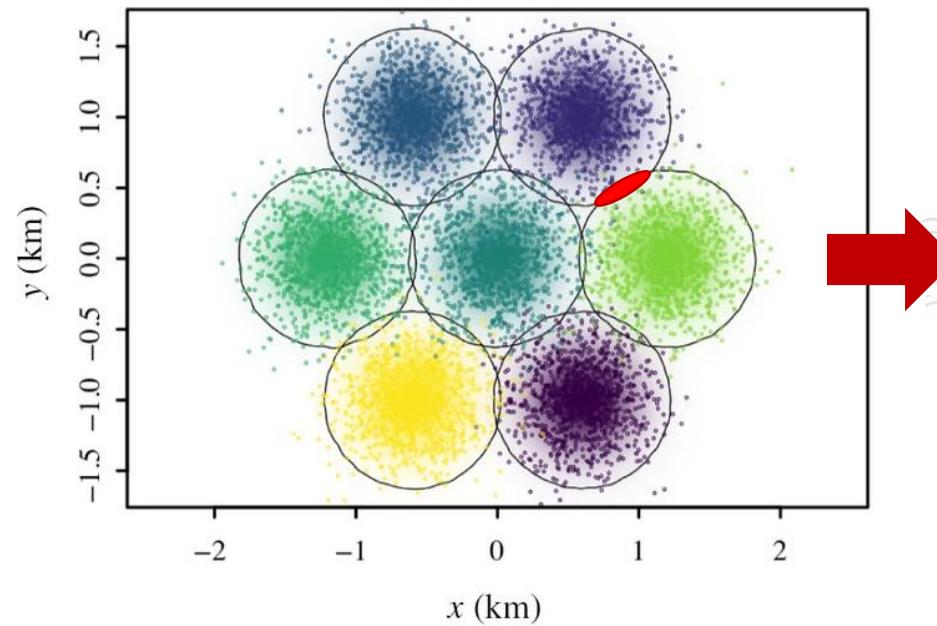
Overlapping home ranges with permeable borders

Simulated tracking data for a population of 7 individuals with equally sized, regularly spaced home ranges.



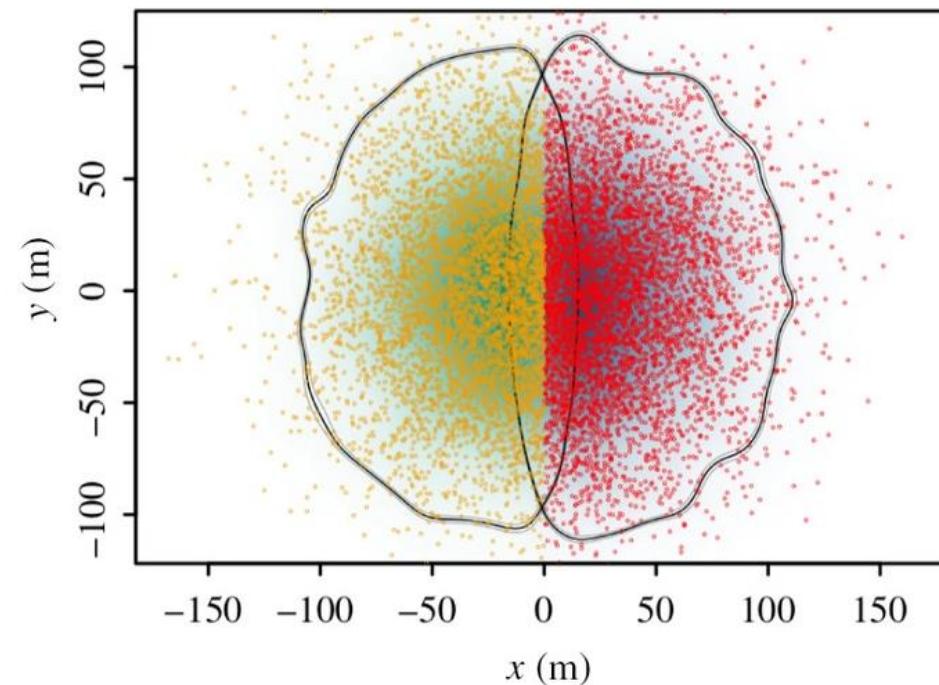
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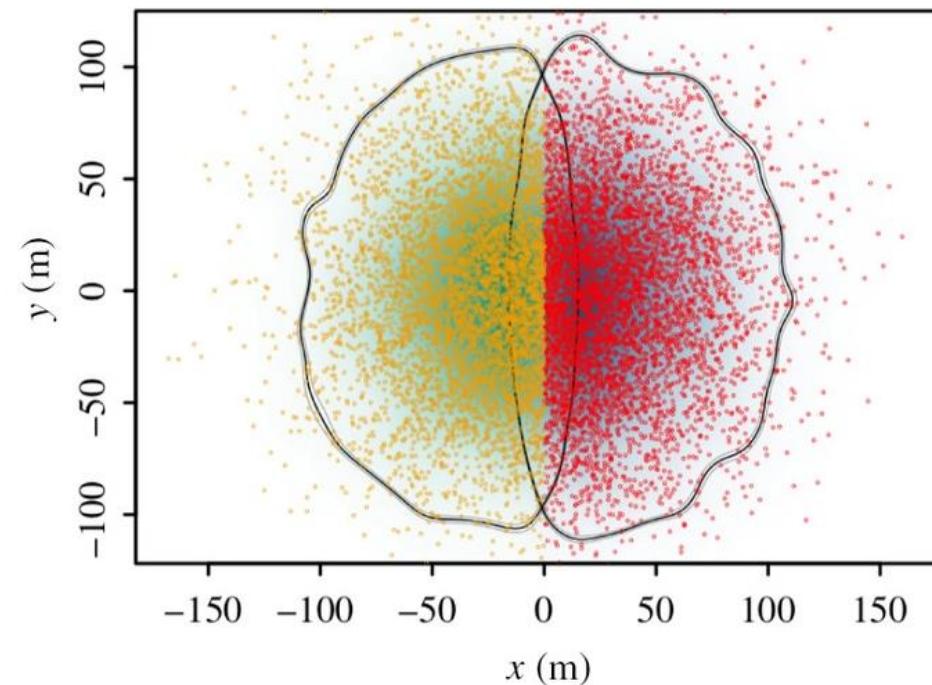
Exclusive home ranges with hard borders.

Simulated tracking data for 2 individuals with a hard territorial border between mutually-exclusive home ranges.

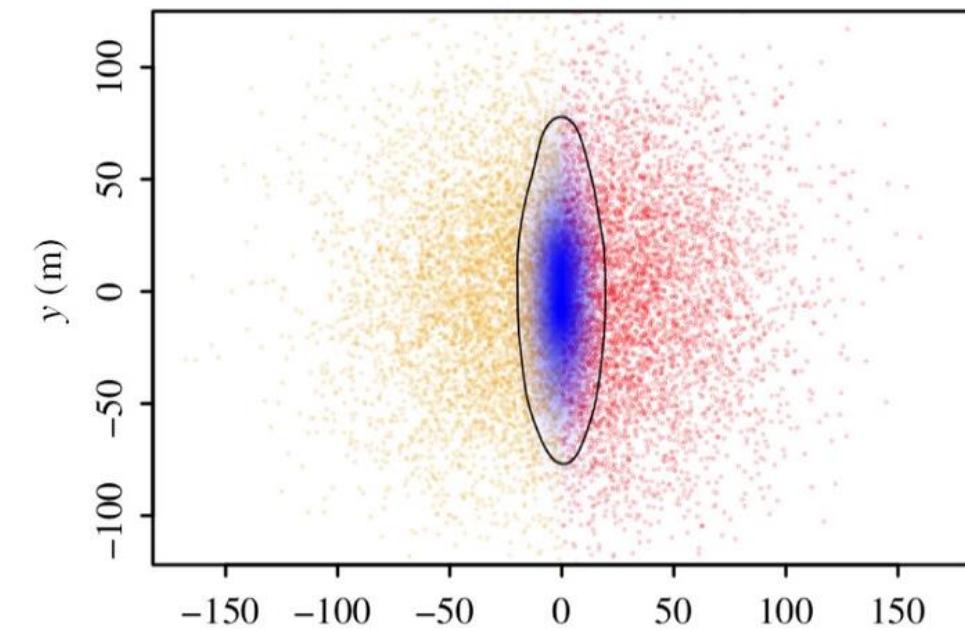


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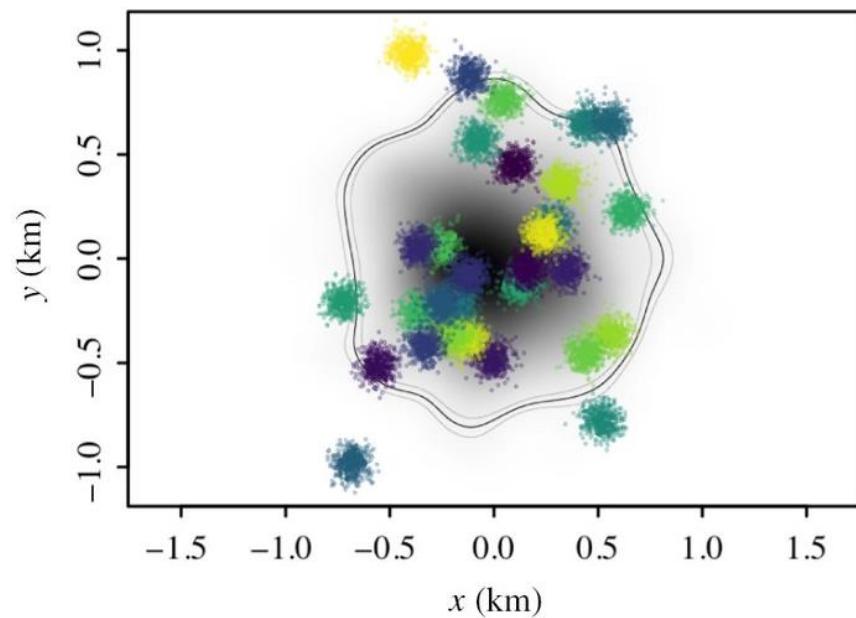


CDE can be used to identify the location of territorial borders.



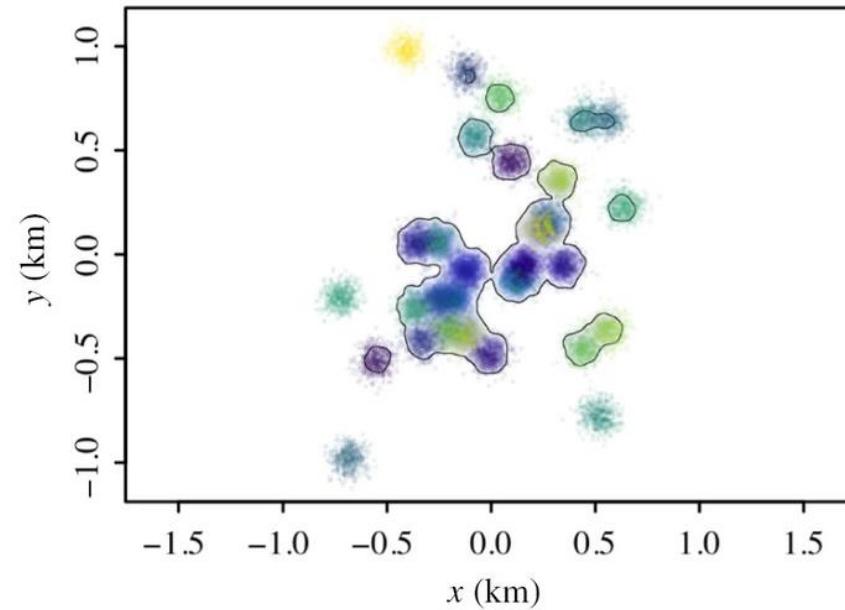
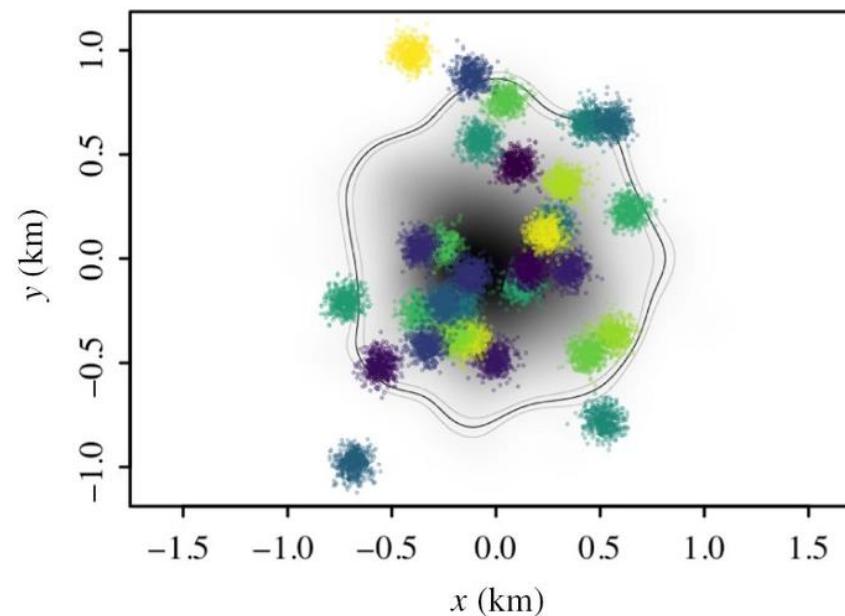
Predator-prey encounters

Simulated tracking data for a predator with a large home range that encompassed a population of 30 prey individuals.



Predator-prey encounters

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WHITE-FACED CAPUCHINS
CEBUS CAPUCINUS



@ John Fader

On BCI, Panama, capuchins are group-living, with intense and potentially lethal **inter-group competition**.



Encounter probability plays an important role in governing **capuchin behavior**.

ESTIMATION ENCOUNTERS

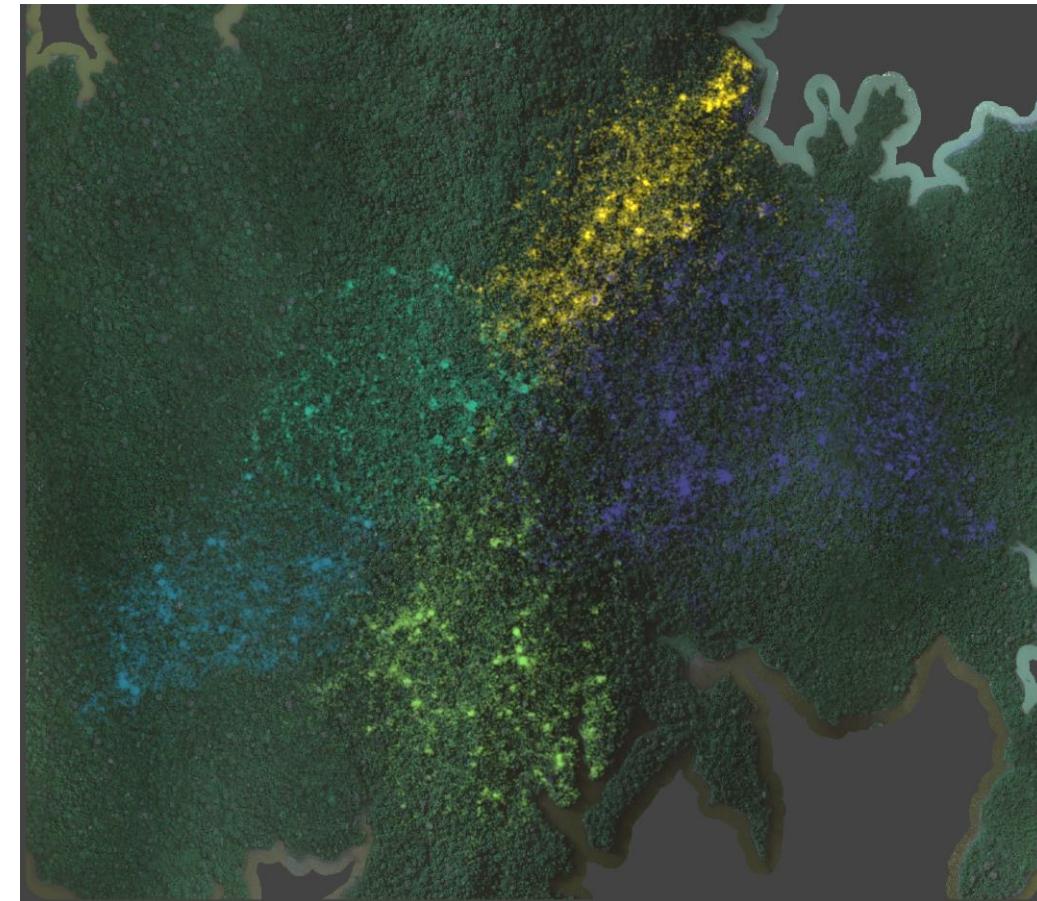
ANIMOVE 2022

WHITE-FACED CAPUCHINS *CEBUS CAPUCINUS*



@ John Fader

CDE estimation on GPS data from 5 individuals
belonging to neighbouring social groups

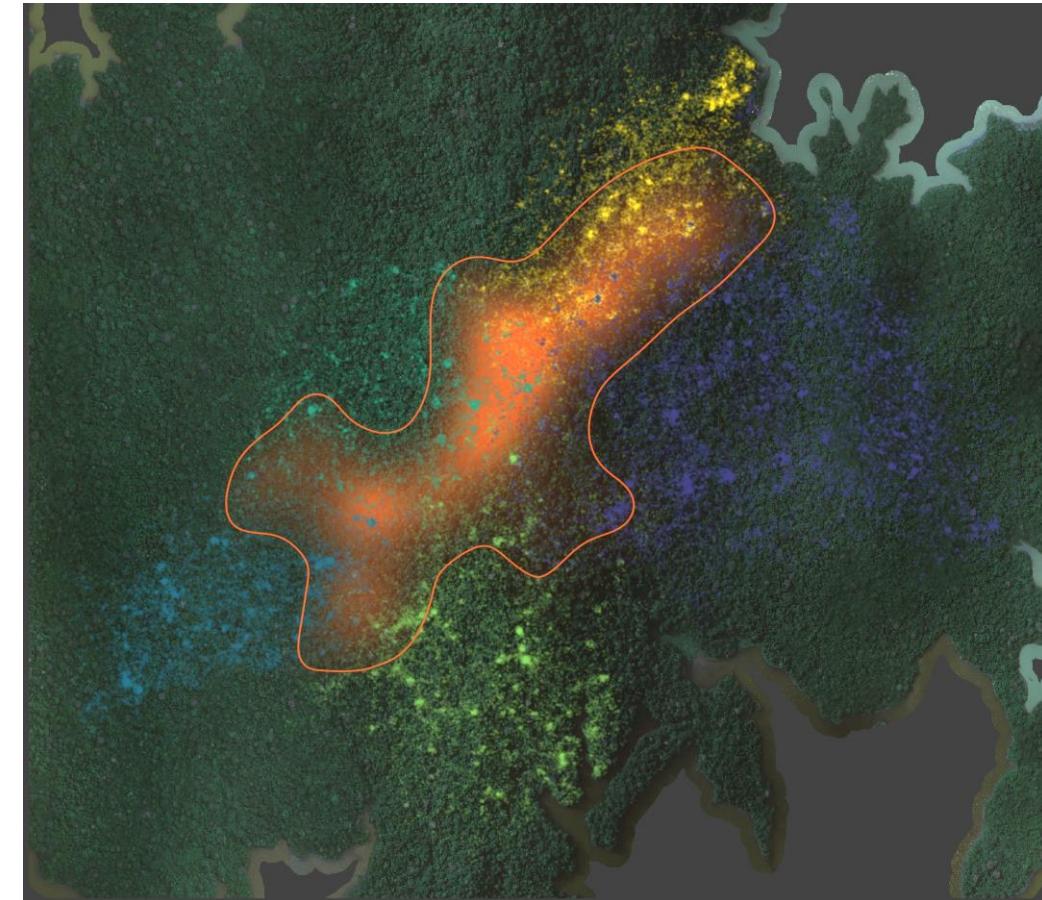


WHITE-FACED CAPUCHINS
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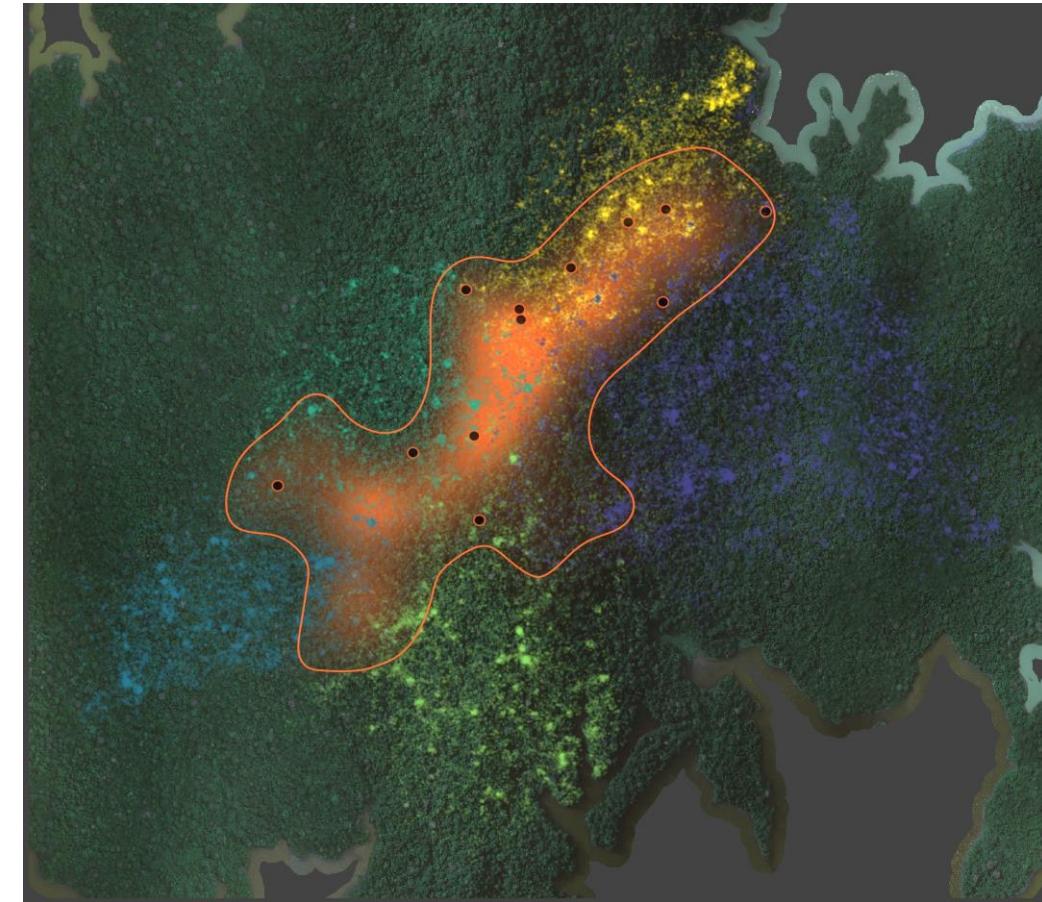


WHITE-FACED CAPUCHINS
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@ John Fader

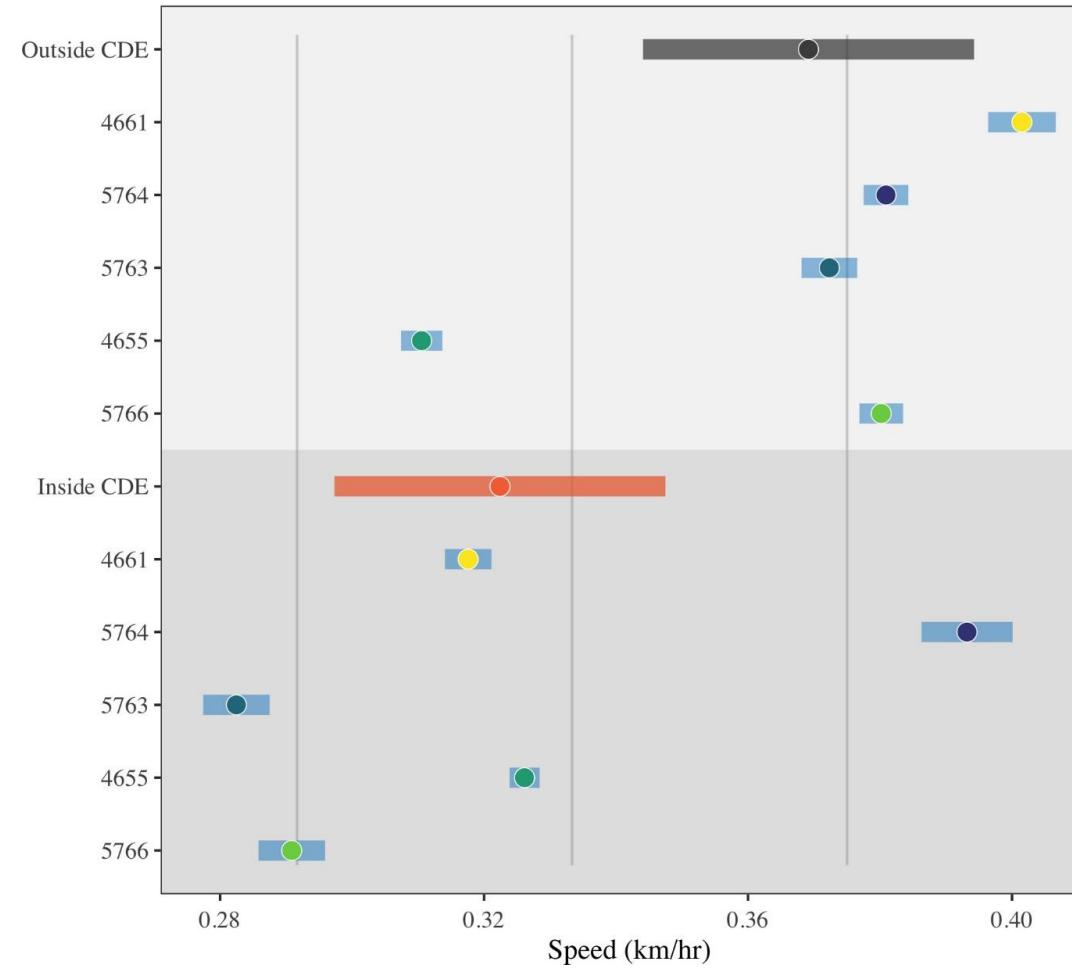
CDE estimation on GPS data from 5 individuals
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WHITE-FACED CAPUCHINS
CEBUS CAPUCINUS



@ John Fader



Capuchins also modified their movement according to local encounter probability, moving significantly more slowly in the 95% CDE area.

SLEEPY LIZARDS
TILIQUA RUGOSA



@ Michael Gardner

The sleepy lizard is a large herbivorous skink from temperate regions of Australia.



Sleepy lizards home ranges often overlap extensively with **conspecifics**.
Kerr & Bull (2006)

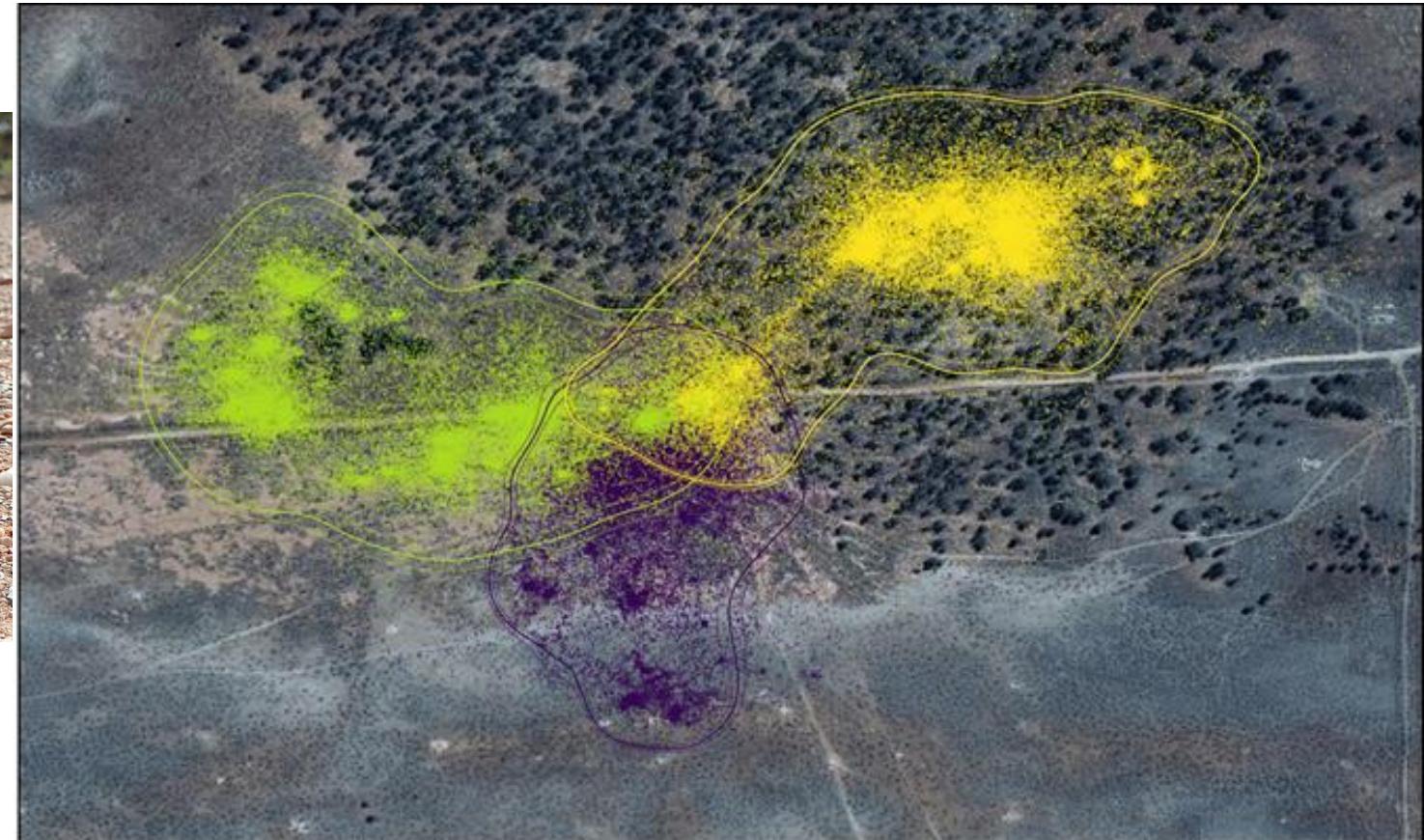
ESTIMATION ENCOUNTERS

ANIMOVE 2022

SLEEPY LIZARDS *TILIQUA RUGOSA*



@ Michael Gardner



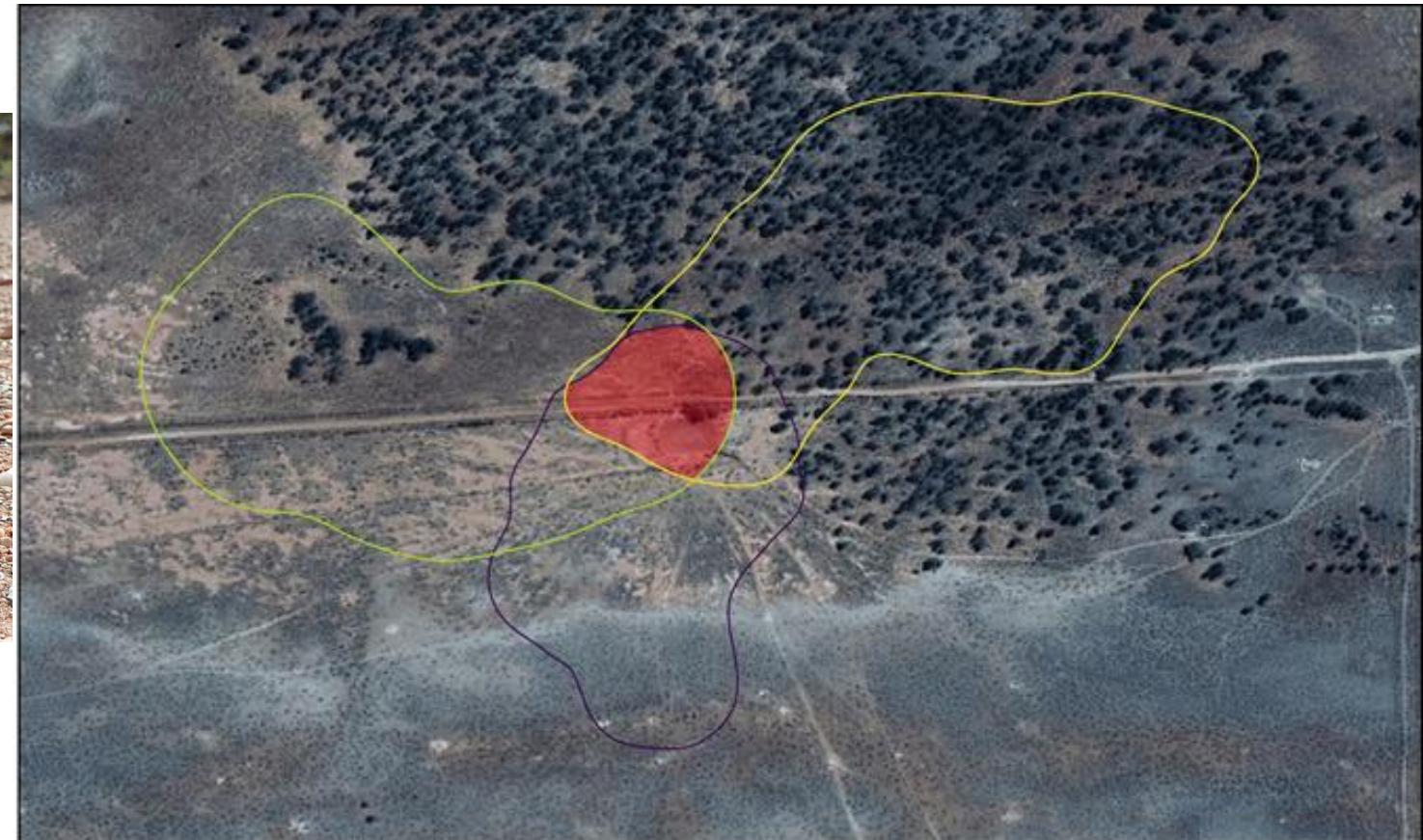
ESTIMATION ENCOUNTERS

ANIMOVE 2022

SLEEPY LIZARDS *TILIQUA RUGOSA*



@ Michael Gardner



ESTIMATION ENCOUNTERS

ANIMOVE 2022

SLEEPY LIZARDS *TILIQUA RUGOSA*



@ Michael Gardner



Conditional Distribution of Encounter events (CDE)

Described in [Noonan et al. \(2021\)](#)

[10.1111/2041-210X.13597](https://doi.org/10.1111/2041-210X.13597)

There are three key assumptions for CDE estimation:

1. Stationarity in the movement processes;
2. Encounters are local events;
3. Movement is uncorrelated across individuals.

Good coverage of the local population is also necessary for the CDE to fully capture the spatial distribution of encounters.



Center for Advanced Systems Understanding (CASUS)
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HOME RANGE META-ANALYSES

USING THE **CTMM R PACKAGE**



Inês Silva, Chris Fleming
i.silva@hzdr.de

 META-ANALYSES

Accurately estimating *area requirements* is of utmost importance for conservation, from the *individual* to the *population level*.

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We want to quantify the effect of covariates, such as **species or taxa, sex, body size, age, movement characteristics, conspecific density, habitat, human influences**, etc...

 META-ANALYSES

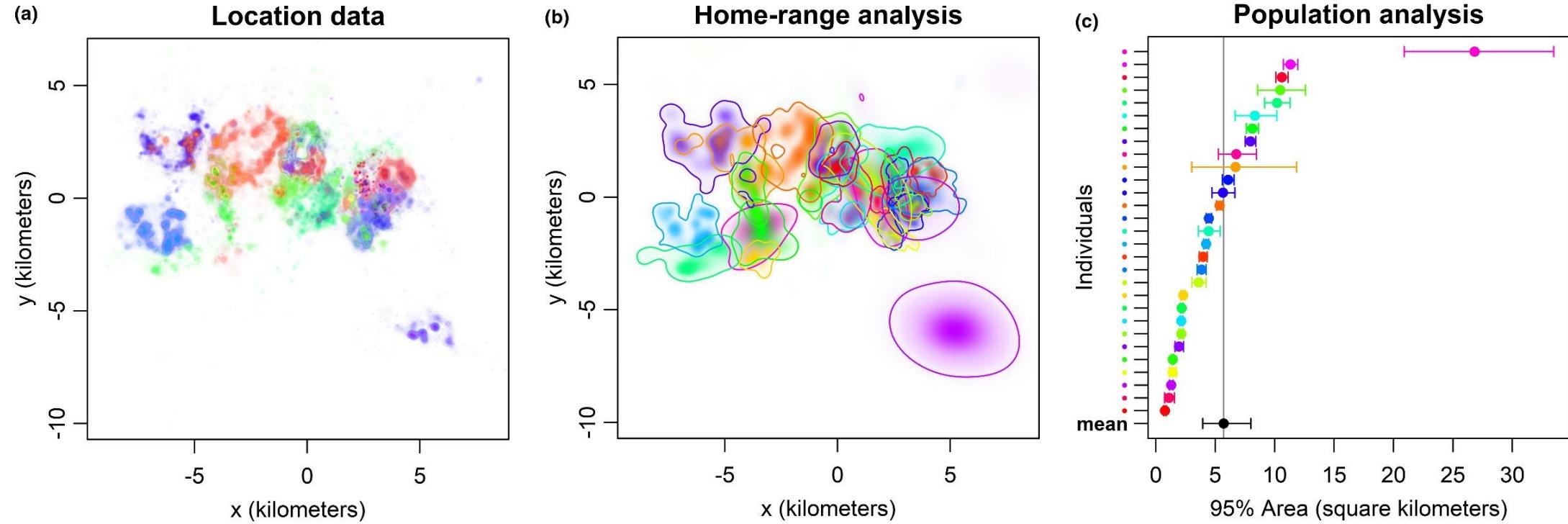
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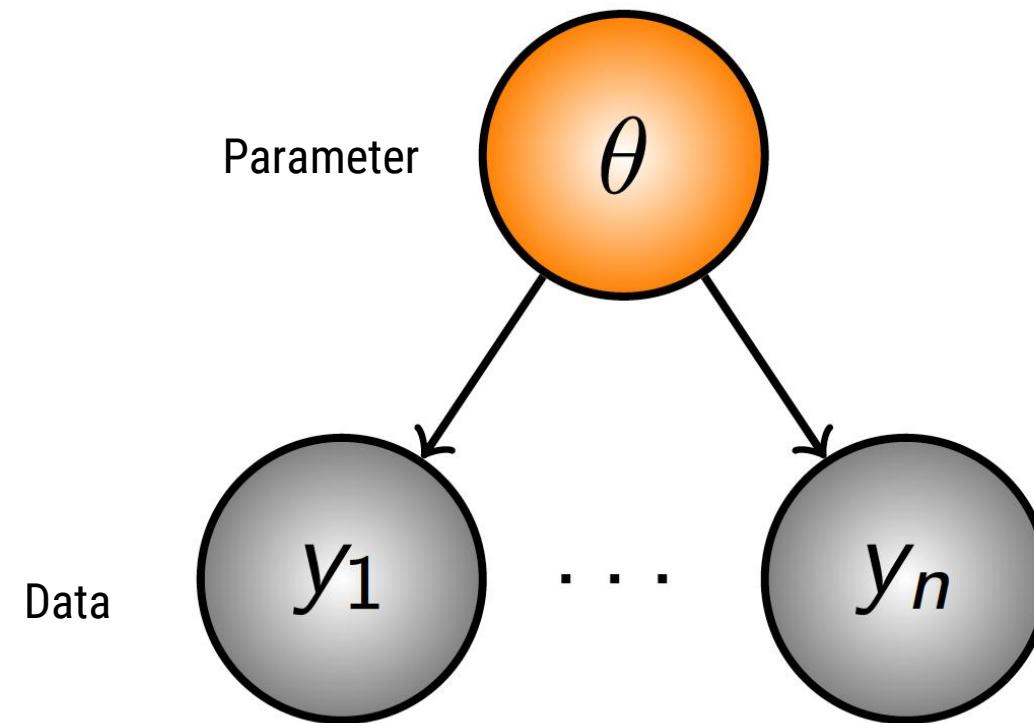


.. Even if we are comparing different populations with **different movement behaviors** or **sampling schedules**.

 META-ANALYSES

NON-HIERARCHICAL MODELS

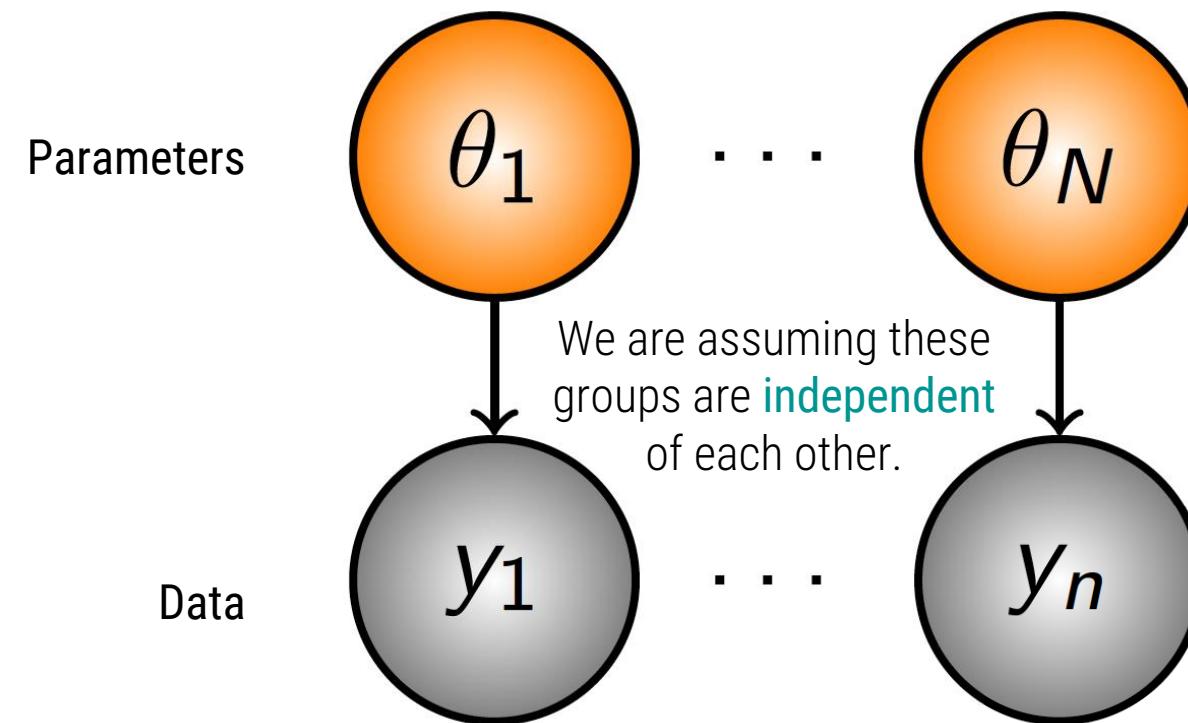
How does data inform parameters?



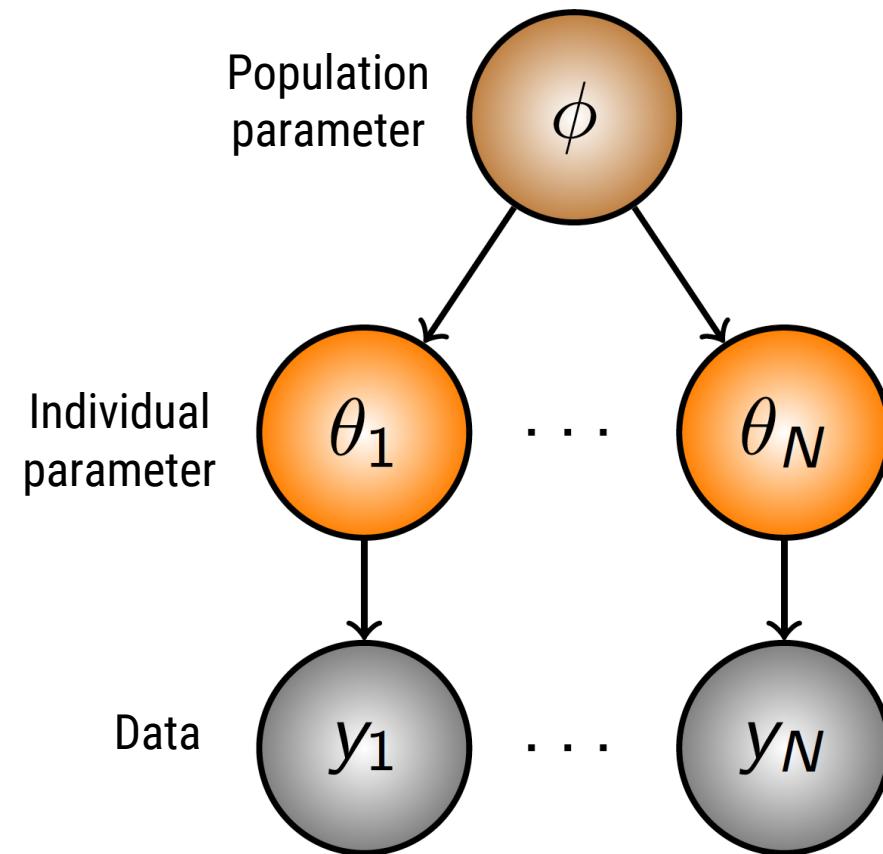
Adapted from [Midway \(2008\)](#)

NON-HIERARCHICAL MODELS

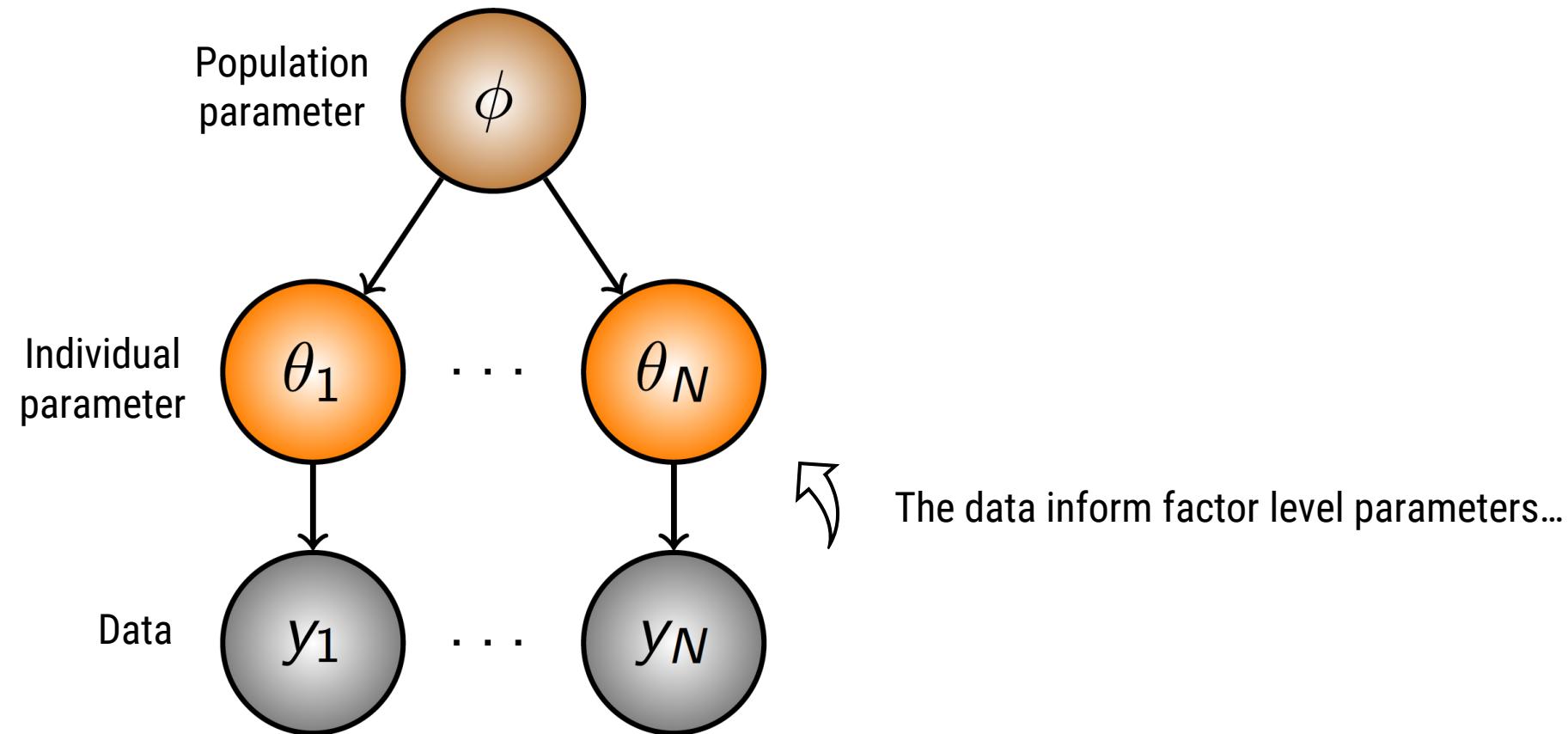
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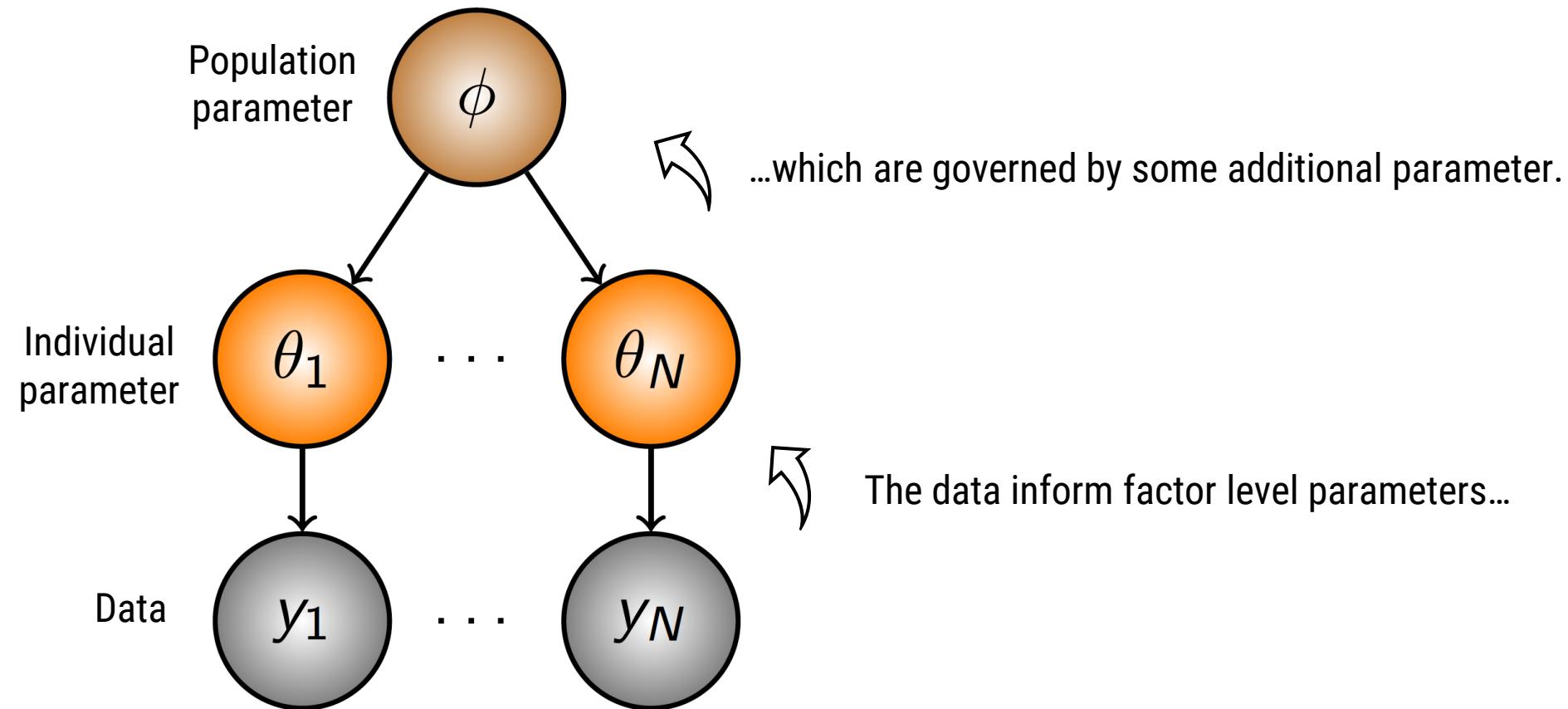
HIERARCHICAL MODELS



HIERARCHICAL MODELS



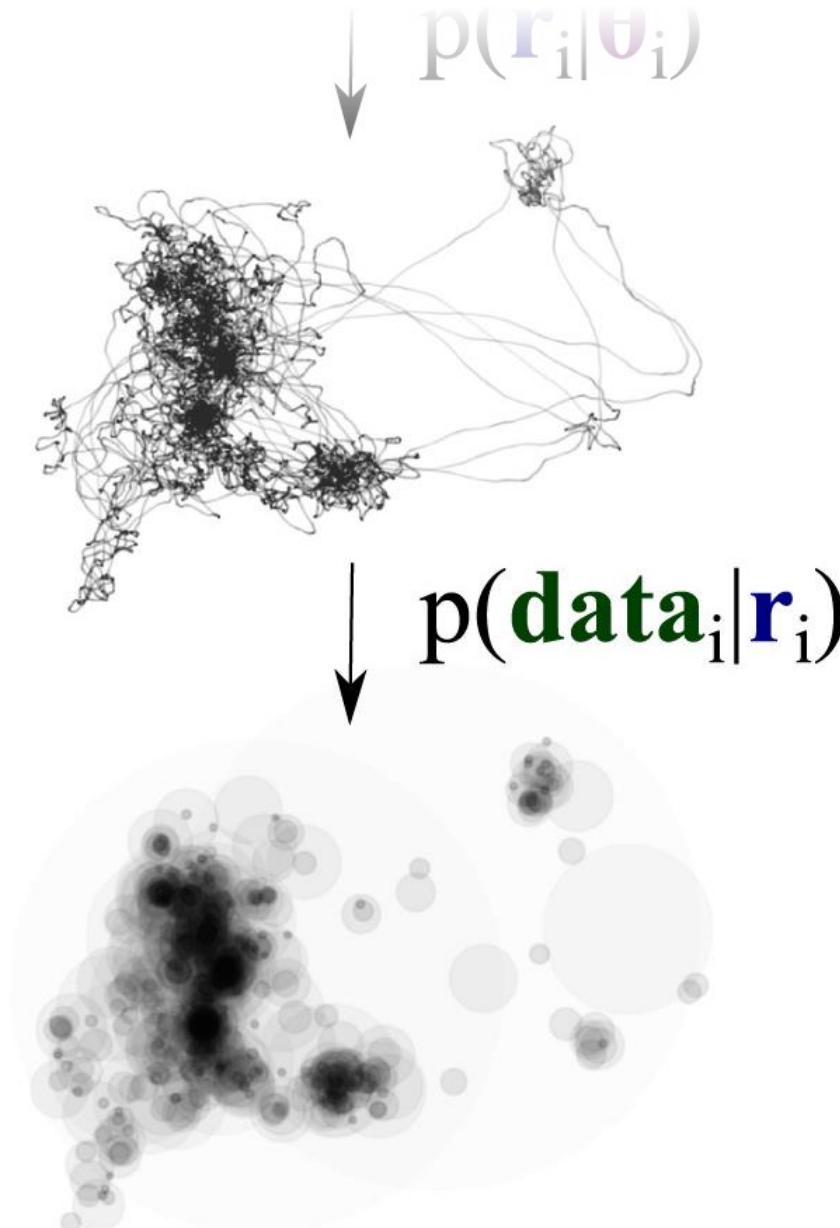
HIERARCHICAL MODELS



Trajectory

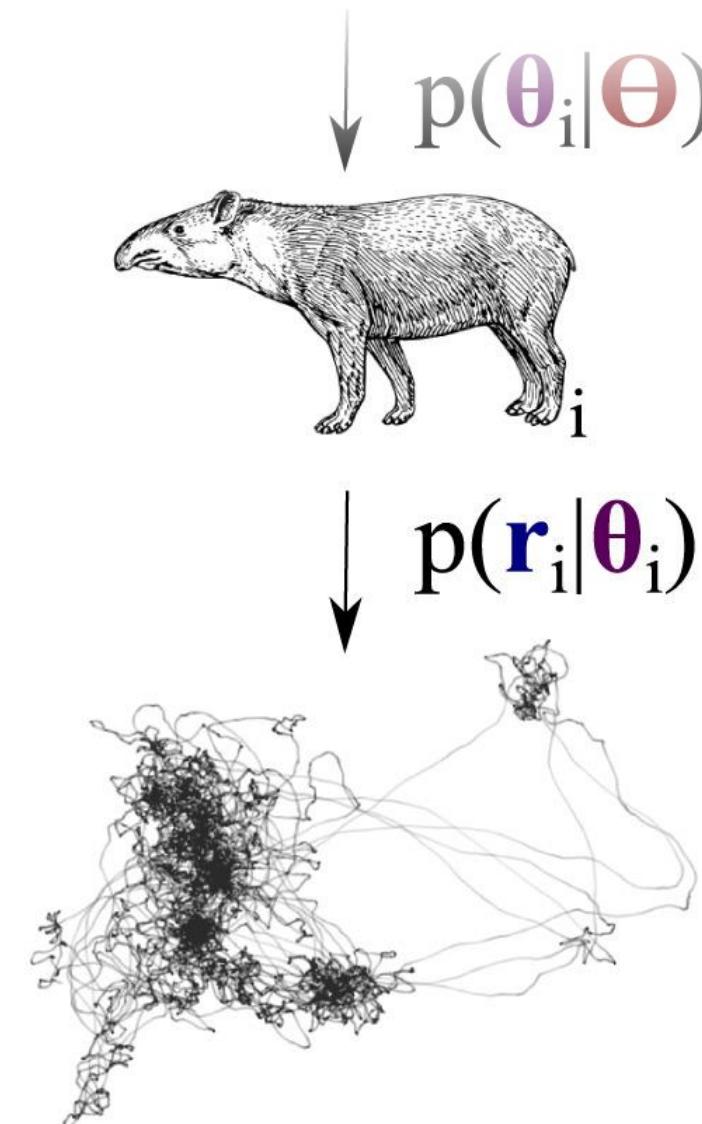
Data

χ^2 inverse-Gaussian meta-analysis

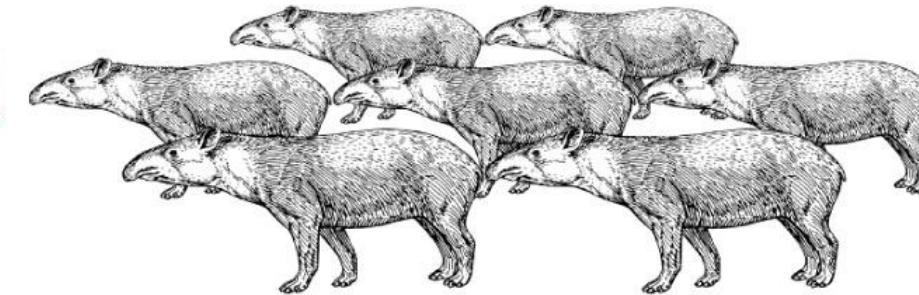


Individual

Trajectory

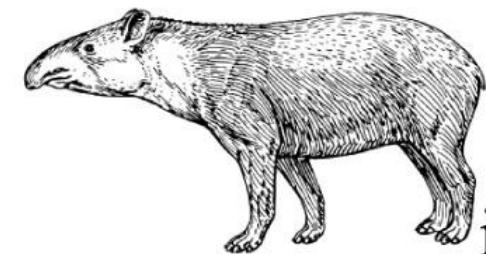


Population



$$\downarrow p(\theta_i | \Theta)$$

Individual

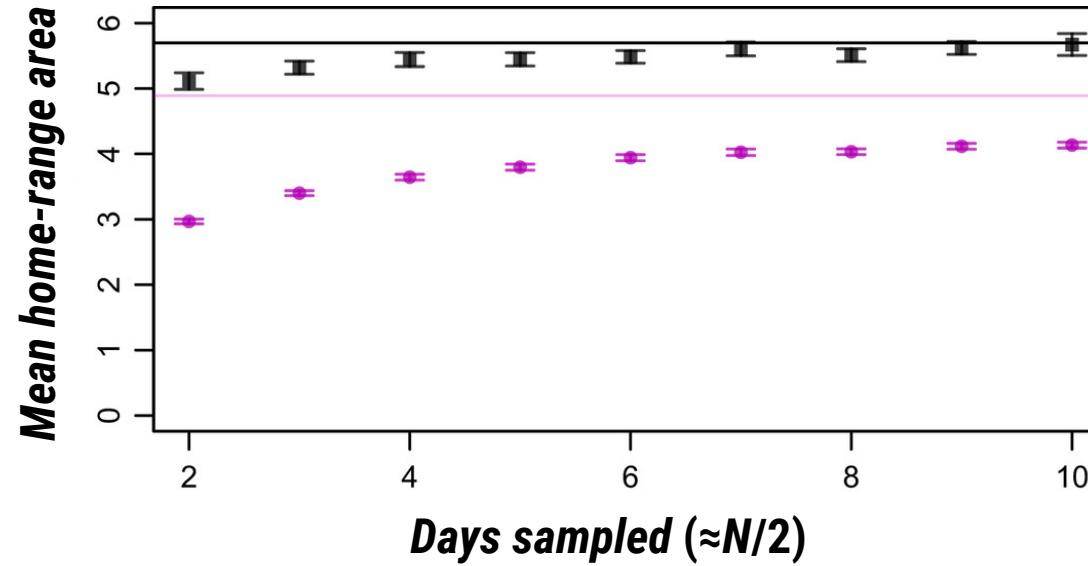


 META-ANALYSES

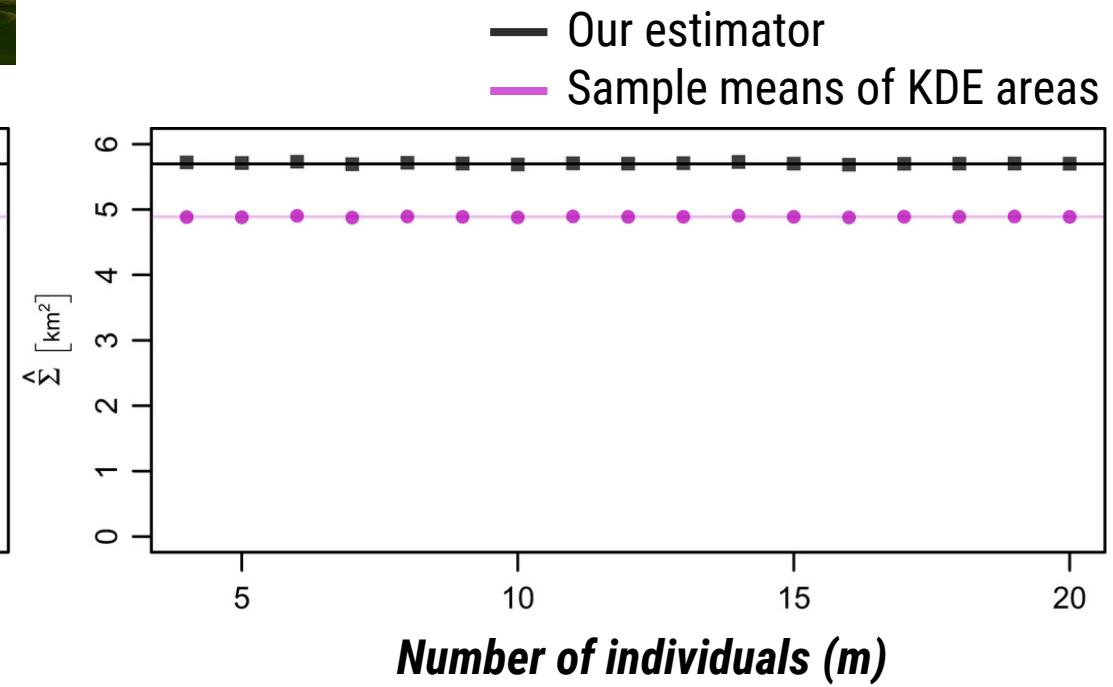
LOWLAND TAPIR

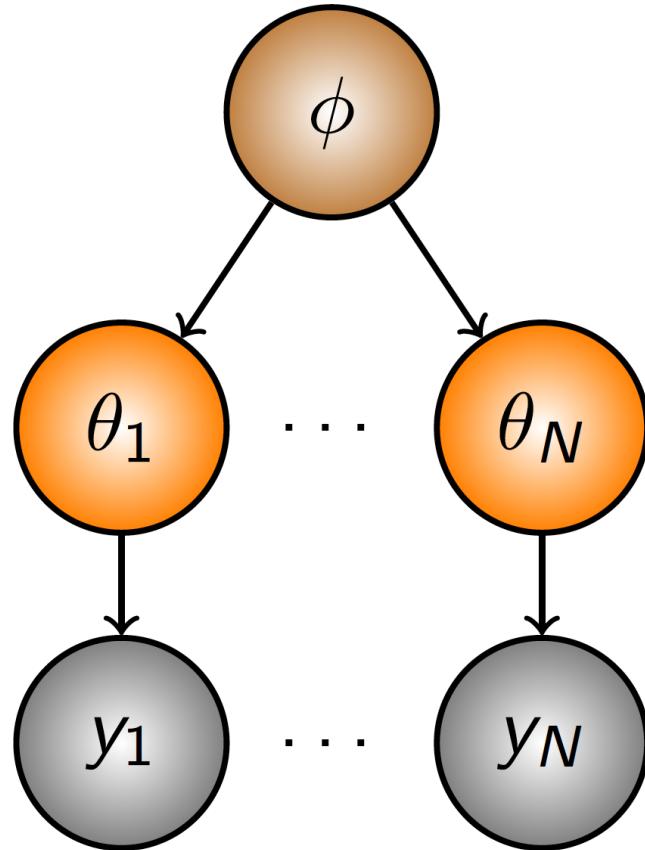
TAPIRUS TERRESTRIS

VU



Tapirs have HR crossing times (τ_p) of **0.72 days**, ranging from **0.05 to 12.8 days**.





Conclusions

This framework facilitates population-level inference with as few as **2–3 observed home range crossings (τ_p)** and similarly small **number of individuals (m)**.

