Estimation of speed and distance travelled

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Introduction to Continuous-Time Movement Modeling for Animal Tracking Data

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Background

A routine analysis

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... and divide that by Δt if speed if the desired metric.

A routine analysis cont.

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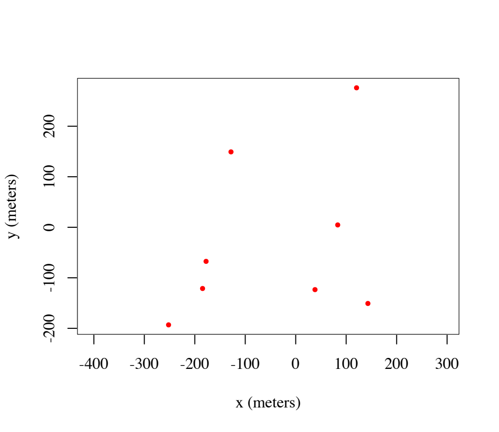

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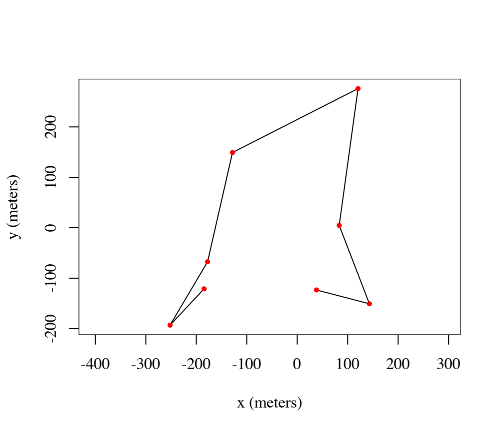

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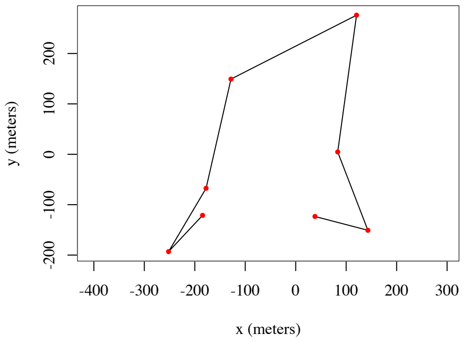
Easy to quantify, but heavily biased



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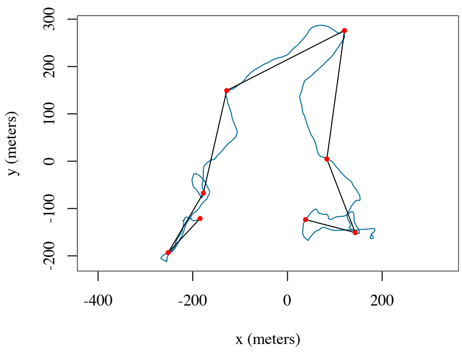

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- People have known this for decades.
  (Bovet & Benhamou, 1988; Reynolds & Laundre, 1990; Rooney et al., 1998; Turchin, 1998; De Solla et al., 1999; Rowcliffe et al., 2012; Sennhenn-Reulen et al., 2017)

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- Solution: Increase the sampling until the straight lines provide a better approximation of a curve (Riemann sum)

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- Few people have been thinking about this
(Ranacher et al. , 2015)

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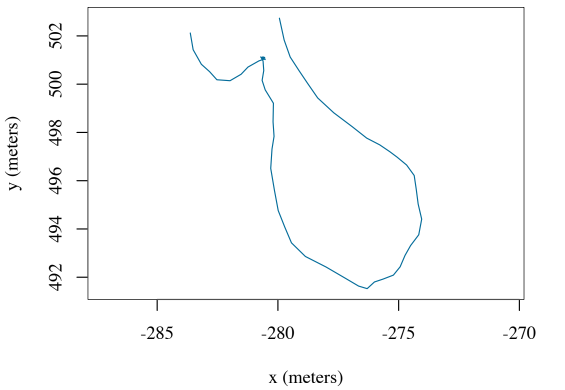

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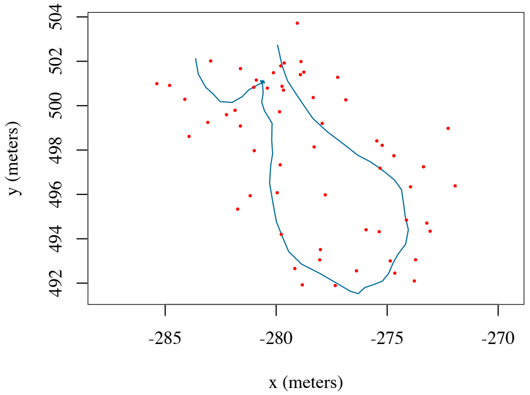

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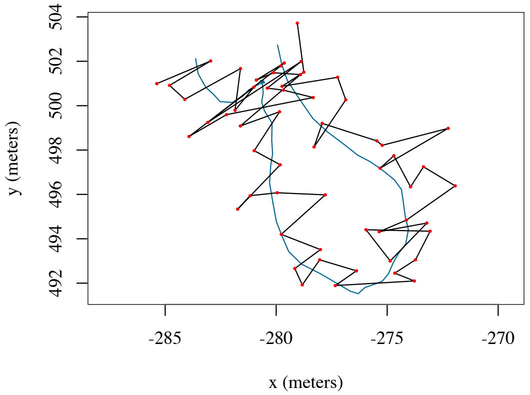
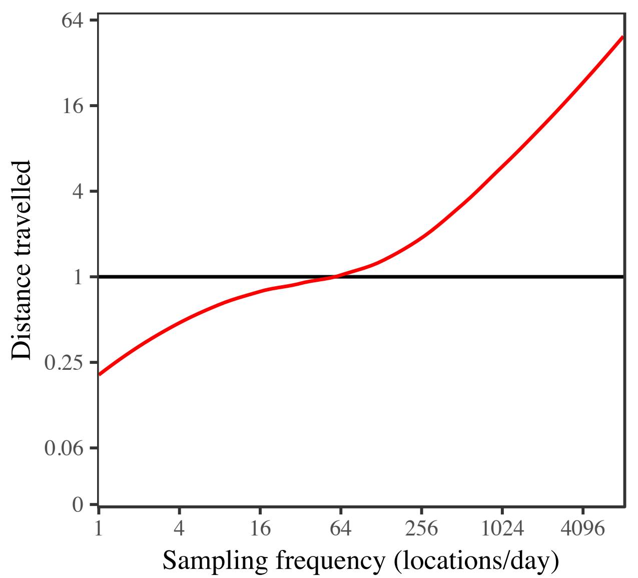
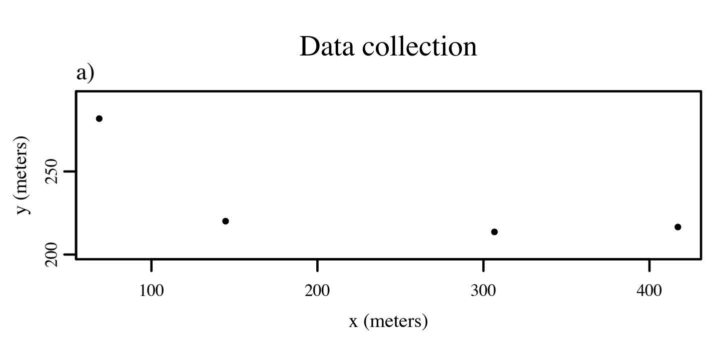


Bias in SLD estimation



CTSD

How does it work?



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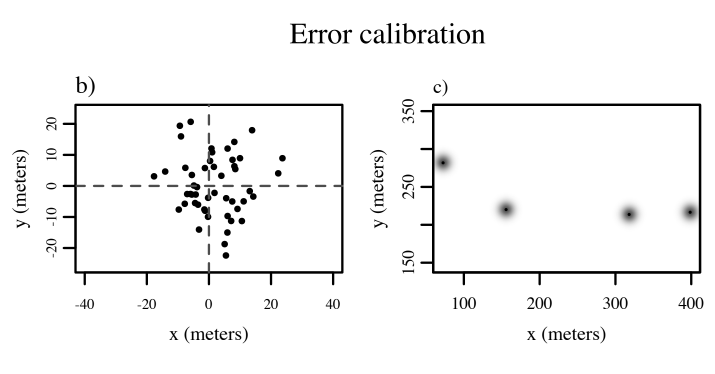

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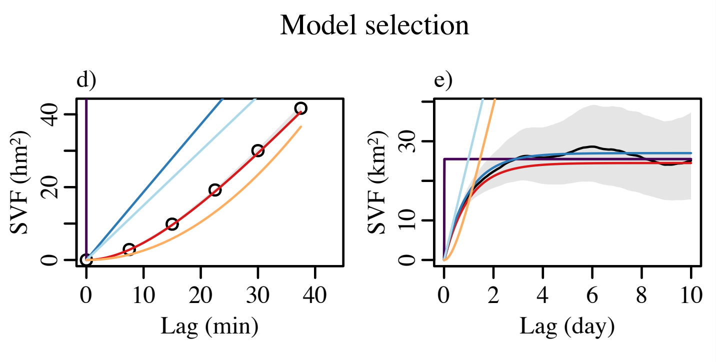

Model requirements

Movement Model	Pos. AC	Vel. AC	H. Range
Ind. Ident. Distr. (IID)	No	No	Yes
Brownian Motion (BM)	Yes	No	No
Ornstein-Uhlenbeck (OU)	Yes	No	Yes
Integrated OU (IOU)	Yes	Yes	No
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Requires a correlated velocity model

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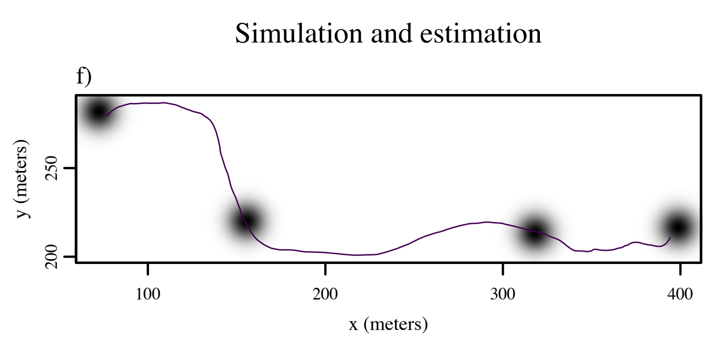

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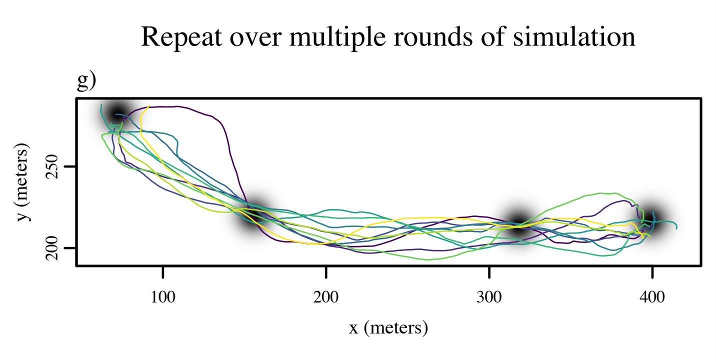

The ensemble

- With the ensemble you get a point estimate (mean).

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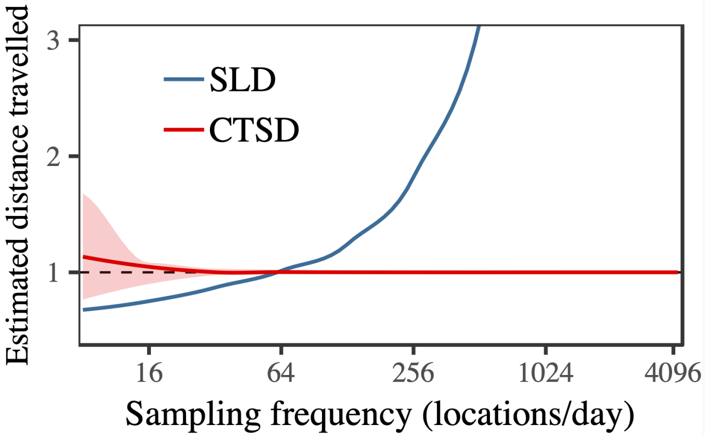
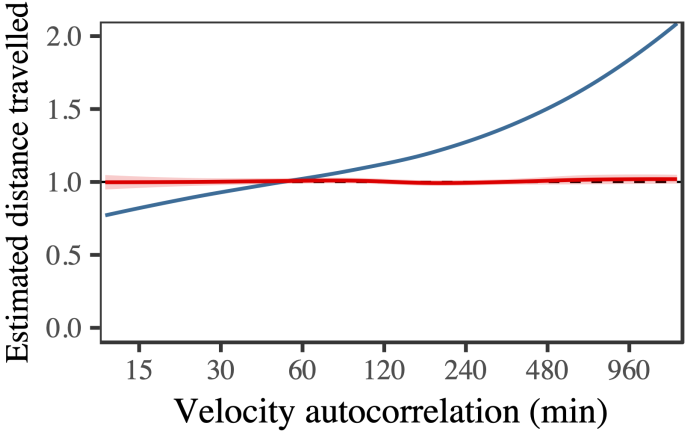
- And variance around the estimate, from which you can get confidence intervals

$$\mathrm{DOF}_{\mathrm{speed}} = \frac{\langle \bar{v} \rangle^2}{2\,\mathrm{VAR}[\widehat{\bar{v}}]} \qquad \mathrm{DOF}_{\mathrm{distance}} = \frac{\langle d \rangle^2}{2\,\mathrm{VAR}[\widehat{d}]} \tag{3}$$

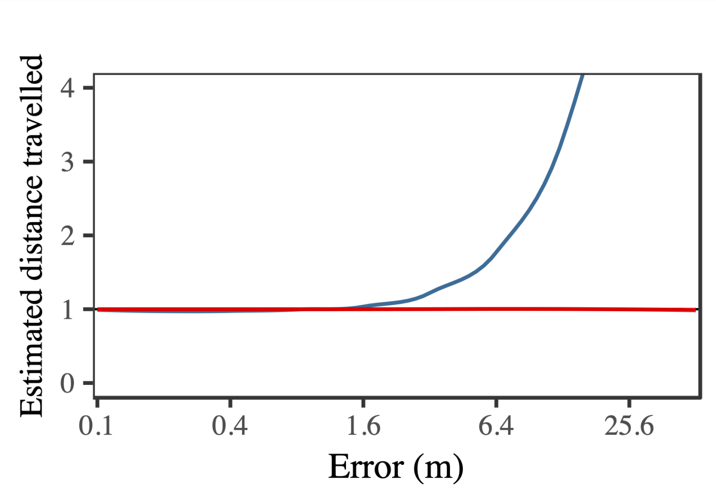
Sampling frequency



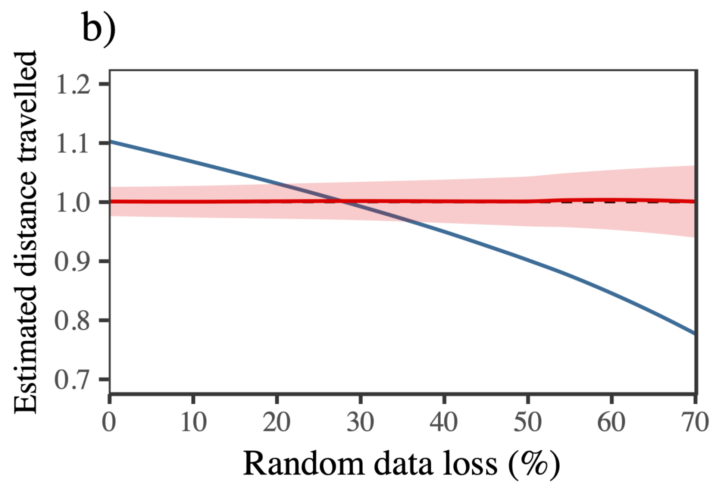
Tortuosity


Estimated distance travelled
2.0
1.5
1.0
0.5
0.0
15
30
60
120
240
480
960
Velocity autocorrelation (min)

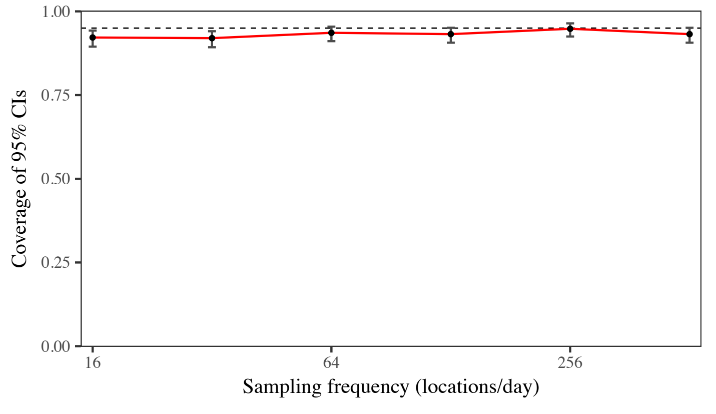
GPS error



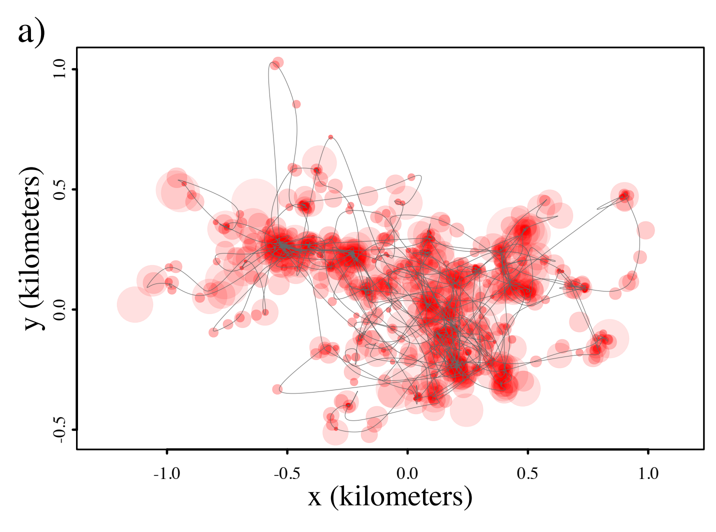
Random data loss



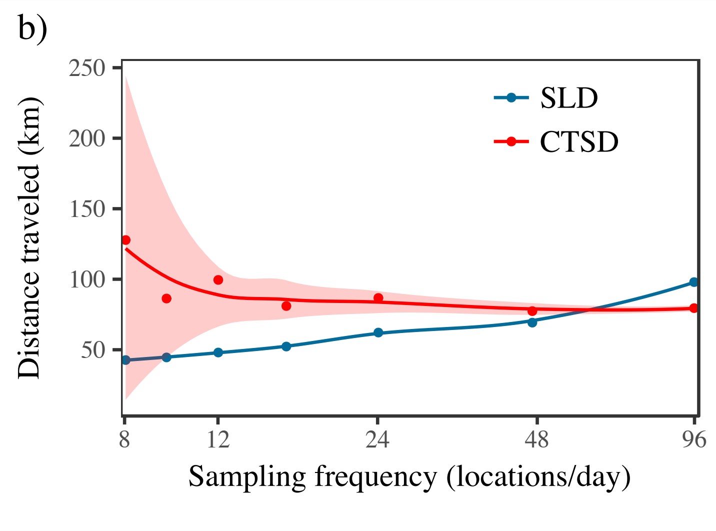
Confidence Intervals



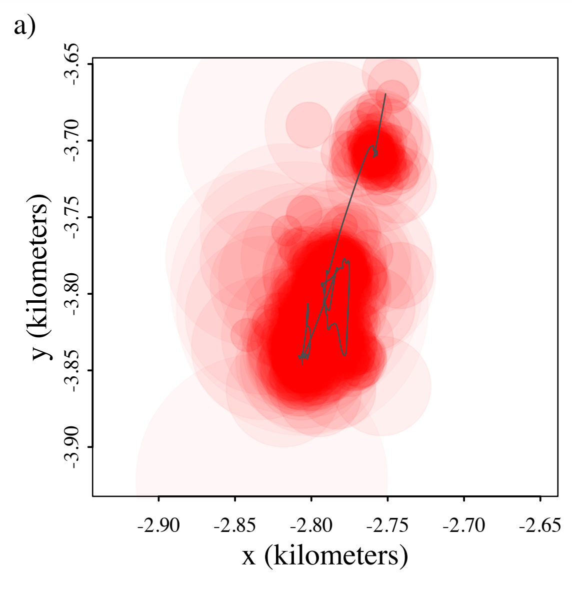
Coati tracking data



Coati CTSD


b)
250
200
150
100
50
Distance traveled (km)
SLD
CTSD
8
12
24
48
96
Sampling frequency (locations/day)

Wood-turtle tracking data



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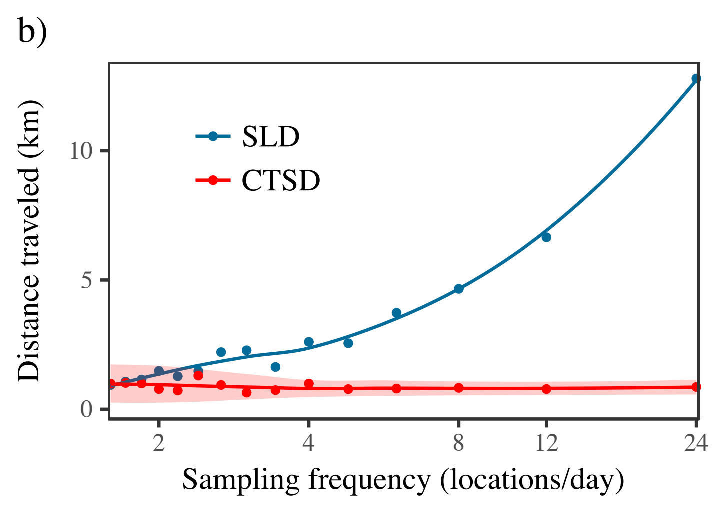
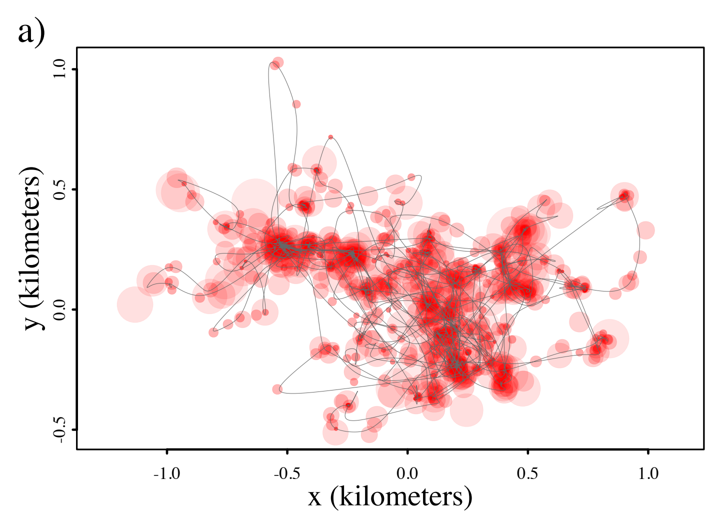


ctmm R script

Instantaneous speeds



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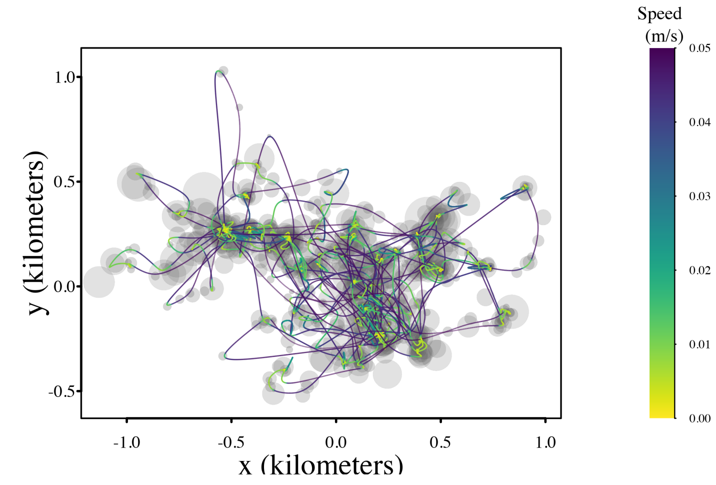
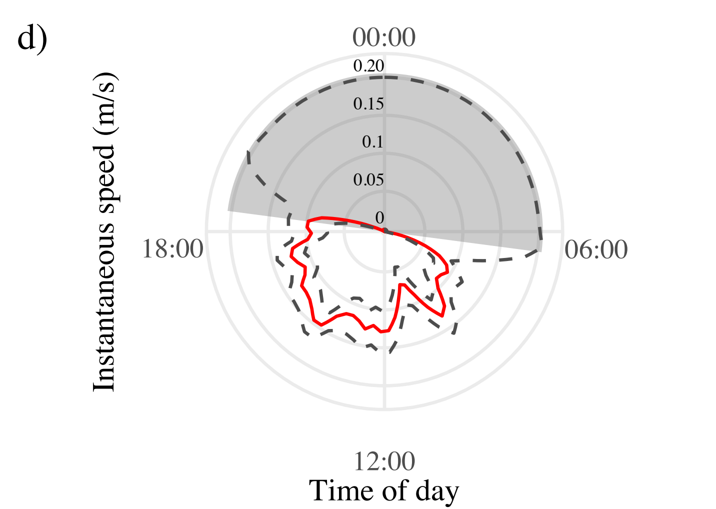


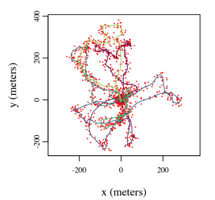
Inst. Speeds: Behavioural descriptive

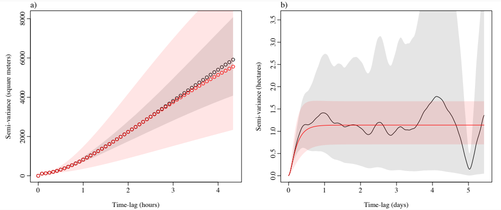


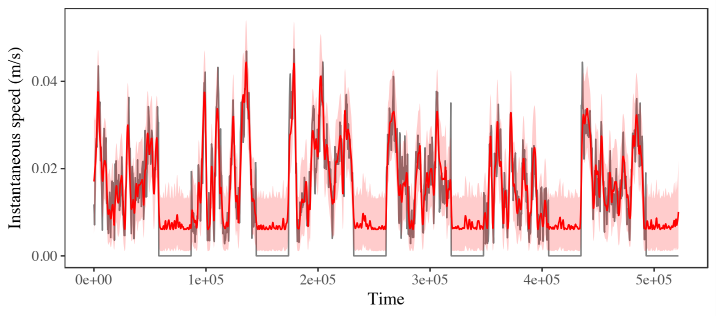
`ctmm` R script

Limitations

Conditional on a fitted model







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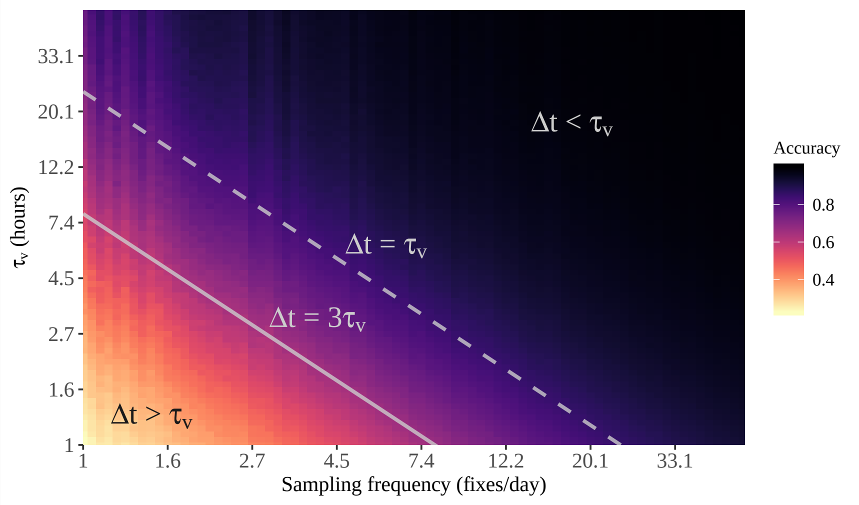

Requires an error model