

Line Transect data in Occupancy Studies: data collection methods and model identifiability

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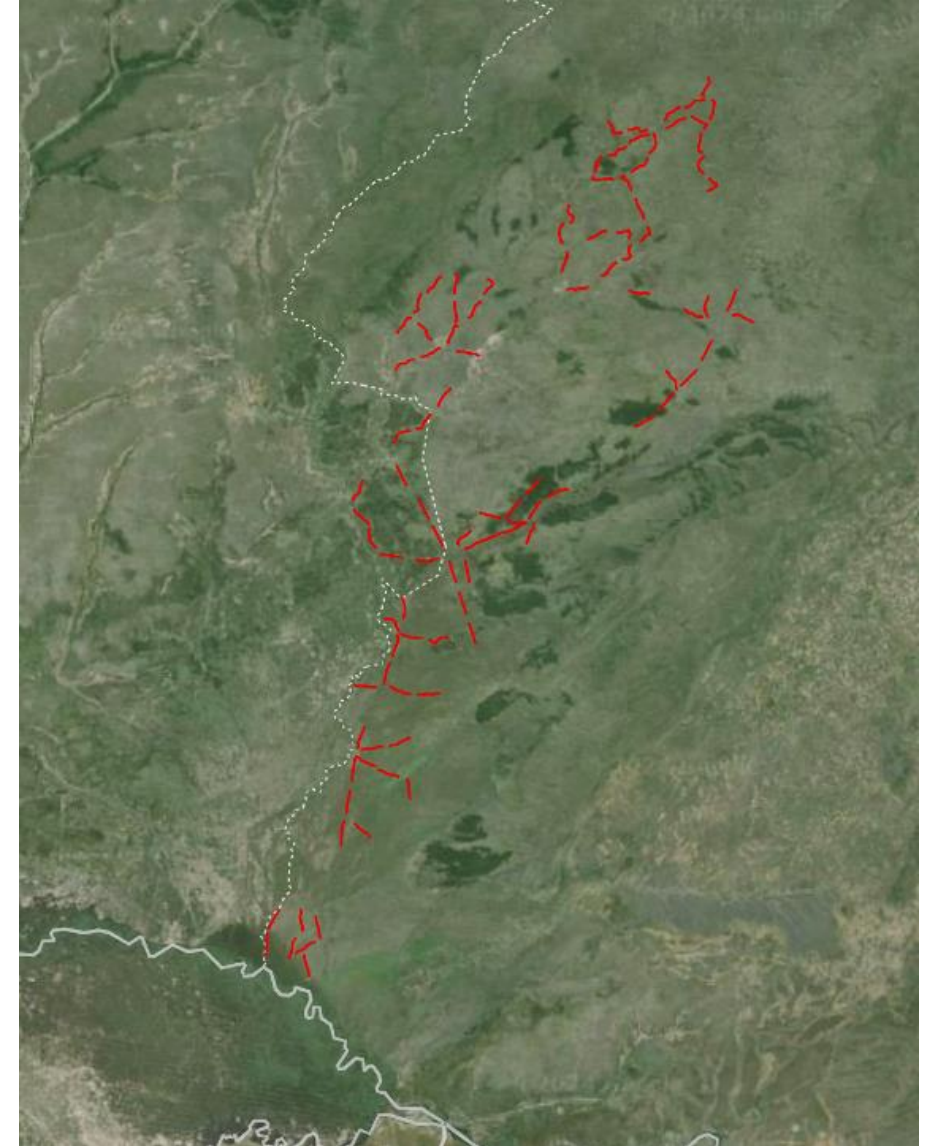
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Motivating data set

[Lines2019]



By Lencer (talk) - own work, used:File:Zambezi river basin-de.svg by Eric Gaba (User:Sting) and User:NNWhttp://www.kavangozambezi.org/the_map.php, CC BY 3.0, <https://commons.wikimedia.org/w/index.php?curid=16751696>

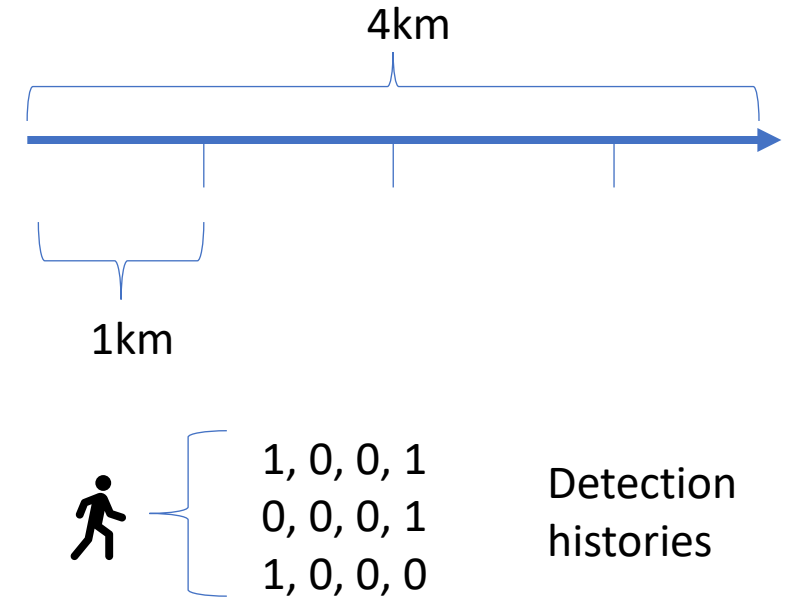


Motivating data set

2015, large scale spoor detection and species sighting survey
102 line transects, each of length 4 km.

Each transect is visited 3 times over the course of 10 days.
Detection/non-detection histories taken.

Detections: Leopard (279), Lion (87), Hyena (237), Wild dog (40).



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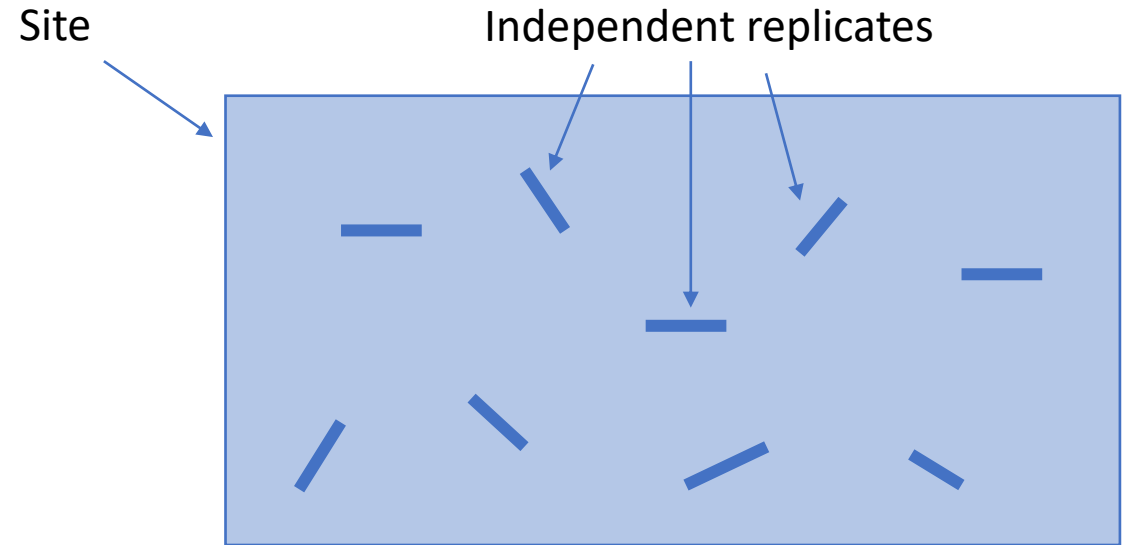
Spatial Replicates

Occupancy studies require replication.

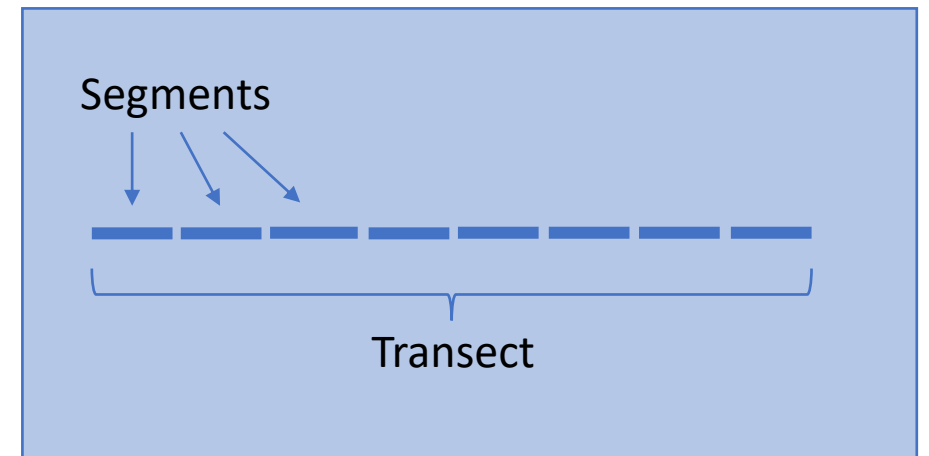
Replication can be spatial as well as temporal.

Established transects at a site are convenient.

Consecutive segments are no longer independent
[Kendall2009].



Random spatial replicates



Consecutive segments

Markovian Segment Occupancy

The model: [Hines2010]

1. Site occupancy

$$z_i \sim \text{Bernoulli}(\psi)$$



Notation:

z_i = occupancy site i

z_{ik} = occupancy segment k , site i

y_{ik} = detection segment k , site i

$\psi = \mathbb{P}(\text{site is occupied})$

$\theta_{01} = \mathbb{P}(\text{segment occupied} \mid \text{previous segment unoccupied})$

$\theta_{11} = \mathbb{P}(\text{segment occupied} \mid \text{previous segment occupied})$

$p = \mathbb{P}(\text{detection} \mid \text{segment is occupied})$

Markovian Segment Occupancy

The model: [Hines2010]

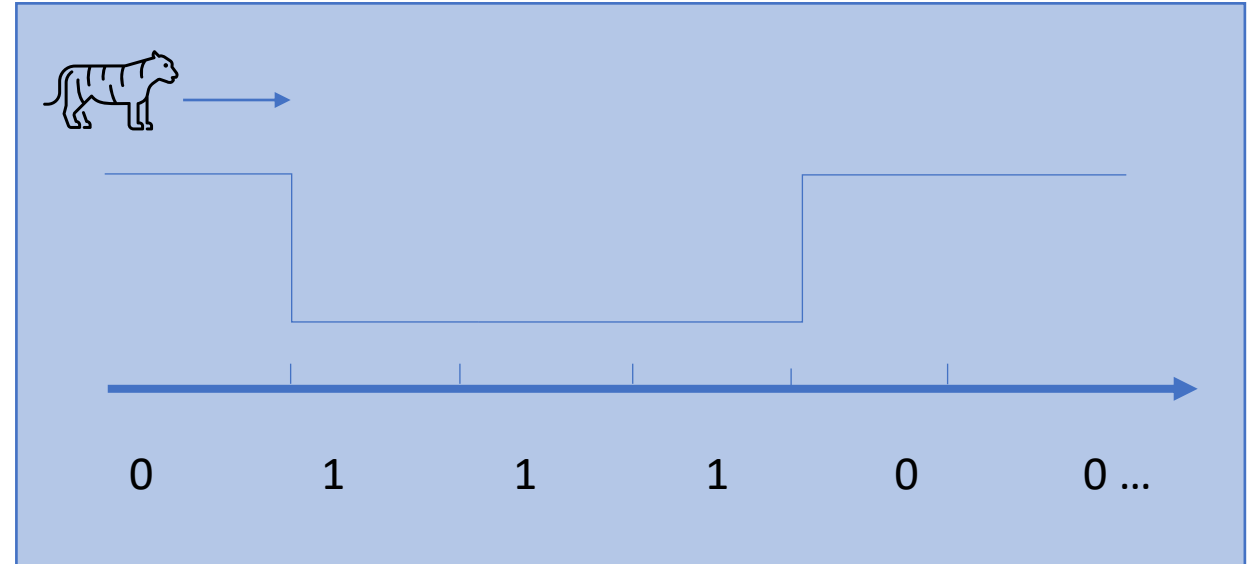
1. Site occupancy

$$z_i \sim \text{Bernoulli}(\psi)$$

2. Segment occupancy

$$z_{ik} | z_i \sim \text{Bernoulli}(z_i \times \theta_{ik})$$

$$\begin{bmatrix} 1 - \theta_{01} & \theta_{01} \\ 1 - \theta_{11} & \theta_{11} \end{bmatrix}$$



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Markovian Segment Occupancy

The model: [Hines2010]

1. Site occupancy

$$z_i \sim \text{Bernoulli}(\psi)$$

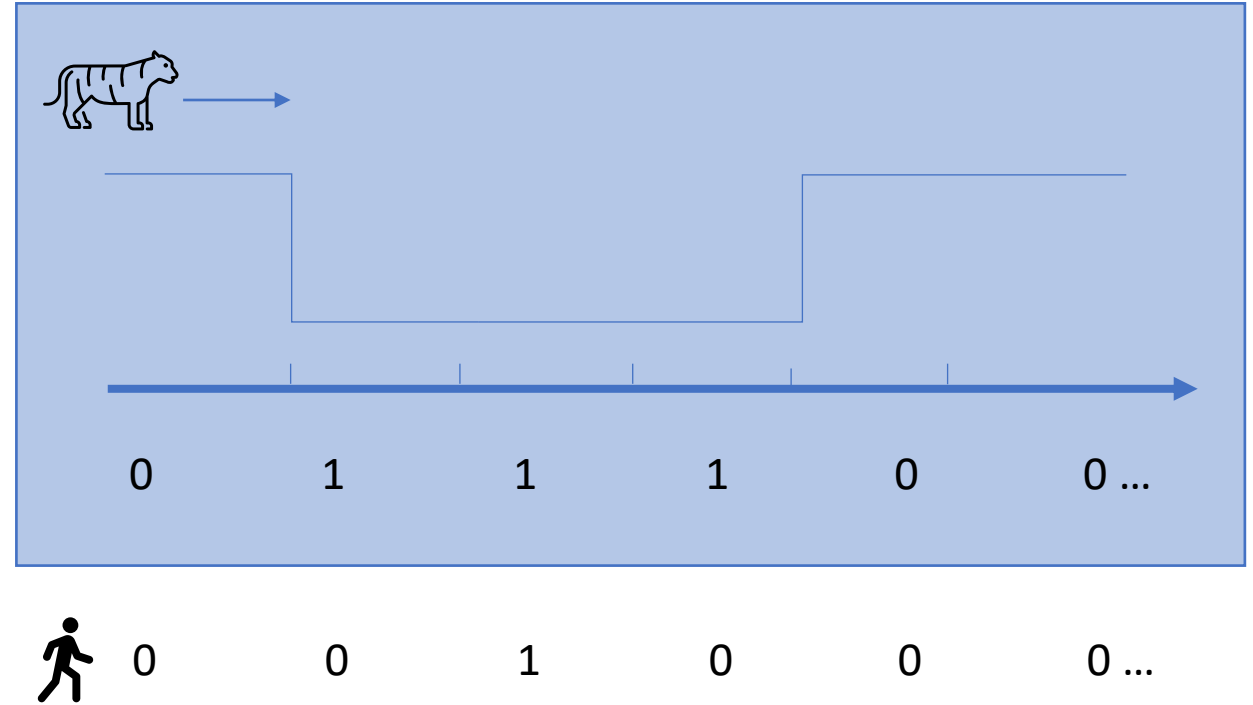
2. Segment occupancy

$$z_{ik} | z_i \sim \text{Bernoulli}(z_i \times \theta_{ik})$$

$$\begin{bmatrix} 1 - \theta_{01} & \theta_{01} \\ 1 - \theta_{11} & \theta_{11} \end{bmatrix}$$

3. Detection

$$y_{ik} | z_{ik} \sim \text{Bernoulli}(z_{ik} \times p)$$



Notation:

z_i = occupancy site i

z_{ik} = occupancy segment k , site i

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$p = \mathbb{P}(\text{detection} \mid \text{segment is occupied})$

Identifiability

Full Model

$$\begin{aligned}z_i &\sim \text{Bernoulli}(\psi) \\ z_{ik}|z_i &\sim \text{Bernoulli}(z_i \times \theta_{ik}) \\ y_{ik}|z_{ik} &\sim \text{Bernoulli}(z_{ik} \times p)\end{aligned}$$

$$\theta_{01} = \theta_{11} = \theta$$


Collapses to

Non-identifiable Model

$$\begin{aligned}z_i &\sim \text{Bernoulli}(\psi) \\ y_{ik}|z_{ik} &\sim \text{Bernoulli}(z_i \times \theta \times p)\end{aligned}$$

Can only identify: $(\psi, \theta p)$

Good news! Can still identify ψ .

Notation:

z_i = occupancy site i

z_{ik} = occupancy segment k , site i

y_{ik} = detection segment k , site i

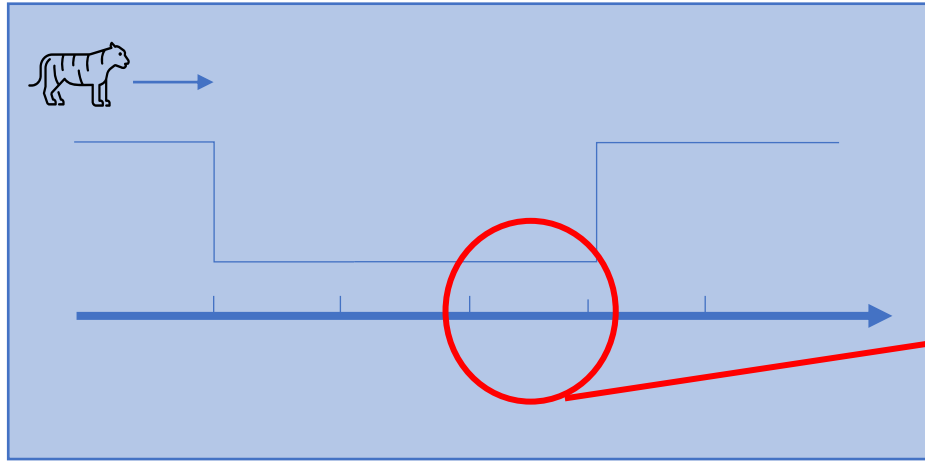
ψ = \mathbb{P} (site is occupied)

θ_{01} = \mathbb{P} (segment occupied | previous segment unoccupied)

θ_{11} = \mathbb{P} (segment occupied | previous segment occupied)

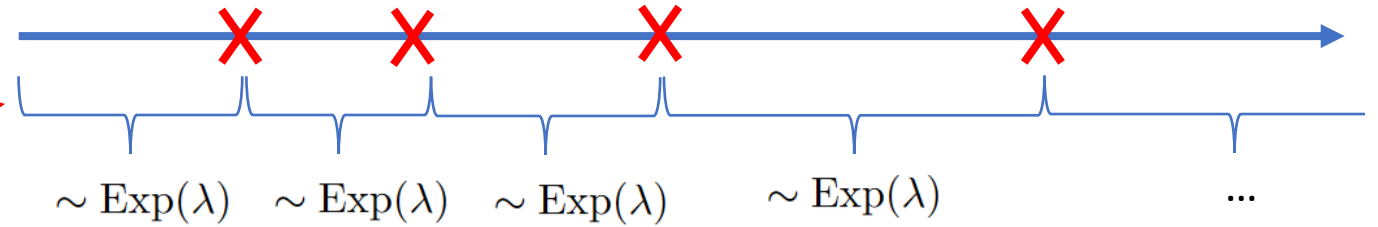
p = \mathbb{P} (detection | segment is occupied)

How do we record data: [Pautrel2024]

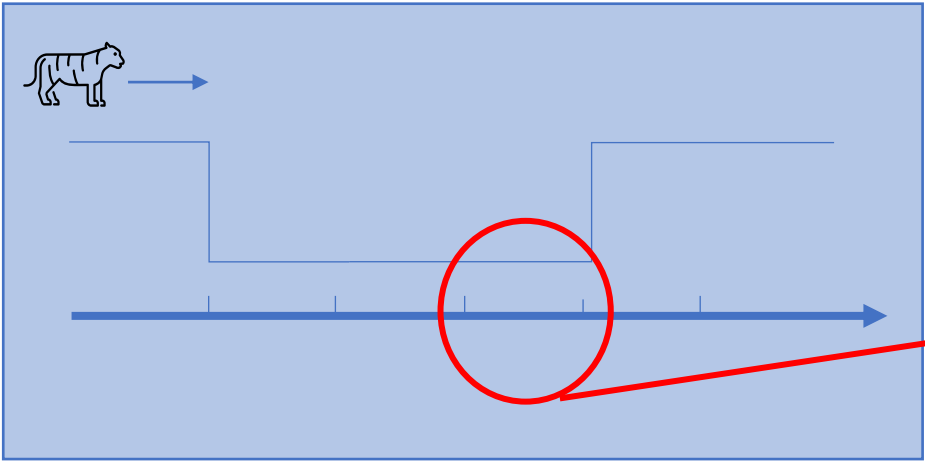


Detections are made at exponential rate λ on occupied segments.

If all segments have length R : $p = 1 - \exp(-\lambda R)$

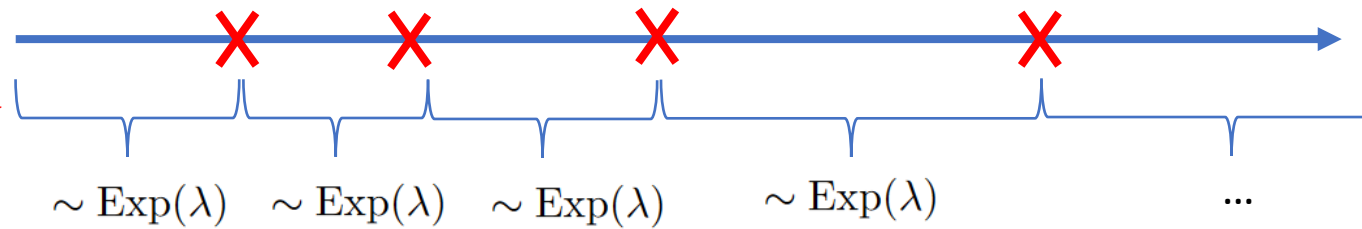


How do we record data: [Pautrel2024]



Detections are made at exponential rate λ on occupied segments.

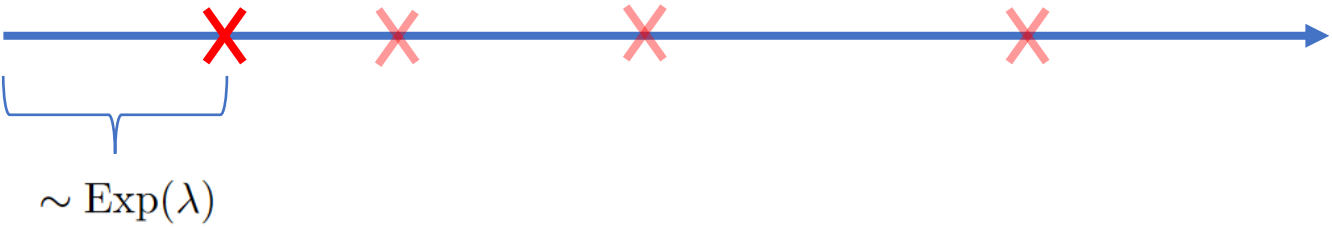
If all segments have length R : $p = 1 - \exp(-\lambda R)$



Single Observation – Discrete vs Continuous

Two Observations

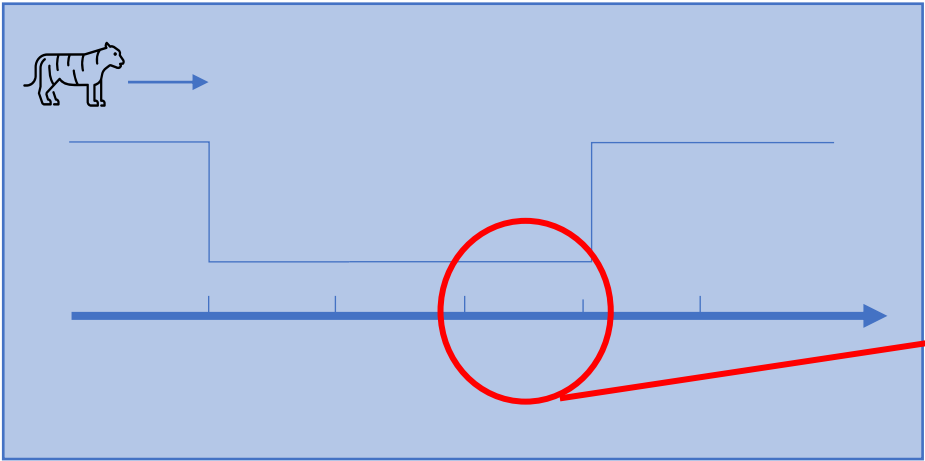
All observations



‘Time to first detection’ [Garrard2008]

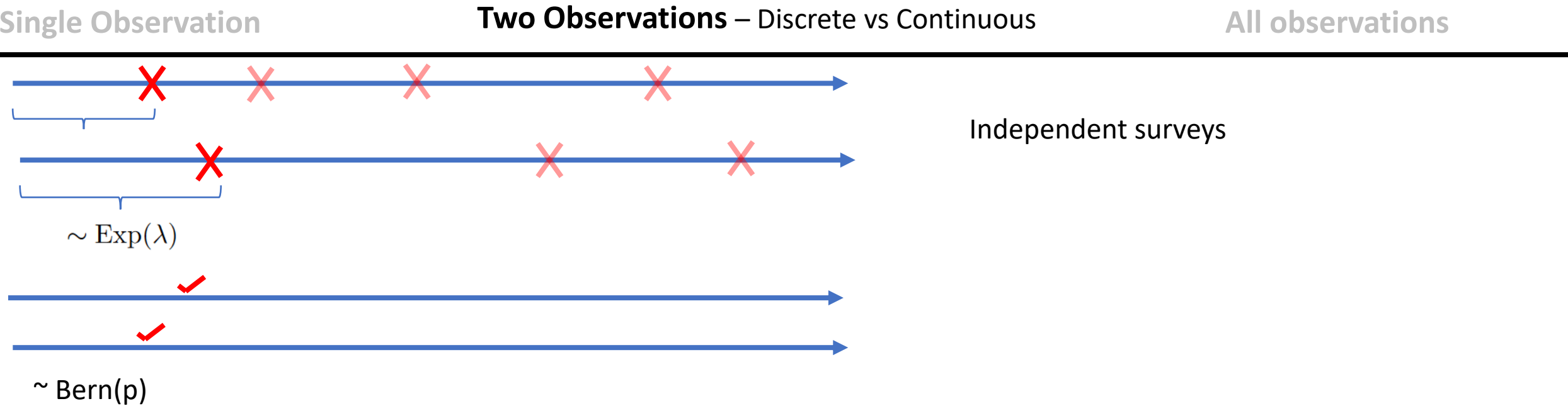
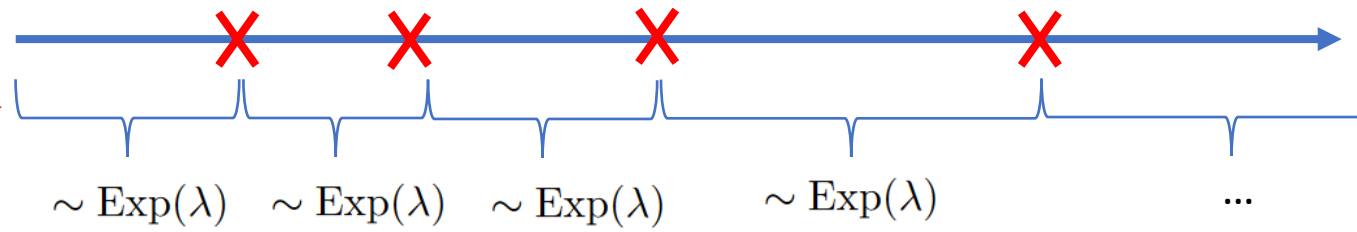


How do we record data: [Pautrel2024]

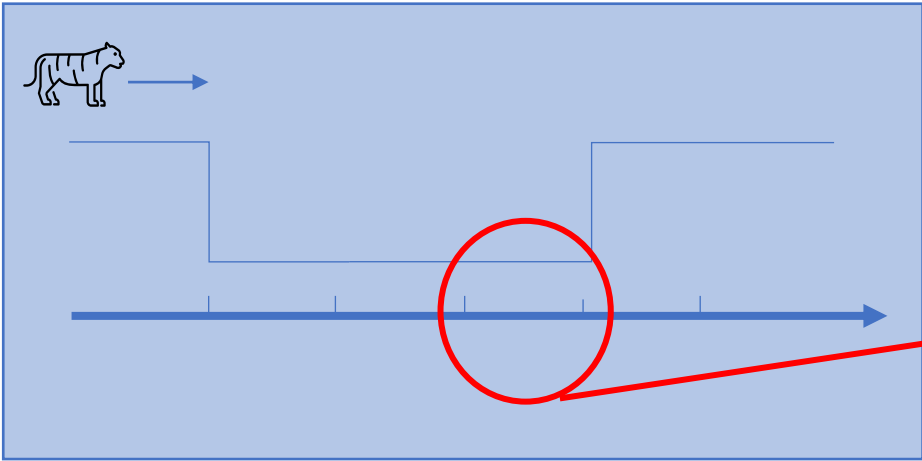


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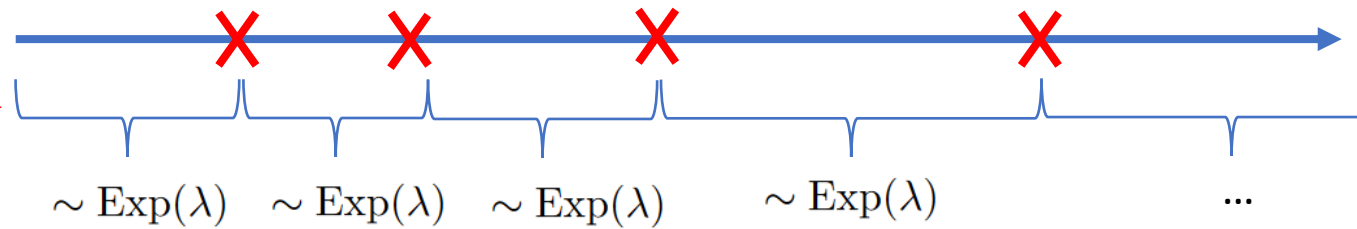


How do we record data: [Pautrel2024]



Detections are made at exponential rate λ on occupied segments.

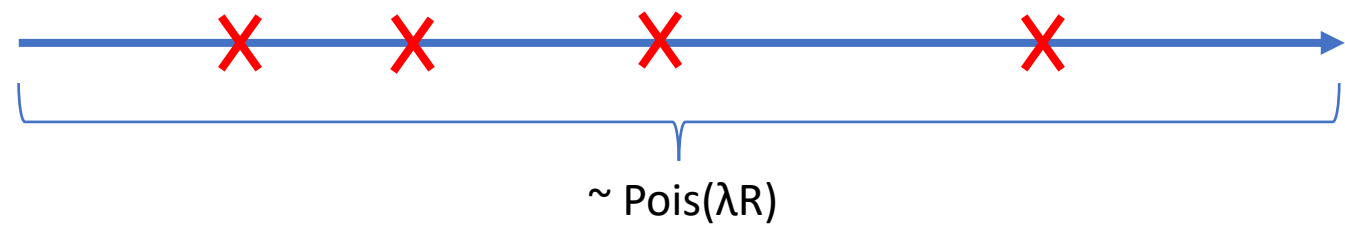
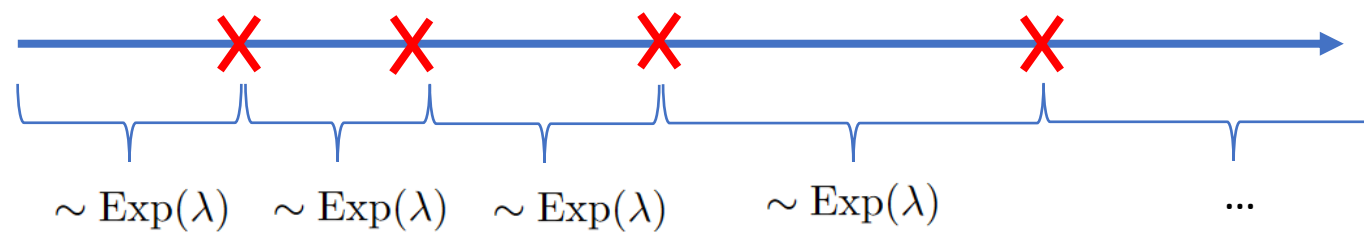
If all segments have length R : $p = 1 - \exp(-\lambda R)$



Single Observation

Two Observations

All observations – Discrete vs Continuous



Count of observations

Summary:

Single Observation

Discrete

Detection/non-detection
 $\sim \text{Bern}(p)$



1, 0, 0, 1, 1, ...

Continuous

Distance to first
detection
 $\sim \text{Exp}(\lambda)$



x1, -, -, x4, x5, ...

\geq Two Observations

Discrete

Two independent
detection\ non-detection
 $\sim \text{Bern}(p)$



1, 0, 0, 1, 1, ...
0, 0, 1, 1, 0, ...

Continuous

Two independent distance
to first detection
 $\sim \text{Exp}(\lambda)$



x1, -, -, x4, x5, ...
-, -, x3, x4, -, ...

All Observations

Discrete

Counts
 $\sim \text{Pois}(\lambda R)$



5, 0, 0, 7, 3, ...

Continuous

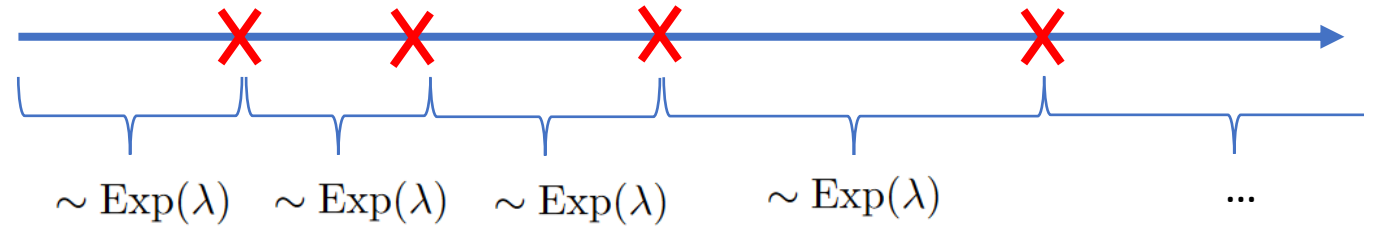
All inter-detection
distances
 $\sim \text{Exp}(\lambda)$



x11, x12, x13, ...
x21, x22, x23, ...
...

Simulations overview

- We simulate:
 1. Site occupancy status
 2. Segment occupancy status
 3. Continuous detections
 4. Discretise as needed



200 sites, 20 segments per transect.

Compare 6 data collection methods.

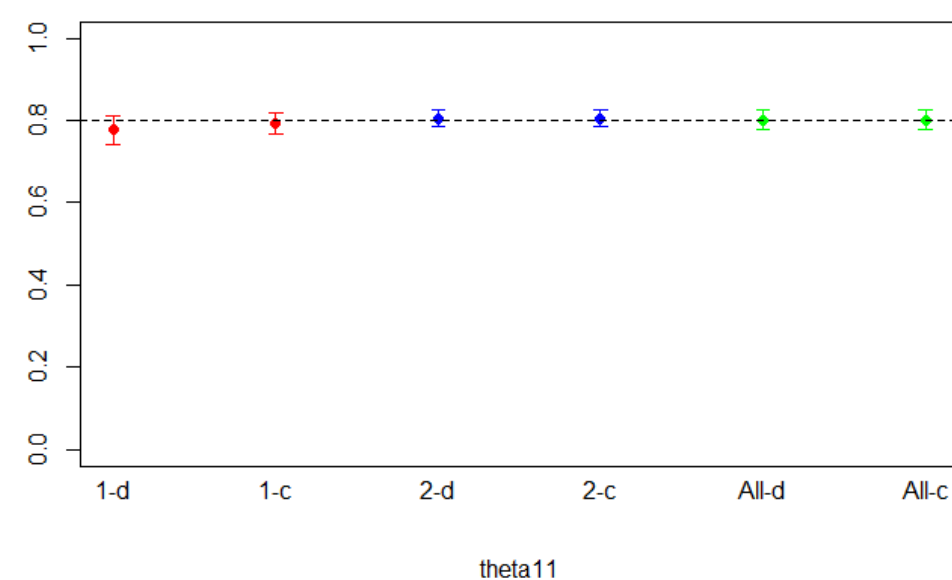
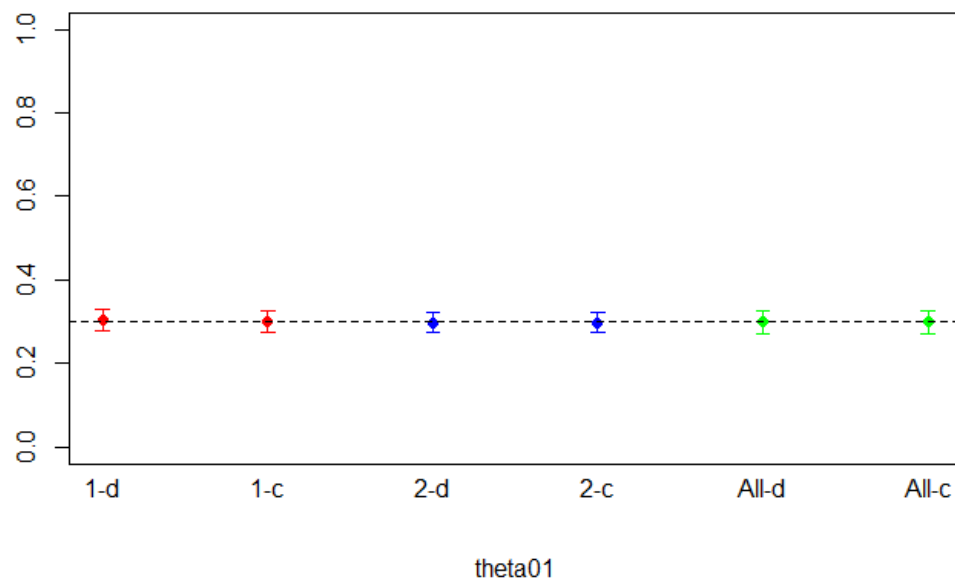
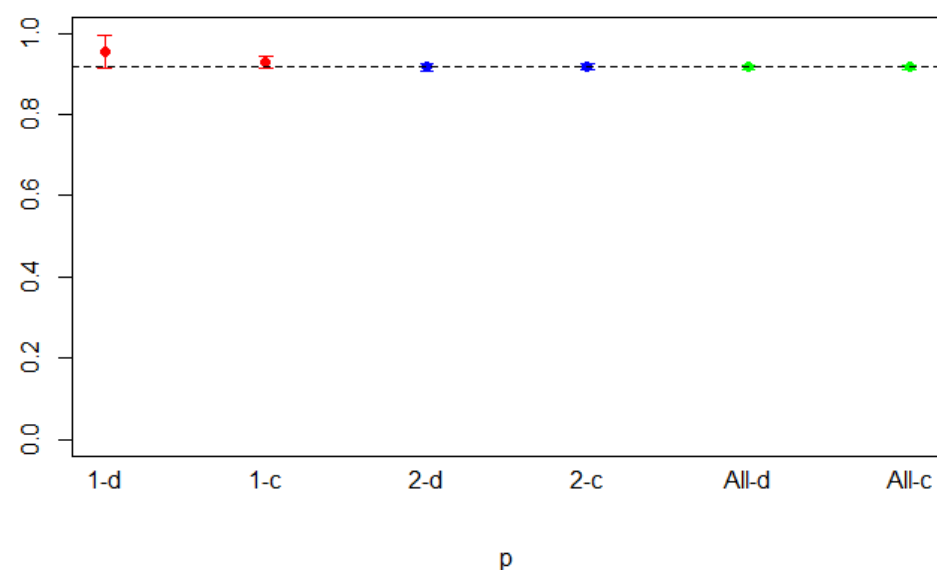
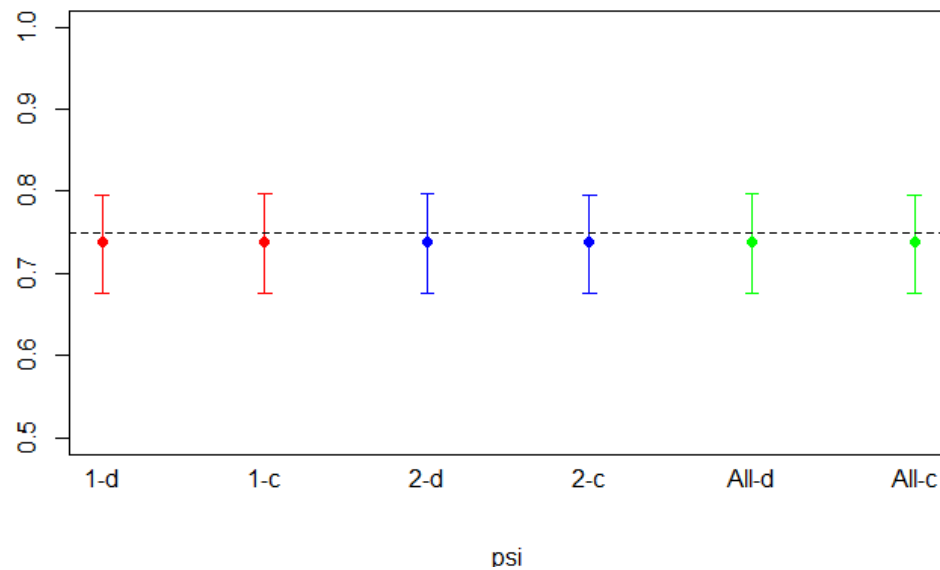
Recall that: $p = 1 - \exp(-\lambda R)$

All models fit in nimble.



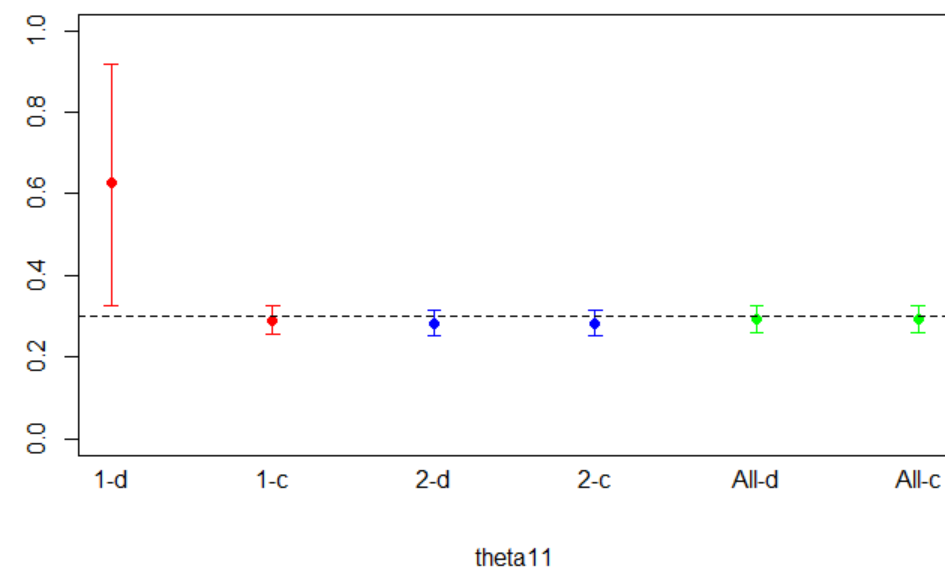
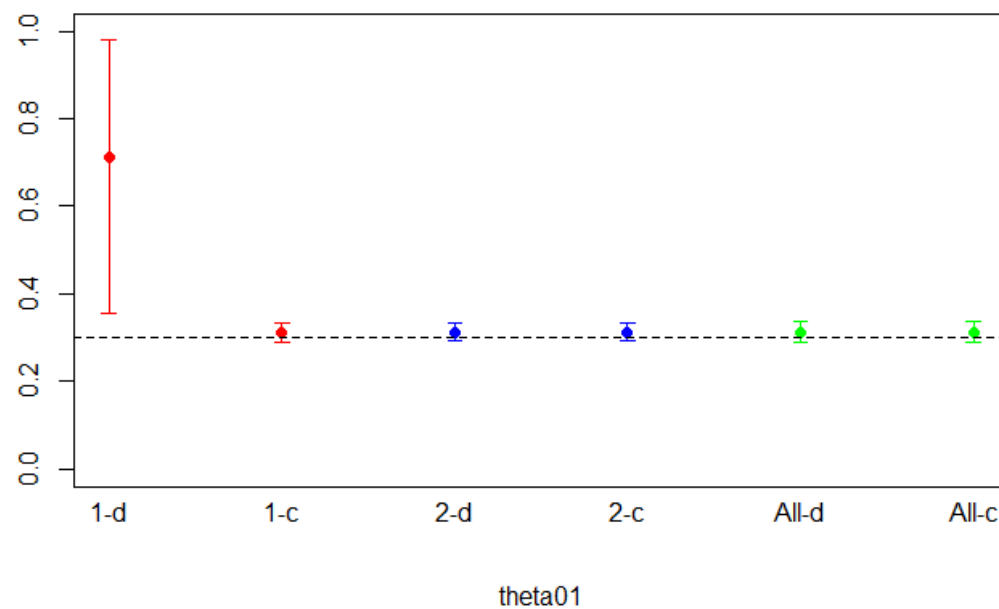
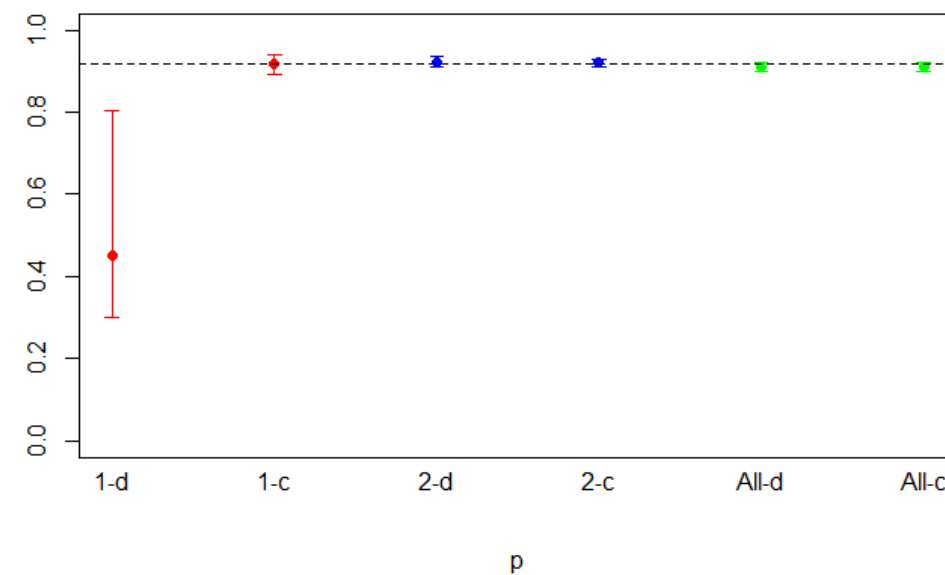
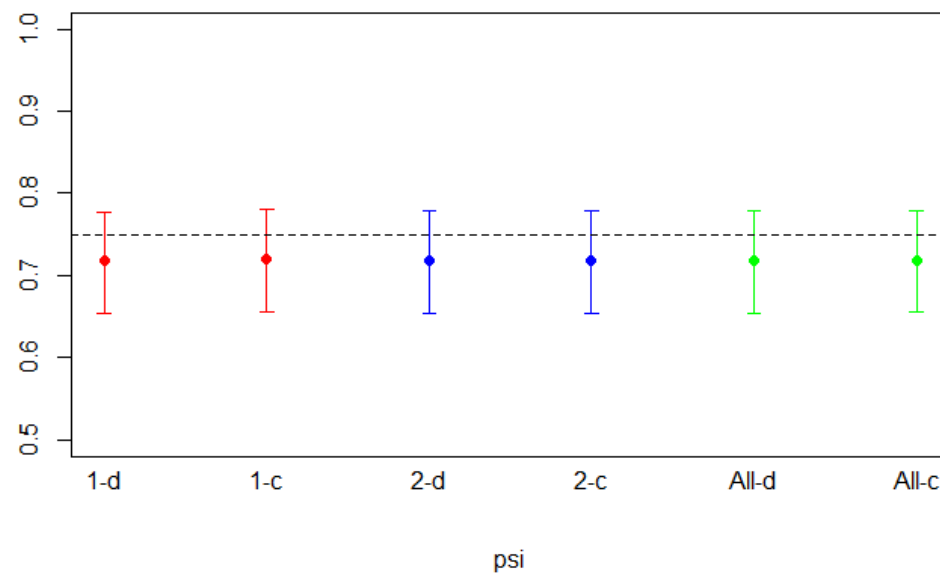
Simulations

$\psi = 0.75$
 $p = 0.918$
 $\theta_{01} = 0.3$
 $\theta_{11} = 0.8$



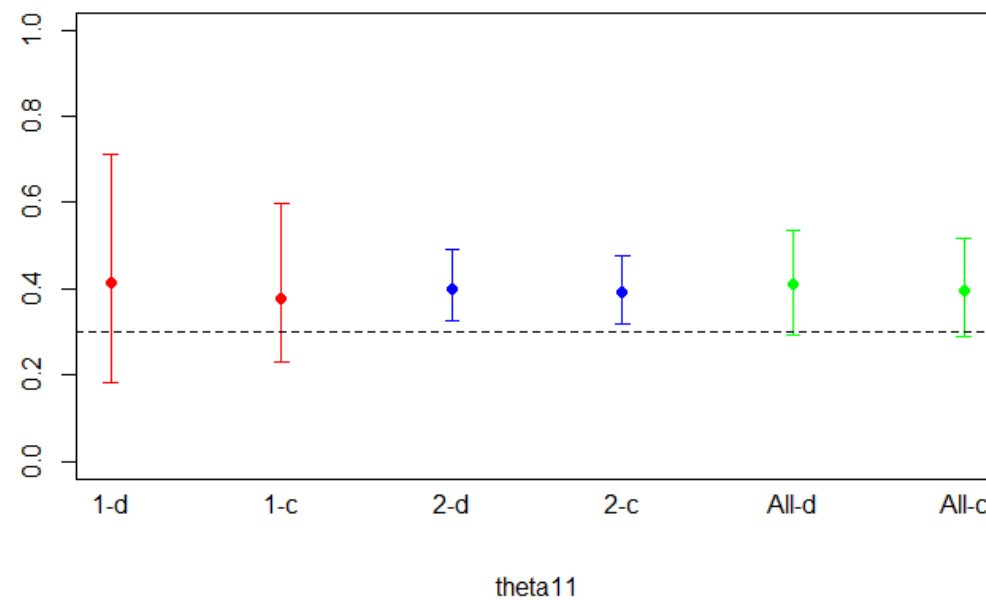
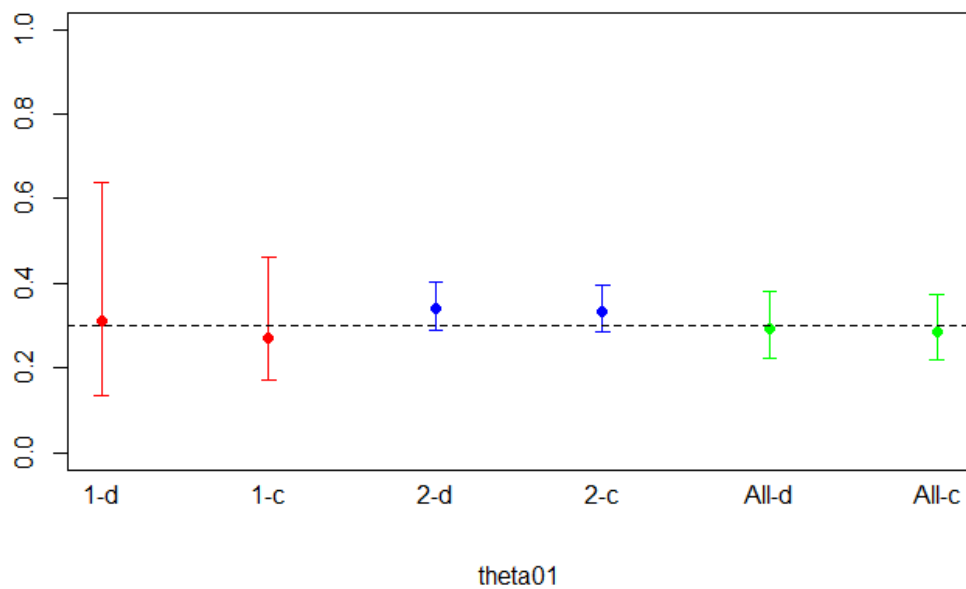
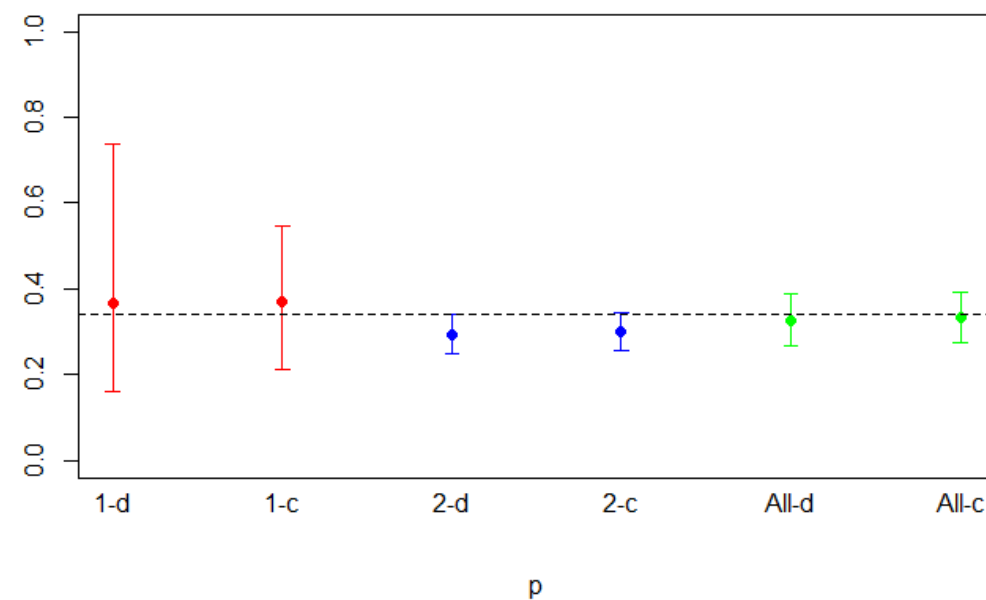
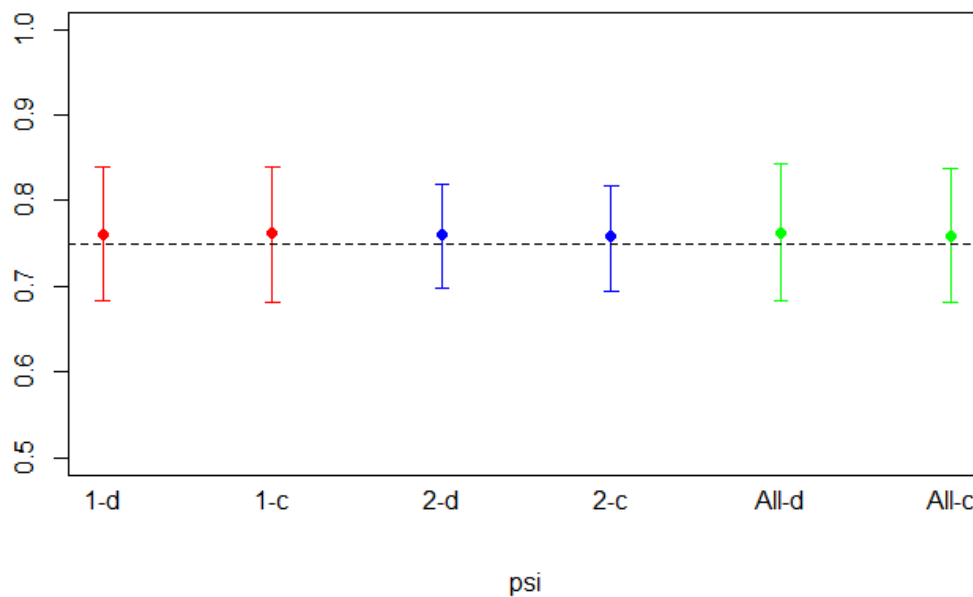
Simulations

$\psi = 0.75$
 $p = 0.918$
 $\theta_{01} = 0.3$
 $\theta_{11} = 0.3$

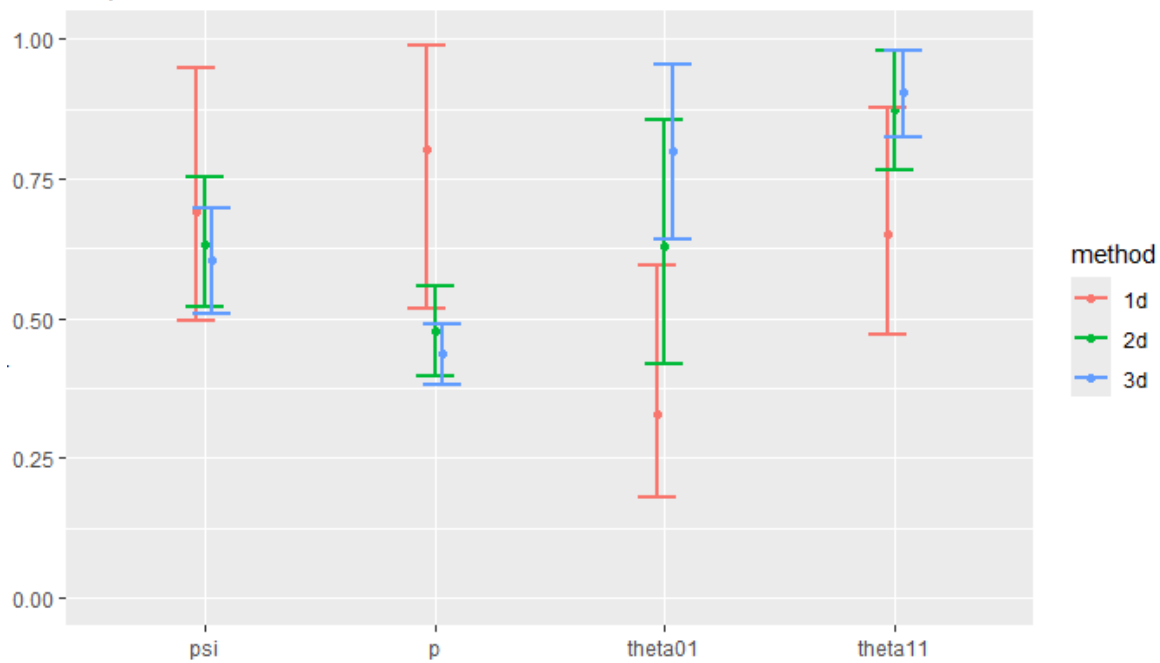


Simulations

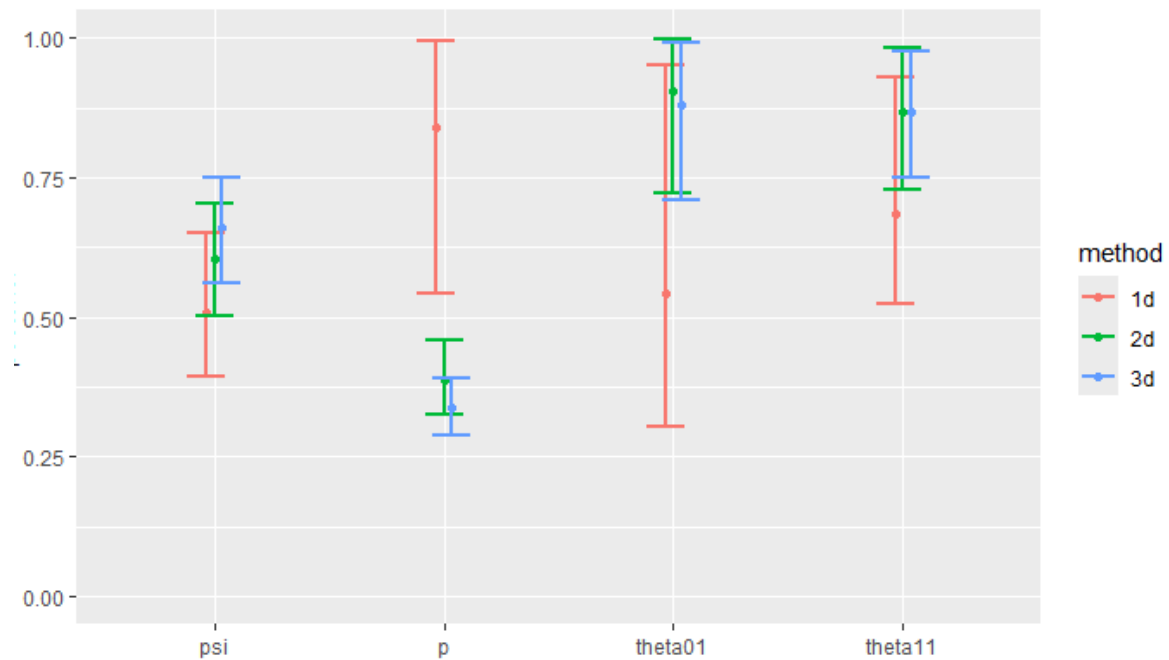
$\psi = 0.75$
 $\rho = 0.340$
 $\theta_{01} = 0.3$
 $\theta_{11} = 0.3$



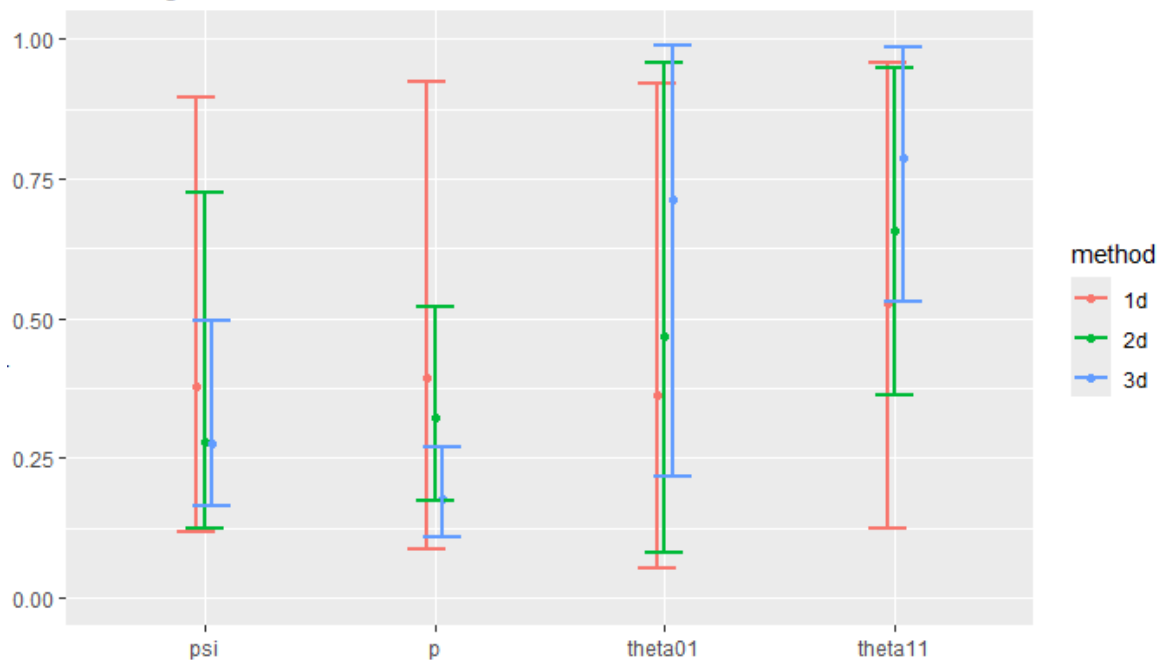
leopard



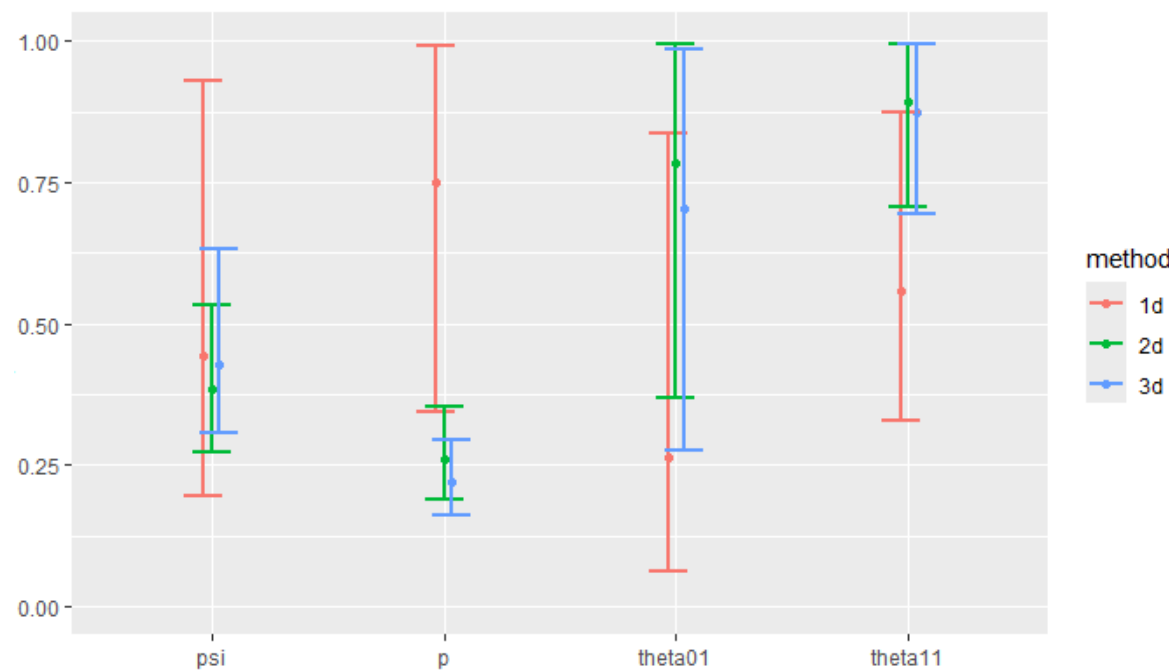
hyena



wild dog



lion



Conclusion

- Three layer occupancy models using Markovian dependence in segment occupancy and a single detection are not identifiable when spatial correlation does not exist.
- We show that using a single time to detection, two or more independent observations, or counts make the model identifiable even when spatial correlation does not exist.
- Site occupancy probabilities perform well even other parameters struggle.

Where next

Discretising transects into segments is often arbitrary. Continuous models for handling spatial correlation include [Guru2011], involving a 2 state Markov Modulated Poisson Process (2-MMPP).

We have other line transect data collected for occupancy models that include perpendicular distances to observations (distance sampling data).

References

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