False positives and false negatives in citizen science monitoring data: should we be worried?

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Introduction

Citizen Science -> large scale data collection

- Essential for species monitoring

Data quality still perceived as major problem

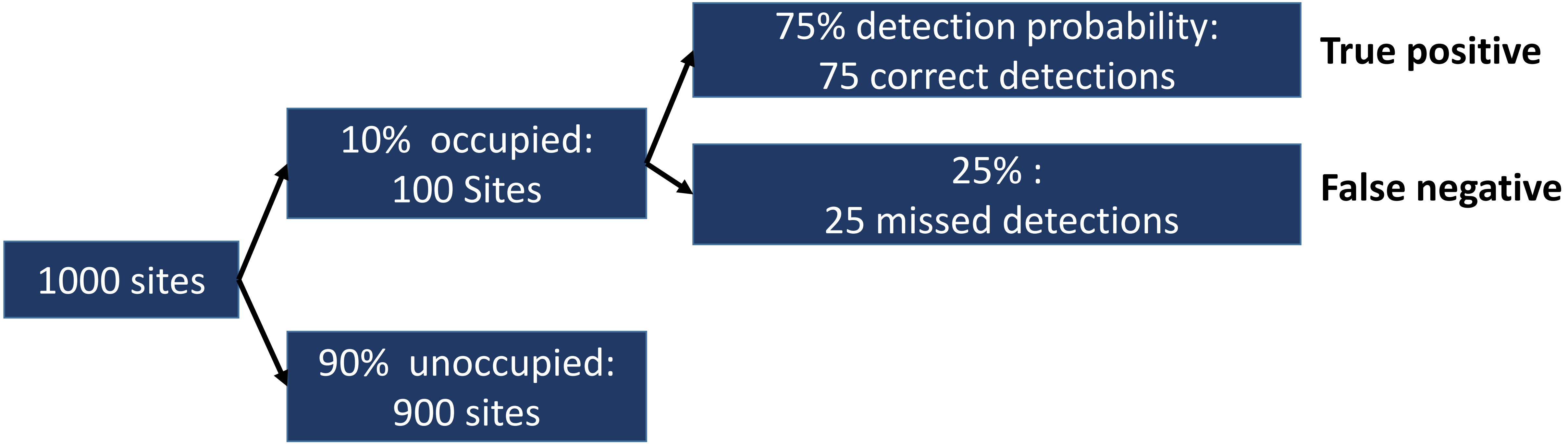
Repeat observations allow modelling of these observer effects

In species monitoring, quality can be characterised as:

- **False negatives**

- **False positives**

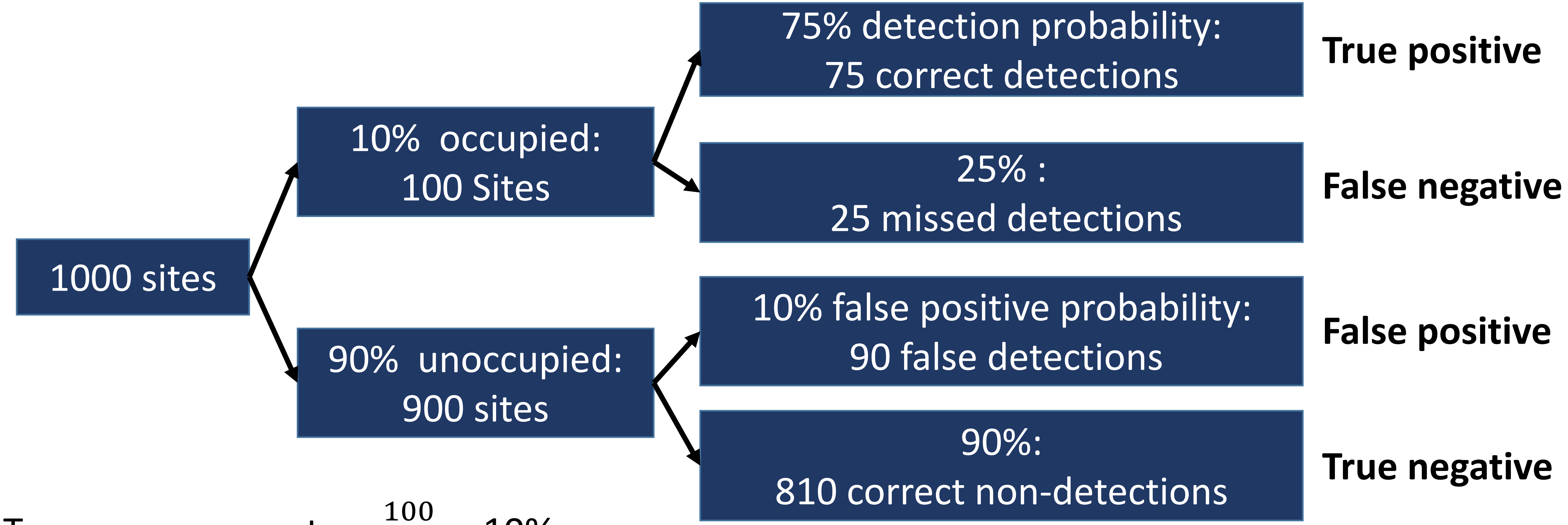
Observation Biases



True occupancy rate $\frac{100}{1000} = 10\%$

Estimated occupancy rate $\frac{75}{1000} = 7.5\%$

Observation Biases

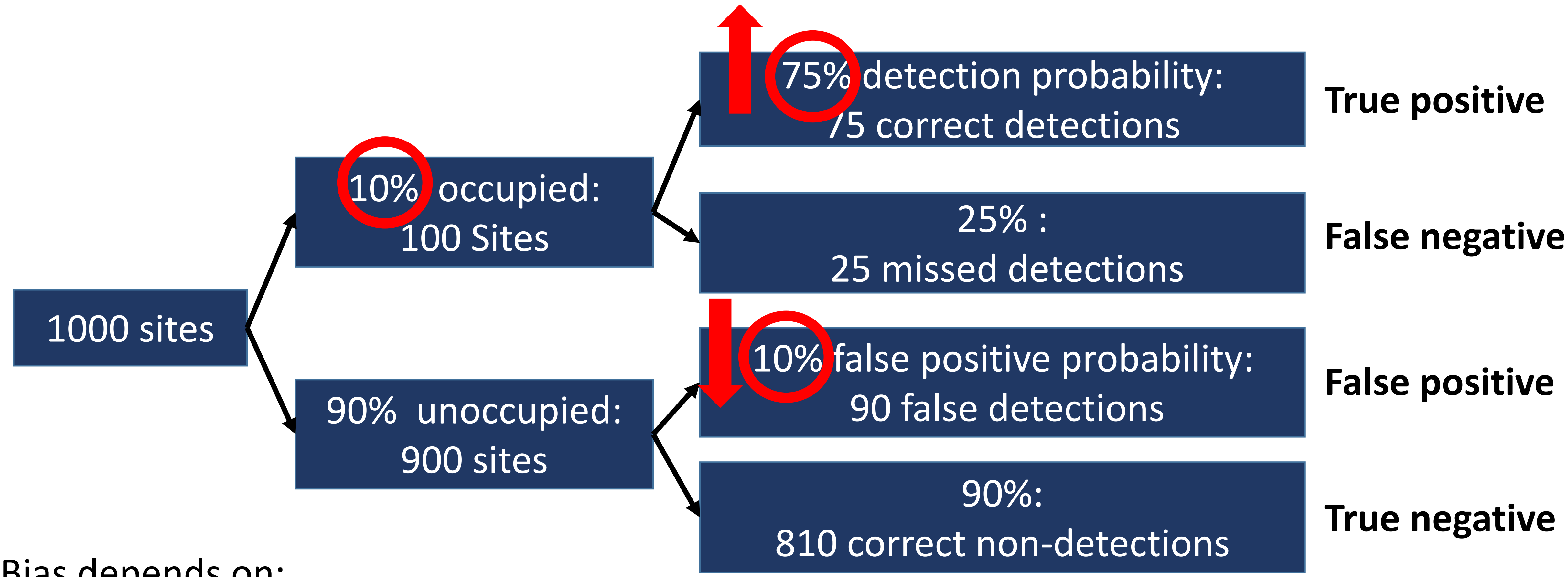


True occupancy rate $\frac{100}{1000}$ = 10%

Estimated occupancy rate $\frac{75+90}{1000}$ = 16.5%

False discovery rate = $\frac{90}{90+75}$ = 55%

Observation Biases



Bias depends on:

- True occupancy
- False positives/imperfect detection rates

More visits = higher cumulative detection probability
= lower cumulative false 'discovery' rate

Observation Biases

10 visits at a site

Possible site histories include:

a) **0000100000**

b) **1101111111**

True positive

False negative

False positive

True negative

Bias depends on:

- True occupancy
- False positives/imperfect detection rates

  More visits = higher cumulative detection probability

  = lower cumulative false-positive rate

Research Objectives

- Estimate prevalence of Imperfect detection
  False positives

- How do these rates bias population trend estimation

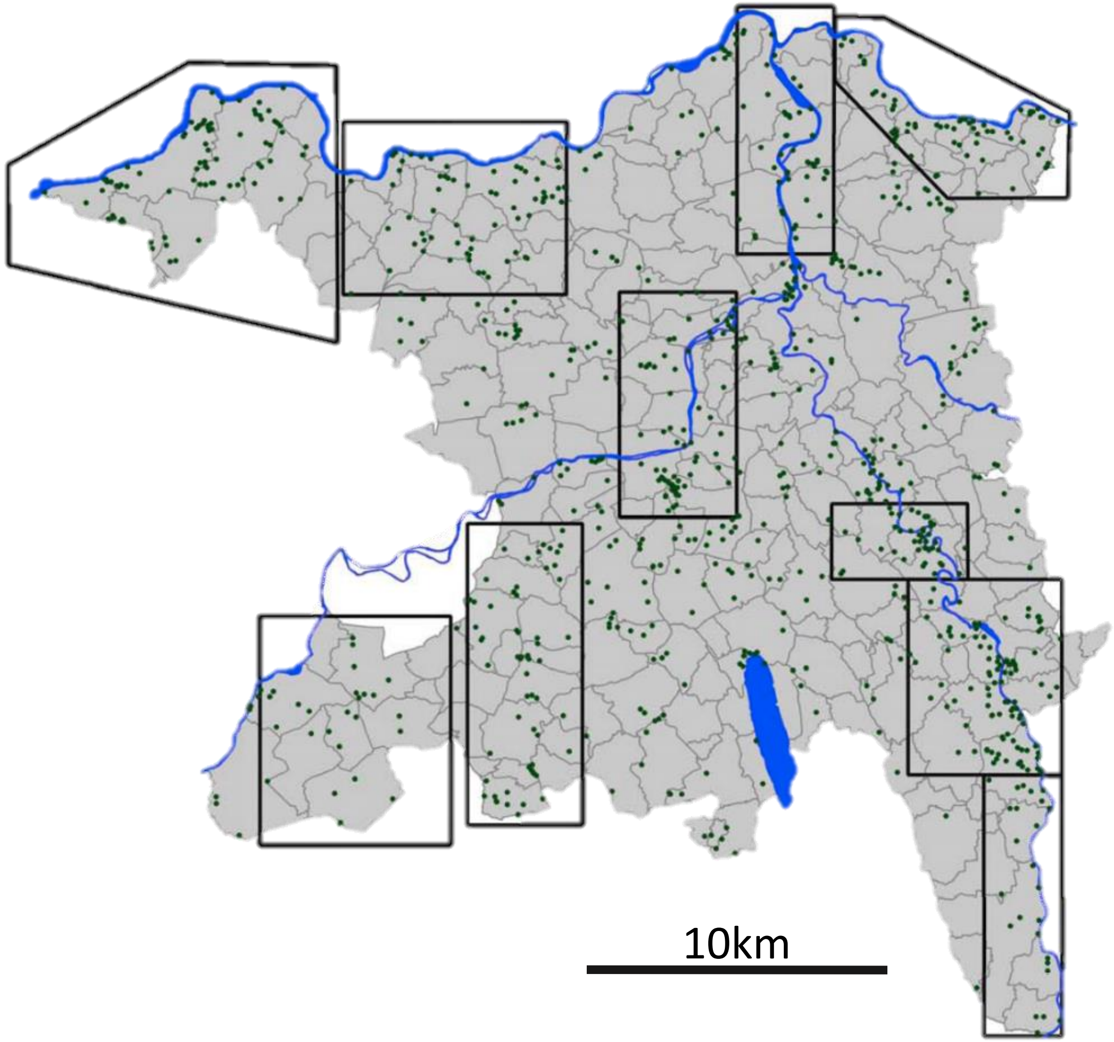
Study System

- 1999-2013
- 1054 sites

10 core areas

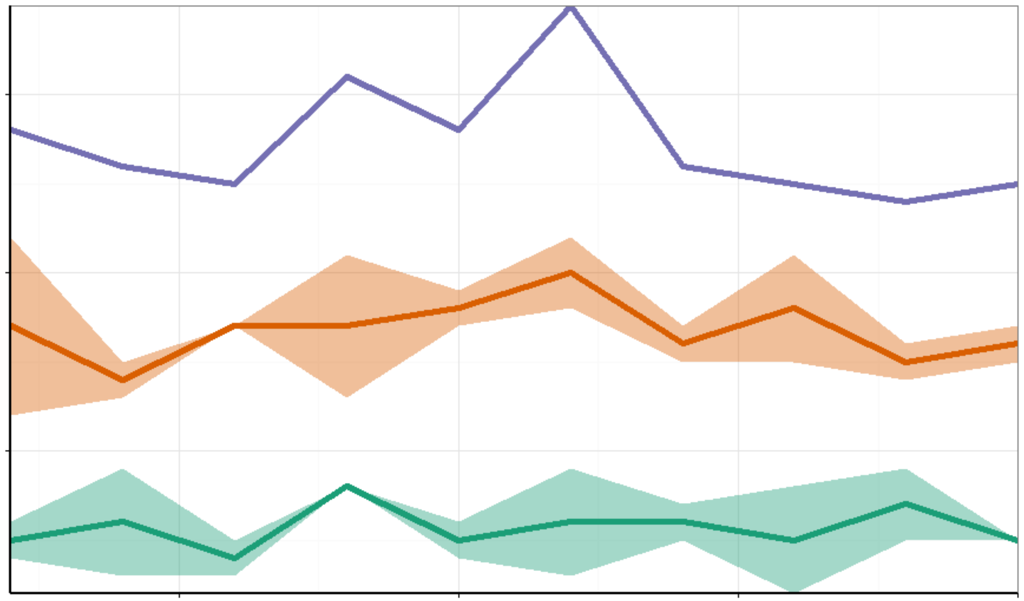
surveyed every 3 years

- 3 surveys/ year
- Counts of all amphibians recorded



Modelling Approach

- Focus on occupancy (not count) data
- Each species separately
- Dynamic occupancy models
  - Occupancy
    - ➢ Trend calculation
  - Survival
  - Colonisation



3 Models:

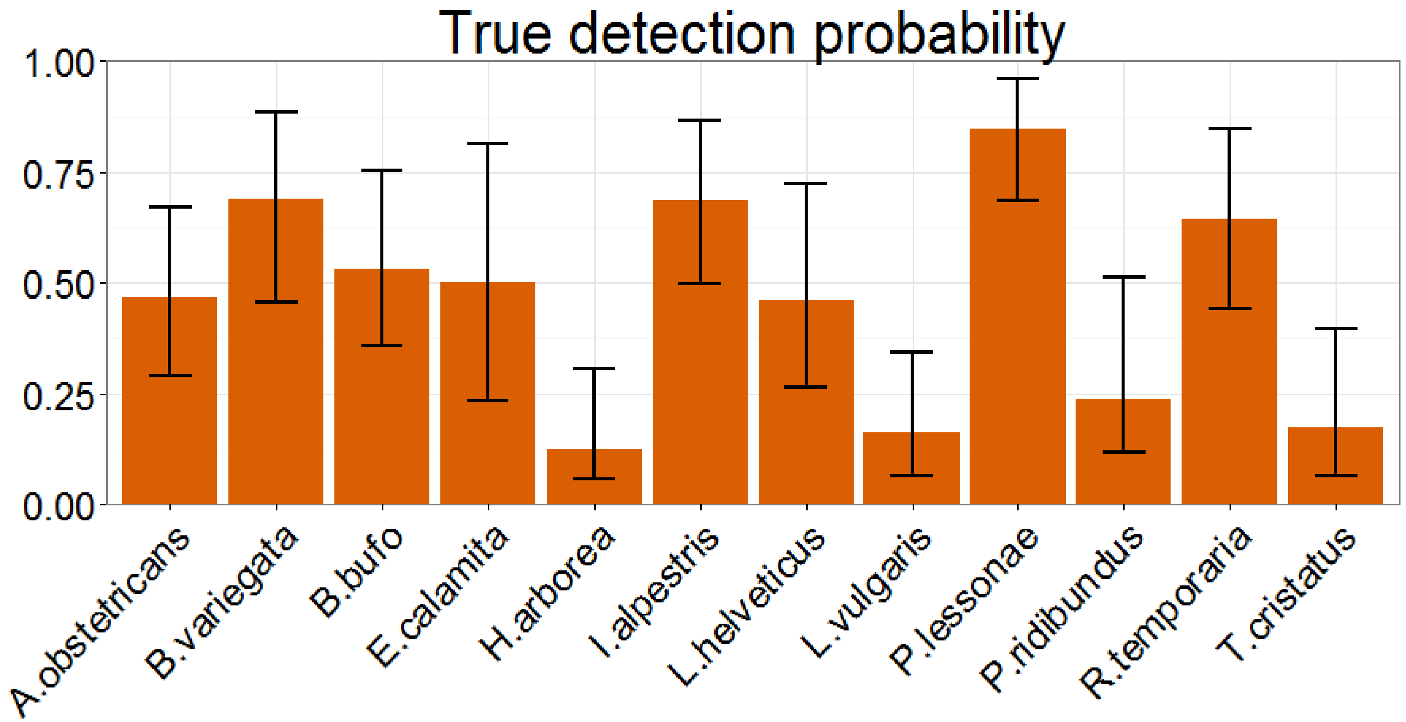
- Naïve - observed data
- False negatives - estimate imperfect detection
- False positives - both imperfect detection and false positives

Preliminary Results: Imperfect detection

Per-visit detection
(when species is present)

Bars= 95% credible intervals

- 12 species
- High variation

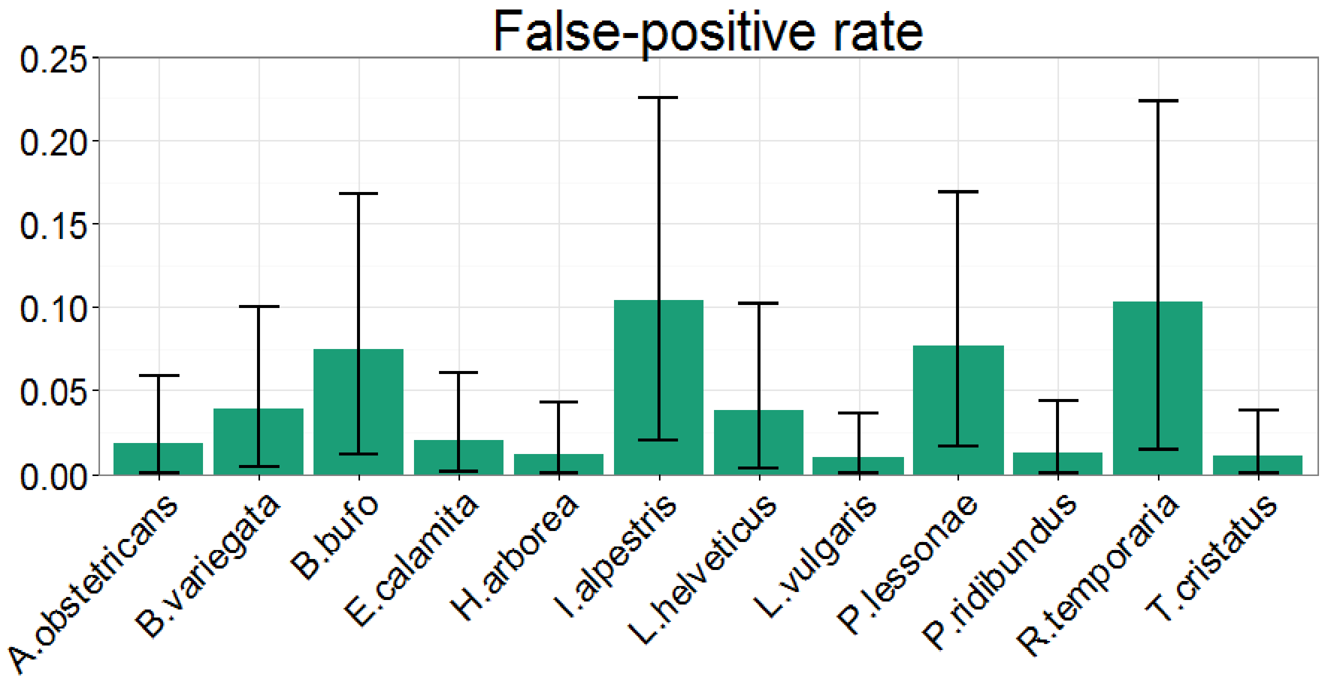


Preliminary Results: False-positives

Per-visit false positives
(when species is absent)

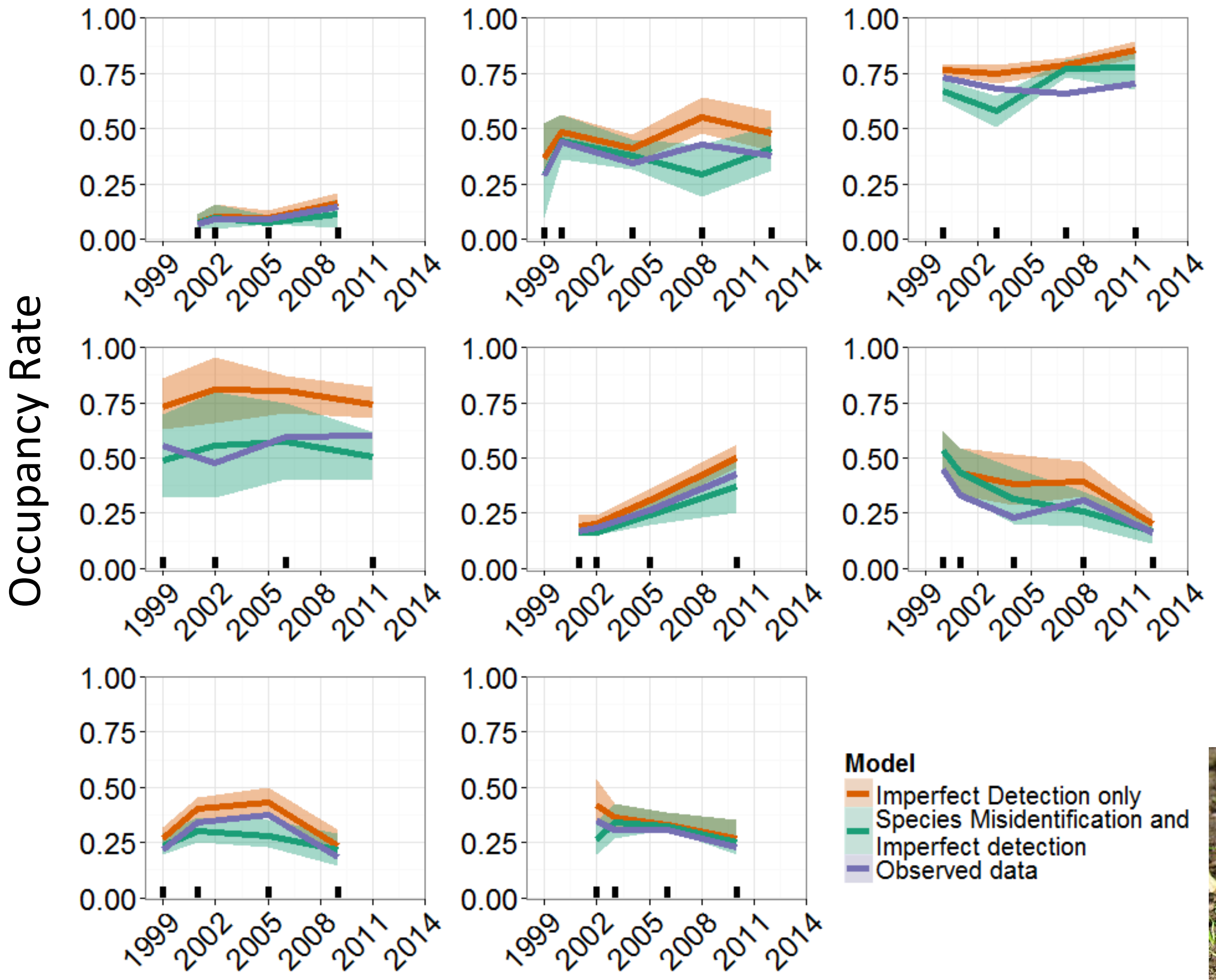
- Relatively low rates
- Common species more problematic

No evidence for “rare-species” bias



Preliminary population trends- Pool frog

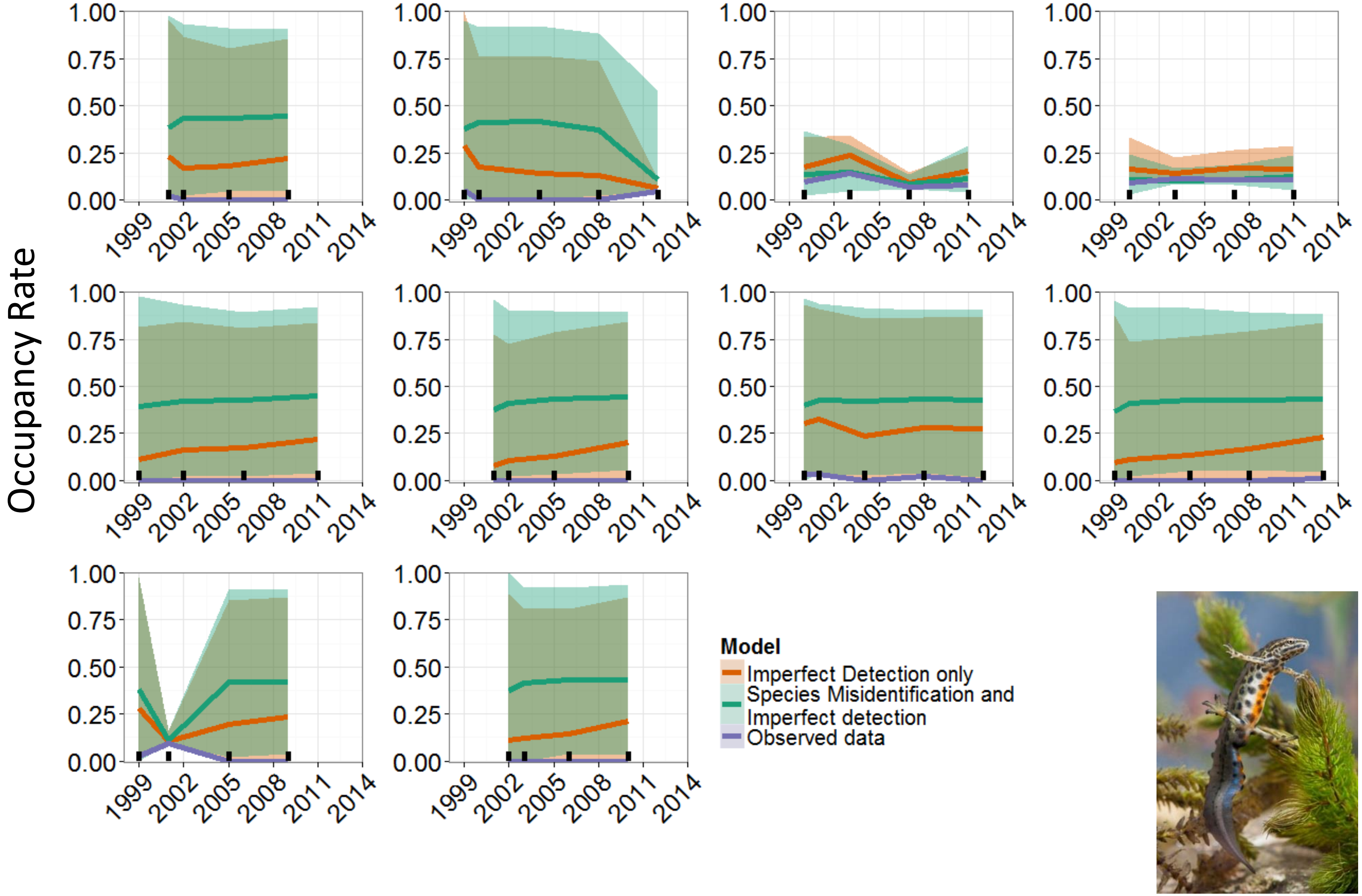
- High true detection (84.5%)
- High false positives (7.7%)
- Trends are qualitatively comparable



Preliminary population trends- Smooth Newt

- Rare species
- Low detection (16.1%)
- Low false positives (1.0%)

- Trend estimates differ qualitatively
- Models overestimate
- Not enough information to draw conclusions



Rare species issues

False positives create large bias

But not enough information to estimate observer effects

1010

Occupied but unseen twice?

Unoccupied with two false positives?

Solution: **Incorporate more information**

- “Confirm” detections
- Incorporate abundance (higher abundance → higher chance of true detection)

➢ Increased estimation of observer effects
➢ Better trend estimates

Conclusions: should we be worried?

Yes: - We know imperfect detection is the norm

- False positives do happen

No: - Problems are not unique to citizen science data

- For non-rare species, population trends remain broadly similar

Rare species: Problematic

➢ Need sufficient information to estimate observation values

Accounting for detection is not complex, but it is important!

- **Need to demonstrate data quality**

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