Inferring the spatial distribution of visceral leishmaniasis burden in India:

The impact of targeted surveillance and considerations for the near- and post-elimination strategy

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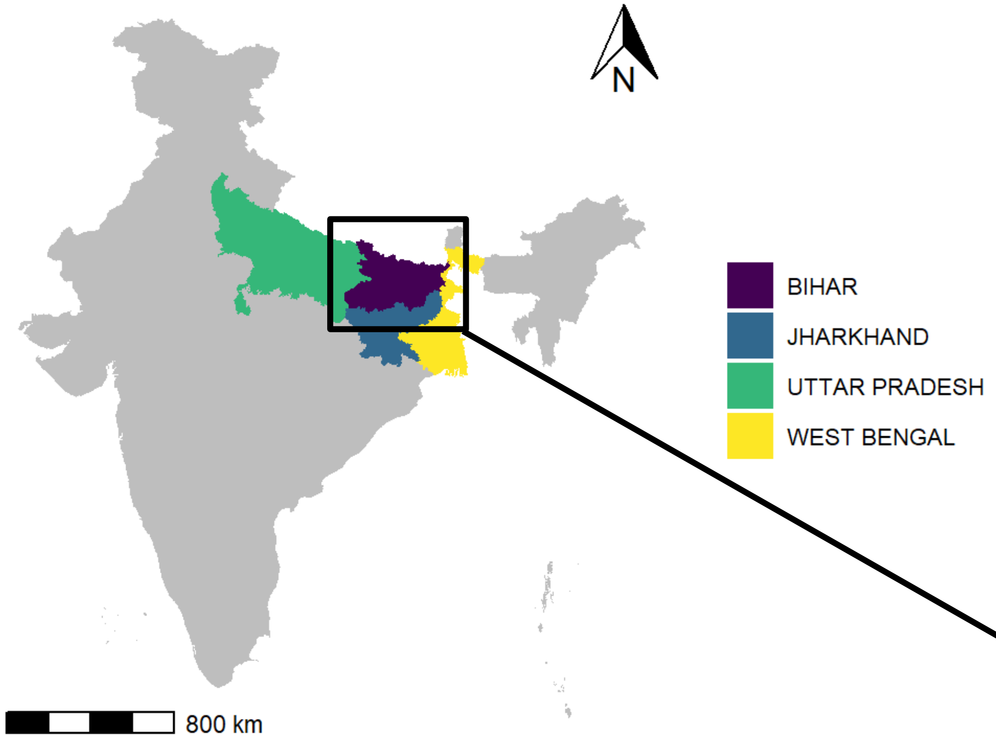
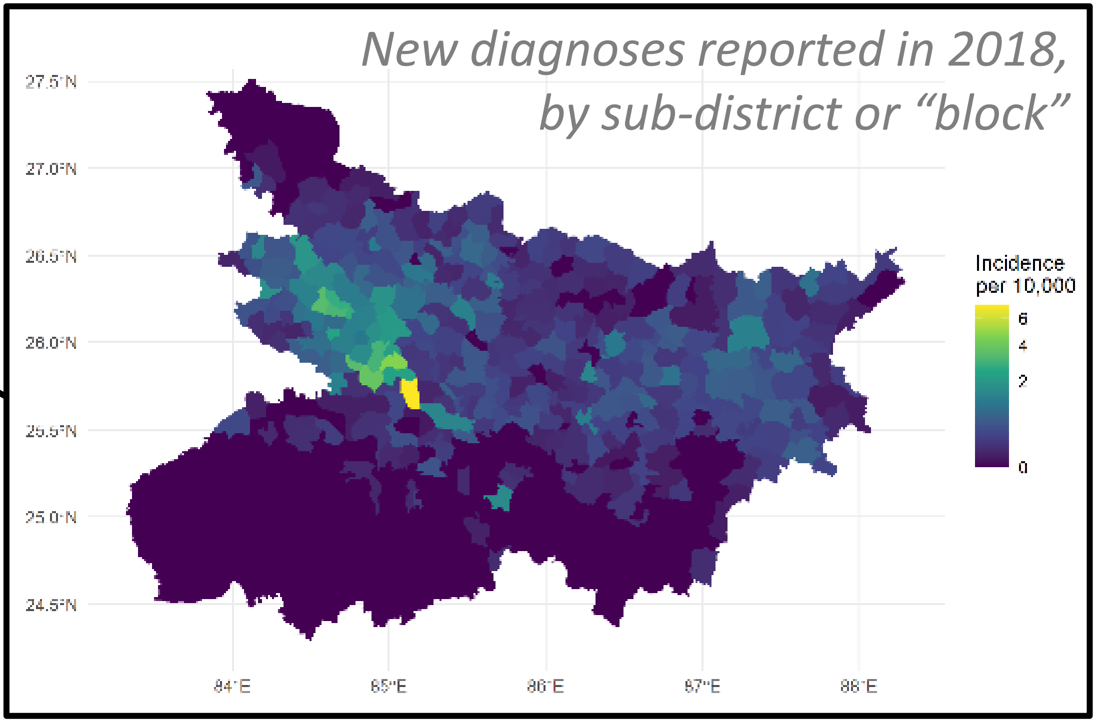
Outline

- Background
  - Epidemiology and surveillance of visceral leishmaniasis in India
- Spatial disaggregation of VL surveillance data
  - Method and validation approach
  - Results & Interpretation
- Exploring the impact of targeted surveillance
  - Spatial variation in promptness of detection
- Conclusions

Background



- No vaccine
- Unclear impact of vector control
- ➢ Prompt case detection crucial for control



VL has been targeted for elimination "as a public health problem" in India:

➢ < 1 case per 10,000 at the block level

Background

What action can be taken in response to observing 10 cases across a region of ~150k people?

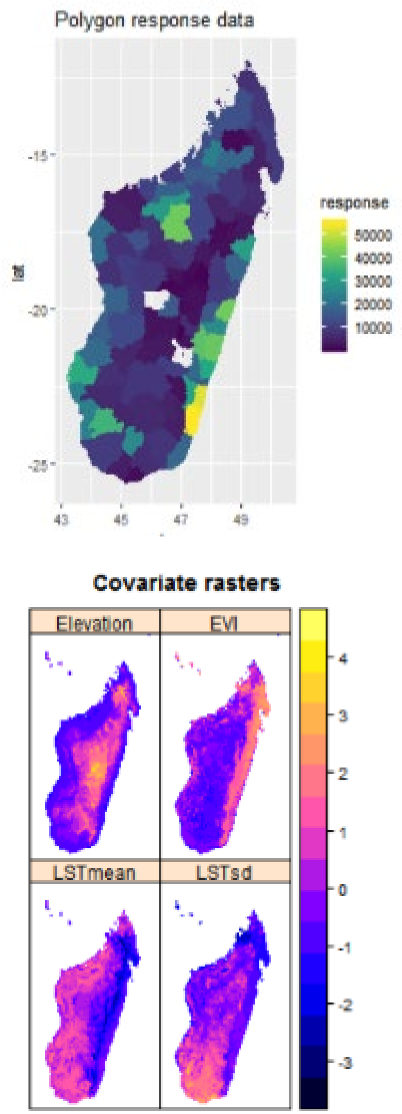
- ➢ Will only get more extreme as elimination is approached

VL appears in local clusters, so target may be met on a block-level but all burden falls in one focal area

- ➢ Is it appropriate/equitable to conclude elimination?

⇨ There is a need for surveillance at a finer scale, *however*, this is resource-intensive

A possible solution – Spatial disaggregation



Areal aggregated data

+

Fine scale spatial covariates

Assumed spatial dependence

Fine scale spatial predictions

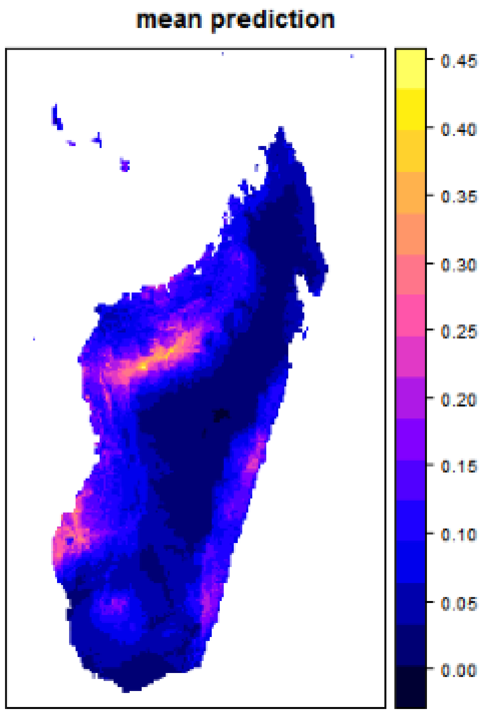


Image source: Arambepola et al. (2021)

Model structure

- Poisson regression defined on pixel level incidence r_{ij}
- Fit to case counts aggregated across areas i, weighted by a population raster a_{ij}

MODEL

$$\log(r_{ij}) = \beta_0 \underbrace{\boxed{+\ \beta X_{ij}}}_{\text{Pixel-level covariates}} \underbrace{\boxed{+\ GP(s_{ij})}}_{\text{Spatial random field}} \underbrace{\boxed{+\ u_i}}_{\text{Area-level IID effect}}$$

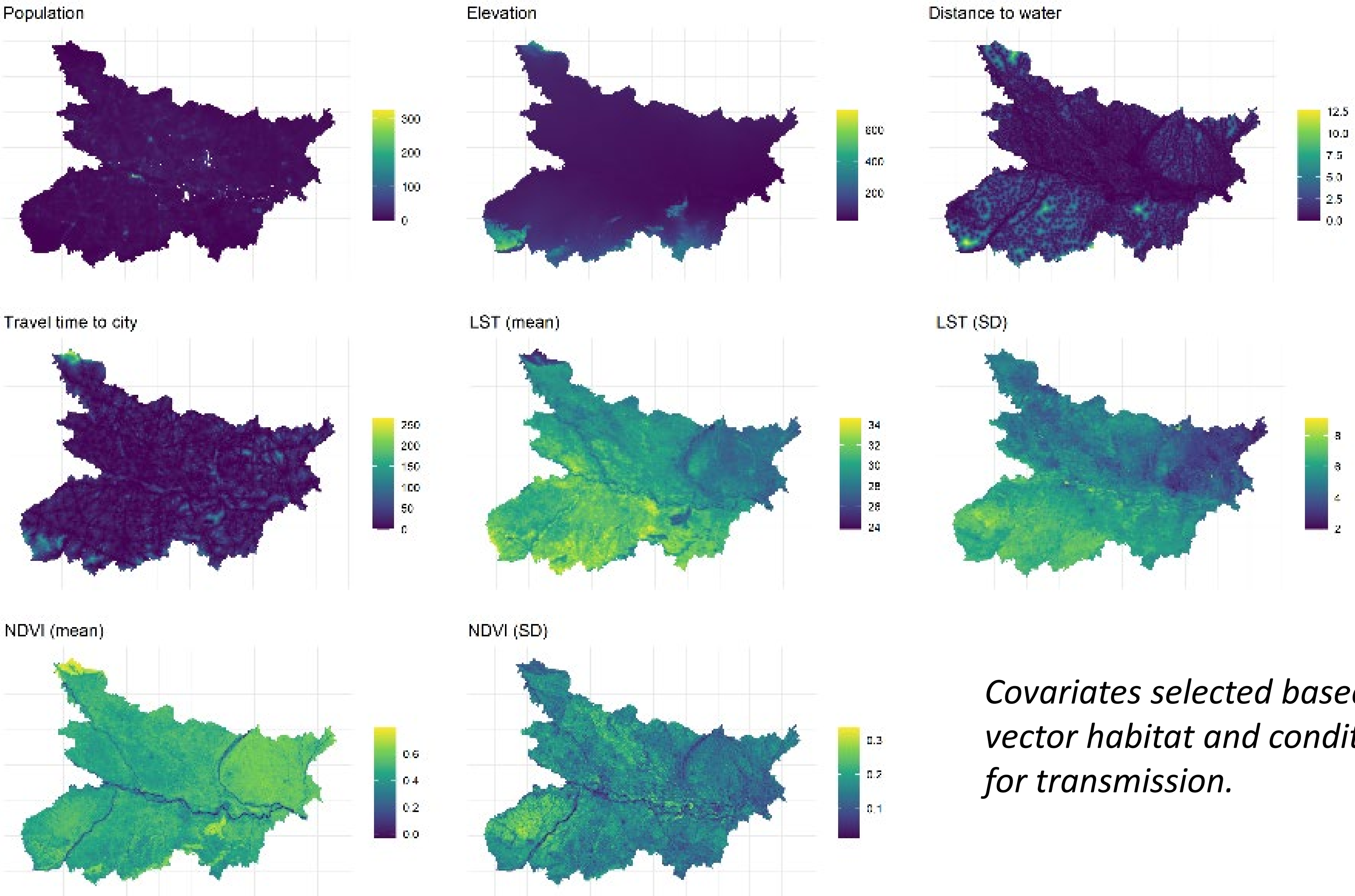
AGGREGATION

$$cases_i = \sum_{j=1}^{N_i} a_{ij} r_{ij}$$

LIKELIHOOD

$$y_i \sim Pois(cases_i)$$

Environmental covariates



Covariates selected based on vector habitat and conditions for transmission.

Constructing a validation set

Validation of disaggregation model predictions is often limited

- Simulation studies
- Point prevalence surveys, other independent data sources

For 2018, GPS coordinates were collected for the village of every diagnosed VL case.

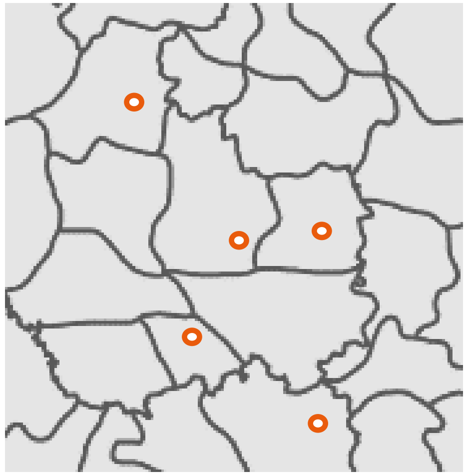
Combined with:

Affected village GPS

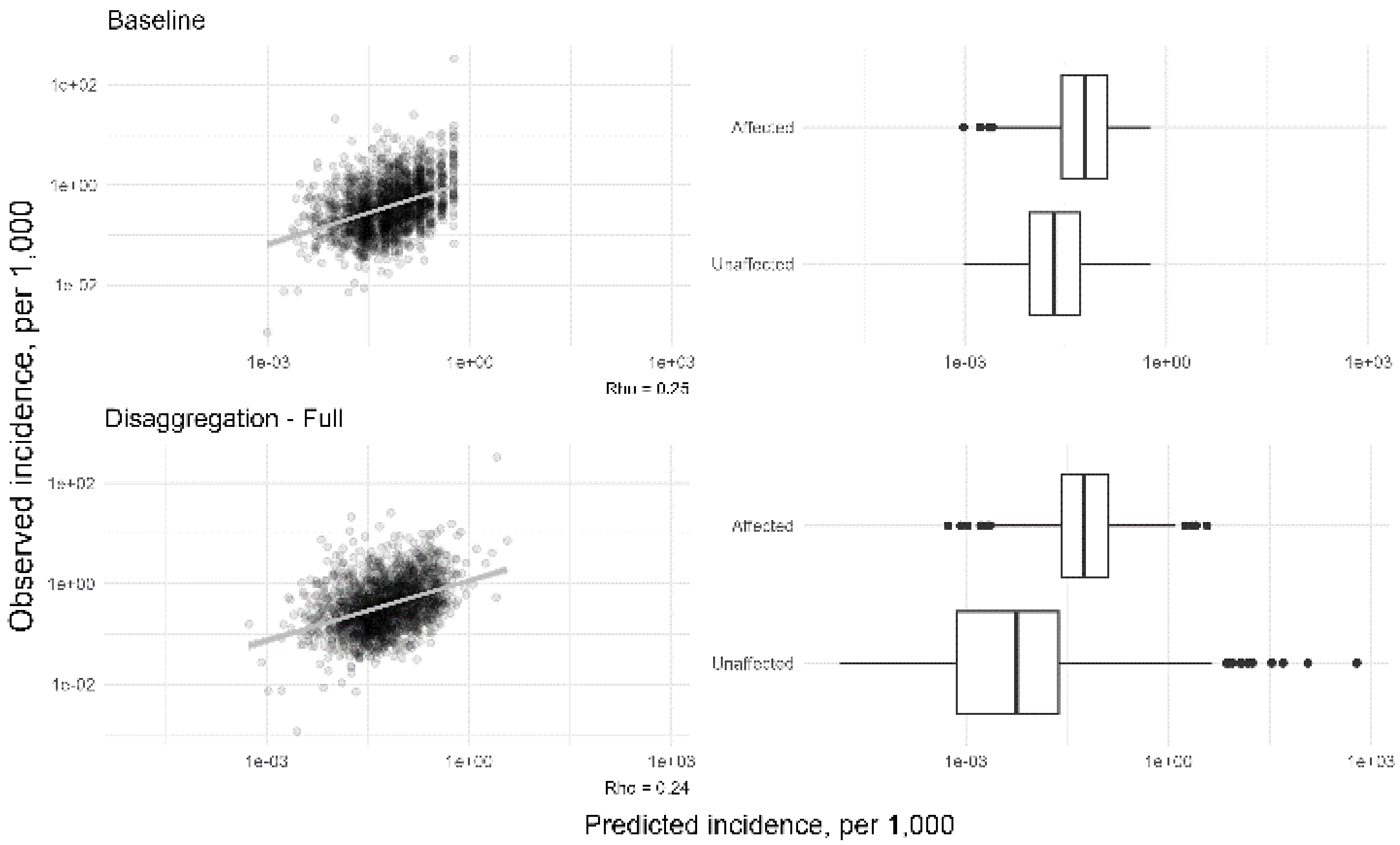
\+ State-wide village shapefiles

\+ Population density raster

⇨ Village level incidence against which to *validate*



Results



[BASELINE]
Uniform incidence across blocks

Disaggregation model

Disaggregation approach doesn't do much better than assuming all villages in a block observe the same incidence rate.

Why are the model predictions so poor?

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Village incidence is not predictable

…from these covariates and assumed correlation structures

- Predictable patterns with environment have deteriorated with sparse incidence
- Population movement rather than local transmission

Validation data are not representative of true village incidence

- Inaccurate village populations / boundaries
- Biased case detection

Spatial targeting of case detection

Prompt detection is a key component of VL control in Bihar

Active case detection (ACD) is *targeted* by village

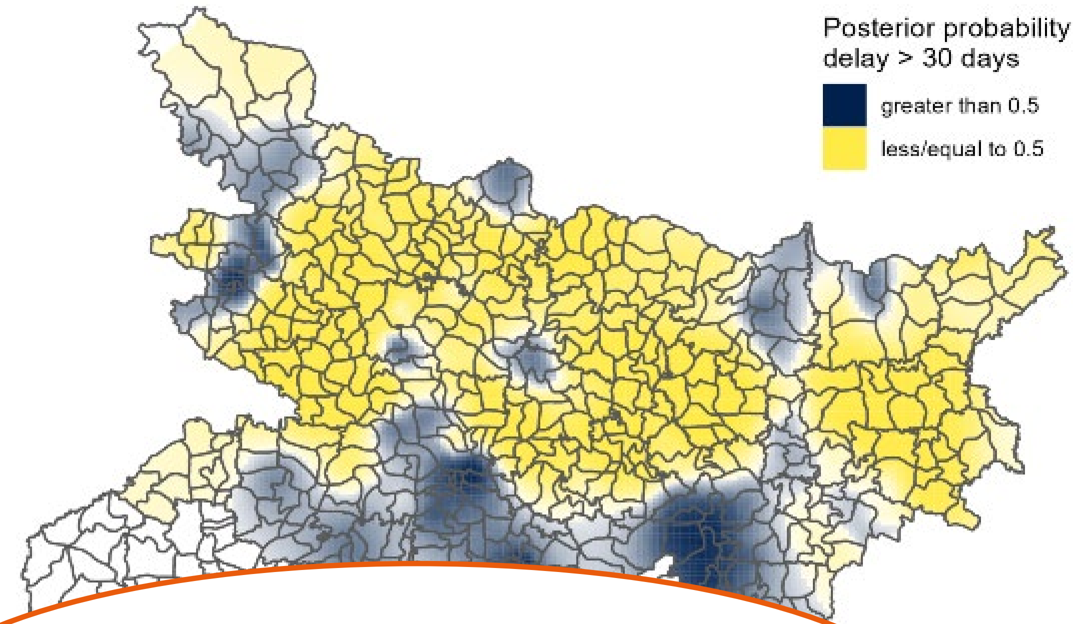
- Detection of one case triggers further investigation
- Logical approach when resources limited and incidence is low and difficult to predict

Inconsistency in case detection over space?
Higher chance of detection in more recently-affected areas?

We can see one aspect of this focal case detection effort in *delays to diagnosis* among detected cases

Spatial variation in promptness of detection

- VL cases diagnosed 2018-19
- Poisson model for days of delay between symptom onset and diagnosis, with residual spatial correlation by village location
- Adjusted for age, HIV, detection route, local endemicity



Evidence of longer delays *outside* the main endemic foci

Could this indicate surveillance in general is weaker in these peripheral areas?

Conclusions

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Is village-level analysis feasible to support elimination?

Surveillance on a coarse administrative level is practical because the area and population is well-defined

- As elimination is approached, this scale becomes less relevant

Disaggregation regression is an appealing tool in such settings

- Desire to scale back investment when incidence low
- Gain detailed inference from more practical high-level surveillance

However, the predictions are challenging to validate

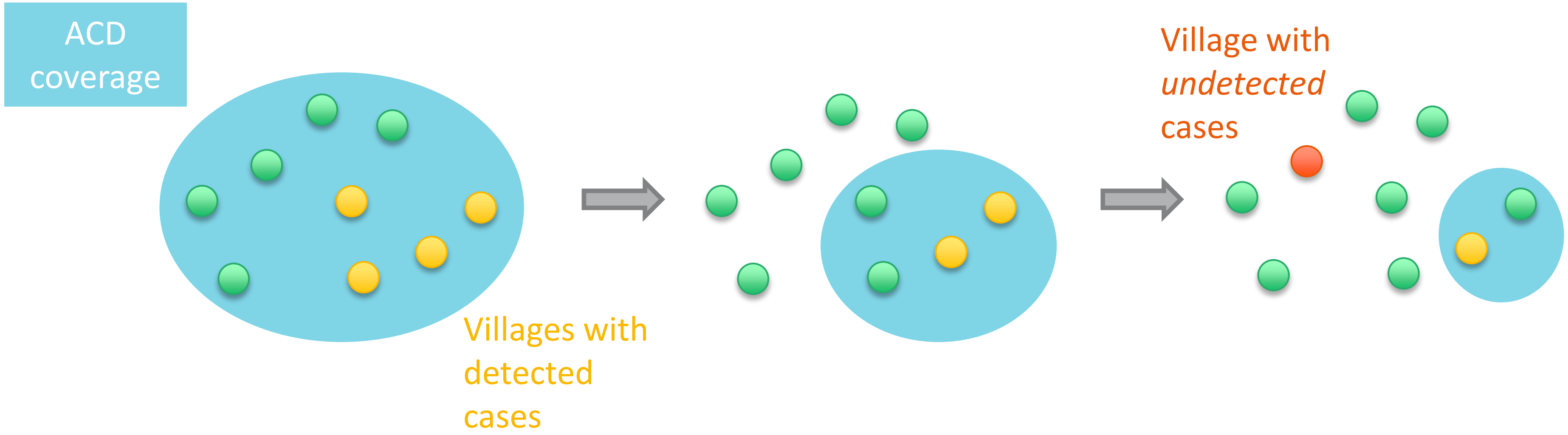
- Uncertainty in representation of true incidence by detected cases

Conclusions

Do we understand the impact of targeted surveillance near- and post- elimination?

A reactive approach to intervention is necessary when resources are finite and incidence cannot be predicted from other sources

However, where the intervention is surveillance itself this creates biases in the data from which we infer the need for intervention



Conclusions

What could be done to improve inference of the spatial distribution of VL near elimination?

- Record data on where and when intensive surveillance activities are implemented
- Monitor number of suspect case referrals between villages/blocks as an indicator of surveillance effort
- Consider “spot-check” surveillance activities in non-endemic areas in addition to reactive ACD
- Maintain community awareness even in areas no longer deemed to be affected

Thanks for listening

- SPEAK India Consortium
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- Prof. Graham Medley, Dr Oliver Brady (LSHTM)
- Dr Tim Lucas (University of Leicester)

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