

SYNTHETIC LIKELIHOOD APPROACH FOR QUANTIFYING MULTI-SCALE EPIDEMIC PROCESSES FROM LARGE AND COMPLEX DATA SETS

APPLICATION TO A VECTOR OF CHAGAS DISEASE

Corentin M. Barbu, Karthik Sethuraman & Michael Z.
Levy

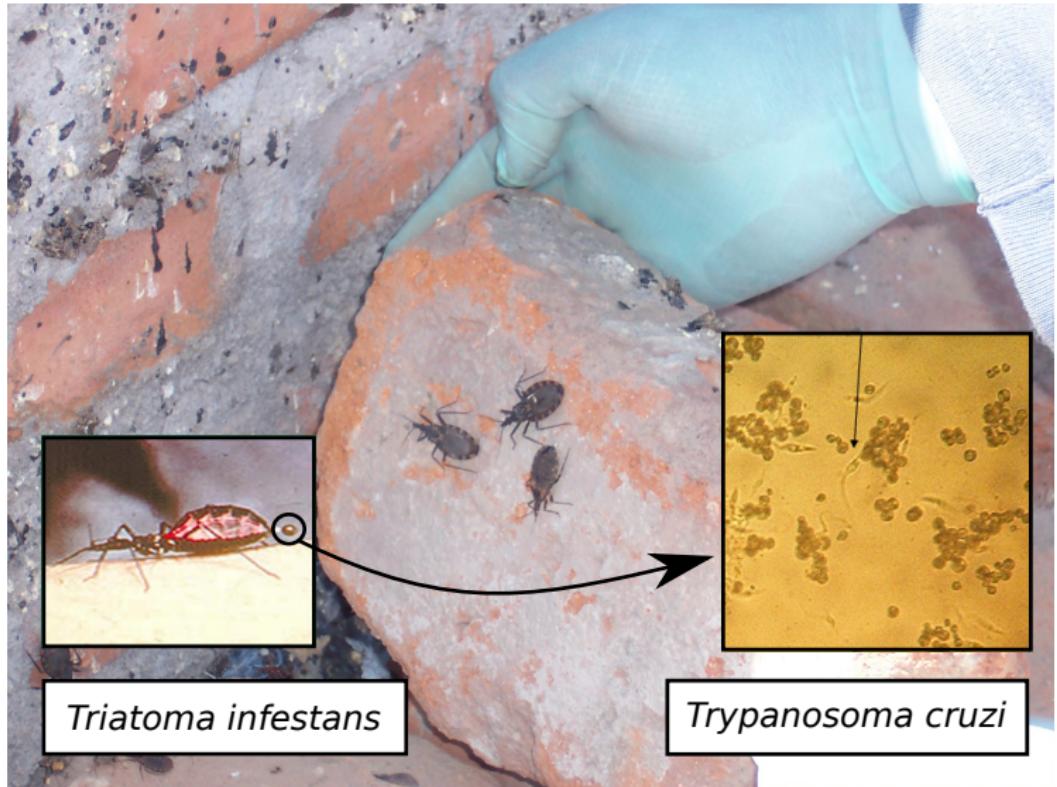
University of Pennsylvania

November 6, 2013

Triatoma Infestans & *Trypanosoma cruzi*

Synthetic
likelihood for
multi-scale
epidemics

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Sethuraman K,
Levy MZ



Why quantifying
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Epidemiological background

The importance of the
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Quantifying the
spatio-temporal
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Separating Temporal and
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A simple stochastic model

The spatial synthetic
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CHAGAS DISEASE CONTROL

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AVAILABLE TREATMENT AND PREVENTION METHODS

- ▶ No vaccine
- ▶ Imperfect treatment
- ▶ Vector control

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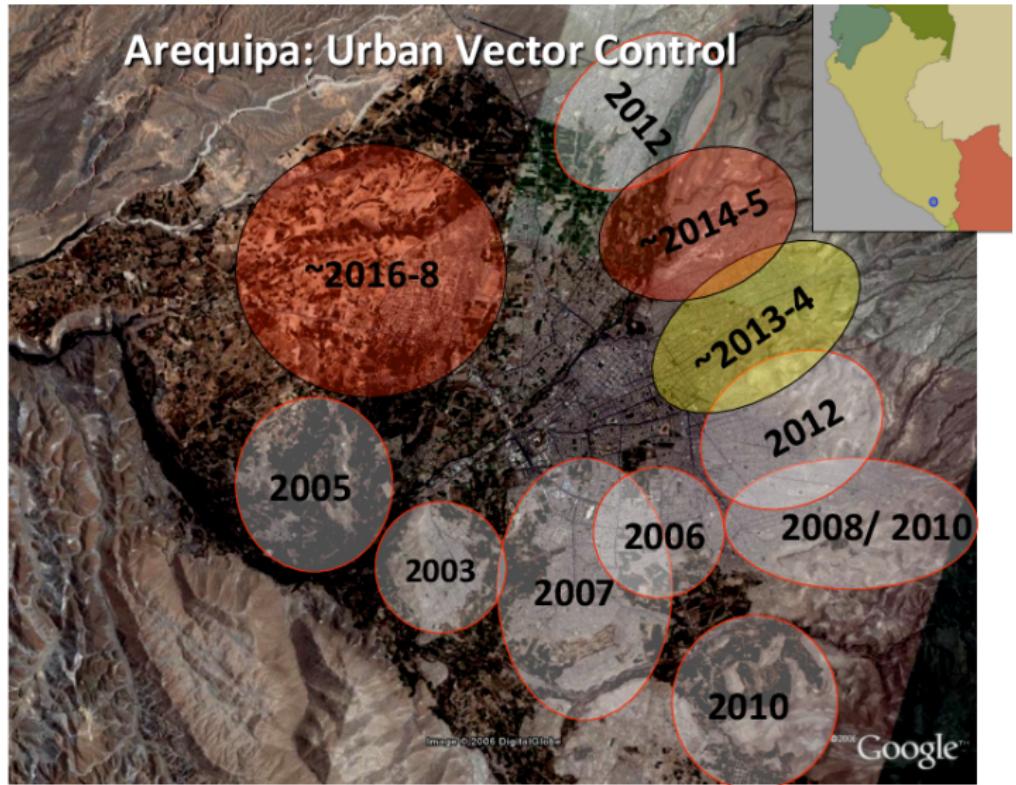
TYPICAL VECTOR CONTROL SEQUENCE

- ▶ Initial treatment (blanket indoor spraying)
- ▶ Surveillance
 - ▶ Community reports → inspections
 - ▶ Infestation → retreatment

THE CONTROL CAMPAIGN IN AREQUIPA

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HALF-WAY EVALUATION

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ATTACK PHASE EVALUATION

- ▶ 10 years to treat half the city
- ▶ 60-85% participation in initial treatment
- ▶ very efficient treatment (>99% households cleared)

SURVEILLANCE



- ▶ redispersal from some non-treated households
- ▶ infected insects

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CAN A REACTIVE SURVEILLANCE BE ENOUGH?

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FOCI R_0 THINKING

As we detect/treat easily neighbors of reporting households:

- ▶ Local dispersal is already dealt with
- ▶ Medium range dispersal may be handled
- ▶ Large scale dispersal is catastrophic

Can we on average control a foci before it generates infestation too far to be handled?

- ▶ Quantification of the dispersal at these three scales

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LEVERAGING COMPLEX DATA

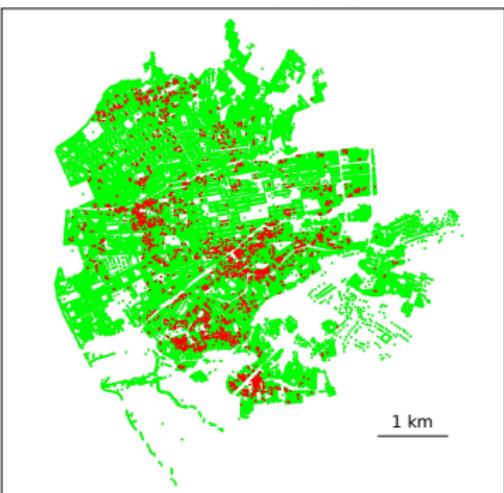
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DECOUPLING SPATIAL AND TEMPORAL SCALE

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- ▶ cross-sectional → spatial patterns different scales

Paucarpata & Mariano Melgar
At blanket spraying



- ▶ longitudinal (400 households) → time

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LEVERAGING COMPLEX DATA

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DECOUPLING SPATIAL AND TEMPORAL SCALE

- ▶ cross-sectional → spatial patterns different scales
- ▶ longitudinal (400 households) → time

Jerusalen
January 2009

Jerusalen
March 2011



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COMBINE AND CONQUER

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Cross-sectional study

- ▶ Unknown time
 - Impossible to fit the rate of movement
- ▶ Large scale
 - Relative rates at different scales

Longitudinal study

- ▶ Known time
 - Fit of the rate of movement
- ▶ Small scale
 - Vague fit of large scale movement

BAYESIAN COMBINATION:

The posterior from cross-sectional study becomes the prior for the longitudinal study.

⇒ The cross-sectional study gives the relative abundance of the dispersal at different spatial scales, the longitudinal a study gives the time-scale.

THE HOP/SKIP/JUMP MODEL

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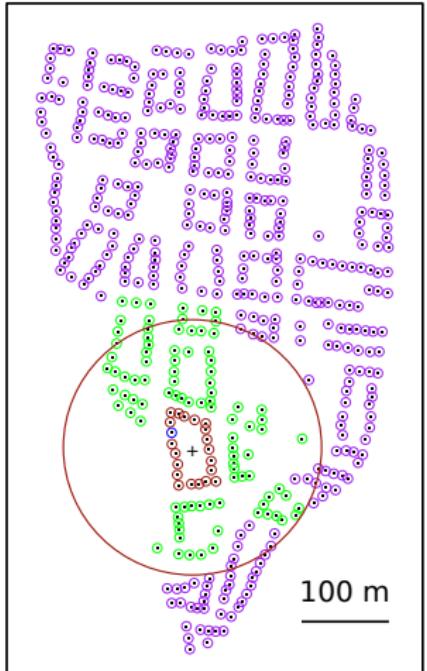
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THE HOP/SKIP/JUMP MODEL OF DISPERSAL

- ▶ hop: within a city-block
- ▶ skip: in neighboring city-blocks
- ▶ Jumps: anywhere

THE SYNTHETIC LIKELIHOOD

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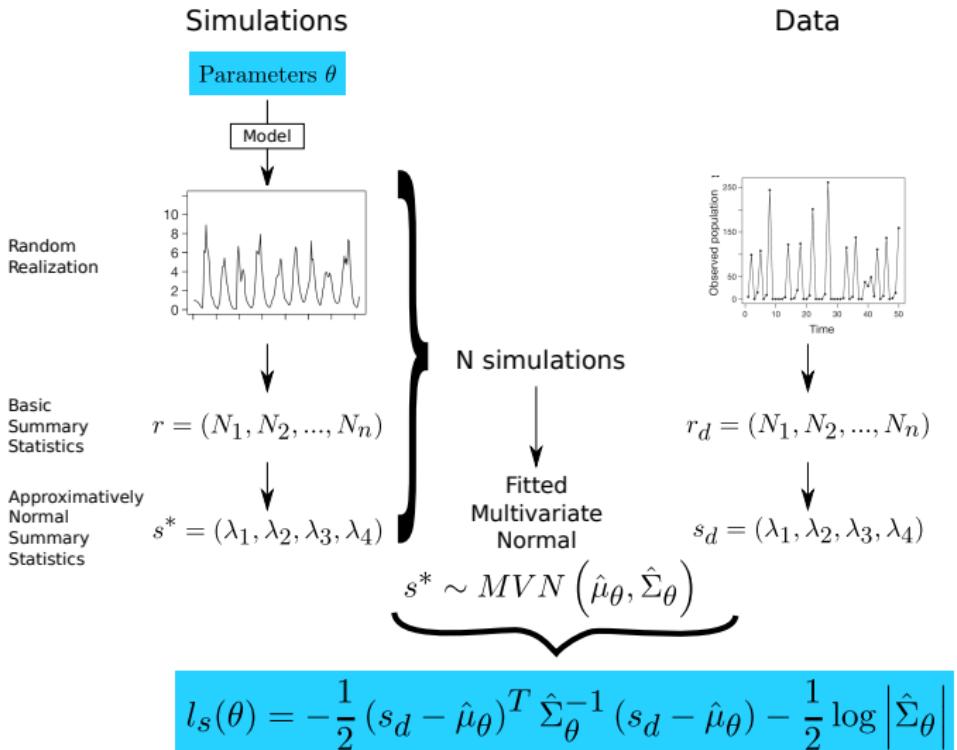
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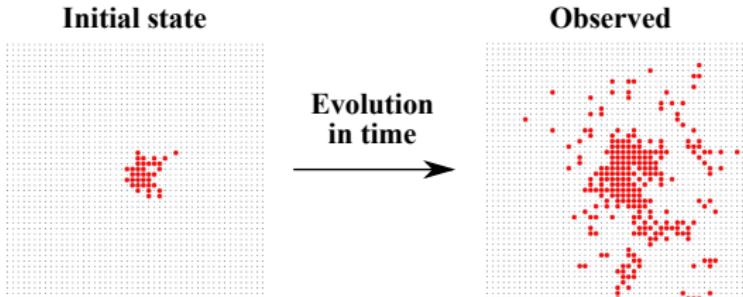


THE SYNTHETIC LIKELIHOOD

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$$Syn.Lik.(\theta) = P(\text{Observed Sum. Stats} | \text{Sum. Stats}(\theta))$$

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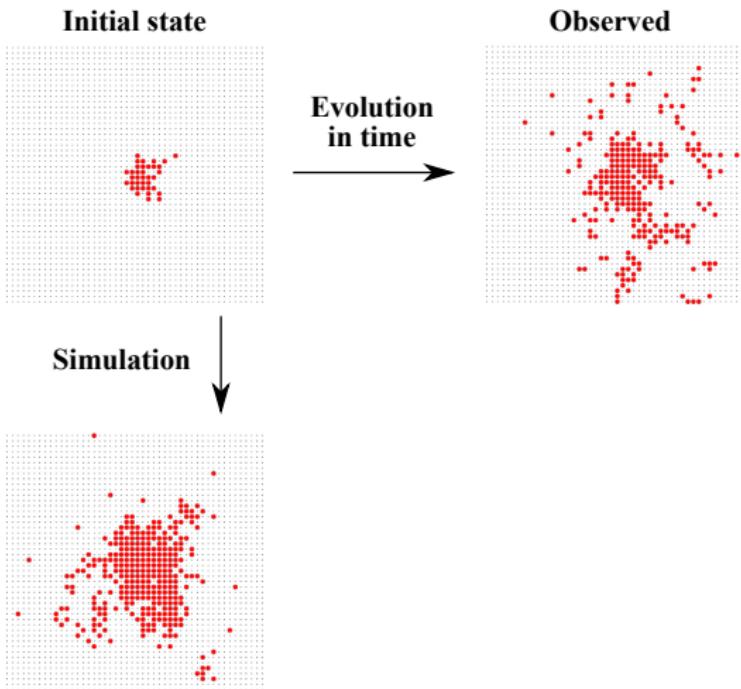
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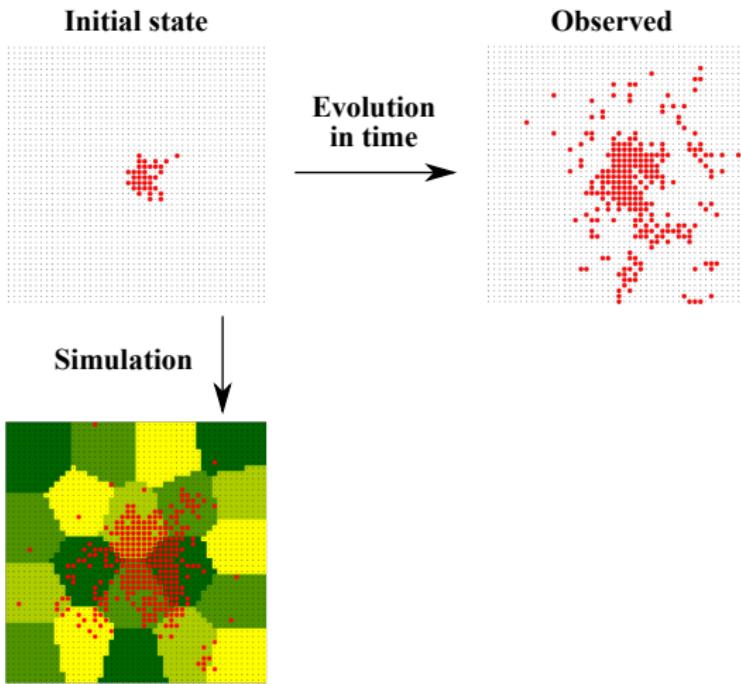
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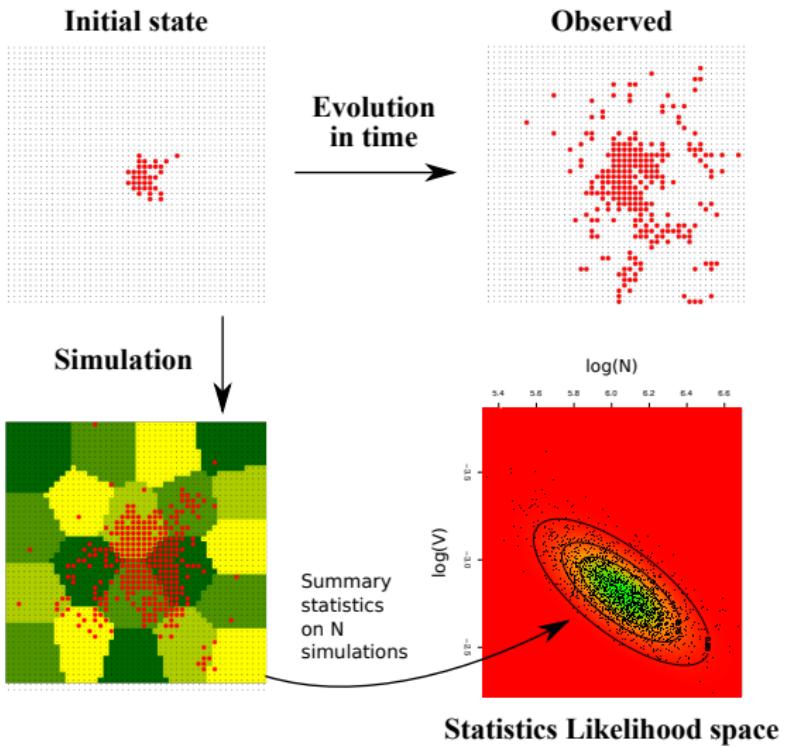
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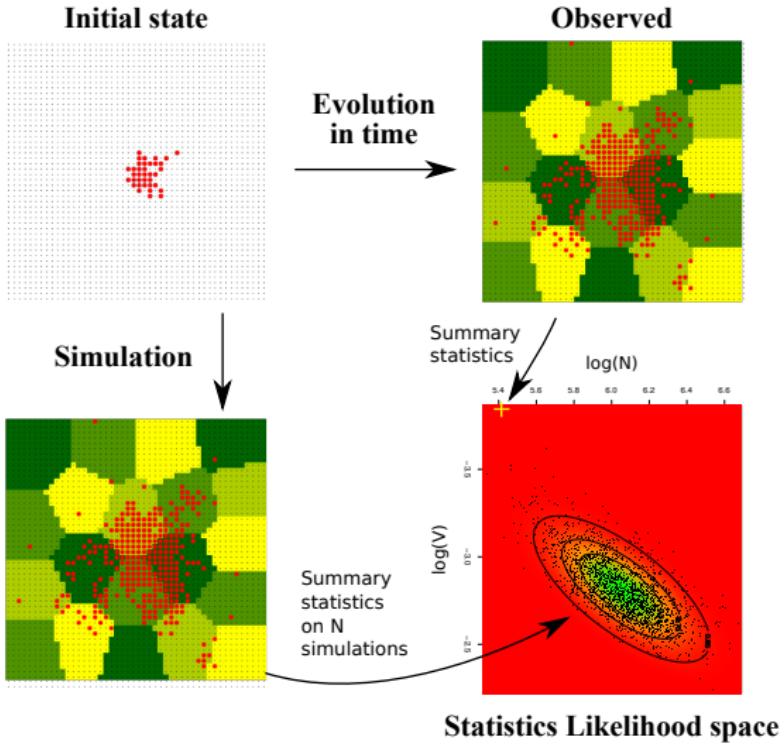
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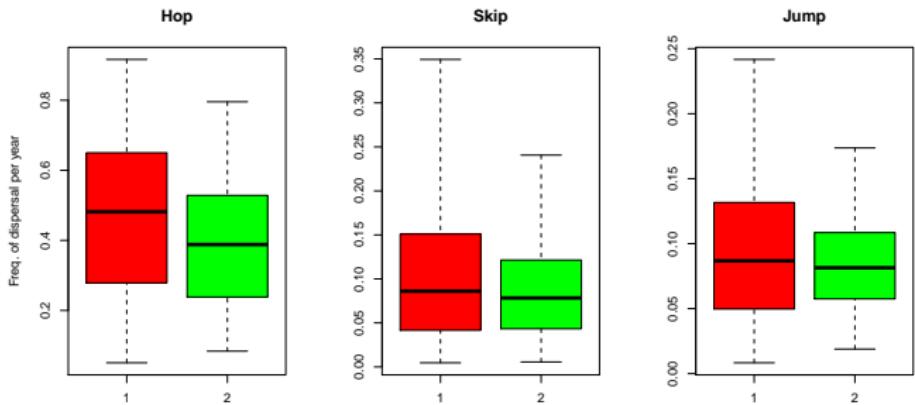
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DISPERSAL FREQUENCY

IMPACT OF THE COMBINED ANALYSIS



MODES OF DISPERSAL

- ▶ hop ~ walk (68% [39-86])
 - ▶ skip ~ flight (16% [0.8-45])
 - ▶ jump ~ passive (15% [3-32])
- ⇒ Mainly active dispersal but significant passive dispersal

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RE-INFESTATION RISK FROM ONE HOUSEHOLD

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AVERAGE TIME TO NEW INFESTATION

Total: 1.8 years [1.0-4.3]

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RE-INFESTATION FROM A SINGLE HOUSEHOLD

Time (years)	Same City Block	Diff. City Block	Neigh. City Blocks	Further away	Total
0.5	0.24	0.11	0.05	0.06	0.35
1.0	0.56	0.29	0.13	0.16	0.85
1.5	0.91	0.56	0.24	0.32	1.48
2.0	1.47	0.99	0.40	0.59	2.46
2.5	1.87	1.48	0.58	0.90	3.35
3.0	2.63	2.50	0.94	1.57	5.14

Average number of households infested, starting from a single household randomly chosen among the households in the cross-sectional study and using 1000 different parameter sets drawn from the posterior of the joint analysis.

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PUBLIC HEALTH IMPACT

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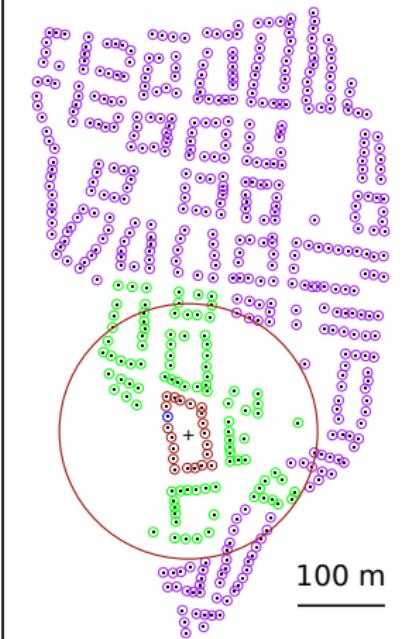
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IMPLICATIONS FOR THE SURVEILLANCE CAMPAIGN

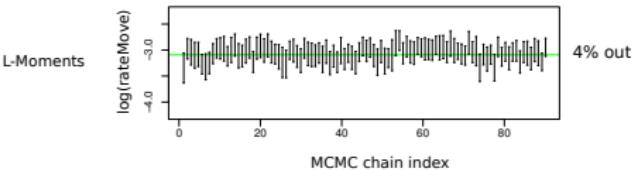
1. Same city-block inspection and treatment can stop epidemics.
2. Inspection of neighboring city-blocks is not efficient.
3. Infestation → treatment time must stay under 2 years.

VALIDATION OF THE ESTIMATES

Synthetic likelihood for multi-scale epidemics

INTERNAL VALIDATIONS

- ▶ Synthetic likelihood approximation: coverage analysis



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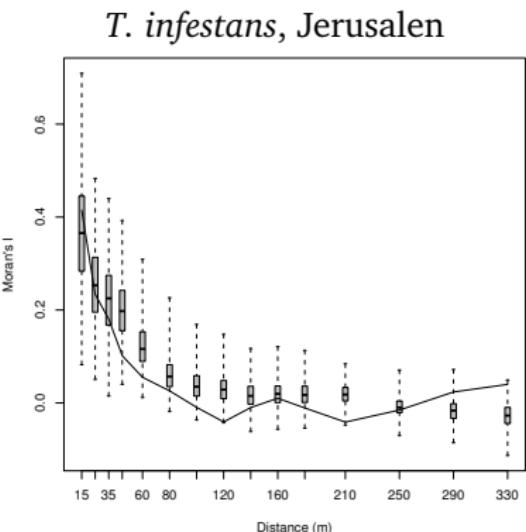
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- ▶ Adequacy of the model: autocorrelation generated by the model



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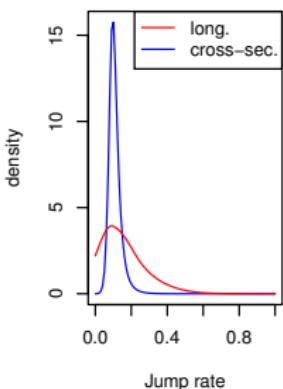
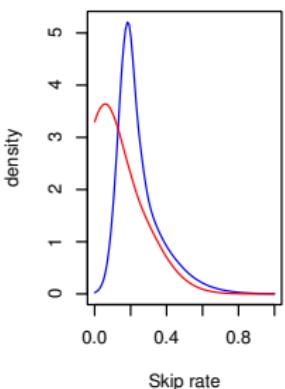
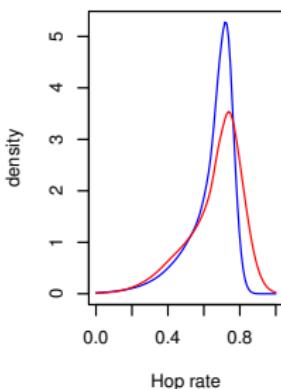
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- ▶ Consistency of the data: similar posteriors for the rates in independent analysis.



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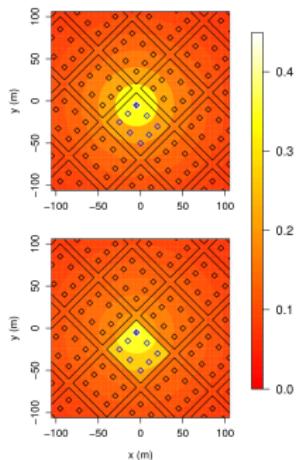
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CONNECTION WITH OTHER APPROACHES

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EPIDEMIOLOGICAL DATA

- ▶ Average number of household found infested in close neighbors of infested, non-treated households, 6 months to 2 years after treatment: 0.27 [0.1-0.6].
- ▶ Autocorrelation analysis ^a

^a Barbu, C. et al. The Effects of City Streets on an Urban Disease Vector PLOS Computational Biology, Public Library of Science, 2013, 9, e1002801

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MICRO-SATELLITE ANALYSIS

- ▶ Micro-satellite analysis (Foley, in prep)



- ▶ Existence of migration at the scale of dozens of kilometers (Foley 2013).

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STRENGTHS AND LIMITATIONS

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EXISTING STRENGTHS

- ▶ Can handle arbitrary complex dispersal models
- ▶ Can combine cross-sectional and longitudinal datasets
- ▶ Can integrate large datasets by “small scale merging”

CURRENTLY WORKING ON

- ▶ Improving joint posteriors passing
- ▶ Improving usability (R package)
- ▶ Adding distance kernel handling

FUTURE DIRECTIONS

- ▶ Accounting for heterogeneity (households, observation)
- ▶ Using information from surveillance phase
- ▶ Integrating genetic information

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FIELD TEAM IN AREQUIPA



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