

Identifying spatiotemporal dynamics of Ebola in Sierra Leone using virus genomes

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INTELLECTUAL VENTURES[®]

Modeling human mobility using physics analogies

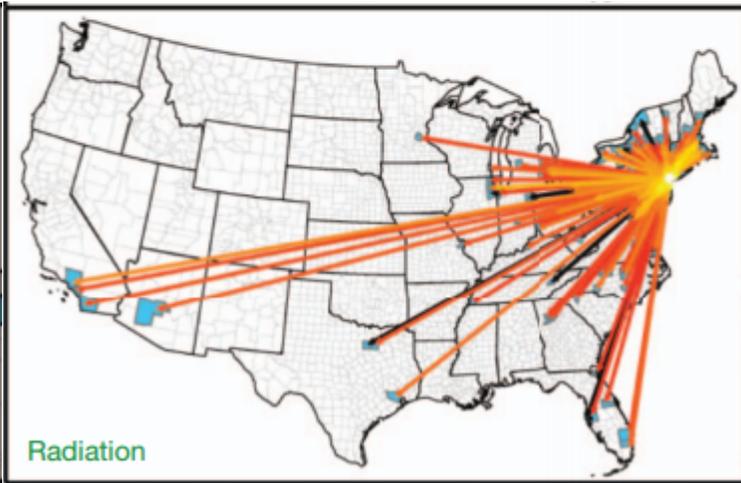


Gravity

Gravity

Ravenstein, E.G.,
J Roy Stat Soc, (1889)

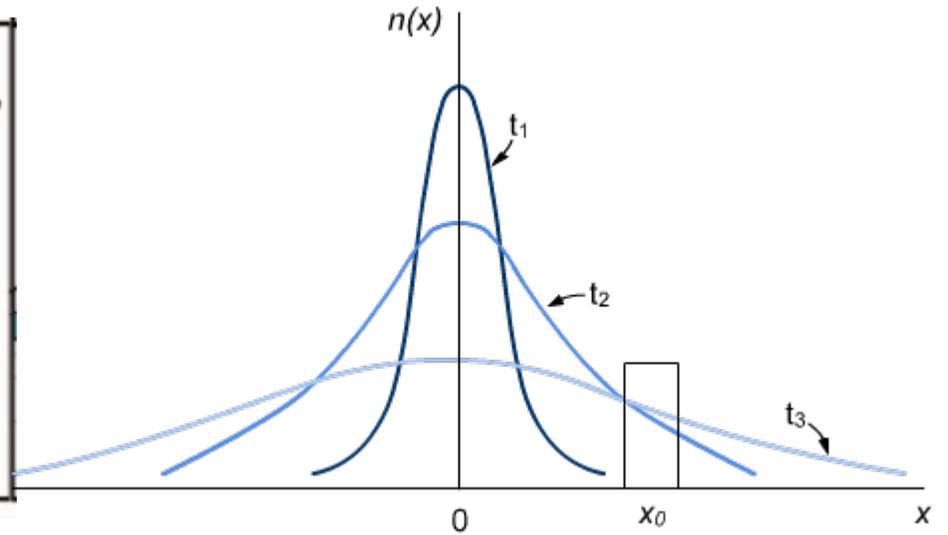
Truscott and Ferguson,
PLoS Comp Bio (2012)



Radiation

Radiation

Simini *et al.* Nature (2012)

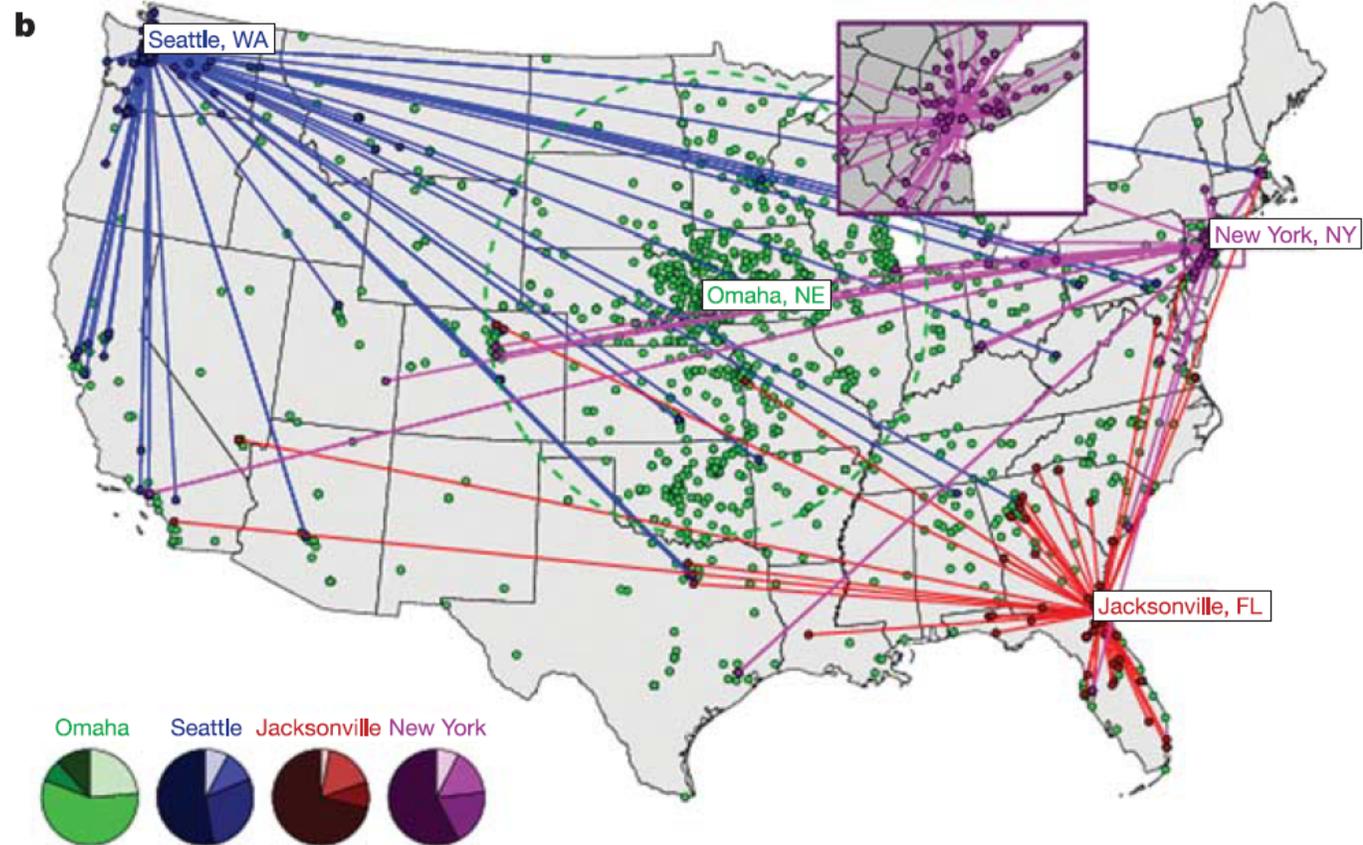
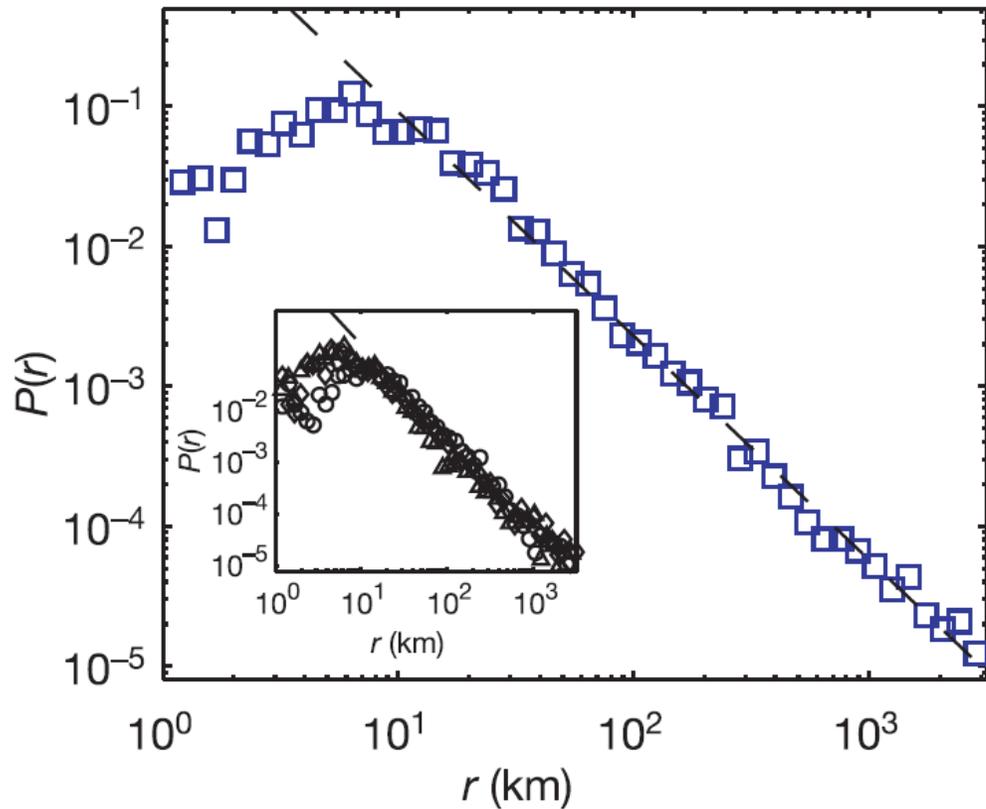


Random walks

Rhee *et al.* IEEE Trans. Networking (2012)

Tracer of human mobility: US banknote random walks

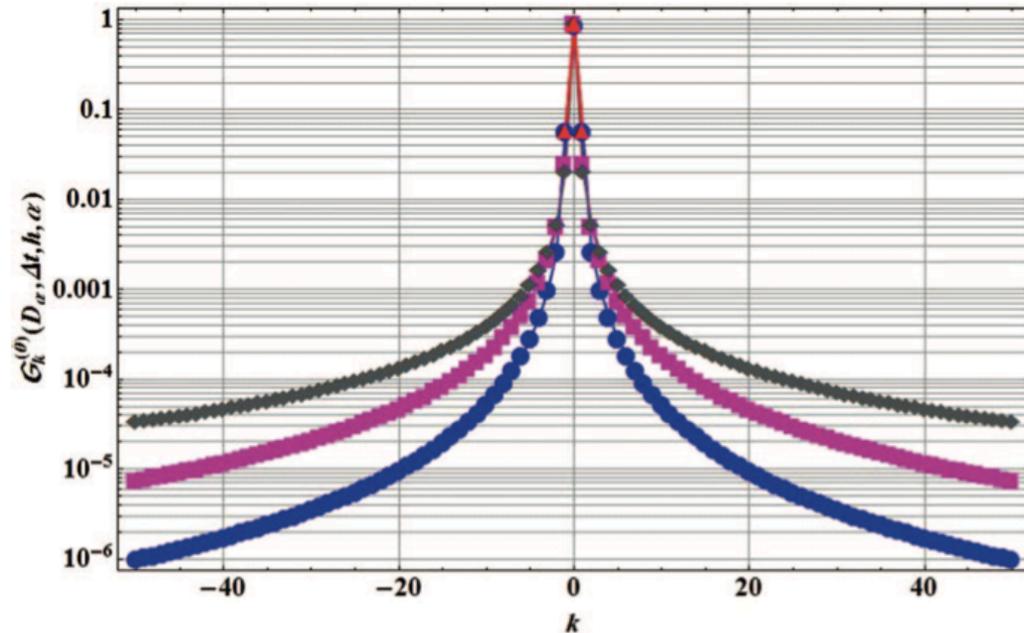
Empirical power law statistics:
Lévy flight: heavy-tailed random walk



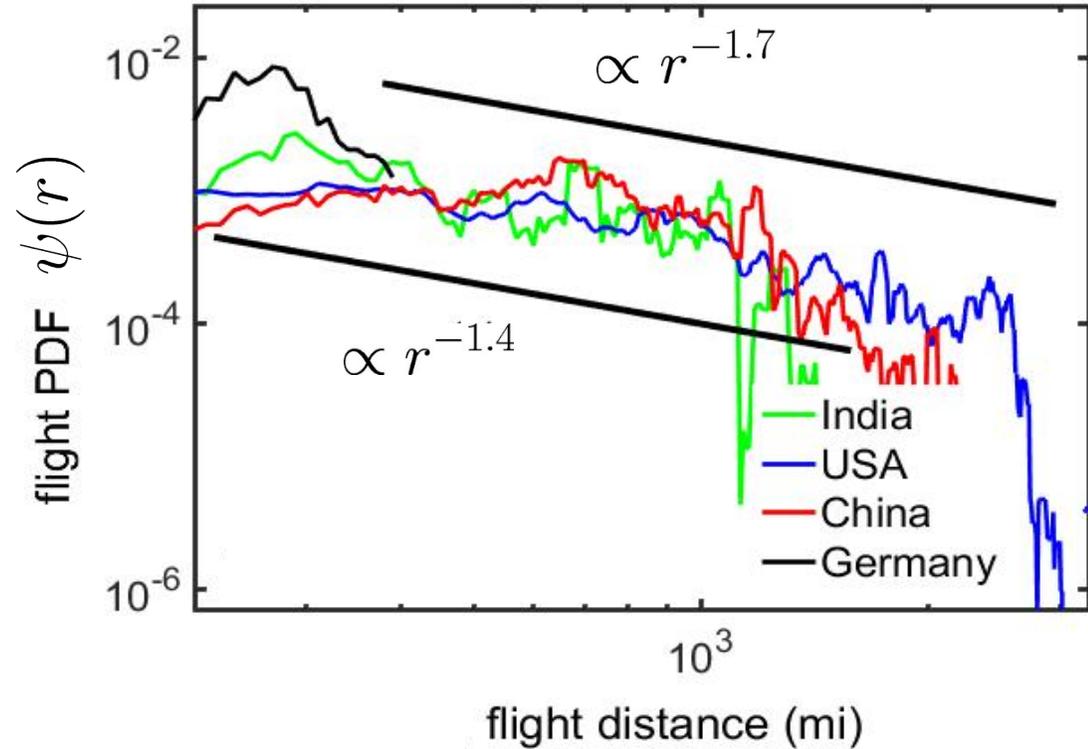
Brockmann, Hufnagel and Geisel, Nature 2006

Lévy flight is a generalization of diffusion

$$\frac{\partial \mathcal{G}}{\partial t} = D_\alpha \frac{\partial^\alpha \mathcal{G}}{\partial |x|^\alpha}$$



Bayati, J Chem. Phys. 2013



Gustafson, Bayati, Eckhoff

Frontiers in Ecology and Evolution, April 2017

We used space-fractional diffusion as a proxy for commercial air traffic to model outbreak dynamics

Tracking Ebola virus in Sierra Leone (2014-2015)

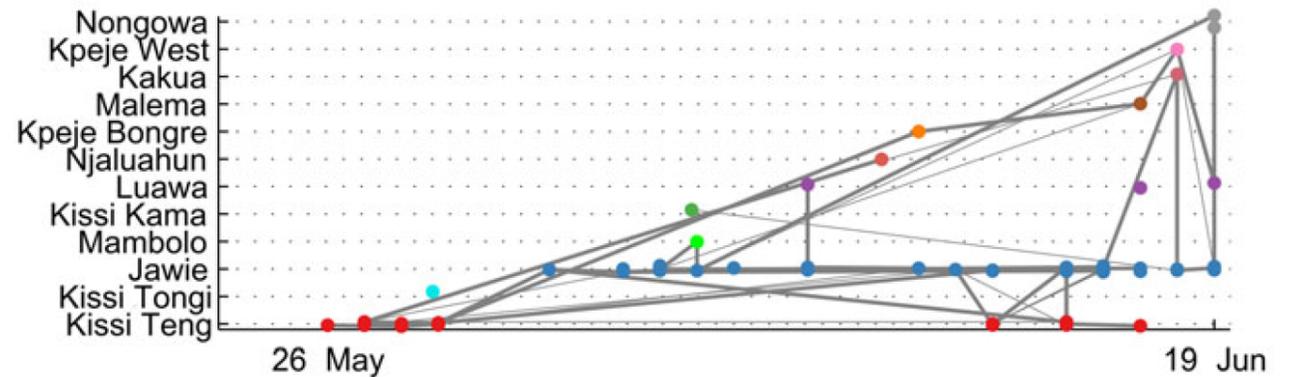
Infections as a tracer of human mobility

Stochastic process

Human behavior is dynamic

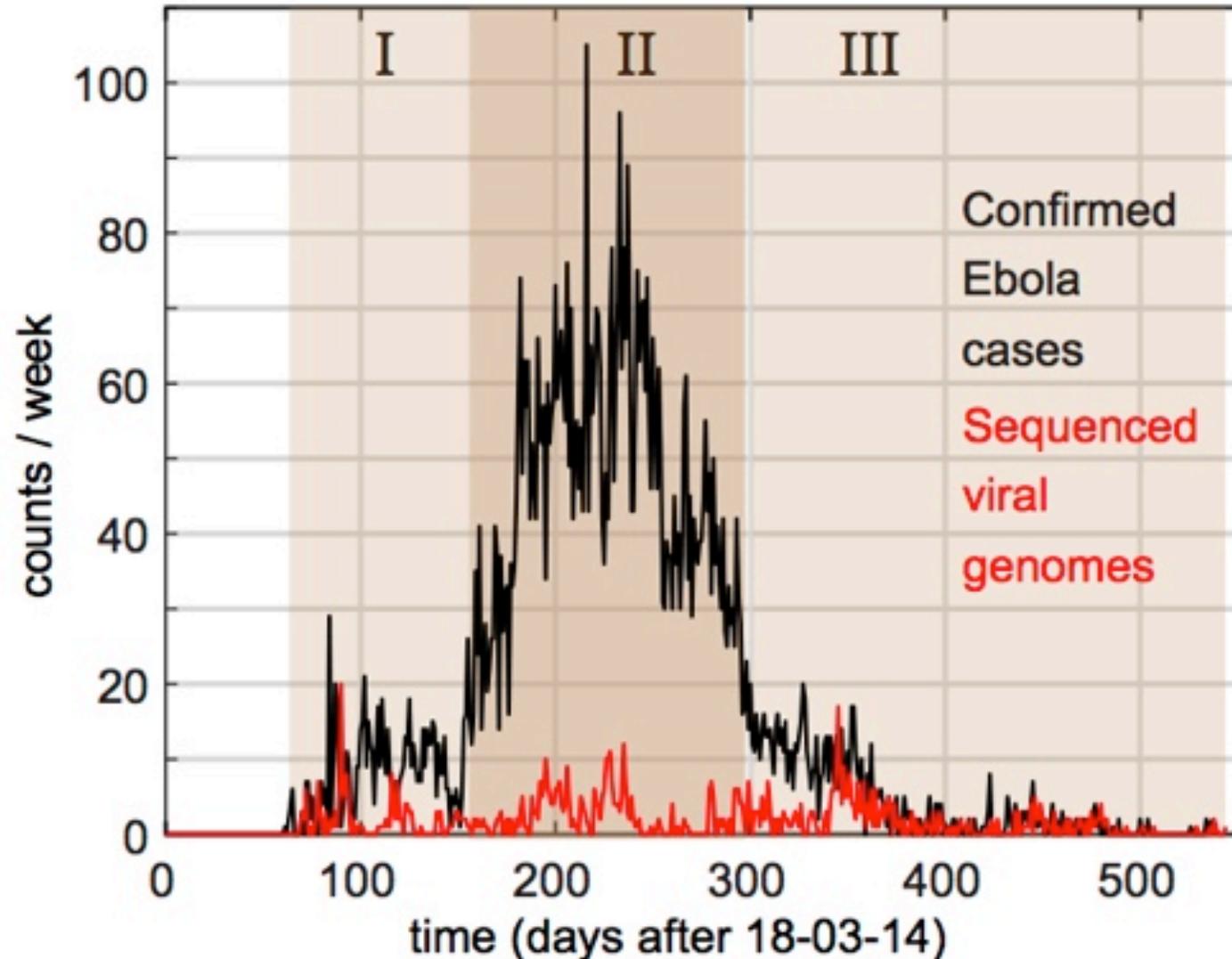
Population landscape is inhomogeneous

Need: a tool to decide which spatial model explains the epidemic dynamics



Famulare and Hu, Int. Health (2015)

A: Sequenced viral genomes track the outbreak



Focus on Sierra Leone

Sequenced cases tracked the course of all cases

Peak of cases in Freetown in December 2014

“Surge” of interventions reduced transmission in Freetown

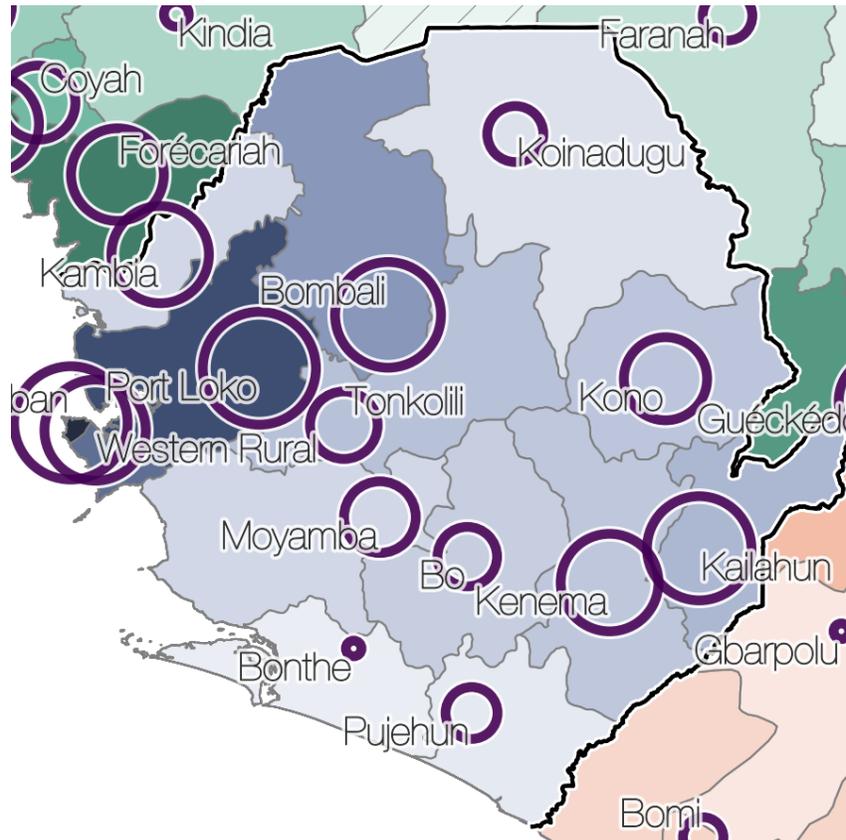
Dudas *et al.* Nature 2017

Fang *et al.* PNAS 2016

Using open data

FASTA file with >1000 district-localized genomes from Sierra Leone

Dudas *et al.* bioRxiv 2016



Sierra Leone data

Arias *et al.* Virus Evolution (2016)

554 sequences

Tong *et al.* Nature (2015)

175 sequences

Park *et al.* Cell (2015)

232 sequences

Gire *et al.* Science (2014)

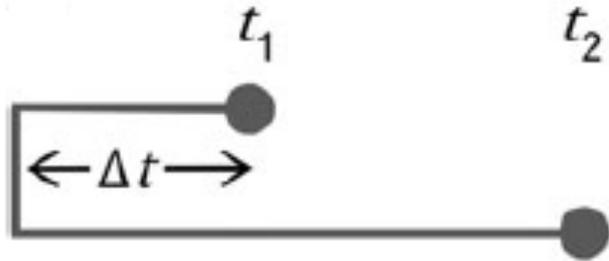
78 sequences

Smits *et al.* Euro Surveillance (2015)

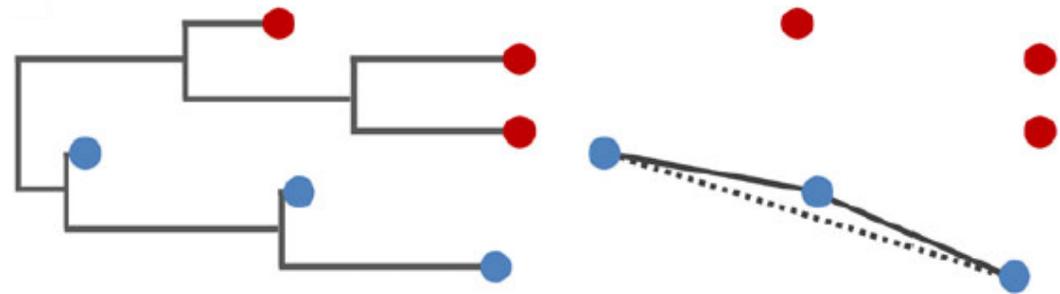
49 sequences

Partially observed transmission network (POTN): fast and adaptable

Famulare and Hu, Int. Health (2015)



Tree that only retains likely direct descendants
Good for finding transmission chains



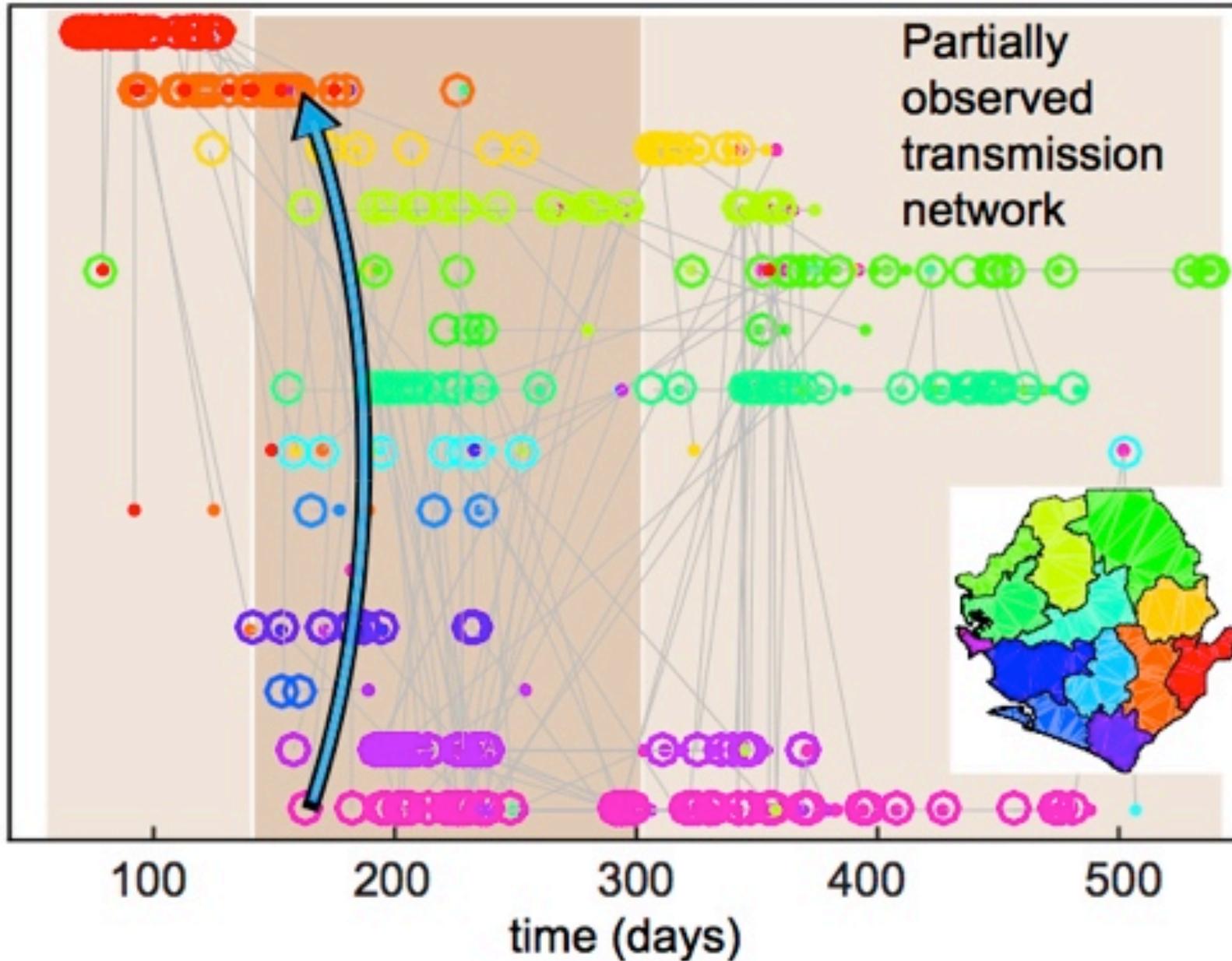
Likelihood ratio

$$H_{12} = \frac{L(\Delta t = 0 | t_1, t_2, d_{12}, \mu)}{L(\Delta t = \hat{\Delta t} | t_1, t_2, d_{12}, \mu)}$$

Poisson mutation model

$$L(\Delta t | t_1, t_2, d_{12}, \mu) = \frac{(\mu(t_2 - t_1 + 2\Delta t))^{d_{12}}}{\Gamma(d_{12} + 1)} \exp(-\mu(t_2 - t_1 + 2\Delta t))$$

B: Genetic linkages infer spatial connectivity



POTN:

$$\mu = 2 \times 10^{-3} \text{ bp/site/year}$$

Gire *et al.* Science 2016

Open circle: origin

Closed dot: destination

No inferred ancestors,
only likely descendants

Pruned to shortest linkages
for plot

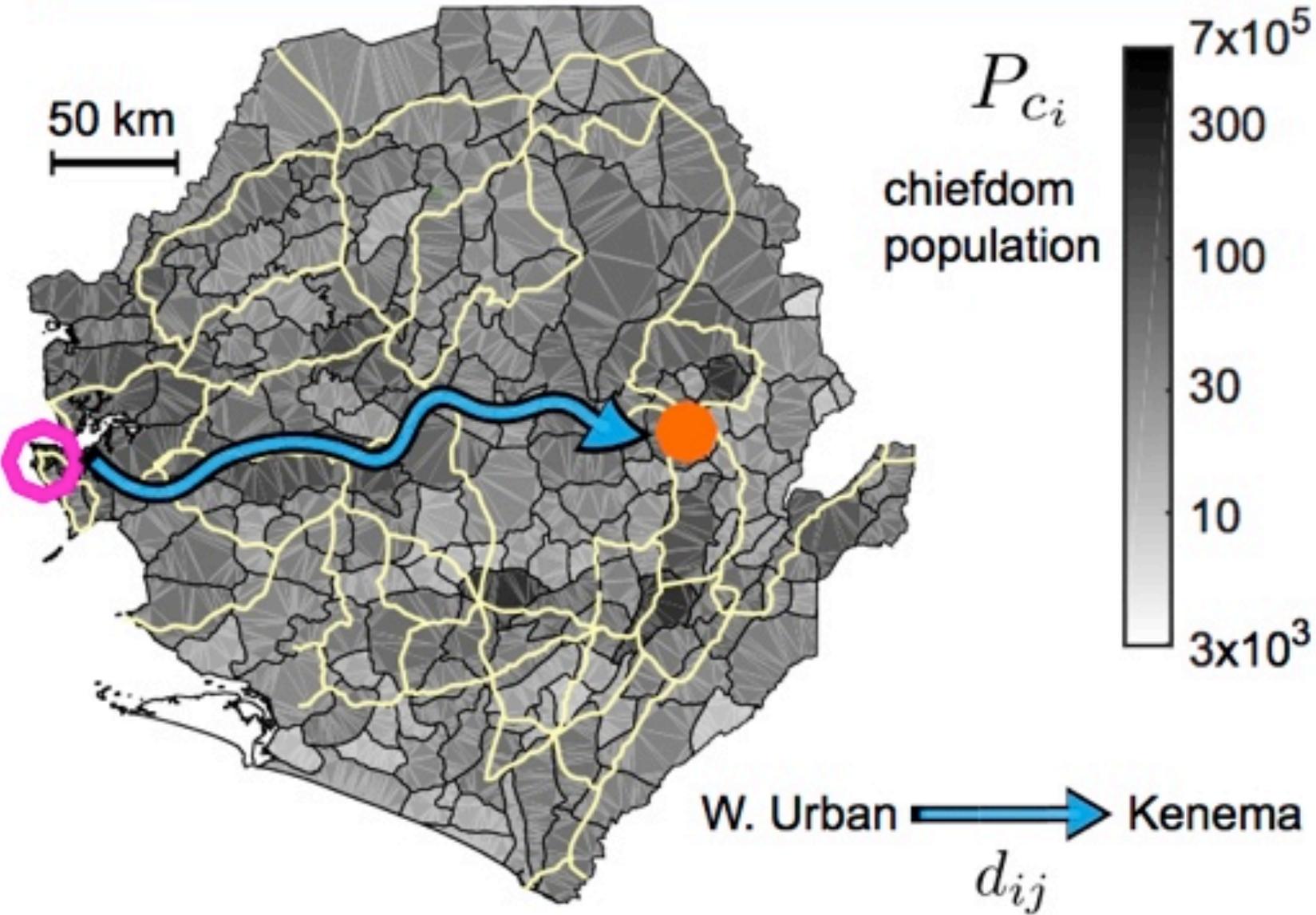
Our innovations

Lévy flight fitting for POTN transmission distances

Dynamic spatial model selection using genetic linkages

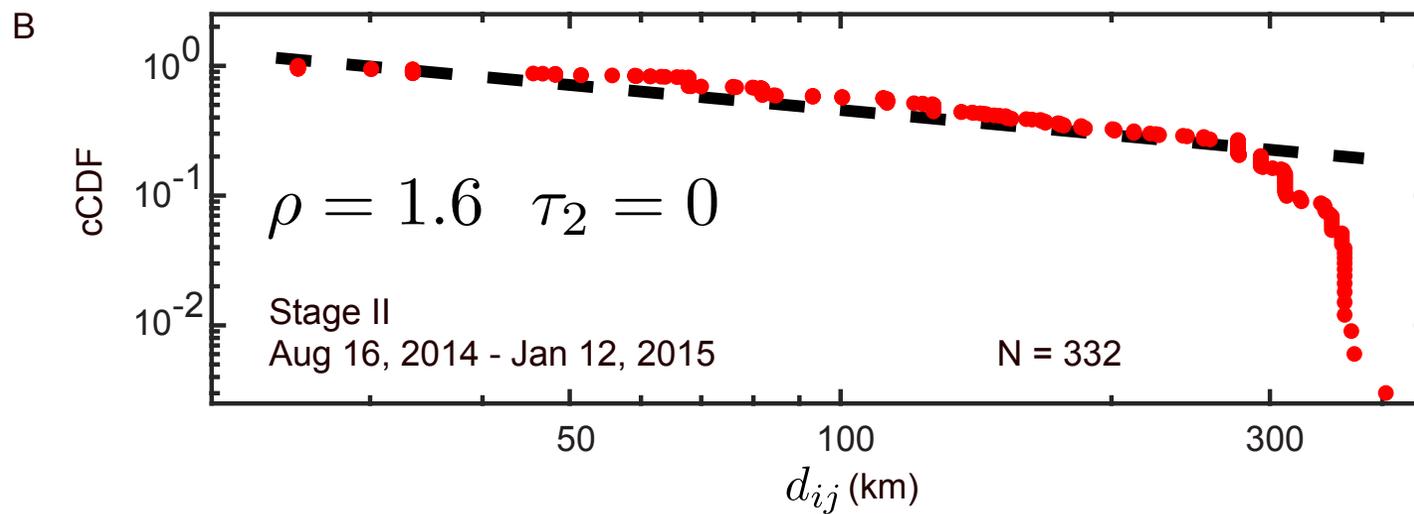
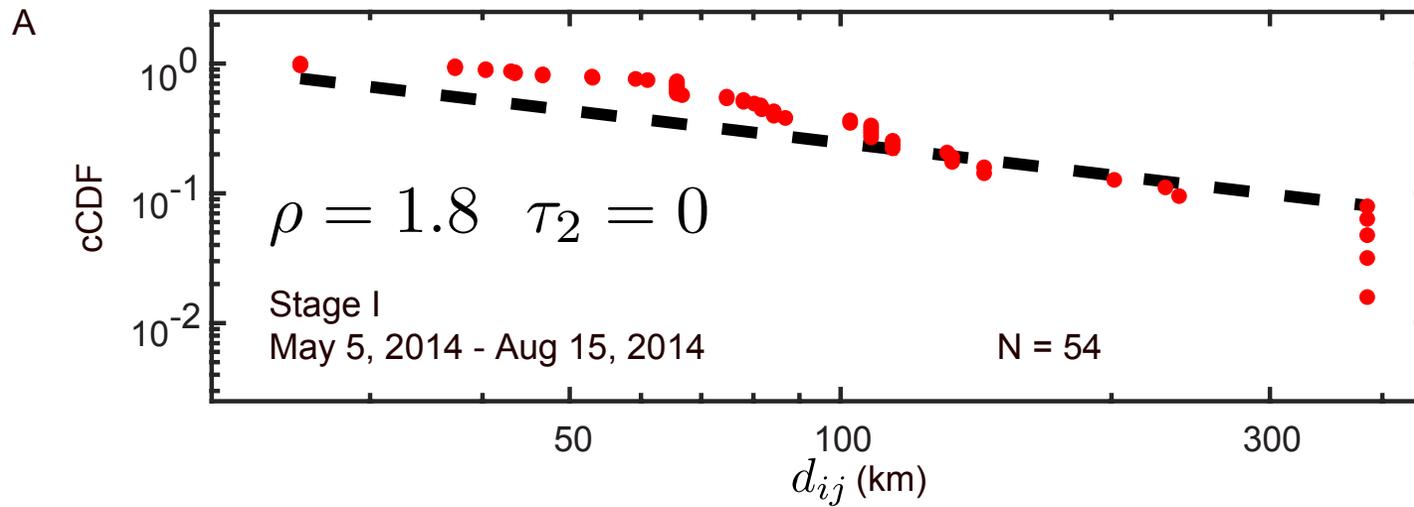
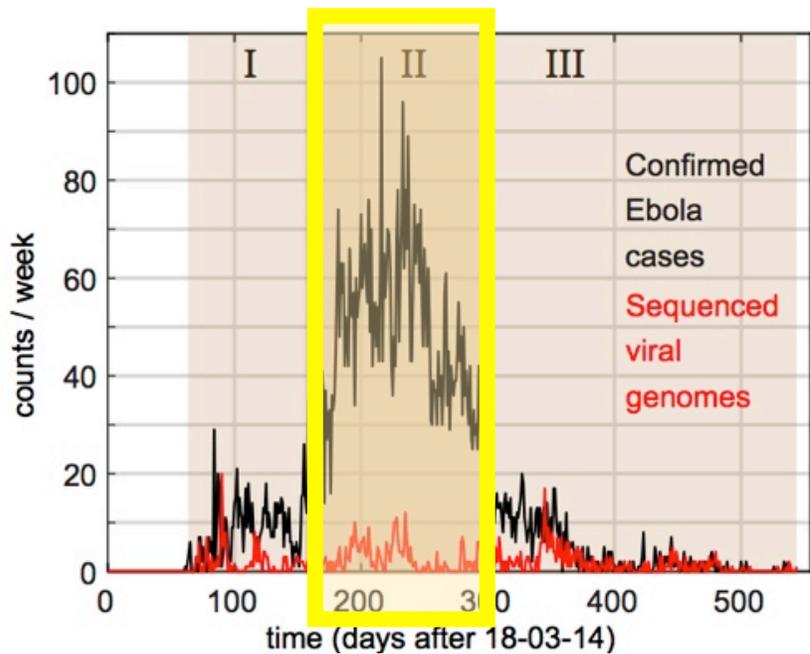
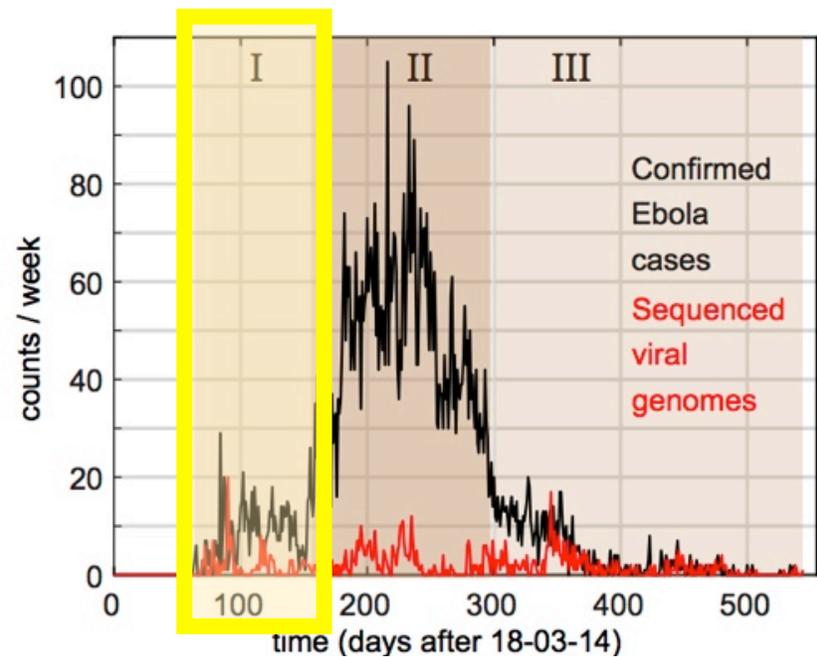
A decision tool for adaptable spatial pattern prediction

C: Population and mobility influence transmission



Driving distances from Google Maps API

Populations from 2010 census



Clauset, Shalizi, and Newman
SIAM Rev., 2009

E: Disease mobility models are calibrated to data

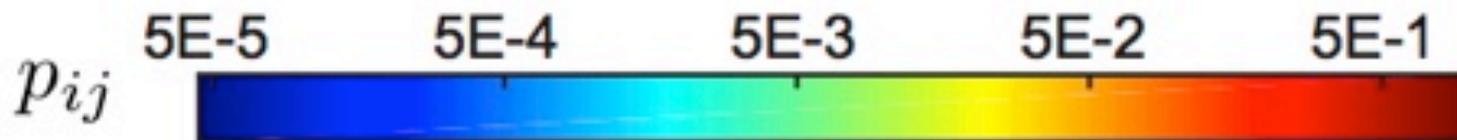
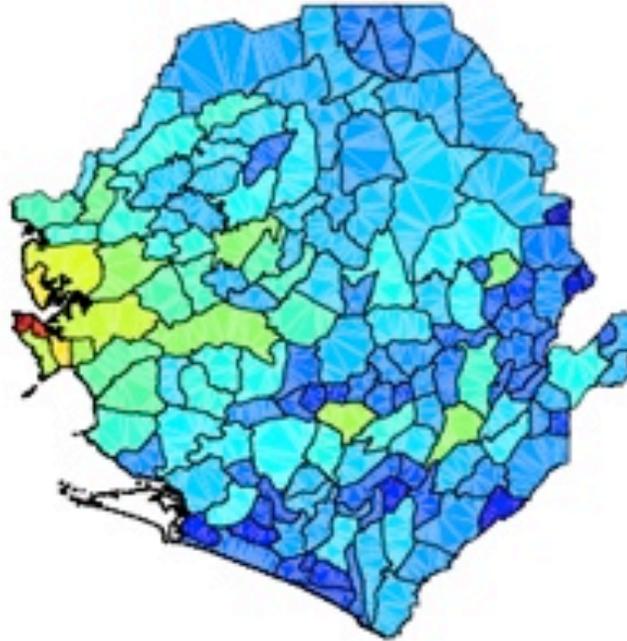
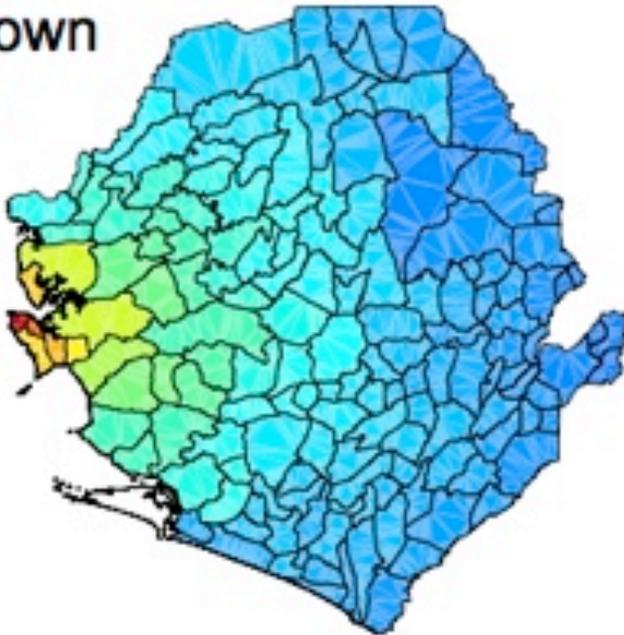
Power law

$$p_{ij}^L = C_i^L \frac{1}{d_{ij}^\rho}$$

Gravity

$$p_{ij}^G = C_i^G \frac{P_{c_i}^{\tau_1} P_{c_j}^{\tau_2}}{d_{ij}^\rho}$$

Freetown
origin



Let the gravity model become a population-weighted random walk

Normalized origin by origin

50% chance of staying in origin chiefdom

Gravity model concentrates probability in population centers

Likelihood ratio for model selection

Power law

$$p_{ij}^L = C_i^L \frac{1}{d_{ij}^\rho}$$

Gravity

$$p_{ij}^G = C_i^G \frac{P_{c_i}^{\tau_1} P_{c_j}^{\tau_2}}{d_{ij}^\rho}$$

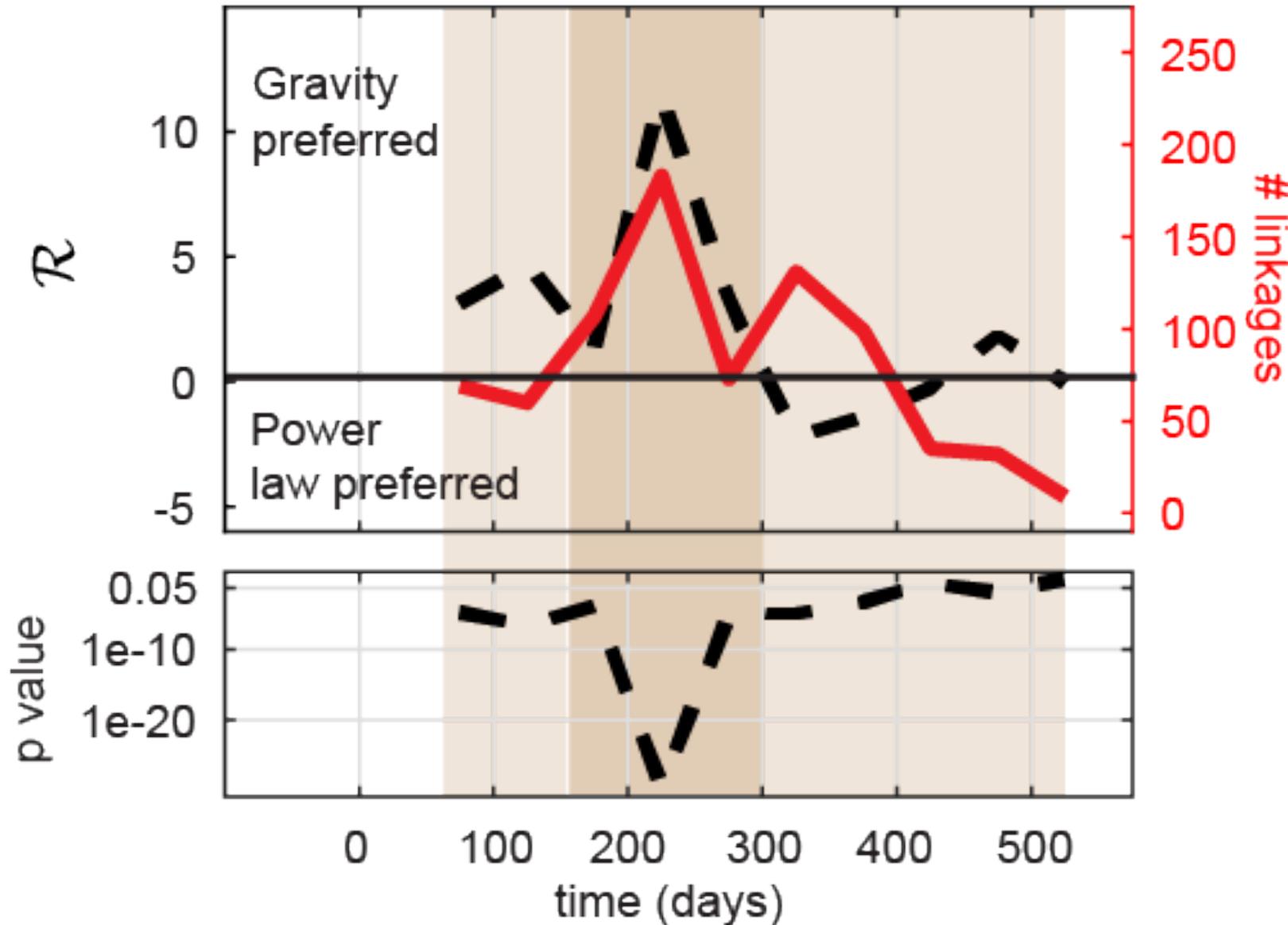
$$\mathcal{R}(\rho, \tau_2) = \sum_S [\ln(p_{ij}^G) - \ln(p_{ij}^L)] / \sqrt{N}$$

N genetic linkages

Two options:

- 1) Compare power law with classical $\tau_2 = 1$ gravity using same ρ
- 2) Scan through ρ and τ_2 to determine maximum likelihood gravity, compare to power law

Switching between Lévy flight and gravity



$$\rho = 1.7 \quad \tau_2 = 1$$

50 day windows

Each window for
descendant linkages

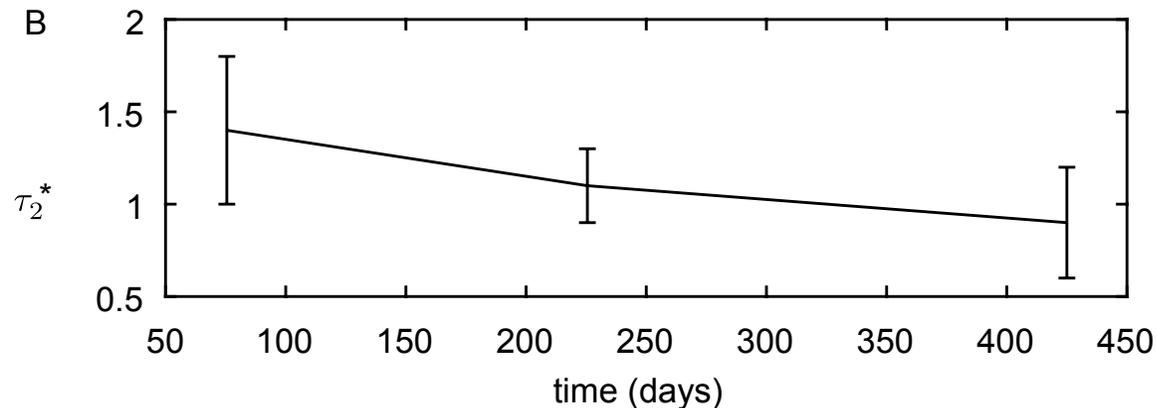
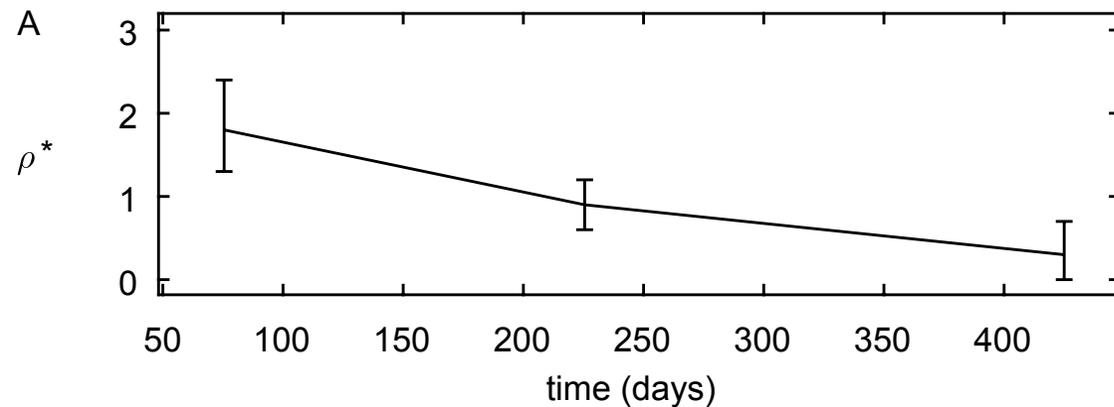
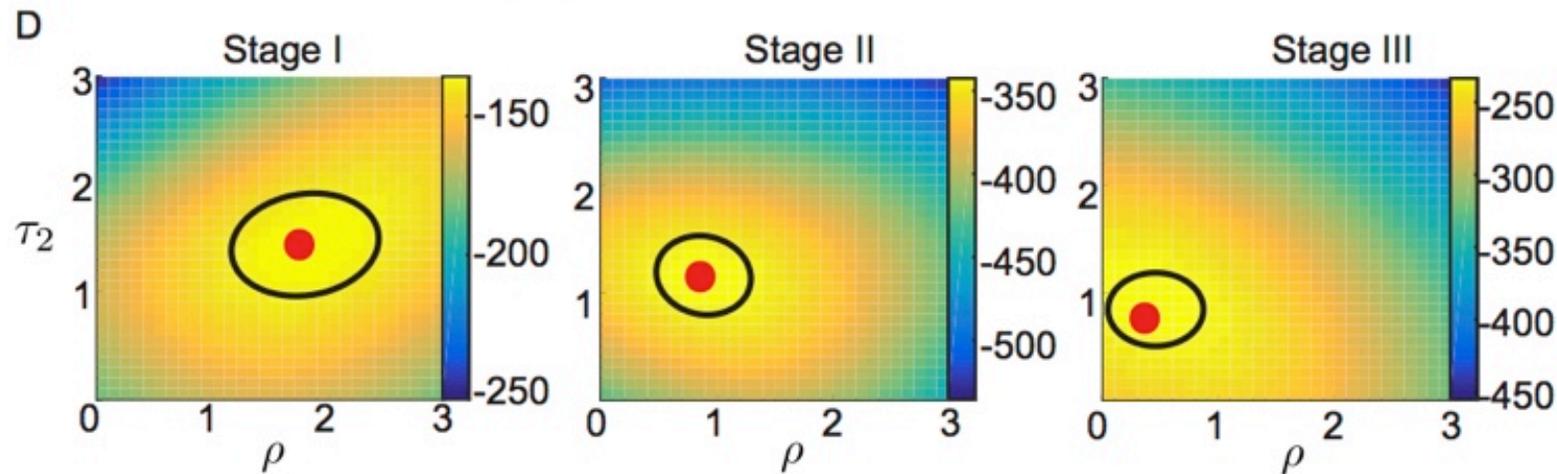
Using median chiefdom
population

Maximum likelihood for gravity model

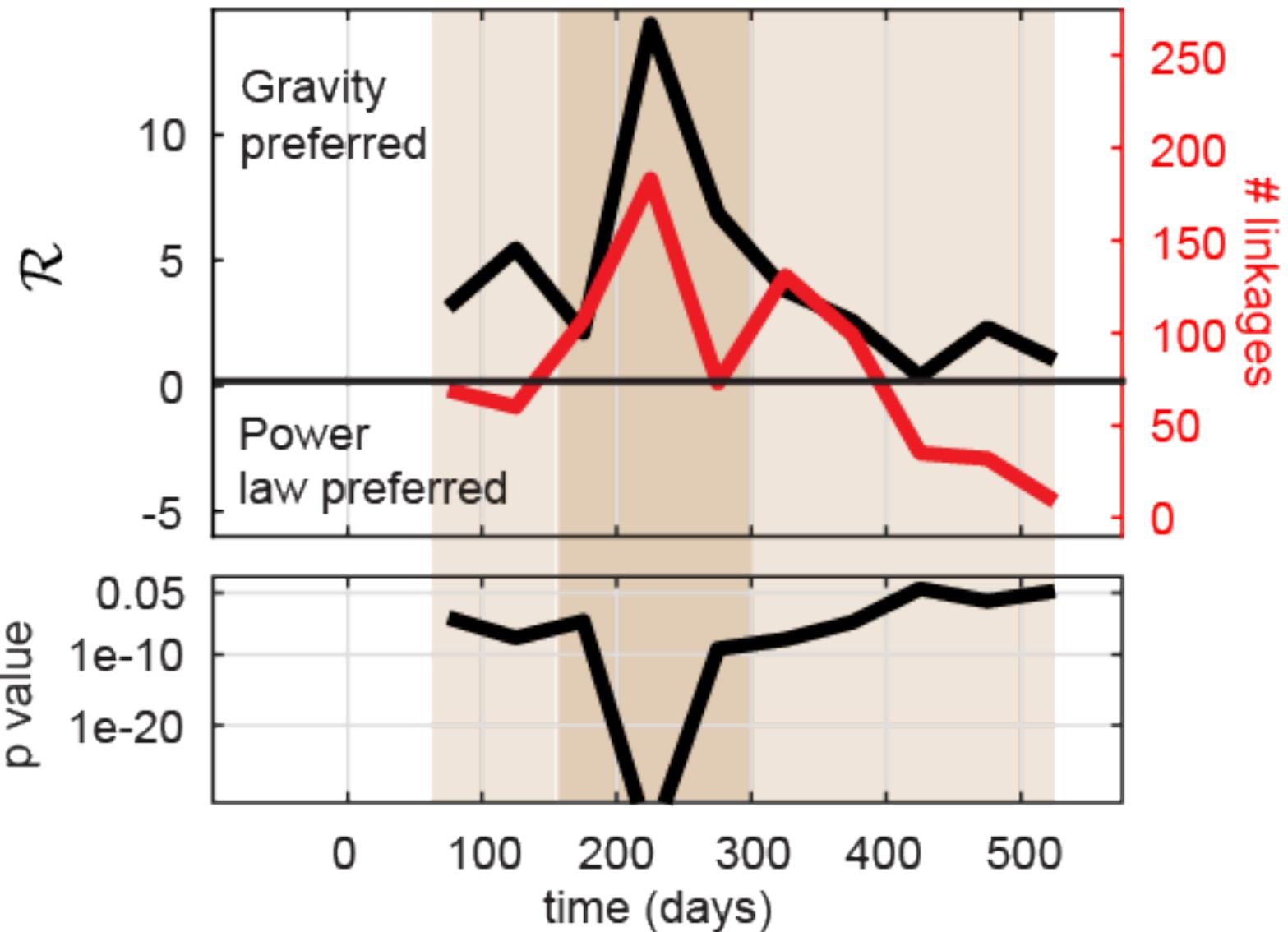
$$p_{ij}^G = C_i^G \frac{P_{c_i}^{\tau_1} P_{c_j}^{\tau_2}}{d_{ij}^\rho}$$

Both population and distance parameters shrink

Uncertainty in fit is high



Trend away from gravity – using MLE estimates



50 day windows

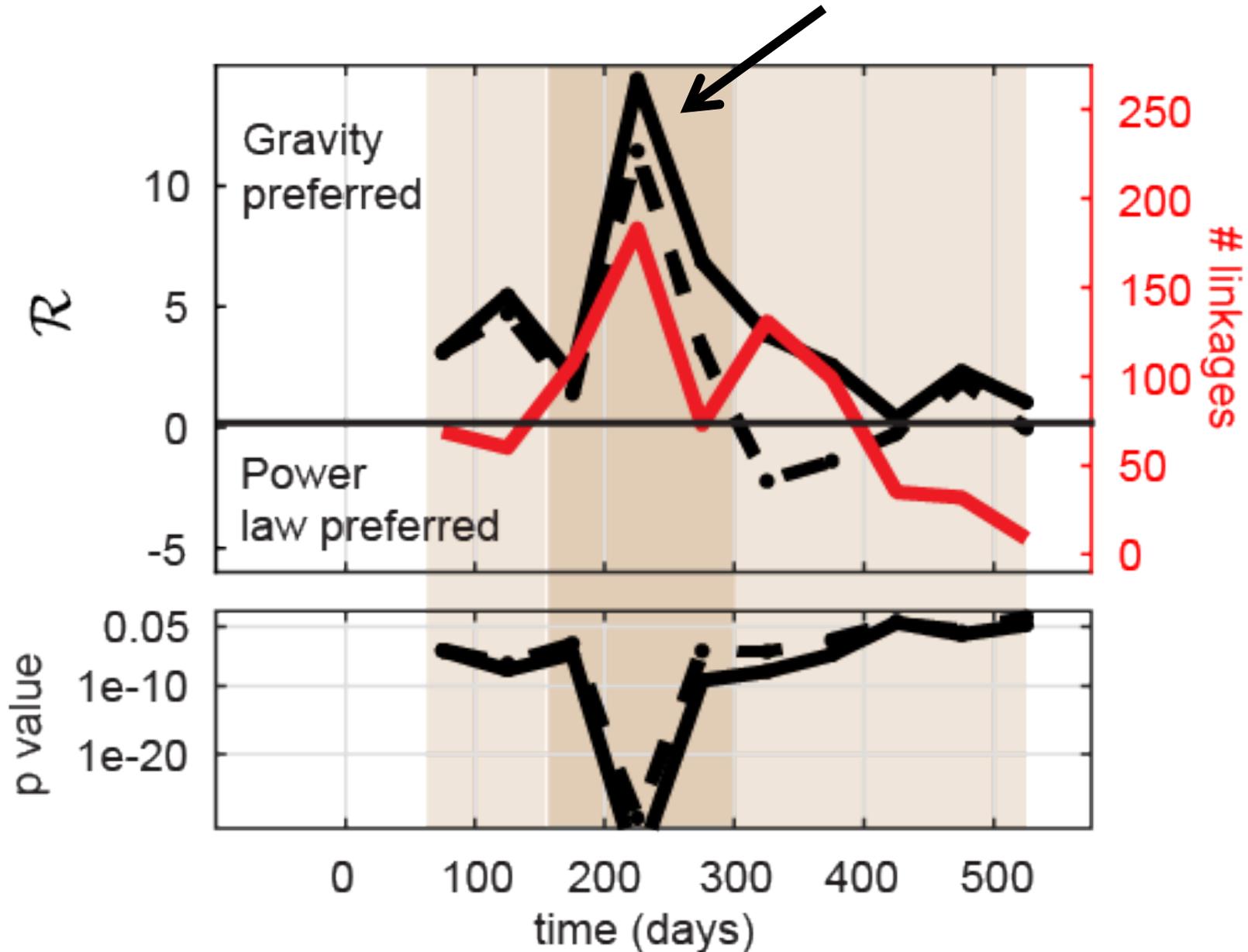
Gravity model preferred until 400 days

Uncertainty in MLE estimate is large

Significance of model preference low after 400 days

Comparison

Intervention surge in Freetown



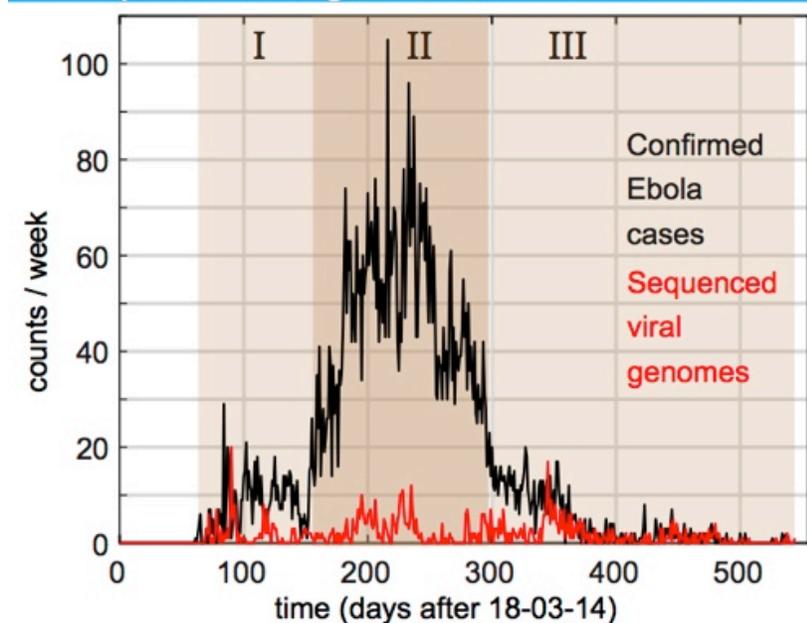
MLE estimates

$$\rho = 1.7 \quad \tau_2 = 1$$

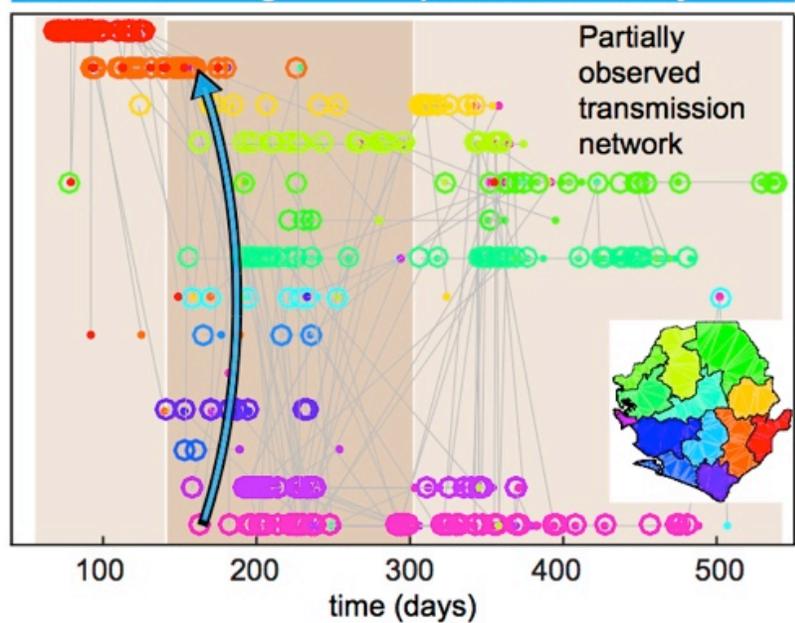
Best to use both methods

Clear success of Operation Western Area Surge

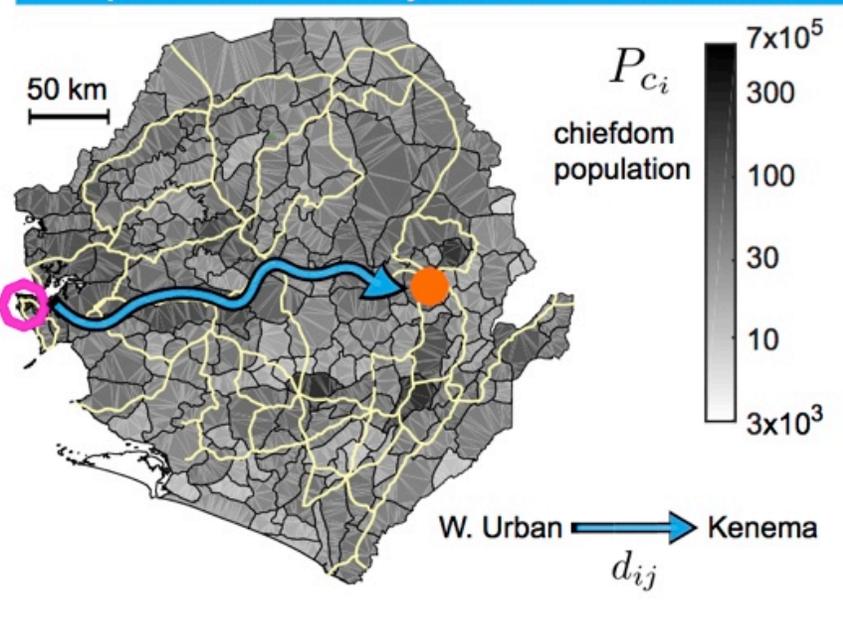
A: Sequenced viral genomes track the outbreak



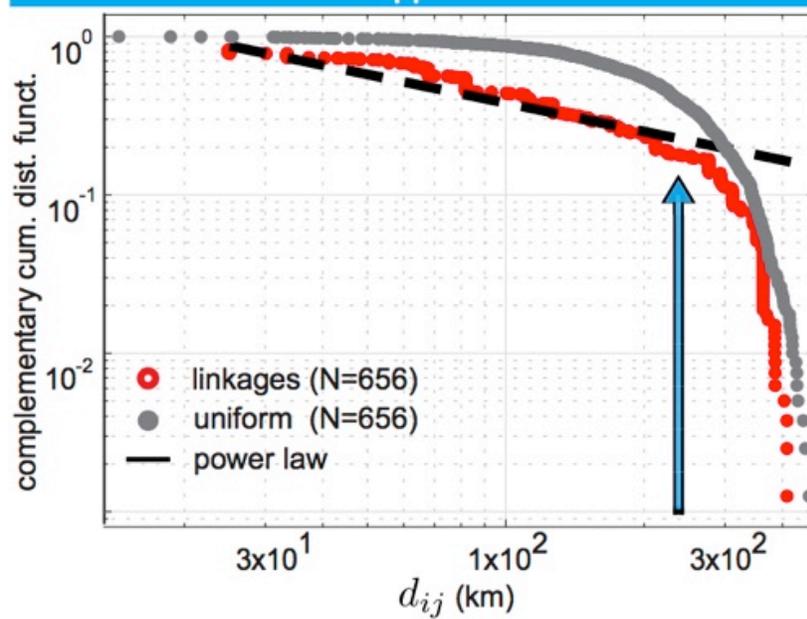
B: Genetic linkages infer spatial connectivity



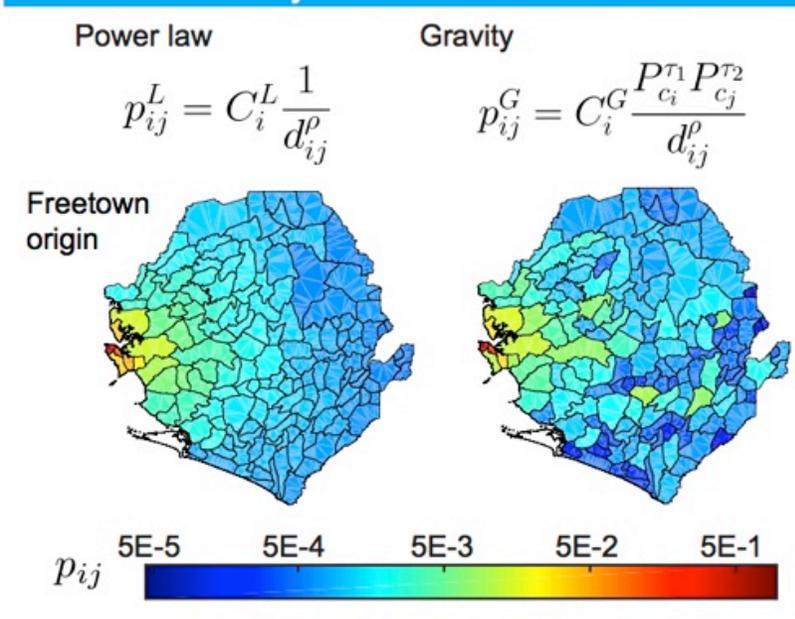
C: Population and mobility influence transmission



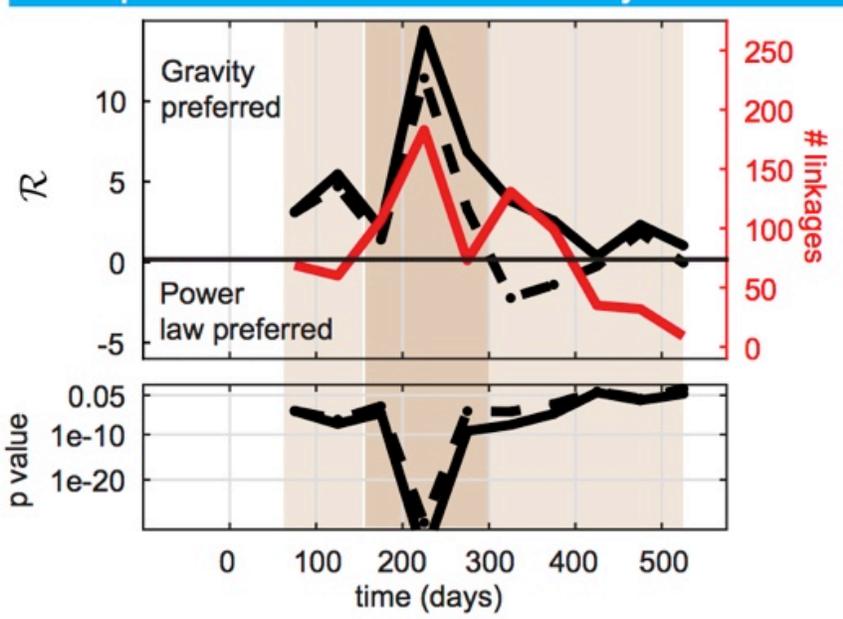
D: Distance statistics support a non-uniform model



E: Disease mobility models are calibrated to data



F: Adaptive model selection identifies dynamics



Summary and next steps

Phylogeography indicates a Lévy flight or weighted Lévy flight / gravity

Population size is not always predictive of transmission pattern

Adaptable model selection for real-time spatial dynamics of outbreaks

Other models and geographies can be implemented for next outbreak

Thanks to

Bill and Melinda Gates, Global Good Fund

and to

Philip Eckhoff

Mike Famulare

Edward Wenger

Ben Althouse

Laurent Hébert-Dufresne

Hao Hu

Joel Miller

Dan Klein

Niall Mangan

Thanks for your attendance