

Impact of Seeding and Spatial Heterogeneity on Metapopulation Disease Dynamics

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Rohit Rajuladevi, Przemek Porebski, Madhav Marathe, Srini Venkatramanan

August 15th, 2022



srini@virginia.edu

epiDAMIK 5.0, co-held with ACM SIGKDD 2022



srniv_venkat



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Motivation

- Epidemic = among/upon (*epi-*) + people (*demos*)
- Epidemics are influenced by
 - Where people live
 - How people move/mix
- in turn influenced by geography
- Implications for importation, interventions, impact



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Study Goal

- Explore the role of population geography on epidemic dynamics
- Leverage real-world demographics combined with *realistic* models of mobility & spread
- Focus on the initial conditions
- Use **epi-** to perform **DaMiK*** on the demic

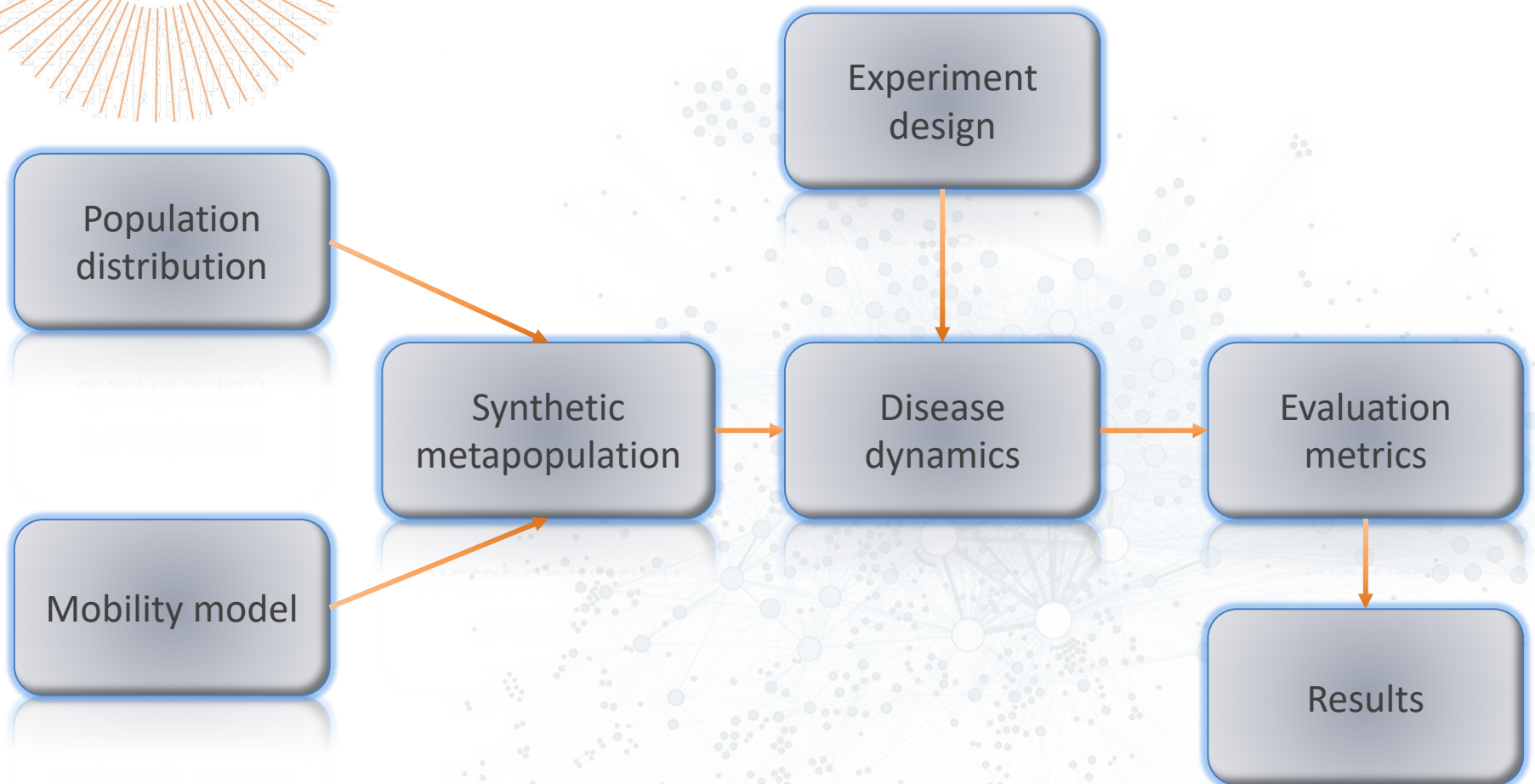
* Data Mining and Knowledge discovery



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Overall framework



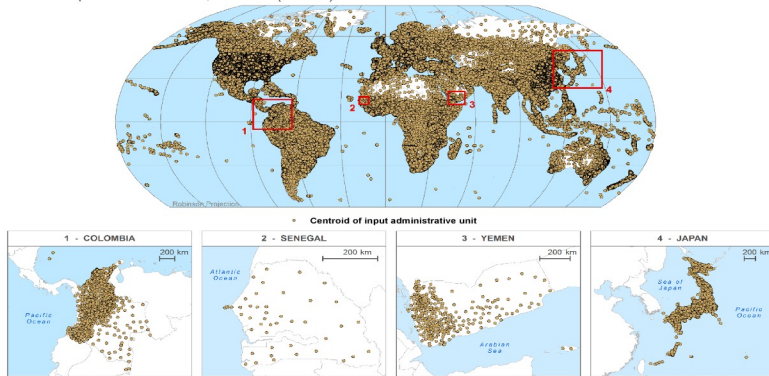
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Population construction

Admin unit populations from GPWv4 + GADMv3.6
(levels 1 & 2 equivalent of state and counties)

Administrative Unit Center Points with Population Estimates, v4.11
Gridded Population of the World, Version 4 (GPWv4)



Gridded Population of the World, Version 4 (GPWv4) Administrative Unit Center Points with Population Estimates, Revision 11 consists of UN WPP-adjusted population estimates and densities for the years 2000, 2005, 2010, 2015 and 2020, the 2010 basic demographic characteristics (age and sex), and administrative name, area, and data context by administrative unit center point (centroid) location. The center points are based on approximately 13.5 million input administrative units used in GPWv4.
Center for International Earth Science Information Network - CIESIN - Columbia University, 2018. Gridded Population of the World, Version 4 (GPWv4).
Science Information Network
https://sedac.ciesin.columbia.edu/data/collection/gpw-v4/

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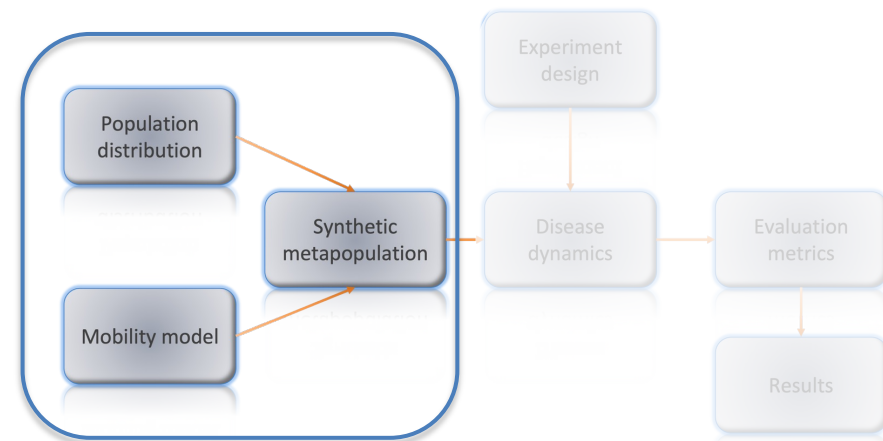
GADM Version 3.6

<https://sedac.ciesin.columbia.edu/data/collection/gpw-v4>
<https://gadm.org/data.html>



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Radiation model of mobility

$$\langle T_{ij} \rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})}$$

m_i - population of source i

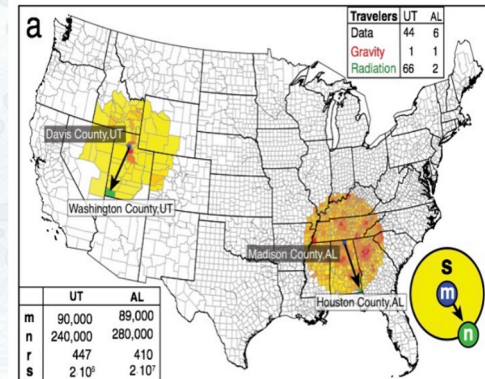
n_j - population of destination j

T_i - total outflow from source i

d_{ij} = distance from i to j

s_{ij} - population residing within d_{ij} of i

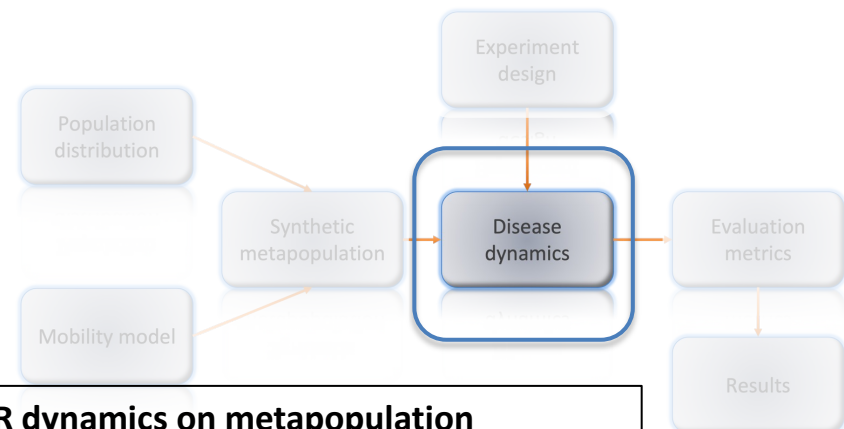
Why radiation model?



Simini, Filippo, et al. "A universal model for mobility and migration patterns." Nature 484.7392 (2012): 96-100.

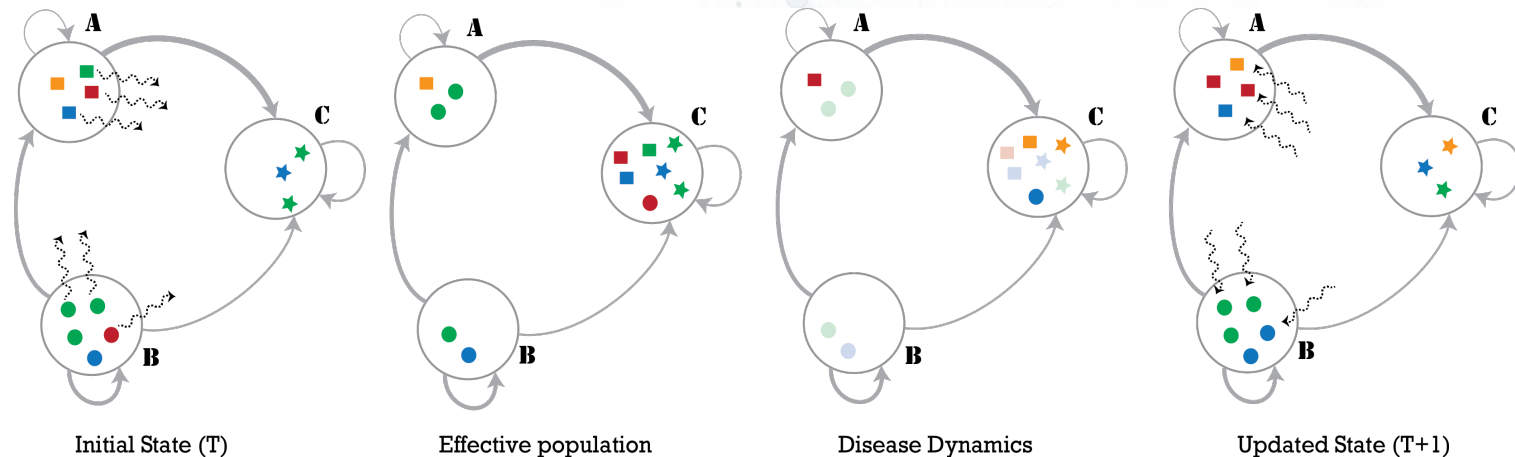
Data publicly available at:
<https://github.com/NSSAC/patchflow-data>

Disease dynamics



PatchSim: Simulation engine for SEIR dynamics on metapopulation

- Deterministic and discrete-time
- Includes functionality for external seeding, vaccination, dynamic control



S → **E** → **I** → **R**

SV et al. "Optimizing spatial allocation of seasonal influenza vaccine under temporal constraints." PLoS computational biology 15.9 (2019): e1007111.

SV et al. "Forecasting influenza activity using machine-learned mobility map." Nature communications 12.1 (2021): 1-12.



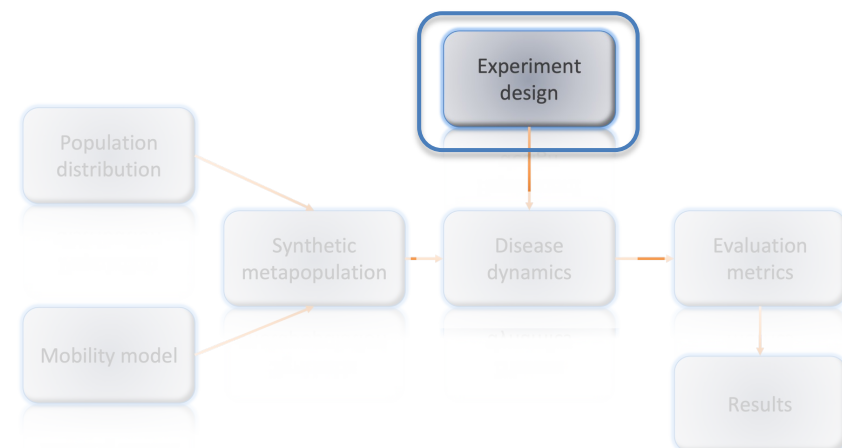
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Code publicly available at:

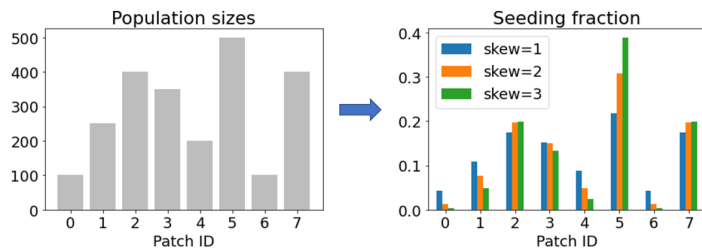
<https://github.com/NSSAC/PatchSim/>

Experiment design

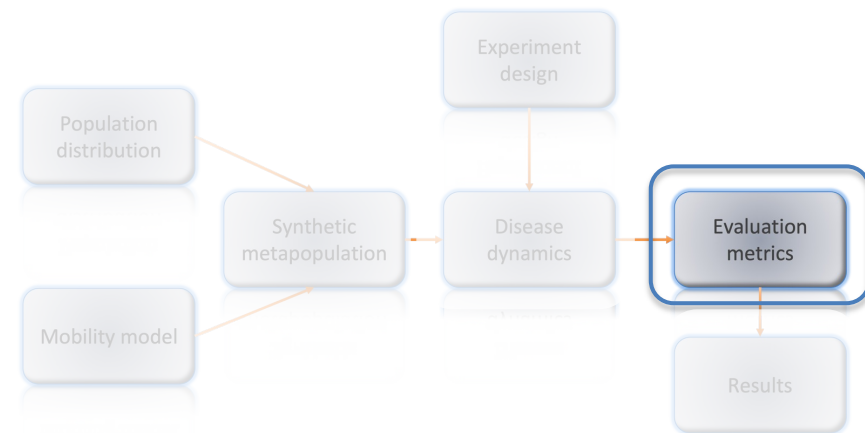


Transmissibility	Cum. Attack Rate (%)
0.45	21.45
0.5	37.47
0.55	49.63
0.6	59.08
0.65	66.52
0.7	72.47

- Admin. level (0-nation, 1-state, 2-county)
- Radiation model outflow (1%, 5%, 10%)
- Transmissibility $\beta \in [0.45, 0.5, \dots, 0.7]$
- Total seed volume fixed (10 per 100k)
- Initial cases in a patch proportional to population: $p_i^{skew} / \sum_i p_i^{skew} \times Total$



Evaluation metrics

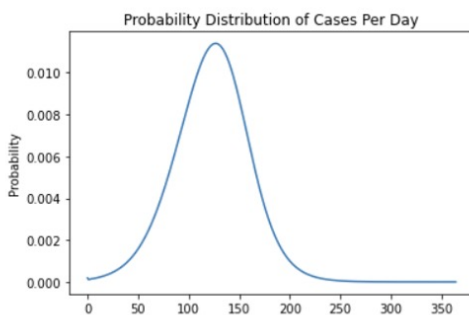
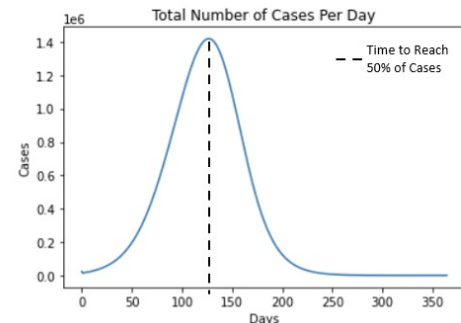


- Shannon Entropy of the normalized epidemic curve

$$H(X) = - \sum_{i=1}^n P(x_i) \log_b P(x_i)$$

Dalziel, Benjamin D., et al. "Urbanization and humidity shape the intensity of influenza epidemics in US cities." *Science* 362.6410 (2018): 75-79.

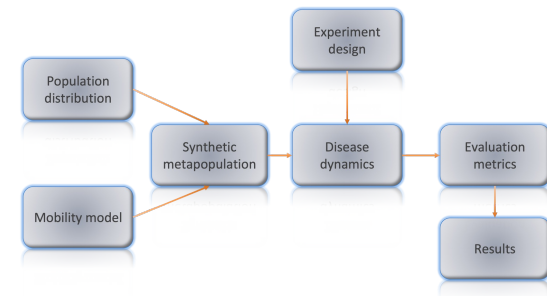
- Number of days to cross 50% of total cases



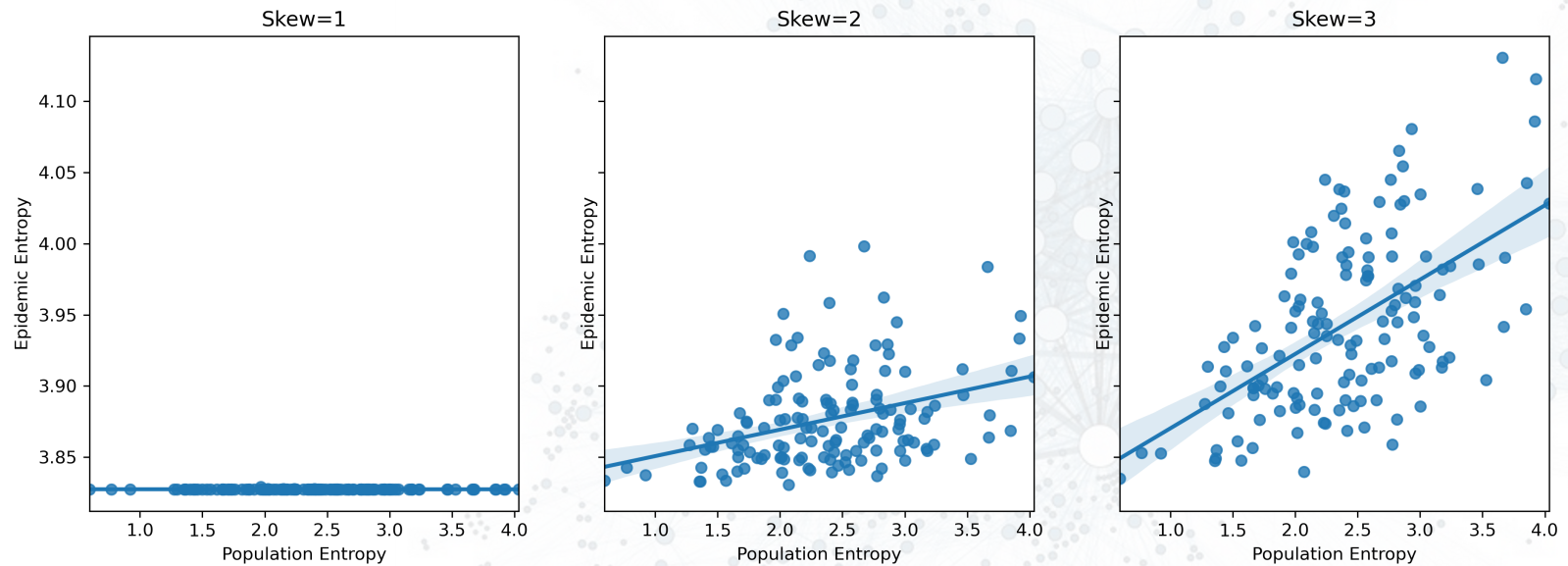
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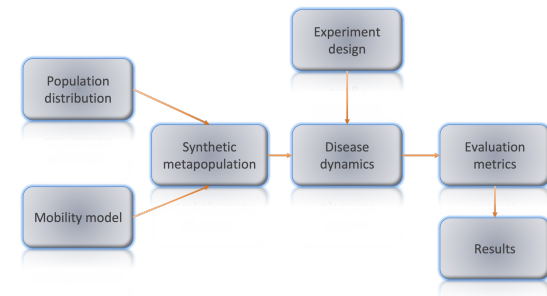
Results - 1



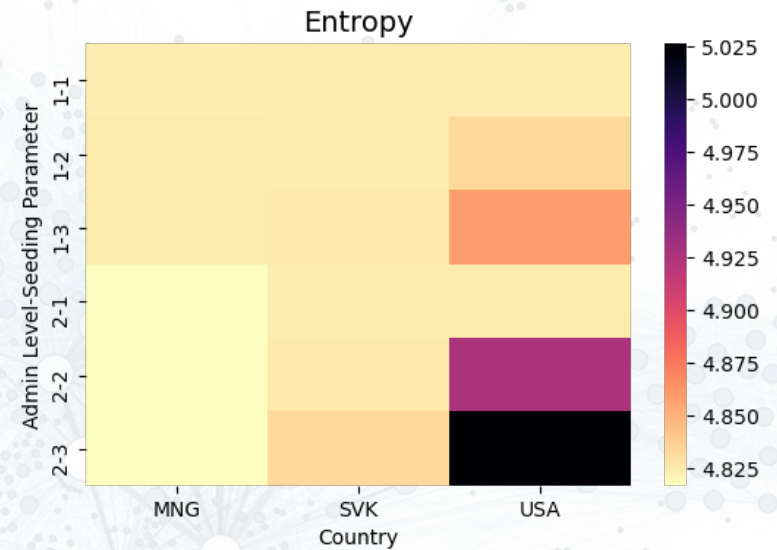
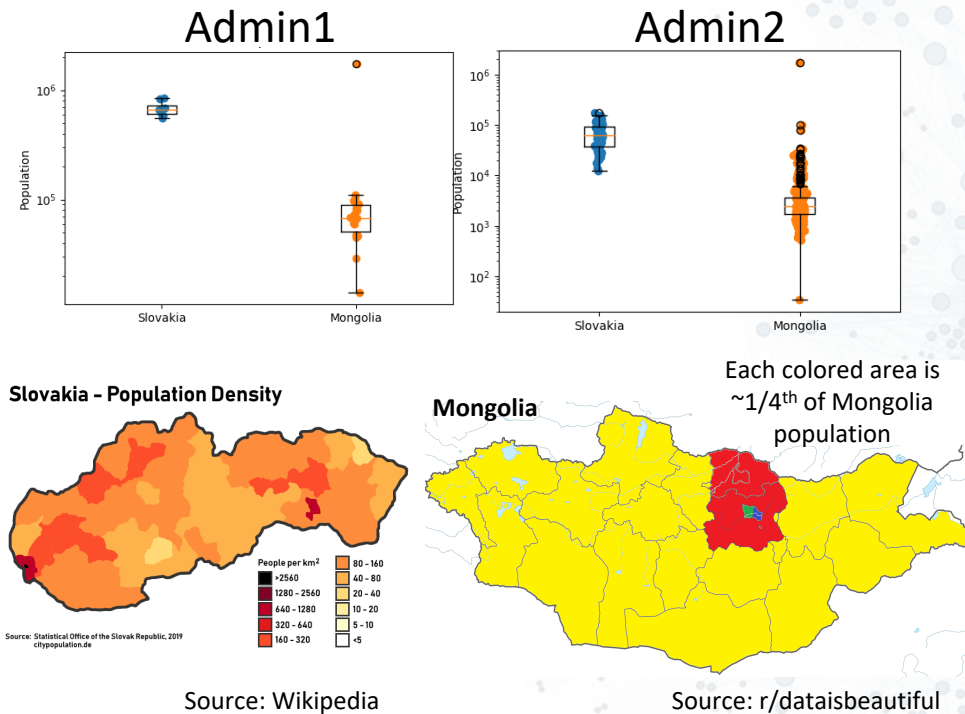
Population entropy influences epidemic entropy at higher skews



Results - 2



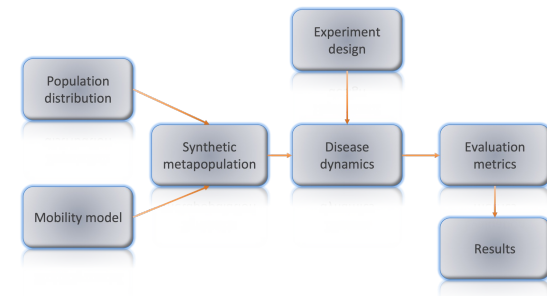
Impact of skew more evident at finer geographic resolutions



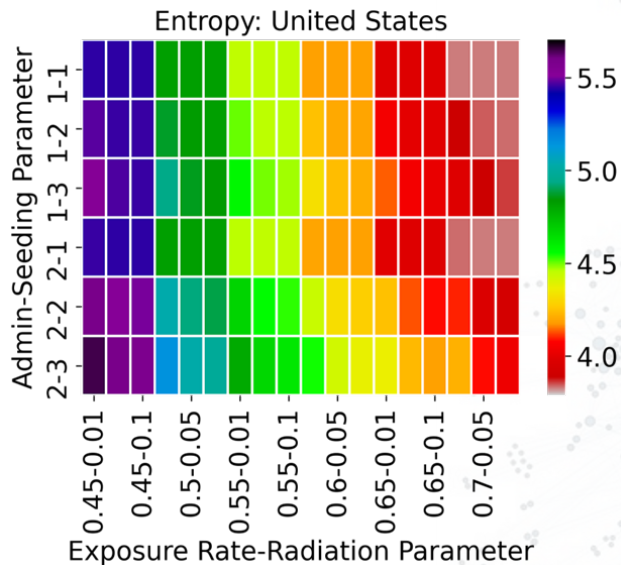
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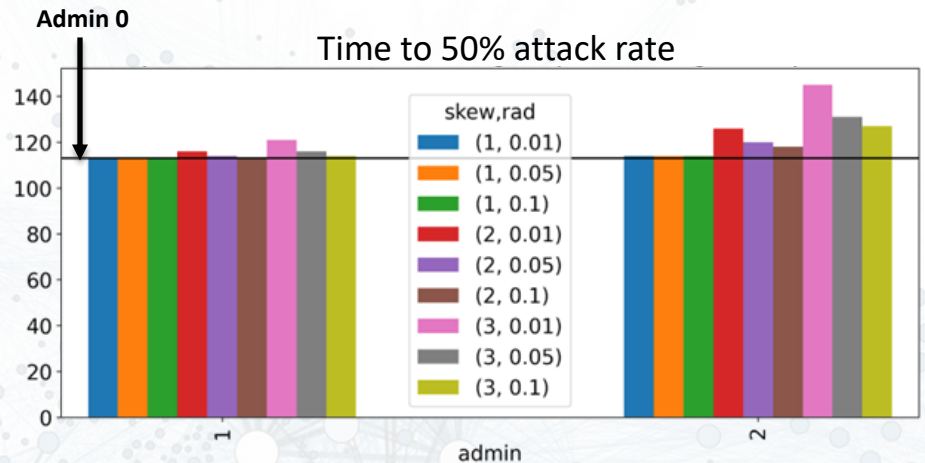
Results - 3



Increased mobility or Increased β
 -> Lower entropy

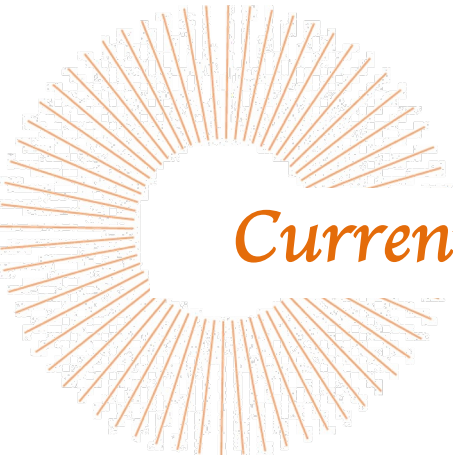


Influence of mobility felt more at higher skews



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Current & Future Work

- Impact of spatial resolution of NPIs (e.g., lockdowns)
- Optimal and equitable vaccination strategies
- Other demographics (age, income), seasonality
- Better network models (multi-modal) & real-world data



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Acknowledgments

This work was supported by NSF RAPID 2027541: COVID-19 Response Support: Building Synthetic Multi-scale Networks, NSF Expeditions 1918656: Collaborative Research: Global Pervasive Computational Epidemiology, DTRA subcontract/ARA S-D00189-15-TO01-UVA.



Thanks to members of Network Systems Science and Advanced Computing Division (NSSAC) & Biocomplexity Institute COVID-19 Response Team.

<https://biocomplexity.virginia.edu/>

<https://nssac.github.io/covid-19/>



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srini@virginia.edu



sriniv_venkat