Impact of Spatial Seeding on Metapopulation Models for Disease Dynamics

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Introduction

- **Metapopulation models combine SEIR models with network models**
- **Metapopulation models provide insights into individual regions without significant computational cost**
- **Distinct features arise from accounting for mobility within the model**

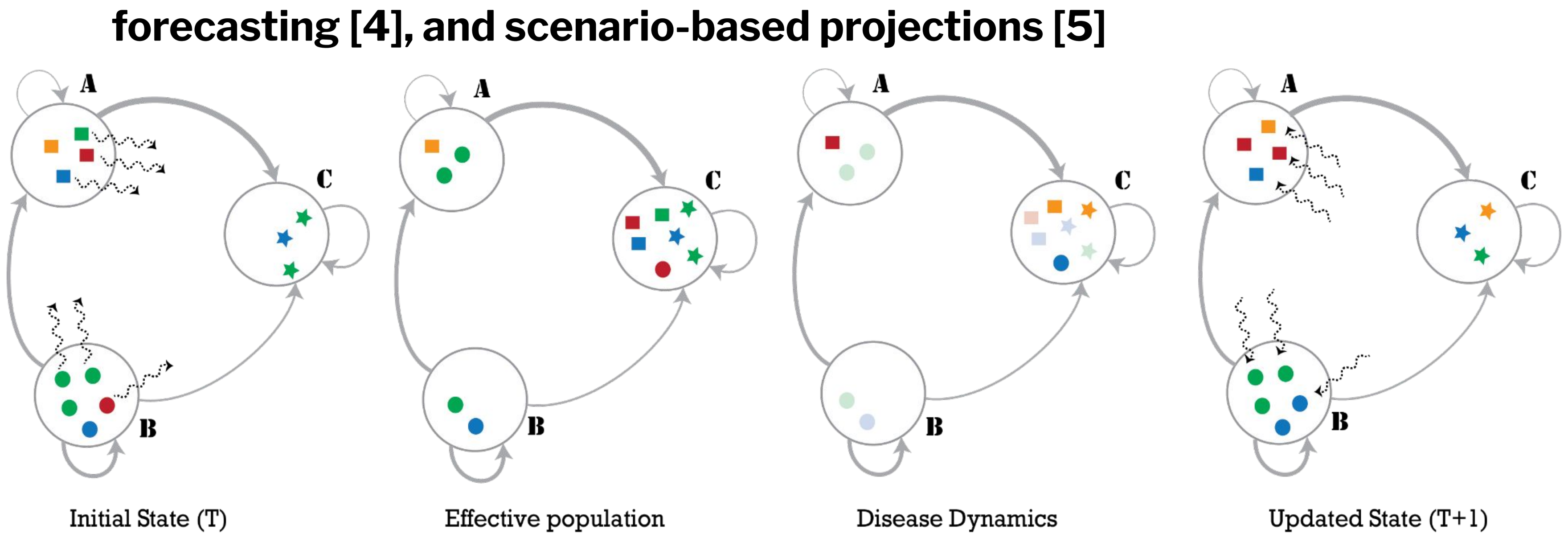
- **PatchSim [1] is a metapopulation model developed at the BII NSSAC**
- **PatchFlow [2] is a repository of datasets containing mobility data from radiation modeling that can be used in PatchSim**
- **The goal is for the results to not only provide insights into PatchSim/PatchFlow itself but also for better pandemic preparedness**

Purpose

- **The purpose of this experiment is to deepen the understanding on mobility and spatial heterogeneity, esp. metapopulation models**
- **Understanding should be brought on how disease spread is altered by different networks and seeding locations**
- **Contrasting with a homogeneous model for entire country**

Patchsim Description

- **Metapopulation based disease model both SEIR models and network models**
  - **SEIR difference equations for dynamics within region**
  - **Network models account for mobility among subregions**
- **Has been used in various contexts including resource allocation [3], forecasting [4], and scenario-based projections [5]**

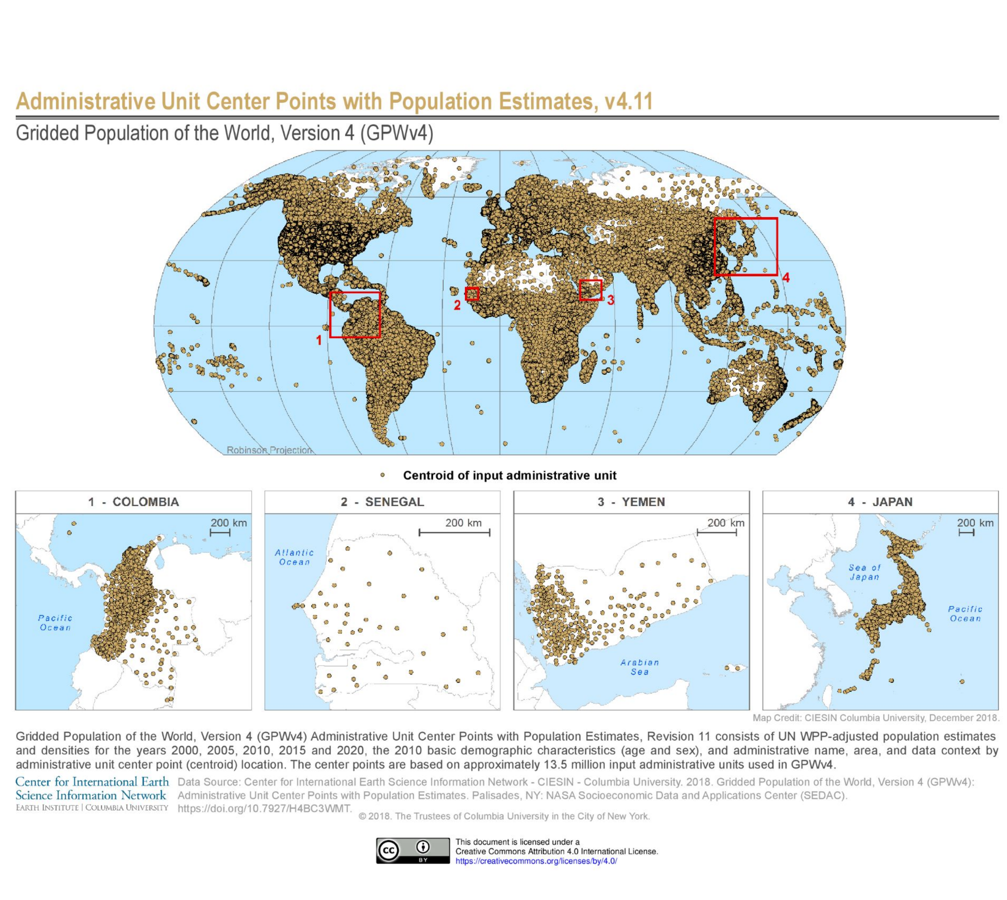


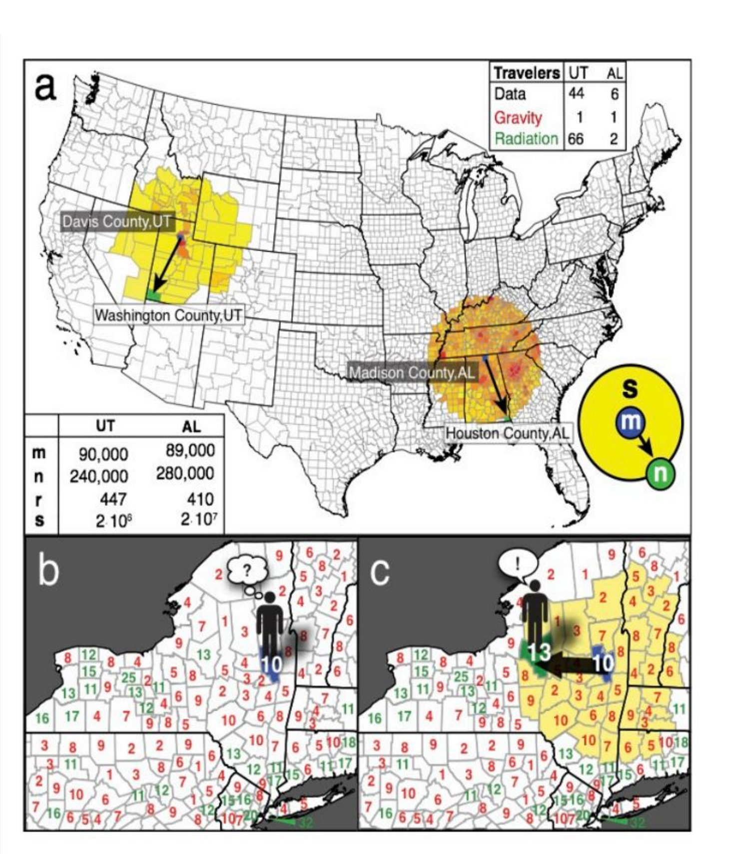
S → E → I → R

PatchSim metapopulation framework

Patchflow Description

- **PatchFlow is a set of precalculated networks for simulating the metapopulation SEIR model at a global level**
- **Country specific mobility networks are based on a radiational model**
- **Population distributions are obtained from Gridded Populations of the World (GPWv4), and administrative regions were obtained from GADM**
- **Admin level is the resolution of the network - for instance admin 1 in USA is states and 2 is counties**
- **The radiation parameter (rad) determines what percent of the population travels in the network [6]**
- **Network and Population files are designed to be compatible with PatchSim**



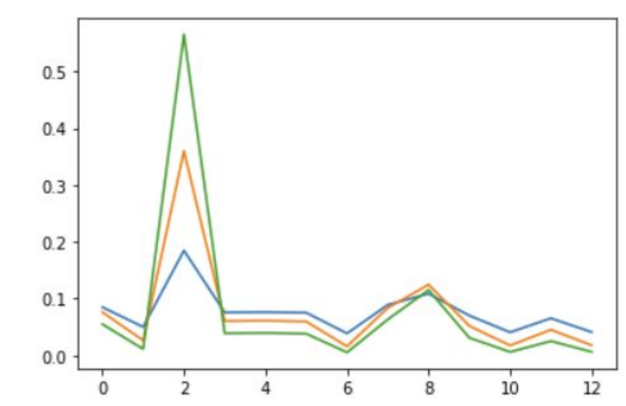


$$\left\langle T_{ij} \right\rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})},$$

- m_i - population of source region i
- n_j - population of destination region j
- T_i - number of commuters from source region i
- d_{ij} = distance from region i to region j
- s_{ij} - population residing within dij from region i

Study Design

- **Independent variables are admin level (admin), radiation parameter (rad), seeding scaler (skew) and exposure rate (β)**
- **Only countries with a population over one million are included**
- **admin0 is a homogeneous SEIR model with one patch, and compared against admin1 and admin2 simulations**
- **rad ∈ [1%, 5%, 10%], skew ∈ [1, 2, 3], β ∈ [0.3, 0.5, 0.7]**
- **Total number of initial cases are a proportion of the national population (20 per 100k)**
- **Initial cases within patches are taken as a proportion relative to the patch's population exponentiated by the skew parameter: $P^{skew} / \Sigma P^{skew} \times$ Total**
- **A higher skew leads to more initial cases concentrated in higher populated patches as shown below (skew = 1, 2, 3)**
- **Such skewing allows the network to play a larger role**
- **Note that due to full connectivity, total attack rate remains unchanged for a given β**



Exposure Rate	Cumulative 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

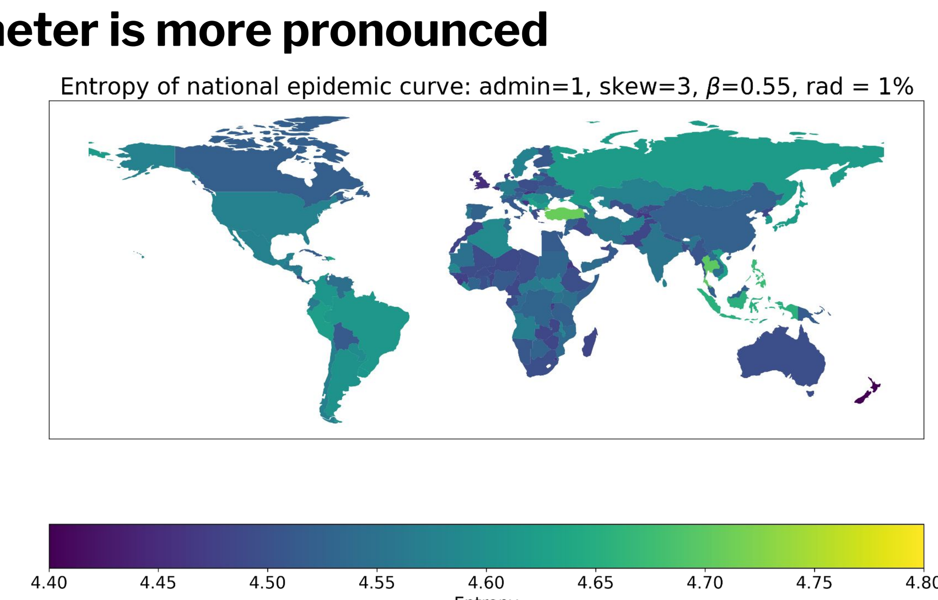
Metrics

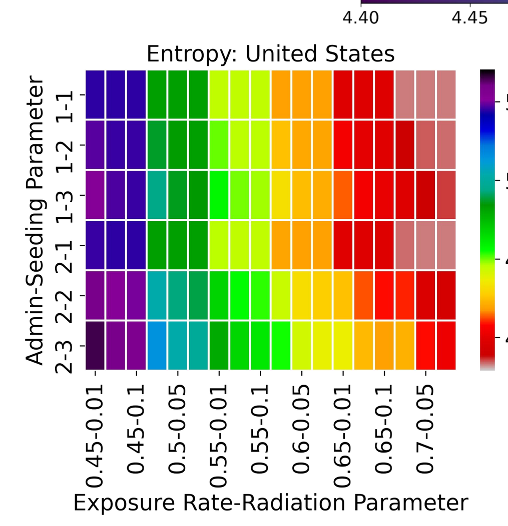
- **Number of days to cross 1%, 50% and 99% of total cases**
- **Shannon Entropy measurements of the normalized epidemic curve [7]**

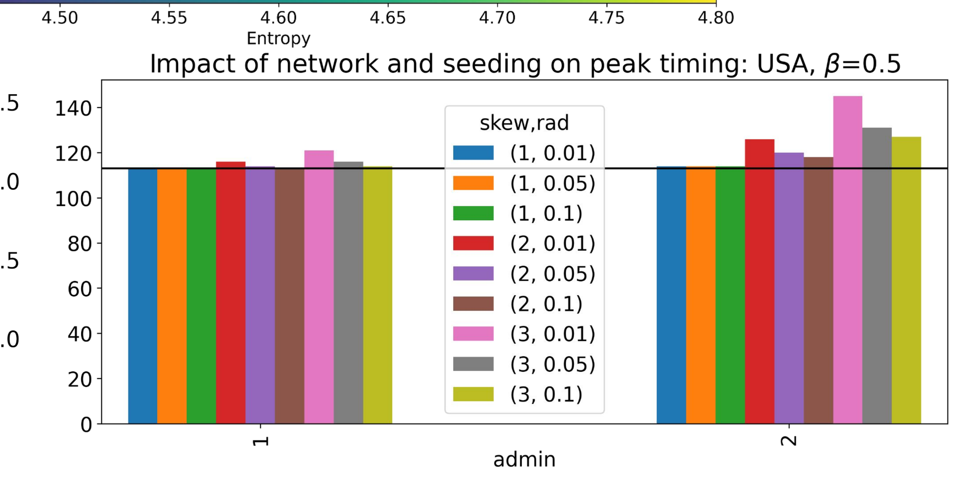
$$H(X) = -\sum_{i=1}^{n} P(x_i) \log_b P(x_i)$$

Initial Results

- **Impact of exposure rate on entropy is non-monotonic**
  - **Higher β lead to sharper epidemics, while lower β leads to faster extinction**
- **With fixed β, as admin level increases, entropy increases due to localized mixing within the regions**
  - **This is further accentuated by the skew in seeding and the rad parameter of the network**
- **Uniform seeding (skew=1) does not significantly change peak times, whereas for higher skew, the effect of rad parameter is more pronounced**







Current and Future Work

- **Impact of core and peripheral seeding using the network [8]**
- **Impact of heterogeneity in prior immunity & vaccination [9]**
- **Role of adaptive interventions at local/global levels [10]**

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