

Metaverse Demystified

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Recent Advances in Contagion Modeling and Simulation at Scale
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Why metapopulations?

- Coined by mathematical ecologist Richard Levins in 1969: Literally "a population of populations"¹
- Networked representations of population interactions in aggregate
 - Valuable intermediate between ordinary differential equation (ODE) models and agent-based models (ABM)
- Key ingredients:
 - Subpopulations of spatially disjoint entities (**Patches**)
 - Linked through connections that represent movement/contact (**Network**)
 - Disease progression represented through compartmental processes (**Dynamics**)
- While patches in general could represent arbitrary groups of entities, in this talk we will mostly focus on spatial grouping.

¹Levins, Richard. "Some demographic and genetic consequences of environmental heterogeneity for biological control." *Bulletin of the ESA* 15.3 (1969): 237-240.

Key concepts in spatial epidemiology

- Diseases often persist through a network where large urban hubs maintain a disease pool and reseed smaller, isolated populations.²
- Traditional geographic distance is often less relevant than “effective distance” based on travel intensity.³
- Multilevel mixing⁴ can be used to include local ‘amplification effects’ in global models.
 - Threshold for global outbreak $R_* = \mu R_G$, where R_G is the reproductive ratio for global contacts and μ is the mean size of a local outbreak within a group

²Balcan, Duygu, et al. "Multiscale mobility networks and the spatial spreading of infectious diseases." *Proceedings of the national academy of sciences* 106.51 (2009): 21484-21489.

³Brockmann, Dirk, and Dirk Helbing. "The hidden geometry of complex, network-driven contagion phenomena." *science* 342.6164 (2013): 1337-1342.

⁴Ball, Frank, Denis Mollison, and Gianpaolo Scalia-Tomba. "Epidemics with two levels of mixing." *The Annals of Applied Probability* (1997): 46-89.

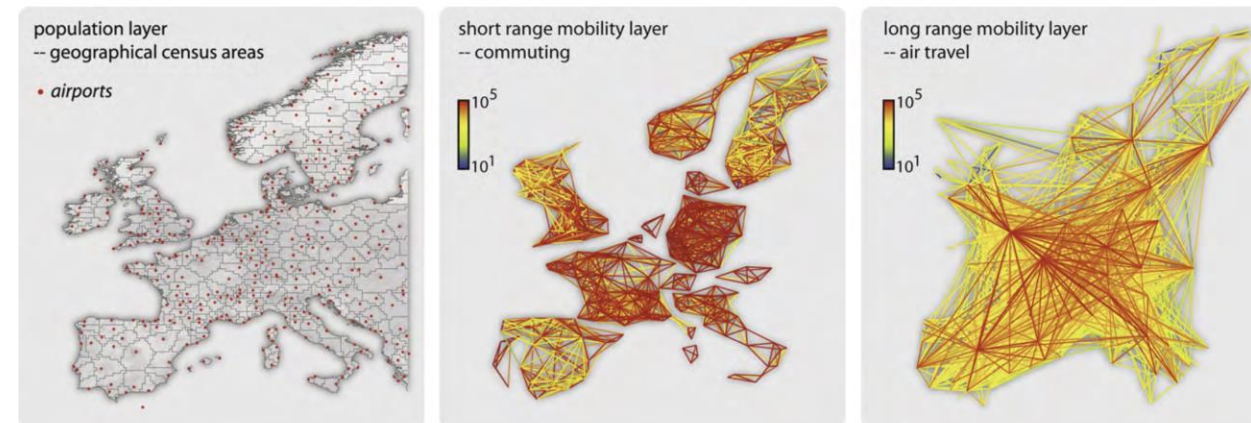
Challenges for Metapopulation models

- **Key challenge⁷:** Clarifying usefulness and limitations of a system of weakly coupled large sub-populations for disease dynamics
- **Modeling Challenges:**
 - Developing models that reflect complex spatial/social population structures
 - Developing a theory for endemic models with household structure
 - Integrating within-host and between-host dynamics ("individual as a habitat")
- **Methodological Challenges:**
 - Creating robust methods for parameter inference during epidemic emergence
 - Developing computationally efficient methods for calculating thresholds and early growth rates

⁷Ball, Frank, et al. "Seven challenges for metapopulation models of epidemics, including households models." *Epidemics* 10 (2015): 63-67.

Global Epidemic and Mobility (GLEaM) Model

- One of the early data-driven attempts at building a multiscale mobility network⁵
- Voronoi tessellation around ~3,300 airport hubs to define patches connected by over 16,800 air travel and commuting fluxes.
- Side-by-side comparison⁶ with stochastic ABM revealed:
 - Good agreement on peak timing
 - Metapopulation model yielded a larger overall incidence (5-10% higher) due to local homogeneity assumption

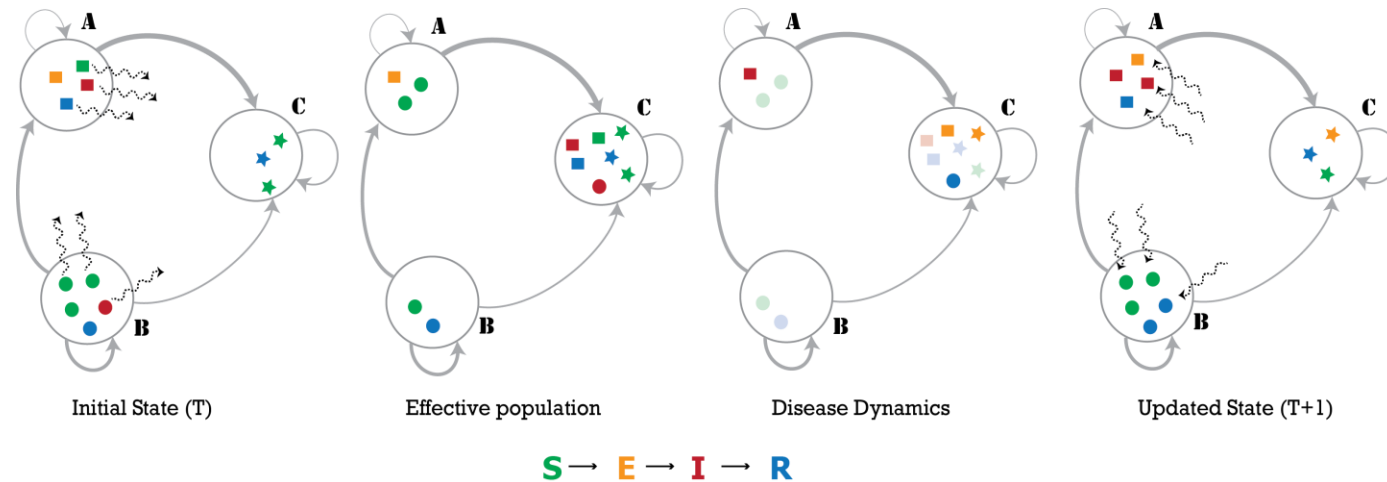


⁵Balcan, Duygu, et al. "Modeling the spatial spread of infectious diseases: The GLEaM computational model." *Journal of computational science* 1.3 (2010): 132-145.

⁶Ajelli, Marco, et al. "Comparing large-scale computational approaches to epidemic modeling: agent-based versus structured metapopulation models." *BMC infectious diseases* 10.1 (2010): 190.

PatchSim

- Open-source simulation engine⁸ for metapopulation SEIR dynamics
 - Travel network results in “effective population” for a given patch on a given day
 - Disease dynamics on effective population is then redistributed to source patches
 - **Flow network $\mathbf{F}$** s.t. $\sum_{j \in \mathcal{N}} F_{ij} = 1$ **Effective population:** $P_i^{\text{eff}} = \sum_{k \in \mathcal{N}} F_{ki} P_i$

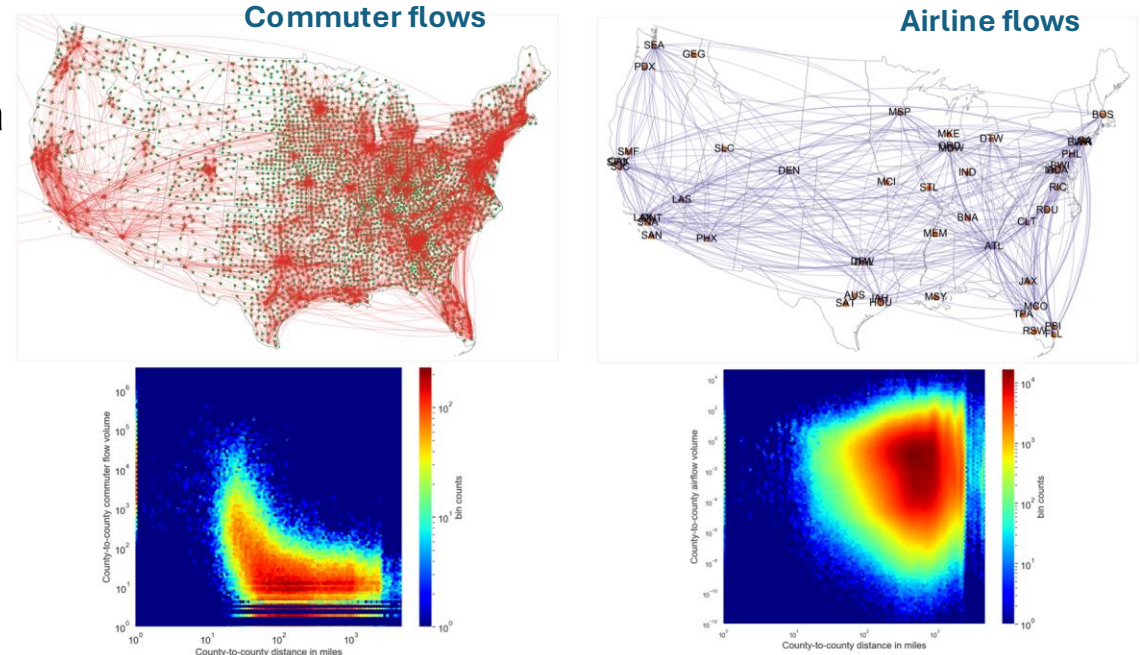


$$\begin{aligned}\Delta S_i &= -X_i - \sum_{j \in \mathcal{N}} F_{ij} \beta \frac{I_j^{\text{eff}}}{P_j^{\text{eff}}} S_i \\ \Delta E_i &= X_i + \sum_{j \in \mathcal{N}} F_{ij} \beta \frac{I_j^{\text{eff}}}{P_j^{\text{eff}}} S_i - \alpha E_i \\ \Delta I_i &= \alpha E_i - \gamma I_i \\ \Delta R_i &= \gamma I_i\end{aligned}$$

⁸Srini Venkatramanan, Parantapa Bhattacharya, Przemek Porebski, Brian Klahn, NSSAC/PatchSim: First official release. <https://github.com/NSSAC/PatchSim>, <https://doi.org/10.5281/zenodo.4313095>

National model for vaccine allocation

- **Problem:** Determining optimal spatial and temporal allocation of limited seasonal influenza vaccines⁹
- **Need:** A lightweight national model to be used within an optimization framework
- **Methodology:** Integrated U.S. domestic airline traffic with county-level commuter data



Mapping inter-airport flows to counties

$$A_{ij}^m = \frac{1}{d_m} \frac{W_{iu}}{\sum_k W_{ku}} \times \frac{W_{jv}}{\sum_l W_{lv}} F_{uv}^m$$

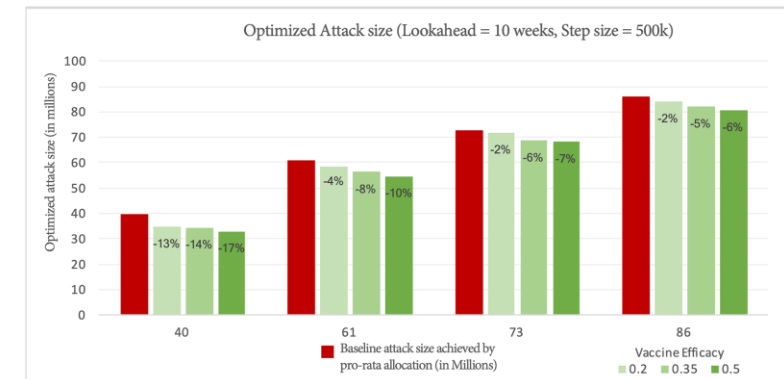
Combining commuter and airline flows

$$O_{ij}^m = C_{ij} + \Delta * A_{ij}^m$$

Aggregated travel matrix

$$\Theta_{ij}^m = \begin{cases} \frac{O_{ii}^m + (P_i - \sum_j O_{ij}^m)}{P_i} & \text{if } i = j \\ \frac{O_{ij}^m}{P_i} & \text{otherwise} \end{cases}$$

- **Key Findings:** Greedy algorithm results in a spatial ring vaccination strategy and improves over pro-rata allocation by up to 15%

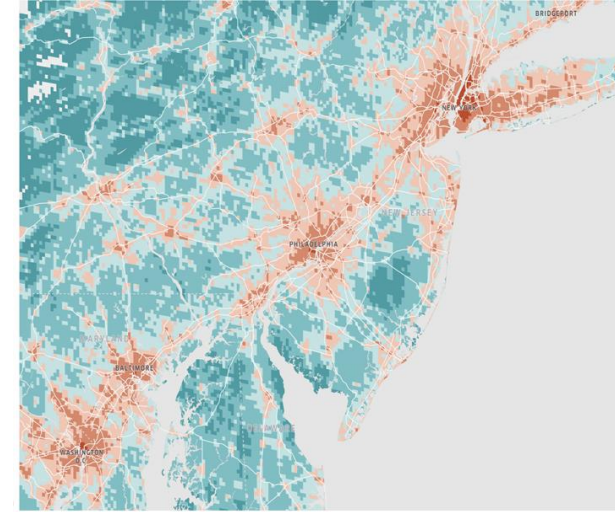


⁹Venkatramanan, Srinivasan, et al. "Optimizing spatial allocation of seasonal influenza vaccine under temporal constraints." *PLoS computational biology* 15.9 (2019): e1007111.

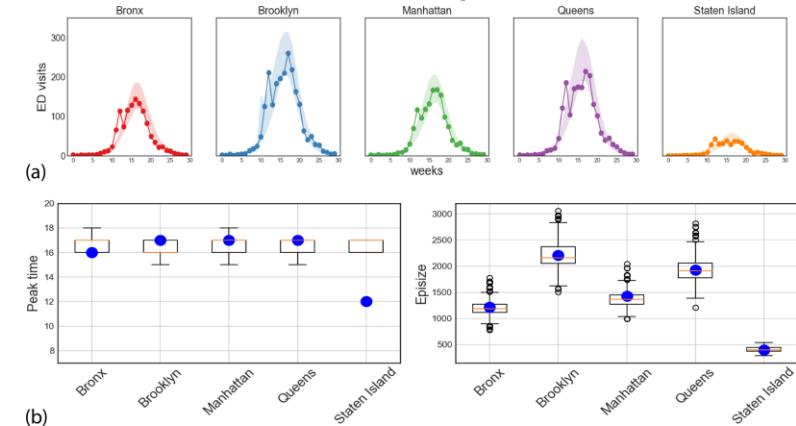
Machine-learned Mobility for Forecasting

- **Question:** Do real-world mobility datasets help improve forecasting efforts?
- **Innovation:** Evaluated Anonymized Mobility Maps (AMM) aggregated from hundreds of millions of smartphones for mechanistic influenza forecasting¹¹
- **Key Finding:** AMM-informed models performed on-par with expensive and sparsely-available census-based commuter surveys.
- **Value:** This proves mobility data from mobile apps can fill critical gaps in real-time epidemic modeling and pandemic preparedness.

AMM patch-level intensity for Northeastern United States



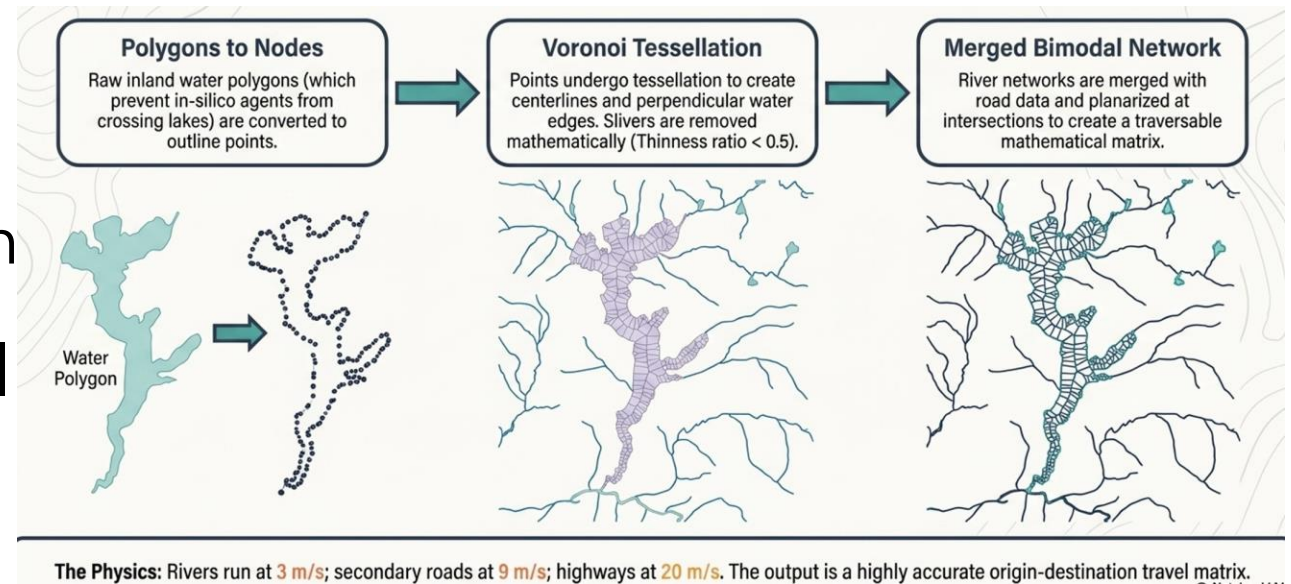
Leave-one-out cross validation performance for NYC boroughs



¹¹Venkatramanan, Srinivasan, et al. "Forecasting influenza activity using machine-learned mobility map." *Nature communications* 12.1 (2021): 726.

Rapid Mobility Assessment in Data-Poor Regions

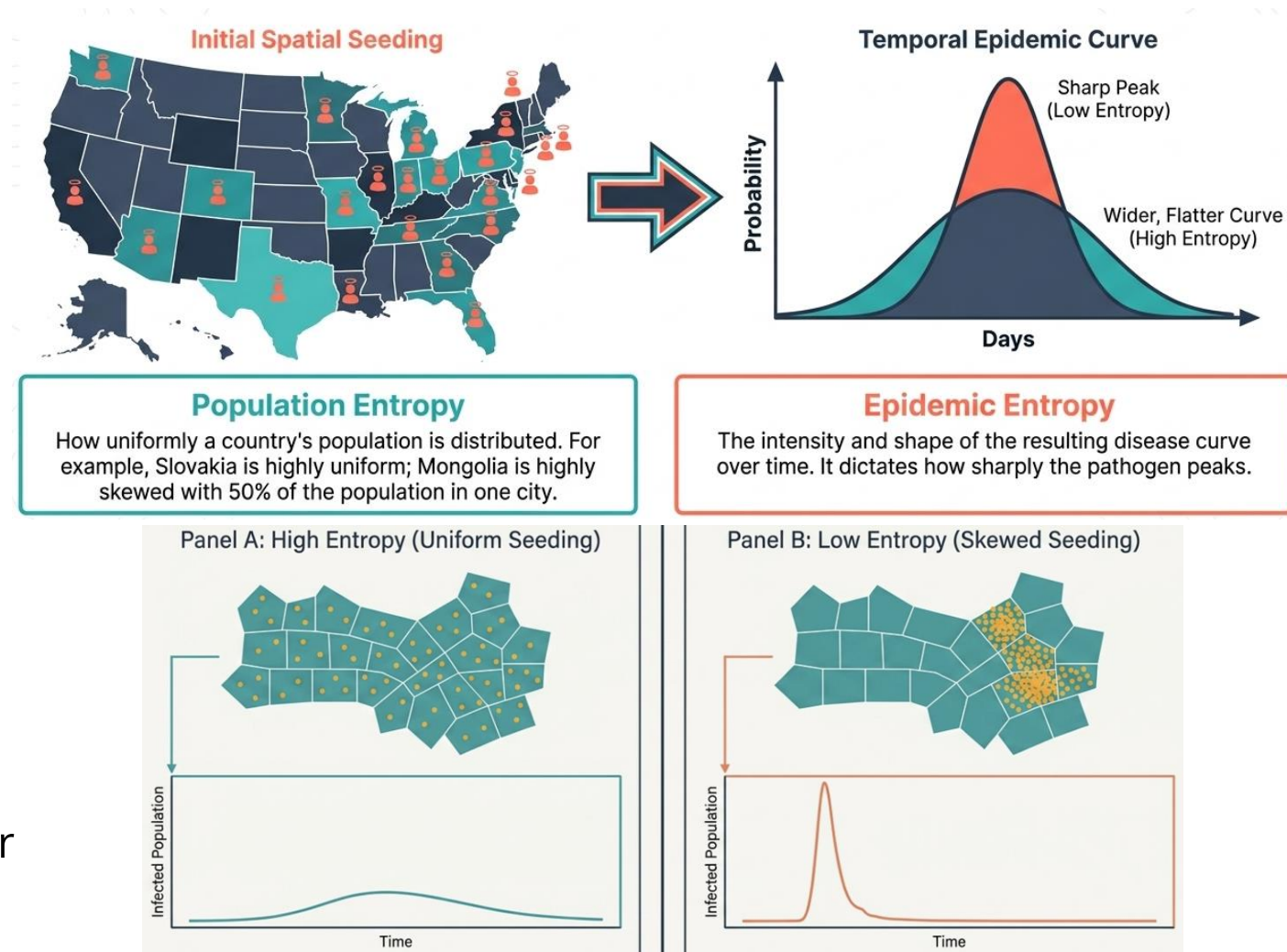
- **Problem:** Modeling spatial risk during Ebola outbreak in the Nord Kivu region (DRC) in 2018
- **Innovation:** Synthesized a bimodal travel network¹⁰ (roads and rivers) for the Democratic Republic of the Congo (DRC).
- **Key Insight:** Movement along the Congo River is a primary driver of risk; ignoring the gravitational attraction of urban centers like Beni leads to highly unrealistic spread patterns



¹⁰Telionis, Pyrros A., et al. "Methods for rapid mobility estimation to support outbreak response." *Health security* 18.1 (2020): 1-15.

Seeding and Spatial Heterogeneity

- **Question:** How does population distribution within a country affect its epidemic dynamics?
- **Innovation:** Introduced **PatchFlow**¹², an open-source dataset of metapopulation networks for 220 countries.
- **Approach:** Uses radiation model with different outflow proportions on administrative divisions from GADM and population data from Gridded Population of the World (GPW).
- **Key Finding:** Higher spatial entropy (uniform population distribution, uniform seeding) correlates with higher temporal entropy (longer, flatter epidemic curves)¹³

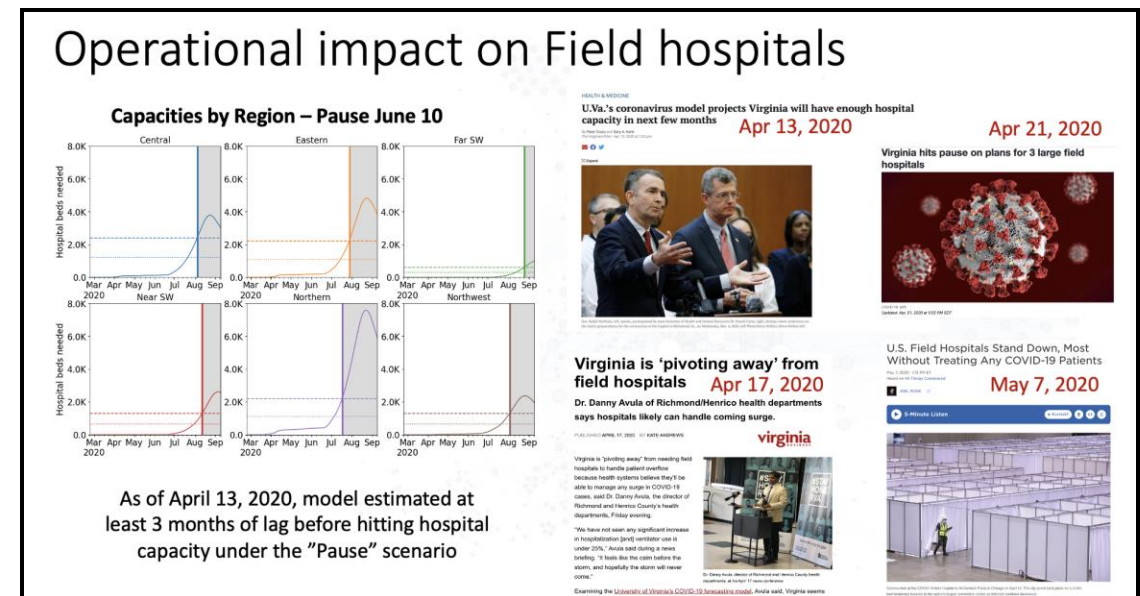
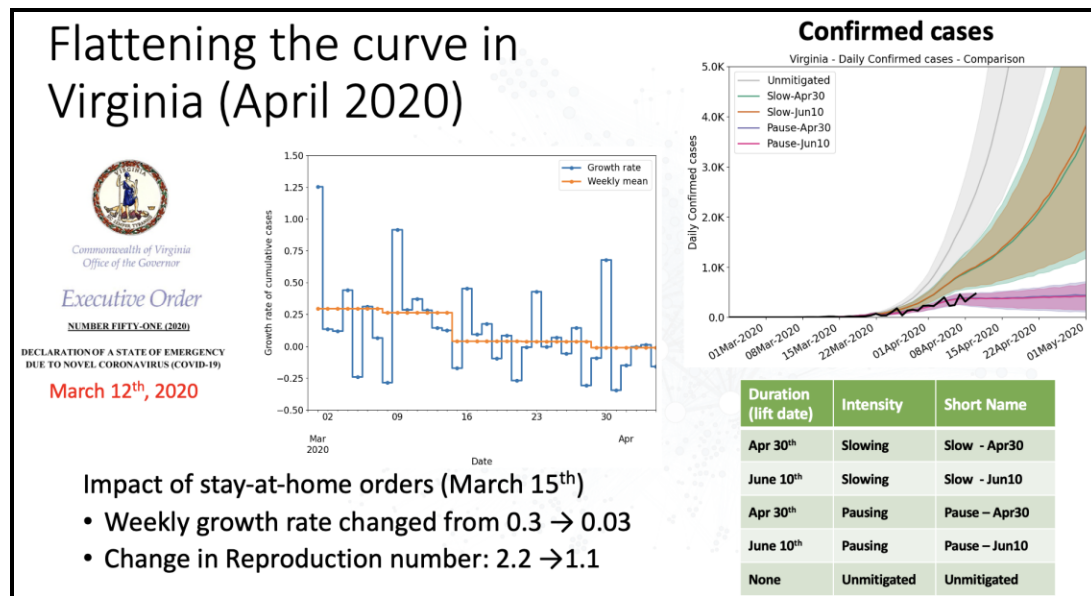


¹²Przemyslaw Porebski, & Srini Venkatramanan. (2021). PatchFlow v1.0 mobility networks (v1.0) [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.4495680>

¹³Rajuladevi, Rohit Srinivas, et al. "Impact of Seeding and Spatial Heterogeneity on Metapopulation Disease Dynamics." *epiDAMIK 5.0: The 5th International workshop on Epidemiology meets Data Mining and Knowledge discovery at KDD 2022*. 2022.

Use of PatchSim for COVID-19 Response

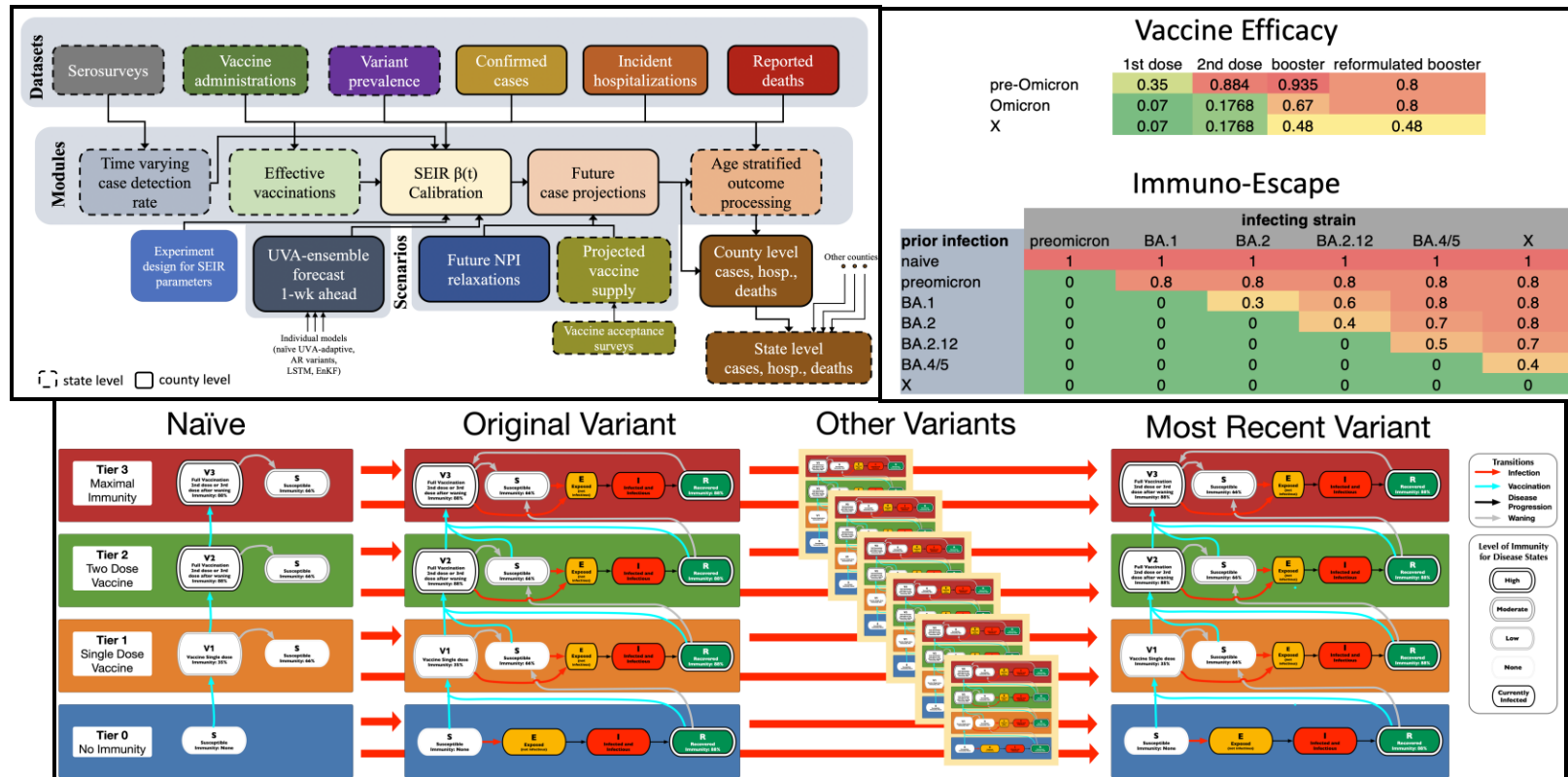
- UVA-BI used PatchSim for providing modeling support to the Commonwealth of Virginia¹⁵ during the pandemic
- **Approach:** County level model with commuter traffic. Implemented interventions as temporal transmissibility changes.
- **Impact:** Saved **\$60-100 million** for the Commonwealth by informing decision to pause construction of field hospitals



¹⁵Lilian Peake, COVID-19 Modeling for Virginia, April 16, 2020.

PatchSim as a simulation engine

- PatchSim variations have also been developed to model tiered multi-strain dynamics¹⁶ within a single patch for CDC Scenario Modeling Hub.
- Ability to represent vaccination and transmissibility schedules makes it quite versatile for real-time response.



¹⁶Porebski, Przemyslaw, et al. "Data-driven mechanistic framework with stratified immunity and effective transmissibility for COVID-19 scenario projections." *Epidemics* 47 (2024): 100761.

Multi-modeling for Decision Support

- **Question:** Is there consensus across modeling approaches¹⁴ for public health relevant decision making for influenza pandemics?
- **Approach** (UVA): Construct 'agentsets' by aggregating the detailed synthetic population by age and county of residence. Resulting quotient graph of the contact network is used to simulate metapopulation dynamics.
- **Key Finding:** Even when models differ in spatial resolution and datasets, ranking of interventions are robust.

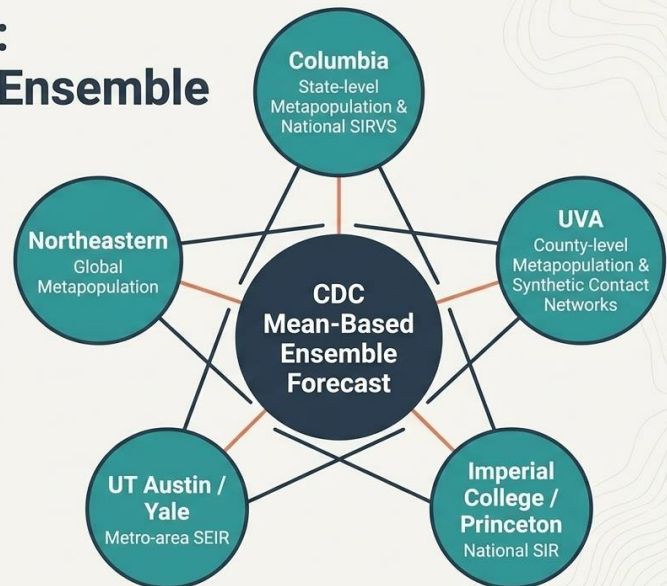
Policy Application: The CDC FluCode Ensemble

The Challenge:

No single mathematical model is perfectly predictive. To inform national policy regarding layered interventions, the CDC funded a network of disparate models.

Scenarios Tested:

- 2009-like H1N1
- PAN1 (High transmission, no immunity)
- PAN2 (High transmission, high severity)



Illnesses Averted Matrix (Ensemble Average)								
Model	ENS	9%	3%	14%	20%	13%	42%	48%
	UVA	4%	0%	4%	15%	8%	34%	40%
	UTA	15%	12%	26%	37%	37%	61%	64%
	NEU	3%	1%	10%	32%	0%	39%	59%
	IMP	4%	1%	6%	33%	39%	58%	55%
	COL2	6%	2%	9%	7%	-6%	29%	25%
	COL	24%	7%	33%	3%	4%	35%	47%
	2009-2	2009-3	2009-4	2009-5	2009-6	2009-7	2009-8	
Scenario								

¹⁴Prasad, Pragati V., et al. "Multimodeling approach to evaluating the efficacy of layering pharmaceutical and nonpharmaceutical interventions for influenza pandemics." *Proceedings of the National Academy of Sciences* 120.28 (2023): e2300590120.

Key Insights and Lessons Learned

- **Strategic Balance:** Metapopulation models provide the "sweet spot" for real-time response—balancing complexity and speed.
- **Data Flexibility:** High-fidelity mobility data from cell phone traces or synthetic bimodal networks based on GIS can drive accurate model construction in regions with varying data availability.
- **Hybrid Synergies:** The future lies in combining metapopulation's scalability with ABM-informed contact matrices within key location types.
- **Preparedness:** Open-source simulators (**PatchSim**) and networks (**PatchFlow**) are vital for rapid "what-if" projection during emerging outbreaks

Resources

PatchSim: <https://github.com/nssac/patchsim>



Funding Acknowledgments:



PatchFlow: <https://github.com/nssac/patchflow-data>

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