

Multi-agent systems for pandemic modeling and response

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AAMAS'21 Tutorial



BIOCOMPLEXITY INSTITUTE

 <https://biocomplexity.virginia.edu>

Slides at: <http://bit.ly/AAMAS21-COVID19-SV>

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Overview

- Background
- Pandemic modeling and MAS
- Agent-based modeling for epidemics
- COVID-19 response examples
- Challenges and path ahead



Who are we?

Biocomplexity Institute & Initiative at the University of Virginia

- 60+ researchers spanning multiple disciplines studying massively interactive systems
- “From molecules to policy”
- Sustained program in computational epidemiology for nearly two decades funded by multiple US federal agencies (DoD, NIH, NSF, CDC)
- Real-time decision support for multiple outbreaks/epidemics: H1N1, Ebola, Zika, COVID-19



Network Systems Science & Advanced Computing Division

- Using the lens of networks to understand complex systems
- Simulation science aided by high-performance computing

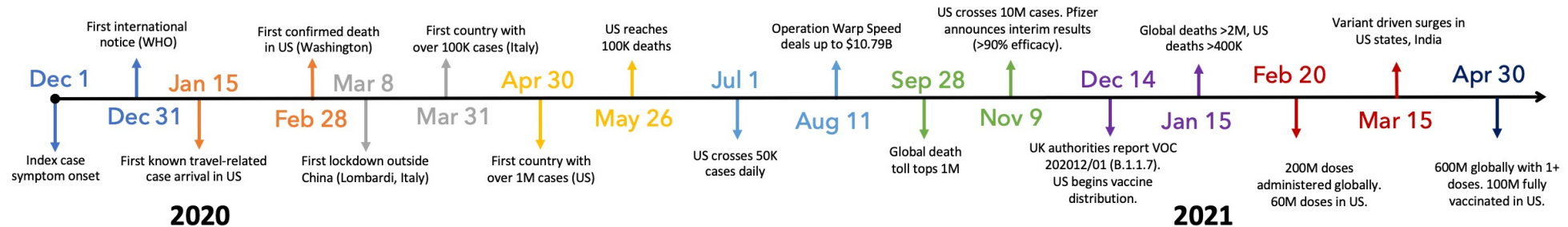


COVID-19 response support

80+ scientists, staff, and students at UVA and collaborating institutions



60+ weeks of modeling briefs to public health agencies



Federal agencies

- U.S. Department of Defense
- Centers for Disease Control
- U.S. Department of Health and Human Services



Commonwealth of Virginia

- Primary modeling for planning and response efforts
- Press conference with Governor's office
- Virginia Department of Emergency Management
- Virginia Department of Health



Virginia Department of
Emergency Management



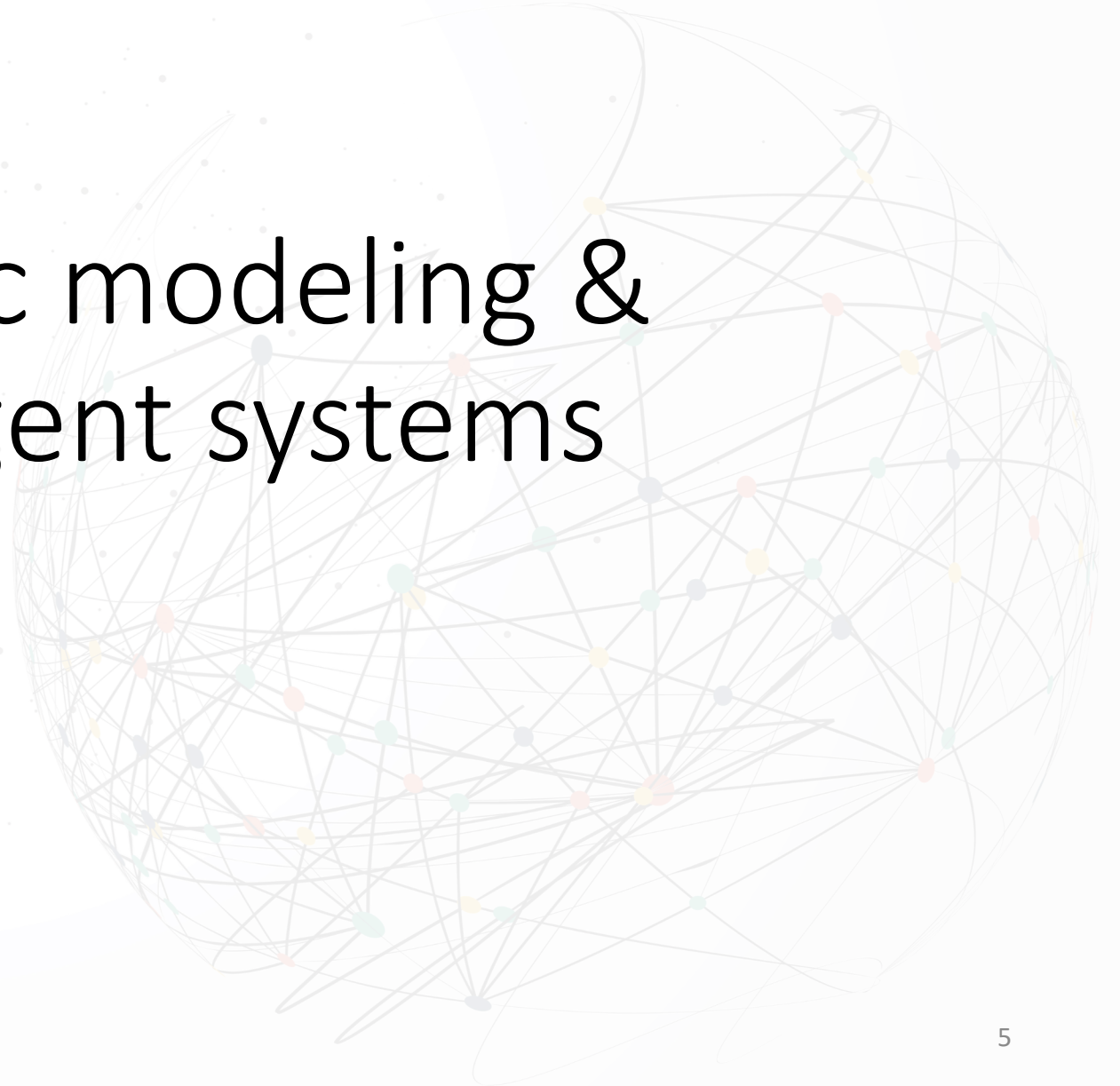
Local agencies

- Local and state hospitals
- Various UVA departments and UVA Medical Center
- Virginia Commonwealth University
- Virginia Hospital and Healthcare Association (comprised of 27-member health systems and 110 community and specialty hospitals)



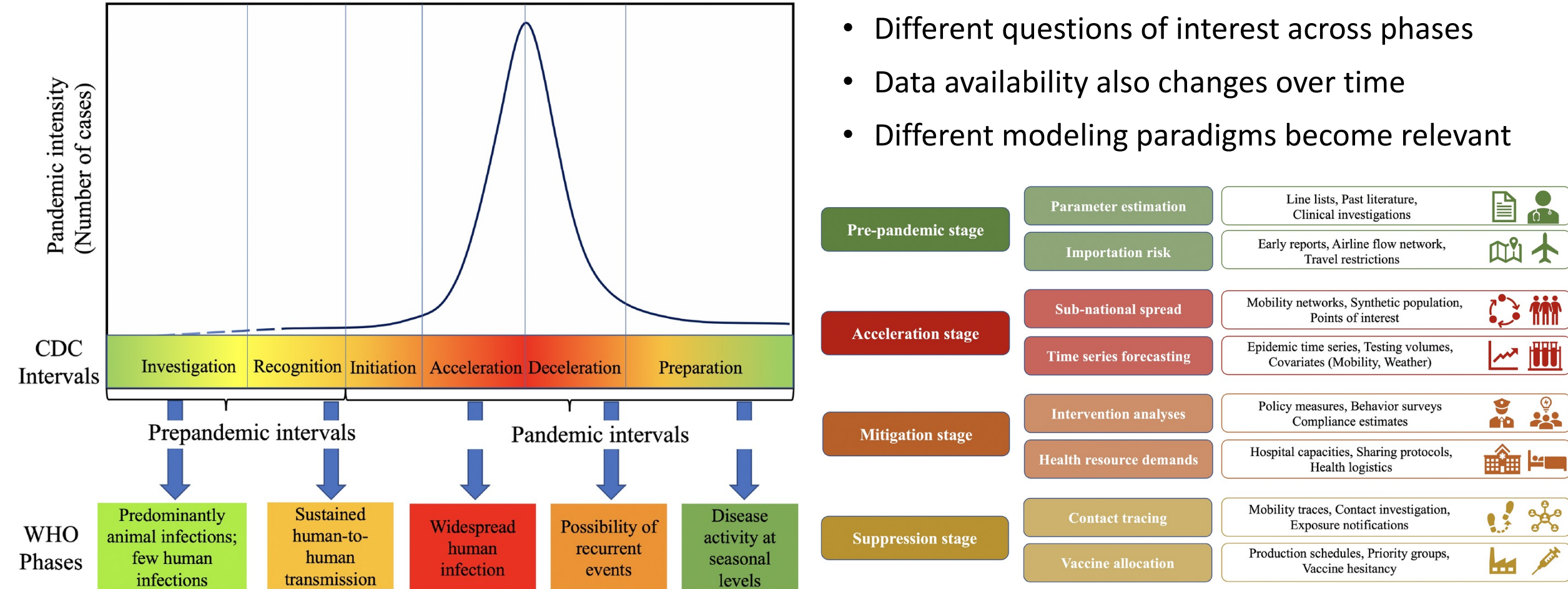
<https://covid19.biocomplexity.virginia.edu/>

Pandemic modeling & Multi-agent systems



Modeling for pandemic phases

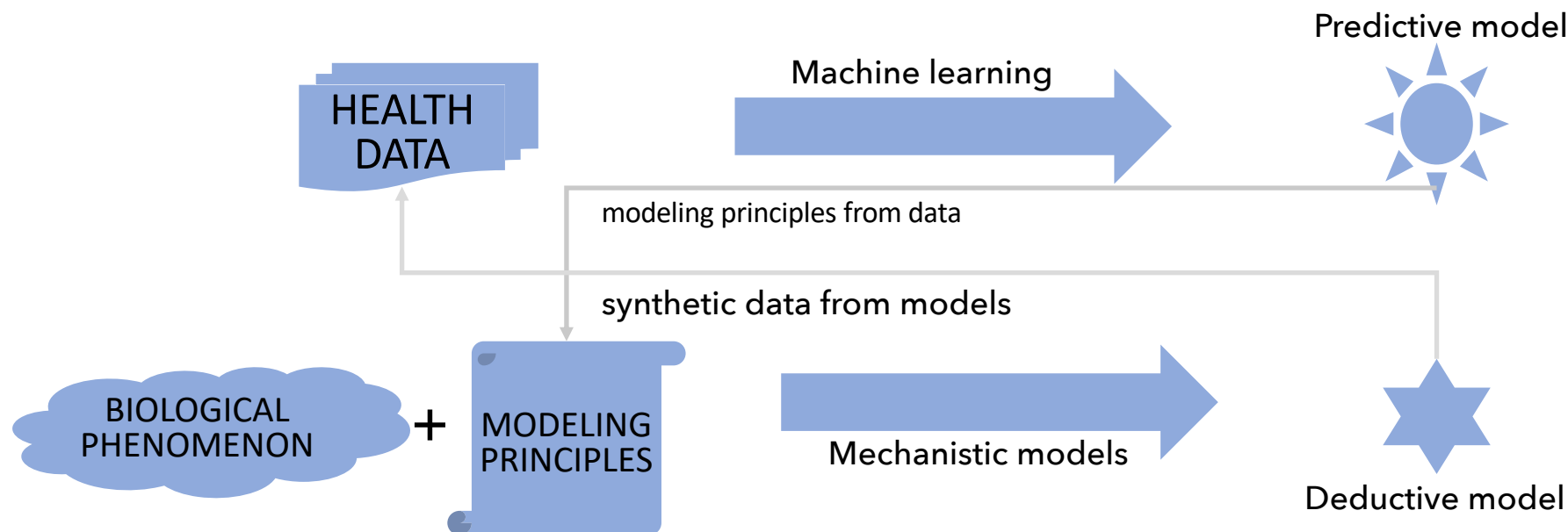
- Different questions of interest across phases
- Data availability also changes over time
- Different modeling paradigms become relevant



Adiga, Aniruddha, et al. "Data-driven modeling for different stages of pandemic response." Journal of the Indian Institute of Science (2020): 1-15

Computational Models

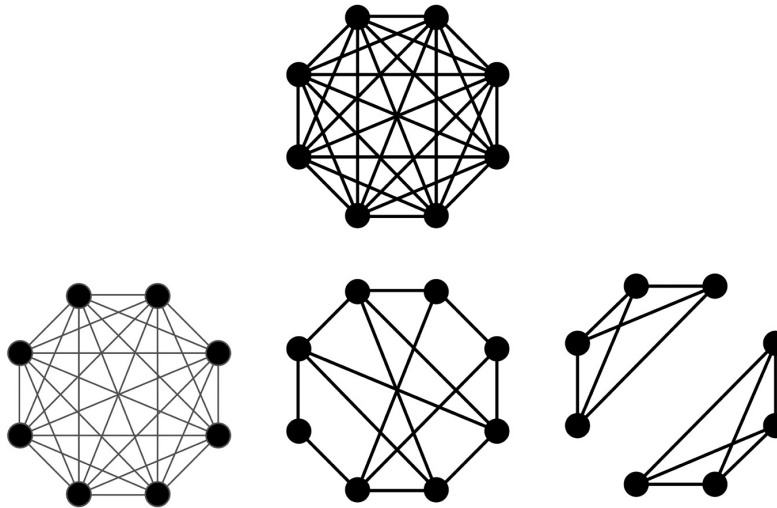
Machine learning models	Mechanistic models
Establishing a statistical (<u>correlation</u>) relationship between inputs and outputs	Establishing a mechanistic (<u>causal</u>) relationship between inputs and outputs
Requires <u>large</u> datasets, often <u>homogeneous linked</u> records	Can work with <u>small</u> datasets coming from <u>diverse</u> sources
Can only make predictions that relate to <u>patterns in the training data</u>	Once validated, can be used for <u>prediction where experiments are difficult</u> to perform



Baker, Ruth E., et al. "Mechanistic models versus machine learning, a fight worth fighting for the biological community?." *Biology letters* 14.5 (2018): 20170660.

Disease modeling - Primer

- SIR model – proposed in 1927 by Kermack and McKendrick
- Early insights into controlling the disease spread
 - Social distancing, Better protection – ↓ transmission/mixing rate
 - Testing and Case isolation - ↓ infectious period
 - Herd immunity and implications for vaccination
- Homogeneous assumption
 - misses network effects
 - spatial and social heterogeneities
 - “reducing contacts by half”

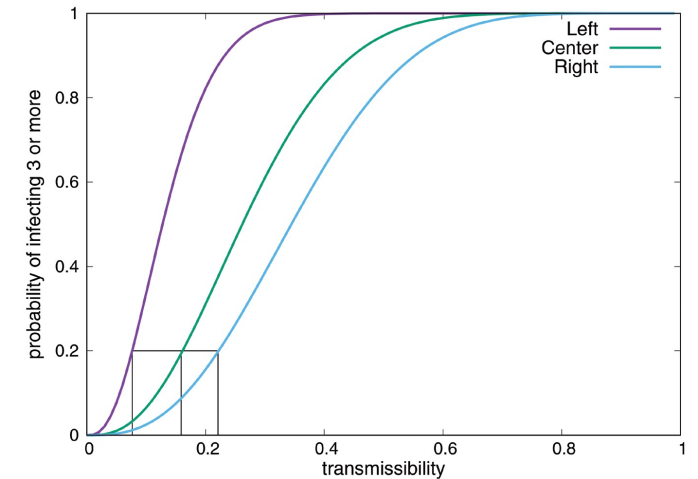


$$\frac{dI}{dt} = \beta IS - \gamma I$$

$$\frac{dS}{dt} = -\beta IS$$

$$\frac{dR}{dt} = \gamma I$$

β - transmission/mixing rate
 $1/\gamma$ - mean infectious period

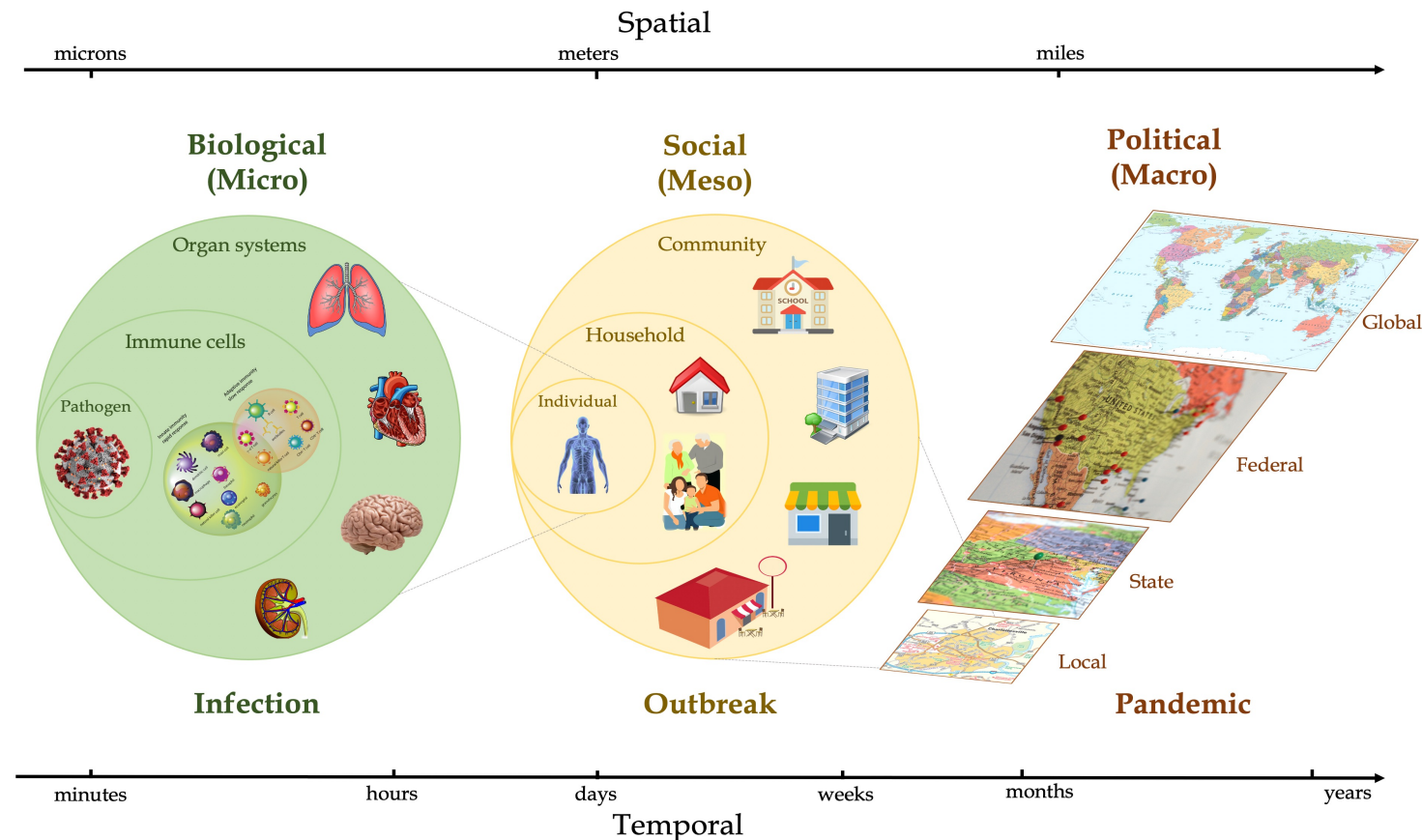


Spatial and temporal scales

- Processes unfolding across multiple scales
 - From within host to global response
- Spatial and Social Interaction Scale
 - Individuals to Communities to Countries

Capturing heterogeneity via multi-scale, multi-theory, multi-level network representations

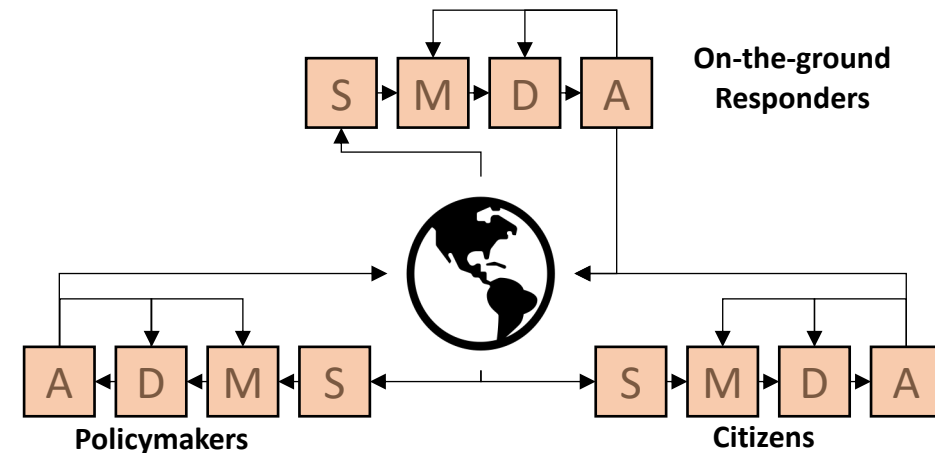
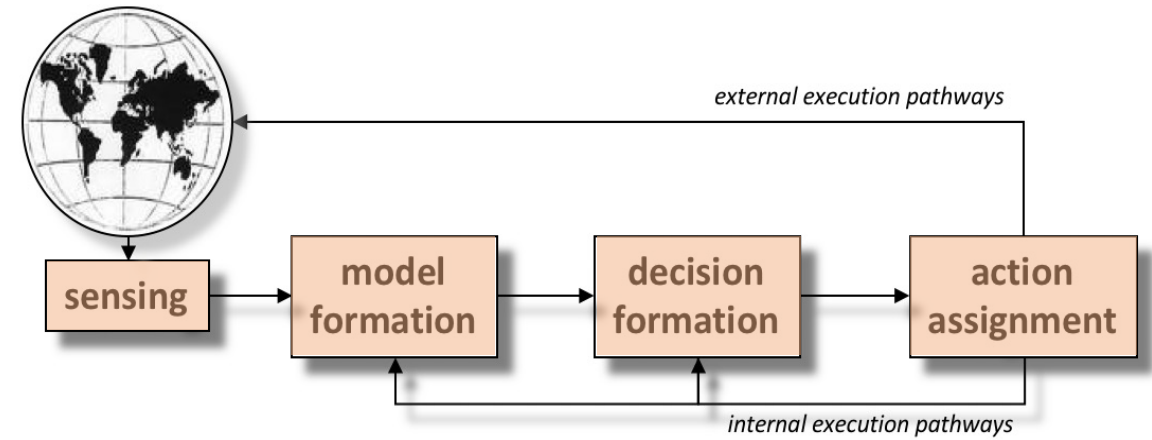
Agent-based representations mostly used in the 'Meso' + partly 'Macro' scale.



Decision making across social scales

- Agent-based representations are also relevant for the decentralized decision making occurring in such systems.
- Individual and collective behavior
 - Varying and sometimes conflicting objectives
 - Information asymmetry & spheres of influence

Context-specific, decentralized information seeking and decision making across socio-political scales



Sources

Census records



Online surveys



Smartphones



Public health



Clinical studies



Datasets

Demographics



Behaviors



Mobility



Surveillance



Interventions



Disease parameters



Sources

Census records



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Mobility



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Interventions



Disease parameters



Models

Analytics



Statistical



Machine learning



Metapopulation

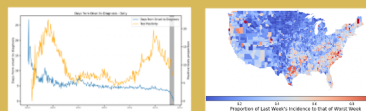


Agent-based

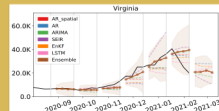


Tasks

Situation assessment



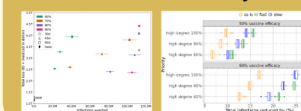
Forecasting



Projections

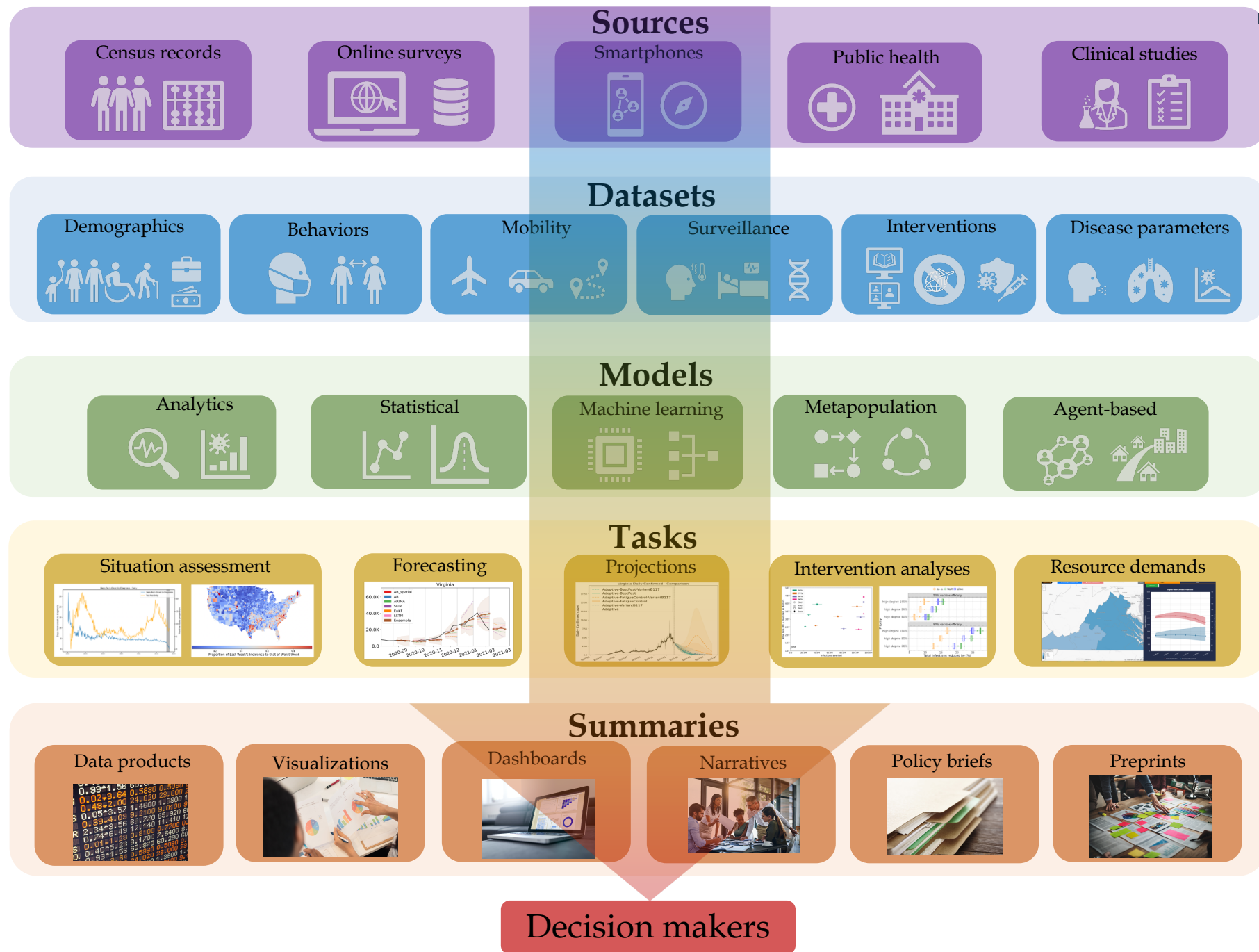


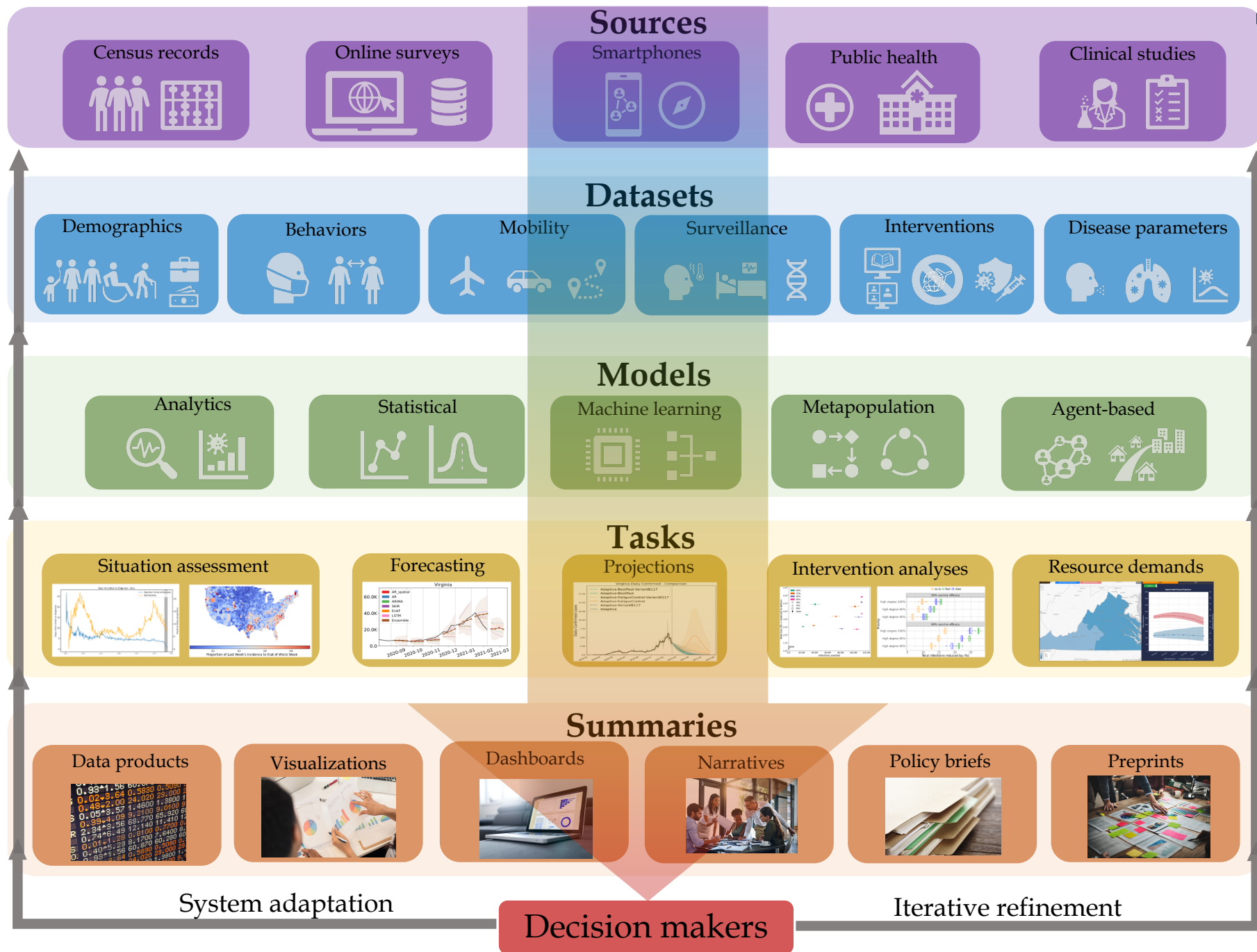
Intervention analyses

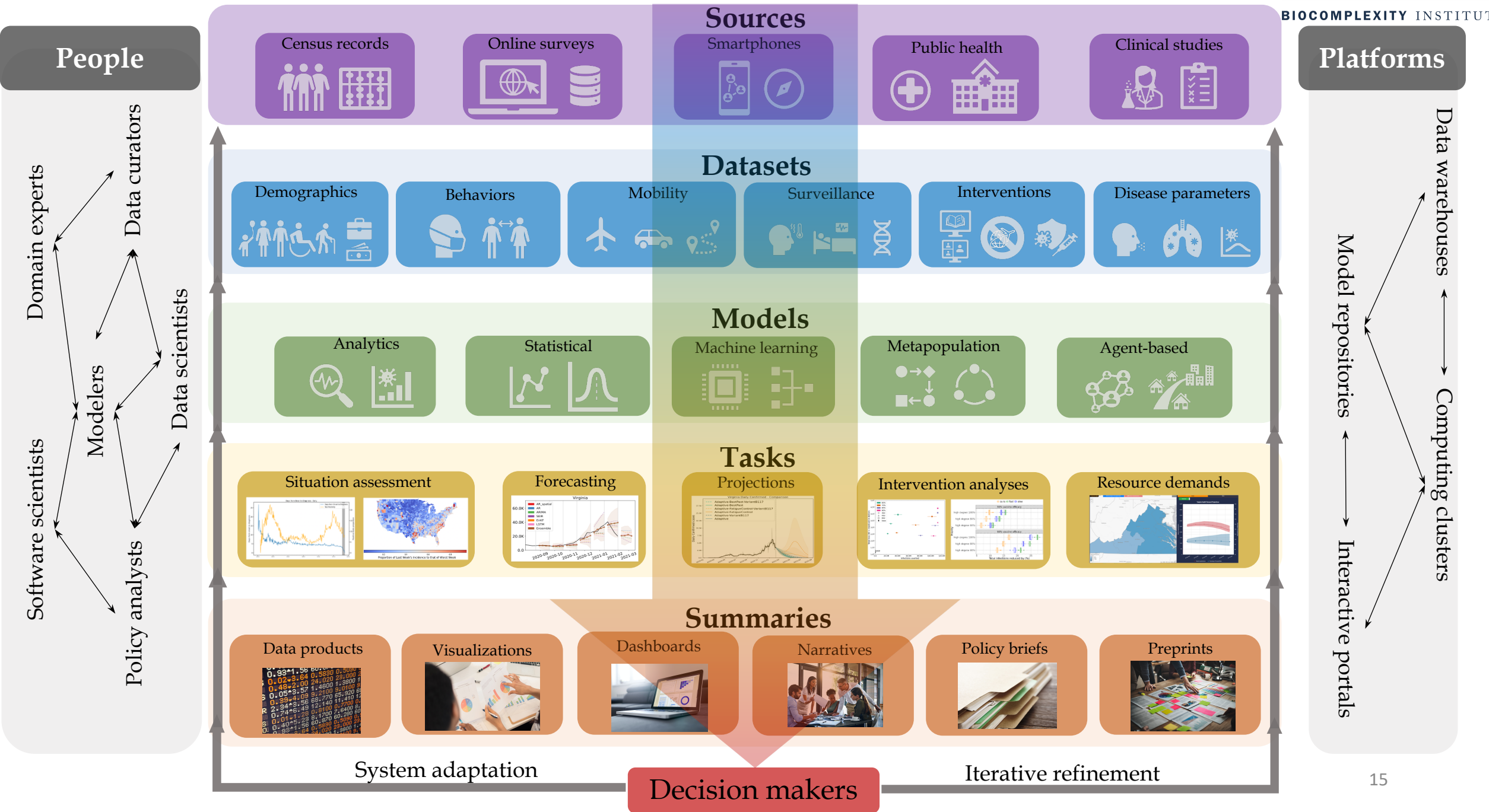


Resource demands









Agent-based modeling for epidemics



History of ABMs for Epidemic modeling

- Early representations were built upon work from other domains (e.g., transportation)

Published: 13 May 2004

Modelling disease outbreaks in realistic urban social networks

Stephen Eubank , Hasan Guclu, V. S. Anil Kumar, Madhav V. Marathe, Aravind Srinivasan, Zoltán Toroczkai & Nan Wang

Nature **429**, 180–184(2004) | [Cite this article](#)

6826 Accesses | **1131** Citations | **161** Altmetric | [Metrics](#)

- Multi-model studies were conducted to evaluate various targeted layered containment strategies for pandemic influenza

Modeling targeted layered containment of an influenza pandemic in the United States

M. Elizabeth Halloran, Neil M. Ferguson, Stephen Eubank, Ira M. Longini Jr., Derek A. T. ...

[+ See all authors and affiliations](#)

PNAS March 25, 2008 105 (12) 4639–4644; <https://doi.org/10.1073/pnas.0706849105>

- Comparisons between different computational approaches have been (and continue to be) studied

Research article | [Open Access](#) | Published: 29 June 2010

Comparing large-scale computational approaches to epidemic modeling: Agent-based versus structured metapopulation models

Marco Ajelli, Bruno Gonçalves, Duygu Balcan, Vittoria Colizza, Hao Hu, José J Ramasco, Stefano Merler & Alessandro Vespignani 

BMC Infectious Diseases **10**, Article number: 190 (2010) | [Cite this article](#)

Use of ABMs for recent epidemics

THE LANCET Infectious Diseases

Volume 15, Issue 2, February 2015, Pages 204-211



Articles

Spatiotemporal spread of the 2014 outbreak of Ebola virus disease in Liberia and the effectiveness of non-pharmaceutical interventions: a computational modelling analysis

Stefano Merler MS ^a, Marco Ajelli PhD ^a, Laura Fumanelli PhD ^a, Marcelo F C Gomes PhD ^b, Ana Pastore y Piontti PhD ^b, Luca Rossi PhD ^c, Dennis L Chao PhD ^d, Prof Ira M Longini Jr PhD ^e, Prof M Elizabeth Halloran DSc ^{d, f}, Prof Alessandro Vespignani PhD ^{b, g} ✉



Epidemics

Volume 22, March 2018, Pages 43-49



Using data-driven agent-based models for forecasting emerging infectious diseases

Srinivasan Venkatramanan ^a ✉, Bryan Lewis ^a ✉, Jiangzhuo Chen ^a ✉, Dave Higdon ^{b, c} ✉, Anil Vullikanti ^{a, d} ✉, Madhav Marathe ^{a, d} ✉

Hybrid agent-based modeling of Zika in the United States

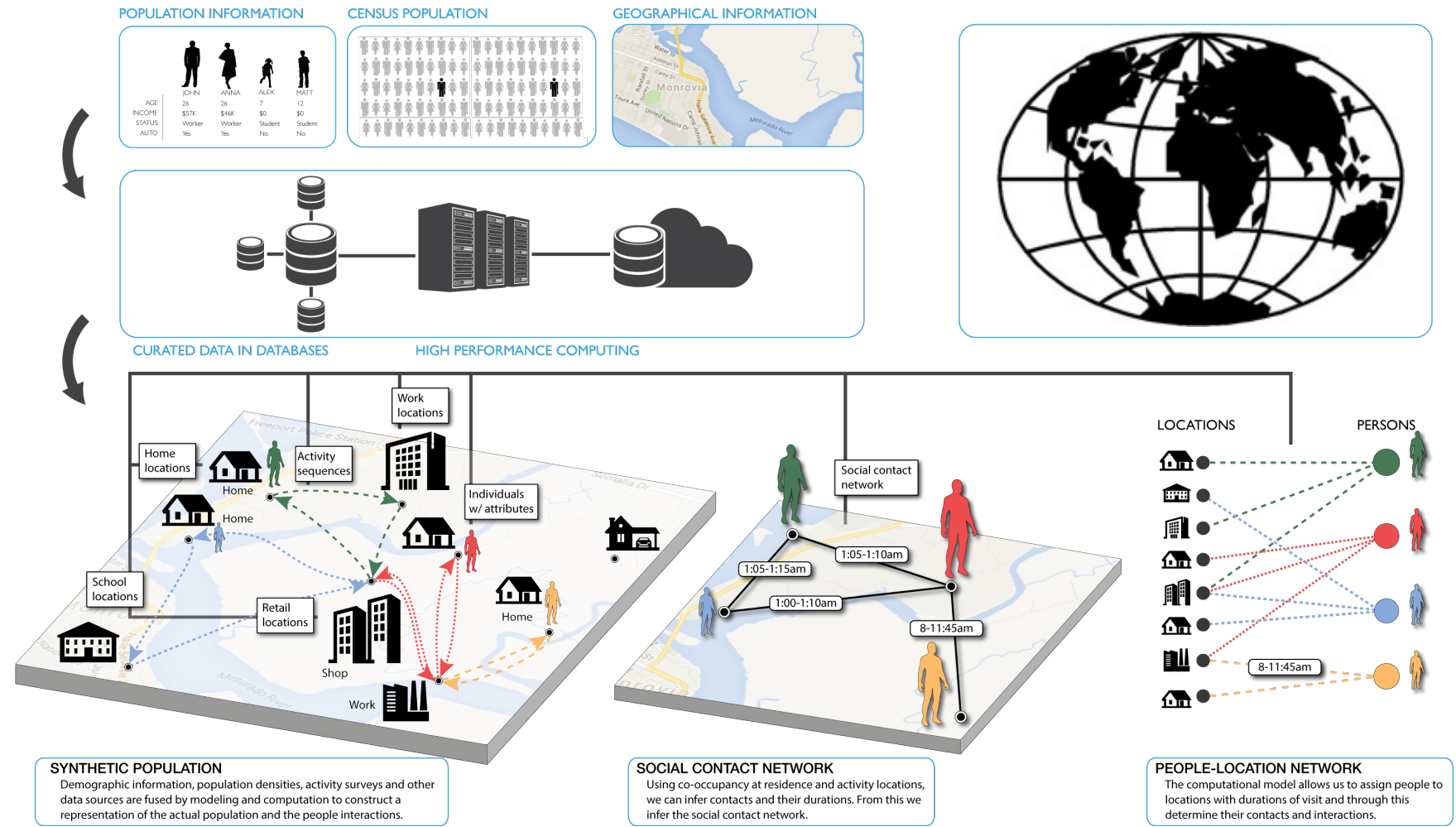


Authors: Chris J. Kuhlman, Yihui Ren, Bryan Lewis, James Schlitt [Authors Info & Affiliations](#)

Publication: WSC '17: Proceedings of the 2017 Winter Simulation Conference • December 2017 • Article No.: 80 • Pages 1–12

Synthetic populations/Digital Twins

- Agent based model for disease dynamics need a synthetic representation of the population
- Age and demographic attributes are essential to capture contact and risk
- Some of the models are spatially explicit with home and activity locations distributed using geo-datasets
- While some models assign contact rates to individuals, others simulate activity patterns which in turn result in contact

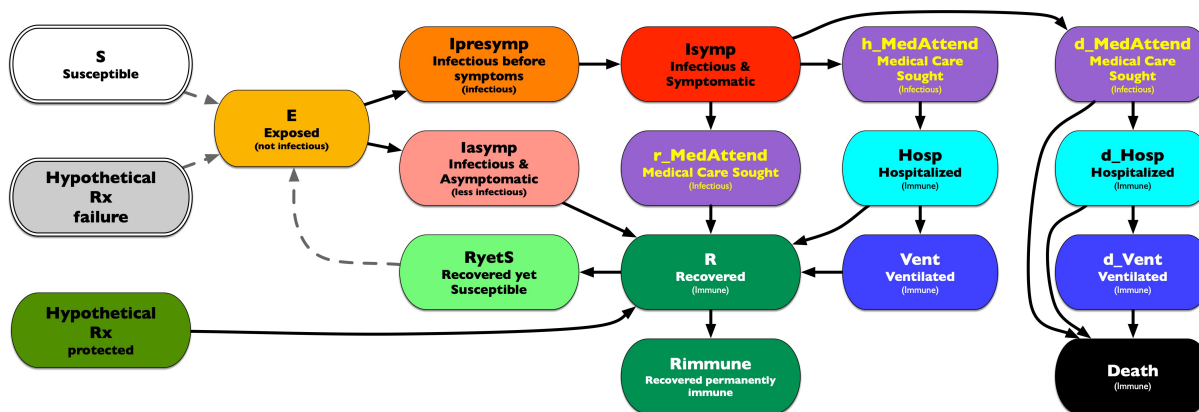


Disease model representation

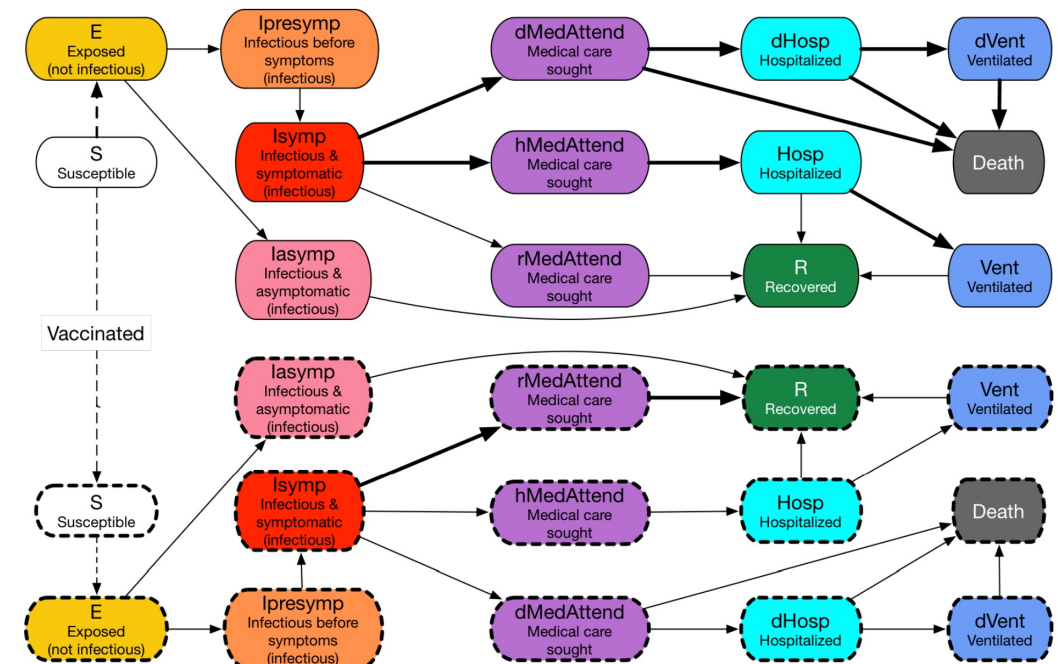
- Detailed within host representation, along with attributes such as care seeking, medical care given, etc.
- Each state has a 'dwell time' distribution as well as transition probabilities to outgoing states
- E.g.: two different ways of modeling vaccine impact and waning immunity

Models calibrated/parameterized based on coordinated planning scenarios
<https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html>

Related reading: Lipsitch, Marc, and Natalie E. Dean. "Understanding COVID-19 vaccine efficacy." *Science* 370.6518 (2020): 763-765.



All-or-nothing vaccine
 Immunity could wane over time



Vaccine reduce likelihoods of infection
 and severity (solid arrows more likely)
 Natural immunity does not wane

Pros and Cons of ABMs

- **Representational Fidelity:**
 - Detailed attributes of the population under study
 - Societal processes that impact disease dynamics
 - Within-agent representation of disease states
- **Corollaries:**
 - Fewer unexplainable parameters (compared to coarse models)
 - Ability to represent complex counterfactuals (one of the central uses of ABMs)
 - Ability to extract various data slices (e.g., demographics, region) for external validation
- **Data intensive:** Requires multiple datasets to realistically setup interaction/contact patterns
- **Modeling intensive:** Lack of data is often supplanted through models which may be difficult to validate
- **Compute intensive:** Due to their high-resolution representations, require significant computation
- **Parameter explosion:** Given the number of parameters, there may be identifiability issues

COVID-19 response examples



#1 Non-pharmaceutical interventions

Neil M Ferguson, Daniel Laydon, Gemma Nedjati-Gilani et al. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College London (16-03-2020), doi: <https://doi.org/10.25561/77482>.

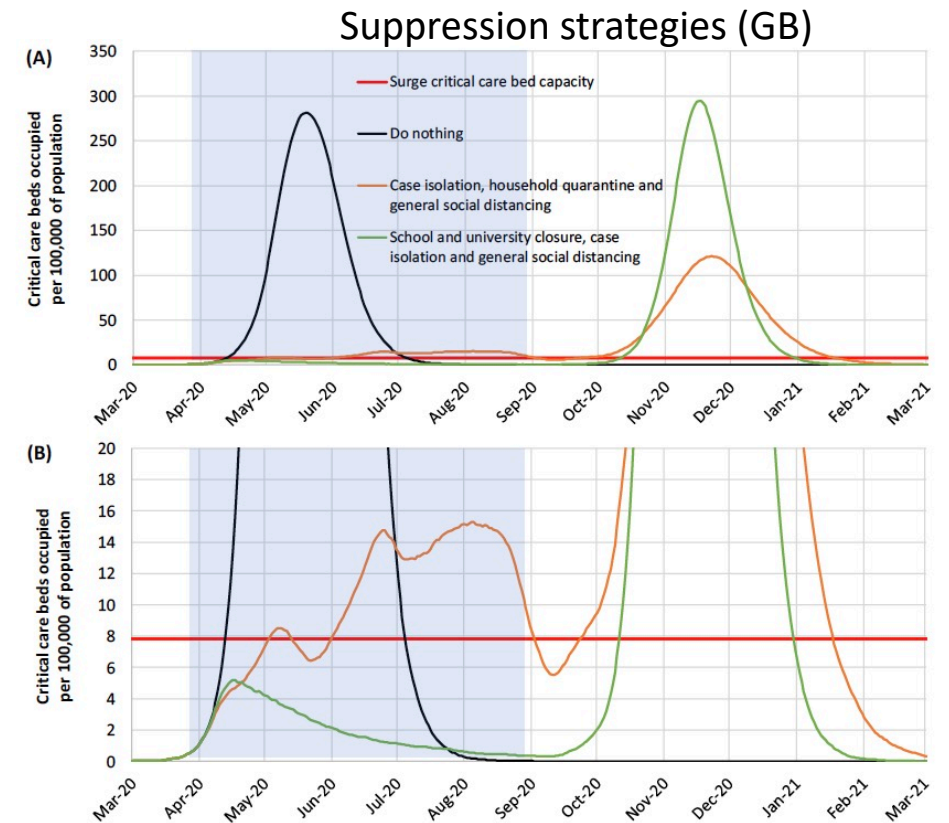
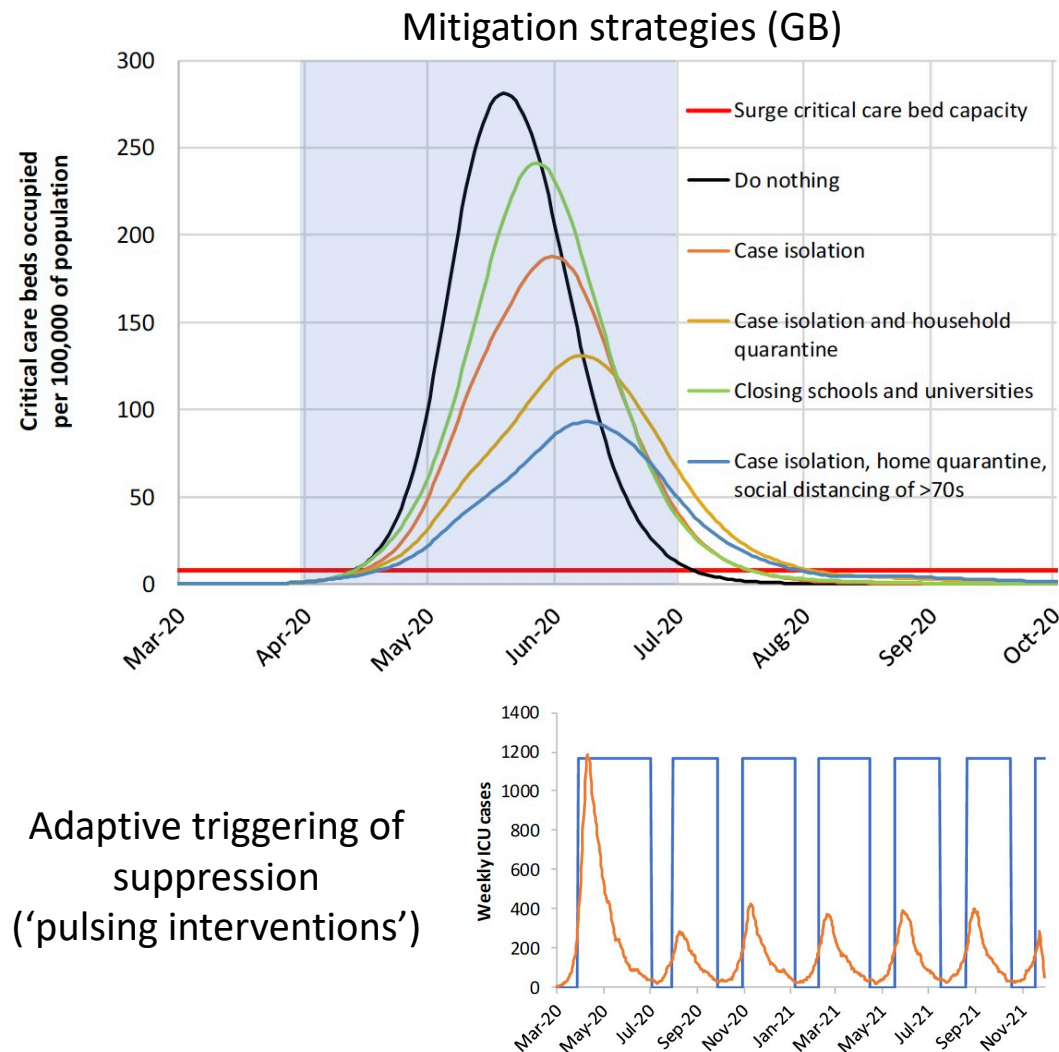
- One of the earliest COVID-19 studies to use an ABM to demonstrate the relative effectiveness of various interventions
- Had a significant impact on policymaking and general public perception of models
- Contacts occur in household, school, workplace or community and the relative rates are assigned to match influenza pandemics
- Disease parameters informed using Wuhan growth rate and other early estimates of incubation/infectious period
- “Suppression” vs “Mitigation”

Label	Policy	Description
CI	Case isolation in the home	Symptomatic cases stay at home for 7 days, reducing non-household contacts by 75% for this period. Household contacts remain unchanged. Assume 70% of household comply with the policy.
HQ	Voluntary quarantine home	Following identification of a symptomatic case in the household, all household members remain at home for 14 days. Household contact rates double during this quarantine period, contacts in the community reduce by 75%. Assume 50% of household comply with the policy.
SDO	Social distancing of those over 70 years of age	Reduce contacts by 50% in workplaces, increase household contacts by 25% and reduce other contacts by 75%. Assume 75% compliance with policy.
SD	Social distancing of entire population	All households reduce contact outside household, school or workplace by 75%. School contact rates unchanged, workplace contact rates reduced by 25%. Household contact rates assumed to increase by 25%.
PC	Closure of schools and universities	Closure of all schools, 25% of universities remain open. Household contact rates for student families increase by 50% during closure. Contacts in the community increase by 25% during closure.

Interventions under study

#1 Non-pharmaceutical interventions

Neil M Ferguson, Daniel Laydon, Gemma Nedjati-Gilani et al. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College London (16-03-2020), doi: <https://doi.org/10.25561/77482>.

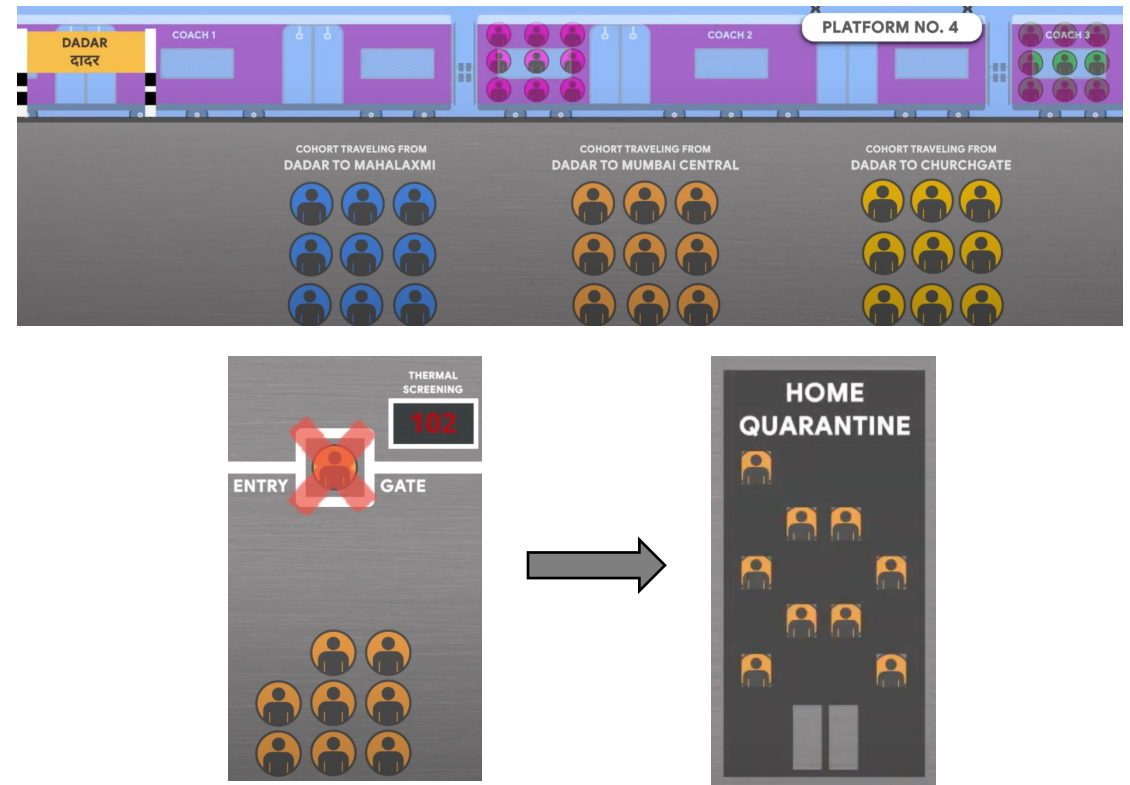


Related reading: Eubank, S., et al. "Commentary on Ferguson, et al., "Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand"." *Bulletin of mathematical biology* 82.4 (2020): 1-7

#2 Special case: Cohorting in public transit

Talekar, Alok, et al. "Cohorting to isolate asymptomatic spreaders: An agent-based simulation study on the Mumbai Suburban Railway.", *arXiv preprint arXiv:2012.12839* (2020). (extended abstract at AAMAS'21)

- Coupling city-scale agent-based simulator for Mumbai with a public-transit interaction module
- Used to understand the impact of various interventions during the phased reopening around Sep-Oct 2020
- Cohorting of passengers by source-destination tuples, and evaluating a policy of 'cohort quarantine' on detecting symptomatic cases
- Highlights how a given base simulator can be 'enhanced' or 'specialized' for targeted case studies

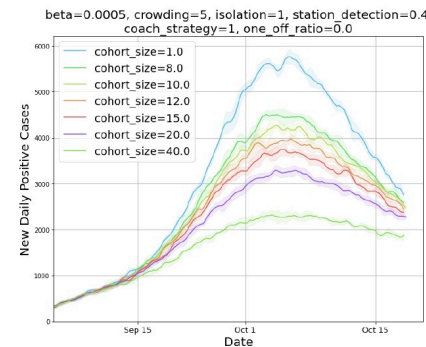


Open source IISc-TIFR city scale simulator available here:
<https://cni-iisc.github.io/epidemic-simulator/docs/index.html>

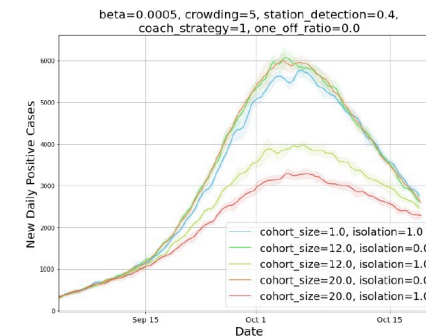
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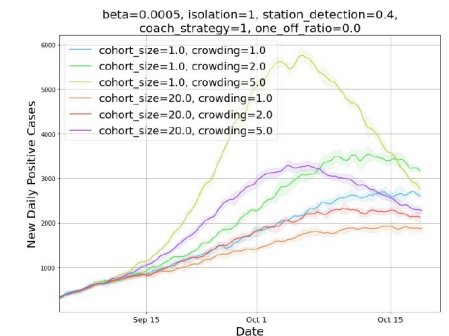
- Greater cohort sizes lead to greater reductions (but more quarantining as well)
- Marginal benefits also increase with cohort size and crowding in the coach
- Better detection strategies at stations and infection control within the coach are crucial
- Marginal benefits of assigning specific coaches to cohorts
- Continuing analyses with comparison to random flow control between hotspots



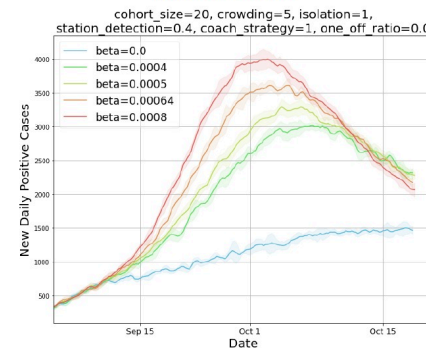
(a) Cohort size



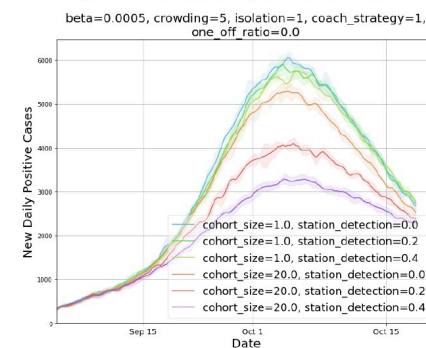
(b) Cohort intervention policy



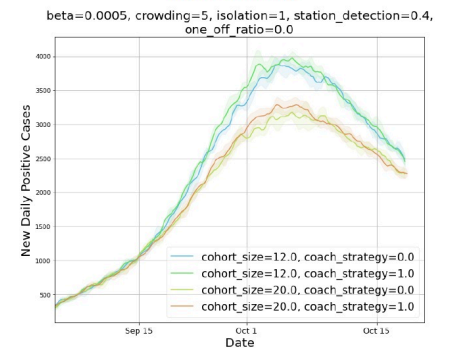
(c) Crowding



(d) β_{coach}



(e) Symptomatic detection at station

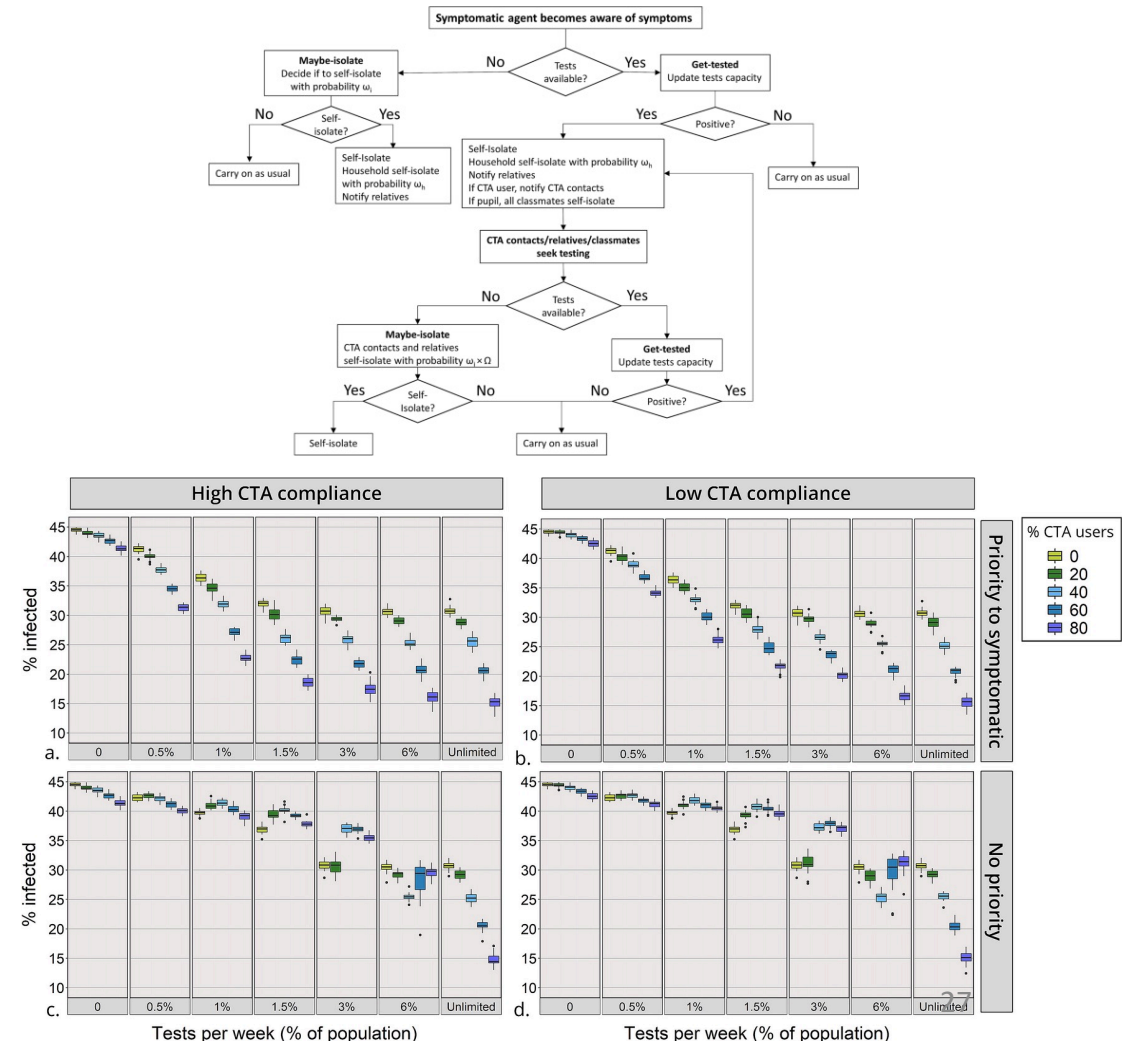


(f) Cohort-to-coach mapping strategy

#3 Special case: Contact tracing

Almagor, Jonatan, and Stefano Picascia. "Exploring the effectiveness of a COVID-19 contact tracing app using an agent-based model." *Scientific reports* 10.1 (2020): 1-11.

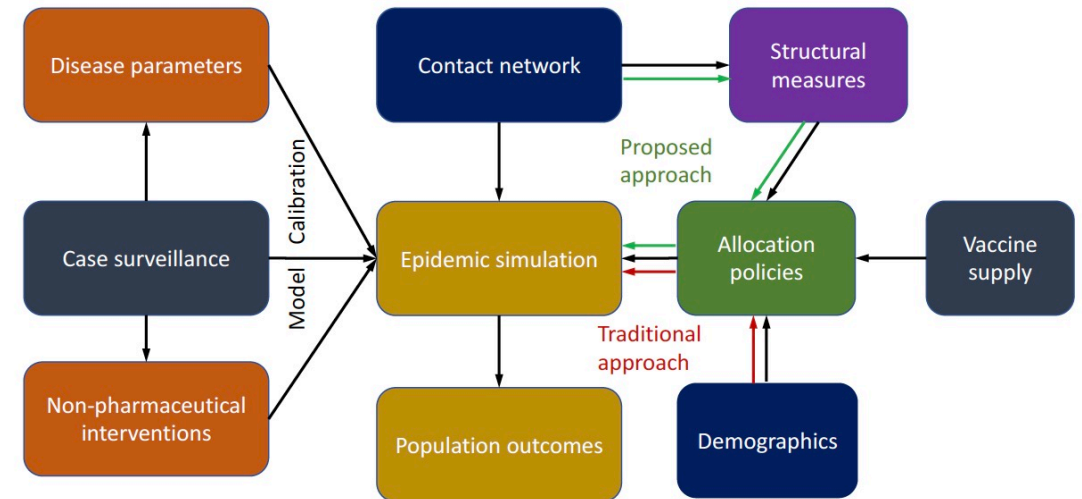
- Contact tracing apps provide an easy way to identify and notify individuals who might have had a potential exposure
- Actual uptake and compliance on the ground is spotty, yet models may allow us to understand their potential impact
- Synthetic representation of Glasgow, Scotland with assumptions on contact structure across household, school, workplace, acquaintance, public-facing, and random
- Model shows that higher adoption along with priority testing at sufficient volumes can significantly reduce the case burden.



#4 Prioritizing vaccine allocations

Chen, Jiangzhuo, et al. "Prioritizing allocation of COVID-19 vaccines based on social contacts increases vaccination effectiveness." *medRxiv* (2021)

- Vaccines allocations are usually prioritized based on age/co-morbidities or occupation status
- Under limited vaccine supply, there might be a need to minimize the overall number of infections, hospitalizations or deaths
- Using a synthetic representation of Virginia (USA), study compares existing priority schemes to degree-based schemes
- Directly related to CS/AI literature on influence maximization (or outbreak minimization) on networks.
- More realistic network, calibrated disease model, and better characterization of constraints and objective functions

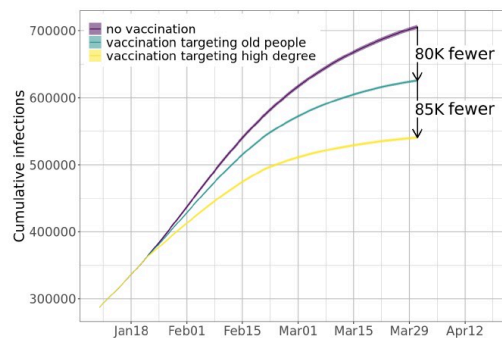


Person-person contact network with 7.6M nodes and 200M edges

#4 Prioritizing vaccine allocations

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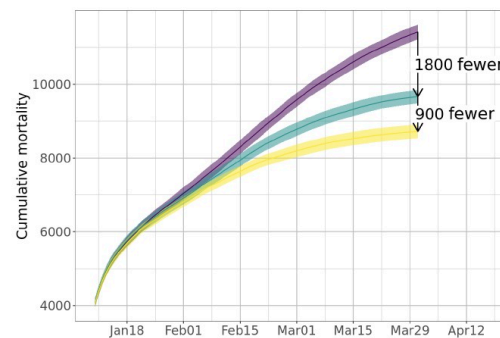
- Approach shows significant reduction across outcomes compared to age-based strategies
- Allocations are based on number of social contacts (degree) and total social proximity time
- In the real world, such structural measures can be estimated with existing digital technology



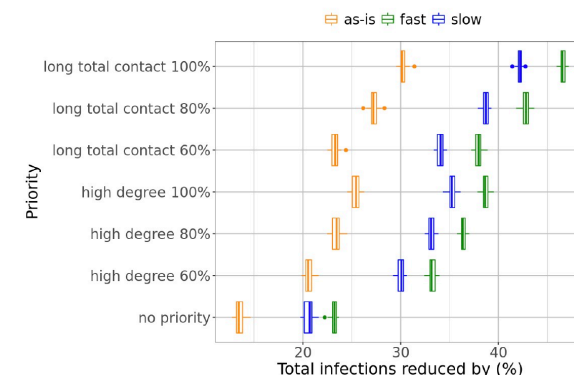
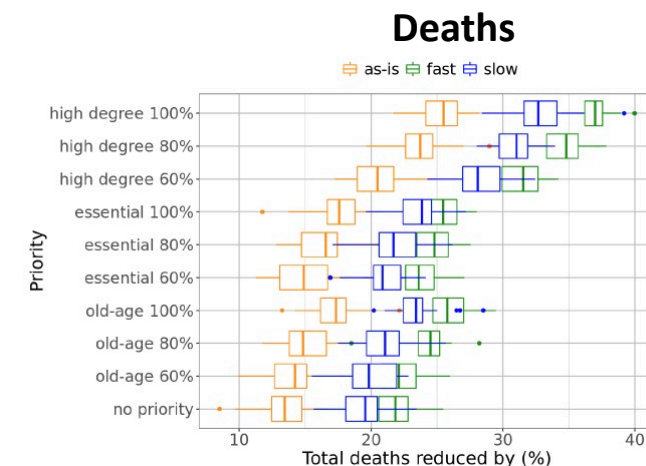
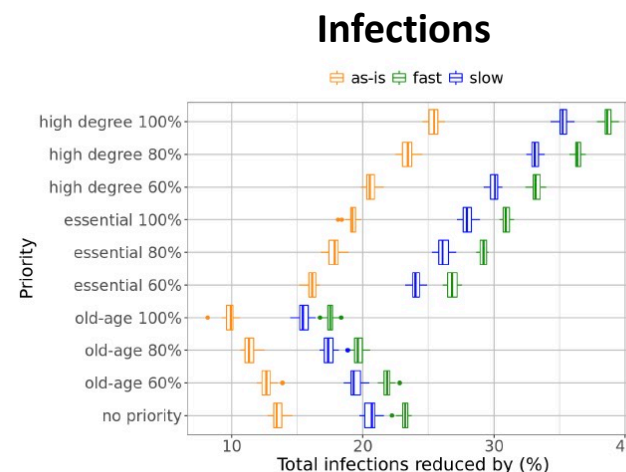
(a) Infections



(b) Hospitalizations



(c) Mortality



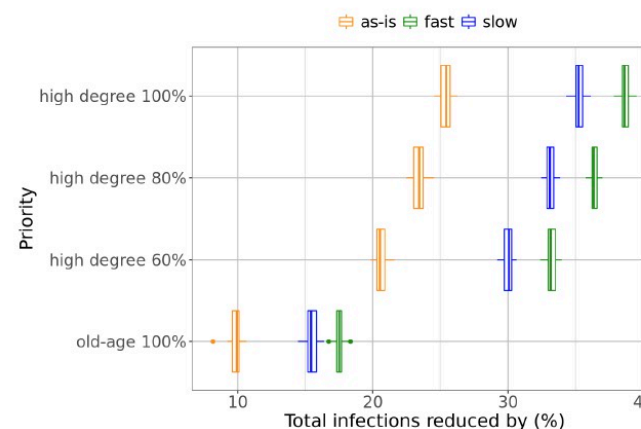
**Degree
vs
Contact
duration**

#4 Prioritizing vaccine allocations

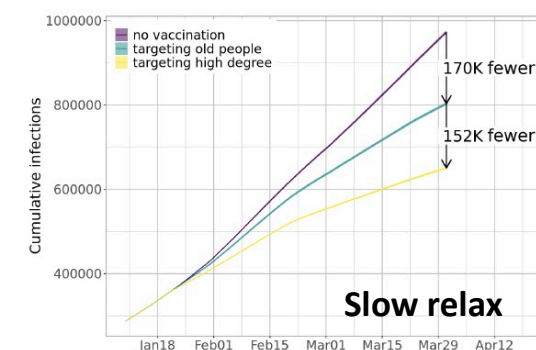
Chen, Jiangzhuo, et al. "Prioritizing allocation of COVID-19 vaccines based on social contacts increases vaccination effectiveness." *medRxiv* (2021)

- Robustness of strategy to:
 - Mis-estimation in social contacts
 - Single dose (i.e., lower vaccine efficacy)
 - Delays in vaccine logistics
 - Under various NPI assumptions
- Results are especially significant for LMICs where combinations of the above are highly likely.

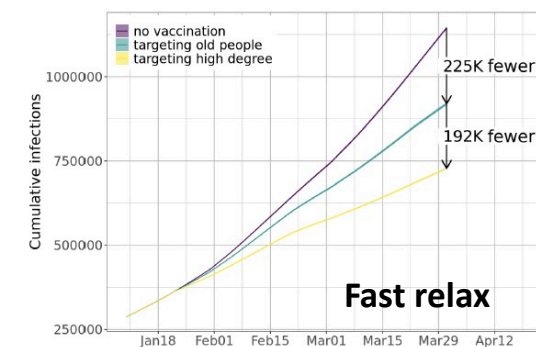
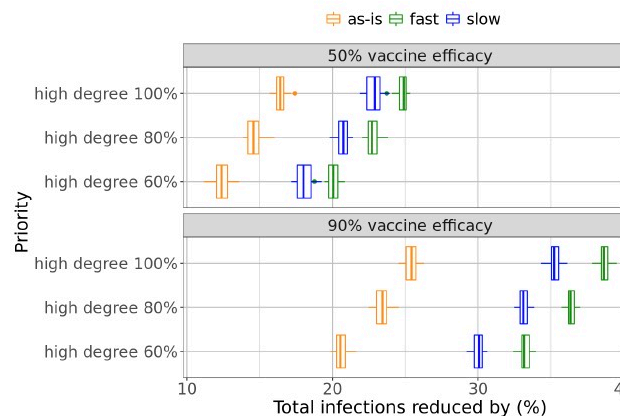
Mis-estimation



NPI relaxations



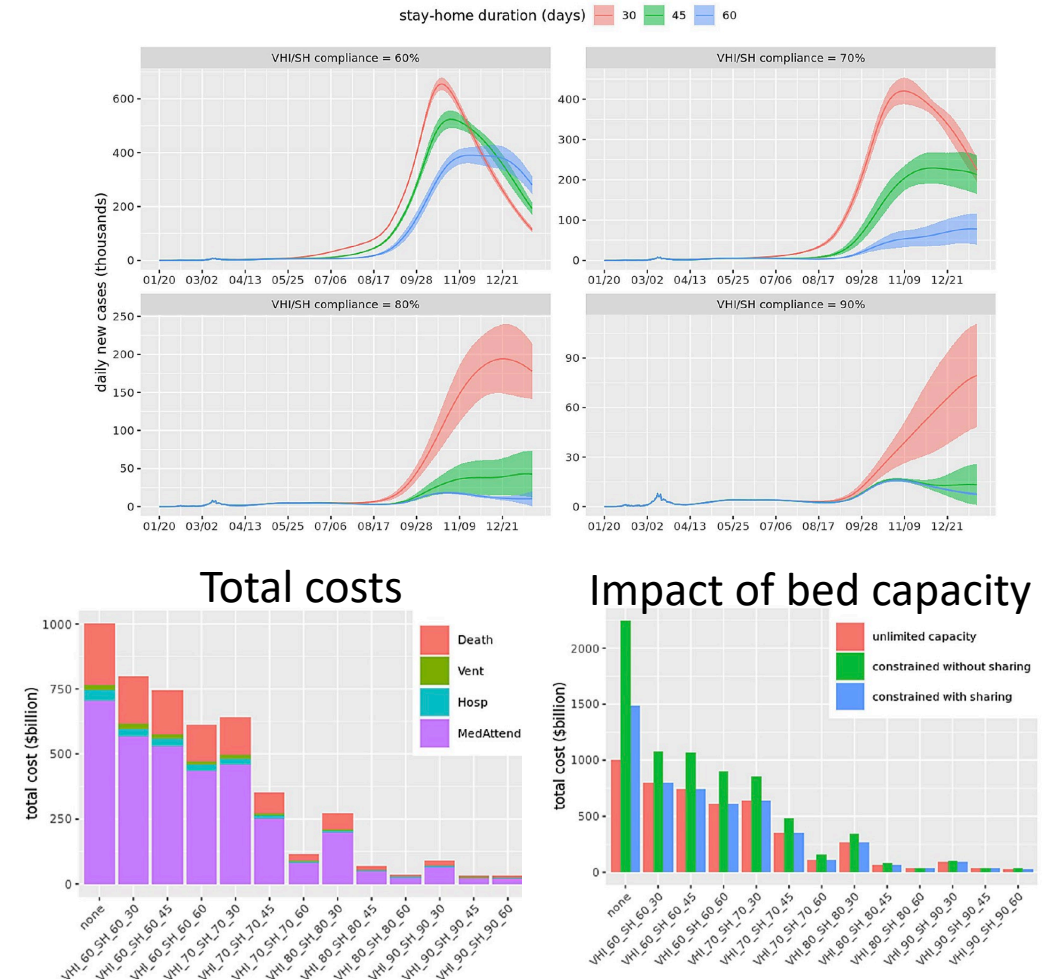
Low efficacy



#5 Medical costs of open economy

Chen, Jiangzhuo, et al. "Medical costs of keeping the US economy open during COVID-19." *Scientific reports* 10.1 (2020): 1-10.

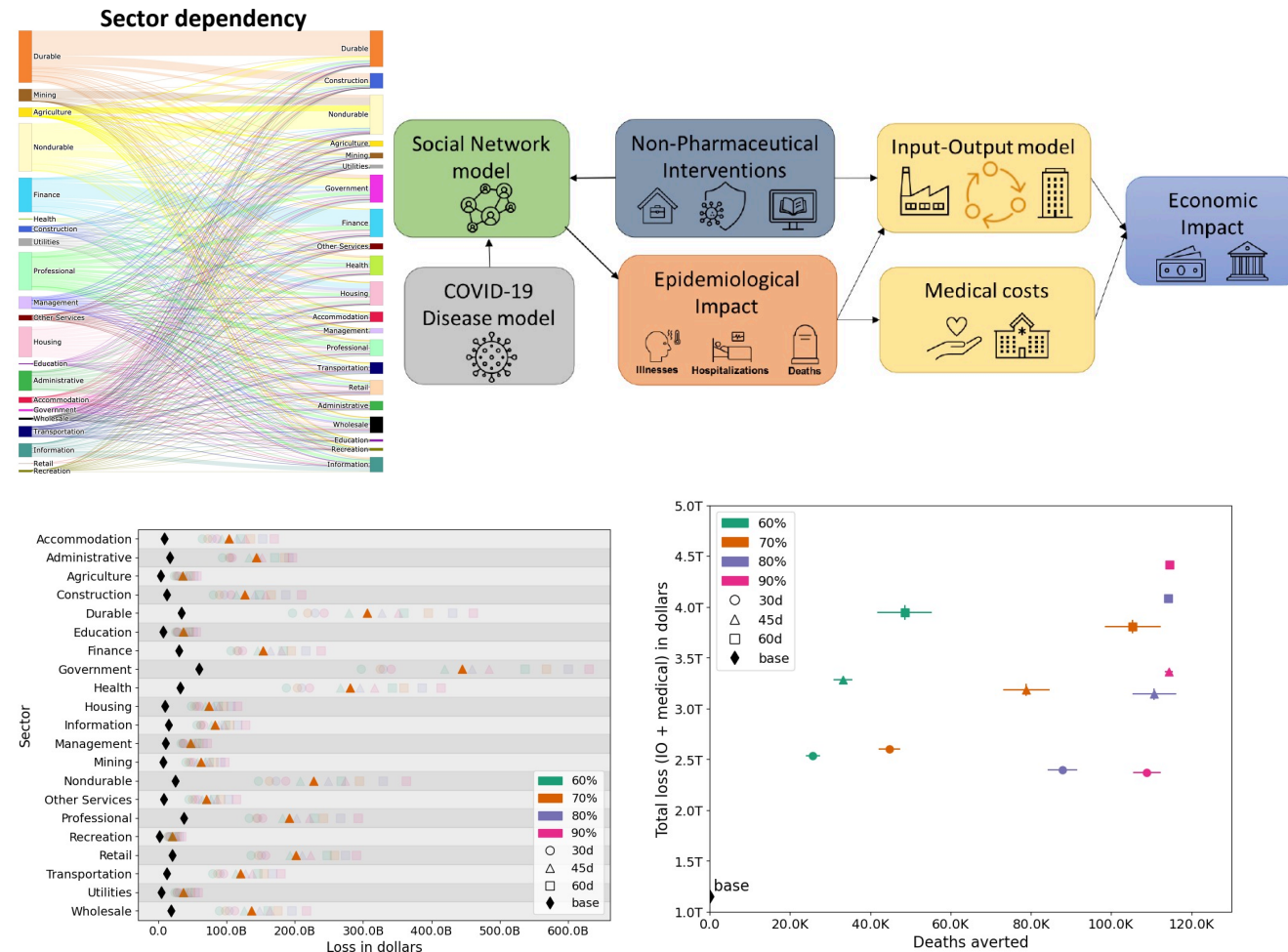
- In addition to epidemiological studies, such analyses can be used to estimate economic costs resulting from disease burden
- Provides a counter-weight to the economic costs due to stringent social distancing measures
- Study compares various stay-at-home and voluntary home isolation compliance levels to the duration of stay-at-home orders
- Simulations performed at a state level for all of US and hospital bed capacities at HRR level are used to estimate shortages.



#6 Multi-sector analyses

Chen, Jiangzhuo, et al. "Epidemiological and Economic Impact of COVID-19 in the US." *medRxiv* (2020)

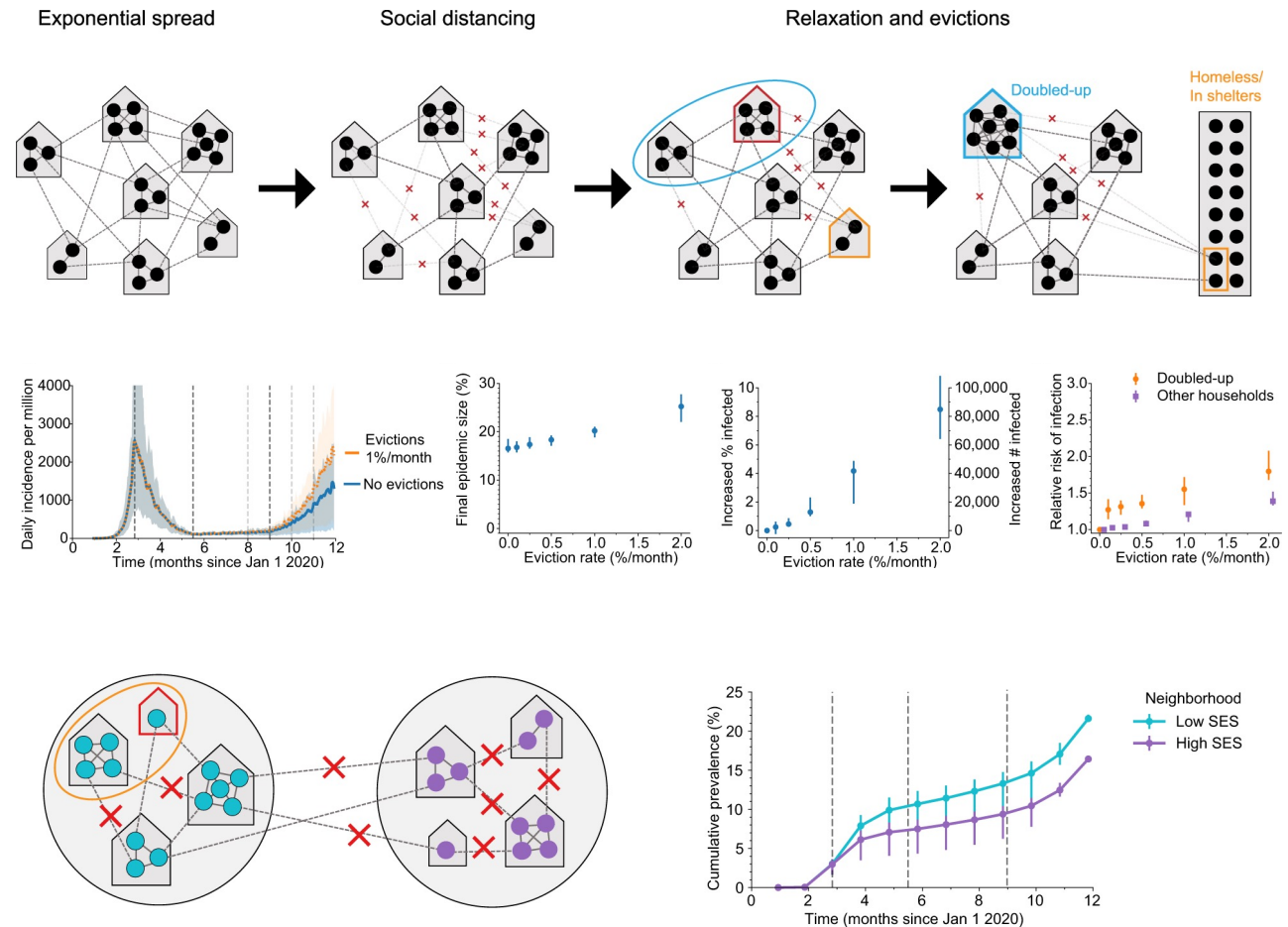
- Additionally, such models can be coupled with economic models (e.g., input-output models) capturing the inter-dependence of various sectors
- Cascading economic costs due to sick-leave, lack of telework, and other sector workforce disruptions
- Non-linear tradeoffs between economic losses and infections/deaths averted.
- Worst hit sectors are not the labor-intensive but ones with high-valued jobs even after accounting for telework
- Low compliance can be traded off with longer shutdowns for similar epi- impact but economic losses vary.



#7 Eviction moratoria and Epidemic risk

Nande, Anjalika, et al. "The effect of eviction moratoria on the transmission of SARS-CoV-2." *Nature Communications* 12.1 (2021): 1-13

- Lifting of eviction moratoria could cause significant changes in household structure
- By modeling 'doubling-up' of households, the study estimates the risks of increased infections due to such orders
- Modeling realistic contact rates for cities and demographic profiles key for estimating heterogeneous impacts
- Higher impact felt in cities with socio-economically segregated neighborhoods

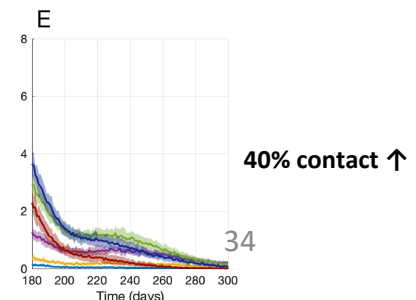
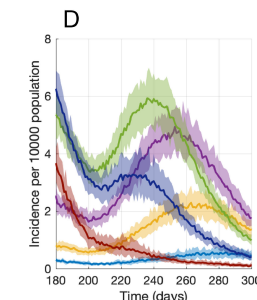
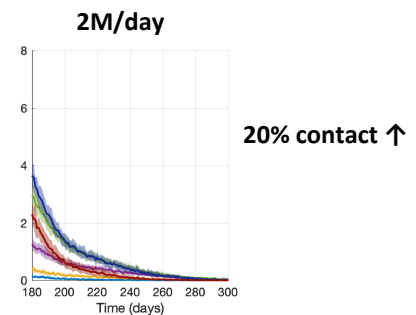
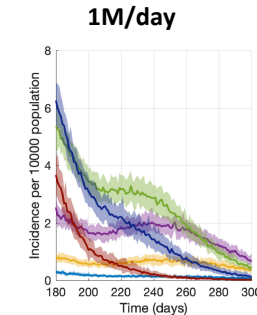
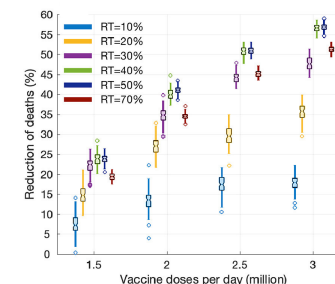
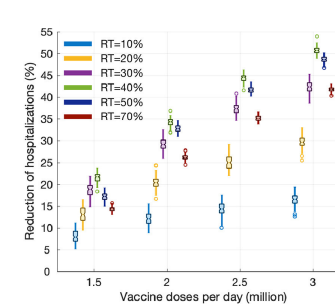
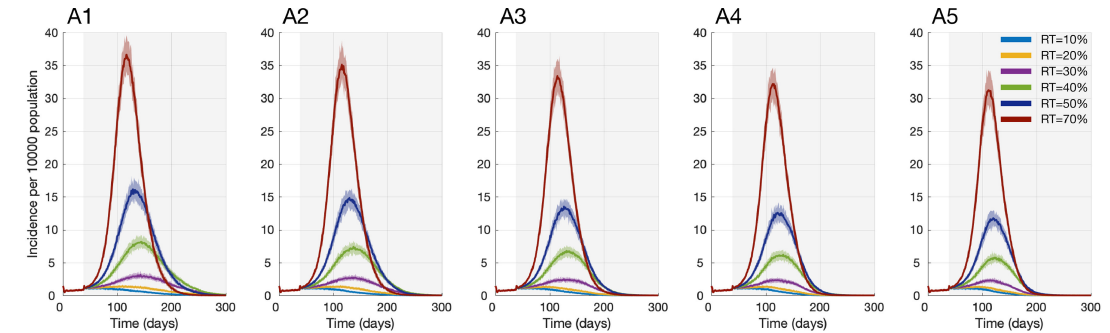


#8 Vaccines versus Variants

Sah, Pratha, et al. "Accelerated vaccine rollout is imperative to mitigate highly transmissible COVID-19 variants." *EClinicalMedicine* 35 (2021): 100865

- Increased prevalence of highly transmissible variants are behind the recent surges across several countries
- The study compares various rates of vaccination under variant prevalence to estimate the relative benefits
- Age-specific risk and contact patterns in the population
- Models SGTF variant (as ~10-70% more transmissible) co-circulating with the wild type (vaccine efficacy unaltered)
- Shows current* rates of vaccinations may not outpace variant surge and increased rollout might be needed to minimize the burden
- This is especially important when NPI compliance rates might be decreasing over time

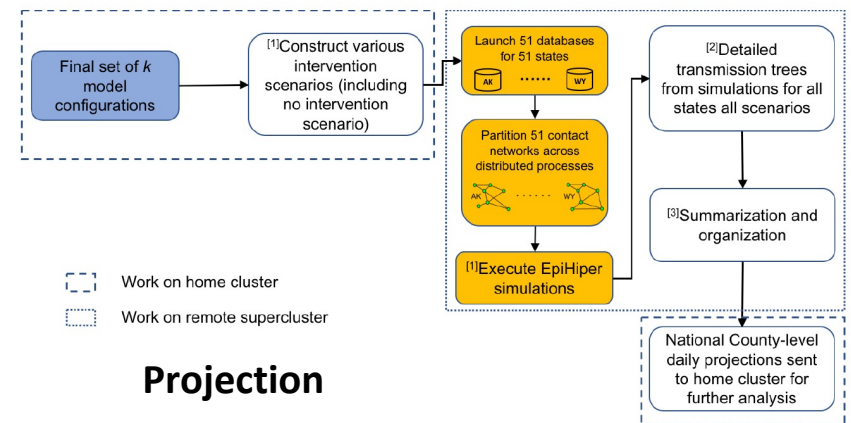
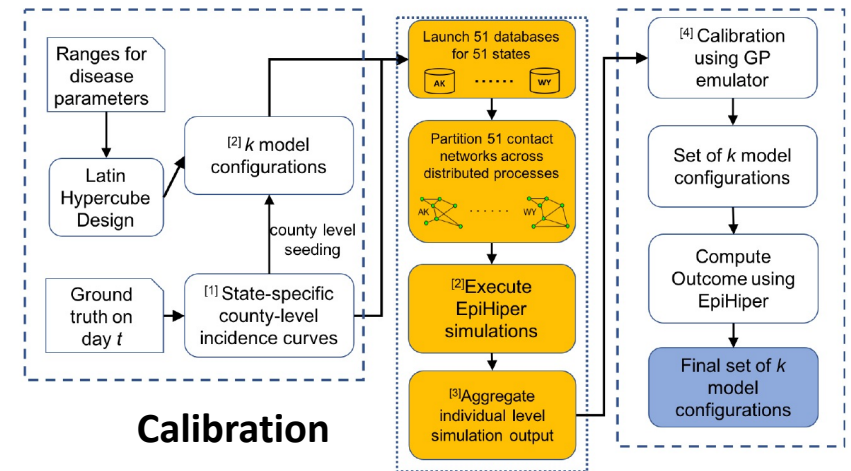
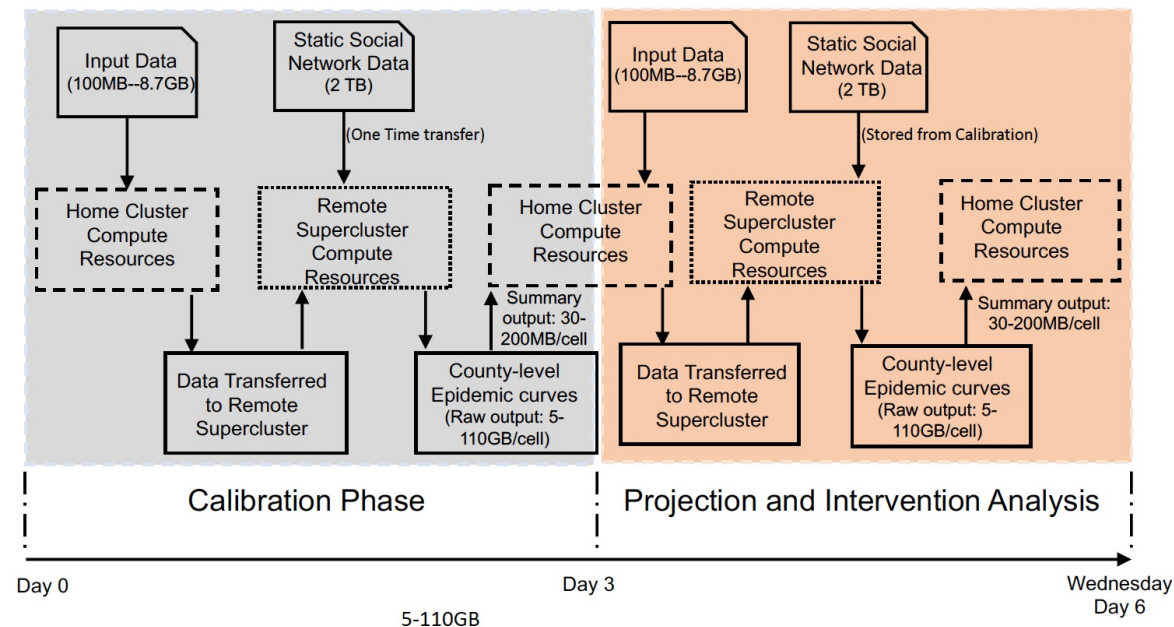
Moderna doses per day: (A1) 1 million; (A2) 1.5 million; (A3) 2 million; (A4) 2.5 million; or (A5) 3 million



Challenges and Path ahead

Scalable epidemiological workflows

- Agent-based models are computationally intensive and often require HPC-enabled workflows to support real-time planning and response
- National scale models (~330M individuals for US and billions of edges)
- Need for hybrid cloud/cluster systems with minimal human intervention (yet to be fully reached)



Machi, Dustin, et al. "Scalable epidemiological workflows to support covid-19 planning and response." *medRxiv* (2021). To appear in IPDPS 2021

Improved decision-making models for agents

- Need better integration of cognitive models into the agent-based simulation
- Studying network effects of existing cognitive/behavioral models
- Coupled contagions (Infodemic + Pandemic) across multiple networks
- Ascertaining the real impact of ‘fog of war’ scenarios
- Will lead to better representation of decision making ‘in the wild’
- Agent ‘types’ to represent hierarchies of decision making
 - individual vs store owner vs policymaker

Bhattacharya, Parantapa, et al. "The Matrix: An agent-based modeling framework for data intensive simulations." *Proceedings of the 18th International Conference on Autonomous Agents and Multi Agent Systems*. 2019.

Live Simulations

- Large-scale agent-based simulations that are **coupled with real-time data feeds**.
 - e.g., mobility traces, social media feeds
- Enables data integration and rapid response during disasters
- Interactive platforms for policymakers (command centers aka war rooms)
- Test-bed for evaluating various theories of human behavior and its interactions
- Relevant thrust areas:
 - Data collection/curation/synthesis/annotation/assimilation
 - Active learning, state estimation, prediction
 - Scalable simulation and analytics platforms

Honorable Mention for the Blue Sky Ideas best paper award AAMAS 2020

Swarup, Samarth, and Henning S. Mortveit. "Live Simulations." *Proceedings of the 19th International Conference on Autonomous Agents and Multiagent Systems*. 2020

Hybrid multi-scale modeling

- Choosing model scale and fidelity adaptively based on data availability
- Coupling agent-based models across scales through emulators
- Incorporating tradeoffs between response time and policy questions into model choice
- Leveraging multi-model ensembles at each scale
- Moving towards truly multi-scale, multi-theory representations of pandemics

Questions?

Slides at: <http://bit.ly/AAMAS21-COVID19-SV>

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