

Large-Scale Agent-Based Epidemiological Modeling

CLSAC 2020: Analytics for Pandemic Decision Support

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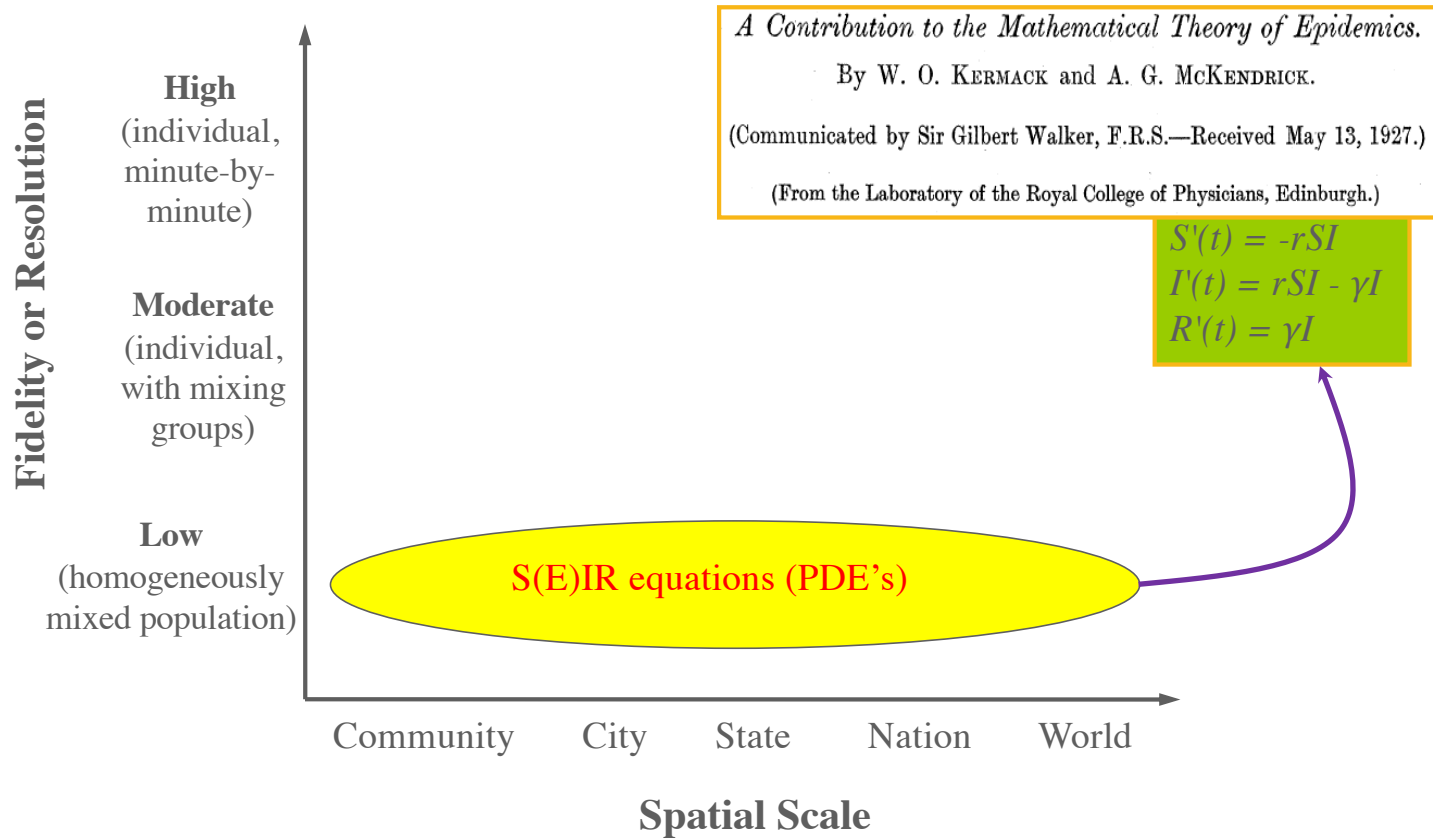
October 6, 2020



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LA-UR-20-27857

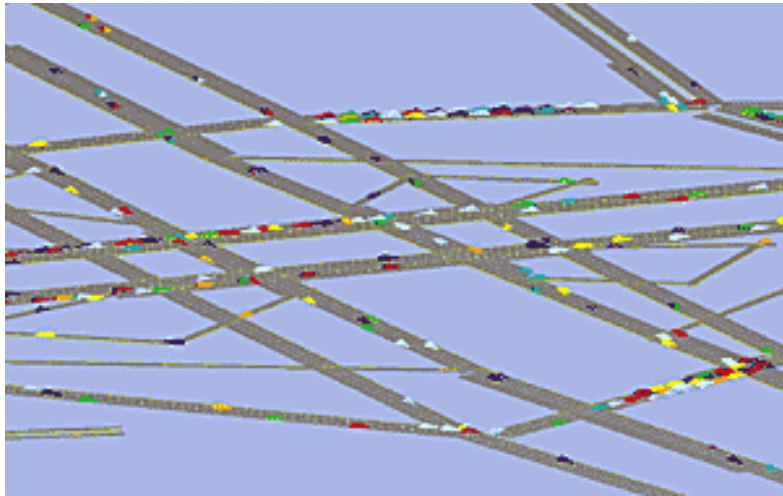
Oversimplified Epidemiological Model Landscape



LANL has a long history applying agent-based simulation to real-world issues

■ Transportation Simulation System (TRANSIMS)

- TRANSIMS is an event-driven agent-based simulation developed at LANL for simulating movement of people on the transportation system



■ The Epidemic Simulation System (EpiSimS) is derived from TRANSIMS

- EpiSimS is an agent-based simulation developed at LANL for simulating the spread of epidemics at the level of individuals



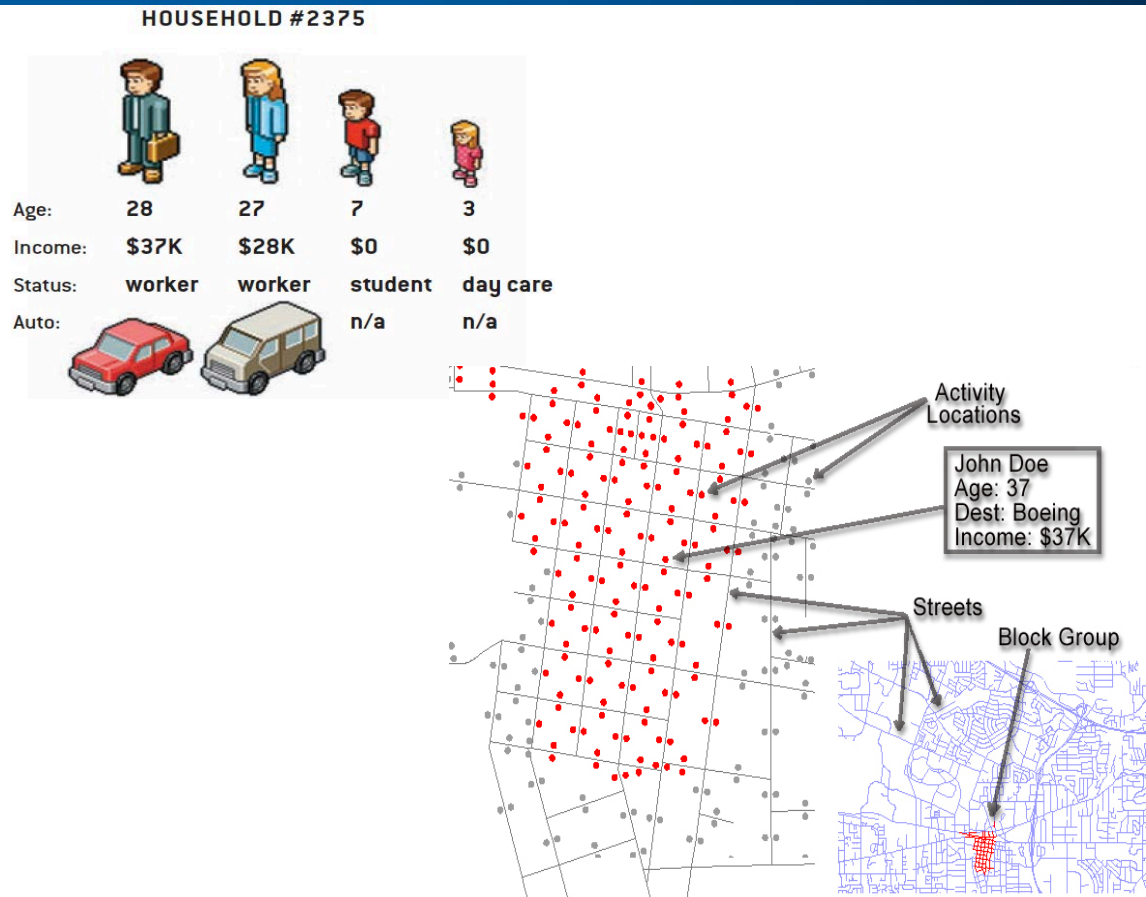
Epidemic Simulation System (EpiSimS)

■ Agent-based model to simulate disease spread in large regions

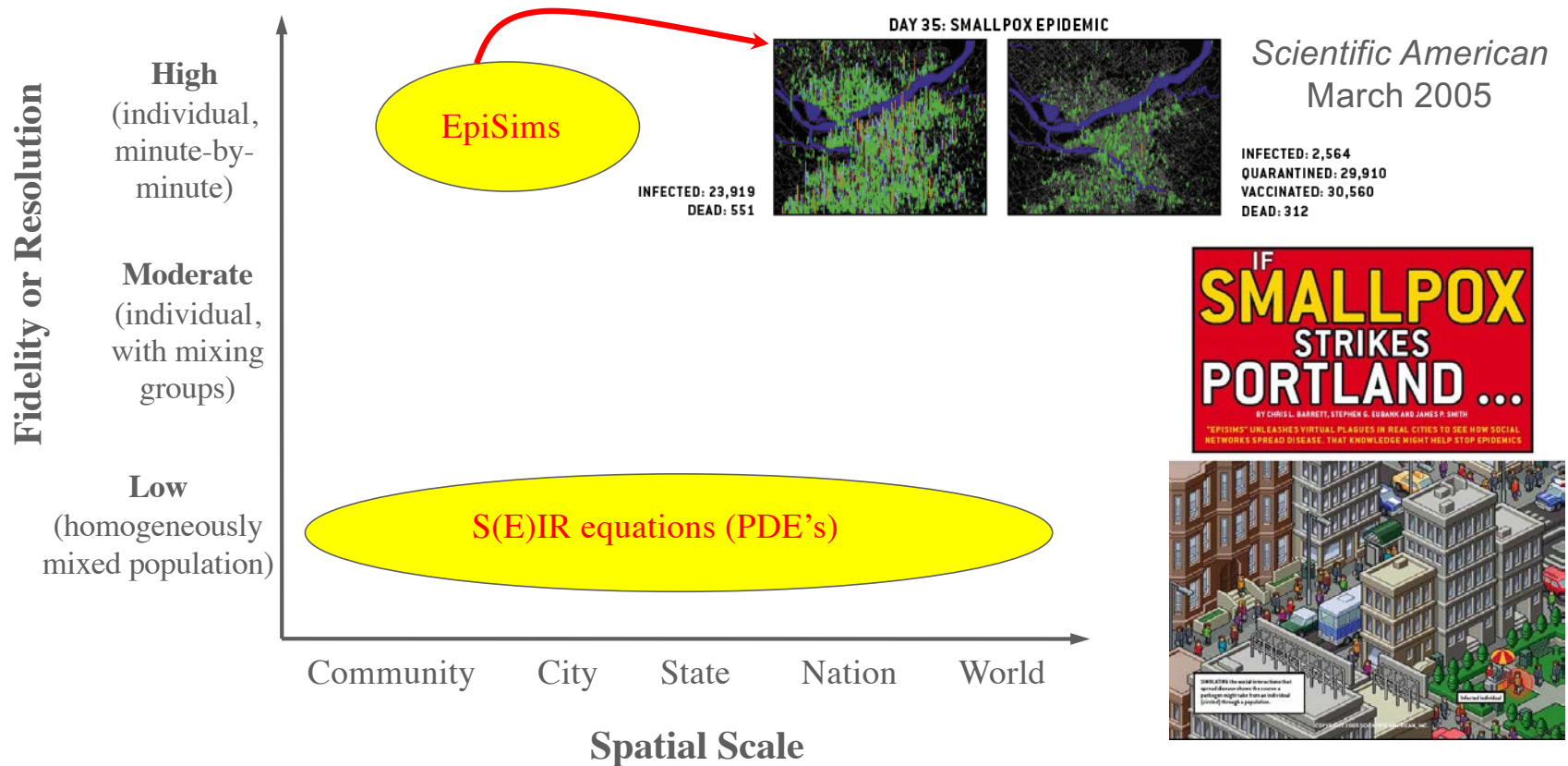
- Detail person-to-person contact on a minute-by-minute basis
- Workforce absenteeism by NAICS
- Explicit geography, demographics, social contact networks, and mitigations

■ Data Sources

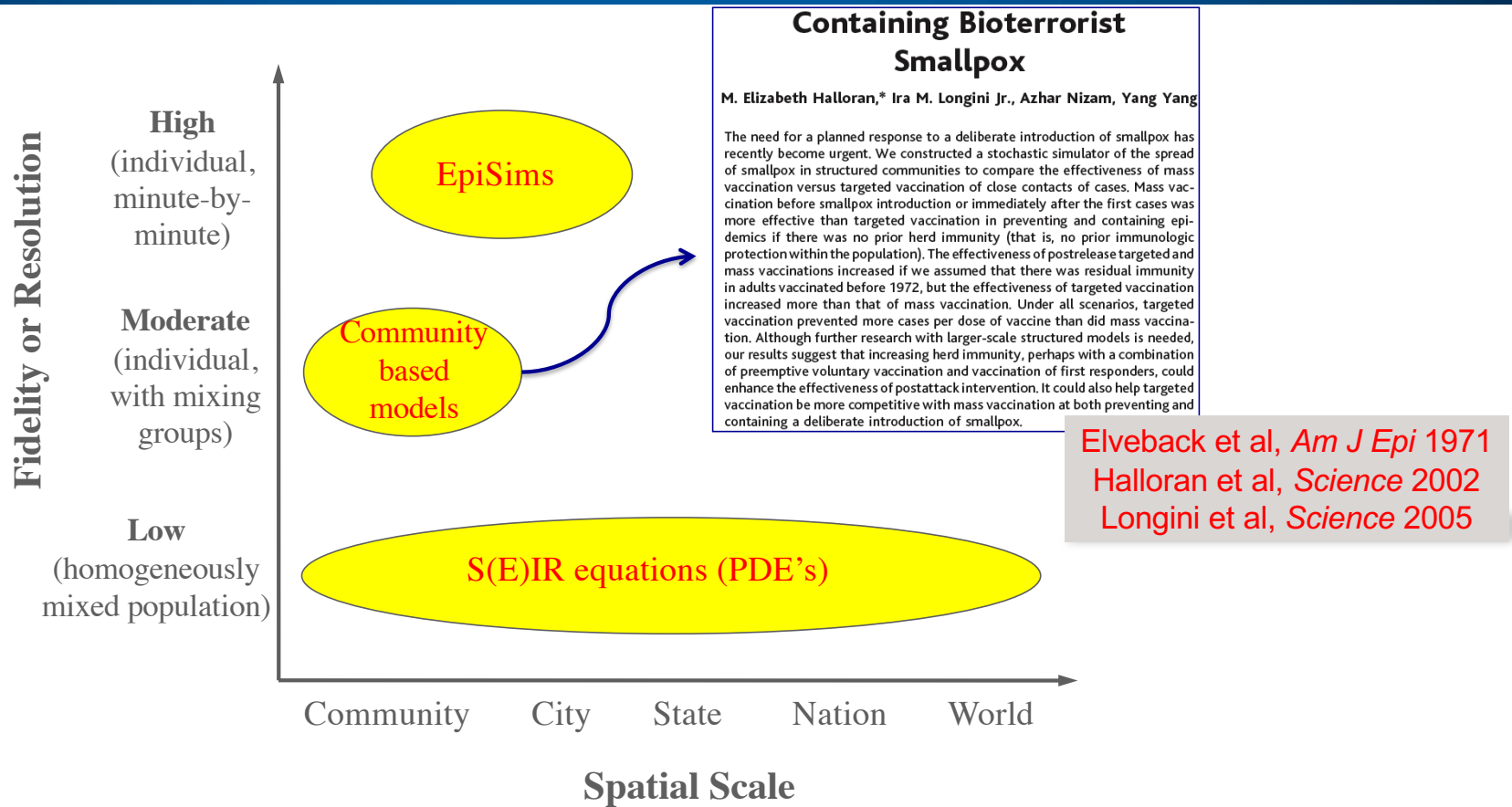
- U.S. Census data
- Dun & Bradstreet business directory
- National Household Transportation Survey from U.S. DOT



Oversimplified Epidemiological Model Landscape

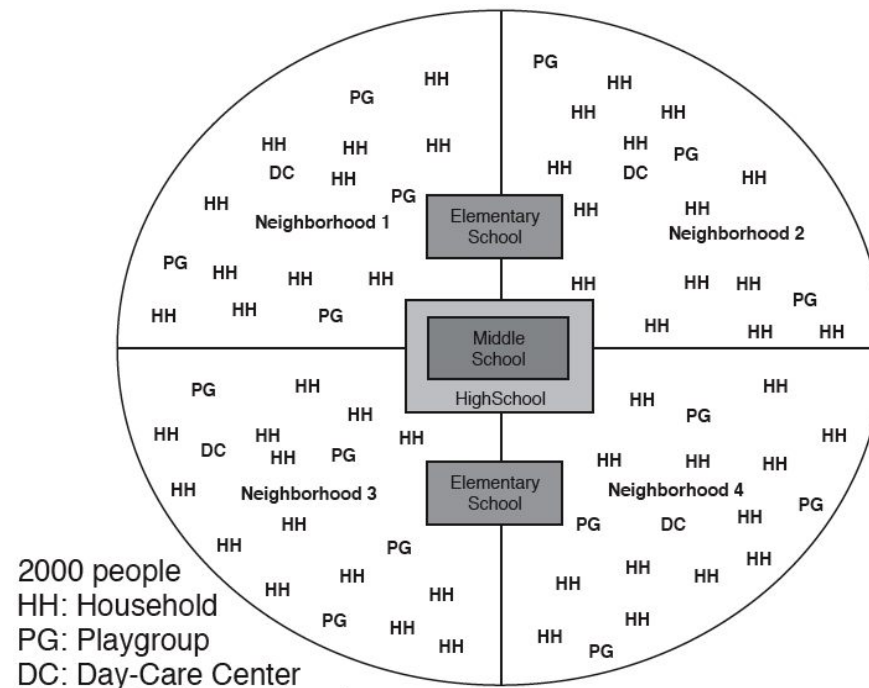


Oversimplified Epidemiological Model Landscape



Person-to-person transmission is represented via contact groups within a ~2000-person model community

Different cultures or modes of transmission may require different sets of contact (mixing) groups.



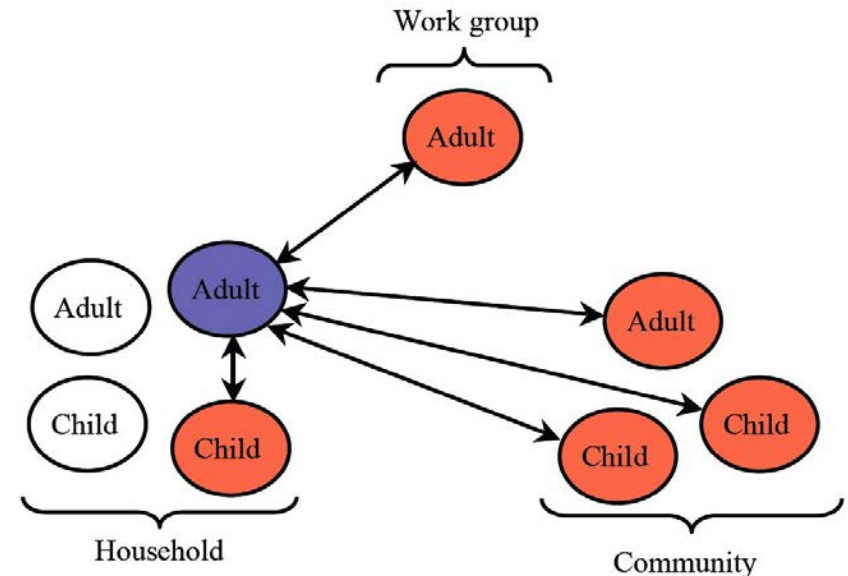
M. E. Halloran *et al*, *Science* 298, 1428 (2002);

I. M. Longini *et al*, *Science* 309, 1083 (2005).

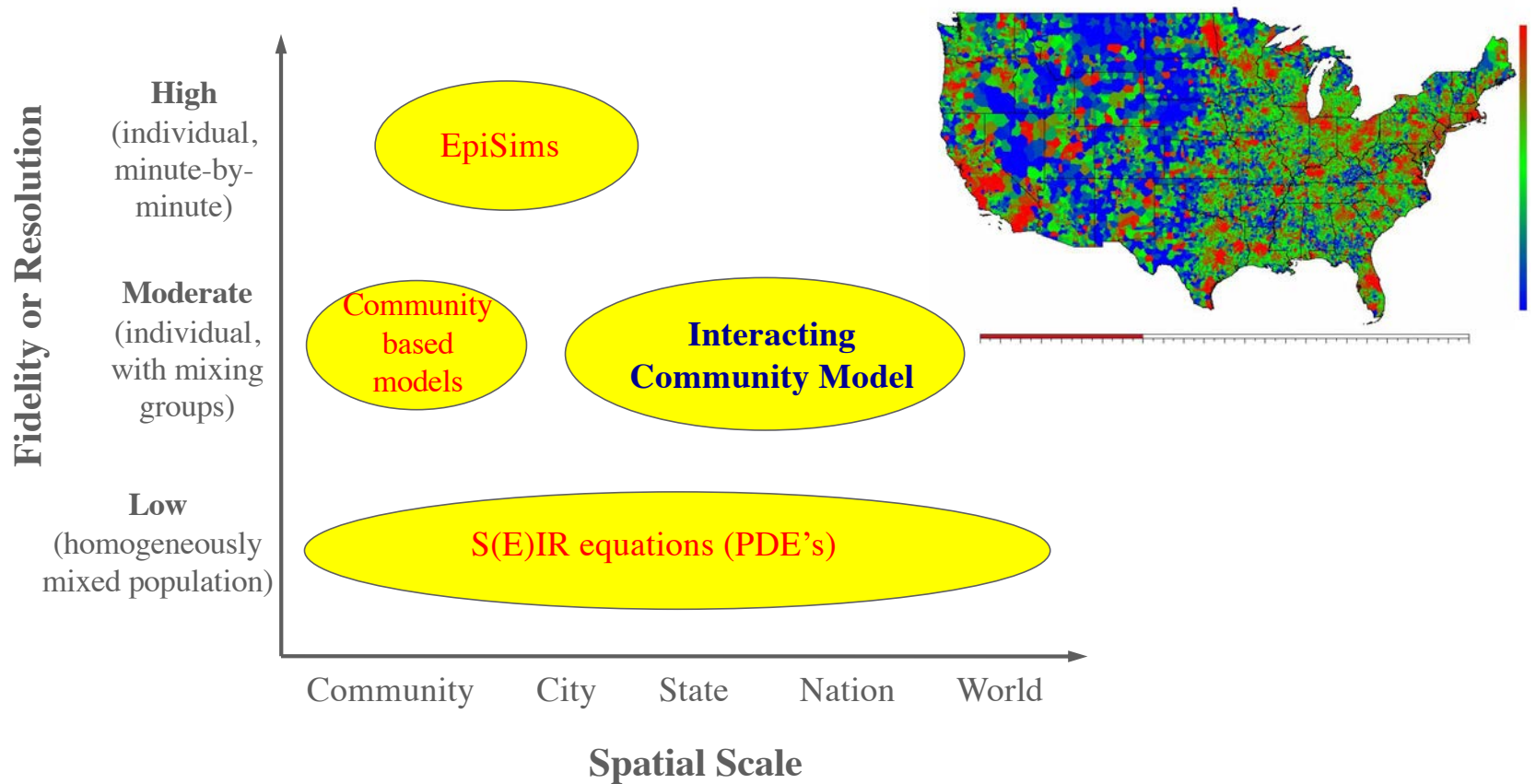
Stochastic Transmission with half-day timesteps

$$P = 1 - (1 - p_{HH}^{c \rightarrow a}) \cdot (1 - p_{WG}^{a \rightarrow a}) \cdot (1 - p_{Comm}^{a \rightarrow a}) \cdot (1 - p_{Comm}^{c \rightarrow a})^2$$

- Person-to-person transmission is represented via **contact groups** within a ~2000-person model community
- Each **susceptible individual** has a **probability** of becoming infected by **infectious individuals** in their contact groups during each 12-hour timestep
- These probabilities may be further modified if the infectious and/or susceptible individuals are adopting **social distancing measures**, taking antivirals, or have been vaccinated



Oversimplified Epidemiological Model Landscape



Agent-based epidemiological methods map directly to particle-based MD simulations

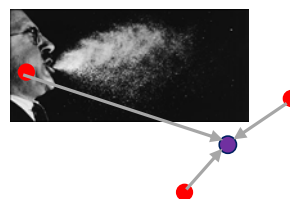
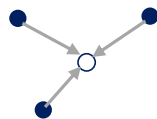
Molecular Dynamics

Agent-Based Epidemiology

Particle type ↔ Individual age, gender, ...
 Particle position, velocity ↔ Individual location
 Internal state variable(s) ↔ Individual disease status

Neighbor list ↔ Contact groups

Interatomic force field ↔ Disease transmission model



Community-level
agent-based
disease spread
models

Classical Mechanics to update
positions and velocities

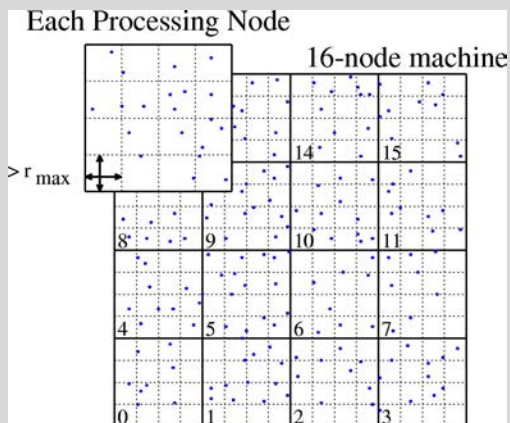


Transportation model

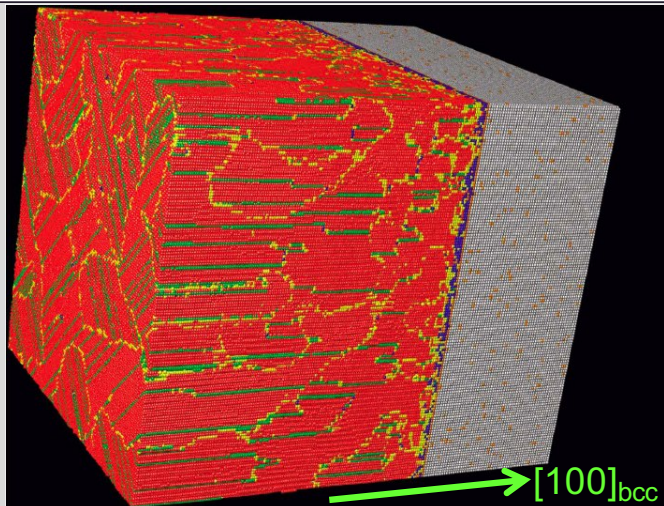
Based on census &
travel data

Scalable Parallel Short-range Molecular dynamics (SPaSM) is a high-performance code for studying large systems of interacting “particles”

- Finite-range (r_{max}) interactions $\Rightarrow O(N)$ computational scaling
- Spatial decomposition on shared and distributed memory architectures
- 1993 IEEE Gordon Bell Performance Prize (50 Gflop/s on LANL/Thinking Machines CM-5)
- 1998 IEEE Gordon Bell Price / Performance Prize (10 Gflop/s on Linux/Alpha Beowulf cluster, \$15/Mflop)
- 2005 IEEE Gordon Bell Prize Finalist (48 Tflop/s on LLNL/IBM BlueGene/L)
- 2008 IEEE Gordon Bell Prize Finalist (369 Tflop/s on LANL/IBM Roadrunner)
- Object-oriented scripting language with parallel visualization and analysis libraries (runtime “steering”)



(David Beazley, Peter Lomdahl)



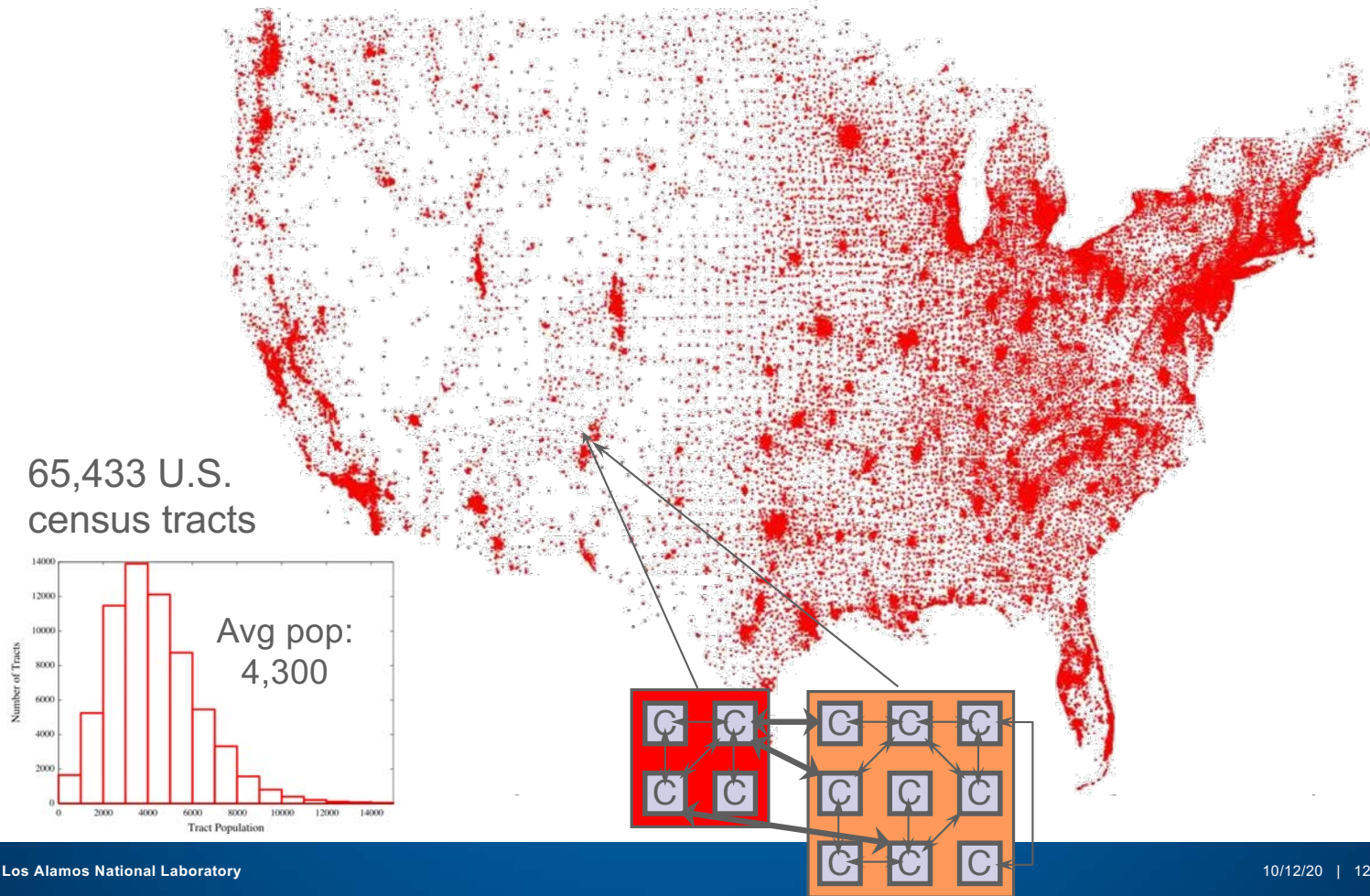
Microscopic View of Structural Phase Transitions Induced by Shock Waves

Kai Kadau,^{1,2*} Timothy C. Germann,³ Peter S. Lomdahl,¹
Brad Lee Holian¹

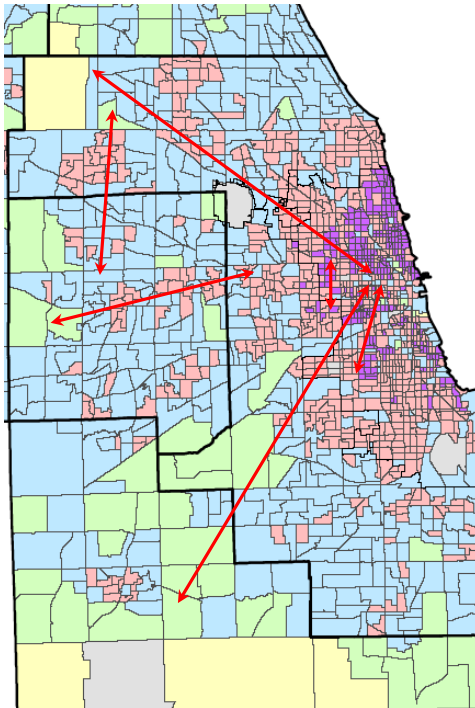
Multimillion-atom molecular-dynamics simulations are used to investigate the shock-induced phase transformation of solid iron. Above a critical shock strength, many small close-packed grains nucleate in the shock-compressed body-centered cubic crystal growing on a picosecond time scale to form larger, energetically favored grains. A split two-wave shock structure is observed immediately above this threshold, with an elastic precursor ahead of the lagging transformation wave. For even higher shock strengths, a single, overdriven wave is obtained. The dynamics and orientation of the developing close-packed grains depend on the shock strength and especially on the crystallographic shock direction. Orientational relations between the unshocked and shocked regions are similar to those found for the temperature-driven martensitic transformation in iron and its alloys.

Science **296**, 1681 (31 May 2002)

U.S. Census population & worker flow data are utilized to construct an interacting community model (“EpiCast”)



Residential and workplace communities for synthetic population matches Census data



We use U.S. Census Bureau data on tract-level demographics and worker-flow, and Dept. of Transportation data on irregular long-range travel to assign fixed residential and workplace communities to each individual, in addition to infrequent visits to more distant communities.

1,344 Cook County (IL) census tracts



Irregular long-distance travel is modeled including three factors

1. **Trip Generation: Which individuals/households make a long distance trip?**

Use age-dependent average number of trips per year to determine the daily probability of making a long-distance trip, then roll the dice for each person every day.

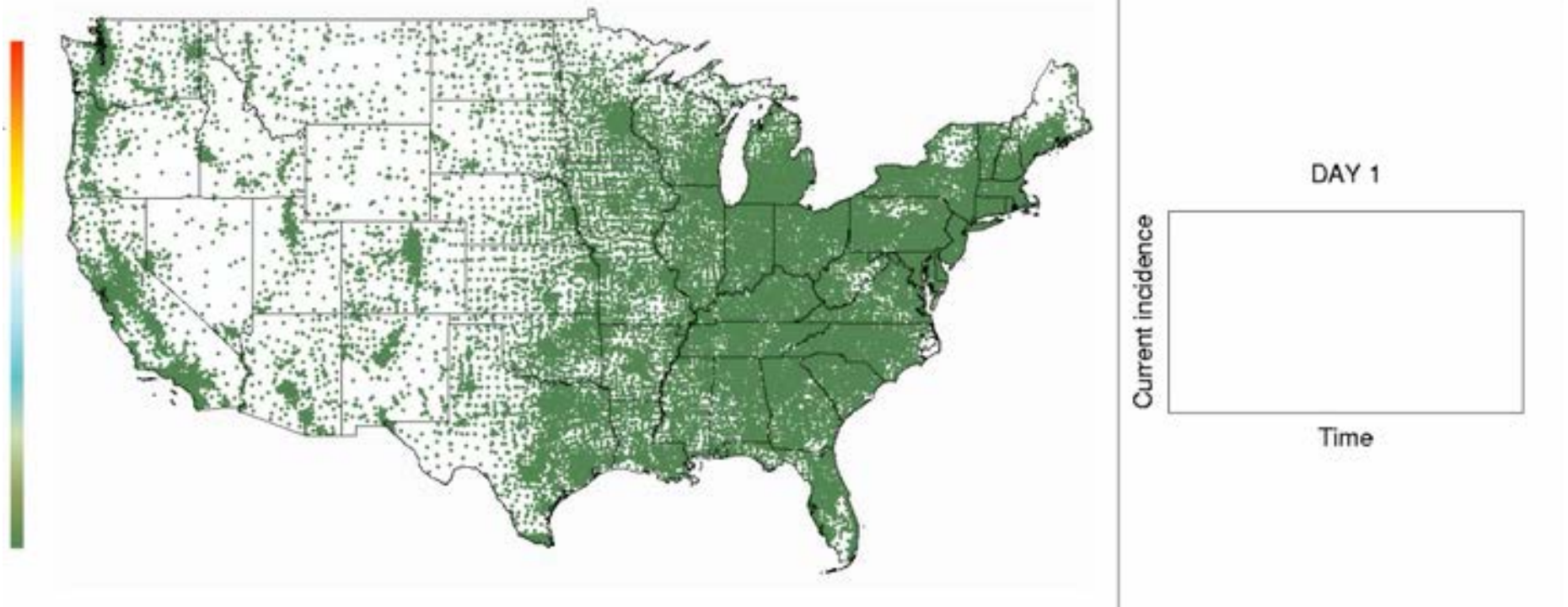
2. **Destination Choice: Where do they go?**

Simplistic gravity model: choose a random community within the simulation (either a 2,000-person residential or a 1,000-person workgroup-only community), without any distance dependence.

3. **Trip Duration: How long do they stay there?**

Use the national statistics on trip duration to choose a duration from 0-13 nights.

Baseline (unmitigated) pandemic, $R_0 = 1.9$



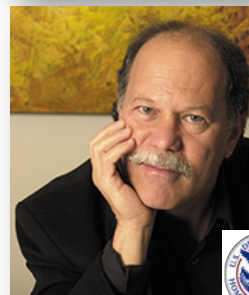
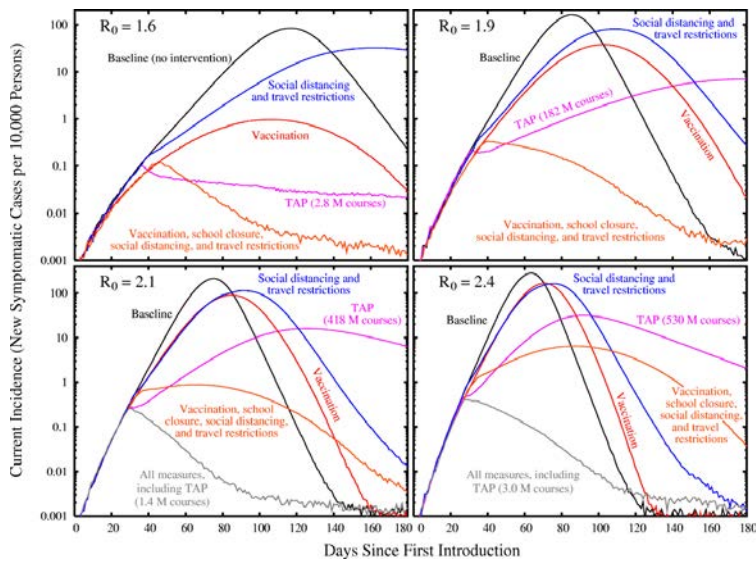
Each Census tract is represented by a dot colored according to its prevalence (number of symptomatic cases at any point in time) on a logarithmic color scale, from 0.3-30 cases per 1,000 residents.

Initial Application of the National EpiCast Model with Tract-level Resolution was to Pandemic Influenza

Mitigation strategies for pandemic influenza in the United States

Timothy C. Germann^{*†}, Kai Kadau^{*}, Ira M. Longini, Jr.[‡], and Catherine A. Macken^{*}

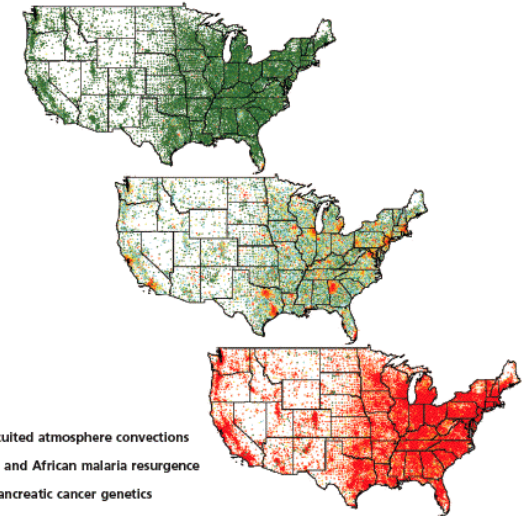
^{*}Los Alamos National Laboratory, Los Alamos, NM 87545; and [‡]Program of Biostatistics and Biomathematics, Fred Hutchinson Cancer Research Center and Department of Biostatistics, School of Public Health and Community Medicine, University of Washington, Seattle, WA 98109



April 11, 2006 | vol. 103 | no. 15 | pp. 5633-6074

PNAS
Proceedings of the National Academy of Sciences of the United States of America www.pnas.org

Intervention simulations for U.S. influenza pandemic



Short-drafted atmosphere convections
Warming and African malaria resurgence
Mouse pancreatic cancer genetics
Poxvirus entry via membrane shedding

SPECIAL REPORT: PREPARING FOR PANDEMIC FLU
IS ANYONE READY FOR THIS GLOBAL KILLER?

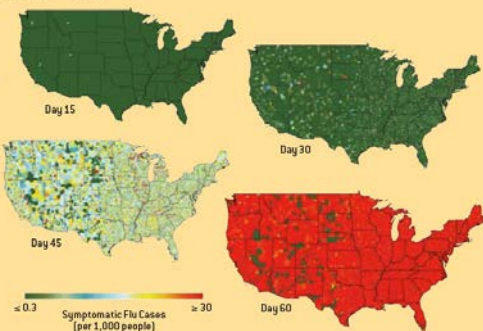
SCIENTIFIC AMERICAN

PANSPERMIA:
Martian Cells
Could Have
Reached Earth

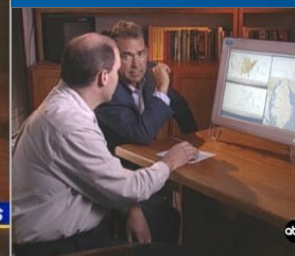
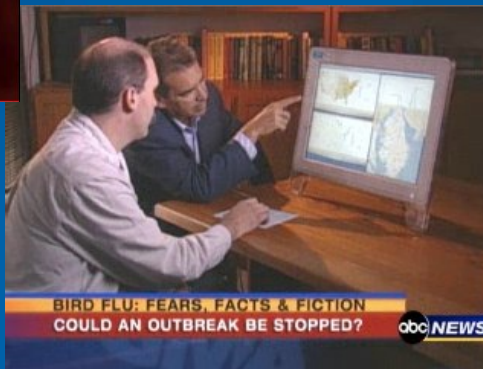
NOVEMBER 2005
WWW.SCIAM.COM

Pandemic Flu Hits the U.S.

A simulation created by researchers from Los Alamos National Laboratory and Emory University shows the first wave of a pandemic spreading rapidly with no vaccine or antiviral drugs employed to slow it down. Colors represent the number of symptomatic flu cases per 1,000 people (see scale). Starting with 40 infected people on the first day, nationwide cases peak around day 60, and the wave subsides after four months with 33 percent of the population having become sick. The scientists are also modeling potential interventions with drugs and vaccines to learn if travel restrictions, quarantines and other disruptive disease-control strategies could be avoided.



ABC's Good Morning America March 13, 2006



Nightline: March 14, 2006

The Economist April 8th 2006

Influenza

Just say "R"

Even a weak vaccine might be useful in an outbreak of influenza

A BRUTAL mathematics governs the spread of an infection. It is tied to what is known as the basic reproductive number, R_0 . Whether the outbreak is of seasonal influenza, Ebola fever or bubonic plague, R_0 tells you, for each person infected, how many others are likely to be infected later. The higher R_0 is, therefore, the harder an infection is to control.

R_0 is one of the many things scientists don't know about the virus that will cause the next pandemic of influenza, because that virus has not yet emerged. This is a problem, because it makes it hard to plan to minimise the impact of that outbreak.

One solution is to produce a virtual world in which various types of virus can be modelled. This is the approach taken by a team led by Timothy Germann, of the Los Alamos National Laboratory in New Mexico, and his colleagues. In a paper published in the *Proceedings of the National Academy of Sciences*, Dr Germann and his team describe a "virtual" population of 281m people distributed across a virtual version of the United States in accordance with census data. They have made assumptions about how often people mix with each other, where they mix (schools, workplaces and homes), and how often and how far they travel. This virtual world

npr



Health News Briefs

Grim Scenario Predicted for Pandemic Flu

NPR.org, December 5, 2005 · Federal health officials meeting with state health authorities today are expected to paint a grim scenario of how a flu pandemic might unfold in America.

A federally financed study used supercomputers to predict what might happen if a virulent and easily spread new strain of flu entered the United States. The study was done by researchers at Emory University and Los Alamos National Laboratory.

They assumed the pandemic virus would leak into the country despite efforts to screen travelers for flu symptoms. If each infected person spread the virus to two others, large outbreaks of flu would occur all over the country within about two months after the virus began to spread. The national epidemic would peak around day 85, with about 4.5 million people falling ill that day. In the end, 122 million Americans may have gotten sick, more than four times the toll in a usual flu season. -- Richard Knox

We weren't prepared for how seriously policy-makers took our simulations....

5 days after the PNAS article:



... Many critical decisions remain to be made. Administration scientists are debating how much vaccine would be needed to immunize against a new strain of avian influenza, and they are weighing data that may alter their strategy on who should have priority for antiviral drugs such as Tamiflu and Relenza.

The new analysis, published in *Proceedings of the National Academy of Sciences*, suggests that instead of giving medicine to first responders and health-care workers, as currently planned, it might be wiser to give the drugs to every person with symptoms and others in the same household, **one senior administration official** said.

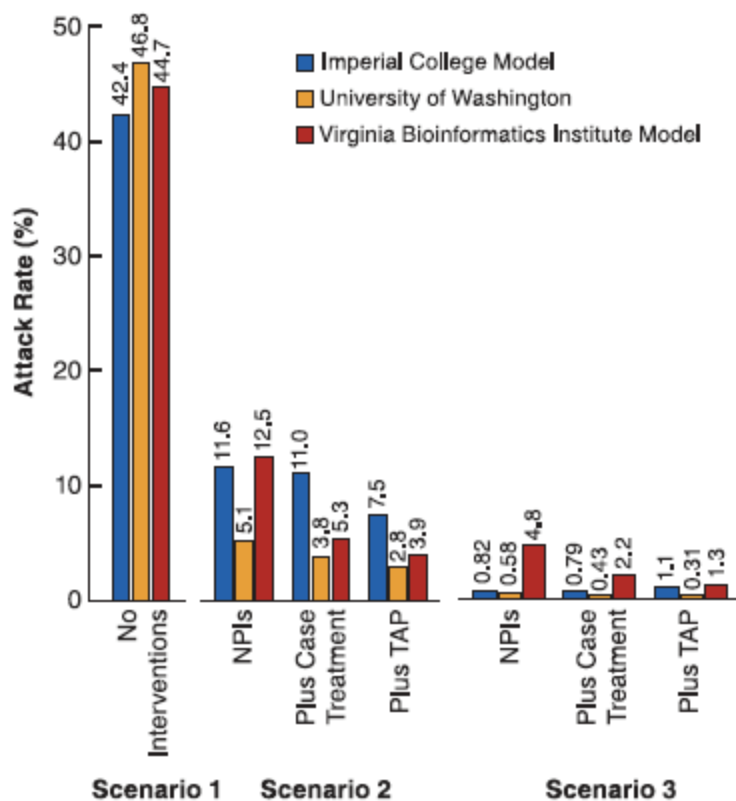
The approach offers “some real hope for communities to put a dent in the amount of illness and death, if we go with that strategy,” **a White House official** said.

U.S. Plan For Flu Pandemic Revealed

Multi-Agency Proposal Awaits Bush's Approval

By Carol Costanzo
Washington Post Staff Writer

Cross-model Comparison of Community-based Targeted Layered Containment Strategies



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. Cummings[§], Bryan Lewis[¶], Shufu Xu[†], Christophe Fraser[§], Anil Vullikanti[¶], Timothy C. Germann[¶], Diane Wagener^{**}, Richard Beckman[¶], Kai Kadau[¶], Chris Barrett[¶], Catherine A. Macken[¶], Donald S. Burke^{††}, and Philip Cooley^{**}

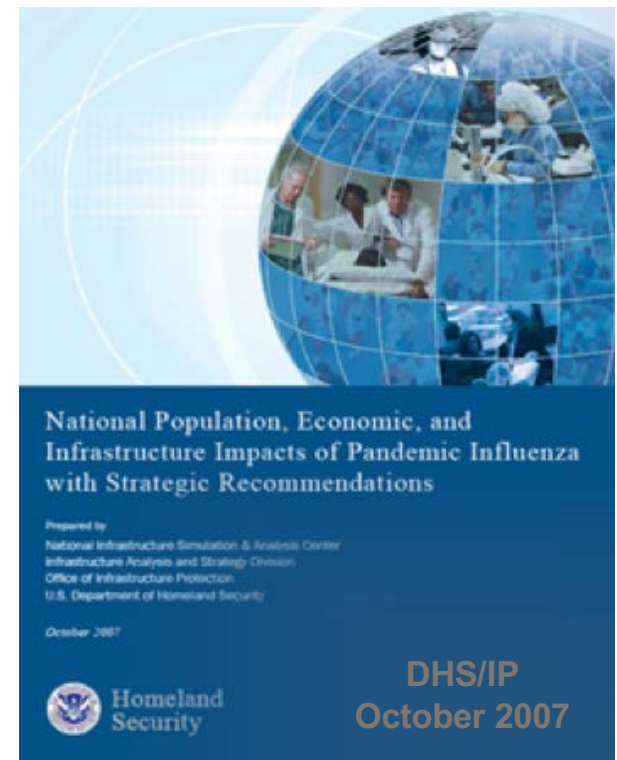
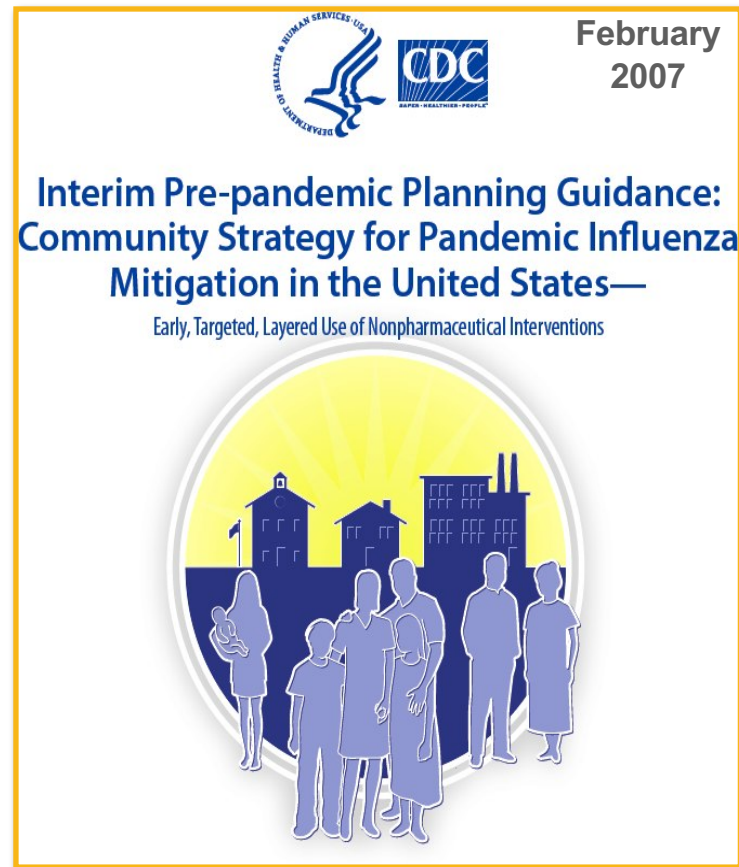
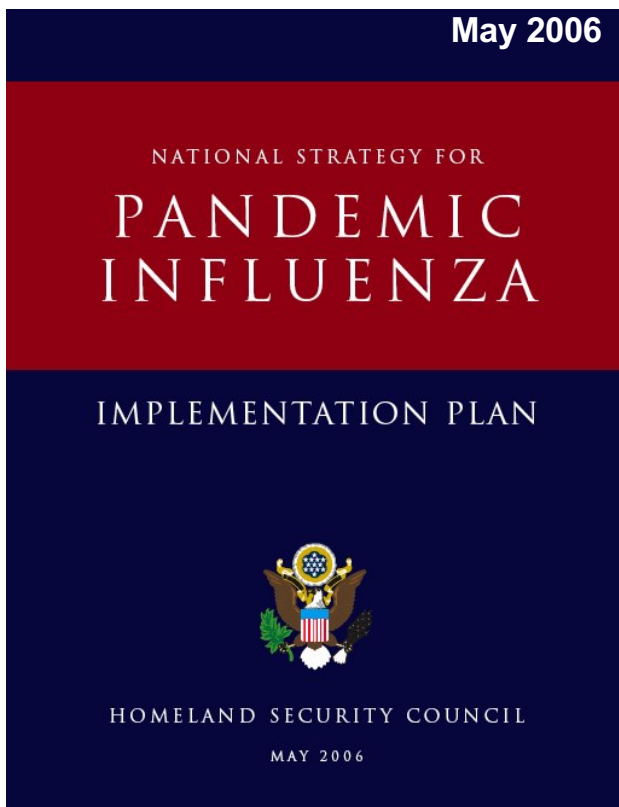
[¶]Virginia Bioinformatics Institute, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061; ^{††}Graduate School of Public Health, University of Pittsburgh, Pittsburgh, PA 15261; ^{**}Research Triangle Institute, Research Triangle Park, NC 27709; [§]Department of Infectious Disease Epidemiology, Imperial College, London W21PG, England; [¶]Los Alamos National Laboratories, Los Alamos, NM 87545; ^{*}Department of Biostatistics, School of Public Health and Community Medicine, University of Washington, Seattle, WA 98195; and [†]Program in Biostatistics and Biomathematics, Division of Public Health Sciences, Fred Hutchinson Cancer Research Center, Seattle, WA 98109

Edited by Barry R. Bloom, Harvard School of Public Health, Boston, MA, and approved January 15, 2008 (received for review July 23, 2007)

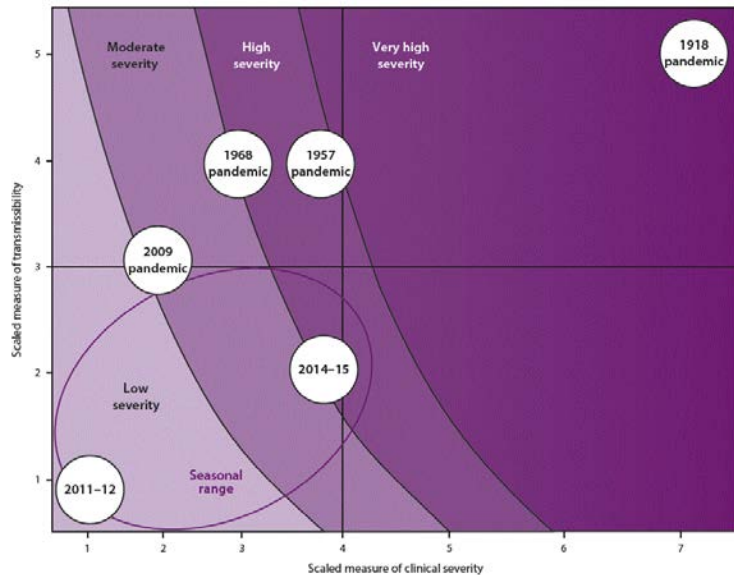
Table 3. Percentage of infections by place and scenario, $R_0 = 1.9$ (2.1) in the Chicago population

	Scenario 1. No intervention			Scenario 2			Scenario 3		
	Imperial	UW	VBI	Imperial	UW	VBI	Imperial	UW	VBI
Illness attack rates	42.4	46.8	44.7	7.3	2.8	3.9	1.1	0.31	1.3
Places									
Home	33.1	39.4	41.1	48.3	58	45.9	50.4	59	36.9
Work	21.8	14.5	28.6	12.9	10	27.8	13.5	10	18.7
School	16.0	18.8	23.3	11.7	11	9.6	9.0	11	2.7
Day care	-	1.1	-	-	0	-	-	0	-
Play group	-	0.8	-	-	0	-	-	0	-
College	-	-	3.3	-	-	12.3	-	-	40.0
Shopping	-	-	2.0	-	-	2.4	-	-	1.0
Neighborhood	-	17.7	-	-	15	-	-	15	-
Neighborhood clusters	-	7.7	-	-	5	-	-	4	-
Other/Community	29.0	0	1.7	26.6	0	2.0	23.8	0	0.8
Totals									
Primary Groups*	70.9	72.7	93.0	72.9	79	83.3	72.9	79	58.3
Community†	29.0	25.4	3.7	26.6	20	4.4	23.8	19	1.8

Large-scale Agent-Based Epidemiological Studies Have Directly Influenced the National Pandemic Planning Process



EpiCast Used to Assess School Dismissal Policies in the Context of the Pandemic Severity Framework



Adapted from C. Reed, M. Biggerstaff, L. Finelli, et al., *Novel framework for assessing epidemiologic effects of influenza epidemics and pandemics*, Emerg Infect Dis **19**, 85–91 (2013)



Los Alamos National Laboratory

Epidemics 28 (2019) 100348

Contents lists available at ScienceDirect

Epidemics

journal homepage: www.elsevier.com/locate/epidemics

School dismissal as a pandemic influenza response: When, where and for how long?

Timothy C. Germann^a, Hongjiang Gao^{b,*}, Manoj Gambhir^{c,d,1}, Andrew Plummer^{b,2}, Matthew Biggerstaff^c, Carrie Reed^c, Amra Uzicanin^b

^a Theoretical Division, Los Alamos National Laboratory, Los Alamos, NM 87545 USA
^b Community Interventions for Infection Control Unit, Centers for Disease Control and Prevention, Atlanta, GA 30329 USA
^c National Center for Immunization and Respiratory Diseases, Centers for Disease Control and Prevention, Atlanta, GA 30333 USA
^d School of Public Health and Preventive Medicine, Monash University, Victoria 3800 Australia

- In partnership with the **CDC Community Interventions for Infection Control Unit (CI-ICU)**, we explored non-pharmaceutical interventions focused on school dismissal, specifically :

- *Threshold trigger: **when** to close*
- *Geographic scale: **where** to close*
- *Duration: for **how long** to close*

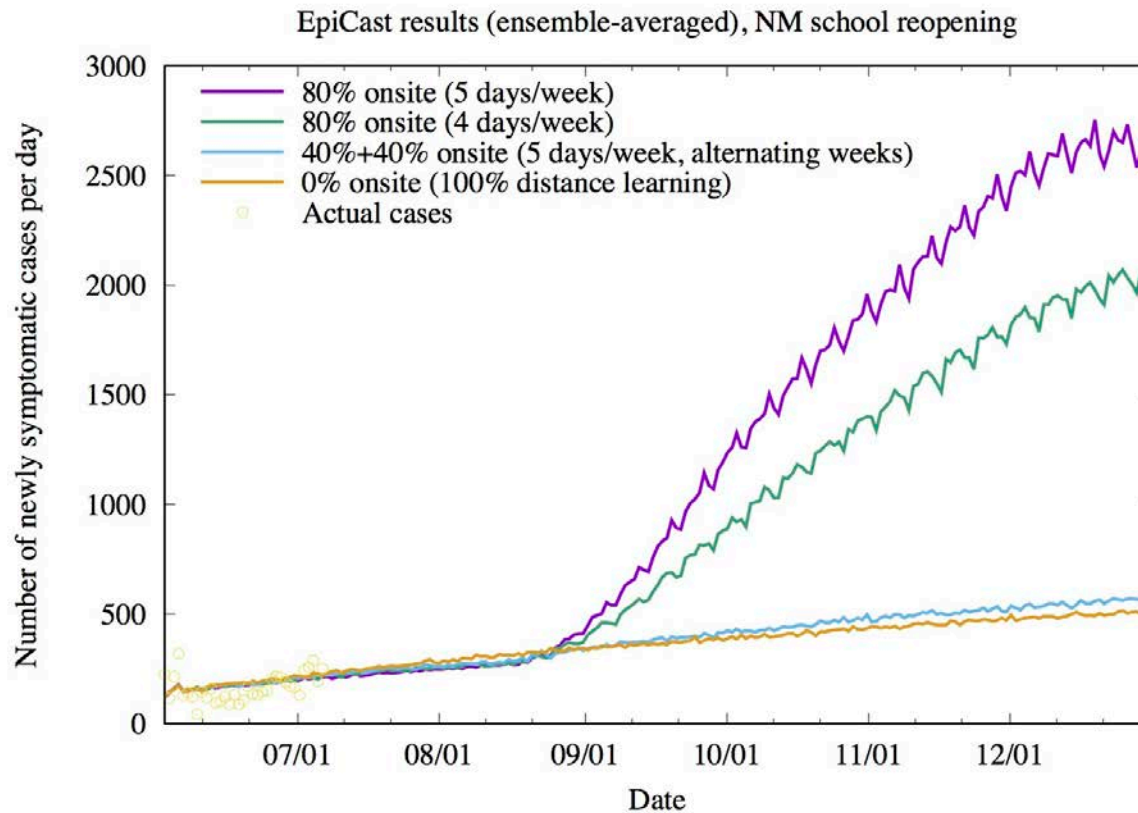
Adapting an influenza model to COVID-19

- **Disease parameters** from CDC's Planning Parameters for COVID-19 Outbreak Scenarios
- **Initial conditions:** Daily counts of diagnosed cases in each county from the NY Times database
- **Mitigations**
 - **Schools** are closed/children contacts reduced by 30% outside the household
 - **Stay-at-home** order is enacted on a county-by-county basis
 - **Workplaces** are assigned 3-digit NAICS codes, which determine whether they are open or closed, allow telework, shift schedules, etc.
 - **Long-distance travel** is assumed to be limited

The image shows a table with 5 columns representing different COVID-19 outbreak scenarios. The rows list various parameters such as 'Case Fatality Rate (CFR)', 'Reproduction Number (R0)', and 'Estimated Total Cases'. To the right of the table is a bar chart showing the percentage of total cases for each scenario: Scenario 1 (Moderate-high severity, low transmissibility) at 40%, Scenario 2 (Moderate-high severity, high transmissibility) at 30%, Scenario 3 (High/very high severity, low transmissibility) at 40%, Scenario 4 (High/very high severity, high transmissibility) at 30%, and Scenario 5 ('Best Case' Scenario 2) at 20%.



The reported daily case counts in each county are used to calibrate the initial conditions (manually or automated*)



*See Peer-Timo Bremer's talk tomorrow on "Cognitive Simulations for COVID-19 Analysis, Exploration, and Scenario Planning" for more advanced multiparameter estimation techniques.

Initial EpiCast/COVID-19 national-level results: first report April 6

EpiCast COVID-19 simulation results – 6 April 2020

EpiCast team*, Los Alamos National Laboratory
 *Contact: Tim Germann, tgg@lanl.gov

NOTE: These are results based on *initial models and parameters for COVID-19, which are being actively refined. Disease natural history and case hospitalization/ICU/ventilator/fatality rates are based on the “best guess” values in the March 20 Planning Parameters for COVID-19 Outbreak Scenarios (PPCOS), and have not been updated to the more recent March 31 document. Contact rates are largely based on prior influenza modeling efforts [1-3], and no recently available mobility/contact data (e.g., through cell phone tracking) has been utilized. Data sources and assumptions are indicated below; suggestions are welcome.*

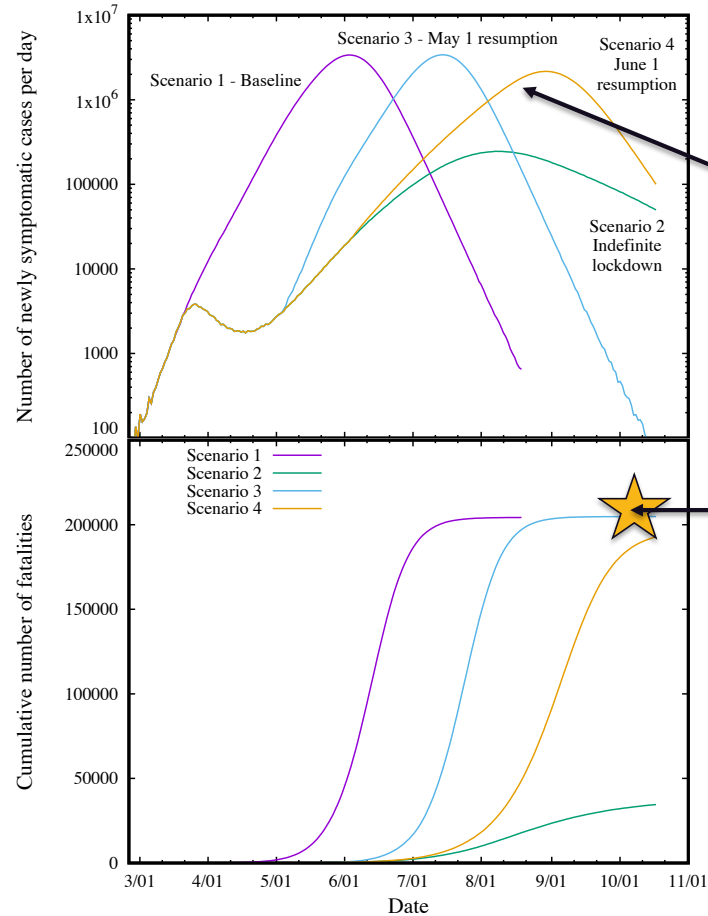
Disease model parameters

Parameter	Value	Source
Doubling time	6.5 days	March 20 PPCOS
Time to symptom onset	Mean ~5 days (range 2-8 days)	“
Serial interval	Mean ~8 days	“
Symptomatic duration	Mean ~6 days (range 3-9 days)	“
Proportion of pre-symptomatic transmission	35%	“
Proportion of infections that are asymptomatic	50%	“
Relative infectiousness of asymptomatic individuals	100%	“
Pre-existing immunity	None	“
Symptomatic case hospitalization ratio (by age groups 0-4, 5-18, 19-29, 30-64, and 65+ years old)	1.25%, 0.5%, 1.25%, 1.5%, 16%	Adapted from March 20 PPCOS
ICU % among those hospitalized (by age)	15%, 20%, 15%, 17%, 15%	“
Ventilated % among those in ICU (by age)	35%, 30%, 45%, 47%, 45%	“
Symptomatic case fatality ratio (by age)	0.01%, .0075%, .045%, .072%, .1%	“

It is further assumed that seasonality (e.g., weakening of transmission in warmer and dryer summer months) effects are negligible and can be ignored.

Simulation Details

EpiCast is an individual-based model, with daily contacts between people in household, workplace, school, neighborhood, and community settings. The primary data source is U.S. Census demographics at the tract level (the ~65,000 tracts are subsets of the ~3000 counties, with typically a few thousand people in each tract), and Census tract-to-tract workerflow data (i.e., how many people live in tract A and work in tract B). This is used to construct a model population with tract-level age and household size demographics, and realistic daily workflow pattern, which captures most of the short-range mobility. In addition, occasional long-distance travel is possible. A 12-hour timestep is used, so (unless on travel) individuals spend the night-time at home and day-time at school or workplace, if they belong to one (and they are open). Additional details are provided in the Supporting Information of [1]. In the original model [1,2], the individual age- and context-specific contact rates that account for the duration and closeness of interactions between pairs of individuals in different settings (home, school, workplace, neighborhood, community, etc.) were uniform across the US. In our recent school dismissal study [3], we allowed for different communities to decide to close their schools at different times, depending upon the current local disease incidence. In our ongoing COVID-19 work, these local policies have been extended to *all* community mitigation measures: school dismissal, workplace closure, shelter-in-place and other social distancing.



“Scenario 4” most nearly describes subsequent behavior (relaxation of social distancing around June 1 leading to a second peak)

We are here

Effects we can model (that most others can't)

- Impact of heterogeneous mixing patterns
- Impact of school/workplace closures by school district, county, or state level
- Impact of workforce impacts by NAICS
- Non-pharmaceutical interventions differentiation by spatial or demographic factors



EpiCast has been used to evaluate school reopening scenarios for the state of New Mexico

Scenario 1: Distance Learning

- All household contacts are increased by 40%
- Daycares are assumed to be closed
- Workplaces are partially opened (consistent with Phase 1)

Scenario 2: Partial Onsite Learning

- Students are stratified into **two non-overlapping** groups
- Students are assumed to go to school for **only 2 days a week**
- Workplaces are partially opened (consistent with Phase 1)

Scenario 3: Onsite Learning

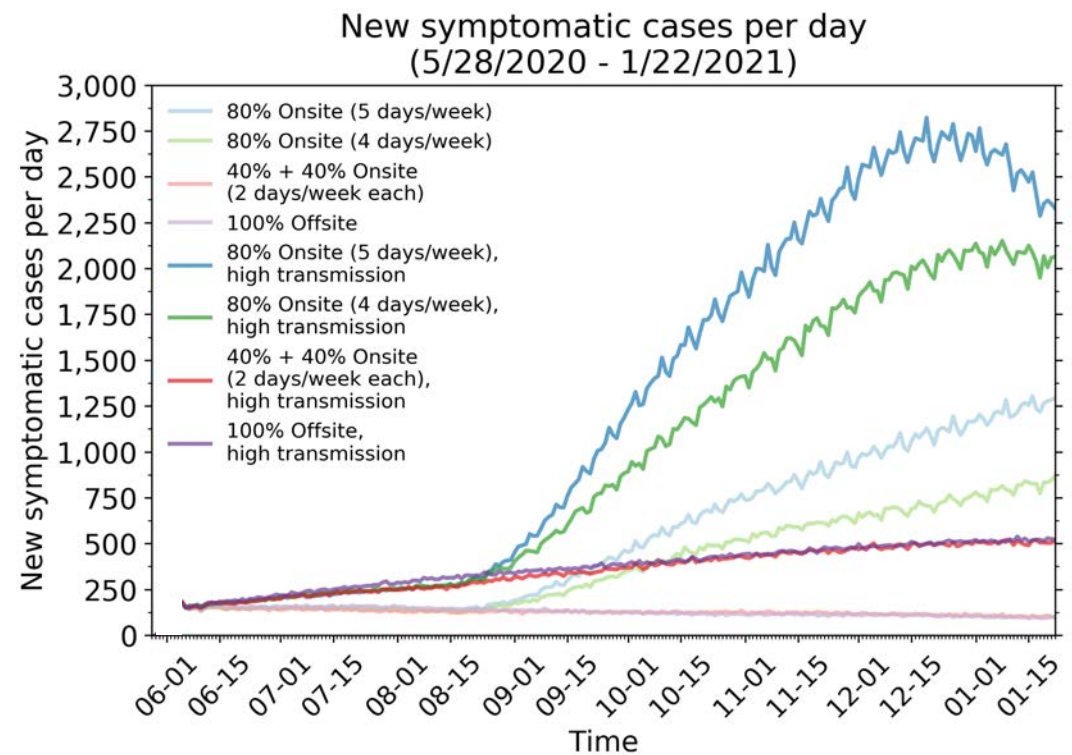
- Schools are assumed to be opened **5 days a week**
- Transmission is reduced by 50% to account for social distancing measures, facemasks, mixing groups, etc.
- Workplaces are partially opened (consistent with Phase 1)

LANL PI: Sara Del Valle (A-1)

EpiCast Results – Overall Trends

Low & High Transmission Scenarios

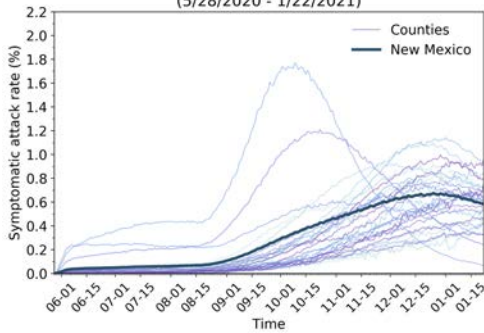
- Lower transmission leads to less cases
- Reducing school attendance by 1 day (**4-day scenario**) has a significant impact
- Two non-overlapping groups of students **2 days a week** leads to less cases and results in similar results as the offsite scenario due to assumed interactions outside school



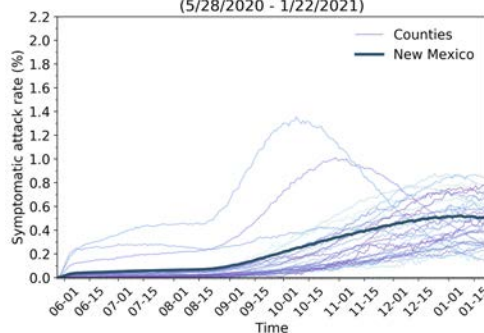
County-level Trends

High Transmission

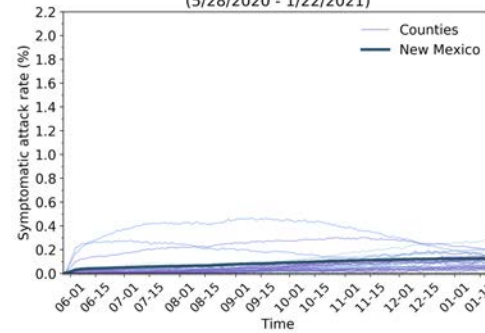
80% Onsite (5 days/week) modified:
Current symptomatic attack rate
(5/28/2020 - 1/22/2021)



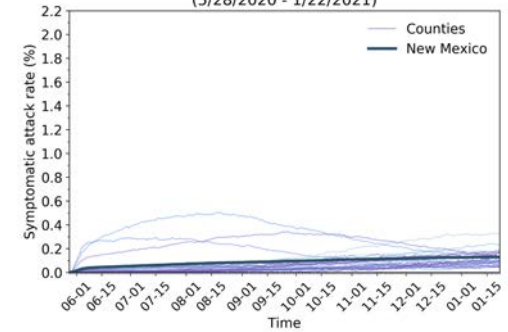
80% Onsite (4 days/week) modified:
Current symptomatic attack rate
(5/28/2020 - 1/22/2021)



40% + 40% Onsite (2 days/week each) modified:
Current symptomatic attack rate
(5/28/2020 - 1/22/2021)

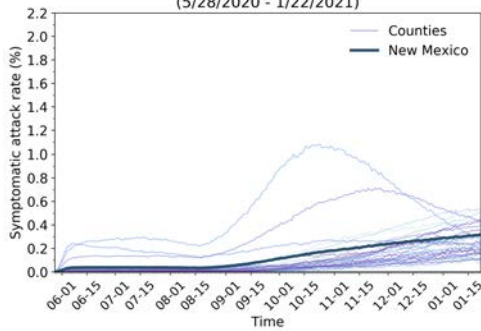


100% Offsite modified:
Current symptomatic attack rate
(5/28/2020 - 1/22/2021)

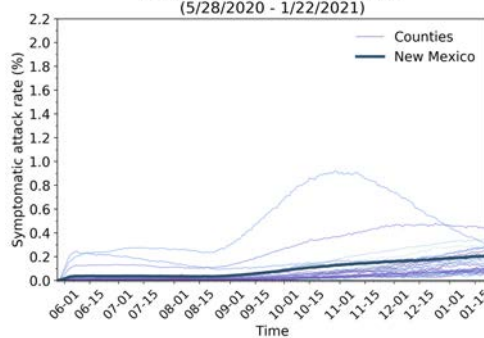


Low Transmission

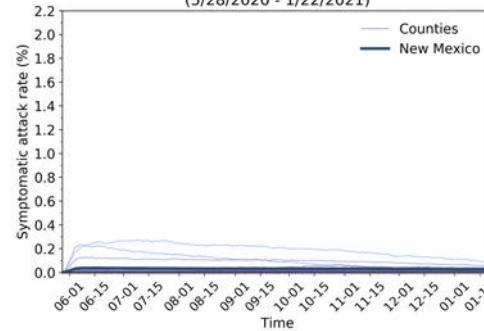
80% Onsite (5 days/week):
Current symptomatic attack rate
(5/28/2020 - 1/22/2021)



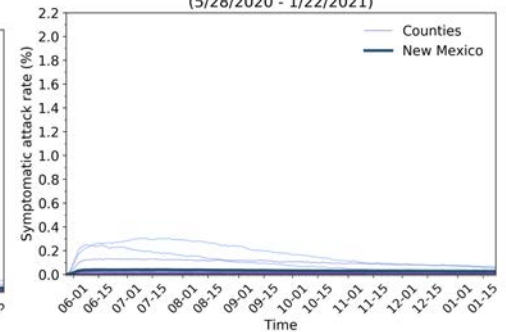
80% Onsite (4 days/week):
Current symptomatic attack rate
(5/28/2020 - 1/22/2021)



40% + 40% Onsite (2 days/week each):
Current symptomatic attack rate
(5/28/2020 - 1/22/2021)



100% Offsite:
Current symptomatic attack rate
(5/28/2020 - 1/22/2021)



LANL simulations (including but not limited to EpiCast) are informing NM policy-makers



Using Data to Drive Decisions



In partnership with Los Alamos National Laboratory (LANL), the state is using the most up-to-date epidemiological models to assess current virus threat level.

A phased entry approach will allow the state to collect and analyze data on the impact of a controlled start on the spread of the virus. This information will be essential to ensure that the state is able to move toward the goal of returning all children to a full school schedule as soon as it can be safely accomplished.

In addition, the phased entry approach will enable New Mexico to use the latest and best data on the impact of reopening in nearby states, as well as to base decisions on emerging, peer-reviewed research on virus transmission rates in children.



National School Reopening Studies

- In collaboration with the CDC, our goal is to assess different school reopening scenarios at a regional and national scales under different phase assumptions using an agent-based simulation.
- In previous EpiCast models, school mixing groups accounted only for transmission between students; teachers and staff were not explicitly included.
- For this work, we associate a workplace with NAICS Subsector Code 611 (Educational Services) with each school, and account for mixing between the teachers, staff, and school children.
- Where necessary, additional workplace(s) are added to achieve an average 14:1 student-to-teacher/staff ratio in each school (based on data from the National Center for Education Statistics).
- Two scenarios were considered, roughly corresponding to "Opening Up America Again" Phases 2 ("Fewer Workplaces") and 3 ("More Workplaces")

Workplace Assumption	Working Status				Reduction in Contacts due to social Distancing		Long Distance Travel
	Full Time	Part-time or Shift	Telework Take-up	Laid Off	Workplace	Other non-household	
Fewer Workplaces	44%	32%	20%	16%	10%	50%	50%
More Workplaces	52%	32%	15%	8%	10%	25%	75%

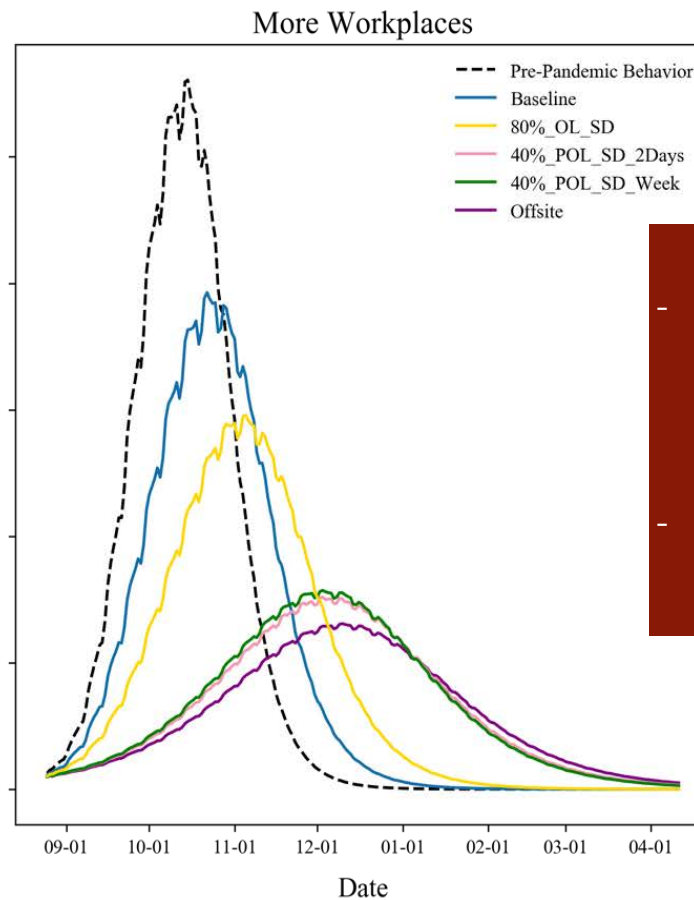
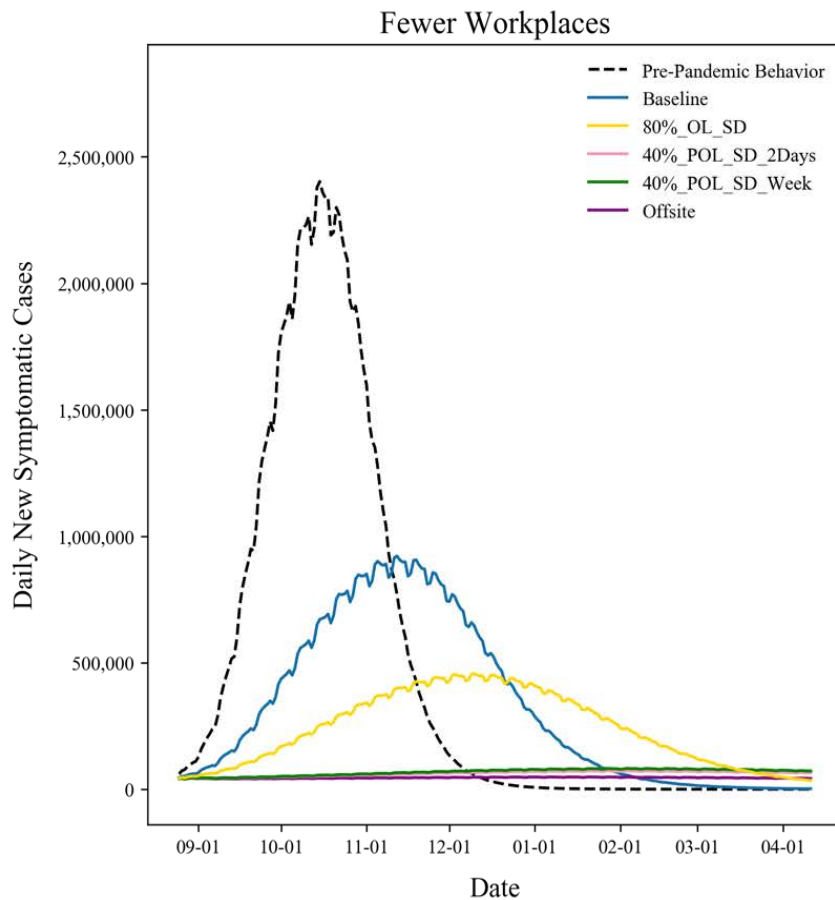
NAICS Sector	NAICS 2-Digit Code	Ability to Telework (Median)
Agriculture & Mining	11	8.1%
Utilities & Construction	21-23	32.7%
Manufacturing	31-33	41.0%
Wholesale	42	26.5%
Retail	44-45	26.5%
Transportation & Warehousing	48-49	32.7%
Information	51-52	80.4%
Finance, Insurance, & Real Estate	52-53	81.1%
Professional and Business Services	54-56	71.6%
Education	61	47.9%
Health & Social Services	62	47.9%
Leisure & Hospitality	71-72	20.3%
Other Services	81	39.9%
Government & Administration	92	57.0%

Several reopening scenarios were considered

- 10-20 sets of alternative school schedules and assumptions were considered, using regional (New Mexico and Chicago-area) models to identify the most important factors.
- Some surveys indicated that even if schools were open, a significant fraction of parents (~20%) would opt for distance learning or home schooling.

Scenario Name	Scenario Code	Scenario Description
Pre-Pandemic Behavior	Pre-Pandemic Behavior	No mitigations, all businesses completely open.
Baseline	Baseline	All students physically in school with some social distancing.
80% Onsite Learning with Reduced Social Distancing	80%_OL_LessSD	All students physically in school.
80% Onsite Learning with Ideal Social Distancing	80%_OL_SD	All students physically in school.
80% Partial Onsite Learning – Alternating Week with Reduced Social Distancing	40%_POL_LessSD_Week	Two non-overlapping cohorts of students – 40% of the students attend one week and the other 40% attend the next week.
80% Partial Onsite Learning – Alternating Days with Reduced Social Distancing	40%_POL_LessSD_2Day	Two non-overlapping cohorts of students – 40% of the students attend for two days/week (Mon/Tue) and the other 40% attend for two days (Thu/Fri). Wednesday off for disinfection.
80% Partial Onsite Learning – Alternating Weeks with Ideal Social Distancing	40%_POL_SD_Week	Two non-overlapping cohorts of students – 40% of the students attend one week and the other 40% attend the next week.
80% Partial Onsite Learning – Alternating Days with Ideal Social Distancing	40%_POL_SD_2Days	Two non-overlapping cohorts of students – 40% of the students attend for two days/week (Mon/Tue) and the other 40% attend for two days (Thu/Fri). Wednesday off for disinfection.
100% Distance Learning	Offsite	No students physically in school.

National Model Results

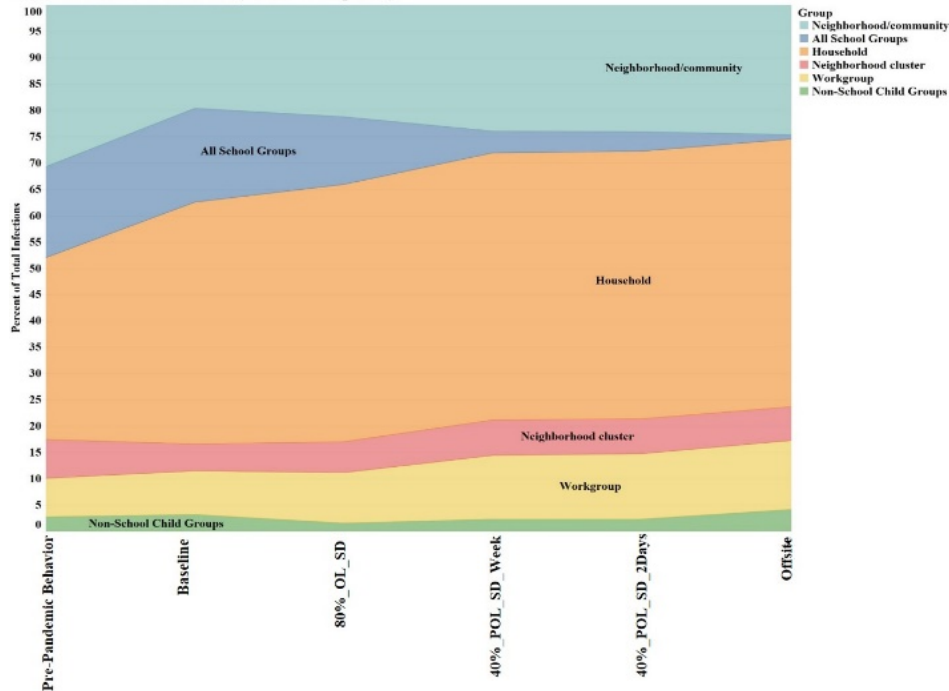


So what?

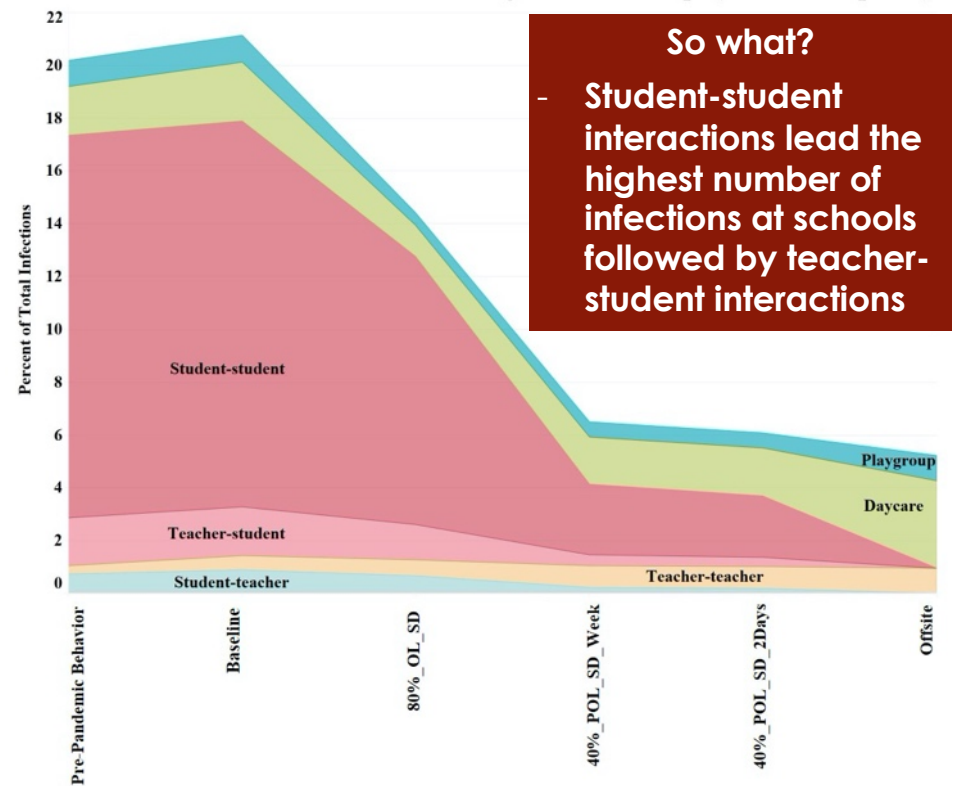
- Reopening schools at 80% attendance levels can result in a secondary wave of infection
- 40% scenarios and offsite levels result in better outcomes

Source of Infection (“Fewer Workplaces”)

National Source of Infection (Fewer Workplaces)



National Source of Infection for School/Young Children Groups (Fewer Workplaces)

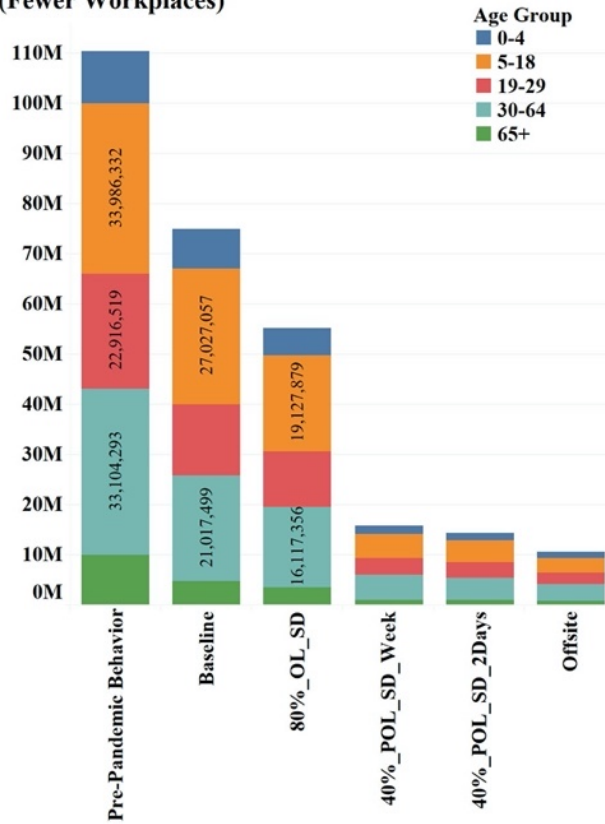


So what?
 - Student-student interactions lead the highest number of infections at schools followed by teacher-student interactions

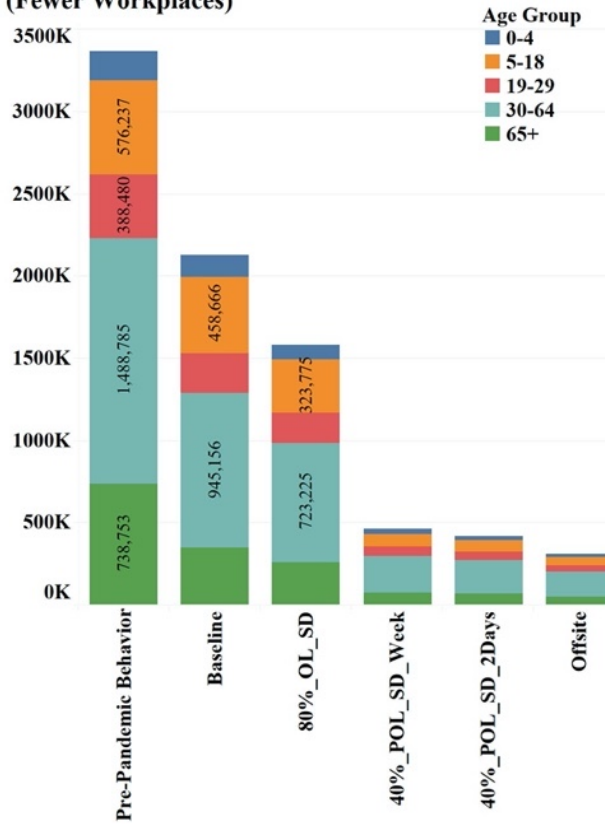
So what?
 - The majority of infections are generated at home followed by neighborhood/community

Case, hospital, and ventilator usage by age group (“Fewer Workplaces”)

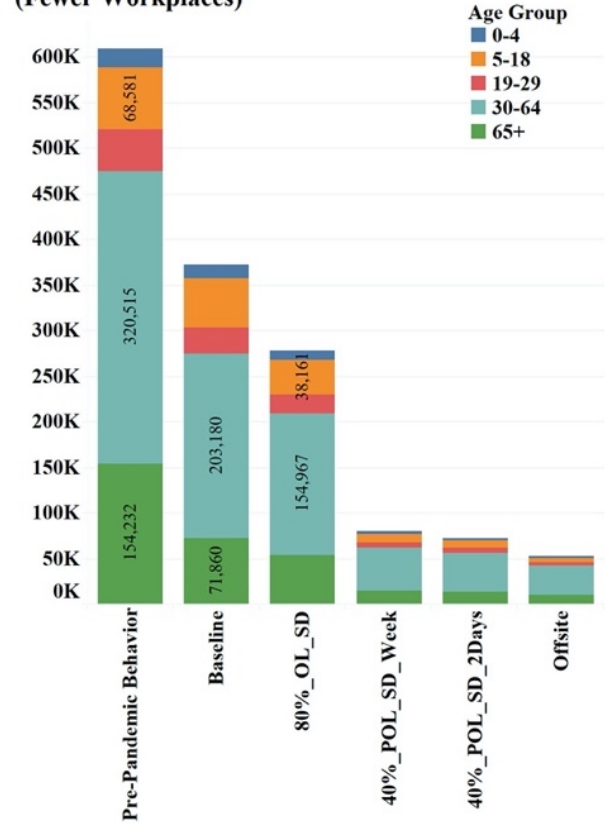
National Cases by Age Group by Scenario (Fewer Workplaces)



National Hospitalizations by Age Group by Scenario (Fewer Workplaces)



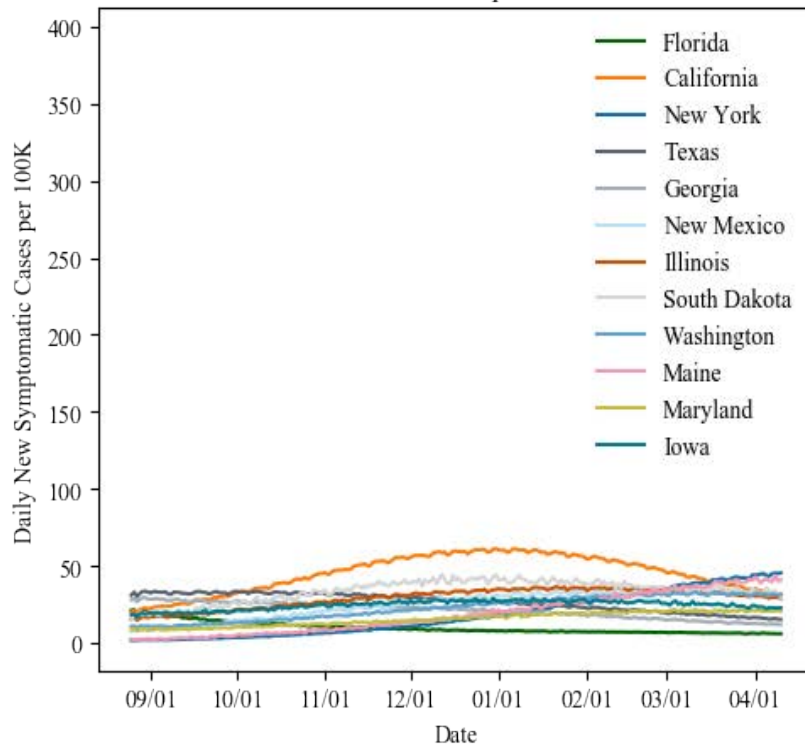
National Ventilators by Age Group by Scenario (Fewer Workplaces)



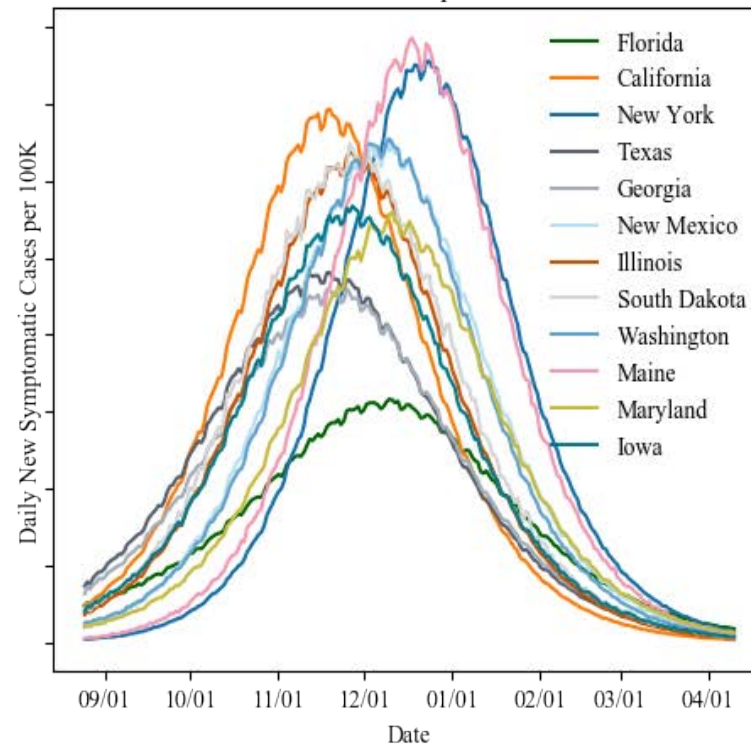
Spatial heterogeneity

40%_POL_SD_Week

Fewer Workplaces



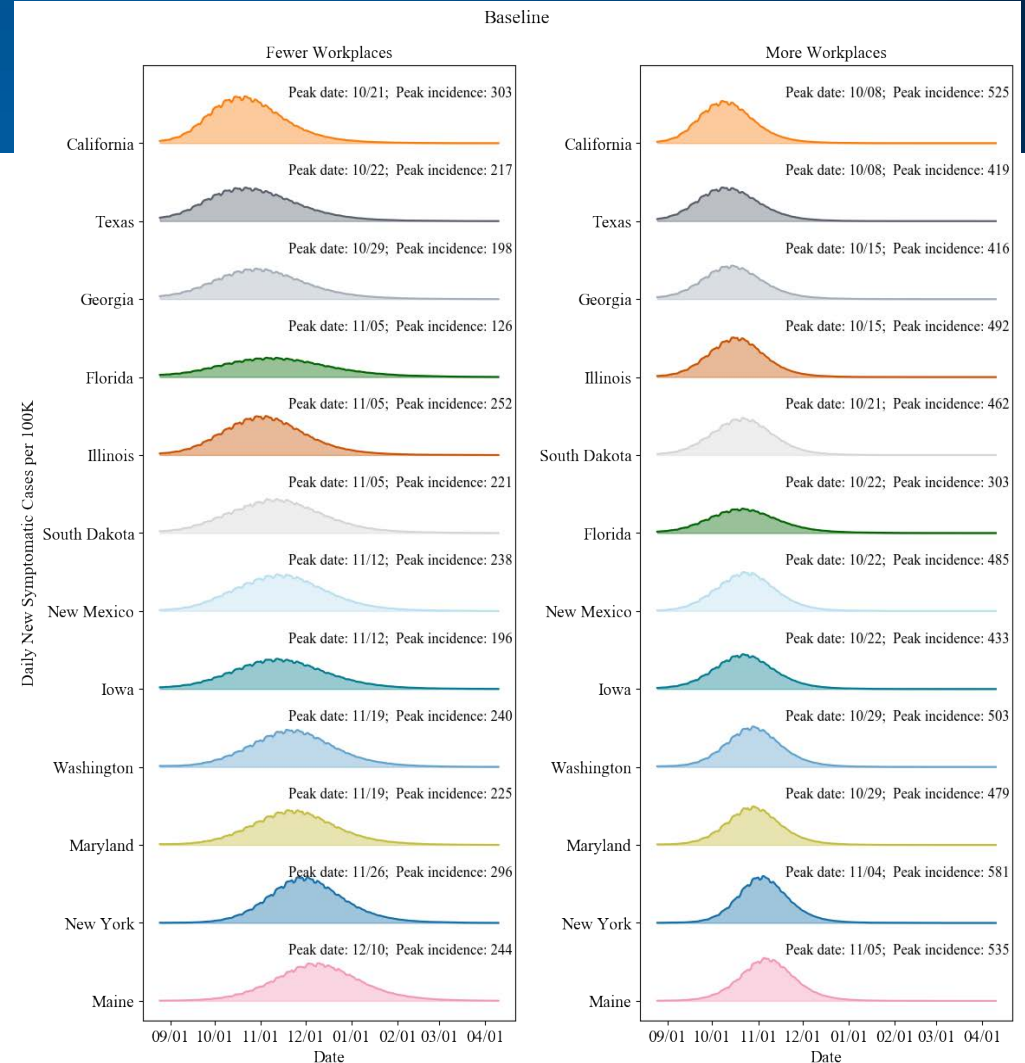
More Workplaces



So what?
Spatial heterogeneity driven by initial conditions, local demographic factors, and phases

Spatial heterogeneity

- For the baseline with Fewer Workplaces, the peak date ranges from October 21st (California) to December 10th (Maine).
- The timing of the peak for each state is dependent on:
 1. The current transmission levels; states with active community spread will reach their peak sooner; and
 2. Announced school reopening dates, which vary from August 3 (Arizona) to September 6 (New York).

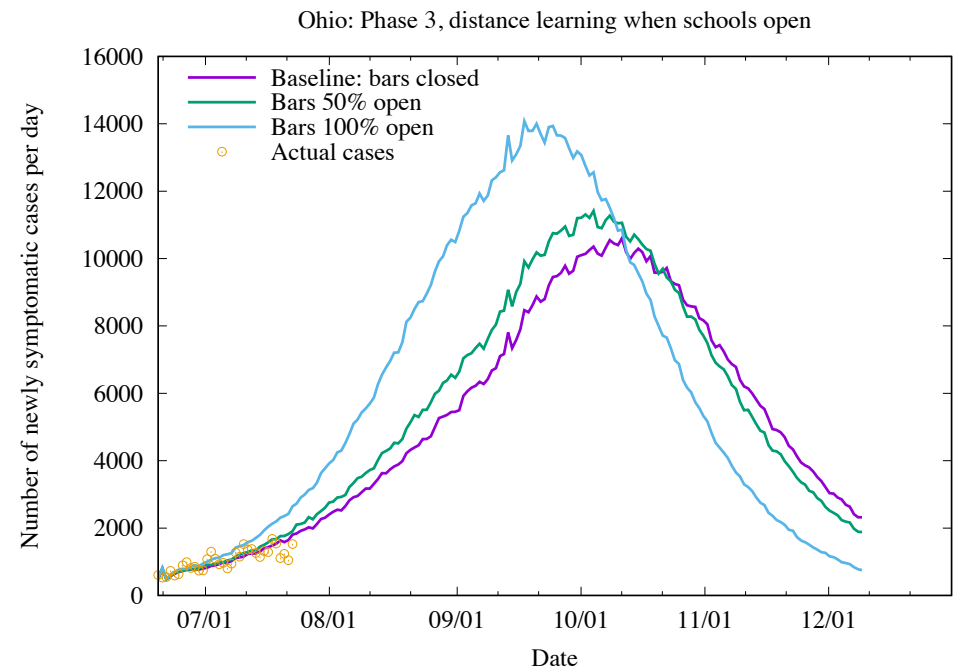
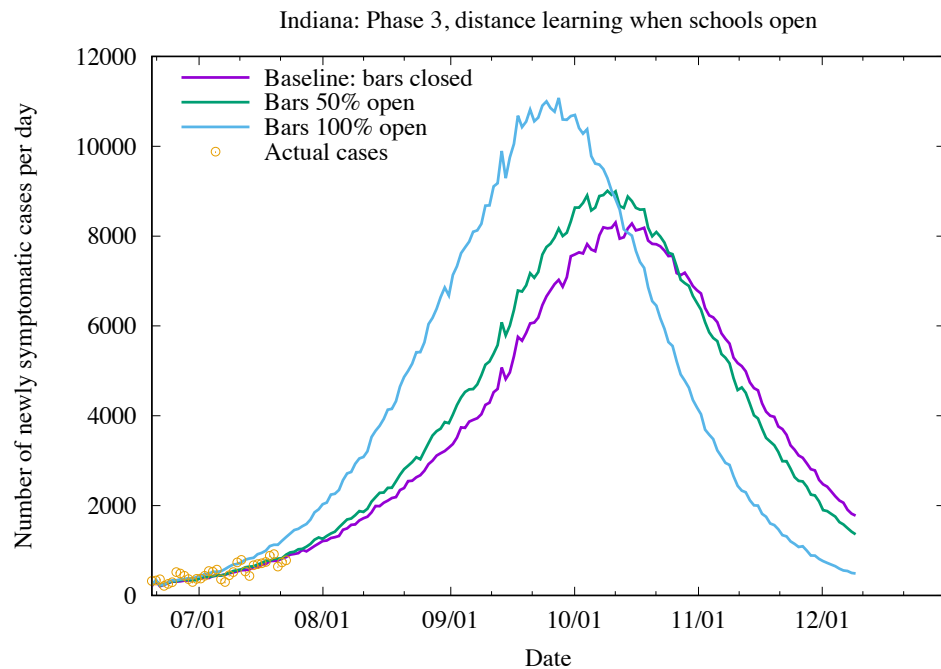


Assumptions: Bars and Restaurants



- **Transmission in large social settings** (bars, restaurants, birthday parties, college fraternities, ...) is important and a key target of policy guidance
- Various pre-COVID studies suggest that **~1/3 of adults visit bars/restaurants at least once a month**, with one stating that “34% said at least once a month; 19% said at least once a week; 3% said every day”
- Data on the % of bar industry revenue across different age groups closely matches (perhaps surprisingly!) the population of those age groups
- We assume that in the “normal” situation with fully open bars and restaurants, a **3%** of adults will participate in this mixing group each day
- Transmission in bars is assume to be similar to inside **household**
- The following results assume **Phase 3** business and social distancing practices, and a **regular 5-day work week** (for open businesses) with maximum telework

Results: Bars and Restaurants



So what?

The effect of opening 50% of bars is small relative to the overall transmission, however opening 100% can lead to significantly larger clinical attack rate

Some key limitations (which are being addressed by ongoing work)

- Identical policies (e.g., workplace restrictions and school schedules) uniformly across all states.
- Testing and contact tracing were not explicitly modeled.
- Uniform policies and behavior (e.g., compliance) assumed throughout the pandemic duration (simulations are through the end of March 2021).
- The model population in EpiCast is based upon the 2000 U.S. Census data, to take advantage of the tract-to-tract work flow data that was last compiled then.
- Epidemiological parameters are assumed to be constant throughout the simulation, but in reality may have spatial and temporal variability during the course of the COVID-19 pandemic.
 - Local weather (e.g., humidity) may affect not only human behavior, but also the dynamics and lifetime of droplets, spray, etc., which affect the transmissibility.
 - As more is learned about the disease course and effective treatments, the case fatality ratio has dropped.

Acknowledgements

- **DOE Data and Computational Coronavirus Tiger Team – (DCT)²**
 - Co-leads: Kathy Yelick (LBNL) and Fred Streitz (LLNL/AITO)
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 - PI: Sara Del Valle (LANL)

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