University of Pittsburgh

Large-scale Social Simulations for Public Health: Computational Challenges and Opportunities

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Carnegie Mellon Seminar

16 Feb 2012

Outline

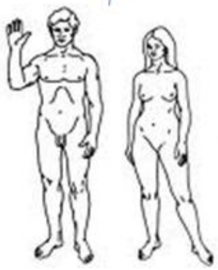
- Public Health Dynamics Lab
- Agent-Based Models of Infectious Disease Dynamics
- FRED: Framework for Reconstruction of Epidemic Dynamics
- Case Studies
- Validation
- Active Areas of Research
    - *Collaborations Welcome!*

Spatial Scales (meters)

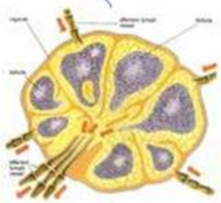
10^8 (Earth)

10^6 (Country)

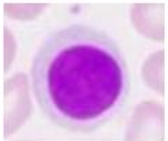
10^3 Kilometer (City)



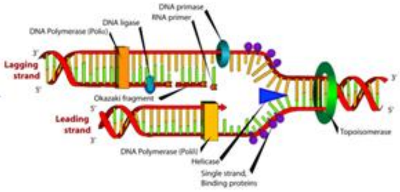
10^0 Meter (Human)



10^-3 Millimeter (Lymph follicle)



10^-6 Micrometer (Cell)



10^-9 Nanometer (Molecule)

Public Health

Medicine

Thanks to Don Burke

University of Pittsburgh Public Health Dynamics Lab

Computational modeling to advance the theory and practice of Public Health

www.phdl.pitt.edu

MISSION: *Promote health and prevent disease*

APPROACH:

- Develop interdisciplinary approaches using computational models to advance the theory and practice of Public Health
- Contribute to "Systems Thinking" in the training of the next generation of Public Health professionals

PHDL Members

and more ...

Major Projects and Partners

Models of Infectious Disease Agent Study (MIDAS)

National Center of Excellence (NIGMS/NIH)

- Real time epidemic parameter estimation
- Applied modeling
- Effects of weather and climate on infectious diseases
- Viral evolution
- Human behavior in epidemics

MIDAS
www.midas.pitt.edu

Vaccine Modeling Initiative (Bill and Melinda Gates Foundation)

- Impact of new vaccine technologies
- Global open source public health data access
- Supply chain models of vaccine distribution in developing countries

VMI
Vaccine Modeling Initiative
www.vaccinemodeling.org

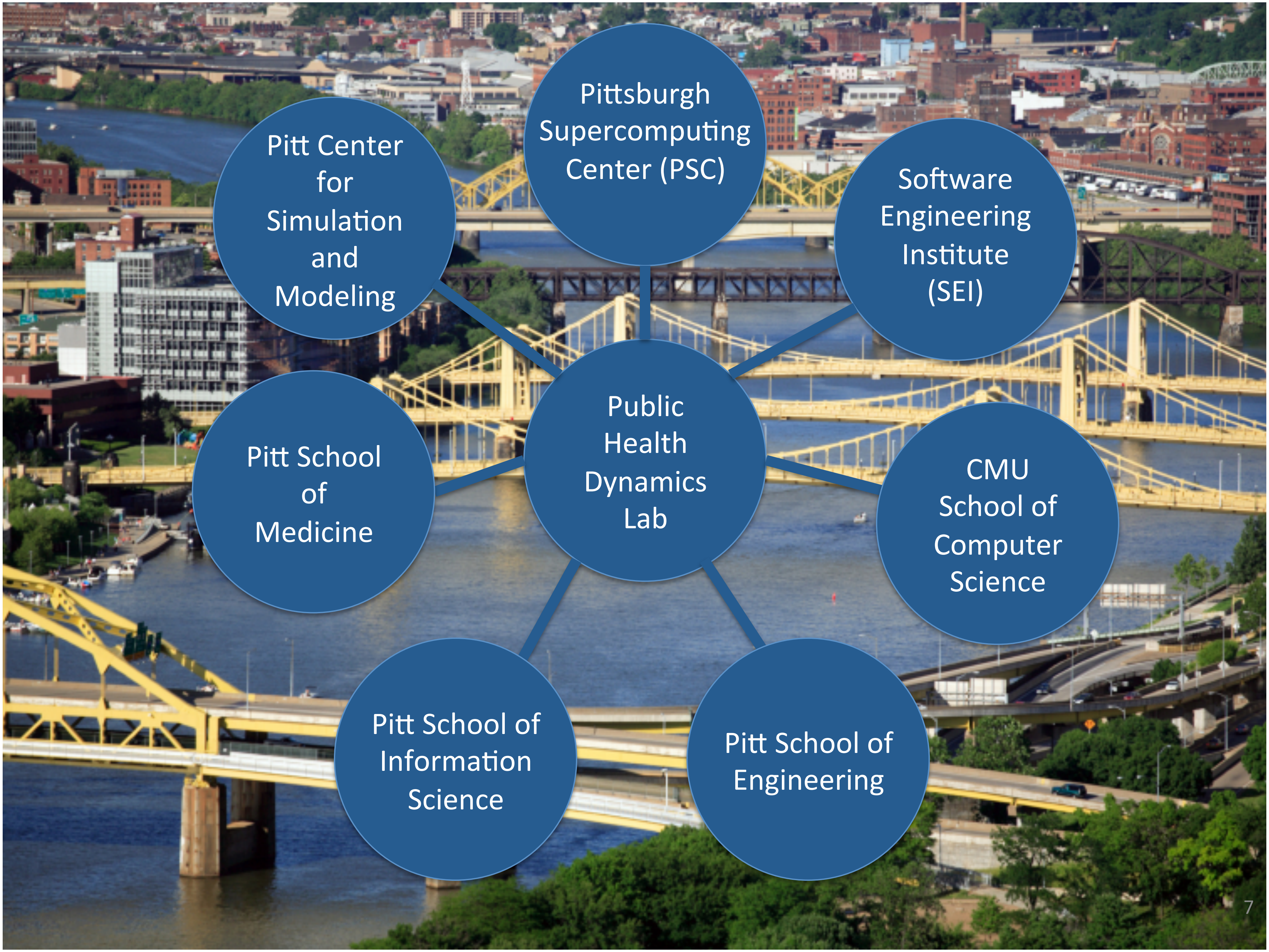
Public Health Adaptive Systems Studies (CDC)

- Data and metrics for populations and public health systems
- Geocoding of public health system capacities
- Network analyses of public health laws and policies
- Behavioral modeling for public health interventions
- Modeling tools for public health decision-making

PHASYS
www.phasys.pitt.edu

Partners:

Allegheny County ACHD Health Department
Pittsburgh Supercomputing Center
Carnegie Mellon University
RODS Laboratory
Johns Hopkins Medicine


Pittsburgh Supercomputing Center (PSC)
Pitt Center for Simulation and Modeling
Software Engineering Institute (SEI)
Public Health Dynamics Lab
Pitt School of Medicine
CMU School of Computer Science
Pitt School of Information Science
Pitt School of Engineering
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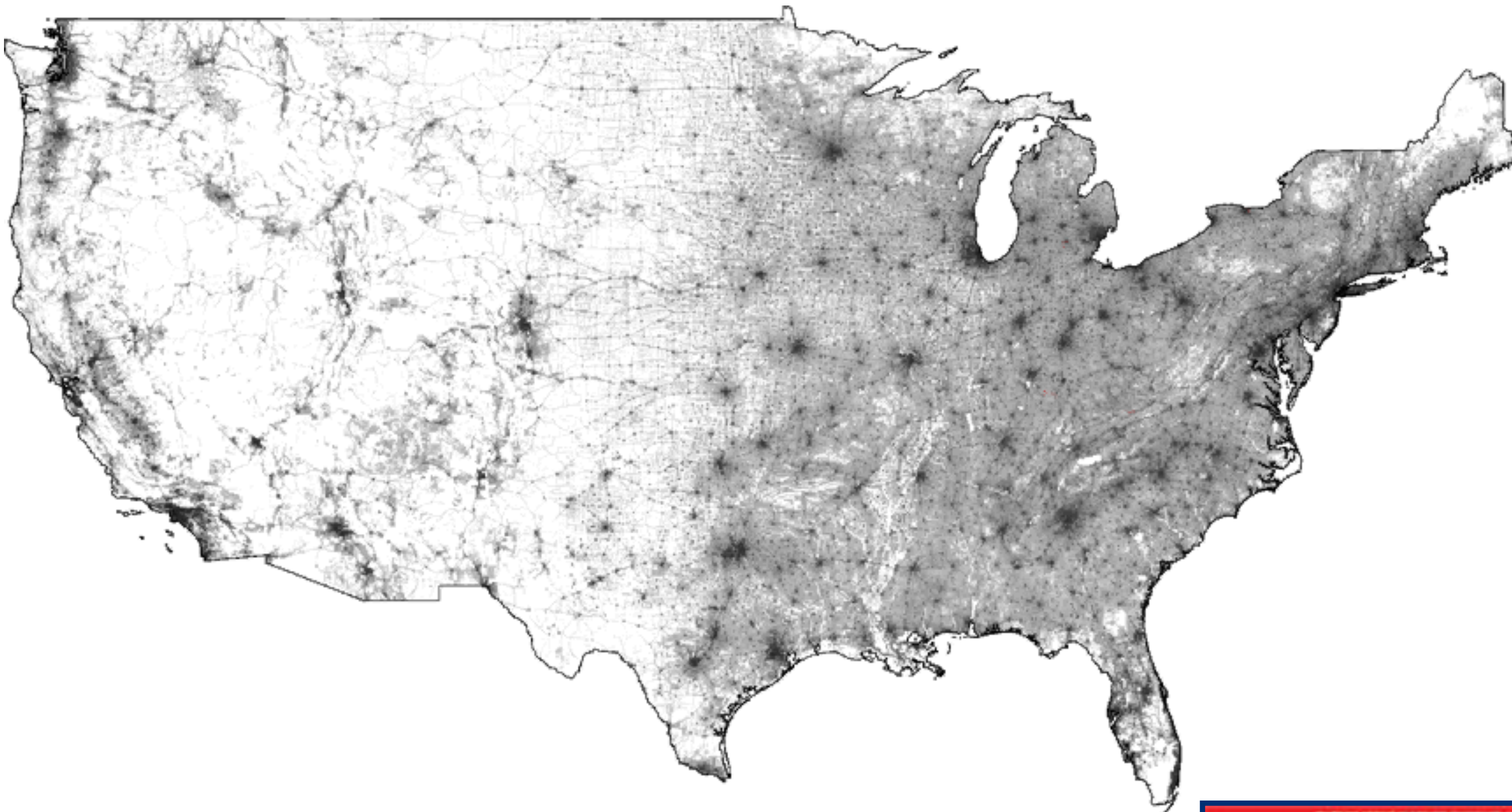
Agent Based Models

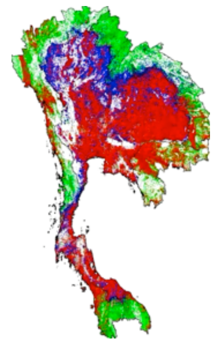
- Agent-based models (ABMs) focus on how interactions among individual agents can result in complex and interesting patterns of population behavior



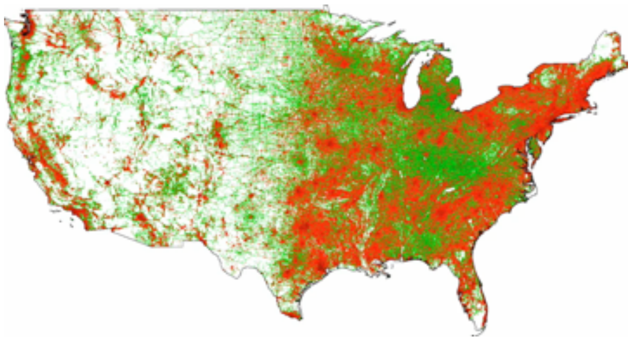
Ferguson NM, Cummings DA, Fraser C, Cajka JC, Cooley PC, Burke DS.
Strategies for mitigating an influenza epidemic
Nature July 27, 2006; 442: 448-52

Agent-Based Models for Infectious Disease

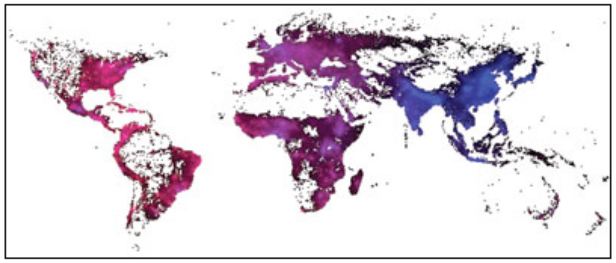
Small-pox
(Epstein et al 2002)
5000 agents



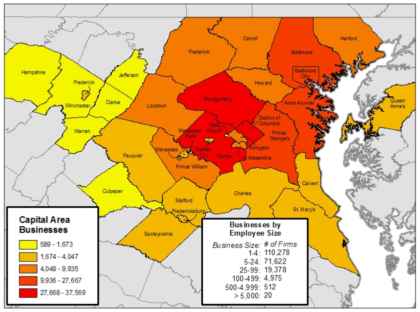
H5N1 Thailand
(Ferguson et al 2005)
85M agents



Influenza Pandemic US
(Ferguson et al, 2006)
273M agents



Global Scale Agent Model
(Parker and Epstein, 2009)
6.5B agents



MIDAS H1N1pdm Model
(Cooley, Brown et al 2009)
Pandemic Planning

FRED: (Pitt, 2011)
Dynamic Demographics,
Health Behavior Models

2009 H1N1 Pandemic Planning

2009 | 2010

University of Pittsburgh Influenza Task Force

Washington, DC

April May June July Aug Sept Oct Nov Dec Jan

ALLEGHENY COUNTY
ACHD
HEALTH DEPARTMENT

pennsylvania
DEPARTMENT OF HEALTH

Commenced work with ASPR and PCAST

Bruce Y. Lee, MD, MBA

Shawn Brown, PhD

CDC
CENTERS FOR DISEASE CONTROL AND PREVENTION

Continued work with ASPR and DHS

School Closure

Vaccination Strategy

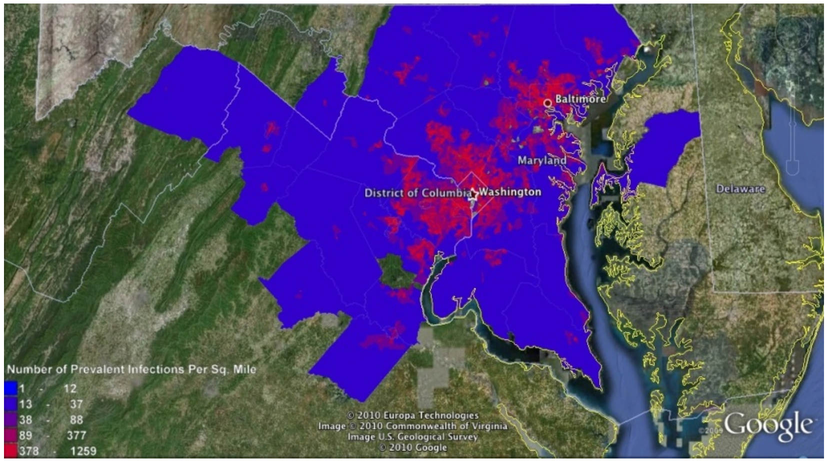
Antiviral Estimates

3rd Wave Scenarios

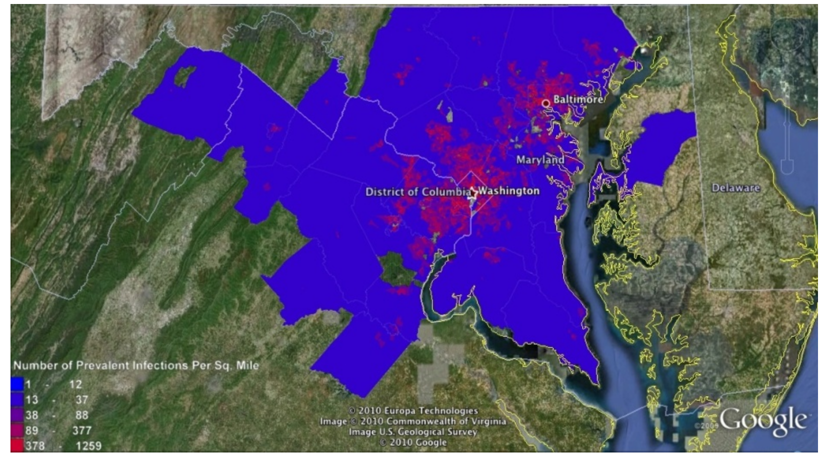
MIDAS Large-Scale ABMs contributed to H1N1 Pandemic National Planning

- Modeled a wide range of hypothetical scenarios for government decision makers
- Effects of epidemic peak timing and vaccine production schedules
- Effects of using adjuvants
- Effects of school closure policies
- Potential antiviral demand
- Effects on healthcare operations (e.g., ventilator demand)
- Possible third wave

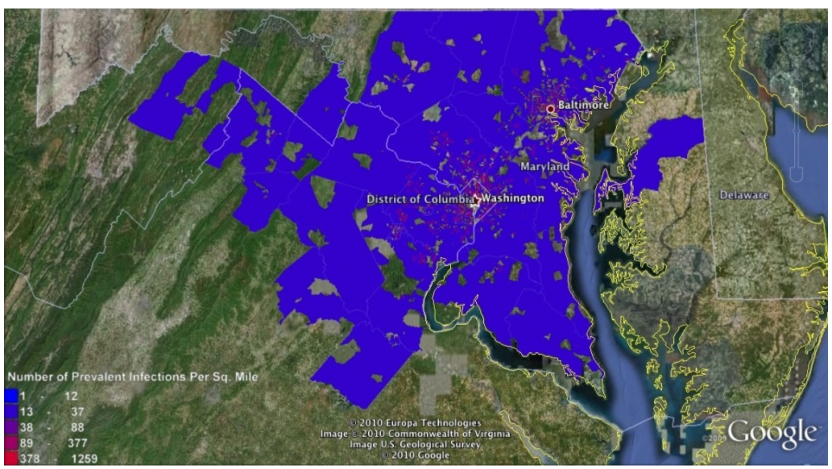
Visualizing the Epidemic Peak in Washington DC Four Scenarios



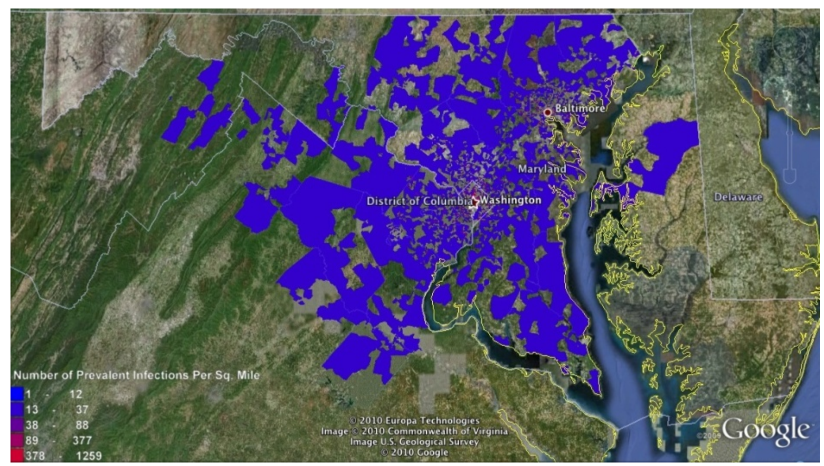
A. 15% serologic attack rate, no mitigation



B. Vaccinate a few weeks before peak



C. Vaccinate a month before the peak



D. Vaccinate a few months before the peak

Requirements arising from H1N1 experience

- Agent-based models with realistic U.S. population
- Support for complex vaccination availability schedules
- Flexible software design to allow rapid response
- Support for the study of human health behaviors
- Support for studies of viral evolution
- Adaptive re-use of research models:
  - real-time decision support
  - training and educational tools

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- Case Studies
- Validation
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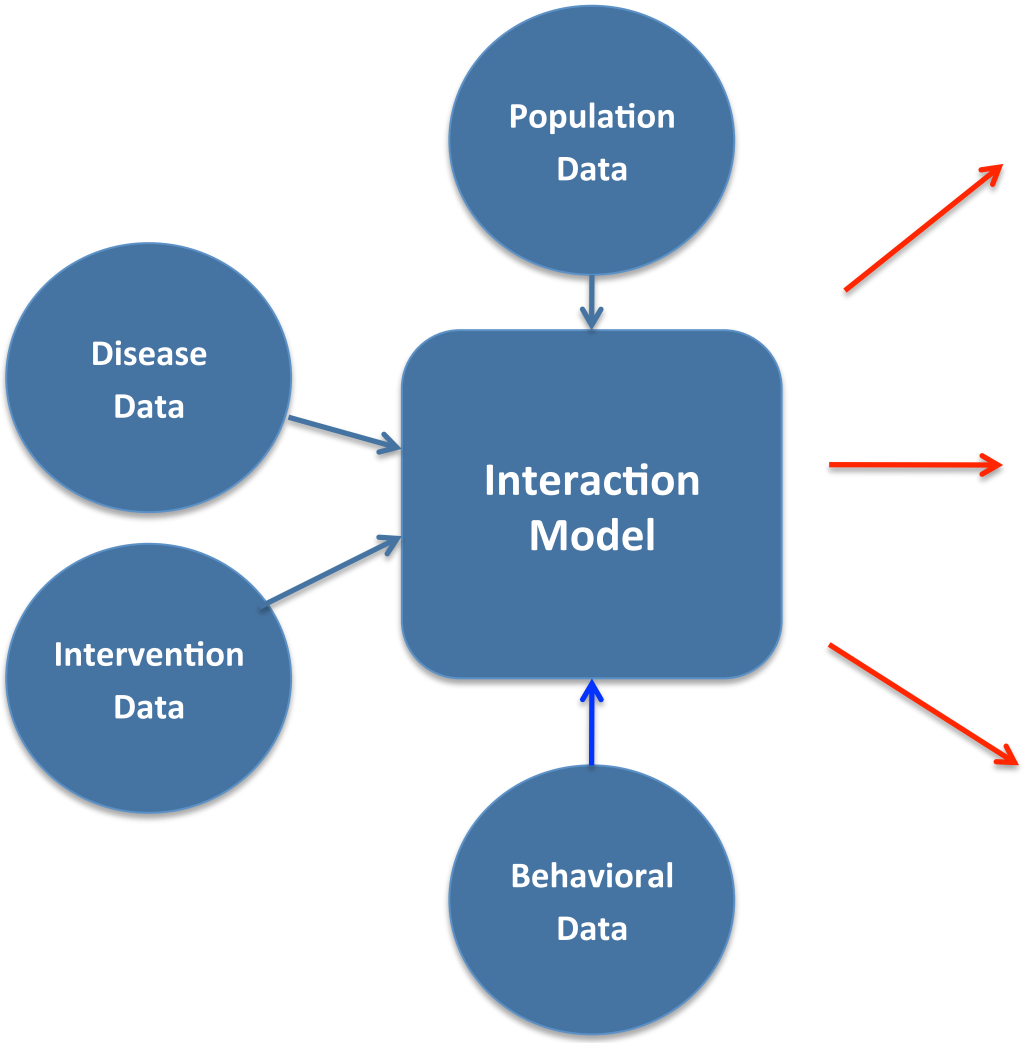
FRED: Framework for Reconstruction of Epidemic Dynamics

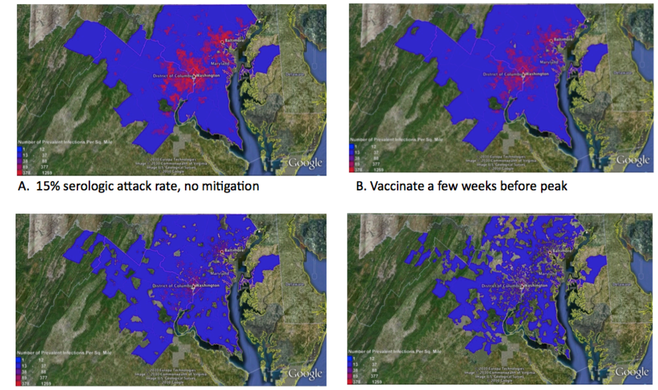
It's a beautiful day in this neighborhood,
A beautiful day for a neighbor.
Would you be mine?
Could you be mine?...

Fred McFeely Rogers, **"Mr. Rogers"** (March 20, 1928 – February 27, 2003) was an American educator, Presbyterian minister, songwriter, and television host. Rogers was the host of the Pittsburgh-based television show *Mister Rogers' Neighborhood*, in production from 1968 to 2001. The show won four Emmy awards.

FRED: Framework for Reconstruction of Epidemic Dynamics



Visualizing the Epidemic Peak in Washington DC -- Four Scenarios

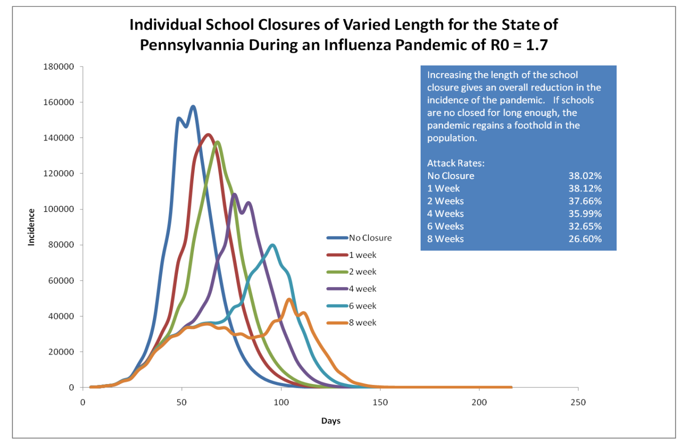


A. 15% serologic attack rate, no mitigation

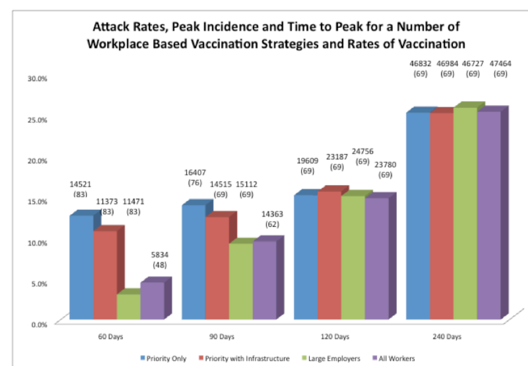
B. Vaccinate a few weeks before peak

C. Vaccinate a month before the peak

D. Vaccinate a few months before the peak

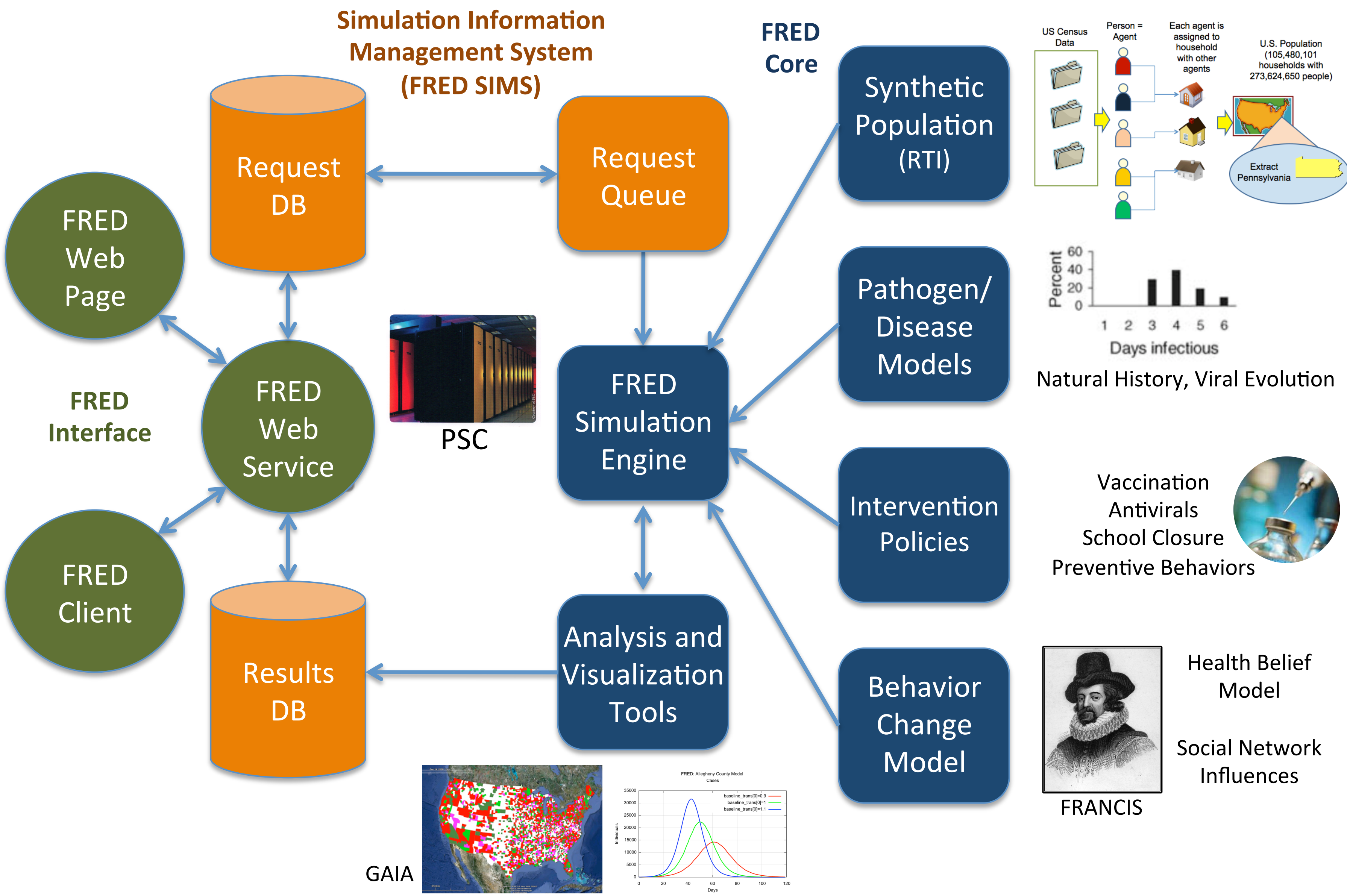


Vaccine Coverage and Timing

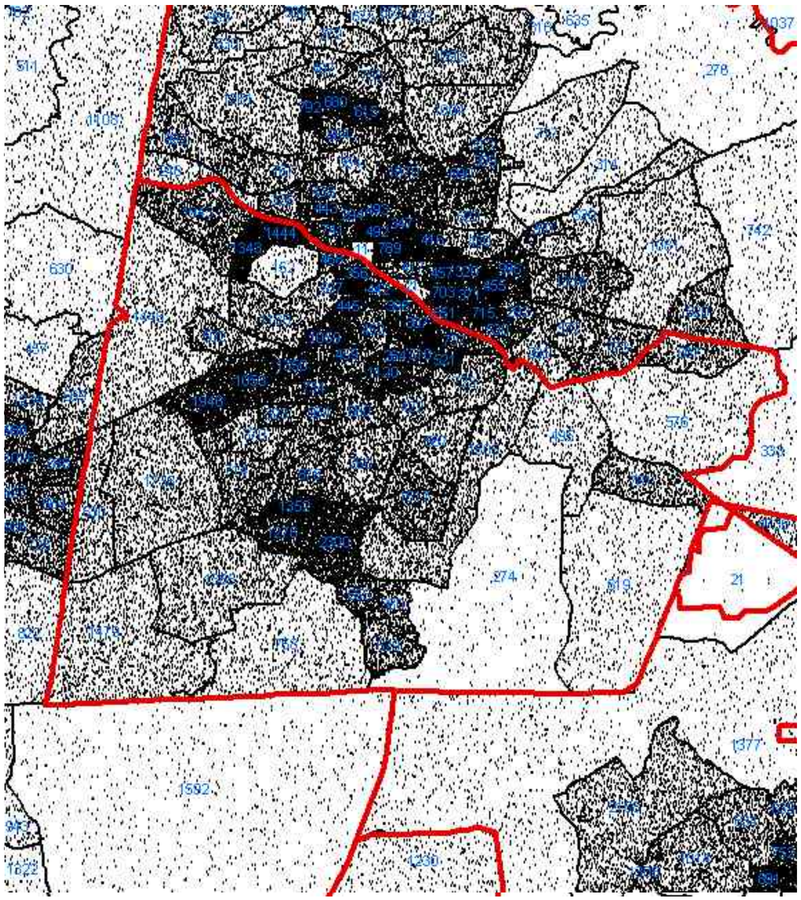


Even though a majority of workers are employed by small businesses, focusing on vaccinating larger firms may be just as effective in epidemic mitigation as trying to vaccinate all employees.

FRED: Framework for Reconstruction of Epidemic Dynamics



Creating a Synthetic Population: Data Inputs and Techniques



Macro/Aggregate Data

- Counties
- Census Tracts
- Block Groups [black outlines]
  - census counts only

Micro/Individual Data

- 5% sample from Public Use Microdata Areas (PUMAs) [red]
- Detailed individual and household info

Household Locations

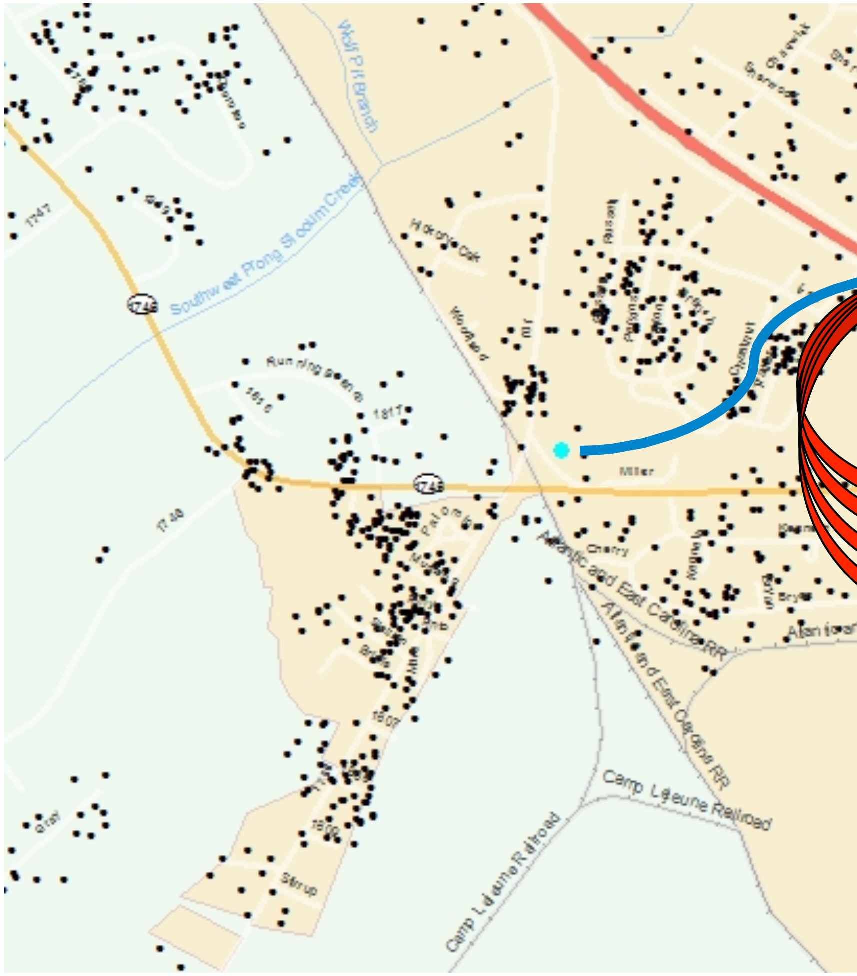
- Based on LandScan data
- 90m grid resoution

Iterative Proportional Fitting

- "Clone" particular records of the 5% PUMS sample to match census counts at block group level

Courtesy of Bill Wheaton, RTI

Example Households and Persons



Household

ID	Persons	Age of HH	Income	Vehicles
9903	4	47	55,000	2

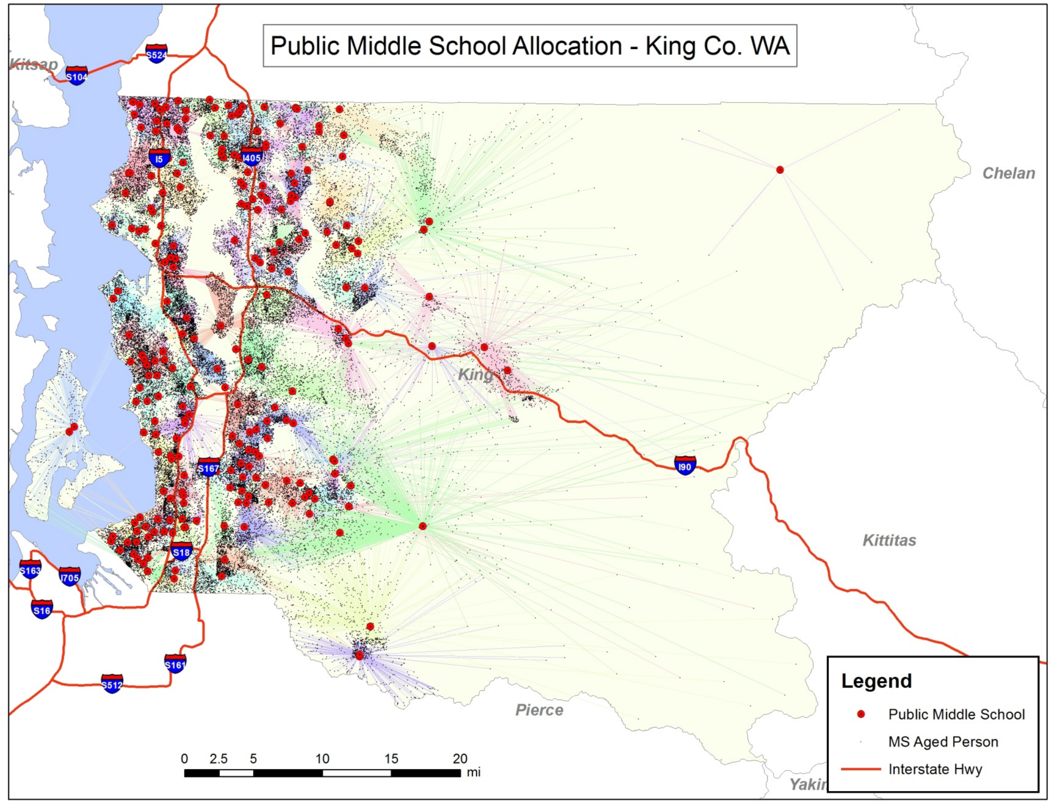
Persons

ID	Person Num	Age	Sex	school_ID	work_ID
9903	1	47	Male	N/A	23401
9903	2	45	Female	N/A	N/A
9903	3	15	Female	18047	N/A
9903	4	10	Female	34789	N/A

Details in: Beckman, Richard J., "Creating Synthetic Baseline Populations", Transportation Research, Vol 30, No.6, pp 415-429, 1996

Schools Assignments

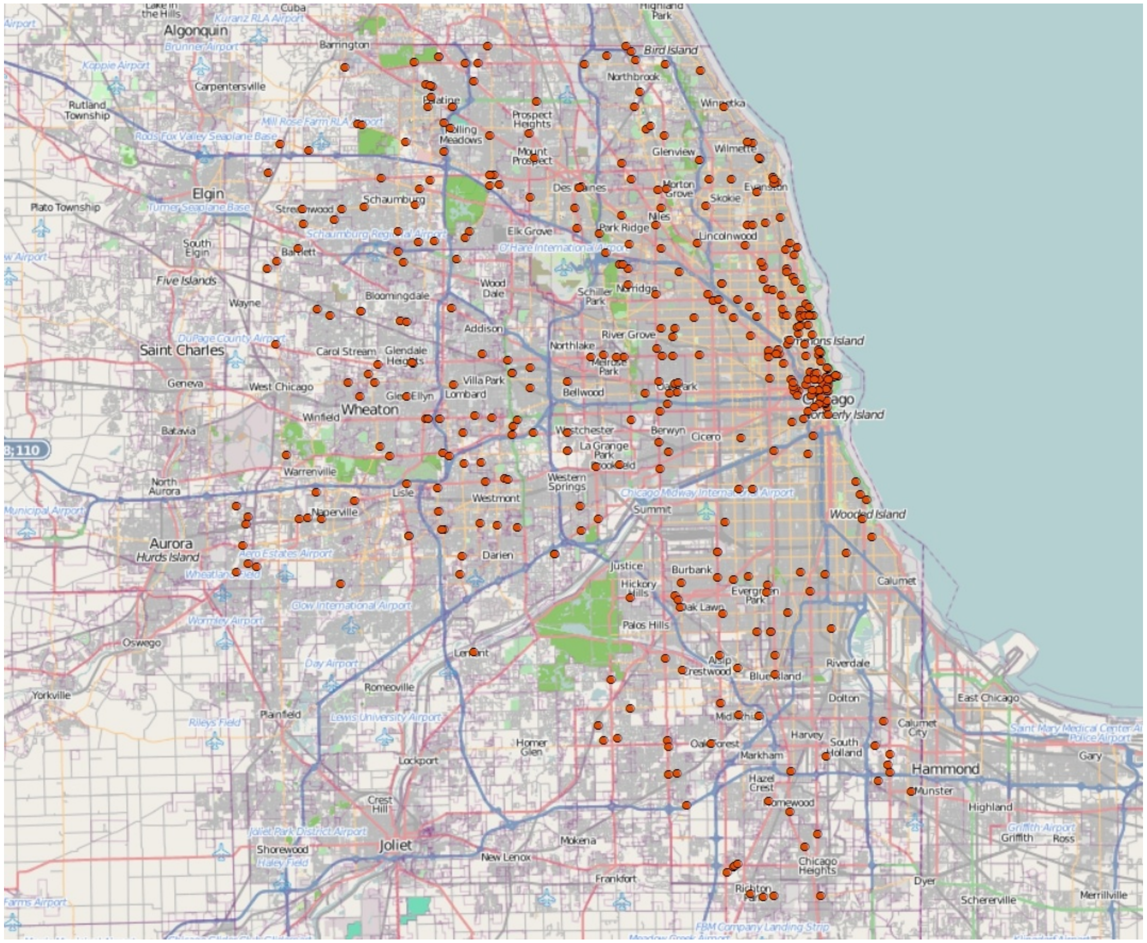
- After creating basic population, assign students to schools
- Based on nationwide database of schools: location; grades, capacity
- Use distance to assign students to school by age/ grade and capacity



Courtesy of Bill Wheaton, RTI

Workplace Assignments

- In general, data is not available to assign workers to specific workplaces based on occupation
- Workplaces are generated based on size distribution and placed by population density
- Workers are assigned to workplaces to match census commuting distances



Courtesy of Bill Wheaton, RTI

U.S. Synthetic Population Results

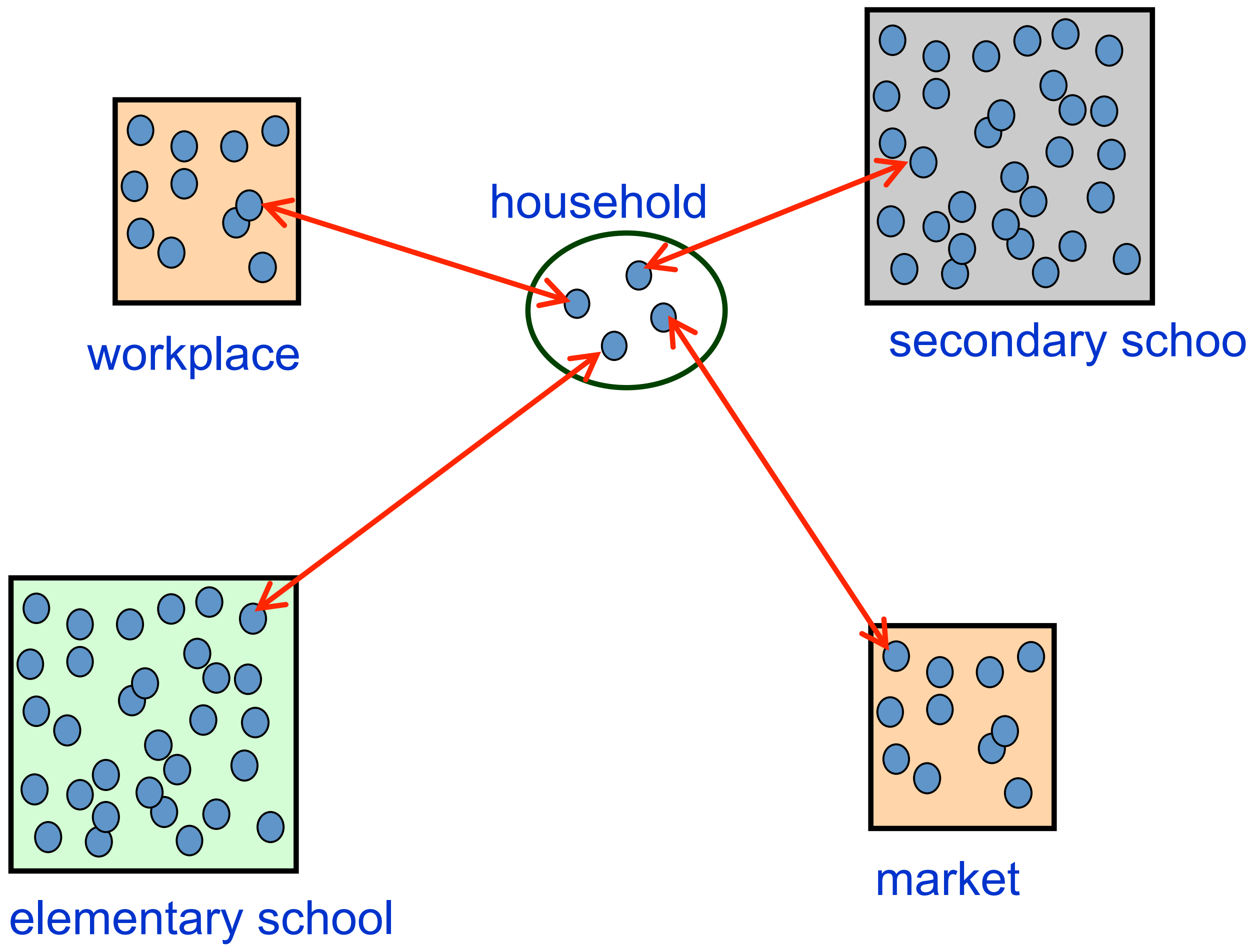
- Persons
  - In households: 273,624,650 generated vs. 281,421,906
    - In Group Quarters: (6,115,802)
  - Individual attributes: age, sex, etc.
- Households
  - 105,480,101 generated vs. 104,926,825 in census
  - Locations matched to LandScan 90m grid data
  - Household attributes: size, age of householder, race, income, etc.
- Workplaces
  - 8,580,092 generated work locations
  - Workers assigned to match census commuting distance data
- Schools
  - 116343 actual school locations
  - Students assigned to match enrollment by age
- Built-in Social Networks: family, school, workplace

Courtesy of Bill Wheaton, RTI

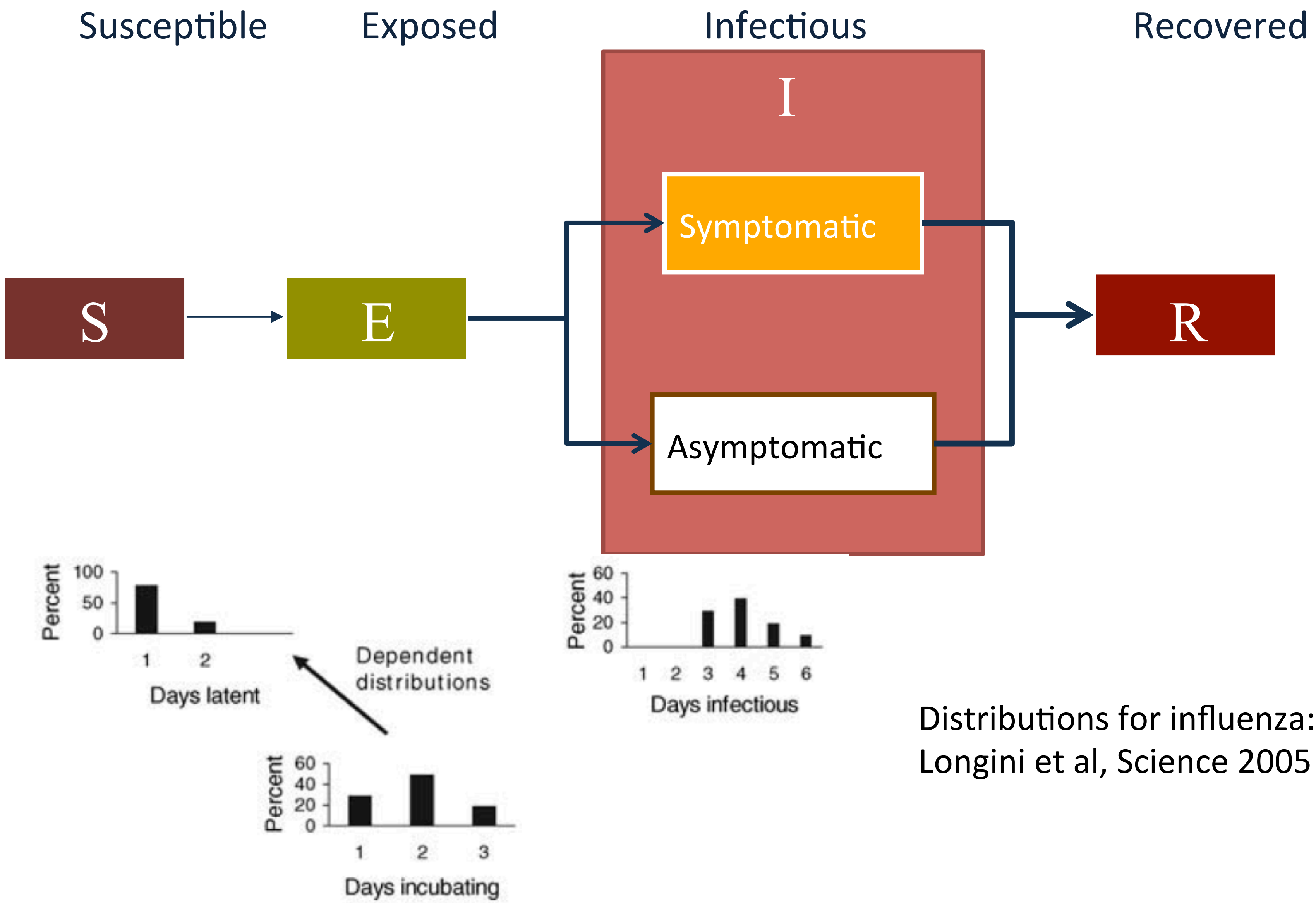
Contact Network Interactions

- Individuals commute to schools/workplaces with realistic distances based on travel data

- Disease transmission probabilities depend on where transmission occurs, and who infects whom



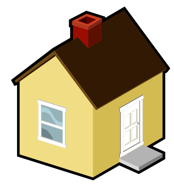
Individual Disease Model



Distributions for influenza:
Longini et al, Science 2005

Place Model

- FRED assumes that all transmission occurs in a given *Place*
- Place types include:
  - Household
  - Community
  - School / Classroom
  - Workplace / Office
  - Additional types can be defined
- Places can have
  - Contact rates
  - Transmission probabilities
  - Geo-location
  - Environmental conditions
    - Temp, humidity
- Place can be extended to include
  - Vectors
  - Fomites



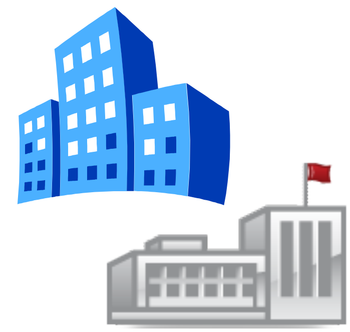


Table 1. Model transmission and person-to-person contact parameter values

Transmission parameters			
Contact group	**Infected**	**Susceptible**	**Transmission probability**[a]
Household	Adult	Adult	0.4
Household	Child	Adult	0.3
Household	Adult	Child	0.3
Household	Child	Child	0.6
Elementary school	Student	Student	0.0435
Middle school	Student	Student	0.0375
High school	Student	Student	0.0315
Workplace	Adult	Adult	0.0575
Hospital	HCW	HCW	0.0575
Hospital	HCW	Patient	0.01
Hospital	Patient	HCW	0.01
Community	All	Child	0.00255
Community	All	Adult	0.00480

Lee et al. Am J Prev Med 2010, based on
Ferguson NM, Cummings DA, Fraser C, Cajka JC, Cooley PC, Burke DS. *Strategies for mitigating an influenza pandemic*. Nature 2006;442(7101):448 –52.

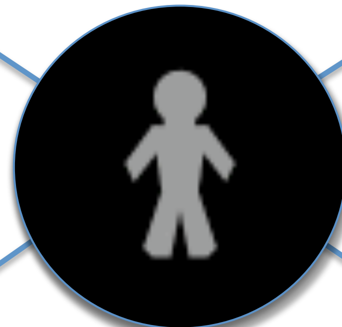
FRED Agent Model

Demographics:
Age
Sex

Agents can age, give birth, die

Health:
Immune Status
Exposure Status
Symptoms

Maintain health history over lifetime of agents



Activity Profile:
Pre-schooler
Student
Worker
Retired

Activity Profiles can change over lifetime of agents

Behavior:
Vaccine Acceptance
Social Distancing
Hand Washing

Models of Health Behavior Change:

- *Stochastic*
- *Social norms / influence*
- *Health Belief Model*
- *Segmented populations*

FRED Daily Cycle

1. Update all agents
   a. Demographics
   b. Health
   c. Health-related decisions
   d. Daily schedule of places to visit

2. Identify all places that have infectious visitors
   a. Find all susceptible visitors

3. Simulate spread of infection in each infectious place:
   a. Schools
   b. Workplaces
   c. Neighborhoods
   d. Households

Intervention Models

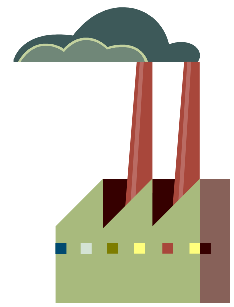
- Pharmaceutical Interventions
  - Vaccines
  - Anti-viral drugs
  - Flexible specification of efficacy
  - Complex availability and delivery schedules
- Non-pharmaceutical Interventions
  - School closure
    - Multiple closure/reopen policies
  - Personal behavior changes
    - Facemasks
  - Travel Restrictions
  - Environmental treatments (future)

Model Calibration

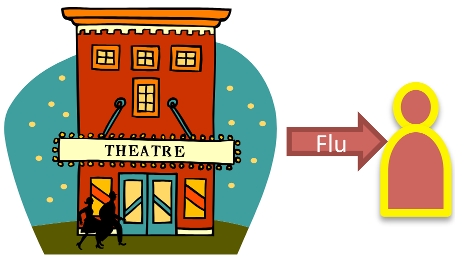
Communities

33%

Workplaces

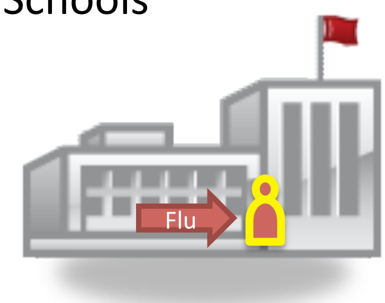


37%

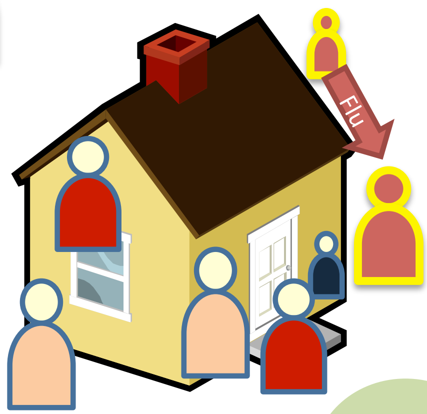


16% infections in schools
21% infections in workplaces

Schools



(Applies to an epidemic R0 = 1.9)

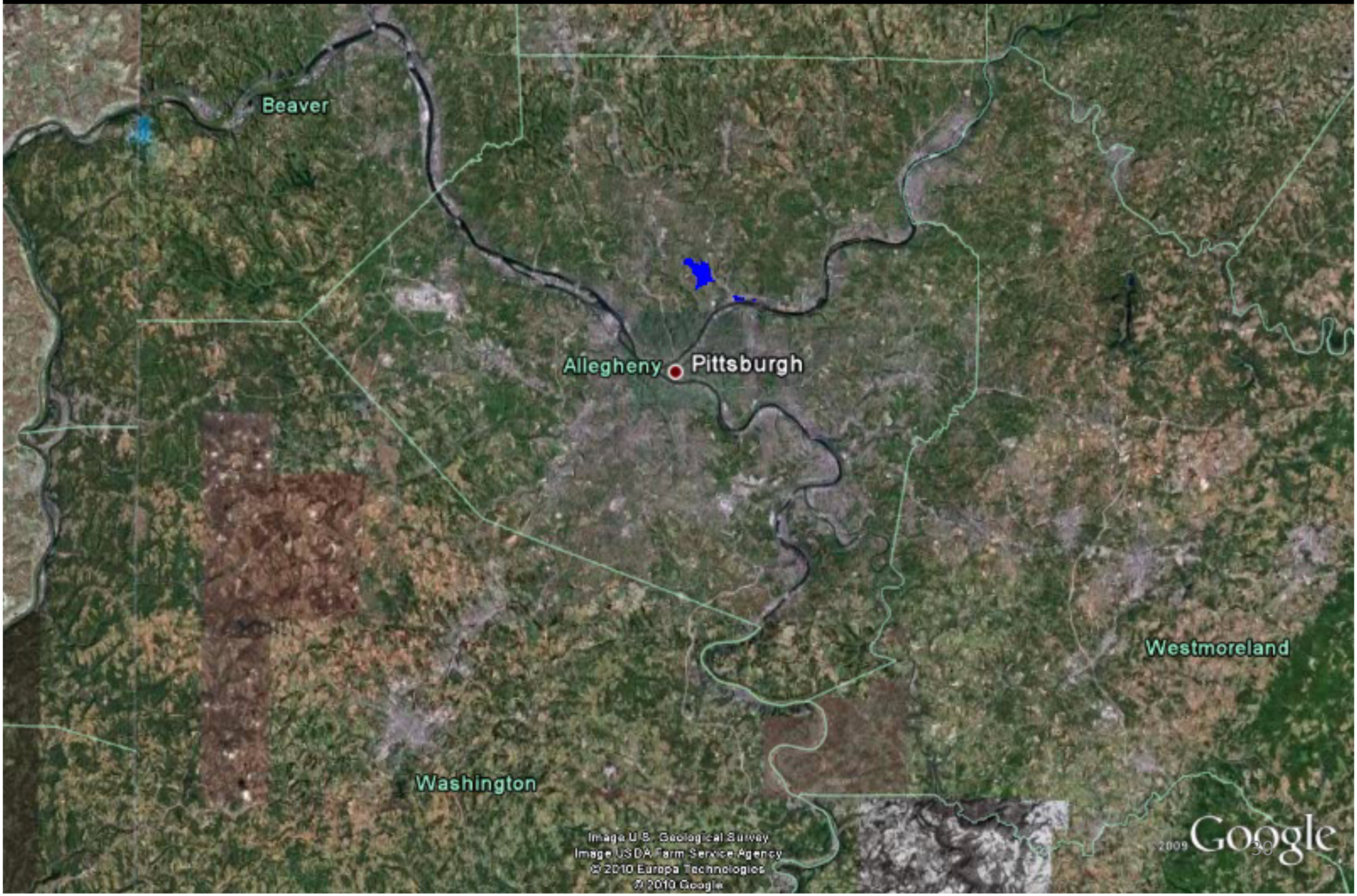


Homes

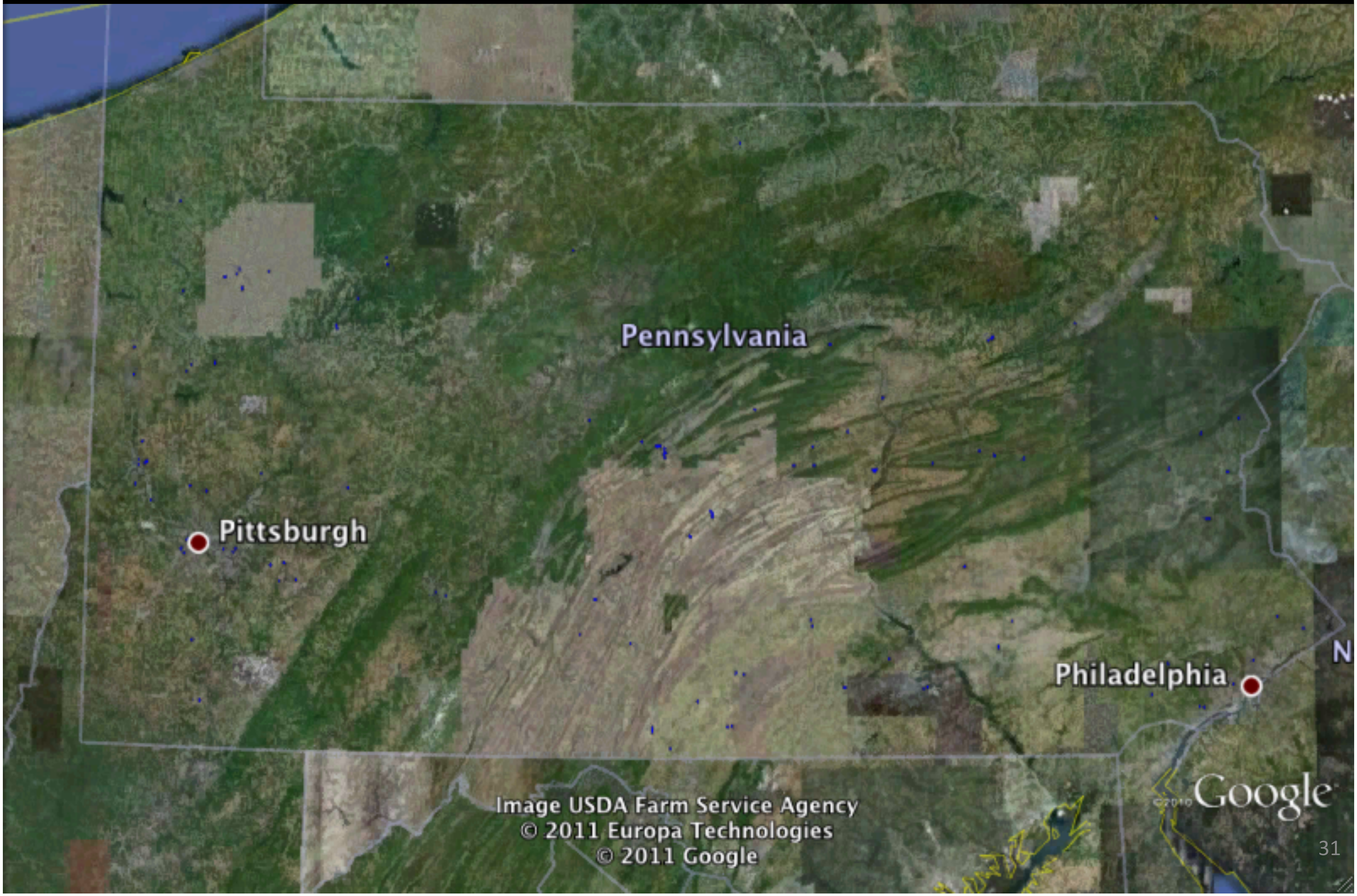
30%

Reference:
Ferguson N, Cummings DAT, Fraser C, Cajka JC, Cooley PC, Burke DS. Strategies for mitigating an influenza pandemic. Nature. July 27, 2006; 442:448-452.

Spread of Pandemic Influenza in Allegheny County, PA



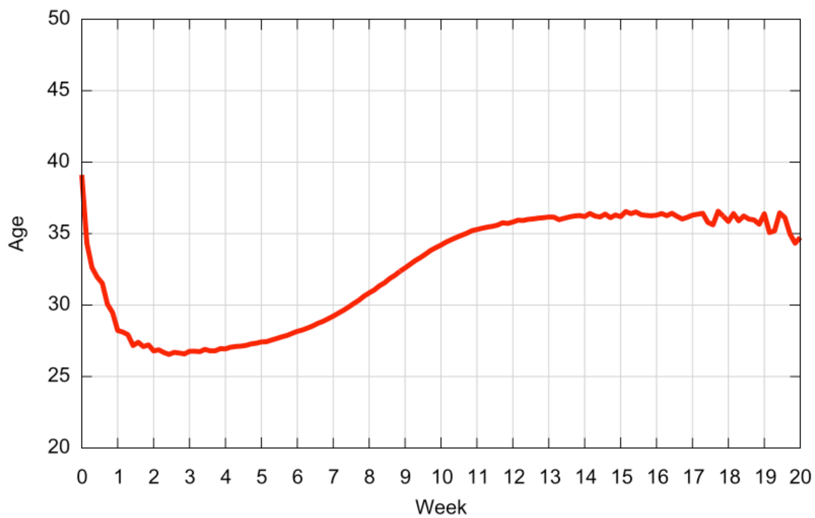
Spread of Pandemic Influenza in PA



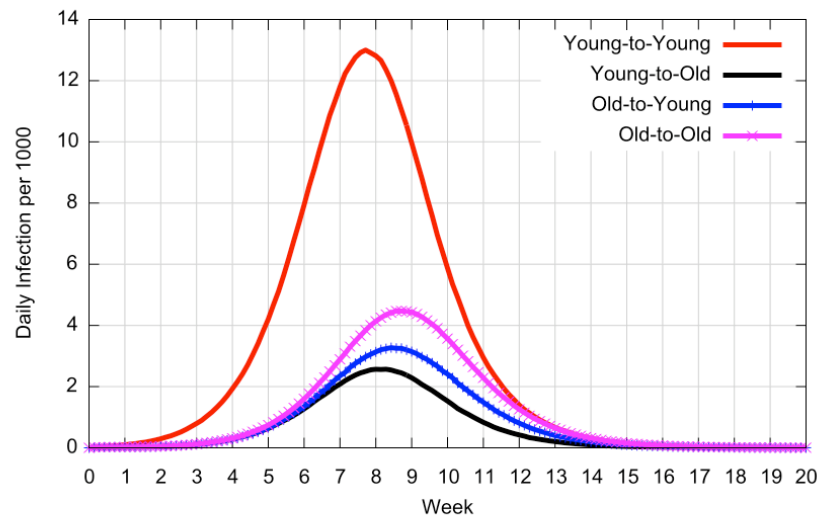
Reconstruction of Detailed Epidemic Dynamics

- Who is infected over time?
- Who infects whom?
- When/Where do infections occur?
- Evaluation of individual-based intervention strategies

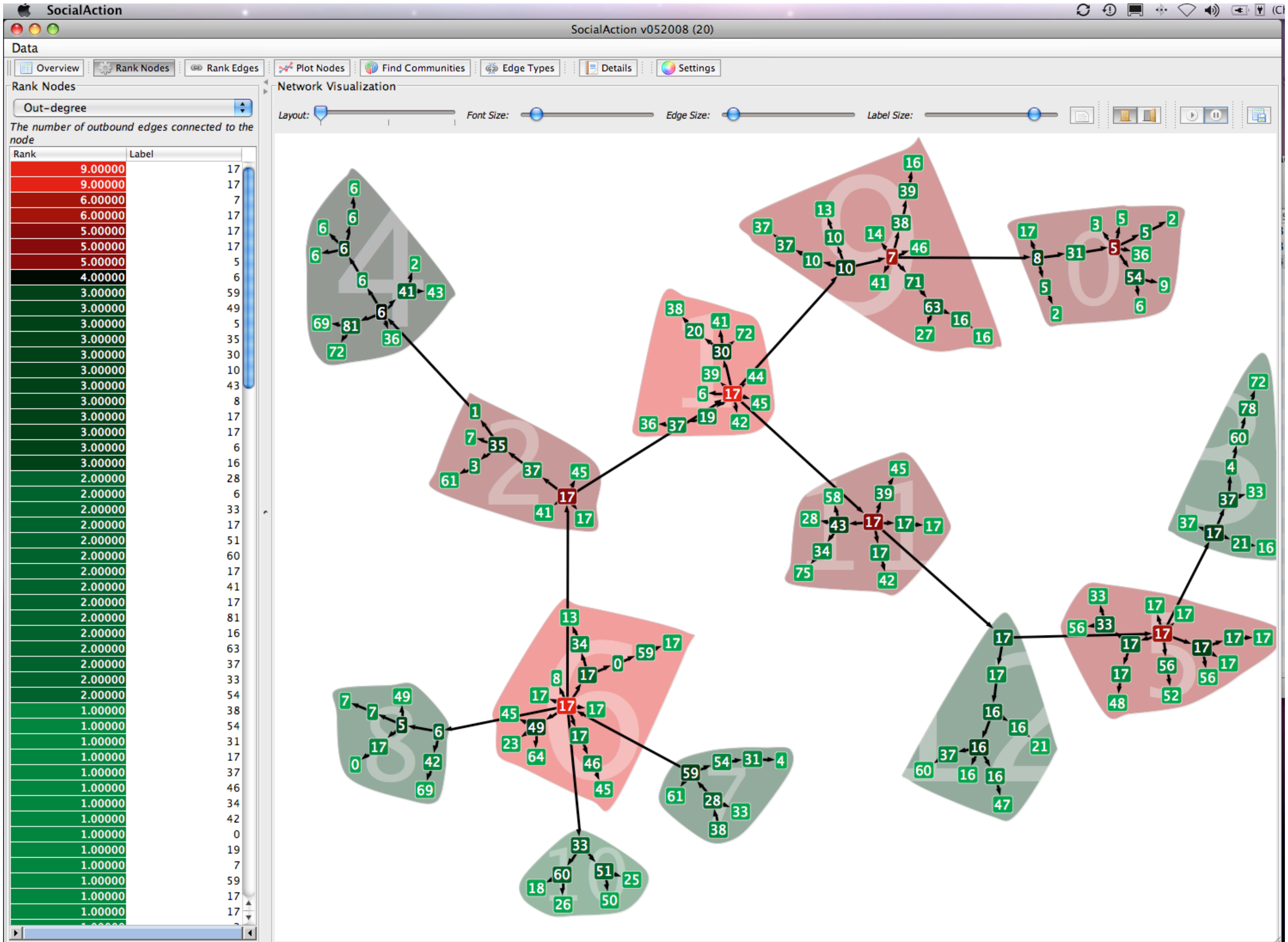
Average Age of Incident Infections
FRED Model of Influenza in Allegheny County



Who Infects Whom?
Age-Stratified Chains of Infections



Transmission Tree Visualization



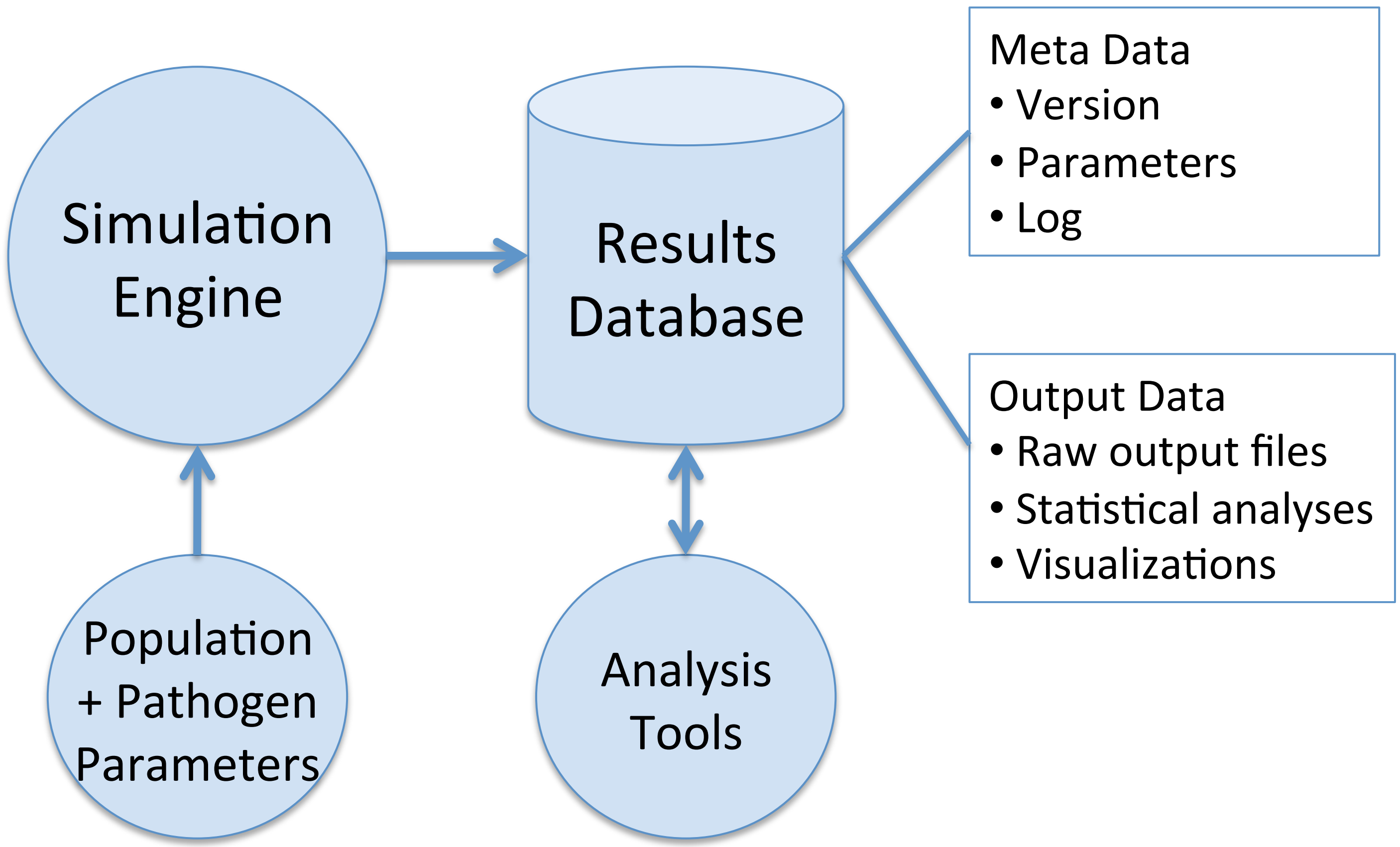
Jiawei Huang, Univ Pitt

FRED: Software Features

- Objected Oriented ABM in C++
- Tested under Linux, OS X, Windows
- Runs on Blacklight supercomputer (PSC)
- Team software development practices
- Simulation data management
- Separate statistical analysis and visualization tools
- Web services interface

Blacklight
Pittsburgh Supercomputing Center

FRED Simulation Information Management System



- Ensures reproducible methods and results
  - Calibration exercises
  - Sensitivity Analyses
  - Optimization runs

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- Public Health Dynamics Lab
- Agent-Based Models of Infectious Disease Dynamics
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- Case Studies
- Validation
- Active Areas of Research
  - *Collaborations Welcome!*

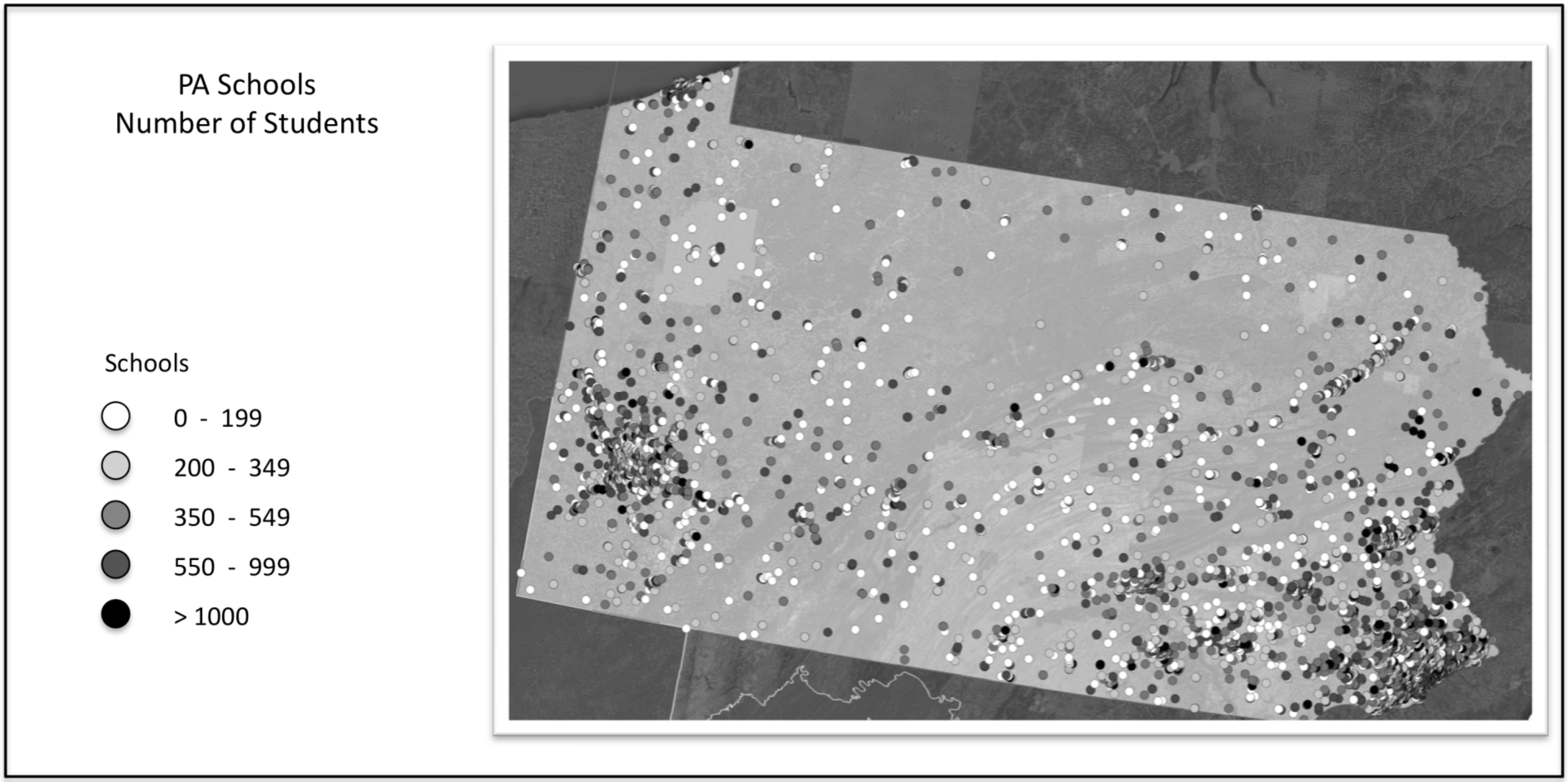
School Closures

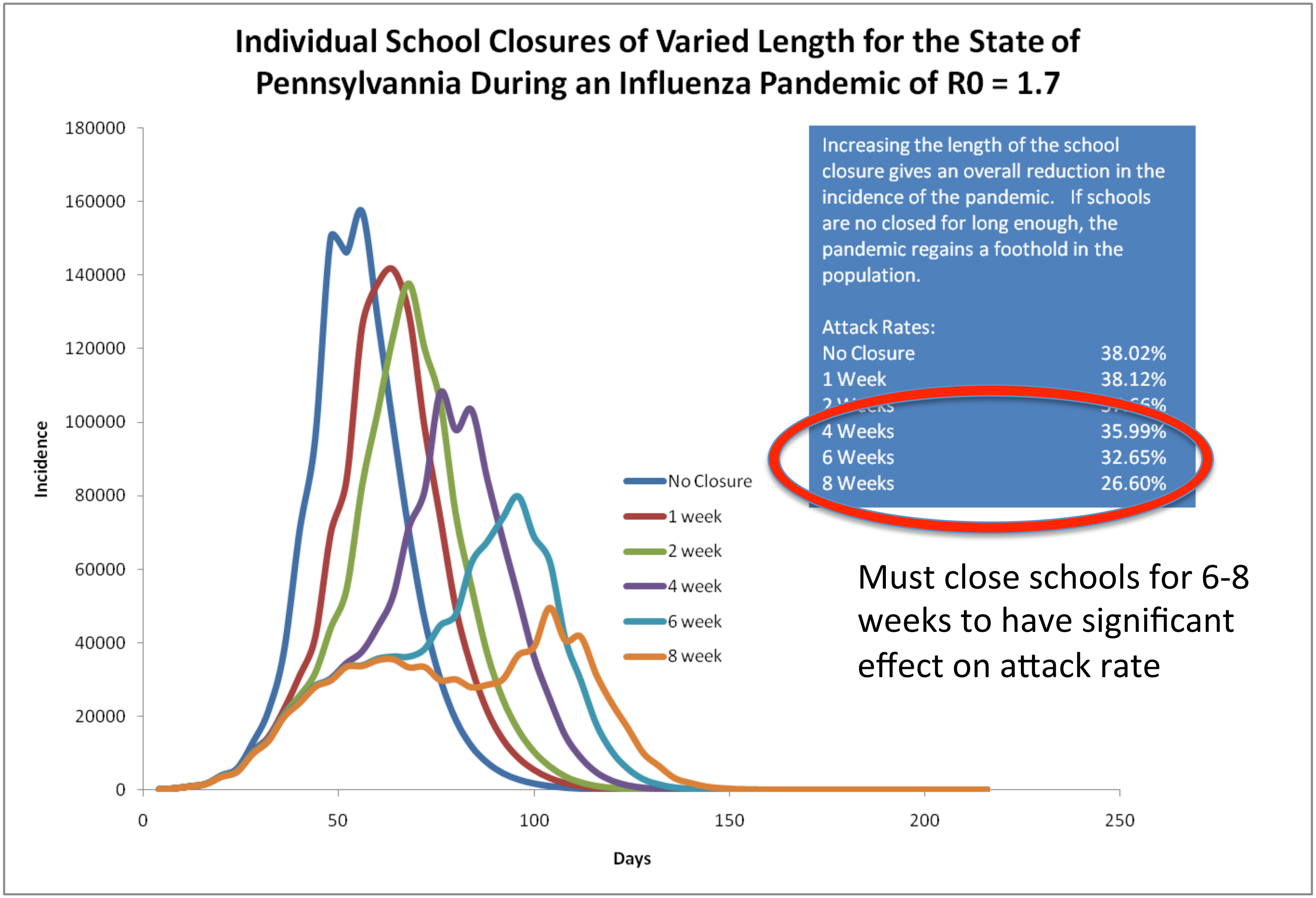
- Lee et al (2010). Simulating school closure strategies to mitigate an influenza epidemic. *J Public Health Manag Pract.* 2010 May-Jun;16(3):252-61. PubMed PMID: 20035236

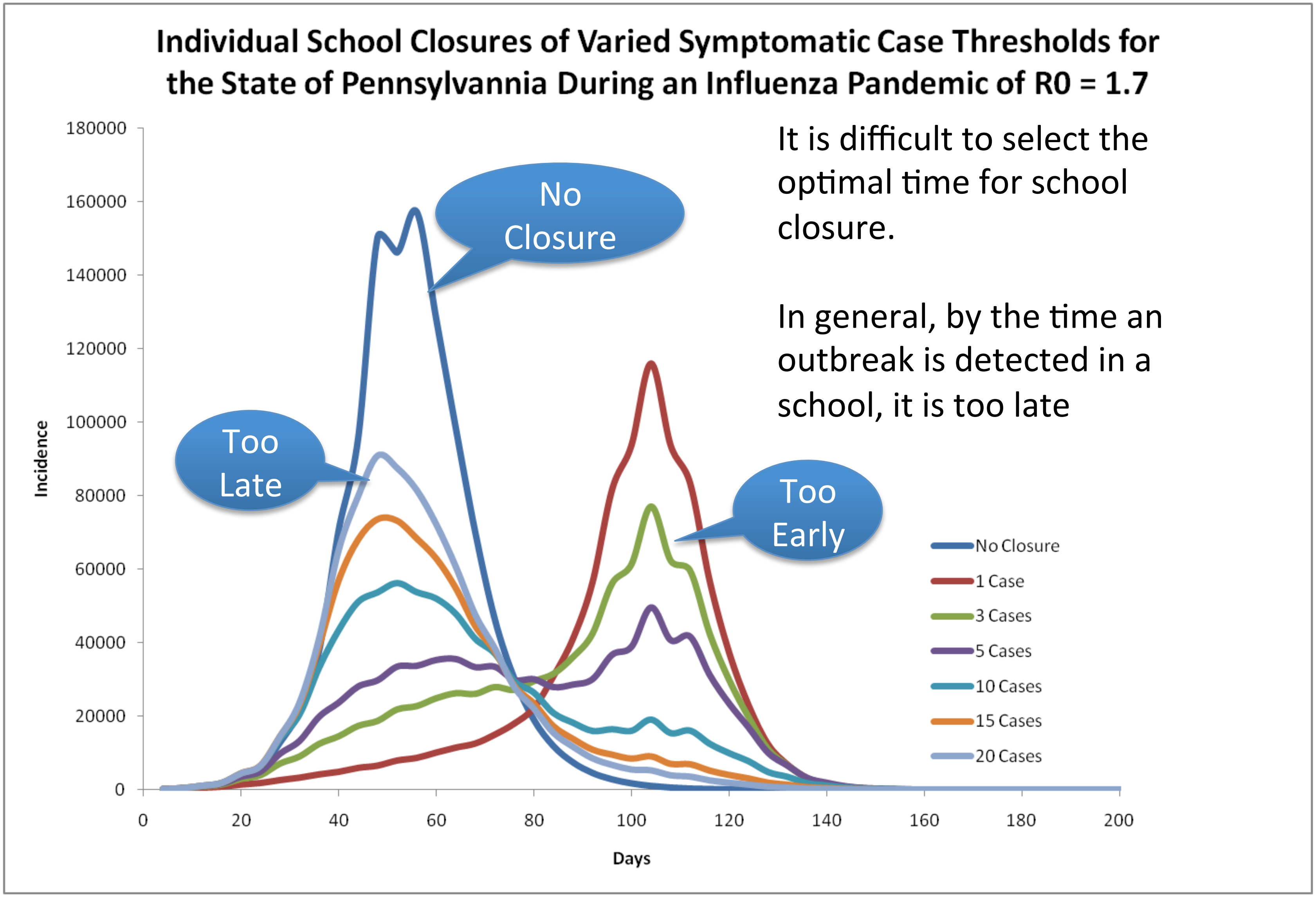
- Brown et al. (2011). Would school closure for the 2009 H1N1 influenza epidemic have been worth the cost?: a computational simulation of Pennsylvania. *BMC Public Health*. 2011 May 20;11(1):353. [Epub ahead of print] PubMed PMID: 21599920

- Potter et al (in press). Preparedness for Pandemics: Does Variation Among States Affect the Nation as a Whole? *J Public Health Manag Pract.* (2012).

Pennsylvania Schools




Individual School Closures of Varied Length for the State of Pennsylvannia During an Influenza Pandemic of R0 = 1.7
Incidence
180000
160000
140000
120000
100000
80000
60000
40000
20000
0
0
50
100
150
200
250
Days
No Closure
1 week
2 week
4 week
6 week
8 week
Increasing the length of the school closure gives an overall reduction in the incidence of the pandemic. If schools are no closed for long enough, the pandemic regains a foothold in the population.
Attack Rates:
No Closure 38.02%
1 Week 38.12%
4 Weeks 35.99%
6 Weeks 32.65%
8 Weeks 26.60%
Must close schools for 6-8 weeks to have significant effect on attack rate


Individual School Closures of Varied Symptomatic Case Thresholds for the State of Pennsylvannia During an Influenza Pandemic of R0 = 1.7
Incidence
180000
160000
140000
120000
100000
80000
60000
40000
20000
0
0
20
40
60
80
100
120
140
160
180
200
Days
No Closure
Too Late
Too Early
No Closure
1 Case
3 Cases
5 Cases
10 Cases
15 Cases
20 Cases
It is difficult to select the optimal time for school closure.
In general, by the time an outbreak is detected in a school, it is too late

Employee Vaccination Coverage

A Computer Simulation of Employee Vaccination to Mitigate an Influenza Epidemic

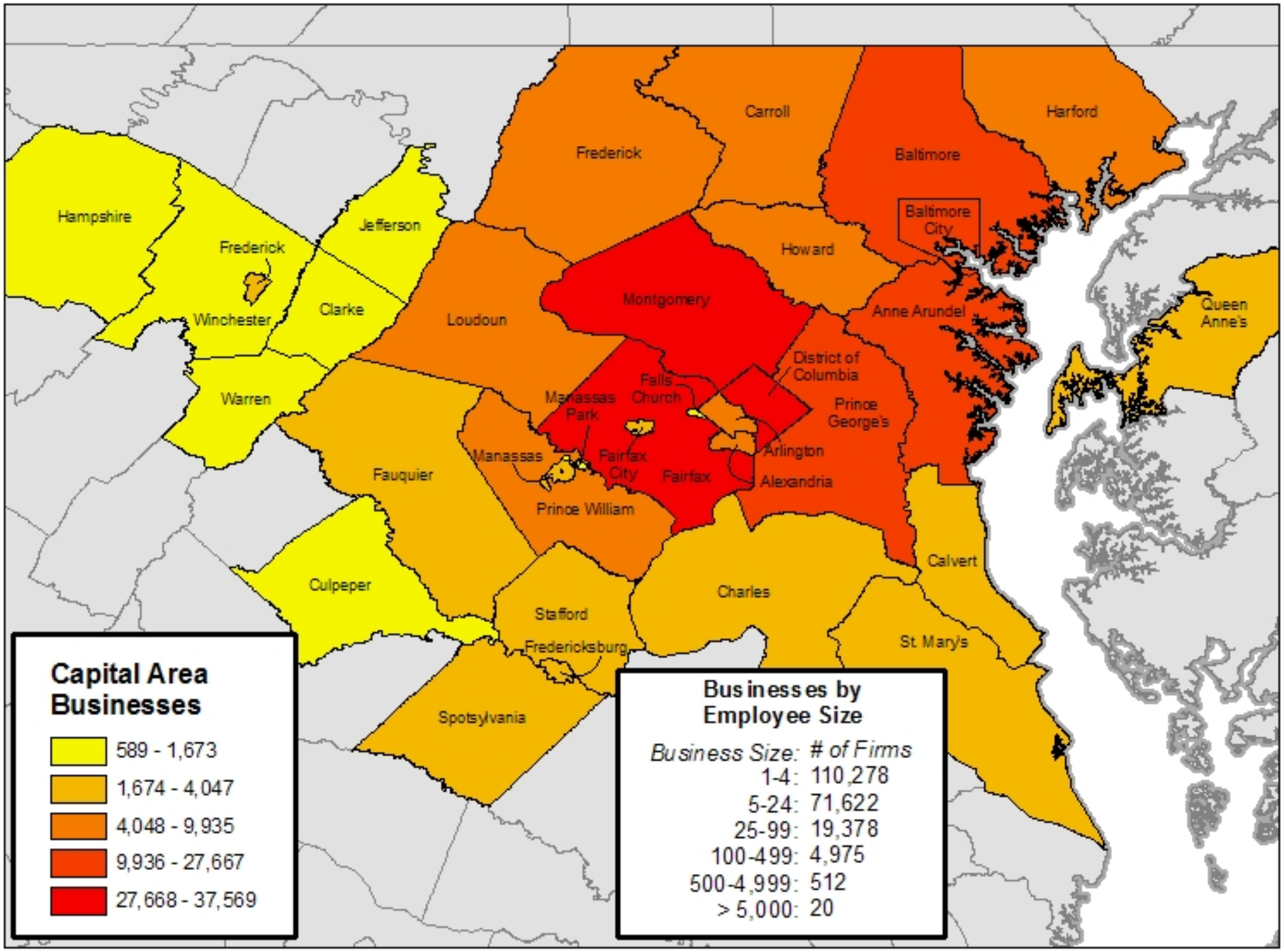
Bruce Y. Lee, MD, MBA, Shawn T. Brown, PhD, Philip C. Cooley, MS, Richard K. Zimmerman, MD, MPH, William D. Wheaton, MA, Shanta M. Zimmer, MD, John J. Grefenstette, PhD, Tina-Marie Assi, MPH, Timothy J. Furphy, MPH, Diane K. Wagener, PhD, Donald S. Burke, MD

Background: Better understanding the possible effects of vaccinating employees is important and can help policymakers and businesses plan vaccine distribution and administration logistics, especially with the current H1N1 influenza vaccine in short supply.

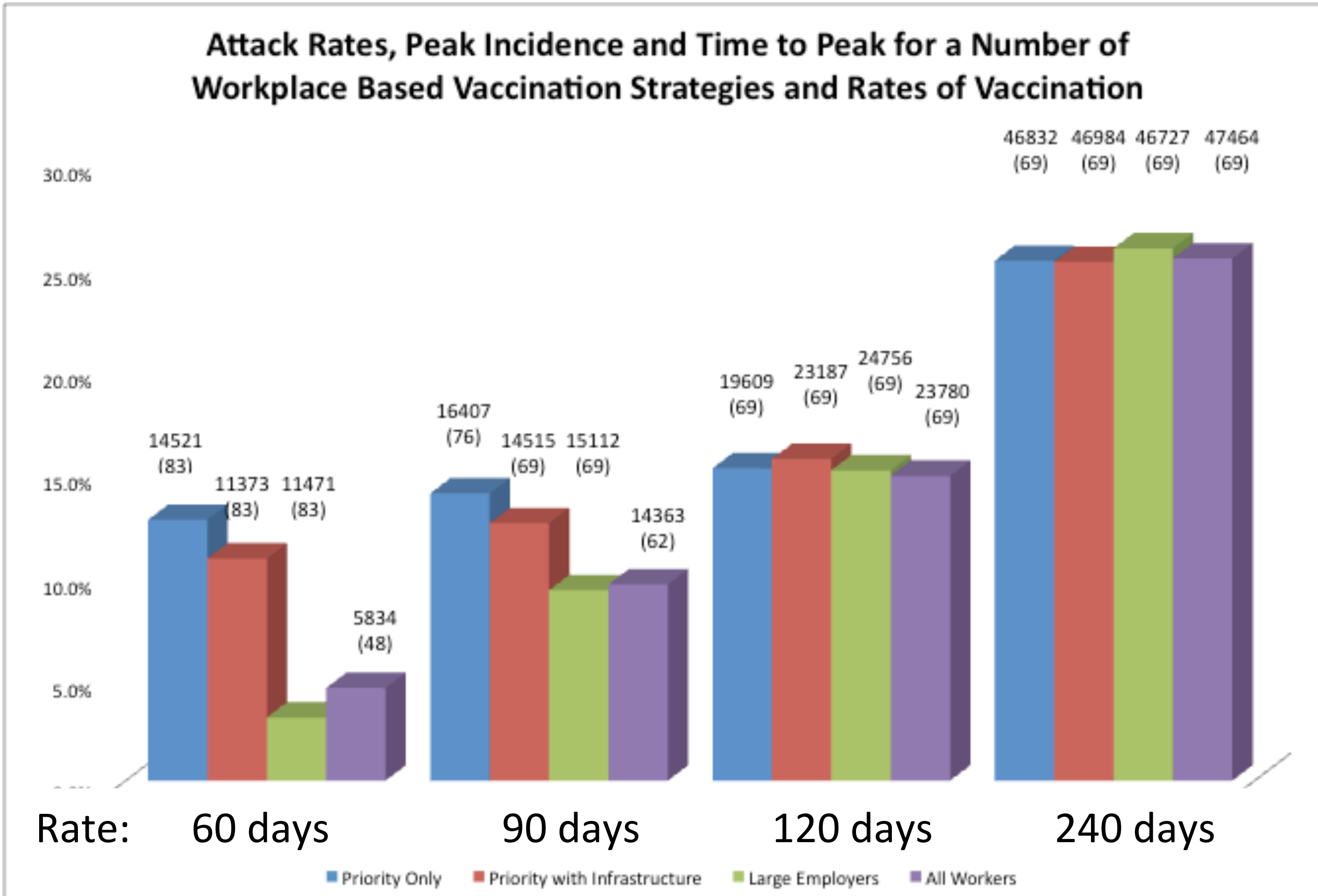
Purpose: This article aims to determine the effects of varying vaccine coverage, compliance, administration rates, prioritization, and timing among employees during an influenza pandemic.

Methods: As part of the H1N1 influenza planning efforts of the Models of Infectious Disease Agent Study network, an agent-based computer simulation model was developed for the Washington DC metropolitan region, encompassing five metropolitan statistical areas. Each simulation run involved introducing 100 infectious individuals to initiate a 1.3 reproductive-rate (R_0) epidemic, consistent with H1N1 parameters to date. Another set of scenarios represented a R_0=1.6 epidemic.

DC Metro Region Workplaces



Vaccine Coverage and Timing



Even though a majority of workers are employed by small businesses, focusing on vaccinating larger firms **(green bars)** may be just as effective in epidemic mitigation as trying to vaccinate all employees **(purple bars)**.

Vaccine Prioritization

Vaccine 28 (2010) 4875–4879

Contents lists available at ScienceDirect

Vaccine

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

Short communication

A computer simulation of vaccine prioritization, allocation, and rationing during the 2009 H1N1 influenza pandemic

Bruce Y. Lee[a,*], Shawn T. Brown[a,b], George W. Korch[c], Philip C. Cooley[d], Richard K. Zimmerman[a], William D. Wheaton[d], Shanta M. Zimmer[a], John J. Grefenstette[a], Rachel R. Bailey[a], Tina-Marie Assi[a], Donald S. Burke[a]

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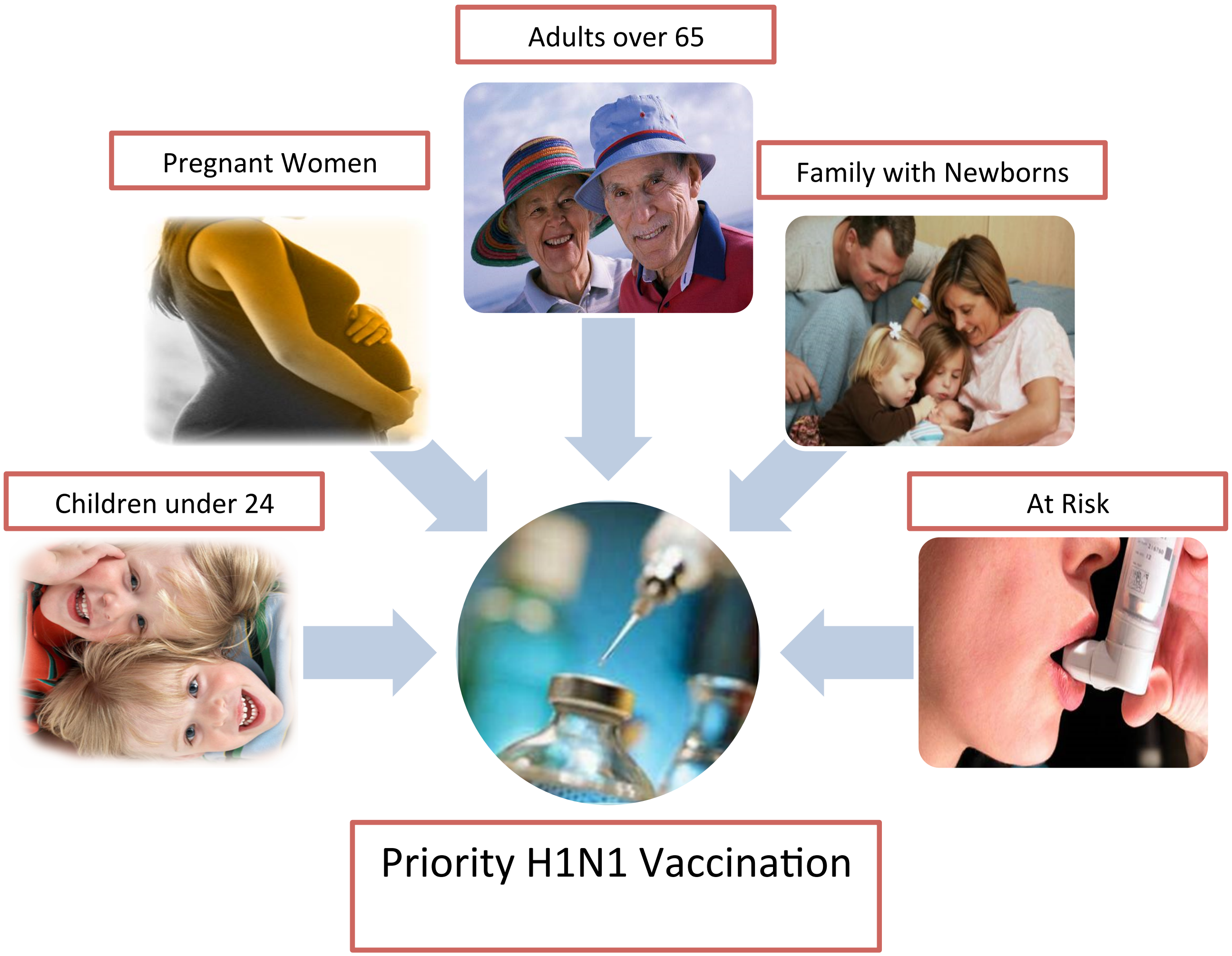
ABSTRACT

In the fall 2009, the University of Pittsburgh Models of Infectious Disease Agent Study (MIDAS) team employed an agent-based computer simulation model (ABM) of the greater Washington, DC, metropolitan region to assist the Office of the Assistant Secretary of Public Preparedness and Response, Department of Health and Human Services, to address several key questions regarding vaccine allocation during the 2009 H1N1 influenza pandemic, including comparing a vaccinating children (i.e., highest transmitters)–first policy versus the Advisory Committee on Immunization Practices (ACIP)–recommended vaccinating at-risk individuals-first policy. Our study supported adherence to the ACIP (instead of a children-first policy) prioritization recommendations for the H1N1 influenza vaccine when vaccine is in limited supply and that within the ACIP groups, children should receive highest priority.

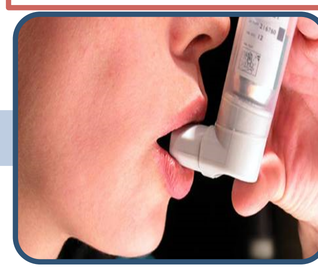
ACIP Recommendation



ACIP Recommendation

Children under 24

At Risk

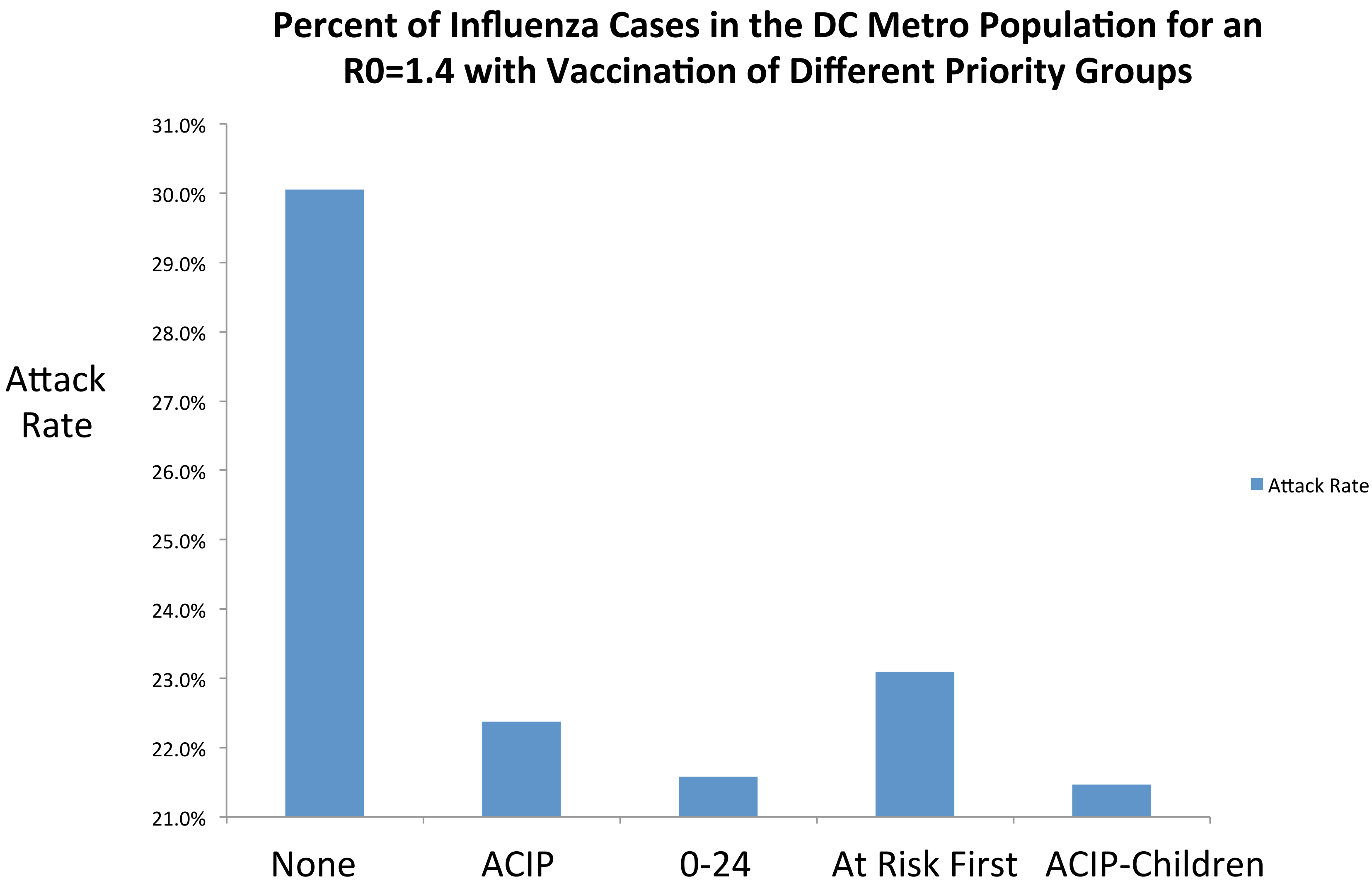


High
Mixing

Priority H1N1 Vaccination

Greater
Hospitalization

ACIP Modeling Results

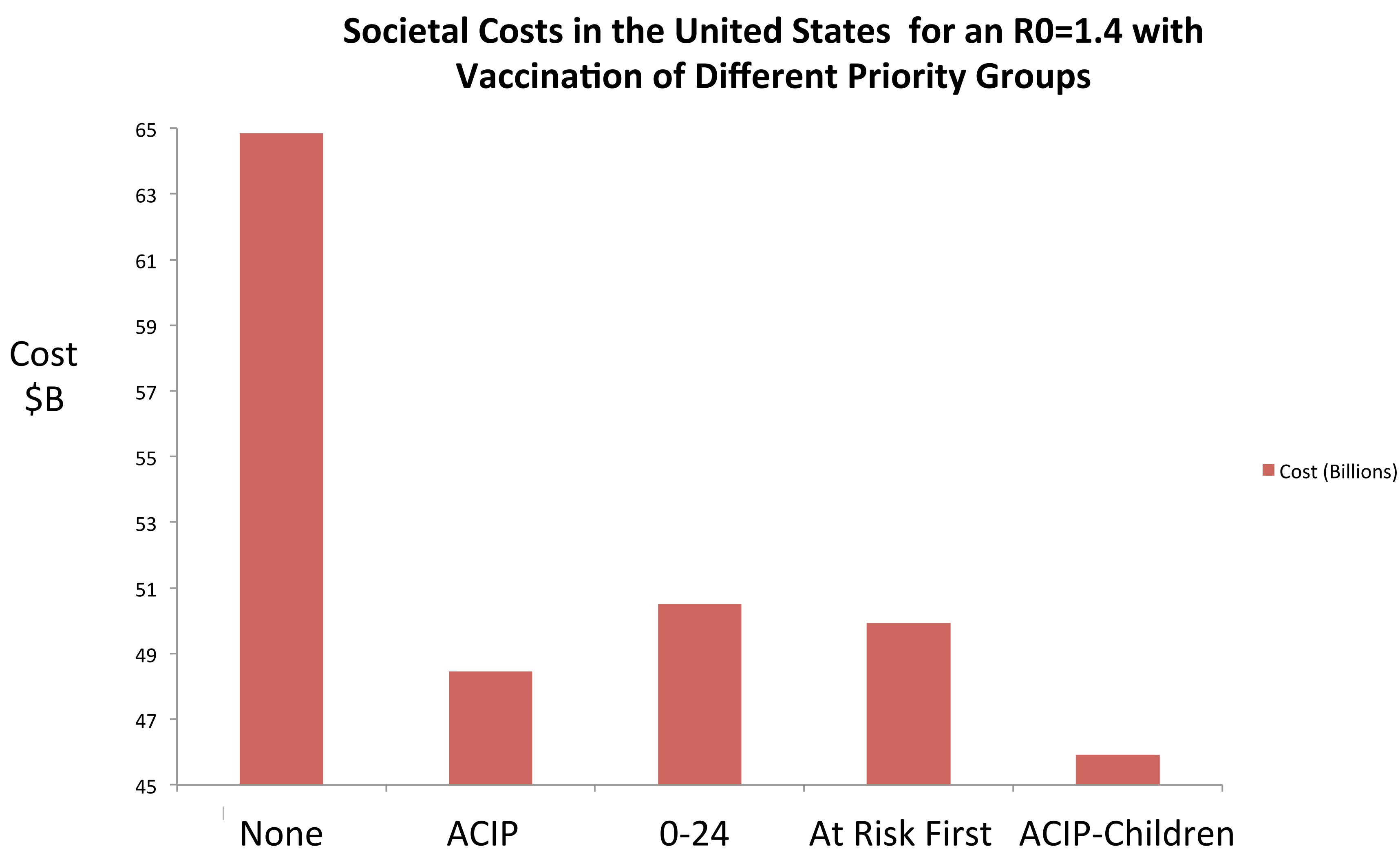


Economic Costs

Table 3
Effects of different vaccination scenarios ($R_0 = 1.3$).

Scenario	Serologic attack rate		DC metro area					United States				
			Hospitalizations		Costs ($US Billion)			Hospitalizations		Costs ($US Billion)		
	Total	At-risk	Total	At-risk	Third party payer	Productivity	Societal	Total	At-risk	Third party payer	Productivity	Societal
No mitigation	30.1%	25.1%	6518	1330	0.06	1.52	1.58	267,312	54,541	2.45	62.39	64.84
Vaccinating ACIP priority	22.5%	17.9%	4187	3002	0.04	1.14	1.18	171,686	123,126	1.73	46.72	48.46
Allowing varying percentages of non-ACIP priority into queue												
25% non-ACIP priority	22.9%	18.6%	4299	3076	0.04	1.16	1.20	176,295	126,144	1.77	47.63	49.40
50% non-ACIP priority	23.3%	19.1%	4414	3183	0.04	1.18	1.22	181,026	130,520	1.81	48.33	50.14
75% non-ACIP priority	23.6%	19.5%	4483	3237	0.04	1.20	1.24	183,827	132,759	1.83	49.09	50.93
100% non-ACIP priority	24.1%	20.0%	4642	3380	0.05	1.22	1.27	190,357	138,611	1.88	50.04	51.92
ACIP priority with 18 year old cut-off instead of 24 year old												
18 year old cut-off	22.7%	17.9%	4167	2981	0.04	1.22	1.26	170,880	122,242	1.57	50.00	51.57
Prioritizing different age groups over ACIP-priority groups												
0–24 year olds	21.5%	18.3%	4223	3105	0.04	1.19	1.23	173,181	127,323	1.52	49.00	50.52
5–11 year olds	21.3%	18.0%	4095	2979	0.04	1.19	1.22	167,915	122,154	1.50	48.68	50.18
25–49 year olds	22.7%	18.8%	4308	3120	0.04	1.26	1.31	176,677	127,946	1.77	51.80	53.57
50 years and above	24.5%	19.7%	4538	3260	0.05	1.36	1.41	186,092	133,673	2.02	55.97	57.99
Vaccinating ACIP priority with varying coverage												
20% vaccine coverage	21.7%	17.5%	4076	2923	0.04	1.10	1.14	167,155	119,849	1.68	45.09	46.77
60% vaccine coverage	23.3%	17.7%	4155	2971	0.04	1.18	1.22	170,388	121,834	1.77	48.41	50.18
80% vaccine coverage	23.9%	19.1%	4427	3152	0.04	1.21	1.26	181,538	129,259	1.84	49.64	51.48
Prioritizing within ACIP priority												
At-risk patients first	23.2%	17.1%	4050	2799	0.04	1.17	1.22	166,074	114,799	1.75	48.18	49.93
Age groups first	21.3%	18.0%	4180	3056	0.04	1.08	1.12	171,419	125,330	1.67	44.24	45.92

ACIP Modeling Results



Effects of Equal Vaccine Distribution

ISSUES FOR THE UNITED STATES

By Bruce Y. Lee, Shawn T. Brown, Rachel R. Bailey, Richard K. Zimmerman, Margaret A. Potter, Sarah M. McGlone, Philip C. Cooley, John J. Grefenstette, Shanta M. Zimmer, William D. Wheaton, Sandra Crouse Quinn, Ronald E. Voorhees, and Donald S. Burke

The Benefits To All Of Ensuring Equal And Timely Access To Influenza Vaccines In Poor Communities

ABSTRACT When influenza vaccines are in short supply, allocating vaccines equitably among different jurisdictions can be challenging. But justice is not the only reason to ensure that poorer counties have the same access to influenza vaccines as do wealthier ones. Using a detailed computer simulation model of the Washington, D.C., metropolitan region, we found that limiting or delaying vaccination of residents of poorer counties could raise the total number of influenza infections and the number of new infections per day at the peak of an epidemic throughout the region—even in the wealthier counties that had received more timely and abundant vaccine access. Among other underlying reasons, poorer counties tend to have high-density populations and more children and other higher-risk people per household, resulting in more interactions and both increased transmission of influenza and greater risk for worse influenza outcomes. Thus, policy makers across the country, in poor and wealthy areas alike, have an incentive to ensure that poorer residents have equal access to vaccines.

AT THE INTERSECTION OF HEALTH, HEALTH CARE, AND POLICY

HealthAffairs

June 2011 Vol. 30 No. 6 healthaffairs.org

Strategies For The 'Decade Of Vaccines'

- H1N1 vaccines were not always distributed equally in 2009
- Used a detailed model of Washington DC region

Conclusions:

- Limiting or delaying vaccine access in poorer counties could raise total number of infections throughout region

Outline

- Public Health Dynamics Lab
- Agent-Based Models of Infectious Disease Dynamics
- FRED: Framework for Reconstruction of Epidemic Dynamics
- Case Studies
- Validation
- Active Areas of Research
    - *Collaborations Welcome!*

Validation Methods (1)

Internal Validity

- Validate the individual mechanisms or assumptions within the model
- Trace the behavior of specific entities in the model to determine if they behave as in the real system
- Does the model produce expected results when some inputs are set to extreme values?

Face Validity

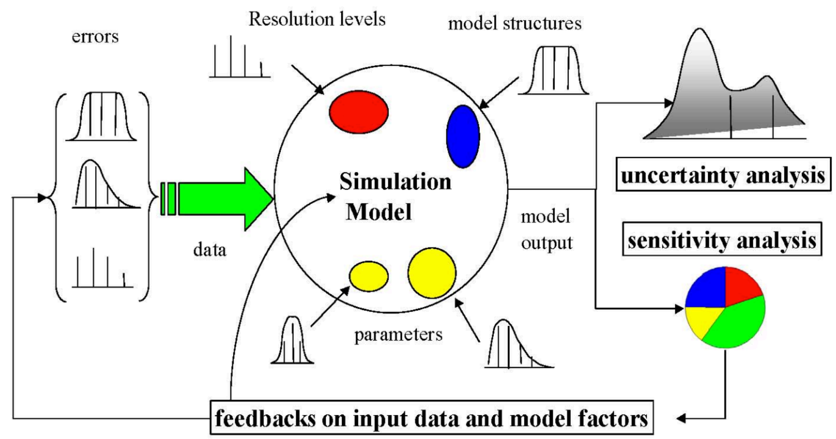
- Does the model produce the expected sequence or distribution of events?
- Does the model produce expected results for input values for which the results are known or easily computed
- Do experts agree that the behavior of the model is reasonable?

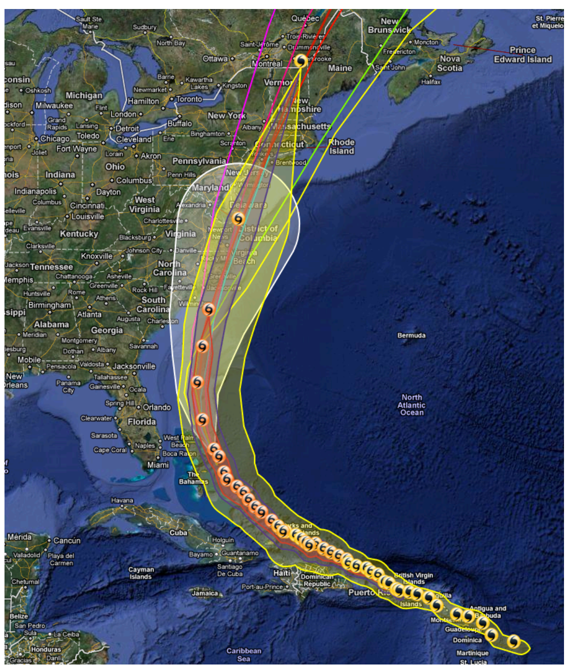
Sargent, 1999

Validation Methods (2)

Sensitivity analysis

- How does the uncertainty in a given parameter affect the model outcome?
- Determine if the more sensitive parameters have been estimated with enough accuracy to support the model outcomes





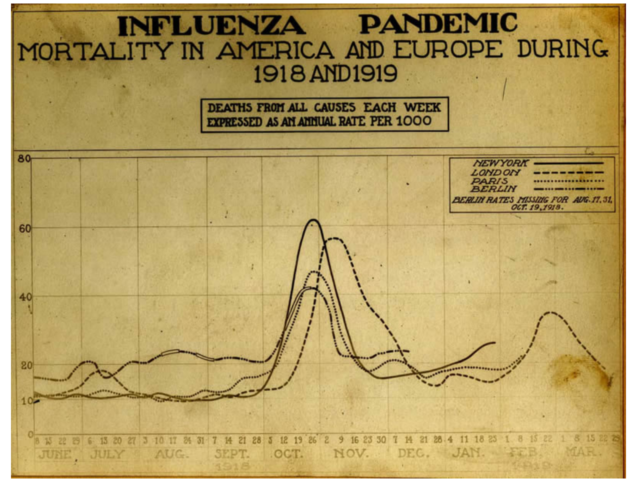
Multi-Model Comparison

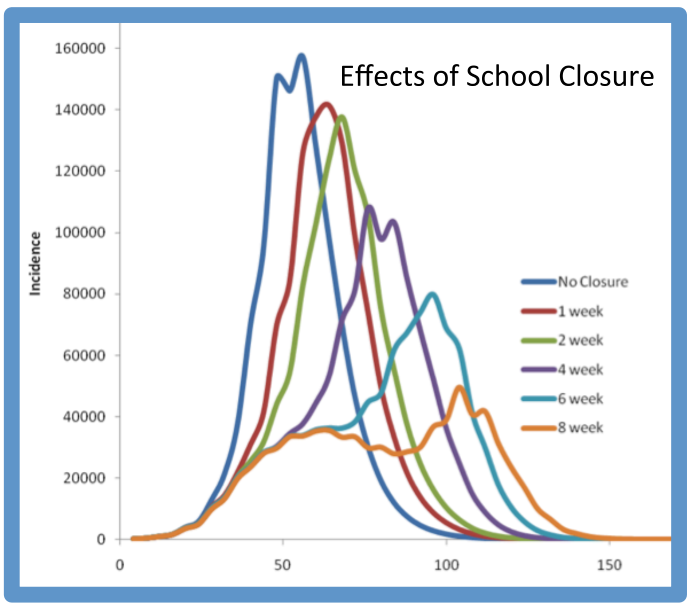
- Compare the model to other models that employ different assumptions and data sources
- Differences may suggest model refinements or new data collection needs

Validation Methods (3)

Historical Data Validation

- Compare the model against historical data, using parameter estimates derived from the historical situation





Predictive Validation

- Use the model to predict the system behavior, and then compare with the system's observed behavior

Nationwide Difference between American Community Survey and Synthetic Population

Variable		Category						
		1	2	3	4	5	6	7
Variable	Age	15-24	25-34	35-44	45-54	55-64	65-74	>74
	Income	<$10K	$10K-$15K	$15K-$25K	$25K-$35K	$35K-$50K	$50K-$100K	>$100K
	Size	1	2	3	4	5	6	7+
	Race	White	Black/AA	Asian	other	2+	N/A	N/A

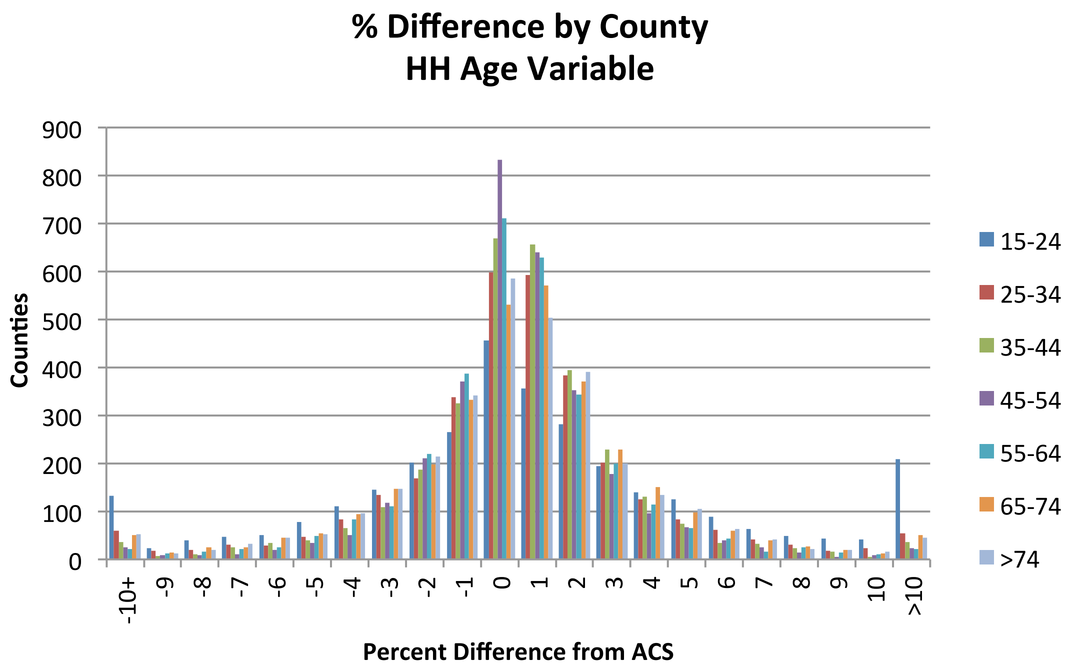
Percentage difference from ACS:

Variable		Category						
		1	2	3	4	5	6	7
Variable	Age	0.151	0.054	0.049	-0.125	-0.048	0.089	-0.004
	Income	0.016	0.139	0.166	0.200	0.202	-0.175	-0.112
	Size	0.065	-0.131	0.059	-0.038	0.206	0.272	0.227
	Race	-0.042	0.075	0.330	0.159	0.340	N/A	N/A

Courtesy W. Wheaton, RTI International

Population Differences by County

- Example of differences in 'Age of Head of Householder' by county:



% Difference

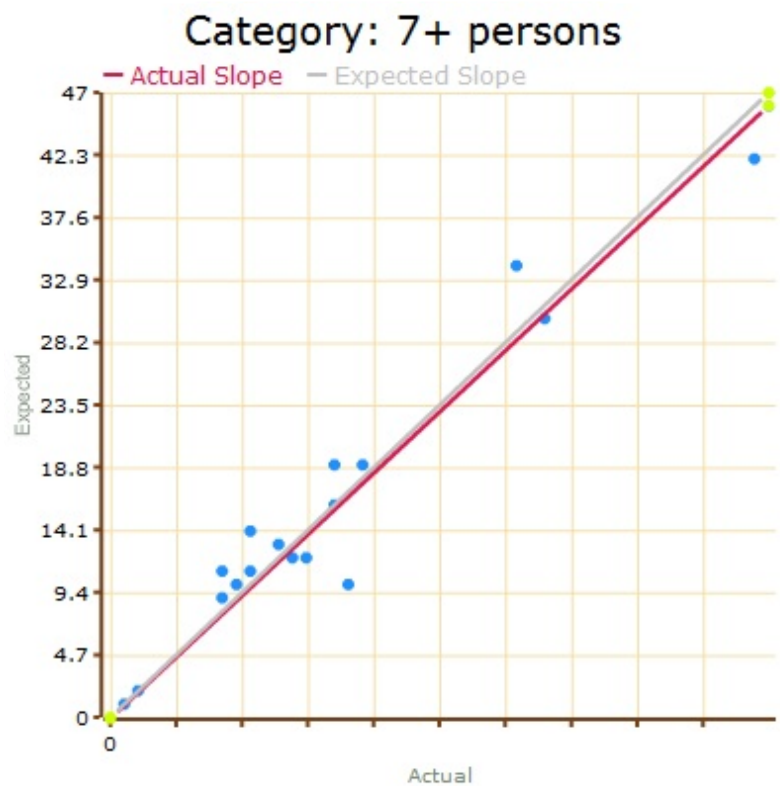
Min	Max	Mean	St Dev.
-66.67*	200.00**	0.08	9.05
-40.48	47.83	0.06	4.49
-66.67	33.33	0.06	3.84
-22.08	25.00	-0.04	2.88
-50.00	29.41	-0.11	3.31
-27.27	34.78	0.05	4.04
-60.00	33.33	-0.08	4.43

* Broadwater, MT: Population 5,612
** Camas County, ID: Population 991

Courtesy of W. Wheaton, RTI International

Sample Comparison between American Community Survey and Synthetic Population

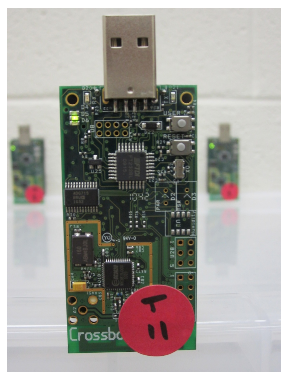
- Graphs for a single Public Use Microdata Area (PUMA)
- Each dot represents one block group



Courtesy of W. Wheaton, RTI International

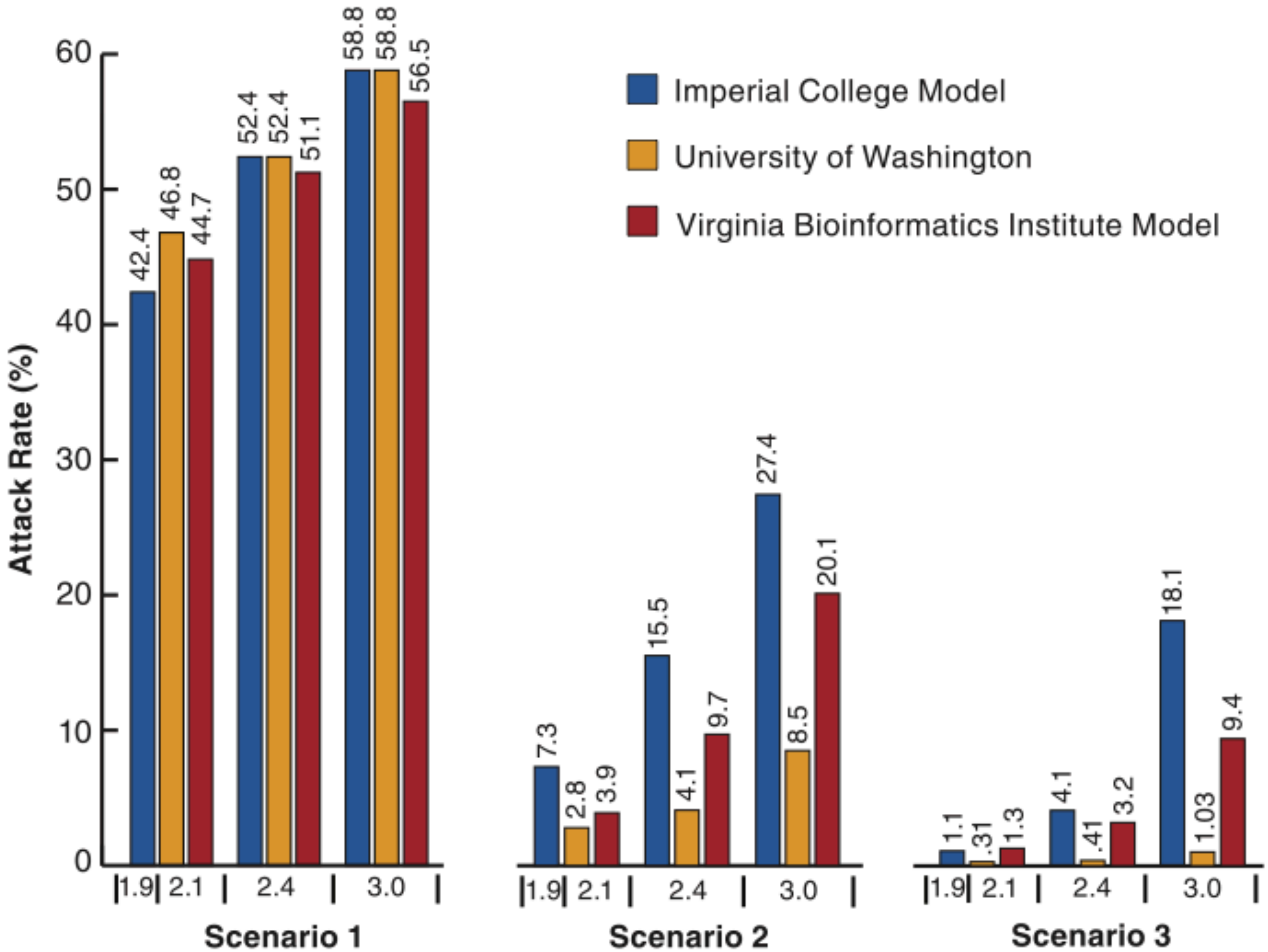
Collecting School Contact Data

- Social Mixing and Respiratory Transmission (SMART) Schools
  - 2011-2013 Pitt Study
  - CDC Funded
  - Measure child-child contact rates in Pittsburgh school
  - Correlate with Flu and stay-at-home behavior



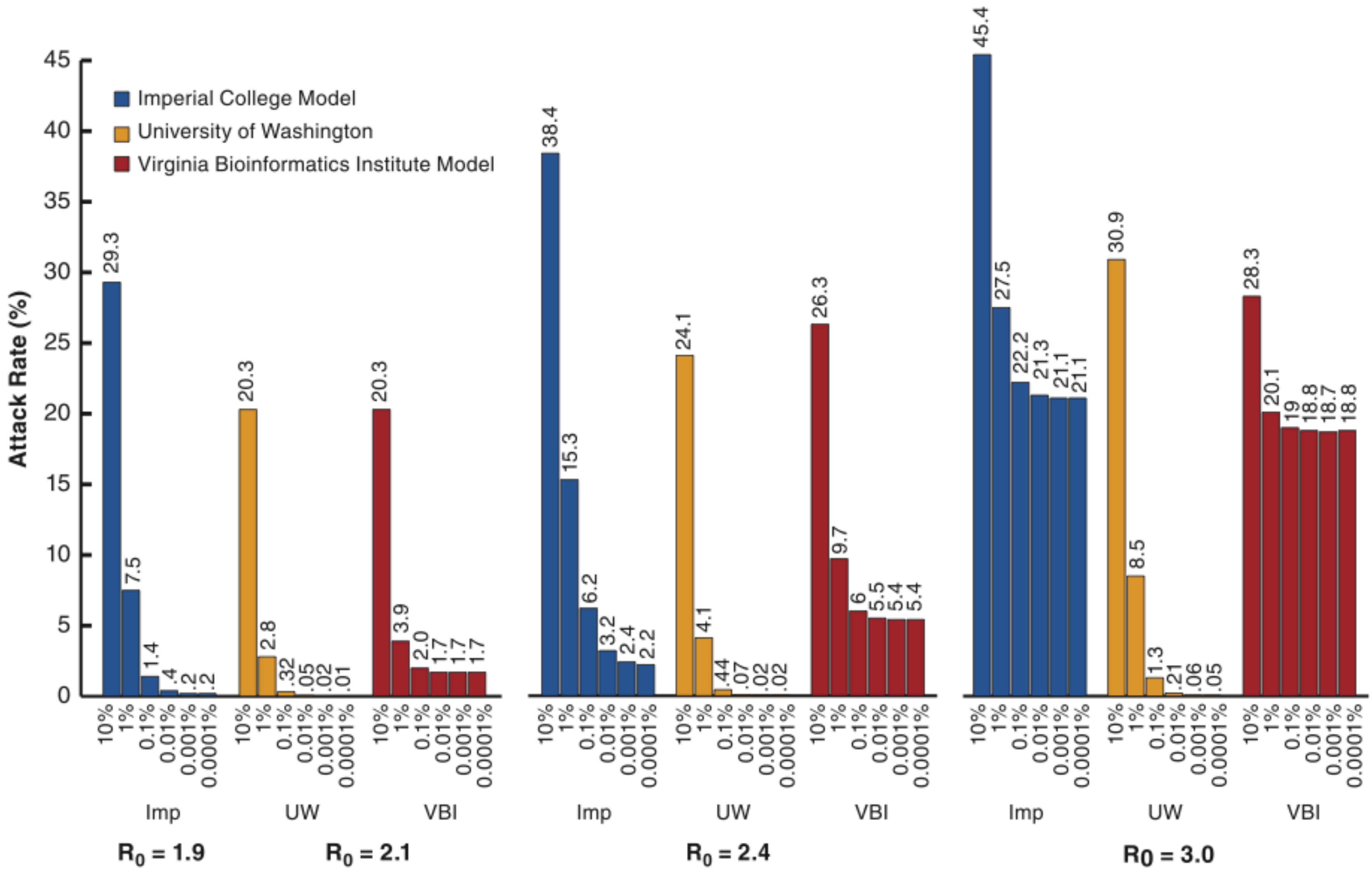
Dave Galloway with motes

Comparing Effect of NPI Compliance across models



Halloran, M. E., Ferguson, N. M., Eubank, S., Jr, I. M., Cummings, D. A., Lewis, B. et al. (2008). Modeling targeted layered containment of an influenza pandemic in the United States. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(12), 4639-4644

Sensitivity to Intervention Thresholds across Models



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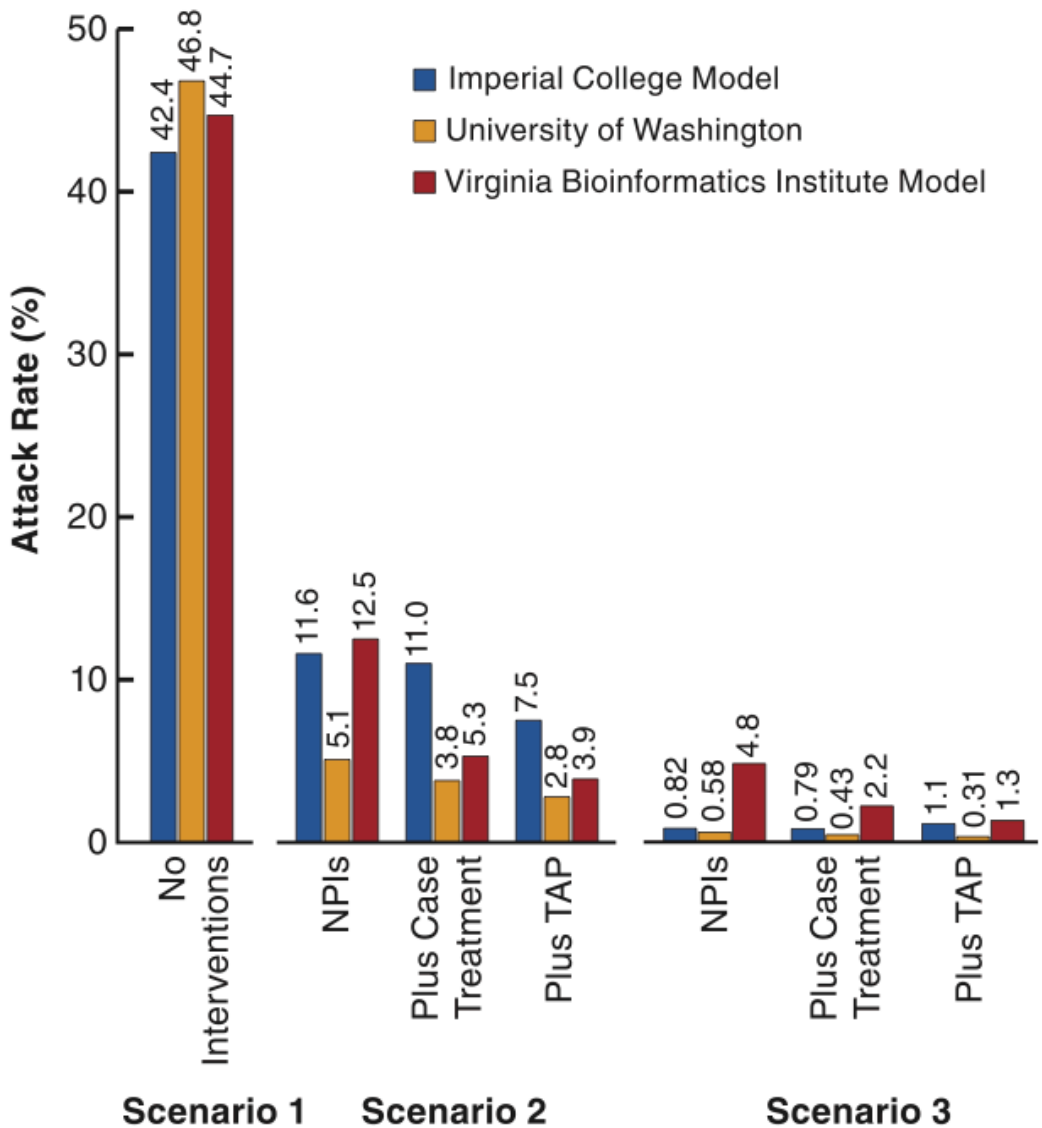
Comparing Alternative Interventions across models



- Non-pharmaceutical intervention (NPI)
- Case Treatment
- Targeted antiviral prophylaxis (TAP)

Halloran, M. E., Ferguson, N. M., Eubank, S., Jr, I. M., Cummings, D. A., Lewis, B. et al. (2008). Modeling targeted layered containment of an influenza pandemic in the United States. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(12), 4639-4644

Data Needs for Model Validation

- Transmission data based on place of infection for known pathogens
  - Household, Schools, Workplaces
  - Health Care Facilities, Group quarters
  - Playgrounds, stores, subways, etc
- Periodic biological surveys
  - Spatial distribution of viral strains
  - Infection rates pre- and post-epidemic
- Periodic health behavior surveys
  - Spatial distribution of vaccine coverage and behavior patterns
  - Measure behaviors pre-, intra- and post-epidemic

Outline

- Public Health Dynamics Lab
- Agent-Based Models of Infectious Disease Dynamics
- FRED: Framework for Reconstruction of Epidemic Dynamics
- Case Studies
- Validation
- Active Areas of Research
    - *Collaborations Welcome!*

Active Areas of Development in FRED

- Transmission Models
  - Respiratory, Oral/fecal, Sexual, Vector
- Viral evolution
  - Resistance
  - Emerging diseases
- Health behavior and decisions
  - Risk Assessment
  - Social Influences
- Models of Human Movement
  - Urban mobility, Short-term Travel, Migration
- Environmental conditions
  - Climate effects, Seasonality

Work in Progress:
Human Behavior Modeling

- Models of Behavior Change
  - Health Belief Model
  - Game Theory
- Health Behaviors being modeled:
  - Vaccine Refusal
  - Personal Hygiene (Face Masks)
  - Social Distancing (Staying home from work)
- Impact of Anti-vaccine Clusters on Measles Outbreak
- Effect of Sick Leave Policies

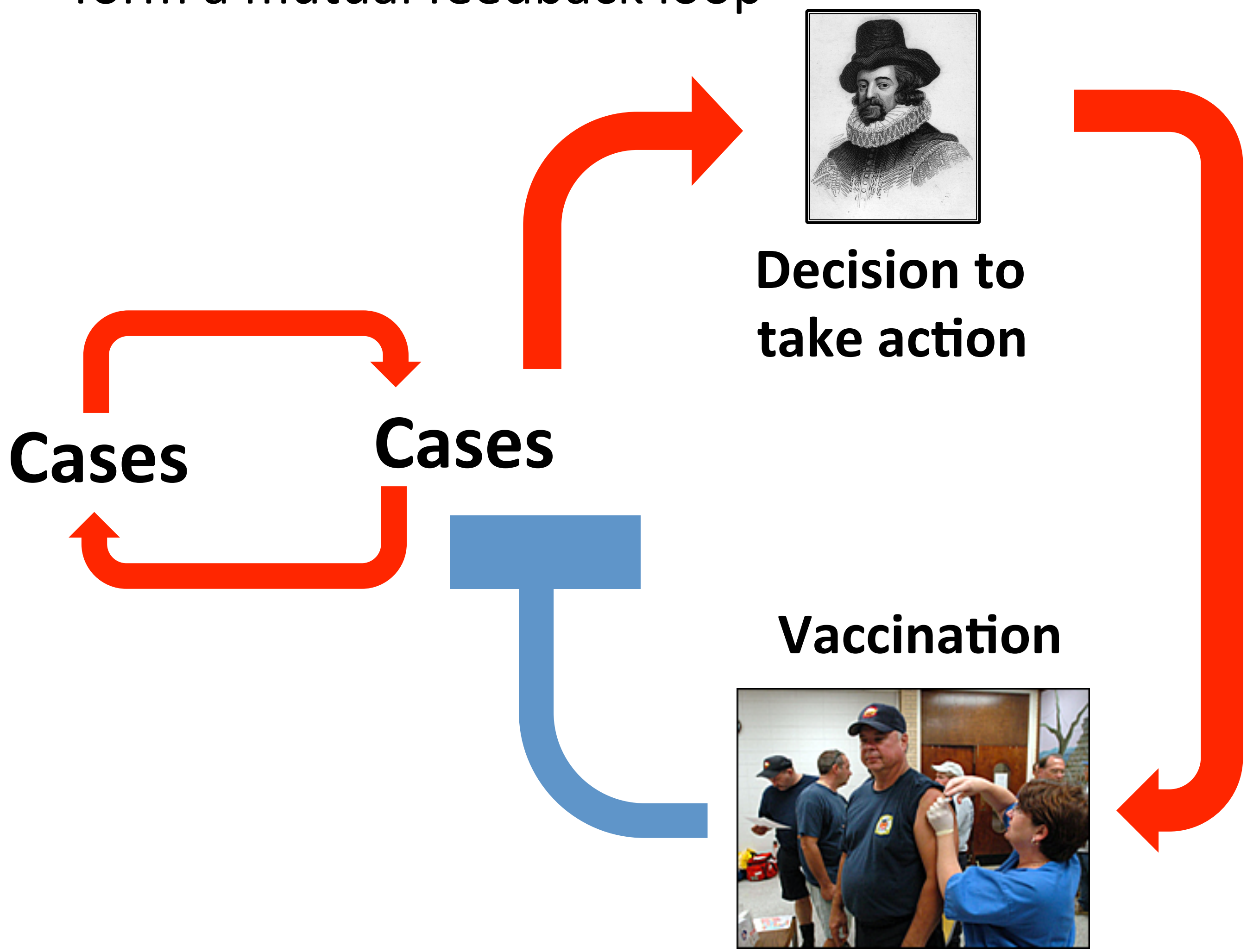
Steve Albert

Eunha Shim

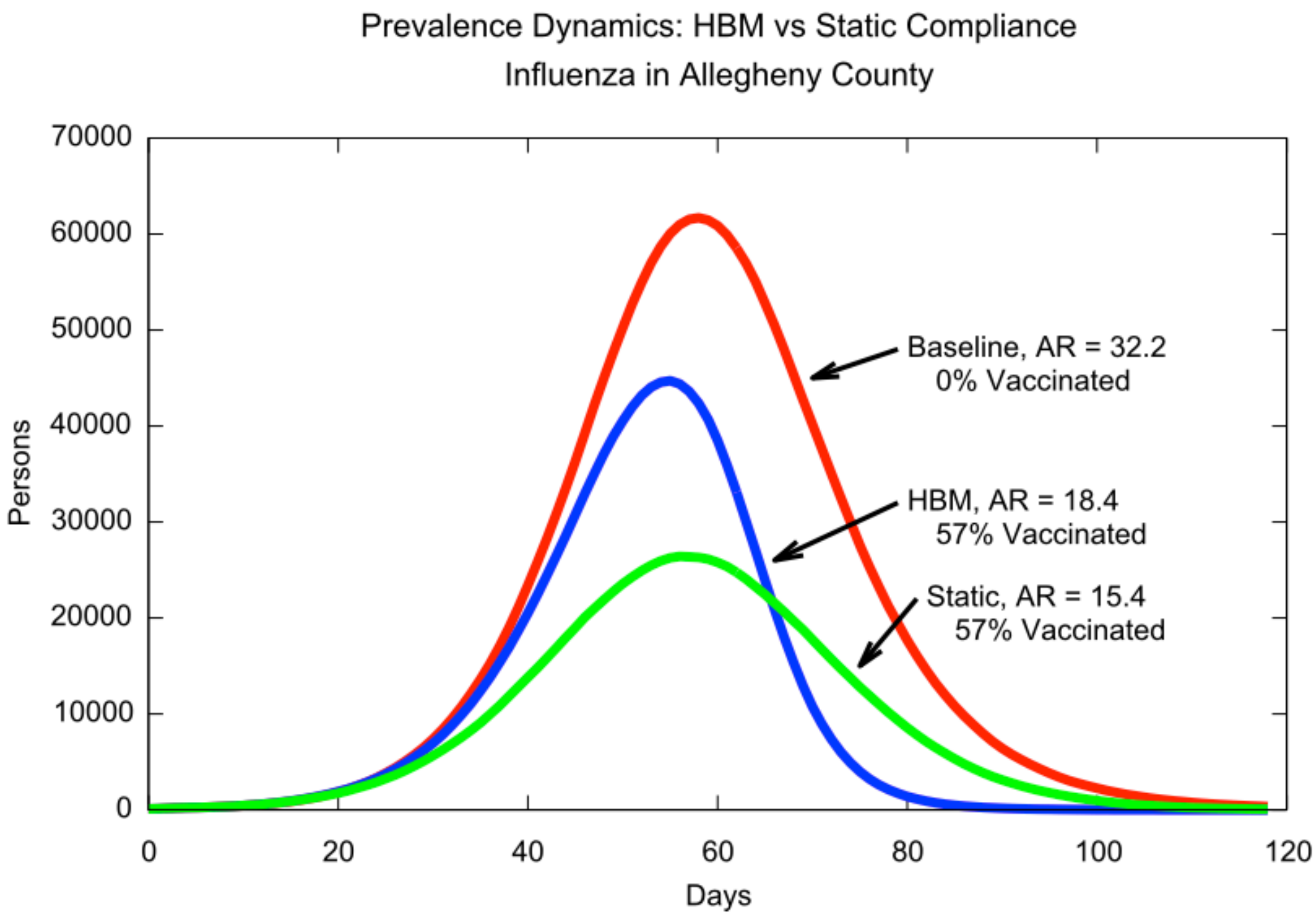
Supriya Kumar

Individual Behaviors and Epidemic Dynamics

- Hypothesis: Individual behaviors and epidemic state form a mutual feedback loop



Assuming constant vaccine compliance underestimates the attack rate and delays the peak, compared to a Health Belief Model



Work in Progress: Viral Evolution


Roni Rosenfeld

- FRED supports multiple circulating pathogens/ strains
- Pathogens can be described in varying levels of details
  - Phenotype, genotype
  - Cross immunogeneticity
- Strain evolution models
  - Mutation rates
  - Evolution of resistance
- Pathogen can be tracked geographically

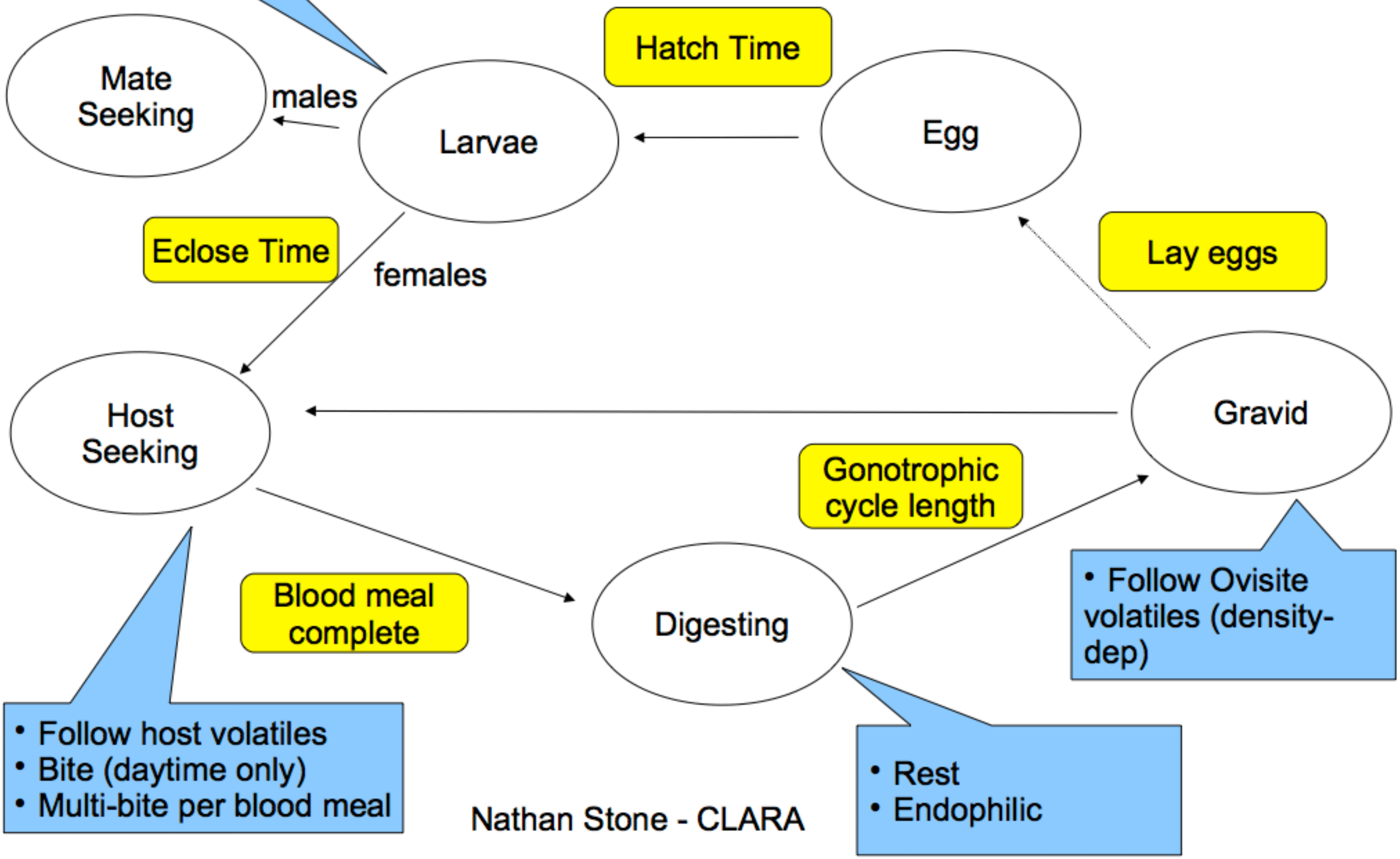
Work in Progress: Vector-Borne Disease

- Dengue
  - Mulitple serotypes
- Complete agent-based mosquito life cycle
  - *Aedes Egypti*
  - Human Biting Behavior, Mobility
- Human-mosquito population interactions
- Mitigations being Modeled
  - Environmental treatments
  - Vector control
  - Wolbachia
  - Vaccination

Shawn Brown

Nathan Stone

Vector Life Cycle



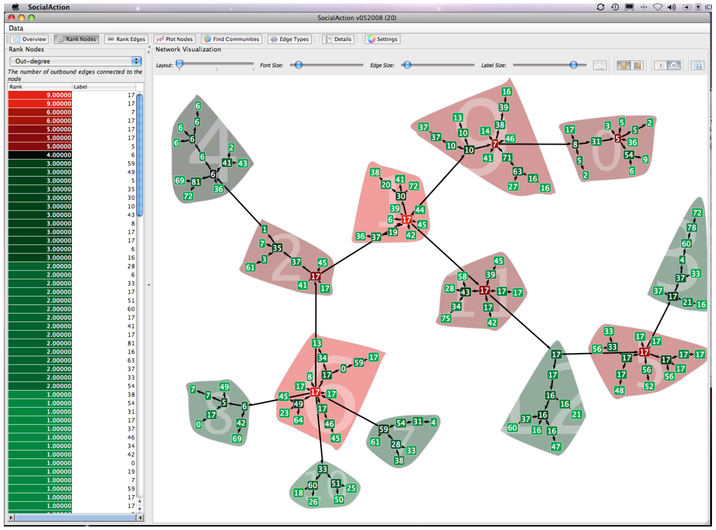
Nathan Stone - CLARA

Work in Progress:
Network Analysis of Disease Dynamics

- Multiyear Epidemics
  - Who gets infected repeatedly / rarely ?
  - What affects epidemic seasonality?

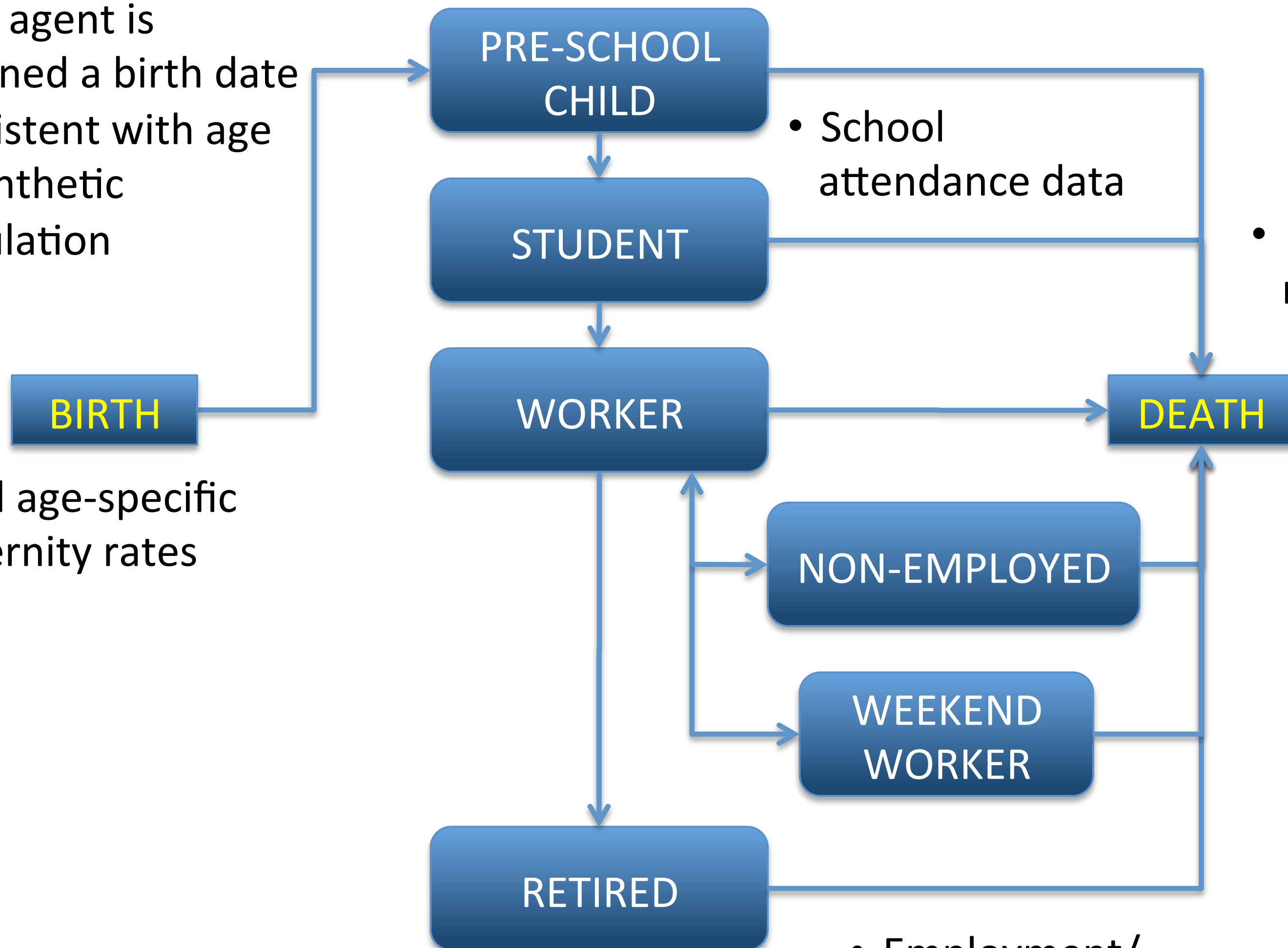
Hasan Guclu

- Population Network Structure
  - Who infects whom?
  - Superspreaders and possible vaccination targets



Agent Models with Births/Deaths/Aging

- Each agent is assigned a birth date consistent with age in synthetic population
- Local age-specific maternity rates



- School attendance data
- Mortality rates
- Employment/ retirement data

Other Potential Health Modeling Applications

- Chronic Conditions and Behaviors
  - Smoking
  - Obesity
- Health Care Systems
  - Supply Chain Analysis
  - Spread of Innovations
  - Health Care Facility Operation
- Preparedness and Response
  - Emergency Services Response
  - Evacuation Behavior

Collaborations Welcome!

FRED Development Team

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Not pictured: Anuroop Sriram, Christopher Tischuk, Jay De Passe, Yu-Ting Weng,

Acknowledgments

- MIDAS: National Institute of General Medical Sciences

www.midas.pitt.edu

- PHASYS: Centers for Disease Control and Prevention

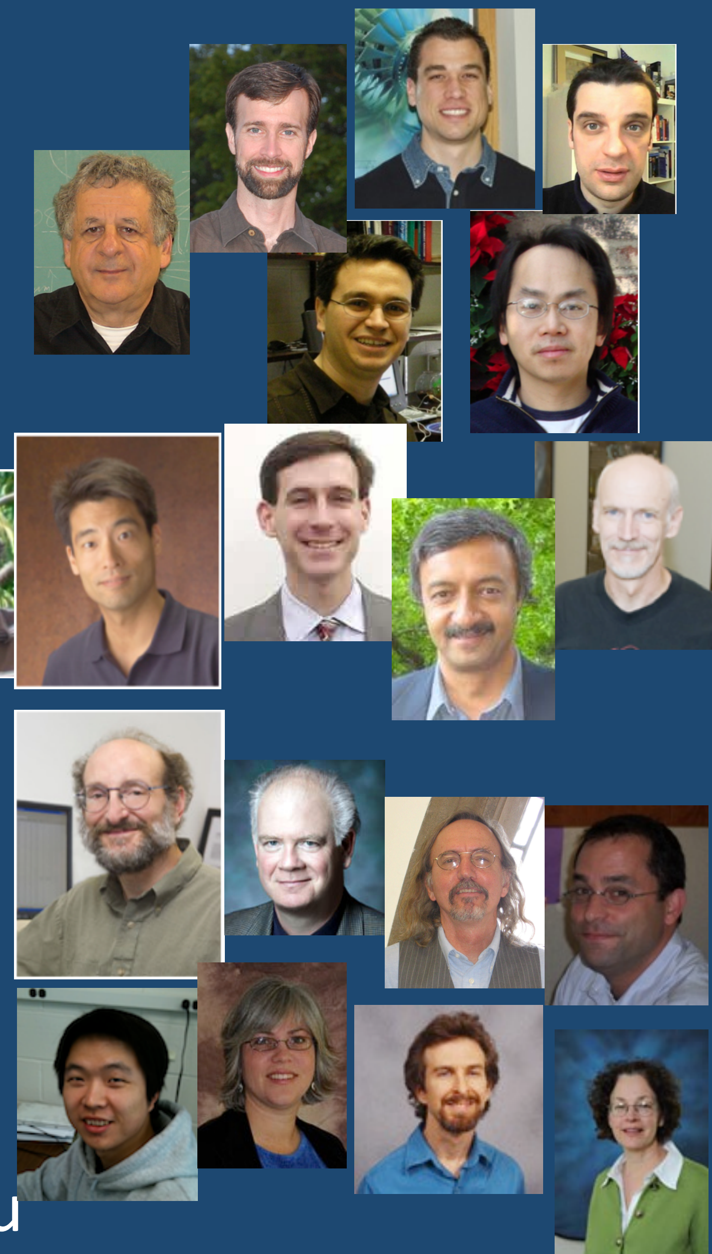
www.phasys.pitt.edu

- VMI: Bill and Melinda Gates Foundation

www.vaccinemodeling.org

- Pittsburgh Supercomputing Center

Thank You!



gref@pitt.edu

www.phdl.pitt.edu