Engineering in Public Health for "Efficient, Effective, and Equitable" Outcomes

Julie Swann, PhD

Industrial and Systems Engineering

Georgia Institute of Technology

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GEORGIA TECH
Health & Humanitarian Logistics Center
A Unit of the Supply Chain & Logistics Institute

Georgia Tech ISyE
Stewart School of Industrial & Systems Engineering

Georgia Institute of Technology

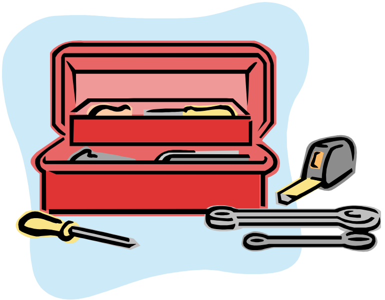
Definitions

- Industrial (and Systems) Engineering is concerned with the design, improvement, and implementation of systems of people, materials, information, equipment, and/or energy
  - Manufacturing systems
  - Military
  - Airlines and road transportation
  - Healthcare
- Public Health can be defined as the "science and art of preventing disease, prolonging life, and promoting health" within and across populations

Material adapted from CDC, Wikipedia, Dictionary.com, Institute of Industrial Engineer websites, or others

What Tools?

- IE and related field of Operations Research (OR) draw upon methods from the mathematical, physical, and social sciences together with systems approaches to specify, optimize, predict, and/or evaluate the results obtained from systems
  - Optimization with mathematical modeling
  - Simulation of systems with uncertainty
  - Statistics and probability
  - Economics and financial analysis
  - Human factors



What Problems in Health?

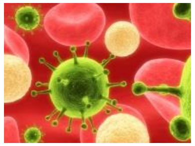
- Decisions where there are
  - Limited resources, or
  - Trade-offs between two elements (e.g., cost and quality-adjusted life years) or
  - Uncertainties in the system or
  - Complex interactions
- There may be one or more goals or objectives, and multiple constraints in the system
- Systems could take different forms
  - Individual (e.g., optimizing radiation treatment within body)
  - Provider (e.g., serving patients in hospitals)
  - Network (e.g., distributing emergency supplies within a state)
  - Population (e.g., policies around infectious diseases)

Some Relevant CDC CIOs

- Center for Global Health
- Office of Infectious Diseases
- Office of Noncommunicable Diseases, Injury and Environmental Health; including
  - Birth Defects and Developmental Disabilities
  - Chronic Disease Prevention and Health Promotion

- Office of Public Health Preparedness and Response

- Office of Surveillance, Epidemiology, and Laboratory Services



- Office of Minority Health and Health Equity
- …

Example Performance Measures

- Efficiency
  - Accomplishment of an outcome with the minimum time, effort, or resources needed
  - "Are we doing things the right way?"
  - Example: are we delivering medicines without unnecessary resources?
- Effectiveness
  - Producing the best or desired outcome
  - "Are we doing the right things?"
  - Example: are we delivering the right medicines for the right population?
- Equity
  - Achieving outcomes that are fair or equitable across a system
  - "Are we impacting all people or places?"
  - Example: is our distribution of medicines equitable?
- Achieving all measures may be desirable, but may not always be possible

Cost

Outcomes

Fair

Examples of IE Health Research

- Population screening policies for diseases
  - Hepatitis C policies for who and how often
- Interventions for diseases spreading across a network
  - H1N1a pandemic using agent-based modeling
  - Post-campaign evaluation of distribution system
- Quantifying and explaining access to care and disparities
  - Pediatric patients across a network
- Predicting disease prevalence in small areas
  - Childhood obesity

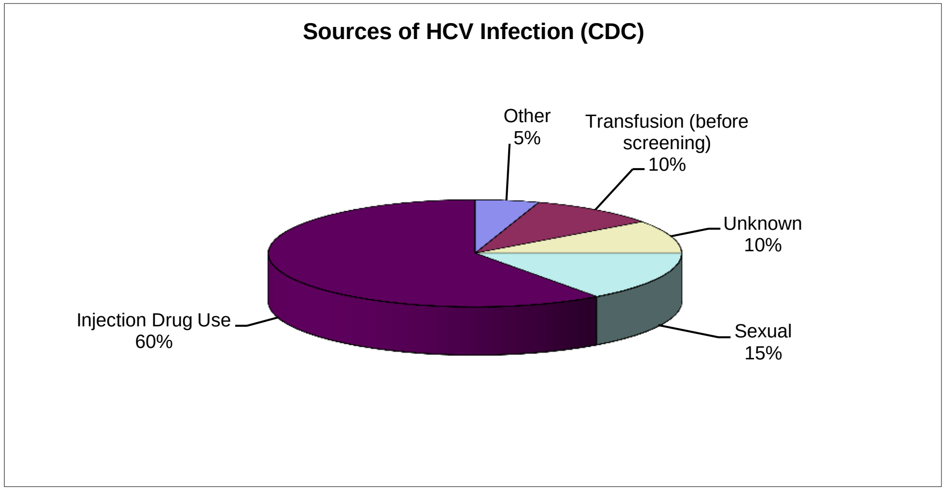
- Work covers multiple collaborations between GT ISyE, CDC, and other health entities, including many researchers not present today

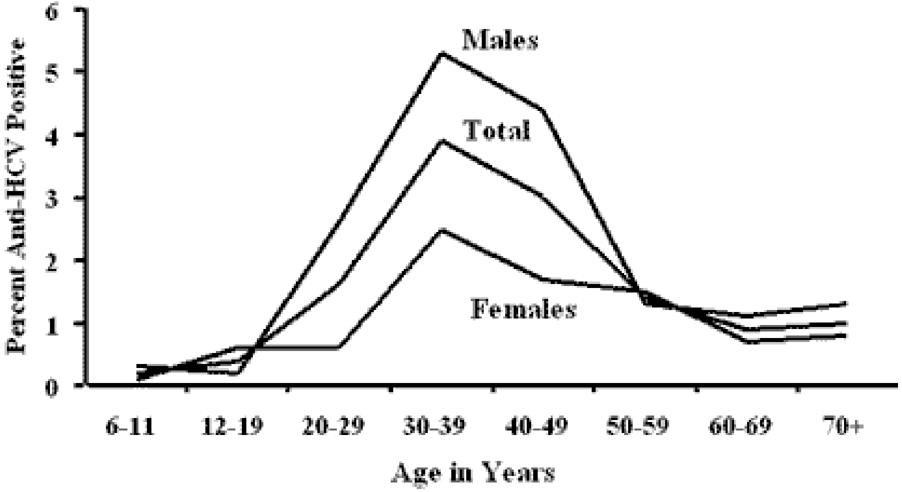
Population Screening Policies

Given a communicable disease, how often should screening of a particular population be performed given their risk characteristics?

Hepatitis C Screening

- Blood-borne Hepatitis C virus (HCV) can cause end-stage liver disease
- Most infected people asymptomatic for decades
  - 3.9 million infected people in US but 48% are unaware
- Treatments are somewhat effective (54%)
- Behavior is important to progression and secondary infections in this disease and others



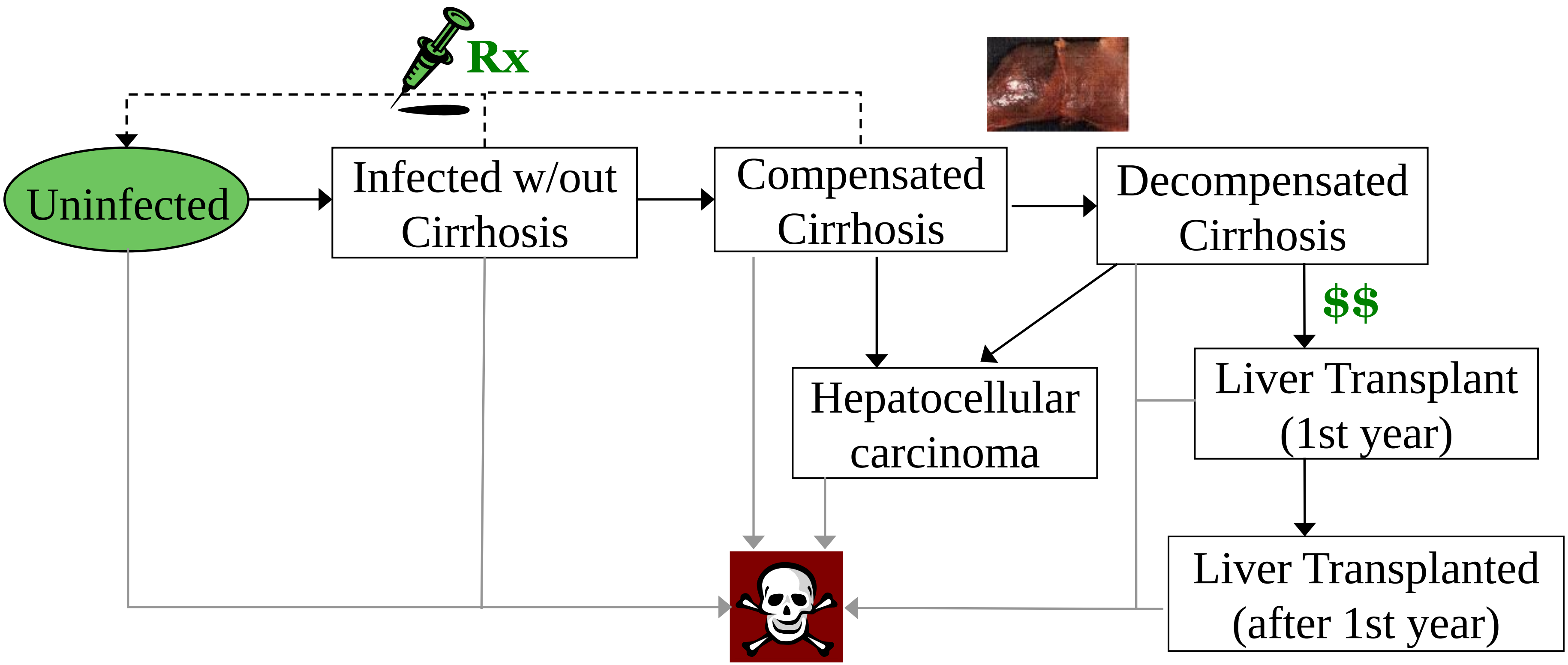


Objectives

- Analyze general models for timing and frequency of testing decisions
  - Disease may be asymptomatic
  - Knowledge can affect behavior (progression or infection)
- Determine appropriate testing and treatment for Hepatitis C with societal perspective
  - Maximize Quality-Adjusted Life Years (QALYs) gained, or
  - Minimize cost to the system, or
  - Consider both

Kirkizlar, E., D. Faissol, P. Griffin, and J. Swann (2010). "Timing of Testing and Treatment for Asymptomatic Diseases." *Mathematical Biosciences* 226:28-37.

Natural History of Disease

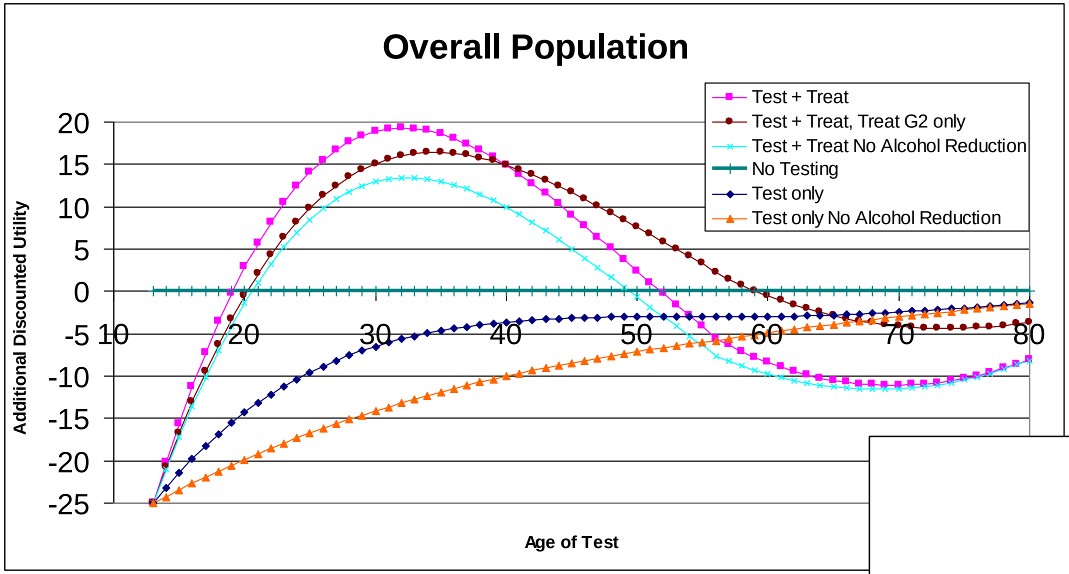


- We use a Markov decision process for testing and treatment
- Model adds that patient's knowledge of disease can slow progression
- Analysis to find "optimal" timing of policies with extensive simulations of other testing policies

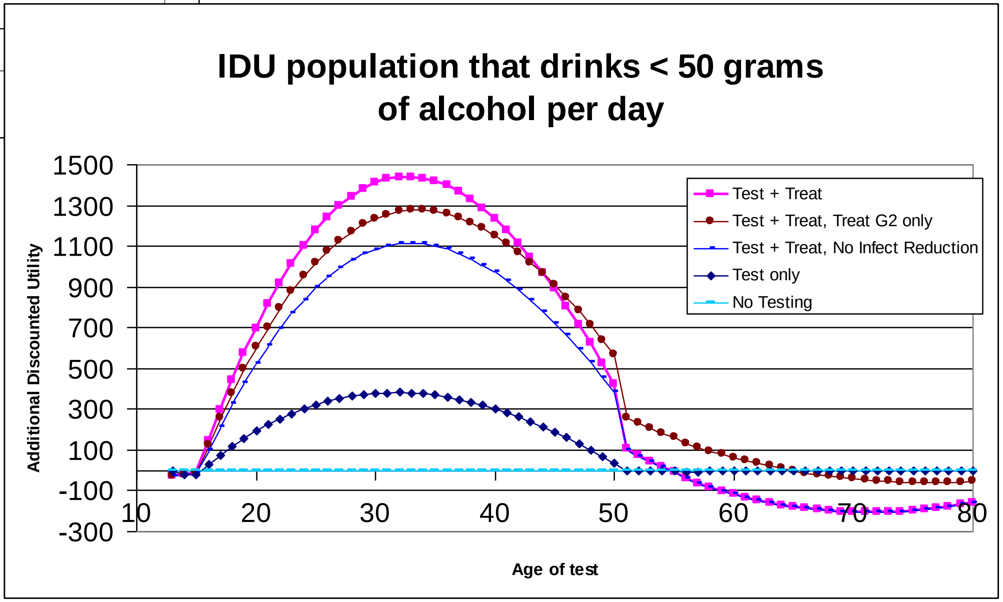
Parameter Estimation

Progression rates of disease [including w/ or w/out alcohol]	Bennett et al (1997); Degos et al (2000); [Freeman et al (2001), Wiley et al (2001); Poynard et al (2001)]
QALYs	Singer (2001); Chong (2003)
Cost of disease	Sullivan et al (2004)
Treatment success rates	Manns et al (2001); Horoldt et al (2006)
Incidence Rates	CDC (2006)
Drop-out & Ineligibility Rates	Fried et al (2002); Jowett (2001)
Genotype factors	Hornberger (2006)

Maximizing the Utility (1 Test)

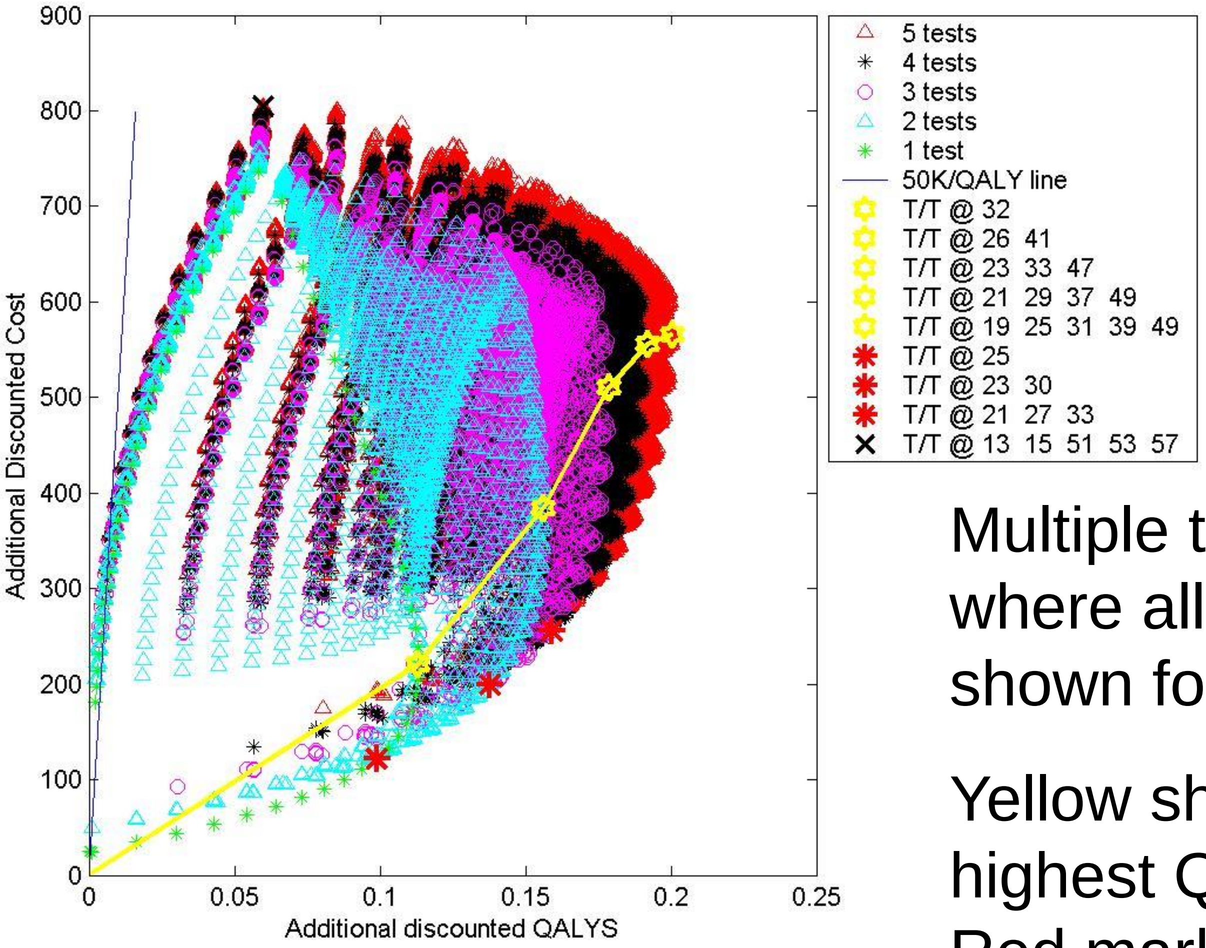


- Testing IDU population has high utility for a wide range of ages
- Should we test more often?



- Testing in middle years captures more infections than early years, and still captures most of the benefit of catching disease early

Cost/Utility Ratio for Multiple Tests



Multiple tests of IDU population where all age combinations are shown for each n-test policy.

Yellow shows policies with highest QALYs for each n-test; Red marks frontier

Most policies are cost-effective

Conclusions

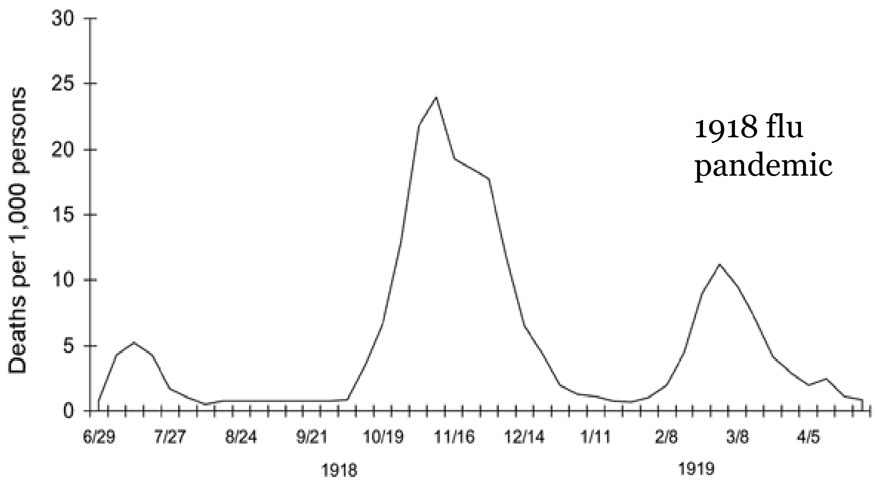
- Testing Recommendations
  - High-risk groups should be tested (multiple times) over a wide range of ages
  - Testing is also at the edge of cost-effectiveness for the general population
- Static interval testing is appropriate for some groups, but dynamic testing can offer improvement
- Similar approaches can be used for a wide variety of diseases
  - Screening of newborn infants (Ayer & Keskinocak, Grosse et al)
  - Various cancers (Ayer)
  - Personalized medicine based on risk factors

Interventions for Epidemics

How might a disease spread over time and space? What are the impacts to changes in the system? How should one design a response system?

Background on Epidemic Work

- Goal
  - Use simulation and modeling to promote better decision making
    - Policies
    - Planning
    - Response
  - Variety of organizational types
    - Government
    - Non-governmental
    - Private Industry



1918 flu pandemic

- Initial modeling performed prior to outbreak of H1N1a in 2009, with evaluation of US vaccine distribution afterwards
- Still relevant, as epidemics still possible (H7N9 or others)

Source: J. K. Taubenberger, D. M. Morens. 1918 Influenza: the Mother of All Pandemics. Emerging Infectious Diseases (2006)

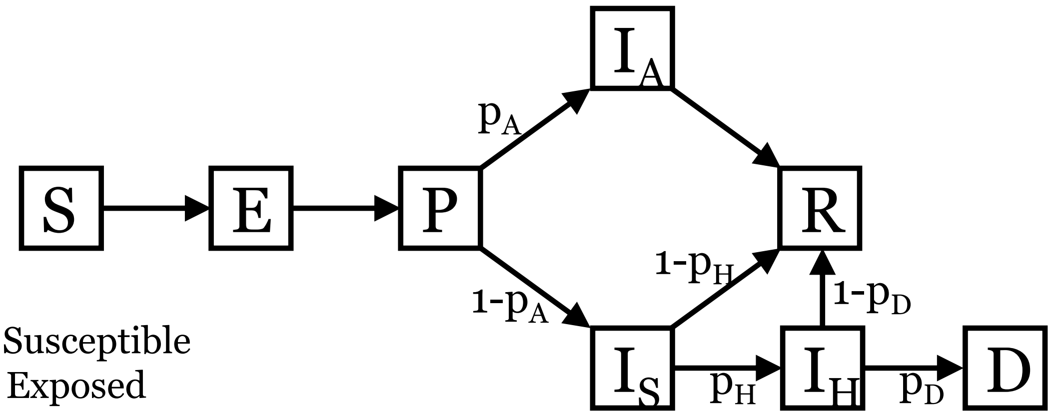
Approach

- Modeling and understanding the disease spread geographically and over time
  - Impact of seasonality and mutation
- Constructing a food distribution network for planning and response
  - Estimating the food need
  - Number of facilities and their locations (over time)
  - Allocation of resources among the facilities
- Analyzing the impact of intervention strategies (i.e., policies)
- Using framework to study other decisions

- Collaborations
  - Food planning in collaboration with American Red Cross Metropolitan Atlanta Chapter
  - H1N1 policy updates to GA Department of Education, and GA-DHR Department of Public Health
  - On loan to CDC during the 2009-2010 H1N1 pandemic

Disease Progression Model

- An individual-based stochastic model (expansion of SEIR)
- 5 age groups (0-5, 6-11, 12-18, 19-64, 65+)



S: Susceptible
E: Exposed
I_P: Presymptomatic
I_A: Asymptomatic
I_S: Symptomatic
R: Recovered
I_H: Hospitalized
D: Dead

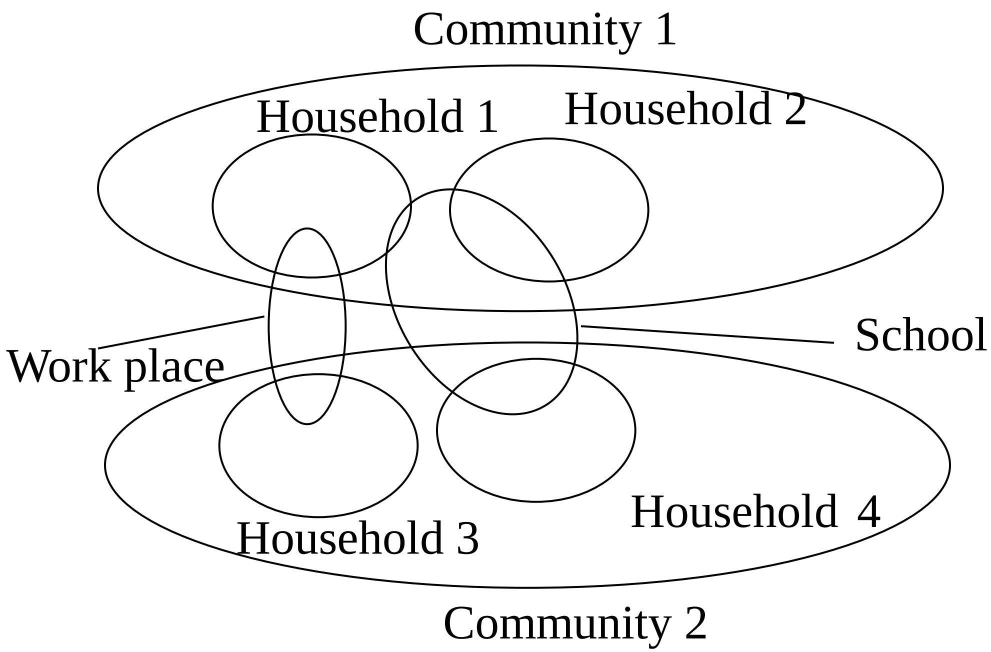
Parameters for pre-H1N1 planning

p_A = 0.4 for adults (19-64) and 0.25 for others [1,2,3,4]
p_H = 0.18 for children between 0 and 5, 0.12 for elderly (65+) and 0.06 for others [1,2]
p_D = 0.344 for elderly and children between 0 and 5 and 0.172 for others [1,6]
Duration of $E + I_P \sim$ Weibull(1.48, 0.47) (including an offset of 0.5 days) [1,5]
Duration of I_P = 0.5 days [1,5]
Duration of $I_S \sim$ Exponential(2.7313) [1]
Duration of $I_A \sim$ Exponential(1.63878) [1]
Duration of $I_H \sim$ Exponential(14) [1,5]

[1] Wu, J. T., S. Riley, C. Fraser, G. M. Leung. 2006. Reducing the impact of the next influenza pandemic using household-based public health interventions. *PLoS Medicine* 3(9) 1532-1540
[2] Longini, I. M., A. Nizam, S. Xu, K. Ungchusak, W. Hanshaoworakul, D. A. T. Cummings, M. E. Halloran. 2005. Containing pandemic influenza at the source. Science 309 1083-1087
[3] Germann, T. C., K. Kadau, I. M. Longini, C. A. Macken. 2006. Mitigation strategies for pandemic influenza in the United States. Proc. Natl. Acad. Sci. 103(15) 5935-5940
[4] Ferguson, N. M., S. Mallett, H. Jackson, N. Roberts, P. Ward. 2003b. A population-dynamic model for evaluating the potential spread of drug-resistant influenza virus infections during community-based use of antivirals. Journal of Antimicrobial Chemotherapy 51 977-990
[5] Ferguson, N. M., D. A. T. Cummings, S. Cauchemez, C. Fraser, S. Riley, A. Meeyai, S. Iamsirithaworn, D. S. Burke. 2005. Strategies for containing an emerging influenza pandemic in Southeast Asia. Nature 437 209-214
[6] Carrat, F., J. Luong, H. Lao, A. Sall, C. Lajaunie, H. Wackernagel. 2006. A "small-world-like" model for comparing interventions aimed at preventing and controlling influenza pandemics. BMC Medicine 4(26)

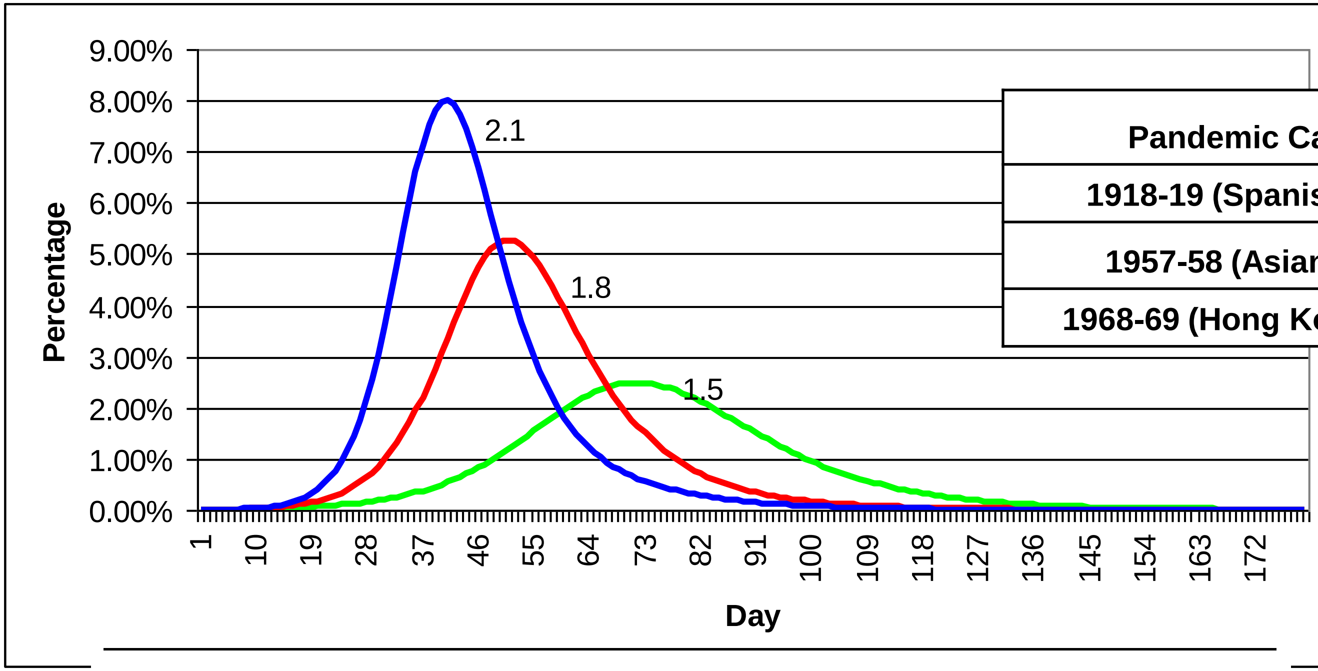
Disease Contact Network

- Households
- Peer groups (work place and schools)
- Community: Census tract-based
  - Population ~ (1500-8000)
- Agent-based Simulation built for state of Georgia
  - Household statistics, work flow data, classroom sizes, age statistics



Flexible model that can be adapted to other states or the entire U.S.

Basic Simulation Estimates for Georgia

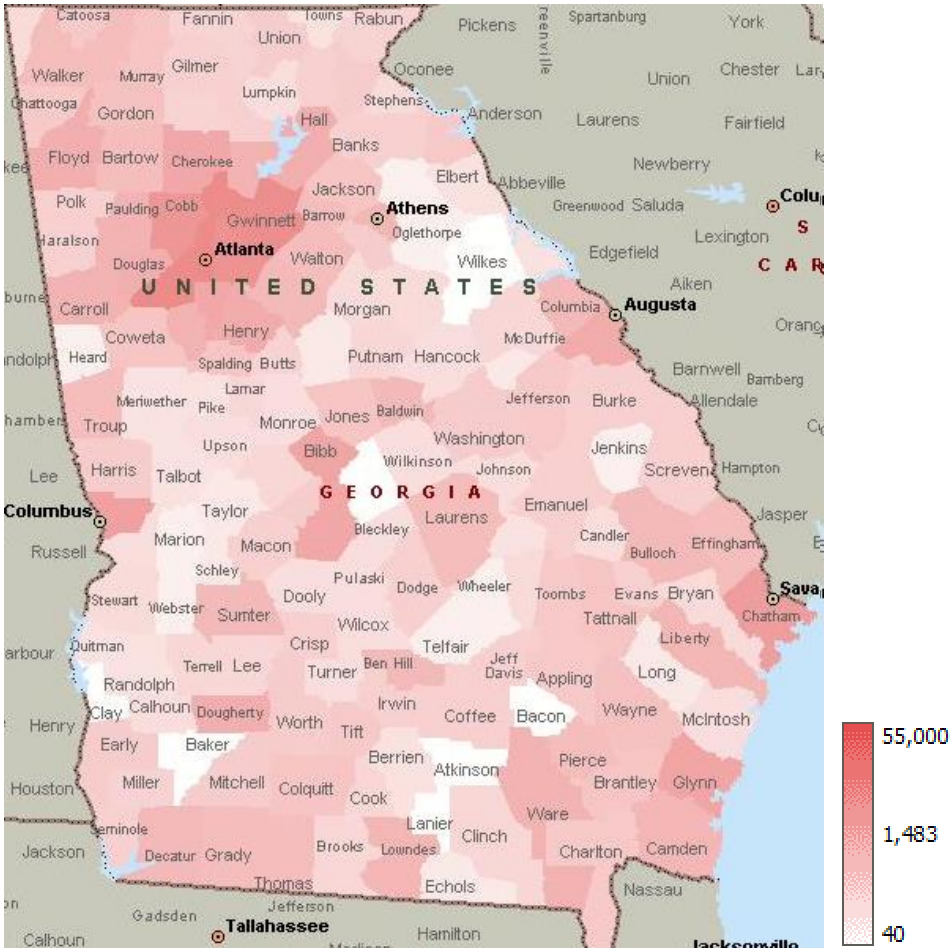


Pandemic Case	R_0 value
1918-19 (Spanish flu)	2-3 [3] or 1.7-2.0 [1]
1957-58 (Asian flu)	1.5-1.7 [1]
1968-69 (Hong Kong flu)	1.89 [2]

R_0 Value	Peak Infectivity	Peak Day	CAR	IAR	Death Ratio
1.5	2.48%	70	32.50%	49.65%	0.57%
1.8	5.27%	50	44.20%	67.49%	0.80%
2.1	8.01%	40	51.27%	78.27%	0.93%

[1]Ferguson, N. M., D. A. T. Cummings, C. Fraser, J. C. Cajka, P. C. Cooley, D. S. Burke. 2006. Strategies for mitigating an influenza pandemic. *Nature* 442 448-452.
[2]Rvachev, L., I. M. Longini. 1985. A mathematical model for the global spread of influenza. Mathematical Biosciences 75 3-22.
[3]Mills, C. E., J. M. Robins, M. Lipsitch. 2004. Transmissibility of 1918 pandemic influenza. Nature 432 904-906.

Example Spread across GA



Day 90 se in Fulton Co.

Disease spreads quickly to populous or "connected" counties, with location and rate varying for different conditions

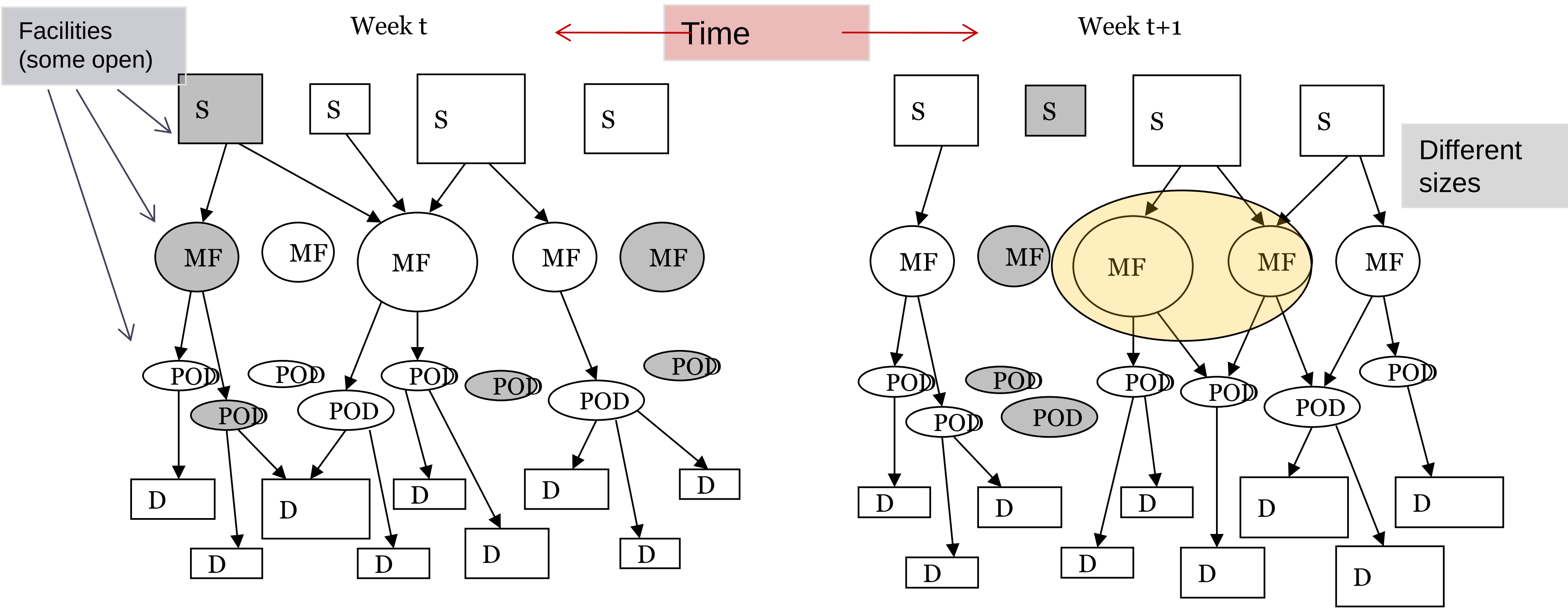
Small area differences may be easier to capture with a model than with surveillance

Number of infections, logarithmic scale

Estimating the food need (Metro Atlanta)

- 3 meals per day
- Several alternatives to calculate the food need
  - Serve the households with
    - An infected (symptomatic or hospitalized) individual
      - All, or only those below 25K income, or below the poverty level
    - All adults infected (symptomatic or hospitalized)
      - All, or only those below 25K income, or below the poverty level
  - Serve the quarantined households
  - Need varies over these scenarios from 250K to 35 Million
- Model captures need across time and space
- Engineering models can help design the distribution system needed

Food Distribution Network

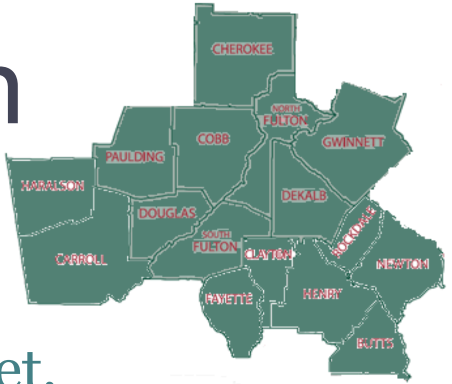


Capacitated Multi-Period Hierarchical Facility Location Problem

- Demand (D): households with needs
- Points of distribution (POD): e.g., located at schools
- Major Facilities (MF): warehousing, storage, cross-docking
- Supply nodes (S): Source of food

Locations are open (shaded) or closed (white) as needed over time

Designing Distribution System

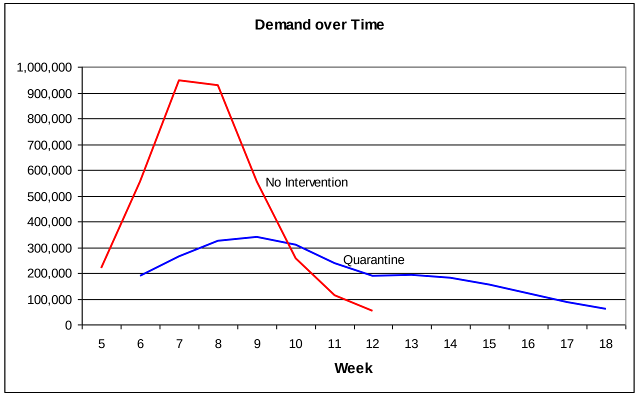


- Performed optimization of network
  - Meet the maximum demand given a limited budget, or minimize cost to serve a particular sized population
- Solved small instances (to study solutions) and large instances (for 1600+ census tracts in metro-Atlanta)
  - The number of major facilities is the most important factor in making the problem hard to solve
- For large problems, heuristics outperform best integer solution found within time limits
- "Static" approach is usually sufficient, but dynamic can be worthwhile if disease estimates are changing
- Results indicate where might be good locations for facilities

Ekici, A., P. Keskinocak, and J. Swann. "Pandemic Influenza Response: Food Distribution Logistics." Forthcoming at *Manufacturing and Service Operations Management*.

Further Analysis of Spread

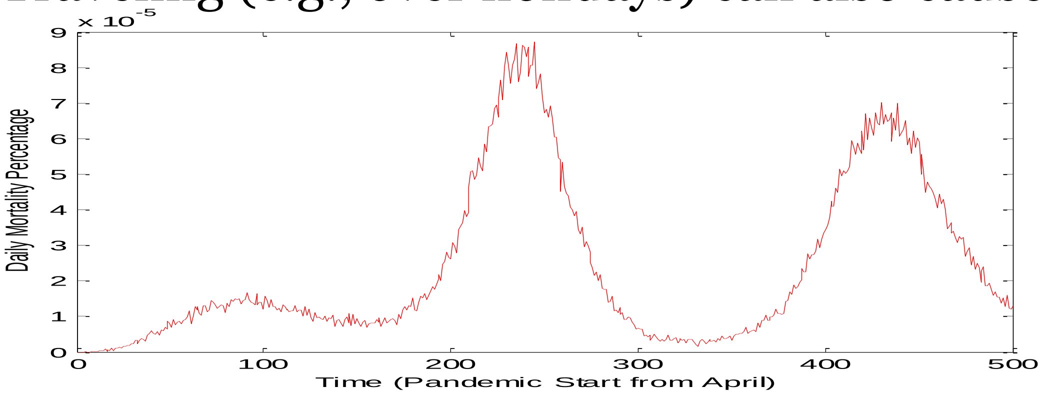
- Impact of household quarantine (weeks 4 – 12) on food need



IMPLICATIONS:
Total demand ↓ 26.70%
Average demand ↓ 55%
Number of open PODs ↓ 50% (stay open for longer)

Capacity bottlenecks ↓

- Seasonality and mutations can cause second or third waves
- Traveling (e.g., over holidays) can also cause wavelets



Can mimic 1918 patterns
- Ro* = 1.5
- Start in April
- Mutant strain emerges at day 275 (Dec)
- ε = 0.3 (start of seasonality)
- δ = 0.015 (related to mutation rate)

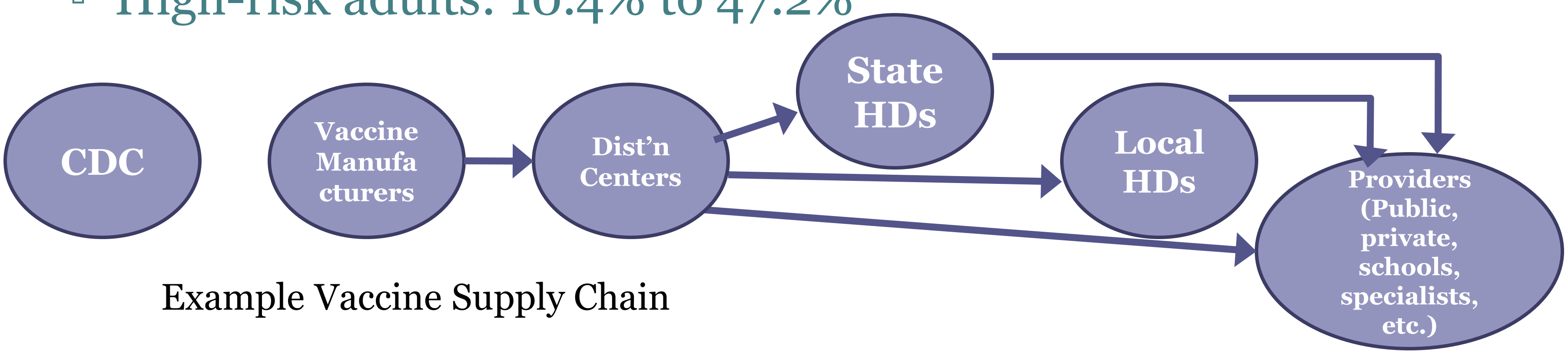
Shi, P., P. Keskinocak, J. Swann, and B. Lee (2010). "Modeling Seasonality and Viral Mutation to Predict the Course of an Influenza Pandemic." *Epidemiology and Infection* Oct;138(10):1472-81.
Shi, P., P. Keskinocak, J. Swann, and B. Lee (2010). "The Impact of Mixing Pattern Changes from Holidays and Traveling on Outcomes during an Influenza Pandemic." *BMC Public Health* 10:778.

Engineering and Epidemics

- Models can test out different strategies
  - What is the value of information (surveillance or vaccine administration) on adapting distribution dynamically?
- What models or logistics are needed for other types of diseases?
  - Cholera study with Task Force for Global Health
  - (Dr. Pinar Keskinocak & Dr. Dima Nazzal, GT HHL Center)
- What can results from 2009-2010 distribution tell us for the future?
  - States differed widely in their vaccination uptake and their distribution systems. Is there a link?

H1N1 Influenza Pandemic

- A national influenza H1N1 vaccination campaign for the H1N1a pandemic began in Fall 2009 and involved federal government working with states and local health departments (HDs), providers, etc.
- Initial allocations to states were pro-rata by population but vaccination coverage rates varied greatly across states
  - Adults: 8.7 to 34.4%
  - Children: 21.3% to 84.7%
  - High-risk adults: 10.4% to 47.2%



Example Vaccine Supply Chain

Objectives

- Find system factors and state decisions that explain variation in coverage rates
  - Supply chain design and processes
  - Population and state characteristics
  - Health infrastructure or behaviors
- Note that
  - Vaccine was in short supply in the first part of the response
  - Priority groups (or subgroups) were targeted
  - States and/or local HDs had different processes and strategies

1. Davila Payan, C., J. Swann and P. Wortley (2012), "Supply Chain and System Factors to Explain H1N1 State Vaccination Rates for Adults in US Emergency Response to Pandemic". Forthcoming at *Vaccine*. (Accepted April 2013).
2. Davila Payan, C., P. Wortley, and J. Swann (2012), "System Factors to Explain H1N1 State Vaccination Rates for Children and High-Risk Adults in US Emergency Response to Pandemic". Cleared by CDC June 2013. Working paper, Georgia Tech.

Approach

- Regression over state vaccination rates for adults, children, and high-risk adults
  - Studied supply chain factors, while controlling for others
  - Limitations of ecological model and the data
  - Adjusted R-squared values 75% or greater

Standardized coefficients when predicting adult coverage

		Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)		2.66E-16	0.06807	3.9E-15	1.00E+00	
c7	% Hispanic	0.378	0.07953	4.753	2.26E-05	***
sf2	Past Flu Coverage	0.3599	0.07928	4.54	0.000045	***
ah36	% Women w/ Pap	0.3002	0.07653	3.923	0.00031	***
sh2	Max # Sites	0.1807	0.07061	2.558	0.01412	*
sh11	% to Specialists	-0.295	0.07788	-3.788	0.000468	***
pw3	% weeks ILI high	-0.4366	0.07362	-5.931	4.61E-07	***
o7	Leadtime	-0.4419	0.07401	-5.97	4.04E-07	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Adjusted R-squared: 0.7637 , Reg p-value: 6.035e-13

Overall Findings

- Strengthening existing seasonal flu vaccination programs, provider infrastructure, and usage of preventive medical programs could be beneficial for emergency response or campaigns with limited supply
- Increase the number of ship-to-sites allowed or underlying provider infrastructure
  - Variable associated with higher vaccination coverage in all groups
- Consider pro-rata allocation that includes children if they are a priority
- Further explore leadtime and order lags
  - E.g., positively correlated with use of third party for redistribution and negatively with shipments per location
  - Ordering and shipping lags may be a function of system design, or efficiency, suggesting monitoring and/or system design changes

- Sending vaccine where there is general access rather than limited access can be beneficial
  - Appears in adult model ("limited access" effect) and high-risk adult models ("general access" effect)

Access to Care and Disparities

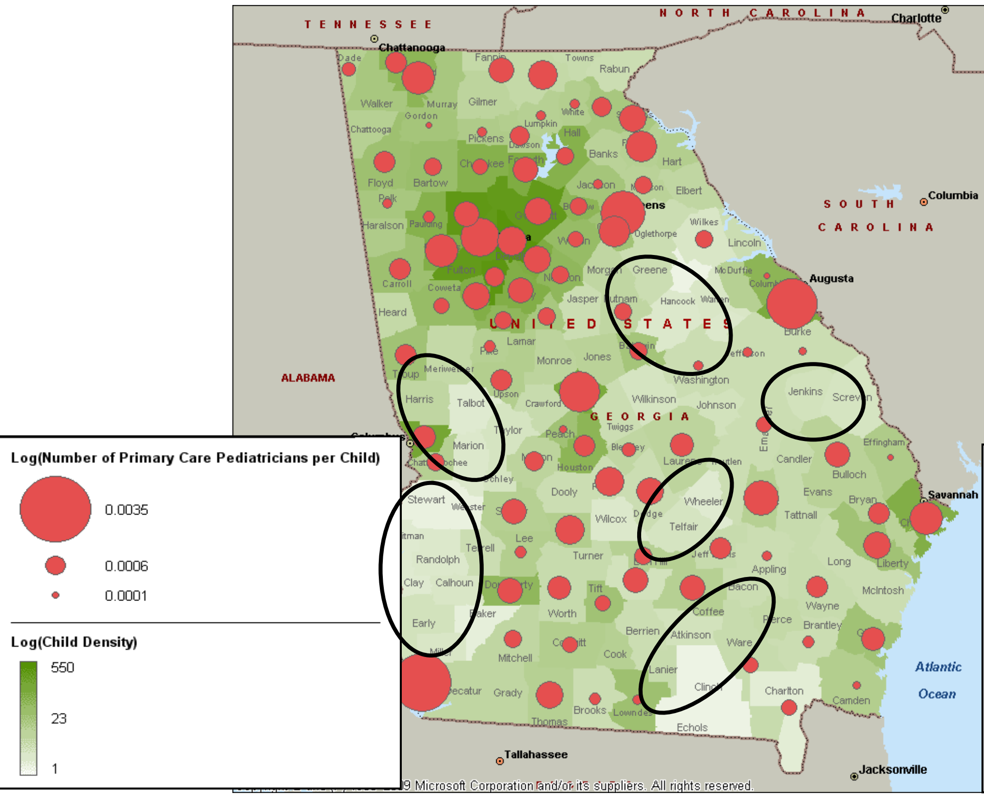
What approaches should be used for quantifying access or disparities over a network? What interventions could result in the most improvements?

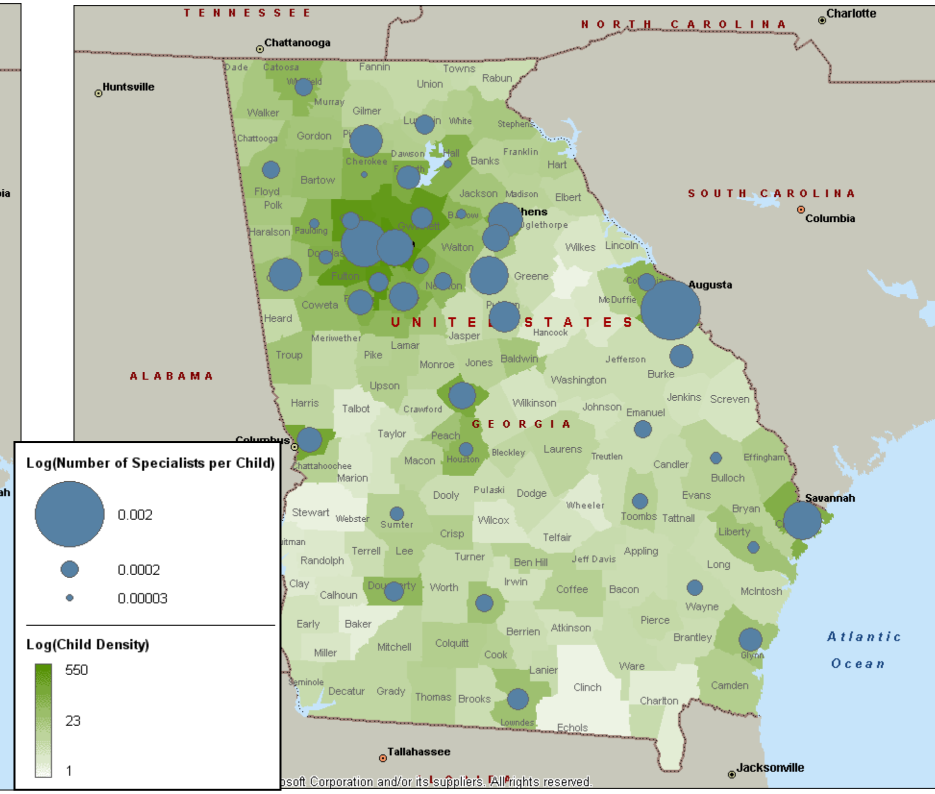
Access to Pediatric Healthcare

- There is a large and increasing discrepancy between the rural and urban supply of pediatricians (Randolph, Pathman 1996)
  - In 1996, 95.5% of counties with populations below 10,000 had no pediatrician and 84.4% of counties with populations below 25,000 had no pediatrician
  - Only 8% of general pediatricians and only 4% of pediatric sub-specialists practice in rural areas, where approximately 20% of children live.
- The U.S. Department of Health and Human Services identifies increasing accessibility of healthcare services as a key step in mitigating the widening disparities of health outcomes of children (Healthy People 2010)
- Inequities in access to healthcare are also associated with higher costs and inconsistency in health treatments (Williams, R.A. 2007)

Pediatricians Per Child in Georgia

- Many counties have no pediatricians
- Specialists are even sparser

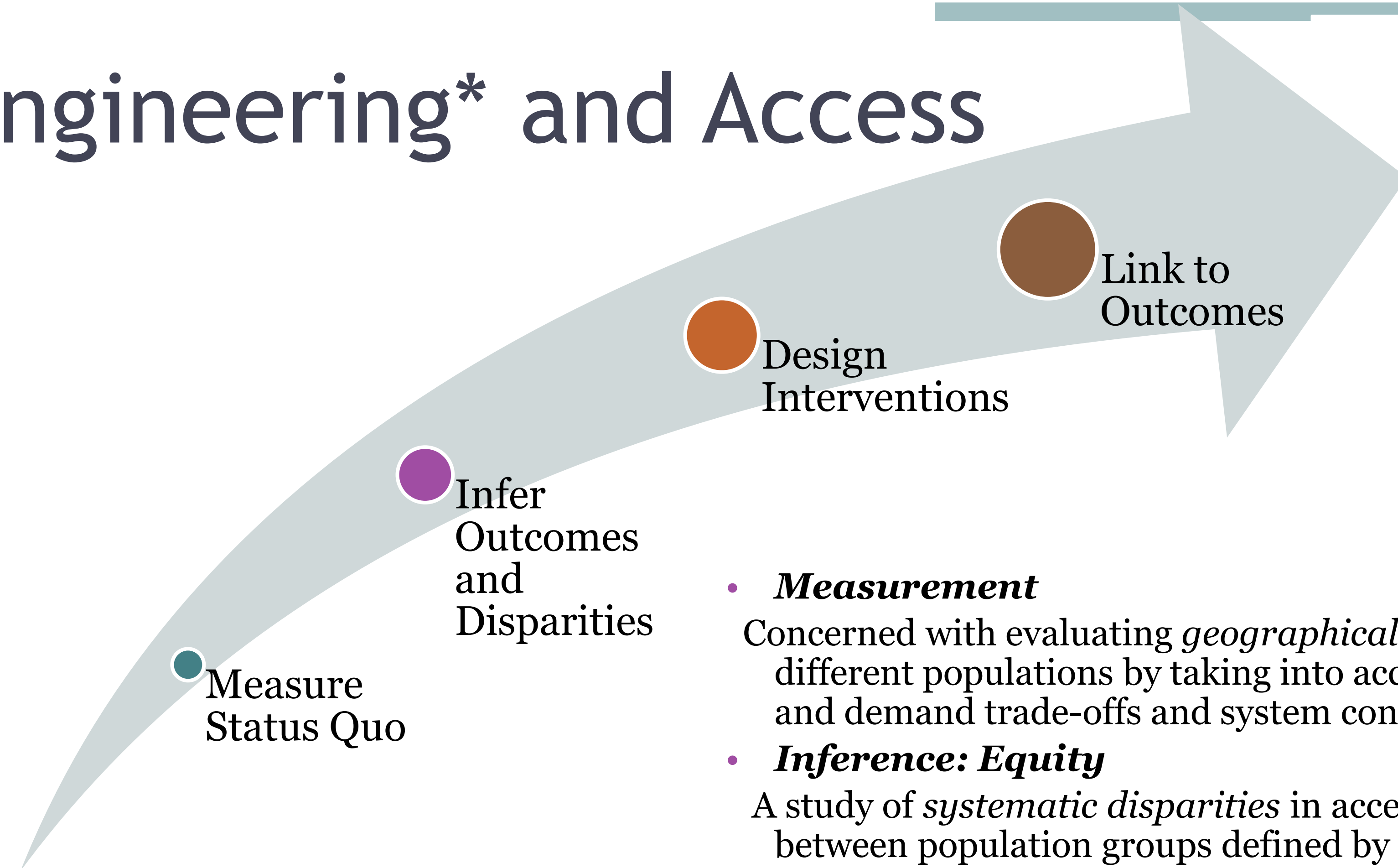




What role does spatial access play in health outcomes?

Data on location of pediatricians is from the 2010 National Provider Identifier (NPI) Registry through the Center for Medicare & Medicaid Services (CMS). Data on population from 2000 Census.

Engineering* and Access



- ***Measurement***

  Concerned with evaluating *geographical access* of different populations by taking into account supply and demand trade-offs and system constraints.
- ***Inference: Equity***

  A study of *systematic disparities* in access to services between population groups defined by geographic location and demographic characteristics.
- ***Designing Interventions***

  Optimization allows one to target interventions or estimate the impact on a complex system
- ***Outcomes***

  Ultimately we want to design interventions likely to positively impact health outcomes or inequities

*Also includes Statistics

Our Approach

- *We use optimization to match supply and demand and quantify access for multiple populations across the network*
  - System constraints
    - Mobility – transportation, cost, infrastructure
    - Capacity – access to supply, system dynamics
    - User choice within network and willingness to travel
  - System can be measured on distance traveled, congestion or scarcity, coverage, or others
- *Our premise: Equity is achieved when there is no systematic association between "potential access" and socioeconomic or other attributes of a population*
  - Use spatial statistics for associations and significance

Optimization Model

Objective: $\min \sum_{i=1}^{n}\sum_{j=1}^{m} d_{ij} * (n_{ij}^{M} + n_{ij}^{O})$

Constraints:

1. $\sum_{i=1}^{n}\sum_{j=1}^{m} \frac{(n_{ij}^{M}+n_{ij}^{O})}{p_i} \geq CR$

2. $\sum_{i=1}^{n} n_{ij}^{M} + n_{ij}^{O} \leq PC \ \forall j$

3. $\sum_{i=1}^{n} n_{ij}^{M} \leq PC * pam_j \ \forall j$

4. $\sum_{j=1}^{m} n_{ij}^{M} * I(d_{ij} \geq 10) \leq m_i^{M} * p_i \ \forall i$

5. $\sum_{j=1}^{m} n_{ij}^{O} * I(d_{ij} \geq 10) \leq m_i^{O} * p_i \ \forall i$

6. $\sum_{i \epsilon C_k} \sum_{j \epsilon C_k} (n_{ij}^{M} + n_{ij}^{O}) \leq AC * md_k \ \forall k$

7. $\sum_{j=1}^{m} n_{ij}^{M} \leq p_i * pom_i \ \forall i$

8. $\sum_{j=1}^{m} n_{ij}^{O} \leq p_i * (1 - pom_i) \ \forall i$

9. $n_{ij}^{M} \geq 0, \ n_{ij}^{O} \geq 0 \ \forall i, \forall j$

Decision Variable:

- Number of children in each census tract assigned to each physician (separately for Medicaid and other populations)

Objective function:

- Minimize travel distance for covered patients

Constraints:

1) Coverage:

- Achieve a minimum coverage level at the state level

2-3) Physician Capacity:

- For each physician, limit assignees by the maximum patient caseload & the estimated number of Medicaid patients they accept

4-5) Patient Mobility:

- For each census tract, limit the assignees to physicians more than 10 miles away by the percentage of the population with cars

6) Dispersion of Congestion:

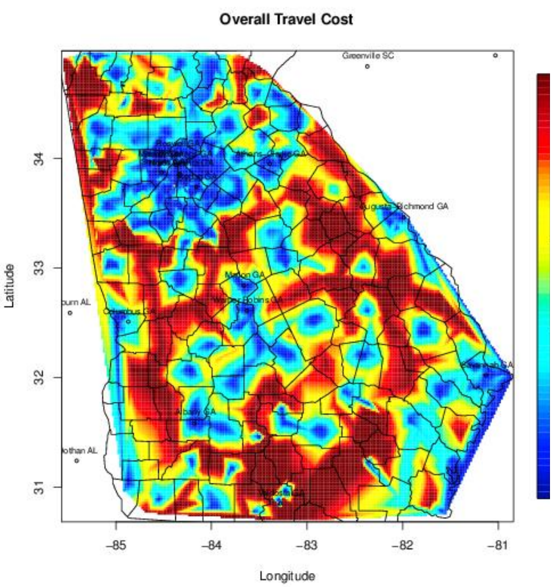
- For each county, ensure that average congestion for physicians is below a threshold level

7-9) Logic of Assignments:

- Assignments less than number of children in population
- No negative assignments

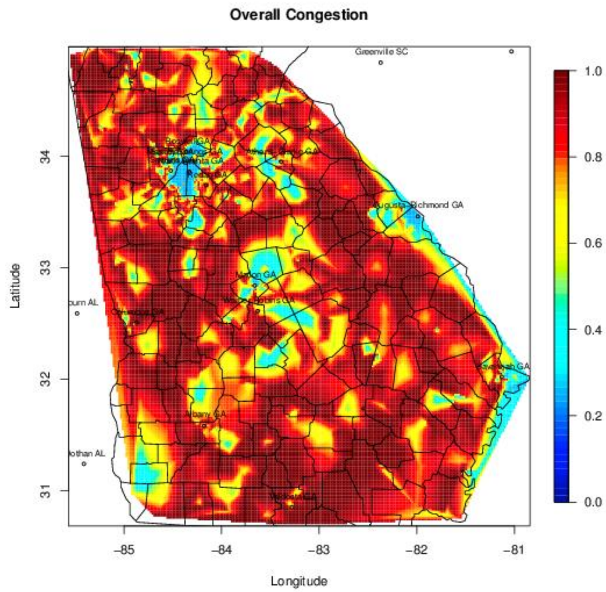
Results*

Distance



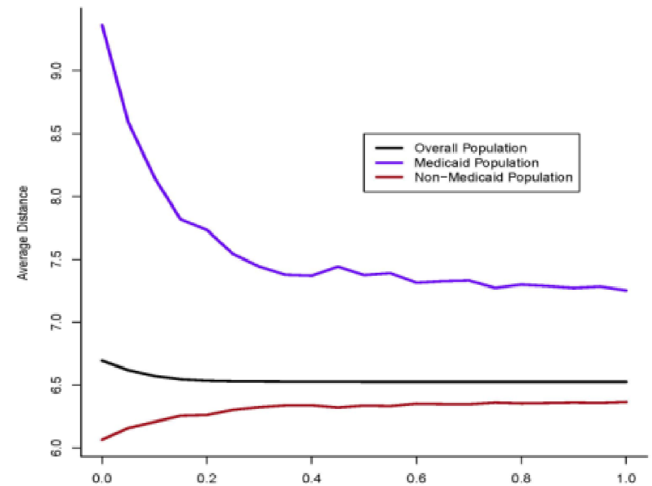
- Urban areas: shorter distances and higher coverage than rural
- Wide variety in distances traveled

Congestion



- Congestion high across state except for some cities

Intervention

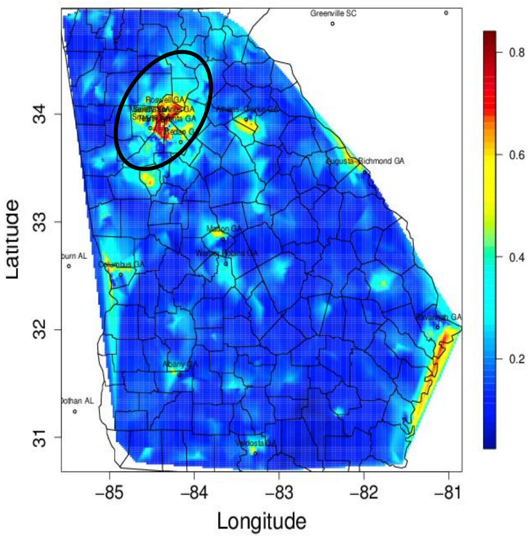


- Increasing participation of MDs taking Medicaid would improve access for Medicaid patients without compromising access for overall population

* Nobles, M., N. Serban, and J. Swann (2012), "Spatial Accessibility of Pediatric Primary Healthcare: Measurement and Inference". Under review at *Technometrics*. Submitted January 2013.

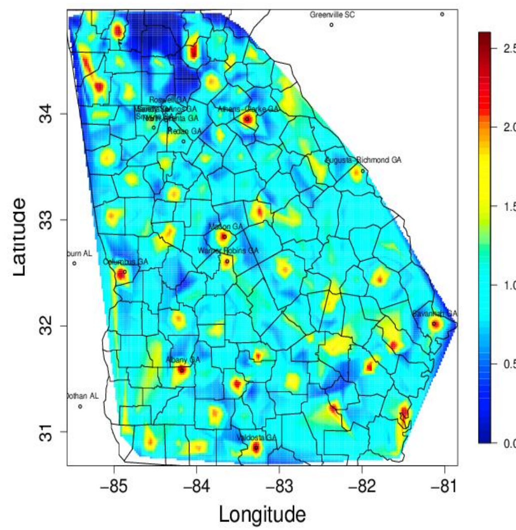
Example Independent Variables for Spatial Regression on Distance

% With Some Higher Education



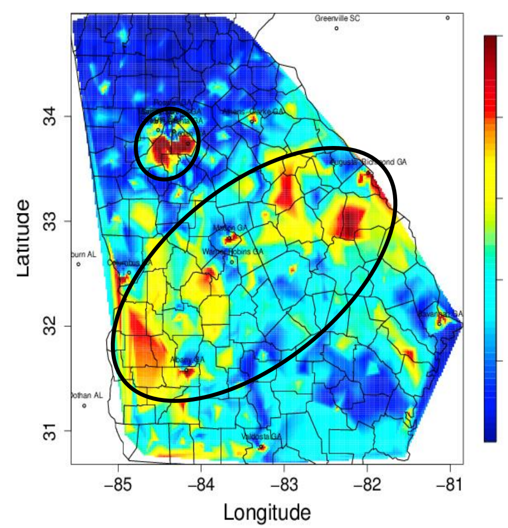
- High primarily in cities

Segregation Ratio



- Ratio > 1 if small surrounding area has less segregation than larger surrounding area
- Tends to be largest in small towns

% Nonwhite



- High in cities and in diagonal band across state

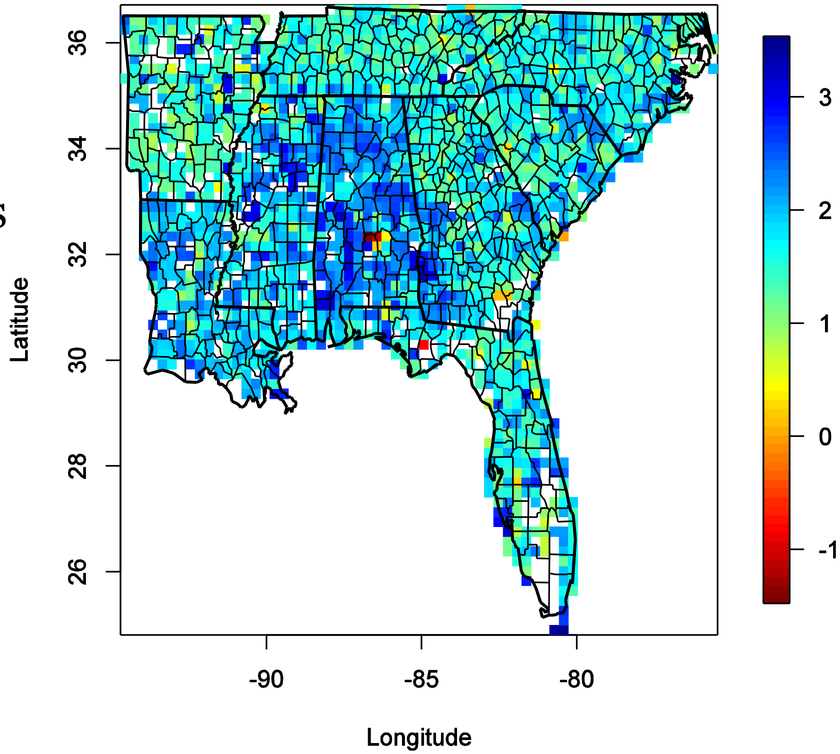
Associations with Accessibility

- Regression with spatially varying coefficients allowed controls for spatial dependence
- Model selection:
  - Estimate many combination sets of predictors
  - Evaluate model performance based on multiple statistical criteria
- Findings:
  - There is unexplained systematic access disparities
  - Factors tend to have a consistent effect on access
- Distance tends to be higher with (higher income, lower education, more segregation compared to community), and nonlinear with population density

	Income	**Percent with Higher Education**	**Unemployment Rate**	**Percent of non-white children**	**Population Density**	**Distance to Nearest Hospitals**	**Diversity Ratio**
Consistent Effect	Yes	Yes	Yes	Yes	Yes	No	Yes
Significant Effect	Yes	Yes	No	No	Yes	Yes	Yes
Type of Effect	Constant	Constant	Constant	Constant	Non Linear	Non Linear or Constant	Constant
Range of Coefficients	[.2, .35]	[-.26, -.15]	[.001, .41]	[-.18, .06]	---	[.11, .13]	[-.24, -.18]

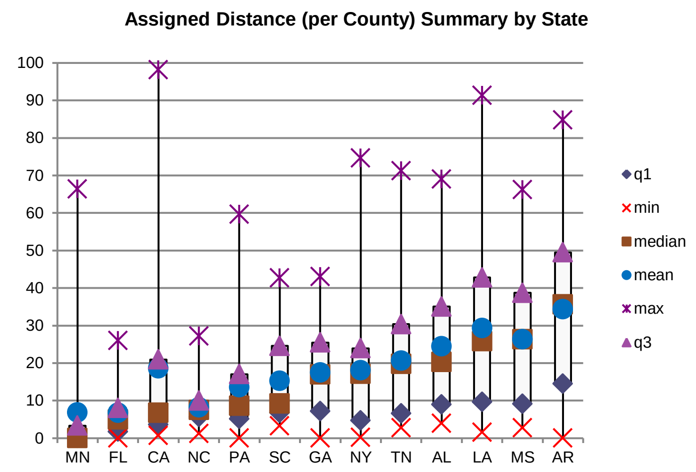
Access for Other Health Services

- Methods, with application to Asthma and Cystic Fibrosis[1]
  - Compares optimization models to other methods including E2SFCA across dense, sparse, and heterogeneous networks
- H1N1: Quantifying and Explaining Access to Vaccine during Shortages[2]
  - Uses vaccine shipments, populations, and modeling
  - Finds that population density is associated with differences in access but that most socioeconomic characteristics are not



1. Li, Zihao, N. Serban, and J. Swann (2013), "Methods to quantify spatial access to health services including Asthma and Cystic Fibrosis", Working paper at Georgia Institute of Technology.
2. Heier Stamm, N. Serban, J. Swann, and P. Wortley (2012), "Quantifying and Explaining Accessibility of H1N1 Vaccine during the 2009 pandemic". Under review at *Management Science*. (Received CDC clearance 2012; Submitted Feb 2013.)

Access to Outcomes to Interventions



- Asthma: Linking Access to Outcomes[1]
  - Distances to asthma care vary greatly over a network
  - Tests the association between spatial access to asthma care and visits to hospital in CA, FL, GA, NC
  - Finds that increased distance is often associated with lower outcomes, especially for children age 4-9
- Designing Interventions for Improved Access and Outcomes
  - What are the pathways to care (especially for Medicaid patients), and what kind of interventions would improve outcomes?
  - How effective would it be to use schools, health departments, or retail clinics for additional services? Where would be most effective, and how many?

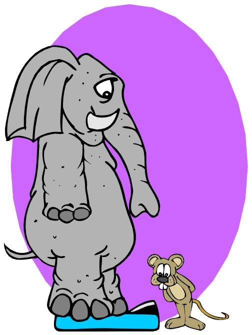
1. Garcia, E, N. Serban, and J. Swann (2013), "Linking Access for Asthma Care to Emergency Department Visits and Hospitalizations", Working paper at Georgia Institute of Technology.

Predicting Disease Prevalence

What is the expected level of disease in each small area, so interventions may be targeted effectively?

Pediatric Obesity

- Pediatric obesity has tripled in the last three decades
- The cost of obesity in the United States totaled about $147 billion in 2008 (Finkelstein, et al 2009)
- Interventions could impact children immediately, and health system for the long-term
- Obesity differs geographically and/or by population characteristics
  - Targeting the interventions (e.g., by area) may be more cost-effective
  - But, survey and surveillance approaches are costly
- Statistical modeling and simulation can be used to project prevalence in "small areas"



Data on Pediatric Obesity

- National Health and Nutrition Examination Survey (NHANES) contains national survey and examination data for all ages[1]
- National Survey of Children's Health (NSCH) provides state-level estimates for ages 10-17 from self-reported surveys[2]
- Arkansas school systems started collected measurements, reported for schools or counties

1. Davila Payan, C., M. DeGuzman, N. Serban, and J. Swann (2012), "Local Estimates of Pediatric Obesity for Informing Interventions in Georgia", Working Paper, Georgia Tech.
2. Zhang X, Onufrak S, Holt JB, Croft JB. A Multilevel Approach to Estimating Small Area Childhood Obesity Prevalence at the Census Block-Group Level. Prev Chronic Dis 2013;10:120252.

Approach: Multilevel Logistic Regression

- Logistic regression for prediction of individuals 2-17 with BMI measured in NHANES (2001-2008)
  - Predicting overweight or obese, defined by 85% BMI)
- Covariates tested
  - Gender
  - Age in months
  - Race/Ethnicity: Hispanic, Non Hispanic (N.H.) Black, Other N. H.
  - Income level at or above 4, 2, 1 times the poverty level
  - Educational Level of household reference person
  - Household size
- Selected variables
  - Individual significance
  - Fit with Census data available for small areas
  - Wald F statistic of overall model

Coefficient	Covariate	Mean	95% C. I.	p-value	Characteristic
β_b	X_b	0.20	(0.05, 0.35)	0.0107	Non Hispanic Black or not
B_{nho}	X_{nho}	-0.34	(-0.57, -0.11)	0.0043	Non Hispanic Other or not
β_h	X_h	0.34	(0.18, 0.50)	0.0001	Hispanic or not
β_e	X_e	-0.58	(-0.78, -0.38)	0.0000	Household representative education level
β_h	X_h	-0.69	(-0.95, -0.43)	0.0000	Household size
β_a	X_a	0.76	(0.59, 0.93)	0.0000	Age in months
β_0	*Intercept*	-0.56	(-0.84, -0.27)	0.0002	Intercept coefficient

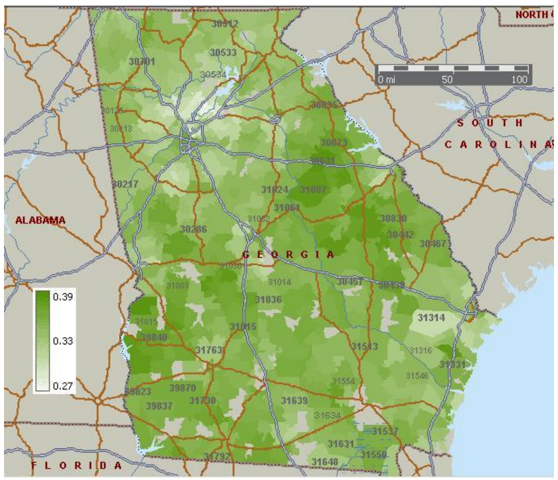
Approach: Simulation across Areas

- Used Census 2000, Summary File 3
  - Each variable stratified by race-ethnicity
  - Missing data in small areas approximated
- In each census tract, generate 1000 virtual individuals using proportions from Census
  - Generate model coefficients from distributions
  - Project likelihood overweight or obese
  - Simulate whether individual is overweight or not
  - Count people overweight or obese in that tract
  - Repeat 1000 times, and calculate 95% confidence intervals

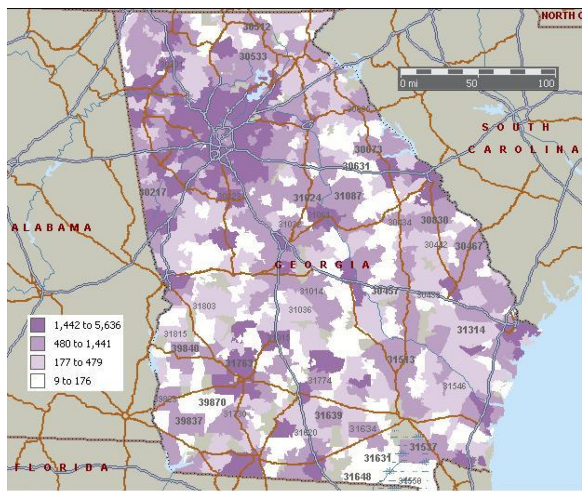
- Also convert estimates to zip codes level

Estimates for Overweight children

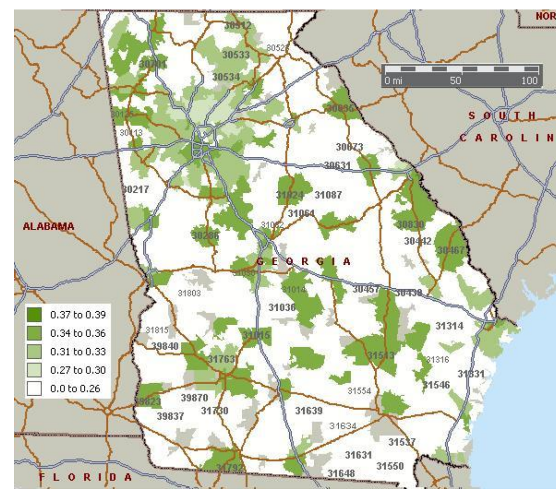
Prevalence (zip codes)



Number of Children



Priority Areas:
Areas that cover ~ 80% of the overweight children in GA



Results used to target interventions by a large healthcare provider in GA

Validation of results

- Cross-validation of model
- Our overweight baseline estimate for children 10 – 17 years old in the state of Georgia is 37.5%, comparable with 37.3% (31.7 - 42.9) in 2007 NSCH
- Comparing results in small areas
  - GT NHANES model to CDC NSCH model with geomarkers
  - Both to estimates of adult obesity in GA
  - Both to school estimates in Arkansas

Research partially funded by seed grant by CDC & Georgia Tech through IPaT

Decision-Support

Modeling can be built into tools, from patients, up to providers, organizations, and policymakers

Scheduling Catch-up Vaccinations

Recommended Immunization Schedule for Persons Aged 0 Through 6 Years—United States • 2010

For those who fall behind or start late, see the catch-up schedule

Vaccine ▼ Age ▶	Birth	1 month	2 months	4 months	6 months	12 months	15 months	18 months	19–23 months	2–3 years	4–6 years
Hepatitis B[1]	HepB	HepB			HepB						
Rotavirus[2]			RV	RV	RV[2]						
Diphtheria, Tetanus, Pertussis[3]			DTaP	DTaP	DTaP	see footnote[3]	DTaP				DTaP
Haemophilus influenzae type b[4]			Hib	Hib	Hib[4]	Hib					
Pneumococcal[5]			PCV	PCV	PCV	PCV				PPSV	
Inactivated Poliovirus[6]			IPV	IPV	IPV						IPV
Influenza[7]					Influenza (Yearly)						
Measles, Mumps, Rubella[8]						MMR		see footnote[8]			MMR
Varicella[9]						Varicella		see footnote[9]			Varicella
Hepatitis A[10]						HepA (2 doses)				HepA Series	
Meningococcal[11]										MCV	

Range of recommended ages for all children except certain high-risk groups

Range of recommended ages for certain high-risk groups

- Many children have late, early or missed vaccinations
- Aim: a freely available and easy to use automated tool for catch-up scheduling using vaccination history and feasibility rules
- Approach: dynamic programming in Excel or other platforms

- H. Smalley, F. Engineer, P. Keskinocak, L. Pickering (2010), “Universal Tool for Vaccine Scheduling – Applications for Children and Adults,” Interfaces., Vol.41, No.5.
- F. Engineer, P. Keskinocak, L. Pickering (2009), "Catch-up Scheduling for Childhood Immunization," Operations Research, Vol.57, No.6, 1307-1319.

Output Charts -- Childhood Catch-up Scheduler

Scenario 1

A 4 month old child who has received 1 dose of *HepB* at birth and one each of *DTaP*, *Hib* and *PCV* at 2 months of age.

Schedule* generated for: on Nov 05, 2010 (11/05/2010)
Birth Date: Jul 04, 2010 (07/04/2010). Current Age: 0 year/s, 4 month/s and 0 week/s

Timeline	0-4 weeks	1-2 months	3-5 months		6-11 months	12-14 months	15-17 months	18-23 months		4-6 years		
Rec. Date ** (mm/dd/yy)	07/04/10	09/02/10	Today 11/05/10	12/03/10	01/04/11	07/04/11	10/04/11	01/04/12	06/04/12	07/04/14	07/04/16	Tally
HepB [1]	AD		CD		OD							3/3
Rota [2]												0/3
DTaP		AD	OD		OD		OD			OD		5/5
Hib [4]		AD	OD		OD	OD						4/4
PCV [5]		AD	OD		OD	OD						4/4
IPV			CD	CD	OD					OD		4/5
MMR [7]						OD				OD		2/2
Var [8]						OD				OD		2/2
HepA [9]						OD		OD				2/2

AD - Administered Dose CD - Catch-up Dose OD - On-time Dose PD - Preemptive Dose

Usage and Dissemination

- The **Desktop Childhood Immunization Scheduler** was available at: http://www.cdc.gov/vaccines/recs/Scheduler/catchup.htm
  107,500+ downloads between June 2008 and March 2012
- **Adult Immunization Scheduler**: http://www.cdc.gov/vaccines/schedules/easy-to-read/adult.html
  49,800+ downloads since January 2010
- **Adolescent Immunization Scheduler**: http://www.cdc.gov/vaccines/schedules/easy-to-read/preteen-teen.html
  30,850+ downloads since March 2011
- **Online Childhood Scheduler**
  125,000+ visits since January 2012, https://www.vacscheduler.org/
  http://www.cdc.gov/vaccines/schedules/easy-to-read/child.html

The Washington Post

For Parents, an Easier Way to Track Vaccines

Tuesday, July 15, 2008

Quick: Which shots have your kids received -- and which do they still need? The Centers for Disease Control and Prevention has a free online tool that can help.

The Catch-Up Immunization Scheduler (go to http://www.cdc.gov/vaccines, click on "immunization schedules," then "Interactive Catchup Schedule") lets you plug in your child's birth date and vaccines given and see what's missing.

U.S.News & WORLD REPORT

A New Tool to Manage Your Child's Vaccine Schedule

THE OFFICIAL NEWSMAGAZINE OF THE AMERICAN ACADEMY OF PEDIATRICS

AAP News

Online scheduler keeps track of missed immunizations

Entrepreneur

Catch-up immunization software.

ScienceDaily

Tool Creates Personalized Catch-up Immunization Schedules For Missed Childhood Vaccinations

Education and Collaborations

- Professional education
  - Health and Humanitarian logistics short courses
  - Sept 2013 and May 2014
  - http://humanitarian.gatech.edu
- Student project teams in classes
  - http://www.isye.gatech.edu/seniordesign
  - http://humanitarian.gatech.edu
- Graduate student and faculty research

Engineering in Public Health for "Efficient, Effective, and Equitable" Outcomes

- Julie Swann
  jswann@isye.gatech.edu or jswann@gatech.edu
  http://humanitarian.gatech.edu
  404-385-3054 (office)

- Other GT ISyE faculty involved in public health
  - Turgay Ayer
  - Ozlem Ergun
  - Dave Goldsman
  - Pinar Keskinocak
  - Eva Lee
  - Nicoleta Serban
  - (and many others)