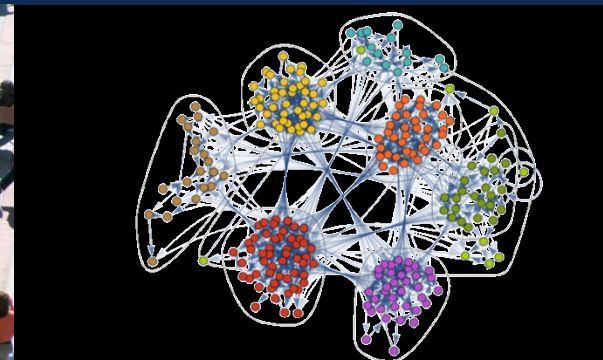


*Exceptional service in the national interest*



# Building Confidence in Complex Systems Models for Reducing Population Health Risks

Theresa Brown

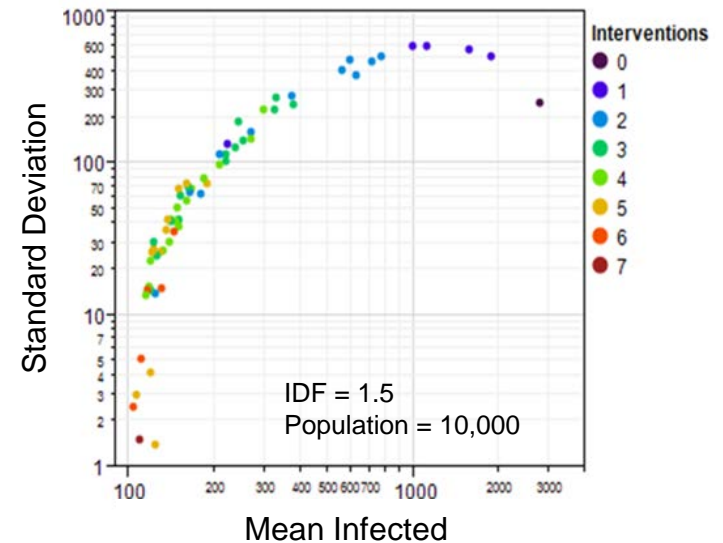
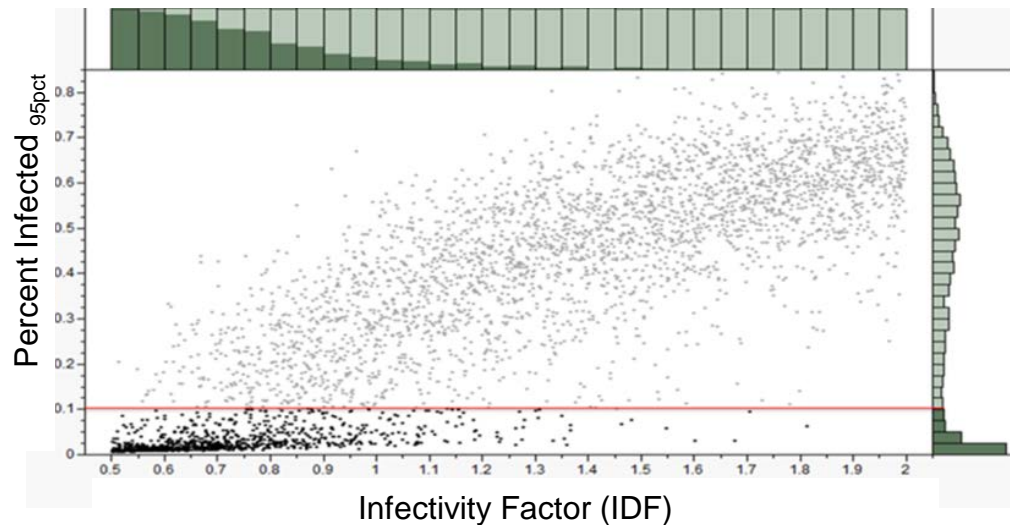
25 February 2016

Complex Systems Design & Management Asia 2016



# Key Takeaways

- ❖ *Experiment with models before implementing strategies in the real system*

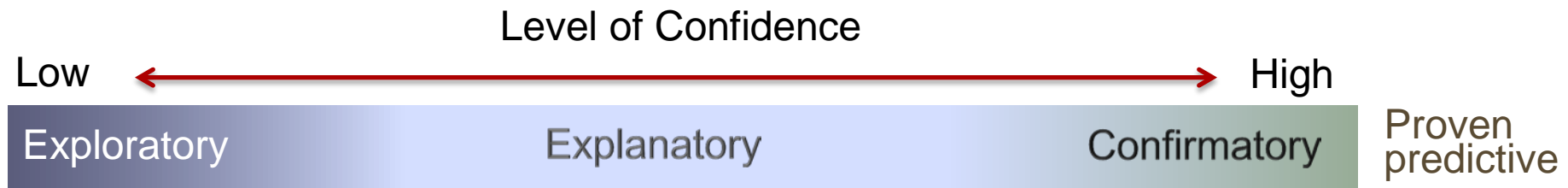


## References:

- **Health Outcomes and Costs of Community Mitigation Strategies for an Influenza Pandemic in the United States**, Daniella J. Perlroth, Robert J. Glass, Victoria J. Davey, Daniel C. Cannon, Alan M. Garber, and Douglas K. Owens. *Clinical Infectious Diseases*, vol. 50, no. 2, p. 165-174. Expedited publication. January 2010 PubMed Summary
- **Effective, Robust Design of Community Mitigation for Pandemic Influenza: A Systematic Examination of Proposed U.S. Guidance**, Robert J. Glass, Victoria J. Davey, H. Jason Min, Walter E. Beyeler, and Laura M. Glass. *PLoS One*, vol. 3, no. 7. July 2008 (2008-0561 J)

# Key Takeaways

- ❖ *Experiment with models before implementing strategies in the real system*
- ❖ *Ambitious but realistic goals for CS models are that they be explanatory and through experimentation and data collection we develop a medium-level of confidence in their predictive capability*

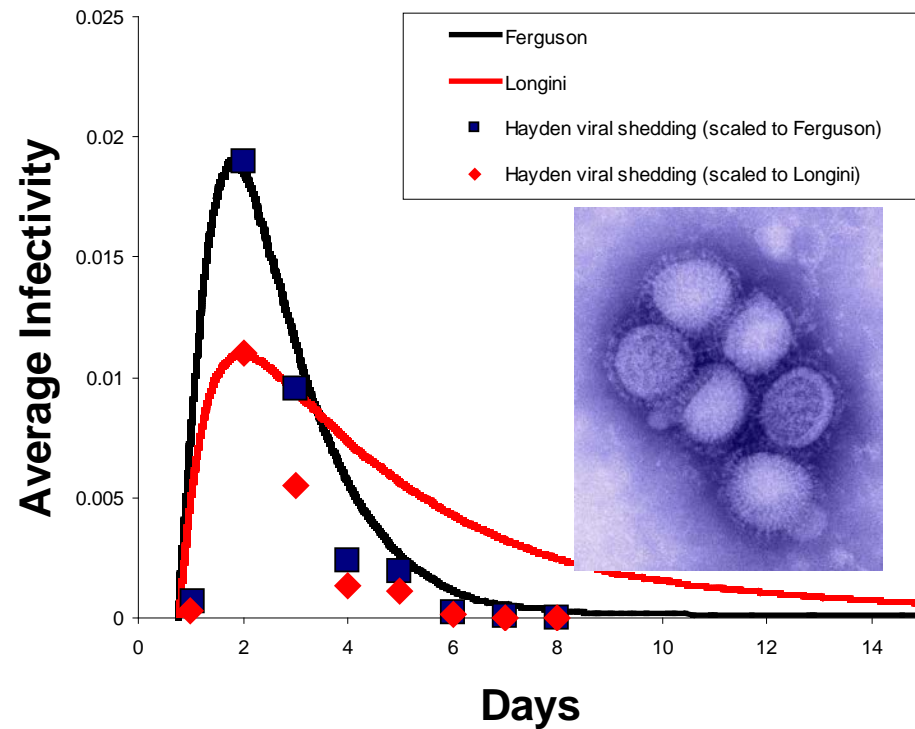


# Key Takeaways

- ❖ *Experiment with models before implementing strategies in the real system*
- ❖ *Ambitious but realistic goals for CS models are that they be explanatory and through experimentation and data collection we develop a medium-level of confidence in their predictive capability*
- ❖ *It will take a global community of practice to achieve these goals*

# Epidemic Control: Central Analysis Questions

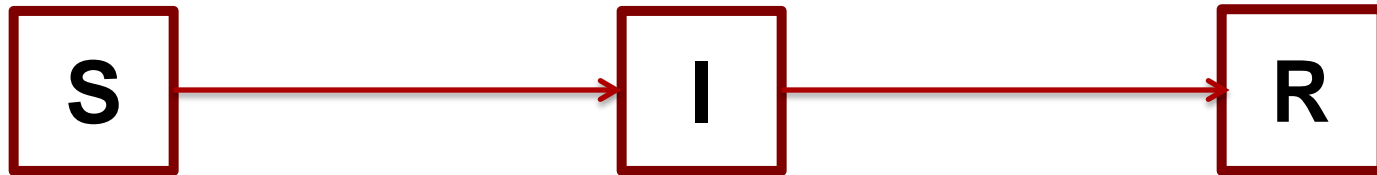
- **Scoping the potential damage:** What is the likely course of development for an outbreak if there is no intervention?
- **Guiding the response:** Which intervention strategies and associated resource deployments provide the best chance of success (fewest expected deaths, for example)?
- **Evolving the system:** How can we prevent future epidemics?



Average population scale infectivity for Ferguson and Longini-like disease manifestations with viral shedding data from Hayden (Hayden, Fritz et al. 1998) scaled to the peak infectivity.

- **Heterogeneity** in the populations is important
  - Populations are not well-mixed
  - **Subpopulation level interaction structures** change over time
  - Mean-field approximation is not a suitable approach
- Individuals within the population **adapt**
  - To cope with disease spread
  - Due to interventions
- **System feedbacks** drive behaviors and disease spread
- These features are commonly observed attributes of complex systems

Hypothesis: epidemic control modeling can better inform development of intervention strategies by directly representing these Complex System attributes.



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

$$\frac{dI}{dt} = \beta SI - \alpha I$$

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

**Average Infected transmits infection to Susceptible with rate  $\beta$**

**Infected Recover with average rate  $\alpha$**

- Describe the population in terms of the number of members in each of a set of discrete states
- First introduced in 1927 (Kermack and McKendrick 1927)
- Several extensions (SEIR), including Legrand et al.'s (2007) Ebola model

# Projection of Ebola Cases Using SEIR Models

- In September 2014, CDC released estimates of Ebola spread in Western Africa (Meltzer et al. 2014)
- Key findings include
  - Exponential growth without intervention
  - As many as 1.4M cases by January 2015
- Projections have been heavily criticized
  - “Avoidable errors in the modelling of outbreaks of emerging pathogens, with special reference to Ebola” (King et al. 2015)
  - WHO reported only 21k Ebola cases by January 2015
  - Concerns about misallocation of resources, “crying wolf”

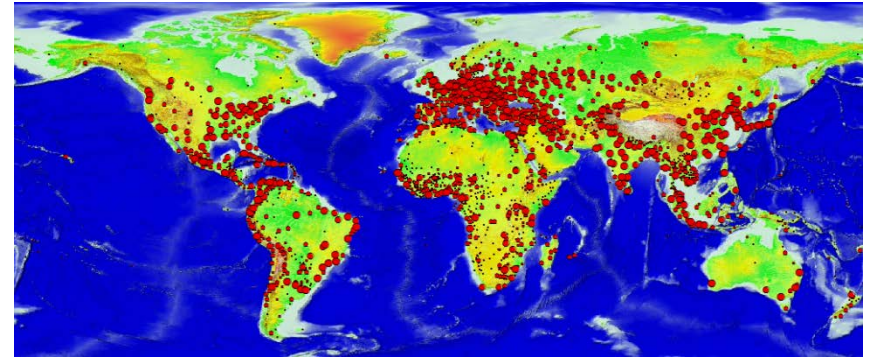
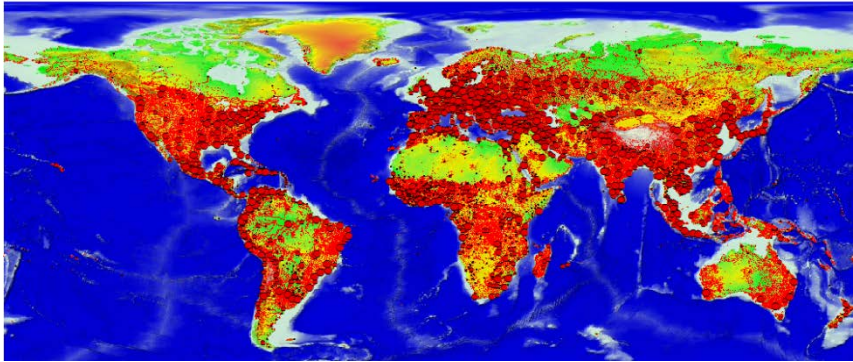
- Omission: population adaptations not represented
  - Population will likely change structure of interactions and behaviors with notification of outbreak
- Assumption: well-mixed, homogeneous spatial distribution of population
  - Social contact structures that are central to disease propagation are not represented
  - Omission of interaction structures limits spectrum of control strategies that can be evaluated
- Meltzer et al. acknowledge several limitations with their estimates

“Spread of modern epidemics is spatially incoherent and chaotic, generically does not bear any metric regularity, and observed spatio-temporal patterns depend sensitively on the outbreak location”.

Helbing et al. 2015  
Journal of Statistical Physics

# Detailed Networks without Supporting Data

- Agent-based models of contact network control on disease have become common since 2007
  - Pros: network structure captures heterogeneity better than compartmental models
  - Cons: Insufficient data to parameterize network structure results in massive new uncertainties

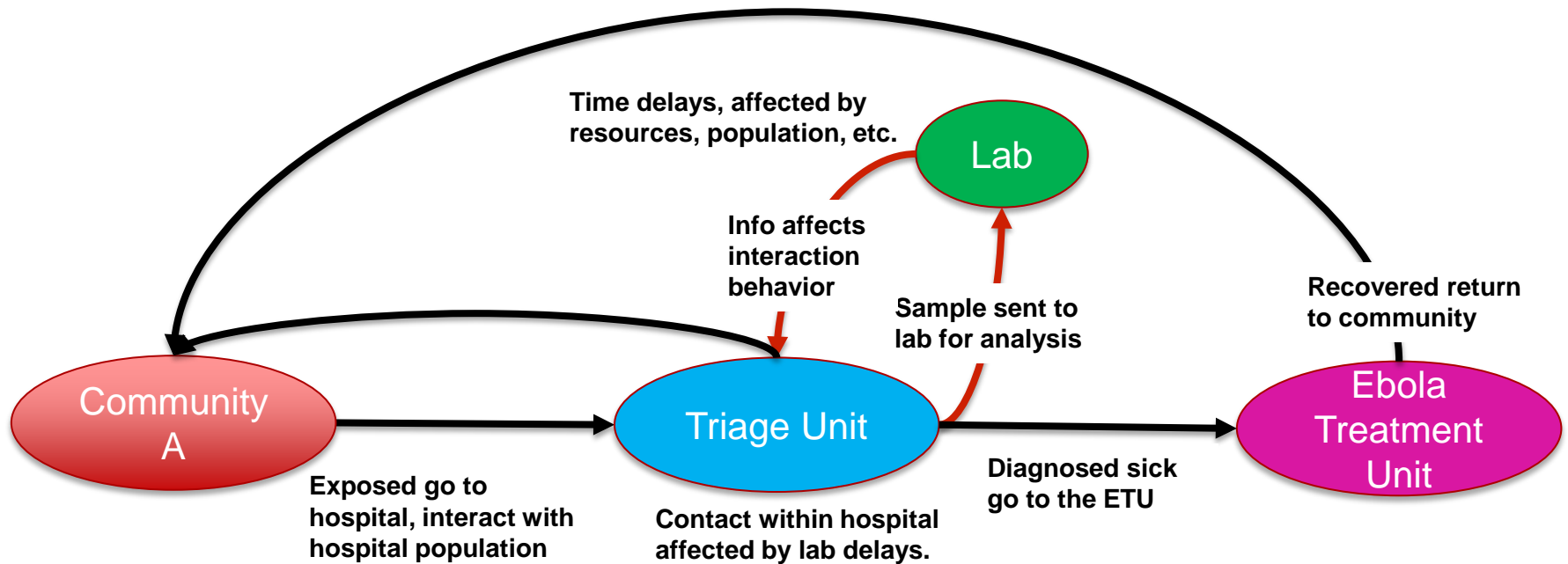


- Agent-based models of contact network control on disease have become common since 2007
  - Pros: network structure captures heterogeneity better than compartmental models
  - Cons: Insufficient data to parameterize network structure results in massive new uncertainties
- Outcomes:
  - Widespread failure to predict disease patterns from very expensive models (e.g. 2009 H1N1).
  - Highly detailed simulations can be misleading when drive for more detail outpaces available information.

**Needed:** A balanced approach which incorporates complexity better than compartmental models without uncertainty problems of “photo-realistic” disease spread simulations

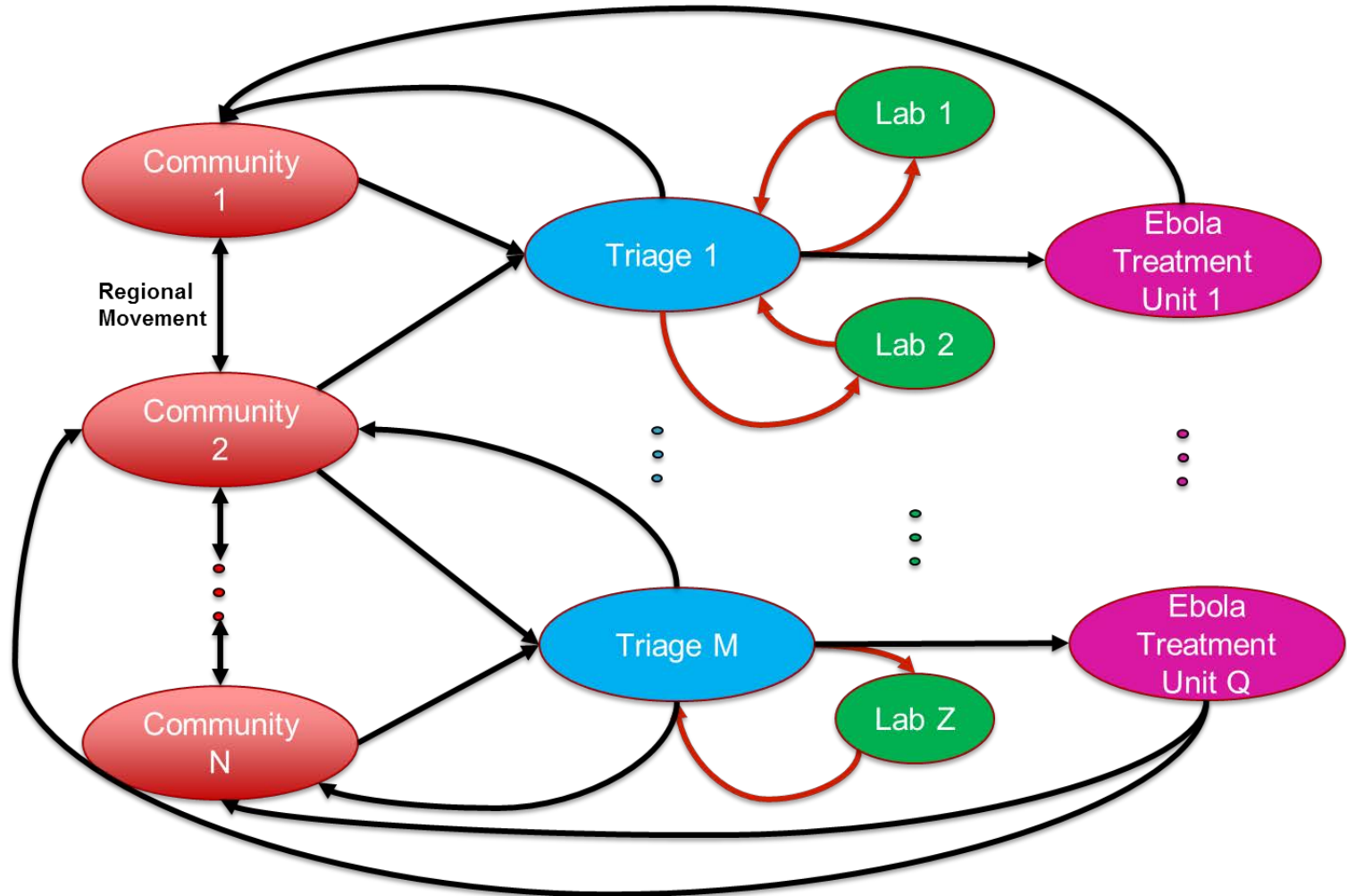
- Represent physical locations
- Represent interactions
  - Within location: SEIR formulation
  - Between locations: determined by interaction structures (e.g., regional movements, institutional controls)
- Represent adaptations and control strategies
  - Information flow affects behavior
  - Modify interaction structures (e.g., isolation)
  - Modify rate constants (e.g., analysis delays, transport times)

# Conceptual Illustration



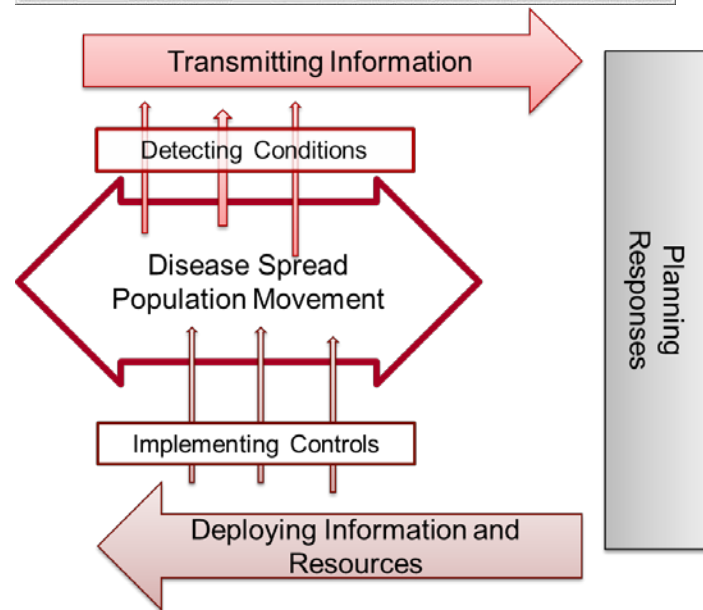
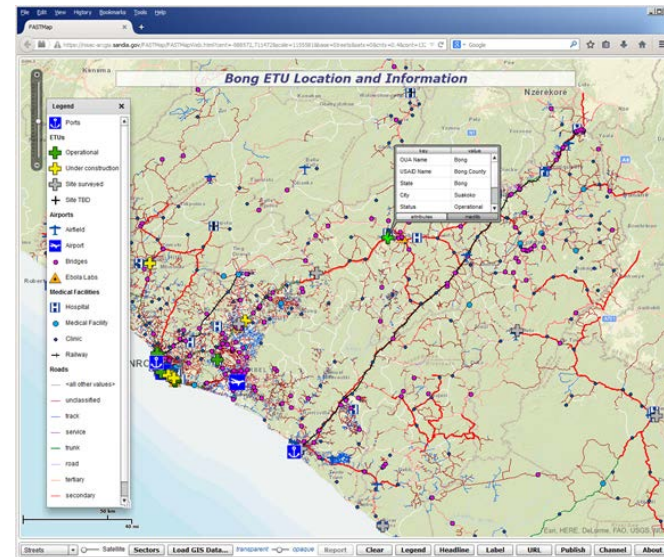
- People Flow
- Information Flow

# Conceptual Illustration: Replicate Across Multiple Units



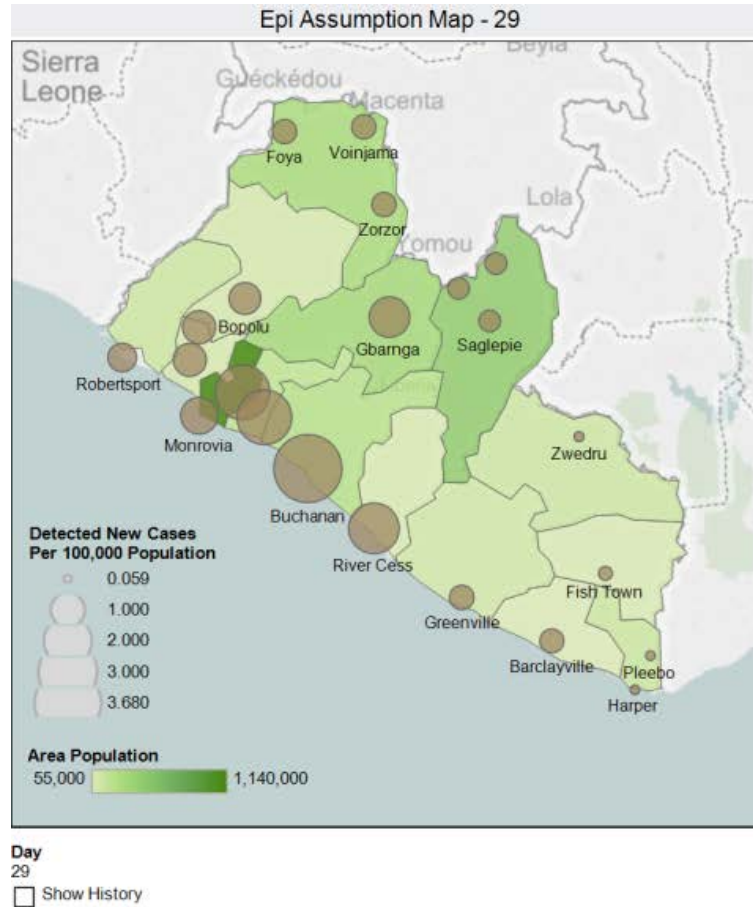
# Conceptual Model Development: What is or could be important in Disease Control: Ebola Example

- State of knowledge (what is known):
  - Disease epidemiology
  - Incidences of disease at various locations
  - Population characteristics including: size and density
  - Important factors in disease spread include: contact networks, interactions and behavioral responses
  - Poor response was likely to lead to significant loss of life
    - Transportation routes and general conditions
    - Administrative limitations (curfew)
    - Lab locations and capacities
- Uncertainties (unknowns due to lack of data):
  - Extent of disease spread
  - Population movements, interactions and responses
  - Sample processing times
  - Which controls and resource deployment strategies will work best

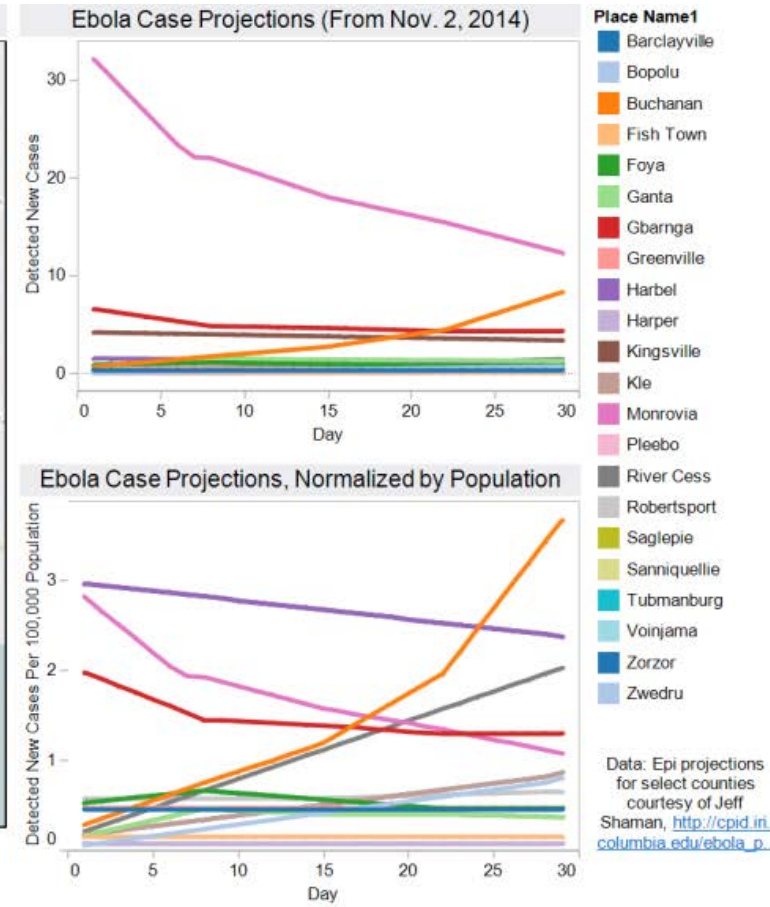


# Ebola disease parameter values and initial conditions Sierra Leone

## Population and Reported Cases



## Projected Cases



# Disease Control: Ebola Test Scenario

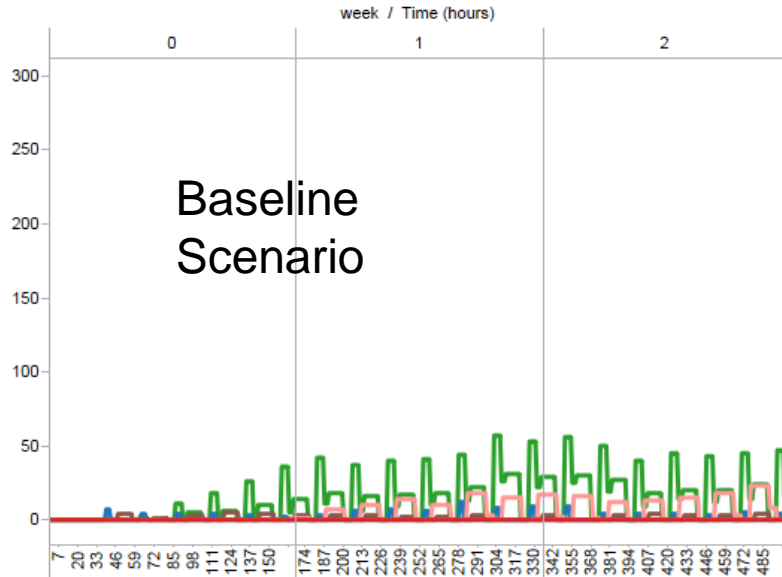
Labs: Samples Awaiting Testing

- Scenario ID
- Null
  - BaseInfBaseTT
  - Spot4InfBaseTT
  - Spot4InfRoute3b

Labs Dynamic  
Samples Awaiting Testing

Hotspot scenario: disease outbreak in rural communities north of Monrovia, Robertsport, Tubmanburg, Klu area patients presenting at Sinje and Tubmanburg clinical facilities

Baseline Scenario



Induces overloading on Island Clinic laboratory

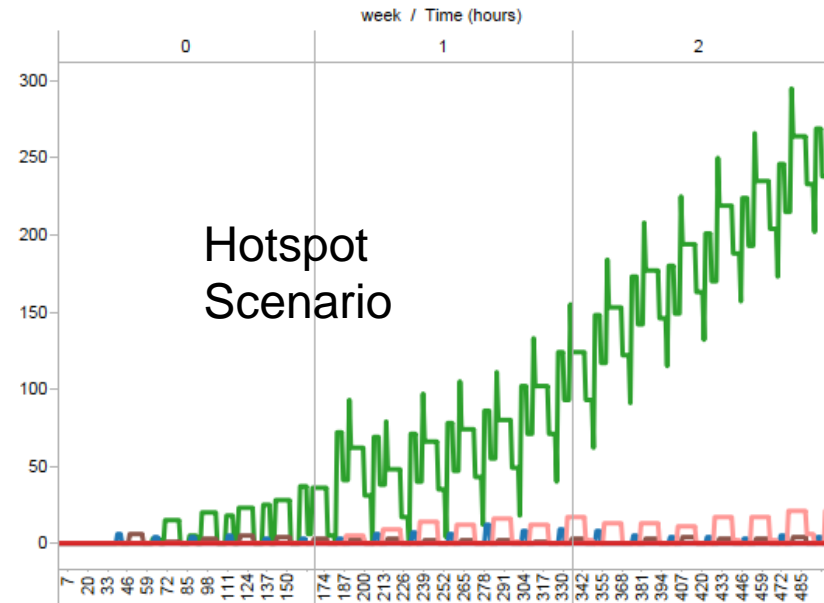
- Island Clinic receiving samples from northern communities and from within Monrovia

Labs: Samples Awaiting Testing

- Scenario ID
- Null
  - Spot4InfBaseTT
  - Spot4InfRoute3b

Labs Dynamic  
Samples Awaiting Testing

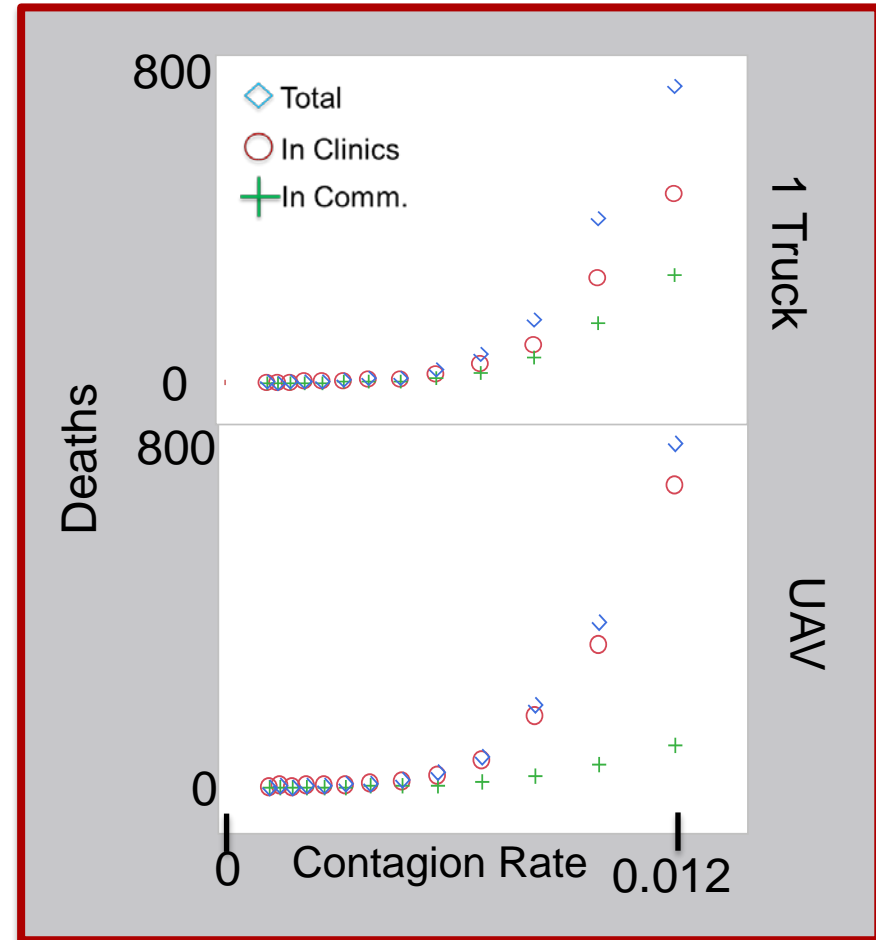
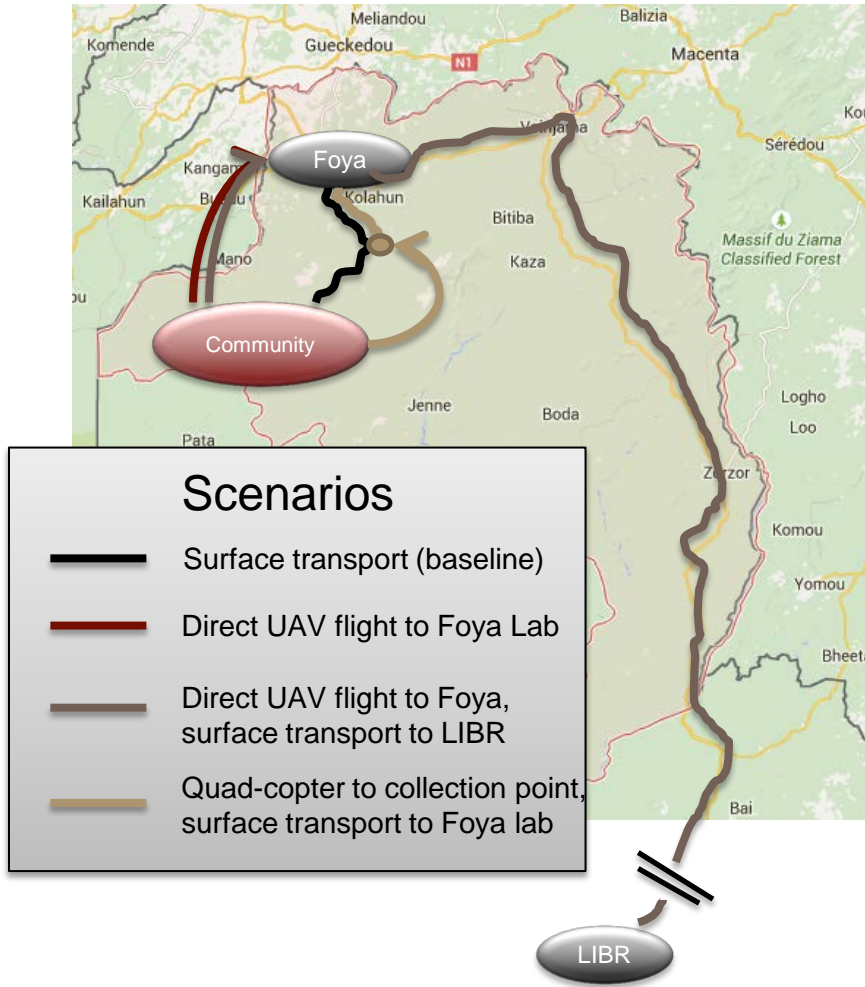
Hotspot Scenario



Lab Name

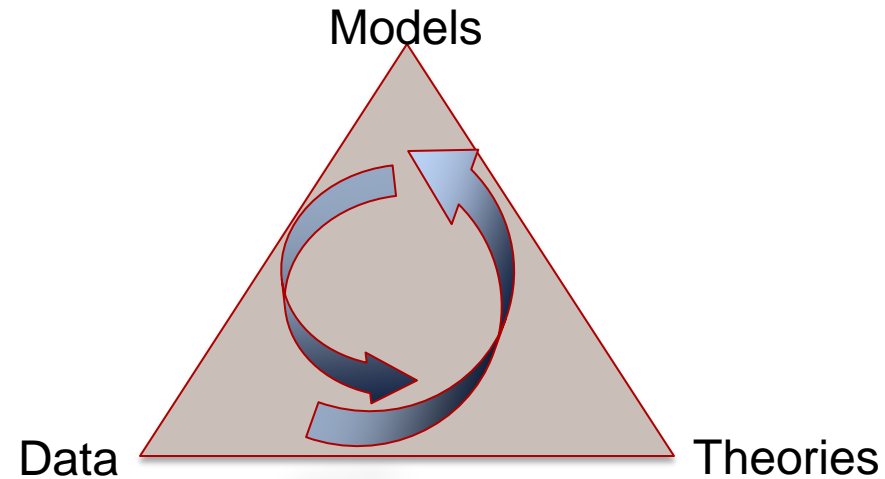
- CDC NIH ELWA Team 2
- MSF ETUc in Foya
- USN NMRC Gbarnga Lab Team 1
- MOH USAMRID Kakata
- NEW Fish Town Lab
- USN NMRC Island Clinic Lab Team 2

# Example Analysis: Ebola Sample Collection and Transport



# Technical Challenges

- Data
- Quantifying data quality, model bias and parameter uncertainty
- Modern sensitivity and uncertainty analysis methods operate on summary scalar outputs while CS models capture processes through time-series data outputs
- Huge numbers of runs required for multivariate testing



## Immediate Research Needs:

- Identifying what is observable and measurable in complex systems
- Categorizing complex systems by their structure, predictability and susceptibility to control
- Developing and testing single-value output that adequately characterize time-series complex system outputs

# Takeaways

- ❖ *Experiment with models before implementing strategies in the real system*
- ❖ *Ambitious but realistic goals for CS models are that they be explanatory and through experimentation and data collection we develop a medium-level of confidence in their predictive capability*
- ❖ *It will take a global community of practice to achieve these goals*

For more information and publications see:  
<http://www.sandia.gov/CasosEngineering>