Ebola response in Liberia: A step towards real-time epidemic science

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http://www.vbi.vt.edu/ndssl

Goals for today's webinar

- Want to introduce the population modeling working group to IMAG and invite you to be a part of the WG
- Describe efforts by two teams (Yale and Virginia Tech) to support Ebola response
- Introduce the use and role of multi-scale population modeling in computational epidemiology

Team

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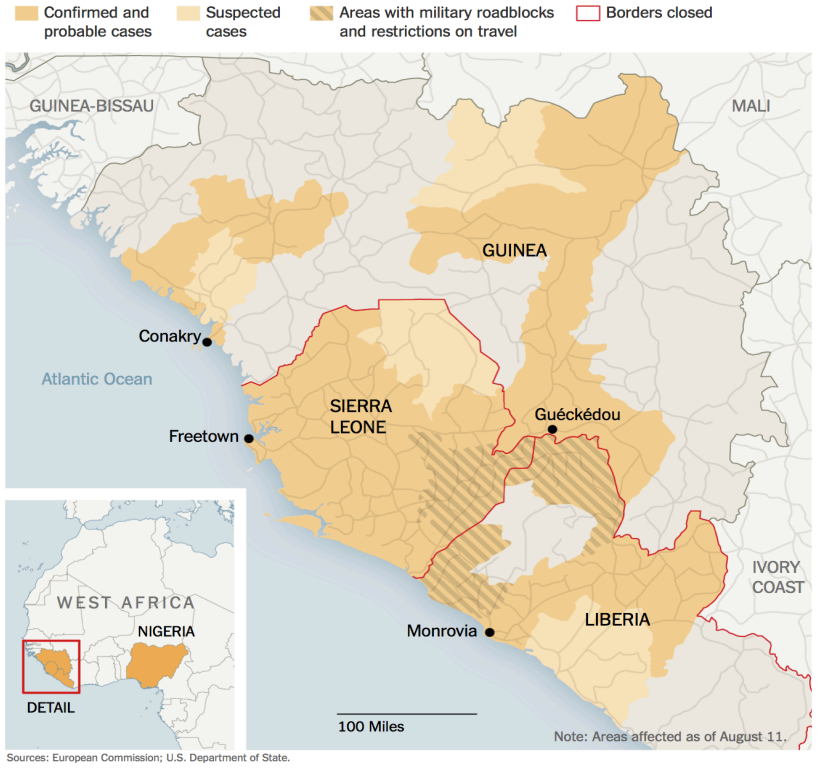
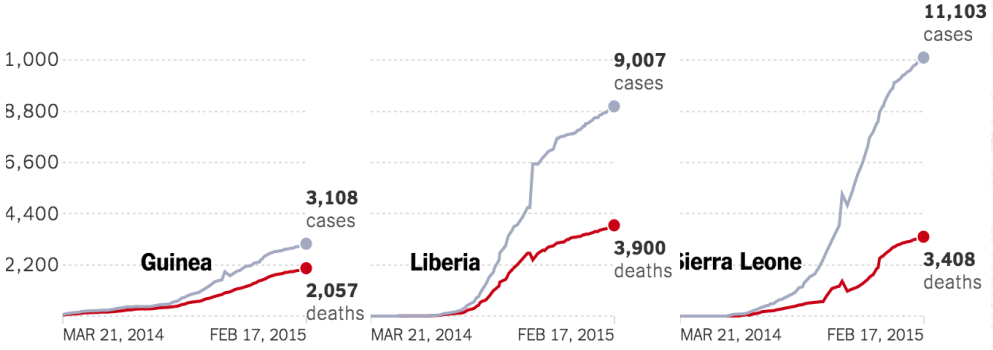
Ebola outbreak in Africa

- Largest Ebola outbreak yet: 5 countries; 24000 cases; 9000 deaths.
- Excellent NY Times webpage: http://www.nytimes.com/interactive/2014/07/31/world/africa/ebola-virus-outbreak-qa.html





Goal: Real-time response

- Before an epidemic
  - (i) Determine the (non)medical interventions required, (ii) feasibility of containment, (iii) optimal size of stockpile, (iv) best use of pharmaceuticals once a pandemic begins
- During an epidemic
  - (i) Quantifying transmission parameters, (ii) Interpreting real-time epidemiological trends, and (iii) assessing impact of interventions.

Harvey V. Fineberg is president of the Institute of Medicine.

Mary Elizabeth Wilson is associate professor of Global Health and Population at the Harvard School of Public Health and associate clinical professor at Harvard Medical School, Boston, MA.

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EDITORIAL

Epidemic Science in Real Time

FEW SITUATIONS MORE DRAMATICALLY ILLUSTRATE THE SALIENCE OF SCIENCE TO POLICY THAN AN epidemic. The relevant science takes place rapidly and continually, in the laboratory, clinic, and community. In facing the current swine flu (H1N1 influenza) outbreak, the world has benefited from research investment over many years, as well as from preparedness exercises and planning in many countries. The global public health enterprise has been tempered by the outbreak of severe acute respiratory syndrome (SARS) in 2002–2003, the ongoing threat of highly pathogenic avian flu, and concerns over bioterrorism. Researchers and other experts are now able to make vital contributions in real time. By conducting the right science and communicating expert judgment, scientists can enable policies to be adjusted appropriately as an epidemic scenario unfolds.

In the past, scientists and policy-makers have often failed to take advantage of the opportunity to learn and adjust policy in real time. In 1976, for example, in response to a swine flu outbreak at Fort Dix, New Jersey, a decision was made to mount a nationwide immunization program against this virus because it was deemed similar to that responsible for the 1918–1919 flu pandemic. Immunizations were initiated months later despite the fact that not a single related case of infection had appeared by that time elsewhere in the United States or the world (www.iom.edu/swinefluaffair). Decision-makers failed to take seriously a key question: What additional information could lead to a different course of action? The answer is precisely what should drive a research agenda in real time today.

In the face of a threatened pandemic, policy-makers will want real-time answers in at least five areas where science can help: pandemic risk, vulnerable populations, available interventions, implementation possibilities and pitfalls, and public understanding. Pandemic risk, for example, entails both spread and severity. In the current H1N1 influenza outbreak, the causative virus and its genetic sequence were identified in a matter of days. Within a couple of weeks, an international consortium of investigators developed preliminary assessments of cases and mortality based on epidemic modeling.*

Specific genetic markers on flu viruses have been associated with more severe outbreaks. But virulence is an incompletely understood function of host-pathogen interaction, and the absence of a known marker in the current H1N1 virus does not mean it will remain relatively benign. It may mutate or acquire new genetic material. Thus, ongoing, refined estimates of its pandemic potential will benefit from tracking epidemiological patterns in the field and viral mutations in the laboratory. If epidemic models suggest that more precise estimates on specific elements such as attack rate, case fatality rate, or duration of viral shedding will be pivotal for projecting pandemic potential, then these measurements deserve special attention. Even when more is learned, a degree of uncertainty will persist, and scientists have the responsibility to accurately convey the extent of and change in scientific uncertainty as new information emerges.

A range of laboratory, epidemiologic, and social science research will similarly be required to provide answers about vulnerable populations; interventions to prevent, treat, and mitigate disease and other consequences of a pandemic; and ways of achieving public understanding that avoid both over- and underreaction. Also, we know from past experience that planning for the implementation of such projects has often been inadequate. For example, if the United States decides to immunize twice the number of people in half the usual time, are the existing channels of vaccine distribution and administration up to the task? On a global scale, making the rapid availability and administration of vaccine possible is an order of magnitude more daunting.

Scientists and other flu experts in the United States and around the world have much to occupy their attention. Time and resources are limited, however, and leaders in government agencies will need to ensure that the most consequential scientific questions are answered. In the meantime, scientists can discourage irrational policies, such as the banning of pork imports, and in the face of a threatened pandemic, energetically pursue science in real time.

– Harvey V. Fineberg and Mary Elizabeth Wilson

10.1126/science.1176297

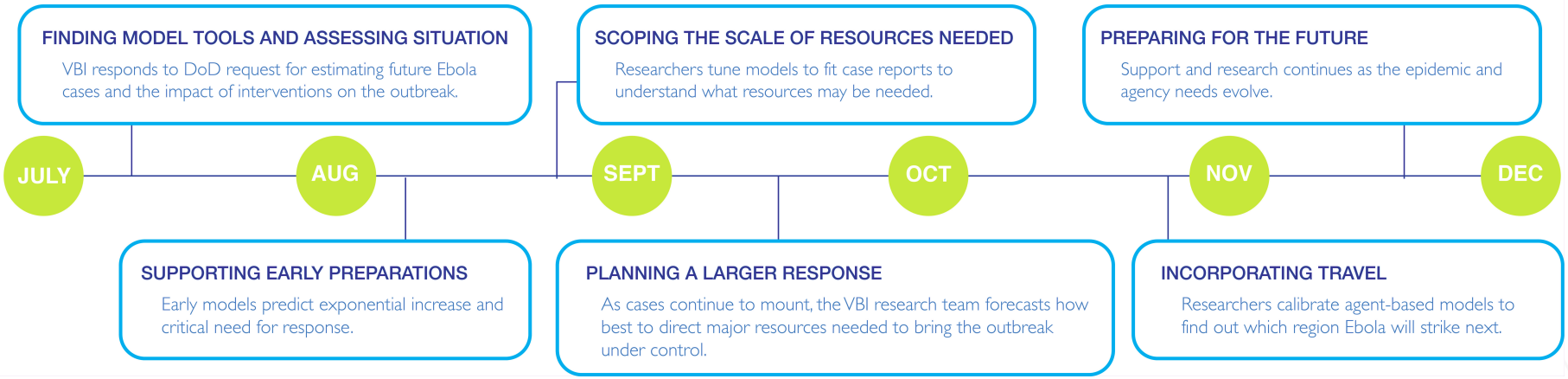
*C. Fraser *et al.*, *Science* 11 May 2009 (10.1126/science.1176062).

Our approach: Informatics for integrated reasoning about situations and actions

- Goal: Build a suite of informatics tools that
  - Synthesize: available data to produce consistent and meaningful representation of the underlying system
  - Provide: range of interpretations of incoming measurements
  - Evaluate: range of response actions and behaviors
  - Monitor: Effect of policy responses evaluation of objectives
- Support coordination among diverse stakeholders
- Want to go beyond prediction
- Build systems, synthetize data and refine as we go along
  - Systems should be useable by analysts and not just by computing experts

Response: Analysis and tools

Our Response Timeline



30 Presentations

1000+ Slides

7 Months of weekly engagement

6+ Case studies

4 Additional requests

5 Countries Synthetic populations & networks

20+ Press articles, interviews, papers

3 New apps

URL: https://www.vbi.vt.edu/ndssl/featured-projects/ebola

Our Ebola Research

Summary
Modeling Updates
Resources
Collaborations
Funding
Blog
Publications

Contact

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Informatics Resources for Ebola Epidemic Response

About Ebola

The latest Ebola outbreak in Western Africa has illuminated the significant threat posed by infectious diseases to human lives and society. The ongoing Ebola outbreak is by far the largest in history. As of October 12, 2014, over 5500 individuals have been confirmed infected and have caused almost 4500 deaths. It has ravaged Guinea, Liberia, Sierra Leone, with smaller outbreaks in Nigeria and Senegal, causing significant social, health and economic impact.

Ebola is a challenging disease to combat. There is no known cure and the mortality rate is high. While its origins are zoonotic in nature, once spread to humans, Ebola can be passed onto another through bodily fluids. The average incubation period is six days, but can last as long as 21 days. During that time, those that are infected are not contagious. However, given the means of transmission, the outbreak can be controlled using proper precautions.

The current web page is created so as to make the data, methods and analysis available to the world community in an attempt to speed up the scientific progress on this important public health crisis.

Synthetic Information


Sierra Leone


Liberia


Guinea


Nigeria

SI Visualizer

Ebola in the News

October 27, 2014
Quartz features Madhav Marathe; crowdsourcing and supercomputing and Ebola

October 27, 2014
NDSSL's Ebola data and Hackathon featured in IBM Smarter Planet Blog

Examples of analytic support for Ebola response

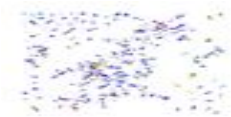
- *Estimating* basic epidemiological parameters for the outbreak
- *Forecasting* the ongoing epidemic with & without control
- *Assessing* the threat of imported cases in the United States causing secondary infections
- *Efficiently allocating* of potential pharmaceutical treatments
- *Location of Emergency treatment centers* and assessing the impact these centers will have on the outbreak
- *Estimating* the need for supplies such as personal protective equipment
- Analyzing Twitter data to assess public mood & sentiments
- Assessing the potential spread of Ebola to Latin American countries

Lessons learned

- Close coordination with analysts and policy makers is critical
  - Helped with problem formulations
  - Led to relevant analysis
  - Led to entirely new research questions and requirements
- Well trained multi-disciplinary team critical
  - Past experiences (e.g. SLE exercises, H1N1 response) allowed the team to be prepared and trained
  - Strong collegiality within the team as well as with DTRA, BARDA, NIH MIDAS and other groups was the key
  - Maintaining a ready team is important - cannot be assembled real-time
- Managing expectations: balancing science and timely response
  - Science is inherently a slow deliberate process, policy makers need results quickly and adaptively
- Utility of the tools developed to support the next epidemic outbreak

SIMDEMICS: A comprehensive Cyber-infrastructure for computational epidemiology

Digital Library



Networks


Results

User Applications

EpiCaster

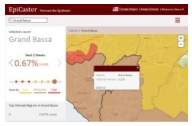
DISimS

EpiViewer

Game Apps

MY4Sight

FluCaster



Simfrastructure: Middleware to support pervasive app ecosystem

- Models
- Simulations
- Forecasting
- Analysis
- Diseases

Compute Resources


HPC Cluster

Individual Sever



Pervasive webapps to support Ebola response
http://www.vbi.vt.edu/ndssl/tools

EpiCaster

Users can view Ebola (or Flu) activity for the past four weeks and view forecast predictions for the next two weeks. They can also view forecast trends and compare them to surveillance data. EpiCaster allows users to see what impact various strategies, such as vaccines and social distancing, have on disease spread.

EpiViewer

EpiViewer is a data repository for epidemiologists. Users can upload and compare Ebola forecasts and surveillance data from a variety of sources and see how forecasts change over time. Users can also load and share their own forecasting predictions.

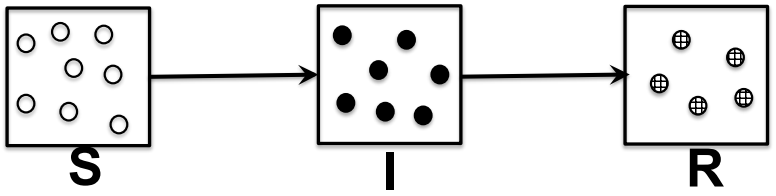
Eyes on the Ground

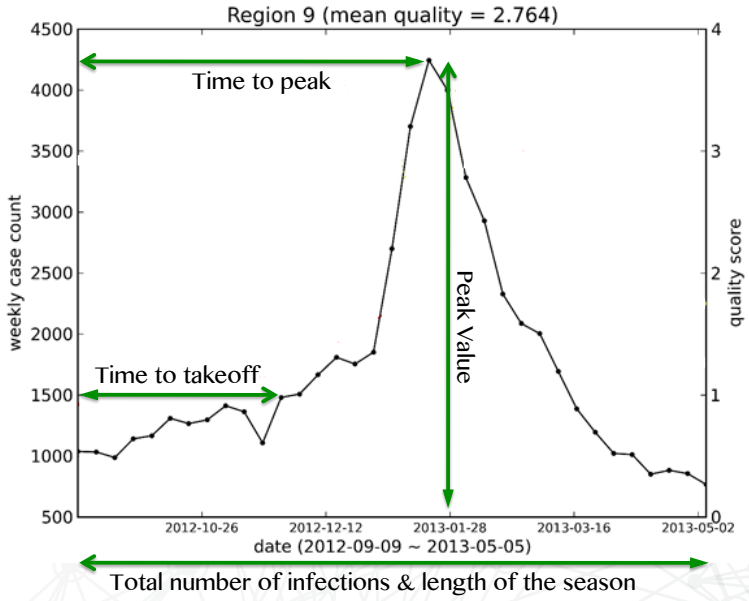
Road conditions can be variable in some of the rural areas in Western Africa. Eyes on the Ground allows people in affected areas to report their road conditions. Other travelers can then view these reports and plan their trips accordingly. This is especially useful when planning the delivery of patients and supplies between cities.

Mass action compartmental models

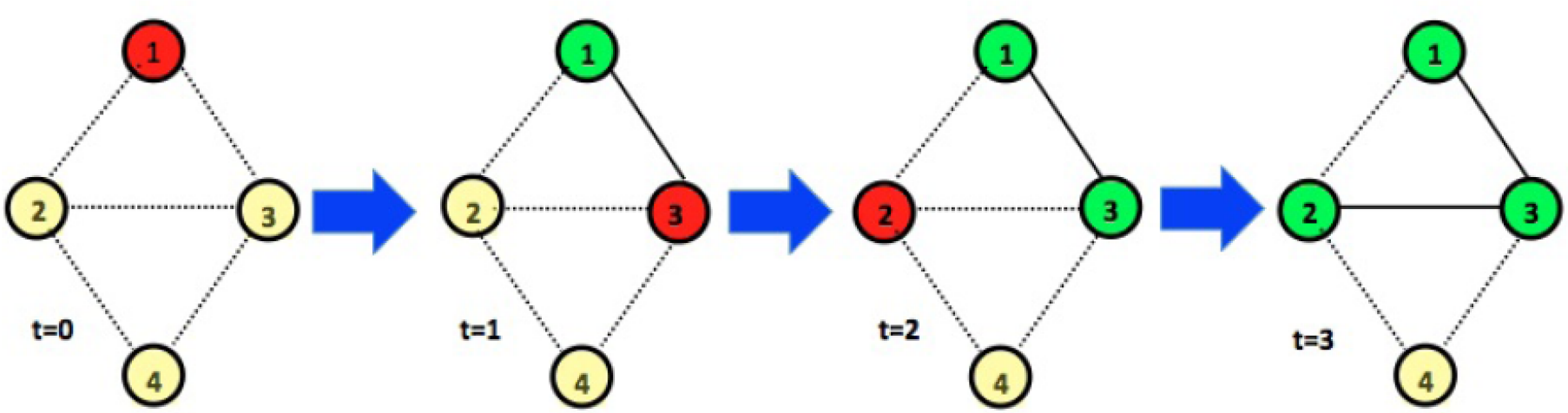
- **Susceptible (S)**: An individual has never had the disease and is susceptible to being infected;
- **Infected (I)**: An individual who currently has the disease and can infect other individuals, and
- **Resistant/Recovered (R)**: An individual does not have the disease, cannot infect others, and cannot be infected (sometimes called removed)

$$\frac{ds}{dt} = -\beta is$$
$$\frac{di}{dt} = \beta is - \gamma i$$
$$\frac{dr}{dt} = \gamma i$$





Networked epidemiology



Fixed point: $R = \{1, 2, 3\}$ and $S = \{4\}$

$$p(1,3)(1-p(1,2))p(2,3)(1-p(2,4))(1-p(3,4))$$

- Each node is in states S (susceptible), I (infectious) or R (recovered)
- Time is discrete
- Each infected node u spreads the infection independently to each susceptible neighbor v with probability $p(u, v)$
- Infected node u recovers after 1 time step
- *Fixed point:* all nodes in states S or R

A Multi-scale modeling approach: networked epidemiology and agent-based models

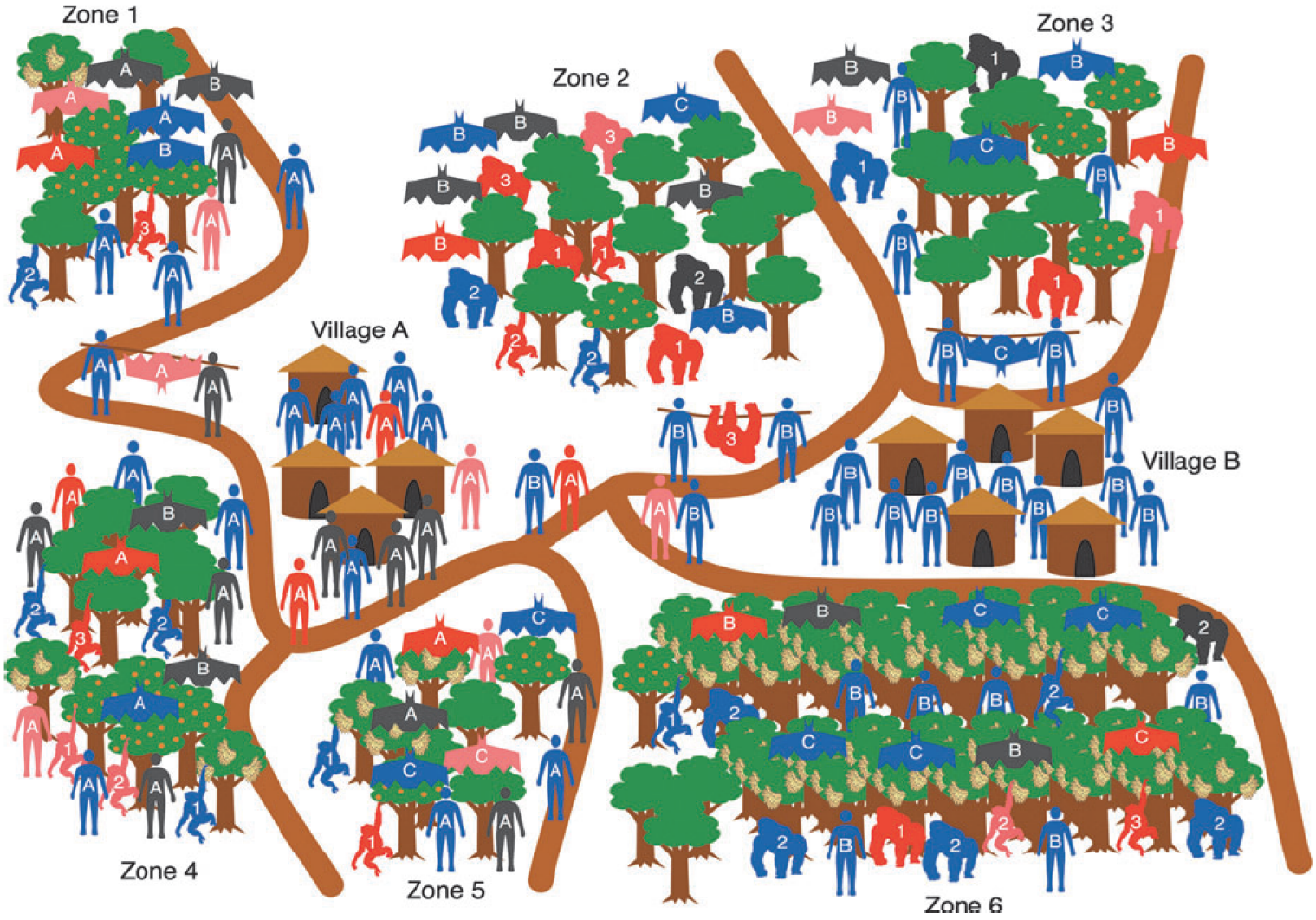
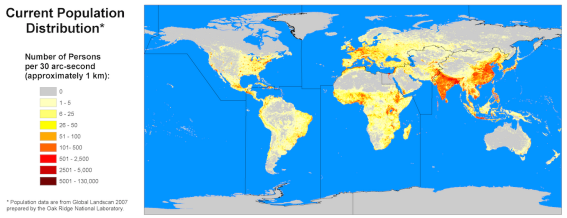


FIG. 7. In an agent-based approach, individual behaviors and interactions can be represented across multiple coupled networks. These interactions can induce changes in the entities, which can, in turn, change which entities they interact with, and the nature of the interactions themselves.

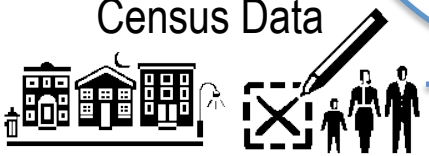
Workflow for synthetic networks and populations

Data at URL: https://www.vbi.vt.edu/ndssl/featured-projects/ebola

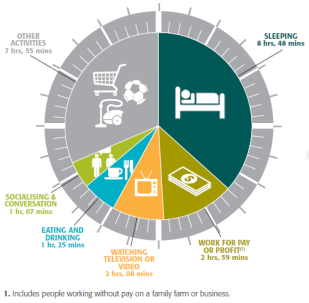
LandScan Population Counts



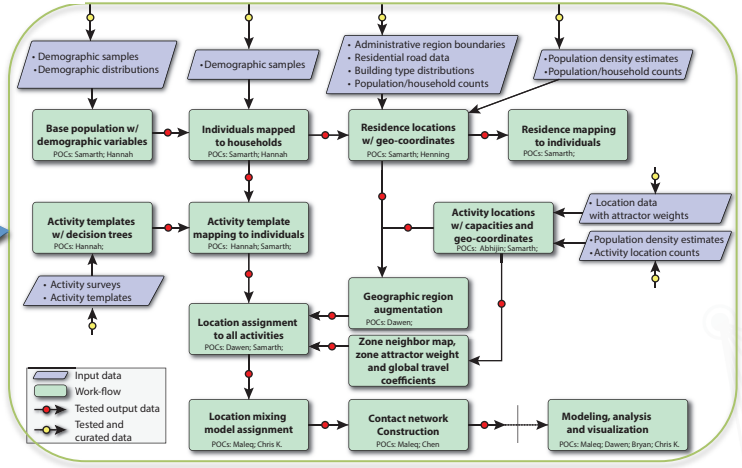
Census Data



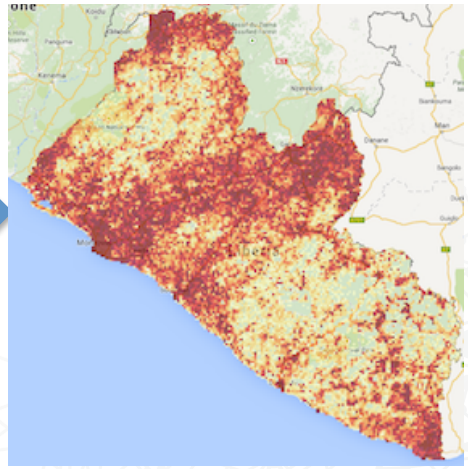
Time Use Surveys



Synthetic Population Pipeline



Synthetic Population

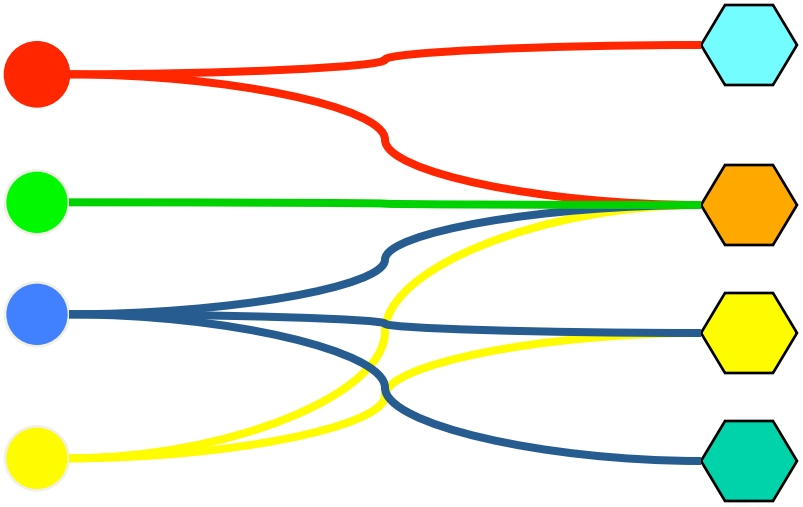


- Automatic execution of workflows
- Integrated data testing
- Data quality measures
- Configuration Management

… Produces synthetic networks are dynamic & relational

People *Locations*

Vertex attributes:
- age
- household size
- gender
- income
- …



Vertex attributes:
- (x,y,z)
- land use
- …

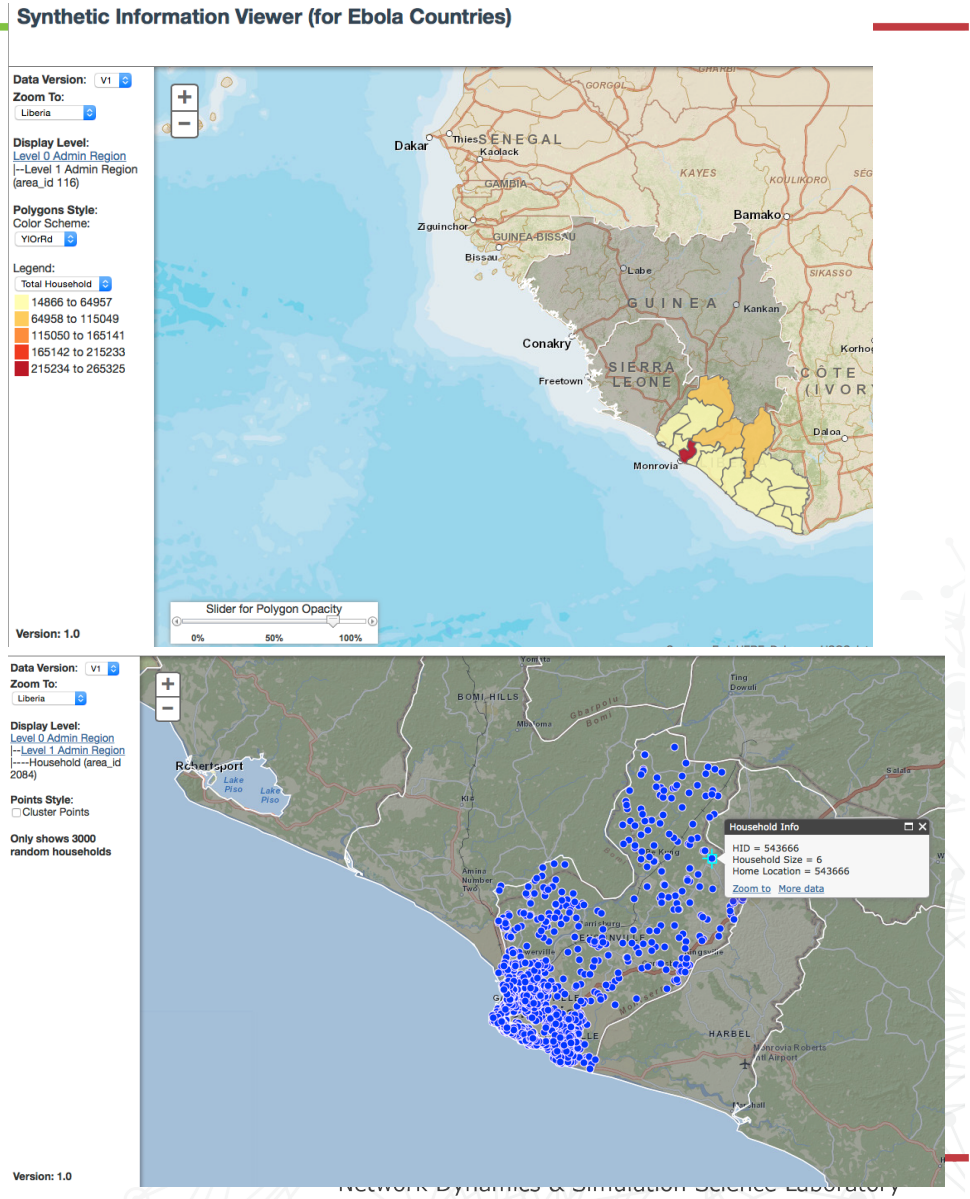
Edge attributes:
- activity type: shop, work, school
- (start time 1, end time 1)
- (start time 2, end time 2)
- …

SIV: ndssl.vbi.vt.edu/apps/siv

SIV: synthetic population visualization tool.

- Each synthetic individual is placed in a household with other individuals and household is located geographically
- Census of our synthetic population is statistically indistinguishable from the original census data.

- Multi-resolution: Explore individual or household level or county level, national attributes
- Users can visualize individual attributes and their interrelationships within a households
- Two versions - US and International



Synthetic West Africa: Demographics

Country	ID	$\|P\|$	n_{HH}	n_H	n_W	n_S	n_C	n_A
Sierra Leone	SLE-v1	5,743,725	989,917	989,917	134,847	9,617	5	23,663,983
Guinea	GIN-v1	11,521,656	2,375,532	2,375,532	250,096	9,317	6	55,069,905
Liberia	LBR-v1	4,092,310	844,066	844,066	88,016	5,477	20	22,202,262
Liberia	LBR-2gp	4,092,310	844,066	844,066	85,395	5,498	25	22,502,300
Liberia	LBR-9gp	4,092,310	844,066	844,066	85,395	5,498	25	20,144,766
Liberia	LBR-ldt	4,092,310	844,066	844,066	88,016	5,477	20	22,202,262

Quantity	**Meaning**
ID	population identifier
$\|P\|$	population size
n_{HH}	number of household units
n_H	number of residence locations
n_W	number of work locations
n_S	number of school locations
n_C	number of colleges
n_A	total number of activities per day

Measure	**Synopsis**
$\|P\|$	size of population
$\|V\|$	number of vertices
$\|E\|$	number of edges
$d_{\min}$	minimal degree
$d_{\max}$	maximal degree
$\bar{D}$	average degree
λ_1	largest eigenvalue of adjacency matrix
λ_2	second largest eigenvalue of adjacency matrix
n_C	number of components
$\|V_{\max}\|$	size of largest components
r	relative size of largest component $\|V_{\max}\|/\|V\|$
D	diameter
n_T	number of labeled (?) triangles
$\bar{c}$	average cluster coefficient

West Africa: Social contact network properties

Population	$\|P\|$	$\|V\|$	$\|E\|$	$d_{\min}$	$d_{\max}$	d	λ_1	λ_2
GIN-v1	11,521,656	11,425,439	183,268,217	0	255	32.69	124.84	124.70
SLE-v1	5,743,725	5,733,911	93,734,286	0	164	32.69	97.84	97.81
LBR-v1	4,092,310	4,084,569	84,789,847	0	249	41.52	125.48	125.34
LBR-2gp	4,092,310	4,077,272	87,255,911	0	254	42.80	126.83	126.41
LBR-9gp	4,092,310	4,077,426	78,830,017	0	250	38.67	111.97	111.93
LBR-ldt	4,092,310	4,079,500	146,386,825	0	721	71.77	202.99	195.47

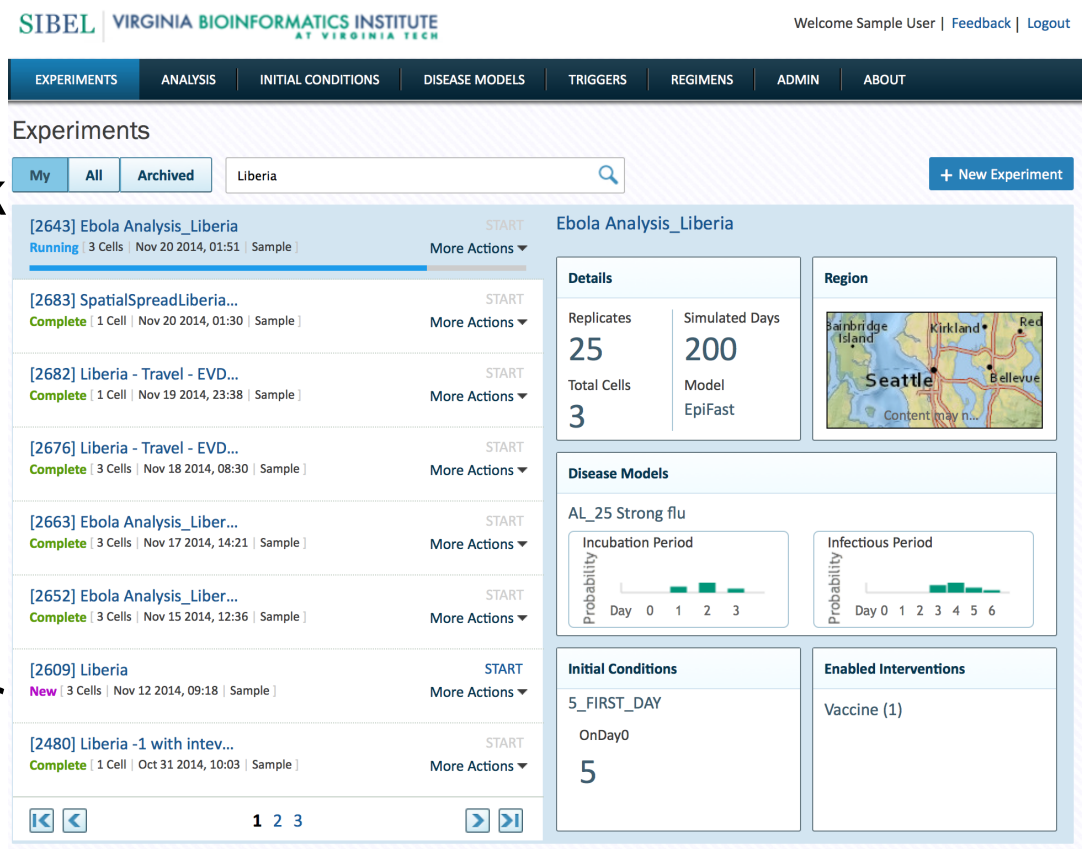
Population	n_C	$\|V_{\max}\|$	r	D	n_T	$\bar{c}$
GIN-v1	115,224	11,113,955	0.973	21	1,457,330,472	0.67
SLE-v1	10,543	5,704,544	0.995	16	683,523,753	0.61
LBR-v1	14,073	4,051,099	0.992	18	720,629,723	0.59
LBR-2gp	10,106	4,053,906	0.994	16	824,000,000	0.59
LBR-9gp	10,014	4,054,303	0.994	17	679,000,000	0.59
LBR-ldt	3,611	4,071,515	0.998	11	1.52841e+09	0.47

High performance computing simulations

Distinguishing Features	EpiSimdemics (SC'09,WSC'10, IPDPS'14)	EpiFast (ICS'09)	Indemics (ICS'10,TOMACS'11)
Solution Method	Interaction-Based Simulation	Combinatorial +discrete time	Interaction-based, Interactive Simulations
Performance 180 days 9M hosts & 40 proc.	**1 min (300K cores) for 300Million nodes**	**~40 seconds**	**15min-1hour**
How was the method used	Modeling detailed interactions at hospitals and funerals	Calibration and forecasting	Contact tracing based detection and interventions
Disease transmission model	Edge as well as vertex based (e.g. threshold functions)	Edge based, independence of infecting events	Edge based
Query and Interventions	Scripted, groups allowed but not dynamic	Scripted and specific groups allowed	Very general: no restriction on groups

SIBEL: http://sibeldemo.vbi.vt.edu/sibel/sibel.html

- Web based tool for in-silico epidemiological experiments based on realistic social network simulations.
- Interactive, easy to use GUI
- Specifies factorial designs to investigate range of parameters
- Useful for planning and course of action of analysis activities for analysts.



Supporting real-time response using pervasive web-apps, multi-scale models and synthetic populations/networks

Ebola Research Activities

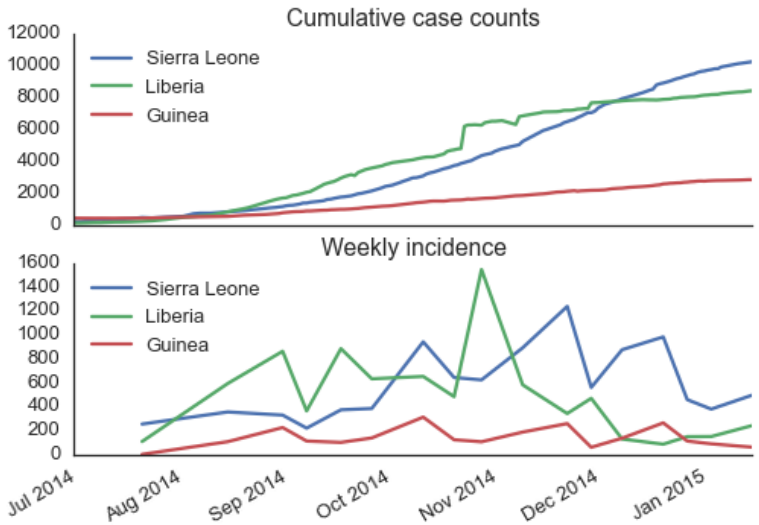
- Situational Awareness
  - Situation reports / Facebook
  - Twitter
- Deterministic Compartmental Model
  - Simple forecasting and many experiments
- Stochastic Compartmental Model
  - Intervention effectiveness, forecasting with stochastic variation
- Network and population synthesis
- Agent-based Simulations
  - US likelihood experiments
  - Adaption of modeling framework to Ebola-like disease transmission and intervention
  - National spread models in West Africa
  - Evaluation of stochasticity
  - Calibration of detailed models
  - Vaccine stockpile experiments

Support for Ebola Related Requests

Supported 4 official requests

- SOUTHCOM
  - Risk assessment of disease spread risk with cases imported to Central and South American nations
- NORTHCOM
  - Risk assessment of disease spread risk with cases imported to Mexico and Caribbean nations
- Regional Contingency Team – Ebola (RCT-E)
  - Risk assessment of disease spread risk with cases imported to surrounding West African nations
- NORTHCOM: Amalgam Dragon
  - Training exercise using hypothetical Ebola as bioterror weapon in US population (prior to West African crisis)

Maintaining Situational Awareness



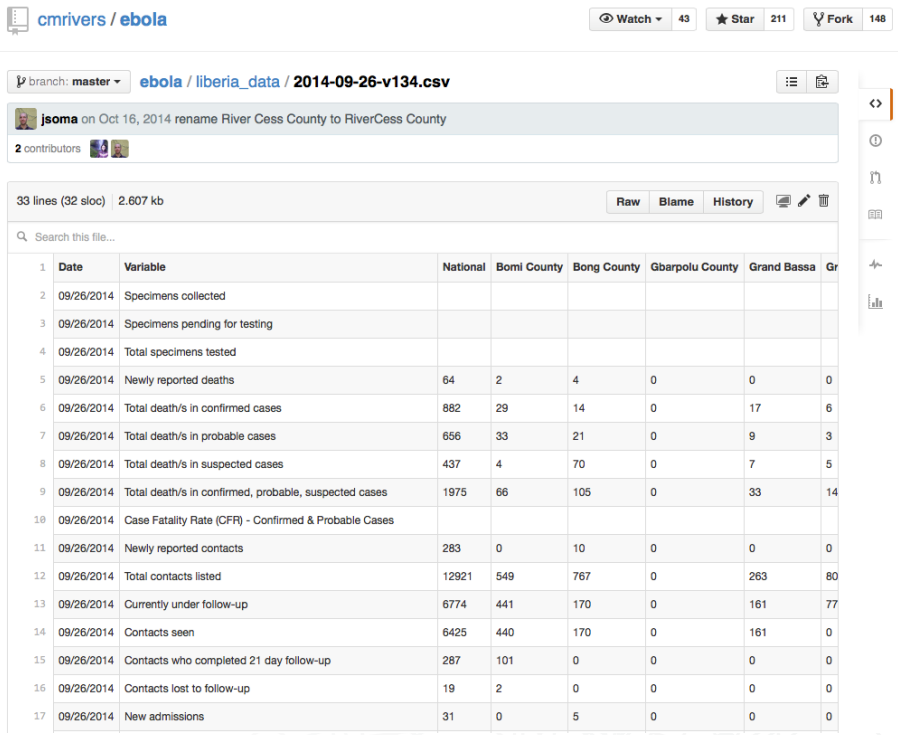
- Keep decision-makers appraised of the situation
  - Up to October, no larger organizations provided such analyses
- Required integration, organization, analysis, and interpretation of multiple sources of information
- Use this understanding to design simulation experiments

Maintaining Situational Awareness

Ebola Case and Death Summary by County

County	DAILY EMAIL REPORT New[1] suspected and probable cases (Alive and Dead)			Laboratory[2] Confirmed Cases (Alive and Dead)	Confirmed Cases on Contact List	Cumulative[3] cases 23 May-FEBUARY 9th 2015				Cumulative deaths[2]
	Total	Suspect	Probable			Total	Suspect	Probable	Confirmed	
Bomi	1	1	0	0	0	319	101	79	139	174
Bong	3	3	0	0	0	601	417	38	150	159
Gbarpolu	0	0	0	0	0	35	16	3	16	13
Grand Bassa	0	0	0	0	0	182	55	73	54	80
Grand Cape Mount	0	0	0	0	0	320	178	52	94	201
Grand Gedeh	0	0	0	0	0	11	8	0	3	6
Grand Kru	0	0	0	0	0	36	14	18	4	27
Lofa	1	1	0	0	0	679	195	146	332	405
Margibi	0	0	0	0	0	1292	460	441	391	582
Maryland	2	2	0	0	0	28	22	2	4	23
Montserrado	31	31	0	0	0	4932	2290	871	1794	2059
Nimba	0	0	0	0	0	337	90	131	116	60
River Gee	3	3	0	0	0	28	16	5	8	16
River Cess	0	0	0	0	0	44	10	10	24	27
Sinoe	0	0	0	0	0	61	36	7	18	26
NATIONAL	41	41	0	0	0	8864	3876	1869	3147	3846

[1] From daily email county reports of aggregated data for that day
[2]Laboratory confirmed cases of suspects and probable cases identified during the preceding days
[3]From individual-level data from the Case Investigation form; cases may be reclassified according to surveillance case definitions ↑Increase in daily reported cases by county ■ County did not report



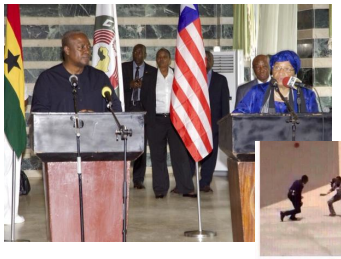
	Date	Variable	National	Bomi County	Bong County	Gbarpolu County	Grand Bassa	Gr
2	09/26/2014	Specimens collected						
3	09/26/2014	Specimens pending for testing						
4	09/26/2014	Total specimens tested						
5	09/26/2014	Newly reported deaths	64	2	4	0	0	0
6	09/26/2014	Total death/s in confirmed cases	882	29	14	0	17	6
7	09/26/2014	Total death/s in probable cases	656	33	21	0	9	3
8	09/26/2014	Total death/s in suspected cases	437	4	70	0	7	5
9	09/26/2014	Total death/s in confirmed, probable, suspected cases	1975	66	105	0	33	14
10	09/26/2014	Case Fatality Rate (CFR) - Confirmed & Probable Cases						
11	09/26/2014	Newly reported contacts	283	0	10	0	0	0
12	09/26/2014	Total contacts listed	12921	549	767	0	263	80
13	09/26/2014	Currently under follow-up	6774	441	170	0	161	77
14	09/26/2014	Contacts seen	6425	440	170	0	161	0
15	09/26/2014	Contacts who completed 21 day follow-up	287	101	0	0	0	0
16	09/26/2014	Contacts lost to follow-up	19	2	0	0	0	0
17	09/26/2014	New admissions	31	0	5	0	0	0

https://github.com/cmrivers/ebola

Situation reports, Facebook updates, WHO reports, etc. were digitized (often from PDF tables) into a more computable CSV format shared via GitHub.

Maintaining Situational Awareness

Most common images:



Prénoms

Garçon		Fille
Noel	↔	Noëlla
Emmanuel	↔	Emmanuela
Daniel	↔	Daniella
Ebo	↔	??????????

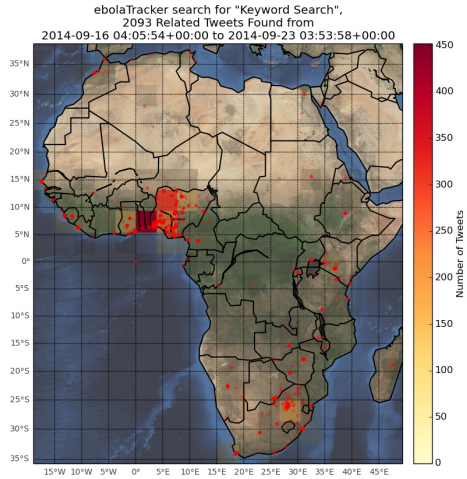
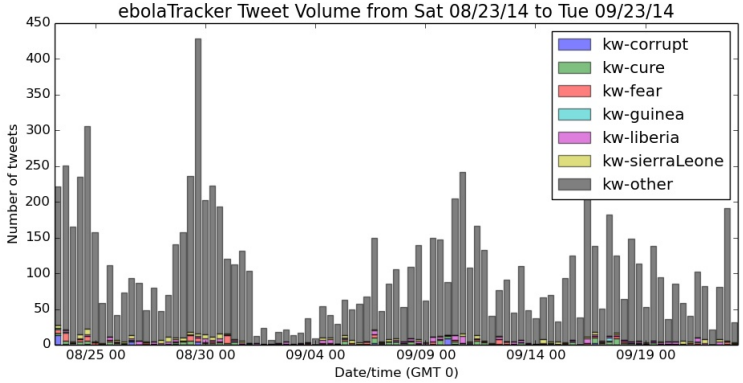
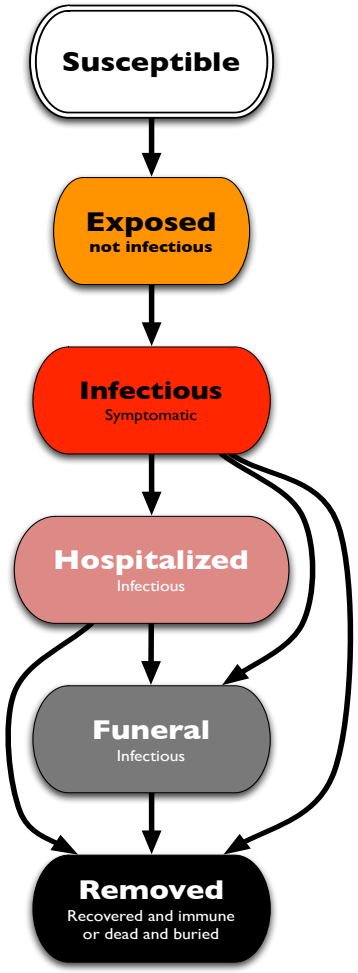


Photo content: Solidarity with Ebola affected countries, Jokes about bushmeat, Ebola risk, names, positive health message



Twitter Scraping began in mid-August, Of any mention of Ebola in Africa. This tool also extracts images from tweets and keeps track of the most popular ones as depicted here (Week of Sept 17-23). The most common tweets this week were about fighting Ebola, and a few jokes indicating a grown fear and awareness of the threat posed by Ebola.

Modeling Ebola: Compartmental model



$$-\frac{1}{N}(\beta_{\mathrm{I}}\mathrm{SI}+\beta_{\mathrm{H}}\mathrm{SH}+\beta_{\mathrm{F}}\mathrm{SF})$$

$$\frac{1}{N}(\beta_{\mathrm{I}}\mathrm{SI}+\beta_{\mathrm{H}}\mathrm{SH}+\beta_{\mathrm{F}}\mathrm{SF})-\alpha\mathrm{E}$$

$$\alpha\mathrm{E}-(\gamma_{\mathrm{h}}\theta_1+\gamma_i(1-\theta_1)(1-\delta_1)+\gamma_{\mathrm{d}}(1-\theta_1)\delta_1)\mathrm{I}$$

$$\gamma_{\mathrm{h}}\theta_1\mathrm{I}-(\gamma_{\mathrm{dh}}\delta_2+\gamma_{i\mathrm{h}}(1-\delta_2))\mathrm{H}$$

$$\gamma_{\mathrm{d}}(1-\theta_1)\delta_1\mathrm{I}+\gamma_{\mathrm{dh}}\delta_2\mathrm{H}-\gamma_{\mathrm{f}}\mathrm{F}$$

$$\gamma_i(1-\theta_1)(1-\delta_1)\mathrm{I}+\gamma_{i\mathrm{h}}(1-\delta_2)\mathrm{H}+\gamma_{\mathrm{f}}\mathrm{F}$$

Epidemiol. Infect. (2007), **135**, 610–621. © 2006 Cambridge University Press
doi:10.1017/S0950268806007217 Printed in the United Kingdom

Understanding the dynamics of Ebola epidemics

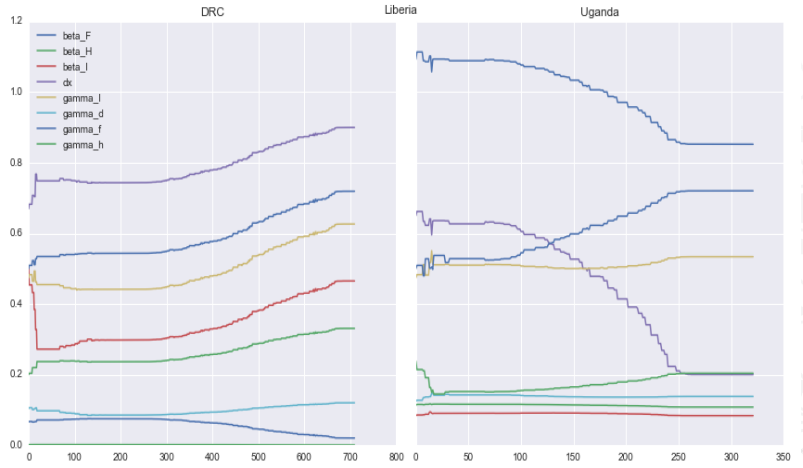
J. LEGRAND*, R. F. GRAIS, P. Y. BOELLE, A. J. VALLERON AND A. FLAHAULT
INSERM, UMR-S 707, Paris, France, and Université Pierre et Marie Curie-Paris 6, UMR-S 707, Paris, France

(Accepted 14 July 2006; first published online 26 September 2006)

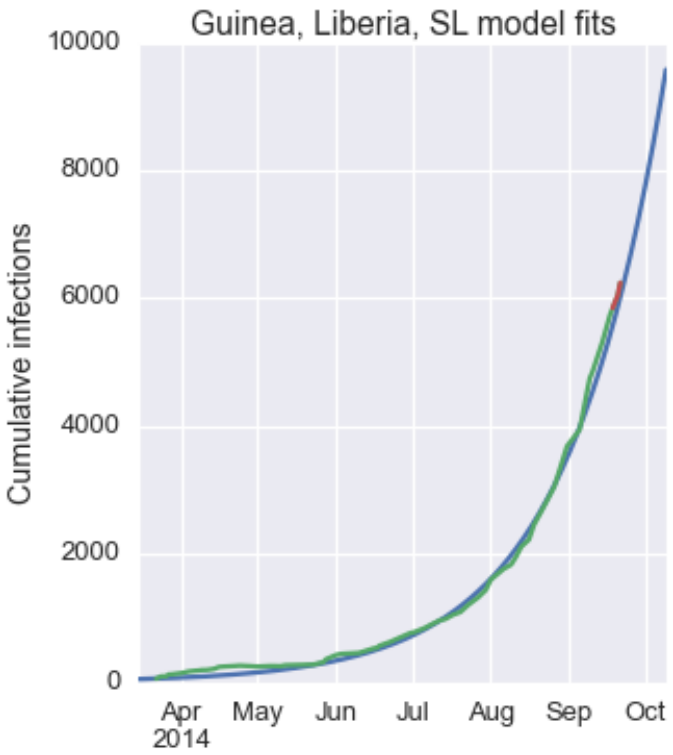
Legrand, J, R F Grais, P Y Boelle, A J Valleron, and A Flahault. "Understanding the Dynamics of Ebola Epidemics" *Epidemiology and Infection* 135 (4). 2007. Cambridge University Press: 610–21. doi:10.1017/S0950268806007217.

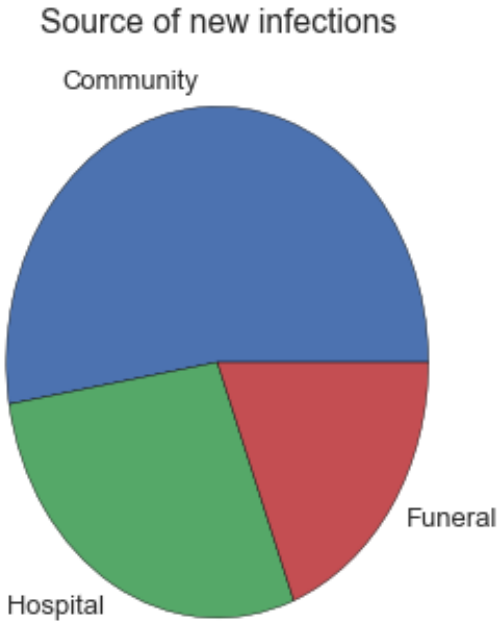
Modeling Ebola: Optimized Fit Process

- Parameters to explored selected
  - Diag_rate, beta_I, beta_H, beta_F, gamma_I, gamma_D, gamma_F, gamma_H
  - Initial values based on two historical outbreak
- Optimization routine
  - Runs model with various permutations of parameters
  - Output compared to observed case count
  - Algorithm chooses combinations that minimize the difference between observed case counts and model outputs, selects “best” one



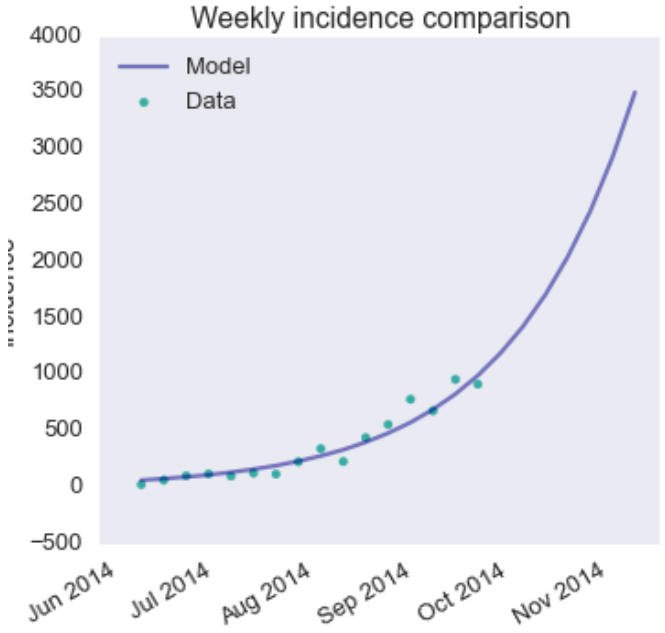
Ebola Model: Estimates

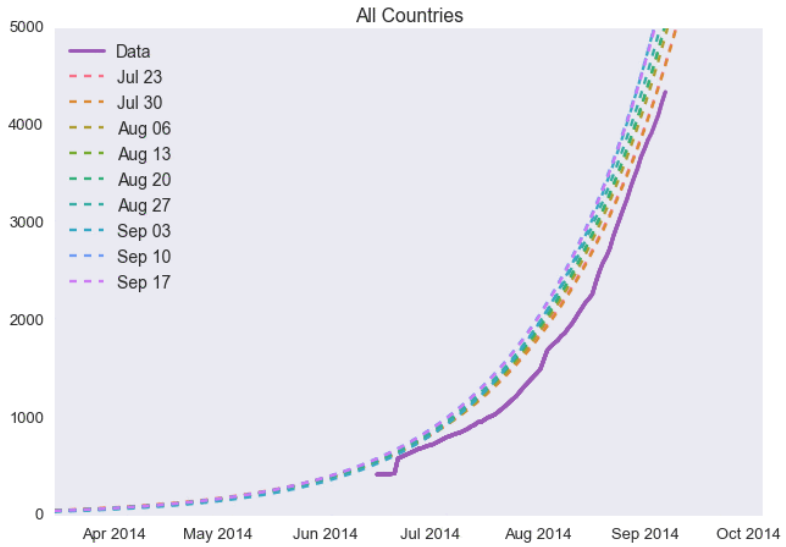




rI: 1.1
rH:0.4
rF:0.3
Overall:1.7

Ebola Model: Estimates

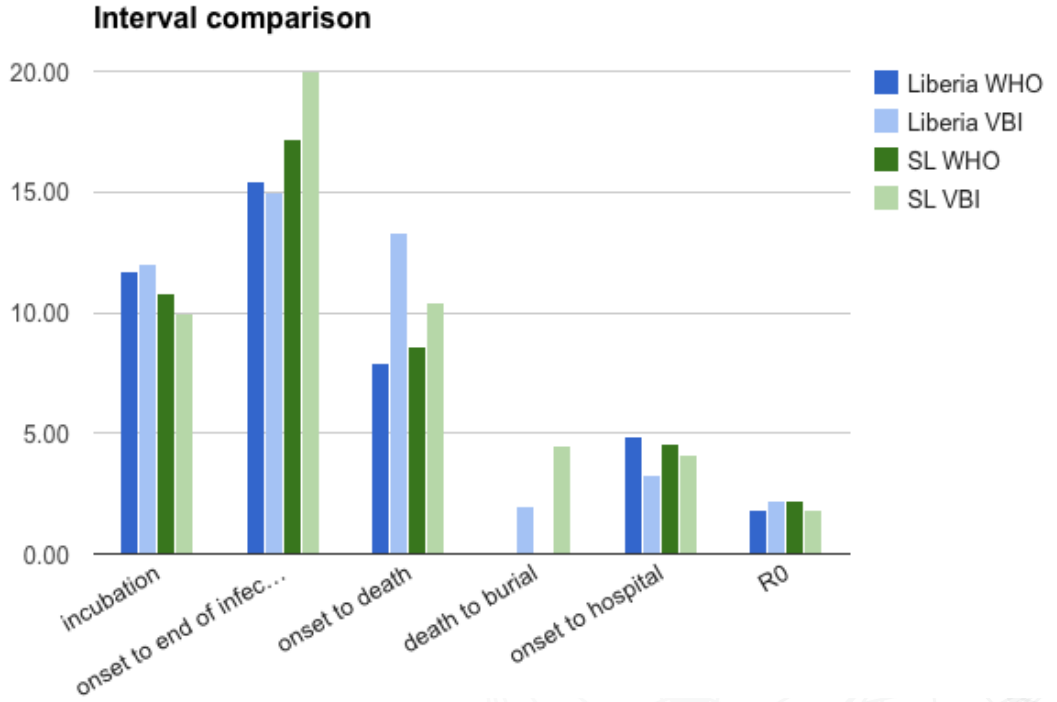




	8/10 – 8/16	8/17 – 8/23	8/24 – 8/30	8/31– 9/6	9/8 – 9/13	9/14- 9/20	9/21 – 9/27	9/28 – 10/4
Actual	231	442	559	783	681	959	--	--
Forecast	336	403	483	578	693	830	994	1191

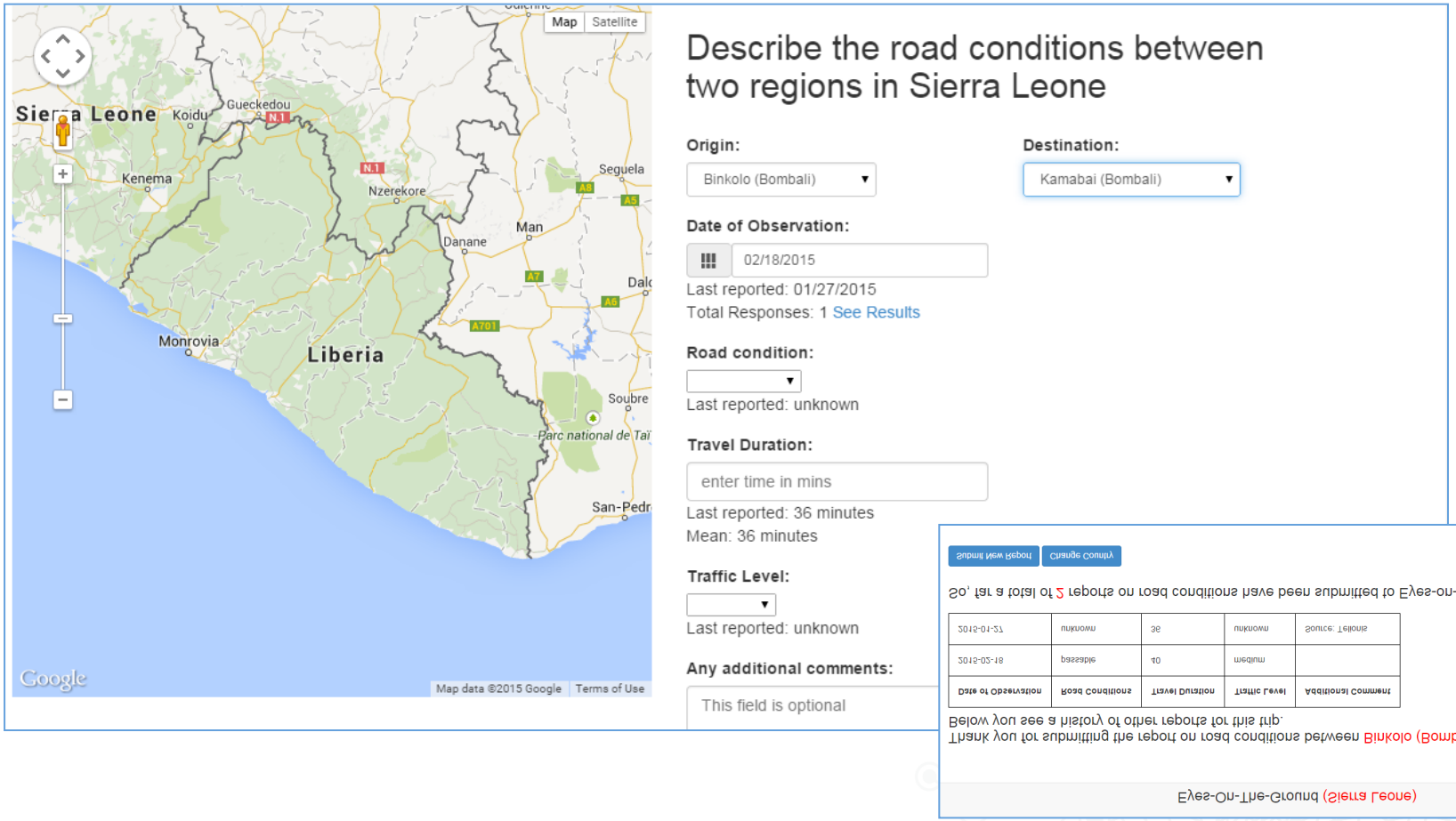
Ebola Model: Evaluation

- Late September WHO published results from the detailed epidemiologic data
- Estimates derived from the fitted compartmental model were very close to that measured by the WHO.



parameter	name	Liberia WHO	Liberia VBI	SL WHO	SL VBI	Vespignani	Althaus	Towers	Nishiura	Fisman	Meltzer
alpha	incubation	11.70	12.00	10.80	10.00	7.0	5.3	5, 7, 10			6
gamma_I	onset to end of infectiousness for survivors	15.4	15.0	17.2	20.0	10.0	5.6 (infectious period)	5, 7, 10 (infectious periods)			6 (infectious period)
gamma_d	onset to death	7.9	13.3	8.6	10.4	9.6					
gamma_f	death to burial		2.0		4.5	2.0					
gamma_h	onset to hospital	4.9	3.2	4.6	4.1	5.0					
What exactly they claim to be measuring varies	R0	1.8	2.2	2.2	1.8	1.8 overall	SL 2.5 & 1.6 Liberia, but has time-decaying beta that puts R < 1 in early July	1.3 SL & 2.1 Liberia	1.4-1-7 overall	8.3 SL & 1.7 Liberia	

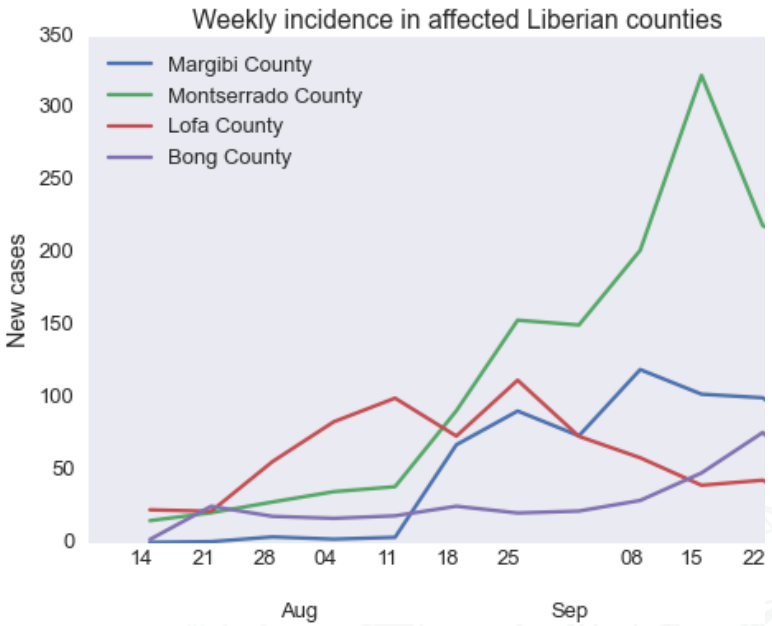
Eyes-on-the-Ground



Provides easy to use, light weight interface to access and submit “on the ground” data to support analyses and simulations.

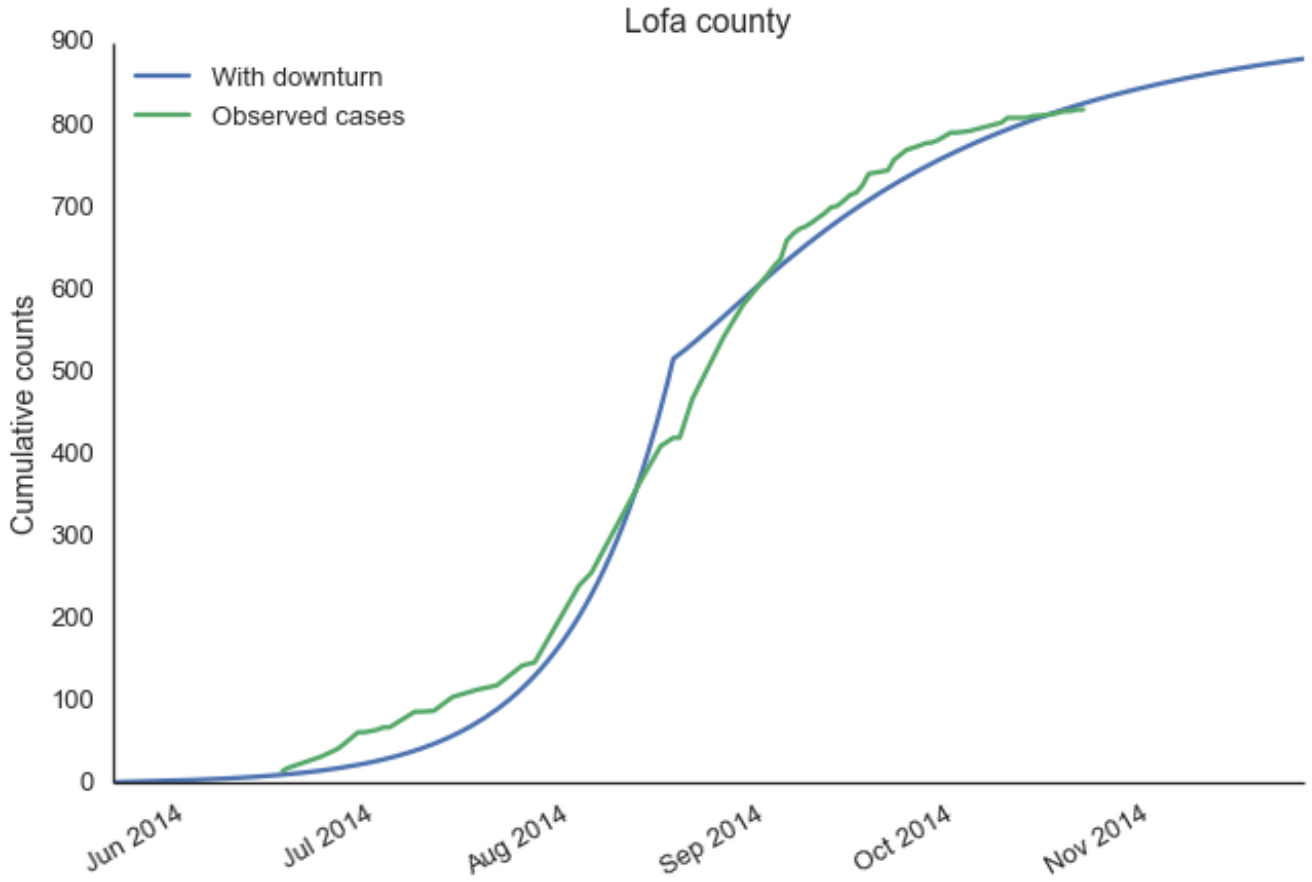
Learning from Lofa

- Lofa county, near the epicenter of the Ebola outbreak
- Grassroots efforts and very active health director educated public and reducing transmission in community



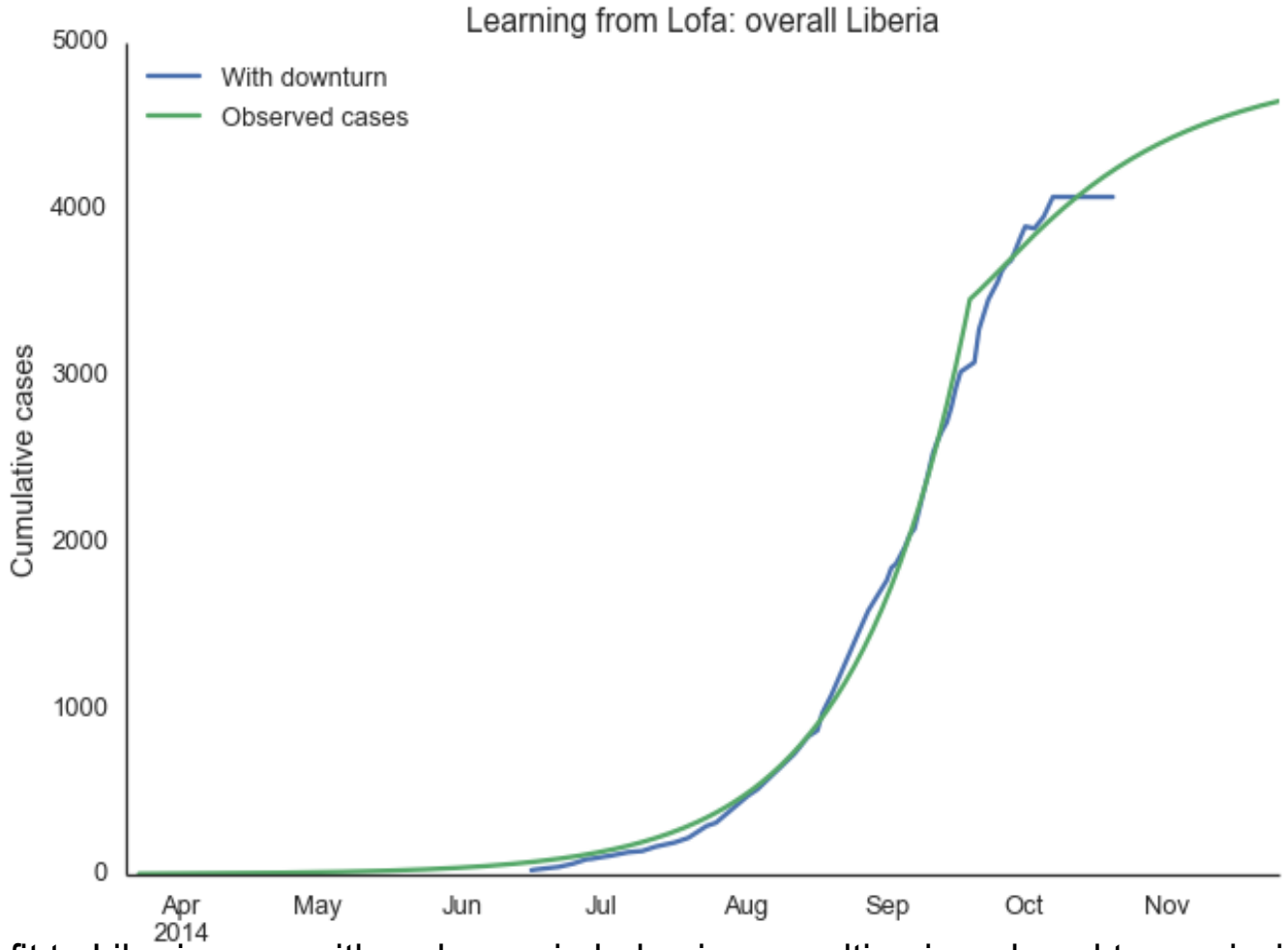
- Experiment: What if the experience of Lofa county can be transferred to Liberia as a whole?

Learning from Lofa



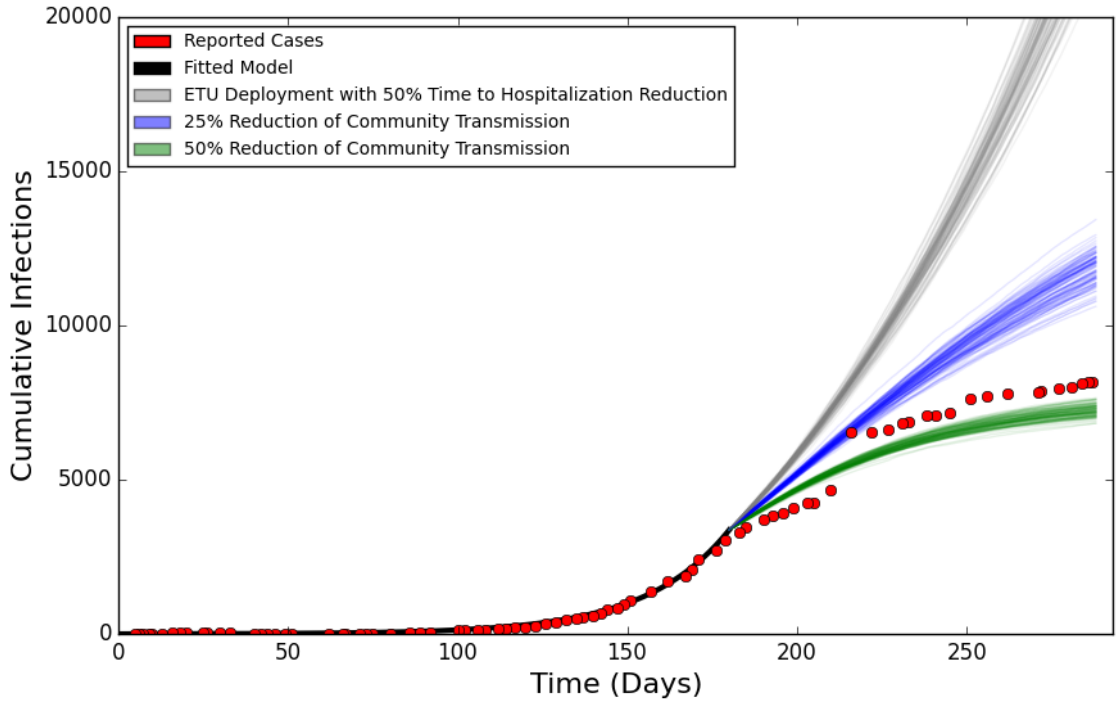
Model fit to Lofa case with a change in behaviors resulting in reduced transmission stating mid-Aug (blue), compared with observed data (green)

Learning from Lofa



Model fit to Liberia case with a change in behaviors resulting in reduced transmission stating Sept 21st (green), compared with observed data (blue)

Impact of ETUs

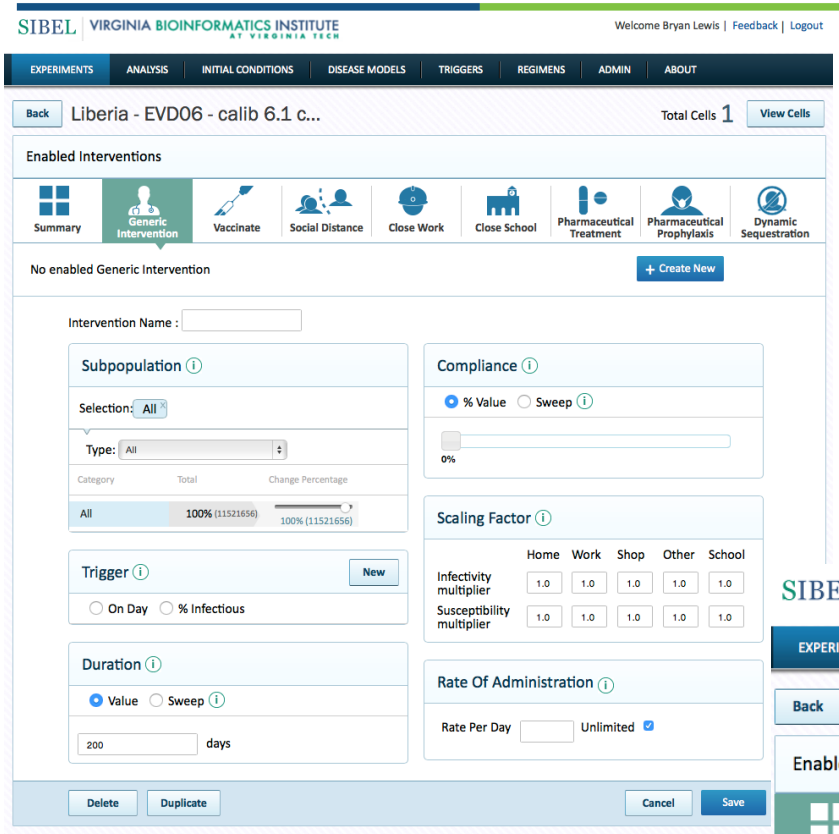


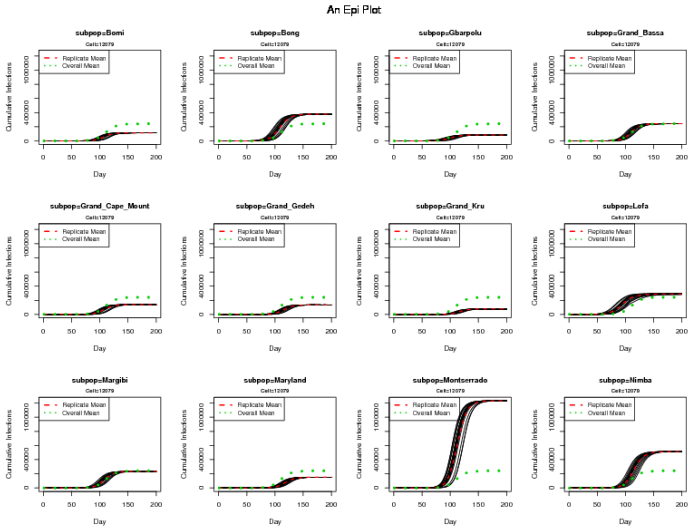
- How effective were the deployed Ebola Treatment Units?
- Significant reductions in community transmission required to match current observations

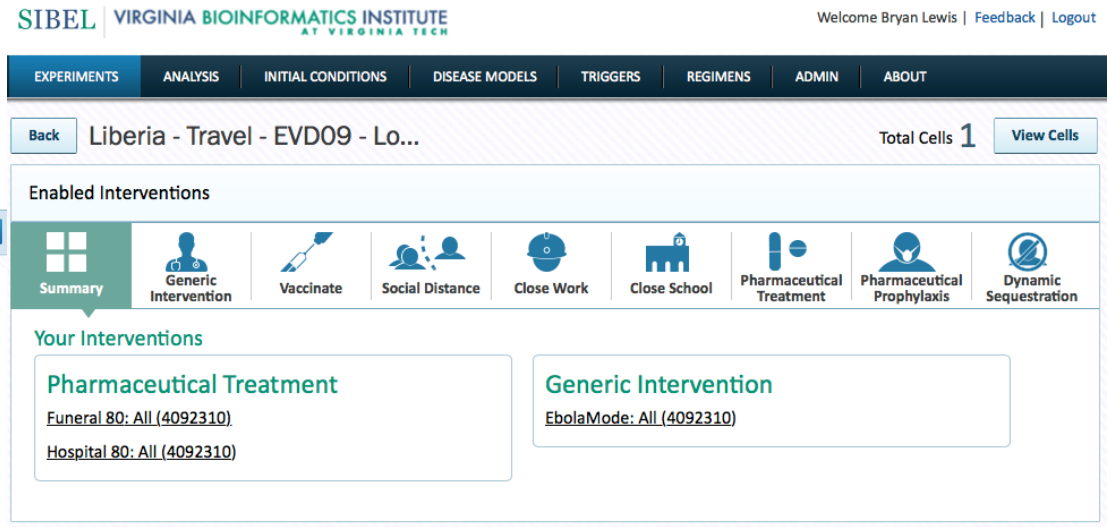
Agent-based Modeling: Challenges

- Rapidly adapting system optimized for airborne transmission to support
  - novel disease model and transmission modes
  - Interventions and populations
- Parameterizing a data intensive model when data is scarce and often inaccurate
- Analysis of a disease process with high levels of variance and stochastic effects

SIBEL Synthetic Information Based Epidemiological Laboratory







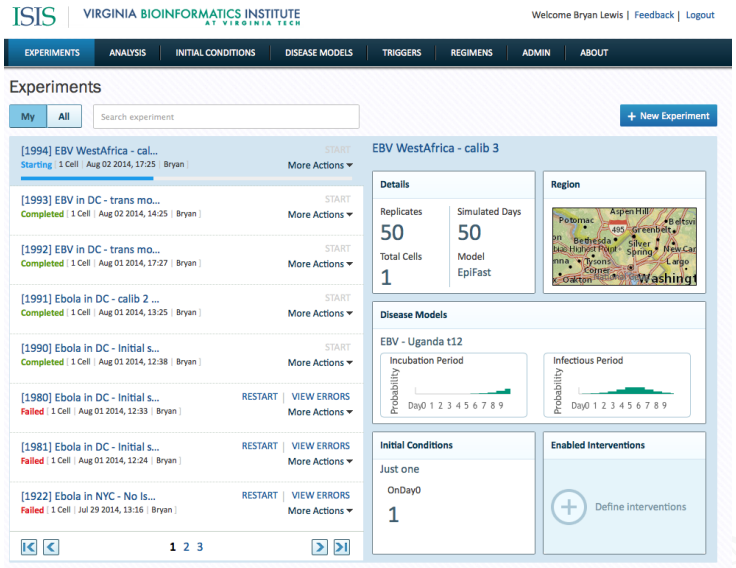
Design, Execute, and Analyze Agent-based simulations of Infectious disease spread

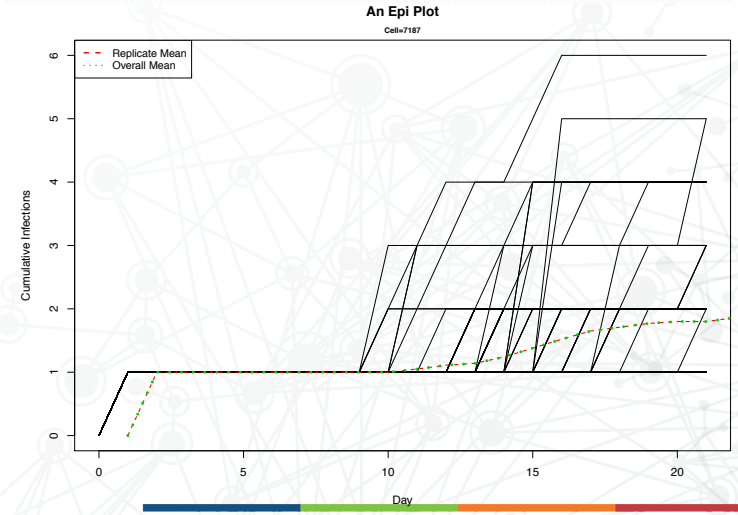
SIBEL extensions and refinements

- Flexible framework for modifications too complex to represent within web interface
- Contact based interventions prototyped
- Refinement of analysis tools
  - Enable interactive overview analyses
  - Tools to allow more flexible detailed analysis (eg custom-defined age groups,etc.)

Agent-based Model in the US

- Early in the outbreak, concern about US spread was a primary question
- Existing US population data and simulation tools were harnessed to address this situation



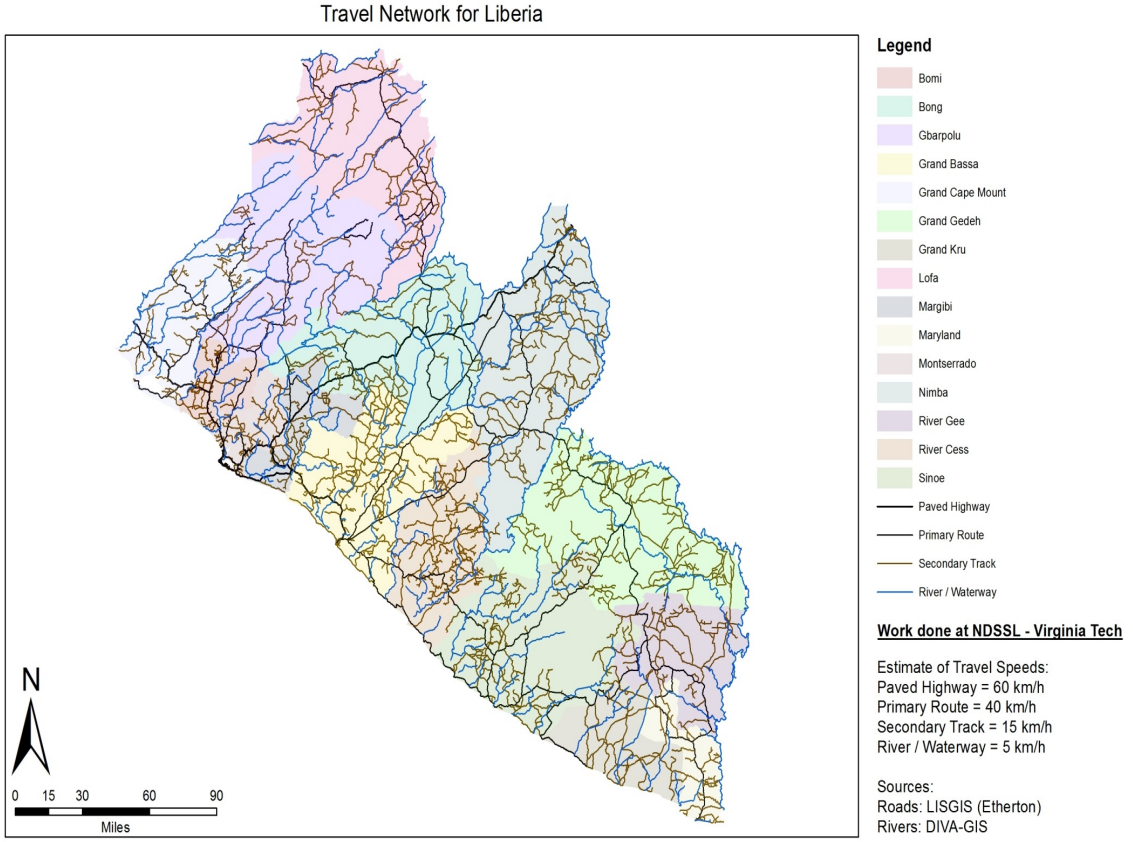


Summary of results:

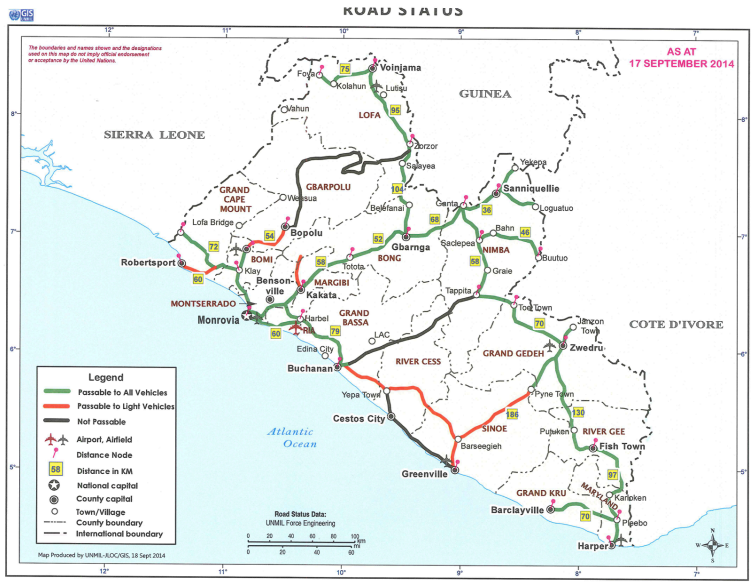
100 replicates
Mean of 0.8 additional cases
Max of 6 cases
Majority only one initial case

National Spread

- Need to understand travel patterns
- Need to know transportation network



National Spread



	Bomi	Bong	Gbarpolu	Grand Bassa	Grand Cape Mount	Grand Gedeh	Grand Kru	Lofa	Margibi	Maryland	Montserrado	Nimba	River Cess	River Gee	Sinoe
Bomi		0.55	0.5	1	0.5	0.425	0.425	0.1	1	0.425	1	0.55	0.1	0.425	0.3
Bong	0.55		0.3	0.55	0.3	1	1	1	1	1	1	1	0.1	1	0.36666666 7
Gbarpolu	0.5	0.3		0.5	0.5	0.425	0.425	0.1	0.5	0.425	0.5	0.3	0.1	0.425	0.3
Grand Bassa	1	0.55	0.5		0.5	0.3	0.3	0.4	1	0.3	1	0.55	0.1	0.3	0.3
Grand Cape Mount	0.5	0.3	0.5	0.5		0.3	0.3	0.3	0.5	0.3	0.5	0.23333333 3	0.1	0.3	0.3
Grand Gedeh	0.425	1	0.425	0.3	0.3		1	1	0.55	1	0.55	1	0.1	1	0.5
Grand Kru	0.425	1	0.425	0.3	0.3	1		1	0.53333333 3	1	0.533333333	1	0.1	1	0.5
Lofa	0.1	1	0.1	0.4	0.3	1	1		0.55	1	0.55	1	0.1	1	0.21428571 4
Margibi	1	1	0.5	1	0.5	0.55	3	0.55		1	1	1	0.1	3	0.3
Maryland	0.425	1	0.425	0.3	0.3	1	1	1	0.53333333 3		0.533333333	1	0.1	1	0.5
Montserrado	1	1	0.5	1	0.5	0.55	3	0.55	1	3		0.55	0.1	3	0.3
Nimba	0.55	1	0.3	0.55	0.233333333	1	1	1	1	1	0.55		0.1	1	0.23333333 3
River Cess	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1		0.1	0.1
River Gee	0.425	1	0.425	0.3	0.3	1	1	1	0.53333333 3	1	0.533333333	1	0.1		0.5
Sinoe	0.3	0.36666666 7	0.3	0.3	0.3	0.5	0.5	0.214285 714	0.3	0.5	0.3	0.23333333 3	0.1	0.5	

Green	1
Red	0.5
Black	0.1

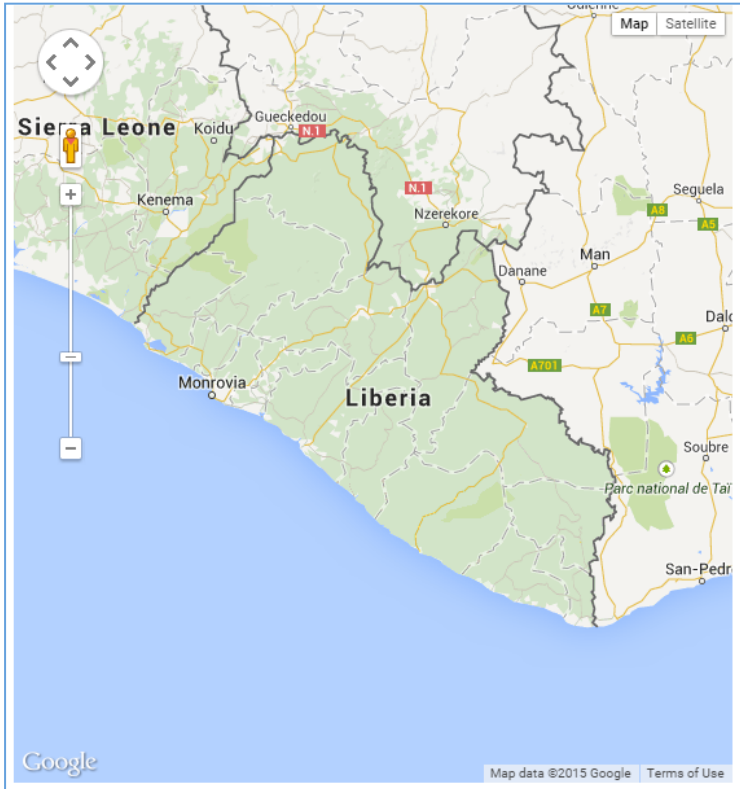
Based on traveling from county capital to county capital

Based on 17SEPT2014 data

During the rainy season this road network is degraded, which influences the amount of travel. This in turn can drive where future cases occur and the overall size of the epidemic. More importantly its critical to understand when trying to decide where to devote resources to combat the epidemic.

Maryland Avenue from Pleebo to Harper (from John Etherton).

Eyes-on-the-Ground



Describe the road conditions between two regions in Sierra Leone

Origin: Binkolo (Bombali)

Destination: Kamabai (Bombali)

Date of Observation: 02/18/2015

Last reported: 01/27/2015

Total Responses: 1 See Results

Road condition:

Last reported: unknown

Travel Duration: enter time in mins

Last reported: 36 minutes

Mean: 36 minutes

Traffic Level:

Last reported: unknown

Any additional comments: This field is optional

Eyes-On-The-Ground (Sierra Leone)

Thank you for submitting the report on road conditions between Binkolo (Bombali) and Kamabai (Bombali). Below you see a history of other reports for this trip.

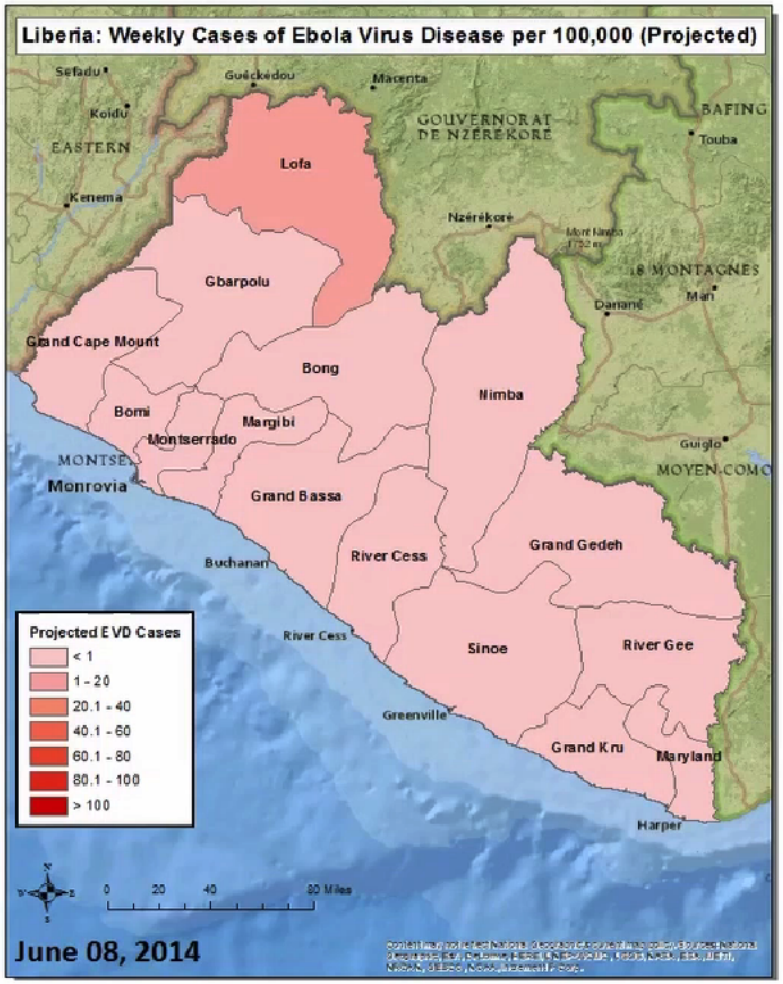
Date of Observation	Road Conditions	Travel Duration	Traffic Level	Additional Comment
2015-02-18	passable	40	medium	
2015-01-27	unknown	36	unknown	Source: Telionis

So, far a total of 2 reports on road conditions have been submitted to Eyes-on-the-Ground for this trip.

Submit New Report | Change Country

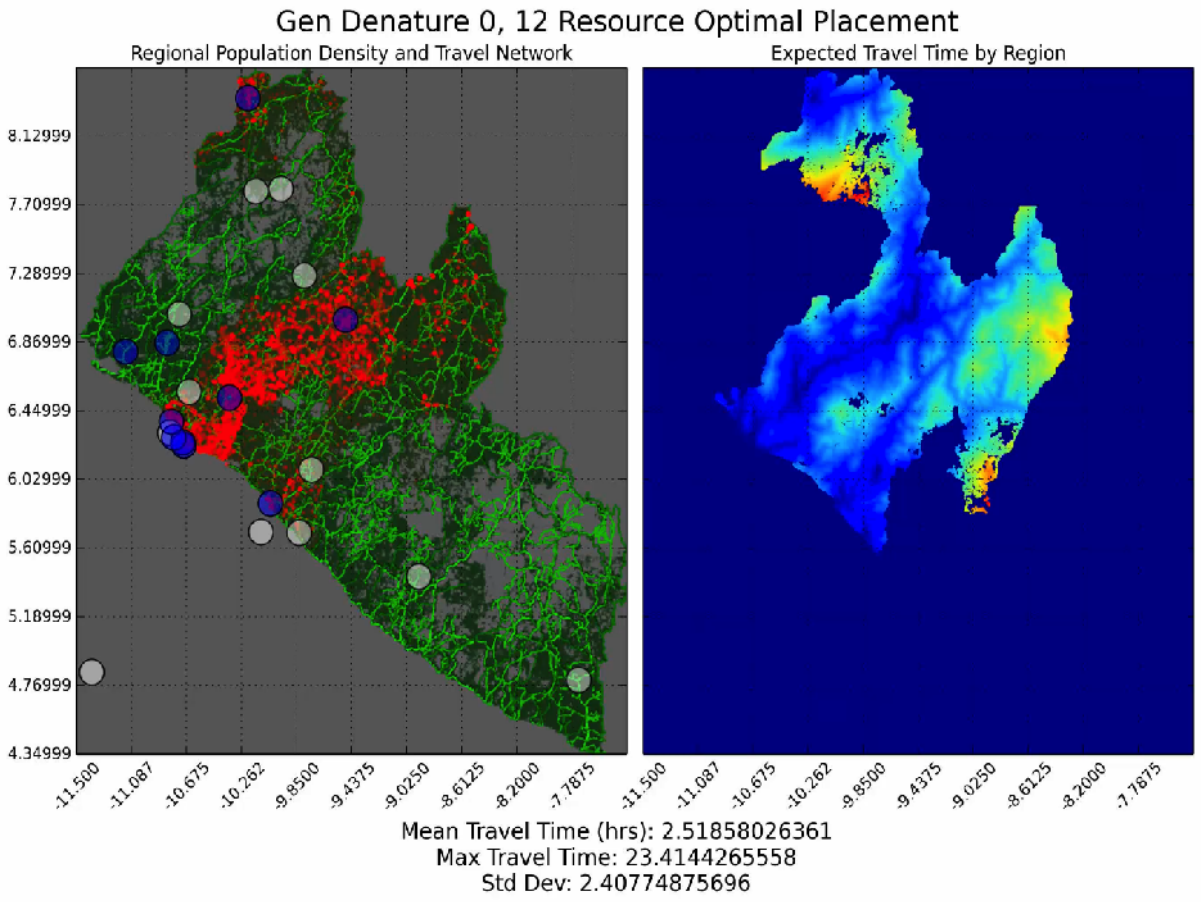
Provides easy to use, light weight interface to access and submit “on the ground” data to support analyses and simulations.

Ebola national model



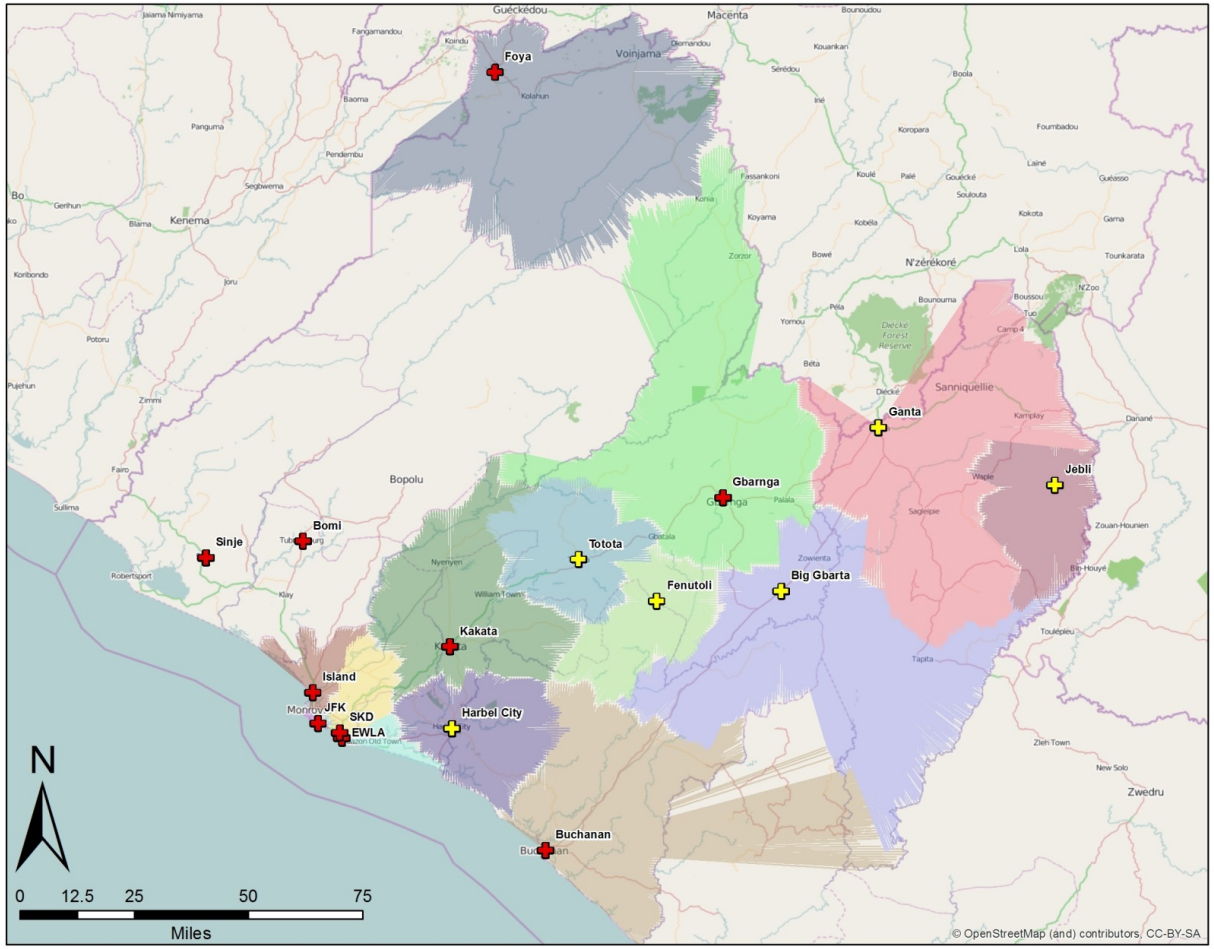
What counties will be affected next?

Optimal Placement of ETUs



Optimal Placement of ETUs

K-median Allocation of 6 new ETUs based on Predicted Ebola Cases on Dec-1st



ETUs	Cases	Long	Lat
All Monrovia	1,442	-10.7505	6.2411
Big Gbarta	246	-9.2951	6.7108
Bomi	1	-10.8207	6.8663
Buchanan	187	-10.0442	5.8834
Fenutoli	105	-9.6912	6.6790
Foya	187	-10.2130	8.3632
Ganta	237	-8.9851	7.2322
Gbarnga	598	-9.4812	7.0084
Harbel City	368	-10.3430	6.2709
Jebli	66	-8.4210	7.0482
Kakata	707	-10.3518	6.5313
Sinje	0	-11.1305	6.8129
Totota	290	-9.9418	6.8106

Legend

- Facility Already Built
- Proposed Facility

Coordinate System: WGS 1984 UTM Zone 29N
Projection: Transverse Mercator
Datum: WGS 1984
false easting: 500,000.0000
false northing: 0.0000
central meridian: -9.0000
scale factor: 0.9996
latitude of origin: 0.0000
Units: Meter

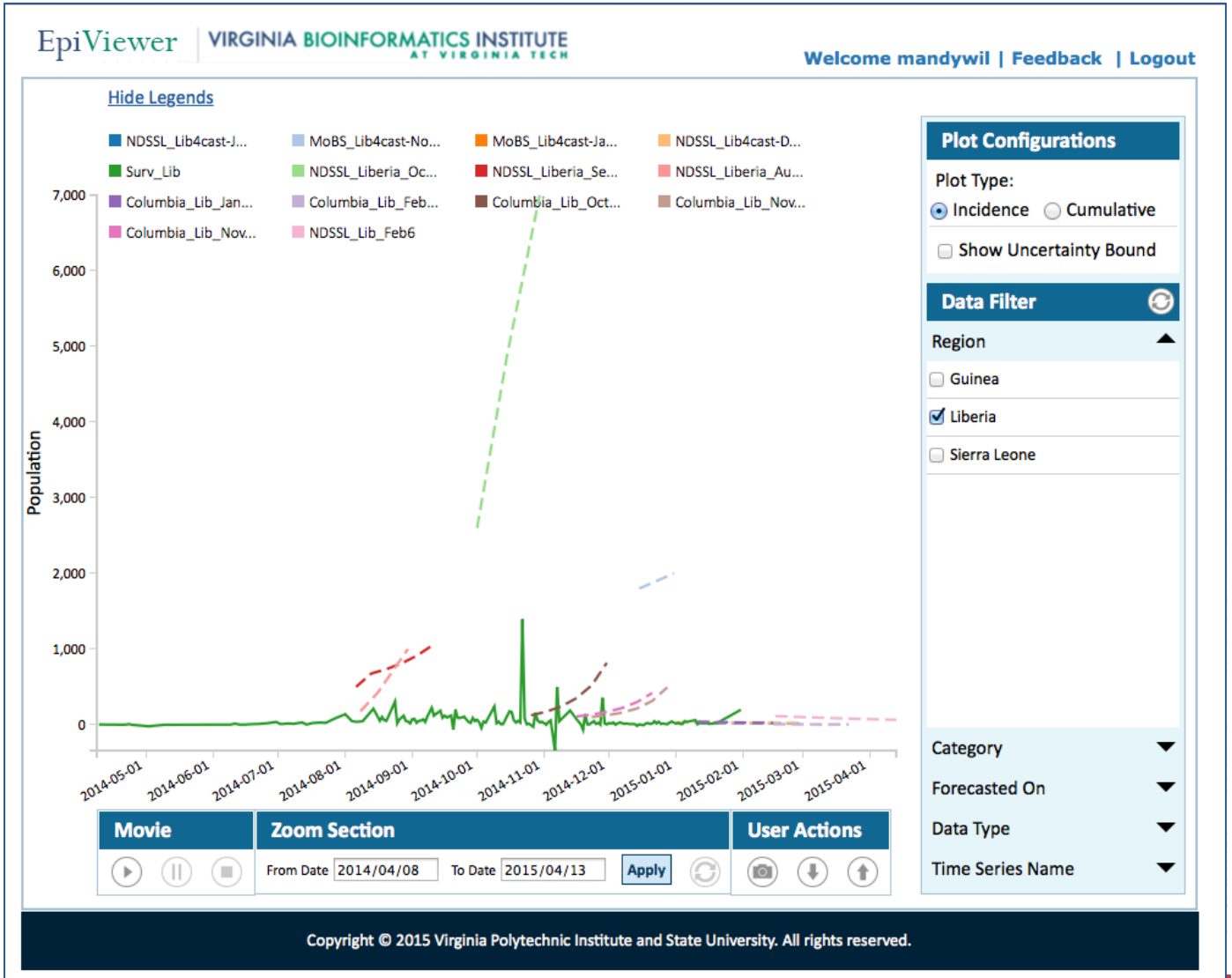
Work done at NDSSL - Virginia Tech

Notes:
- Based on County Level ODE Model
- No demand on Sinje
- Minimal Demand on Bomi

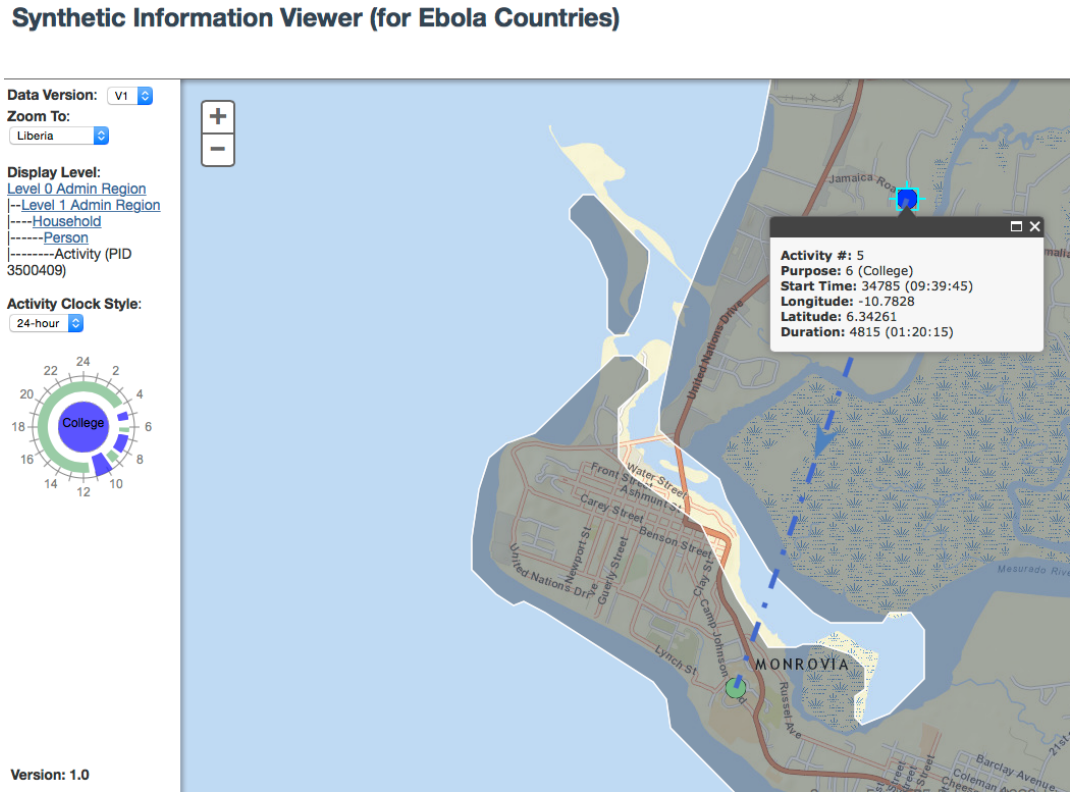
Sources:
Pop: LandScan 2013
Roads: LISGIS (Etherton)
Rivers: DIVA-GIS

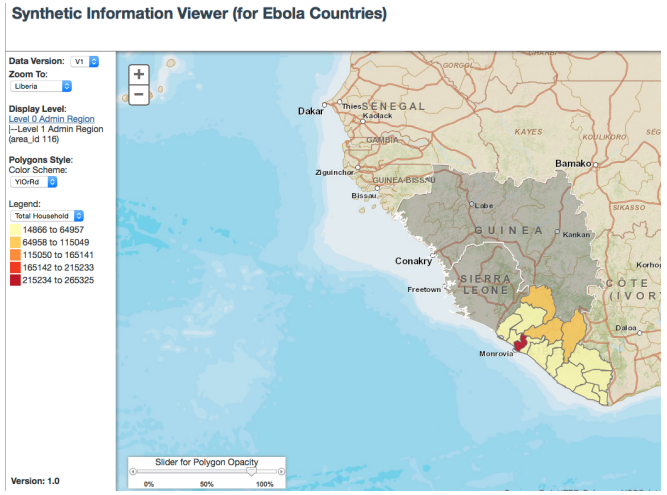
EpiViewer

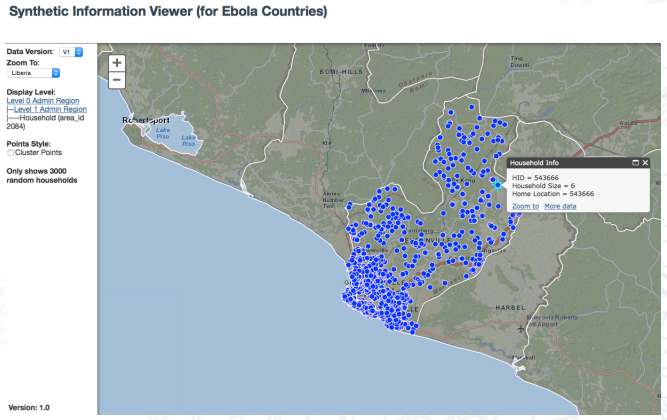
EpiViewer graphs Ebola surveillance and forecasting data from a variety of sources so trends and correlations may be made. Users can limit the graphs via a number of data filters, and they can also specify incidence or cumulative numbers. This data can be downloaded (either manually or by API.) While this tool was built specifically for Ebola, it can easily be extended to support other epidemics.



Agent-based Modeling

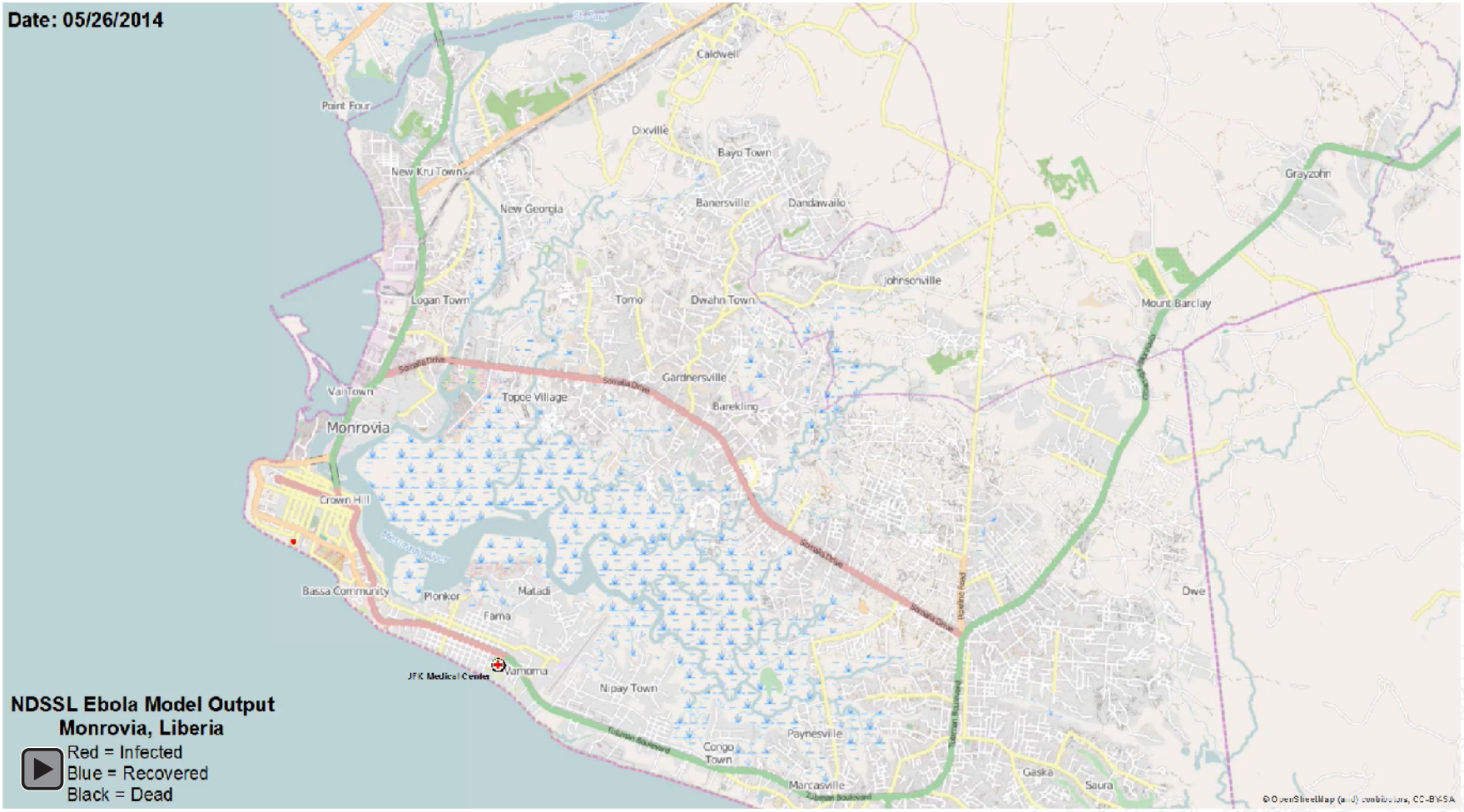




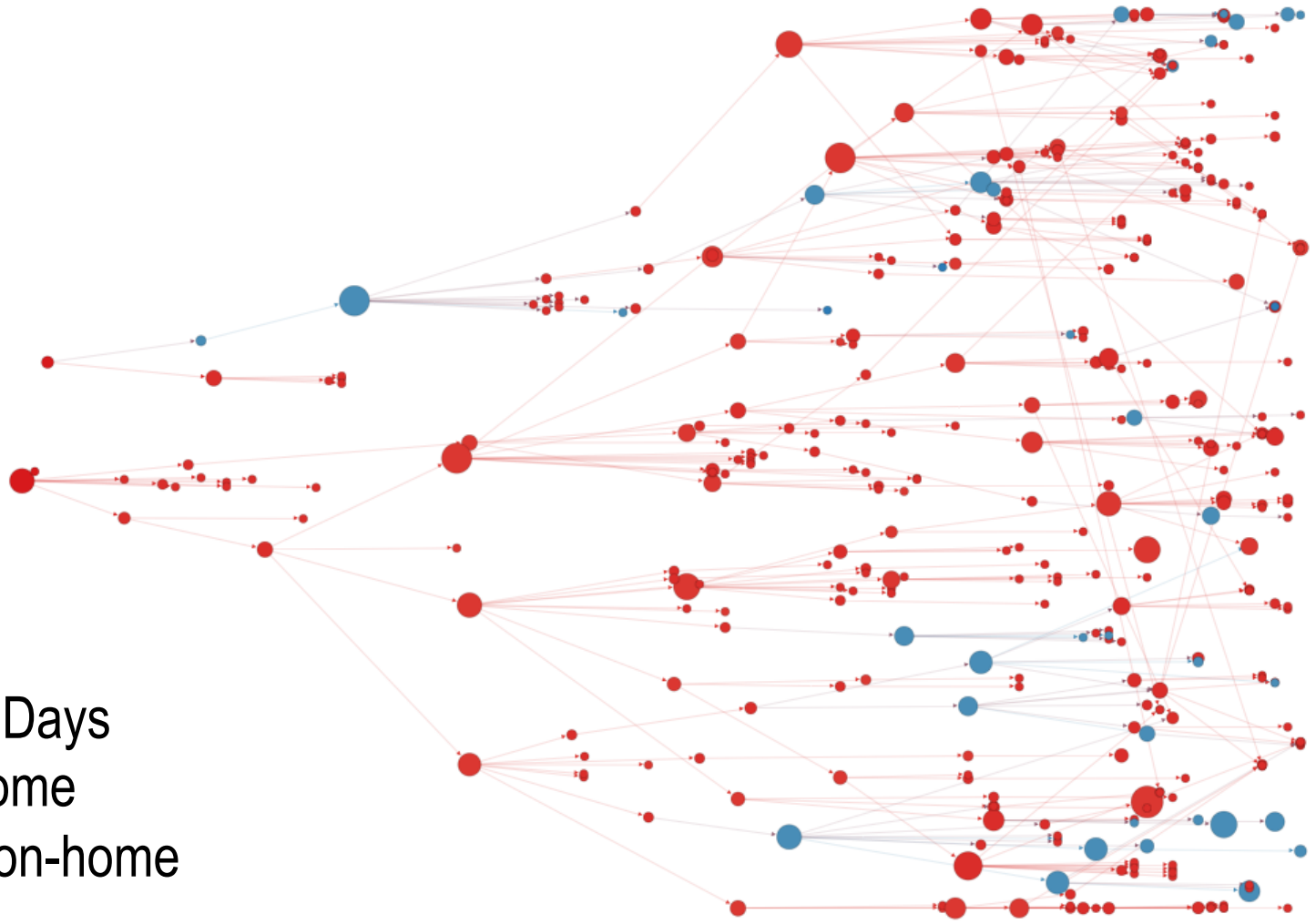


- Each individual represented, interactions drive transmission
  - Includes household, school, and work activities

Agent-based Modeling



Transmission Trees



X-axis is Days
Red is home
Blue is non-home

On going Work

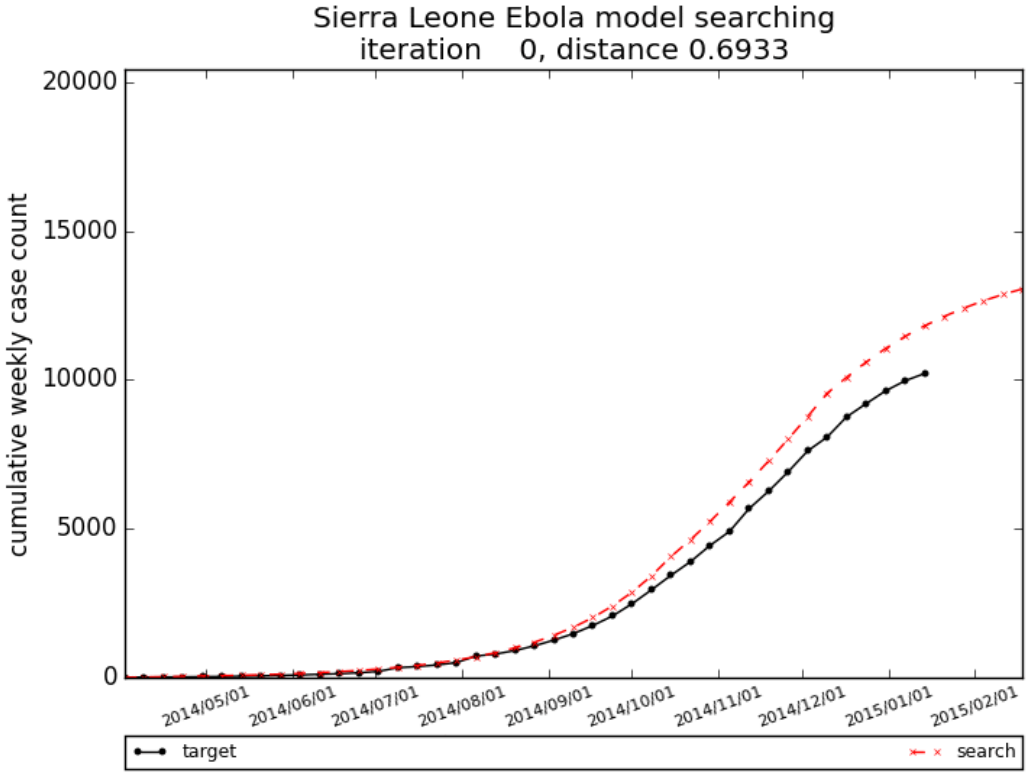
- Stochastic Extinction
  - Role of chance in initial spread and propagation of emerging diseases
- Complex Calibrations
  - Calibrating with multiple constraints (eg geo-spatial and temporal)
- Vaccine studies
  - Using detailed agent based studies to evaluate vaccine properties and guide design of field studies

Behavioral Adaptation

- Can we understand and estimate the impact of behavioral changes while the outbreak is on going?
- Details included in this ABM can provide a variety of structurally valid behaviors matching observations
  - These can be used to design field studies or epidemiologic analyses for confirming or disconfirming these behaviors
  - Can be used directly in estimating impacts, forecasting future cases, further exploring other counterfactuals

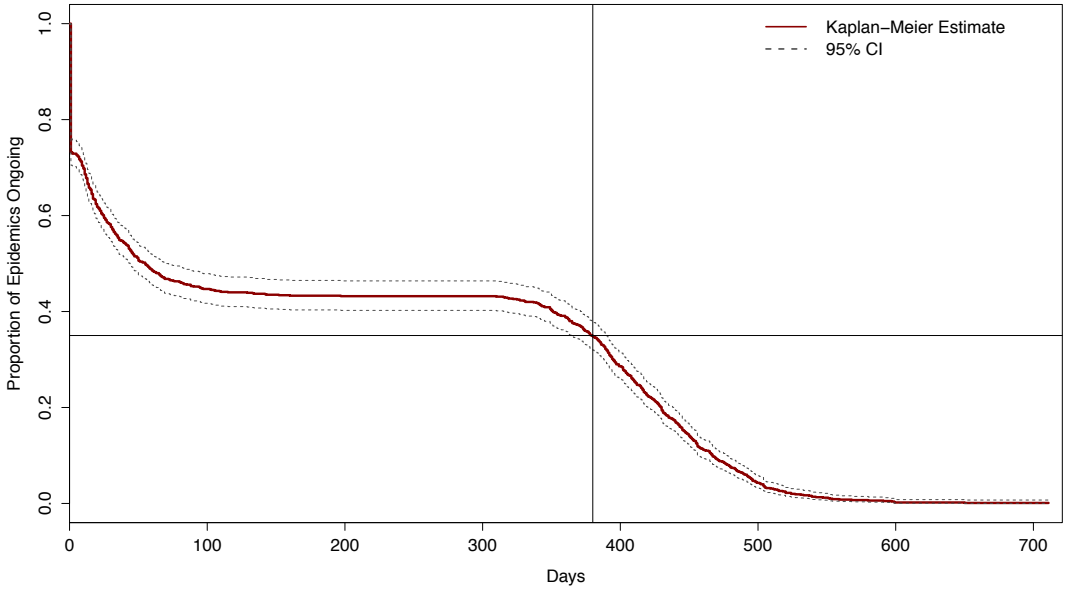
ABM Calibration system

- Automated disease model / scenario search wrapped around full ABM simulations
- Use in upcoming RAPIDD Ebola forecasting Challenge



Stochastic Extinction

- How likely is an outbreak of this size and kind?
  - Parameterize and calibrate model to observed values
  - Look at distribution of outbreaks produced (1000 sims)
- Prelim Results:
  - Same parameters that produce this outbreak produce many smaller ones and larger ones



Vaccine Studies

- What are sufficient requirements of a vaccine and vaccine campaign to mitigate future outbreaks of this caliber?
  - Using parameters that generate large outbreaks roll out vaccine campaigns of various sizes, designs, and efficacy to estimate impacts

- Design of Vaccine trials greatly debated
  - Simulations assisted in evaluation of novel designs made to combat problem of declining incidence

Summary and key insights

- Public health epidemiology is a complex system problem.
  - Responding to future pandemics challenging due to emerging global trends
  - Epidemics, contact networks, behaviors & policies coevolve during a pandemic
- Advances in computing & big data, have created new opportunities to support real-time epidemiology.
  - Simdemics: Network-based Computational Epidemiology -- Highly resolved, captures complex social and epidemic interactions
  - Role of multi-scale modeling and synthetic information
  - Leads to a qualitative change in the way public policies are supported
- Tools and experiences prove useful to prepare for the next outbreak

Publications

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Thank you

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