Lost in Space: How GeoHealth can help us find our way

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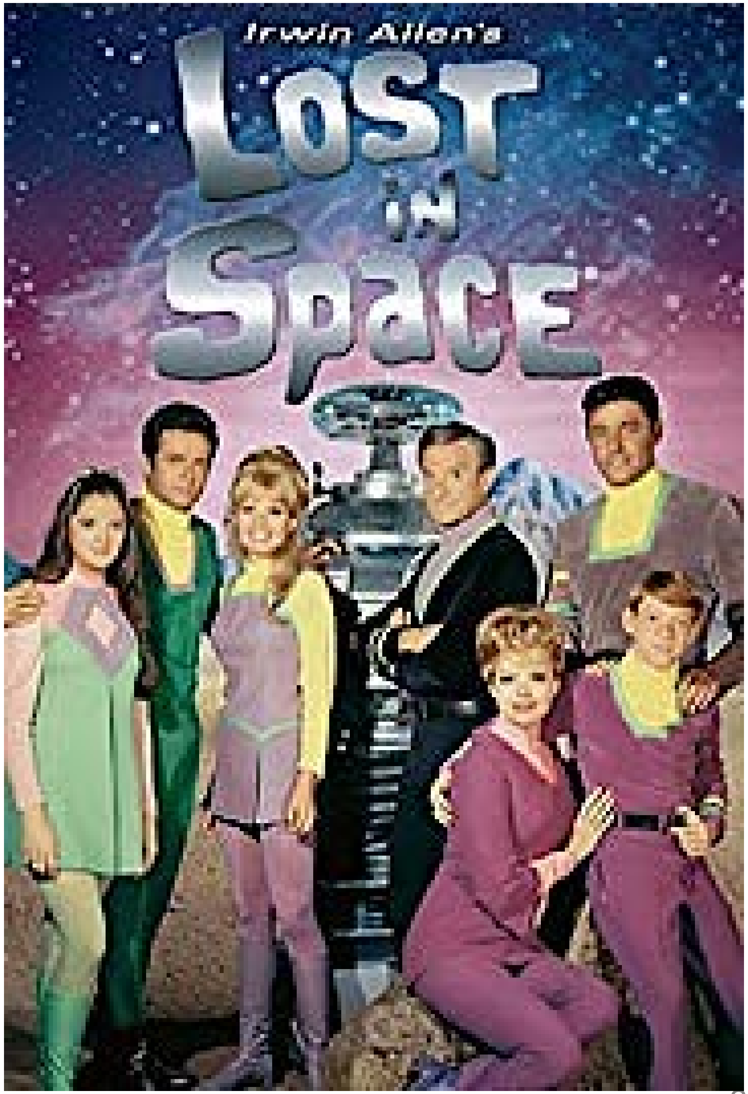
Global Health Consortium

Agenda

- Are we lost?
- Finding our path
- The GeoHealth Framework
- Zombies
- Applying GeoHealth to emerging challenges in Global Public Health
- Path to the Future
- Cool Stuff



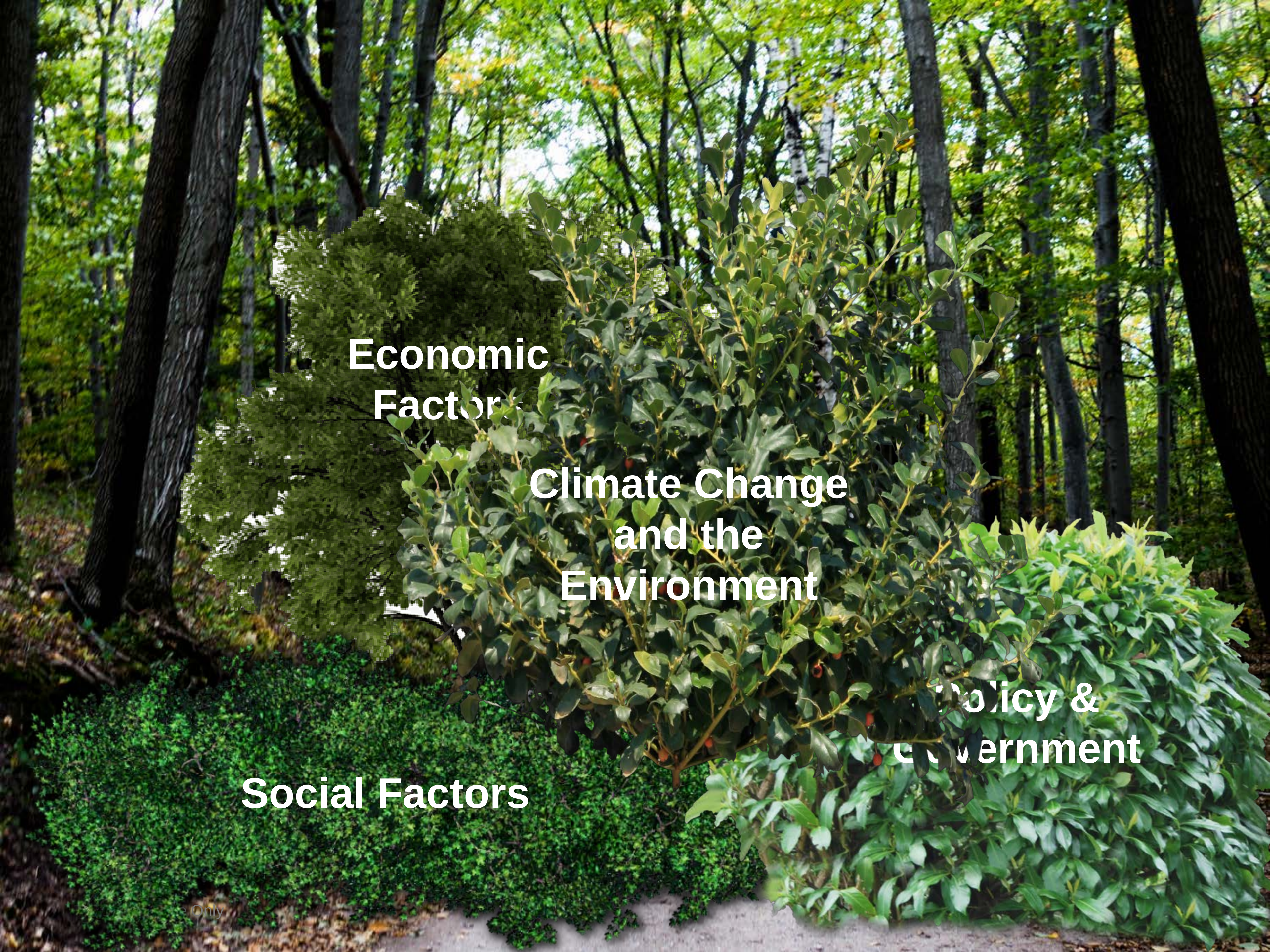
Are we lost?

- Highly complex disease systems
- Multitude of simultaneously-operating causal factors
- Highly specialized training
- A swiftly shifting landscape

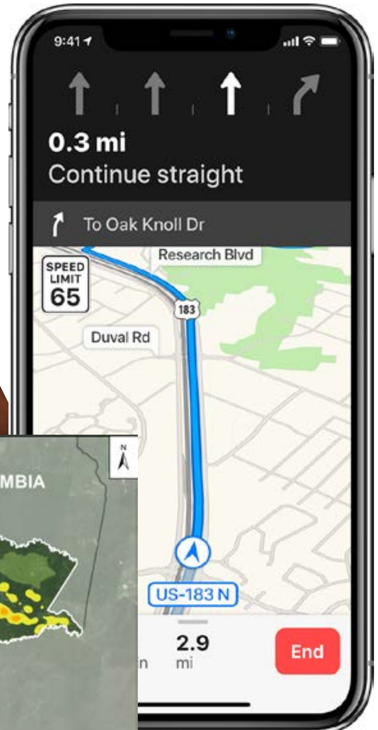
Finding our path

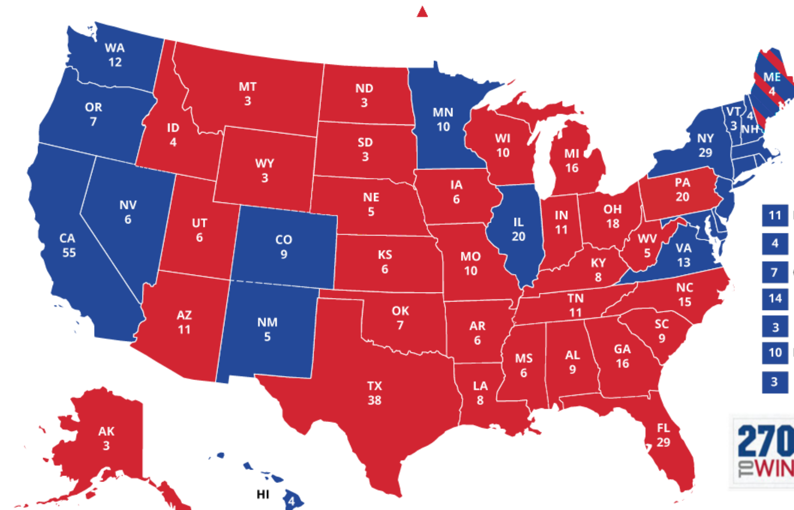
Elimination **Control**

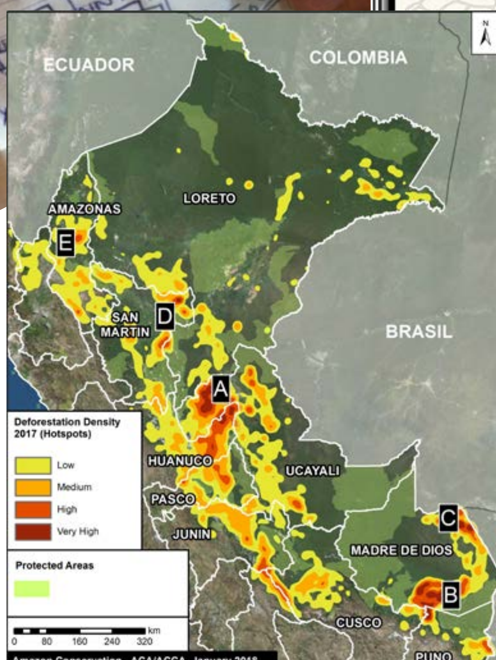
Data


Economic
Climate Change
and the
Environment
Social Factors

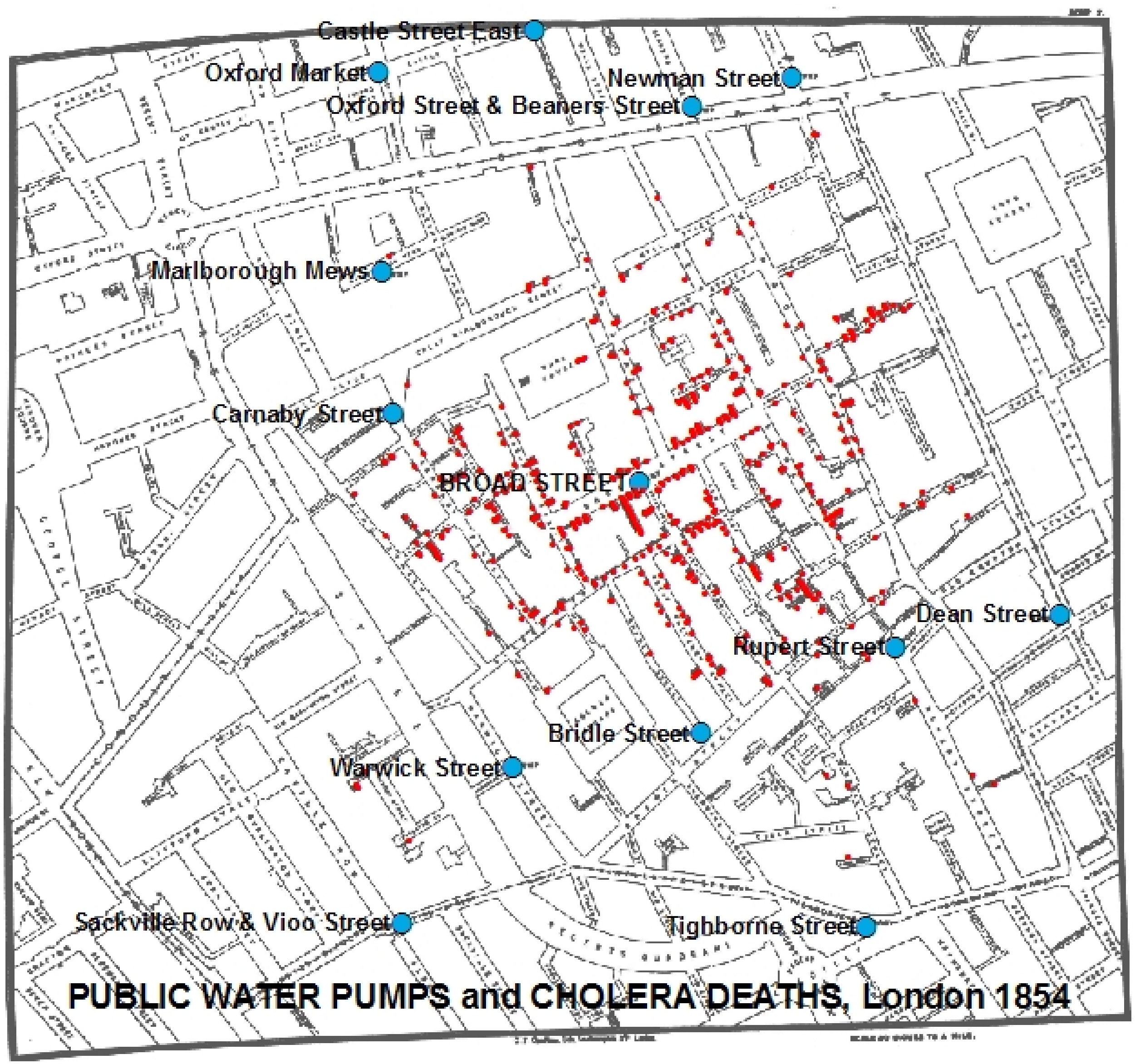
What do we do when we’re lost?







A famous example



Human attention to the spatial distribution of the *outcomes* and *causes* of disease, and consideration of the relationship to natural systems, is contributing to an awareness of the increasing usefulness of geospatial data to global health – which has given rise to a ***new field of research***:

GeoHealth

Safeguarding human health through the application of spatial analysis to epidemiology and health systems.

The GeoHealth Framework

- Space
  - Geospatial analysis
  - Environmental data
- Policy
  - Global
  - Local
- Systems
  - Ecosystems
  - Healthcare and Delivery
- Social
  - Psychosocial, Behavior
  - Social Media and Networks
- Individual
  - Characteristics
  - Disease incidence

Products

- Static Maps: disease incidence, tree cover, health access points
  - To understand the problem – where is the zombie outbreak currently occurring?
- Dynamic maps: traffic maps, migration, rainfall, erosion
  - To evaluate changes in the problem – how quickly is the zombie outbreak spreading? Whic
- Interactive maps: influe of relationships across
  - Given known risk factors, likely to occur?

In: Infectious Disease Modelling Research Progress ISBN 978-1-60741-347-9
Editors: J.M. Tchuenche and C. Chiyaka, pp. 133-150

Chapter 4

When Zombies Attack!: Mathematical Modelling of an Outbreak of Zombie Infection

Philip Munz[1,*], ***Ioan Hudea***[1,†], ***Joe Imad***[2,‡], ***Robert J. Smith?***[3,§]
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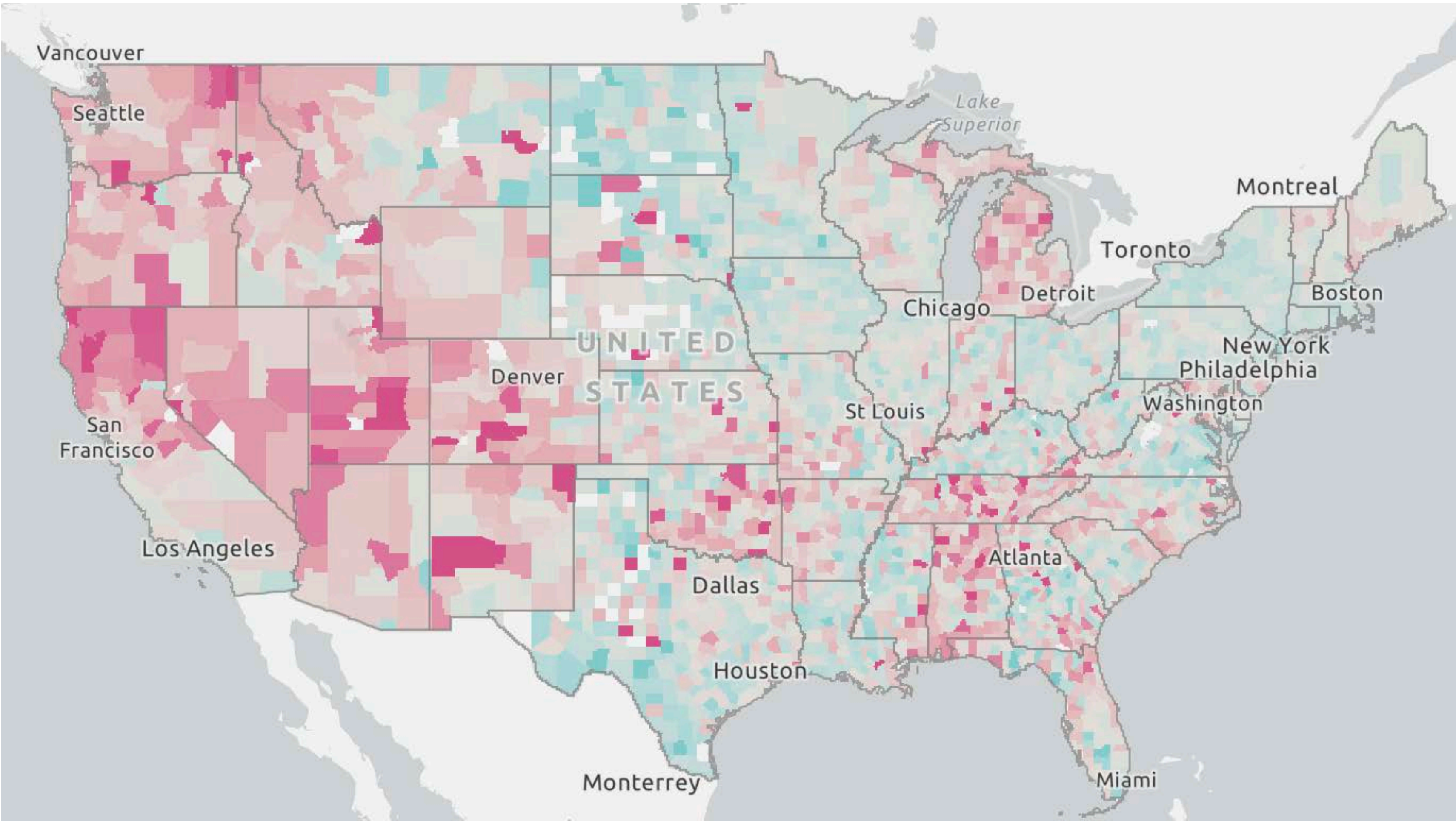
[2]Department of Mathematics, The University of Ottawa,
585 King Edward Ave, Ottawa ON K1N 6N5, Canada
[2]Department of Mathematics and Faculty of Medicine, The University of Ottawa,
585 King Edward Ave, Ottawa ON K1N 6N5, Canada

Applications

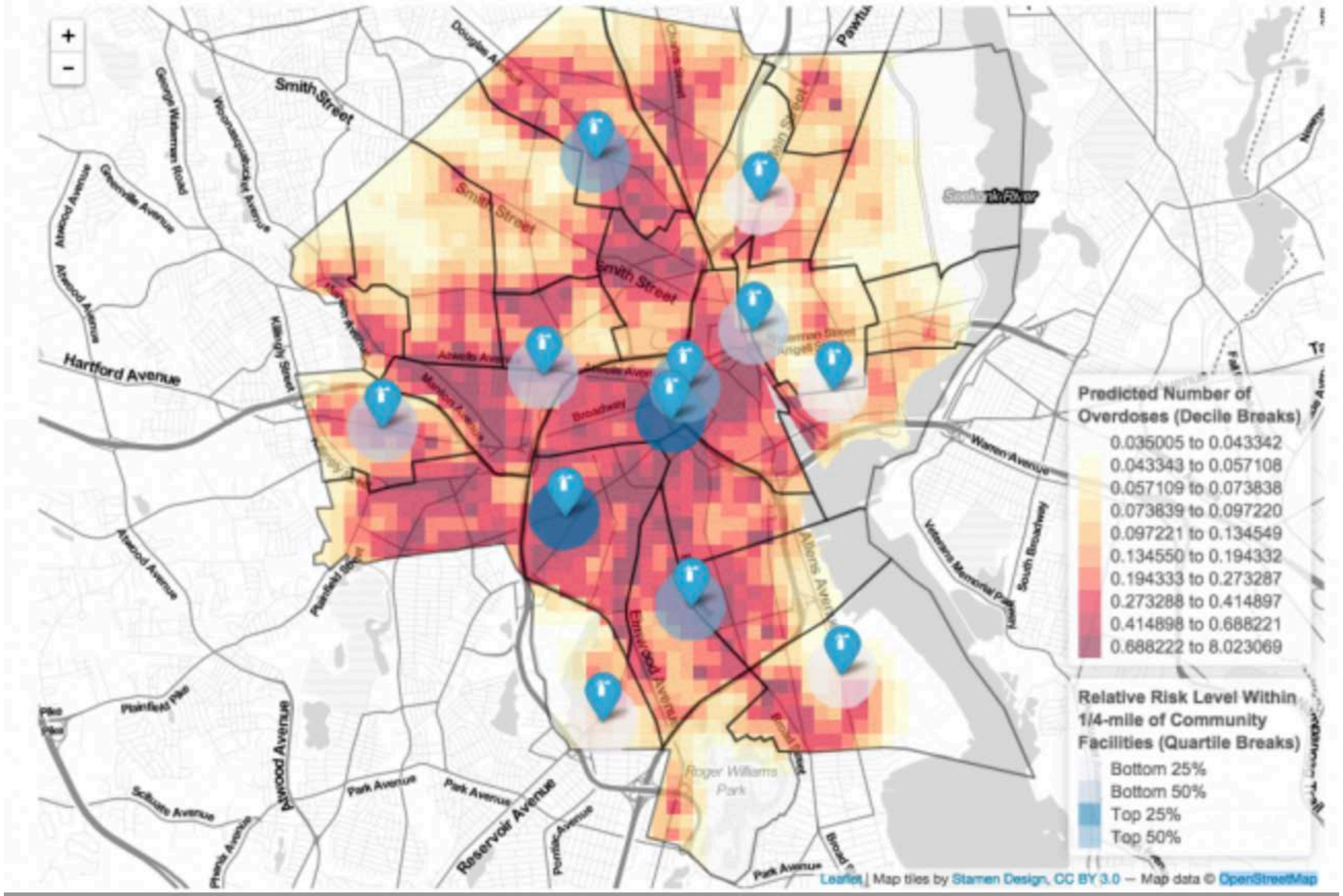
- Disease Surveillance
- Arboviruses and climate change
- Maternal and child health services
- Cancer screening
- Climate policy
- Diabetes
- Alzheimers
- *Homo Necrosis Zombifis*
- *…*

Static Example – Opioid Epidemic



- The Opioid Mapping Initiative

Dynamic Example – Opioid Epidemic



MAP SHOWING OVERDOSE RISK AND THE LOCATIONS OF FIRE STATIONS THROUGHOUT THE CITY.

- Harvard's Map of the Month: Providence Healthy Communities Office

Static Becomes Dynamic Example – Disparities

- http://storymaps.esri.com/stories/2018/mapping-incomes/index.html

LiveSlides web content

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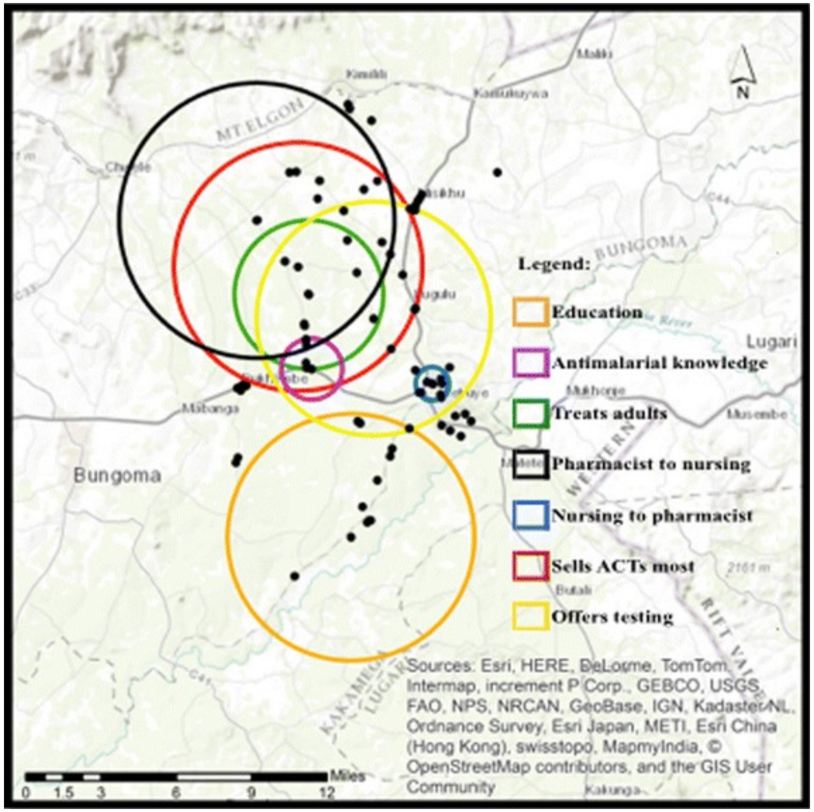
Finding statistical significance in Space

- Malaria elimination efforts in Webuye, Bongoma, Kenya
- Outbreak data was well tracked and available
- Delay in correct treatment was associated with outbreak clusters
- Measuring determinants to antimalarial dispensation
- Rural areas = lower pharmacy training levels, fewer shops offering Dx testing
- Urban areas = lower nursing training levels



Rusk A, Highfield L, Wilkerson JM, Harrell M, Obala A, Amick B. Spatial distribution and cluster analysis of retail drug shop characteristics and antimalarial behaviors as reported by private medicine retails in western Kenya: informing future interventions." Int J Health Geogr. 2016; 15:9

Areas of Risk & Intervention Successes

- Disease risk in 2006 & 2010 = Incidence rates from clinical reports, population data from AfriPop, climatic and environmental conditions from NASA
- Intervention effects = logit change in risk as *f* of climatic and seasonal condition changes, intervention coverage, income, education, age, adherence, housing
- Interactions with endemicity levels accounts via regional intervention effects calculations

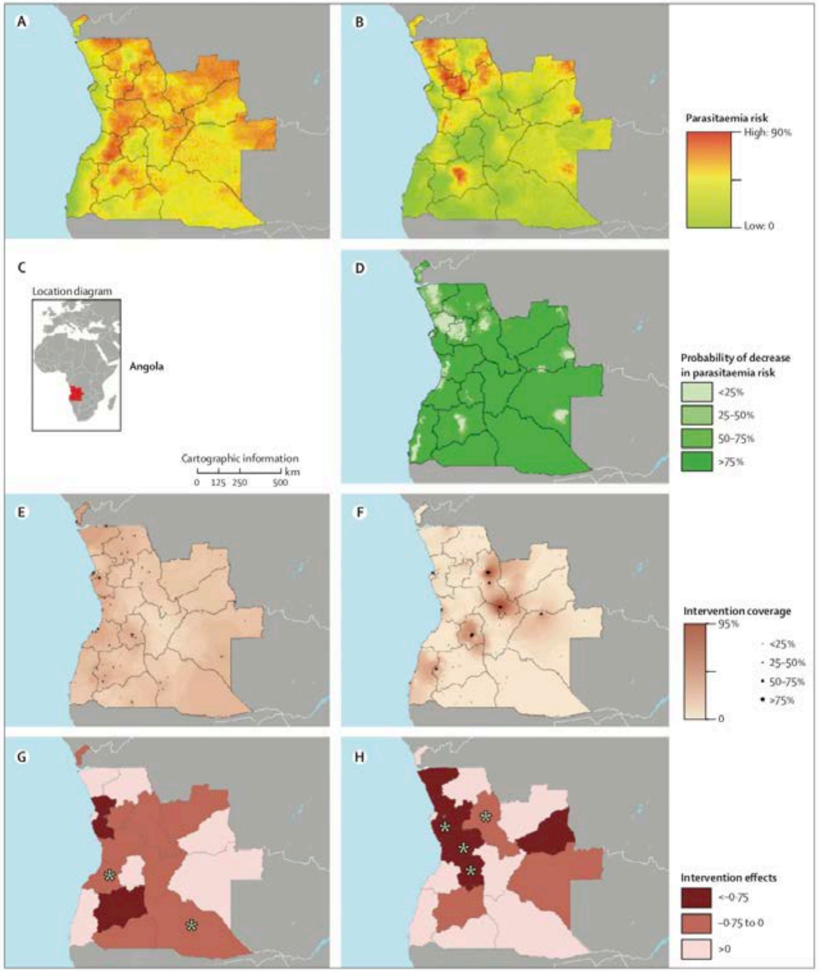


Figure 1: Angola
Predicted parasitaemia risk in 2006 (A) and 2010 (B), location diagram and cartographic information (C), probability of observing a decline in the period 2006–10 (D), ITN (E) and IRS (F) coverage maps, estimated effects of interventions: ITN (G) and IRS (H) (median plotted). ITN=insecticide-treated nets. IRS=Indoor residual spraying. *Statistically significant effect.

Giardina, Kasasa, Sie, Utzinger, Tanner, Vounatsou. Effects of vector-control interventions on changes in risk of malaria parasitaemia in sub-Saharan Africa; a spatial and temporal analysis. 2014; 2

Controlling for spatial confounding – Drug Resistance

- Static
- Interactive

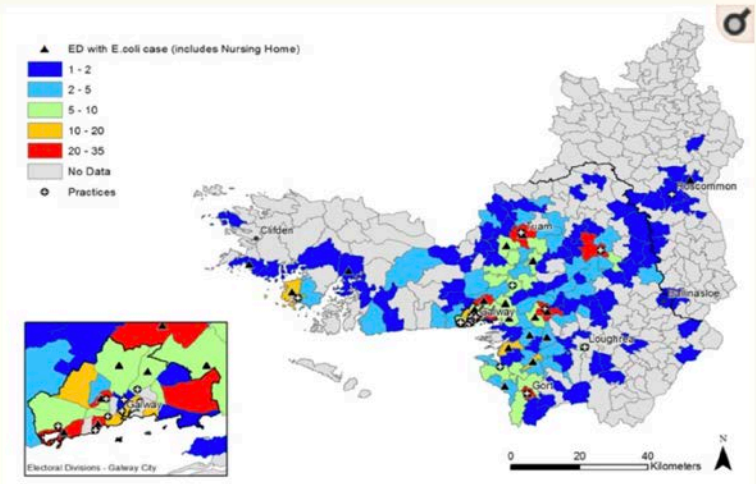


Figure 1

Distribution and frequency of *E. coli* urinary tract infection (UTI) cases, practices and nursing homes in the study region at electoral division level.

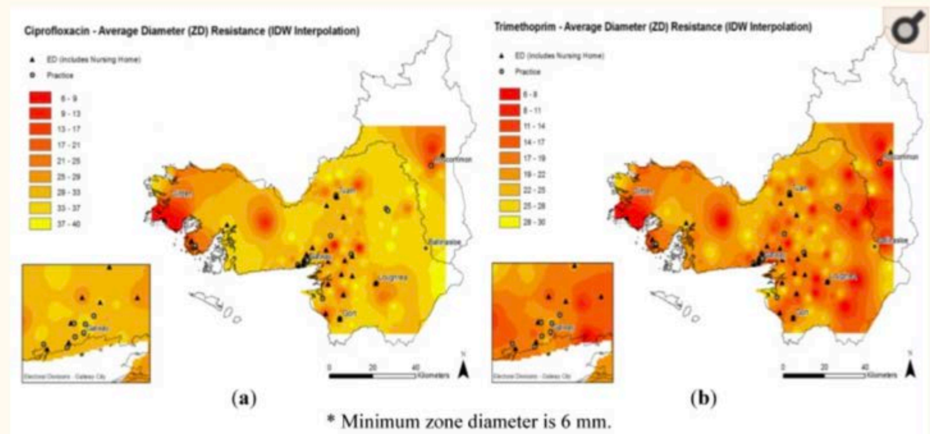


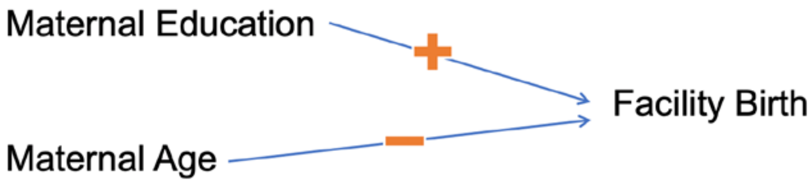
Figure 2

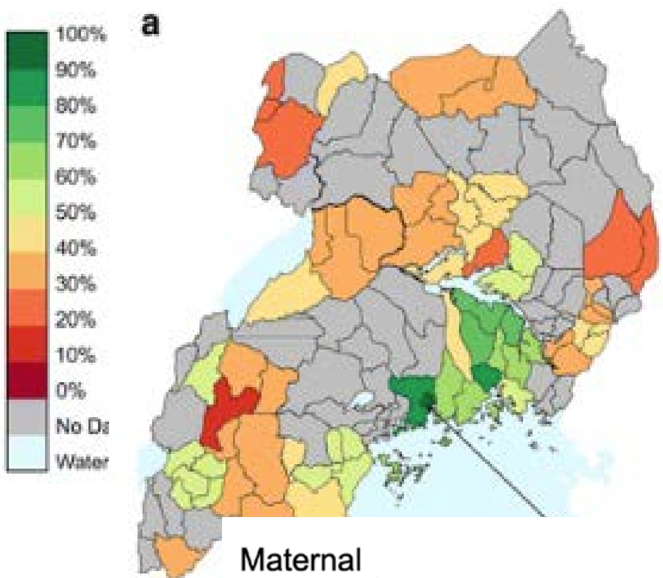
Average antimicrobial susceptibility results * for *E. coli* isolates for (**a**) ciprofloxacin (left) and (**b**) trimethoprim (right).

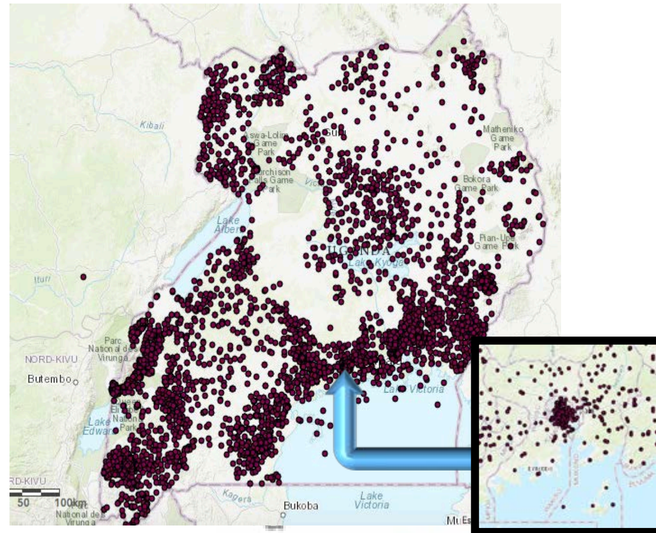
- Distribution of *E. coli* cases in West Ireland
  - Corresponds with population density
- Heat maps of Ciprofloxacin and Trimethoprim resistance
  - Informs prescribing practices (Kiffer et al, 2011)

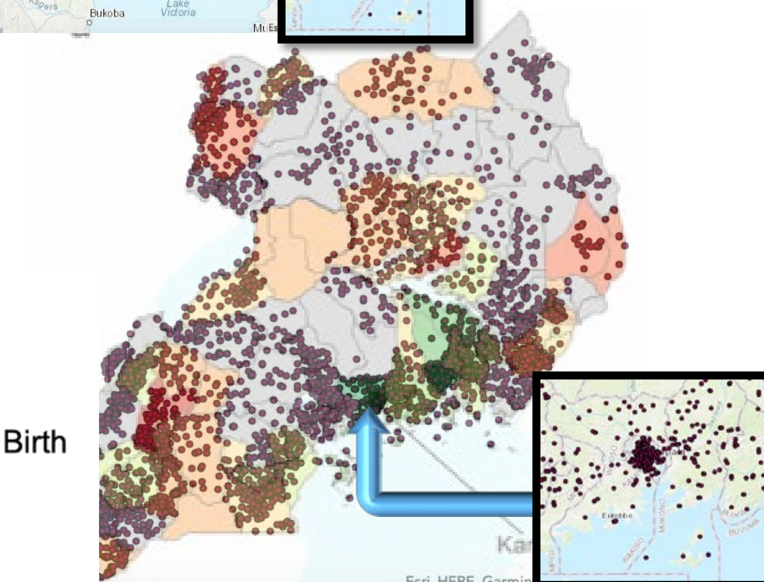
Galvin, Bergin, et al. “Exploratory spatial mapping of the occurrence of antimicrobial resistance in E. coli in the community. Antibiotics 2013; 2(3): 328-338

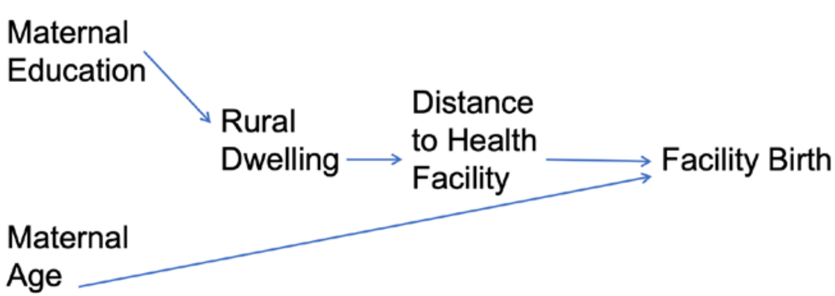
Controlling for confounding WITHOUT space





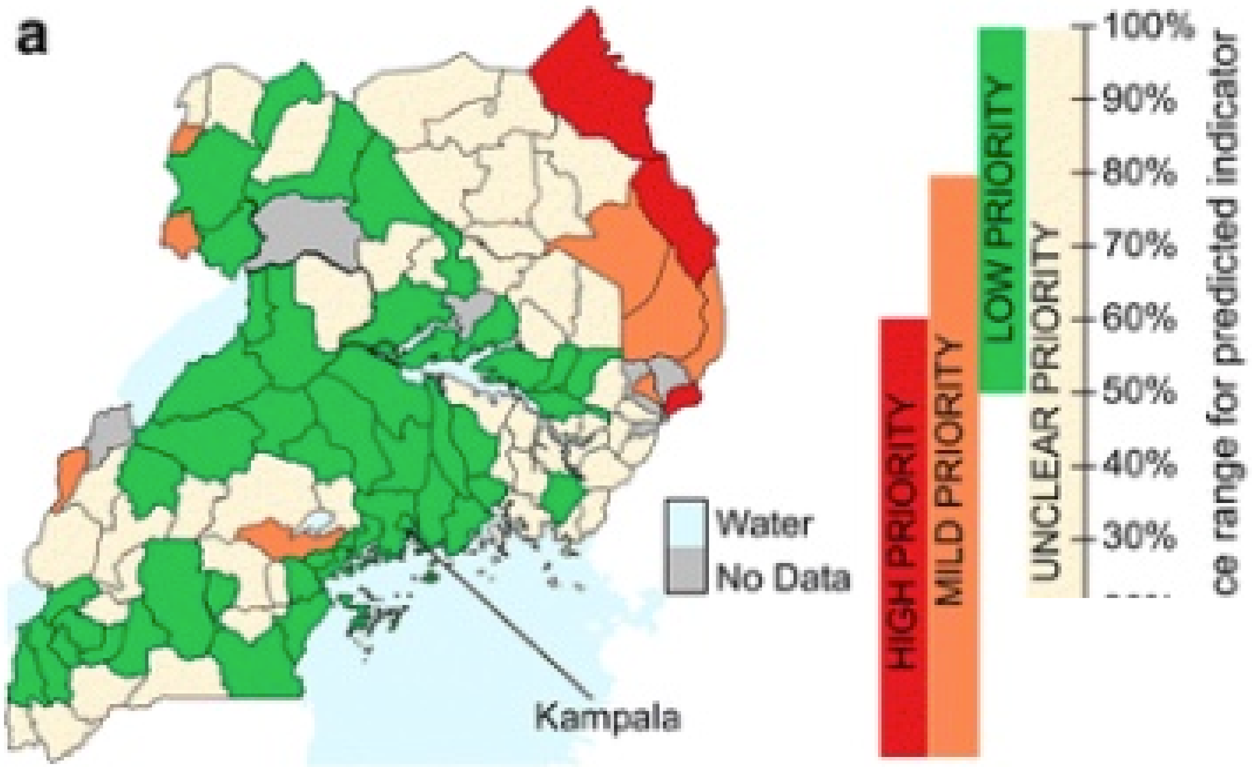


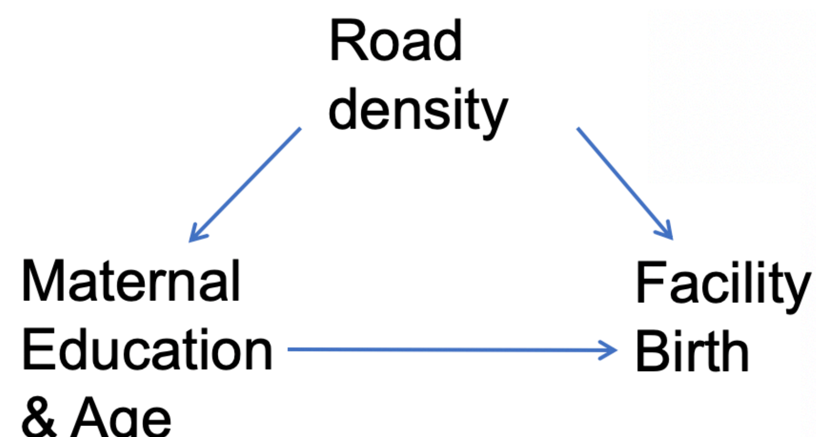




Sprague et al. Assessing delivery practices of mothers over time and over space in Uganda, 2003–2012. *Emerg Theme in Epi* 2016 *13:9*

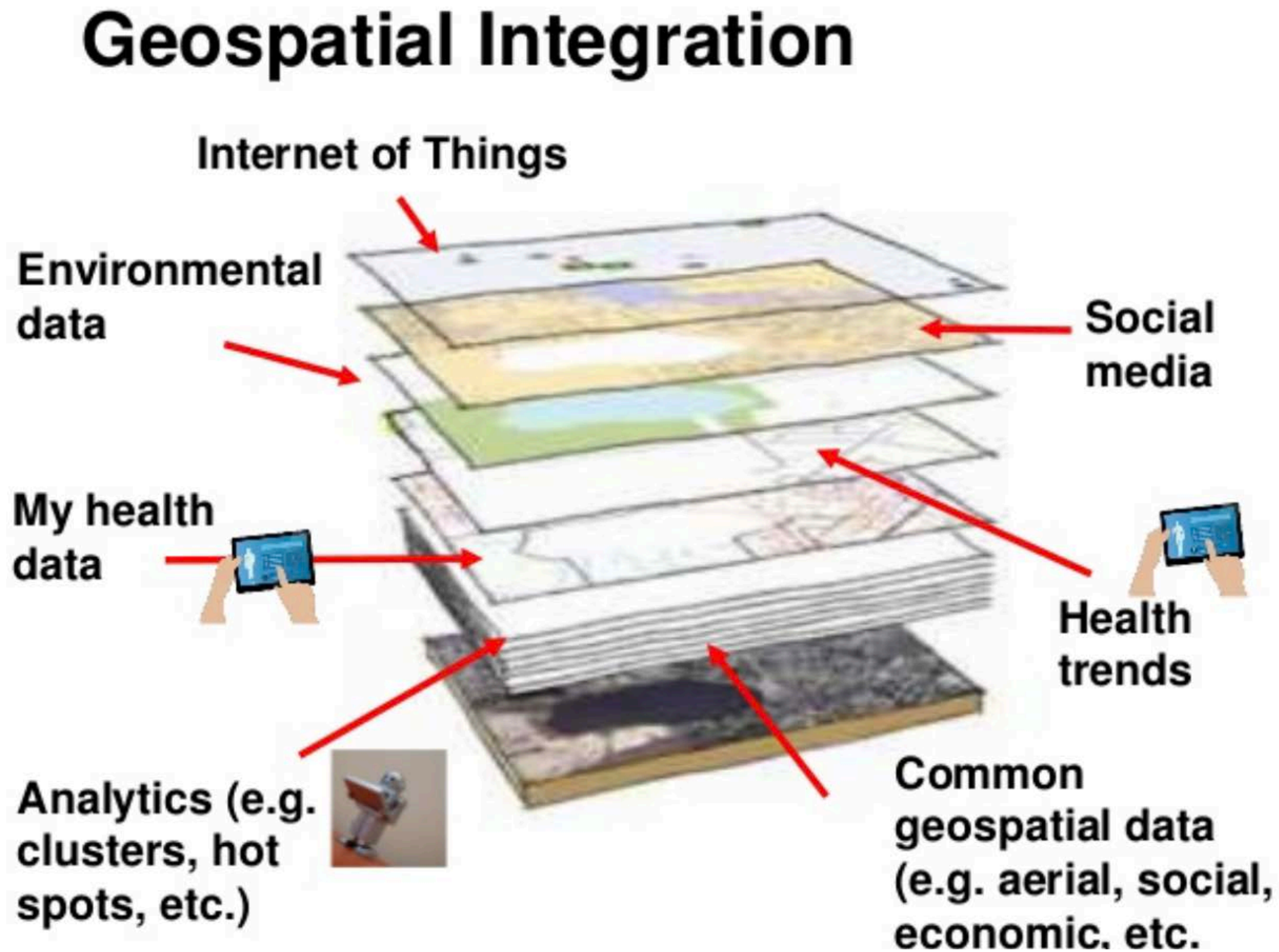
Controlling for confounding WITH space

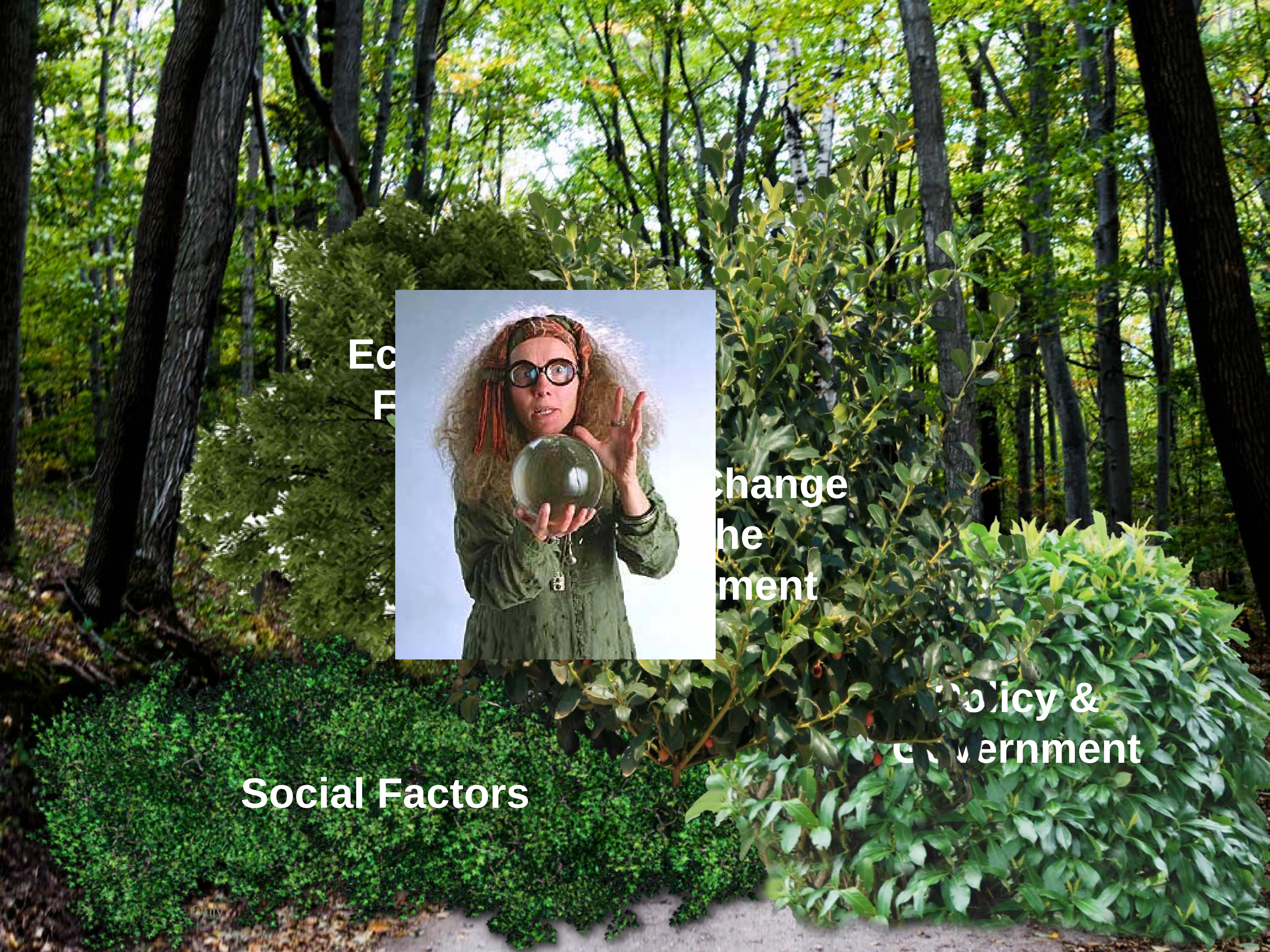




Sprague et al. Assessing delivery practices of mothers over time and over space in Uganda, 2003–2012. *Emerg Theme in Epi* 2016 *13:9*

A layered view – BIG DATA

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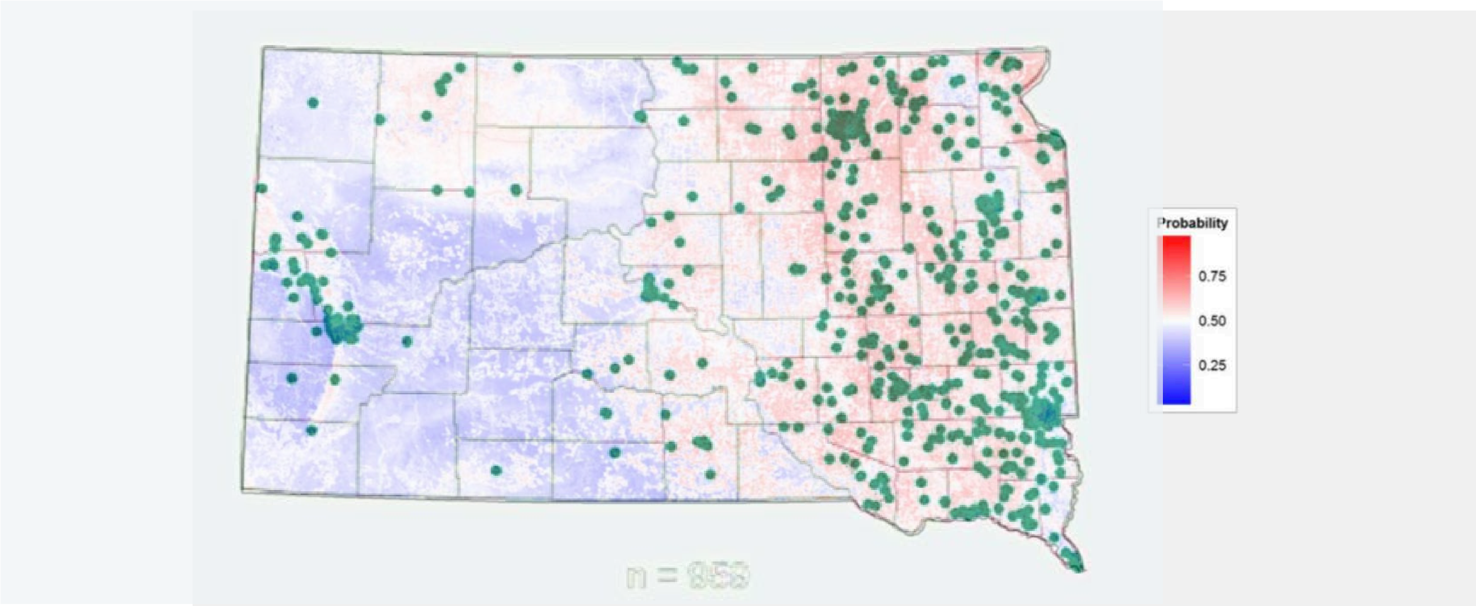
Social Factors

Path to the Future

- Predicting West Nile Virus based on NLDAS climate, land cover, soil, and demographic data



Wimberly, MC “Mapping and forecasting mosquito-borne disease risk” Applied Remote Sensing Training www.nasa.gov SDSU

Path to the Future

- Predicting Zika Virus distribution using temperature, rainfall, vector distribution data, vector reproduction model estimates, historical climate data, population distribution data
- Predicted distribution of Zika risk, involvement of *Ae. Albopictus* as a competent vector, and the causal contribution of the 2015 El Niño weather event.
- For more on machine learning: Bhatt, et al. "Improved prediction accuracy for disease risk mapping using Gaussian process stacked generalization." JR Soc Interface 2017

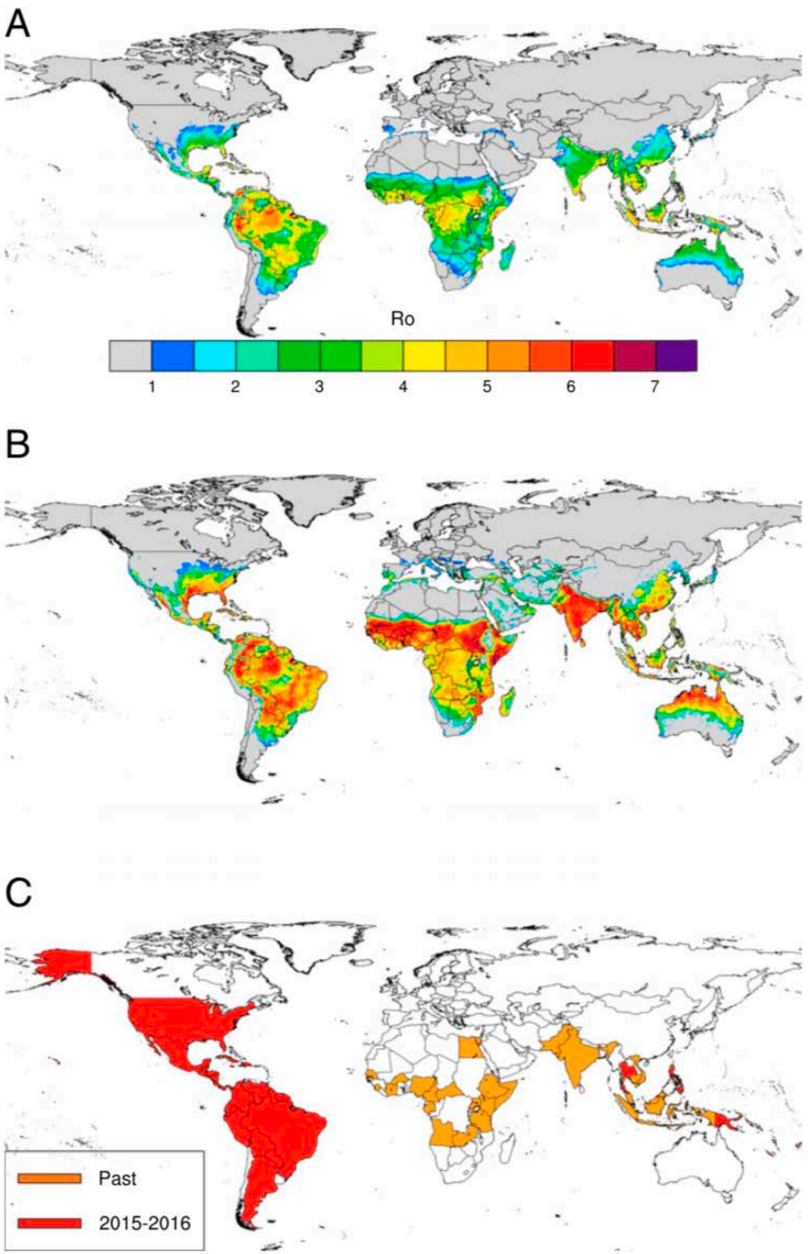
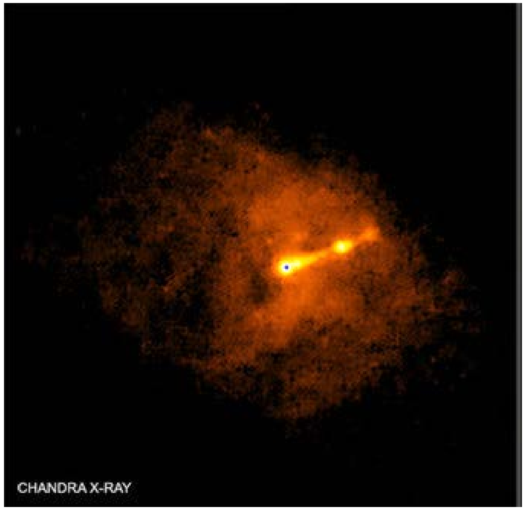


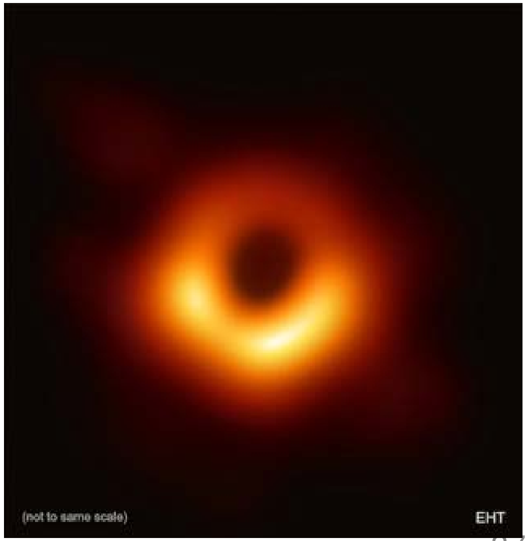
Fig. 1. Observed and simulated ZIKV distribution. (*A*) Mean annual R_0 (calculated over the period 1980–2015), (*B*) annual R_0 peak that represents the largest monthly value over the whole time period (1980–2015), and (*C*) past and recent (2015–2016) countries with reported ZIKV circulation.

Caminade, Baylis et al. "Global Risk model for vector-borne transmission of Zika virus reveals the role of El Nino 2015" PNAS 2016

The Future is Spatial

- Mapping behaviors
  - Geospatial behavioral plurality by outcome
- Integrating systems
  - Healthcare utilization, neighborhood and individual resource & risk mapping
  - Network and service area analysis
  - Environment analysis to monitor & manage disease
- Informing policy
  - Allocating resources
  - Reducing disparities
  - Predicting patterns
  - Targeting interventions





Cool Stuff to Check Out

- Harvard's Map Monday: https://datasmart.ash.harvard.edu/civic-data/data-visualization
- The Opioid Mapping Initiative: http://opioidmappinginitiative-opioidepidemic.opendata.arcgis.com
- The Malaria Atlas Project (MAP): https://map.ox.ac.uk
- Global Forest Change Maps: https://globalforestwatch.org
- Mapping the Millennium Development Goals with The Lancet: https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(17)31758-0/fulltext
- Visualizing geographic data: http://storymaps.esri.com
- The master data visualizer: https://www.ted.com/talks/hans_rosling_shows_the_best_stats_you_ve_ever_seen

Acknowledgements

FIU

Robert Stempel College of Public Health & Social Work

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