

Modeling Ebola

Tachikawa infectious boot camp, 2019

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https://github.com/dushoff/Generation_talks

Outline

Dynamic modeling of infectious diseases

Early Ebola models

- Process error and observation error

- Projection models

Some simple models

- Burial transmission

- Dynamic effects of sub-clinical infections

- More on \mathcal{R}

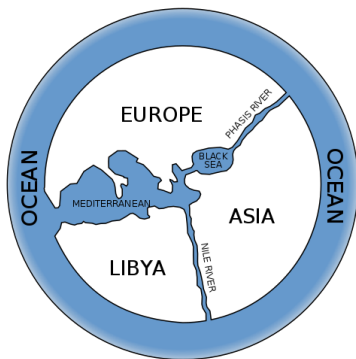
Forecasting

Ethics

- The statistical power and validity of Ebola vaccine trials

Conclusions

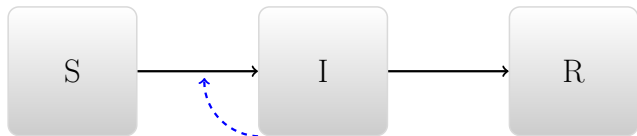
Models



- ▶ A model is a simplified view of the world
- ▶ Allows linking between assumptions and outcomes

Dynamic models

Connect scales



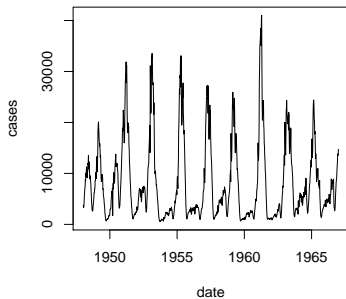
Small-scale events \Leftrightarrow Large-scale patterns and outcomes

Measles

Dynamic modeling connects scales

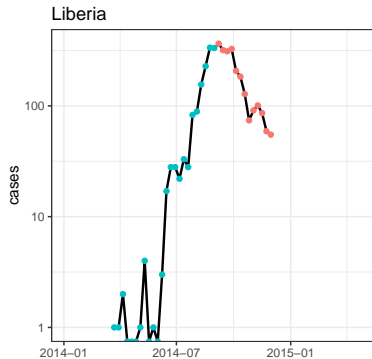


Measles reports from England and Wales



Ebola

Dynamic modeling connects scales

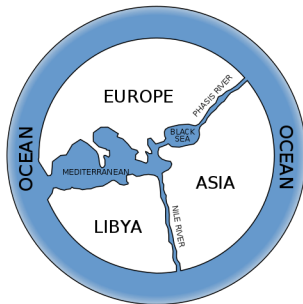


Statistics and theory

- ▶ Dynamical models are required to bridge scales
- ▶ Statistical frameworks are required to interpret noisy data
- ▶ We need tools that can incorporate dynamical mechanisms into frameworks that allow statistical inference
- ▶ Simple dynamical theories allow clearer interpretation and inspire better techniques

Questions

- ▶ Your model is not reality
- ▶ But it may help you answer a specific research question
- ▶ The model you use should be tailored to your question
 - ▶ What are the relevant details?



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Process error and observation error

- ▶ **Observation error:** we don't observe the world perfectly
- ▶ **Process error:** we think our dynamical system has a fundamental random component
 - ▶ This is usually the only way to model processes where we treat individuals as individuals
- ▶ Doing both of these things is hard

Lekone and Finkenstadt, 2006

- ▶ Modeled a small 1995 Ebola outbreak in DR Congo
- ▶ Used latent variables to consider both process error and observation error
- ▶ Result: More realistic model \implies more uncertainty
- ▶ DOI: *10.1111/j.1541-0420.2006.00609.x*

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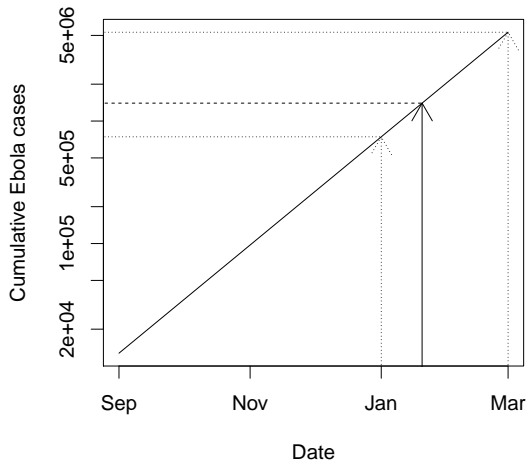
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The CDC projection

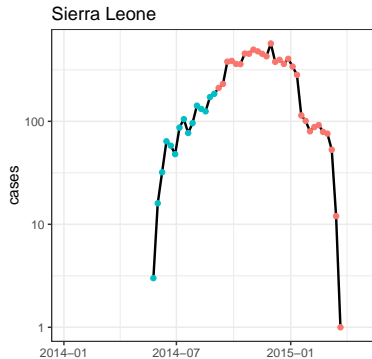
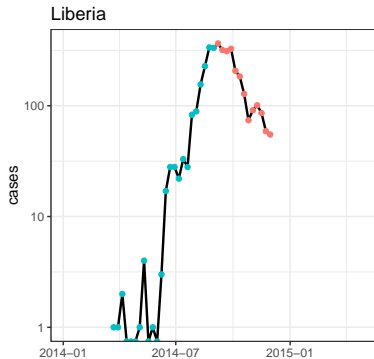
- ▶ Meltzer 2014 estimated > 1 million cases by “Jan 20, 2015” unless effective action was taken
- ▶ Model contained contained many compartments for infected people
 - ▶ disease stage, linkage to treatment
- ▶ Very crude handling of contact patterns, susceptibles



Projection models

- ▶ Wrong level of detail
- ▶ But they did address a question:
 - ▶ Does the West Africa Ebola epidemic have the potential to be a global crisis?

The epidemic

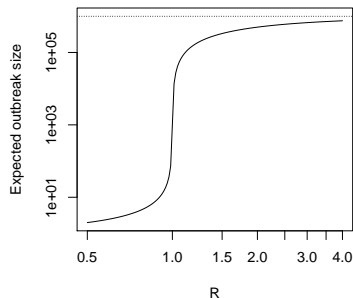


Ebola outbreaks

- ▶ Before 2014, most Ebola outbreaks were either
 - ▶ very small, or
 - ▶ pretty large (compared to some estimate of population at risk in a remote village)
- ▶ More or less consistent with simple picture

Predicted outbreak size

- ▶ Simple models argue that outbreaks should (almost always) be:
 - ▶ Very small (sub-critical), or
 - ▶ Very large (at the scale of the population)



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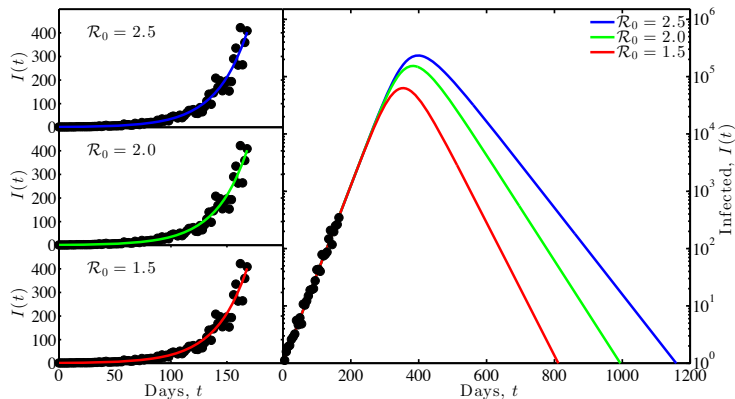
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Ebola outbreak (repeat)



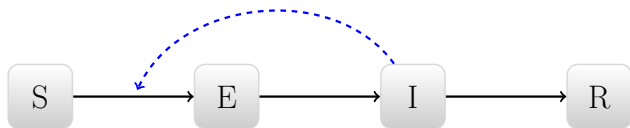
$C \approx 1$ month.

Post-death transmission and safe burial

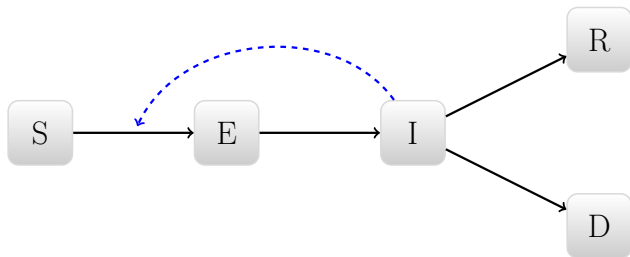
- ▶ What proportion of Ebola spread occurs before vs. after death?
- ▶ Highly context dependent
 - ▶ Funeral practices, disease knowledge
- ▶ What if it's more than we think?
 - ▶ Disease spreads slower?
- ▶ *Weitz and Dushoff Scientific Reports 5:8751.*



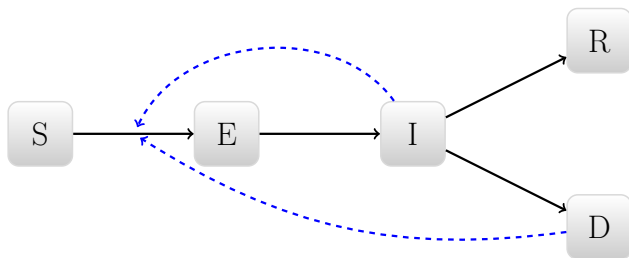
Standard disease model (present)



Disease model including post-death transmission (present)



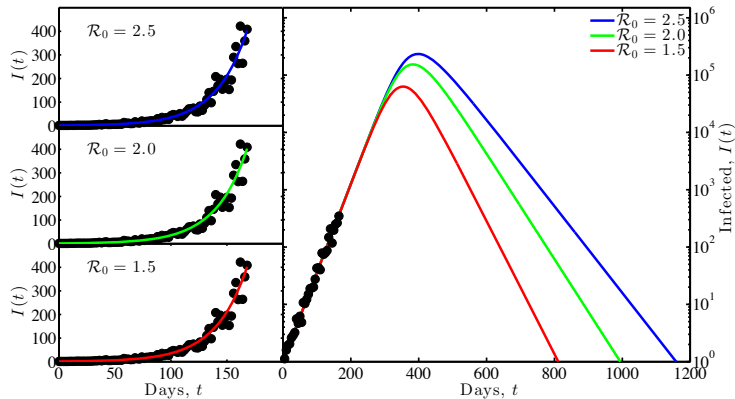
Disease model including post-death transmission



Ebola burial example

- ▶ Burial transmission increases the mean generation interval
 - ▶ *Increases* estimate of \mathcal{R}
- ▶ ...increases variation
 - ▶ *Decreases* estimate of \mathcal{R}
- ▶ So what's the result?
 - ▶ It feels like it should increase
 - ▶ The filtered mean approach tells us: shifting transmission later must increase the estimate

Scenarios (repeat)



Summary

- ▶ Different parameters can produce indistinguishable early dynamics
- ▶ More after-death transmission implies
 - ▶ Higher \mathcal{R}_0
 - ▶ Larger epidemics
 - ▶ Larger importance of safe burials
- ▶ $r = \text{strength something} \times \text{generation speed something}$

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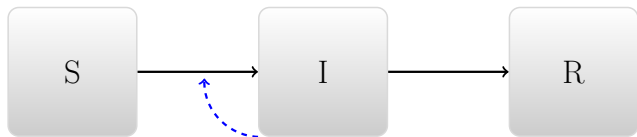
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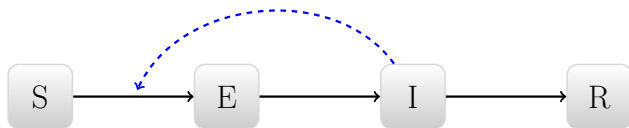
Dynamic effects of sub-clinical infections

- ▶ People with no history of clinical Ebola illness have Ebola-specific antibodies:
 - ▶ In forests where animals carry Ebola
 - ▶ In places where past Ebola outbreaks have occurred
- ▶ What if $\approx 50\%$ of infected people have *sub-clinical* infection?
- ▶ *Bellan et al. Lancet 384:1499–1500, October 2014*

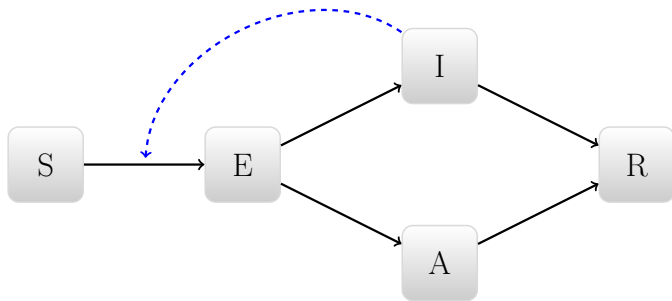
Standard epidemic model (present)



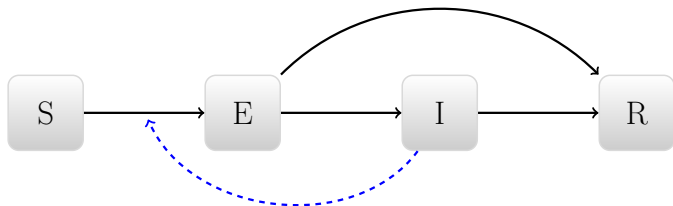
Add an exposed class (present)



Add sub-clinical immunity



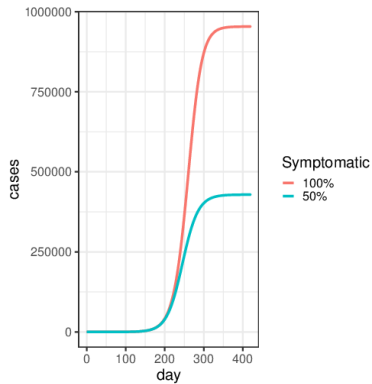
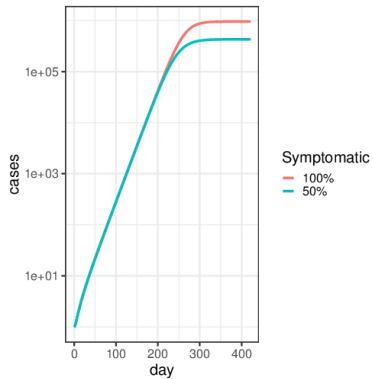
Simplify



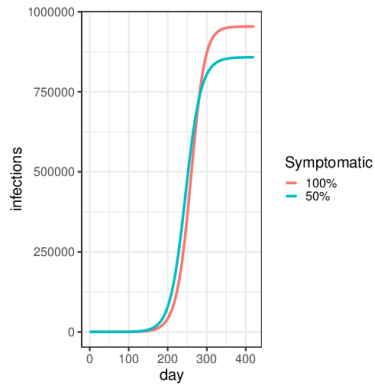
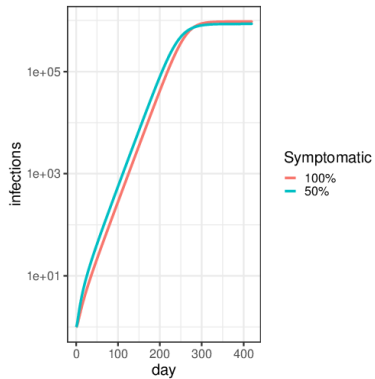
What is the effect of sub-clinical immunity?

- ▶ What do we already know?
 - ▶ Parameters and starting conditions?
 - ▶ Incidence time series?

Ebola cases



Ebola *infections*



Estimation

- ▶ Indirect evidence
 - ▶ Not enough information, and too many complications
 - ▶ Population structure, changes through time
- ▶ Direct evidence
 - ▶ Easy: how common is sub-clinical infection?
 - ▶ More evidence is available now
 - ▶ ... but not as much as we expected.
 - ▶ Hard: how protected are people who recover from it?

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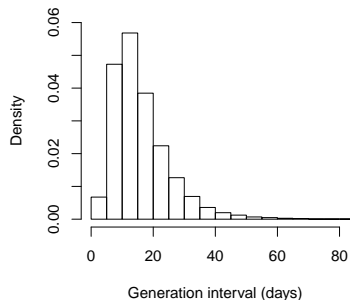
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Fitting to Ebola (repeat)

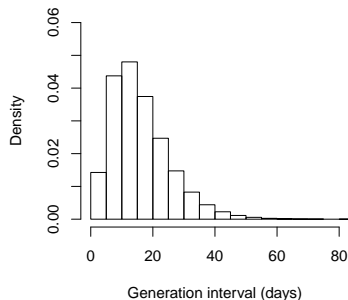
- ▶ Simulate generation intervals based on data and approach from WHO report
- ▶ Use both lognormals and gammas
 - ▶ WHO used gammas
 - ▶ Lognormals should be more challenging

Approximating the distribution (repeat)

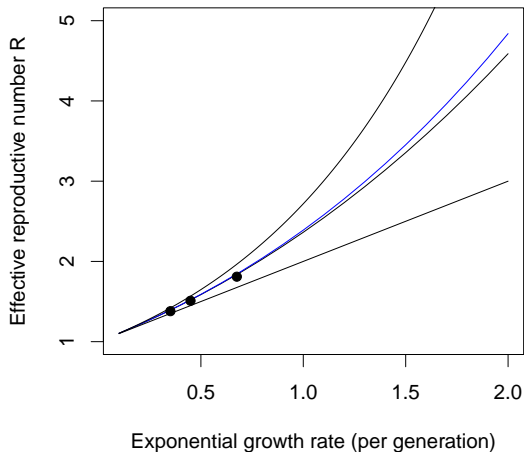
Lognormal SEIR



Single-gamma approximation



Approximating the curve (repeat)



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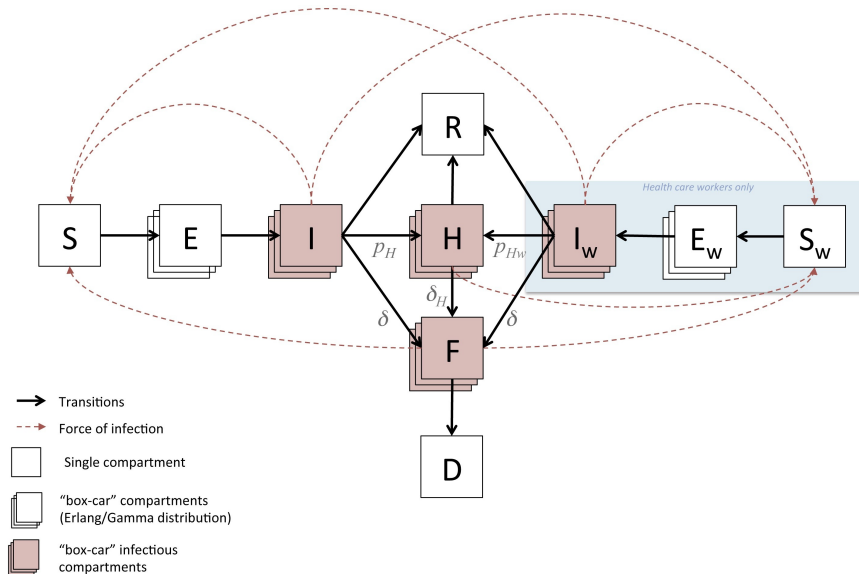
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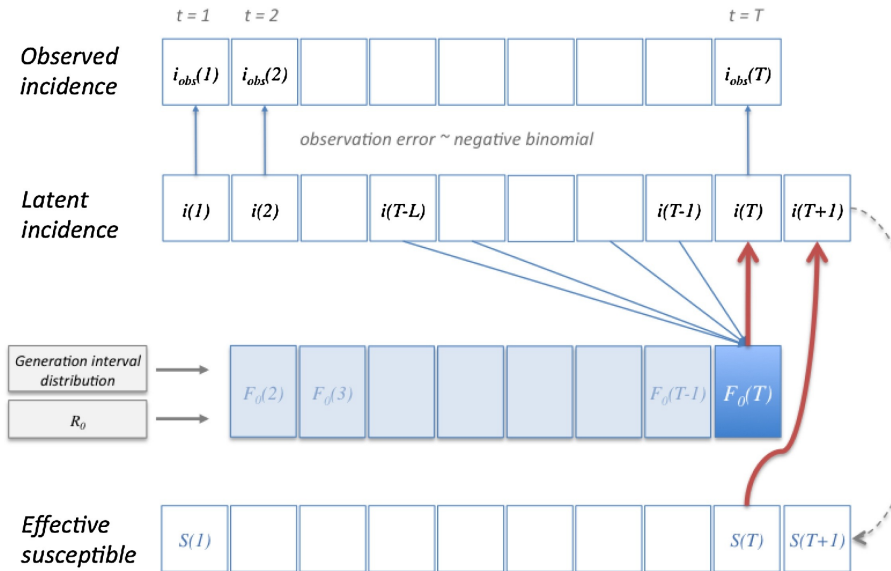
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Compartment model approaches

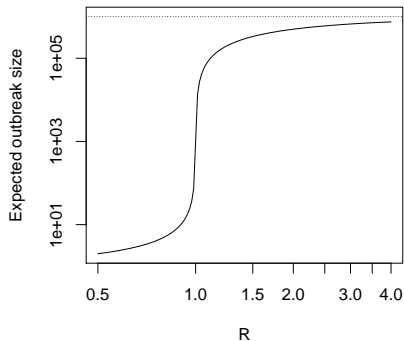


Discrete-time renewal equation



What else do we need to add? (present)

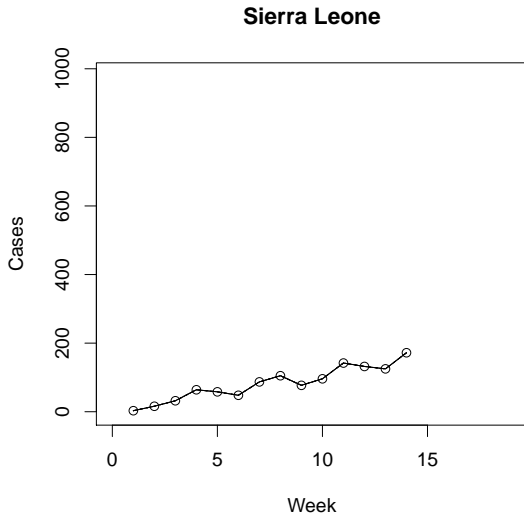
Why do we see medium-sized epidemics?



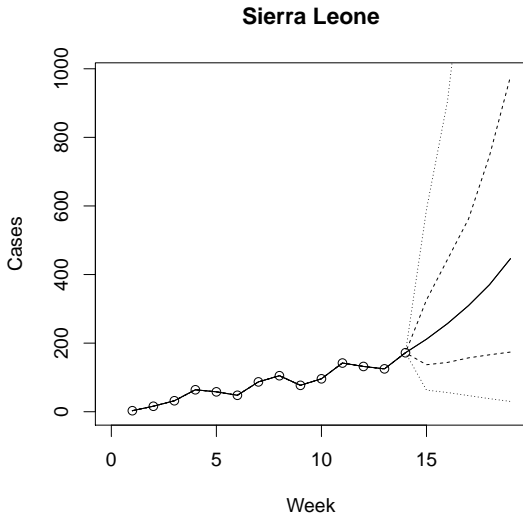
Relevant detail

- ▶ The things we are good at estimating and modeling may not be sufficient to forecast Ebola spread
- ▶ We don't know enough about:
 - ▶ contact structures
 - ▶ beliefs and behaviours

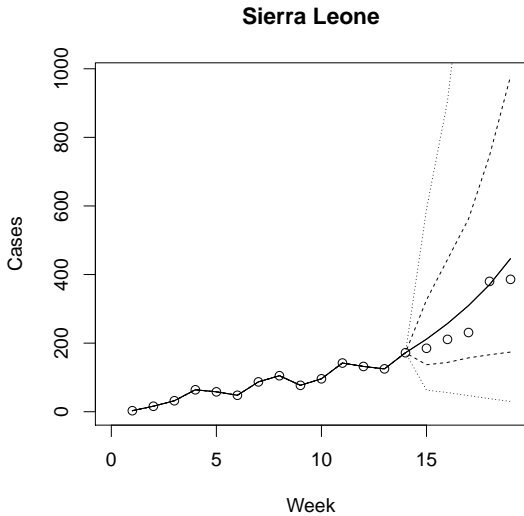
Report what we don't know? (present)



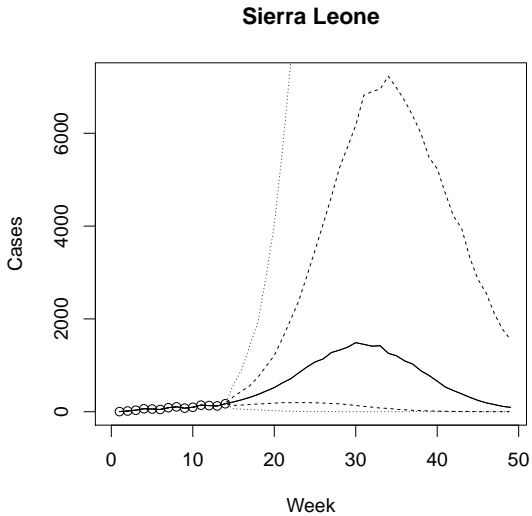
What we don't know (present)



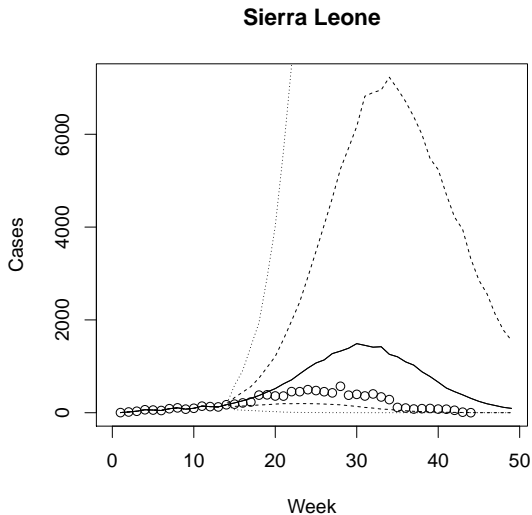
What we don't know (present)



What we don't know (present)



What we don't know!



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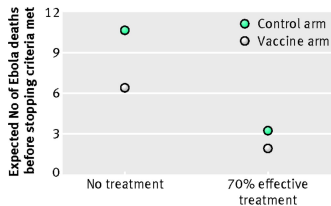
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- ▶ History of abuse → strong rules
- ▶ In general, you can't put public good ahead of participant interests
- ▶ It's hard to achieve clinical equipoise – would *you* want to be in the control arm?
- ▶ *Bellan et al., BMJ 2014;349:g7518*



Vaccine trials

- ▶ What are the *ethics* of controlled trials in the middle of a deadly epidemic?
- ▶ What are the *logistics* of controlled trials on the down-slope of an epidemic?

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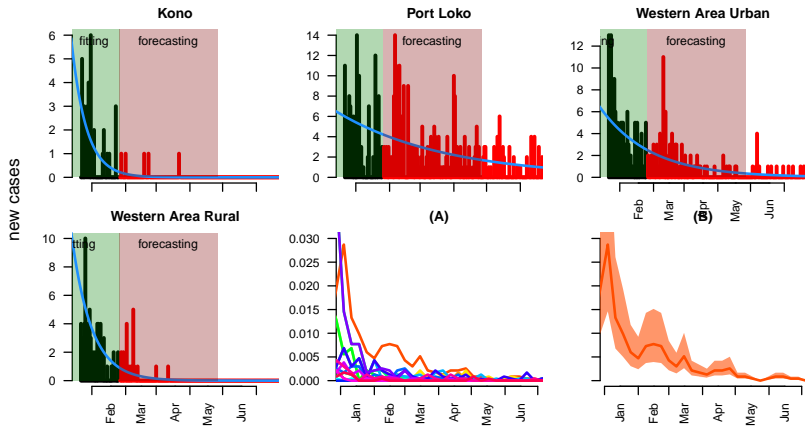
Randomized controlled trials

- ▶ The gold standard of medical evidence
- ▶ A plan is made, and then participants are individually and randomly assigned to **treatment** and **control** groups
- ▶ Control groups sometimes get something that is meant to be good for their health, too
 - ▶ E.g., a meningococcal vaccine

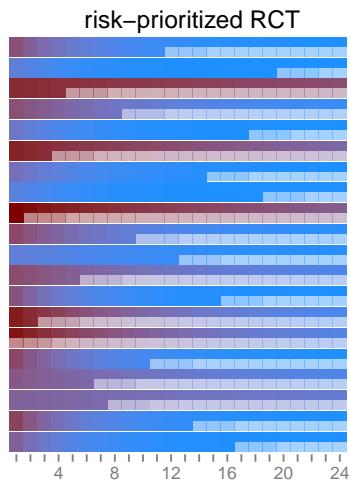
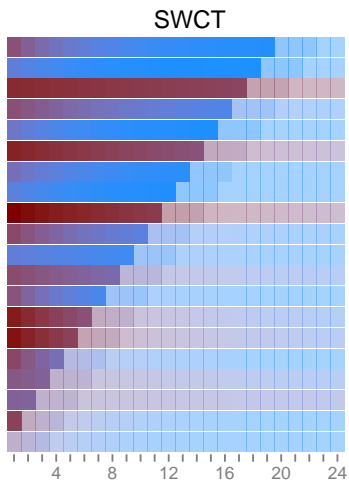
Stepped-wedge controlled trials (SWCT)

- ▶ Sometimes it's unethical to delay vaccination (or other treatment) to participants
- ▶ You still can't necessarily vaccinate everyone at once
- ▶ It may be possible to evaluate efficacy by randomizing the *order* in which people are vaccinated
 - ▶ A free lunch!
- ▶ This is a relatively *fragile* idea
 - ▶ Not as powerful as RCT
 - ▶ If RCT is not ethical, then it's also not ethical to make logistical concessions to study objectives

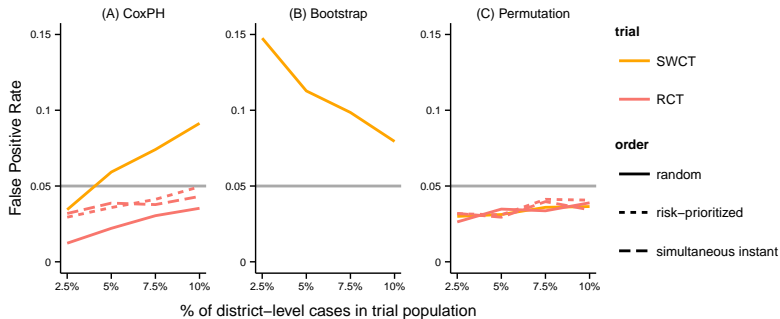
Simulated incidence



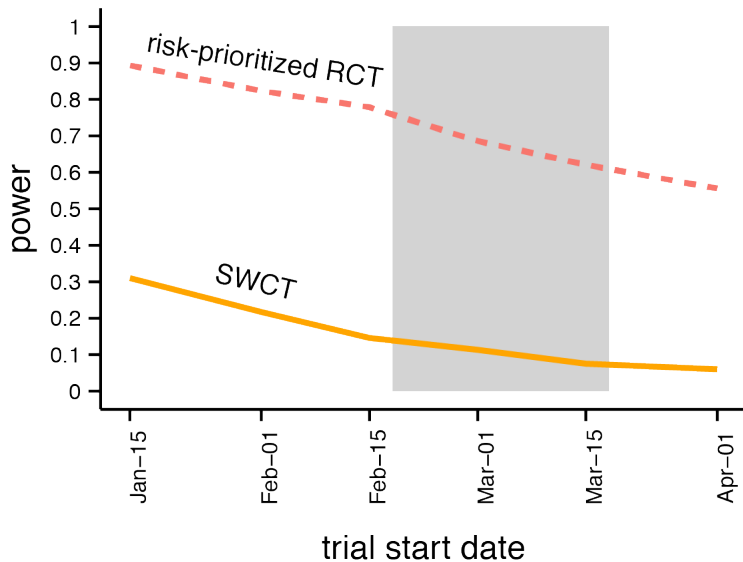
Vaccine rollout scenarios



Statistical validity



Statistical power



Summary

- ▶ Spatiotemporal variation undercuts SWCT
 - ▶ Reduces power
 - ▶ Reduces or eliminates ethical advantages
- ▶ RCTs surprisingly robust to all kinds of issues
 - ▶ Also allow prioritization
- ▶ Permutation tests can rescue statistical validity
- ▶ Changing landscapes
 - ▶ Hard to do an Ebola vaccine trial when incidence is very high or very low

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- ▶ Dynamic models allow us to explore the meaning of *scientific* hypotheses
- ▶ They are most useful when they help us understand mechanisms in a scientific way
 - ▶ Don't trust mathematical results that you can't explain
- ▶ We need to recognize what we don't know
 - ▶ Use statistical methods
 - ▶ Recognize when your uncertainty is large