Digital health and computational epidemiology

Lesson 16

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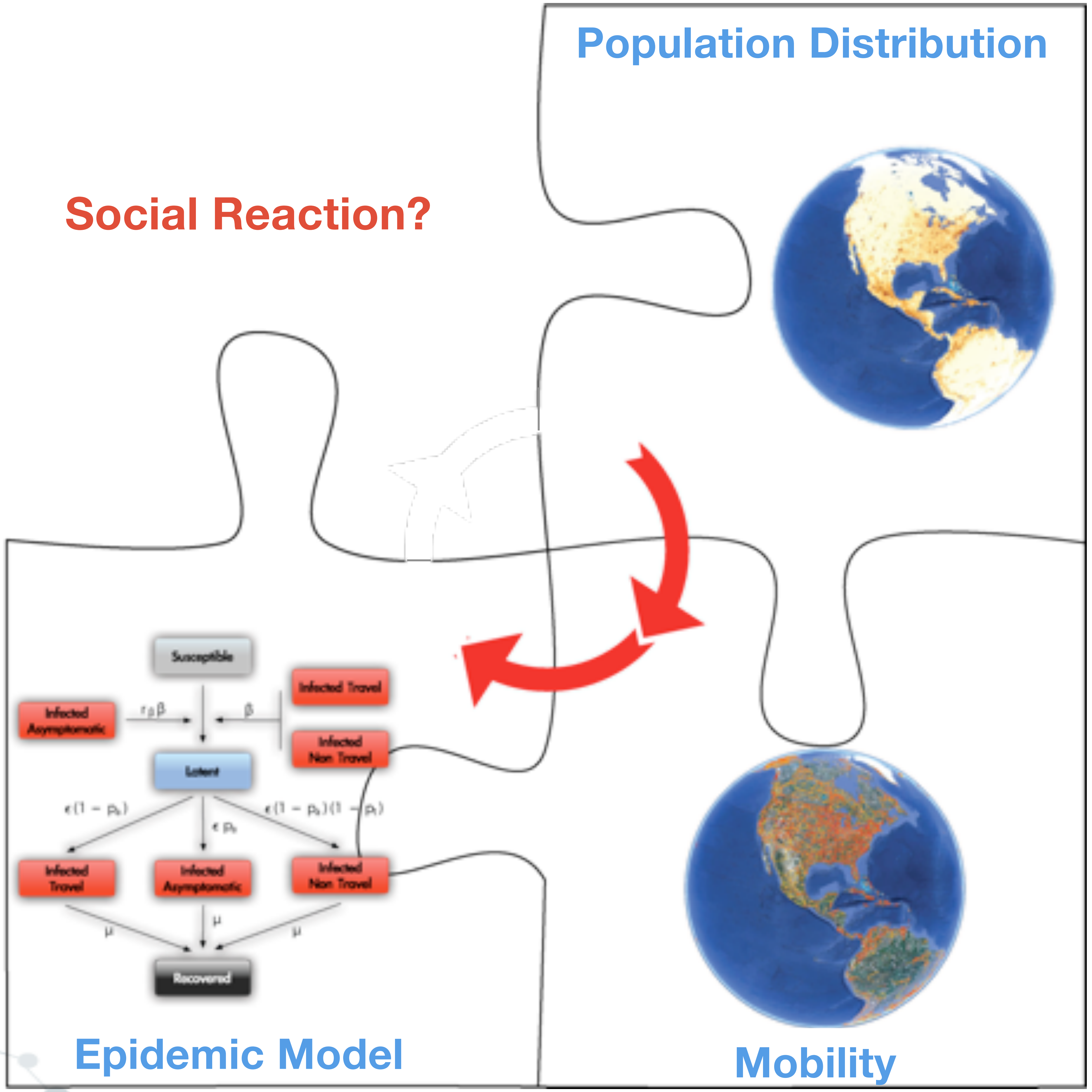
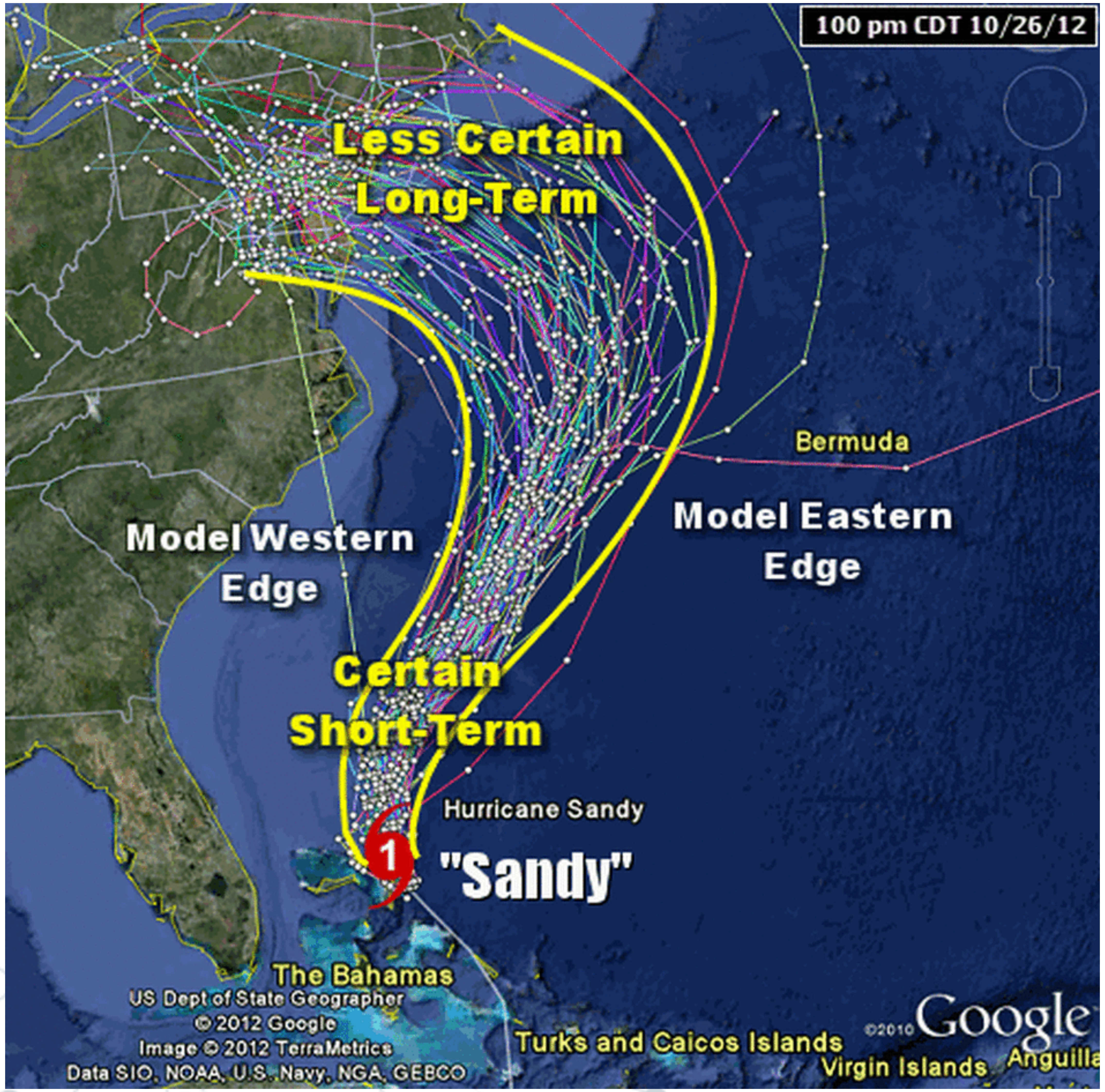
Human behaviour and epidemics

The missing piece of the puzzle



Infectious disease forecasting?



- As an hurricane approaches the mainland, people will react to its predicted trajectory by taking shelter.
- This will not change the hurricane's path which is of course independent from people reactions.
- In epidemic forecasting, individuals will change behaviour as the pathogen spreads but this will in turn change the outbreak dynamics.
- Forecasting efforts need to integrate human adaptation.

Human behaviour

- How do people adapt their behaviours in response to the spreading of infectious diseases?
- How such changes can affect the unfolding of the disease?
- Can we model these changes with mathematical or numerical methods?
- Can we collect digital data to understand these phenomena?

Capturing human behaviour

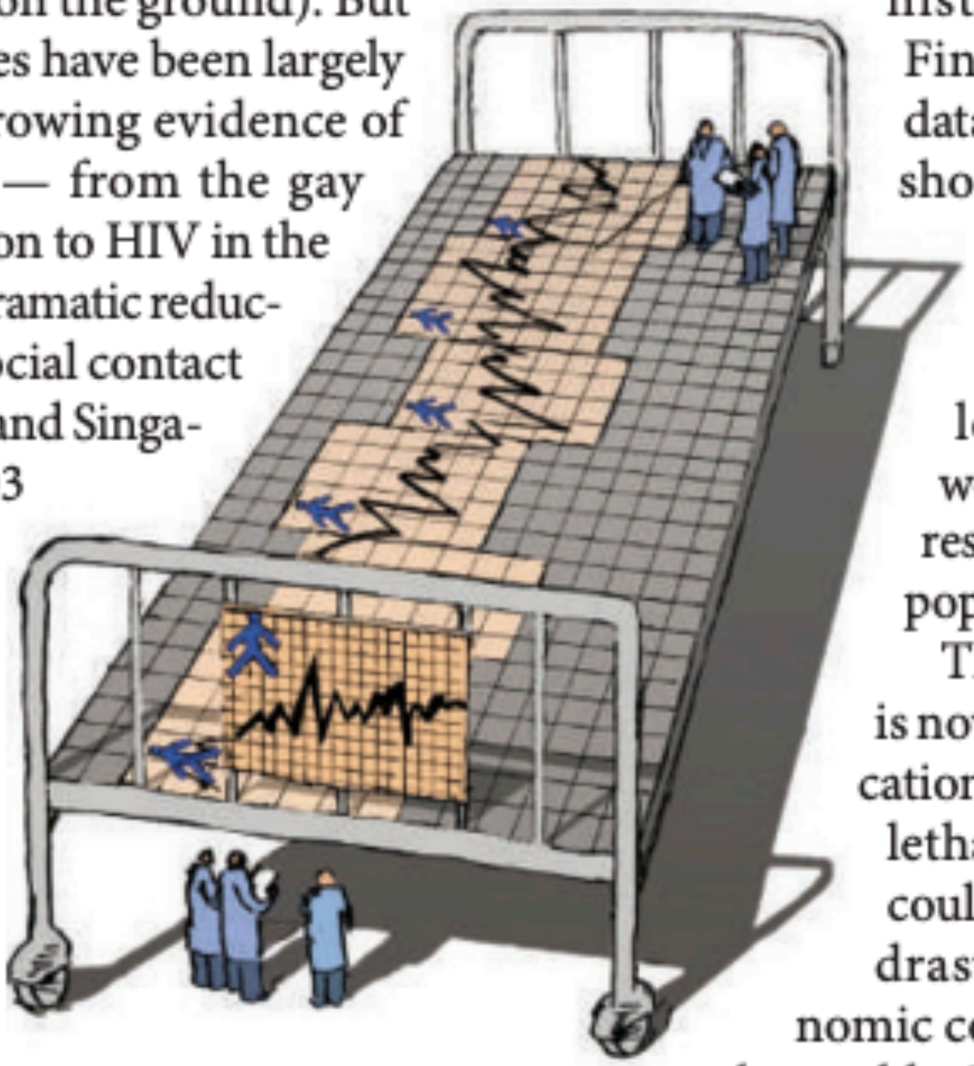
Understanding the dynamics of infectious-disease transmission demands a holistic approach, yet today's models largely ignore how epidemics change individual behaviour.

Neil Ferguson

We live in an ever more connected, mobile and interdependent world, where small perturbations can have unpredictable and sometimes far-reaching effects. The paradox is that we increasingly demand predictability. From climate to car design, we expect the future to be anticipated, risks assessed and solutions to be rational. We have to be 'on top' of everything — including threats from infectious diseases.

In response to this trend, policy-makers increasingly turn to epidemic models as a tool in tackling potentially catastrophic outbreaks, from Britain's foot-and-mouth epidemic of 2001 and SARS in 2003 to the pandemic threat now posed by the H5N1 strain of avian flu. Better data, significantly boosted computer power and theoretical advances — particularly from the social sciences — have endowed models with a new realism. Yet fundamental limitations remain in how well they capture a key social parameter: human behaviour.

The subtlety in epidemic modelling lies in how the processes of human contact that underlie transmission and the biology of the host–pathogen interaction are represented. It is in this area that social science has had the greatest impact. Past models represented societies as 'compartments' of identical individuals all mixing randomly; the new paradigm is social networks characterized by either casual or intimate contact — the former being more relevant for respiratory diseases, the latter for sexually are one way that behaviour can change, but people may also spontaneously modify their behaviour to reduce perceived risk. Public-health measures are often examined prospectively in models (although many retrospective studies of outbreaks only crudely capture the complexity of controls implemented on the ground). But individual responses have been largely ignored, despite growing evidence of their importance — from the gay community's reaction to HIV in the early 1980s, to the dramatic reduction in travel and social contact seen in Hong Kong and Singapore during the 2003 SARS epidemic. Even absenteeism resulting from illness or caring for sick dependants can significantly affect close-contact networks, by removing people from workplaces.



J. KAPUSTA/IMAGES.COM

By modifying the contact network, behavioural changes during an epidemic can give dynamics very different from the kind predicted by simple models. Most basic models assume that all parameters are static, but in fact people's responses often shift as an epidemic progresses. Individuals are most likely to change their contact patterns when mortality or the perception of risk is high, and resume normal life as the perceived risk declines. A case in point of research need to be pursued. The first is controlled epidemiological intervention studies to determine how modifying contact networks affects disease transmission. Another will be the integrated collation and analysis of epidemiological and, preferably, quantitative social data from historical epidemics. Finally, protocols and data-collection systems should be designed to track the number of people infected per day in a future lethal outbreak as well as the behavioural response of the affected population.

The time for this work is now: global communications mean that a novel lethal disease outbreak could trigger potentially drastic social and economic consequences across the world within days.

From a public-health perspective, the goal is improving our ability to predict and control epidemics — but that may first require new sociological models that are both predictive and quantitative. So the interdisciplinary approach remains vital, this time at the interface of epidemiology, sociology and the history of medicine.

Beyond public health, what is there in this enterprise to motivate sociologists, anthropologists or historians? Under-

ESSAY

Putting the pieces together

Capturing human behaviour

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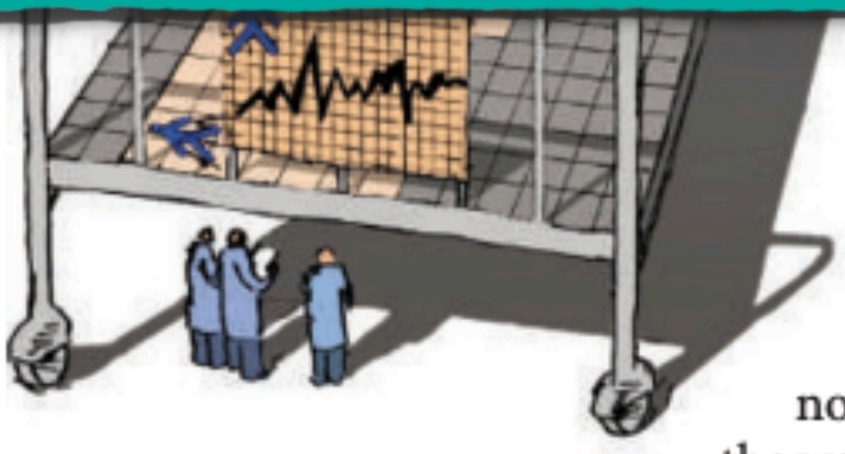

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Human behaviour

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REVIEW

Modelling the influence of human behaviour on the spread of infectious diseases: a review

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Nine challenges in incorporating the dynamics of behaviour in infectious diseases models

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Review

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Behavioural change models for infectious disease transmission: a systematic review (2010–2015)

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We review behavioural change models (BCMs) for infectious disease transmission in humans. Following the Cochrane collaboration guidelines and the

Classic approach

Several variations of the classic SIR model, to account for additional compartments: those who have information about the disease, who are scared, etc…

Common assumptions:

- behavior is driven by prevalence of the disease
- as prevalence increases, more people will change their habits
- as the epidemic dies out, people will get back to normal

The spread of awareness

The spread of awareness and its impact on epidemic outbreaks

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	Transition	Rate
Infection	$S_i + I_j \to I_i + I_j$	$(1 - \rho^i)\hat{\beta}$
Recovery	$I_i \to R_i$	γ
Information transmission	$X_i + X_{j>(i+1)} \to X_i + X_{i+1}$	$\hat{\alpha}$
Information fading	$X_i \to X_{i+1}$	λ
Information generation	$I_i \to I_0$	ω

- Information transmission and epidemic spreading are coupled
- Information transmission is modelled as a simple contagion.
- Information fades with with time

The spread of awareness

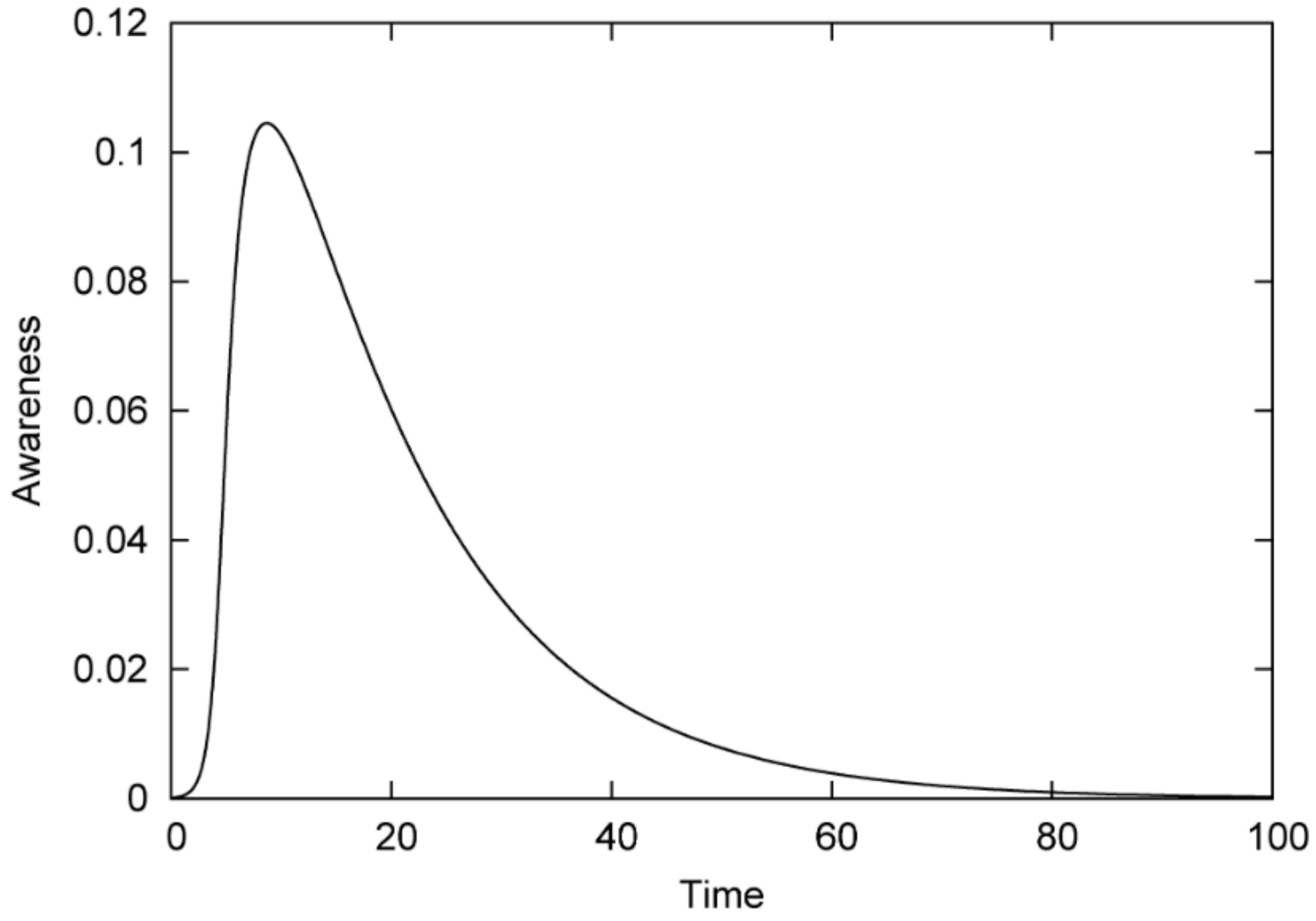

Fig. 1. Awareness $g(\rho, t)$ in the well-mixed population as a function of time for a given $\rho < 1$ if information is not replenished by the presence of the disease.

$$\begin{cases} \dfrac{dS}{dt} = -\beta' \dfrac{SI}{N} \\ \dfrac{dI}{dt} = \beta' \dfrac{SI}{N} - \mu I \\ \dfrac{dR}{dt} = \mu I \end{cases}$$

$$\beta' = \beta[1 - f(\rho, \{S_i(t)\})]$$

$$f(\rho, \{S_i(t)\}) = \sum_i (S_i(t)/S(t))\rho^i$$

is the **total amount of awareness** in the susceptible population at any given time t

The spread of awareness

- In this model, the epidemic threshold is not affected by the awareness, unless we have an initial number of aware individuals in the population.
- Awareness arises only through the process of information generation coupled to the parameter and infected I.
- This becomes relevant only once there are many infected and only then we can observe the effect of $\beta' < \beta$
- Even with an unchanged epidemic threshold the outbreak peak will be reduced by the effect of awareness and the final size of the epidemic can be much lower than the classic SIR model.

Classes of behavioural models

- For a general integration of behavioural effects, we can introduce a new compartment S^F that represents those susceptible who adopt precautionary measures (F stands for “fear”).
- The S^F are **less susceptible** to the infection ($\beta \to r_\beta \beta$) with $r_\beta < 1$
- We need to define the dynamics of the new compartment:
    - Case I: **Local, prevalence-based** spread of the fear.
    - Case II: **Global, prevalence-based** spread of the fear.
    - Case III: **Local, belief-based spread** of the fear.

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Towards a Characterization of Behavior-Disease Models

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1 Center for Complex Networks and Systems Research, School of Informatics and Computing, Indiana University, Bloomington, Indiana, United States of America, 2 Linkalab, Center for the Study of Complex Networks, Cagliari, Sardegna, Italy, 3 Pervasive Technology Institute, Indiana University, Bloomington, Indiana, United States of America, 4 Institute for Scientific Interchange (ISI), Torino, Italy

Recovery from fear

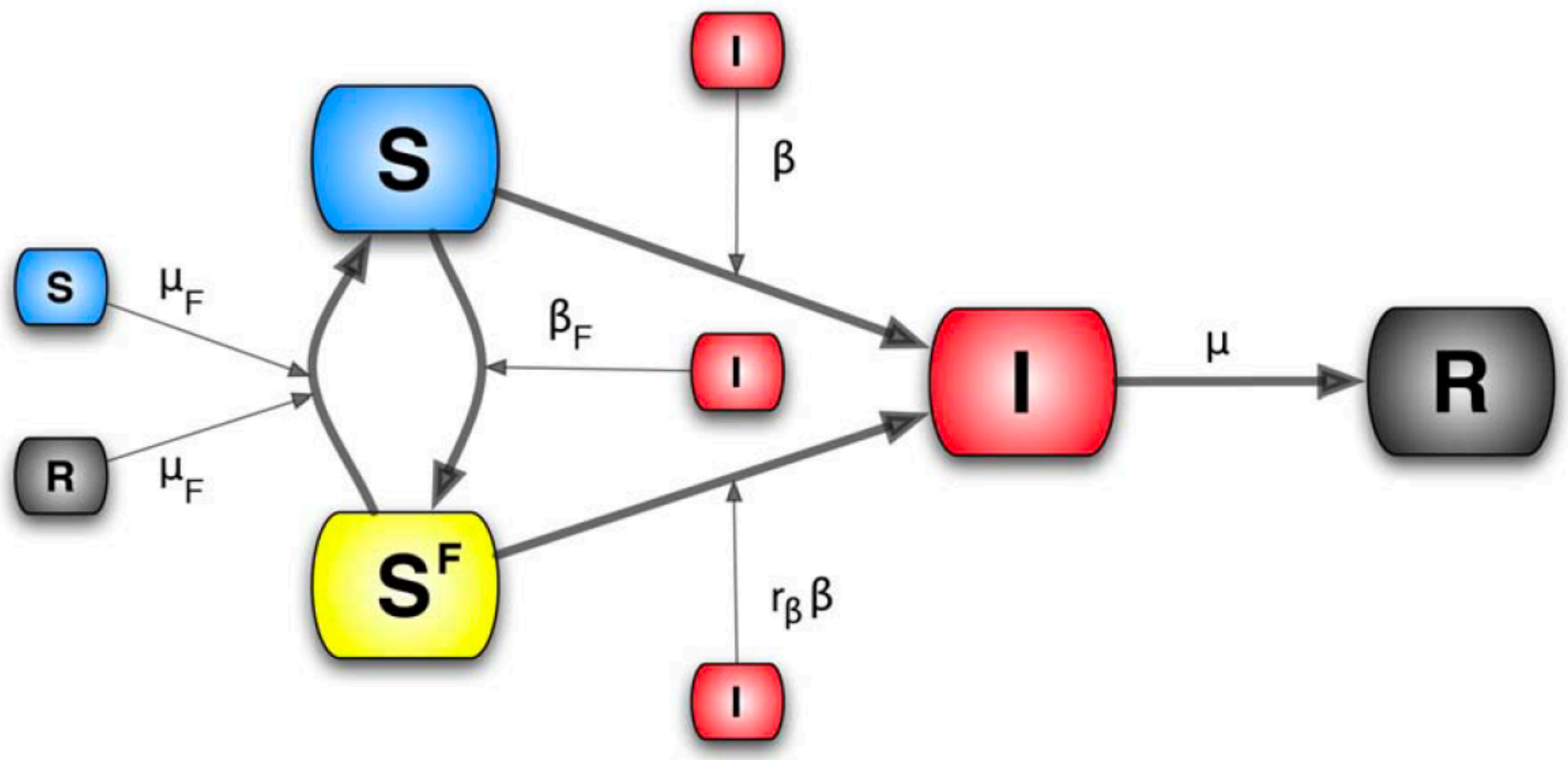
- Individuals can recover from the fear of the disease with two mechanisms:
  - Spontaneously, as memory decays but on **long time scales (not considered here)**
  - Due to the interaction with other individuals who behave normally:

$$S + S^F \xrightarrow{\mu_F} 2S \qquad\qquad R + S^F \xrightarrow{\mu_F} R + S$$

We note that only susceptible individuals can be “scared”. This is a limiting

Case I

- **Local, prevalence-based** spread of the fear.



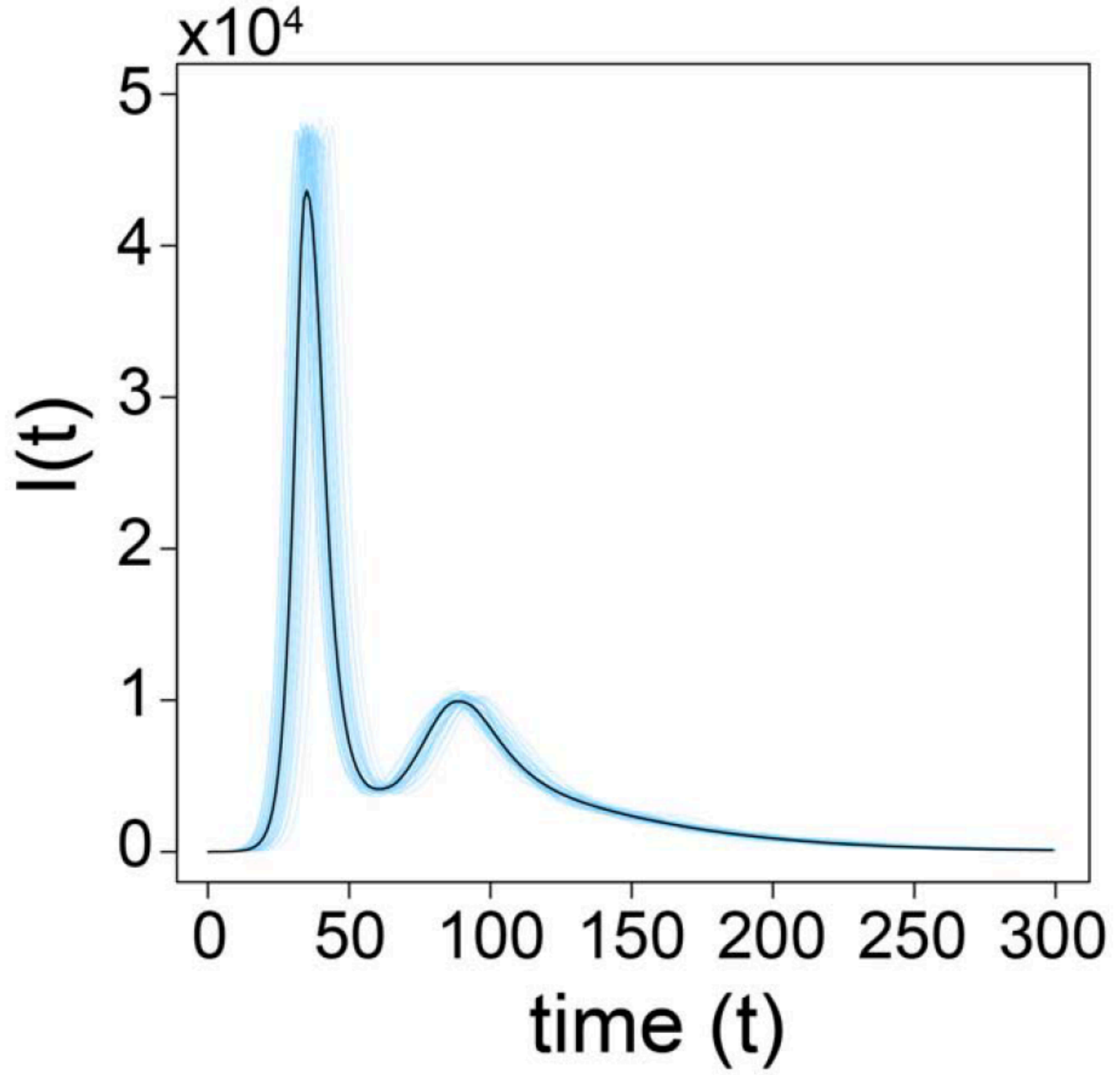
$$d_t S(t) = -\beta S(t)\frac{I(t)}{N} - \beta_F S(t)\frac{I(t)}{N} + \mu_F S^F(t)\left[\frac{S(t)+R(t)}{N}\right],$$

$$d_t S^F(t) = -r_\beta \beta S^F(t)\frac{I(t)}{N} + \beta_F S(t)\frac{I(t)}{N} - \mu_F S^F(t)\left[\frac{S(t)+R(t)}{N}\right],$$

$$d_t I(t) = -\mu I(t) + \beta S(t)\frac{I(t)}{N} + r_\beta \beta S^F(t)\frac{I(t)}{N},$$

$$d_t R(t) = \mu I(t),$$

Multiple peaks



Case II

- **Global, prevalence-based** spread of the fear.

$$d_t S(t) = -\beta S(t)\frac{I(t)}{N} - \beta_F S(t)\left[1-e^{-\delta I(t)}\right] + \mu_F S^F(t)\left[\frac{S(t)+R(t)}{N}\right],$$

$$d_t S^F(t) = -r_\beta \beta S^F(t)\frac{I(t)}{N} + \beta_F S(t)\left[1-e^{-\delta I(t)}\right] - \mu_F S^F(t)\left[\frac{S(t)+R(t)}{N}\right],$$

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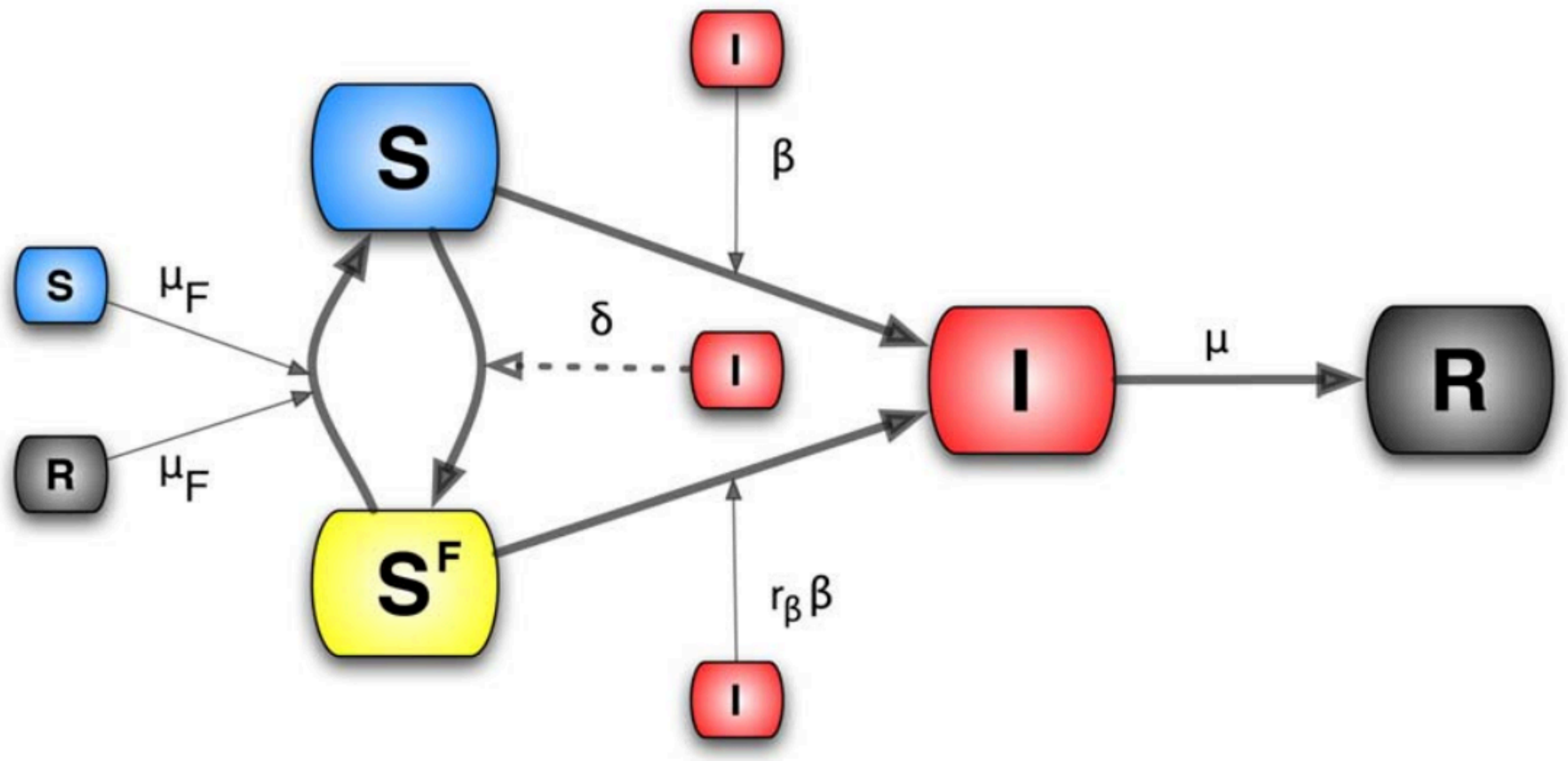

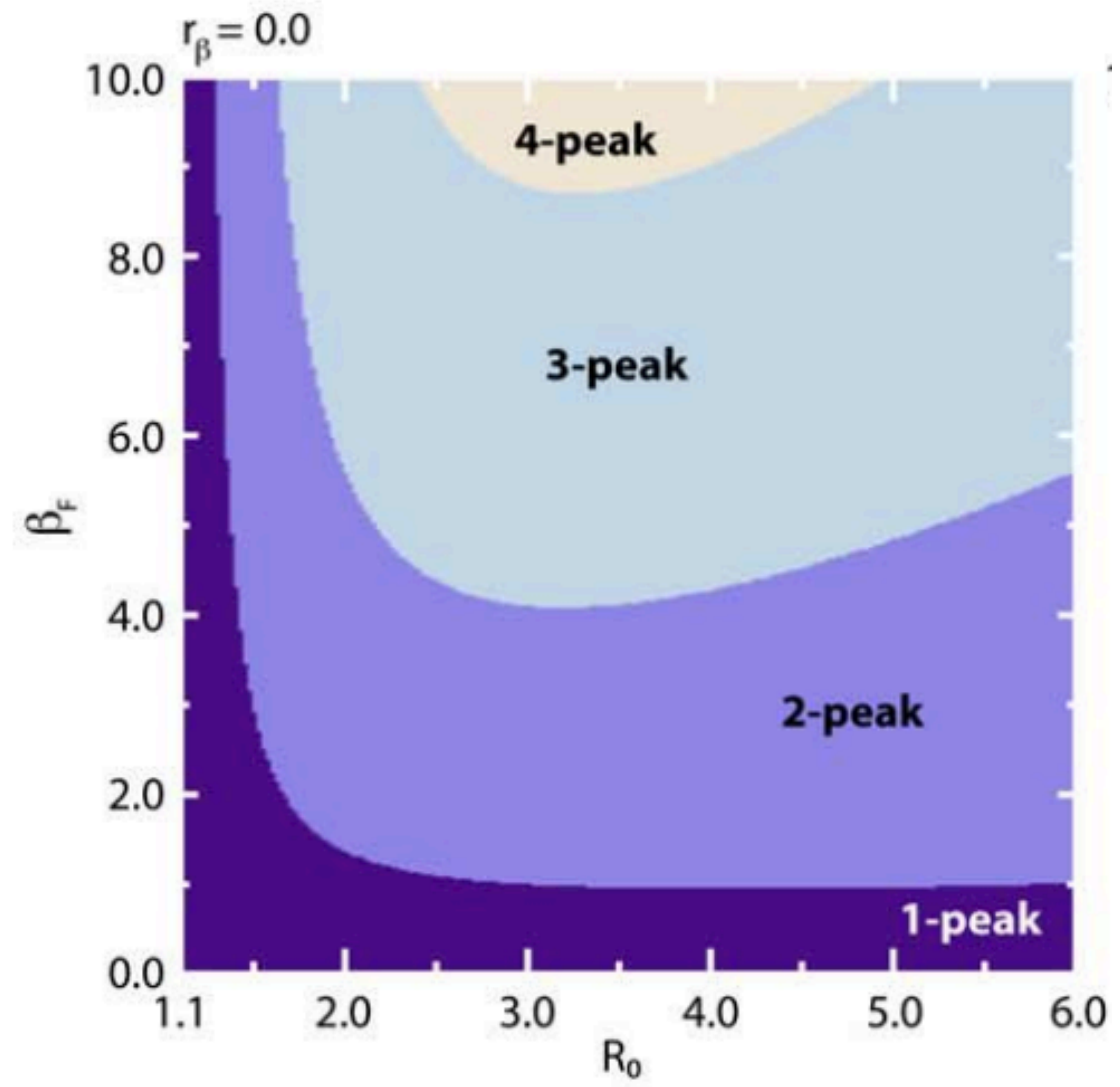

Case III

- **Local, belief-based** spread of the fear.

$$d_tS(t) = -\beta S(t)\frac{I(t)}{N} - \beta_F S(t)\left[\frac{I(t)+\alpha S^F(t)}{N}\right]$$
$$+\mu_F S^F(t)\left[\frac{S(t)+R(t)}{N}\right],$$
$$d_tS^F(t) = -r_\beta \beta S^F(t)\frac{I(t)}{N} + \beta_F S(t)\left[\frac{I(t)+\alpha S^F(t)}{N}\right]$$
$$-\mu_F S^F(t)\left[\frac{S(t)+R(t)}{N}\right],$$
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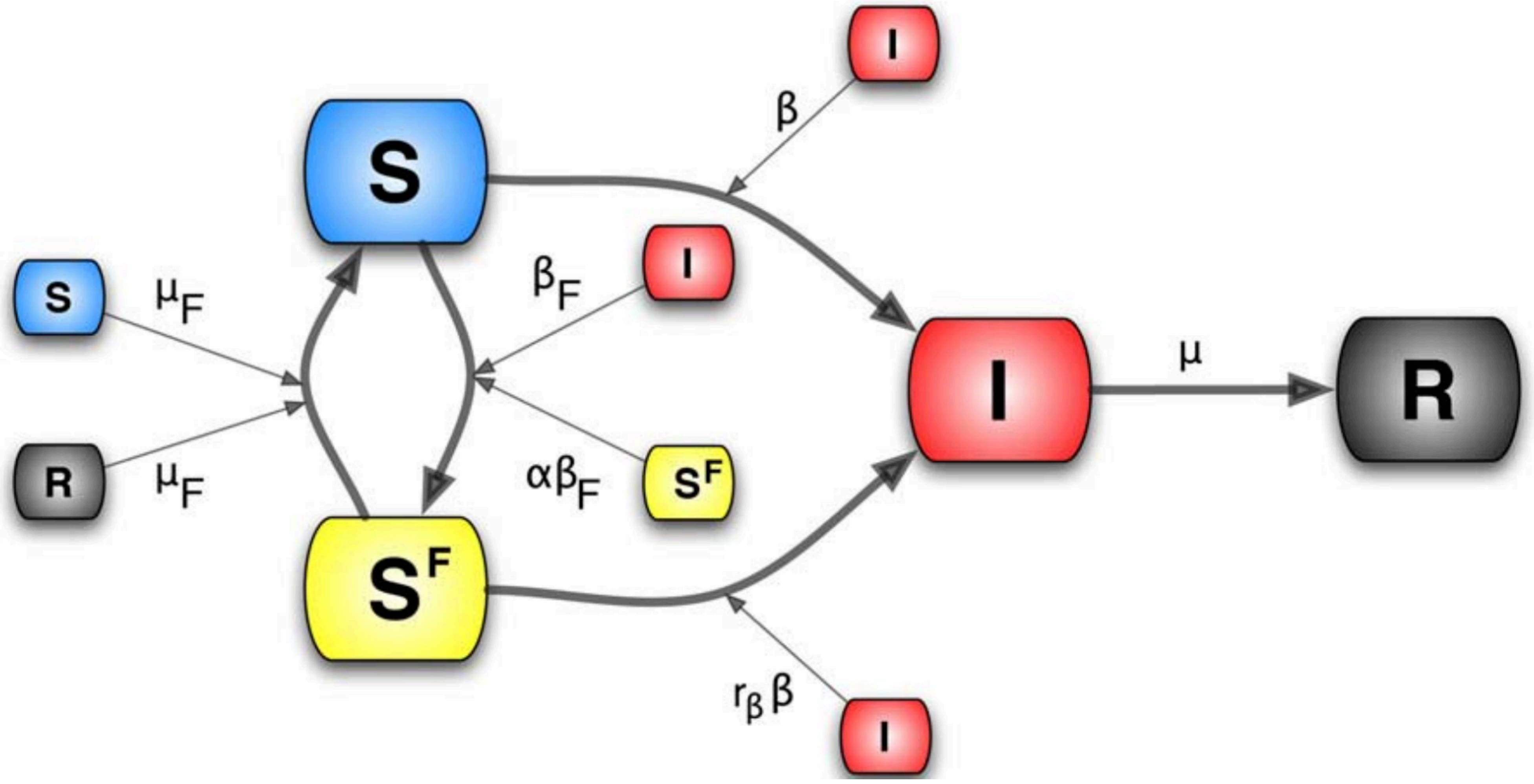
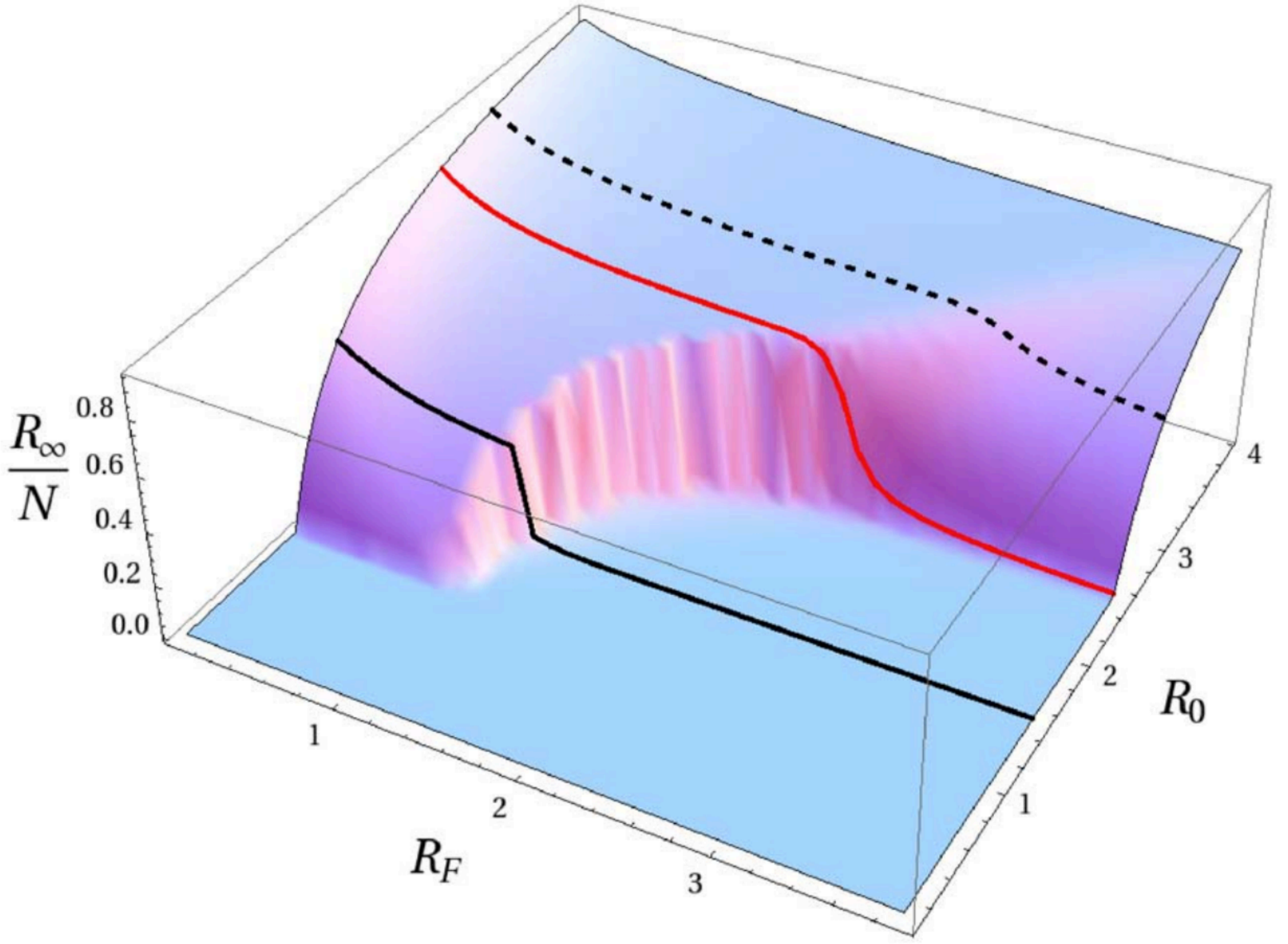
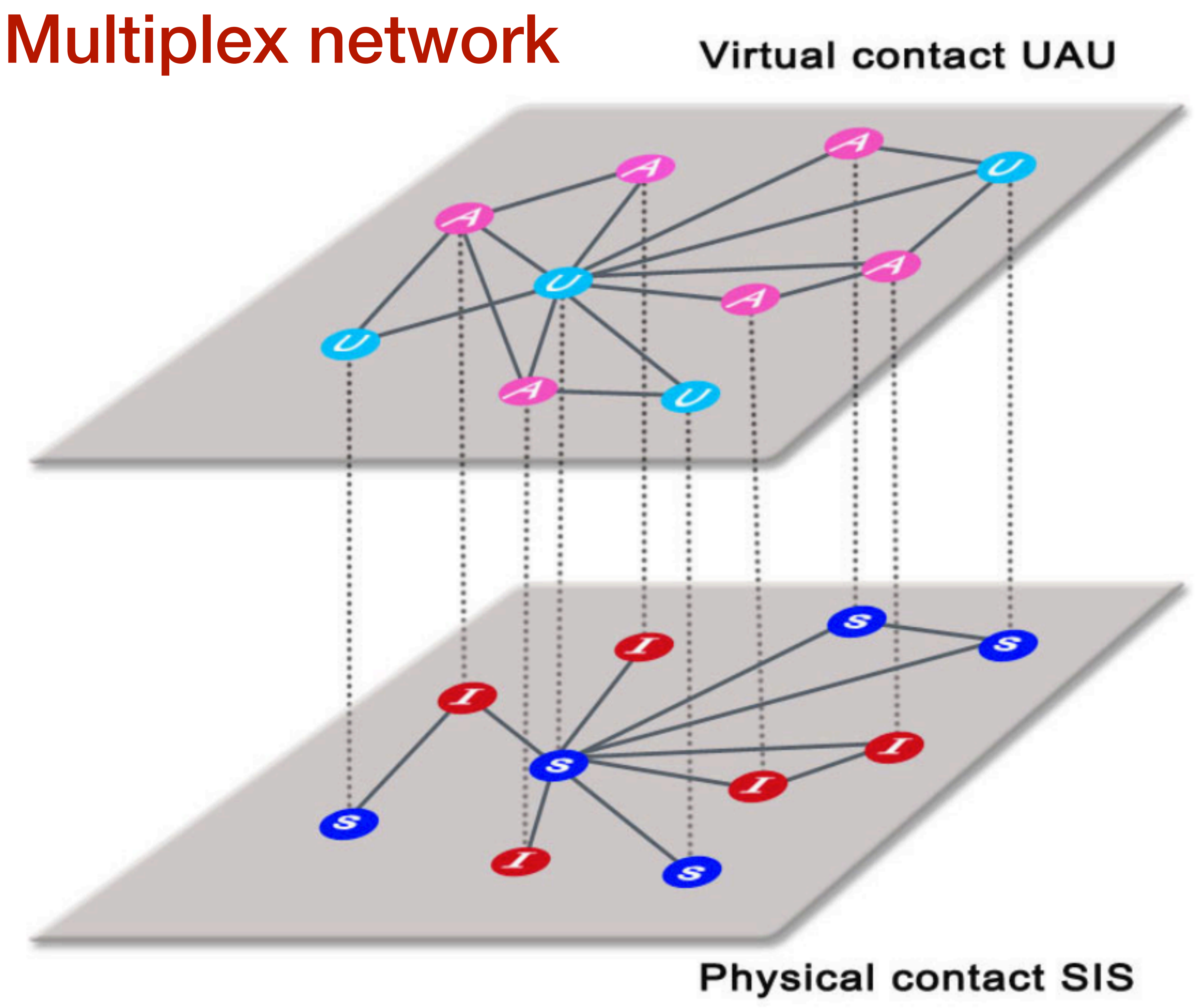




Networks

- The upper layer (virtual contact) is supporting the spreading of awareness, nodes have two possible states: unaware (U) or aware (A)
- The lower layer (physical contact) corresponds to the network where the epidemic spreading takes place.
- The nodes are the same actors than in the upper layer, but here their state can be: susceptible (S) or infected (I).



Epi-economics

- Since decades, economists have modelled human decision-making with mathematical equations.
- The combination of decision-making theory from economics and epidemic modelling is called “epi-economics”
- **Several approaches can be found in the literature:**
    - **Mechanistic behavior:** Agents’ actions are determined by the current state of the epidemic.
    - **Rule-of-thumb behavior:** Agents act to maximize an objective different (and typically simpler) than maximizing their own welfare**.**
    - **Individually optimal (forward-looking) behavior:** Agents’ actions are individually optimal given others’ current and future behaviors.

For a review see: *David McAdams, The Blossoming of Economic Epidemiology, Annual*

Data sources

Only 15% of the papers on the subject published between 2010 and 2015 were based on empirical data, most models being “purely theoretical and lack representative data and a validation process”
(*Verlest et al. J. R. Soc. Interface 2016*)

The COVID-19 pandemic has dramatically changed the landscape by providing the first case in human history of behavioral changes induced by an epidemic being monitored in real-time through mobile devices used by millions of individuals

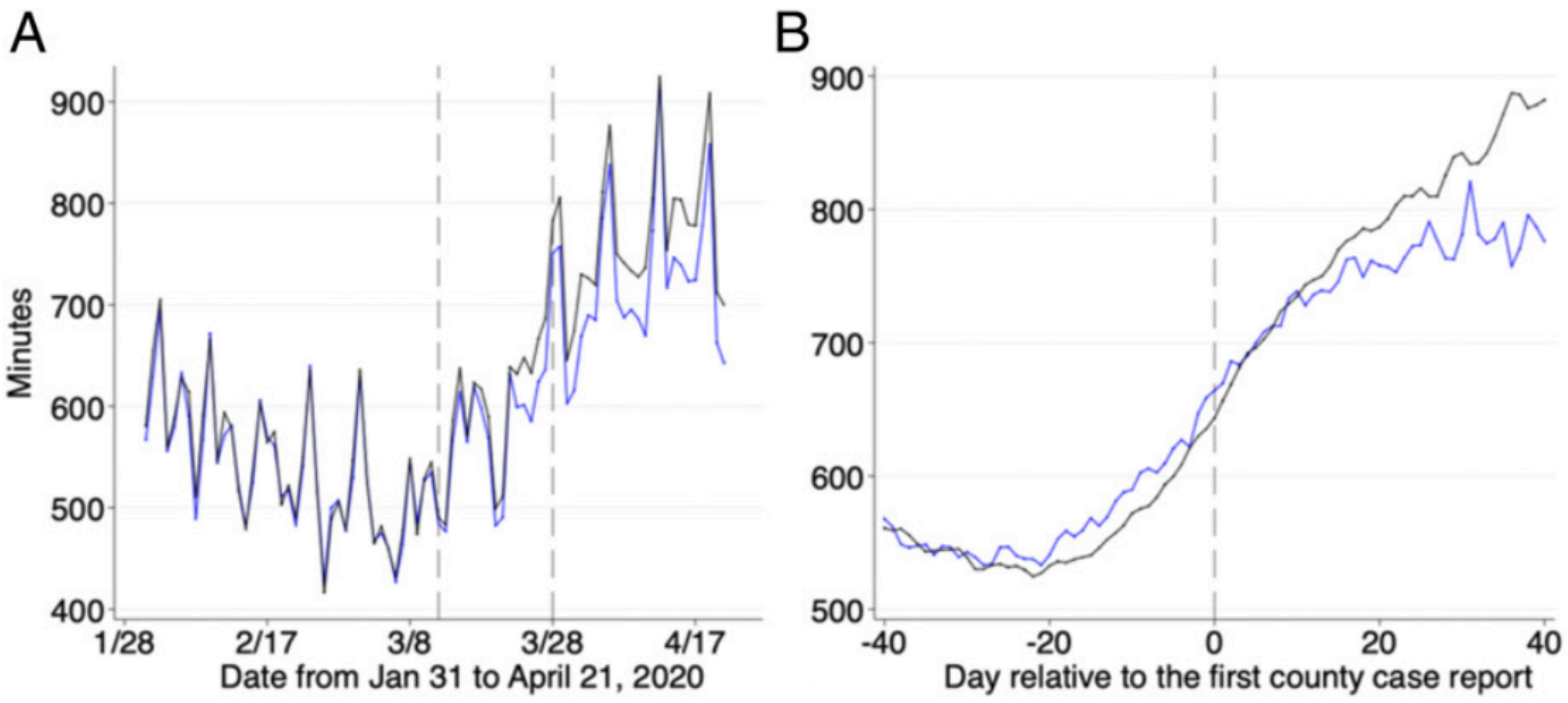
Empirical analysis

Check for updates

Measuring voluntary and policy-induced social distancing behavior during the COVID-19 pandemic

Youpei Yan[a], Amyn A. Malik[b,c], Jude Bayham[d], Eli P. Fenichel[a,1], Chandra Couzens[e], and Saad B. Omer[b,c,e,f]

[a]School of the Environment, Yale University, New Haven, CT 06511; [b]Yale Institute for Global Health, New Haven, CT 06510; [c]Department of Internal Medicine, Yale School of Medicine, New Haven, CT 06510; [d]Department of Agricultural and Resource Economics, Colorado State University, Fort Collins, CO 80523; [e]Department of Epidemiology of Microbial Diseases, Yale School of Public Health, New Haven, CT 06510; and [f]Yale School of Nursing, Orange, CT 06477



Trends for the mean time at home in minutes for counties never receiving stay-at-home policies (**blue lines**) and counties receiving a stay-at-home policy (**black lines**)

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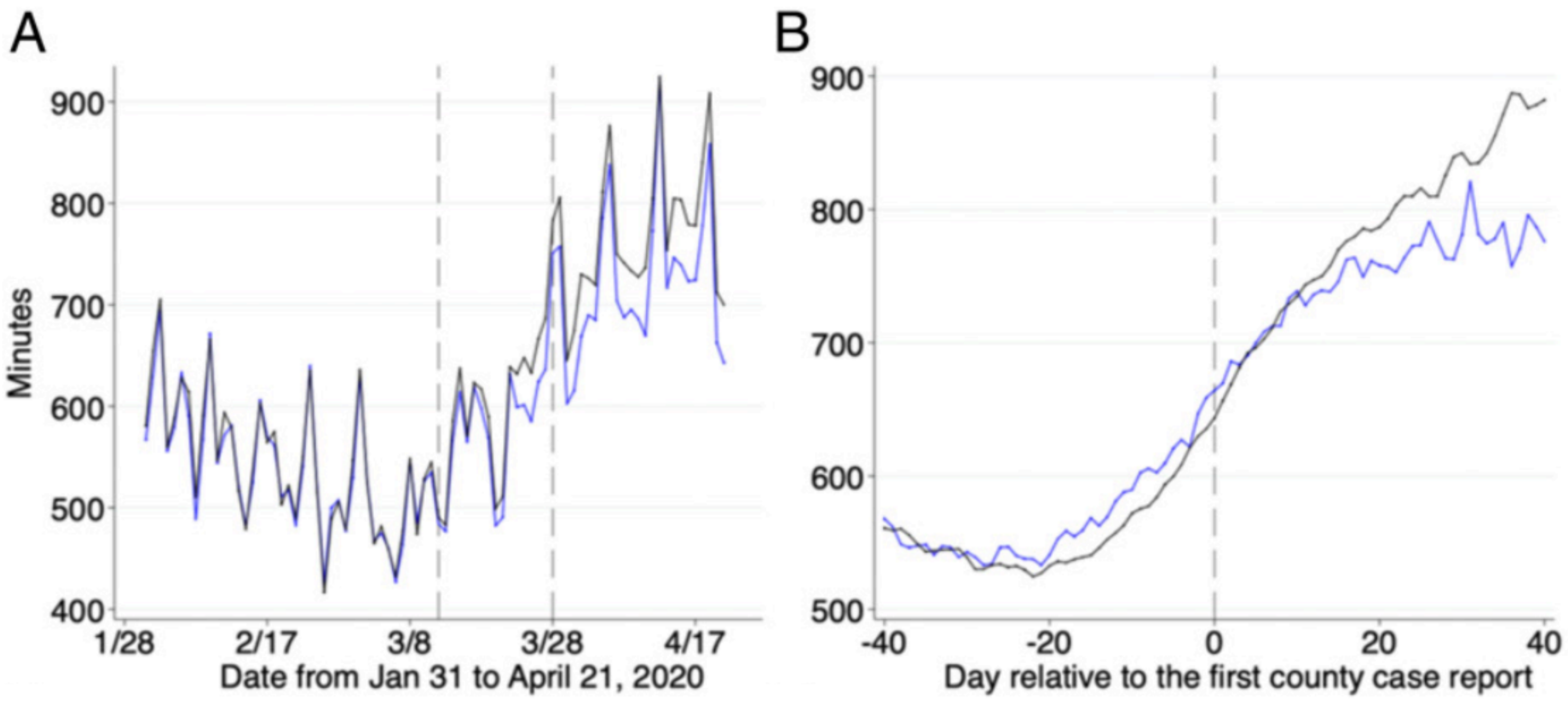

- Americans showed nontrivial voluntary behavioral changes in response to COVID-19 risk.
- The magnitude of voluntary response likely would have increased with increasing cases.
- Mandates kept more people home earlier in the epidemic, and timing is critical.

Conclusions

- Integrating human behaviour in epidemic models remains an open challenge. There is no universal model and different disciplines provide different approaches (economics, psychology, behavioural sociology, etc.)

- Digital sources provide for the first time a benchmark to test theories and models.

- One question arises: do we need a model of behaviour? Can we just measure the changes in behaviour from digital sources and plug them into epidemic models?

- Do models become more accurate when considering behavioural changes?

The end!