淡江大學熊貓講座 TAMKANG CLEMENT AND CARRIE CHAIR Modelling epidemic/ with diffu/ion

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3.19 ²⁰ (Tue), 14:00-16:00 守謙國際會議中心有蓮廳 理學院 數學學系 敬邀

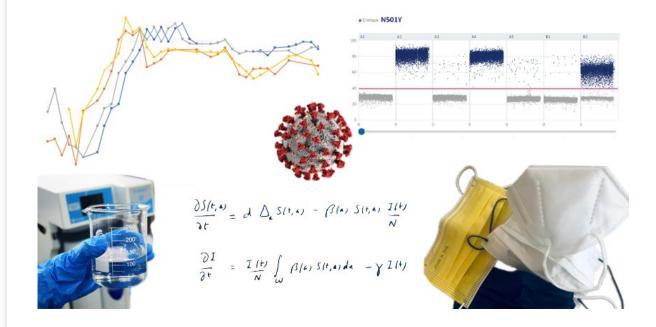


Modelling the Propagation of Epidemics with Diffusion

Henri Berestycki (EHESS, Paris, and Univ. of Maryland, College Park

- Tamkang Clement and Carrie Chair
- 19 March 2024

I. INTRODUCTION



Epidemics have always existed in human history

Epidemics: diseases transmitted by contagion Invasion of populations causing deaths or illnesses Then diminish in severity, or disappear, or become endemic Recurrences

Some historic pandemics

"Spanish flu" in 1918-19 caused over 50 million deaths worldwide

"Black death" (plague) in the 14th century, arrived in Europe from Asia in 1346, wiped 1/3 of population in Europe between 1346 and 1350

Japanese smallpox, 735-737, killed 1/3 of population in Japan

Many endemic diseases with large mortality: tuberculosis, measles, malaria, HIV/ AIDS

Pandemics: major concern of public health

In the 21st century:

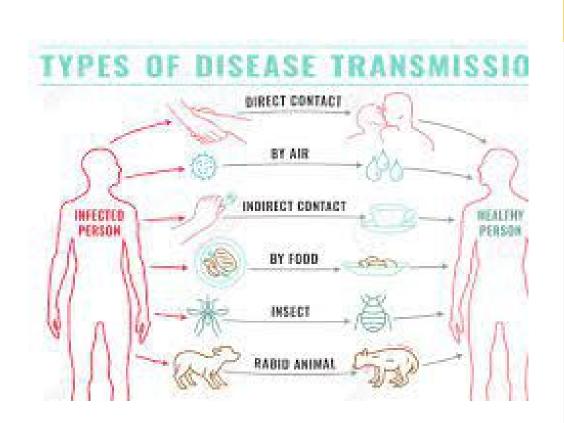
- SARS-CoV (2002-2003)
- H1N1 (2009)

• ...

- Ebola (1976, 2013)
- MERS-CoV (2012)
- HIV/AIDS (estimated to have killed 43 million worldwide)
- SARS-CoV-2 or COVID-19, Dec. 2019 (estimated between 7 and 35 million deaths worldwide)

Epidemics: Communicable diseases

- Epidemics: Direct transmission through individual-to-individual contact
- Contagion mechanism: physical contacts, by particles in the air, insects, animals...

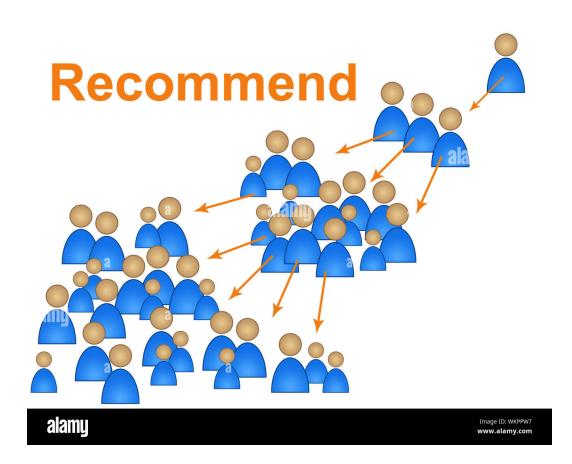


Mathematical modelling of epidemics

- Mathematical laws describing dynamics of an epidemics
- Understanding spreading
- Forecasting
- Devising ways to control it

Many other phenomena with contagion

- Dynamics of opinions
- Social norms
- Spreading on social networks
- Marketing: the Bass model and variants
- Adoptions of new technologies...



Compartmental Models in Epidemiology

- Introduction of compartmental models, beginning of 20 th century: Ross, Hammer...
- Large, homogeneous population (notion of density)
- Population divided into **compartments** :
 - Susceptibles \rightarrow Infected \rightarrow Removed (recovered)
 - Exposed, Asymptomatic, Hospitalized,...
- Describe flow of populations from one compartment to another

Ronald Ross (1857-1932)

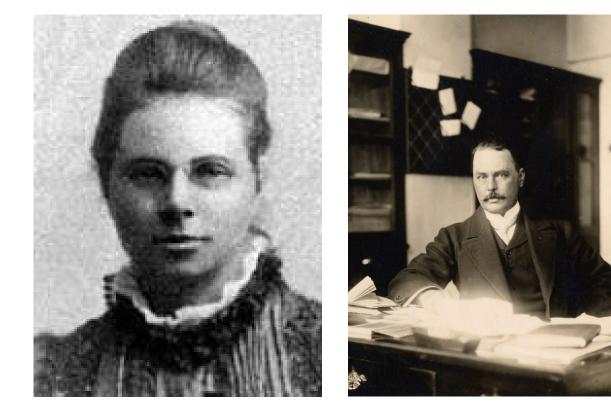
- MD, worked in the Indian Medical Service
- Discoverer of malaria transmission
- Second Nobel Prize in Physiology or Medicine (1902)
- A polymath:
 - Poet
 - Novelist, Playwriter
 - Artist
 - Musician
 - Mathematician





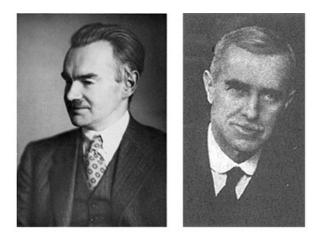
Ronald Ross and Hilda Hudson

- An application of the theory of probabilities to the study of a priori pathometry, part I (1916)
- II and III with Hilda Hudson (1917)
- Papers in geometry



II. The SIR Model

Ross, Hammer, Kermack and McKendrick (all working in public health medical services)



W. Kermack (1898-1970), A.G. McKendrick (1976-1943)



Kermack and McKendrick Model of Epidemiology (1927)

- Large, homogeneous population (density)
- 3 compartments :

Susceptibles \rightarrow Infected \rightarrow Removed

- I contaminates S until removed \rightarrow R
- Removal and contamination rates depend on duration of infection
- Contamination depends on transmission rate

The SIR system

 A system of Ordinary Differential Equations (ODEs)

$$\begin{cases} \frac{dS}{dt} = -\beta SI, \\\\ \frac{dI}{dt} = \beta SI - \gamma I, \\\\ \frac{dR}{dt} = \gamma I \end{cases}$$

 β = Transmission rate (depends on number of contacts, transmissibility, social distancing etc...

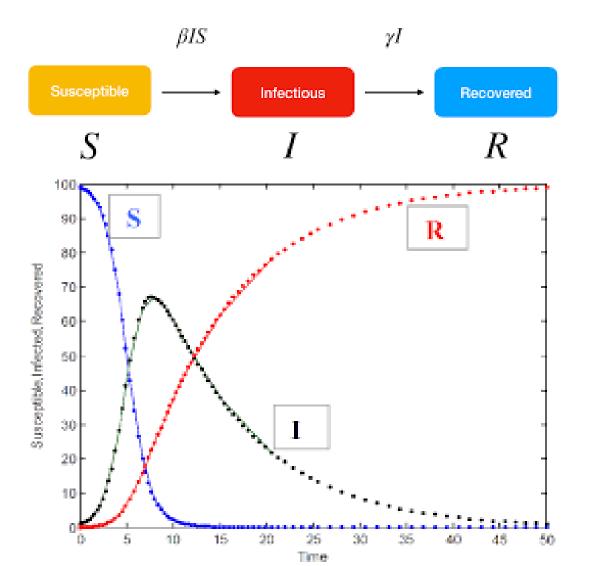
 $\beta = \tau \chi~$ = product of rate of transmission upon contact by rate of social contact

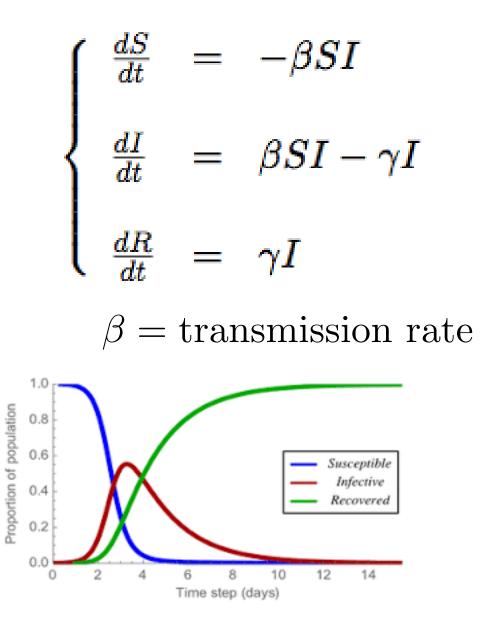
 $\frac{-}{\gamma}$ = Duration of infection

 $R_0 = \frac{\beta S_0}{\gamma}~$ = Basic reproduction number, to be compared with 1

The parameters of the SIR model

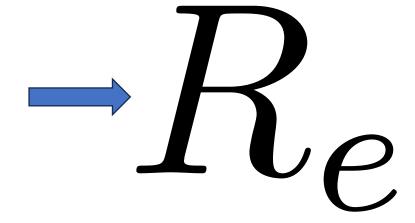
Classical SIR model



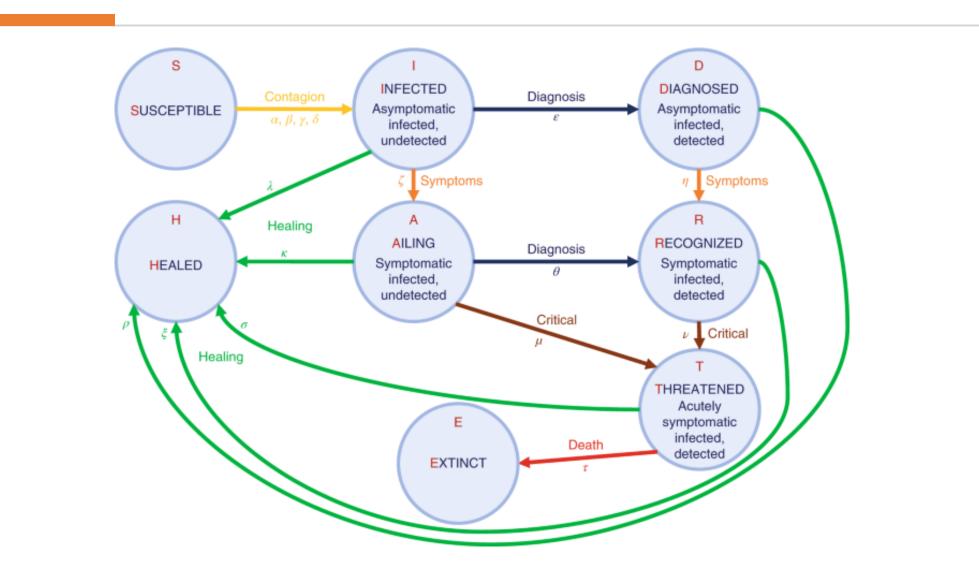


SIR model widely used

- Monitoring the progression of an epidemic
- Effective reproduction number compared to 1
- Forecasting, how fast does it grow, is it receding?
- Public health policy : reducing the transmission



Adding new compartments \implies many extensions, variants. Example:



Diffusion

- SIR : a description in a homogenous and isolated group
- How does the epidemic spread from a country to another, from a city to another, or even in neighborhoods?
- Diffusion
- Diffusion in epidemiology comes under several different guises

"As a matter of fact, all epidemiology, concerned as it is with the variation of disease from time to time or from place to place must be considered mathematically, if it is to be considered scientifically at all."

Sir Ronald Ross Nobel Price in Physiology 1902



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Sir Ronald Ross Nobel Price in Physiology 1902

The variation of disease from time to time or from place to place





III. Spatial Diffusion of Epidemics

Non-local (spatial) spreading - Kendall (1965)

$$S = S(t, x), I = I(t, x), \quad x \in \mathbb{R}^N$$

K(x, y) = Probability that individual at location y will infect individual at location x

$$\begin{cases} \partial_t S(t,x) = -\beta S(t,x) \int K(x,y) I(t,y) dy \\\\ \partial_t I(t,x) = \beta S(t,x) \int K(x,y) I(t,y) dy - \gamma I(t,x) \end{cases} \end{cases}$$

Kendall was motivated by the study of rabies in Britain propagated by foxes

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Spatial variations

"from place to place"

Time variations

"from time to time"

First model by Kendall involved non-local spreading (continuous)

Spatial diffusion with non-local spreading



A vast mathematical literature since

A model (discrete) with non-local transmission and applications to Covid-19 data in France:

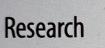


L. Roques, HB et al., Royal Soc. Open Science (December 2020)

Spatial spreading

ROYAL SOCIETY OPEN SCIENCE

royalsocietypublishing.org/journal/rsos



Cite this article: Poques L, Bonnefon O, Baudrot V, Soubeyrand S, Berestycki H. 2020 A parsimonious approach for spatial transmission and heterogeneity in the COVID-19 propagation. *R. Soc. Open Sci.* **7**: 201382. https://doi.org/10.1098/rsos.201382

Check for

Received: 3 August 2020 Accepted: 7 December 2020 A parsimonious approach for spatial transmission and heterogeneity in the COVID-19 propagation

L. Roques¹, O. Bonnefon¹, V. Baudrot¹, S. Soubeyrand and H. Berestycki^{2,3}

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Raw data on the number of deaths at a country level generally indicate a spatially variable distribution of COVID-19 incidence. An important issue is whether this pattern is a

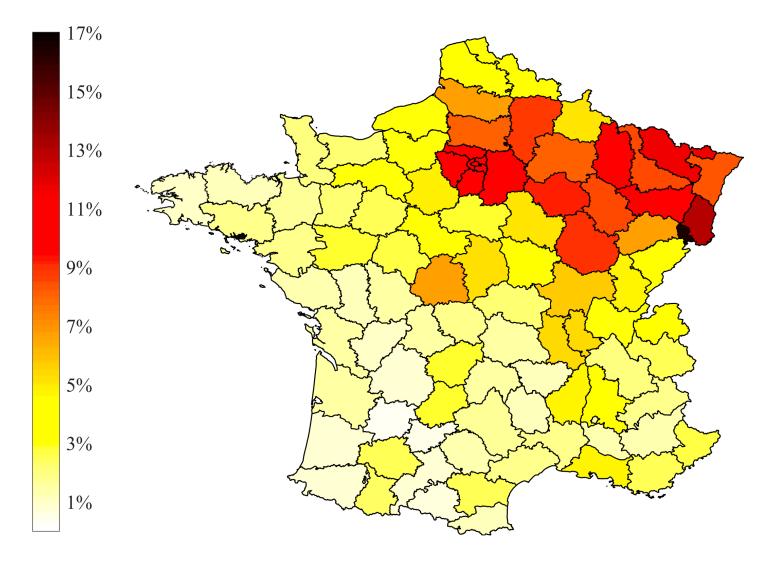
Inspired from earlier work on social contagion: https ://www.nature.com/ articles/s41598-017-18093

With L. Bonnasse-Gahot et al.

Propagation of the 2005 riots in France



Départements (counties) of France



Graph of n_d départements (counties) in France

$$S = S_k(t), \quad I = I_k(t), \quad R = R_k(t) \quad k = 1, \dots, n_d$$

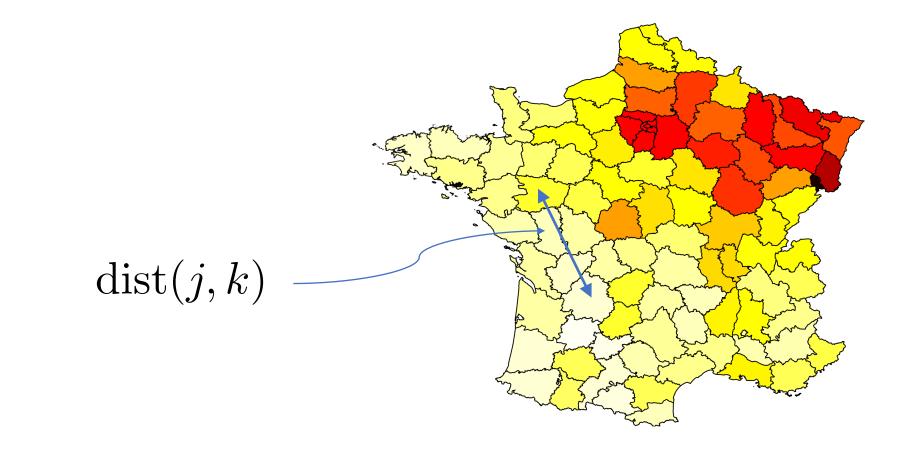
$$\begin{cases} \partial_t S_k(t) = -\frac{\rho(t)}{N_k} S_k(t) \Sigma_{j=1}^{n_d} w_{j,k} I_j(t) \\\\ \partial_t I_k(t) = \frac{\rho(t)}{N_k} S_k(t) \Sigma_{j=1}^{n_d} w_{j,k} I_j(t) - \gamma I_k(t) \\\\ \partial_t R_k(t) = \gamma I_k(t) \end{cases}$$
Analogous to
$$\begin{cases} \partial_t S(t, x) = -\beta S(t, x) \int K(x, y) I(t, y) dy \\\\ \partial_t I(t, x) = \beta S(t, x) \int K(x, y) I(t, y) dy - \gamma I(t, x) \end{cases}$$

Weights W_{j,k}

- Power law decay in the distance
- dist(*j*,*k*) : distance from centroids of counties *j* and *k*
- *d*₀ a scale parameter
- d_0 and δ global parameters

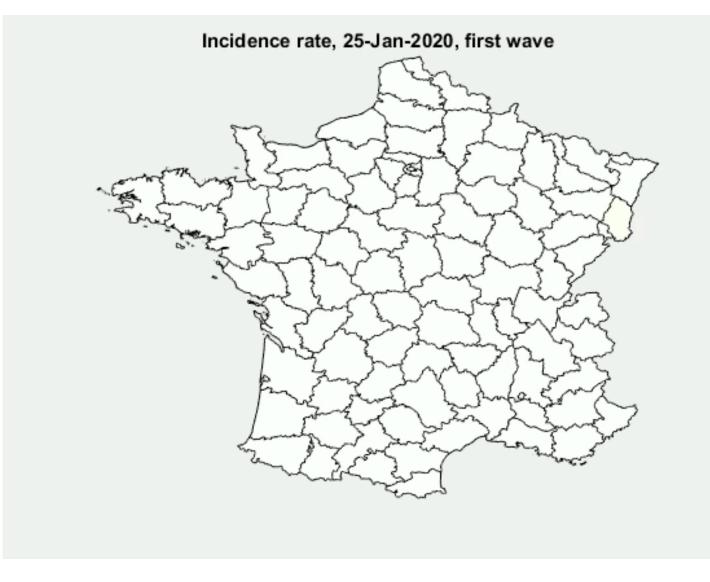
$$w_{j,k} = \frac{1}{1 + (\operatorname{dist}(j,k)/d_0)^{\delta}}$$

Distance between two counties



Incidence rate

- Simulation of the model
- Localized initial cases
- Evolution January -December 2020
- Public health measures (lockdown) reflected in coefficient $\rho(t)$
- Darker colors = higher incidence rates



Using the model

- Good qualitative agreement with the observed spatial dynamics of the COVID epidemics in France
- Few parameters to fit globally
- Use for forcasting
- Study the impact of public health measures
- In particular effects of
 - Lockdown to reduce transmission rate
 - Travel restrictions

Testing effects of measures : Limiting movement vs limiting transmission per contact

Comparing 4 strategies

- 1. No restrictions
- 2. Restriction on intercounty travel
- 3. Reduction of contact rate at national level (social distancing etc.)
- 4. Reduction of contact rate *and* restriction on intercounty travel

Testing strategies Forecasting the effects in daily number of deaths in France

- 1. No restrictions
- 2. Restricting intercounty travel
- 3. Reducing contact rate (social distancing etc.)
- 4. Reducing contact rate and restricting intercounty travel

 10^{4} Strategy 1 Strategy 2 Strategy 3 Daily number of deaths Strategy 4 10^{3} 10^{2} 10 35 5 10 15 20 25 30 40 Number of days

Logarithmic scale

Daily number of deaths due to a new outbreak in logarithmic scale; comparis gement strategies. The number of deaths is computed over the whole country Local diffusion in epidemiology: spatial spreading Random movement of susceptible and infected

$$S = S(t, x), I = I(t, x), \quad x \in \mathbb{R}^{N}$$

$$\begin{cases} \partial_{t}S - \mu_{S}\Delta S = -\beta SI \\ \partial_{t}I - \mu_{I}\Delta I = +\beta SI - \gamma I \end{cases}$$
Spatial ra of individ

Spatial random movement of individuals

Activity/susceptibility models a general class of models

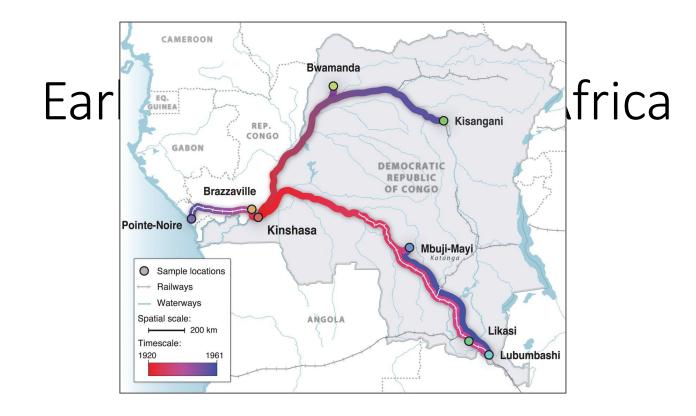
- Many different type of models : predator - prey, riots, social behavior,...
- HB, S Nordmann, L. Rossi : *Modeling the propagation of riots, collective behaviors, and epidemics,*

<u>Mathematics in Engineering</u> 2022, <u>Volume 4</u>, <u>Issue 1</u>: 1-53. doi: <u>10.3934/mine.2022003</u>

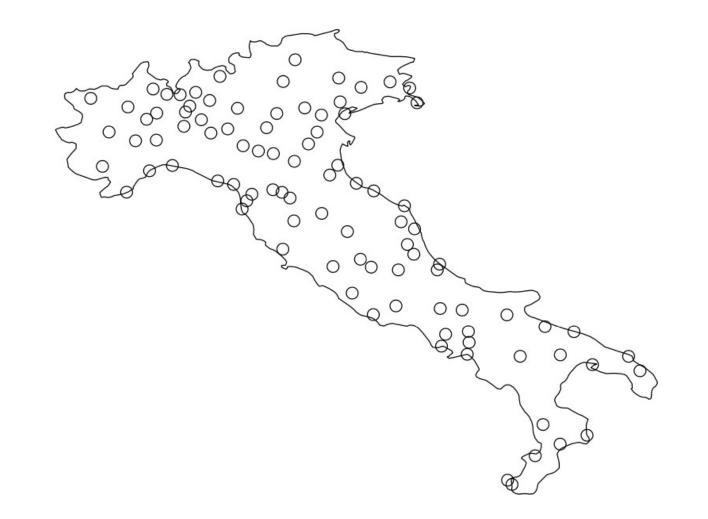


IV. Propagation of epidemics along roads

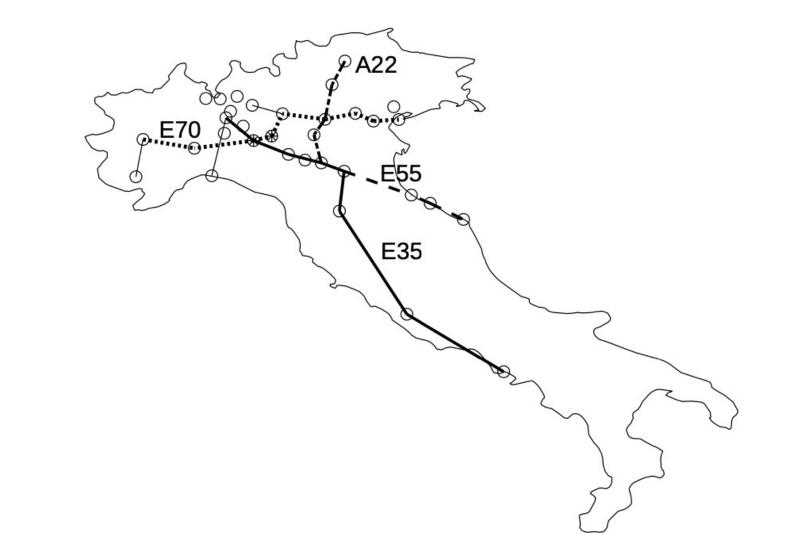
(roads, railways, waterways...)



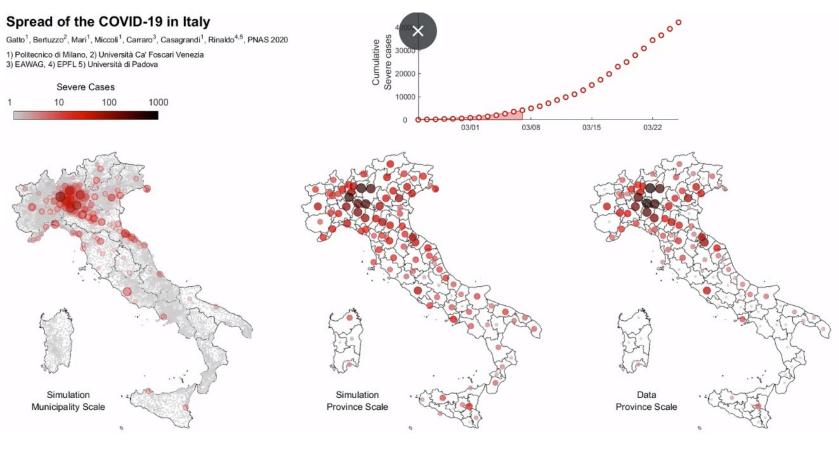
[Faria et al., *The early spread and epidemic ignition of HIV-1 in human populations*, Science (2014)]



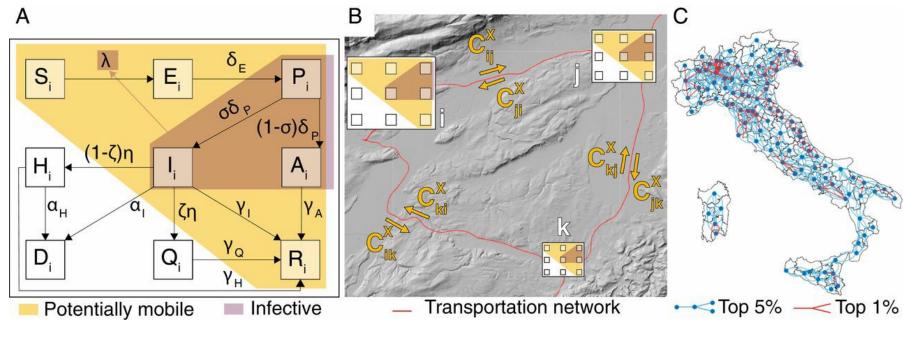
[Sebastiani et al., Il Coronavirus ha viaggiato in autostrada (2020)]



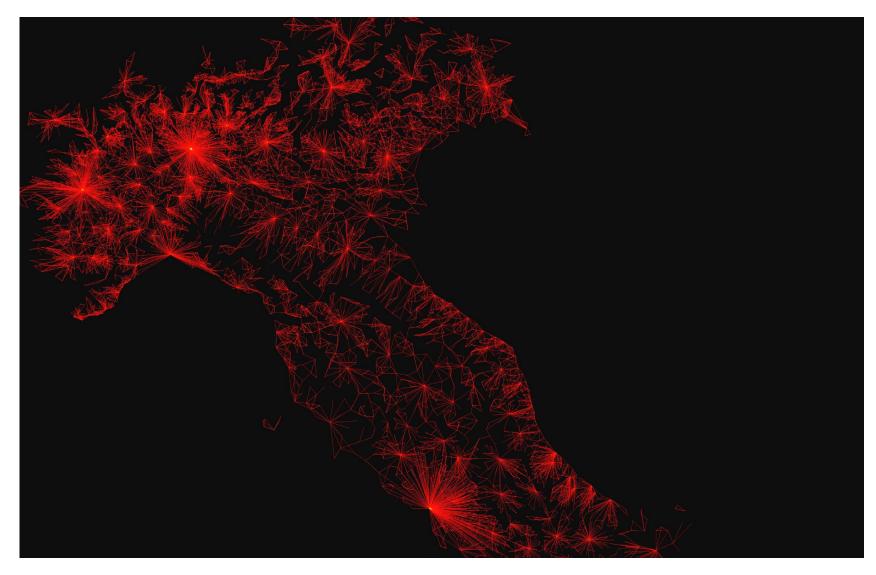
Sebastiani et al., The Coronavirus travelled on expressways (2020)



[Gatto et al., PNAS (2020)]



[Gatto et al., PNAS (2020)]



[Gatto et al., PNAS (2020)]

Diffusion in epidemiology: Rapid diffusion along roads

Berestycki, H., Roquejoffre, JM. & Rossi, L.
Propagation of Epidemics Along Lines with Fast Diffusion. *Bull Math Biol* 83, 2 (2021).
https://doi.org/10.1007/s11538-020-00826-8

The SIRT model

- Large population, domain : a half plane limited by a line.
 - Susceptibles \rightarrow Infectives in the domain.
 - A new compartment : Travelling Infectives on the line.
- I contaminate S at constant rate until removed.
- Infectives
 - move in the domain, travel on the line.
- Line and plane exchange infectives at constant rate.
- At t = 0 a (small) density of infectives is introduced

Model in the halfspace $\{y > 0\}$

- The line : $(x, 0), x \in \mathbb{R}$.
- Unknowns :
 - Susceptibles/Infective : densities *S*(*t*, *x*, *y*), *I*(*t*, *x*, *y*).
 - T(t, x) : density of travelling infectives.

• Parameters :

- *S*₀ : initial density of susceptibles.
- α : removal rate of infectives, β : transmission rate of infection.
- μ : transmission rate between line and half plane.
- v : transmission rate between half plane and line.
- *d* : diffusion in the domain, *D* : diffusion on the line.

Basic reproduction number :

The SIRT model in a half-plane

Spreading speed

■ If
$$c > c_{SIR}^{T}$$
 then $(u(t, x), v(t, x, y)) \rightarrow 0$ if $k \ge ct$.
■ If $c < c_{SIR}^{T}$ then $(u(t, x), v(t, x, y)) \rightarrow (u^{*}, v^{*})$ if $k \le ct$.

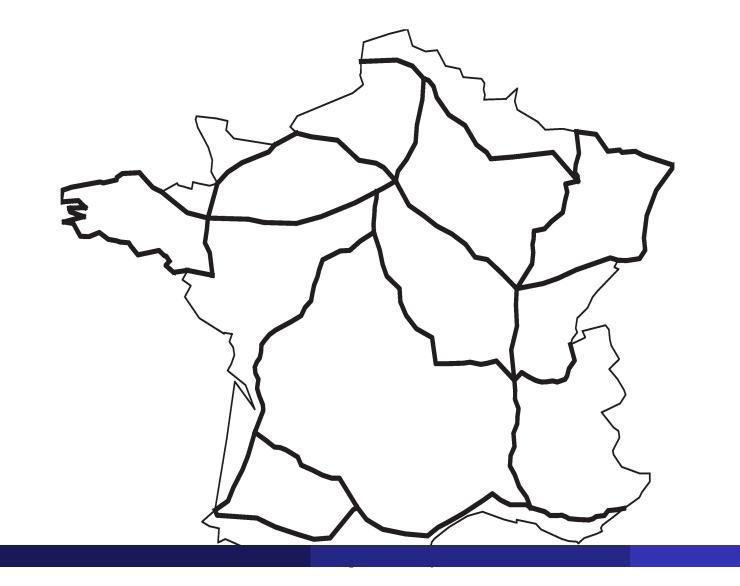
1 If
$$D \le 2d$$
, then $c_{SIR}^T = c_{SIR}$
2 If $D > 2d$, then $c_{SIR}^T > c_{SIR}$
If x is large, $I(t, x, y)$ peaks around $t \sim \frac{x}{c_{SIR}^T}$.

An important outcome: Propagation may be fast even if *R*⁰ close to 1!

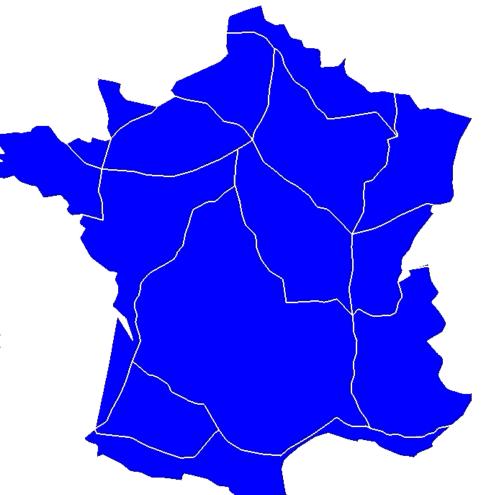
1/48/53

Simulation : France with major expressways

Epressways : traffic≥15000 cars / day.



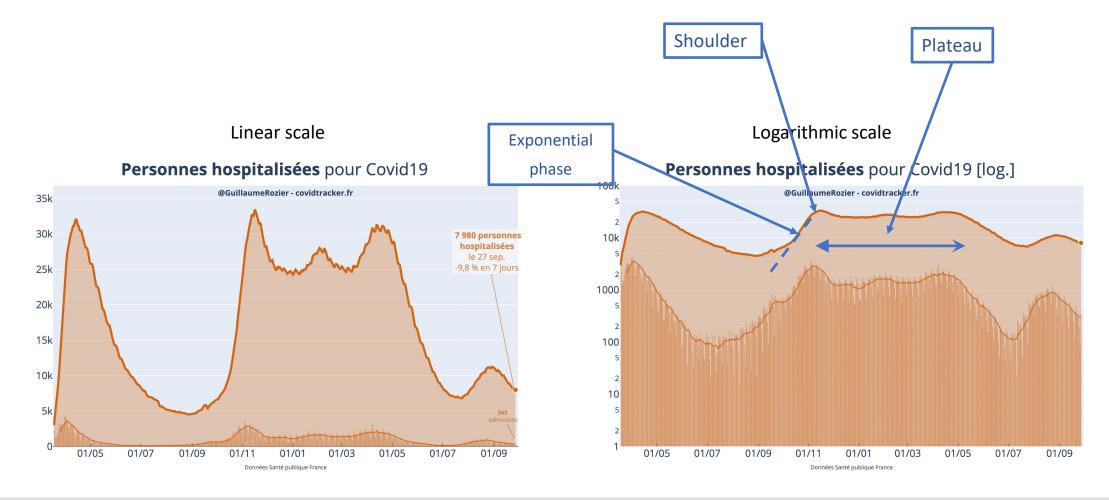
Simulation of COVID propagation in France using the SIRT model with major roads

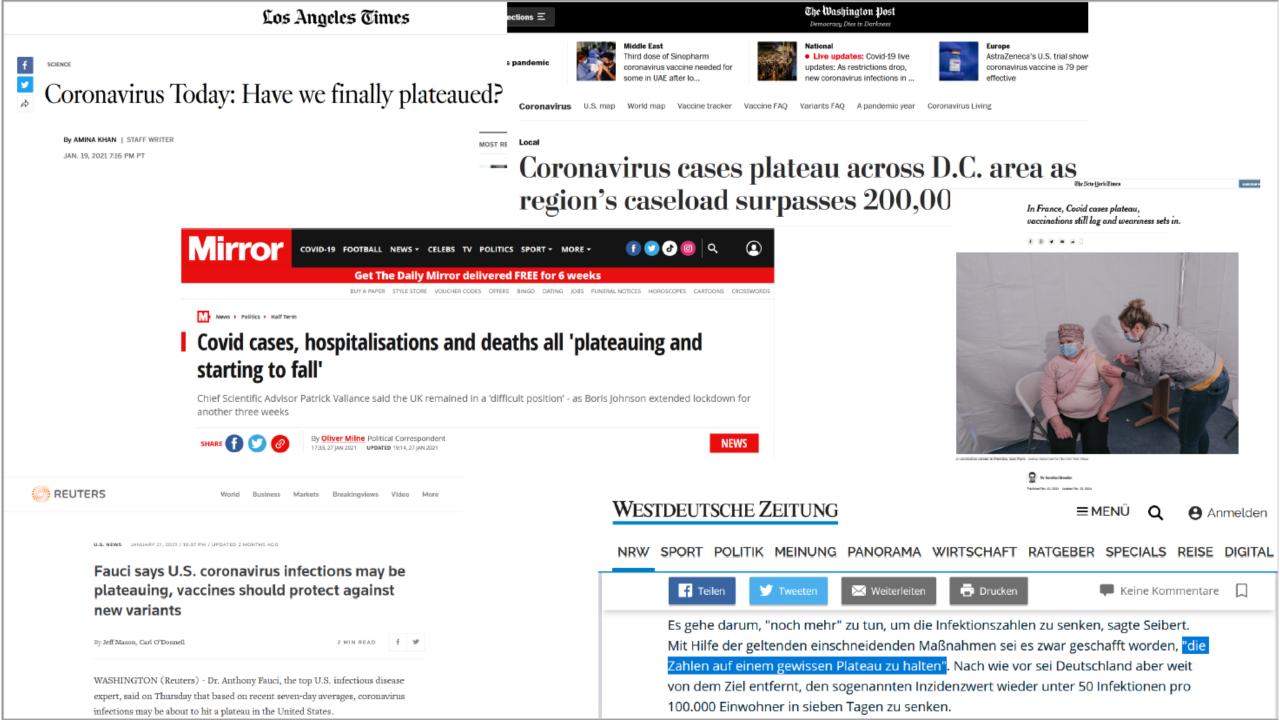


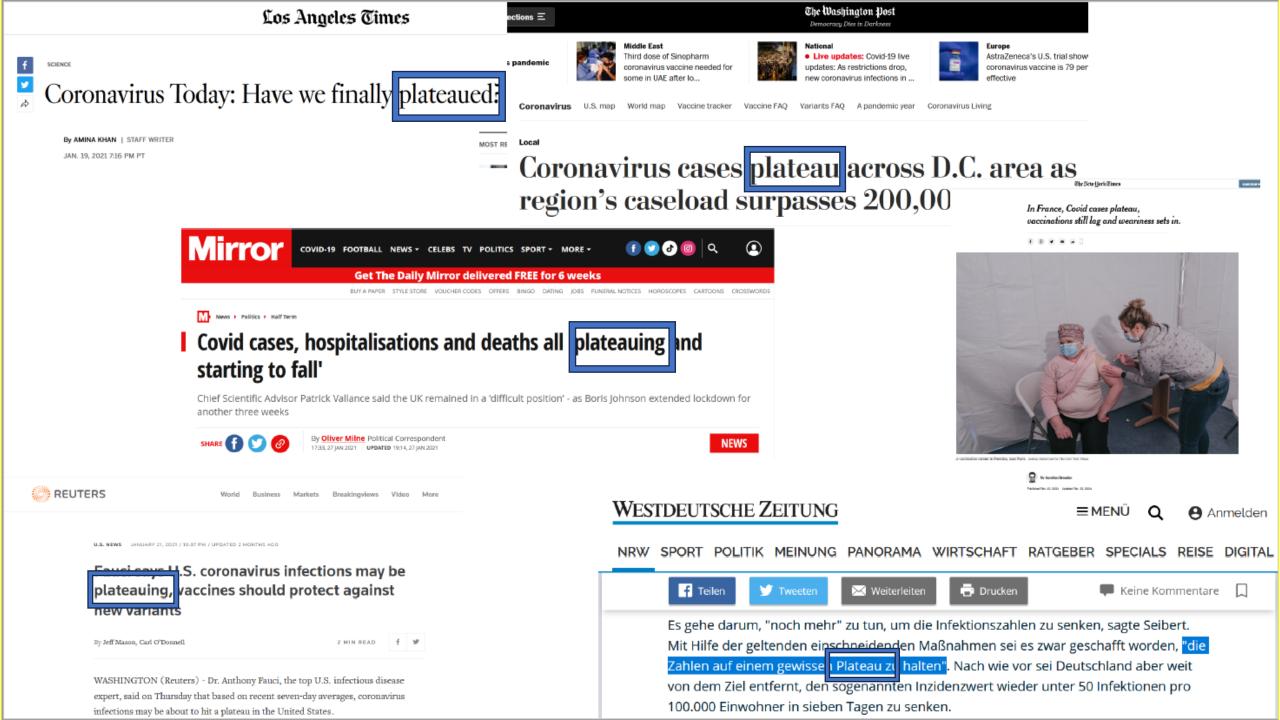
Good qualitative agreement with observed spreading of covid

V. Social Diffusion

Observed complex dynamics : **Epidemic plateaus** Hospitalized (7 days moving average)







Why are there plateaus ?

Complex dynamics of epidemics

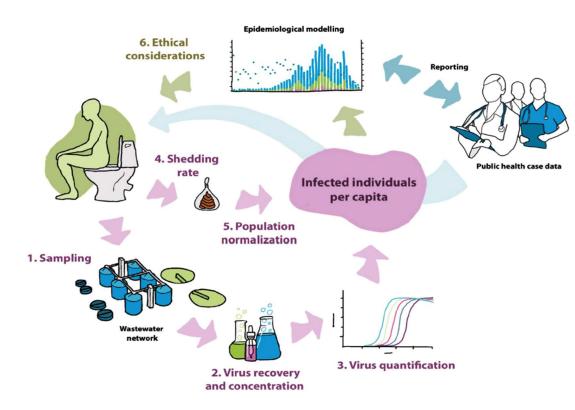
Starting with an observation from wastewater measures in South of France

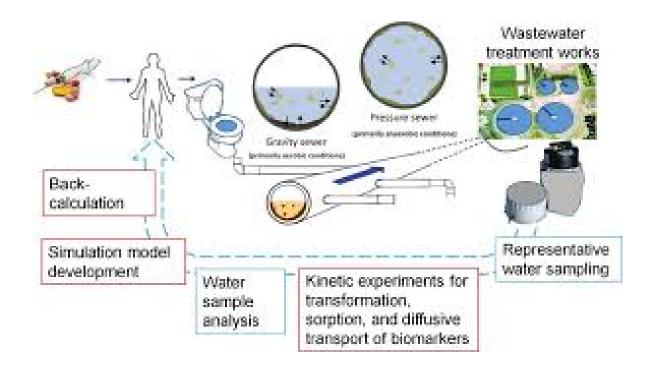
Why are there plateaus and rebounds ?

- Effects of public health policy ?
- Effects of awareness ?
- Effects of *fatigue* ?
- We claim that plateaus, rebounds etc. result from the *intrinsic dynamics* of epidemics
- Observations from Wastewater based epidemiology (WBE)
- WBE: game changer in epidemiology,
 - New possibilities
 - Many challenges, including mathematical



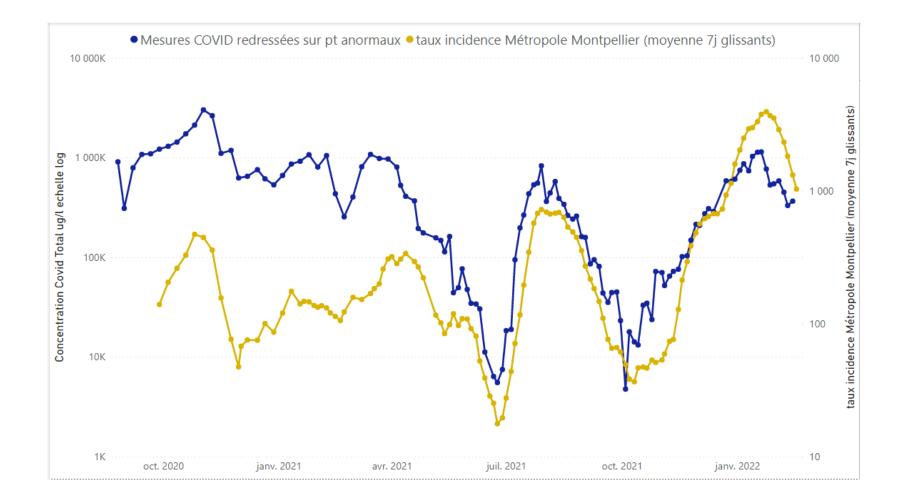
Wastewater Based Epidemiology



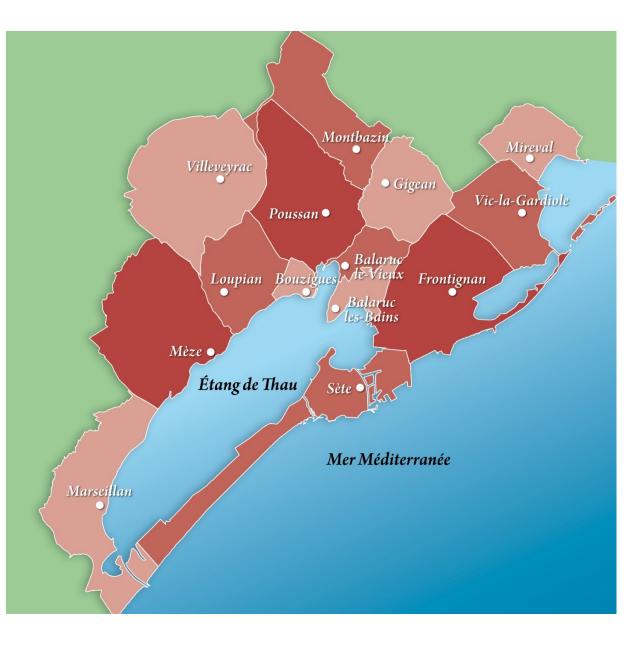




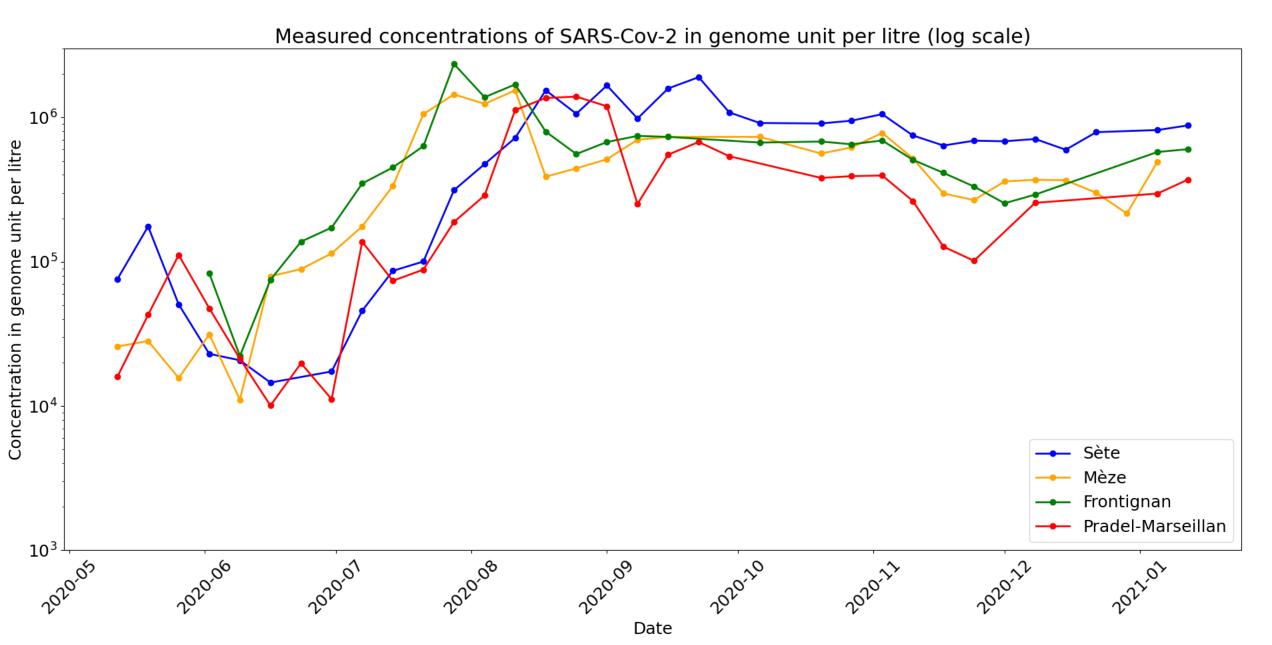
Measures in Montpellier



Thau lagoon map



Wastewater based epidemiology: the Thau lagoon experiment



A new model involving diffusion: Heterogeneous behaviors and Social Diffusion



AIM TO UNDERSTAND SOME COMPLEX FEATURES IN EPIDEMICS

IN PARTICULAR, *PLATEAUS* AND *REBOUNDS*

DIFFUSION HERE IS SOCIAL DIFFUSION

scientific reports

Check for updates

OPEN Plateaus, rebounds and the effects of individual behaviours in epidemics

Henri Berestycki^{1,2^I}, Benoît Desjardins^{3,4}, Bruno Heintz⁴ & Jean-Marc Oury⁴

Plateaus and rebounds of various epidemiological indicators are widely reported in Covid-19 pandemics studies but have not been explained so far. Here, we address this problem and explain the appearance of these patterns. We start with an empirical study of an original dataset obtained from highly precise measurements of SARS-CoV-2 concentration in wastewater over nine months in several treatment plants around the Thau lagoon in France. Among various features, we observe that the concentration displays plateaus at different dates in various locations but at the same level. In order to understand these facts, we introduce a new mathematical model that takes into account the heterogeneity and the natural variability of individual behaviours. Our model shows that the distribution of risky behaviours appears as the key ingredient for understanding the observed temporal patterns of epidemics.



- $a \in (0,1)$ defines an indicator of risky behavior of susceptibles
- The infection transmission rate $a \mapsto \beta(a)$ is an increasing function of *a*
- S(t,a) the density of individuals at time *t* associated with risk parameter *a*
- Epidemiological *I*(*t*) the total number of infected model with • *R*(*t*) the number of removed individuals heterogeneous behavior and social diffusion
 - γ^{-1} : the inverse of typical duration (in days) of the disease
 - *d* a positive diffusion coefficient

PDE model with heterogeneous behavior and social diffusion

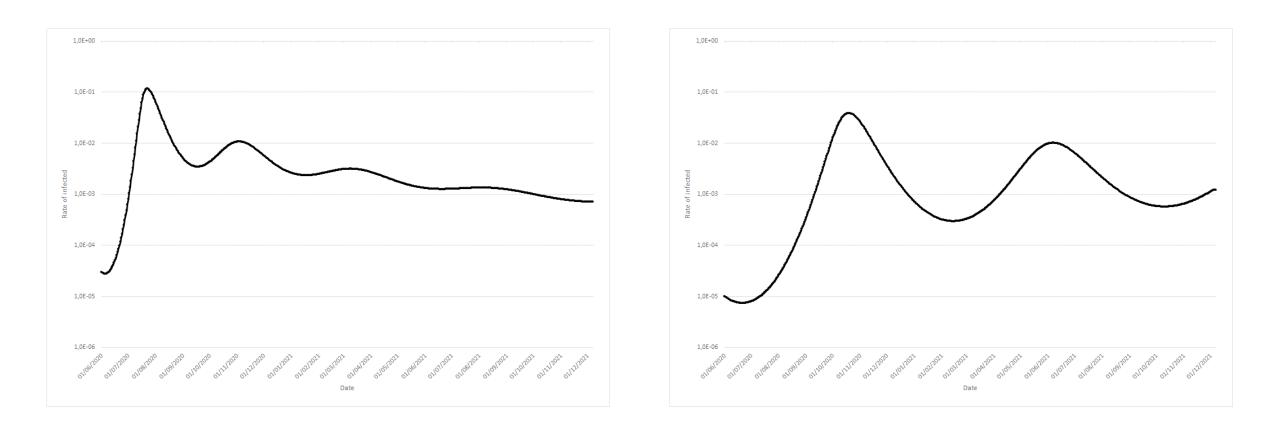
$$\partial_a S(t,0) = \partial_a S(1,0) = 0$$
 if $d > 0$.

 \cap

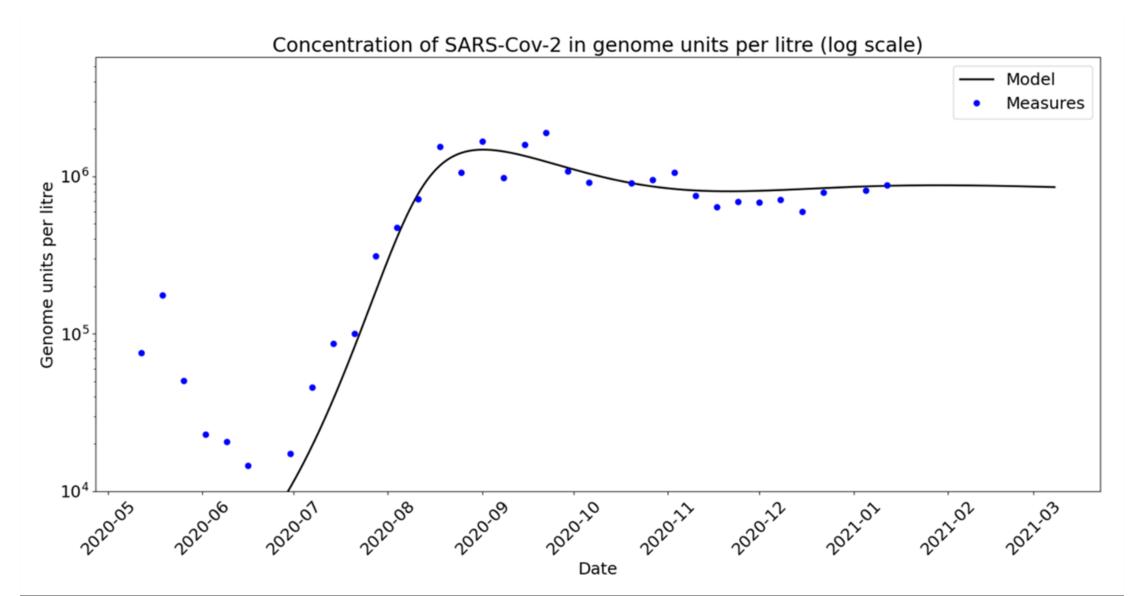
$$\begin{cases} \frac{\partial S(t,a)}{\partial t} = d \, \frac{\partial^2 S(t,a)}{\partial a^2} - \beta(a) S(t,a) \frac{I(t)}{N}, \\ \frac{dI(t)}{dt} = \frac{I(t)}{N} \int_0^1 \beta(a) S(t,a) \, da - \gamma I(t), \\ \frac{dR(t)}{dt} = \gamma I(t), \end{cases}$$

 $S(0,a) = S_0(a), \quad I(0) = I_0, \text{ and } R(0) = 0,$

Simulations: plateaus and rebounds



Model calibration on Thau lagoon data (Sète)



Conclusions

- "epidemiology, [...] variation of disease from time to time or from place to place..."
- Models with diffusion allow one to consider complex phenomena in epidemics
- Diffusion comes in various guises in epidemiology
- Spatial propagation
- Propagation on networks
- Modeling the effect of roads
- Taking into account behavioral heterogeneity and variability
- Generate complex dynamics with plateaus and rebounds
- Open new mathematical challenges
- New modelling developments in epidemiology and social sciences