Mathematical modeling of infectious disease epidemics

Eugenio Valdano

Pierre Louis Institute of Epidemiology and Public Health (IPLESP) - Sorbonne Outbreaks Modeling Center (SUMOC)

INSERM - Sorbonne Université - Paris, France

www.evmodelers.org - eugenio.valdano@inserm.fr

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From science to health

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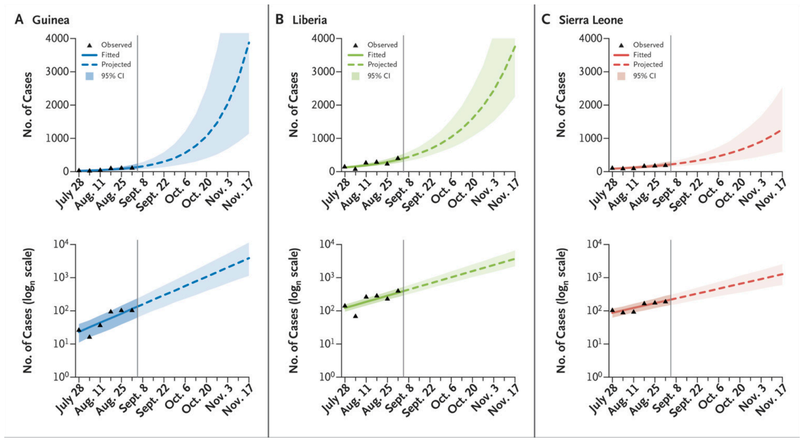
iPLesp

SUMOC
Sorbonne Université
Modeling Outbreaks Center

WHY DO WE MODEL EPIDEMICS OF INFECTIOUS DISEASE?

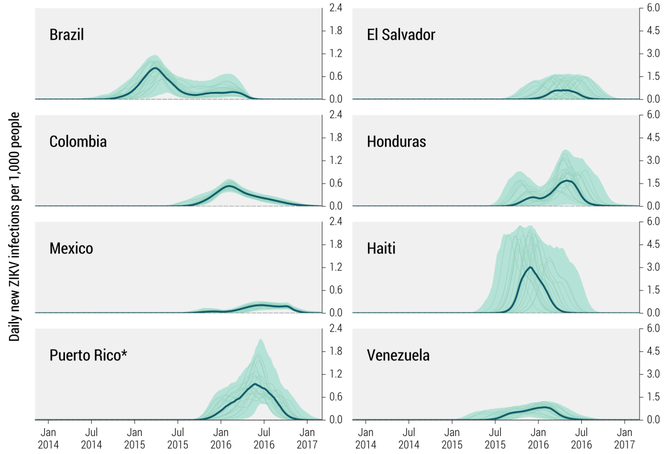
WHAT CAN MATHEMATICAL MODELS DO?

1. FORECAST / PROJECTIONS



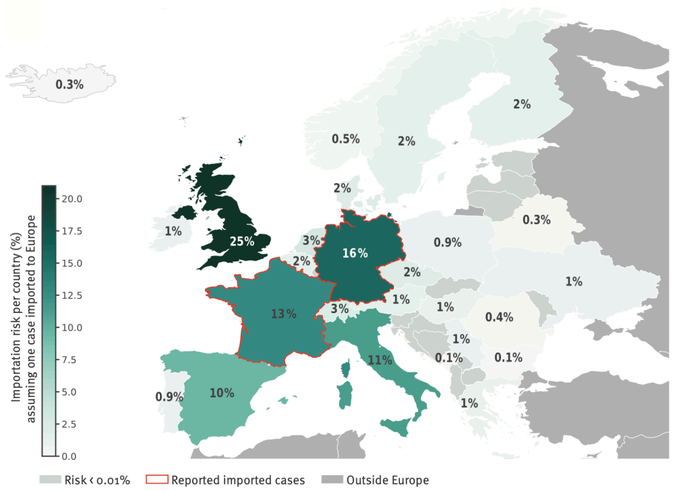
Ebola epidemic in West Africa

WHO team (2014) NEJM



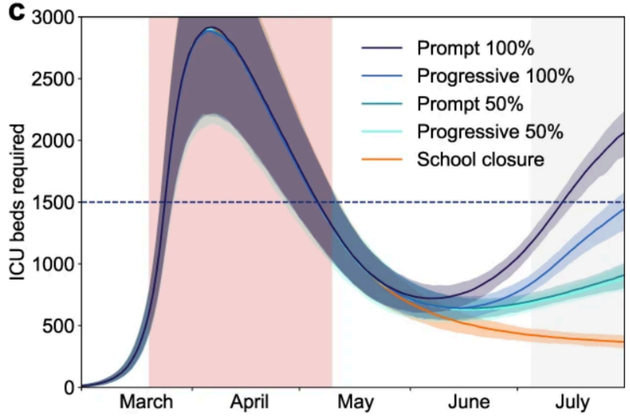
Zika in Latin America

Zhang et al (2017) PNAS



early COVID-19 importation

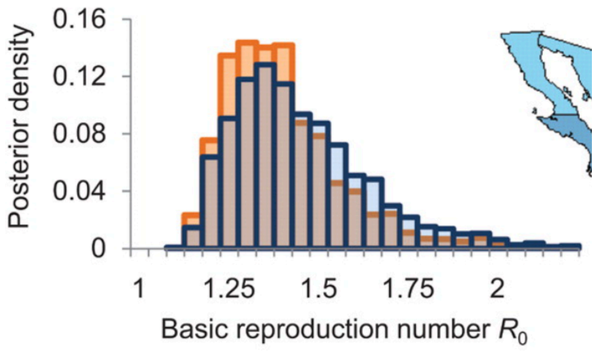
Pullano et al (2020) Eurosurv



impact of school closures on COVID-19

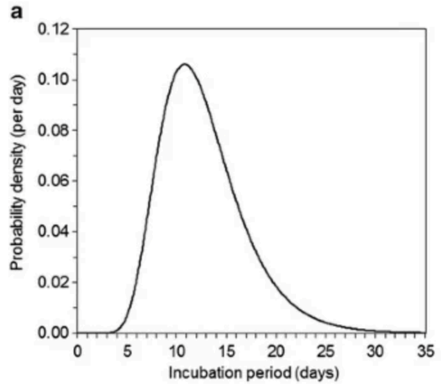
De Domenico et al (2021) Nat Comm

2. ESTIMATE OF UNKNOWN PARAMETERS/FEATURES



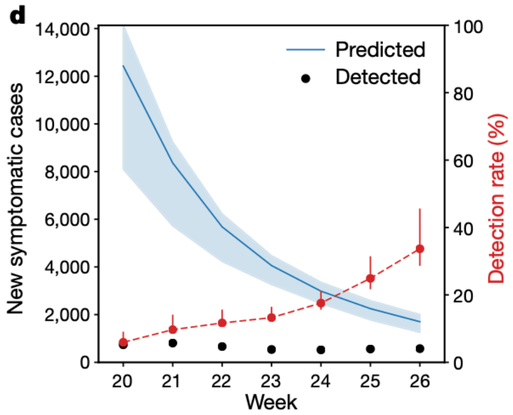
R0 of H1N1

Frase et al. (2009) Science



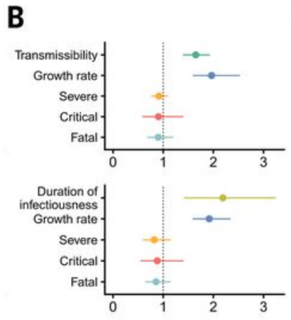
Ebola - distribution of incubation period

Chowell et al. (2014) BMC Med



COVID-19 detection rate

Pullano et al. (2021) Nature

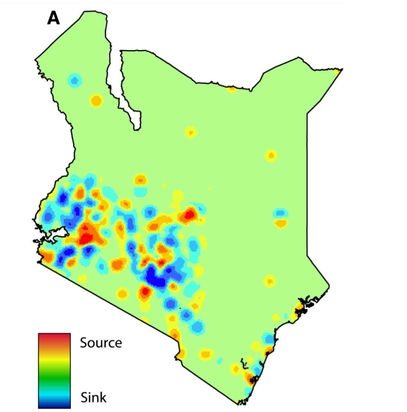


stratum. We estimate that the new variant has a 43 to 90% higher reproduction number (range of 95% credible intervals, 38 to 130%) than preexisting variants. Similar increases are observed in Denmark, Switzerland, and the United States. The most parsimonious explanation for this increase in the reproduction number is that people infected with VOC 202012/01 are more infectious than people infected with a preexisting variant, although there is also reasonable support for a longer infectious period and multiple mechanisms may be operating. Our estimates of

transmission advantage of COVID-19 Alpha variant vs wild-type

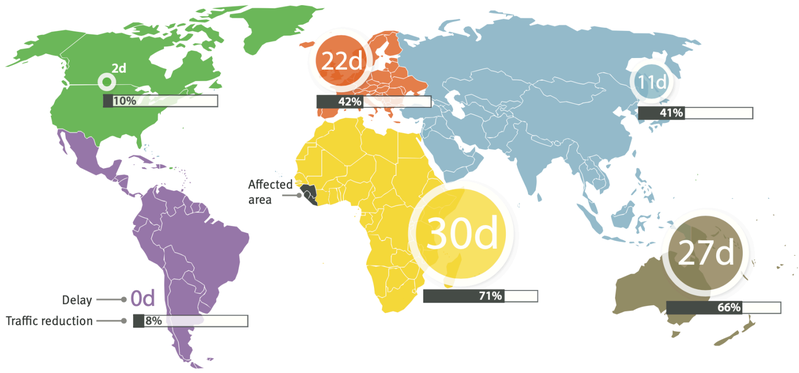
Davies et al. (2021) Science

3. UNDERSTAND MECHANISMS - DISENTANGLE EFFECTS



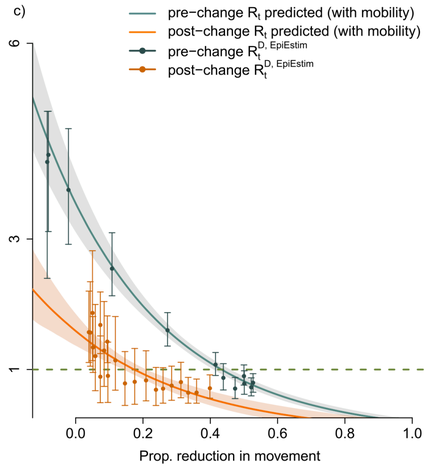
spatial dynamics of malaria in Kenya

Wesolowski et al. (2012) Science



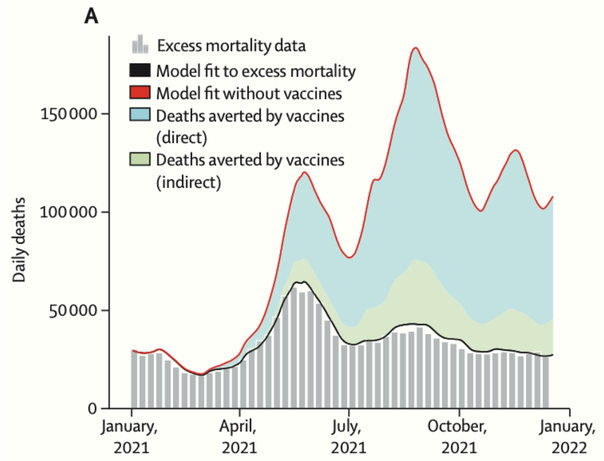
impact of travel restrictions on the spread of Ebola

Poletto et al. (2014) Eurosurveillance



human mobility vs COVID-19 R_t

Nouvellet et al. (2021) Nat Comm



COVID-19: deaths averted by vaccines

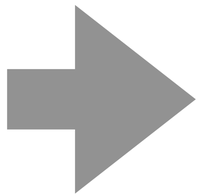
Watson et al. (2022) Lancet Inf Dis

(EPIDEMIC) MODELING

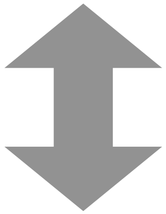
THEORY

- biomathematics
- physics / complex systems science
- network science
- computer science

MODEL



OUTPUT



VALIDATION DATA

INPUT DATA

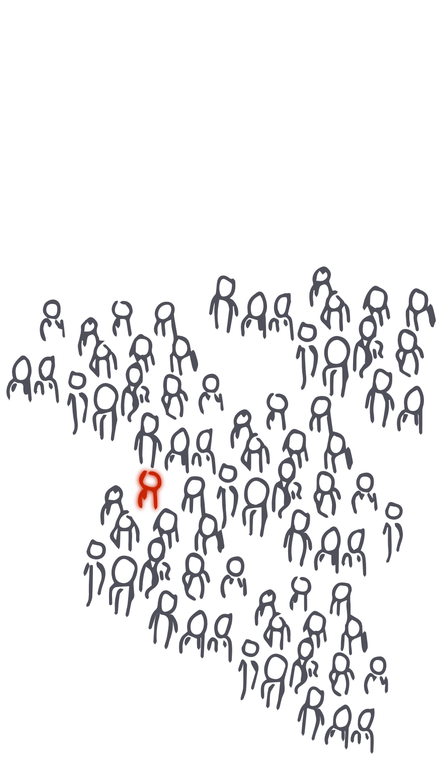
- disease natural history
- pathogen phylogenetics
- epidemic surveillance
- human behavior, contacts & mobility

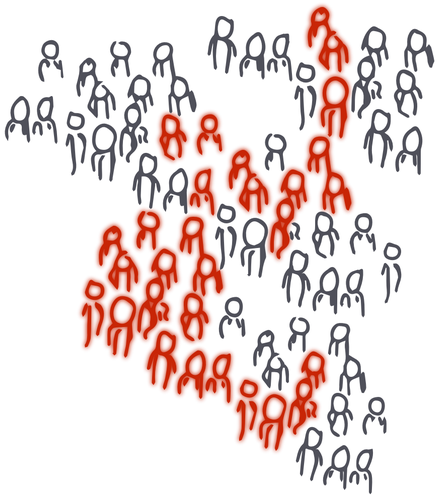
EPIDEMIC GRAPH DIAGRAMS TO ESTIMATE EPIDEMIC RISK

[EV et al (2023) Nature Communications]

MEASURING EPIDEMIC RISK: THE EPIDEMIC THRESHOLD

reproduction ratio R_t: average number of secondary infections that one case generates



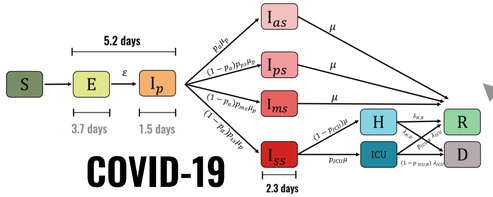


outbreak / endemicity ($R_t > 1$)

epidemic threshold ($R_t = 1$)

disease extinction ($R_t < 1$)

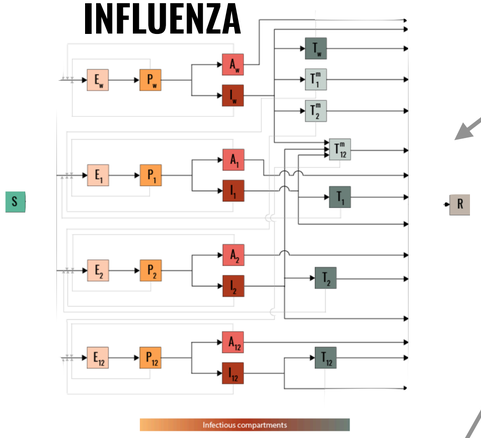
MEASURING EPIDEMIC RISK: THE EPIDEMIC THRESHOLD



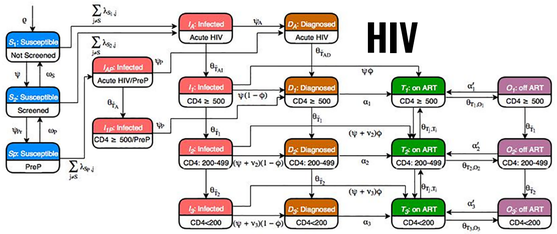
COVID-19

Di Domenico et al 2020 BMC Med

INFLUENZA



HIV



REALISTIC

DISEASE PROGRESSION

SIMPLIFIED

next-generation matrix

[Diekmann et al 1990 J Math Biol]

SIS/SIR + homogeneous mixing

annealed networks

[Pastor-Satorras Vespignani 2001 PRL
Newman 2002 PRE]

&

quenched networks

[Wang et al 2003
Gómez et al 2010 Europhys Lett]

infection propagator

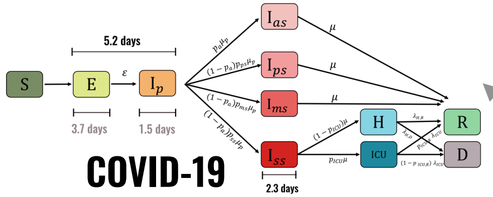
[Valdano et al 2015 PRX]

SIMPLIFIED

POPULATION MIXING & CONTACTS

REALISTIC

MEASURING EPIDEMIC RISK: THE EPIDEMIC THRESHOLD



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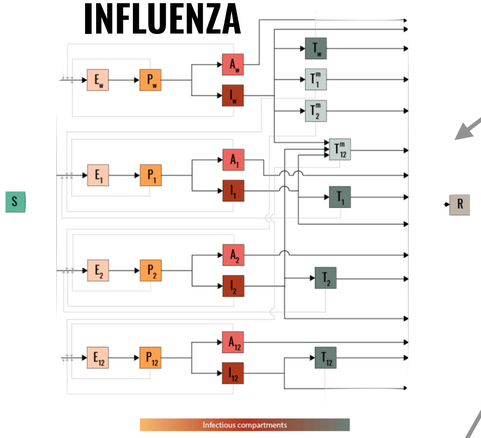

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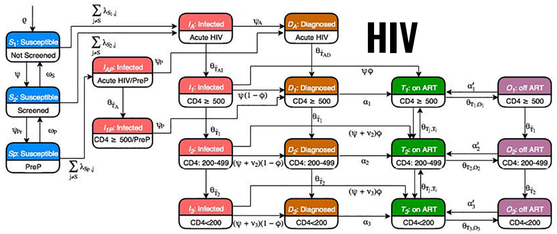

REALISTIC

DISEASE PROGRESSION

SIMPLIFIED

next-generation matrix
[Diekmann et al 1990 J Math Biol]

NEITHER SIMPLIFICATION IS ACCEPTABLE

SIS/SIR + homogeneous mixing

annealed networks
[Pastor-Satorras Vespignani 2001 PRL
Newman 2002 PRE]
&
quenched networks
[Wang et al 2003
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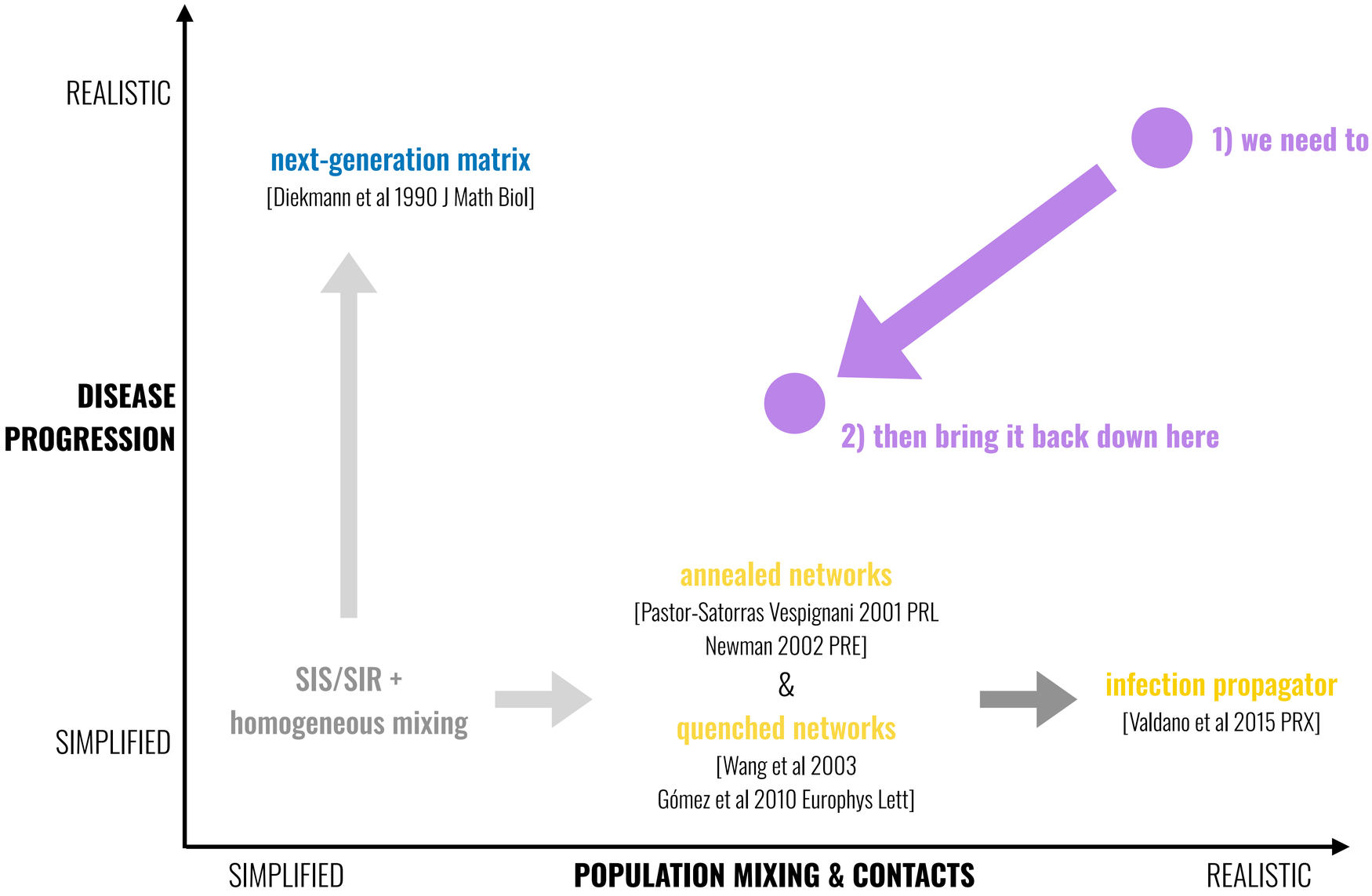
SIMPLIFIED — **POPULATION MIXING & CONTACTS** — REALISTIC

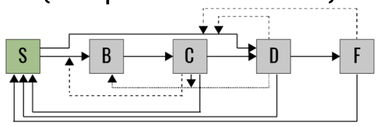
MEASURING EPIDEMIC RISK: THE EPIDEMIC THRESHOLD



EPIDEMIC GRAPH DIAGRAMS

DISEASE EVOLUTION

(compartmental model)



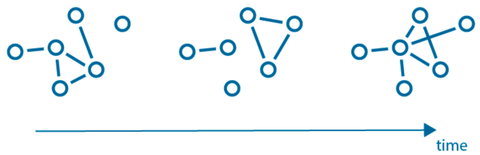
compartment
S: susceptibles
B,C,D,F: other compartments

Reactions

①	$B \to C$	with rate	γ_{BC}	spontaneous transitions
	$C \to D$		γ_{CD}	
	$D \to F$		γ_{DF}	
	$C \to S$		μ_{CS}	to S
	$D \to S$		μ_{DS}	
	$F \to S$		μ_{FS}	
②	$S + C \to B + C$		λ_{CB}	transmission processes w/ S
	$S + D \to 2D$		λ_{DD}	
	$S + F \to D + F$		λ_{FD}	
③	$D + C \to B + C$		ω_{DCB}	transmission processes w/o S

MIXING

(time-evolving contact network)



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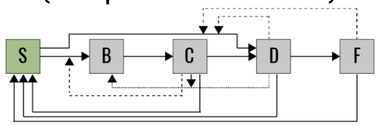

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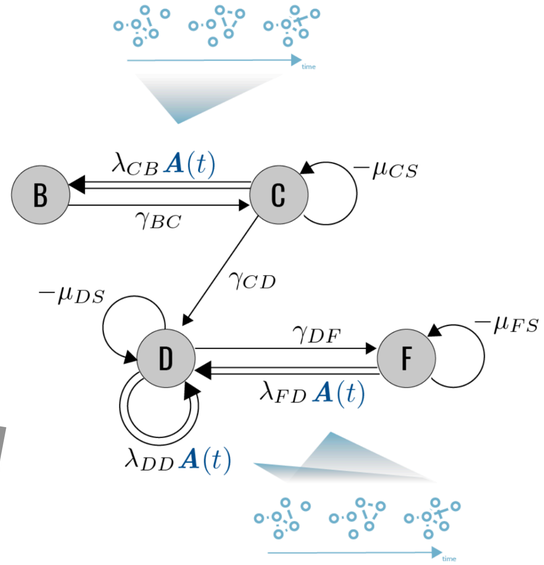
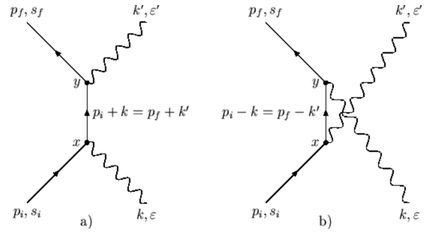
EPIDEMIC GRAPH DIAGRAM



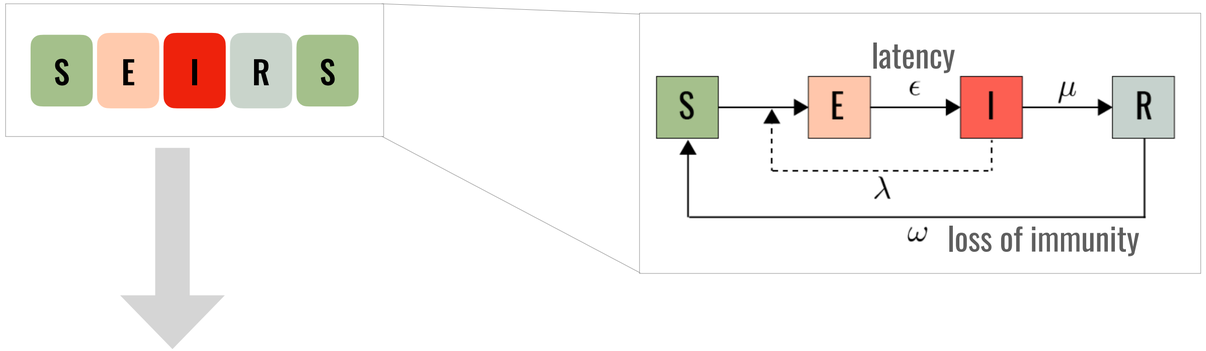
(wishful) analogy with

Feynman rules & diagrams

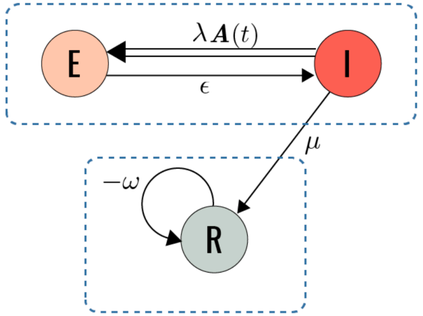


- graphical representations
- tools to perform calculations
- rules to build them and simplify them
- compute things directly from them

EXAMPLE: LATENCY & LOSS OF IMMUNITY

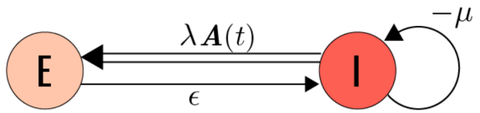


build the EGD



CUT

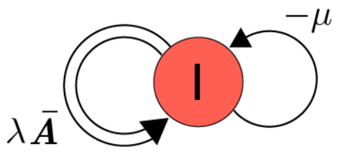
1. time to loss of immunity plays no role



NO temporal structure in the contact network

SHRINK

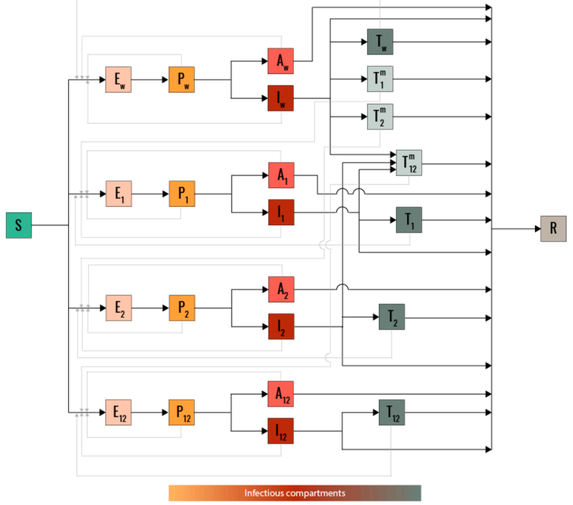
2. latency impacts the threshold through its interplay with the underlying contact network



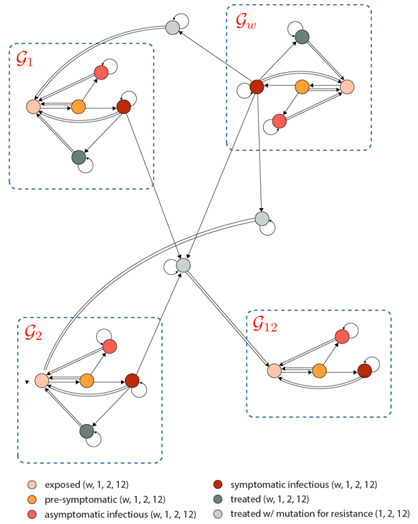
S I S

EXAMPLE: INFLUENZA WITH RESISTANCE TO ANTIVIRALS

influenza with strains resistant to antivirals

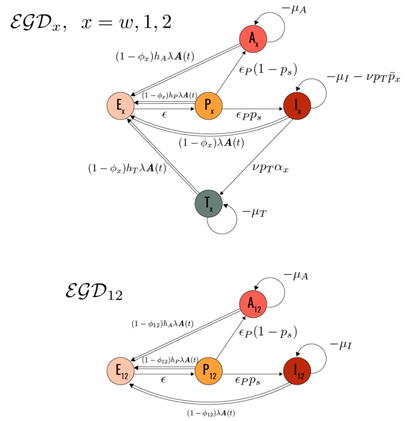


build the EGD



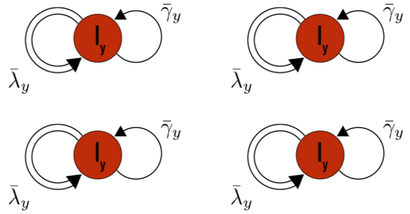
CUT

[keep only strongly connected components]



ZIP

[only one node has incoming double links]



decoupled SIS models

DISTRIBUTION OF PREVENTION: NONSELECTIVE VS RISK-BASED

[Steinegger et al (2022) Nature Communications]

PrEP AMONG MSM

PrEP: Pre-Exposure Prophylaxis of HIV

prevents HIV acquisition during unprotected sex

most common formulation

- emtricitabine / tenofovir disoproxil fumarate (Truvada®)
- **pill** taken daily (or on demand)

MSM: men-having-sex-with-men

- disproportionately at risk for HIV infection
- stigma & criminalization make many communities hard-to-reach

Globally, the risk of acquiring HIV is 26 times higher among MSM compared to the general population.

source: who.int

PrEP OFTEN RECOMMENDED TO HIGH-RISK MSM

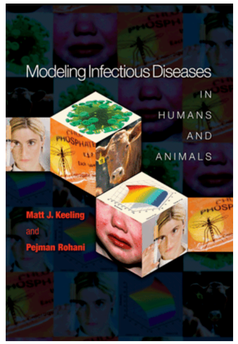
2002

PHYSICAL REVIEW E, VOLUME 65, 036104

Immunization of complex networks

Romualdo Pastor-Satorras[1] and Alessandro Vespignani[2]

2007



long-established theory: TARGETED IMMUNIZATION

you should immunize those at high risk of spreading the disease

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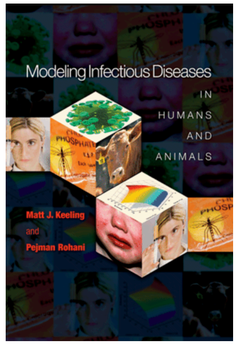

long-established theory: TARGETED IMMUNIZATION

you should immunize those at high risk of spreading the disease

PrEP **guidelines** often **risk-based (targeted)**

	Eligibility criteria	Preferred regimen	Event-driven option*	Monitoring recommendations	Discontinuation
WHO[3,11]	All people who are HIV-negative and are at substantial risk of acquiring HIV, prioritising subpopulations with 3% or higher annual HIV incidence in the absence of PrEP	Oral, containing tenofovir disoproxil fumarate	Yes, for MSM	HIV testing every 3 months; renal function testing every 6 months; HBV surface antigen; HCV antibody; adherence counselling; STI testing	If a person is no longer at risk and can remain at low risk: continue daily PrEP for 28 days after last HIV exposure; MSM using daily or event-driven 2-1-1 PrEP regimen should take a single pill daily for two days after the last sex act
Centers for Disease Control and Prevention and United States Public Health Service[10]	Adult (≥18 years) MSM, heterosexual men and women, or people who inject drugs are at substantial risk if they have an HIV-positive partner; a recent STI; a high number of partners; inconsistently use or do not use condoms; are sex workers; and people who inject drugs with a HIV-positive injecting partner or share injection equipment	Daily oral fixed dose combination tenofovir disoproxil fumarate (300 mg) plus emtricitabine (200 mg)	No	HIV testing every 3 months; renal function testing every 6 months; adherence counselling, behavioural risk reduction; STI testing (every 3–6 months)	Discuss alternative risk reduction strategies; document HIV status, reason for discontinuation, and medication adherence or sexual risks; continue medication for 7–10 days after the last exposure
International Antiviral Society–USA[11]	All populations with an annual HIV incidence of 2% or more	Oral fixed dose combination tenofovir disoproxil fumarate (300 mg) plus emtricitabine (200 mg)	Yes, for MSM with infrequent sexual exposures and without hepatitis B virus	HIV and STI testing every 3 months; renal function testing every 6 months	Continue medication for 1 week after the last sexual exposure
European AIDS Clinical Society[12]	Adults at high-risk of acquiring HIV infection, specifically HIV-negative MSM or transgender populations who do not use condoms consistently with casual partners; HIV-positive partners not on treatment; recent STI, use of post-exposure prophylaxis, or chemsex might increase HIV risk; and for HIV-negative heterosexual men and women who inconsistently use a condom and have multiple partners whom are likely to be HIV-positive and not on treatment	Oral fixed dose combination tenofovir disoproxil fumarate (300 mg) plus emtricitabine (200 mg)	Yes, for MSM	HIV testing every 3 months; hepatitis B virus surface antigen testing; STI screen when initiating PrEP and regularly; renal function and bone mineral density according to tenofovir disoproxil fumarate guidelines[12]	Not mentioned
British HIV Association[13]	MSM and trans women at elevated risk of HIV with condomless anal sex; heterosexual men and women with condomless sex with known HIV-positive partners (not virally suppressed)	Oral fixed dose combination tenofovir disoproxil fumarate (300 mg) plus emtricitabine (200 mg); tenofovir disoproxil fumarate alone can be offered to heterosexual men and women with emtricitabine contraindication	Yes, for MSM	HIV and STI testing every 3 months; HCV screening every 3 months in MSM, trans women, and those at risk of HCV; renal function and bone mineral density according to tenofovir disoproxil fumarate guidelines	Continue PrEP 48 h after last sexual risk if HIV risk is through anal sex; continue for 7 days after last sexual risk if HIV risk is through vaginal sex
Australasian Society of HIV, Viral Hepatitis, and Sexual Health Medicine[14]	All people at risk of HIV infection	Oral fixed dose combination tenofovir disoproxil fumarate (300 mg) plus emtricitabine (200 mg)	Yes, for MSM	HIV and STI testing every 3 months; renal function and bone mineral density according to tenofovir disoproxil fumarate guidelines	Duration depends on persistence of HIV risk; on-demand PrEP stopped with a single tablet for 2 days after the last exposure; daily PrEP should be continued for 28 days after last exposure
South African HIV Clinicians Society[15]	Any sexually active MSM or transgender person; heterosexual men and women especially if HIV-positive partners not confirmed (virologically suppressed) or partner status unknown; those with recent STI; multiple sexual partners; sex workers; and those inconsistently using or not using condoms	Oral fixed dose combination tenofovir disoproxil fumarate (300 mg) plus emtricitabine (200 mg)	–	HIV testing every 3 months; renal function testing at 1 and 4 months, then every 12 months; STI screen (syndromic or testing, depending on resources) every 6 months	28 days after the last potential exposure to HIV-infected fluids if not at continued substantial risk of HIV acquisition

HBV=hepatitis B virus. HCV=hepatitis C virus. MSM=men who have sex with men. PrEP=pre-exposure prophylaxis. STI=sexually transmitted infection. *Also known as the 2-1-1 regimen by the International Antiviral Society–USA.

Table 1: PrEP initiation, monitoring, and discontinuation

Rutstein et al (2020) Lancet HIV

PROBLEM: risk metrics may

1. have low accuracy in some communities
2. be hard to implement
3. reinforce stigma

CURRENT **CONUNDRUM**

target according to risk

BUT

risk is hard to measure and may be inequitable

SOLUTION: **targeting may not be the best-performing strategy!**

IMPERFECT PROTECTION

PrEP efficacy among **MSM: 40**-to-**86%**
[Grant et al 2010 NEJM, Molina et al 2015 NEJM, Jourdain et al 2022 Lancet PH]

→ possibility of **breakthrough** infections

THEY ARE THE SAME PEOPLE!
(think about #contacts)

two types of individual risk:

high **risk** of **exposure**

↑

those with the **highest probability** of **breakthrough** infections

high **risk** of **transmission** once infected

↑

those who you **want** to **target**

IMPERFECT PROTECTION

PrEP efficacy among **MSM: 40-to-86%**
[Grant et al 2010 NEJM, Molina et al 2015 NEJM, Jourdain et al 2022 Lancet PH]

→ possibility of **breakthrough** infections

THEY ARE THE SAME PEOPLE!
(think about #contacts)

TRADEOFF

two types of individual risk:

high **risk** of **exposure**

those with the **highest probability** of **breakthrough** infections

high **risk** of **transmission** once infected

those who you **want** to **target**

BAD: breakthrough infection means "wasted" dose

GOOD: avoid superspreading events

A BIT OF THEORY

SIS model

parameters

λ: transmission rate

μ: recovery rate

ε: efficacy of prevention

p_k: probability of having contact rate k

g_k: fraction of immunized among those with contact rate k

$$\begin{cases} \dot{x}_k = -\mu x_k + \dfrac{\lambda}{\langle k \rangle} k(1-x_k)\xi \\ \dot{y}_k = -\mu y_k + \dfrac{\lambda}{\langle k \rangle}(1-\epsilon)k(1-y_k)\xi \\ \xi = \displaystyle\sum_k k p_k \left[(1-g_k)x_k + g_k y_k\right] . \end{cases}$$

variables

x_k: probability of being infectious given c.r. k and **no immunization**

y_k: probability of being infectious given c.r. k and **immunization**

prevalence: $I[g,x,y] = \displaystyle\sum_k p_k \left[(1-g_k)x_k + g_k y_k\right]$

RESPONSE FUNCTION

1. nobody is immunized

$g_k = 0 \quad \forall k$

2. I start providing vaccines/prophylaxis to a specific risk class

set a specific $k \longrightarrow g_k$ starts going up from zero

3. what is the benefit on the overall epidemic?

impact on $I[g, x, y]$ (overall prevalence)

RESPONSE FUNCTION

1. nobody is immunized → $g_k = 0 \quad \forall k$
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RESPONSE FUNCTION $$f(k) = -\frac{1}{p_k}\frac{dI}{dg_k}\bigg|_{g=0}$$

high value ⟺ immunizing in class k has a strong effect on disease circulation (lower I)

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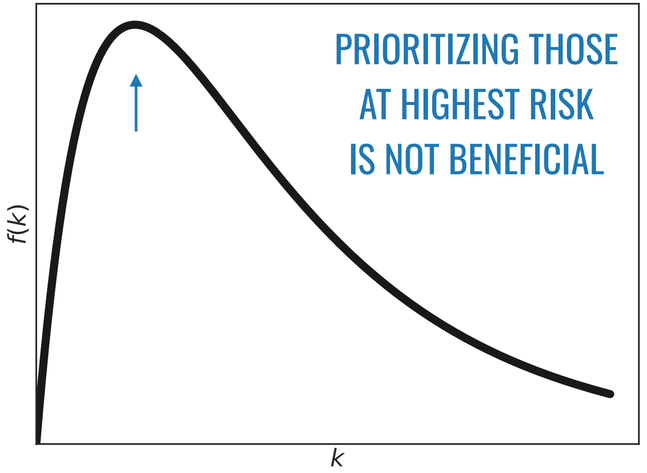
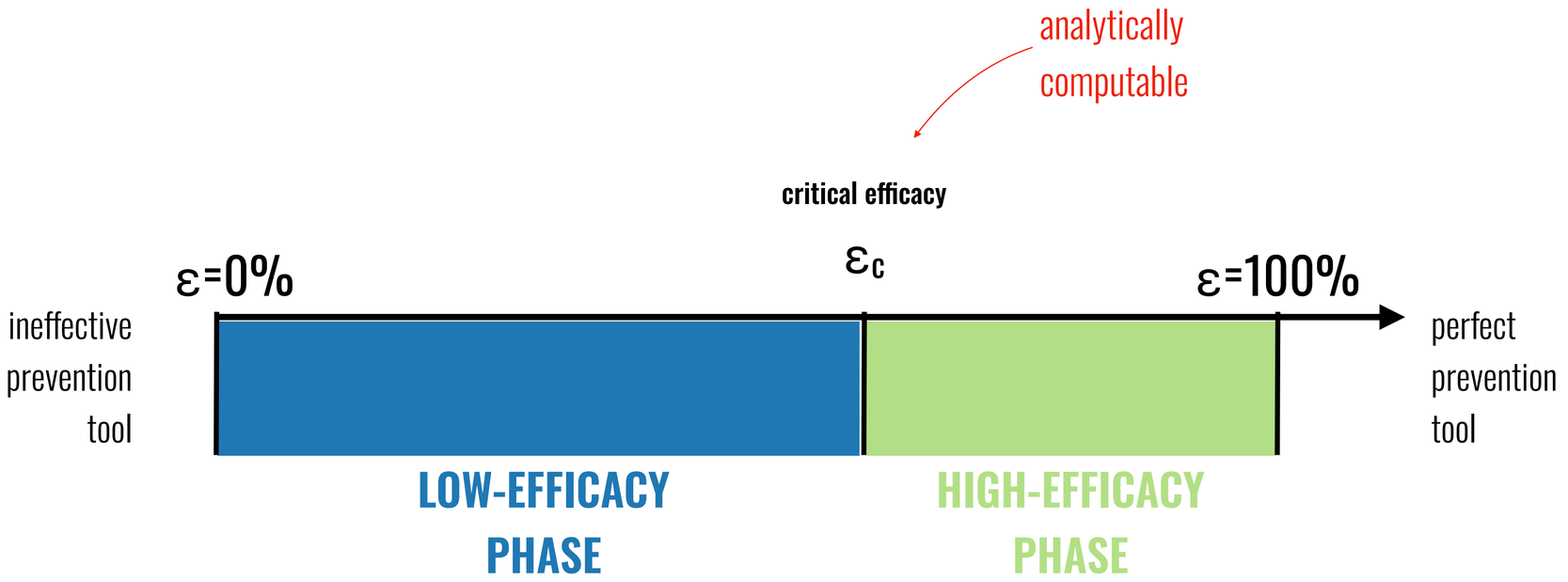


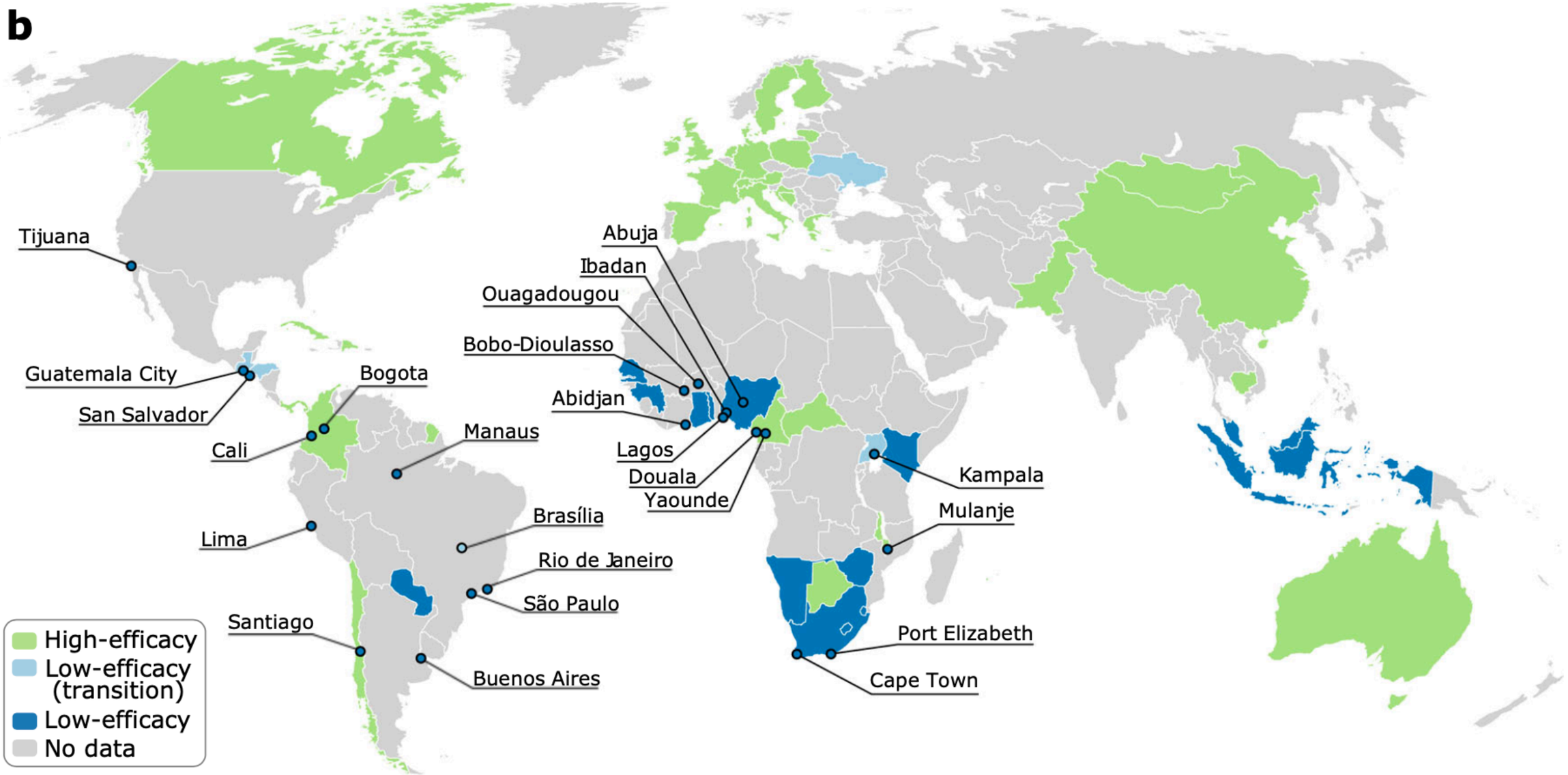
CRITICAL EFFICACY



efficacy above critical efficacy → **targeting** those at **highest risk** (hubs) is optimal

efficacy below critical efficacy → **providing prevention non-selectively** (at random) outperforms targeting

RISK-BASED PrEP DISTRIBUTION MAY NOT BE OPTIMAL EVERYWHERE



58 countries, 24 cities (tot 82) high-efficacy region: 34 low-efficacy region: 40

FOUNDATION MODELS FOR TABULAR DATA TO MODEL EPIDEMICS

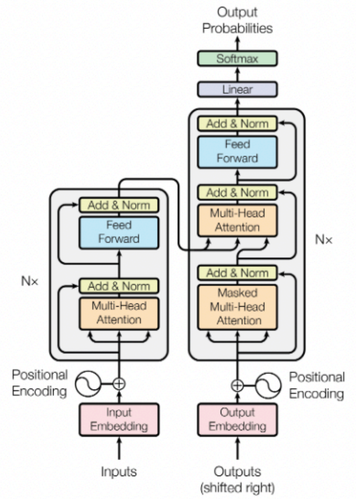
[Kalahasti et al (2025) medRxiv pre-print]

WHAT ARE FOUNDATION MODELS?

large-scale, pre-trained **machine learning models** that can be adapted to **many tasks** with no or **little retraining**

- **Scale**: Trained on massive datasets with millions/billions of parameters
- **Self-supervised learning**: Learns from unlabelled data
- **Transfer Learning**: Can apply knowledge to new domains and tasks
- **Few-shot/Zero shot Learning**: Require minimal examples to adapt to new tasks
- **Domain Adaptability**: Can be fine-tuned across multiple domains

transformer-based architectures



Vaswani et al.
Attention is all you need
Advances in Neural Information Processing Systems (2017)

WHAT GOOD ARE FOUNDATION MODELS TO US?

foundation models work well with textual data

 GPT

 BERT

 LECHAT

 LLAMA

 CLAUDE

have revolutionized

- natural language processing
- computer vision
- image generation

problem: you typically don't describe epidemic spread with text or images.

WHAT GOOD ARE FOUNDATION MODELS TO US?

foundation models work well with textual data

GPT BERT LECHAT

LLAMA CLAUDE

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- natural language processing
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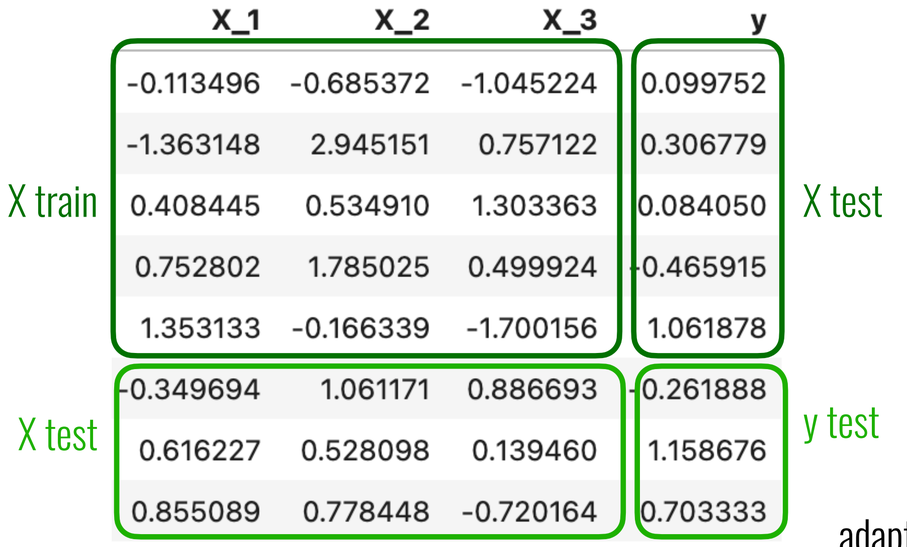
- image generation

problem: you typically don't describe epidemic spread with text or images.

NEW FIELD:

foundation models for tabular data



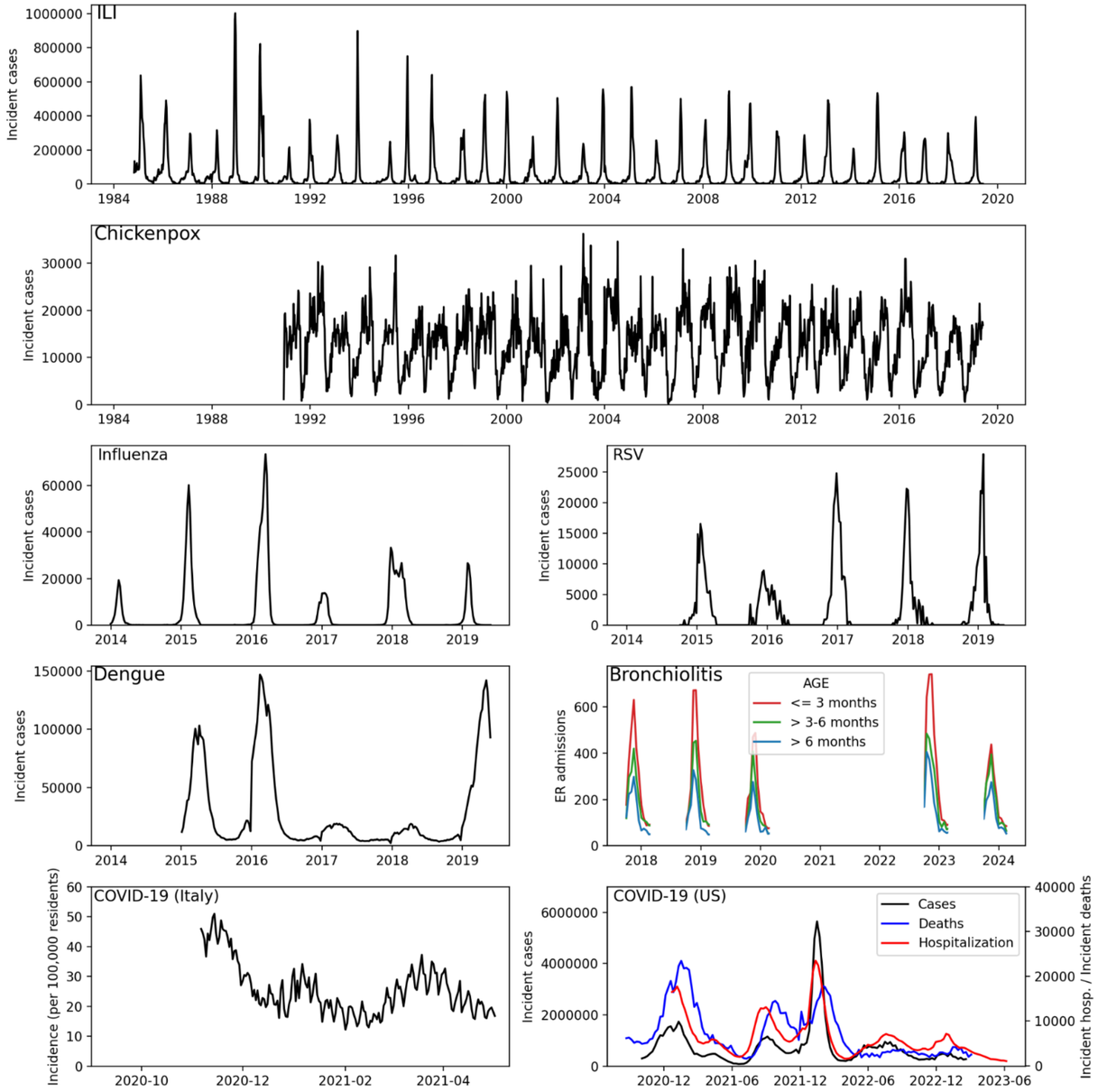
adapted from Hollmann et al (2025) Nature

TABULAR (→TIME SERIES) FOUNDATION MODELS

model	features	size (# param)
TimesFM	developed by	7G
LagLlama	based on Llama	1.2G
TabPFN-TS	synth data	11M
TimeGPT	based on GPT	3.5G
Chronos	based on T5	2.8G

- none of them trained on epi data
- no re-training (zero-shot)
- except some hyperparam tuning (for few models)

TESTING ACROSS EPIDEMIC CONTEXTS



- multiple diseases
- multiple pathogens
- multiple countries (France, Italy, Brazil)
- multiple indicators (cases, ER admissions, hospitalizations)
- multiple transmission routes
- multiple dataset sizes

SHORT-TERM FORECASTS: TabPFN vs SotA

the US COVID-19 Forecast Hub **ensemble forecast**

from up to 110 independent forecasts

COVID-19 ForecastHub

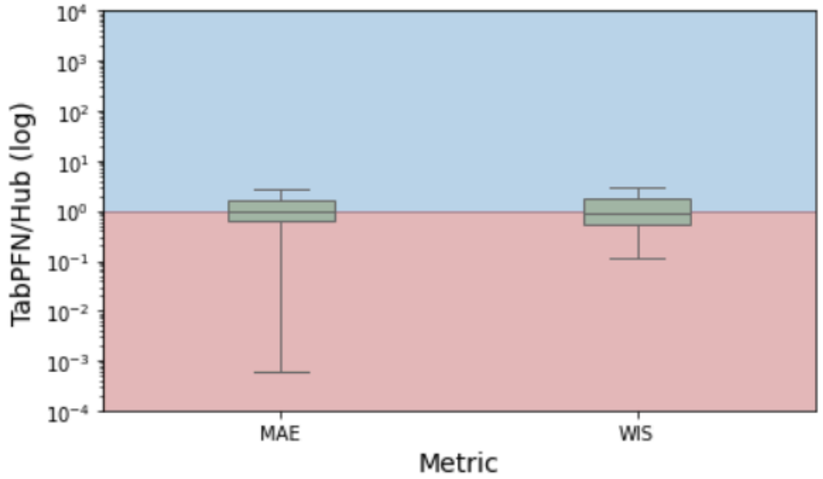
RESEARCH ARTICLE | STATISTICS

Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the United States

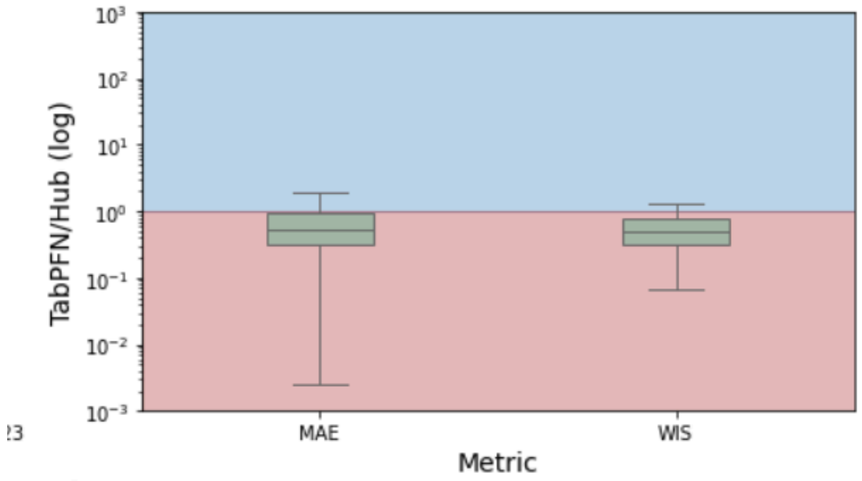
Estee Y. Cramer, Evan L. Ray, Velma K. Lopez, Johannes Bracher, Andrea Brennen, Alvaro J. Castro Rivadeneira, Aaron Gerding, Tilmann Gneiting, Katie H. House, Yuxin Huang, Dasuni Jayawardena, Abdul H. Kanji, Ayush Khandelwal, Khoa Le, Anja Mühlemann, Jarad Niemi, Apurv Shah, Ariane Stark, Yijin Wang, Nutcha Wattanachit, Martha W. Zorn, Youyang Gu, Sansiddh Jain, Nayana Bannur, Ayush Deva, Mihir Kulkarni, Srujana Merugu, Alpan Raval, Siddhant Shingi, Avtansh Tiwari, Jerome White, Neil F. Abernethy, Spencer Woody, Maytal Dahan, Spencer Fox, Kelly Gaither, Michael Lachmann, Lauren Ancel Meyers, James G. Scott, Mauricio Tec, Ajitesh Srivastava, Glover E. George, Jeffrey C. Cegan, Ian D. Dettwiller, William P. England, Matthew W. Farthing, Robert H. Hunter, Brandon Lafferty, Igor Linkov, Michael L. Mayo, Matthew D. Parno, Michael A. Rowland, Benjamin D. Trump, Yanli Zhang-James, Samuel Chen, Stephen V. Faraone, Jonathan Hess, Christopher P. Morley, Asif Salekin, Dongliang Wang, Sabrina M. Corsetti, Thomas M. Baer, Marisa C. Eisenberg, Karl Falb, Yitao Huang, Emily T. Martin, Ella McCauley, Robert L. Myers, Tom Schwarz, Daniel Sheldon, Graham Casey Gibson, Rose Yu, Liyao Gao, Yian Ma, Dongxia Wu, Xifeng Yan, Xiaoyong Jin, Yu-Xiang Wang, YangQuan Chen, Lihong Guo, Yanting Zhao, Quanquan Gu, Jinghui Chen, Lingxiao Wang, Pan Xu, Weitong Zhang, Difan Zou, Hannah Biegel, Joceline Lega, Steve McConnell, V. P. Nagraj, Stephanie L. Guertin, Christopher Hulme-Lowe, Stephen D. Turner, Yunfeng Shi, Xuegang Ban, Robert Walraven, Qi-Jun Hong, Stanley Kong, Axel van de Walle, James A. Turtle, Michal Ben-Nun, Steven Riley, Pete Riley, Ugur Koyluoglu, David DesRoches, Pedro Forli, Bruce Hamory, Christina Kyriakides, Helen Leis, John Milliken, Michael Moloney, James Morgan, Ninad Nirgudkar, Gokce Ozcan, Noah Piwonka, Matt Ravi, Chris Schrader, Elizabeth Shakhnovich, Daniel Siegel, Ryan Spatz, Chris Stiefeling, Barrie Wilkinson, Alexander Wong, Sean Cavany, Guido España, Sean Moore, Rachel Oidtman, Alex Perkins, David Kraus, Andrea Kraus, Zhifeng Gao, Jiang Bian, Wei Cao, Juan Lavista Ferres, Chaozhuo Li, Tie-Yan Liu, Xing Xie, Shun Zhang, Shun Zheng, Alessandro Vespignani, Matteo Chinazzi, Jessica T. Davis, Kunpeng Mu, Ana Pastore y Piontti, Xinyue Xiong, Andrew Zheng, Jackie Baek, Vivek Farias, Andreea Georgescu, Retsef Levi, Deeksha Sinha, Joshua Wilde, Georgia Perakis, Mohammed Amine Bennouna, David Nze-Ndong, Divya Singhvi, Ioannis Spantidakis, Leann Thayaparan, Asterios Tsiourvas, Arnab Sarker, Ali Jadbabaie, Devavrat Shah, Nicolas Della Penna, Leo A. Celi, Saketh Sundar, Russ Wolfinger, Dave Osthus, Lauren Castro, Geoffrey Fairchild, Isaac Michaud, Dean Karlen, Matt Kinsey, Luke C. Mullany, Kaitlin Rainwater-Lovett, Lauren Shin, Katharine Tallaksen, Shelby Wilson, Elizabeth C. Lee, Juan Dent, Kyra H. Grantz, Alison L. Hill, Joshua Kaminsky, Kathryn Kaminsky, Lindsay T. Keegan, Stephen A. Lauer, Joseph C. Lemaitre, Justin Lessler, Hannah R. Meredith, Javier Perez-Saez, Sam Shah, Claire P. Smith, Shaun A. Truelove, Josh Wills, Maximilian Marshall, Lauren Gardner, Kristen Nixon, John C. Burant, Lily Wang, Lei Gao, Zhiling Gu, Myungjin Kim, Xinyi Li, Guannan Wang, Yueying Wang, Shan Yu, Robert C. Reiner, Ryan Barber, Emmanuela Gakidou, Simon I. Hay, Steve Lim, Chris Murray, David Pigott, Heidi L. Gurung, Prasith Baccam, Steven A. Stage, Bradley T. Suchoski, B. Aditya Prakash, Bijaya Adhikari, Jiaming Cui, Alexander Rodriguez, Anika Tabassum, Jiajia Xie, Pinar Keskinocak, John Asplund, Arden Baxter, Buse Eylul Oruc, Nicoleta Serban, Sercan O. Arik, Mike Dusenberry, Arkady Epshteyn, Elli Kanal, Long T. Le, Chun-Liang Li, Tomas Pfister, Dario Sava, Rajarishi Sinha, Thomas Tsai, Nate Yoder, Jinsung Yoon, Leyou Zhang, Sam Abbott, Nikos I. Bosse, Sebastian Funk, Joel Hellewell, Sophie R. Meakin, Katharine Sherratt, Mingyuan Zhou, Rahi Kalantari, Teresa K. Yamana, Sen Pei, Jeffrey Shaman, Michael L. Li, Dimitris Bertsimas, Omar Skali Lami, Saksham Soni, Hamza Tazi Bouardi, Turgay Ayer, Madeline Adee, Jagpreet Chhatwal, Ozden O. Dalgic, Mary A. Ladd, Benjamin P. Linas, Peter Mueller, Jade Xiao, Yuanjia Wang, Qinxia Wang, Shanghong Xie, Donglin Zeng, Alden Green, Jacob Bien, Logan Brooks, Addison J. Hu, Maria Jahja, Daniel McDonald, Balasubramanian Narasimhan, Collin Politsch, Samyak Rajanala, Aaron Rumack, Noah Simon, Ryan J. Tibshirani, Rob Tibshirani, Valerie Ventura, Larry Wasserman, Eamon B. O'Dea, John M. Drake, Robert Pagano, Quoc T. Tran, Lam Si Tung Ho, Huong Huynh, Jo W. Walker, Rachel B. Slayton, Michael A. Johansson, Matthew Biggerstaff, and Nicholas G. Reich Authors Info & Affiliations

Edited by Kenneth Wachter, University of California, Berkeley, CA; received July 24, 2021; accepted January 24, 2022

April 8, 2022 | 119 (15) e2113561119 | https://doi.org/10.1073/pnas.2113561119

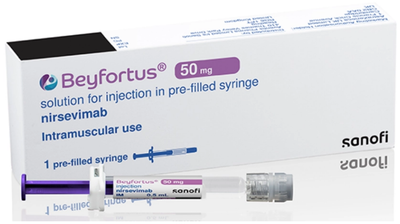


CASES



HOSPITALIZATIONS

BEYOND FORECASTS: POLICY EVALUATION



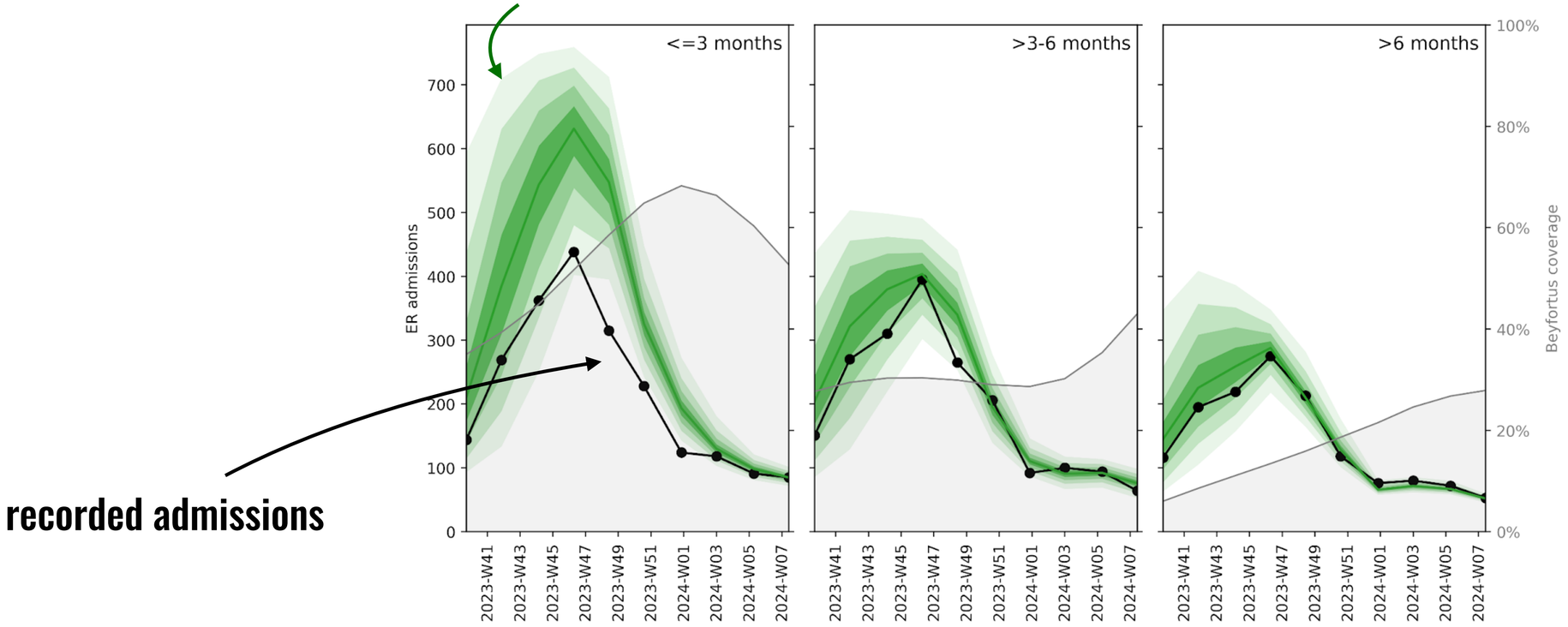
- respiratory syncytial virus (**RSV**) causes bronchiolitis in **newborns**
- monitoring **ER admissions** in Paris
- season 2023-24: introduction of **nirsevimab** immunization
- case-control study to estimate **effectiveness** in averting all-cause bronchiolitis ER admissions

	≤3 months (n=940)	>3–6 months (n=642)	>6–12 months (n=1204)
Attended paediatric emergency department (all-cause bronchiolitis; N=864)			
Received nirsevimab	77/217 (35%)	47/315 (15%)	54/332 (16%)
Did not receive nirsevimab	140/217 (65%)	268/315 (85%)	278/332 (84%)
Effectiveness (95% CI)	52% (29 to 68)	59% (36 to 74)	27% (–9 to 51)

Carbajal et al. (2024) Lan Child & Adol Health

TabPFN to estimate the effectiveness of nirsevimab immunization

TabPFN "counterfactual": admissions observed in the absence of the immunization campaign



From that we could predict the effectiveness

- <=3 months - 56% (CI : 10%-77%)
- > 3-6 months - 45% (-20%,75%)
- >6 months - 13% (-50%,174%)

vs

	≤3 months (n=940)	>3–6 months (n=642)	>6–12 months (n=1204)
Attended paediatric emergency department (all-cause bronchiolitis; N=864)			
Received nirsevimab	77/217 (35%)	47/315 (15%)	54/332 (16%)
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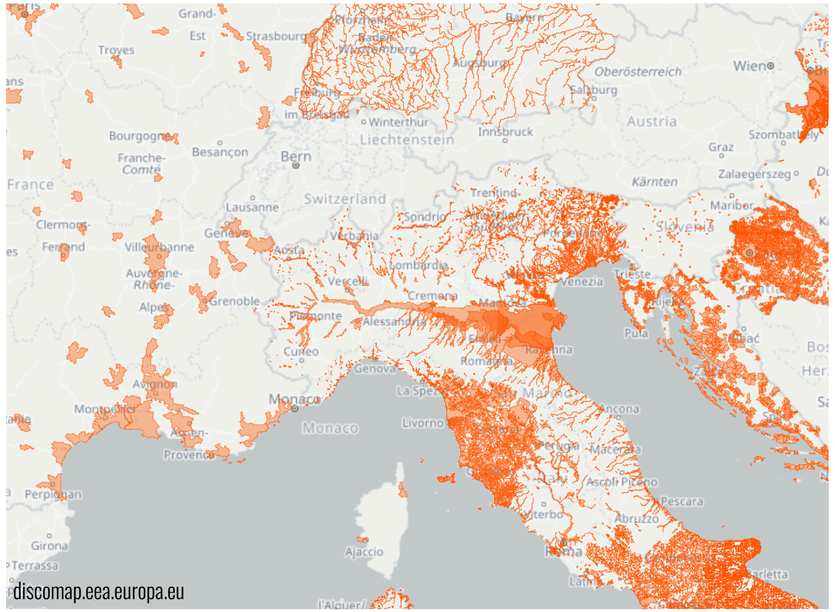
EXTREME WEATHER EVENTS AND THE SPREAD OF RESPIRATORY PATHOGENS

[Ascione et al (2025) EPJ Data Science]

FLOODS IN EMILIA ROMAGNA, ITALY - MAY 2023

- 50,000 displaced
- 10 bn EUR in damage



THE LANCET

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REVIEW · Volume 404, Issue 10465, P1847-1896, November 09, 2024 Download Full Issue

The 2024 report of the *Lancet* Countdown on health and climate change: facing record-breaking threats from delayed action

Marina Romanello, PhD [a] · Maria Walawender, MSPH [a] · Shih-Che Hsu, PhD [b] · Annalyse Moskeland, MSc [i] · Yasna Palmeiro-Silva, PhD [a] · Daniel Scamman, EngD [c] · et al. Show more

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EFFECT ON LOCAL AND SPATIAL MIXING

COLOCATION MAPS by Meta

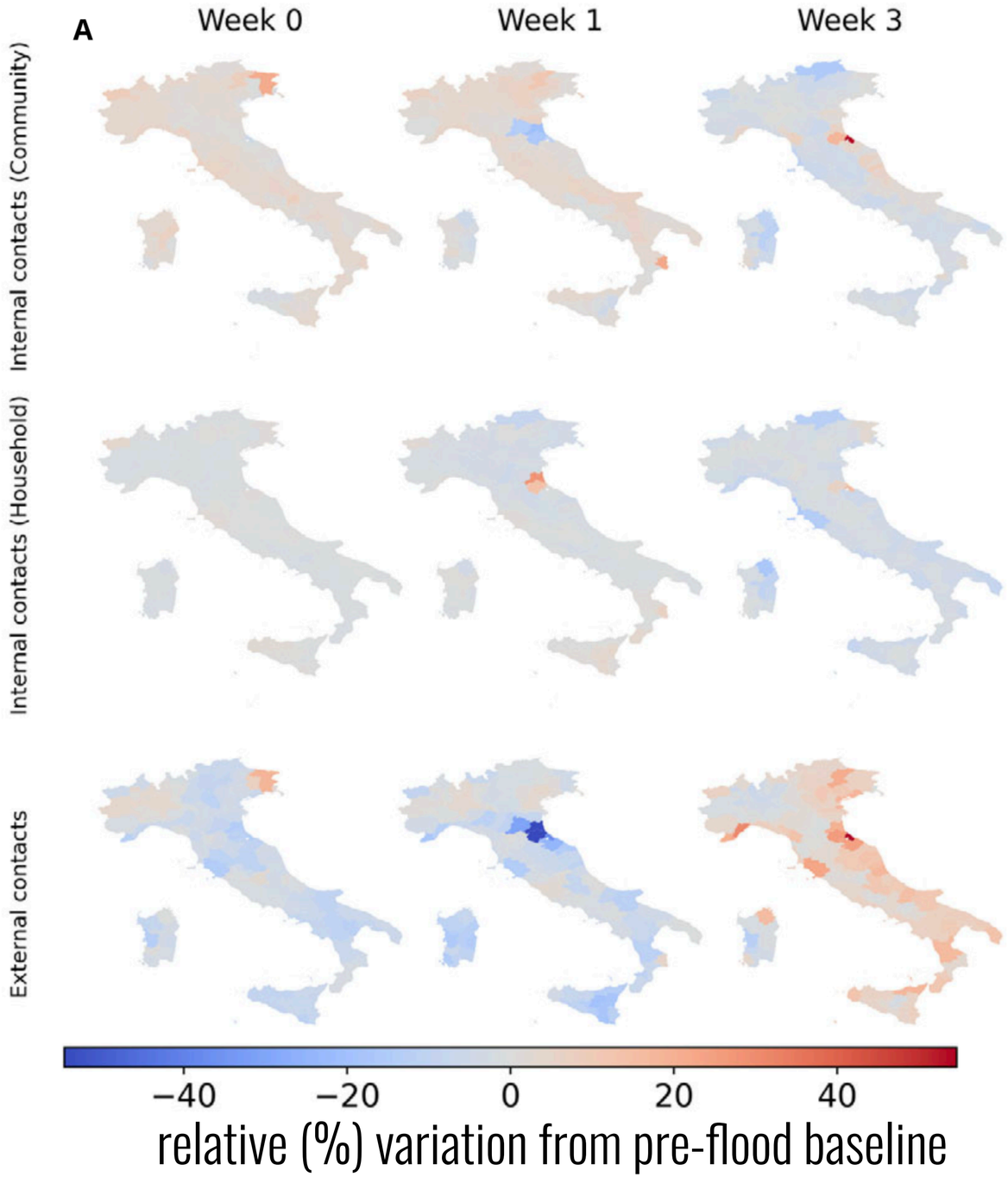
- from smartphone GPS traces
- GDPR-compliant

Ref: Iyer et al. (2023) Epidemics

HOUSEHOLD CONTACTS

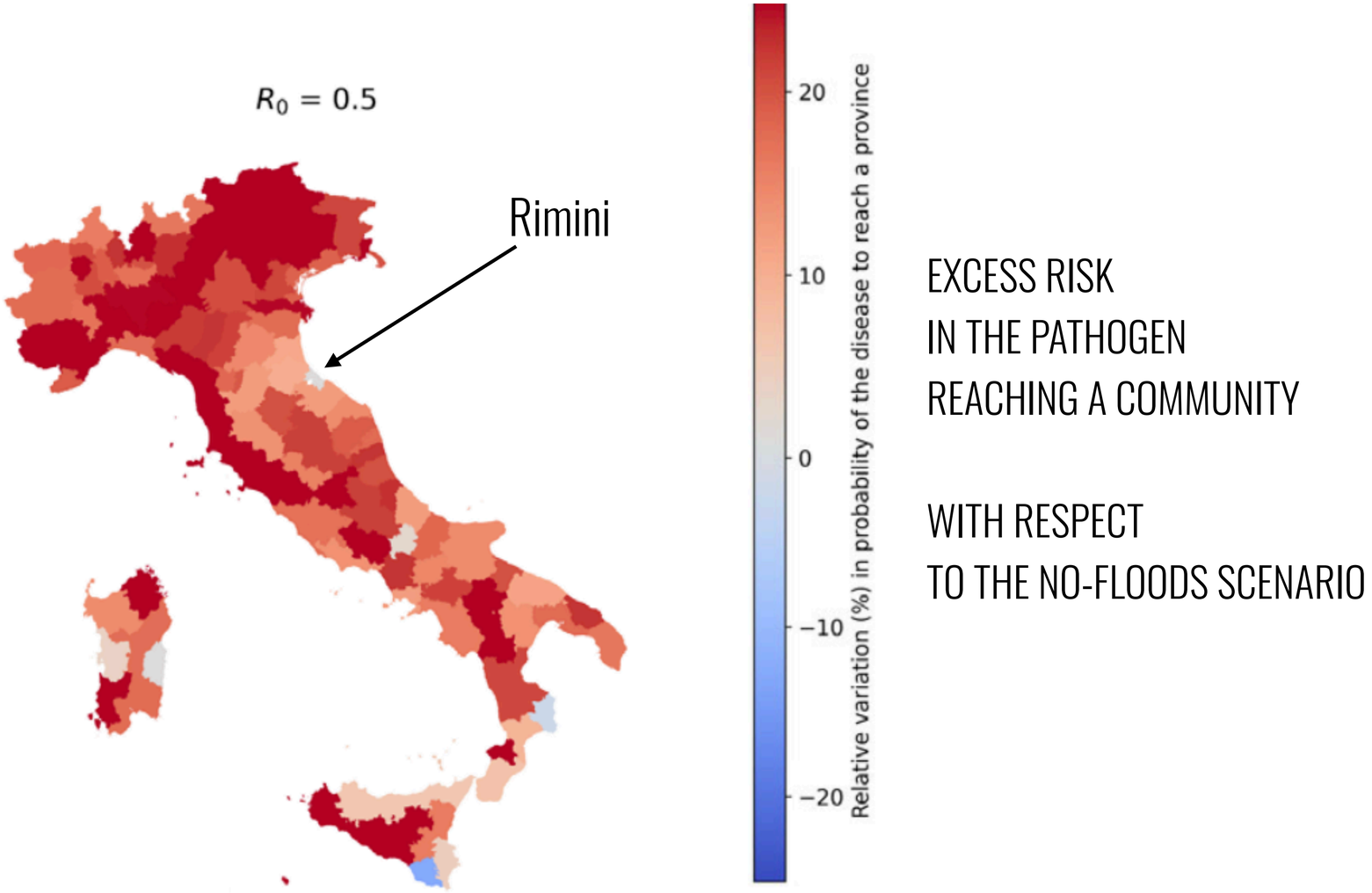
COMMUNITY CONTACTS

INTER-COMMUNITY CONTACTS



Ascione et al (2025) EPJ Data Science

FLOODS → SPATIAL MIXING → EPIDEMIC OUTCOMES



EXCESS RISK
IN THE PATHOGEN
REACHING A COMMUNITY

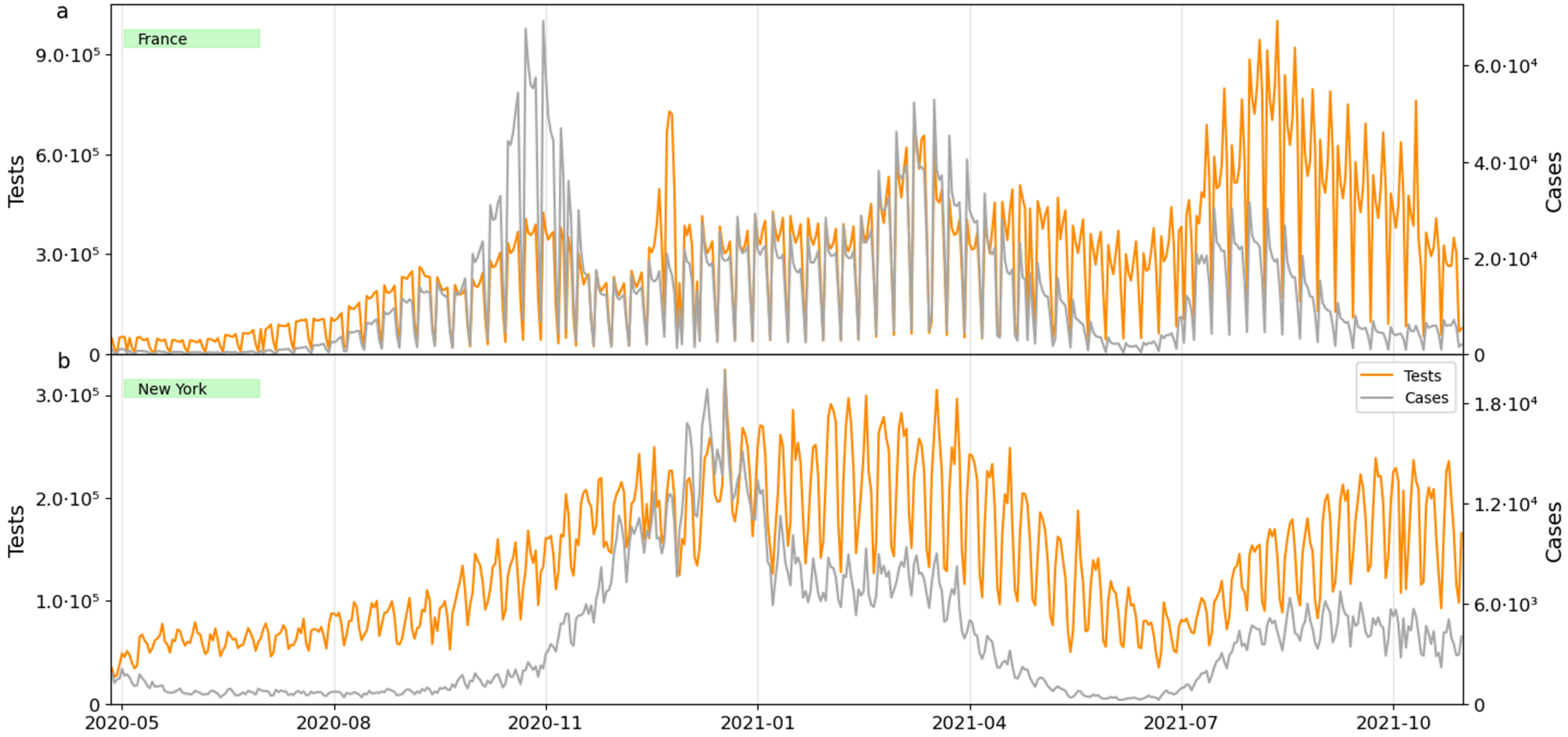
WITH RESPECT
TO THE NO-FLOODS SCENARIO

Ascione et al (2025) EPJ Data Science

RAINFALL AND EPIDEMIOLOGICAL SURVEILLANCE (COVID-19)

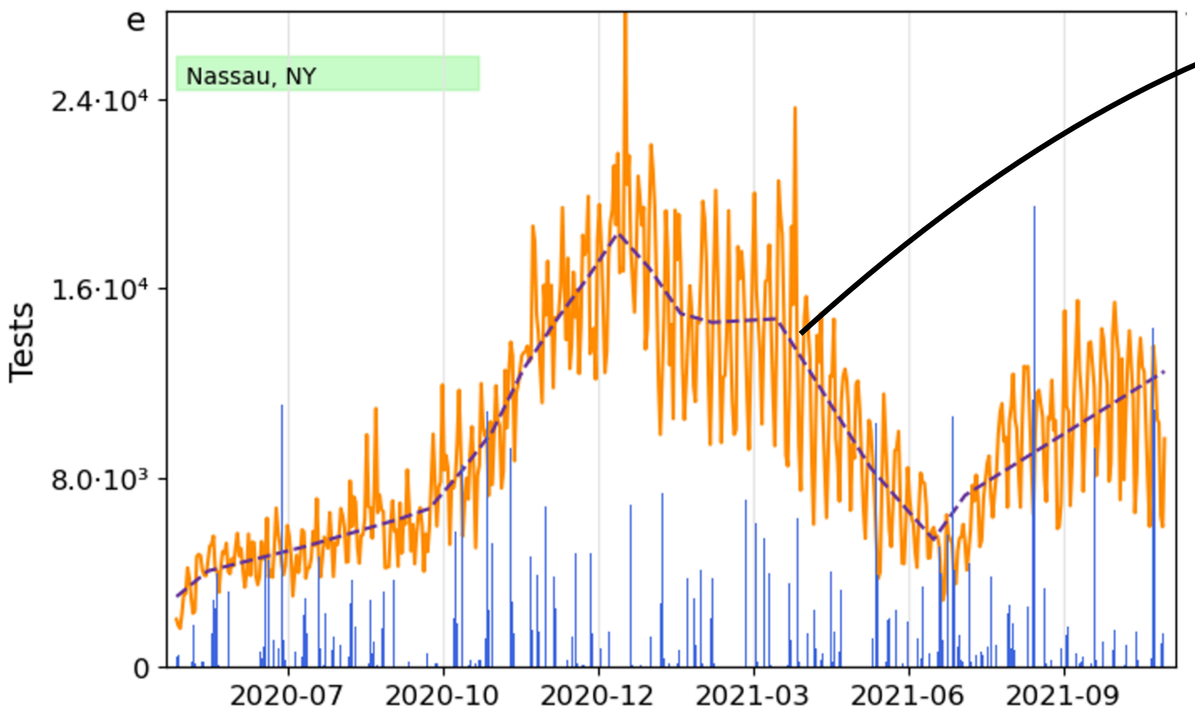
FRANCE

NEW YORK STATE (US)



Caruso et al (2025) medRxiv pre-print

DETECTING THE EFFECT OF RAINFALL ON THE DAILY NUMBER OF COVID-19 TESTS



trend + weekly components

$$\mu(t) = \mathbb{E}[N(t)] = O(t)\ \exp\left[q + \alpha\, x(t)\right]$$

rainfall

number of daily tests

$$N(t) \sim \text{Poisson}\left[\mu(t)\right]$$

Caruso et al (2025) medRxiv pre-print

DETECTING THE EFFECT OF RAINFALL ON THE DAILY NUMBER OF COVID-19 TESTS

FRANCE

Trend/periodicity setup	Weekly component	AIC	Effect of rain (Δ)
additive	Day-of-week cat. variable	18,114,846	*Not included*
additive	Day-of-week cat. variable	18,054,556	-9.91 (-9.99, -9.83)
additive	From Prophet	26,913,692	*Not included*
additive	From Prophet	26,840,430	-10.73 (-10.80, -10.65)
multiplicative	Day-of-week cat. variable	15,248,971	*Not included*
multiplicative	Day-of-week cat. variable	15,209,547	-8.07 (-8.17, -7.99)
multiplicative	From Prophet	14,856,229	*Not included*
multiplicative	From Prophet	**14,810,057**	-8.69 (-8.76, -8.61)

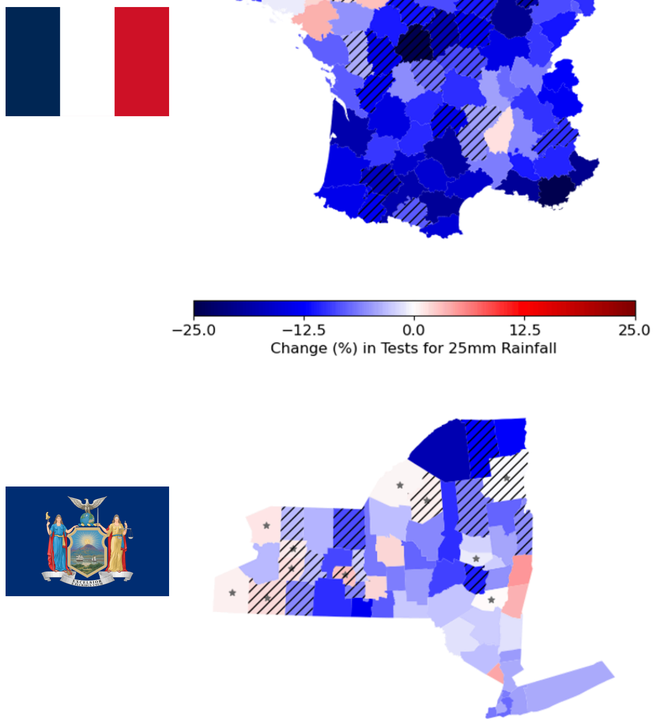
NEW YORK STATE

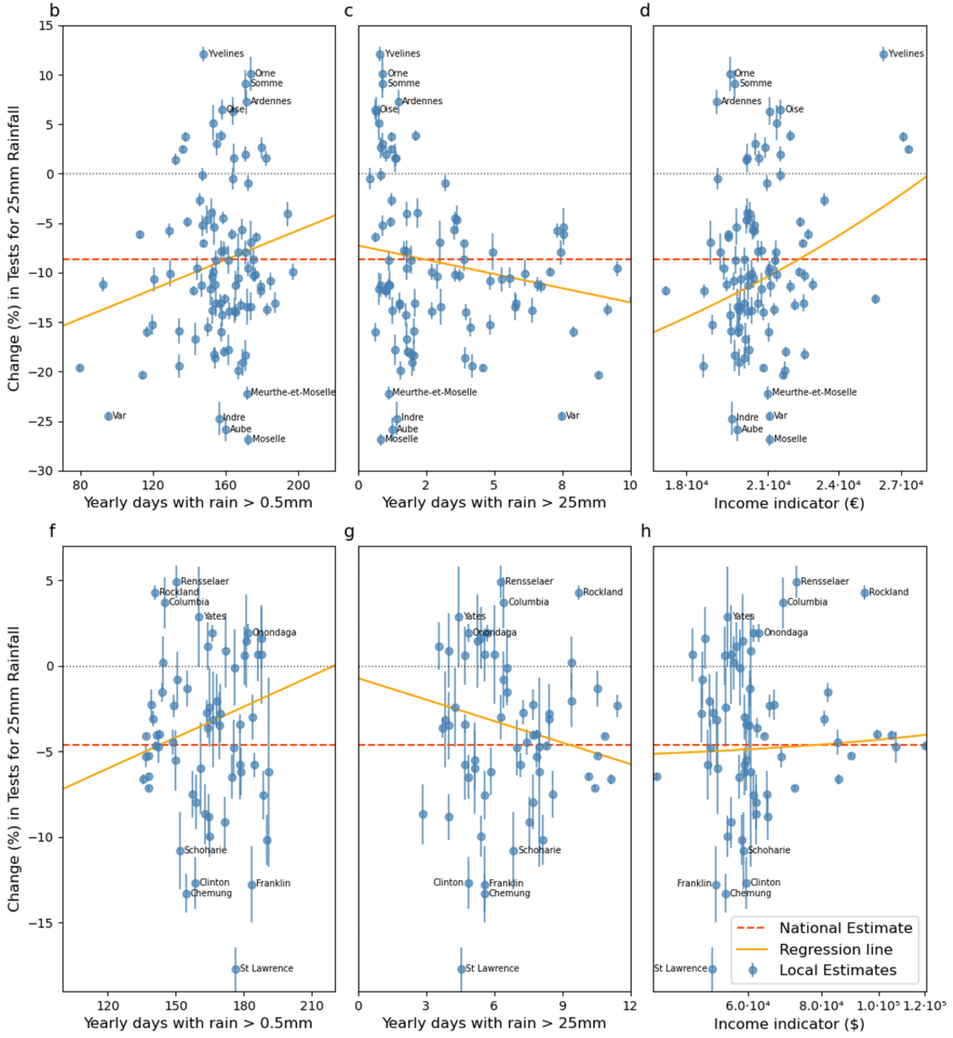
Trend/periodicity setup	Weekly component	AIC	Effect of rain (Δ)
additive	Day-of-week cat. variable	4,533,723	*Not included*
additive	Day-of-week cat. variable	4,512,424	-4.50 (-4.56, -4.44)
additive	From Prophet	5,690,903	*Not included*
additive	From Prophet	5,673,806	-4.05 (-4.11, -3.99)
multiplicative	Day-of-week cat. variable	4,522,195	*Not included*
multiplicative	Day-of-week cat. variable	4,500,870	-4.50 (-4.56, -4.44)
multiplicative	From Prophet	4,256,053	*Not included*
multiplicative	From Prophet	**4,233,541**	-4.62 (-4.68, -4.56)

effect of rain = percentage change in tests attributable to 25 mm of rainfall

Caruso et al (2025) medRxiv pre-print

COMPOUND VULNERABILITIES: SE + DISEASE + CLIMATE ADAPTATION





- **Climate adaptation**: more rainy days → weaker effect of rain: showing community adaptation
- **Limits of adaptation**: no adaptation to heavy rain
- **Spontaneous adaptation insufficient**: need for structural, top-down interventions
- **Socioeconomic vulnerability**: stronger test reductions in poorer communities
- **Compounding risks**: poverty + climate change + infectious disease vulnerability intersect, requiring coordinated mitigation strategies

Caruso et al (2025) medRxiv pre-print

www.evmodelers.org

scientific publications: www.evmodelers.org/publication/

available internships: www.evmodelers.org/job/

Internship - Mobility-informed risk mapping

We are looking for an intern to join our research on integrating large-scale, high-resolution mobility data to build exposure risk maps for infectious disease epidemics. The data will be provided by Meta - see this for how we used similar data.

Internship - Foundation models for epidemic modeling and public health policy evaluation

We are looking for an intern to apply foundation models to modeling epidemics and informing public health strategies (e.g., immunization campaigns, mobility restrictions). Candidates will be 1st-year or 2nd-year master students in computer science, machine learning, physics applied mathematics, engineering or other relevant fields.

Internship - Low-dimensional representations of realistic, heterogeneous epidemic models

We are looking for an intern to join our research on on devising and applying complex systems physics and deep learning methods to finding low-dimensional interpretable representations of realistic epidemic processes.

eugenio.valdano@inserm.fr

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