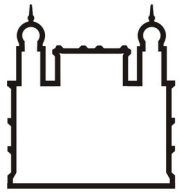

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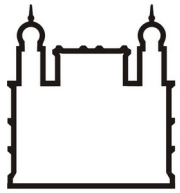
Surveillance systems: The Experience of InfoGripe

Marcelo F C Gomes

MAVE: Grupo de Métodos Analíticos em Vigilância Epidemiológica (PROCC/Fiocruz e EMAp/FGV)

Fiocruz, PROCC



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Public health research in times of pandemics: preparedness, surveillance, and communication

Marcelo F C Gomes

MAVE: Grupo de Métodos Analíticos em Vigilância Epidemiológica (PROCC/Fiocruz e EMAp/FGV)

Fiocruz, PROCC

Collaborators

Usefull MAVE links:

Repository: http://bit.ly/mave-repo-fiocruz
COVID-19 reports:
https://bit.ly/mave-covid19-relatorios-fiocruz
Data: http://bit.ly/mave-infogripe-dados-fiocruz

InfoGripe:
http://info.gripe.fiocruz.br
Weekly reports: http://bit.ly/mave-infogripe-fiocruz

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- Marcelo F C Gomes

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Surveillance and timeline

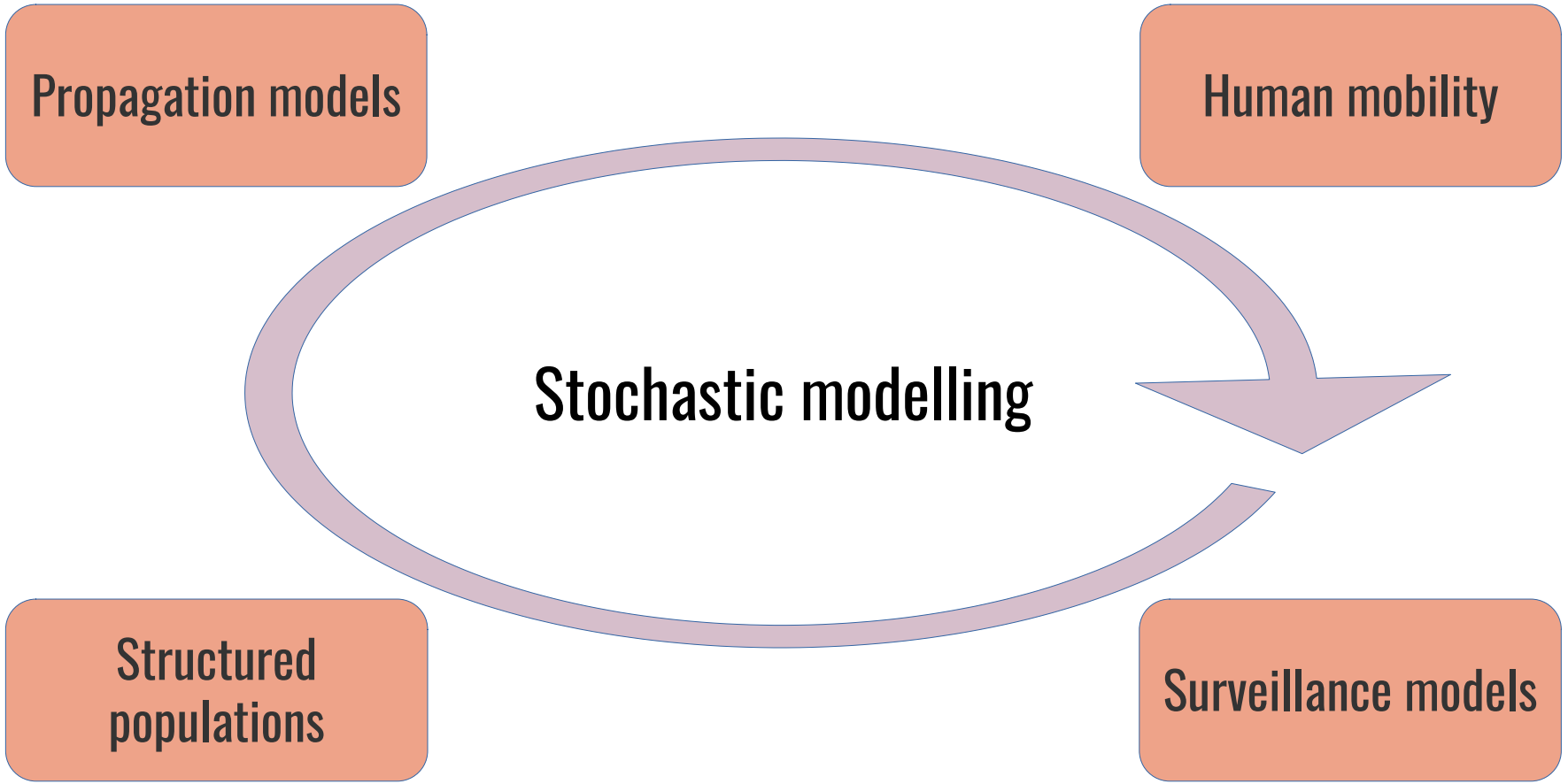
Timeline

Epidemiological events

Points of entry identification; spreading potential; mitigation scenarios	(Re)Analysis based on identified points-of-entry	Situation analysis and projections	Impact assessment; identification of risk-groups	Vaccination strategies

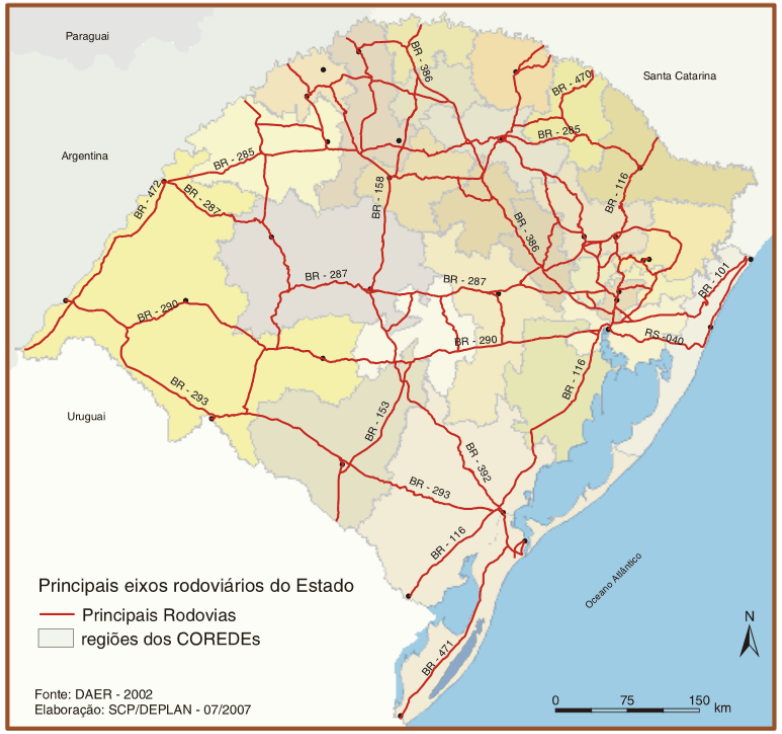
Examples of study of interest

Epidemiology and public health surveillance



Preparation phase

Human mobility networks

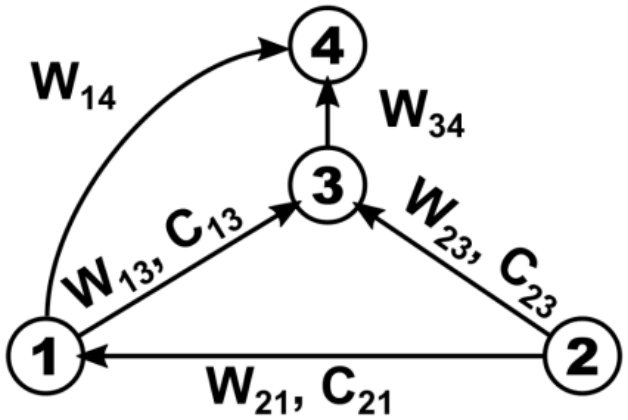


Human mobility networks

- Challenges:
  - Brazilian airline data:
    - Public data:
      - Passengers from A to B as final destination: B is the endpoint, but A might not be the starting one.
      - Passengers from A to B for connecting flights: B is not the endpoint, and A might not be the starting one either.
    - Alternative for detailed travel information: proprietary data.
  - Ground transportation:
    - Public data:
      - Intercity commuting for work/study for every municipality only available through official Census: once every 10 years (at least).
      - Lots of data regarding vehicle volume on roads/highways, number of buses between cities, or hierarchical areas of influence: not with actual people flow or a clear proxy for modeling purposes.
    - Alternative for detailed origin-destination data: proprietary cellphone data and driving apps (gmaps, waze, …). Publicly shared data do not provide aggregated info on detailed origin-detination (even intercity, let alone inside a given city).

Human mobility networks

- Challenges:
  - Brazilian airline data:
    - Public data:
      - Passengers from A to B as final destination: B is the endpoint, but A might not be the starting one.
      - Passengers from A to B for connecting flights: B is not the endpoint, and A might not be the starting one either.



$$\Omega_{ij} = W_{ij}\left(1 - \frac{C_{.i}}{W_{i.}}\right) + \sum_k \frac{C_{ik}}{W_{i.}} W_{kj}$$

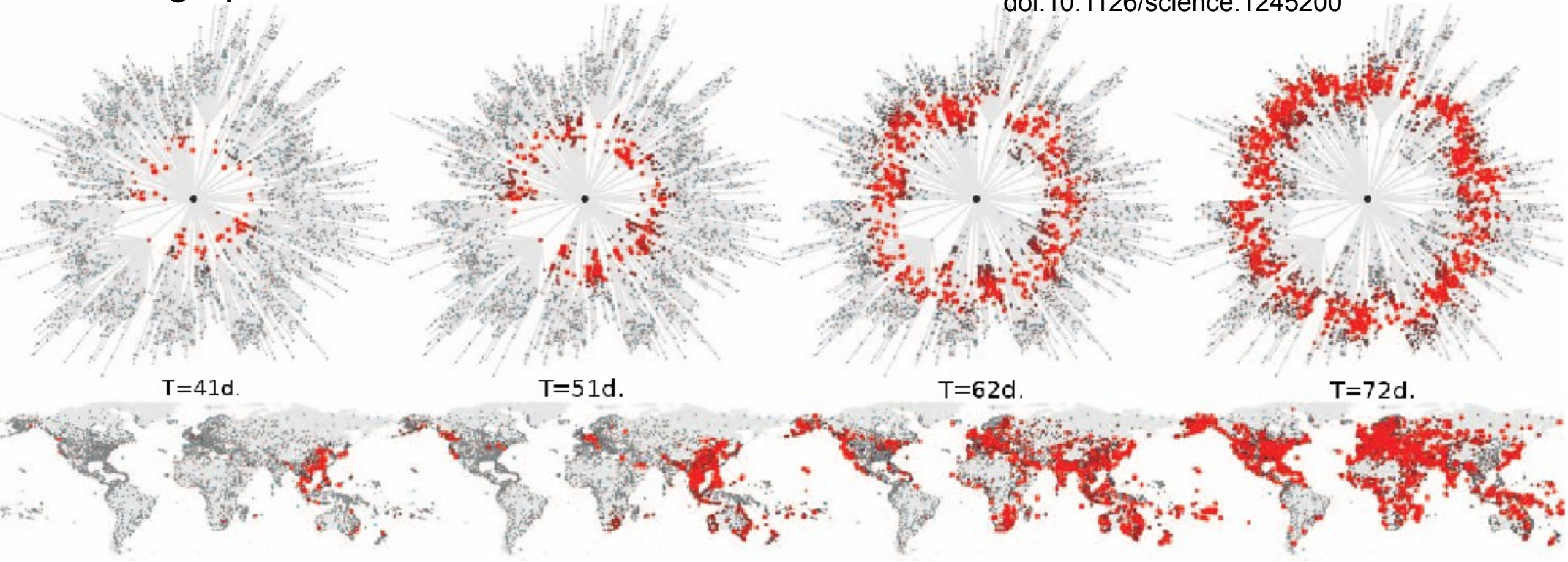
Fig 1. Example of a small directed weighted network with information structure as provided in the Brazilian airline database. Each node represents an airport, and the edges represent passengers flying between them. Weights represent the number of passengers on direct flights from airport i to j (W_{ij}) and passengers from airport i taking a connecting flight at j (C_{ij}).

The introduction of dengue follows transportation infrastructure changes in the state of Acre, Brazil: A network-based analysis
Lana et al. 2017. Plos NTD. DOI:10.1371/journal.pntd.0006070

Propagation routes

Geographic distance x Network distance

Brockmann & Helbing, 2013, *Science,* doi:10.1126/science.1245200



- Gautreau, A., Barrat, A., & Barthélemy, M. (2008). Global disease spread: Statistics and estimation of arrival times. Journal of Theoretical Biology, 251(3), 509–522. doi:10.1016/j.jtbi.2007.12.001

- Iannelli, F., Koher, A., Brockmann, D., Hövel, P., & Sokolov, I. M. (2017). Effective distances for epidemics spreading on complex networks. Physical Review E, 95(1). doi:10.1103/physreve.95.012313

Propagation routes: basic theory

Geographic distance x Network distance

- Gautreau, A., Barrat, A., & Barthélemy, M. (2008). Global disease spread: Statistics and estimation of arrival times. Journal of Theoretical Biology, 251(3), 509–522. doi:10.1016/j.jtbi.2007.12.001

- Iannelli, F., Koher, A., Brockmann, D., Hövel, P., & Sokolov, I. M. (2017). Effective distances for epidemics spreading on complex networks. Physical Review E, 95(1). doi:10.1103/physreve.95.012313

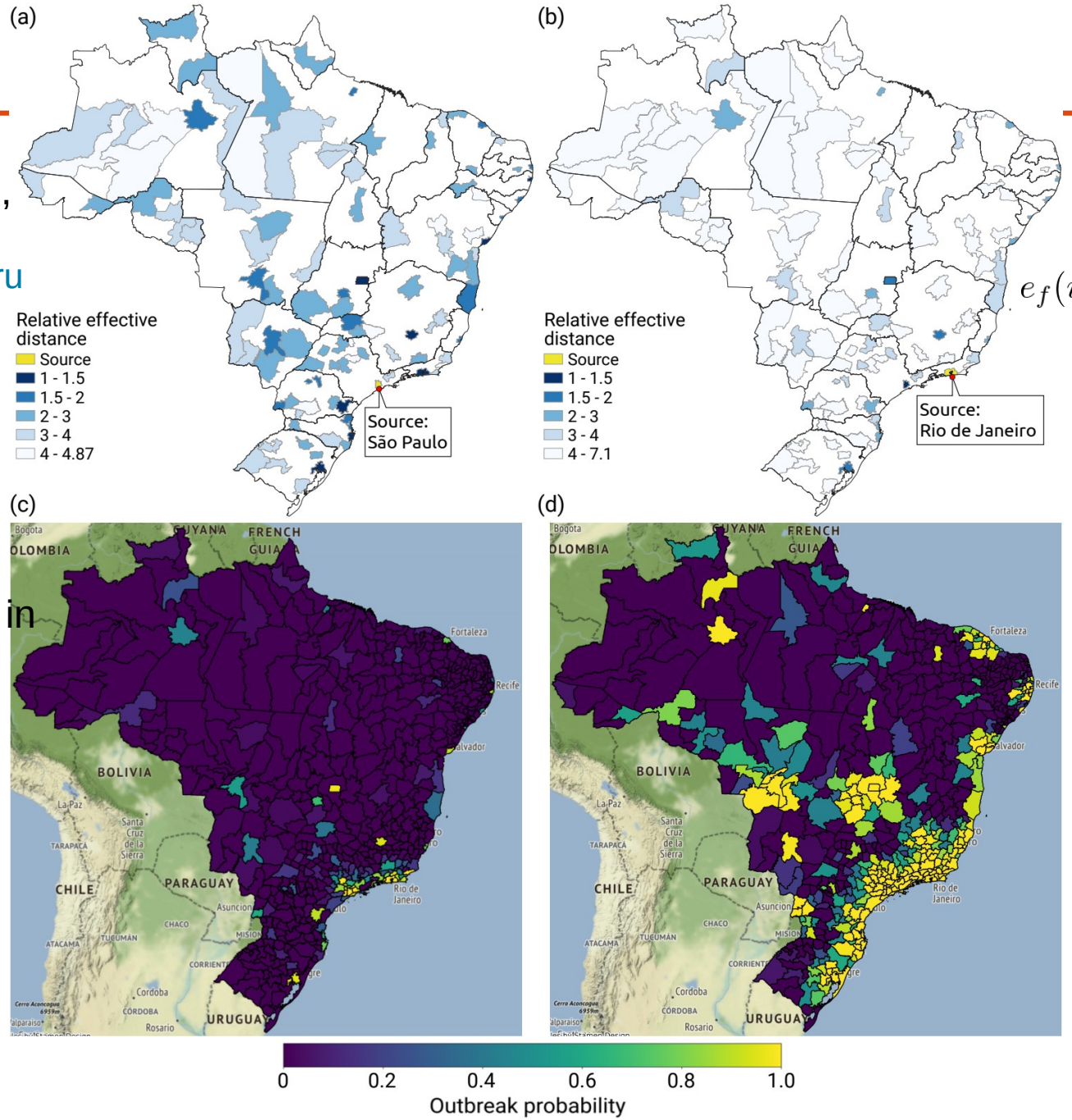
Key facts:
- based on Rvachev-Longini model (Rvachev L A and Longini I M, 1985 Math. Biosci. 75 3);
- analytical results based on SI or SIR models;
- assumes that invasion occurs during exponential growth phase, that is $I(t) \sim I_0 e^{\lambda t}$

Exposure

Estimates published March 23 & 25, 2020.
http://bit.ly/mave-covid19-relatorio2-fiocruz

Medrxiv:
https://doi.org/10.1101/2020.03.19.20039131

Plos One:
Assessing the spread of COVID-19 in Brazil: Mobility, morbidity and social vulnerability
https://doi.org/10.1371/journal.pone.0238214

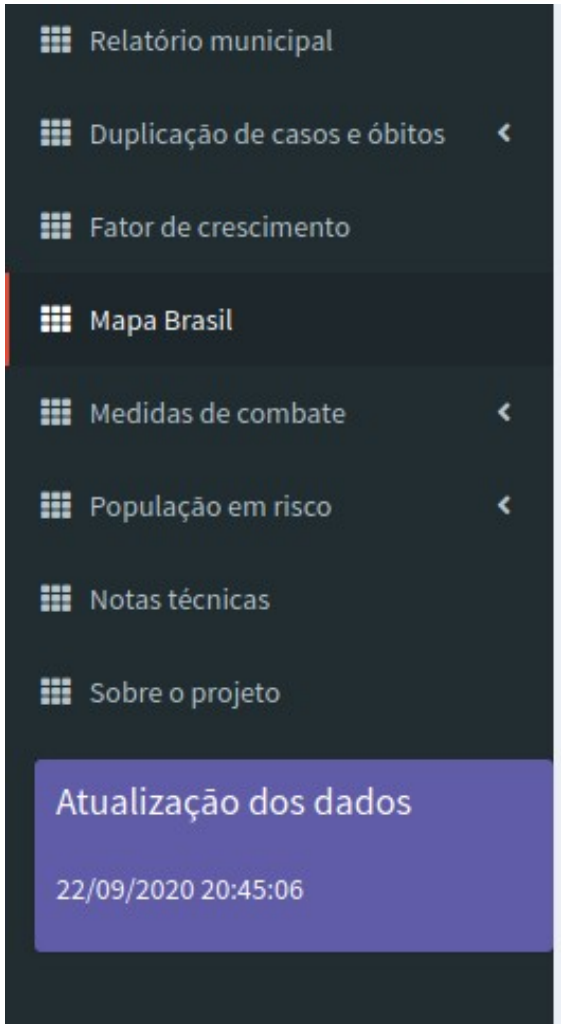


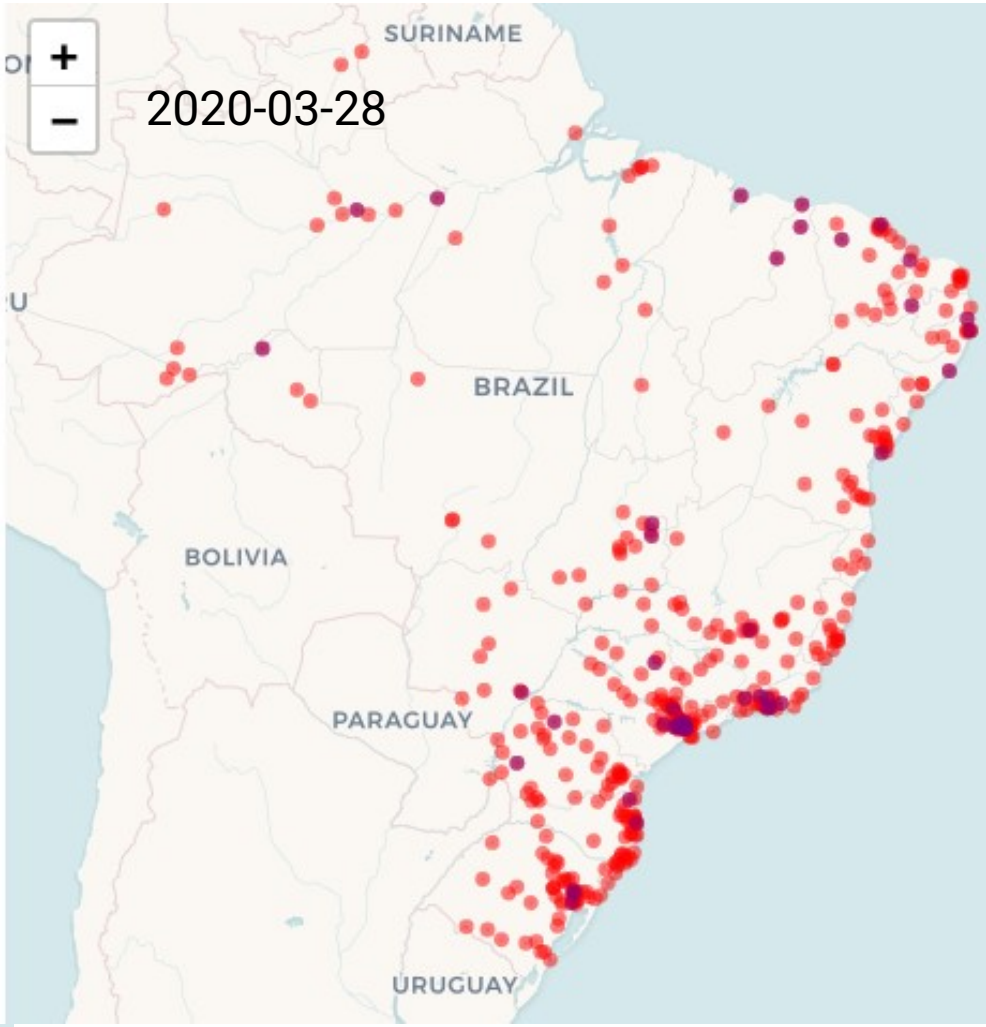
$$e_f(i,j) = \frac{E_f(i,j)}{\min_k E_f(i,k)}$$

$$p_j = 1 - (\frac{1}{R_0})^{I_j}$$

$$I_j = k\tau \sum_i f_{i,j} \frac{I_i}{N_i}$$

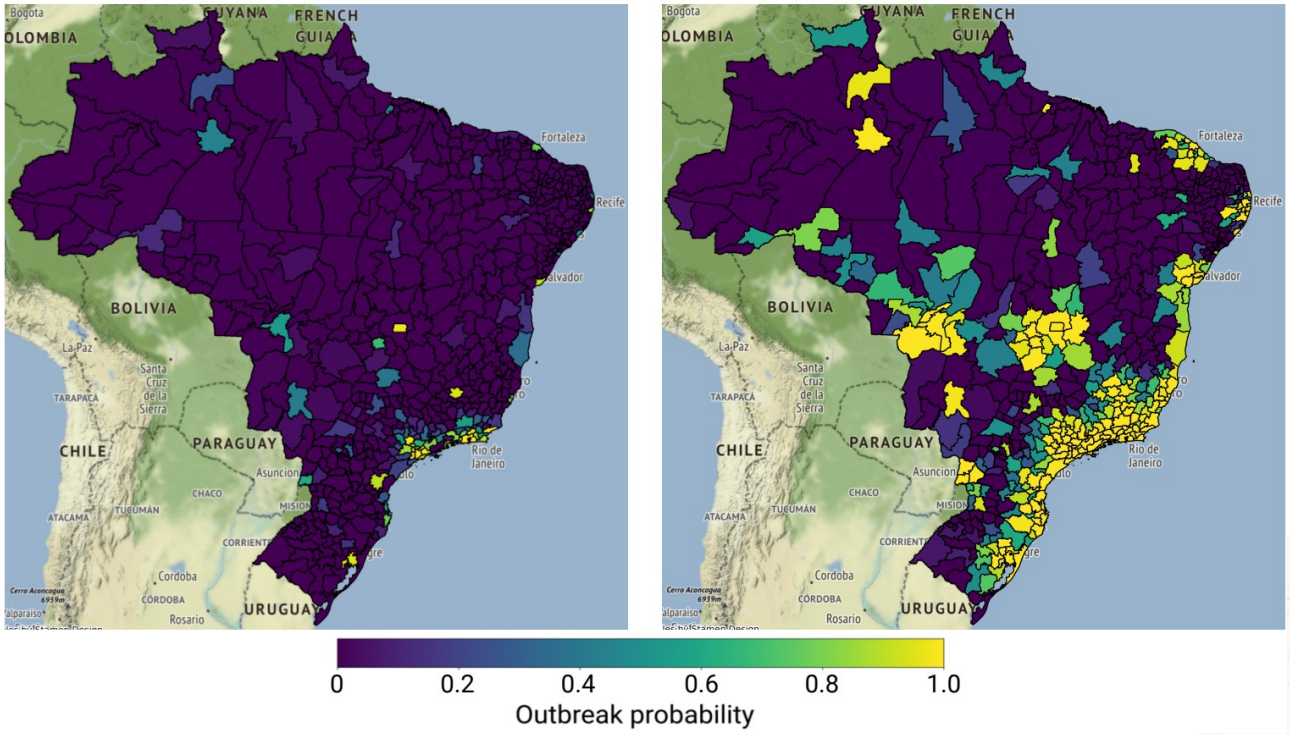
Data as of 2020-09-22





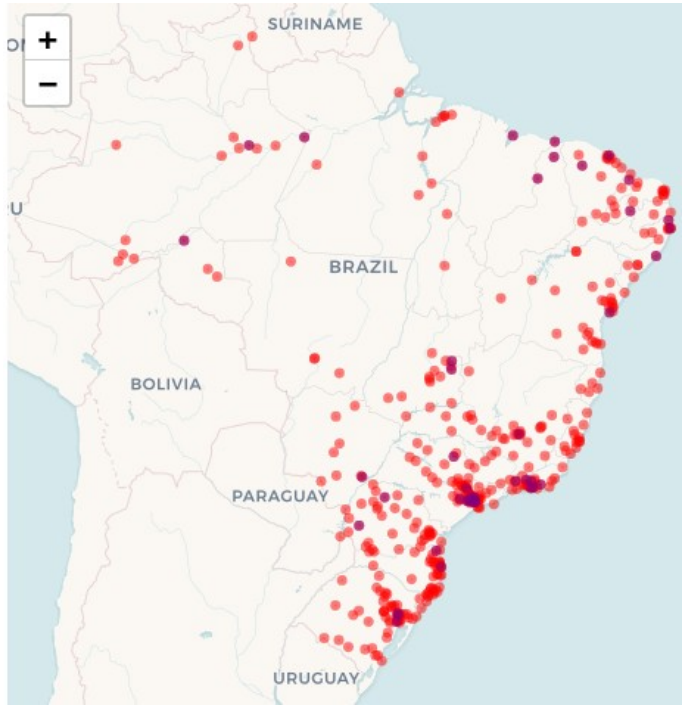
https://bigdata-covid19.icict.fiocruz.br/

Data as of 2020-09-22



2020-03-10

2020-03-28



Mitigation strategies: time saved before invasion

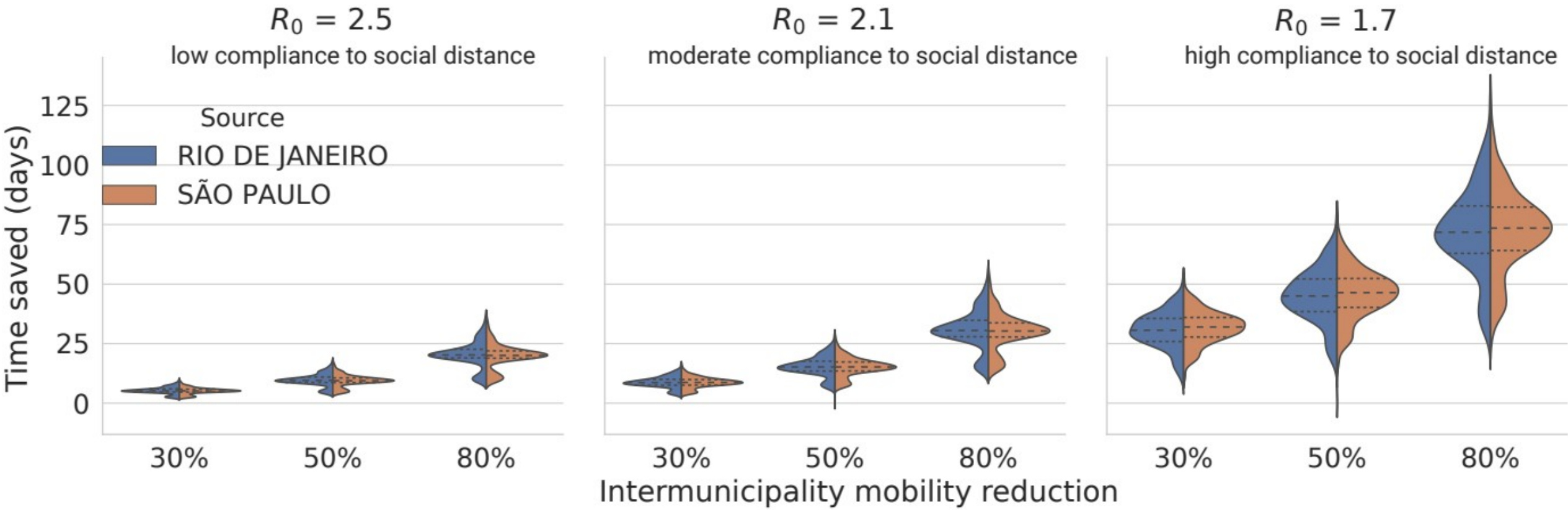
Effective distance d_{ij} and time to invasion T_{ij}

$$T_{i,j} = \frac{d_{ij}}{\gamma(R_0 - 1)}$$

Effective distance ~ 1/travel flow. The less individuals traveling per time unit, the greater the effective distance.

R_0 ~ infection rate. The lower the transmissibility or contact rate, the lower the reproductive number.

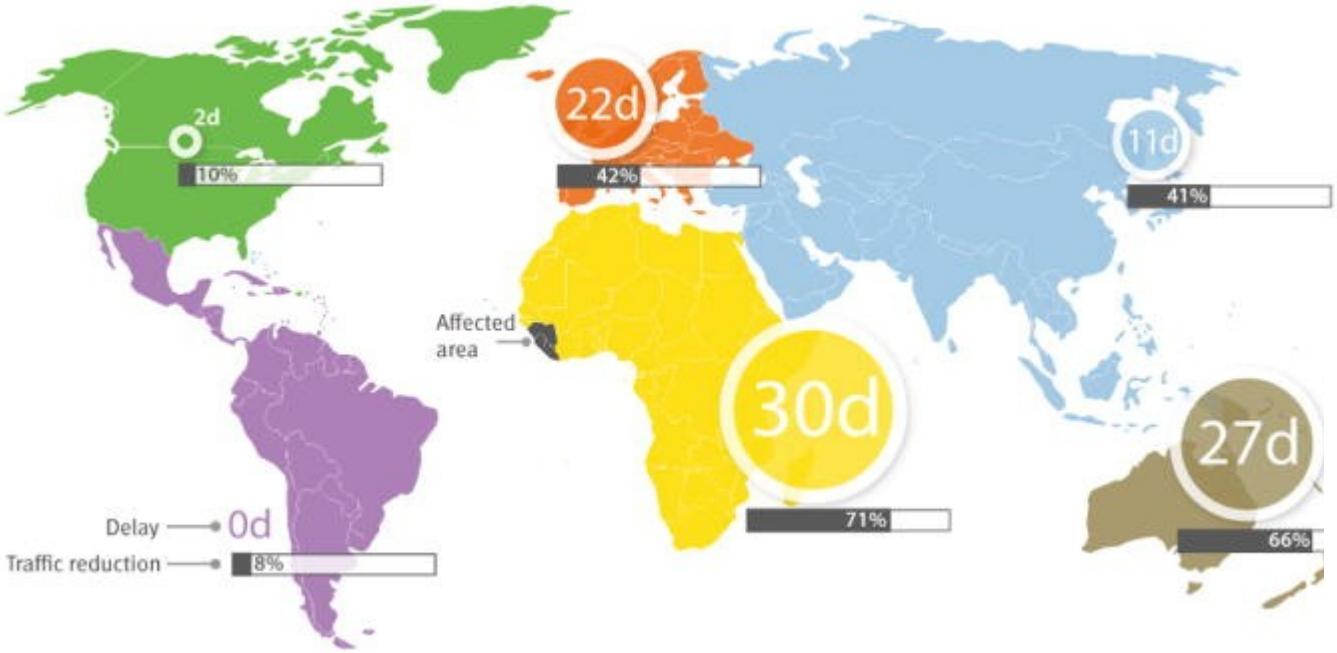
Mitigation strategies: time saved before invasion



$$T_{i,j} = \frac{d_{ij}}{\gamma(R_0 - 1)}$$

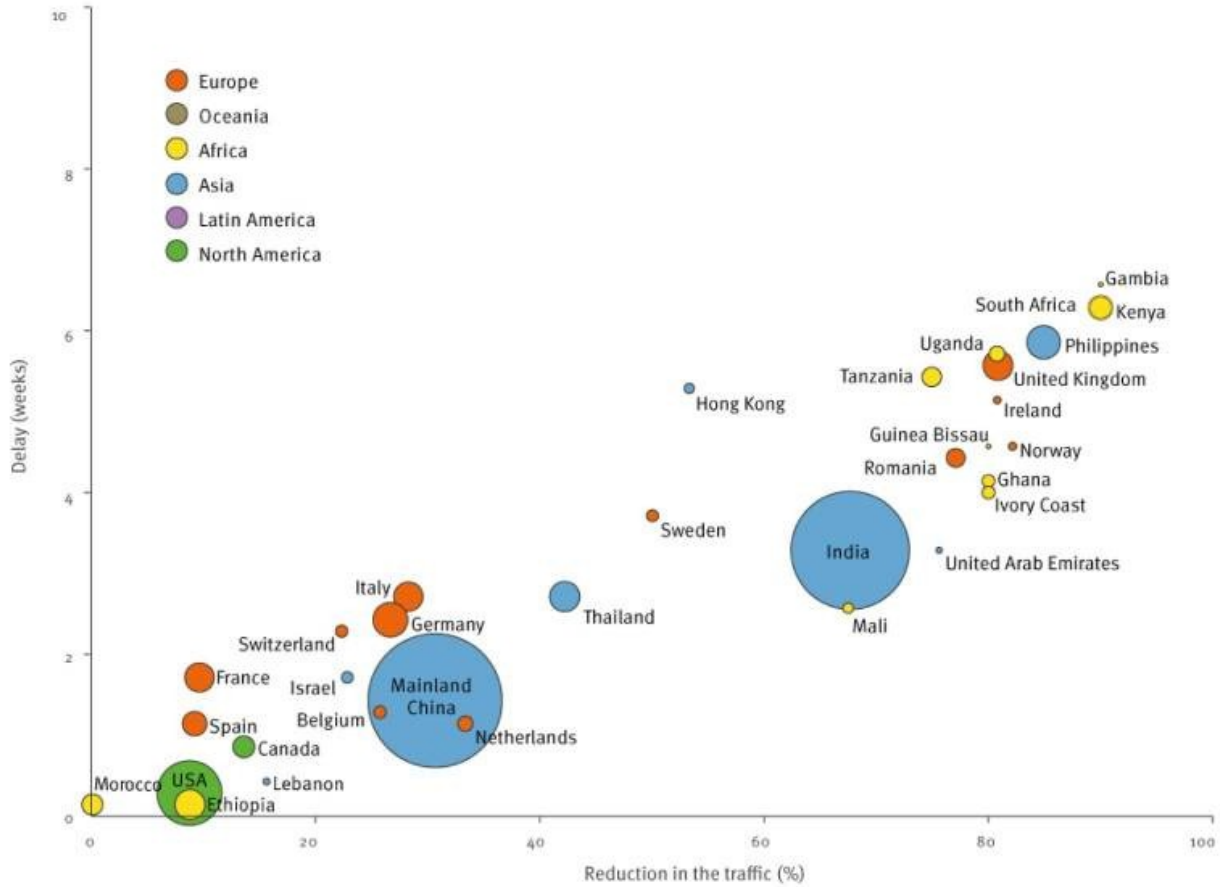
Estimates published on March 23 & 25, 2020.
http://bit.ly/mave-covid19-relatorio2
Medrxiv: https://doi.org/10.1101/2020.03.19.20039131
By Municipality: https://bit.ly/mave-covid19-estados2020-04-01

Travel restrictions: the case of Ebola 2014

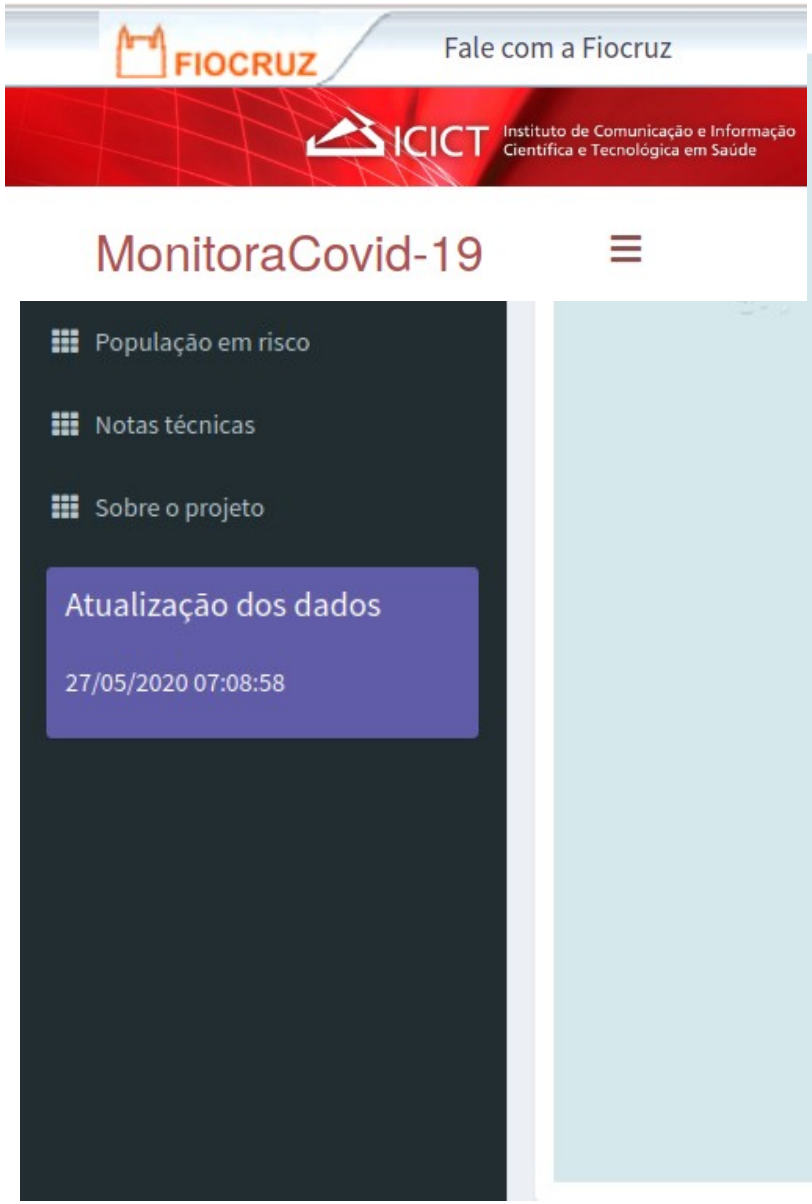


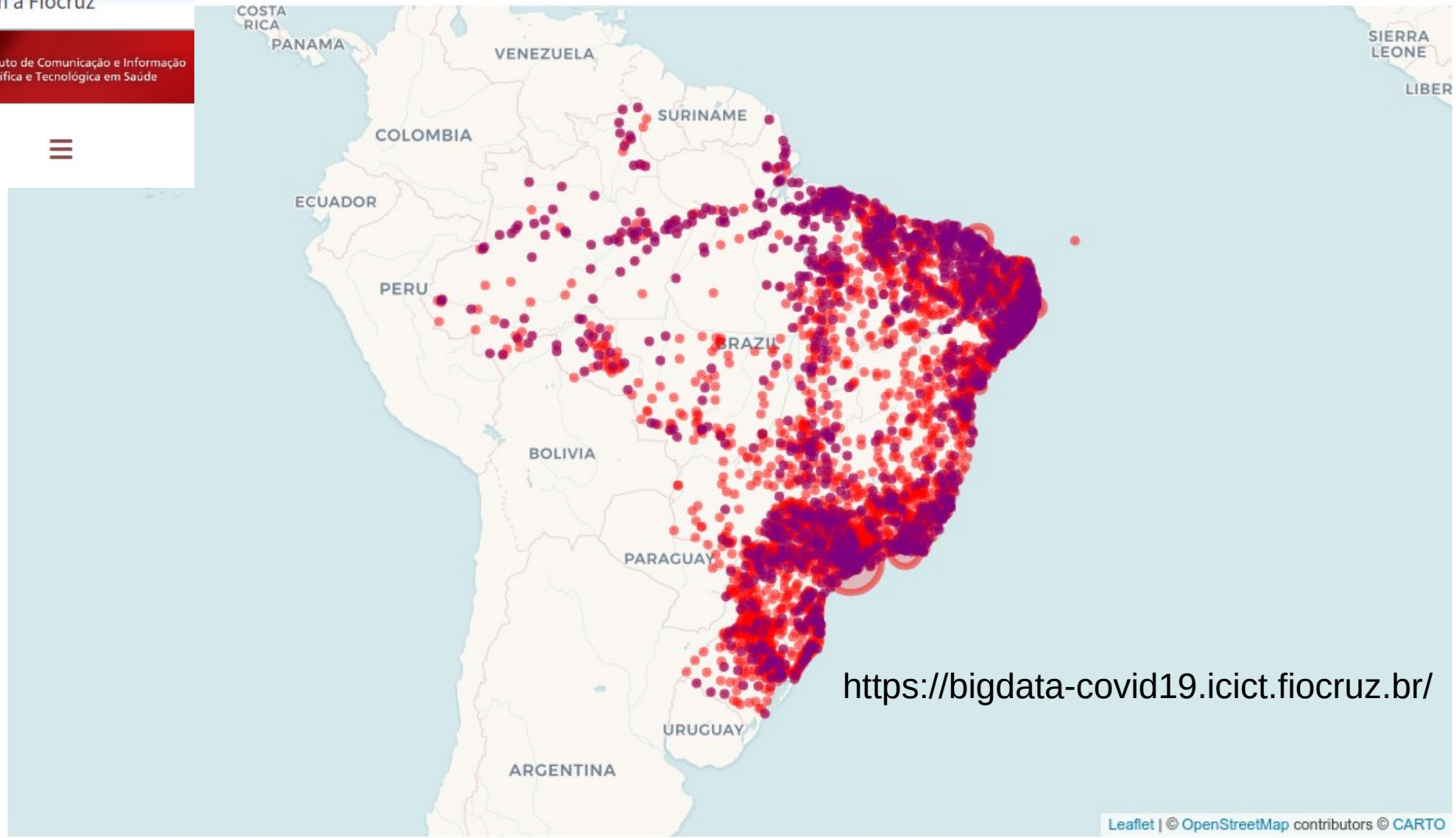
In general, "[…] a 50% travel reduction produces a delay [in risk of case importation] equal to the doubling time of the number of cases."

Poletto et al. Euro Surveill. 2014
doi: 10.2807/1560-7917.es2014.19.42.20936.



2020-05-27





https://bigdata-covid19.icict.fiocruz.br/

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Epidemiological surveillance

COVID-19 in Brasil: data sources?

- Official databases:
  - Severe Acute Respiratory Sindrome (SARI): "*Síndrome respiratória aguda Grave (SRAG)*", Sivep-gripe
  - Non-SARI COVID-19 (ILI): e-SUS VE
  - State or municipal spreadsheets/dashboards

- Federal Government panel: *"Painel Croronoavírus"*
  - https://covid.saude.gov.br/

ILI and COVID-19: challenges

Mild cases identified by ILI surveillance: ambulatory cases and private labs' positive cases

- Heterogeneous testing criteria and method between municipalities:
  - Hinders municipal-level comparisons;
  - Non-uniform state level aggregation (data collection bias).

- Testing criteria and method varying over time:
  - Hinders temporal evolution evaluation.
  - Hinders its usage as projection models' input.

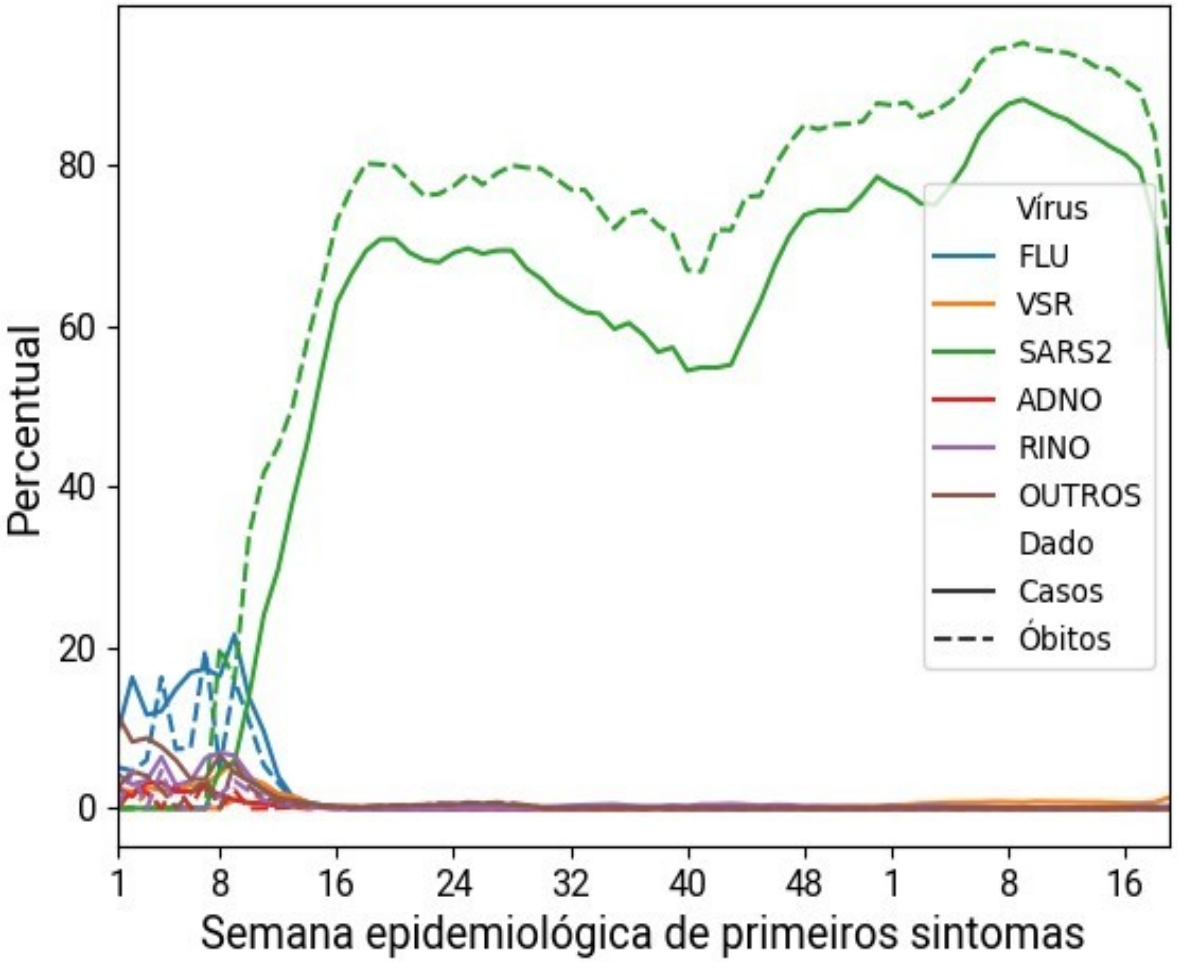
- Why not run RT-PCR on all ILI cases?
  - State labs (LACENs) already overwhelmed by SARI.

SARI: What is it?

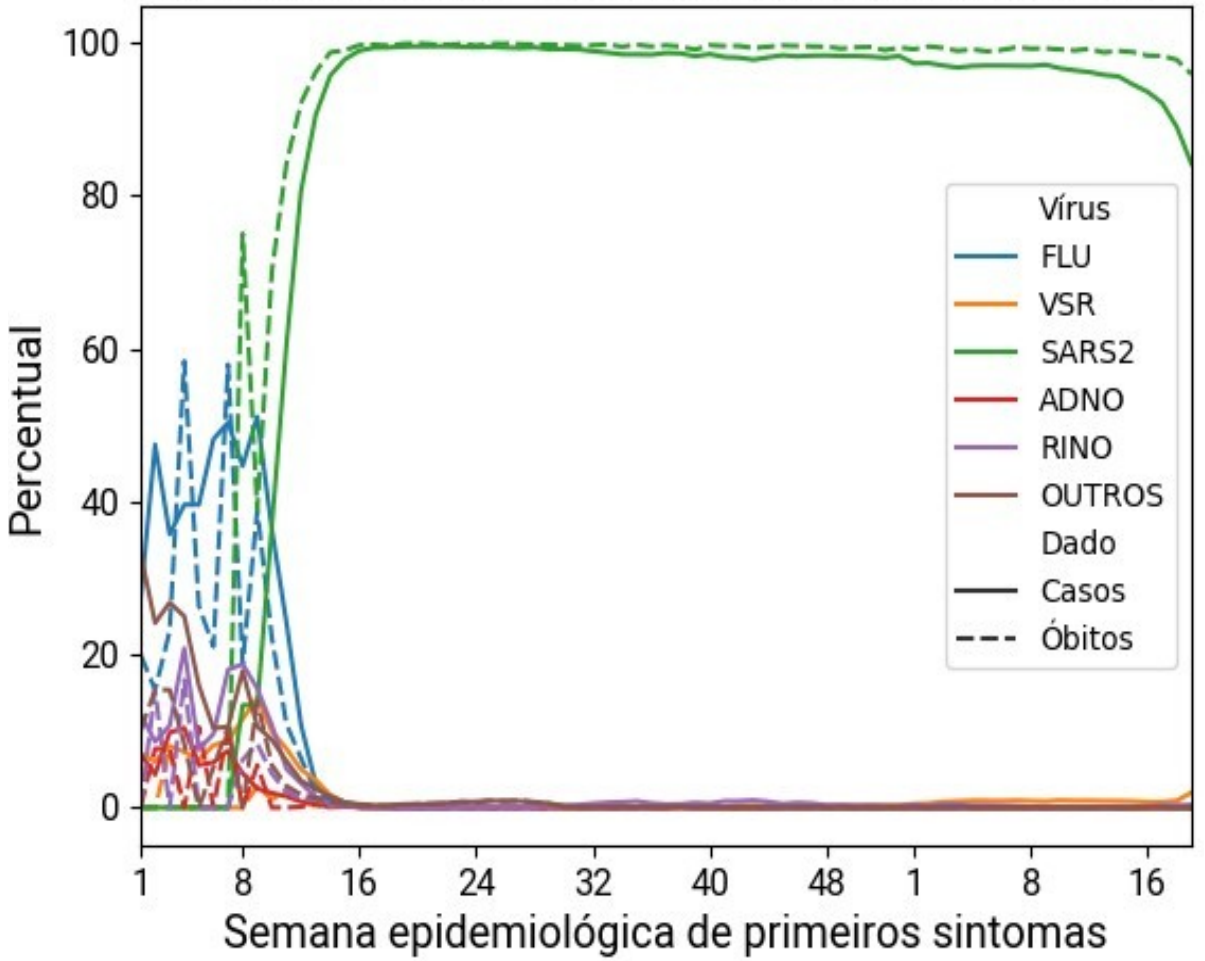
- Per historical definition, in line with WHO's recommendation (not to be confused with SARS):
  - Fever (dropped) +
  - Coaghing OR sore throat +
  - Dyspnea OR oxigen saturation < 95% OR difficulty breathing +
  - Hospitalization OR death

SARI and COVID-19 in Brazil

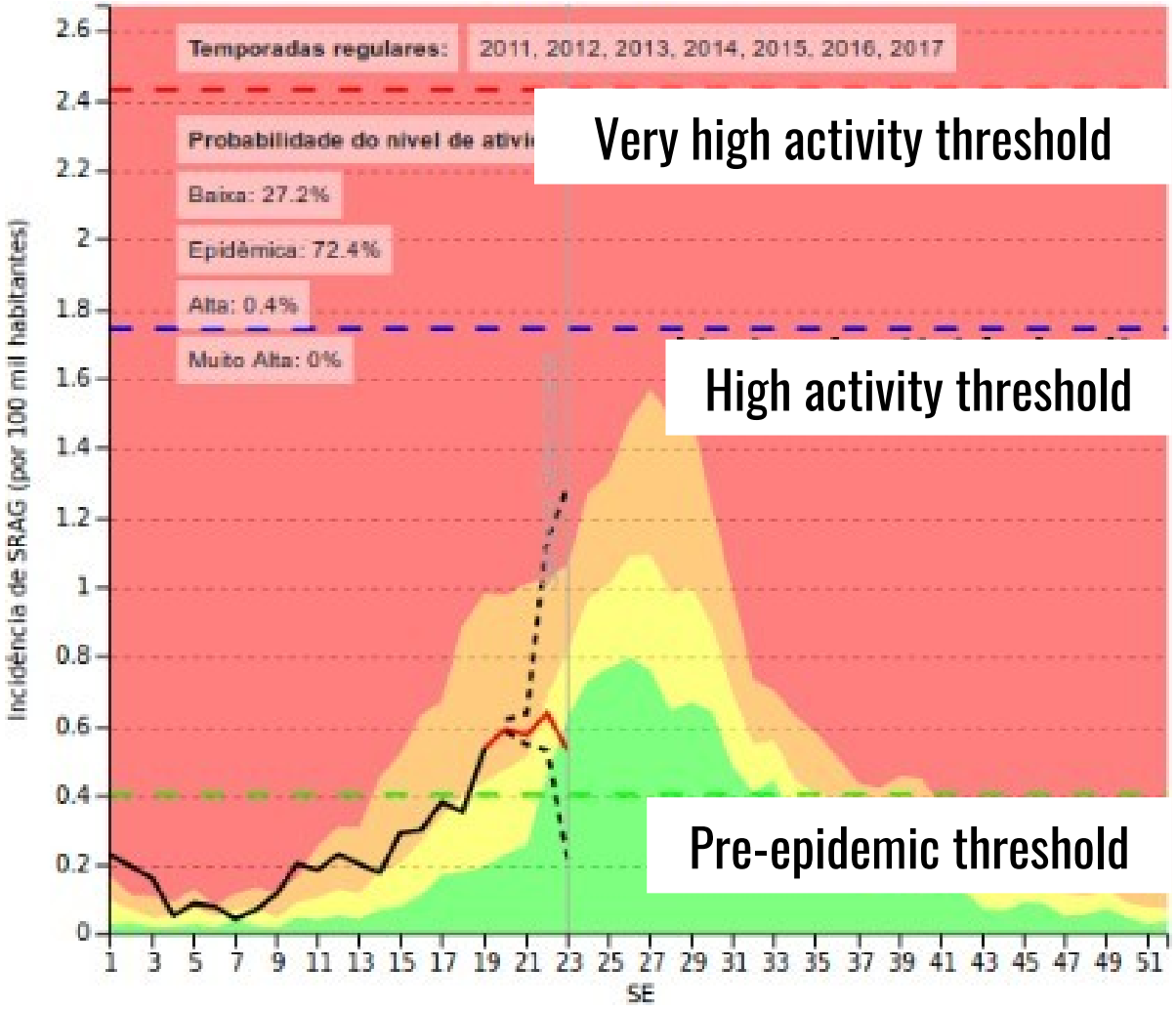
Positivity among tested cases

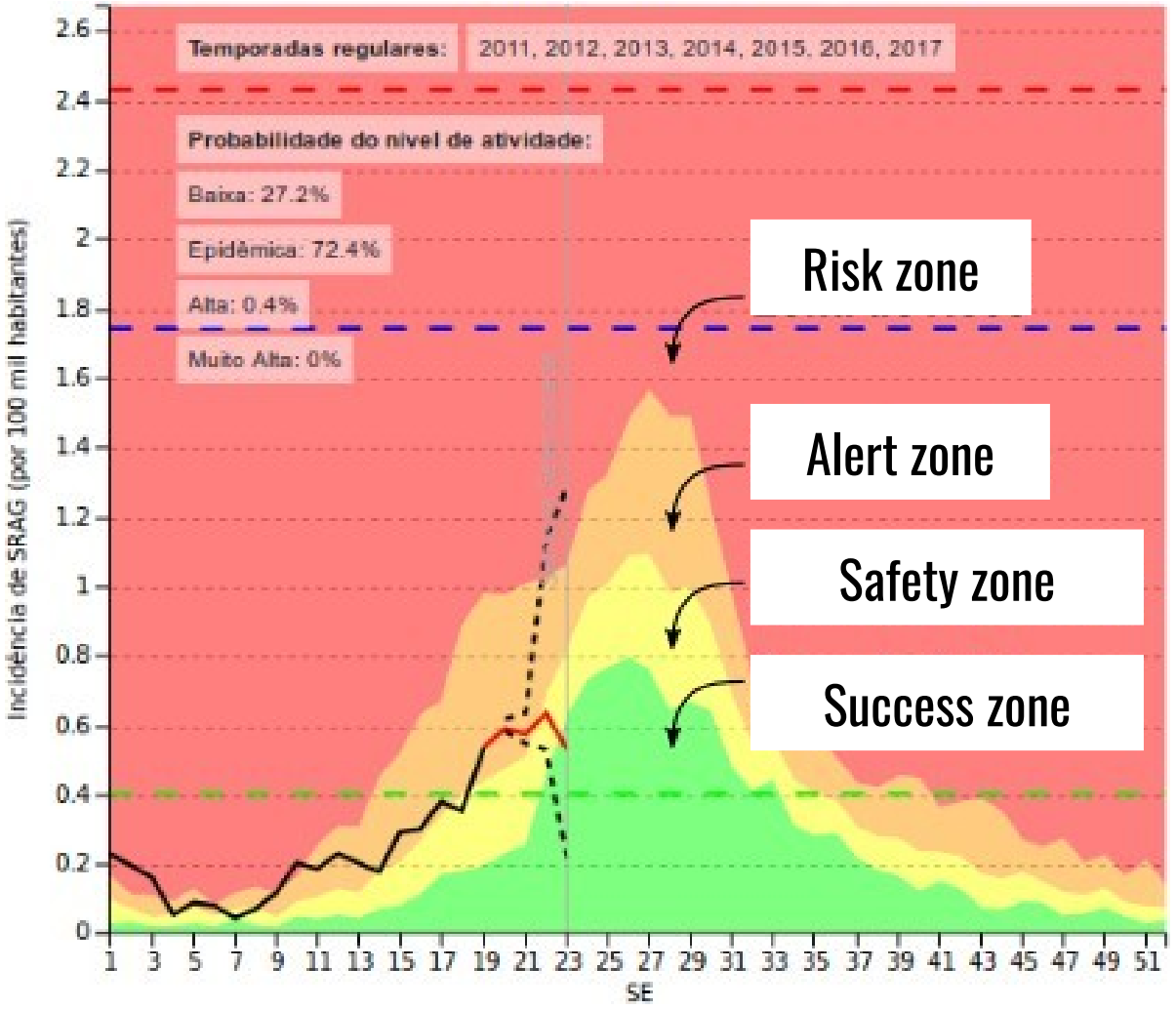


Viral identification among positive cases



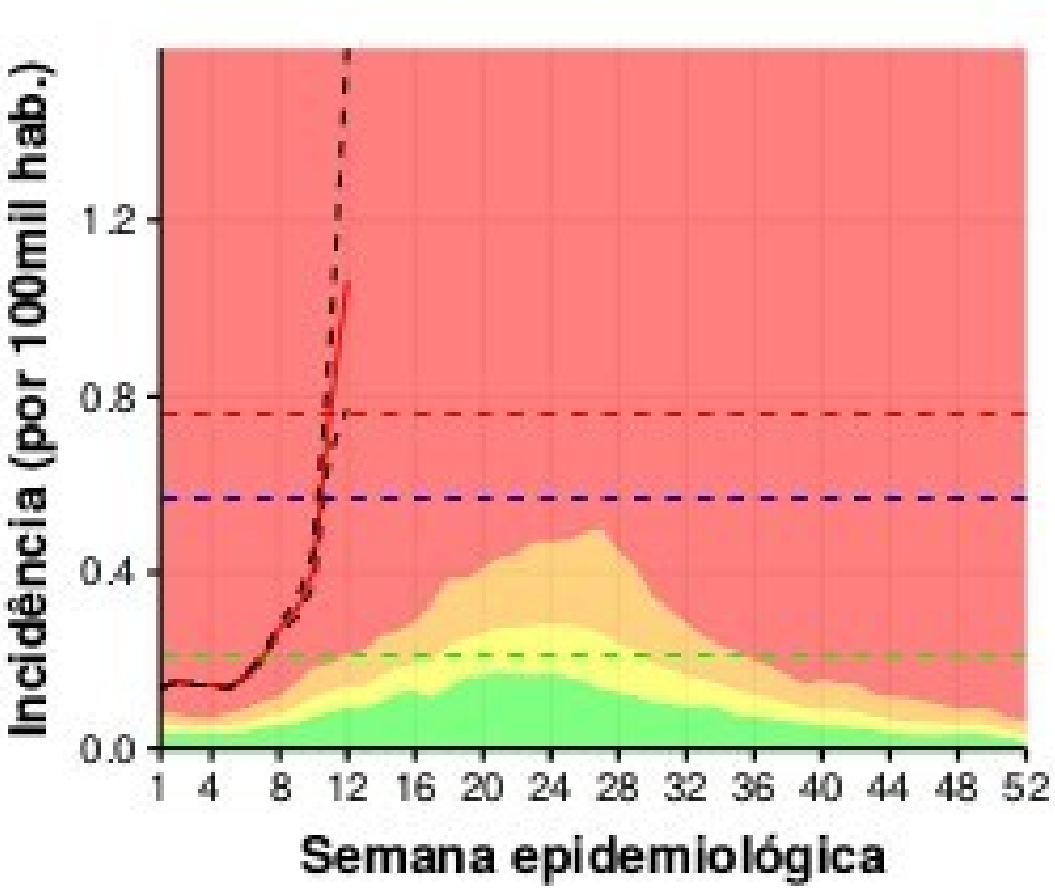
Seasonal profile and activity thresholds

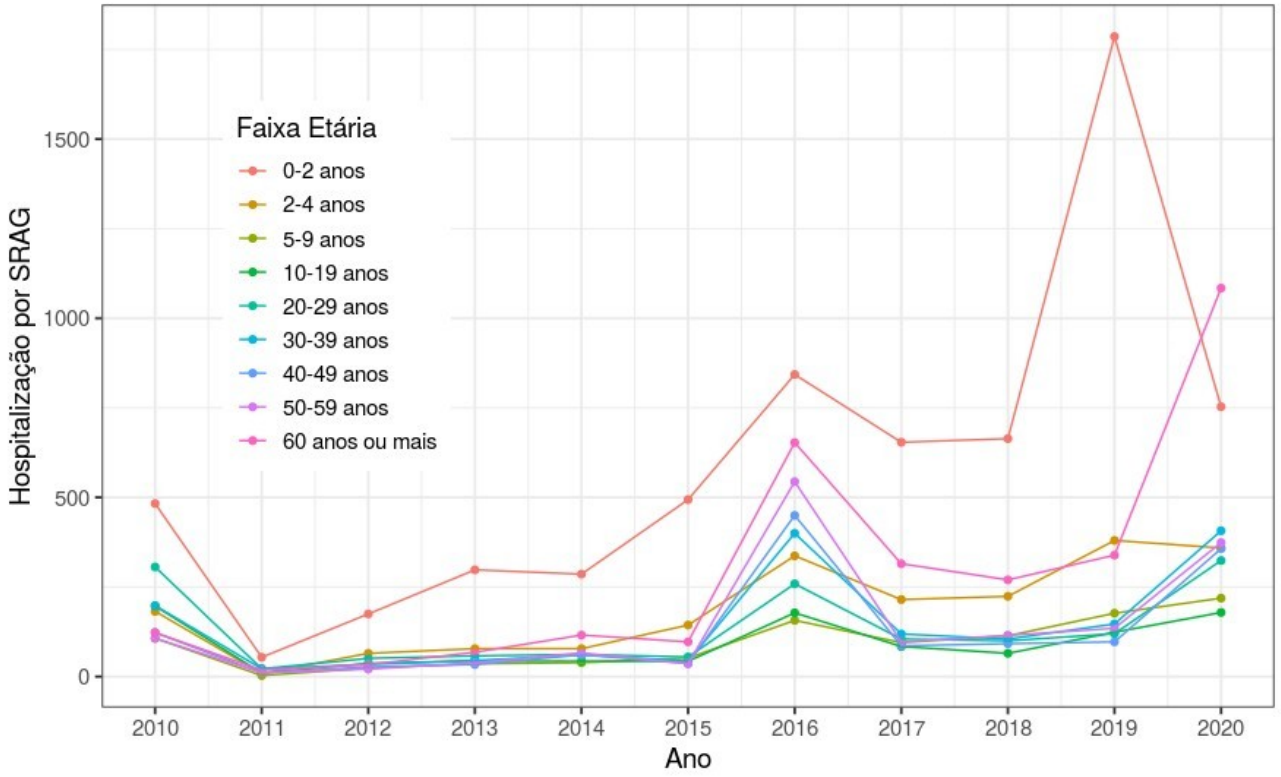




MEM – Moving Epidemics Method
Vega et al. 2013 DOI:10.1111/j.1750-2659.2012.00422.x.
Vega et al. 2015 DOI:10.1111/irv.12330.

Detection timeliness: week 12 2020





COVID-19 and hospitalizations for SARI in Brazil: a comparison up to the 12th epidemiological week of 2020
Bastos et al., http://dx.doi.org/10.1590/0102-311X00070120

Case counts

Counting cases...

From math:

New cases =

(cumulative cases as of today) -

(cumulative cases as of yesterday)

Counting cases...

From data collection:

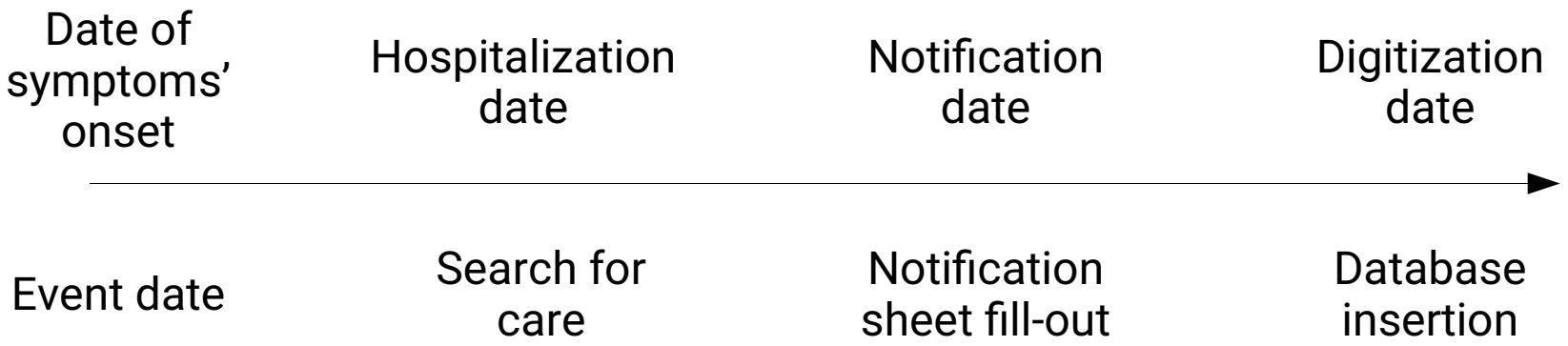
cumulative cases as of today =
cumulative as of yesterday
+ new cases registered
– duplicates identified
– discarded cases

Counting cases...

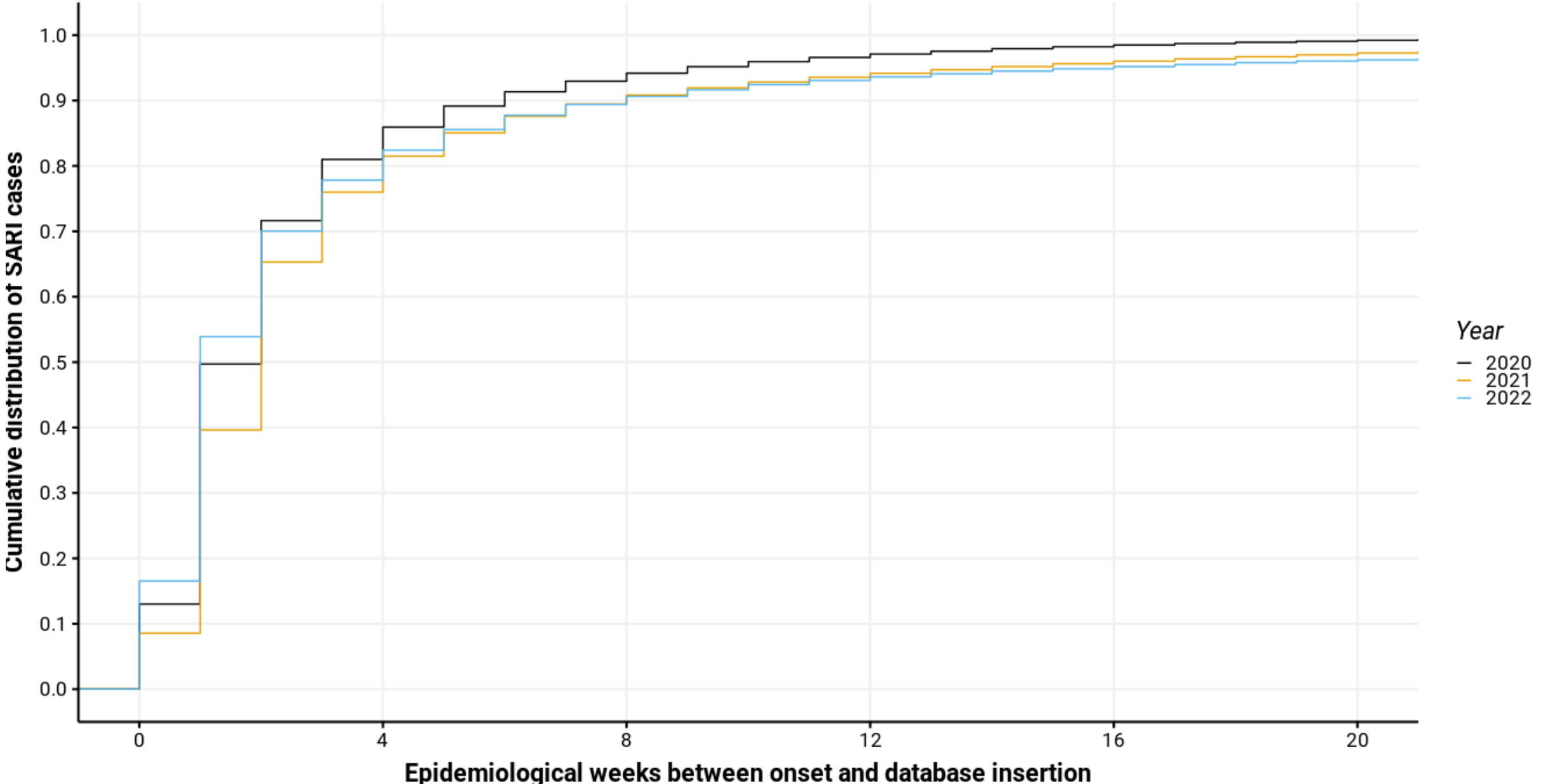
cumulative cases as of today =
cumulative as of yesterday
+ new cases registered
– duplicates identified
– discarded cases

(cumulative cases as of today) –
(cumulative cases as of yesterday)

From case occurrence to database entry

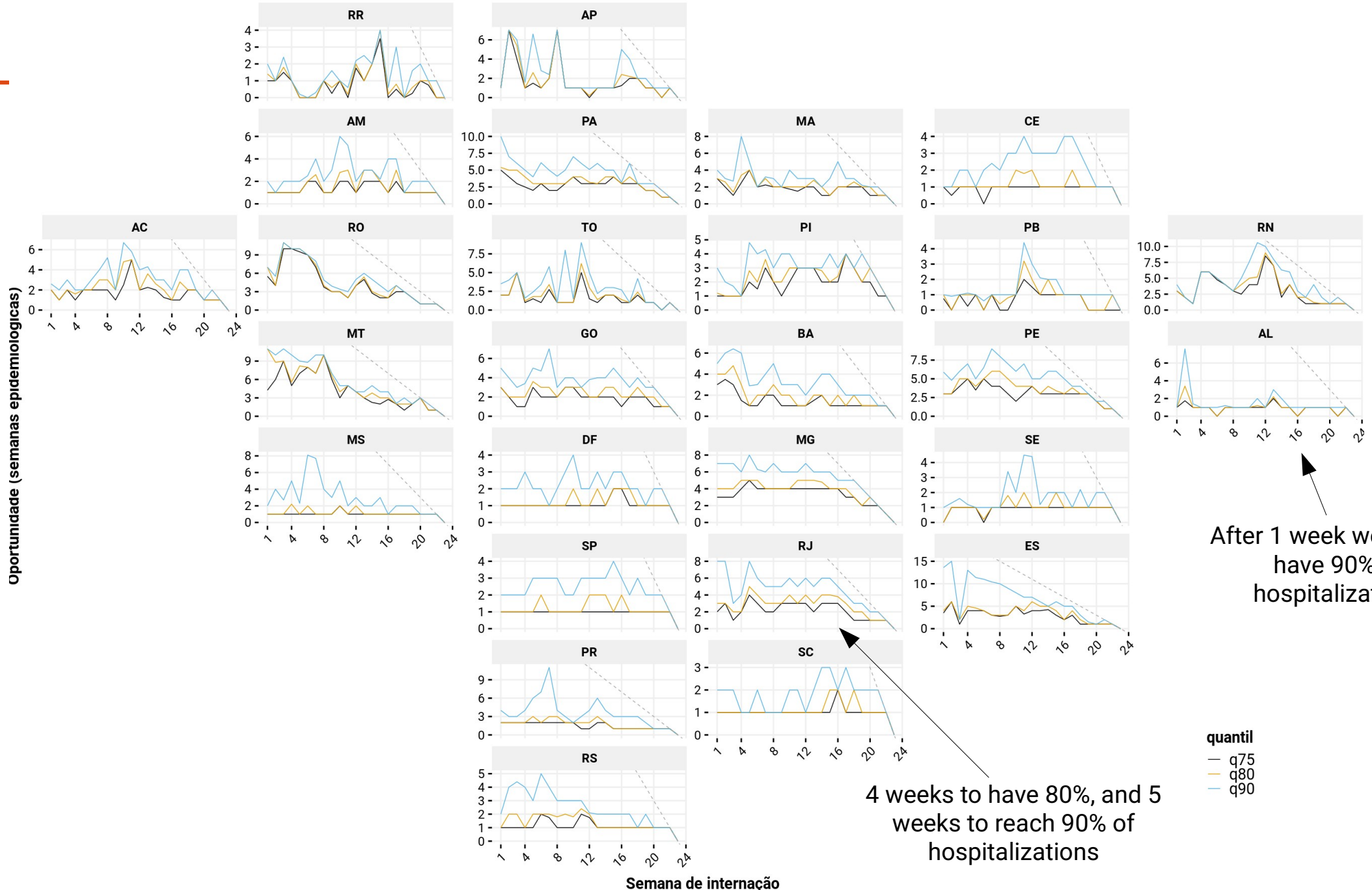


Challenge: time to database insertion (backfill)



Oportunidade de digitação em relação à internação

Dados digitados até a semana epidemiológica 2023 24



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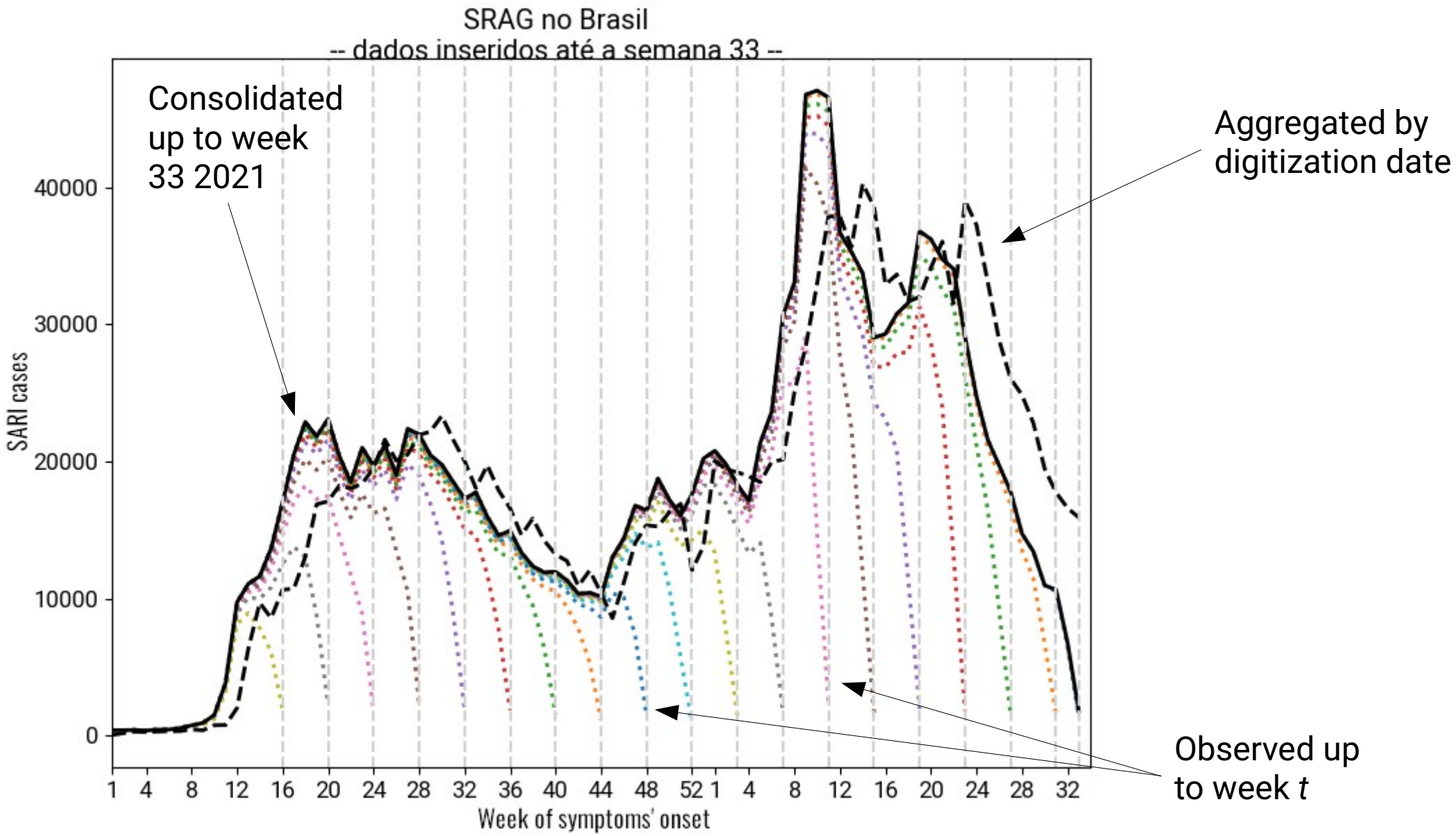

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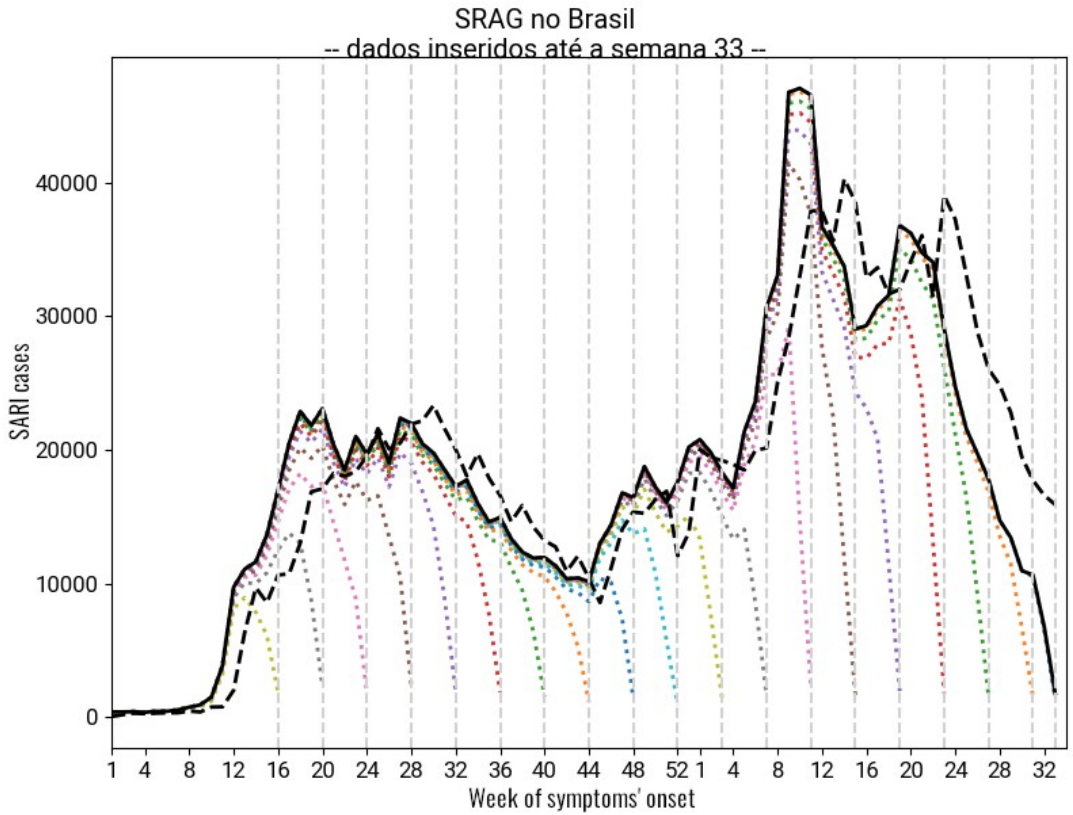
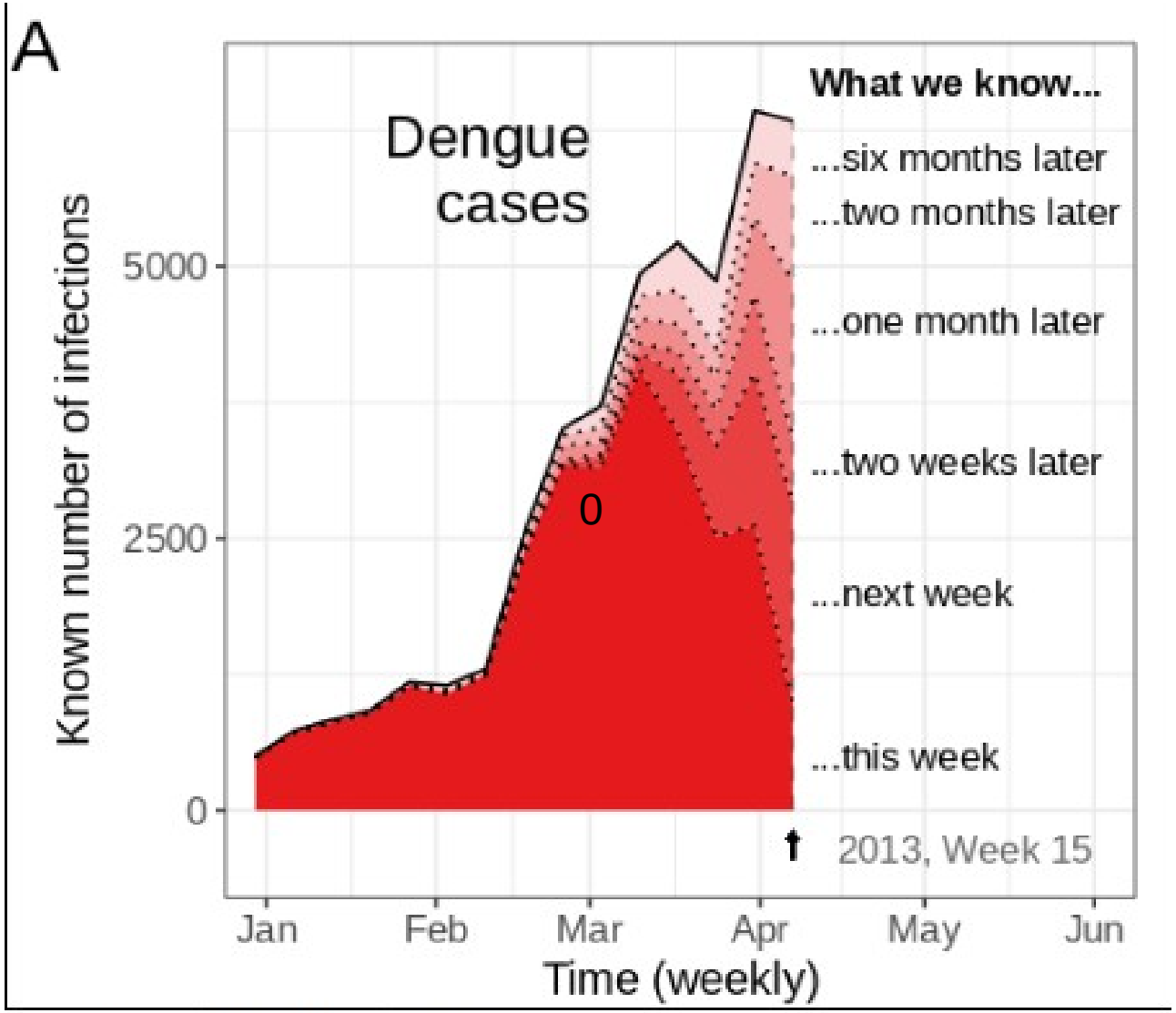
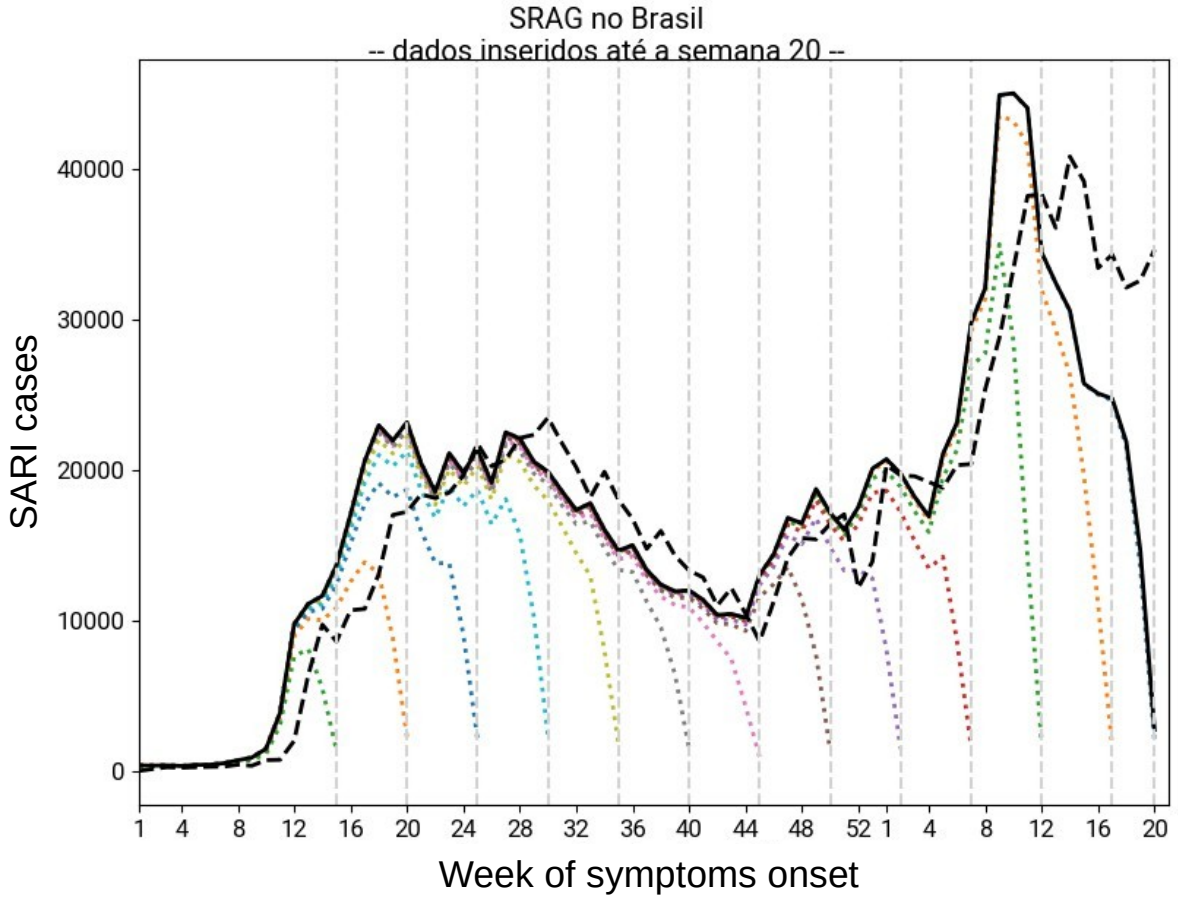
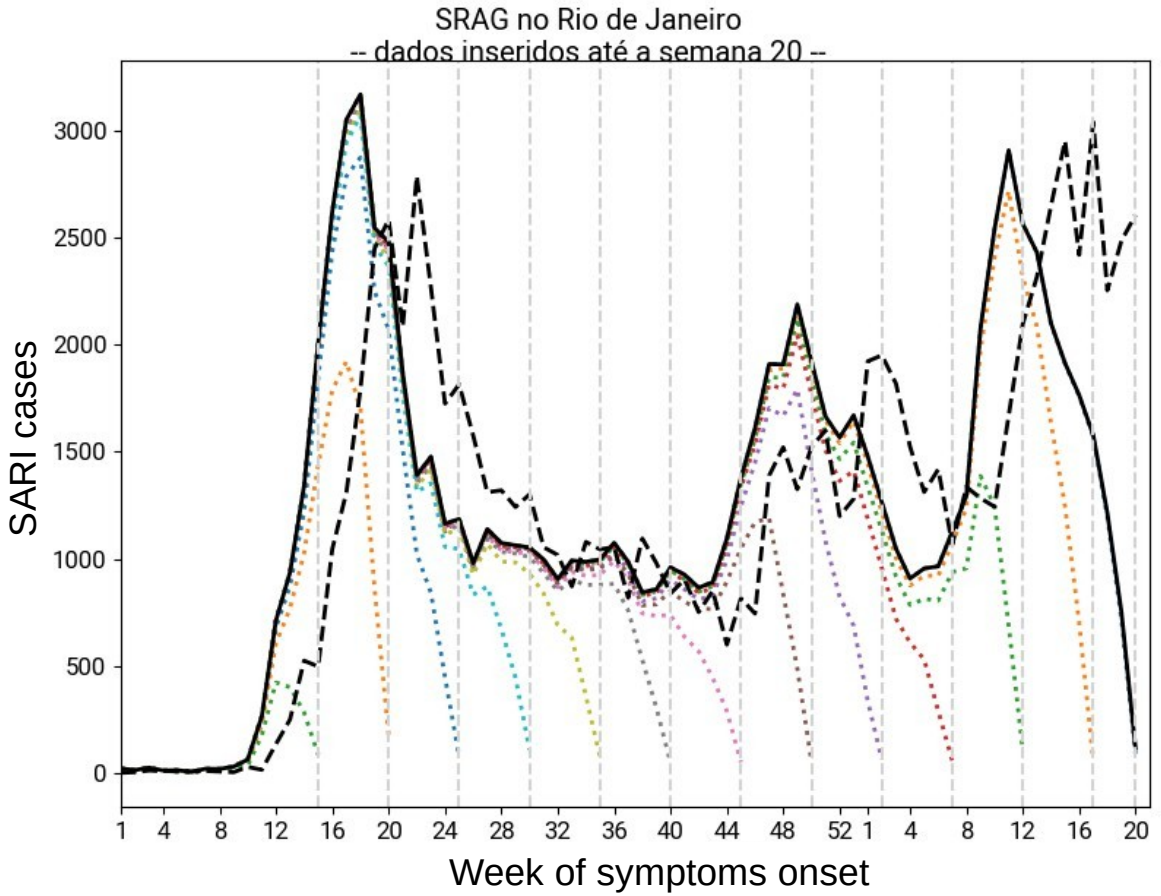




Time of event vs notification vs digitization





http://info.gripe.fiocruz.br

InfoGripe's weekly reports: http://bit.ly/mave-infogripe-fiocruz

Time of event vs notification vs digitization

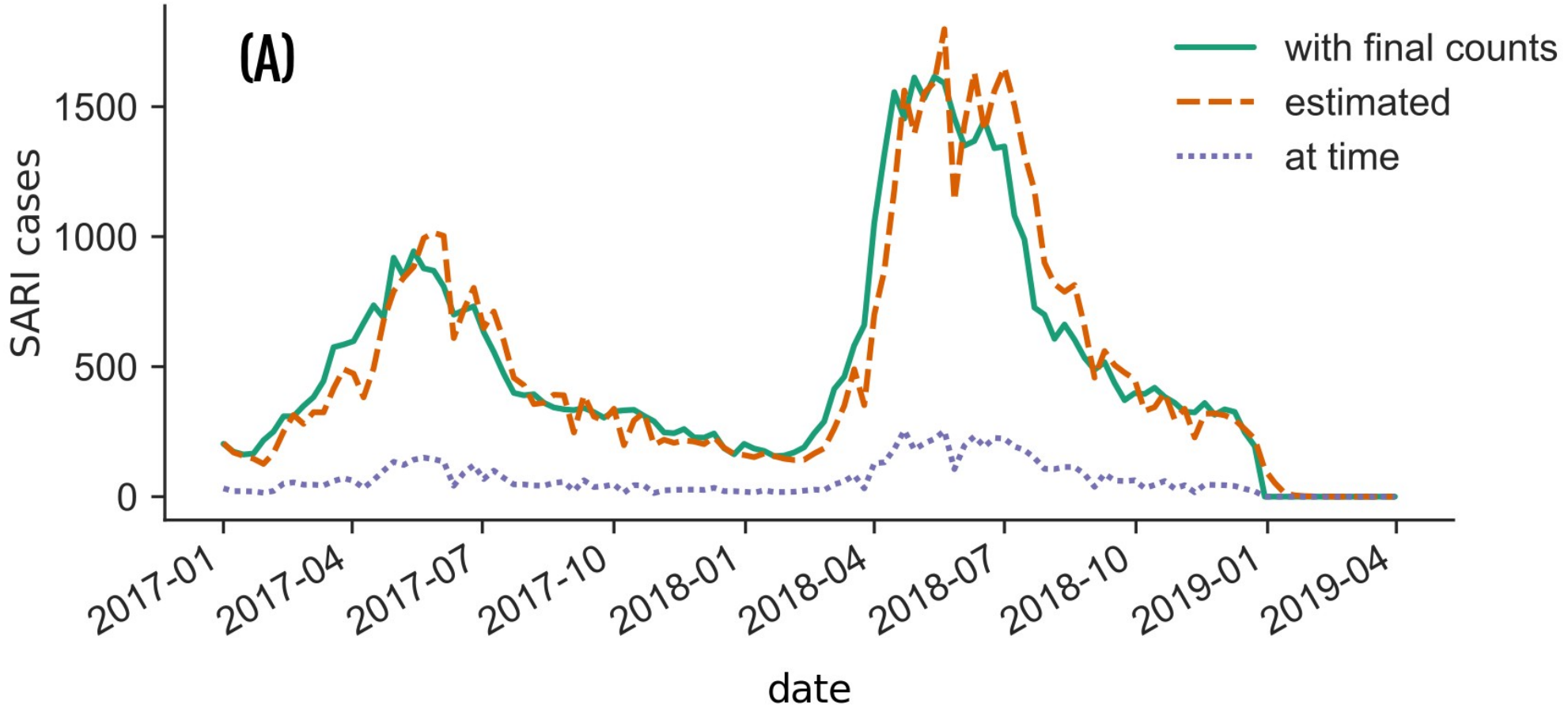
Time	0	1	2	⋯	D-2	D-1	D	N	
1	$n_{1,0}$	$n_{1,1}$	$n_{1,2}$		$n_{1,D-2}$	$n_{1,D-1}$	$n_{1,D}$	N_1	Observations
2	$n_{2,0}$	$n_{2,1}$	$n_{2,2}$	⋯	$n_{2,D-2}$	$n_{2,D-1}$	$n_{2,D}$	N_2	
3	$n_{3,0}$	$n_{3,1}$	$n_{3,2}$		$n_{3,D-2}$	$n_{3,D-1}$	$n_{3,D}$	N_3	
⋮		⋮				⋮			
T-D	$n_{T-D,0}$	$n_{T-D,1}$	$n_{T-D,2}$		$n_{T-D,D-2}$	$n_{T-D,D-1}$	$n_{T-D,D}$	N_{T-D}	
T-D+1	$n_{T-D+1,0}$	$n_{T-D+1,1}$	$n_{T-D+1,2}$		$n_{T-D+1,D-2}$	$n_{T-D+1,D-1}$	$n_{T-D+1,D}$	N_{T-D+1}	Nowcasting
T-D+2	$n_{T-D+2,0}$	$n_{T-D+2,1}$	$n_{T-D+2,2}$		$n_{T-D+2,D-2}$	$n_{T-D+2,D-1}$	$n_{T-D+2,D}$	N_{T-D+2}	
T-2	$n_{T-2,0}$	$n_{T-2,1}$	$n_{T-2,2}$		$n_{T-2,D-2}$	$n_{T-2,D-1}$	$n_{T-2,D}$	N_{T-2}	
T-1	$n_{T-1,0}$	$n_{T-1,1}$	$n_{T-1,2}$		$n_{T-1,D-2}$	$n_{T-1,D-1}$	$n_{T-1,D}$	N_{T-1}	
T	$n_{T,0}$	$n_{T,1}$	$n_{T,2}$	⋯	$n_{T,D-2}$	$n_{T,D-1}$	$n_{T,D}$	N_T	
T+1	$n_{T+1,0}$	$n_{T+1,1}$	$n_{T+1,2}$		$n_{T+1,D-2}$	$n_{T+1,D-1}$	$n_{T+1,D}$	N_{T+1}	Forecasting
T+2	$n_{T+2,0}$	$n_{T+2,1}$	$n_{T+2,2}$		$n_{T+2,D-2}$	$n_{T+2,D-1}$	$n_{T+2,D}$	N_{T+2}	
⋮		⋮		⋯		⋮			
T+K	$n_{T+K,0}$	$n_{T+K,1}$	$n_{T+K,2}$		$n_{T+K,D-2}$	$n_{T+K,D-1}$	$n_{T+K,D}$	N_{T+K}	

$$n_{t,d} \sim \text{NegBin}(\lambda_{t,d}, \phi),\ \lambda_{t,d} > 0,\ \phi > 0$$

$$\log(\lambda_{t,d}) = \mu + _t + \beta_d + \mathbf{x}'_{t,d}\gamma$$

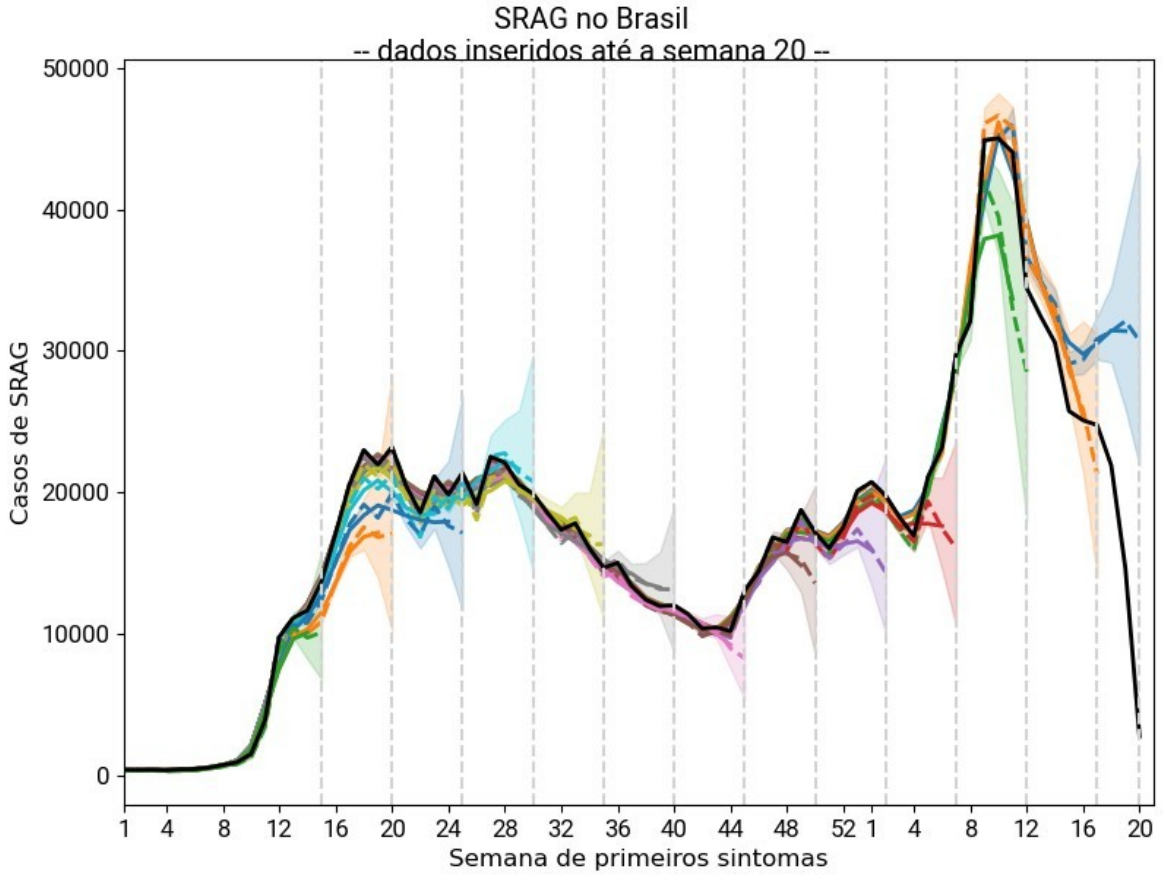
Bastos, LS, Economou, T, Gomes, MFC, et al.
A modelling approach for correcting reporting delays in disease surveillance data. Statistics in Medicine. 2019; 38: 4363– 4377.
https://doi.org/10.1002/sim.8303

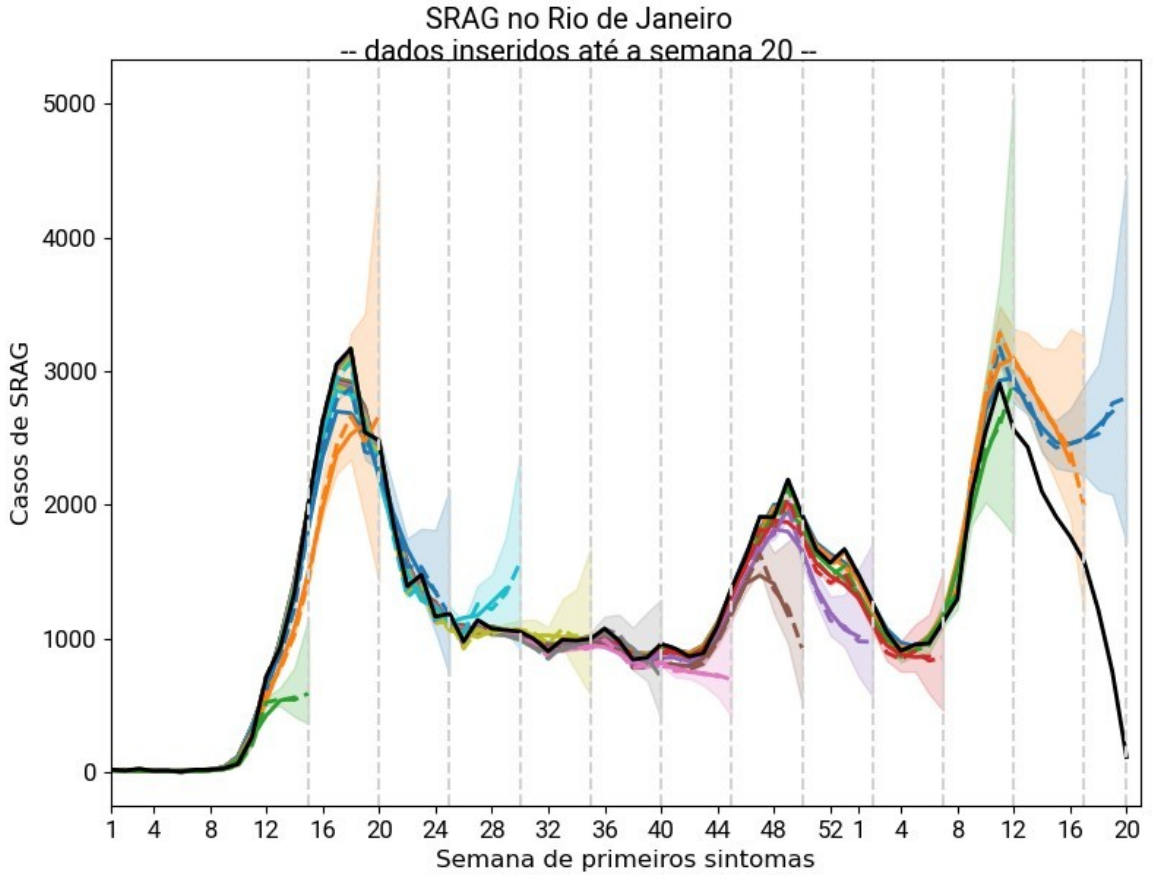
Time of event vs notification vs digitization



Bastos, LS, Economou, T, Gomes, MFC, et al.
A modelling approach for correcting reporting delays in disease surveillance data. Statistics in Medicine. 2019; 38: 4363– 4377.
https://doi.org/10.1002/sim.8303

Time of event vs notification vs digitization





http://info.gripe.fiocruz.br

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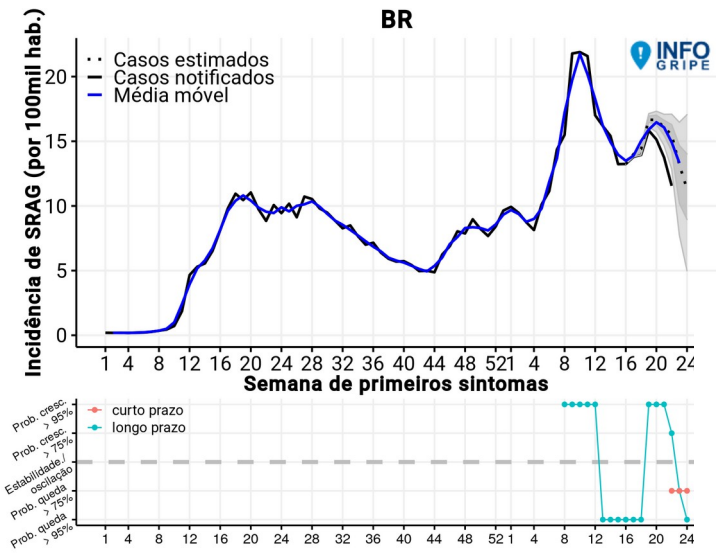
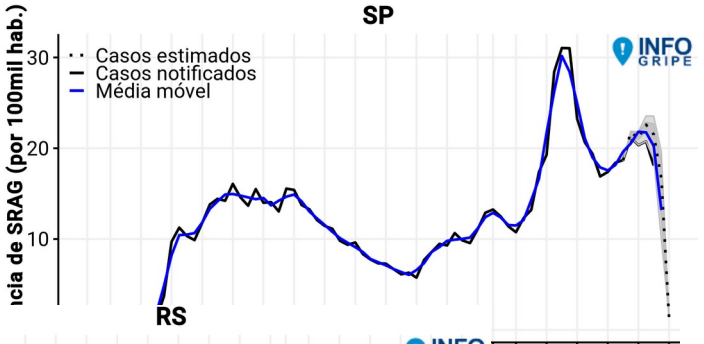
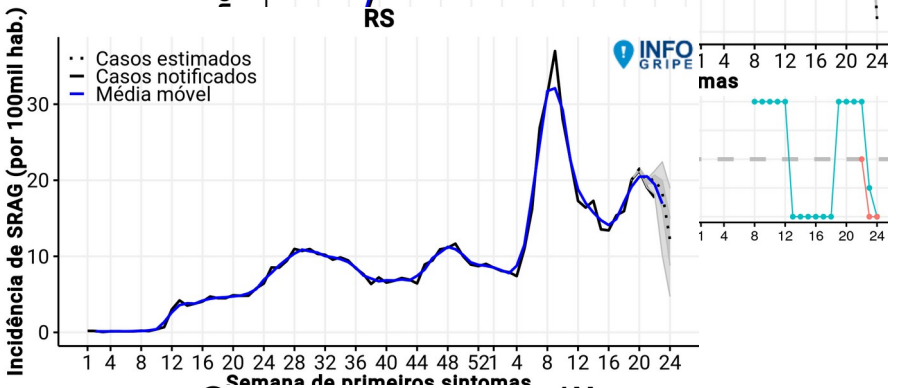
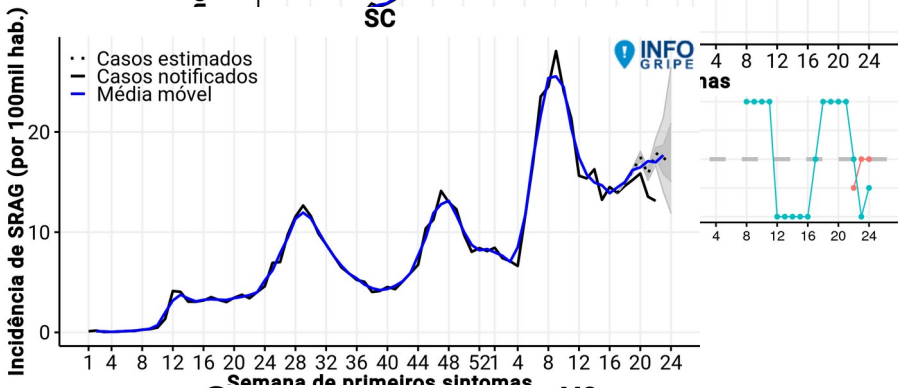
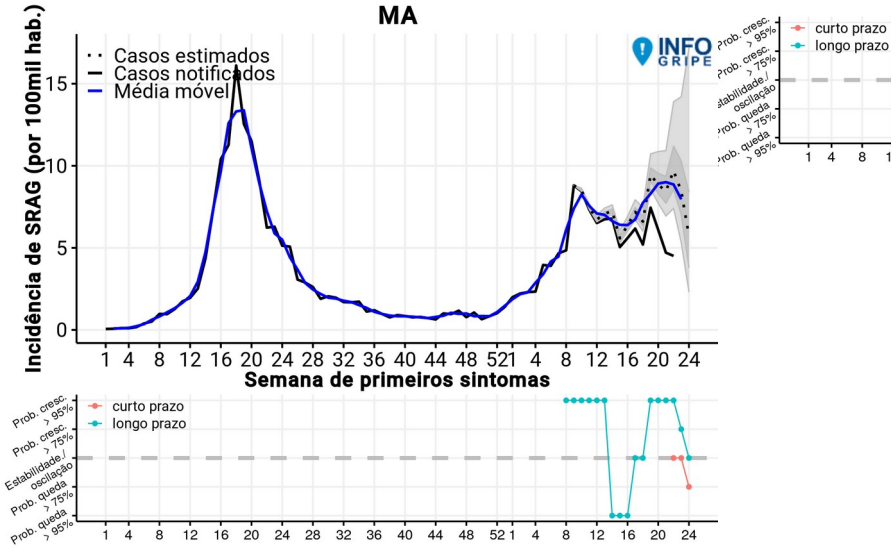
Situation analysis (week 24 2021)

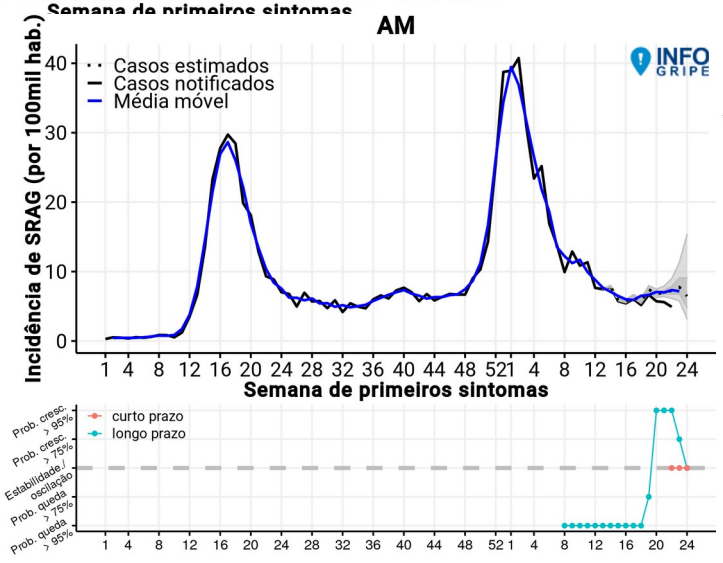


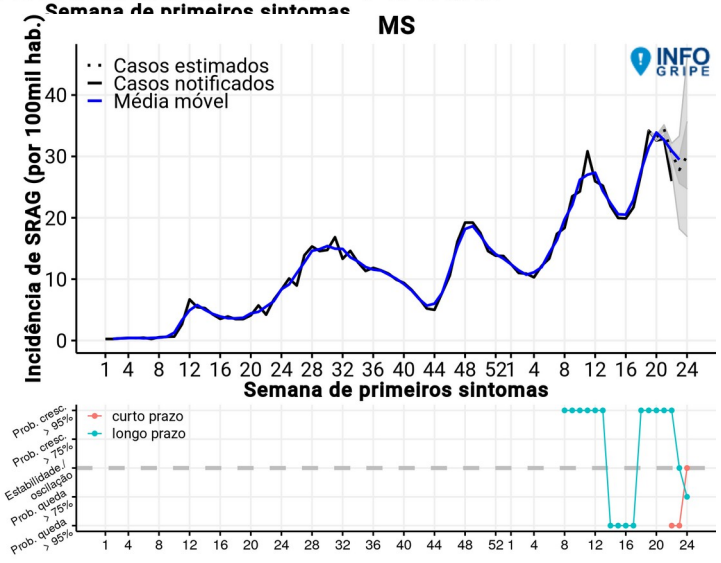




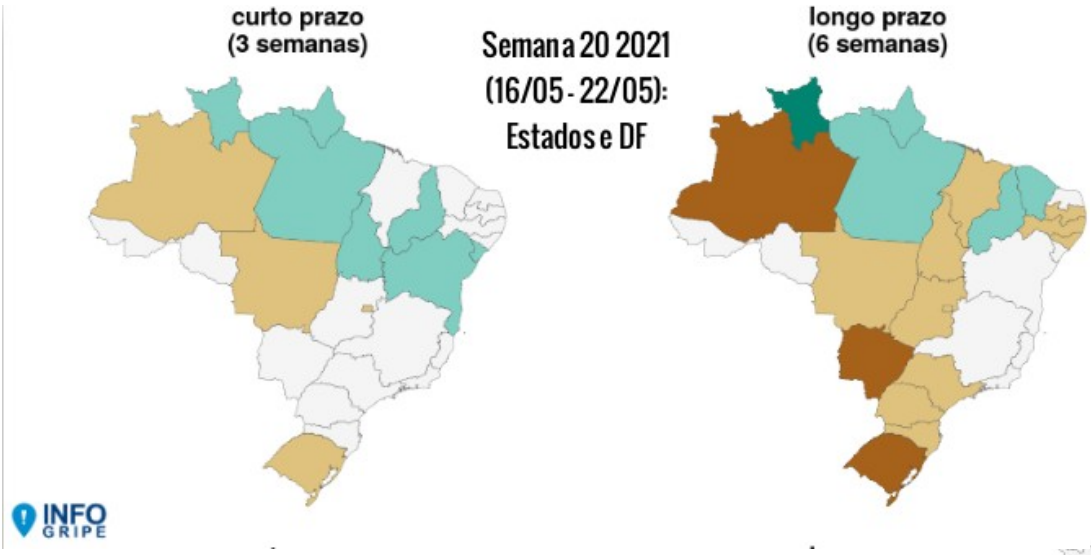




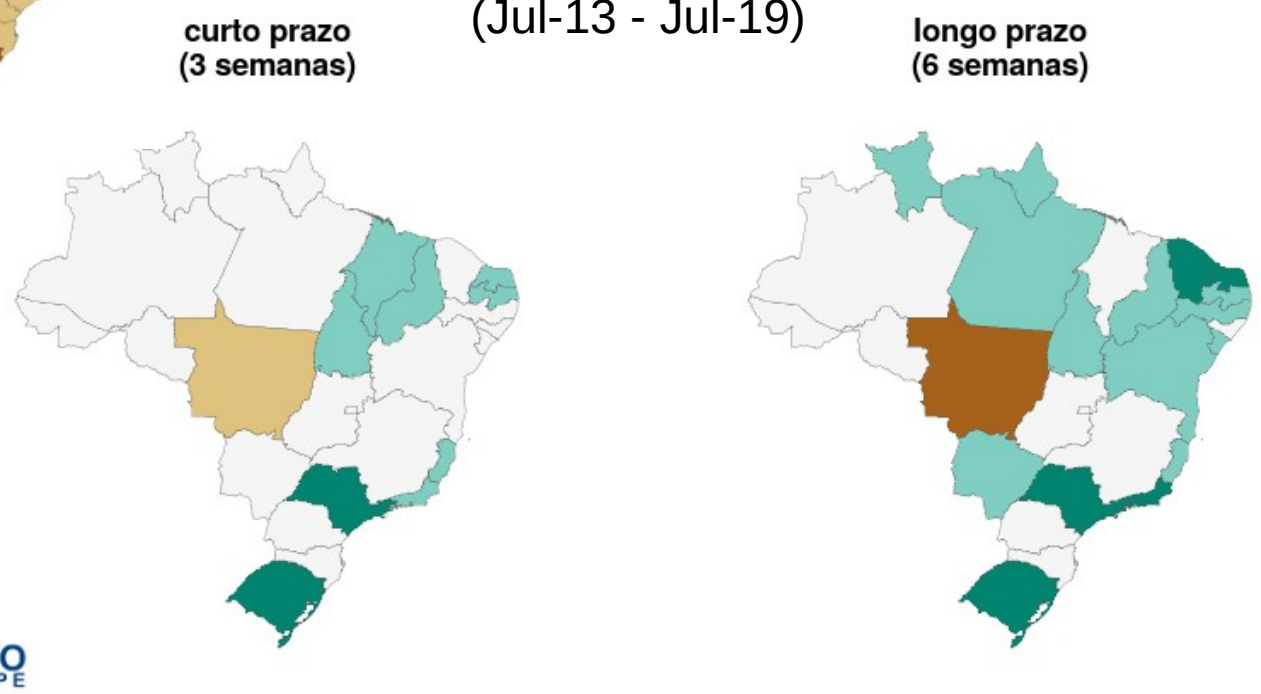




Situation analysis



Week 24 2021
(Jul-13 - Jul-19)



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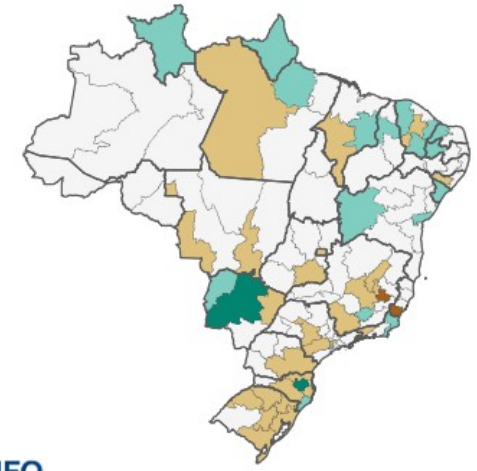
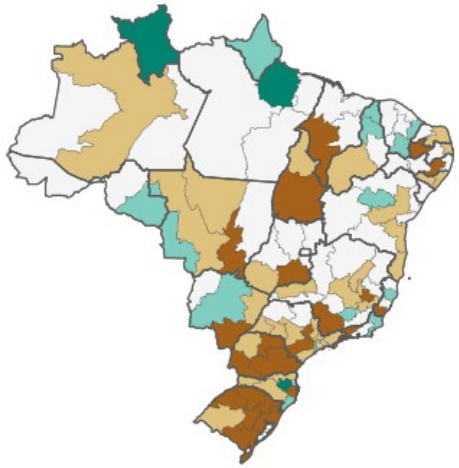
Situation analysis: macrorregions of health

curto prazo
(3 semanas)

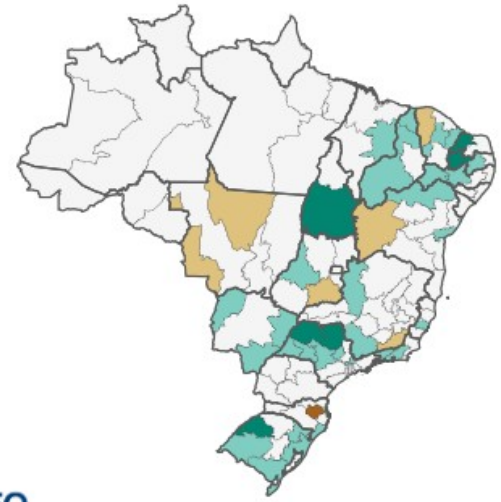


longo prazo
(6 semanas)

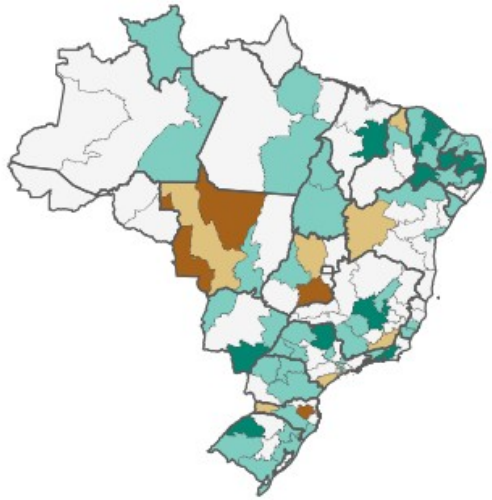


INFO GRIPE

curto prazo
(3 semanas)



longo prazo
(6 semanas)



INFO GRIPE

- Increase prob. > 95%
- Increase prob. > 75%
- Stability/Oscill.
- Decrease Prob.> 75%
- Decrease Prob.> 95%

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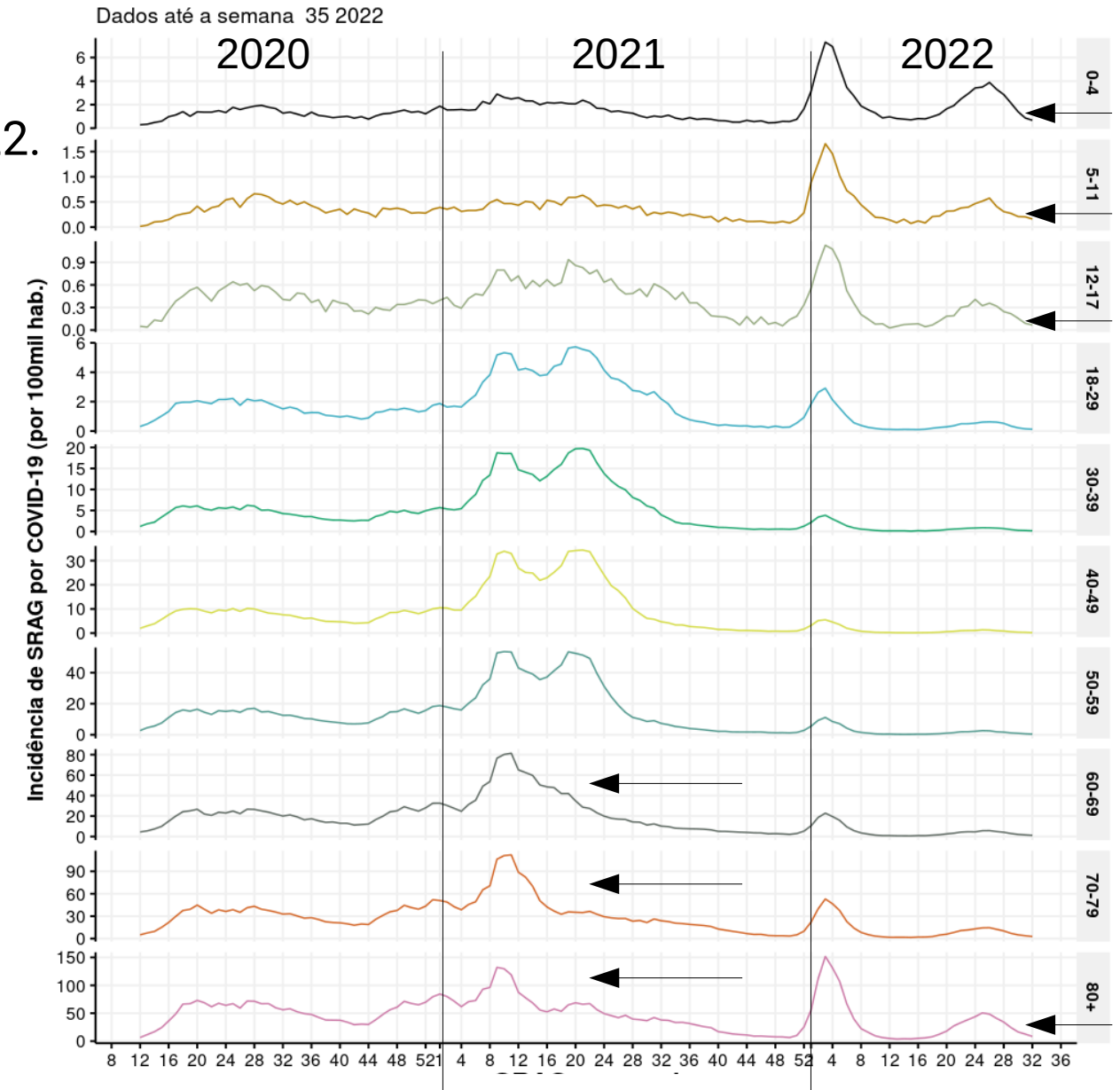
INFO GRIPE

Age stratification

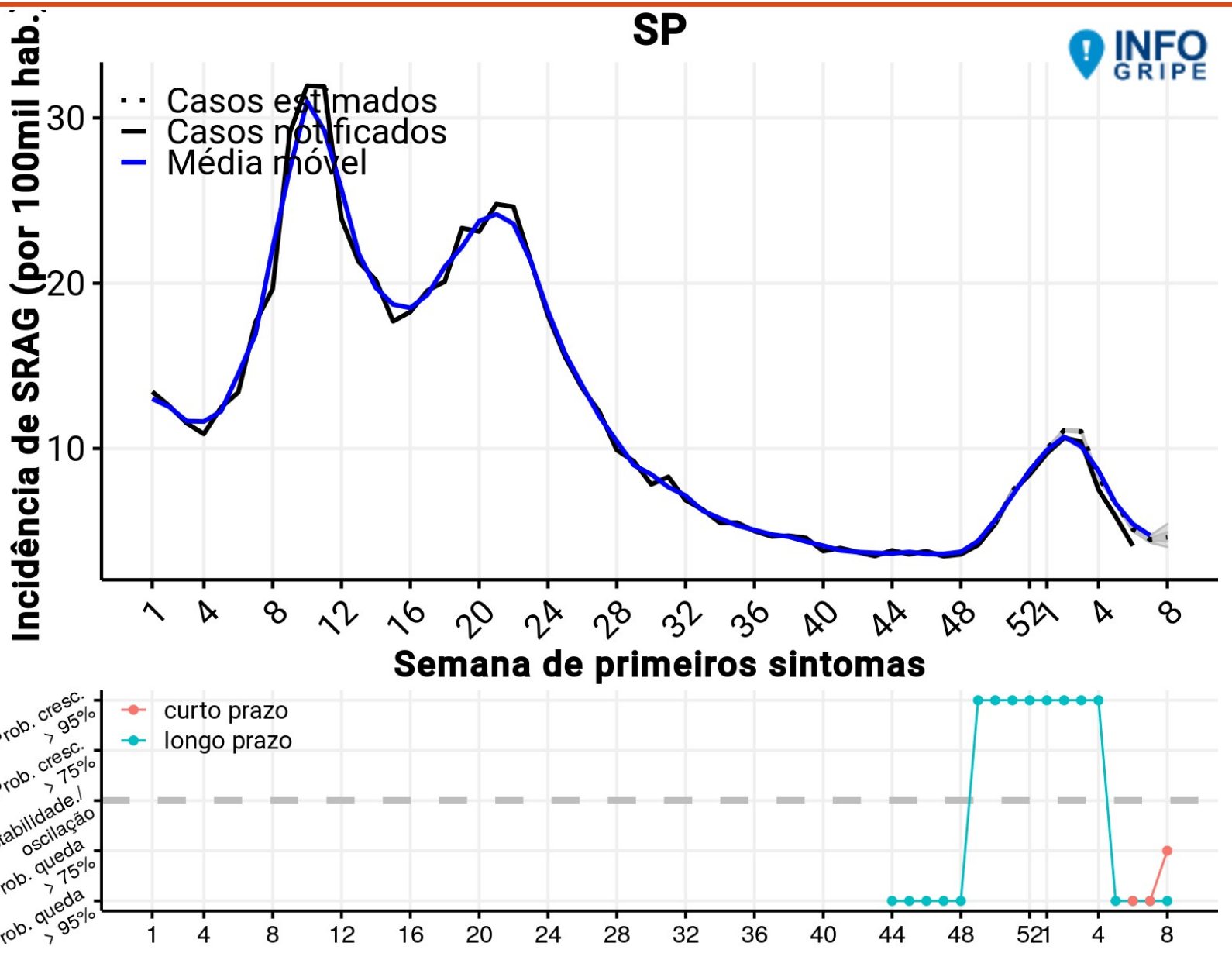
Incidence by age group

SARI by SARS-CoV-2
week 12 2020 to 33 2022.

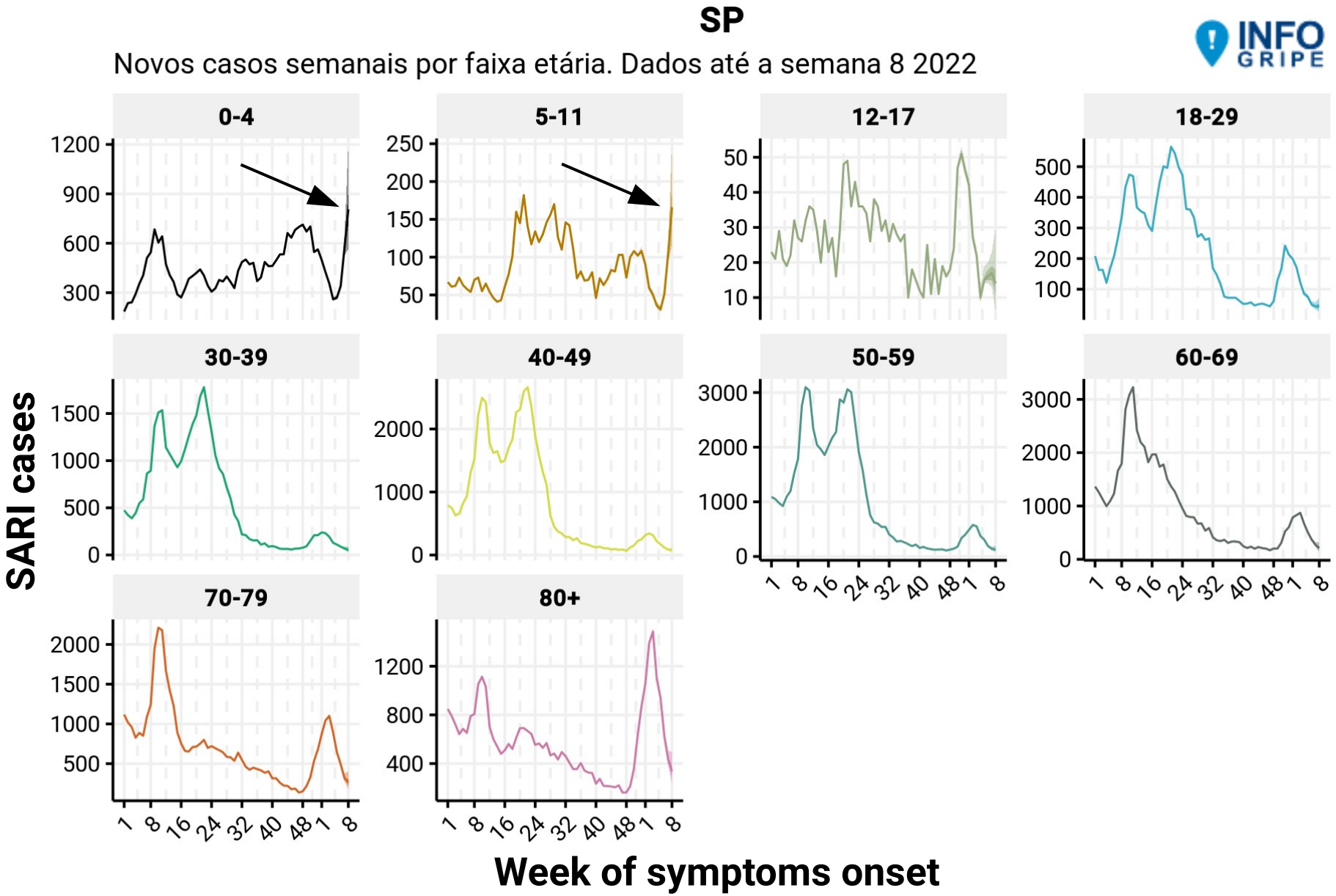
Data extracted at week
35 2022.



Situation at week 8 2022

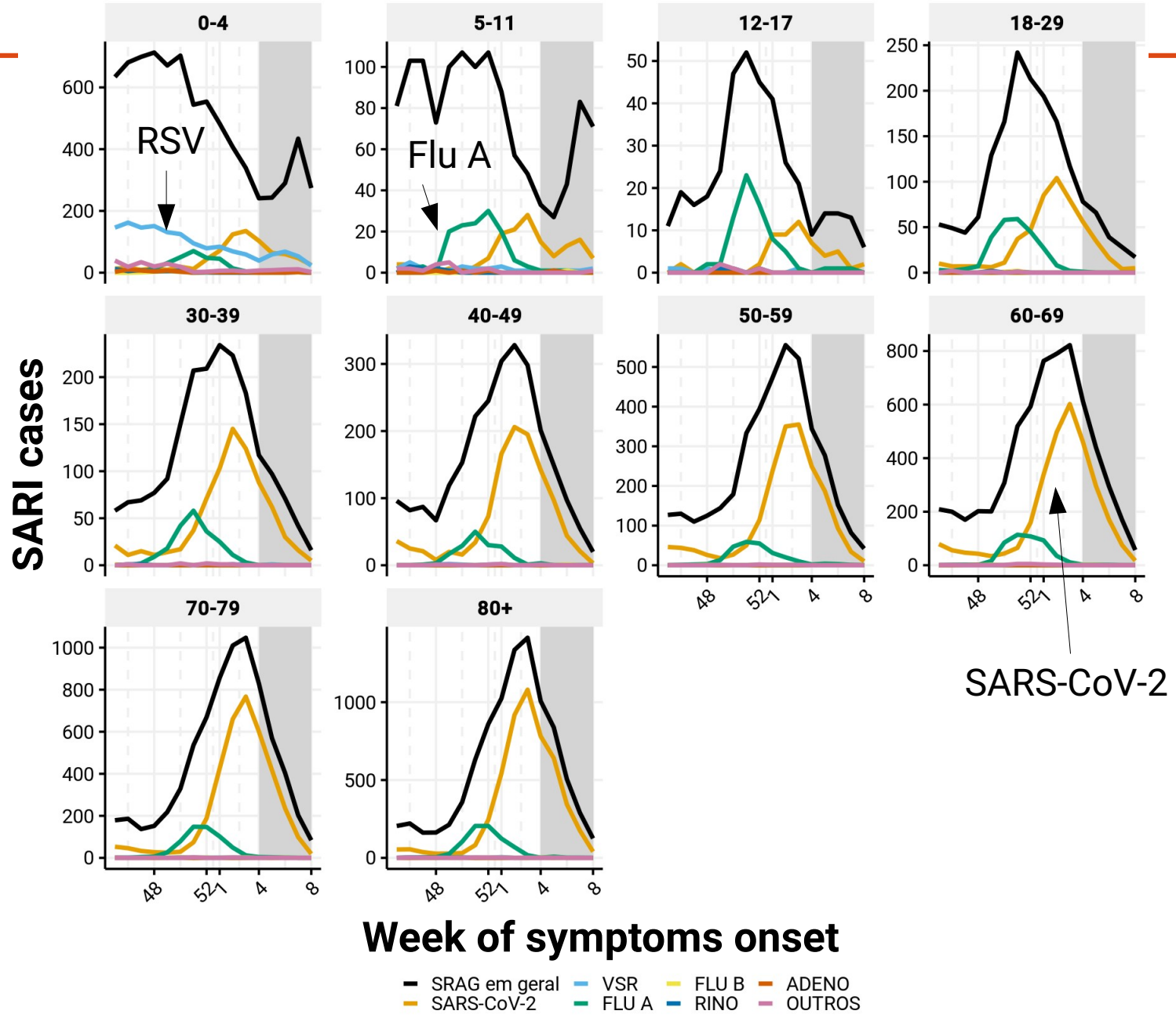


Situation at week 8 2022

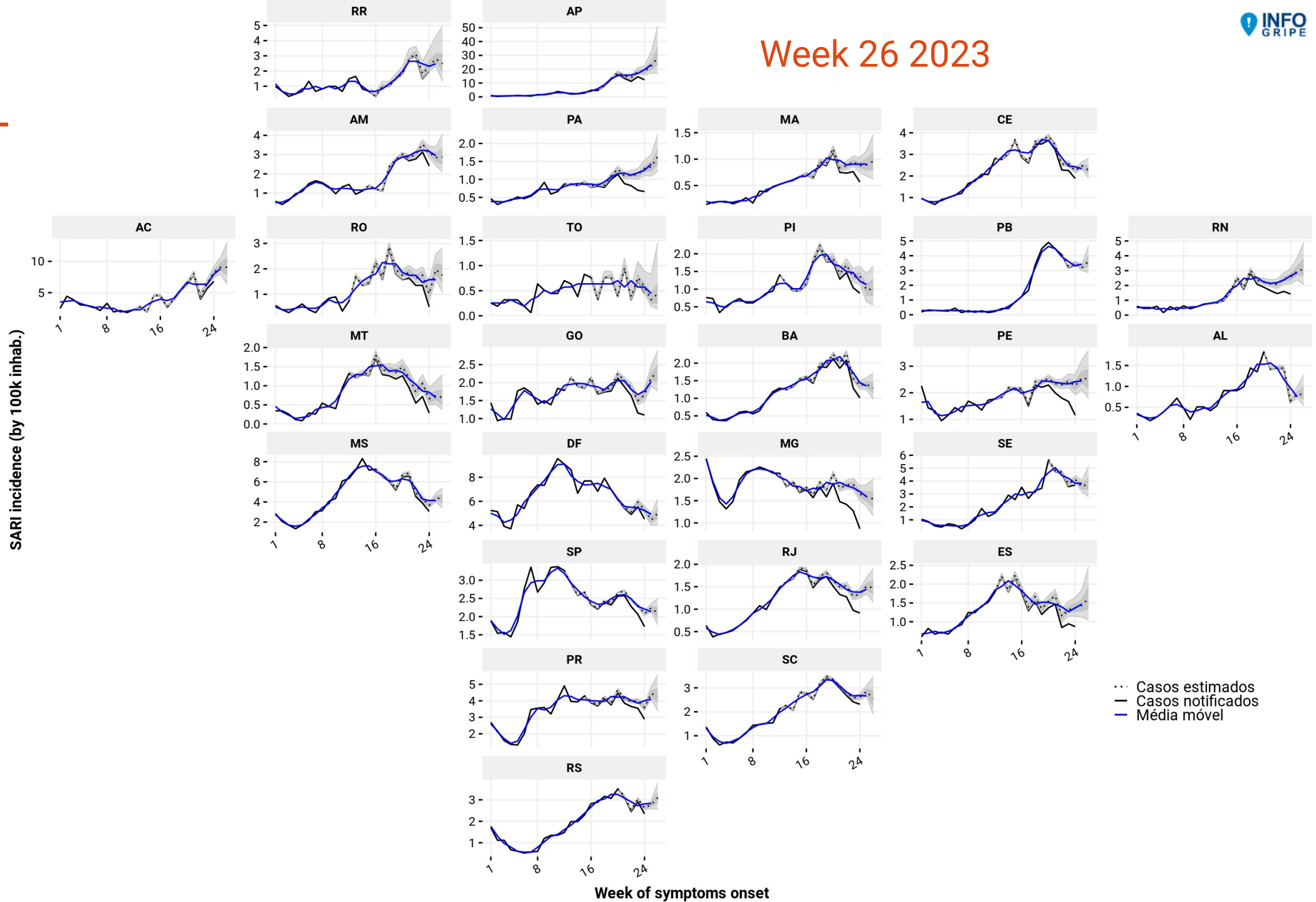


São Paulo

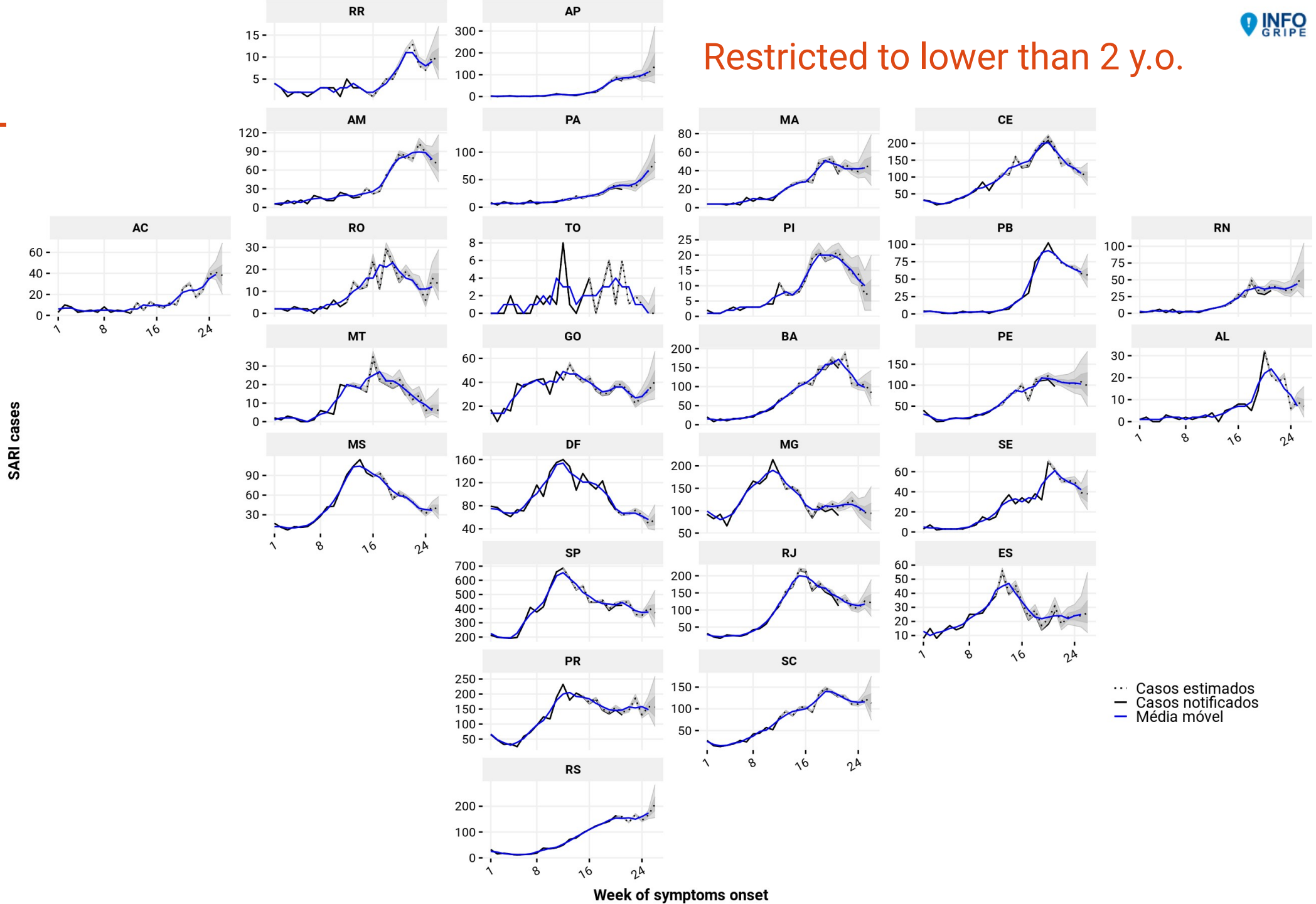
Novos casos semanais por faixa etária. Dados até a semana 8 2022.
Para semanas recentes os dados são parciais (área cinza).



Week 26 2023


RR
AP
AM
PA
MA
CE
AC
RO
TO
PI
PB
RN
MT
GO
BA
PE
AL
MS
DF
MG
SE
SP
RJ
ES
PR
SC
RS
SARI incidence (by 100k inhab.)
Week of symptoms onset
Casos estimados
Casos notificados
Média móvel

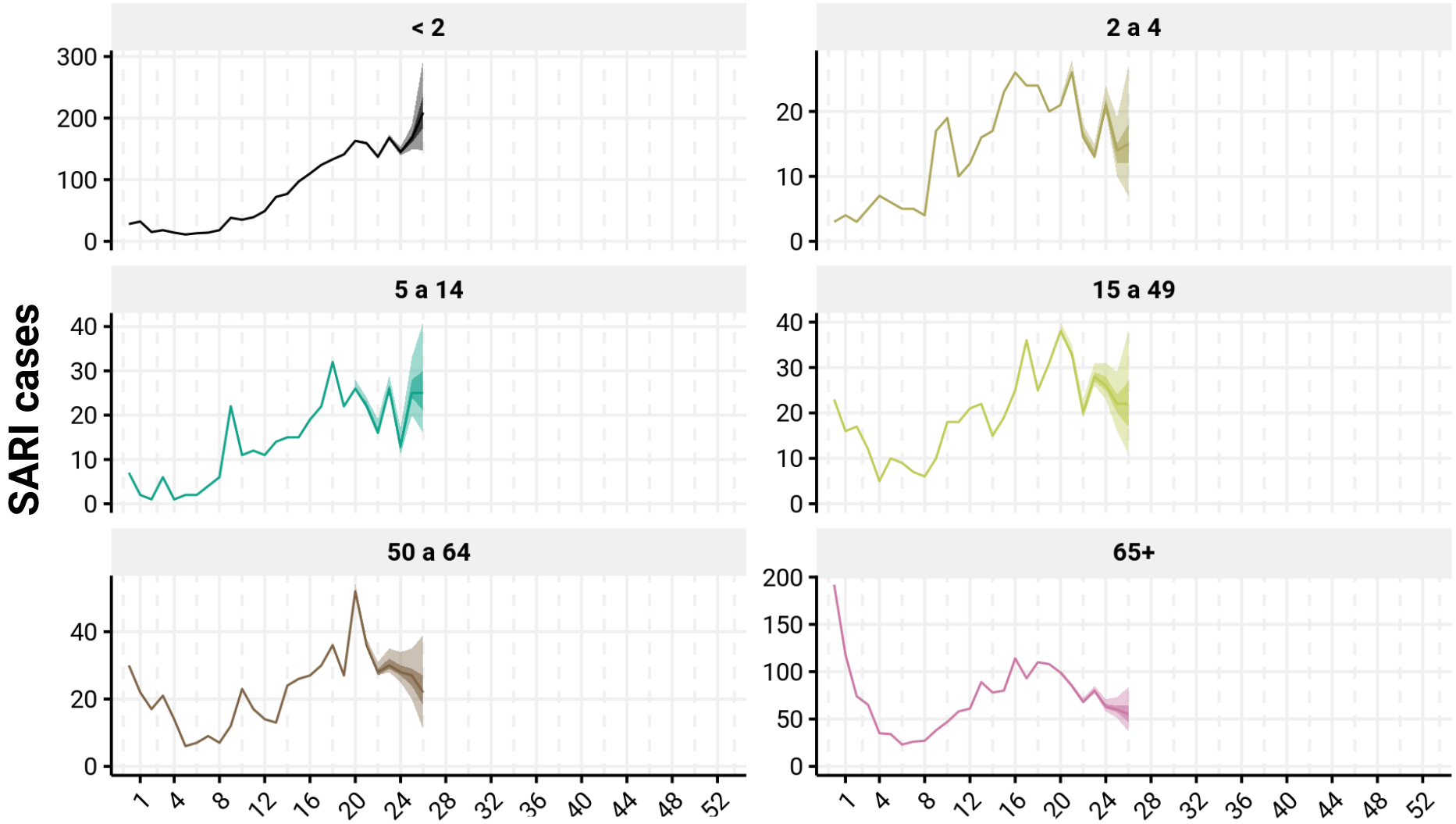
Restricted to lower than 2 y.o.



RS

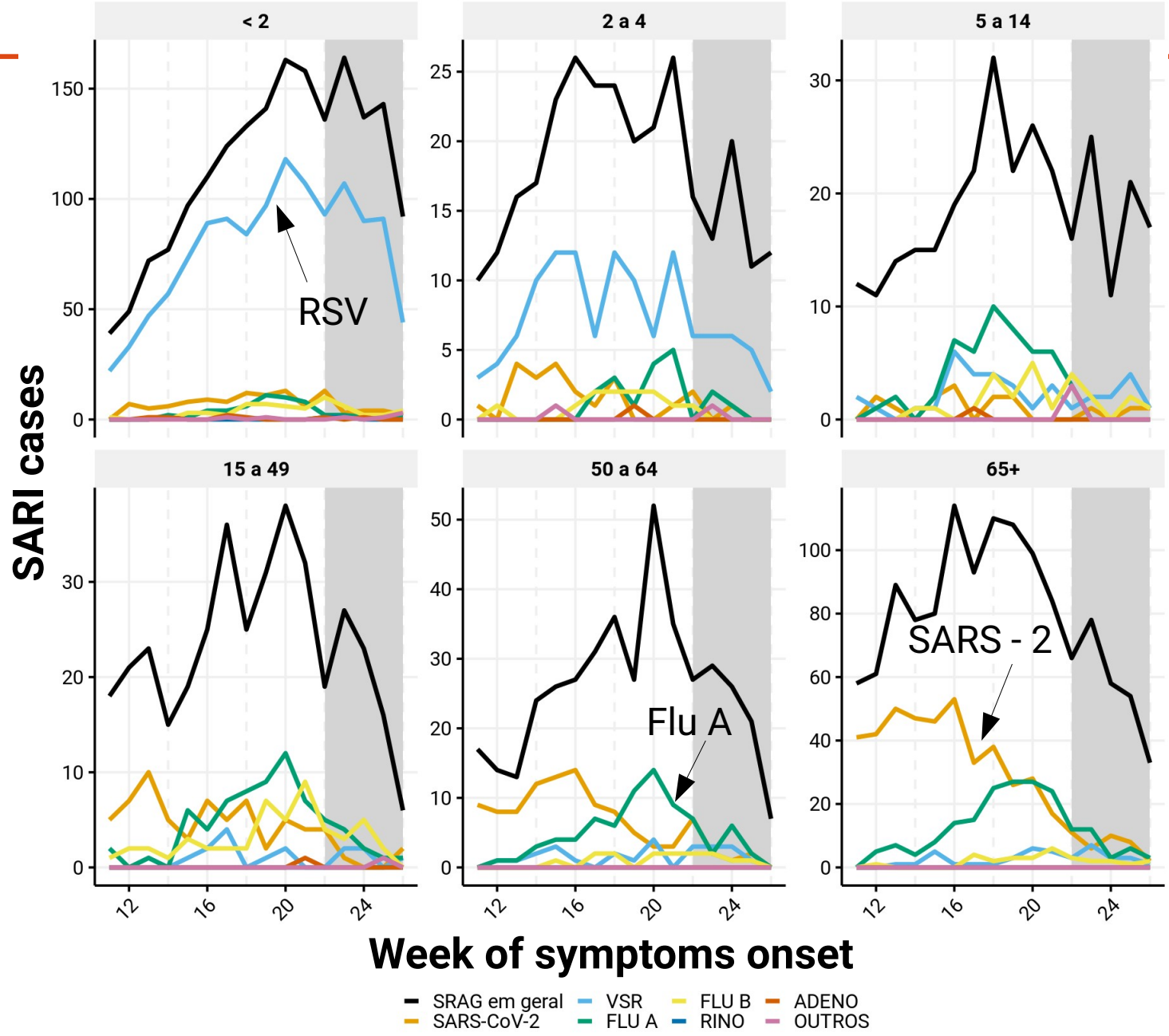
INFO GRIPE

Novos casos semanais por faixa etária. Dados até a semana 26 2023



Rio Grande do Sul

Novos casos semanais por faixa etária. Dados até a semana 26 2023.
Para semanas recentes os dados são parciais (área cinza).



Thanks!

Usefull MAVE links:

Repository: http://bit.ly/mave-repo-fiocruz
COVID-19 reports:
https://bit.ly/mave-covid19-relatorios-fiocruz
Data: http://bit.ly/mave-infogripe-dados-fiocruz

InfoGripe:

http://info.gripe.fiocruz.br
Weekly reports: http://bit.ly/mave-infogripe-fiocruz

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