Subnational analysis of the Initial Phase of the COVID-19 epidemic in Brazil

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MACHINE LEARNING & GLOBAL HEALTH NETWORK

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Background

Brazil was one of the most badly affected countries during the initial outbreak of the COVID-19 pandemic. In response to the rapid spread of the virus, the policy makers implemented extensive public health measures to reduce the transmission, including closure of retail services, schools, restricting transportation and travel. Specific interventions were implemented at a state level, with substantial variation between the states. A better understanding of the epidemiological origins and the impact of those interventions is required to guide future policy decisions.

Aim: Assess the impact of impact of non-pharmaceutical interventions on curbing transmission of COVID-19 across the states of Brazil in the first stage of the epidemic.

Methods

- Data: state-stratified COVID-19 deaths from [1] and [2] up to 9th May 2020 and Google Mobility data [3]
- Model: we extend the model from [4, 5] by incorporating uncertainty around deaths underreporting
- Partially-pooled hierarchical Bayesian model for 18 states
- State- and time-varying reproduction number is estimated using mobility data (t-time, m-state, k-mobility covariate, sigma-logistic function)

$$R_{t,m} = R_{0,m} \cdot \sigma(-(\sum_{k=1}^{4}(\alpha_k + \beta_{m,k})X_{t,m,k}) - \epsilon_{m,w_m(t)})$$

- Observed deaths *d* are generated with earlier infections *i*, where an infection fatality ratio *ifr* has a delay distribution π

$$d_{t,m} = \text{ifr} \sum_{\tau<t} i_{\tau,m}\pi_{t-\tau,m}$$

$$i_{t,m} = R_{t,m} \sum_{\tau<t} i_{\tau,m}g_{t-\tau,m}$$

- Daily deaths are modelled by

$$D_{t,m} \sim \text{Negative Binomial}\left(d_{t,m}, d_{t,m} + \frac{d_{t,m}^2}{\phi}\right),\ \phi \sim N(0,5)$$

Results

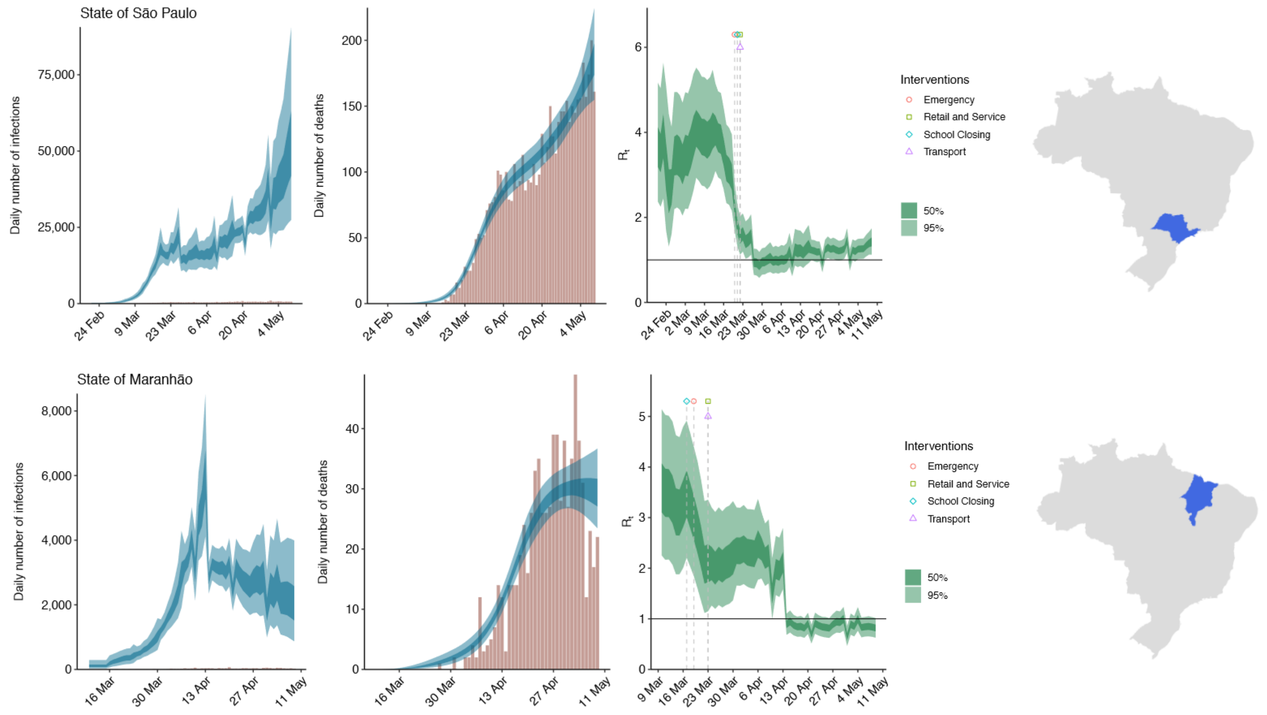

Fig.1 Estimates of numbers of infections, deaths and R_t for 2 states. Left: daily number of infections, blue bands are predicted infections, dark blue 50% credible interval (CI), light blue 95% CI. Middle: daily number of deaths, brown bars are reported deaths, blue bands are predicted deaths, CI as in left plot. Right: time-varying reproduction number R_t. If the R_t is above 1, the number of infections continues to grow. Icons are interventions shown at the time they occurred.

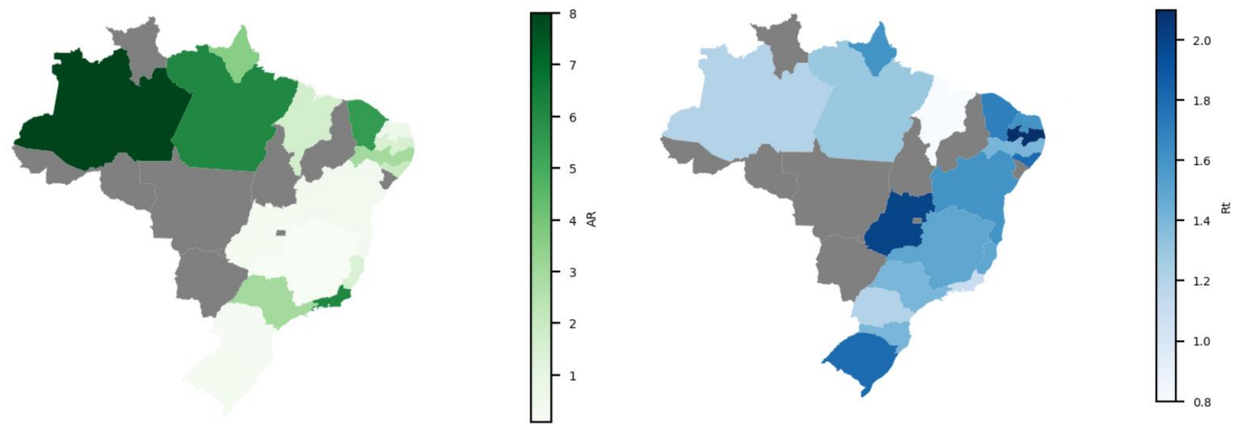

Fig. 2 Mean posterior estimate of attack rate (AR, left) and reproduction number (R_t) on the 9th May 2020 across the states of Brazil. Gray states were not analysed.

Discussion

- Our results support geographical variation, highlighting specifically the variation in the likely timing of epidemic take-off that has led to the asynchronous epidemics that have emerged across different states.
- Despite the reductions introduced by the NPIs, our results also show that the changes in population mobility covariates were not stringent enough to reduce R_t below 1 in many states.

References

[1] covid.saude.gov.br
[2] opendatasus.saude.gov.br/dataset/bd-srag-2020
[3] google.com/covid19/mobility/
[4] Flaxman et al. 2020, Nature
[5] Unwin et al. 2020, Nature Comms

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