State-specific Projection of COVID-19 Infection and Evaluation of Three Major Control Measures

Shi Chen[1], Qin Li[1*], Song Gao[2*], Yuhao Kang[2], Xun Shi[3]

1 Department of Mathematics, University of Wisconsin-Madison, Madison, WI 53706, USA

2 GeoDS Lab, Department of Geography, University of Wisconsin-Madison, Madison, WI 53706, USA

3 Department of Geography, Dartmouth College, Hanover, NH 03755, USA

WISCONSIN UNIVERSITY OF WISCONSIN–MADISON

Introduction

To combat the spread of COVID-19, actions have been taken in various dimensions, including discouraging travels, curbing non-essential interactions, and increasing test capacity. However, it is still unclear what control and intervention measures would have actual effect, especially to what extent, on abating the spread of COVID-19.

- In this study, we developed a travel-network-based susceptible-exposed-infectious-removed (SEIR) model that characterizes infections by state and incorporates inflows and outflows of interstate travelers.
- We chose to use three parameters that can directly correspond to practical control measures, and quantify their impact on the final output of the model.

Model

The parameters and model specification are defined as follows:

$$\begin{cases} \frac{\mathrm{d}S_i}{\mathrm{d}t} = -\frac{b_i S_i (U_i + \gamma E_i)}{P_i} + \sum_{j\neq i} \alpha_t n_{ij} \frac{S_j}{P_j} - \sum_{j\neq i} \alpha_t n_{ji} \frac{S_i}{P_i} \\ \frac{\mathrm{d}E_i}{\mathrm{d}t} = \frac{b_i S_i (U_i + \gamma E_i)}{P_i} - \frac{E_i}{D_e} + \sum_{j\neq i} \alpha_t n_{ij} \frac{E_j}{P_j} - \sum_{j\neq i} \alpha_t n_{ji} \frac{E_i}{P_i} \\ \frac{\mathrm{d}I_i}{\mathrm{d}t} = r_i \frac{E_i}{D_e} - c_I \frac{I_i}{D_c} - (1-c_I)\frac{I_i}{D_l} \\ \frac{\mathrm{d}U_i}{\mathrm{d}t} = (1-r_i)\frac{E_i}{D_e} - c_U \frac{U_i}{D_c} - (1-c_U)\frac{U_i}{D_l} + \sum_{j\neq i} \alpha_t n_{ij} \frac{U_j}{P_j} - \sum_{j\neq i} \alpha_t n_{ji} \frac{U_i}{P_i} \\ \frac{\mathrm{d}R_i}{\mathrm{d}t} = c_I \frac{I_i}{D_c} + (1-c_I)\frac{I_i}{D_l} + c_U \frac{U_i}{D_c} + (1-c_U)\frac{U_i}{D_l} \end{cases} .$$

S: susceptible, E: exposed, I: reported, U: unreported, R: removed, $P = S + E + U$. n_{ij}: the flow from state j to i. b_i: transmission rate. r_i: reporting rate of state. D_e: the latent period.

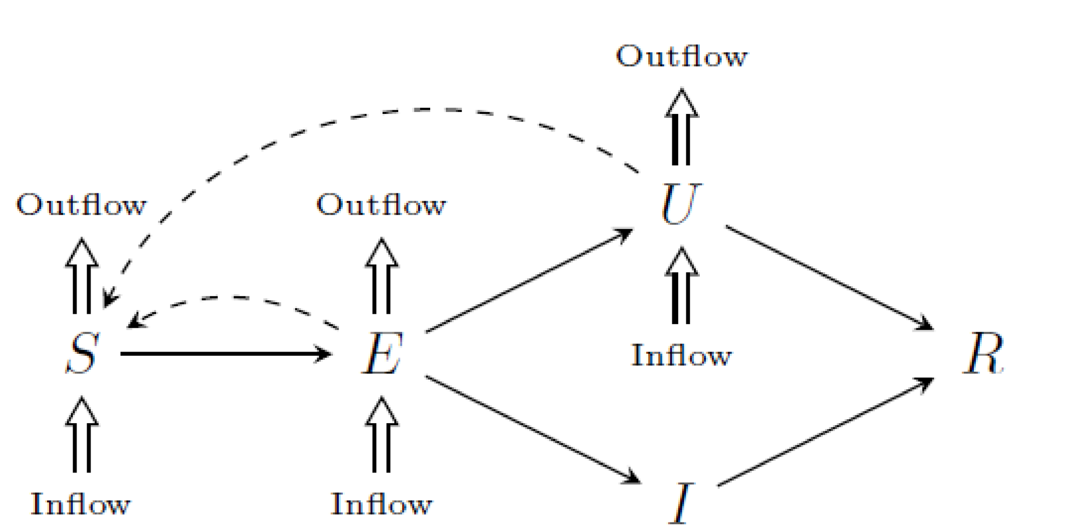

Fig. 1: Illustration of the travel flow-network augmented susceptible-exposed-infectious-removed model.

Results

We set $r = 1 - \alpha_r(1 - r_0)$ and $b = \alpha_b b_0$, with r_0 and b_0 being inferred parameters. (A) and (B) in Fig. 2 reveals that once the epidemic has reached a certain stage, the difference caused by the relatively small number of imported cases is insignificant. From Fig. 3, It can be seen that merely raising r cannot fully make basic reproduction rate $R_e < 1$.

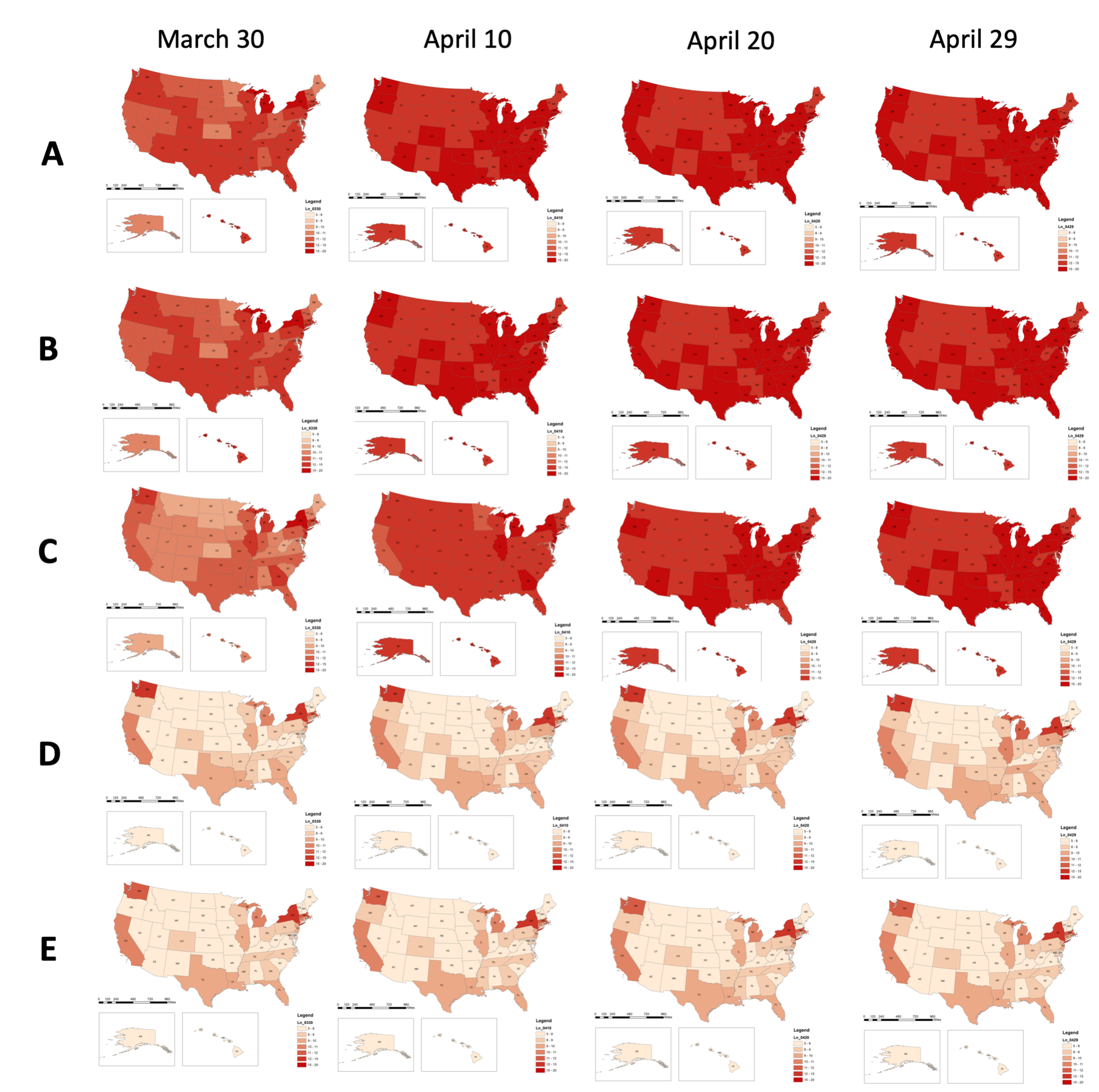

Fig. 2: Left: the spatiotemporal distribution of predicted infected population. $\alpha_t = 1$ unless otherwise mentioned. (A) $\alpha_r = \alpha_b = 1$; (B) $\alpha_r = \alpha_b = 1$, $\alpha_t = 0.05$; (C) $\alpha_r = 0.1$ and $\alpha_b = 1$; (D) $\alpha_r = 1$ and $\alpha_b = 0.1$; (E) $\alpha_r = 0.1$, $\alpha_b = 0.1$.

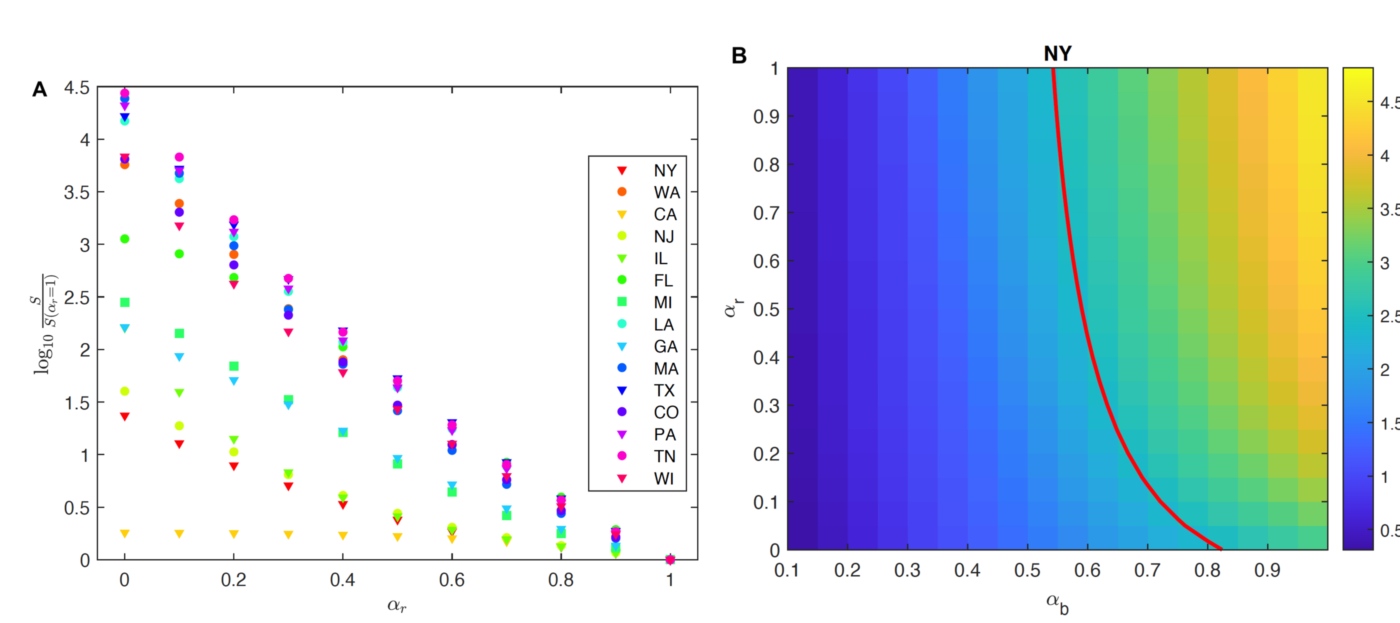

Fig. 3: Left: susceptible population as a function of α_r. Right: the basic reproduction number for different α_b and α_r.

References

[1] K. Law, A. Stuart, and K. Zygalakis. "Data assimilation". In: *Cham, Switzerland: Springer* 214 (2015).

Discussion

To mitigate the spread of COVID-19 in these states, a proactive approach needs to be taken to prevent the exposed population from potentially infecting other susceptible people. In Fig 4, we plot the increase of infections in terms of the temporal lag in putting a person into quarantine (D_q). The longer one waits to inform and isolate the exposed population, the more infected people one observes.

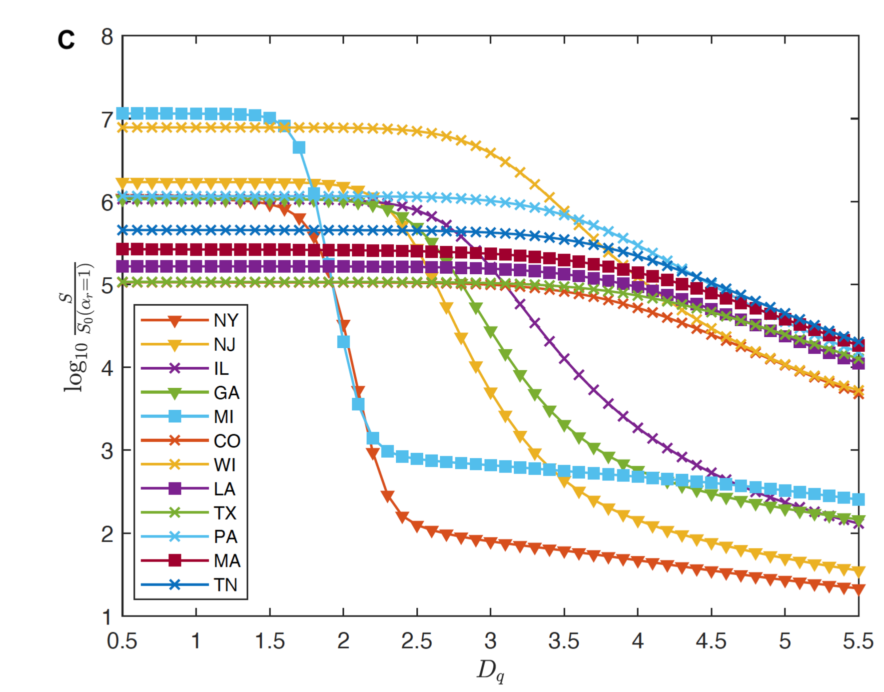

Fig. 4: Susceptible population for different D_q. S significantly depends on the period from expose to quarantine.

Data and Parameter Fitting

We employed daily and state specific historical data (I) to incrementally calibrate the parameters $u = (b_i, r_i, I_i, E_i, S_i, U_i, R_i)$ in the model. With $P_{n-1|n-1}(u)$ being the probability density of u at t_{n-1}, we evolve the model to obtain prior density $P_{n|n-1}(u)$ at t_n. Then confirmed cases $d_n = (I_i^n)$ is incorporated to update posterior density. We choose to utilize Ensemble Kalman Filter which is steered towards analyzing systems having high dimensional state variables [1]. The mobility data is collected from the SafeGraph business venue database.

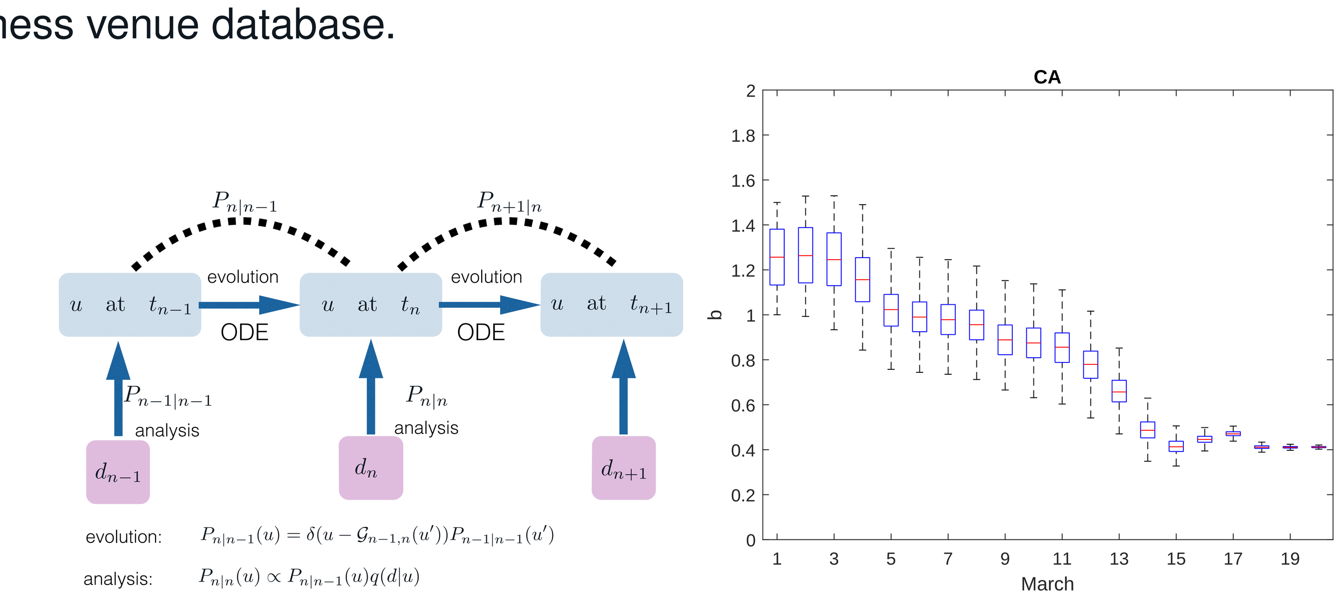

Fig. 5: Left: flowchart of data assimilation. $\mathcal{G}_{n-1,n}$ is the forward map by running the ODE from t_{n-1} to t_n. Right: Inferred transmission rate b of CA during the data assimilation stage.