Spatiotemporal transmission dynamics of COVID-19 pandemic and its impact on critical healthcare capacity

MODEL DESCRIPTION

We developed a spatial deterministic compartmental mathematical model to simulate the dynamics of confirmed COVID-19 cases, COVID-19-related hospitalizations and ICU admissions, and COVID-19-related deaths in Ohio. The model incorporated spatial connectivity information by county. The COVID-19 spatial was formulated as a system of coupled nonlinear differential equations that stratify the population into compartments according to spatial risk group, infection status, hospitalization, and disease stage. The model stratified the population into four different spatial groups depending on spatial risk characteristics of the county. The spatial risk groups were defined as following, Group 1: counties with airports; Group 2: counties surrounding the counties with airports; Group 3: counties with main highways crossing the county; and Group 4: counties not surrounding counties with airports or being crossed by main highways. Each group has its own dynamic of the disease and the directional connections between groups are assumed to be by flow of infections between the different groups at specific rates. The dynamic of the disease transmission and infection complications in each group was modeled using seven epidemiological compartments for the susceptible, infected, recovered, hospitalized, ICU admitted, recovered after hospitalization, and death population. Susceptible individuals in each spatial group are at risk of being exposed to infection at varying hazard rates, which are group- and time dependent, to capture the variability in the risk of exposure and the impact of public health interventions.

Susceptible individuals in Group i (i= 1, 2, 3, 4) get infected at a group specific hazard rate λ_i . Infected individuals can recover at a rate δ , or can get hospitalized at rate η_i . Infected individuals can die of COVID-19 infection complications without get hospitalized at rate ψ .

Hospitalized individuals can recover at rate σ or an get admitted to ICU at rate ω_i . COVID-19 infection complications admitted to ICU can recover at a rate ξ , or patients die at a rate μ_i . Spatial risk groups are connected by a flow of infections between groups in which infections from Group 1 flow to Group 2 at a rate ϕ , and infections from Group 2 flow to Group 3 at a rate τ . Group 4 is infected from Group 2 at a rate γ and from Group 3 at a rate α . We assumed that a non-pharmaceutical intervention is implemented at t_{interv} and generates a reduction ε in the hazard rate of infection. Figure S1 illustrates the schematic diagram of the model.

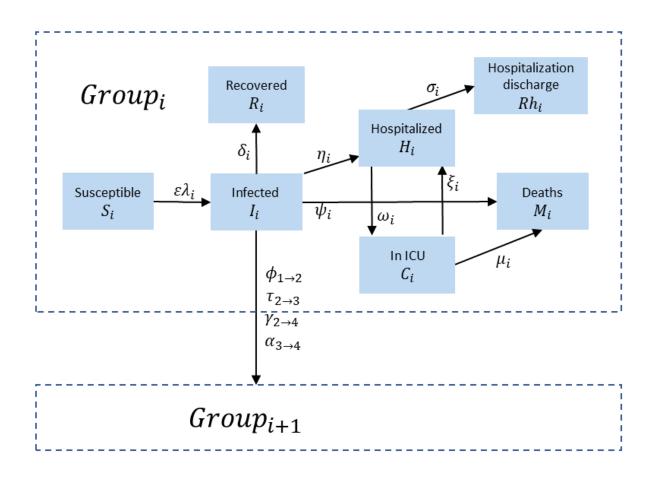


Figure S1. Schematic diagram for the Susceptible-Infected-Hospitalized-Recovered-Dead (SIHRD) COVID-19 deterministic compartmental model

The above formulations result in a system of differential equations describing COVID-19 model in four spatial risk groups as follows,

Group 1: counties with airports

$$\begin{split} \frac{dS_1}{dt} &= -\varepsilon \lambda_1 S_1 (I_1/N_1) \\ \frac{dI_1}{dt} &= \varepsilon \lambda_1 S_1 (I_1/N_1) - I_1 (\delta + \eta_1 + \psi) \\ \frac{dH_1}{dt} &= \eta_1 I_1 + \xi C_1 - H_1 (\omega_1 + \sigma) \\ \frac{dC_1}{dt} &= \omega_1 H_1 - C_1 (\mu_1 + \xi) \\ \frac{dM_1}{dt} &= \mu_1 C_1 + \psi I_1 \\ \frac{dR_1}{dt} &= \delta I_1 \\ \frac{dRh_1}{dt} &= \sigma H_1 \end{split}$$

Group 2: counties surrounding counties with airports

$$\begin{split} \frac{dS_2}{dt} &= -S_2(\phi(I_1/N_1) + \varepsilon \lambda_2(I_2/N_2)) \\ \frac{dI_2}{dt} &= S_2(\phi(I_1/N_1) + \varepsilon \lambda_2(I_2/N_2)) - I_2(\delta + \eta_2 + \psi) \\ \frac{dH_2}{dt} &= \eta_2 I_2 + \xi C_2 - H_2(\omega_2 + \sigma) \\ \frac{dC_1}{dt} &= \omega_2 H_2 - C_2(\mu_2 + \xi) \\ \frac{dM_1}{dt} &= \mu_2 C_2 + \psi I_2 \\ \frac{dR_1}{dt} &= \delta I_2 \\ \frac{dRh_1}{dt} &= \sigma H_2 \end{split}$$

Group 3: counties with main highways

$$\begin{split} \frac{dS_3}{dt} &= -S_3(\tau(I_2/N_2) + \varepsilon \lambda_3(I_3/N_3)) \\ \frac{dI_3}{dt} &= S_3(\tau(I_2/N_2) + \varepsilon \lambda_3(I_3/N_3)) - I_3(\delta + \eta_3 + \psi) \\ \frac{dH_3}{dt} &= \eta_3 I_3 + \xi C_3 - H_3(\omega_3 + \sigma) \\ \frac{dC_3}{dt} &= \omega_3 H_3 - C_3(\mu_3 + \xi) \\ \frac{dM_3}{dt} &= \mu_3 C_3 + \psi I_3 \\ \frac{dR_3}{dt} &= \delta I_3 \\ \frac{dRh_3}{dt} &= \sigma H_3 \end{split}$$

Group 4: Low risk counties not surrounding counties with airports and without main highways

$$\begin{split} \frac{dS_4}{dt} &= -S_4(\gamma(I_2/N_2) + \alpha(I_3/N_3) + \varepsilon \lambda_4(I_4/N_4)) \\ \frac{dI_4}{dt} &= S_4(\gamma(I_2/N_2) + \alpha(I_3/N_3) + \varepsilon \lambda_4(I_4/N_4)) - I_4(\delta + \eta_4 + \psi) \\ \frac{dH_4}{dt} &= \eta_4 I_4 + \xi C_4 - H_4(\omega_4 + \sigma) \\ \frac{dC_4}{dt} &= \omega_4 H_4 - C_4(\mu_4 + \xi) \\ \frac{dM_4}{dt} &= \mu_4 C_4 + \psi I_4 \\ \frac{dR_4}{dt} &= \delta I_4 \\ \frac{dRh_4}{dt} &= \sigma H_4 \end{split}$$

Table S1. Definition of population variables

Symbol	Definition
S_{i}	Susceptible population in group <i>i</i>
I_{i}	Infected population in group <i>i</i>
H_{i}	Hospitalized population in group <i>i</i>
C_i	Population admitted into ICU in group <i>i</i>
R_i	Recovered population in group i
Rh_i	Population discharged from hospitals in group <i>i</i>
M_{i}	Deaths in group <i>i</i>
N_{i}	Total population in group <i>i</i>

 Table S2. Definition of parameters

Symbol	Definition	Estimated value	Justification
$\lambda_i; i=1,2,3,4$	Hazard rate of infection for spatial risk group <i>i</i>	1= 0.41 2= 0.34 3= 0.23 4= 0.13	Fitted parameter
ε	Reduction of the hazard rate after interventions	if $t_{interv} \le$ March 22 $\varepsilon = 1$ If $t_{interv} >$ March 23 $\varepsilon = 0.27$	Fitted parameter
1/8	Natural recovery rate without hospitalization	4.35 days	Fitted parameter
$\eta_i; i=1,2,3,4$	Hospitalization rate for spatial risk group <i>i</i>	1= 0.05 2= 0.07 3= 0.07 4= 0.14	Fitted parameter
ω_i ; $i=1,2,3,4$	Admission rate of ICU admission rate in spatial risk group <i>i</i>	1= 0.04 2= 0.06 3= 0.04 4= 0.07	Fitted parameter
ξ	Recovery rate from ICU	0.06	Fitted parameter
σ	Discharge rate from hospital	0.08	Fitted parameter
$\mu_i \; ; \; i=1,2,3,4$	Mortality rate for individuals in ICU in spatial risk group <i>i</i>	1= 0.22 2= 0.17 3= 0.05 4= 0.25	Fitted parameter
Ψ	Mortality rate for infected individuals	0.01	Fitted parameter

φ	Rate of infection flow from group 1 to group 2	0.04	Fitted parameter
τ	Rate of infection flow from group 2 to group 3	0.08	Fitted parameter
γ	Rate of infection flow from group 3 to group	0.02	Fitted parameter
α	Rate of infection flow from group 2 to group 4	0.03	Fitted parameter

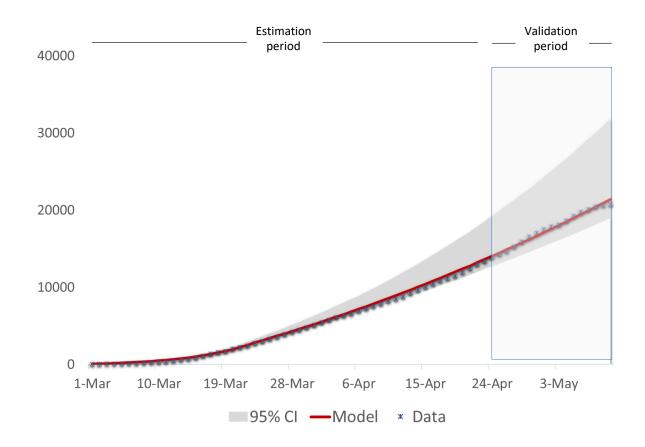


Figure S2. Out-of-sample validation of the model. We used data from March 01 to April 25 as the estimation period for model fitting. Data from April 26 to May 10 were used as the validation period for assessing the accuracy of model estimations

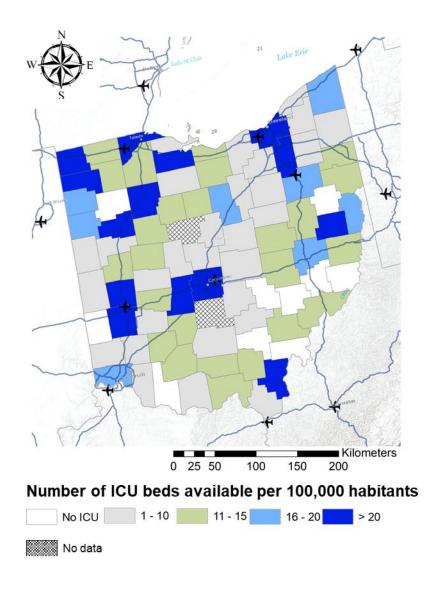


Figure S3. Distribution of the number of ICU available per 100,000 habitants in each county in Ohio, U.S. Maps were created using ArcGIS® by ESRI version 10.3 (http://www.esri.com)