Spread of COVID-19 through Georgia, USA. Near-term projections and impacts of social distancing via a metapopulation model

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Abstract

The COVID-19 global pandemic has caused over two and a half million recorded cases and over 170,000 deaths as of April 21, 2020. Epidemiological forecasts at the country and/or state level have helped to shape public health interventions. However, such models leave a scale-gap between the spatial resolution of actionable information (i.e. the county or city level) and that of modelled viral spread. States and nations are not homogeneously mixed and different areas may vary in disease risk and severity. For example, COVID-19 has age-stratified risk. Similarly, ICU units, PPE and other vital equipment are not equally distributed within states. Here, we implement a county-level epidemiological framework to assess and forecast COVID-19 spread through Georgia, where 818 people have died from COVID-19 and 20,166 cases have been documented as of April 21, 2020. We find that county level forecasts trained on heterogeneity in place due to clustered events can continue to predict epidemic spread over multi-week periods, potentially of service to efforts to prepare medical resources, manage supply chains, and develop targeted public health interventions. We find that premature removal of social distancing could lead to rapid increases in cases or the emergence of sustained plateaus of elevated fatalities.

1 Introduction

COVID-19 is a global pandemic which has (as of April 21, 2020) caused more than two and a half million reported cases and over 170,000 reported fatalities worldwide. Empirical evidence suggests that a large proportion of cases are asymptomatic [1, 2] making transmission an often 'invisible' occurrence which increases challenges for disease control efforts. Public health responses to help curb transmission of COVID-19 have far reaching health, economic, social and emotional consequences, and depend on epidemiological models. However, these models are often developed at large-spatial scales that do not necessarily factor in local information about e.g. population demographics, travel patterns, ICU capacity [3]. We seek to model this heterogeneity to better understand how COVID-19 will be transmitted across spatial scales that can be translated into local surveillance and action. Our effort is similar in spirit to multiple models that also aim to bring actionable information to local scales (e.g., [4, 5, 6]).

To tailor models to locales, we extended an age-structured epidemiological model with eight epidemiological states, including sub-acute and critical hospitalisations (as in [7, 8]). The use of an age-specific model is essential given that the elderly are more severely impacted [9, 7, 10]; additional comorbidities include obesity and environmental factors which could be incorporated into future work. We extend this model to incorporate space using a meta-population modelling framework that implicitly accounts for transport between county-level 'patches', by assuming that the mixing population can be broken into two categories: the local patch population; and a commuter patch population. We define the commuter

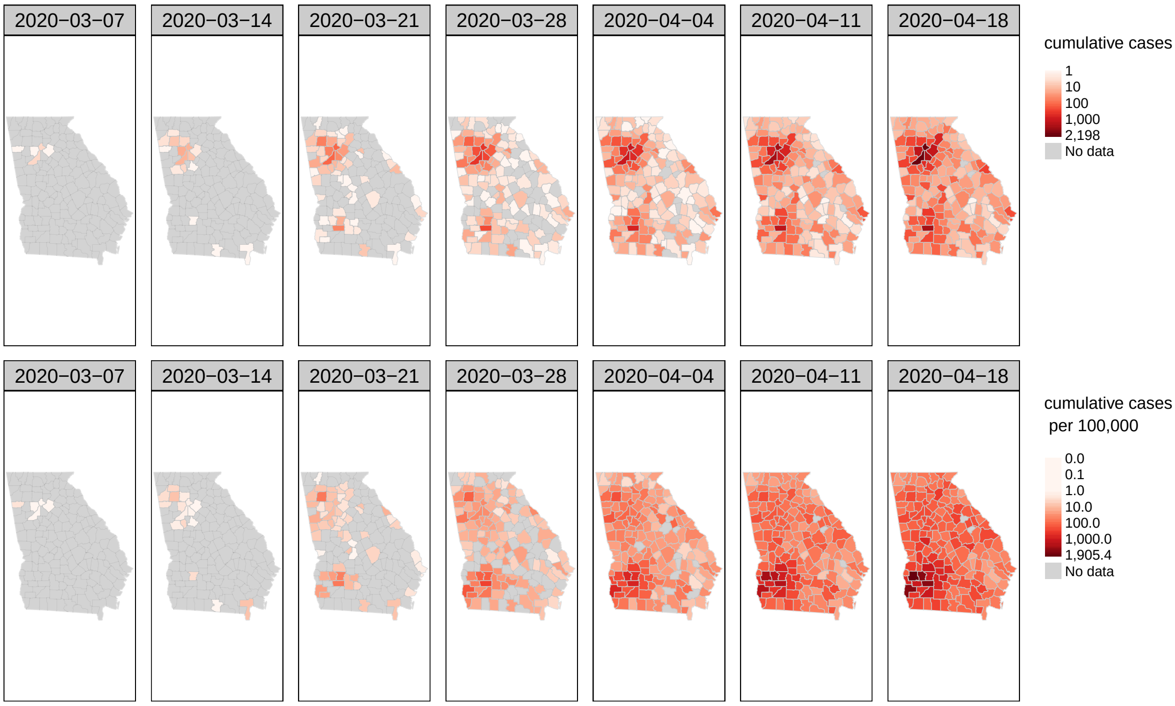

Figure 1: Weekly time-lapse of cumulative recorded cases of COVID-19 data (top) and cumulative case data per 100,000 people (bottom) in Georgia counties using data obtained from The New York Times county-level COVID-19 dataset, based on reports from state and local health agencies.

patch population as the local population who stay within a patch, minus those who leave to visit other patches, plus those who travel into the patch from other patches. We term this the Metapopulation AGe-structured Epidemiological (MAGE) model. While this framework could be applied generically, in this work we focus on modelling the spread of COVID-19 through counties in Georgia, where previous work predicts that thousands of deaths could occur [8]. However, such state level models do not capture local commuting patterns, or availability of resources and crisis-support that will be useful to inform public health interventions.

As of April 21, 2020 over 818 people have died from COVID-19 in the state of Georgia, with over 20,000 recorded cases, and these numbers will soon be surpassed and outdated. The first recorded case was in Metropolitan Atlanta in early March, but the city of Albany in Southern Georgia also became a hotspot of cases after a large extended family and their friends contracted the disease [11]. COVID-19 has spread across the whole state (Figure 1, absolute (top) and per capita (bottom) cumulative cases), with only two counties not reporting any cases as of April 18th. While Atlanta and Albany are hotspots for COVID-19, Southwestern Georgia as a whole is disproportionately affected when normalized by population size. This heterogeneity in infection rates indicates a need to understand community transmission at local scales. It is also important to note that recorded cases are only a proxy for COVID-19 spread as there is a delay of a few days between taking a test and the results being recorded. Additionally, many of those in Georgia who have been exposed to COVID-19 have not been tested – because they were ineligible for testing, were unable to access or unwilling to seek tests, or were asymptomatic and did not realize they were carrying the disease. The number of actual cases is much higher. Ascertaining how much higher is an ongoing research challenge. Here, we use reported case and fatality data, and data for county demographics and commuter patterns, coupled with a mechanistic mathematical model to project COVID-19 spread in Georgia.

2 Methods

2.1 Mathematical model of COVID-19 spatial spread

We model COVID-19 spread through Georgia using 159 connected patches (i.e. counties), where individuals are classified as being in one of eight epidemiological states. Five of the eight epidemiological states are allowed to move, and potentially transmit the disease, between counties: susceptible S, exposed E, infected asymptomatic I_A, infected symptomatic I_S, and recovered R. Additionally, we consider that some symptomatic cases require hospital care that can be sub-acute $I_{h,sub}$ or critical $I_{h,crit}$, where critical hospitalisation may result in death D. Furthermore, individuals are stratified by age – we consider nine age classes: 0-9, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, and over 80. This model has a total of $159 \times 8 \times 9 = 11,488$ state variables. To model the spatial spread of COVID-19 we assume that local individuals spend their time mixing with either the local population; or with a commuting population, which accounts for commuting between counties. The time spent mixing with either "local" or "commuting" populations is mediated by the weights w_L and w_C. Commutes are used to signify movement between counties, although much of the population is no longer commuting. To account for this we mediate transmission rates by a physical distancing (a.k.a. social distancing) factor κ. The system of nonlinear differential equations governing this metapopulation model with age-structured epidemiology can be described for patch i and age a as follows:

$$
\begin{aligned}
\frac{dS(i,a)}{dt} &= -\overbrace{\kappa\beta_S S(i,a)\left(w_L\frac{I_{S,L}(i)}{N_L(i)} + w_C\frac{I_{S,C}(i)}{N_C(i)}\right)}^{new\ cases\ from\ symptomatic\ contact} - \overbrace{\kappa\beta_A S(i,a)\left(w_L\frac{I_{A,L}(i)}{N_L(i)} + w_C\frac{I_{A,C}(i)}{N_C(i)}\right)}^{new\ cases\ from\ asymptomatic\ contact} \\
\frac{dE(i,a)}{dt} &= \overbrace{\kappa\beta_S S(i,a)\left(w_L\frac{I_{S,L}(i)}{N_L(i)} + w_C\frac{I_{S,C}(i)}{N_C(i)}\right)}^{new\ cases\ from\ symptomatic\ contact} + \overbrace{\kappa\beta_A S(i,a)\left(w_L\frac{I_{A,L}(i)}{N_L(i))} + w_C\frac{I_{A,C}(i)}{N_C(i)}\right)}^{new\ cases\ from\ asymptomatic\ contact} - \overbrace{\gamma_E E(i,a)}^{onset\ of\ infectiousness} \\
\frac{dI_A(i,a)}{dt} &= \overbrace{p(a)\gamma_E E(i,a)}^{asymptomatic\ onset} - \overbrace{\gamma_A I_A(i,a)}^{recovery} \\
\frac{dI_S(i,a)}{dt} &= \overbrace{(1-p(a))\gamma_E E(i,a)}^{symptomatic\ onset} - \overbrace{\gamma_S I_S(i,a)}^{transfer\ from\ I_S} \\
\frac{dI_{h,sub}(i,a)}{dt} &= \overbrace{h(a)(1-\xi(a))\gamma_S I_S(i,a)}^{subcritical\ cases} - \overbrace{\gamma_h I_{h,sub}(i,a)}^{recovery\ from\ I_{h,sub}} \\
\frac{dI_{h,crit}(i,a)}{dt} &= \overbrace{h(a)\xi(a)\gamma_S I_S(i,a)}^{critical\ (ICU)\ cases} - \overbrace{\gamma_h I_{h,crit}(i,a)}^{transfer\ from\ I_{h,crit}} \\
\frac{dR(a)}{dt} &= \overbrace{\gamma_A I_A(i,a)}^{recovery\ from\ I_A} + \overbrace{(1-h(a))\gamma_S I_S(i,a)}^{recovery\ from\ I_S} + \overbrace{\gamma_h I_{h,sub}(i,a)}^{recovery\ from\ I_{h,sub}} + \overbrace{(1-\mu)\gamma_h I_{h,crit}(i,a)}^{recovery\ from\ I_{h,crit}} \\
\frac{dD(i,a)}{dt} &= \overbrace{\mu\gamma_h I_{h,crit}(i,a)}^{mortality}
\end{aligned} \tag{1}
$$

where $I_{S,L}$ and $I_{S,C}$ are the total number (across all age classes) of symptomatic infectious individuals; $I_{A,L}$ and $I_{A,C}$ are the total number of asymptomatic infectious individuals; and N_L and N_C are the total number of living individuals during "local" and "commuting" times. For local times:

$$I_{S,L}(i) = \sum_a I_S(i,a) \tag{2}$$

$$I_{A,L}(i) = \sum_a I_A(i,a) \tag{3}$$

$$N_L(i) = \sum_a \left(S(i,a) + E(i,a) + I_A(i,a) + I_S(i,a) + I_{h,sub}(i,a) + I_{h,crit}(i,a) + R(i,a)\right). \tag{4}$$

To capture commutes we introduce the transport matrix M that contains the proportion of people who move from patch i to patch j. We describe how the transport matrix is constructed in Supporting Information S1. Diagonal elements of M are negative and describe the proportion of people who leave the current patch. The current patch is indexed by the column elements; such that each column sums to 0. Hospitalized or deceased individuals are removed from the commuting population. Thus, the commuter populations for each patch can be computed by multiplying the transport matrix (159x159) by a vector of a particular age and epidemiological state across all nodes (159x1) to find the net population change during commuter times (159x1). We denote these net changes with hats (an example calculation is shown in the Supporting Information equation 9). We can then calculate the commuting population components as:

$$I_{S,C}(i) = I_{S,L}(i) + \sum_a \hat{I}_S(i,a) \tag{5}$$

$$I_{A,C}(i) = I_{A,L}(i) + \sum_a \hat{I}_A(i,a) \tag{6}$$

$$N_C(i) = N_L(i) + \sum_a \left(\hat{S}(i,a) + \hat{E}(i,a) + \hat{I}_A(i,a) + \hat{I}_S(i,a) + \hat{R}(i,a)\right). \tag{7}$$

Model parameters are chosen based on the Imperial College London Model [9] (Tables 1 and 2).

Parameter	Meaning	Value
β_a	Asymptomatic transmission rate	0.3/day
β_s	Symptomatic transmission rate	0.6/day
$1/\gamma_e$	Mean exposed period	4 days
$1/\gamma_a$	Mean asymptomatic period	6 days
$1/\gamma_s$	Mean symptomatic period	6 days
$1/\gamma_h$	Mean hospital period	10 days
w_L	Relative time in local phase	2/3
w_C	Relative time in commuting phase	1/3

Table 1: Epidemiological characteristics.

Age class	Frac. Asymptomatic (p)	Hospital Frac. (h)	ICU (given hospitalization) Frac. (ξ)
0-9	0.95	0.001	0.05
10-19	0.95	0.003	0.05
20-29	0.9	0.012	0.05
30-39	0.8	0.032	0.05
40-49	0.7	0.049	0.063
50-59	0.6	0.102	0.122
60-69	0.4	0.166	0.274
70-79	0.2	0.243	0.432
80+	0.2	0.273	0.709

Table 2: Age-stratified risk for COVID-19. Of note, the model assumes that 50% of ICU cases die. Parameters in line with [9, 7].

2.2 Initialising the model

In order to make projections at a county-level, we use data released by the Georgia Department of Public Health on the March 28, 2020, around the time social distancing measures were introduced, to set county-level initial conditions in the model. We have two methods of setting initial conditions for model simulations.

2.2.1 State-level modelling:

In the state-level model (SLM) approach, we initialize an outbreak with a single person aged 20-29 in a Georgia-wide model (spatial features removed), and simulate the epidemiological dynamics forwards in time until the number of recorded deaths at the state level on the 28th March 2020 is reached. We then assign this distribution to the county level proportional to the number of deaths recorded in each county. Counties with no recorded deaths are assigned an equally distributed portion of deaths whose reporting county is unknown.

2.2.2 County simulation method:

In the county simulation method (CSM), we initialize an outbreak with a single person aged 20-29 in both Fulton County (metro. Atlanta) and Dougherty County (city of Albany). We then simulate the MAGE model forward in time looking county-by-county until the number of reported dead in that county is reached, and record the distribution of people in that county across the different epidemiological states. If no deaths are recorded, we run the simulation until the number of hospitalized cases is reached - assumed to be 20% of the recorded cases; or the fractional equivalent of 0.5 deaths in the county in the event no cases were recorded. When this operation has been performed for each county, we patch together the distributions across epidemiological states county-by-county and use this as the initial condition for the model projections.

2.3 Social distancing

We implement social distancing by reducing the transmission rates β_S and β_A. We assume that initially no social distancing occurs when setting the initial conditions for the model on the 28th March 2020. In our forward projections we assume social distancing policies result in 0%, 50% or 75% reductions in transmission rates. To model potential future scenarios, we also consider the consequences of relaxing social distancing measures (back to the baseline) on May 15, 2020.

2.4 Data and software availability

Georgia county data was obtained from the US Census Bureau. Commuting data was obtained from US Census LODES [12]. County-level COVID-19 case and death counts were obtained from the Georgia Department of Public Health COVID-19 Daily Status Report (https://dph.georgia.gov/covid-19-daily-status-report); and from The New York Times county-level COVID-19 dataset, based on reports from state and local health agencies (https://github.com/nytimes/covid-19-data). ICU capacity data was obtained from the Kaiser Health news analysis of hospital cost reports filed to the Centers for Medicare and Medicaid services. Aggregated regions in the excess capacity analysis are the regions of the Georgia Regional Coordinating Hospital (RCH) System (https://southhealthdistrict.com/programs-services/emergency-prep/healthcare-preparedness-coalitions/). The MAGE model was developed in Julia [13] and numerical integration was performed using a 5(4) order adaptive time-stepping method [14] implemented in the DifferentialEquations.jl [15] package. Visualisations were made using the R packages tmap [16] and sf [17]. All code for simulations and plotting is available at https://www.github.com/WeitzGroup/MAGEmodel_covid19_GA and is archived [18].

3 Results

3.1 Short-term projections

Models were initialized using data for March 28, 2020. Simulations were projected forward for five weeks. At the state level (Fig 2), we find that the state-level model (SLM) and county simulation method (CSM) simulations have similar initial conditions with respect to fatality, but differ in their description of cumulative exposed individuals. The CSM method assumes nearly 2x more people have initially been exposed to the virus than in the SLM method. This suggests that between 50,000 and 100,000 people

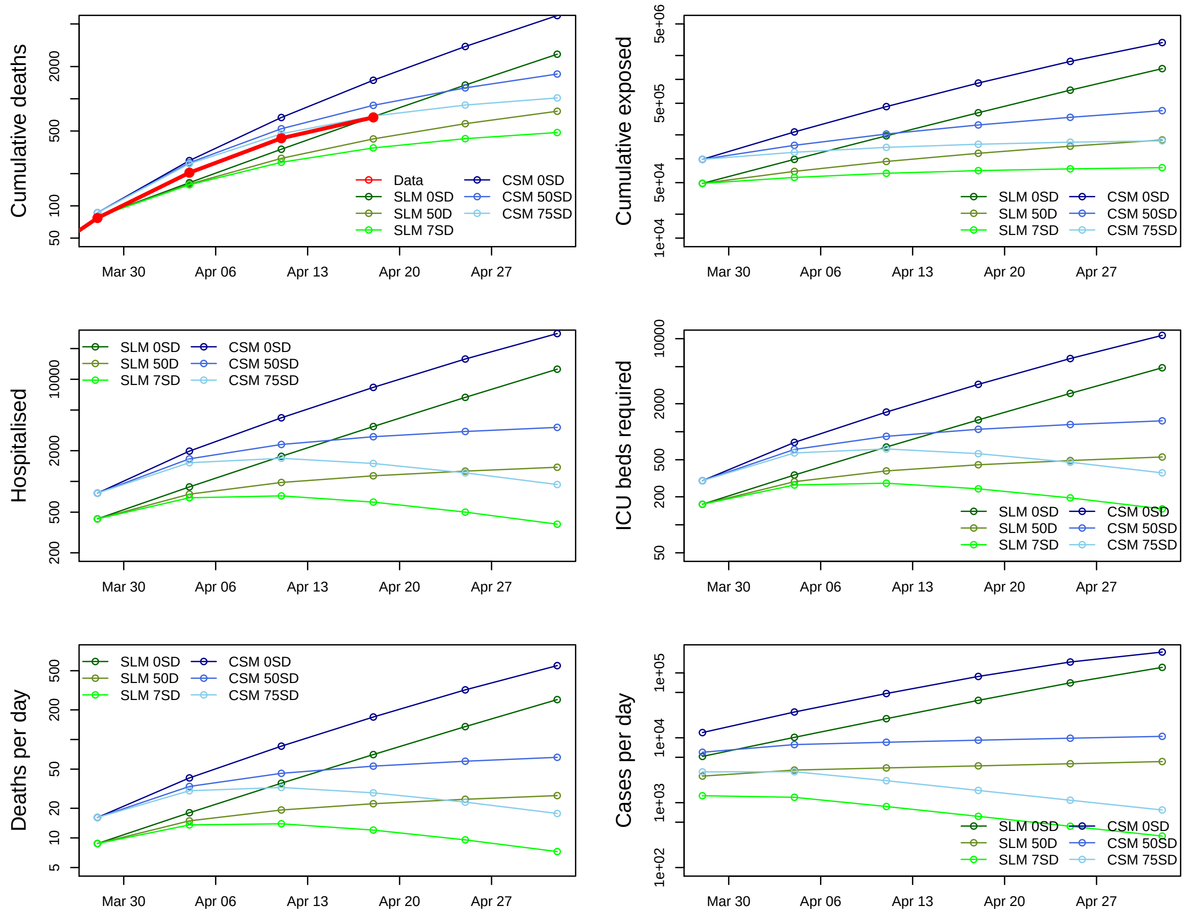

Figure 2: Short-term COVID-19 projections for the state of Georgia from March 28, 2020 to May 2, 2020. Projections initialized with the state level model (SLM) are shown in green, whilst those in blue are initialized with the county simulation method (CSM). Lines are shown with no social distancing (0SD), with a 50% reduction in transmission via social distancing (50SD) and with a 75% reduction in transmission via social distancing (75SD). Note values are shown on log-scales.

had encountered COVID-19 by March 28, 2020. While these may appear to be large numbers we note these estimates are inline with previous work on 'NowCasting' and ascertainment bias [19] and that these numbers are small relative to the total population in Georgia. Qualitatively the dynamics of SLM and CSM simulations with the same reduction in social distancing appears similar, though the CSM simulations have a higher baseline than the SLM. We can treat these differences as an analysis of varying the initial conditions.

Our projections all initially appear consistent with cumulative death records; and it takes weeks for the simulations to diverge (and to see the impact of social distancing policies). Social distancing interventions were projected to slow the increase in cumulative deaths. Currently the data appears to sit between the SLM and CSM curves for a 50% reduction in transmission via social distancing; and nearly on top of the 75% reduction in transmission curve CSM simulation. Related data suggests Georgia has reduced mobility by around 40-60% on average since March 28 [20], which seems consistent with a reduction in transmission by around 50%. The rate of increase for cumulative deaths appears to be beginning to decrease in the recorded data. In the short term we find that social distancing may have already prevented hundreds of deaths, as well as reduced hospital demand, and new case and death rates relative to baseline scenarios with no intervention.

In figure 3 we report cumulative deaths and projected cumulative deaths at the county level. Reports show that most fatalities occured in Fulton County and Dougherty County inline with the locations with most prevalence of recorded cases (see figure 1). In contrast to recorded cases, there are a large number of counties which appear to have no COVID-19 related fatalities at present. The distribution of cumulative deaths appears generally consistent with simulation projections. CSM simulations appear to capture the distribution of cumulative deaths across Eastern counties such as Chatham County, Richmond County and Ware County better than the SLM simulations. In part, this is due to there only being 30 counties with reported fatalities on the 28th March 2020.

We additionally show projected new cases per day at the county level in figure S2, projected new deaths per day are shown at county level in figure S3. These show Dougherty County and Fulton County as hotspots for disease spread and severity, but with active and ongoing community transmission across the whole state, even under a 50% transmission reduction scenario. The total number of projected hospitalized cases (sub-acute and critical) are shown in figure S4; and the demand for ICU beds - assumed as the number of critical hospitalized cases - are projected in figure S5.

To account for disparities in ICU availability we find the ratio of ICU demand to ICU capacity which is projected in figure 4. As many counties do not have ICU units, we base our analysis of capacity relative to demand on Georgia's Regional Coordinating Hospital System. Here values above one show that demand exceeds capacity in that region. We do note that this analysis does not consider the use of ICU beds for non-COVID-19 cases, meaning that in reality ICU services are likely under even more pressure. With no social distancing interventions we find that all (CSM) or almost all (SLM) regions are above baseline capacity by the May 2, 2020. In the CSM simulations demand is nearly 10x over capacity in the Oconee and Hamilton Medical Center regions. Here, we note that our model does not include a dynamic feedback between available capacity and demand. This means that our baseline simulations may underestimate the severity of the impact of COVID-19 as many may die when medical facilities are overstretched. In scenarios where social distancing reduces transmission by 50% we find that hospital systems are more resilient within this timeframe with only a few regions exceeding capacity. In general, we find that Phoebe Putney Memorial Hospital region will surpass capacity first, followed by the Hamilton Medical Center region and then the region for the Oconee Medical Center. We find that the Georgia Health Sciences Medical Center may be most prepared to meet demand within its region.

3.2 Medium-term projections with the removal of social distancing

In the medium term it is useful to consider when things may return to business as usual [21]. In order to do this, we extend our projections through from the 28th March to July 4, 2020. In these scenarios we see that epidemic may peak in June if no interventions were applied, that with extreme social distancing (more than current levels) then cases could decrease and could curtail by late May, or under a 50% reduction in transmission via social distancing the epidemic may be "plateauing" - where the numbers of inpatients vs. outpatients appears near balanced through and beyond July.

To explore what would happen if lockdown policies are relaxed in the medium term we create additional scenarios, shown in figure 6, considering that social distancing returns to baseline levels on the May 15, 2020. When this scenario is applied we see an uptick in new cases and a return of increasing COVID-19 hospitalisations and fatalities, regardless of the previous level of social distancing. We note that in doing so we see similar rates of increase across cases, hospitalisations and fatalities as in the baseline scenarios. Social distancing flattens the curve, but if social distancing is released, the intensity of spread increases. In addition, the curve appears to reach the same maximum demand magnitudes for hospital beds and ICU beds as in the baseline case. In effect, social distancing shifts the epidemic curve to a later time point.

4 Discussion

The model framework we developed here incorporates transit and spatial distributions of population, age-structure and explicit epidemiological compartments. Additionally, it explicitly accounts for asymptomatic carriers and subacute and critical hospitalisations. As such, the MAGE framework is more complex than simple SIR compartmental models (e.g. [5]), and contains explicit information relevant for policy making, but is less complex than other more detailed approaches e.g. agent based modelling approaches [4]. A potential benefit of our framework is that it remains reasonably tractable both philosophically – it is possible to see and understand the rules that drive epidemiological dynamics; but also computationally. These characteristics may be appealing for policy makers [22] and for future modelling efforts [23].

Figure 3: Weekly COVID-19 deaths in Georgia. Top: cumulative recorded COVID-19 deaths. 2nd and 3rd rows: projections from March 28th 2020 with no social distancing interventions using the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation. 4th and 5th rows: projections from March 28th 2020, with a 50% reduction in transmission via social distancing, for the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation.

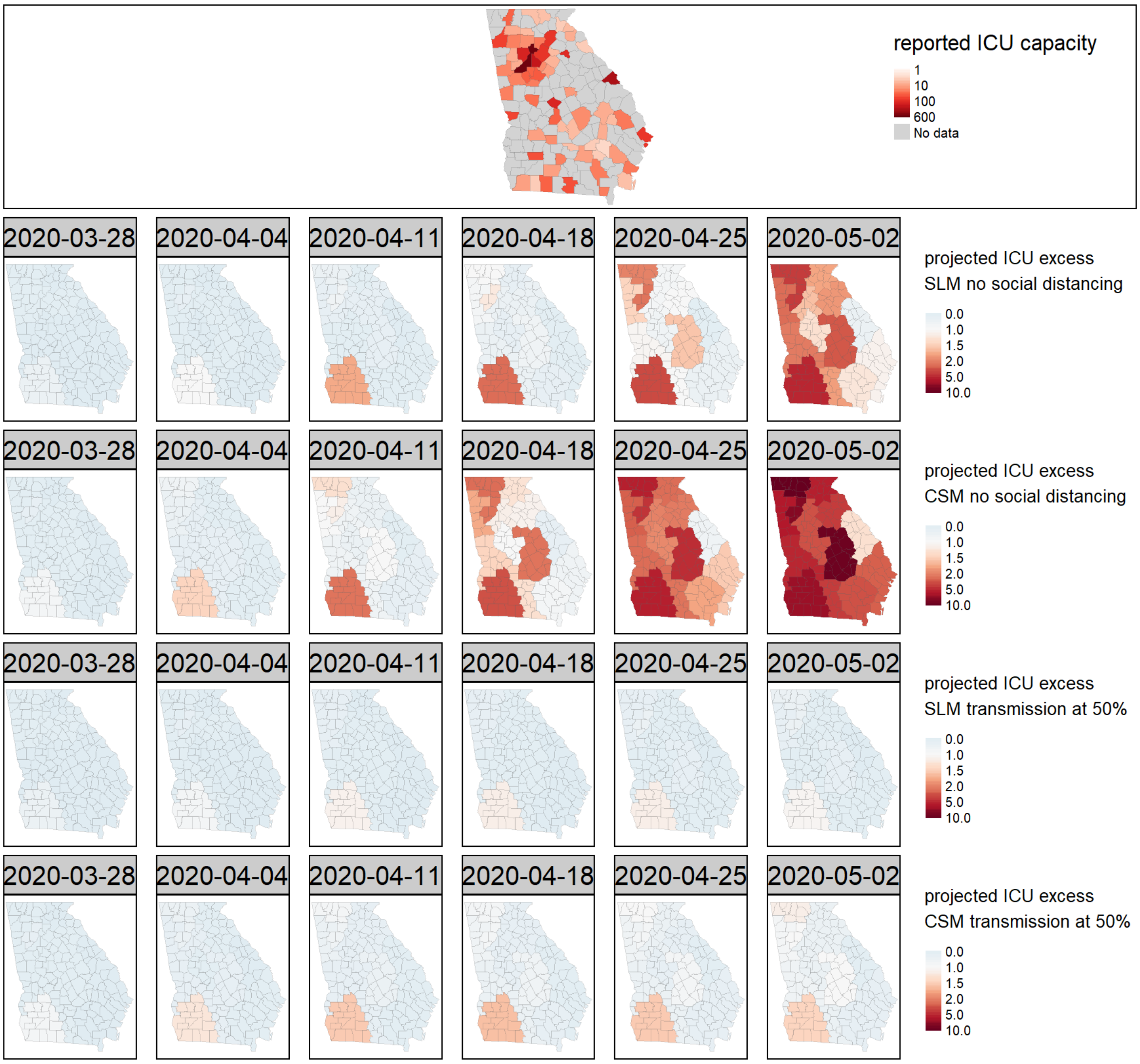

Figure 4: Projected excess ICU demand aggregated to hospital regions. A value equal to one is the point at which demand meets capacity. A value of two means demand is double capacity. Top row shows ICU capacity across counties. Rows two and three show Georgia Regional Coordinating Hospital System region aggregated details about ICU capacity relative to demand in scenarios with no social distancing. Rows three and four show the same under scenarios with a 50% reduction in COVID-19 transmission via social distancing.

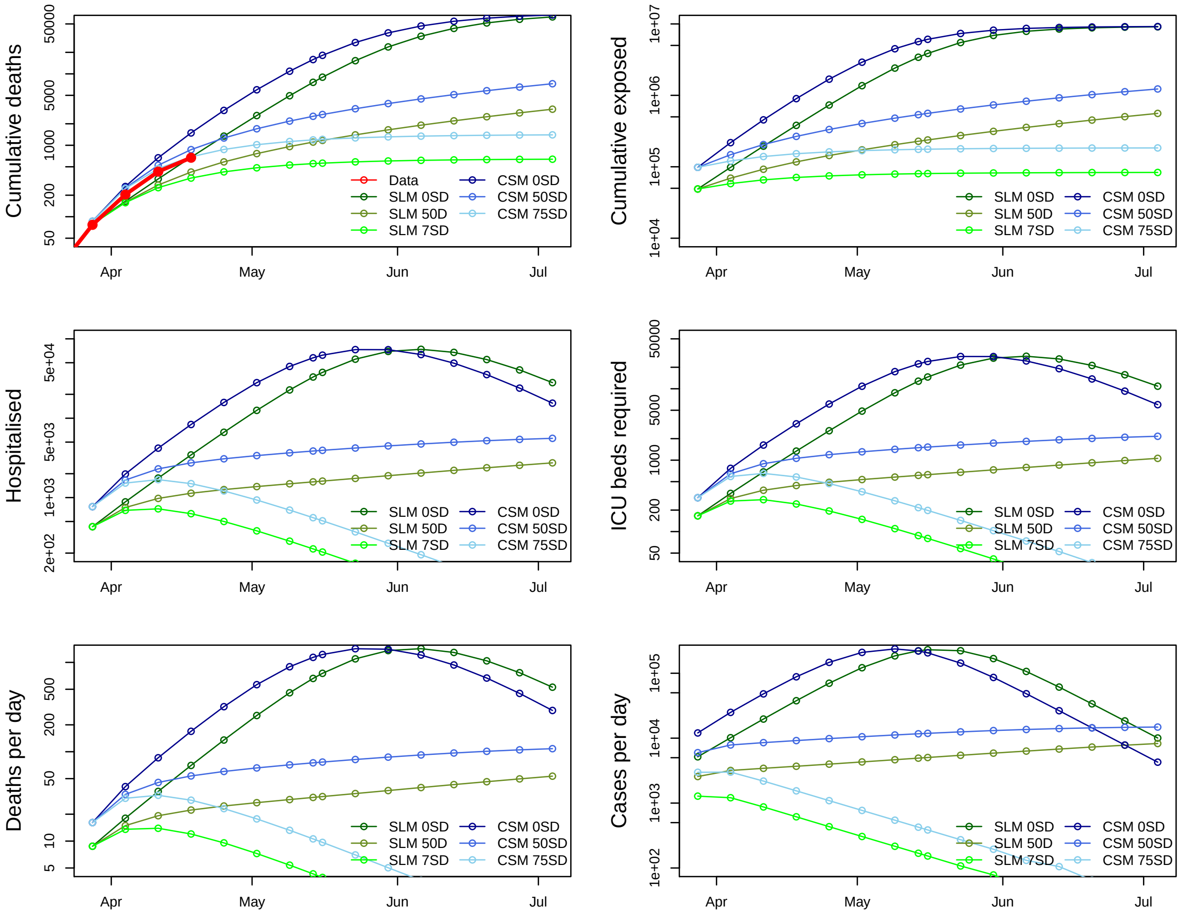

Figure 5: Medium-term COVID-19 projections for the state of Georgia from March 28, 2020 to July 4, 2020 assuming no changes in social distancing. Projections initialized with the state level model (SLM) are shown in green, whilst those in blue are initialized with the county simulation method (CSM). Lines are shown with no social distancing (0SD), with a 50% reduction in transmission via social distancing (50SD) and with a 75% reduction in transmission via social distancing (75SD). Note values are shown on log-scales.

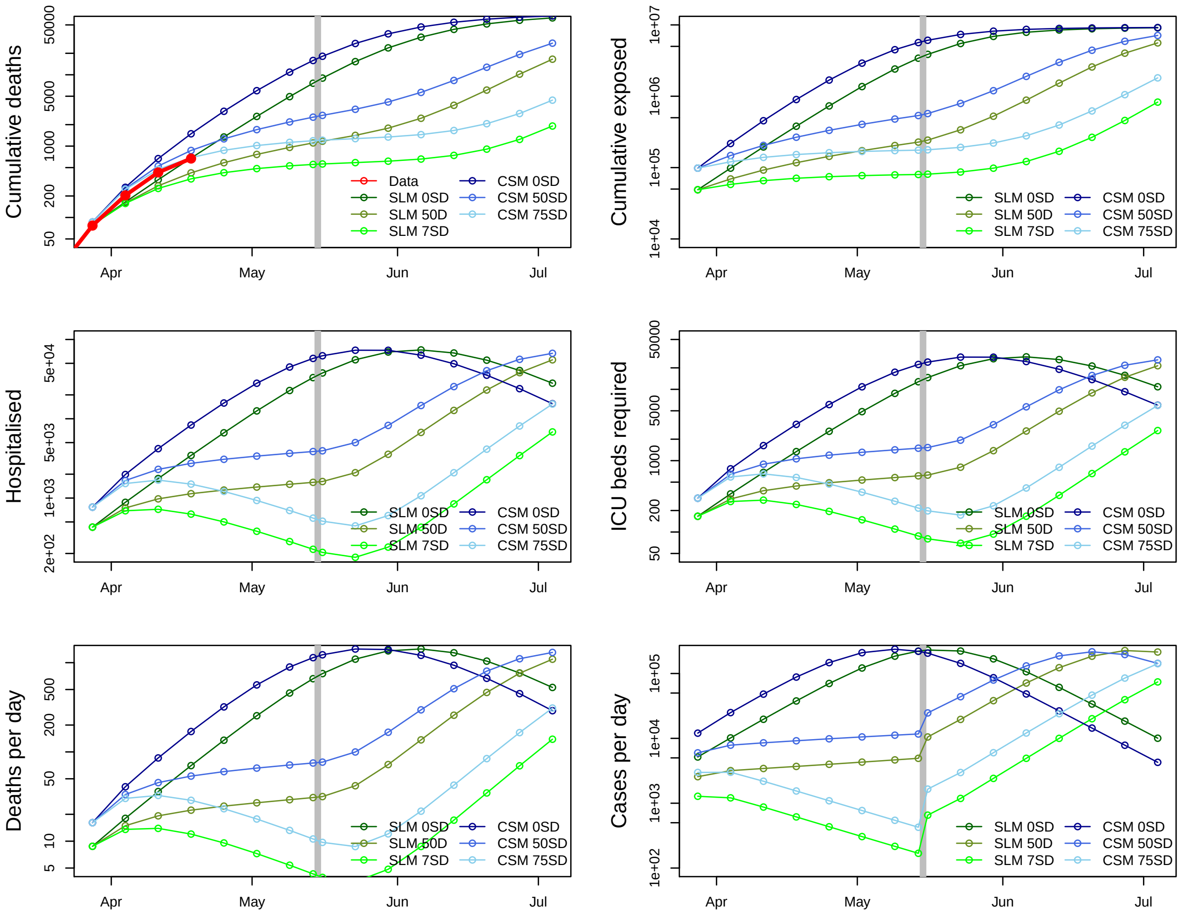

Figure 6: Medium-term COVID-19 projections for the state of Georgia from March 28, 2020 to July 4, 2020 assuming lockdown is removed on May 15, 2020 (vertical grey line). Projections initialized with the state level model (SLM) are shown in green, whilst those in blue are initialized with the county simulation method (CSM). Lines are shown with no social distancing (0SD), with a 50% reduction in transmission via social distancing (50SD) and with a 75% reduction in transmission via social distancing (75SD). Note values are shown on log-scales.

Many types of models have been developed or adapted to attempt to understand the spread of COVID-19, with a variety of assumptions. Since infection dynamics remain uncertain, and as behaviour modification in response to public health advice varies across locales, it is hard to predict changes over time. These models predict different potential outcomes given various scenarios [24]. We recognize that forecasting remains uncertain – indeed the variation in initial conditions in our study lead to either underestimates, or overestimates of the current state, and this study should not be implemented in isolation but in tandem with other predictive studies.

Public awareness of and policies implementing social distancing – as well as job losses associated with COVID-19 – have altered personal mobility patterns. Additional data is required to attempt to constrain how commuting patterns (as assumed here) may be altered by COVID-19 at local scales. For example, counties with extraction, manufacturing, utilities, business management, agriculture, retail trade, transportation and warehousing, and wholesale trade have reduced their mobility the least [25]. Counties with high levels of finance and insurance, professional, scientific and technical employment have reduced their mobility the most [25]. Exploring epidemiological dynamics in the context of different socio-economic groups is an important future challenge.

As mentioned, forecasts for Georgia with social distancing suggest in excess of 10,000 fatalities by the end of September 2020 [8]. Currently, there are no proven therapies for COVID-19 [26]. Social distancing has been the preliminary public health intervention to reduce spread of COVID-19, enhanced and supported by local and national stay-at-home orders. However, this type of intervention strategy may fail if it is relaxed too soon [9, 27, 28] and is already coming into scrutiny by members of the public. Other interventions such as serological shielding [7], digital contract tracing [29] and COVID-19 vaccinations [30] hold promise when they can be integrated as part of strategic decision making.

Our results suggest that the implementation of social distancing policies has potentially already saved hundreds of lives, and is likely to save thousands of lives in the long term. However, if Georgia were to retain current social distancing measures until May 15, 2020, it will not be enough to end the epidemic in Georgia. The same can be said if social distancing interventions are relaxed sooner. There are opposing tensions between holding down lock-down to reduce disease transmission, and economic, social and personal wellbeing of individuals and businesses [21]. Lock-down cannot easily be sustained for months on end, but we must recognize the danger associated with releasing individuals from lock-down. Georgia must carefully monitor this virus as the population remains immunologically naïve; and our simulations suggest the relative number of immune individuals are likely few – suggesting that we are a long way from herd-immunity. COVID-19 will remain an ongoing threat in Georgia, and globally – potentially into 2021 or beyond [28]. Future lock-downs and other forms of sustained interventions may be necessary to protect the general population and ensure medical facilities are able to treat patients. We caution that at this time it is too soon to claim success and that Georgia must remain vigilant in the months to come.

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Supporting Information

S1 Construction of the transport matrix

In order to use commuting data in the MAGE model we need to construct what we term the transport matrix, from Origin-Destination datasets. The origin-destination (OD) data shows an absolute number of recorded commutes with origins on the rows and destinations on the columns; and includes data on within-county commutes. We find the total number of commutes originating within each county by summing across the rows of the OD dataset; and use these sums to find the proportions of commutes from each county to other counties. The diagonal elements of this matrix (diag(Mat) denote the proportion of within-county commutes. We replace these diagonal elements with $-(1 - diag(Mat))$ i.e. the negative of the proportion of out-of-county commutes. Finally, we transpose this matrix (i.e. placing the destinations on the rows and origins on the columns) to create the transport matrix. This structure is made clear in the next section.

S2 Example of net change in population

Let us define a transport matrix w in a network consisting of three nodes (A,B,C):

$$M = \begin{pmatrix} -M_{A,out} & M_{B\to A} & M_{C\to A} \\ M_{A\to B} & -M_{B,out} & M_{C\to B} \\ M_{A\to C} & M_{B\to C} & -M_{C,out} \end{pmatrix} \tag{8}$$

where $M_{X\to Y}$ represents the proportion of the population in node X moving to patch Y. The columns sum to zero as the diagonal element in each column is the negative of the sum of all other column elements. To calculate population net change we multiply the transport matrix by the states of interest - e.g. the susceptible pool in age class 30-39 across the three patches. The calculation for each coupled age-epidemiological state is as follows:

$$\hat{S} = \begin{pmatrix} -M_{A,out} & M_{B\to A} & M_{C\to A} \\ M_{A\to B} & -M_{B,out} & M_{C\to B} \\ M_{A\to C} & M_{B\to C} & -M_{C,out} \end{pmatrix} \begin{pmatrix} S_A \\ S_B \\ S_C \end{pmatrix} = \begin{pmatrix} -M_{A,out} \cdot S_A + M_{B\to A} \cdot S_B + M_{C\to A} \cdot S_C \\ M_{A\to B} \cdot S_A - M_{B,out} \cdot S_B + M_{C\to B} \cdot S_C \\ M_{A\to C} \cdot S_A + M_{B\to C} \cdot S_B - M_{C,out} \cdot S_C \end{pmatrix} \tag{9}$$

S3 County demographics

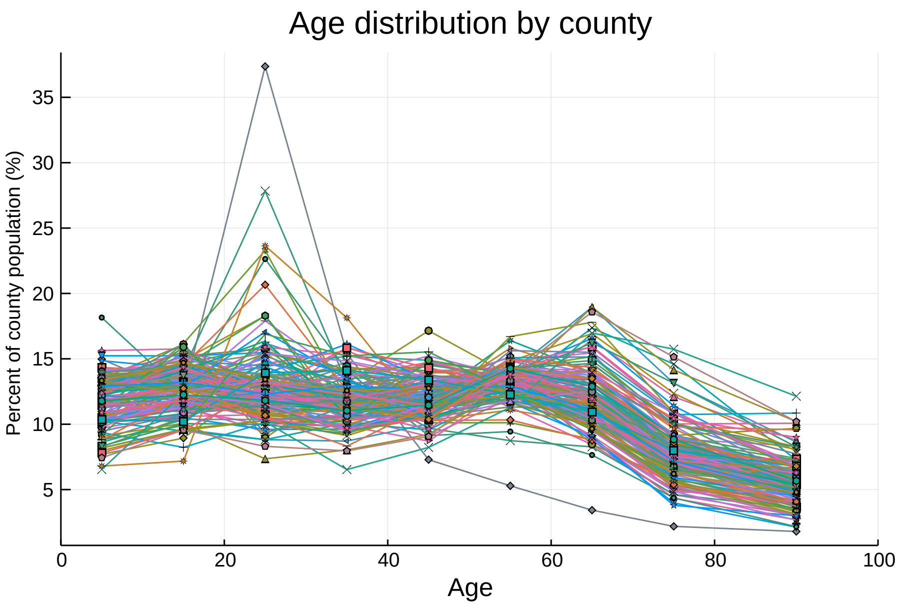

Figure S1: County-level age-structures shown as lines for each of Georgia's 159 counties per the U.S. Census American Community Survey (2017). Spikes in the 20-29 age class are counties with large universities.

S4 Short-term projection maps

Figure S2: Projected new cases per day. 1st and 2nd rows: projections from March 28th 2020 with no social distancing interventions using the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation. 3rd and 4th rows: projections from March 28th 2020, with a 50% reduction in transmission via social distancing, for the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation.

Figure S3: Projected new deaths per day. 1st and 2nd rows: projections from March 28th 2020 with no social distancing interventions using the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation. 3rd and 4th rows: projections from March 28th 2020, with a 50% reduction in transmission via social distancing, for the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation.

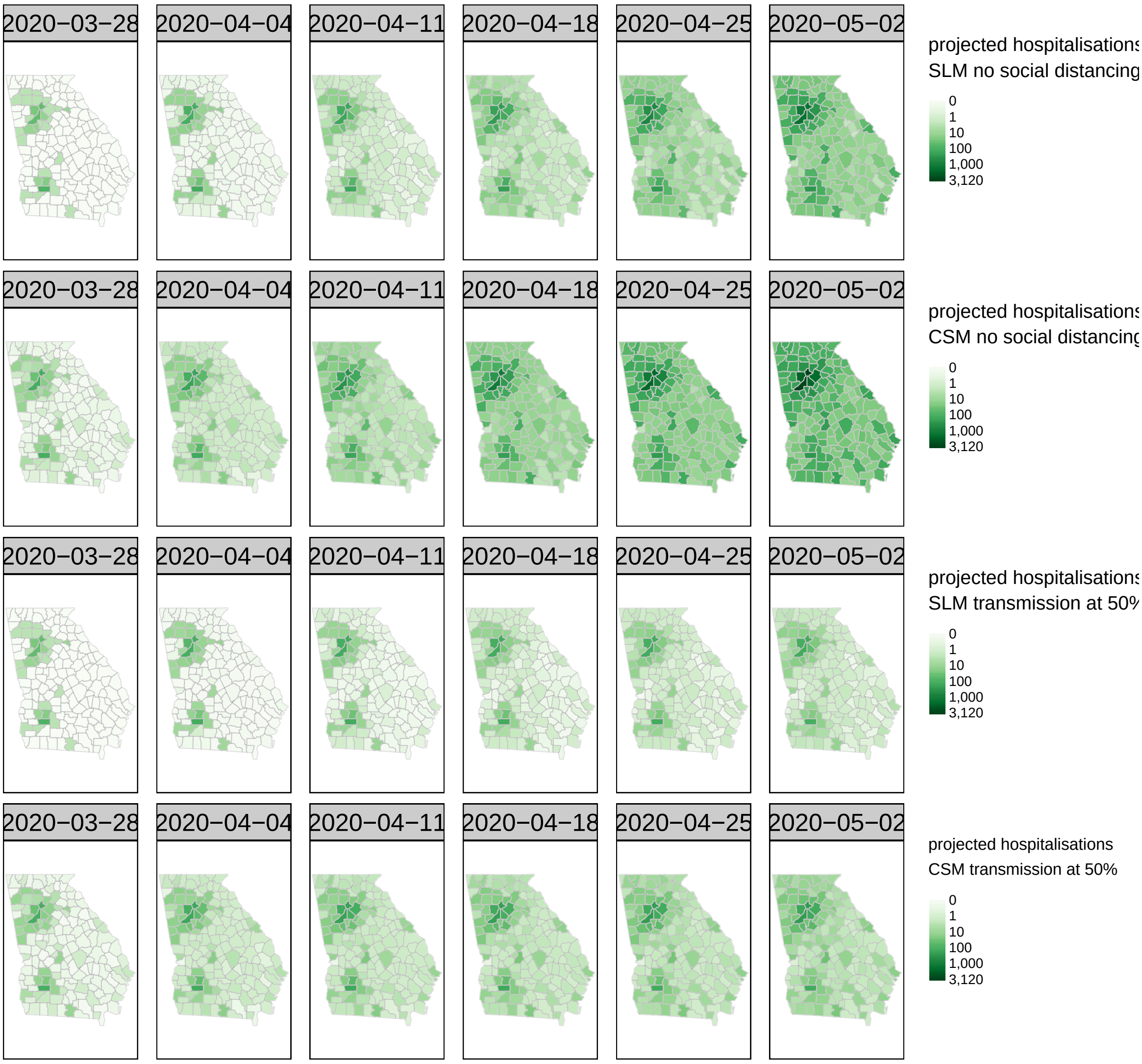

Figure S4: Projected hospitalized (total). 1st and 2nd rows: projections from March 28th 2020 with no social distancing interventions using the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation. 3rd and 4th rows: projections from March 28th 2020, with a 50% reduction in transmission via social distancing, for the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation.

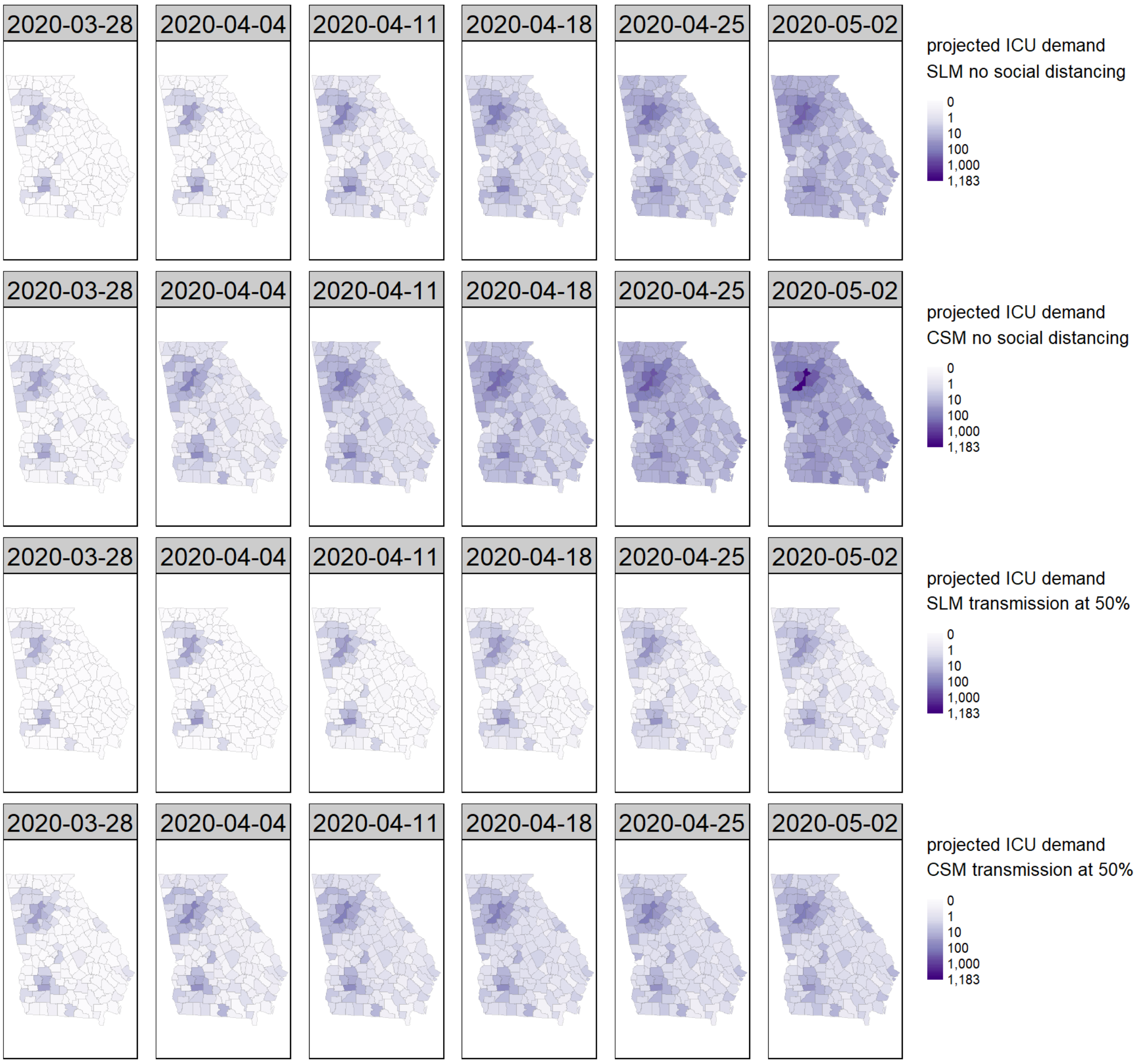

Figure S5: Projected ICU demand. 1st and 2nd rows: projections from March 28th 2020 with no social distancing interventions using the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation. 3rd and 4th rows: projections from March 28th 2020, with a 50% reduction in transmission via social distancing, for the state-level model (SLM) initialisation and the county-level simulation (CSM) initialisation.