

Forecasting the impact of the first wave of the COVID-19 pandemic on hospital demand and deaths for the USA and European Economic Area countries

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Summary

Background: Hospitals need to plan for the surge in demand in each state or region in the United States and the European Economic Area (EEA) due to the COVID-19 pandemic. Planners need forecasts of the most likely trajectory in the coming weeks and will want to plan for the higher values in the range of those forecasts. To date, forecasts of what is most likely to occur in the weeks ahead are not available for states in the USA or for all countries in the EEA.

Methods: This study used data on confirmed COVID-19 deaths by day from local and national government websites and WHO. Data on hospital capacity and utilisation and observed COVID-19 utilisation data from select locations were obtained from publicly available sources and direct contributions of data from select local governments. We develop a mixed effects non-linear regression framework to estimate the trajectory of the cumulative and daily death rate as a function of the implementation of social distancing measures, supported by additional evidence from mobile phone data. An extended mixture model was used in data rich settings to capture asymmetric daily death patterns. Health service needs were forecast using a micro-simulation model that estimates hospital admissions, ICU admissions, length of stay, and ventilator need using available data on clinical practices in COVID-19 patients. We assume that those jurisdictions that have not implemented school closures, non-essential business closures, and stay at home orders will do so within twenty-one days.

Findings: Compared to licensed capacity and average annual occupancy rates, excess demand in the USA from COVID-19 at the estimated peak of the epidemic (the end of the second week of April) is predicted to be 9,079 (95% UI 253–61,937) total beds and 9,356 (3,526–29,714) ICU beds. At the peak of the epidemic, ventilator use is predicted to be 16,545 (8,083–41,991). The corresponding numbers for EEA countries are 120,080 (119,183–121,107), 32,291 (32,157–32,425) and 28,973 (28,868–29,085) at a peak of April 6. The date of peak daily deaths varies from March 30 through May 12 by state in the USA and March 27 through May 4 by country in the EEA. We estimate that through the end of July, there will be 60,308 (34,063–140,381) deaths from COVID-19 in the USA and 143,088 (101,131–253,163) deaths in the EEA. Deaths from COVID-19 are estimated to drop below 0.3 per million between May 4 and June 29 by state in the USA and between May 4 and July 13 by country in the EEA. Timing of the peak need for hospital resource requirements varies considerably across states in the USA and across regions of Europe.

Interpretation: In addition to a large number of deaths from COVID-19, the epidemic will place a load on health system resources well beyond the current capacity of hospitals in the USA and

EEA to manage, especially for ICU care and ventilator use. These estimates can help inform the development and implementation of strategies to mitigate this gap, including reducing non-COVID-19 demand for services and temporarily increasing system capacity. The estimated excess demand on hospital systems is predicated on the enactment of social distancing measures within three weeks in all locations that have not done so already and maintenance of these measures throughout the epidemic, emphasising the importance of implementing, enforcing, and maintaining these measures to mitigate hospital system overload and prevent deaths.

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Introduction

The Coronavirus Disease 2019 (COVID-19) pandemic started in Wuhan, China, in December 2019¹ and has since spread to the vast majority of countries.² As of April 16, twelve countries have recorded more than a thousand deaths: Italy, USA, Spain, France, UK, Iran, China, Netherlands, Germany, Belgium, Canada, and Switzerland. COVID-19 is not only causing mortality but is also putting considerable stress on health systems, with large case numbers and many patients needing critical care including mechanical ventilation. Estimates of the potential magnitude of COVID-19 patient volume – particularly at the local peak of the epidemic – are urgently needed for USA and European hospitals still early in the epidemic to effectively manage the rising case load and provide the highest quality of care possible.

COVID-19 scenarios and forecasts have largely been based on mathematical compartmental models that capture the probability of moving between susceptible, exposed, and infected states, and then to a recovered state or death (SEIR models). Many SEIR or SIR models have been published or posted online.^{3–20} In general, these models assume random mixing between all individuals in a given population. While results of these models are sensitive to starting assumptions and thus differ between models considerably, they generally suggest that given current estimates of the basic reproductive rate (the number of cases caused by each case in a susceptible population), 25% to 90% of the population could eventually become infected unless mitigation measures are put in place and maintained.^{6,20} Based on reported case-fatality rates, these projections imply that there would be millions of deaths in the USA and Europe due to COVID-19. Individual behavioural responses and government-mandated social distancing (school closures, non-essential service closures, and shelter-in-place orders), however, can dramatically influence the course of the epidemic. As of April 14, 2020, for Wuhan City in China – and also for at least 12 additional regions in Italy (Liguria, Lombardia, Emilia-Romagna, Marche, Lazio, Campania), Spain (Community of Madrid, Castile and Leon, Catalonia, Navarre), and the USA (King County, Snohomish County) – strict social distancing has led to the peak of the first wave of the epidemic, implying that the effective reproduction number ($R_{\text{effective}}$) has dropped below unity in these settings. Planning tools based on SEIR models provide high-level information across populations. Few of these planning models have forecasted peaks in deaths or cases and subsequent declines. Using reported case numbers and models based on those for health service planning is also not ideal because of widely varying COVID-19 testing rates and strategies. For example, countries such as Germany, Iceland, and South Korea

have undertaken widespread testing, while in the USA and elsewhere, limited test availability has led to largely restricting testing, particularly early in the epidemic, to those with more severe disease or those who are at risk of serious complications.

An alternative strategy is to focus on modelling the empirically observed COVID-19 population death rate curves, which directly reflect both the transmission of the virus and the infection-fatality rates in each specific community. Deaths are likely more accurately reported than cases in settings with limited testing capacity, where tests are usually prioritised for the more severely ill patients. Hospital service need is likely to be highly correlated with deaths, given predictable disease progression probabilities by age for severe cases. In this study, we use statistical modelling to implement this approach and derive state-specific and country-specific forecasts with uncertainty for deaths and for health service resource needs and compare these to available resources in the USA and countries in the European Economic Area (EEA). This model is regularly updated to incorporate new data for the location of interest as well as data from other locations.

Methods

The modelling approach in this study is divided into four components: (i) identification and processing of COVID-19 data; (ii) statistical model estimation for population death rates as a function of time since the death rate exceeds a threshold in a location; (iii) predicting time to exceed a given population death threshold in locations early in the pandemic; and (iv) modelling health service utilisation as a function of deaths. Additional information on the determination of hospital resource utilisation and capacity is provided in Appendix A; details on curve fitting methods, quantification of uncertainty, and a full specification of the statistical model are available in Appendix B. This study complies with the Guidelines for Accurate and Transparent Health Estimates Reporting (GATHER) statement.²¹

Data identification and processing

Local government, national government, and WHO websites, and third-party aggregators^{22–26} were used to identify data on confirmed COVID-19 deaths by day of death at the first administrative level (state or province, hereafter “admin 1”). Data on licensed bed and ICU capacity and average annual utilisation by location were obtained from a variety of sources for most countries to estimate baseline capacities; observed COVID-19 utilisation data were obtained for a range of countries and USA states providing information on inpatient and ICU use or were imputed from available resources (Appendix A). Other parameters were sourced from the scientific literature and an analysis of available patient-level data. Age-specific data on the relative population death rate by age are available from China,²⁸ Italy,²⁹ South Korea,³⁰ the USA,^{31,32} Netherlands,³³ Sweden,³⁴ and Germany²³ and show a strong relationship with age (Figure 1).

Using the average observed relationship between the population death rate and age, data from different locations can be standardised to the age structure using indirect standardisation (Appendix B). For the estimation of statistical models for the population death rate, only admin 1 locations with an observed death rate greater than 0.31 per million ($\exp(-15)$) were used. This

threshold was selected by testing which threshold minimised the variance of the slope of the death rate across locations in subsequent days.

Government declarations were used to identify the day that different jurisdictions implemented various social distancing policies (school closures, closures of non-essential services focused on bars and restaurants, stay-at-home or shelter-in-place orders, and the deployment of severe travel restrictions) following the New Zealand government COVID-19 alert schema.³⁵ Data on timings of interventions were compiled by checking national and state governmental websites, executive orders, and newly initiated COVID-19 laws, and cross-referencing other policy compilation resources (see Supplementary Information). Covariates of days with expected exponential growth in the cumulative death rate were created using information on the number of days after the death rate exceeded 0.31 per million that six different social distancing measures were mandated by local and national governments: school closures, partial non-essential business closures, complete non-essential business closures, restricting group gatherings, stay-at-home recommendations, and severe local travel restrictions including public transport closures. To derive weighting schemes for each of the social distancing mandates, we determined the effect of social distancing measures on mobility data published by Google (average of retail, workplace, and transit mobility dimensions),³⁶ Descartes Lab (distance travelled)³⁷ and Safegraph (time spent at home)³⁸ using random effects regression where the dependent variable was the log of mobility measures with social distancing measures as a series of dummy variables. The three different weighting schemes were used to create covariates for an ensemble of three models (Appendix B, section 5). For locations that have not yet implemented all of the closure measures, we assumed that the remaining measures will be put in place within 3 weeks. This lag between reaching a threshold death rate and implementing more aggressive social distancing was combined with the observed period of exponential growth in multiple locations that reached their peak after Level 4 social distancing from the New Zealand alert schema³⁵ was implemented, adjusted for the median time from incidence to death. For ease of interpretation of statistical coefficients, this covariate was normalised so the value for Wuhan was 1.

Statistical model for the cumulative death rate

We developed a curve-fitting tool to fit a nonlinear mixed effects model to the available administrative cumulative death data. See Appendix B: Curvefit Tool and Analyses for greater detail. The cumulative death rate for each location is assumed to follow a parametrised Gaussian error function:

$$D(t; \alpha, \beta, p) = \frac{p}{2} \Psi(\alpha(t - \beta)) = \frac{p}{2} \left(1 + \frac{2}{\sqrt{\pi}} \int_0^{\alpha(t-\beta)} \exp(-\tau^2) d\tau \right)$$

where the function Ψ is the Gaussian error function (written explicitly above), p controls the maximum cumulative death rate at each location, t is the time since death rate exceeded $\exp(-15)$, β (beta) is a location-specific inflection point (time at which rate of increase of the daily death rate is maximum), and α (alpha) is a location-specific growth parameter. Other sigmoidal functional forms (alternatives to Ψ) were considered but did not fit the data as well. Data were fit to the log of the death rate in the available data, using an optimisation framework described in Appendix B. For data-rich cases, we also developed linear curve fitting extension, where after a

Gaussian curve in daily death is obtained, we fit the data to a weighted combination (with constraints on weights) of such curves propagated forward and backward in time. The resulting models can capture more complex behavior in the data.

An ensemble of three models was used to produce the estimates. In all models, we parametrised the time-axis shift parameter β to depend on a covariate based on time from when the initial $\ln(\text{death rate})$ exceeds $\exp(-15)$ to the implementation of social distancing. The models differed by the definition of the social distancing covariate. In each model, the value of the covariate multiplier was obtained by fitting a joint model on all the locations that were considered to have peaked; that is, the generalisable information from these locations was the impact that social distancing had on the time to reach the inflection point. Using 13 locations where peak deaths had occurred as of April 14, 2020 – China (Wuhan City), Italy (Liguria, Lombardia, Emilia-Romagna, Marche, Lazio, Campania), Spain (Community of Madrid, Castile and Leon, Catalonia, Navarre), and the USA (King County, Snohomish County) – we fit mixed effects models to get the mean and variance of the relationship between the social distancing covariates and the peak time, and used this information to build priors for location-specific estimates.

We use hospitalization data to generate additional short-term predicted deaths (pseudo-data). On average, the time between hospitalization and death is 8 days. Using location-specific hospitalization data which has more than 10 deaths, we estimate the ratio of cumulative deaths to cumulative hospitalizations up to 8 days in the past. We use this ratio to generate pseudo-data for 8 days, and incorporate this pseudo-data into the CurveFit model. Details are given in Section 11 of Appendix B.

For locations with fewer than 18 days, we use the following analysis. For each type of model (based on definition of the covariate), we considered both “short-range” and “long-range” variants, to explain existing data and forecast long-term trends, respectively. In the former case, covariate multipliers could deviate from those estimated using peaked locations, while in the latter, the joint model fit from peaked locations had a larger impact on the final covariate multiplier. The two remaining parameters (not modelled using covariates) were allowed to vary among locations to fit location-specific data. Uncertainty for every model was obtained using the predictive validity framework that analyses errors in predicting out-of-sample observations. Using these methods, we obtain model realisations using draws, for both short- and long-term models across the forecast horizon. We then obtain forecasts that linearly interpolate between short-term and long-term models, with next days closely following short-term models and long-term forecasts following long-term models. Finally, we ensemble these draws across the model types (based on the definition of the social distancing covariate).

For locations with 18 or more days, we first fit a long-term model, borrowing strength from peaked locations and obtaining location-specific representative daily deaths Gaussian curves. We then fit a linear combination of 13 of the inferred Gaussian curves from the long-term model, placed two days apart (12 days back from the inferred peak to 12 days forward of the inferred peak). We then ensemble across draws for different model types. See Appendix B (section 11) for full details.

The dataset age-standardised to the age-structure of California is shown in Figure 2.

Time to threshold death rate

All states except Wyoming have deaths greater than 0.31 per million (e-15) and more than 2 deaths and were included in the model estimation along with data on 66 other admin 1 locations. For other USA states or locations in the EEA, we estimated the expected time from the current case count to reach the threshold level for the population death rate model. Using the observed distribution of the time from each level of case count to the threshold death rate for all admin 1 locations with data, we estimated this distribution. We used the mean and standard deviation of days from a given case count to the future threshold death rate to develop the probability distribution for the day each state will cross over the threshold death rate, and then we applied the death rate epidemic curve after crossing the threshold.

Hospital service utilisation microsimulation model

From the projected death rates, we estimated hospital service utilisation using an individual-level microsimulation model – additional details are provided in Appendix A. We simulated deaths by age using the average age pattern (Figure 1). For each simulated death, we estimated the date of admission using the median length of stay for deaths from available data (six days). Simulated individuals requiring admission who were discharged alive were generated using the location-specific ratios of admissions to deaths; where location-specific ratios were not available we used the EEA pooled estimate for other EEA countries and the USA pooled estimate for other USA states. An age pattern of the ratio was based on available data (Appendix A). The age-specific fraction of admissions requiring ICU care was based on data from the USA. The fraction of ICU admissions requiring invasive ventilation was estimated as 85%. To determine daily bed and ICU occupancy and ventilator use, we applied median lengths of stay of eight days for those not requiring ICU care and discharged alive and 20 days for those admissions with ICU care, with 13 of those days in the ICU.³⁹

Role of the funding source

The funders of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report. The authors had access to the data in the study and the final responsibility to submit the paper.

Results

By aggregating forecasts across location, we determined the overall trajectory of expected health-care needs in different categories and deaths, as shown in Figure 3 for the USA (Panel A) and for EEA countries (Panel B). These figures highlight the earlier beginning of the epidemic in EEA countries compared to the USA. The USA projected peak was reached on April 15 with almost 3,500 deaths daily. In EEA the peak was on April 6 with more than 4,000 deaths daily but with a flatter peak, reflecting the considerable variability in the timing of the epidemic by country. Our estimated peak hospital demand was 68,884 (95% UI 34,599–175,312) beds, 18,269 (9,621–44,223) ICU beds and 16,545 (8,083–41,991) ventilators in the USA; for EEA nations the corresponding numbers were 120,080 (119,183–121,107) hospital beds, 32,291 (32,157–32,425) ICU beds, and 28,973 (28,868–29,085) ventilators.

The peak of daily deaths varies considerably between EEA countries and subnational locations (Figure 4, Panel A) and USA states (Panel B). Several regions in Italy reached their peak by the end of March, with parts of Spain, France, Netherlands, Norway, Denmark, Greece, and Estonia following suit by the beginning of April. Other countries such as the UK, Germany, and Sweden are at the peak or are approaching the peak. In the USA, states with earlier peaks include Washington, Nevada, Arizona, Montana and Florida. States at the peak or just approaching the peak include Texas, California and parts of New England. States in the middle of the country, including North Dakota, South Dakota, Iowa and Wyoming are expected to peak later.

Figure 5 shows total excess demand for the USA (panel A) and EEA countries (panel B) overall. In the USA, peak excess demand for hospitalisation above usual capacity was estimated as 9,079 (95% UI 253–61,937); ICU bed excess demand was 9,356 (3,526–29,714). We estimated that EEA countries experienced a peak excess demand above usual capacity for total beds of 28,270 (0 to 126,788) at peak; the ICU bed shortfall was 16,090 (15,973–16,211). Excess demand is concentrated in particular countries and USA states as shown in Figure 6, which shows the percentage excess demand for ICU beds by location: in the USA (panel A), excess demand for ICU beds is concentrated in New York, New Jersey, Connecticut, Wyoming, Michigan, Rhode Island, and Massachusetts; in the EEA (panel B), ICU excess demand above usual capacity is particularly high in Sweden, Spain, Northern Ireland, Italy, France, and Belgium. We have not been able to estimate current ventilator capacity; however, the number of ventilators per person implied by the peak (Figure 3) also suggests potentially large gaps in availability of ventilators.

Figure 7 shows the expected cumulative death numbers with 95% uncertainty intervals for the USA (Panel A) and EEA (Panel B). In the USA, the average forecast suggests 60,308 deaths, but the range is large, from 34,063 to 140,381 deaths. The figure shows that uncertainty widens markedly as the peak of the epidemic approaches, given that the exact timing of the peak is uncertain. In the EEA, 91,972 (95% UI 91,212–93,620) deaths have already been recorded so far, with the majority of these coming from Italy, Spain, and France. Our forecast suggests a cumulative total of 143,088 (101,131–253,163) deaths in the EEA. A large number of these deaths are projected to occur in the UK (13,759 observed to date; 37,521 [17,625–89,385] total), Sweden (1,333 observed to date; 5,890 [1,965–16,883] total), Germany (3,570 observed to date; 4,957 [3,697–9,379] total) and France (18,485 observed to date; 22,555 [19,455–29,314] total).

Figure 8 shows a map of the cumulative number of deaths per capita by location for the USA and EEA. In Europe, the highest number of estimated cumulative deaths per capita are in Italy – particularly the northern regions – Spain, Belgium, Sweden and the UK. In the USA, states with the highest per capita deaths are New York, Rhode Island, New Jersey, Connecticut, Massachusetts, Wyoming, Louisiana, and Michigan.

Figure 9 shows the date by location by which projected daily deaths drop below 0.3 per million. As expected, there is a strong correlation between the timing of the peak daily death and when the daily death rate will drop below this threshold. In Europe, countries where this will happen later include the UK, Norway, Denmark, Sweden and the Netherlands. In the USA, states that will not cross this threshold until the end of May include South Dakota, North Dakota, Iowa, Oklahoma, Arkansas and Utah.

Results for each location are accessible through a visualisation tool at

<http://covid19.healthdata.org/projections> – the estimates presented in this tool will be continually updated as new data are incorporated and ultimately will supersede the results in this paper. Summary information on cumulative deaths, the date of peak demand, the peak demand, peak excess demand, and aggregate demand are provided for each location in Table 1.

Discussion

This study has generated estimates of predicted health service utilisation and deaths due to COVID-19 by day through the end of July for all USA states and EEA countries, assuming that social distancing efforts will continue until deaths reach a very low level. The analysis shows large gaps between need for hospital services and usual capacity, especially for inpatient and ICU beds. A similar or perhaps even greater gap for ventilators is also likely, but detailed state or country data on ventilator capacity are not available to directly estimate that gap. Uncertainty in the time course of the epidemic, its duration, and the peak of utilisation and deaths is large, particularly for when locations are early in the epidemic and where there are few deaths. Given this, it is critical to update these projections as the pandemic progresses and new data are collected. Uncertainty will also be reduced as we gain more knowledge about the epidemic peak and subsequent decline in daily deaths across more than 13 locations. A critical aspect to the size of the peak is when aggressive measures for social distancing are implemented in each state, region, or country and for how long they are maintained. Delays in implementing government-mandated social distancing and relaxing policies will have an important effect on the resource gaps that health systems will be required to manage.

Our estimates of excess demand show that hospital systems have already or will face difficult choices to continue providing high-quality care to their patients in need. This model was first developed for use by the UW Medicine system in Washington state, and the practical experience of that system provides insight into how it has been useful for planning purposes. From the perspective of planning for the UW Medicine system, these projections immediately made apparent the need to rapidly build available capacity. Strategies to do so included suspending elective and non-urgent surgeries and procedures, while supporting surge planning efforts and reconfiguration of medical/surgical and ICU beds across the system. These targets also supported a proactive discussion regarding the potential shift from current standards of care to crisis standards of care, with the goal to do the most good for the greatest number in the setting of limited resources.

There are a variety of options available to deal with the situation, some of which have already been implemented or are being implemented. One option is to reduce non-COVID-19 patient use. In the USA and in many EEA countries, local, state, or national governments have cancelled elective procedures⁴⁰⁻⁴⁵ and many, but not all, hospitals have complied. This decision has significant financial implications for USA health systems, however, as elective procedures are a major source of revenue.⁴⁶ Also, aggressive social distancing policies reduce not only the transmission of COVID-19 but will likely have the added benefit of reducing health-care utilisation due to other causes such as injuries.⁴⁷ Reducing non-COVID-19 demand alone will not be sufficient, and strategies to increase capacity are also clearly needed. This includes setting up additional beds by repurposing unused operating rooms, pre- and post-recovery rooms, procedural areas, medical and nursing staff quarters, and hallways.

Currently, one of the largest constraints on effective care may be the lack of ventilators. One supplement to ventilator capacity is using anesthesia machines freed up by deferring or cancelling elective surgeries. Other options go beyond the capacity or control of specific hospitals. The use of mobile military resources has the potential to address some capacity limitations, particularly in the USA given the differently timed epidemics across states. Other innovative strategies will need to be found, including the construction of temporary hospital facilities as has been done in Wuhan,⁴⁸ Washington state,⁴⁹ New York,^{50,51} Italy,⁵² France,⁵³ and Spain.⁵⁴

In this study, we have quantified the potential gap in physical resources, but there is an even larger potential gap in human resources (HR). Expanding bed capacity beyond licensed bed capacity may require an even larger increase in the HR to provide care. The average annual bed-day utilisation rate in the US is 66% and ranges from 46% to 92% among EEA countries. Many hospital systems are staffed appropriately at their usual capacity utilisation rate, and expanding even up to, but then potentially well beyond, licensed capacity will require finding substantial additional HR. Strategies include increasing overtime, training operating room and community clinic staff in inpatient care or physician specialties in COVID-19 patient care, rehiring recently separated workers, and the use of volunteers. In academic health systems such as UW Medicine, clinical faculty time can be redirected from research and teaching to clinical care during the COVID-19 surge. A more concerning HR bottleneck identified, given the need for ICU care for COVID-19 patients, is for ICU nurses, for which there are very limited options for increasing capacity. In addition to HR, what should not be overlooked is the increased demand for supplies ranging from personal protective equipment (PPE), medication, and ventilator supplies to basics such as bed linen. Add to these the need to expand other infrastructure required to meet the COVID-19 surge, such as information technology (IT) for electronic medical records. The overall financial cost over a short period of time is likely to be enormous, particularly when juxtaposed against the substantial reductions in revenue for many hospitals due to the cancellation of elective procedures and the broader economic consequences of social distancing mandates.

Our model suggests that the timing of the implementation of social distancing mandates is a critical determinant of peak demand and cumulative deaths. Mobility data derived from cell phone use has provided the basis for evaluating the importance of the different social distancing mandates included in the social distancing covariate. It is important to note the social distancing mandates do not capture all variation in mobility, and that the data in some locations suggests behavioural change prior to the introduction of these mandates. Understanding what drives individual change, e.g. levels of awareness or fear of the pandemic or the private sector implementing remote work policies prior to government mandates, will be important for understanding what may drive the change in behaviour after official social distancing mandates are relaxed, which is now beginning in some European countries and US States.

Based on our experience thus far, we have derived important insights into the epidemic trajectories and health service demand as data have accumulated. These have led to improved forecasts reflecting both new data and method refinements.^{55,56} For this reason, we are continuing to revise the model as new data are available, providing an updated forecast for health service providers, governments, and the public. In some regions that have peaked, such as regions in Italy like Liguria, or New York, the duration of the peak is much longer than in other

places such as Madrid. The mixture model we use accommodates this longer peak but it remains unclear why some communities have the prolonged peak and others do not. The prolonged peak leads to substantially increased total mortality. There is also marked variation across locations in how steeply the epidemic curve rises, captured by the alpha parameter in our model. Understanding why some locations have an epidemic like New York and others like Washington State will be important to make robust forecasts in other regions of the world.

Any attempt to forecast the COVID-19 epidemic has many limitations. Only a limited number of locations with generalised epidemics have reached the peak in terms of daily deaths, and only one has currently brought new cases to near zero, namely Wuhan. Many other locations, including all other provinces in China, have so far successfully contained transmission, preventing a general outbreak. Modelling based on one completed epidemic, at least for the first wave, and many incomplete epidemics is intrinsically challenging. The main limitation of our study is that observed epidemic curves for COVID-19 deaths define the likely trajectory. In this study, we do include a covariate meant to capture the timing of social distancing measures and their effect on various measures of population mobility. Our model also relies on the accuracy of reporting of deaths due to COVID-19; reports suggest that in some locations not all deaths may be included in country reported totals.^{57,58} Our models explicitly take into account variation in age-structure, which is a key driver of all-age mortality. But these efforts at quantification do not take into account many other factors that may influence the epidemic trajectory: sex, the prevalence of co-morbidity, population density, individual behavior change not captured by mobility metrics, and a host of other individual factors that may potentially influence the immune response. We also have not explicitly incorporated the effect of reduced quality of care due to stressed and overloaded health systems beyond what is captured in the data. For example, the higher mortality rate in Italy may in part be due to policies around restricting invasive ventilation in the elderly. The model ensemble used does suggest that locations with faster increases in the death rate are likely to have greater peak caseload and cumulative deaths, but our uncertainty intervals are appropriately large. Finally, it is critical to note that we restrict our projections to the first wave of the pandemic under a scenario of continued implementation of social distancing mandates and do not yet incorporate the possibility of a resurgence or subsequent waves. This is an essential area for future work.

Conclusion

COVID-19 is an extraordinary challenge to health and the health-care system. In this study, we forecast a large excess of demand for hospital bed-days and ICU bed-days and our estimate of 1,584,737 (95% UI 1,050,954–3,082,999) deaths in the USA and EEA from the first wave of pandemic is an alarming number. This number could be substantially higher if excess demand for health system resources is not addressed and if social distancing policies are not continued, vigorously implemented, and enforced. This planning model will hopefully provide an up-to-date tool for improved hospital resource allocation.

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Figure 1

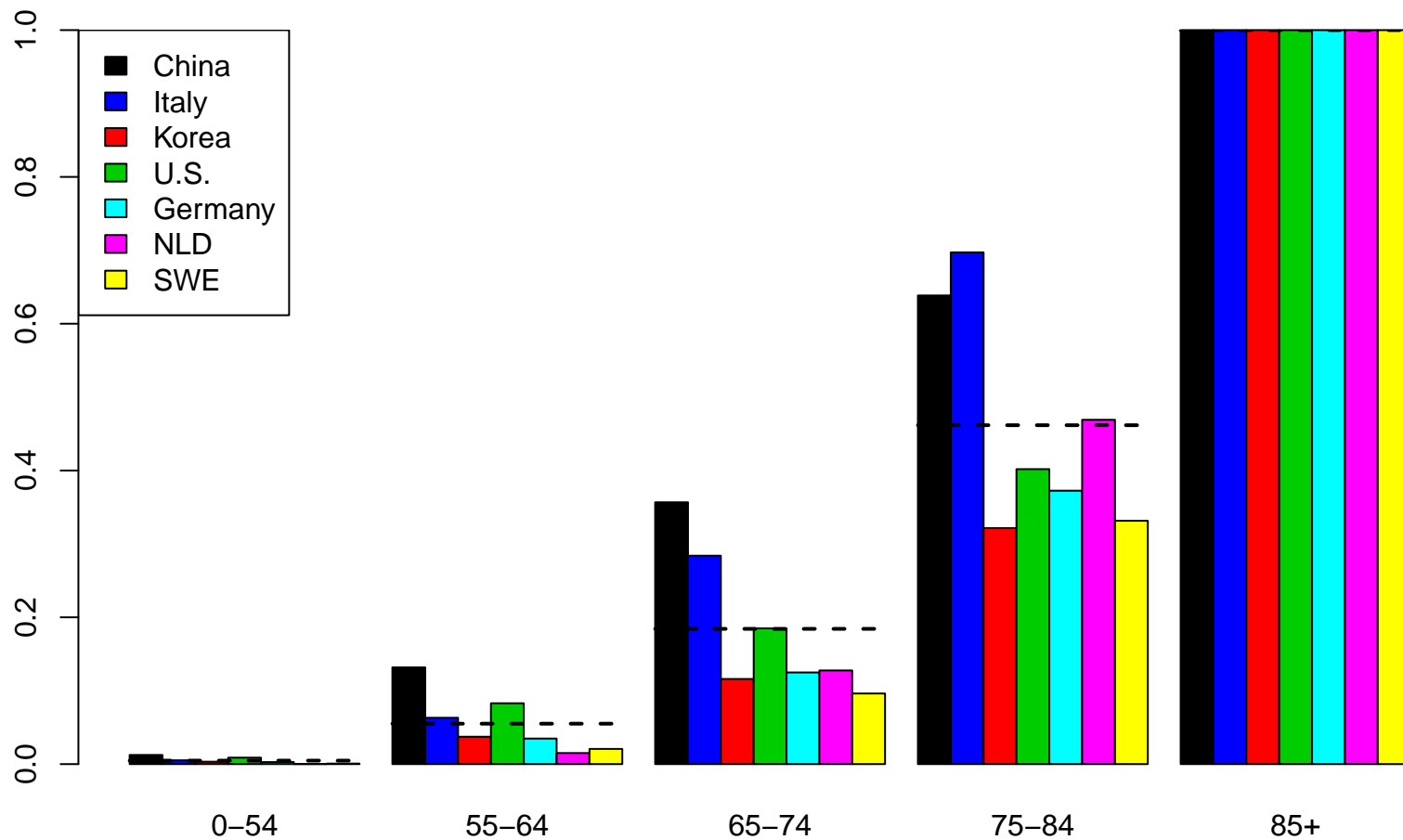


Figure 2. Death rate data age-standardized to California as a function of time since a threshold death rate of 0.3 per million.

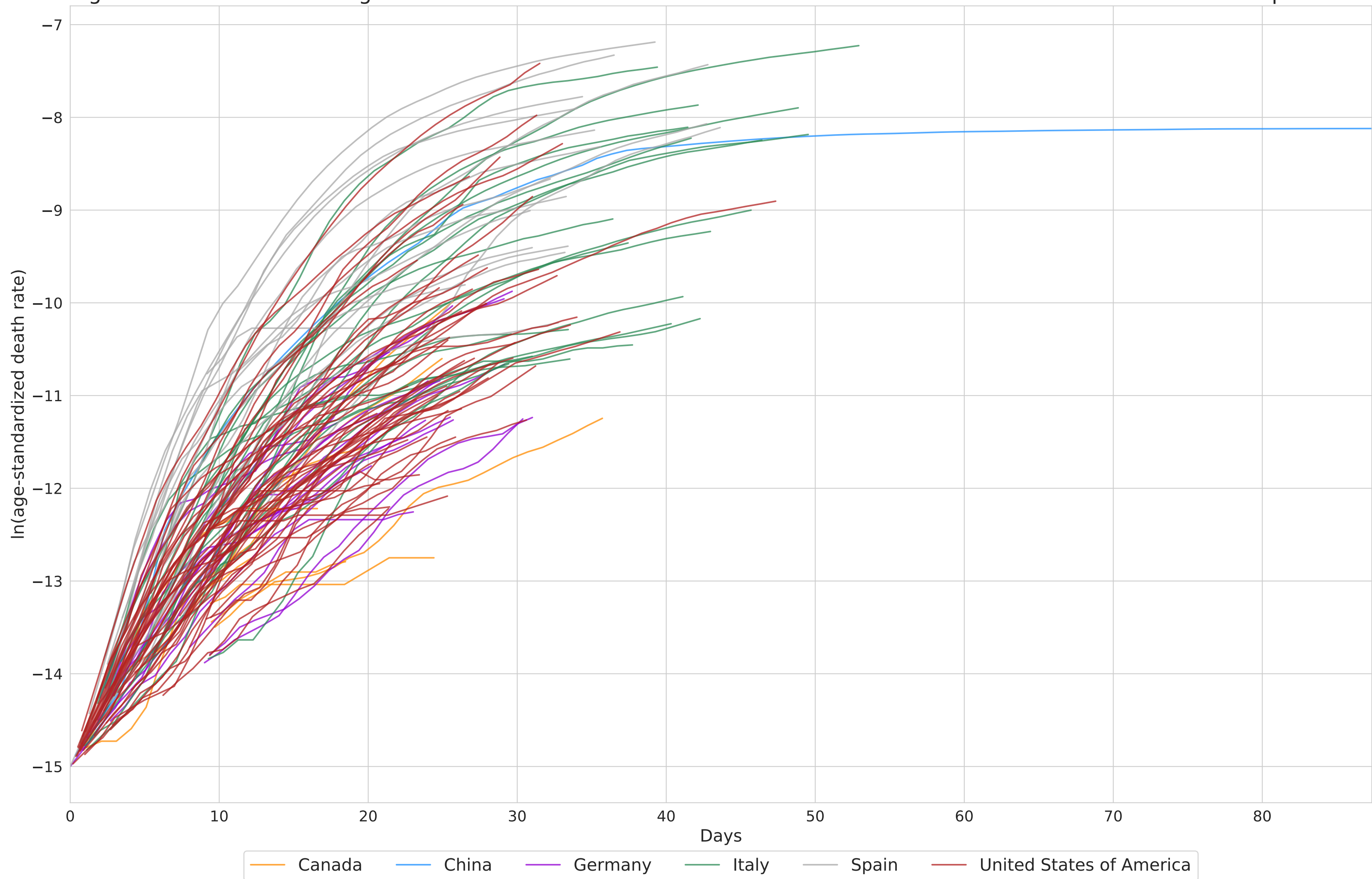


Figure 3A - USA

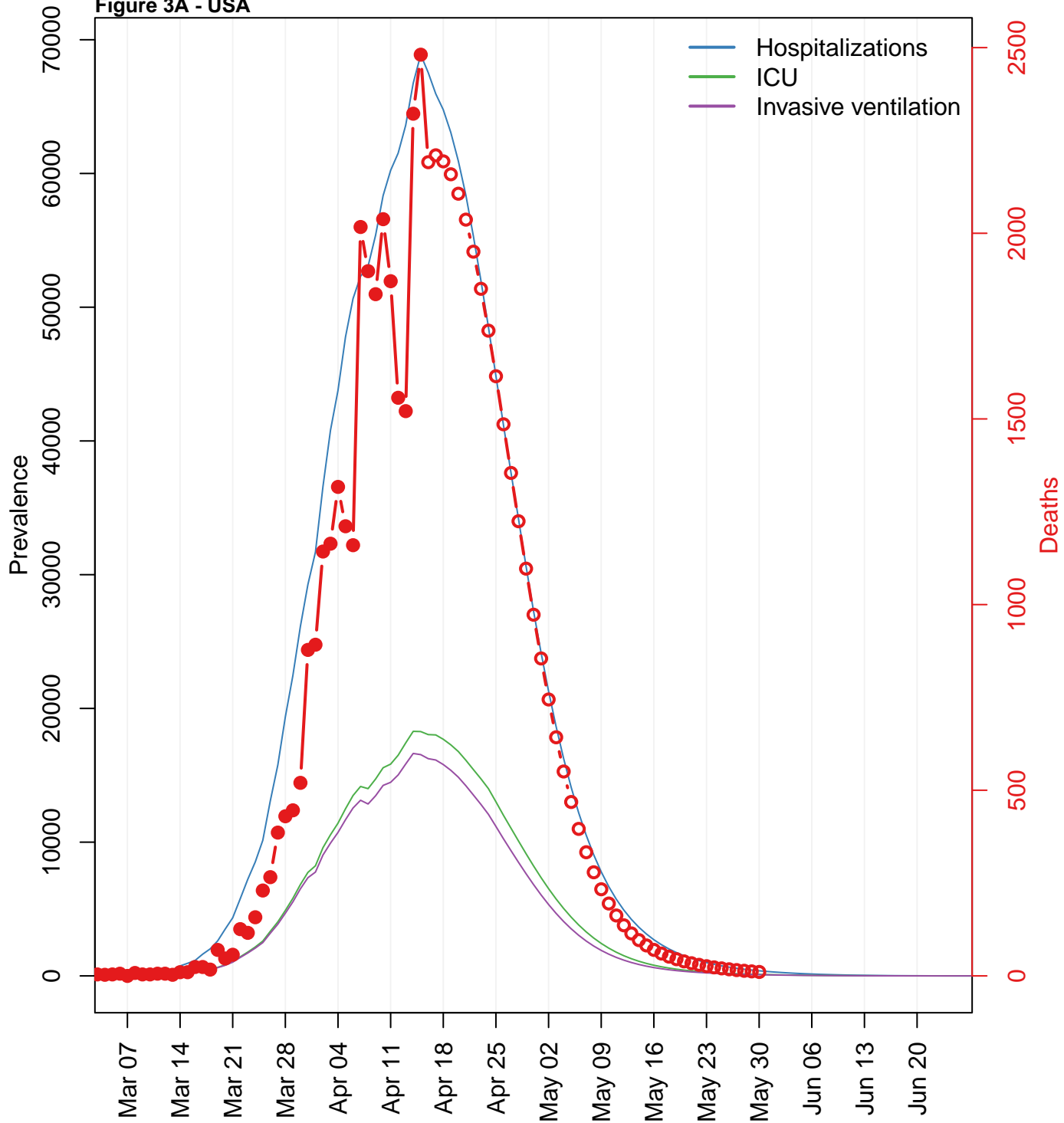


Figure 3B - EEA

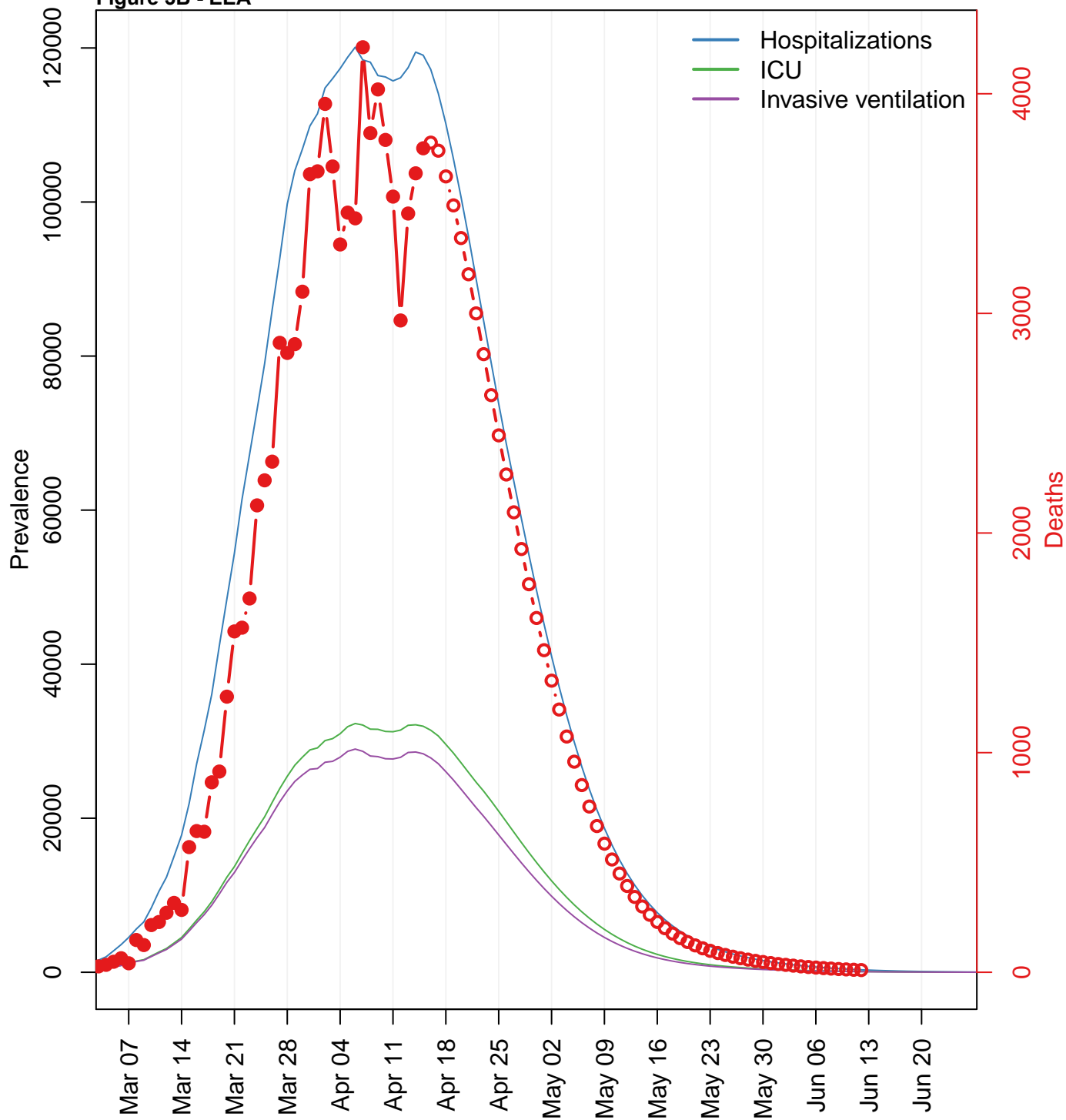


Figure 4. Date of peak of daily deaths by state

A. United States

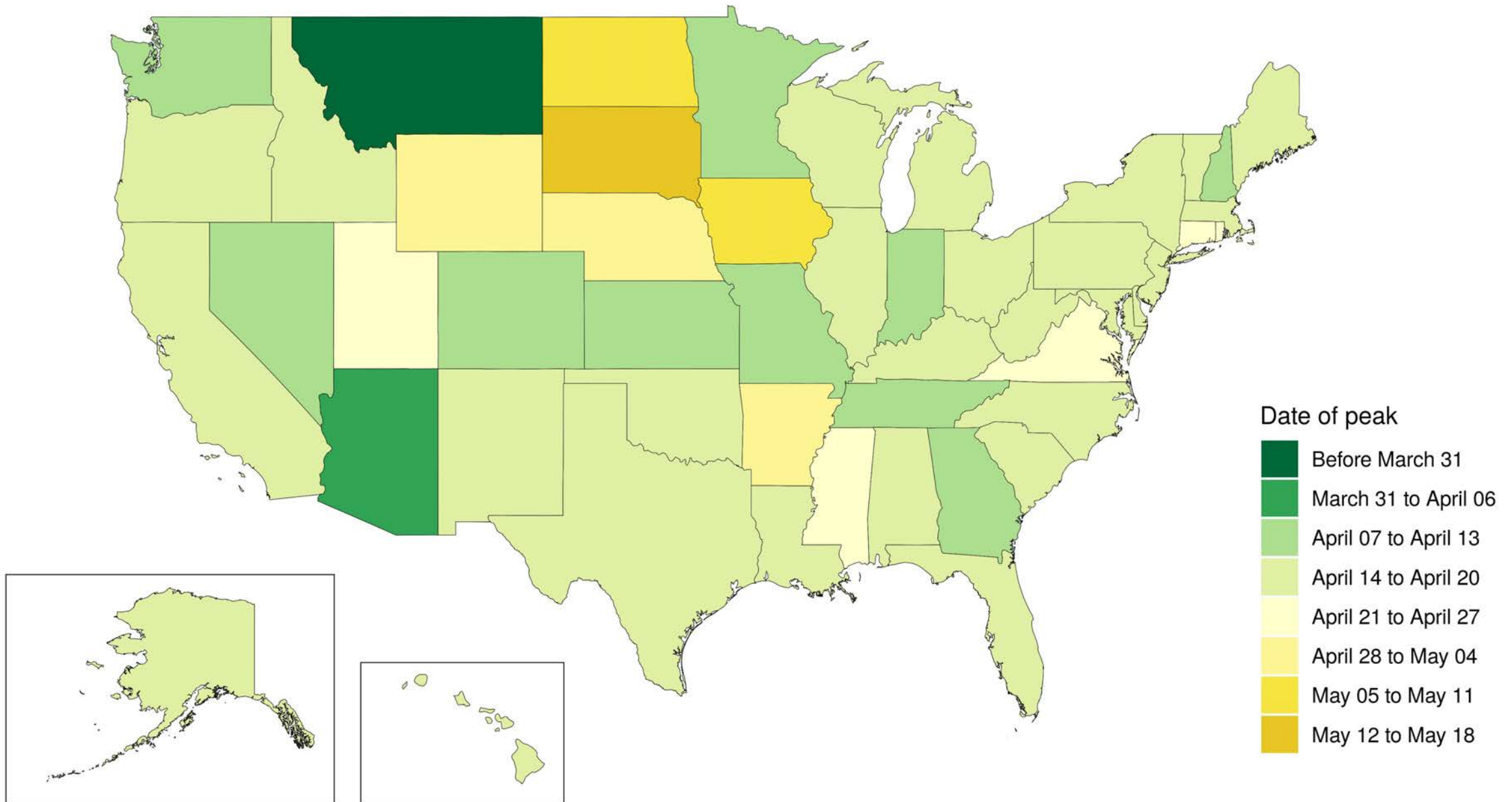


Figure 4. Date of peak of daily deaths by location
B. European Economic Area

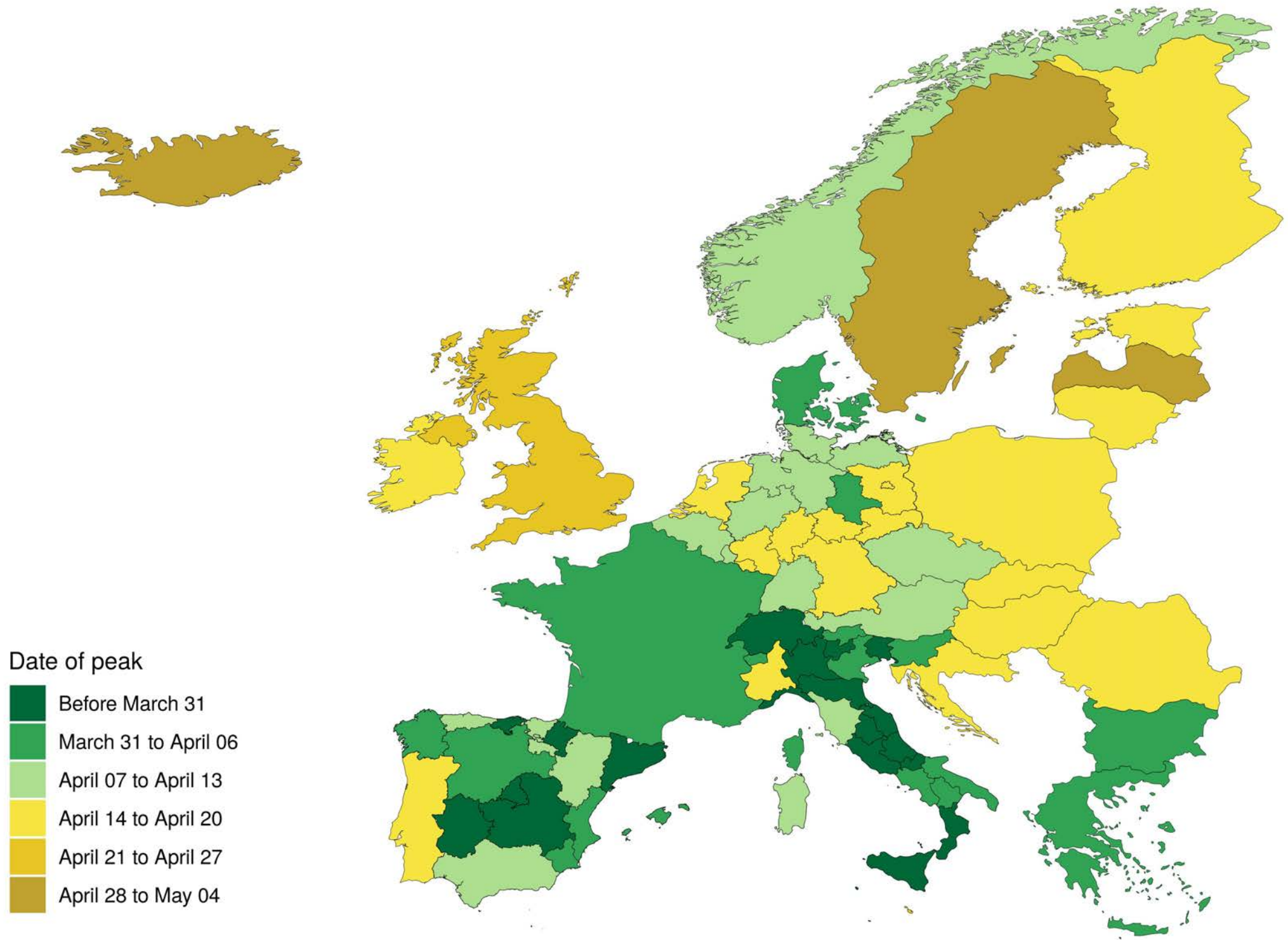


Figure 5A - USA

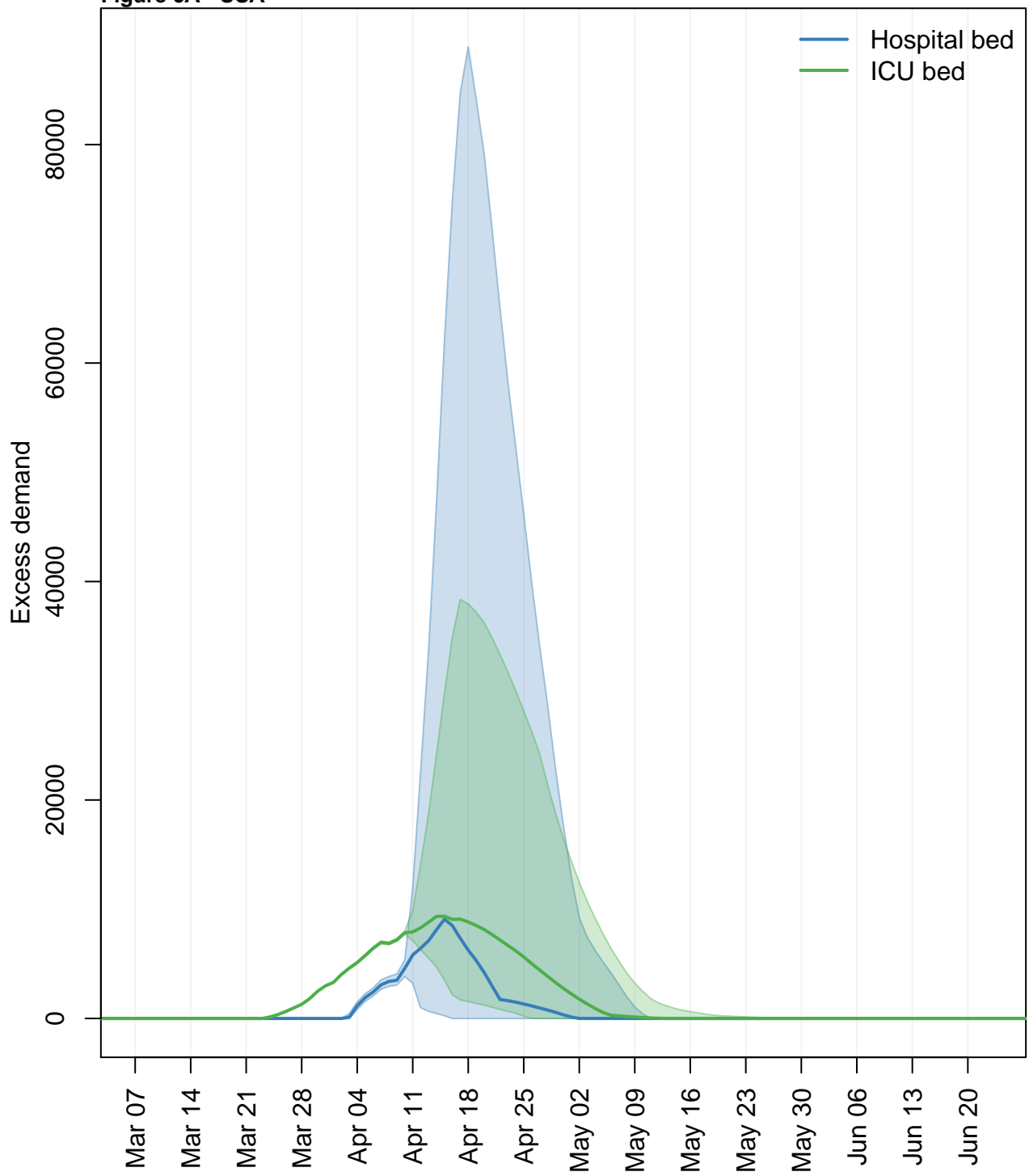


Figure 5B - EEA

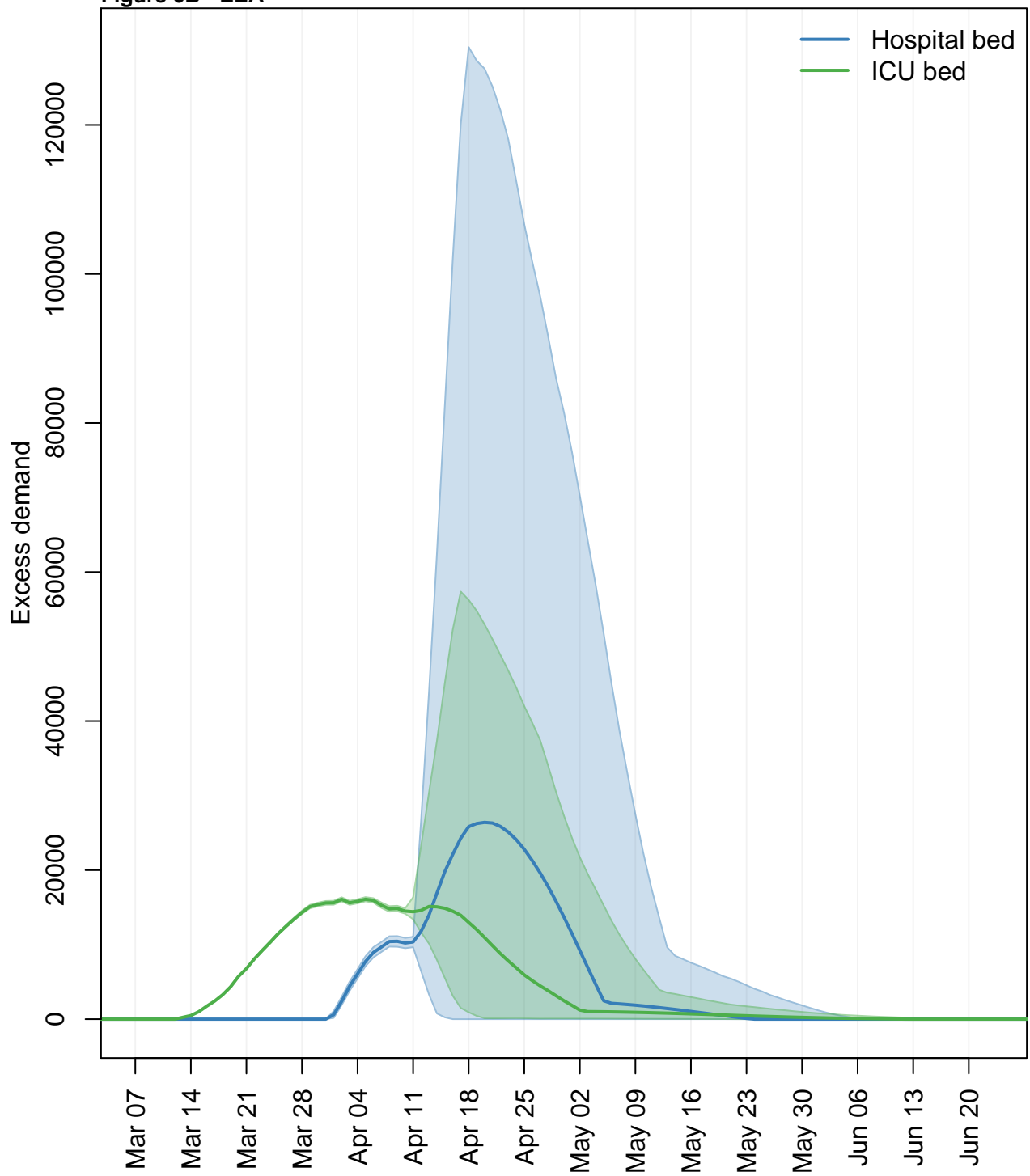


Figure 6A. United States

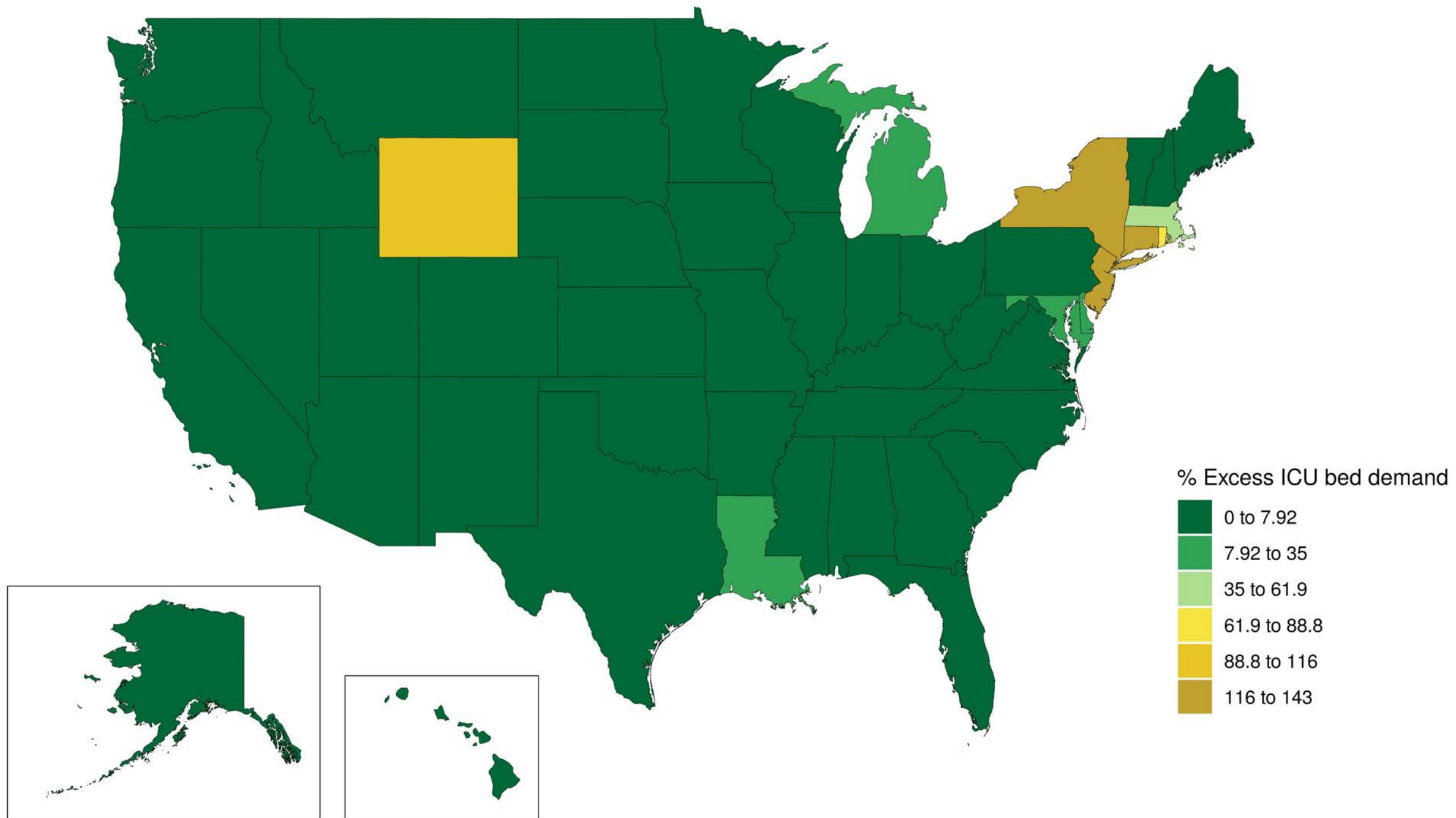


Figure 6B. European Economic Area

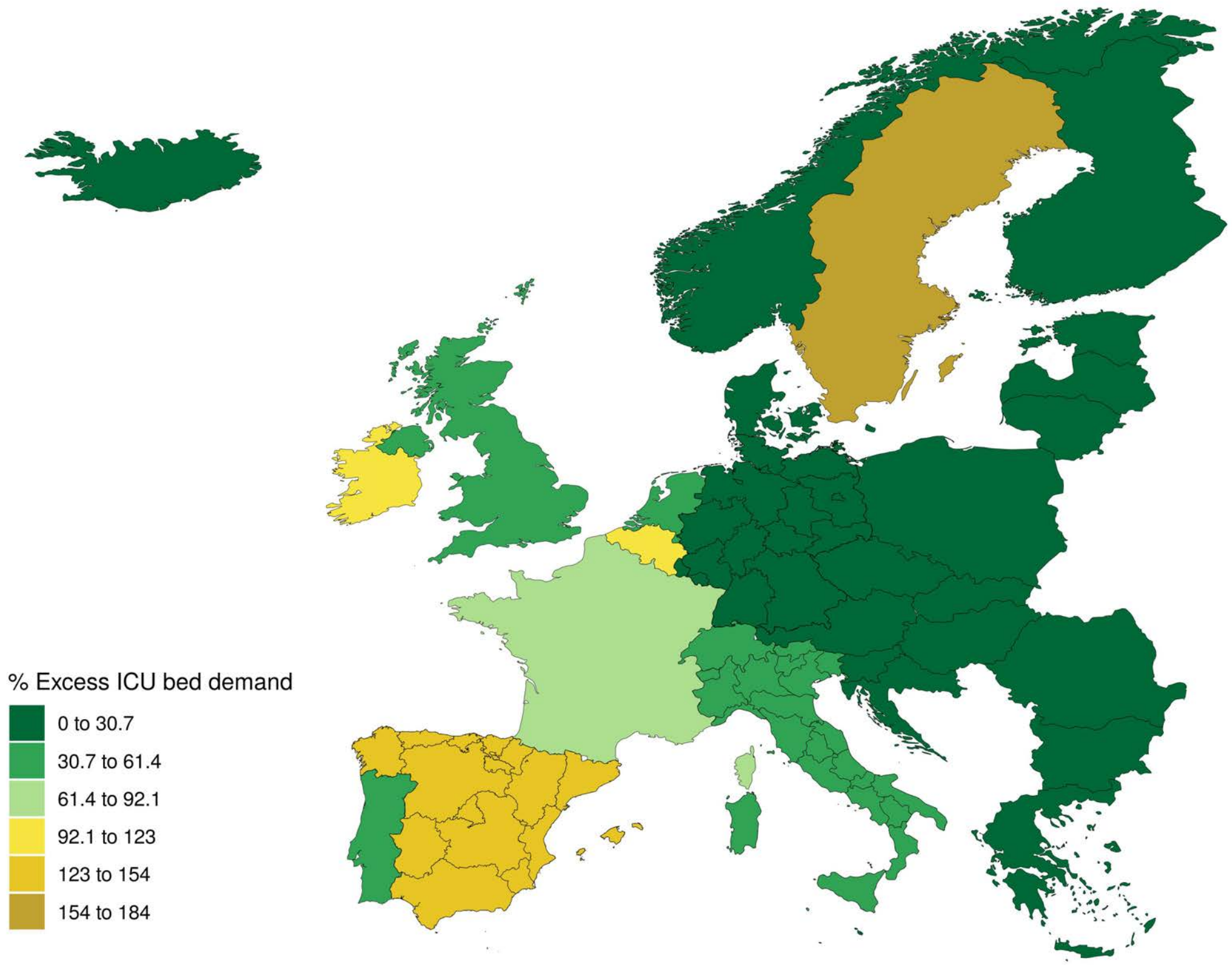


Figure 7A -- USA

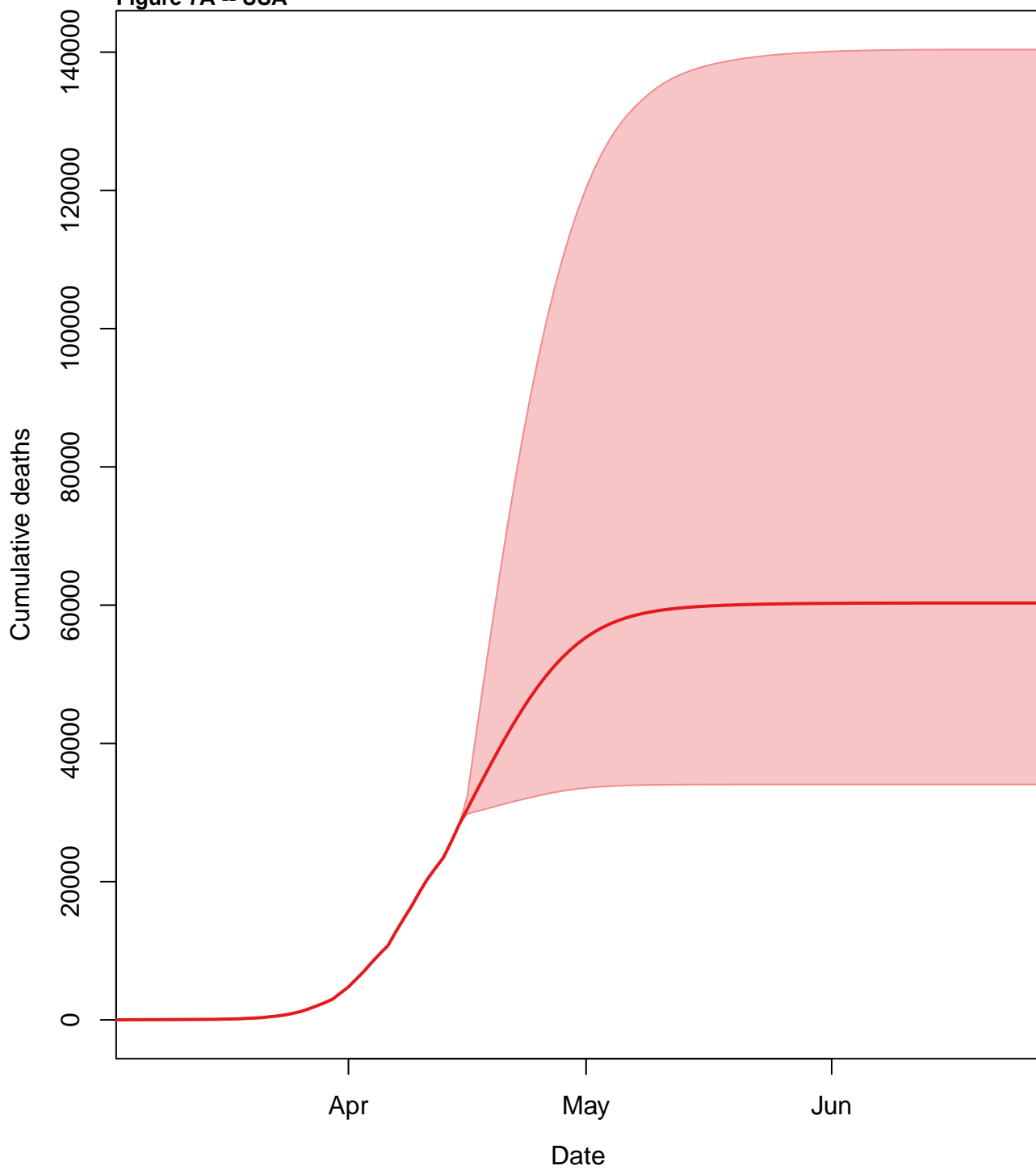


Figure 7B - EEA

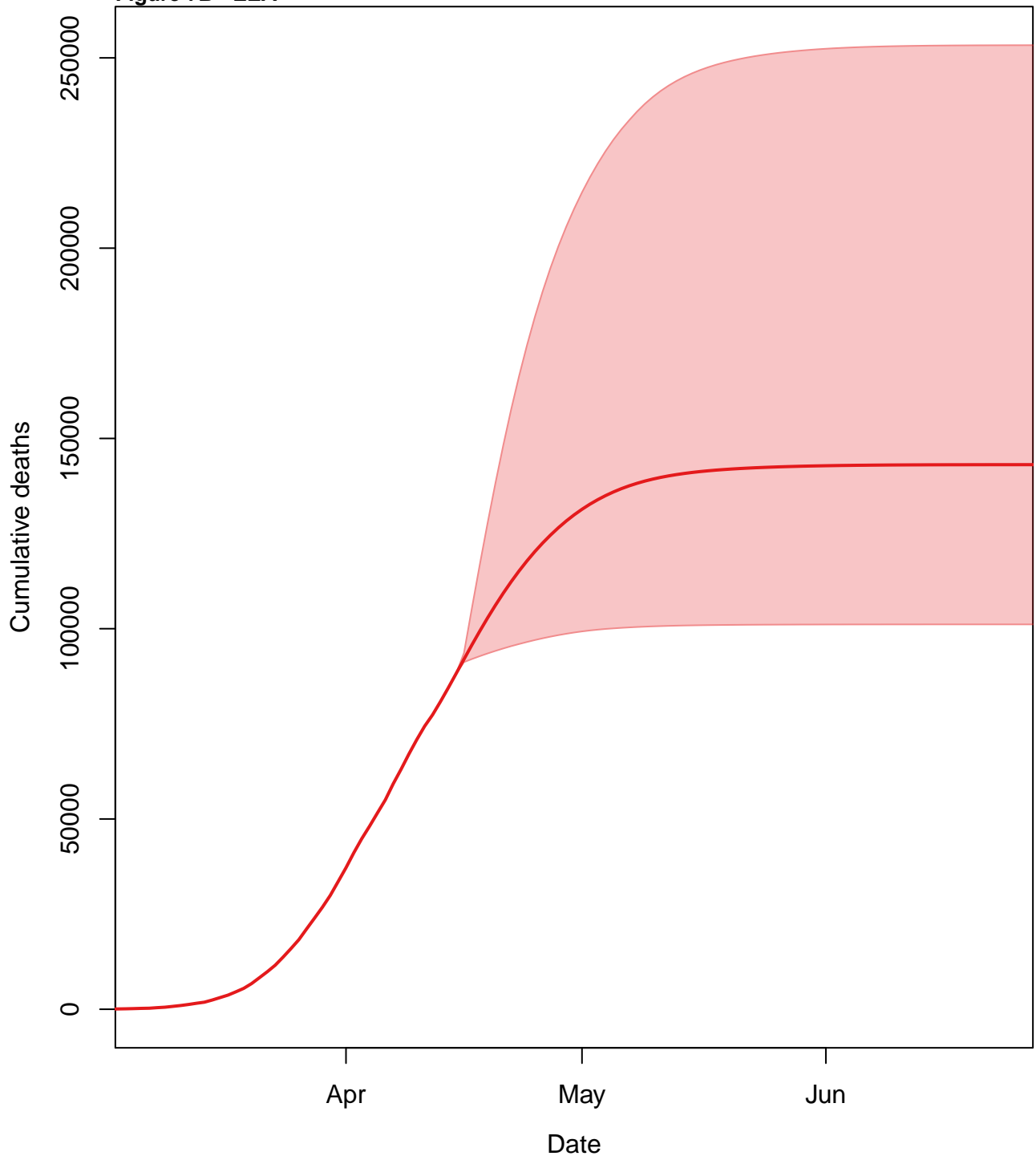


Figure 8. Expected mean cumulative death per 100,000 population

A. United States

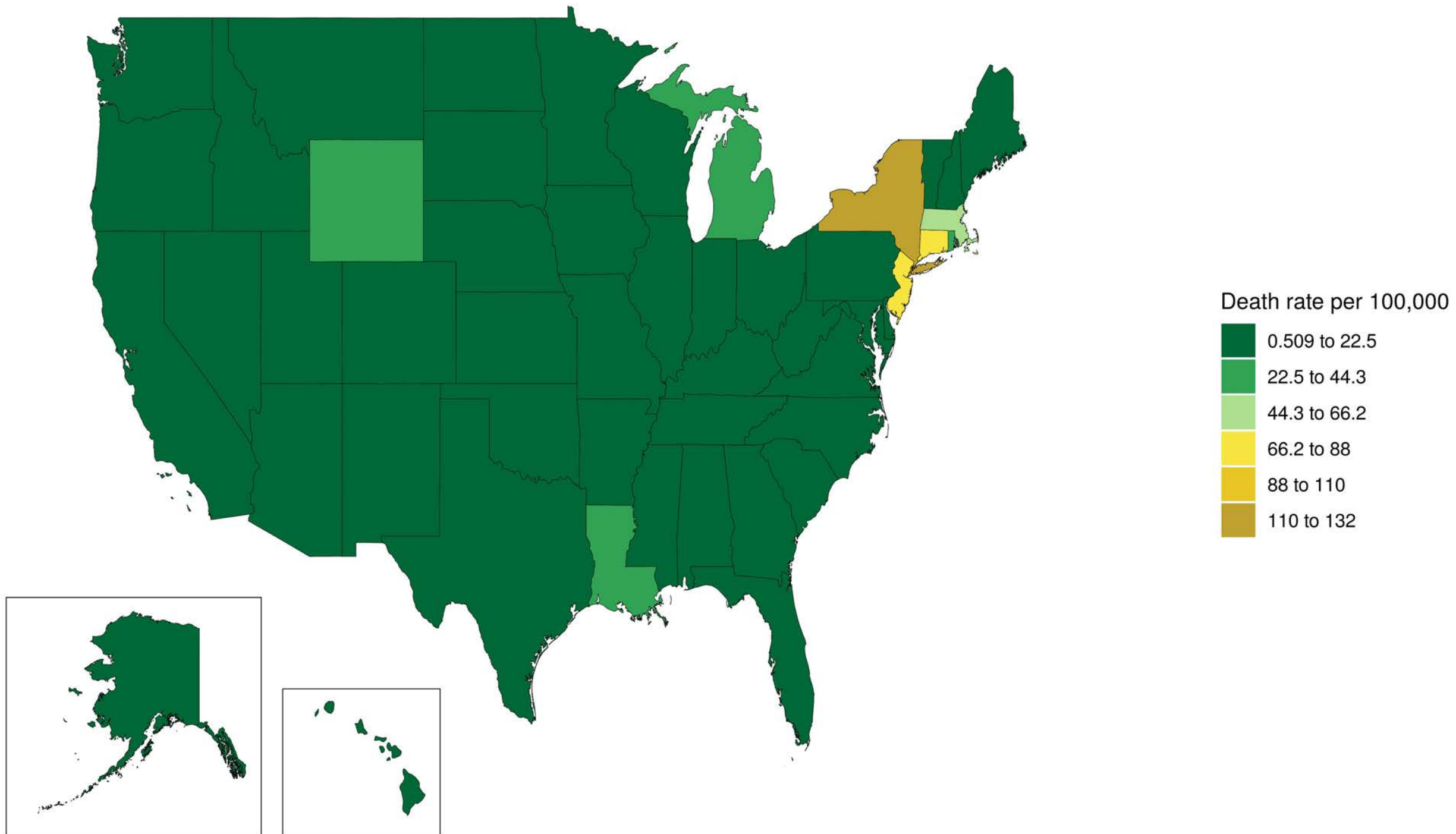
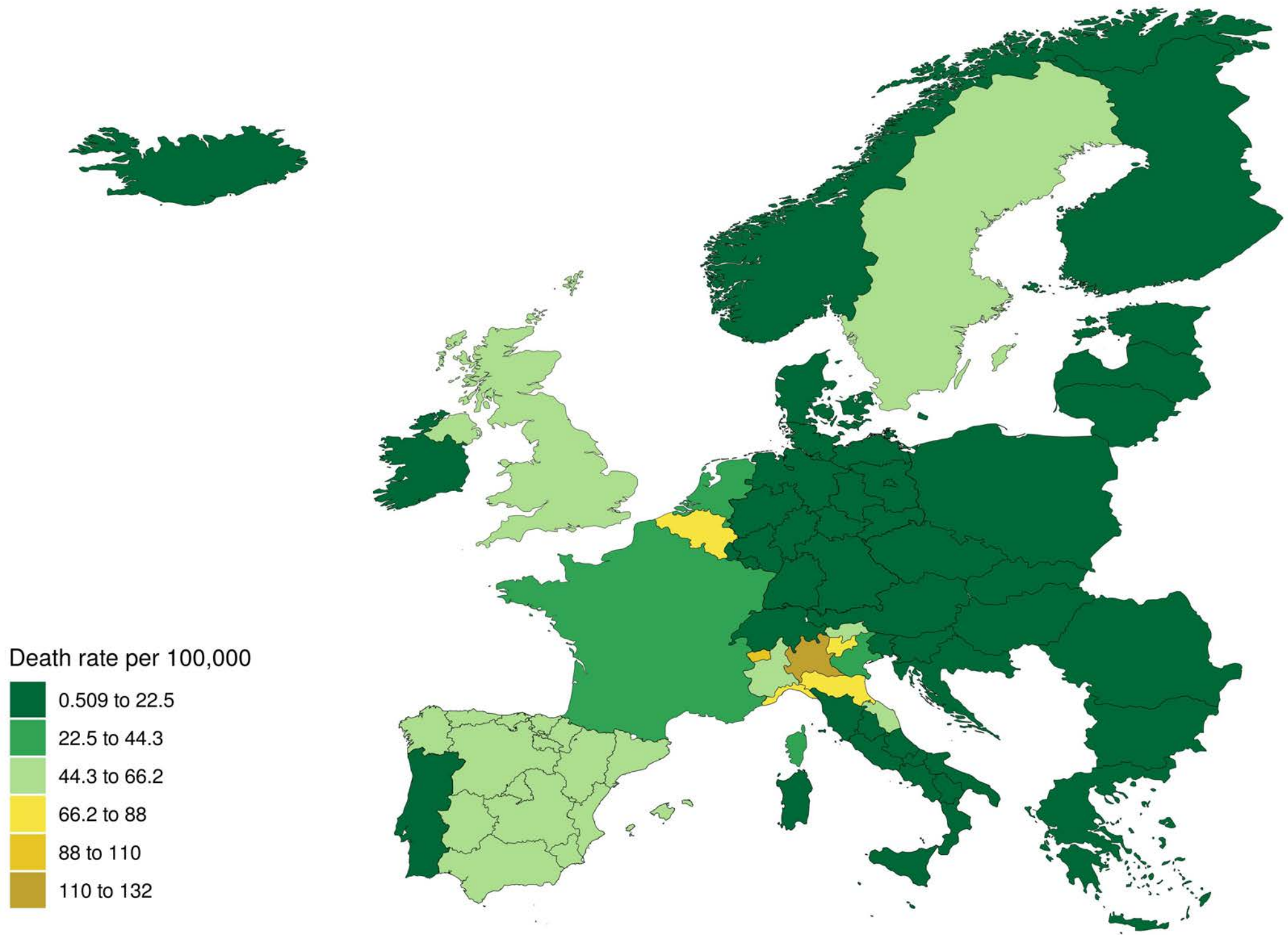


Figure 8. Expected mean cumulative death per 100,000 population
B. European Economic Area



Date at Which the Daily Death Rate Drops Below 0.3 per Million

- > May 31
- May 17 - May 31
- May 3 - May 17
- April 19 - May 3
- April 5 - April 19
- March 22 - April 5

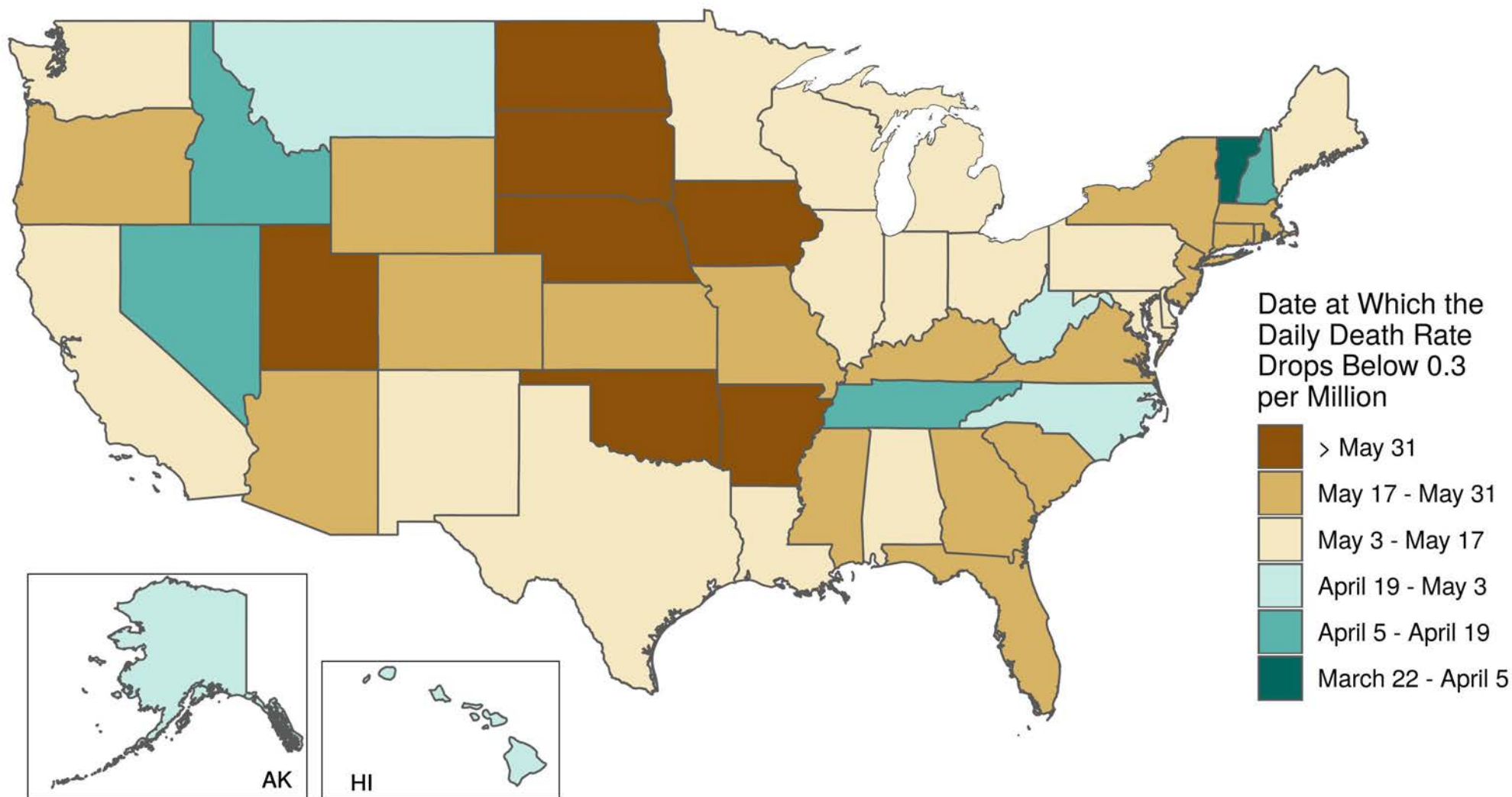


Figure 9B-- EEA

Date at Which the
Daily Death Rate
Drops Below 0.3
per Million

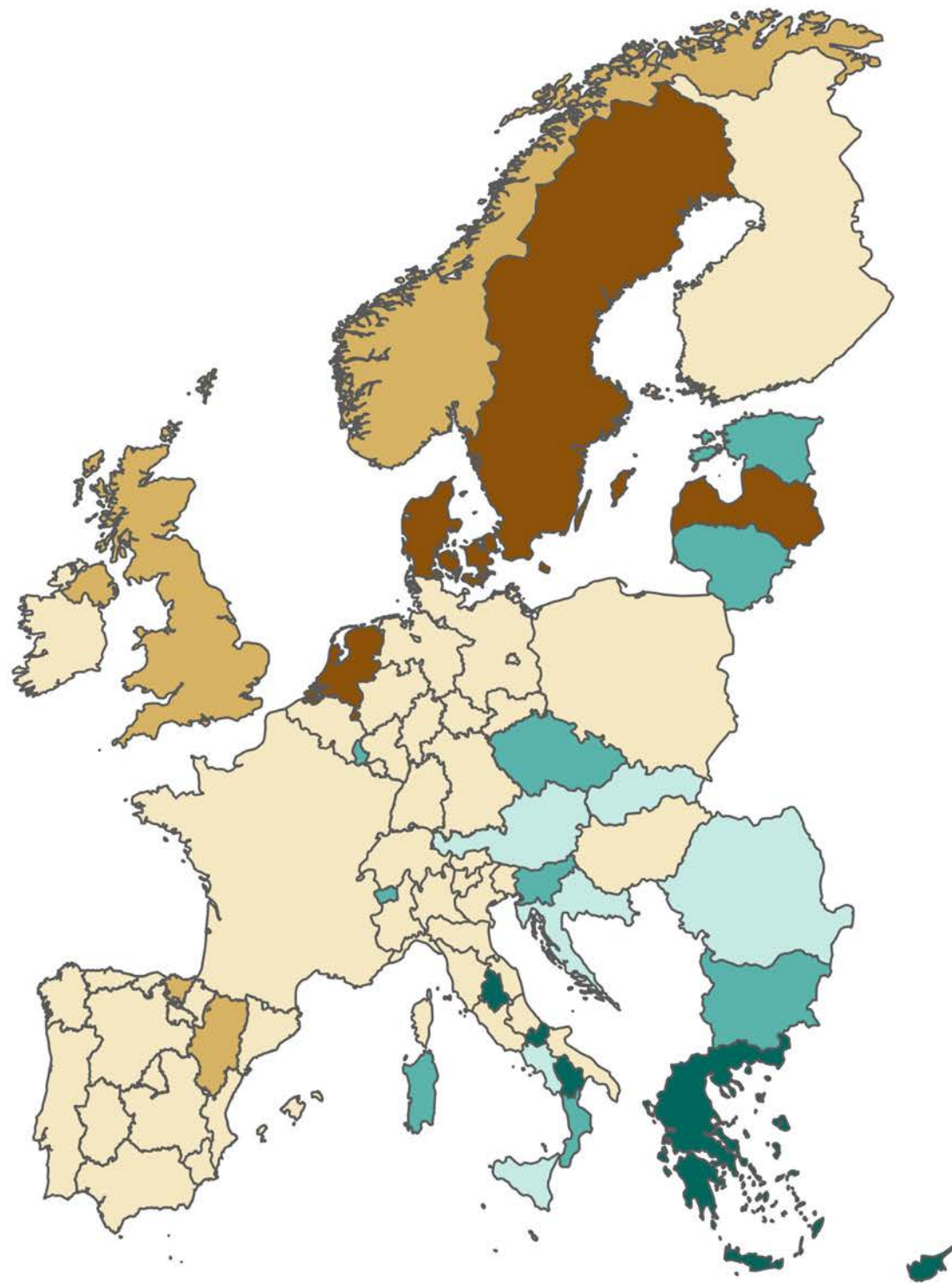


Table 1. Summary information on deaths, peak demand, peak excess demand, and aggregate demand, by location

Location name	Cumulative Deaths	Date of Peak Hospital use	Beds Used at Peak	ICU Beds Used at Peak	Ventilators Used at Peak	Excess Bed Demand	Excess ICU Demand	Cumulative Bed Days	Cumulative ICU Days	Cumulative Ventilator Days
Austria	457 (414–593)	04/06/2020 (04/06/2020–04/17/2020)	703 (679–801)	183 (179–220)	165 (163–197)	0 (0–0)	0 (0–0)	703 (13321–20478)	4062 (3608–5343)	3600 (3204–4719)
Belgium	8039 (5416–15180)	04/11/2020 (04/11/2020–04/18/2020)	10321 (9994–27826)	2730 (2544–7094)	2432 (2320–6603)	0 (0–1078)	1931 (1746–6295)	10321 (171751–506232)	70826 (47069–134970)	62930 (41880–119972)
Bulgaria	47 (38–86)	04/12/2020 (04/11/2020–04/17/2020)	70 (61–187)	19 (17–47)	17 (16–44)	0 (0–0)	0 (0–0)	70 (1138–3134)	425 (315–800)	376 (281–699)
Croatia	56 (35–114)	04/14/2020 (04/12/2020–04/18/2020)	97 (64–280)	25 (19–68)	23 (17–64)	0 (0–0)	0 (0–0)	97 (1044–4082)	498 (294–1052)	442 (262–923)
Cyprus	18 (14–33)	03/28/2020 (03/28/2020–04/18/2020)	37 (30–83)	8 (8–19)	8 (7–17)	0 (0–0)	0 (0–0)	37 (446–1528)	169 (116–344)	146 (103–298)
Czechia	194 (170–274)	04/09/2020 (04/09/2020–04/15/2020)	358 (340–535)	89 (86–136)	79 (78–123)	0 (0–0)	0 (0–0)	358 (5711–10170)	1766 (1508–2541)	1555 (1333–2228)
Denmark	683 (354–1637)	04/18/2020 (04/04/2020–04/18/2020)	549 (520–1885)	139 (131–438)	124 (119–405)	0 (0–0)	47 (39–346)	549 (11663–58026)	6155 (3103–14980)	5436 (2744–13196)
Estonia	57 (36–135)	04/03/2020 (04/03/2020–04/18/2020)	79 (70–211)	20 (18–50)	18 (17–48)	0 (0–0)	0 (0–9)	79 (1034–4639)	501 (297–1214)	445 (266–1076)
Finland	118 (76–257)	04/13/2020 (04/11/2020–04/18/2020)	150 (137–400)	40 (38–102)	37 (35–94)	0 (0–0)	0 (0–41)	150 (2278–8531)	1043 (644–2279)	926 (576–2019)
France	22555 (19455–29314)	04/02/2020 (04/02/2020–04/16/2020)	25795 (25297–32686)	6975 (6907–8803)	6266 (6213–7968)	0 (0–0)	5214 (5146–7042)	25795 (612478–957724)	197059 (168591–258463)	175462 (150150–229655)
Germany	4957 (3697–9379)	04/11/2020 (04/11/2020–04/17/2020)	6322 (6241–16734)	1778 (1637–4432)	1596 (1481–4130)	0 (0–0)	0 (0–0)	6322 (114421–296138)	42929 (31823–81389)	38317 (28433–72531)
Bavaria	1431 (1086–2741)	04/11/2020 (04/11/2020–04/17/2020)	1809 (1760–4998)	514 (473–1322)	461 (428–1236)	0 (0–0)	0 (0–0)	1809 (33175–87392)	12393 (9306–23942)	11062 (8328–21320)
Berlin	159 (81–455)	04/16/2020 (04/11/2020–04/18/2020)	260 (147–1023)	69 (38–259)	64 (36–245)	0 (0–0)	0 (0–0)	260 (2327–14389)	1374 (670–3984)	1226 (603–3521)
Brandenburg	70 (54–126)	04/15/2020 (04/05/2020–04/17/2020)	119 (108–313)	34 (28–80)	31 (27–76)	0 (0–0)	0 (0–0)	119 (1535–4141)	604 (447–1104)	539 (401–983)
Bremen	26 (21–50)	04/09/2020 (04/09/2020–04/18/2020)	48 (42–95)	13 (12–26)	12 (11–24)	0 (0–0)	0 (0–0)	48 (553–1654)	230 (165–445)	205 (149–394)
Hamburg	139 (84–321)	04/16/2020 (04/06/2020–04/18/2020)	217 (159–606)	60 (45–156)	55 (42–146)	0 (0–0)	0 (0–0)	217 (2433–10064)	1205 (700–2751)	1075 (629–2447)
Hesse	290 (196–644)	04/14/2020 (04/11/2020–04/18/2020)	423 (360–1221)	117 (98–315)	106 (90–295)	0 (0–0)	0 (0–0)	423 (5809–20528)	2515 (1652–5607)	2245 (1481–4988)
Lower Saxony	326 (253–569)	04/11/2020 (04/11/2020–04/17/2020)	461 (441–974)	124 (121–257)	114 (112–235)	0 (0–0)	0 (0–0)	461 (7553–18495)	2820 (2142–5025)	2517 (1917–4454)
Mecklenburg–Vorpommern	17 (13–35)	04/03/2020 (04/03/2020–04/17/2020)	35 (30–79)	9 (9–19)	9 (8–18)	0 (0–0)	0 (0–0)	35 (330–1195)	151 (99–314)	135 (91–279)
North Rhine–Westphalia	841 (692–1239)	04/11/2020 (04/11/2020–04/16/2020)	1187 (1153–2098)	321 (306–552)	286 (281–512)	0 (0–0)	0 (0–0)	1187 (21113–39503)	7285 (5924–10804)	6501 (5294–9643)
Rhineland–Palatinate	170 (93–498)	04/16/2020 (04/11/2020–04/18/2020)	252 (153–1096)	67 (44–274)	61 (41–260)	0 (0–0)	0 (0–0)	252 (2680–15767)	1473 (774–4321)	1315 (695–3848)
Saarland	116 (71–267)	04/11/2020 (04/11/2020–04/17/2020)	195 (181–484)	52 (41–122)	48 (39–114)	0 (0–0)	0 (0–0)	195 (2077–8513)	1006 (603–2312)	898 (540–2054)
Saxony–Anhalt	36 (27–74)	04/09/2020 (04/09/2020–04/18/2020)	54 (47–166)	15 (14–45)	14 (13–42)	0 (0–0)	0 (0–0)	54 (716–2464)	315 (213–655)	281 (193–584)
Saxony	137 (94–276)	04/16/2020 (04/11/2020–04/17/2020)	201 (169–517)	57 (45–131)	52 (41–124)	0 (0–0)	0 (0–0)	201 (2765–8860)	1182 (796–2412)	1055 (714–2152)
Schleswig–Holstein	70 (55–113)	04/10/2020 (04/10/2020–04/18/2020)	110 (100–190)	28 (26–53)	25 (24–49)	0 (0–0)	0 (0–0)	110 (1553–3738)	609 (454–1002)	543 (408–892)
Thuringia	67 (45–135)	04/14/2020 (04/11/2020–04/16/2020)	112 (96–211)	31 (26–54)	29 (24–50)	0 (0–0)	0 (0–0)	112 (1255–4305)	576 (367–1161)	514 (330–1037)
Greece	119 (105–176)	04/01/2020 (04/01/2020–04/17/2020)	149 (137–246)	41 (40–68)	38 (36–63)	0 (0–0)	0 (0–0)	149 (2880–5705)	1018 (852–1566)	912 (769–1398)
Hungary	305 (153–795)	04/18/2020 (04/10/2020–04/18/2020)	507 (342–1907)	129 (85–435)	116 (79–408)	0 (0–0)	0 (0–0)	507 (5076–27919)	2757 (1357–7156)	2433 (1199–6297)
Iceland	19 (9–81)	04/06/2020 (04/06/2020–05/04/2020)	20 (16–72)	5 (4–18)	5 (4–16)	0 (0–0)	0 (0–5)	20 (236–3114)	175 (68–773)	153 (62–676)
Ireland	890 (516–2297)	04/15/2020 (04/11/2020–04/18/2020)	1410 (1149–5741)	327 (271–1201)	294 (245–1122)	0 (0–2438)	256 (200–1130)	1410 (19072–90886)	8379 (4763–22025)	7316 (4171–19214)
Italy	26007 (23589–31056)	03/28/2020 (03/28/2020–04/17/2020)	24029 (23651–24429)	6681 (6630–6825)	6089 (6046–6249)	0 (0–0)	4622 (4571–4766)	24029 (702638–951530)	222179 (199885–266815)	199048 (179250–238960)
Abruzzo	286 (255–354)	03/29/2020 (03/29/2020–04/18/2020)	322 (306–347)	91 (88–102)	84 (82–93)	0 (0–0)	0 (0–0)	322 (7219–11051)	2437 (2110–3073)	2185 (1900–2743)
Basilicata	23 (22–30)	03/31/2020 (03/31/2020–04/15/2020)	36 (31–43)	10 (9–12)	9 (9–11)	0 (0–0)	0 (0–0)	36 (541–1000)	197 (167–266)	176 (153–237)
Calabria	77 (73–94)	03/31/2020 (03/31/2020–03/31/2020)	130 (120–141)	33 (32–34)	30 (29–31)	0 (0–0)	0 (0–0)	130 (2044–3196)	665 (593–847)	594 (535–753)
Campania	316 (294–372)	03/23/2020 (03/23/2020–04/15/2020)	394 (374–419)	107 (104–110)	94 (92–97)	0 (0–0)	0 (0–0)	394 (9413–13085)	2819 (2550–3382)	2498 (2264–2990)
Emilia–Romagna	3297 (3065–3764)	03/26/2020 (03/26/2020–03/26/2020)	2727 (2634–2828)	784 (769–799)	705 (694–717)	0 (0–0)	0 (0–0)	2727 (87661–114738)	27950 (25536–32304)	25092 (22981–28980)
Friuli–Venezia Giulia	256 (230–312)	03/29/2020 (03/29/2020–03/29/2020)	241 (229–255)	68 (66–70)	62 (61–65)	0 (0–0)	0 (0–0)	241 (6383–9640)	2166 (1889–2691)	1945 (1703–2409)
Lazio	376 (335–464)	03/30/2020 (03/30/2020–04/15/2020)	381 (365–431)	103 (100–120)	93 (91–109)	0 (0–0)	0 (0–0)	381 (9920–15050)	3248 (2820–4093)	2902 (2529–3644)
Liguria	1046 (914–1290)	03/27/2020 (03/27/2020–04/18/2020)	799 (776–994)	244 (240–290)	221 (217–268)	0 (0–0)	0 (0–0)	799 (24640–36922)	8677 (7451–10830)	7838 (6743–9778)
Lombardia	13162 (12220–15146)	03/27/2020 (03/27/2020–03/27/2020)	13311 (12956–13654)	3715 (3666–3767)	3371 (3332–3412)	0 (0–0)	0 (0–0)	13311 (363813–476190)	112990 (103300–131753)	101090 (92642–117739)
Marche	879 (804–1026)	03/29/2020 (03/29/2020–03/29/2020)	904 (876–935)	260 (256–265)	237 (233–240)	0 (0–0)	0 (0–0)	904 (22598–30732)	7407 (6652–8749)	6660 (6001–7853)
Molise	16 (16–16)	03/19/2020 (03/19/2020–03/19/2020)	28 (24–33)	8 (8–9)	8 (7–8)	0 (0–0)	0 (0–0)	28 (367–605)	135 (117–158)	121 (108–139)
Piemonte	2882 (2365–3876)	04/12/2020 (04/11/2020–04/18/2020)	2665 (2570–4430)	746 (734–1242)	681 (673–1142)	0 (0–0)	0 (0–0)	2665 (67471–116914)	24351 (19743–33335)	21881 (17756–29822)
Provincia autonoma di Bolzano	273 (237–337)	03/31/2020 (03/31/2020–03/31/2020)	409 (390–428)	113 (111–116)	104 (102–106)	0 (0–0)	0 (0–0)	409 (7129–11229)	2382 (2005–2996)	2121 (1792–2663)
Provincia autonoma di Trento	402 (341–556)	03/26/2020 (03/26/2020–04/18/2020)	448 (429–627)	116 (113–172)	105 (103–160)	0 (0–0)	0 (0–0)	448 (10092–17737)	3471 (2873–4860)	3101 (2575–4336)
Puglia	383 (330–480)	04/01/2020 (04/01/2020–04/17/2020)	440 (421–467)	115 (113–126)	107 (105–114)	0 (0–0)	0 (0–0)	440 (9882–15658)	3320 (2787–4238)	2962 (2500–3766)
Sardegna	92 (85–120)	04/06/2020 (04/06/2020–04/15/2020)	140 (130–165)	38 (37–46)	35 (34–42)	0 (0–0)	0 (0–0)	140 (2408–4014)	799 (696–1073)	714 (626–953)
Sicilia	208 (192–252)	03/27/2020 (03/27/2020–03/27/2020)	269 (252–285)	69 (67–78)	64 (62–70)	0 (0–0)	0 (0–0)	269 (5727–8398)	1817 (1615–2242)	1619 (1447–1993)
Toscana	724 (633–913)	04/11/2020 (04/11/2020–04/17/2020)	701 (677–994)	198 (194–281)	180 (178–258)	0 (0–0)	0 (0–0)	701 (17870–27400)	6114 (5251–7804)	5496 (4735–7006)
Umbria	55 (55–60)	03/26/2020 (03/26/2020–03/26/2020)	75 (67–83)	23 (22–24)	21 (20–22)	0 (0–0)	0 (0–0)	75 (1398–1951)	466 (429–532)	420 (390–475)

Location name	Cumulative Deaths	Date of Peak Hospital use	Beds Used at Peak	ICU Beds Used at Peak	Ventilators Used at Peak	Excess Bed Demand	Excess ICU Demand	Cumulative Bed Days	Cumulative ICU Days	Cumulative Ventilator Days
Valle d'Aosta	135 (122–178)	03/31/2020 (03/31/2020–03/31/2020)	198 (185–211)	55 (53–57)	50 (49–52)	0 (0–0)	0 (0–0)	198 (3392–5682)	1156 (999–1557)	1035 (900–1389)
Veneto	1118 (1001–1415)	03/26/2020 (03/26/2020–04/16/2020)	1084 (1051–1465)	298 (293–403)	270 (266–369)	0 (0–0)	0 (0–0)	1084 (29857–44885)	9613 (8477–12327)	8596 (7601–10997)
Latvia	80 (11–285)	04/26/2020 (04/07/2020–04/25/2020)	91 (14–330)	24 (4–87)	22 (4–79)	0 (0–0)	0 (0–23)	91 (162–10786)	705 (53–2882)	626 (45–2559)
Lithuania	39 (32–69)	04/10/2020 (04/10/2020–04/17/2020)	68 (60–140)	17 (17–37)	16 (16–34)	0 (0–0)	0 (0–0)	68 (900–2367)	345 (260–617)	307 (234–544)
Luxembourg	116 (71–265)	04/06/2020 (04/06/2020–04/18/2020)	153 (140–487)	35 (34–106)	32 (31–99)	0 (0–0)	0 (0–70)	153 (2322–9997)	1073 (624–2469)	941 (550–2173)
Netherlands	6814 (4035–14051)	04/16/2020 (04/03/2020–04/18/2020)	5761 (4908–15311)	1452 (1269–3569)	1303 (1133–3339)	0 (0–0)	533 (350–2650)	5761 (133187–501154)	61396 (35169–129013)	54221 (31230–114002)
Norway	280 (167–624)	04/07/2020 (04/07/2020–04/18/2020)	282 (265–828)	73 (71–194)	66 (64–180)	0 (0–0)	0 (0–93)	282 (5510–23323)	2547 (1462–5904)	2243 (1294–5206)
Portugal	980 (661–2003)	04/16/2020 (04/11/2020–04/18/2020)	1096 (952–3928)	302 (266–996)	271 (240–940)	0 (0–0)	190 (154–884)	1096 (20181–63950)	8507 (5650–17513)	7588 (5050–15593)
Poland	646 (337–2020)	04/16/2020 (04/11/2020–04/18/2020)	771 (678–3389)	196 (180–753)	174 (163–702)	0 (0–0)	0 (0–0)	771 (11554–72641)	5904 (3011–18409)	5195 (2656–16211)
Romania	618 (413–1489)	04/16/2020 (04/07/2020–04/18/2020)	923 (749–4173)	241 (188–1034)	215 (170–973)	0 (0–0)	0 (0–0)	923 (13782–53650)	5561 (3656–13879)	4913 (3233–12219)
Slovakia	252 (41–955)	04/18/2020 (04/19/2020–04/18/2020)	1123 (149–4409)	237 (33–935)	226 (30–886)	0 (0–0)	49 (0–747)	1123 (1506–37134)	2374 (378–9002)	2072 (331–7865)
Slovenia	70 (61–105)	04/06/2020 (04/06/2020–04/18/2020)	124 (113–177)	30 (29–48)	28 (27–44)	0 (0–0)	0 (0–8)	124 (1803–3718)	622 (507–951)	552 (454–840)
Spain	23680 (20269–31608)	03/29/2020 (03/29/2020–04/17/2020)	26474 (26066–35145)	6961 (6905–9398)	6343 (6302–8652)	0 (0–3355)	5597 (5541–8034)	26474 (637743–1018635)	206496 (175544–276670)	183962 (156513–246374)
Andalucia	1099 (950–1492)	04/06/2020 (04/06/2020–04/16/2020)	1486 (1445–1900)	414 (408–515)	377 (372–470)	0 (0–0)	0 (0–0)	1486 (29342–48738)	9583 (8150–13152)	8539 (7278–11707)
Aragon	759 (605–1056)	04/04/2020 (04/04/2020–04/16/2020)	815 (786–1182)	234 (230–318)	210 (207–289)	0 (0–0)	0 (0–0)	815 (18687–34310)	6620 (5204–9286)	5897 (4642–8263)
Asturias	225 (172–410)	04/09/2020 (04/09/2020–04/17/2020)	284 (269–768)	75 (73–201)	68 (67–189)	0 (0–0)	0 (0–0)	284 (5126–13353)	1966 (1455–3556)	1752 (1301–3175)
Balearic Islands	154 (131–228)	03/28/2020 (03/28/2020–04/16/2020)	203 (190–333)	53 (51–88)	49 (47–81)	0 (0–0)	0 (0–0)	203 (3868–7619)	1340 (1099–2016)	1194 (986–1796)
Canary Islands	115 (107–134)	03/28/2020 (03/28/2020–03/28/2020)	195 (181–211)	53 (52–55)	49 (47–50)	0 (0–0)	0 (0–0)	195 (3115–4594)	999 (888–1209)	890 (797–1071)
Cantabria	173 (137–295)	03/31/2020 (03/31/2020–04/17/2020)	212 (198–475)	55 (53–124)	49 (48–115)	0 (0–0)	0 (0–0)	212 (4080–9799)	1507 (1158–2616)	1342 (1035–2324)
Castilla–La Mancha	2475 (1959–3630)	04/08/2020 (04/08/2020–04/17/2020)	2432 (2362–4882)	656 (646–1251)	587 (579–1161)	0 (0–0)	0 (0–0)	2432 (60936–118300)	21584 (16887–31923)	19230 (15077–28405)
Catalonia	4743 (4100–6320)	03/29/2020 (03/28/2020–04/17/2020)	6281 (6028–6928)	1657 (1626–1826)	1526 (1502–1687)	0 (0–0)	0 (0–0)	6281 (125495–206956)	41367 (35004–55711)	36852 (31290–49585)
Community of Madrid	7867 (7181–9195)	03/24/2020 (03/24/2020–03/24/2020)	9182 (8895–9492)	2398 (2358–2440)	2176 (2147–2210)	0 (0–0)	0 (0–0)	9182 (221673–303231)	68614 (61563–81483)	61125 (54960–72519)
Extremadura	468 (378–700)	03/28/2020 (03/28/2020–04/17/2020)	561 (539–931)	148 (145–244)	135 (133–226)	0 (0–0)	0 (0–0)	561 (11587–22901)	4083 (3236–6173)	3637 (2889–5493)
Galicia	378 (324–518)	03/31/2020 (03/31/2020–04/16/2020)	530 (507–615)	133 (130–163)	124 (122–149)	0 (0–0)	0 (0–0)	530 (9859–17020)	3296 (2767–4562)	2936 (2474–4052)
La Rioja	345 (279–515)	04/06/2020 (04/06/2020–04/17/2020)	384 (365–640)	105 (102–171)	95 (93–156)	0 (0–0)	0 (0–0)	384 (8494–17097)	3013 (2383–4593)	2684 (2130–4073)
Murcia	129 (111–196)	04/02/2020 (04/02/2020–04/17/2020)	210 (197–308)	56 (54–82)	51 (49–77)	0 (0–0)	0 (0–0)	210 (3270–6519)	1123 (929–1727)	1000 (832–1539)
Navarre	319 (270–469)	03/29/2020 (03/29/2020–04/16/2020)	436 (416–647)	113 (111–167)	104 (102–156)	0 (0–0)	0 (0–0)	436 (8166–15535)	2778 (2290–4171)	2475 (2049–3705)
Valencian Community	1220 (1016–1762)	03/30/2020 (03/30/2020–04/17/2020)	1505 (1461–2394)	395 (389–630)	361 (356–585)	0 (0–0)	0 (0–0)	1505 (31510–57416)	10640 (8738–15508)	9480 (7803–13803)
Sweden	5890 (1965–16883)	04/29/2020 (04/11/2020–04/21/2020)	4173 (2350–13825)	1099 (652–3672)	979 (577–3235)	2365 (542–12017)	1020 (573–3593)	4173 (62421–568761)	52143 (17091–151841)	46270 (15174–134608)
United Kingdom	37521 (17625–89385)	04/20/2020 (04/08/2020–04/18/2020)	42407 (27463–132942)	10646 (6947–31240)	9577 (6312–28710)	24642 (9698–115177)	3865 (166–24459)	42407 (600161–3074135)	337062 (157746–800822)	297904 (139414–707443)
United States of America	60308 (34063–140381)	04/15/2020 (04/11/2020–04/18/2020)	68884 (57922–226051)	18286 (15494–54755)	16631 (14188–51508)	9079 (3857–88921)	9356 (7718–38347)	68884 (1049489–4558549)	523419 (292547–1228976)	466888 (261704–1093763)
Alabama	295 (145–802)	04/17/2020 (04/11/2020–04/18/2020)	329 (219–1245)	96 (64–350)	89 (60–331)	0 (0–0)	0 (0–0)	329 (3706–21985)	2421 (1167–6624)	2193 (1061–6010)
Arizona	267 (158–682)	04/10/2020 (04/10/2020–04/18/2020)	312 (294–1061)	77 (74–237)	69 (67–220)	0 (0–0)	0 (0–0)	312 (5395–26079)	2454 (1403–6486)	2155 (1239–5699)
Arkansas	158 (37–527)	04/30/2020 (04/12/2020–05/02/2020)	129 (74–519)	32 (20–128)	28 (19–112)	0 (0–0)	0 (0–0)	129 (1188–19809)	1453 (320–4942)	1276 (283–4332)
California	1658 (1068–3548)	04/14/2020 (04/11/2020–04/18/2020)	2753 (2240–8233)	633 (516–1741)	563 (465–1608)	0 (0–0)	0 (0–0)	2753 (41690–144832)	15911 (10103–34295)	13827 (8795–29771)
Colorado	715 (389–1944)	04/17/2020 (04/11/2020–04/18/2020)	842 (799–3677)	205 (193–786)	181 (172–739)	0 (0–0)	0 (0–232)	842 (14205–73527)	6656 (3586–18172)	5828 (3149–15942)
Connecticut	2732 (1163–8601)	04/16/2020 (04/11/2020–04/18/2020)	3886 (2737–16784)	935 (639–3798)	860 (596–3504)	2148 (999–15046)	836 (540–3699)	3886 (39775–312943)	24819 (10391–79660)	21865 (9160–70188)
Delaware	143 (64–404)	04/17/2020 (04/11/2020–04/19/2020)	260 (162–954)	57 (31–196)	50 (29–178)	0 (0–258)	16 (0–155)	260 (2415–17243)	1392 (589–3993)	1205 (514–3451)
District of Columbia	170 (87–424)	04/15/2020 (04/11/2020–04/18/2020)	290 (238–918)	68 (53–197)	61 (49–180)	0 (0–0)	2 (0–131)	290 (3093–17063)	1607 (795–4112)	1402 (698–3572)
Florida	1363 (775–3430)	04/14/2020 (04/11/2020–04/18/2020)	1535 (1386–5229)	405 (362–1251)	367 (332–1180)	0 (0–0)	0 (0–0)	1535 (24580–113743)	12021 (6705–30351)	10675 (5966–26980)
Georgia	1369 (670–3828)	04/15/2020 (04/05/2020–04/18/2020)	1358 (1079–5783)	350 (287–1291)	311 (262–1209)	0 (0–0)	0 (0–702)	1358 (22705–140596)	12398 (5967–36009)	10936 (5278–31752)
Hawaii	38 (10–121)	04/18/2020 (04/01/2020–04/18/2020)	116 (20–434)	26 (6–100)	25 (5–95)	0 (0–0)	0 (0–55)	116 (294–4448)	353 (84–1122)	310 (75–987)
Idaho	63 (41–145)	04/10/2020 (04/10/2020–04/18/2020)	119 (109–309)	29 (25–73)	26 (24–67)	0 (0–0)	0 (0–0)	119 (1354–5481)	583 (358–1357)	511 (316–1184)
Illinois	2259 (1212–5054)	04/17/2020 (04/11/2020–04/18/2020)	3459 (2672–11295)	837 (638–2464)	752 (581–2310)	0 (0–0)	0 (0–1333)	3459 (43782–190312)	20895 (11093–47173)	18327 (9744–41412)
Indiana	903 (519–2529)	04/15/2020 (04/10/2020–04/18/2020)	1374 (1134–5590)	329 (264–1212)	294 (237–1130)	0 (0–0)	0 (0–506)	1374 (18792–94944)	8390 (4762–23466)	7349 (4176–20542)
Iowa	624 (106–2603)	05/07/2020 (04/11/2020–05/08/2020)	580 (137–2723)	148 (35–699)	132 (33–621)	0 (0–0)	0 (0–453)	580 (3537–93259)	5634 (942–24278)	4973 (830–21439)
Kansas	187 (88–500)	04/17/2020 (04/09/2020–04/18/2020)	250 (207–843)	58 (51–180)	51 (46–160)	0 (0–0)	0 (0–0)	250 (3307–20908)	1824 (810–4860)	1579 (709–4199)
Kentucky	407 (160–1213)	04/21/2020 (04/08/2020–04/21/2020)	455 (313–1806)	110 (70–421)	97 (62–378)	0 (0–0)	0 (0–0)	455 (5660–46733)	3789 (1455–11540)	3318 (1275–10092)
Louisiana	1685 (1269–2767)	04/14/2020 (04/11/2020–04/18/2020)	2619 (2355–5469)	648 (563–1265)	576 (505–1154)	0 (0–0)	171 (86–788)	2619 (47125–107918)	15783 (11750–26198)	13798 (10287–22824)
Maine	51 (27–134)	04/16/2020 (04/11/2020–04/19/2020)	83 (53–274)	19 (13–58)	17 (12–53)	0 (0–0)	0 (0–0)	83 (916–5449)	486 (235–1300)	424 (207–1131)

Location name	Cumulative Deaths	Date of Peak Hospital use	Beds Used at Peak	ICU Beds Used at Peak	Ventilators Used at Peak	Excess Bed Demand	Excess ICU Demand	Cumulative Bed Days	Cumulative ICU Days	Cumulative Ventilator Days
Maryland	914 (373–3160)	04/18/2020 (04/09/2020–04/18/2020)	2405 (1455–11111)	441 (258–1857)	376 (228–1629)	0 (0–7150)	175 (0–1591)	2405 (20439–178003)	10363 (4145–35424)	8658 (3467–29604)
Massachusetts	3236 (1289–9426)	04/18/2020 (04/10/2020–04/18/2020)	2830 (1967–10962)	964 (685–3581)	906 (656–3459)	0 (0–6114)	687 (408–3304)	2830 (27062–211980)	24872 (9684–73469)	22963 (8946–67939)
Michigan	3304 (2131–6780)	04/10/2020 (04/10/2020–04/18/2020)	4748 (4615–14655)	1158 (1139–3347)	1048 (1033–3110)	0 (0–4501)	416 (397–2605)	4748 (74403–250353)	30192 (19234–63001)	26566 (16956–55325)
Minnesota	195 (95–605)	04/18/2020 (04/10/2020–04/18/2020)	293 (230–1350)	69 (53–278)	62 (48–259)	0 (0–0)	0 (0–0)	293 (3379–23752)	1838 (855–5748)	1604 (751–5002)
Mississippi	369 (150–1298)	04/23/2020 (04/06/2020–04/21/2020)	410 (271–1985)	102 (64–482)	90 (58–428)	0 (0–0)	0 (0–142)	410 (5225–49082)	3421 (1349–12188)	2999 (1186–10683)
Missouri	362 (188–1027)	04/15/2020 (04/09/2020–04/18/2020)	474 (382–1913)	120 (94–424)	107 (85–397)	0 (0–0)	0 (0–0)	474 (6508–37351)	3322 (1694–9446)	2919 (1493–8278)
Montana	17 (8–43)	04/17/2020 (03/30/2020–04/17/2020)	40 (24–163)	10 (7–39)	9 (6–37)	0 (0–0)	0 (0–0)	40 (224–1671)	152 (63–414)	134 (56–367)
Nebraska	127 (21–479)	05/01/2020 (04/06/2020–04/29/2020)	101 (46–438)	25 (11–110)	22 (10–98)	0 (0–0)	0 (0–0)	101 (644–17975)	1169 (178–4524)	1027 (158–3971)
Nevada	257 (149–562)	04/07/2020 (04/07/2020–04/18/2020)	364 (344–1219)	87 (83–256)	79 (77–237)	0 (0–0)	0 (0–73)	364 (5554–23196)	2455 (1372–5511)	2135 (1198–4795)
New Hampshire	55 (32–127)	04/15/2020 (04/10/2020–04/18/2020)	95 (79–296)	24 (18–68)	21 (17–63)	0 (0–0)	0 (0–0)	95 (1033–4793)	503 (276–1186)	442 (245–1035)
New Jersey	6952 (4160–14367)	04/15/2020 (04/11/2020–04/18/2020)	10480 (8644–27673)	2568 (2078–6284)	2324 (1902–5855)	2665 (829–19858)	2103 (1614–5819)	10480 (146278–527991)	63655 (37795–133132)	55973 (33286–117091)
New Mexico	80 (36–229)	04/18/2020 (04/10/2020–04/18/2020)	118 (102–458)	29 (25–104)	26 (23–96)	0 (0–0)	0 (0–0)	118 (1169–8794)	739 (314–2196)	649 (278–1926)
New York	21812 (13623–42798)	04/15/2020 (04/10/2020–04/17/2020)	17346 (16061–49532)	6039 (5567–16551)	5603 (5208–15854)	4336 (3051–36522)	5321 (4849–15833)	17346 (295917–954519)	167923 (104084–329040)	154958 (96145–303878)
North Carolina	251 (156–529)	04/15/2020 (04/11/2020–04/18/2020)	523 (368–1366)	123 (90–304)	112 (81–281)	0 (0–0)	0 (0–0)	523 (5585–20350)	2342 (1420–4965)	2050 (1247–4337)
North Dakota	149 (9–652)	05/04/2020 (04/10/2020–05/06/2020)	137 (20–630)	34 (5–157)	30 (4–138)	0 (0–0)	0 (0–71)	137 (255–24256)	1375 (73–6065)	1207 (65–5327)
Ohio	716 (429–1645)	04/15/2020 (04/11/2020–04/18/2020)	1230 (934–3759)	300 (226–847)	274 (207–794)	0 (0–0)	0 (0–0)	1230 (14924–60064)	6547 (3863–15215)	5760 (3401–13374)
Oklahoma	359 (149–1166)	04/15/2020 (04/06/2020–04/20/2020)	359 (250–1396)	86 (64–335)	77 (58–299)	0 (0–0)	0 (0–0)	359 (5161–45818)	3331 (1333–11331)	2919 (1174–9939)
Oregon	131 (69–318)	04/17/2020 (04/08/2020–04/18/2020)	173 (145–603)	38 (33–116)	33 (30–105)	0 (0–0)	0 (0–0)	173 (2815–14748)	1326 (662–3262)	1138 (571–2797)
Pennsylvania	1707 (914–4555)	04/15/2020 (04/11/2020–04/18/2020)	3926 (3359–14724)	773 (612–2512)	663 (549–2291)	0 (0–329)	0 (0–1469)	3926 (45991–236824)	18443 (9717–49122)	15578 (8226–41512)
Rhode Island	438 (121–1656)	04/23/2020 (04/09/2020–04/24/2020)	610 (224–2628)	152 (56–655)	136 (52–587)	0 (0–1833)	111 (15–614)	610 (3996–58949)	3976 (1062–15072)	3505 (941–13269)
South Carolina	217 (127–469)	04/15/2020 (04/10/2020–04/18/2020)	277 (254–777)	68 (60–173)	62 (55–158)	0 (0–0)	0 (0–0)	277 (4394–18076)	2014 (1136–4422)	1764 (999–3878)
South Dakota	94 (7–378)	05/10/2020 (04/02/2020–05/08/2020)	102 (18–501)	26 (5–128)	23 (4–114)	0 (0–0)	0 (0–54)	102 (177–14900)	849 (52–3823)	748 (47–3362)
Tennessee	231 (136–470)	04/04/2020 (04/04/2020–04/18/2020)	282 (267–690)	71 (69–158)	65 (63–144)	0 (0–0)	0 (0–0)	282 (4630–17481)	2104 (1222–4392)	1853 (1078–3868)
Texas	957 (472–2520)	04/15/2020 (04/11/2020–04/18/2020)	1364 (1092–4851)	308 (242–1025)	270 (218–933)	0 (0–0)	0 (0–0)	1364 (18370–104777)	9239 (4451–24648)	8017 (3875–21418)
Utah	202 (40–753)	04/24/2020 (04/10/2020–04/25/2020)	332 (75–1304)	69 (16–270)	58 (14–229)	0 (0–0)	0 (0–100)	332 (1805–39658)	2192 (407–8194)	1849 (347–6921)
Vermont	40 (33–75)	04/01/2020 (04/01/2020–04/17/2020)	54 (48–158)	14 (13–36)	12 (12–34)	0 (0–0)	0 (0–2)	54 (995–2825)	364 (272–702)	321 (244–617)
Virginia	763 (277–2465)	04/23/2020 (04/10/2020–04/24/2020)	1110 (745–4374)	243 (124–949)	208 (111–815)	0 (0–0)	0 (0–620)	1110 (12399–114439)	7849 (2787–25114)	6706 (2385–21462)
Washington	694 (611–883)	04/05/2020 (04/05/2020–04/18/2020)	1043 (1008–1108)	241 (237–260)	216 (213–233)	0 (0–0)	0 (0–0)	1043 (22444–35187)	6515 (5606–8436)	5692 (4913–7359)
West Virginia	22 (12–58)	04/14/2020 (04/12/2020–04/18/2020)	47 (30–170)	11 (8–39)	10 (8–37)	0 (0–0)	0 (0–0)	47 (338–2145)	196 (96–538)	173 (86–472)
Wisconsin	302 (211–609)	04/11/2020 (04/11/2020–04/18/2020)	425 (403–1172)	108 (99–274)	95 (90–253)	0 (0–0)	0 (0–102)	425 (7243–22391)	2766 (1885–5601)	2432 (1665–4931)
Wyoming	243 (44–948)	04/30/2020 (04/24/2020–05/01/2020)	670 (117–3024)	150 (21–663)	137 (18–611)	0 (0–1955)	106 (0–619)	670 (803–44921)	2276 (223–10788)	1991 (178–9590)

Appendix A: Health Care Utilization and Capacity

1. Hospital Resource Use Simulation

The hospital use micro-simulation is run for each projected death and is run across time and across death-draws.

For each death, we:

1. Simulate the age of the deceased using normalized estimated mortality rates as the probability for belonging to that age. That is, we assign the death to $ageBin_i$ with probability $MR_{ageBin_i}(loc)/\sum_i MR_{ageBin_i}(loc)$. Call this A_D . See Age-Pattern of Mortality Rate Estimation section below for further details.
2. We determine how many days prior to death the deceased entered the hospital. Based on initial data from New York State we set this to be 6 days prior to death.
3. We assign the deceased to an ICU bed for their entire admittance period.
4. Based on A_D , we use $H:D_{A_D}$ to estimate the number of individuals of the same age group that would have entered the hospital on the same day as the deceased to result in 1 death in that age group on the date of death. This age-hospital-cohort will pass through the hospital and all are assumed to survive. See section on Hospitalization to Death Ratio Estimation section below for further details.
5. For each individual in the age-hospital-cohort, they have a 6.3% chance of getting admitted to the ICU (see note below on derivation of 6.3%).
 - a. Those that visit the ICU are assumed to have a hospital stay of 20 days, the middle 13 of which are in the ICU.
 - b. Those that don't visit the ICU are released after 8 days.
6. To determine ventilation use, we assume 85% of individuals in the ICU require invasive mechanical ventilation based on data from New York State.

By performing this simulation for each death, and each associated member of the age-hospital-cohort, we are able to summarize future hospital usage needs for general beds, ICU beds, and ventilators. Finally, using a combination of data sources, we compare the estimated number of general beds and ICU beds with availability.

Notes:

1. Based on hospital data from New York State up through Mar 31, 2020, the average ICU bed counts to hospital census was 25%. Given the assumptions about lengths of stay for

those who die, those who recover, and their duration in the ICU, the conditional probability of a recovering patient going to the ICU was back calculated to be 6.3% to keep the long-term ICU usage at 25%.

2. Age-pattern of Mortality Rate Estimation

To determine the age-pattern of mortality, we assembled available data from the following countries: China, Italy, South Korea, USA, Netherlands, Sweden, Germany. A continuous model relating age and mortality from which the average mortality for any discrete age bins can be aggregated. We assume a Poisson model for death counts and fit a monotonically increasing (shape-constrained) generalized additive model (SCAM) for mortality as a function of age, using the medians of each of the N_{loc} age bins, $ageBin_i^M(loc)$:

$$\begin{aligned} \log(E[MortalityRate_{AgeBin_i}(loc)](loc)) \\ = \log(Pop_{AgeBin_i}(loc)(loc) + f_1(ageBin_i^M(loc)) + \dots + f_k(ageBin_i^M(loc))), \end{aligned}$$

where $f()$ are monotonically increasing P-splines, and k , the number of bases functions, is between 6 and 8 and tuned for different locations. This yields continuous mortality rates by age: $MR_a(loc)$.

Similarly, assuming a Poisson model, we fit a generalized additive model (GAM) to population as a function of age, using the age groups specified in the mortality data for each location:

$$\log(E[Pop_{AgeBin_i}(loc)](loc)) = g_1(ageBin_i^M(loc)) + \dots + g_k(ageBin_i^M(loc)),$$

where $g()$ are penalized thin-plate regression splines, and k , the number of bases functions, is between 6 and 8 and tuned for different locations. This yields continuous population by age: $pop_a(loc)$.

The estimated continuous mortality rate curves are then aggregated using population weights to the pre-determined $ageBin(CDC)$ s:

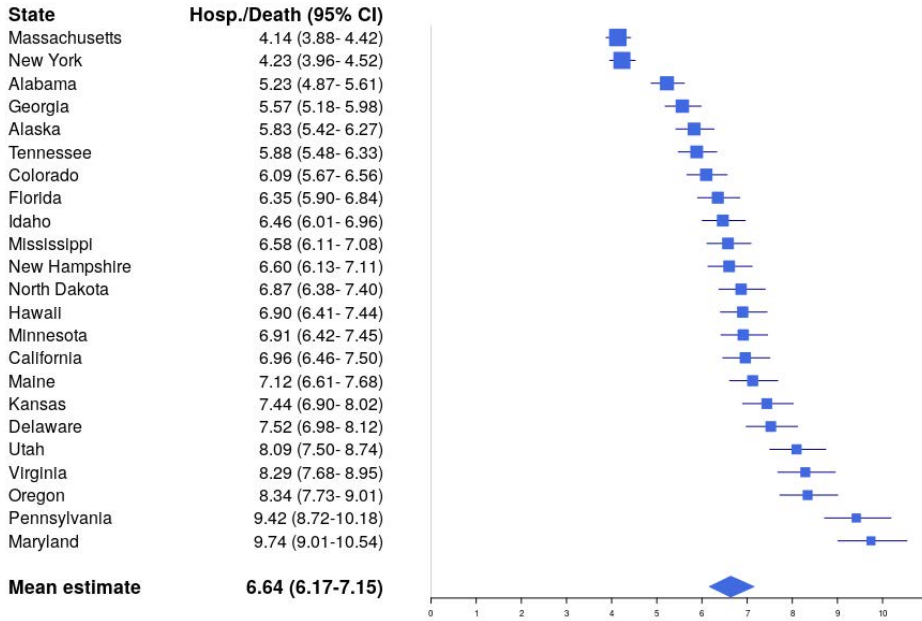
$$MR_{ageBin_i(CDC)}(loc) = \frac{\sum_{a \in ageBin_i(CDC)} MR_a(loc) * pop_a(loc)}{\sum_{a \in ageBin_i(CDC)} pop_a(loc)}.$$

3. Hospitalization to Death Ratio Estimation

To determine hospitalization, we use hospital to deaths ratios estimated directly from hospitalization and mortality data in the US and Europe. We assembled data from the following countries and US states:

We analyzed hospitalization to death ratios using random effects meta-analysis. Where available we used the location-specific ratio shown in the figure below and in the absence of data used the corresponding pooled effect for countries in Europe and states in the US.

Random effects meta-analysis of the ratio of hospital admission to deaths by location



As the hospitalization to death ratios are for all-ages only, to estimate the age-pattern of the hospitalization to death ratio, we used the age distribution of hospitalization to death ($H:D$) in the US to estimate the age-distribution for other countries and states:

$$H:D_{ageBin}(loc) = \frac{H:D_{ageBin}(US) * H:D_{allAge}(loc)}{(H:D_{ageBin}(US) * D_{ageBin}(loc))/D_{allAge}(loc)}$$

4. Imputation of hospital resources

Data on licensed bed and ICU capacity and average annual utilization were obtained from a variety of sources (see Table 1 below). We imputed the estimate of ICU beds in Malta by multiplying the number of total beds in Malta by the average ratio of ICU beds over total beds for every EEA country where we had data for both total beds and ICU beds and the data source(s) had the same year start and year end during which the data were extracted. For some EEA countries, we used estimates of critical care beds as a proxy for ICU beds. We imputed ICU utilization for all EEA countries, with the exception of Spain, Bulgaria, and Germany. To impute ICU utilization for every location except for the UK, we multiplied total bed utilization in each location by the average ratio of ICU bed utilization over total bed utilization for every EEA

country where we had data for both total bed utilization and ICU bed utilization and the data source(s) had the same year start and year end during which the data were extracted. To calculate ICU utilization in the UK, we first estimated the average number of ICU beds occupied in the UK by multiplying an estimate of ICU beds in the UK in 2013 by an estimate of the critical care occupancy rate in England in 2020. We then divided our estimate of the average number of ICU beds occupied by our most recent estimate of ICU beds in the United Kingdom – which includes ICU beds that have been added or converted to ICU beds since the COVID-19 outbreak began – to estimate ICU utilization in the UK.

Table 1. List of sources used for determining or imputing health care capacity by location

Country	Source	Citation
Australia	ANZICS Centre for Outcome and Resource Evaluation Report 2018	Australian and New Zealand Intensive Care Society (ANZICS). ANZICS Centre for Outcome and Resource Evaluation Report 2018. Australian and New Zealand Intensive Care Society (ANZICS), 2019.
Australia	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Austria	How is Intensive Care Reimbursed? A Review of Eight European Countries	Bittner M-I, Donnelly M, van Zanten ARH, Andersen JS, Guidet B, Javier Trujillano Cabello JJ, Gardiner S, Fitzpatrick G, Winter B, Joannidis M, Schmutz A. How is Intensive Care Reimbursed? A Review of Eight European Countries. <i>Ann Intensive Care</i> . 2015; 3(37).
Austria	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Austria	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Belgium	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med</i> . 2012; 38: 1647–53.
Belgium	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Belgium	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Bulgaria	Bulgaria Health System Review 2012	European Observatory on Health Systems and Policies, World Health Organization (WHO). Bulgaria Health System Review 2012. Brussels, Belgium: European Observatory on Health Systems and Policies, 2012.
Bulgaria	Public Health Statistics Bulgaria Annual 2019	Ministry of Health (Bulgaria), National Center of Public Health and Analyses (Bulgaria). Public Health Statistics Bulgaria Annual 2019. Sofia, Bulgaria: National Center of Public Health and Analyses (Bulgaria), 2019.
Bulgaria	Public Health Statistics Bulgaria Annual 2018	Ministry of Health (Bulgaria), National Center of Public Health and Analyses (Bulgaria). Public Health Statistics Bulgaria Annual 2018. Sofia, Bulgaria: National Center of Public Health and Analyses (Bulgaria), 2018.

Country	Source	Citation
Bulgaria	Public Health Statistics Bulgaria Annual 2001	Ministry of Health (Bulgaria), National Center for Health Informatics (Bulgaria). Public Health Statistics Bulgaria Annual 2001. Sofia, Bulgaria: National Center for Health Informatics (Bulgaria), 2001.
Croatia	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Croatia	WHO COVID-19 Health System Response Monitor Croatia Policies March 30, 2020	World Health Organization Regional Office for Europe (WHO/Europe). WHO COVID-19 Health System Response Monitor Croatia Policies March 30, 2020. Copenhagen, Denmark: World Health Organization Regional Office for Europe (WHO/Europe), 2020.
Croatia	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.
Croatia	WHO Hospital Bed Density Data by Country	World Health Organization (WHO). WHO Hospital Bed Density Data by Country. Geneva, Switzerland: World Health Organization (WHO).
Cyprus	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Cyprus	WHO COVID-19 Health System Response Monitor Cyprus Policies April 5, 2020	World Health Organization Regional Office for Europe (WHO/Europe). WHO COVID-19 Health System Response Monitor Cyprus Policies April 5, 2020. Copenhagen, Denmark: World Health Organization Regional Office for Europe (WHO/Europe), 2020.
Cyprus	WHO Hospital Bed Density Data by Country	World Health Organization (WHO). WHO Hospital Bed Density Data by Country. Geneva, Switzerland: World Health Organization (WHO).
Cyprus	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.
Czech Republic	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Czech Republic	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Czech Republic	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.
Denmark	How is Intensive Care Reimbursed? A Review of Eight European Countries	Bittner M-I, Donnelly M, van Zanten ARH, Andersen JS, Guidet B, Javier Trujillano Cabello JJ, Gardiner S, Fitzpatrick G, Winter B, Joannidis M, Schmutz A. How is Intensive Care Reimbursed? A Review of Eight European Countries. <i>Ann Intensive Care.</i> 2015; 3(37).
Denmark	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Denmark	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Estonia	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.

Country	Source	Citation
Estonia	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Estonia	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Finland	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.
Finland	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Finland	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
France	How is Intensive Care Reimbursed? A Review of Eight European Countries	Bittner M-I, Donnelly M, van Zanten ARH, Andersen JS, Guidet B, Javier Trujillano Cabello JJ, Gardiner S, Fitzpatrick G, Winter B, Joannidis M, Schmutz A. How is Intensive Care Reimbursed? A Review of Eight European Countries. <i>Ann Intensive Care.</i> 2015; 3(37).
France	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
France	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2002	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2002. Federal Health Monitoring (Germany), 2002.
Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2003	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2003. Federal Health Monitoring (Germany), 2003.
Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2004	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2004. Federal Health Monitoring (Germany), 2004.
Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2005. Federal Health Monitoring (Germany), 2005.

Country	Source	Citation
	Occupancy/Billing Days) 2005	
Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2006	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2006. Federal Health Monitoring (Germany), 2006.
Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2007	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2007. Federal Health Monitoring (Germany), 2007.
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Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2012	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2012. Federal Health Monitoring (Germany), 2012.
Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals -

Country	Source	Citation
	(Cases and Occupancy/Billing Days) 2013	Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2013. Federal Health Monitoring (Germany), 2013.
Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2014	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2014. Federal Health Monitoring (Germany), 2014.
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Germany	Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2016	Federal Health Monitoring (Germany), Federal Statistical Office (Germany), Robert Koch Institute (Germany). Germany Intensive Care in Hospitals - Number of Hospitals, Beds and Stays (Cases and Occupancy/Billing Days) 2016. Federal Health Monitoring (Germany), 2016.
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Germany	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Germany	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Germany	Variation in critical care services across North America and Western Europe	Wunsch H, Angus DC, Harrison DA, Collange O, Fowler R, Hoste EA, de Keizer NF, Kersten A, Linde-Zwirble WT, Sandiumenge A, Rowan KM. Variation in critical care services across North America and Western Europe. <i>Crit Care Med</i> . 2008; 36(10): 2787-93, e1-9.
Greece	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med</i> . 2012; 38: 1647-53.
Greece	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Greece	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.

Country	Source	Citation
Hungary	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.
Hungary	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Hungary	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
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Iceland	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Iceland	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Ireland	How is Intensive Care Reimbursed? A Review of Eight European Countries	Bittner M-I, Donnelly M, van Zanten ARH, Andersen JS, Guidet B, Javier Trujillano Cabello JJ, Gardiner S, Fitzpatrick G, Winter B, Joannidis M, Schmutz A. How is Intensive Care Reimbursed? A Review of Eight European Countries. <i>Ann Intensive Care.</i> 2015; 3(37).
Ireland	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Ireland	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
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Italy	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Italy	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Latvia	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.
Latvia	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Latvia	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.

Country	Source	Citation
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Lithuania	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Lithuania	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Luxembourg	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.
Luxembourg	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Luxembourg	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Malta	WHO COVID-19 Health System Response Monitor Malta Policies March 30, 2020	World Health Organization Regional Office for Europe (WHO/Europe). WHO COVID-19 Health System Response Monitor Malta Policies March 30, 2020. Copenhagen, Denmark: World Health Organization Regional Office for Europe (WHO/Europe), 2020.
Malta	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Malta	WHO Hospital Bed Density Data by Country	World Health Organization (WHO). WHO Hospital Bed Density Data by Country. Geneva, Switzerland: World Health Organization (WHO).
Netherlands	WHO COVID-19 Health System Response Monitor Netherlands Policies April 2, 2020	World Health Organization Regional Office for Europe (WHO/Europe). WHO COVID-19 Health System Response Monitor Netherlands Policies April 2, 2020. Copenhagen, Denmark: World Health Organization Regional Office for Europe (WHO/Europe), 2020.
Netherlands	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Netherlands	WHO Hospital Bed Density Data by Country	World Health Organization (WHO). WHO Hospital Bed Density Data by Country. Geneva, Switzerland: World Health Organization (WHO).
Netherlands	How is Intensive Care Reimbursed? A Review of Eight European Countries	Bittner M-I, Donnelly M, van Zanten ARH, Andersen JS, Guidet B, Javier Trujillano Cabello JJ, Gardiner S, Fitzpatrick G, Winter B, Joannidis M, Schmutz A. How is Intensive Care Reimbursed? A Review of Eight European Countries. <i>Ann Intensive Care.</i> 2015; 3(37).
Netherlands	Variation in critical care services across North America and Western Europe	Wunsch H, Angus DC, Harrison DA, Collange O, Fowler R, Hoste EA, de Keizer NF, Kersten A, Linde-Zwirble WT, Sandiumenge A, Rowan KM. Variation in critical care services across North America and Western Europe. <i>Crit Care Med.</i> 2008; 36(10): 2787-93, e1-9.
New Zealand	ANZICS Centre for Outcome and Resource Evaluation Report 2018	Australian and New Zealand Intensive Care Society (ANZICS). ANZICS Centre for Outcome and Resource Evaluation Report 2018. Australian and New Zealand Intensive Care Society (ANZICS), 2019.
Norway	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.

Country	Source	Citation
Norway	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
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Poland	Poland Available Health Facility Resources for COVID-19 Response as of April 2020	Poland Available Health Facility Resources for COVID-19 Response as of April 2020.
Poland	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Poland	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Portugal	EUROSTAT Hospital Beds by Type of Care	Eurostat. EUROSTAT Hospital Beds by Type of Care. Luxembourg City, Luxembourg: Eurostat.
Portugal	Organization for Economic Co-operation and Development Data - Hospital Beds	Organization for Economic Co-operation and Development (OECD). Organization for Economic Co-operation and Development Data - Hospital Beds. Paris, France: Organization for Economic Co-operation and Development (OECD), 2018.
Portugal	The Variability of Critical Care Bed Numbers in Europe	Rhodes A, Ferdinande P, Flaatten H, Guidet B, Metnitz PG, Moreno RP. The Variability of Critical Care Bed Numbers in Europe. <i>Intensive Care Med.</i> 2012; 38: 1647–53.
Romania	Romania Hospital Beds for Certain Medical Specialties, at the End of the Year 1990-2018	National Institute of Statistics (Romania). Romania Hospital Beds for Certain Medical Specialties, at the End of the Year 1990-2018. Bucharest, Romania: National Institute of Statistics (Romania).

Appendix B: CurveFit Tool and Analyses

Abstract

This Appendix gives details for the `CurveFit` program and related analyses, including age standardization, and peak detection, which are used together with the tool to obtain the estimates for the Covid-19 death rates in the public-facing tool <https://covid19.healthdata.org/>. The report includes methods used to create the initial estimates, as well as updates that have been developed over the last three weeks. The tool allows multiple functional forms, covariates, link functions, and prior specifications, that can be used as we learn more about Covid-19. A Gaussian form for daily deaths remains the workhorse functional form used thus far. To fit distributions of daily deaths, which exhibit asymmetry and flat peaks across locations, we fit a linear combination of Gaussian atoms to the data. Uncertainty is estimated in all cases using a model-agnostic predictive validity framework, also detailed in the report. The mathematical methods are open source, and the repository cited in the introduction is updated as the work continues to evolve.

1. Introduction

Overview. The `CurveFit` package, available at <https://github.com/ihmeuw-msca/CurveFit>, is used by IHME to estimate and forecast deaths across locations¹. General changes in data, covariates, and models are described on the main website² as the approach evolves.

The forecasts for Covid-19 deaths and equipment need assume that:

- (1) All social distancing measures that are in place will stay in place.
- (2) Any remaining restrictions will be put in place within a fixed number of days.

The time before the remaining social distancing measures are to be implemented was assumed to be 7 days prior to April 17 forecasts, and 21 days for forecast published on April 17 and afterwards.

CurveFit Model. `CurveFit` supports parametrized curves that can be fit to data, modeling parameters using covariates, and post-processing, such as fitting linear combinations of `CurveFit` models. We focus on parametric and semi-parametric inference (in contrast to fully nonparametric inference, e.g. fitting tools with splines [10]) for several reasons:

- Parametric functions capture key signals from noisy data due to simple parametrization.
- Parameters are interpretable, and can be modeled using covariates in a transparent way.
- Parametric forms allow for more stable inversion approaches, for current and future work.
- Parametric functions impose rigid assumptions that make forecasting more stable.

Roadmap. The Appendix proceeds as follows. Age-standardization, an important pre-processing step done for each forecasted location before running `CurveFit`, is described in Section 2. For the Covid model, we considered sigmoidal shapes, described in Section 3. Assumptions on noise and relationships between locations are specified through the statistical model, discussed in Section 4. Covariate definitions for original and updated analyses are given in Section 5. Assumptions and expert knowledge can be communicated to the model through priors and constraints, described in Section 6. All estimation is carried out using an optimization procedure, described in Section 7. The extended model that fits a constrained linear combination of Gaussian atoms discovered by fitting the basic `CurveFit` model is given in Section 8. Posterior uncertainty is estimated from the fits using a prediction validity framework described in Section 9. Automatic peak detection used to get a set of likely peaked locations for further expert vetting using splines with shape constraints is detailed in Section 10. Current settings used to obtain fits are summarized in Section 11.

2. Age Standardization

In an effort to control for the confounding effect of age structure variation across the geographic units for which we estimate COVID-19 deaths, we run separate model pipelines for each location,

¹<https://covid19.healthdata.org/projections>

²<http://www.healthdata.org/covid/updates>

standardizing all data to that location's population age structure. The key pre-processing step before the analysis is to convert the reported cumulative deaths in our dataset into death rates using the most recent available population data from the Global Burden of Disease 2019 study.

We use the average age pattern of COVID-19 mortality rates in 10-year age bands up to a terminal group 80+ based on data from Hubei, Italy, Republic of Korea, and the United States as a reference mortality rate by age m_a^r . We then derive an implied mortality rate m_l^i using those data and the age-specific population of each location in the model dataset $p_{a,l}$.

$$m_l^i = \sum_{a=[0-9]}^{[80+]} \frac{m_a^r \times p_{a,l}}{p_l}$$

We can then adjust the reference age pattern by the ratio of the observed mortality rate on a given location-day $m_{l,d}^o$ to the implied mortality rate to produce a series of age-specific mortality rates $m_{a,l,d}$ representative of each datapoint.

$$\{m_{a,l,d}\}_{a=[0-9]}^{[80+]} = \{m_a^r\}_{a=[0-9]}^{[80+]} \frac{m_{l,d}^o}{m_l^i}$$

Lastly, we apply the population structure in the model location p_{m_l} to the age-specific mortality rates created from each data point, resulting in an age-standardized mortality rate $m_{l,d}^{as}$.

$$m_{l,d}^{as} = \frac{\sum_{a=[0-9]}^{[80+]} m_{a,l,d} \times p_{a,m_l}}{p_{m,l}}$$

The natural log of the age-standardized mortality rate is then used as input data to the CurveFit model.

3. Functional Form for Covid-19

We considered several functional forms to model the death rate of the Covid-19 virus. Based on currently available data, the log rate starts slowly, increases quickly, and then flattens out again as either social distancing or saturation goes into effect. This is the classic sigmoid shape. We first tried building the analysis using the sigmoidal function

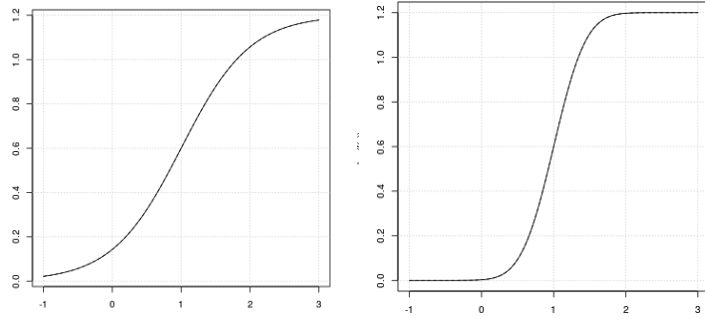


Figure 1. Expit function \tilde{D} (left) and ERF function D (right). The ERF function fits the available Covid-19 data better than Expit.

$$\tilde{D}(t; \alpha, \beta, p) = \frac{p}{1 + \exp(-\alpha(t - \beta))}$$

where p controls the level, β the shift, and α the growth. **Here and below, we refer to fundamental quantities, here p, β, α as parameters.**

We then discovered that the ERF error function provided a better fit to the data:

$$D(t; \alpha, \beta, p) = \frac{p}{2} \Psi(\alpha(t - \beta)) = \frac{p}{2} \left(1 + \frac{2}{\sqrt{\pi}} \int_0^{\alpha(t-\beta)} \exp(-\tau^2) d\tau \right)$$

CurveFit allows the user to specify an arbitrary parameterized functional form, so that other models could be considered as more data becomes available. We can fit in four spaces:

- Log space: $\log(\text{data})$ vs. $\log(D)$

- Linear space: data vs. D
- Derivative of log space: increments of log data vs. derivative of $\log(D)$
- Derivative of linear space: increments of data vs. derivative of D .

For the D functional form, the three parameters are:

- Level: p controls the maximum asymptotic level that the rate can reach
- Slope: α controls the speed of the infection
- Inflection: β is the time at which the rate of change of D is maximal.

These interpretations are clear from the following derivative computations:

Logistic Function.

$$\begin{aligned}\tilde{D}(t) &= \frac{p}{1 + \exp(-\alpha(t - \beta))} = p(1 + \exp(-\alpha(t - \beta)))^{-1} \\ \tilde{D}'(t) &= p\alpha(1 + \exp(-\alpha(t - \beta)))^{-2} \exp(-\alpha(t - \beta)) = \frac{p\alpha}{\exp(\alpha(t - \beta)) + 2 + \exp(-\alpha(t - \beta))} \\ \tilde{D}''(t) &= \frac{-p\alpha^2 (\exp(\alpha(t - \beta)) - \exp(-\alpha(t - \beta)))}{(\exp(\alpha(t - \beta)) + 2 + \exp(-\alpha(t - \beta)))^2}\end{aligned}$$

It is clear that $\tilde{D}'(t)$ is maximized at $t = \beta$, since the numerator of \tilde{D}'' is then equal to 0, that is the infection point occurs at $t = \beta$. Plugging in, the maximum value of \tilde{D}' is given by

$$\tilde{D}'(t)_{\max} = \frac{p\alpha}{4}.$$

We can also obtain a simple expression for $D''(t)$ at $t = 0$:

$$\tilde{D}''(0) = p\alpha^2 \frac{(\exp(\alpha\beta) - \exp(-\alpha\beta))}{(\exp(-\alpha\beta)) + 2 + \exp(\alpha\beta))^2} \quad (1)$$

ERF Function.

$$\begin{aligned}D(t) &= \frac{p}{2} \left(1 + \frac{2}{\sqrt{\pi}} \int_0^{\alpha(t-\beta)} \exp(-\tau^2) d\tau \right) \\ D'(t) &= \frac{p\alpha}{\sqrt{\pi}} \exp(-\alpha^2(t - \beta)^2) \\ D''(t) &= \frac{-2p\alpha^3}{\sqrt{\pi}} \exp(-\alpha^2(t - \beta)^2) (t - \beta)\end{aligned}$$

It is clear that $D'(t)$ is maximized at $t = \beta$, since at that value $D''(t) = 0$. Plugging in, the maximum value of $D'(t)$ is given by

$$D'(t)_{\max} = \frac{p\alpha}{\sqrt{\pi}}.$$

For the ERF function, we also have a simple expression for the rate of change of daily deaths at $t = 0$:

$$D''(0) = \frac{2p\alpha^2}{\sqrt{\pi}} (\alpha\beta) \exp(-(\alpha\beta)^2) \quad (2)$$

In both functional forms, the maximal D' expressions are proportional to $p\alpha$, and the rates of changes D'' at $t = 0$ (and at other specified times) are strongly dependent on the quantity $\alpha\beta$.

Asymmetric Extensions. We also considered asymmetric forms, such as a switched Gaussian devised by one of the team members. For the ongoing analyses, we still use a symmetric form, but fit to data using a linear combination of the inferred peaks described in Section 8. This approach has proven robust, while also fitting a variety of asymmetric data without relying on a particular functional form with additional parameters.

To capture variation across location, we have to model the relationships of parameters using covariates and random effects. These specifications are given in the next section.

4. Statistical Specification

Statistical assumptions link parameters together across locations. Statistical models introduce variables that can be inferred to describe these relationships. **CurveFit** allows any parameter to be specified using both a link function and covariates using the generalized linear modeling framework [7]:

$$\text{parameter} = \text{LinkFunction}(\text{covariate} * \text{multiplier} + \text{random effect}).$$

The covariate value is provided by the user (for example, a measure of social distancing), while the multiplier and random effect are both variables that are solved for using an optimization procedure from the data. **Here and below, we use ‘variables’ to refer to quantities solved for by an algorithm.** We use the word ‘parameters’ only when talking about (α, β, p) .

For the Covid-19 model, there are two link functions:

- identity for modeling the β parameter, and
- exponential function to ensure that α and p parameters are positive.

The ability to parametrize by covariates is a key functionality of the model. For example, the only covariate used in the death rate model for the current estimate is based on the duration between a threshold of the rate and social distancing policy, and this covariate drives the inference of the covariate multiplier for the inflection point or the level in the models we consider for the analysis. As more data becomes available, **CurveFit** can be used to incorporate additional understanding to further link the covariates.

To finish the specification, we give an important modeling example that is used for current estimates. The covariate links the inflection points β_l across locations l . The observation model is

$$\log(\text{cumulative death rate in location } l \text{ at time } t) = \log(D(t; \alpha_l, \beta_l, p_l)) + \text{error}_{l,t}$$

and the remaining specification is

$$\begin{aligned}\alpha^l &= \exp(\mu_\alpha + u_\alpha^l) \\ \beta_l &= (\mu_\gamma + u_\gamma^l) \text{Covariate}^l \\ p^l &= \exp(\mu_p + u_p^l)\end{aligned}\tag{3}$$

In this example,

- μ_α and μ_p are intercepts (in log space) that capture average behavior of parameters α^l and p^l across locations
- u_α^l and u_p^l are random effects that multiplicatively adjust $\exp(\mu_\alpha)$ and $\exp(\mu_p)$ to each location
- μ_γ is the average covariate multiplier that controls the peak β
- u_γ^l are random effects on slope that adjust the covariate multiplier to each location.

5. Covariate Definitions

The covariate in the **CurveFit** model (3) is very important in being able to predict the peak. The information used to construct the covariate has evolved between the initial posting of the model and the current iteration, and the procedure is briefly described here. The procedure describes creation of multiple covariates by treating the available information differently, to create a set of models in the model pool that are then ensembled to create the final estimates as discussed in Section 11.

5.1. Social Distancing Covariates Prior to Social Mobility Data

Before social distancing data was available and had been processed by the team, government mandates across locations were used to construct the covariate to capture social distancing (see Supplementary Information). Specifically, covariates of days with expected exponential growth in the cumulative death rate were created using information on the number of days after the death rate exceeded 0.31 per million to the day when 4 different social distancing measures were mandated by local and national governments: school closures, non-essential business closures, stay-at-home recommendations, and severe local travel restrictions including public transport closures. Three different weighting schemes to create covariates were considered:

1. Days with 1 measure were counted as 0.67 equivalents, days with 2 measures as 0.334 equivalents and with 3 or 4 measures as 0;

2. Days with 1 measure were counted as 0.86, 2 measures as 0.57, and 3 or 4 as 0
3. Days with 1 or 2 measures are counted fully, and 3 or 4 counted as 0.

For locations that have not yet implemented all of the closure measures, the forecasts assumed that the remaining measures would be put in place within 1 week of the data of analysis. This lag between reaching a threshold death rate and implementing more aggressive social distancing was combined with the observed period of exponential growth in the cumulative death rate seen in Wuhan after Level 4 social distancing was implemented, adjusted for the median time from incidence to death. For ease of interpretation of statistical coefficients, this covariate was normalized so the value for Wuhan was 1.

5.2. Using Social Mobility Data

The model run on April 17 and future updates use population-level mobility data to better reflect how populations are changing their behavior once distancing mandates are implemented. That means we now inform our model predictions by including information on how populations are responding to different distancing measures.

We use social mobility data from Descartes Labs³, SafeGraph⁴, and Google (via their COVID-19 Community Mobility Reports)⁵ in relation to each type of distancing policy implemented. All three mobility datasets are available for the US, while the Google mobility dataset is the only one that includes European countries.

Each dataset is analyzed separately to estimate the percentage reduction in mobility associated with each of our six social distancing measures. We then use these estimates as weights to construct a single covariate for predicting the epidemic peak in each location, see Table 1. We produce three distinct versions of the social distancing covariate (i.e., one based on data from Descartes Lab, one from SafeGraph, and one from Google). We run the COVID-19 death model for each of the three versions of the social distancing covariate and then ensemble them into a single set of predictions.

Table 1. Mobility weights

	Any Gathering Restrictions	Stay at Home	Ed. Fac. Closed	Any Business Closures	Non-ess. Serv. Closed
Descartes	0.129	0.206	0.274	0.212	0.178
Google	0.222	0.081	0.37	0.176	0.151
Safegraph	0.206	0.277	0.201	0.141	0.175

We use “Any gathering restrictions” as an incremental implementation of “People instructed to stay at home”, so the full mandate is the sum of weights in the first two columns of Table 1. The same is true of “Any business closures” and “Non-essential services closed”. Using these values, we determine the weighted average of days without each mandate. For example, when using Descartes data, the weighted average for a given location using Table 1 is computed as below:

$$0.129 * (\text{Days without any gathering restrictions}) + 0.206 * (\text{Days without a stay home order}) + 0.274 * (\text{Days with open educational facilities}) + 0.212 * (\text{Days without any business closure}) + 0.178 * (\text{Days without a non-essential services closed order}).$$

As done in Section 5.1, this composite measure is then combined with the empirical closure to peak duration (21 days), and normalized based on the Wuhan value (so Wuhan has value 1). Since switching to these weights, we have also revised the duration of time before unimplemented mandates are presumed to be in place from 1 week to 3 weeks in the future from the day at which the forecast is obtained.

6. Specifying Priors and Constraints

The *CurveFit* tool lets the user specify prior knowledge using two interfaces: Bayesian priors and constraints. Both types of information can be used to inform estimation of all parameters and covariate multipliers. In the sections below we discuss simple priors, box constraints, and functional priors.

6.1. Simple priors

CurveFit assumes that prior distributions are Gaussian $N(\mu, \sigma^2)$, where the parameter μ encodes the prior belief, while σ^2 specifies confidence in this belief.

³<https://github.com/descarteslabs/DL-COVID-19>

⁴<https://www.safegraph.com/dashboard/covid19-commerce-patterns?is=5e8b94eac6a05447bd786ae9>

⁵<https://www.google.com/covid19/mobility/>

6.2. Box constraints

Constraints are assumed to be simple bound constraints, that is, we can specify

$$\text{lower bound} \leq \text{parameter} \leq \text{upper bound}$$

for any parameter we wish to infer. Since the functional form D is highly nonlinear, constraints are very useful in stabilizing the numerical solution of the inference problem and communicating model assumptions about parameters in a simple way. Constraints guarantee that parameters will stay in a certain range, but do not prescribe any particular value in that range.

6.3. Functional priors

The behavior of nonlinear curves often depends on coupled relationships between parameters. For example, rates of change of daily deaths D'' depend on all three parameters (p, α, β) , see (1) and (2), and strongly depend on the quantity $\alpha\beta$. **CurveFit** therefore allows functional priors, which for the logistic functions can be written as

$$f(\alpha, \beta, p) \sim N(\mu, \sigma^2).$$

These priors can be used when the generalizable quantity (i.e. information we learn from locations with a lot of data) is a function of the modeled parameters.

7. Optimization Procedure

The final optimization problem includes the GLM specifications such as (3), along with Gaussian priors (simple and functional) and bound constraints. The fitting problem in the current version of **CurveFit** is thus a bound-constrained nonlinear least squares problem. To solve this optimization problem, we use the L-BFGS-B algorithm [11], implemented in **SciPy**⁶.

The L-BFGS-B algorithm requires derivatives of the objective function. We use numerical differentiation, implemented using the complex step method, to compute these derivatives for any user-specified functional form [5]. Complex step is a simple variant of Algorithmic Differentiation (AD) [2]. More sophisticated packages are being tested, but if adopted will impact speed of the method rather than results.

Since the curves are highly nonlinear, the nonlinear least squares problem is highly nonconvex, and therefore initialization is important. When fitting a joint model for multiple locations, we initialize values of the random effects parameters to their location-specific fits, and then run the full optimization model as specified in Section 4 from this starting point.

8. Curve Fitting Extension Using Gaussians Atoms

As we see more and more data across locations, it is clear that while some peaks follow the classic Gaussian shape in daily deaths, many do not. Some peaks are wider, some trajectories are asymmetric, and overall there is a fair amount of variation in the shape of the curves we see directly in the data.

To balance model flexibility (fitting data) with generalizability (forecasting potential epidemic trajectories), we use a semi-parametric modeling framework, building on the basic **CurveFit** result. The steps are as follows:

- We fit a particular **CurveFit** model to a given location using the social distancing covariate, to fit its γ multiplier, α , and p (see (3)). This gives the atom specification for the next step.
- Given the atom, we use a semi-parametric fit of staggered atoms to data. Specifically, we consider a basis of staggered atoms 13 days, with peaks 2 days apart, centered at the inferred peak from step 1. We fit the weights to the data as described below.

Fitting procedure. Given a set of atomic functions of time $f_i(t)$, and all observations y_t for a given location, we fit the following model:

$$y_t = \sum_{i=1}^{13} w_i f_i(t) + \epsilon.$$

⁶<https://docs.scipy.org/doc/scipy/reference/optimize.minimize-lbfgsb.html>

The resulting models generalize the basic model used so far and better capture the signals in the data – in particular the fitted combinations of curves can be asymmetric, and exhibit flatter regions. Overall the approach better captures the variation in the epidemic trends that we see. At the same time, the extended model is can still be used to forecast into the future just as in the original single atom case.

We want to fit the data as a non-negative combination of atoms. We also put upper bound constraints of 1 on each weight. The full fitting problem is given by

$$\min_{\{0 \leq w_i \leq 1\}} \sum_t \left(y_t - \sum_{i=1}^{13} w_i f_i(t) \right)^2. \quad (4)$$

Problem (4) is a bound-constrained linear least squares problem, in particular convex, and easy to solve. It is analogous to a spline, except that the atoms are highly structured – simple replicates of the peak inferred from the data. Since (4) is a least squares problem with bound constraints, we also use the L-BFGS-B routine to solve it.

Uncertainty for any model fit (including the basic fit and the extension) is computed using the predictive validity framework, described in the next section.

9. Uncertainty Quantification

CurveFit provides draws – random realizations of the mean function – for individual locations used in the model estimation. Location-specific samples then inform aggregate uncertainty of downstream estimates. To make these draws, **CurveFit** can use sampling based on either approximated model-based uncertainty, or based on predictive validity. While uncertainty for the initial forecasts (updated March 30-April 1st) were made using model-based uncertainty (Section 9.1), the uncertainty for the forecasts on April 5th were computed via the predictive validity framework (Section 9.2).

9.1. Model-based uncertainty

We partition the uncertainty as coming from two sources: fixed effects and random effects. Fixed effects in the model are average parameters across locations, and covariate multipliers. Random effects are specific to location. Estimates of uncertainty for both pieces of the model come from asymptotic statistical approximations (Fisher information) together with the likelihood.

Fixed Effects. For any estimator obtained by solving a nonlinear least squares problem

$$\hat{\theta} = \arg \min_{\theta} := \frac{1}{2\sigma^2} \|y - f(\theta; X)\|_{\Sigma^{-1}}^2$$

we can approximate posterior covariance using the inverse of the Fisher information matrix:

$$\mathcal{I}(\theta) = V[\nabla \mathcal{M}(\theta)] = V[J_{\theta}^T \Sigma^{-1} (f(\theta; X) - y)] = J_{\theta}^T \Sigma^{-1} J_{\theta}$$

where

$$J_{\theta} := \nabla_{\theta} f(\theta; X)|_{\theta=\hat{\theta}} \quad (5)$$

is the Jacobian of $f(\theta)$ evaluated at the computed estimate $\hat{\theta}$. We therefore get

$$V(\hat{\theta}) = \mathcal{I}(\hat{\theta})^{-1} = (J_{\hat{\theta}}^T \Sigma^{-1} J_{\hat{\theta}})^{-1} \quad (6)$$

Random Effects. To estimate the variance at each location, we first obtain an empirical variance-covariance matrix using the random effect fits by location, denoted by V_0 .

Given a location with no observations, its uncertainty will be driven by V_0 , which captures the variation across location. However, if a location has data, we can obtain a location-specific fit and uncertainty estimates using the location-specific likelihood. That is, with the prior V_0 , the likelihood changes to

$$\hat{\theta}_i = \arg \min_{\theta} := \frac{1}{2} \theta^T V_0^{-1} \theta + \frac{1}{2\sigma^2} \|y_i - f_i(\theta; X_i)\|_{\Sigma_i^{-1}}^2$$

and then we have

$$V_i(\hat{\theta}) = ((J_i)_{\hat{\theta}}^T \Sigma_i^{-1} (J_i)_{\hat{\theta}} + V_0^{-1})^{-1}. \quad (7)$$

9.2. Predictive Validity

The newer approach **CurveFit** uses to estimate uncertainty is based on studying how the model performs in predicting deaths out of sample, and generalizing that performance into the future. The framework is agnostic to the model, that is, any model that generates forecasts can be used. The key invariant is that when obtaining residuals for a specific location, all the other data for all the other locations are available to the model for the estimation. The main goal is to evaluate how well the model predicts for future time points in a location given everything we know so far up to the current time point.

The natural quantities to consider when analyzing and generalizing these errors are

- How many data points we have, and
- How far out we are forecasting.

To obtain the out of sample errors, for each location, we hold out part of the existing data points and compute the residual between the held out data and the fitted curves. We iterate this process, first holding out all data points except the first point, all the way through to only holding out the last data point, fitting on all others [4]. After this analysis, for each location, we have a triangular residual matrix with one axis corresponding to the number of data points used to fit the curve and the other axis represents how far are we predicting out. Using mathematical notation, we have:

$$r_{n,i}^l = \text{pred}_{n,t_n+i}^l - \text{obs}_{t_n+i}^l, \quad i = 1, \dots \quad (8)$$

where l is the index of location, n is the number of data points, t_n^l is the time index for the n -th data point in location l , and i represents how far we are predicting into the future. Table 2 shows a simple hypothetical example how these residuals would be tabulated across two locations with 5 and 6 datapoints.

Table 2. Tabulating estimation errors at two hypothetical locations with 5 and 6 total datapoints.

Using datapoints:					
5	$\{r_{5,1}^2\}$				
4	$\{r_{4,1}^1, r_{4,1}^2\}$	$\{r_{4,2}^2\}$			
3	$\{r_{3,1}^1, r_{3,1}^2\}$	$\{r_{3,2}^1, r_{3,2}^2\}$	$\{r_{3,3}^2\}$		
2	$\{r_{2,1}^1, r_{2,1}^2\}$	$\{r_{2,2}^1, r_{2,2}^2\}$	$\{r_{2,3}^1, r_{2,3}^2\}$	$\{r_{2,4}^2\}$	
1	$\{r_{1,1}^1, r_{1,1}^2\}$	$\{r_{1,2}^1, r_{1,2}^2\}$	$\{r_{1,3}^1, r_{1,3}^2\}$	$\{r_{1,4}^1, r_{1,4}^2\}$	$\{r_{1,5}^2\}$
Predicting out:	1	2	3	4	5

Prediction space. The evaluation of residuals in (8) can be done in any space, not only to spaces where we fit the data. Specifically, in the current models we fit the data in the log cumulative death rate space, and evaluate the residual in the log daily death rate space. Log cumulative space is more robust to vagaries of the data, but we want to evaluate predictions in log daily death, and we expect less correlated residuals in log daily death space.

Aggregation and smoothing. To account for low data availability for specific locations we choose to analyze residuals in across all locations together rather than in specific locations. More specifically, if one location only has three data points, in order to understand how well we will predict 10 time points into the future past those three data points for this location, we need to utilize information about predictive validity from other locations with more data where we have held out all but the first three data points and predicted 10 time points into the future.

To do this aggregation over location of the residual matrix, for each number of data point n and forecasting horizon i , we obtain mean and standard deviation of the residual by,

$$\mu_{n,i} = \text{mean}(\{r_{\hat{n},\hat{i}}^i : |\hat{n} - n| \leq a, |\hat{i} - i| \leq b\})$$

$$\sigma_{n,i} = \text{std}(\{r_{\hat{n},\hat{i}}^i : |\hat{n} - n| \leq a, |\hat{i} - i| \leq b\})$$

where a and b are the window size for the number of data points and forecasting horizon, and we include the data across locations when compute the mean and standard deviation. To get the estimates, we use $a = b = 5$. Since some number of data points n and forecasting horizons i pairs only have a couple of contributing locations (for example, only a handful of locations have over 30 data points), we average the mean and standard deviations obtained from the aggregation step over the same window size. After smoothing, we have clearer trends in the relationship between the number of data points, the forecasting horizon and the standard deviation of the residuals. An example of the result of this aggregation and smoothing process is shown in Figure 2.

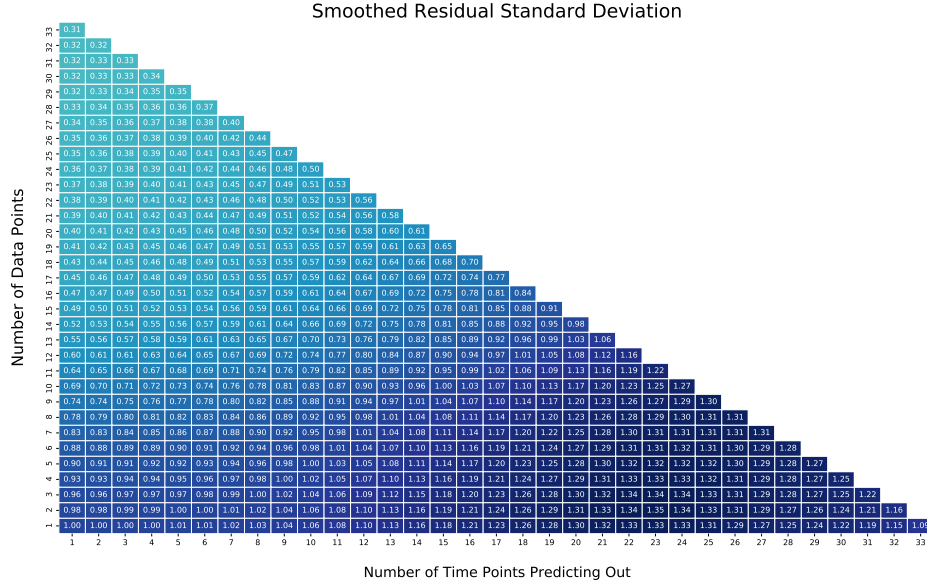


Figure 2. Smoothed standard deviation matrix.

Extrapolating averaged mean, standard deviation, and coefficient of variation values. We need to extrapolate the above matrix to new prediction horizon and number of data point combinations. For example, in Table 2, we don't have any predictive validity results where we had 5 data points and predicted out 5 into the future. In the current approach we use a simple extrapolation technique to extend this table, first extrapolating available quantities to the right, and then down. Continuing with the example in Table 2, we get the array in Table 3.

Table 3. Extrapolating residual matrices to new prediction horizons and number of datapoints

Pred / num:	1	2	3	4	5	6	7	⇒
↑	↑	↑	↑					
6	$\hat{\sigma}_{6,1} = \sigma_{5,1}$	$\hat{\sigma}_{6,2} = \sigma_{5,1}$	⇒					
5	$\sigma_{5,1}$	$\hat{\sigma}_{5,2} = \sigma_{5,1}$	$\hat{\sigma}_{5,3} = \sigma_{5,1}$	⇒				
4	$\sigma_{4,1}$	$\sigma_{4,2}$	$\hat{\sigma}_{4,3} = \sigma_{4,2}$	$\hat{\sigma}_{4,4} = \sigma_{4,2}$	⇒			
3	$\sigma_{3,1}$	$\sigma_{3,2}$	$\sigma_{3,3}$	$\hat{\sigma}_{3,4} = \sigma_{3,3}$	$\hat{\sigma}_{3,5} = \sigma_{3,3}$	⇒		
2	$\sigma_{2,1}$	$\sigma_{2,2}$	$\sigma_{2,3}$	$\sigma_{2,4}$	$\hat{\sigma}_{2,5} = \sigma_{2,4}$	$\hat{\sigma}_{2,6} = \sigma_{2,4}$	⇒	
1	$\sigma_{1,1}$	$\sigma_{1,2}$	$\sigma_{1,3}$	$\sigma_{1,4}$	$\sigma_{1,5}$	$\hat{\sigma}_{1,6} = \sigma_{1,5}$	$\hat{\sigma}_{1,7} = \sigma_{1,5}$	⇒

Generating draws for predictive validity-based uncertainty. Once we have residual standard deviation computed across all observed values of forecast horizon and number of data points, and extrapolated to future values, we generate random errors appropriately around the mean curve to simulate draws.

Specifically, for one draw, we generate one realization from a standard normal distribution and then add on that amount of noise scaled by the standard deviation from Table 3 to the mean curve for each prediction horizon, given the amount of data currently observed for that location. We do this for any number of draws (for a given model this will typically be ≥ 200 draws). Currently, we are only incorporating standard deviation of the residuals into the uncertainty and not the mean of the residuals.

10. Peak Analysis

In this section, we describe analyses to detect which locations have peaked, and what the likely durations of these peaks might be. The technology to do this uses splines, and a brief primer on splines is first provided in Section 10.1. The peak detector is then briefly described in Section 10.2, while the duration detector is described in Section 10.3.

10.1. Splines and Spline Shape Constraints

A spline basis is a set of piecewise polynomial functions with designated degree and domain. If we denote polynomial order by p , and the number of knots by k , we need $p + k$ basis elements s_j^p , which can be generated recursively.

Given such a basis, we can represent any dose-response relationship as the linear combination of the spline basis elements, with coefficients $\beta \in \mathbb{R}^{p+k}$ that are fit to data:

$$f(t) = \sum_{j=1}^{p+k} \beta_j^p s_j^p(t). \quad (9)$$

We can impose shape constraints such as monotonicity, concavity, and convexity on splines. Constraints on splines have been developed in the past through reformulation techniques, see e.g. [8]. We use explicit constraints instead.

Monotonicity. Spline monotonicity across the domain of interest follows from monotonicity of the spline coefficients [1]. Given coefficients

$$\beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_n \end{bmatrix},$$

the curve $f(t)$ in (9) is monotonically nondecreasing when

$$\beta_1 \leq \beta_2 \leq \dots \leq \beta_n$$

and *monotonically non-increasing* if

$$\beta_1 \geq \beta_2 \geq \dots \geq \beta_n.$$

Convexity and Concavity. For any twice continuously differentiable function $f : \mathbb{R} \rightarrow \mathbb{R}$, convexity and concavity are captured by the signs of the second derivative. Specifically, f is convex if $f''(t) \geq 0$ is everywhere, an concave if $f''(t) \leq 0$ everywhere. We can compute $f''(t)$ for each interval, and impose linear inequality constraints on these expressions.

10.2. Peak Detector

When running the model, we use peaked locations to obtain relationships between peaks and social distancing covariates. Here we detail an automatic peak detector to give a list of potential peaked locations for further expert vetting. For example, from the data set from 04/10/2020, the detector selects 31 candidates from 107 locations, largely reduced the search space, and then expert consensus is used to select the final 19 locations from this reduced set.

The detector works as follows. Since the cumulative death rate is modeled using the ERF function, we know that the log daily death rate should roughly follow a quadratic function with negative curvature. When the location reaches its peak, the log daily death curve should have either almost reached or passed the part of this curve where the tangent line is horizontal, see e.g. Emilia-Romagna in Figure 3.

To detect whether this has happened, we fit a quadratic B-spline to each location in the log daily death rate space using the `Xspline` package [9], and compute the minimum of the absolute value of the derivatives of the fitted curve. We use two knots, at 0 and 100; `Xspline` allows functionality for computing derivatives of any fitted splines. To detect whether a location has peaked, we choose a threshold and declare peaks when the minimum absolute derivative is less than this threshold (we use `5e-3` to get 31 locations). To make the detector more accurate, we impose the requirement that the second order derivative of the spline should be negative and we require the number of the observations has to be greater or equal to 20.

10.3. Peak Duration

As more and more locations starting to decline in the daily death, we observe that many locations have a flat peak of variable duration. To estimate the duration of the peak, we extend the idea of the peak detector, fitting a concave quadratic spline in the log daily death space, also using the `Xspline` package. This approach can capture the flat shape at the top of the peak, while denoising the data through the concavity assumption. After fitting the spline, we compute derivatives of the curve in the log daily death space. Given a threshold, we obtain the duration of the peak by the difference between points where the relative derivative (as a fraction of maximum observed derivative) crosses the threshold on each side of the peak.

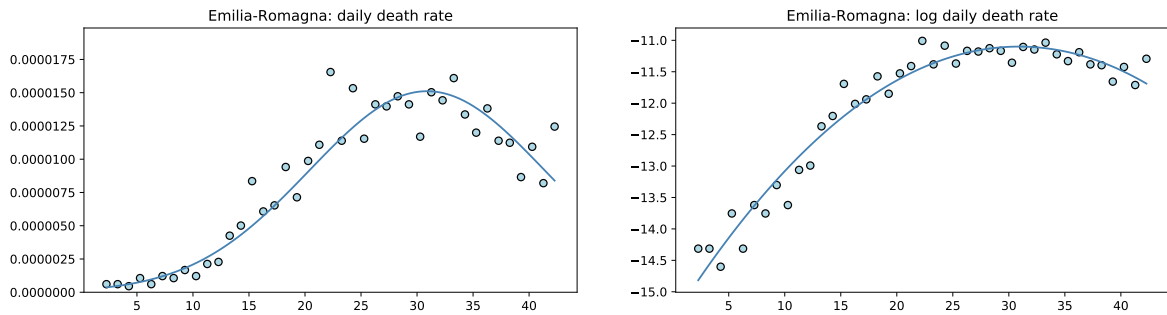


Figure 3. Peaked detector example for Emilia-Romagna. Dots are the data in daily and log daily death space and curve are the spline fits.

11. Model Specification for Estimates

The final results use an a model ensemble, where models in the ensemble differ by definition of the social distancing covariate. Final estimates and uncertainty are created at the draw level. When we have fewer than 18 datapoints, each draw from a particular model (using a particular social distancing covariate) interpolates draws between short-range and long-range models. When we have 18 or more datapoints, we use the linear Gaussian extended model. These analyses are explained in detail below, along with common settings and assumptions. At the end we document the ensemble.

11.1. Data processed outside of the JHU Pipeline

France. Due to out-of-hospital deaths being reported differentially to in-facility deaths in France, we have been redistributing French data. Using data from Sante Publique⁷ cumulative deaths in hospital are kept distinct from deaths reported in EHPAD (Établissement d’hébergement pour personnes âgées dépendantes) and EMS (Établissements medico-sociaux). We have redistributed the deaths reported in the latter sector proportionate to the daily deaths reported in hospitals.

Spanish subnationals. With subnational locations in Spain missing from JHU, we have instead used the Daily governmental reports from the Centro de Coordinación de Aleras y Emergencias Sanitarias (CCASES)⁸.

Catalonia addendum. In the Spanish governmental report Number 78 dated 17th April 2020, it was noted that there was a discrepancy between reported tabulations, and that reported by Salud Pública de Cataluña (Sub-direcció General de Vigilància I Reposta a Emergències de Salut Pública). For the epidemiological dates 16th April onwards, we instead report the number of deaths indicated by the Catalanian Government instead⁹

Germany. With subnational locations in Germany missing from JHU, we have instead used the daily epidemiological reports from the Robert Koch Institute¹⁰

Wuhan City, Hubei Province, China. With sub-provincial data missing from JHU, we have instead manually extracted the time series of deaths as reported by the Health Commission of Hubei Province¹¹ in their daily situation report press releases.

Wuhan City addendum. On the 16th April 2020, Wuhan City death numbers were increased by 1290 deaths, and cases by 325. We have subtracted these numbers from the subsequent days of reported cases and deaths since these deaths are known not to have occurred on the 16th April 2020, but across the months previously. We are currently withholding these deaths from the model.

United States.

- Illinois. Due to repeated inconsistencies in reported cumulative total deaths between JHU and the Illinois Department of Public Health, we replaced the JHU time series with one derived from the Illinois Department of Public Health instead¹². Given the lack of an historical archive,

⁷<https://dashboard.covid19.data.gouv.fr/>

⁸<https://www.mscbs.gob.es/profesionales/saludPublica/ccayes/alertasActual/nCov-China/situacionActual.htm>

⁹<https://analisi.transparenciacatalunya.cat/Salut/Incid-ncia-de-la-COVID-19-a-Catalunya/623z-r97q>

¹⁰https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Situationsberichte/Gesamt.html

¹¹<http://wjw.hubei.gov.cn/fbjd/dtyw/>

¹²<http://www.dph.illinois.gov/topics-services/diseases-and-conditions/diseases-a-z-list/coronavirus>

we used The COVID Tracking Project's¹³ archive of preserved screenshots to reconstruct the historical time series of reported total cumulative deaths.

- New York. Due to the mid-outbreak of stratification of confirmed and probable deaths in New York City, we derived an alternative data processing workflow for New York City and therefore New York State. We replaced the JHU New York City time series with the New York Times New York City time series¹⁴ which more closely tracks with the time series of confirmed deaths as indicated by New York City Health¹⁵. To account for the reporting of probable deaths, for the most recent day of reporting, we take the difference between the New York City Health total number of deaths (i.e. the sum of probable and confirmed deaths) and subtract the New York Times reported deaths for that day, and re-distribute the remainder proportionate to the daily deaths reported by New York Times.
- Washington. Due to the unique high-intensity epidemic in the Life Care Kirkland facility in Washington state [6, 3] we have modeled this facility separately from the general population. Furthermore, as our initial development of the model was focused on King and Snohomish counties in Washington state, we have also stratified these 2 counties from the rest of Washington state. In other words, for Washington state, we model 3 populations explicitly: (i) the Life Care Kirkland facility; (ii) the remainder of the King and Snohomish county population; and (iii) all other counties in Washington state. Data was collected directly from each County Health Department, with metadata on whether deaths were reported from the Life Care Kirkland facility retained.

11.2. Pre-processing

11.2.1. Short-term Pseudo-Death data from Hospitalizations

We use what we know about the timing of the disease to generate additional short-term predicted deaths (pseudo-data) from hospitalizations and use these in our model. On average, the time between hospitalization and death is 8 days. Using location-specific hospitalization data which has more than 10 deaths, we build simple measure that can help predict deaths:

$$R_{d/h} = \frac{\text{cumulative deaths up to time } t}{\text{cumulative cases up to time } t - 8}$$

If a location has more than 10 deaths, we then use a location-specific ratio and current case loads to generate ‘pseudo-data’ for the next 8 days, and incorporate this pseudo-data into the model, with a fractional weight of $\frac{1}{5}$ so the model fits to real data much more strongly than pseudo-data. If a location has fewer than 10 days, we use the average ratio and location-specific cases to predict location-specific deaths in the next 8 days.

11.2.2. Moving average smoothing of daily deaths

We use a 3-day moving average across times $(t - 1, t, t + 1)$ in the space where we fit the model, log age-standardized cumulative death rate. For the first day, where $t = 0$, we project the average difference in smoothed values from $t = 1$ to $t = 3$ back from $t = 1$. For the last day, where $t = N$, we project the average difference in smoothed values from $t = N - 3$ to $t = N - 1$ forward. We drop the last day from analysis if there are no new deaths reported.

11.3. Model functional form, variables, and bounds.

All of the models in the ensemble follow (3).

Measurement model.

$$\log(\text{cumulative death rate in location } l \text{ at time } t) = \log(D(t; \alpha^l, \beta^l, p^l)) + \epsilon_t^l$$

Statistical model for parameters.

$$\begin{aligned}\alpha^l &= \exp(\mu_\alpha + u_\alpha^l) \\ \beta_l &= (\mu_\gamma + u_\gamma^l) \text{Covariate}^l \\ p^l &= \exp(\mu_p + u_p^l)\end{aligned}$$

¹³<https://covidtracking.com/>

¹⁴<https://github.com/nytimes/covid-19-data>

¹⁵<https://www1.nyc.gov/site/doh/covid/covid-19-data.page>

Error model.

$$\begin{aligned}
\epsilon_t^l &\sim N(0, \sigma_\epsilon^2) \\
u_\alpha^l &\sim N(0, \sigma_\alpha^2) \\
u_\gamma^l &\sim N(0, \sigma_\gamma^2) \\
u_p^l &\sim N(0, \sigma_p^2).
\end{aligned} \tag{10}$$

Simple bound constraints are also used, and Table 4 shows bounds that apply to all models. The error model assumptions are set differentially, depending on the model, as explained in the next sections.

Table 4. Parameter bounds and prior values common across all models. * The interpretation for β assumes the same value of the social distancing covariate value as in Wuhan (normalized to 1).

Parameter	Bounds	Interpretation
μ_α	$(-\infty, 0]$	$0 \leq \alpha \leq 1$
μ_γ	$[15, 100]$	$15 \leq \beta \leq 100^*$
μ_p	$[-15, -6]$	$\exp(-15) \leq p \leq \exp(-6)$

11.4. Low-Data Case: Fewer Than 18 Daily Death Datapoints

For locations that have fewer than 18 points of daily data, we generate forecasts that transition from short-term to long-term models. This also is the way all forecasts were generated before the April 17, 2020 update, so we give full details below.

11.4.1. Short-term models

Short-term models are specified to fit the data. In order to obtain location specific models we

- First fit peaked locations jointly to get a prior distribution
- Fit to individual locations using the prior we obtained from peaked locations.

Fitting to peaked locations. In order to obtain some of the statistics (10), we first fit a joint model on the ‘peaked’ locations, obtained using the peak detector in Section 10.2 followed by expert vetting of the candidates. To consider later points more than earlier points, we set

$$\sigma_t = \frac{1}{0.1 + t^2}. \tag{11}$$

With this specification of measurement error, we fit the joint model with bounds from Table 4 and set $\sigma_\alpha = \sigma_p = \infty$, and $\sigma_\gamma = 10$. From the resulting empirical distribution of γ_l in the peaked locations, we then get a mean $\bar{\mu}_\gamma$ and standard deviation σ_γ that we can use as a prior when fitting individual locations.

Fitting individual locations. The individual fits are done completely independently, so each location is fit with its own fixed-effects only model:

$$\begin{aligned}
\alpha^l &= \exp(\mu_\alpha^l) \\
\beta_l &= (\mu_\gamma^l) \text{Covariate}^l \\
p^l &= \exp(\mu_p^l) \\
\mu_\gamma^l &\sim N(\bar{\mu}_\gamma, \sigma_\gamma^2)
\end{aligned}$$

with only the prior on μ_γ^l informed by the joint fit. The variables (α^l, p^l) can adapt to each location, still subject to bounds in Table 4. The standard deviations are still given by (11).

11.4.2. Long-term models

The purpose of long-term models is to forecast far away, following more closely those locations that have already peaked. Just as in the short-term case, the strategy is

- First fit peaked locations jointly to get a prior distribution
- Fit to individual locations using the prior we obtained from peaked locations.

The list of peaked locations is the same as for the short-term models, but the remaining specifications are different.

Fitting to peaked locations. In order to obtain some of the statistics (10), we again fit a joint model on the ‘peaked’ locations.

For long-term models, we let standard errors follow a different functional form, that still emphasizes the latter points but not as strongly:

$$\sigma_t = \frac{1}{1.0 + t} \quad (12)$$

We also let the strength of the σ_γ depend on the timeliness of the datapoint, so later values have more influence on the inferred multipliers. Specifically we use the formula

$$\sigma_\gamma(t) = 10^{\min(0, \max(-1, t/10 - 1.5))}, \quad (13)$$

which varies between 0.1 and 1, in contrast to the value 10 used in the short-term model.

Finally, for the tight model we use a functional prior (see Section 6.3)

$$\alpha\beta \sim N(\exp(0.7), 0.1) \quad (14)$$

where the value $\exp(0.7)$ was obtained by fitting a regression in log-space for the quantity $\alpha\beta$ to the slopes at $t = 14$ days for data rich locations. We impose a prior on $\alpha\beta$ because this term determines the behavior of slopes of the trajectory of daily deaths $D''(t)$, see e.g. (2).

The peaked locations again determine a mean $\bar{\mu}_\gamma$ and standard deviation σ_γ that we use as a prior when fitting individual locations.

Fitting to individual locations. The individual fits are again done independently, so each location is fit with its own fixed-effects only model:

$$\begin{aligned} \alpha^l &= \exp(\mu_\alpha^l) \\ \beta_t &= (\mu_\gamma^l) \text{Covariate}^t \\ p^l &= \exp(\mu_p^l) \\ \mu_\gamma^l &\sim N(\bar{\mu}_\gamma, \sigma_\gamma^2) \end{aligned}$$

with only the prior on μ_γ^l informed by the joint fit (using the long-term specifications). The variables (α^l, p^l) can adapt to each location, still subject to bounds in Table 4. The standard deviations are given by (12), and the functional prior (14) is also used for each individual location.

11.4.3. Combining draws from long-term and short-term models

For each location, the previous sections explain how we get long-term and short-term location-specific fitted models, that are informed by priors estimated using peaked locations. Given a location, we use the predicted validity framework of Section 9.2 to obtain 200 draws from each of the long-term and short-term location-specific variants.

To create the combined 200 draws that transition smoothly from the short-term to the long-term regime, we use simple linear interpolation in log increment space:

$$\text{increment of log D} = \lambda(t)[\text{increment of log D (long)}] + (1 - \lambda(t))[\text{increment of log D (short)}]$$

where

$$\lambda(t) = \min\left(1, \max\left(0, \frac{t - t_s}{t_e - t_s}\right)\right).$$

and where t_s and t_e are start and end times for the period of interest, starting with the last datapoint and continuing to the end of the forecast horizon. The resulting draw is then constructed by aggregating the joint increments over (t_s, t_e) .

We illustrate these steps all together using New York as an example. Figure 4 shows four plots. The short-term models are everywhere indicated using a red curve, while the long-term models are shown using green. The blue curve interpolates between these at the draw level in daily death space. Uncertainty in the plots is generated using the predictive validity framework, as described in Sections 6 and 7.

11.5. Default Case: 18 or More Daily Death Datapoints

For all locations where we have 18 or more datapoints, we no longer use the short-term strategy. Instead we use the extended model strategy detailed in Section 8.

Specifically, we follow the following steps:

- Fit a long-term specification as described in Section 11.4.2. For each location, this gives a Gaussian atom that has its own (γ, α, p) parameters.

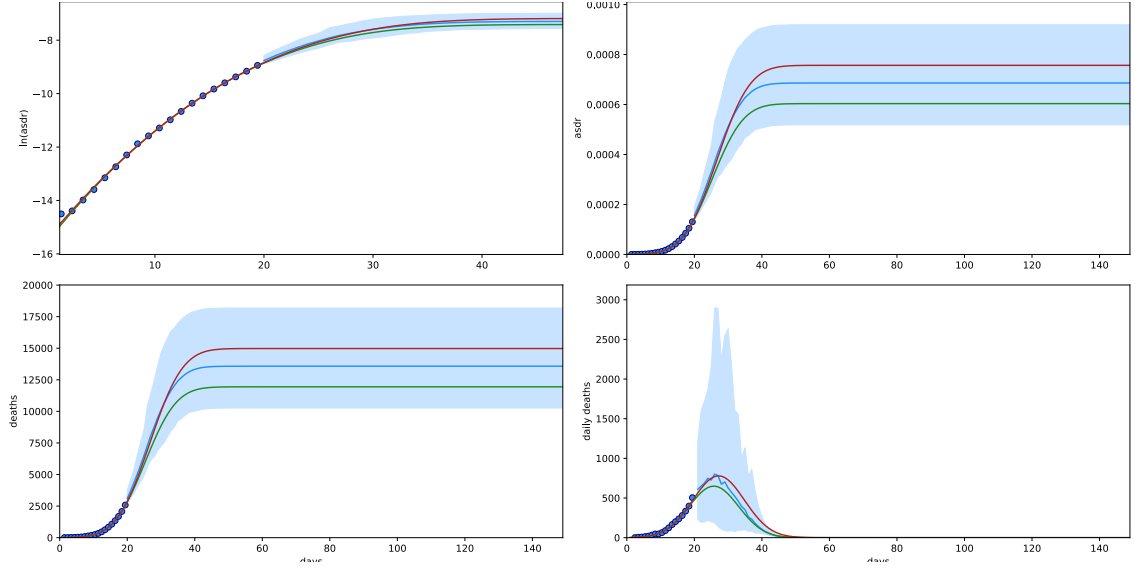


Figure 4. New York fits using the strategy in Section 11.4 (analysis and data from April 6). Top left: log cumulative death rate. Top right: cumulative death rate. Bottom right: cumulative deaths. Bottom left: daily deaths. Uncertainty using the PV framework is shown using blue shading. The short-term model is indicated by the red curve, while the long-term model is indicated by the green curve. The mean forecast, shown using the blue line, interpolates between the short-term and long-term models in daily death space.

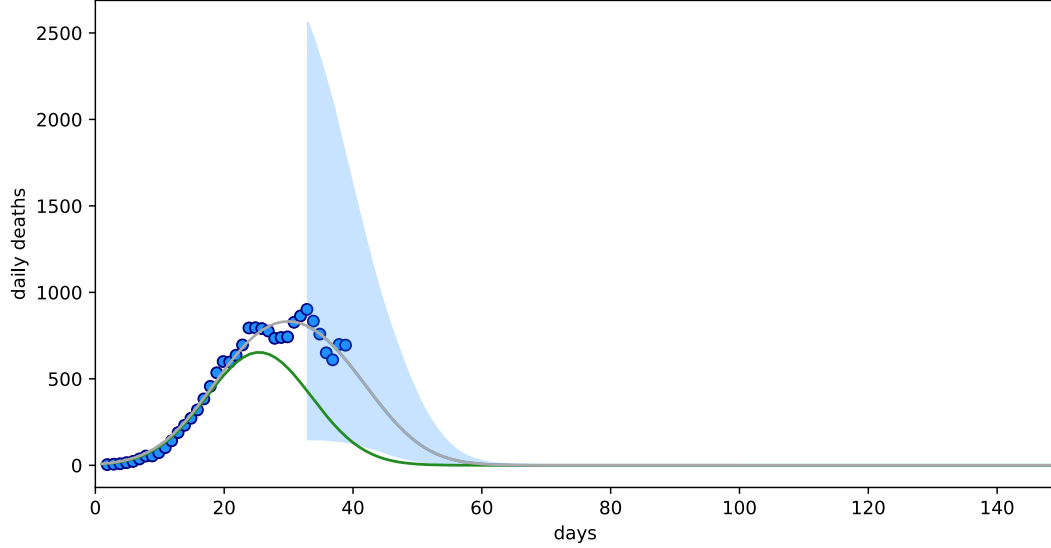


Figure 5. NY fits in daily death space, using the strategy in Section 11.5 (analysis and data from April 16). The long-term model, shown in green, is strongly tied to the social distancing covariate under-estimates the deaths time series and cannot adjust to the peak duration. The fitted linear combination of Gaussians, shown in grey, is fit as described in Section 8, uses the green fit as an atom, and fits much better to the data. Uncertainty estimates (shown using blue shading) for the entire procedure are obtained through the predictive validity framework described in Section 9.

- Fit location-specific combination of Gaussians using the 13 staggered peaks strategy given in Section 8.

The effects of this approach are as follows:

1. We borrow strength across locations in obtaining the relationship between the social distancing covariate and the peak times for places that have peaked.
2. We obtain location-specific Gaussian atoms that use the borrowed strength from the first step, and adjust the shape of the Gaussian atom to each specific location.
3. The final location-specific forecasts for data-rich locations use a combination of these atoms fit to the data at each location, captures individual variation, including asymmetric epidemic shapes, flat peaks, and other anomalies.

11.6. Ensemble over different covariate definitions.

The final estimates are created by an ensemble, at the draw level, across different model types. Models differed by definition of the social distancing covariate. The construction of these covariates (both for the initial and more recent estimates) is described in Section 5.

Once we have a set of covariates to ensemble over, the statistical specification and fitting procedure of each model type is specified exactly as in the previous sections. The final ensemble was created by equally weighting draws from each type of covariate model. The process is illustrated for New York in Figure 6 showing differences in data, analysis, and covariates between April 6th and April 16th.

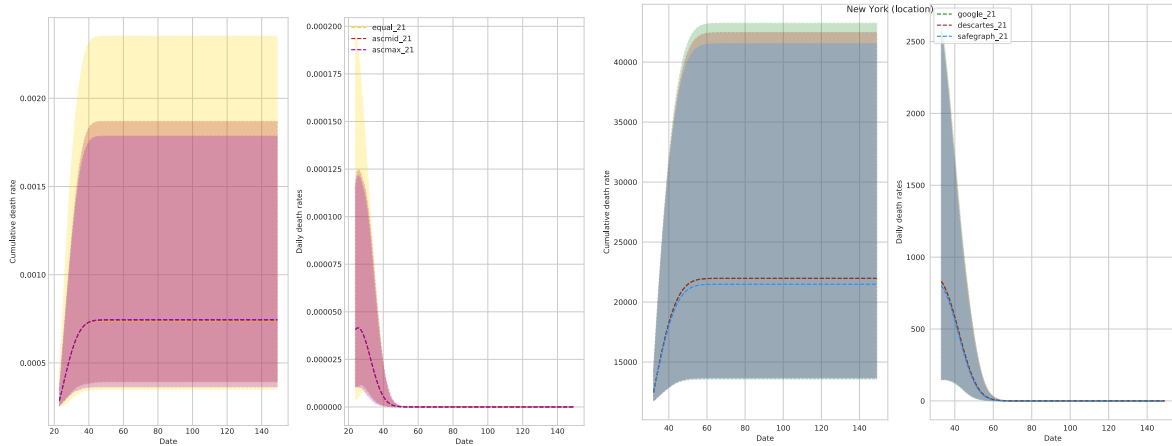


Figure 6. New York forecasts of three covariate models that are incorporated into a final ensemble. Left panel: data, analysis, and covariates from April 6th for cumulative and daily death rates, using the analysis detailed in Section 11.4. Right panel: data, analysis, and covariates from April 16 for cumulative and daily death counts using the analysis detailed in Section 11.5. Covariate definitions for these dates are described in Section 5.

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Supplementary Information: Timing of implementation and references for social distance measures by location

Location	Country	admin 1 unit name	Mass gathering restrictions	Stay at Home Order	Educational facilities closed	Initial business closures	Non-essential services closed	Travel severely limited	Source Mass gathering restrictions	Source Stay at Home Order	Source Educational facilities closed	Source Initial business closure	Source Non-essential services closed	Source Travel severely limited
Baden-Wuerttemberg	Germany	Baden-Wuerttemberg	full implementation	21.03.2020	17.03.2020	full implementation	21.03.2020	not implemented	https://stm.baden-wuerttemberg.de/fileadmin/redaktion/dateien/PDF/Coronainfos/20032_2_Rechtsverordnung_englisch.pdf	https://stm.baden-wuerttemberg.de/fileadmin/redaktion/dateien/PDF/Coronainfos/20032_165_Corona.pdf	https://stm.baden-wuerttemberg.de/fileadmin/redaktion/dateien/PDF/200317_STM_VO_165_Corona.pdf	https://stm.baden-wuerttemberg.de/fileadmin/redaktion/dateien/PDF/Coronainfos/20032_2_Rechtsverordnung_englisch.pdf	https://stm.baden-wuerttemberg.de/fileadmin/redaktion/dateien/PDF/Coronainfos/20032_2_Rechtsverordnung_englisch.pdf	
Bavaria	Germany	Bavaria	full implementation	21.03.2020	16.03.2020	17.03.2020	21.03.2020	not implemented	https://www.stmtp.bayern.de/presse/ausgangsbeschraenkung-in-bayern-wegen-coronavirus-pandemie-gesundheitsministerin-humt/	https://www.stmtp.bayern.de/presse/ausgangsbeschraenkung-in-bayern-wegen-coronavirus-pandemie-gesundheitsministerin-humt/	https://www.stmtp.bayern.de/presse/ausgangsbeschraenkung-in-bayern-wegen-coronavirus-pandemie-gesundheitsministerin-humt/	https://www.stmtp.bayern.de/presse/ausgangsbeschraenkung-in-bayern-wegen-coronavirus-pandemie-gesundheitsministerin-humt/	https://www.stmtp.bayern.de/presse/ausgangsbeschraenkung-in-bayern-wegen-coronavirus-pandemie-gesundheitsministerin-humt/	
Berlin	Germany	Berlin	full implementation	23.03.2020	23.03.2020	14.03.2020	23.03.2020	not implemented	https://www.berlin.de/corona/en/measures/	https://www.berlin.de/corona/en/measures/	https://www.berlin.de/corona/massnahmen/verordnung/	https://www.berlin.de/corona/massnahmen/verordnung/	https://www.berlin.de/corona/massnahmen/verordnung/	
Brandenburg	Germany	Brandenburg	full implementation	17.03.2020	18.03.2020	full implementation	17.03.2020	not implemented	https://www.maerkisch-oderland.de/de/datei/anzeigen/id/18585,1249/sars-cov-2-eindv.pdf	https://www.maerkisch-oderland.de/de/datei/anzeigen/id/18585,1249/sars-cov-2-eindv.pdf	https://www.maerkisch-oderland.de/de/datei/anzeigen/id/18585,1249/sars-cov-2-eindv.pdf	https://www.maerkisch-oderland.de/de/datei/anzeigen/id/18585,1249/sars-cov-2-eindv.pdf	https://www.maerkisch-oderland.de/de/datei/anzeigen/id/18585,1249/sars-cov-2-eindv.pdf	
Bremen	Germany	Bremen	full implementation	22.03.2020	16.03.2020	full implementation	20.03.2020	not implemented	https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1733248	https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1733248	https://www.senatspressestelle.bremen.de/detail.php?gsid=bremen1456331761.de&asle	https://www.senatspressestelle.bremen.de/pressemitteilungen-14647d-1464&skip=20	https://www.senatspressestelle.bremen.de/pressemitteilungen-14647d-1464&skip=20	
Hamburg	Germany	Hamburg	full implementation	22.03.2020	16.03.2020	15.03.2020	not implemented	not implemented	https://www.hamburg.de/allgemeinverfuegungen/13746326/2020-03-22-voruebergende-kontaktbeschraenkungen/	https://www.hamburg.de/allgemeinverfuegungen/13746326/2020-03-22-voruebergende-kontaktbeschraenkungen/	https://www.hamburg.de/coronavirus/pressemitteilungen/13721230/20-15-03-03-ik-massnahmen-corona-virus/	https://www.thelocal.de/20200316/coronavirus-restrictions-whats-closed-and-whats-open-in-germany	https://www.thelocal.de/20200316/coronavirus-restrictions-whats-closed-and-whats-open-in-germany	
Hesse	Germany	Hesse	full implementation	22.03.2020	16.03.2020	15.03.2020	not implemented	not implemented	https://www.hessen.de/presse/pressemitteilung/gemeinsame-leitlinien-von-bund-und-laendern-weiter-verschaert	https://www.hessen.de/presse/pressemitteilung/gemeinsame-leitlinien-von-bund-und-laendern-weiter-verschaert	https://www.hessen.de/presse/pressemitteilung/wir-muessen-die-ausbreitung-der-infektionen-verlangsamen	https://www.thelocal.de/20200316/coronavirus-restrictions-whats-closed-and-whats-open-in-germany	https://www.hessen.de/presse/pressemitteilung/gemeinsame-leitlinien-von-bund-und-laendern-weiter-verschaert	
Mecklenburg-Western Pomerania	Germany	Mecklenburg-Western Pomerania	full implementation	23.03.2020	16.03.2020	full implementation	18.03.2020	not implemented	https://www.regierung-mv.de/Aktuell/7id=158736&processor=processor.sa.pressemitteilung	https://www.regierung-mv.de/Aktuell/7id=158736&processor=processor.sa.pressemitteilung	https://www.regierung-mv.de/Aktuell/7id=158508&processor=processor.sa.pressemitteilung	https://www.regierung-mv.de/Aktuell/7id=158587&processor=processor.sa.pressemitteilung	https://www.regierung-mv.de/Aktuell/7id=158587&processor=processor.sa.pressemitteilung	
Lower Saxony	Germany	Lower Saxony	full implementation	23.03.2020	16.03.2020	full implementation	27.03.2020	not implemented	https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1733248	https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1733248	https://www.niedersachsen.de/Coronavirus/erlasse-und-allgemeinverfuegung/erlasse-und-allgemeinverfuegung-186628.html	https://www.niedersachsen.de/politik_staet/gesetzte_verordnungen_un-d_sonstige_vorschriften/aktuelle_verkundungsblaetter/download-verkundungsblaetter-108794.html	https://www.niedersachsen.de/politik_staet/gesetzte_verordnungen_un-d_sonstige_vorschriften/aktuelle_verkundungsblaetter/download-verkundungsblaetter-108794.html	
North Rhine-Westphalia	Germany	North Rhine-Westphalia	full implementation	23.03.2020	16.03.2020	26.02.2020	23.03.2020	not implemented	https://www.land.nrw.de/pressemitteilung/landesregierung-beschliesst-weitreichendes-kontaktverbot-und-weitere-massnahmen-zur	https://www.land.nrw.de/pressemitteilung/landesregierung-beschliesst-weitreichendes-kontaktverbot-und-weitere-massnahmen-zur	https://www.land.nrw.de/pressemitteilung/ministerin-gebauer-die-landesweite-einstellung-des-unterrichtsbetriebs-ist-eine	https://www.mags.nrw/erlasse-des-nrw-gesundheitsministeriums-zur-bekampfung-der-corona-pandemie	https://www.mags.nrw/erlasse-des-nrw-gesundheitsministeriums-zur-bekampfung-der-corona-pandemie	
Rhineland-Palatinate	Germany	Rhineland-Palatinate	full implementation	22.03.2020	16.03.2020	full implementation	23.03.2020	not implemented	https://corona.rlp.de/de/aktuelles/detail/news/News/detail/bund-und-laender-einigen-sich-auf-erweiterung-von-corona-schutzmassnahmen-1/	https://corona.rlp.de/de/aktuelles/detail/news/News/detail/bund-und-laender-einigen-sich-auf-erweiterung-von-corona-schutzmassnahmen-1/	https://www.spiegel.de/international/germany/germany-states-move-to-close-educational-and-daycare-facilities-a-e9c13296-002b-484b-88bc-e14ea295f110	https://www.thelocal.de/20200316/coronavirus-restrictions-whats-closed-and-whats-open-in-germany		
Saarland	Germany	Saarland	full implementation	21.03.2020	16.03.2020	15.03.2020	not implemented	not implemented	https://www.saarland.de/SID-80EAC3AE-AB42DE56/254312.htm	https://www.saarland.de/SID-80EAC3AE-AB42DE56/254312.htm	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	
Saxony	Germany	Saxony	full implementation	23.03.2020	23.03.2020	full implementation	23.03.2020	not implemented	https://www.coronavirus.sachsen.de/amtliche-bekanntmachungen.html	https://www.coronavirus.sachsen.de/amtliche-bekanntmachungen.html	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	
Saxony-Anhalt	Germany	Saxony-Anhalt	full implementation	22.03.2020	16.03.2020	full implementation	24.03.2020	not implemented	https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1733248	https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1733248	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	https://www.sachsen.sachsen.de/download/AllgV-Corona-Schulen-und-Kita-23032020.pdf	
Schleswig-Holstein	Germany	Schleswig-Holstein	full implementation	24.03.2020	16.03.2020	14.03.2020	24.03.2020	not implemented	https://www.schleswig-holstein.de/DE/Landesregierung/Presse/PI/2020/MP/200323_Erlass.h.html	https://www.schleswig-holstein.de/DE/Landesregierung/Presse/PI/2020/MP/200323_Erlass.h.html	https://www.schleswig-holstein.de/DE/Landesregierung/VIII/Presse/PI/2020/200313_VIII_Corona_Schulen_Kitas.html?sessionid=5514E56F90C51709719600398EC4CCD2_delivery1-master	https://www.schleswig-holstein.de/DE/Landesregierung/Presse/PI/2020/MP/200323_Erlass.h.html	https://www.schleswig-holstein.de/DE/Landesregierung/Presse/PI/2020/MP/200323_Erlass.h.html	
Thuringia	Germany	Thuringia	full implementation	22.03.2020	17.03.2020	15.03.2020	not implemented	not implemented	https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1733248	https://www.bundesregierung.de/breg-de/themen/coronavirus/besprechung-der-bundeskanzlerin-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1733248	https://www.spiegel.de/international/germany/germany-states-move-to-close-educational-and-daycare-facilities-a-e9c13296-002b-484b-88bc-e14ea295f110	https://www.thelocal.de/20200316/coronavirus-restrictions-whats-closed-and-whats-open-in-germany	https://www.thelocal.de/20200316/coronavirus-restrictions-whats-closed-and-whats-open-in-germany	
Andalucia	Spain	Andalucia	full implementation	15.03.2020	14.03.2020	full implementation	15.03.2020	not implemented	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	
Aragon	Spain	Aragon	full implementation	15.03.2020	14.03.2020	full implementation	15.03.2020	not implemented	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	
Principado de Asturias	Spain	Principado de Asturias	full implementation	15.03.2020	14.03.2020	full implementation	15.03.2020	not implemented	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	
Islas Baleares	Spain	Islas Baleares	full implementation	15.03.2020	14.03.2020	full implementation	15.03.2020	not implemented	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	
Islas Canarias	Spain	Islas Canarias	full implementation	15.03.2020	14.03.2020	full implementation	15.03.2020	not implemented	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	
Cantabria	Spain	Cantabria	full implementation	15.03.2020	14.03.2020	full implementation	15.03.2020	not implemented	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	
Castilla-La Mancha	Spain	Castilla-La Mancha	full implementation	15.03.2020	14.03.2020	full implementation	15.03.2020	not implemented	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	https://www.boe.es/boe/dias/2020/03/14/pdfs/BOE-A-2020-3692.pdf	
Castilla y Leon	Spain	Castilla y Leon	full implementation											

Location	Country	admin 1 unit name	Mass gathering restrictions	Stay at Home Order	Educational facilities closed	Initial business closures	Non-essential services closed	Travel severely limited	Source Mass gathering restrictions	Source Stay at Home Order	Source Educational facilities closed	Source Initial business closure	Source Non-essential services closed	Source Travel severely limited
Alaska	USA	Alaska	24.03.2020	28.03.2020	16.03.2020	17.03.2020	28.03.2020	28.03.2020	https://gov.alaska.gov/wp-content/uploads/sites/2/03232020-SOA-COVID-19-Health-Mandate-009.pdf	https://gov.alaska.gov/wp-content/uploads/sites/2/03232020-COVID-19-Health-Mandate-010-Attachment-A.pdf	https://gov.alaska.gov/wp-content/uploads/sites/2/03132020-COVID-19-Health-Mandate-001.pdf	https://gov.alaska.gov/wp-content/uploads/sites/2/03.16.20-COVID-19-Health-Mandate-002.pdf	https://gov.alaska.gov/wp-content/uploads/sites/2/03232020-COVID-19-Health-Mandate-010-Attachment-A.pdf	https://gov.alaska.gov/wp-content/uploads/sites/2/04132020-COVID-MANDATE-012-Alaska-Small-Community-Emergency-Travel-Order.pdf
Arizona	USA	Arizona	full implementation	30.03.2020	16.03.2020	not implemented	not implemented	not implemented	https://azagovernor.gov/file/34365/download?token=6YdWos-F	https://azagovernor.gov/file/34365/download?token=6YdWos-F	https://www.azed.gov/communications/2020/03/10/guidance-to-schools-on-covid-19/	https://www.healthy.arkansas.gov/images/uploads/pdf/Directive_03_10_2020_final.pdf		
Arkansas	USA	Arkansas	27.03.2020	not implemented	17.03.2020	19.03.2020	not implemented	not implemented	https://governor.arkansas.gov/images/uploads/executiveOrders/EO_20-10_.pdf	http://adecm.arkansas.gov/ViewApprovedMemo.aspx?id=4328	https://www.healthy.arkansas.gov/images/uploads/pdf/Directive_03_10_2020_final.pdf			
California	USA	California	11.03.2020	19.03.2020	19.03.2020	full implementation	19.03.2020	not implemented	https://www.gov.ca.gov/2020/03/11/california-public-health-experts-mass-gatherings-should-be-postponed-or-canceled-statewide-to-slow-the-spread-of-covid-19/	https://covid19.ca.gov/img/Executive-Order-N-33-20.pdf	https://edsources.org/2020/california-k-12-schools-closed-due-to-the-coronavirus/624984	https://covid19.ca.gov/img/Executive-Order-N-33-20.pdf	https://covid19.ca.gov/img/Executive-Order-N-33-20.pdf	
Colorado	USA	Colorado	19.03.2020	26.03.2020	23.03.2020	17.03.2020	26.03.2020	not implemented	https://drive.google.com/file/d/1AaKv87qLUHUR59bl_q0L24rCChair/fiew	https://drive.google.com/file/d/1O1EDCY6-A6QBkx2DmCSf8B8BD0OI3k/view	https://www.colorado.gov/pacific/sites/default/files/atoms/files/Bars-ZdJueEJ_vvVw3dWk/view	https://www.colorado.gov/pacific/sites/default/files/atoms/files/Bars-ZdJueEJ_vvVw3dWk/view	https://drive.google.com/file/d/1O1EDCY6-A6QBkx2DmCSf8B8BD0OI3k/view	
Connecticut	USA	Connecticut	12.03.2020	not implemented	17.03.2020	16.03.2020	23.03.2020	not implemented	https://portal.ct.gov/-/media/Office-of-the-Governor/Executive-Orders/Lamont-Executive-Orders/Executive-Order-No-7.pdf?la=en	https://portal.ct.gov/-/media/Office-of-the-Governor/Executive-Orders/Lamont-Executive-Orders/Executive-Order-No-7C.pdf?la=en	https://portal.ct.gov/-/media/Office-of-the-Governor/Executive-Orders/Lamont-Executive-Orders/Executive-Order-No-7D.pdf?la=en	https://portal.ct.gov/-/media/Office-of-the-Governor/Executive-Orders/Lamont-Executive-Orders/Executive-Order-No-7H.pdf?la=en		
Delaware	USA	Delaware	16.03.2020	24.03.2020	16.03.2020	16.03.2020	24.03.2020	not implemented	https://governor.delaware.gov/wp-content/uploads/sites/24/2020/03/State-of-Emergency_Modified-03162020.pdf	https://governor.delaware.gov/wp-content/uploads/sites/24/2020/03/Fifth-Modification-to-State-of-Emergency-03222020.pdf	https://governor.delaware.gov/wp-content/uploads/sites/24/2020/03/School-Letter-Governor-Carney-03132020.pdf	https://governor.delaware.gov/wp-content/uploads/sites/24/2020/03/Second-Modification-to-the-State-of-Emergency.pdf	https://governor.delaware.gov/wp-content/uploads/sites/24/2020/03/Fourth-Modification-to-State-of-Emergency-03222020.pdf	
Florida	USA	Florida	03.04.2020	03.04.2020	17.03.2020	17.03.2020	not implemented	not implemented	https://www.flgov.com/wp-content/uploads/orders/2020/EO_20-91-compressed.pdf	https://www.flgov.com/wp-content/uploads/orders/2020/EO_20-91-compressed.pdf	https://www.flgov.com/wp-content/uploads/orders/2020/EO_20-68.pdf			
Georgia	USA	Georgia	24.03.2020	03.04.2020	18.03.2020	24.03.2020	not implemented	not implemented	https://gov.georgia.gov/document/2020-executive-order/03232001/download	https://gov.georgia.gov/document/2020-executive-order/04022001/download	https://gov.georgia.gov/document/2020-executive-order/03162001/download			
Hawaii	USA	Hawaii	17.03.2020	25.03.2020	19.03.2020	17.03.2020	25.03.2020	not implemented	https://governor.hawaii.gov/newsroom/latest-news/proper-use-of-covid-19-tests-impertative-there-is-a-current-shortage-of-hand-sanitizers-and-toilet-paper-in-hawaii-in-part-because-of-the-publics-over-reaction-to-covid-19-the-hawai/	https://hawaii.covid19.com/statewide-stay-at-home-effective-march-25-2020-through-april-30-2020/	http://www.hawaiipublicschools.org/ConnectWithUs/MediaRoom/Presaleads/Pages/HIDOC-extends-school-closures-implements-remote-work-to-maintain-essential-functions.aspx	https://governor.hawaii.gov/newsroom/latest-news/proper-use-of-covid-19-tests-impertative-there-is-a-current-shortage-of-hand-sanitizers-and-toilet-paper-in-hawaii-in-part-because-of-the-publics-over-reaction-to-covid-19-the-hawai/	https://hawaii.covid19.com/wp-content/uploads/2020/03/2003162-ATG_Third-Supplementary-Proclamation-for-COVID-19-signed-12.pdf	
Idaho	USA	Idaho	full implementation	25.03.2020	23.03.2020	full implementation	25.03.2020	not implemented	https://coronavirus.idaho.gov/wp-content/uploads/sites/127/2020/04/amended-statewide-stay-home-order_041520.pdf	https://coronavirus.idaho.gov/wp-content/uploads/sites/127/2020/04/amended-statewide-stay-home-order_041520.pdf	https://boardofed.idaho.gov/resources/covid-19-school-operations-guidance/	https://coronavirus.idaho.gov/wp-content/uploads/sites/127/2020/04/amended-statewide-stay-home-order_041520.pdf	https://coronavirus.idaho.gov/wp-content/uploads/sites/127/2020/04/amended-statewide-stay-home-order_041520.pdf	
Illinois	USA	Illinois	13.03.2020	21.03.2020	17.03.2020	16.03.2020	21.03.2020	not implemented	https://www2.illinois.gov/Pages/Executive-Orders/ExecutiveOrder2020-04.aspx	https://www2.illinois.gov/ISNews/21288-Gov_Pritzker_Stay_at_Home_Order.pdf	https://www2.illinois.gov/Documents/ExecOrders/2020/ExecutiveOrder2020-05.pdf	https://www2.illinois.gov/Pages/ExecutiveOrders/ExecutiveOrder2020-07.aspx	https://www2.illinois.gov/Pages/ExecutiveOrders/ExecutiveOrder2020-10.aspx	https://www2.illinois.gov/ISNews/21288-Gov_Pritzker_Stay_at_Home_Order.pdf
Indiana	USA	Indiana	12.03.2020	25.03.2020	19.03.2020	16.03.2020	24.03.2020	not implemented	https://calendar.in.gov/site/gov/event/gov-holcomb-announces-new-steps-to-protect-public-from-covid-19/	https://www.in.gov/gov/files/Executive_Order_20-08_Stay_at_Home.pdf	https://www.doe.in.gov/sites/default/files/health/ideo-covid-19-update-3192020.pdf	https://www.in.gov/gov/files/ExecutiveOrder20-04furtherOrderforPublicHealthEmergency.pdf	https://www.in.gov/gov/files/Executive_Order_20-08_Stay_at_Home.pdf	
Iowa	USA	Iowa	17.03.2020	not implemented	04.04.2020	17.03.2020	not implemented	not implemented	https://governor.iowa.gov/sites/default/files/documents/Public%20Health%20Proclamation%20-%202020.03.17.pdf	https://governor.iowa.gov/sites/default/files/documents/Public%20Health%20Proclamation%20-%202020.04.02.pdf	https://governor.iowa.gov/sites/default/files/documents/Public%20Health%20Proclamation%20-%202020.04.02.pdf	https://governor.iowa.gov/sites/default/files/documents/Public%20Health%20Proclamation%20-%202020.03.17.pdf		
Kansas	USA	Kansas	17.03.2020	30.03.2020	17.03.2020	not implemented	not implemented	not implemented	https://governor.kansas.gov/wp-content/uploads/2020/03/20-04-Executed.pdf	https://governor.kansas.gov/wp-content/uploads/2020/03/EO20-16.pdf	https://governor.kansas.gov/wp-content/uploads/2020/03/EO20-07-Executed.pdf			
Kentucky	USA	Kentucky	19.03.2020	not implemented	20.03.2020	16.03.2020	26.03.2020	not implemented	https://governor.ky.gov/attachments/20200319_Order_Mass-Gatherings.pdf		https://content.govdelivery.com/accounts/KYDE/bulletins/28181c1	https://governor.ky.gov/attachments/20200316_Order_Restaurant-Closure.pdf	https://governor.ky.gov/attachments/20200325_Executive-Order_2020-257_Healthy-at-Home.pdf	
Louisiana	USA	Louisiana	13.03.2020	23.03.2020	16.03.2020	17.03.2020	22.03.2020	not implemented	https://gov.louisiana.gov/assets/ExecutiveOrders/27-IBE-2020-COVID-19.pdf	https://gov.louisiana.gov/index.cfm/newsroom/detail/2427	https://gov.louisiana.gov/assets/ExecutiveOrders/27-IBE-2020-COVID-19.pdf	https://gov.louisiana.gov/assets/ExecutiveOrders/IBE-EO-30.pdf	https://gov.louisiana.gov/assets/Proclamations/2020/IBE-33-2020.pdf	
Maine	USA	Maine	18.03.2020	02.04.2020	16.03.2020	18.03.2020	25.03.2020	not implemented	https://www.maine.gov/governor/mills/sites/maine.gov.governor.mills/files/inline-files/EXECUTIVE%20Order%20on%20Protect%20Public%20Health%20.pdf	https://www.wmtw.com/article/maine-school-closures-coronavirus-covid19/31619144	https://www.maine.gov/governor/mills/sites/maine.gov.governor.mills/files/inline-files/EXECUTIVE%20Order%20on%20Protect%20Public%20Health%20.pdf	https://www.maine.gov/governor/mills/sites/maine.gov.governor.mills/files/inline-files/Ar%20Order%20Regarding%20Essential%20Businesses%20and%20Operations%20_0.pdf		
Maryland	USA	Maryland	16.03.2020	30.03.2020	16.03.2020	16.03.2020	23.03.2020	not implemented	https://governor.maryland.gov/wp-content/uploads/2020/03/Executive-Order-Amending-Large-Gatherings.pdf	http://marylandpublicschools.org/Pages/default.aspx	https://governor.maryland.gov/wp-content/uploads/2020/03/Executive-Order-Amending-Large-Gatherings.pdf	https://governor.maryland.gov/wp-content/uploads/2020/03/Gatherings-THIRD-AMENDED-3.23.20.pdf		
Massachusetts	USA	Massachusetts	13.03.2020	not implemented	17.03.2020	17.03.2020	24.03.2020	not implemented	https://www.mass.gov/doc/order-prohibiting-gatherings-of-more-than-250-people/download	https://www.mass.gov/info-details/covid-19-state-of-emergency	https://www.mass.gov/doc/march-16-2020-large-gathering-at-25-people-order/download	https://www.mass.gov/doc/march-23-2020-essential-services-and-revised-gatherings-order/download		
Michigan	USA	Michigan	13.03.2020	24.03.2020	16.03.2020	16.03.2020	23.03.2020	not implemented	https://www.michigan.gov/whitmer/0,9309,7-387-90499_90705-521595--00.html	https://www.michigan.gov/whitmer/0,9309,7-387-90499_90705-521595--00.html	https://www.michigan.gov/whitmer/0,9309,7-387-90499_90705-521595--00.html	https://www.michigan.gov/whitmer/0,9309,7-387-90499_90705-521595--00.html		
Minnesota	USA	Minnesota	24.03.2020	27.03.2020	18.03.2020	17.03.2020	not implemented	not implemented	https://www.sos.ms.gov/Education-Publications/ExecutiveOrders/1463.pdf	https://www.leg.state.mn.us/archive/execorders/20-20.pdf	https://education.mn.gov/mde/index.html	https://mn.gov/governor/assets/2020_03_16_EO_20_04_Bars_Restaurants_tcm1055-423380.pdf		
Mississippi	USA	Mississippi	24.03.2020	03.04.2020	19.03.2020	24.03.2020	03.04.2020	not implemented	https://www.sos.ms.gov/Education-Publications/ExecutiveOrders/1463.pdf	https://www.sos.ms.gov/Pages/Gov-Reeves-Announces-Extended-School-Closures.aspx	https://www.sos.ms.gov/Education-Publications/ExecutiveOrders/1463.pdf	https://www.sos.ms.gov/Education-Publications/ExecutiveOrders/1466.pdf		
Missouri	USA	Missouri	23.03.2020	06.04.2020	23.03.2020	23.03.2020	not implemented	not implemented	https://governor.mo.gov/press-releases/archive/governor-parson-directs-dhss-director-require-social-distancing-statewide	https://content.govdelivery.com/attachments/MOGOV/2020/04/03/file_attachments/1419322/Stay%20at%20Home%20Missouri%20Order.pdf	https://dese.mo.gov/communications/coronavirus-covid-19-information	https://governor.mo.gov/press-releases/archive/governor-parson-directs-dhss-director-require-social-distancing-statewide		
Montana	USA	Montana	24.03.2020	26.03.2020	15.03.2020	20.03.2020	26.03.2020	not implemented	http://governor.mt.gov/Portals/16/Closure%20Extensions%20and%20SocialDistancing.pdf?ver=2020-03-24-164313-497	https://covid19.mt.gov/Portals/223/Documents/Stay%20at%20Home%20Directive.pdf?ver=2020-03-26-173332-177	https://news.mt.gov/governor-bullock-directs-the-closure-of-public-k-12-schools-for-two-weeks-strongly-recommends-social-distancing-measures-to-slow-the-spread-of-covid-19	http://governor.mt.gov/Portals/16/Directive%20on%20Bars%20and%20Restaurants.pdf?ver=2020-03-20-103134-937	https://covid19.mt.gov/Portals/223/Documents/Stay%20at%20Home%20Directive.pdf?ver=2020-03-26-173332-177	
Nebraska	USA	Nebraska	16.03.2020	not implemented	02.04.2020	19.03.2020	not implemented	not implemented	https://governor.nebraska.gov/press/gov-ricketts-further-limits-events-gatherings-prevent-covid-19-spread	https://www.education.ne.gov/publichealth/known-school-closures/	https://www.dropbox.com/s/sk9Selfp6bnets/DHM%203.19.2020.pdf?dl=1			
Nevada	USA	Nevada	24.03.2020	31.03.2020	16.03.2020	18.03.2020	21.03.2020	not implemented	http://gov.nv.gov/News/Emergency_Orders/2020/2020-03-31_-_COVID-19_Declaration_of_Emergency_Directive_007/	http://www.doe.nv.gov/uploadedFiles/ndedoe/vgov/content/home/declarationofEmergencyDirectiveSchools.pdf	http://gov.nv.gov/News/Emergency_Orders/2020/2020-03-18_-_COVID-19_Declaration_of_Emergency_Directive_002/	http://gov.nv.gov/News/Emergency_Orders/2020/2020-03-20_-_COVID-19_Declaration_of_Emergency_Directive_003/		
New Hampshire	USA	New Hampshire	16.03.2020	27.03.2020	16.03.2020	16.03.2020	28.03.2020	not implemented	https://www.governor.nh.gov/news-media/emergency-orders/documents/emergency-order-2.pdf	https://www.governor.nh.gov/news-media/emergency-orders/documents/emergency-order-17-1.pdf	https://www.governor.nh.gov/news-media/emergency-orders/documents/emergency-order-2.pdf	https://www.governor.nh.gov/news-media/emergency-orders/documents/emergency-order-17		

Location	Country	admin 1 unit name	Mass gathering restrictions	Stay at Home Order	Educational facilities closed	Initial business closures	Non-essential services closed	Travel severely limited	Source Mass gathering restrictions	Source Stay at Home Order	Source Educational facilities closed	Source Initial business closure	Source Non-essential services closed	Source Travel severely limited
South Carolina	USA	South Carolina	18.03.2020	07.04.2020	16.03.2020	18.03.2020	not implemented	not implemented	https://governor.sc.gov/sites/default/files/Documents/Executive-Orders/2020-03-17%20of%20the%20Executive%20Order%20No.%202020-10%20-%20Directing%20Additional%20Emergency%20Measures%20due%20to%20COVID-19.pdf	https://governor.sc.gov/sites/default/files/Documents/Executive-Orders/2020-04-06%20of%20the%20Executive%20Order%20No.%202020-21%20-%20Stay%20at%20Home%20or%20Work%20Order.pdf	https://governor.sc.gov/sites/default/files/Documents/Executive-Orders/2020-03-15%20of%20the%20Executive%20Order%20No.%202020-09%20-%20Closing%20Schools%20and%20Canceling%20Events%20Other%20Provisions%20due%20to%20COVID-19.pdf	https://governor.sc.gov/sites/default/files/Documents/Executive-Orders/2020-03-17%20of%20the%20Executive%20Order%20No.%202020-10%20-%20Directing%20Additional%20Emergency%20Measures%20due%20to%20COVID-19.pdf	https://governor.sc.gov/sites/default/files/Documents/Executive-Orders/2020-03-31%20of%20the%20Executive%20Order%20No.%202020-17%20-%20Closure%20of%20Non-Essential%20Businesses.pdf	
South Dakota	USA	South Dakota	06.04.2020	not implemented	16.03.2020	not implemented	not implemented	not implemented	https://sdsos.gov/general-information/executive-actions/executive-orders/assets/2020-12.PDF		https://www.youtube.com/watch?v=Nijuy-HlICw			
Tennessee	USA	Tennessee	23.03.2020	02.04.2020	20.03.2020	23.03.2020	01.04.2020	not implemented	https://sos.tn.gov/files.tnsosfiles.com/forms/exec-order-lee17.pdf	https://publications.tnsosfiles.com/pub/execorders/exec-orders-lee23.pdf	https://www.tn.gov/governor/news/2020/3/16/governor-lee-issues-lee23.pdf	https://sos.tn.gov/files.tnsosfiles.com/forms/exec-order-lee17.pdf	https://publications.tnsosfiles.com/pub/execorders/exec-orders-lee2.pdf	
Texas	USA	Texas	21.03.2020	02.04.2020	19.03.2020	21.03.2020	not implemented	not implemented	https://gov.texas.gov/uploads/files/press/EO-GA_08_COVID-19_preparedness_and_mitigation_FINAL_03-19-2020_1.pdf	https://gov.texas.gov/news/post/governor-abbott-issues-executive-order-implementing-essential-services-and-activities-protocols	https://gov.texas.gov/uploads/files/press/EO-GA_08_COVID-19_preparedness_and_mitigation_FINAL_03-19-2020_1.pdf	https://gov.texas.gov/uploads/files/press/EO-GA_08_COVID-19_preparedness_and_mitigation_FINAL_03-19-2020_1.pdf		
Utah	USA	Utah	19.03.2020	not implemented	16.03.2020	19.03.2020	not implemented	not implemented	https://coronavirus.utah.gov/wp-content/uploads/Restaurant-Pub-HiH-Order-1.pdf	https://rules.utah.gov/wp-content/uploads/Governors_Coronavirus_Directive_for_Utah.pdf	https://governor.utah.gov/2020/03/13/gov-herbert-announces-two-week-dismissal-of-utahs-public-schools/	https://coronavirus.utah.gov/wp-content/uploads/Restaurant-Pub-HiH-Order-1.pdf	https://rules.utah.gov/wp-content/uploads/Governors_Coronavirus_Directive_for_Utah.pdf	
Vermont	USA	Vermont	13.03.2020	24.03.2020	18.03.2020	17.03.2020	25.03.2020	not implemented	https://governor.vermont.gov/sites/scott/files/documents/EO%202001-20%20Declaration%20of%20State%20of%20Emergency%20in%20Response%20to%20COVID-19%20and%20National%20Guard%20Call-Out.pdf	https://governor.vermont.gov/sites/scott/files/documents/ADDENDUM%206%20TO%20EXECUTIVE%20ORDER%2001-20.pdf	https://governor.vermont.gov/press-release/gov-scott-orders-orderly-closure-vermont-prek-12-schools-week	https://governor.vermont.gov/sites/scott/files/documents/ADDENDUM%206%20TO%20EXECUTIVE%20ORDER%2001-20_0.pdf	https://governor.vermont.gov/sites/scott/files/documents/ADDENDUM%206%20TO%20EXECUTIVE%20ORDER%2001-20.pdf	
Virginia	USA	Virginia	24.03.2020	30.03.2020	16.03.2020	17.03.2020	24.03.2020	not implemented	https://www.governor.virginia.gov/media/governorvirginiagov/executive-actions/EO-53-Temporary-Restrictions-Due-To-Novel-Coronavirus-(COVID-19).pdf	https://www.governor.virginia.gov/newsroom/all-releases/2020/march/headline-854442.en.html	https://www.governor.virginia.gov/sites/default/files/declarations/20-13%20Coronavirus%20Restaurants-Bars%20%28tmp%29.pdf	https://www.governor.virginia.gov/media/governorvirginiagov/executive-actions/EO-53-Temporary-Restrictions-Due-To-Novel-Coronavirus-(COVID-19).pdf	https://www.governor.virginia.gov/sites/default/files/declarations/20-13%20Coronavirus%20Restaurants-Bars%20%28tmp%29.pdf	
Washington	USA	Washington	11.03.2020	23.03.2020	13.03.2020	16.03.2020	25.03.2020	not implemented	https://www.governor.wa.gov/sites/default/files/20-07%20Coronavirus%20%28tmp%29.pdf	Complete sub-location set	https://www.governor.wa.gov/sites/default/files/declarations/20-08%20Coronavirus%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-13%20Coronavirus%20Restaurants-Bars%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-16%20Coronavirus%20No%20Visitors%20LC%20%28tmp%29.pdf	
Life Care Center, Kirkland, WA	USA	Washington	11.03.2020	17.03.2020	11.03.2020	16.03.2020	25.03.2020	17.03.2020	https://www.governor.wa.gov/sites/default/files/20-07%20Coronavirus%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-16%20Coronavirus%20No%20Visitors%20LC%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-08%20Coronavirus%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-13%20Coronavirus%20Restaurants-Bars%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-25%20Coronavirus%20Stay%20Safe-Stay%20Healthy%20%28tmp%29%20%28002%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-16%20Coronavirus%20No%20Visitors%20LC%20%28tmp%29.pdf
Other Counties, WA	USA	Washington	11.03.2020	23.03.2020	13.03.2020	16.03.2020	25.03.2020	not implemented	https://www.governor.wa.gov/sites/default/files/20-07%20Coronavirus%20%28tmp%29.pdf	https://www.governor.wa.gov/news-media/inslee-announces-statewide-school-closures-expansion-limits-large-gatherings	https://www.governor.wa.gov/sites/default/files/declarations/20-13%20Coronavirus%20Restaurants-Bars%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-25%20Coronavirus%20Stay%20Safe-Stay%20Healthy%20%28tmp%29%20%28002%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-13%20Coronavirus%20Restaurants-Bars%20%28tmp%29.pdf	
King and Snohomish Counties (excluding Life Care Center), WA	USA	Washington	11.03.2020	23.03.2020	11.03.2020	16.03.2020	25.03.2020	not implemented	https://www.governor.wa.gov/sites/default/files/20-07%20Coronavirus%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-25%20Coronavirus%20Stay%20Safe-Stay%20Healthy%20%28tmp%29%20%28002%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-08%20Coronavirus%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-13%20Coronavirus%20Restaurants-Bars%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-25%20Coronavirus%20Stay%20Safe-Stay%20Healthy%20%28tmp%29%20%28002%29.pdf	
USA	USA	Washington	11.03.2020	17.03.2020	11.03.2020	16.03.2020	25.03.2020	not implemented	https://www.governor.wa.gov/sites/default/files/20-07%20Coronavirus%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-16%20Coronavirus%20No%20Visitors%20LC%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-08%20Coronavirus%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-13%20Coronavirus%20Restaurants-Bars%20%28tmp%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-25%20Coronavirus%20Stay%20Safe-Stay%20Healthy%20%28tmp%29%20%28002%29.pdf	https://www.governor.wa.gov/sites/default/files/declarations/20-16%20Coronavirus%20No%20Visitors%20LC%20%28tmp%29.pdf
West Virginia	USA	West Virginia	24.03.2020	25.03.2020	14.03.2020	18.03.2020	24.03.2020	not implemented	https://www.wvinsurance.gov/Portals/0/pdf/pressrelease/WVStayHomeOrder.pdf?ver=2020-03-23-152606-773	https://www.wvinsurance.gov/Portals/0/pdf/pressrelease/WVStayHomeOrder.pdf?ver=2020-03-23-152606-773	https://governor.wv.gov/News/press-releases/2020/Pages/COVID-19-UPDATE-Gov.-Justice.-Department-of-Education-issue-updated-guidance-on-school-closures-in-West-Virginia.aspx	https://governor.wv.gov/Documents/2020%20Executive%20Orders/Executive-Order-March-18-2020.pdf	https://www.wvinsurance.gov/Portals/0/pdf/pressrelease/WVStayHomeOrder.pdf?ver=2020-03-23-152606-773	
Wisconsin	USA	Wisconsin	17.03.2020	25.03.2020	18.03.2020	17.03.2020	25.03.2020	not implemented	https://content.godvelivery.com/accounts/WIGOV/bulletins/2817964_attachments/1409408/Health%20Order%20N%202312%20Safer%20At%20Home.pdf	https://evers.wi.gov/Documents/COVID19/K-12FAQ_3.15.20.pdf	https://drive.google.com/file/d/1XtW20VfYbgBVB8aYrVWnBAdpvyk/view	https://evers.wi.gov/Documents/COVID19/UPDATEDOrder10People.pdf	https://content.godvelivery.com/accounts/WIGOV/bulletins/2817964_attachments/1409408/Health%20Order%20N%202312%20Safer%20At%20Home.pdf	
Wyoming	USA	Wyoming	20.03.2020	not implemented	19.03.2020	19.03.2020	not implemented	not implemented	https://health.wyo.gov/wp-content/uploads/2020/03/March-20-gatherings-order.pdf		https://drive.google.com/file/d/1XtW20VfYbgBVB8aYrVWnBAdpvyk/view	https://drive.google.com/file/d/1XtW20VfYbgBVB8aYrVWnBAdpvyk/view		
District of Columbia	USA	District of Columbia	13.03.2020	30.03.2020	16.03.2020	16.03.2020	25.03.2020	not implemented	https://coronavirus.dc.gov/sites/default/files/dc/sites/coronavirus/release_content/attachments/DOH_Rulemaking_Mass-Gatherings.pdf	https://coronavirus.dc.gov/stayhome	https://dcps.dc.gov/coronaviruslatest	https://mayor.dc.gov/sites/default/files/dc/sites/mayor/mv/publication/Attachments/MO-Prohibition-on-Mass-Gatherings-During-Public-Health-Emergency.pdf	https://mayor.dc.gov/sites/default/files/dc/sites/mayor/mv/release_content/attachments/Mayor%27s%20Order%202020-05%20Closure%20of%20Non-Essential%20Businesses%20and%20Prohibitions.pdf	
Abruzzo	Italy	Abruzzo	full implementation	11.03.2020	05.03.2020	full implementation	11.03.2020	22.03.2020	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	https://www.muir.gov.it/web/guest/-/coronavirus-azzolina-attivita-didattiche-sospese-fino-al-15-marzo	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.trovanorme.salute.gov.it/norme/dettaglioAtto?id=73728	
Basilicata	Italy	Basilicata	full implementation	11.03.2020	05.03.2020	full implementation	11.03.2020	22.03.2020	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	https://www.muir.gov.it/web/guest/-/coronavirus-azzolina-attivita-didattiche-sospese-fino-al-15-marzo	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.trovanorme.salute.gov.it/norme/dettaglioAtto?id=73728	
Provincia autonoma di Bolzano	Italy	P.A. Bolzano	full implementation	11.03.2020	05.03.2020	full implementation	11.03.2020	22.03.2020	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	https://www.muir.gov.it/web/guest/-/coronavirus-azzolina-attivita-didattiche-sospese-fino-al-15-marzo	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.trovanorme.salute.gov.it/norme/dettaglioAtto?id=73728	
Calabria	Italy	Calabria	full implementation	11.03.2020	05.03.2020	full implementation	11.03.2020	22.03.2020	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	https://www.muir.gov.it/web/guest/-/coronavirus-azzolina-attivita-didattiche-sospese-fino-al-15-marzo	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.trovanorme.salute.gov.it/norme/dettaglioAtto?id=73728	
Campania	Italy	Campania	full implementation	11.03.2020	05.03.2020	full implementation	11.03.2020	22.03.2020	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	https://www.muir.gov.it/web/guest/-/coronavirus-azzolina-attivita-didattiche-sospese-fino-al-15-marzo	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.trovanorme.salute.gov.it/norme/dettaglioAtto?id=73728	
Emilia-Romagna	Italy	Emilia Romagna	07.03.2020	11.03.2020	01.03.2020	07.03.2020	11.03.2020	22.03.2020	https://www.bbc.com/news/world-middle-east-51787238	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	https://www.muir.gov.it/web/guest/-/coronavirus-azzolina-attivita-didattiche-sospese-fino-al-15-marzo	https://www.bbc.com/news/world-middle-east-51787238	http://www.trovanorme.salute.gov.it/norme/dettaglioAtto?id=73728	
Friuli-Venezia Giulia	Italy	Friuli Venezia Giulia	full implementation	11.03.2020	05.03.2020	full implementation	11.03.2020	22.03.2020	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299	http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-202				

Location	Country	admin 1 unit name	Mass gathering restrictions	Stay at Home Order	Educational facilities closed	Initial business closures	Non-essential services closed	Travel severely limited	Source Mass gathering restrictions	Source Stay at Home Order	Source Educational facilities closed	Source Initial business closure	Source Non-essential services closed	Source Travel severely limited
Finland	Finland		12.03.2020	not implemented	18.03.2020	18.03.2020	04.04.2020	25.03.2020	https://www.covid19healthsystem.org/mainpage.aspx		https://yle.fi/uutiset/osasto/news/finland_closes_schools_declares_state_of_emergency_over_coronavirus/11260062	https://www.covid19healthsystem.org/mainpage.aspx	https://vnk.fi/en/article/-/asset_publisher/ravtsemiskleiden-toimintaa-ajotetaan-ja-valmiuslain-mukaisia-toimivaltuuksia-jatketaan	https://www.reuters.com/article/us-health-coronavirus-finland/finland-restricts-movement-to-and-from-capital-region-to-reduce-coronavirus-spread-idUSKBN21C34H
Sweden	Sweden		11.03.2020	not implemented	not implemented	not implemented	not implemented	not implemented	https://www.covid19healthsystem.org/mainpage.aspx		https://www.government.se/articles/2020/03/the-governments-work-in-the-area-of-education-in-response-to-the-coronavirus/			https://www.government.se/press-releases/2020/04/the-ministry-for-foreign-affairs-advises-against-travel-to-all-countries-up-to-15-june-2020/
Portugal	Portugal		full implementation	19.03.2020	16.03.2020	16.03.2020	19.03.2020	09.04.2020	https://www.politico.eu/article/portugal-quarantine-measures-coronavirus-covid19-antonio-costa-shutdown-state-of-emergency/	https://www.politico.eu/article/portugal-quarantine-measures-coronavirus-covid19-antonio-costa-shutdown-state-of-emergency/	https://dre.pt/home/-/dre/130243053/details/maximized	https://www.covid19healthsystem.org/mainpage.aspx	https://www.politico.eu/article/portugal-quarantine-measures-coronavirus-covid19-antonio-costa-shutdown-state-of-emergency/	https://www.portugal.gov.pt/pt/gc22/comunicacao/noticia?i=governo-lm1ta-circulacao-intermunicipal-no-periodo-da-pascoa
Croatia	Croatia		09.03.2020	17.03.2020	16.03.2020	full implementation	19.03.2020	23.03.2020	https://www.covid19healthsystem.org/mainpage.aspx	https://www.hzja.hr/wp-content/uploads/2020/03/letak_samoizolacija.pdf	https://www.vecernji.hr/vijesti/plenikovic-hrvatska-i-svijet-u-ratu-su-protiv-virusa-i-panike-1385524	https://www.reuters.com/article/us-health-coronavirus-croatia/croatia-closes-most-services-shops-fighting-coronavirus-idUSKBN21538C	https://www.reuters.com/article/us-health-coronavirus-croatia/croatia-closes-most-services-shops-fighting-coronavirus-idUSKBN21538C	https://hr.usembassy.gov/covid-19-information-2/
Netherlands	Netherlands		10.03.2020	not implemented	15.03.2020	12.03.2020	not implemented	not implemented	https://www.covid19healthsystem.org/mainpage.aspx		https://www.reuters.com/article/us-health-coronavirus-netherlands/netherlands-to-close-schools-restaurants-in-coronavirus-fight-idUSKBN2120KG	https://www.covid19healthsystem.org/mainpage.aspx		
Belgium	Belgium		13.03.2020	18.03.2020	14.03.2020	13.03.2020	18.03.2020	not implemented	https://www.covid19healthsystem.org/mainpage.aspx	https://www.belgium.be/en/news/2020/coronavirus_reinforced_measures	https://www.belgium.be/en/news/2020/coronavirus_phase_2_maintained_transition_federal_phase_and_additional_measures	https://www.covid19healthsystem.org/mainpage.aspx	https://www.belgium.be/en/news/2020/coronavirus_reinforced_measures	
Slovakia	Slovakia		12.03.2020	not implemented	12.03.2020	full implementation	16.03.2020	08.04.2020	http://www.uvwrz.sk/index.php?option=com_content&view=article&id=4082:informacia-k-zakazu-organizovano-anusporadiva-hromadne-podujatia-portovej-kulturnej-spoloenskej-i-inej-povahy&catid=250:koronavirus-2019-ncov&Itemid=153	https://www.reuters.com/article/us-health-coronavirus-slovakia/slovakia-closes-schools-stops-international-travel-to-battle-coronavirus-idUSKBN20220R	https://spectator.sme.sk/c/22359303/new-measures-national-emergency-and-further-limits-to-business.html	https://spectator.sme.sk/c/22359303/new-measures-national-emergency-and-further-limits-to-business.html	https://spectator.sme.sk/c/22378841/slovakia-to-fine-people-for-non-essential-easter-travels.html	
Lithuania	Lithuania		full implementation	15.03.2020	16.03.2020	14.03.2020	15.03.2020	not implemented	https://www.lrt.lt/naujienos/lietuvoje/2/1151427/skvernells-pranese-kad-sestadieni-bus-primtas-sprendimas-del-karantino-salies-mastu	https://www.lrt.lt/naujienos/lietuvoje/2/1151427/skvernells-pranese-kad-sestadieni-bus-primtas-sprendimas-del-karantino-salies-mastu	https://www.covid19healthsystem.org/mainpage.aspx	https://www.lrt.lt/naujienos/lietuvoje/2/1151427/skvernells-pranese-kad-sestadieni-bus-primtas-sprendimas-del-karantino-salies-mastu		
Latvia	Latvia		13.03.2020	not implemented	12.03.2020	not implemented	not implemented	not implemented	https://www.covid19healthsystem.org/mainpage.aspx		https://www.reuters.com/article/us-health-coronavirus-lithuania/lithuania-and-latvia-close-schools-ban-large-public-gatherings-over-coronavirus-idUSKBN20225W			
Estonia	Estonia		13.03.2020	not implemented	16.03.2020	13.03.2020	not implemented	not implemented	https://news.err.ee/1063224/estonian-government-declares-emergency-situation-against-coronavirus		https://news.reuters.com/article/us-health-coronavirus-estonia/estonia-closes-schools-bans-public-events-over-coronavirus-idUSKBN2100RQ	https://news.err.ee/1063224/estonian-government-declares-emergency-situation-against-coronavirus		
Poland	Poland		10.03.2020	24.03.2020	12.03.2020	31.03.2020	not implemented	not implemented	https://zdrowie.trojmiasto.pl/Odwołano-wszystkie-imprezy-masowe-n143077.html	https://www.premier.gov.pl/en/news/news/prime-minister-in-the-battle-against-the-coronavirus-we-must-reduce-our-mobility-to-an.html	https://www.premier.gov.pl/en/news/news/prime-minister-we-have-decided-to-close-all-educational-institutions-and-universities.html			
Czechia	Czechia		10.03.2020	16.03.2020	10.03.2020	10.03.2020	14.03.2020	not implemented	https://www.mzcr.cz/dokumenty/mimoradna-opatreni-ministerstva-zdravotnictvi-zakazuj-konani-hromadnych-akci-na_18698_4107_1.html	https://www.vlada.cz/cz/media-centrum/aktualne/rozeceni-vlady-o-zakazu-volneho-pohybu-osob-180358/	https://www.vlada.cz/en/media-centrum/aktualne/due-to-the-spread-of-coronavirus-the-government-has-banned-cultural-sporting-and-social-events-involving-over-100-people-schools-are-to-be-closed-180201/	https://www.mzcr.cz/dokumenty/mimoradna-opatreni-ministerstva-zdravotnictvi-zakazuj-konani-hromadnych-akci-na_18698_4107_1.html	https://www.vlada.cz/en/media-centrum/aktualne/the-government-is-strengthening-preventive-measures-in-relation-to-the-coronavirus-closing-shops-and-restaurants-to-the-public-for-ten-days-180337/	
Slovenia	Slovenia		12.03.2020	20.03.2020	16.03.2020	full implementation	15.03.2020	16.03.2020	https://www.covid19healthsystem.org/mainpage.aspx	https://www.gov.si/en/news/2020-03-19-ordinance-on-the-temporary-prohibition-of-public-gathering-at-public-meetings-and-public-events-and-other-events-in-public-places-in-the-republic-of-slovenia/	https://www.gov.si/en/news/2020-03-12-slovenia-to-declare-an-epidemic-and-temporarily-close-kindergartens-and-schools/	https://www.gov.si/en/news/2020-03-15-decisions-adopted-by-the-government-to-contain-covid-19-epidemic/	https://www.gov.si/en/news/2020-03-15-decisions-adopted-by-the-government-to-contain-covid-19-epidemic/	https://www.gov.si/en/news/2020-03-15-the-government-adopts-an-ordinance-on-the-temporary-ban-and-restrictions-on-public-transport-of-passengers-in-the-republic-of-slovenia/
Denmark	Denmark		18.03.2020	not implemented	16.03.2020	18.03.2020	not implemented	not implemented	https://www.covid19healthsystem.org/mainpage.aspx	https://www.reuters.com/article/us-health-coronavirus-denmark/denmark-extends-coronavirus-lockdown-until-april-13-idUSKBN21A2DV	https://polit.dk/coronavirus-i-danmark/en-english/new-measures-against-covid-19	https://www.covid19healthsystem.org/mainpage.aspx	https://www.dr.dk/nyheder/politik/faa-overblikket-over-de-nye-corona-tiltag-se-hvad-du-ikke-maa-fra-i-dag-klokken-10	https://www.covid19healthsystem.org/countries/denmark/livinghit.aspx?Section=1.2%20Physical%20distancing&Type=Section
Norway	Norway		12.03.2020	not implemented	12.03.2020	12.03.2020	not implemented	not implemented	https://www.helsedirektoratet.no/nyheter/the-norwegian-directorate-of-health-has-issued-a-decision-to-close-schools-and-other-educational-institutions	https://helsenorge.no/koronavirus/barnehager-og-skoler	https://www.helsedirektoratet.no/nyheter/the-norwegian-directorate-of-health-has-issued-a-decision-to-close-schools-and-other-educational-institutions	https://www.bag.admin.ch/bag/en/home/krankheiten/ausbrueche-epidemien-pandemien/aktuelle-ausbrueche-epidemien/novel-cov/massnahmen-des-bundes.html	https://www.bag.admin.ch/bag/en/home/krankheiten/ausbrueche-epidemien-pandemien/aktuelle-ausbrueche-epidemien/novel-cov/massnahmen-des-bundes.html	https://www.bsg.ox.ac.uk/research/publications/variation-government-responses-covid-19
Switzerland	Switzerland		28.02.2020	not implemented	13.03.2020	full implementation	16.03.2020	not implemented	https://www.admin.ch/gov/en/start/documentation/media-releases.msg-id-78289.html	https://www.admin.ch/gov/de/start/dokumentation/medienmitteilung.en.msg-id-78437.html	https://www.bag.admin.ch/bag/en/home/krankheiten/ausbrueche-epidemien-pandemien/aktuelle-ausbrueche-epidemien/novel-cov/massnahmen-des-bundes.html	https://www.bag.admin.ch/bag/en/home/krankheiten/ausbrueche-epidemien-pandemien/aktuelle-ausbrueche-epidemien/novel-cov/massnahmen-des-bundes.html	https://www.bsg.ox.ac.uk/research/publications/variation-government-responses-covid-19	https://www.bsg.ox.ac.uk/research/publications/variation-government-responses-covid-19
Hungary	Hungary		12.03.2020	28.03.2020	16.03.2020	12.03.2020	16.03.2020	not implemented	https://www.covid19healthsystem.org/mainpage.aspx	https://koronavirus.gov.hu/cikkek/megjelent-kijarasi-korlatozasrol-szolo-rendelet	https://www.theguardian.com/world/2020/mar/12/how-do-coronavirus-containment-measures-vary-across-europe	https://www.covid19healthsystem.org/mainpage.aspx	https://www.reuters.com/article/us-health-coronavirus-bulgaria-emergency/bulgaria-closes-schools-restricts-travel-over-coronavirus-idUSKBN21015D	
Bulgaria	Bulgaria		13.03.2020	17.03.2020	13.03.2020	full implementation	13.03.2020	21.03.2020	https://www.reuters.com/article/us-health-coronavirus-bulgaria-emergency/bulgaria-closes-schools-restricts-travel-over-coronavirus-idUSKBN21015D	https://www.covid19healthsystem.org/countries/bulgaria/countrypage.aspx	https://dv.parliament.bg/DVWeb/showMaterialDV.jsp?idMat=147150	https://dv.parliament.bg/DVWeb/showMaterialDV.jsp?idMat=147150	https://dv.parliament.bg/DVWeb/showMaterialDV.jsp?idMat=147150	https://www.covid19healthsystem.org/countries/bulgaria/countrypage.aspx
Romania	Romania		06.03.2020	23.03.2020	11.03.2020	full implementation	21.03.2020	not implemented	https://www.covid19healthsystem.org/mainpage.aspx	https://stirioficiale.ro/hotarari/ordonanta-militara-nr-3-din-24-03-2020-privind-masuri-de-prevenire-a-raspadirii-covid-19	https://www.bsg.ox.ac.uk/research/publications/variation-government-responses-covid-19	https://stirioficiale.ro/hotarari/ordonanta-militara-nr-2-din-21-03-2020-privind-masuri-de-prevenire-a-raspadirii-covid-19	https://stirioficiale.ro/hotarari/ordonanta-militara-nr-2-din-21-03-2020-privind-masuri-de-prevenire-a-raspadirii-covid-19	https://www.reuters.com/article/health-coronavirus-romania/romania-imposes-curfew-to-slow-coronavirus-spread-idUSL8N2BE0XD
Greece	Greece		08.03.2020	23.03.2020	11.03.2020	12.03.2020	22.03.2020	23.03.2020	https://www.covid19healthsystem.org/mainpage.aspx	https://www.bloomberg.com/news/articles/2020-03-22/greece-to-impose-lockdown-to-contain-spread-of-coronavirus	https://www.covid19healthsystem.org/mainpage.aspx	https://www.covid19healthsystem.org/mainpage.aspx	https://www.covid19healthsystem.org/countries/greece/livinghit.aspx?Section=1.2%20Physical%20distancing&Type=Section	https://forma.gov.gr/docs/faq-lockdown-en.pdf
Luxembourg	Luxembourg		13.03.2020	not implemented	16.03.2020	full implementation	18.03.2020	not implemented	https://www.covid19healthsystem.org/mainpage.aspx	https://msan.gouvernement.lu/en/actualites.gouvernement%2Ben%2Bactualites%2Btoutes_actualites%2Bcommuniqués%2B2020%2B03-mars%2B12-cdg-extraordinaire-coronavirus.html	https://msan.gouvernement.lu/en/actual			