Ensemble Forecasts of Coronavirus Disease 2019 (COVID-19) in the U.S.

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***The findings and conclusions in this report are those of the authors and do not necessarily represent the views of the Centers for Disease Control and Prevention.

Abstract

Background

The COVID-19 pandemic has driven demand for forecasts to guide policy and planning. Previous research has suggested that combining forecasts from multiple models into a single "ensemble" forecast can increase the robustness of forecasts. Here we evaluate the real-time application of an open, collaborative ensemble to forecast deaths attributable to COVID-19 in the U.S.

Methods

Beginning on April 13, 2020, we collected and combined one- to four-week ahead forecasts of cumulative deaths for U.S. jurisdictions in standardized, probabilistic formats to generate real-time, publicly available ensemble forecasts. We evaluated the point prediction accuracy and calibration of these forecasts compared to reported deaths.

Results

Analysis of 2,512 ensemble forecasts made April 27 to July 20 with outcomes observed in the weeks ending May 23 through July 25, 2020 revealed precise short-term forecasts, with accuracy deteriorating at longer prediction horizons of up to four weeks. At all prediction horizons, the prediction intervals were well calibrated with 92-96% of observations falling within the rounded 95% prediction intervals.

Conclusions

This analysis demonstrates that real-time, publicly available ensemble forecasts issued in April-July 2020 provided robust short-term predictions of reported COVID-19 deaths in the United States. With the ongoing need for forecasts of impacts and resource needs for the COVID-19 response, the results underscore the importance of combining multiple probabilistic models and assessing forecast skill at different prediction horizons. Careful development, assessment, and communication of ensemble forecasts can provide reliable insight to public health decision makers.

Introduction

The outbreak of Coronavirus Disease 2019 (COVID-19) in Wuhan, China, in late December 2019 quickly spread around the world, resulting in formal recognition of COVID-19 as a global threat by the World Health Organization on January 30, 2020 (Promed 2019; World Health Organization 2020). Subsequent rapid, global spread of SARS-CoV-2, the virus that causes COVID-19, drove an urgent need for forecasts of the timing and intensity of future transmission and the locations with the highest risk of spread to inform risk assessment and planning.

Multiple studies of epidemic forecasting have shown that ensemble forecasts, which incorporate multiple model predictions into a combined forecast, consistently perform well and often outperform most if not all individual models (Viboud et al. 2018; Johansson et al. 2019; McGowan et al. 2019; Reich, Brooks, et al. 2019). Ensemble approaches are in widespread use in other fields such as economics (Timmermann 2006; Busetti 2014) and weather forecasting (Leutbecher and Palmer 2008). Ensemble models can distill information across multiple forecasts and are a robust option for decision making and policy planning, especially in situations where extensive historical data on individual model performance are not available.

Here, we summarize a collaborative effort between the U.S. Centers for Disease Control and Prevention (CDC), 21 largely academic research groups, five private industry groups, and two government-affiliated groups. Starting in April 2020, this consortium, called the COVID-19 Forecast Hub (https://covid19forecasthub.org), developed shared forecasting targets and data formats, then constructed, evaluated, and communicated the results of ensemble forecasts for U.S. deaths attributable to COVID-19. Deaths due to COVID-19 are a proximate indicator of burden on health care systems and a critical measure of health impact.

Methods

Beginning on April 13, 2020 and every Monday thereafter, we collected probabilistic one-, two-, three-, and four-week ahead forecasts of the total number of deaths due to COVID-19 that would be reported by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (Dong, Du, and Gardner 2020) by the Saturday of each week for U.S. states and territories and the United States overall. Prediction intervals (e.g., 95% or 50%) characterize uncertainty which point forecasts are unable to characterize. Thus, each participating team provided the median of the predictive distribution and 11 prediction intervals ranging from a 10% prediction interval to a 98% prediction interval. Participating groups were able to use the methods and data sources they deemed appropriate to generate the forecasts (Reich et al. 2020).

On April 27, after two weeks of consistent submissions, we began aggregating individual forecasts of cumulative deaths to construct a weekly ensemble forecast (hereafter referred to as "ensemble"). To be eligible for inclusion in the ensemble, a model had to submit a valid forecast for all four week-ahead horizons (details on validation in Supplemental Figure 1). The total number of individual models included in the ensemble forecasts ranged from six (April 27) to 20 (June 15 and 29). Ensemble forecasts for specific locations often included fewer models because some models did not include forecasts for all locations. The ensemble forecast was constructed as an equally-weighted average of forecasts from all eligible models. Specifically, the endpoints of each prediction interval in the ensemble forecast were calculated as the average of the corresponding quantiles across all individual model forecasts (Busetti 2014). Ensemble forecasts were constructed by researchers at the University of Massachusetts Amherst and posted publicly by CDC each week.

We evaluated ensemble forecasts of cumulative deaths in the United States compared to reported deaths for only weeks which had previous forecasts at all four prediction horizons (one- to four-weeks ahead). For example, we did not evaluate forecasts for the week ending May 2, because only a one-week ahead ensemble forecast was available, making comparison across horizons impossible. Overall, we compared forecasts across nine weeks of observations, from the week ending May 23 through the week ending July 25, 2020. We evaluated the performance of ensemble forecasts across all locations and weeks where at least two individual models contributed to the ensemble; this included 2,512 of the 2,561 possible forecasts during the evaluation timeframe for different locations and forecast horizons. Reported cumulative death data for this evaluation were downloaded from the CSSE repository on July 26, 2020.

We evaluated the error of the ensemble with mean absolute error (MAE), the mean difference between the forecasted and observed values, and calibration with prediction interval coverage. Prediction interval coverage was calculated by determining the frequency with which the prediction interval contained the eventually observed outcome. In a model that accurately characterizes uncertainty, the prediction interval level will correspond closely to the frequency of eventually observed outcomes that fall within that prediction interval. For example, eventually observed values should be within the 95% prediction interval approximately 95% of the time. Because the ensemble prediction intervals were calculated by averaging individual models, the ensemble prediction intervals typically were not whole numbers and almost never included predictions of no new deaths in a given week. We therefore assessed interval coverage for the original ensemble and for the rounded ensemble. We rounded the interval endpoints to a whole number conservatively, rounding the lower limits of prediction intervals down and the upper limits of prediction intervals up.

The forecast data and submission instructions are available in a public GitHub repository (Reich et al. 2020). Analyses were performed in R (https://www.R-project.org/) and all code used to construct the ensemble forecasts and reproduce the analyses in this manuscript is available in a separate public GitHub repository (E. Ray 2020).

Results

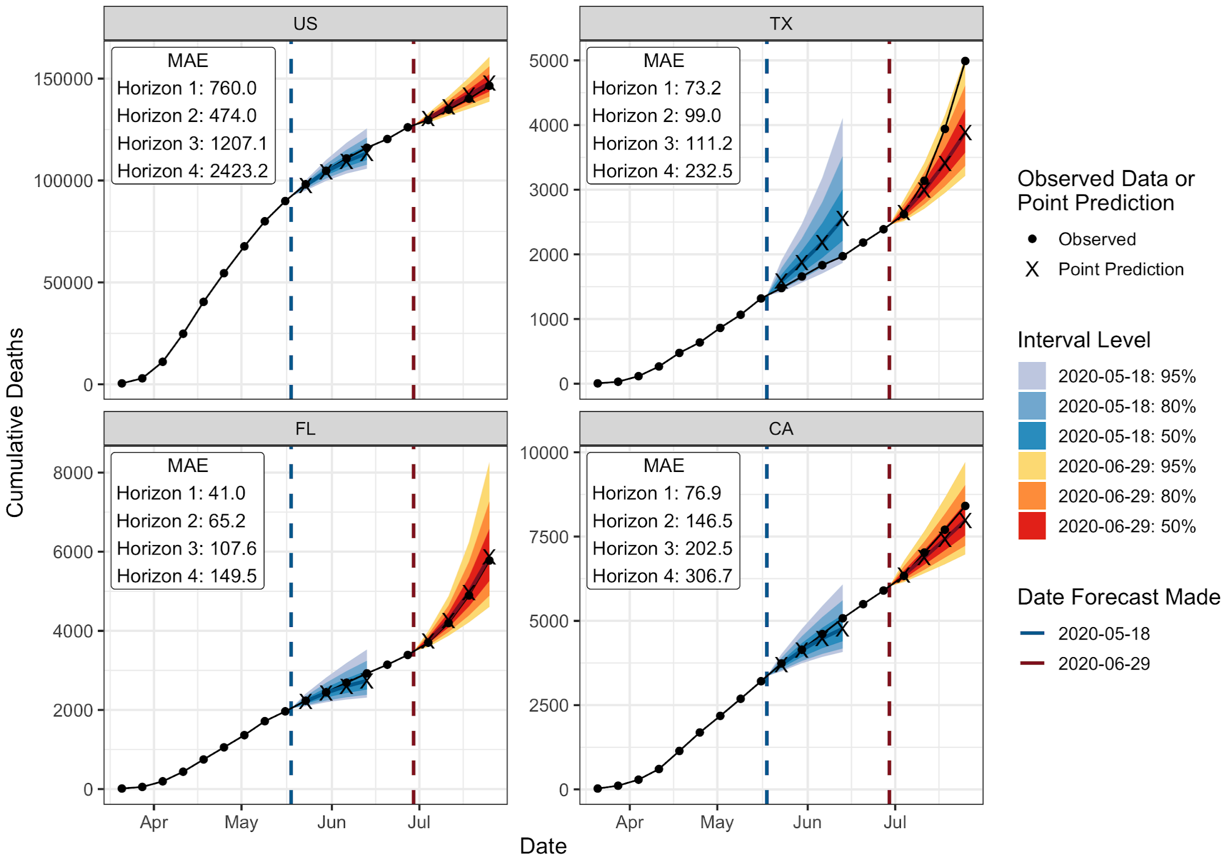

Figure 1: Reported deaths and example forecasts. Reported cumulative deaths due to Coronavirus Disease 2019 (COVID-19) from March 21 to July 25 as of July 26, 2020 (black points) for the United States (US) and the three states with highest reported deaths in the week ending July 25 (Texas [TX], Florida [FL] and California [CA]). Forecasts are one-through four-week ahead predicted medians and 50%, 80%, and 95% prediction intervals from the ensemble forecasts created on May 18 and June 29. Forecasts from these two dates are shown as examples. Ensemble forecasts were made every week starting April 27, 2020 (not shown, available at (Reich et al. 2020)). The mean absolute error (MAE) is the mean of the difference between the forecasted and observed values across all forecasts at each horizon (one- to four-weeks ahead) for which the target was observed as of July 26.

Comparing forecasts to the reported death data for the weeks ending May 23 through July 25, 2020, the ensemble point forecasts were accurate and precise at short-term prediction horizons, with a general increase in error at longer horizons (Figure 1, Supplemental Figure 2, Supplemental Table 1). Specifically, on average across all locations, the mean absolute error (MAE) of four-week ahead point predictions was more than three times the MAE of one-week ahead predictions. For example, the national-scale one-week ahead MAE indicated an average difference of 760 deaths from the eventually observed values, while the four-week ahead forecasts had a MAE of about 2,400 deaths (Figure 1).

The ensemble forecasts were also well calibrated, with prediction intervals that covered the observed data with the expected frequency (Table 1, Supplemental Figure 3). The 50% prediction intervals were conservative; they captured 50-55% of observations for all forecast horizons with the original forecasts, and 57-65% with the conservatively rounded, whole number forecasts. In contrast, the original 95% prediction intervals captured only 87-90% of observations. After rounding, the 95% prediction intervals were better calibrated, with coverage rates of 92-96%. Rounding had a particularly clear impact on forecasts for weeks with no reported deaths as many ensemble forecasts had lower prediction bounds just above zero due to one or more individual forecasts being greater than zero. For example, rounding changed the 95% coverage for 120 forecasts and 99 of those were for weeks with no new deaths. While the forecasts were less precise at longer horizons (greater MAE), they remained calibrated.

		Observed Prediction Interval Coverage Forecast Horizon (weeks ahead)			
	Measure	1	2	3	4
Original Ensemble Forecasts	50% Coverage	53.3%	50.5%	51.6%	54.6%
	95% Coverage	87.3%	87.0%	89.2%	90.1%
Rounded Ensemble Forecasts	50% Coverage	65.1%	59.9%	57.9%	57.7%
	95% Coverage	95.6%	93.2%	93.8%	92.8%

Table 1: Observed prediction interval coverage for deaths reported May 23 through July 25, 2020 indicating calibration for ensemble forecasts of cumulative deaths in locations with at least two valid individual forecasts. The top section summarizes the original ensemble forecasts, and the bottom section summarizes the ensemble forecasts after rounding the lower limits of prediction intervals down and the upper limits of prediction intervals up.

Discussion

The spread of COVID-19 has driven a continually adapting global response. Substantial uncertainty persists about the disease's trajectory, and robust forecasts of COVID-19 activity can help inform decision making in the face of this uncertainty. The COVID-19 Forecast Hub was created to rapidly collect, aggregate, ensemble, and evaluate forecasts in real-time. The resulting forecasts were published on the CDC website starting on April 27, 2020, (Centers for Disease Control and Prevention 2020) and were used to develop summary messages about the trajectory of the outbreak in the United States. These early results indicate that ensemble forecasts at the national and state-level were accurate, with mean absolute errors well below the maximum number of new deaths reported per week, and well-calibrated, with reasonable prediction interval coverage, especially when evaluated using rounded prediction intervals. These forecasts can be used as situational awareness and planning tools to inform a variety of planning and response decisions such as the implementation of mitigation strategies, the distribution of resources, or vaccine trial site selection (Dean et al. 2020; Wallinga, van Boven, and Lipsitch 2010; Lipsitch et al. 2011).

It is critical that forecasts used to inform public health decisions accurately characterize their uncertainty, and these ensemble forecasts achieved that goal. The ensemble forecasts were conservative for more central prediction intervals such as the 50% prediction interval which captured 50-60% of observations, but were well calibrated at the more important, extreme intervals after rounding. In outbreak forecasting, extreme errors can lead to suboptimal decision-making, such as unexpected shortages in or oversupply of resources. A well-calibrated forecast reduces this risk. For example, only 1% of outcomes should exceed the 99% prediction quantile, and this occurred for 1.4% of forecasts made by the COVID-19 Forecast Hub ensemble.

Although the ensemble performed well, there are many avenues for further improvement. The ensemble forecast weighted the models equally, but weighting based on historical performance may improve forecast skill (McAndrew and Reich 2019; Reich, McGowan, et al. 2019; Viboud et al. 2018; E. L. Ray and Reich 2018; Yamana, Kandula, and Shaman 2016; Reis et al. 2019; Brooks et al. 2018). However, any weighting method will need to be dynamic and allow for the incorporation of new models, potential changes in existing models, and the different sets of locations forecasted by each model.

The ensemble forecasts evaluated here only looked four weeks into the future. Although probabilistic forecasts at longer horizons may characterize uncertainty correctly, in this study we observed significant widening of prediction intervals and degrading precision of point forecasts, even at horizons of three- to four-weeks ahead. This raises concerns about the reliability of forecasts at longer horizons of weeks to months. In addition to current transmission dynamics and mitigation measures, long-term forecasts must also predict changes in mitigation and human behavior to inform projections. Uncertainties about data, behavior, and mitigation measures compound at longer horizons and may further reduce precision and accuracy.

This analysis indicates that ensemble forecasts of cumulative mortality generated in real-time at the national and state level during the first six months of the COVID-19 outbreak in the United States were accurate and well-calibrated. Given this and the previous performance of probabilistic ensemble forecasts for multiple infectious diseases, we encourage decision makers to consider the use of multiple models and ensemble forecasts rather than single model forecasts for future risk assessment and planning needs.

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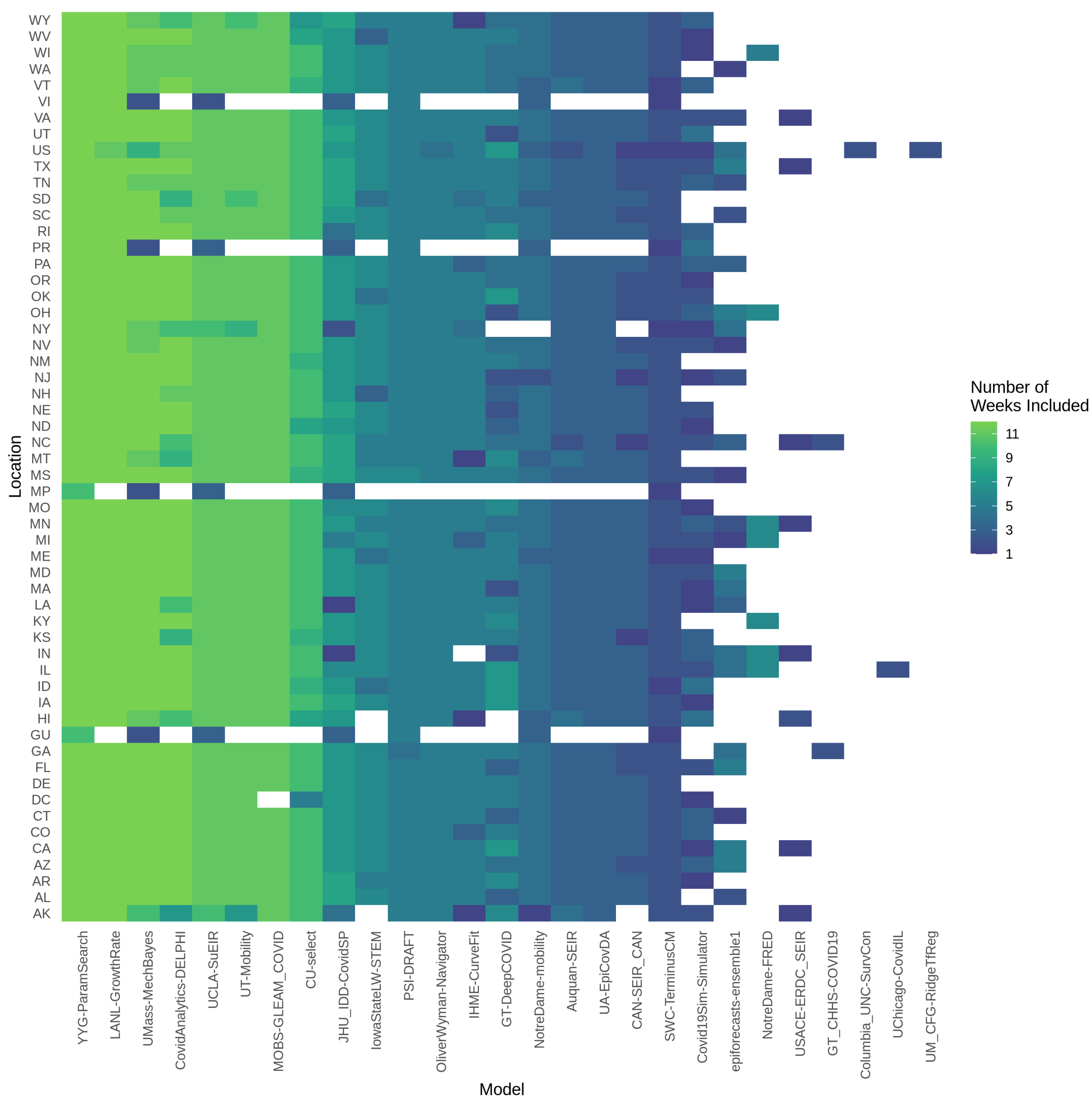
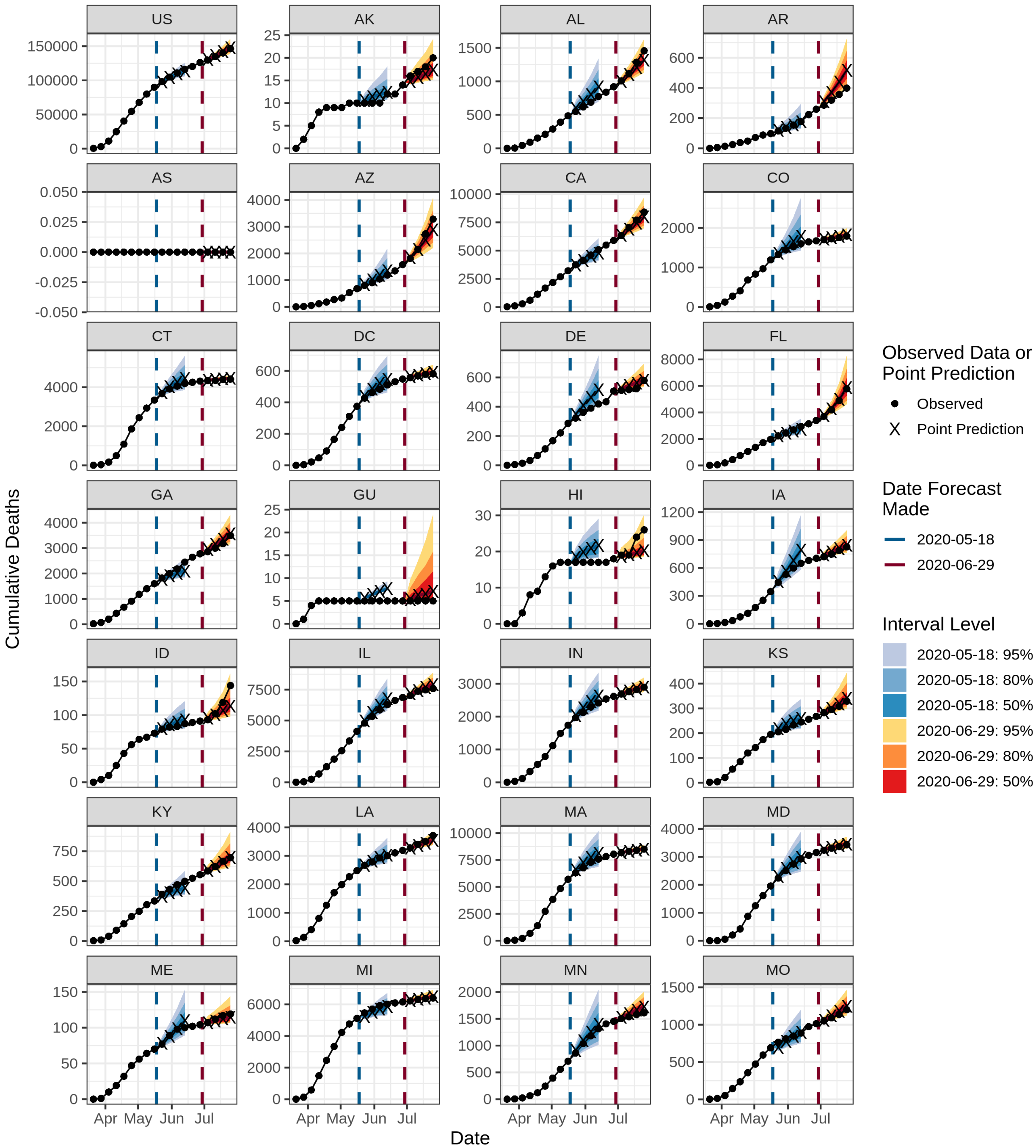
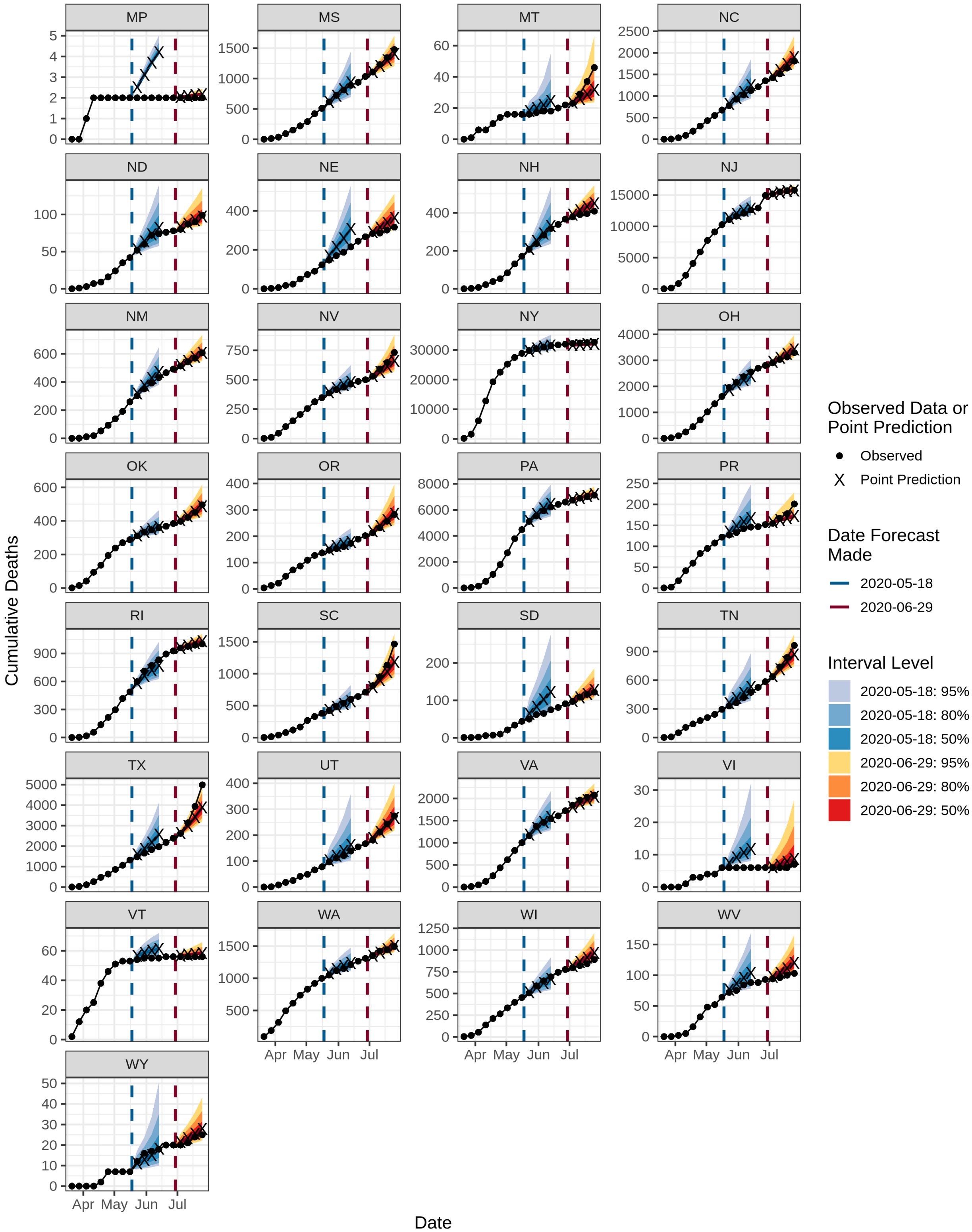
Supplement

Supplemental Figure 1: The number of times each contributing model was in the ensemble forecast for each location. An empty cell indicates that the model was not included in a forecast for the given location. The number of individual models included varied because of differences in number of submissions, locations included in submissions, and the following criteria for individual forecasts: (1) a forecast had to include all four week-ahead horizons, (2) the one week ahead forecast for cumulative deaths should not assign probability more than 0.1 to a reduction in cumulative deaths relative to already reported deaths, and (3) at each quantile level, predictions should be non-decreasing over the four prediction horizons. Abbreviations for each location are shown in Supplemental Table 1.



Supplemental Figure 2: Reported cumulative deaths due to COVID-19 for the US and states and territories from March 21 to July 25 as of July 26, 2020. Forecasts are 1- through 4-week ahead predicted medians and 50%, 80%, and 95% prediction intervals from the ensemble forecasts created on May 18 and June 29. Forecasts from these two dates are shown as examples; ensemble forecasts were made every week starting April 27, 2020 (not shown, available at (Reich et al. 2020)). Abbreviations for each location are shown in Supplemental Table 1.

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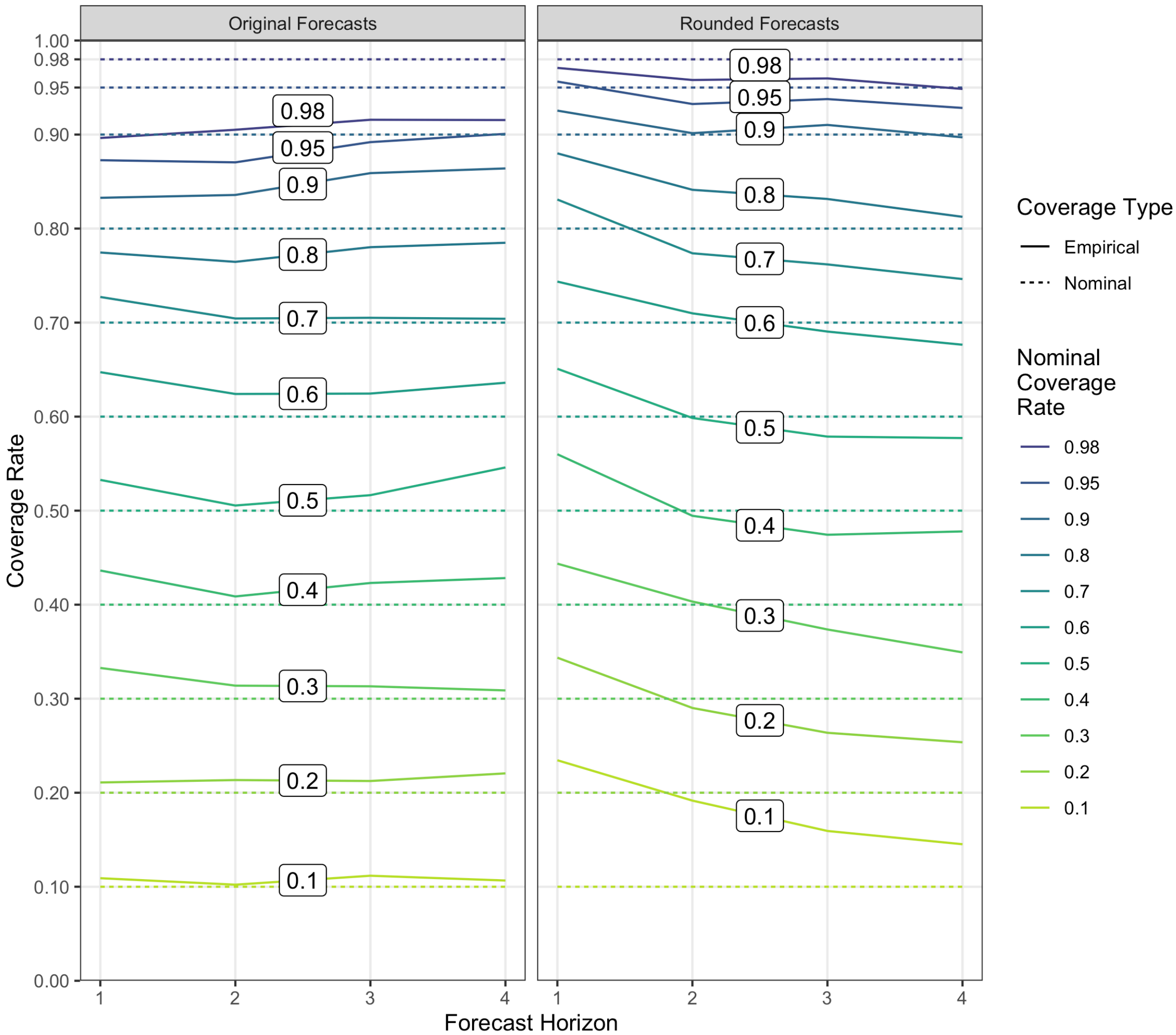
Date Forecast Made
2020-05-18
2020-06-29
Interval Level
2020-05-18: 95%
2020-05-18: 80%
2020-05-18: 50%
2020-06-29: 95%
2020-06-29: 80%
2020-06-29: 50%

Supplemental Table 1: MAE for cumulative deaths reported May 23 through July 25, the maximum number of deaths reported per week up through the week ending July 25, and the cumulative deaths reported through the week ending July 25. All reported data were collected on July 26, 2020. Locations are sorted in decreasing order of cumulative deaths. The top row summarizes MAE for all locations other than American Samoa, for which 0 deaths were observed during the evaluation period.

		Mean absolute error (MAE)					
Location abbreviation	Location name	1-week horizon	2-week horizon	3-week horizon	4-week horizon	Maximum weekly deaths	Cumulative Deaths
-	All	49.1	68.4	112.1	175.4		
US	United States	760.0	474.0	1,207.1	2,423.2	15,665	146,460
NY	New York	512.3	500.4	601.7	694.4	6,667	32,608
NJ	New Jersey	293.1	560.6	818.0	830.3	2,024	15,776
MA	Massachusetts	65.8	101.0	177.3	448.4	1,326	8,510
CA	California	76.9	146.5	202.5	306.7	706	8,408
IL	Illinois	104.6	209.5	263.4	272.6	790	7,589
PE	Pennsylvania	36.2	135.3	281.0	485.5	1,084	7,124
MI	Michigan	107.5	132.0	137.1	149.3	973	6,400
FL	Florida	41.0	65.2	107.6	149.5	882	5,777
TX	Texas	73.2	99.0	111.2	232.5	1,051	4,990
CT	Connecticut	26.3	59.2	94.5	202.4	779	4,413
LA	Louisiana	11.8	19.5	48.0	98.9	461	3,715
GA	Georgia	51.1	110.2	161.5	184.7	325	3,494
MD	Maryland	35.2	89.9	150.7	255.0	454	3,433
OH	Ohio	44.7	92.5	136.0	203.4	346	3,297
AZ	Arizona	31.4	52.1	97.7	133.7	579	3,286
IN	Indiana	24.5	66.5	124.2	232.2	375	2,895

		Mean absolute error (MAE)					
Location abbreviation	Location name	1-week horizon	2-week horizon	3-week horizon	4-week horizon	Maximum weekly deaths	Cumulative Deaths
VI	Virginia	47.3	95.4	138.1	187.4	211	2,075
NC	North Carolina	32.1	73.9	130.4	193.5	163	1,811
CO	Colorado	18.1	53.6	80.3	140.2	273	1,794
MN	Minnesota	30.1	94.3	186.1	305.1	175	1,611
WA	Washington	13	17.3	24.2	27.3	180	1,494
MS	Mississippi	18.2	26.3	62.5	92.3	132	1,478
SC	South Carolina	14.4	25.9	45.8	67.9	330	1,465
AL	Alabama	16.2	26.5	50.9	78.6	172	1,456
MO	Missouri	26	41.2	56.8	72.9	122	1,200
RI	Rhode Island	13	25.4	34.9	79.8	122	1,002
TN	Tennessee	12.3	17.3	20.3	42.4	126	964
WI	Wisconsin	16.4	37.9	64.0	101.4	83	891
IA	Iowa	15.6	44.1	93.8	201.6	100	826
NV	Nevada	9.6	19.3	22.9	28.1	86	732
KY	Kentucky	8.8	17.4	32.2	60.6	61	696
NM	New Mexico	5.9	11.5	18.1	26.6	68	607
DC	Washington DC	7.9	19.5	32.6	47.8	75	581
DE	Delaware	15.7	26.5	35.0	38.9	73	579
OK	Oklahoma	4.3	11.0	20.0	27.2	58	496
NH	New Hampshire	6.5	10.0	18.2	34.1	47	409

		Mean absolute error (MAE)					
Location abbreviation	Location name	1-week horizon	2-week horizon	3-week horizon	4-week horizon	Maximum weekly deaths	Cumulative Deaths
AR	Arkansas	7.2	16.6	18.2	15.9	47	399
KS	Kansas	3.6	11.6	23.3	55	35	329
NE	Nebraska	10.7	24.8	47.6	105.1	33	316
OR	Oregon	3.8	7.0	8.6	10.6	26	282
UT	Utah	6.9	11.5	19.2	27.8	31	274
PR	Puerto Rico	4.9	7.9	13.0	16.8	24	201
ID	Idaho	2.1	3.4	5.1	9.2	25	144
SD	South Dakota	4.8	6.5	12.2	21.1	13	122
ME	Maine	2.1	4.9	8.3	14.4	15	119
WV	West Virginia	3.3	6.0	10.7	16.9	16	103
ND	North Dakota	3.6	6.7	11.4	17.7	12	99
VT	Vermont	1.1	2.7	6.0	10.7	13	56
MO	Montana	1.2	1.4	2.7	5.2	9	46
HI	Hawaii	0.7	1.6	3.3	4.2	5	26
WY	Wyoming	1.0	2.1	2.7	3.6	5	25
AK	Alaska	1.0	1.4	1.7	2.4	3	20
VI	Virgin Islands	0.6	1.4	2.0	2.6	2	7
GU	Guam	0.3	0.6	0.8	1.1	3	5
MP	Northern Mariana Islands	2.4	3.0	3.8	4.8	1	2
AS	American Samoa	0.0	0.0	0.0	0.0	0	0



Supplemental Figure 3: Calibration for ensemble predictions of cumulative deaths in locations with at least two valid individual models submitted. We report calibration of prediction intervals from forecasts for weeks ending May 23 to July 25, 2020, the set of observed weeks with previous forecasts at all four time horizons at the time of writing. Lines are labeled with the nominal coverage rate; a well calibrated forecast will have empirical coverage rate equal to the nominal coverage rate.

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