Supplementary material for "Interval forecasts of weekly incident and cumulative COVID-19 mortality in the United States: A comparison of combining methods" by KS Taylor and JW Taylor

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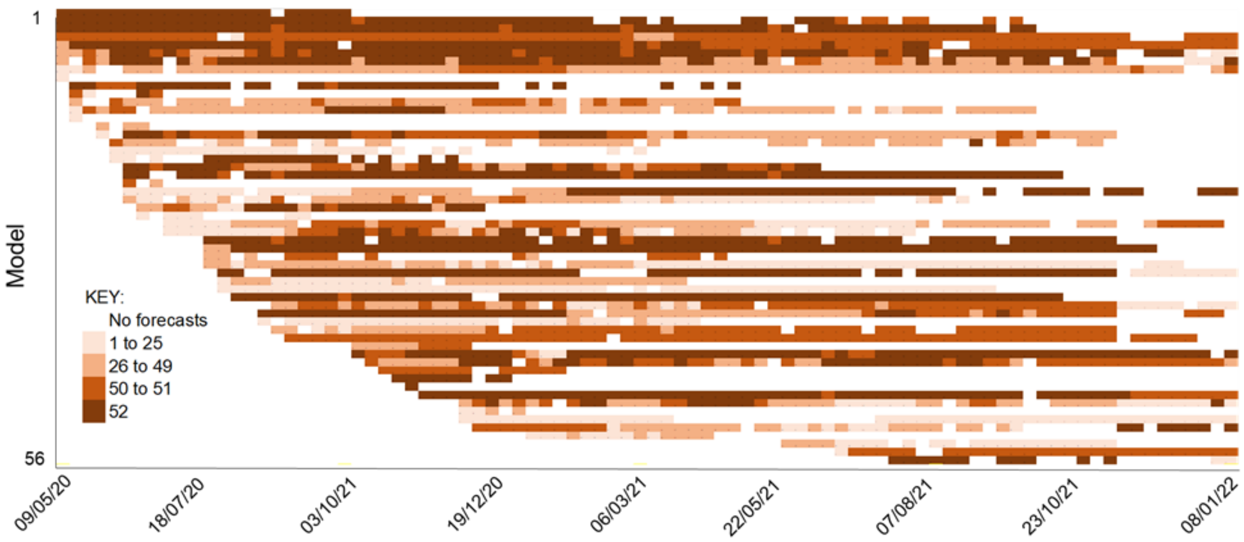

S1 Figure. Data availability for forecasts of cumulative COVID-19 deaths. * Based on information recorded on the COVID19 Hub with citations as recorded on 25/2/22; [a] Only provided forecasts of numbers of cumulative COVID-19 deaths; [b] Only provided forecasts of numbers of incident COVID-19 deaths.

S1 Table. Individual forecasting models

Contributors	Short model name	Model description*	Access and licencing information Citations
Wattanachit N, Ray EL, Reich N	COVID hub-ensemble	An ensemble, or model average, of submitted forecasts to the COVID-19 Forecast Hub.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/COVIDhub-ensemble https://www.medrxiv.org/content/10.1101/2020.08.19.20177493v1
COMPARTMENTAL			
Tomar V, Jain C	Auquan-SEIR [a]	Modified SEIR model with compartments for reported and unreported infections. Non-linear mixed effects curve-fitting.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/Auquan-SEIR
Panano B.	BPangano-RtDriven	Projects infections and deaths for 223 locations using an SIR model.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/BPagano-RtDriven https://bobpagano.com/covid-19-modeling/
Carlson E, Henderson M, Kelly C, Kofman I, Zhang X	CovidActNow-SEIR_CAN	SEIR model forecasts of cumulative deaths, incident deaths, incident hospitalizations by fitting predicted cases, deaths, and hospitalizations to the observations.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/CovidActNow-SEIR_CAN
Li ML, Bouardi HT, Lami OS, Trikalinos TA, Trichakis NK, Bertsimas D	CovidAnalytics-DELPHI	SEIR model augmented with underdetection and interventions. Projections account for reopening and assume interventions would be re-enacted if cases continue to climb.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/CovidAnalytics-DELPHI https://www.covidanalytics.io/DELPHI_documentation_pdf
Chhatwal J, Ayer T, Linas B, Dalgic O, Mueller P, Adee M, Ladd MA, Xiao J	Covid19Sim-Simulator	An interactive tool that uses a validated SEIR compartment model.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/Covid19Sim-Simulator
Pei S, Yamana T, Kandula S, Yang W, Galanti M, Shaman J	CU-select	Metapopulation county-level SEIR model for projecting future COVID-19 incidence and deaths. This forecast is the scenario we believe to be most plausible given the current setting.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/CU-select https://doi.org/10.1101/2020.03.21.20040303 https://www.medrxiv.org/content/10.1101/2020.05.04.20090670v2

Pei S, Yamana T, Kandula S, Yang W, Galanti M, Shaman J	CU-nochange	This metapopulation county-level SEIR model assumes that current contact rates will remain unchanged in the future.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/CU-nochange https://doi.org/10.1101/2020.03.21.20040303
Max A, Epshteyn A, Kang B, Li C-L, Sava D, Parish D, Miller D, Kanal E, Liu H, Nakhost H, Jones I, Lai J, Repenning J, Yoon J, Ramasamy K, Zhang L, Le L, Nikoltchev M, Siegler M, Dusenberry M, Yoder N, Rozenfeld O, Rangaswamy P, Sinha R, Xie R, Arik S, Singh S, Tsai T, Pfister T, Menon V, Karande V, Y, Li Y	Google-Harvard-CPF	Our model improves upon standard compartmental models by using temporally and spatially rich data, and integrating covariate encodings into compartment transitions via end-to-end learning.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/Google_Harvard-CPF https://arxiv.org/abs/2008.00646
Lemaitre JC, Bi Q , Hulse JD, Grabowski MK, Grantz KH, Kaminsky J, Lauer SA, Lee EC, Meredith HR, Perez-Saez J, Truelove SA, Keegan LT, Kaminsky K, Shah S, Wills J, Aquilanti P-Y, Raman K, Subramaniyan A, Thursam G, Tran A.	JHU_IDD-CovidSP	County-level metapopulation model with commuting and stochastic SEIR disease dynamics with social-distancing indicators.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/JHU_IDD-CovidSP https://doi.org/10.1038/s41598-021-86811-0
Kinsey M, Tallaksen K, Obrecht RF, Asher L, Costello C, Kelbaugh M, Wilson S	JHUAPL_Bucky	Metapopulation model using public mobility data. Local parameters (case reporting rates, doubling times, etc) are estimated using data from CSSE and CDC scenario 5. Primary output is case incidence.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/JHUAPL-Bucky
Baek J, Farias V, Georgescu A, Levi R, Sinha D, Wilde J, Zheng A	MITCovAlliance-SIR	SIR model trained on public heath regions. SIR parameters are functions of static demographic and time-varying mobility features. Two-stage approach that first learns magnitude of peak infections.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/MITCovAlliance-SIR https://arxiv.org/abs/2006.06373
Vespignani A, Chinazzi M, Davis JT, Mu K, Pastore y Piontti A, Samay N,	MOBS-GLEAM_COVID	Metapopulation, age structured SLIR model. Superimposed on the worldwide population and	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-

Xiong X, Halloran ME, Longini IM, Dean NE, Viboud C, Sun K, Litvinova M, Gioannini C, Rossi L, Ajelli M		mobility layers is an agent-based epidemic model that defines the infection and population dynamics. Makes predictions about the future that are dependent on the assumption that current interventions continue.	processed/MOBS-GLEAM_COVID https://uploads-ssl.webflow.com/58e6558acc00ee8e4536c1f5/5e8bab44f5baae4c1c2a75d2_GLEAM_web.pdf
Gao Z, Li C, Zheng S, Bian J, Xie X, LiuT-Y	MSRA-DeepST	A deep spatio-temporal network with knowledge based SEIR as a regularier under the assumption of spatio-temporal process in pandemic of different regions.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/MSRA-DeepST
Espana G, Oidtman R, Cavany S, Costello A, Wieler A, Lerch A, Barbera C, Poterek M, Tran Q, Moore S, Perkins A	NotreDame-Mobility	Ensemble of nine models that are identical except that they are driven by different mobility indices from Apple and Google. The model underlying each is a deterministic, SEIR-like model.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/NotreDame-mobility
Koyluoglu U, Milliken J	OliverWyman-Navigator	Forecasts and scenario analysis for Detected and Undetected cases and death counts following a compartmental formulation with non-stationary transition rates.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/OliverWyman-Navigator
Turtle J, Ben-Nun M, Riley P	PSI-DRAFT	A stochastic/deterministic, single-population SEIRX model that stratifies by both age distribution and disease severity and includes generic intervention fitting.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/PSI-DRAFT
Shi Y, Shah T, Ban X	RPI-UW-Mob_Collision	A mobility-informed simplified SIR model motivated by collision theory.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/RPI-UW-Mob-Collision https://www.medrxiv.org/content/10.1101/2020.07.25.20162016v1
Snyder TL, Wilson DD	SWC-TerminusCM	Mechanistic compartmental model using disease parameter estimates from literature. It uses Bayesian inference to predict the most likely model parameters.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/SWC-TerminusCM
Cobey S, Arevalo P, Baskerville E, Carran S, Gostic K, McGough L, Ranjeva S, Wen F	UChicago-COVIDIL	Compartmental, age-structured SEIR model that infers past SARS-CoV-2 transmission rates and forecasts mortality under current and hypothetical public health interventions.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UChicago-CovidIL

Gu Q, Xu P, Chen J, Wang L, Zou D, Zhang W	UCLA-SuEIR	Variant of the SEIR model considering both untested and unreported cases. The model considers reopening and assumes susceptible population will increase after the reopen.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UCLA-SuEIR https://www.medrxiv.org/content/10.1101/2020.05.24.20111989v1
Chen YQ, Zhao Y, Guo L	UCM-MESALab-FoGSEIR	FoGSEIR model is a modification of integer order SEIR model considering fractional integrals. The model considers the age structure and reopening intervention to minimize infections and deaths.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UCM_MESALab-FoGSEIR
Sheldon D, Gibson G, Reich N	UMass-MechBayes	Bayesian compartmental model with observations on cumulative case counts and cumulative deaths. Model is fit independently to each state. Model includes observation noise and a case detection rate.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UMass-MechBayes
Mayo ML, Rowland MA, Parno MD, Detwiller ID, Farthing MW, England WP George GE	USACE-ERDC_SEIR	The ERDC SEIR model makes predictions of several variables (e.g., reported new/cumulative cases per day, etc.). Model parameters are estimated using historical data using Bayesian inference.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/USACE-ERDC_SEIR
Jain S, Tiwari A, Deva A, Kulkarni M, Shingi S, Bannur N, White J, Merugu S, Raval A	Wadhwani_AI-BayesOpt	A novel model-agnostic Bayesian optimization ("BayesOpt") approach for learning the parameters of our SEIR model from observed data.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/Wadhwani_AI-BayesOpt
Gu Y	YYG-ParamSearch	Based on the SEIR model with hyperparameter optimization to make daily projections regarding COVID-19 infections and deaths in 50 US states. The model accounts for state reopenings and its effects on infections and deaths.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/YYG-ParamSearch https://covid19-projections.com/about/
NON-COMPARTMENTAL			
O'Dea E	CEID-Walk	A random walk model with drift. A least squares line is fitted to the tail observations of a target time series to estimate the drift and step variance of a random walk model.	https://github.com/reichlab/covid19-forecast-hub/blob/master/data-processed/CEID-Walk/metadata-CEID-Walk.txt

Green A, Hu A, Jahja M, Ventura V, Wasserman L, Tibshirani Rob, Shankar V, Bien J, Brooks L, Narasimhan B, Rajanala S, Rumack A, Simon N, Sharpnack J, McDonald D(University of British Columbia), Ryan Tibshirani (Senior author, and the Delphi COVID-19 Response Team	CMU-Timeseries [b]	A basic AR-type time series model fit using case counts and deaths as features.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/CMU-TimeSeries
Wang Y, Zeng D, Wang Q, Xie S	Columbia_UNC-SurvCon	Survival-convolution model with piece-wise transmission rates that incorporates latent incubation period and provides time-varying effective reproductive number.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/Columbia_UNC-SurvCon https://www.frontiersin.org/article/10.3389/fpubh.2020.00325
Ray EL, Tibshirani R	COVIDhub-baseline	Baseline prediction model.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/COVIDhub-baseline
Kalantari R, Zhou M.	DDS-NBDS	Jointly modeling daily deaths and cases using a negative binomial distribution based nonparametric Bayesian generalized linear dynamical system.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/DDS-NBDS https://dds-covid19.github.io/
Sherratt K, Bosse N, Abbott S, Hellewell J, Meakin S, Munday J, Funk S	epiforecasts-ensemble1	A deaths forecast using the renewal equation and time-series forecasts of the time-varying reproduction number.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/epiforecasts-ensemble1 https://doi.org/10.12688/wellcomeopenres.16006.1
Keskinocak P, Aglar BEO, Baxter A, Asplund J, Serban N	GT_CHHS-COVID19	Agent-based simulation model to project COVID19 infection spread.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/GT_CHHS-COVID19
Prakash BA, Rodriguez A, Cui J, Tabassum A, Adhikari B, Sun J, Xiao D, Qiang C	GT-DeepCOVID	Data-driven approach based on deep learning for forecasting mortality and hospitalizations using syndromic, clinical, demographic, mobility and point-of-care data.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/GT-DeepCOVID

Murry C and the IHME-CurveFitTeam	IHME-CurveFit	Non-linear mixed effects curve-fitting. This model makes predictions about the future that are dependent on the assumption that current interventions continue.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/IHME-CurveFit https://www.medrxiv.org/content/10.1101/2020.03.27.20043752v1
Wang L, Wang G, Gao L, Li X, Yu S, Kim M, Wang Y, Gu Z.	IowaStateLW-STEM	A nonparametric space-time disease transmission model. The projections assume that the data used is reliable, the future will continue to follow the current pattern, and current interventions will remain the same till the end of forecasting period.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/IowaStateLW-STEM https://arxiv.org/abs/2004.14103
Chiang W-H, Mohler G	IUPUI-HkPrMobiDyR	Hawkes processes with Dynamic reproduce number.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/IUPUI-HkPrMobiDyR https://doi.org/10.1101/2020.06.06.20124149
Marshall M, Gardner L, Drew C, Burman E, Nixon K	JHU_CSSE-DECOM	County-level, empirical machine learning model driven by epidemiological, mobility, demographic, and behavioral data.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/JHU_CSSE-DECOM
Karlem D	Karlen-pypm	Discrete-time difference equations with long periods of constant transmission rate	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/Karlen-pypm https://arxiv.org/abs/2007.07156
Osthus D, Del Valle S, Manore C, Weaver B, Castro L, Shelley S, Smith M, Spencer J, Fairchild G, Travis Pitts T, Gerts D, Dauelsberg L, Daughton A, Gorris M, Hornbein B, Israel D, Parikh N, Shutt D, Ziemann A	LANL-GrowthRate	Statistical dynamical growth model accounting for population susceptibility. Makes predictions about the future, unconditional on particular intervention strategies.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/LANL-GrowthRate
Gao Z, Li C, Cao W, Zheng S, Bian J, Xie X, Liu TY, Zhang S, Ferres JL	Microsoft-DeepSTIA [a]	A deep spatio-temporal network with intervention and hospital gate under the assumption of spatio-temporal process in pandemic of different regions.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/Microsoft-DeepSTIA
Espana G, Oidtman R, Cavany S, Costello A, Wieler A,	NotreDame-FRED	Agent-based model developed for influenza with parameters modified to	https://github.com/reichlab/covid19-forecast-

Lerch A, Barbera C, Poterek M, Tran Q, Moore S, Perkins A		represent the natural history of COVID-19	hub/tree/master/data-processed/NotreDame-FRED
Walraven R	RobertWalraven-ESG	Multiple skewed gaussian distribution peaks fitted to raw data.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/RobertWalraven-ESG
Nagraj VP, Turner SD, Hulme-Lowe C	SigSci_TS	Time series forecasting using ARIMA for case forecasts and lagged cases for death forecasts.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/SigSci-TS
McConnell S, Donaldson B	SteveMcConnell_COVIDComplete	A near-term fatality prediction model that calculates and uses fatality trends at the national and state level, trends in positive virus tests and total virus tests, and age-related demographics for state forecasts. Model forecasts are based on predicting near-term deaths from recent positive virus tests.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/SteveMcConnell-CovidComplete https://stevemcconnell.com/covid
Bieggel H, Lega J	UA-EpiCovDA	SIR mechanistic model with data assimilation. EpiCovDA is an extension of the EpiGro model. Model parameters are fit to Covid-19 data using a variational data assimilation method. A prior distribution of the parameters is estimated by fitting an SIR Incidence-Cumulative Cases curve to data from states that had at least 1000 cases by 04/01/2020.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UA-EpiCovDA
Jin X, Wang Y-X, Yan X	UCSB-ACTS	This data-driven machine learning model makes predictions by referring to other regions with similar growth patterns and assuming the similar development will take place in the current region.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UCSB-ACTS
Wu D, Gao L, M Yian, Yu R, Vespignani A, Chinazzi M, Davis JT, Mu K, Pastore y Piontti A, Xiong X	UCSD-NEU_DeepGLEAM	Combines the signal of a discrete stochastic epidemic computational model GLEAM with a deep learning spatiotemporal forecasting framework to further improve predictions.'	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UCSD_NEU-DeepGLEAM
Corsetti S, Schwarz T	UMich-RidgeTfReg	Nation-level model of confirmed cases and deaths	https://github.com/reichlab/covid19-forecast-

		based on ridge regression. No assumptions made about social distancing.	hub/tree/master/data-processed/UMich-RidgeTfReg
Zhang-James Y, Hess J, Chen S, Wang D, Morley CP, Faraone SV.	UpstateSU_GRU [b]	County-level forecast using recurrent neural network seq2seq model with the Gated recurrent units (GRU)	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UpstateSU-GRU
Srivastava A, Prasanna VK, Xu FT	USC-SI_kJalpha [b]	A heterogeneous infection rate model with human mobility for epidemic modeling. Our model adapts to changing trends and provide predictions of confirmed cases and deaths.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/USC-SI_kJalpha https://arxiv.org/abs/2007.05180
Srivastava A, Prasanna VK, Xu FT	USC-SI_kJalpha_RF	A heterogeneous infection rate model with human mobility for epidemic modeling. Our model adapts to changing trends and provide predictions of confirmed cases and deaths. We build a random forest, based on the output of USC_SIkJalpha model along with the data on the cumulative case/death, weekly increase, and previous increase. We then sample trees to generate quantile forecasts	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/USC-SI_kJalpha_RF https://arxiv.org/abs/2007.05180
Woody S, et al. at the University of Texas	UT-Mobility	This model makes predictions assuming that social distancing patterns, as measured by anonymized mobile-phone GPS traces, remain constant in the future. Only models *first-wave deaths*.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/UT-Mobility
Mehrotra P, Ivan JI, and the Walmart Labs COVID-19 Team	WalmartLabsML_LogForecasting [a]	A logistic growth prophet forecasting model fit using case counts and deaths as features.The Model is built by Prophet model with logistic growths to forecast the US cumulative deaths. By sampling from uniform distribution to get the quantiles.	https://github.com/reichlab/covid19-forecast-hub/tree/master/data-processed/WalmartLabsML-LogForecasting

* Based on information recorded on the COVID19 Hub with citations as recorded on 18/5/21; [a] Only provided forecasts of numbers of cumulative COVID-19 deaths; [b] Only provided forecasts of numbers of incident COVID-19 deaths.

S2 Table. For incident mortality, 95% interval MIS and MWIS for each prediction horizon.

Method	95% interval MIS					MWIS				
	All	U.S.	High	Med	Low	All	U.S.	High	Med	Low
1 week ahead										
Mean	650	7216	1032	434	98	42.3	677.4	58.9	23.6	7.2
Median	633	8477	908	429	99	40.9	684.3	55.0	22.7[b]	7.2
Ensemble	633	8931	891	424	97	41.1	704.0	54.5	22.6[ab]	7.1[a]
Sym trim	628	7572	951	427	97	41.6[b]	676.1	57.5	22.7[b]	7.1[a]
Exterior trim	663	7756	1030	441	101	43.3	693.8	60.9	23.6	7.3
Interior trim	614	7286	952	405[ab]	91[ab]	42.5	684.3	59.3	23.2[b]	7.2
Envelope	2249	20811	4746	654	254	140.0	2057.9	228.2	60.2	18.8
Inv score	595[b]	7169[a]	891[b]	414[b]	92[bc]	40.7[b]	656.1[b]	55.9[b]	23.1[b]	7.1[ab]
Inv score tuning	577[a]	7285	822[a]	419	94	39.5[ab]	625.0[a]	53.5[ab]	23.5	7.1[a]
Previous best	719	10217	996	481	121	46.4	715.8	63.9	27.8	8.2
2 weeks ahead										
Mean	744	8237	1217	469	106	54.6	813.5	84.0	27.3	8.0
Median	656	8355	946	467	102	47.1	814.4	62.3	25.9[b]	7.8[ab]
Ensemble	684	10151	936	457	102	47.7	854.3	62.1	25.8[ab]	7.8[ab]
Sym trim	716	8383	1132	463	102	53.6	809.8	82.3	26.2[b]	7.9[b]
Exterior trim	768	8945	1237	477	108	77.9	830.9	154.0	27.3	8.1
Interior trim	750	8209	1267	443	102	58.6	816.8	96.5	26.8[b]	8.0
Envelope	3220	27179	7049	828	372	249.4	2656.4	508.1	75.5	23.0
Inv score	649[b]	7586	989[b]	452[a]	97[ab]	53.0	763.2[b]	82.5	26.7[b]	7.9[b]
Inv score tuning	606[ab]	7479[a]	845[a]	465	102	45.7[a]	727.8[a]	61.6[a]	27.4	8.0
Previous best	794	10706	1092	570	138	55.6	906.9	74.3	33.1	9.5
3 weeks ahead										
Mean	801	8813[a]	1344	477	109	58.5	941.5	85.2	29.7	8.6
Median	731	9992	1046	498	103	54.1	965.5	71.3	29.2	8.3[a]
Ensemble	727	10531	1016	487	102	53.4	947.9	70.3	29.1[a]	8.3[a]
Sym trim	795	9603	1270	487	110	58.4	966.0	84.0	29.4	8.4
Exterior trim	857	10455	1401	497	107	73.1	969.2	128.2	30.0	8.5
Interior trim	780	8910	1285	469	107	61.0	957.2	92.4	29.4	8.6
Envelope	3749	46863	6995	1062	655	251.0	3460.1	446.6	87.8	29.8
Inv score	707[b]	8974	1079[b]	460[a]	96[a]	56.2[b]	881.2[b]	82.3	29.3	8.3[ab]
Inv score tuning	664[a]	9009	912[a]	480	107	52.4[a]	880.4[a]	69.6[a]	30.3	8.7
Previous best	885	11273	1242	658	145	65.7	1121.8	86.0	38.1	10.9
4 weeks ahead										
Mean	924	12738	1403	510	163	66.6	1156.6	92.2	33.6	10.0
Median	873	11671	1302	560	122	64.1	1193.6	83.9	32.7[a]	9.2[a]
Ensemble	864	11602	1283	558	120[ac]	63.9	1192.9	83.3	32.8	9.2[a]
Sym trim	917	12301	1396	550	134	66.9	1199.0	91.5	33.1	9.3
Exterior trim	1009	14588	1539	546	145	74.4	1204.8	112.9	34.2	9.7
Interior trim	925	12765	1411	508	158	68.3	1173.2	96.5	33.4	10.0
Envelope	6135	128559	8219	1643	1342	295.7	4984.5	452.3	115.6	43.5
Inv score	809[b]	12128	1161[b]	481[abc]	121	63.2[b]	1073.1[a]	87.8[b]	32.7[ab]	9.5
Inv score tuning	781[a]	10751[a]	1115[a]	516	125	62.5[a]	1099.7	82.4[a]	34.3	9.8
Previous best	1093	13519	1594	778	177	80.2	1500.4	100.6	43.2	13.4

Lower values are better. [a] best method for each horizon in each column; [b] score is significantly lower than the mean combination; [c] score is significantly lower than the median combination.

S3 Table. For incident mortality, calibration for all locations.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	5.2	2.8	2.8	3.7	5.8	2.9	1.4	3.1	3.3	4.1
2.5	7.0	4.3	4.2	5.3	7.6	3.8	1.4	4.8	4.7	5.6
5	8.9	6.0	5.8	6.9	9.7	5.3	1.5	6.9	6.6	7.6
10	12.9	9.5	9.0	10.2	14.1	8.0	1.5	10.8	10.1	12.2
15	17.0	13.0	12.5	13.8	18.2	11.6	1.6	15.0	14.3	16.9
20	20.8	16.6	16.0	17.1	22.2	15.1	1.7	19.1	18.4	20.9
25	24.9	20.6	19.9	20.9	26.4	18.7	1.8	23.1	22.8	24.9
30	29.0	24.7	24.0	25.0	30.9	22.6	1.9	27.4	27.0	29.1
35	33.7	29.2	28.5	29.3	36.0	27.3	2.1	32.0	31.6	33.2
40	38.6	33.6	33.0	34.1	41.4	32.6	2.5	36.5	36.0	36.7
45	43.4	38.2	37.9	39.0	47.0	38.4	3.0	41.4	41.0	40.9
50	49.2	43.6	44.1	44.5	48.1	44.4	3.9	46.9	46.4	44.7
55	56.0	49.7	51.3	50.9	49.9	58.1	95.7	54.0	52.6	49.0
60	61.4	54.8	56.3	56.3	56.0	63.7	96.5	59.4	57.6	52.6
65	66.6	59.4	60.7	61.3	61.9	69.2	97.2	64.6	62.7	56.9
70	71.8	63.9	65.1	66.2	67.3	74.3	97.9	69.9	67.6	61.4
75	76.3	68.5	69.7	70.8	72.1	79.0	98.4	74.7	72.5	65.6
80	81.2	73.0	74.2	75.8	77.4	83.4	98.8	79.8	77.7	70.4
80	85.5	78.2	79.3	80.8	81.8	87.6	99.1	84.7	82.8	74.9
90	89.7	83.0	83.8	85.9	86.4	91.4	99.4	89.5	87.4	79.7
95	93.7	88.4	89.1	90.9	90.8	95.1	99.6	94.0	92.6	85.9
97.5	95.9	91.5	92.1	93.8	93.4	97.0	99.7	96.4	95.4	89.6
99	97.5	93.9	94.3	95.5	95.4	98.3	99.8	97.9	97.1	92.3

S4 Table. For incident mortality, calibration for U.S.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	0.3	0.7	1.7	0.0	0.7	0.3	0.0	0.0	0.0	2.4
2.5	1.7	1.4	2.4	1.4	1.7	1.4	0.0	0.3	0.3	3.4
5	2.8	2.1	3.1	2.8	2.8	1.0	0.0	2.1	2.4	4.8
10	3.5	2.8	4.1	3.5	3.5	1.7	0.0	2.8	3.1	7.9
15	5.9	4.1	6.2	5.2	5.9	2.8	0.0	4.1	6.2	10.7
20	8.3	5.9	8.3	6.2	8.3	4.8	0.3	6.5	8.3	17.3
25	11.4	9.0	11.4	9.6	12.1	7.9	0.3	10.7	11.1	17.9
30	15.5	15.5	17.6	15.9	16.2	11.0	0.3	13.1	14.8	21.7
35	22.1	18.6	20.4	18.6	22.1	17.6	0.3	18.7	18.6	21.7
40	25.6	24.2	28.0	23.8	27.3	22.8	0.7	22.1	21.4	22.4
45	32.1	30.0	33.1	29.3	38.0	28.3	1.0	27.6	23.8	26.5
50	37.7	35.2	38.0	34.5	38.0	33.5	1.4	33.5	29.0	29.3
55	45.2	40.7	43.4	41.4	41.1	47.0	95.9	43.1	36.5	31.3
60	51.8	44.9	48.3	45.2	48.7	53.5	96.9	48.3	44.2	33.4
65	57.0	50.7	53.1	52.1	55.9	61.4	97.6	56.2	51.4	37.5
70	64.5	58.6	60.0	59.3	60.4	65.5	98.3	63.1	55.9	41.7
75	70.0	64.5	63.8	65.1	68.3	72.4	99.0	69.7	63.1	46.5
80	75.5	68.3	67.6	69.3	73.8	78.3	99.3	78.3	70.7	54.4
80	81.4	74.1	73.7	77.2	80.0	83.1	99.3	83.8	79.0	60.3
90	86.9	79.6	81.0	83.4	85.5	89.6	99.7	89.6	85.2	65.4
95	93.5	89.6	89.6	92.4	90.3	94.8	99.7	95.5	92.4	79.3
97.5	95.9	92.7	92.7	94.1	92.4	95.9	100.0	97.9	96.2	91.7
99	99.3	94.5	94.8	96.6	94.8	99.3	100.0	99.0	96.2	94.5

S5 Table. For incident mortality, calibration for high mortality locations.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	2.6	1.5	1.5	1.5	3.2	1.8	0.3	1.4	1.5	3.1
2.5	4.2	2.8	2.8	3.0	4.9	2.6	0.4	2.6	2.7	4.1
5	5.8	4.1	4.0	4.5	6.5	3.9	0.4	4.4	4.2	6.2
10	8.9	6.5	6.4	7.1	10.1	5.7	0.4	7.2	6.7	10.4
15	12.9	9.3	9.1	10.6	14.1	9.1	0.5	10.9	10.4	14.1
20	16.4	12.7	12.5	13.8	17.9	12.3	0.6	14.8	14.0	17.9
25	20.4	16.5	16.3	17.3	22.0	15.2	0.8	18.4	18.2	21.6
30	24.8	20.4	20.4	21.4	26.6	18.9	0.8	22.6	22.5	25.3
35	29.6	25.4	25.5	26.0	32.0	23.2	0.9	27.8	27.4	30.8
40	35.1	30.4	30.7	31.1	38.0	28.9	1.1	32.7	32.4	35.6
45	40.5	35.2	35.8	36.4	43.5	35.2	1.4	38.3	37.8	39.7
50	46.6	40.9	41.6	42.1	45.2	41.3	1.7	44.2	43.8	43.5
55	52.4	46.9	48.3	48.6	47.1	55.2	96.4	51.0	50.2	48.4
60	58.2	52.7	53.8	54.5	52.8	61.4	97.3	57.0	55.3	52.8
65	64.1	57.8	59.0	60.6	59.4	67.3	98.0	63.0	61.6	57.2
70	69.8	62.6	63.9	65.9	65.5	72.4	98.3	68.8	66.8	62.0
75	75.0	67.6	68.7	71.3	71.2	77.7	98.8	74.2	72.4	65.9
80	80.7	72.8	74.2	77.2	76.8	83.0	99.1	80.1	78.2	71.9
85	85.6	78.6	79.8	82.5	81.7	87.4	99.4	85.7	83.4	76.6
90	90.5	84.0	84.6	87.8	86.9	91.6	99.6	91.0	88.6	81.5
95	94.6	89.6	90.1	92.2	91.4	95.6	99.7	95.1	93.5	88.2
97.5	96.8	92.8	93.3	95.0	94.4	97.4	99.8	97.4	96.3	91.5
99	98.2	95.1	95.4	96.4	96.0	98.4	99.9	98.6	97.7	93.4

S6 Table. For incident mortality, calibration for medium mortality locations.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	3.7	1.8	1.8	2.5	4.4	1.7	0.5	2.0	2.1	3.1
2.5	5.6	2.9	2.9	4.1	6.1	2.7	0.5	3.4	3.6	4.9
5	7.4	4.6	4.5	5.6	8.2	4.0	0.5	5.4	5.5	6.6
10	11.7	8.1	7.9	9.0	13.0	6.9	0.6	9.6	9.1	11.4
15	15.7	11.4	11.4	12.9	16.9	10.5	0.6	14.0	13.4	17.0
20	19.7	15.2	14.9	16.1	21.0	13.8	0.7	18.1	17.9	21.0
25	24.1	19.2	18.8	20.0	25.4	17.8	0.8	22.5	22.5	25.1
30	28.5	23.7	23.2	24.4	30.7	21.7	0.9	27.1	27.0	29.8
35	33.9	28.3	28.0	29.2	36.4	26.8	1.2	32.4	32.1	33.5
40	39.1	33.0	32.7	34.1	42.3	32.6	1.5	37.2	36.8	36.5
45	44.1	38.4	38.3	39.8	49.6	38.8	1.9	42.7	42.4	40.7
50	50.9	44.6	45.1	45.9	50.7	45.5	2.6	48.9	48.4	44.5
55	57.4	51.1	52.5	52.8	52.0	59.2	96.0	55.8	54.9	49.4
60	62.6	56.5	57.6	58.5	57.8	64.7	96.5	61.0	60.2	53.8
65	67.6	61.2	62.3	63.3	63.6	69.9	97.1	66.1	65.1	59.1
70	72.4	65.5	66.7	67.8	69.1	74.9	97.9	71.2	69.8	63.5
75	76.3	70.5	71.6	72.5	73.3	79.3	98.2	75.6	74.4	68.1
80	81.3	74.5	75.7	77.3	78.3	83.4	98.7	80.8	79.9	73.1
85	85.7	79.4	80.4	82.5	83.0	87.6	99.0	85.4	85.0	77.3
90	89.9	84.2	84.9	86.9	87.4	91.4	99.3	90.2	89.1	81.4
95	94.1	89.2	89.7	91.4	91.6	95.2	99.6	94.3	93.7	87.2
97.5	96.2	91.9	92.5	94.0	93.9	96.9	99.7	96.6	96.3	90.3
99	97.6	94.5	94.9	95.8	95.9	98.1	99.7	97.9	97.0	92.7

S7 Table. For incident mortality, calibration for low mortality locations.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	9.2	5.9	5.8	7.1	10.0	6.1	3.8	6.4	6.2	6.3
2.5	11.2	8.0	7.7	8.7	12.1	7.1	3.8	8.5	7.8	8.0
5	13.3	10.0	9.5	10.7	14.7	9.1	3.8	11.2	10.3	10.4
10	18.4	14.9	13.9	14.7	19.4	12.6	3.8	16.0	14.9	15.8
15	22.9	19.7	18.1	18.4	24.1	16.3	3.8	20.6	19.9	20.4
20	27.1	23.6	22.3	22.9	28.8	20.8	4.0	25.4	24.4	24.2
25	31.7	28.6	26.6	27.1	33.2	24.8	4.2	29.7	28.7	28.6
30	35.6	32.9	31.0	31.3	37.2	28.9	4.4	34.2	32.8	32.8
35	39.7	37.1	35.0	35.4	41.7	33.9	4.7	38.2	37.0	36.6
40	44.1	41.3	38.8	40.2	46.6	38.8	5.3	42.4	41.2	40.1
45	48.4	45.1	42.9	44.1	51.0	44.1	6.2	46.5	45.5	44.5
50	53.2	49.6	49.7	49.1	52.0	49.8	8.1	51.2	50.2	48.3
55	61.5	55.7	57.6	55.6	54.3	63.8	96.5	59.1	56.1	52.4
60	67.1	60.1	62.2	60.5	61.7	68.6	97.3	64.6	61.1	54.7
65	71.9	64.1	65.8	64.7	67.2	74.0	98.0	68.9	65.4	58.6
70	76.8	68.0	69.5	69.3	71.7	79.0	98.6	73.3	70.1	63.3
75	80.8	71.9	73.4	72.8	75.8	82.8	99.2	77.5	74.4	67.9
80	85.3	75.8	77.3	77.1	80.8	87.2	99.5	81.8	78.8	72.0
85	89.0	80.7	81.9	81.4	84.0	90.6	99.7	86.4	83.5	76.3
90	92.1	85.1	85.8	86.6	88.0	93.5	99.8	90.8	87.9	81.7
95	95.4	90.1	90.7	91.9	92.0	96.3	99.9	95.0	93.1	87.0
97.5	97.3	93.0	93.6	94.7	94.4	98.0	100.0	97.0	95.7	90.7
99	98.7	94.9	95.3	96.3	96.6	99.1	100.0	98.8	97.6	93.0

S8 Table. For cumulative mortality, 95% interval MIS and MWIS for each prediction horizon.

Method	95% interval MIS					MWIS				
	All	U.S.	High	Med	Low	All	U.S.	High	Med	Low
1 week ahead										
Mean	6283	107370	9357	2445	1101	202	3806	283	78	34
Median	2355 [ab]	29080 [b]	4791 [b]	465 [ab]	237 [b]	93 [ab]	1567 [b]	158 [b]	24 [ab]	11 [ab]
Ensemble	2364 [b]	30211 [b]	4749 [bc]	470 [b]	235 [ab]	93 [ab]	1559 [ab]	157 [abc]	24 [ab]	11 [ab]
Sym trim	2723 [b]	32310 [b]	5376 [b]	694 [b]	359 [b]	101 [b]	1652 [b]	171 [b]	28 [b]	13 [b]
Exterior trim	5642 [b]	92082 [b]	8593 [b]	2205 [b]	1043 [b]	166 [b]	2893 [b]	246 [b]	63 [b]	29 [b]
Interior trim	2444 [b]	23852	4379 [ab]	1075 [b]	619 [b]	134 [b]	2120 [b]	206 [b]	52 [b]	26 [b]
Envelope	5076 [b]	97199	7209 [b]	1941 [b]	659 [b]	780	17437	927	329	103
Inv score	3737 [b]	30588 [b]	6840 [b]	1878 [b]	914 [b]	130 [b]	1865 [b]	208 [b]	54 [b]	27 [b]
Inv score tuning	4225 [b]	22738 [b]	7784	2961	842	128 [b]	1644 [b]	214 [b]	57 [b]	24 [b]
Previous best	5232	20629 [ab]	9196	5120	473	130 [b]	1609 [b]	218 [b]	69	17 [b]
2 weeks ahead										
Mean	5912	89926	9250	2463	1080	227	3907	335	92	37
Median	2574 [ab]	26967 [b]	5222 [b]	788 [ab]	278 [ab]	123 [ab]	1966 [b]	201 [b]	43 [ab]	16 [ab]
Ensemble	2630 [b]	30649 [b]	5164 [ab]	800 [b]	279 [b]	124 [b]	2038 [b]	199 [ab]	43 [ab]	16 [ab]
Sym trim	2894 [b]	28487 [b]	5792 [b]	1000 [b]	384 [b]	131 [b]	1994 [b]	218 [b]	47 [b]	18 [b]
Exterior trim	5687 [b]	85822	8922 [b]	2370 [b]	1056	196 [b]	3127 [b]	303 [b]	80 [b]	33 [b]
Interior trim	3157 [b]	25998 [b]	6126	1334 [b]	667 [b]	208	2518 [b]	387	71 [b]	31 [b]
Envelope	6525	114668	9762	2510	942	954	19297	1278	384	121
Inv score	3785 [b]	24350 [b]	7121 [b]	2088	937	162 [b]	2135 [b]	266 [b]	71 [b]	32 [b]
Inv score tuning	4301 [b]	19548 [ab]	7940	3198	869	154 [b]	1933 [ab]	254 [b]	75 [b]	29 [b]
Previous best	5684	27102 [b]	9635	5597	559	166 [b]	2100 [b]	266 [b]	95	23
3 weeks ahead										
Mean	4971	78958	8254	1800	507	235	4203	355	89	27
Median	2873 [b]	29160	5671 [b]	1077 [b]	326 [b]	156 [b]	2488 [b]	247 [b]	63 [ab]	20 [ab]
Ensemble	2907 [b]	31733	5617 [b]	1082 [b]	328 [b]	155 [ab]	2484 [b]	245 [ab]	64 [b]	20 [ab]
Sym trim	3040 [b]	34160	5832 [b]	1138 [b]	320 [b]	162 [b]	2591 [b]	258 [b]	65 [b]	20 [ab]
Exterior trim	5034	80925	8288	1843	508	212 [b]	3552 [b]	332 [b]	81 [b]	25 [b]
Interior trim	3293	31080	6874	1069 [ab]	301 [b]	252	3136	491	73 [b]	23 [b]
Envelope	8114	147130	11750	3032	1381	1081	21951	1499	403	113
Inv score	2908 [b]	27823	5911 [b]	1070 [b]	277 [ab]	172 [b]	2627 [b]	285 [b]	67 [b]	21 [b]
Inv score tuning	2791 [ab]	24017 [ab]	5604 [ab]	1231 [b]	290 [b]	159 [b]	2385 [ab]	257 [b]	69 [b]	21 [b]
Previous best	3764	36374	7336	1664	373 [b]	183 [b]	2793	280	90	24
4 weeks ahead										
Mean	4993	73035	8425	1985	568	271	4706	410	109	32
Median	3335 [b]	35545	6373 [b]	1352 [ab]	384 [b]	200 [ab]	3306	307 [b]	85 [ab]	26 [ab]
Ensemble	3384 [b]	39995	6248 [b]	1368 [b]	383 [b]	200 [ab]	3338	302 [ab]	86 [b]	26 [ab]
Sym trim	3517 [b]	41194	6527 [b]	1435 [b]	375 [b]	208 [b]	3423	320 [b]	88 [b]	26 [ab]
Exterior trim	5188	76633	8726	2092	544	254 [b]	4195	397	103 [b]	30 [b]
Interior trim	3920	40403	7794	1403 [b]	417 [b]	311	3960	592	96 [b]	30 [b]
Envelope	11944	258403	14536	4241	2558	1292	25886	1789	490	151
Inv score	3286 [b]	33773	6369 [b]	1356 [b]	340 [ab]	216 [b]	3355	346 [b]	89 [b]	26 [ab]
Inv score tuning	3187 [ab]	32193 [a]	5943 [ab]	1558 [b]	354 [b]	201 [b]	3117 [a]	312 [b]	92 [b]	27 [b]
Previous best	4465	48258	8206	2146	466	240	3820	358	121	32

Lower values are better. [a] best method for each horizon in each column; [b] score is significantly lower than the mean combination; [c] score is significantly lower than the median combination.

S9 Table. For cumulative mortality, calibration for all locations.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	18.0	3.2	3.3	4.8	19.1	3.1	1.3	5.1	4.6	4.4
2.5	20.0	4.5	4.6	6.1	21.2	4.2	1.4	7.3	6.3	6.2
5	22.1	6.2	6.3	7.8	23.7	5.8	1.5	10.1	8.5	9.0
10	26.0	9.6	9.6	11.0	28.2	8.9	1.6	14.9	12.0	13.8
15	29.9	12.9	13.1	14.5	32.3	12.1	1.7	19.5	16.3	18.0
20	33.6	16.6	16.7	17.8	36.2	15.5	1.7	23.5	20.1	21.7
25	37.2	20.2	20.6	21.3	39.9	19.5	1.9	27.6	24.4	25.8
30	41.1	24.3	24.8	25.7	44.0	23.6	2.0	32.0	28.9	30.2
35	44.9	29.1	29.4	30.2	48.2	27.9	2.3	36.2	33.4	34.2
40	48.9	33.5	33.8	34.7	52.6	32.7	2.5	40.8	38.1	38.0
45	53.1	38.1	38.4	39.4	55.6	38.7	3.1	45.5	43.2	42.0
50	58.0	43.7	44.8	45.6	56.5	45.1	4.0	51.3	48.9	46.1
55	63.5	50.4	52.2	52.5	57.5	66.0	95.0	58.0	55.3	50.9
60	67.9	55.7	57.4	58.0	60.9	70.5	95.7	63.0	60.5	55.3
65	71.8	60.3	61.8	62.7	65.6	74.1	96.3	67.6	64.9	59.0
70	75.4	64.7	66.1	67.1	69.4	77.7	96.8	71.8	69.6	62.9
75	78.9	69.0	70.4	71.4	73.4	81.2	97.3	75.6	73.9	67.0
80	82.1	73.5	74.7	75.7	76.7	84.5	97.7	79.7	78.1	71.0
85	85.4	77.9	78.9	80.2	80.4	87.9	98.1	83.8	82.5	75.7
90	88.6	82.3	83.0	84.8	84.0	90.9	98.4	87.6	86.7	80.1
95	92.1	87.0	87.6	89.1	88.6	94.3	98.8	91.8	90.8	85.5
97.5	94.1	90.1	90.4	91.8	91.3	96.2	99.1	94.4	93.3	88.9
99	95.8	92.3	92.5	93.9	93.6	97.6	99.3	96.1	95.3	91.7

S10 Table. For cumulative mortality, calibration for U.S.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	16.0	0.0	0.6	1.3	16.3	0.0	0.0	1.6	0.0	0.0
2.5	17.0	0.0	0.6	1.3	17.3	0.0	0.0	2.9	0.3	0.0
5	18.3	0.0	0.6	1.6	18.6	0.0	0.0	5.5	1.0	1.9
10	18.9	1.6	1.9	3.6	19.9	0.0	0.0	7.5	2.6	10.1
15	21.9	3.6	4.9	6.5	22.2	2.3	0.0	10.4	5.2	11.7
20	22.5	6.8	7.1	7.8	24.2	4.5	0.0	12.4	8.8	14.3
25	25.8	8.8	9.4	9.4	25.8	6.2	0.0	13.7	12.7	18.3
30	27.8	13.0	14.3	12.4	28.1	10.4	0.0	18.3	15.0	22.5
35	30.4	16.0	17.6	17.6	32.4	15.0	0.0	21.2	17.6	23.8
40	34.7	19.6	20.5	19.3	35.3	19.6	0.0	23.8	20.2	26.4
45	37.9	23.8	24.5	25.2	38.9	24.5	0.6	27.4	24.8	32.3
50	43.5	29.4	30.4	32.4	41.5	30.1	1.0	31.4	28.8	38.5
55	48.1	35.0	36.0	37.0	43.2	48.4	91.9	38.3	35.9	43.8
60	51.0	38.9	40.2	40.6	45.2	51.7	92.5	43.9	43.9	46.4
65	54.3	41.2	43.5	42.5	49.4	55.0	93.2	47.4	47.1	47.1
70	58.3	44.9	45.2	46.8	53.1	58.3	93.8	51.4	52.7	50.0
75	61.2	51.4	51.1	52.7	56.0	63.2	95.5	58.0	56.0	54.0
80	64.8	57.3	56.9	57.9	59.9	67.8	96.8	63.5	60.9	60.2
85	71.7	62.9	62.2	66.1	66.8	76.2	97.7	70.1	68.4	65.7
90	76.9	69.1	69.1	75.6	74.3	81.5	99.0	77.9	77.3	71.6
95	84.7	79.5	78.5	84.4	82.1	87.3	99.7	85.1	88.0	89.9
97.5	89.3	84.4	82.4	87.0	85.7	91.9	100.0	91.6	92.9	89.3
99	92.3	87.7	85.4	89.6	89.0	94.5	100.0	95.2	95.5	95.5

S11 Table. For cumulative mortality, calibration for high mortality locations.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	19.0	4.8	4.9	5.6	20.3	4.4	2.3	5.5	5.5	5.1
2.5	21.1	6.0	6.0	6.8	22.6	5.2	2.3	7.5	7.0	6.9
5	23.1	7.6	7.6	8.0	24.9	6.7	2.4	9.8	8.4	9.5
10	26.8	10.4	10.4	11.0	29.1	9.6	2.5	14.3	11.2	13.5
15	30.4	13.0	13.3	14.0	32.8	12.8	2.5	18.4	14.5	17.9
20	33.8	16.5	16.6	17.6	36.5	15.7	2.7	22.4	17.5	22.1
25	37.4	20.4	21.0	21.0	40.4	19.3	3.0	26.4	21.9	26.2
30	41.0	24.5	25.4	25.7	44.3	23.1	3.2	30.6	26.5	30.5
35	44.6	29.7	30.4	30.2	48.1	27.8	3.3	35.0	31.1	35.2
40	48.8	33.9	35.2	34.8	52.7	32.5	3.5	40.0	36.3	39.9
45	53.2	38.9	40.2	40.0	56.0	39.6	3.8	45.5	42.8	43.9
50	58.4	44.6	46.3	46.2	57.2	45.7	4.1	51.4	49.2	48.5
55	63.3	51.3	53.3	52.2	58.0	66.6	97.0	58.1	56.1	55.1
60	68.4	57.3	59.2	58.7	61.7	71.6	97.8	63.8	62.3	60.3
65	72.7	62.3	64.2	64.3	66.5	75.2	98.2	69.0	67.0	64.1
70	76.6	67.5	69.1	69.3	70.7	78.8	98.6	73.4	72.3	68.0
75	80.6	72.2	73.7	74.3	75.3	82.7	98.9	78.2	77.3	72.2
80	83.8	76.7	78.0	78.2	78.5	86.2	99.0	82.3	81.5	76.6
85	87.4	81.1	82.3	83.1	82.1	90.1	99.3	86.4	86.0	80.8
90	90.9	85.6	86.6	87.8	85.6	93.0	99.5	90.4	89.2	86.0
95	94.1	90.3	91.1	92.1	90.9	95.8	99.6	94.3	93.2	89.9
97.5	95.9	93.5	93.9	94.5	93.1	97.4	99.7	96.9	95.5	92.9
99	97.4	95.7	95.7	96.4	95.2	98.4	99.8	98.3	97.6	94.4

S12 Table. For cumulative mortality, calibration for medium mortality locations.

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	17.7	1.5	1.6	2.7	18.9	1.8	0.2	3.6	3.1	3.3
2.5	19.8	2.7	2.8	4.2	21.1	2.8	0.3	6.0	5.0	4.9
5	22.0	4.2	4.4	5.8	23.8	4.0	0.4	8.9	7.3	8.2
10	26.0	7.6	7.7	9.1	28.2	7.2	0.4	13.7	10.6	13.6
15	29.9	10.5	10.7	12.5	32.6	10.5	0.4	18.4	15.5	17.3
20	33.8	14.1	14.4	15.6	36.8	14.4	0.5	22.9	19.4	20.8
25	37.6	18.0	18.2	19.3	40.6	18.7	0.5	27.3	23.9	24.9
30	42.2	22.6	23.1	24.6	44.8	23.1	0.6	32.3	28.8	29.8
35	46.7	27.8	28.3	29.4	49.8	27.3	0.9	36.9	34.2	33.9
40	50.6	32.7	33.2	34.4	54.1	32.6	1.1	41.8	39.4	37.4
45	54.9	37.7	38.1	39.4	57.3	38.5	1.6	46.0	44.3	42.5
50	60.0	44.3	45.2	46.3	58.0	45.6	2.2	52.7	50.8	47.1
55	65.4	52.0	53.3	54.2	58.9	68.0	96.5	59.2	57.1	51.9
60	69.8	57.6	58.8	59.8	62.8	72.3	97.1	64.5	62.7	56.2
65	73.6	62.4	63.2	64.8	67.5	76.0	97.5	69.0	67.5	60.4
70	77.2	66.8	67.5	69.2	71.4	79.6	98.0	73.5	72.3	65.1
75	80.7	70.7	71.6	73.2	75.3	82.7	98.5	77.1	76.7	69.6
80	83.8	75.3	76.2	77.8	78.5	86.1	98.9	81.4	80.9	73.3
85	87.4	80.1	80.9	82.2	82.4	89.3	99.2	85.9	85.6	77.6
90	90.6	84.9	85.6	86.8	86.2	92.1	99.4	89.7	89.6	81.6
95	94.2	89.4	89.8	91.0	90.5	95.5	99.6	94.0	93.0	86.9
97.5	96.1	92.6	92.9	94.0	93.3	97.0	99.7	96.1	95.4	90.4
99	97.5	94.7	94.9	96.0	95.6	98.1	99.9	97.6	97.0	93.0

S13 Table. For cumulative mortality, calibration for low mortality locations

Quantile	Mean	Median	Ensemble	Sym trim	Exterior trim	Interior trim	Envelope	Inv score	Inv score tuning	Previous best
1	17.0	3.5	3.5	4.4	18.4	3.9	1.5	4.7	4.6	5.4
2.5	19.3	5.4	5.4	6.0	20.7	5.6	1.8	7.1	6.2	7.1
5	21.7	7.6	7.5	8.5	23.9	7.9	1.9	10.8	9.4	10.1
10	26.7	11.8	11.8	12.7	29.8	12.1	2.0	16.1	14.3	15.3
15	31.2	16.6	16.4	17.1	34.6	15.8	2.0	21.6	19.3	20.2
20	35.6	21.1	20.8	21.4	39.0	20.0	2.1	26.0	24.9	24.1
25	39.5	25.3	25.3	25.2	43.2	24.7	2.2	30.7	28.9	29.0
30	43.6	29.4	29.4	29.2	48.2	29.2	2.3	35.1	33.7	33.5
35	47.6	34.5	33.9	33.9	52.6	33.0	2.7	39.6	37.8	37.5
40	52.1	39.0	37.9	38.6	57.0	37.8	3.1	44.4	42.1	41.5
45	56.9	43.5	42.5	43.5	60.3	43.5	4.2	49.7	47.3	44.7
50	62.2	48.9	50.0	50.0	60.4	50.2	5.8	55.3	52.8	48.4
55	68.9	55.3	58.0	57.2	61.6	71.0	97.4	63.4	59.7	52.1
60	73.4	60.1	62.7	62.4	64.8	75.3	98.1	67.8	64.3	56.7
65	77.4	64.6	66.7	66.5	69.8	79.1	98.7	72.4	68.5	60.3
70	81.6	69.0	71.1	71.0	73.5	83.0	99.1	76.6	72.8	63.8
75	84.8	73.7	75.8	74.9	77.7	86.3	99.3	80.4	77.0	68.1
80	88.2	78.4	79.8	79.5	81.5	89.4	99.6	84.4	81.2	72.0
85	90.8	82.6	83.9	84.3	85.1	92.0	99.7	88.4	85.5	77.6
90	93.5	86.7	87.3	88.4	88.2	94.7	99.9	91.5	89.8	81.9
95	96.5	91.2	92.0	92.4	92.7	97.2	100.0	95.1	93.7	87.0
97.5	98.0	94.0	94.2	94.8	95.0	98.4	100.0	97.4	95.9	91.1
99	99.1	96.0	96.2	96.8	96.7	99.3	100.0	98.8	97.4	93.3

S14 Table. Sensitivity analysis for incident mortality, skill scores of the 95% interval MIS and MWIS after excluding locations for which there were noticeable changes in reporting patterns.

	95% interval MIS					MWIS				
Method	**All**	**U.S.**	**High**	**Med**	**Low**	**All**	**U.S.**	**High**	**Med**	**Low**
Mean	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Median	9.9	-4.0	16.8	-1.8	16.3	6.0	-1.9	8.5	3.0	7.5
Ensemble	11.2	-11.4	18.7 [a]	-0.1	17.0 [a]	6.4 [a]	-3.1	9.4 [a]	3.4 [a]	7.5 [a]
Sym trim	9.4	-2.3	15.2	1.3	13.1	4.4	-1.7	4.9	2.3	6.8
Exterior trim	-2.3	-12.8	-3.3	-5.0	2.7	0.5	-3.1	0.5	-1.5	3.1
Interior trim	4.3	-0.5	3.0	5.1	4.9	0.5	-1.2	0.1	1.2	0.3
Envelope	-239.0	-503.8	-253.8	-168.2	-313.1	-258.5	-266.6	-297.2	-220.8	-267.4
Inv score	12.5 [a]	3.1	17.2	6.4 [a]	15.2	4.4	6.0	6.9	2.7	3.7
Inv score tuning	8.6	6.7 [a]	16.5	0.2	9.8	1.6	7.1 [a]	6.1	-1.5	-0.1
Previous best	-20.8	-23.5	-12.4	-35.2	-13.5	-22.7	-18.3	-13.8	-25.1	-30.3

Shows percentages. Higher values are better. [a] best method in each column.

S15 Table. Sensitivity analysis for cumulative mortality, skill scores of the 95% interval MIS and MWIS after excluding locations for which there were noticeable changes in reporting patterns.

	95% interval MIS					MWIS				
Method	**All**	**U.S.**	**High**	**Med**	**Low**	**All**	**U.S.**	**High**	**Med**	**Low**
Mean	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Median	69.7 [a]	65.4	66.8 [a]	64.9 [a]	77.4 [a]	46.2 [a]	43.9	43.2	42.4	53.5 [a]
Ensemble	69.4	62.0	66.5	64.7	77.1	46.1	43.3	43.5 [a]	42.3 [a]	52.9
Sym trim	65.4	61.0	61.2	60.5	74.2	43.1	41.9	40.4	38.6	50.8
Exterior trim	5.7	4.0	5.4	3.1	9.2	12.5	17.2	12.1	10.2	15.2
Interior trim	47.4	65.3	49.6	47.9	42.6	18.9	29.4	21.3	19.7	14.4
Envelope	-56.4	-76.8	-47.9	-49.3	-74.4	-346.5	-408.8	-349.7	-356.5	-327.0
Inv score	34.0	66.6	41.7	28.5	27.7	24.9	39.9	29.6	23.1	20.3
Inv score tuning	22.4	71.8 [a]	28.9	2.8	30.0	24.4	45.4 [a]	28.8	20.4	22.4
Previous best	27.5	62.1	23.0	-15.9	59.9	19.4	37.9	17.8	7.4	32.1

Shows percentages. Higher values are better. [a] best method in each column.