Supplement

Supplementary information: *Predictive performance of multi-model ensemble forecasts of COVID-19 across European nations*

Participating teams

The following teams participated in the European Forecast Hub by contributing forecasts over the study period. Information below is taken from metadata provided by each team.

Team	Authors	Methods	Metadata
BIOCOMSC	Martí Català, Enric Álvarez, Sergio Alonso, Daniel López, Clara Prats	Empirical model based on cases and deaths dynamics.	BIOCOMSC-Gompertz
University of Cologne Covid Metrics	Tom Zimmermann, Arne Rodloff	Forecasts are based on TBATS - models (DeLivera, Hyndman and Snyder (2011)) and are updated daily for each German state.	CovidMetrics-epiBATS
Epiforecasts / London School of Hygiene and Tropical Medicine	Nikos Bosse, Sam Abbott, Sebastian Funk	Semi-mechanistic estimation of the time-varying reproduction number for latent infections mapped to reported cases/deaths.	epiforecasts-EpiNow2
epiforecasts	Sam Abbott	A Bayesian autoregressive model using weekly incidence data, application of the forecast.vocs R package.	epiforecasts-weeklygrowth
epiMOX	Giovanni Ardenghi, Giovanni Ziarelli, Luca Dede', Nicola Parolini, Alfio Quarteroni	Compartmental model SUIHTER	epiMOX-SUIHTER
European COVID-19 Forecast Hub	Katharine Sherratt, Nikos Bosse, Sebastian Funk	An ensemble, or model average, of submitted forecasts to the European COVID-19 Forecast Hub.	EuroCOVIDhub-ensemble
Frankfurt Institute for Advanced Studies & Forschungszentrum Jülich	Maria V. Barbarossa, Jan Fuhrmann, Stefan Krieg, Jan H. Meinke	An extended SEIR model with additional compartments for undetected cases	FIAS_FZJ-Epi1Ger
Helmholtz Zentrum fuer Infektionsforschung	Isti Rodiah, Berit Lange, Pratizio Vanella, Alexander Kuhlmann, Wolfgang Bock	Deterministic SEIR type model	HZI-AgeExtendedSEIR

Team	Authors	Methods	Metadata
ICM / University of Warsaw	Rafał Bartczuk, Łukasz Górski, Magdalena Gruziel-Słomka, Artur Kaczorek, Jan Kisielewski, Antoni Moszyński, Karol Niedzielewski, Jędrzej Nowosielski, Maciej Radwan, Franciszek Rakowski, Marcin Semeniuk, Jakub Zieliński	Agent-based model	ICM-agentModel
IEM Health	Brad Suchoski, Steve Stage, Heidi Gurung, Sid Baccam	SEIR model projections for daily incident confirmed COVID cases and deaths by using AI to fit actual cases observed.	IEM_Health-CovidProject
ILM	Stefan Heyder, Thomas Hotz	Extended Kalman filter based on reproduction equation	ILM-EKF
Fraunhofer Institute for Industrial Mathematics ITWM	Jan Mohring, Neele Leithäuser, Michael Helmling	Integral equation model based on age cohorts taking into account vaccination and testing. The parameters are adjusted to the counted cases and deaths.	itwm-dSEIR
ITWW	Przemyslaw Biecek, Viktor Bezborodov, Marcin Bodych, Jan Pablo Burgard, Stefan Heyder, Thomas Hotz, Tyll Krüger	Forecasts of county level incidence based on regional reproduction numbers.	ITWW-county_repro
JBUD	Jozef Budzinski	Heavily modified infection-age SIR-X model with waning immunity, vaccinations, seasonality and undetected cases.	JBUD-HMXK
MOCOS group	Marek Bawiec, Marcin Bodych, Tyll Krueger, Tomasz Ozanski, Barbara Pabjan, Agata Migalska, Przemyslaw Biecak, Viktor Bezborodov, Ewa Szczurek, Ewaryst Rafajłowicz, Ewa Rafajłowicz, Wojciech Rafajłowicz	Agent-based microsimulation model	MOCOS-agent1
Masaryk University	Andrea Kraus, David Kraus	ARIMA model with outlier detection fitted to transformed weekly aggregated series.	MUNI-ARIMA
Department of Mathematics and Statistics Masaryk University Team	Veronika Eclerova, Lenka Pribylova	SEIAR model with A compartment of absent unobserved infected estimated from hospital data with incorporated mobility data dependence; optimized to the compartment of all exposed (unobserved included)	MUNI_DMS-SEIAR
Grzegorz Redlarski	Grzegorz Redlarski	Modified SIR method, applied to all districts. Forecasts for districts are summed up.	PL_GRedlarski-DistrictsSum
prolix	Loïc Pottier	Offsets obtained by correlations, best linear approximation of reproduction rates (using vaccination approximation) by least euclidean distance, and linear prediction.	prolix-euclidean
Robert Walraven	Robert Walraven	Multiple skewed gaussian distribution peaks fit to raw data	RobertWalraven-ESG

Team	Authors	Methods	Metadata
Swiss Data Science Center / University of Geneva	Ekaterina Krymova, Dorina Thanou, Benjamin Bejar Haro, Tao Sun, Gavin Lee, Elisa Manetti, Christine Choirat, Antoine Flahault, Guillaume Obozinski	The Trend Model predicts daily cases and deaths using linear extrapolation on the linear or log scale of the underlying trend estimated by a robust LOESS seasonal-trend decomposition model.	SDSC_ISG-TrendModel
Statgroup19	Marco Mingione, Pierfrancesco Alaimo Di Loro	Richards' curve based generalized growth model	Statgroup19-richards
Statgroup19	Marco Mingione, Pierfrancesco Alaimo Di Loro	Richards' curve based generalized growth model taking into account spatial dependence	Statgroup19-spatialrichards
Universidad Carlos III de Madrid	David E. Singh, Miguel Guzman Merino, Maria Cristina Marinescu, Jesus Carretero, Alberto Cascajo Garcia	Agent-based parallel simulator that models individual interactions extracted from social networks and demographical data.	UC3M-EpiGraph
University of Ljubljana, Faculty of Health Sciences Team	Janez Zibert	SEIHR model extended with compartments for hospitals, intensive care units, asymptomatic cases, separate submodels for vaccinated and unvaccinated, divided to 5 age subgroups of population	ULZF-SEIRC19SI
UMass-Amherst	Dan Sheldon, Graham Gibson, Nick Reich	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.	UMass-MechBayes
UNED	José L. Aznarte, César Pérez, José Almagro, Pedro Álvarez, Álvaro Ortiz, Fernando Blat	Bayesian time series models with ARIMA noise and fixed transfer functions for each input.	UNED-PreCoV2
UNIPG_UNIMIB_USI_UNINSUBRIA	Francesco Bartolucci, Fulvia Pennoni, Antonietta Mira	Bayesian Dirichlet-Multinomial models for counts of patients in mutually exclusive and exhaustive categories such as hospitalized in regular wards and in intensive care units, deceased and recovered	UpgUmibUsi-MultiBayes
University of Southern California	Ajitesh Srivastava, Frost Tianjian Xu	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.	USC-SIkJalpha
University of Virginia, Bio-complexity COVID-19 Response Team	Aniruddha Adiga, Lijing Wang, Srinivasan Venkatramanan, Akhil Sai Peddireddy, Benjamin Hurt, Przemyslaw Porebski, Bryan Lewis, Madhav Marathe, Jiangzhou Chen, Anil Vullikanti	An ensemble of multiple methods such as auto-regressive (AR)models with exogenous variables, Long short-term memory (lSTM) models,Kalman filter and PatchSim (an SEIR model).	UVA-Ensemble

Summary of evaluated forecasts

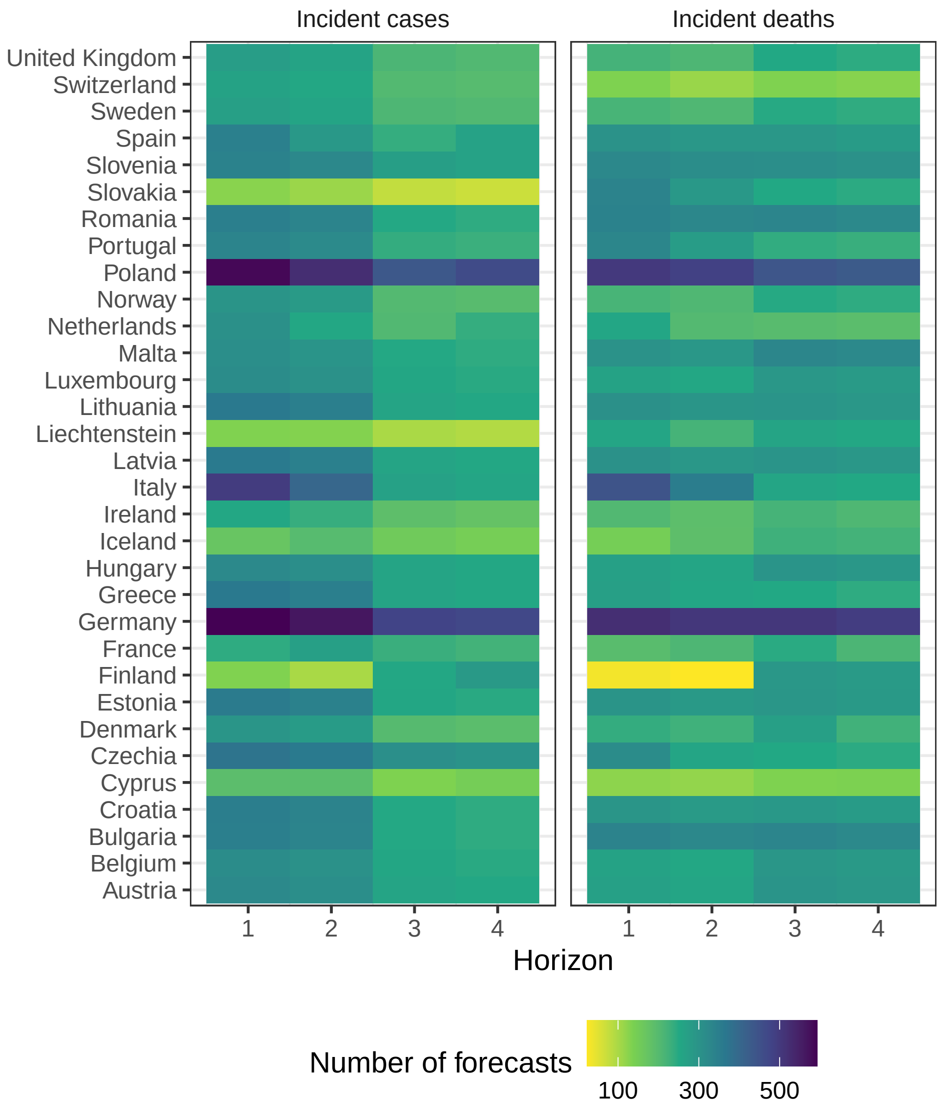

Figure 1: Total number of forecasts included in evaluation, by target location, week ahead horizon, and variable

Comparison of contributed forecasts and the Hub ensemble

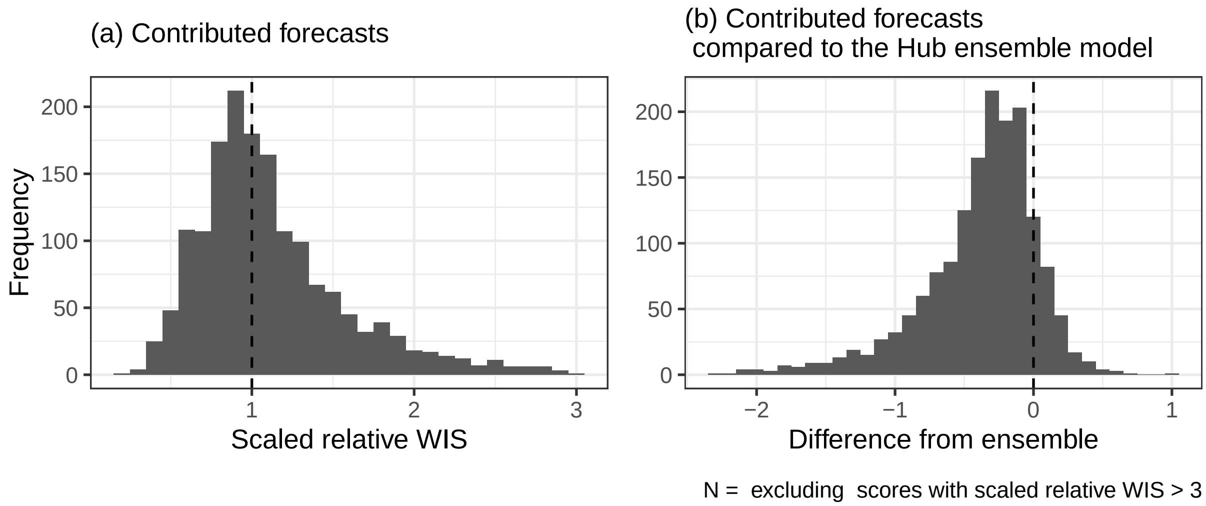

Figure 2: Comparison of scores between participating model forecasts and Hub ensemble of all available forecasts for each target

EPIFORGE guidelines for reporting of epidemic forecasting research

Table 2: EPIFORGE guidelines (Pollet et. al., 2021)

Section of manuscript	Item	Checklist item	Reported on page
Title/Abstract	1	Describe the study as forecast or prediction research in at least the title or abstract	1
Introduction	2	Define the purpose of study and forecasting targets	4
Methods	3	Fully document the methods	4,5,6,7,8
Methods	4	Identify whether the forecast was performed prospectively, in real time, and/or retrospectively	5
Methods	5	Explicitly describe the origin of input source data, with references	5
Methods	6	Provide source data with publication, or document reasons as to why this was not possible	see Github epiforecasts/euro-hub-ensemble
Methods	7	Describe input data processing procedures in detail	5,6
Methods	8	State and describe the model type, and document model assumptions, including references	5,6, Supplement Table 1
Methods	9	Make the model code available, or document the reasons why this was not possible	see Github epiforecasts/euro-hub-ensemble
Methods	10	Describe the model validation, and justify the approach	5,6
Methods	11	Describe the forecast accuracy evaluation method used, with justification	6,7
Methods	12	Where possible, compare model results to a benchmark or other comparator model, with justification of comparator choice	6,7

Section of manuscript	Item	Checklist item	Reported on page
Methods	13	Describe the forecast horizon, with justification of its length	5
Results	14	Present and explain uncertainty of forecasting results	8,9,10,11,12
Results	15	Briefly summarize the results in nontechnical terms, including a nontechnical interpretation of forecast uncertainty	12,13,14
Results	16	If results are published as a data object, encourage a time-stamped version number	see Github epiforecasts/euro-hub-ensemble
Discussion	17	Describe the weaknesses of the forecast, including weaknesses specific to data quality and methods	12,13,14
Discussion	18	If the research is applicable to a specific epidemic, comment on its potential implications and impact for public health action and decision-making	14,15
Discussion	19	If the research is applicable to a specific epidemic, comment on how generalizable it may be across populations	15

Following:

Pollett S, Johansson MA, Reich NG, Brett-Major D, Del Valle SY, Venkatramanan S, Lowe R, Porco T, Berry IM, Deshpande A, Kraemer MUG, Blazes DL, Pan-Ngum W, Vespigiani A, Mate SE, Silal SP, Kandula S, Sippy R, Quandelacy TM, Morgan JJ, Ball J, Morton LC, Althouse BM, Pavlin J, van Panhuis W, Riley S, Biggerstaff M, Viboud C, Brady O, Rivers C. Recommended reporting items for epidemic forecasting and prediction research: The EPIFORGE 2020 guidelines. PLoS Med. 2021 Oct 19;18(10):e1003793. doi: 10.1371/journal.pmed.1003793. PMID: 34665805; PMCID: PMC8525759.