Supplement

 $\label{lem:continuous} \begin{tabular}{ll} Supplementary information: $Predictive performance of multi-model ensemble forecasts of $COVID-19$ across $European nations$ \end{tabular}$

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.

Model	Affiliation	Methods	Metadata
BIOCOMSC-Gompertz	BIOCOMSC	Empirical model based on cases and deaths dynamics.	Metadata
CovidMetrics-epiBATS	University of Cologne Covid Metrics	Forecasts are based on TBATS - models (DeLivera, Hyndman and Snyder (2011)) and are updated daily for each German state.	Metadata
epiforecasts-EpiNow2	Epiforecasts / London School of Hygiene and Tropical Medicine	Semi-mechanistic estimation of the time-varying reproduction number for latent infections mapped to reported cases/deaths.	Metadata
epiforecasts-weeklygrowth	epiforecasts	A Bayesian autoregressive model using weekly incidence data, application of the forecast.vocs R package.	Metadata
epiMOX-SUIHTER	epiMOX	Compartmental model SUIHTER	Metadata
EuroCOVIDhub-ensemble	European COVID- 19 Forecast Hub	An ensemble, or model average, of submitted forecasts to the European COVID-19 Forecast Hub.	Metadata
FIAS_FZJ-Epi1Ger	Frankfurt Institute for Advanced Studies & Forschungsze trum Jülich	An extended SEIR model with additional compartments for undetected cases	Metadata

Model	Affiliation	Methods	Metadata
HZI-AgeExtendedSEIR	Helmholtz Zentrum fuer Infektions- forschung	Deterministic SEIR type model	Metadata
ICM-agentModel	ICM / University of Warsaw	Agent-based model	Metadata
IEM_Health-CovidProject	IEM Health	SEIR model projections for daily incident confirmed COVID cases and deaths by using AI to fit actual cases observed.	Metadata
ILM-EKF	ILM	Extended Kalman filter based on reproduction equation	Metadata
itwm-dSEIR	Fraunhofer Institute for Industrial Mathe- matics ITWM	cohort based, integral equation	Metadata
ITWW-county_repro	ITWW	Forecasts of county level incidence based on regional reproduction numbers.	Metadata
JBUD-HMXK	JBUD	Heavily modified infection-age SIR-X model with waning immunity, vaccinations, seasonality and undetected cases.	Metadata
MOCOS-agent1	MOCOS group	Agent-based microsimulation model	Metadata
MUNI-ARIMA	Masaryk University	ARIMA model with outlier detection fitted to transformed weekly aggregated series.	Metadata
MUNI_DMS-SEIAR	Department of Mathe- matics and Statistics Masaryk University Team	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)	Metadata
PL_GRedlarski-DistrictsSum	Grzegorz Redlarski	Modified SIR method, applied to all districts. Forecasts for districts are summed up.	Metadata

Model	Affiliation	Methods	Metadata
prolix-euclidean	prolix	Offsets obtained by correlations, best linear approximation of reproduction rates (using vaccination approximation) by least euclidean distance, and linear prediction.	Metadata
RobertWalraven-ESG	Robert Walraven	Multiple skewed gaussian distribution peaks fit to raw data	Metadata
SDSC_ISG-TrendModel	Swiss Data Science Center / University of Geneva	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.	Metadata
Statgroup19-richards		Richards' curve based generalized growth model	Metadata
Statgroup19-spatialrichards	Statgroup19	Richards' curve based generalized growth model taking into account spatial dependence	Metadata
UC3M-EpiGraph	Universidad Carlos III de Madrid	_	Metadata
ULZF-SEIRC19SI	University of Ljubljana, Faculty of Health Sciences Team	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	Metadata
UMass-MechBayes	UMass- Amherst	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.	Metadata
UpgUmibUsi-MultiBayes	UNIPG_UN	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	Metadata

Model	Affiliation	Methods	Metadata
USC-SIkJalpha	University of Southern California	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.	Metadata
UVA-Ensemble	University of Virginia, Biocom- plexity COVID- 19 Response Team	An ensemble of multiple methods such as auto-regressive (AR)models with exogenous variables, Long short-term memory (ISTM) models, Kalman filter and PatchSim (an SEIR model).	Metadata

Summary of evaluated forecasts

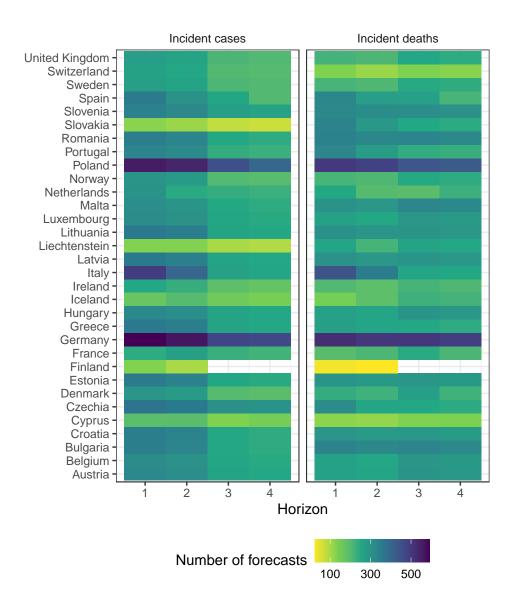


Figure 1: Total number of forecasts included in evaluation, by target location, week ahead horizon, and variable

Comparison of contributed forecasts and the Hub ensemble

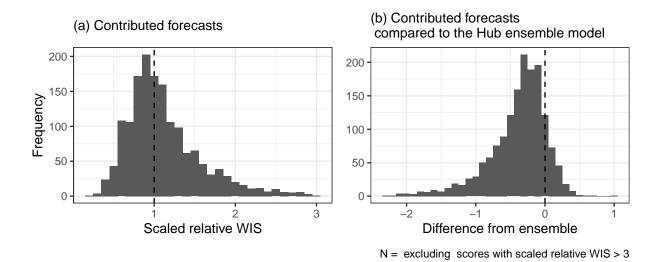


Figure 2: Comparison of scores between participating model forecasts and Hub ensemble of all available forecasts for each target

EPIFORGE guidelines for reporting of epidemic forecasting research

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

Section of manuscript It	em Checklist item	Reported on page
Title/Abstract	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 :	Fully document the methods	4,5,6,7,8
Methods	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	Provide source data with publication, or document reasons as to why this was not possible	see Github epiforecasts/euro- hub-ensemble
Methods	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 13		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	Iten	n 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.