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ALADIN in Poland

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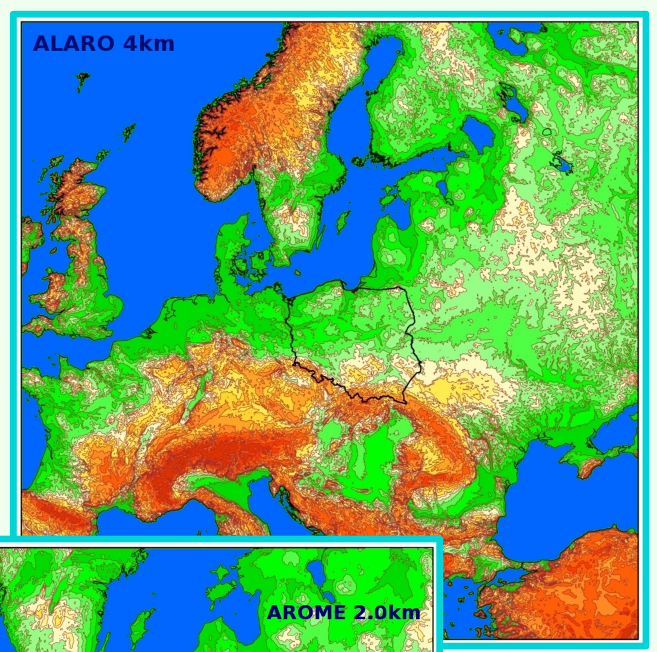
Operational Forecasts

ALARO-v1B NH (CY43T2)

E040 domain:

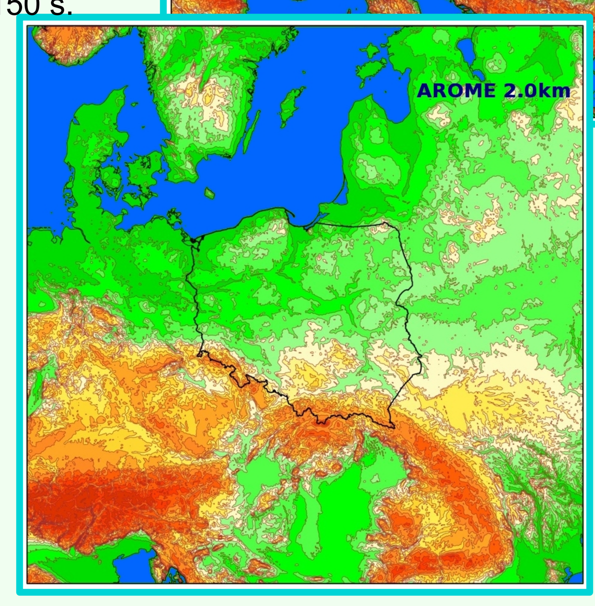
4.0 km horizontal resolution, 789x789 grid points, 70 vertical model levels on a Lambert projection with 3h coupling frequency and 1h output, coupling zone with 8 points; Runs 4 times per day (00,06,12 and 18) with 72 hours forecast range; LBC from ARPEGE with 9.4 km horizontal resolution; Time step 150 s.



AROME (CY43T2)

P020 domain:

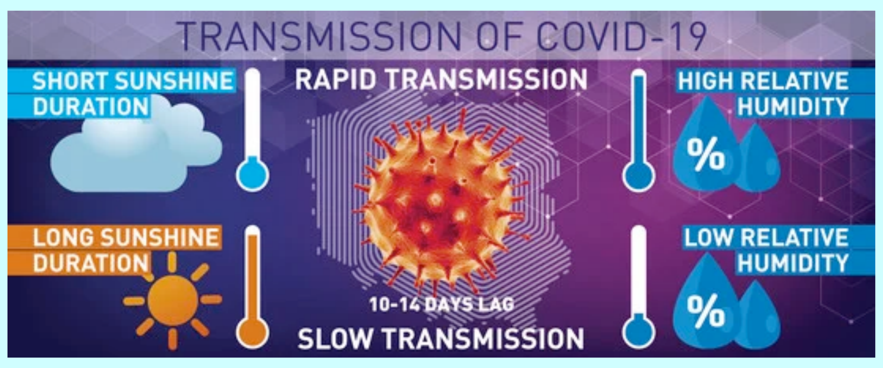
2.0km horizontal resolution, 799x799 grid points, 70 vertical model levels on a Lambert projection with 1h coupling frequency and 1 hour output. 4 runs per day (00,06,12 and 18) with 30 hours forecast range; LBC from ALARO 4.0 km; Time step 50s.



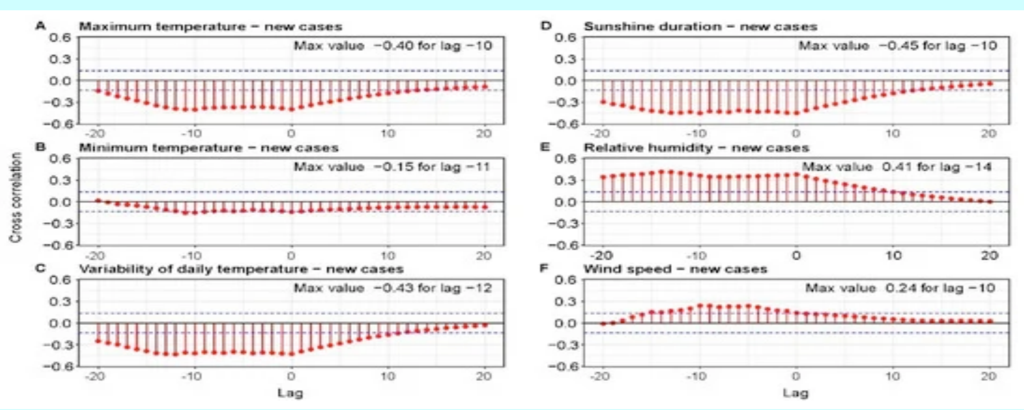
Operational machine characteristics

Cluster of HP BL460c_GEN8 servers connected with Infiniband network, OS Scientific Linux 6, Intel Xeon E5-2690 processors – with maximum 1552 cores (97 nodes with 16 cores each), each core RAM 128 GB, disc array – 64 TB.

Impact of Meteorological Conditions on the Dynamics of the COVID-19 Pandemic in Poland



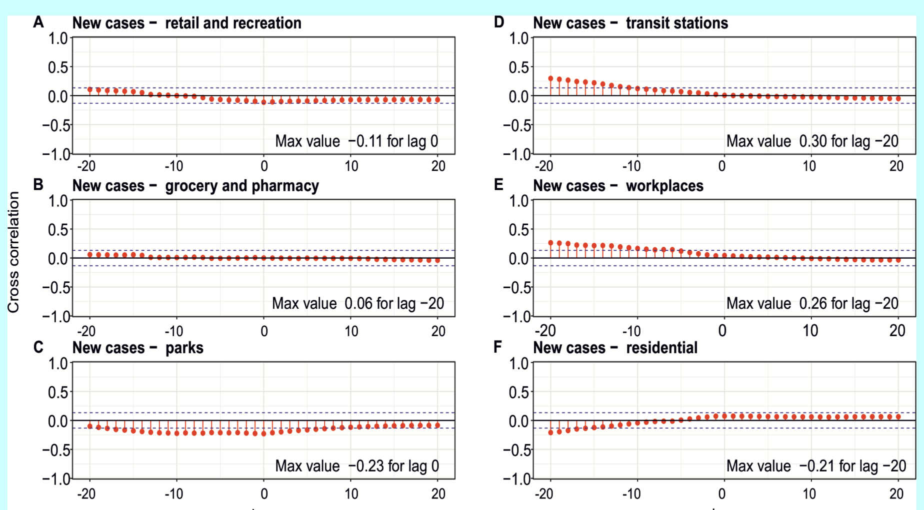
Data on a daily number of laboratory-confirmed COVID-19 cases and the number of COVID-19-related deaths were gathered from the official governmental website. Meteorological observations from 55 synoptic stations in Poland were used. Moreover, reports on the movement of people across different categories of places were collected. A cross-correlation function, principal component analysis and random forest were applied.



Cross-correlation between number of new cases and meteorology parameters: maximum daily temperature (A), minimum daily temperature (B), variability of daily temperature (C), sunshine duration (D), relative humidity (E), wind speed (F). The 95% confidence bounds are plotted in blue.

The results show that the maximum value of correlation was obtained with a sunshine duration equal to −0.45 with time lag of −10 days, daily temperature range (−0.43) with a similar time lag, maximum daily temperature (-0.4). A high positive correlation (0.41) and time lag equal to –14 days indicate that an increase in humidity causes an increase in the number of infections.

To determine whether weather conditions affect mobility and mobility affects COVID-19, or whether weather has a direct impact on the pandemic dynamics, we calculated CCF between new COVID-19 cases/new deaths and mobility. Our study showed that, although meteorological parameters were correlated with mobility, their correlation with the dynamics of COVID-19 pandemic was stronger than mobility data. Therefore, we can state that meteorological parameters such as sunshine duration and relative humidity had a direct impact on the dynamic of COVID-19 pandemic in Poland

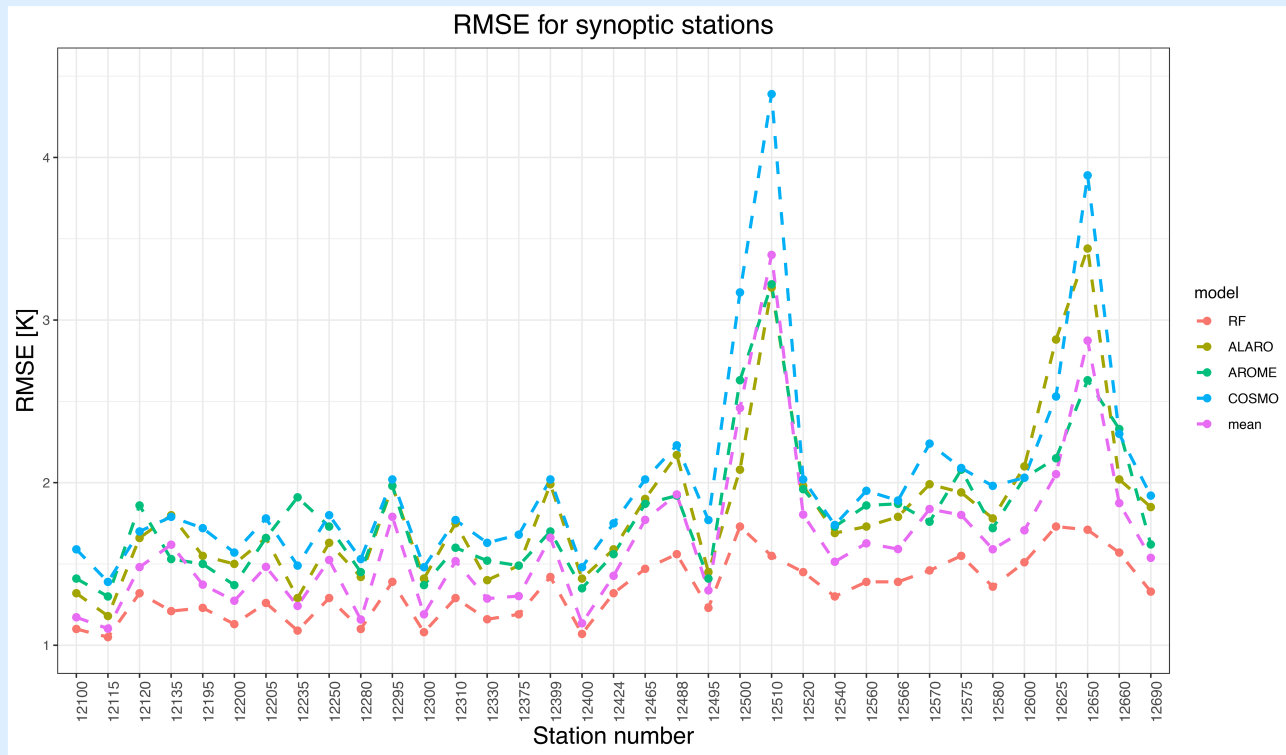


Cross-correlation between COVID-19 new cases and mobility data: (A) retail and recreation, (B) grocery and pharmacy, (C) parks, (D) transit stations, (E) workplaces, (F) residential.

Bochenek, B.; Jankowski, M.; Gruszczynska, M.; Nykiel, G.; Gruszczynski, M.; Jaczewski, A.; Ziemianski, M.; Pyrc, R.; Figurski, M.; Pinkas, J. Impact of Meteorological Conditions on the Dynamics of the COVID-19 Pandemic in Poland. Int. J. Environ. Res. Public Health 2021, 18, 3951. https://doi.org/10.3390/ijerph18083951

Machine-learning-based post-processing of 2-m air temperature model output – a multi-model approach

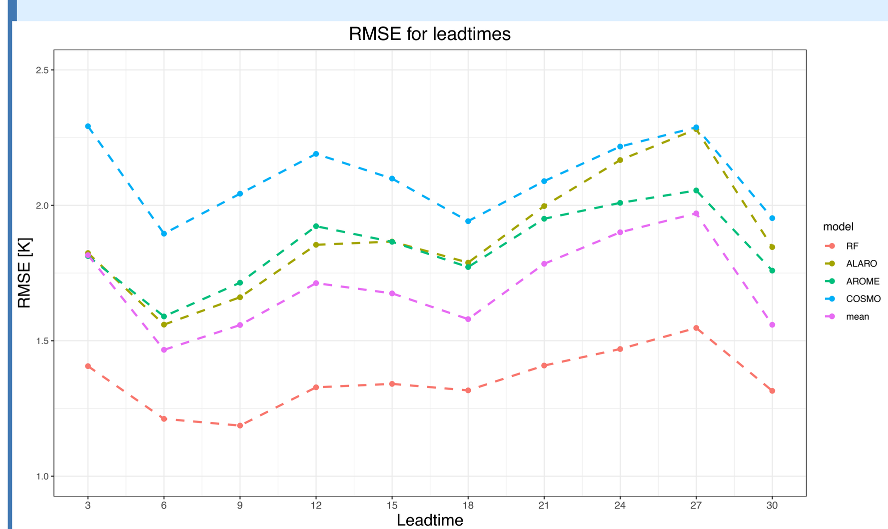
In the experiment forecasted 2m temperatures from three operational models (ALARO 4km, AROME 2km and COSMO 7km) were compared with observed 2m temperature SYNOP values. A machine learning algorithm *Random Forest Approach* was applied (package *randomForest* in R), which uses a collection of decision trees (random forest) with increased performance and can use both classification and regression techniques depending upon the user and target or categories needed. In our case each decision tree, based on the respective predictor variables, was trained on different model and finally Random Forest took the average of the results from all the decision trees.

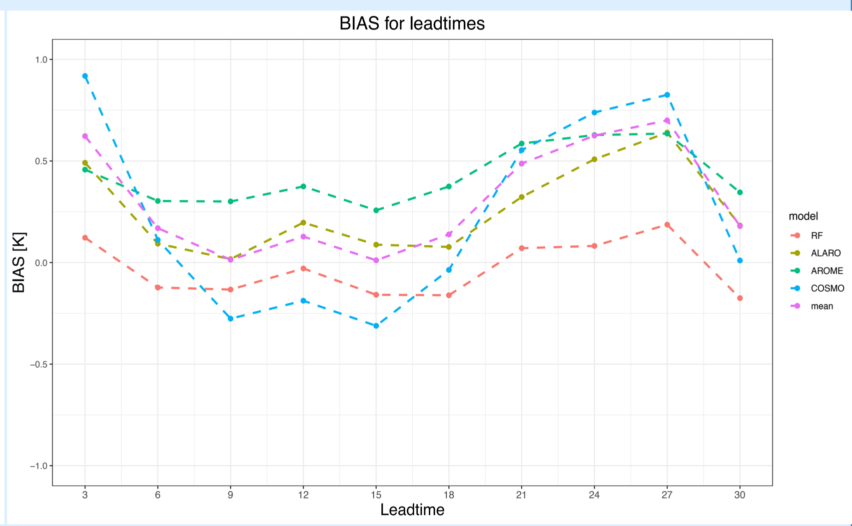


Averaged for each synop station (on all leadtimes and test days) 2m temperature RMSE of ALARO, AROME, COSMO forecasts and random forest (RF).

For building a random forest all models datasets were used with the same specification:

- sampling frequency:3h with leadtime: 3-30h;
- predictors comprise also month, day of the year, hour and leadtime;
- training was conducted on the two years period (2018-2019), which gave around 6800 cases,





Averaged for each leadtime (on all stations and test days) 2m temperature RMSE of ALARO, AROME, COSMO, mean of models (mean) and random forest (RF).

Averaged for each leadtime (on all stations and test days) 2m temperature BIAS of ALARO, AROME, COSMO, mean of models (mean) and random forest (RF).

Built random forest was tested on dates from 2020 and compared with forecasta of each of previously used models. Results were verified by calculating RMSE for 35 selected SYNOP stations from different regions in Poland (lowlands, uplands and mountains) . On figures they are named by its numbers.

Conclusions:

- RMSE reduction occurred at every station, with an avarage of 16%;
- The biggest improvement occured for mountain-top stations (12510,12650), probably because models were strongly biased there;
- Training error (on the right) is slighty higher in highlands (from 12500 on) than in lowlands;
- The biggest training errors are noticeable for stations 12500 and 12625, which lays in a bottoms of valleys at the mountains;
- Some predictors with information about topography and cloudiness//insolation should be added to training data;
- Although random forest performs better than the best of three models only in 30-40% of forecasts, its impact is the most visible when considering big errors (over 5°C) – e.g. for Cracow (12566) random forest made such an error only 4 times, while COSMO 20 times, ALARO – 21 and AROME – 23.