MS/CS “Green Book’ Report 2024

Section 1: Background

* 1.1 Country

Germany

* 1.2 Author(s)

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* 1.3 Organisation

German Weather Service, DWD

* Section 2: Summary of major highlights

Section 3: Forecast Products

3.1. Direct use of ECMWF forecast products

*** a) Medium Range (e.g. for high impact weather forecasting)**

- Use of IFS deterministic and ensemble and also some of the AI models run at ECMWF as further reference for evaluating own numerical weather forecasts.
- OpenCharts for interpretation of predicted pattern across Europe for the next week for a weekly (pre-operational) newsletter about sub-seasonal temperature forecast in Germany for the next 4 weeks

*** b) Extended Range (monthly)**

- Data for operational system of sub-seasonal forecast in Germany and adjacent river catchment areas

*** c) Long Range (seasonal)**

- Currently WMO – Long Range Forecast Multi-Model Ensemble or COPERNICUS C3S seasonal charts for comparison with the German seasonal prediction system and for a monthly (pre-operational) newsletter about seasonal temperature forecast in Germany for the next 6 months

*** d) CAMS and Fire-related output (ecCharts mainly)**

3.2. Cycle 48r1

* a) <u>Positive</u> impacts of model cycle 48r1

- Verification scores are dominated by the interannual variability, nothing that can be attributed to the new model cycle unambiguously.
- Mainly we use monthly forecast, but currently once a week. The switch to a continuous time series without spatial resolution change is less complicated. And the increasing number of ensemble members in monthly forecast is much better for statistics in prediction.

* b) <u>Negative</u> impacts of model cycle 48r1

c) Systematic changes in forecast output since model cycle 48r1 was implemented

3.3: Derived Fields

- Yes, we do. For Germany and adjacent river catchment areas we downscale/bias-adjust the extended range forecast data sets (all ensemble members) by an empirical-statistical downscaling method (EPISODES) in 5 km x 5 km spatial resolution. After that we calculate the anomaly for ensemble mean and probabilistic predictions and compare the reforecasts with observations for verification (= prediction skill). Results are shown on www.dwd.de/climatepredictions.
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3.4: Artificial Intelligence (AI) / Machine Learning (ML) techniques

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- We use the IFS high resolution forecast of meteorological fields together with the CAMS forecast of the air quality parameters NO_2, O_3, $PM_{2.5}$ and PM_{10}. The CAMS forecast and the meteorological fields are fed together with station measurements of the respective air quality parameters into our Model Output Statistics system. This system is specifically dedicated to the processing of air quality parameters and was developed in the project LQ-WARN. With the machine learning approach, the CAMS forecast is refined at the stations and the forecast quality is significantly improved. The resulting operational product is a point forecast of the parameters NO_2, O_3, $PM_{2.5}$ and PM_{10} at roughly 150 to 400 stations (depending on the parameter) throughout Germany. Currently we are modifying our procedure so that it is capable of producing continuous maps based on the point forecasts. In the future it is planned to derive a product that includes probabilities of exceeding a threshold, for example of specific pollution levels of the above-mentioned parameters.

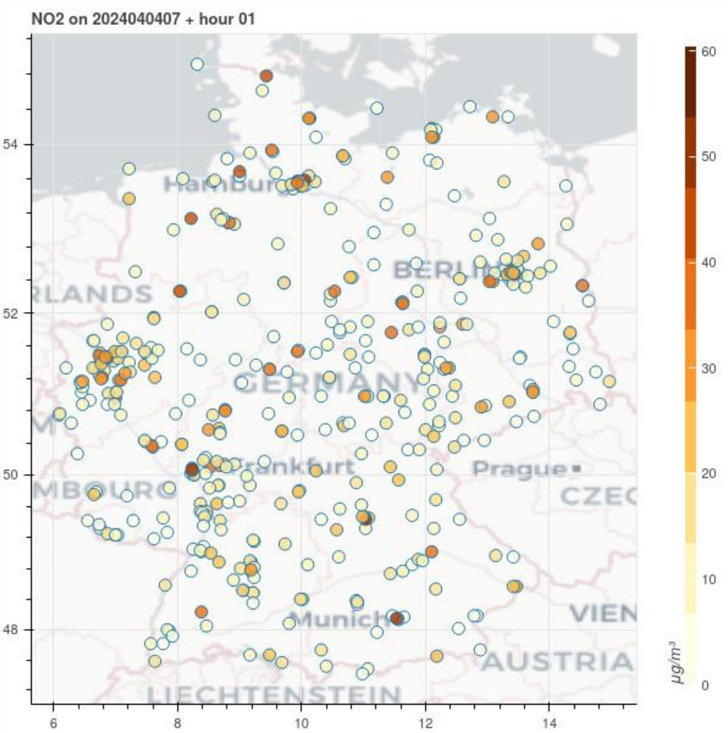

Figure 1: NO_2 forecast over Germany at all air quality stations produced by the LQ-WARN MOS system.

- No, we don't currently use AI or ML techniques, but we see several opportunities to improve the prediction through these techniques, e.g. bias correction, subsampling of ensemble members.

3.5: Dynamical Adaptation

- Yes, we do. Besides the provision of high-resolution and bias-adjusted data sets by EPISODES (see section 3.3), e.g. for hydrological models of partner institutes to predict hydrological runoffs on German rivers with shipping traffic, we use these datasets for our own agrometeorological model (AMBAV Global) to predict agriculturally relevant water balance components, e.g. soil moisture.

3.6: Data-driven (AI) models

* a) ECMWF's real-time AI model initiative

- Making plots and data available certainly helps building trust un AI model capabilities. The amount of AI models run multiple times each day and the already now available model fields are impressive.
- It should be considered to extent the base-time range for the AI Products in the charts catalogue to illustrate the high predictive power especially at longer lead-times. Right now base-time reached back to 4-5 days only.

* b) Use of AI forecasts for operational purposes

- No feedback

Section 4: Verification

4.1 <u>Raw model output</u> from ECMWF, and other operational models/ensembles

a) Short Range and Medium Range

- DWD uses IFS deterministic and ensemble forecast with our in house verification system for comparison with our operational forecasting systems. Significant trends are hard to identify on our own small domain. In the northern hemisphere e.g. we notice that a continuous improvement of our forecast system has given us the lead in forecast performance for many surface variables in the first forecast days (Fig 2). We also notice a quality drop of ECMWF cloud forecasts (N in Fig 2)

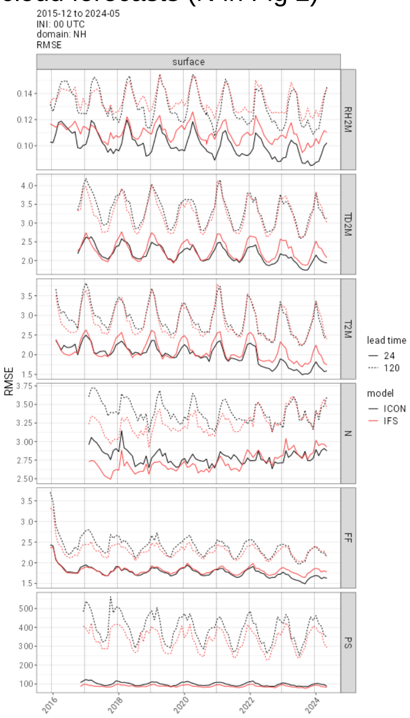

Figure 2: RMSE for northern hemisphere 24h and 120h surface forecasts of ICON (black) and IFS (red), Initialization at 12UTC.

- AIFS, PANGU, Graphcast forecast produced at ECMWF are verified against observations (SYNOP, TEMP etc.) in order to quantify the differences compared to in house NWP and also to serve as a reference for own AI developments. We notice the very strong performance of the AI Models compared to traditional NWP models. In case of AIFS this is also true when comparing against SYNOP. AIFS has less pronounced humidity and temperature biases compared to Graphcast or Pangu but all AI models seem to have problems forecasting wind (Fig. 3). Looking at the spatial distribution of forecast errors this can be attributed mainly to lower level and coastal areas. The 6h precipitation forecasts of AIFS are also of good quality with a strong bias for low precipitation rates.

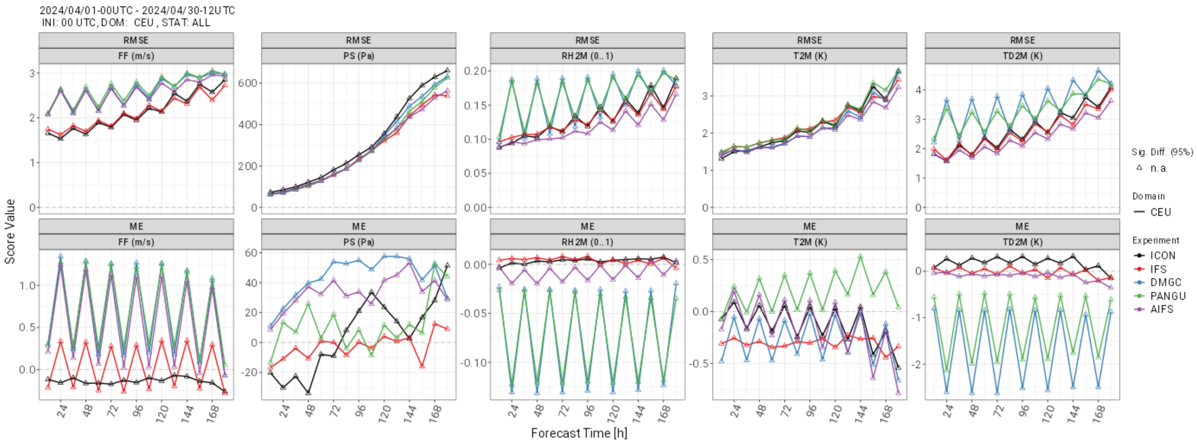

Figure 3: RMSE and Mean Error of ICON, IFS, Graphcast (DMGC), Pangu and AIFS 00UTC forecast over Europe against SYNOP observations in April 2024.

b) Extended Range (Monthly) and Long Range (Seasonal)

- If we start the sub-seasonal prediction once a week on Monday, the verification runs automatically. For the world and Europe, we analyse 2m mean temperature and precipitation of raw model output from ECMWF. But for Germany and adjacent river catchment areas it is only relevant how well the bias-adjusted and downscaled data are. Have a look at https://www.dwd.de/EN/ourservices/kvhs_en/2_expert/z_skill/week/weekly_node.html. Currently we analyse the Ranked Probability Skill Score (RPSS) for probabilistic predictions and the correlation coefficient and Mean Squared Error Skill Score (MSESS) for ensemble mean predictions.

  For long-range forecasts, we only evaluate our own model system on this website. We plan to use multi-model data for the future outlook for Germany and will soon start with first tests. For the (pre-operational) newsletter we use skill information from ECMWF and Copernicus websites.

4.2 Post-processed products and/or tailored products delivered to users

- The verification of post-processed products has so far been carried out for Germany (per grid box, region, city), Europe and the world (per grid box) for the skill scores described in section 4.1. We show these products on our website https://www.dwd.de/EN/ourservices/kvhs_en/2_expert/start_node.html

  Currently, this is provided for 2m mean temperature, precipitation and soil moisture under grass (0-60 cm depth) only. But we are developing further indicators related to heat and dryness to be provided on our website

4.3 Subjective verification

- To build multi-model long-range forecasts we gather skill information on all WMO seasonal forecast models from Copernicus or other platforms. For each forecast time period we only select those models reaching a distinct level of skill for Germany to build the multi-model outlook

4.4 Case Studies

- We evaluated the probabilistic multi-model winter temperature forecasts for Germany in 2022/2023 issued in autumn and winter 2022 in the pre-operational newsletter. Generally, the probabilistic forecast matched quite well with observed temperature conditions.

a) Case Study 1

b) Case Study 2

Section 5: Output Requests

a) Product request 1: *add a title / short-form summary here in bold*

DWD presents subseasonal, seasonal and decadal predictions on a common website (www.dwd.de/climatepredictions). For a better comparison between all timescales of this 'seamless prediction' (e.g. anomalies w.r.t. to common reference period based on hindcasts) and better verification of extended range forecast we would need a reforecast with lead times up to 46-days for **30 years**. Currently, the reference period for seasonal and decadal predictions is 1991-2020 as recommended by WMO.

b) Product request 2: *add a title / short-form summary here in bold*

ERA5-Land is a high-resolution reanalysis and can therefore be applied well to regional processes and impact models. Unfortunately some important parameters are not provided, for example **sea level pressure, maximum and minimum temperature or 10m wind gust**

Section 6: References

Robrecht et al., 2022 on the improvement of air quality forecasts in Germany using CAMS

1. Overview of Climate Predictions @ DWD Website:

Basic climate predictions: https://www.dwd.de/EN/ourservices/kvhs_en/1_basic/start_basic.html
Expert climate predictions: https://www.dwd.de/EN/ourservices/kvhs_en/2_expert/start_node.html

Paxian, A., Mannig, B., Tivig, M., Reinhardt, K., Isensee, K., Pasternack, A., Hoff., A., Pankatz, K., Buchholz, S., Wehring, S., Lorenz, P., Fröhlich, K., Kreienkamp, F., Früh., B. (2023): The DWD climate predictions website: Towards a seamless outlook based on subseasonal, seasonal and decadal predictions. Clim. Serv. DOI: https://doi.org/10.1016/j.cliser.2023.100379

2. Overview of EPISODES – DWD empirical-statistical downscaling method:

https://www.dwd.de/DE/leistungen/episodes/episodes.html

Kreienkamp, F., Paxian, A., Früh, B., Lorenz, P., Matulla, C., 2019: Evaluation of the empirical-statistical downscaling method EPISODES. Climate Dynamics 52, 991-1026. https://link.springer.com/article/10.1007/s00382-018-4276-2

3. Overview of AMBAV Global - DWD agrometeorological model (only in German):

https://www.dwd.de/DE/fachnutzer/landwirtschaft/dokumentationen/allgemein/ambav-20_v15_doku.html?nn=807458&lsbId=782452

Braden, H., 2012: Agrarmeteorologische Modelle des Wasser- und Energiehaushalts im Deutschen Wetterdienst. Promet 38, 11-19.
https://www.dwd.de/DE/leistungen/pbfb_verlag_promet/inhalt_promethefte/38_1_2_inh_pdf.pdf?__blob=publicationFile&v=7

Herbst, M., Falge, E., Frühauf, C., 2021: Regionale Klimamodellierung - Perspektive Landwirtschaft. In: Regionale Klimamodellierung II - Anwendungen. Deutscher Wetterdienst (Hrsg.), Promet 104, 55-62.
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Section 7: Additional comments and Feedback

Please provide here any additional comments on topics that have not been covered in any of the sections above.