Regional Cooperation for
Limited Area Modeling in Central Europe

LACE
nwp central europe

ACCORD
A Consortium for COnvection-scale modelling Research and Development

LACE verification activities

Authors: Doina-Simona Tașcu with contributions of LACE partners

GeoSphere Austria
DHMZ
Czech Hydrometeorological Institute
OMSZ
IMGW
METEO ROMANIA
SHMÚ
ARSO METEO Slovenia

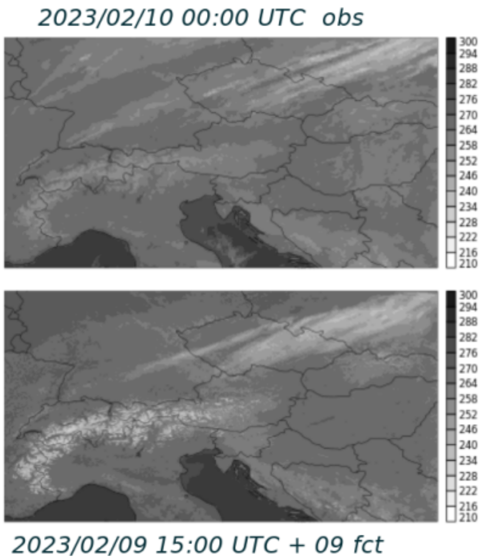
OUTLINE

- HARP usage @LACE
- Subjective verification approaches
- Model output post-processing
- Database of cases

HARP usage @Austria

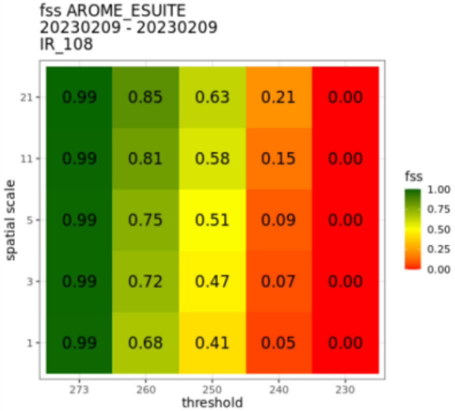
Verification of simulated IR channels in HARP

- over Austria domain
- MSG 2 – SEVIRI: Infrared 10.8 µm (Brightness Temperatures)
- AROME esuite - simulated infrared channel



Score: Fraction Skill Score (FSS)

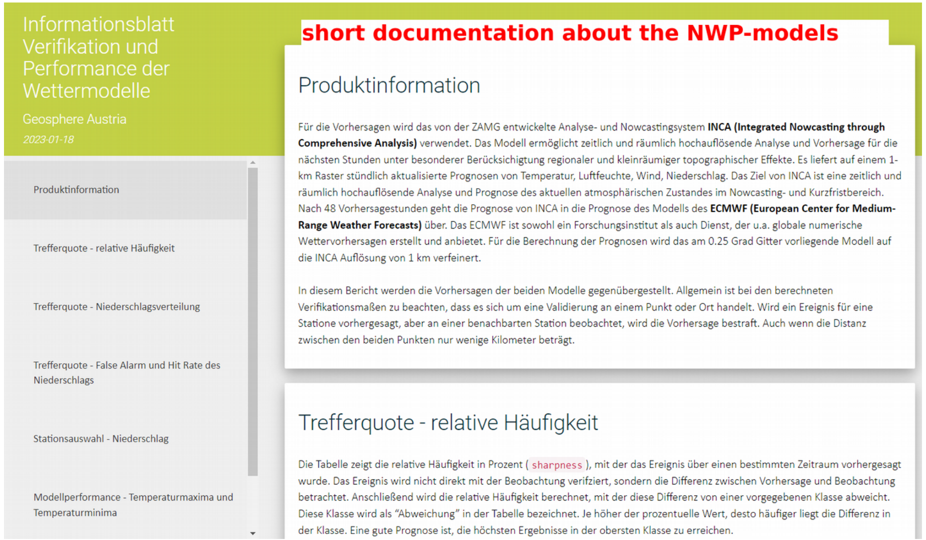
- Window sizes: 1, 3, 5, 11, 21
- Thresholds:
  - 273 K (0-degree Celsius)
  - 260 K (supercooled water droplets)
  - 250 K (convective initiation)
  - 240 / 230 K (overshooting tops)



HARP usage @Austria

Generation of a Fact Sheet based on model verification with HARP using Markdown

- provides an easy accessible and easy to understand evaluations of model performance
- fact sheets tailored to the needs of specific customer are created



Informationsblatt Verifikation und Performance der Wettermodelle

Geosphere Austria

2023-01-18

Produktinformation

Trefferquote - relative Häufigkeit

Trefferquote - Niederschlagsverteilung

Trefferquote - False Alarm und Hit Rate des Niederschlags

Stationsauswahl - Niederschlag

Modellperformance - Temperaturmaxima und Temperaturminima

short documentation about the NWP-models

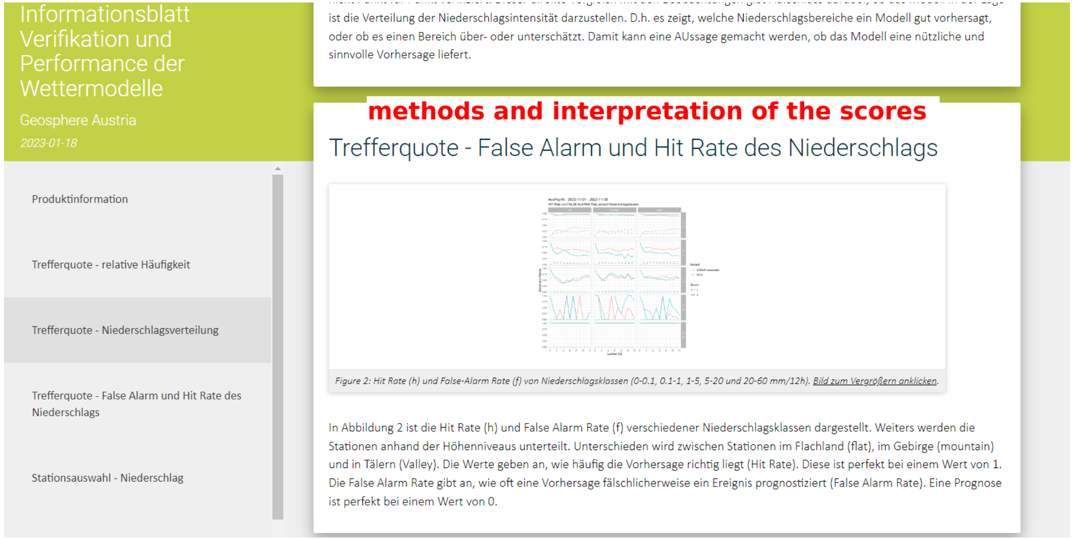
Produktinformation

Für die Vorhersagen wird das von der ZAMG entwickelte Analyse- und Nowcastingsystem **INCA (Integrated Nowcasting through Comprehensive Analysis)** verwendet. Das Modell ermöglicht zeitlich und räumlich hochauflösende Analyse und Vorhersage für die nächsten Stunden unter besonderer Berücksichtigung regionaler und kleinräumiger topographischer Effekte. Es liefert auf einem 1-km Raster stündlich aktualisierte Prognosen von Temperatur, Luftfeuchte, Wind, Niederschlag. Das Ziel von INCA ist eine zeitlich und räumlich hochauflösende Analyse und Prognose des aktuellen atmosphärischen Zustandes im Nowcasting- und Kurzfristbereich. Nach 48 Vorhersagestunden geht die Prognose von INCA in die Prognose des Modells des **ECMWF (European Center for Medium-Range Weather Forecasts)** über. Das ECMWF ist sowohl ein Forschungsinstitut als auch Dienst, der u.a. globale numerische Wettervorhersagen erstellt und anbietet. Für die Berechnung der Prognosen wird das am 0.25 Grad Gitter vorliegende Modell auf die INCA Auflösung von 1 km verfeinert.

In diesem Bericht werden die Vorhersagen der beiden Modelle gegenübergestellt. Allgemein ist bei den berechneten Verifikationsmaßen zu beachten, dass es sich um eine Validierung an einem Punkt oder Ort handelt. Wird ein Ereignis für eine Statione vorhergesagt, aber an einer benachbarten Station beobachtet, wird die Vorhersage bestraft. Auch wenn die Distanz zwischen den beiden Punkten nur wenige Kilometer beträgt.

Trefferquote - relative Häufigkeit

Die Tabelle zeigt die relative Häufigkeit in Prozent (`sharpness`), mit der das Ereignis über einen bestimmten Zeitraum vorhergesagt wurde. Das Ereignis wird nicht direkt mit der Beobachtung verifziert, sondern die Differenz zwischen Vorhersage und Beobachtung betrachtet. Anschließend wird die relative Häufigkeit berechnet, mit der diese Differenz von einer vorgegebenen Klasse abweicht. Diese Klasse wird als "Abweichung" in der Tabelle bezeichnet. Je höher der prozentuelle Wert, desto häufiger liegt die Differenz in der Klasse. Eine gute Prognose ist, die höchsten Ergebnisse in der obersten Klasse zu erreichen.



Informationsblatt Verifikation und Performance der Wettermodelle

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Trefferquote - relative Häufigkeit

Trefferquote - Niederschlagsverteilung

Trefferquote - False Alarm und Hit Rate des Niederschlags

Stationsauswahl - Niederschlag

ist die Verteilung der Niederschlagsintensität darzustellen. D.h. es zeigt, welche Niederschlagsbereiche ein Modell gut vorhersagt, oder ob es einen Bereich über- oder unterschätzt. Damit kann eine AUssage gemacht werden, ob das Modell eine nützliche und sinnvolle Vorhersage liefert.

methods and interpretation of the scores

Trefferquote - False Alarm und Hit Rate des Niederschlags

Figure 2: Hit Rate (h) und False-Alarm Rate (f) von Niederschlagsklassen (0-0.1, 0.1-1, 1-5, 5-20 und 20-60 mm/12h). *Bild zum Vergrößern anklicken.*

In Abbildung 2 ist die Hit Rate (h) und False Alarm Rate (f) verschiedener Niederschlagsklassen dargestellt. Weiters werden die Stationen anhand der Höhenniveaus unterteilt. Unterschieden wird zwischen Stationen im Flachland (flat), im Gebirge (mountain) und in Tälern (Valley). Die Werte geben an, wie häufig die Vorhersage richtig liegt (Hit Rate). Diese ist perfekt bei einem Wert von 1. Die False Alarm Rate gibt an, wie oft eine Vorhersage fälschlicherweise ein Ereignis prognostiziert (False Alarm Rate). Eine Prognose ist perfekt bei einem Wert von 0.

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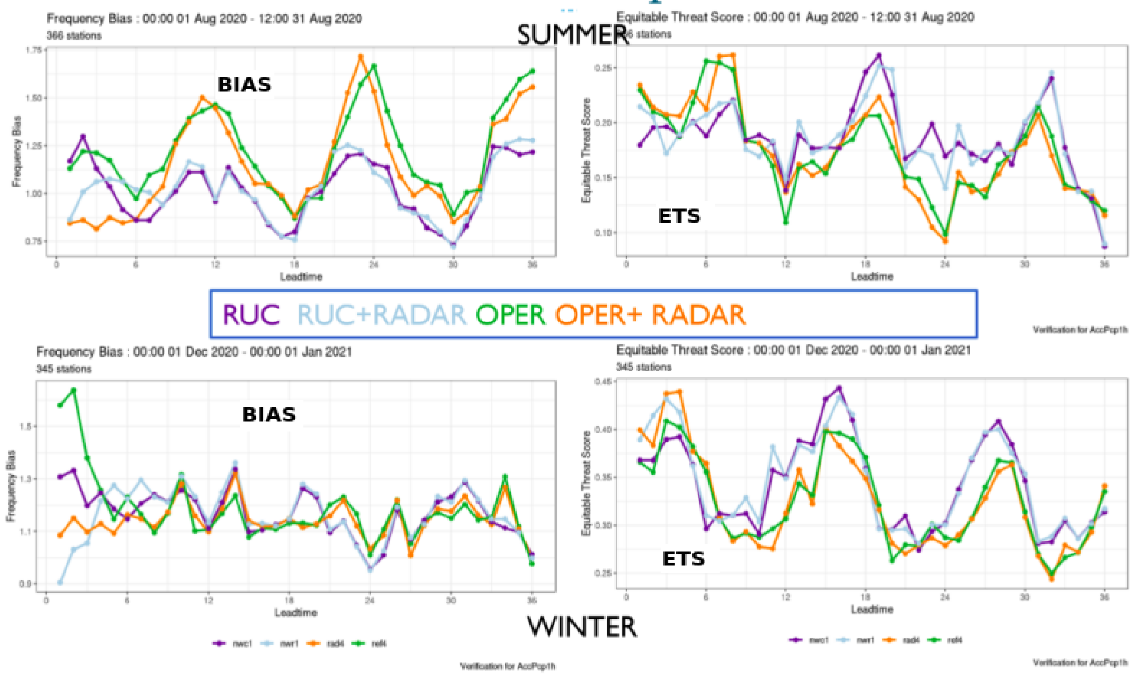
HARP usage @Slovenia

- automatic objective verification
- weekly and monthly scores
- traditional parameters

Performance of RUC & impact of radar data



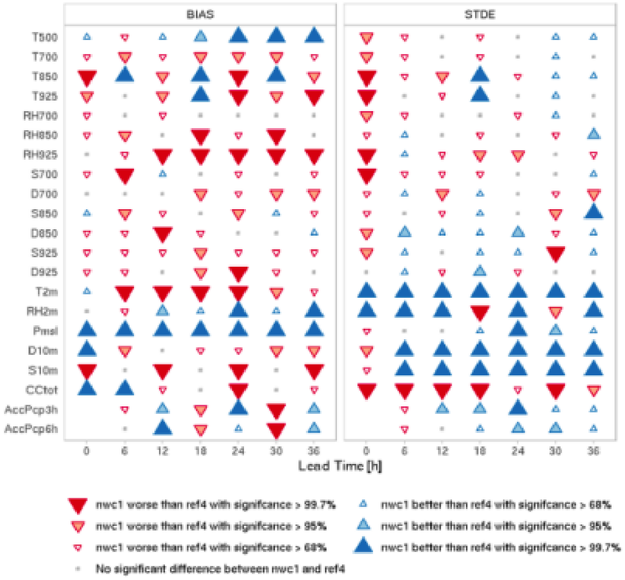
2 mm/h precipitation threshold

HARP usage @Slovenia

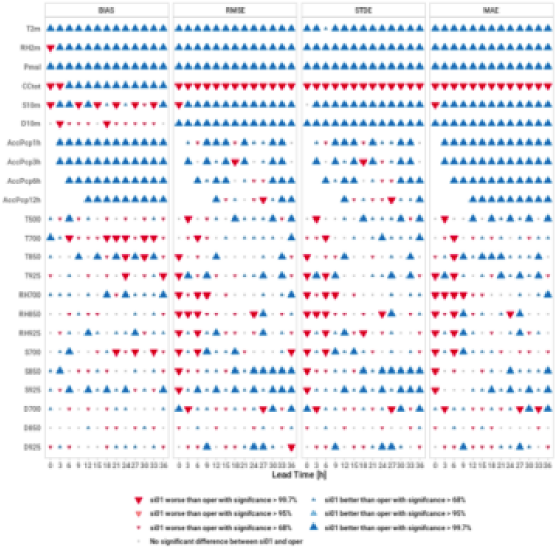
- automatic objective verification
- weekly and monthly scores
- scorecards

Performance of RUC

RUC (1.3 km) vs. OPER (4.4 km)

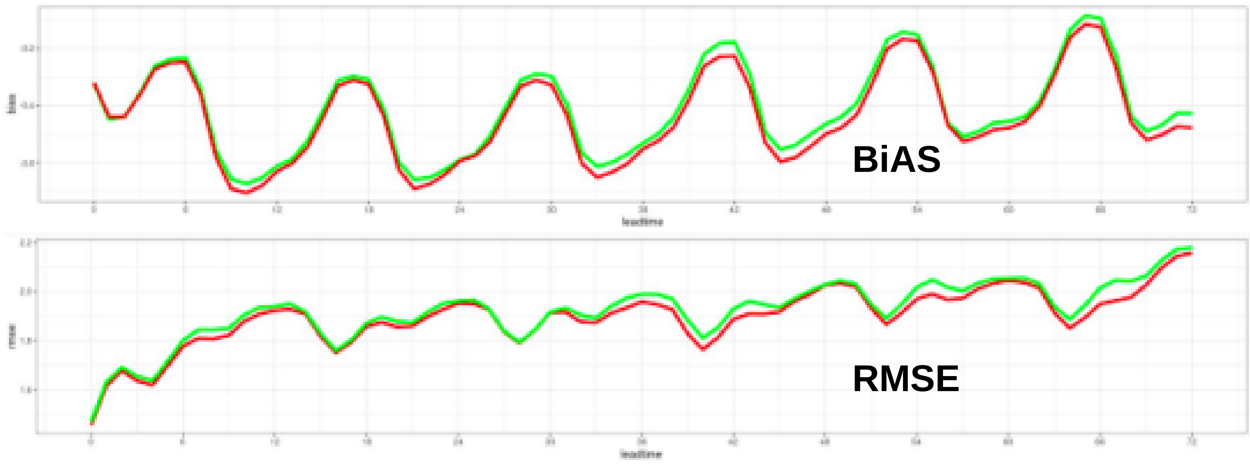


RUC (1.3 km) vs. OPER (4.4 km)
April and May 2022



HARP usage @Slovakia

- Validation of HPC3 operational system vs HPC2

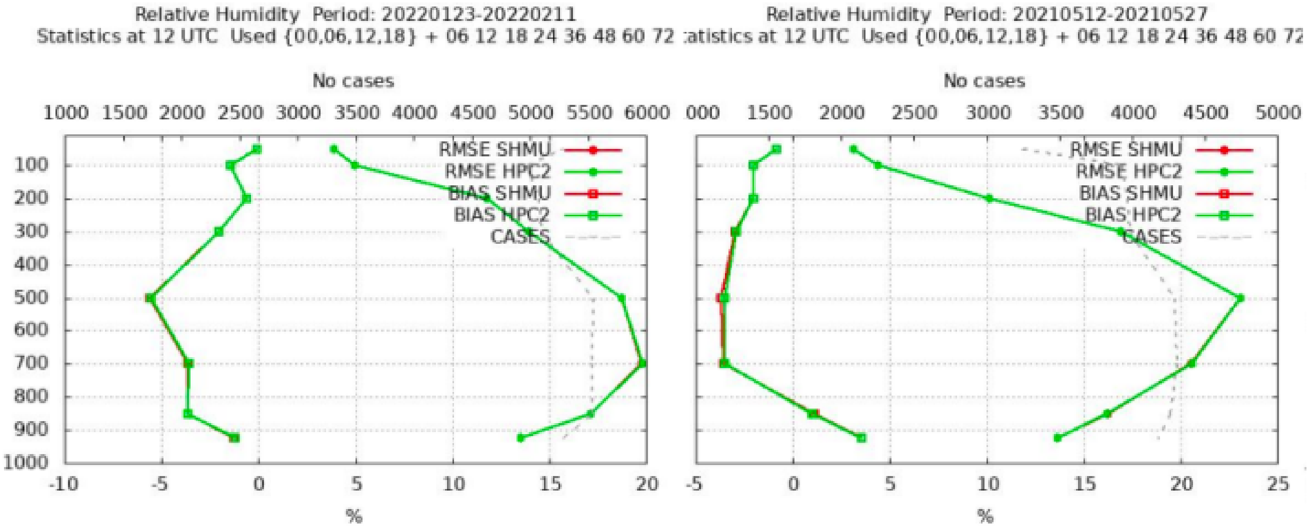


- T2m
- 20.01.2022, 00UTC – 21.02.2022, 12 UTC
- 95 stations
- HPC2 – green, HPC3 - red

HARP usage @Slovakia

- Validation of HPC3 operational system vs HPC2

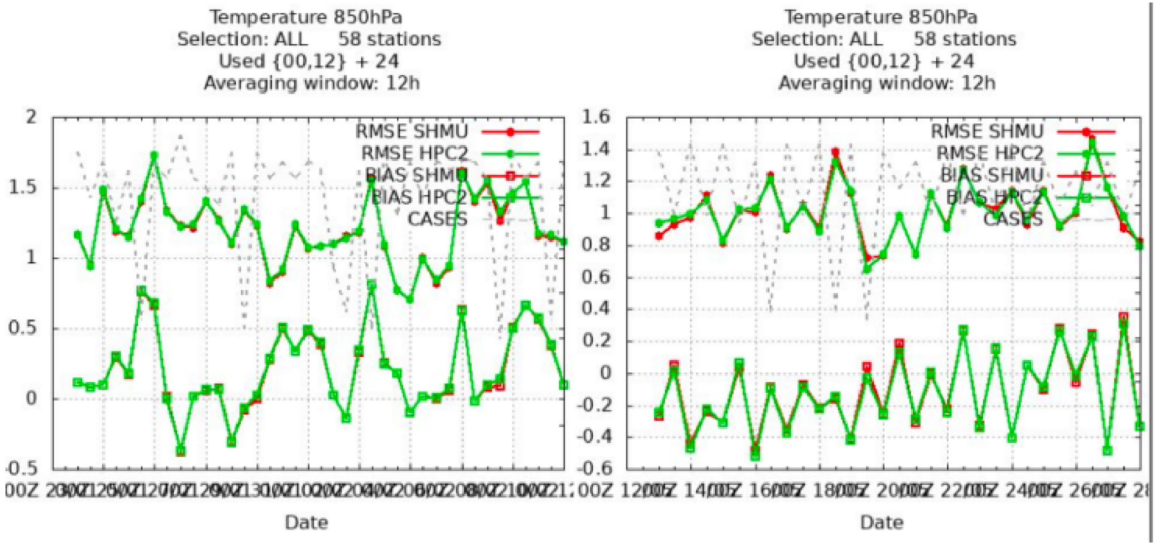
- RH2m
- BIAS and RMSE
- 23.01.2022 - 11.02.2022 (left)
- 12.05.2021 - 27.05.2021 (right)



HARP usage @Slovakia

- Validation of HPC3 operational system vs HPC2

- T850
- RMSE and BIAS
- 23.01.2022 - 11.02.2022 (left)
- 12.05.2021 - 27.05.2021 (right)



HARP usage @Slovakia

OBSOUL in HARP update - *Martin Petráš* and Alena Trojáková

- two obsoul data format:
  1. GTS EU data: *obsoul_1_xxxxxx_hu_YYYYMMDDHH*
  2. Non GTS data (National data): obsoul_1_xxxxxy_[hu,cz,sk,si,ro,pl,at,cr]_YYYYMMDDHH

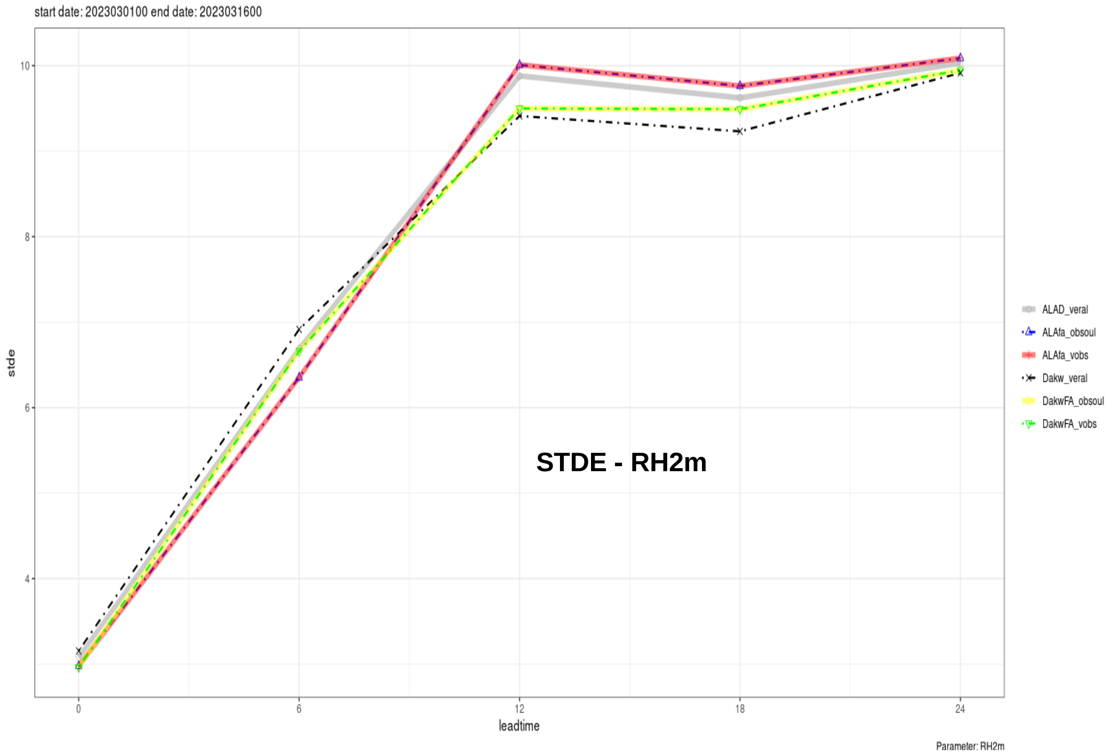
Differences in structure between GTS and non-GTS formatting:

- specific station identifications (CZ,HU, ...) for non-GTS data
- GTS data contains SYNOP data with station IDs having only integers
- SHIP data in GTS obsoul files - partially or fully string IDs
- non-GTS data - less parameters (T2m,wind,RH2m…)
- GTS data - more parameters, up to 6 parameters with not predefined order

HARP usage @Slovakia

OBSOUL in HARP update - *Martin Petráš* and *Alena Trojáková*

- Compare verification scores
  - Compare verification scores using multiple setups:
    - **Different observation sources**:
      - vobs
      - obsoul
    - **Verification tools**:
      - Harp
      - Veral

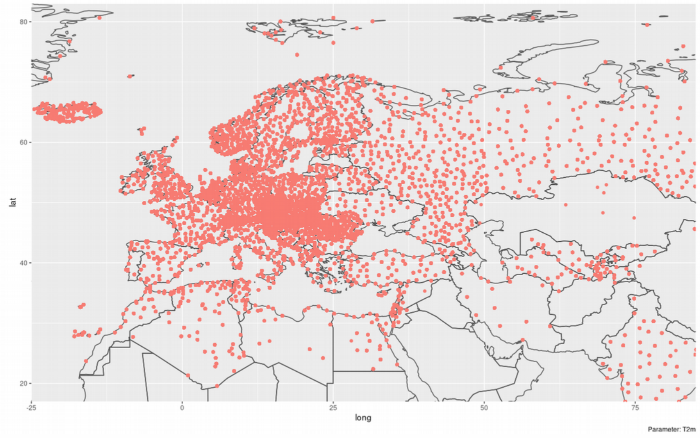


HARP usage @Slovakia

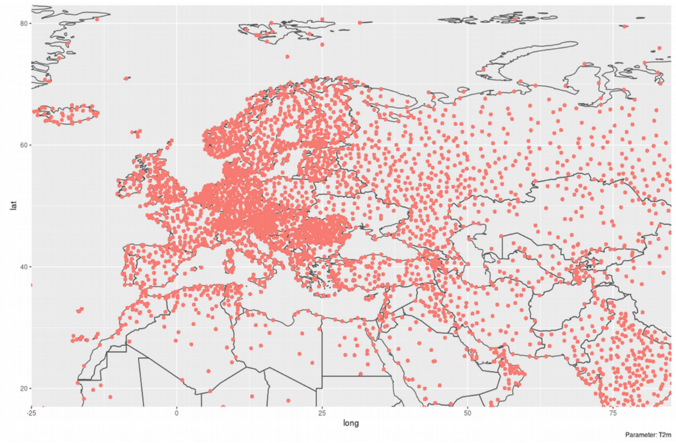
OBSOUL in HARP update - *Martin Petráš* and Alena Trojáková

- Quality control :
- ❑ - writing/reading obsoul from SQLite
- ❑ - comparing station data from different sources

T2m obsoul



T2m vobs



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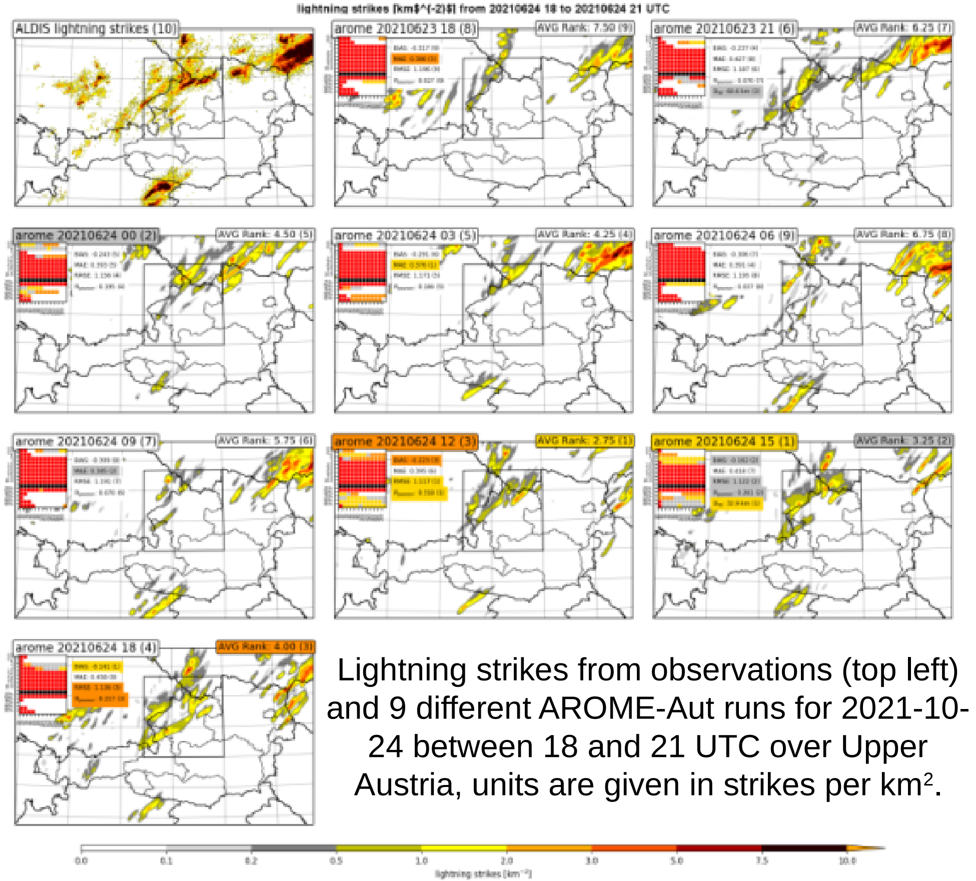
Panelification @Austria

- extended to hail and lightning: good indicators of strong convection
- for lightning: MODIS-Data is read from a local database and converted into a grided field of lightning strikes and compared to the lightning density from AROME
- for hail: a threshold approach will be used



Lightning strikes from observations (top left) and 9 different AROME-Aut runs for 2021-10-24 between 18 and 21 UTC over Upper Austria, units are given in strikes per km².

GeoSphere Austria DHMZ Czech Hydrometeorological Institute OMSZ IMGW METEO ROMANIA SHMU ARSO METEO Slovenia

Visualization of 2D vertical cross-sections in Python @Croatia

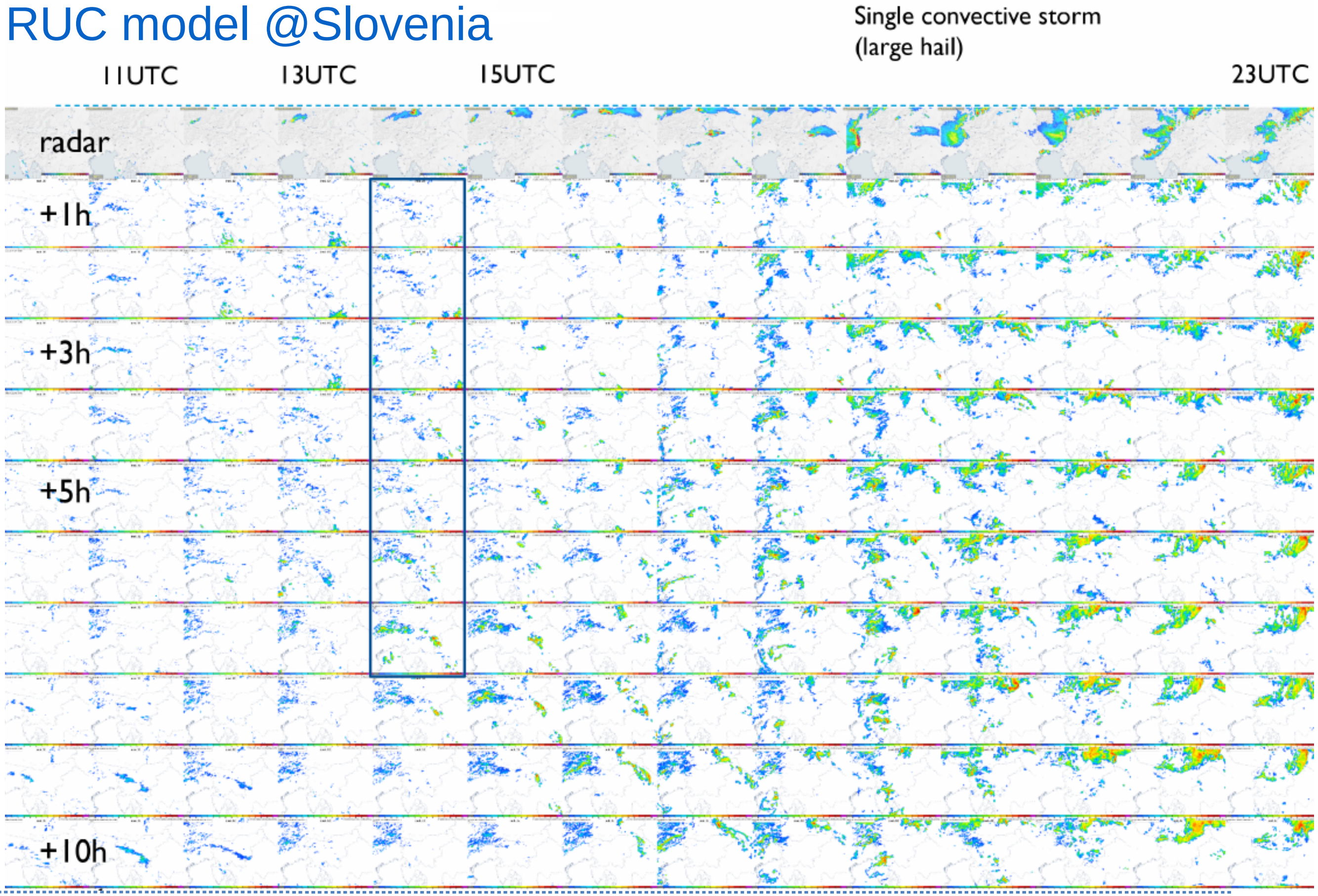
- a python-based verification dashboard started to be developed
- it enables interactive work (selection of location(s), score(s), etc.)
- ongoing work on the selection of verification measures and representative stations, which would be used to validate operational model configuration and postprocessing on a regular basis (e.g., monthly/yearly)
- work on methods for data quality control
- create an interactive system for real-time comparison of measured and modeled time series of near-surface parameters (python-based)

Subjective validation of 1.3 km RUC model @Slovenia

- to evaluate the quality of the 1.3 km model, especially to run consistency and the ability to simulate the (severe) weather events while they are in progress
- the main focus is on the development of the convection, particularly the onset of convection and the positioning of the convective systems
- to study the performance of the assimilation to capture the current ongoing convection activity by comparing two top row
- to study the consistency of the model from run to run by comparing each column individually

Subjective validation of 1.3 km RUC model @Slovenia

- the procedure is to plot a time series of radar images in the top row
- below that a large panel of many consecutive outputs - the same time of validity
- the lead time increases towards the bottom, in such view, an individual run lies on the diagonal



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Machine learning post-processing methods on AROME-EPS forecasts @Hungary

- the EMOS technique for global radiation - the distribution of predictions was approximated with censored normal (*CN*) or censored logistic (*CL*) functions
- 31-day rolling training period
- 7 stations of OMSZ measuring network
- 11 members of AROME-EPS, 00 UTC, using nearest gridpoint approach
- the CRPS of the improved probabilistic forecast could be reduced by 16-18% with respect to the CRPS of the raw AROME-EPS (Schulz et al., 2021)
- CN-EMOS method proved to be numerically somewhat more stable

Schulz, B., El Ayari, M., Lerch, S., Baran, S., 2021: Post-processing numerical weather prediction ensembles for probabilistic solar irradiance forecasting. Sol. Energy 220, 1016–1031.

Machine learning post-processing methods on AROME-EPS forecasts @Hungary

- also, a multilayer perceptron (MLP) machine learning method based on TN or LN distributions
- 3 wind farms observation in the NW Hungary and corresponding AROME-EPS forecasts at hub height (100m) at nearest grid points were used
- a 51-day long training period
- MLP was the most successful, with CRPS improved by 10-15% of the raw EPS (Baran and Baran, 2021)

Baran, S. and Baran, Á., 2021: Calibration of wind speed ensemble forecasts for power generation. Időjárás 125, 4.

Machine learning post-processing methods on AROME-EPS forecasts @Hungary

- the ongoing work: on integrating the received code into the operating system
- the improved forecasts is produced daily: every station and every 15 minutes by determining 11 equal quantiles from the given distribution function
- each method handles each lead time independently

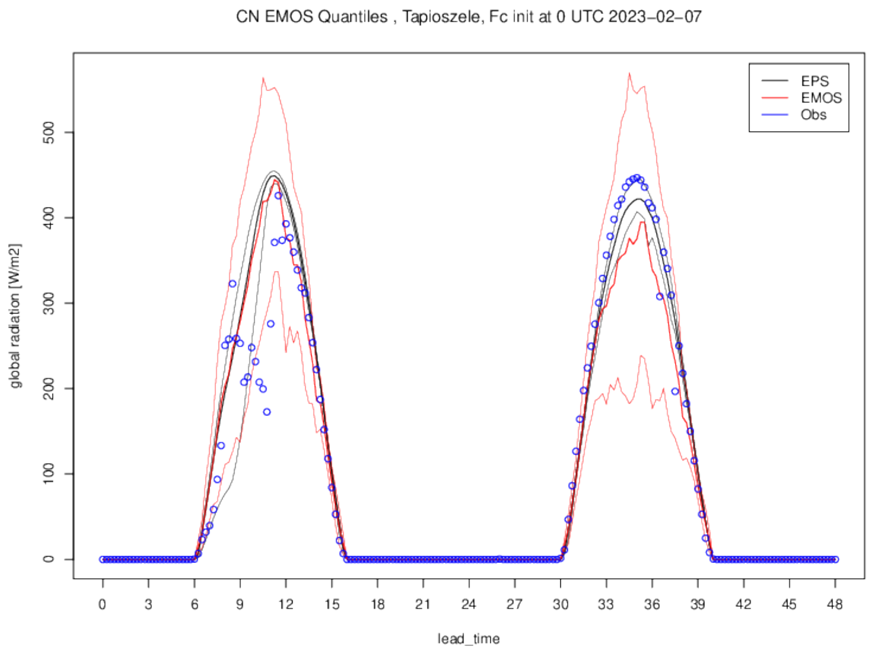
The running procedure consists of 3 steps:

- the collection of forecast data for the given day and observations
- the EMOS fitting and the MLP training run on a separate computers
- verification is done for the forecasts of the preceding day: some statistics are calculated for the previous period of about one week, and also a few simple meteograms and verification plots are produced to compare the improved forecast and the raw AROME-EPS.

Machine learning post-processing methods on AROME-EPS forecasts @Hungary

Ensemble meteogram for radiation on 7 February 2023 based on raw AROME-EPS forecasts:

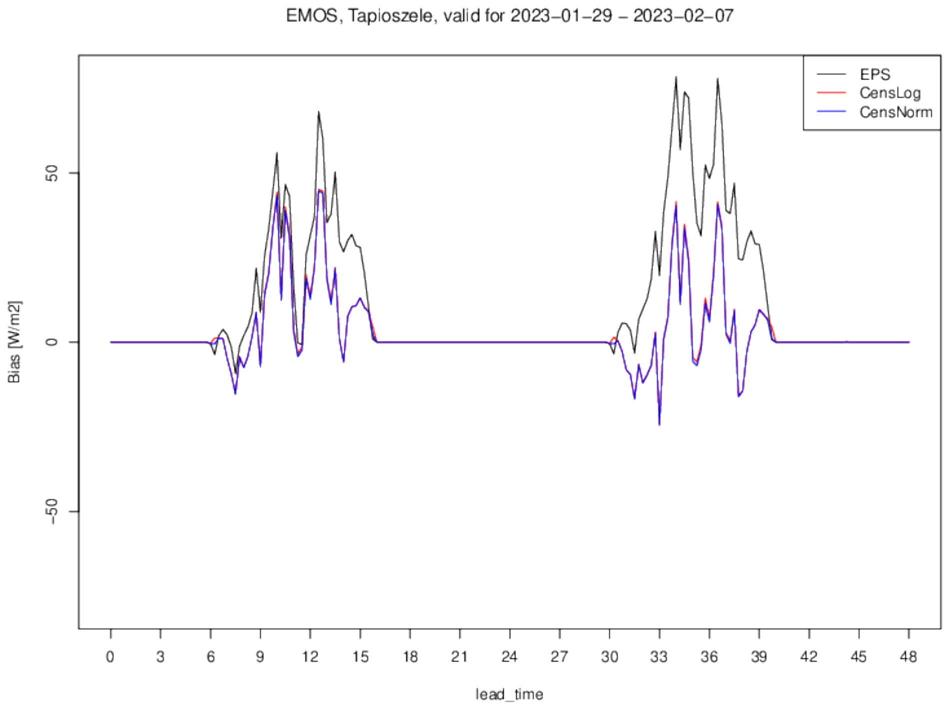
- ensemble mean in ***black***
- minimum and maximum in *grey*
- on CN-EMOS: ensemble mean estimated from the corrected distribution function with *thick red* line, upper and lower quantiles with *thin red lines*
- observations with *blue circles*



Machine learning post-processing methods on AROME-EPS forecasts@Hungary

Bias of ensemble mean for radiation:

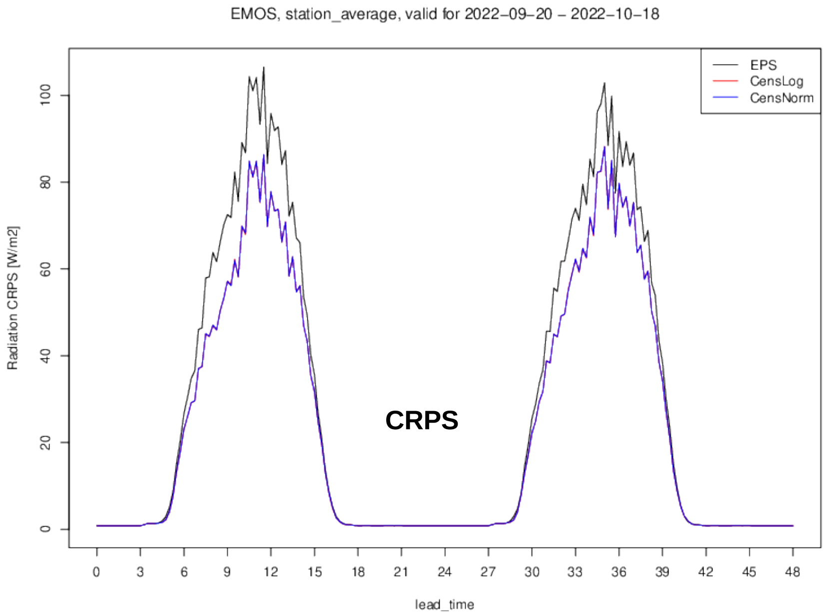
- 29 January and 7 February 2023 based on raw AROME-EPS forecasts (***black***)
- CN-EMOS (*blue*)
- CL-EMOS (*red*).
- for station of Tápiószele.

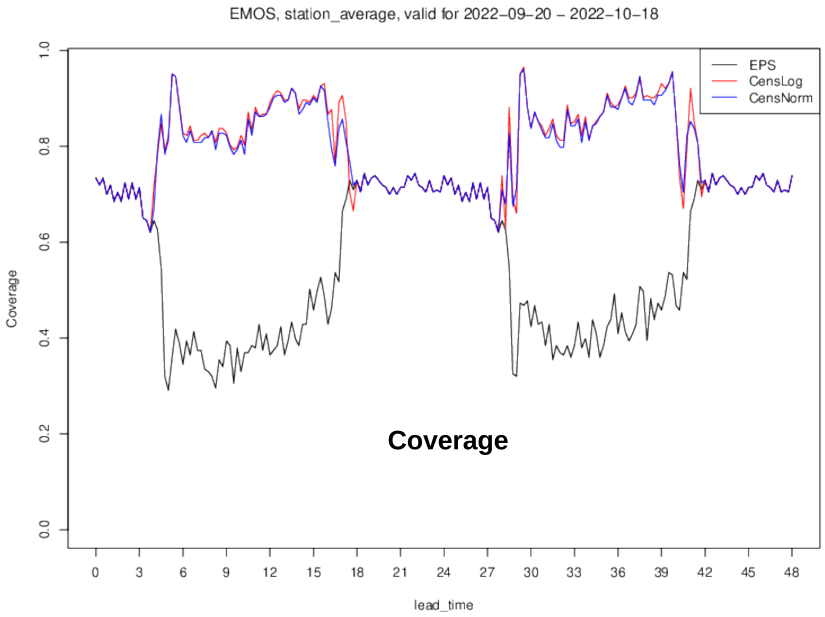


Machine learning post-processing methods on AROME-EPS forecasts @Hungary

- test was done on the current operational AROME-EPS which is downscaling of ECMWF-ENS

Global radiation for 7 stations, 20.09.2022 - 18.10.2022





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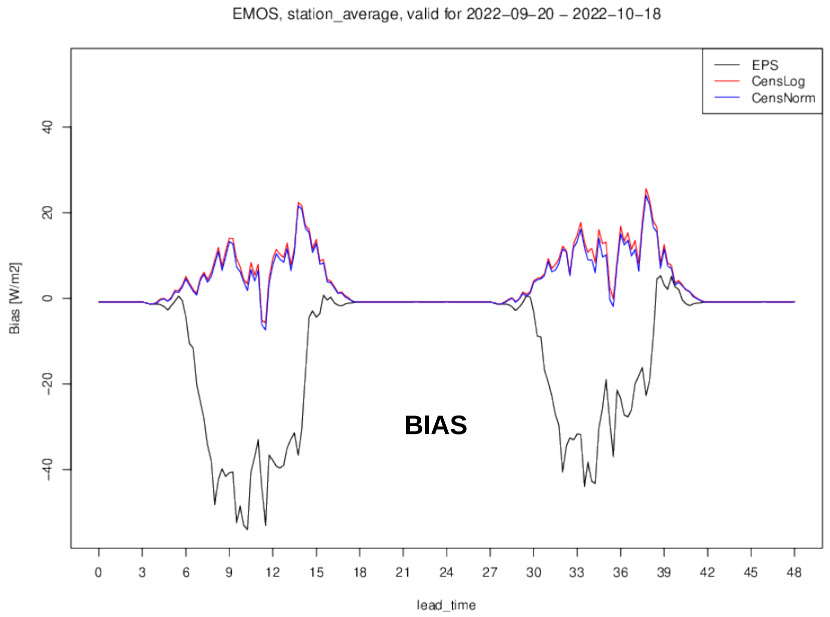

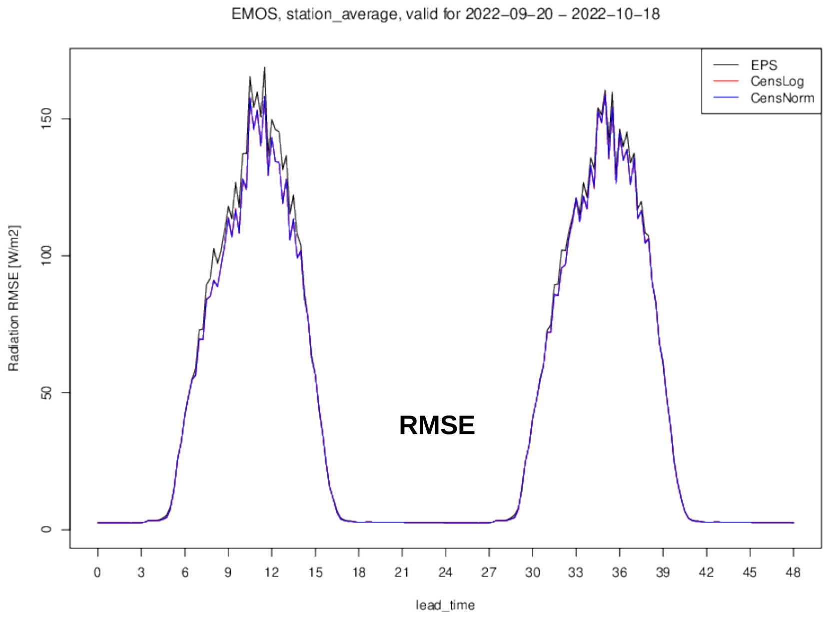

Machine learning post-processing methods on AROME-EPS forecasts@Hungary

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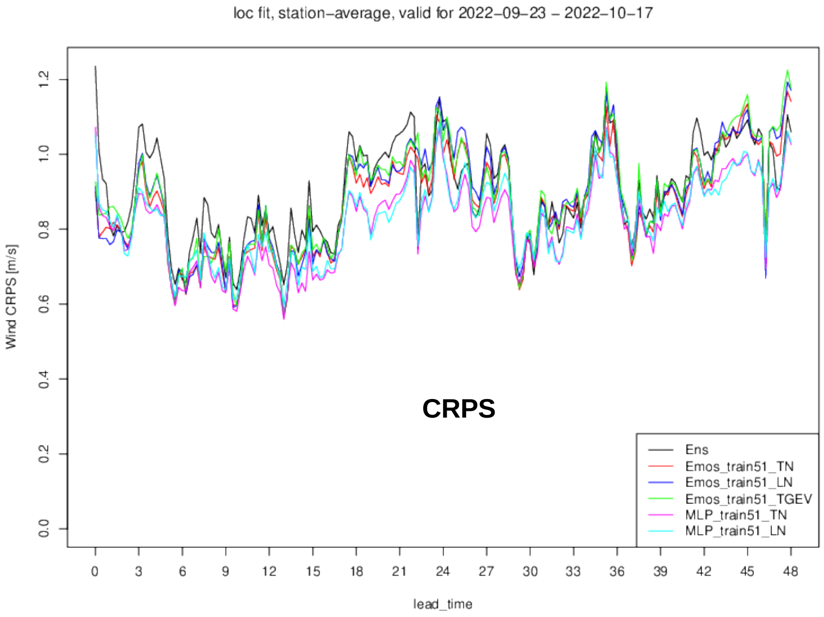
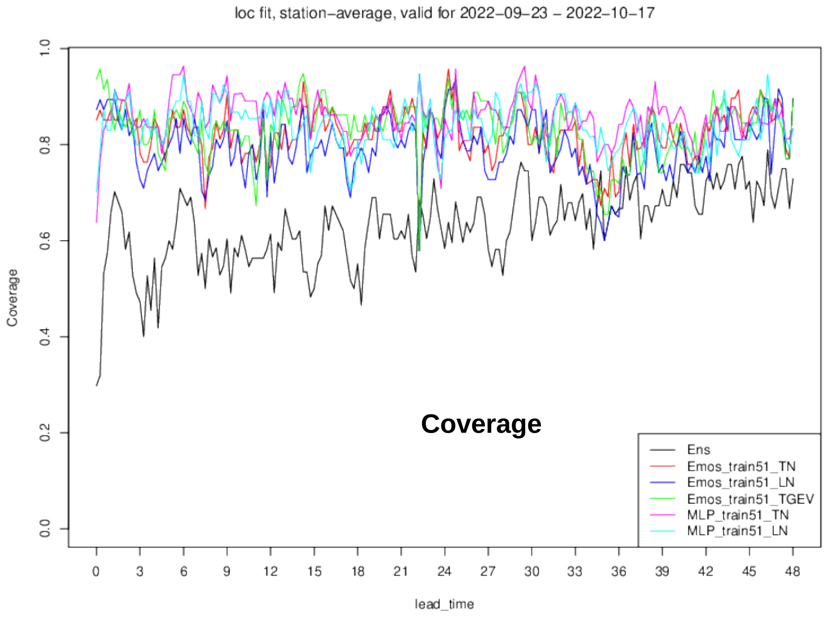
100m wind forecasts for 3 stations, 23.09.2022 – 17.10.2022





Machine learning post-processing methods on AROME-EPS forecasts@Hungary

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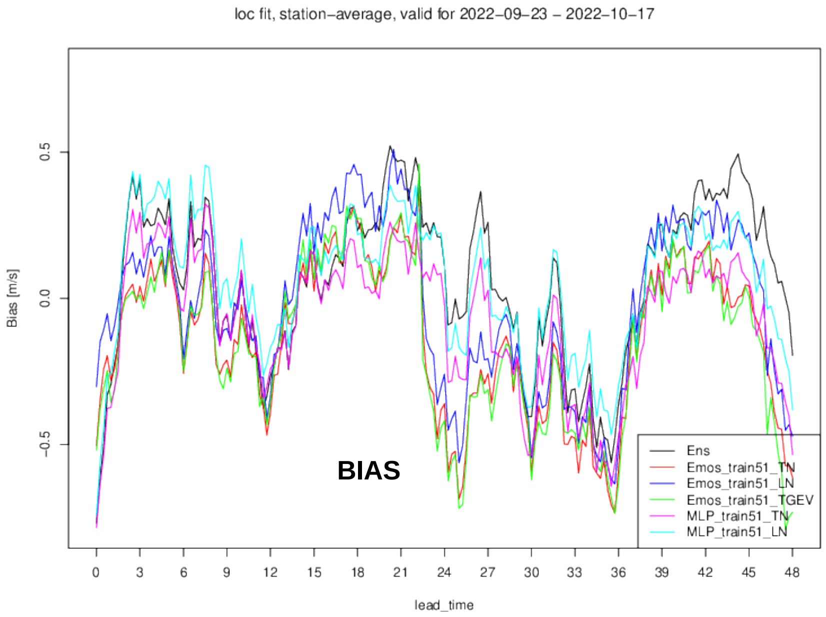
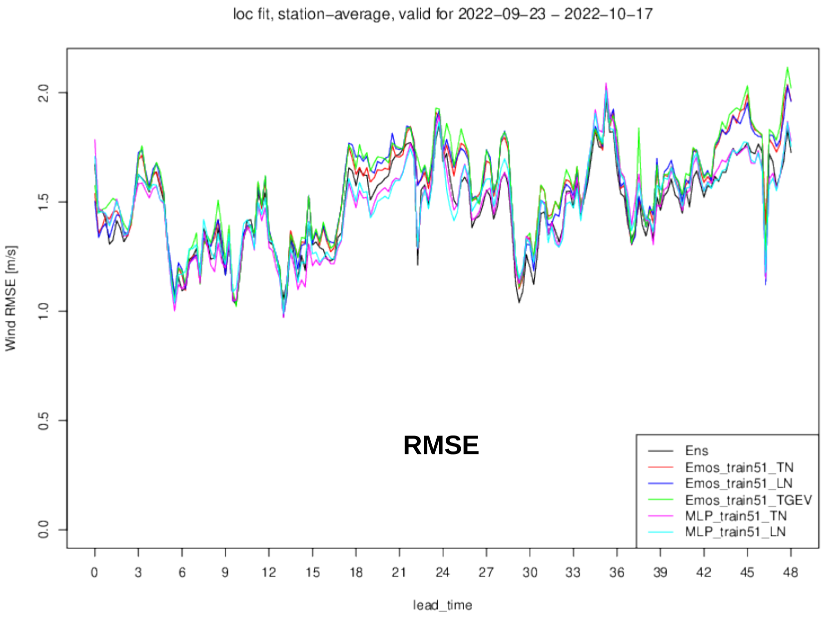




Machine learning post-processing methods on AROME-EPS forecasts @Hungary

- in general, the operational AROME-EPS is underdispersive and biased, both features seem to be improved after the post-processing

- an improvement in CRPS does not mean an improvement in RMSE of ensemble mean to the same extent, i.e. end users should consider the probability information and not only EPS mean

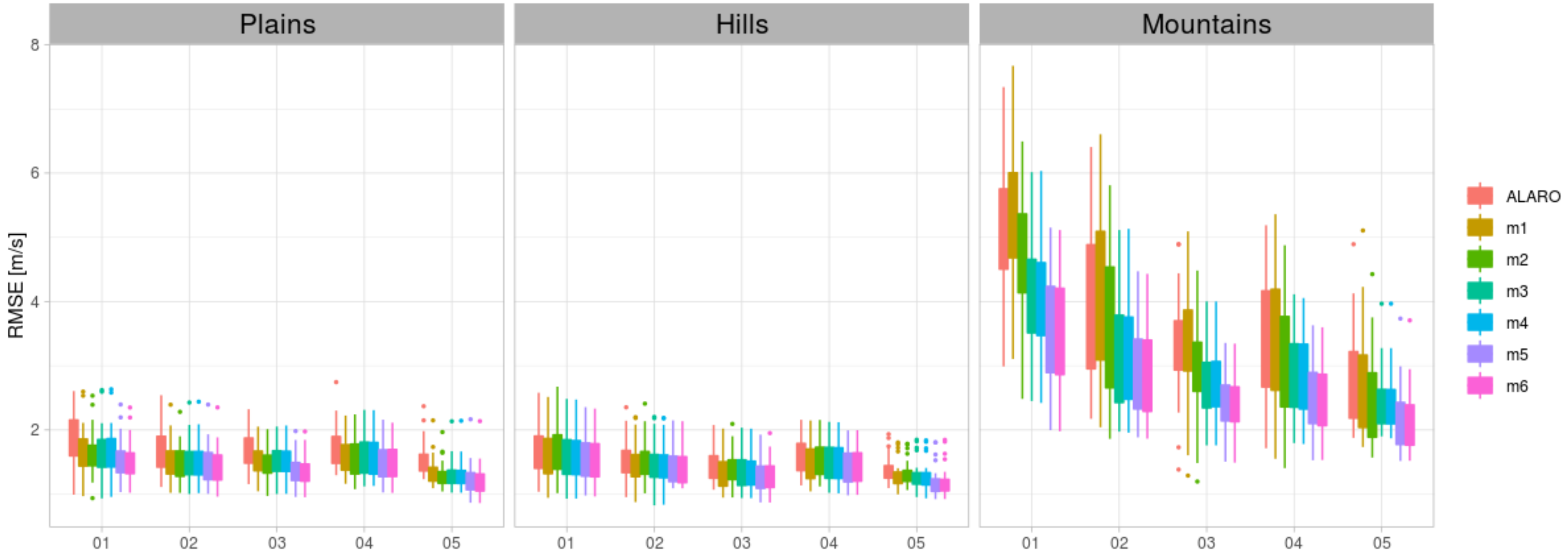
GAM (Generalized Additive Models) models to estimate wind speed @Romania

- a post processing method of the model output was tested for wind speed forecast of ALARO - GAM (Generalized Additive Models)
- several GAM models were defined: differ mostly in the predictors they use in the regression equation:
  - *m1* - a simple regression model (one single predictor which - wind speed simulated by ALARO)
  - *m2* - takes into consideration the coordinates (latitude and longitude) of the point where is applied
  - *m3* - includes the altitude of the station
  - *m4* - includes the simulated wind direction
  - m5 - adds the 24 hours lagged simulated wind speed
  - *m6* - takes into consideration two local characteristics: the distance to the Black Sea and the number of urban pixels within 3 km radius for the point considered

GAM (Generalized Additive Models) models to estimate wind speed @Romania

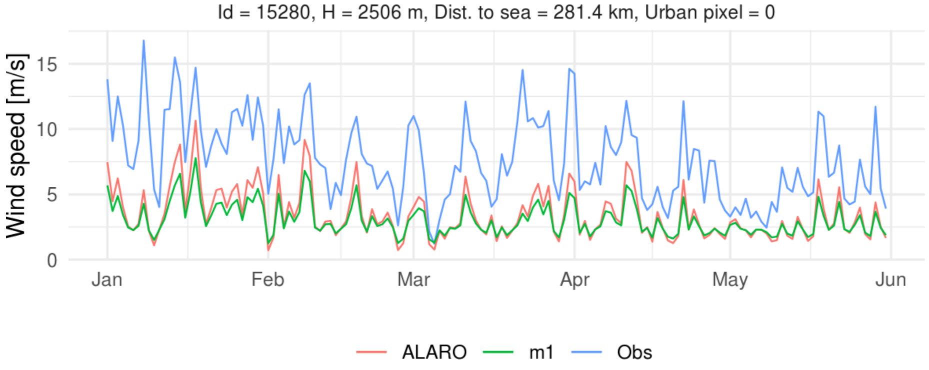
- All 6 models were applied for 2021 training period
- the wind speed estimation for the period January – May 2022
- 157 meteorological stations in Romania

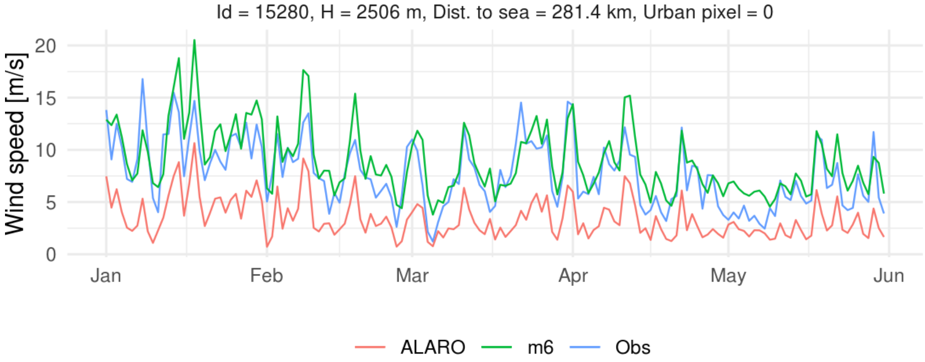
GAM (Generalized Additive Models) models to estimate wind speed @Romania



- the models show different results, depending on the month or altitude of the station
- improvements are more visible for mountain stations, mostly for models m5 and m6
- this result shows the significance of adding more predictors in the regression model

GAM (Generalized Additive Models) models to estimate wind speed @Romania





- daily mean wind speed for station Vf. Omu (located at 2506 m altitude)
- model m1 shows very slight differences compared to ALARO in this case and both underestimate the real wind speed
- model m6 leads to wind speeds more closer to registered values

Database of cases

Organization | Operational activities | RC LACE Projects | Documents | Actions | Data base of cases | Forum | Events | Private zone

> Data base of cases

Data base of cases

Idea is to have Data base for Cases studies. All suggestions and new cases are welcome.

Short description	Event date	Category	Country	name	Forecast & Report
EPS - Case studies report 2021	2021		A	Wastl Clemens	Report
Record rainfall in Italy, A-LAEF (case study)	04 October 2021		SK	Martin Belluš	Report
High spread and underestimation of 2m temperature over snow cover in case of the warm air advection	22 February 2021		SK	André Simon, Martin Belluš	Report
Temperature forecasts in very cold weather	12-13 February 2021		SK	André Simon	Report
False model advection of warm air over Bratislava	07 February 2021		SK	André Simon	Report

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Thank you for your attention.

GeoSphere Austria

DHMZ

Czech Hydrometeorological Institute

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METEO ROMANIA

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