PP MILEPOST – description, results after one year

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Introduction

The main goal of the Priority Project – provide methods of post-processing based on Machine-Learning (MLP), including Artificial Neural Networks (ANN).

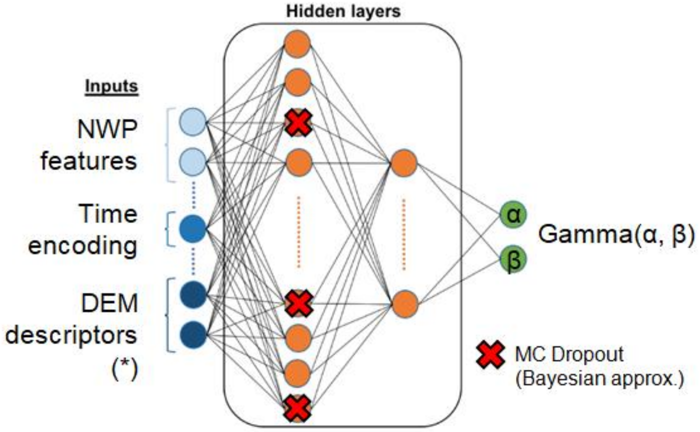
Results – the assessment of a relation(s) between numerical forecasts in terms of Direct Model Output (DMO) and MLP, including verification.

All proposed methods should eventually be delivered to interested ones in the form of software packages for advanced post-processing.

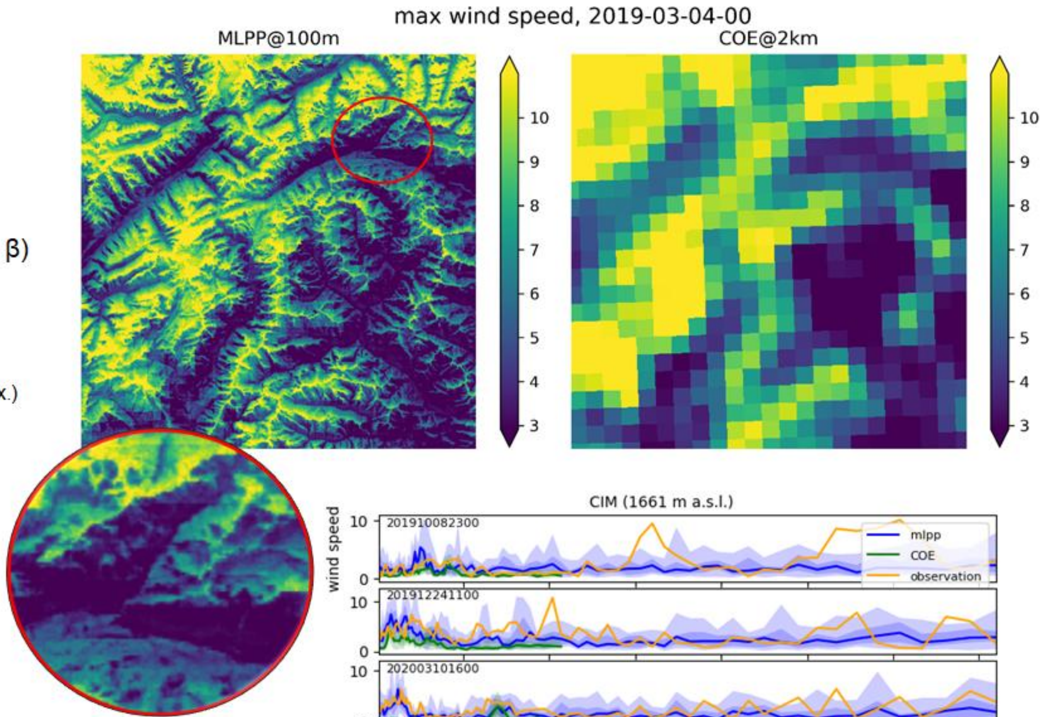
Tasks

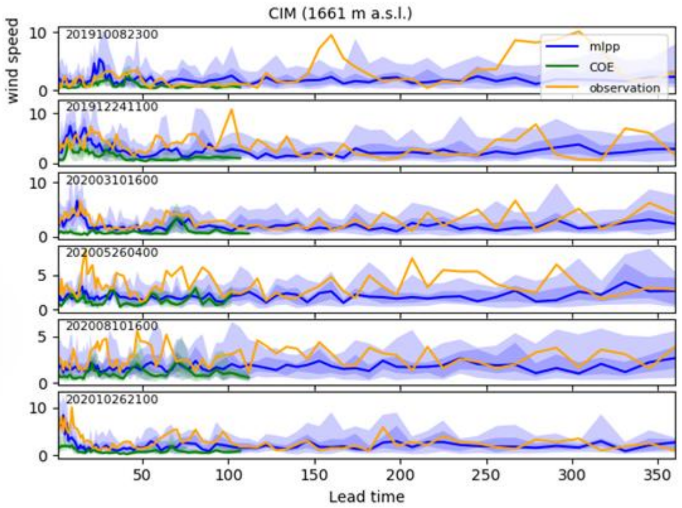
- General survey of Machine Learning – ended, report(s) planned as a final deliverable(s)
- Set-up, research and application of ANNs
- Set-up, research and application of other ML techniques
- General ML-based post-processing and verification: definition of comparison setup – a testbed to establish an evaluation framework.

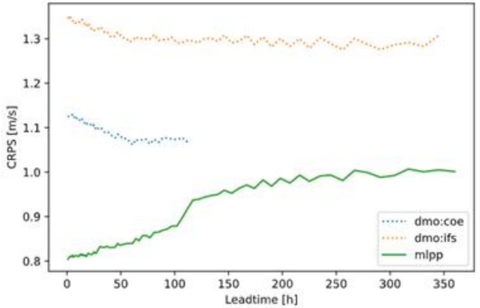
Seamless postprocessing of multi-model NWP surface wind forecasts with deep learning

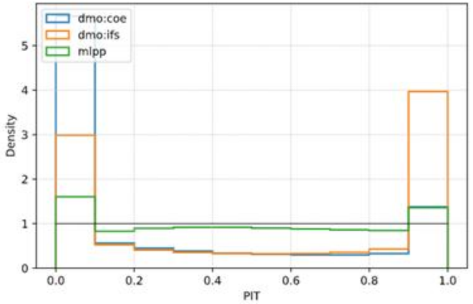


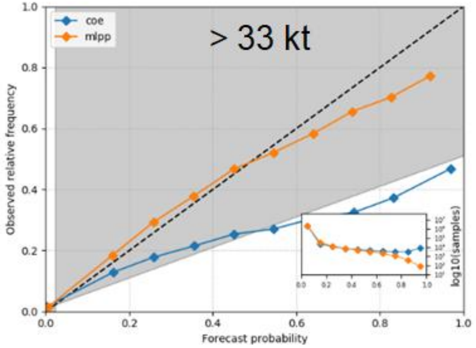
(*) https://github.com/MeteoSwiss/topo-descriptors









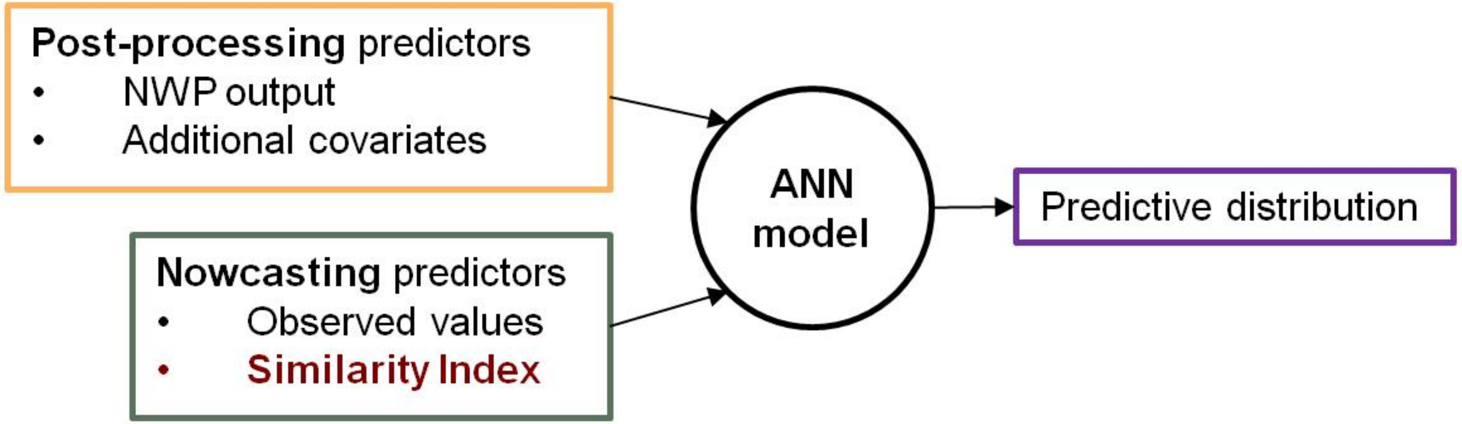


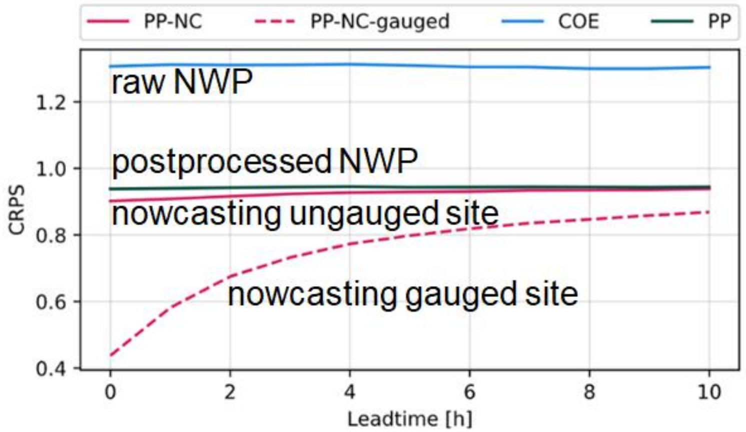
- Aleatoric uncertainty
- Epistemic uncertainty

NWP sources
- COSMO-1 (1km, +33h, det)
- COSMO-E (2 km, +120h, 21 memb.)
- IFS-ENS (18 km, +360h, 51)

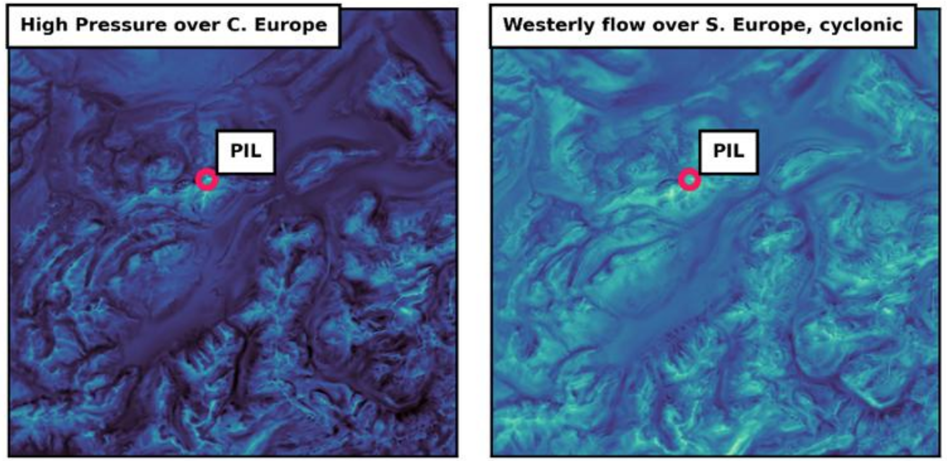
Data split:
- train (2016-2018, 300 stations)
- val (2019, 100 stations)
- test (2020, 100 stations)

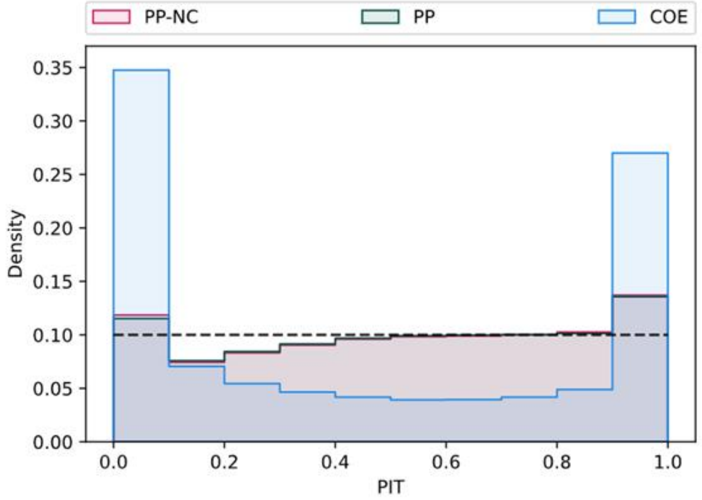
Nowcasting of surface wind speed using probabilistic, explainable deep learning





Similarity Index: a model estimation of the correlation of wind speed between any pair of locations, as a function of their position and geomorphological setting.





Latest news from MeteoSwiss:

Investigation in progress: the use of **Generative Adversarial Networks** (GANs) for post-processing weather forecasts with particular focus on hourly precipitation fields.

The main goal of this work: to write a python package that can serve as a base for further research and development.

Ph.L.Bykov, Hydrometeorological Research Center of the Russian Federation

Correction of the COSMO-Ru fields in the troposphere using the convolutional neural network

Problem: To use the near-surface, SYNOP-based correction to calculate the post-processed fields in the troposphere.

The dataset contains ~640 000 pairs of the COSMO-Ru6-ENA 0-72h forecast and high-resolution radiosonde BUFR profile.

Corrected fields: temperature *T*, water vapor *Qv*, pressure *p.*

ML model: e.g. for temperature *T* :

$$T_{corr}(z) = T_{\mathrm{cosmo}}(z) + f(z)[T_{corr}(2m) - T_{\mathrm{cosmo}}(2m) + b(z) - b(2m)],$$

where $f(z) \in [0,1]$ and *b(z)* is the 1D (vertical column) convolutional neural network outputs; $T_{corr}(2m)$ is corrected forecast, calculated with take into account the last SYNOP data.

Plans: apply to wind profiles.

$100 * MAE \log p$

The hydrostatic regularizer

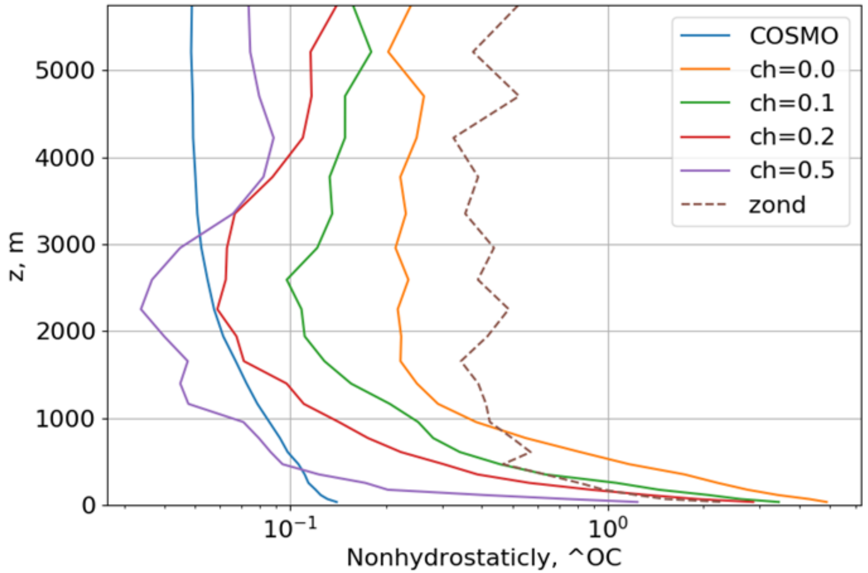
- We estimate the non-hydrostaticity of the corrected profiles by formula

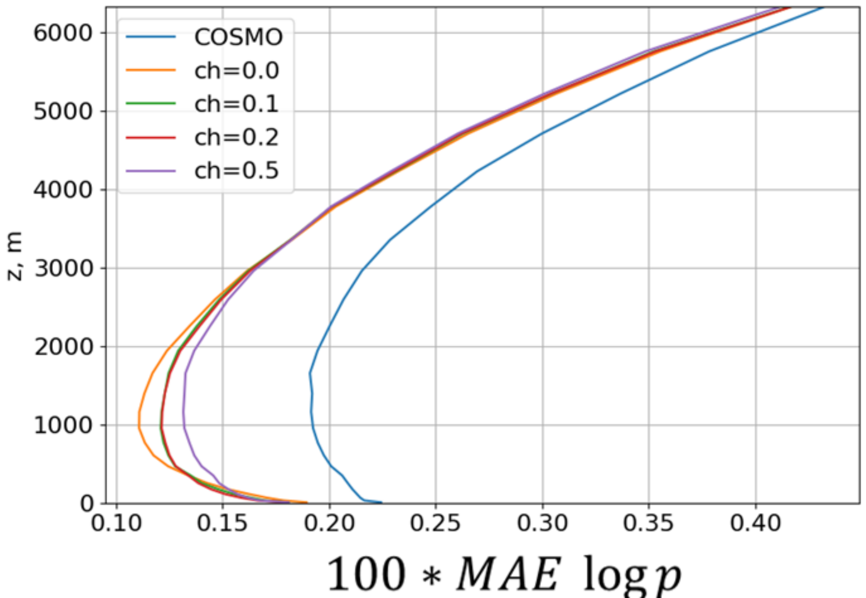
$$e_{hydro}(z_{i+1/2}) = e\left(\frac{1}{2}\left(T_{E,corr}(z_i) + T_{E,corr}(z_{i+1})\right), -\frac{g}{R}\frac{z_{i+1} - z_i}{\log\frac{p_{corr}(z_{i+1})}{p_{corr}(z_i)}}\right)$$

and add it into the loss functional as the additional regularization :

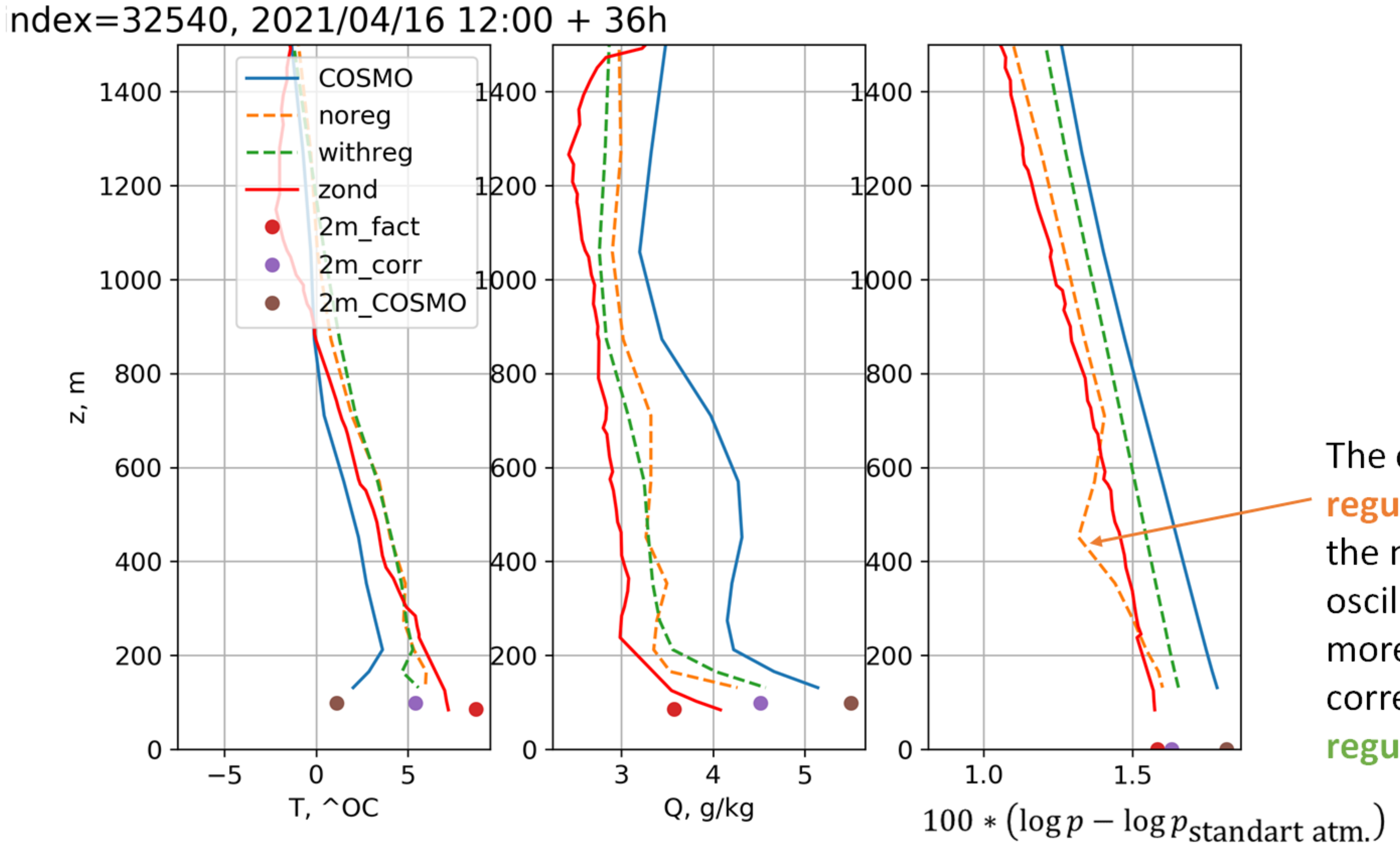
$$L = \int\left[e(T_{zond}, T_{corr}) + e(Q_{zond}, Q_{corr}) + 1000e(\log p_{zond}, \log p_{corr}) + \boldsymbol{c_h e_{hydro}}\right]p_{\text{cosmo}}(z)dz \rightarrow min.$$

- **The hydrostaticity conflicts with the best accuracy of the post-processed pressure profile in the lower 3000 m layer**





The regularization reduces the artefacts



The correction **without regularization** produces the non-physical oscillations, but it is more accurate than the correction **with regularization**

Other ML techniques. WLR – an alternative for ANN

$$f(x) = y = a \cdot x + b$$

$$\chi^2(a,b) = \sum_{i=1}^{n} \frac{(y_i - a \cdot x_i - b)^2}{\sigma_i^2}$$

$$w_i = 1/\sigma_i^2$$

$$\frac{\partial \chi^2}{\partial a} = 0 = -2\sum_{i=1}^{n} w_i\, x_i (y_i - a \cdot x_i - b)$$

$$\frac{\partial \chi^2}{\partial b} = 0 = -2\sum_{i=1}^{n} w_i\, (y_i - a \cdot x_i - b)$$

Initial weights – sigma values calculated from archive measurements vs. forecasts for initial period.
From the ”zero” approximation – compute the value of sum of (squares of) residues.

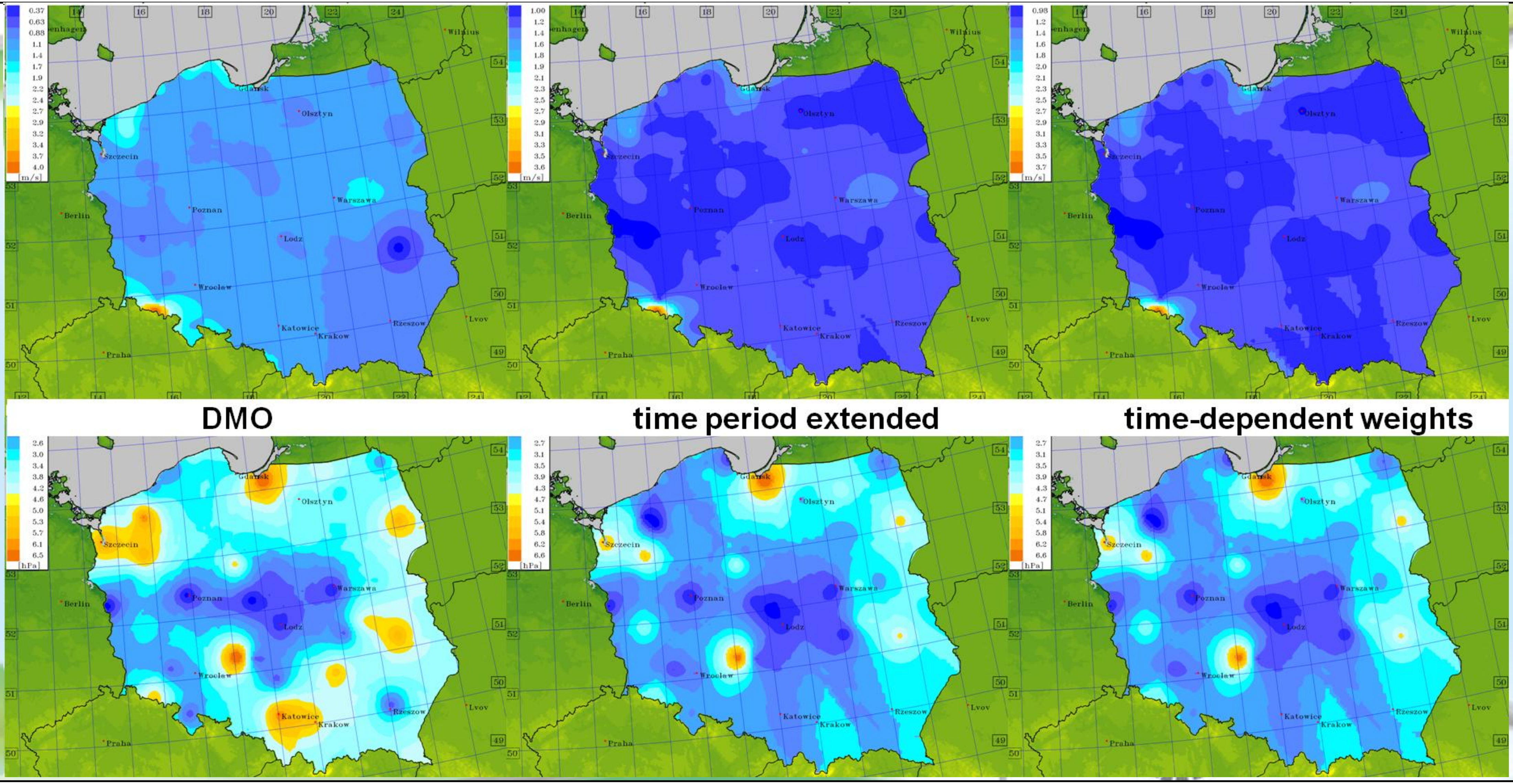
$$RES = \sum_{i=1}^{n} (y_i - a \cdot x_i - b)^2$$

Set an arbitrary threshold.
If RSS is above it – modify weights w_i accordingly (time-dependency and/or extend learning period).

WMLR recalculation must be performed with changed weights to achieve the assumed convergence criterion

WMLR – an alternative for ANN – results

U10M MAE



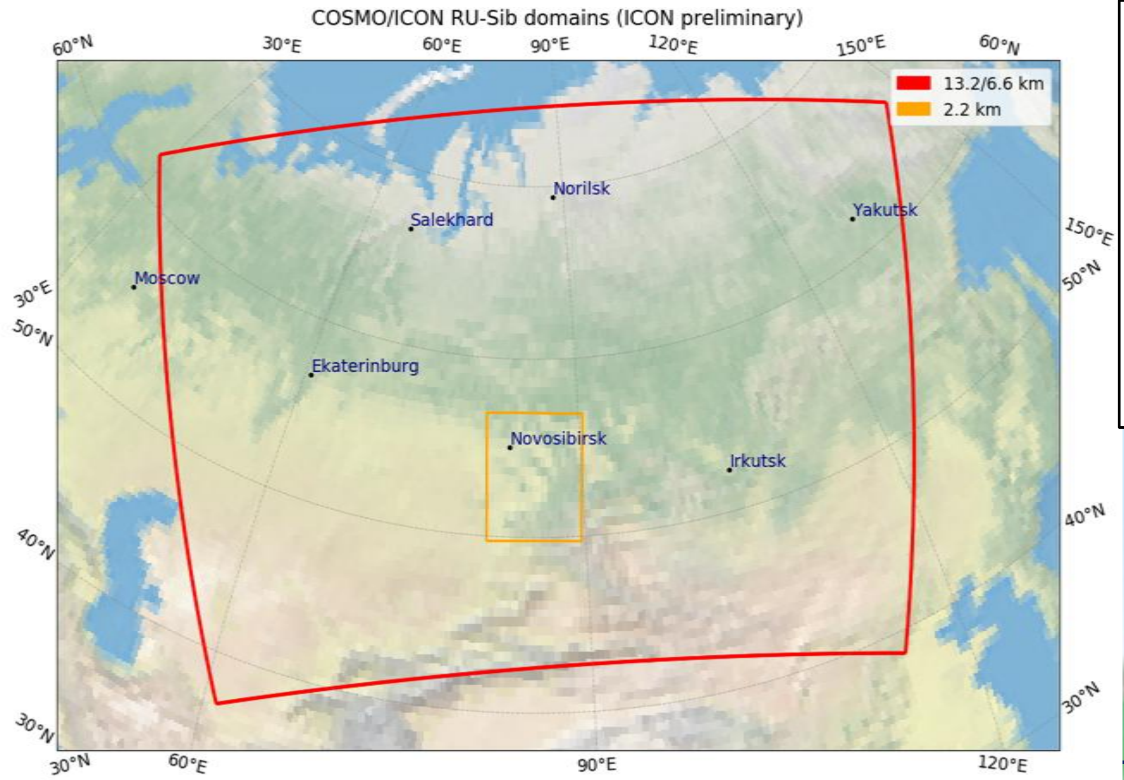
PS MAE

SibNigmi (RHM) team

The new team from the Siberian Research Meteorological Institute (Novosibirsk, Russia, Roshydromet) has joined WG4/MILEPOST PP in July 2021. The team is involved in the research process on the application of ML technology to postprocessing forecasts of rare phenomena (e.g. thunderstorms).

The current research topic is learning efficiency using the Decision Tree classifiers and Neural Networks to forecast storms (for the non-convective mode of the Cosmo model) and to compare with DMO with the supported convective mode (the results of LPI COSMO and ICON were analyzed).

The scheme can be extended to other rare phenomena.



COSMO v 5.03 (13.2 km), v 5.09 (6.6, 2.2 km)
ICON v 2.6.2.2
Direct variable: LPI (>= 2 J/kg) from 2.2 domain
NN (Sequential,3 hidden layers)
and ML(Decision Tree)
52 variables (direct model output and calculations) from
13.2 COSMO domain

SibNigmi (RHM) team

- To investigate frames of usability ML technologies for postprocessing and rare phenomena forecasting.
- To compare effectivity of various approaches of ML.
- To develop recommendation for training dataset building (e.g. balancing, number of cases and events)

Current status: under processing.

Current results:

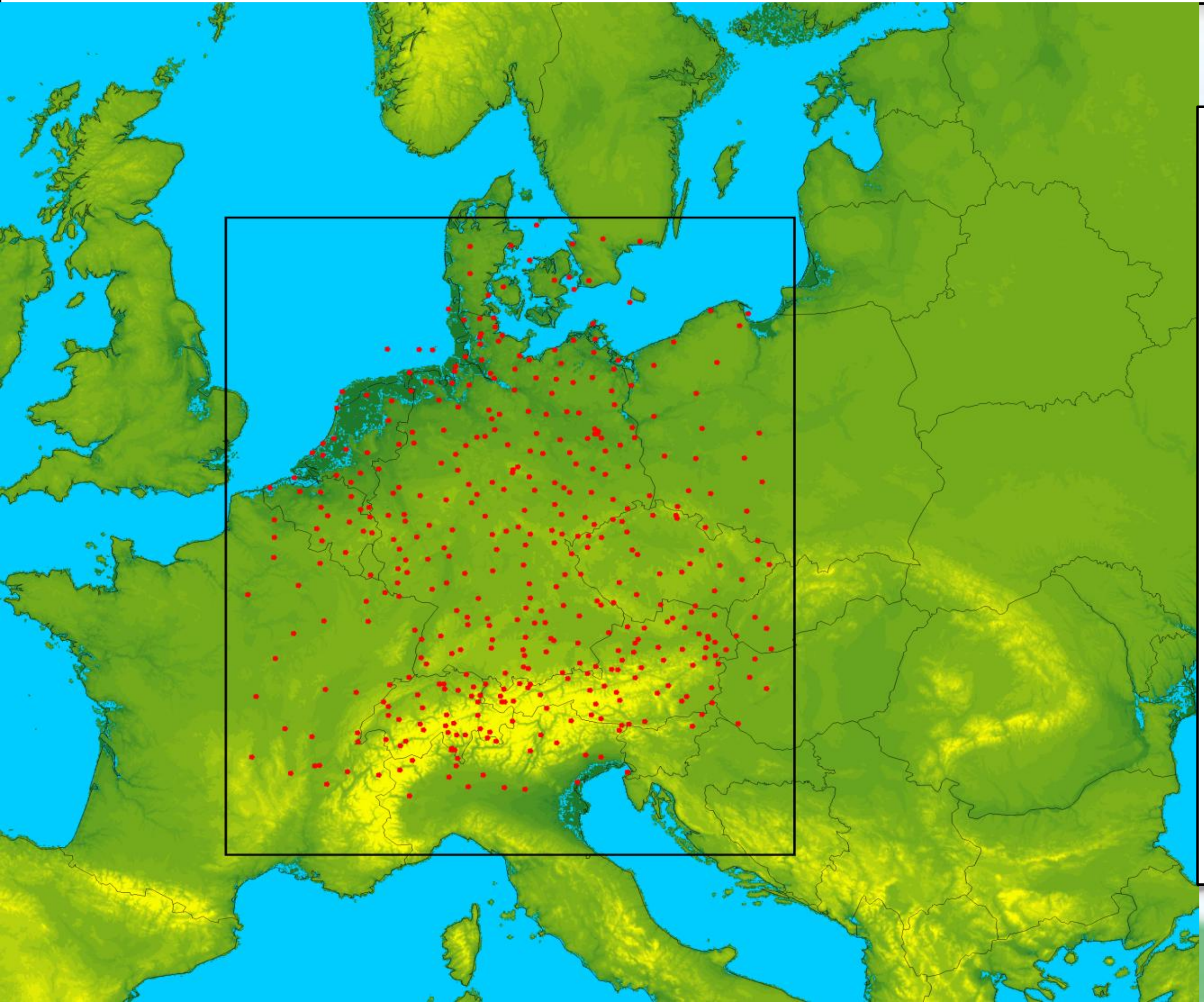
The quality of the training dataset affects the result to a much greater than the algorithm of ML applied.

For classification tasks Decision Trees provides similar NN output with much better calculation costs.

The right balancing of training set (positive and negative, and other factors distribution) is extremely important for all types of ML approaches.

Database from DWD (for common verification/test setup)

Data gathered from COSMO-DE-EPS (Dec. 2010 up to 14. May 2018) and from COSMO-D2-EPS since 15 May 2018 until Dec. 2020.



Variables:

- TMIN_2M, TMAX_2M, T_G;
- VMAX_10M;
- CLCT, CLCL, CLCM, CLCH;
- PMSL;
- U_10M, V_10M;
- T_2M, TD_2M;
- RAIN_GSP, SNOW_GSP, TOT_PREC;
- HBAS_SC, HTOP_SC;
- ASOB_S, ATHB_S, ALB_RAD;
- W_SNOW;

At 500, 700, 850, 950, 1000 hPa:

- Temp, RelHum, Geopot, U/V/Omega

Column-integrated Soil Moisture, **1, 2, 6, 18, 54cm**.

Conclusions

There are many possibilities of ML configuration – "**please choose wisely**".

If ANN cannot be implemented – there are simpler alternatives that are less demanding in terms of resources and/or computing power. **Weighted LS** is a good example.

A large database **is available for the evaluation of ML** schemes (thanks to Susanne Theis and Reinhold Hess) – interested parties should refer to Susanne for the possibility of using it for research purposes.

Thank you for your attention