# ANN post-processing of EPS

Andrzej Mazur, Grzegorz Duniec

*Institute of Meteorology and Water Management – National Research Institute, Warsaw, Poland 61 Podlesna str., PL-01-673 Warsaw, Poland*

## 1 Introduction

The results from research on COSMO-EPS, carried out at IMWM, are presented. The operational EPS set-up is based on perturbations of soil surface-area index of the evaporating fraction of grid points over land. Long-term evaluation results of different methods of EPS-post-processing. As a general rule, using Artificial Neural Network (ANN) values of EPS mean are significantly closer to observation of air temperature/dew point temperature or wind speed than those calculated as simple average or Multi-linear Mean. Extensive tests conducted during the COTEKINO Priority Project proved that small perturbations of selected soil parameter were sufficient to induce significant changes in the forecast of the state of atmosphere and to provide qualitative selection of a valid member of an ensemble (Duniec and Mazur, 2014). Changes of c_soil*) had a significant impact on values of air temperature, dew point temperature and relative humidity at 2m agl., wind speed/direction at 10m agl., and surface specific humidity (ibidem). The usage of an idea of time-lagged initial and boundary conditions allowed obtaining a valid ensemble and using it efficiently in an operational mode. Further work is intended to focus on "tuning" ensemble performance and to provide quantitative quality scores. For this purpose the random number generator combined with perturbations of initial soil surface temperature and the dependence of amplitude of perturbation on soil type will be implemented in the COSMO model.

While the set of equally weighted time-lagged forecasts improve short-range forecasts, the further progress may also be sought by adopting a regression approach to compute set of weights for different time-lagged ensemble members. EPS runs operationally at IMWM since January, 2016. It covers 4 runs/day, with 48 hours forecasts, 20 members/4 groups (using Time-lagged Ics/BCs; see Duniec G. et al. (2016); conf. Fig.1 below). Amplitude of perturbation of c_soil depends on type of soil (clay, sand, peat etc). [5]

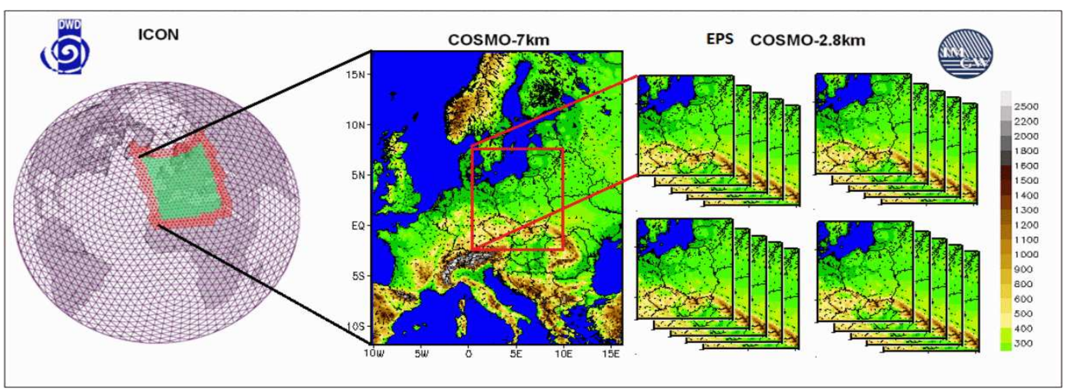


Figure 1: EPS operational configuration

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[5]*) surface-area index of the evaporating fraction of gridpoints over land

Table 1: Deterministic model(s) – source of ICs/BCs for operational EPS **ibidem)**

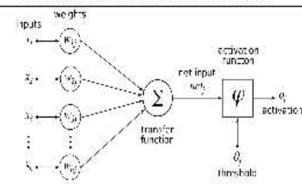
| Model | Grid size NxMxL | Forecast length(h) | Resolution(km) |
|---|---|---|---|
| ICON (DWD) | 2949120 triangles | 78 | 13 |
| COSMO v. 5.01 | 415x460x40 | 13 | 7 |
| COSMO v. 5.01$\hat{*}$ | 380x405x50 | 78 | 2.8 |

## 2 Some Formulas

Details of the deterministic models configuration are as follows:

Forecasts of air temperature and dew point temperature at 2m agl., surface pressure and windspeed at 10m agl., as well as other fields are available. As a result, plots/chart of EPS mean, spread, probabilities of threshold exceedance are prepared in the routine manner. Results are subsequently stored for further research (e.g. skill-spread relation) Results of EPS forecasts are subsequently calibrated. Three basic methods of calibration were examined as shown in Fig.2 – simple arithmetic mean (SM), multilinear regression mean (MLR) and artificial neural network mean (ANN).

Table 2. Ensemble calibration – Simple Mean (SM) vs. multilinear regression (MLR) mean vs. ANN mean

| Simple Mean*) | Multilinear regression **) | Artificial Neural Network***) |
|---|---|---|
| | |  |
| $x$ – forecast values, $y$ – ensemble mean, $m$ – # members | y – corrected forecasts – (new) ensemble mean, x – matrix of raw forecast values/parameters, β – weights (from previous fcsts.) | 24 input neurons ([illegible] + λ,φ + ts,tc) 5 neurons in a single hidden layer activation function: hyperbolic tangent |

*) Simple avg. – arithmetic mean, m=20 members;
**) # of predictors: n=24=20 members+geo.coords+lead/fcst.time;
***) Trained on data from July 2016 to March 2018, tested on data of April 2018

Figure 2: Ensemble calibration – Simple Mean (SM) vs. multilinear regression (MLR) mean vs. ANN mean

## 3 Results – comparison of results for three methods of post-processing.

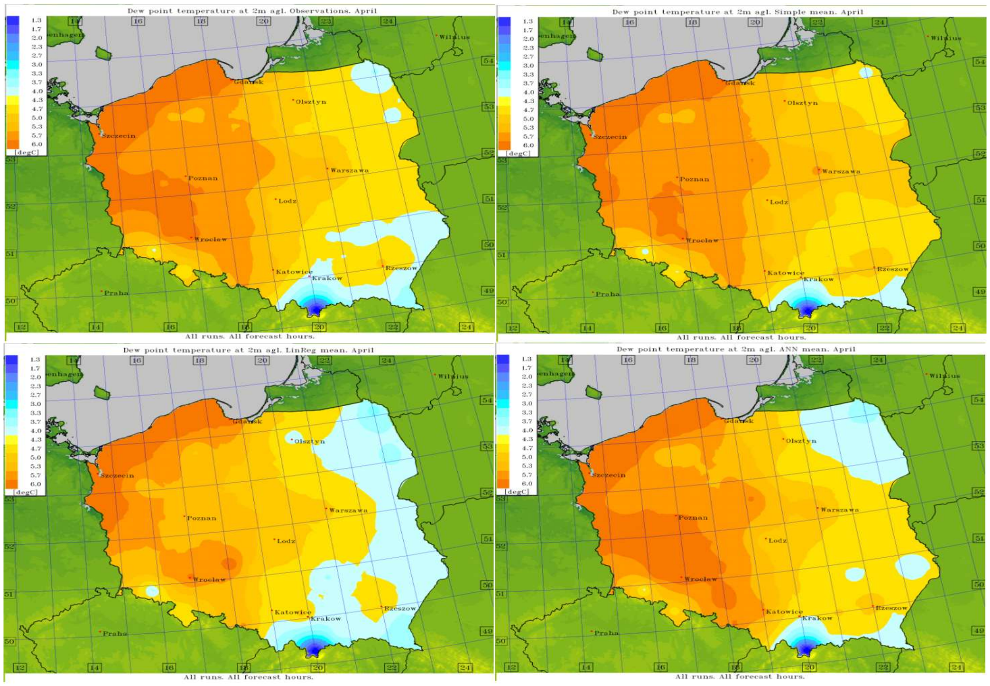



Figure 3: Spatial distribution of dew point temp. at 2m: mean observations (upper left), simple mean (upper right), MLR mean (24 predictors, lower left) and ANN mean (24 input neurons, lower right). All avg. values for April 2018.

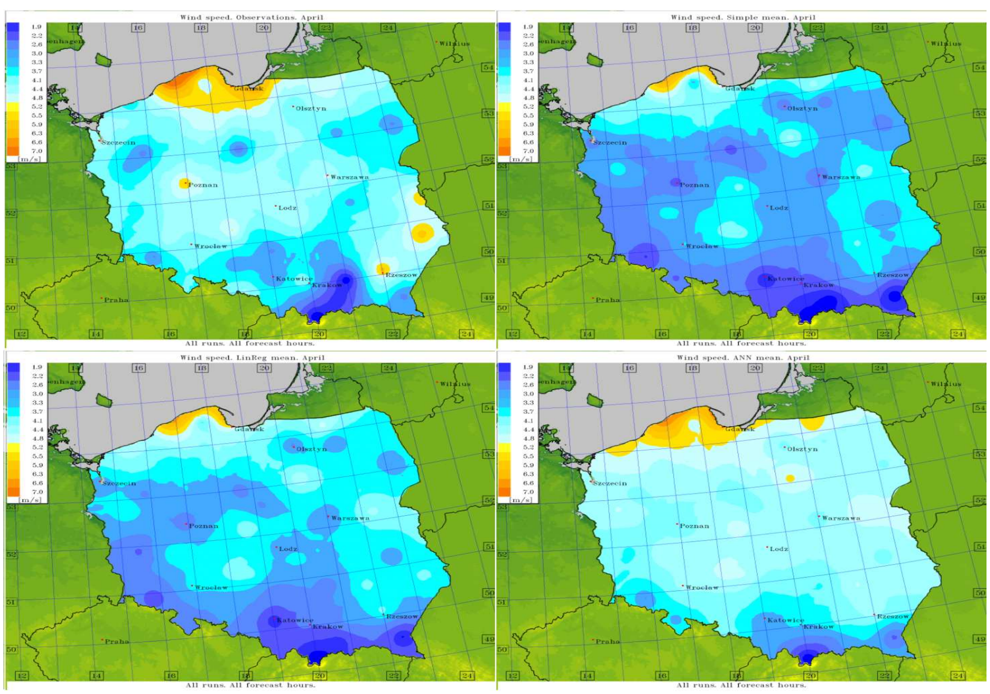



Figure 4: Spatial distribution of wind speed at 10m: mean observations (upper left), simple mean (upper right), MLR mean (24 predictors, lower left) and ANN mean (24 input neurons, lower right). All avg. values for April 2018.

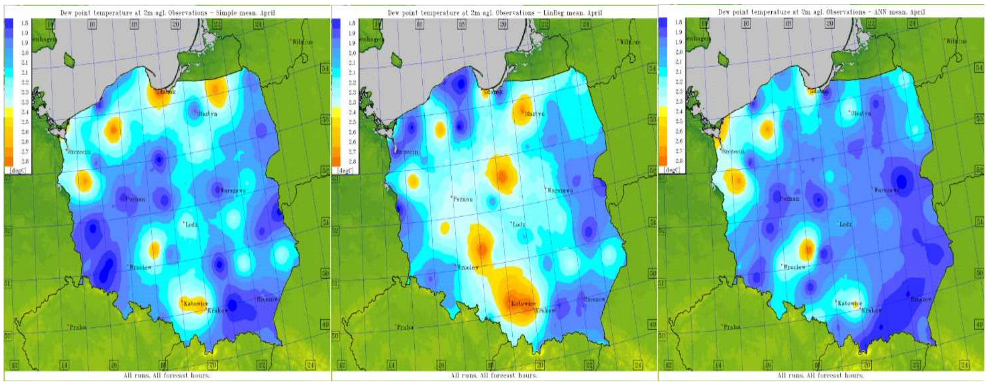


Figure 5: Spatial distribution of Mean Absolute Error (MAE) for dew point temp. at 2m, April 2018. Left: observations vs. simple mean; middle: observations vs. MLR mean; right: observations vs. ANN mean.

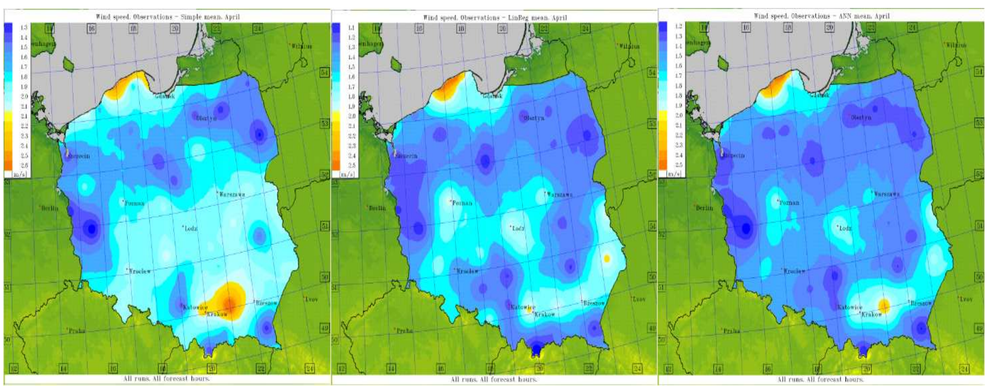


Figure 6: Spatial distribution of Mean Absolute Error (MAE) for wind speed at 10m, April 2018. Left: observations vs. simple mean; middle: observations vs. MLR mean; right: observations vs. ANN mean.

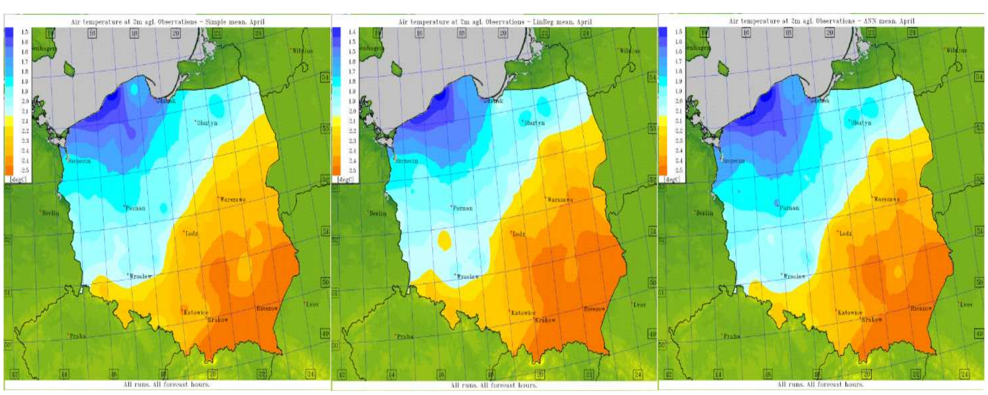


Figure 7: Spatial distribution of Mean Absolute Error (MAE) for air temp. at 2m, April 2018. Left: observations vs. simple mean; middle: observations vs. MLR mean; right: observations vs. ANN mean.

Table 2: Basic statistics for different post-processing methods, as calculated for April, 2018 (ME – mean error, MAE – mean absolute error, RMSE – root-mean square error, MinE – minimum error, MaxE – maximum error)

| Means | ME | MAE | RMSE | MinE | MaxE |
|---|---|---|---|---|---|
| **Dew point** | | | | | |
| SM | 0.253 | 2.009 | 2.812 | -12.4 | 15.1 |
| MLR | -0.310 | 1.989 | 2.755 | -12.3 | 14.8 |
| ANN | -0.244 | 1.981 | 2.750 | -11.2 | 14.8 |
| **Air temp.** | | | | | |
| SM | 0.771 | 2.369 | 3.443 | -14.600 | 18.100 |
| MLR | 0.475 | 2.252 | 3.206 | -14.500 | 16.600 |
| ANN | 0.066 | 2.214 | 3.135 | -13.600 | 15.500 |
| **Windspeed** | | | | | |
| SM | -0.618 | 1.737 | 2.297 | -13.6 | 13.6 |
| MLR | 0.113 | 1.488 | 1.978 | -7.8 | 13.2 |
| ANN | -0.200 | 1.436 | 1.814 | -6.1 | 13.2 |

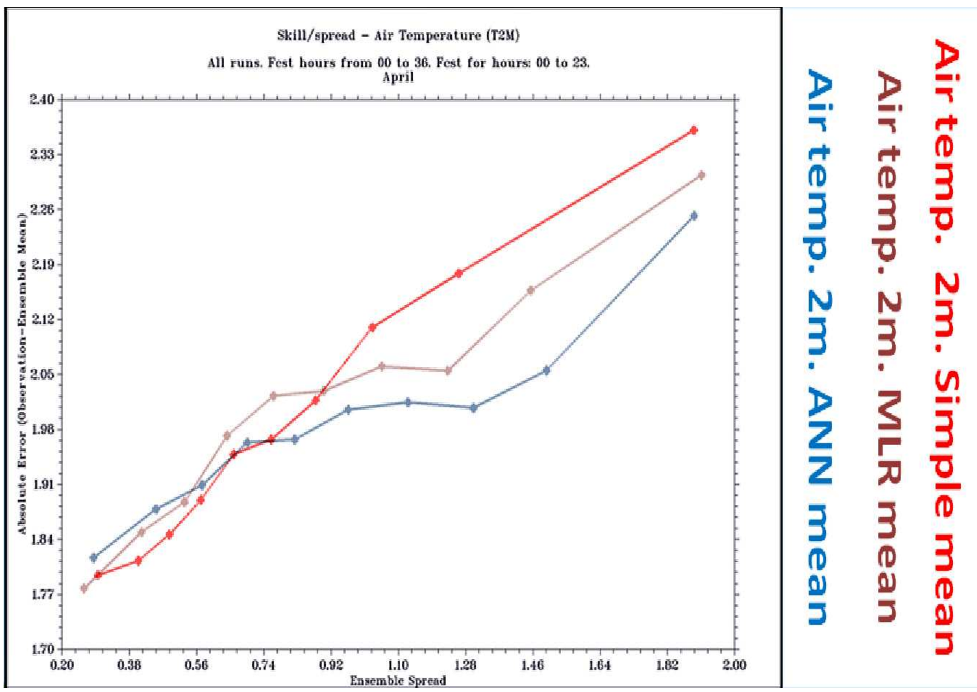



Figure 8: Skill/spread relation for air temp. at 2m, April 2018.

## 4 Conclusions

Except for single case of mean error for windspeed results of ANN post-processing gives evidently the best results in terms of statistic evaluation and skill-spread relation (see Fig. 7). Keeping in mind arguments against ANN (complicated pre- and post-processing, need for big data sets and huge computational resources, long computational time for training) one can say that this method, with ready-to-use dedicated software with source codes (FORTRAN) is sophisticated yet elegant and intuitive concept. Improvement in preliminary case study can be clearly observed and forecasts are getting better and better with the extension of learning period, which is a key reason to go on with ANN in an operational EPS.

Artificial Neural Network is linked to the DMO, to extend the learning period. In the operational mode 24 predictors is set (values from twenty ensemble members + spatio-temporal coordinates). The system is set in an (quasi)operational mode (slight delay due to calculations). Results are collected four times per day, so the structure of ANN can be updated frequently

The results in a poster form were presented at 40th EWGLAM/25th SRNWP Workshop in Salzburg, Austria, October 2018.

# References

[1] Duniec, G. and Mazur, A. (2014): COTEKINO Priority Project – Results of Sensitivity Tests, COSMO Newsletter, 14, **106-113**.

[2] Duniec, G., Interewicz, W., Mazur, A. and Wyszogrodzki, A. (2016): Operational Setup of the COSMO-based, Time-lagged Ensemble Prediction System at the Institute of Meteorology and Water Management – National Research Institute. Met. Hydrol. Water Manage. (2017) vol. 5; (2): **43-51**.

[3] Mazur, A. and Duniec, G. (2017): SPRED PP activities at IMWM-NRI. Presented at COSMO GM, Jerusalem, Israel.

[4] Mazur, A., Duniec, G. and Interewicz, W. (2018): Introductory activities in PP APSU at IMWM-NRI and results of ANN post-processing of EPS forecasts. Presented at COSMO GM, Sankt Petersburg, Russia.