Influence of Perturbation Type on Results of EPS Forecasts of Surface Elements

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1 Introduction

Abstract

The results from research on COSMO-EPS, carried out at IMWM, are presented. The operational EPS (Ensemble Prediction System) set-up is based on perturbations of soil surface-area index of the evaporating fraction of grid points over land. In the research mode, six different types of perturbation is additionally applied. Long-term evaluation results of different methods of EPS-post-processing is presented in the paper. As a general rule, using Artificial Neural Network (ANN) values of EPS mean are significantly closer to observation of air temperature/dew point temperature/surface pressure or wind speed than those computed as deterministic forecast.

Introduction

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$\hat{*}$) 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)*. Other approaches of perturbation (as presented in previous work) would result in different forecast, expecting even a synergy while combining perturbation methods for the same run(s). The research has been carried out for the entire year 2011. For the ANN training results from January to October have been set. Methods *(approaches)* have been tested on results from November 2011. [4].

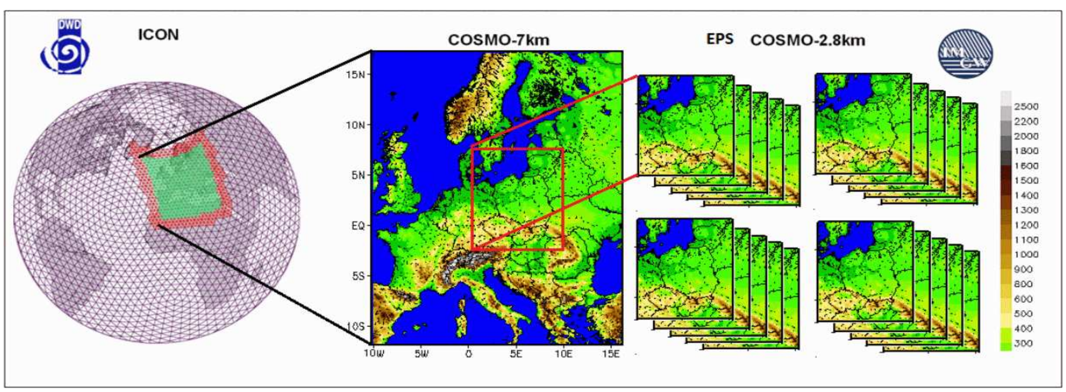

Figure 1: EPS operational configuration *(Duniec et al., 2016)*

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[4]*)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

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 exceedances are prepared in the routine manner. Results in a raw form are subsequently stored for further research research (e.g. skill-spread relation) and simultaneously calibrated.

Artificial Neural Network(ANN) mean(s) in this research have been compared with direct results from "deterministic" forecasts (DET). ANN in this resarch consisted of 24 input neurons (20 members, geographical coordinates, forecast start and forecast hour; there were 5 neurons set in a single hidden layer, with hyperbolic tangent accepted as the activation function.

The following perturbations were considered:

a) *c_ soil*-perturbation of a parameter describing evaporation from soil(described above);
b) *eff-coeff*-perturbation of the collection efficiency coefficient;
c) *eff-c_ soil*-perturbation of the collection efficiency coefficient together with c_soil;
d) *laf-pert*-perturbation of the surface temperature of the soil;
e) *laf-c_ soil*-perturbation of soil surface temperature in the set of initial conditions with c_soil;
f) *laf-eff*-perturbation of the soil surface temperature (as in *e*) with the collection efficiency coefficient(b);
g) *eps-all*-perturbation of all the above quantities (fields and parameters) at the same time;
h) *operational* perturbation of c_soil with a different random number generator (Duniec et al., 2016), operational runs

3 Results – comparison of results for different methods of perturbations.

Table 2: Basic statistics for different perturbation methods with ANN post-processing, compared with values from deterministic runs, as calculated for November, 2011 (ME – mean error, MAE – mean absolute error, RMSE-root-mean square error, MinE-minimum error, MaxE-maximum error)

Means	ME	MAE	RMSE	MaxE	MinE
Dew point					
c_soil	-0.11338	1.45981	1.99090	12.30946	-9.88111
eff-coeff	-0.01667	1.47110	2.00072	11.11471	-9.41829
eff-c_soil	0.04247	1.45814	1.98011	11.53134	-9.92467
eps-all	-0.00854	1.49234	2.02759	11.24309	-9.09813
laf-pert	-0.04460	1.46721	1.99155	10.89753	-9.27700
laf-c_soil	0.01080	1.51334	2.04447	10.83230	-8.87939
laf-eff	-0.05678	1.46489	1.99521	10.47621	-9.37223
operational	0.02424	1.46355	1.98274	10.49569	-9.10767
deterministic	-0.40246	1.58561	2.18141	13.04700	-10.08800
Air temp					
c_soil	0.17387	1.77275	2.32496	10.93927	-15.88361
eff-coeff	-0.15550	1.77681	2.34730	11.16211	-16.14814
eff-c_soil	-0.08983	1.76932	2.34525	10.54141	-16.63289
eps-all	0.07055	1.77859	2.34857	10.31766	-15.89856
laf-pert	0.09633	1.78876	2.34243	10.67038	-14.61441
laf-c_soil	0.06539	1.76116	2.31501	10.84628	-15.06645
laf-eff	-0.18840	1.77813	2.33403	10.50841	-15.01652
operational	-0.13666	1.78166	2.34402	10.80536	-15.59283
deterministic	0.44751	1.90295	2.62627	11.77100	-12.86600
Windspeed					
c_soil	0.04309	1.17025	1.58737	9.72965	-9.05961
eff-coeff	-0.07475	1.17811	1.59937	9.64747	-9.06740
eff-c_soil	0.02018	1.16574	1.58048	9.74929	-9.87465
eps-all	0.04844	1.16578	1.58195	9.74003	-6.55868
laf-pert	0.10026	1.17006	1.58576	9.77432	-5.21126
laf-c_soil	-0.04346	1.17756	1.60043	10.00780	-11.41867
laf-eff	-0.07655	1.17344	1.58327	9.63682	-7.45664
operational	-0.03980	1.17237	1.59618	9.70848	-10.99594
deterministic	-0.26905	1.30687	1.88147	12.76900	-3.03400
Pressure					
c_soil	0.00985	1.60175	2.08209	32.14813	-23.20300
eff-coeff	0.06719	1.63273	2.10419	31.09039	-24.85364
eff-c_soil	-0.13769	1.68544	2.20423	30.00128	-22.65503
eps-all	0.01005	1.64700	2.14694	31.19647	-22.99243
laf-pert	-0.10553	1.65470	2.14979	30.91657	-23.75635
laf-c_soil	-0.08059	1.64437	2.15423	30.03619	-23.26672
laf-eff	-0.12735	1.59559	2.08393	30.57135	-25.36975
operational	-0.01102	1.65513	2.15091	30.22253	-23.53040
deterministic	1.03752	4.22822	8.11503	26.29303	-47.95404
Green color denotes best values,red – worst values					

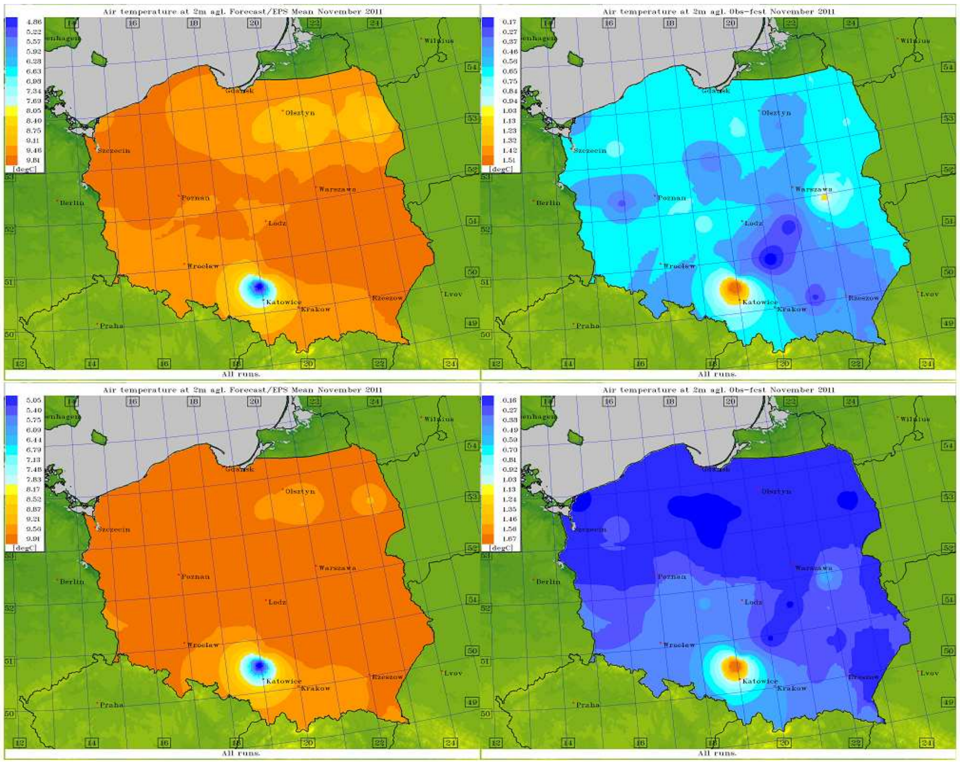

Figure 2: Spatial distribution of air temperature at 2m: ANN (eff-c_soil) mean (upper left) and skill (upper right), deterministic mean forecast (lower left) and skill (lower right).All avg. values for November 2011

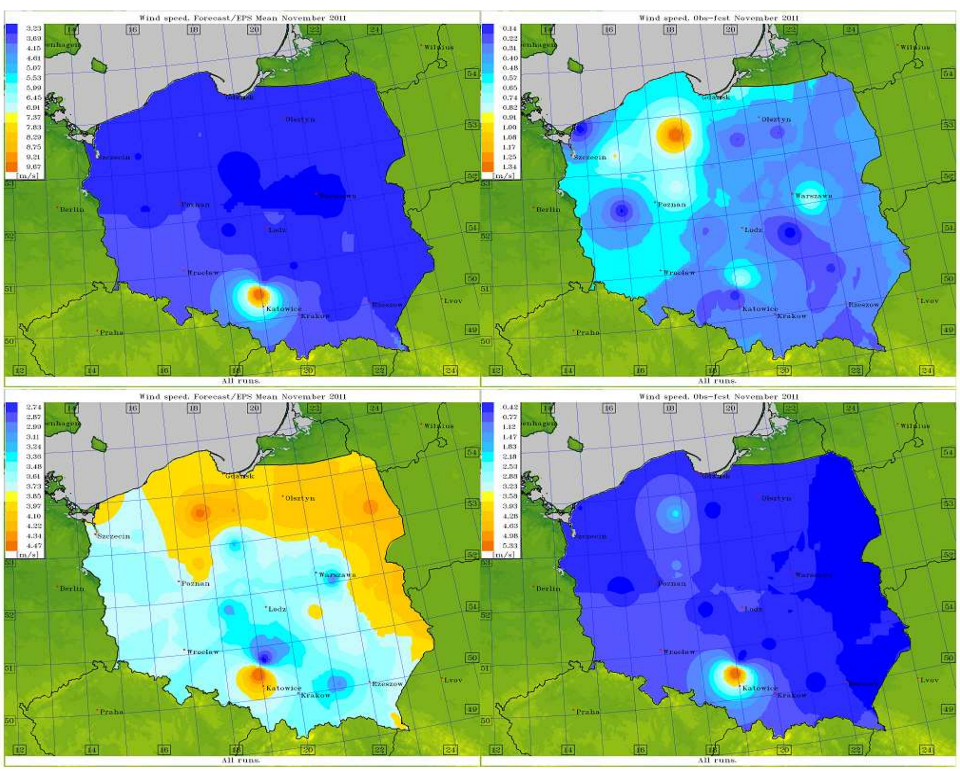

Figure 3: Spatial distribution of wind speed at 10m: ANN (eff-c_soil) mean (upper left) and skill (upper right), deterministic mean forecast (lower left) and skill (lower right). All avg. values for November 2011

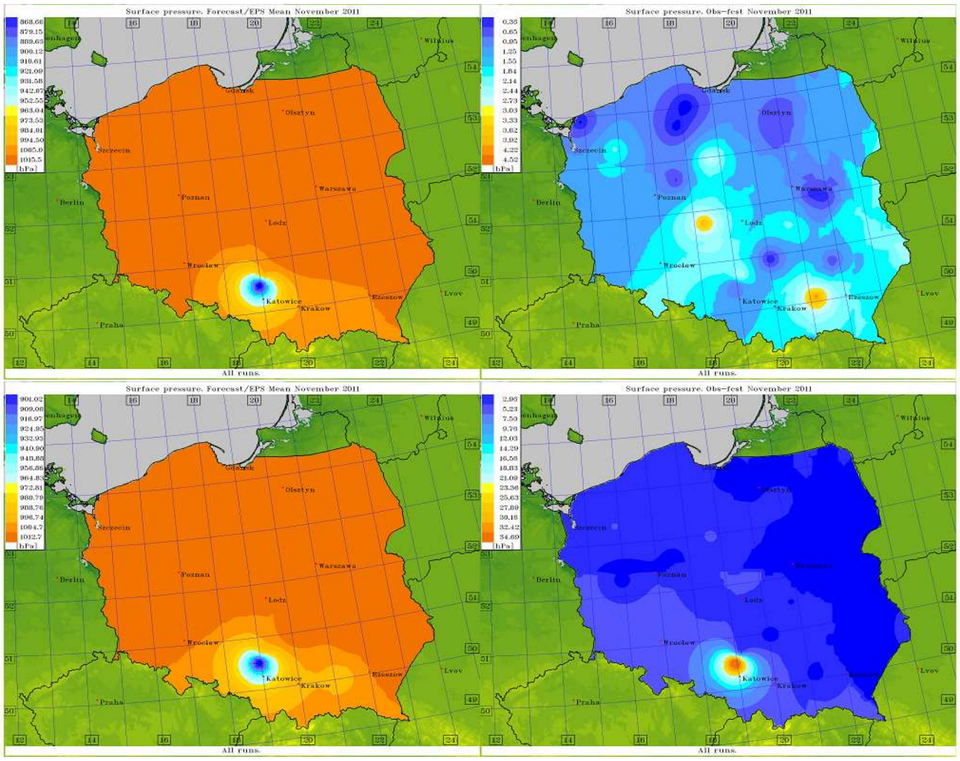

Figure 4: Spatial distribution of surface pressure: ANN (c_soil) mean (upper left) and skill (upper right), deterministic mean forecast (lower left) and skill (lower right). All avg. values for November 2011

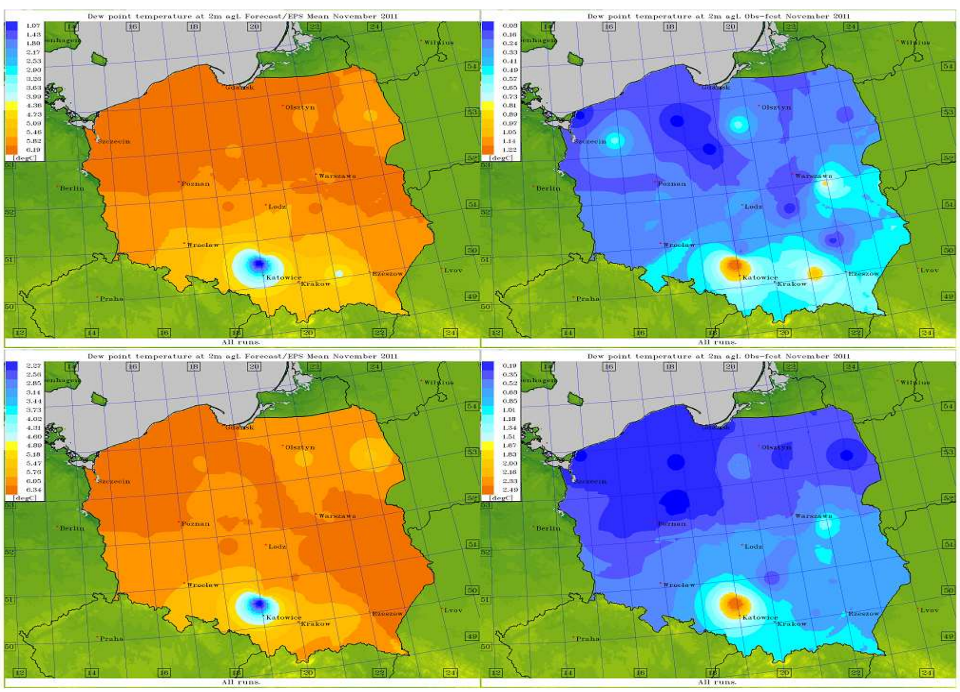

Figure 5: Spatial distribution of dew point temperature at 2m: ANN (eff-c_soil) mean (upper left) and skill (upper right), deterministic mean forecast (lower left) and skill (lower right). All avg. values for November 2011

4 Conclusions

Except for few cases of min/max errors results of ANN postprocessing gives evidently the best results in terms of statistic evaluation in comparison to "deterministic" forecast. 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. However, there was no effect of synergy with combining perturbation methods and objects. Yet, c_soil alone and with combination with some other perturbation methods seemed to be the best as far as overall statistics is concerned (see *Table 2* and *Figures 2-5*).

The results in a poster form to be presented partially at ICCARUS in Offenbach, Germany, March 2019 and partially at EGU General Assembly in Vienna, Austria, April 2019.

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.