



# **SPRED PP activities at IMWM-NRI**

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## Introduction



1. Operational since January, 2016
2. 4 runs per day, 36 hours forecasts, 20 members in 4 groups
3. Forecasts of T2M, TD2M, PS, U10M, TOT\_PREC...
4. Other elements' forecasts also available (specific, dedicated)
5. Immediate post-processing (probabilities, charts and plots...)
6. Results stored for further investigations (skill-spread relation)

# Ensemble Prediction System – operational setup and status

## Setup

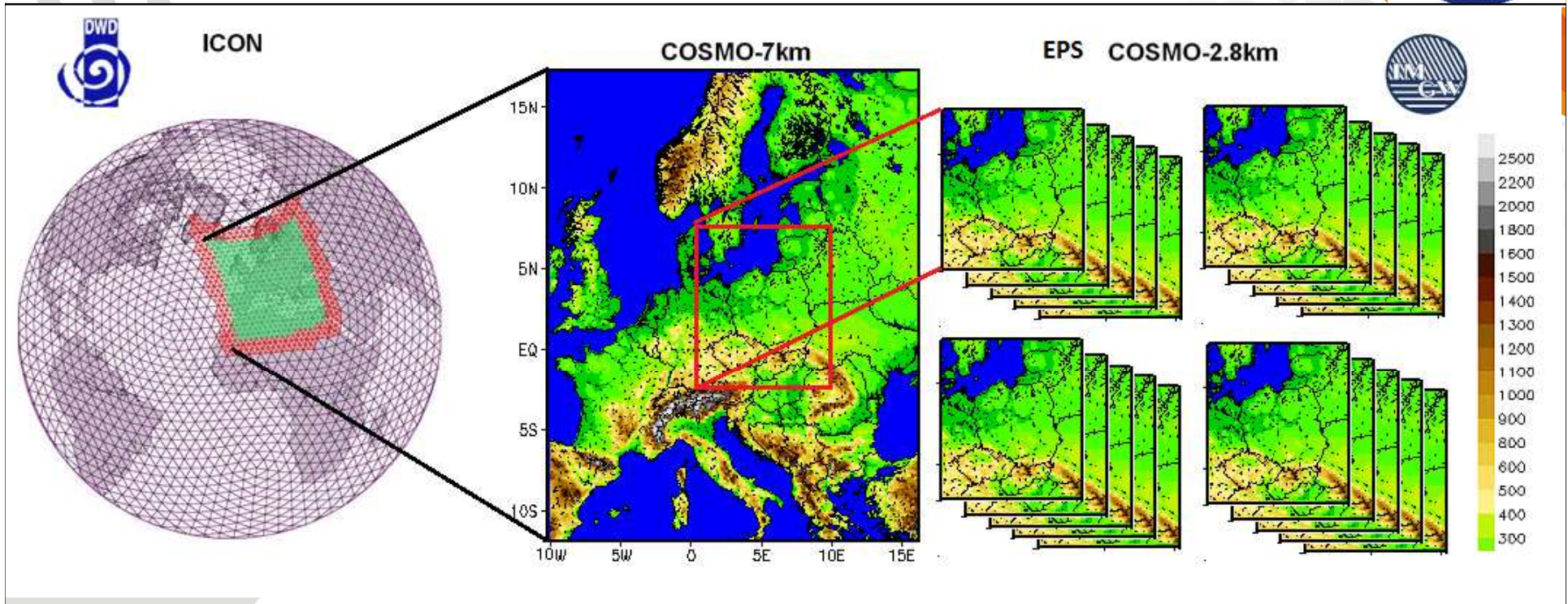
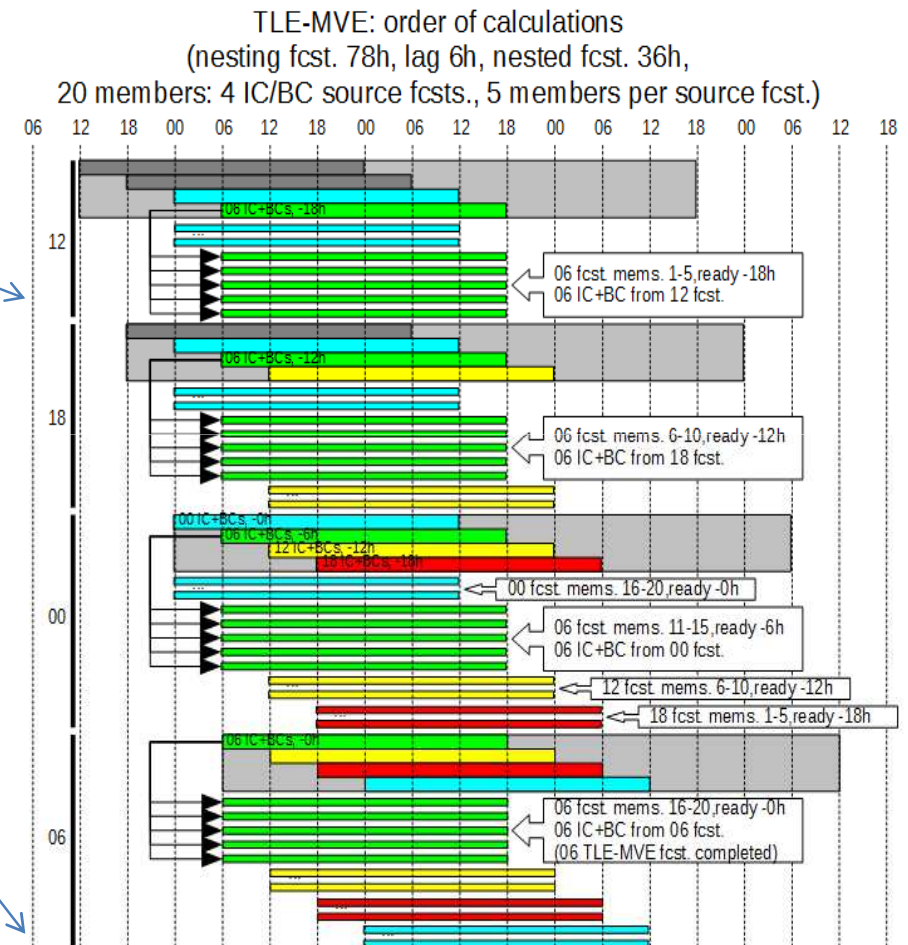


Table 1. Details of the deterministic models configuration.

Model	Resolution	Grid size NxMxL	Forecast length [h]
ICON (DWD)	13	2949120 triangles	78
COSMOv5.01	7	415x460x40	78
COSMOv5.01	2.8	380x405x50	36



TLE-MVE: general concept  
(nesting fcst. 78h, lag 6h, nested fcst. 36h,  
20 members: 4 IC/BC source fcsts., 5 members per source fcst.)

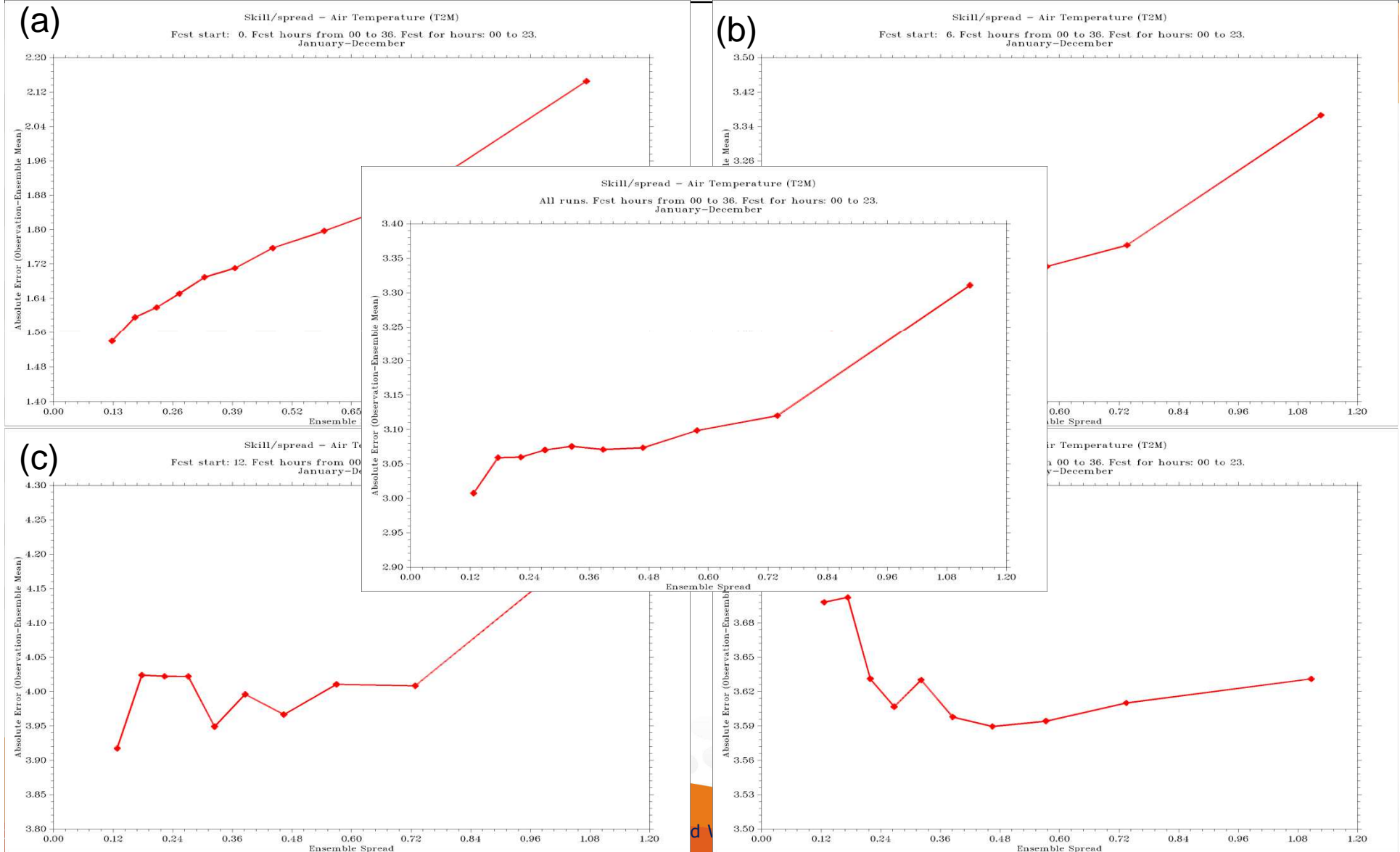


TLE – Time-Lagged Ensemble; MVE – Model-Varied Ensemble

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## Task 1 – Study of the spread/skill relation

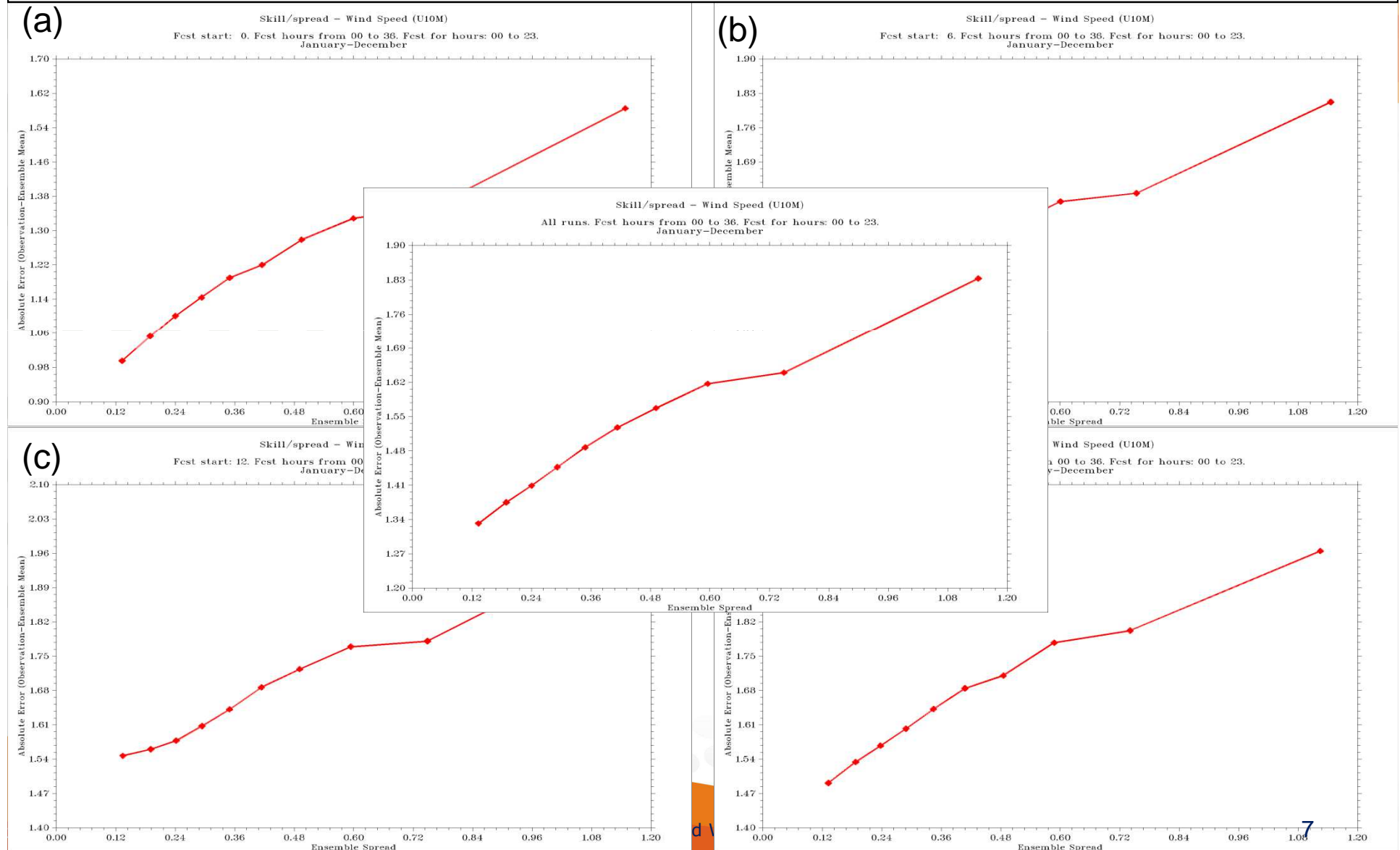
(a) Skill-Spread diagram for T2M, 00h run. (b) ..., 06h run. (c) ..., 12h run. (d) ..., 18h run. Average values for 2016



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# Task 1 – Study of the spread/skill relation

(a) Skill-Spread diagram for U10M, 00h run. (b) ..., 06h run. (c) ..., 12h run. (d) ..., 18h run. Average values for 2016

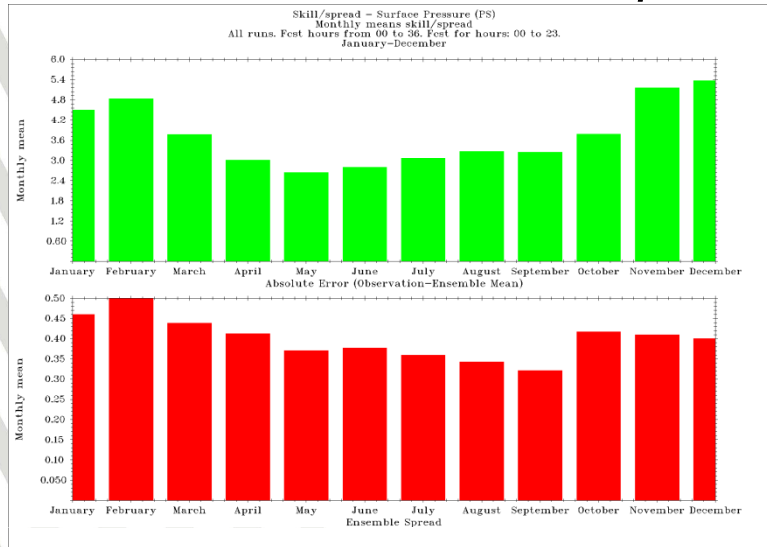


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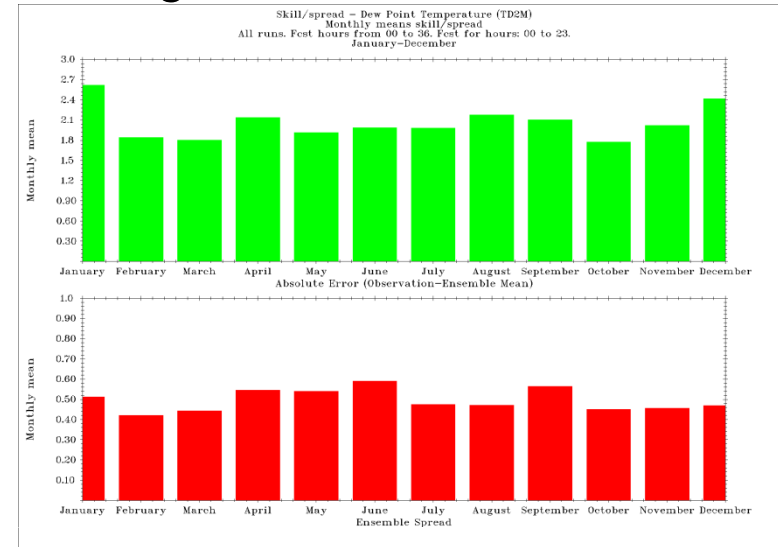
## Task 1 – Study of the spread/skill relation

### *Skill-Spread monthly averages*

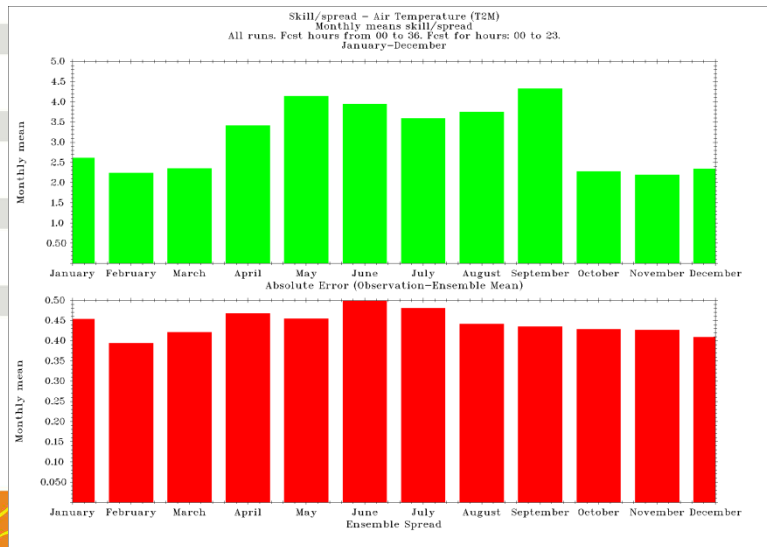
(a)



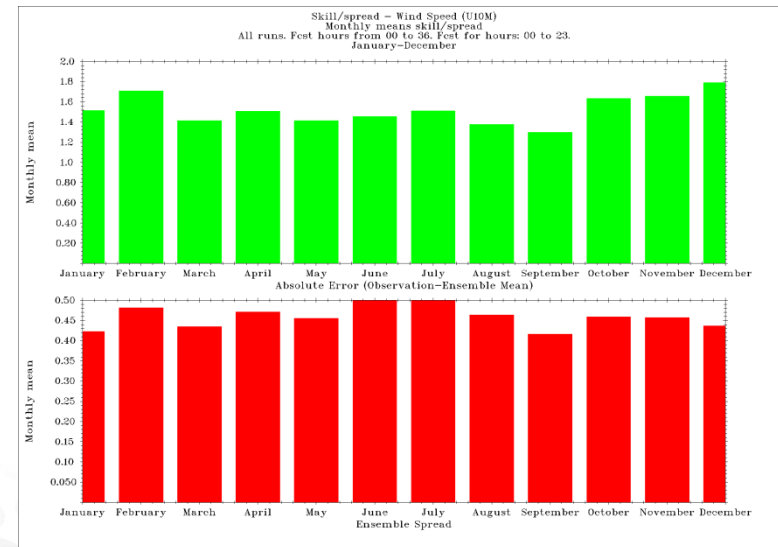
(b)



(c)



(d)

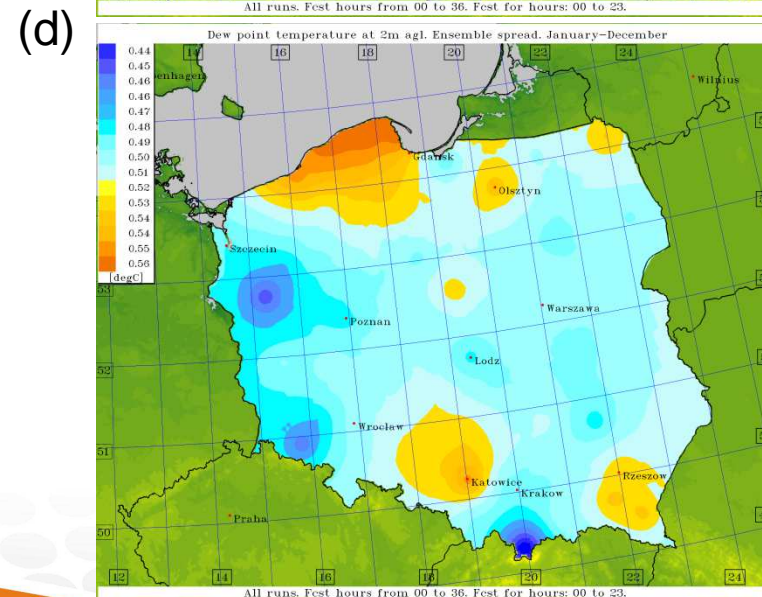
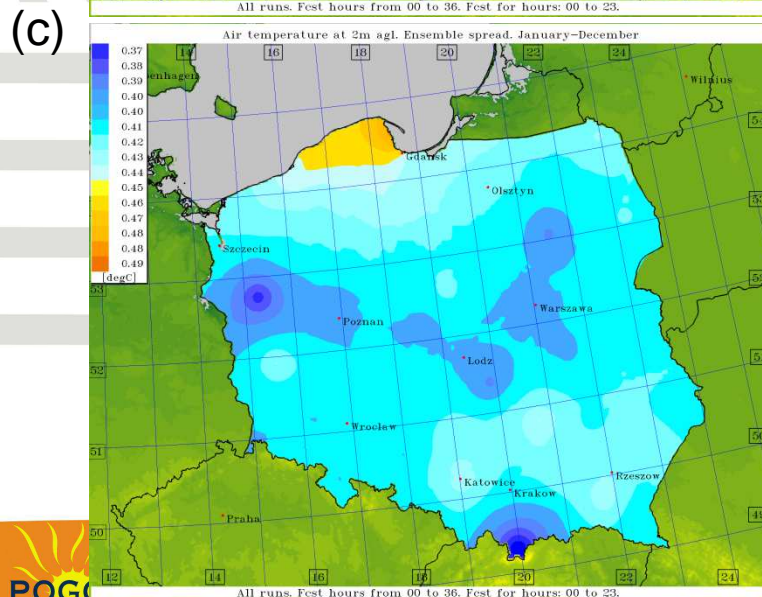
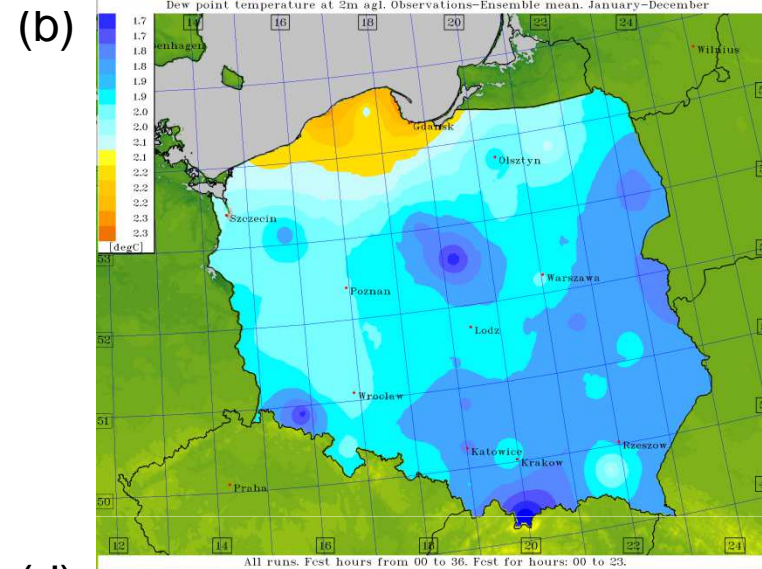
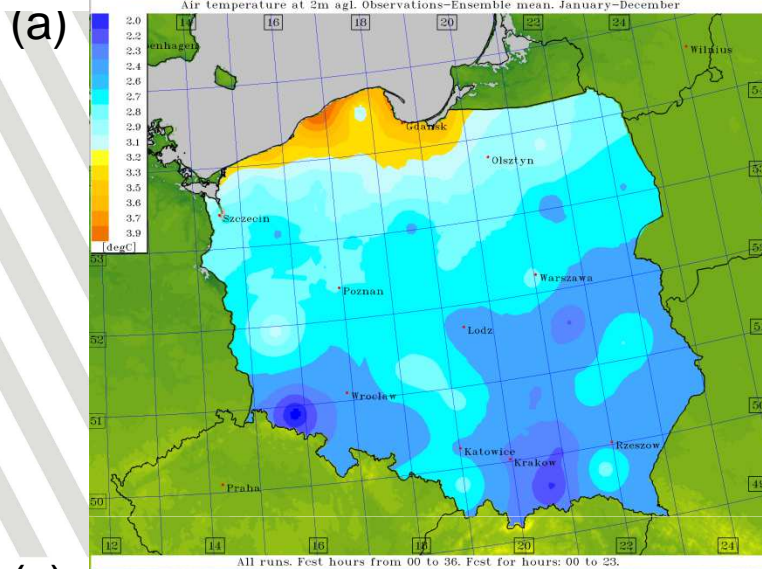




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# Task 1 – Study of the spread/skill relation

## *Skill-Spread spatial distribution*



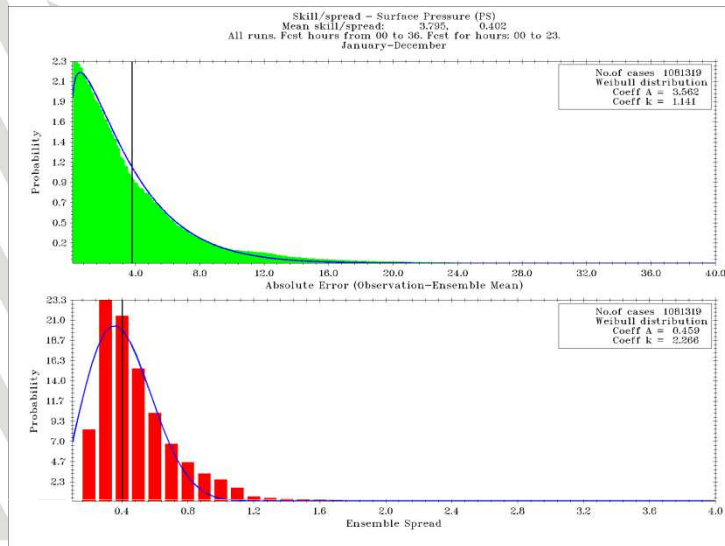
Avg. skill (up)/spread (down); T2M, TD2M (all runs, all fcst hours, Jan-Dec)

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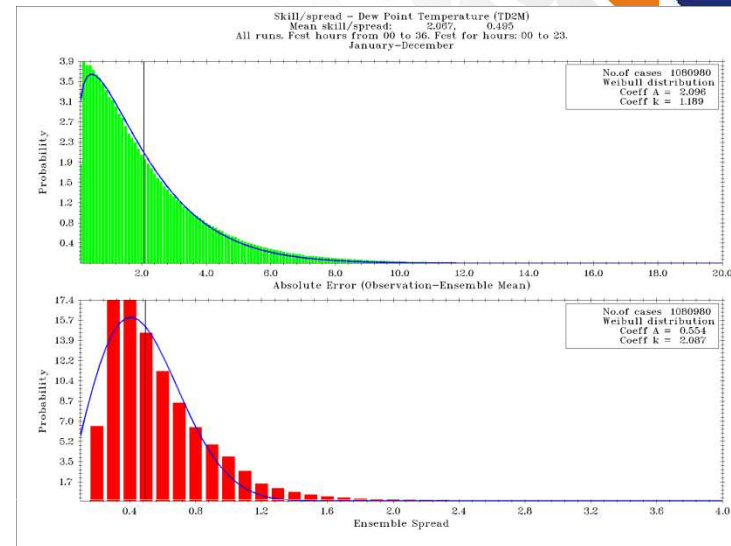
# Task 1 – Study of the spread/skill relation

## Skill-Spread statistics

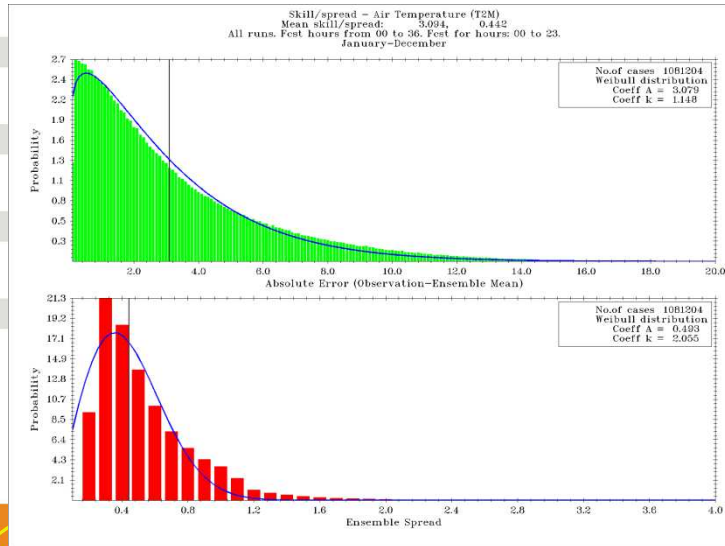
(a)



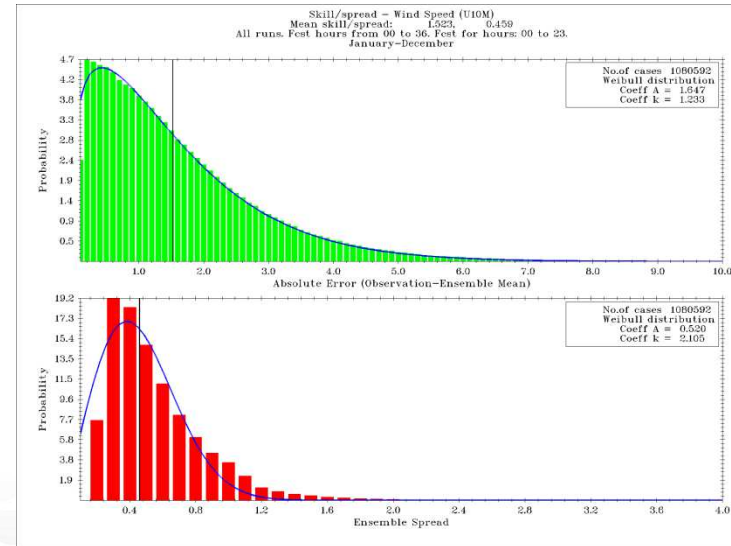
(b)



(c)



(d)



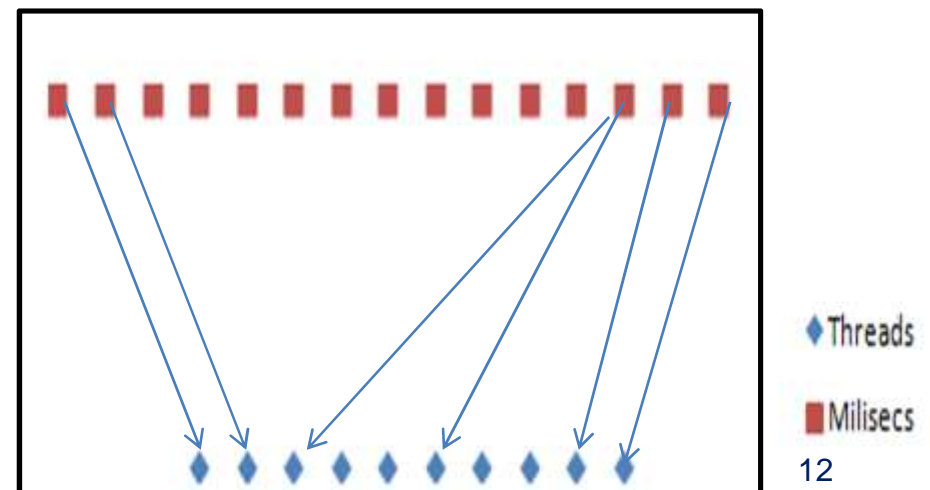
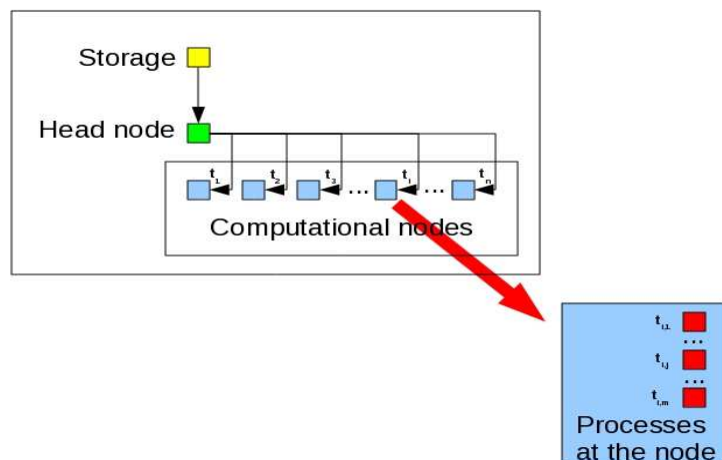
## Conclusions – Task 1 – operational runs

- Skill/spread relation was studied thoroughly, using operational EPS results. Study has been carried out for months, seasons, entire year and, simultaneously, for runs (00, 06, 12, 18), forecast hours (0-36) and hours (0-23).
- Average spread is in general 2x to 10x lower than skill measured as MAE.
- Spatial relations (Poland) – skill is in general better (i.e., smaller,) for central and southern part – probably due to EPS generation. Spread is bigger in central and northern part of Poland
- Similarly for time relation (monthly means) – skill is in general better (i.e., smaller) for warm months – probably due to EPS generation Spread is bigger for warm months – probably due to EPS generation
- Spread values – Weibull's distribution with shape coefficient  $k$  about 2 (low variability), while for MAE shape coefficient is closer to 1 – close to exponential distribution (high variability)
- Scale coef.  $A$  is bigger (3x to 10x) for MAE (wide) than for spread (sharp).

## Activities in the frame of PP SPRED – Task 1

### *Motivation for new initialisation (seed) of RNG*

- Seed of RNG is based on machine time (in general, milliseconds).
- On fast machines seed may be identical for all processes (threads).
- More threads – increased probability of an occurrence of identical seeds .
- Operational setup: 400 threads vs. 999 msecs
- On fast machines you do not have 999 msecs, but much, much less!!!





## Activities in the frame of PP SPRED – Task 1

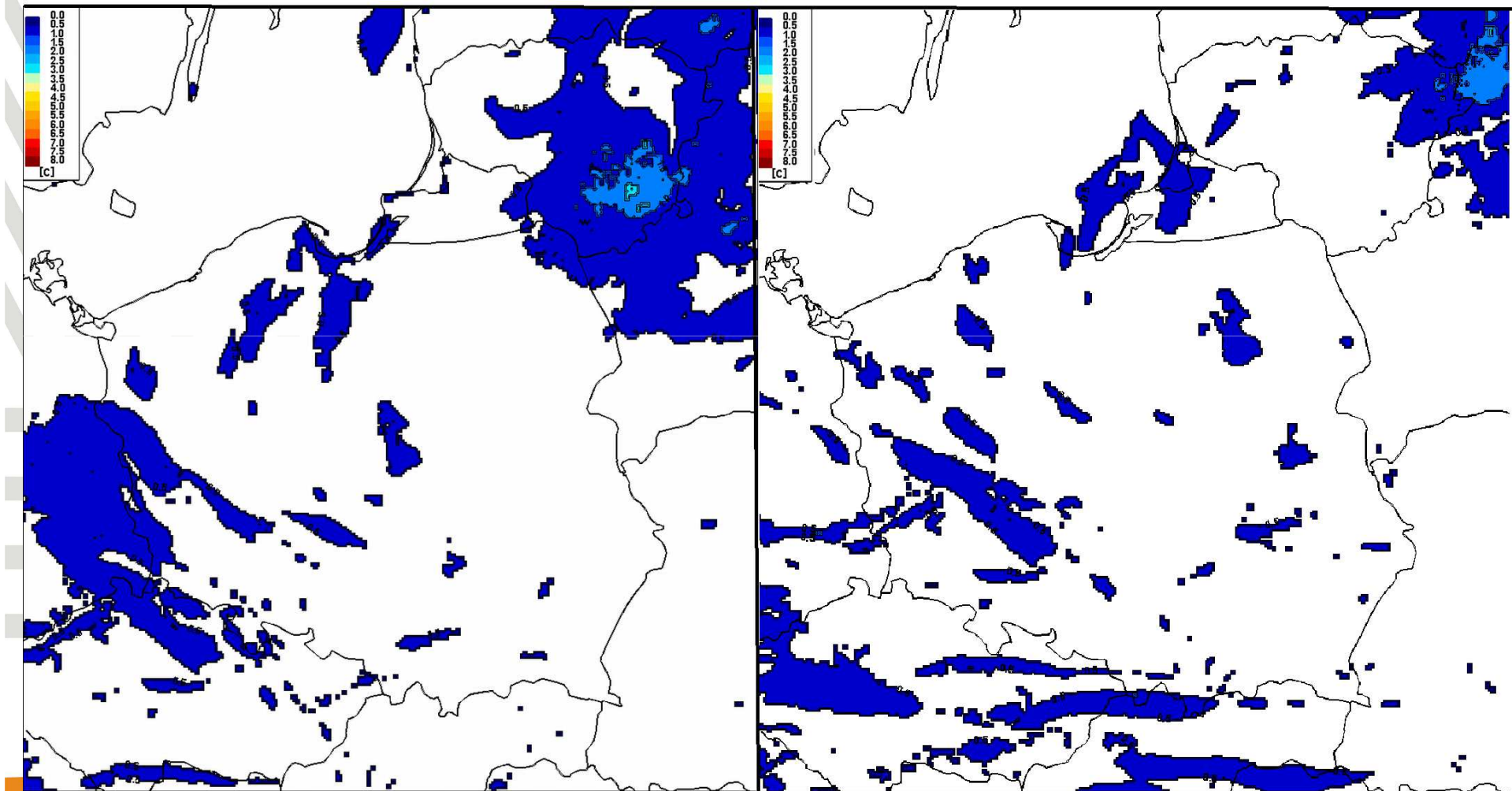
*Results (archive runs, June 2013, no time-lagged lcs/BCs)*

<b>Spread values</b>	<b>Reference (previous operational RNG)</b>	<b>Modified RNG</b>	
<b>T2m (K)</b>			
Mean	0.108191	0.238555	←
Max	2.262	2.458	
<b>TD2m (K)</b>			
Mean	0.118675	0.272361	←
Max	3.284	3.536	
<b>Rel. hum. (%)</b>			
Mean	0.705627	2.120926	←
Max	12.261	14.758	
<b>U10m (m/s)</b>			
Mean	0.139599	0.180653	←
Max	2.041	2.903	
<b>Pressure (hPa)</b>			
Mean	0.023892	0.027456	←
Max	0.747	0.652	
<b>Tot. precip. (mm)</b>			
Mean	0.286905	0.379897	←
Max	13.203	18.515	

## Activities in the frame of PP SPRED – Task 1

### *Results – old vs. new RNG*

Start of forecast: 2016-12-02 06:00



T2M spread for new (left) and old (right) RNG; 12 hour of forecast

## Conclusions – new RNG



- Very efficient (spread) – especially on fast machines
- More "realistic" in spread' spatio-temporal distribution
- Operational since January 2017
- First statistics to be available shortly

## Task 3 – Lower boundary perturbation

### *Perturbation of other fields/parameters: soil surface temperature and collection efficiency coefficient*

- Soil surface temperature (analysis – *laf*) was perturbed using described RNG
- An amplitude of perturbation was related to the soil type (clay, sand, peat etc.).
- Additional constraints applied – an average perturbation over the entire domain is set to zero via normalization of perturbation values.

Collection efficiency coefficient  $E_c$  (*eff-coeff*) describes the efficiency with which a drop intercepts and unites with the smaller drops it overtakes.

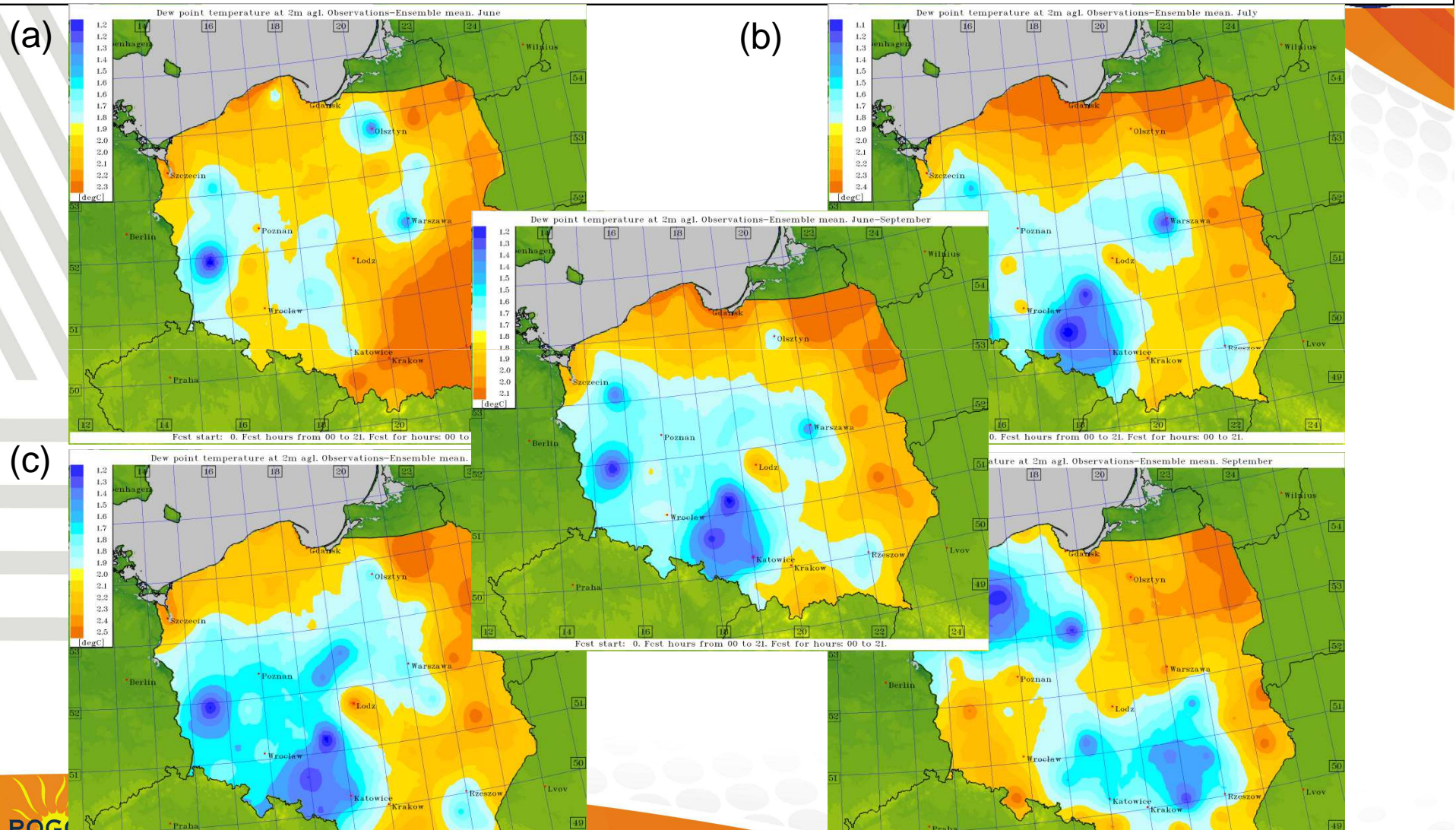
- $E_c$  is largely determined by the relative airflow around the falling drop.
- Smaller particles may be carried out of the path of the collector drop ( $E_c < 1$ ) or droplets not in the geometrical sweep-out volume may collide with the large drop due to turbulence or electric effects ( $E_c > 0$ ).
- In COSMO  $E_c$  is assumed constant and equal to 0.8.
- Perturbation was effective only for non-zero precipitation ☺.

- Combinations of all perturbations were also examined.



## Task 3 – Lower boundary perturbation

MAE (skill) spatial distribution for TD2M, (a) June (*eff-coef*), (b) July (*c-soil*), (c) August (*eff-coef*), (d) September (*c-soil*).



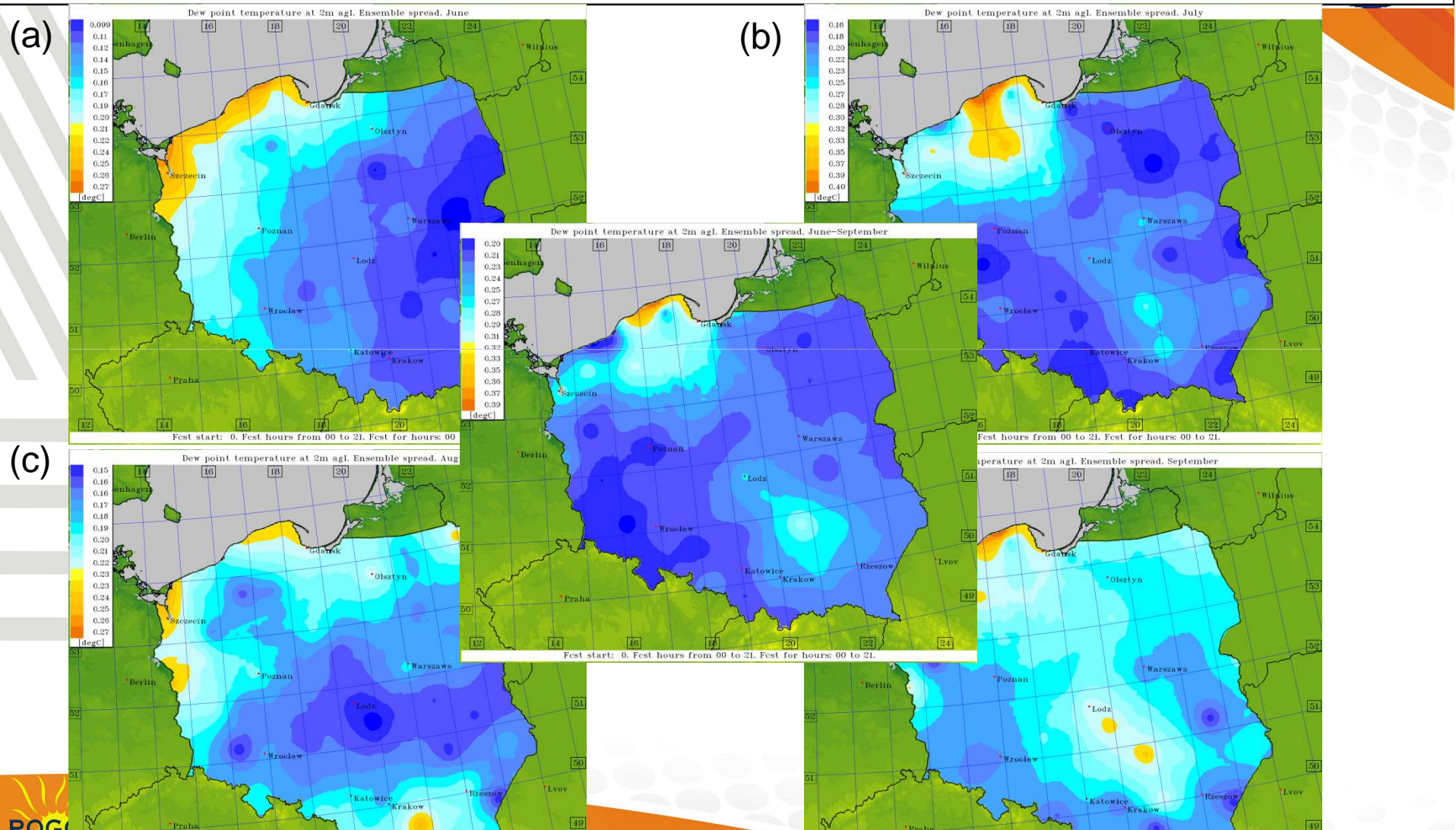
*c-soil* perturbation combined with sfc temperature perturbation (*laf-c-soil*)



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## Task 3 – Lower boundary perturbation

Spread spatial distribution for TD2M, (a) June (*eff-coef*), (b) July (*c-soil*), (c) August (*eff-coef*), (d) September (*c-soil*).

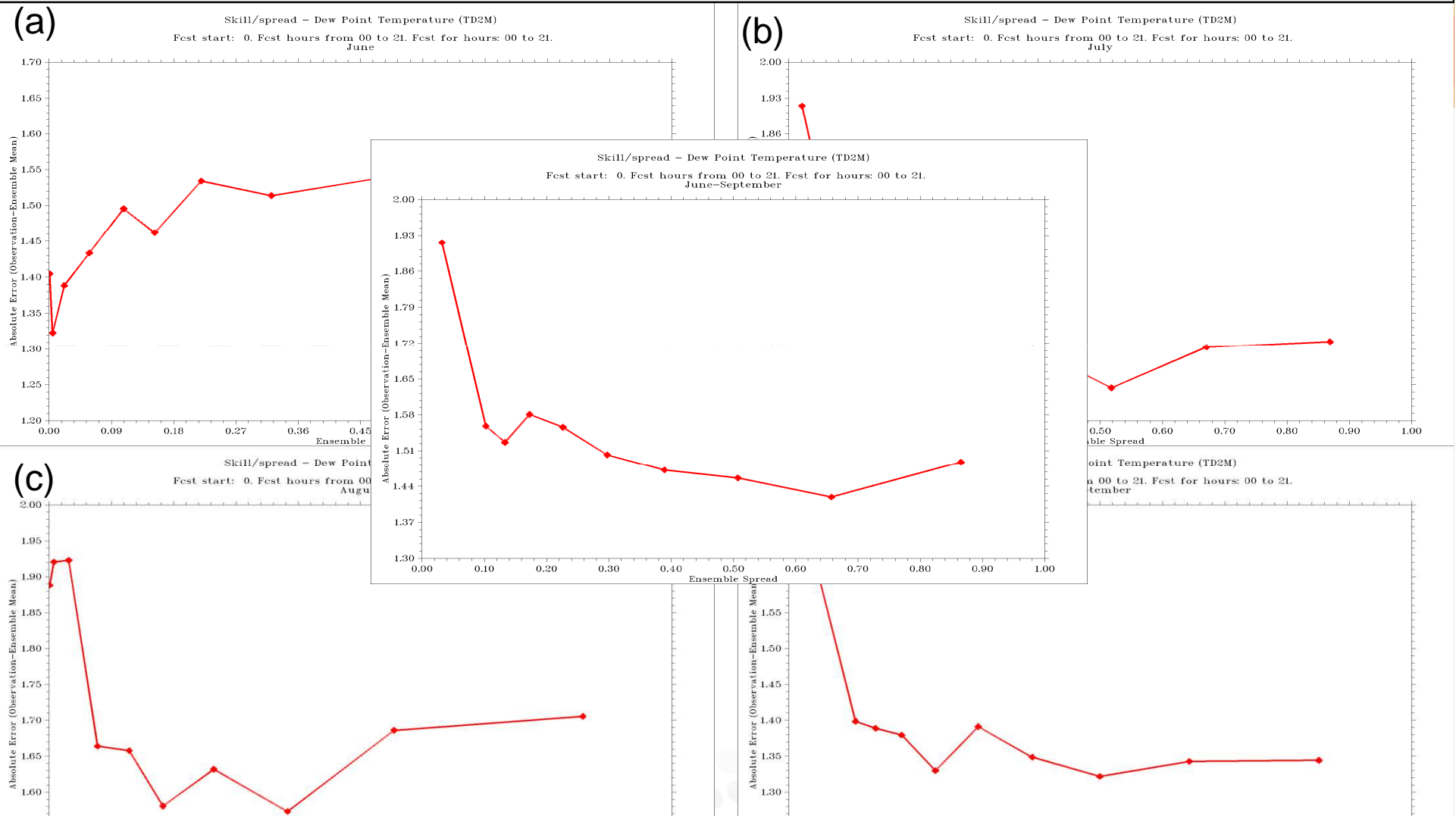


*c-soil* perturbation combined with sfc temperature perturbation (*laf-c-soil*)

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## Task 3 – Lower boundary perturbation

Skill-Spread diagram for TD2M, (a) June (*eff-coef*), (b) July (*c-soil*), (c) August (*eff-coef*), (d) September (*c-soil*).

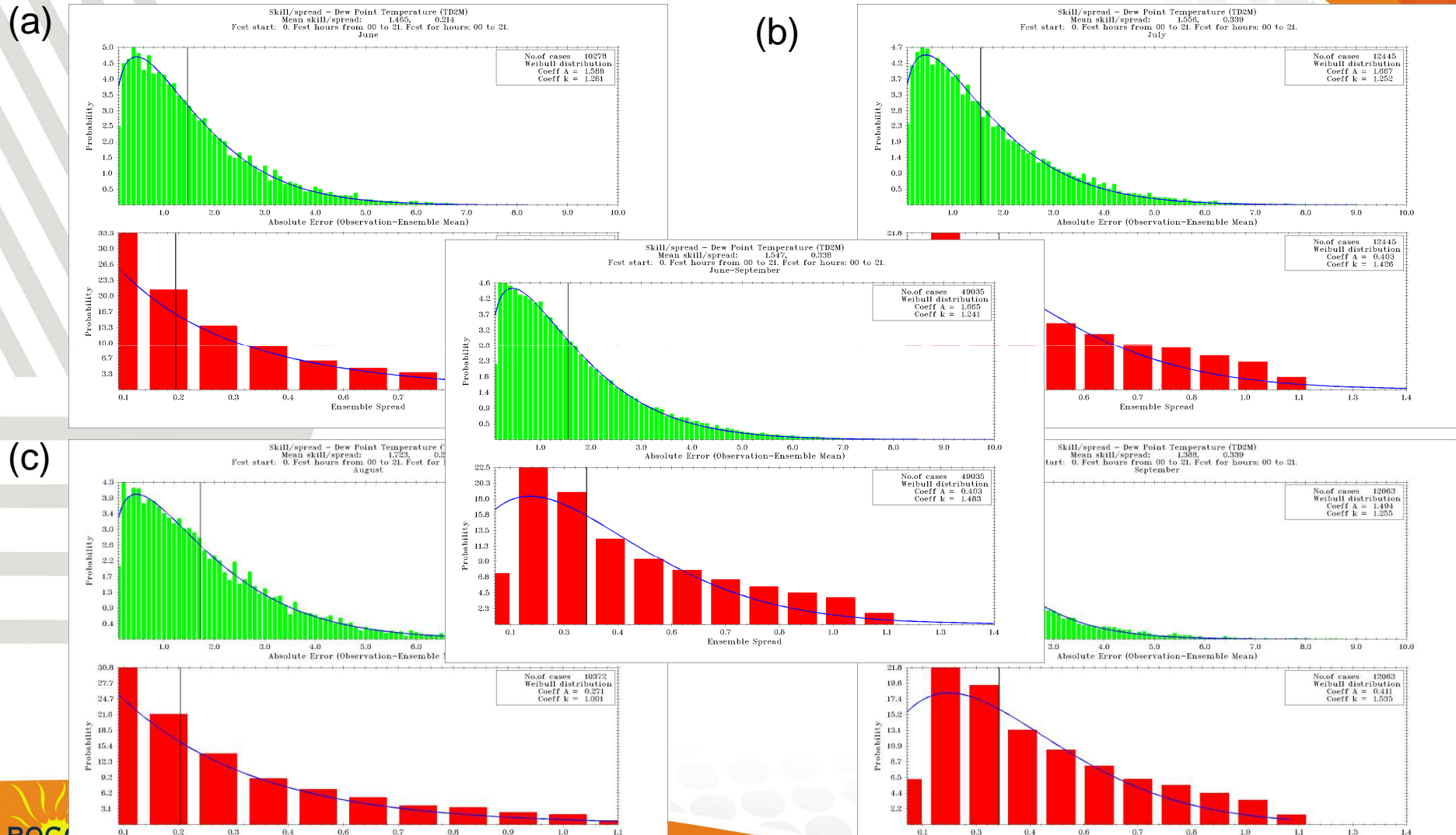


*c-soil* perturbation combined with sfc temperature perturbation (*laf-c-soil*)

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## Task 3 – Lower boundary perturbation

Skill-Spread statistics for TD2M, (a) June (*eff-coef*), (b) July (*c-soil*), (c) August (*eff-coef*), (d) September(*c-soil*).



*c-soil* perturbation combined with sfc temperature perturbation (*laf-c-soil*)

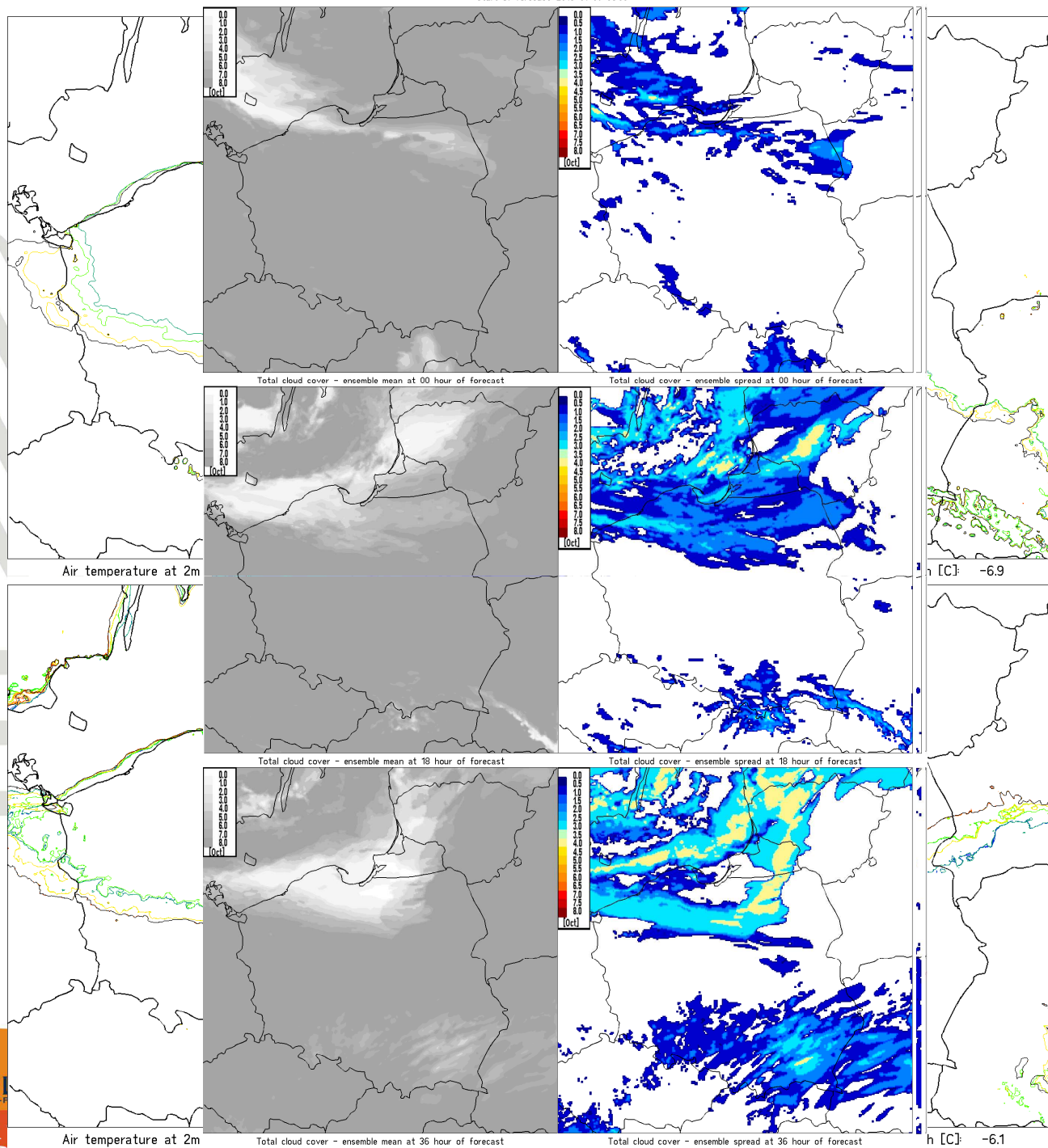


## Conclusions – Task 3

Most effective perturbation schemes (combinations) in terms of MAE and spread, avg. for Jun-Aug, 2013:

Period/Field	TD2m	T2m	U10m
<i>June</i>	eff-coef	@	@ (~ eff-c-soil)
<i>July</i>	c-soil	eff-coef	@ (~ laf-c-soil)
<i>August</i>	eff-coef	eff-coef	@ (~ laf)
<i>September</i>	c-soil	eff-coef	@
<i>Jun-Sep</i>	laf-c-soil	eff-coef	@

@ – hard to say  
"~" – "itsy-bitsy"



n



## Task 4 – Post-processing and interpretation

### *Ensemble calibration*



(Multi)Linear regression approach – compute weights for different ensemble members.

$$\begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix} = \begin{pmatrix} x_{11} & \dots & x_{1p} \\ x_{21} & \dots & x_{2p} \\ \dots & \dots & \dots \\ x_{n1} & \dots & x_{np} \end{pmatrix} \cdot \begin{pmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_p \end{pmatrix}$$

$y$  – corrected (calibrated) forecast(s) – (new) ensemble mean,

$X$  – matrix of input forecast values [& parameters],  $\beta$  – weights

$$\beta_i = f(\lambda, \varphi, t_s, t_c, m)$$

$x$  –  $T2M$ ,  $U10M$ ,  $TD2M$ ,  $PS$

$\lambda, \varphi$  – geo. coordinates

$t_s, t_c$  – forecast start, current hour,  $m$  – # member

## Task 4 – Post-processing and interpretation

Linear regression results:

Fields	Predictors <sup>*)</sup> →	24	22	20	Simple avg. <sup>**) </sup>
	↓ MAE				
<b>U10M</b>	Avg.	1.168	1.182	1.187	1.373
	Max	1.748	1.754	1.783	2.519
<b>T2M</b>	Avg.	2.327	2.481	2.483	2.606
	Max	3.173	3.466	3.475	3.628
<b>TD2M</b>	Avg.	1.634	1.646	1.651	1.736
	Max	1.957	1.993	1.989	2.006
<b>PS</b>	Avg.	2.725	2.727	2.785	2.864
	Max	11.284	11.286	10.589	11.786
<b>TOT_PREC</b>	Avg.	0.967	0.972	0.973	0.808
	Max	1.677	1.679	1.693	1.514

<sup>\*)</sup> Predictors: 20 – members (history, learning); 22 – 20 + geo.coords.; 24 – 20 + geo.coords. + forecast start + current hour,

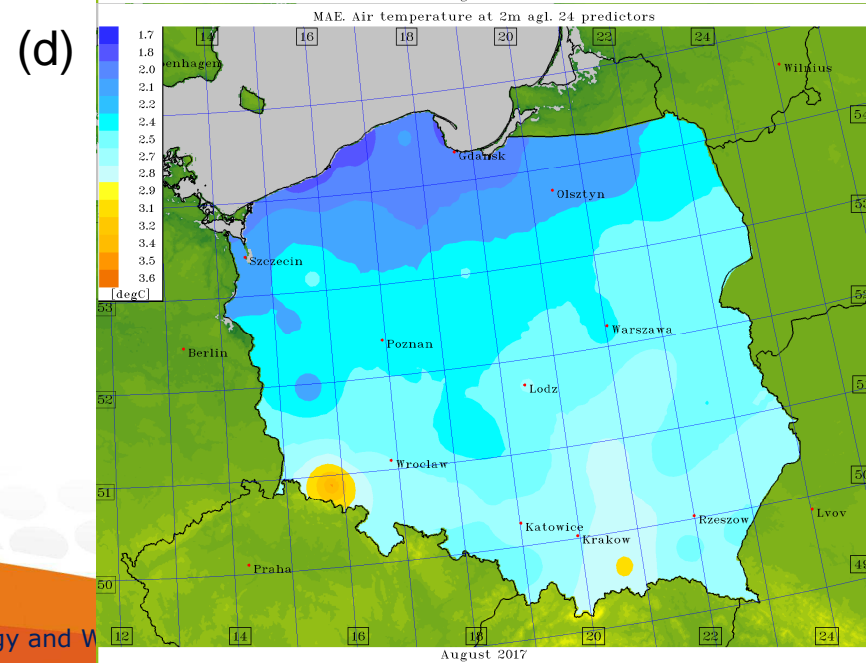
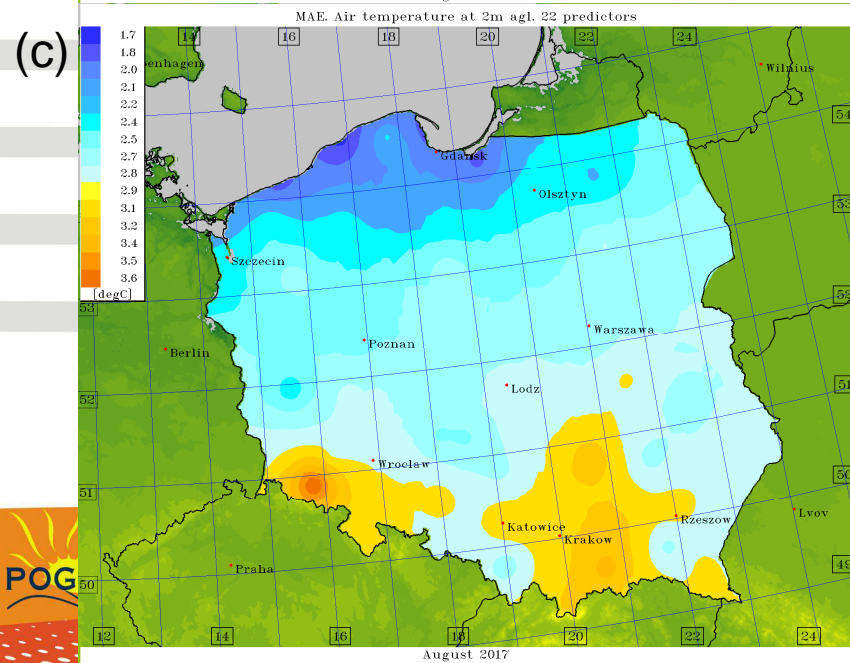
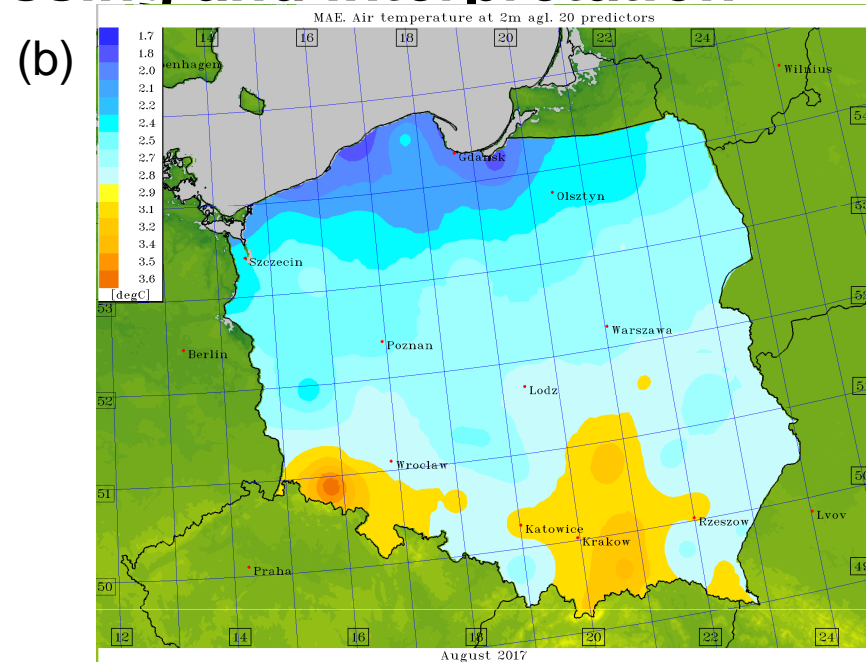
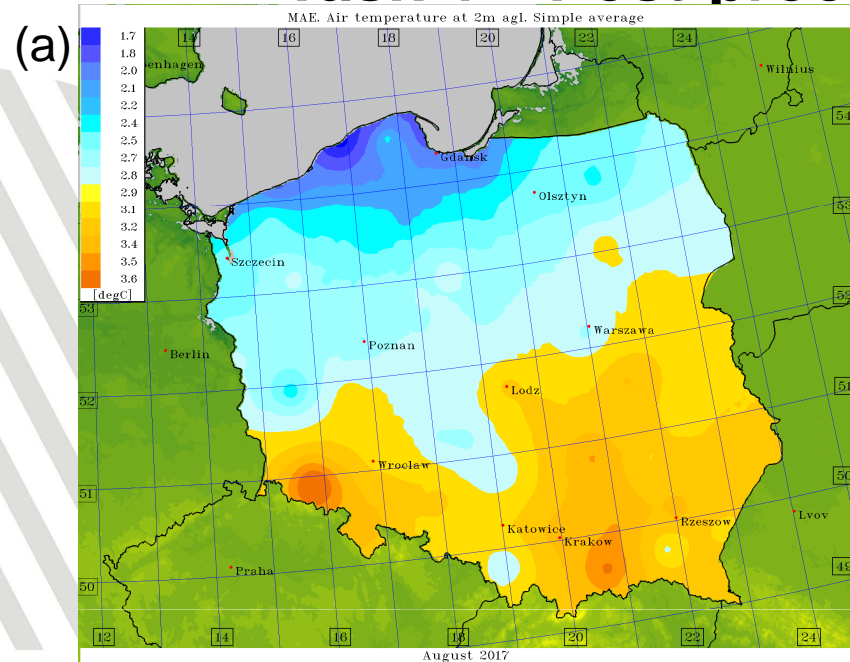
<sup>\*\*)</sup>  Simple averaging – 20 members mean (current forecast)

Learning: July 1<sup>st</sup>, 2016 – July 31<sup>st</sup>, 2017

Testing: August 1<sup>st</sup>, 2017 – August 31<sup>st</sup>, 2017

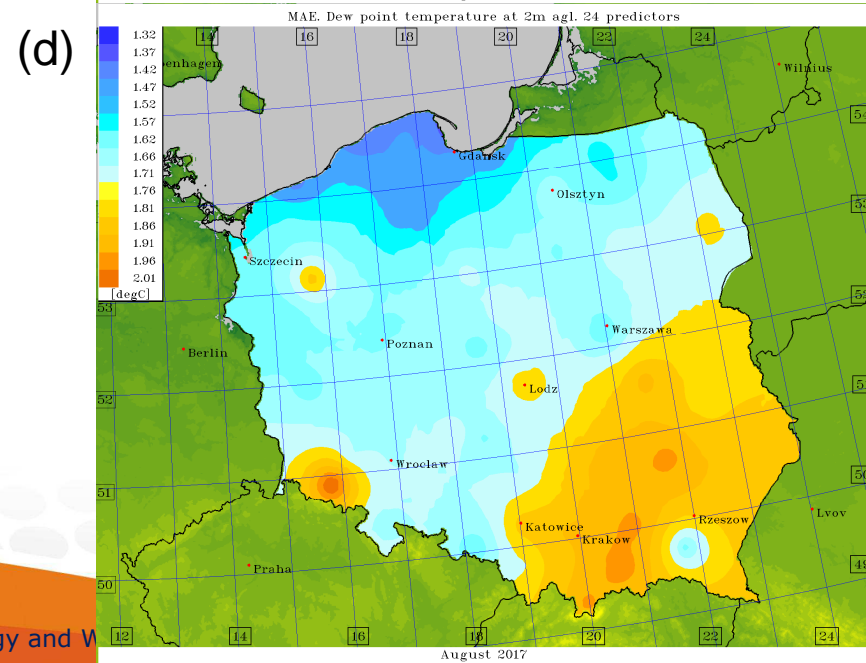
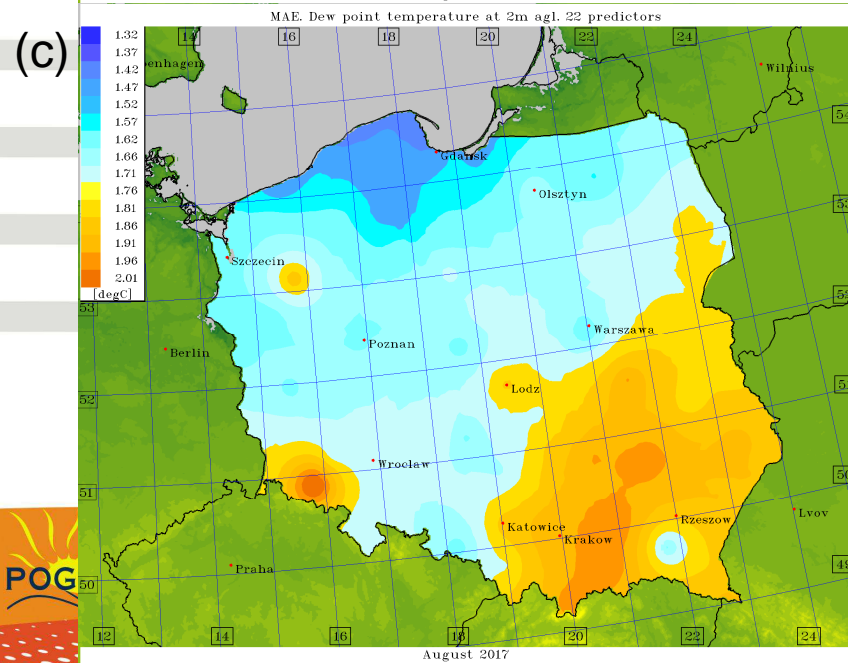
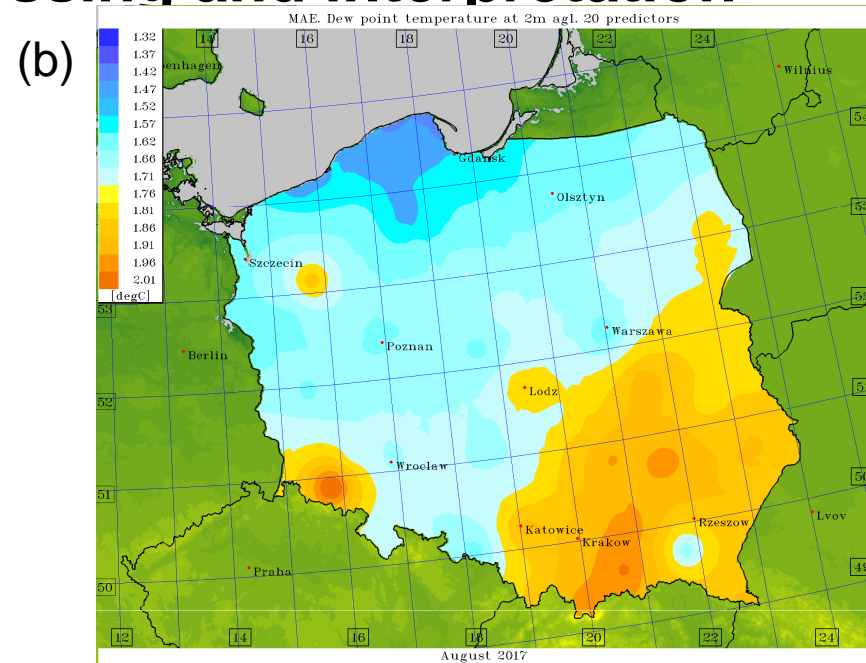
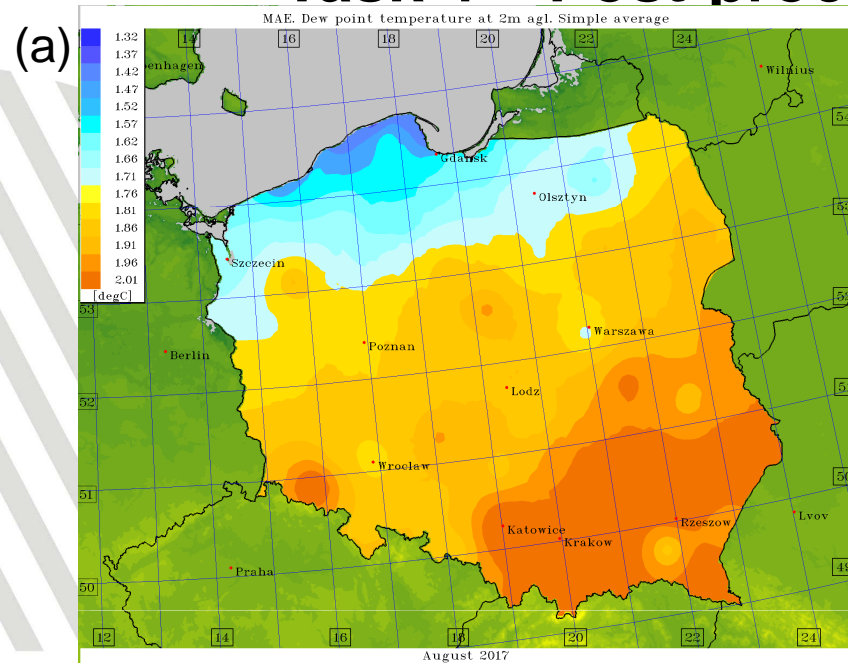


# Task 4 – Post-processing and interpretation



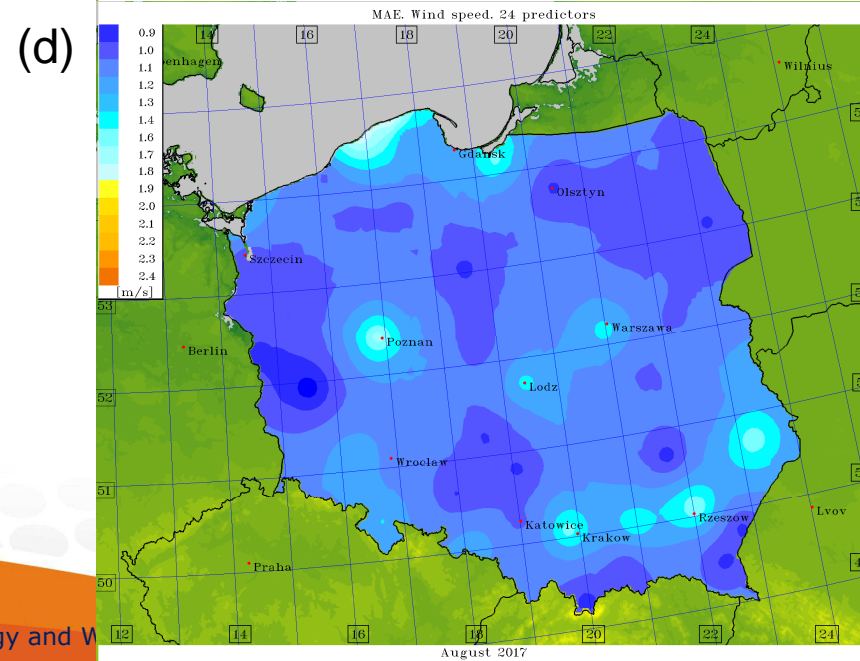
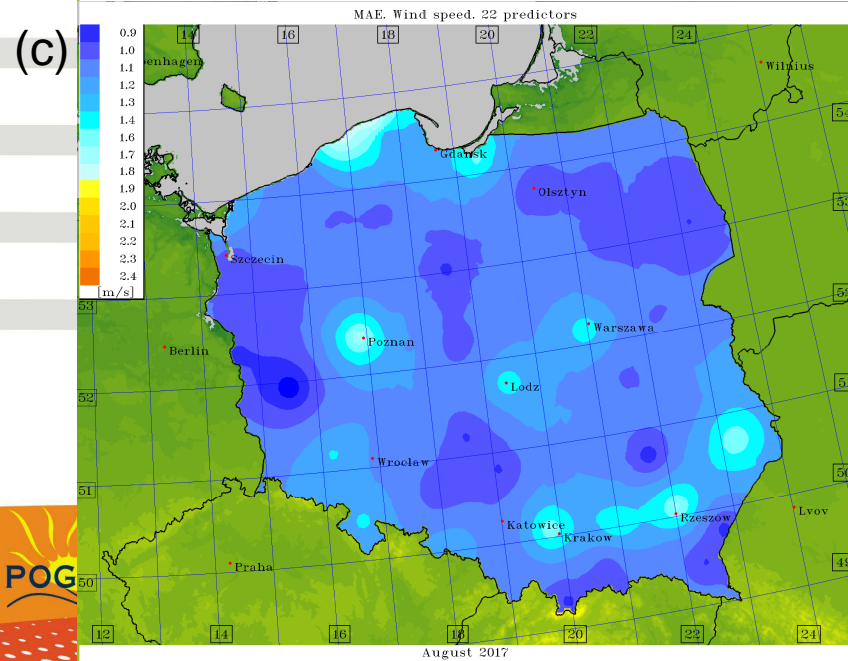
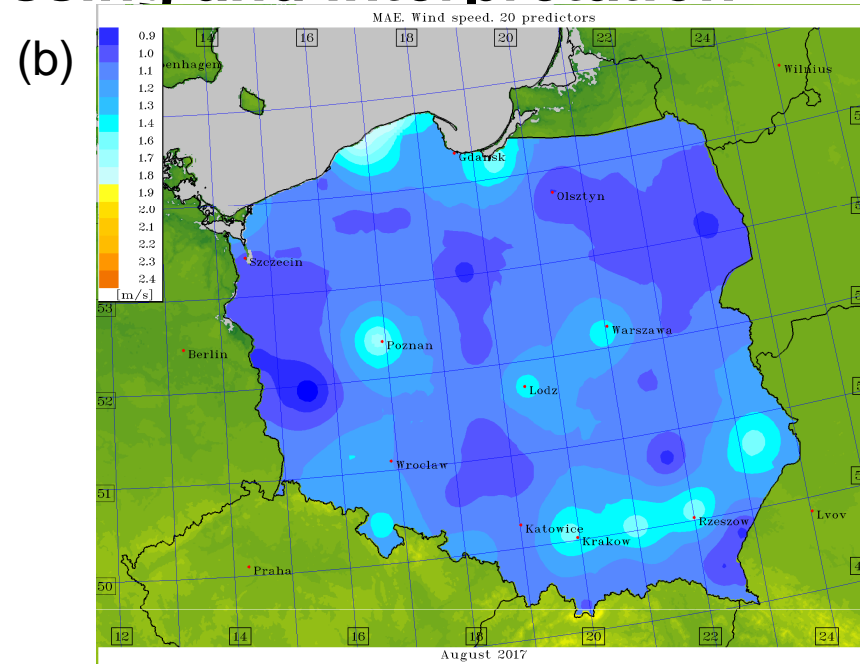
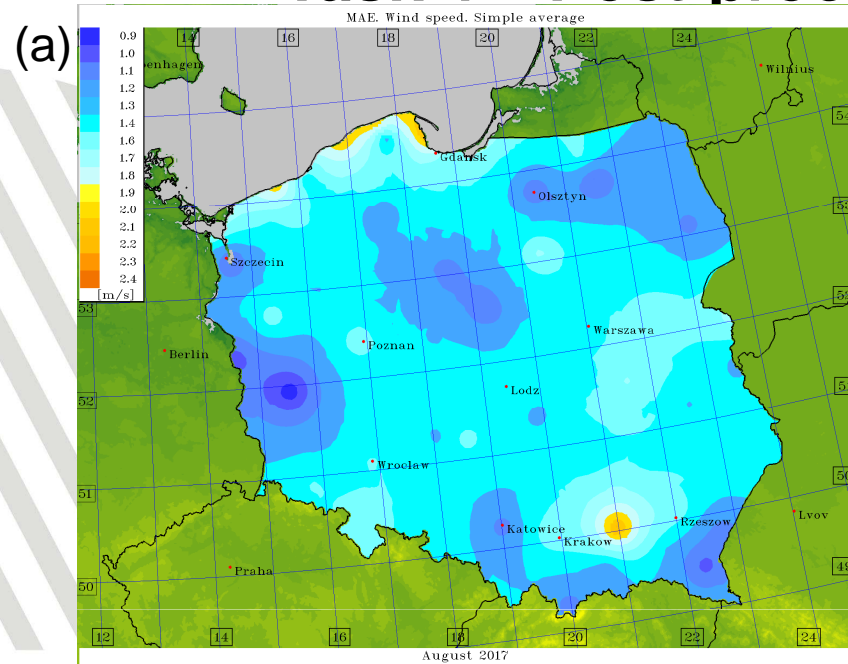
Temperature

# Task 4 – Post-processing and interpretation



Dew point

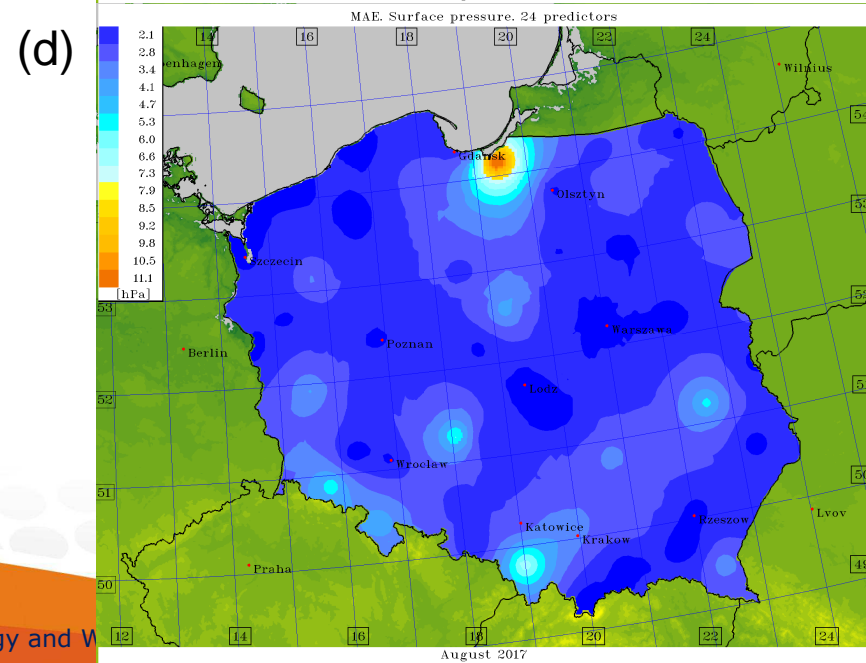
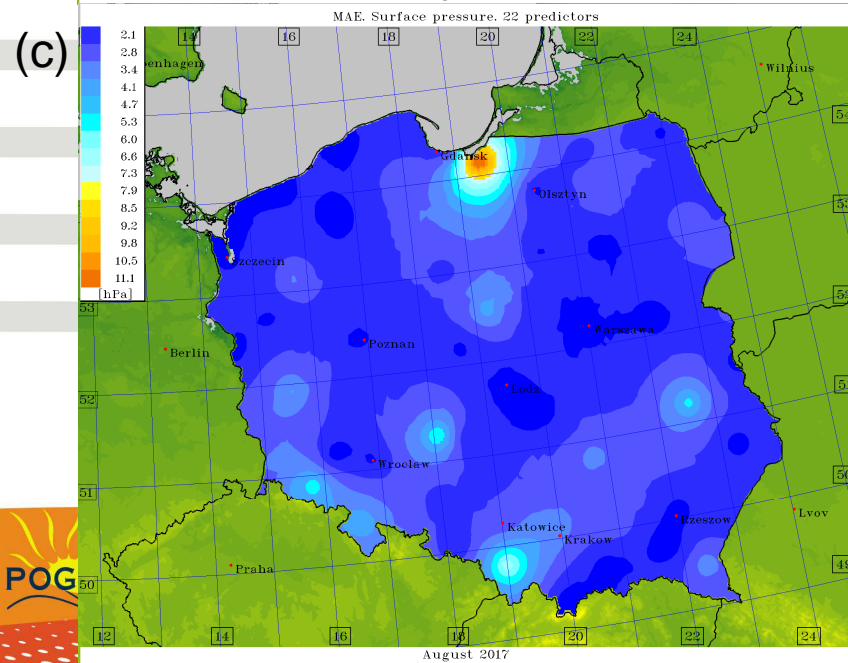
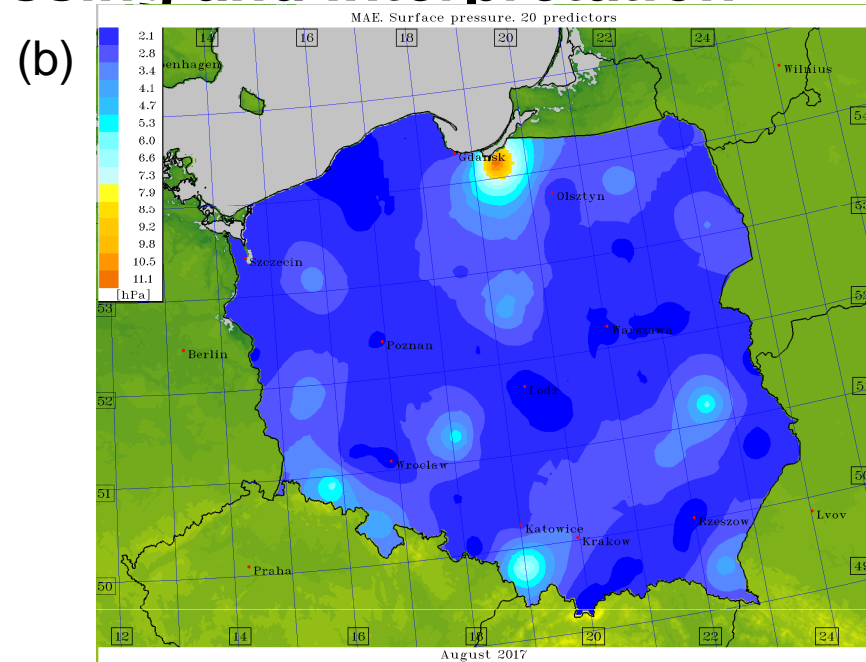
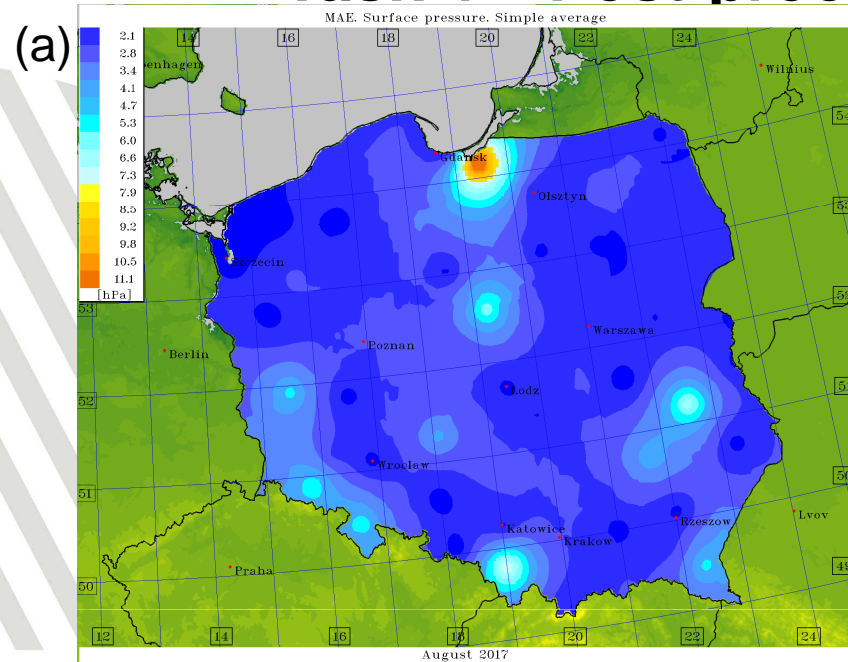
# Task 4 – Post-processing and interpretation



Wind speed



# Task 4 – Post-processing and interpretation

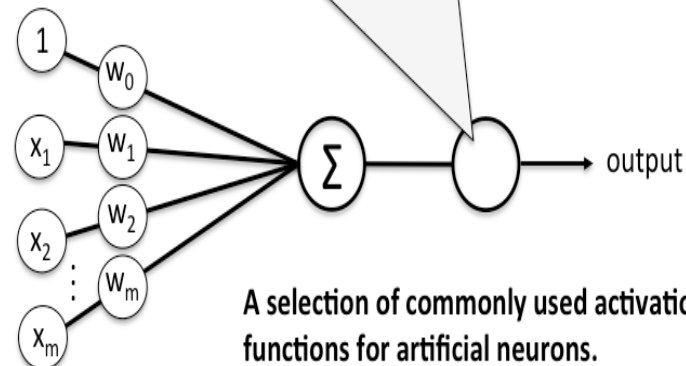
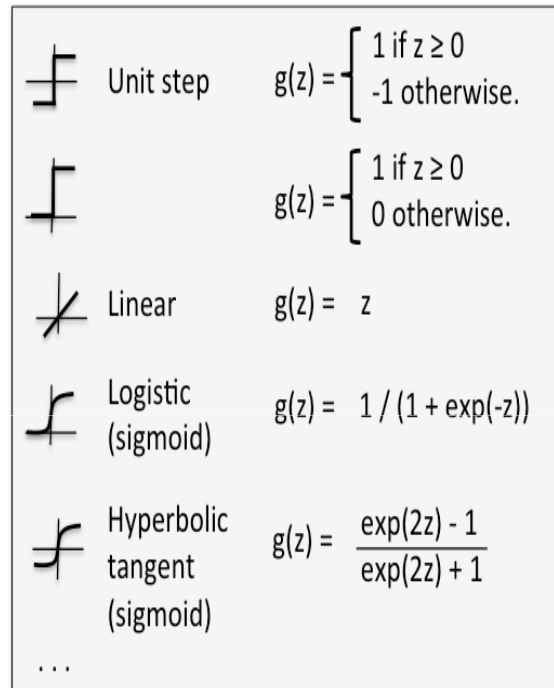
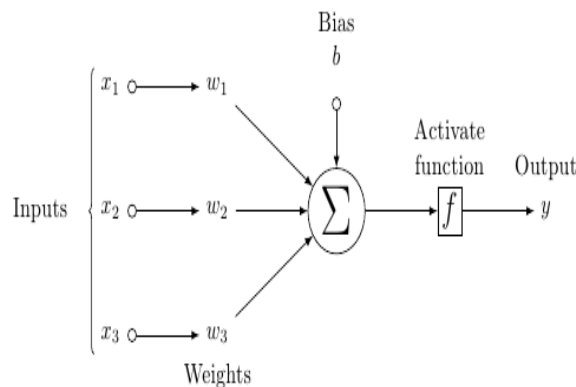
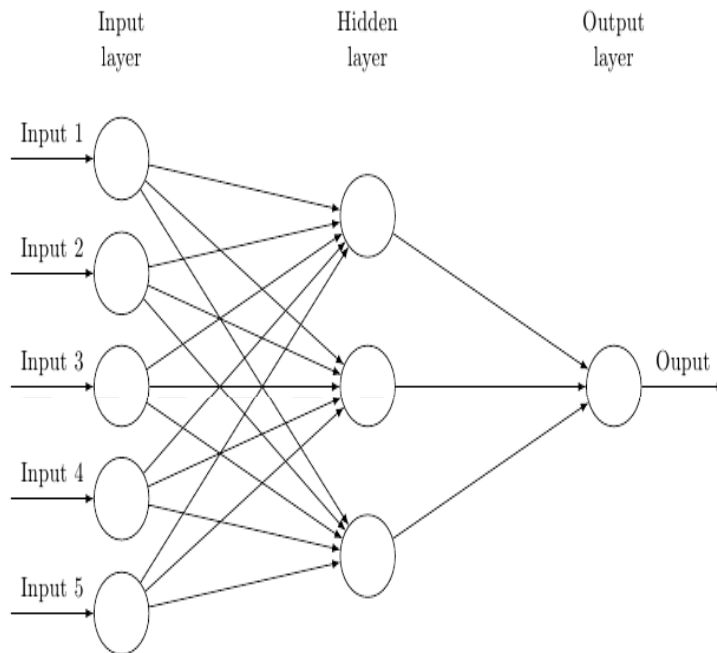


Surface pressure



## Task 4 – Post-processing and interpretation

### *Artificial Neural Network – an alternative for linear regression*



A selection of commonly used activation functions for artificial neurons.

## Task 4 – Post-processing and interpretation

### *Artificial Neural Network – an alternative for linear regression*

#### Setup:

1. 24/22/20 input neurons ( $t_s, t_c + \lambda, \varphi + 20$  members)
2. 5 neurons in a single hidden layer (referring to 4 blocks of TL-ICs/BCs and spatio-temporal coordinates – blocked) except for precipitation – 1 neuron in hidden layer (~ logistic regression).
3. Every element (temperature, wind speed, pressure, etc.) treated independently.
4. Activation function: hyperbolic tangent (symmetric with respect to origin of 0,0).
5. Training method: backward propagation of errors (back-prop).
6. Optimization: gradient descent.

## Task 4 – Post-processing and interpretation

ANN results:

Fields	Input neurons <sup>*)</sup> →	24	22	20	Simple avg. <sup>**) </sup>
	↓ MAE				
<b>U10M</b>	Avg.	0.409	0.416	0.430	1.373
	Max	1.324	1.361	1.538	2.519
<b>T2M</b>	Avg.	0.266	0.275	0.451	2.606
	Max	0.924	1.144	1.302	3.628
<b>TD2M</b>	Avg.	0.268	0.305	0.365	1.736
	Max	0.906	0.999	1.238	2.006
<b>PS</b>	Avg.	2.398	2.405	2.595	2.864
	Max	11.683	11.464	9.708	11.786
<b>TOT_PREC</b>	Avg.	0.131	0.127	0.219	0.808
	Max	0.739	0.741	0.505	1.514

<sup>\*)</sup> *Input neurons: 20 – members (history, learning); 22 – 20 + geo.coords.;*

*24 – 20 + geo.coords. + forecast start + current hour,*

<sup>\*\*) Simple averaging – 20 members mean (current forecast)</sup>

Learning: July 1<sup>st</sup>, 2016 – July 31<sup>st</sup>, 2017

Testing: August 1<sup>st</sup>, 2017 – August 31<sup>st</sup>, 2017

## **Task 4 – Post-processing and interpretation**

### *Artificial Neural Network – an alternative for linear regression*

#### Pros:

1. Ready-to-use dedicated software (Fortran-95).
2. Sophisticated yet elegant and intuitive concept.
3. Improvement in preliminary case study was observed,

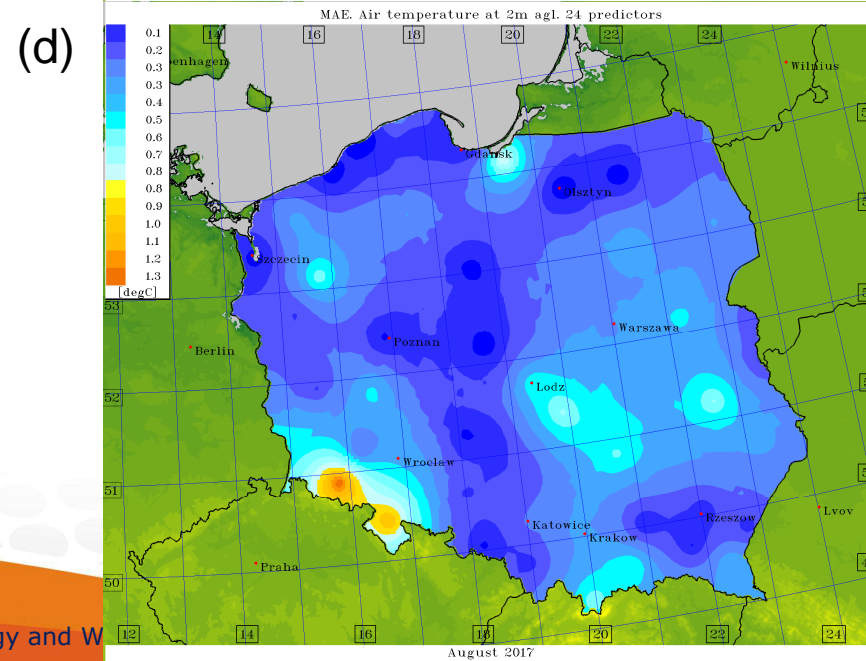
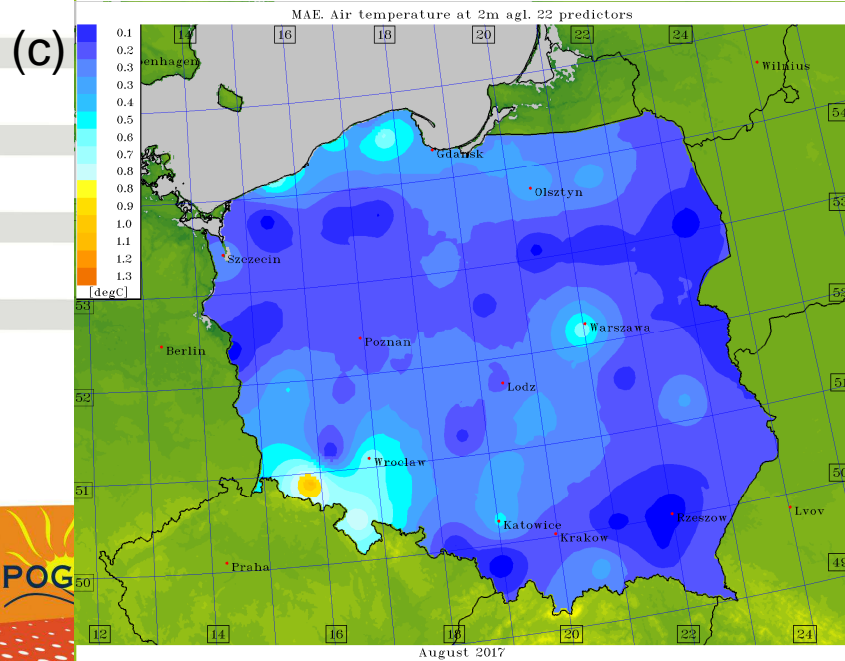
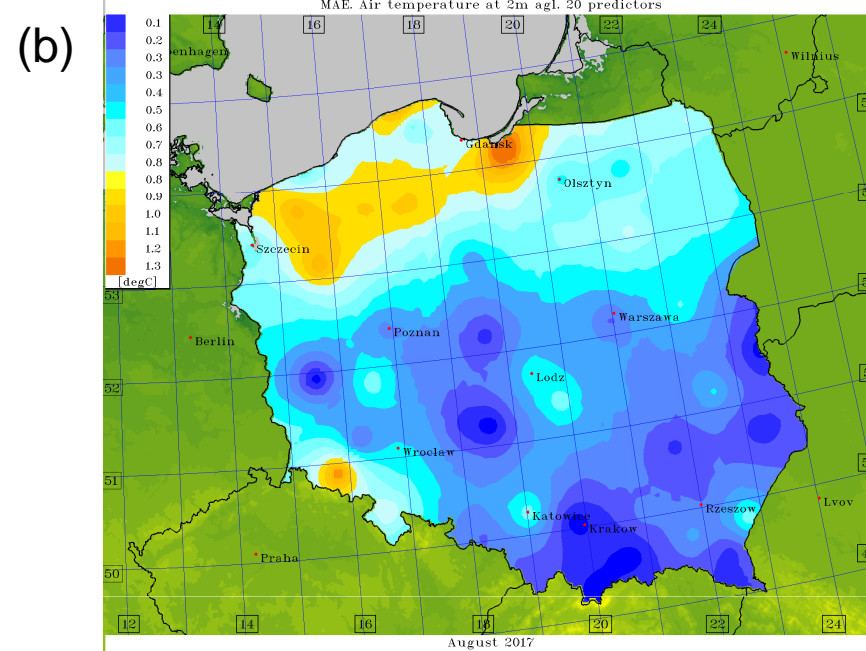
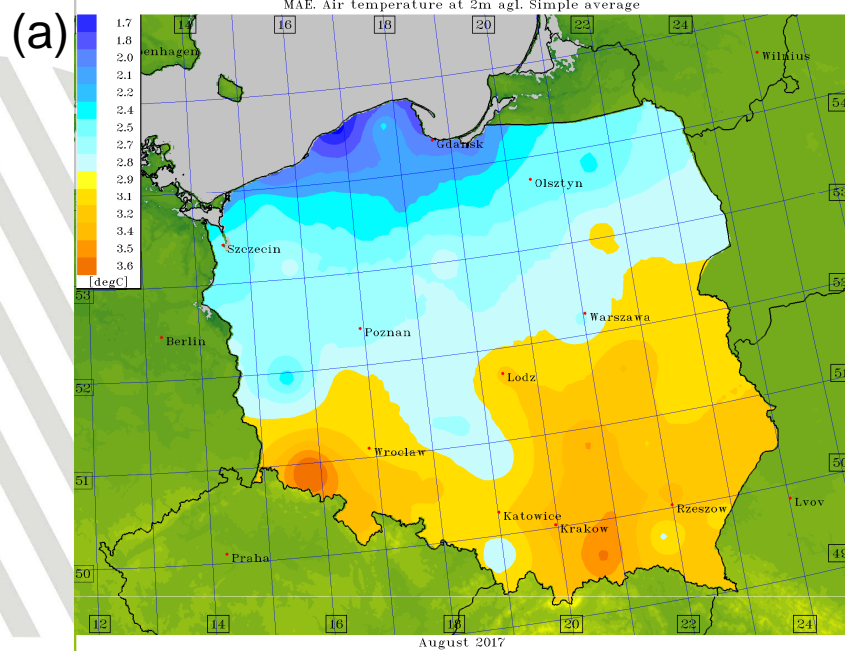
however...

#### Cons:

1. Complicated pre- and post-processing
2. Need for big data sets (archives), and for relatively huge computational resources
3. Long computational time for training
4. Improvement vs. linear regression (w. spatial adjustment) not very significant ...
5. Not true anymore! Festina lente!

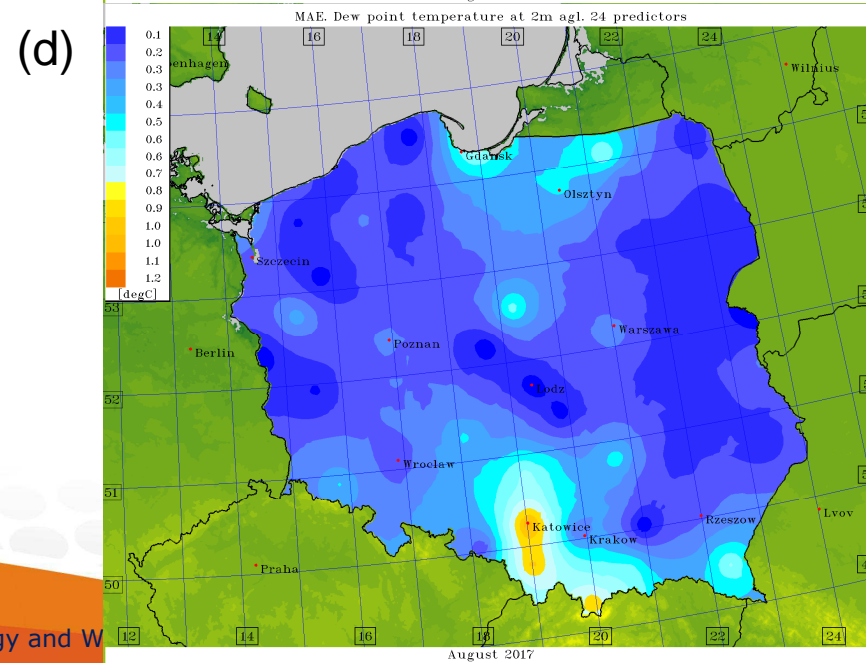
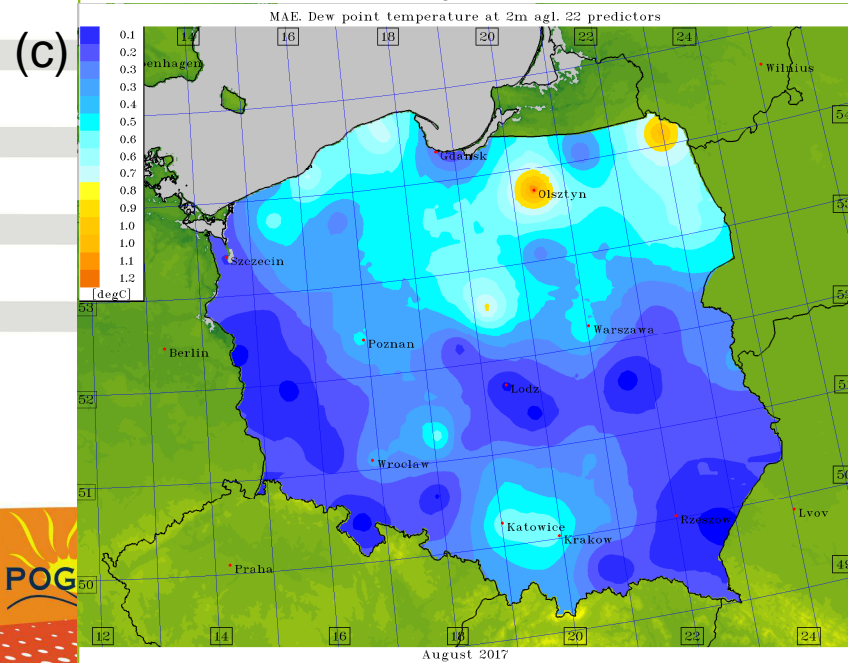
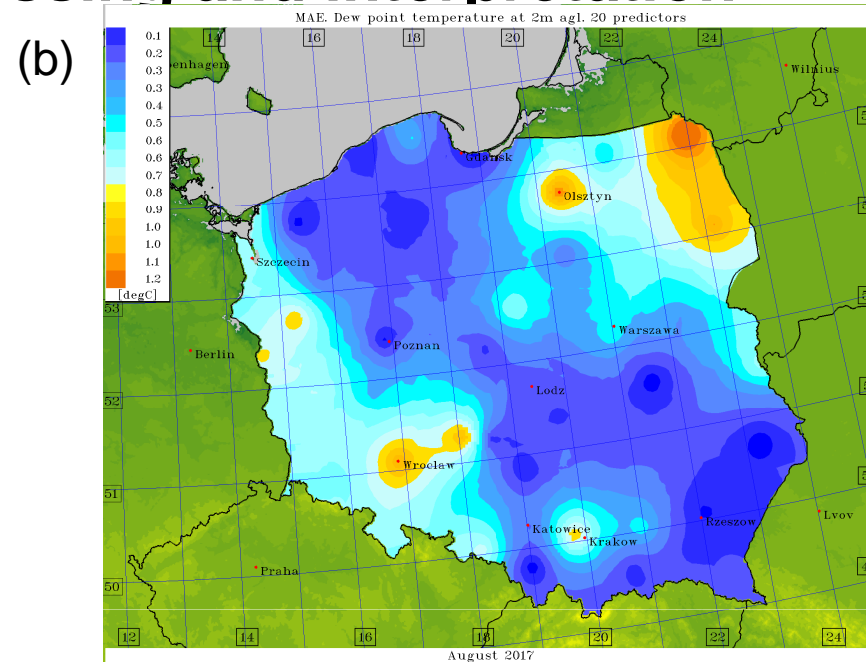
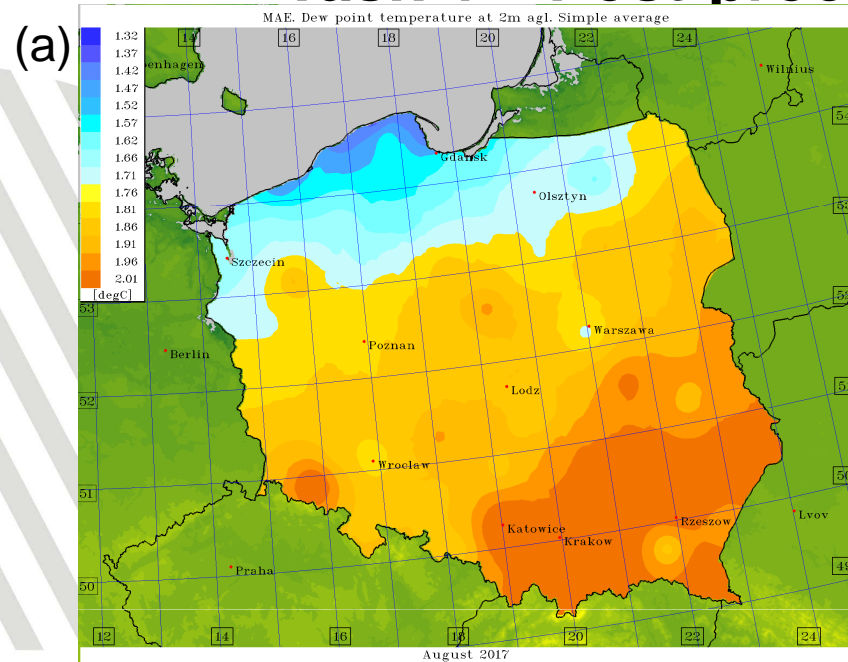


# Task 4 – Post-processing and interpretation



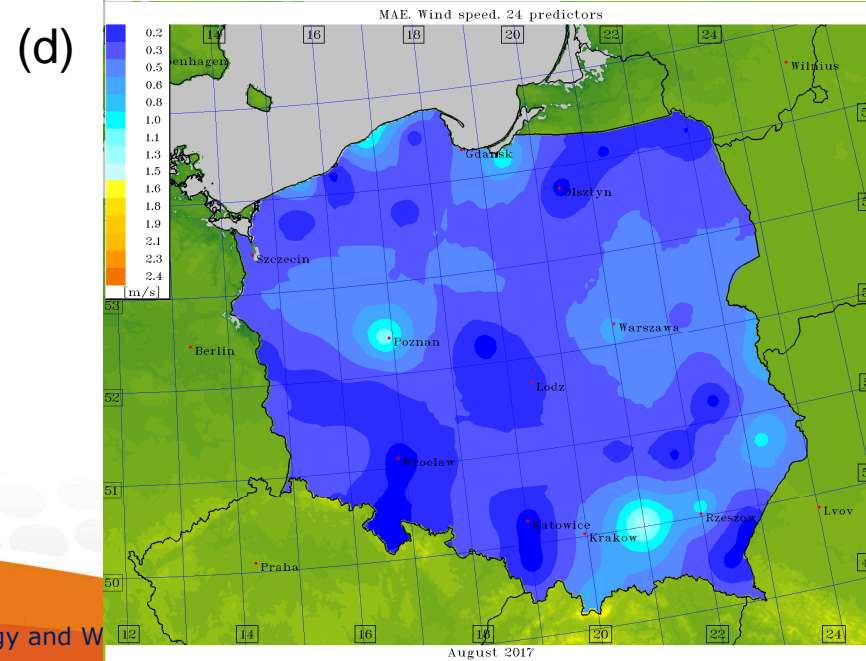
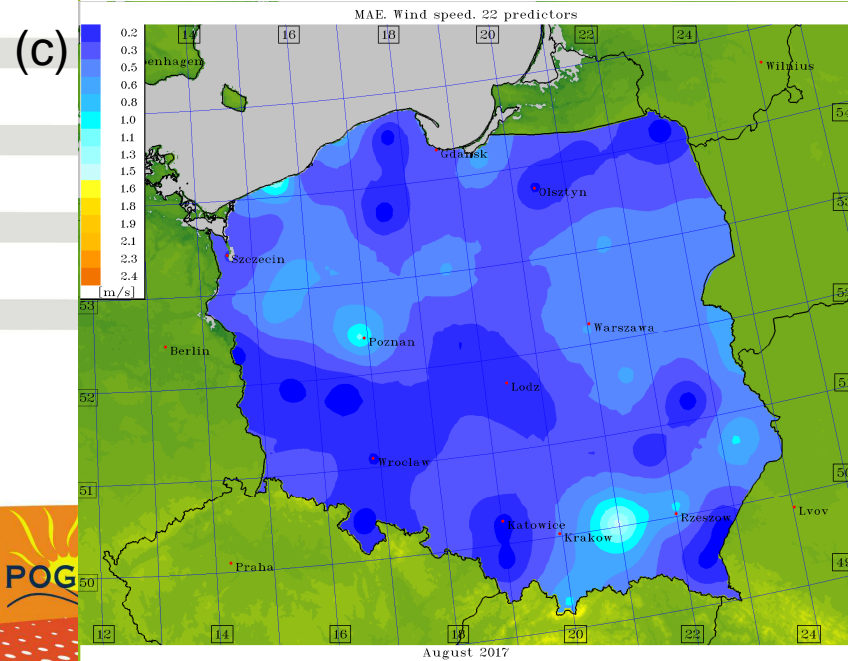
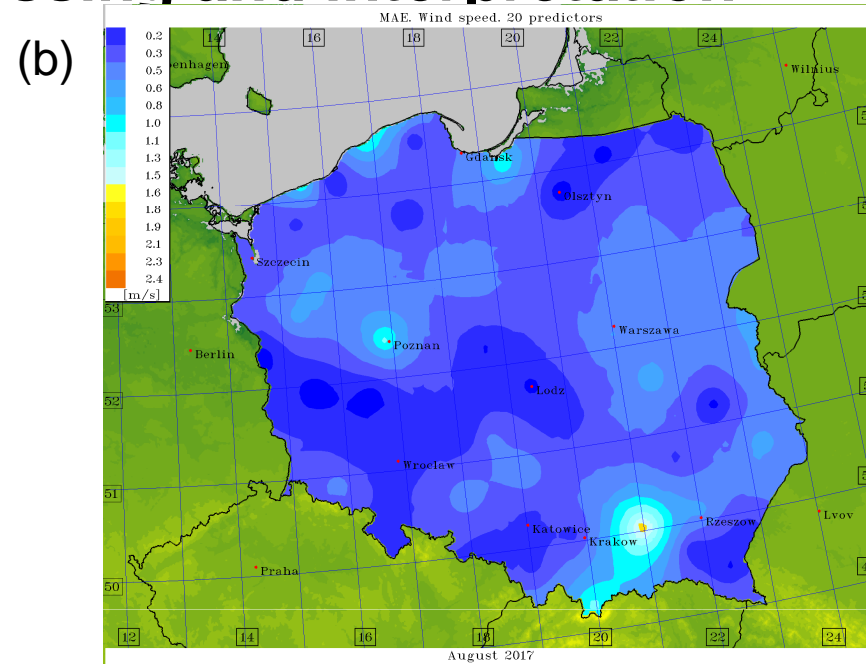
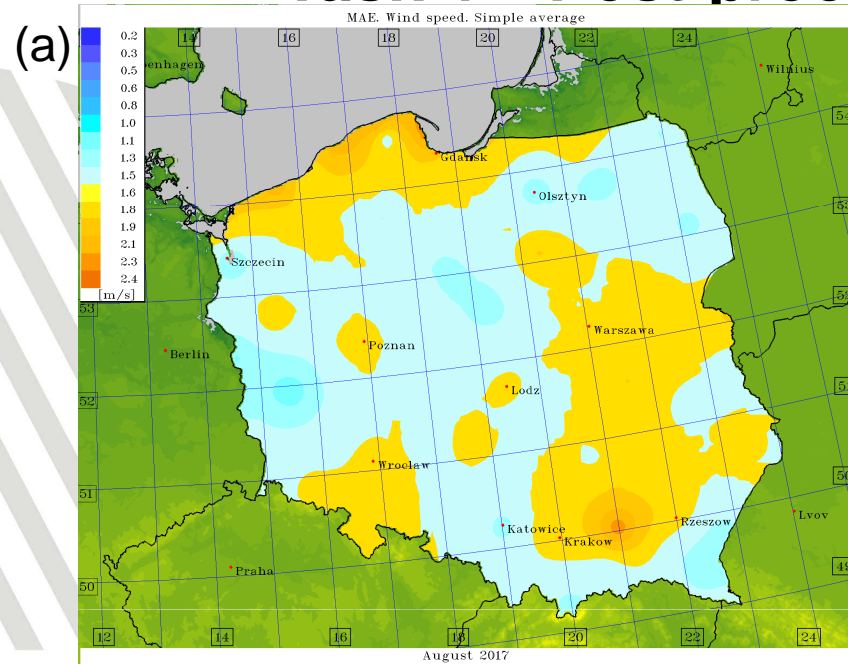
Temperature

# Task 4 – Post-processing and interpretation



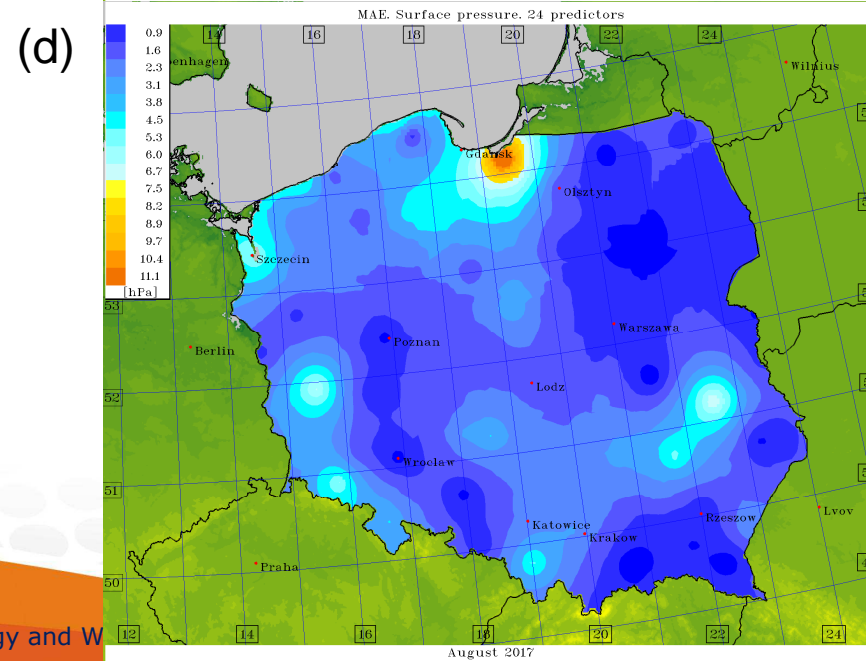
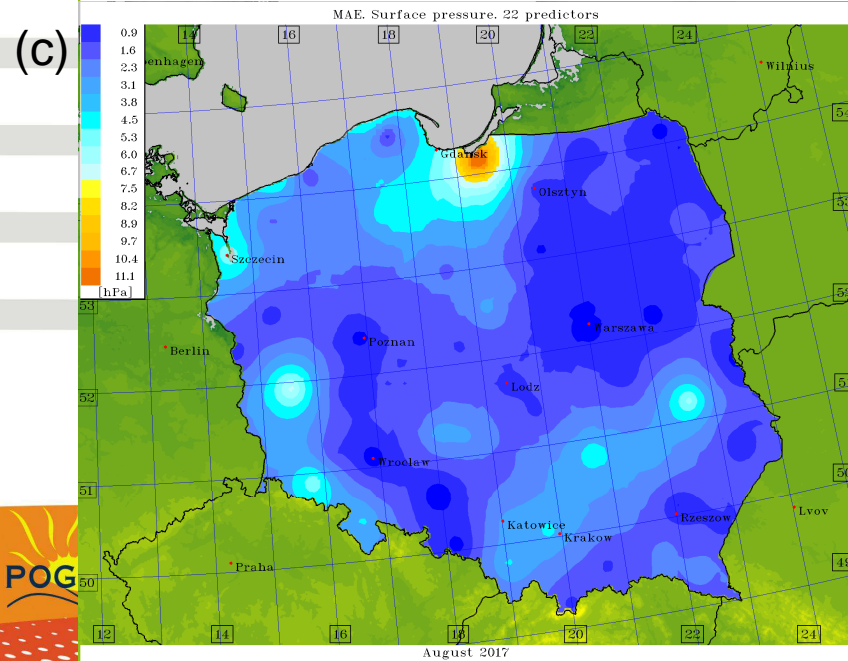
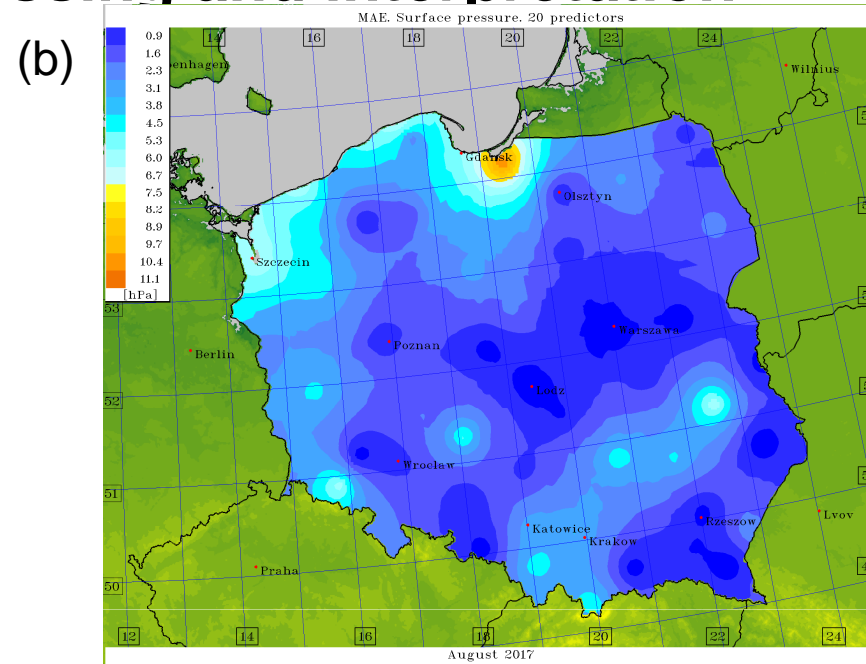
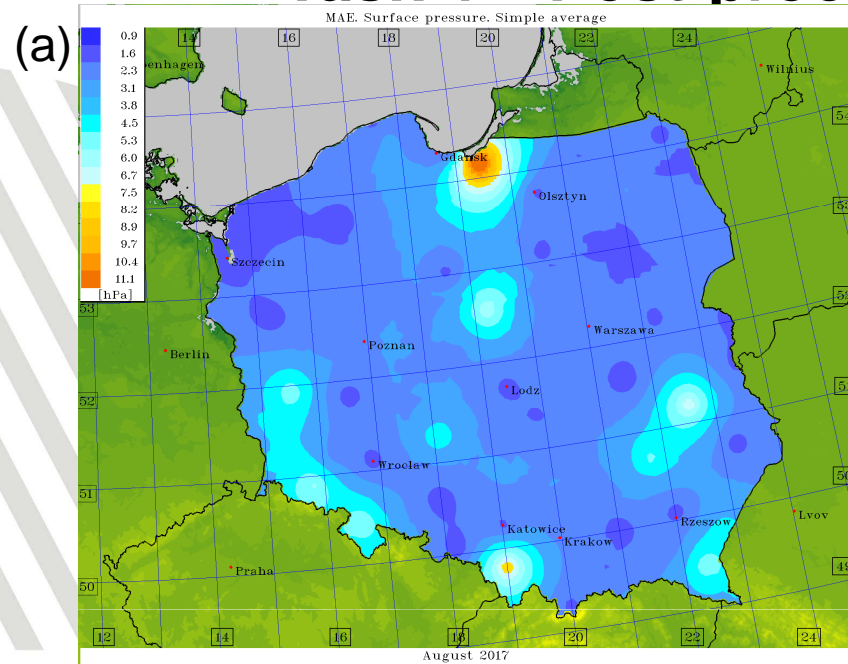
Dew point

# Task 4 – Post-processing and interpretation



Wind speed

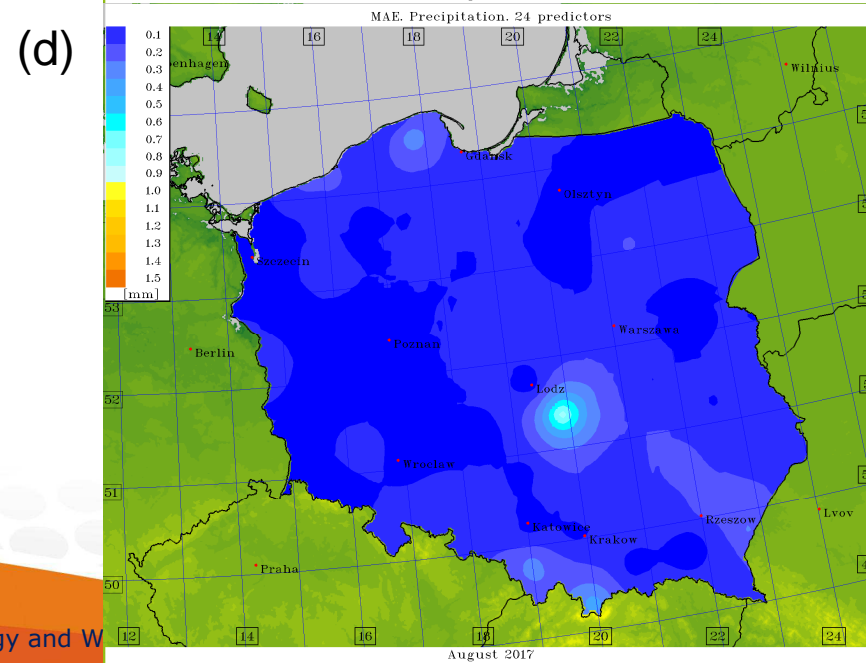
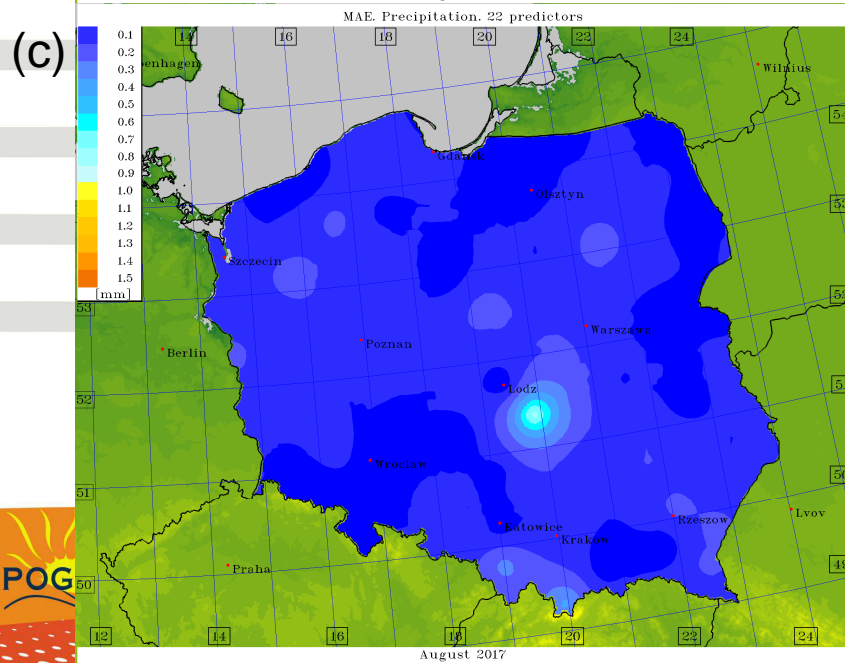
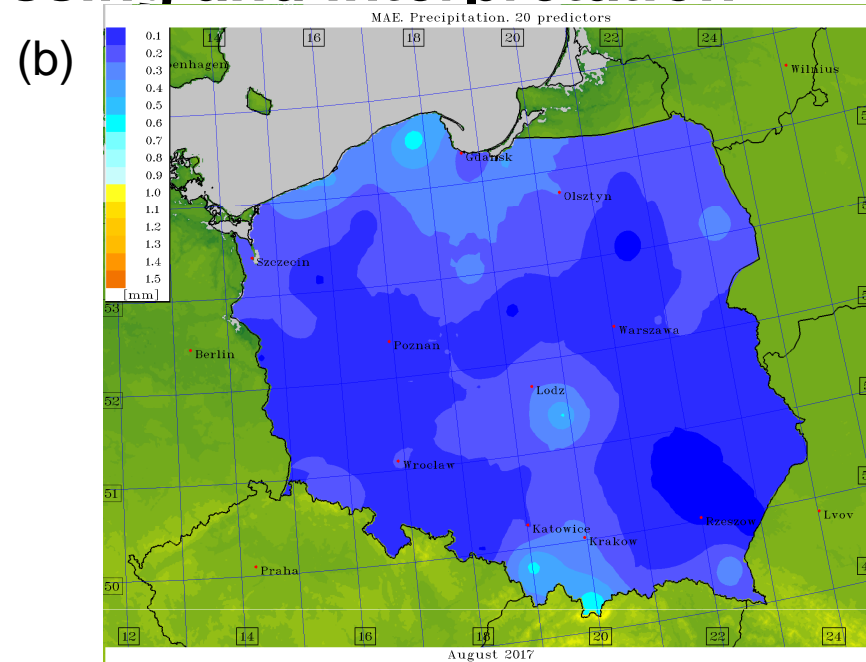
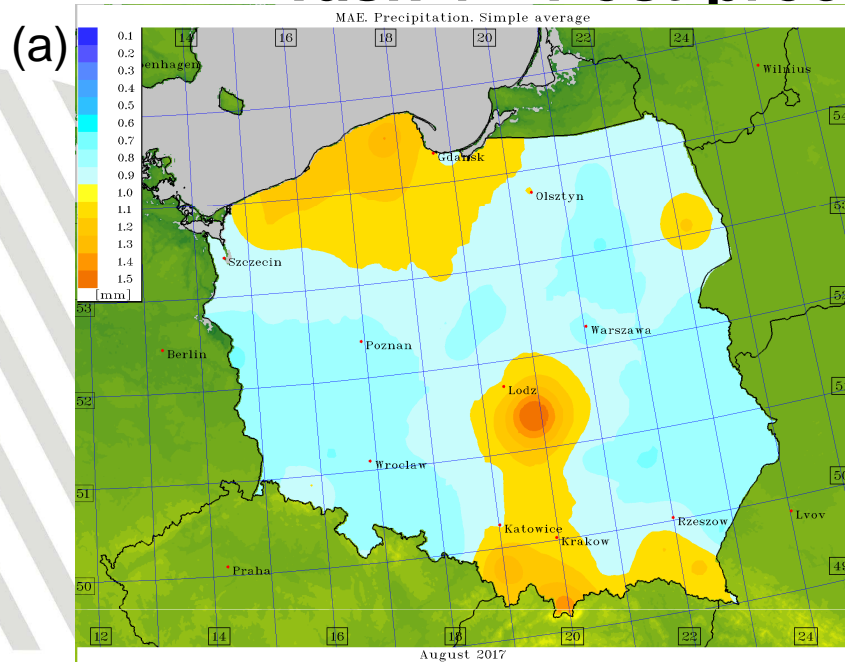
# Task 4 – Post-processing and interpretation



Surface pressure



# Task 4 – Post-processing and interpretation



Precipitation

## **Conclusions – Post-processing and interpretation**

- Significant improvement, esp. of ANN! (perhaps due to longer learning period?)
- "More predictors" – in general – means "better forecast", but also "longer calculations" – compromise to be established
- To be operational very shortly – next month(s)
- Some fields may be treated with ANN, others (pressure?) – linear regression
- Looking forward for the new PP.
- Enough time to think about changing the name eg. to EMBASSy (EnseMBle forecASts Skill vs. Spread determination) or EMBOSS (EnseMBle fOrecasts Skill vs. Spread estimation)?

