Improving existing post-processing methods:
Use of MLR, adaptive/recursive LMS and ANN techniques

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Report on sub-task 4.2 of COSMO Priority Project AWARE (Appraisal of Challenging WeAther FoREcasts)

Contents

i. Introduction

In contrary to other sub-tasks (e.g. 2.1, 3.1) in the Priority Project, the main goal in this activities was the verification against observations of various post-processed results. It means that the effectiveness of post-processing is assessed, not the FR parameterization itself as follows:

$$FR = \left(\frac{W}{14.66}\right)^{4.54}$$

with *W* being updraft velocity, calculated as

$$W = 0.3 \cdot \sqrt{2 \cdot CAPE}$$

As it was already used in sub-tasks 2.1 and 3.1, *FR* is to be limited with the temperatures of top/bottom cloud temperatures, *CTT* and *CBT*, respectively

$$if\ CTT > -15℃\ FR = FR \cdot \left[max\left(0.01, \frac{-CTT}{15.0}\right)\right]$$

and

$$if\ CBT < -5℃\ FR = FR \cdot \left[max\left(0.01, \frac{15.0 + CBT}{10.0}\right)\right]$$

And again, another limitation is due to lack of convective clouds – if (forecasted) cloud cover is below 25%, *FR* is set equal to zero. Moreover, case was selected to verification if (for both observations and forecasts) maximum value over the entire domain was greater than 20 strikes/hour , and the duration of the storm was greater than 6 hours.

Observation data (intercloud- and cloud-to-ground lightnings) came from the Polish lightning detection network PERUN, covering Poland and nearest vicinity - parts of neighbouring countries.

The quality of (any) post-processing used in the study was assessed via continuous verification - MAE, RMSE - only. Methods using contingency table nor other discrete verification methods were not used.

ii. Methods

Various methods of post-processing used in the study essentially belonged to the class of Least Mean Squares (LMS) methods and the Artificial Neural Network (ANN) method.

1. *Multi-Linear Regression (MLR)* – class of LMS method with multidimensional input data vector, yet constant over time. Marking corrected forecasts as *y*, DMO (Direct Model Output) as *h*, and weight values (to be determined) as *b*, the method diagram looks as follows.

$$\hat{y}_n = \sum_{j=0}^{J} b_j h_{nj}$$

Solution for regression coeffs

$$\bar{b} = (\hat{H}^T \hat{H})^{-1} \hat{H}^T \bar{y},$$

where

$$\hat{H} = \begin{bmatrix} 1 & h_{11} & \dots & h_{1J} \\ 1 & h_{21} & \dots & h_{2J} \\ \dots\dots & & h_{nj} & \dots \\ 1 & h_{N1} & \dots & h_{NJ} \end{bmatrix}; \bar{y} = \begin{bmatrix} y_0 \\ y_1 \\ \dots \\ y_N \end{bmatrix}; \bar{b} = \begin{bmatrix} b_0 \\ b_1 \\ \dots \\ b_J \end{bmatrix}$$

Figure 1. Flow chart of the MLR procedure

2. *Adaptive/Recursive LMS methods.* Basic scheme of the method is presented below. The most important here – from the post-processing point of view – was the forgetting factor *λ*, that described how long older data should be "remembered".

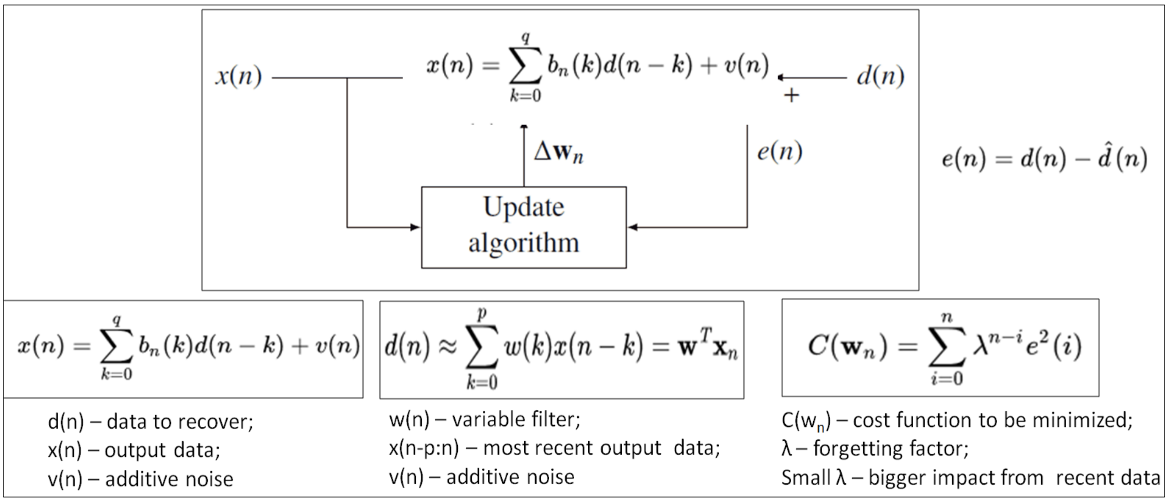

Figure 2. Flow chart of the RLMS procedure

3. Artificial Neural Networking (ANN) – dealing with post-processing for both EPS- and deterministic forecasts

Inputs to the net were, apart from (time lagged) values of DMO, geographical coordinates λ,φ, and t_s,t_c – lead time and current time of forecast. Basic idea of the ANN is presented in the diagram below. Transfer function was assumed linear, activation function – hyperbolic tangent. The main factor that was modified in the assessment process was the number of hidden neutrons of the net.

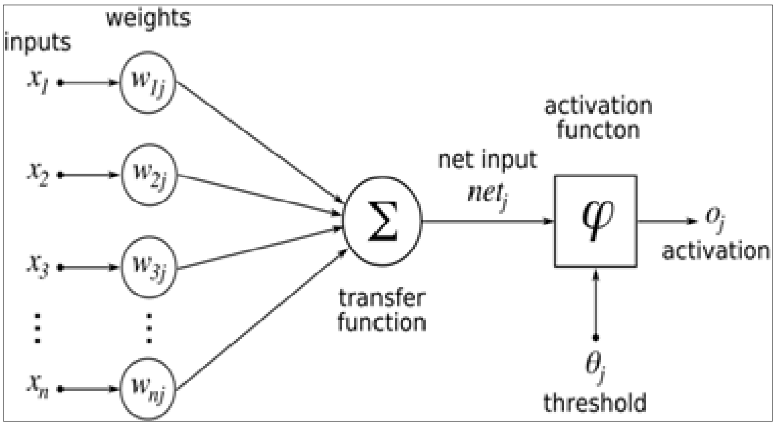

Figure 3. Schematic depiction of ANN

Space lag (cross-) correlation approach

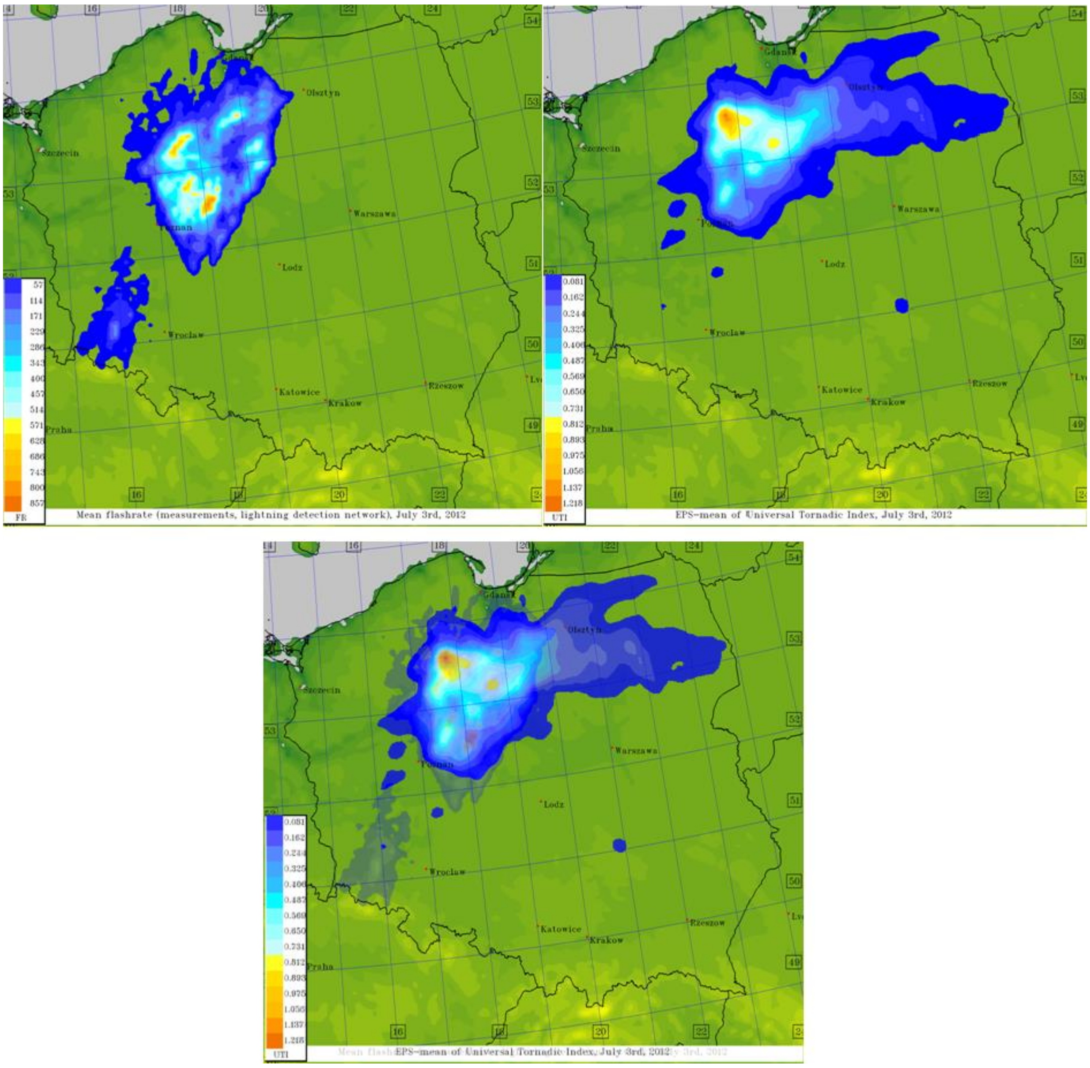

Figure 4. Introduction to cross-correlation procedure

Similarly as in subtask 2.1/3.1. cross-correlation procedure was applied. To remind a basic idea of the approach: when overlap the upper left (observations field) and the upper right (forecasts) panels (Fig. 4), in most cases they do not match (lower panel, Fig. 4). It is possible to improve the forecast by using the cross-correlation (or space lag correlation) method. To do this (using the example from the figure above) one should:

- Calculate coordinates of ”centres of mass” for both distribution patterns (observations vs. forecasts).
- Compute vector of displacement (VOD) of forecasts to observations as a difference of the two above.
- Displace linearly every value of forecasts field by the vector of displacement.

In operational work, VOD is calculated from previous model runs (as compared to observations). It is then assumed to remain constant throughout the next run.

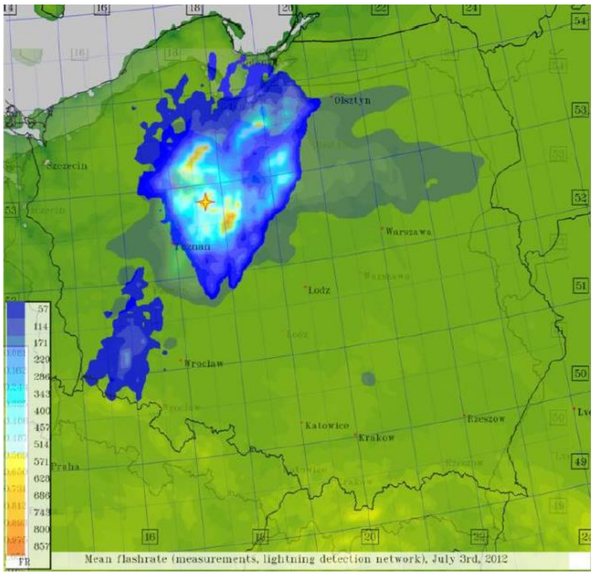

Figure 5. Result of cross-correlation procedure

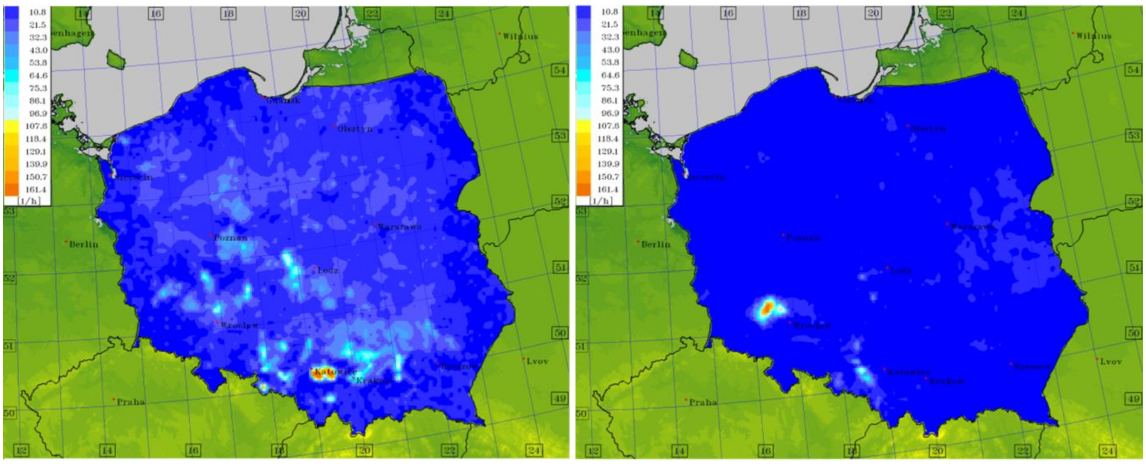

Figure 6. Sample values of (observations – forecasts) for flash rate (lightning frequency). Left - direct model output results, right panel - corrected with VOD procedure.

iii. Examples and detailed results

Various set-ups of post-processing of various methods have been tested over the seven-years period (2011-2017). The learning/testing period: 2011-2016 and the entire 2017 as period for verification were selected. The following table lists the Mean Error, Mean Absolute Error and Root Mean Square Error values for the various set-ups in the evaluated methods of post-processing.

	ME	MAE	RMSE
ANN 4 hidden neurons	0.8406	1.6856	11.8038
ANN 3 hidden neurons	0.4088	1.8395	11.8919
RLS λ=0.95	0.1203	2.1109	12.3525
RLS λ=1.00	0.0538	2.1911	12.7302
MLR 6 predictors	0.5957	2.1503	13.0064
MLR 3 predictors	1.0369	2.2140	13.4703

The following table shows the same results, but using the cross-correlation procedure and Vector Of Displacement approach.

	ME	MAE	RMSE
ANN 6 hidden neurons	0.0036	1.6283	11.5729
ANN 3 hidden neurons	-0.0775	1.6971	11.7552
RLS λ=0.95	1.2364	2.0847	12.1510
RLS λ=1.00	-0.7295	2.1130	12.4476
MLR 6 predictors	0.6641	2.1769	12.9326
MLR 4 predictors	1.2260	2.1990	13.3877

The figures below show exemplary results for the average MAE/RMSE values for Direct Model Output and after using the VOD procedure.

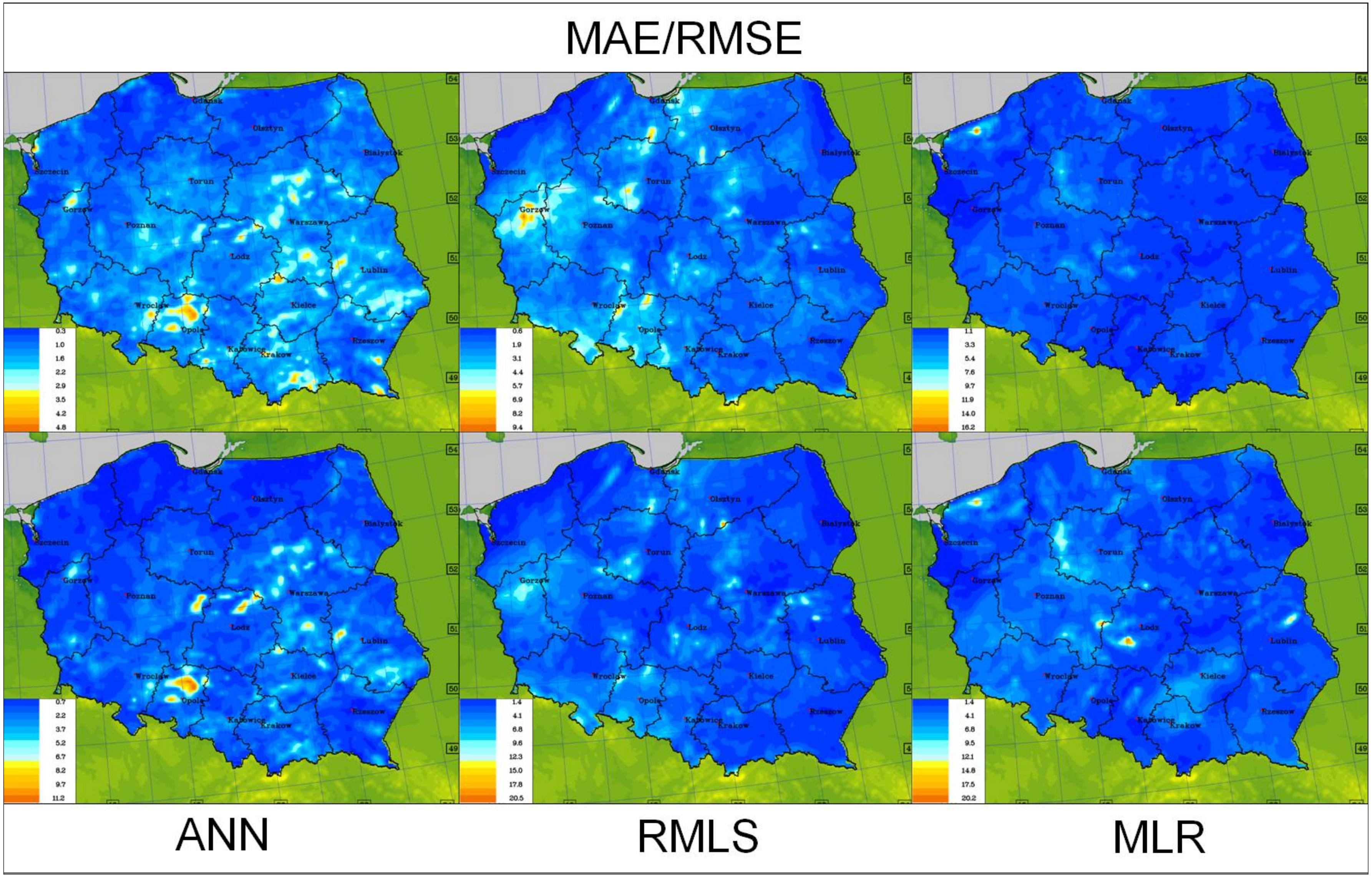

Figure 7. Results for the average MAE/RMSE values for Direct Model Output of Flash Rate (observation vs. forecasts)

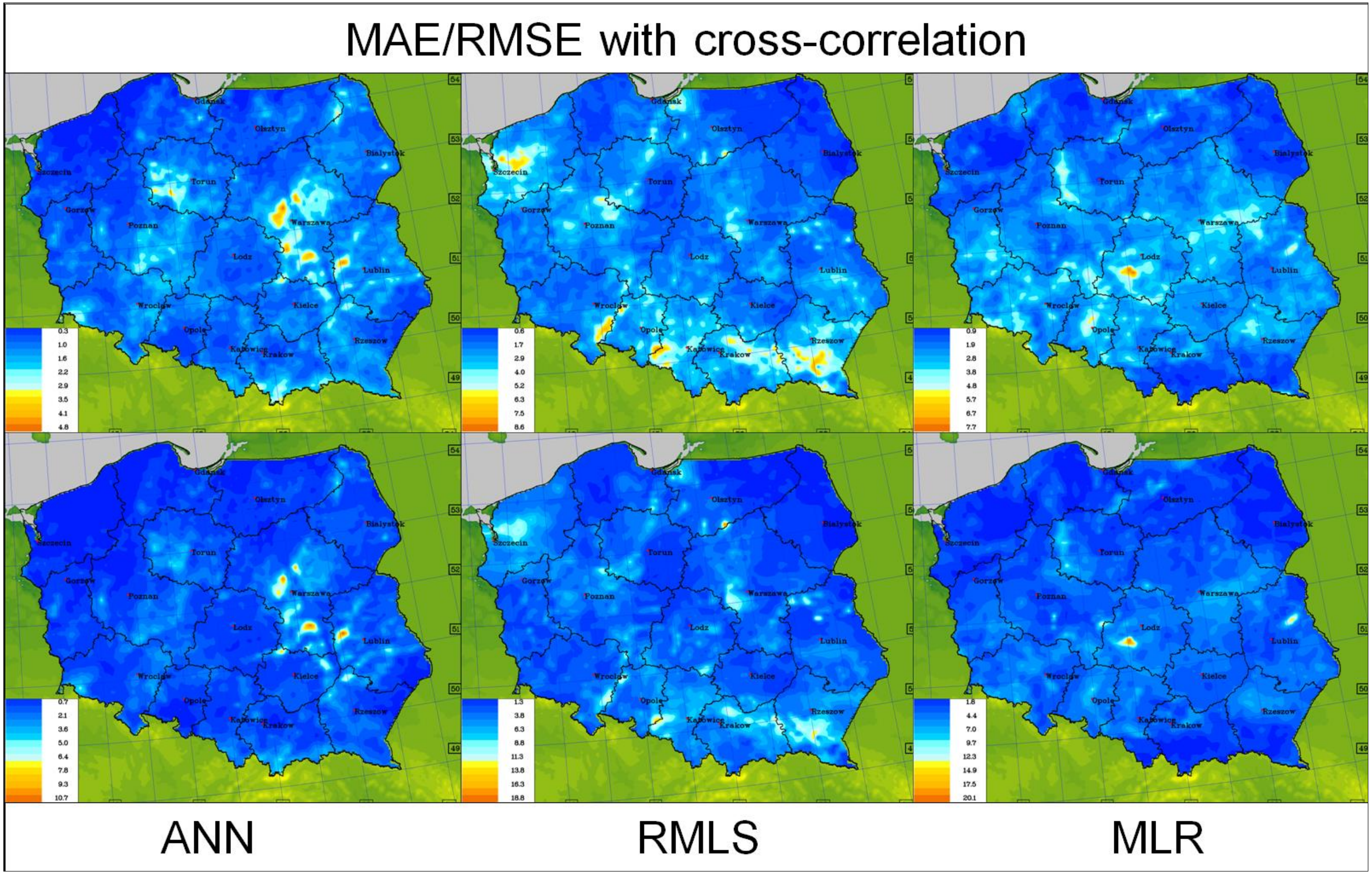

Figure 8. As in Fig. 7, but after using the VOD (cross-correlation) procedure

iv. Conclusions

Best method?

Of all the methods, ANN appears to be the best, basing on the results expressed as the MAE and RMSE. This confirms the results that has been already obtained in post-processing with EPS.

… With VOD?

When VOD procedure is applied to MAE/RMSE, slight improvement can be seen in comparison to direct verification, with a maxima of MAE/RMSE shifted towards centre of the domain. A similar effect was recognized for all values.

The Recursive/Adaptive Least Mean Square method not necessarily works as good as expected (i.e. the results are not better than the ANN results), but they are much better compared to the standard Multi-Line Regression approach.

Further research?

Extended works are planned to improve the Flash Rate post-processing methods, however, in the frame of the newly established Priority Project MILEPOST (MachIne Learning-based POST-processing).