Representing Microphysical Uncertainty in Convective-Scale Data Assimilation Using Additive Noise

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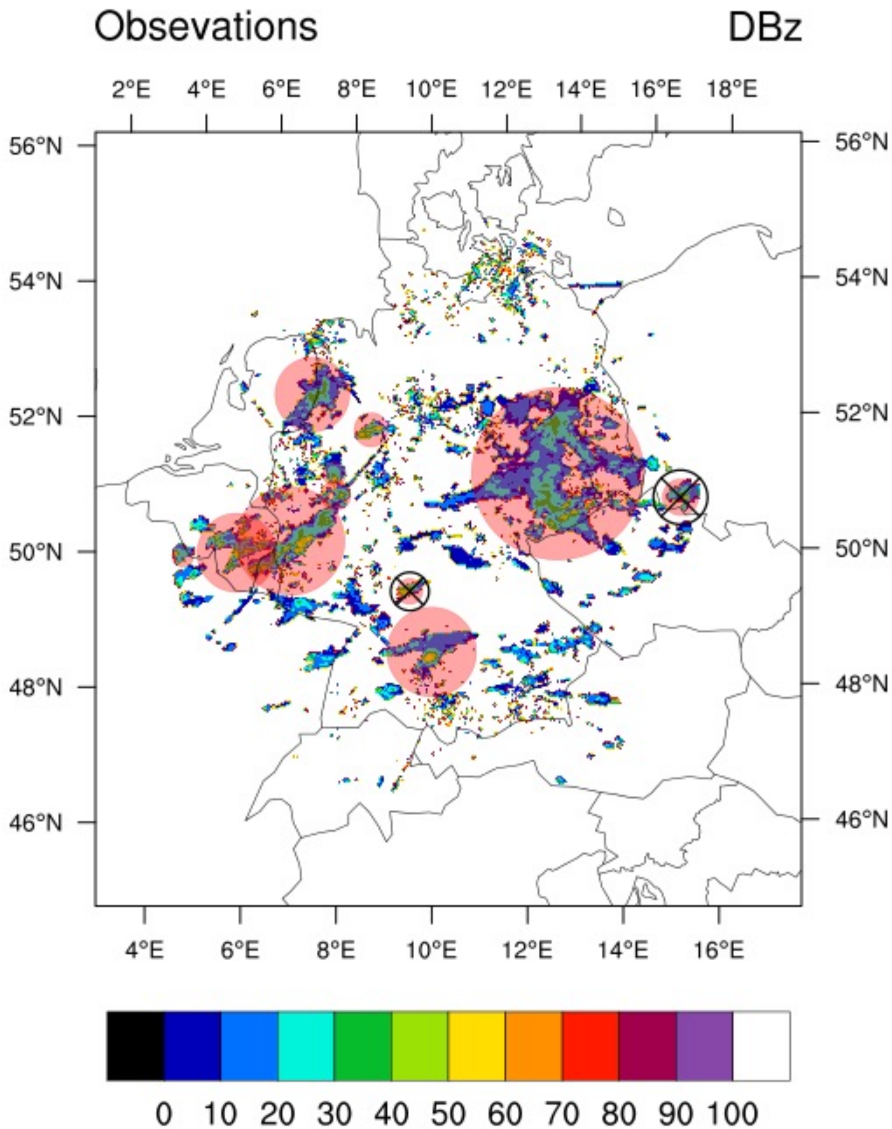
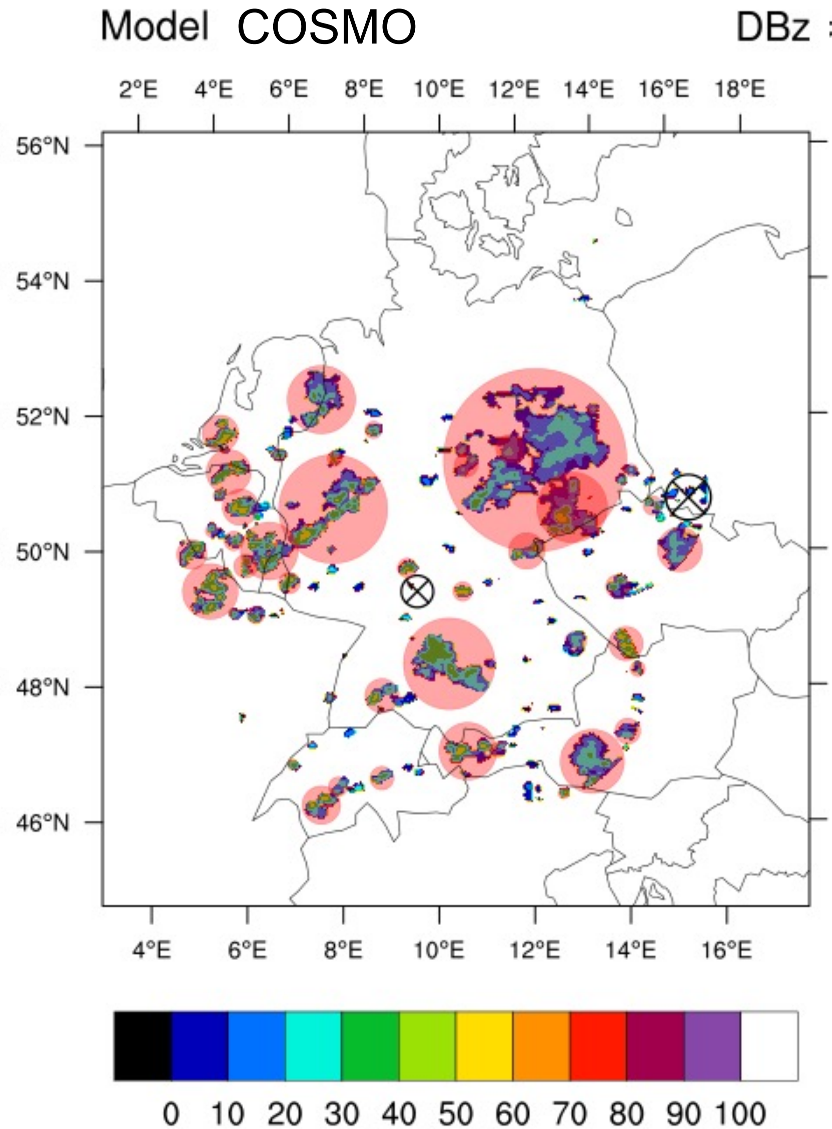

Obsevations
DBz
2°E 4°E 6°E 8°E 10°E 12°E 14°E 16°E 18°E
56°N 54°N 52°N 50°N 48°N 46°N
4°E 6°E 8°E 10°E 12°E 14°E 16°E
0 10 20 30 40 50 60 70 80 90 100


Model COSMO
DBz
2°E 4°E 6°E 8°E 10°E 12°E 14°E 16°E 18°E
56°N 54°N 52°N 50°N 48°N 46°N
4°E 6°E 8°E 10°E 12°E 14°E 16°E
0 10 20 30 40 50 60 70 80 90 100

Additive noise

ICON DA

$$\mathbf{x}^{a(i)} \leftarrow \mathbf{x}^{a(i)} + \alpha_a \boldsymbol{\eta}^{(i)} + \alpha_a^{s} \boldsymbol{\eta}^{(i)s} \qquad \boldsymbol{\eta}^{(i)} = \tilde{\mathbf{B}}^{\frac{1}{2}} \gamma$$

$\eta^{(i)s}$ for unresolved scales model error samples calculated as difference between COSMO 2.8 km and 1.4 km **offline for a different historical time**

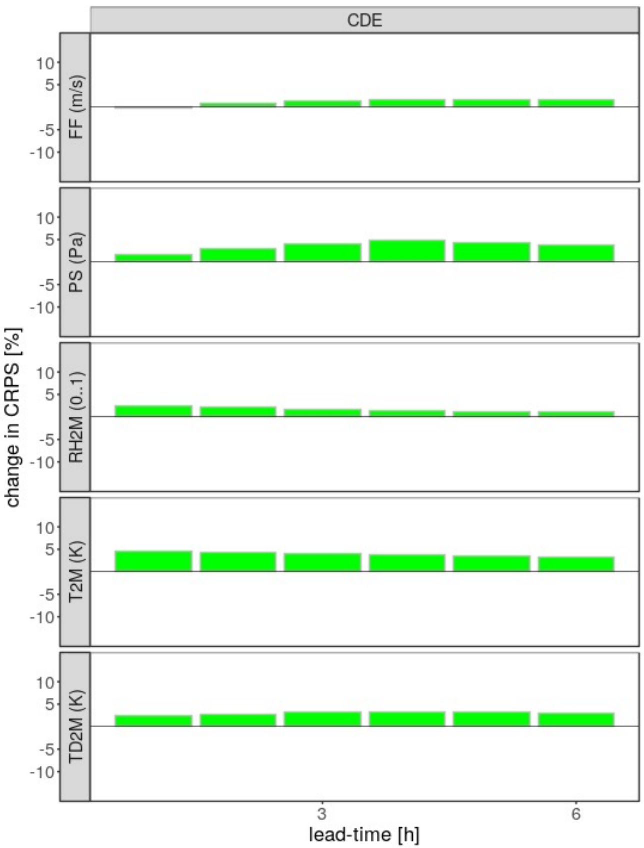
$\boldsymbol{\eta}^{(i)}$ velocity u, v, temperature, pressure and relative humidity qv are perturbed

$\boldsymbol{\eta}^{(i)s}$ velocity u, v, **w,** temperature and relative humidity qv are perturbed using randomly chosen sample from historical data base

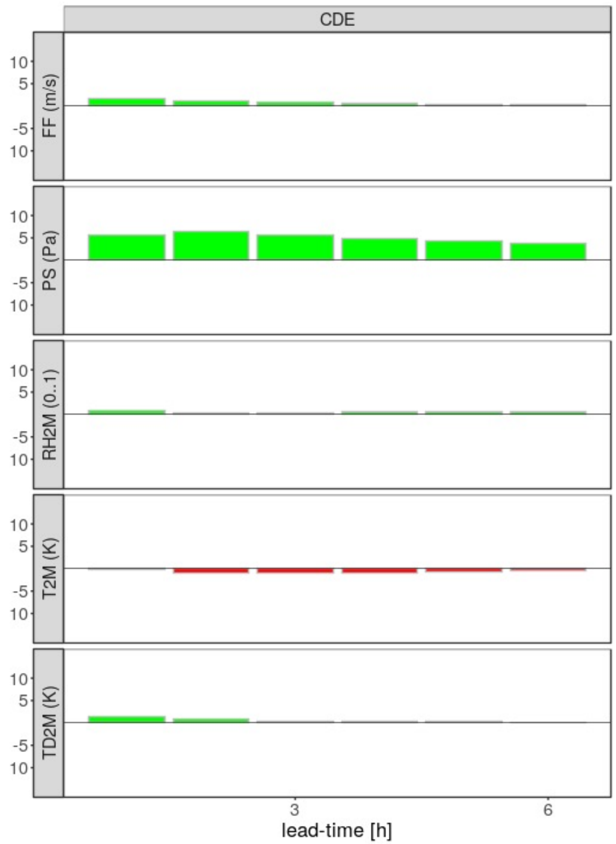
DA: 40 members, KENDA, EMVORADO, **All hydrometeors updated with LETKF**
20 members are used for 6-h ensemble forecasts, initiated at 10, 11, …, 18:00 UTC
Observation error: 10 dBZ for reflectivity, 1h updates

Zeng et al. 2018,2019

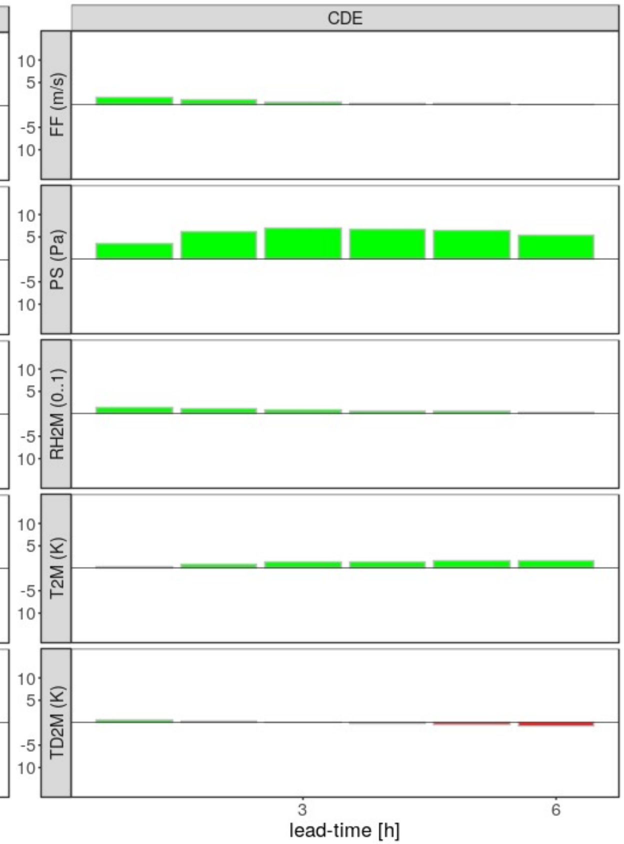
E SAN vs. E LAN



E LAN vs. E LAN + SAN NW



E LAN + SAN NW vs. E LAN + SAN



Relative difference of CRPS in percentage. Strong forcing conditions

Uncertainty in microphysics

ICON DA

$$\mathbf{x}^{a(i)} \leftarrow \mathbf{x}^{a(i)} + \alpha_a \boldsymbol{\eta}^{(i)} + \alpha_a^{\mathrm{m}} \boldsymbol{\eta}^{(i)\mathrm{m}} \qquad \boldsymbol{\eta}^{(i)} = \tilde{\mathbf{B}}^{\frac{1}{2}} \gamma$$

$\eta^{(i)\mathrm{m}}$ representing uncertainty in **m**icrophysics, as a difference between simulations with one and two-moment scheme

$\eta^{(i)\mathrm{m}}$ qi, qr, qg, qs, qc are perturbed using randomly chosen sample from historical data base

In addition to LAN, in which velocity u, v, temperature, pressure and relative humidity qv are perturbed

Samples calculated for historic case

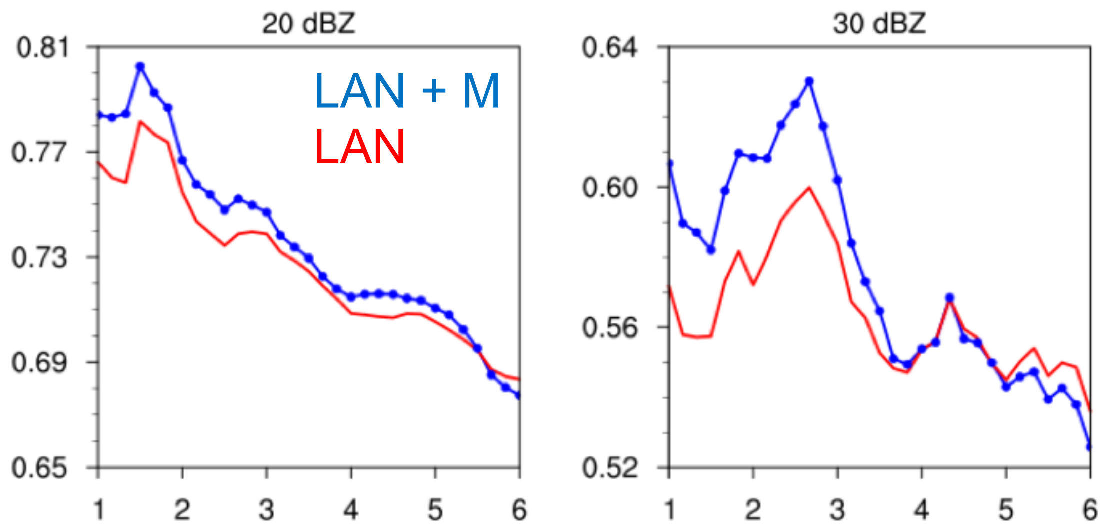
Uncertainty in microphysics

ICON DA

$$\mathbf{x}^{a(i)} \leftarrow \mathbf{x}^{a(i)} + \alpha_a \boldsymbol{\eta}^{(i)} + \alpha_a^{\mathrm{m}} \boldsymbol{\eta}^{(i)\mathrm{m}} \qquad \boldsymbol{\eta}^{(i)} = \tilde{\mathbf{B}}^{\frac{1}{2}} \boldsymbol{\gamma}$$

$\eta^{(i)\mathrm{m}}$ qi, qr, qg, qs, qc are perturbed using randomly chosen sample from historical data base

FSS (70 km)



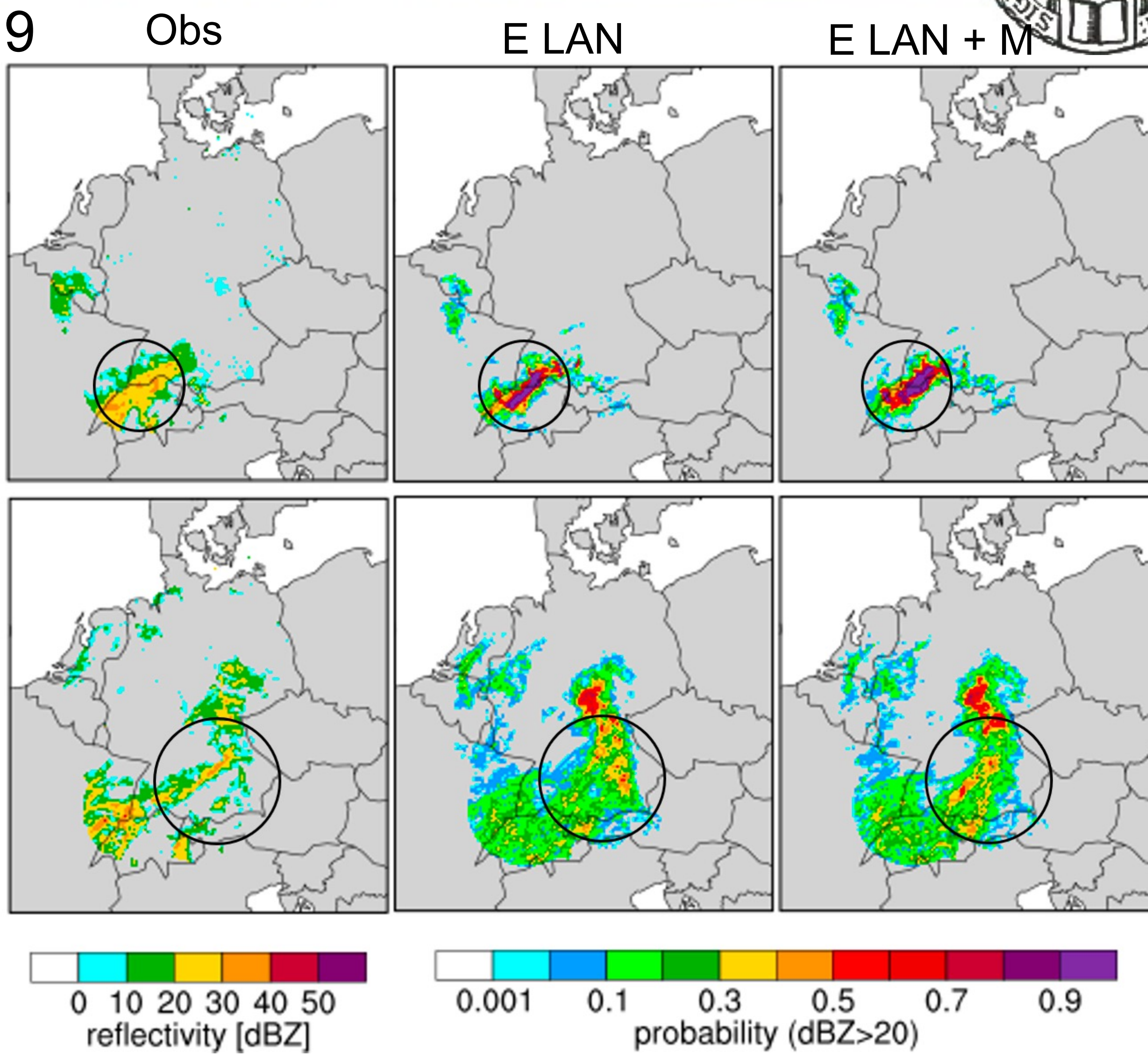
12:00 09 June, 2019

1. Column: Reflectivity composite

Initial time

2.&3. Columns: What percent of ensemble members exceed 20 dBZ

6 h



Conclusion

- The higher resolution models are able to resolve **strongly nonlinear dynamics and start to resolve physical processes that have traditionally been parameterized** such as, for example, convection.
- Small-scale additive noise **based on model truncation error or microphysics error** improves large-scale additive inflation for short-term precipitation forecast.
- Further improvement over additive **model truncation error** can be obtained by adding time variable information from data or on weather regime (Zeng et al. 2020).
- Still to be shown for time variable microphysics error.

References

Feng, Y., T. Janjic, Y. Zeng, A.Seifert, J. Min, 2021, Representing Microphysical Uncertainty in Convective-scale Data Assimilation using Additive Noise, JAMES, 13, e2021MS002606.

Zeng, Y., T. Janjic, A. de Lozar, S. Rasp, U. Blahak, A. Seifert, G. C. Craig, 2020, Comparison of methods accounting for subgrid-scale model error in convective-scale data assimilation, Mon. Wea. Rev., 148, 2457-2477.

Zeng, Y., T. Janjic, A. de Lozar, U. Blahak, M. Sommer, H. Reich, A. Seifert, 2019: Representation of model error for data assimilation on convective scale: additive noise based on truncation error, JAMES, 11, 752–770.

Zeng. Y. T. Janjic, A. de Lozar, U. Blahak, H. Reich, C. Keil, A. Seifert, 2018, Representation of model error in convective-scale data assimilation: Additive noise, relaxation methods and combinations, JAMES,10, 2889–2911.

Gustafsson, N. et al. 2018: Survey of data assimilation methods for convective-scale numerical weather prediction at operational centres. Q.J.R. Meteorol. Soc. Q. J. R. Meteorol. Soc. , 144, 1218-1256

Schraff, C., H. Reich, A. Rhodin, A. Schomburg, K. Stephan, A. Perianez, and R. Potthast, 2016: Kilometre-scale ensemble data assimilation for the Cosmo model (KENDA). Quart. J. Roy. Meteor. Soc., 142, 1453–1472.