Representation of model error in convective scale data assimilation

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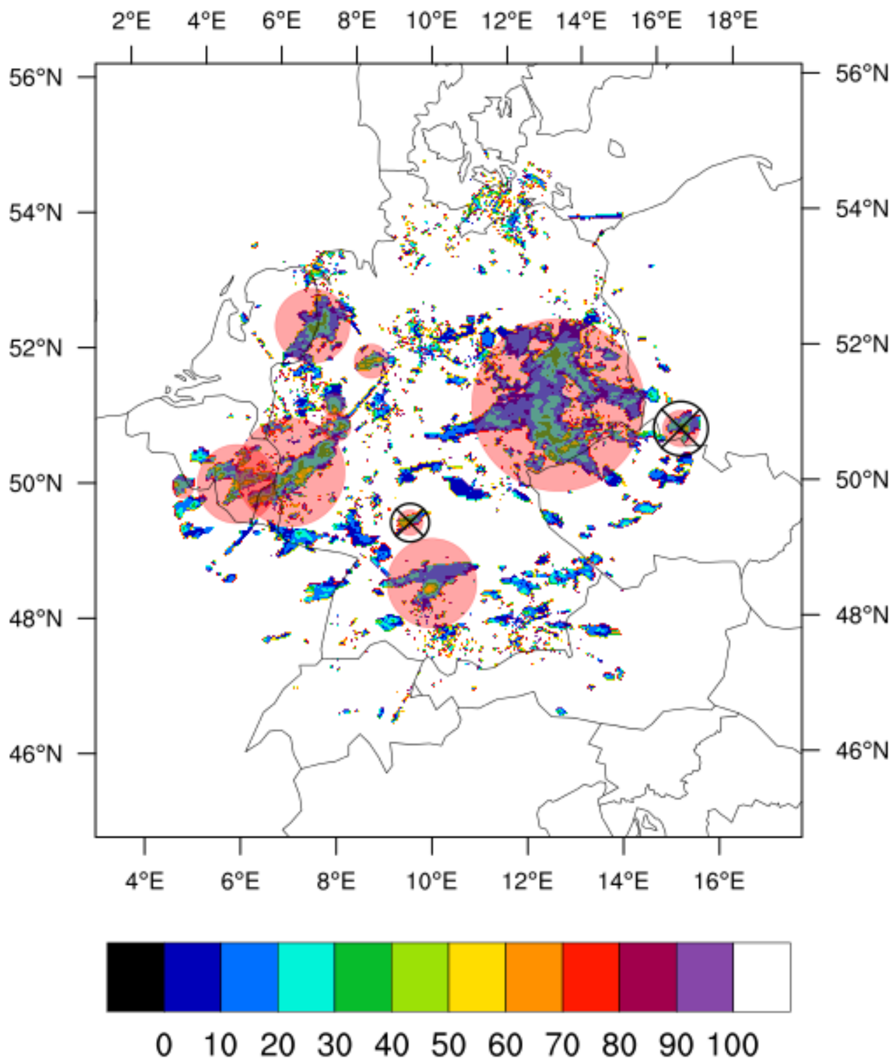
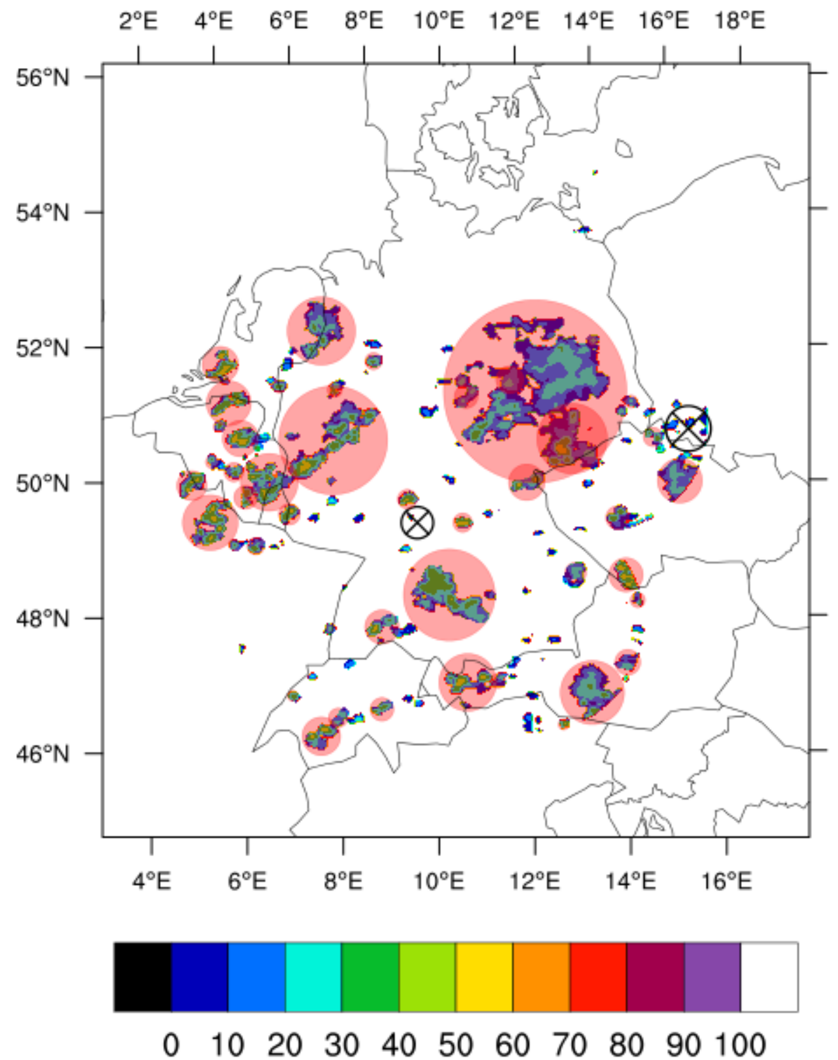
Obsevations DBz



Model COSMO DBz



How can we best characterize **uncertainty of the convection permitting model** for data assimilation and ensemble forecasting?

Our goals:

- Improvement of short term forecast **up to 6h**

- Better use of radar reflectivity data

Methods

- Parameter estimation (Ruckstuhl and Janjic, MWR 2020),EGU2020-7163
- Stochastic boundary layer perturbations (Kober and Craig, JAS,2016)
- Warm bubble (Zeng et al. 2020, MWR)
- Additive noise (Zeng et al. 2019, JAMES) will be primarily presented.

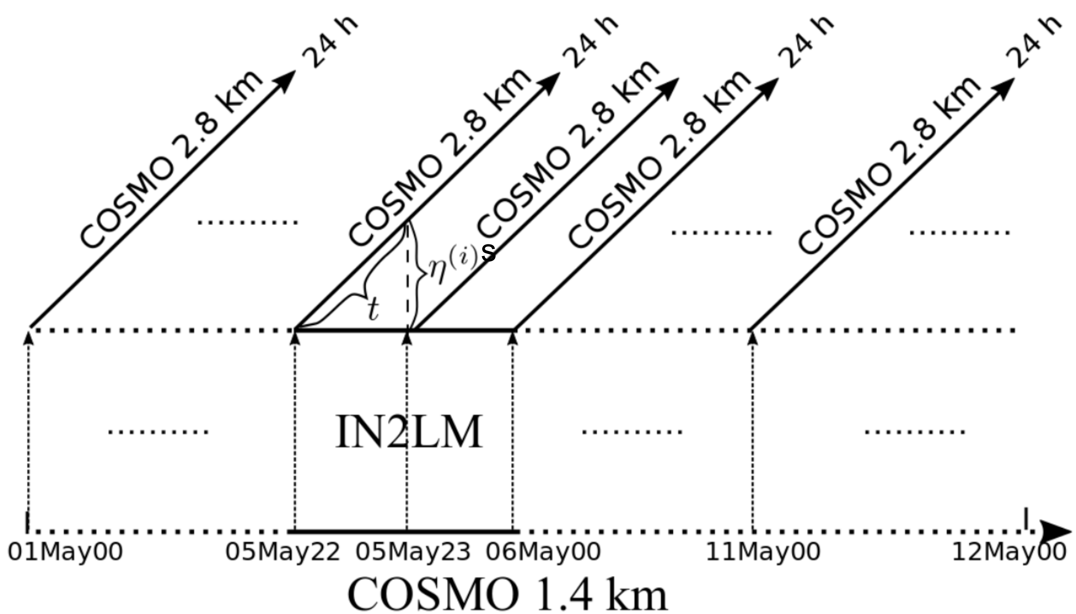
- **K**ilometer-Scale **En**semble **D**ata **A**ssimilation (KENDA, Schraff et al. 2016) based on **LETKF** (Hunt et al. 2007)
- 40-member COSMO ensemble with ICON lateral boundary conditions
- Each member consists of the prognostic variables of velocity, temperature, pressure perturbation, specific humidity, cloud water and ice, rain, snow, and graupel.
- 1h updates using conventional data + radar reflectivity
- **LETKF** also for radar reflectivity, using forward operator EMVORADO (Zeng et al. 2016)

Additive noise

ICON DA

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

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



t taken 1h

288 samples

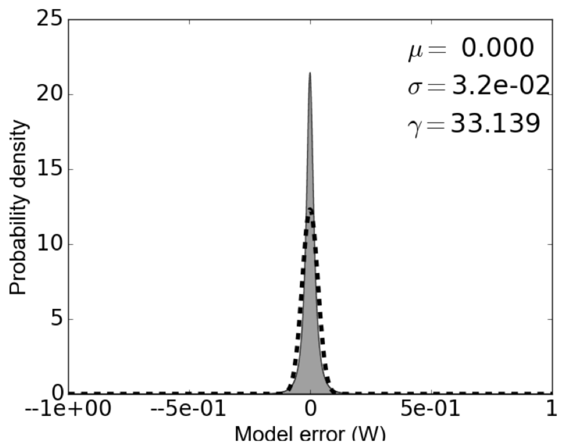
Samples calculated for historic case in 2014

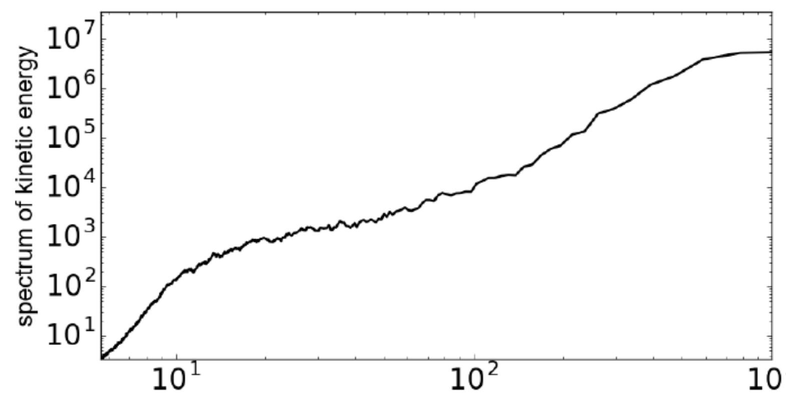
Properties of model error samples

w

Spectrum of large scale perturbations

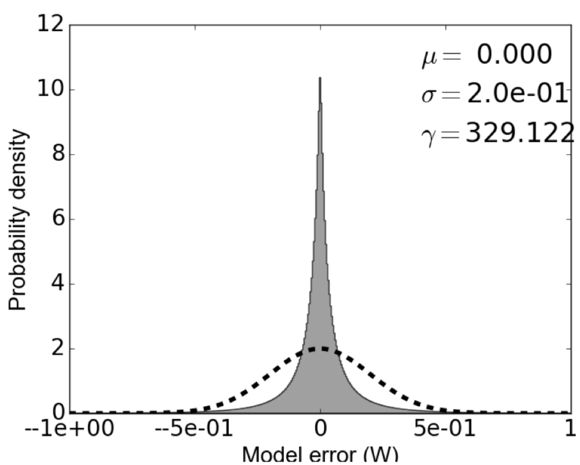
13km

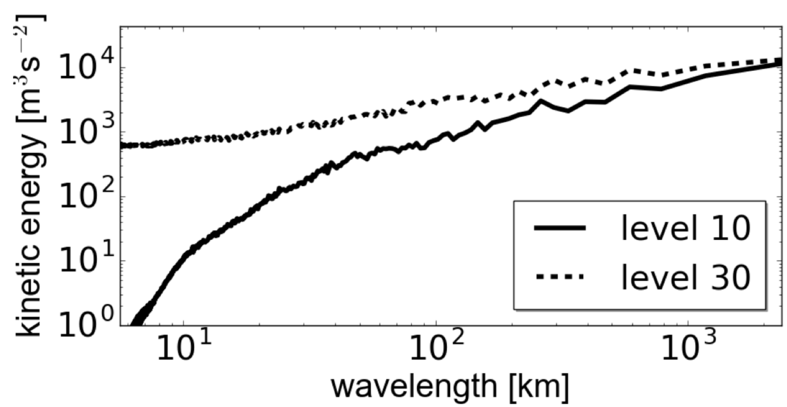




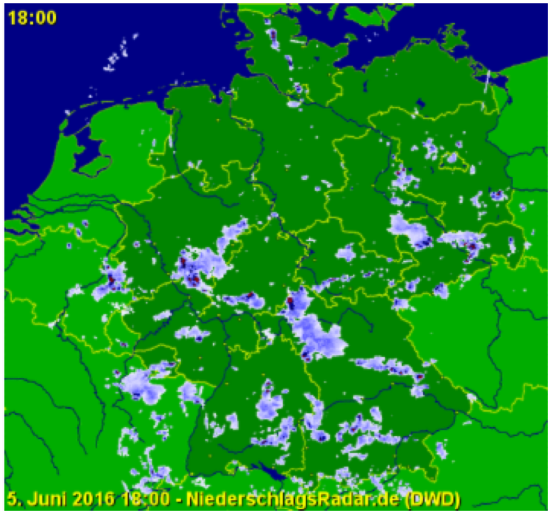
Spectrum of small scale perturbations

3km





Experimental design:



Period: 2 week period starting 00:00 UTC 27 **May 2016, strong and weak forcing**

Size of ensemble: 40 members for DA
20 members are used for 6-h ensemble forecasts, initiated at
10, 11, …, 18:00 UTC
Observation error: 10 dBZ for reflectivity

Experimental design:

$$\mathbf{x}^{a(i)} \leftarrow \mathbf{x}^{a(i)} + \alpha_a \boldsymbol{\eta}^{(i)} + \alpha_a^{s} \boldsymbol{\eta}^{(i)s}$$

ELAN

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

α_a tuned to 0.1, α_a^{s} = 0

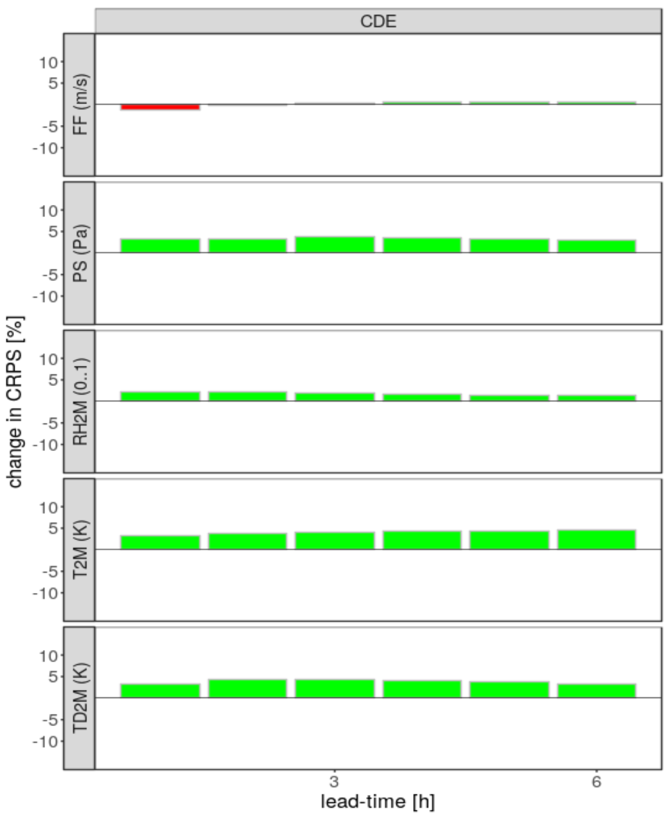
ESAN

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

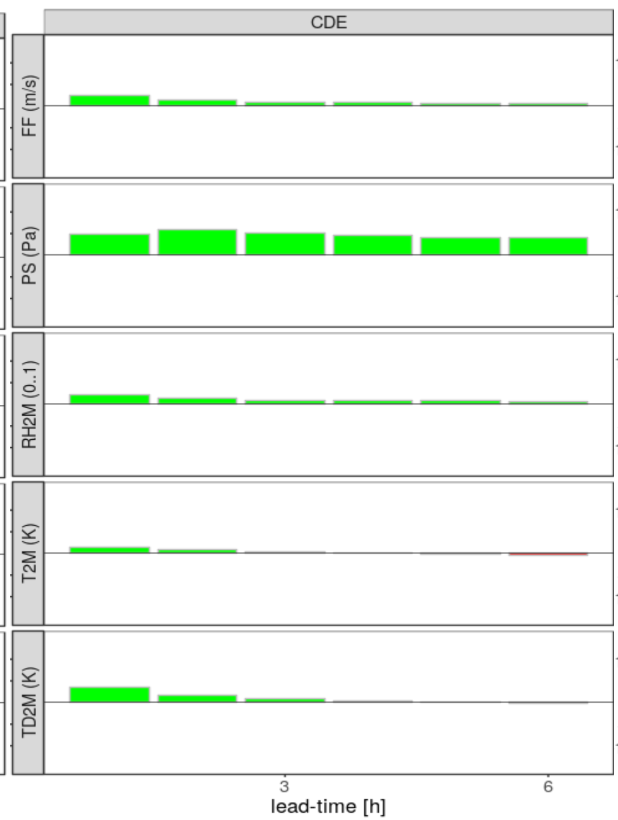
α_a 0, α_a^{s} = 1.25

ELAN0.1SAN1.25 combination
ELAN0.1SAN1.25NW experiment in which w is not perturbed

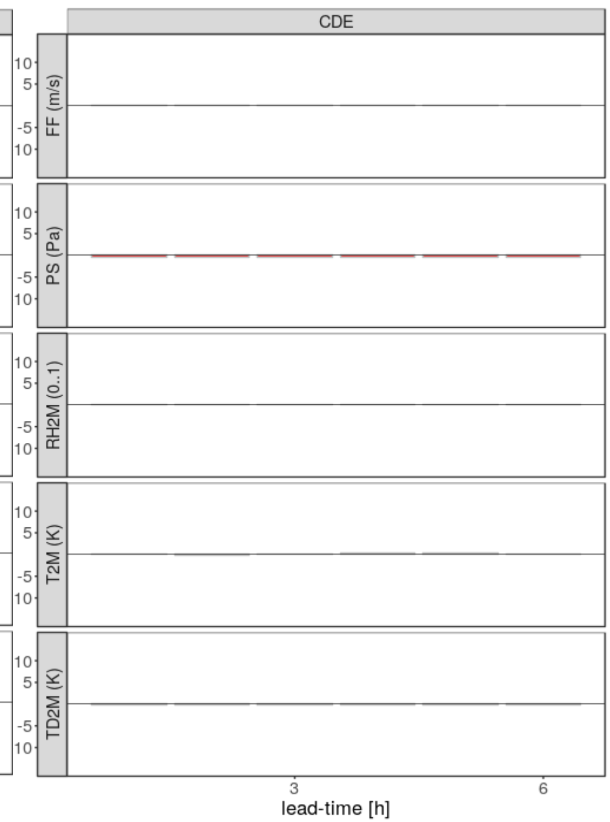
E SAN1.25 vs. E LAN0.10



E LAN0.10 vs.
E LAN0.10SAN1.25NW



E LAN0.10SAN1.25NW
vs. E LAN0.10SAN1.25



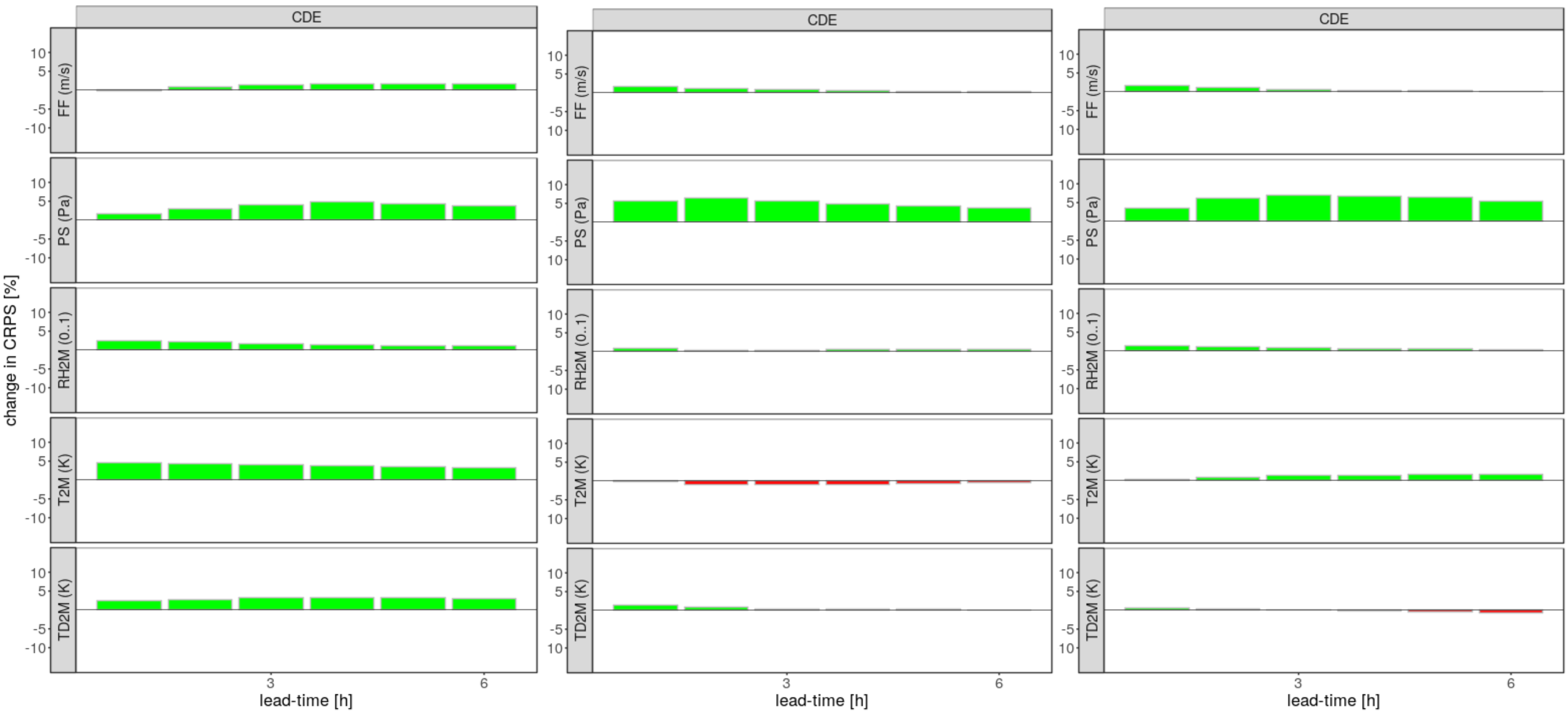
Relative difference of CRPS in percentage. Weak forcing conditions.

Green is better

E SAN1.25 vs. E LAN0.10

E LAN0.10 vs. E LAN0.10SAN1.25NW

E LAN0.10SAN1.25NW vs. E LAN0.10SAN1.25



Relative difference of CRPS in percentage. Strong forcing conditions

Green is better

12:00 06 June, 2016

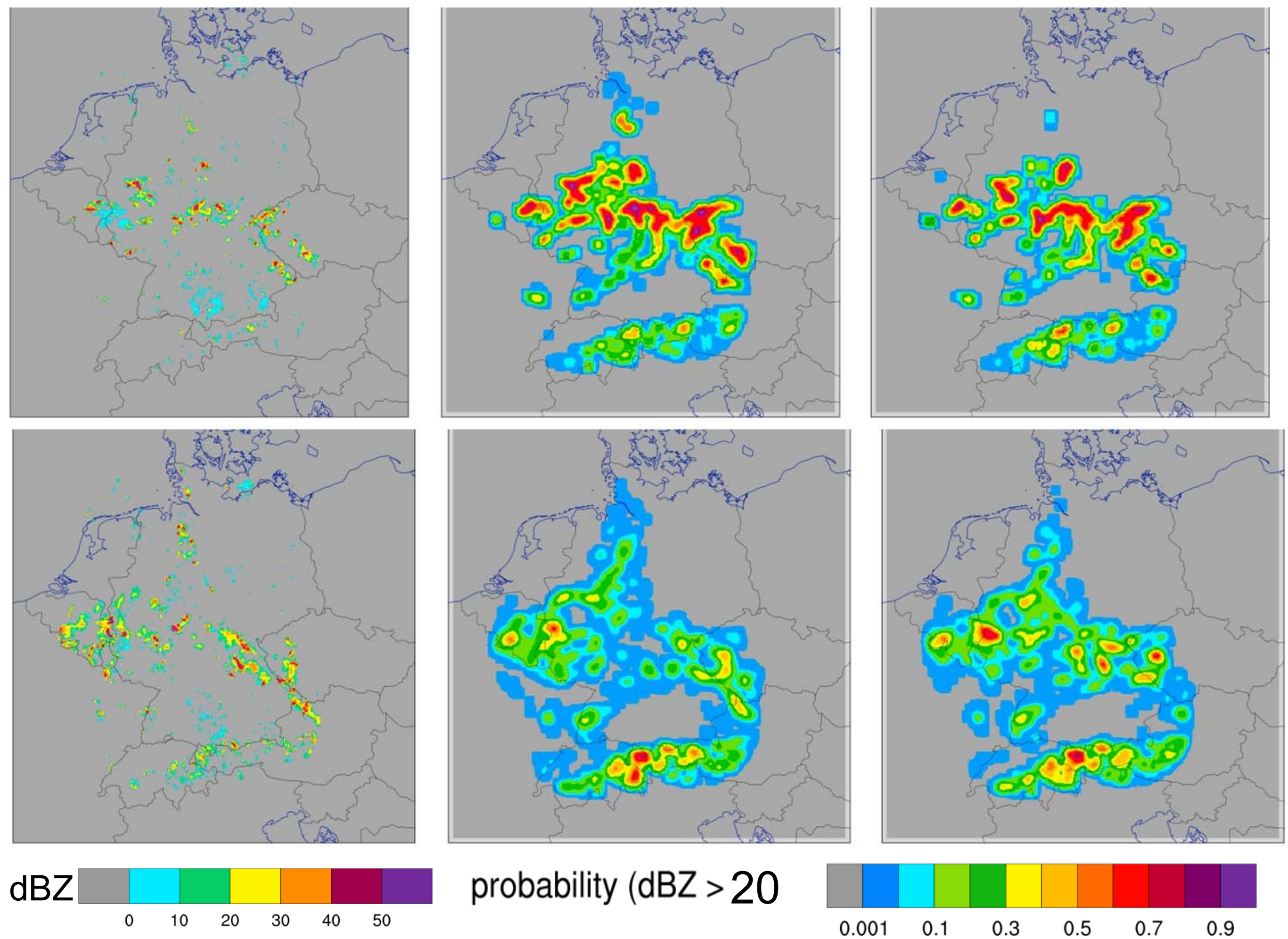
Obs | E LAN0.10 | E LAN0.10SAN1.25

1. Column: Reflectivity composite

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

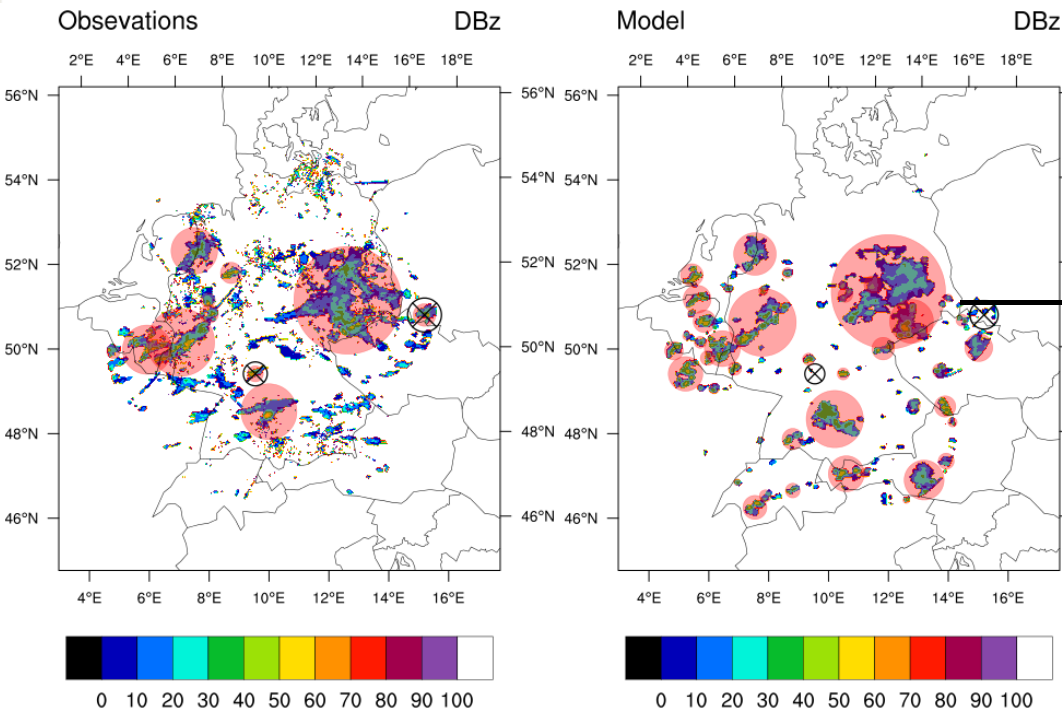
Initial time

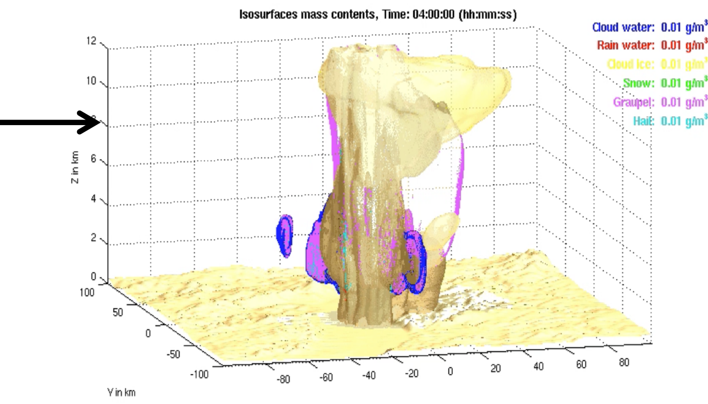
3 h



Warm bubble in DA

(Zeng et al. 2020, MWR)





- Start forming bubbles in areas where radar observations show a convective cell, but there is none in model 15 min before assimilation time in each ensemble member.
- Bubbles warm an area~10x10kmx2km with ~0.01 K/s, in period of 15 minutes.
- Depending on dynamical conditions in each member, cells may or may not develop. Note assimilation hourly using only last 5 min of radar data.

Physically based **S**tochastic **P**erturbations scheme (**PSP**, Kober and Craig 2016)

$$\left(\frac{\partial \Phi}{\partial t}\right)_{\text{total}} = \left(\frac{\partial \Phi}{\partial t}\right)_{\text{param}} + \alpha_{\text{tuning}} \eta \frac{1}{\tau_{\text{eddy}}} \frac{l_{\text{eddy}}}{\Delta x_{\text{eff}}} \sqrt{\overline{\Phi'^2}}$$

$\Phi \in T, q_v, w$; $\tau_{\text{eddy}} = 10$ minutes; $\Delta x_{\text{eff}} = 5\Delta x$; $\alpha_{\text{tuning}} = 7.2$; $l_{\text{eddy}} = 1$ km

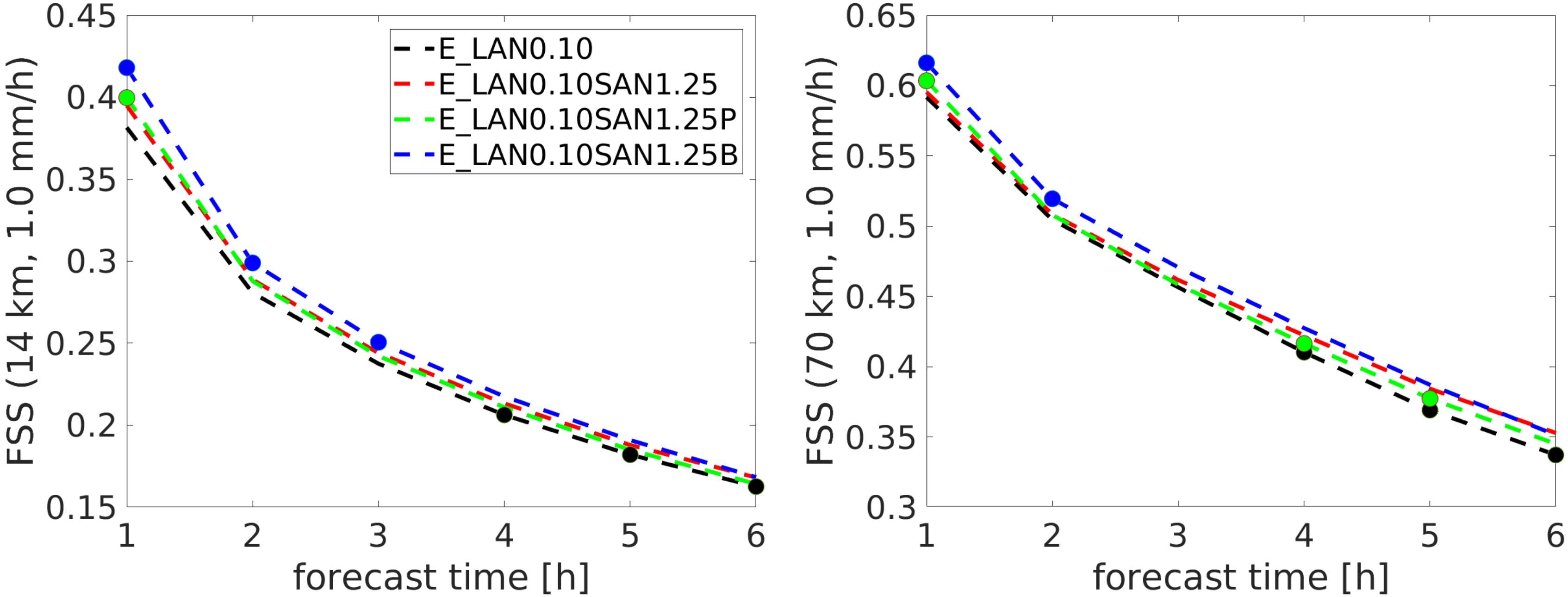
$\sqrt{\overline{\Phi'^2}}$ is the subgrid standard deviation; η is a two-dimensional random field

ELAN0.1SAN1.25 represents model error only via climatological information

It was also combined with PSP or warm bubble (Zeng et al. 2020)

ELAN0.1SAN1.25P = ELAN0.1SAN1.25 +PSP

ELAN0.1SAN1.25B = ELAN0.1SAN1.25 +Warm Bubble



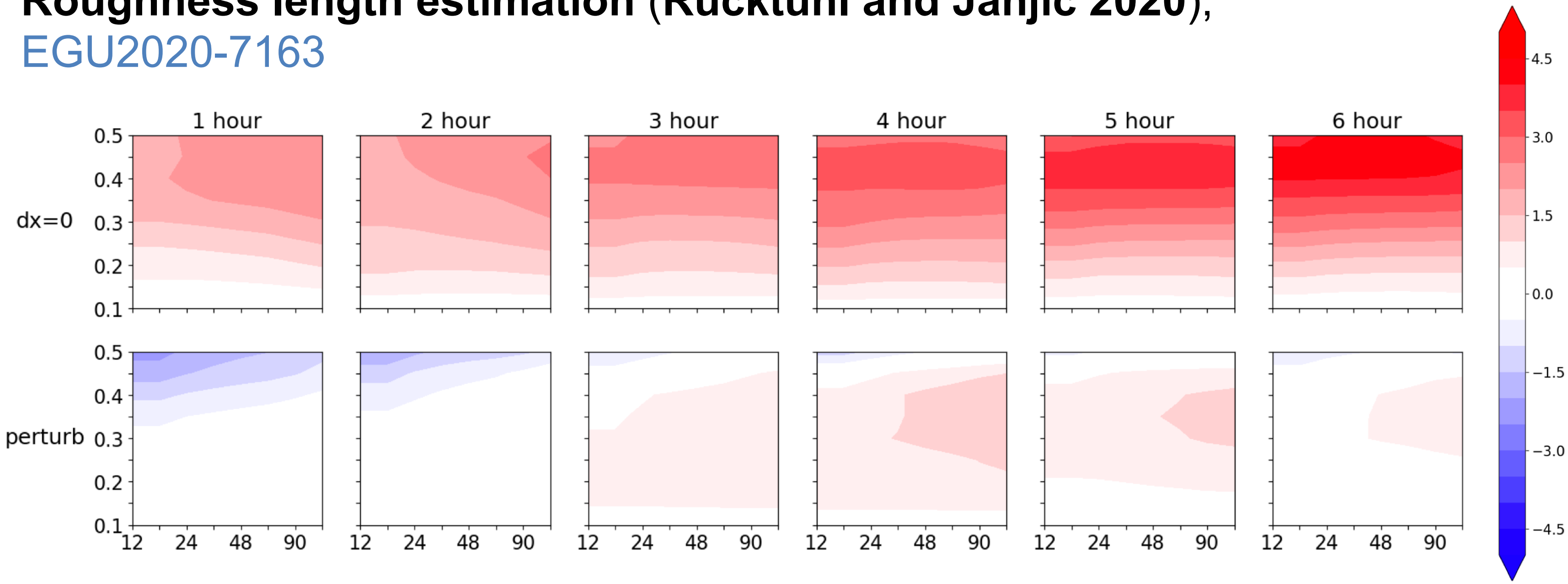
Warm bubble in DA, adds new cells missing in the model and therefore time dependent information.

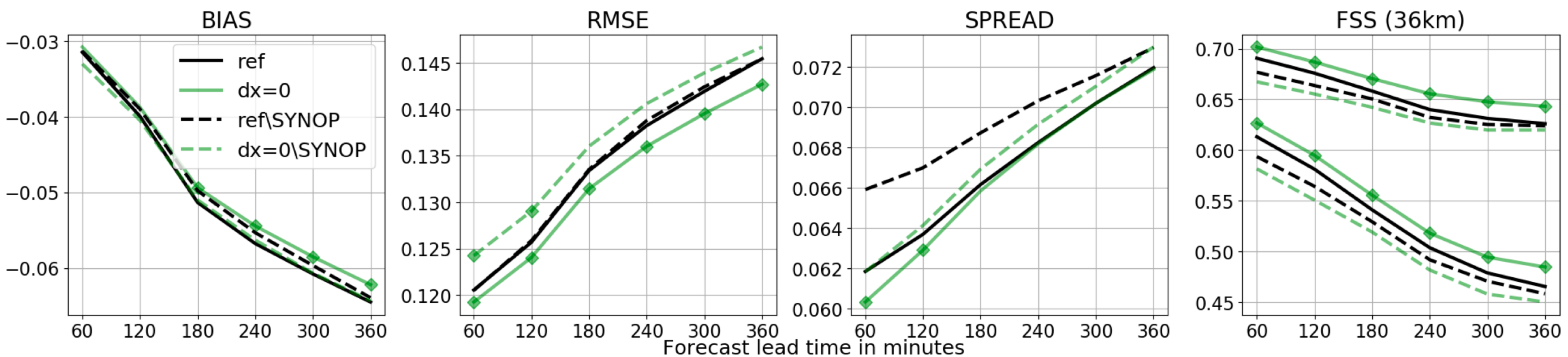
PSP also adds regime dependent information during DA.

Both further improve FSS scores.

Roughness length estimation (Rucktuhl and Janjic 2020),

EGU2020-7163





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.
- However model error still exists.
- Small-scale additive noise based on model truncation error improves large-scale additive inflation for short-term precipitation forecast.
- Further improvement can be obtained by adding time variable information from data or on weather regime.
- Can we do better through improvements in additive noise algorithm?

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MIM

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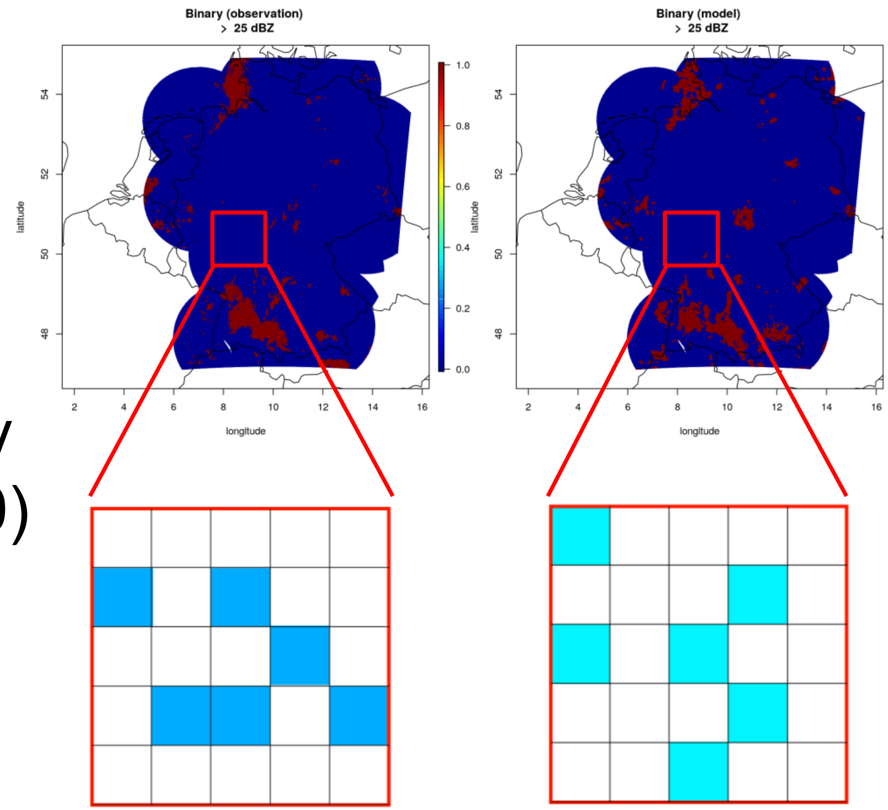
➢ Fraction Skill Score (**FSS**, Roberts & Lean, 2008)

FSS for a fixed treshold value (of reflectivity or rain) and resolution

$$FSS = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}(P_{fcst} - P_{obs})^2}{\frac{1}{N}\sum_{i=1}^{N}P_{fcst}^2 + \frac{1}{N}\sum_{i=1}^{N}P_{obs}^2}$$

- Continuous ranked probability score (**CRPS**, Hersbach 2000)
- False alarm rate **FAR** ratio of false alarms to sum of false alarms and hits for a fixed treshold values



P_{obs}= 6/25 P_{fcst} = 6/25

Figure from M.Hoff, DWD

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RTPP scheme with 0.75 (Zhang et al 2004)

$$\mathbf{X}^a \leftarrow (1-\alpha_p)\mathbf{X}^a + \alpha_p \mathbf{X}^b$$

Additive noise with samples from ICON's B matrix with 0.1

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

RTPS scheme with 0.95 (Whitaker and Hamill 2012)

$$\sigma^a \leftarrow (1-\alpha_s)\sigma^a + \alpha_s\sigma^b \qquad \mathbf{X}^a \leftarrow \left(\alpha_s \frac{\sigma^b - \sigma^a}{\sigma^a} + 1\right)\mathbf{X}^a$$

Whitaker and Hamill 2012, using two-level primitive equation global model: "when model error is the dominant source of unrepresented background errors, additive inflation alone outperforms any combination of RTPS and additive inflation."

Similar conclusion Zeng et al, JAMES 2018

Histogram of small scale model error samples