Representation of model error for data assimilation on convective scale

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Background information:

- Kilometre-scale ENsemble Data Assimilation (**KENDA**) system operationally run at DWD since May 2016 (Schraff et al. (2016))
- Data assim. scheme: Local Ensemble Transform Kalman Filter (**LETKF**)
- "Sufficient" background (analysis) spread σ^b (σ^a) to represent **sampling error** (due to limited size of ensemble) and **model error:**
  - **Adaptive multi. inflation** (Anderson (2008)): $\mathbf{P}^b = \frac{1}{N-1}\mathbf{X}^b\mathbf{X}^{b^T} \leftarrow \alpha\mathbf{P}^b$
  - **Relaxation method:**

    1. Relaxation to prior perturbations (**RTPP**, Zhang et al. (2004))

       $\mathbf{X}^a \leftarrow (1-\alpha_p)\mathbf{X}^a + \alpha_p\mathbf{X}^b$ operational α_p = 0.75

    2. Relaxation to prior spread (**RTPS**, Whitaker and Hamill (2012))

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

       e.g., α_s = 0.95 (Bick et al. (2016))

  - **Additive inflation:** $\mathbf{x}^{a(i)} \leftarrow \mathbf{x}^{a(i)} + \alpha_a\boldsymbol{\eta}^{(i)}$

    Currently in KENDA: random samples of climatological background error covariances from global EnVar data assimilation system for ICON.
    We call it "**large-scale**" additive inflation, denoted by "**AIL**",
    operational α_a= 0.1

Motivation

Whitaker and Hamill (2012) compare combinations of AIL (based on truncation error of 12-h forecast) with RTPS using two-level primitive equation global model. Ensemble size is 200, so sampling error is very small

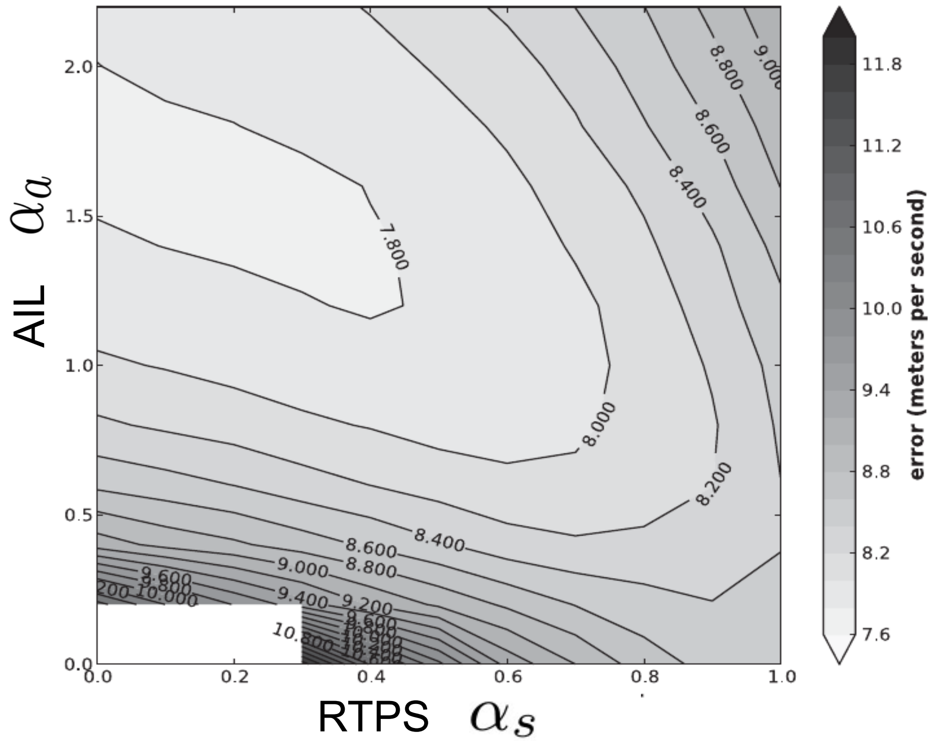


Fig.: Contours of the ensemble mean background error using combinations of AIL and RTPS

" when model error is the dominant source of unrepresented background errors, additive inflation alone outperforms any combination of RTPS and additive inflation."

Model error is prevailing at convective-scale

Question: AIL, RTPP/RTPS or else for convective-scale data assimilation?

Outline

1. Comparison of AIL, RTPP and combination
2. Comparison of AIL, RTPS and combination
3. Introduction of additive inflation based on model truncation error for KENDA
4. Conclusion and outlook

Experimental design:

Period: 00:00 UTC 27 May 2016 – 00:00 UTC 03 June 2016

Weather situation: atmospheric blocking, stationary thunderstorms

Observations: conventional data (AIREP, TEMP, PILOT, SYNOP) + radar reflectivity

Data assim. scheme: LETKF (also for radar reflectivity, using forward operator EMVORADO (Zeng et al. (2016))

Assimilation window: one hour

Size of ensemble: 40 members, and 20 members are used for 6-h ensemble forecasts, initiated at 10, 11, …, 18:00 UTC

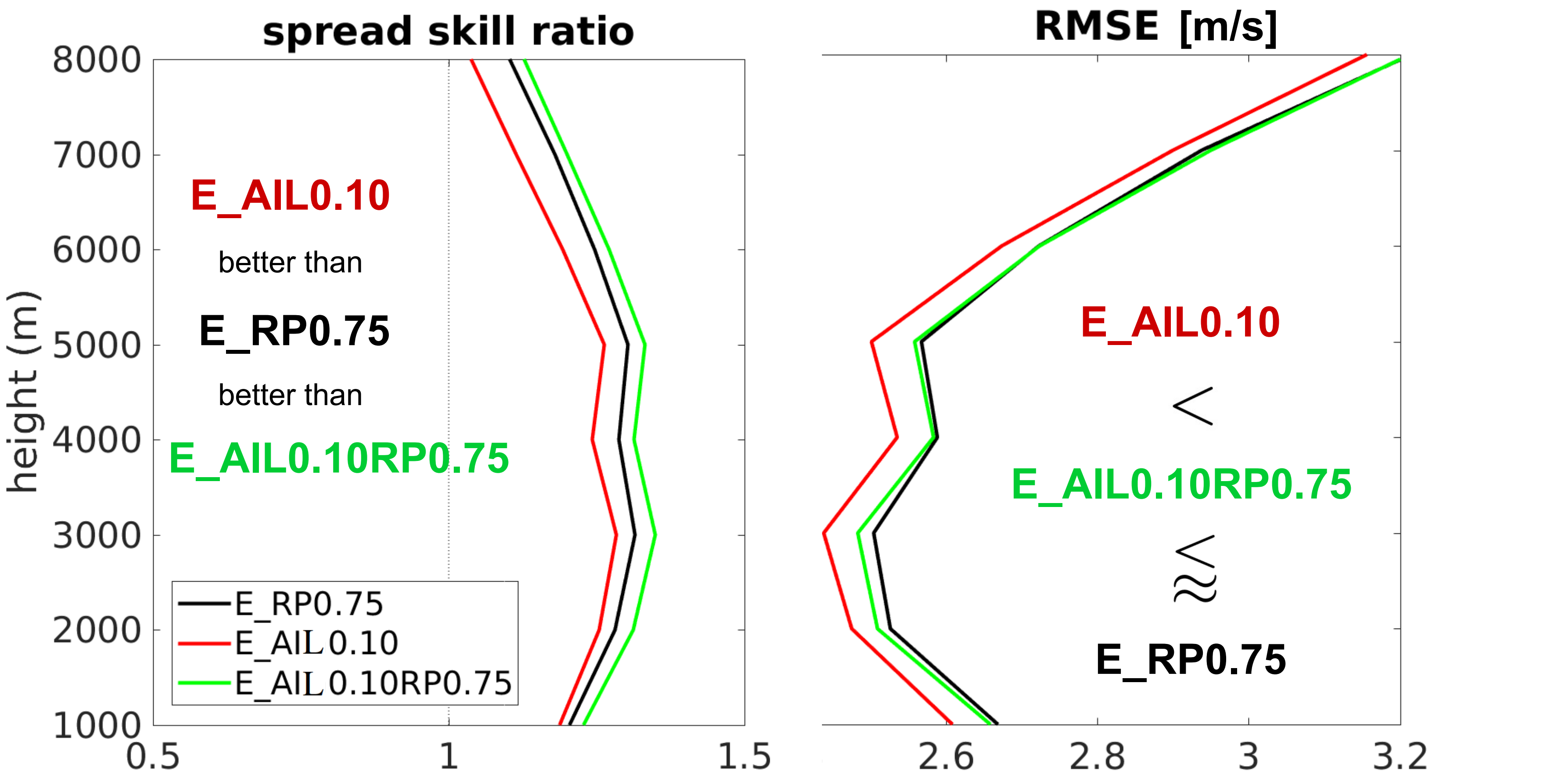
Localization: adaptive horizontal localization for conventional data, constant horizontal localization (16 km) for reflectivity

Observation error: 10 dBZ for reflectivity

Study I: Comparison of AIL and RTPP (spread skill ratio & RMSE)

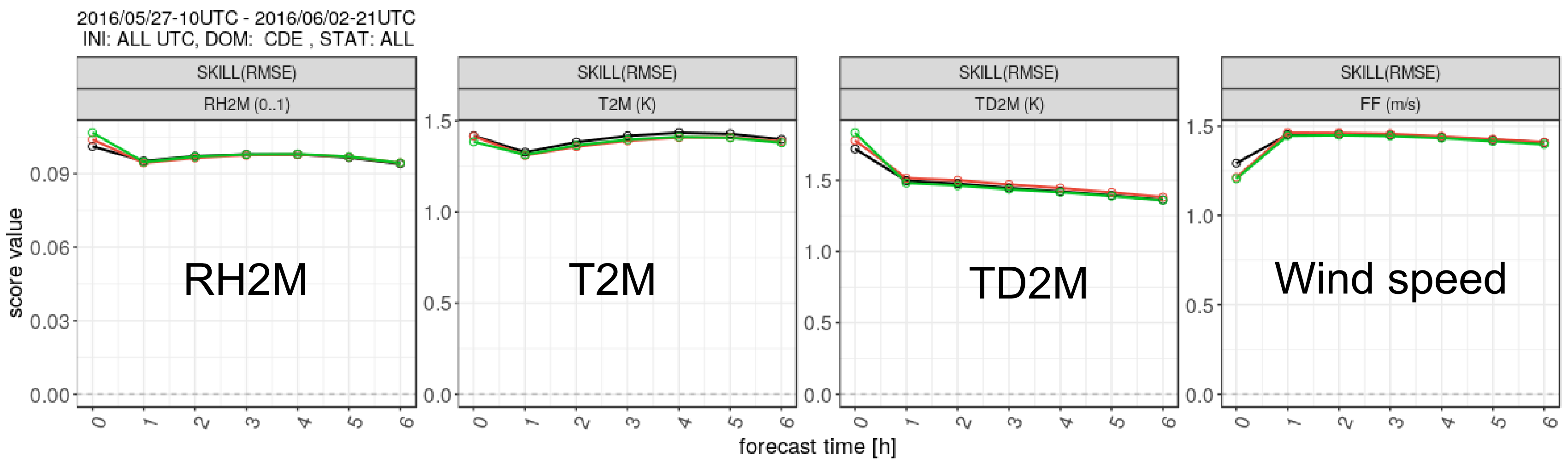
E_RP0.75 : RTPP (α_p = 0.75) only; **E_AIL0.10**: AIL (α_a = 0.1) only

E_AIL0.10RP0.75: AIL (α_a = 0.1) + RTPP (α_p = 0.75)



Verification of first guess ensemble against **Radial Wind** within assim. cycles

Study I: Comparison of AIL and RTPP (RMSE of ensemble forecast)

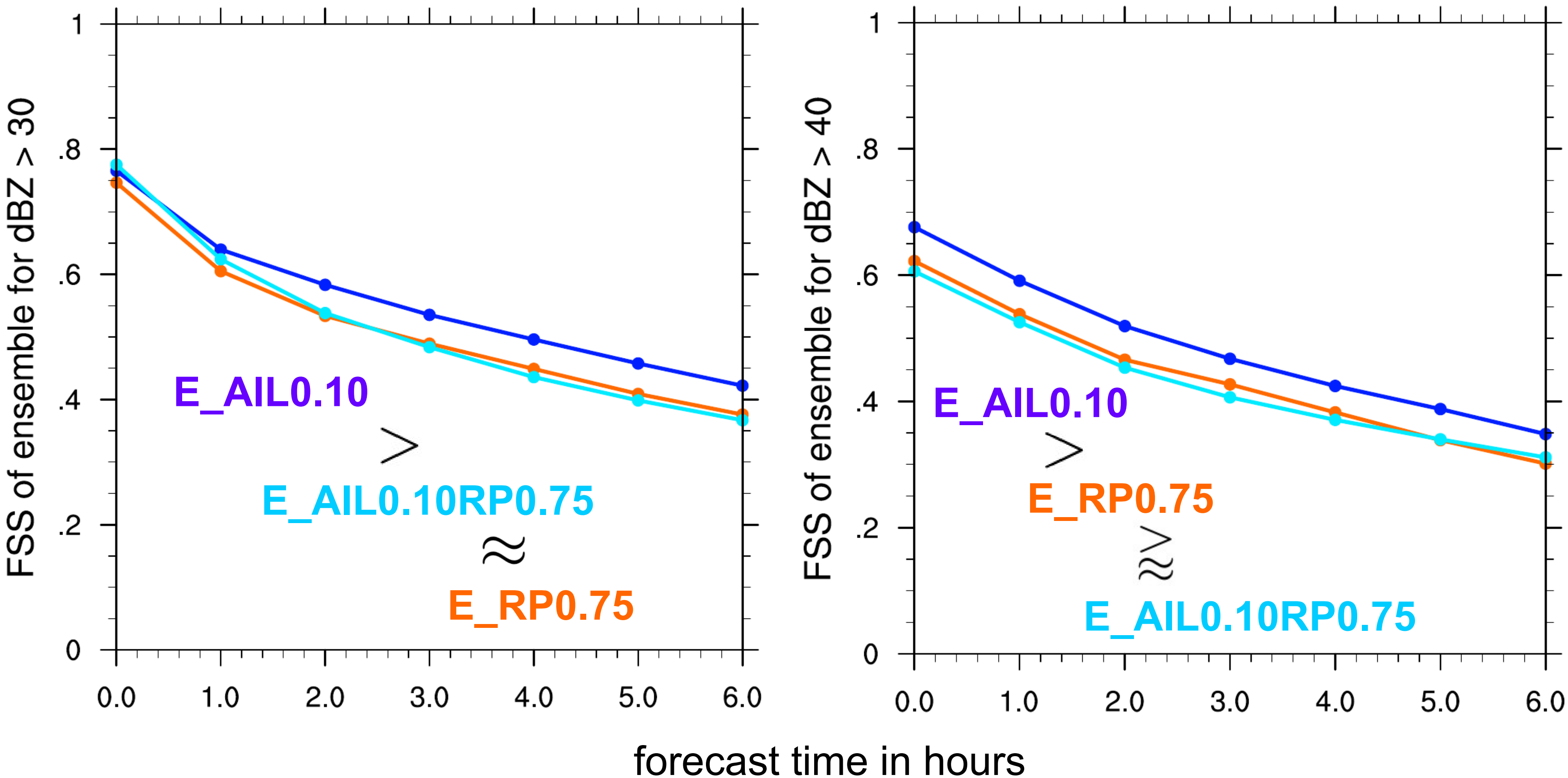


Verification of 6-h ensemble forecast against SYNOP

E_RP0.75 ≈ **E_AIL0.10** ≈ **E_AIL0.10RP0.75**

Study I: Comparison of AIL and RTPP (Fraction skill score (FSS) of reflectivity in ensemble forecast)

FSS with scale of 30 km for different thresholds 30 and 40 dBZ: the higher, the better

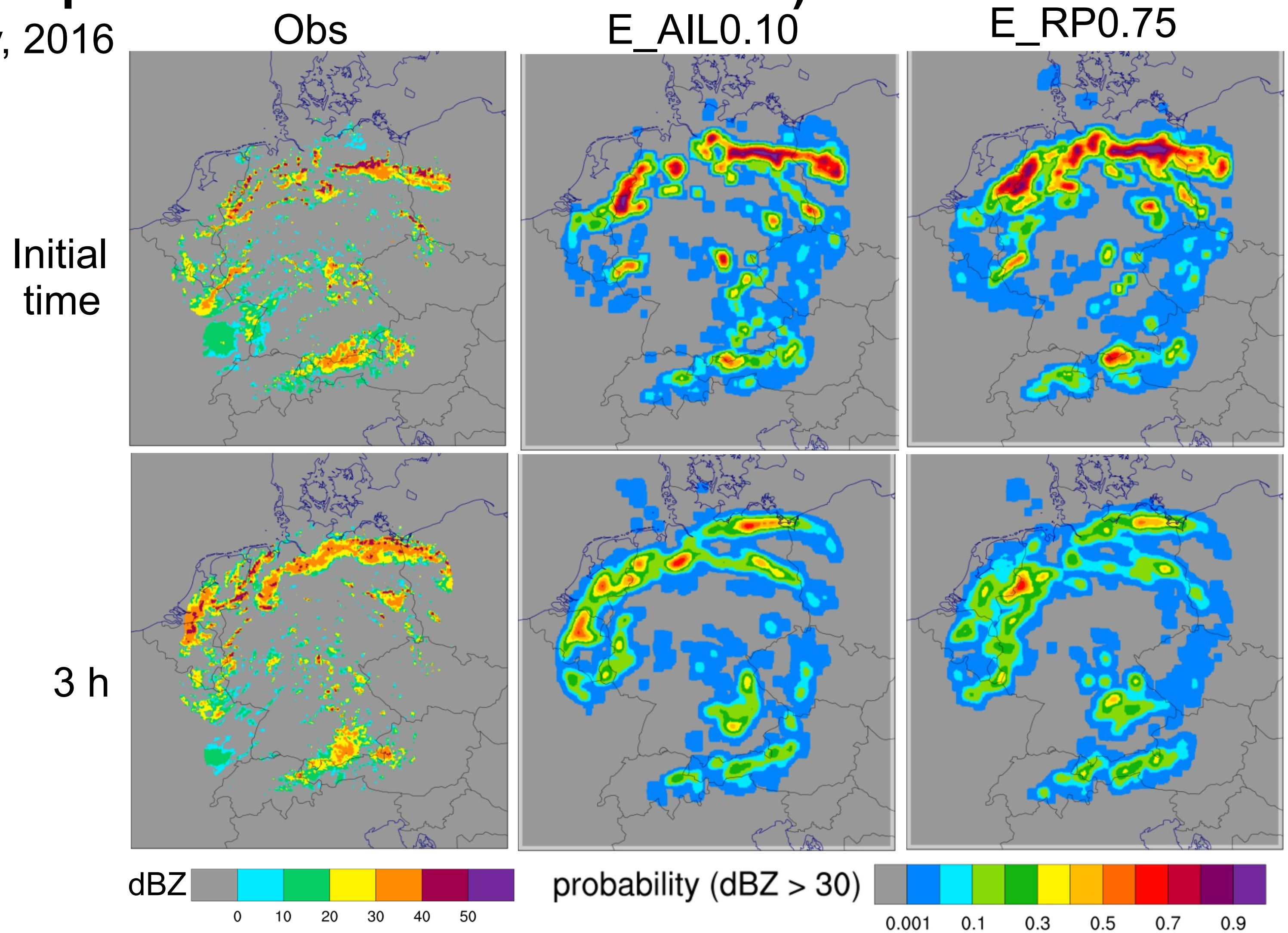


Study I: Comparison of AIL and RTPP (reflectivity composite in initial time & forecast)

14:00 30 May, 2016

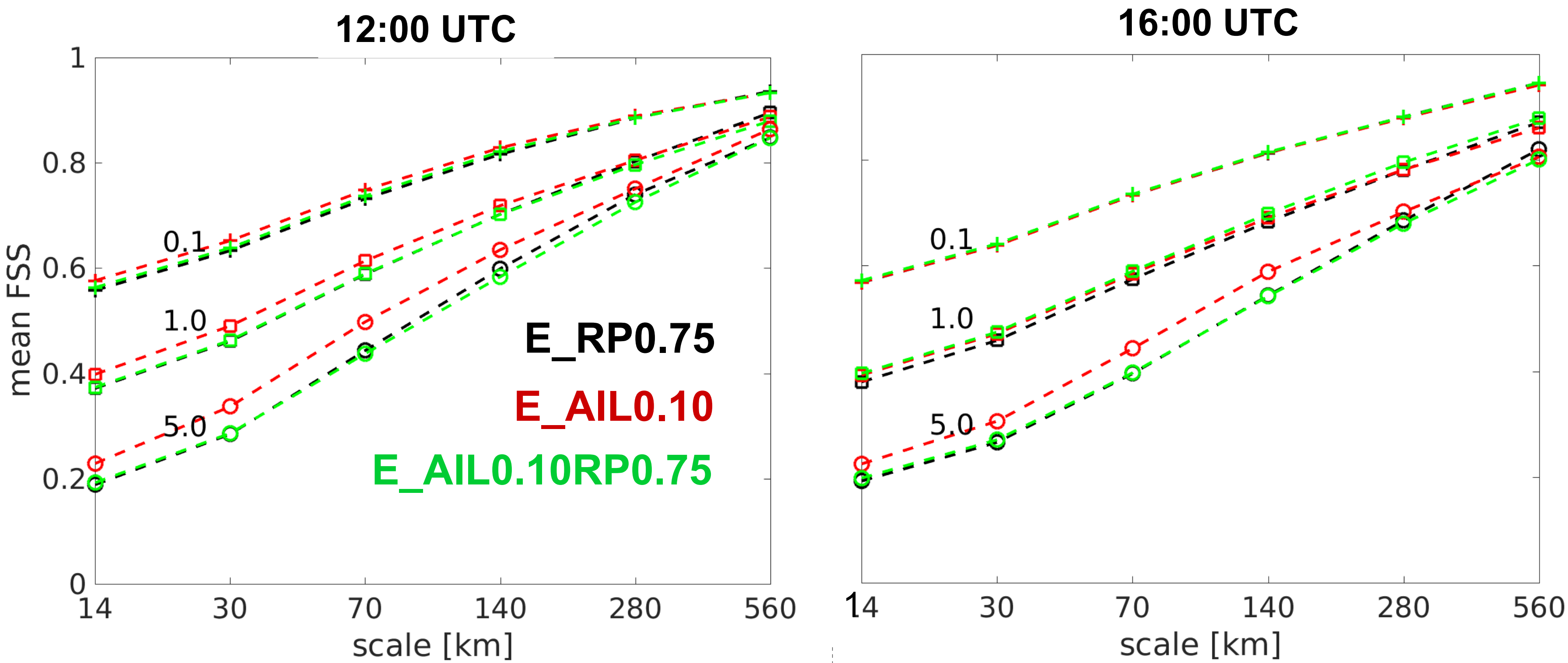
1. Column: Reflectivity composite

2.&3. Columns: How much percent of ensemble members exceed 30 dBZ



Study I: Comparison of AIL and RTPP (Fraction skill score of precipitation forecast)

FSS for different precip. rate thresholds 0.1, 1.0 & 5.0 mm/h and scales 14,…, 560 km

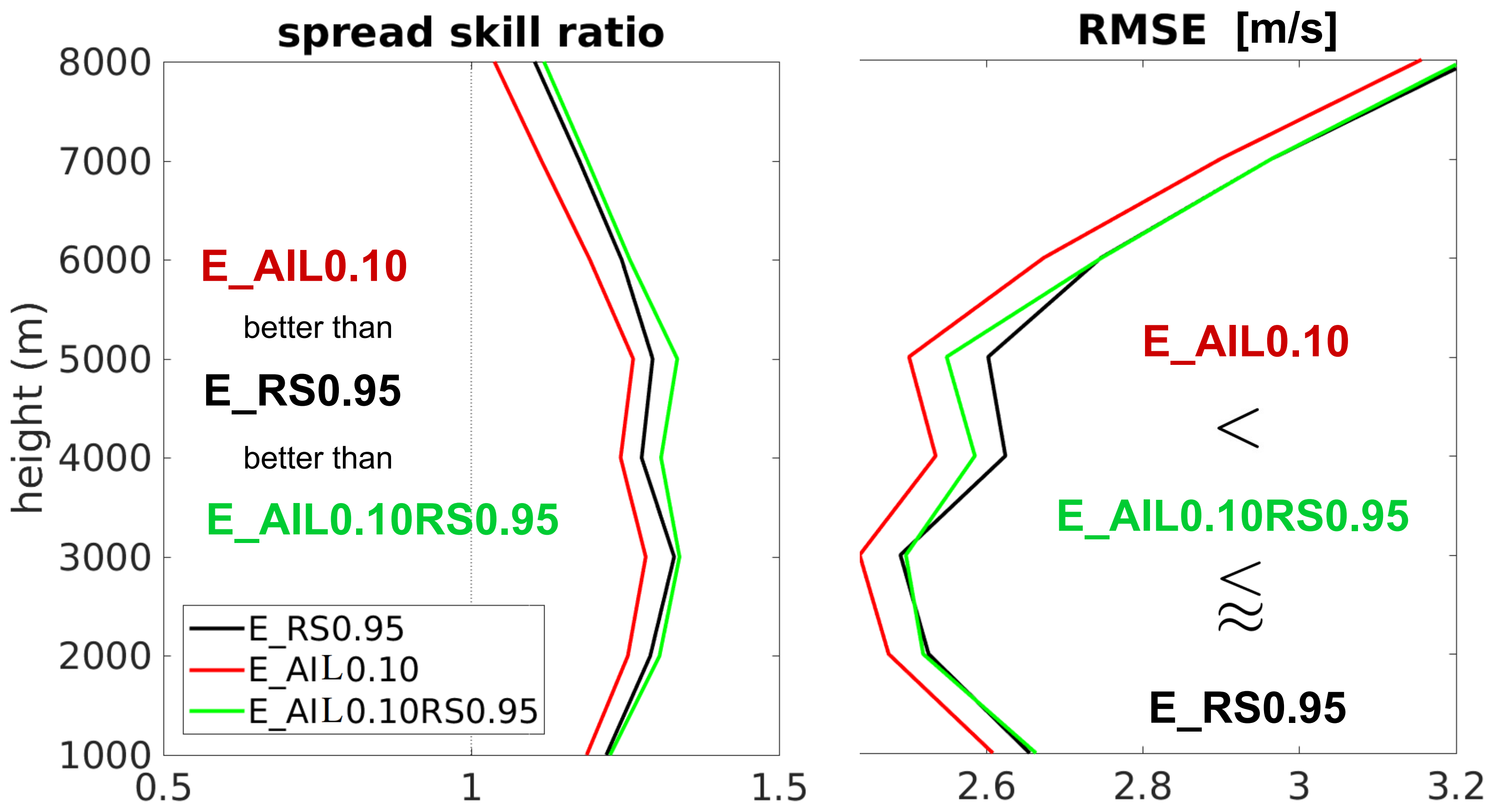


	12:00 UTC	16:00 UTC
0.1 mm/h:	E_AIL0.10 $\gtrapprox$ E_AIL0.10RP0.75 ≈ E_RP0.75	E_AIL0.10 ≈ E_AIL0.10RP0.75 ≈ E_RP0.75
1.0 mm/h:	E_AIL0.10 > E_AIL0.10RP0.75 ≈ E_RP0.75	E_AIL0.10 ≈ E_AIL0.10RP0.75 ≈ E_RP0.75
5.0 mm/h:	E_AIL0.10 > E_AIL0.10RP0.75 ≈ E_RP0.75	E_AIL0.10 > E_AIL0.10RP0.75 ≈ E_RP0.75

Study II: Comparison of AIL and RTPS (spread skill ratio & RMSE)

E_RS0.95 : RTPS (α_s = 0.95) only; **E_AIL0.10** : AIL (α_a = 0.1) only

E_AIL0.10RS0.95: AIL (α_s = 0.1) + RTPS (α_a = 0.95)



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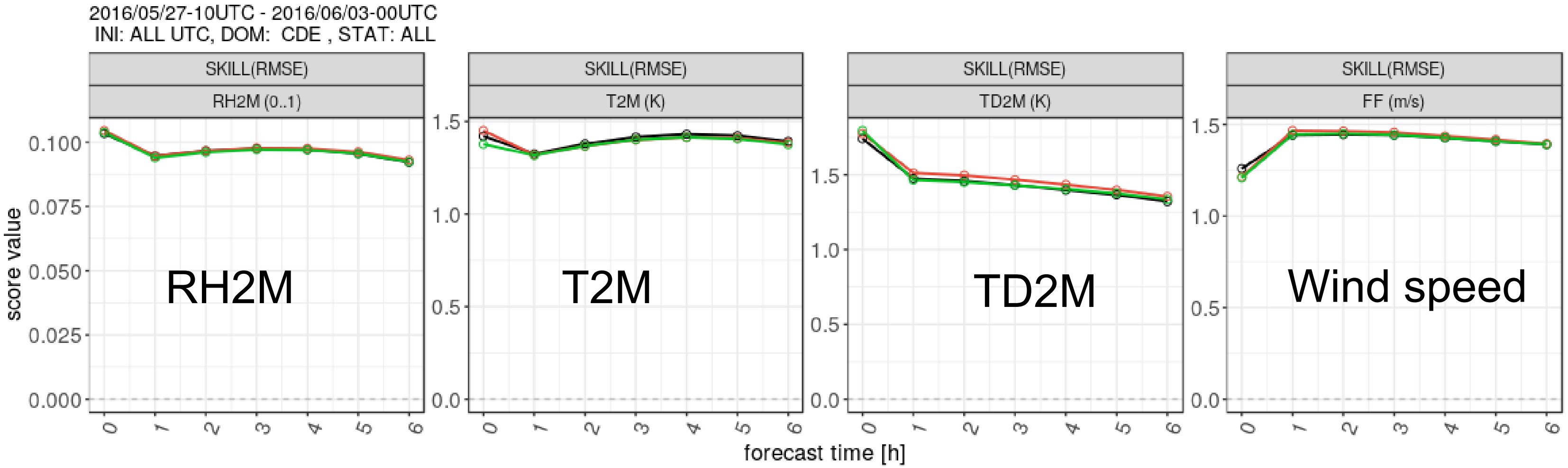
Study II: Comparison of AIL and RTPS (RMSE of ensemble forecast)



Verification of 6-h ensemble forecast against SYNOP

E_RS0.95 ≈ E_AIL0.10 ≈ E_AIL0.10RS0.95

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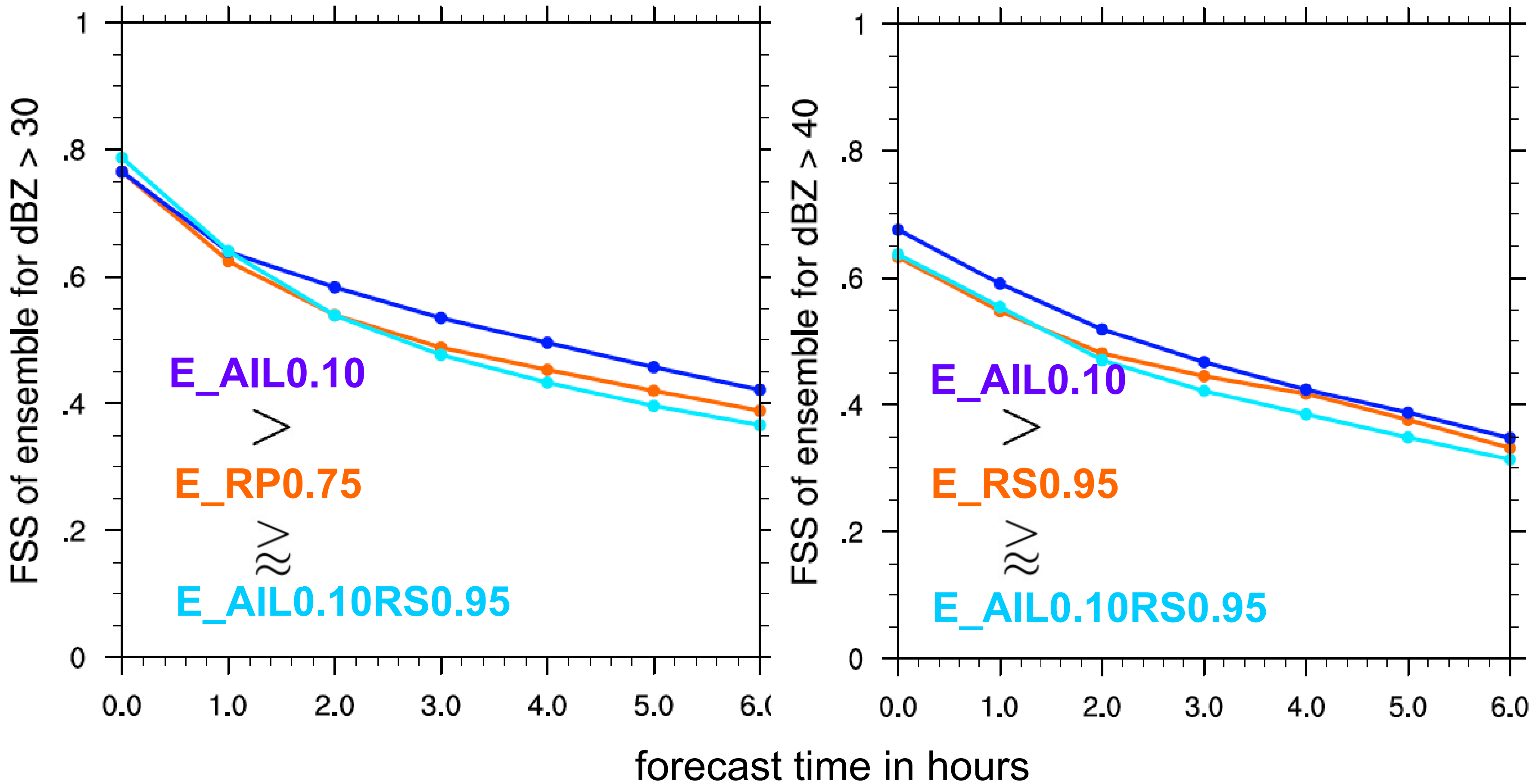
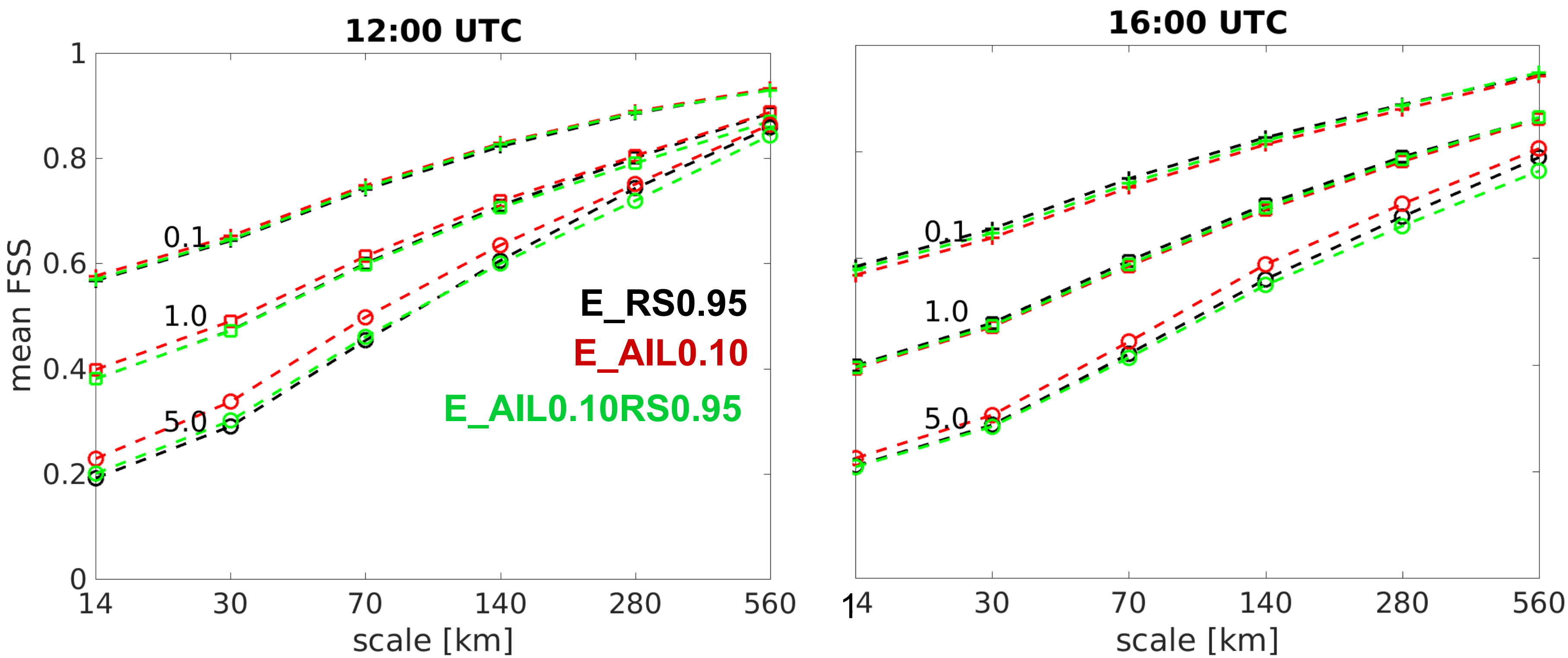


Study II: Comparison of AIL and RTPS (Fraction skill score of precipitation forecast)

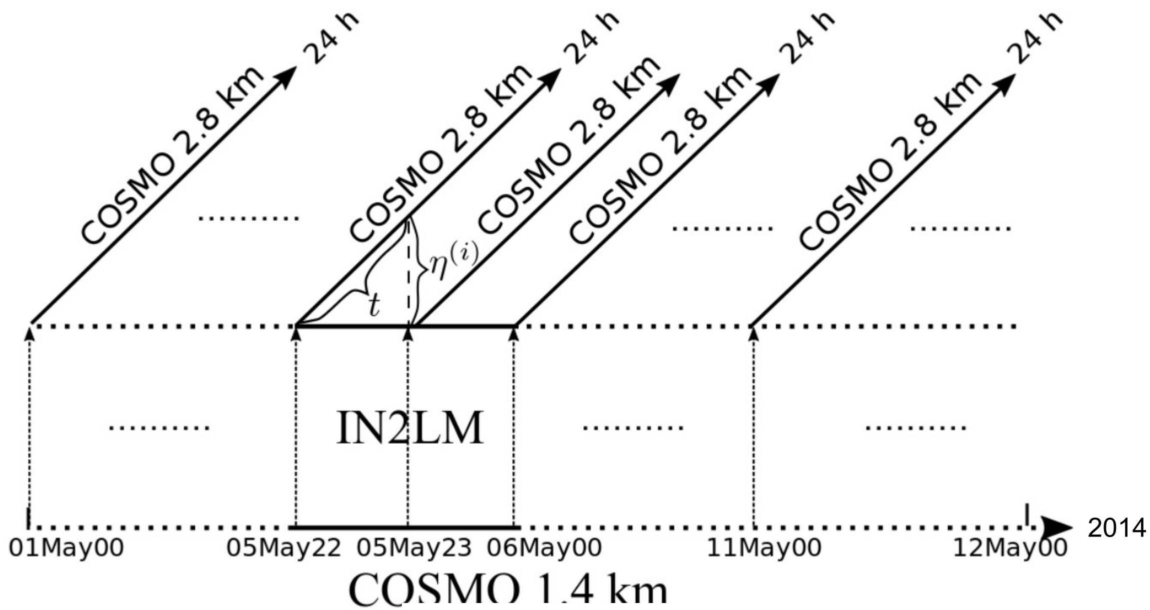
FSS for different precip. rate thresholds 0.1, 1.0 & 5.0 mm/h and scales 14,…, 560 km



	12:00 UTC	16:00 UTC
0.1 mm/h:	E_AIL0.10 $\approx$ E_AIL0.10RS0.95 $\approx$ E_RS0.95	E_AIL0.10 $\approx$ E_AIL0.10RS0.95 $\approx$ E_RS0.95
1.0 mm/h:	E_AIL0.10 $\gtrapprox$ E_AIL0.10RS0.95 $\approx$ E_RS0.95	E_AIL0.10 $\approx$ E_AIL0.10RS0.95 $\approx$ E_RS0.95
5.0 mm/h:	E_AIL0.10 $>$ E_AIL0.10RS0.95 $\approx$ E_RS0.95	E_AIL0.10 $>$ E_AIL0.10RS0.95 $\approx$ E_RS0.95

Introduction of additive inflation based on model truncation error for KENDA (Whitaker and Hamill (2012))

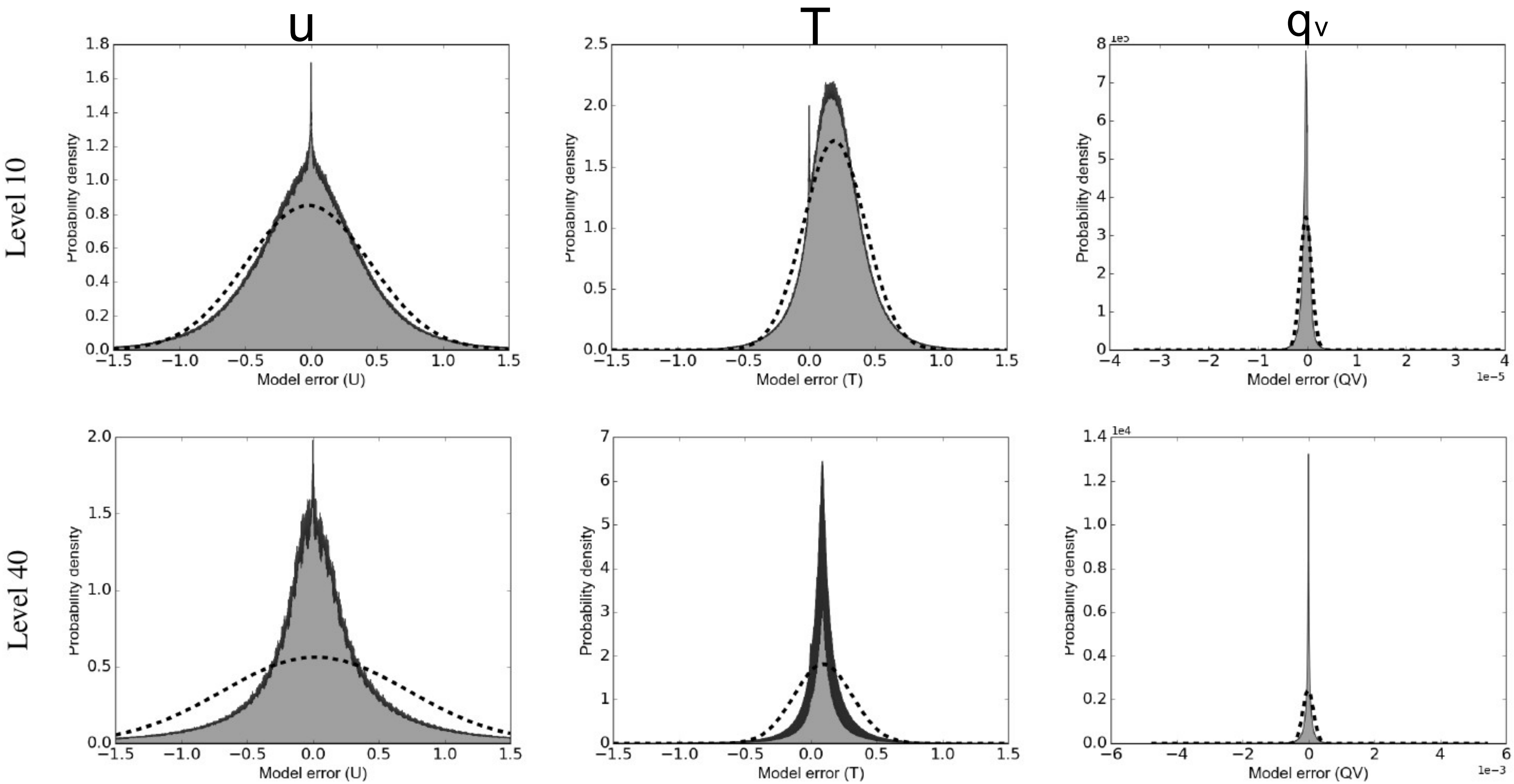
- Model truncation error is one of important sources of model error
- The refinement of the horizontal resolution improves the convective-scale precip. forecasts (e.g., Clark et al. (2016))
- Creation of sample archive for model truncation error



- Approach: choose t = 1 hour, $\mathbf{x}^{a(i)} \leftarrow \mathbf{x}^{a(i)} + \alpha_b \boldsymbol{\eta}^{(i)}$

  $\boldsymbol{\eta}^{(i)}$ samples represent **unresolved/small-scale** model error
  We call it “small-scale” additive inflation, denoted by “**AIS**”

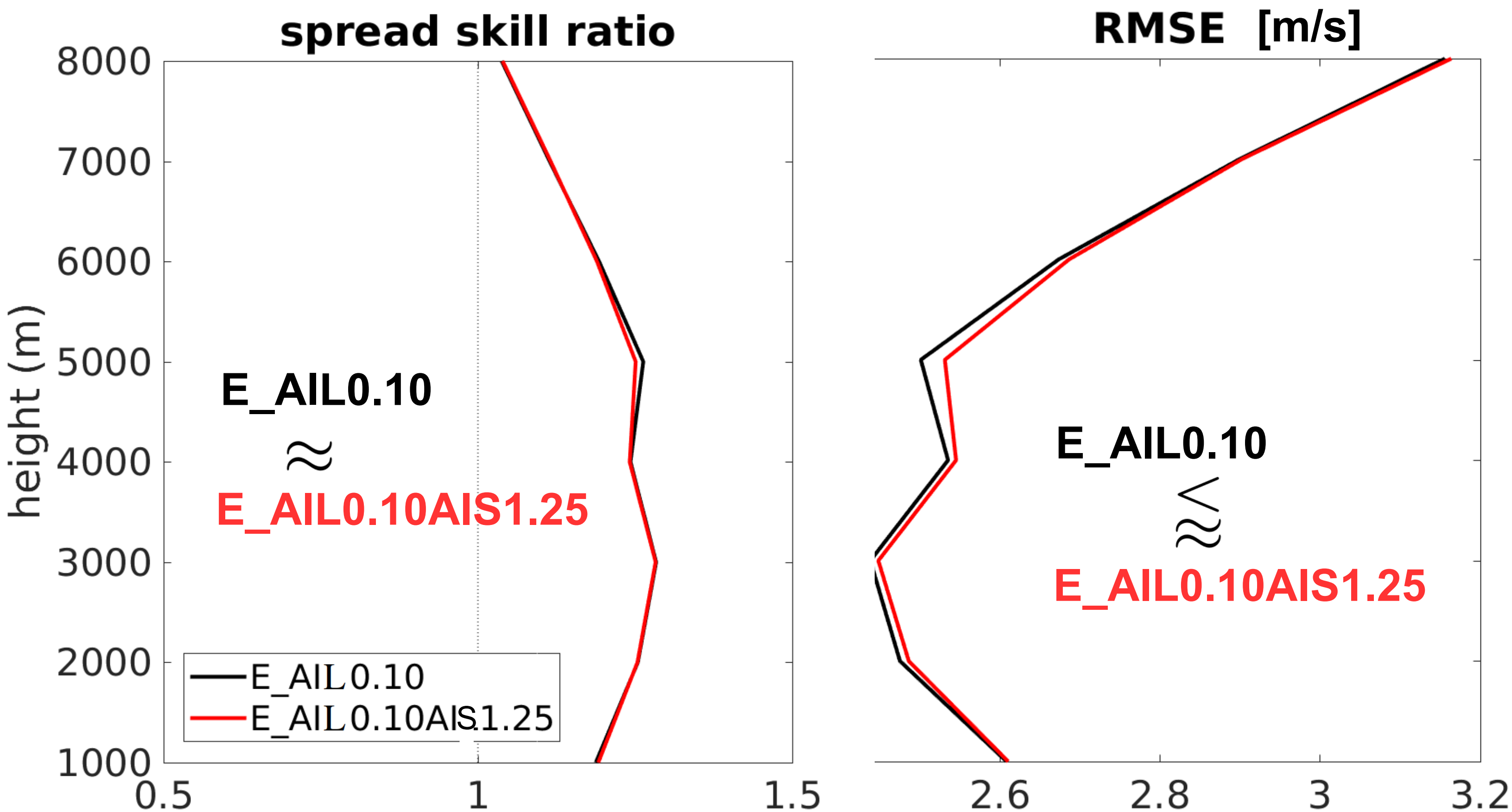
Introduction of additive inflation based on model truncation error
(Histogram of model error samples)



Study III: Comparison of AIL and AIL+AIS(spread skill ratio & RMSE)

E_AIL0.10: AIL ($\alpha_a = 0.1$) only

E_AIL0.10AIS1.25: AIL ($\alpha_a = 0.1$) +
AIS ($\alpha_b = 1.25$) with u, v, T, q_v perturbed



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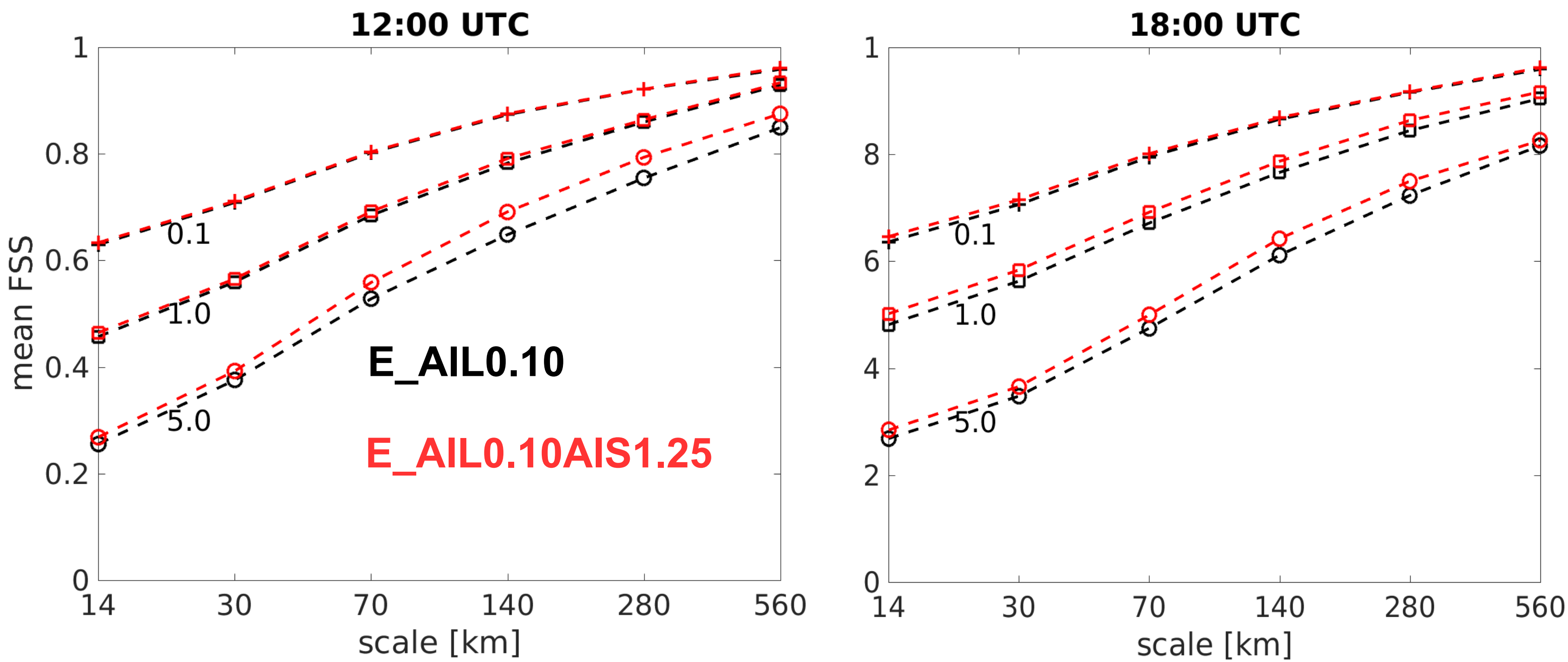
Study III: Comparison of AIL and AIL+AIS (Fraction skill score of precipitation forecast)

FSS for different precip. rate thresholds 0.1, 1.0 & 5.0 mm/h and scales 14,…, 560 km



	12:00 UTC	18:00 UTC
0.1 mm/h:	E_AIL0.10AIS1.25 $\approx$ E_AIL0.10	E_AIL0.10AIS1.25 $\approx$ E_AIL0.10
1.0 mm/h:	E_AIL0.10AIS1.25 $\approx$ E_AIL0.10	E_AIL0.10AIS1.25 $\approx$ E_AIL0.10
5.0 mm/h:	E_AIL0.10AIS1.25 $>$ E_AIL0.10	E_AIL0.10AIS1.25 $\gtrapprox$ E_AIL0.10

Conclusion and Outlook

Conclusion:

1. Large-scale additive inflation alone outperforms RTPP, RTPS and combination both in cycling and short-term precip. forecast for convective-scale data assimilation

2. Small-scale additive inflation based on model truncation error further improves large-scale additive inflation for short-term precip. forecast

Outlook:

1. To tune small-scale additive inflation

2. To compare small-scale additive inflation with warm bubbles and stochastic boundary layer perturbations

3. Papers in preparation:

Y. Zeng, T. Janjic, A. de Lozar, U. Blahak, M. Sommer, H. Reich, A. Seifert, 2018: Representation of model error for data assimilation on convective scale. Part I: Additive noise based on model truncation errors.

Y. Zeng, T. Janjic, A. de Lozar, U. Blahak, A. Seifert, S. Rasp, G. C. Craig, 2018: Representation of model error for data assimilation on convective scale. Part II: Comparison of additive noise and differently specified boundary layer uncertainties.

Reference

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Thank you for your attention

Surface pressure tendency of during one day cycling