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The impact of localization and observation averaging for convective-scale data assimilation in a simple stochastic model

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1 Motivation

• New generation of high resolution NWP models are cloud resolving. To assimilate high resolution fields, data assimilation systems have to be able to deal with sources of information like radar where conventional methods are likely to have **difficulties because of:**

1. nonlinearity: Rapid evolution of convective clouds **2. non-Gaussianity:** Clouds and precipitation produce highly intermittent fields

3. no geostrophic or comparable balance constraints: Some of the most powerful strategies to reduce the dimensionality of the system are not applicable

• Currently simple models (Lorenz 1995, Ehrendorfer 2008) are used but they are not intended for convective scale.

2 Goals

• Use a simple system that represents the key features of nonlinearity and intermittency of convection to investigate **two strategies** for coping with problems in ensemble data assimilation:

1. Observation averaging: Average data over a large region to reduce the dimensionality of the system and improve the Gaussianity → Loss of accuracy

2. Localization: Consider observations only in the vicinity of a point to reduce dimensionality → Possible loss of dynamical consistency

• We use the **Ensemble Transform Kalman Filter** (Bishop et al. 2001), LETKF (Hunt et al. 2007) and **Sequential Importance Resampling** (van Leeuwen 2009).

3 Stochastic convection model

• Simple toy model to produce a changing number of clouds
• Convective dynamics are specified as a **birth-death process**

■ **Squares:** position of clouds
Red line: ensemble mean
Green line: ensemble spread

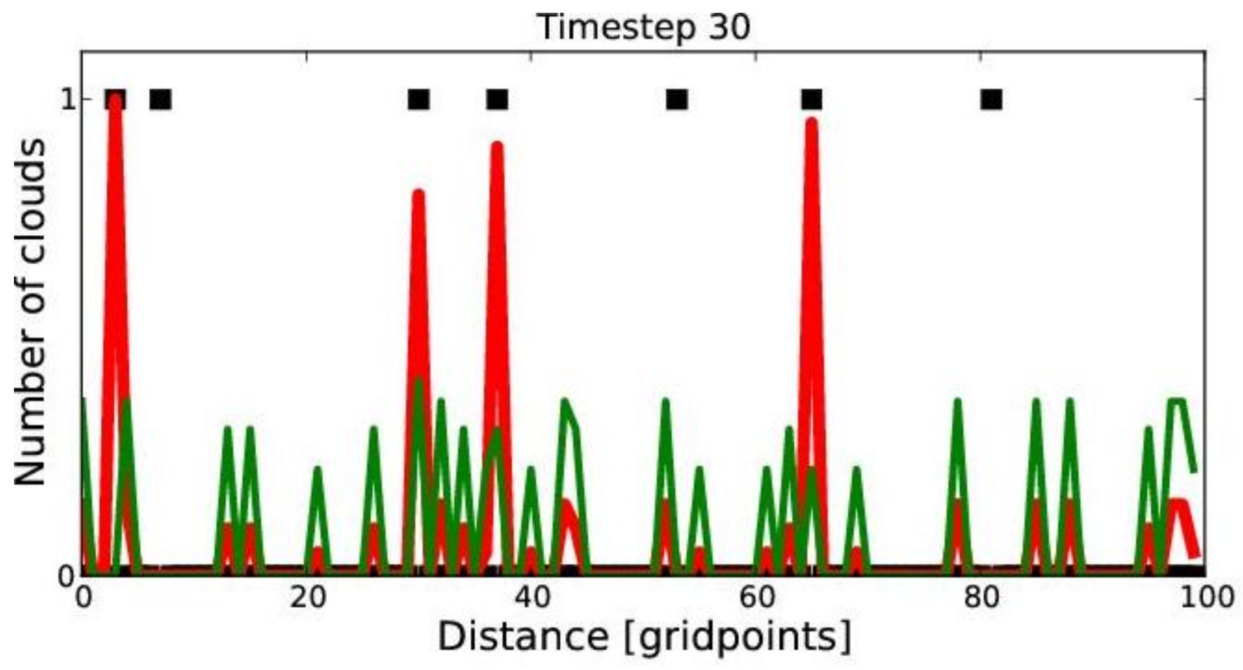

Figure 1. Example of an assimilation with the ETKF and a 20 member ensemble

4 Results – Example runs

SIR:
• Hl3000: Almost perfect after 100 steps
• Hl30: constant big error after 40 steps

ETKF:
• Hl3000: slowly converges to a small error
• Hl30: Does not get better than 0.8

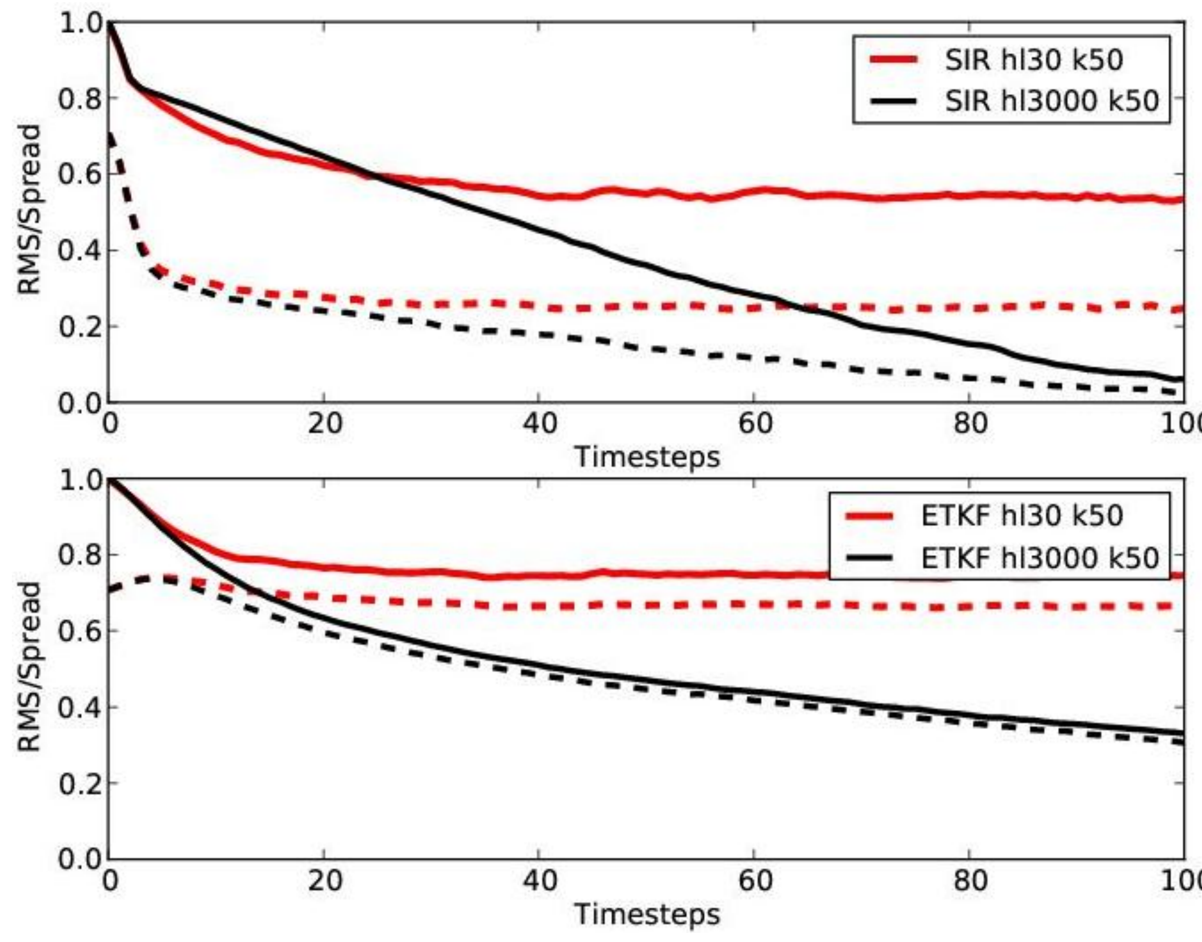

Figure 2. RMSE (solid line) and ensemble spread (dashed) for an **ensemble size of 50** with time.

5 Results – Changing ensemble size

SIR:
- Hl3000: SIR is almost perfect
- Hl30: Decreases slowly with bigger ensemble. Still at 0.4 with 200 members

ETKF:
- Hl3000: Error only decreases significantly up to 40 members
- Hl30: Almost no improvement

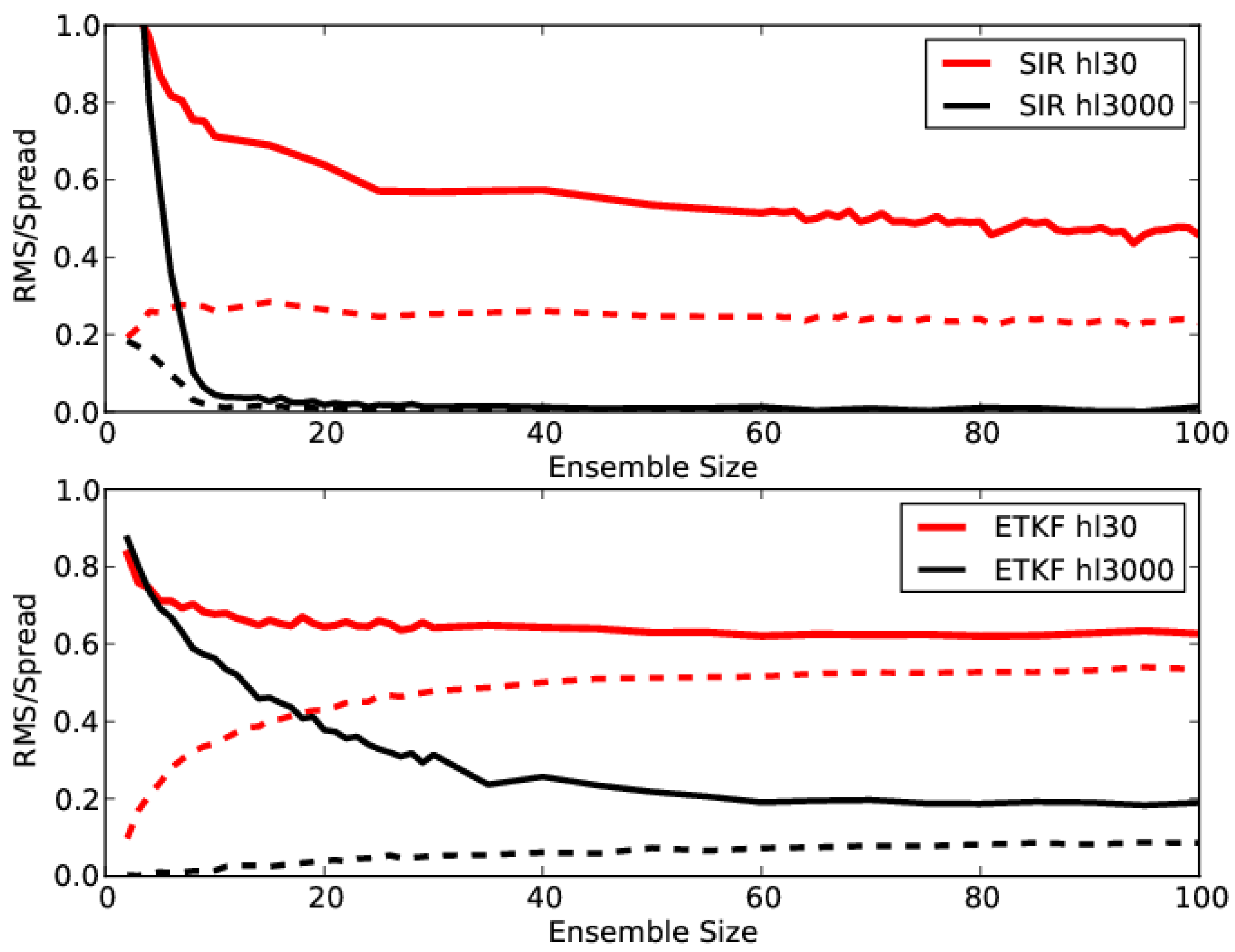

Figure 3. Final error (solid) and spread (dashed) for different ensemble sizes.

6 Results – Localization and averaging

ETKF:
• Averaging **enables ETKF to assimilate** with smaller ensembles where the standard and local versions fail

SIR:
• **Localization has a huge effect**, especially for the faster evolving problem
• Averaging is as good as Localization

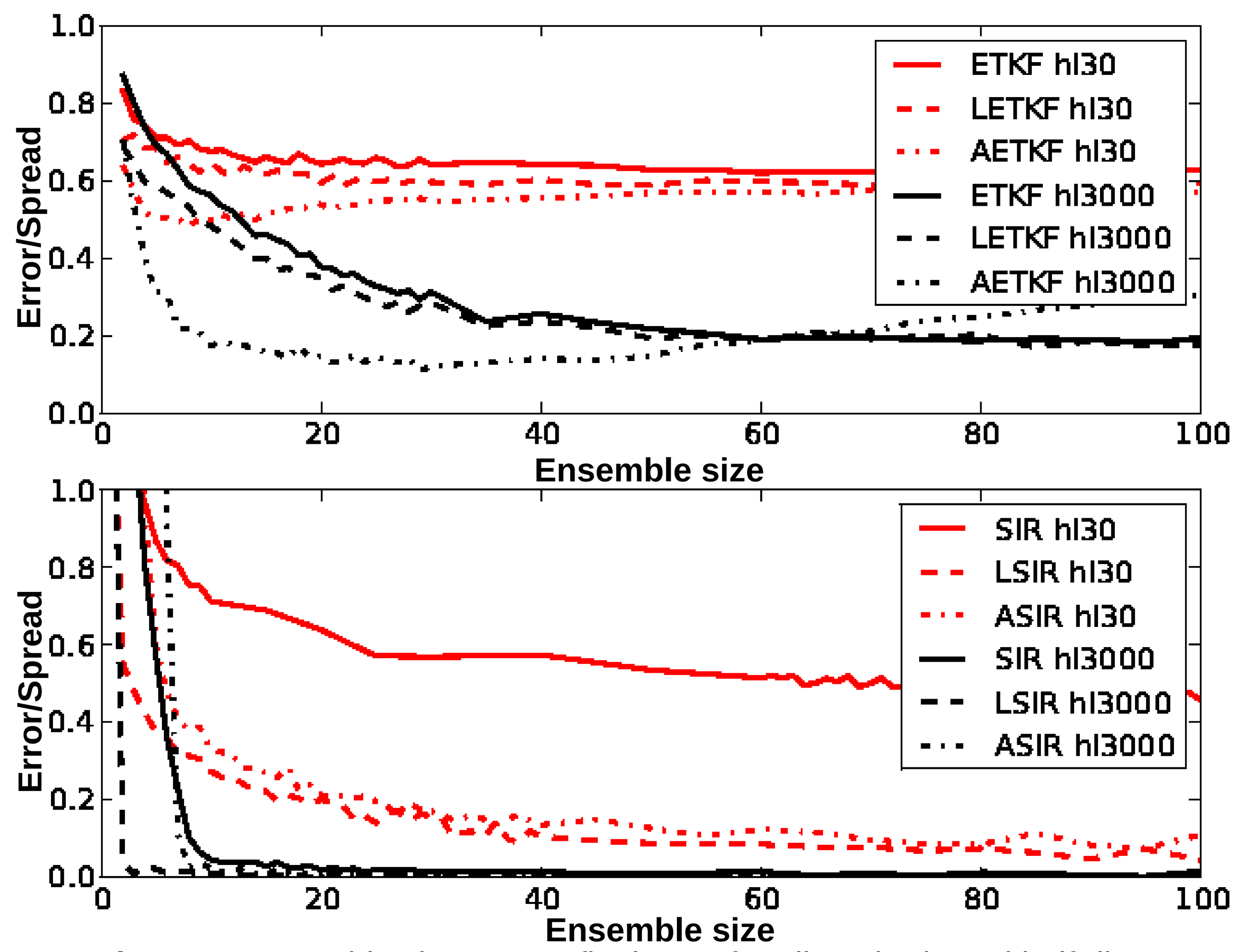

Figure 4. Ensemble size versus final error for all methods and half -lives.

7 Conclusions and Outlook

- Introduced a stochastic model that captures the key features of convective-scale data assimilation
- Both standard methods fail when posed with the dynamical situation
- SIR can give good results, but ensemble size is related to the dimensionality of the problem
- Localization works very well for the SIR and has a smaller effect for the ETKF
- Averaging seems more useful for the ETKF, especially for small ensembles

Next steps:
- Use a more complex model (modified shallow-water model) to test interaction with gravity waves
- Do idealised tests with COSMO/KENDA

8 References

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