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

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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, resulting in a stochastic component to the evolution of the field
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: **Observation averaging** and **Localization**

• Long-term goal for HErZ is a **hierarchy of models**. Couple a stochastic model for convection with a series of dynamical models of increasing complexity like: barotropic wave (coupling of convection to larger scales), 1-D shallow water (wave interactions), 2-D shallow water (potential organization), rotating shallow water (balance).

## 3 Stochastic Model

- Produces a changing number of clouds at every grid point
- Convective dynamics are specified as a **birth-death process**

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

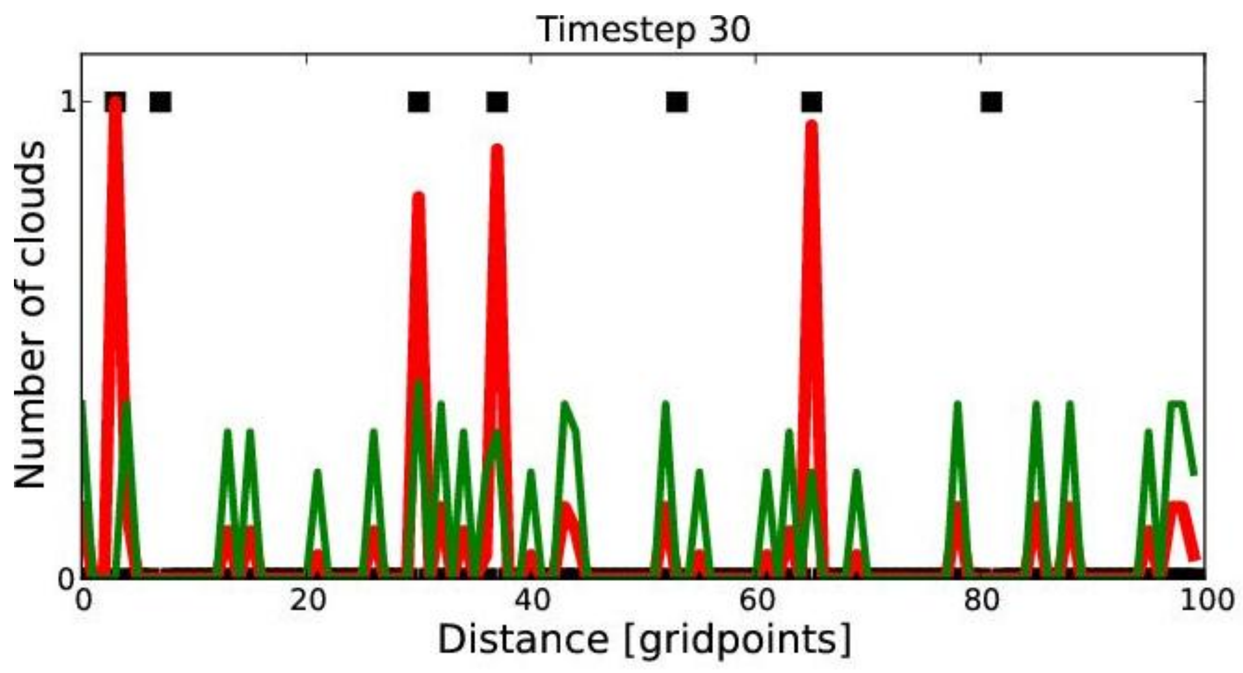



**Figure 1.** Example of an assimilation with the ETKF and a 20 member ensemble

## 4 Results – Ensemble size

**SIR** (van Leeuwen, 2009)**:**
- Hl3000: SIR is almost perfect
- Hl30: Decreases slowly with bigger ensemble. Still at 0.4 with 200 members

**ETKF** (Hunt et al, 2007)**:**
- Hl3000: Error only decreases significantly up to 40 members
- Hl30: Almost no improvement

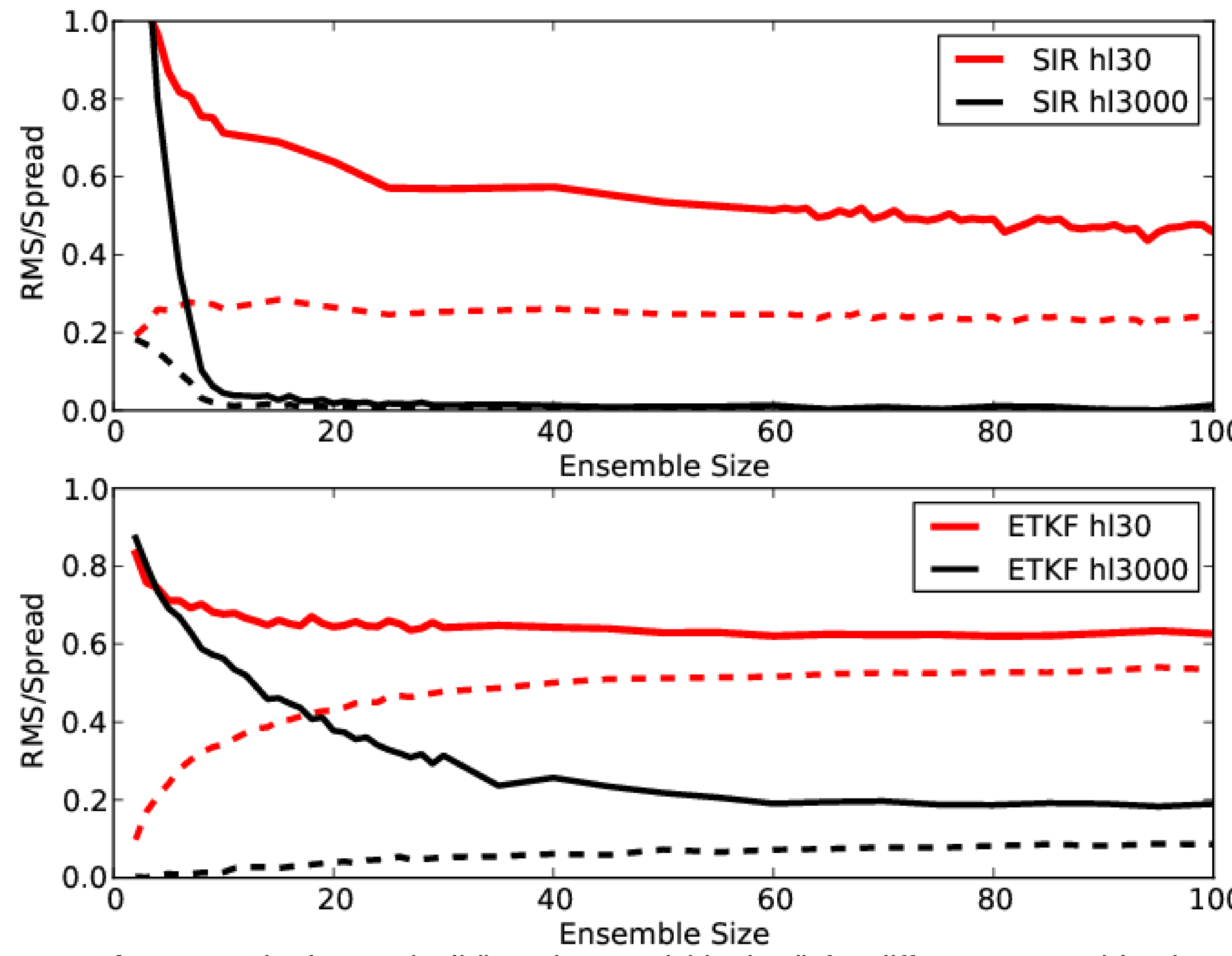



**Figure 2**. Final error (solid) and spread (dashed) for different ensemble sizes.

## 5 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 rapidly evolving system
• Averaging is as good as Localization

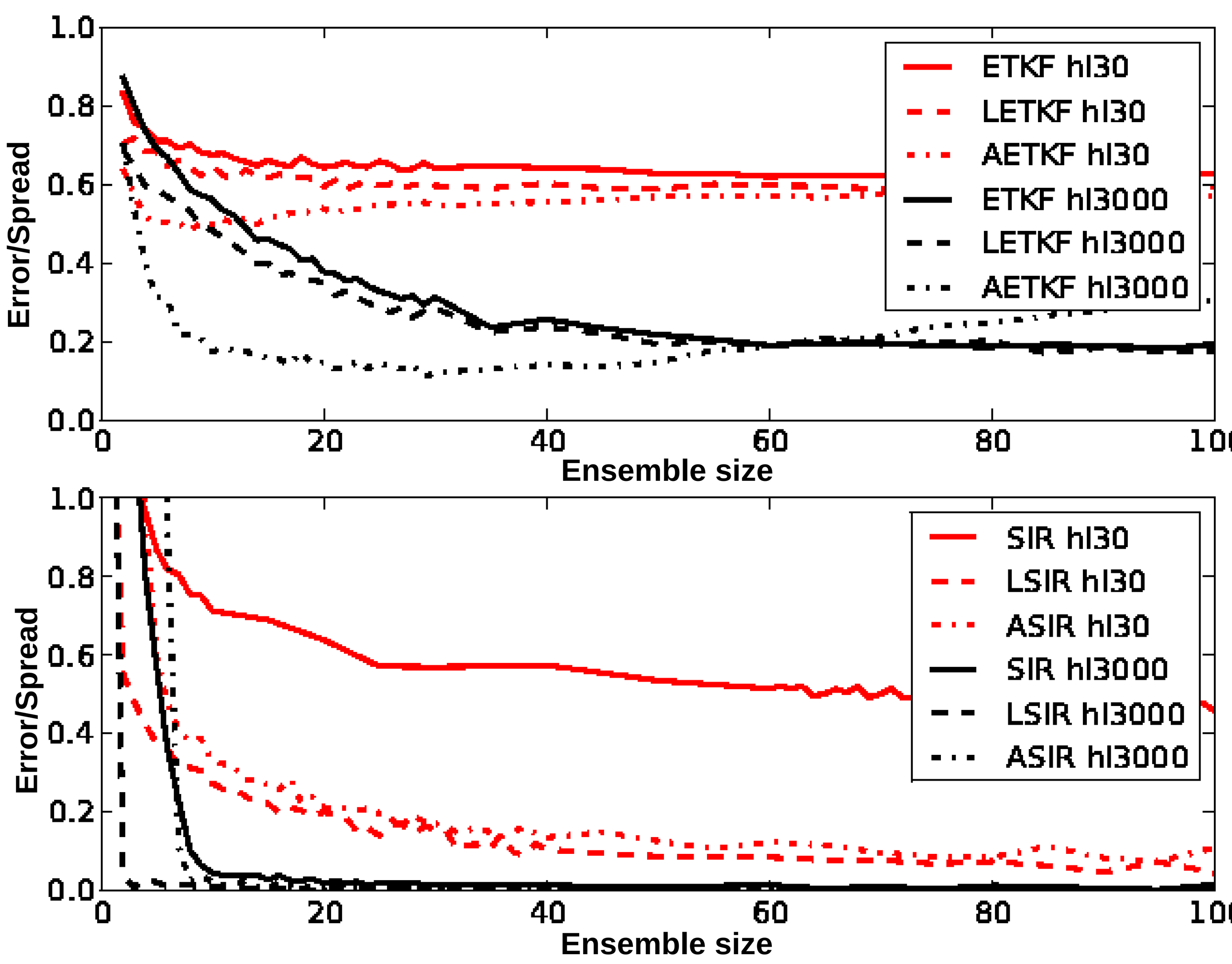



**Figure 3**. Ensemble size versus final error for all methods and half -lives.

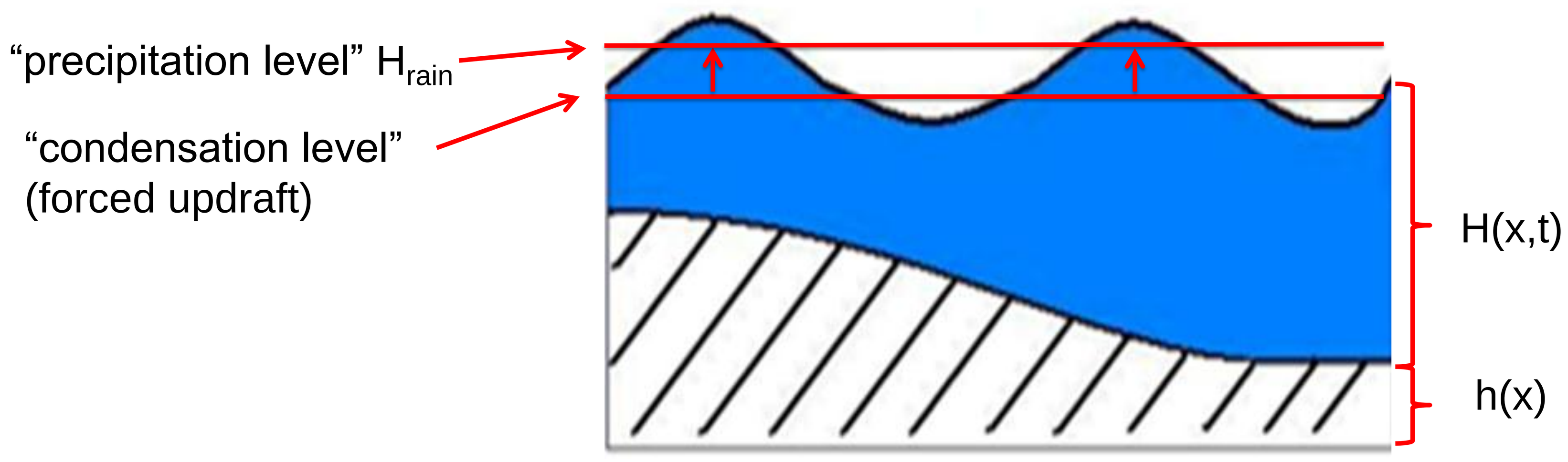
## 6 Modified shallow water model

- Toy model that includes stochastic noise and "precipitating" updrafts
- In updraft regions the water level is artificially forced to rise
- An additional variable, precipitation, is introduced into the equations

$$\frac{\partial r}{\partial t} + u\frac{\partial r}{\partial x} = -\alpha r - \begin{cases} \beta \frac{\partial}{\partial x} u, & (H+h) > H_{rain} \text{ and } \frac{\partial u}{\partial x} < 0 \\ 0, & else \end{cases}$$

- Rain imposes a downward force into the momentum equation.

- **Motivation:**
- Gravity waves and physical constraints make the model more realistic
- This corrects the too strong simplification of the simple model where the lack of correlation between grid points makes localization an almost perfect approach
- Find new sensitivities to localization and averaging




## 7 Conclusions

- Introduced two stochastic models that capture 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 well for the SIR and has a smaller effect for the ETKF
- The results point to specific problems that are likely to limit the performance of certain DA methods for cumulus convection, and provide indications regarding how they can be improved

## 8 Outlook

- Repeat experiments from the simple model with the shallow water model
- Test using the new model to evaluate the sensitivity of the methods to model resolution and resolution difference between model and truth
- Produce an isolated storm to experiment with a situation closer to reality
- Put a small mountain into the domain

## 9 References

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