Multi-scale Localization in Ensemble-based Data Assimilation

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Motivation

- Due to the limited ensemble size, sampling error may be problematic.
- \odot Localization plays an essential role.
 - Distance-dependent localization is applied to error covariance and reduces the sampling errors.
 No localization
 Localized





Analysis increments from a single profile observation (20 members)

 Higher resolution models require narrower localization which limits the influence of observations.

Approach

 Motivated by Buehner (2012), we construct analysis increments as a sum of high- (h) and low- (l) wavenumber components.



Longer-range covariance

 We apply spatial smoothing to the ensemble perturbations to reduce noise in longer-range covariance.

Full-range (T30) analysis increment

Analysis increment from reducedresolution (T21) ensemble perturbations



Larger-scale localization

○ Applying a 1000-km (larger scale) localization.

Full-range (T30) analysis increment

Analysis increment from reducedresolution (T21) ensemble perturbations



Smaller-scale structure

• Applying a 500-km (smaller scale) localization.

Full-range (T30) analysis increment

Analysis increment from reducedresolution (T21) ensemble perturbations



Merging the two scales

Original covariance with 500-km (smaller scale) localization



Preserve the smaller-scale structure in short range

$$\delta x = \delta x_h + \delta x_l$$

Large-scale covariance with 1000-km (larger scale) localization



Merging the shorter and longer ranges

 \circ We merge the high (*h*) and low (*l*) wavenumber components.



Summary of the algorithm

- Compute the analysis increment regularly (with smaller-scale localization)
- 2. Compute the analysis increment with smoothed ensemble perturbations (with larger-scale localization)
- 3. Compute the analysis increment with smoothed ensemble perturbations (with smaller-scale localization)
- 4. Take the difference between 2 and 3
- 5. Add 1 and 4



Settings of perfect model experiments

	CTL(L=500)	CTL(L=1000)	Test
Model	SPEEDY, T30L7 (Molteni 2003)		
Observation	Radiosonde-like		
Ensemble size	20		
Localization scale	500 km (small)	1000 km (large)	500 km 1000 km

○ Test experiment: Dual Localization LETKF

RMSE (Q, Z=1) at each wavenumber

23-month average global analysis error power spectrum.



Successfully reducing the errors at all scales.

General improvements for mid-level U

23-month average RMS errors



 Successfully improving analysis RMS errors in the Northern Hemisphere.



Impressive improvements for low-Q

23-month average RMS errors



 Greatly improving analysis RMS errors almost everywhere.



Summary

- Dual-localization LETKF analysis showed promising results.
 - Improvements at almost all scales
 - Improvements almost everywhere for all variables
 - Impressive improvements for humidity
- Drawback: LETKF computations are tripled.
- Future plans
 - Improving the algorithm for saving computations.
 - Applying to higher-resolution models
 - Multi-scale considerations are more important with higher resolutions.

Thank you for your attention !



Power spectrum (U, Z=4)

23-month average global analysis error power spectrum.



○ Successfully reducing the errors slightly.

Power spectral



Small and large scale localization

 Regular analysis increments at the full resolution (T30) with two different localization scales:



Reducing sampling noise in a longer range

 We apply spatial smoothing to the ensemble perturbations to reduce noise in longer-range covariance.



Longer-range component

