Correlation length scales in background/observation error covariances and how they influence filter performance

Yue (Michael) Ying

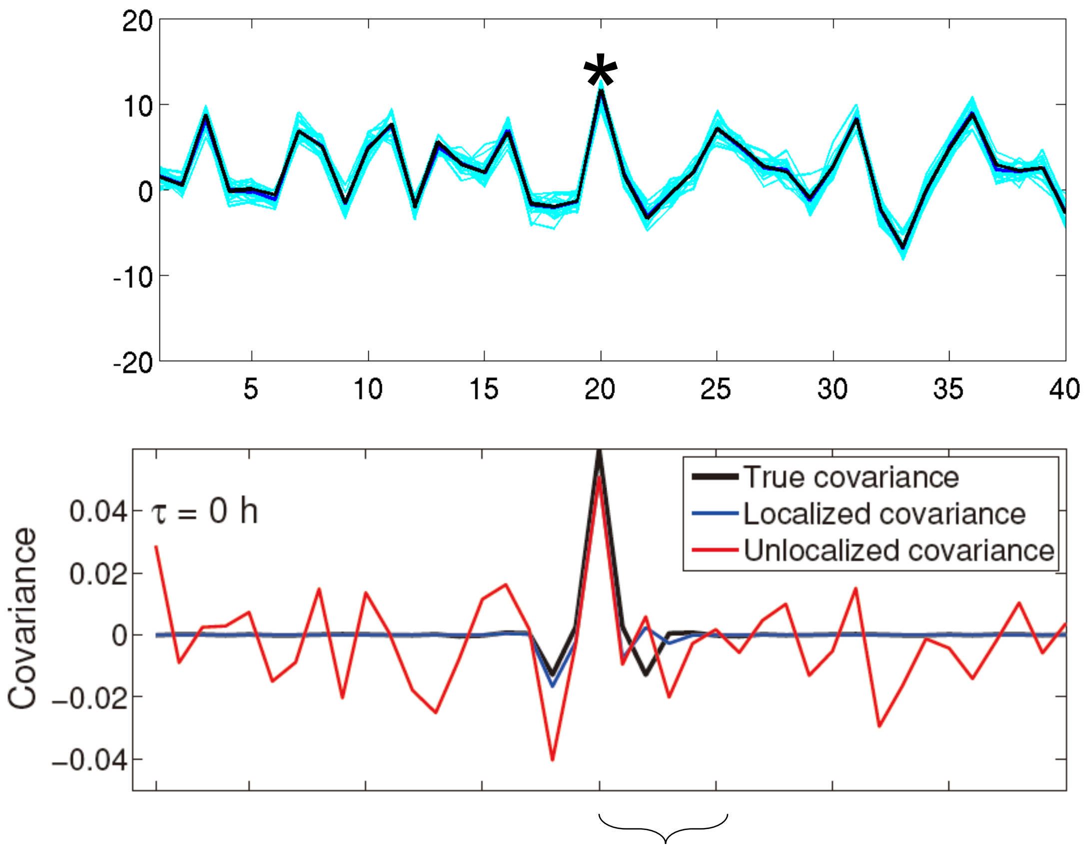
Fuqing Zhang

Jeffery Anderson

Groupmeeting, Aug 2017

Why is error covariance important?

Consider a single-variable system, e.g. Lorenz (1996) model.



correlation length scale

Covariance propagates observed information in space/time

- covers unobserved variables
- enhance observed variables

Ensemble-estimated covariance is noisy, therefore requires localization.

What is the appropriate localization distance?

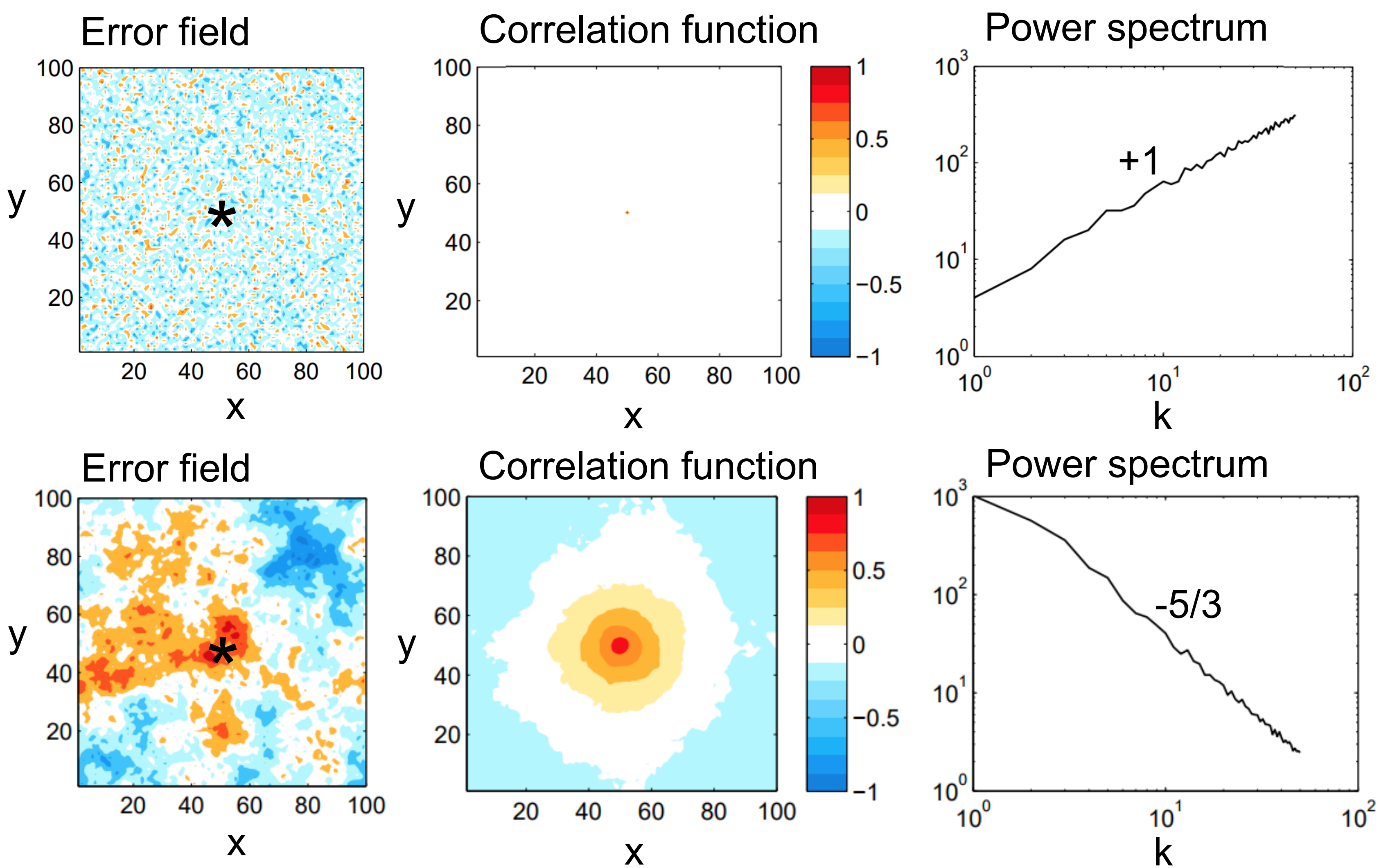
- Zhen and Zhang (2014) adaptive algorithm
- Anderson and Lei (2013) empirical localization functions

Covariance is flow-dependent!

(also variable-, scale-dependent?)

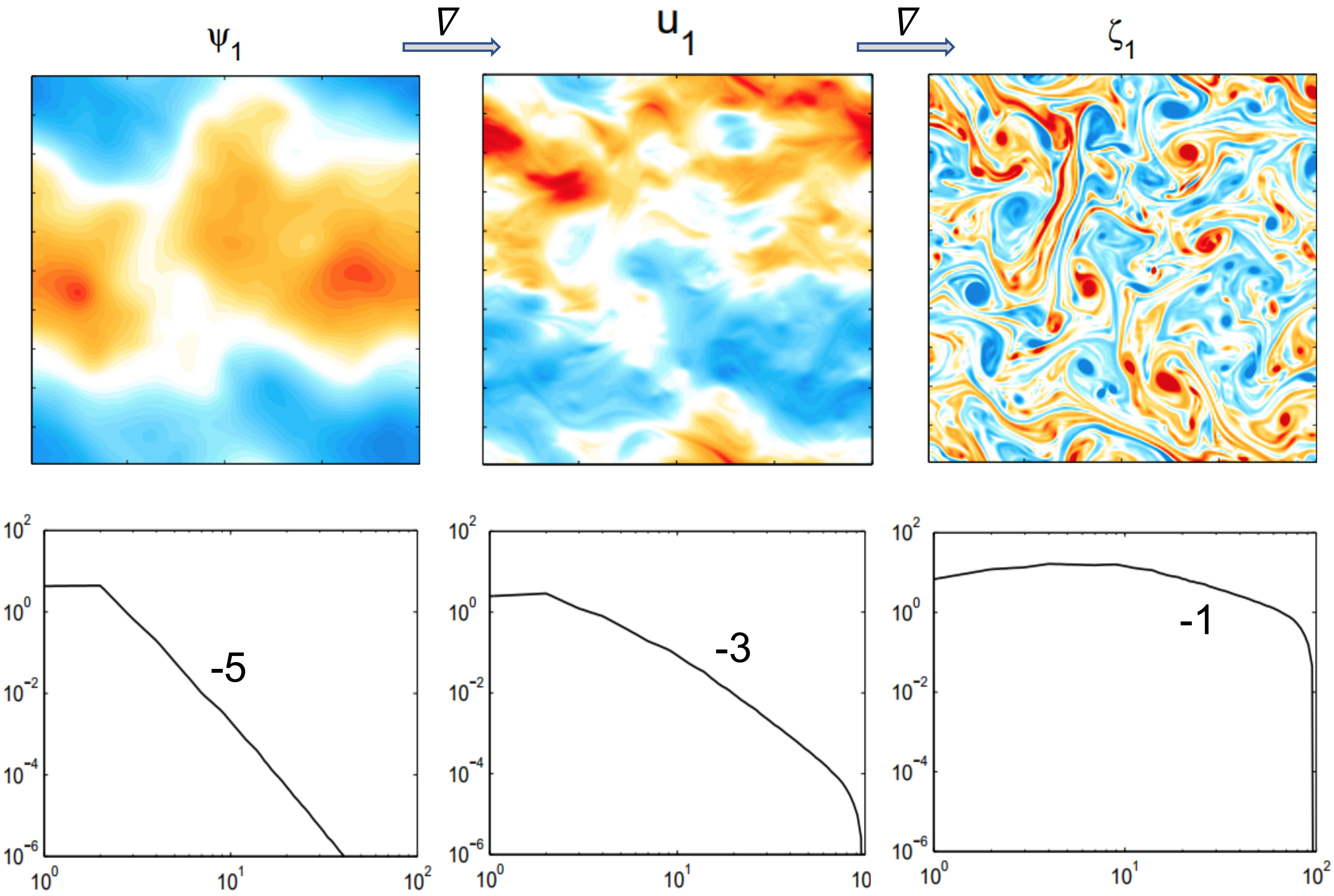
Correlation length scale (L) in background error

L=0, white noise, all variables must be observed.
Luckily, atmosphere has L>0, like a red noise. Its spectrum determines L.

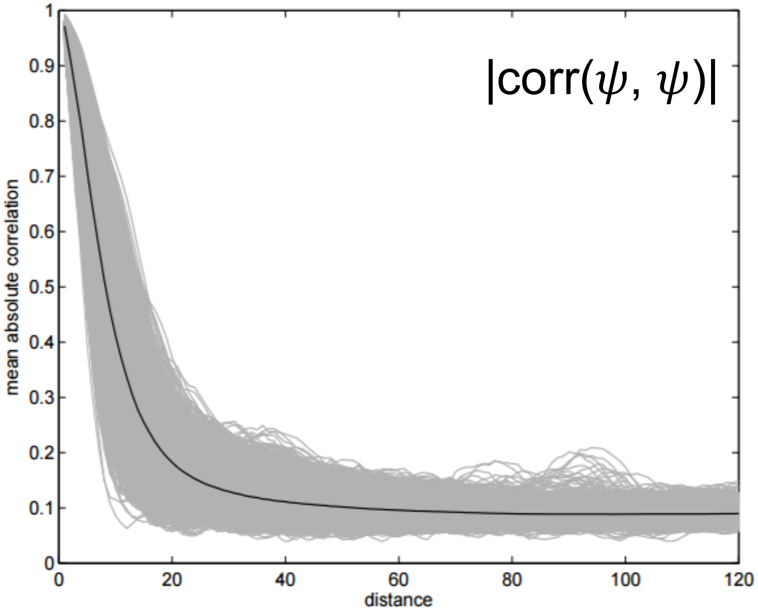


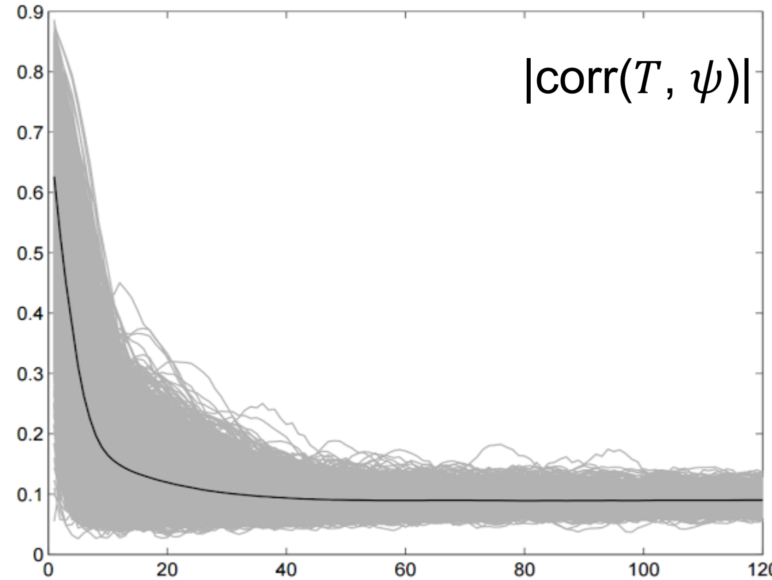
Variable dependence for L

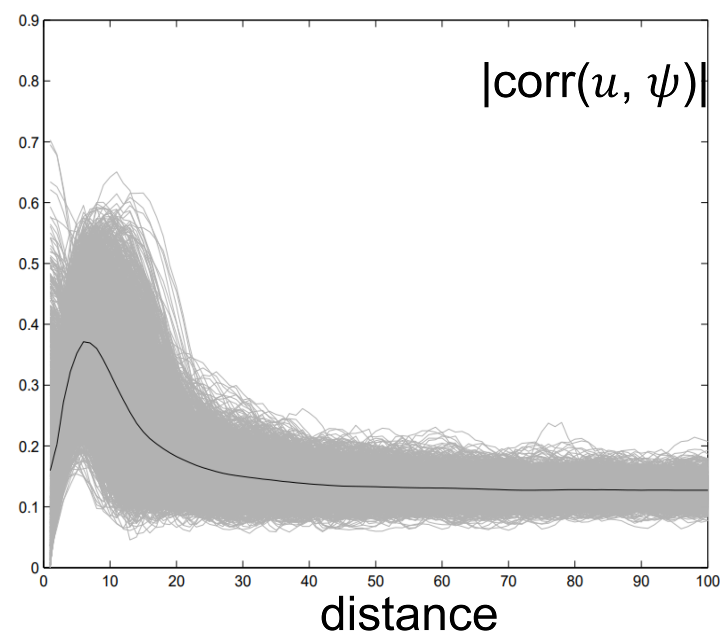
Two-layer QG model, different power-law for each variable:



Cross-variable correlation functions





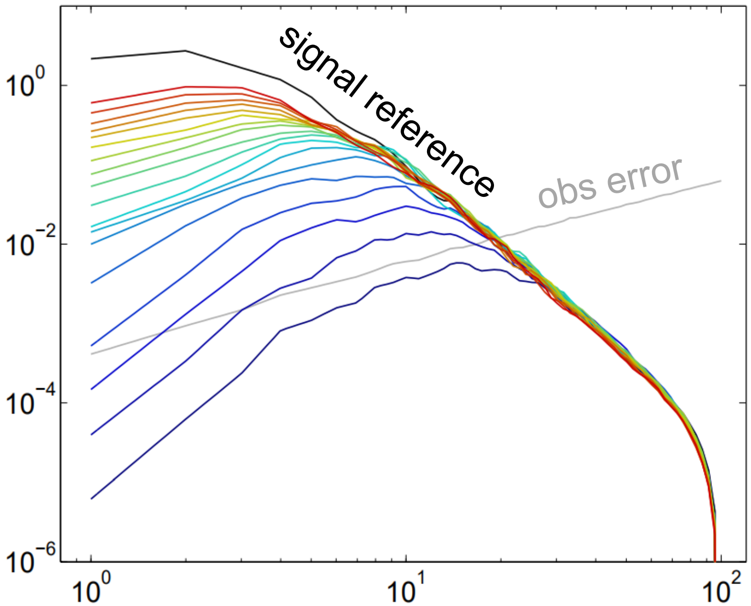


Time evolution of L

Free ensemble run: L increase over time as error saturates upscale.

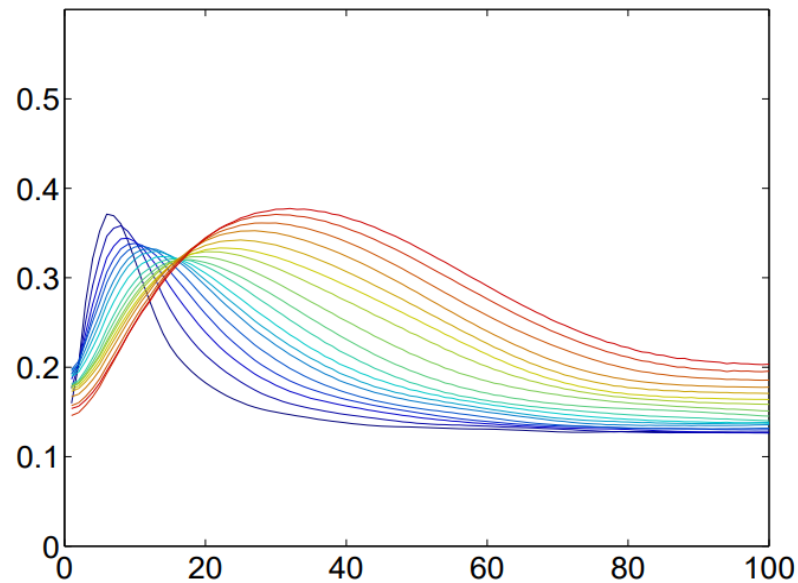
With cycling data assimilation: L finds a quasi-steady value.

KE spectrum



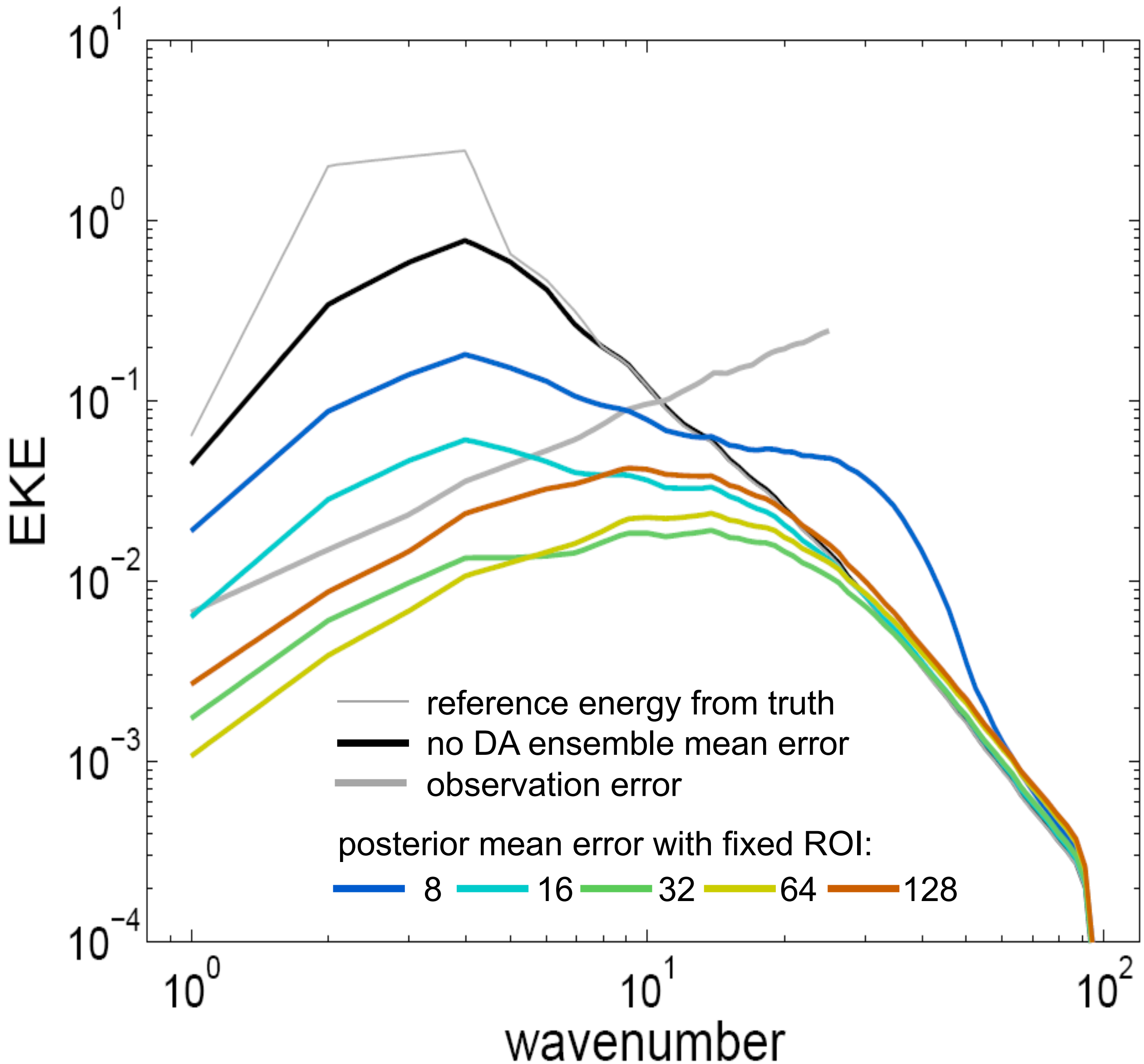
k

mean absolute correlation (u, ψ)



distance
(grid points)

Impact of background L on filter performance

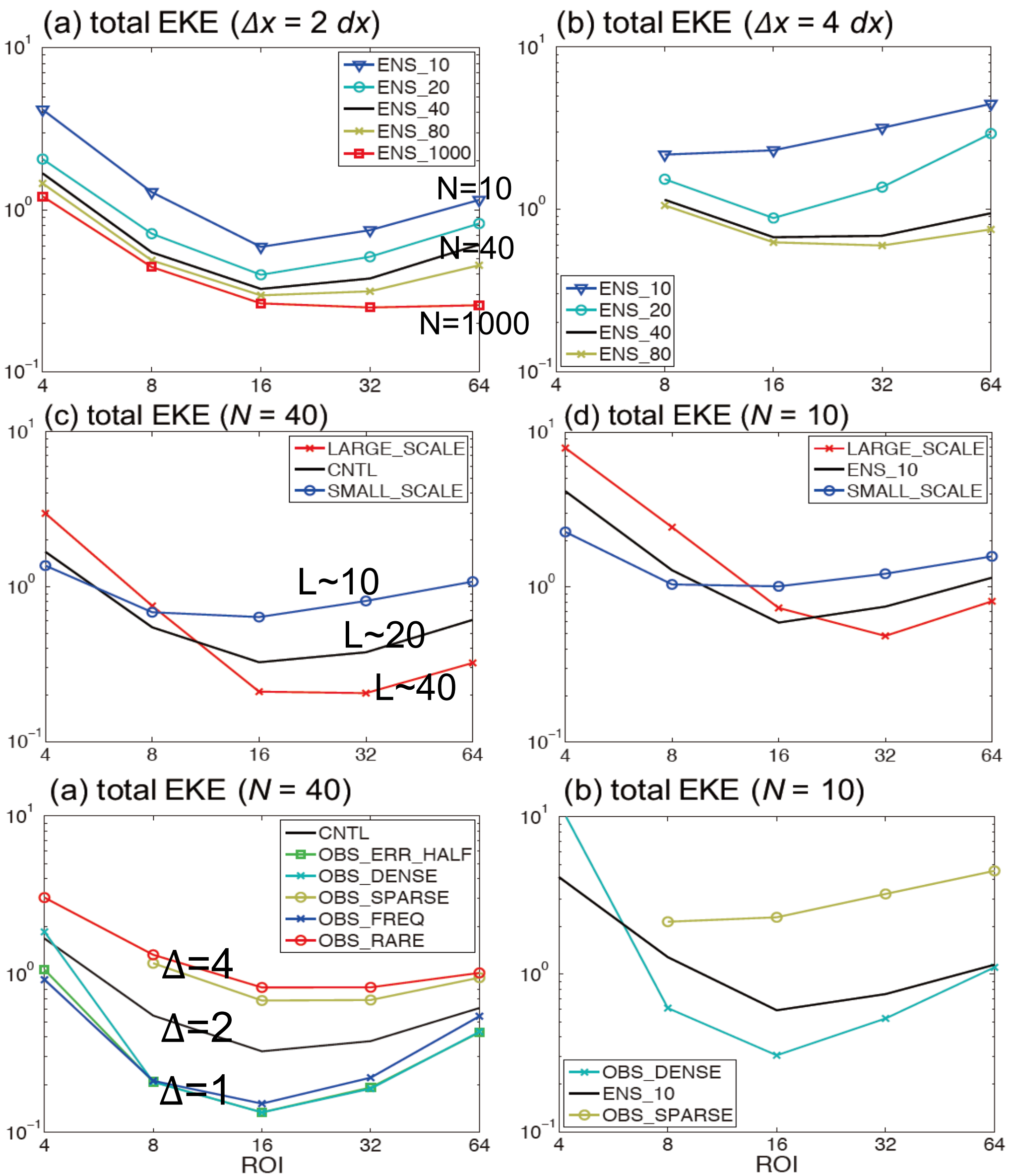


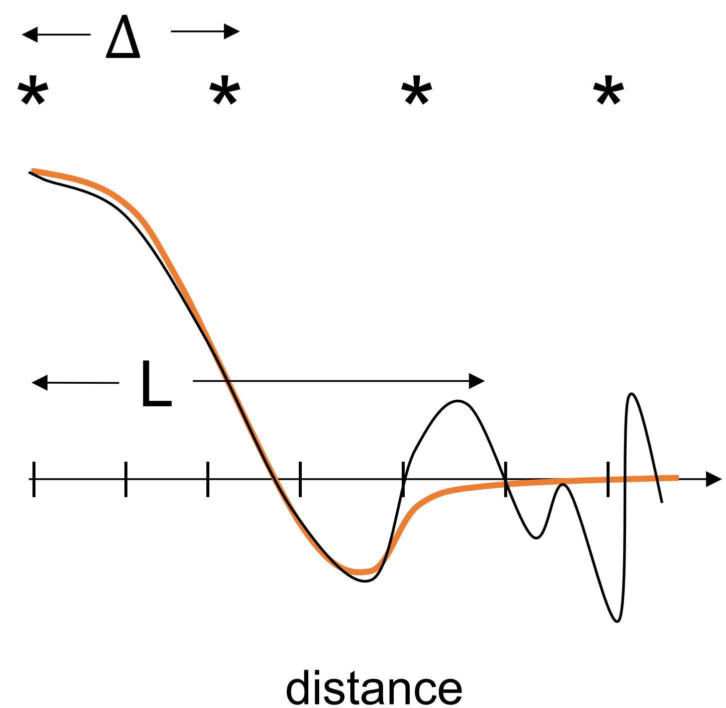
N=40 member
background L~50
observation interval Δ=4

Best-performing localization ROI is matching L

Large scale favors larger ROI.

Complication in the codependence among
ensemble size N, correlation scale L, observation interval Δ





L in correlated observation error

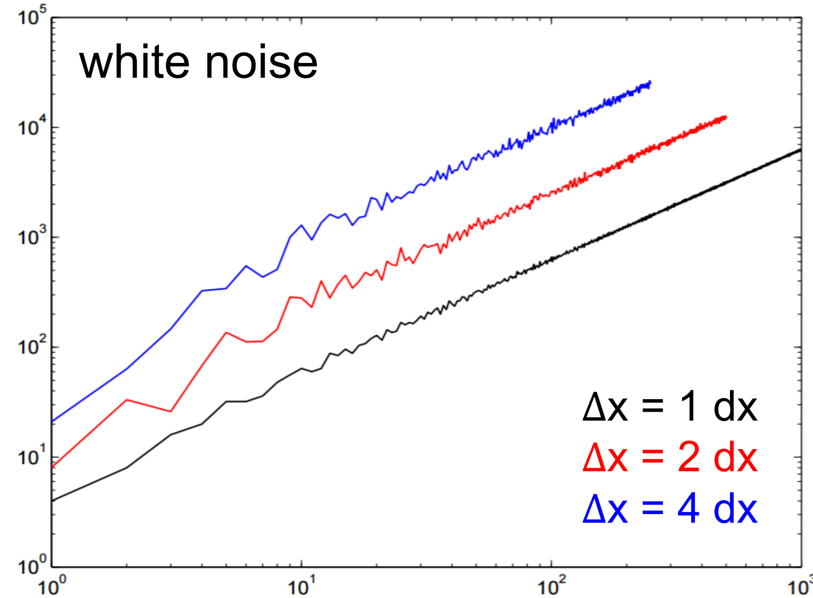
EnKF (square root algorithm) assumes *uncorrelated* observation error: instrument errors are white noise.

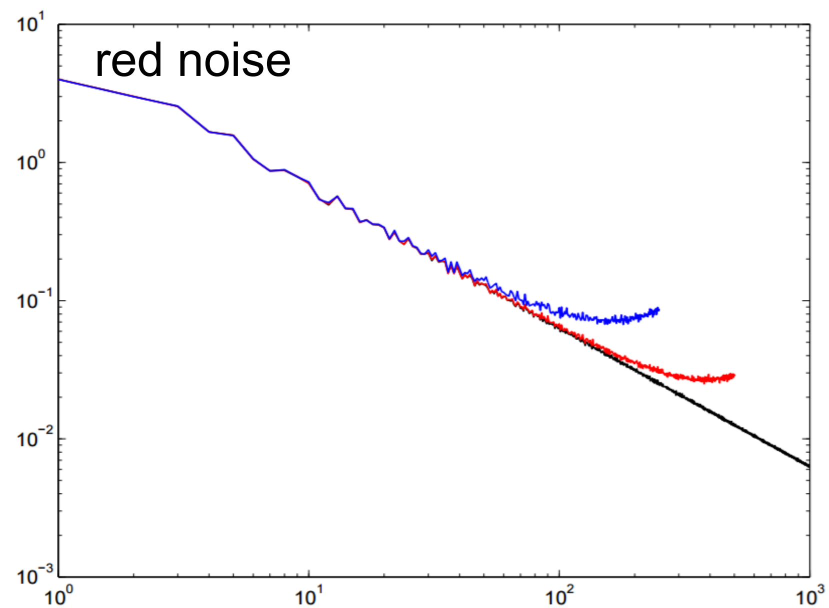
According to information theory: more (uncorrelated) observations -> less uncertainty

However, observation errors can be correlated:

- preprocessing
- error of representation
- observation operator

Correlated error means additional observation does not increase information content as much.



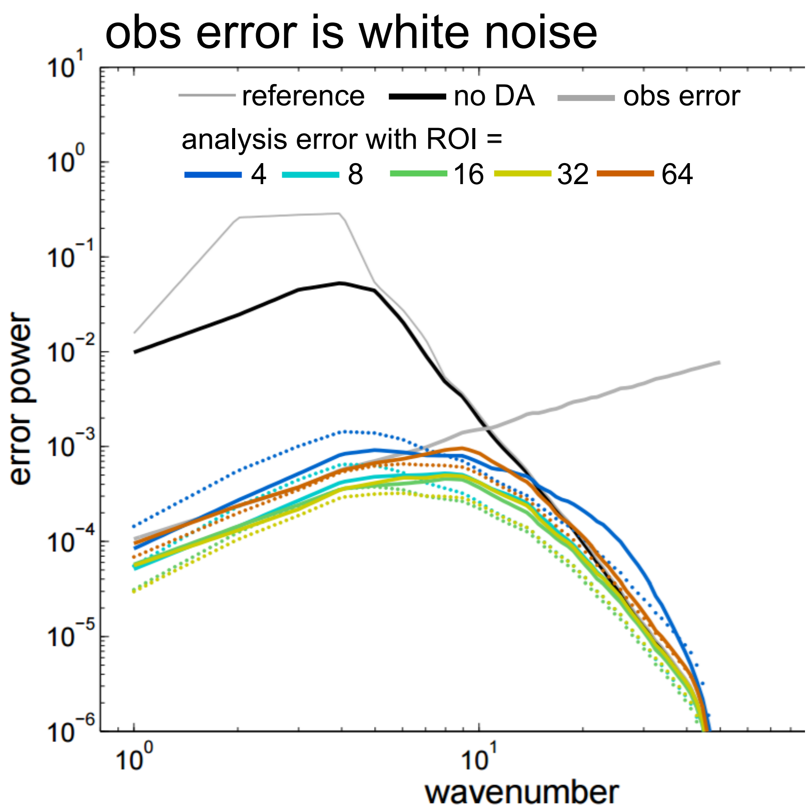


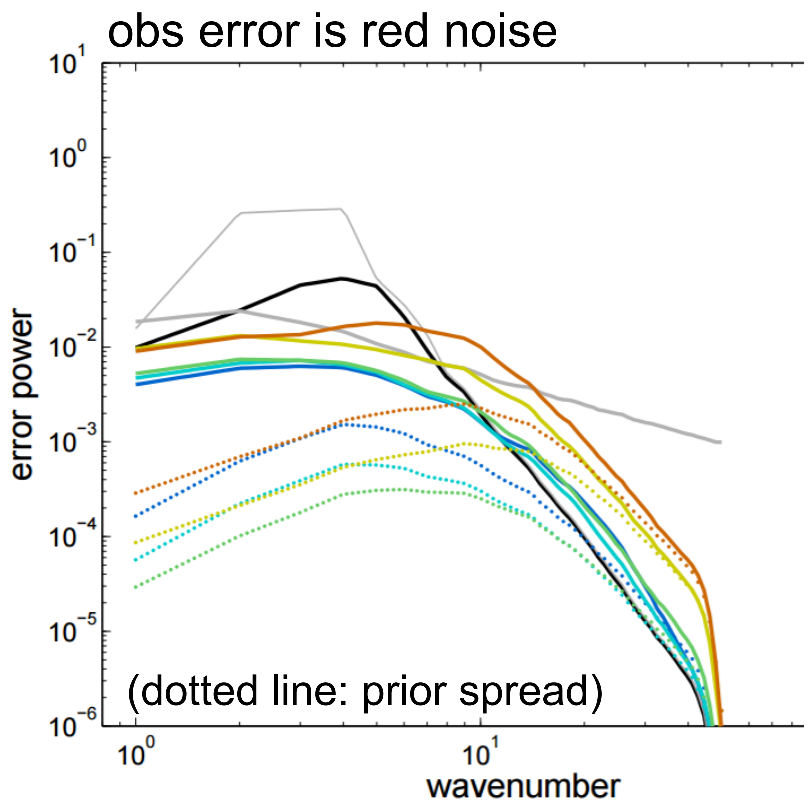
Treating correlated error in ensemble filters

- Ignore it: suboptimal analysis + ensemble spread is reduced too much.

- inflate observation error variance

- account for correlation with a full-rank observation error covariance (in ETKF)



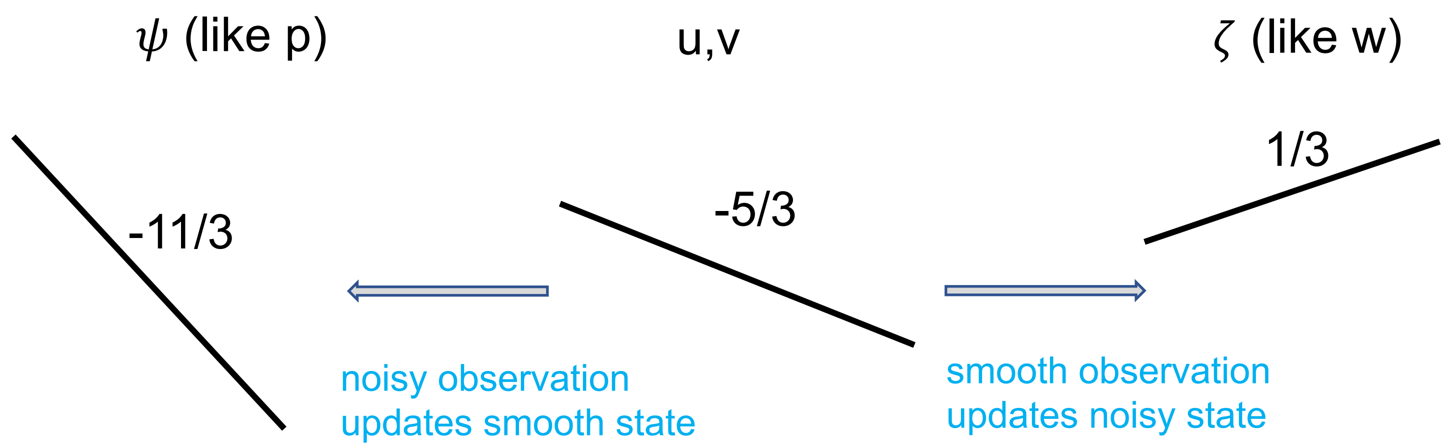


Consider real atmosphere data assimilation…

Unlike QG, there are several state variables with different spectral slope coupled with dynamic equations

For example, a wind observation will be used to update *p* and *w* as well as wind itself.

Errors in *p* and *w* will feedback into wind during forecast step.



Plans for further experiments

In QG, change state variable from ψ to *u*, *v*,
then test assimilating ψ and ζ to update *u*, *v*.

Assimilate *u*, *v* observation to update state variable ψ and ζ, some how couple the two corresponding wind analysis (averaging) to form the final state.

Assimilate *u*, *v* to update *u*, *v*, but draw observation error with correlation length scale from 0 to 2L.