Ensemble-based estimates of information content in observational data extractable by data assimilation methods

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Collaborators
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OUTLINE

- Information measures in ensemble subspace
- Experimental results employing various dynamical models
- Conclusions
- Future plans

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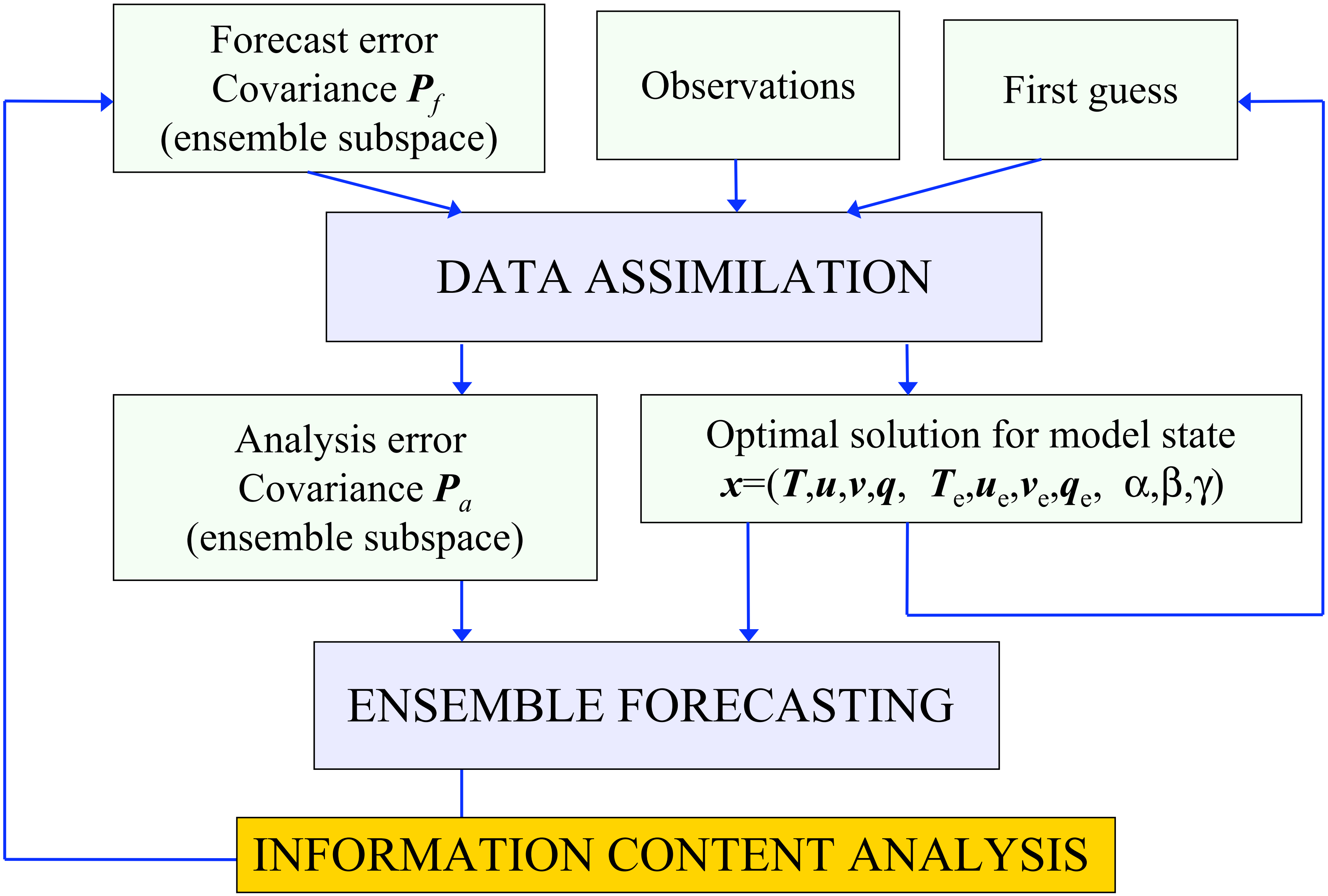
Ensemble Data Assimilation



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Information measures in ensemble subspace

(Bishop et al. 2001; Wei et al. 2005; Zupanski et al. 2005, 2006)

$$\boldsymbol{C} = \boldsymbol{Z}^T \boldsymbol{Z}$$

$\boldsymbol{C}$ **- information matrix in ensemble subspace of dim** $Nens$ **x** $Nens$

$$z^i = R^{-1/2} H[M(x + p_f^i)] - R^{-1/2} H[M(x)]$$

z^i **- are columns of Z**

$$\boldsymbol{x} - \boldsymbol{x}_b = \boldsymbol{P}_f^{1/2} (\boldsymbol{I} + \boldsymbol{C})^{-1/2} \zeta$$

ζ **- control vector in ensemble space of dim** $Nens$

$\boldsymbol{x}$ **- model state vector of dim** $Nstate >> Nens$

Degrees of freedom (DOF) for signal *(Rodgers 2000)*:

$$d_s = tr[(\boldsymbol{I} + \boldsymbol{C})^{-1} \boldsymbol{C}] = \sum_i \frac{\lambda_i^2}{(1 + \lambda_i^2)}$$

λ_i^2 **- eigenvalues of C**

Shannon information content,
or entropy reduction

$$h = \frac{1}{2} \sum_i \ln(1 + \lambda_i^2)$$

Errors are assumed Gaussian in these measures.

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Basic characteristics of Maximum Likelihood Ensemble Filter (MLEF)

(Zupanski 2005; Zupanski and Zupanski 2006)

- **MLEF is similar to 4dvar because it seeks a maximum likelihood solution (i.e., minimum of J).**
- **It is also similar to EnKF methods because it uses ensembles to calculate forecast error covariance.**
- **MLEF uses the same definition of matrix C as in the ETKF (Bishop et al. 2001).**
- **It has a built-in capability to estimate and reduce several major sources of forecast uncertainties simultaneously: Initial conditions, model error, boundary conditions, and empirical parameters.**

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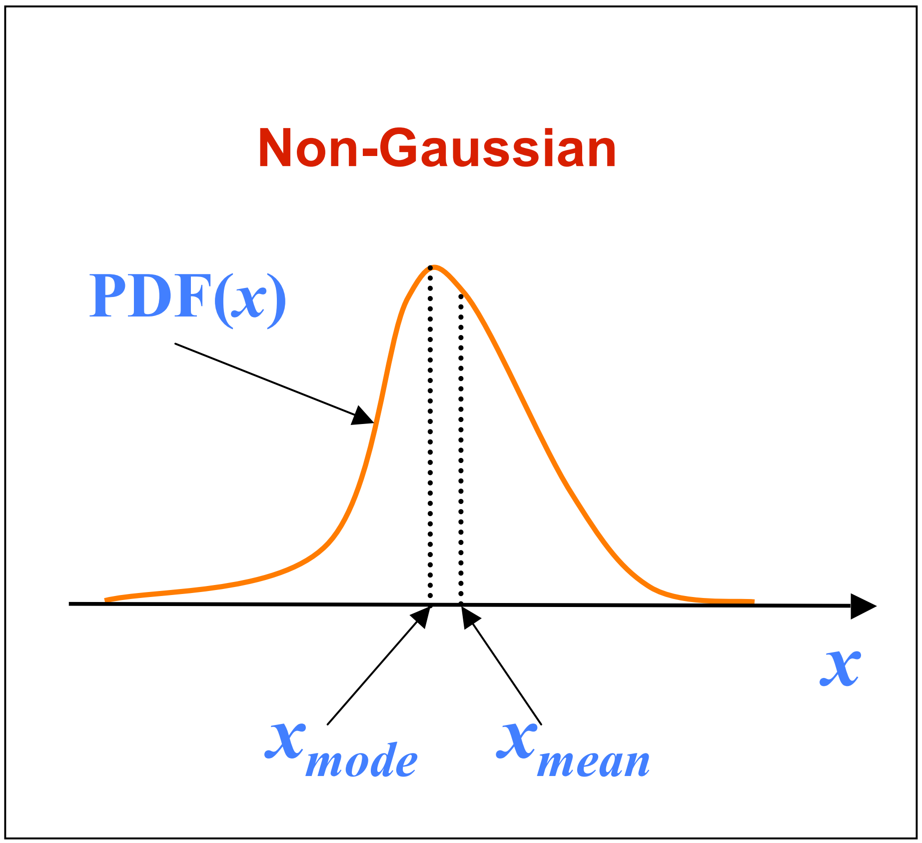
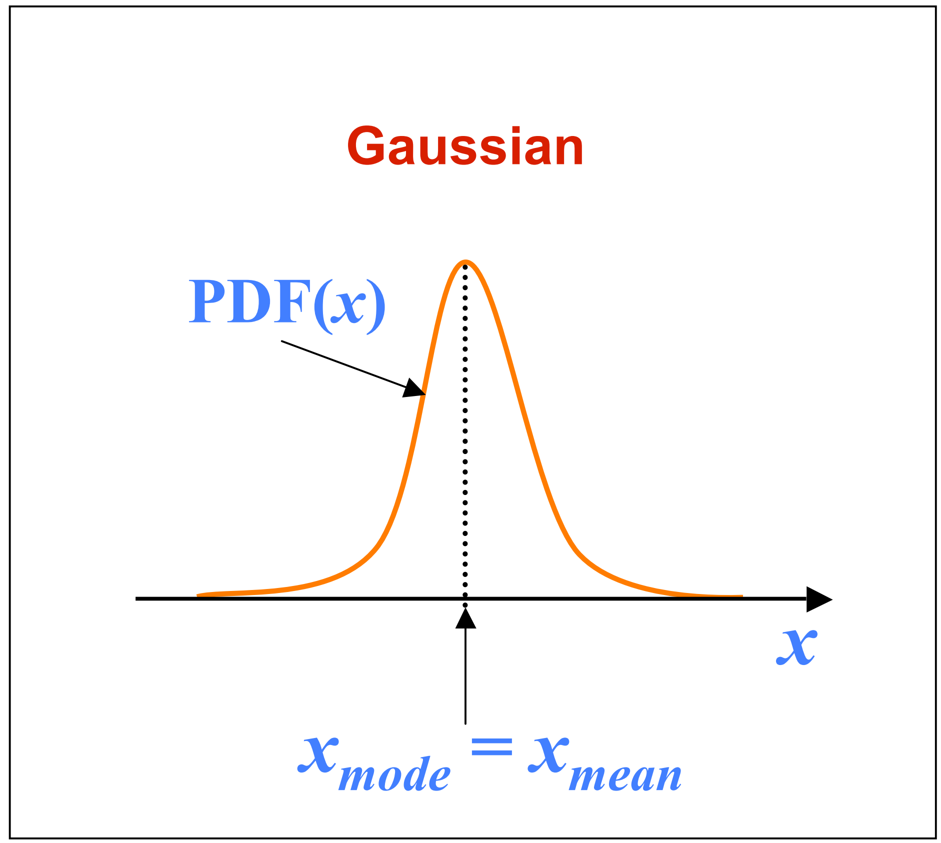
MODE vs. MEAN

MLEF involves an iterative minimization of functional *J* $\Rightarrow x_{mode}$

Minimum variance methods (EnKF) calculate ensemble mean $\Rightarrow x_{mean}$





Different results expected for non-Gaussian PDFs

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Experiments

Atmospheric models:

- **GEOS-5** single column model: Assimilation of T and q
  (In collaboration with Athur Hou and Sara Zhang, NASA)

- **RAMS** model: Assimilation of u,v,w,p,th, and r
  (In collaboration with Louie Grasso and Mark DeMaria, CSU)

Carbon transport models:

- **PCTM** model: Global CO2-flux inversion (estimation of weekly CO2-fluxes)
  (In collaboration with Scott Denning and Ravi Lokupitiya, CSU)

- **LPDM** model: Regional (mesoscale) CO2-flux inversion (estimation of model bias in daily CO2-fluxes)
  (In collaboration with Scott Denning, Marek Uliasz and Andrew Schuh, CSU, and Peter Rayner, CEA/LSCE France)

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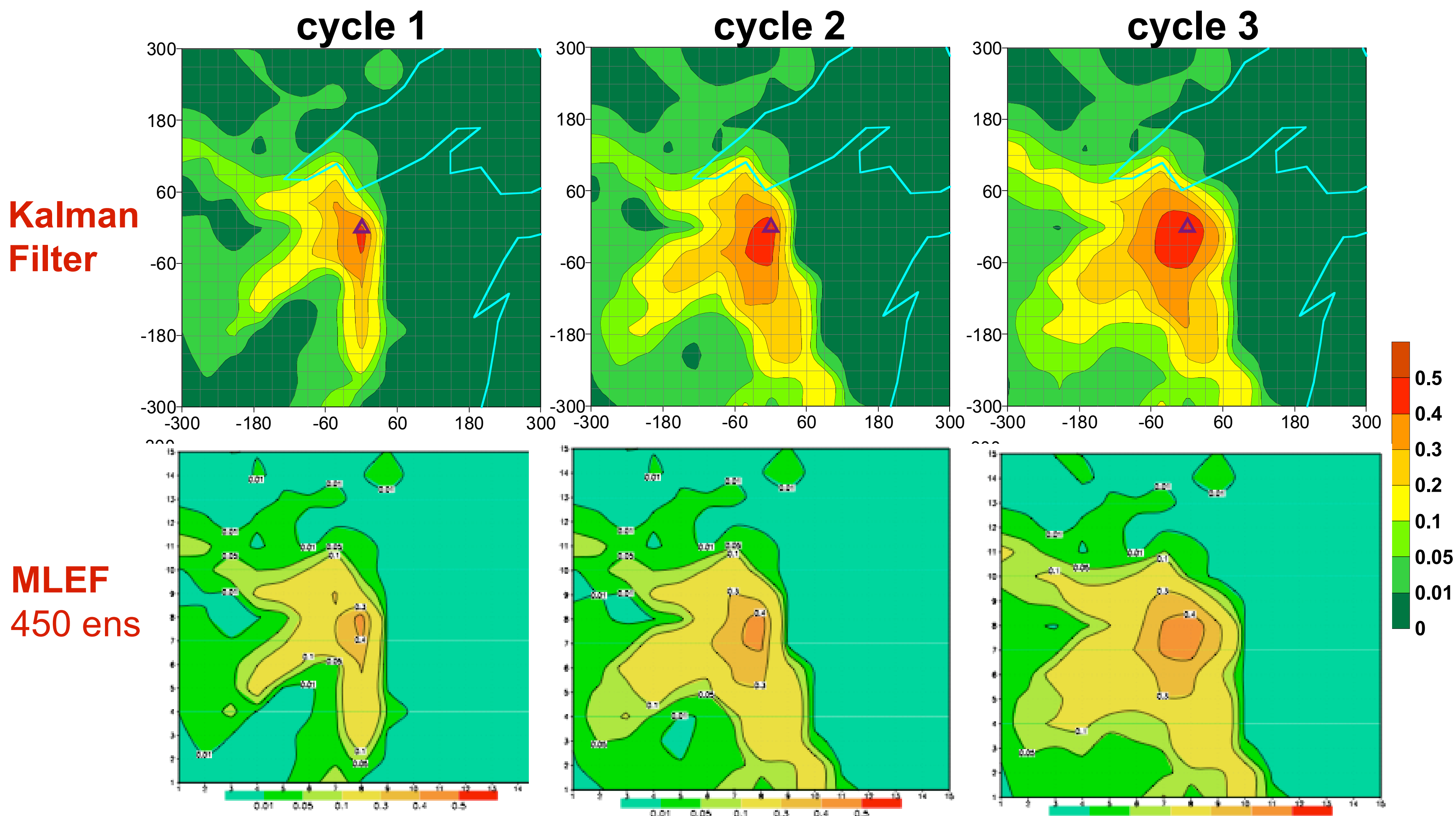
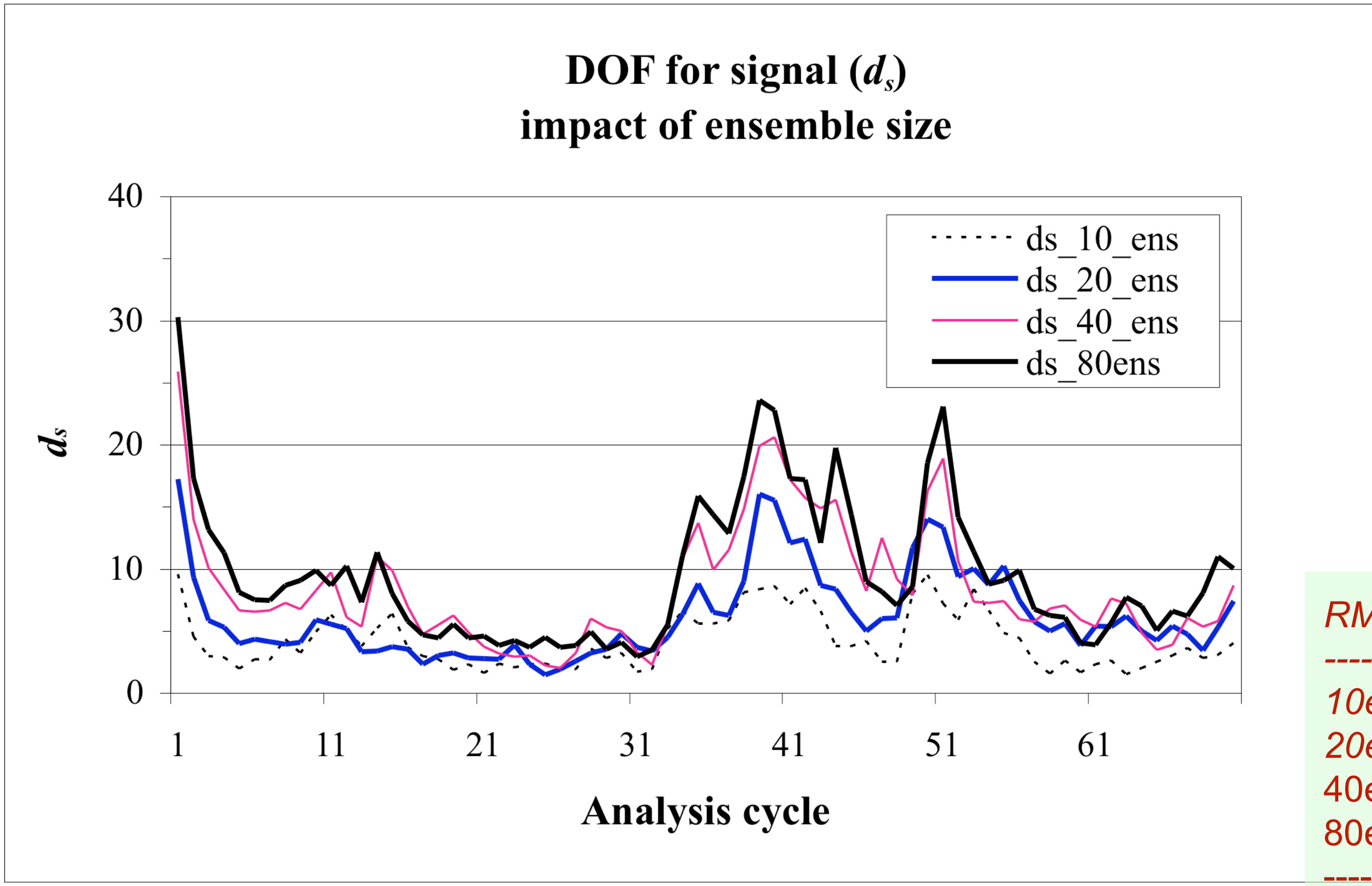
LPDM model: Estimation of respiration bias
Reduction of uncertainty (σ_0-σ), Nstate=450, Nobs=600, three 5-day data assimilation cycles



This is a sanity check of the full-rank MLEF solution: it is equal to the Kalman filter solution for linear models (e.g., LPDM model).

GEOS-5 Single Column Model: DOF for signal (Nstate=80; Nobs=80, seventy 6-h DA cycles, assimilation of simulated T,q observations)



DOF for signal varies from one analysis cycle to another due to changes in atmospheric conditions.

RMS Analysis errors for T, q:

10ens ~ 0.50K; 0.566g/kg

20ens ~ 0.32K; 0.462g/kg

40ens ~ 0.27K; 0.417g/kg

80ens ~ 0.20K; 0.362g/kg

No_obs ~ 0.82K; 0.656g/kg

Small ensemble size (10 ens), even though not perfect, captures main data signals.

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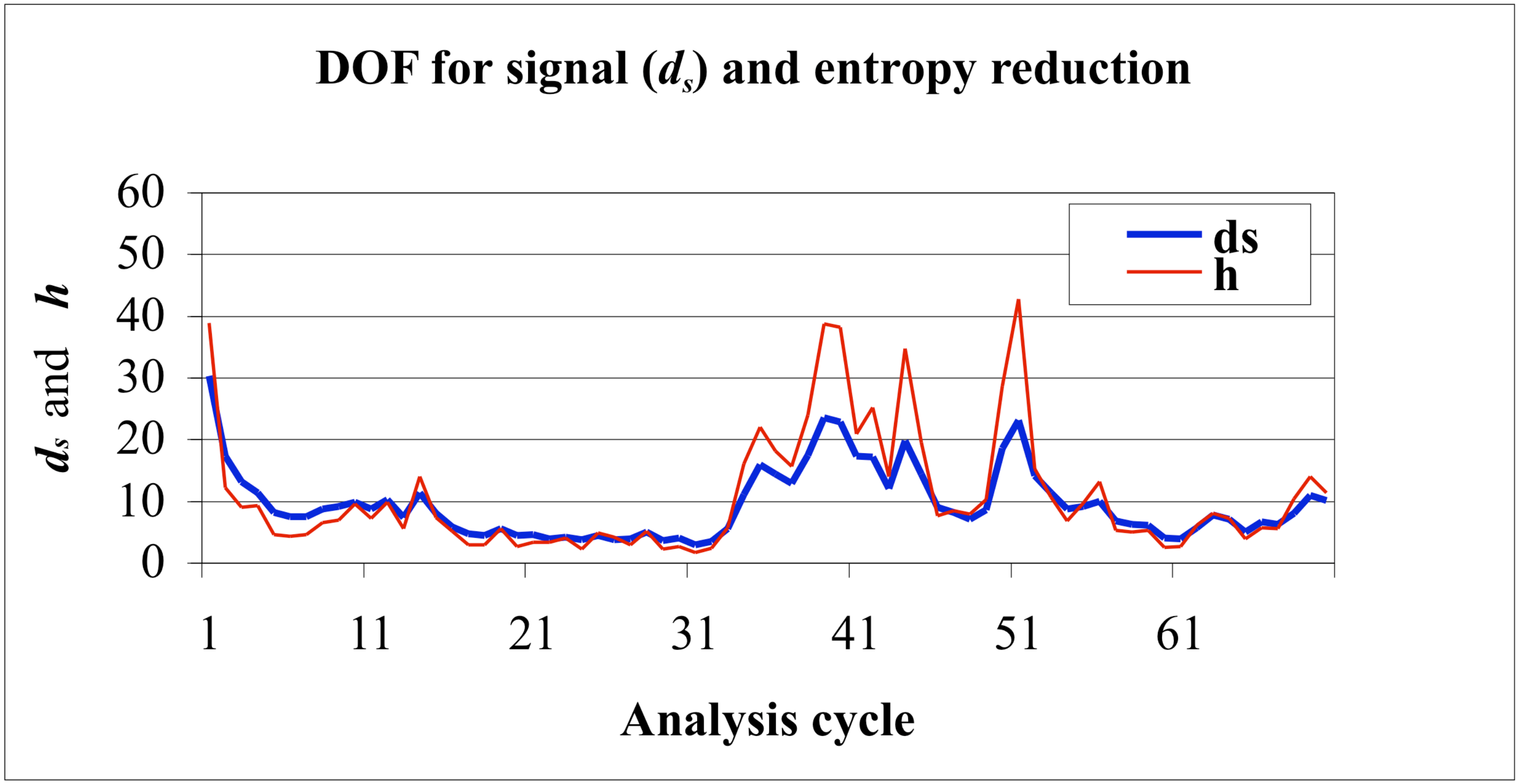

DOF for signal and entropy reduction are very similar information measure. Main difference: the valued of DOF are always ≤ Nens.

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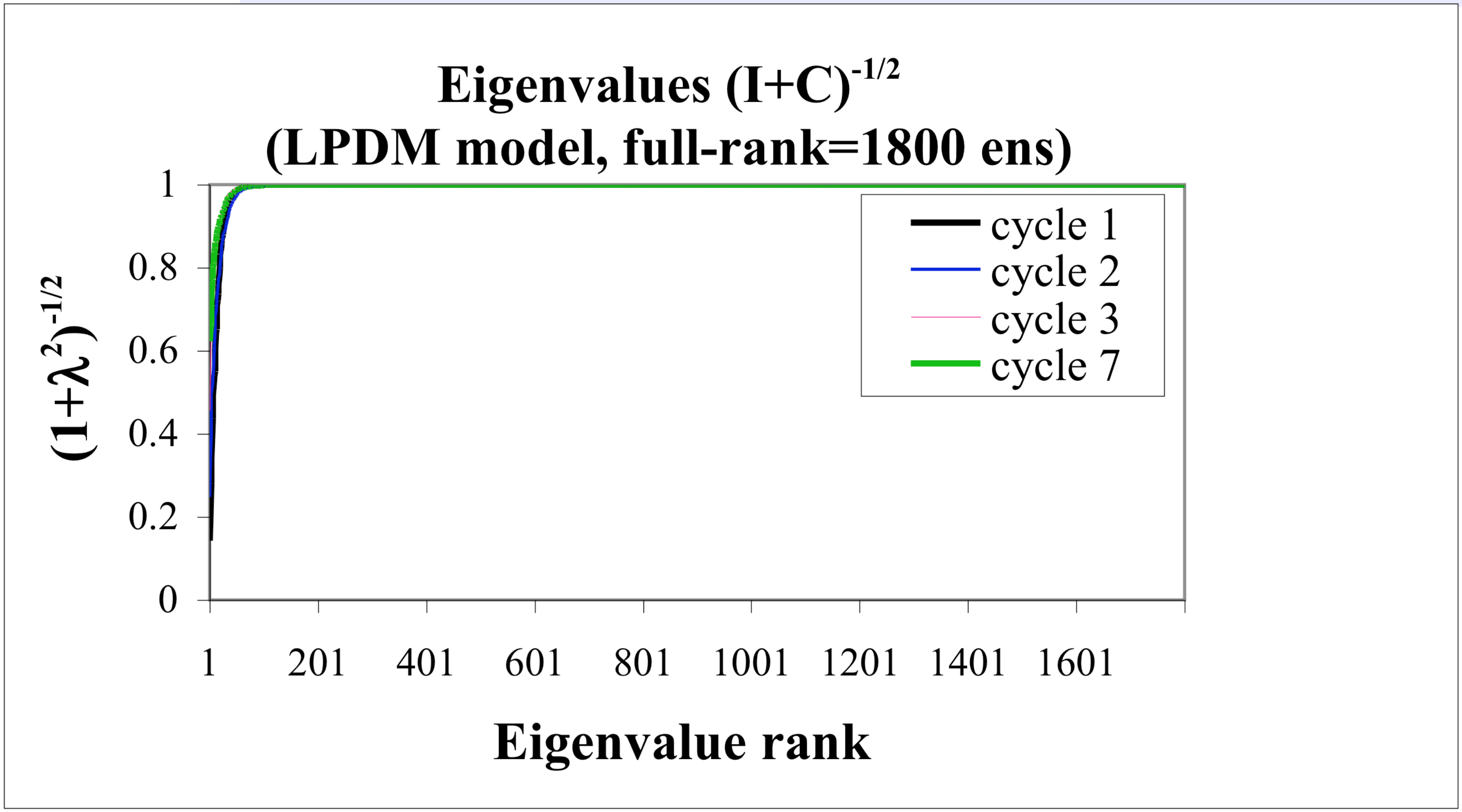
LPDM Model CO2-flux BIAS estimation: Eigenvalue spectrum of $(I+C)^{-1/2}$ (Nstate=1800; Nobs=1200, Nens=1800, seven 10-day DA cycles, assimilation of simulated C02 observations from a tall tower)



The the number of effective DOF of this system is between 10 and 20. We do not need 1800 ensembles!

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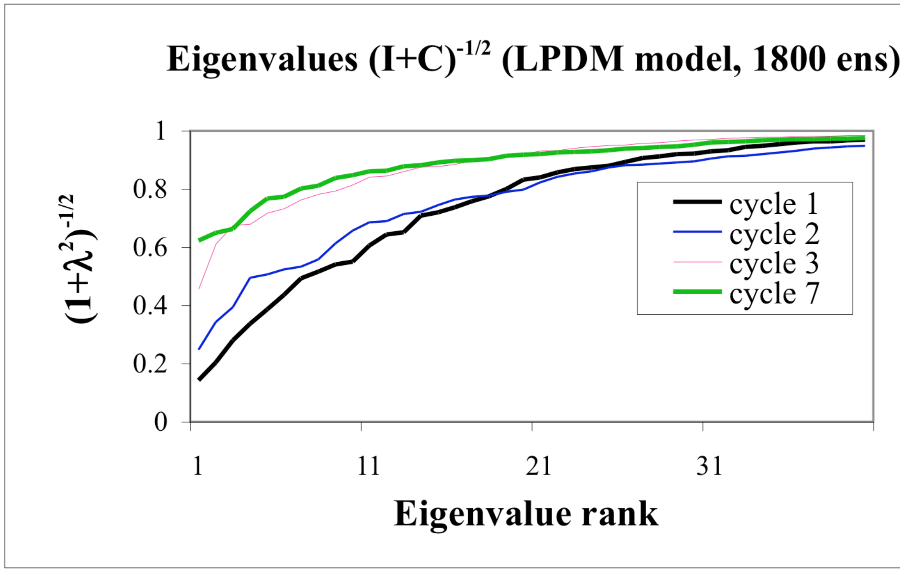
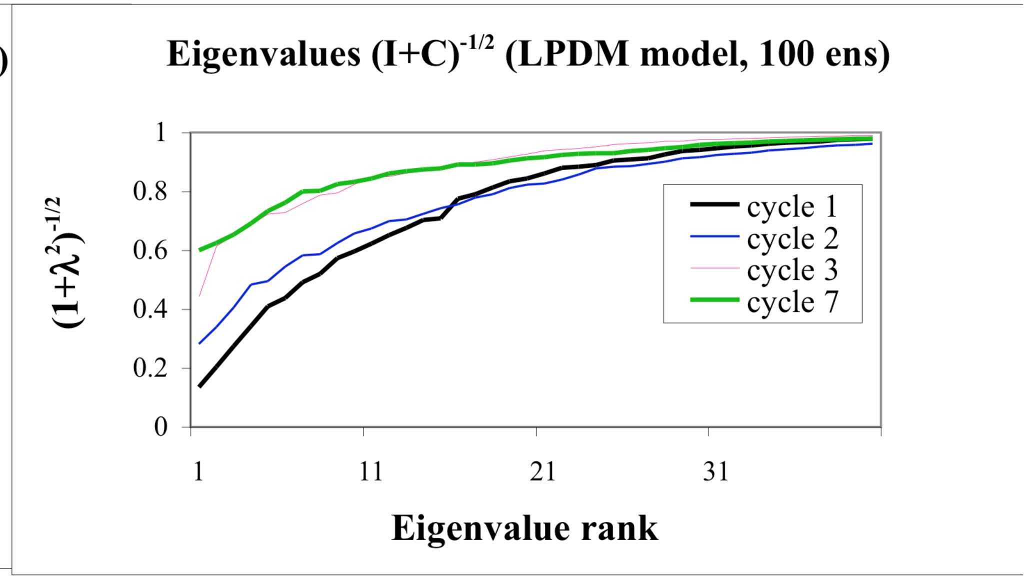
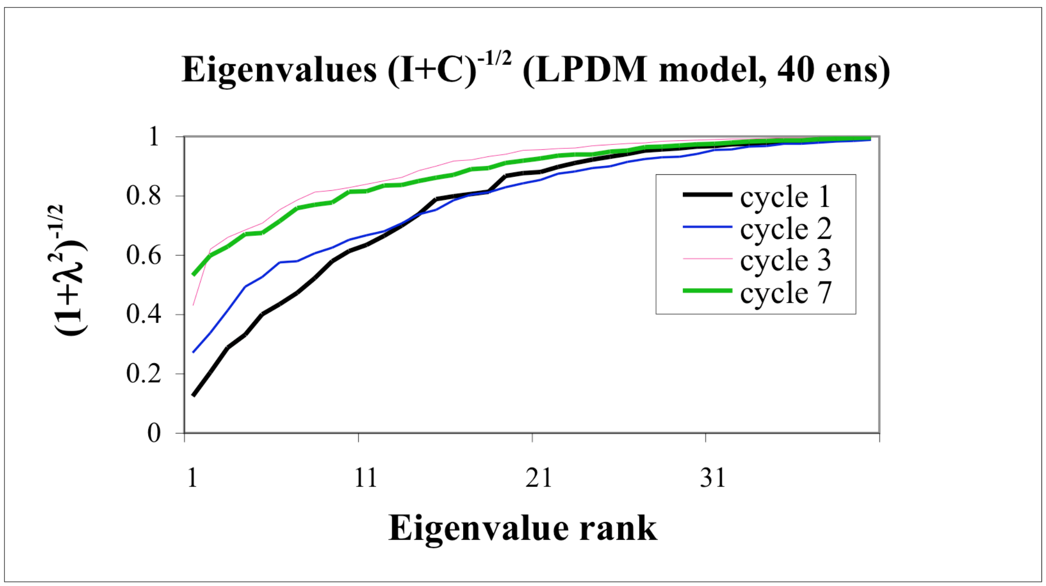
LPDM Model CO2-flux BIAS estimation: Eigenvalue spectrum of $(I+C)^{-1/2}$ (First 40 eigenvalues, Nens = 1800, 100, and 40)







Eigenvalue spectrum is very similar for all 3 ensemble sizes!

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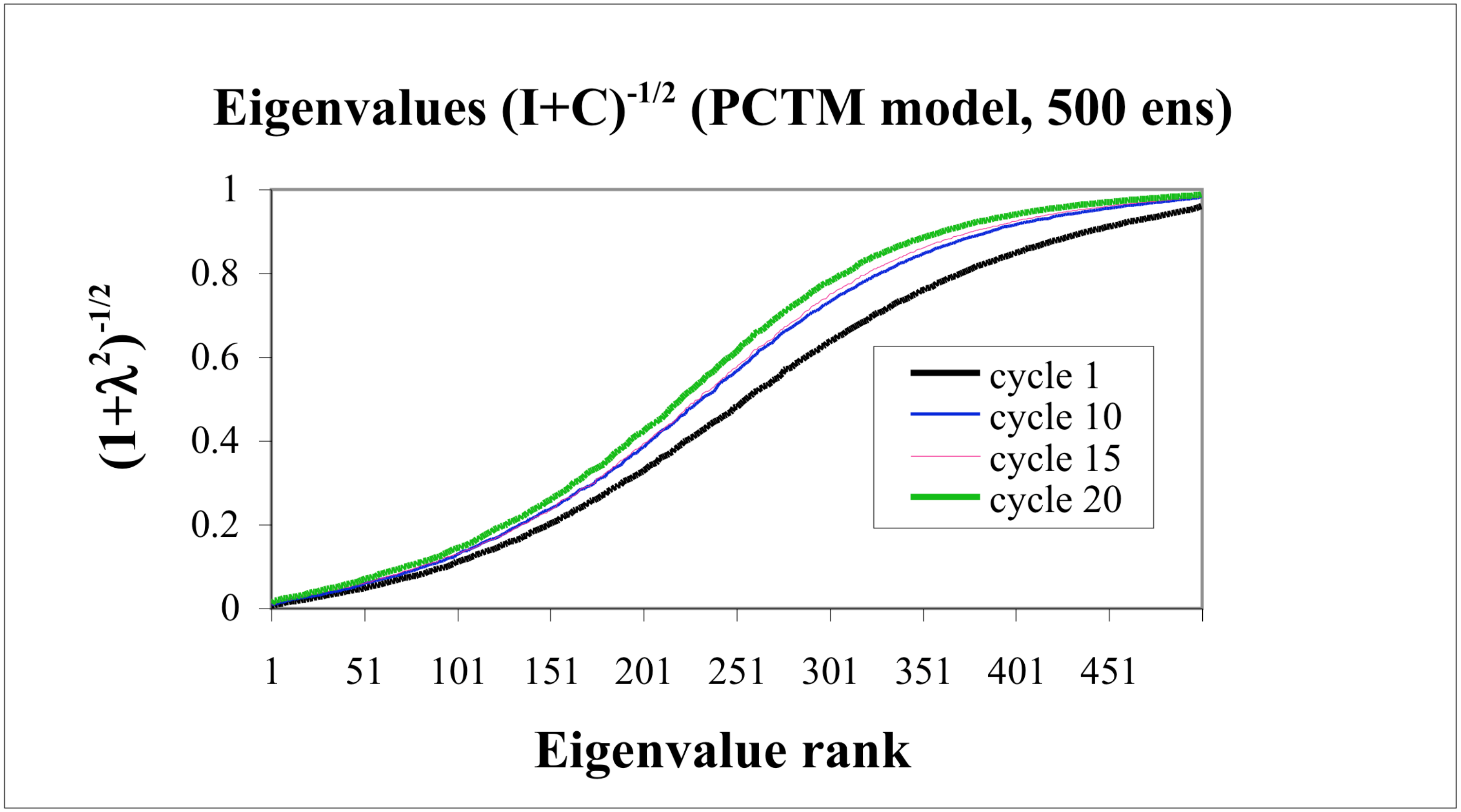
PCTM Global Model CO2-flux estimation: Eigenvalue spectrum of C (Nstate=13104, Nobs=13104, fully observed system, Nens= 500)



Ensemble size of 500 is adequate for describing all DOFs of this fully observed system.
In later cycles more eigenvalues are approaching value 1 (no information).

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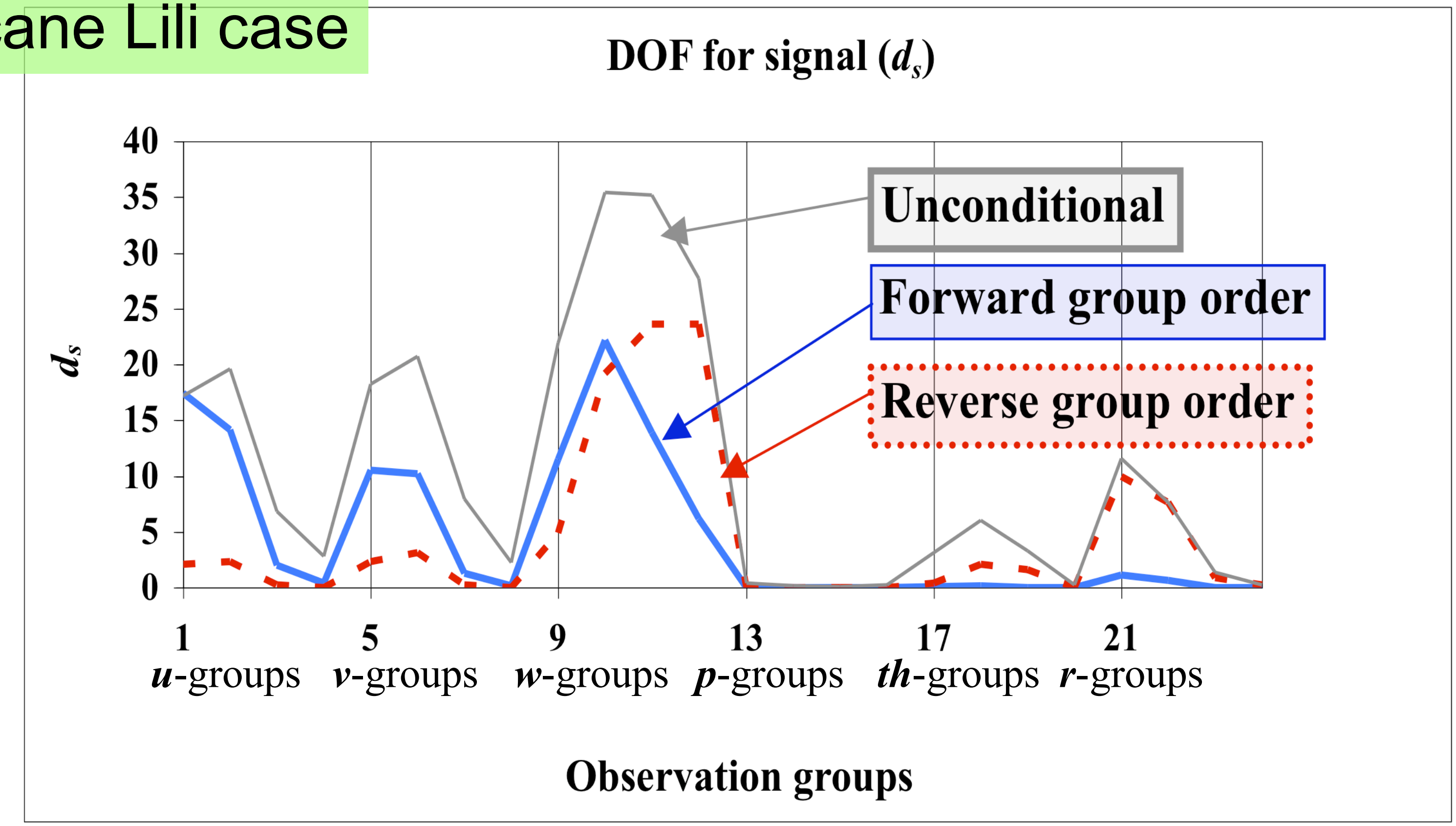
RAMS Model:
Assimilation of simulated observations: u, v, w, p, th, and r groups of observations assimilated successively (Nstate=54000, Nobs=7200, Nens= 50)

Hurricane Lili case



Conditional information content analysis depends on the group order. Unconditional information content analysis produces largest information content, and does not depend on the group order.

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Conclusions and Future Plans

❑ Experience from different dynamical models (e.g., atmospheric and carbon transport models) indicates that information measures, defined in ensemble subspace, are reliable measures of effective DOF.

❑ These measures can be used for many different applications: estimation of information content of data, defining adequate ensemble size, defining adequate control variables for data assimilation, optimally combining different observations, quality control, and data thinning.

❑ Main advantages of using ensemble-based approaches for information content analysis are: flow-dependent error covariance, and small dimensions of information matrix C (*Nens* x *Nens*).

❑ There are indications that a relatively small ensemble size might be sufficient for meaningful information content analysis.

❑ Future Plans: Collaboration with NCEP/EMC on estimating information content of NCEP operational data.

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