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Challenges of Data Assimilation in MMF

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Outline

- **Challenges of multi-scale modeling framework (MMF)**

- **Assimilation-prediction as a single mathematical problem**

  - Kolmogorov equation
  - feasible for realistic applications, for the first time

- **New (old) look at data assimilation: model errors, uncertainty**

  - we knew about it before from the theory, now we can estimate them from observations

- **Extended role of data assimilation: How data assimilation can help in MMF development and applications?**

  - feasibility of a single assimilation-prediction system opens new avenue of opportunities for data assimilation applications

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Challenges of multi-scale modeling framework (MMF)

- **Cloud-scale interaction**
- **Climate scale interaction**
- **Interaction between scales**
    - Nonlinearity
    - Uncertainty transfer
- **Atmospheric-chemical processes**
- **Small-scale interaction between atmosphere and land**

Question:

How to make a computationally efficient data assimilation, without sacrificing the quality? Never before such a complex system was used to simulate such a wide range of scales !

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General Principles

Most general formulation of the assimilation-prediction problem:

Kolmogorov (Fokker-Planck) equation

$$\frac{\partial p(x,t)}{\partial t} = -\frac{\partial [p(x,t) f(x,t)]}{\partial x} + \frac{1}{2}\frac{\partial^2 [p(x,t) g^2(x,t)]}{\partial x^2}$$

p – probability density

f – dynamical model

g – stochastic forcing (model error)

- **Prediction:** Estimate of the *forecast* probability density
- **Data Assimilation:** Estimate of the *initial* probability density

Implications to weather and climate: THERE IS ONLY ONE SYSTEM !

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General Principles

Two fundamental theoretical and practical sources for improvement of the assimilation-prediction:

(1) Kalman filtering (includes Kolmogorov equation)

(2) Deterministic chaos (strange attractors)

Most (if not all) known data assimilation methodologies derived, or closely related to the Kalman filtering theory:

- **Optimal interpolation**
- **Variational methods (3D-var, 4D-var)**
- **Ensemble Kalman filters**

The notion of strange attractors implies an existence of a low-dimensional subspace (small number of degrees of freedom)

- **Ensemble forecasting**
- **Ensemble Kalman filters**

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What do we want from PDF?

(1) Commonly estimated statistical (PDF) parameters

- Mean (Monte Carlo KF - EnKF, minimum variance – standard KF)
- Mode (Maximum of PDF: variational, MLEF)

- **Identical for Gaussian PDF and linear models, differ for nonlinear problems**
- **Differ for sample-derived mean and mode parameters**
- **Differ for non-Gaussian PDFs**

(2) An estimate of the PDF width (uncertainty)

- **Covariance, standard deviation**
- **Ensemble spread**

- **Calculate more than one parameter, if feasible**
- **Use all that can improve the knowledge of PDF**

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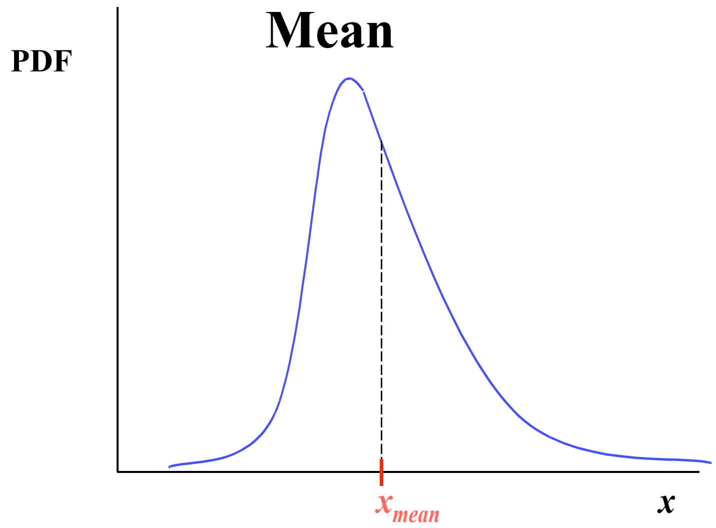
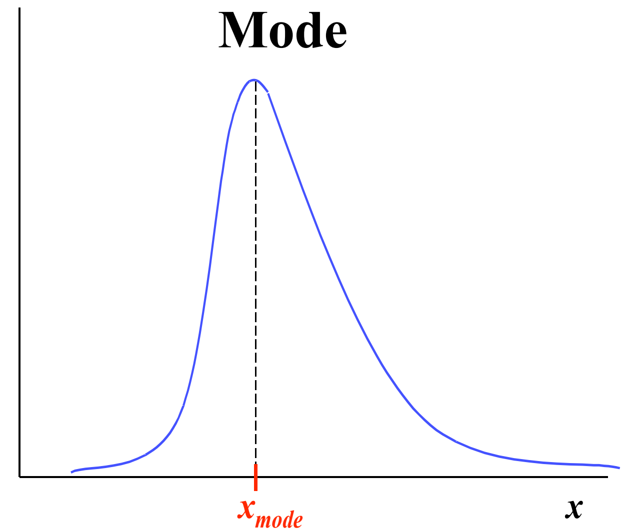
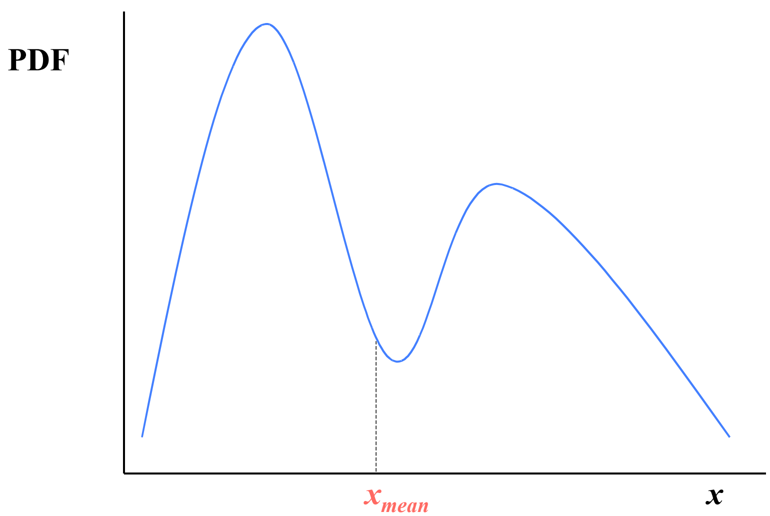
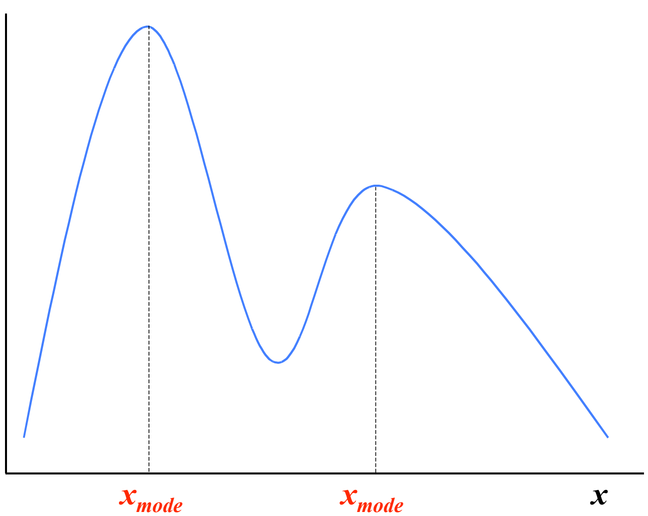
What is optimal?
Statistical parameters







Dynamical state



Dynamical state

Data assimilation

What are the control variable for a prediction model?

- **Initial conditions**
  - best known
- **Model error (including bias)**
  - very little known, yet it may have a dominant impact on the prediction
- **Empirical model parameters**
  - Limited knowledge, often based on a small, inadequate sample of cases
- **Lateral boundary conditions (if needed)**

Can it all be adjusted simultaneously?

- **Yes, and it should be (augmented control variable)**
- **There is an overlap between the model error and empirical model parameters, but it is unknown in practice**

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Data assimilation using EnKF and related ensemble methods

- **At present, the most general, computationally feasible data assimilation approach**
  - need further testing in most complex environment

- **Single algorithm is used for data assimilation and (ensemble) prediction**
  - sample approach to Kolmogorov equation and deterministic chaos

- **Can account for model error - new development**
  - adjustment of model error and its covariance

- **Algorithmically simple, efficient development and maintenance**

- **Suitable for high-performance computing (HPC)**

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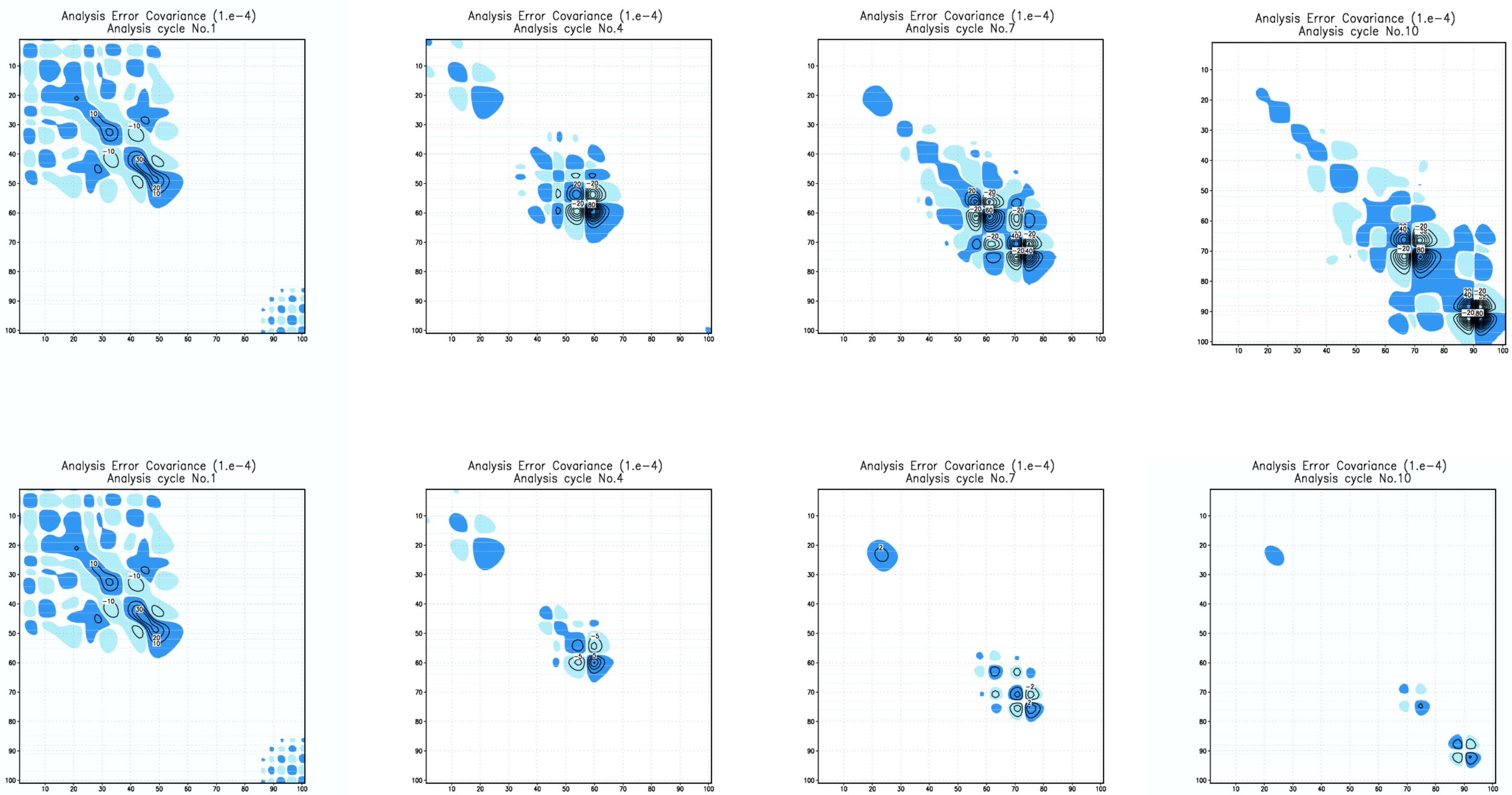
Analysis Error Covariance (MLEF with KdVB model)

Cycle No. 1 | **Cycle No. 4** | **Cycle No. 7** | **Cycle No. 10**

In-situ

Targeted



Targeted (intelligently placed) observations improve ensemble DA performance

From Zupanski 2004, MWR
[Available at ftp://ftp/cira.colostate.edu/milija/MLEF_mwr.pdf]

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Possible issues with MMF applications

- **How many ensembles can we realistically do with MMF?**
  - simultaneous integration of a climate and cloud-system resolving models (CSRM) is quite demanding
  - what is the ultimate goal for resolution of CSRM (impact on climate)

- **Exploit the statistical aspect of CSRM**
  - each 'grid-box' of a climate model includes a sample of CSRM realizations

- **Explore new avenues**
  - adjust only statistical PDF parameters for the cloud-scales
  - no need for CSRM ensembles, PDF information is already given
  - control forecast using most complex model, ensembles used only for the climate component

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Why is model error so important in data assimilation?

- **Data assimilation system that employs a model is more sensitive to the model performance (as it should be)**

- **There is an overlap between the model error and the choice of empirical model parameters, but it is unknown in practice**

  - best to have both the model error and parameters as components of control variable

- **Data assimilation is the most efficient way to learn about model errors, from the comparison with observations**

  - model bias

  - empirical parameters

Why not use data assimilation to learn about model biases and parameter values, and eventually correct the model itself?

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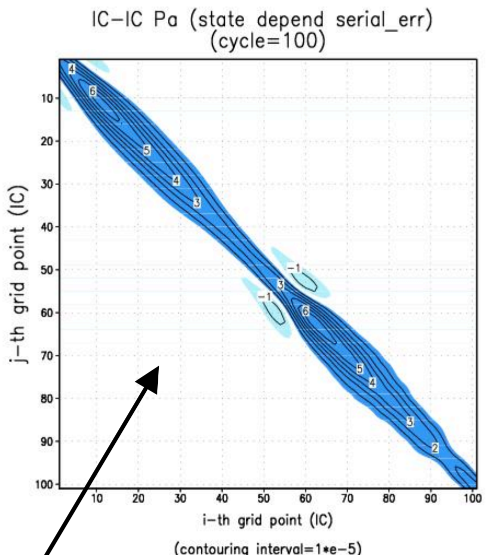
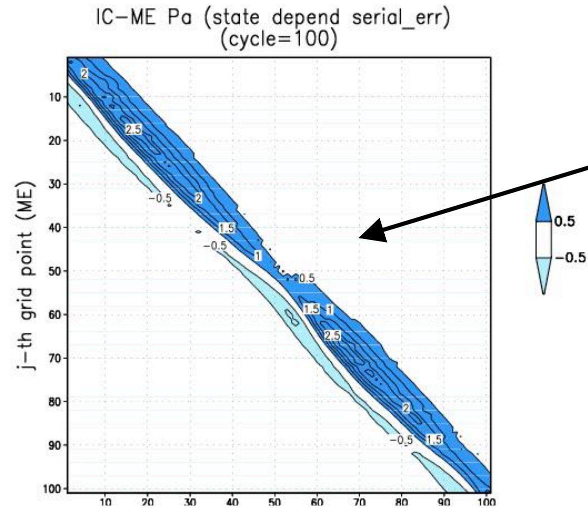
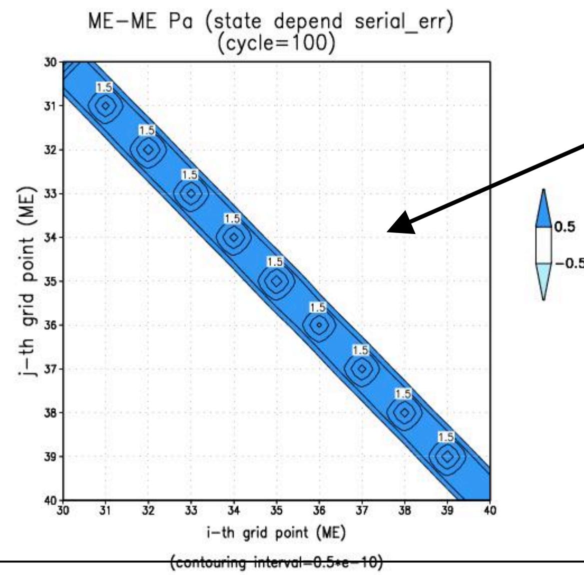
Ensemble data assimilation with KdVB model

Augmented analysis error covariance matrix







Cross-covariance between **model error** (bias) and **initial conditions**

[most significant impact of model error - new]

Auto-covariance for **initial conditions**

Auto-covariance for **model error** (bias)

From Zupanski and Zupanski 2004, MWR
[Available at ftp://ftp/cira.colostate.edu/milija/MLEF_model_err.pdf]

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How to use data assimilation ?

- **Traditional role**

  - model evaluation and validation against observations
  - first develop the model, than worry about data assimilation

Model development issues:

- initial model testing with adequately defined empirical parameters and constants will be beneficial
- debugging: model error adjustment in data assimilation will point to programming errors, as well as to the real biases
- facilitated testing in large sample of cases

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Additional role for data assimilation in model development

- **Data assimilation and prediction are a single system, why not test them together?**

  - speed-up development of a robust model (and data assimilation)

  - it will be used together later anyway

- **Empirical model parameters**

  - from the very beginning of model development and testing, the parameters used will be adequately estimated from observations, no need to wait

  - even if assimilated observations cannot directly relate to the scales and processes represented by parameters, other observations will improve parameter estimation through the implicit use of model equations

- **Model error (bias)**

  - may point to the incorrectly specified equations, facilitate debugging

  - actual model biases and errors will be known early in model development, therefore it may be possible to correct the model equations

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New component to model development effort

- **In order to be used during the initial model development, data assimilation ought to be:**
  - easy to upgrade, accommodate for evolving model and observations
  - does not require considerable changes

EnKF and related ensemble methods

- **Require only minor addition to the model**
  - read control variable (initial conditions, model error, parameters)
  - no change required when adding new subroutines and processes to the model

- **Simultaneous testing of the assimilation-prediction system**
  - robustness of the system, and the model greatly enhanced
  - saves considerable time
  - probabilistic (PDF) evaluation of the prediction system

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Implications

- The assimilation-prediction system is a unified system (e.g., Kolmogorov equation), and it can only be beneficial if treated as such from the very beginning in development, to obtain optimal results

- Most general way to optimally introduce observations in model development is through data assimilation

- Learn about model errors and biases early, possibly correct them

- Find about appropriate values for empirical parameters and constants, even before all scales and types of observations are included

- Data assimilation component of the system can be viewed as a new tool for model development and testing

  - evaluate interaction between the scales
  - uncertainty transfer, especially between cloud-scales and climate
  - can be used in probabilistic (e.g. ensemble prediction), or deterministic sense (deterministic, control prediction)

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