

# **Ensemble Kalman Filter**

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# The Ensemble Kalman Filter (EnKF)

- Represents error statistics using an ensemble of model states.
- Evolves error statistics by ensemble integrations.
- “Variance minimizing” analysis scheme operating on the ensemble.



- Monte Carlo, low rank, error subspace method.
- Converges to the Kalman Filter with increasing ensemble size.
- Fully nonlinear error evolution, contrary to EKF.
- Assumption of Gaussian statistics in analysis scheme.

# The error covariance matrix

Define ensemble covariances around the ensemble mean

$$\mathbf{C}_{\psi\psi}^f \simeq (\mathbf{C}_{\psi\psi}^f)^e = \overline{(\boldsymbol{\psi}^f - \overline{\boldsymbol{\psi}^f})(\boldsymbol{\psi}^f - \overline{\boldsymbol{\psi}^f})^T}$$

$$\mathbf{C}_{\psi\psi}^a \simeq (\mathbf{C}_{\psi\psi}^a)^e = \overline{(\boldsymbol{\psi}^a - \overline{\boldsymbol{\psi}^a})(\boldsymbol{\psi}^a - \overline{\boldsymbol{\psi}^a})^T}$$

- The ensemble mean  $\overline{\boldsymbol{\psi}}$  is the best-guess.
- The ensemble spread defines the error variance.
- The covariance is determined by the smoothness of the ensemble members.
- A covariance matrix can be represented by an ensemble of model states (not unique).

# Dynamical evolution of error statistics

- Each ensemble member evolves according to the model dynamics which is expressed by a stochastic differential equation

$$d\psi = \mathbf{g}(\psi)dt + \mathbf{h}(\psi)dq.$$

- The probability density  $f$  then evolve according to Kolmogorov's equation

$$\frac{\partial f}{\partial t} + \sum_i \frac{\partial (g_i f)}{\partial \psi_i} = \frac{1}{2} \sum_{i,j} \frac{\partial^2 f (\mathbf{h} \mathbf{C}_{qq} \mathbf{h}^T)_{ij}}{\partial \psi_i \partial \psi_j}.$$

- This is the fundamental equation for evolution of error statistics and can be solved using Monte Carlo methods.

# Analysis scheme (1)

- Given an ensemble of model forecasts,  $\psi_j^f$ , defining forecast error covariance

$$\mathbf{C}_{\psi\psi}^f \simeq (\mathbf{C}_{\psi\psi}^f)^e = \overline{(\psi^f - \bar{\psi}^f)(\psi^f - \bar{\psi}^f)^T}.$$

- Create an ensemble of observations

$$\mathbf{d}_j = \mathbf{d} + \boldsymbol{\epsilon}_j,$$

with

- $\mathbf{d}$ , the real observations,
- $\boldsymbol{\epsilon}_j$ , a vector of observation noise,
- $\overline{\boldsymbol{\epsilon}\boldsymbol{\epsilon}^T} = (\mathbf{C}_{\boldsymbol{\epsilon}\boldsymbol{\epsilon}})^e \simeq \mathbf{C}_{\boldsymbol{\epsilon}\boldsymbol{\epsilon}}$ .

# Analysis scheme (2)

- Update each ensemble member according to

$$\psi_j^a = \psi_j^f + (\mathbf{C}_{\psi\psi}^f)^e \mathbf{M}^T \left( \mathbf{M} (\mathbf{C}_{\psi\psi}^f)^e \mathbf{M}^T + \mathbf{C}_{\epsilon\epsilon} \right)^{-1} \left( d_j - \mathbf{M} \psi_j^f \right)$$

- Thus, the update of the mean becomes

$$\bar{\psi}^a = \bar{\psi}^f + (\mathbf{C}_{\psi\psi}^f)^e \mathbf{M}^T \left( \mathbf{M} (\mathbf{C}_{\psi\psi}^f)^e \mathbf{M}^T + \mathbf{C}_{\epsilon\epsilon} \right)^{-1} \left( d - \mathbf{M} \bar{\psi}^f \right).$$

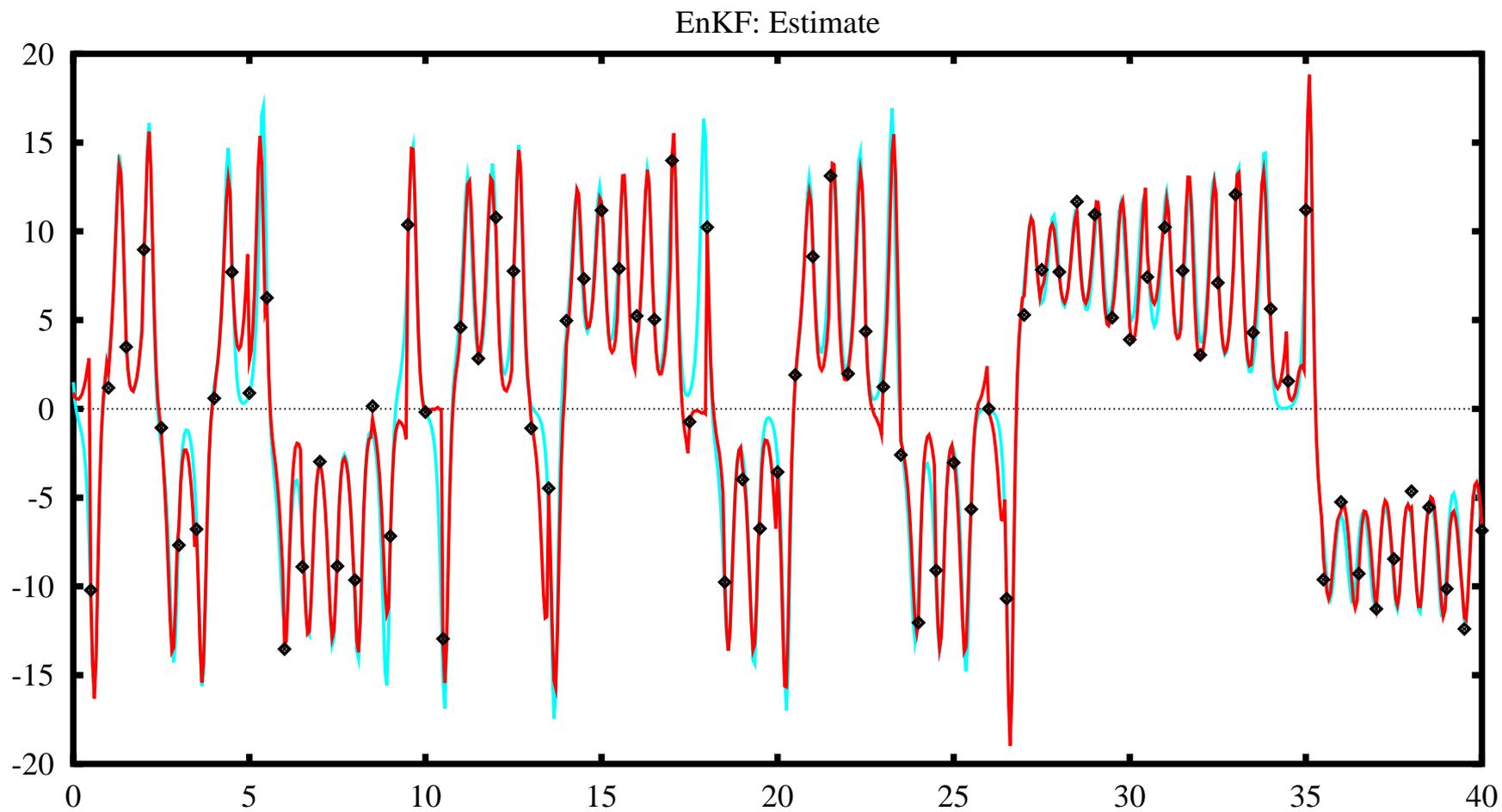
- The posterior error covariance becomes

$$\begin{aligned} (\mathbf{C}_{\psi\psi}^a)^e &= (\mathbf{C}_{\psi\psi}^f)^e \\ &\quad - (\mathbf{C}_{\psi\psi}^f)^e \mathbf{M}^T \left( \mathbf{M} (\mathbf{C}_{\psi\psi}^f)^e \mathbf{M}^T + \mathbf{C}_{\epsilon\epsilon} \right)^{-1} \mathbf{M} (\mathbf{C}_{\psi\psi}^f)^e. \end{aligned}$$

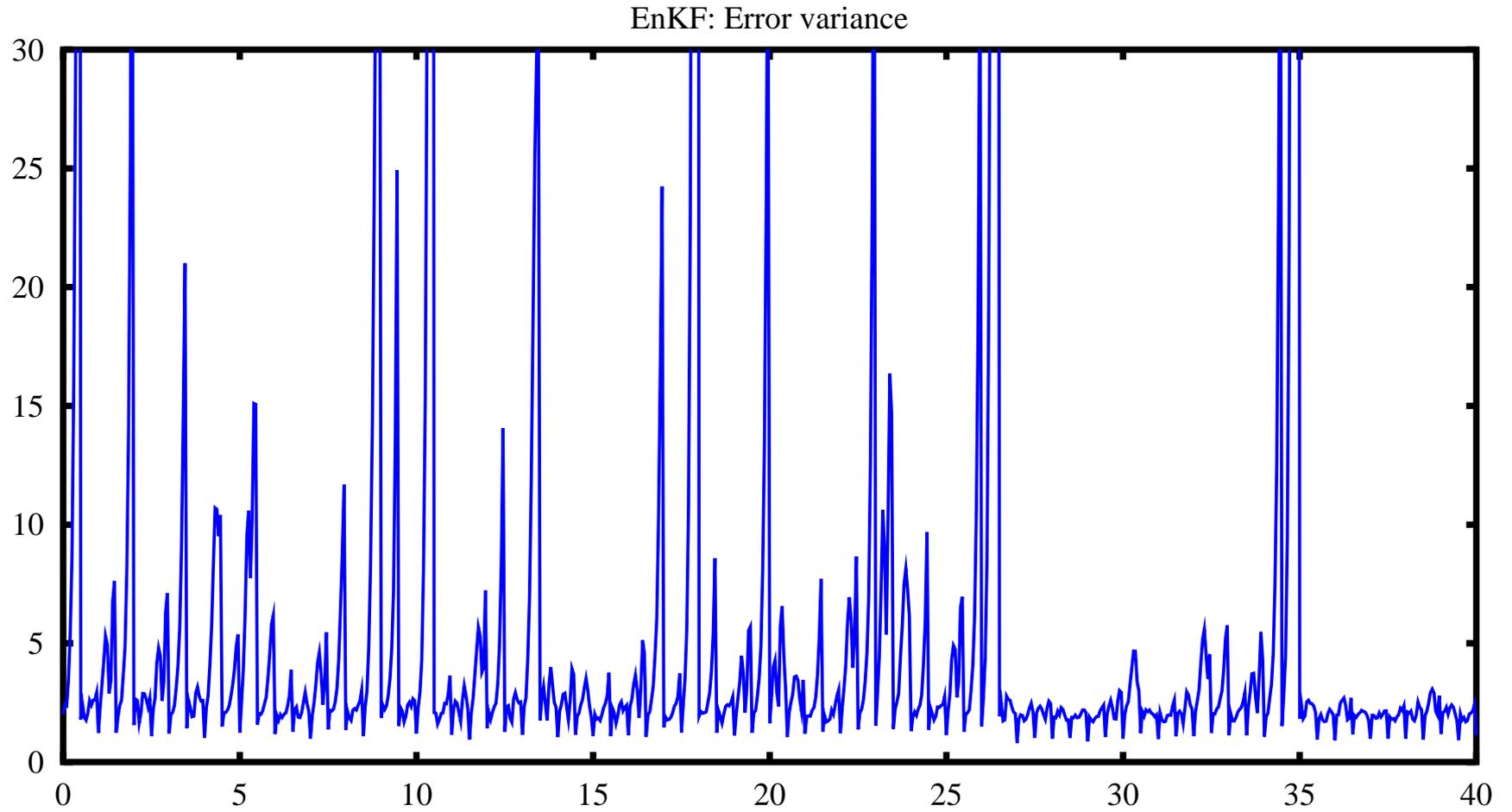
# Example: Lorenz model

- Application with the chaotic Lorenz model
- Illustrates properties with highly nonlinear dynamical models.
- From Evensen (1997), MWR.

# EnKF solution



# EnKF error variance



# Summary: Lorenz model

- The EnKF works well with highly nonlinear dynamical models.
- There is no linearization in the evolution of error statistics.
- Methods using tangent linear or adjoint operators have problems with the Lorenz equations:
  - limited by the predictability time,
  - limited by the validity time of tangent linear operator.
- Can we expect the same to be true for more complex models with large state spaces?

# Analysis equation (1)

- Define the ensemble matrix

$$\mathbf{A} = (\boldsymbol{\psi}_1, \boldsymbol{\psi}_2, \dots, \boldsymbol{\psi}_N) \in \mathfrak{R}^{n \times N}.$$

- The ensemble mean is (defining  $\mathbf{1}_N \in \mathfrak{R}^{N \times N} \equiv 1/N$ )

$$\overline{\mathbf{A}} = \mathbf{A}\mathbf{1}_N.$$

- The ensemble perturbations become

$$\mathbf{A}' = \mathbf{A} - \overline{\mathbf{A}} = \mathbf{A}(\mathbf{I} - \mathbf{1}_N).$$

- The ensemble covariance matrix  $(\mathbf{C}_{\psi\psi})^e \in \mathfrak{R}^{n \times n}$  becomes

$$(\mathbf{C}_{\psi\psi})^e = \frac{\mathbf{A}'(\mathbf{A}')^T}{N - 1}.$$

# Analysis equation (2)

- Given a vector of measurements  $\mathbf{d} \in \mathfrak{R}^m$ , define

$$\mathbf{d}_j = \mathbf{d} + \boldsymbol{\epsilon}_j, \quad j = 1, \dots, N,$$

stored in

$$\mathbf{D} = (\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_N) \in \mathfrak{R}^{m \times N}.$$

- The ensemble perturbations are stored in

$$\mathbf{E} = (\boldsymbol{\epsilon}_1, \boldsymbol{\epsilon}_2, \dots, \boldsymbol{\epsilon}_N) \in \mathfrak{R}^{m \times N},$$

thus, the measurement error covariance matrix becomes

$$\mathbf{C}_{\epsilon\epsilon}^e = \frac{\mathbf{E}\mathbf{E}^T}{N-1}.$$

# Analysis equation (3)

- The analysis equation can now be written

$$\mathbf{A}^a = \mathbf{A} + (\mathbf{C}_{\psi\psi})^e \mathbf{M}^T \left( \mathbf{M} (\mathbf{C}_{\psi\psi})^e \mathbf{M}^T + \mathbf{C}_{\epsilon\epsilon} \right)^{-1} (\mathbf{D} - \mathbf{M}\mathbf{A}).$$

- Defining the innovations  $\mathbf{D}' = \mathbf{D} - \mathbf{M}\mathbf{A}$  and using previous definitions:

$$\mathbf{A}^a = \mathbf{A} + \mathbf{A}' (\mathbf{M}\mathbf{A}')^T \left( (\mathbf{M}\mathbf{A}') (\mathbf{M}\mathbf{A}')^T + \mathbf{C}_{\epsilon\epsilon} \right)^{-1} \mathbf{D}'.$$

i.e., analysis expressed entirely in terms of the ensemble

# Analysis equation (4)

- Define  $S = \mathcal{M}A'$  and  $C = SS^T + C_{\epsilon\epsilon}$ .
- Use  $A' = A(I - \mathbf{1}_N)$ .
- Use  $\mathbf{1}_N S^T \equiv 0$ .

$$\begin{aligned} A^a &= A + A' S^T \left( S S^T + C_{\epsilon\epsilon} \right)^{-1} D' \\ &= A + A(I - \mathbf{1}_N) S^T C^{-1} D' \\ &= A \left( I + S^T C^{-1} D' \right) \\ &= AX \end{aligned}$$

# Remarks

- $(C_{\psi\psi})^e$  never computed but indirectly used to determine  $\mathcal{M}(C_{\psi\psi})^e \mathcal{M}^T = SS^T$ .
- Covariances only needed between observed variables at measurement locations.
- Analysis may be interpreted as:
  - combination of forecast ensemble members, or,
  - forecast plus combination of covariance functions.
- Accuracy of analysis is determined by:
  - the accuracy of  $X$ ,
  - the properties of the ensemble error space.

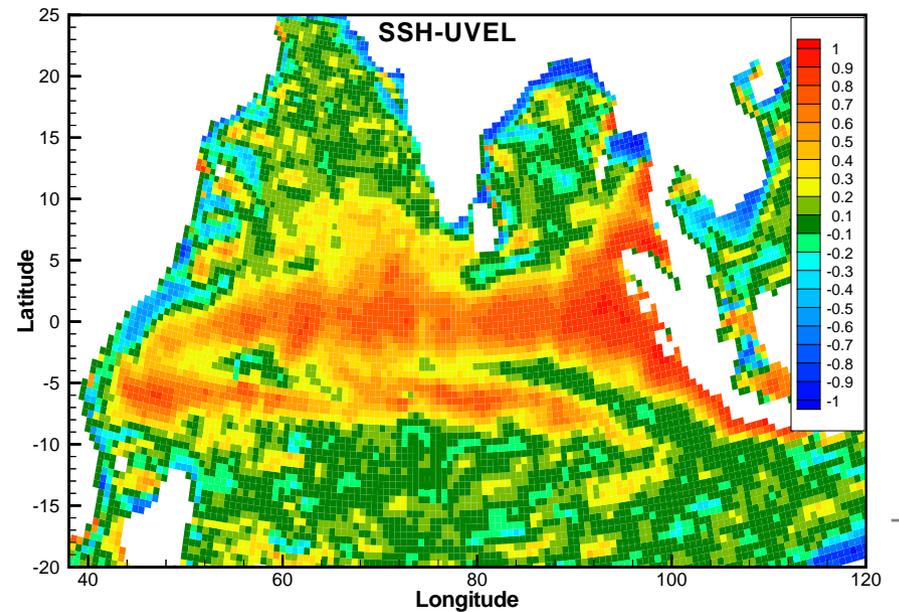
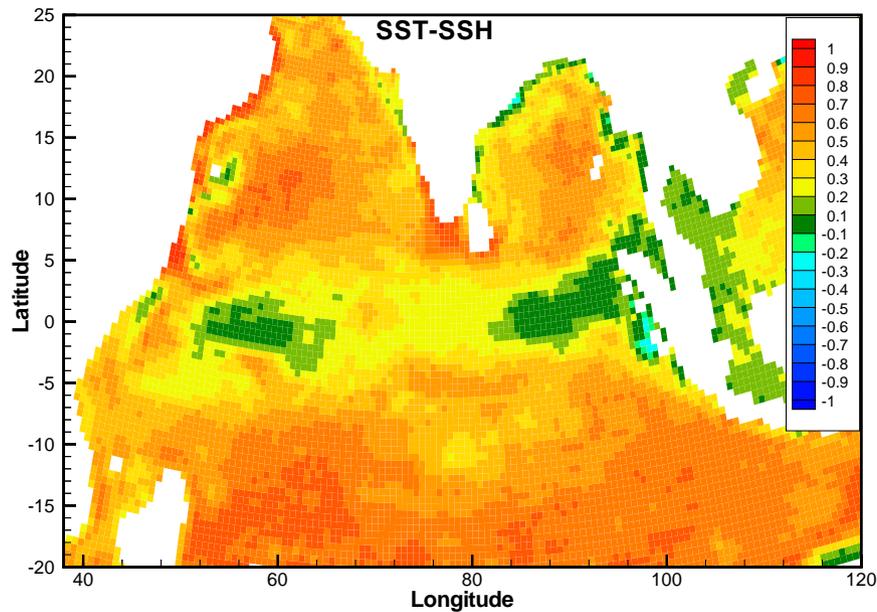
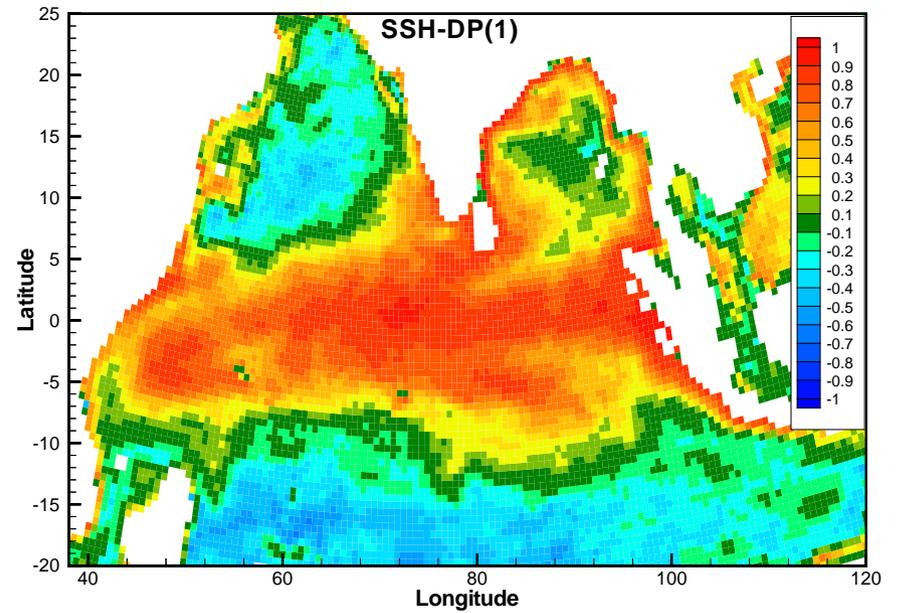
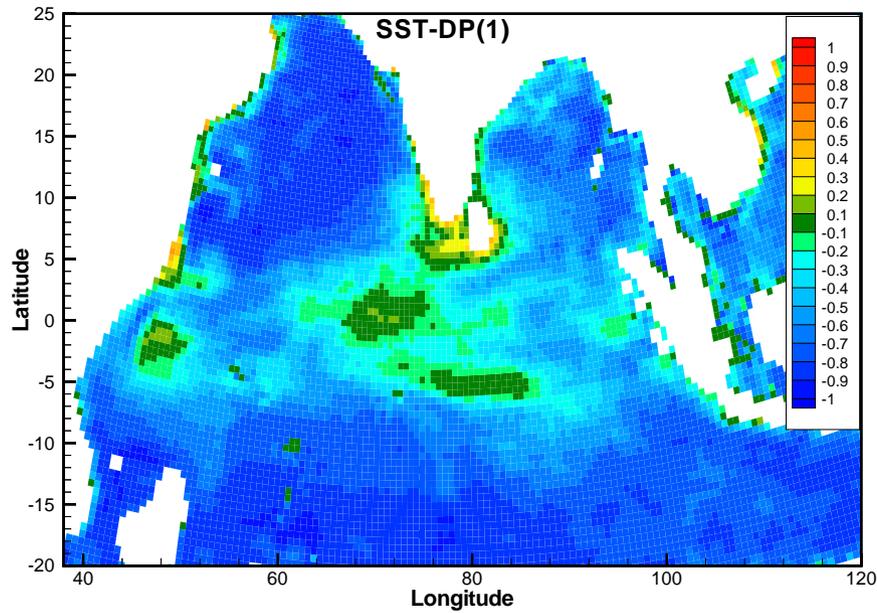
# Remarks

- For a linear model, any choice of  $X$  will result in an analysis which is also a solution of the model.

# Examples of ensemble statistics

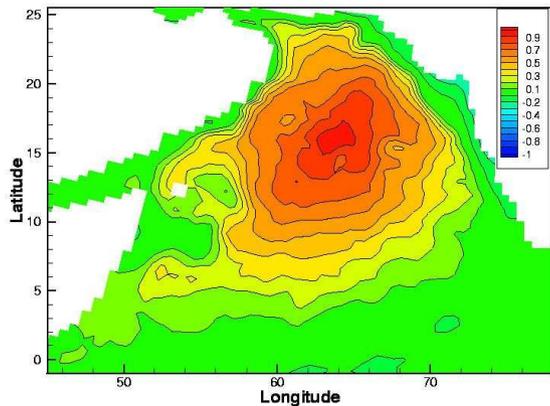
- Taken from Haugen and Evensen (2002), Ocean Dynamics.
- OGCM (MICOM) for the Indian Ocean.
- Assimilation of SST and SLA data.

# Spatial correlations

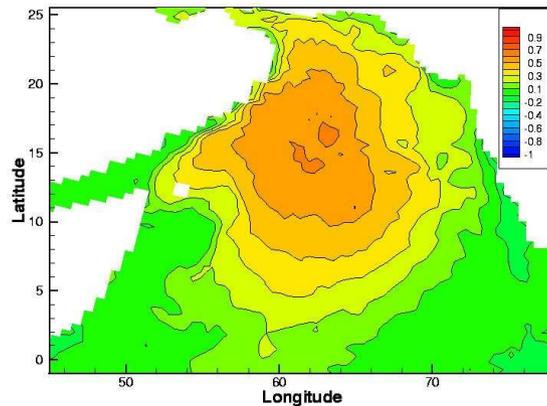


# Correlation functions

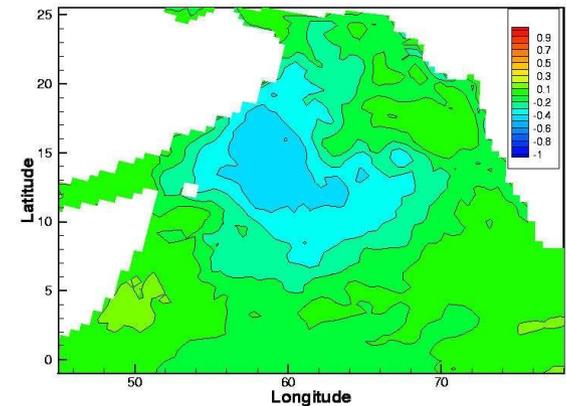
## SSH-SSH



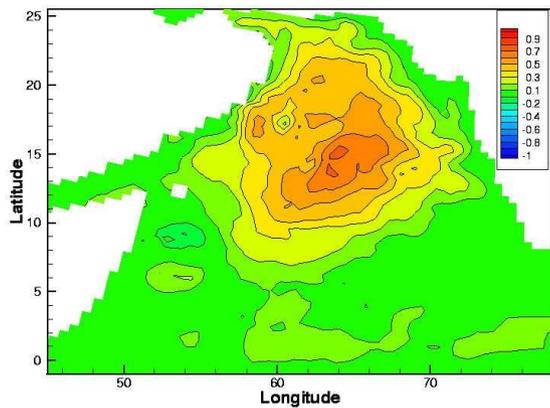
## SSH-SST



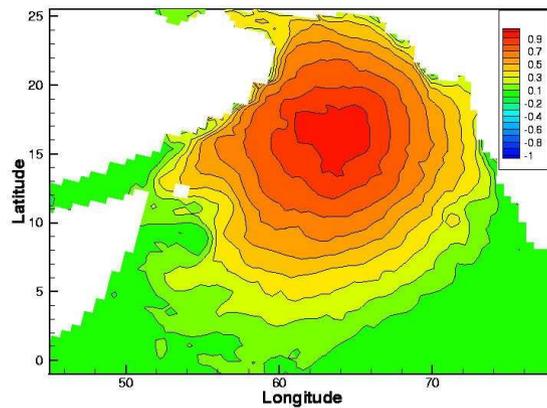
## SSH-DP



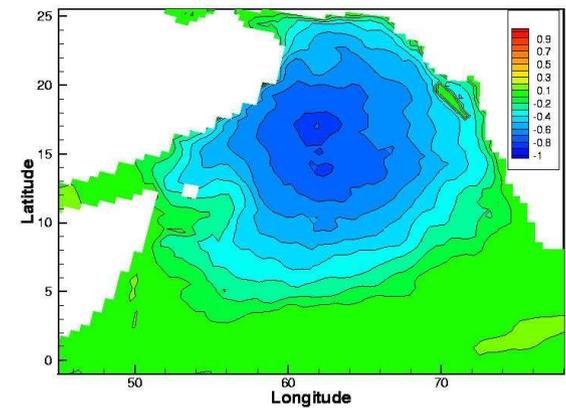
## SST-SSH



## SST-SST

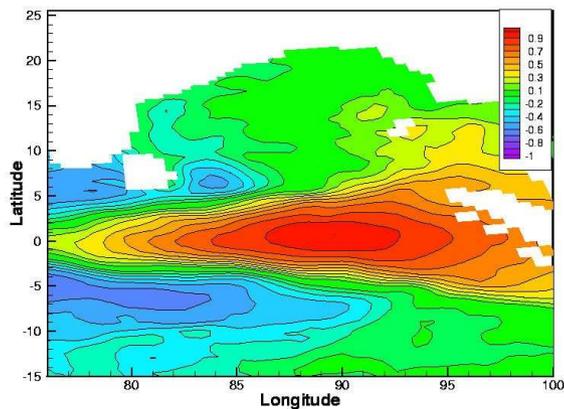


## SST-DP

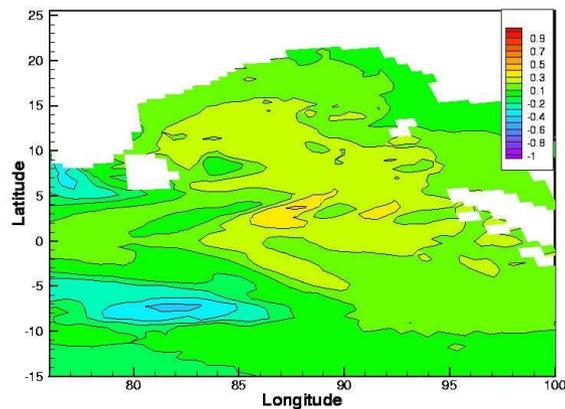


# Correlation functions

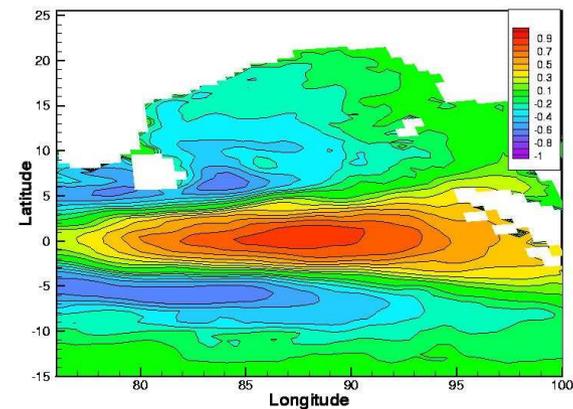
## SSH-SSH



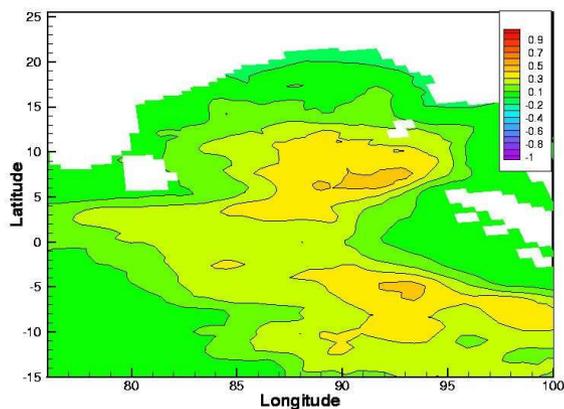
## SSH-SST



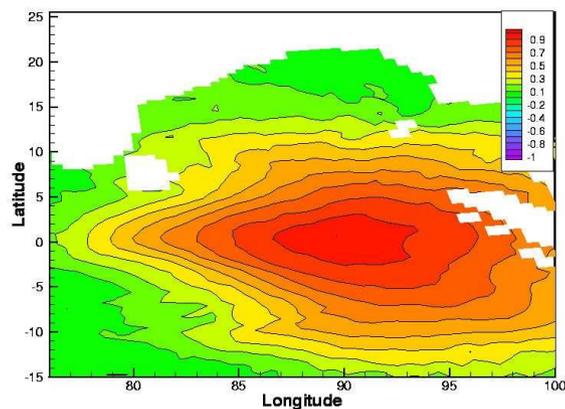
## SSH-DP



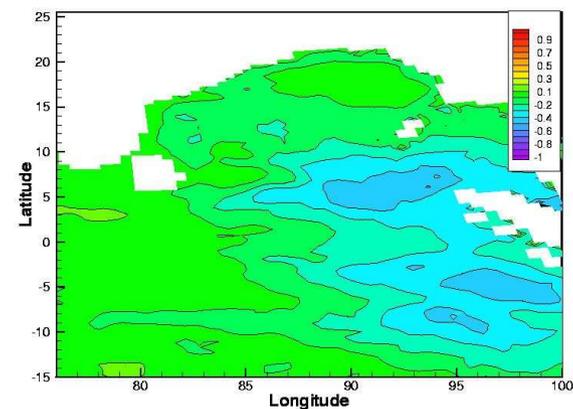
## SST-SSH



## SST-SST



## SST-DP



# Time-Depth: Temperature

