Coupled Ocean Atmosphere Ensemble Prediction

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Objectives Coupled Ensemble Prediction

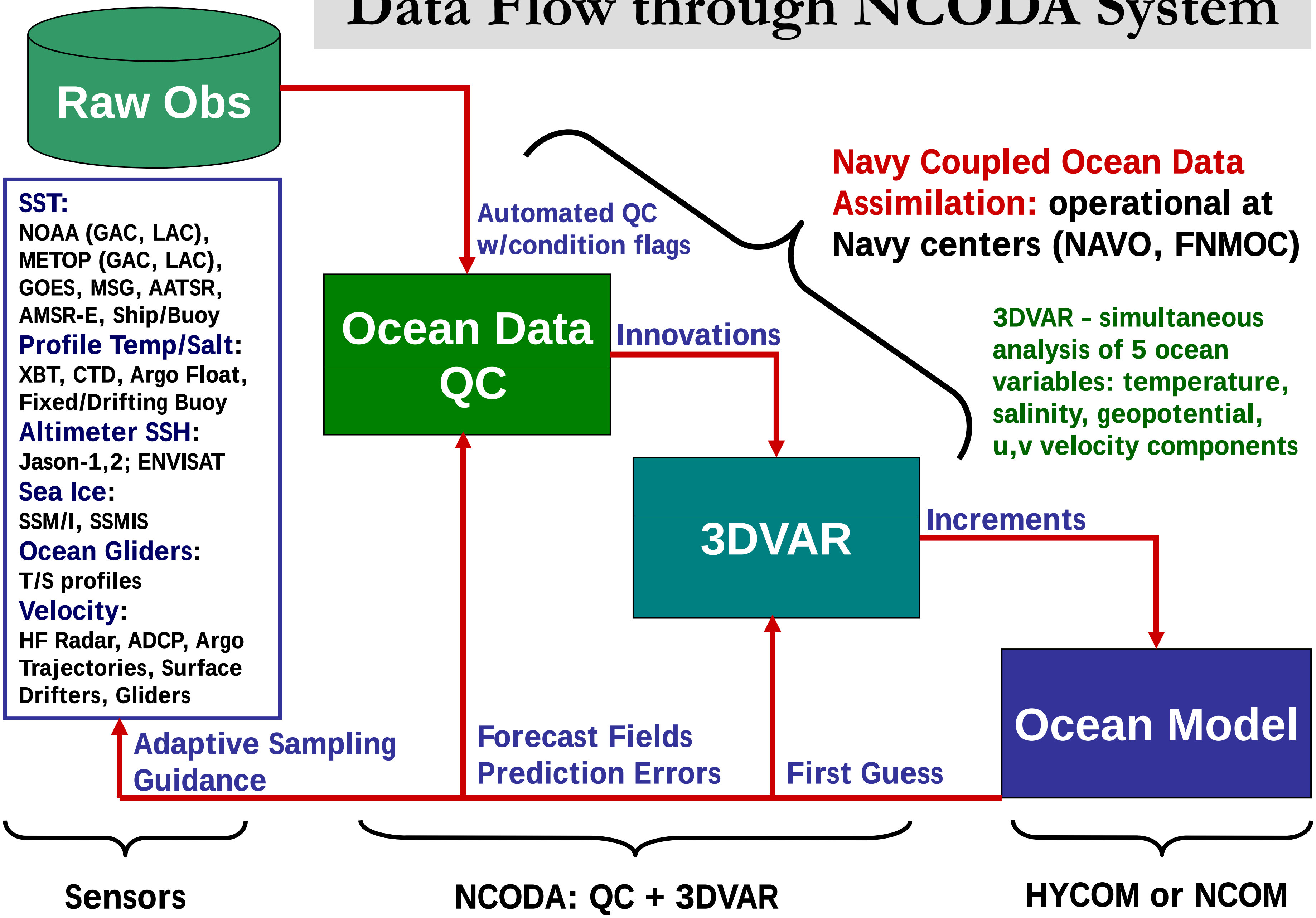
Coupling: The ocean and atmosphere are coupled in nature. The coupling constrains the range of possible states.

Ensembles: To take into account major sources of uncertainty in non-deterministic dynamics, system forcing, and initial state, in order to provide estimates of environment forecast uncertainty

System Components

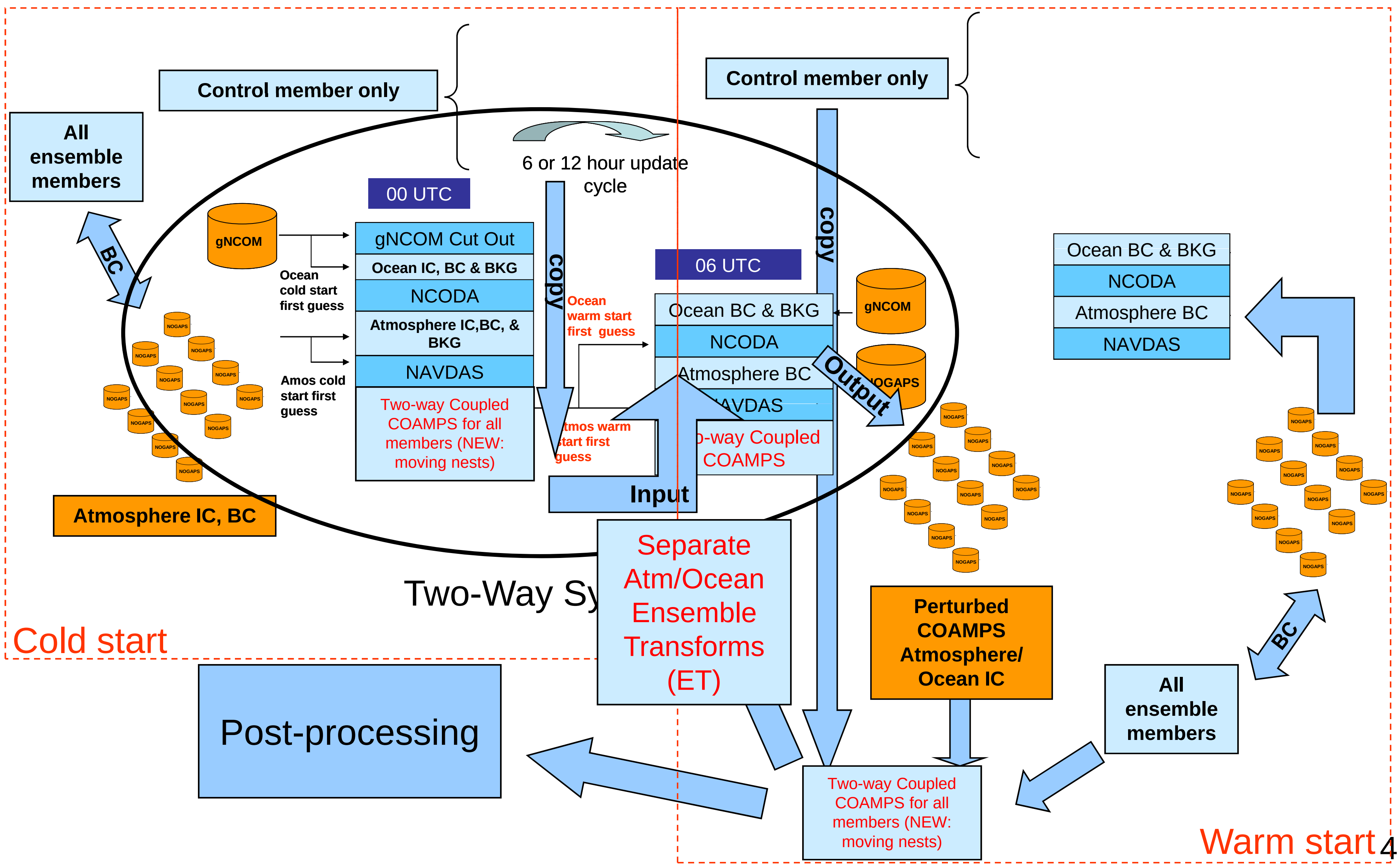
Atmospheric Model:	Coupled Ocean Atmosphere Mesoscale Prediction System **(COAMPS)**
Ocean Model:	Navy Coastal Ocean Model **(NCOM)**
Atm Data Assimilation:	Navy Atmospheric Variational Data Assimilation System **(NAVDAS-3DVAR)**
Ocn Data Assimilation:	Navy Coupled Ocean Data Assimilation **(NCODA-3DVAR)**
Coupling:	Earth System Modeling Framework **(ESMF)**

Data Flow through NCODA System



Coupled Ensemble Prediction

Development of the Two-Way Coupled Ensemble System



Coupled Ensemble Prediction

The Ensemble Transform (ET) Ensemble Generation

(Bishop and Toth 1999, Bishop et al., 2009)

analysis perturbations = forecast perturbations x transformation matrix constrained by analysis error variances (P_a)

$$X_a = X_f \, T \qquad X_a^T P_a^{-1} X_a = n\,I$$

$$X_a = \begin{pmatrix} a_1(1) & a_2(1) & \dots & a_m(1) \\ a_1(2) & a_2(2) & \dots & a_m(2) \\ a_1(3) & a_2(3) & \dots & a_m(3) \\ \vdots & \vdots & \dots & \vdots \\ a_1(n) & a_2(n) & \dots & a_m(n) \end{pmatrix} \quad X_f = \begin{pmatrix} f_1(1) & f_2(1) & \dots & f_m(1) \\ f_1(2) & f_2(2) & \dots & f_m(2) \\ f_1(3) & f_2(3) & \dots & f_m(3) \\ \vdots & \vdots & \dots & \vdots \\ f_1(n) & f_2(n) & \dots & f_m(n) \end{pmatrix} \quad P_a = \begin{pmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & \sigma_n^2 \end{pmatrix}$$

n= number of parameters m=number of ensemble members

Atmosphere variables are *u, v, T, q* and ocean variables are *u, v, T, S*

- With a large ensemble, only one Transformation matrix (T) that includes both atmospheric and oceanic variables could be used.
- With a smaller ensemble (<100), two distinct T's that include all state variables (one for atmosphere and one for ocean) is used.

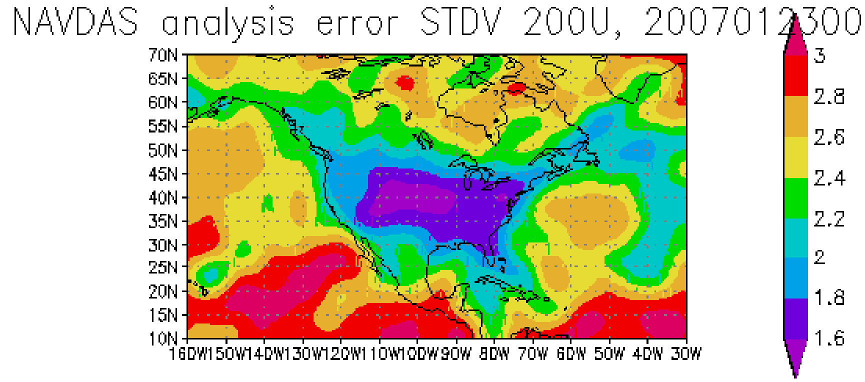
- Accurate knowledge of analysis error variances (P_a) in both fluids is critical.
- *T* derived from the atmospheric estimate of P_a is incapable of directly controlling the magnitude of oceanic perturbations (and vice versa).

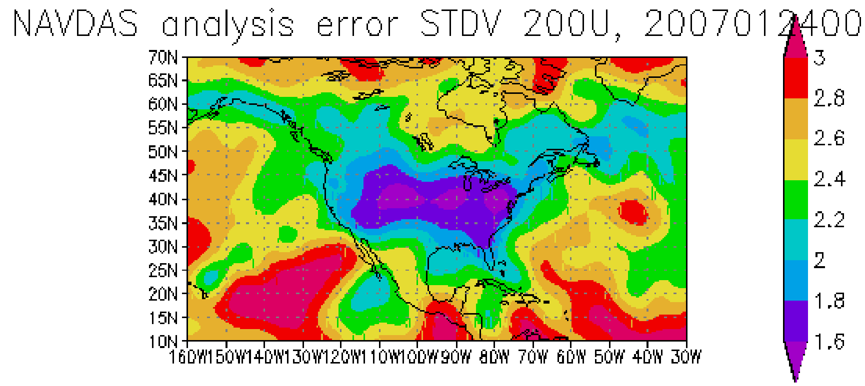
NAVDAS Analysis Error

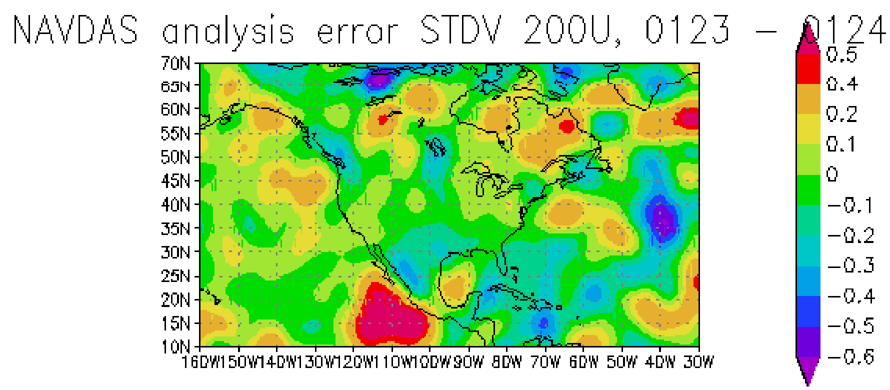
NAVDAS analysis error variance estimates of temperature for different update cycles

Estimates show considerable spatial variability.

Estimates show temporal variability owing to cycle-to-cycle changes in the observing systems.

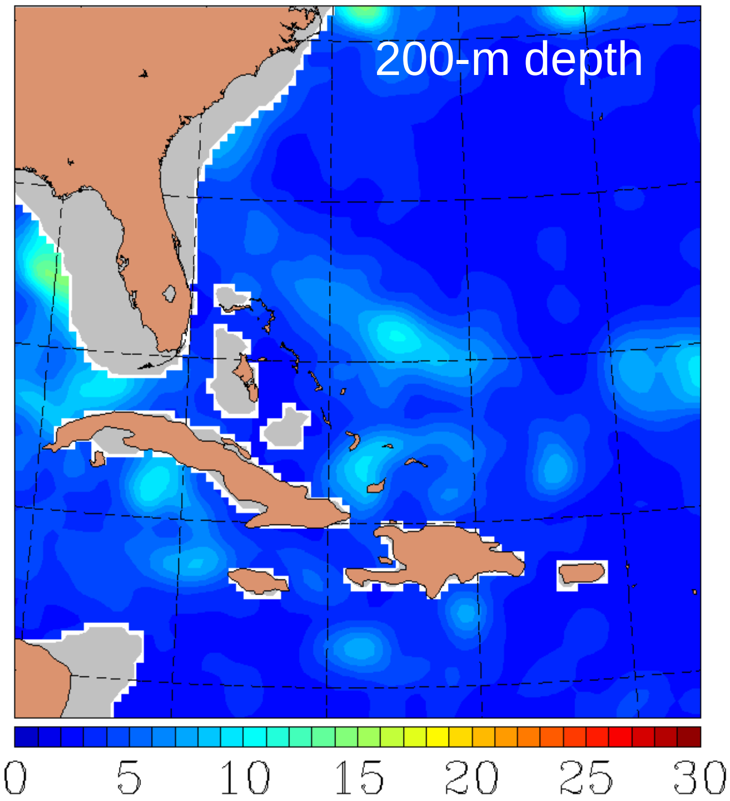






NCODA Background Error Variances (P_f)

Hanna: 2008090112-2008090700



Velocity Errors (cm/s)

Adaptive, evolve with time
Two Components:

1. Model variability – time history of forecast differences at update cycle interval.
2. Model data errors – time history of analyzed increment fields.

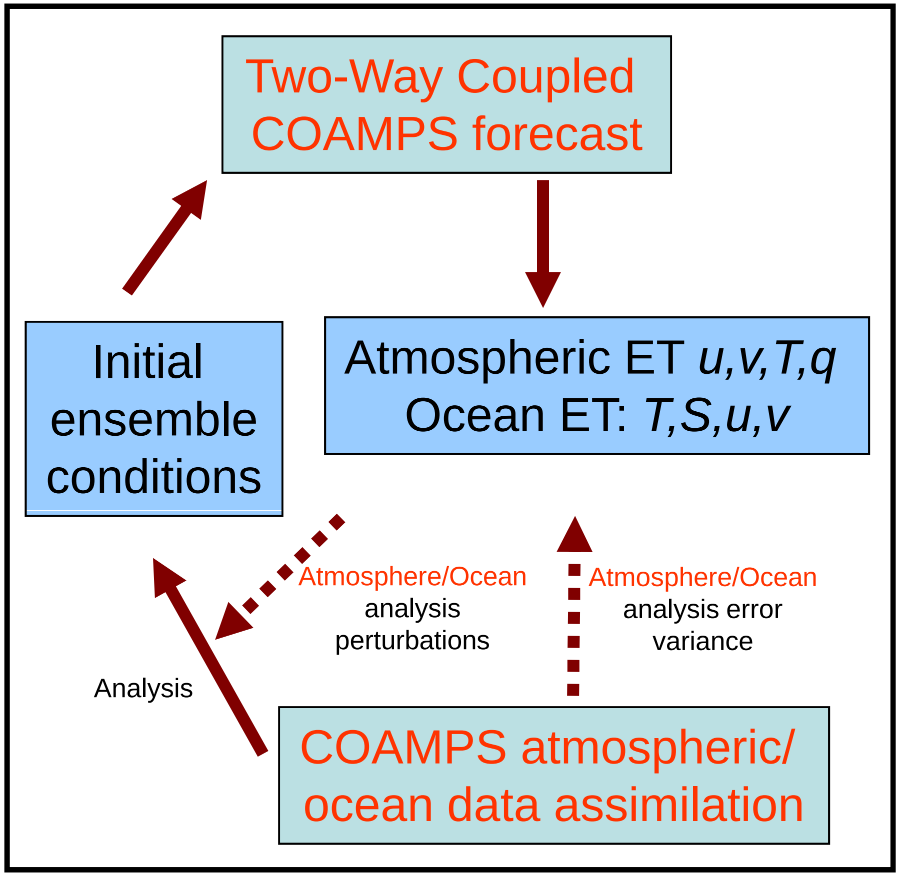
Time scales used to form these 10-day time-mean estimates computed from ratio of spatially varying correlation length scales and velocity fields

- model variability dominates error variances in high-flow regimes
- model data error dominates error variances in low-flow regimes

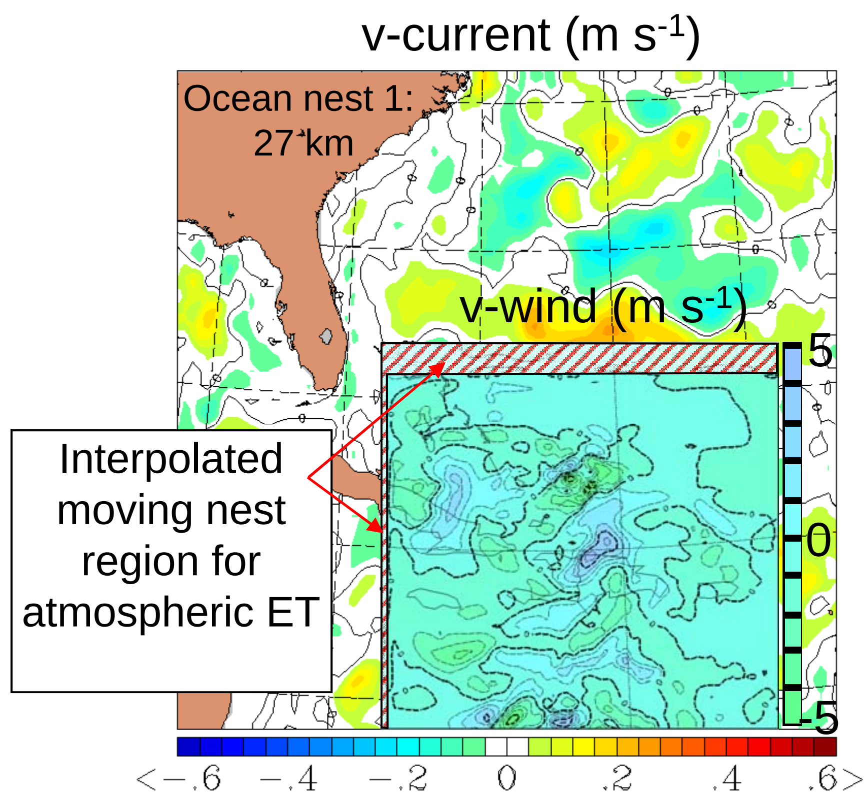
$$P_a = P_f - P_f H^T [H P_f H^T + R]^{-1} H P_f$$

Coupled Ensemble Prediction

Atmosphere/Ocean ET



Example of analysis perturbations:

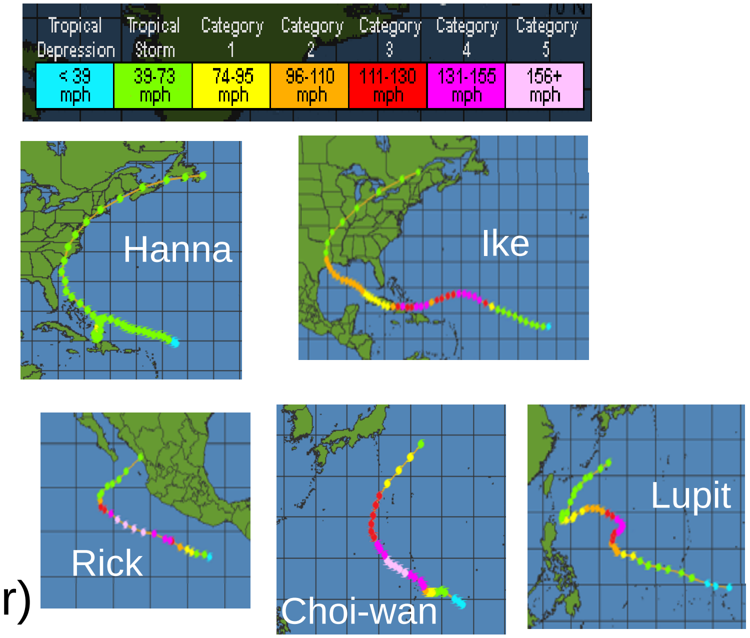


Hanna (2008090112-2008090700)

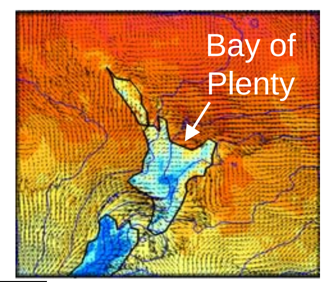
Coupled Ensemble system features: separate atmospheric and oceanic ETs; atmospheric moving nest ET capability

Coupled Ensemble Prediction: Coupled Experiments

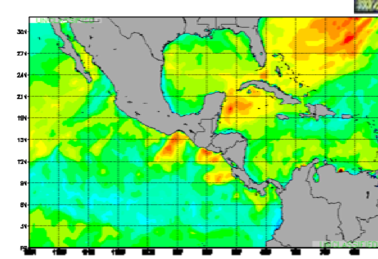
- Moving nest tropical cyclone cases
  - Using NOGAPS T119 banded ET as cold start and lateral boundary conditions
    - September 2008
      - Hanna (08L: 1-7 September)
      - Ike (09L: 5-12 September)
    - September-October 2009
      - Rick (20E: 15-21 October)
      - Choi-wan (15W: 12-20 September)
      - Lupit (22W: 14-25 October)



- ABCANZ case study
  - America, Britain, Canada, Australia, New Zealand experiment
  - 23 Feb – 5 Mar 2009 field program at Bay of Plenty, NZ
  - Focus on EM/radar propagation



- Piracy case study
  - Central America
  - Focus on Risk Management tools/applications



COAMPS 27-km operational Cent-Am

Coupled Ensemble Prediction

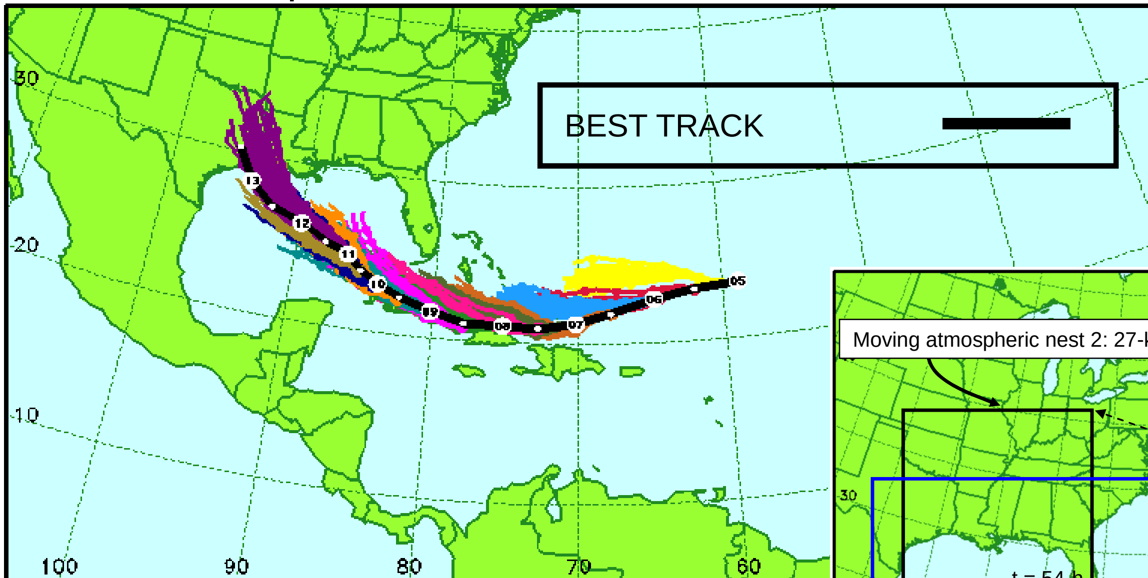
IKE: Cold Start at 2008090500; 29 members

Atmosphere: 81-, 27-km Ocean: 27-km

TC tracks

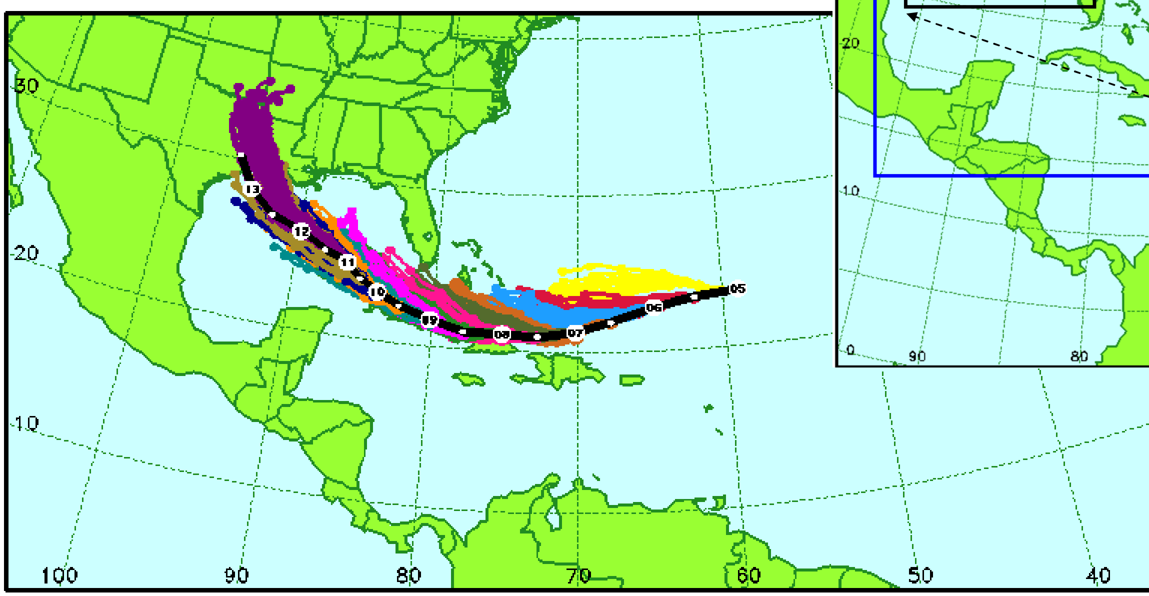
Coupled

(56-h fcsts)



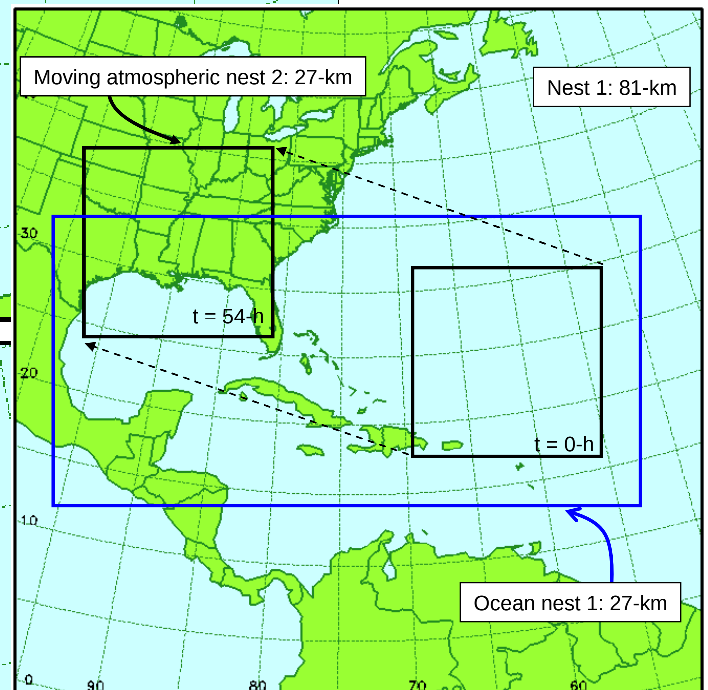
Uncoupled

(60-h fcsts)



• 27-km moving nest 2

• 12-h data assimilation cycle



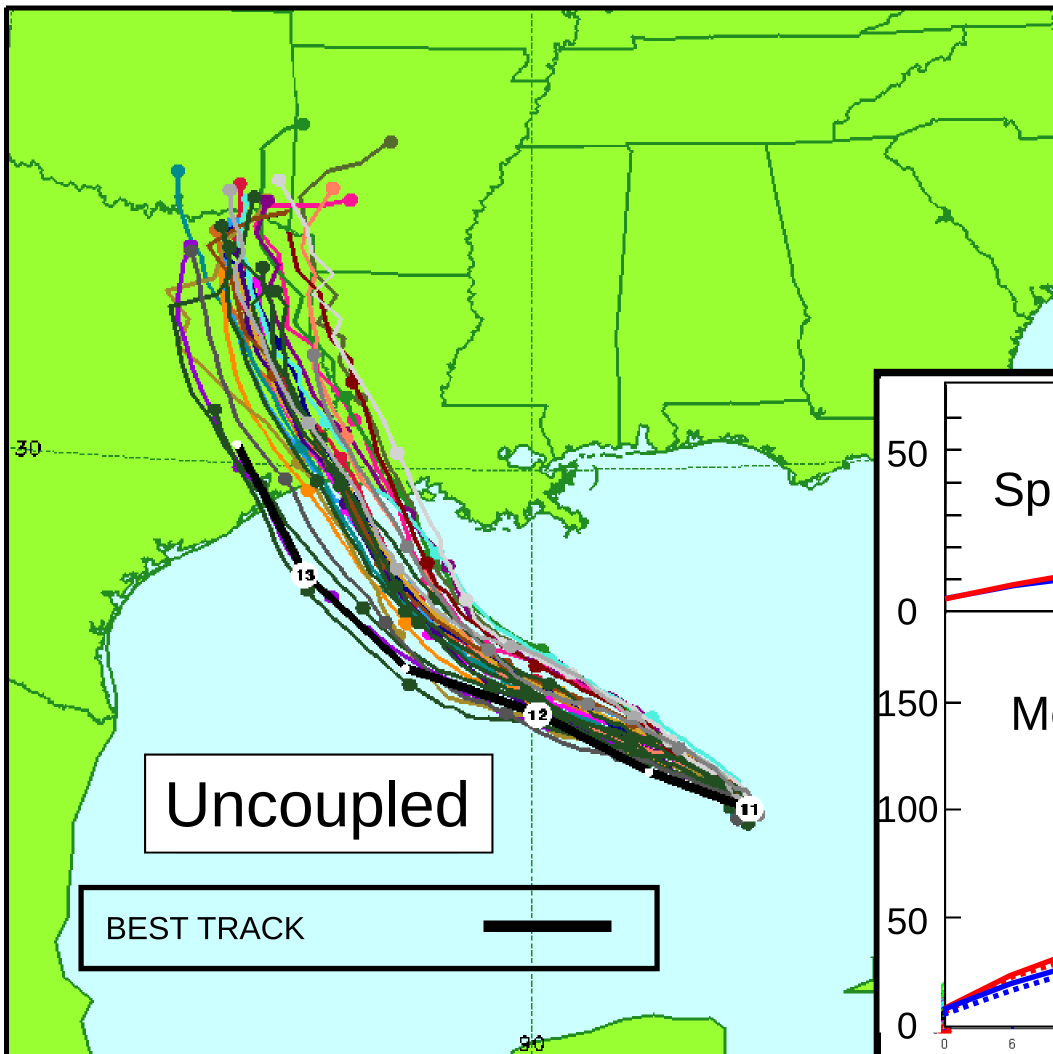
• Lateral BC: NOGAPS T119 ensemble

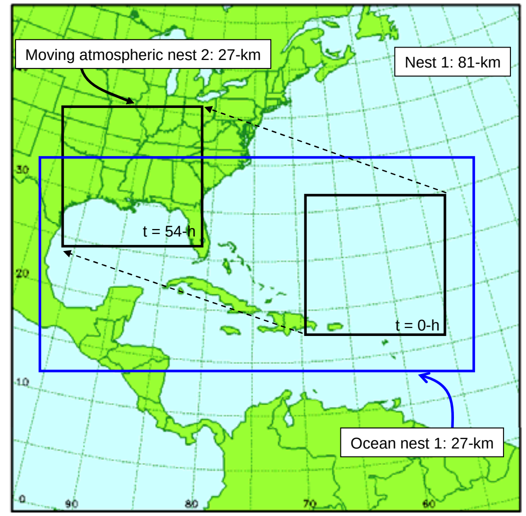
Coupled Ensemble Prediction

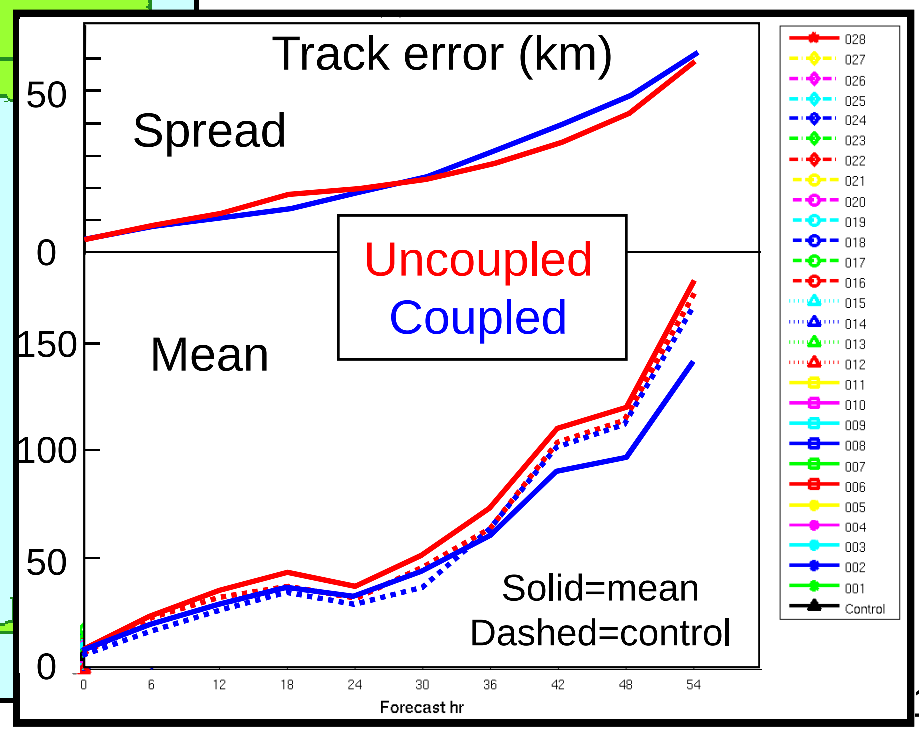
IKE: Cold Start at 2008090500; 29 members

Atmosphere: 81-, 27-km Ocean: 27-km

Nest 2: TC forecast track from 2008091100



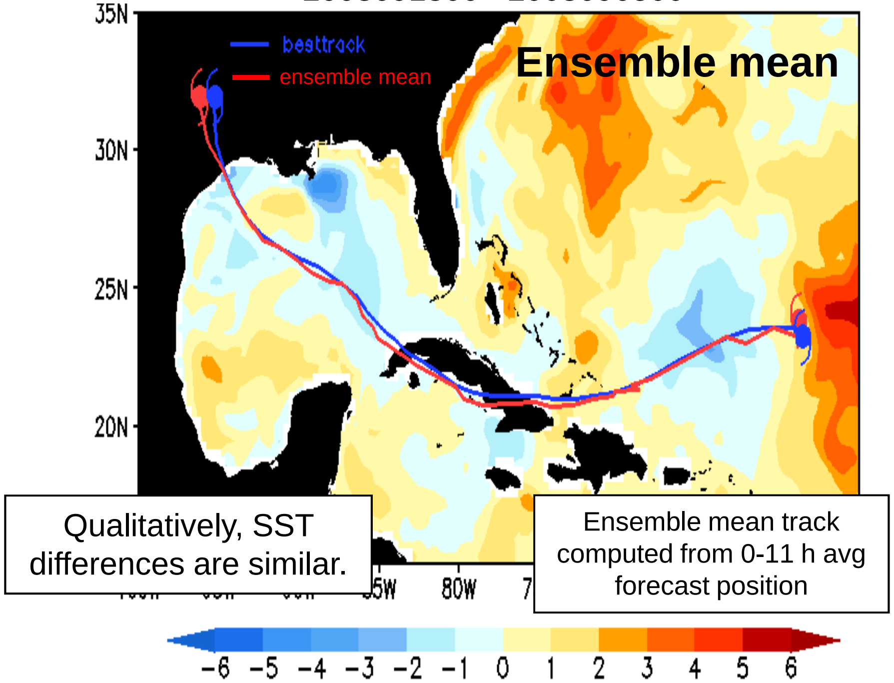




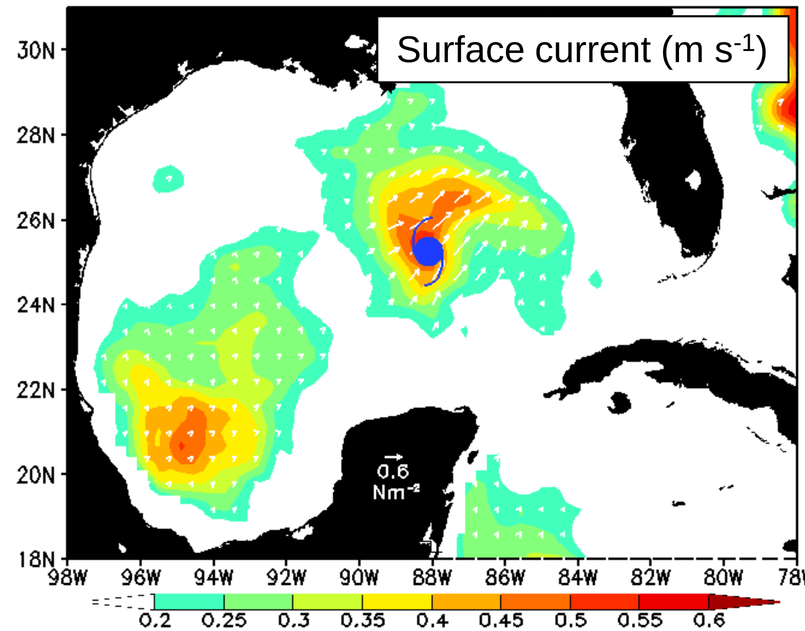
Coupled Ensemble Prediction

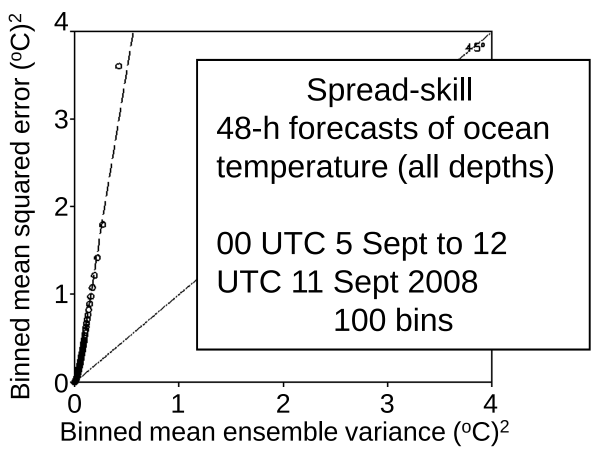
Air-Ocean Variability (Ike: 2008090500-2008091300)

Sea Surface Temperature Difference (°C)
2008091300 - 2008090500



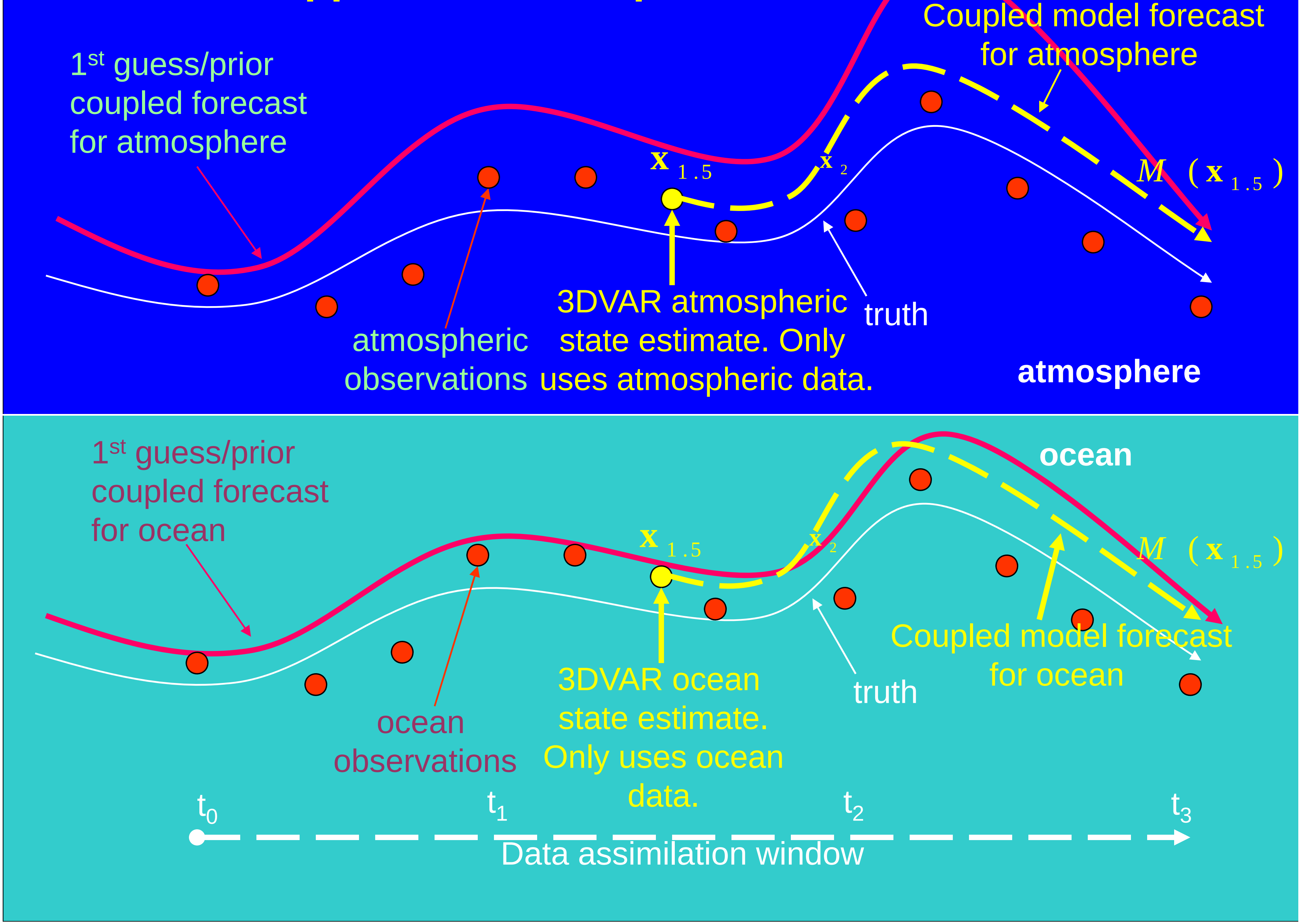
Ensemble spread
24-h forecast valid 2008091112



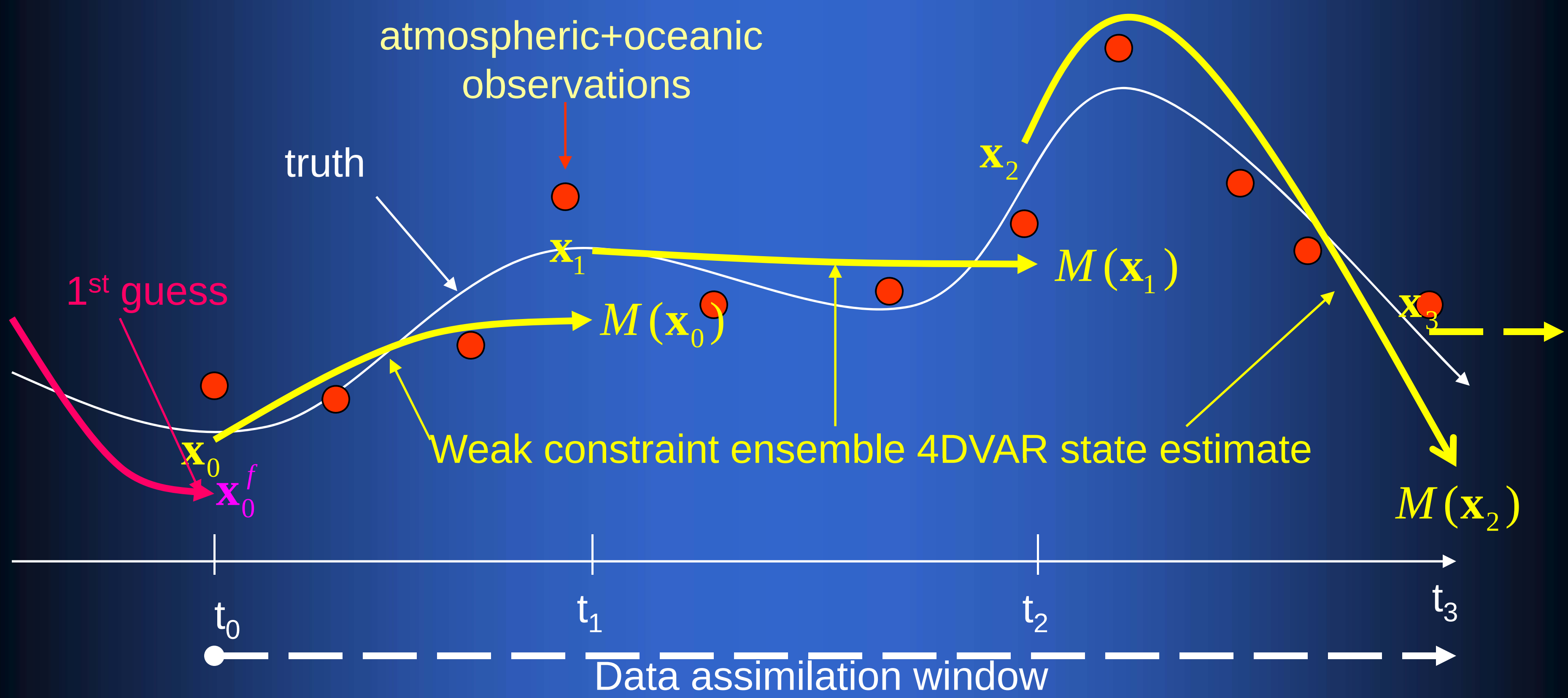


- The coupled system allows for investigation of **coupled** air-sea interaction processes.
- The coupled system for coarse resolution ocean (27-km) test cases of Hanna and Ike is very under-dispersive.
- Moving to higher resolution model grids.

Current DA approach for coupled model



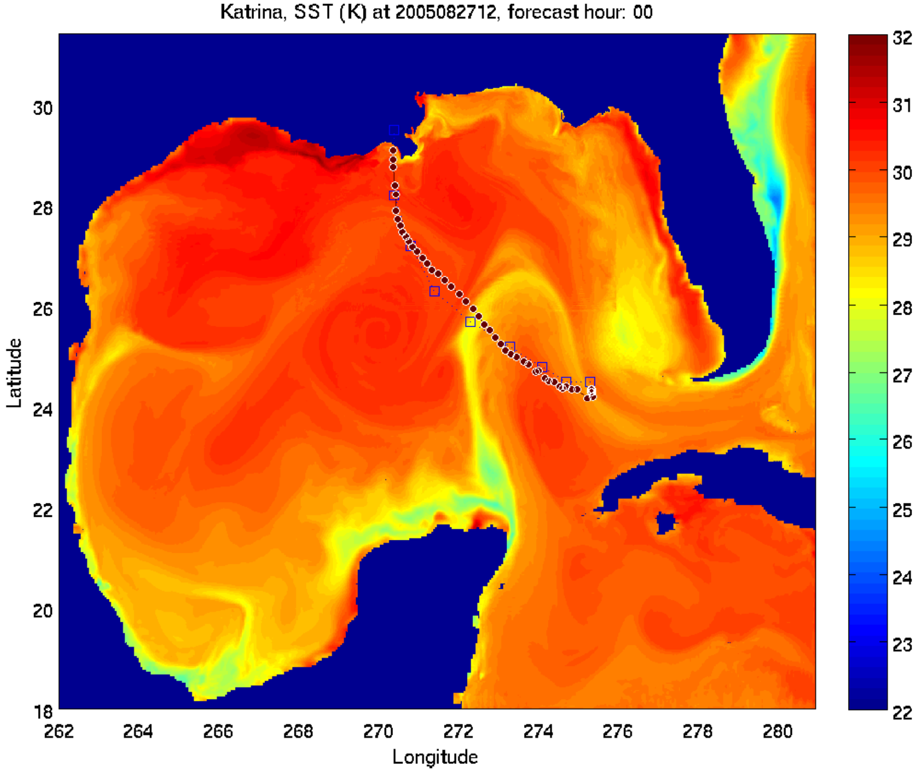
Coupled DA approach, atmosphere and ocean are treated as a single coherent system

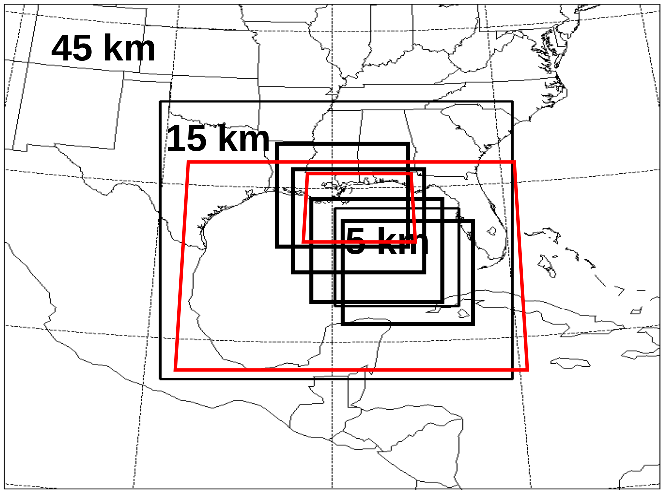


Ocean observations correct atmospheric states and atmospheric observations correct ocean states.

Coupled DA Application: Tropical Cyclone

Definition Coupled DA:
- observation in one fluid creates an innovation in the other fluid





- COAMPS (45, 15, 5 km moving)
- NCOM (5, 1.67 km)
- Initialized 12Z Aug. 27, 2005
- 48 h Forecast

TC wind stress causes upwelling, upwelling cools ocean surface, cool ocean surface moderates TC intensity.

Coupled DA Challenges

Coupled model ensemble provides plausible forecast states constrained by coupled dynamics

Coupled DA via classical adjoint/TLM approach costly to develop and maintain

Ensemble covariances from coupled model ensemble enable coupled DA

- issue of spurious sample covariances associated with small ensemble size

Challenges:

- find the most effective method of attenuating spurious correlations
- implement adaptive covariance localization functions to enable 4D ensemble based DA

Decoupled DA versus Coupled DA

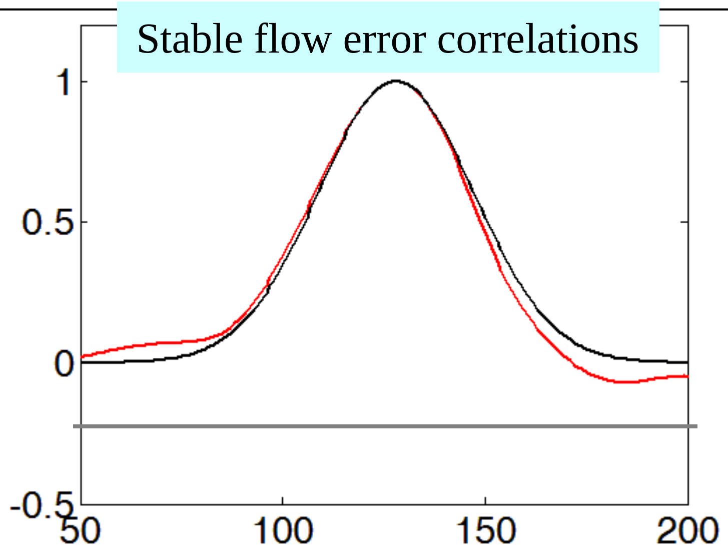
Decoupled 3DVAR Systems

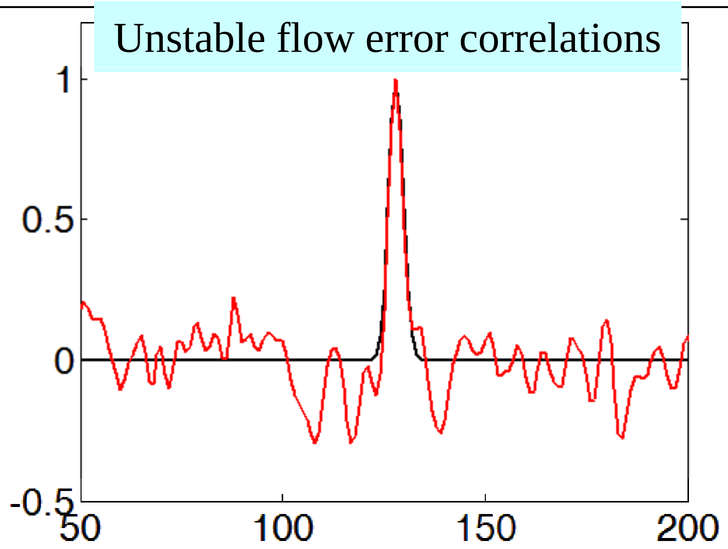
1. Separate analyses for ocean and atmosphere
2. Atmospheric data do not improve ocean. Ocean data do not improve atmosphere.
3. Difficult to produce balanced coupled model initial states.
4. Does not use ensemble covariances in either fluid.
5. No 4D covariance so use of data separated in time fundamentally incorrect.

Coupled 4D System

1. Single analysis: bottom of the ocean to top of the atmosphere
2. Atmospheric data improve ocean - ocean data improve atmosphere.
3. Enables the production of highly balanced coupled initial states.
4. Uses ensemble covariances in and between fluids.
5. Flow adaptive ensemble localization gives 4D covariances. Handles data correctly across assimilation time window.

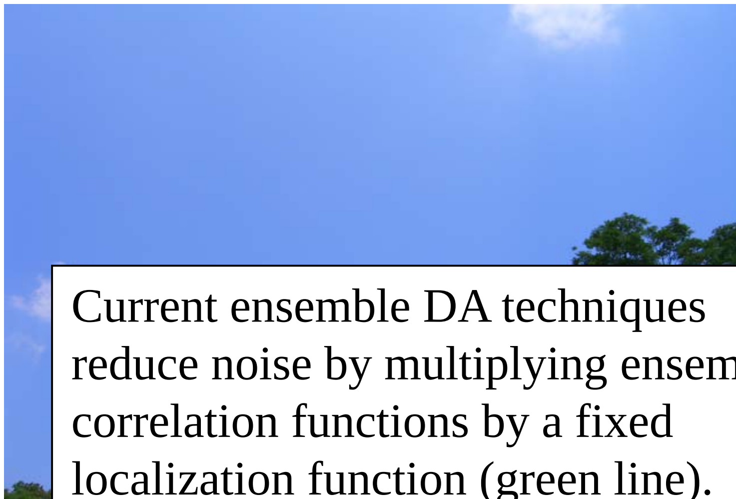
Adaptive Ensemble Covariance Localization

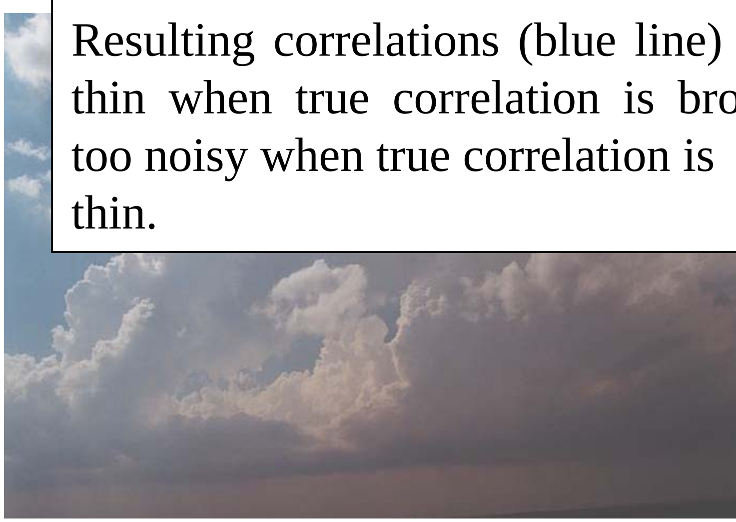




Ensembles give flow dependent, but ***noisy*** correlations

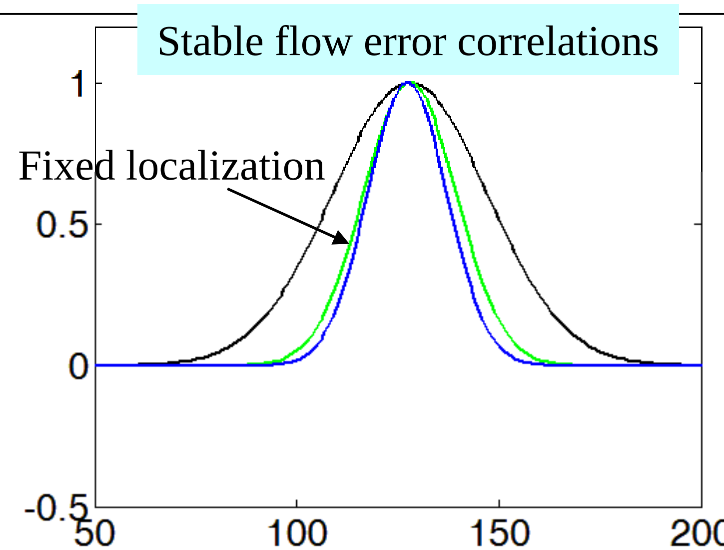
Adaptive Ensemble Covariance Localization

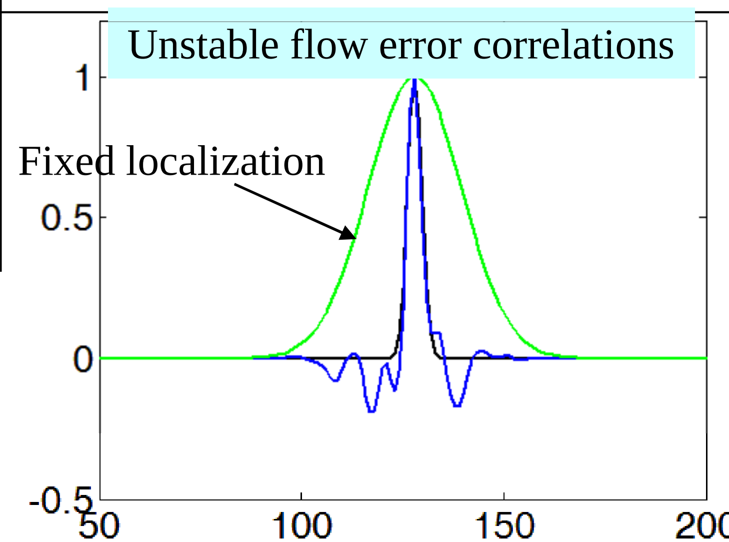




Current ensemble DA techniques reduce noise by multiplying ensemble correlation functions by a fixed localization function (green line).

Resulting correlations (blue line) are too thin when true correlation is broad and too noisy when true correlation is thin.

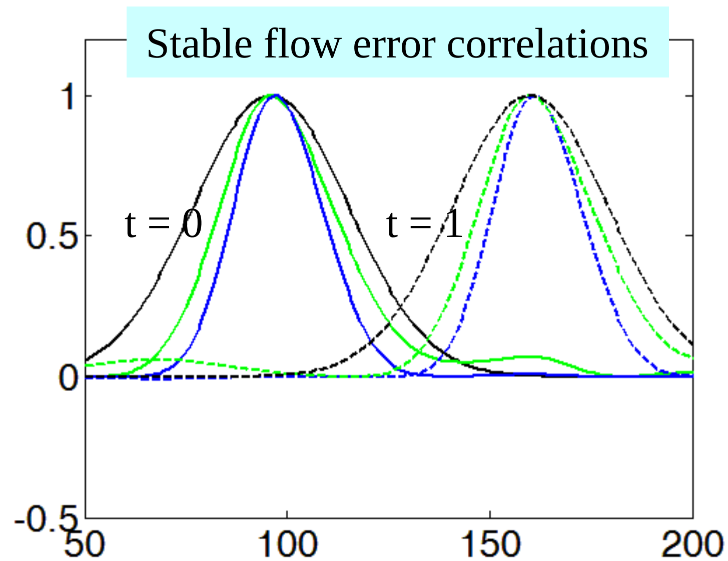


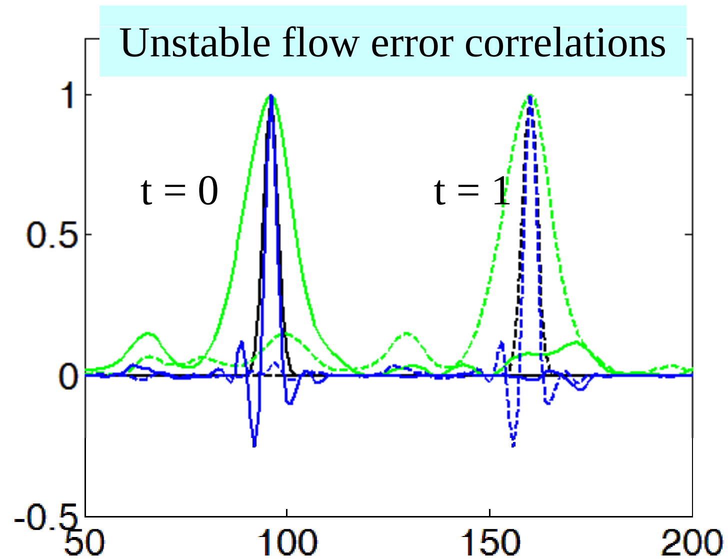


Adaptive Ensemble Covariance Localization

Modulation functions based on smoothed ensemble correlations provide scale adaptive and propagating localization functions.

These moving localization functions enable ensemble based 4D DA.





Localization adapts to width and propagation of true error correlations

Bishop and Hodyss (2007)

Modulated Ensembles and Localization

Bishop and Hodyss (2009a, 2009b) Tellus

Consider covariance of mth and nth elements of $\left(\underline{\mathbf{z}}_k \odot \underline{\mathbf{z}}_j^s \odot \underline{\mathbf{z}}_i^s\right)$ given by

$$\sum_{k=1}^{K}\sum_{j=1}^{K}\sum_{i=1}^{K}\left(z_{mk}z_{mj}^{s}z_{mi}^{s}\right)\left(z_{nk}z_{nj}^{s}z_{ni}^{s}\right)=\left(\sum_{k=1}^{K}z_{mk}z_{nk}\right)\left(\sum_{j=1}^{K}z_{mj}^{s}z_{nj}^{s}\right)\left(\sum_{i=1}^{K}z_{mi}^{s}z_{ni}^{s}\right)=\left(\underline{\mathbf{P}}_K^f \odot \underline{\mathbf{C}}^s \odot \underline{\mathbf{C}}^s\right)_{mn}$$

where $\underline{\mathbf{P}}_K^f = \sum_{k=1}^{K} \underline{\mathbf{z}}_k \underline{\mathbf{z}}_k^T$ and $\underline{\mathbf{C}}^s = \sum_{j=1}^{K} \underline{\mathbf{z}}_j^s \underline{\mathbf{z}}_j^{sT}$. Hence,

$$\sum_{k=1}^{K}\sum_{j=1}^{K}\sum_{i=1}^{K}\underbrace{\left(\underline{\mathbf{z}}_k \odot \underline{\mathbf{z}}_j^s \odot \underline{\mathbf{z}}_i^s\right)}_{\text{Modulated ensemble member}}\left(\underline{\mathbf{z}}_k \odot \underline{\mathbf{z}}_j^s \odot \underline{\mathbf{z}}_i^s\right)^T = \underline{\mathbf{Z}}_D \underline{\mathbf{Z}}_D^T = \underline{\mathbf{P}}_K^f \odot \underline{\mathbf{C}}^s \odot \underline{\mathbf{C}}^s$$

Thus, the covariance of the modulated ensemble is the localized ensemble covariance.

For $K = 128$, the modulated ensemble contains over 2 million members. Up to $K^2\left(K+1\right)/2 = 1{,}056{,}768$ of these are likely to be linearly independent.

Modulated ensembles enable global 4DVAR

Given : $P_f = Z_D Z_D^T$ where Z_D is the large, modulated ensemble

Step 1 is to solve for v:

$$\{[R^{-1/2} H Z_D][R^{-1/2} H Z_D]^T + I\}v = R^{-1/2}[y - H(x_f)]$$

Step 2 is the post-multiply :

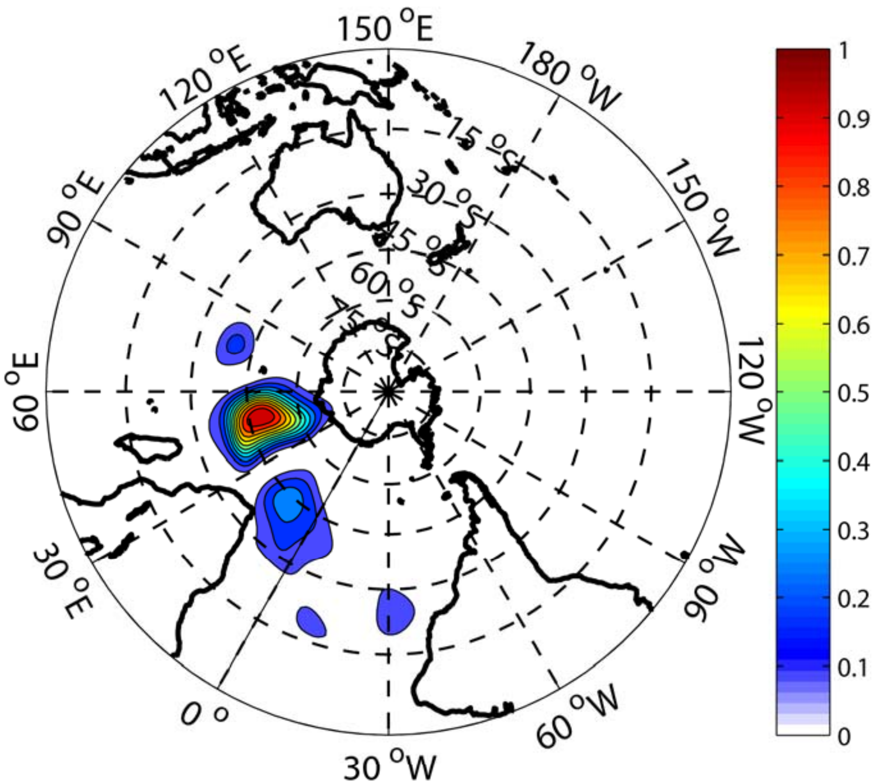
$$x_a - x_f = Z_D [R^{-1/2} H Z_D]^T v$$

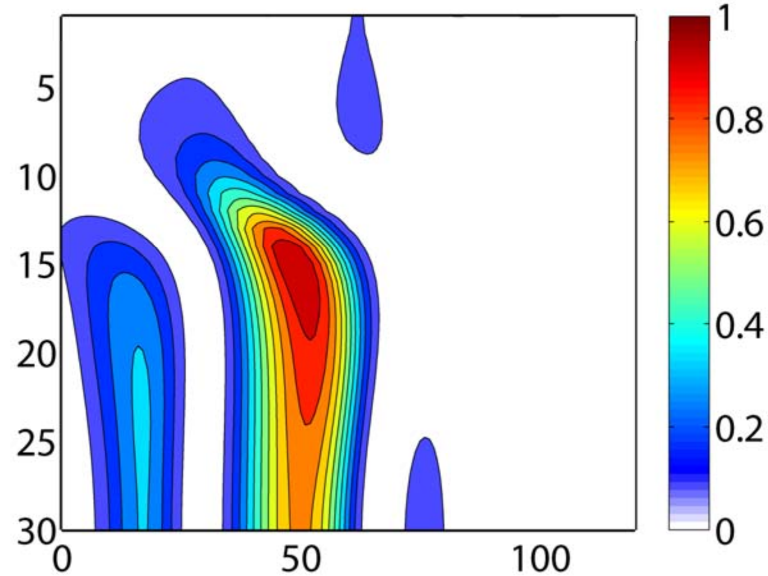
- Incremental and non-incremental 4DVAR are possible
- Hybrid mixes of ensemble-based TLMs and static covariances are possible

Application to global NWP model

Example of a column of the localization $\underline{\mathbf{C}}_s \odot \underline{\mathbf{C}}_s$ with $K = 128$

06Z

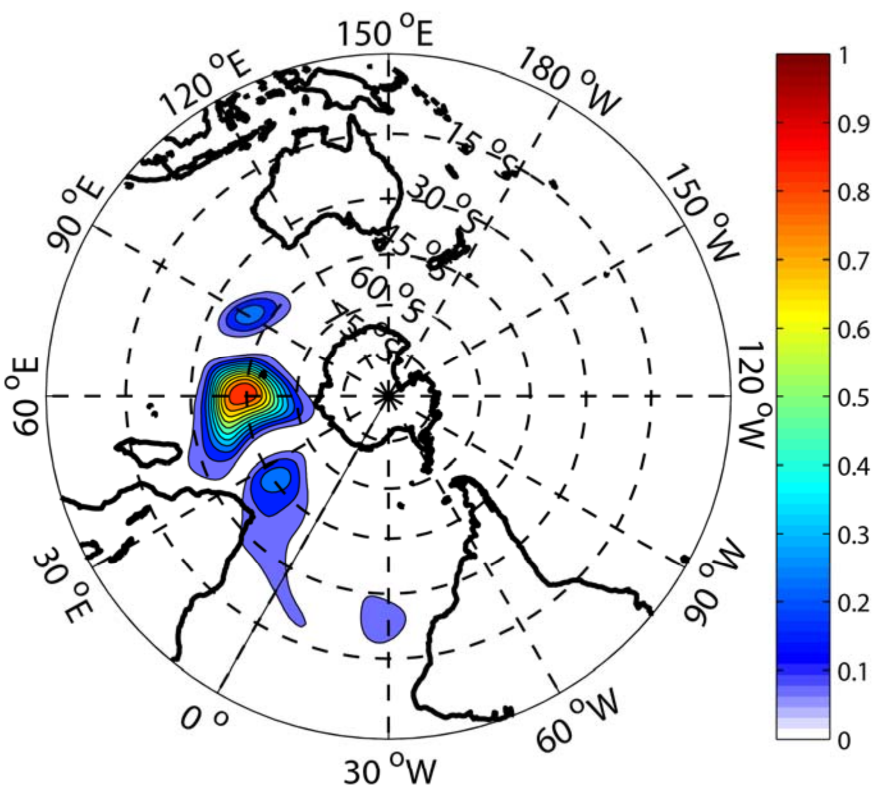


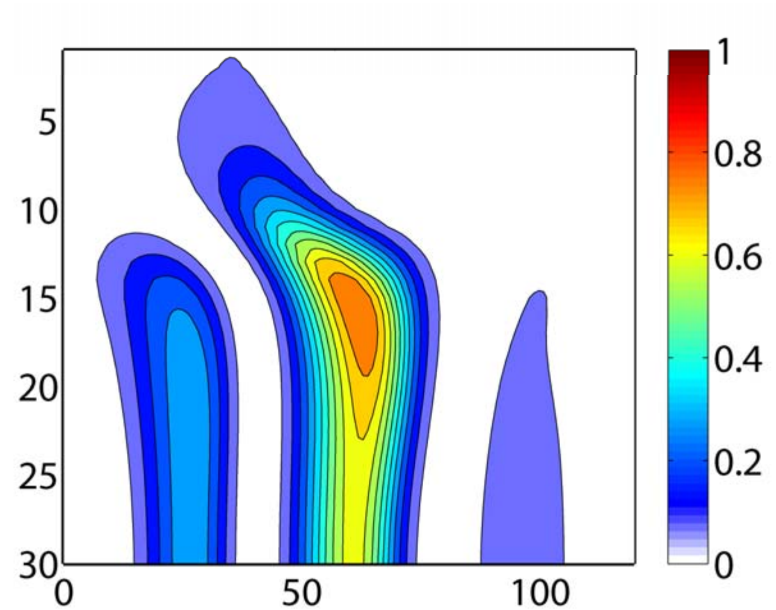


Application to global NWP model

Example of a column of the localization $\underline{\mathbf{C}}_s \odot \underline{\mathbf{C}}_s$ with $K = 128$

18Z



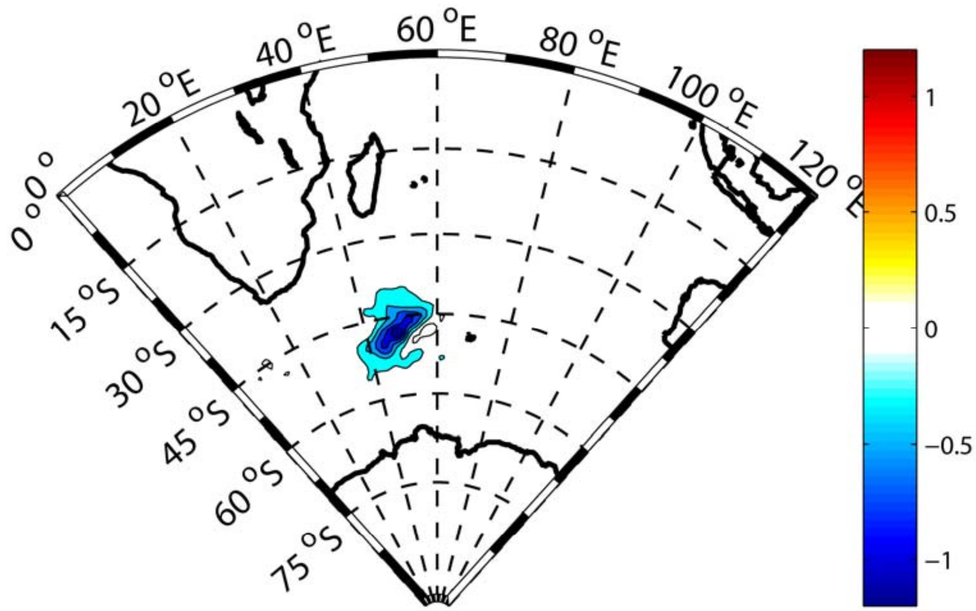


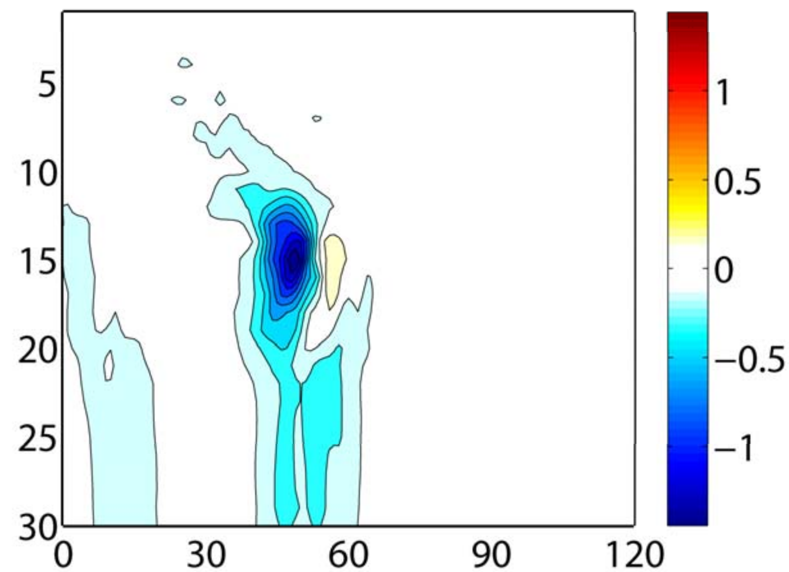
Ensemble based localization moves ~500 km in 6 hrs

4D Localized Ensemble Covariance

Example of a column of $\underline{\mathbf{P}}_K^f \odot \underline{\mathbf{C}}_s \odot \underline{\mathbf{C}}_s$ with $K = 128$

<*vv*> Increment 06Z

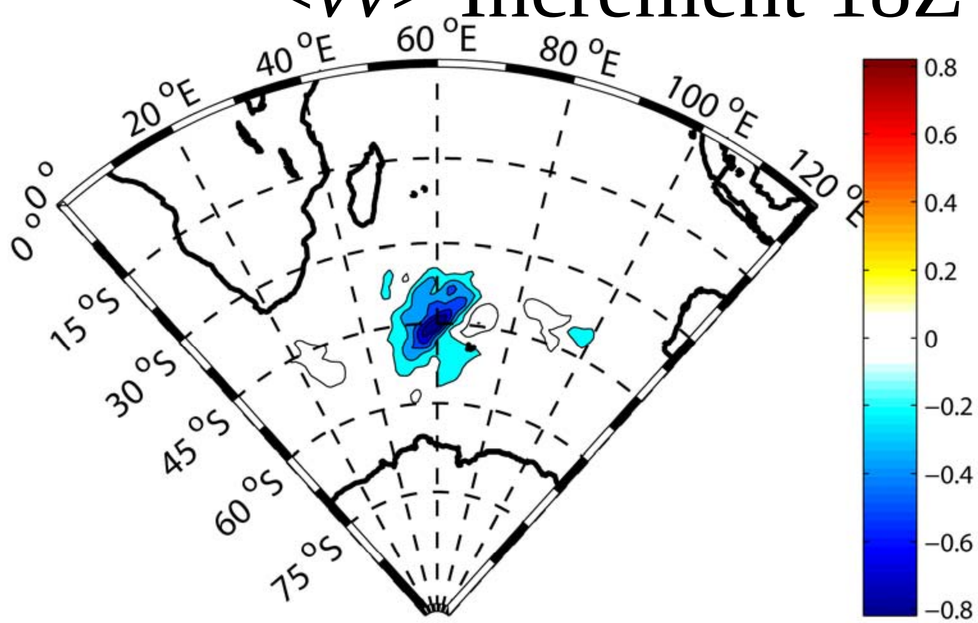


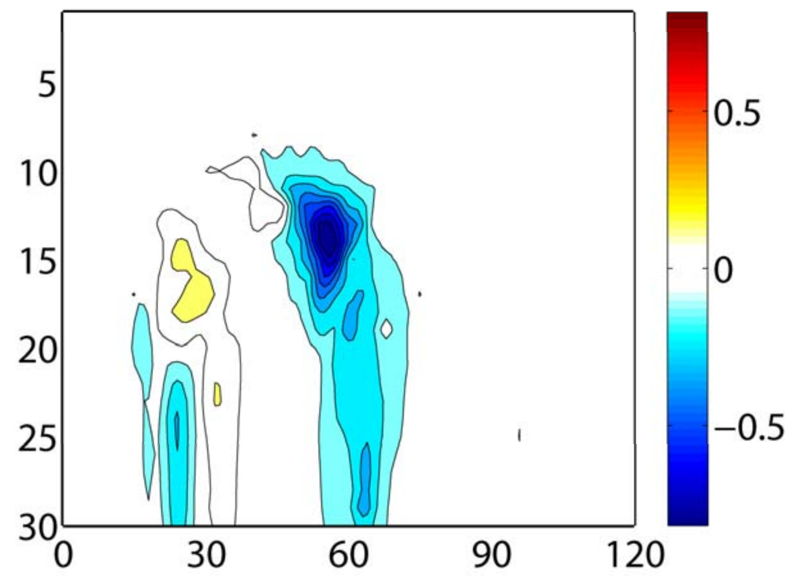


4D Localized Ensemble Covariance

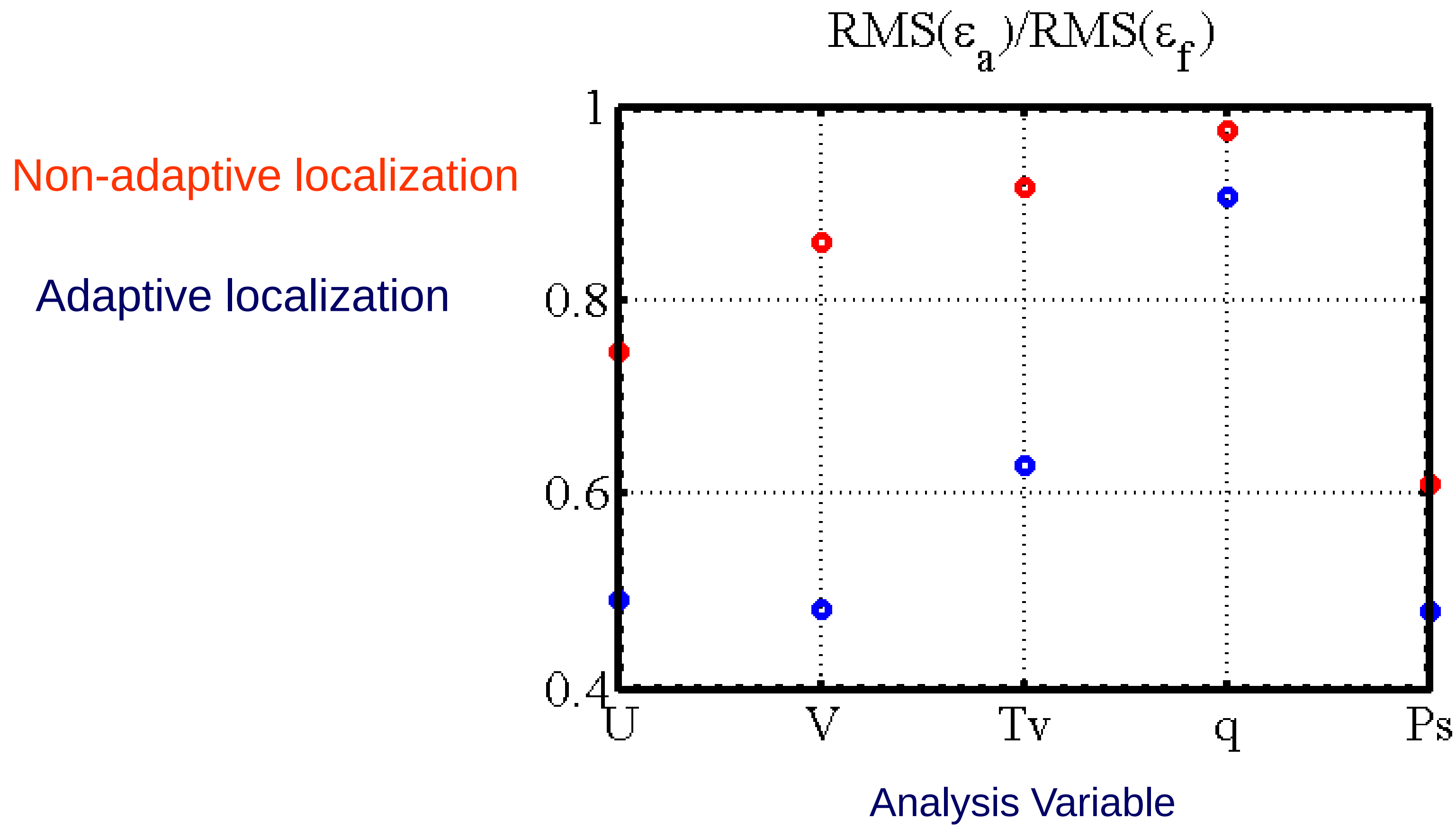
Example of a column of $\underline{\mathbf{P}}_K^f \odot \underline{\mathbf{C}}_s \odot \underline{\mathbf{C}}_s$ with $K = 128$

<*vv*> Increment 18Z





Adaptive vs. Non-adaptive Localization: Twin Data Experiment



Normalized RMS analysis error as a function of analysis variable

~200,000 observations of U, V,T assimilated at 6, 12, and 18 Z

Coupled Ensemble Prediction: Conclusions

- Developed coupled ensemble prediction capability
  - within COAMPS framework allowing rapid relocation to new areas
- Coupled ensembles provide for probabilistic prediction
  - demonstrated with relatively coarse resolution tropical cyclone case
- Ensemble based DA system presented
  - adaptive localization of ensemble covariances account for propagation and scale variations of forecast error distributions
  - huge modulated ensembles enable 4D-VAR global solve using an ensemble based TLM
  - adaptively localized covariances beat operational covariances in NWP idealized twin-data experiments
  - straightforward to import coupled model ensembles into ensemble based DA system for truly coupled assimilation (work in progress)

References: Coupled Ensemble Model System Components

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