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Data assimilation for the coupled ocean-atmosphere

Eugenia Kalnay, Tamara Singleton, Steve Penny, Takemasa Miyoshi, Jim Carton

Thanks to the UMD Weather-Chaos Group, to Daryl Kleist and to the India Monsoon Mission

Outline

- Traditional approaches.
- Thesis of Tamara Singleton (DA with toy coupled model).
- The LETKF and Running in Place.
- Steve Penny: 7 years ocean reanalysis.
- Steve Penny: New EnKF-based hybrid.
- Shaoqing Zhang: GFDL coupled EnKF.
- Our planned approach to coupled LETKF (India Monsoon Mission)
- Questions:
  - Can we do a robust coupled SST analysis? SSH? Scatterometer winds?
  - Should we do LETKF-RIP? Short windows for the ocean and atm.?
  - Should we do Gaussian Transformation (Lien et al.)
  - Should we do Proactive QC with Ens. Fcst. Sens. to Obs. (EFSO)?
- Discussion

Traditional approaches

"In a typical coupling scheme for an ocean-atmosphere model, the ocean model passes SST to the atmosphere, while the atmosphere passes back heat flux components, freshwater flux, and horizontal momentum fluxes." (Neelin, Latif & Jin, 1994)

SST in the ocean model is frequently nudged from Reynolds SSTs, not assimilated from observations.

SSH may not be even be used.

The data assimilation <u>windows</u> are very different for the ocean and the atmosphere.

Tamara Singleton’s thesis

Data Assimilation Experiments with a Simple Coupled Ocean-Atmosphere Model

Questions she addressed:

-- Which is more accurate: 4D-Var or EnKF?

-- Is it better to do an ocean reanalysis separately, or as a single coupled system?

-- ECCO is a version of 4D-Var where both the initial state and the surface fluxes are control variables. This allows ECCO to have very long windows (decades) and estimate the surface fluxes that give the best analysis.

Is ECCO the best approach for ocean reanalysis?

Simple Coupled Ocean-Atmosphere System

3 coupled Lorenz models: A slow "ocean" component strongly coupled with a fast "tropical atmosphere component", in turn weakly coupled with a fast "extratropical atmosphere" (Peña and Kalnay, 2004).

Model Parameter Definitions

Variables	Description	Values
c, c_z, c_e	Coupling coefficient	$c, c_z = 1$ $c_e = 0.08$
τ	time scale	$\tau = 0.1$
σ, b, and r	Lorenz parameters	$\sigma=10$, $b=8/3$, and $r=28$
k_1, k_2	Uncentering parameters	$k_1=10$ $k_2 = -11$

Extratropical atmosphere

$$\dot{x}_e = \sigma(y_e - x_e) - c_e(x_t + k_1)$$
$$\dot{y}_e = rx_e - y_e - x_e z_e - c_e(y_t + k_1)$$
$$\dot{z}_e = x_e y_e - bz_e$$

Tropical atmosphere

$$\dot{x}_t = \sigma(y_t - x_t) - c(X + k_2) - c_e(x_e + k_1)$$
$$\dot{y}_t = rx_t - y_t - x_t z_t + c(Y + k_2) + c_e(y_e + k_1)$$
$$\dot{z}_t = x_t y_t - bz_e + c_z Z$$

Ocean

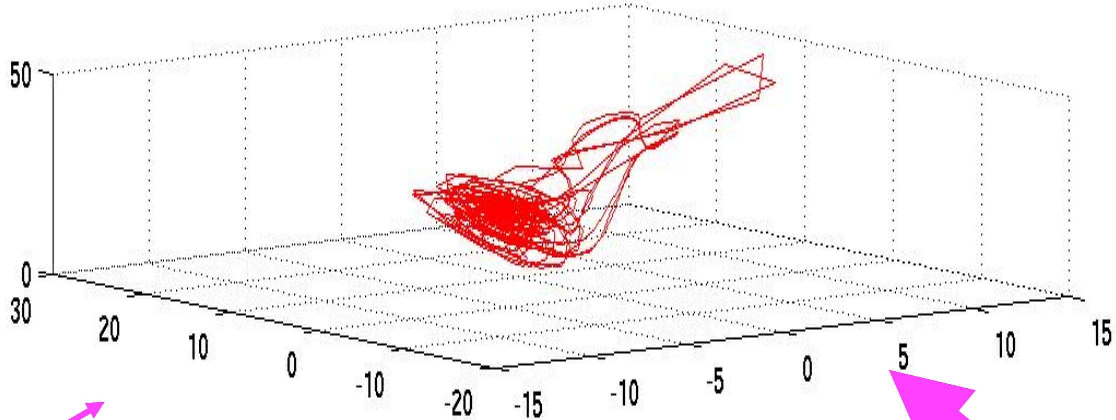
$$\dot{X} = \tau\sigma(Y - X) - c(x_t + k_2)$$
$$\dot{Y} = \tau rX - \tau Y - \tau XZ + c(y_t + k_2)$$
$$\dot{Z} = \tau XY - \tau bZ + c_z z_t$$

Model State: $[x_e, y_e, z_e, x_t, y_t, z_t, X, Y, Z]^T$

Simple Coupled Ocean-Atmosphere Model (Peña and Kalnay, 2004)

Tropical Atmosphere

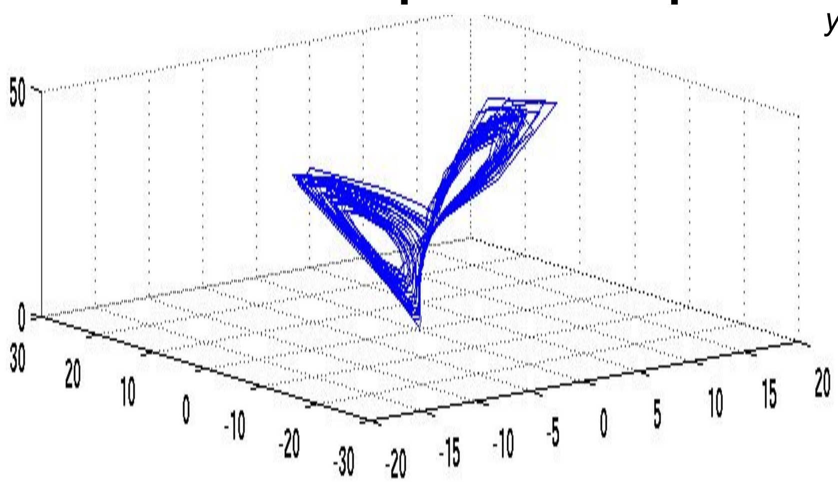
Coupling strength

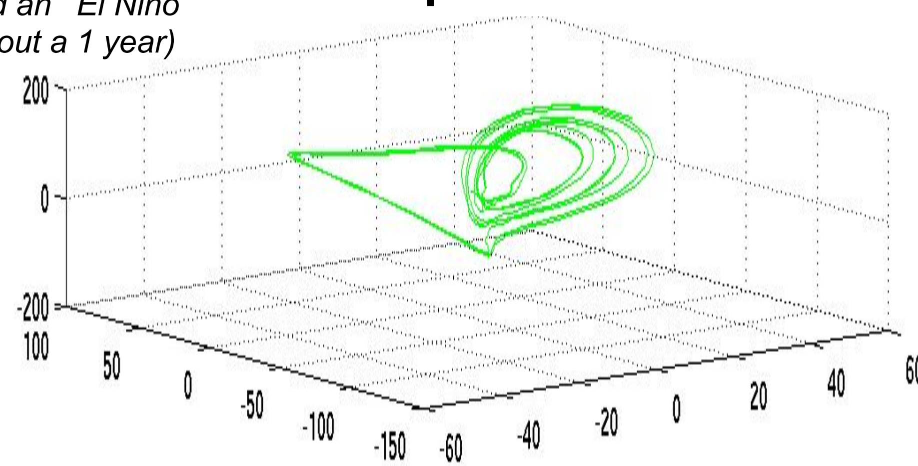


Extra-tropical Atmosphere

Ocean is vacillating between a "normal year" (lasts from ~3-8 years) and an "El Nino" (lasts about a 1 year)

Tropical Ocean

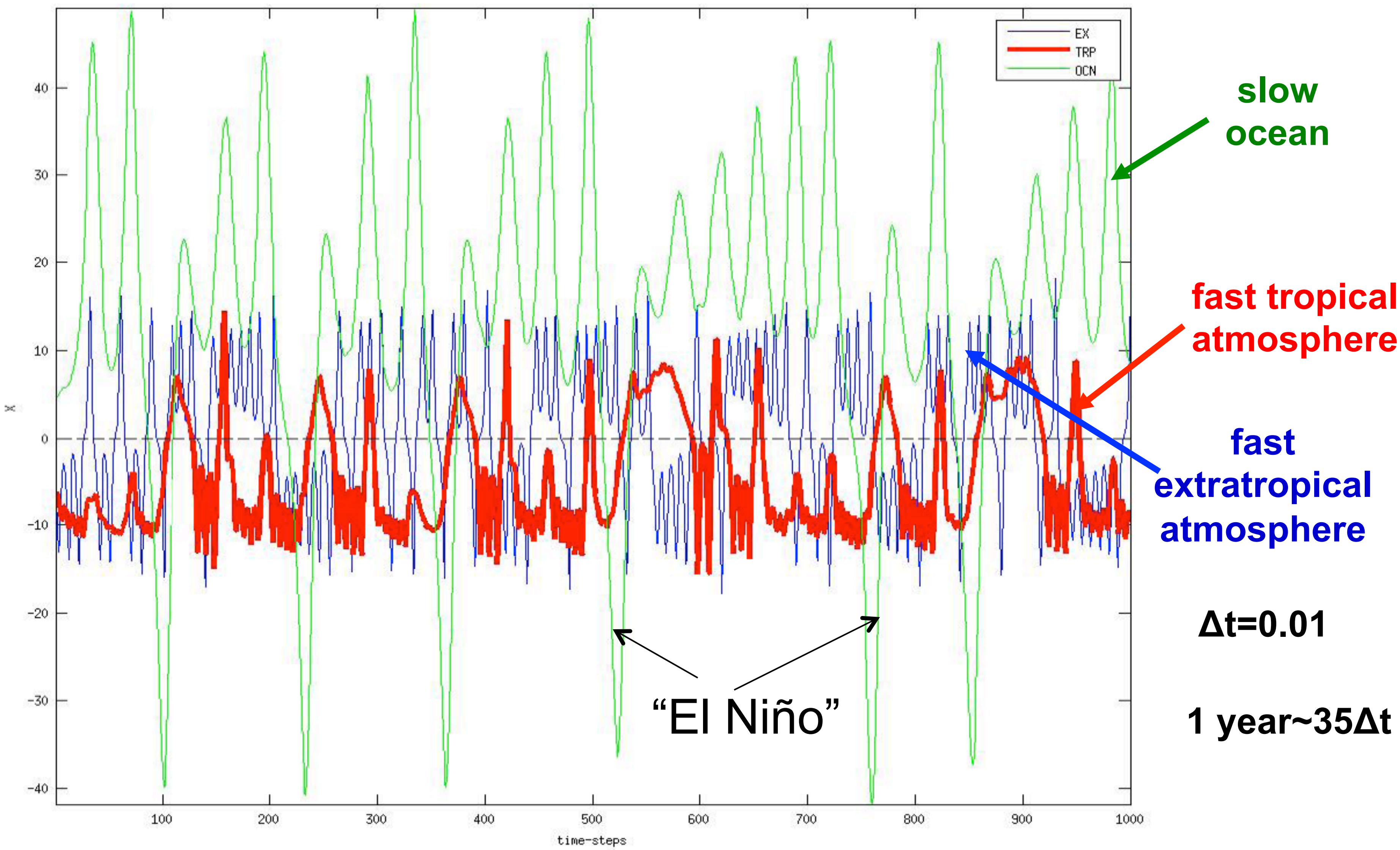




We do OSSEs with this simple coupled model

Simple Coupled Ocean-Atmosphere Model (Peña and Kalnay, 2004)

Time series of the x-component



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4D-Var/ETKF Data Assimilation Summary

- **We developed a 4D-Var data assimilation system for the simple coupled ocean-atmosphere model**
- We found that **lengthening the assimilation window** and **applying QVA improves the 4D-Var analysis**.
- **Tuning the amplitude of the background error covariance has an impact on the performance of the assimilation**.
- **EnKF-based methods (LETKF & ETKF-QOL) compete with 4D-Var analyses** for short and long assimilation windows.
- For much **longer assimilation windows, 4D-Var outperforms the EnKF-based methods**

- **Short windows are good for ETKF**
- **Long windows are good for 4D-Var**
- **Optimal accuracy similar for 4D-Var and ETKF**

ECCO-like 4D-Var

- The consortium for Estimating the Circulation and Climate of the Ocean (ECCO) is a collaboration of a group of scientists from the MIT, JPL, and the Scripps Institute of Oceanography

- The main characteristic of ECCO is that they include surface fluxes as control variables.
  - This allows them to have exceedingly long assimilation windows in 4D-Var (e.g. 10 years or even 50 years).
  - They used NCEP Reanalysis fluxes (Kalnay et al, 1996) as a first guess.

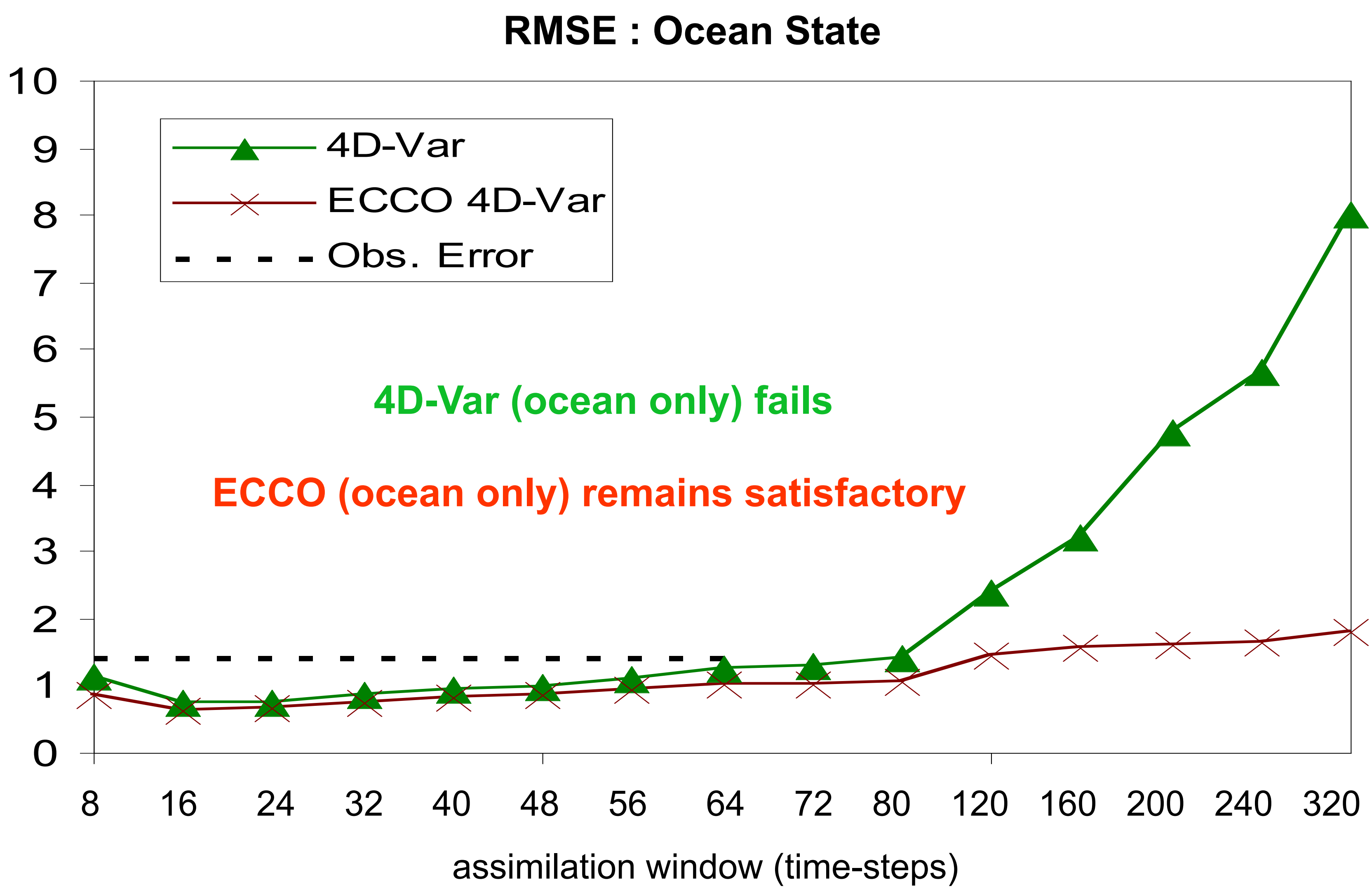
- ECCO used 4D-Var to estimate the initial ocean state and surface fluxes (Stammer et al., 2004; Kohl et al., 2007) in a 50-year reanalysis

Comparison of ECCO-like & Ocean 4D-Var

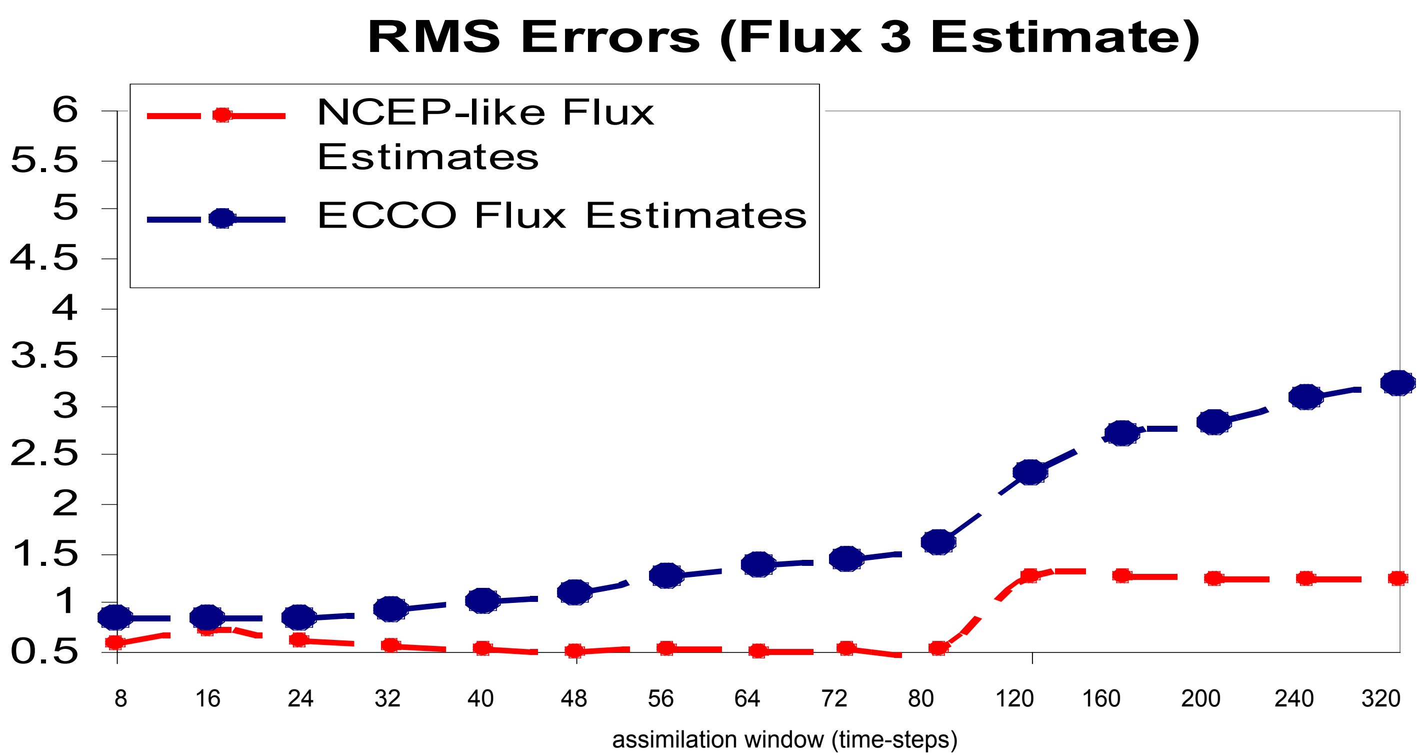
QVA APPLIED

OCEAN ONLY

Obs. s.d error = 1.41 for ocean



Are the ECCO fluxes more accurate?



ECCO does not improve the flux estimates

Answers to the Research Questions

Questions:

-- Which is more accurate: 4D-Var or EnKF?

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Both EnKF and 4D-Var are similar and most accurate when coupled, but uncoupled (ocean only) reanalyses are fairly good.

Answers to the Research Questions

Questions:

-- Which is more accurate: 4D-Var or EnKF?

Fully coupled EnKF (with short windows) and 4D-Var (with long windows) have about the same accuracy.

-- Is it better to do the ocean reanalysis separately, or as a single coupled system?

Both EnKF and 4D-Var are similar and most accurate when coupled, but uncoupled (ocean only) reanalyses are quite good.

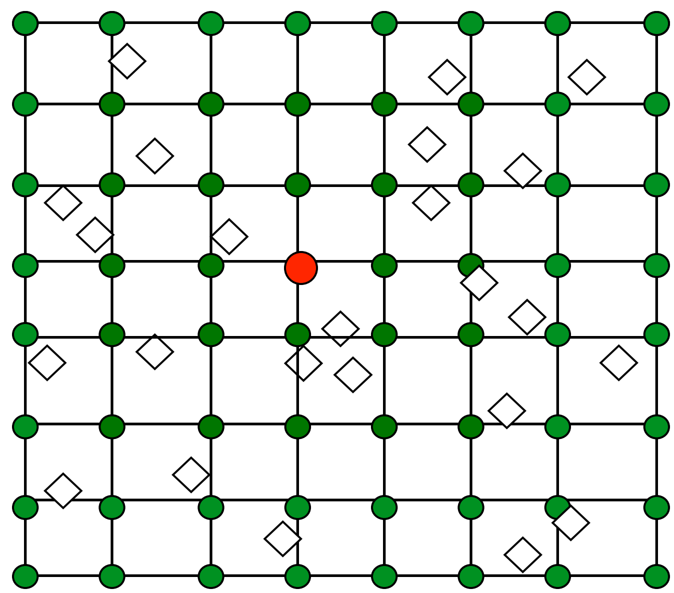
-- Is ECCO 4D-Var with both the initial state and the surface fluxes as control variables the best approach?

In our simple ocean model 4D-Var cannot remain accurate with very long windows. Our ECCO reanalysis remained satisfactory with very long windows but at the expense of less accurate fluxes.

LETKF: Localization based on observations

Perform data assimilation in a local volume, choosing observations

The state estimate is updated at the central grid red dot

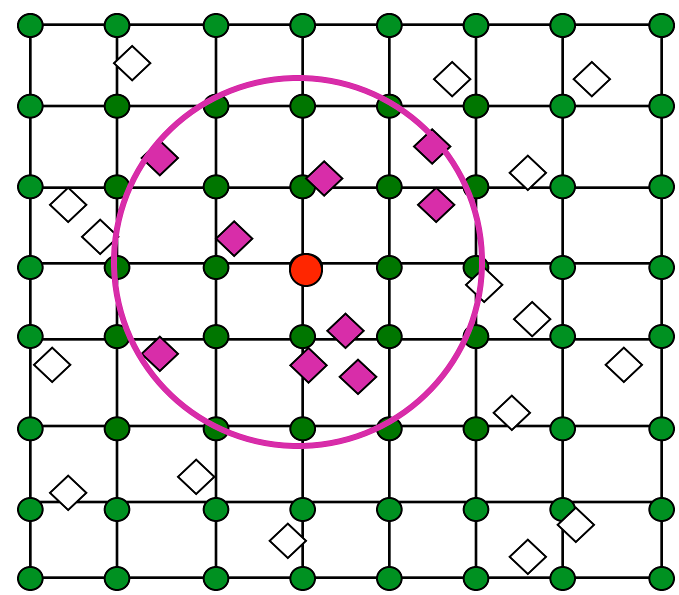


LETKF: Localization based on observations

Perform data assimilation in a local volume, choosing observations

The state estimate is updated at the central grid red dot

All observations (purple diamonds) within the local region are assimilated



The LETKF algorithm can be described in a single slide!

Local Ensemble Transform Kalman Filter (LETKF)

Globally:

Forecast step: $\mathbf{x}^b_{n,k} = M_n\left(\mathbf{x}^a_{n-1,k}\right)$

Analysis step: construct $\mathbf{X}^b = \left[\mathbf{x}^b_1 - \overline{\mathbf{x}}^b \mid \ldots \mid \mathbf{x}^b_K - \overline{\mathbf{x}}^b\right];$

$$\mathbf{y}^b_i = H(\mathbf{x}^b_i); \mathbf{Y}^b_n = \left[\mathbf{y}^b_1 - \overline{\mathbf{y}}^b \mid \ldots \mid \mathbf{y}^b_K - \overline{\mathbf{y}}^b\right]$$

Locally: Choose for each grid point the observations to be used, and compute the local analysis error covariance and perturbations in ensemble space:

$$\tilde{\mathbf{P}}^a = \left[(K-1)\mathbf{I} + \mathbf{Y}^T\mathbf{R}^{-1}\mathbf{Y}\right]^{-1}; \mathbf{W}^a = [(K-1)\tilde{\mathbf{P}}^a]^{1/2}$$

Analysis mean in ensemble space: $\overline{\mathbf{w}}^a = \tilde{\mathbf{P}}^a\mathbf{Y}^{bT}\mathbf{R}^{-1}(\mathbf{y}^o - \overline{\mathbf{y}}^b)$

and add to $\mathbf{W}^a$ **to get the analysis ensemble in ensemble space.**

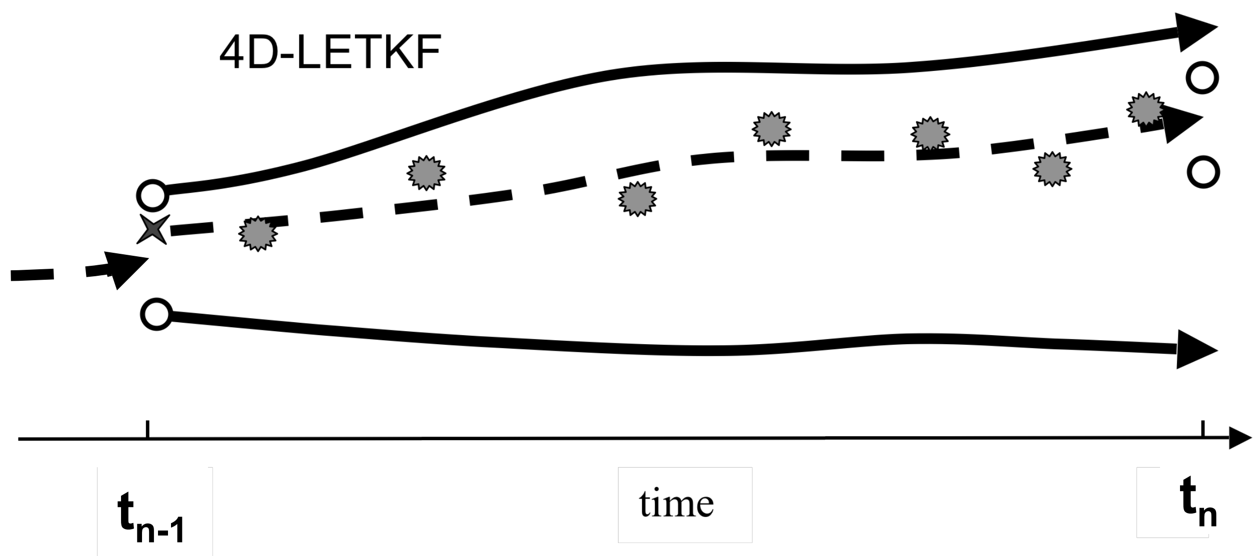
The new ensemble analyses in model space are the columns of $\mathbf{X}^a_n = \mathbf{X}^b_n\mathbf{W}^a + \overline{\mathbf{x}}^b$ **. Gathering the grid point analyses forms the new global analyses. Note that the the output of the LETKF are analysis weights** $\overline{\mathbf{w}}^a$ **and perturbation analysis matrices of weights** $\mathbf{W}^a$**. These weights multiply the ensemble forecasts.**

Promising new tools for the LETKF (1)

1.) **Running in Place** (Kalnay and Yang, QJ 2010, Yang, Kalnay, and Hunt, MWR, 2012)

- It extracts more information from observations by using them more than once.
- Useful during spin-up (e.g., hurricanes and tornados).
- It uses the "no-cost smoother", Kalnay et al., Tellus, 2007b.
- Typhoon Sinlaku (Yang et al., 2012, 2013)
- 7-years of Ocean Reanalysis (Penny, 2011, Penny et al., 2013).

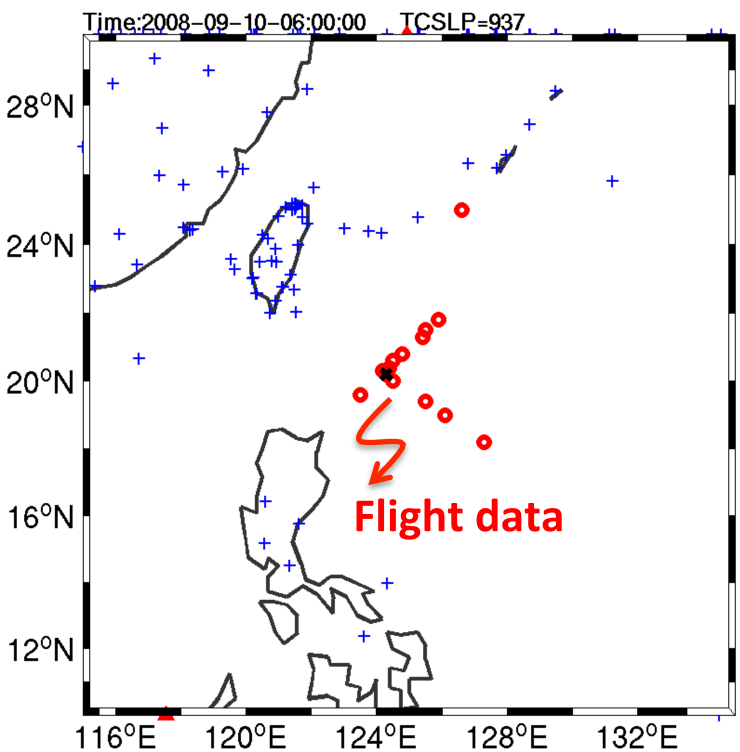
No-cost LETKF smoother (×): apply at t_{n-1} the same weights found optimal at t_n. It works for 3D- or 4D-LETKF



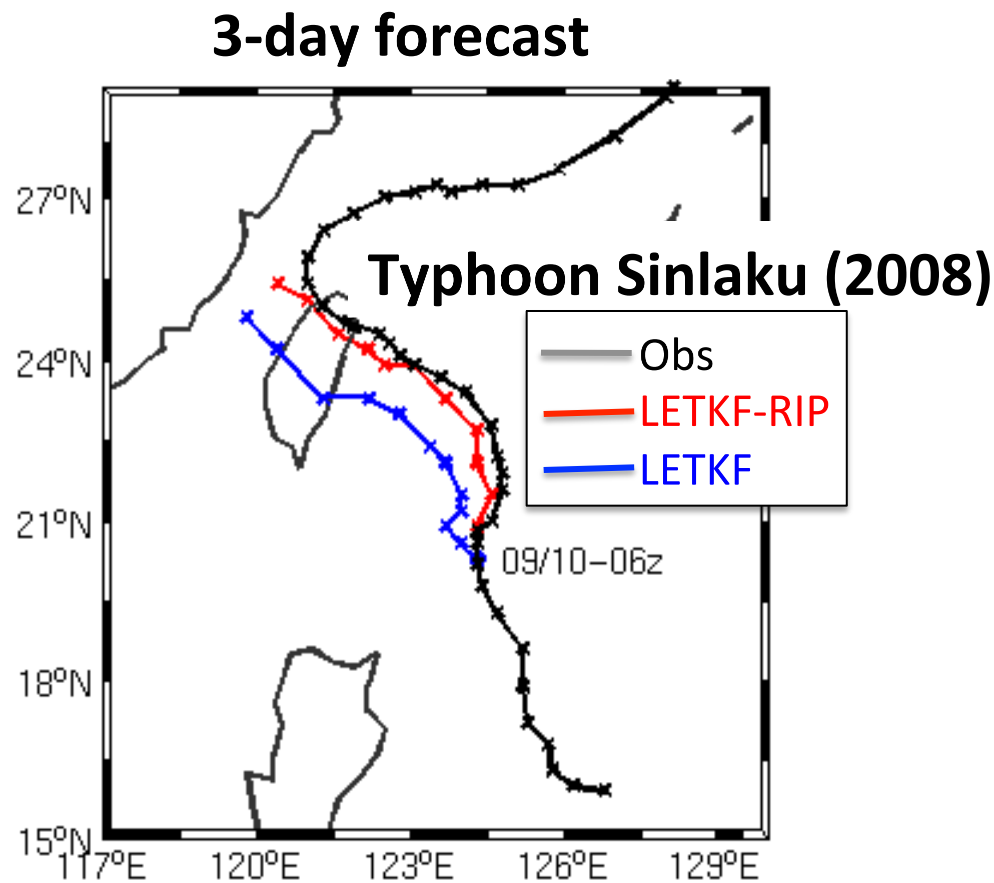
The no-cost smoother makes possible:

- ✓ Quasi Outer Loop (QOL)
- ✓ "Running in place" (RIP) for faster spin-up
- ✓ Use of future data in reanalysis
- ✓ Ability to use longer windows and nonlinear perturbations

LETKF-RIP with real observations (Typhoon Sinlaku, 2008)



SYNOP(+),SOUND(△),
DROPSONDE(○),
Typhoon center (X)



RIP uses better the "limited observations"!

Courtesy of Prof. Shu-Chih Yang (NCU, Taiwan)

An application of LETKF-RIP to ocean data assimilation

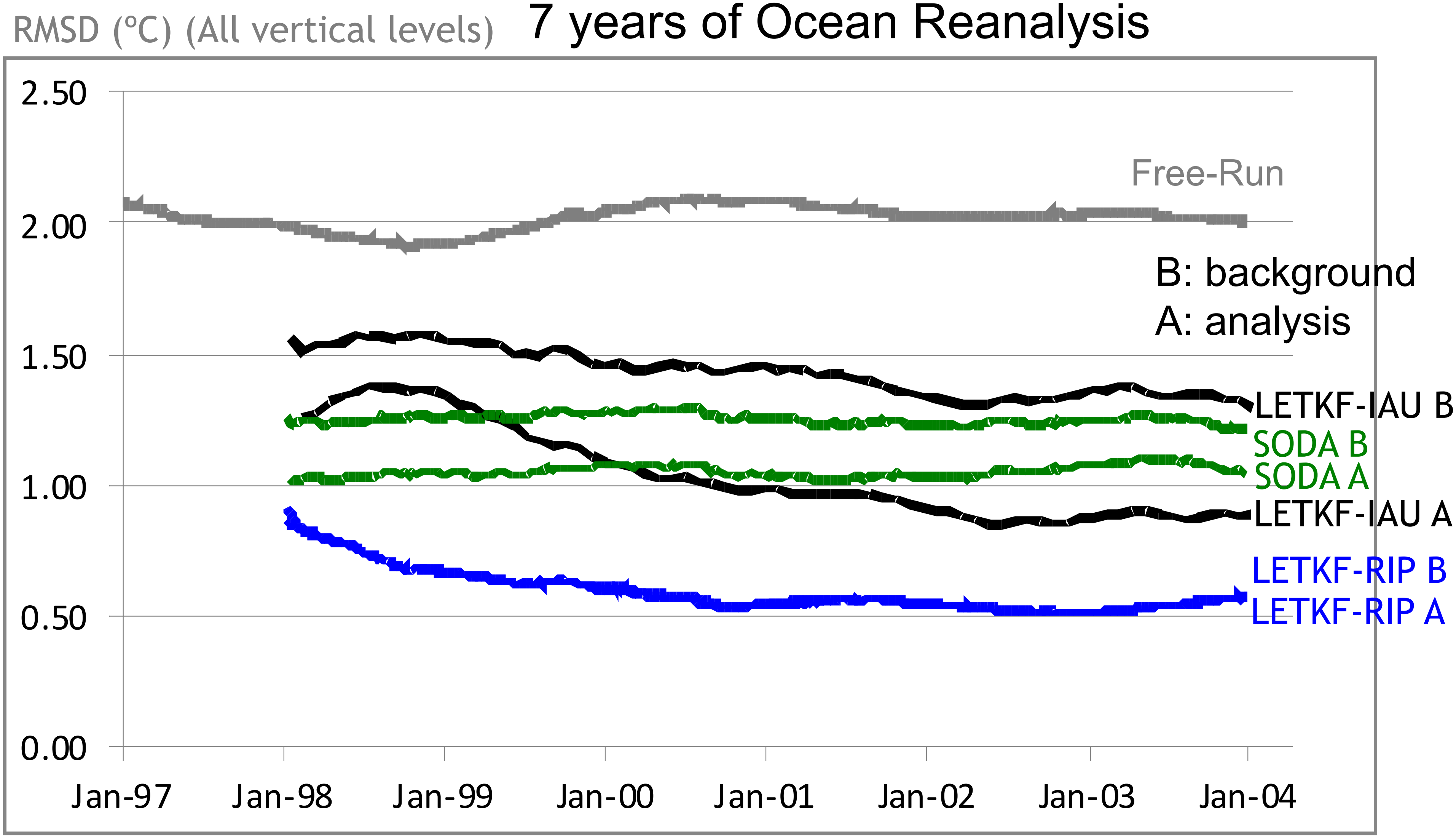
Data Assimilation of the Global Ocean using 4D-LETKF and MOM2

Steve Penny's thesis

Advisors: E Kalnay, J Carton, K Ide, B. Hunt, T Miyoshi, G Chepurin

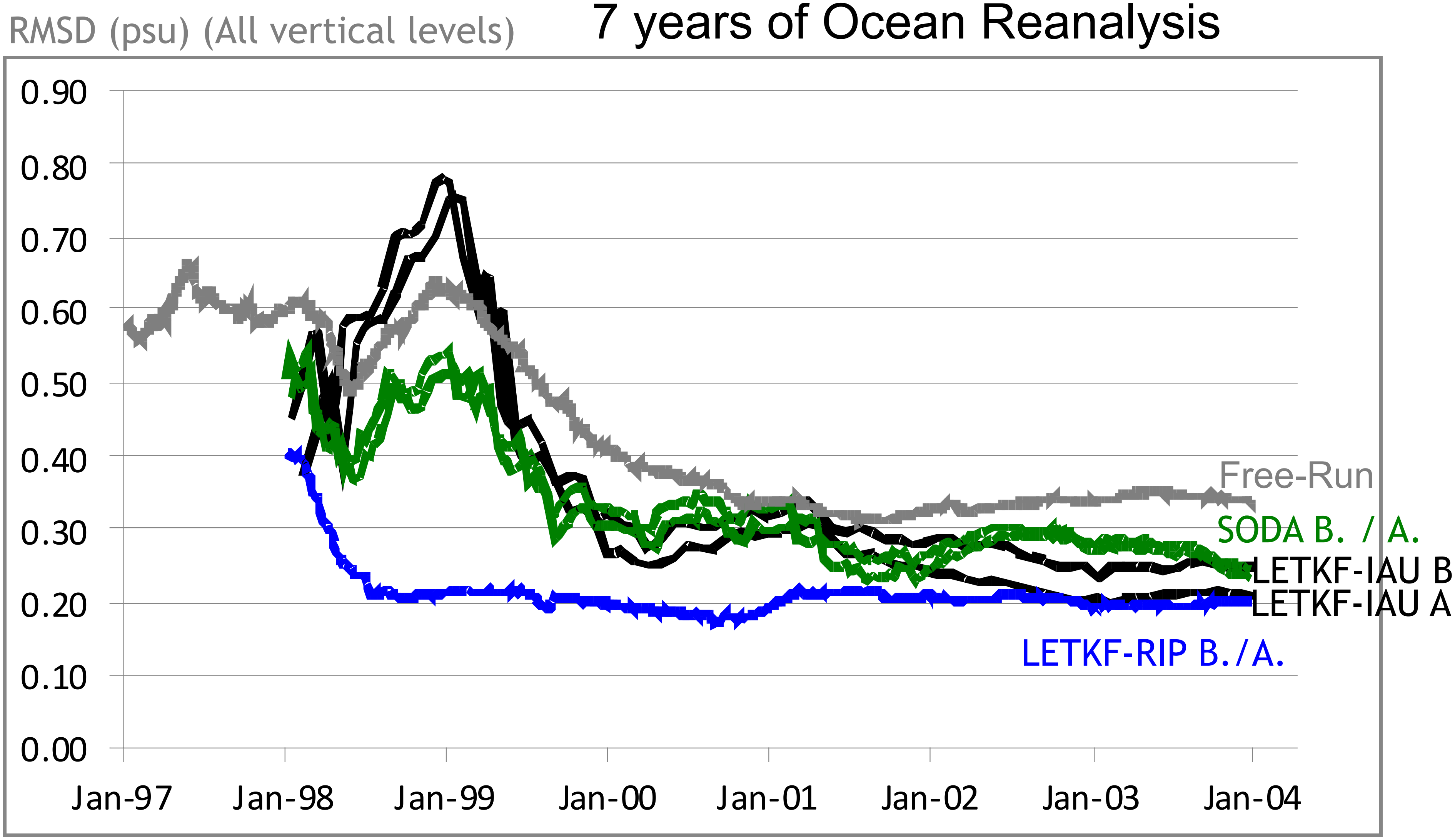
Penny (now at UMD/NCEP) implemented the LETKF with either IAU or RIP and compared it with SODA (OI)

7 years of Ocean Reanalysis



Global RMS(O-F) of Temperature (°C),
12-month moving average
LETKF (with **IAU**), **SODA** and LETKF with **RIP**

7 years of Ocean Reanalysis



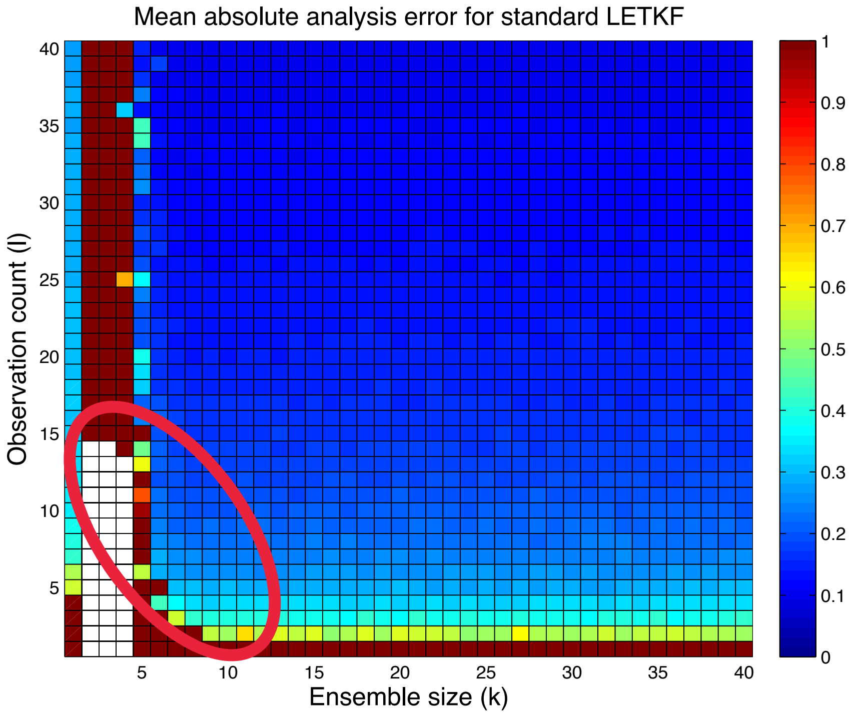
Global RMS(O-F) of Salinity (psu),
12-month moving average
LETKF (with **IAU**), **SODA** and LETKF with **RIP**

How about hybrids between Var and EnKF?

- So far hybrids have been created combining an existing Var system with an ensemble to provide the flow dependence of the background error covariance.
- **We would like to start with a well-developed EnKF (like the LETKF) and add a simple local 3D-Var that provides the full rank that the ensemble lacks.**
- Steve Penny developed a simple, locally Gaussian 3D-Var for this purpose, and tested it on the Lorenz-96, a 40 variable model.
- He plots the analysis error as a function of the number of ensemble members (2 to 40) and the number of observations (1 to 40).

An ensemble based hybrid with a simple local 3D-Var (Steve Penny) applied to the Lorenz 96 model

Standard LETKF



This is the corner where we are in ocean EnKF: too few obs, too few ensembles

The total model dimension is K=40

The LETKF is extremely accurate as long as k>7, number of obs>7.

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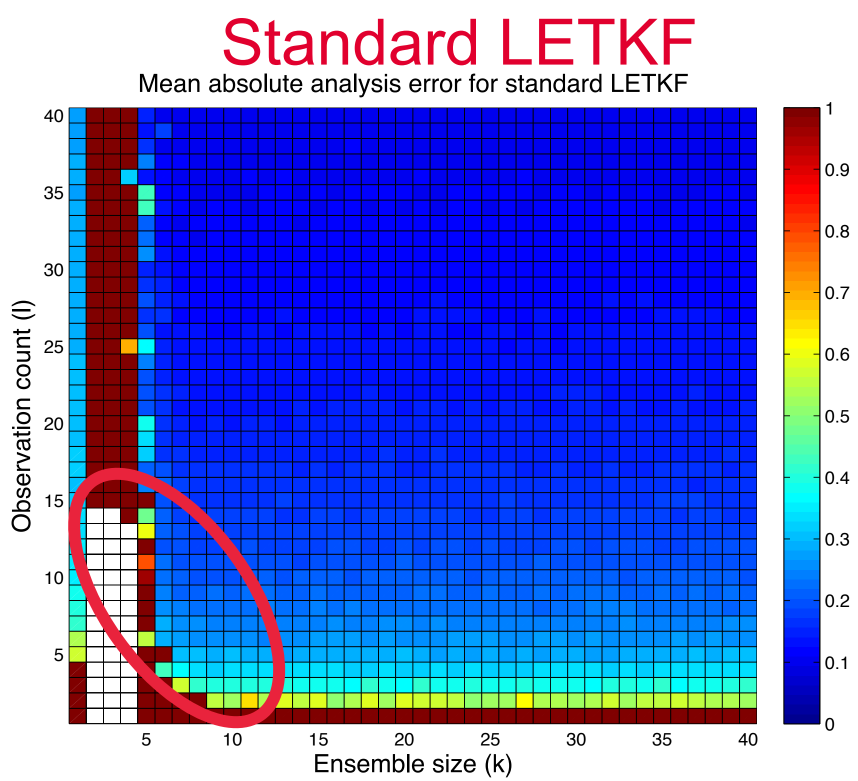
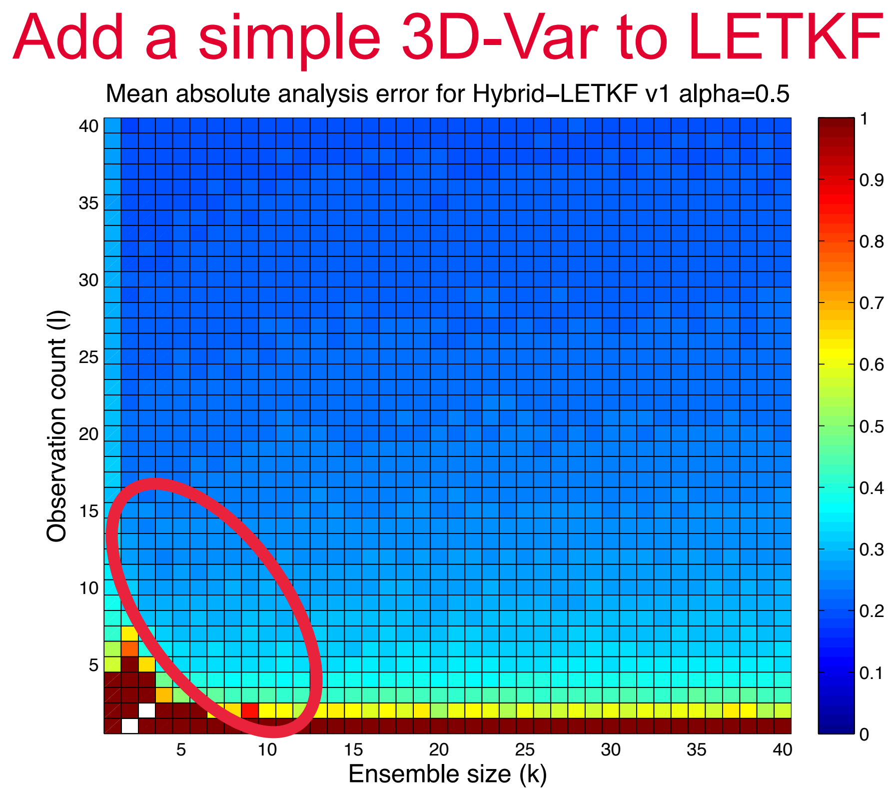
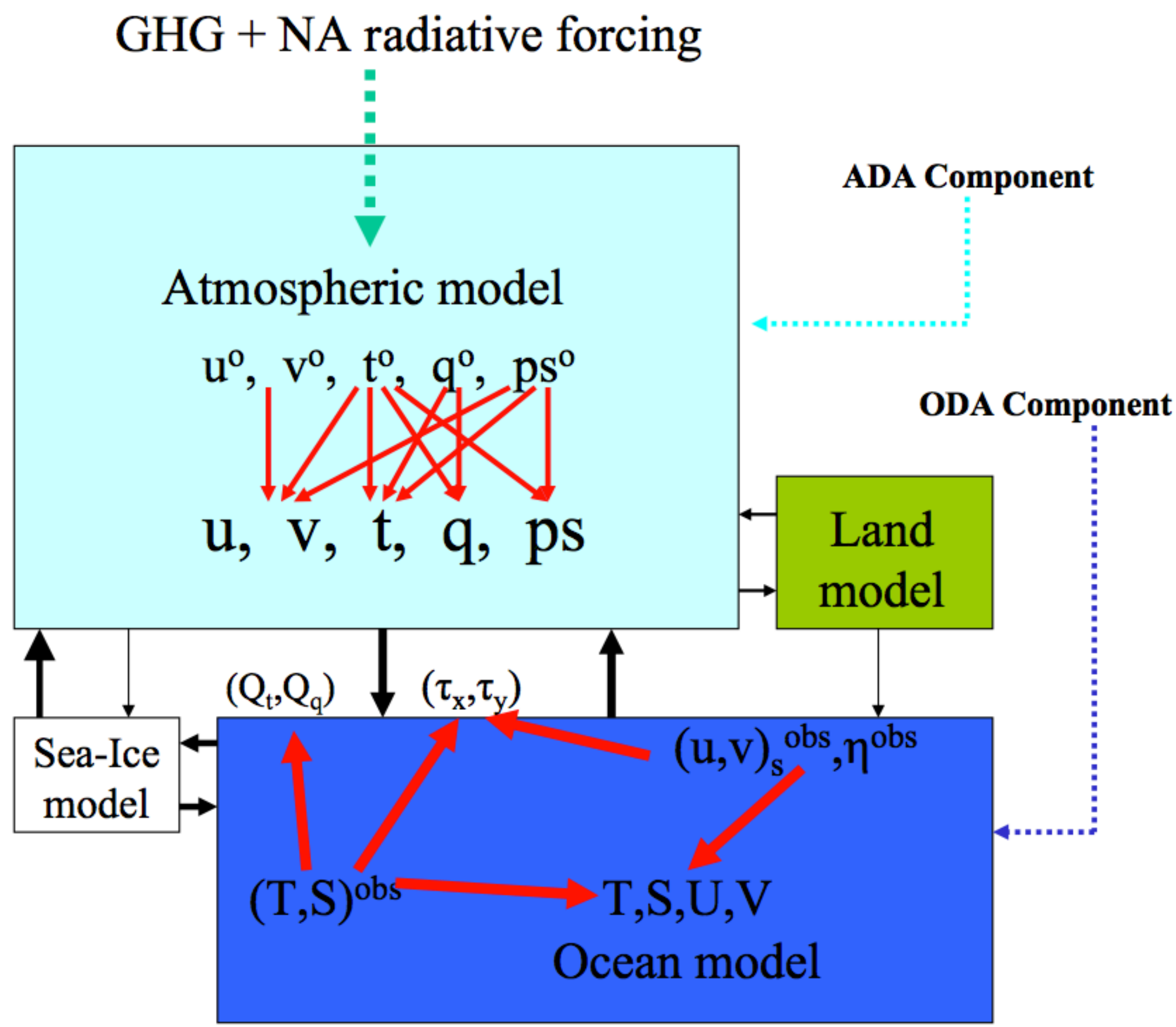


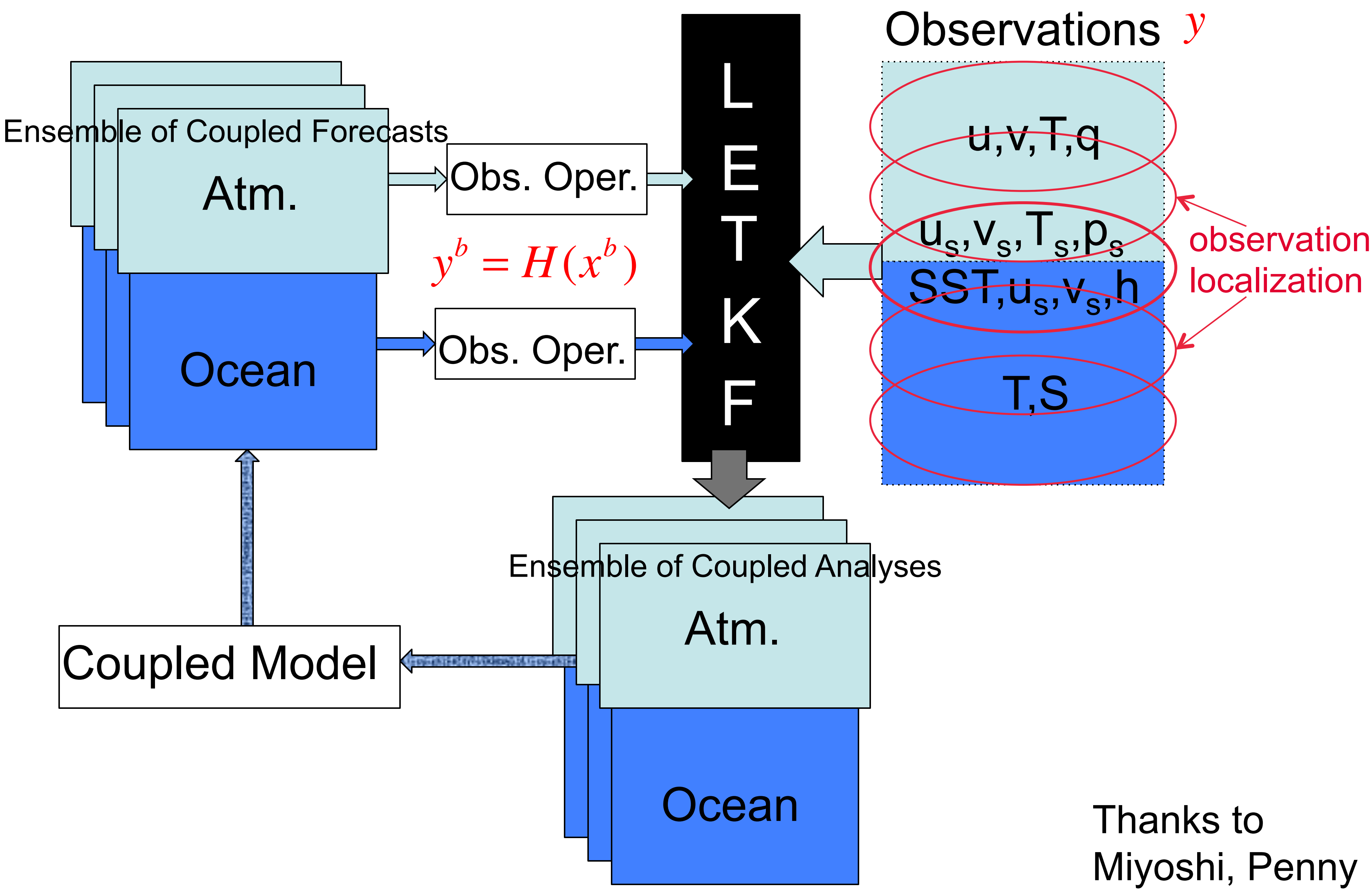


The hybrid LETKF-simple 3D-Var is more robust for few ensemble members and few observations, as in the ocean.

S. Zhang et al.: GFDL Coupled Ocean-Atm EnKF Data Assimilation



Basic idea for our coupled LETKF assimilation



Thanks to
Miyoshi, Penny

Summary: ideas/questions for future coupled ocean-atmosphere EnKF

- Toy model: coupled assimilation and short windows are more accurate for LETKF even if ocean has longer time scales.
- Running in Place (RIP) extracts more information from the observations and allows the use of shorter windows.
- A new hybrid LETKF+simple 3D-Var would make the system more robust with fewer ensemble members and observations.
- For the coupled (India Monsoon Mission) CFS system, we will test the use of 6hr (short) windows for the ocean as well as the atmosphere assimilation.
- Assimilate SST and SSH observations directly.
- Localization of observations near the surface should allow for atm.-ocean interaction through the background error covariance

Summary: ideas/questions for future coupled ocean-atmosphere EnKF

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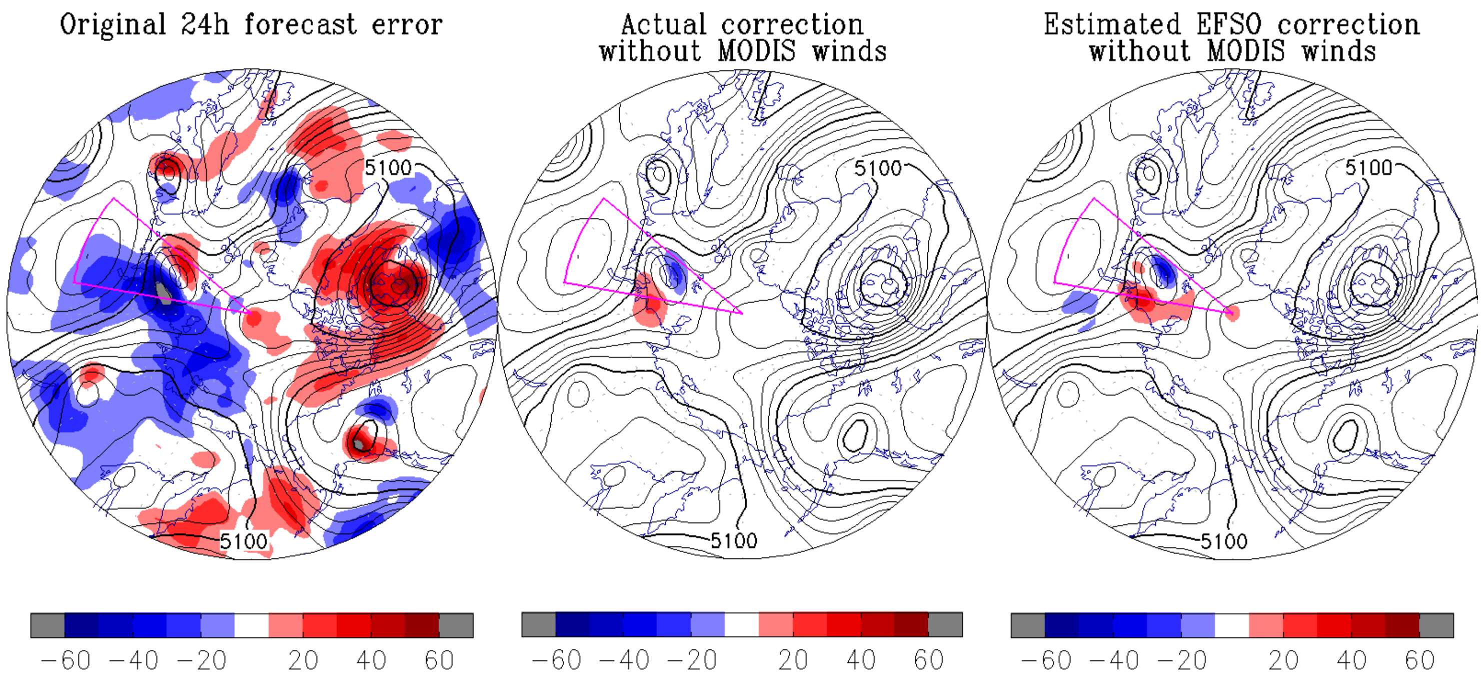
Thanks!

“Proactive QC” with Ens. Fcst. Sens. to Obs.

Bad observations can be identified by EFSO and withdrawn from the data assimilation



After identifying with EFSO the observations (MODIS polar winds) producing bad 24hr regional forecasts, the withdrawal of these winds reduced the regional forecast errors by 39%, as estimated by EFSO. (Ota et al., 2013)

Promising new tools for the LETKF (2)

2. Effective assimilation of Precipitation (Guo-Yuan Lien, Eugenia Kalnay and Takemasa Miyoshi, 2013)

- Assimilation of precipitation has generally failed to improve forecasts beyond a day.
- A new approach deals with non-Gaussianity, and assimilation of both zero and non-zero precipitation.
- Rather than changing moisture to force the model to rain as observed, the LETKF changes the potential vorticity.
- The model now "remembers" the assimilation, so that medium range forecasts are improved.

How to transform precipitation *y* to a Gaussian y_{transf}

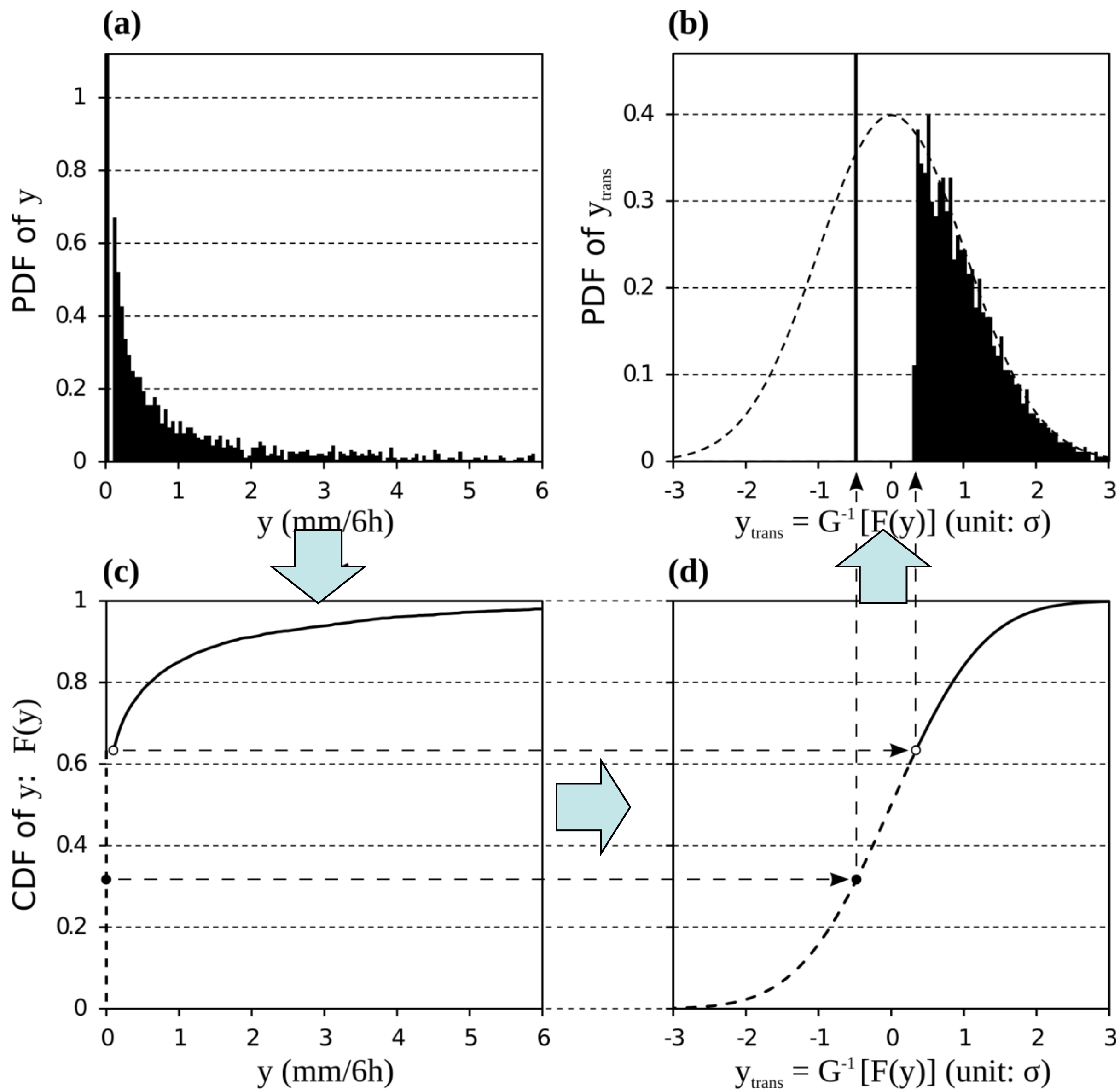
Start with pdf of *y*=rain at every grid point.

"No rain" is like a delta function that we cannot transform.

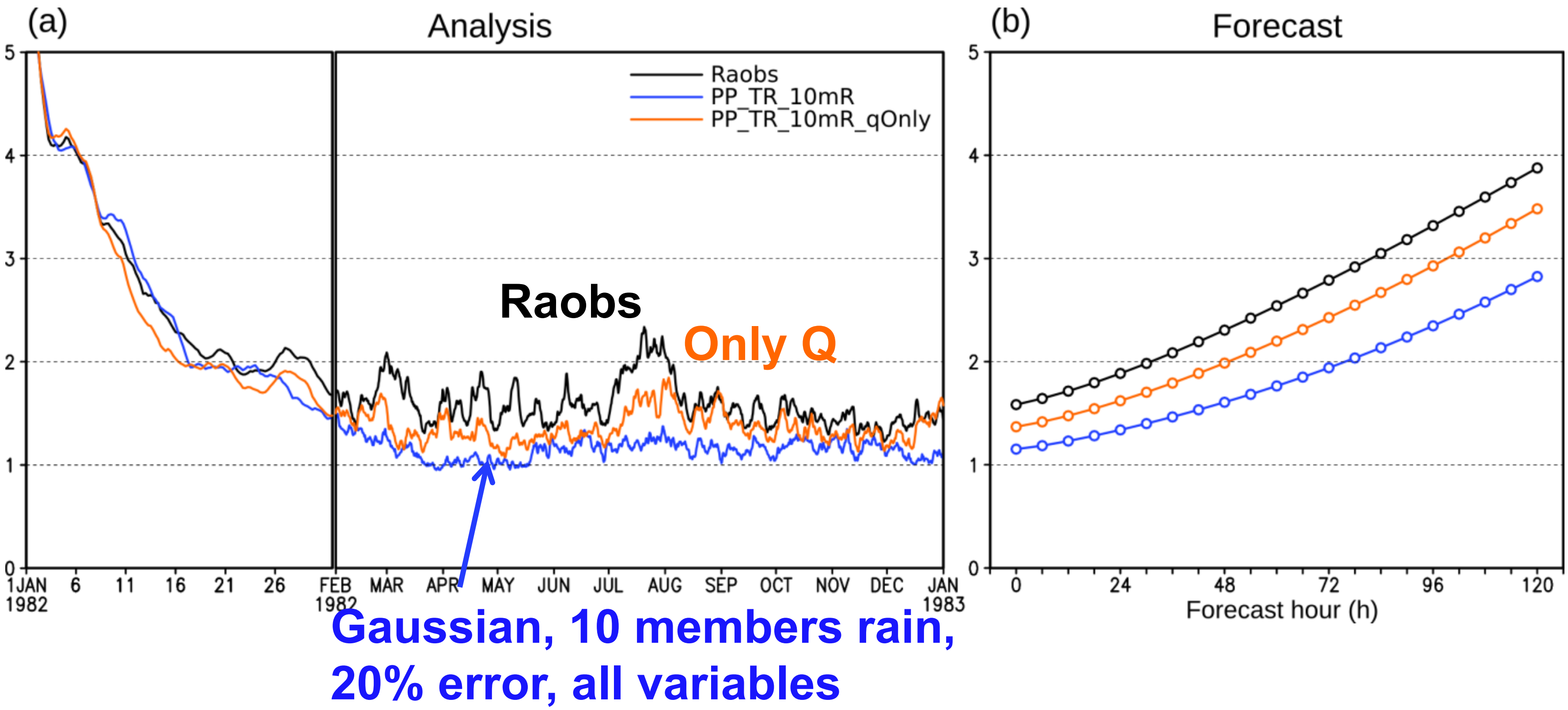
We assign all "no rain" to the median of the no rain CDF.

We found this works as well as more complicated procedures.

It allows to assimilate both rain and no rain.



$$G^{-1}(x) = \sqrt{2}\,erf^{-1}(2x-1)$$



- **Main result:** **with at least 10 ensemble members raining in order to assimilate an obs, updating all variables (including vorticity), with Gaussian transform, and rather accurate observations (20% errors), the analyses and forecasts are much improved!**
- **Updating only Q is much less effective.**
- **The 5-day forecasts maintain the advantage!**