

Recent Advances in EnKF: Running in Place, Assimilation of Rain, Ensemble Forecast Sensitivity to Observations

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UMD Weather-Chaos Group: **Kayo Ide**, **Brian Hunt**, Ed Ott,
and students (Guo-Yuan Lien, Yan Zhou, Adrienne Norwood,
Erin Lynch, Yongjing Zhao, Daisuke Hotta)

Also: **Y Ota**, Juan Ruiz, C Danforth, M Peña

RIKEN, Japan, 26/02/13

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., 2012)
- Very good results!
- **Shu-Chih Yang’s talk this afternoon**

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. The model now “remembers” the assimilation, so that that medium range forecasts are improved.
- **Guo-Yuan Lien’s talk tomorrow**

Promising new tools for the LETKF(3)

3. Forecast Sensitivity to Observations and “proactive QC”

(with Y Ota, T Miyoshi, J Liu, and J Derber)

A simpler, more accurate formulation for the Ensemble Forecast Sensitivity to Observations (EFSO, Kalnay et al., 2012, Tellus).

- Ota et al., 2012 tested it with the NCEP EnSRF-GFS operational system using all operational observations.
- Allows to identify “bad observations” after 12 or 24hr, and then repeat the data assimilation without them: “proactive QC”.

Promising new tools for the LETKF(4, 5)

4. Estimation of surface fluxes as evolving parameters

(Kang et al., 2011, 2012)

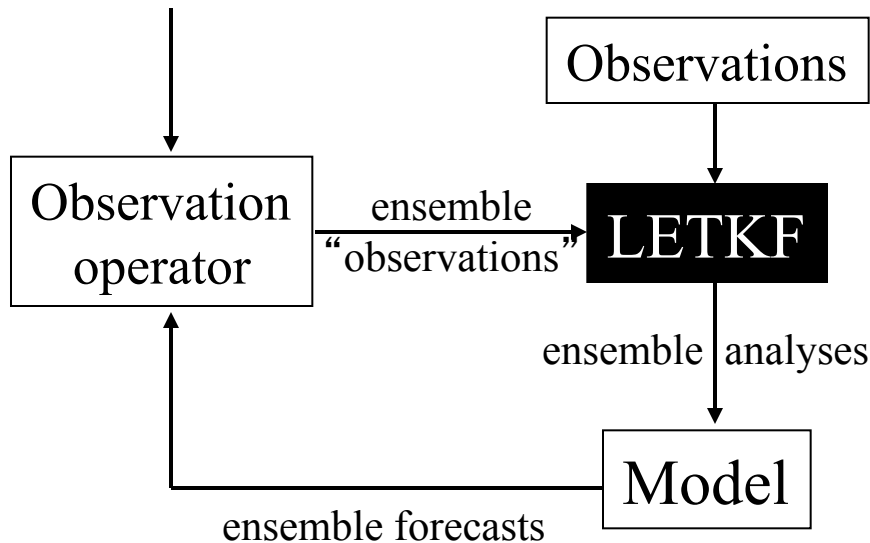
- **Ji-Sun Kang's talk tomorrow**

5. Application of ensemble forecast sensitivity to data assimilation (Shu-Chih Yang, E. Kalnay, thanks to T. Enomoto)

- We apply the idea of ensemble sensitivity to the spin-up problem.
- **Very promising!!**

Local Ensemble Transform Kalman Filter (Ott et al, 2004, Hunt et al, 2004, 2007) (a square root filter)

(Start with initial ensemble)

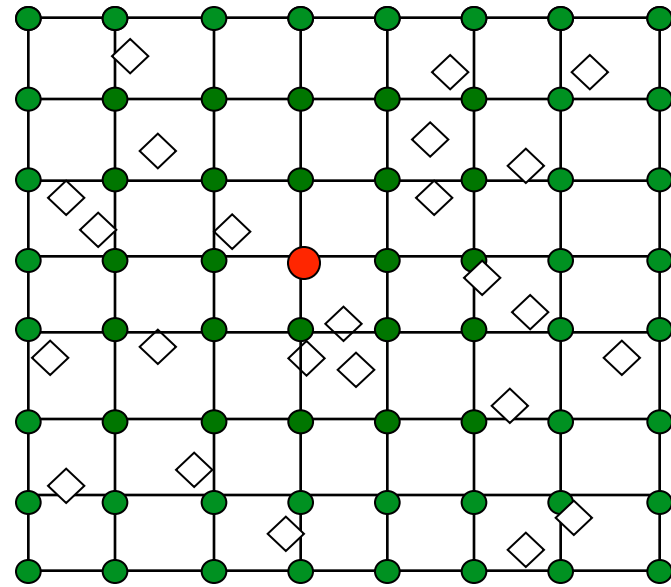


- Model independent (black box)
- **Obs. assimilated simultaneously at each grid point**
- 100% parallel
- No **adjoint** needed
- 4D LETKF extension
- **Computes the weights for the ensemble forecasts explicitly**

Localization based on observations

Perform data assimilation in a local volume, choosing observations

The state estimate is updated at the central grid **red** dot

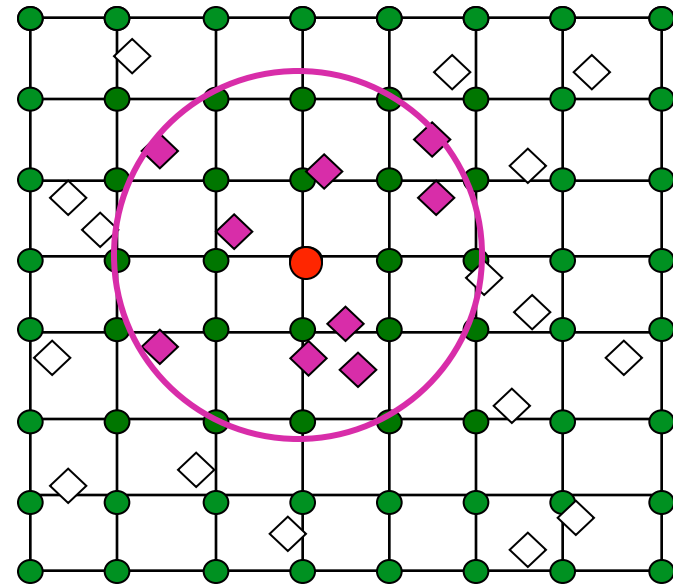


Localization based on observations

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: $\mathbf{x}_{n,k}^b = M_n(\mathbf{x}_{n-1,k}^a)$

Analysis step: construct $\mathbf{X}^b = [\mathbf{x}_1^b - \bar{\mathbf{x}}^b \mid \dots \mid \mathbf{x}_K^b - \bar{\mathbf{x}}^b]$;

$$\mathbf{y}_i^b = H(\mathbf{x}_i^b); \mathbf{Y}_n^b = [\mathbf{y}_1^b - \bar{\mathbf{y}}^b \mid \dots \mid \mathbf{y}_K^b - \bar{\mathbf{y}}^b]$$

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

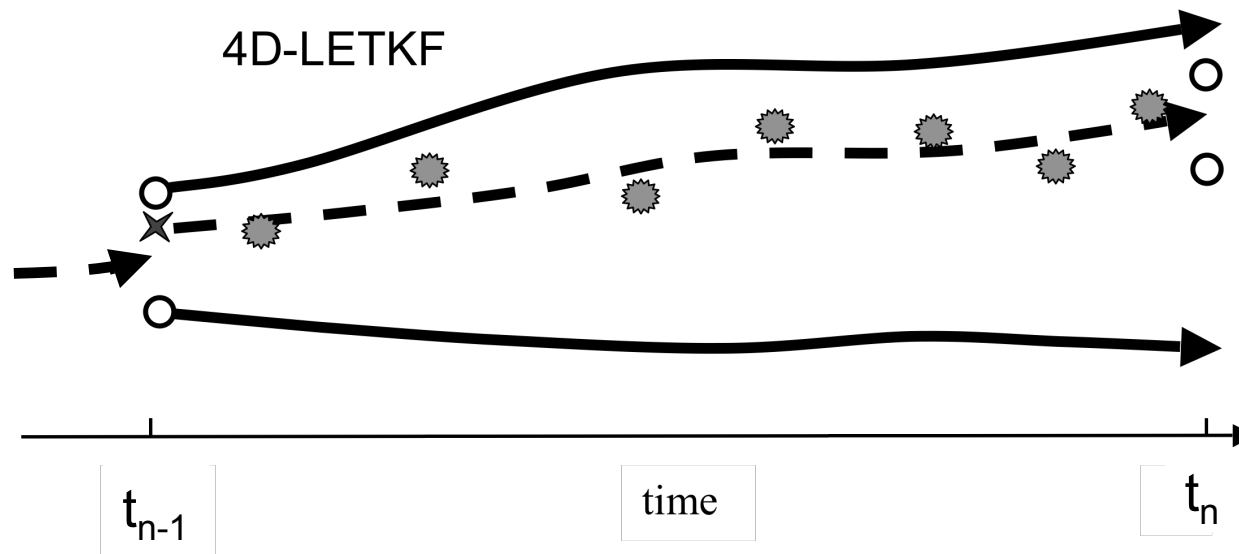
$$\tilde{\mathbf{P}}^a = [(K-1)\mathbf{I} + \mathbf{Y}^b \mathbf{R}^{-1} \mathbf{Y}^{bT}]^{-1}; \mathbf{W}^a = [(K-1)\tilde{\mathbf{P}}^a]^{1/2}$$

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

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 $\mathbf{X}_n^a = \mathbf{X}_n^b \mathbf{W}^a + \bar{\mathbf{x}}^b$. Gathering the grid point analyses forms the new **global analyses**. Note that the the output of the LETKF are analysis weights $\bar{\mathbf{w}}^a$ and perturbation analysis matrices of weights \mathbf{W}^a . **These weights multiply the ensemble forecasts.**

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

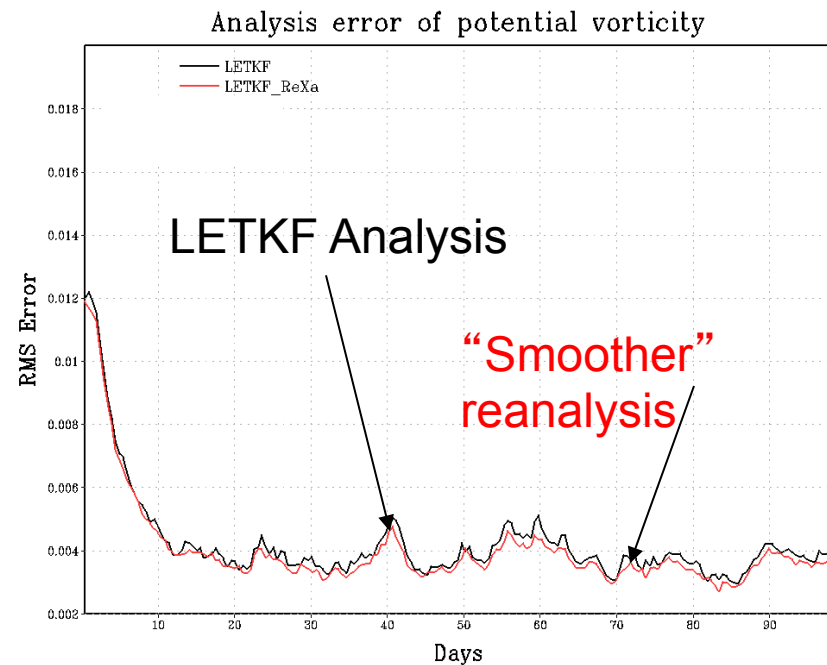
No-cost LETKF smoother first tested on a QG model: it works...

LETKF analysis at time n

$$\bar{\mathbf{x}}_n^a = \bar{\mathbf{x}}_n^f + \mathbf{X}_n^f \bar{\mathbf{w}}_n^a$$

Smoother analysis at time $n-1$

$$\tilde{\mathbf{x}}_{n-1}^a = \bar{\mathbf{x}}_{n-1}^f + \mathbf{X}_{n-1}^f \bar{\mathbf{w}}_n^a$$



Very simple smoother: apply the final weights at the beginning of the window. **It allows assimilation of future data, and assimilating data more than once.**¹¹

Nonlinearities, “QOL” and “Running in Place”

Quasi Outer Loop: similar to 4D-Var: use the final weights to correct only the mean initial analysis, keeping the initial perturbations. Repeat the analysis once or twice. It centers the ensemble on a more accurate nonlinear solution.

Lorenz -3 variable model RMS analysis error

	4D-Var	LETKF	LETKF +QOL	LETKF +RIP
Window=8 steps	0.31	0.30	0.27	0.27
Window=25 steps	0.53	0.68	0.47	0.35

“Running in Place” smoothes both the **analysis** and the **analysis error covariance** and iterates a few times...

An application of LETKF-RIP to ocean data assimilation

Data Assimilation of the Global Ocean using 4D-LETKF, SODA(OI) and MOM2

Steve Penny's thesis
defense

April 15, 2011

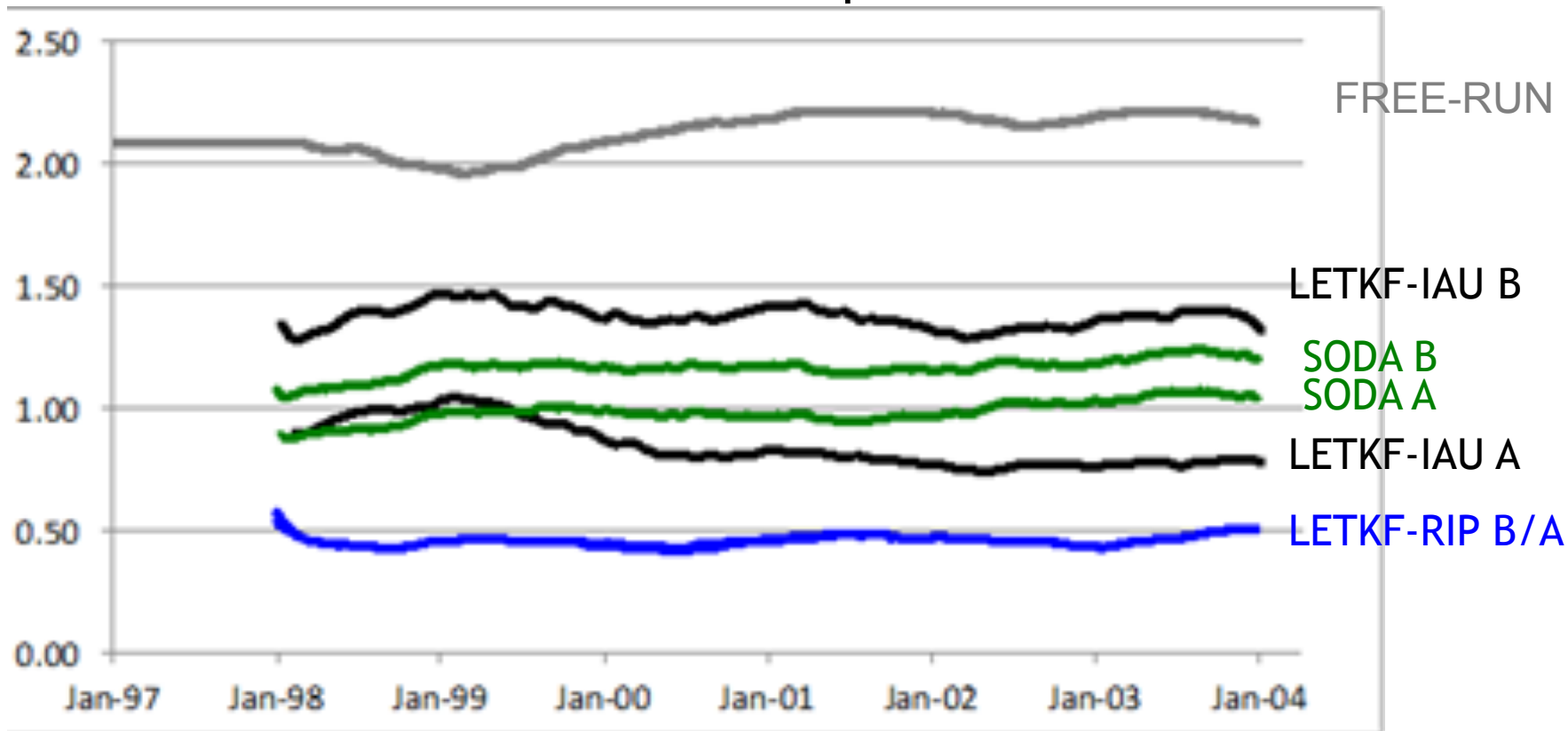
Advisors: E Kalnay, J Carton, K Ide, T Miyoshi, G Chepurin

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

RMSD (°C) (All vertical levels)

7 years of Ocean Reanalysis Temperature

B: background
A: analysis



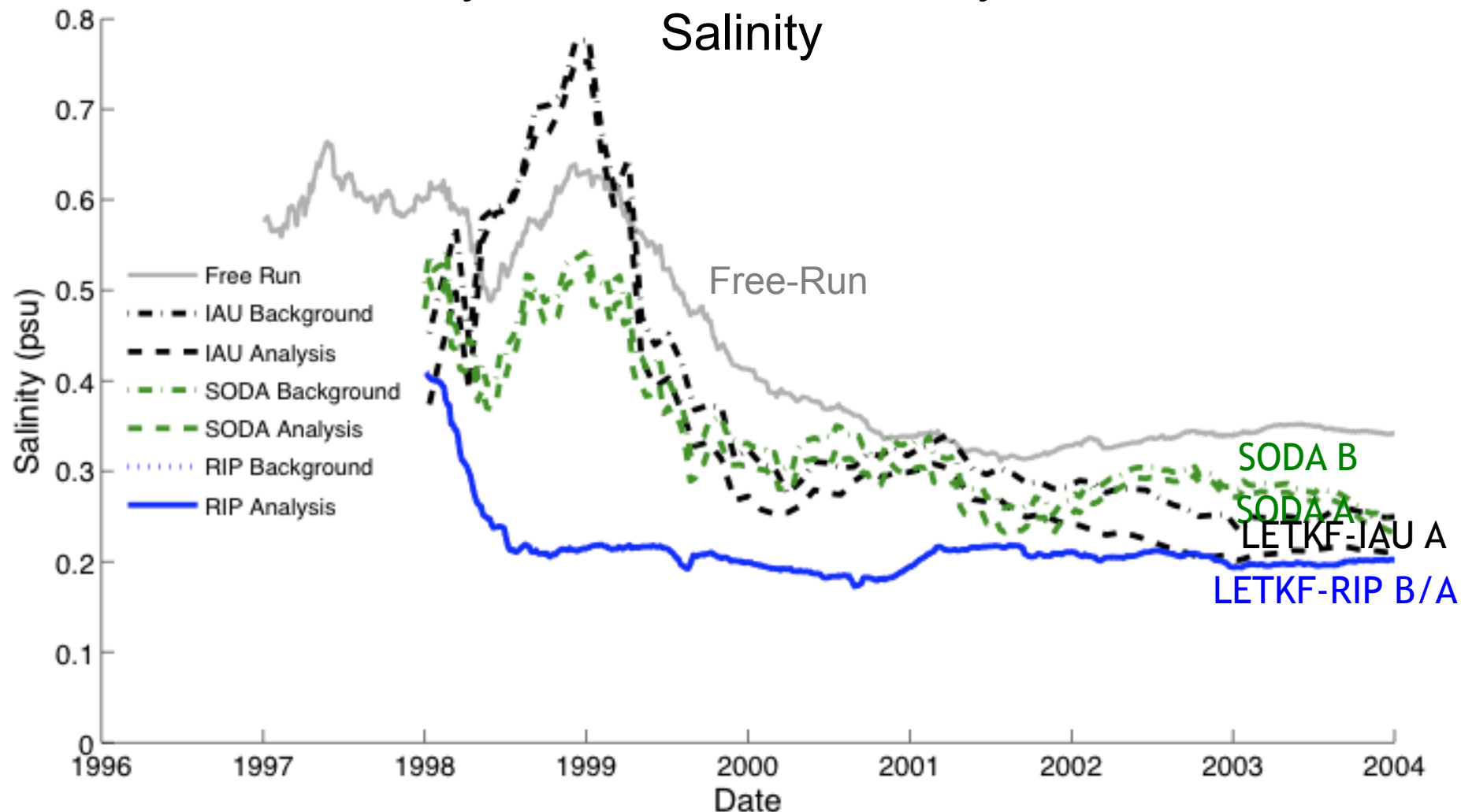
Global RMS(O-F) of Temperature (°C),
12-month moving average

LETKF (with **IAU**), **SODA** and LETKF with **RIP**

RMSD (psu) (All vertical levels)

B: background
A: analysis

7 years of Ocean Reanalysis Salinity



Global RMS(O-F) of Salinity (psu),
12-month moving average

LETKF (with **IAU**), **SODA** and LETKF with **RIP**

Why is LETKF-RIP so much better than SODA or LETKF-IAU for the ocean reanalysis?

- The ocean observations are too sparse for a standard EnKF, or even OI/3D-Var with a short (5-day) window.
- SODA and LETKF-IAU used a much longer window (30 days) in order to hammer the system with the available observations.
- LETKF-RIP uses a 5-day window but re-uses the observations in order to extract more information.

Summary for LETKF-RIP (or QOL)

- Kalman Filter is optimal for a linear, perfect model.
- During spin-up, or when the ensemble perturbations grow nonlinearly, EnKF is not optimal, since it does not extract enough information from the observations.
- The LETKF “no-cost” smoother (or, equivalently, the 4D-EnSRF) allows LETKF-RIP to use the observations more than once, and thus extract much more information.
- This shortens the spin-up and produces more accurate forecasts with the same observations.
- For linear models RIP converges to the same optimal KF solution but with spread reduced by $\sim \sqrt{N}$
- For long windows and nonlinear perturbations, RIP advances in smaller steps and approaches the true attractor more “softly”.

(2) Effective Assimilation of Precipitation

(Guo-Yuan Lien, E. Kalnay and T Miyoshi)

- Guo-Yuan's talk tomorrow

How do we transform precipitation y to a Gaussian y_{transf} ?

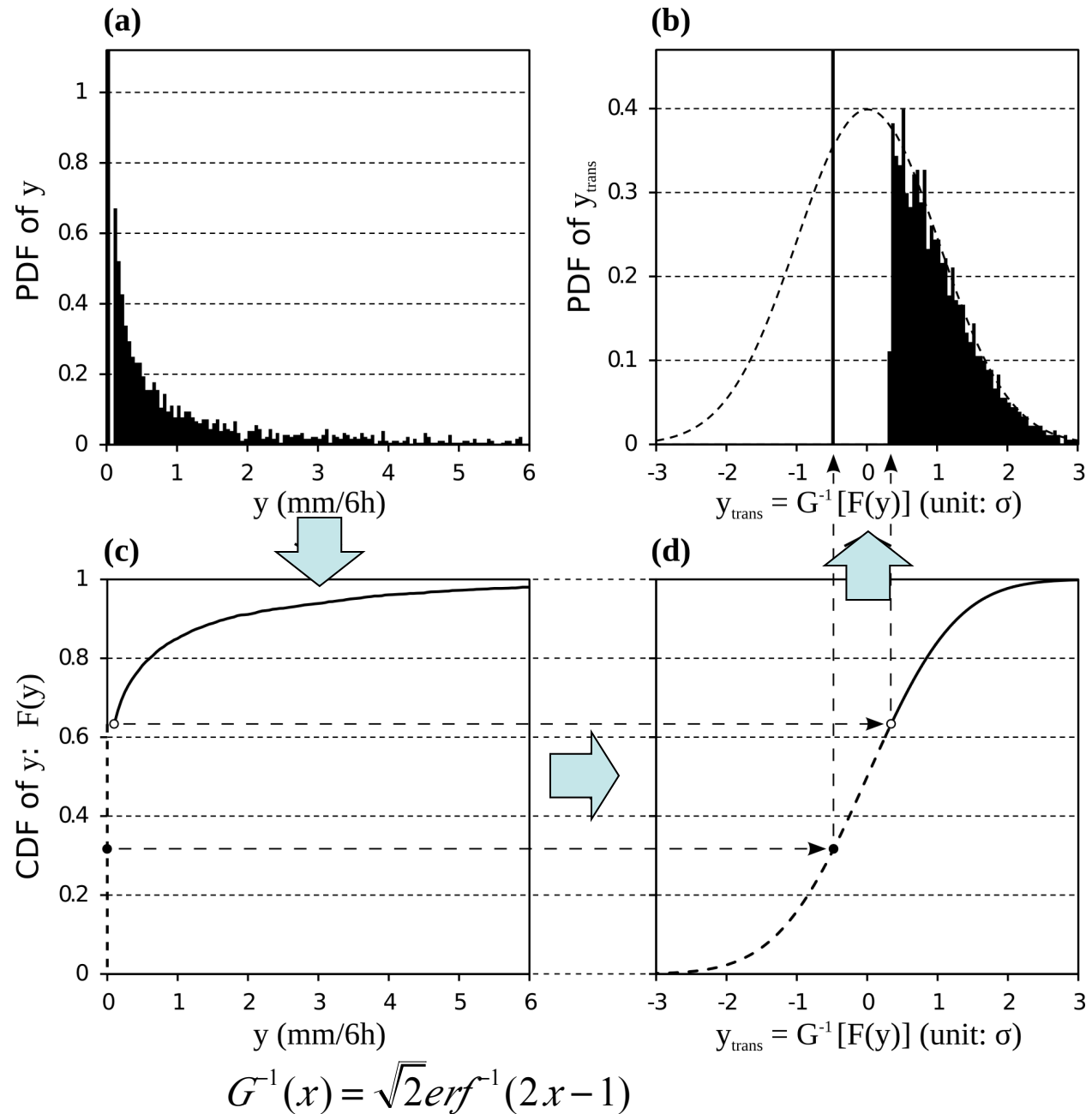
Start with pdf of y =rain at every grid point.

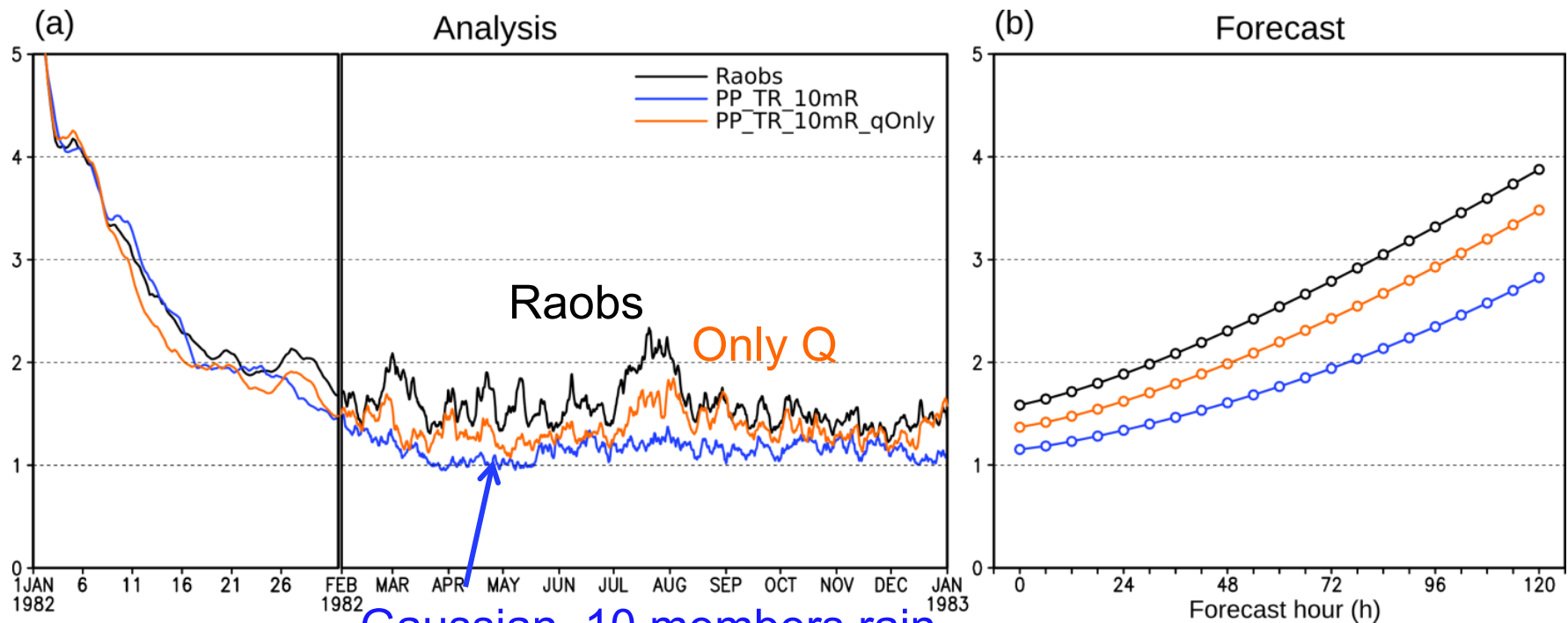
“No rain” is like a delta function that we cannot transform.

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.

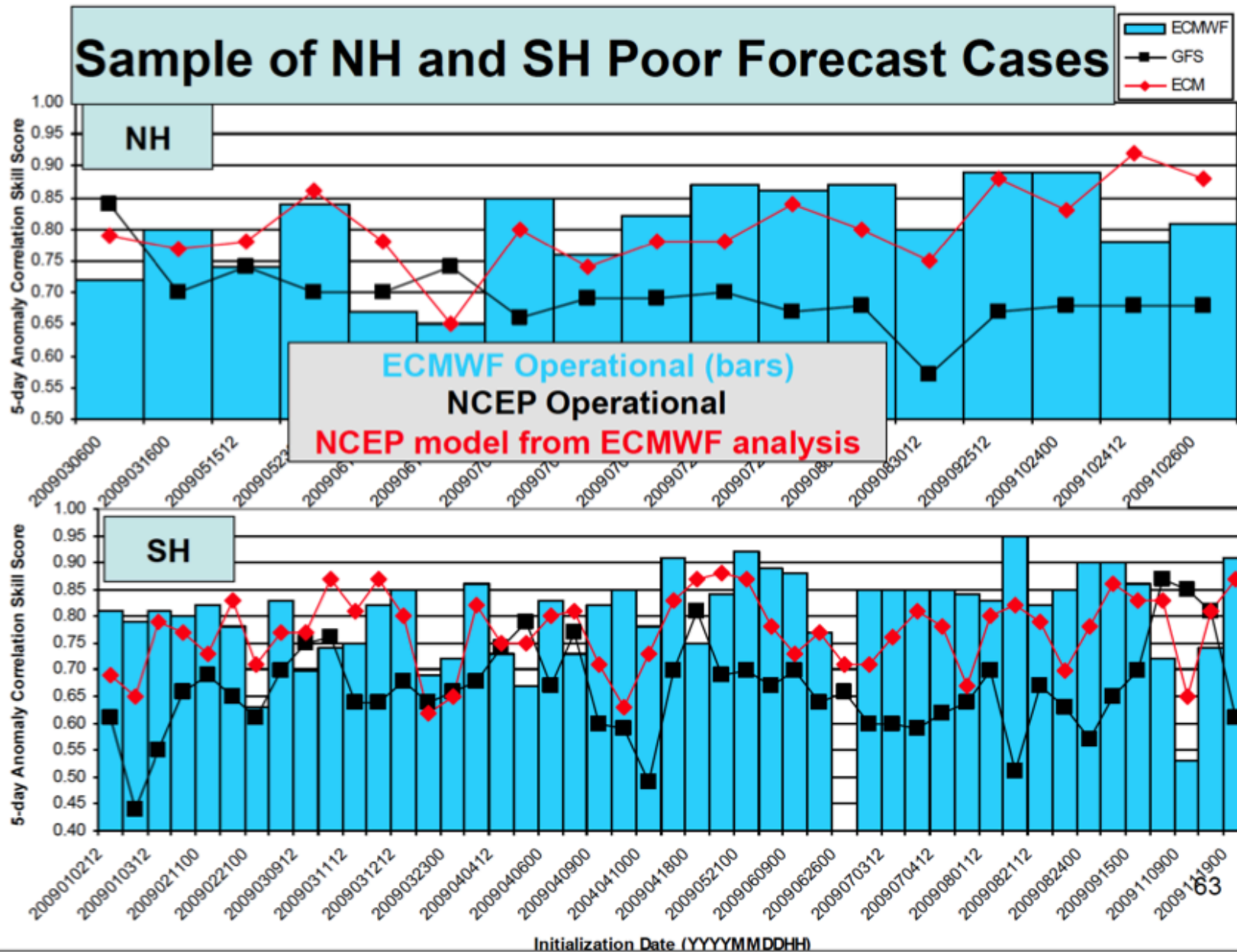




Gaussian, 10 members rain,
20% error, all variables

- **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.**

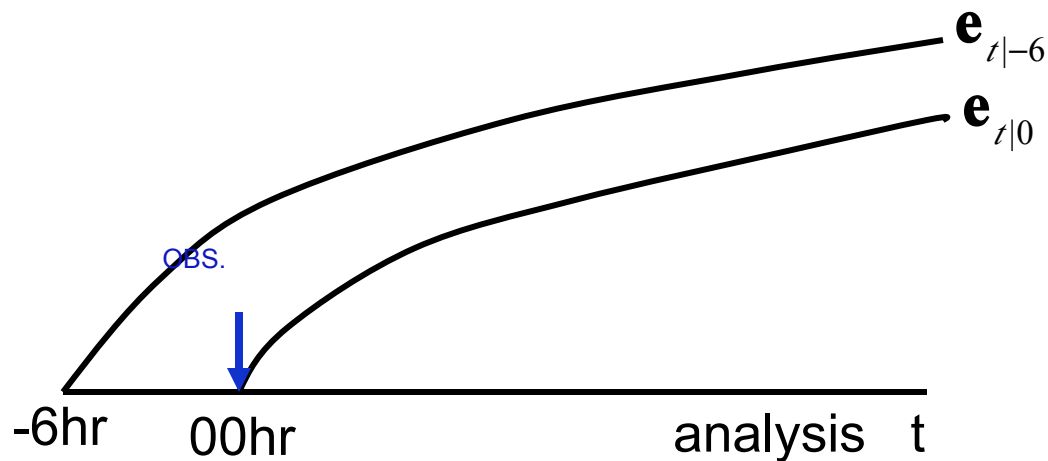
The NCEP 5-day skill dropout problem



Ensemble Forecast Sensitivity to Observations

“Adjoint sensitivity without adjoint” (Liu and K, 2008, Li et al., 2010)

Here we show a **simpler, more accurate formulation**
(Kalnay, Ota, Miyoshi: Tellus, 2012)



$$\mathbf{e}_{t|0} = \bar{\mathbf{x}}_{t|0}^f - \bar{\mathbf{x}}_t^a$$

(Adapted from Langland and Baker, 2004)

The **only** difference between $\mathbf{e}_{t|0}$ and $\mathbf{e}_{t|-6}$ is the **assimilation of observations** at 00hr:

$$(\bar{\mathbf{x}}_0^a - \bar{\mathbf{x}}_{0|-6}^b) = \mathbf{K}(\mathbf{y} - H(\mathbf{x}_{0|-6}^b))$$

➤ Observation impact on the reduction of forecast error:

$$\Delta \mathbf{e}^2 = (\mathbf{e}_{t|0}^T \mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^T \mathbf{e}_{t|-6}) = (\mathbf{e}_{t|0}^T - \mathbf{e}_{t|-6}^T)(\mathbf{e}_{t|0} + \mathbf{e}_{t|-6})$$

Ensemble Forecast Sensitivity to Observations

$$\begin{aligned}\Delta \mathbf{e}^2 &= (\mathbf{e}_{t|0}^T \mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^T \mathbf{e}_{t|-6}) = (\mathbf{e}_{t|0}^T - \mathbf{e}_{t|-6}^T)(\mathbf{e}_{t|0} + \mathbf{e}_{t|-6}) \\ &= (\bar{\mathbf{x}}_{t|0}^f - \bar{\mathbf{x}}_{t|-6}^f)^T (\mathbf{e}_{t|0} + \mathbf{e}_{t|-6}) \\ &= [\mathbf{M}(\bar{\mathbf{x}}_0^a - \bar{\mathbf{x}}_{0|-6}^b)]^T (\mathbf{e}_{t|0} + \mathbf{e}_{t|-6}), \text{ so that}\end{aligned}$$

$$\Delta \mathbf{e}^2 = [\mathbf{MK}(\mathbf{y} - H(\mathbf{x}_{0|-6}^b))]^T (\mathbf{e}_{t|0} + \mathbf{e}_{t|-6})$$

Langland and Baker (2004), Gelaro, solve this with the adjoint:

$$\Delta \mathbf{e}^2 = [(\mathbf{y} - H(\mathbf{x}_{0|-6}^b))]^T \mathbf{K}^T \mathbf{M}^T (\mathbf{e}_{t|0} + \mathbf{e}_{t|-6})$$

This requires the adjoint of the model \mathbf{M}^T and of the data assimilation system \mathbf{K}^T (Langland and Baker, 2004)

Ensemble Forecast Sensitivity to Observations

Langland and Baker (2004):

$$\begin{aligned}\Delta \mathbf{e}^2 &= \left[\mathbf{MK}(\mathbf{y} - H(\mathbf{x}_{0|-6}^b)) \right]^T (\mathbf{e}_{t|0} + \mathbf{e}_{t|-6}) \\ &= \left[(\mathbf{y} - H(\mathbf{x}_{0|-6}^b)) \right]^T \mathbf{K}^T \mathbf{M}^T (\mathbf{e}_{t|0} + \mathbf{e}_{t|-6})\end{aligned}$$

With EnKF we can use the original equation without “adjoining”:

Recall that $\mathbf{K} = \mathbf{P}^a \mathbf{H}^T \mathbf{R}^{-1} = 1 / (K - 1) \mathbf{X}^a \mathbf{X}^{aT} \mathbf{H}^T \mathbf{R}^{-1}$ so that

$$\mathbf{MK} = \mathbf{MX}^a (\mathbf{X}^{aT} \mathbf{H}^T) \mathbf{R}^{-1} / (K - 1) = \mathbf{X}_{t|0}^f \mathbf{Y}^{aT} \mathbf{R}^{-1} / (K - 1)$$

Thus,

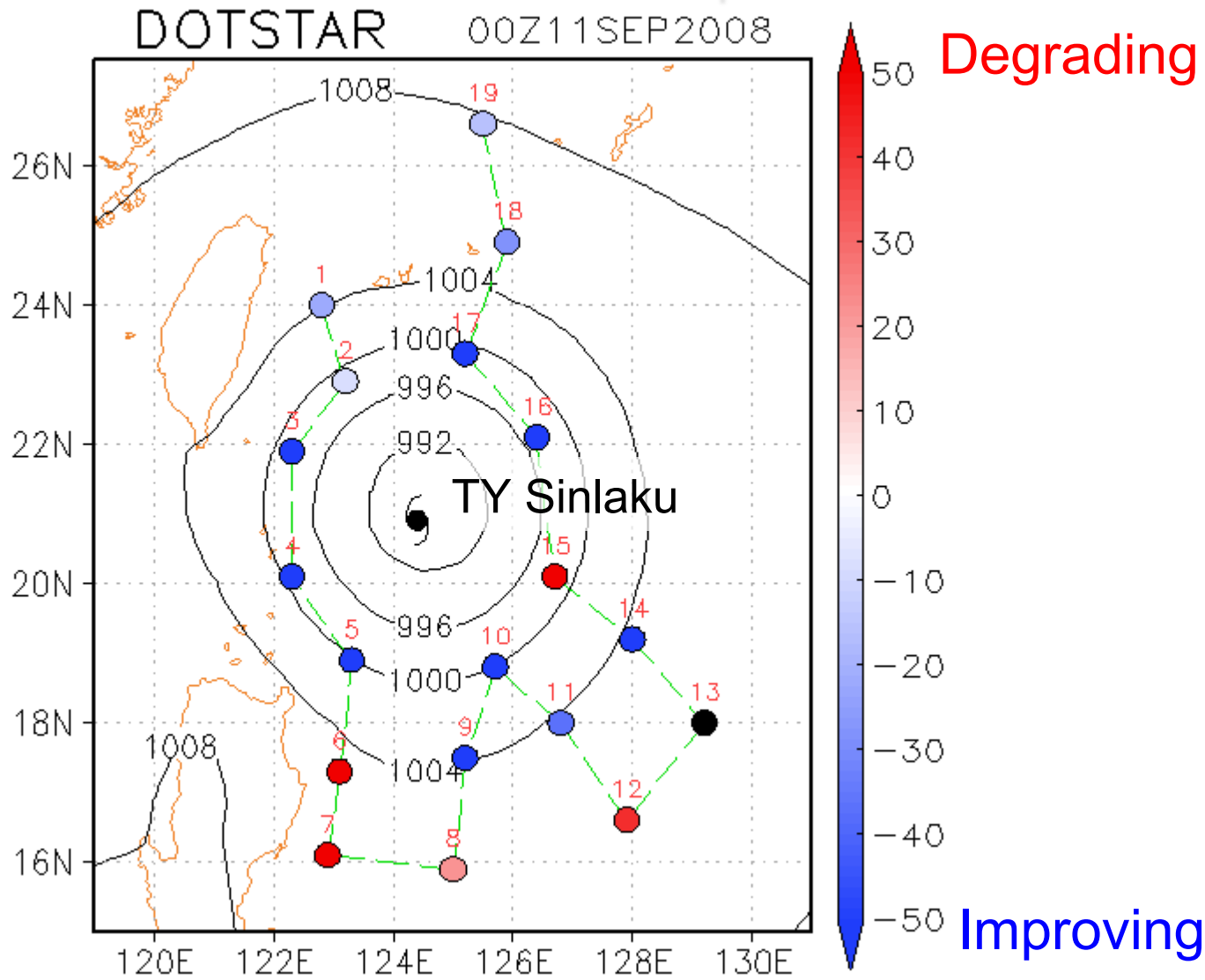
$$\begin{aligned}\Delta \mathbf{e}^2 &= \left[\mathbf{MK}(\mathbf{y} - H(\mathbf{x}_{0|-6}^b)) \right]^T (\mathbf{e}_{t|0} + \mathbf{e}_{t|-6}) \\ &= \left[(\mathbf{y} - H(\mathbf{x}_{0|-6}^b)) \right]^T \mathbf{R}^{-1} \mathbf{Y}_0^a \mathbf{X}_{t|0}^{fT} (\mathbf{e}_{t|0} + \mathbf{e}_{t|-6}) / (K - 1)\end{aligned}$$

This uses the **available nonlinear** forecast ensemble products.

Impact of dropsondes on a Typhoon

(Kunii et al. 2012)

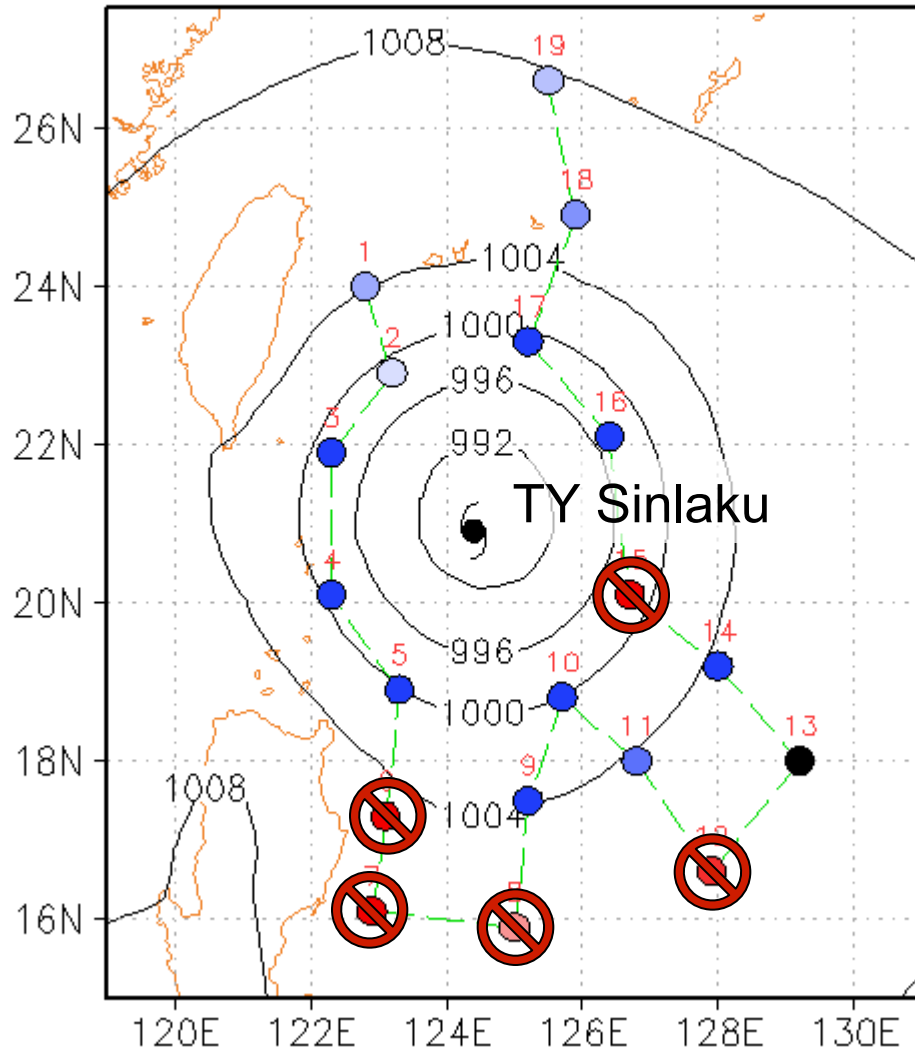
Estimated observation impact



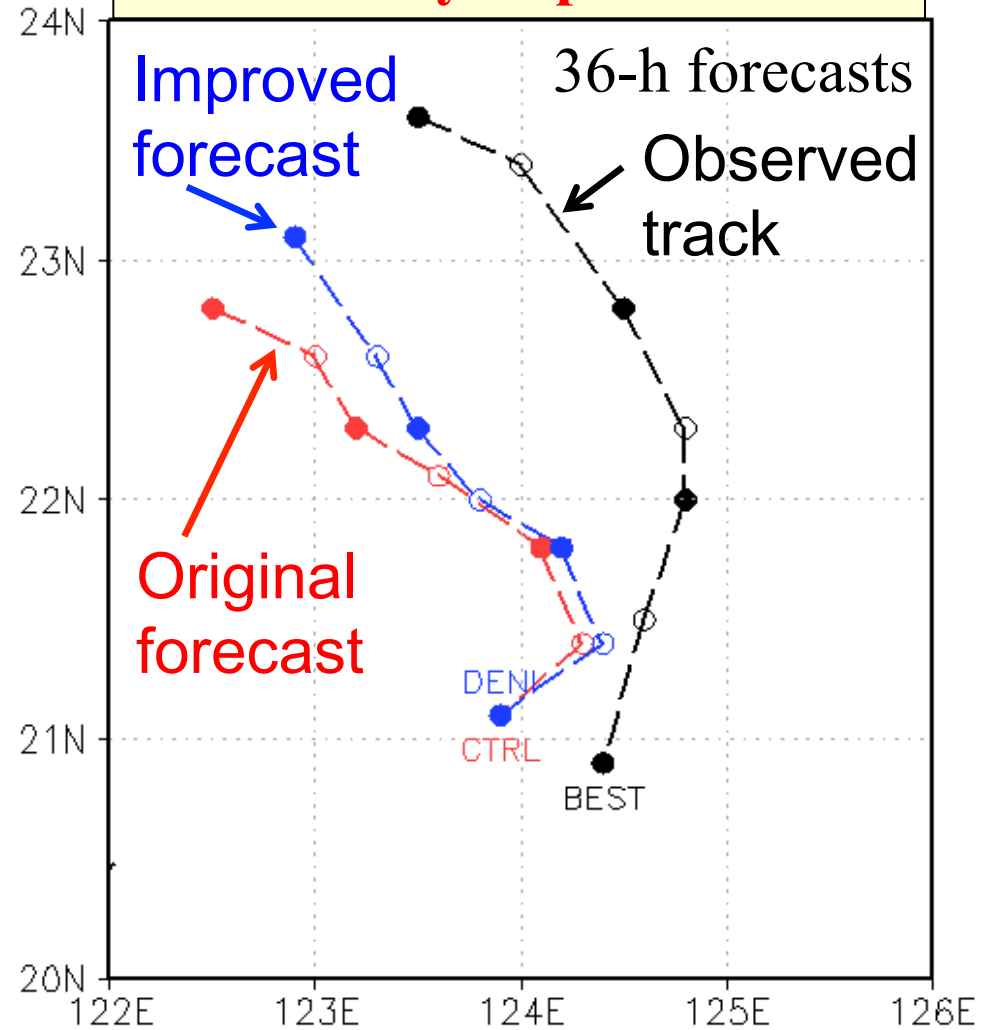
Denying negative impact data improves forecast!

Estimated observation impact

DOTSTAR 00Z11SEP2008



Typhoon track forecast is actually improved!!



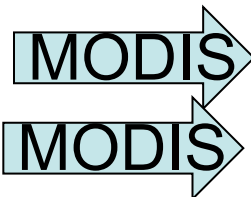
Ota et al. 2013: Applied EFSO to NCEP GFS/ EnSRF using all operational observations. **Determined regional 24hr “forecast failures”**

- Divide the globe into 30x30° regions
- Find all cases where the 24hr regional forecast error is at least 20% larger than the 36hr forecast error verifying at the same time, and
- where the 24hr forecast has errors at least twice the time average.
- Identify the top observation type that has a negative impact on the forecast.
- Found 7 cases of 24hr forecast skill dropout

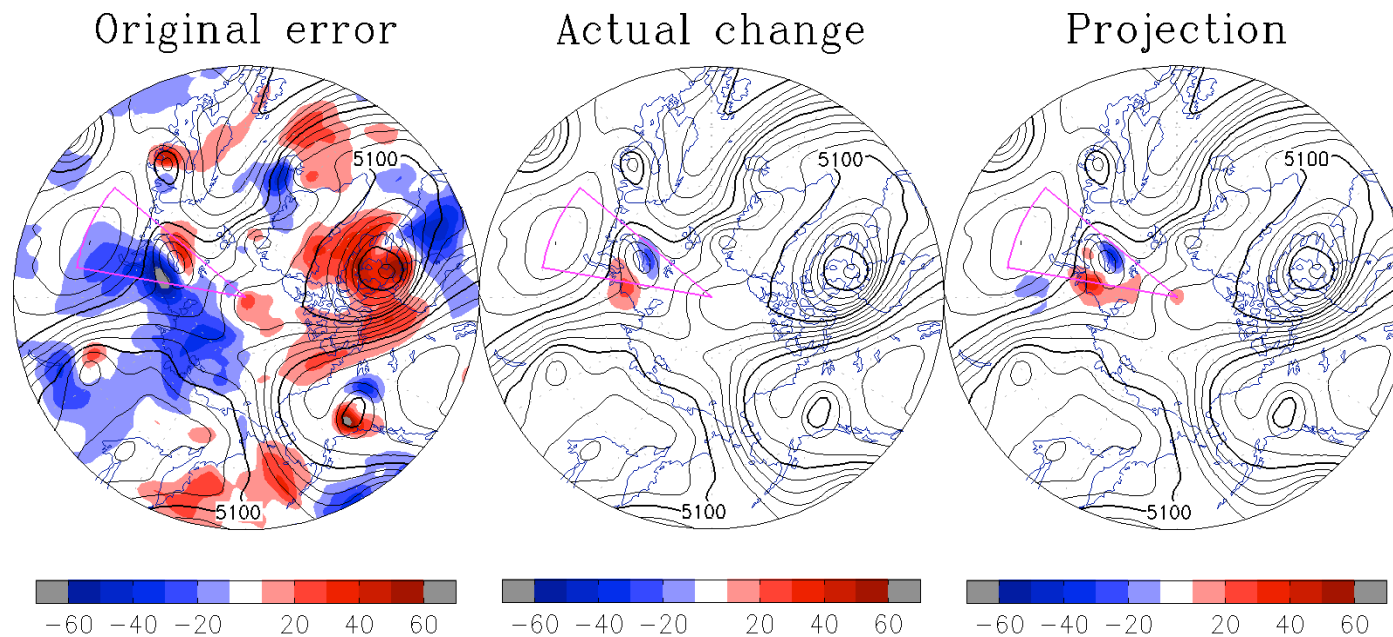
24-hr forecast error correction (Ota et al.)

- identified 7 cases of large 30°x30° regional errors,
 - rerun the forecasts denying bad obs.
 - the forecast errors were substantially reduced
- this could be applied to improve the 5-day skill dropouts

Initial	Area	Size	Rate	N	Denied observation	Change
12 UTC JAN 10	90S~60S 100E~130E	2.04	1.20	1	GPSRO (80S~60S, 90E~120E) ASCAT (60S~50S, 100E~120E)	-6.6%
06 UTC JAN 12	50N~80N 150E ~ 180	2.18	1.40	1	AMSUA (ch4: 45N~75N, 160E~170W, ch5:40N~55N, 155E~180, NOAA15 ch6: 50N~75N, 140E~170W, ch7: 70N~80N, 130E~170E)	-11.4%
00 UTC JAN 16	30N~60N 30W~0	2.13	1.31	2	Radiosonde wind (Valentia, Ireland), ASCAT (40N~47N, 20W~10W, 50N~55N, 35W~30W)	-1.0%
12 UTC JAN 22	90S~60S 130E~160E	2.34	1.22	2	AMSUA (ch5: 65S~50S, 90E~110E, 60S~50S, 120E~127E, ch6: 60S~45S, 110E~125E)	-2.2%
06 UTC FEB 2	50N~80N 150W~120W	3.10	1.32	4	IASI (35N~45N, 155W~150W) NEXRAD (55N~60N, 160W~135W)	-5.5%
18 UTC FEB 6	60N~90N 50E~80E	2.06	1.71	2	MODIS_Wind (60N~90N, 30E~90E)	-39.0%
18 UTC FEB 6	90S~60S 20W~10E	3.56	1.22	1	MODIS_Wind (80S~50S, 30W~0)	-22.5%

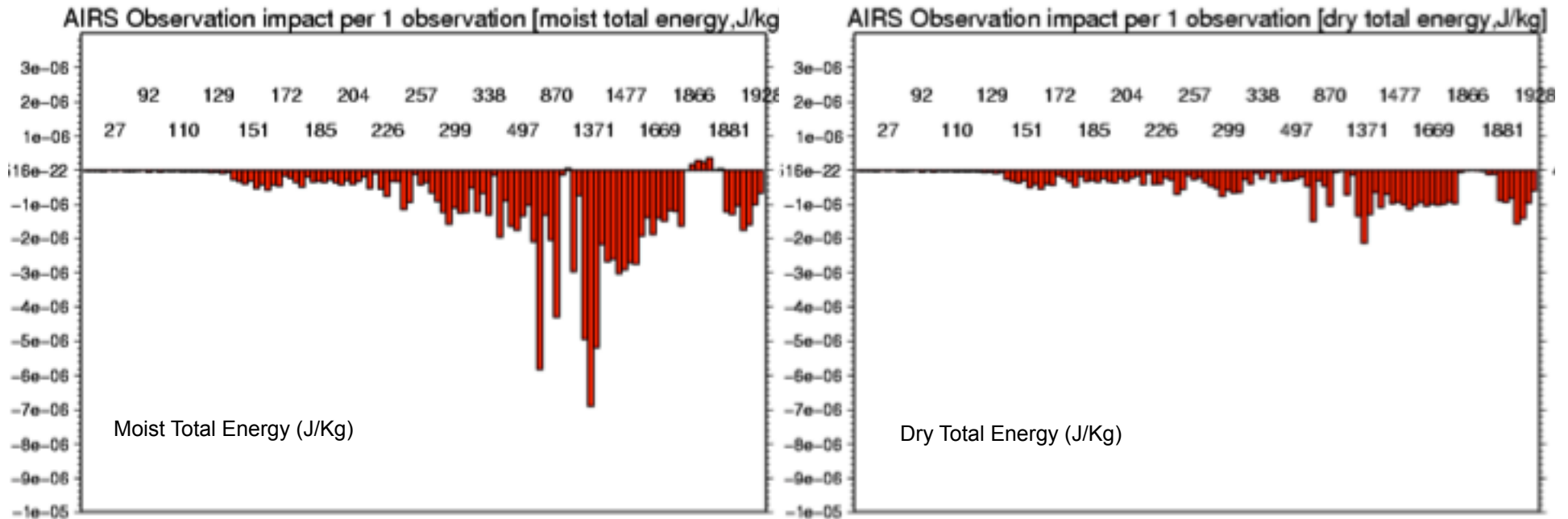


“Proactive” QC: Bad observations can be identified by EFSO and withdrawn from the data assimilation



After identifying MODIS polar winds producing bad 24 hr regional forecasts, the withdrawal of these winds reduced the forecast errors by 39%, as projected by EFSO.

Other applications: Impacts of Observing Systems



The EnKF formulation is nonlinear and thus allows computing Moist Total Energy and estimate more accurately the impact of the channels on the moisture forecast. Adjoint formulation needs TLM.

Promising new tools for the LETKF(4, 5)

4. Estimation of surface fluxes as evolving parameters

(Kang et al., 2011, 2012)

- **Kang's talk tomorrow**

5. Application of ensemble forecast sensitivity to data assimilation (Shu-Chih Yang, E. Kalnay, thanks to T. Enomoto)

- **New!!!**
- Very promising!!

Ensemble Sensitivity: Application to Data Assimilation and the Spin-up Problem

Assume we are in a window of the LETKF with an ensemble of K members

$$\mathbf{x}_{i,t}^b = M(\mathbf{x}_{i,t-1}^a)$$

Since the window is short,

$$\delta \mathbf{x}_{i,t}^b = \mathbf{x}_{i,t}^b - \bar{\mathbf{x}}_t^b \approx \mathbf{M}(\delta \mathbf{x}_{i,t-1}^a)$$

Define the vectors of analysis and forecast perturbations:

$$\mathbf{X}_{t-1}^a = [\delta \mathbf{x}_{1,t-1}^a, \dots, \delta \mathbf{x}_{K,t-1}^a]; \quad \mathbf{X}_t^b = [\delta \mathbf{x}_{1,t}^b, \dots, \delta \mathbf{x}_{K,t}^b]$$

We want to find the linear combination of analysis perturbations that will grow fastest:

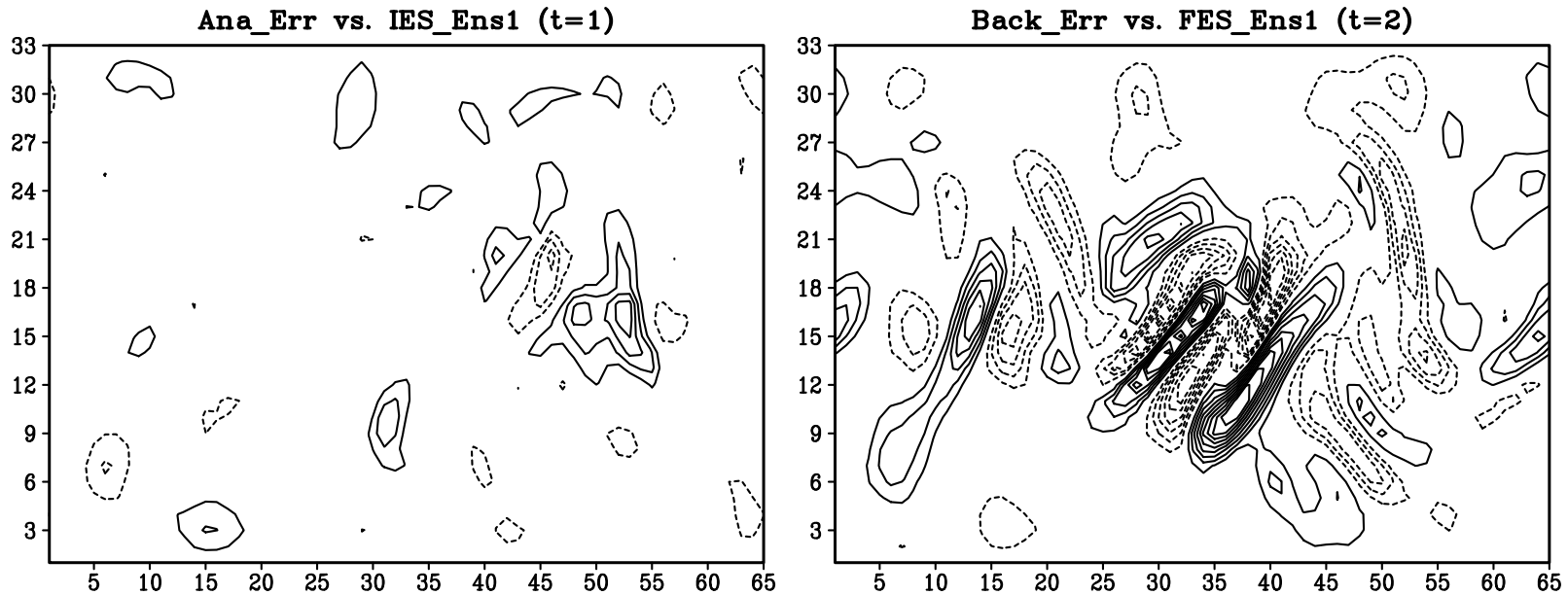
$$\delta \mathbf{x}_{t-1}^a = \mathbf{X}_{t-1}^a \mathbf{p}; \quad \delta \mathbf{x}_t^b = \mathbf{X}_t^b \mathbf{p}$$

with optimal coefficients $\mathbf{p} = [p_{t,1}, \dots, p_{t,K}]$

We can use the equation in Enomoto et al (2007) (see derivation in Yang and Kalnay, 2013):

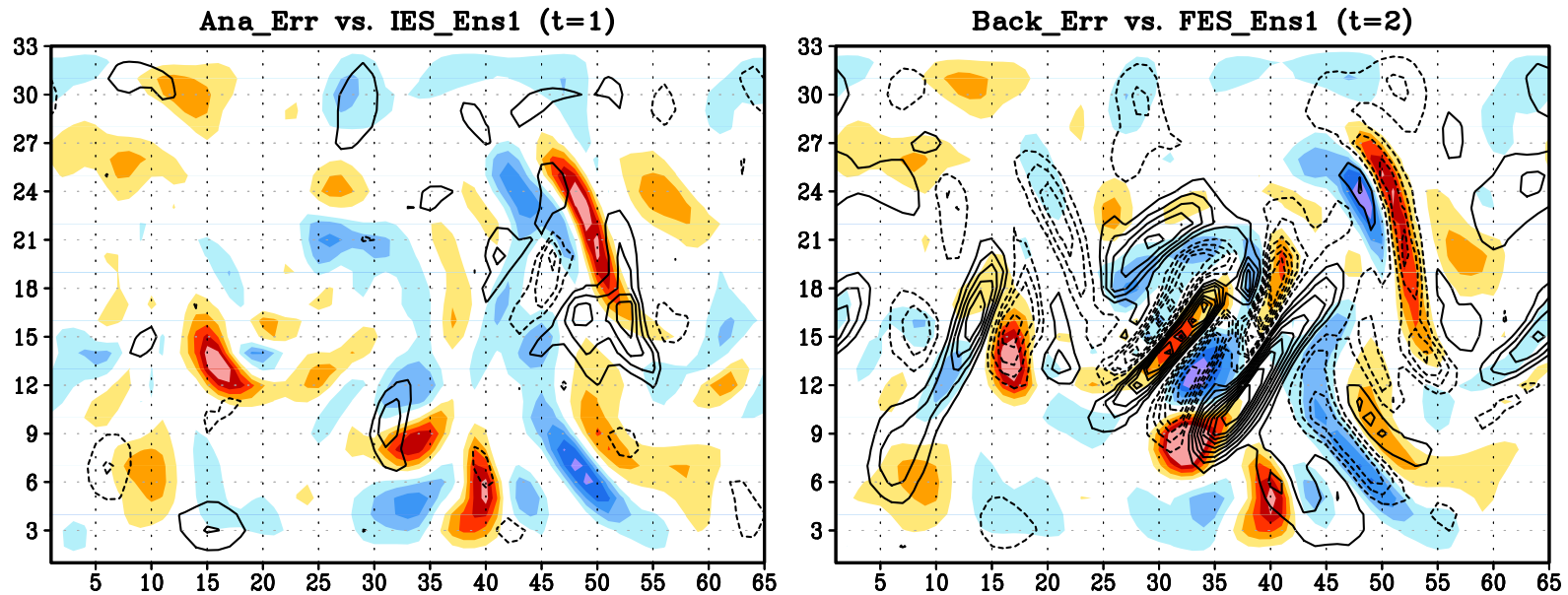
$$(\mathbf{X}_{t-1}^{aT} \mathbf{C}_I \mathbf{X}_{t-1}^{aT})^{-1} (\mathbf{X}_t^{bT} \mathbf{C}_F \mathbf{X}_t^{bT}) \mathbf{p} = \lambda \mathbf{p}$$

We tested this with a QG model starting with a random ensemble that satisfies the B_{3D-Var} .
The initial optimal perturbation after 6hr grows into a final perturbation after 12 hrs:



Is this fast growing perturbation related to the background errors?

We tested this with a QG model starting with a random ensemble that satisfies the B_{3D-Var} .
The initial optimal perturbation after 6hr grows into a final perturbation after 12 hrs:



Is this fast growing perturbation related to the background errors?

YES!!!

Summary and the future

- RIP can extract more information from observations and accelerate spin-up. Examples: Typhoon Sinlaku and Ocean.
- EnKF can be used to assimilate and remember precipitation information, using a Gaussian Transform and other ideas.
- The Ensemble Forecast Sensitivity to Observations can be used to detect observations that give bad *regional* 6, 12 or 24hr forecasts. This allows repeating analysis without bad observations: “proactive QC” and monitoring.
- We can estimate surface fluxes of carbon, heat and moisture with the LETKF as evolving parameters.
- Ensemble Sensitivity can be used to improve the LETKF spinup.
- **EnKF is a newer, simpler, powerful technology.**
- **More potential not yet exploited:**
 - **Estimation and correction of model errors and parameters (Ruiz et al, Danforth et al, Kang et al)...**

Comparison of 4D-Var and EnKF

Bold is the best option

Characteristics of DA system	4D-Var	EnKF
Scalable?	No	Yes
Needs TLM and Adjoint of Model	Yes	No
Needs TLM and Adjoint of Obs. Operator	Yes	No
Full rank B	Yes	No
Flow dependent B	No	Yes
Optimal Assimilation Window	Long	Short