Data Assimilation Studies on Typhoon Sinlaku (2008) using the WRF-LETKF system

Takemasa Miyoshi and Masaru Kunii

University of Maryland, College Park

miyoshi@atmos.umd.edu

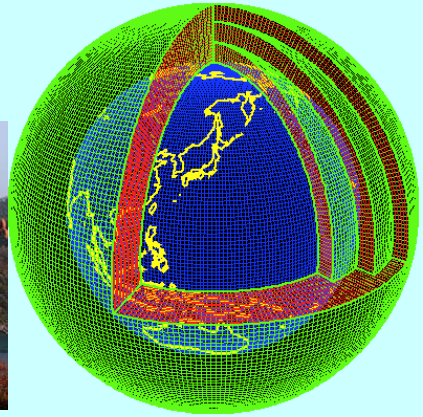
With many thanks to
E. Kalnay, K. Ide, B. Hunt, UMD Weather-Chaos group,
C. Bishop, P. Black (NRL), S.-C. Yang (Taiwan), and H. Li (China)

Data Assimilation (DA)

Observations

Data Assimilation

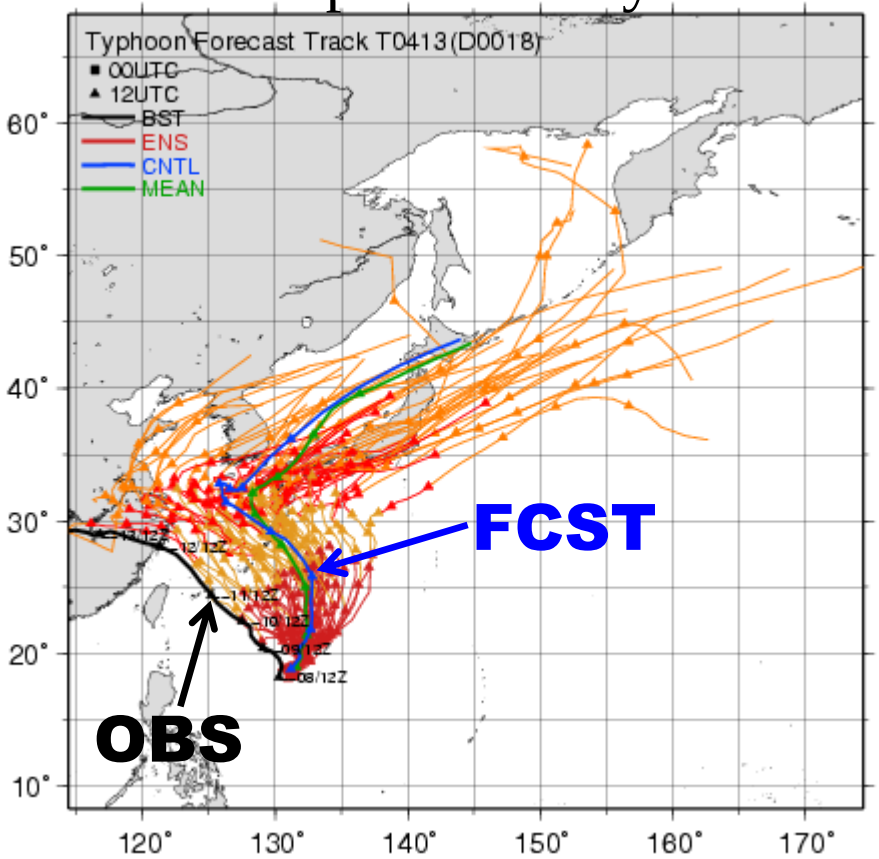
Numerical models



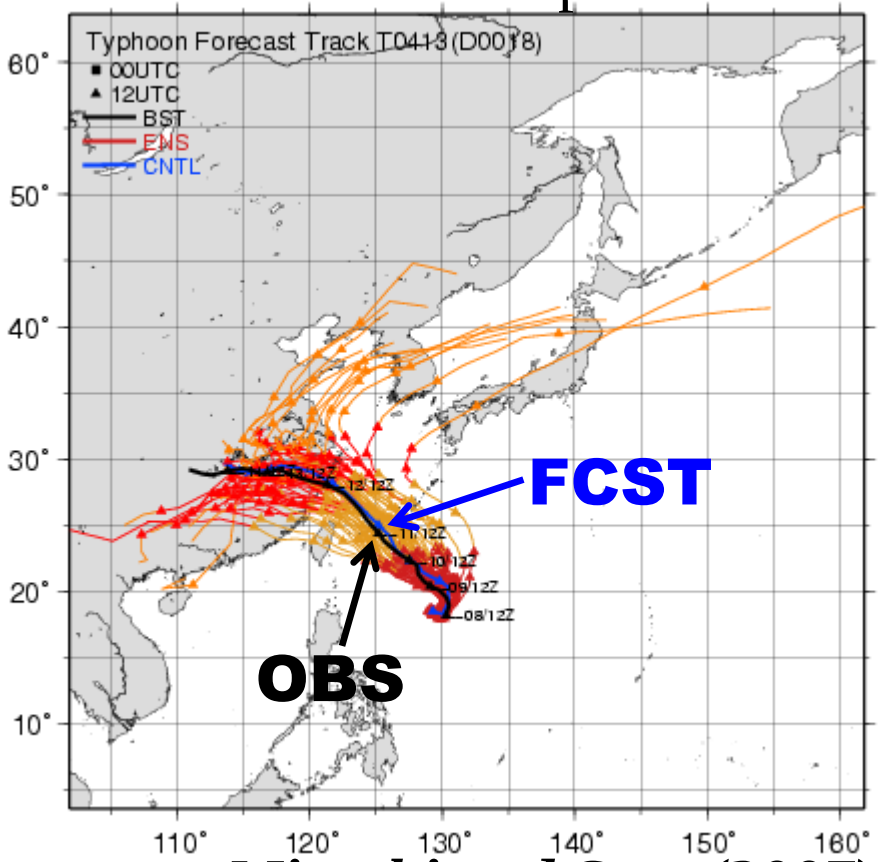
Data assimilation best combines observations and a model, and brings synergy.

DA has an impact.

SV w/ 4D-Var
JMA operational system



LETKF
under development



Miyoshi and Sato (2007)

Using the same NWP model and observations.
DA matters!

My approach

- *Local Ensemble Transform Kalman Filter* (LETKF, Hunt et al. 2007)
- *Application to various systems*

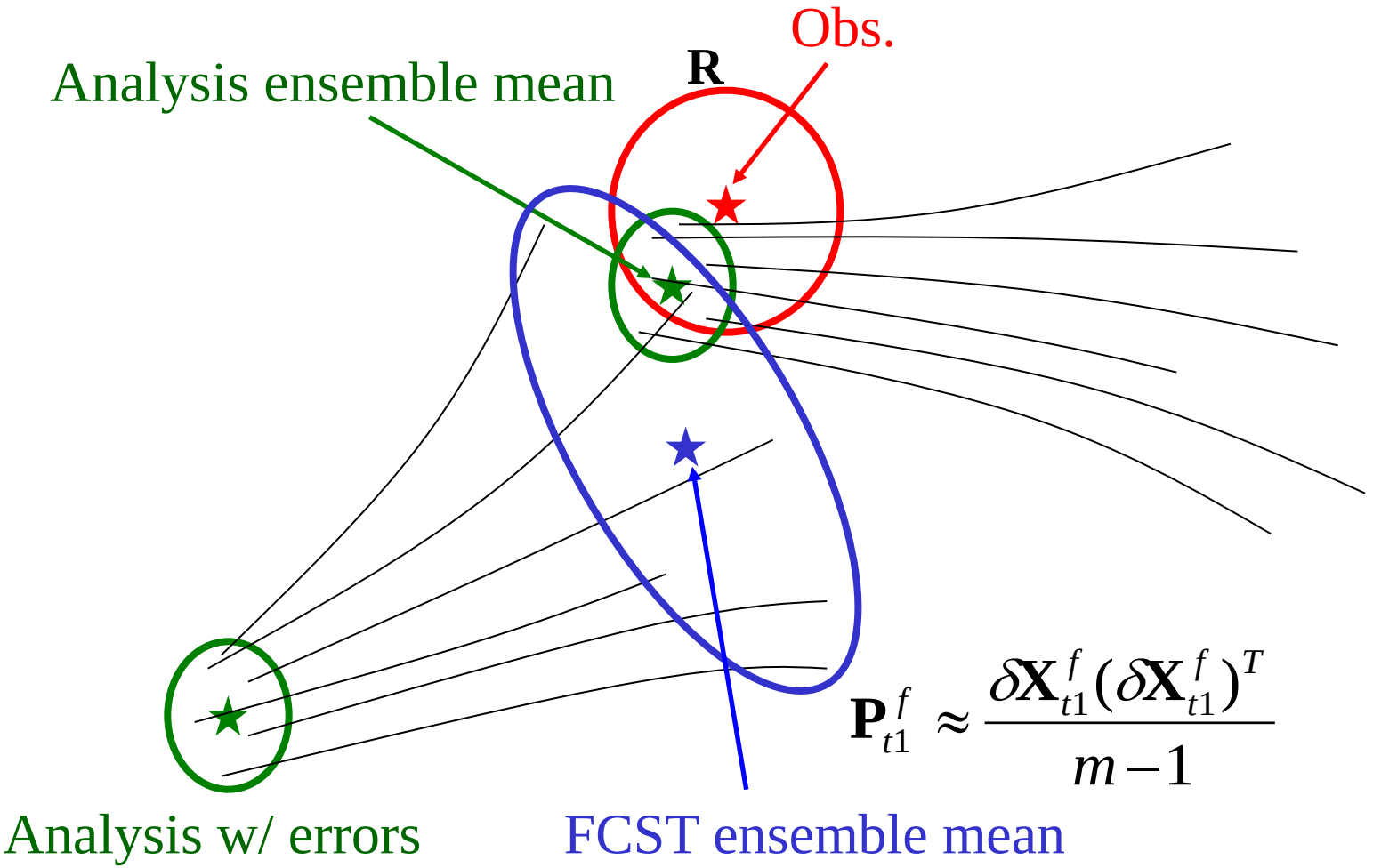
1 Toy models (e.g., Lorenz model)

2 Intermediate AGCM (SPEEDY model, Molteni 2003)

3 Real systems (e.g., operational models)

- *New ideas for improvements*
  - Examples:
    - Satellite bias correction (Miyoshi et al. 2010, Whitaker and Miyoshi 2011)
    - Adaptive Inflation (Miyoshi 2011)
    - Ensemble Sensitivity (Liu and Kalnay 2008, Liu et al. 2009)

Ensemble Kalman Filter (EnKF)



$$\mathbf{P}_{t1}^{f} \approx \frac{\delta\mathbf{X}_{t1}^{f}(\delta\mathbf{X}_{t1}^{f})^{T}}{m-1}$$

LETKF (Local Ensemble Transform Kalman Filter)

Analysis is given by a linear combination of forecast ensemble:

$$\mathbf{X}^a = \overline{\mathbf{x}}^f + \delta\mathbf{X}^f \mathbf{T}$$

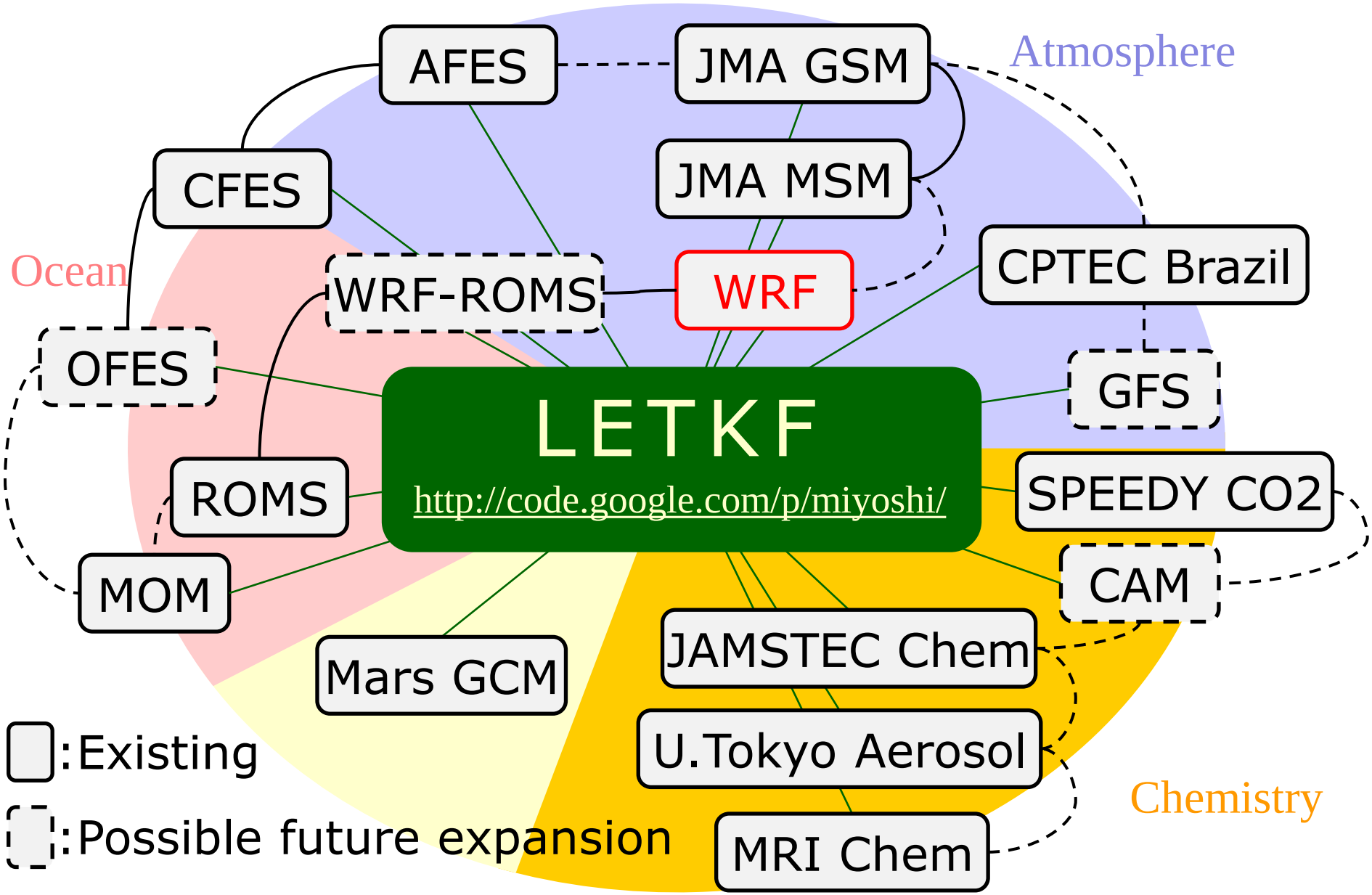
Ensemble Transform Matrix
(ETKF, Bishop et al. 2001; LETKF, Hunt et al. 2007)

$$\mathbf{T} = \underbrace{\tilde{\mathbf{P}}^a (\delta\mathbf{Y})^T \mathbf{R}^{-1} (\mathbf{y}^o - \overline{H(\mathbf{x}^f)})}_{\text{ensemble mean update}} + \underbrace{[(m-1)\tilde{\mathbf{P}}^a]^{1/2}}_{\text{uncertainty update}}$$

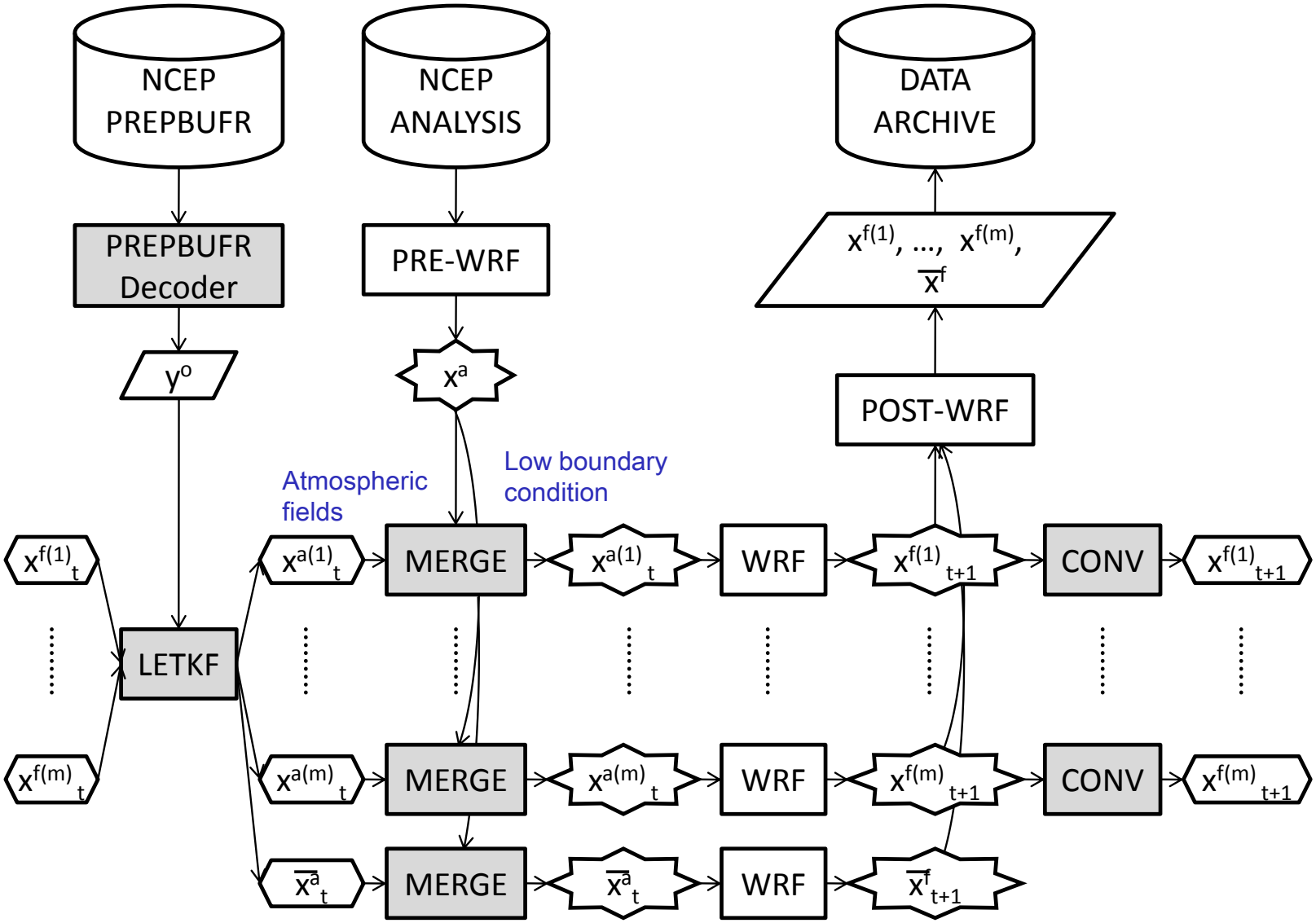
$$\tilde{\mathbf{P}}^a = [(m-1)\mathbf{I}/\rho + (\delta\mathbf{Y})^T \mathbf{R}^{-1} \delta\mathbf{Y}]^{-1}$$

Analysis error covariance in the ensemble subspace

LETKF applications



WRF-LETKF flowchart



Experimental settings

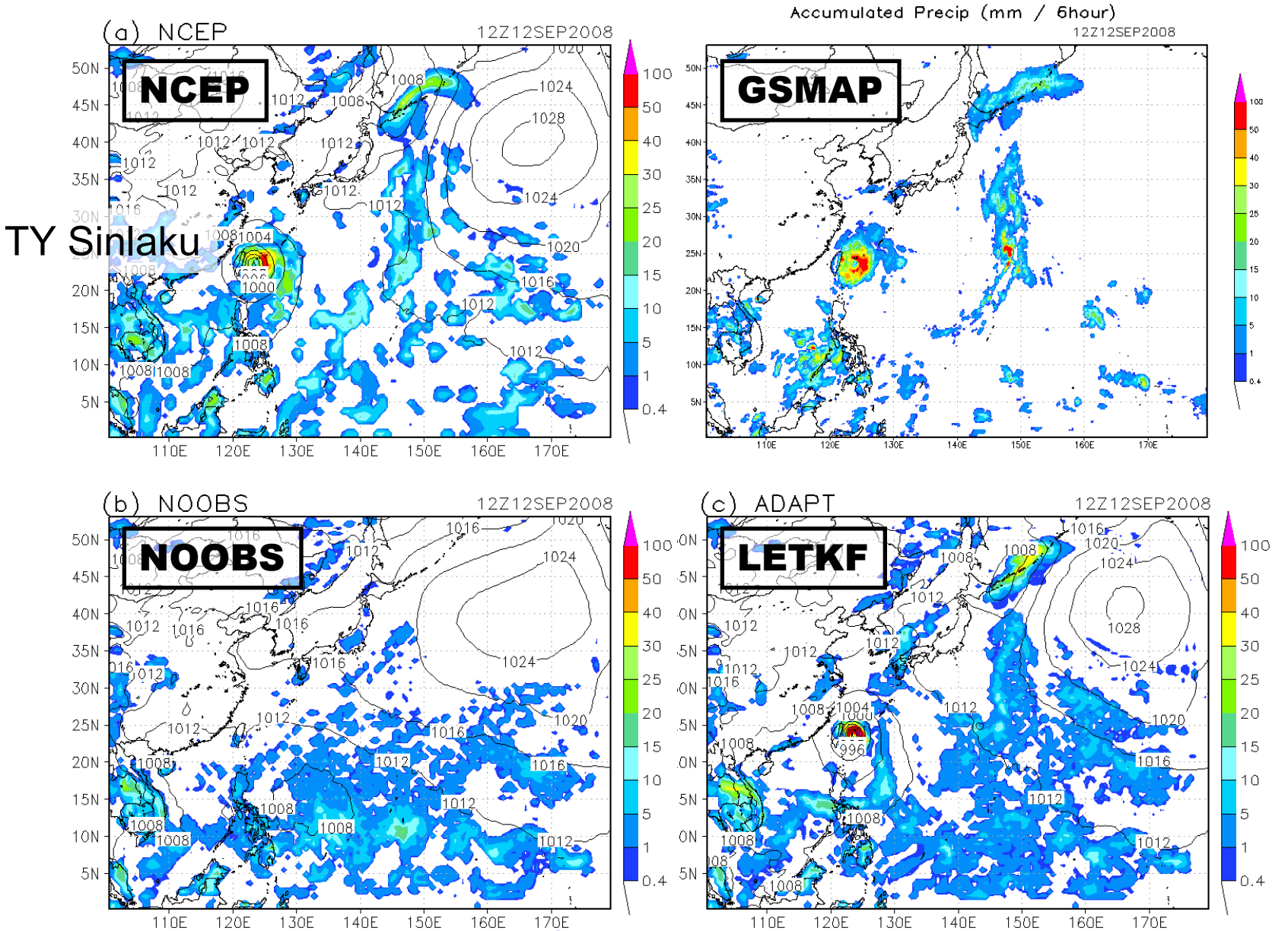
- *LETKF settings*

Ensemble size	20
Lateral boundary conditions	Unperturbed
Covariance inflation	Adaptive (Miyoshi 2010) Fixed 20% (smaller above level 20)
Covariance localization	400 km, 0.4 ln p
Analyzed variables	u, v, w, T, ph, qv, qc, qr

- *WRF settings*

Domain size	136(137) x 108(109) x 39(40)
Horizontal grid spacing	~ 60 km
WRF version	WRF-ARW 3.2

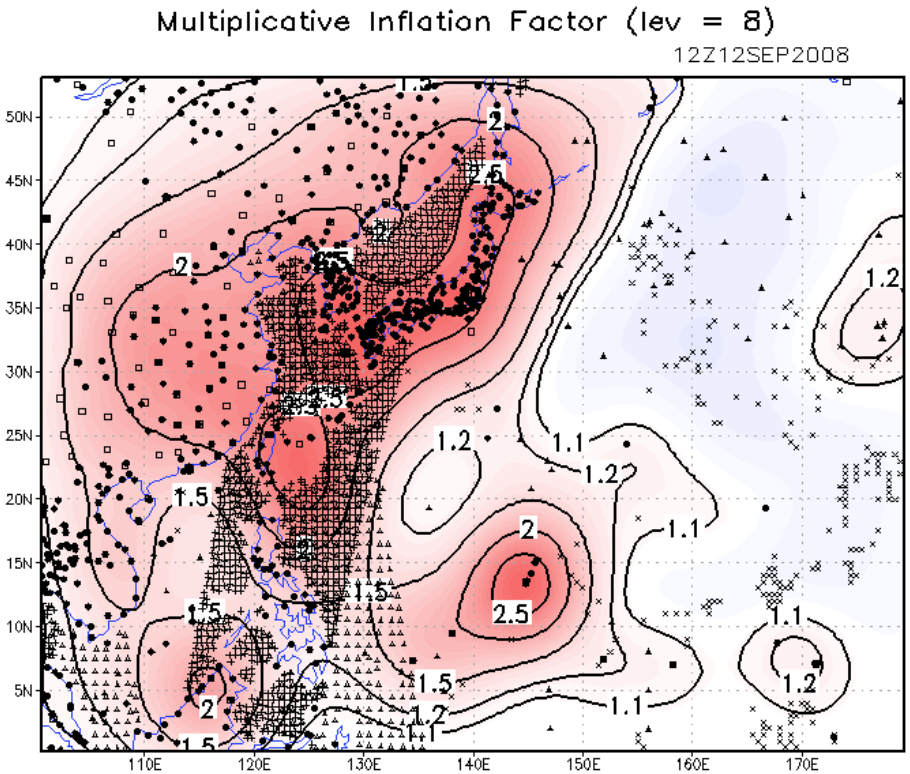
6-hr Forecast at 12Z 12 Sep. 2008



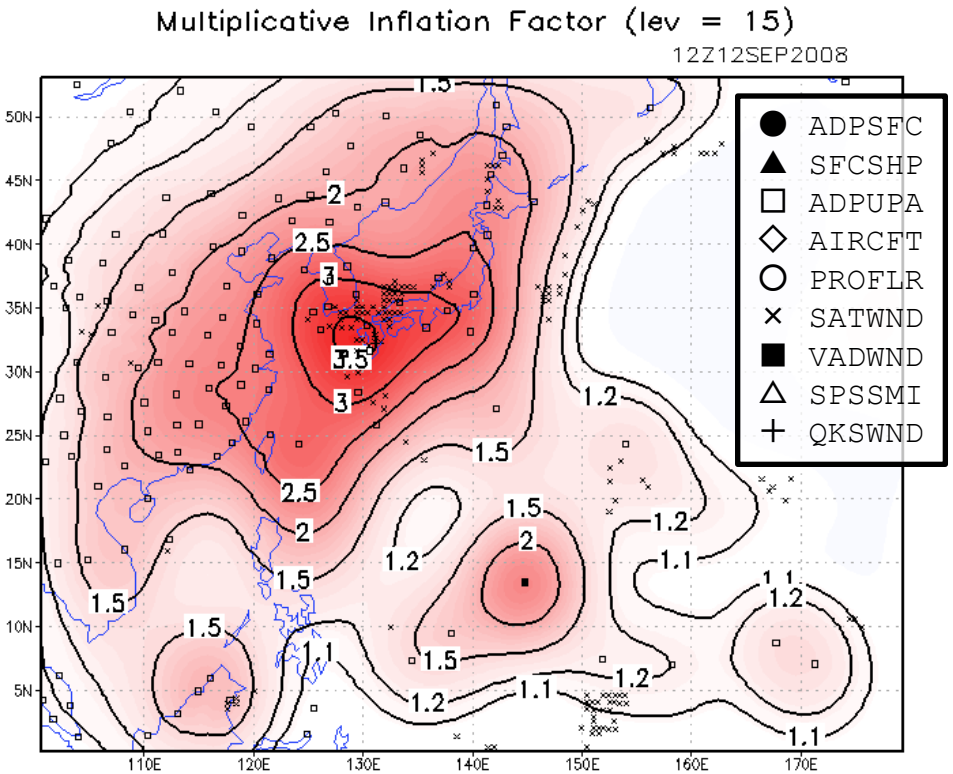
after 9 days cycle

Adaptive inflation

Lower troposphere



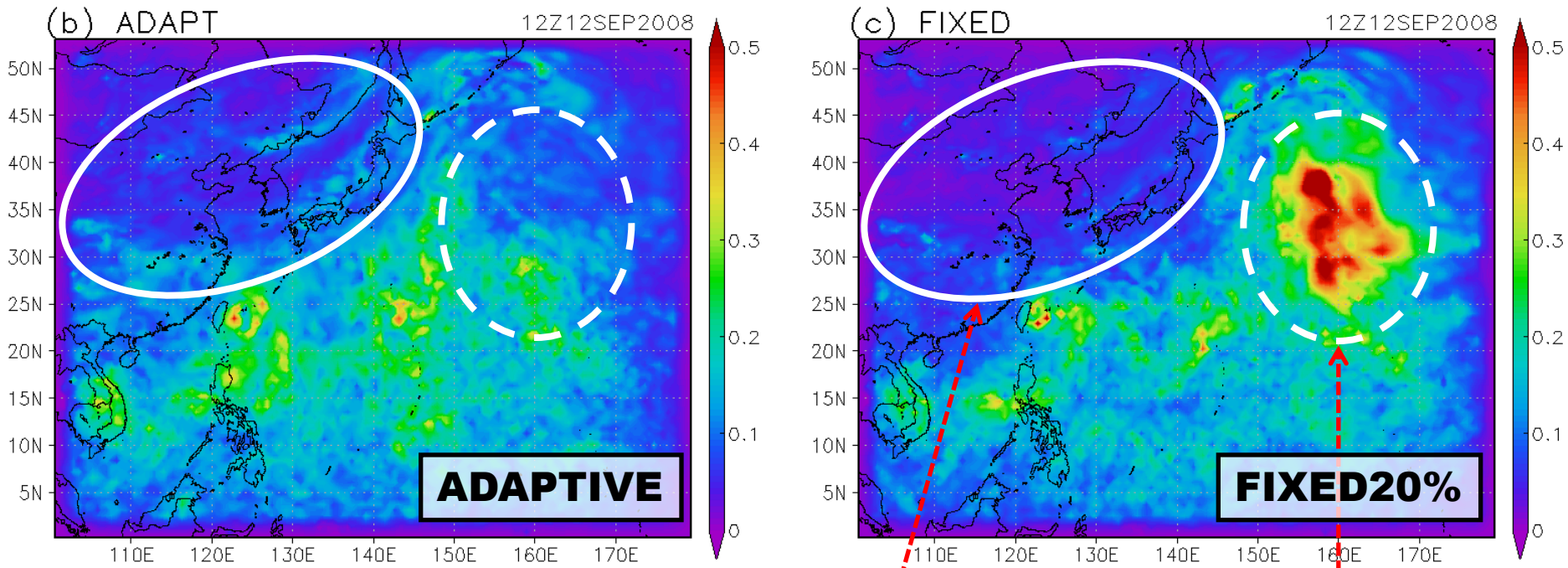
Middle troposphere



- Adaptive inflation accounts for imperfections such as model errors and limited ensemble size.
- Large adaptive inflation > 100 % (2.0) appears occasionally and is appropriate in limited regions.

Miyoshi and Kunii (2011)

Ensemble spread (T500)



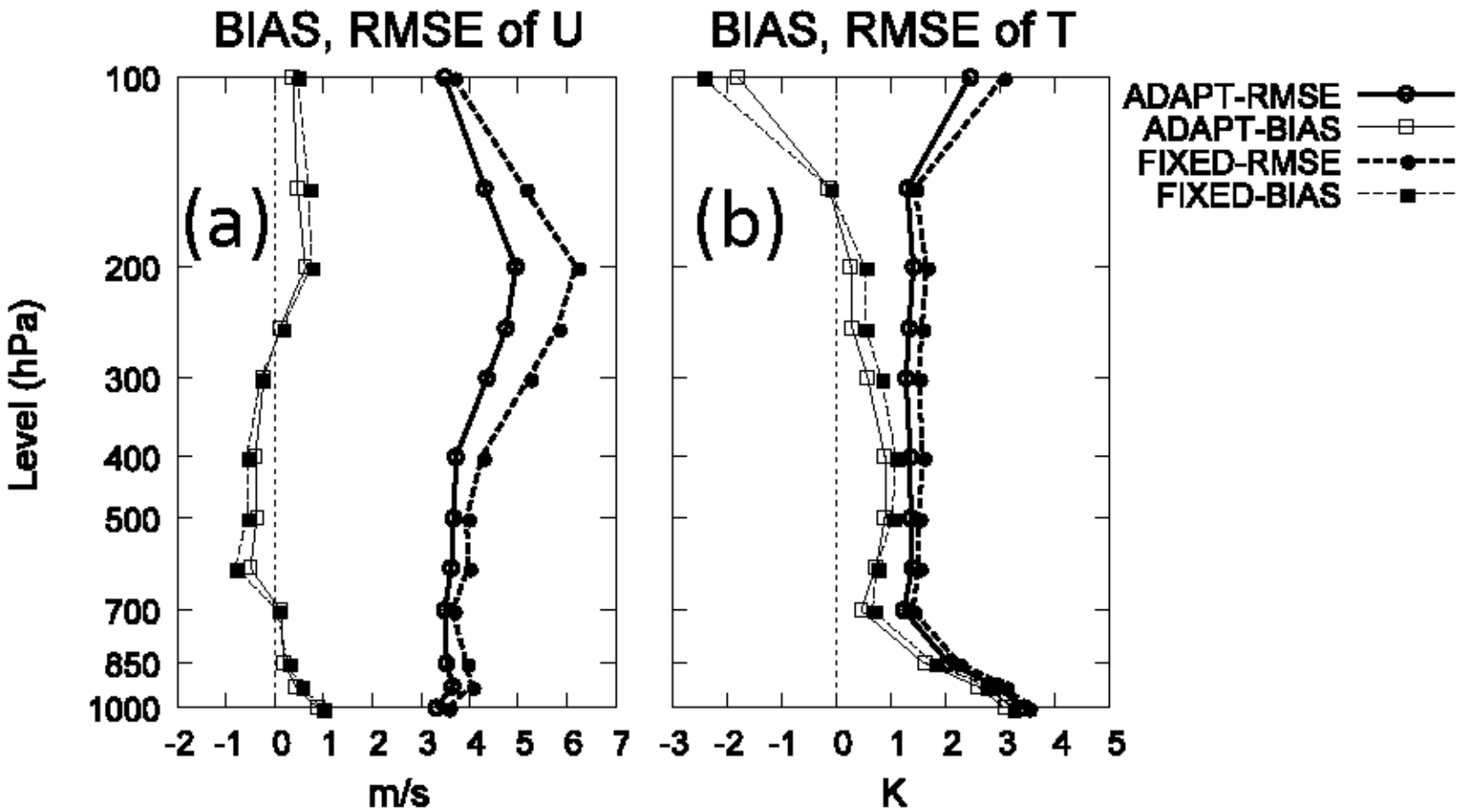
Adaptive inflation improves the ensemble spread.

under-dispersive with dense obs

over-dispersive with sparse obs

Miyoshi and Kunii (2011)

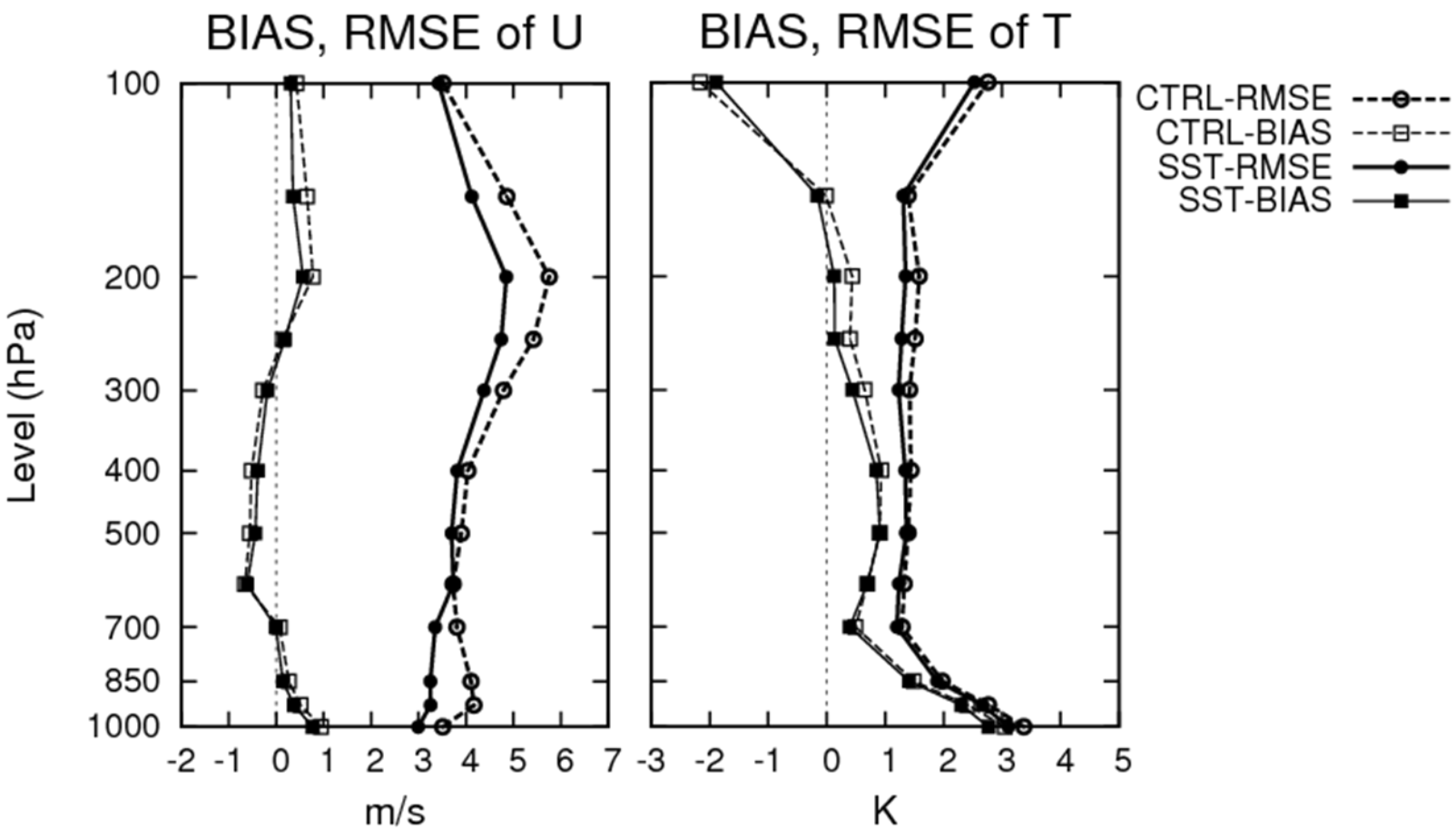
6-hr forecast vs. radiosondes



Adaptive inflation reduces the RMSE and BIAS consistently.

Miyoshi and Kunii (2011)

Impact of SST perturbations



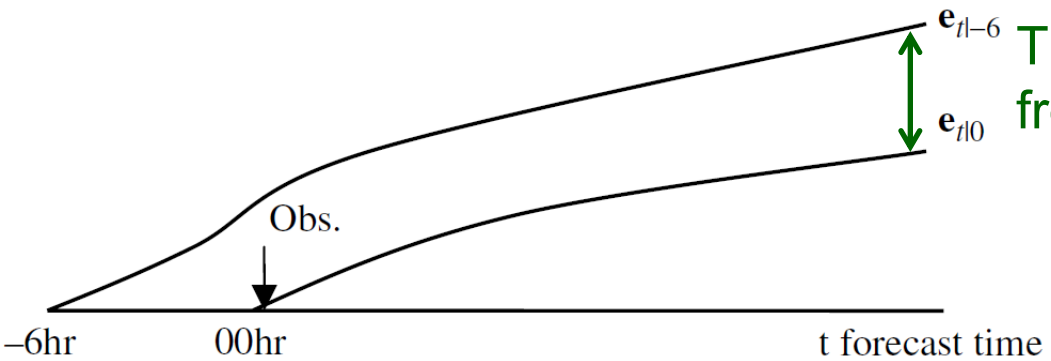
SST perturbations reduce the RMSE and BIAS consistently.

ENSEMBLE SENSITIVITY

– estimating impact of observations –

Ensemble sensitivity

- **Observation impact** is calculated without an adjoint model. *(Liu and Kalnay 2008)*



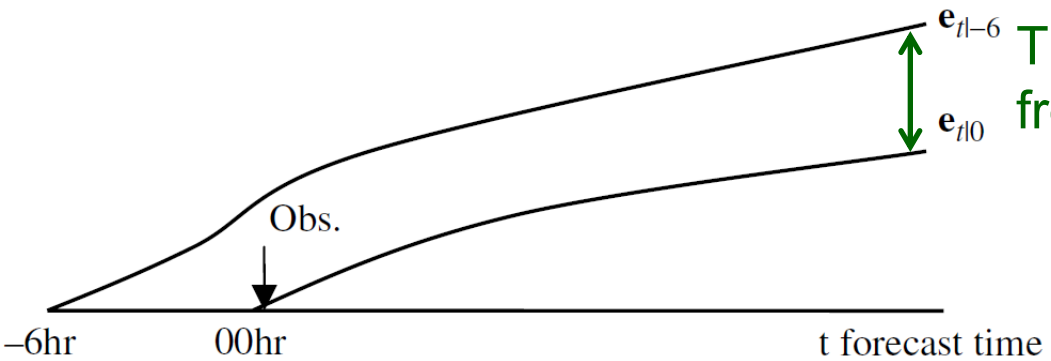
This difference comes from obs at 00hr

$$J = \frac{1}{2}\left(\mathbf{e}_{t|0}^{\mathrm{T}}\mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^{\mathrm{T}}\mathbf{e}_{t|-6}\right)$$

$$\cong \left[\mathbf{e}_{t|-6} + \frac{1}{2}\mathbf{X}_{t|-6}^{\mathrm{f}}\widetilde{\mathbf{K}}_0\mathbf{v}_0\right]^{\mathrm{T}}\mathbf{X}_{t|-6}^{\mathrm{f}}\widetilde{\mathbf{K}}_0\mathbf{v}_0$$

Ensemble sensitivity

- **Observation impact** is calculated without an adjoint model. *(Liu and Kalnay 2008)*



This difference comes from obs at 00hr

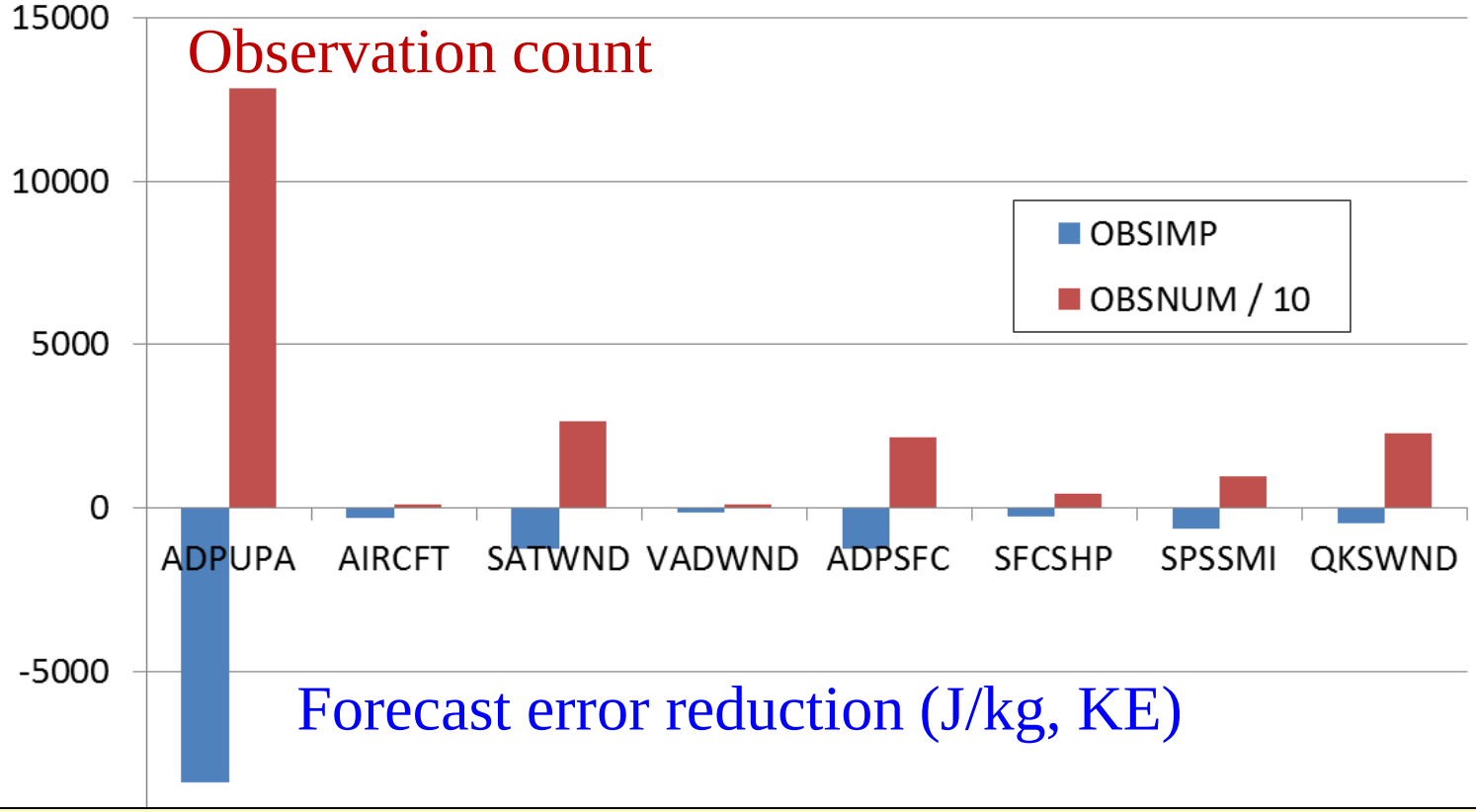
$$J = \frac{1}{2}\left(\mathbf{e}_{t|0}^{\mathrm{T}}\mathbf{e}_{t|0} - \mathbf{e}_{t|-6}^{\mathrm{T}}\mathbf{e}_{t|-6}\right)$$

$$\cong \left[\mathbf{e}_{t|-6} + \frac{1}{2}\mathbf{X}_{t|-6}^{\mathrm{f}}\widetilde{\mathbf{K}}_0\mathbf{v}_0\right]^{\mathrm{T}}\mathbf{X}_{t|-6}^{\mathrm{f}}\widetilde{\mathbf{K}}_0\mathbf{v}_0$$

- We applied the above method to real observations **for the first time!** *(Kunii, Miyoshi, and Kalnay 2011)*

Observation impact for each type

Observation impact for each observation type
(except for satellite radiances)
(9/8 12 UTC – 9/12 12UTC, NW Pacific)

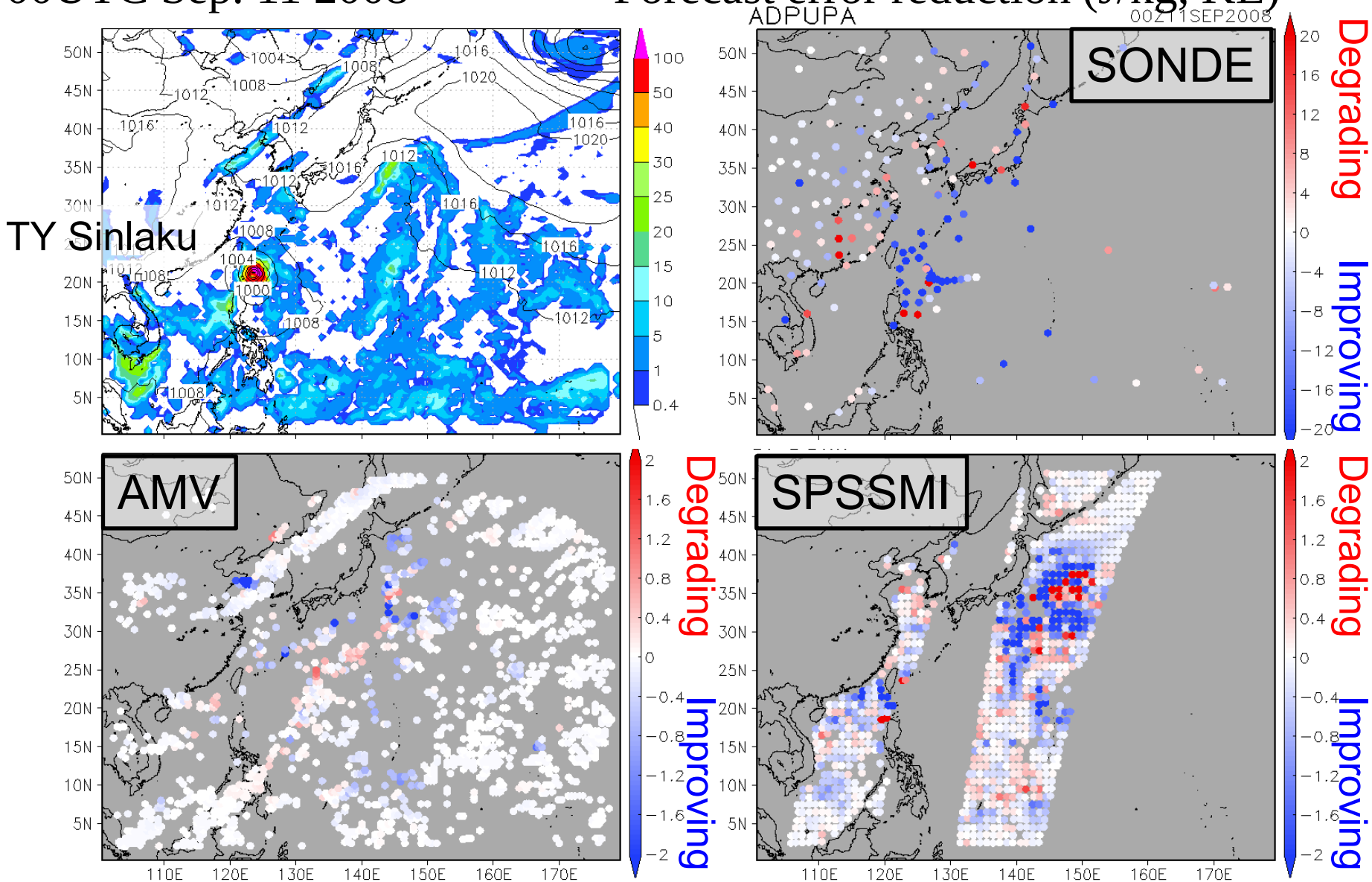


All types of observations reduce the forecast error.
Upper soundings (ADPUPA) have the largest impact.

Impact of each observation

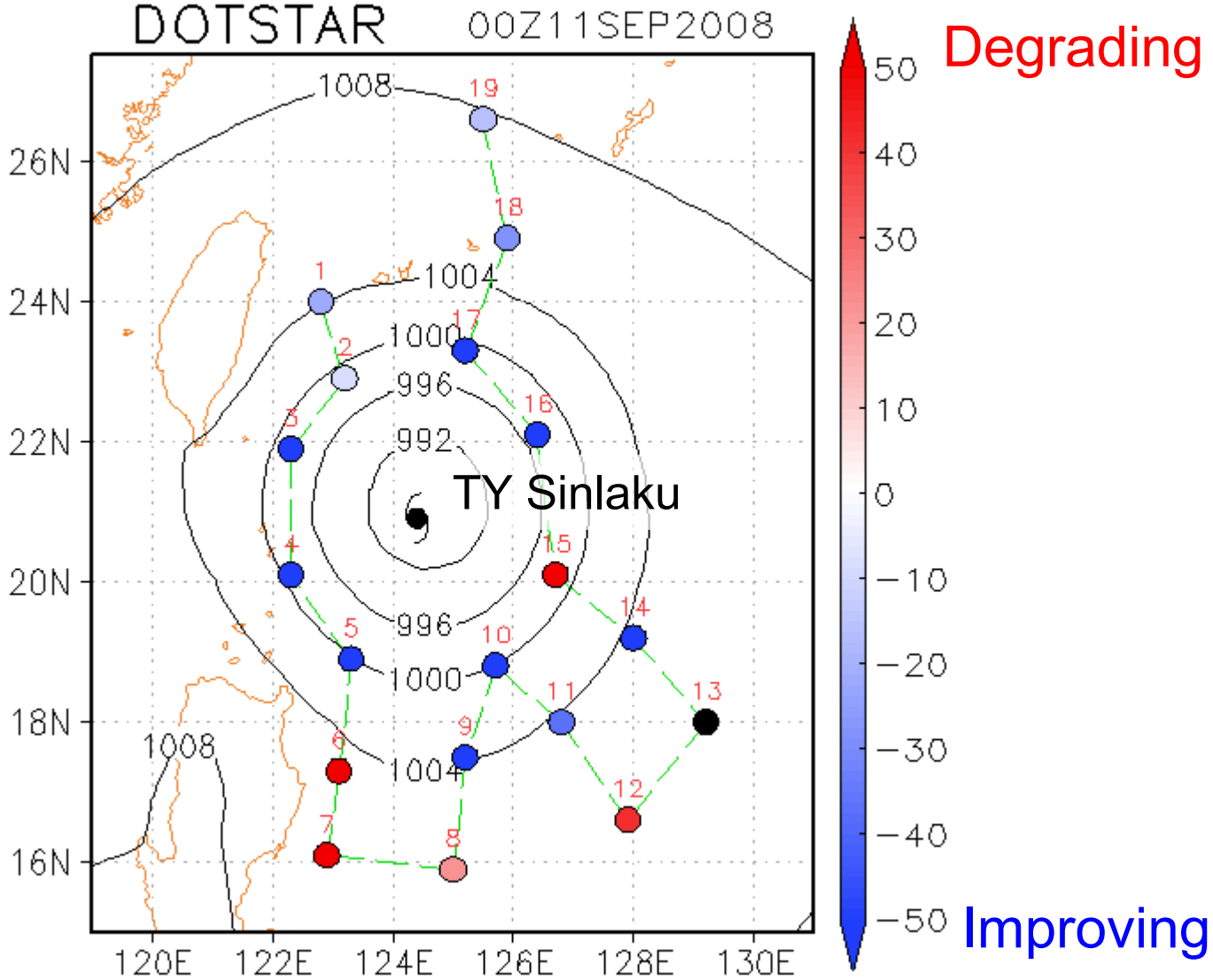
00UTC Sep. 11 2008

Forecast error reduction (J/kg, KE)



Impact of dropsondes on a Typhoon

Estimated observation impact

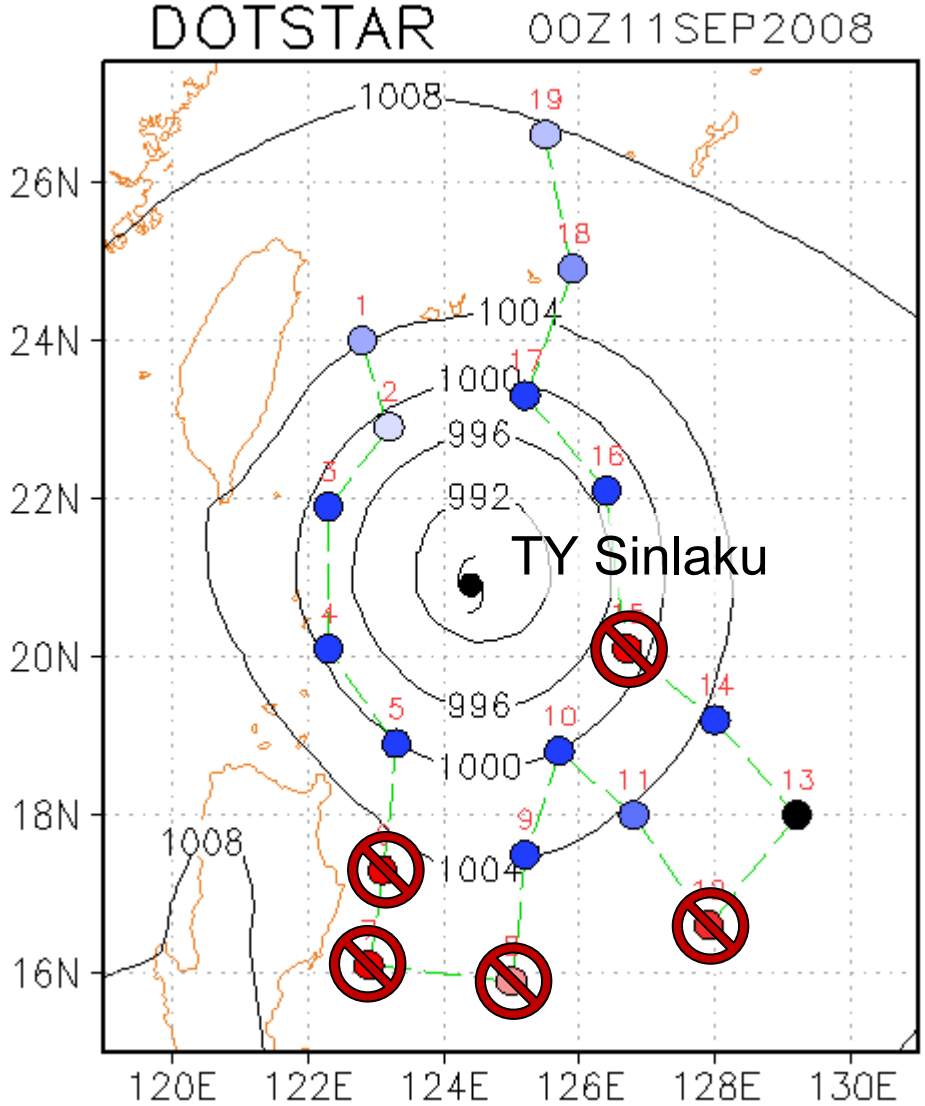


Degrading

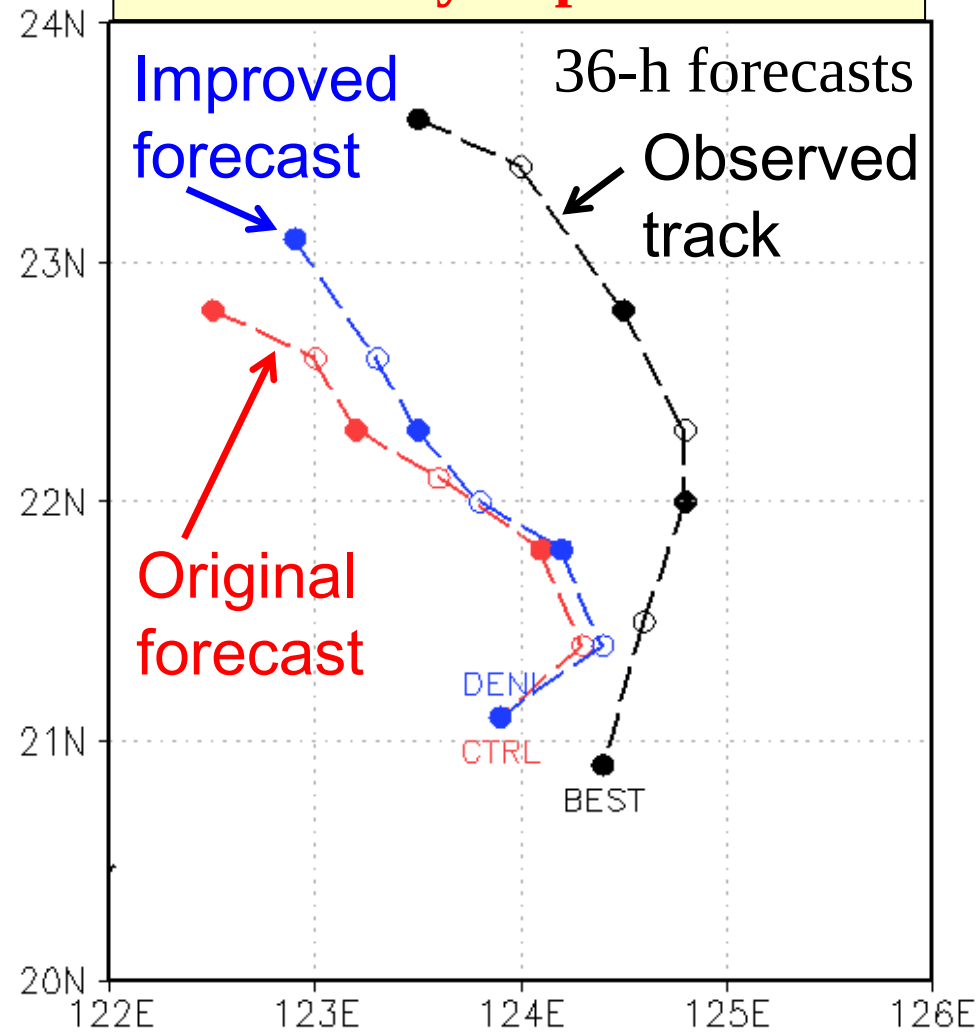
Improving

Denying negative impact data improves forecast!

Estimated observation impact

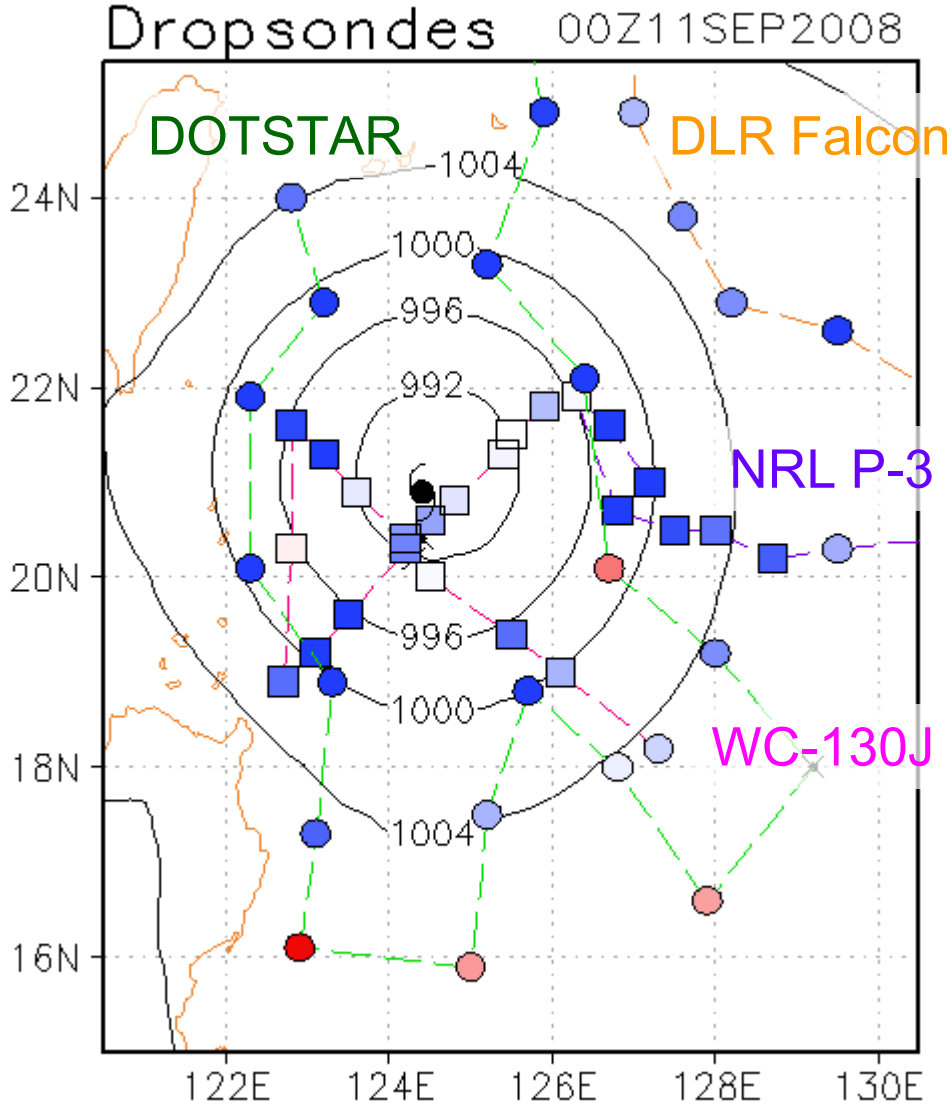


Typhoon track forecast is actually improved!!



A new question arises.

Impact of multiple flights



○ Upper level (> 600 hPa)
□ Lower level (< 600 hPa)

At what stages of TC lifecycle evolution are upper level dropsondes more important?

(Inspired by discussions with Peter Black)

An exciting study on the observing strategies

This is currently ongoing…

FUTURE PLANS

Plans

- *More focusing on TC intensity forecasting*
  - Investigating air-sea coupled covariance around TC
  - Higher-resolution experiments to resolve TC structures
  - Predictability studies by ensemble prediction
  - More TCS-08 case studies
    - More analysis of the impact of aircraft observations
      - Impacts of lower-level and upper-level flights at each stage
    - Use of AIRS retrievals
    - Use of rapid-scan cloud images
    - Direct assimilation of best-track data
  - Possibly, further ITOP-10 case studies
    - Cases with joint DOTSTAR and WC-130J missions

The LETKF code is available at:

http://code.google.com/p/miyoshi/