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Hybridデータ同化システムを用いたメソ気象予測
(A meso hybrid EnKF-4DVAR system based on the JMA nonhydrostatic model)

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1. Introduction

- What is 4DVAR?

  (1) Define a cost function J

  (2) Find the initial state $\mathbf{x}_0$ that yields the smallest J with the constraint of model dynamics.

- Cost function

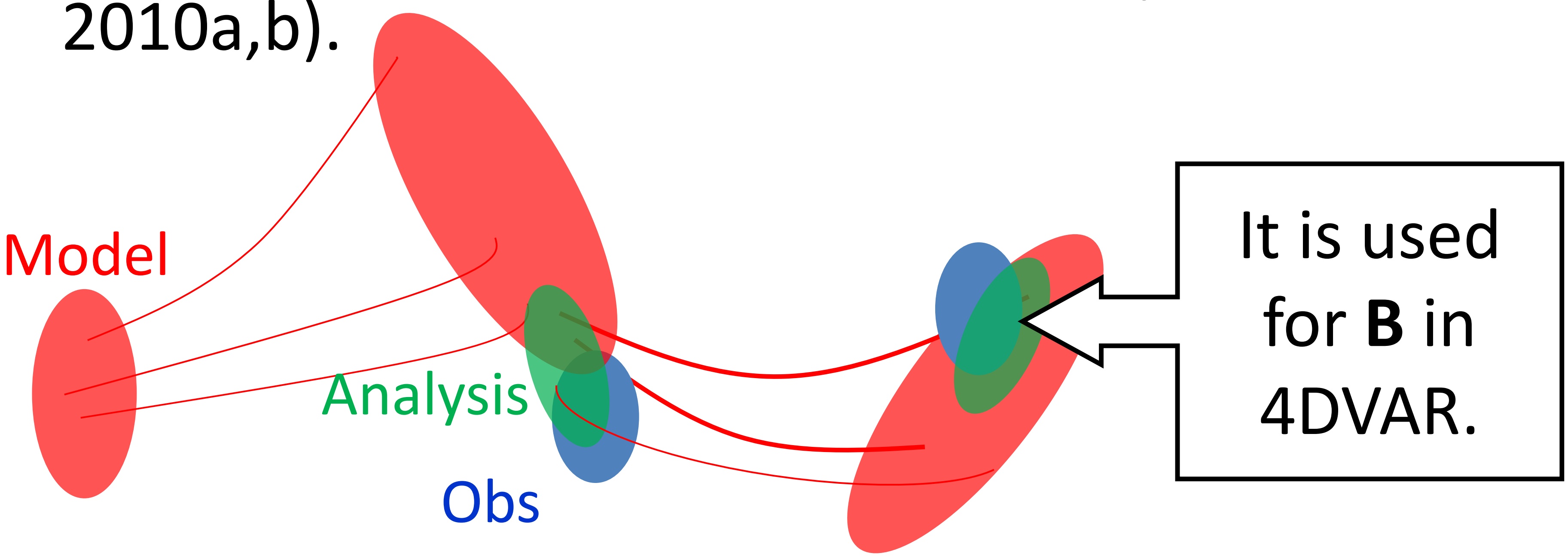
J_B = Difference b/w the first guess and the analysis initial state

$$J = \frac{1}{2}(\mathbf{x}_0 - \mathbf{x}_\mathrm{b})^\mathrm{T}\mathbf{B}^{-1}(\mathbf{x}_0 - \mathbf{x}_\mathrm{b})$$
$$+ \frac{1}{2}\sum_t (\mathbf{y}_t - \mathbf{H}\mathbf{x}_t)^\mathrm{T}\mathbf{R}^{-1}(\mathbf{y}_t - \mathbf{H}\mathbf{x}_t)$$

J_O = Difference b/w observation and model variables

Hybrid DA system

- 4DVAR system needs prescribed **B**
- How to construct **B**?
  - ➢NMC method (conventional): Statistics of the past forecasts --> climatological
  - ➢Hybrid: EnKF- or ensemble-based perturbations
- For global-scale forecasts, hybrid systems shows better skill than NMC-based 4DVAR (Buehner et al. 2010a,b).



Motivation: A meso hybrid system

- The benefit of hybrid DA system can be more pronounced for predicting severe weather events because NMC-based **B** merely represents climatological error covariances.
- Nevertheless, so far, only a few studies have focused on mesoscale weather prediction using a hybrid EnKF-4DVAR system (Poterjoy & Zhang, 2014).
- We evaluate the potential of a hybrid system in terms of predicting severe weather events from a deterministic point of view by comparing:
  - NMCFDV: adjoint-based 4DVAR using NMC-based **B**
  - LETKF: Local Ensemble Transform Kalman filter
  - HYBRID: Same as NMCFDV but also using LETKF-based **B**

2. Methodology

Implementation of HYBRID

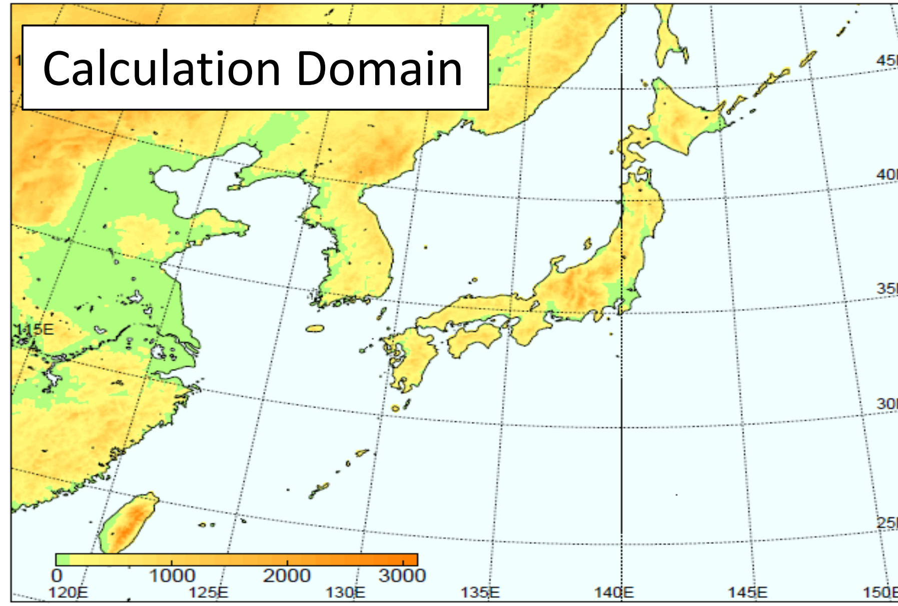
- Localization
  --> No. But we applied neighboring ensemble method (Aonashi et al. 2013)
  --> $\mathbf{B}_{ens}=\mathbf{X}\mathbf{X}^T$, $(\mathbf{B}_{ens})^{1/2}=\mathbf{X}$
- Interaction between 4DVAR and EnKF
  --> one-way (LETKF based **B** --> 4DVAR)
- Do we mix $\mathbf{B}_{NMC}$ and $\mathbf{B}_{ens}$?
  --> $\mathbf{B}_{Hybrid} = 0.1\mathbf{B}_{NMC} + 0.9\mathbf{B}_{ens}$

JNoVA (4DVAR)

- "JMA-nonhydrostatic model" based 4DVAR (Honda 2005)
- Forecast model coordinate dx=5km, 50 layers
- Adjoint model coordinate dx=15km, 40 layers
- Assimilation window = 3-h
- L-BFGS (Liu and Nocadel, 1999)
- Background error cov. $\mathbf{B}_{NMC}$ Statistics based on differences b/w 12h forecast and 6 h forecast (Jan 2005-Dec 2005).

$\mathbf{B}_{ens}$

3 x 3 Neighboring, N = 459 member



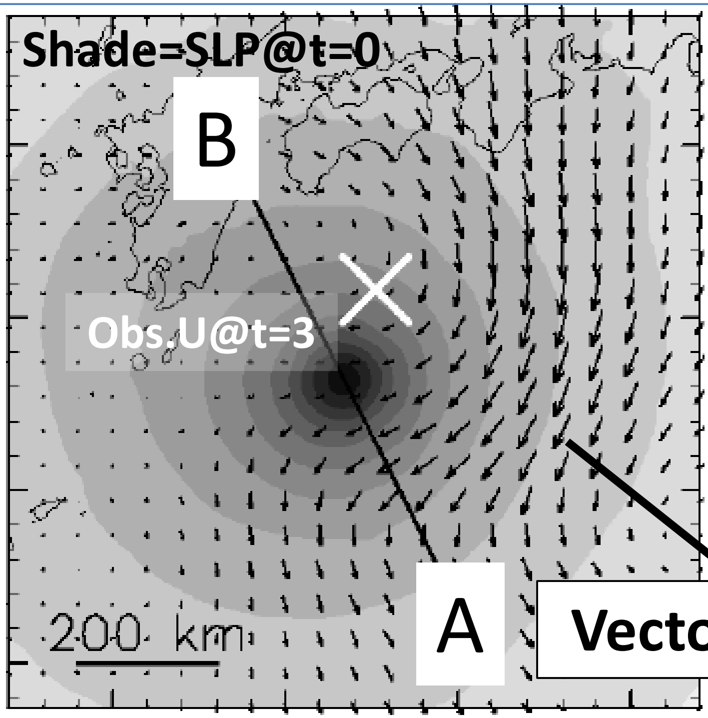
NHM-LETKF (LETKF)

- "JMA-nonhydrostatic model" based LETKF (Kunii 2014)
- Analysis system dx = 15km, 50 layers
- 6-h DA update cycles
- Localization scale = 200km
- Adaptive inflation (Miyoshi 2011)
- 51 members

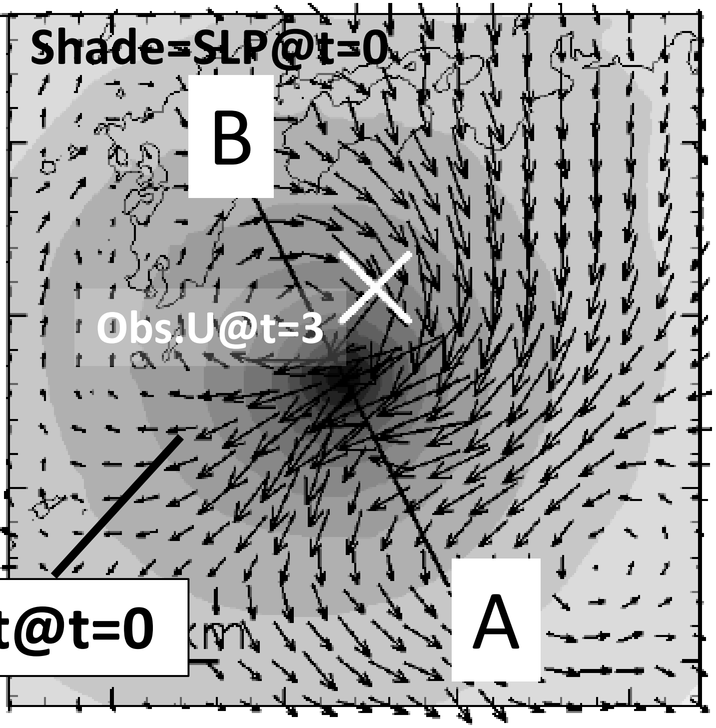
Increment @ t=0 h as a response to single-obs. DA around a TC: Obs.@ t=3 h

- Increment is physically reasonable in HYBRID.

NMCFDV: (δU_{NMC}, δV_{NMC})



HYBRID (δU_{hyb}, δV_{hyb})



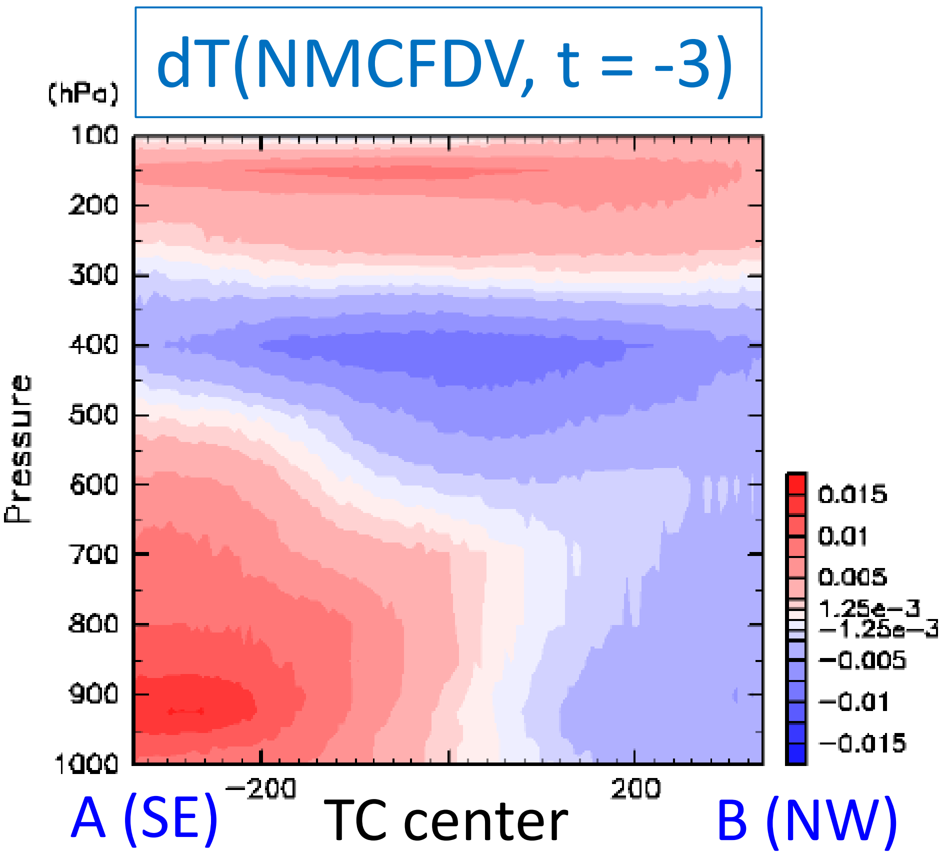
Vector=Increment@t=0

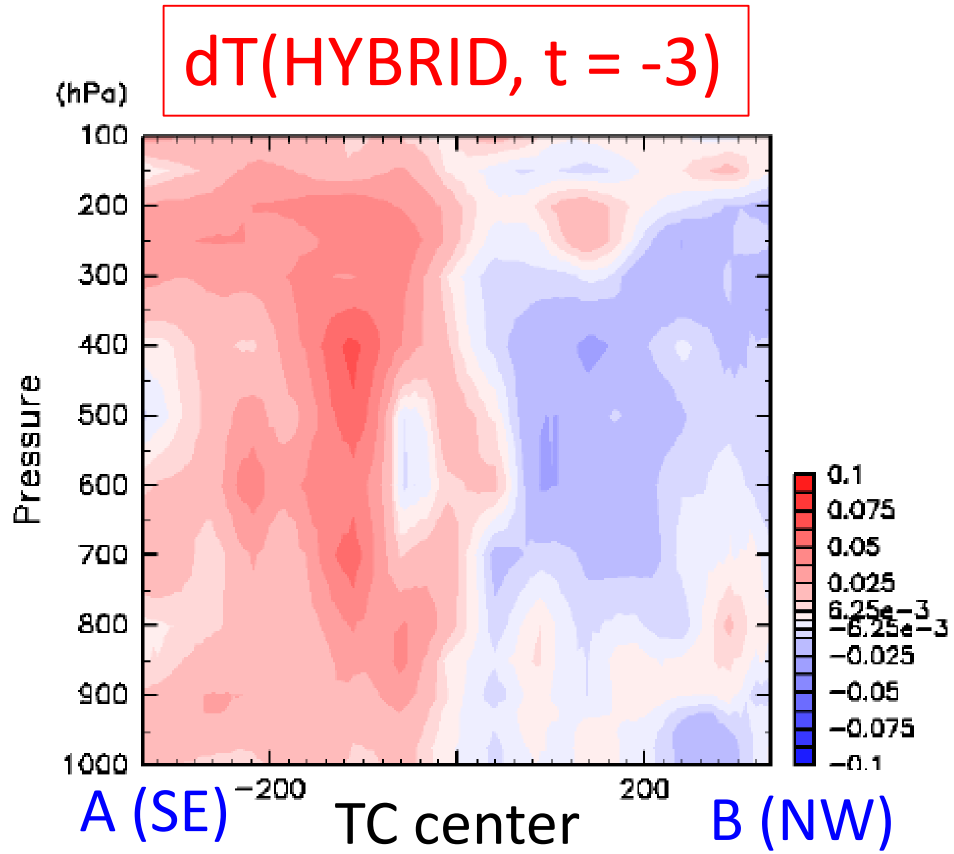
Increment irrelevant to TC structure

Southeastward displacement of TC

Vertical cross section of δT at t = 0 h

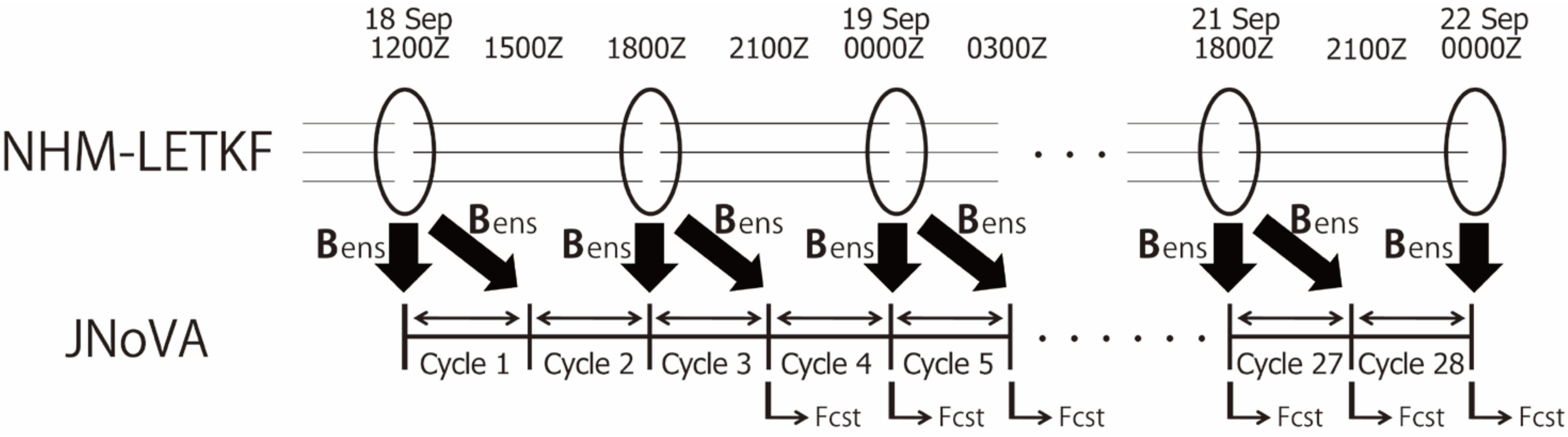
- δT in NMCFDV exhibits vertical nodes which is not likely to be associated with TC dynamics.
- δT in HYBRID reflects a displacement of TC as represented by deep layer shift of warm core





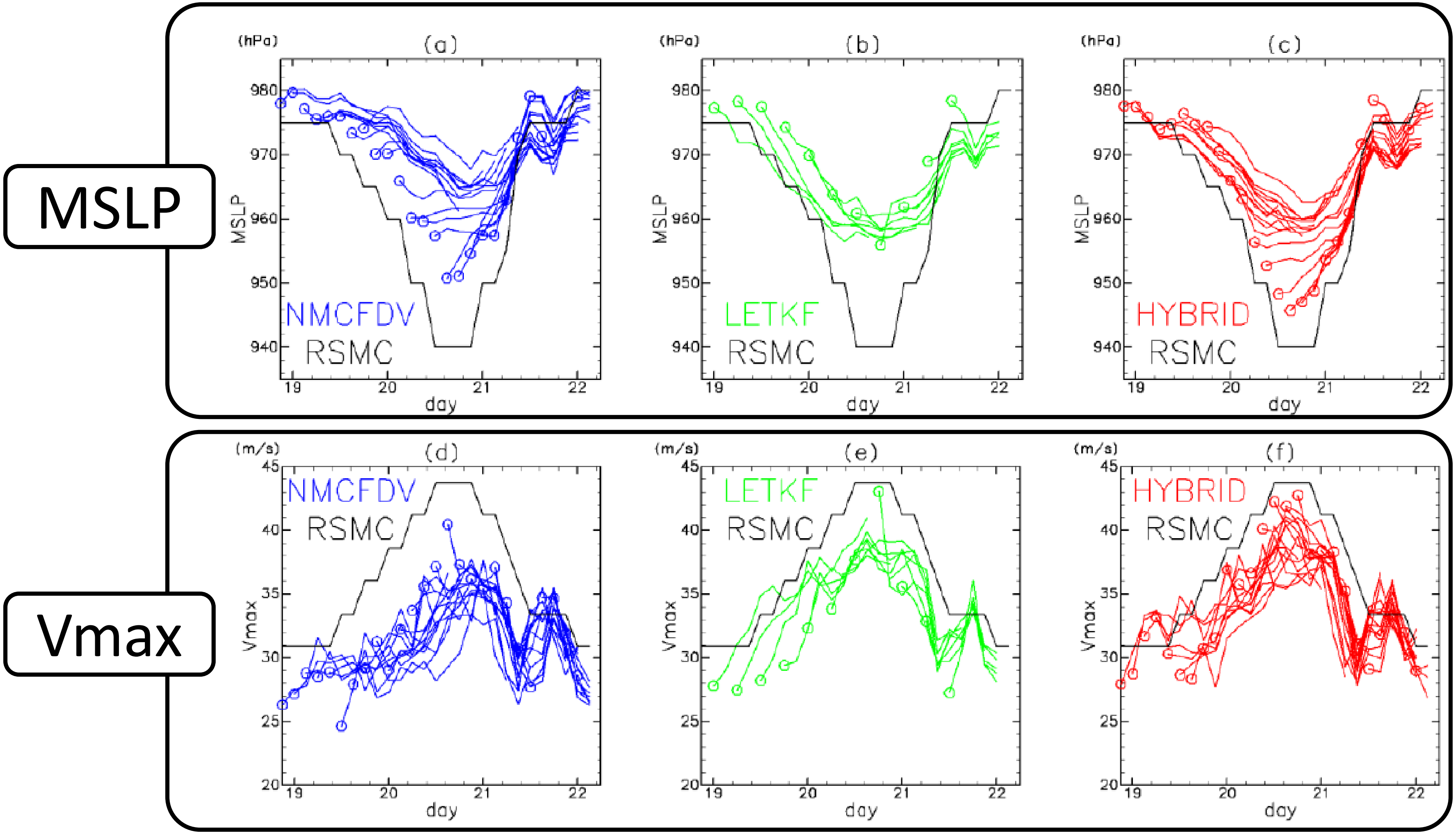
Real data assimilation: TC Roki (2011)

- 36-h forecasts (⊿x=5km) initialized by the analysis field based on NMCFDV, LETKF and HYBRID.
- NHM-LETKF has an update cycle of 6-h and 4DVAR has 3-h assimilation window. Thus,
  - NMCFDV and HYBRID: Every 3-h --> 26 forecasts
  - LETKF: Every 6-h --> 13 forecasts from ensemble-mean
- Time-schedule of HYBRID



TC intensity forecasts over 26 (13) cycles

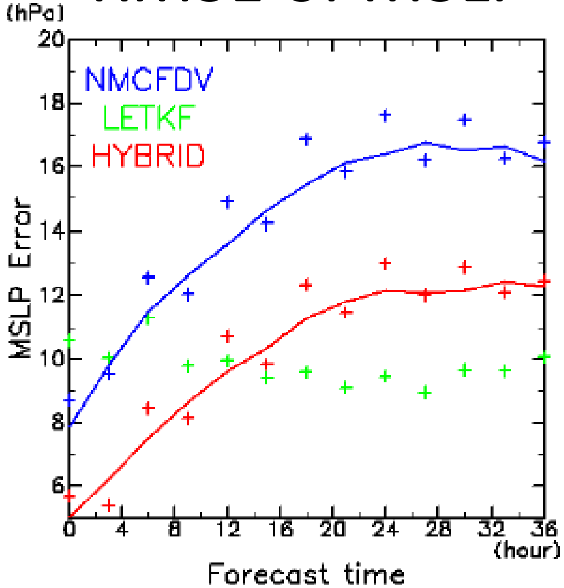
- TCs do not sufficiently intensify when initialized by NMCFDV.
- Analysis TCs are weakly reproduced in LETKF.



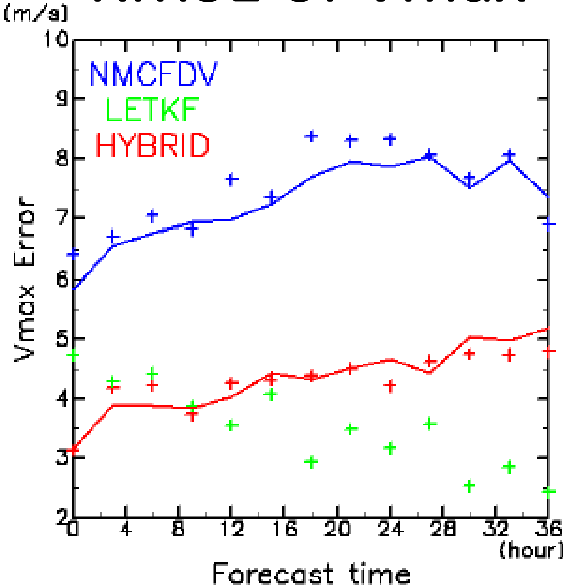
RMSE of MSLP, Vmax and Track

- HYBRID is better than NMCFDV (Improvement rates are about 20% for TC intensity and 10% for TC track).
- LETKF is the worst for the short-term prediction but the best for relatively long-term prediction.

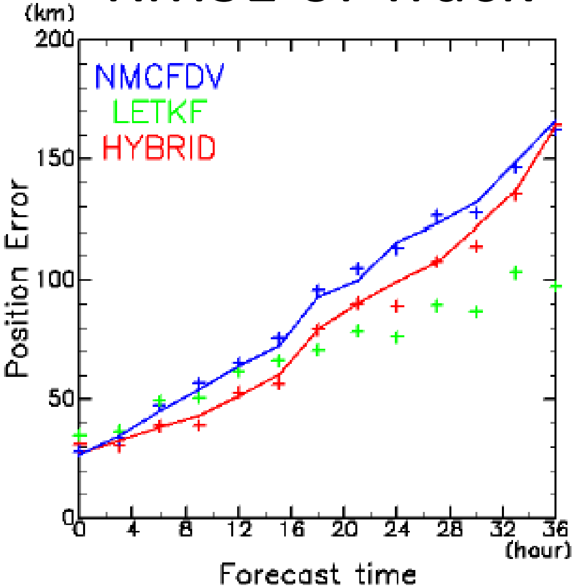
RMSE of MSLP



RMSE of Vmax



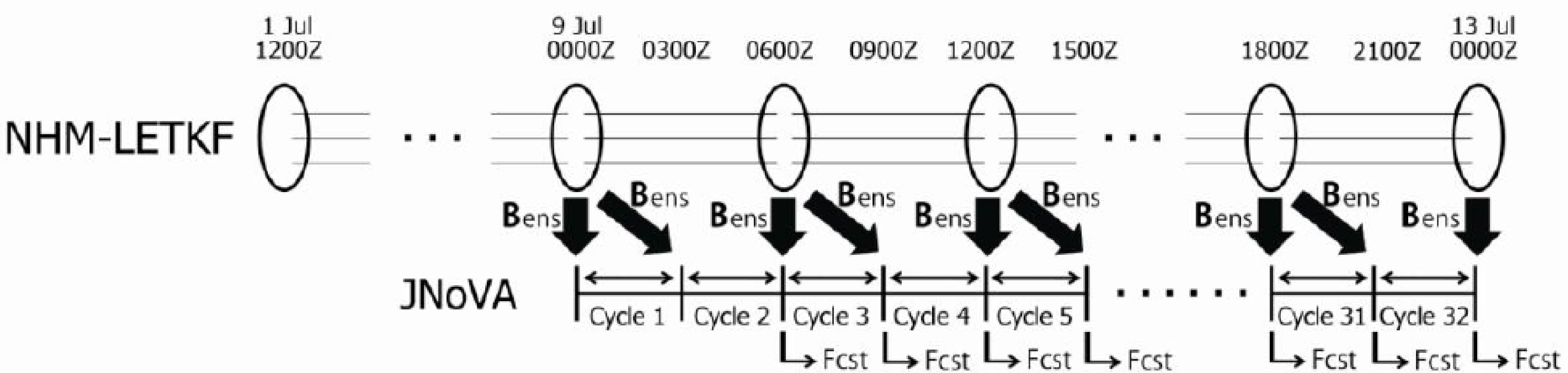
RMSE of Track



Solid line: 26 cycles, +: 13 LETKF-update cycles

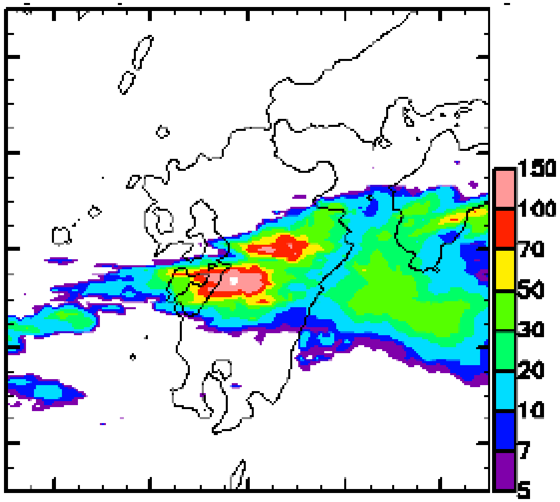
Real data assimilation: Local heavy rainfall events in Kyushu (2012)

- Experiment setting almost same as the TC prediction
- 18-h forecasts initialized by the analysis field based on NMCFDV, LETKF and HYBRID.
- 31 cycles for NMCFDV & HYBRID, 16 cycles for LETKF
- Time schedule for HYBRID

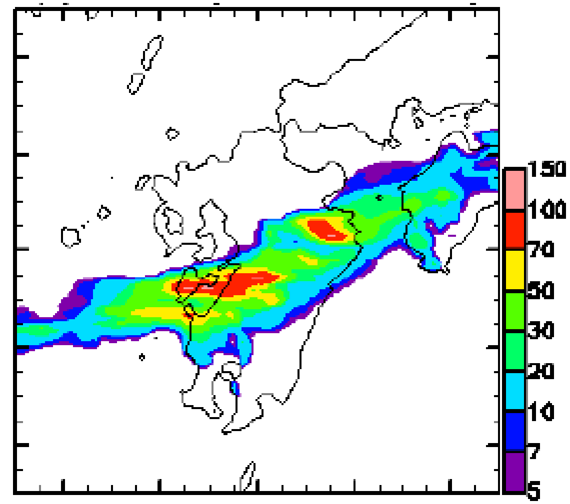


3-h accumulated rainfall (7/12 06-09LST)

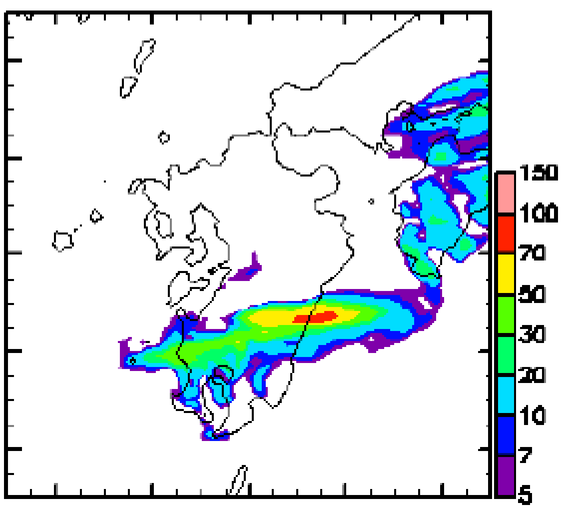
Radar/Rain-gauge analysis



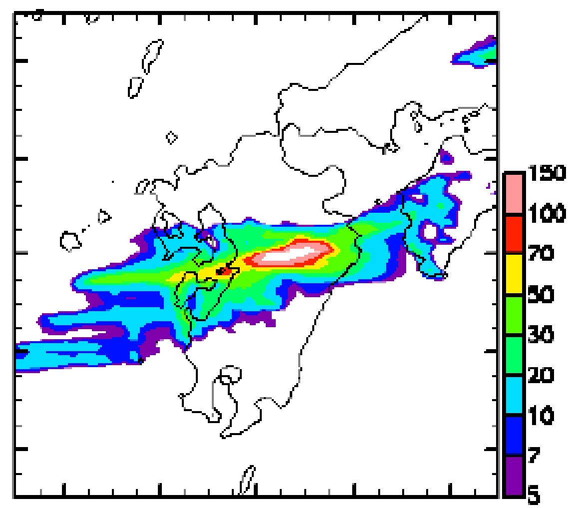
LETKF (FT = 15-18 h)



NMCFDV (FT = 15-18 h)

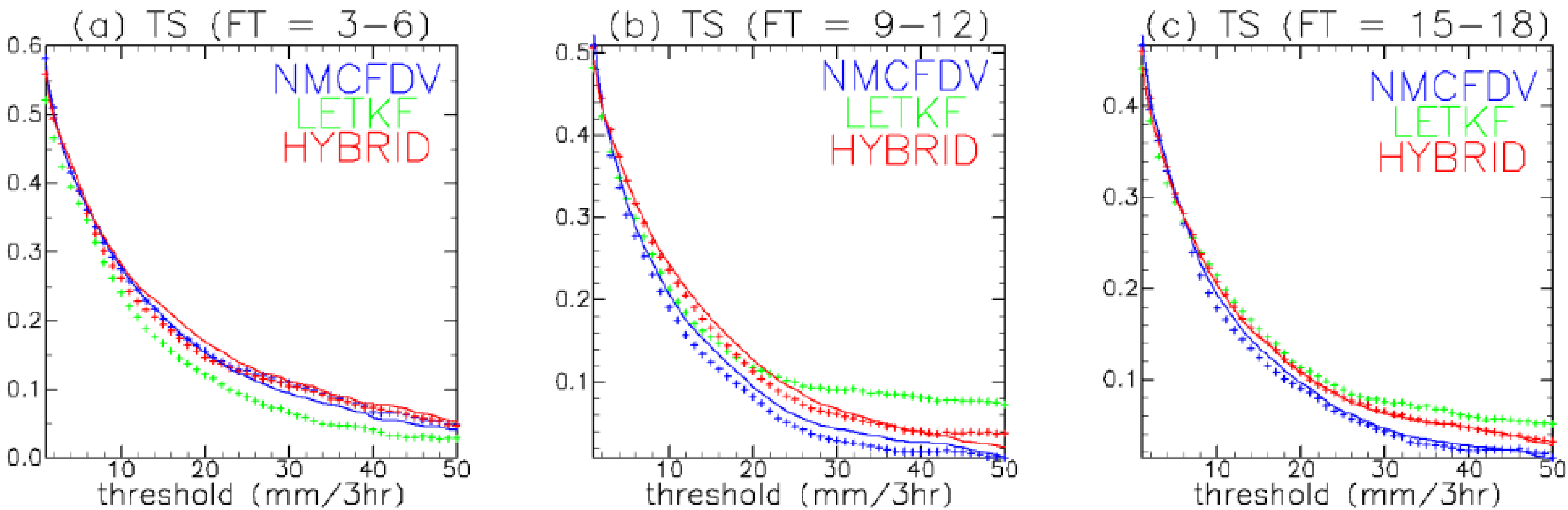


HYBRID (FT = 15-18 h)



Threat scores

- HYBRID is better than NMCFDV, particularly for very intense rainfall.
- HYBRID is the best for short-term prediction of heavy rainfall but LETKF is the best for relatively long-term prediction.



Solid line: 31 cycles, +: 16 LETKF-update cycles

Summary

- We developed a meso HYBRID DA system by using JMA-NHM based 4DVAR and EnKF.
- Single-observation experiment:
  - Increments in HYBRID reflects a TC dynamics, while NMC-based 4DVAR does not.
- Real DA experiments: TC and heavy rainfall
  - HYBRID is better than NMC-based 4DVAR.
  - HYBRID: short-term fcsts, LETKF: long-term fcsts
- Open question: Why does a winner change?