Jan. 18th, 2012

JCSDA Seminar

Ensemble-Based Variational Assimilation Method to Incorporate Microwave Imager Data into a Cloud-Resolving Model

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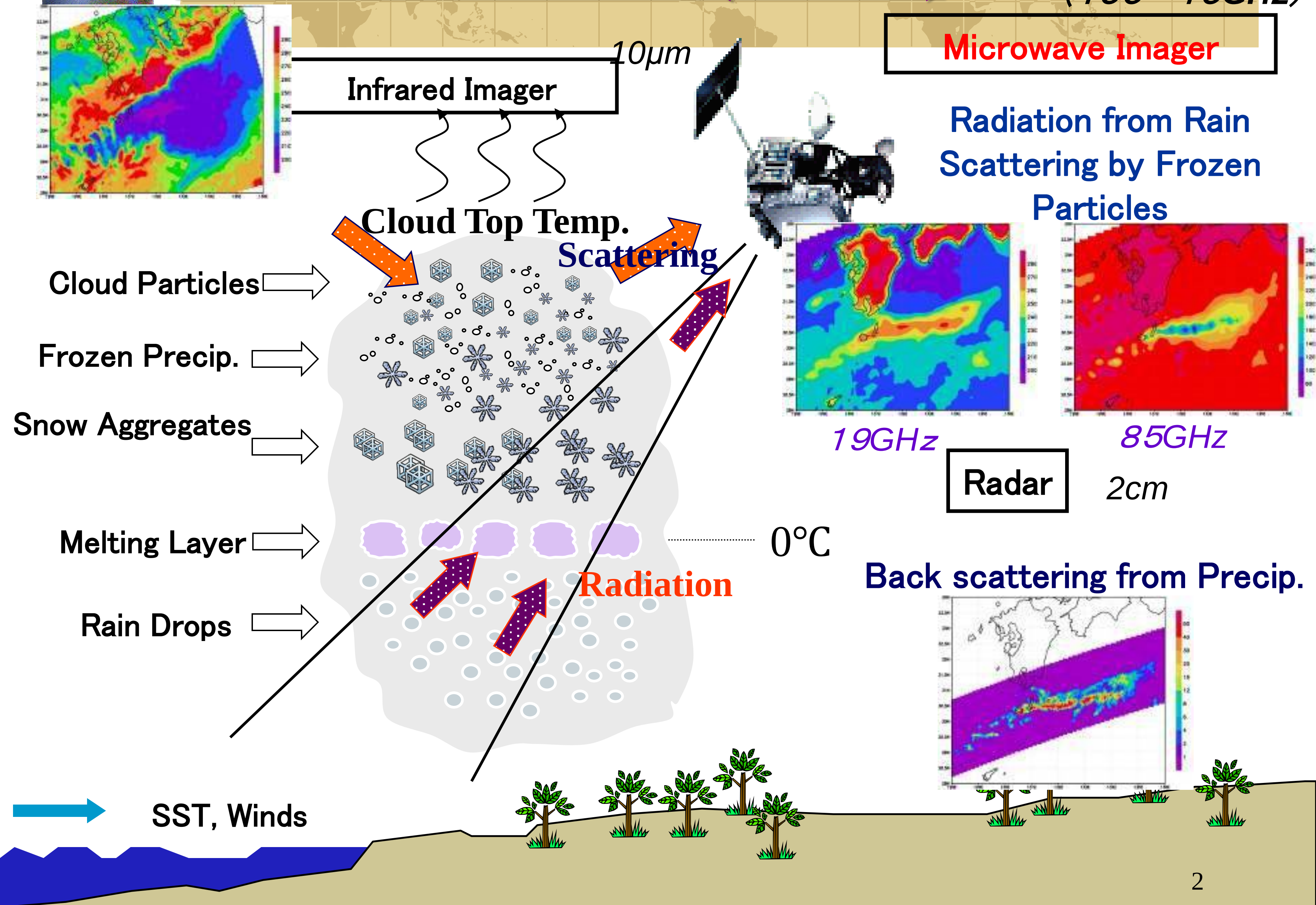
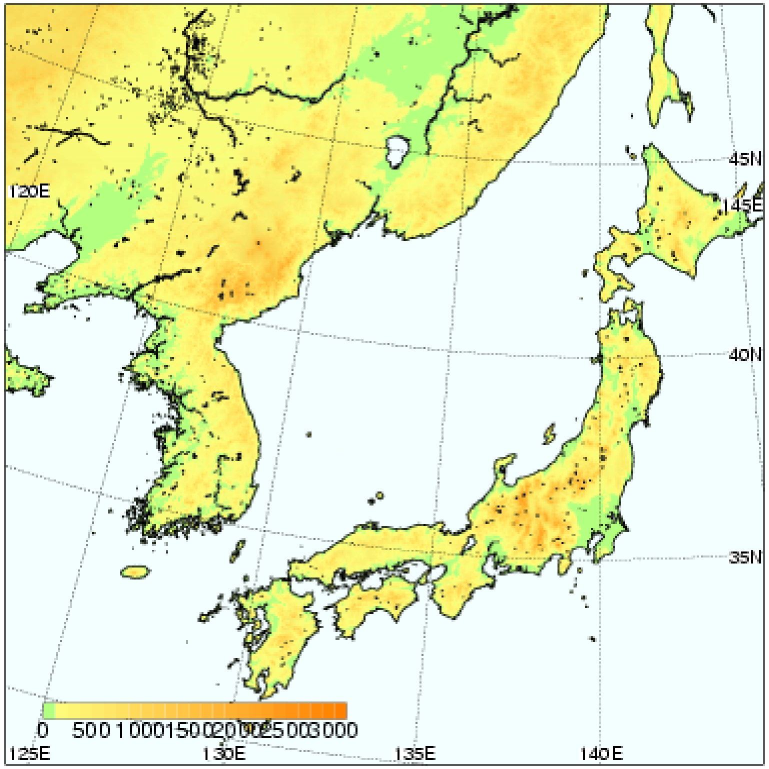
Satellite Observation (TRMM)



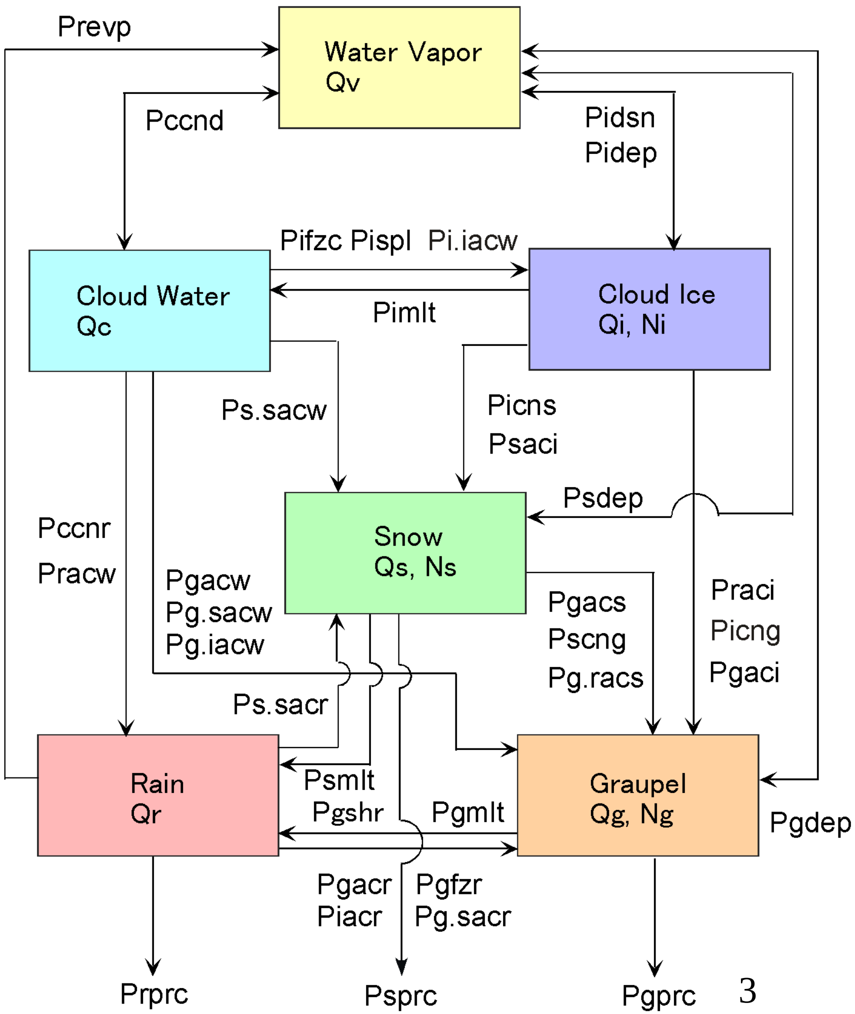
Cloud-Resolving Model used

JMANHM (Saito et al,2001)

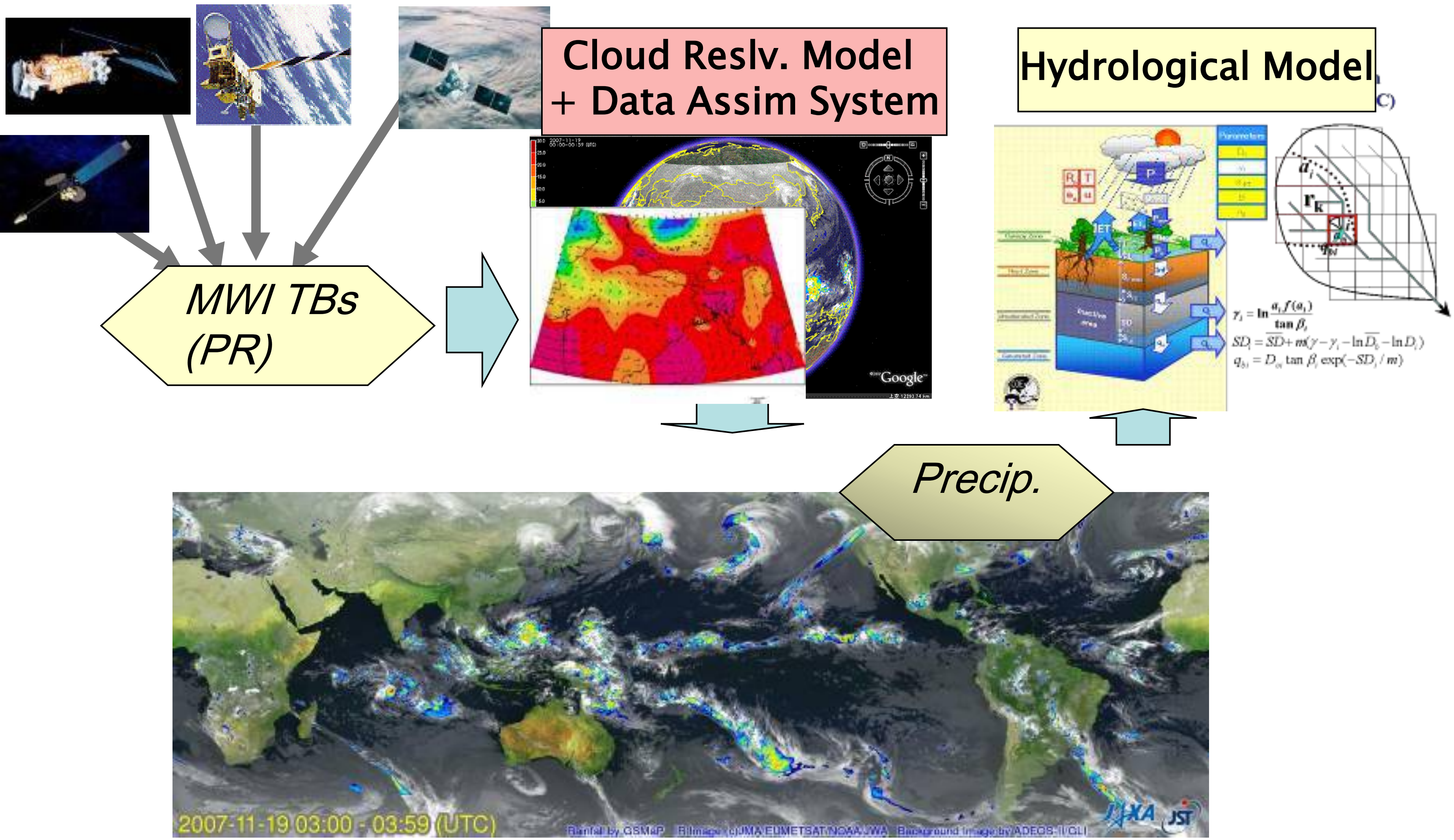
- **Resolution: 5 km**
- **Grids: 400 x 400 x 38**
- **Time interval: 15 s**



Explicitly forecasts 6 species of water substances



Goal: Data assimilation of MWI TBs into CRMs



OUTLINE

- Introduction
- Ensemble-based Variational Assimilation (EnVA)
  - Methodology
  - Problems in EnVA for CRM
- Displacement error correction (DEC)+EnVA
  - Methodology
  - Application results for Typhoon CONSON (T0404)
- Sampling error damping method for CRM EnVA
  - Sample error-damping methods of previous studies
  - Check the validity of presumptions of these methods

Ensemble-based Variational Assimilation (EnVA)

- Methodology

(Lorenc 2003, Zupanski 2005)

- Problems in EnVA for CRM
  - Displacement error
  - Sampling error

EnVA: min. cost function in the Ensemble forecast error subspace

- Minimize the cost function with non-linear Obs. term.

$$J_x = 1/2(\vec{X} - \vec{X}_f)P_f^{-1}(\vec{X} - \vec{X}_f) + 1/2(Y - H(\vec{X}))R^{-1}(Y - H(\vec{X}))$$

- Assume the analysis error belongs to the Ensemble forecast error subspace （Lorenc, 2003):

$$\vec{X} - \vec{X}^f = P_e^{f/2} \circ \Omega \qquad \Omega = [\vec{w}_1, \vec{w}_2, , , , , \vec{w}_N]$$

$$P_e^{f/2} = [\vec{X}_1^f - \vec{X}^f, \vec{X}_2^f - \vec{X}^f, , , , \vec{X}_N^f - \vec{X}^f]$$

- Forecast error covariance is determined by localizatior

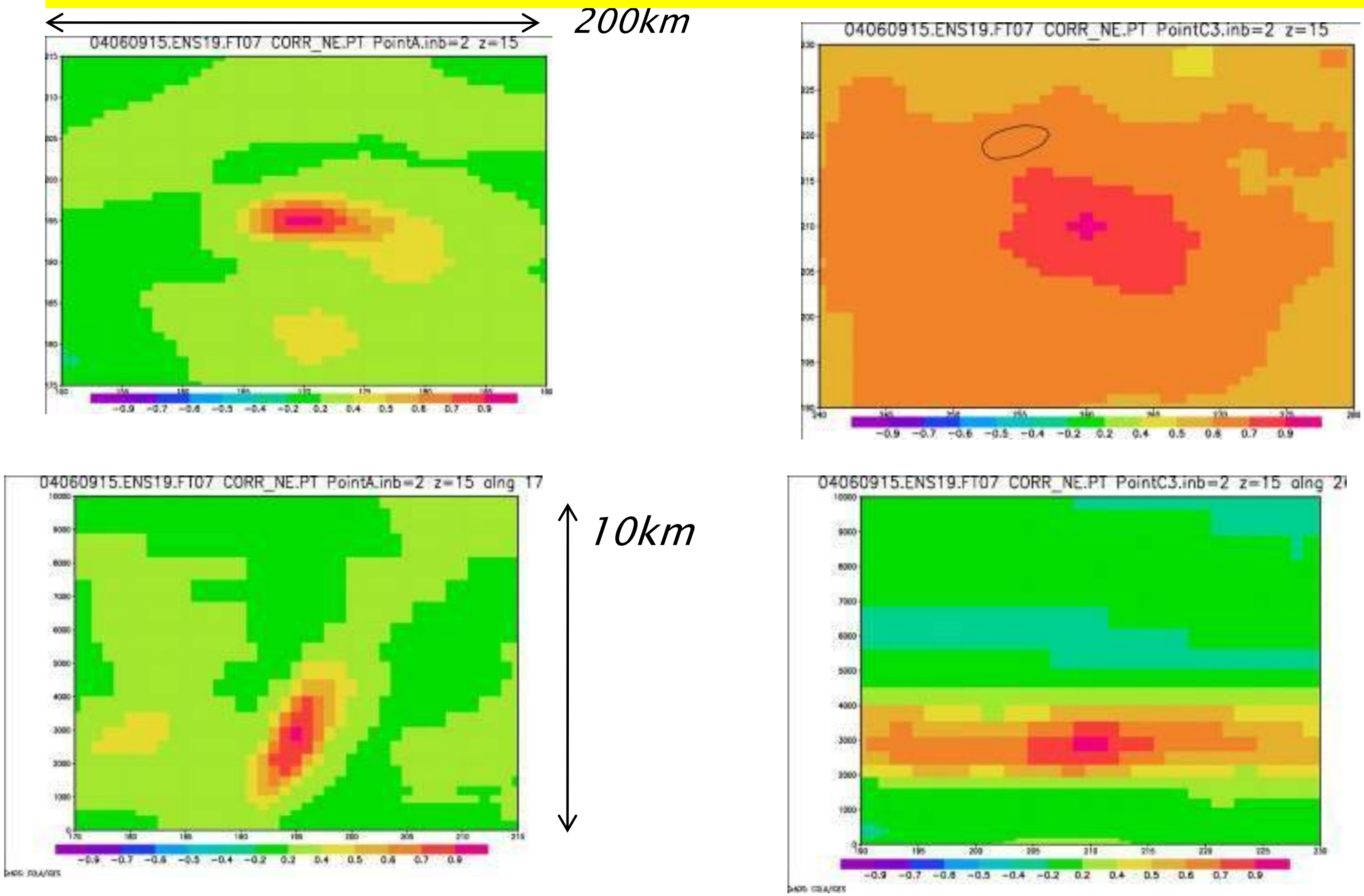
$$P^f = P_e^f \circ S$$

- Cost function in the Ensemble forecast error subspace：

$$J(\Omega) = 1/2\, trace\{\Omega^t S^{-1} \Omega\} + 1/2\{H(\vec{X}(\Omega)) - Y\}^t R^{-1}\{H(\vec{X}(\Omega)) - Y\}$$

Why Ensemble-based method?:

To estimate the flow-dependency of the error covariance



Ensemble forecast error corr. of PT (04/6/9/22 UTC)

Why Variational Method ?

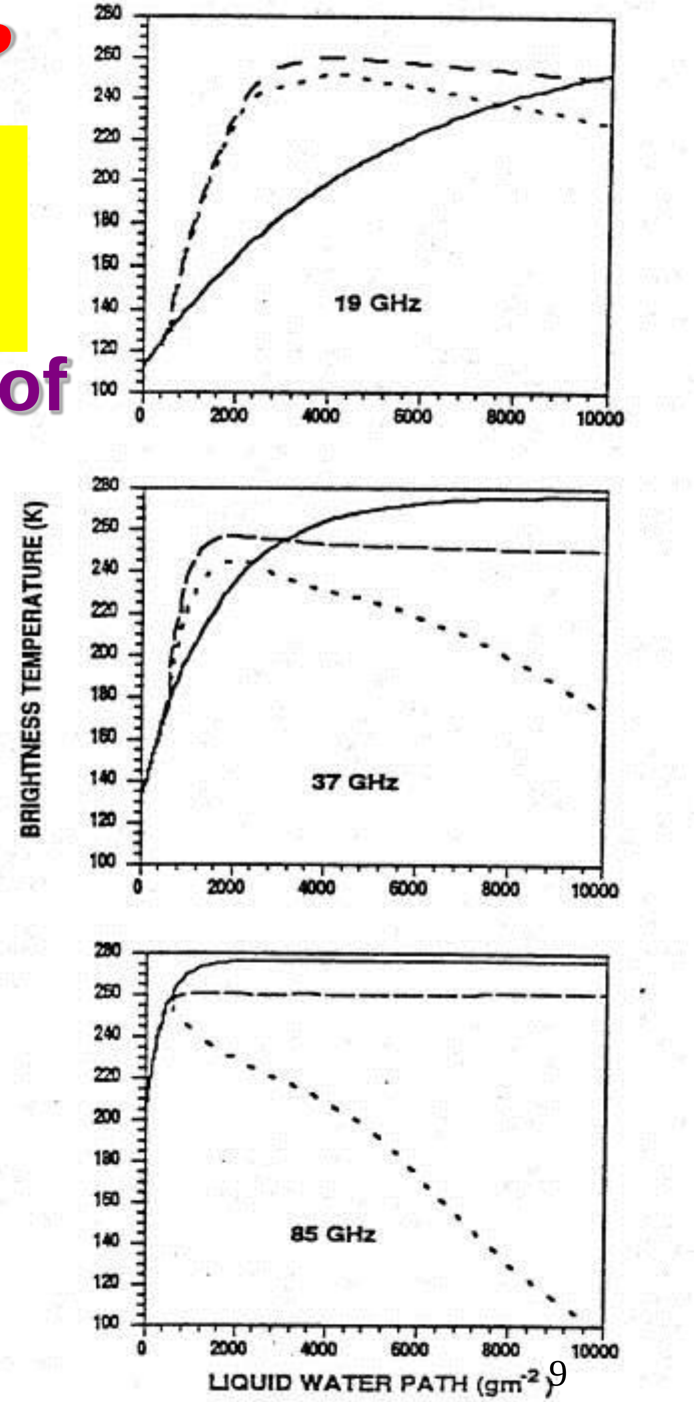
To address the non-linearity of TBs

MWI TBs are non-linear function of various CRM variables.

- TB becomes saturated as optical thickness increases:

$$T - TB \approx (1-\varepsilon_s)Te^{-2\tau/\mu},$$
$$when\ T \approx T_s$$

- TB depression mainly due to frozen precipitation becomes dominant after saturation.



Detection of the optimum analysis

- Detection of the optimum Ω_a, w_a by minimizing J where Ω is diagonalized with U eigenvectors of S:

  $$\chi_i(m) = 1/d_m \{U^t \Omega\}_i(m)$$

- Approximate the gradient of the observation with the finite differences about the forecast error:

  $$\partial H(\vec{X})/\partial\Omega \sim \{H(\vec{X} + \alpha\delta p_i^f) - H(\vec{X})\}/\alpha$$

- To solve non-linear min. problem, we performed iterations.

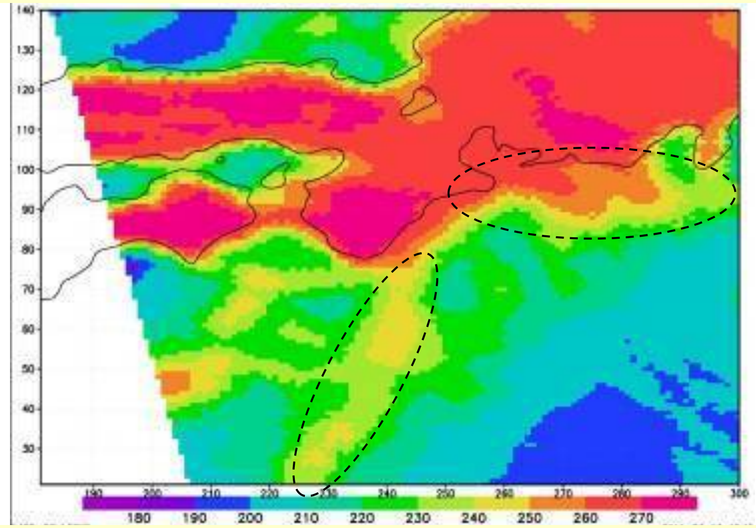
- Following Zupanski (2005), we calculated the analysis of each Ensemble members, $\vec{X}_i^a$ from the Ensemble analysis error covariance.

Problem in EnVA (1): Displacement error

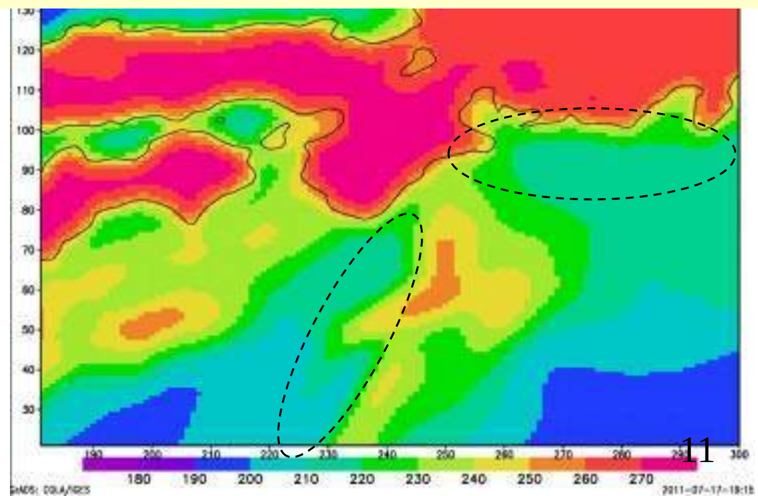
- **Large scale displacement errors of rainy areas between the MWI observation and Ensemble forecasts**

- **Presupposition of Ensemble assimilation is not satisfied in observed rain areas without forecasted rain.**

AMSRE *TB18v* (2003/1/27/04z)

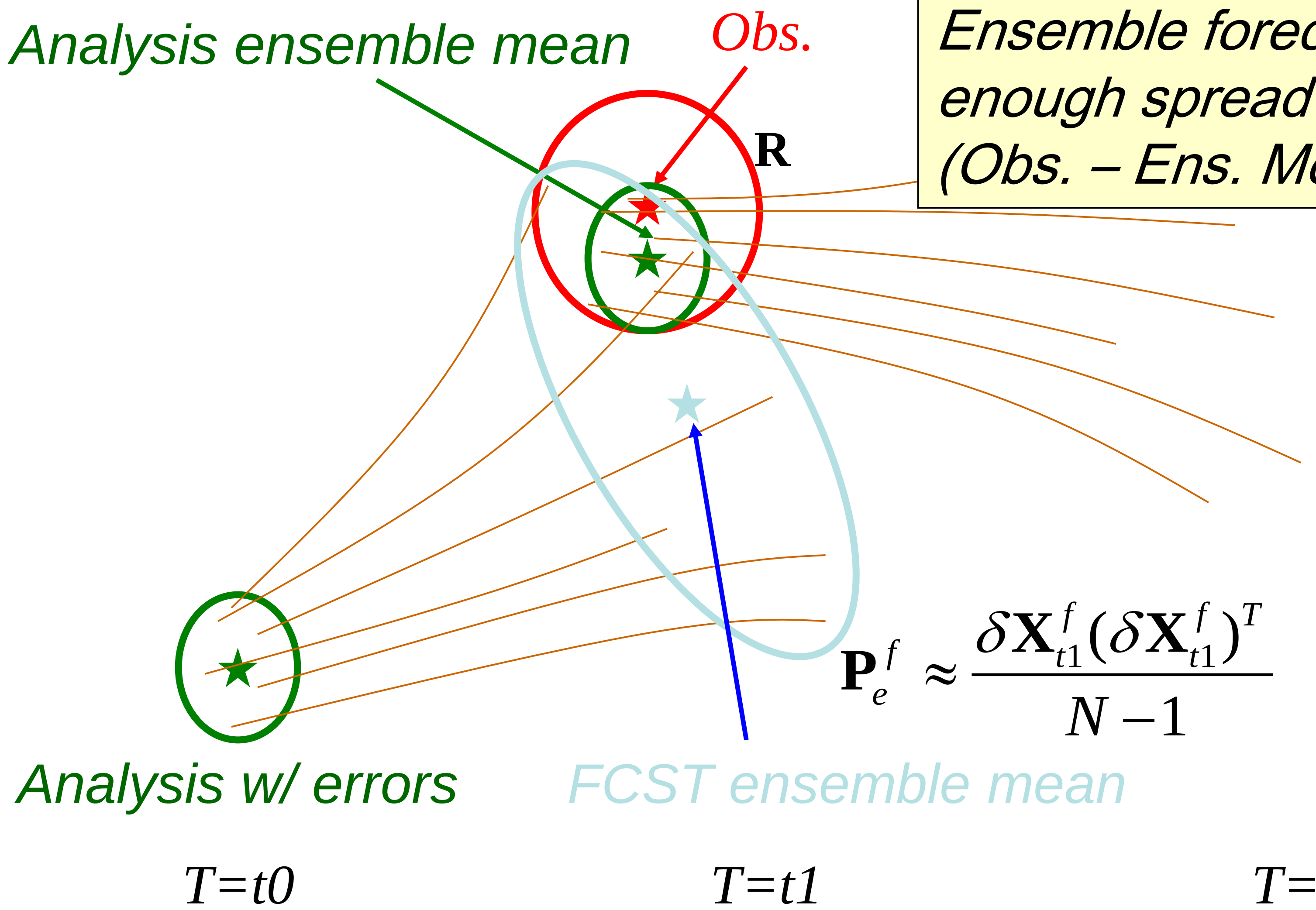


Mean of Ensemble Forecast (2003/1/26/21 UTC FT=7h）



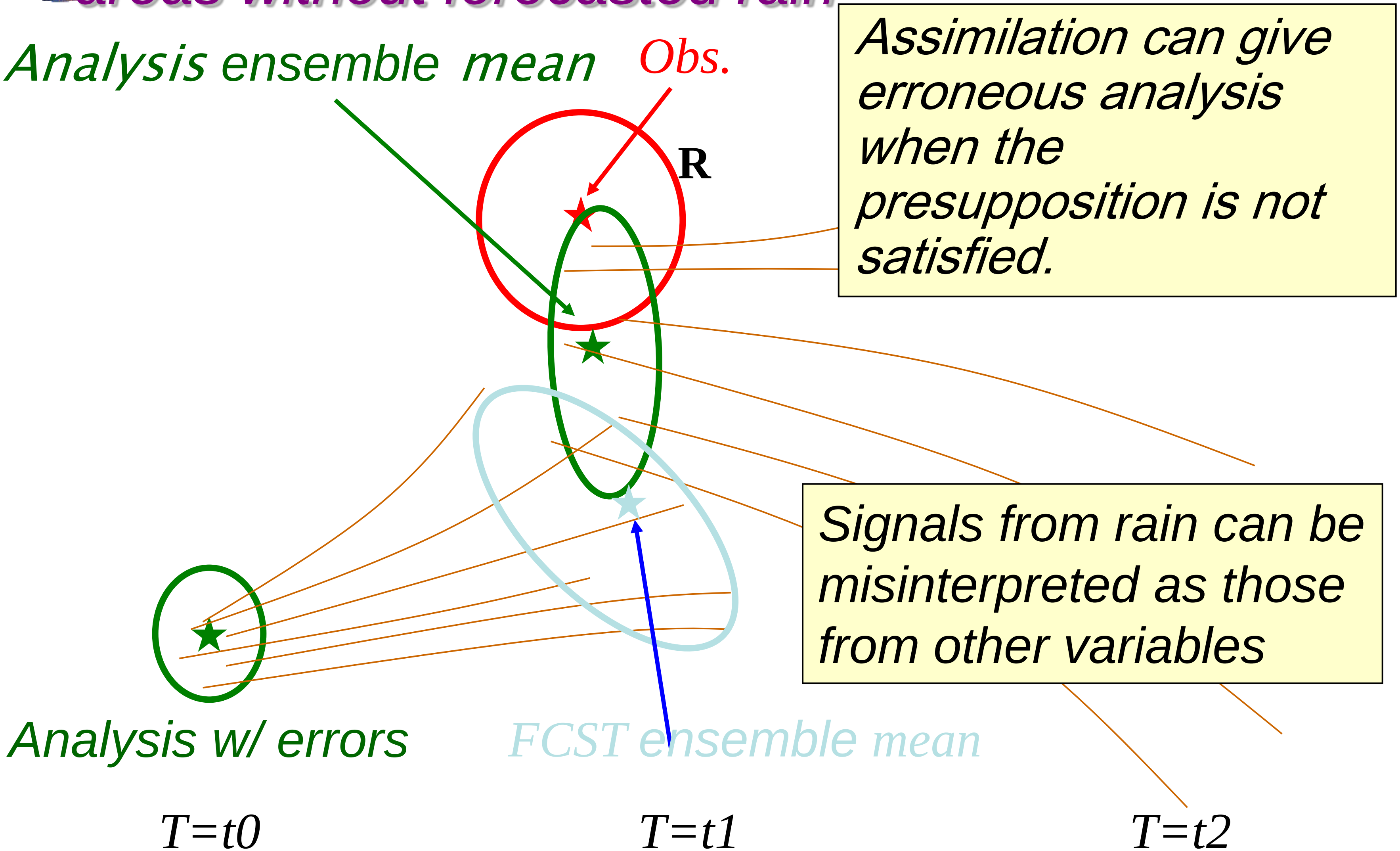
Presupposition of Ensemble-based assimilation

Ensemble forecasts have enough spread to include (Obs. – Ens. Mean)



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

Ensemble-based assimilation for observed rain areas without forecasted rain



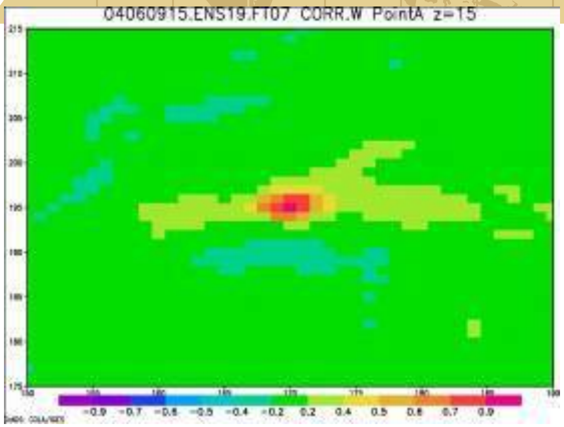
Displacement error correction is needed!

Problem in EnVA (2): Sampling error

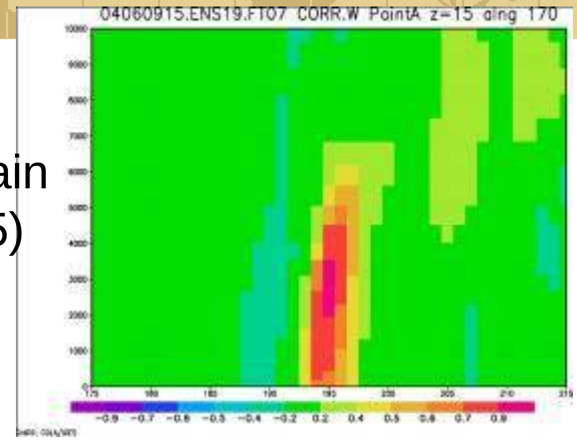
Forecast error corr. of W (04/6/9/15z 7h fcst)

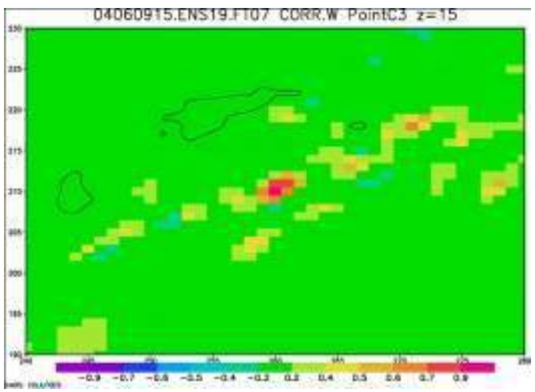
200 km

200 km

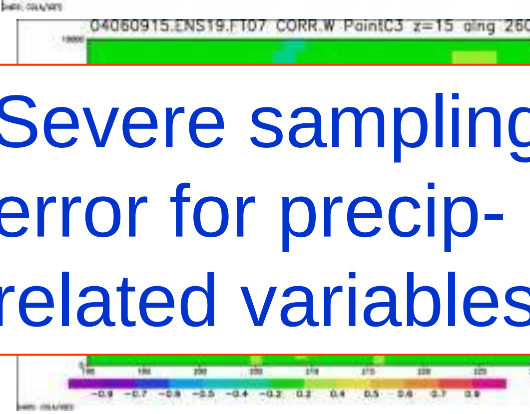


Heavy rain
(170,195)

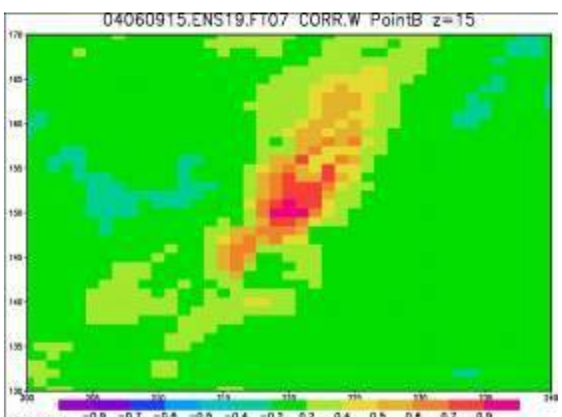




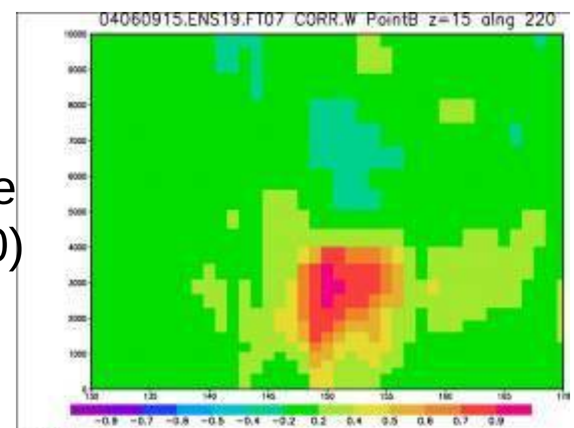
Weak ra
(260,210



Severe sampling error for precip-related variables



Rain-free
(220,150)



Displacement error correction (DEC)+EnVA

- Methodology
- Application results for Typhoon CONSON (T0404)
  - Case
  - Assimilation Results
  - Impact on precipitation forecasts

Displaced Ensemble variational assimilation method

In addition to $\vec{X}$, we introduced $\vec{d}$ to assimilation.

The optimal analysis value maximizes：

$$\arg\max P(\vec{X},\vec{d}\,|\,Y,\bar{X}^f)$$

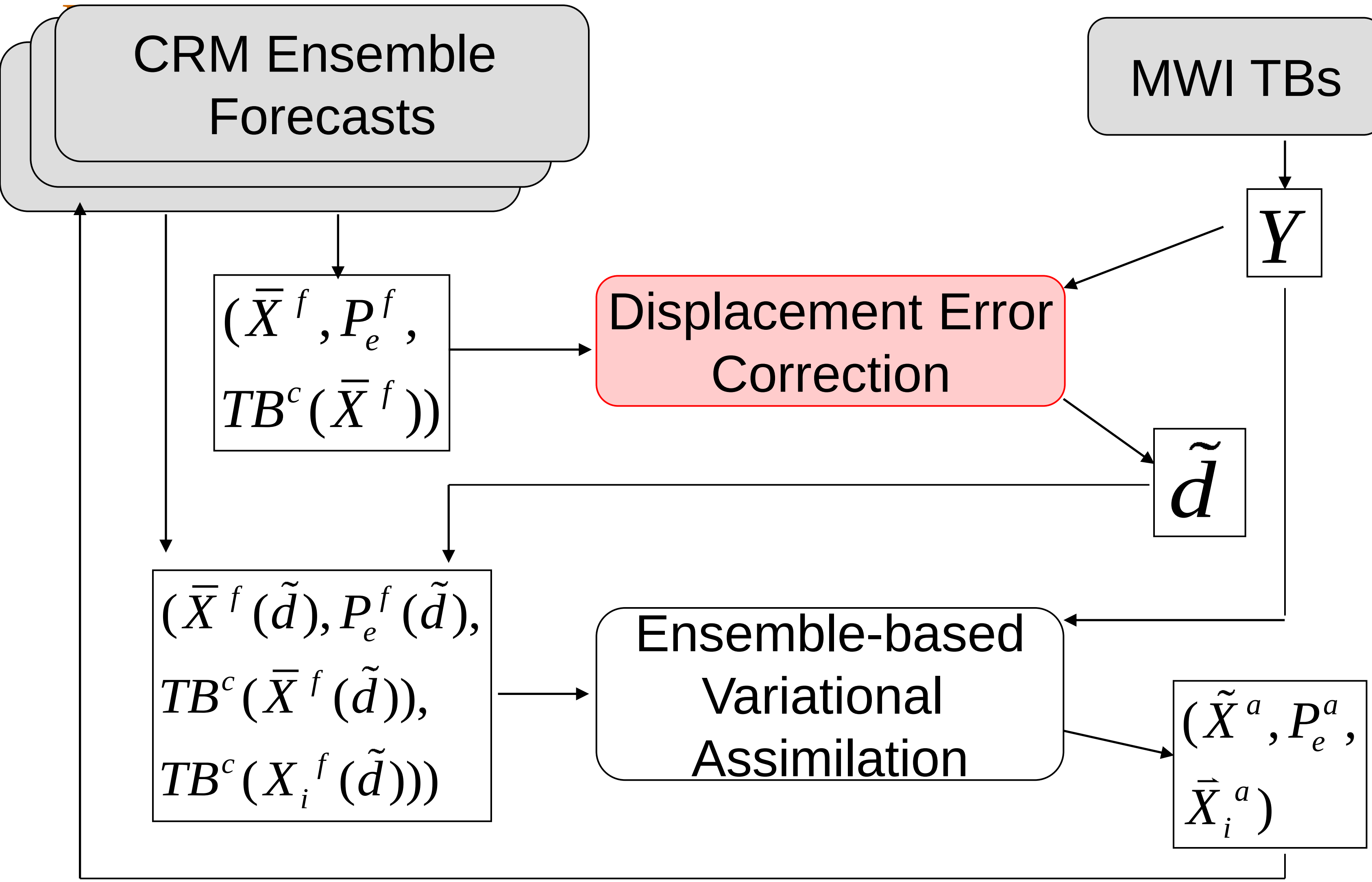
$$P(\vec{X},\vec{d}\,|\,Y,\bar{X}^f)=P(\vec{d}\,|\,Y,\bar{X}^f)P(\vec{X}\,|\,\vec{d},Y,\bar{X}^f)$$

Assimilation results in the following 2 steps:

1) DEC scheme to derive $\vec{d}^a$ from $P(\vec{d}\,|\,Y,\bar{X}^f)$

2)EnVA scheme using the DEC Ensembles to derive $\vec{X}^a$ from $P(\vec{X}\,|\,\vec{d}^a,Y,\bar{X}^f)$

Assimilation method



DEC scheme: min. cost function for d

- Bayes' Theorem

$$P(\vec{d} \mid Y, \bar{X}^f) = P(Y, \bar{X}^f \mid \vec{d}) P(\vec{d}) / P(Y, \bar{X}^f)$$

- $P(Y, \bar{X}^f \mid \vec{d})$ can be expressed as the cond. Prob. of Y given $\bar{X}^f(\vec{d})$:

$$P(Y, \bar{X}^f \mid \vec{d}) = \exp\{-1/2\,(Y - H(\bar{X}^f(\vec{d}))^t R^{-1}(Y - H(\bar{X}^f(\vec{d}))\}$$

- We assume Gaussian dist. of $P(\vec{d})$: $P(\vec{d}) = \exp\{-(|\vec{d}|^2 / 2\sigma_d^2)\}$

where σ_d is the empirically determined scale of the displacement error.

- We derived the large-scale pattern of $\tilde{d}$ by minimizing J_d (Hoffman and Grassotti ,1996) :

$$J_d = \frac{1}{2}(Y - H(\bar{X}^f(\vec{d})))^t R^{-1}(Y - H(\bar{X}^f(\vec{d})))\} + |\vec{d}|^2 \Big/ 2\sigma_d^2$$

Detection of the large-scale pattern of optimum displacement

- We derived the large-scale pattern of $\tilde{d}$ from J_d, following Hoffman and Grassotti (1996) :

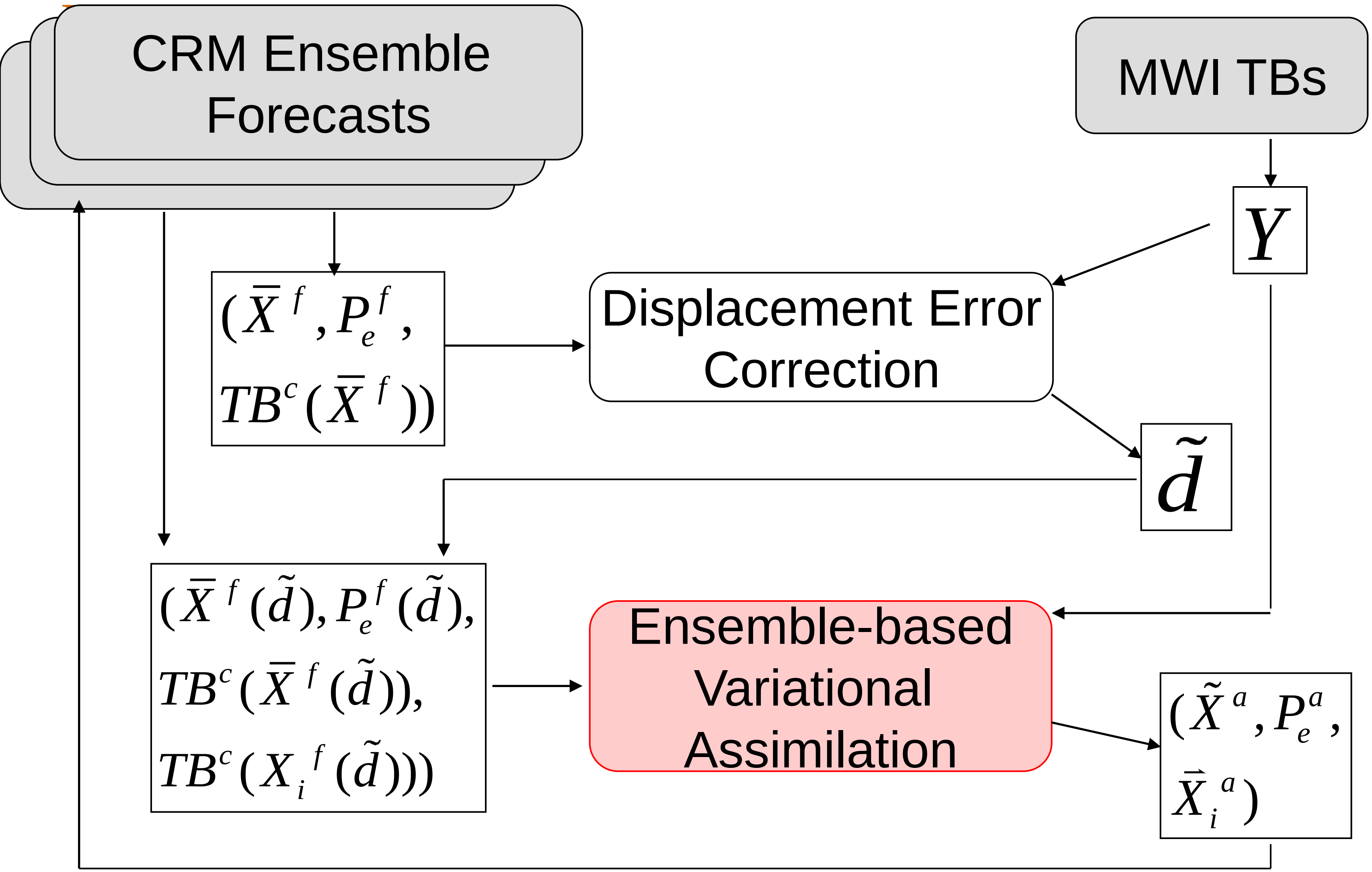
$$J_d = \frac{1}{2}(Y - H(\bar{X}^f(\vec{d})))^t R^{-1}(Y - H(\bar{X}^f(\vec{d})))\} + \left|\vec{d}\right|^2 / 2\sigma_d^2$$

- We transformed $\vec{d}$ into the control variable in wave space, $\vec{r}$ using the double Fourier expansion.

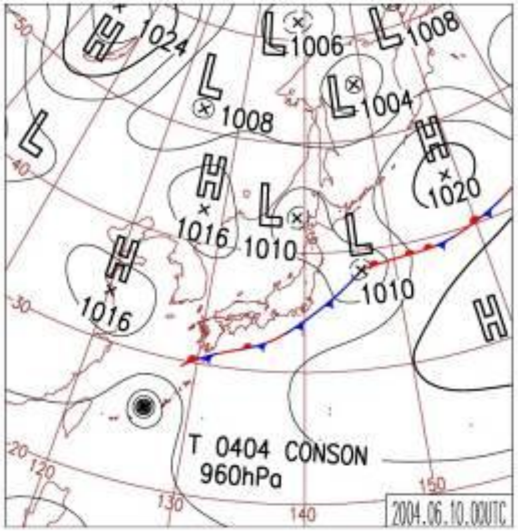
- We used the quasi-Newton scheme (Press et al. 1996) to minimize the cost function in wave space.

- we transformed the optimum $\vec{r}$ into the large-scale pattern of $\vec{d}$ by the double Fourier inversion.

Assimilation method

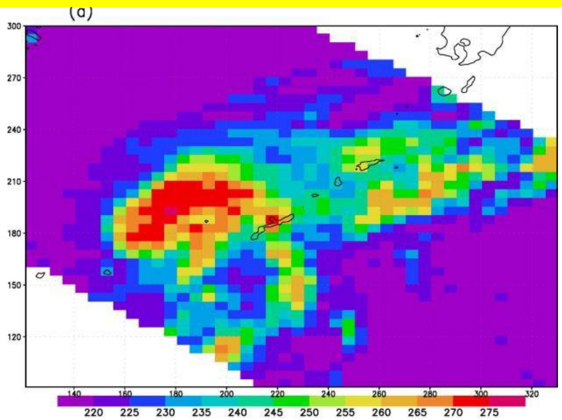


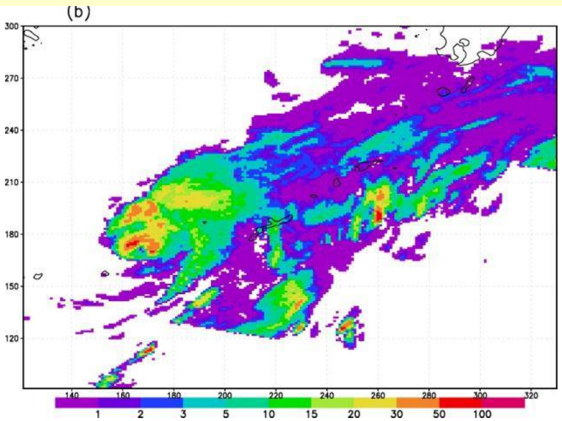
Case (2004/6/9/22 UTC) TY CONSON



Assimilate TMI TBs (10v, 19v, 21v) at 22UTC

RAM (mm/hr)





Cloud-Resolving Model used

JMANHM (Saito et al,2001)

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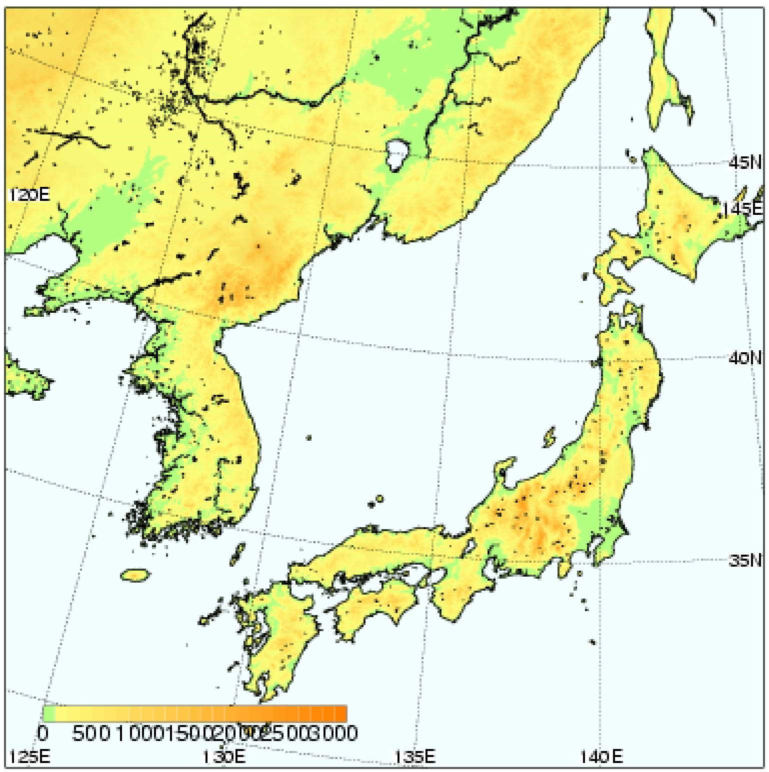
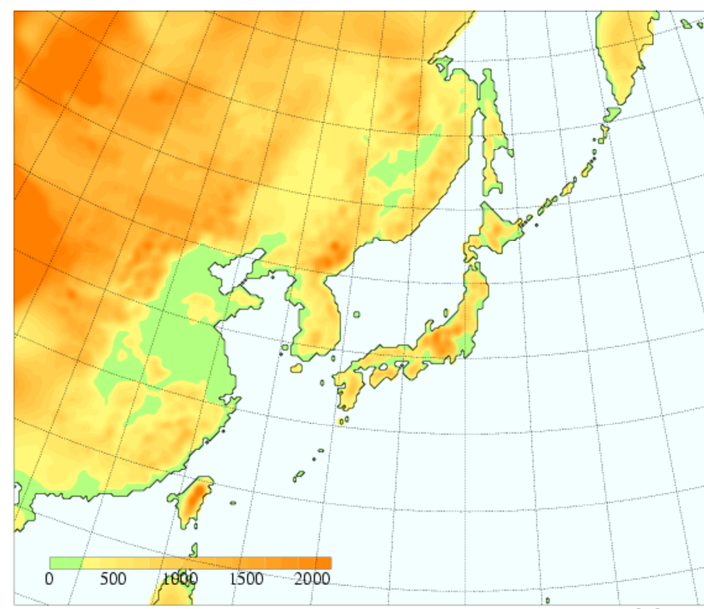


Initial and boundary data

JMA's operational regional model

- **Basic equations :** Hydrostatic primitive
- **Precipitation scheme:** Moist convective adjustment + Arakawa-Schubert + Large scale condensation
- **Resolution:** 20 km
- **Grids:** 257 x 217 x 36

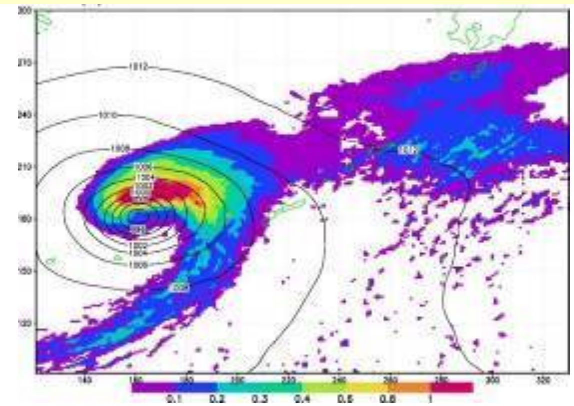


Ensemble Forecasts & RTM code

Ensemble forecasts

- 100 members started with perturbed initial data at 04/6/9/15 UTC (FG)
- Geostrophically-balanced perturbation (Mitchell et al. 2002) plus Humidity

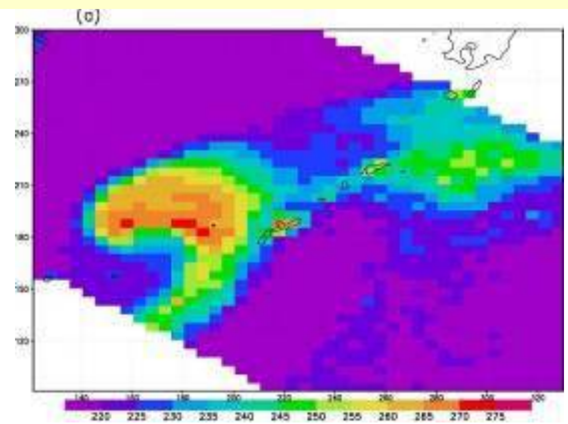
Ensemble mean (FG)
Rain mix. ratio



RTM: Guosheng Liu (2004)

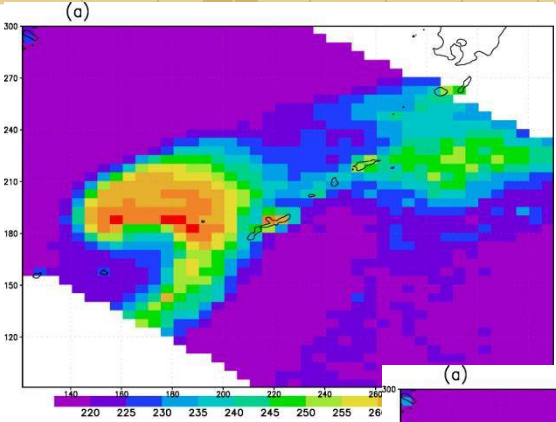
- *One-dimensional model (Plane-parallel)*
- *Mie Scattering (Sphere)*
- *4 stream approximation*

TB19v cal. from FG

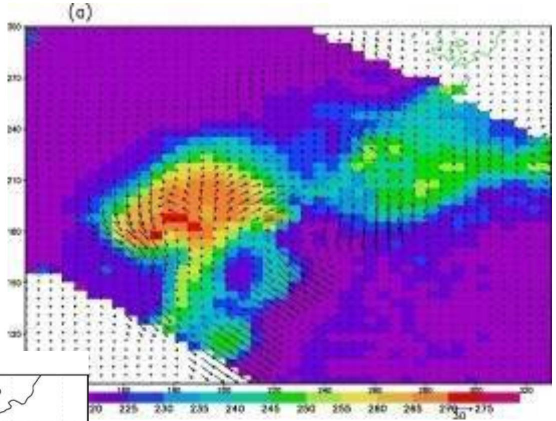


TB19v from TMI and CRM outputs

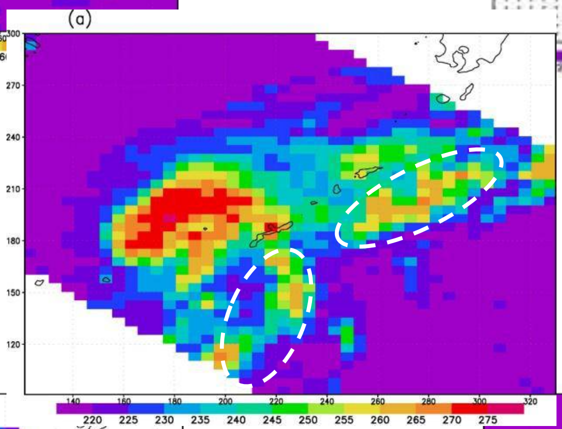
FG : First guess



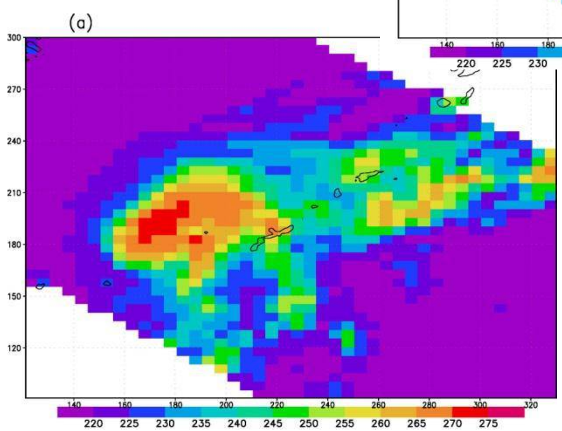
DE : After DEC



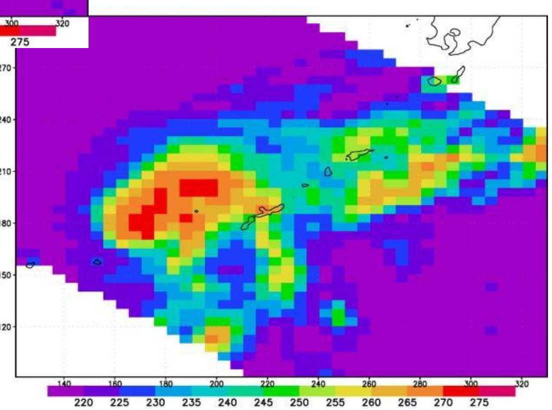
TMI



ND: NoDE+ EnVA



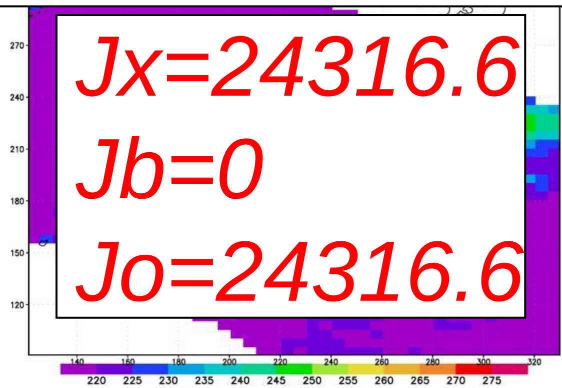
CN : DE+ EnVA



Post–fit residuals

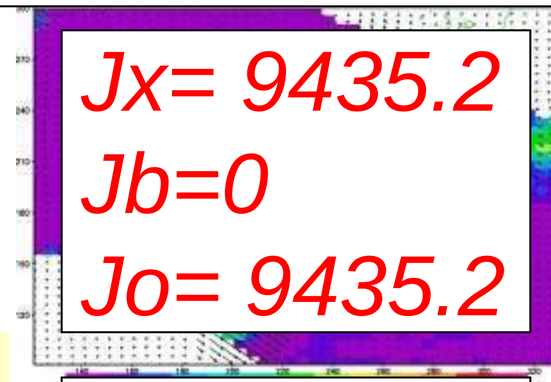
$$J_x = 1/2(\vec{X}-\bar{X}_f)P_f^{-1}(\vec{X}-\bar{X}_f)+1/2(Y-H(\vec{X}))R^{-1}(Y-H(\vec{X}))$$

FG:



Jx=24316.6
Jb=0
Jo=24316.6

DE:

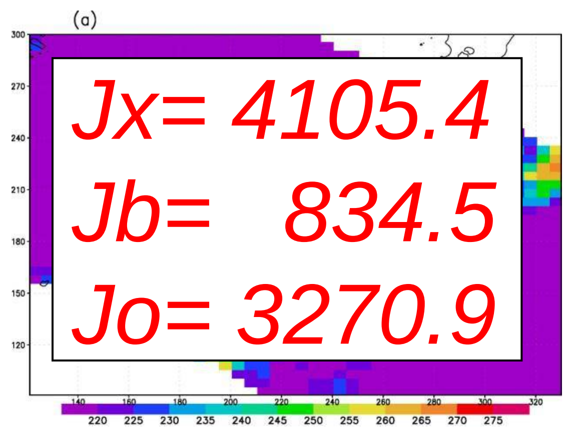


Jx= 9435.2
Jb=0
Jo= 9435.2

LN: DE+ EnVA. 1st

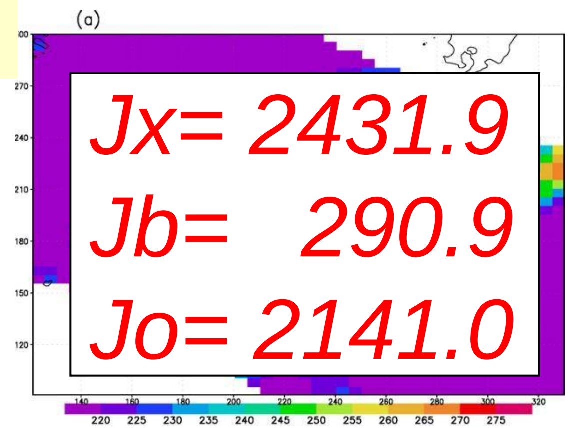
Jx= 6883.0
Jb= 14.5
Jo= 6868.4

ND:



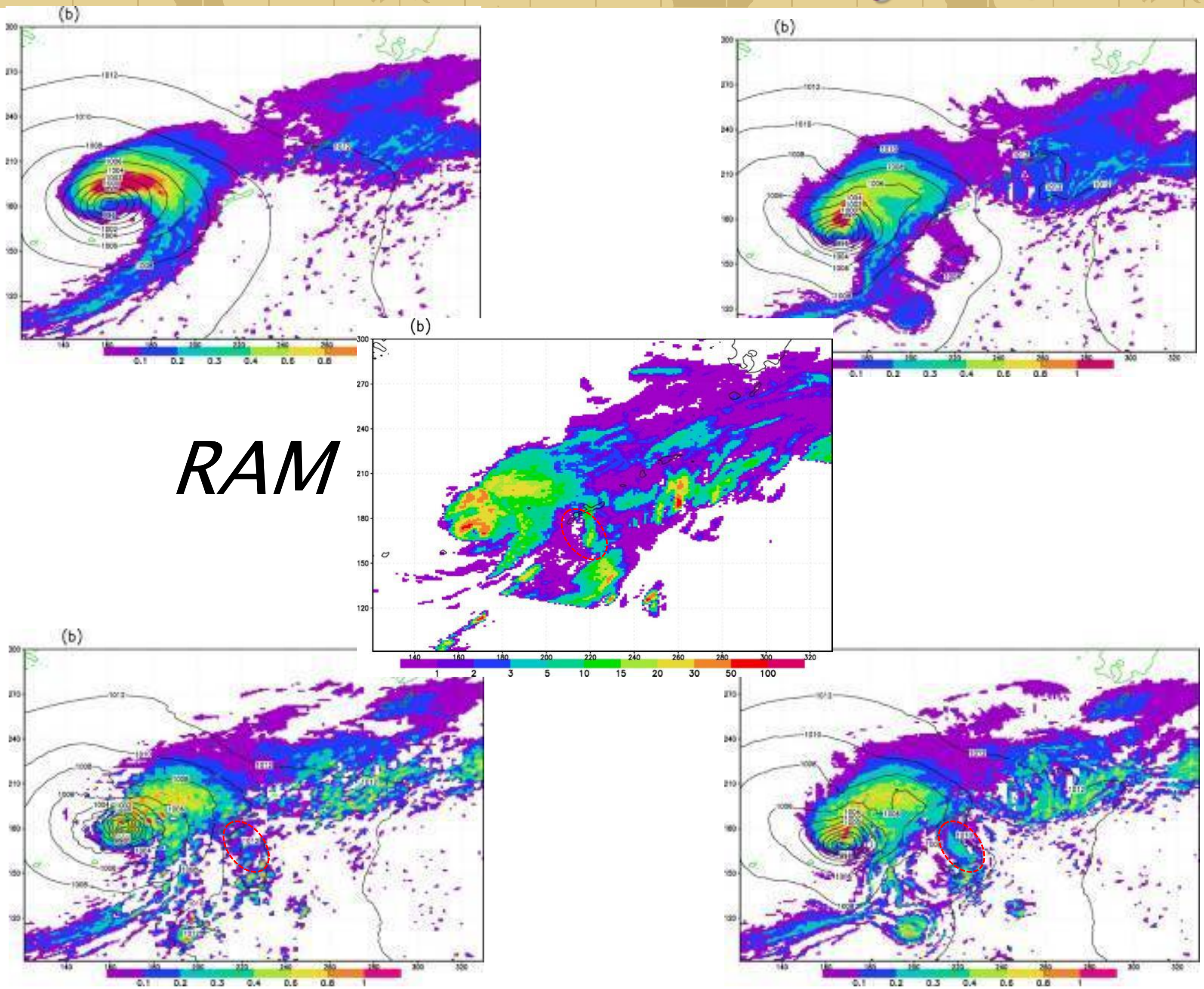
Jx= 4105.4
Jb= 834.5
Jo= 3270.9

CN:

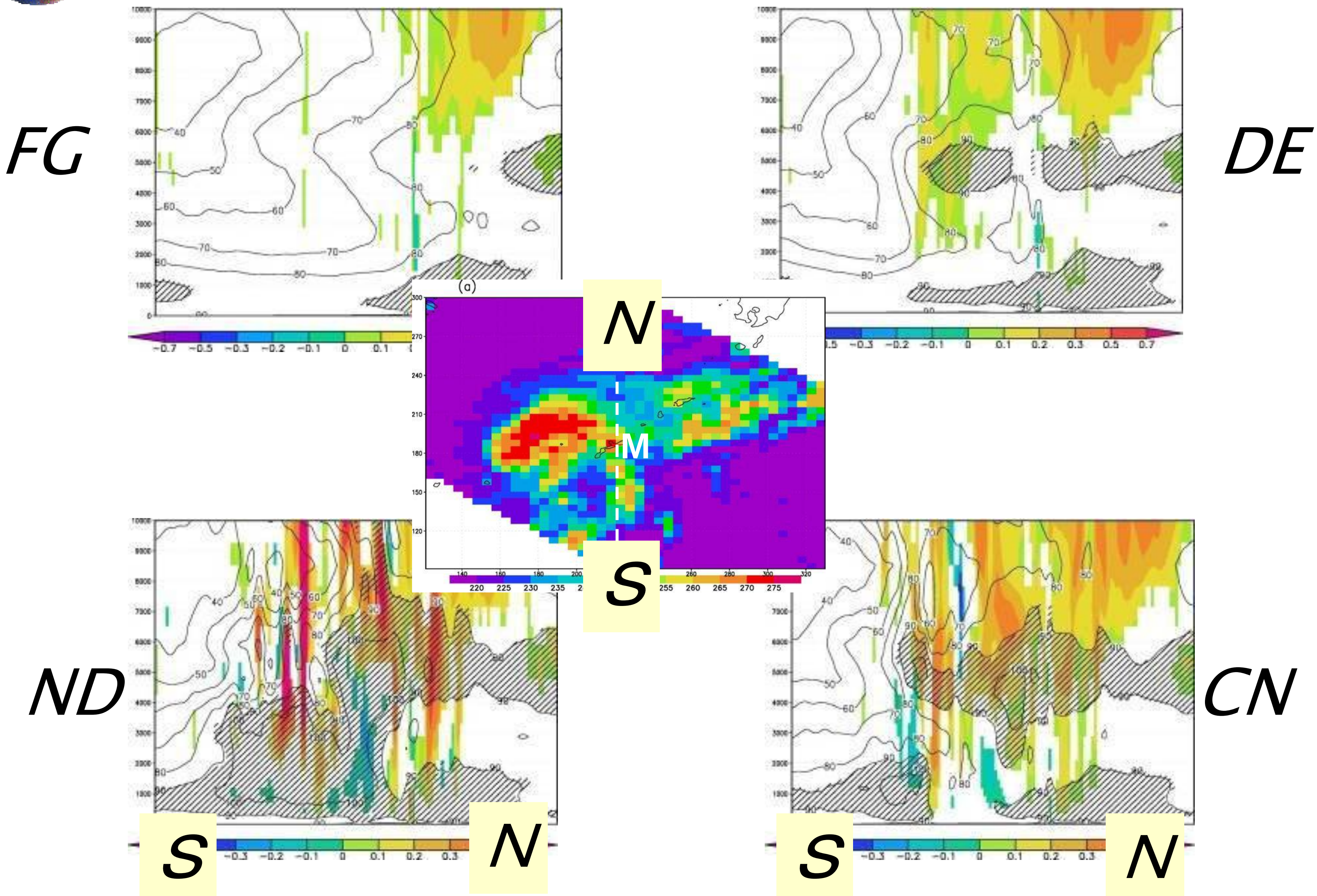


Jx= 2431.9
Jb= 290.9
Jo= 2141.0

RAM and Rain mix. ratio analysis (z=930m)

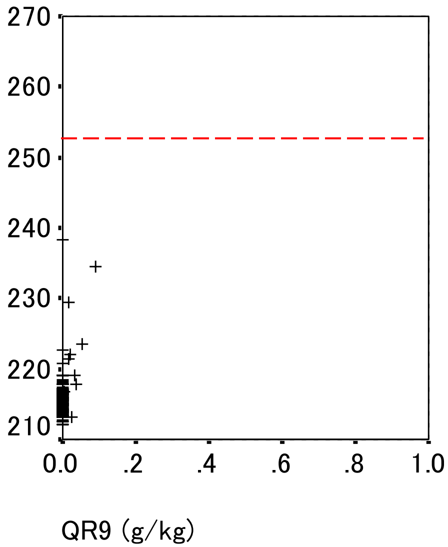


RH(contours) and W(shades) along N-S

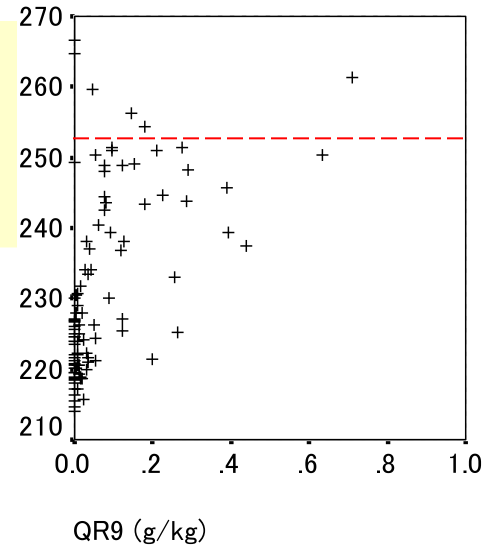


CRM Variables vs. TBc at Point M

FG

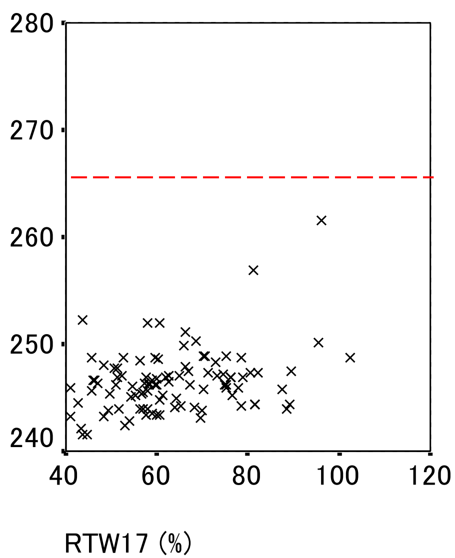


Qr(930m) vs.TB19v

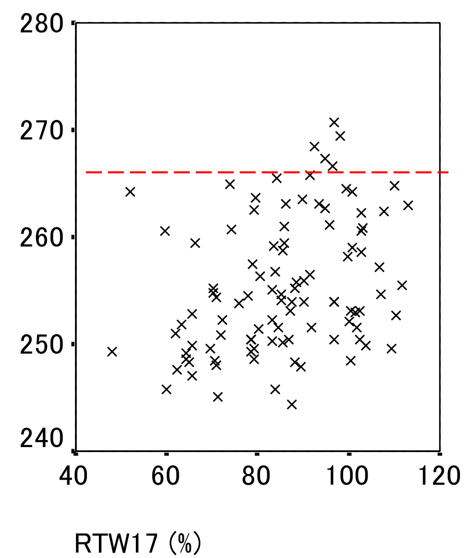


DE

FG



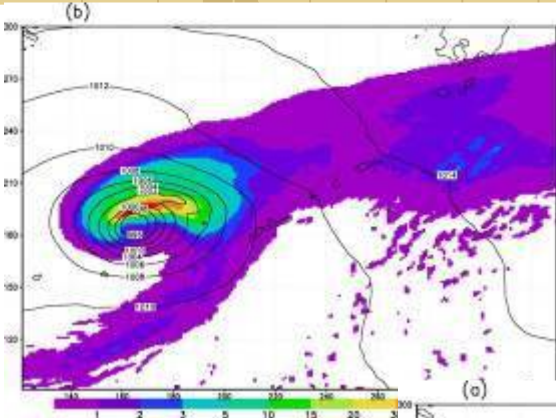
RTW (3880m) vs.TB21v



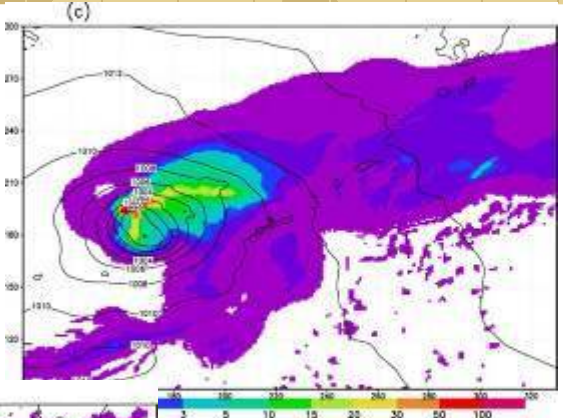
DE

Hourly Precip. forecasts (FT=0-1 h) 22-23Z 9t

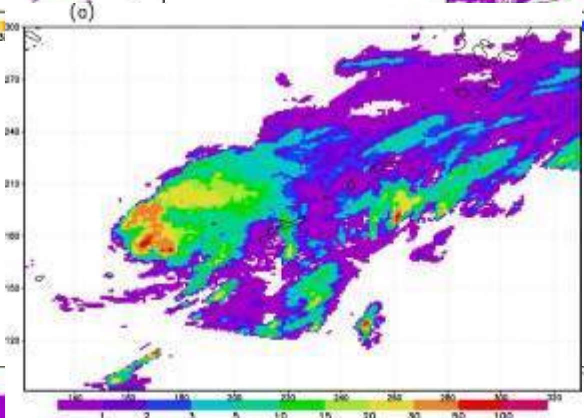
FG



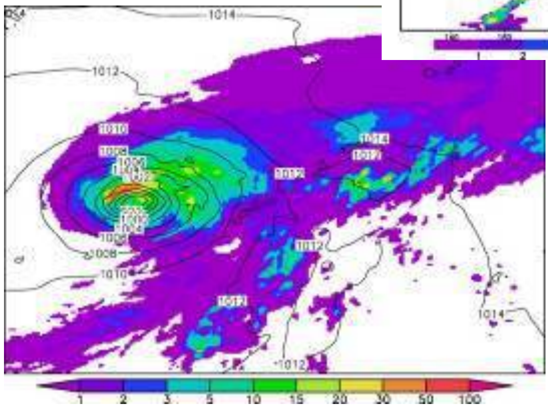
DE



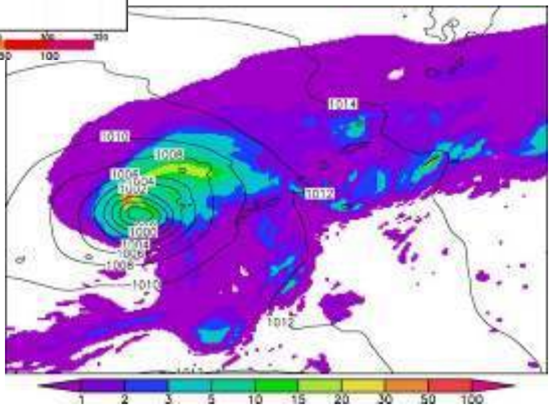
RAM



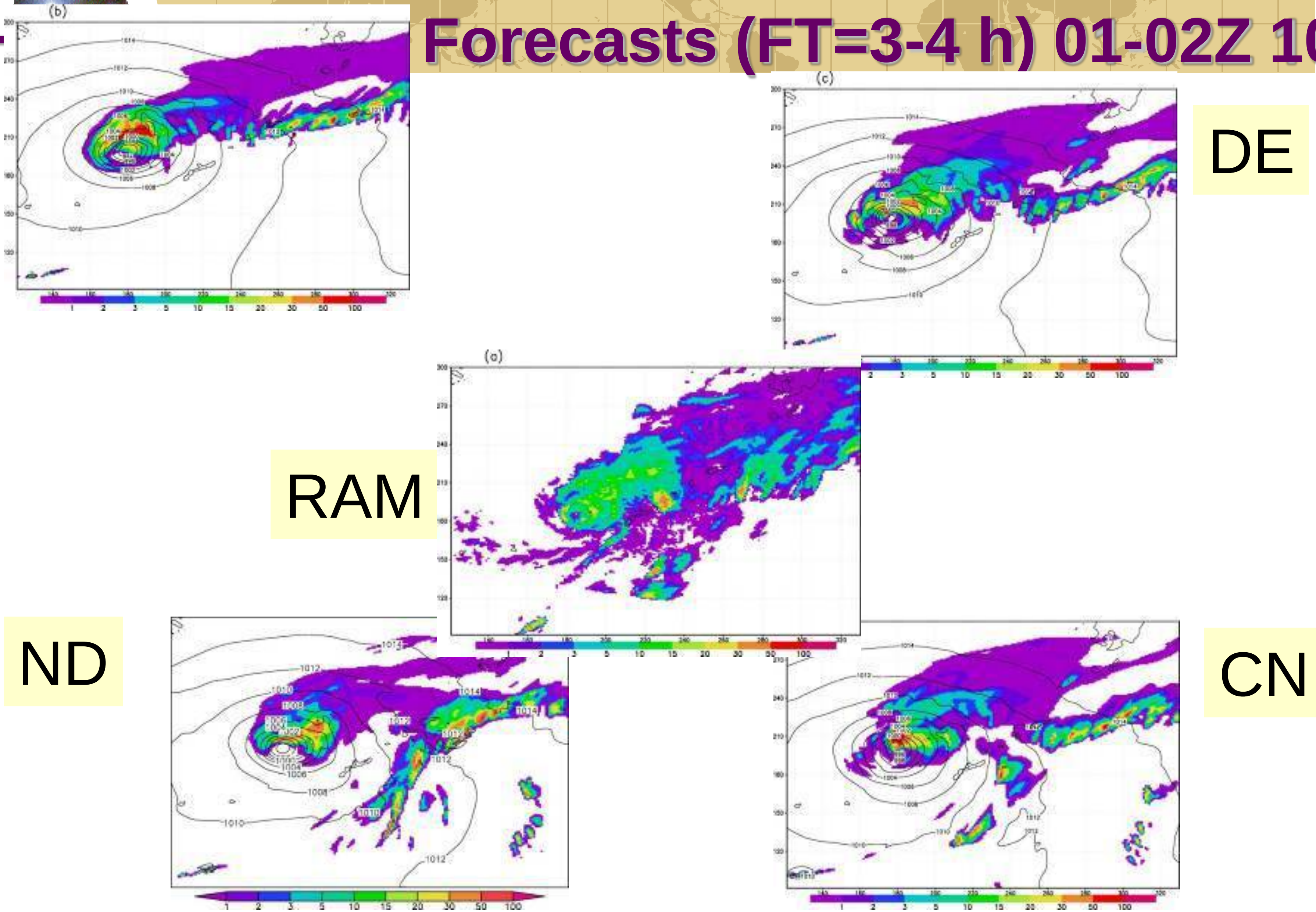
ND



CN



H Forecasts (FT=3-4 h) 01-02Z 10th



Summary

- Ensemble-based data assimilation can give erroneous analysis, particularly for observed rain areas without forecasted rain.
- In order to solve this problem, we developed the Ensemble-based assimilation method that uses Ensemble forecast error covariance with displacement error correction.
- This method consisted of a displacement error correction scheme and an Ensemble-based variational assimilation scheme.

Summary

- We applied this method to assimilate TMI TBs (10, 19, and 21 GHz with vertical polarization) for a Typhoon case (9th June 2004).
- The results showed that the assimilation of TMI TBs alleviated the large-scale displacement errors and improved precip forecasts.
- The DEC scheme also avoided misinterpretation of TB increments due to precip displacements as those from other variables.

Sampling error damping method for CRM EnVA

- Sample error-damping methods of previous studies
- Check the validity of presumptions of these methods

Sample error-damping methods of previous studies

- Spatial Localization (Lorenc, 2003)

$$C_{sp}(x1,x2)=C_{ENS}(x1,x2)\,S(\Delta_{1,2})$$

- Spectral Localization (Buehner and Charron, 2007)

$$\hat{C}_{sl}(k1,k2)=\hat{C}_{ENS}(k1,k2)\,\hat{L}_{sl}(k1,k2)$$

  - When transformed into spatial domain

$$C_{sl}(x1,x2)=\int C_{ENS}(x1+s,x2+s)L_{sl}(s)ds$$

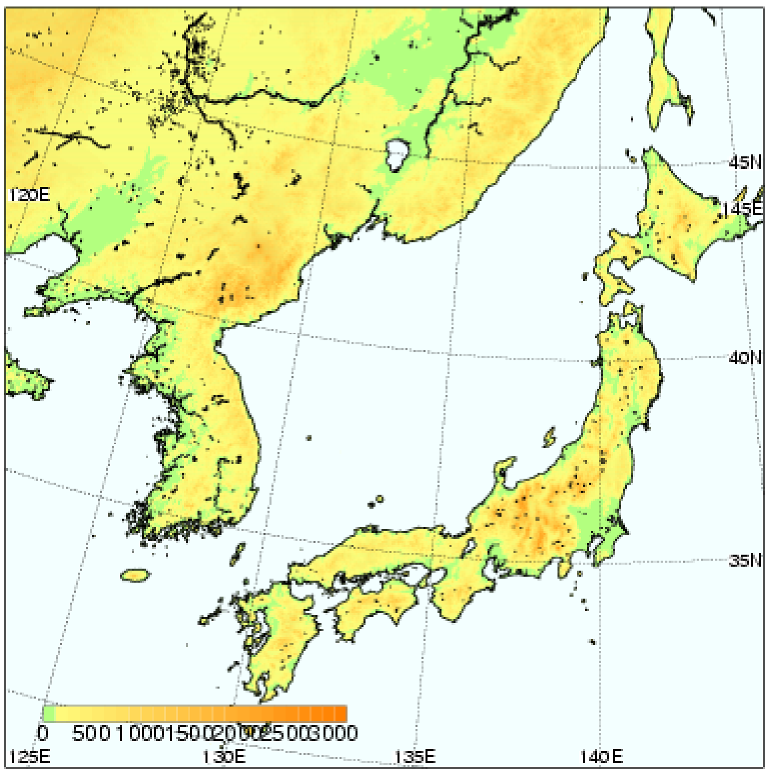
- Variable Localization (Kang, 2011)

$$C_{v}(v1,v2)=C_{ENS}(v1,v2)\,\delta(v1,v2)$$

Cloud-Resolving Model used

JMANHM (Saito et al,2001)

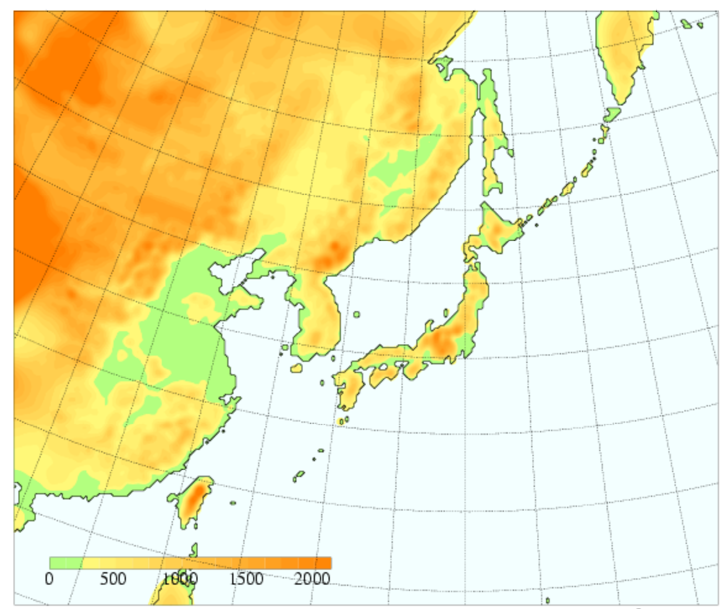
- **Resolution: 5 km**
- **Grids: 400 x 400 x 38**
- **Time interval: 15 s**



Initial and boundary data

JMA's operational regional model

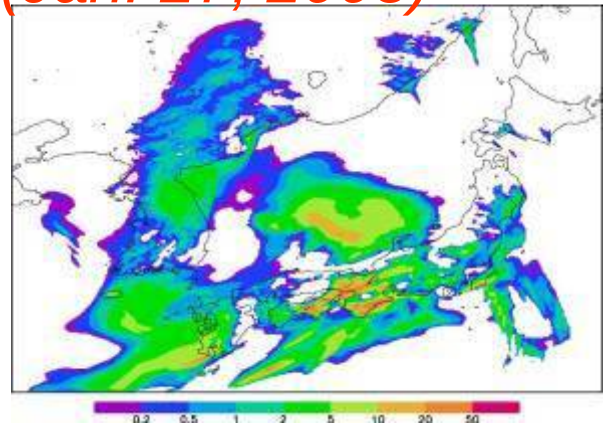
- **Basic equations :** Hydrostatic primitive
- **Precipitation scheme:**
  Moist convective adjustment
  + Arakawa-Schubert
  + Large scale condensation
- **Resolution:** 20 km
- **Grids:** 257 x 217 x 36



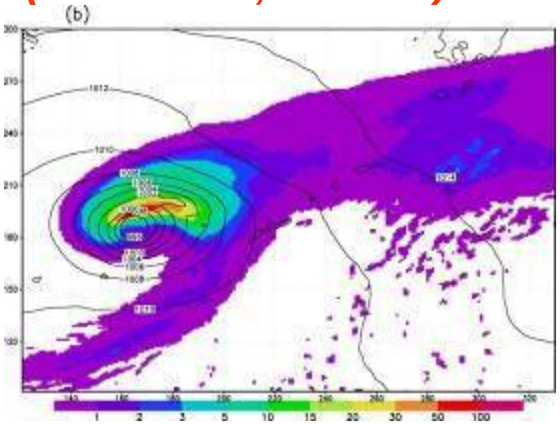
Ensemble Forecasts

- 100 members started with perturbed initial data
- Geostrophically-balanced perturbation plus Humidity
- Random perturbation with various horizontal and vertical scales (Mitchell et al. 2002)

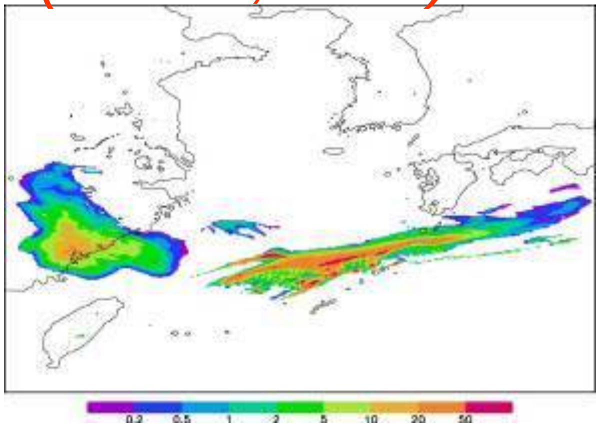
Extra-tropical Low (Jan. 27, 2003)



Typhoon CONSON (June. 9, 2004)



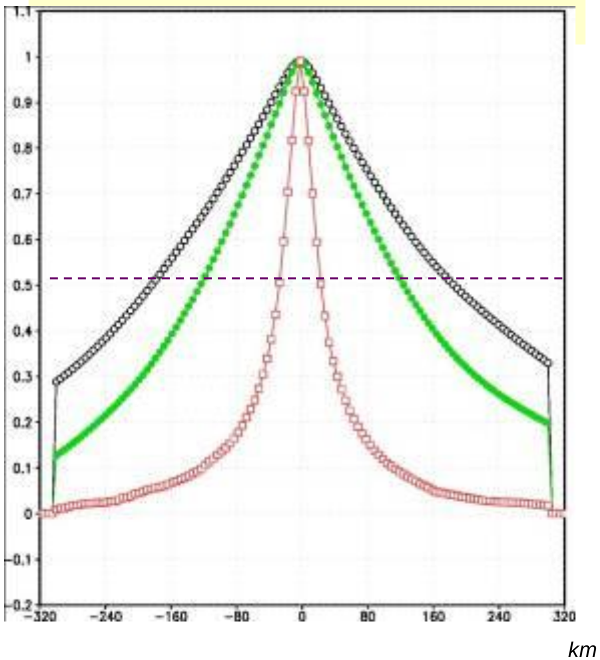
Baiu case (June 1, 2004)



Horizontal correlation of ensemble forecast error (H~ 5000 m) : Typhoon

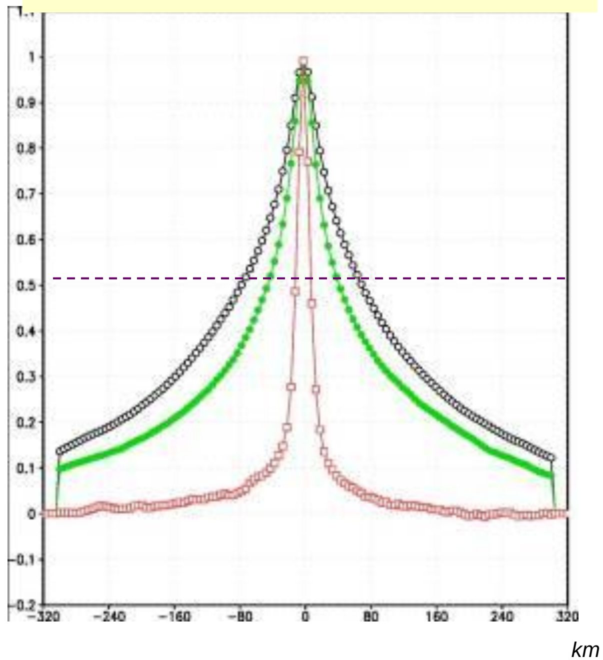
（black: U, green:RHW2, red :W）

Rain-free area



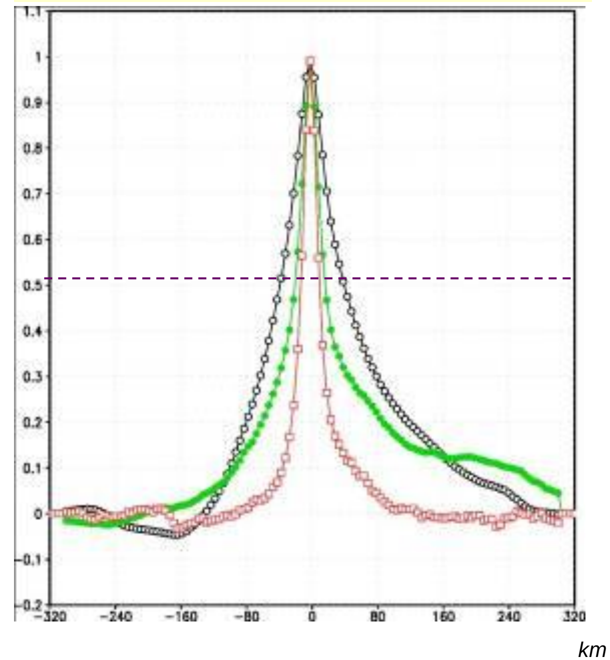
Weak Precip

PR 1-3 mm/hr



Heavy Precip

PR >10mm/hr

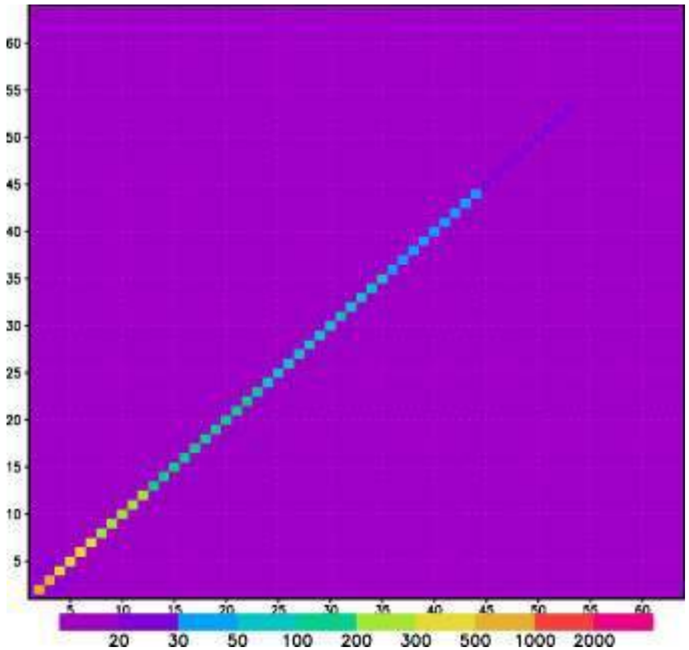


Simple spatial localization is not usable.

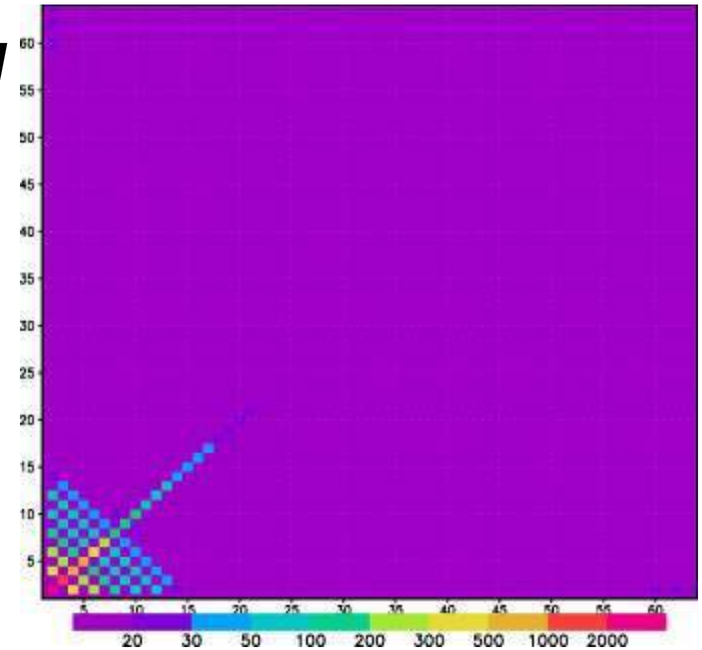
2) Horizontal correlation scales of (U, V, PT, RH) decreased (160 km -> 40 km) with precipitation rate.

Power spectral of horizontal ensemble forecast error (H~5000m) : Typhoon

W



U

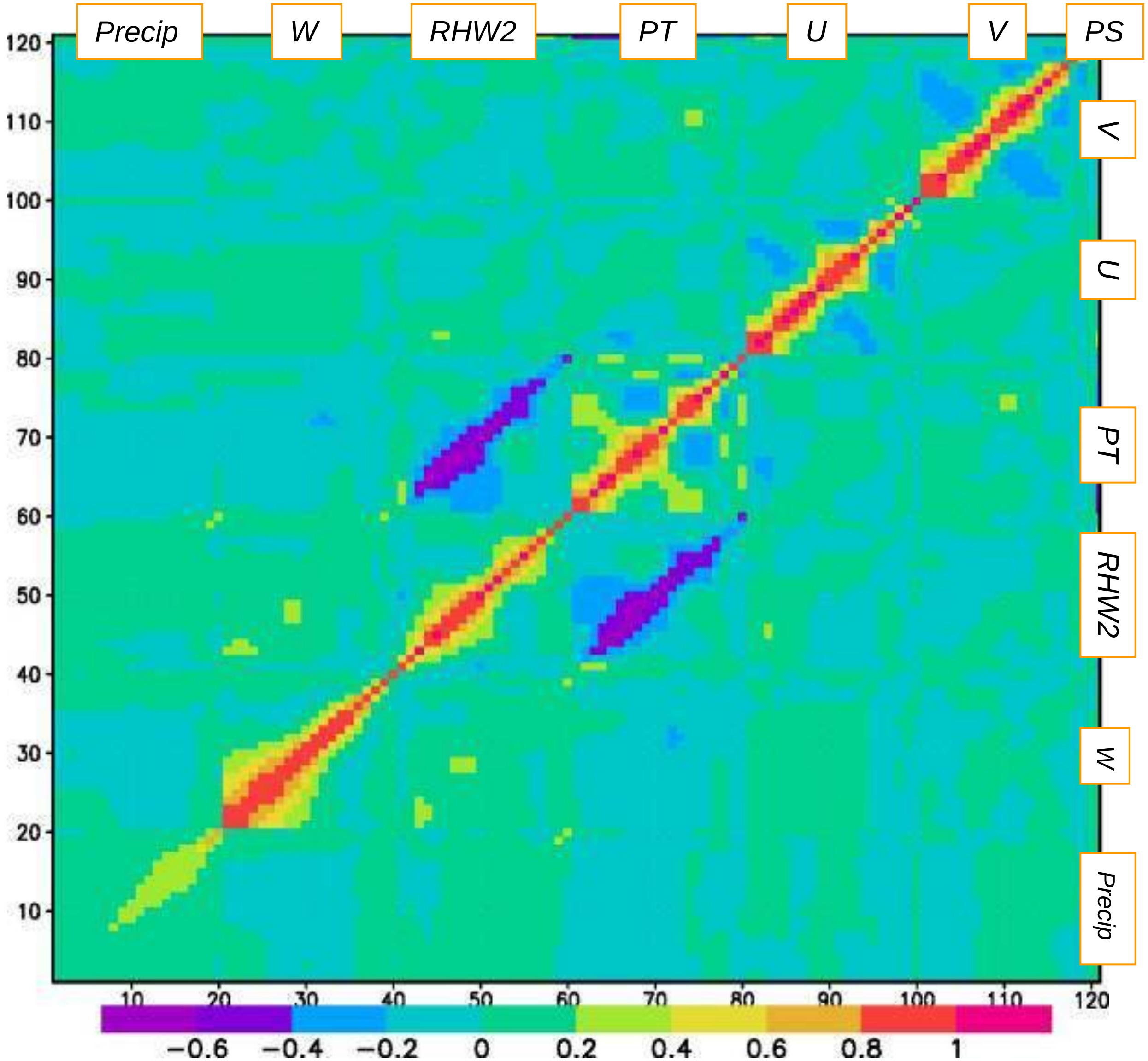


Spectral localization may be applicable.

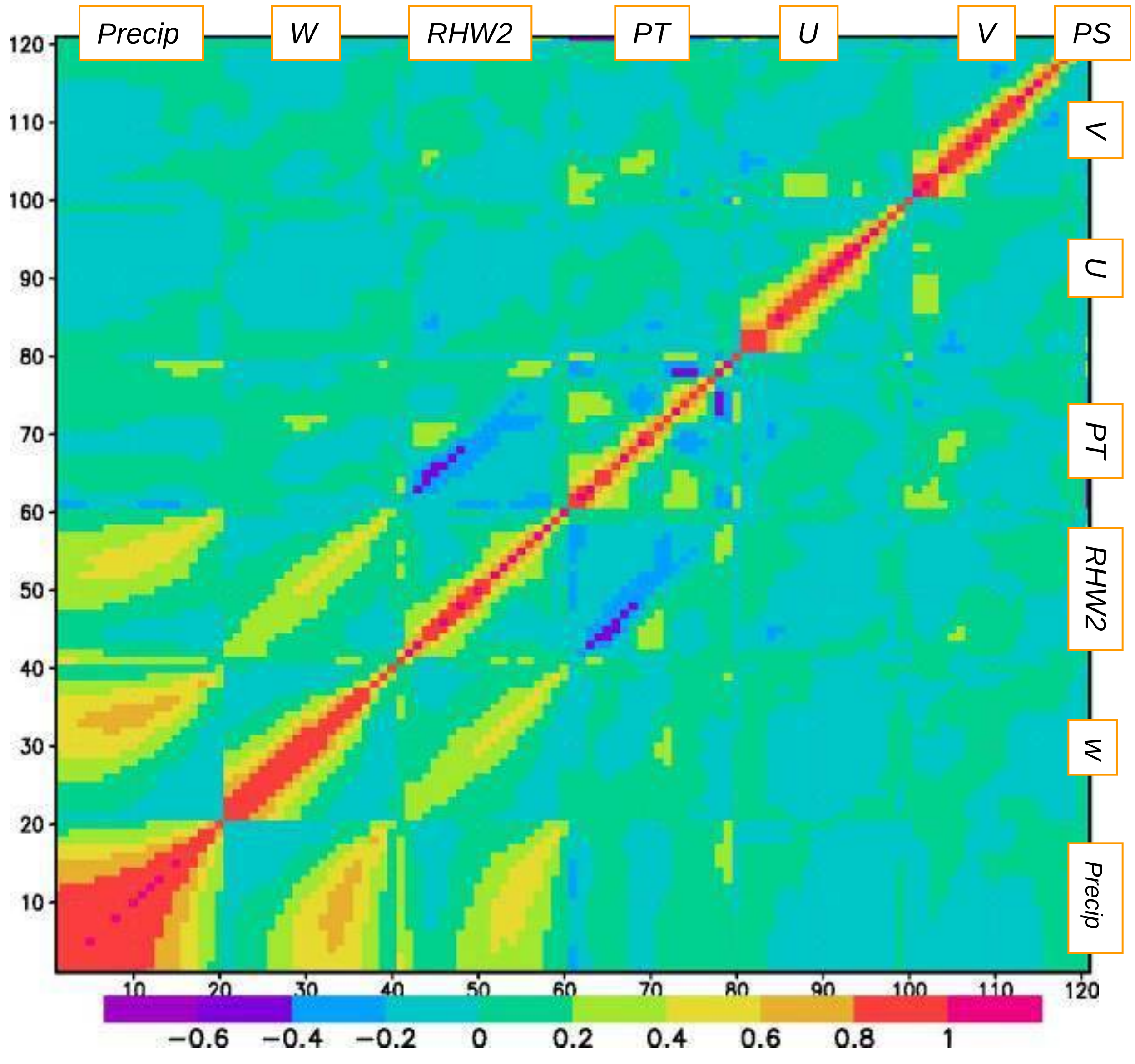
mplitudes

2) The presumption of the spectral localization "Correlations in spectral space decreases as the difference in wave number increases" is valid.

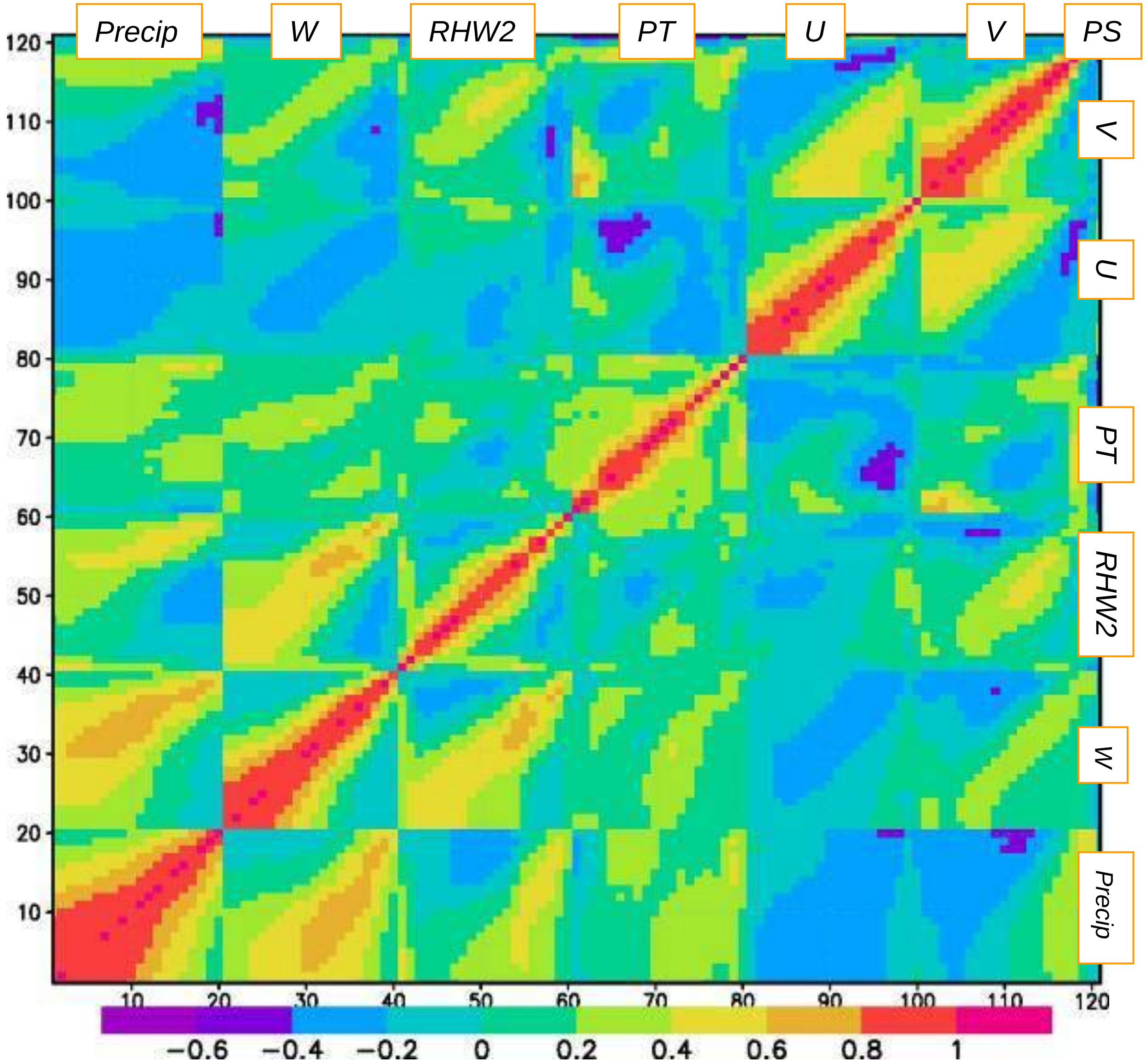
Cross correlation of CRM variables in the vertical (Typhoon): Rain-free areas



Cross correlation of CRM variables in the vertical (Typhoon): Weak rain *(1-3 mm/hr)*



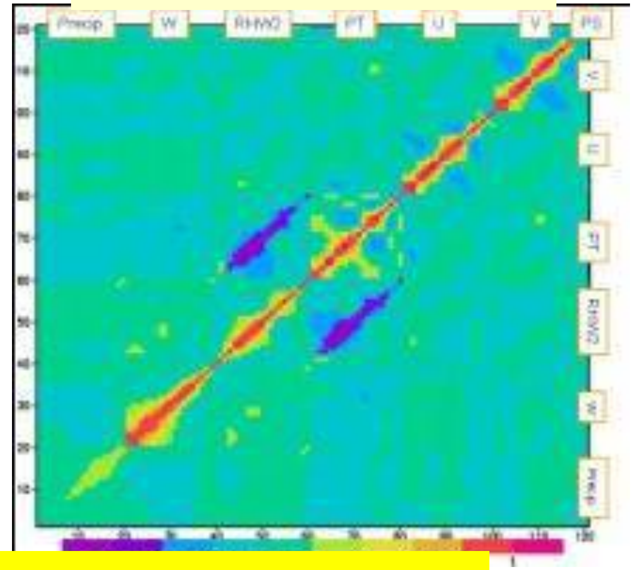
Cross correlation of CRM variables in the vertical (Typhoon):Heavy rain (>10mm/hr)



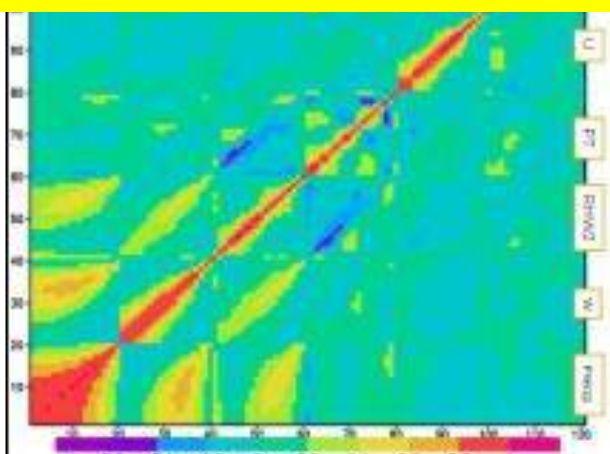
Cross correlation of CRM variables in the vertical (Typhoon)

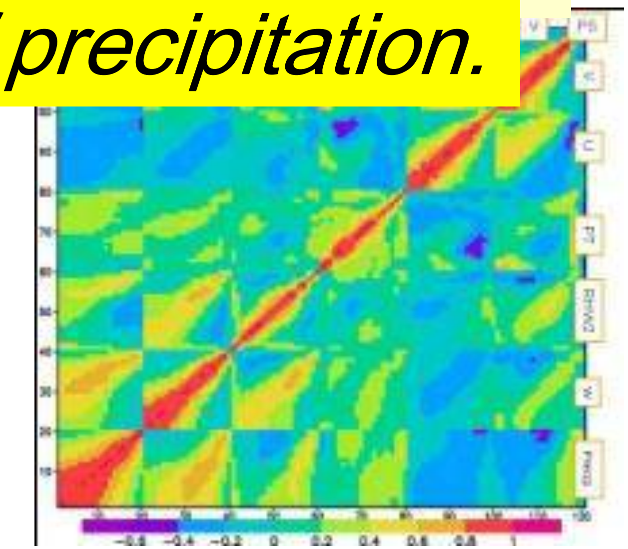
1)Cross correlation between precipitation-related variables and other variables increases with precipitation rate.
2) Variables can be classified in terms of precipitation rate.

Rain-free areas



Variable localization needs classification in terms of precipitation.





Introducing sampling error damping ideas to EnVA

- Spetctal Localization >
  - Use of ensemble forecasts at neighboring grid points
- Heterogeneity of forecast covariance >
  - Classification of CRM variables and assumption of zero cross correlation between different classes.

Summary

- We checked the validity of presumptions of the sampling error damping methods.

- Simple spatial localization is not usable.
- Spectral localization may be applicable.
- Variable localization needs classification in terms of precipitation.
- We should consider heterogeneity of the forecast covariance (Michel et al, 2011).

Summary

- Ensemble-based Variational Assimilation (EnVA)
  - Methodology
  - Problems in EnVA for CRM
- Displacement error correction (DEC)+EnVA
  - Methodology
  - Application results for Typhoon CONSON (T0404)
- **Sampling error damping method for CRM EnVA**
  - **Sample error-damping methods of previous studies**
  - **Check the validity of presumptions of these methods**

Thank you for your attention.

End