Assimilation of GPM/DPR in Km-scale Hybrid-4DVar system

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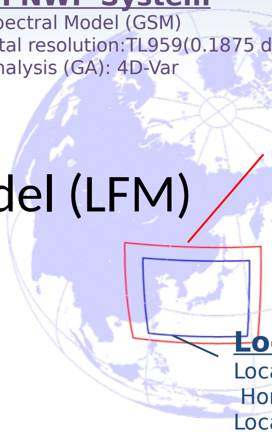
Operational Meso-scale NWP system in JMA

- Main purpose
  - Providing disaster prevention information and aviation weather forecast
- Meso-Scale model (MSM) and Local Forecast Model (LFM)
  - 3-ice 6-class cloud microphysics process scheme
    - Prognostic hydrometeors
      - Water vapor, cloud, rain, ice, snow and graupel
    - These hydrometeor profiles are needed to calculate reflectivity and radiance in data assimilation.
- Meso-Scale Analysis (MA)
  - 4D-Var data assimilation system
    - **Hydrometeors are not control variables.**

Global NWP System
Global Spectral Model (GSM)
Horizontal resolution:TL959(0.1875 deg)
Global Analysis (GA): 4D-Var



Meso-Scale NWP System
Meso-scale model (MSM)
Horizontal resolution: 5 km
Meso-Scale Analysis (MA): 4D-Var

Local NWP System
Local Forecast model (LFM)
Horizontal resolution: 2 km
Local Analysis (LA):3D-Var Analysis cycle

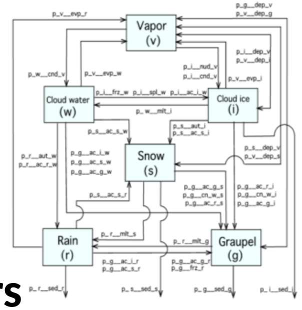


Figure 3.5.2: Cloud microphysical processes in the MSM. For a list of symbols, see Table 3.5.1.

➡ **<u>Future Plan</u>: Hybrid-4DVar with control variable of hydrometeors**

Current state of GPM/DPR assimilation at JMA

- In the operational Meso-Scale NWP system
  - Traditional 4DVAR
    - Climatological background error covariance
    - Hydrometeors are “**not**” control variables.
  - **GPM/DPR assimilation method**
    - Indirect assimilation (1D+4DVAR)
    - Assimilation of relative humidity profile retrieved from reflectivity
- **Operational assimilation of GPM/DPR started in March 2016.**

Further Utilization of GPM/DPR

- Characteristics of DPR
  - **3-D information of hydrometeors**
  - **Sensitivity to snow particles**
  - Covering not only land area, but also sea area

can not be utilized in the current system

- Benefit of the utilization of DPR in DA
  - Improvement of hydrometeors reproducibility in initial time
    -> Improvement of precipitation forecast
- Useful way to achieve the goal for MSM purpose

Next step of DPR assimilation

<u>Indirect assimilation</u>

using retrieved RH profiles
in **traditional 4DVAR**

<u>Direct assimilation</u>

using reflectivity (KuPR, KaPR) profiles
in **new Hybrid-4DVAR**

Formulation of Flow-dependent Assimilation

Cost function

$$J = \frac{1}{2}\beta_n^2 \delta\mathbf{x}_{n0}^T \mathbf{B}_{NMC}^{-1} \delta\mathbf{x}_{n0} + \frac{1}{2}\beta_e^2 \delta\mathbf{x}_{e0}^T \mathbf{B}_{ENS}^{-1} \delta\mathbf{x}_{e0}$$

$$+ \frac{1}{2}\sum_t \left(\mathbf{H}\mathbf{M}_t \delta\mathbf{x}_0 - \mathbf{d}_t\right)^T \mathbf{R}_t^{-1} \left(\mathbf{H}\mathbf{M}_t \delta\mathbf{x}_0 - \mathbf{d}_t\right)$$

1. Observation term

2. Climatological term

- BG covariance is given by statistics of forecast error.

3. Flow-dependent term

- BG covariance is estimated from ensemble forecasts.
- This term measures the fit based on the flow-dependent background error **in various meteorological situations.**

1-moment Cloud microphysics optimized for DA

Cloud particle

PSD: mono-dispersion

Mass

$$m_c = \frac{\pi}{6} \rho_c D^3 \; [\mathrm{kg}]$$

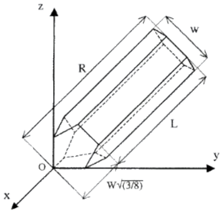
Rain and graupel particle

PSD: exponential

Mass

$$m_{r,g} = \frac{\pi}{6} \rho_{r,g} D^3 \; [\mathrm{kg}]$$

Ice particle



Heymsfield and Iaquinta (2000)

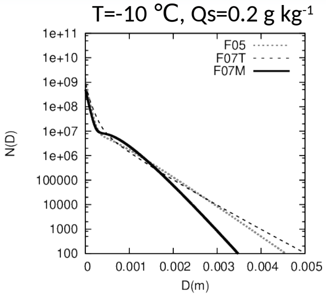
PSD: mono-dispersion

$$n_x(D) = N_x \delta\left(D - \bar{D}_x\right)$$

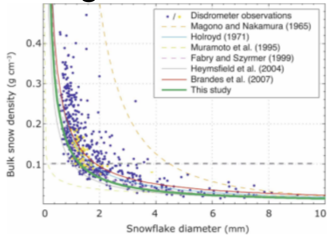
Mass

$$m_i = 7.0 \times 10^{-3} D^2 \; [\mathrm{kg}]$$

Snow particle



Ice <--> large snow flake



Thompson et al. (2008)

PSD: exponential + modified gamma

For midlatitude cloud (Field et al. 2007)

$$n_x(D) = \frac{\mathcal{M}_2^4}{\mathcal{M}_3^3}\left[\kappa_0 \exp\left(-\frac{\mathcal{M}_2}{\mathcal{M}_3}\Lambda_0 D\right) + \kappa_1 \left(\frac{\mathcal{M}_2}{\mathcal{M}_3} D\right)^{\mu} \exp\left(-\frac{\mathcal{M}_2}{\mathcal{M}_3}\Lambda_1 D\right)\right]$$

Mass

$$m_s = 6.9 \times 10^{-2} D^2 \; [\mathrm{kg}]$$

Bulk snow density

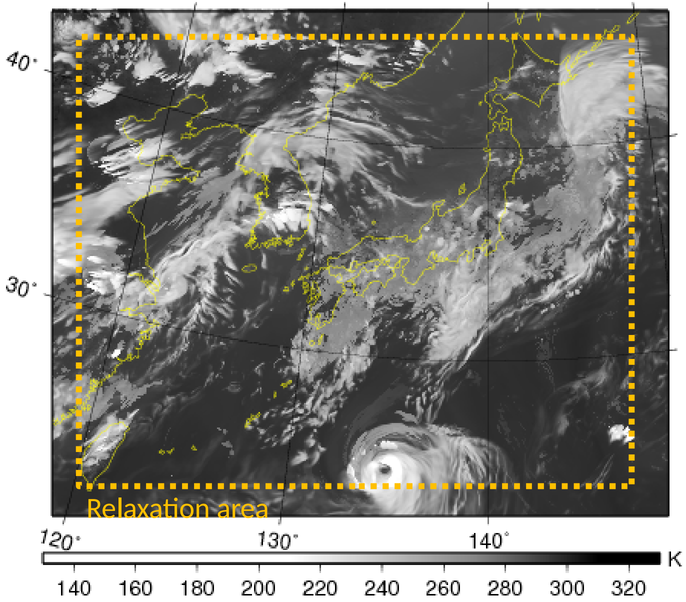
$$\rho_s = 1.3 \times 10^{-1} D^{-1} \; [\mathrm{kg\ m^{-3}}]$$

TL/AD of cloud microphysics are needed for reflectivity and cloudy radiance direct assimilation.

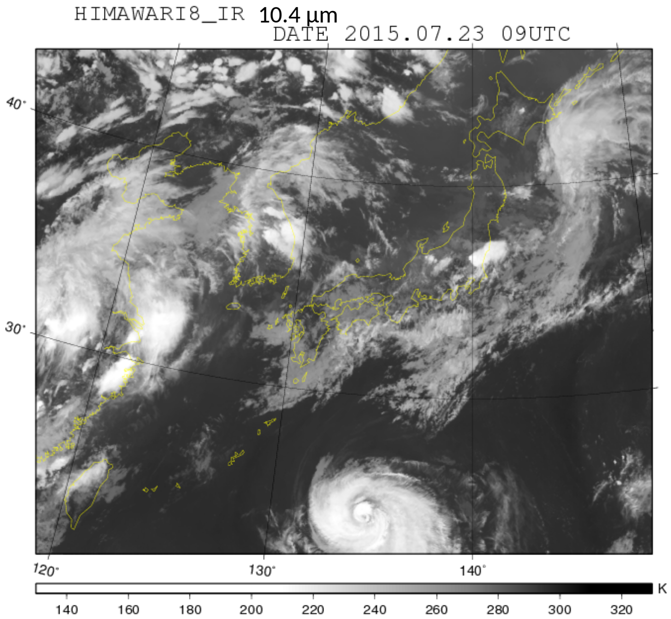
Comparison of Simulation and Observation

Simulation

Horizontal resolution: 2 km, Lead time: 9-hour
Shape: non-spherical, Snow-PSD: exponential+gamma



Observation (Himawari-8 AHI)



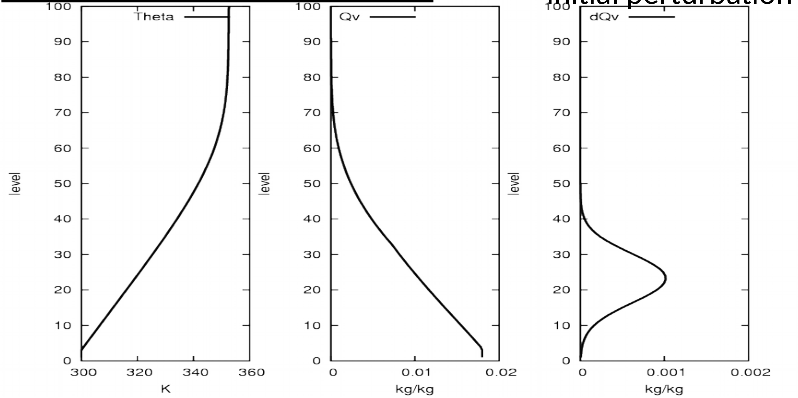
Test Case using Single Column Model

	Single column TL/AD model based on KiD*
Variables	P(pressure), T(temperature), Qv(specific humidity), Qx(mixing ratio of hydrometeors x) x=cloud, rain, ice, snow and graupel
Vertical resolution / number of level	160 m / 100 levels
Time step	5 sec

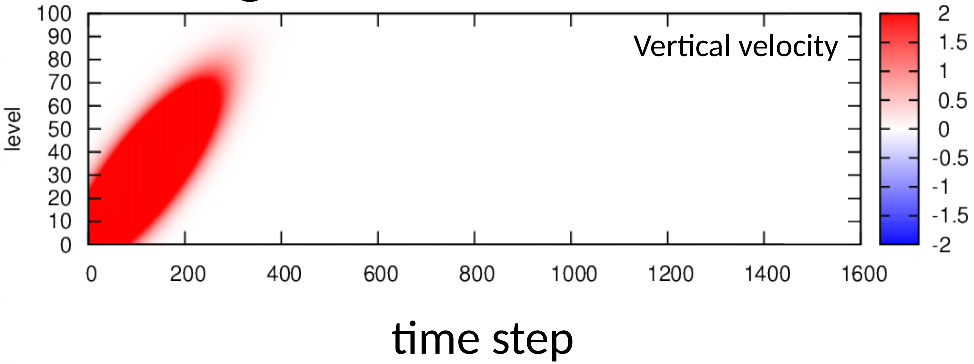
* Shipway and Hill (2012)

Initial condition

initial perturbation

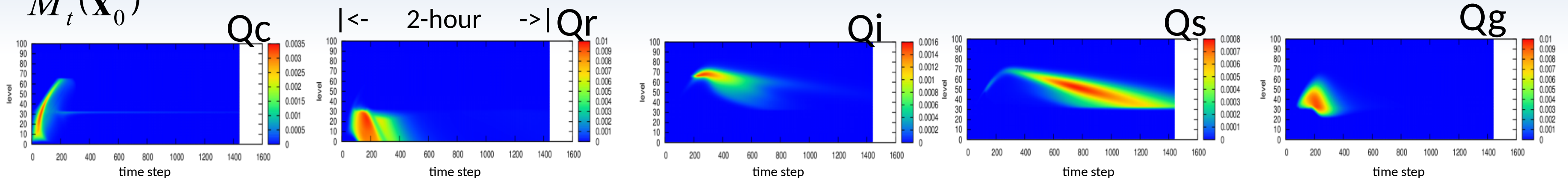


Forcing

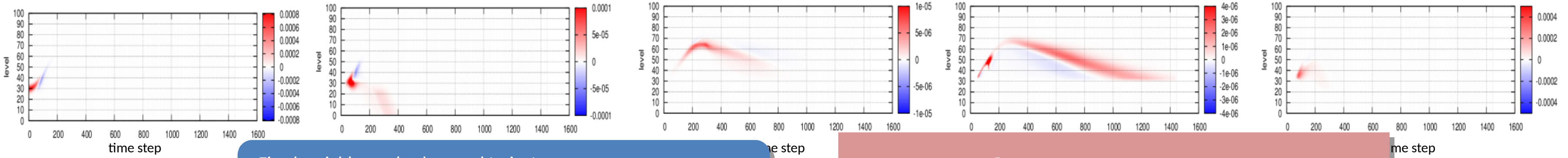


Tangent Linearization of Microphysics Scheme

$M_t(\mathbf{x}_0)$



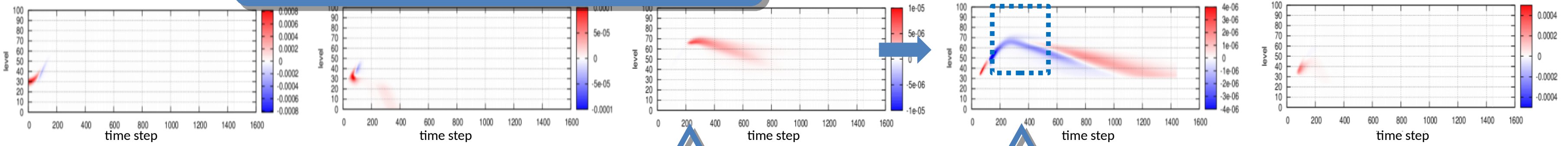
$M_t(\mathbf{x}_0 + \delta\mathbf{x}) - M_t(\mathbf{x}_0)$



TL is almost consistent.

$\mathbf{M}_t\delta\mathbf{x}$

Fixed variables on background trajectory
- Air density and pressure
- Diffusivity of water vapor, thermal conductivity of air

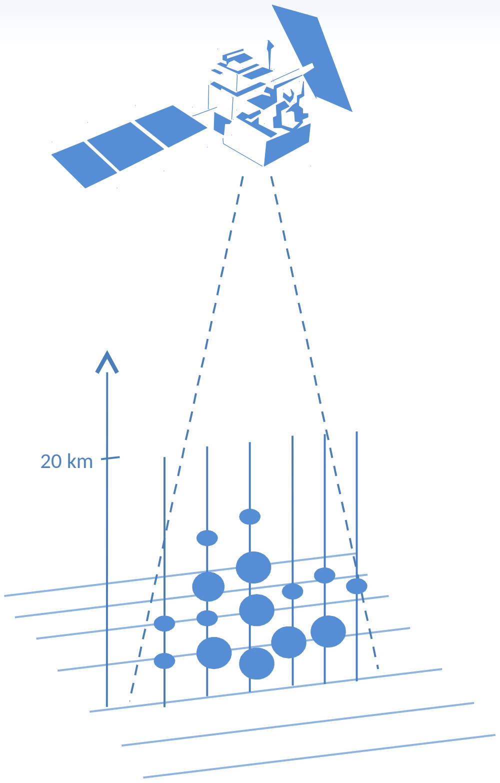


Nucleation is a strongly nonlinear process.

Snow error is originated from difference in ice perturbation

Enhancement of space-borne radar simulator

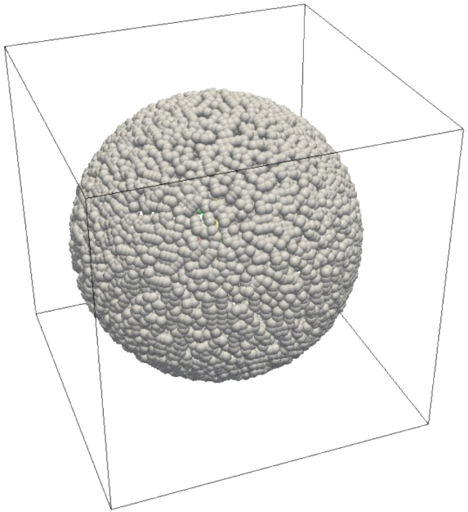
- **<u>Space-borne radar simulator</u>**
    - Simplified because of reducing computation cost
  - Beam: Not-bending
    - Ignoring the slant beam path and beam width
  - Effective particle: Rain, snow and graupel
    - Ignoring cloud water and cloud ice particles
  - Size distribution
    - rain and graupel: Exponential distribution
    - snow: Exponential + modified gamma distribution
  - Particle type
    - Spherical or Non-spherical particle
  - Scattering calculation
    - LUT (Lorenz-Mie, DDA)
    - Single scattering



Shape of snow particle for scattering

Spherical snow

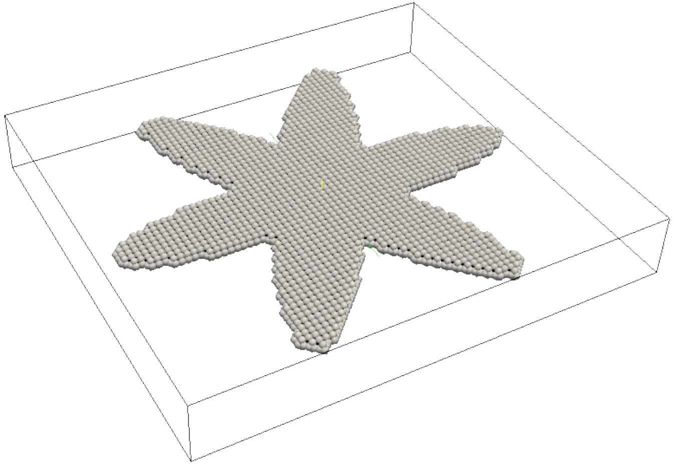
Scattering: Lorentz-Mie



In current method, snow particles are assumed as spherical particle.

Type-A snowflakes in Liu(2008)

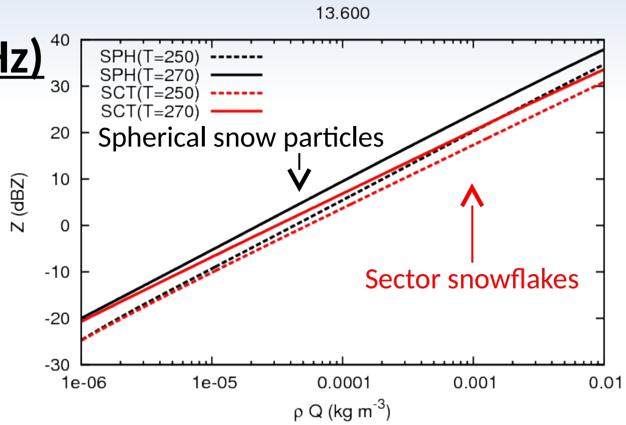
Scattering: DDA(Discrete Dipole Approximation)

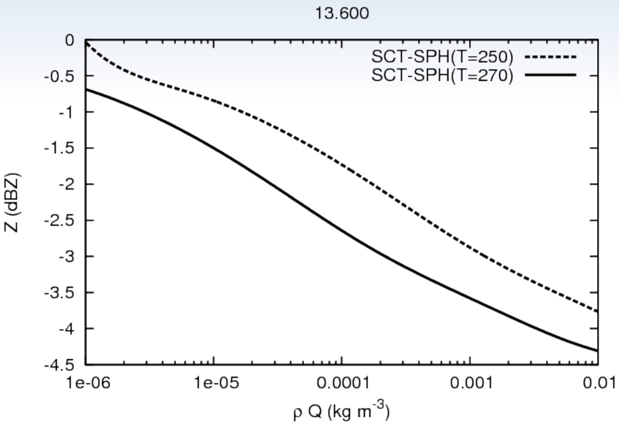


These dipoles by DDSCAT 7.3

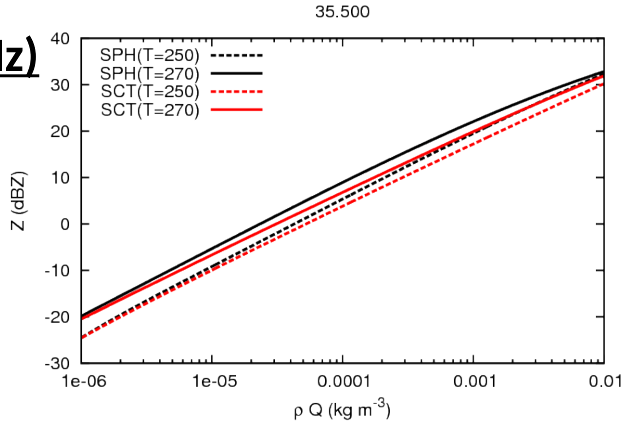
Radar Reflectivity of Snow

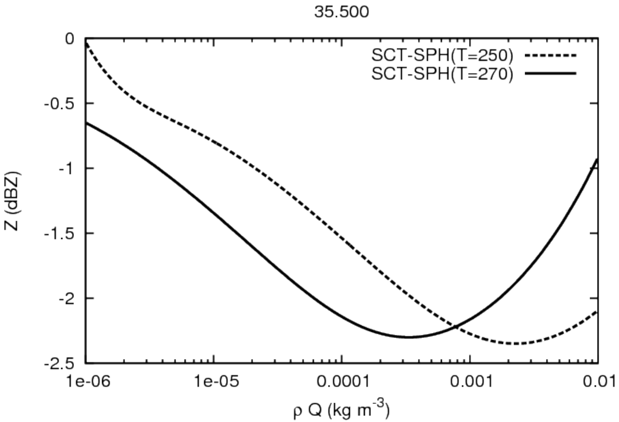
KuPR(13.6GHz)





KaPR(35.5GHz)



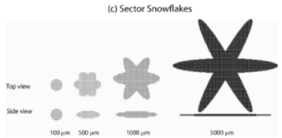


PSD: exponential + modified gamma (Field et al. 2007)

Bulk density:

$$\rho_s = 1.3\times10^{-1} D^{-1} \left[\mathrm{kg\ m^{-3}}\right]$$

SCT Liu(2008)



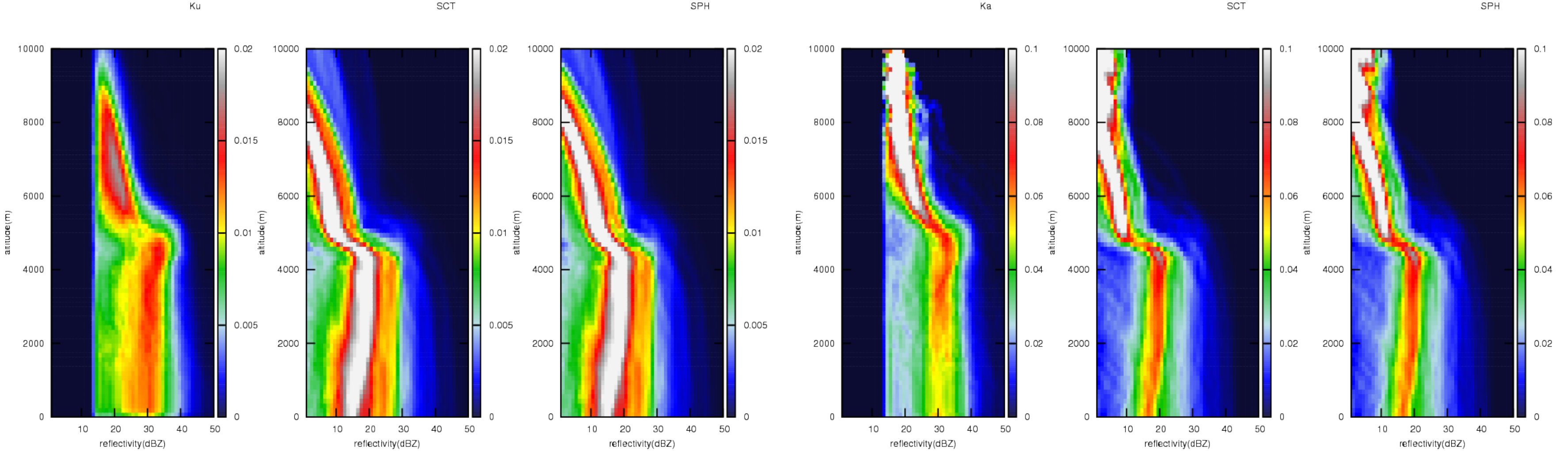
Small Large

CFADs of radar reflectivity

Contour frequency by altitude diagrams (CFADs)

KuPR — **Observation** | **Simulation(SCT)** | **Simulation(SPH)**

KaPR — **Observation** | **Simulation(SCT)** | **Simulation(SPH)**



SCT: sector of snowflakes
SPH: spherical particle of snow

SCT is weaker than SPH, however model bias is larger than difference of particle shape.

Tangent-linear and Adjoint of Radar Simulator

Function of reflectivity calculation

$$Z(Q+\delta Q, T+\delta T) - Z(Q,T) = \frac{\partial Z}{\partial Q}\delta Q + \frac{\partial Z}{\partial T}\delta T$$

$$= \mathbf{Z} \cdot \begin{pmatrix} \delta Q \\ \delta T \end{pmatrix}$$

$\mathbf{Z}$: Tangent-linear operator

$\mathbf{Z}^T$: Adjoint operator

Similarity between $Z(Q,T)$ and $\mathbf{Z}$.

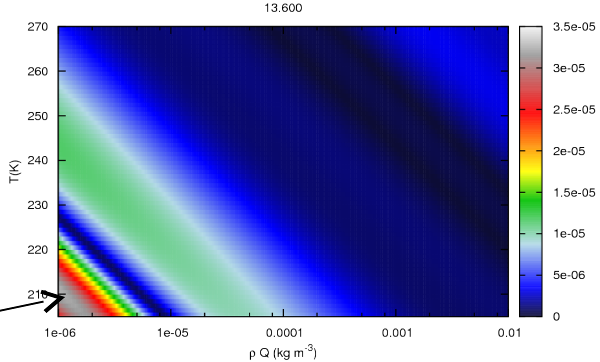
$$\left| \mathbf{Z} \cdot \begin{pmatrix} \delta Q \\ \delta T \end{pmatrix} - \left(Z(Q+\delta Q, T+\delta T) - Z(Q,T) \right) \right|$$

$$\delta Q = Q \times 10^{-3}, \delta T = T \times 10^{-3}$$

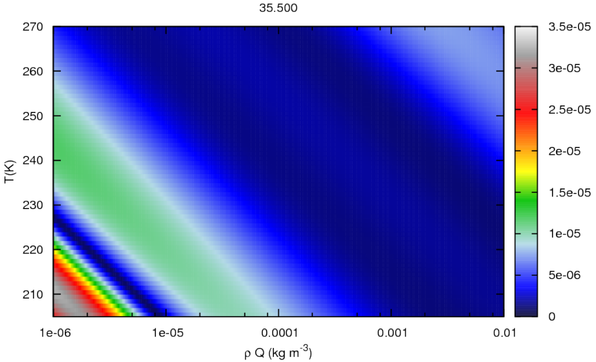
Error increases in low temperature and low mass.

(Maximum error ~ 3.e-5 dBZ)

KuPR (snow)



KaPR (snow)



Formulation of Flow-dependent Assimilation

Cost function

$$J = \frac{1}{2}\beta_n^2 \delta\mathbf{x}_{n0}^T \mathbf{B}_{NMC}^{-1} \delta\mathbf{x}_{n0} + \frac{1}{2}\beta_e^2 \delta\mathbf{x}_{e0}^T \mathbf{B}_{ENS}^{-1} \delta\mathbf{x}_{e0}$$

$$+ \frac{1}{2}\sum_t \left(\mathbf{HM}_t \delta\mathbf{x}_0 - \mathbf{d}_t\right)^T \mathbf{R}_t^{-1} \left(\mathbf{HM}_t \delta\mathbf{x}_0 - \mathbf{d}_t\right)$$

1. Observation term

2. Climatological term

- BG covariance is given by statistics of forecast error.

3. Flow-dependent term

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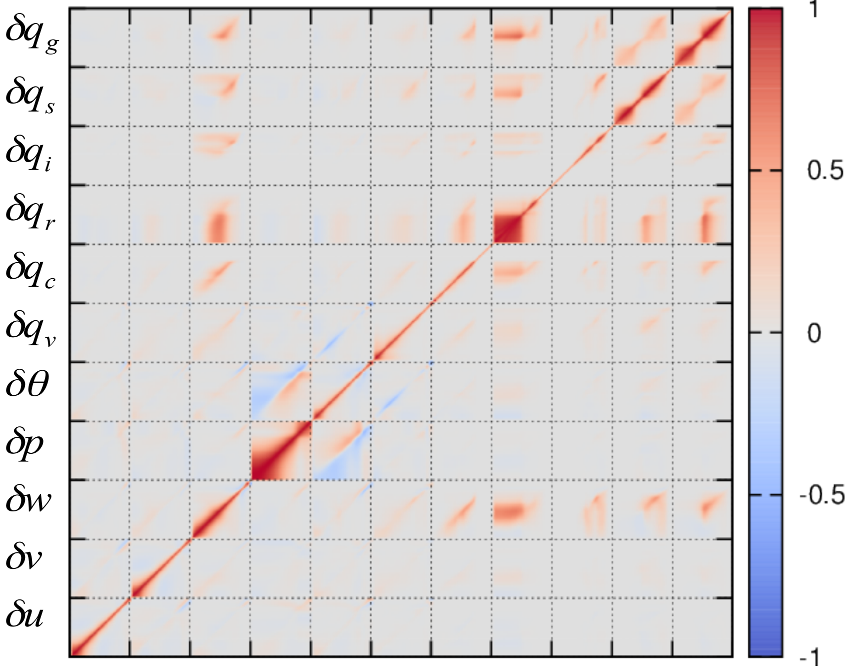
- This term measures the fit based on the flow-dependent background error **in various meteorological situations.**

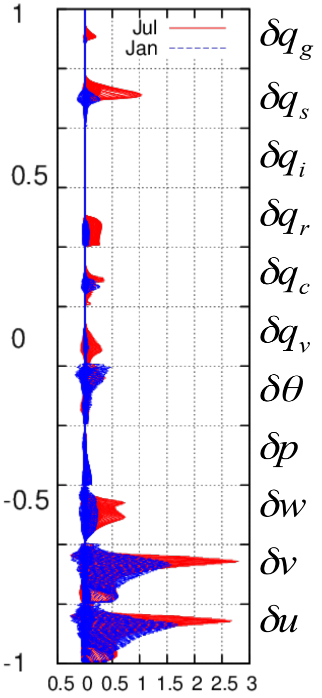
Statistical BG Error Vertical Covariance

$$\mathbf{B}_{NMC} = \left\langle \mathbf{x}_{6h} - \mathbf{x}_{3h}, (\mathbf{x}_{6h} - \mathbf{x}_{3h})^T \right\rangle$$

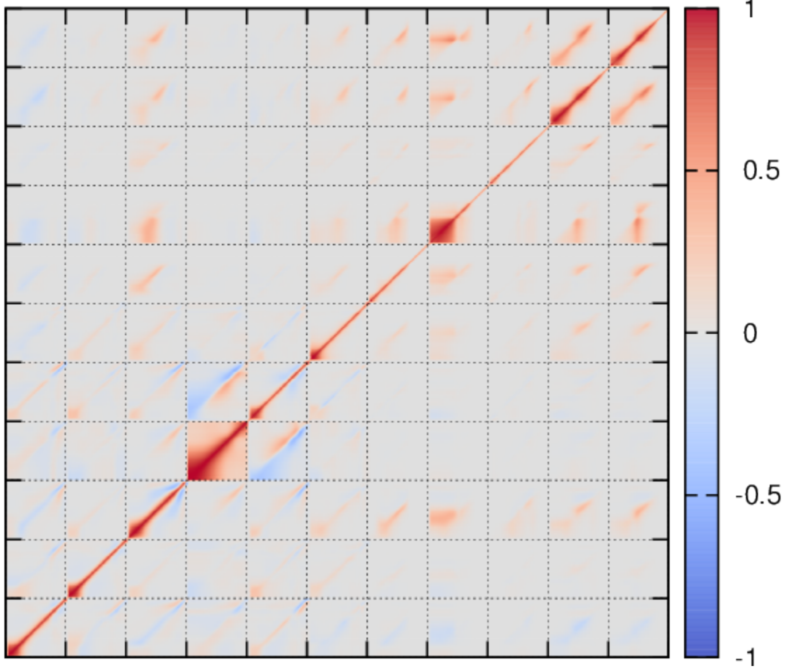
Correlation in Jul (sample # 8x31 forecasts)



Covariance



Correlation in Jan (sample # 8x31 forecasts)



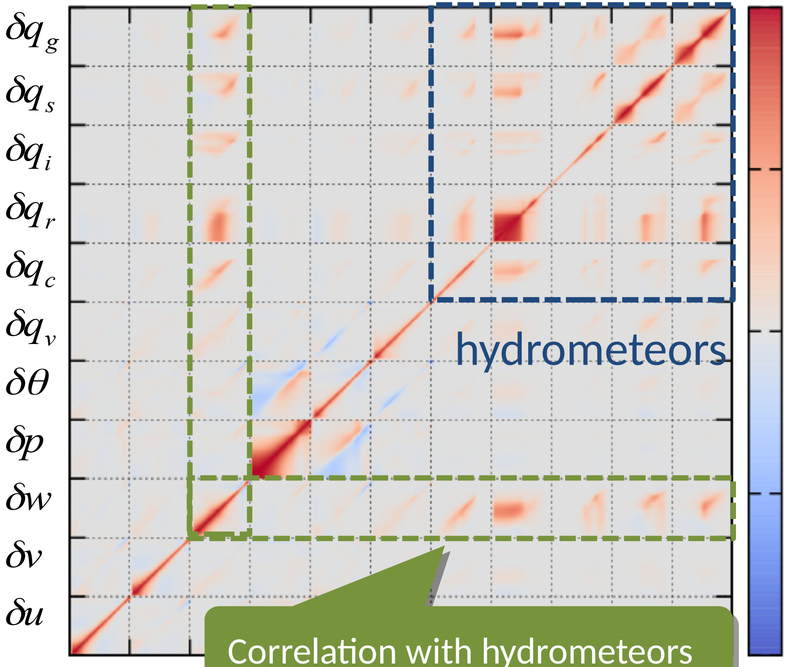
* Cov are rescaled

Statistical BG E

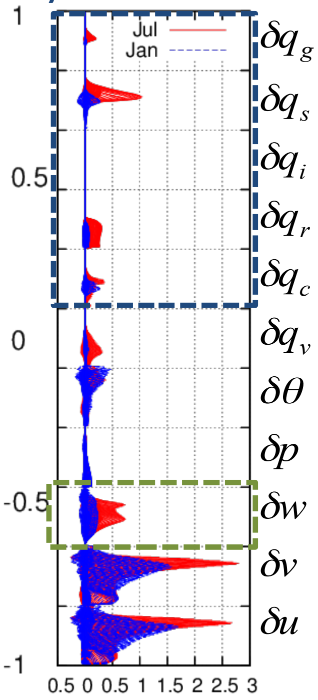
$$\mathbf{B}_{NMC} = \left\langle \mathbf{x}_{6h} - \mathbf{x}_{3h}, \left(\mathbf{x}_{6h} - \mathbf{x}_{3h}\right)^{T} \right\rangle$$

Dependence on seasons and meteorological situations
-> We need flow-dependent BG Error covariance.

Correlation in Jul (sample # 8x31 forecasts)



Cova
hydro meteors



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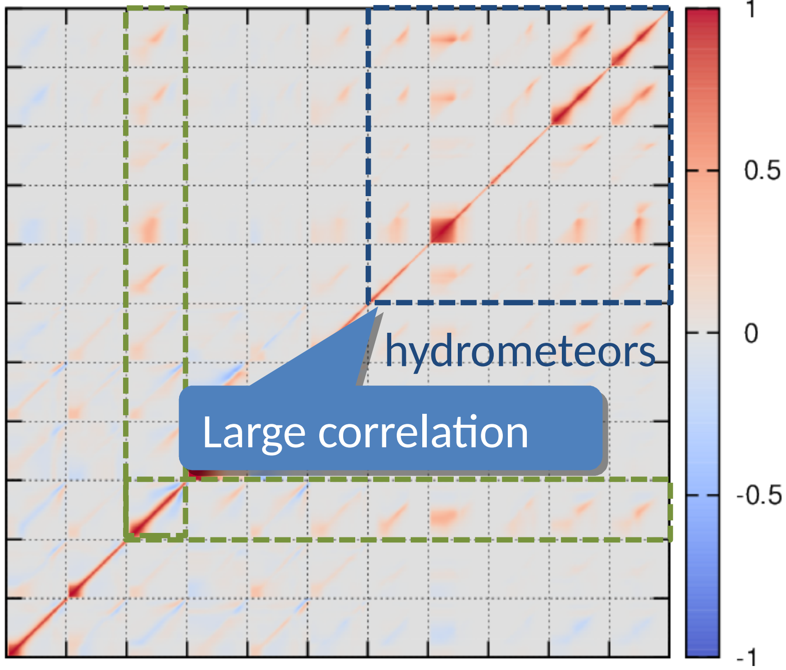

Simplification of Background Error Covariance

Analysis variables

$$\delta \mathbf{x}^T = \left(\delta u, \delta v, \delta T_g, \delta p_s, \delta\theta, \underline{\delta W_g, \delta\mu_p, \delta q_c, \delta q_r, \delta q_i, \delta q_s, \delta q_g}\right)$$

Additional variables in this study

Rank reduction

- Horizontal velocity
  - Weak correlations between δu and δv
- Vertical velocity
  - Effect is lost on early time.
- Pressure
  - Substituted with hydrostatic pressure

$$\begin{array}{c|c}
 & \delta u \quad \delta v \quad \delta T_g\ \delta p_s\ \delta\theta \quad \delta W_g\ \delta\mu_p \quad \delta q_c\ \delta q_r\ \delta q_i\ \delta q_s\ \delta q_g \\
\hline
\begin{array}{c} \delta u \\ \delta v \\ \delta T_g,\ \delta p_s,\ \delta\theta \\ \delta W_g,\ \delta\mu_p \\ \delta q_c,\ \delta q_r,\ \delta q_i,\ \delta q_s,\ \delta q_g \end{array} &
\begin{pmatrix}
\mathbf{B}_u & & & & \\
 & \mathbf{B}_v & & & \\
 & & \mathbf{B}_t & & \\
 & & & \mathbf{B}_\mu & \\
 & & & & \mathbf{B}_q
\end{pmatrix}
\end{array}$$

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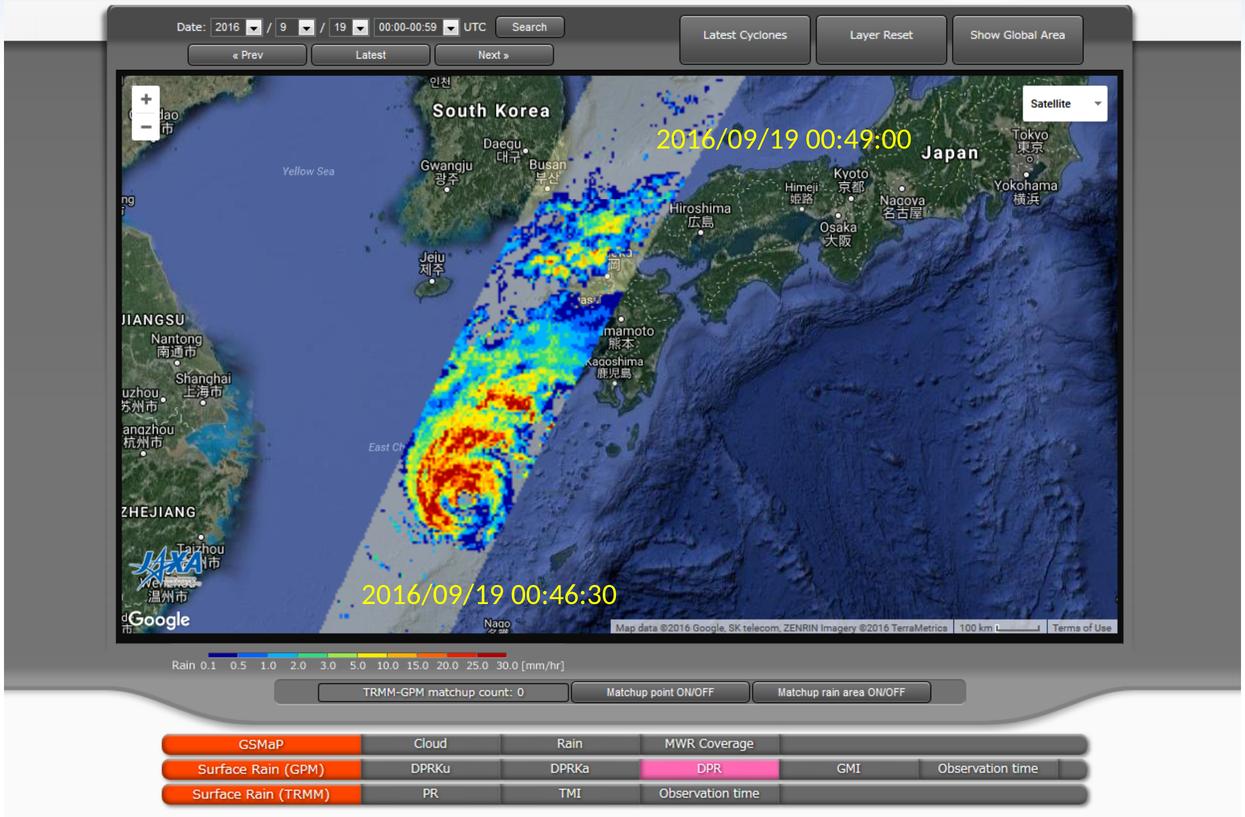
Extended control variable method (Lorenc 2003)

Impact Experiment using Real Observation Data

GPM Near-realtime Monitor (http://sharaku.eorc.jaxa.jp/trmm/RT3/index.html)



Impact Experiment using Real Observation Data

Now investigating .
Bias correction is needed.

<u>GPM/DPR</u>

Corrected Ze (L2 Standard product)

- Liquid-phase: Use
- Solid-phase: Reject

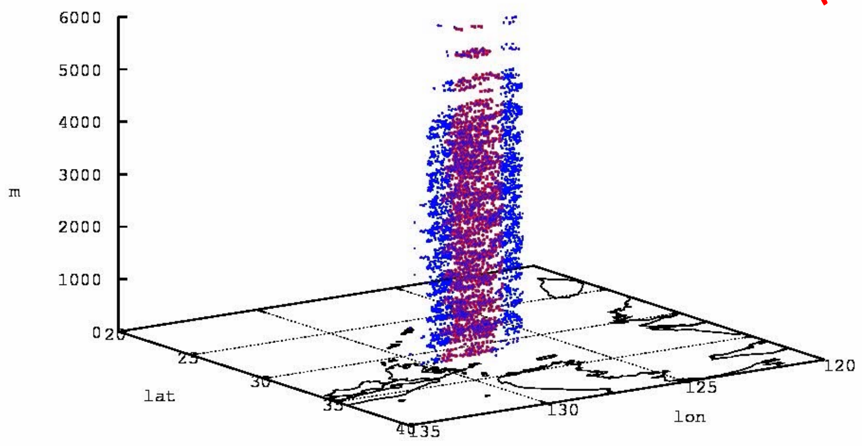
<u>Super Observation</u>

Averaging area: 15x15 km^2

<u>Thinning</u>

Vertical interval: 500 m

- KuPR(35.5GHz)
- KaPR(13.6GHz)



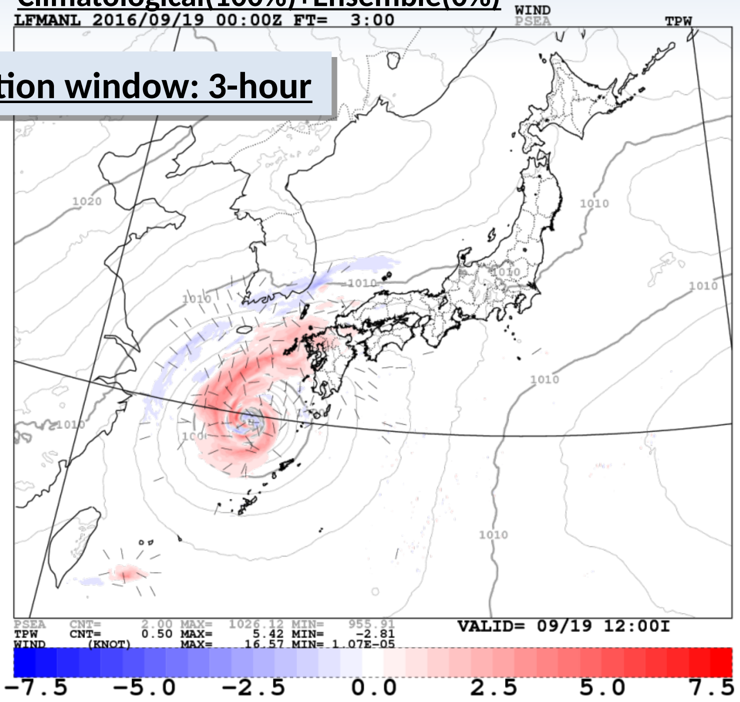
after QC and thinning

Analysis Increments

Assimilation window: 3-hour

Traditional DA

Climatological(100%)+Ensemble(0%)

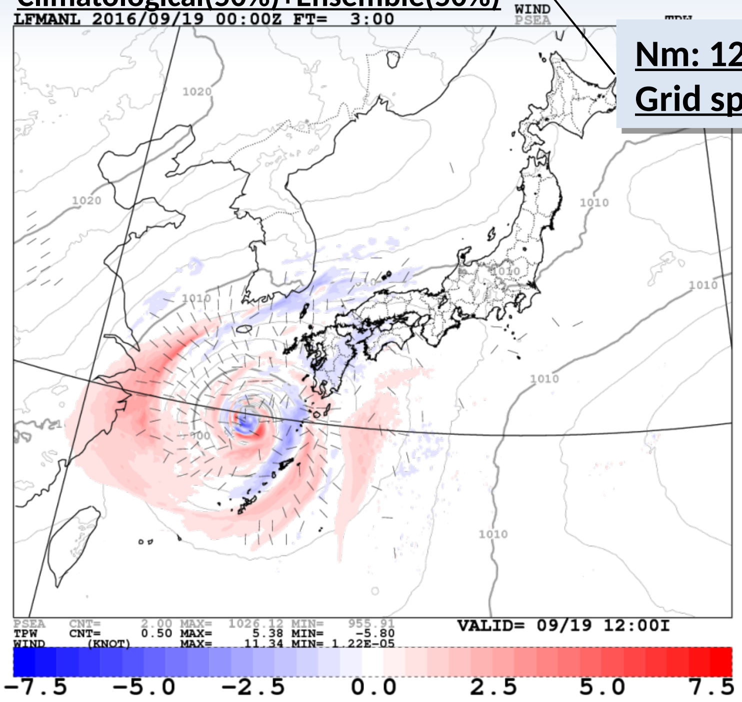


Color shade: Total Precipitable Water
Barbs: Surface Wind

Hybrid DA

Climatological(50%)+Ensemble(50%)

Nm: 12+1
Grid spacing: 5 km



Localization radius was set to 300 km.

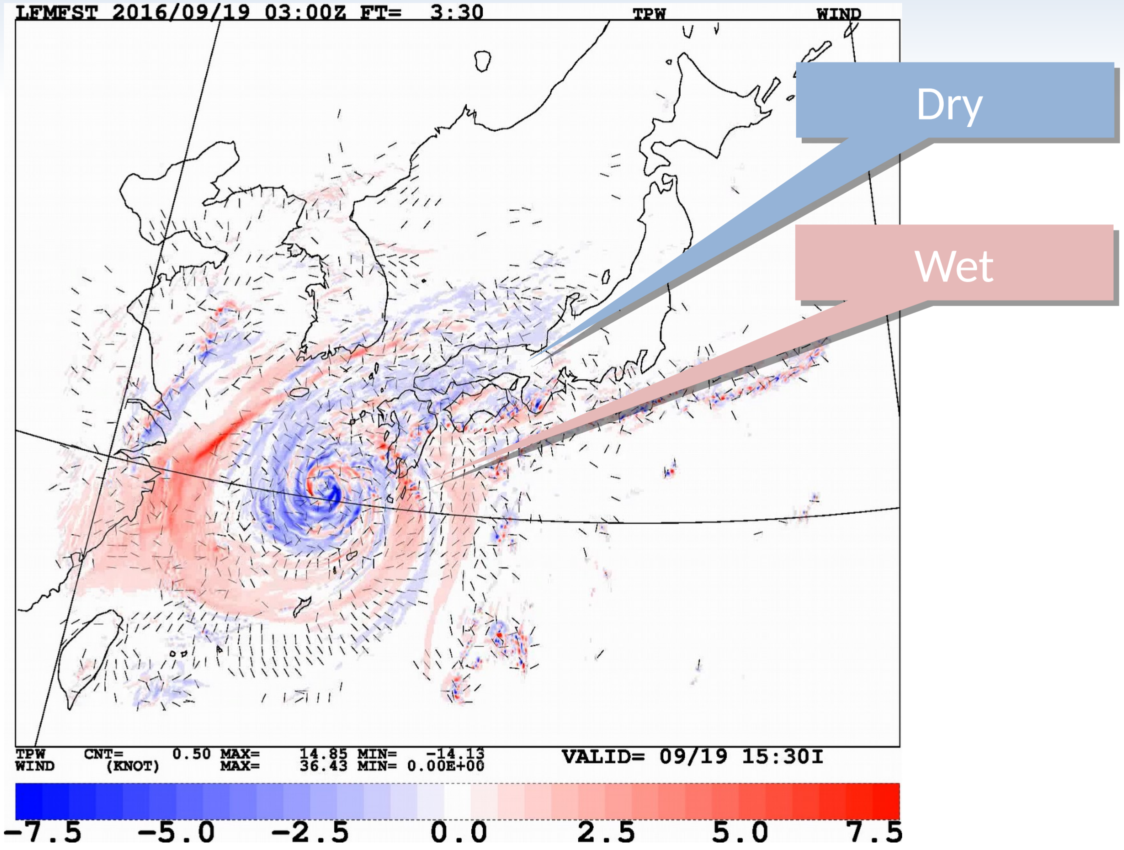
Traditional DA v.s Hybrid DA

<u>CNTL</u>
Forecast from Traditional DA

<u>TEST</u>
Forecast from Hybrid DA

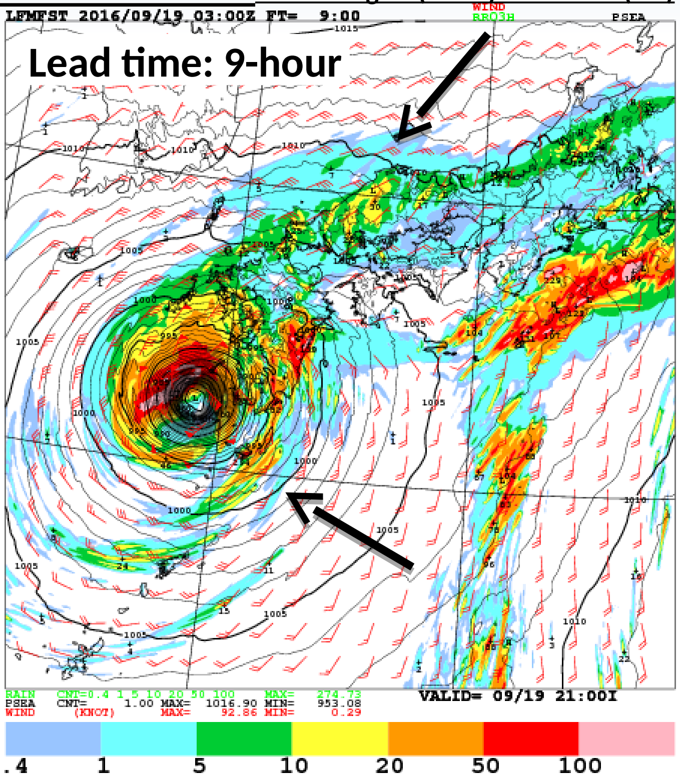
<u>Forecast</u>
Grid spacing: 2 km

<u>TEST – CNTL</u>
Color shade: Total Precipitable Water
Barbs: Surface Wind

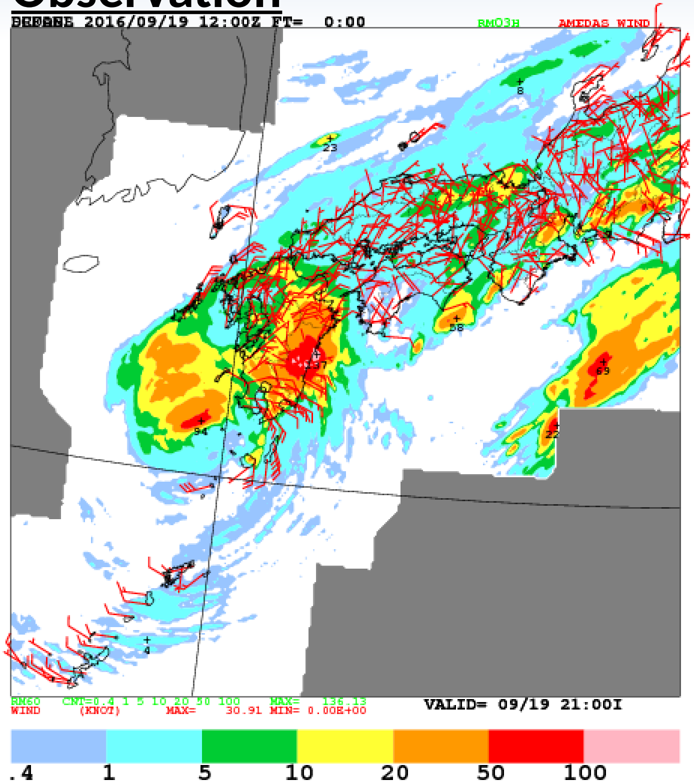


Precipitation of Forecast

Traditional DA Climatological(100%)+Ensemble(0%)

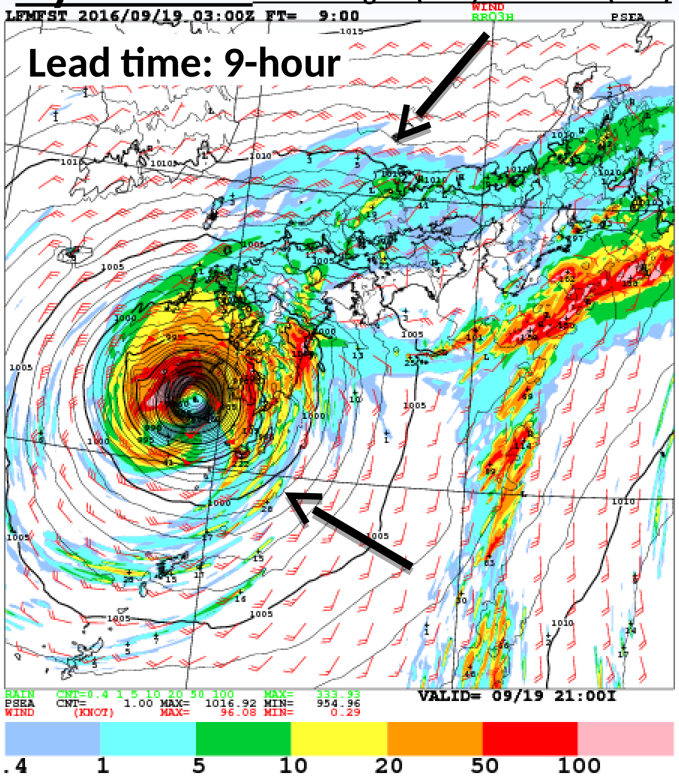


Observation

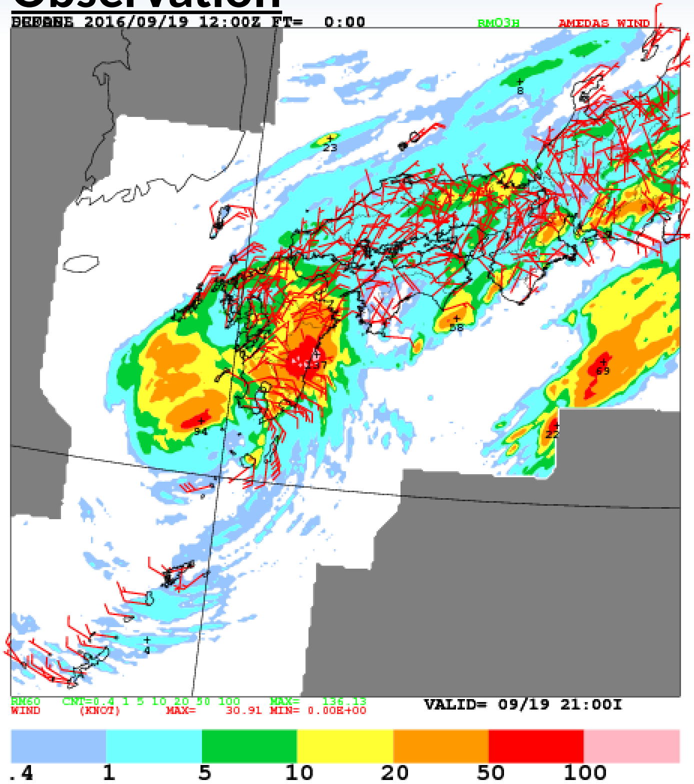


Precipitation of Forecast

Hybrid DA Climatological(50%)+Ensemble(50%)



Observation

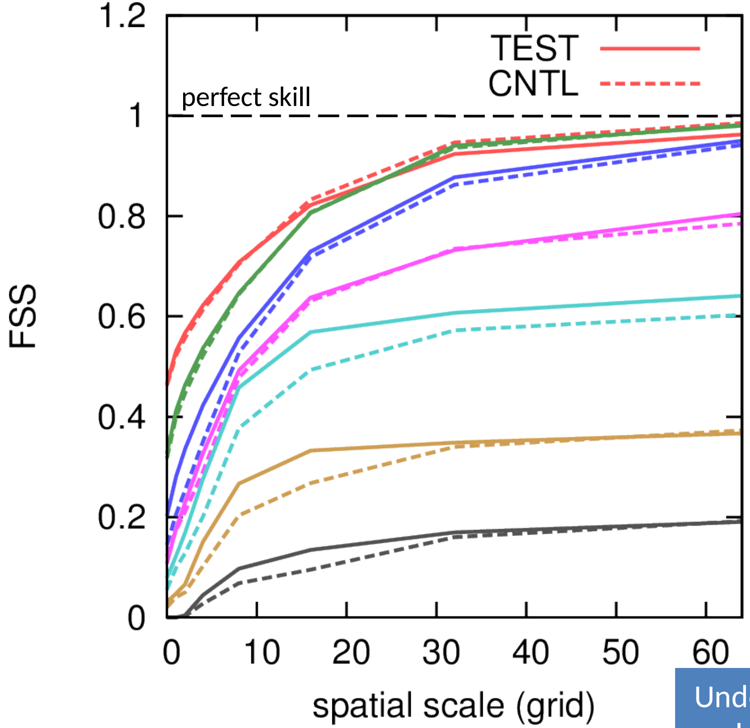


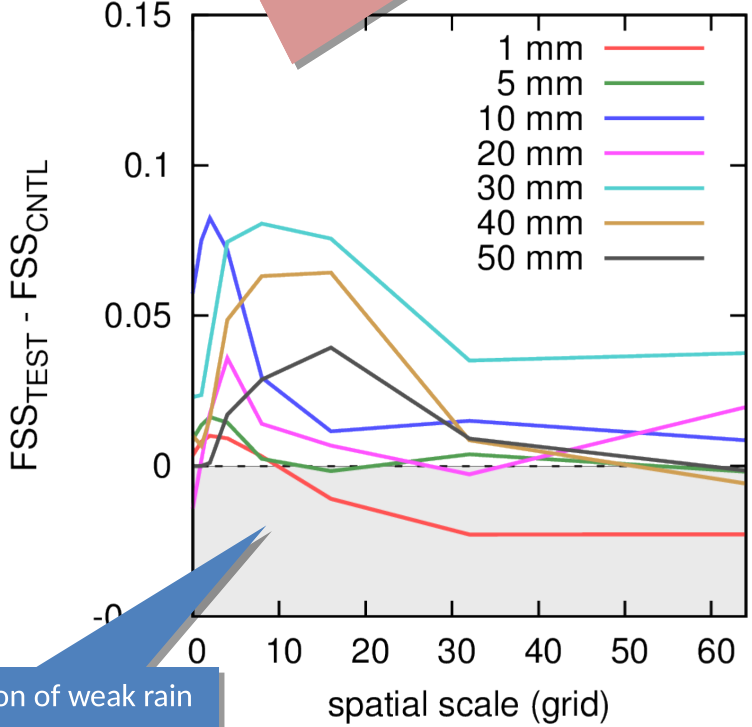
Fractions Skill Score

CNTL: Traditional DA

TEST: Hybrid DA

Improvement of heavy rain rate





Under estimation of weak rain on largescale

Summary

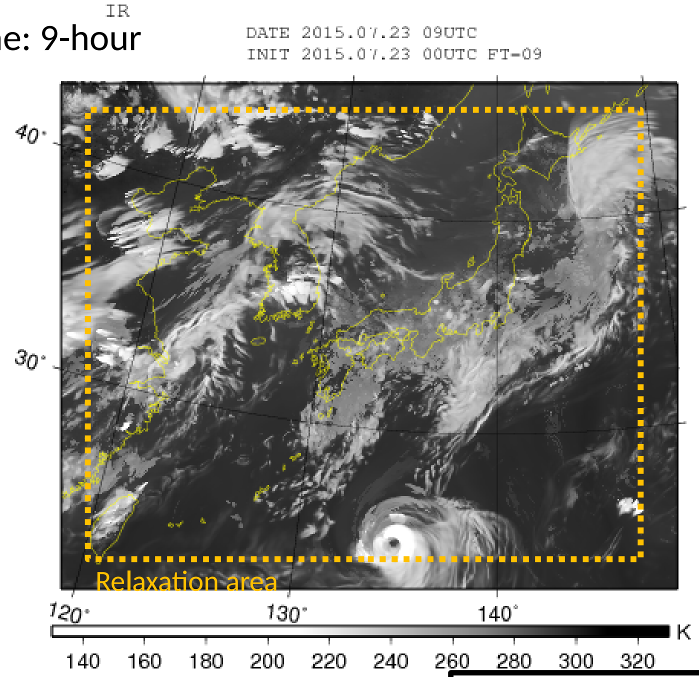
- Development of Hybrid 4D-Var
  - TL/AD of cloud-microphysics scheme
    - The TL model grows the perturbation smoothly in almost processes.
  - Benefit of flow-dependent DA
    - Analysis increments based of flow-dependent
    - Improvement of precipitation forecast
- Development of space-borne radar simulator with TL/AD
  - Reflectivity of non-spherical particles
  - Model bias is larger than difference of scattering method.
- Future work
  - Enhancement of quality control and bias correction for solid particles.
  - More case studies targeting severe weather event.
  - Statistical verification of long-term.

THANK YOU FOR YOUR ATTENTION

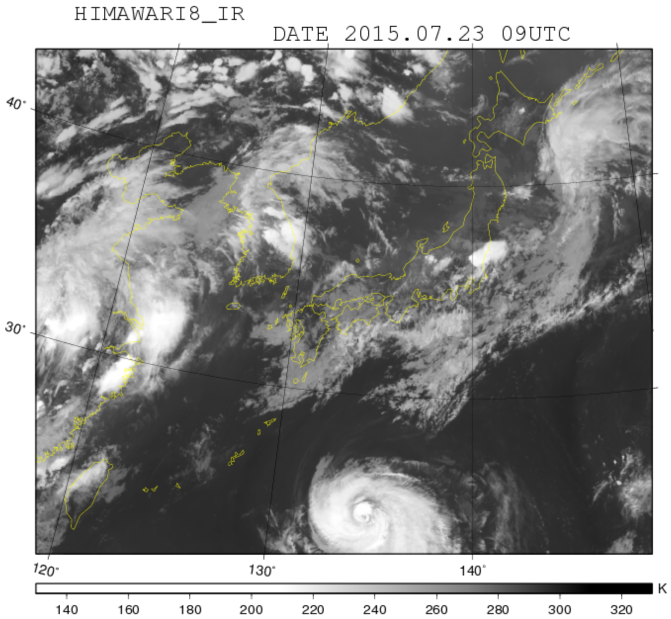
Infrared imager 10.6 µm
Comparison of Simulation and Observation

Shape: non-spherical, Snow-PSD: exponentioal+gamma

Lead time: 9-hour
F05



Observation (Himwari-8 AHI)

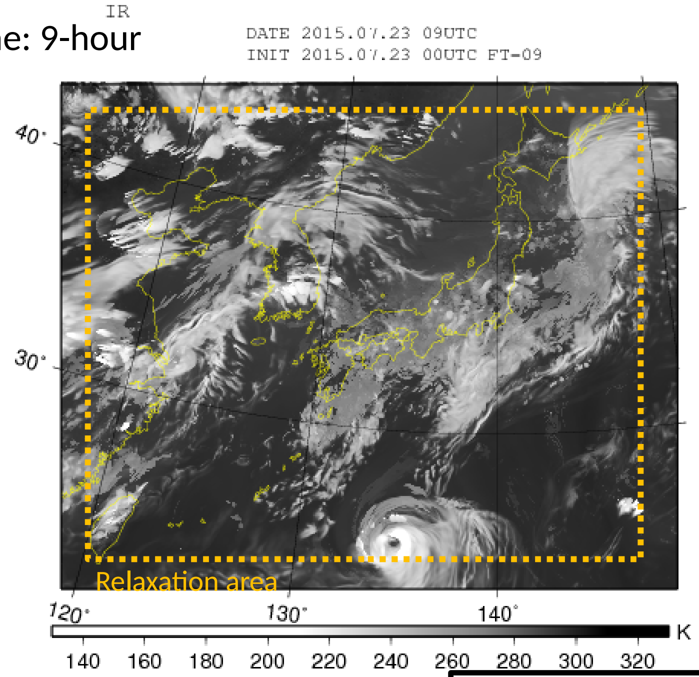


Similar brightness

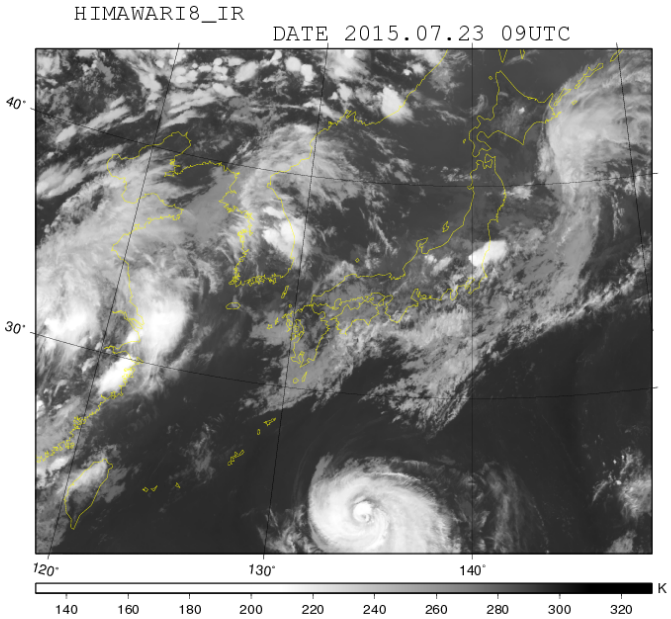
Infrared imager 10.6 µm
Comparison of Simulation and Observation

Shape: non-spherical, Snow-PSD: exponentioal+gamma

Lead time: 9-hour
F07M



Observation (Himwari-8 AHI)

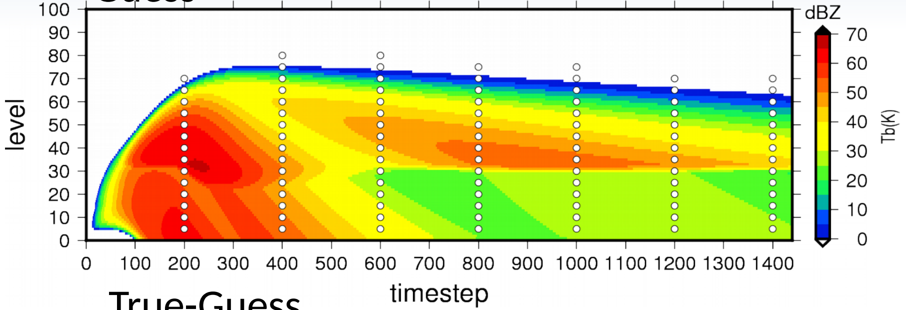


Similar brightness

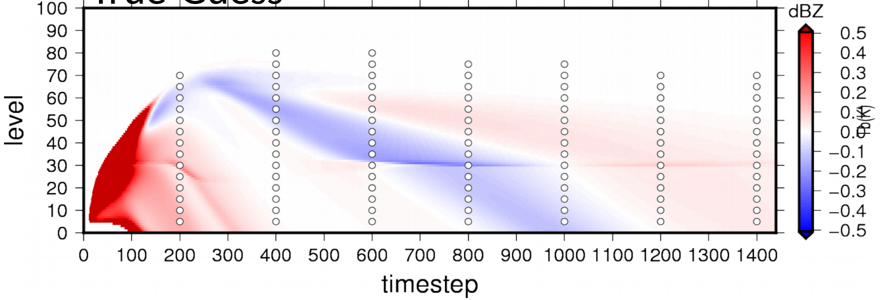
Function of AD Model of Cloud Microphysics in Identical Twin

Reflectivity (KuPR)

Guess



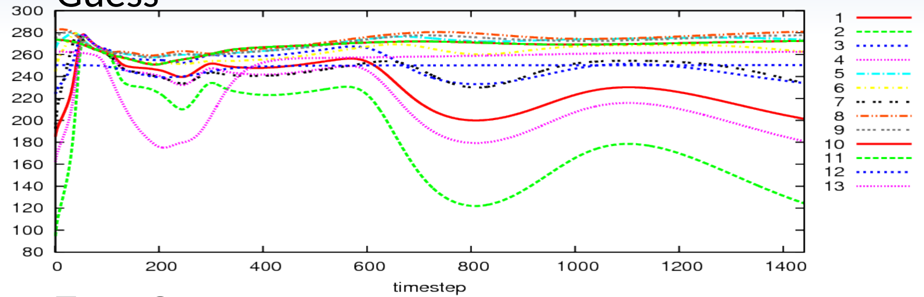
True-Guess



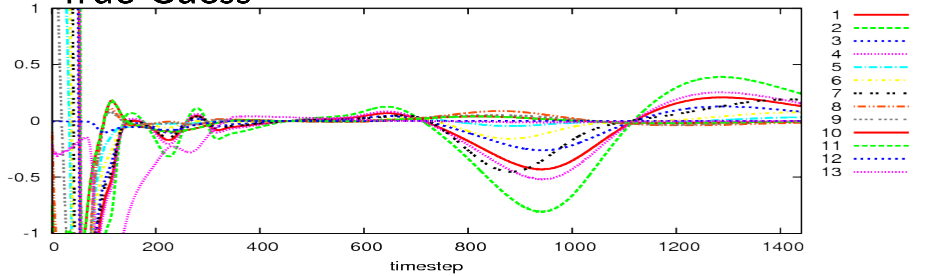
○: Pseudo Observation points

Brightness temperature (GMI)

Guess



True-Guess

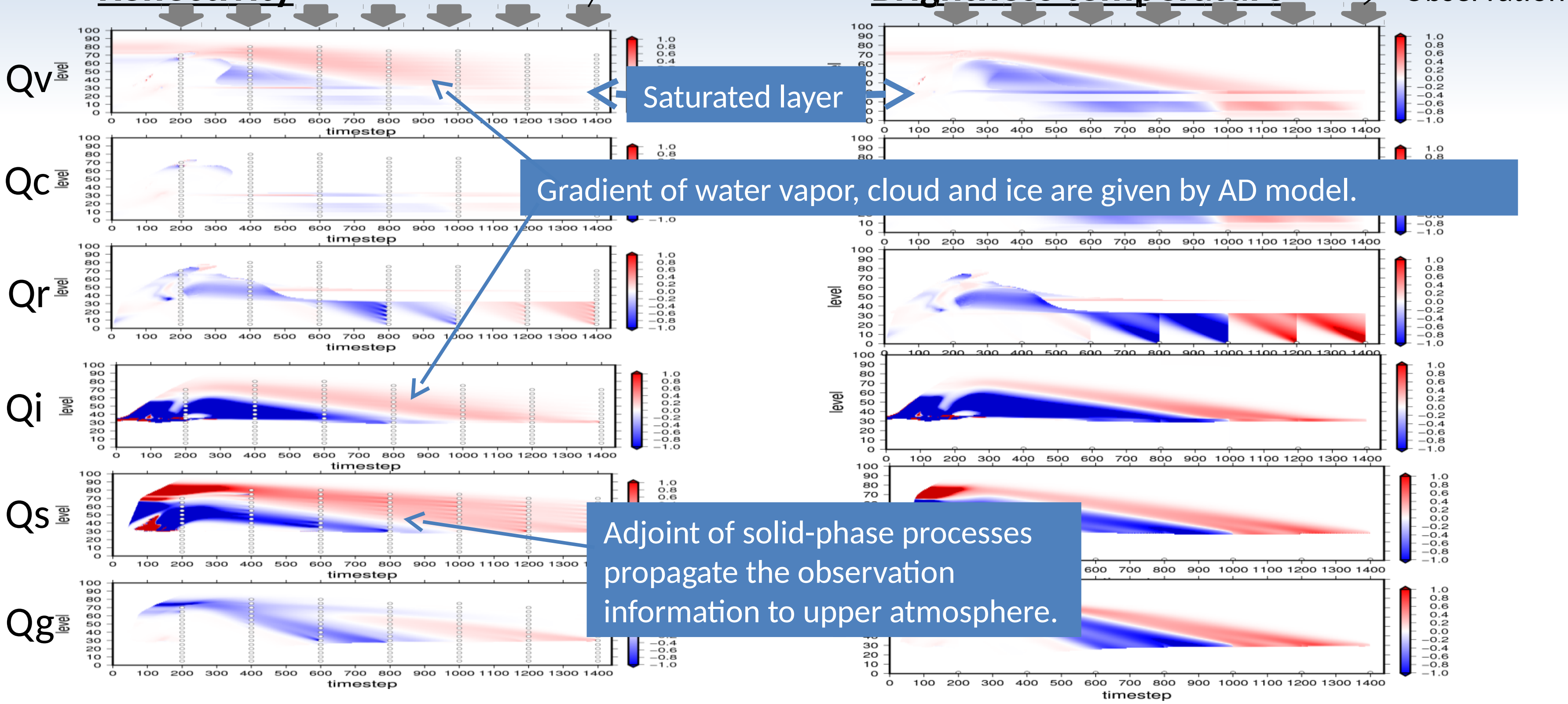


RTTOVSCATT (rttov11.3)

Satellite: GPM, Sensor: GMI, Frequency: 1) 10.65 GHz(V), 2) 10.65 GHz(H), 3) 18.7 GHz(V), 4) 18.7 GHz(H), 5) 23.8 GHz, 6) 36.5 GHz(V), 7) 36.5 GHz(H), 8) 89.0 GHz(V), 9) 89.0 GHz(H), 10) 165.5 GHz(V), 11) 165.5 GHz(H), 12) 183.31±3 GHz, 13) 183.31±8 GHz

Gradient Vector from pseudo observation

Reflectivity | **Brightness temperature**

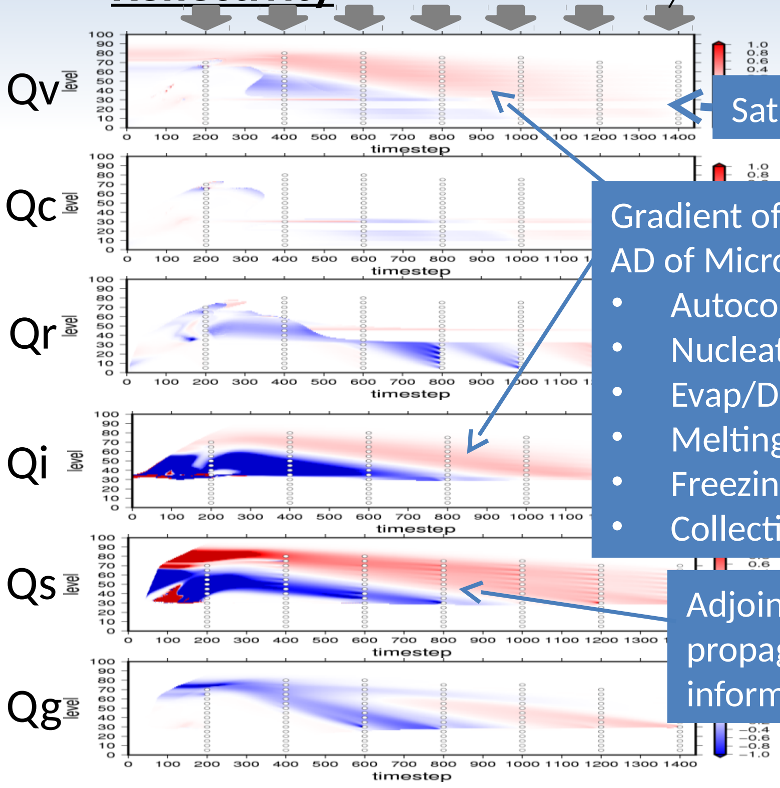


Gradient vector

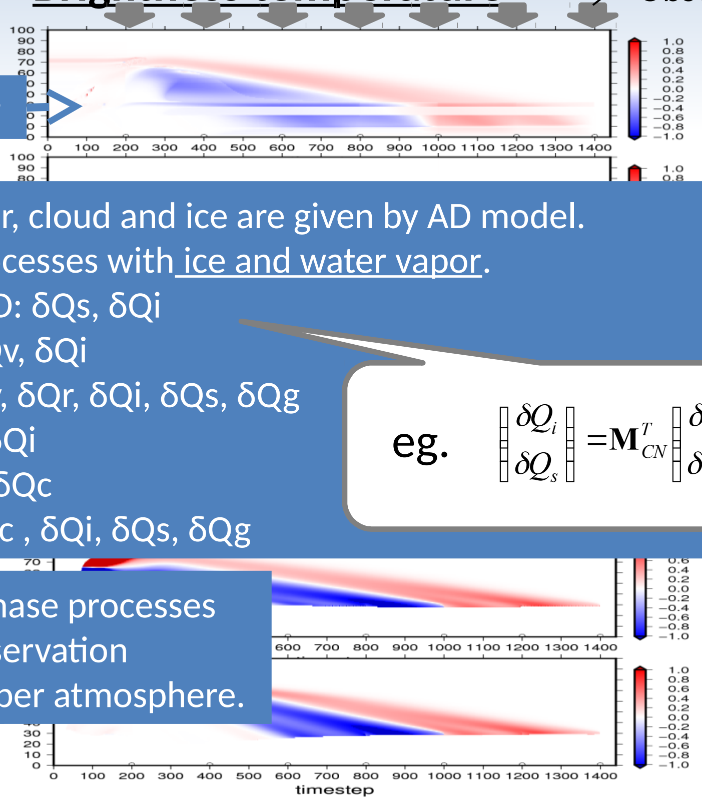
$$\mathbf{M}^T\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H}\mathbf{M}\delta\mathbf{x}$$

Gradient Vector from pseudo observation

Reflectivity



Brightness temperature



Saturated layer

Gradient of water vapor, cloud and ice are given by AD model.
AD of Microphysics Processes with ice and water vapor.

- Autoconversion_AD: δQs, δQi
- Nucleation_AD: δQv, δQi
- Evap/Dep_AD: δQv, δQr, δQi, δQs, δQg
- Melting_AD: δQr, δQi
- Freezing_AD: δQi, δQc
- Collection_AD: δQc , δQi, δQs, δQg

eg. $$\begin{bmatrix} \delta Q_i \\ \delta Q_s \end{bmatrix} = \mathbf{M}_{CN}^{T} \begin{bmatrix} \delta Q_i \\ \delta Q_s \end{bmatrix}$$

Adjoint of solid-phase processes propagate the observation information to upper atmosphere.

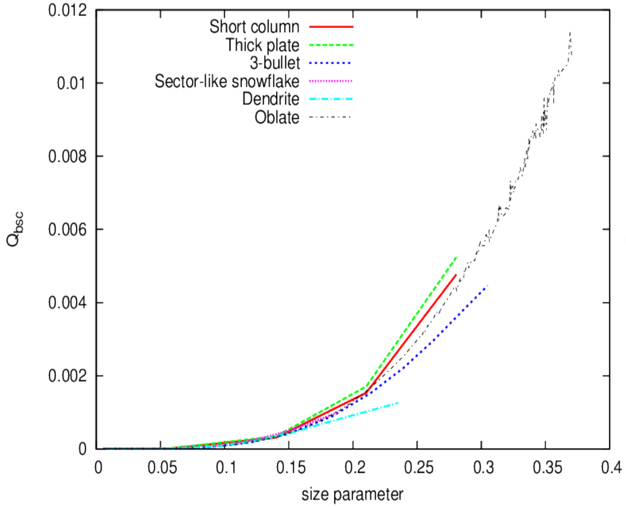
Gradient vector

$$\mathbf{M}^T\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H}\mathbf{M}\delta\mathbf{x}$$

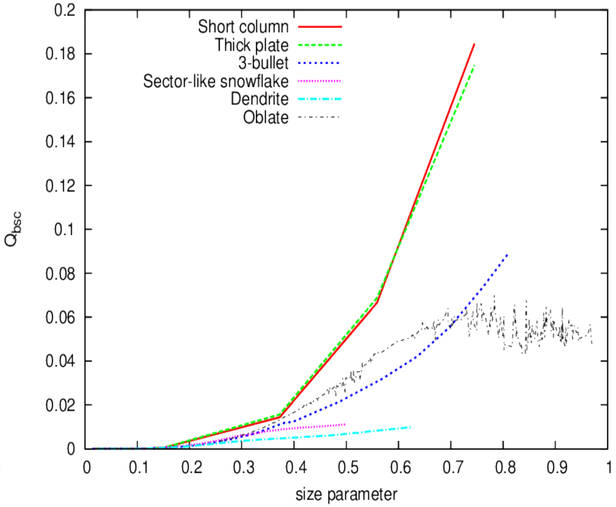
2. Enhancement of quality control and space-borne radar simulator

- SCATDB (Liu 2008, Honeyager et al. 2016)
  - Database of scattering coefficients for non-spherical particle.

13GHz



36GHz



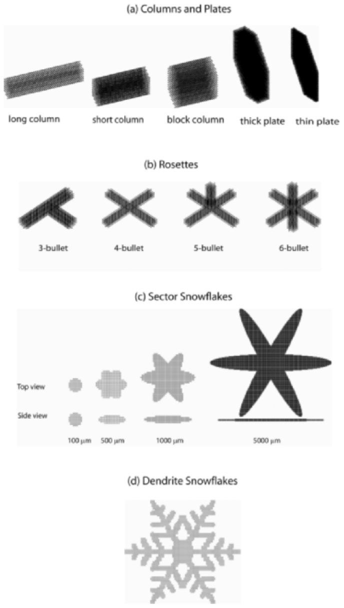


FIG. 1. Shapes of (a) columns and plates, (b) rosettes, (c) sector snowflakes, and (d) dendrite snowflakes. The drawings are made of small dots that are the dipoles used in DDA model simulations.

Liu (2008)

Flow-dependent Term

- Extended control variable method (Lorenc 2003)

The flow-dependent method is employed extended control variables method.

Background error covariance

Mixing the climatological BG error and the ensemble estimated BG error

Preconditioning

Control variables

Extended control variables

$$\delta\mathbf{x}_0^b = \beta_n \mathbf{B}_{NMC}^{1/2} \delta\chi_n + \beta_e \mathbf{B}_{ENS}^{1/2} \delta\chi_e$$

The analysis variable is given by control variable and extended control variables.

$$\mathbf{B}_{ENS}^{1/2} = \frac{1}{\sqrt{N-1}} \left[\mathrm{diag}\,\delta\mathbf{x}_{e_1} \mathbf{L}^{1/2}, \cdots, \mathrm{diag}\,\delta\mathbf{x}_{eN} \mathbf{L}^{1/2} \right]$$

Spatial localization

Cost function

$$J = \frac{1}{2} \delta\chi_n^T \delta\chi_n + \frac{1}{2} \delta\chi_e^T \delta\chi_e + J_o$$