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Introduction and Recent Advances of Data Assimilation

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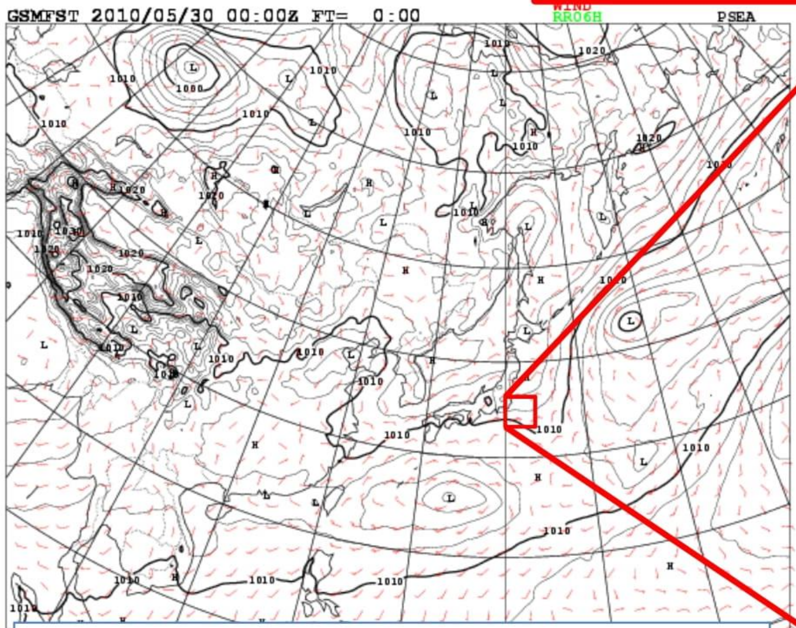
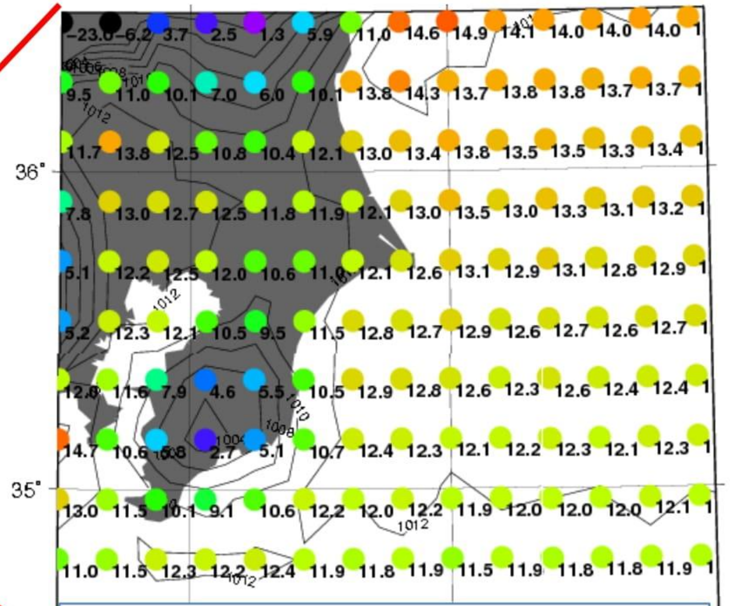
Objective Analysis

- Analyze atmospheric state $\mathbf{x}_t$ at a given time t numerically. Here $\mathbf{x}_t$ is a set of all the variables on all the grid points
    - 1,312,360(Number of horizontal grids)x(1(P)+60(Layer)x4(UVTQ)) ≈316e6

How determine this huge amount of data, accurately ?



$P_{MSL(Mean\ Sea\ Level)}$
Weather map around Japan

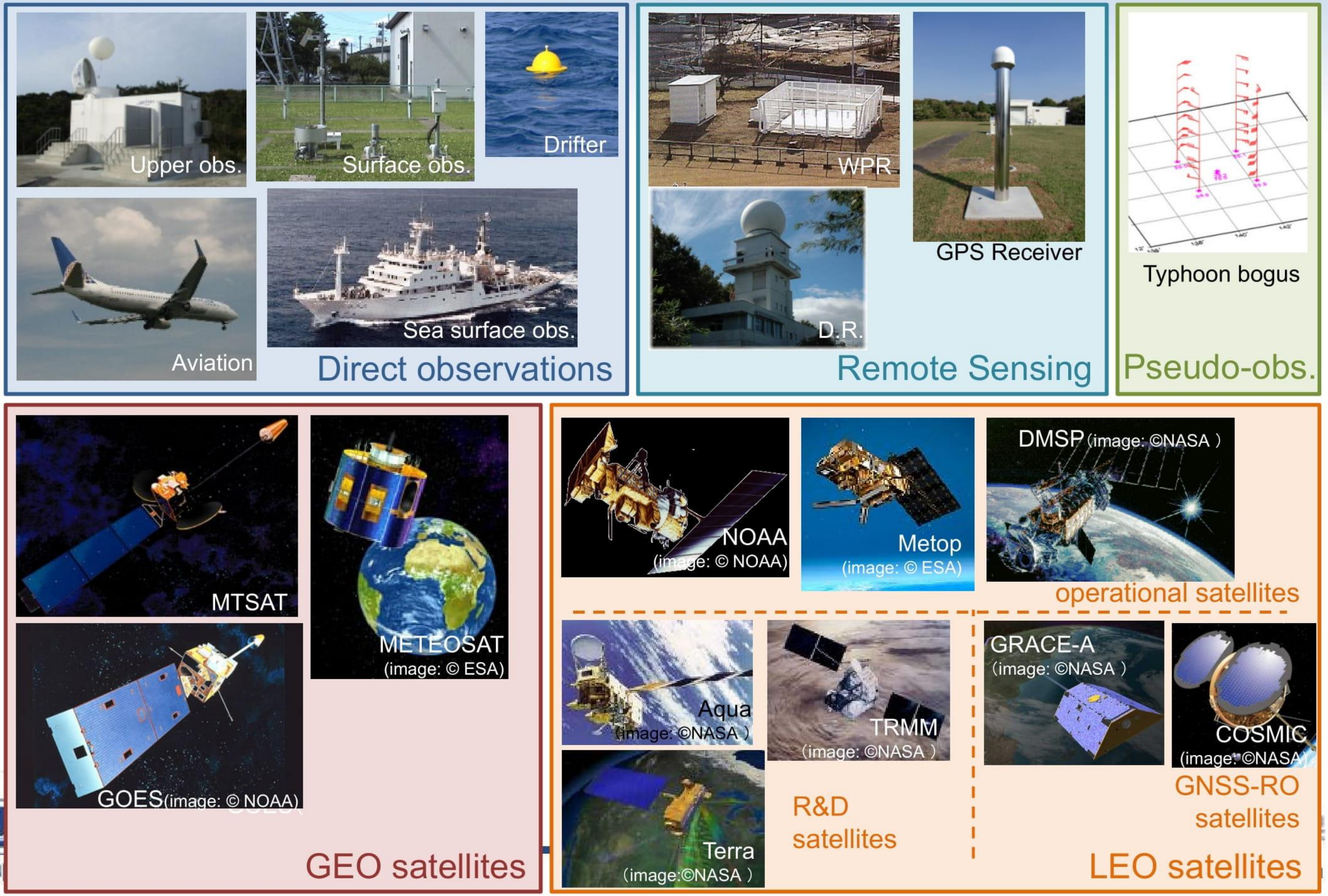


P_S-1000
Original GPV distribution
many values are included in this small box.

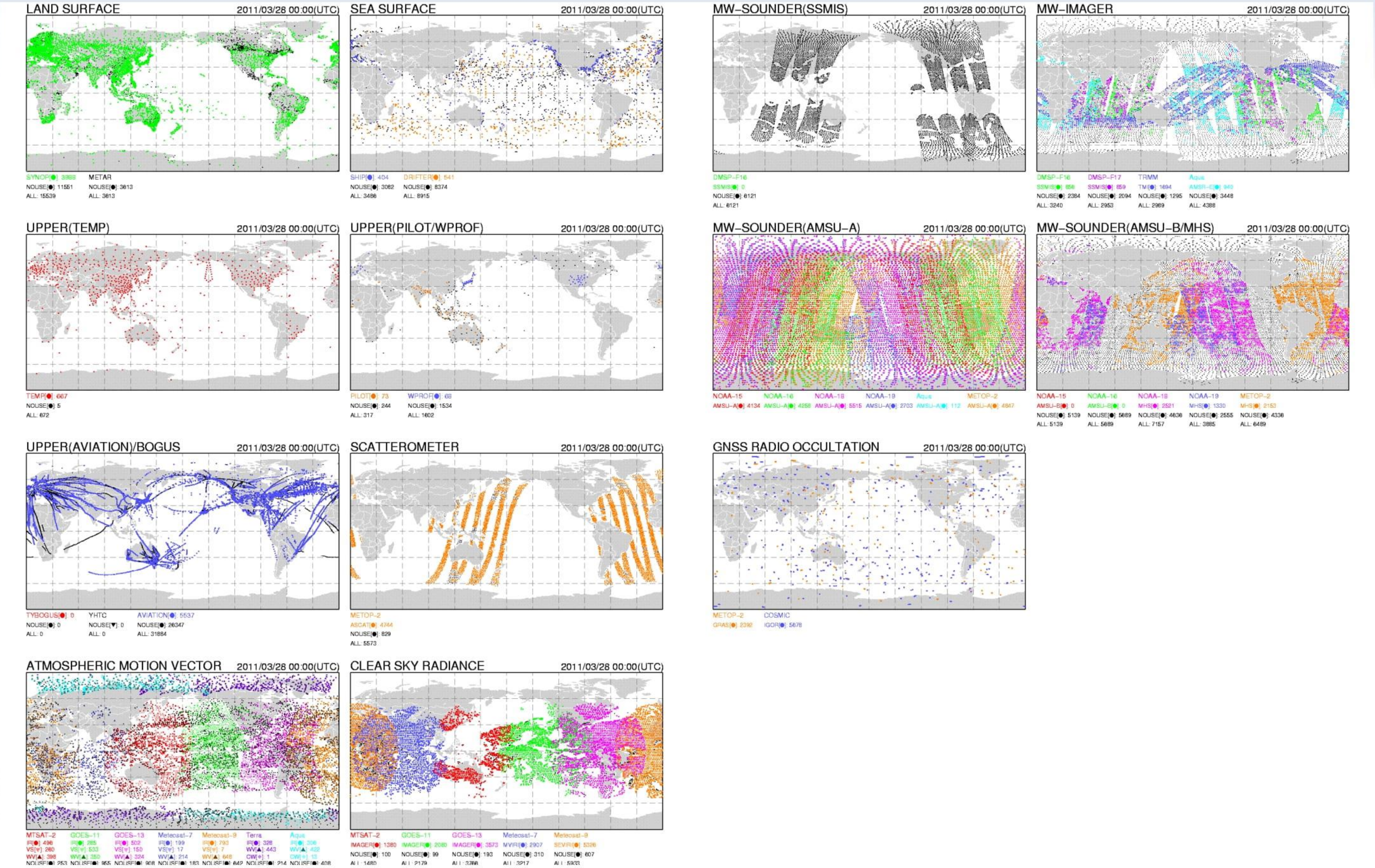
Available data for objective analysis #1

- A variety of observations
  - ☺: The data reflects real atmospheric state
    - 😐: while it includes observation error
  - ☹: All the variables on all the grid points are NOT available

Observations assimilated in NWP



Data coverage (Global cycle analysis)



Data coverage with IR image #1/2

SYNOP
Land surface only

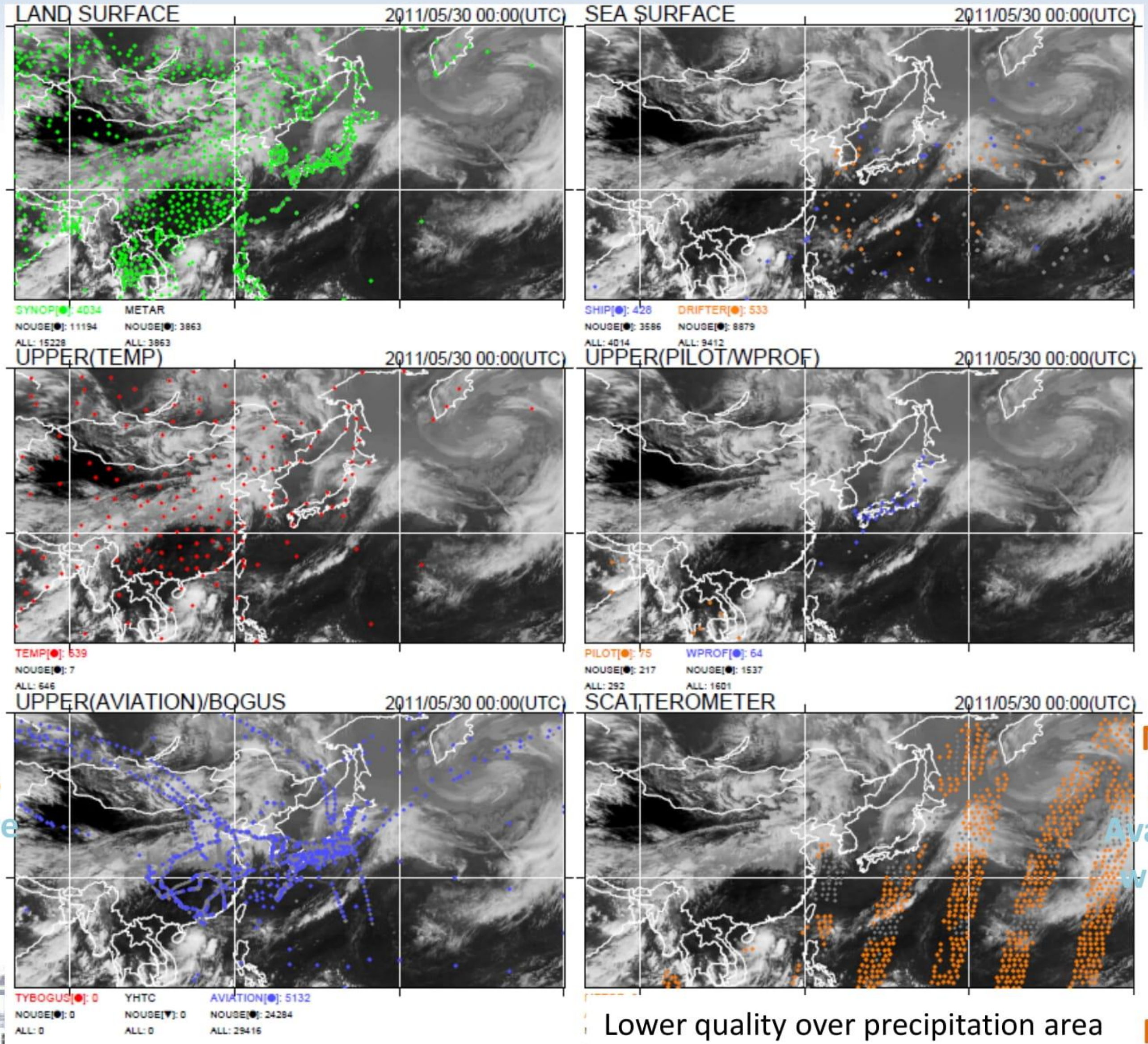
SHIP/BUOY
Sea Surface only, sparse

TEMP
Mostly over land area

WPRF/PILOT
Only over land area

Aviation/ Typhoon bogus
Flight passes are mostly fixed

MW scatterometer (Sea surface wind)
Available over ocean with moderate wind



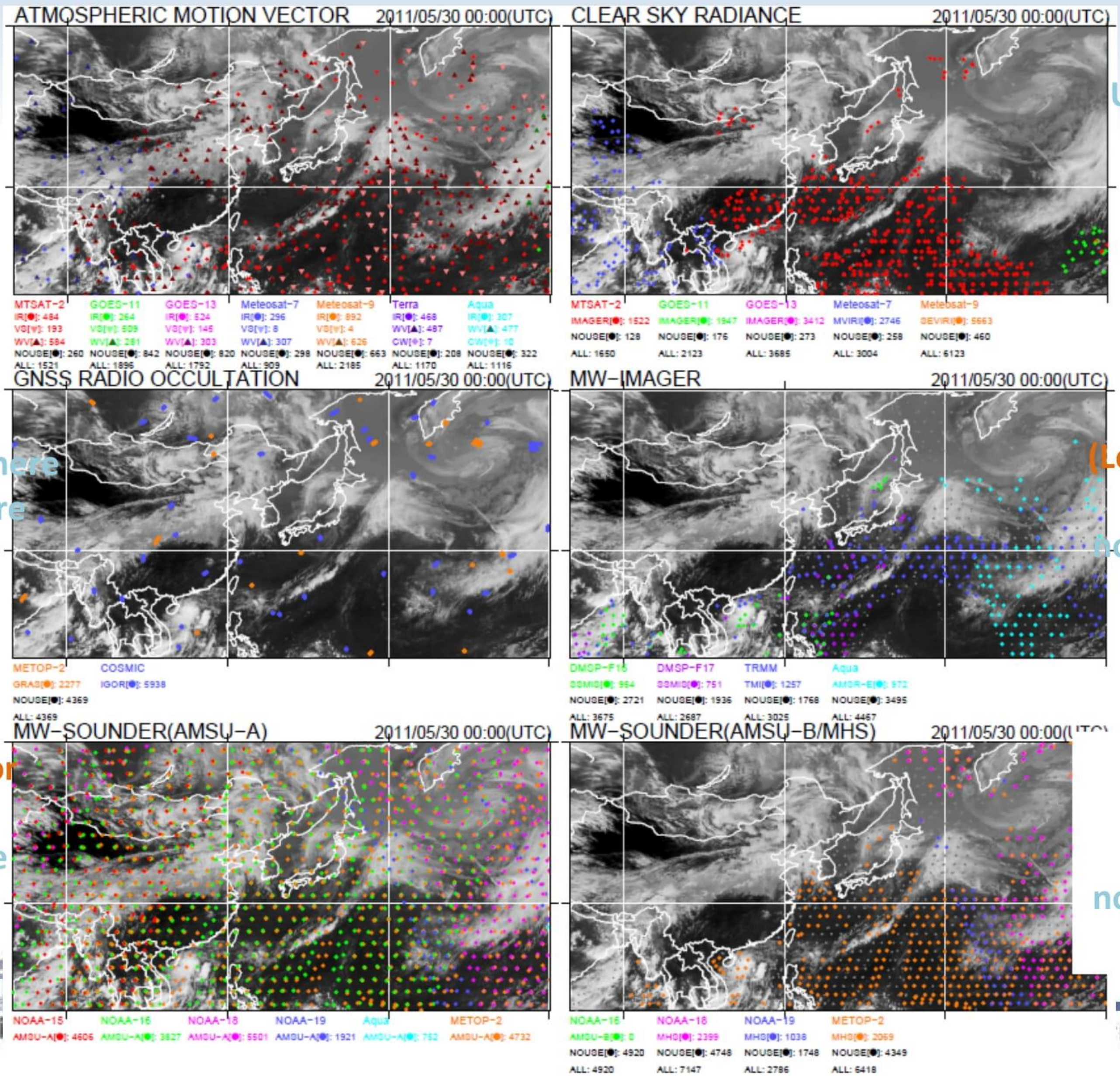
Lower quality over precipitation area
Weak bias for strong wind

MW：Microwave

Data coverage with IR image #2/2

AMV
Cannot be produced from thick cloud

GEO-CSR
Upper troposphere
Only over clear sky area



GPS-RO
Upper troposphere and stratosphere

MW Imager (Lower troposphere)
Only over ocean
not assimilated over precipitation area

MW sounder for temperature
Depends on the atmospheric condition

MW sounder for water vapor
Only over ocean
not assimilated over precipitation area

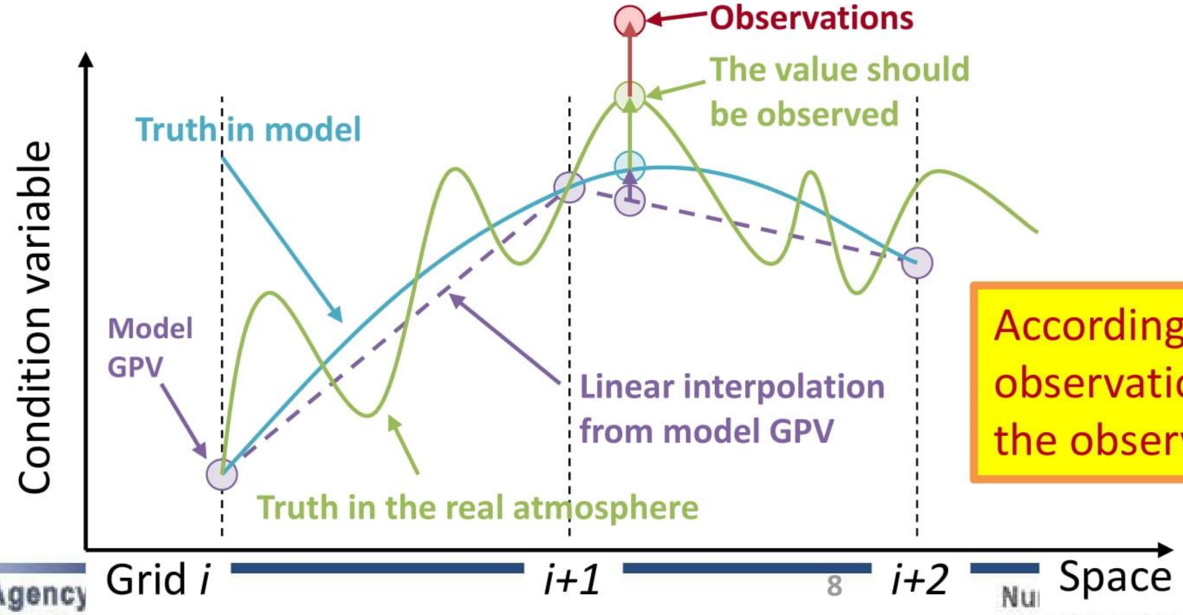
気象庁
Japan Meteorologi

rediction Division

Observation Error

- Observation error is composed by measurement error, representative error, and conversion error
  - Measurement error： The error from the instrument
  - Representative error: The error from spatial quantization
    - Perturbation from small scale phenomena is considered as “Error”
  - Conversion error: The error from observation operator
    - Ex) The error from interpolation method difference (wave/linear/cubic)

Since it cannot be represented in the NWP model



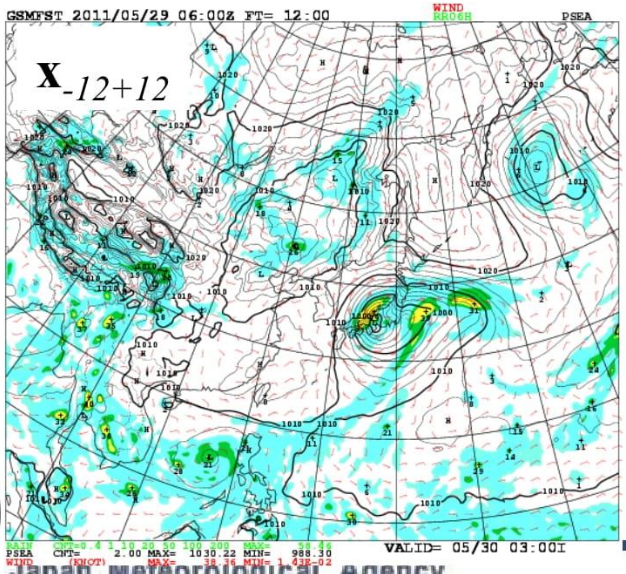
Accordingly, all the observation includes the observation error !

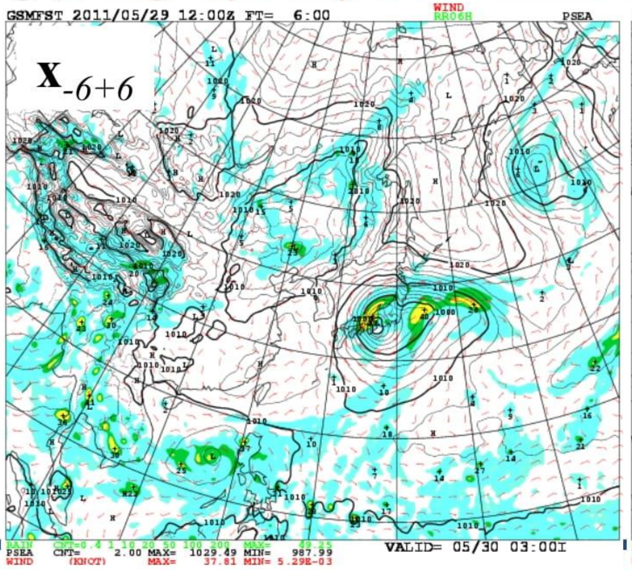
Available data for objective analysis #2

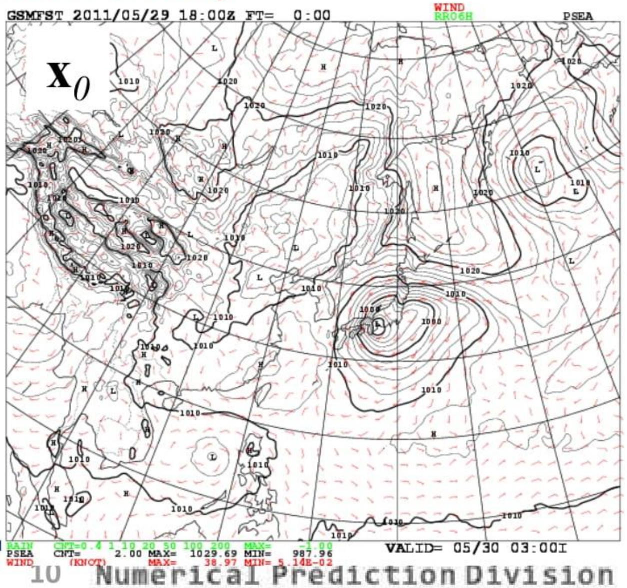
- NWP forecast GPV (the first guess)
  - ☺: All the variables on all the grid points are available
    - 😐: while it includes forecast error
  - ☹: It is NOT assured the forecast reflects real atmospheric state

Forecast values

- (Ex.) Forecast from the last analysis $\mathbf{x}_{-dt+dt}$
  - Background / First Guess
  - Ex. the case for global NWP system dt=6[hr]
    - 6-hours forecast from the analysis at 6-hours before
      - The forecast error should not be large if the forecast time was not so long (if high quality NWP model was used).







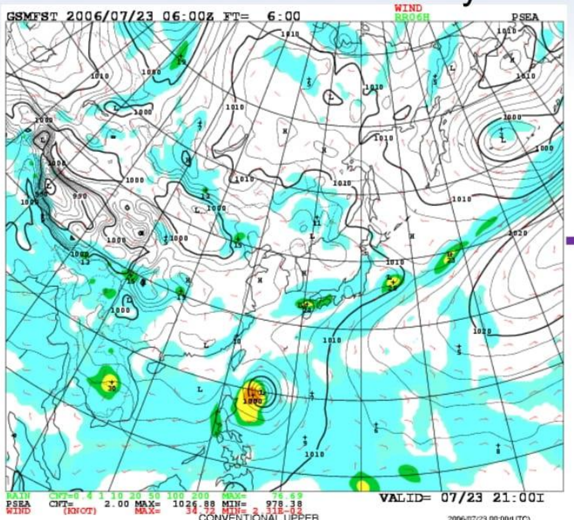
Data Assimilation (DA)

- Available data for objective analysis
  - A variety of observations
    - ☺: The data reflects real atmospheric state
      - » 😐: while it includes observation error
    - ☹: All the variables on all the grid points are NOT available
  - NWP forecast GPV (the first guess)
    - ☺: All the variables on all the grid points are available
      - » 😐: while it includes forecast error
    - ☹: It is NOT assured the forecast reflects real atmospheric state
- DA: Use the "☺" points from each data
  - Corrects the first guess with a variety of observations
    - "Assimilate a variety of observations with NWP GPV"

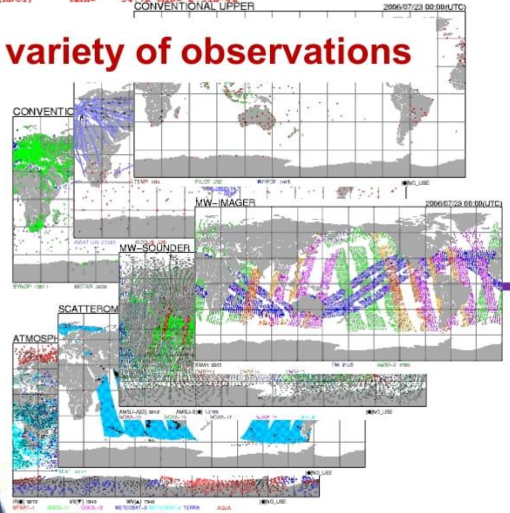
DA system

The first guess

Forecast from the last analysis

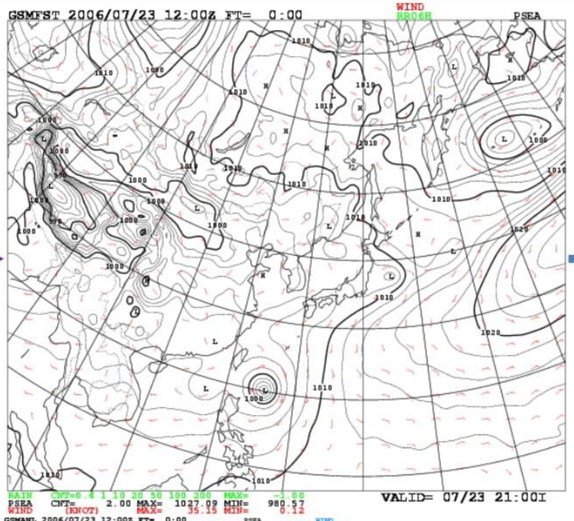


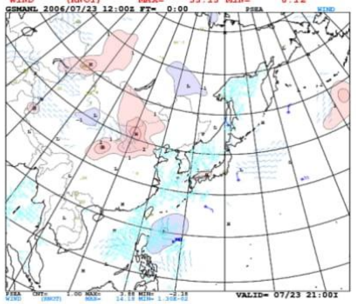
A variety of observations



DA

Analysis (Initial condition)

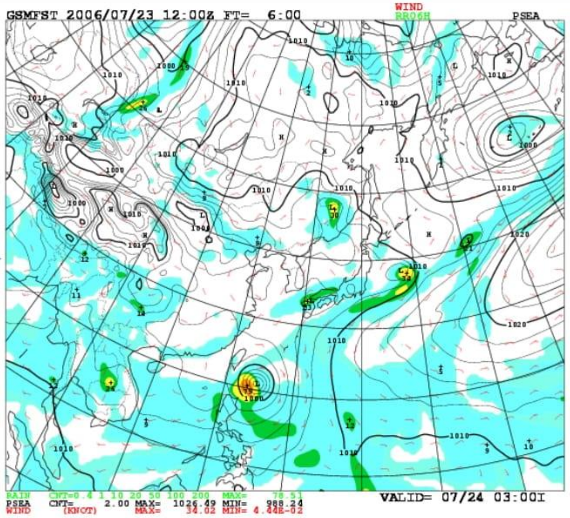




Increments

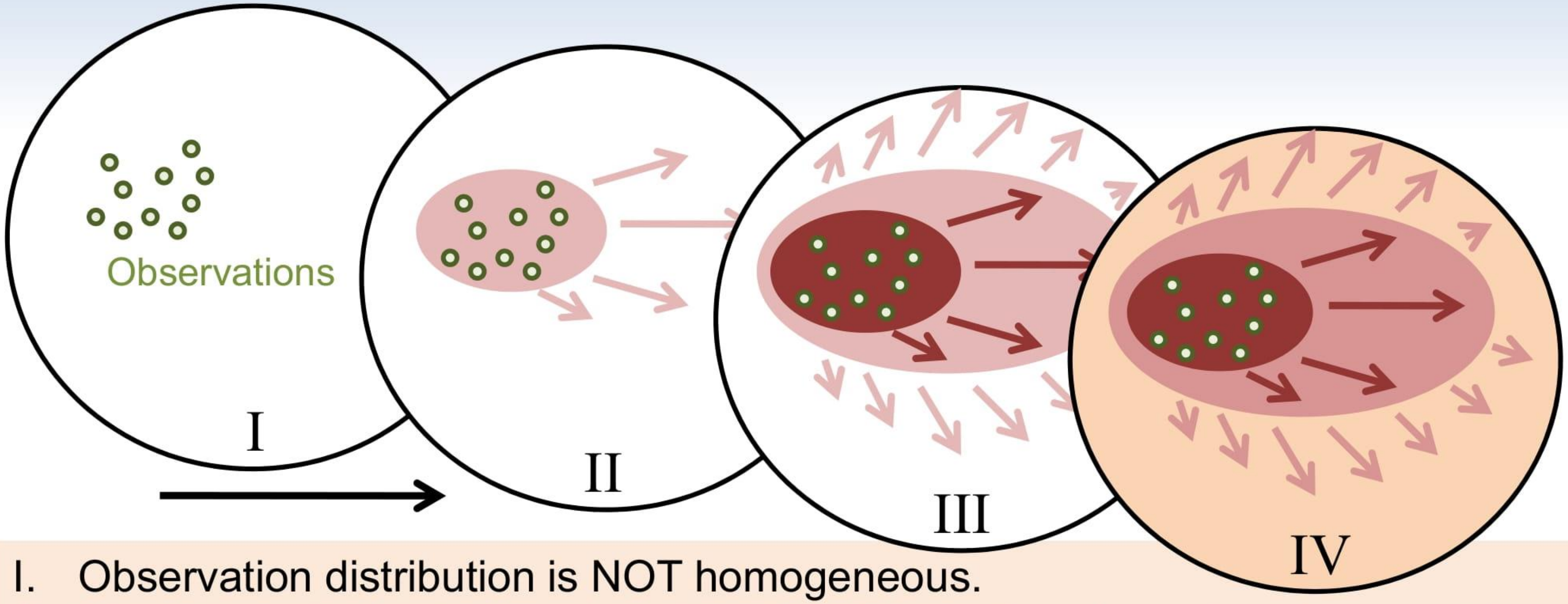
NWP

forecast from this analysis



DA system:
The first guess is corrected by using a variety of observations.
If the first guess was the forecast from the last analysis, this system would be operated cyclically.
➔ **Analysis and forecast cycle**

Analysis and forecast cycle



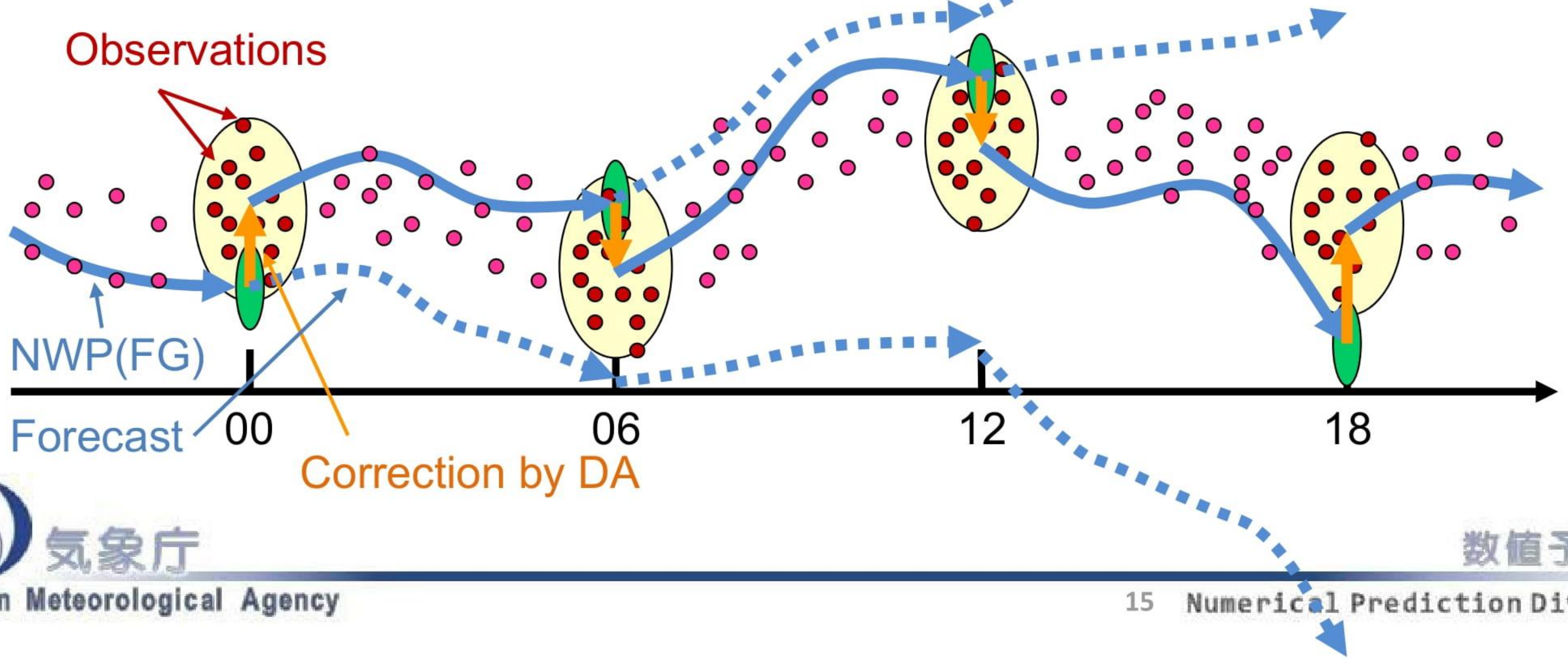
I. Observation distribution is NOT homogeneous.
II. The atmospheric state surrounding the observations is analyzed accurately. The well analyzed atmospheric state is transported by the atmospheric flow in the forecast to the external area.
III. In the next DA, the atmospheric state surrounding the observations is analyzed more accurately. The better analyzed atmospheric state was transported in the next forecast more widely.
IV. With this cyclic operation, the atmospheric state over the observation-poor area will be analyzed with the better accuracy.

Techniques for DA

- Two major approaches:
  - Minimum variance estimation
    - →Minimize the analysis error variance
      - Optimum Interpolation (OI) [used for surface analysis]
      - Ensemble Kalman filtering (EnKF)
  - Maximum likelihood estimation
    - →Find the maximum of likelihood function
    - ←→Minimize the cost function
      - 3 dimensional variational method (3D-Var) [used for LA]
      - **4 dimensional variational method (4D-Var) [used for GA/MA]**

Analysis and forecast cycle

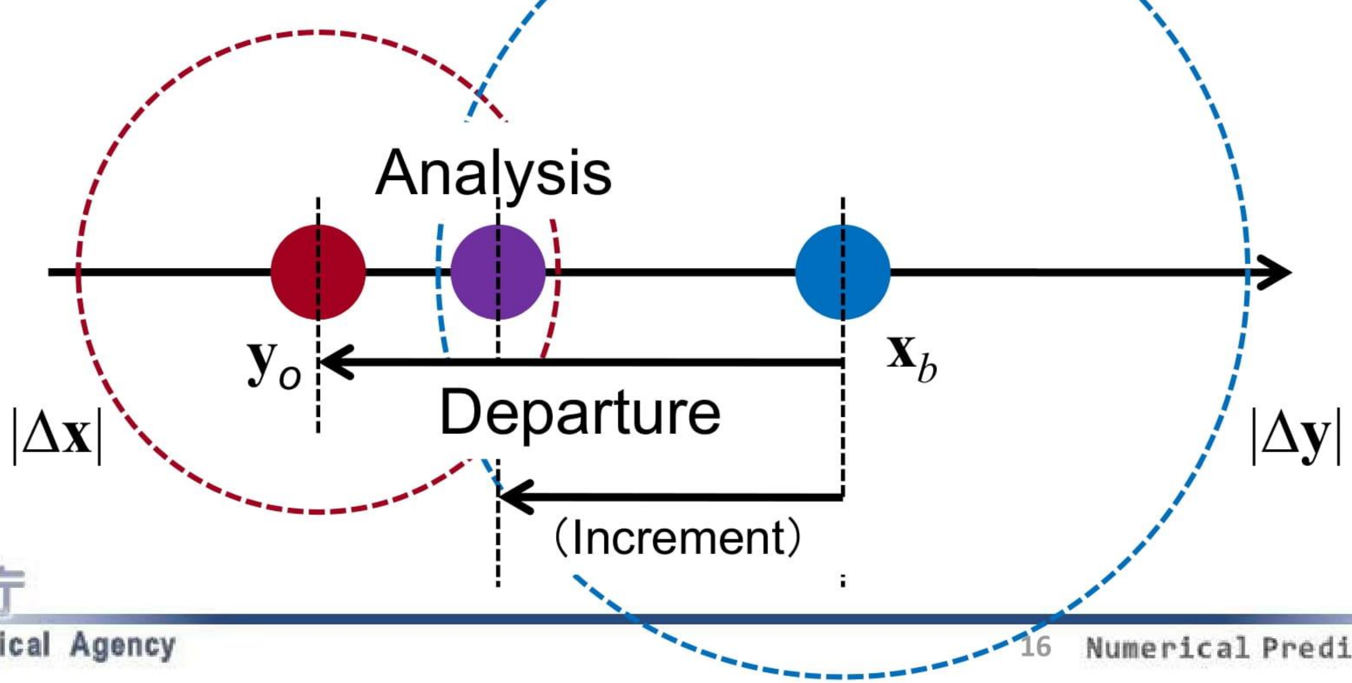
- Forecast error grows along forecast time
  - Short interval DA cycle maintains the analysis accuracy and the following forecast accuracy.
    - It is hard to correct the state in one analysis if the error of the first guess was too large



Determine the correction amount

(by using expected error information)

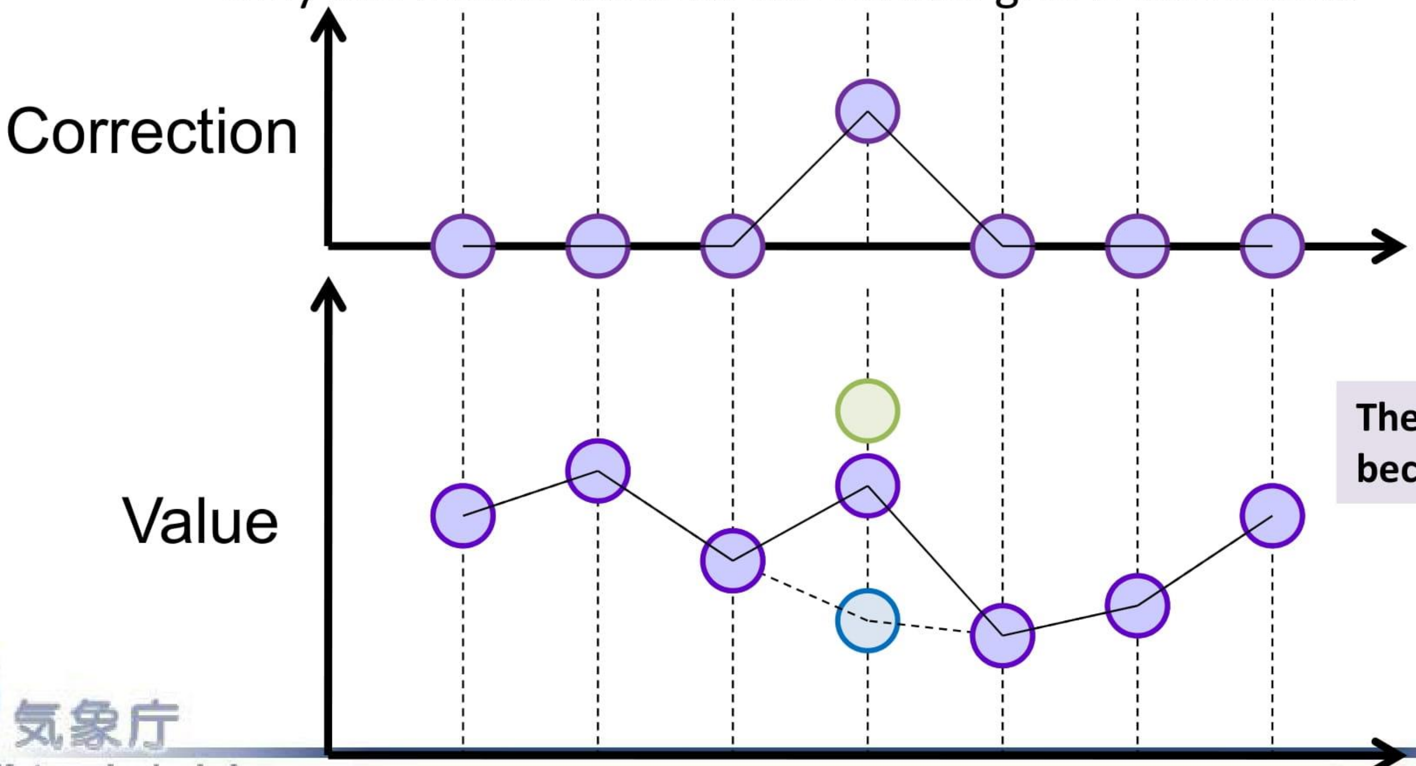
- Forecast (background) value $\mathbf{x}_b$ contains error $\Delta\mathbf{x}$
- Observed value $\mathbf{y}_o$ contains error $\Delta\mathbf{y}$
  - The expected errors $|\Delta\mathbf{x}|$ $|\Delta\mathbf{y}|$ can be estimated by statistics
  - With this information, the most likelihood value is estimated ➔ analyzed value $\mathbf{x}_a$



Correction for surrounding grids

Background error covariance

- When error was found in the model at a certain grid
  - The surrounding grids must have the resemble errors
  - If the background error covariance was NOT considered
    - Only the model value at the certain grid is corrected.

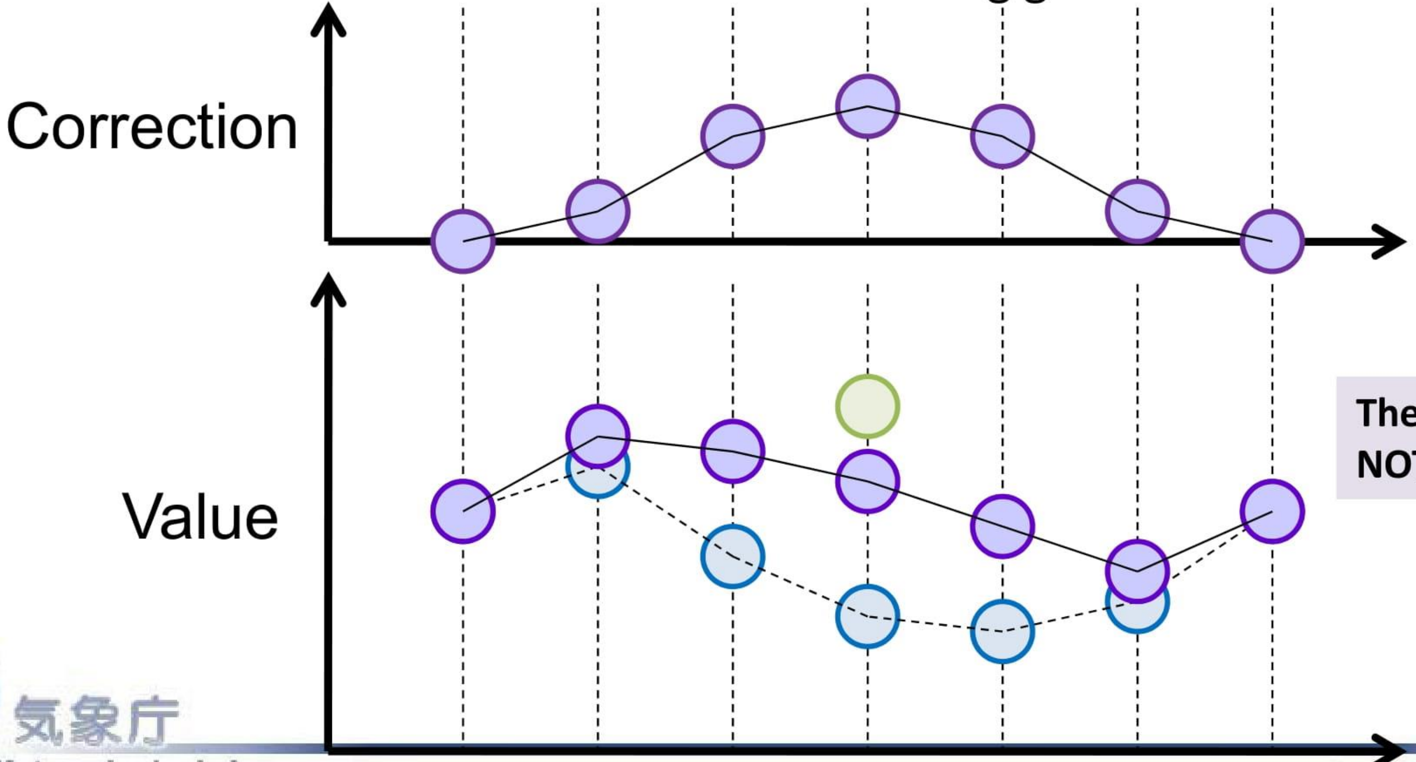


The corrected field becomes unrealistic

Correction for surrounding grids

Background error covariance

- When error was found in the model at a certain grid
  - The surrounding grids must have the resemble errors
  - If the background error covariance was considered
    - The model values at the surrounding grids are also corrected.



The corrected field is NOT unrealistic

Variational method

- Define the cost function J as

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

  - It is an index for the deviation of the analysis $\mathbf{x}_a$ against the first guess $\mathbf{x}_b$ and the one against observation $\mathbf{y}_o$.
    - Size of $\mathbf{x}$ is O(8), Size of $\mathbf{y}$ is O(5)
    - $\mathbf{B}$:Background error covariance $<\Delta\mathbf{x}^{\mathrm{T}}\Delta\mathbf{x}>$
    - $\mathbf{R}$:Obsrvation error covariance $<\Delta\mathbf{y}^{\mathrm{T}}\Delta\mathbf{y}>$
    - H:Observation operator
      - The operator calculates the value corresponding to the observation using GPV $\mathbf{x}$

These matrices are simplified with various assumptions in the actual implementation (It is impossible to estimate explicitly)

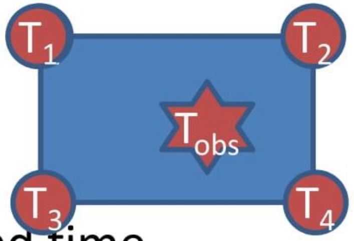
  - $\mathbf{x}_a$ is estimated by non-linear optimization algorithm (iterative method) with using $\nabla_{\mathbf{x}} J$

$$\nabla_{\mathbf{x}} J = \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_{\mathrm{b}}) + \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}(H\mathbf{x}-\mathbf{y}_{\mathrm{o}})$$

- $\mathbf{H}$:Tangent linear of H/ $\mathbf{H}^{\mathrm{T}}$: Adjoint operator (transpose of $\mathbf{H}$)

Observation operator

- Observation operator
  - The operator to produce the value corresponding to the target observations from NWP GPVs.
    - Thus, it is an observation simulator
    - Simple example：Temperature (model variables)
      - Just an interpolation of GPVs for the location and time



    - Complicated example：Satellite radiance
      - Integrate the emission and absorption of radiance vertically

$$TB = \int B \frac{d\tau}{dz} dz + (1-\varepsilon)\tau^2 \int \frac{B}{\tau^2}\frac{d\tau}{dz} dz + \tau_{srf}\varepsilon_{srf} B$$
$$= H(\mathbf{T}, \mathbf{q}, \nu, \theta, \mathbf{x}_{srf})$$

$$\because \tau = \tau(\nu, \theta, \mathbf{T}, \mathbf{q}), B = B(\nu, T), \varepsilon = \varepsilon(\nu, \theta, \mathbf{x}_{srf})$$

τ: Transmittance
ε: Emissivity
B: Plank function
θ: Irradiance angle
ν: Frequency
$\mathbf{T}$: Temperature profile
$\mathbf{q}$: Specific humidity profile
$\mathbf{x}_{srf}$: Surface parameters

Tangent linear/Adjoint operator

- An example for wind speed

Observation operator

$$WS = H(\mathbf{x}) = H(u,v) = \sqrt{u^2 + v^2}$$

Tangent linear operator

$$\mathbf{H} = \begin{pmatrix} \dfrac{u}{\sqrt{u^2+v^2}} & \dfrac{v}{\sqrt{u^2+v^2}} \end{pmatrix}$$

$$WS\delta WS = u\delta u + v\delta v \leftarrow d\left(WS^2 = u^2 + v^2\right)$$

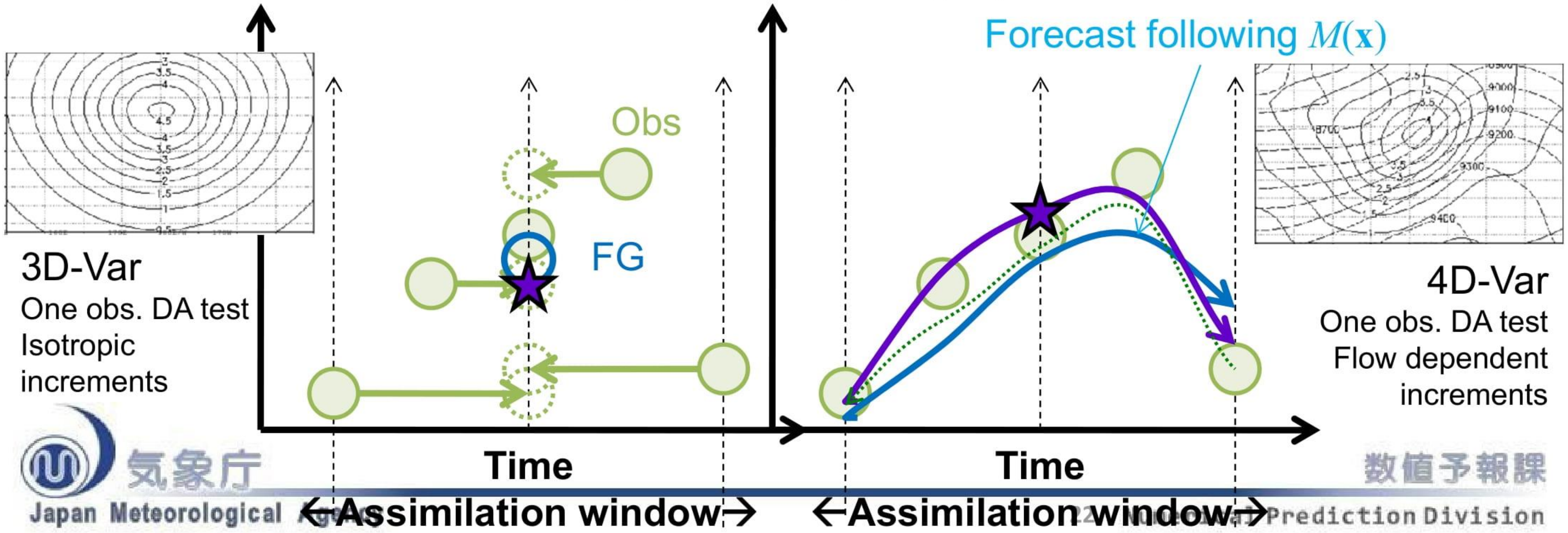
$$\delta WS = \frac{u\delta u + v\delta v}{\sqrt{u^2+v^2}} = \begin{pmatrix} \dfrac{u}{\sqrt{u^2+v^2}} & \dfrac{v}{\sqrt{u^2+v^2}} \end{pmatrix} \begin{pmatrix} \delta u \\ \delta v \end{pmatrix}$$

Adjoint operator

$$\mathbf{H}^{\mathrm{T}} = \begin{pmatrix} \dfrac{u}{\sqrt{u^2+v^2}} \\ \dfrac{v}{\sqrt{u^2+v^2}} \end{pmatrix} \quad \begin{pmatrix} \overline{\delta u} \\ \overline{\delta v} \end{pmatrix} = \begin{pmatrix} \dfrac{u}{\sqrt{u^2+v^2}} \\ \dfrac{v}{\sqrt{u^2+v^2}} \end{pmatrix} \overline{\delta WS}$$

3D-Var/4D-Var

- 3D-Var: NOT consider the time evolution of the state
  - Obs. are compared with the GPV at the analysis time
    - It is supposed the obs. was performed at the analysis time
- 4D-Var: consider the time evolution of the state
  - Obs. are compared with the GPV, which are integrated to the observation time by model M. (FGAT: first guess at the appropriate time)
  - The difference is integrated back by using adjoint model $\mathbf{M}^T$



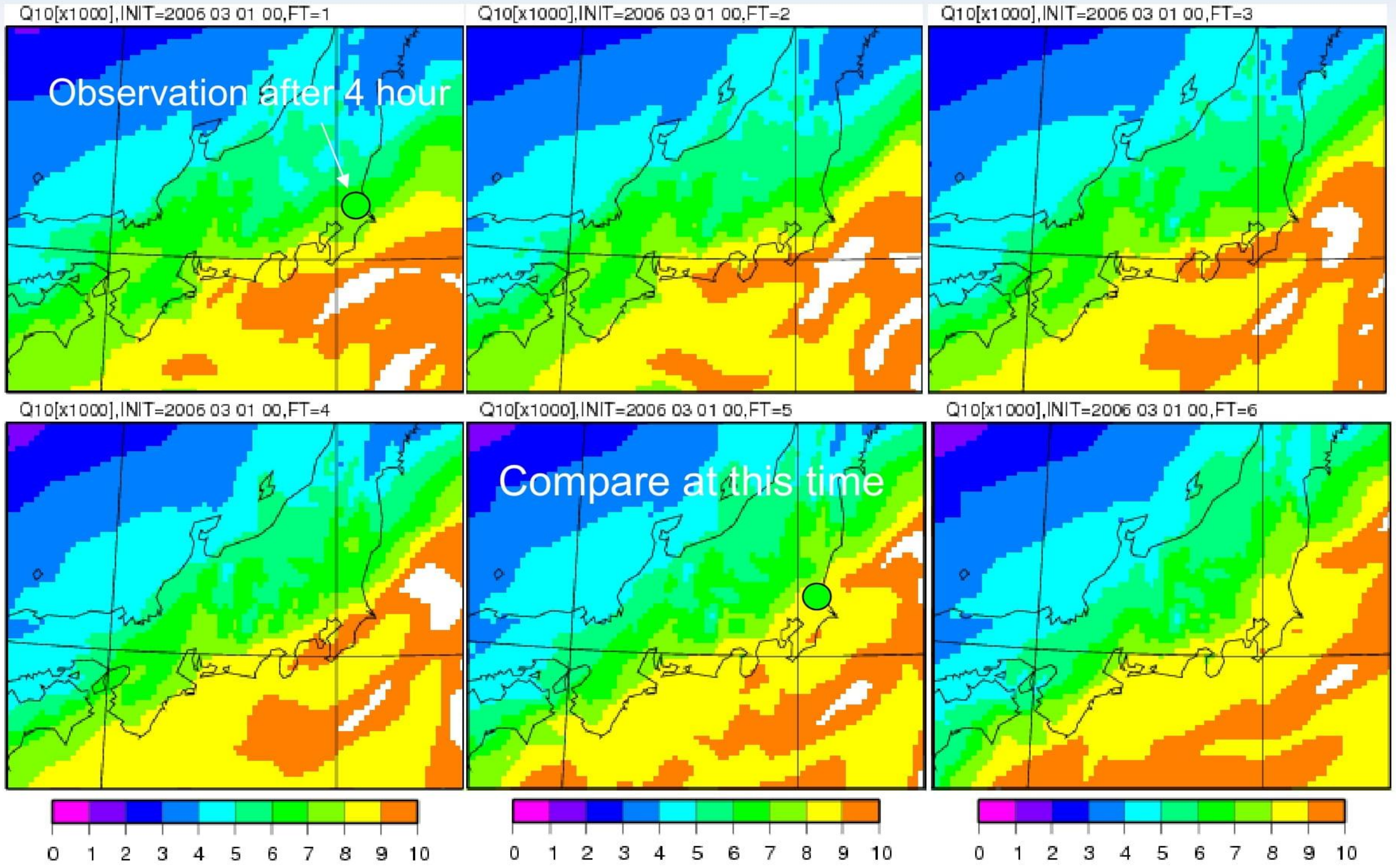
Procedures of the variational method

- In case of Wind speed assimilation:
  - Loop for cost function minimization
    - Convert analysis variables into forecast variables (ST, VP, … → U, V, …)
    - # Integrate the GPVs to the observation time with the model
    - Interpolation of GPVs for the observation point
    - Calculate wind speed by using the interpolated u, v
    - **Subtract the observation y, and divided by variance R**
    - Estimate u’, v’ by using adjoint operator for wind speed
    - Estimate GPVs’ by using adjoint operator for interpolation
    - # Integrate back the GPVs’ to the initial time with the adjoint model
    - Estimate analysis variables’ by using adjoint operator for the conversion
    - **Estimate the total gradient by adding the gradient from bkg term**
      - » Take difference of $\mathbf{x}_a$ and $\mathbf{x}_b$, multiplied by $\mathbf{B}^{-1}$
    - Use non linear optimization algorithm for estimating the correction amount.
      - » → Exit if cost function J was converged. Otherwise, Repeat to the top.
  - End after convert the variables.

is a step for 4D-Var

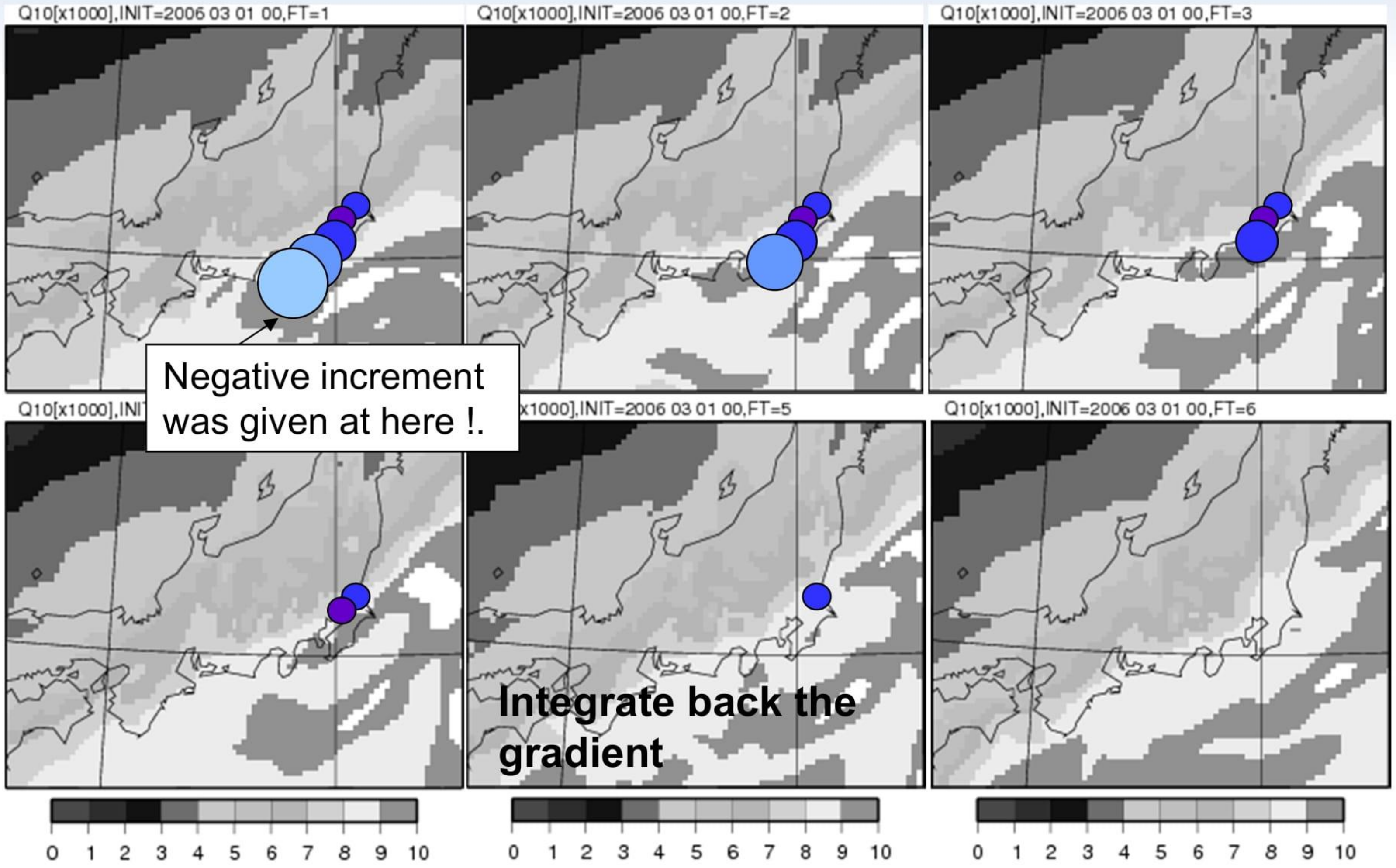
Schematic image of DA

for water vapor at 4 hours after



Schematic image of DA

for water vapor at 4 hours after



ENSEMBLE DA

– Ensemble Kalman Filter (EnKF) –

Kalman Filter

$t = i - 1 \qquad \boldsymbol{x}_{i-1}^{a}, \mathbf{P}_{i-1}^{a}$

Forecast

$$\boldsymbol{x}_i^f = M(\boldsymbol{x}_{i-1}^a) + \eta$$

$$\mathbf{P}_i^f = \mathbf{M}\mathbf{P}_{i-1}^a\mathbf{M}^{\mathrm{T}} + \mathbf{Q}_{i-1}$$

$t = i$

Analysis

$$\mathbf{K}_i = \mathbf{P}_i^f\mathbf{H}_i^{\mathrm{T}}\left(\mathbf{H}_i\mathbf{P}_i^f\mathbf{H}_i^{\mathrm{T}} + \mathbf{R}_i\right)^{-1}$$

$$\boldsymbol{x}_i^a = \boldsymbol{x}_i^f + \mathbf{K}_i\left(\boldsymbol{y}_i^o - H_i\left(\boldsymbol{x}_i^f\right)\right)$$

$$\mathbf{P}_i^a = (\mathbf{I} - \mathbf{K}_i\mathbf{H}_i)\mathbf{P}_i^f$$

Difficulties in KF

- **Dimension Problem**
  - Calculation of inverse matrix

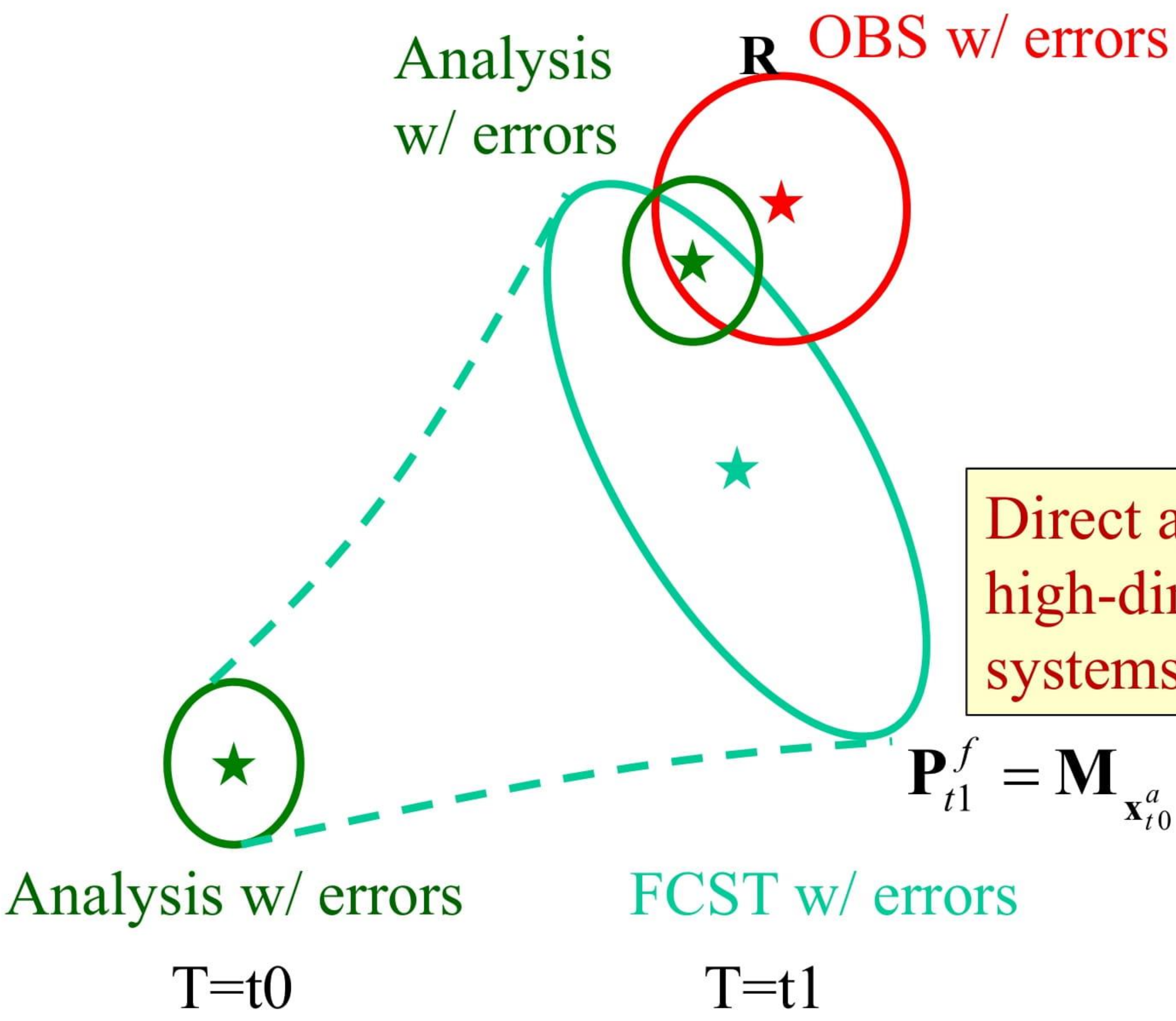
    ↑Reduce the rank of observations（Serial filter）

- **Integration of Pf**
  - Carry out the time integration by tangent linear model 2N times ! (N≒10^7)

→ Reduce rank

SEEK filter，**EnKF**

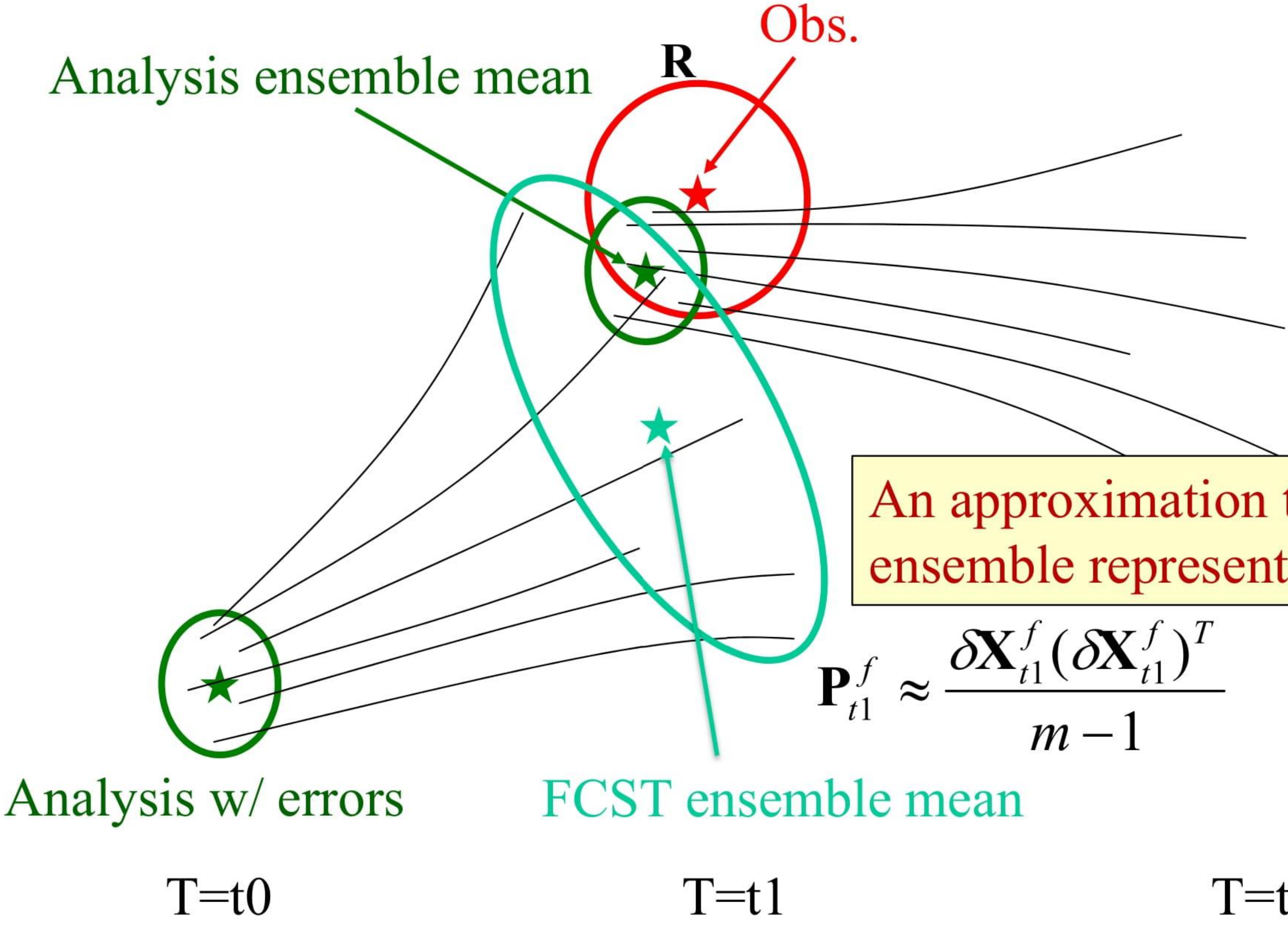
Kalman Filter (KF)



Direct application to high-dimensional systems is prohibitive.

$$\mathbf{P}_{t1}^{f} = \mathbf{M}_{\mathbf{x}_{t0}^{a}} \mathbf{P}_{t0}^{a} \mathbf{M}_{\mathbf{x}_{t0}^{a}}^{T}$$

Ensemble Kalman Filter (EnKF)



An approximation to KF with ensemble representations

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

Approximation in KF

Approximation of the forecast error covariance matrix

$$\mathbf{P}_i^f = \left\langle \delta \boldsymbol{x}_i^f \left(\delta \boldsymbol{x}_i^f \right)^{\mathrm{T}} \right\rangle \approx \frac{1}{m-1} \sum_{k=1}^{m} \left(\boldsymbol{x}_i^{f(k)} - \overline{\boldsymbol{x}_i^f} \right) \left(\boldsymbol{x}_i^{f(k)} - \overline{\boldsymbol{x}_i^f} \right)^{\mathrm{T}}$$

$$\overline{\boldsymbol{x}_i^f} = \frac{1}{m} \sum_{k=1}^{m} \boldsymbol{x}_i^{f(k)}$$

Approximation of the Kalman gain matrix

$$\mathbf{K}_i = \mathbf{P}_i^f \mathbf{H}_i^{\mathrm{T}} \left(\mathbf{H}_i \mathbf{P}_i^f \mathbf{H}_i^{\mathrm{T}} + \mathbf{R}_i \right)^{-1}$$

$$\mathbf{P}_i^f \mathbf{H}_i^{\mathrm{T}} = \left\langle \delta \boldsymbol{x}_i^f \left(\delta \boldsymbol{x}_i^f \right)^{\mathrm{T}} \right\rangle \mathbf{H}_i^{\mathrm{T}} \approx \frac{1}{m-1} \sum_{k=1}^{m} \left(\boldsymbol{x}_i^{f(k)} - \overline{\boldsymbol{x}_i^f} \right) \left(H_i \boldsymbol{x}_i^{f(k)} - \overline{H_i \boldsymbol{x}_i^f} \right)^{\mathrm{T}}$$

$$\mathbf{H}_i \mathbf{P}_i^f \mathbf{H}_i^{\mathrm{T}} = \left\langle \mathbf{H}_i \delta \boldsymbol{x}_i^f \left(\mathbf{H}_i \delta \boldsymbol{x}_i^f \right)^{\mathrm{T}} \right\rangle \approx \frac{1}{m-1} \sum_{k=1}^{m} \left(H_i \boldsymbol{x}_i^{f(k)} - \overline{H_i \boldsymbol{x}_i^f} \right) \left(H_i \boldsymbol{x}_i^{f(k)} - \overline{H_i \boldsymbol{x}_i^f} \right)^{\mathrm{T}}$$

$$\overline{H_i \boldsymbol{x}_i^f} = \frac{1}{m} \sum_{k=1}^{m} H_i \boldsymbol{x}_i^{f(k)}$$

Analysis and ensemble update

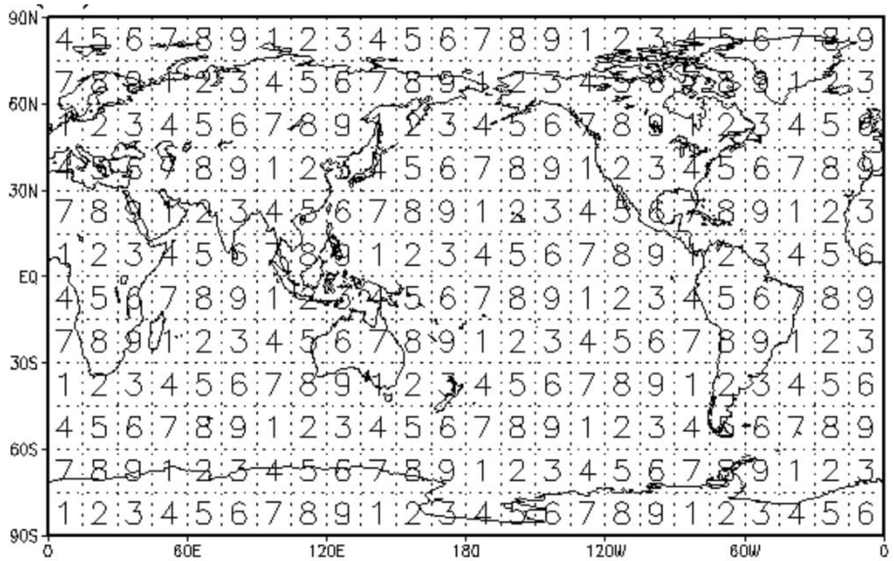
- Perturbed Observation Method (PO)
  - Analysis for each member
  - Analysis error covariance are under estimated theoretically

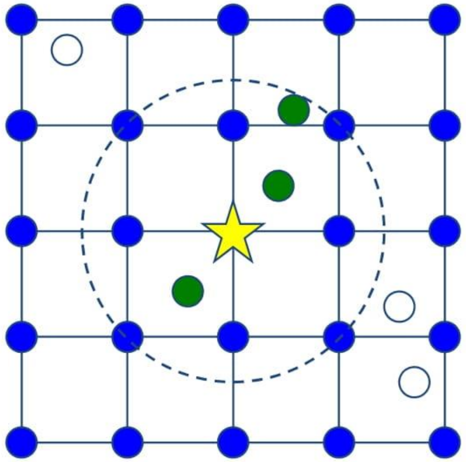
- Square Root Filter (SRF)
  - Analysis for ensemble mean
  - Serial EnSRF, **LETKF**

LETKF (Local Ensemble Transform Kalman Filter)

Each grid point is treated independently.

→ *essentially perfectly parallel*





Multiple observations are treated simultaneously.

LETKF (Local Ensemble Transform Kalman Filter)

Kalman gain matrix:

$$\mathbf{K}_i = \mathbf{P}_i^f \mathbf{H}_i^{\mathrm{T}} \left(\mathbf{H}_i \mathbf{P}_i^f \mathbf{H}_i^{\mathrm{T}} + \mathbf{R}_i\right)^{-1}$$

$$= \frac{1}{m-1} \mathbf{X}_i^f \left(\mathbf{X}_i^f\right)^{\mathrm{T}} \mathbf{H}_i^{\mathrm{T}} \left(\mathbf{H}_i \frac{1}{m-1} \mathbf{X}_i^f \left(\mathbf{X}_i^f\right)^{\mathrm{T}} \mathbf{H}_i^{\mathrm{T}} + \mathbf{R}_i\right)^{-1}$$

$$= \mathbf{X}_i^f \left(\mathbf{Y}_i^f\right)^{\mathrm{T}} \left[\mathbf{Y}_i^f \left(\mathbf{Y}_i^f\right)^{\mathrm{T}} + (m-1)\mathbf{R}_i\right]^{-1}$$

$$\boldsymbol{y}_i^{f(k)} = H\left(\boldsymbol{x}_i^{f(k)}\right); \;\; \mathbf{Y}_i^f = \left[\boldsymbol{y}_i^{f(1)} - \overline{\boldsymbol{y}_i^f} \,|\, \dots \,|\, \boldsymbol{y}_i^{f(m)} - \overline{\boldsymbol{y}_i^f}\right] = \mathbf{H}\mathbf{X}_i^f$$

$$= \mathbf{X}_i^f \left[(m-1)\mathbf{I} + \left(\mathbf{Y}_i^f\right)^{\mathrm{T}} \mathbf{R}_i^{-1} \mathbf{Y}_i^f\right]^{-1} \left(\mathbf{Y}_i^f\right)^{\mathrm{T}} \mathbf{R}_i^{-1}$$

LETKF (Local Ensemble Transform Kalman Filter)

Analysis error covariance in ensemble space:

$$\widetilde{\mathbf{P}}_i^a = \left[(m-1)\mathbf{I} + \left(\mathbf{Y}_i^f\right)^{\mathrm{T}} \mathbf{R}_i^{-1} \mathbf{Y}_i^f\right]^{-1} \qquad cf.\ \mathbf{P}_i^a = \left[\left(\mathbf{P}_i^f\right)^{-1} + \mathbf{H}_i^{\mathrm{T}} \mathbf{R}_i^{-1} \mathbf{H}_i\right]^{-1}$$

$$\mathbf{K}_i = \mathbf{X}_i^f \widetilde{\mathbf{P}}_i^a \left(\mathbf{Y}_i^f\right)^{\mathrm{T}} \mathbf{R}_i^{-1} = \mathbf{X}_i^f \widetilde{\mathbf{K}}_i$$

Ensemble mean update in model space:

$$\begin{aligned}\overline{\boldsymbol{x}_i^a} &= \overline{\boldsymbol{x}_i^f} + \mathbf{K}_i \left(\boldsymbol{y}_i^o - \overline{\boldsymbol{y}_i^f}\right) \\ &= \overline{\boldsymbol{x}_i^f} + \mathbf{X}_i^f \widetilde{\mathbf{P}}_i^a \left(\mathbf{Y}_i^f\right)^{\mathrm{T}} \mathbf{R}_i^{-1} \left(\boldsymbol{y}_i^o - \overline{\boldsymbol{y}_i^f}\right)\end{aligned}$$

LETKF (Local Ensemble Transform Kalman Filter)

Ensemble perturbations in ensemble space:

$$\mathbf{W}^a = \left[(m-1)\widetilde{\mathbf{P}}_i^a\right]^{1/2}$$

Ensemble perturbations in model space:

$$\begin{aligned}\mathbf{X}_i^a &= \mathbf{X}_i^f \mathbf{W}^a \\ &= \mathbf{X}_i^f \left[(m-1)\widetilde{\mathbf{P}}_i^a\right]^{1/2}\end{aligned}$$

LETKF (Local Ensemble Transform Kalman Filter)

In practice, the implementation of the LETKF algorithm requires the following steps:

$$\mathbf{Y}_i^f = \mathbf{H}\mathbf{X}_i^f$$

$$\widetilde{\mathbf{P}}_i^a = \left[(m-1)\mathbf{I} + \left(\mathbf{Y}_i^f\right)^{\mathrm{T}}\mathbf{R}_i^{-1}\mathbf{Y}_i^f\right]^{-1}$$

$$\mathbf{K}_i = \mathbf{X}_i^f\widetilde{\mathbf{P}}_i^a\left(\mathbf{Y}_i^f\right)^{\mathrm{T}}\mathbf{R}_i^{-1}$$

$$(m-1)\mathbf{I} + \left(\mathbf{Y}_i^f\right)^{\mathrm{T}}\mathbf{R}_i^{-1}\mathbf{Y}_i^f = \mathbf{U}\mathbf{D}\mathbf{U}^{\mathrm{T}}$$

$$\overline{\boldsymbol{x}_i^a} = \overline{\boldsymbol{x}_i^f} + \mathbf{K}_i\left(\boldsymbol{y}_i^o - \overline{\boldsymbol{y}_i^f}\right)$$

$$\mathbf{X}_i^a = \mathbf{X}_i^f\left[(m-1)\widetilde{\mathbf{P}}_i^a\right]^{1/2}$$

$$\boldsymbol{x}_i^{a(k)} = \overline{\boldsymbol{x}_i^a} + \mathbf{X}_i^{a(k)}$$

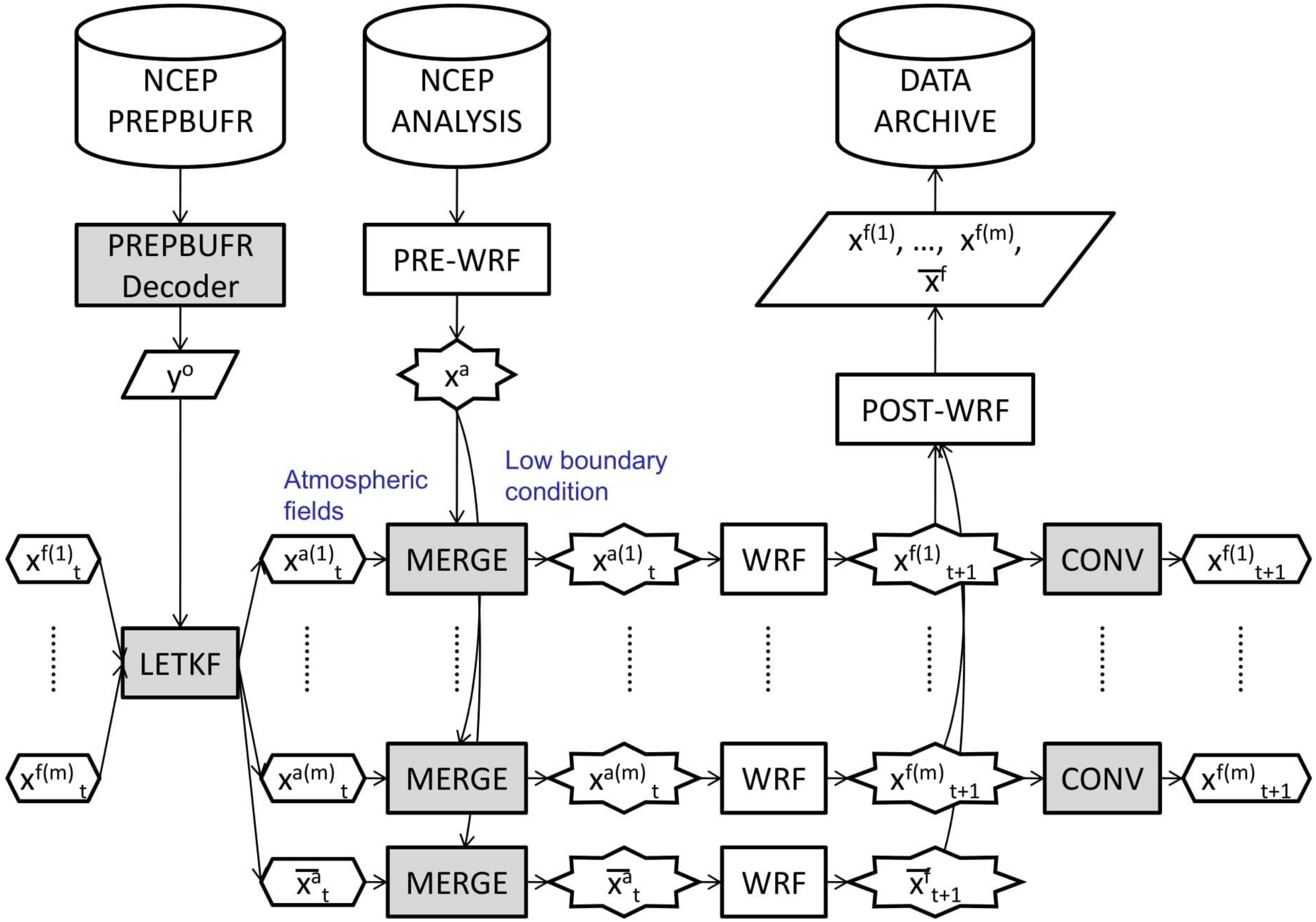
WRF-LETKF

Community Model

- **WRF-ARW**
  - See WRF-ARW TUTRIALS
    http://www.mmm.ucar.edu/wrf/users/supports/tutorial.html

- **LETKF**
  - Available at:
    http://code.google.com/p/miyoshi/

WRF-LETKF flowchart



Experimental settings

- ***LETKF settings***

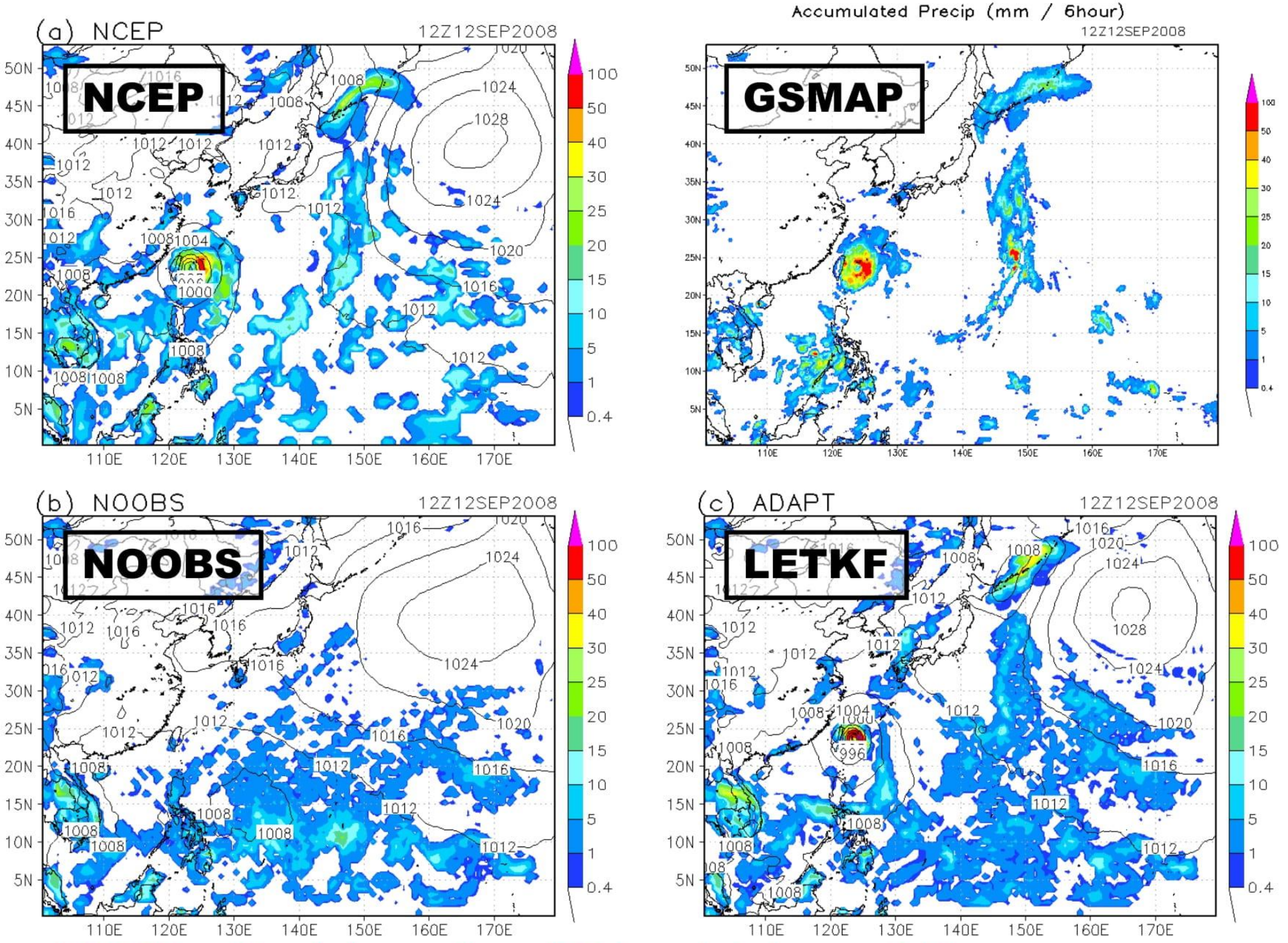
Ensemble size	20
Lateral boundary conditions	Unperturbed
Covariance inflation	Adaptive (Miyoshi 2010) Fixed 20% (smaller above level 20)
Covariance localization	400 km, 0.4 ln p
Analyzed variables	u, v, w, T, ph, qv, qc, qr
Observation data	NCEP PREPBUFR

- ***WRF settings***

Domain size	137 x 109 x 40
Horizontal grid spacing	~ 60 km
WRF version	WRF-ARW 3.2.1

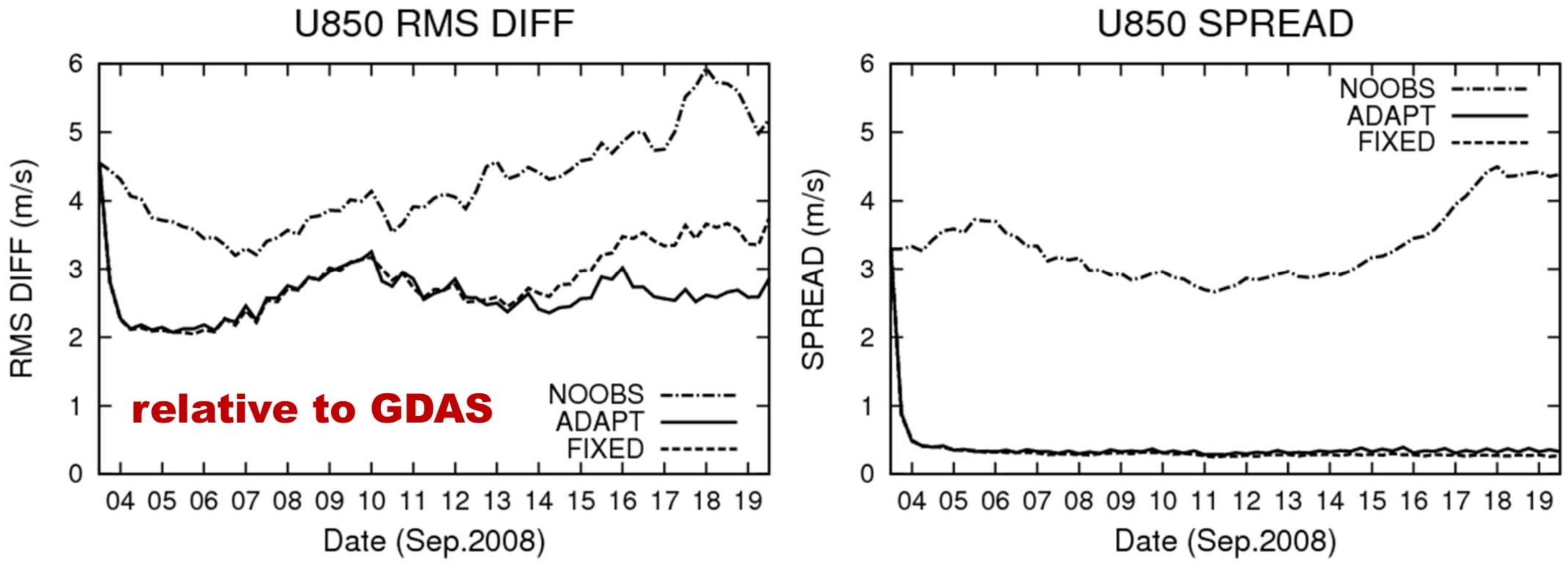
WRF-LETKF working properly

WRF 6-h forecast using each initial field (after 9 days cycle)



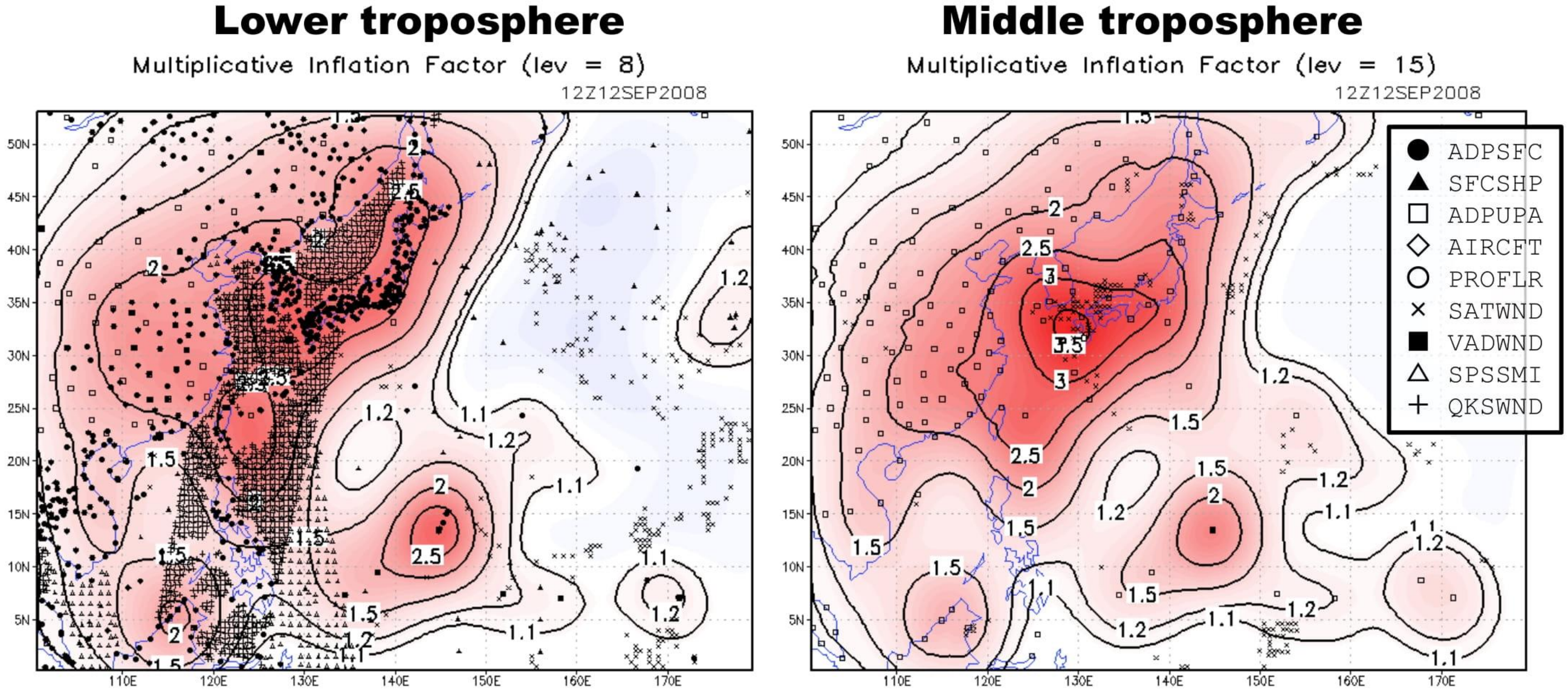
NOOBS: without observations (BC is updated every 6-h)

Time series (U850)



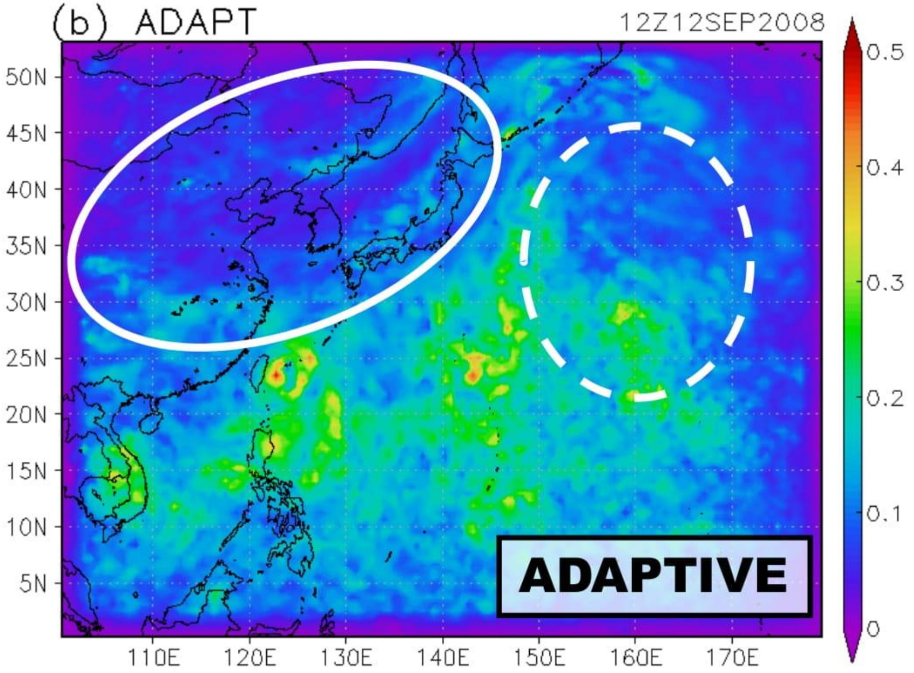
- LETKF performs properly.
- ADAPT shows significantly smaller RMS after 10 days cycle.
  - It takes a while to spin-up the adaptive inflation parameters
- Lateral boundary does not dominate the inner domain.

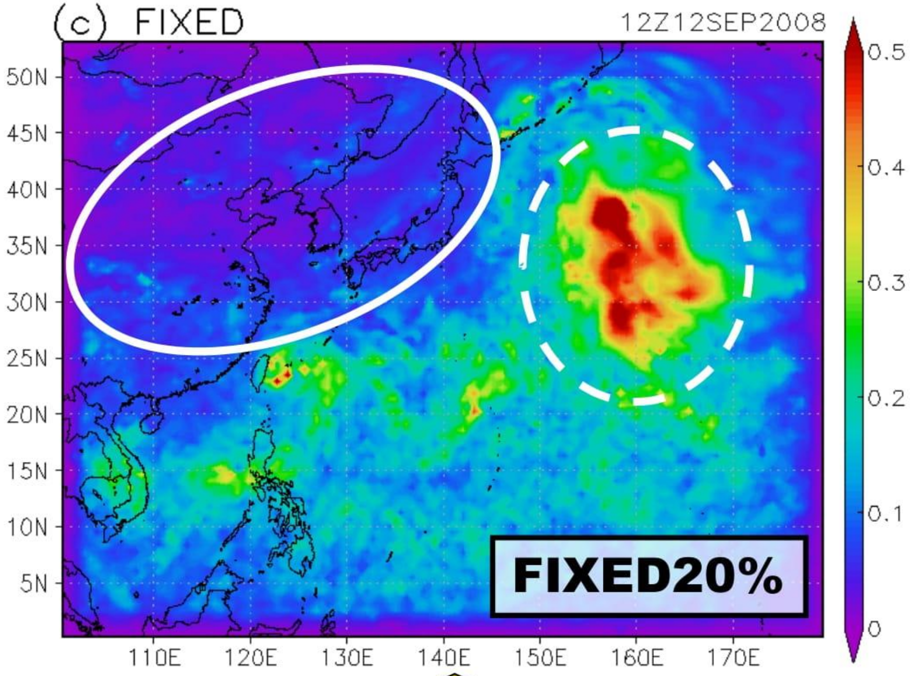
Adaptive inflation



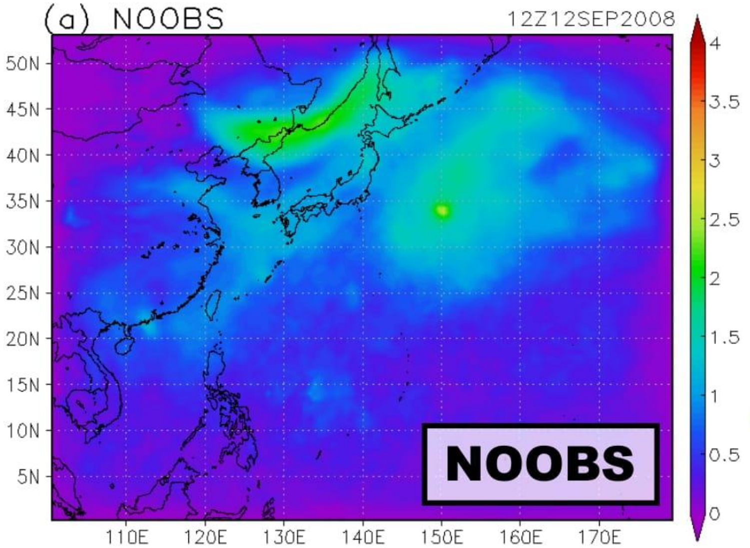
- Adaptive inflation accounts for imperfections such as model errors and limited ensemble size.
- The large adaptive inflation values are estimated over the densely observed areas, which make the ensemble spread significantly larger in the densely observed areas.

Ensemble spread (T500)



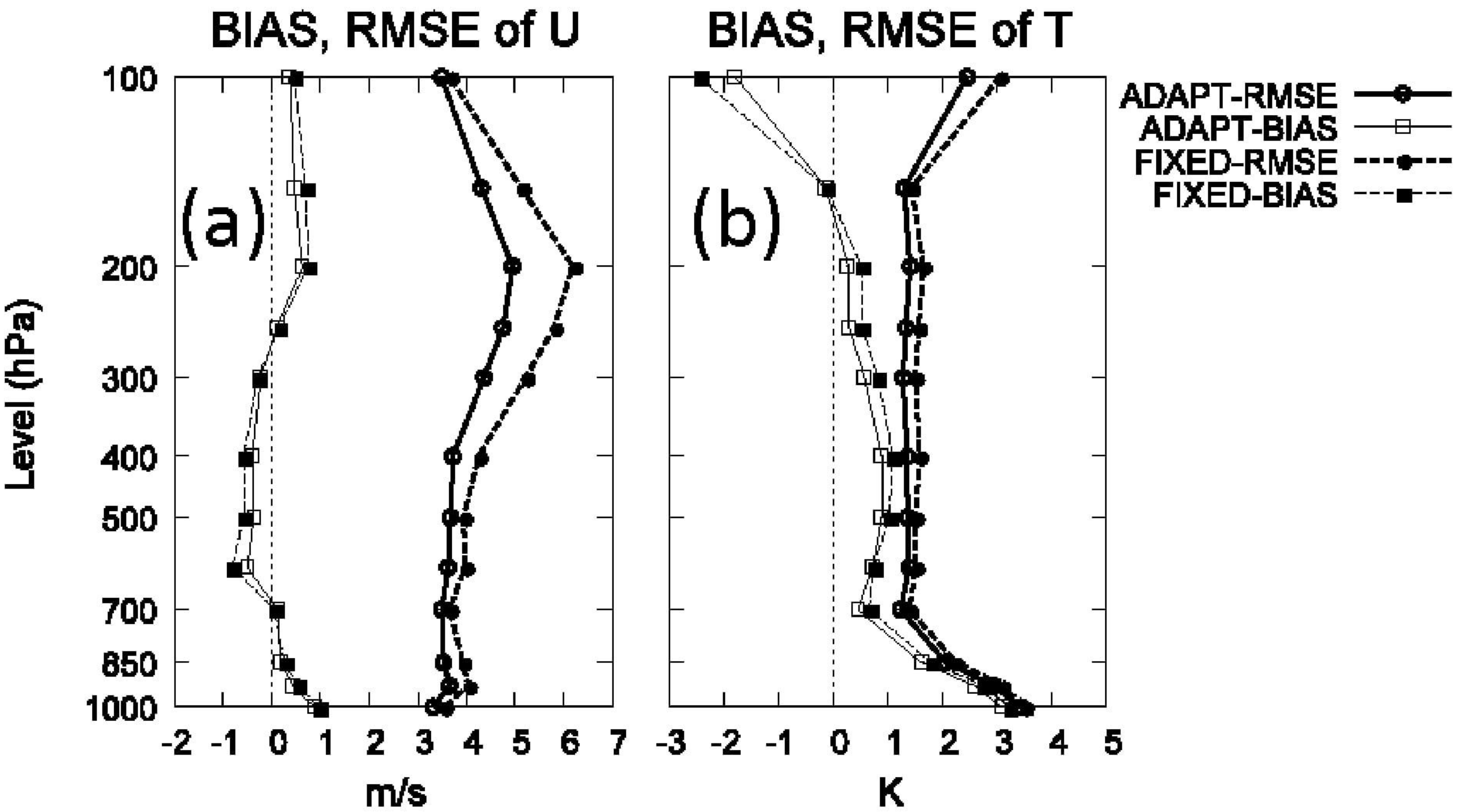


Too small (large) over the densely (sparsely) observed areas



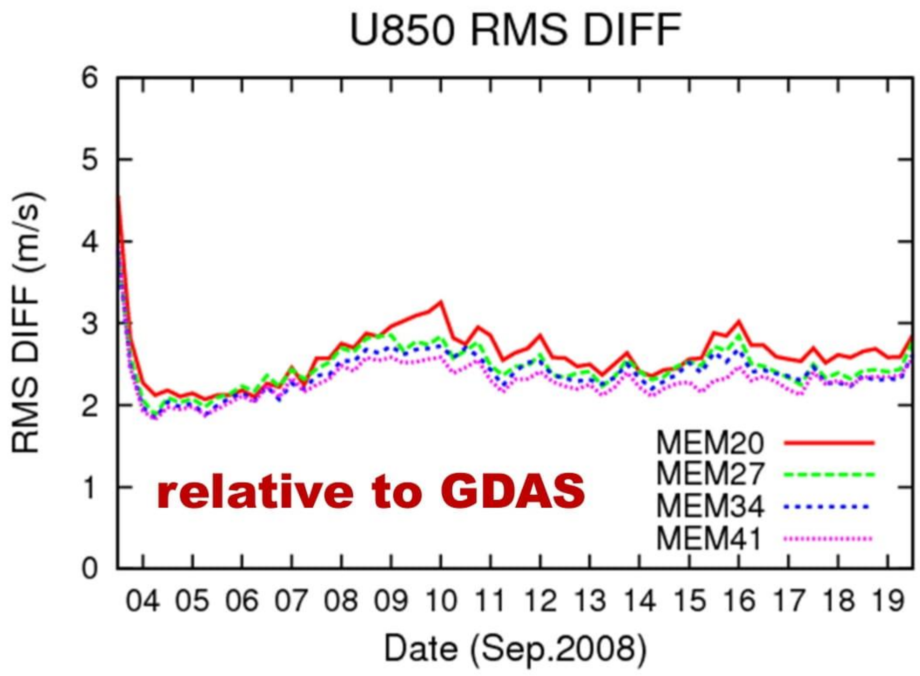
Unperturbed BC is limited near the boundaries

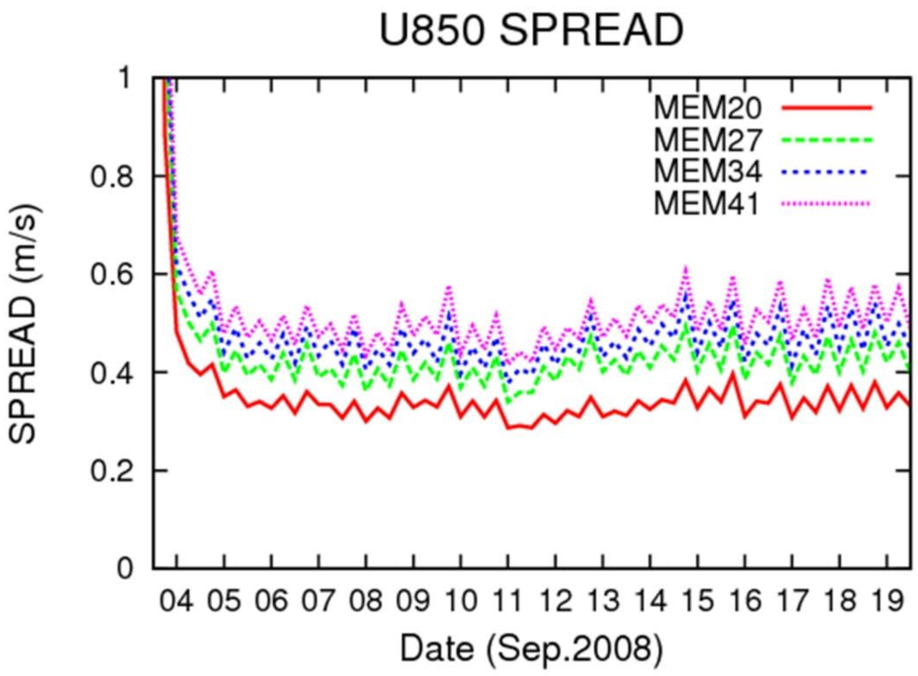
6-hr forecast vs. radiosondes



➢ Adaptive inflation performs well.

Sensitivity to the ensemble size

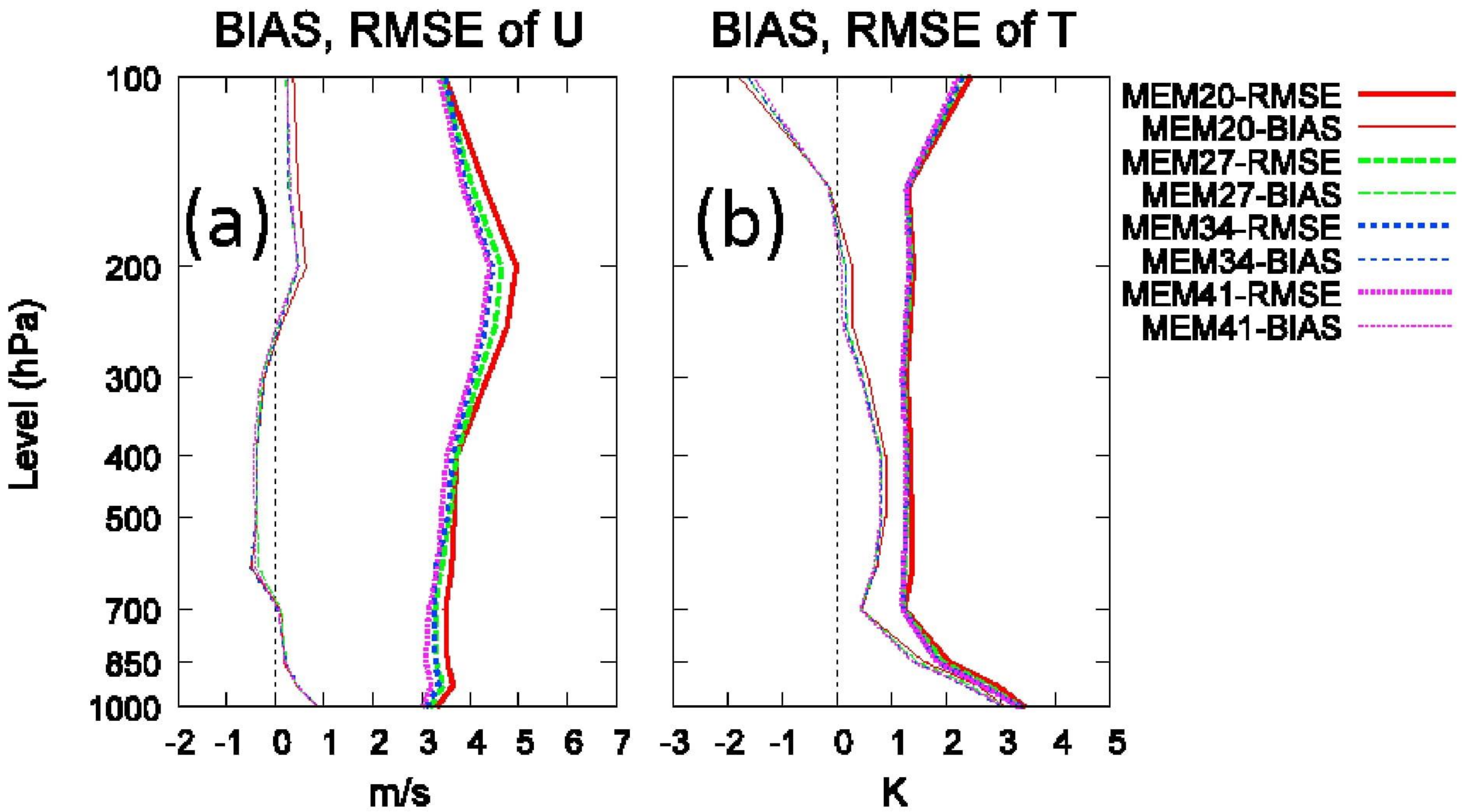




➢ Consistently better with more members.

➢ More members, the larger the ensemble spread.

Sensitivity to the ensemble size



- Consistently better with more members.
- For temperature, increasing the ensemble size more than 27 does not show much improvement.

Conclusions

- The WRF-LETKF system performed properly with real observations.
- Adaptive inflation performed very well.
- More ensemble members yielded consistently better analyses.
  - Roughly linear increase of the computational time