Data assimilation for local rainfall near Tokyo on 18 July 2013 using EnVAR with observation space localization

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What is EnVAR?

Data Assimilation

Analysis $\mathbf{x}_0$ is provided from First guess $\mathbf{x}_0^f$ and Observation $\mathbf{y}_t$.

$\mathbf{x}_0$ takes a maximum likelihood value when cost function J is minimum ($\nabla J=0$).

Background term | Observation term

Cost Function

$$J=\frac{1}{2}\left(\mathbf{x}_0-\mathbf{x}_0^f\right)^T\mathbf{B}^{-1}\left(\mathbf{x}_0-\mathbf{x}_0^f\right)+\frac{1}{2}\sum_t\left[H\left(M_t\left(\mathbf{x}_0\right)\right)-\mathbf{y}_t\right]^T\mathbf{R}_t^{-1}\left[H\left(M_t\left(\mathbf{x}_0\right)\right)-\mathbf{y}_t\right]$$

Gradient

$$\nabla J\equiv\frac{\partial J}{\partial\mathbf{x}_0}=\mathbf{B}^{-1}\left(\mathbf{x}_0-\mathbf{x}_0^f\right)+\sum_t\left[\frac{\partial H\left(M_t\left(\mathbf{x}_0\right)\right)}{\partial\mathbf{x}_0}\right]^T\mathbf{R}_t^{-1}\left[H\left(M_t\left(\mathbf{x}_0\right)\right)-\mathbf{y}_t\right]$$

Several methods are classified using how to solve $\nabla J=0$.

Method	Background covariance	How to solve x_0	How to calculate
3DVAR,4DVAR	Statistic	Implicitly	With adjoint of M and H
Hybrid-4DVAR	Ensemble-based	Implicitly	With adjoint of M and H
EnKF (LETKF)	Ensemble-based	<u>Explicitly</u>	Ensemble approximation
EnVAR	Ensemble-based	<u>Implicitly</u>	Ensemble approximation

EnVAR provides analysis implicitly without adjoint models

EnVAR with observation space localization

Analysis

$$\overline{\mathbf{x}_t^a} = \overline{\mathbf{x}_t^f} + \sum_j \delta\mathbf{x}_{t,j}^f \circ \mathbf{w}_j$$

Analysis valuable is transformed from **x** to **w**

Background error covariance

$$\mathbf{B} = \frac{1}{M-1}\mathbf{L} \circ \sum_j \delta\mathbf{x}_{0,j}^f \delta\mathbf{x}_{0,j}^{f\,T}$$

Localization factor

i: analysis points
k: observation points
t: time slots
j: ensemble members

Then,

Gradient of J

$$\frac{\partial J}{\partial w_{ij}} = (M-1)w_{ij} + \sum_{k,t} L_{ik}\delta H_{kj,t} R_{k,t}^{-1}\left[H_k\left(\overline{\mathbf{x}_t^a}\right) - y_{k,t}\right]$$

Observation error variance

Perturbation of H

Observation operator (non-linear)

- Localization factor in observation term } Similar to LETKF
- Equivalent to B-localization
- Globally defined J

} Different from LETKF

Observation system simulation experiments with SPEEDY model

Number of members: **20**

Assimilation window: **6 hours**

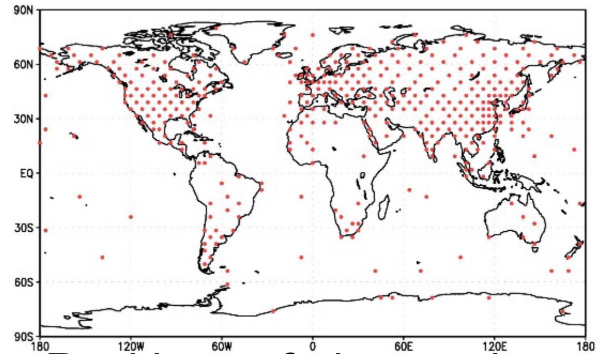
Localization radius: σ_H=**1000(km)**, σ_V=**0.1(sigma)**

Observations: **U, V, T, RH, Ps**

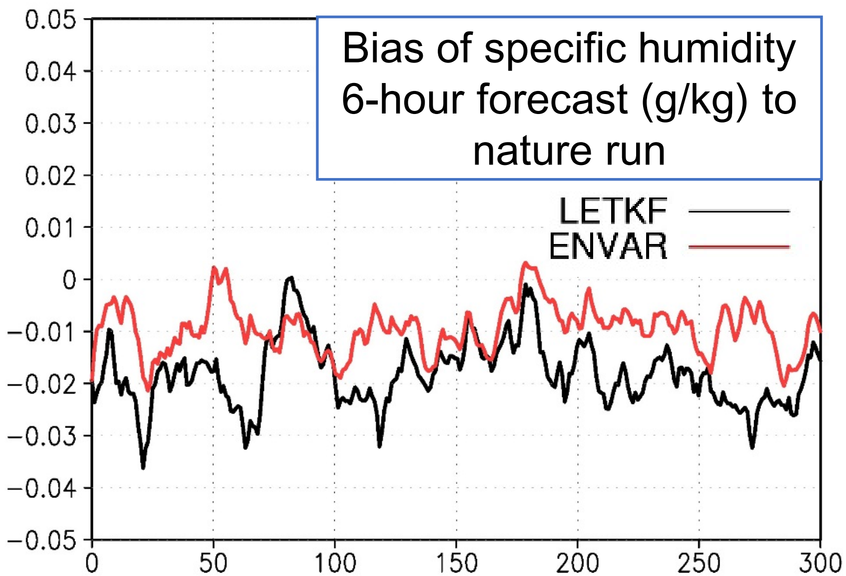
Inflation: **Multiplicative (=1.1)**

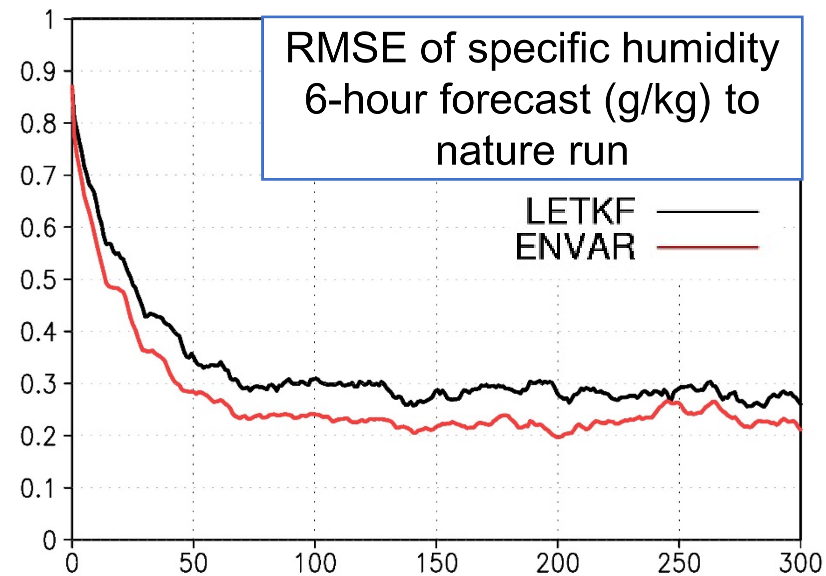
Analysis time: **Center of the window (t=3h)**

Observation time: **t=1h, 3h, 5h**



Positions of observations

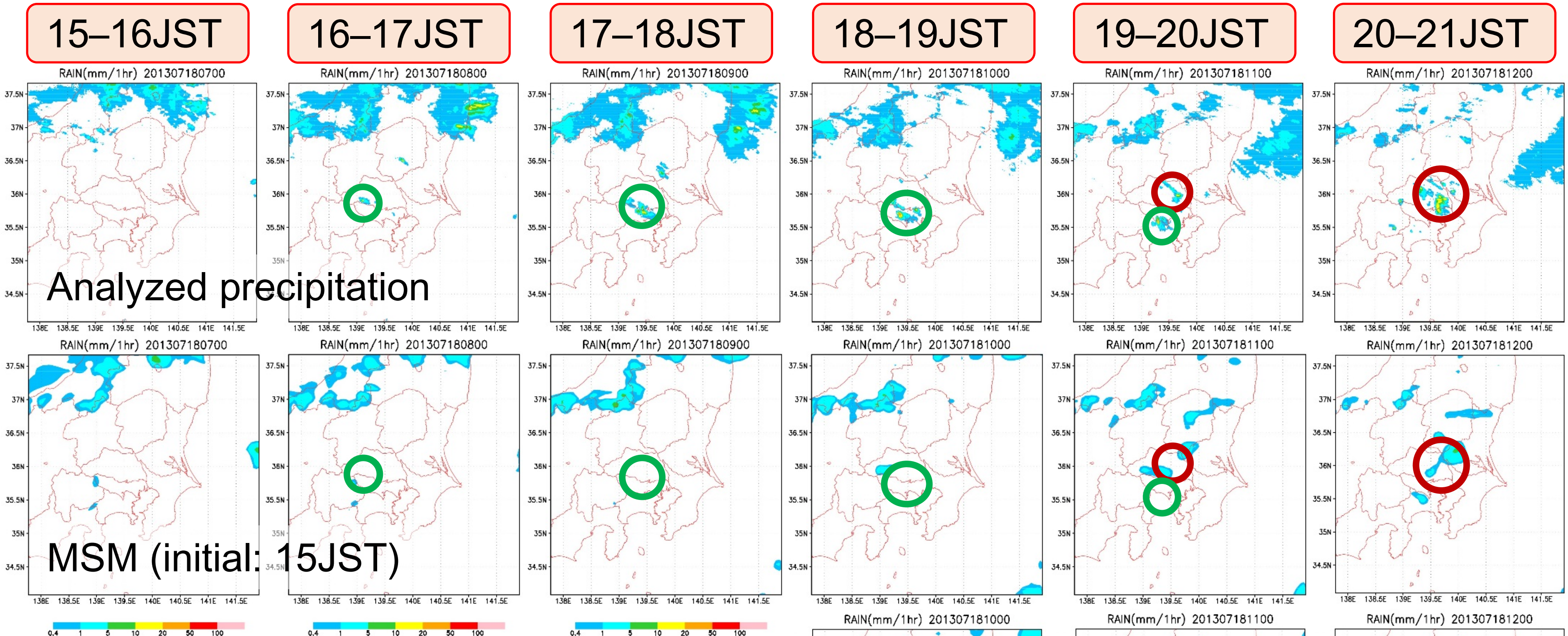


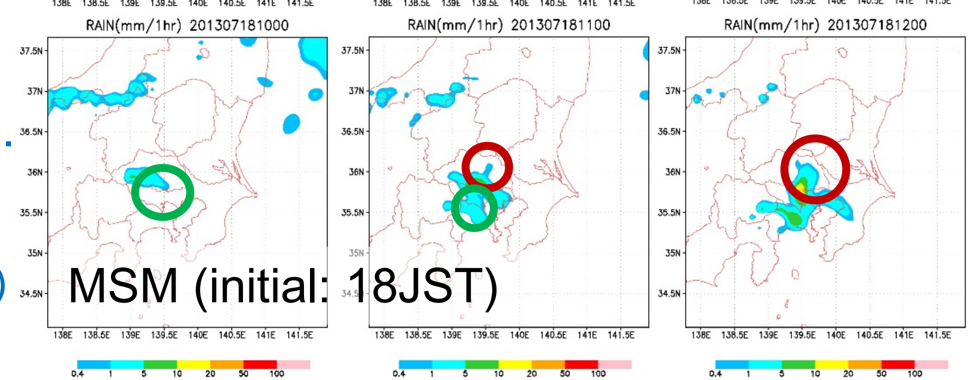


Number of forecast-analysis cycles (every 6 hour)

Is EnVAR better than LETKF in real obs. data assimilation?

Local Rainfall on 18 July 2013





- Two precipitation systems were generated.
- Accurate forecast is difficult.

(even though the initial condition included rainfall)

Dense observations are expected to improve forecasts

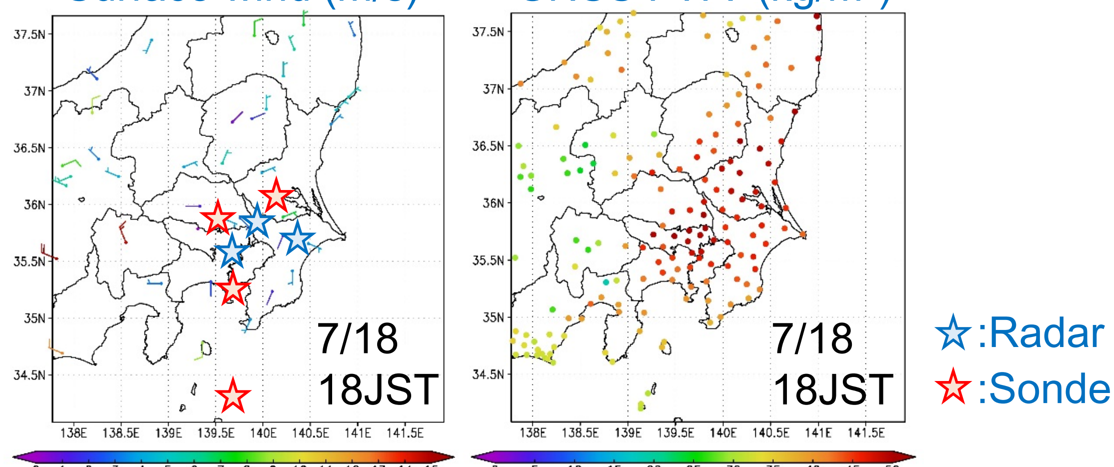
Assimilated Dense Observations

Observation	Elements	Frequency	
Surface (JMA Surface observation and AMeDAS)	U, V, T	every 10 minutes	
GNSS	PWV	every 10 minutes	
Radar	Radial wind	every 10 minutes	Kashiwa, Haneda, Narita
Radiosonde	U, V, T, RH	every 3 hours	Tsukuba, Urawa, Yokosuka, Ryofu Maru

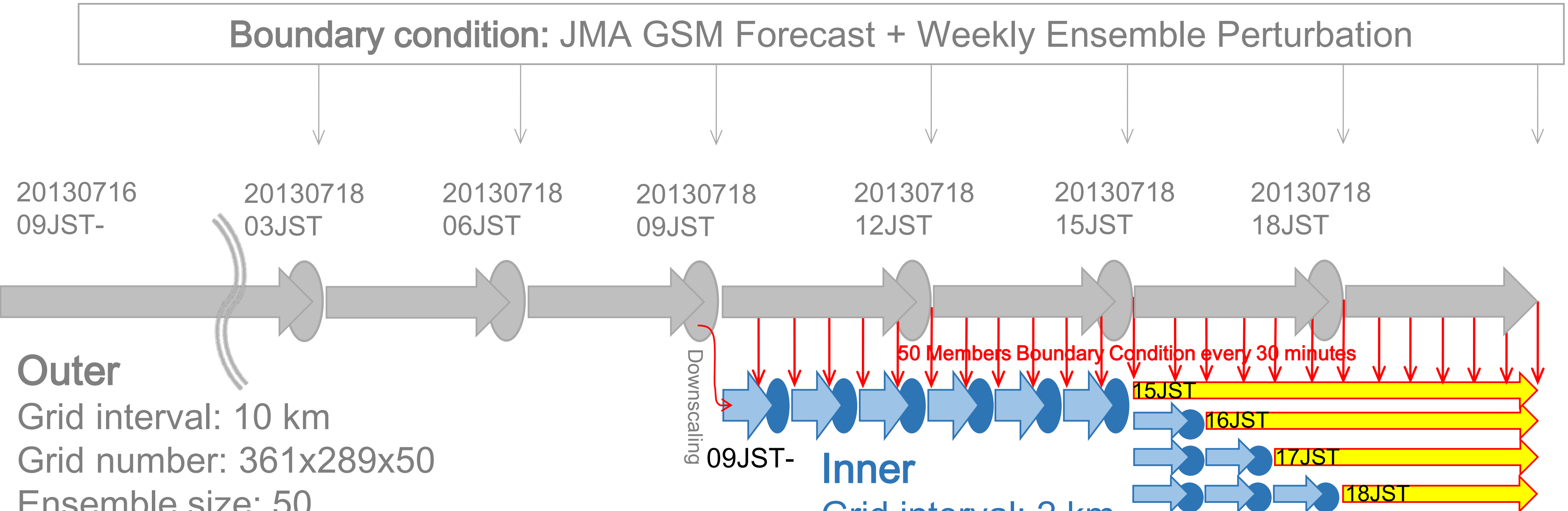
Setting

Horizontal localization: 20 km
Vertical localization: 0.1 lnP
(PWV is not localized vertically)
Multiplicative inflation parameter: 1.2
Observation error:
- U, V: 1 m/s
- T: 1 K
- RH: 10%
- PWV: 5 kg/m^2
- Radial wind: 3 m/s

Surface wind (m/s) GNSS PWV (kg/m^2)



Flow of Assimilation Experiments

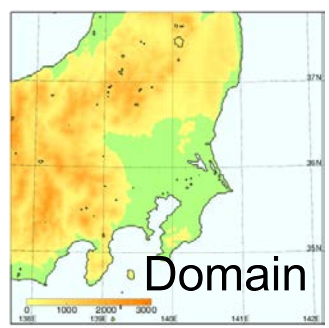


Outer
Grid interval: 10 km
Grid number: 361x289x50
Ensemble size: 50
Analysis window: 3 hour
(Operational Observations used in JMA Meso-DA every 30 minutes)

Inner
Grid interval: 2 km
Grid number: 200x200x60
Ensemble size: 50
Analysis window: 1 hour

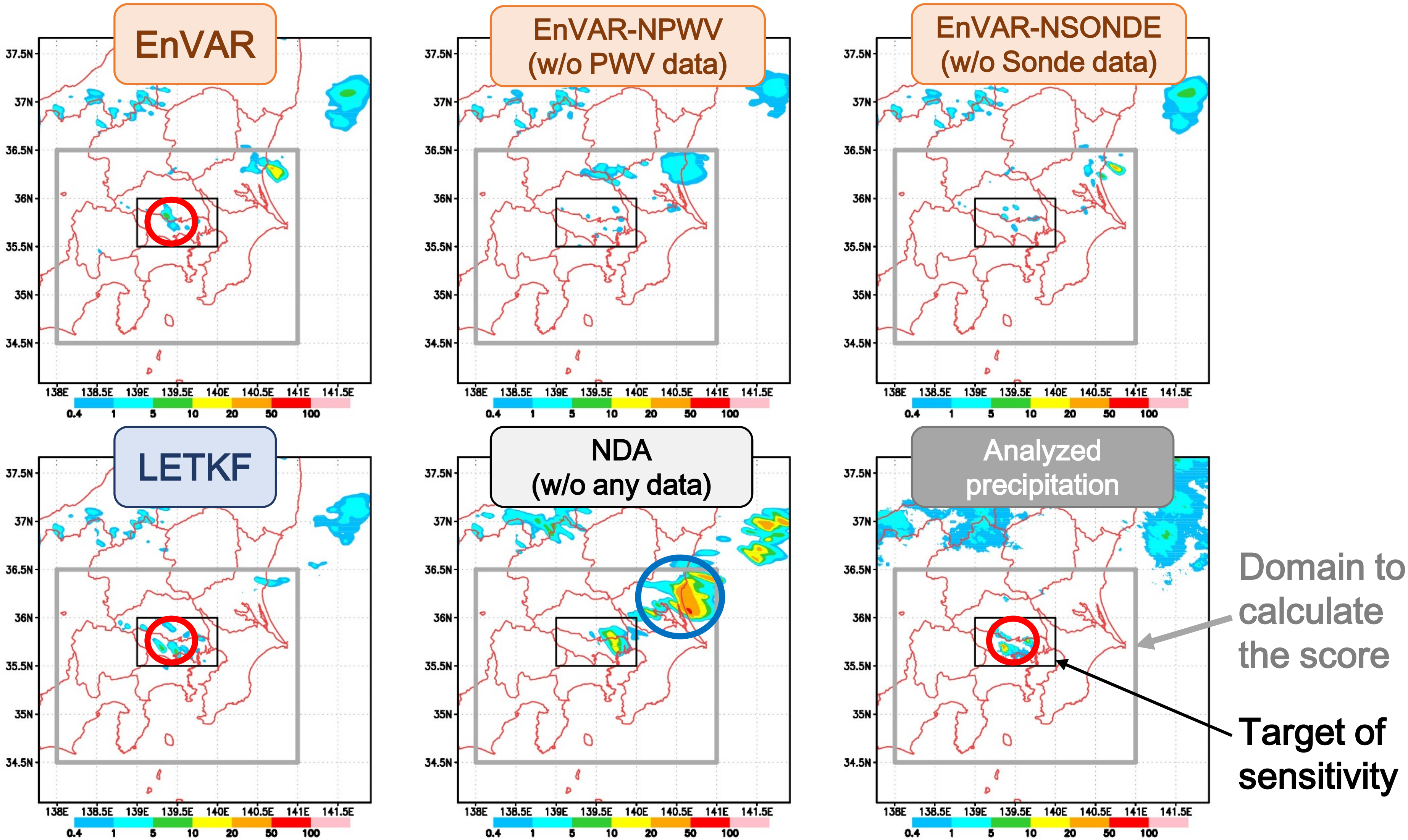
Extended Forecast

: Ensemble Forecasts
: Analysis (LETKF or EnVAR)



Target:
Local rain near Tokyo
in 20130718 17-21JST

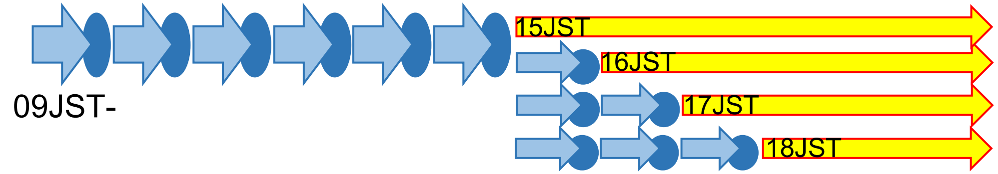
Comparison of 1-h Rainfall in 18-19 JST



Good impacts of PWV and Sonde data assimilation

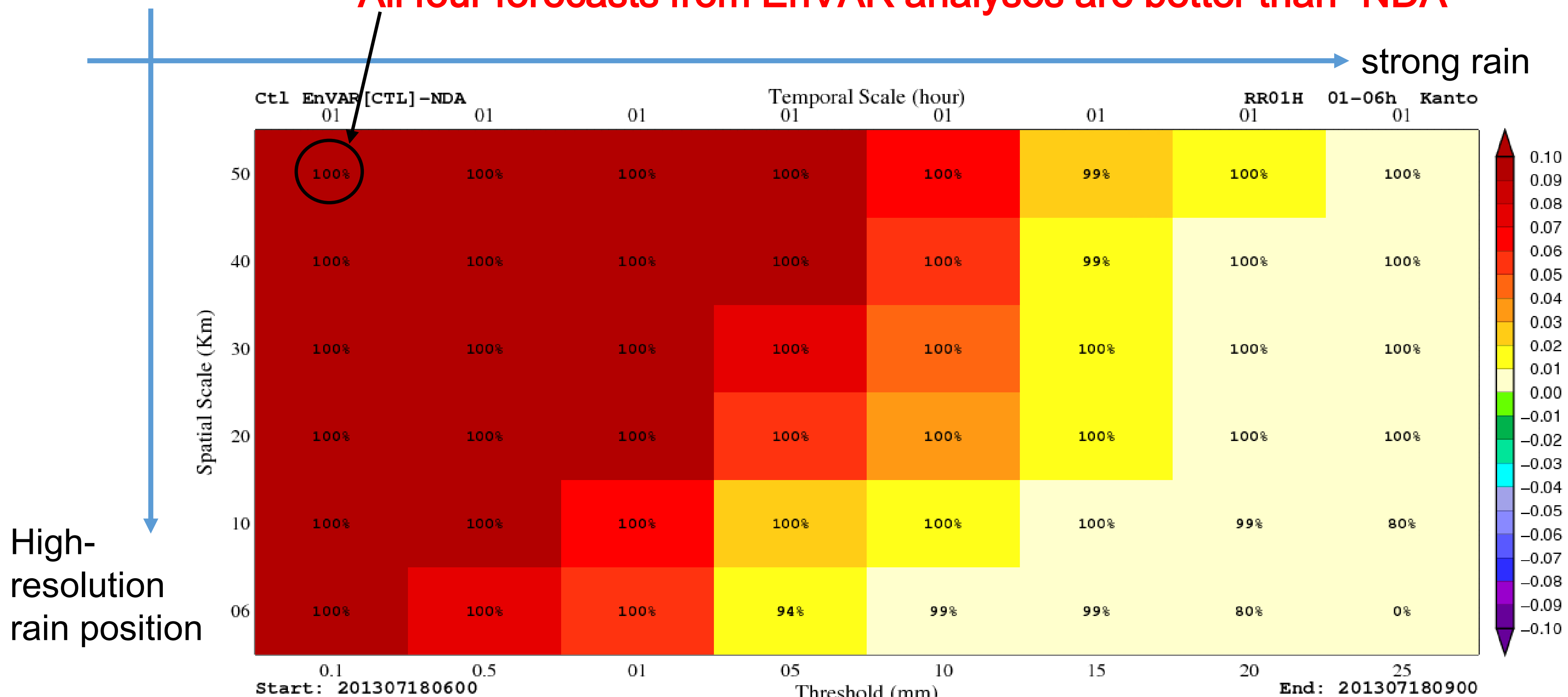
Are Fractions Skill Scores improved?

$$FSS = 1 - \frac{\left[\sum_i (O_i - F_i)\right]^2}{\left[\sum_i O_i\right]^2 + \left[\sum_i F_i\right]^2}$$



O_i : number density of **observed** rainfall in i-th fraction
F_i : number density of **forecast** rainfall in i-th fraction

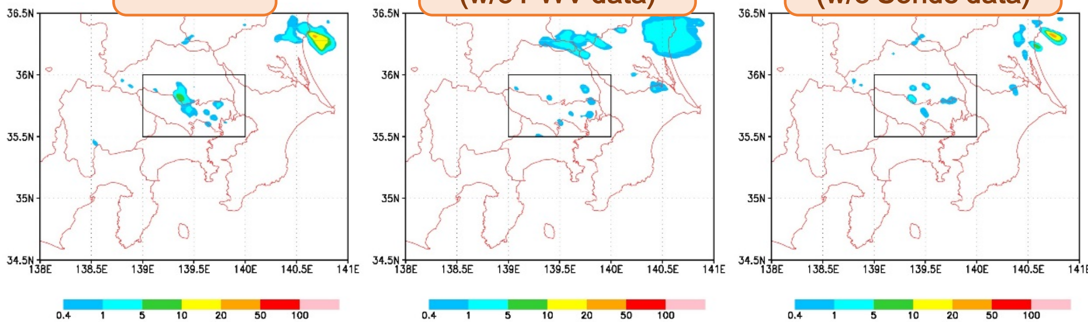
All four forecasts from EnVAR analyses are better than “NDA”



Impact of Dense Observations

Rainfall in 18-19 JST

EnVAR | EnVAR-NPWV (w/o PWV data) | EnVAR-NSONDE (w/o Sonde data)

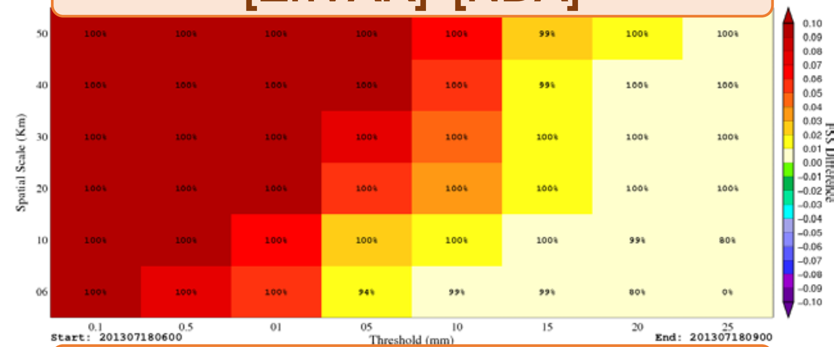


- PWV data greatly improved rainfall forecasts.

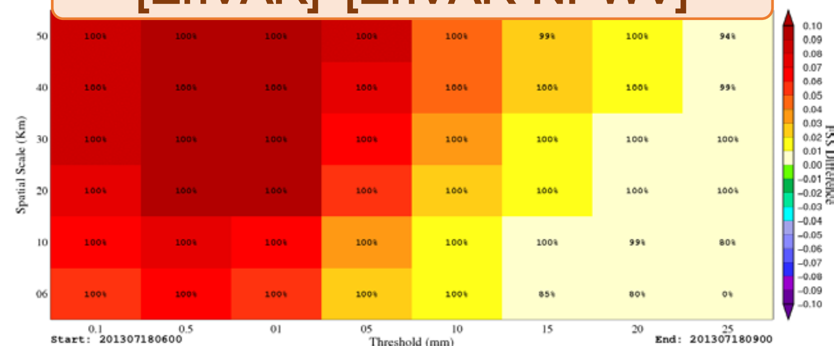
- Radiosonde data also improved weak rain forecasts.

Both PWV and radiosonde data could improve rainfall forecasts

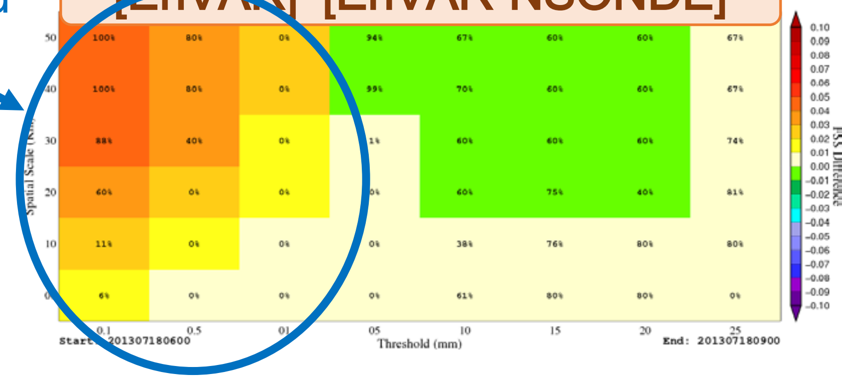
[EnVAR]–[NDA]



[EnVAR]–[EnVAR-NPWV]

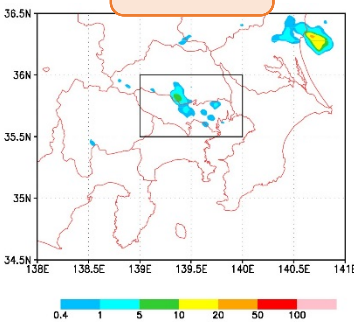


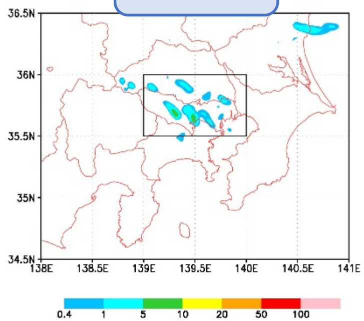
[EnVAR]–[EnVAR-NSONDE]



EnVAR v.s. LETKF

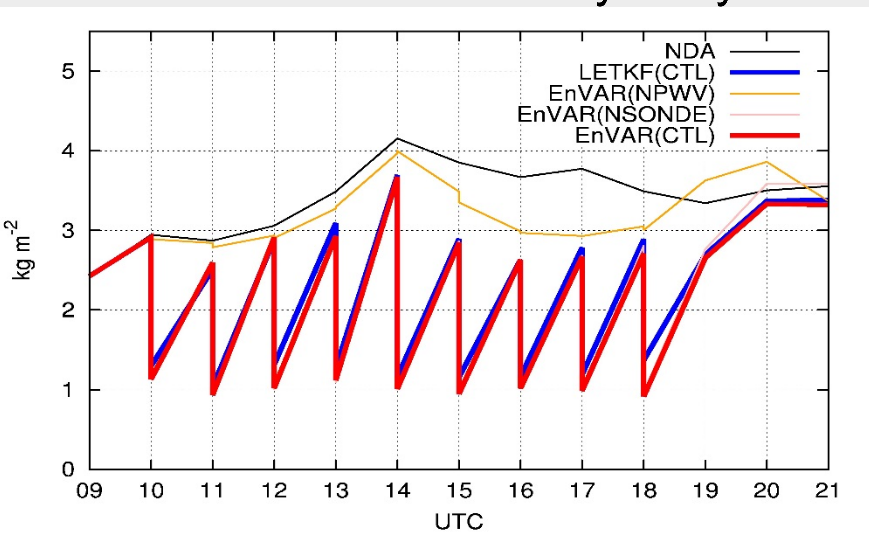
Rainfall in 18-19 JST



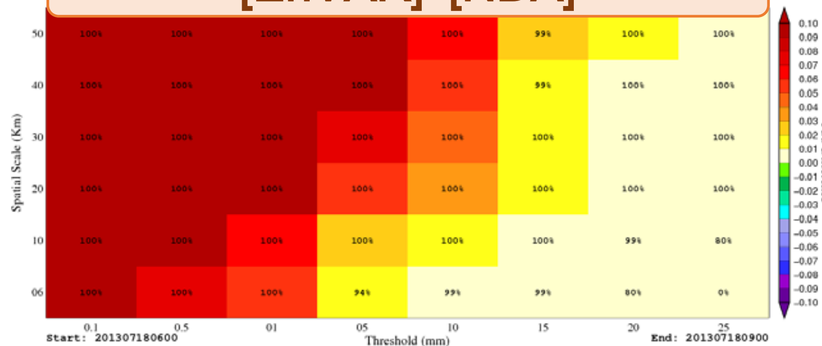


- Difference between EnVAR and LETKF is small

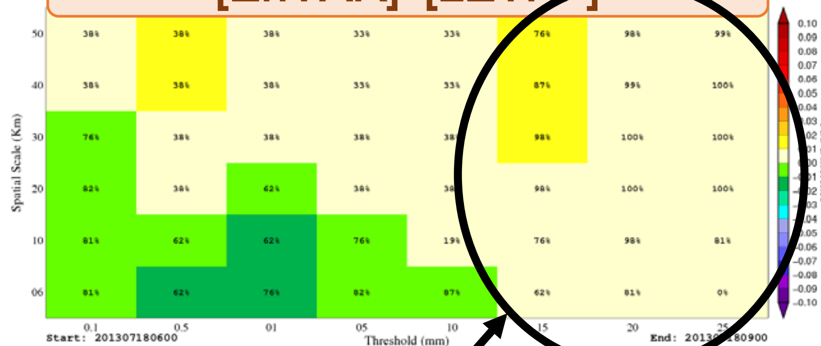
Time series of RMS of (O–A) and (O–F) of PWV in the forecast-analysis cycles



[EnVAR]–[NDA]



[EnVAR]–[LETKF]



In EnVAR, strong rainfall (> 15 mm/hr) forecasts are slightly better than that of LETKF

Correlation between Rainfall and Initial States

Correlation between J and x_n

$$\mathrm{CORR}(i,j) = \frac{\sum_m \left(J_m - \overline{J}\right)\left(x_m(i,j) - \overline{x_m(i,j)}\right)}{\sqrt{\sum_m \left(J_m - \overline{J}\right)^2}\sqrt{\sum_m \left(x_m(i,j) - \overline{x_m(i,j)}\right)^2}}$$

i, j : grid number, **m**: ensemble member

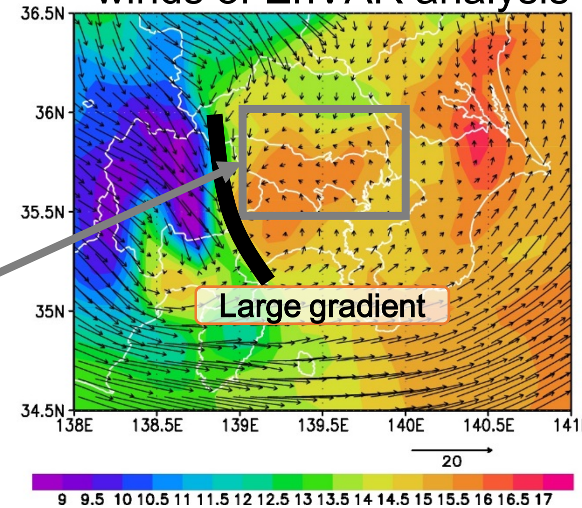
J_m : 1-h rainfall (18–19JST) averaged in this area

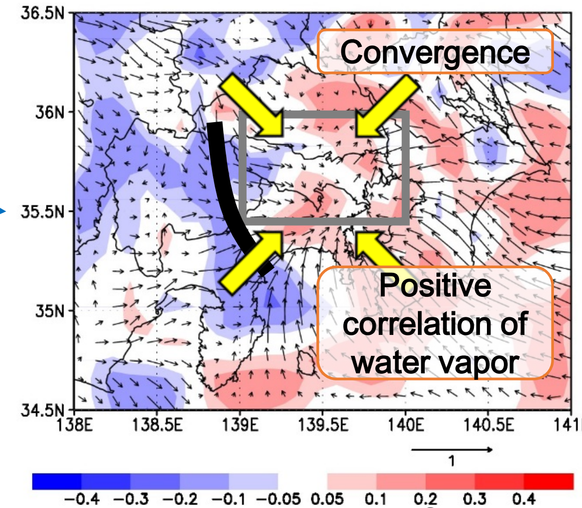
$x_m(i,j)$: variables in 0–1 km height at 18JST

If winds point to the direction of vectors in this figure, rainfall becomes stronger

Low-level convergence is correlated to rainfall intensity

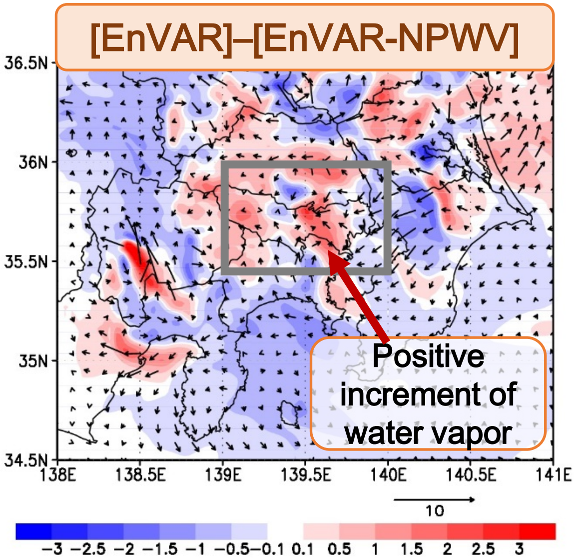
0–1 km water vapor and winds of EnVAR analysis

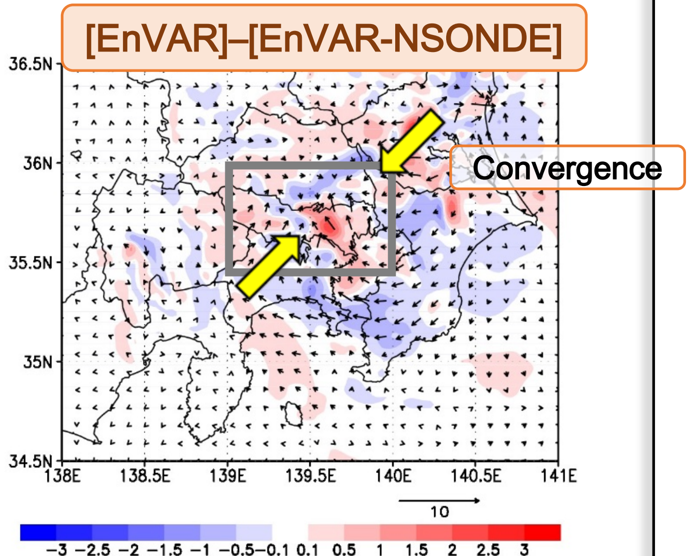


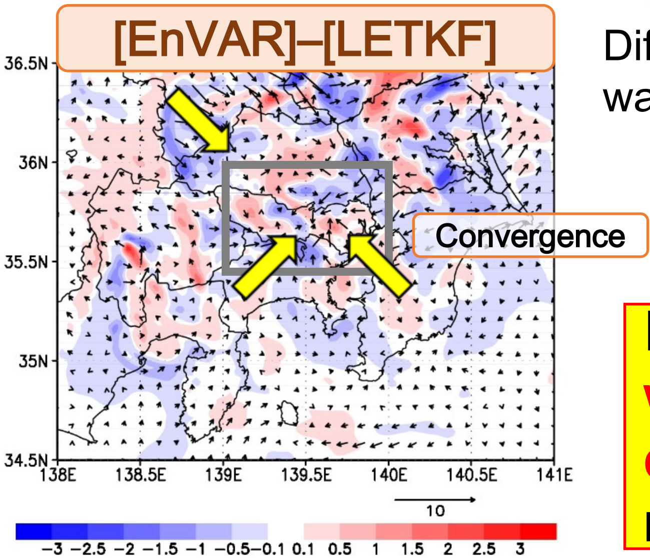


Correlation between rainfall and 0–1km water vapor and winds calculated by 51-member EnVAR

Difference of Low-level variables



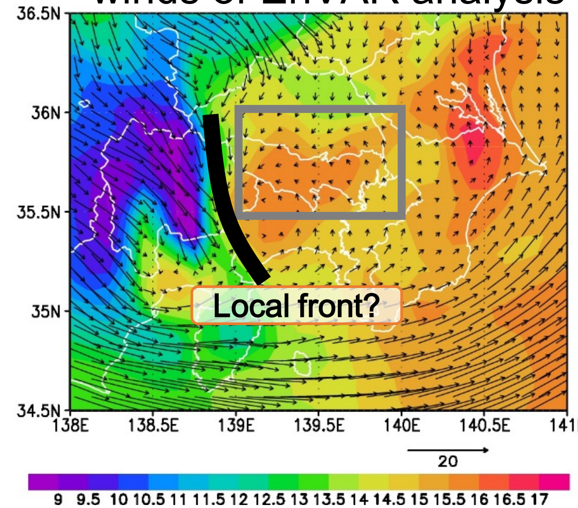


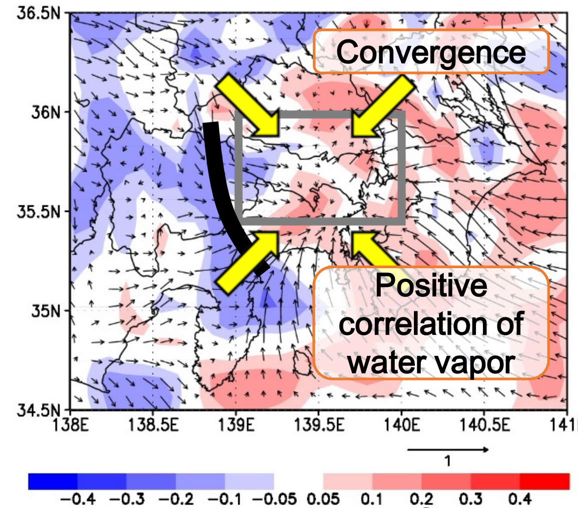


Difference of 0–1km water vapor and winds

Increment of low-level water vapor and convergence makes rainfall stronger

0–1 km water vapor and winds of EnVAR analysis





Correlation between rainfall and 0–1km water vapor and winds calculated by 51-member EnVAR

Summary

<u>We assimilated dense obs. for the local rainfall near Tokyo</u>

- Impact of dense PWV and Radiosonde obs.
  - **PWV improved rainfall forecast through correcting low-level water vapor**
  - **Sonde obs. improved rainfall forecast through correcting low-level winds**

- Comparison between LETKF and EnVAR
  - **EnVAR can make the analysis which is closer to obs. than LETKF.**
  - **Improvement of rainfall forecast by using EnVAR is small**

- Correlation to rainfall based on ensemble forecasts
  - **<u>Low-level water vapor and convergence made local rainfall stronger</u>**

Are these impacts general? Verification in longer period requires.

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