

Model Parameter Estimation Using Ensemble Data Assimilation: – A Case with the NICAM and GSMap –

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²The University of Tokyo, Japan

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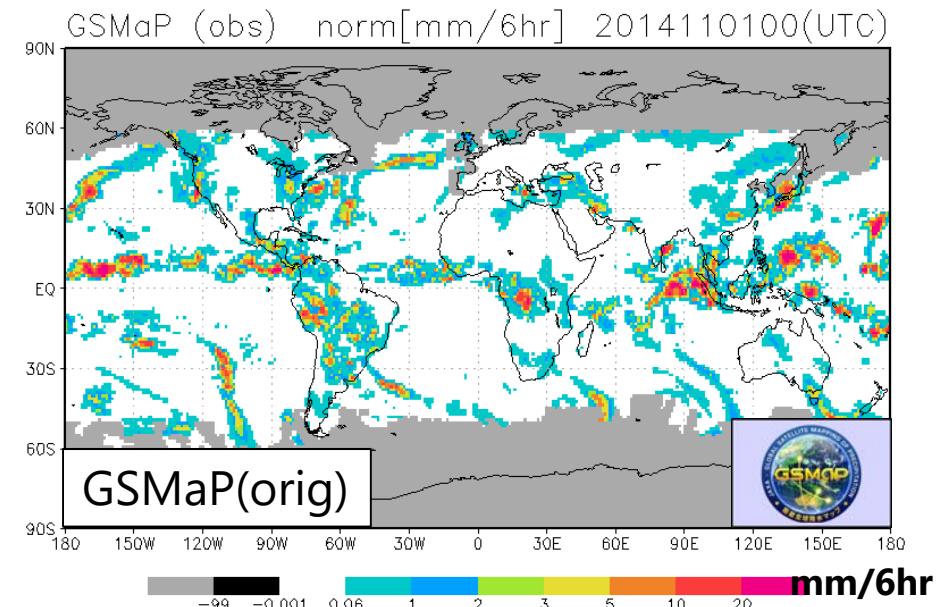
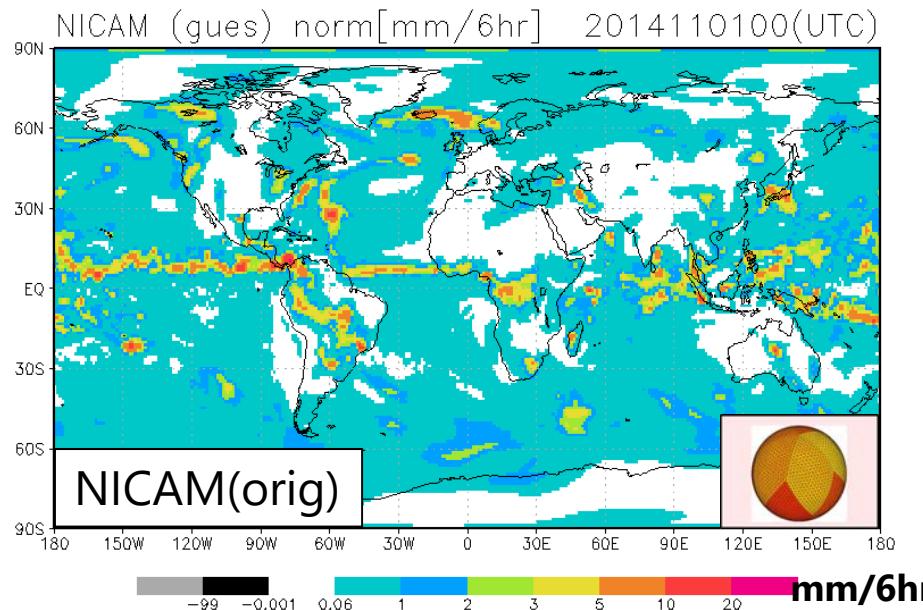
Goals

- To improve NWP using satellite-derived precipitation following *Lien et al. (2013, 2016a,b)*
- To produce a new precipitation product through data assimilation
 - **STEP1: State Estimation**
 - STEP2: Parameter Estimation

Experimental Setting

- **Numerical Model**
 - NICAM (Satoh and Tomita 2004, Satoh et al. 2008, 2014)
 - GL6 (approx. 110 km resolution)
- **Observations**
 - CTRL: PREPBUFR: only upper sounding data (ADPUPA)
 - TEST: + GSMAp Gauge (Ushio et al. 2009)
 - with Gaussian transformation
- **Data assimilation**
 - LETKF (Hunt et al. 2007)
 - NICAM-LETKF (Terasaki et al. 2015) with 36 members
 - 3D-LETKF
 - Localization: 400 km for horizontal & $0.4 \log(p)$ for vertical
 - Relaxation to prior perturbation (Zhang et al. 2004; $\alpha = 0.7$)

Gaussian Transformation



Gaussian Transformation

$$F^G(\tilde{y}) = F(y) \Leftrightarrow \tilde{y} = F^{G^{-1}}[F(y)] \Leftrightarrow y = F^{-1}[F^G(\tilde{y})]$$

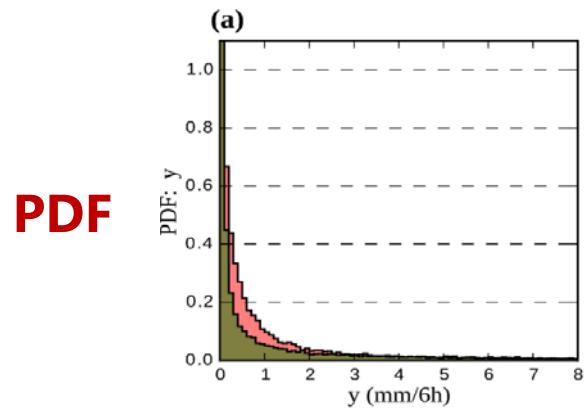
Forward transform (mm/6hr \rightarrow sigma) Inverse transform (sigma \rightarrow mm/6hr)

y : original variable (mm/6hr)

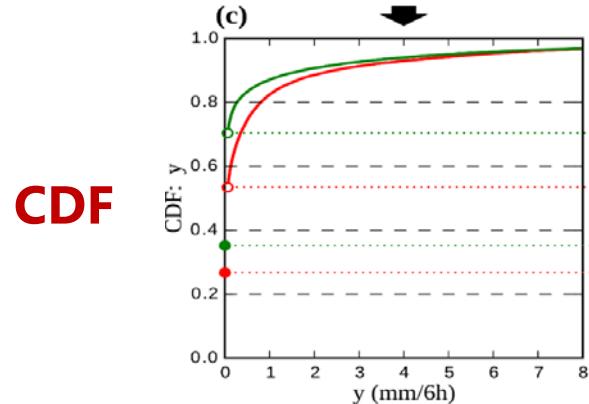
$F()$: CDF of original variable

\tilde{y} : Transformed variable (sigma)

$F^G()$: CDF of Gaussian distribution



—: Model
—: Obs.



Original variable

Step 0: Obtain PDF & CDF

Lien et al. (2013, 2016)

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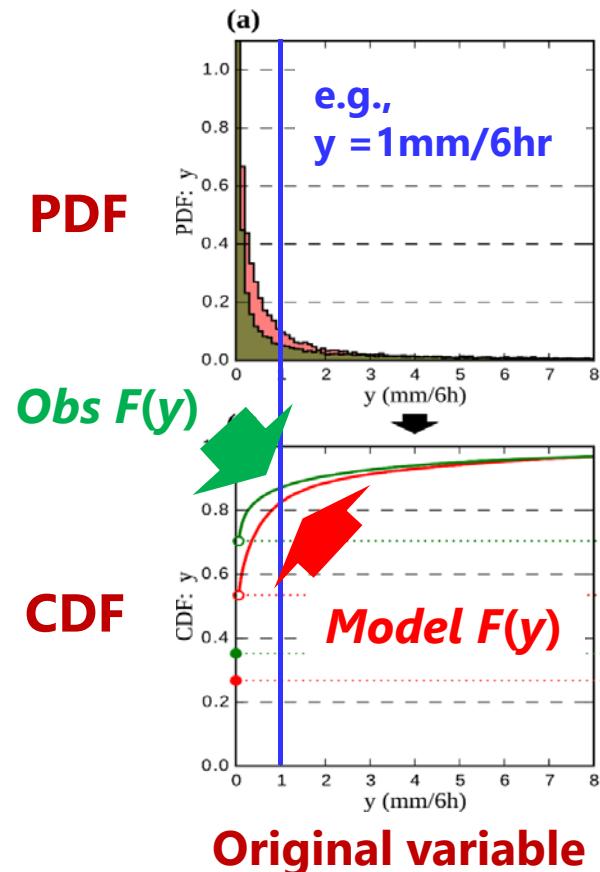
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—: Model
—: Obs.

Step 0: Obtain PDF & CDF

Step 1: Compute $F(y)$

Lien et al. (2013, 2016)

Gaussian Transformation

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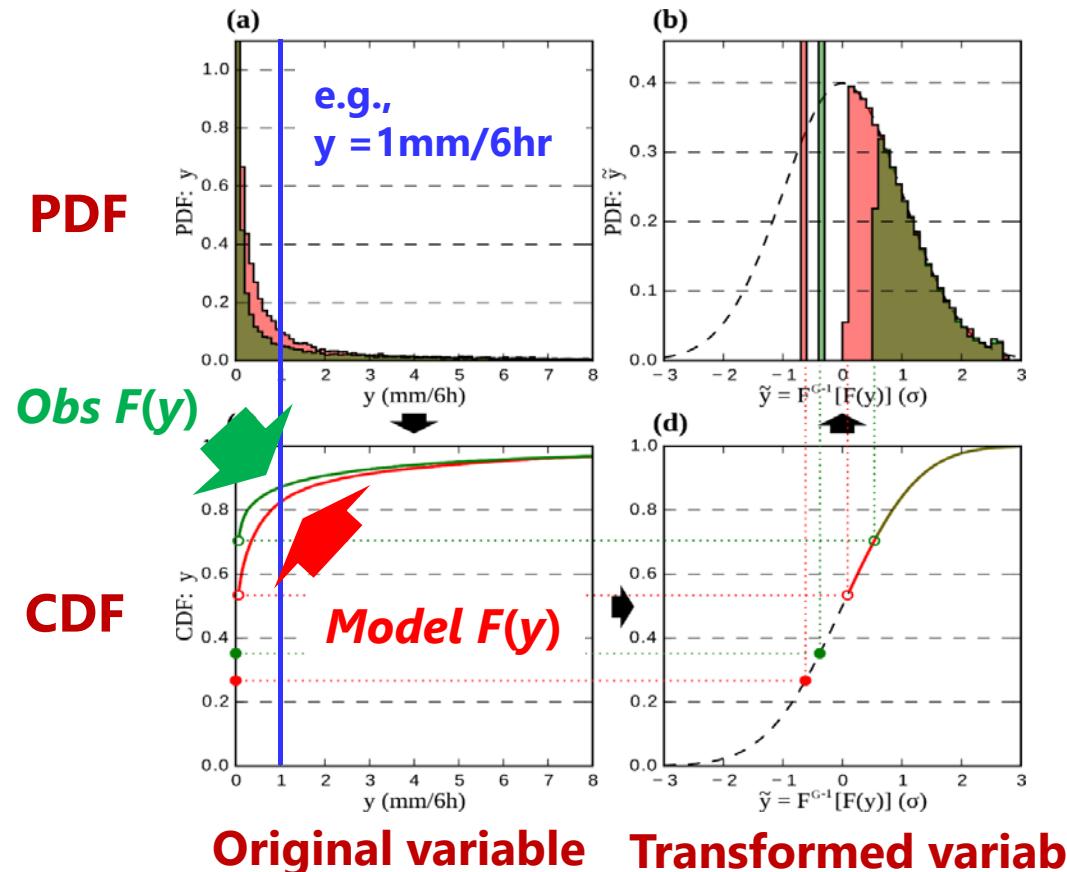
Inverse transform (sigma \rightarrow mm/6hr)

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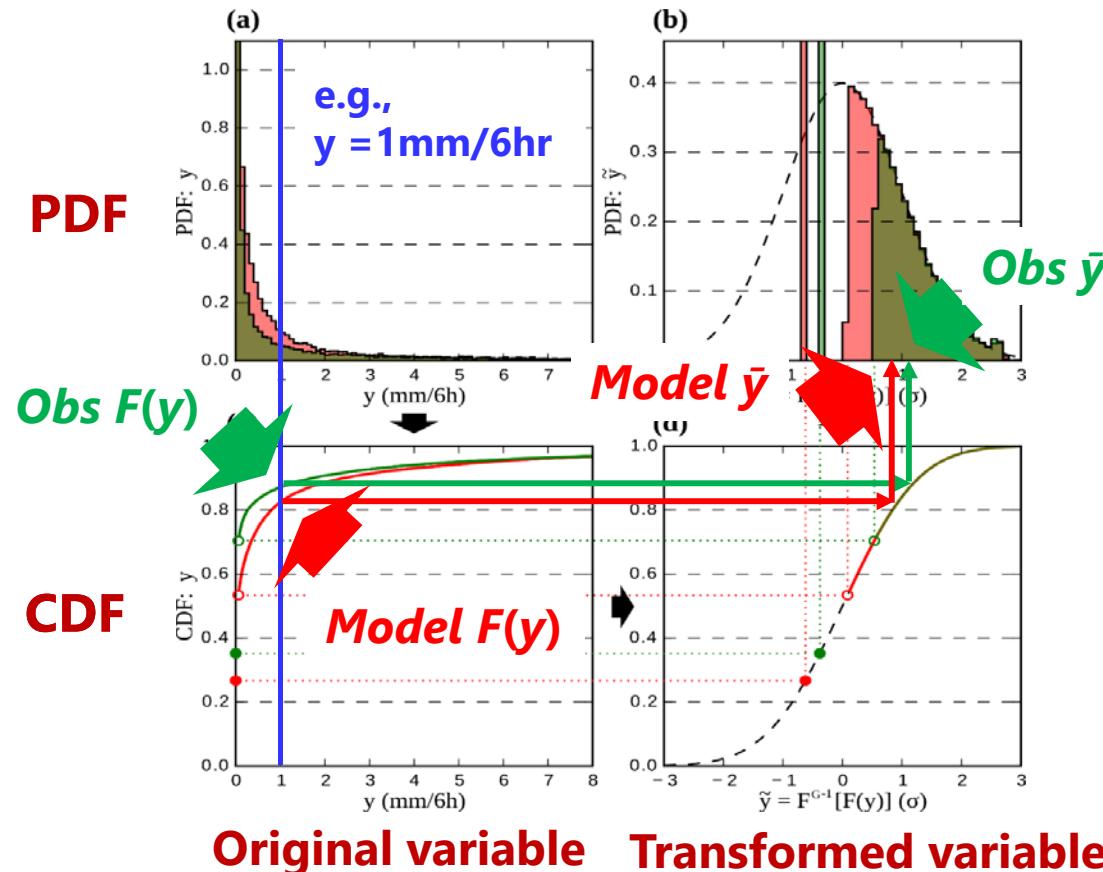
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—: Model
—: Obs.

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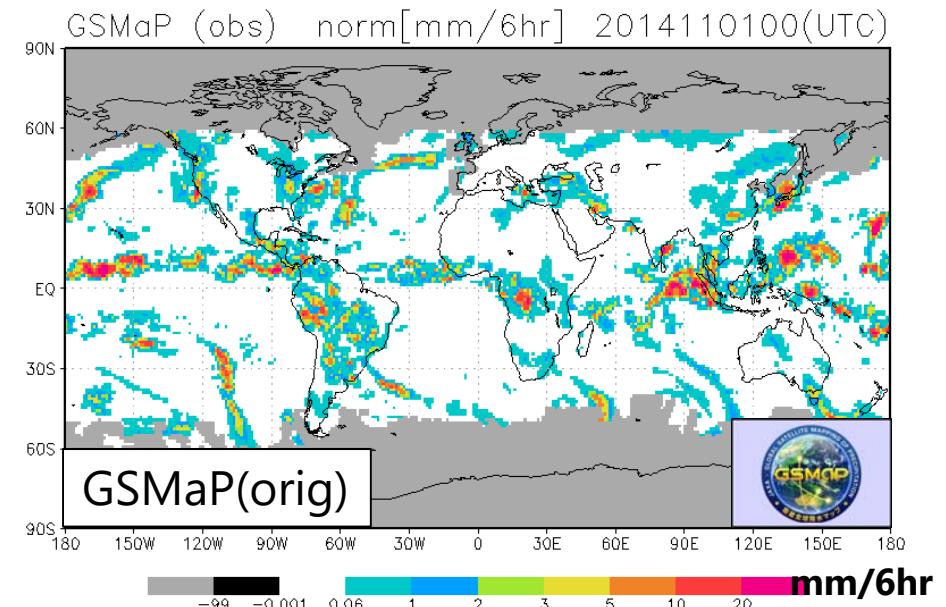
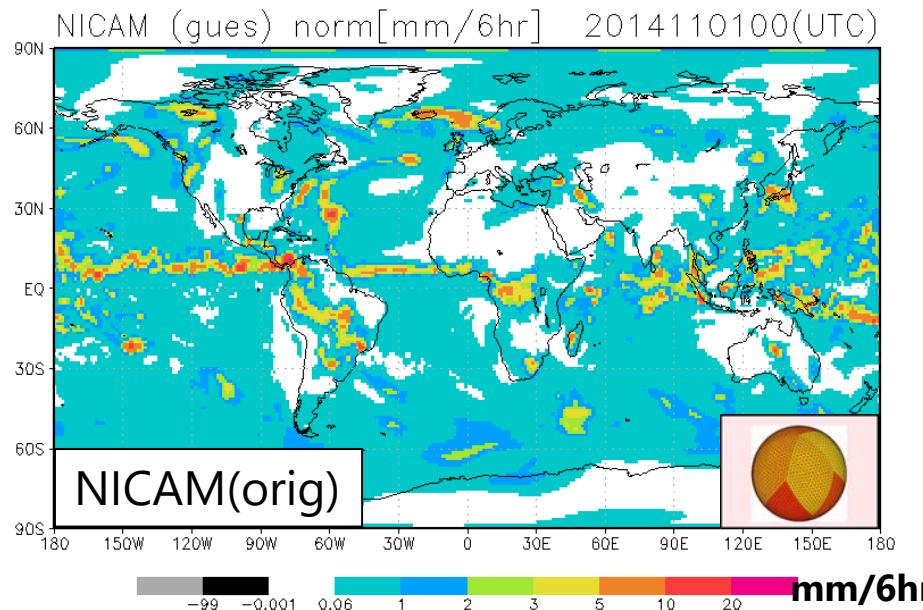
Step 1: Compute $F(y)$

Step 2: Compute

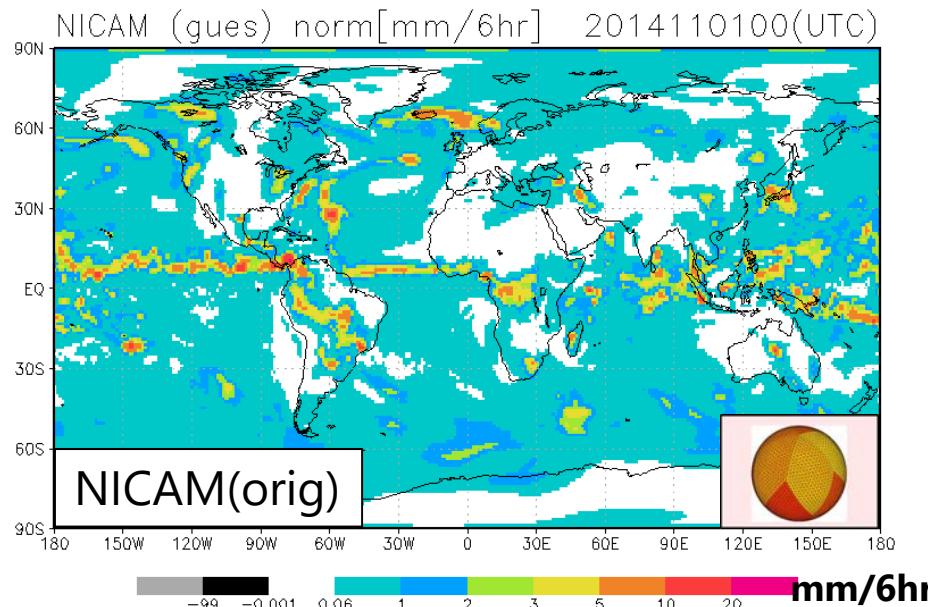
$$\tilde{y} = F^{G^{-1}}[F(y)]$$

Lien et al. (2013, 2016)

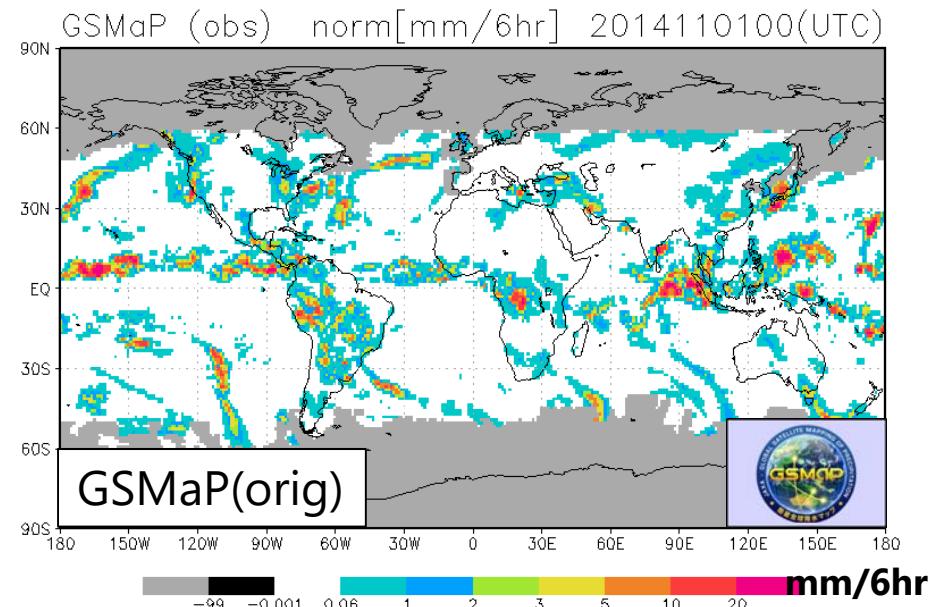
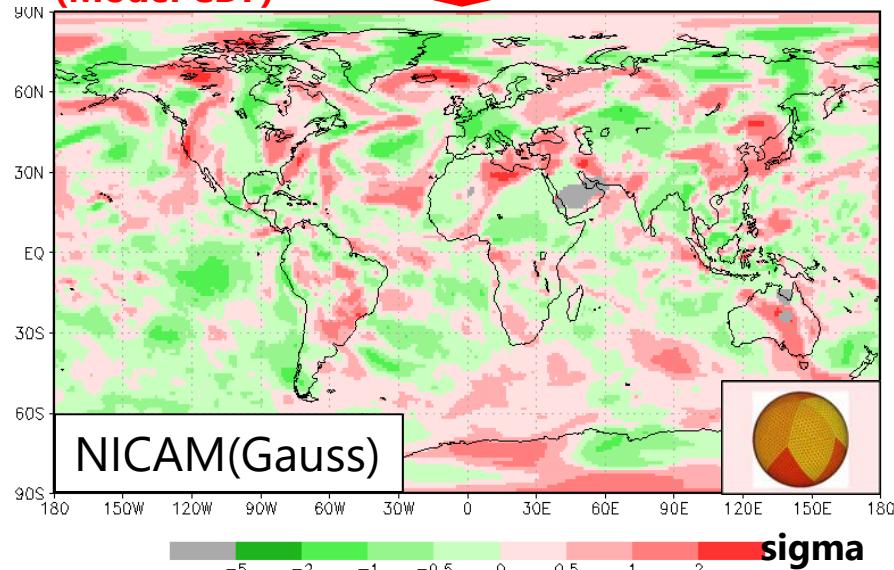
Gaussian Transformation



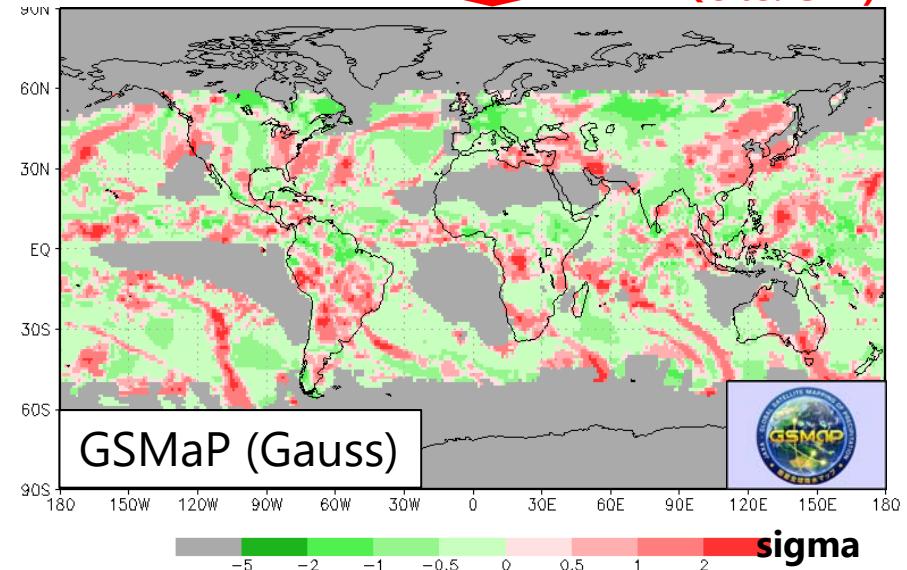
Gaussian Transformation



Transformation
(Model CDF)

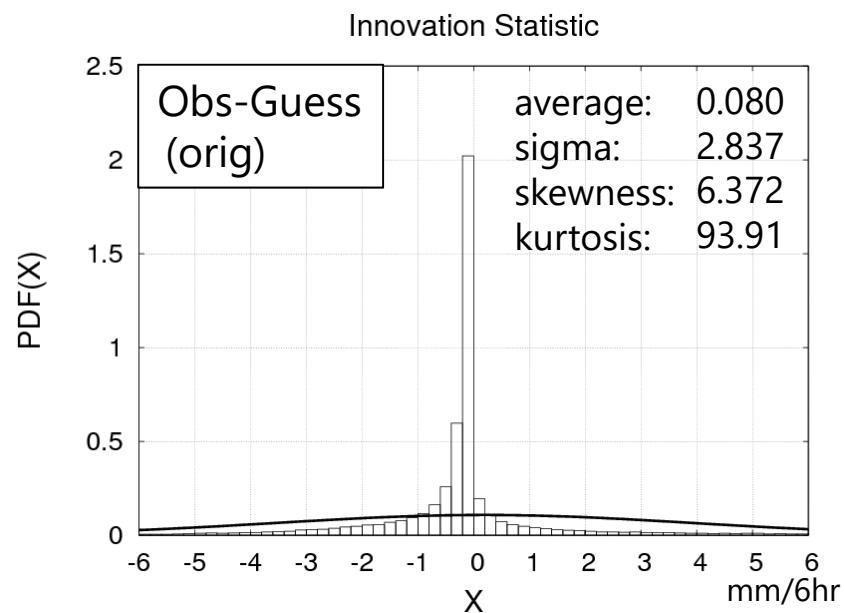


Transformation
(Obs. CDF)

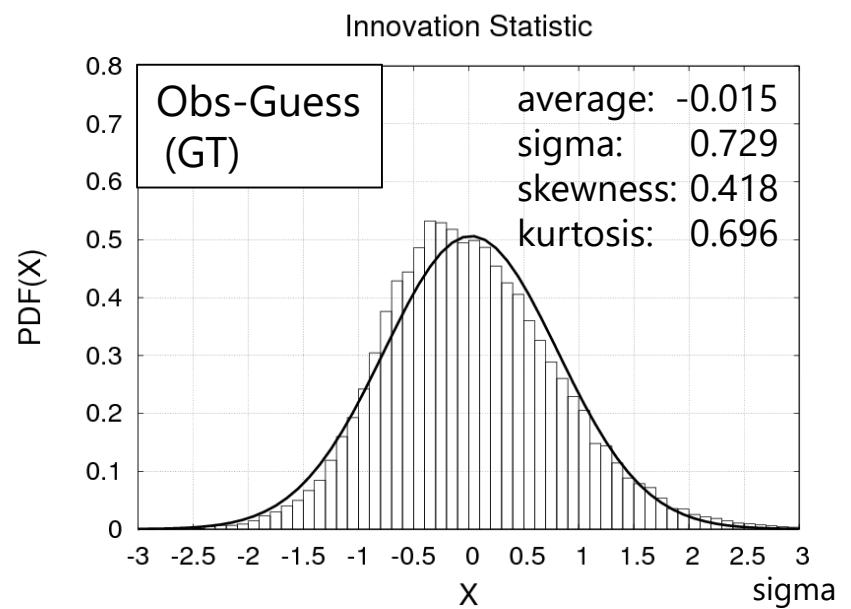


w/wo Gaussian Transformation

wo Gaussian-Transformation



w Gaussian-Transformation



More Gaussian

Sampling period : 2014110100 - 2014110118

Inverse Transformation

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Forward transform (mm/6hr → sigma)

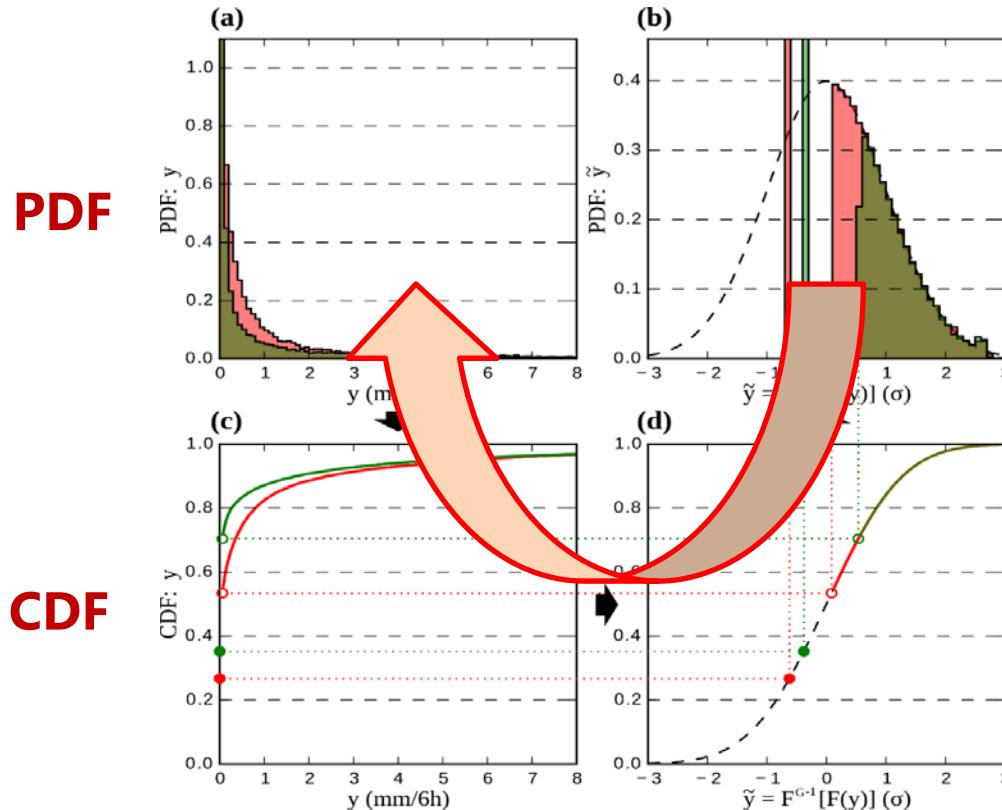
Inverse transform (sigma → mm/6hr)

y : original variable (mm/6hr)

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PDF

CDF

Original variable

Transformed variable

—: Model
—: Obs.

Step 0: Obtain PDF & CDF

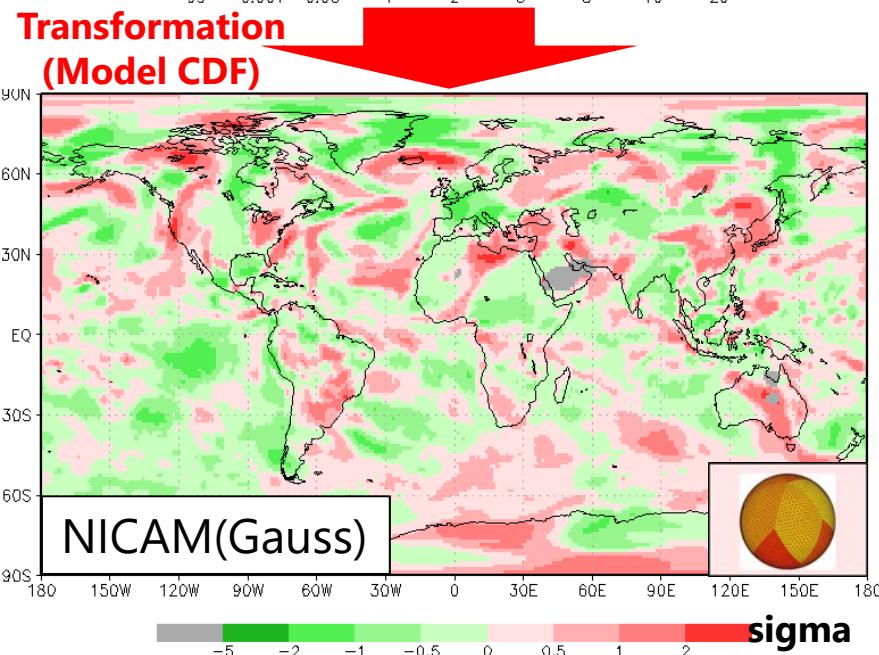
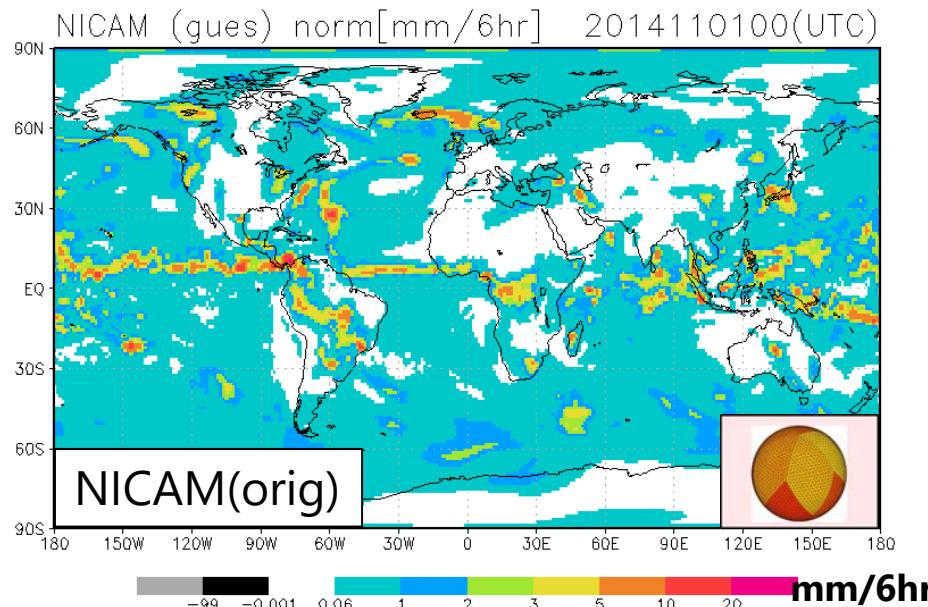
Step 1: Compute $F(y)$

Step 2: Compute

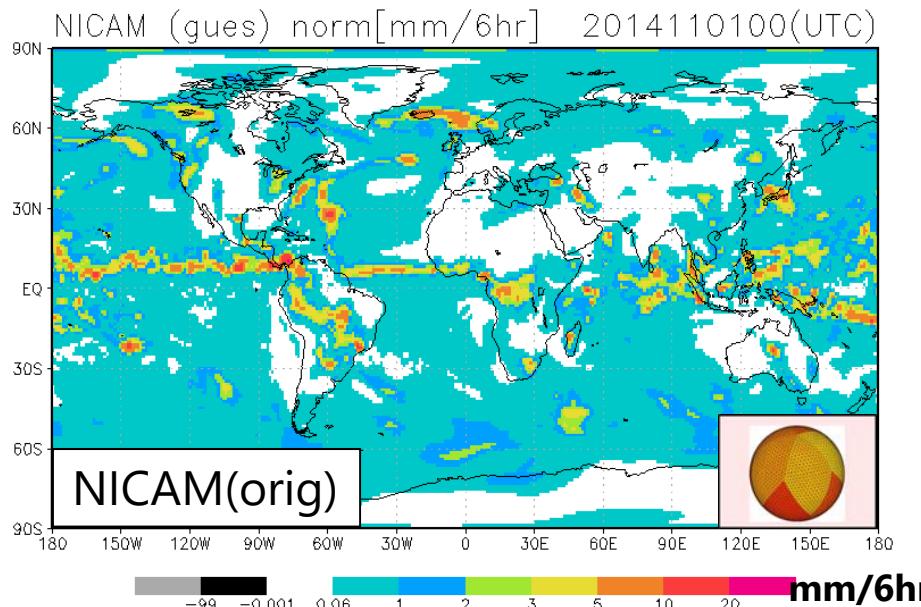
$$\tilde{y} = F^{G^{-1}}[F(y)]$$

Lien et al. (2013, 2016)

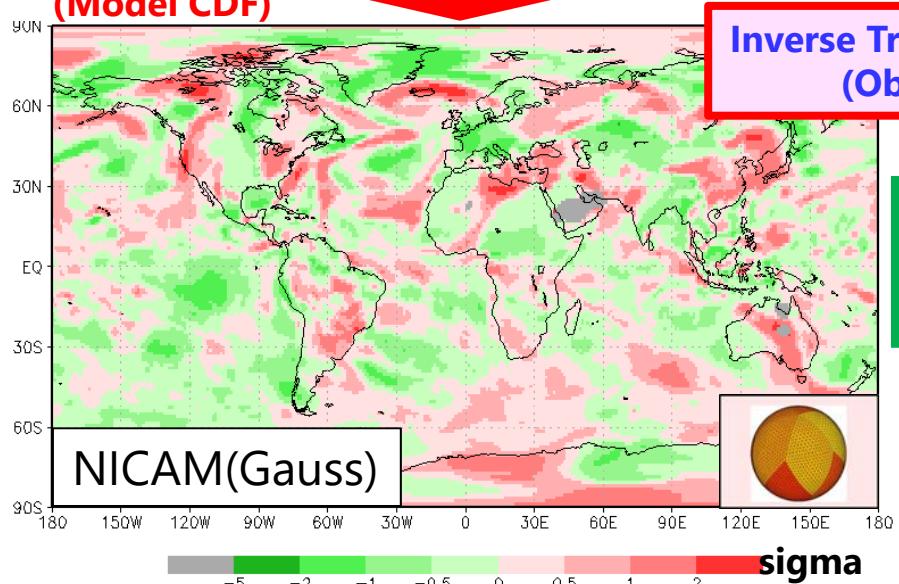
Forward/Inverse Transformations



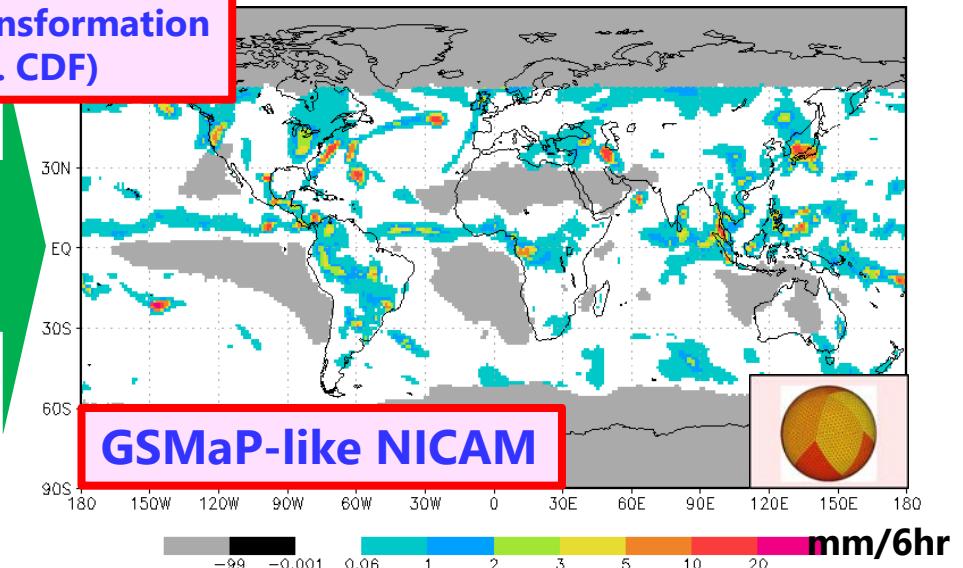
Forward/Inverse Transformations



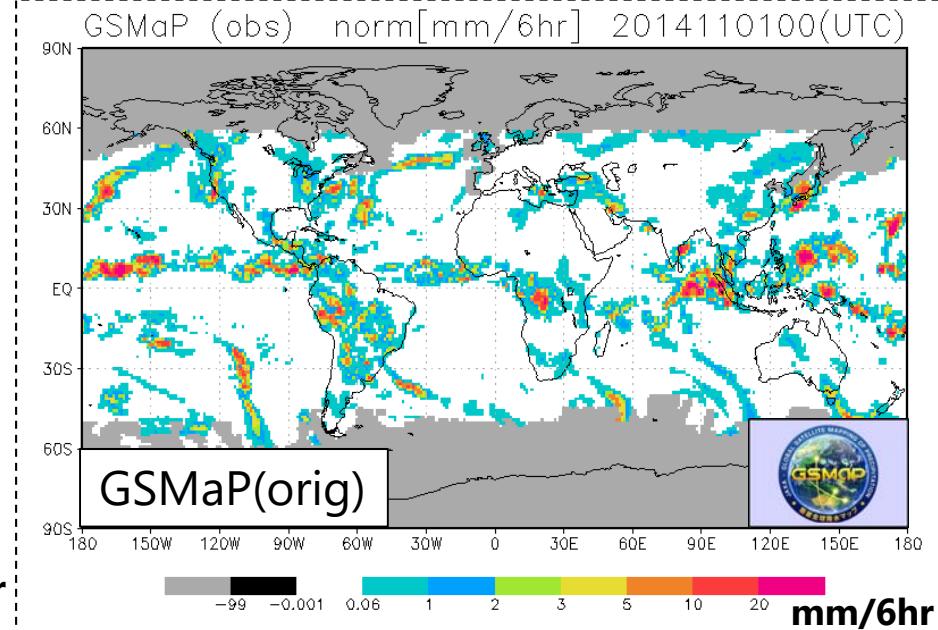
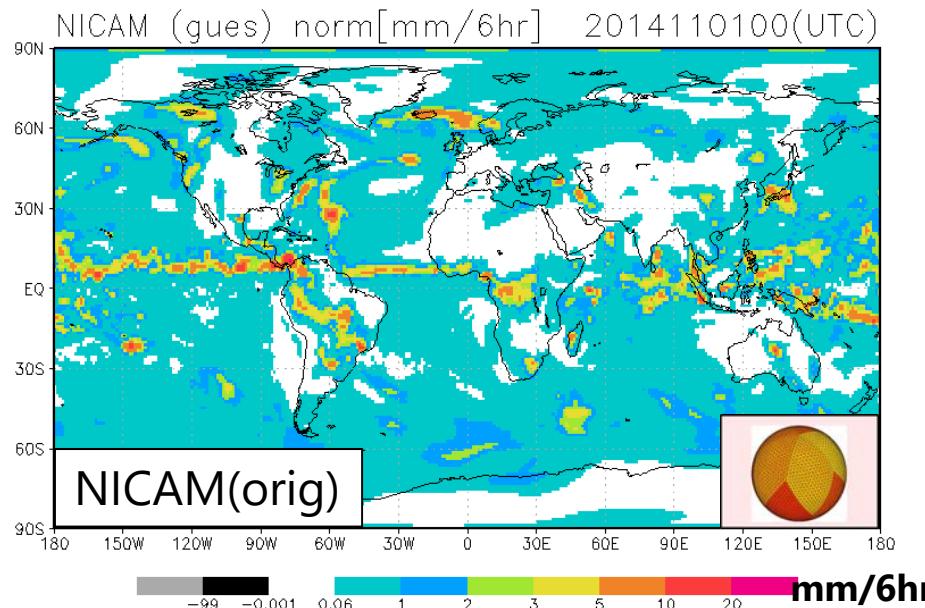
Transformation
(Model CDF)



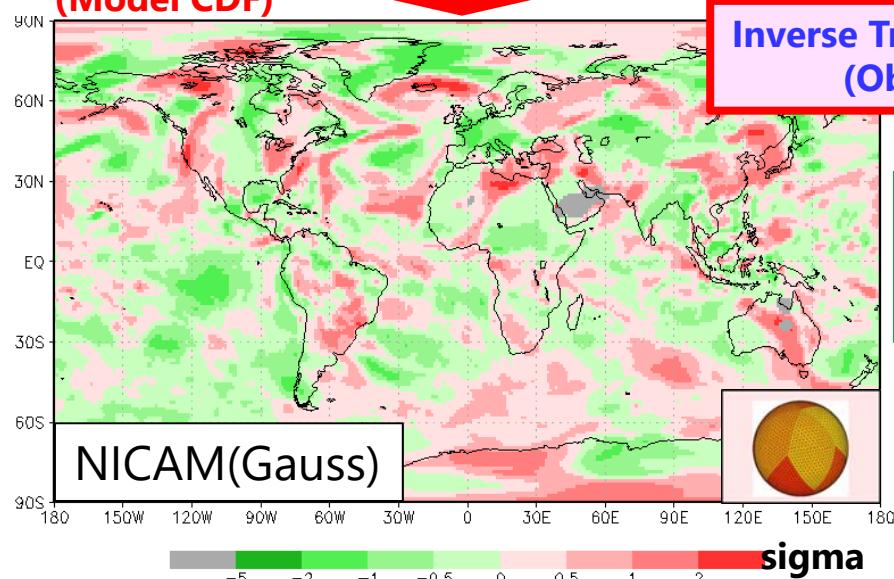
Inverse Transformation
(Obs. CDF)



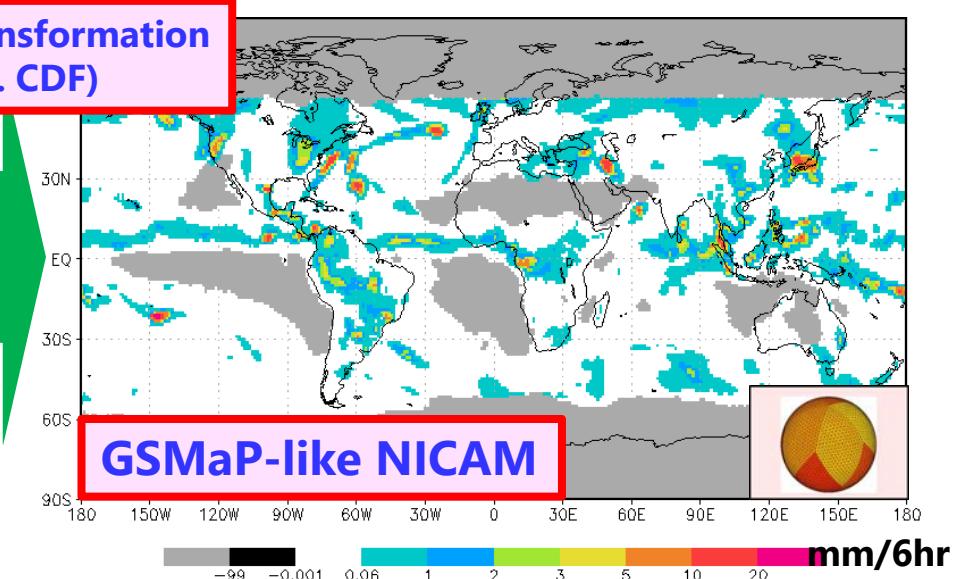
Forward/Inverse Transformations



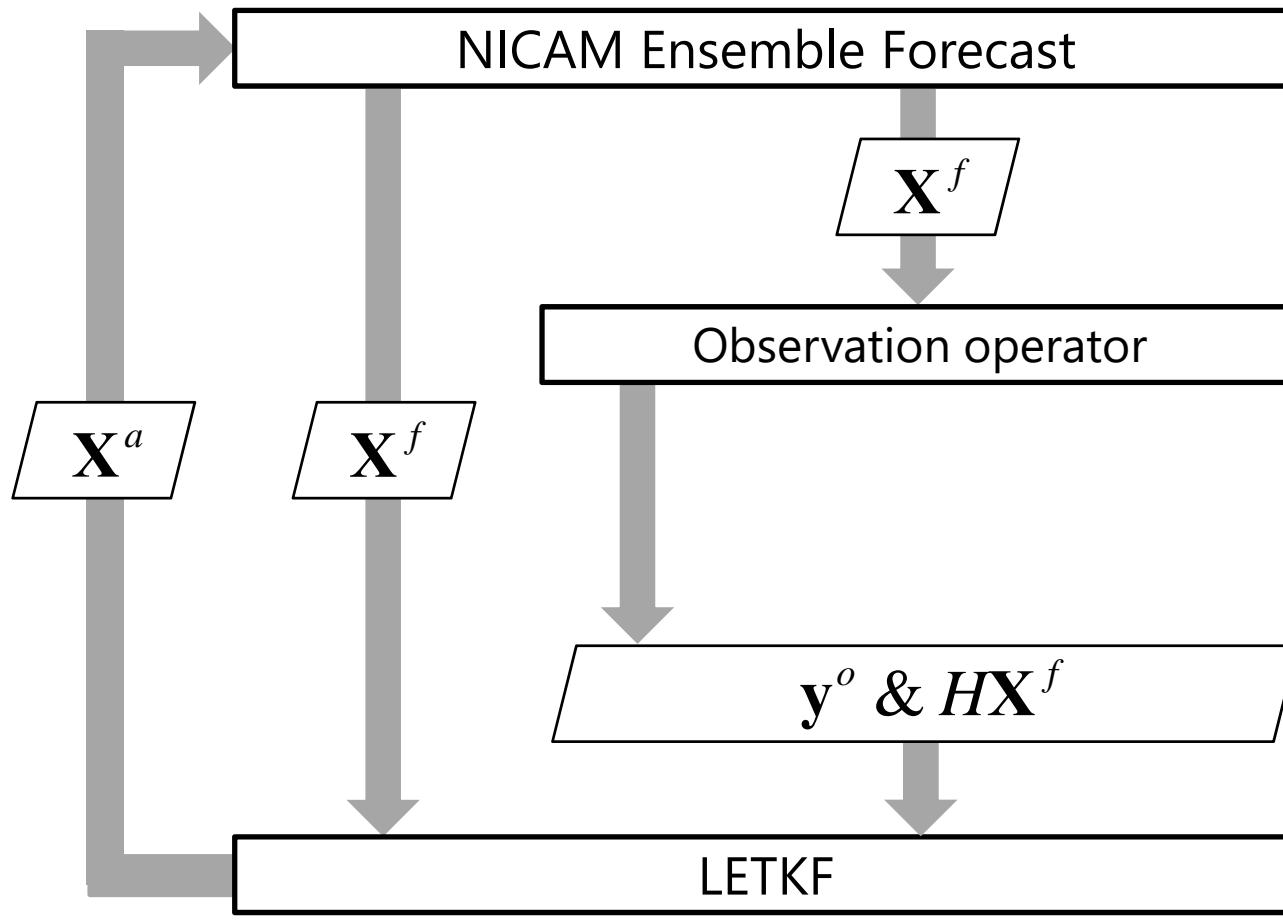
Transformation
(Model CDF)



Inverse Transformation
(Obs. CDF)



Assimilation of GSMP by NICAM-LETKF

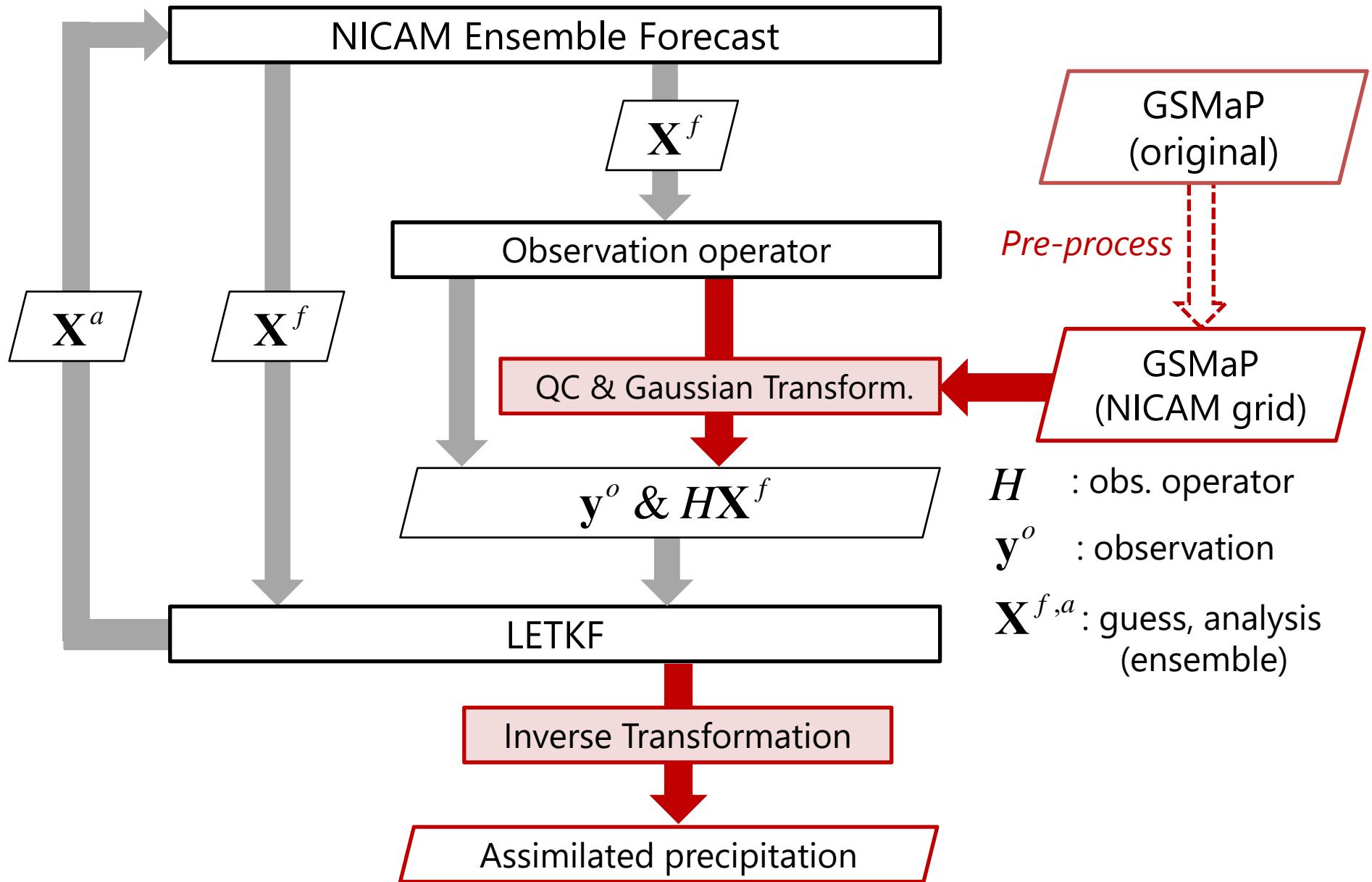


H : obs. operator

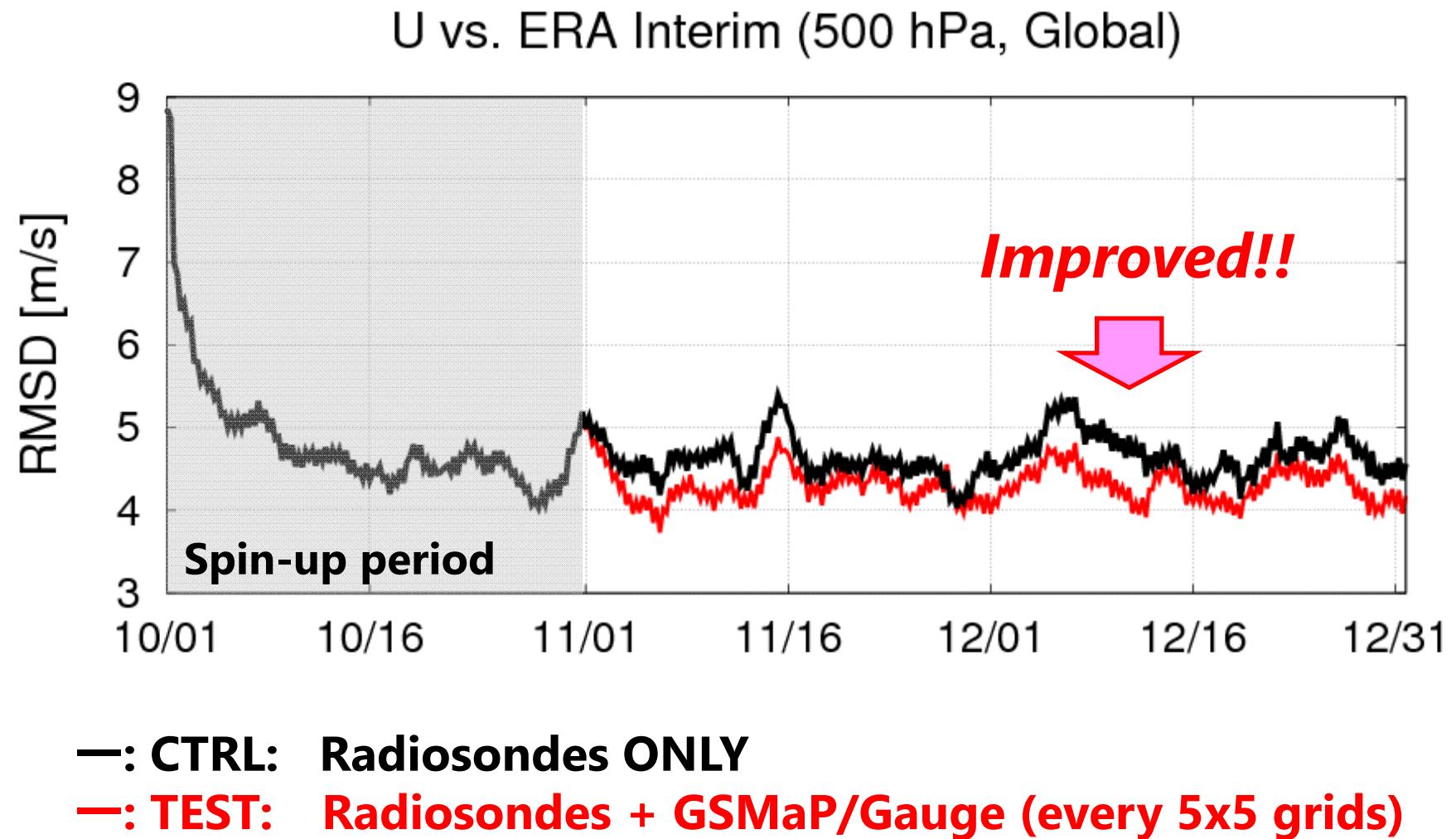
y^o : observation

$X^{f,a}$: guess, analysis
(ensemble)

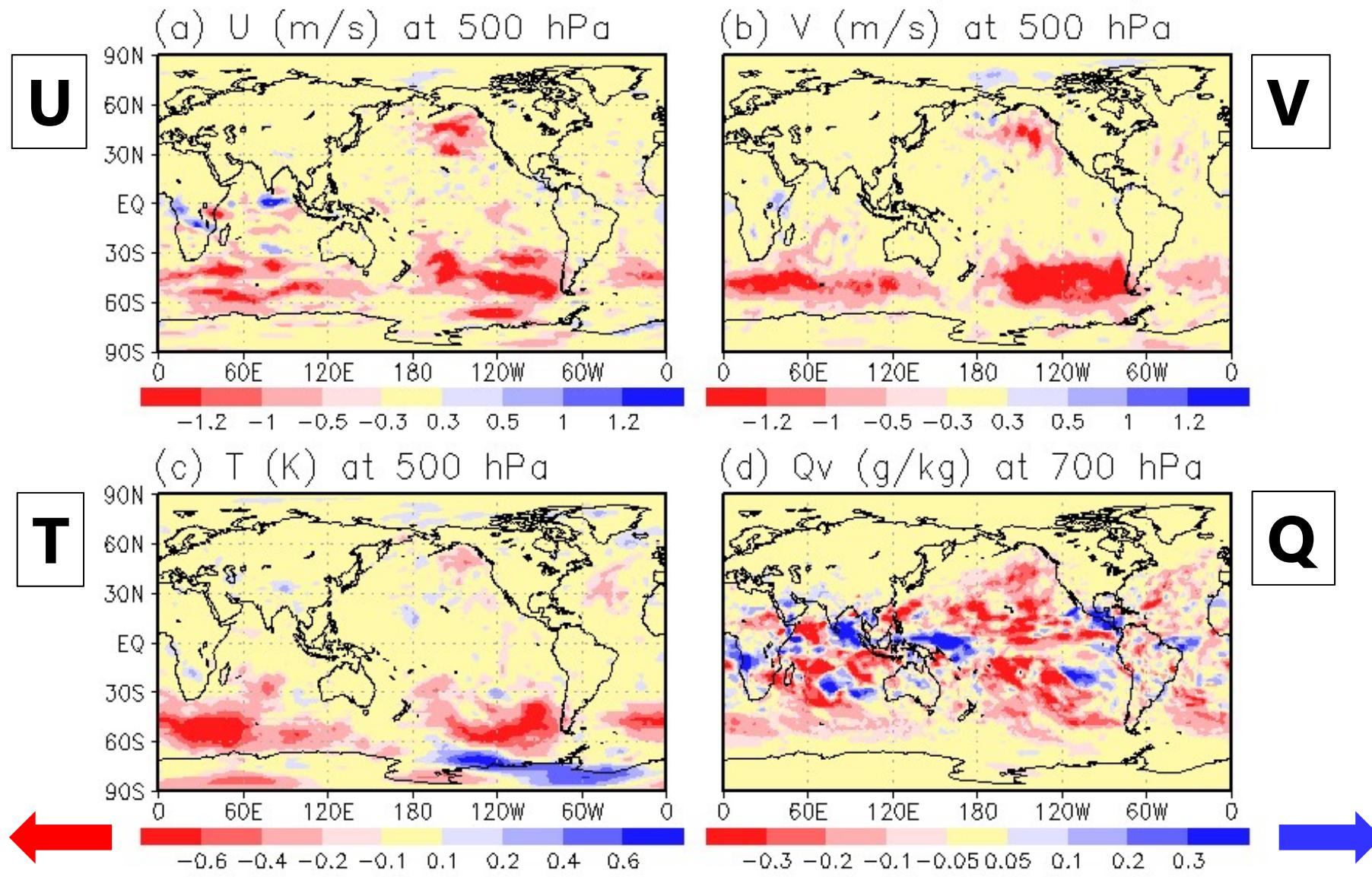
Assimilation of GSMAp by NICAM-LETKF



RMSDs relative to ERA Interim (in 2014)



MADs relative to ERA Interim (in 2014)

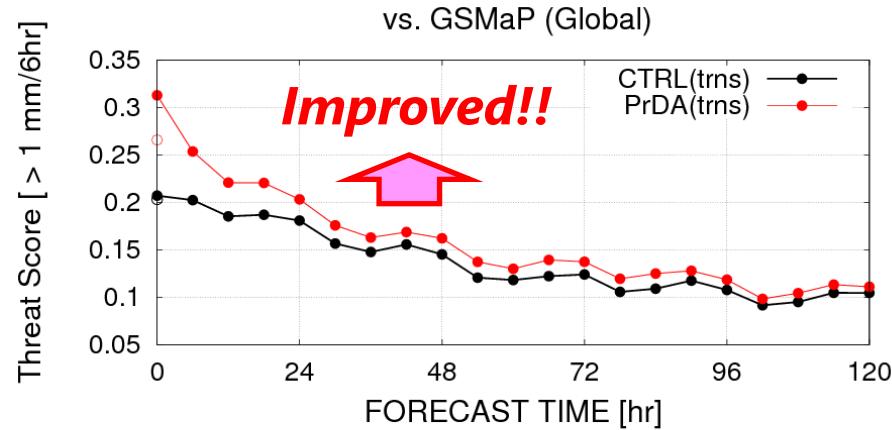


Improved by GSMap DA

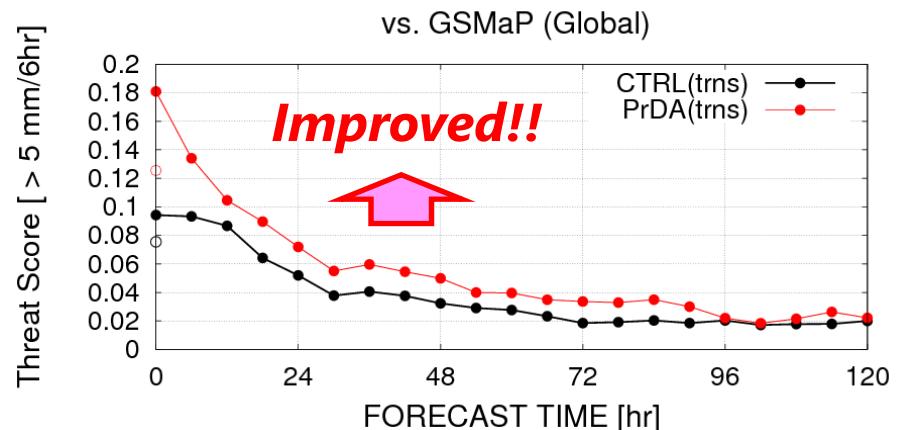
Degraded by GSMap DA

RMSDs: 120 hr Forecasts vs. GSMap/Gauge

Threat Score ($\geq 1 \text{ mm/6hr}$)



Threat Score ($\geq 5 \text{ mm/6hr}$)



—: Radiosondes ONLY
—: Radiosondes + GSMap/Gauge

Precipitation forecasts are improved !!!

Average over 8 ensemble forecasts from different initial dates

Outline

- STEP1: State Estimation
- **STEP2: Parameter Estimation**

Summary

- Assimilating GSMP precipitation with NICAM-LETKF
 - State estimation
 - Gaussian Transformation works well
 - Analyses and forecasts are improved
 - Parameter estimation
 - Precipitation forecasts are improved
 - Dry bias in the lower troposphere is improved

Kotsuki S., Miyoshi T., Terasaki K., Lien G.Y. and Kalnay E.:

Assimilating the Global Satellite Mapping of Precipitation Data with the Nonhydrostatic Icosahedral Atmospheric Model NICAM. JGR-Atmosphere (in revision)