Ensemble Data Assimilation of GSMaP Precipitation into the Nonhydrostatic Global Atmospheric Model NICAM

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[2]University of Maryland, College Park, Maryland, USA

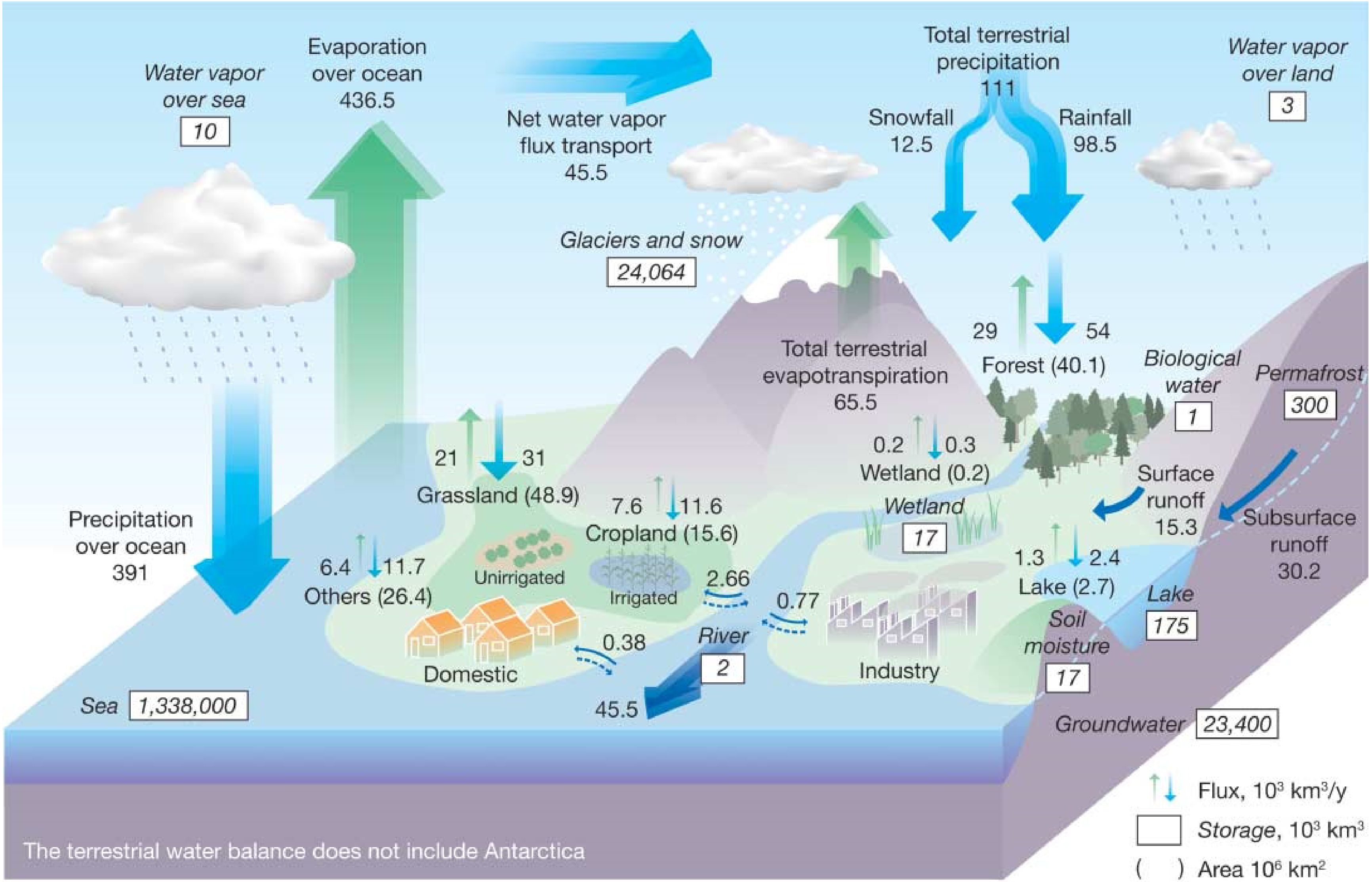
AICS

Data Assimilation Team

K computer

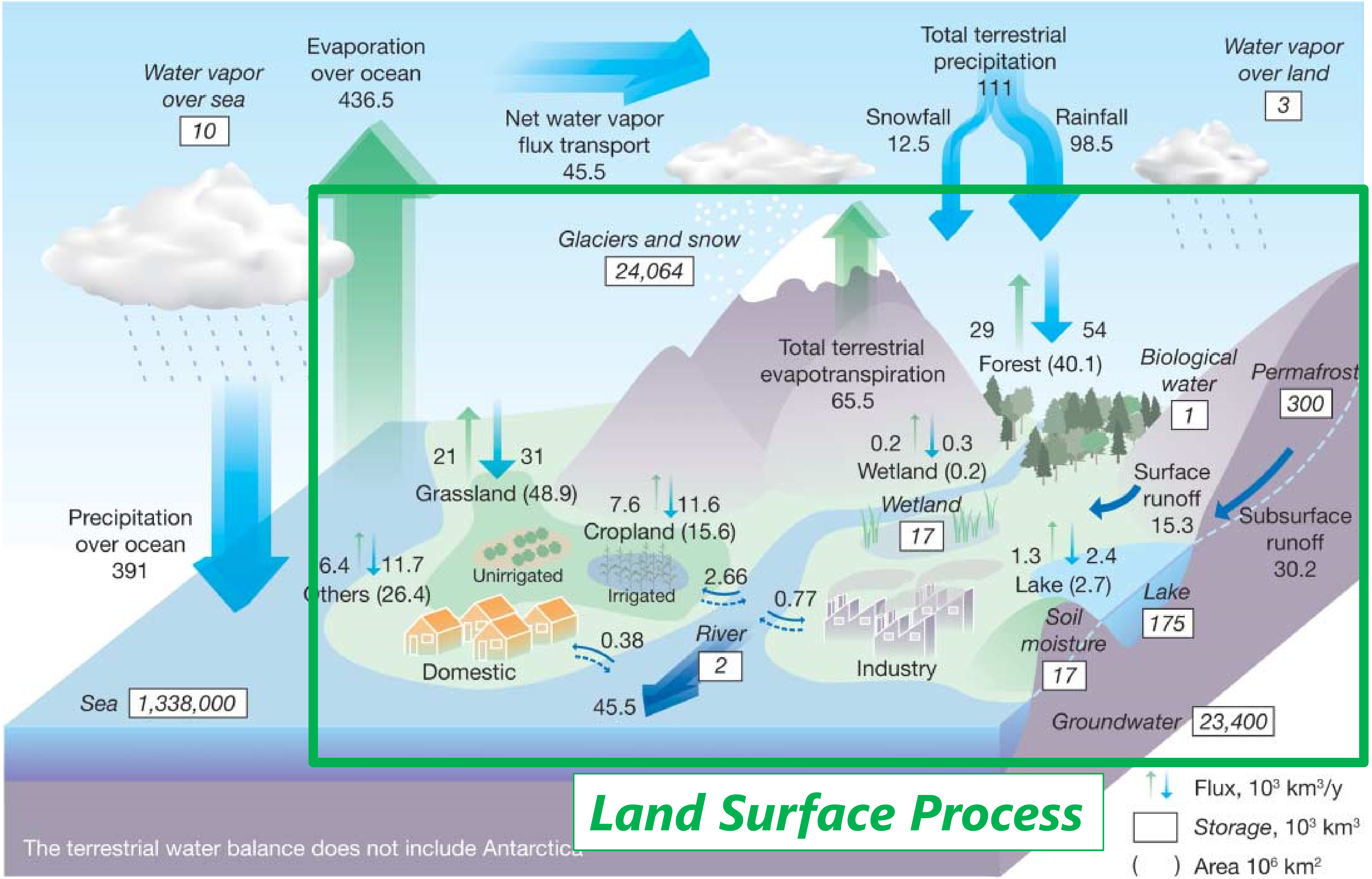
Data Assimilation Seminar, Dec 25, 2015@ RIKEN-AICS

Motivation



Oki and Kanae (2006)

Motivation



Oki and Kanae (2006)

Outline

- Assimilating GSMaP with NICAM-LETKF
  - Introduction
  - Gaussian Transformation
  - DA-cycle experiments
  - Forecast experiments
- Estimation of global crop calendar with NDVI
  - Current status and challenges

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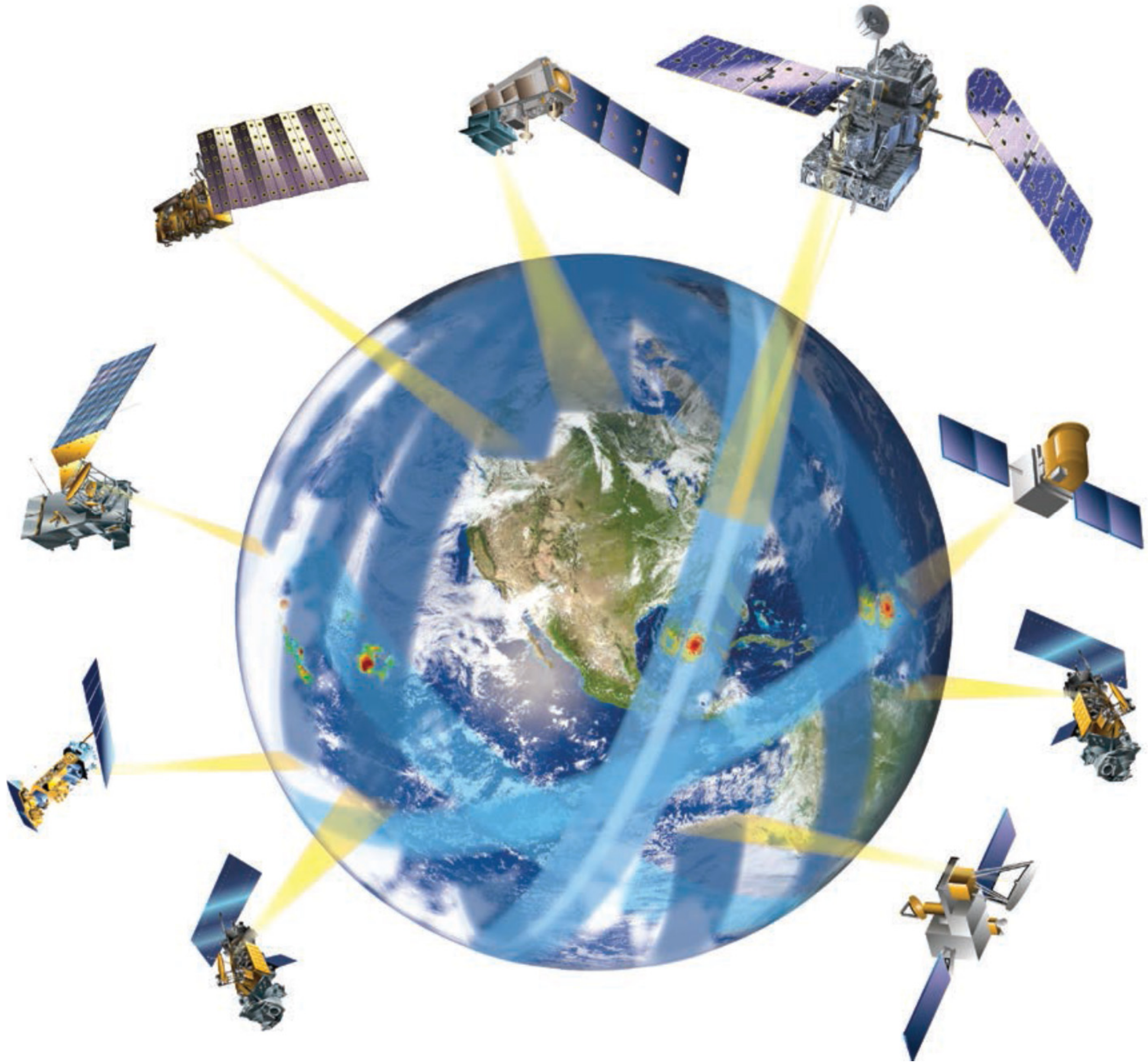
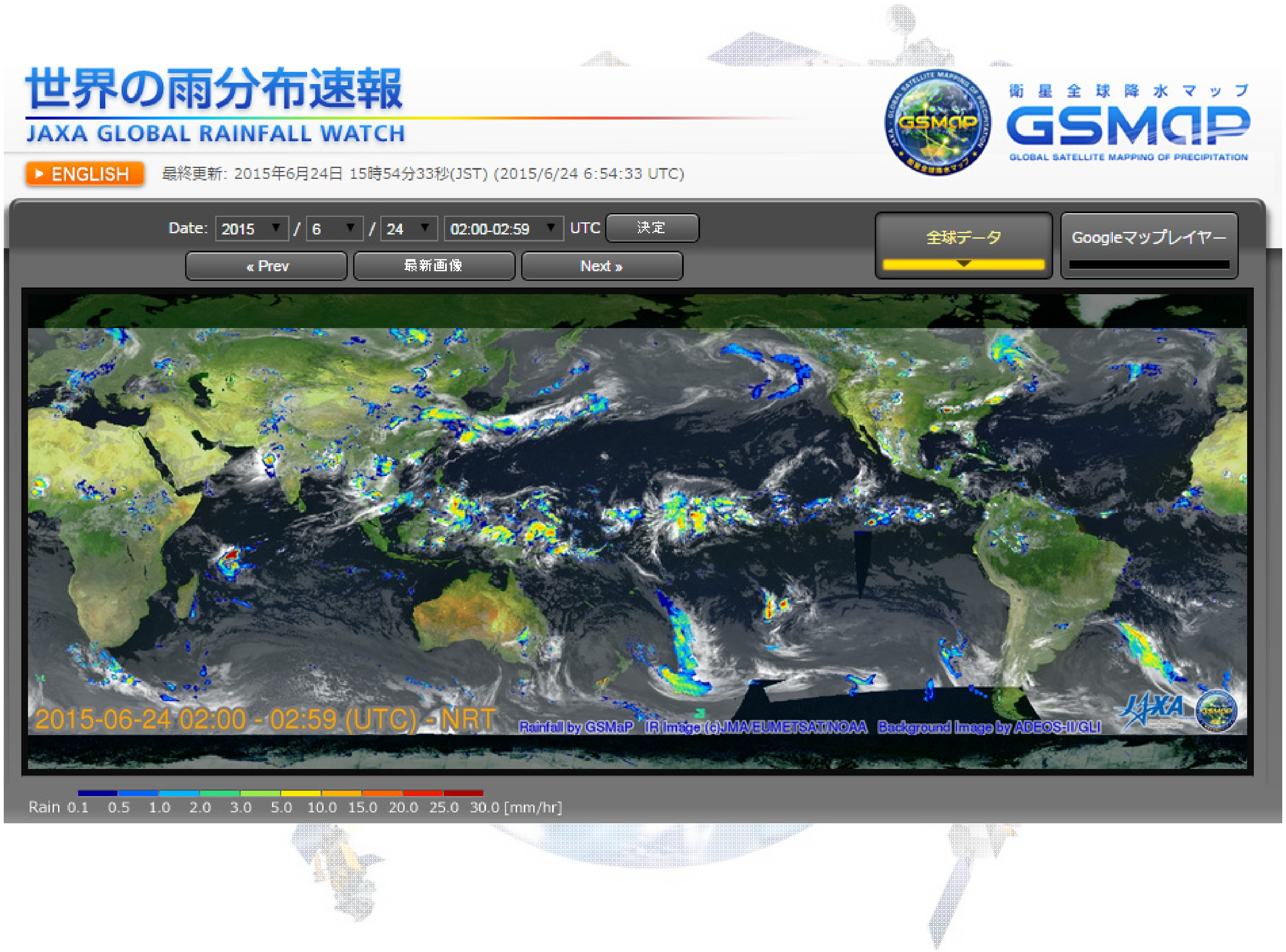
GPM: Global Precipitation Measurement



Hou et al. 2014

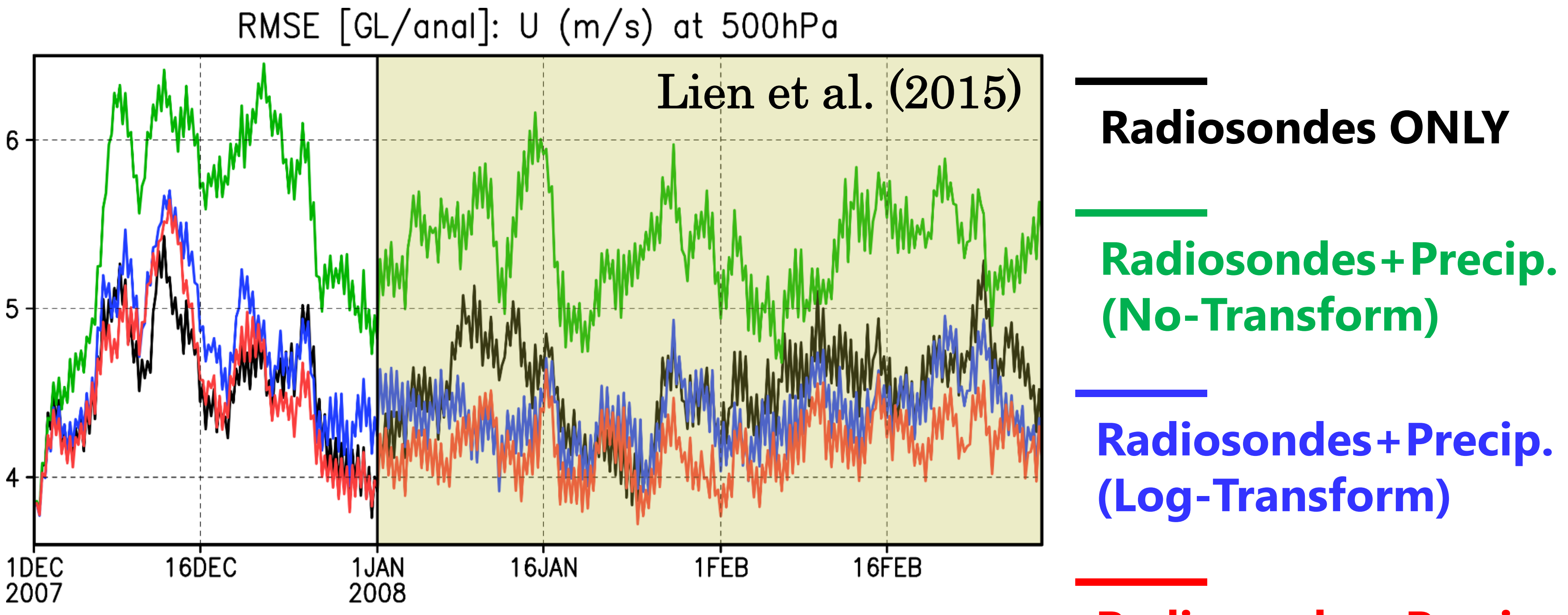
GPM: Global Precipitation Measurement



Hou et al. 2014

Goals

- <u>To improve NWP</u> using satellite-derived precipitation data following ***Lien et al. (2013, 2015a, 2015b)***
- <u>To produce a new precipitation product</u> through data assimilation



Improvement achieved with GFS-LETKF
(U-wind @ 500 hPa)

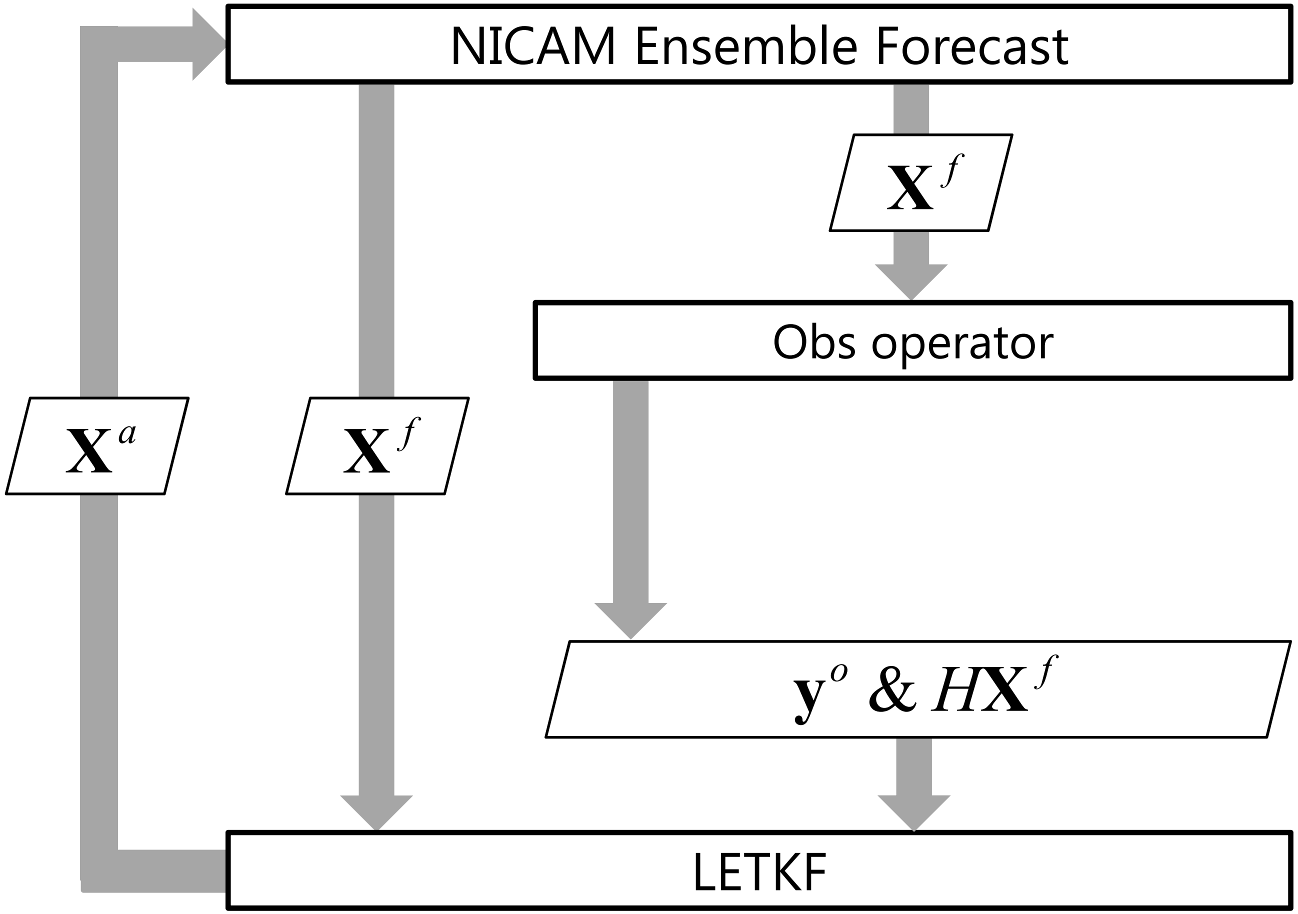
Experimental Setting

- **Numerical Model**
  - NICAM (Satoh and Tomita 2004, Satoh et al. 2008, 2014)
    - GL6 (approx. 110 km resolution)

- **Observations**
  - CTL: Radiosondes
  - EXP: Radiosondes + 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; α = 0.7)

NICAM-LETKF (Terasaki et al. 2015)

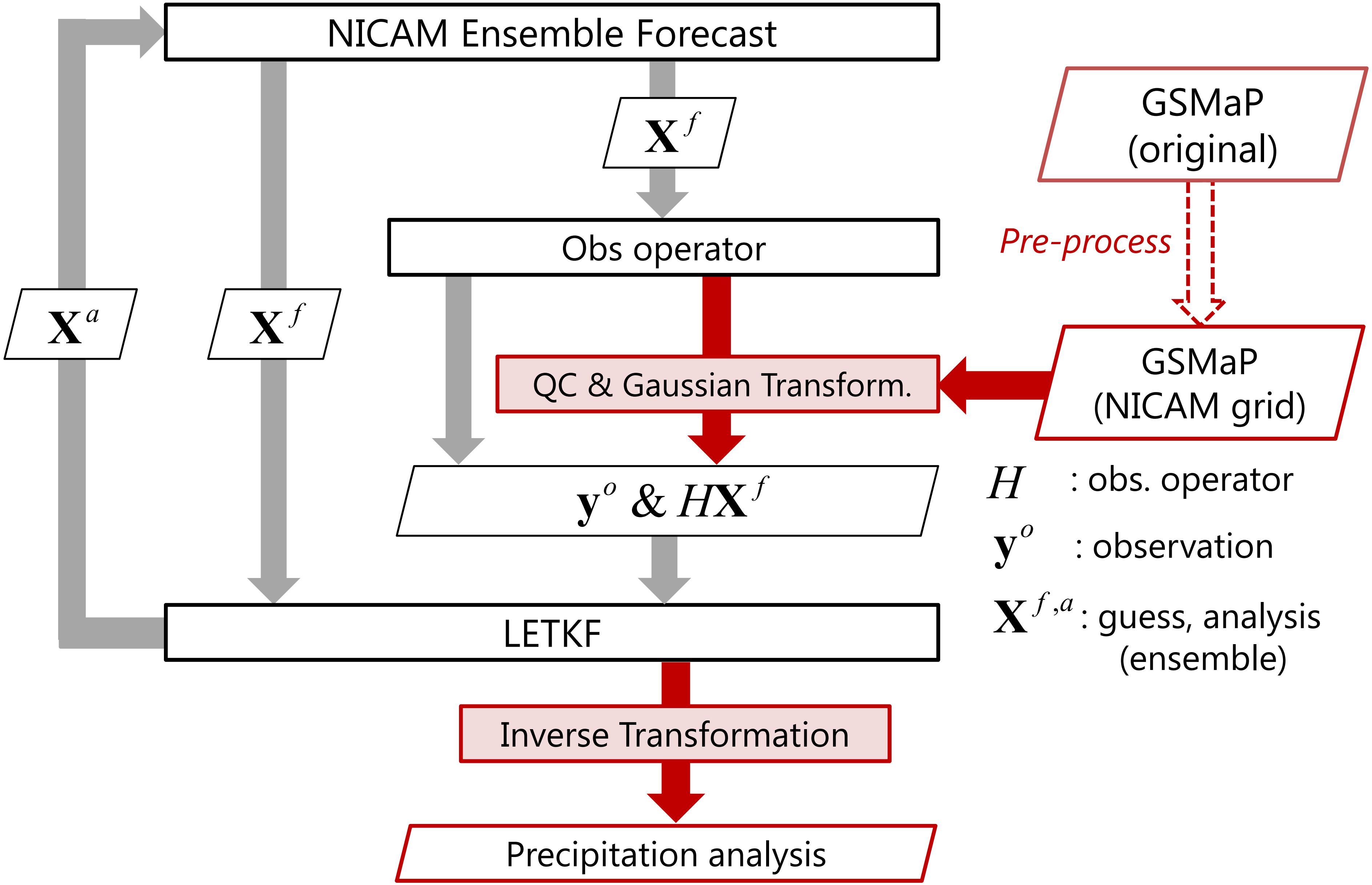


H : obs. operator

$\mathbf{y}^o$: observation

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

Assimilation of GSMaP by NICAM-LETKF



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Gaussian Transformation

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

Forward transform (mm/6hr→sigma) Inverse transform (sigma→mm/6hr)

y : original variable (mm/6hr)

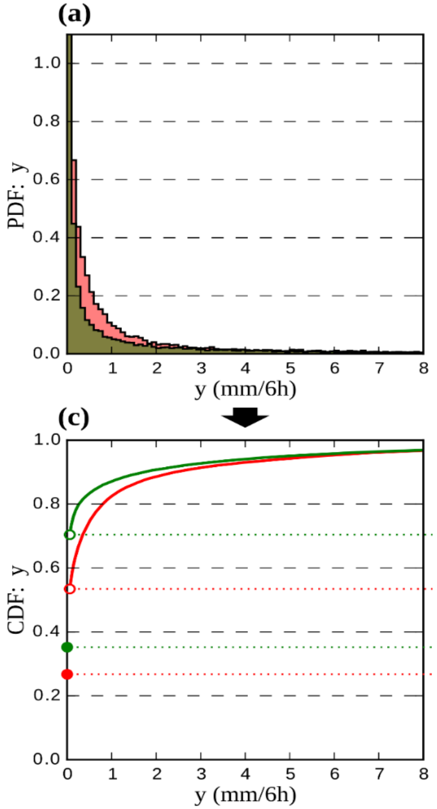
$F()$: CDF of original variable

$\tilde{y}$: Transformed variable (sigma)

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

PDF

CDF



Original variable

—: Model
—: Obs.

Step 0: Obtain PDF & CDF

Lien et al. (2013, 2015)

Gaussian Transformation

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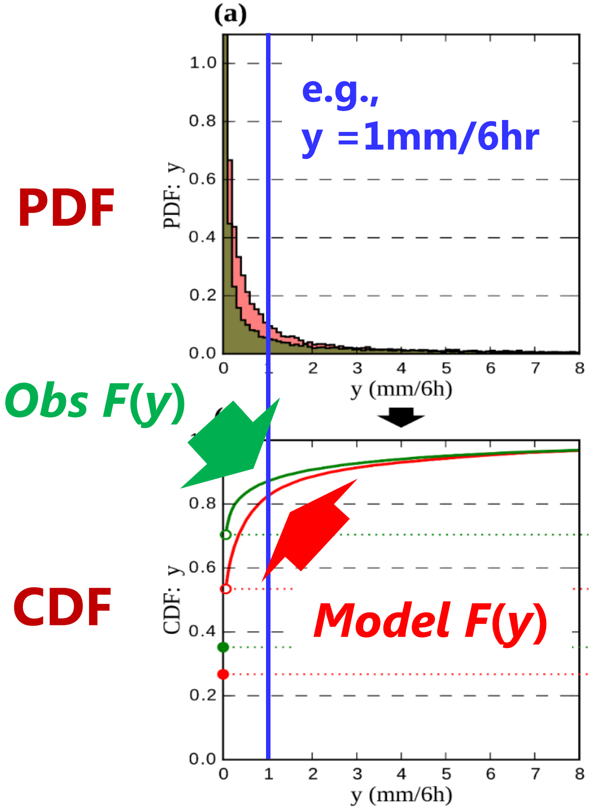

CDF

Original variable

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—: Obs.

Step 0: Obtain PDF & CDF

Step 1: Compute $F(y)$

Lien et al. (2013, 2015)

Gaussian Transformation

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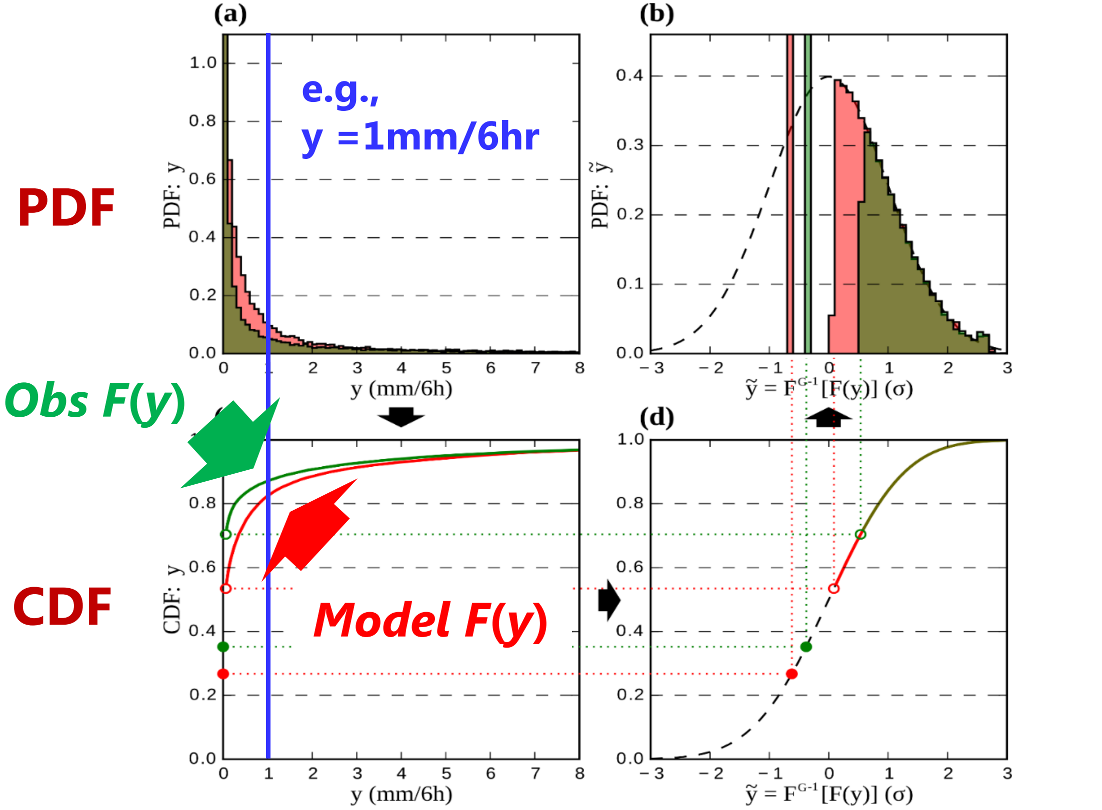

Original variable Transformed variable

—: Model

—: Obs.

Step 0: Obtain PDF & CDF

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Lien et al. (2013, 2015)

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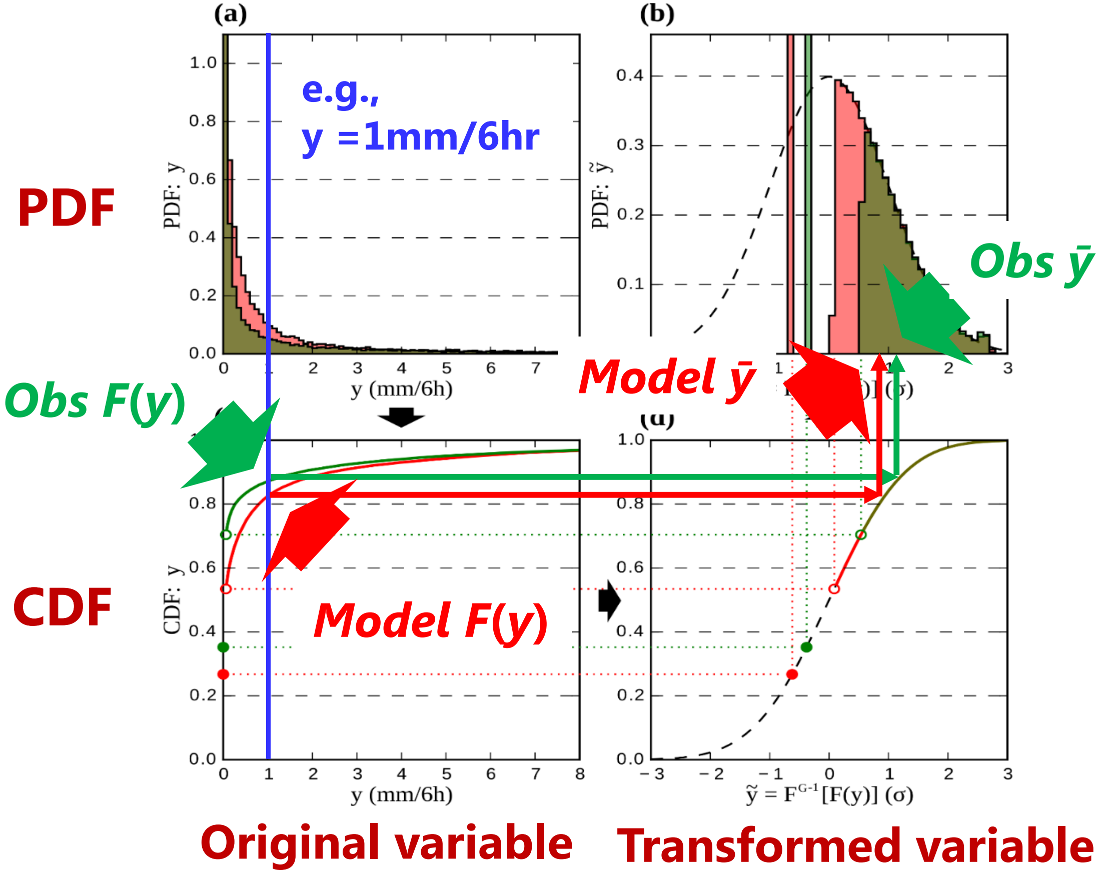

—: Model

—: Obs.

Step 0: Obtain PDF & CDF

Step 1: Compute $F(y)$

Step 2: Compute

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

Lien et al. (2013, 2015)

Gaussian Transformation

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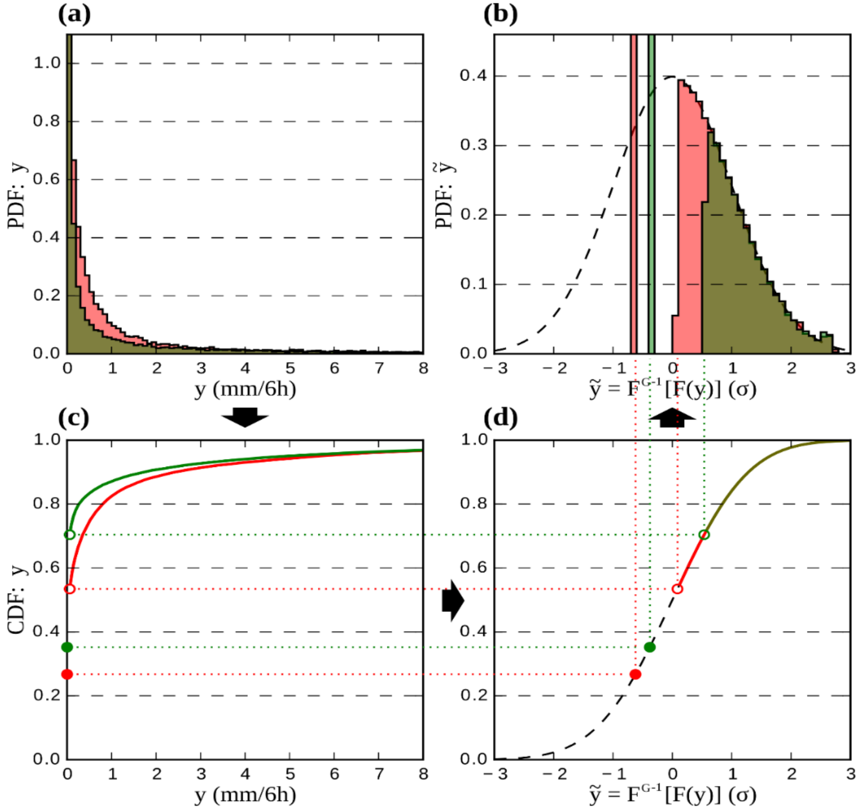


Original variable **Transformed variable**

—: Model

—: Obs.

Step 0: Obtain PDF & CDF

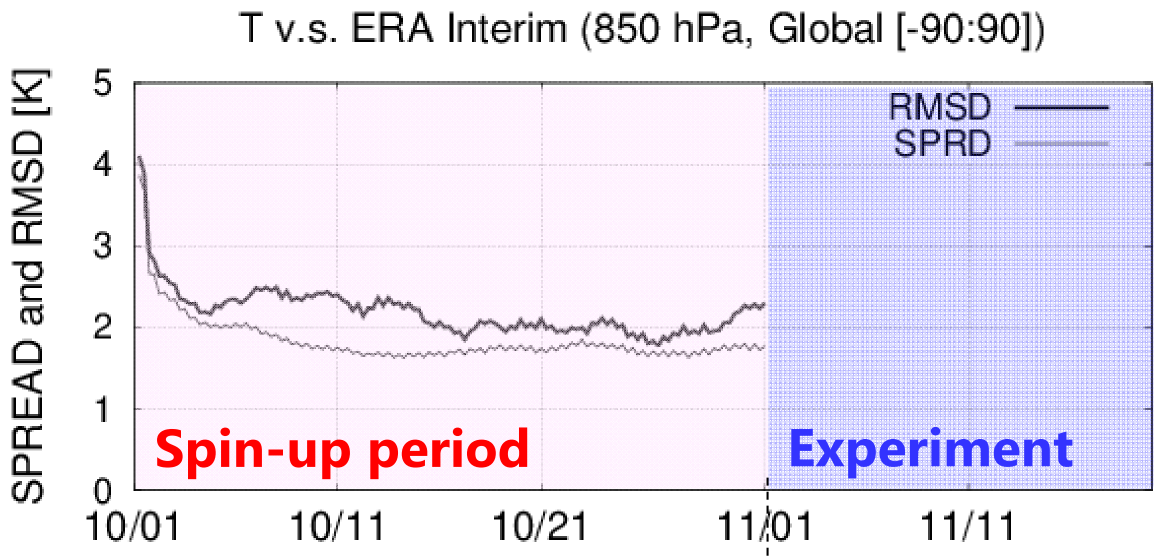
Step 1: Compute $F(y)$

Step 2: Compute

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

Lien et al. (2013, 2015)

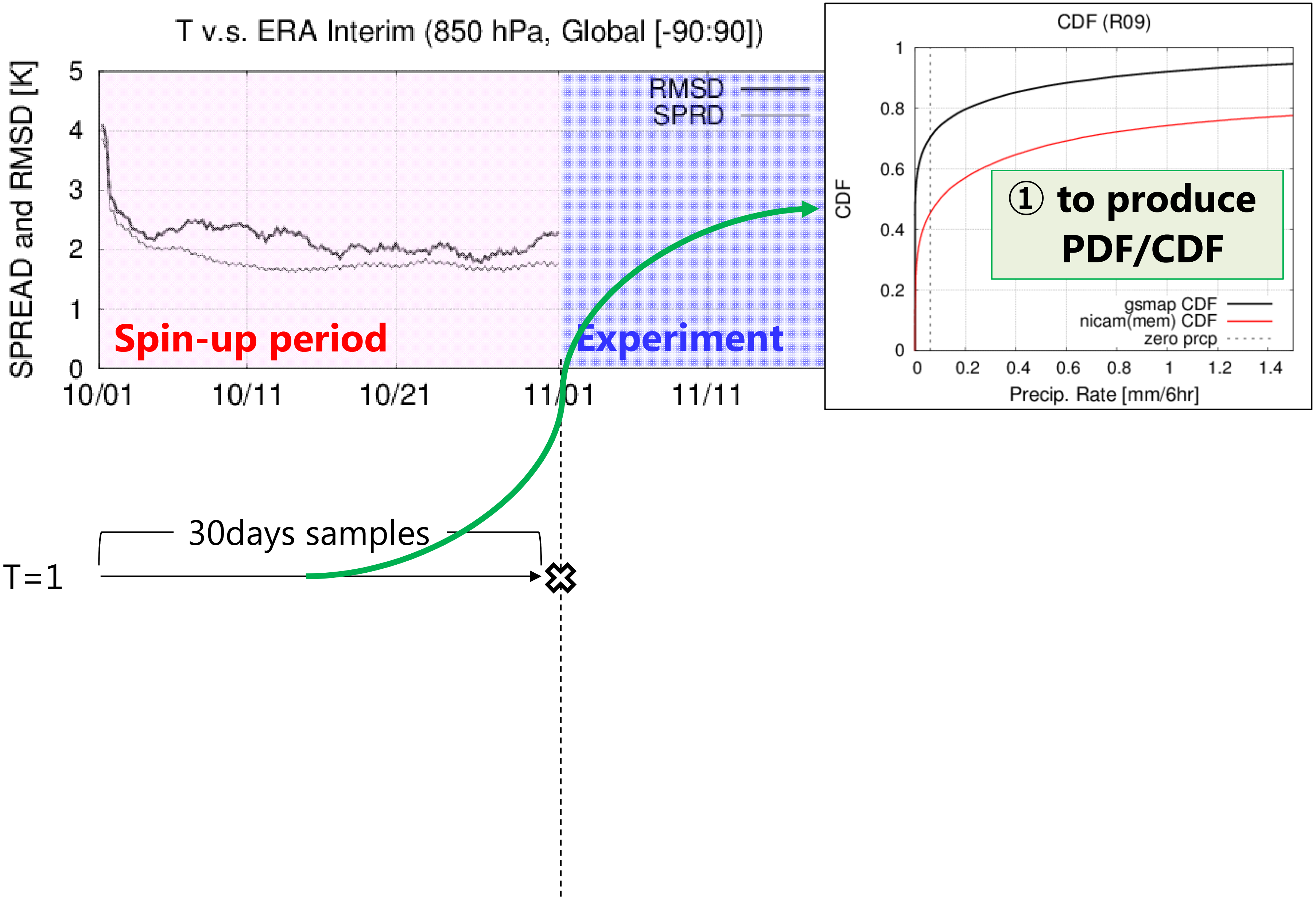
PDF/CDF production



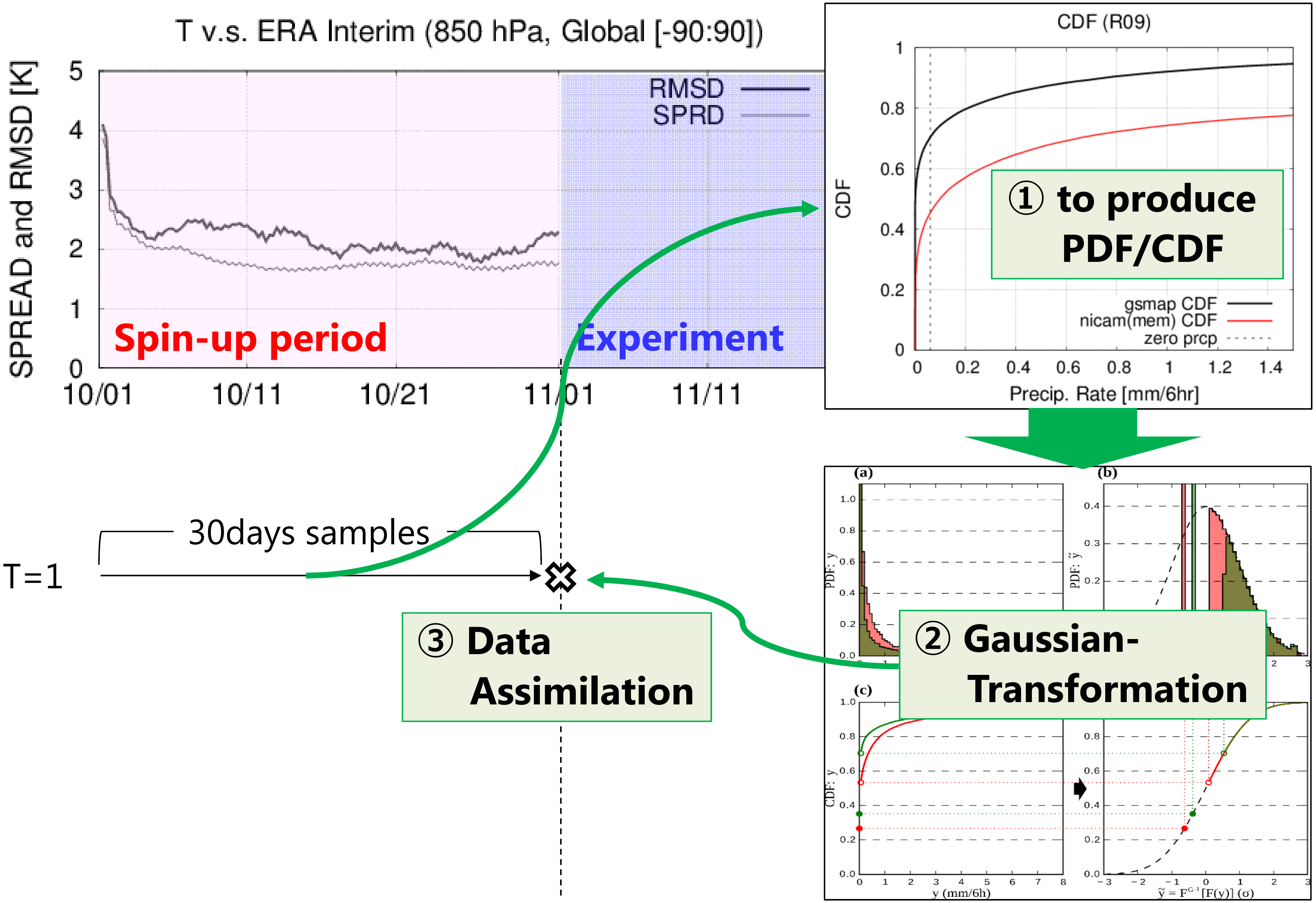
30days samples

T=1

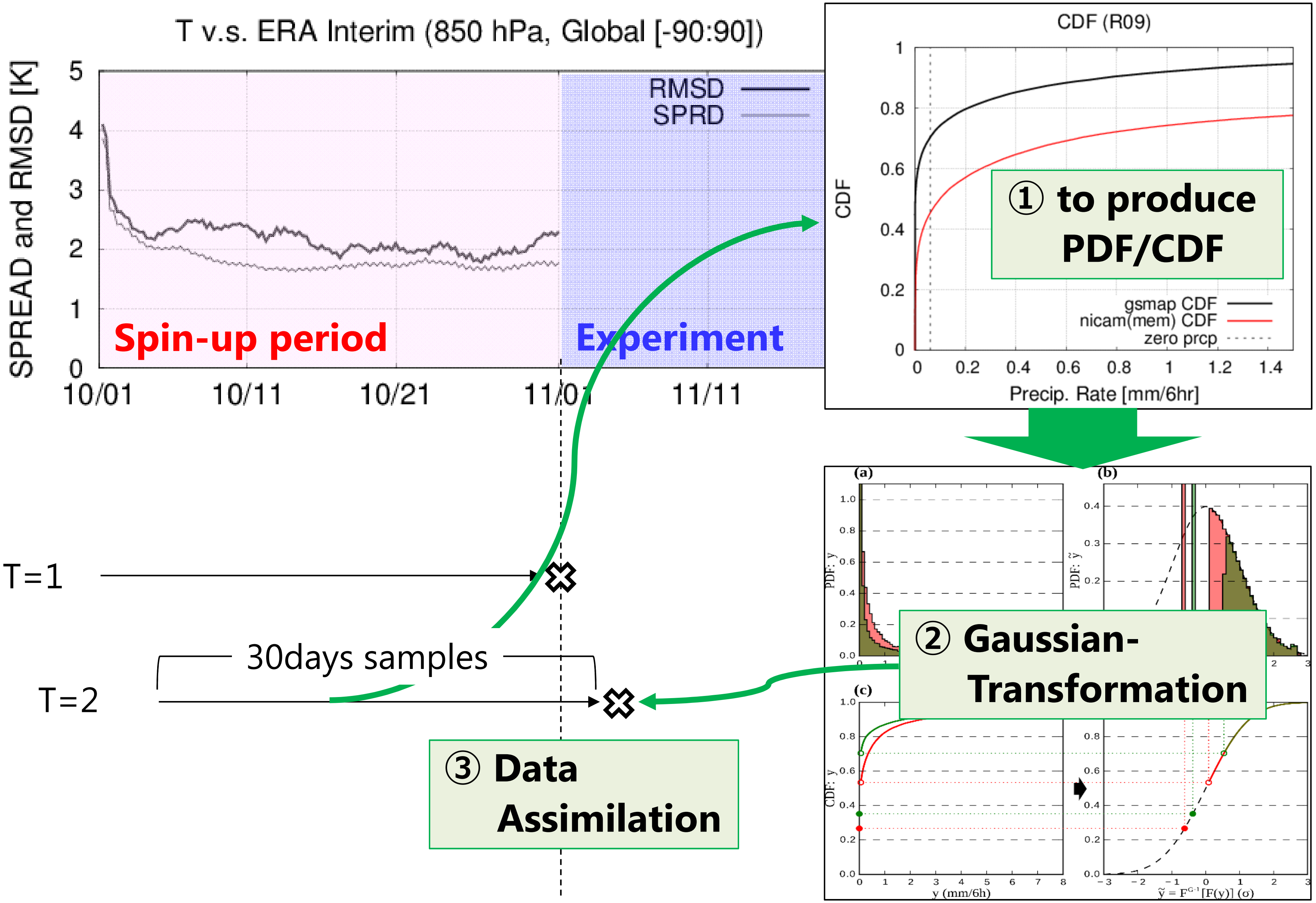
PDF/CDF production



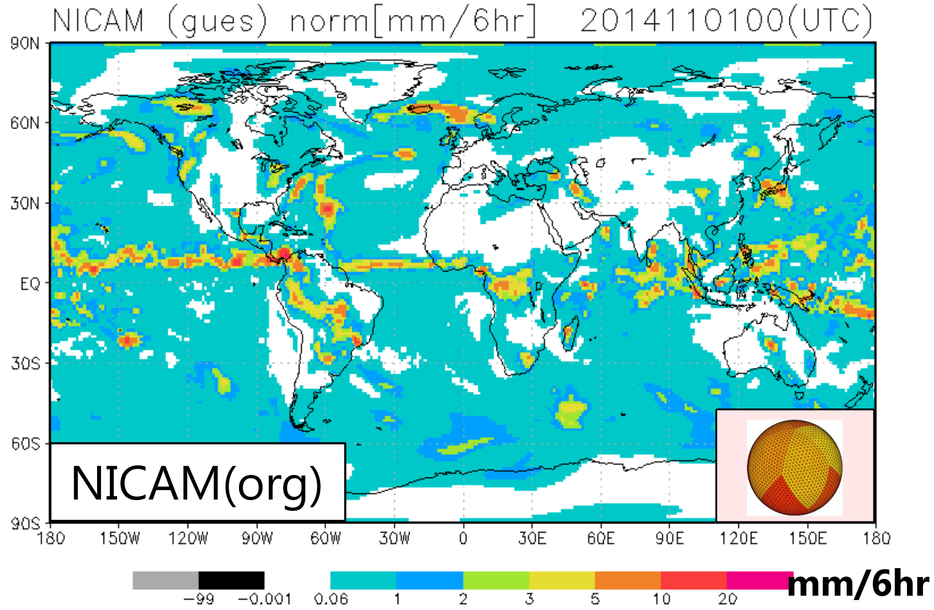
PDF/CDF production

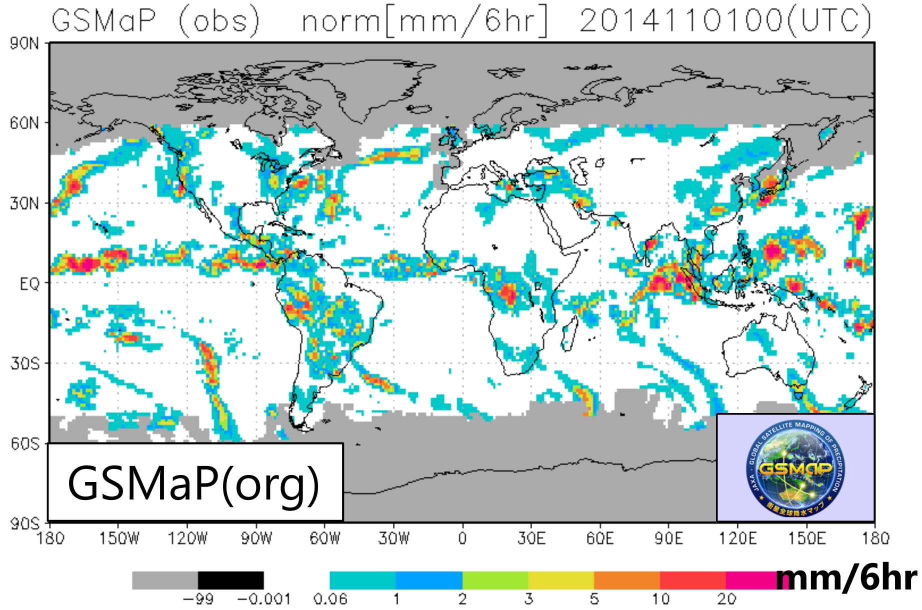


PDF/CDF production

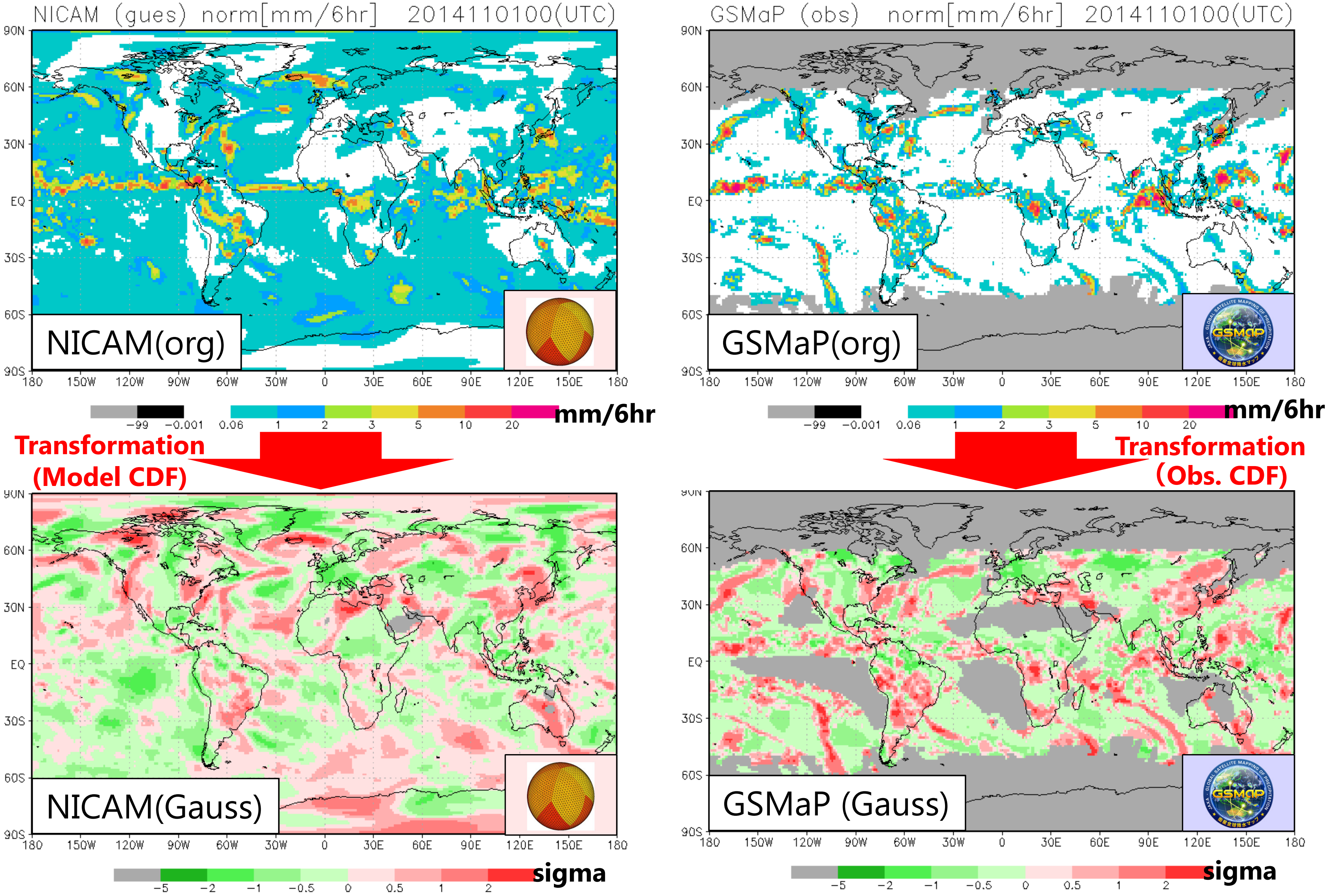


Gaussian Transformation



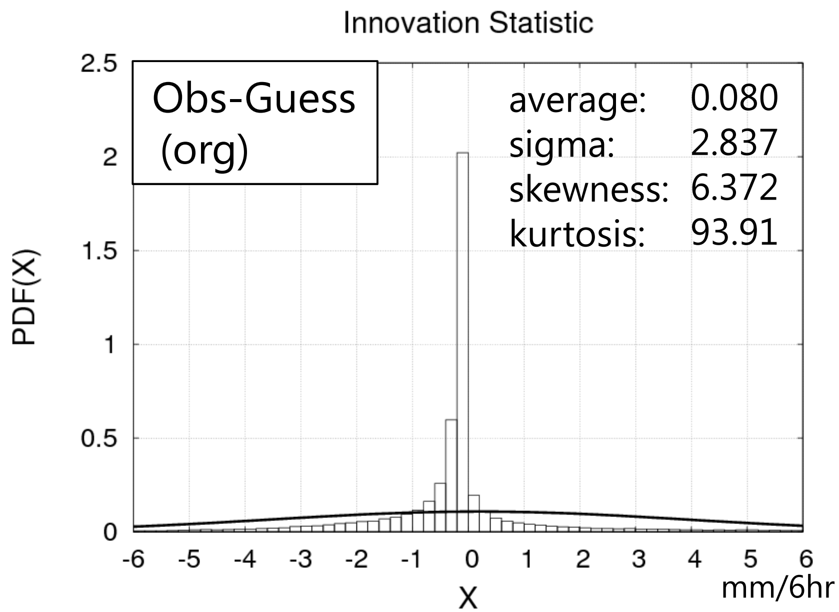


Gaussian Transformation

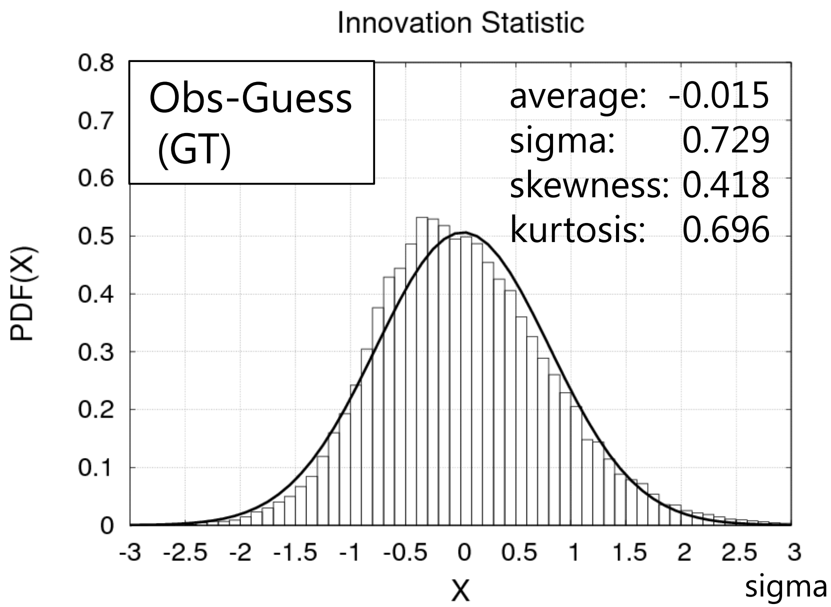


w/wo Gaussian Transformation

wo Gaussian-Transformation



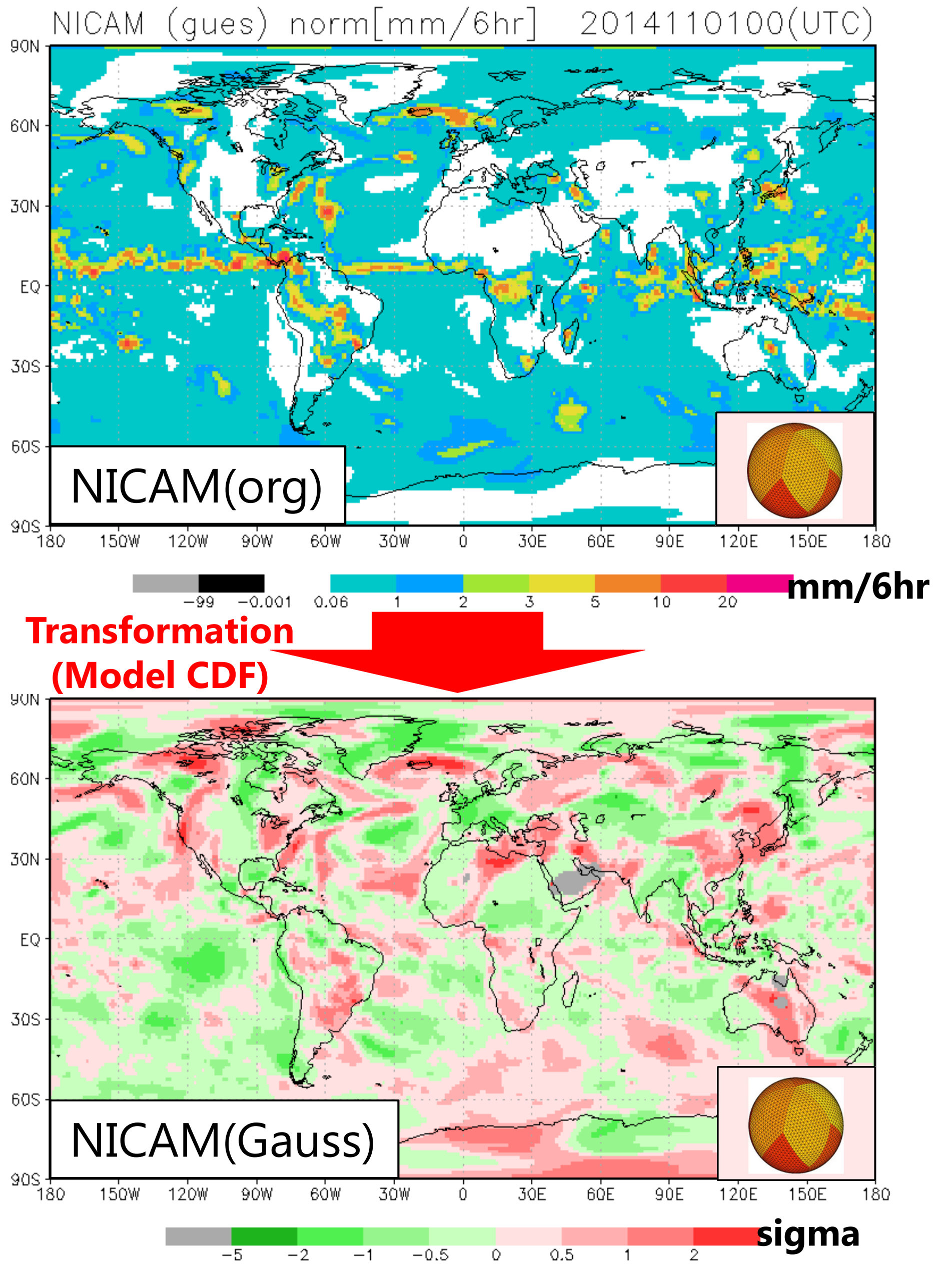
w Gaussian-Transformation



More Gaussian

Sampling period : 2014110100 - 2014110118

Forward/Inverse Transformations



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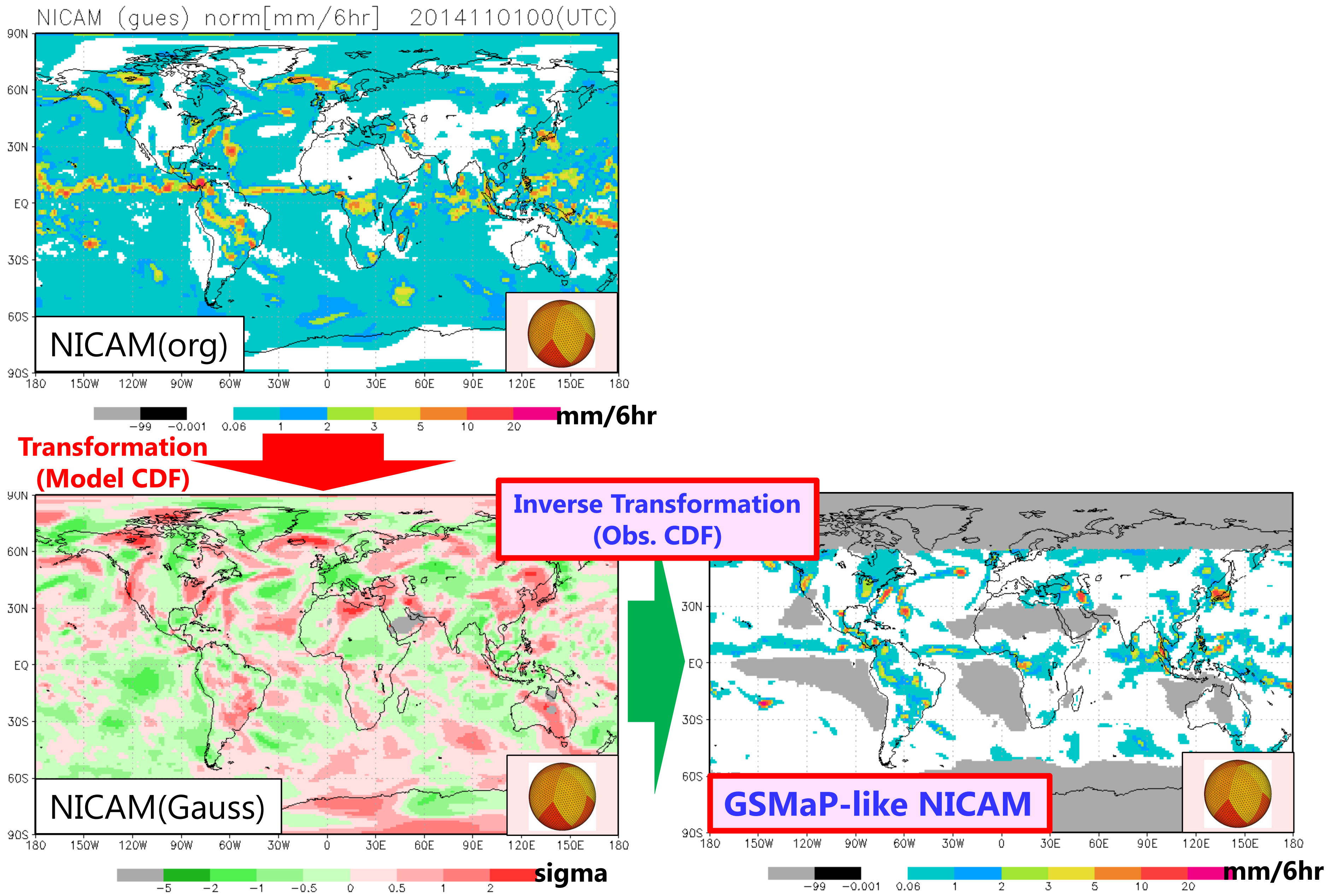

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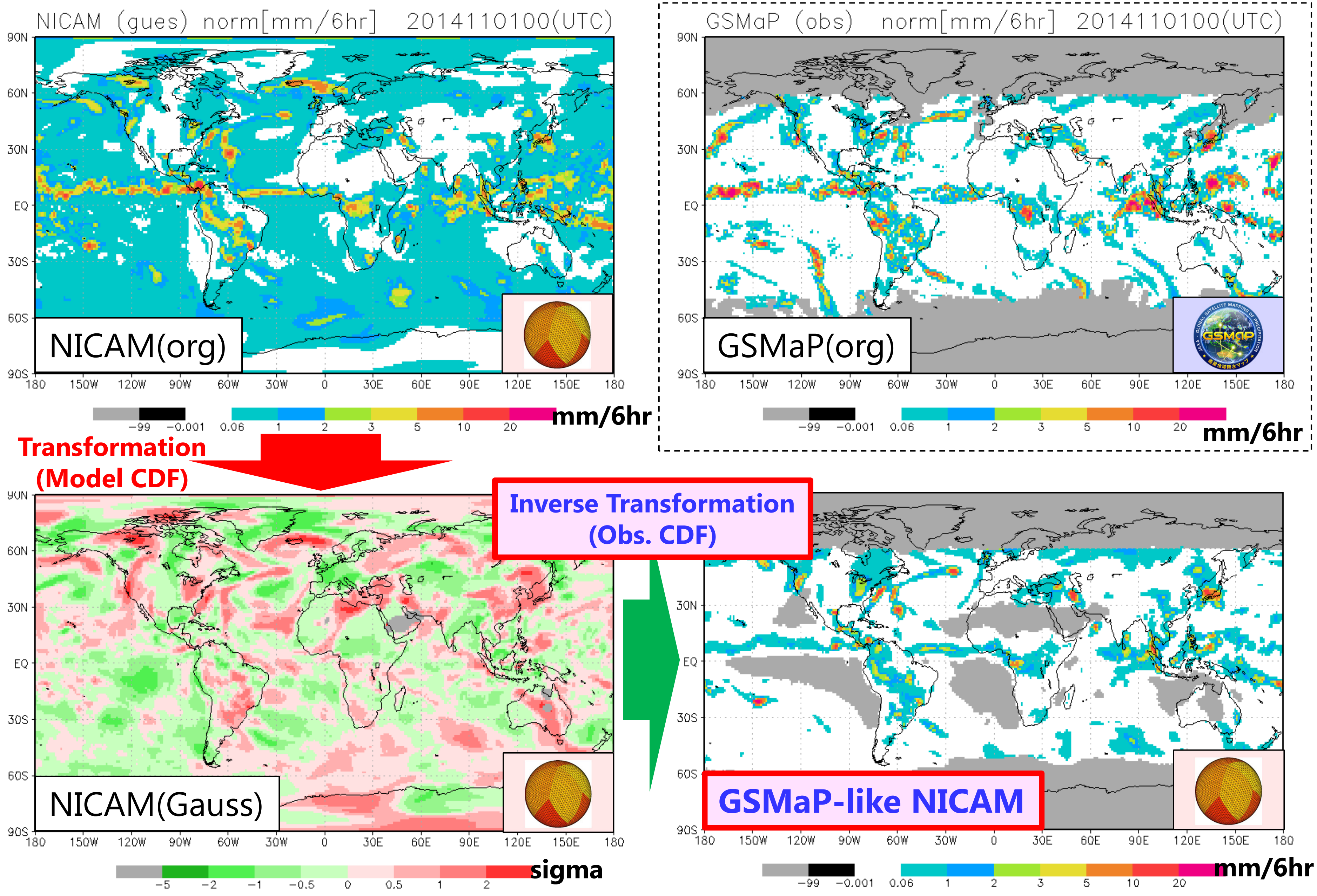
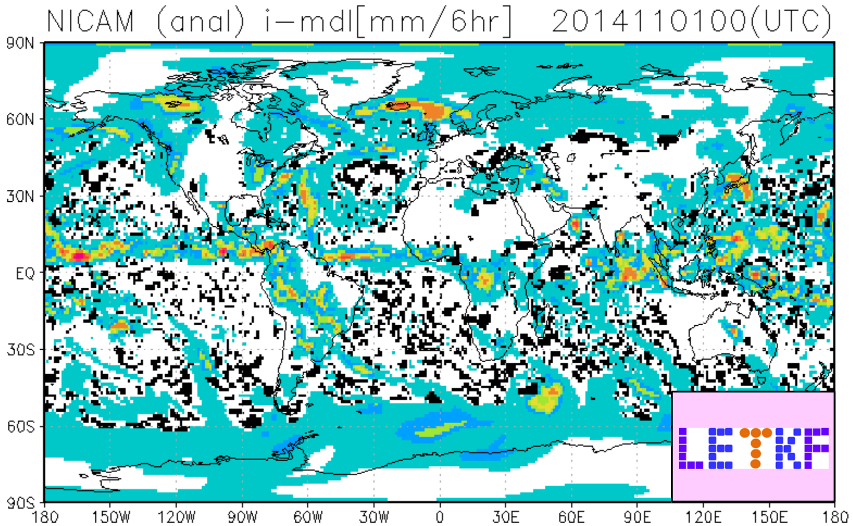


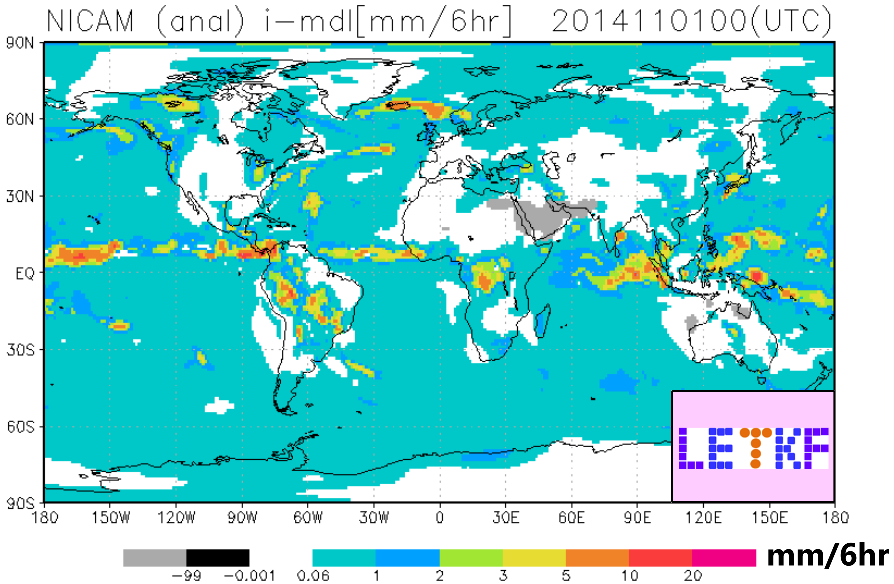
Precipitation after the first analysis

No-Transform (NT)

Noisy field w/ negative values

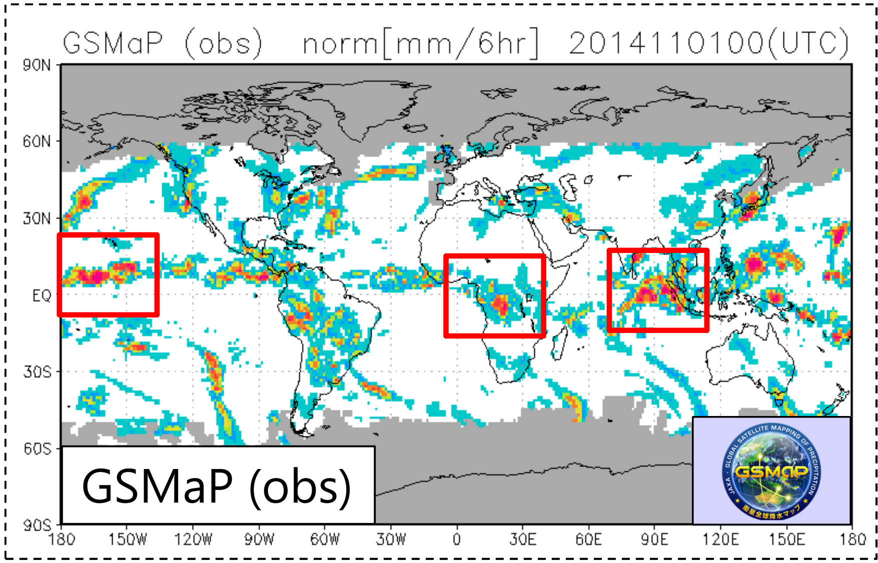


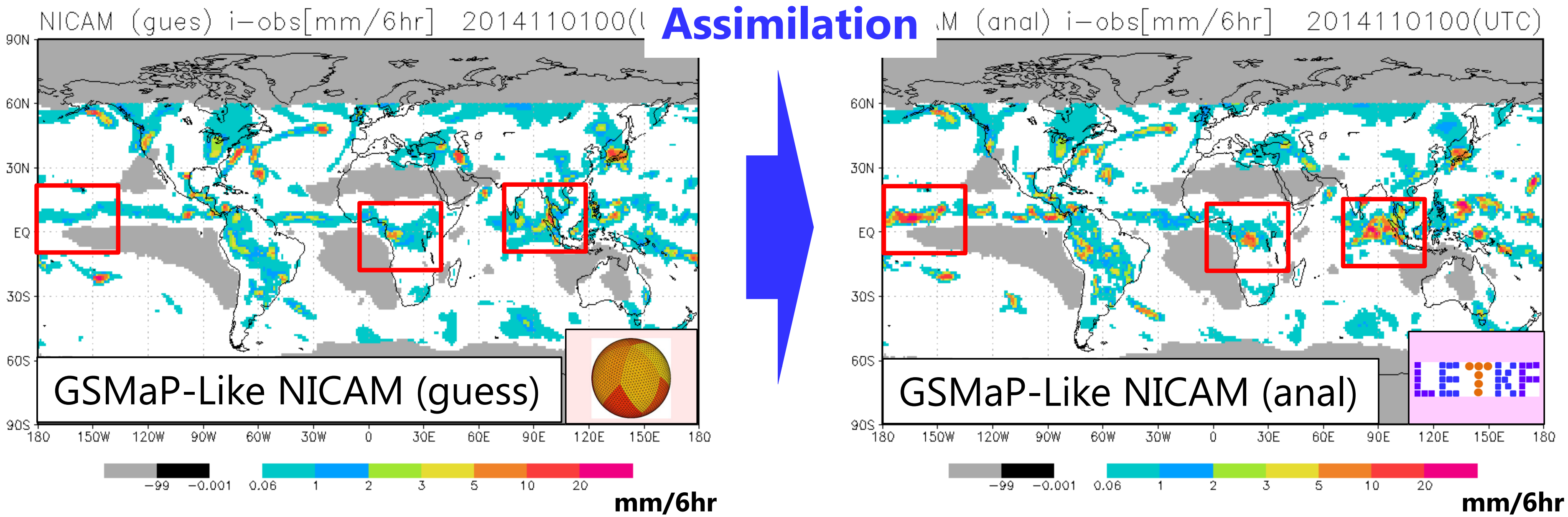
Gaussian-Transform (GT)



Precipitation after the first analysis

Improvement in precipitation field





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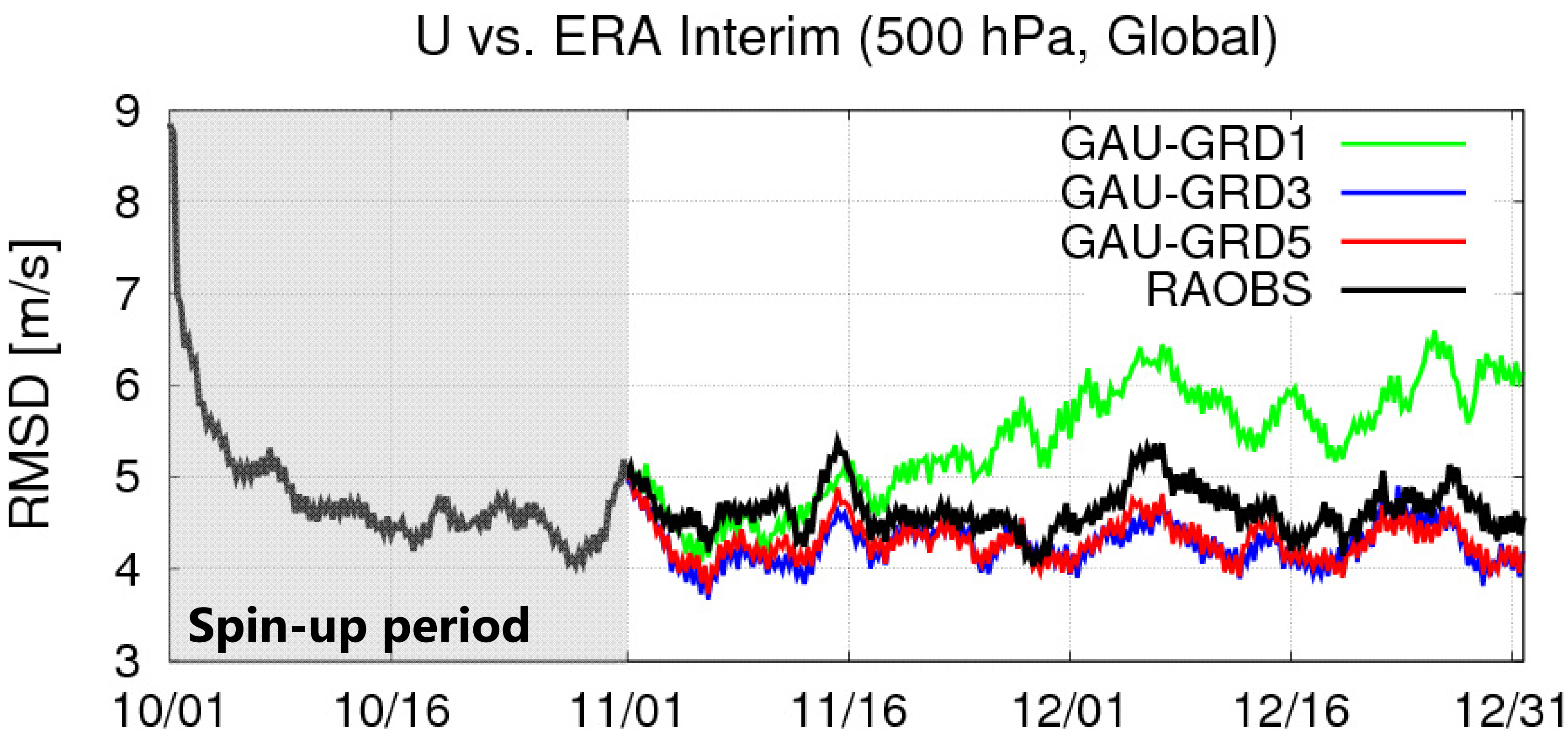
RMSDs relative to ERA Interim (in 2014)



—: Raobs: Radiosondes ONLY

—: GRD1: Radiosondes + GSMaP/Gauge (ALL)

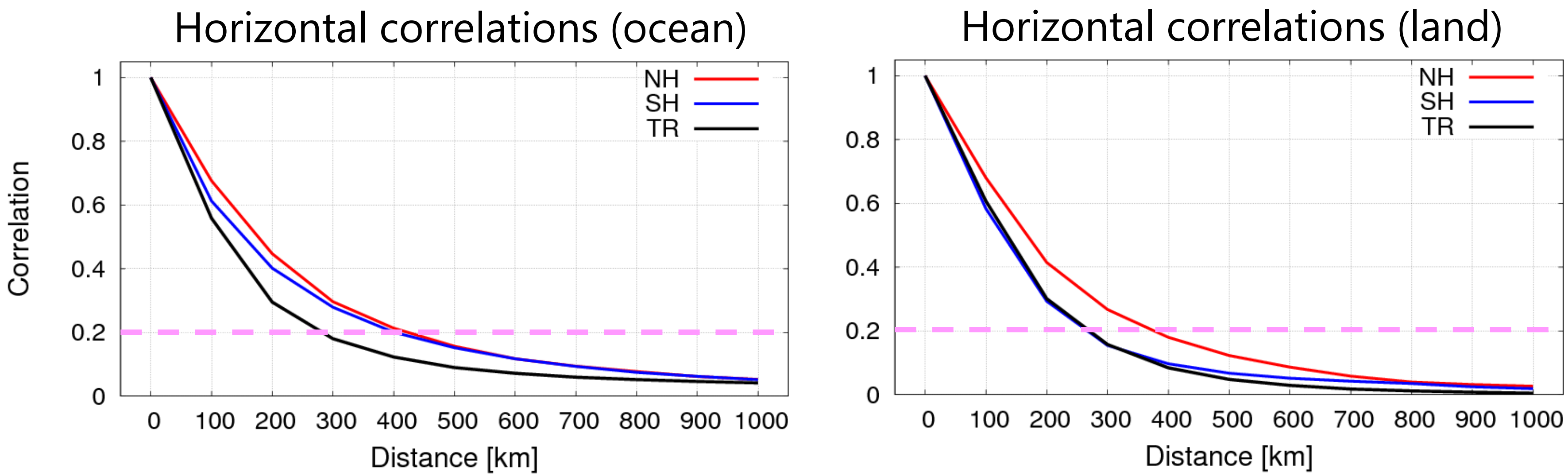
—: GRD3: Radiosondes + GSMaP/Gauge (every 3x3 grids)

—: GRD5: Radiosondes + GSMaP/Gauge (every 5x5 grids)

Desrozier's diagnostics (for precip. obs)

$$\mathbf{R} = \left\langle \mathbf{d}^a \left(\mathbf{d}^b\right)^{\mathrm{T}} \right\rangle \qquad \mathbf{d}^{a(b)} = \mathbf{y}^o - H\mathbf{x}^{a(b)}$$

Desroziers et al. (2005)



NOTE: Diagnosed with <u>suboptimal</u> experiment GRD1

2014/12/01 – 2014/12/31

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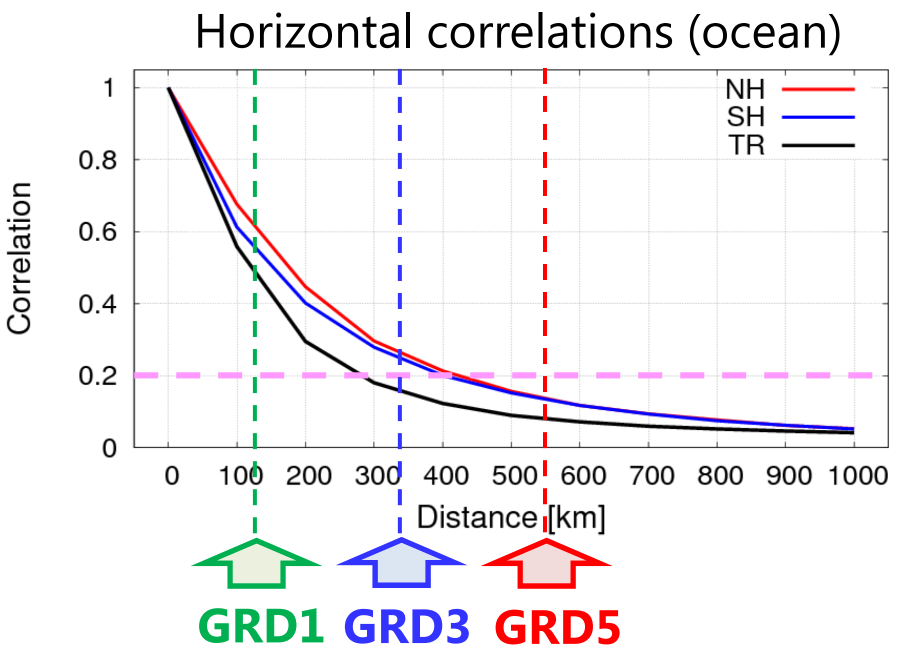
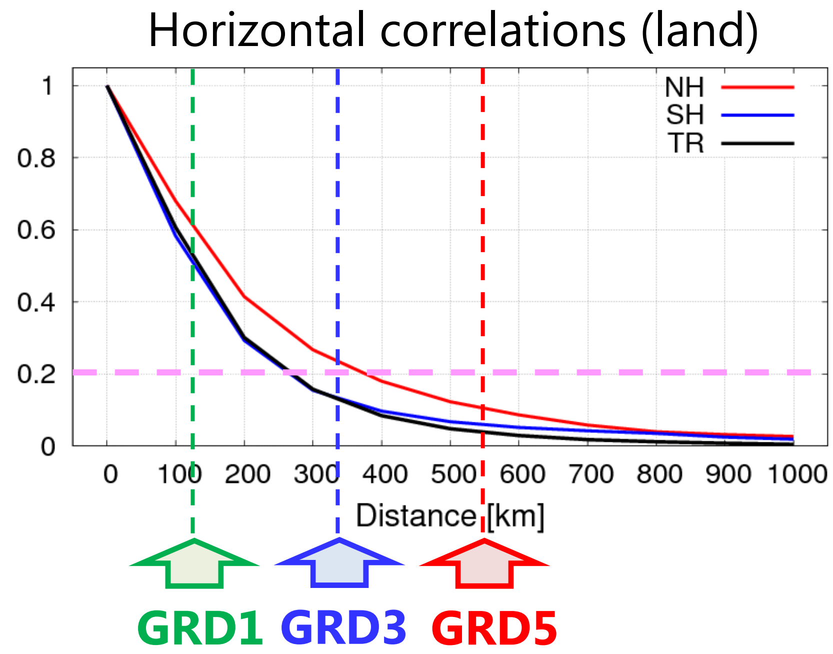


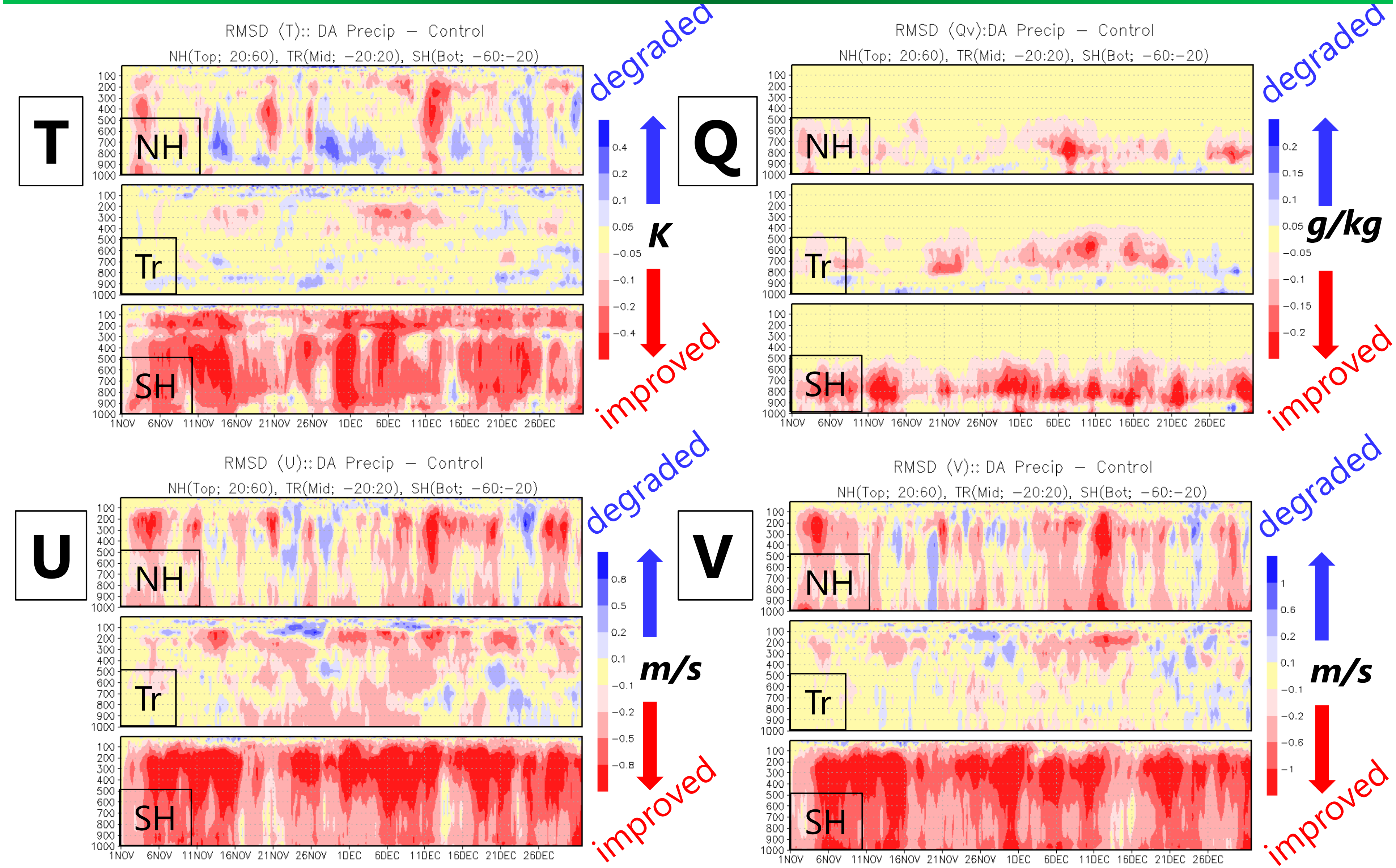


Strong horizontal correlation !!!

NOTE: Diagnosed with <u>suboptimal</u> experiment GRD1

2014/12/01 – 2014/12/31

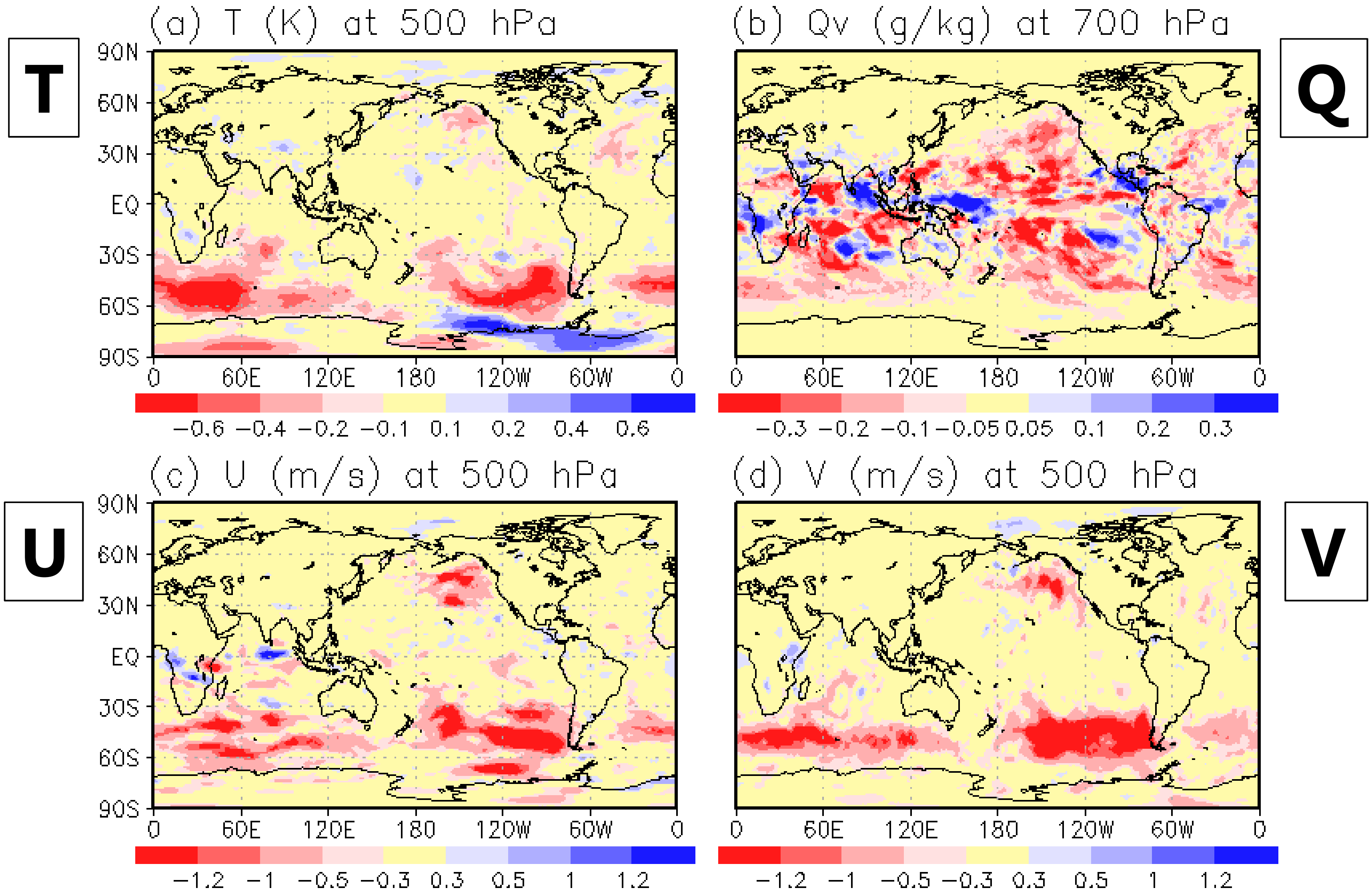
Best experiment (RMSD changes)



RMSD (GRD5) — RMSD (Raobs)

Best experiments (MAE changes)

45-days average (2014/11/17-2014/12/31)



improved ← **RMSD (GRD5) — RMSD (Raobs)** → *degraded*

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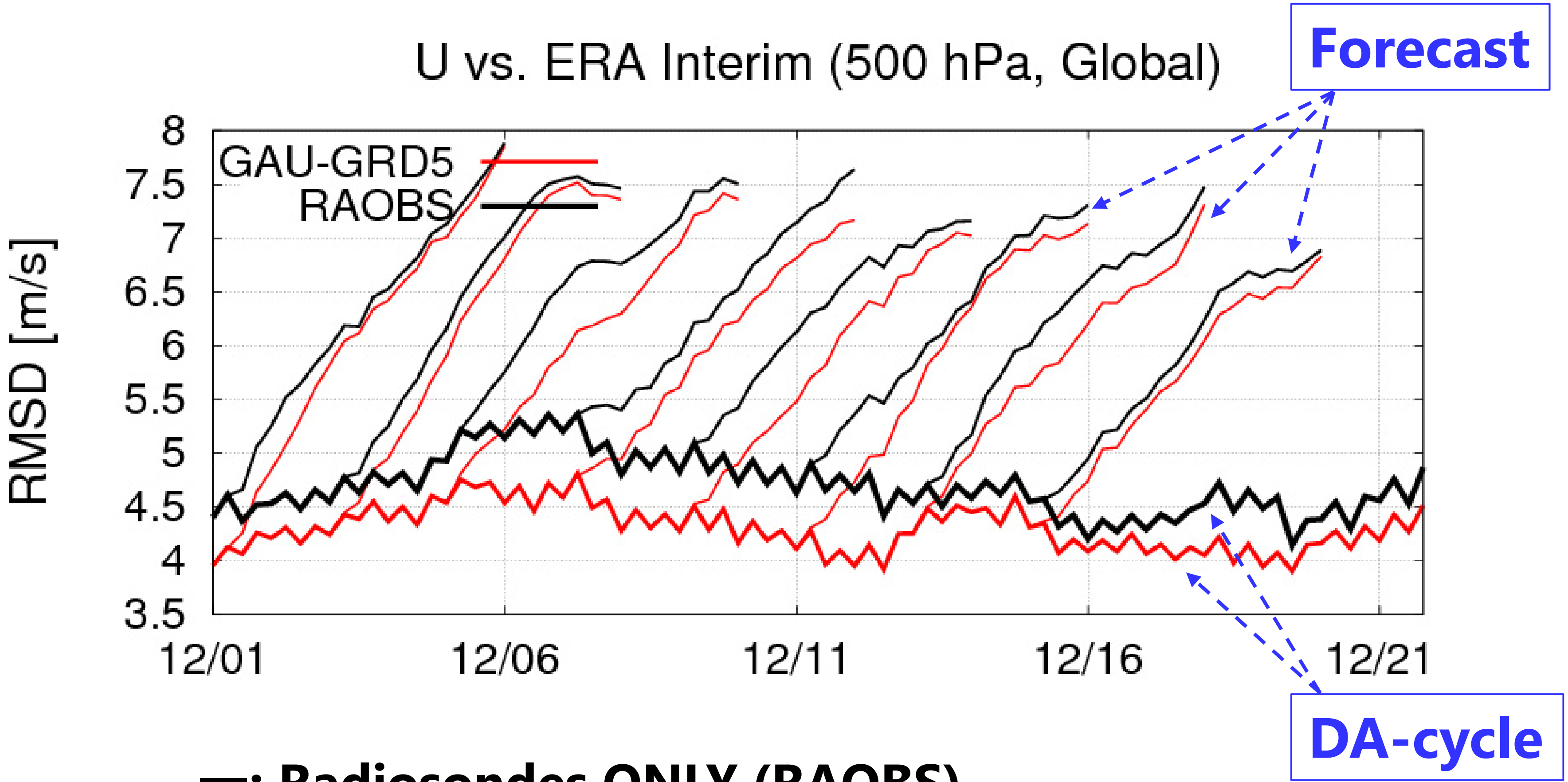
RMSDs: 120h Forecasts vs. ERA Interim



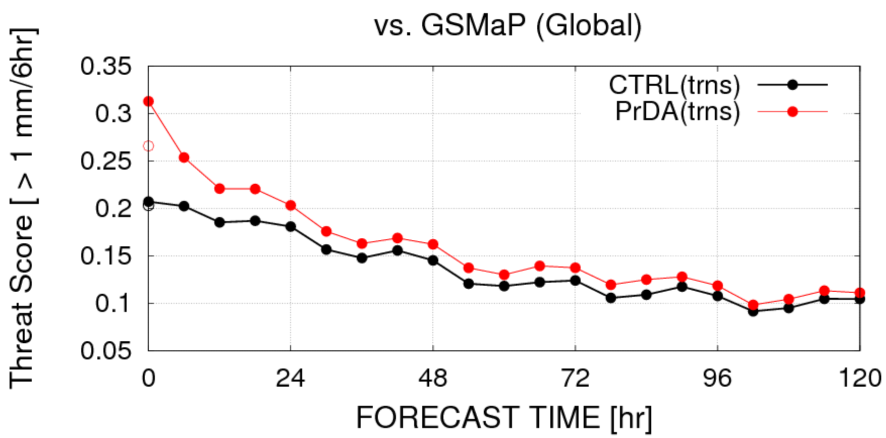
—: Radiosondes ONLY (RAOBS)

—: Radiosondes + GSMaP/Gauge (GRD5)

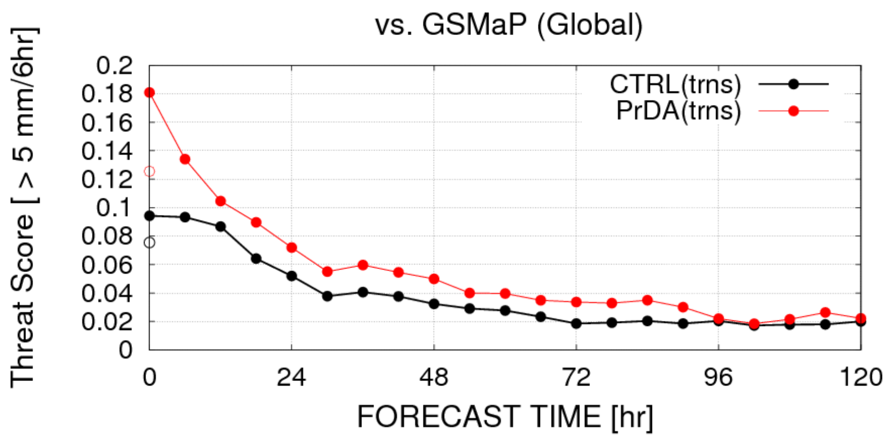
Validation with mean of ensemble forecasts from different initial dates

RMSDs: 120 hr Forecasts vs. GSMaP/Gauge

Threat Score (≥ 1 mm/6hr)



Threat Score (≥ 5 mm/6hr)



—: Radiosondes ONLY (RAOBS)

—: Radiosondes + GSMaP/Gauge (GRD5)

Precipitation forecasts are improved !!!

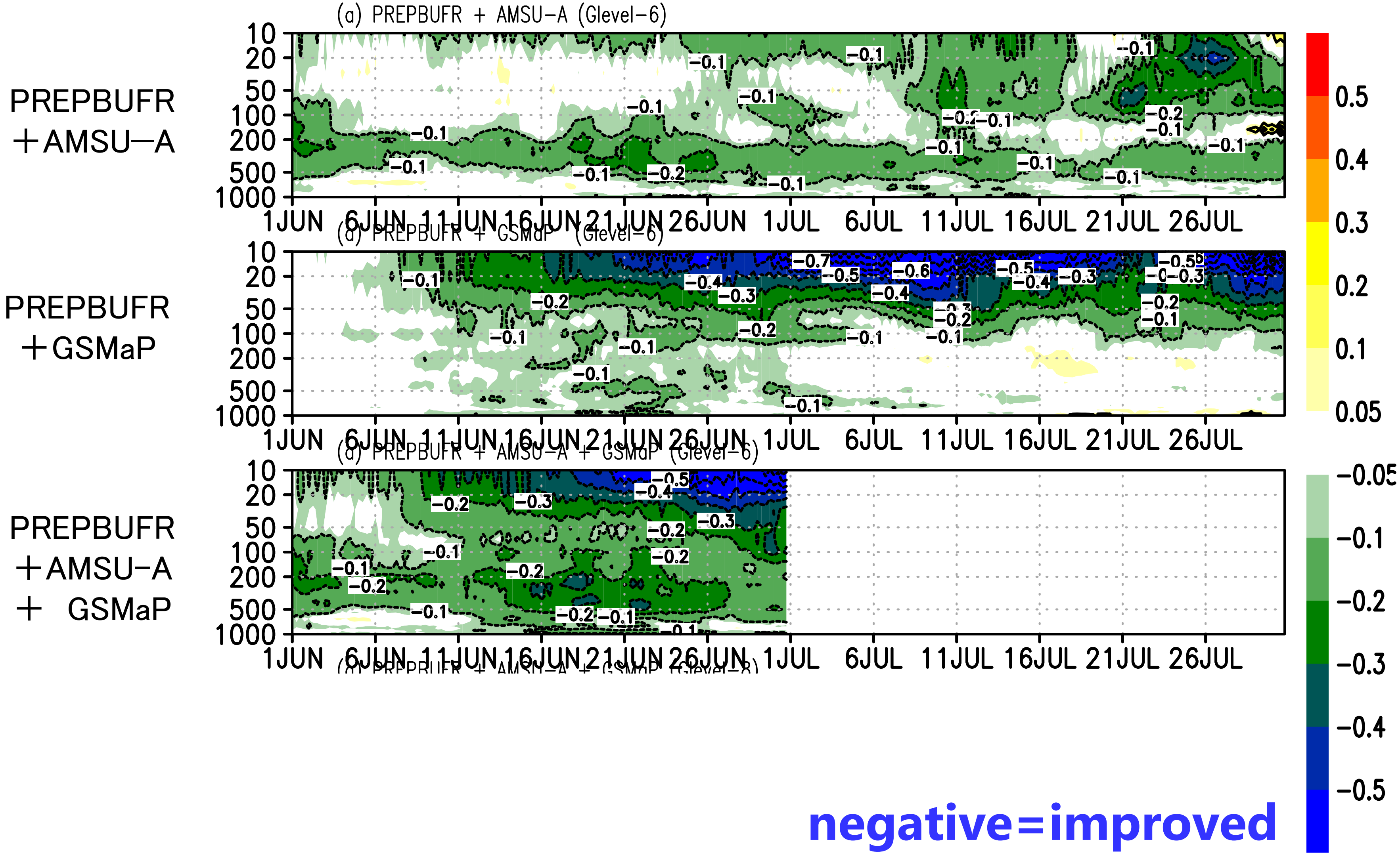
Average over 8 ensemble forecasts from different initial dates

Summary

- Lien et al. (2015) approach works well with NICAM-LETKF & GSMaP
  - Observation data thinning was essential
    - Horizontal obs error correlation of precipitation

Summary

RMSD improvements relative to CTRL (PREPBUFR) experiment



Thanks to Dr. Terasaki

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Estimation of Global Crop Calendar

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www.hydrol-earth-syst-sci.net/19/4441/2015/
doi:10.5194/hess-19-4441-2015

Volume 19, issue 11

Research article

05 Nov 2015

SACRA – a method for the estimation of global high-resolution crop calendars from a satellite-sensed NDVI

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[2]Disaster Prevention Research Institute, Kyoto University, Kyoto, Japan

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Revised: 05 Oct 2015 – Accepted: 15 Oct 2015 – Published: 05 Nov 2015

Abstract. To date, many studies have performed numerical estimations of biomass production and agricultural water demand to understand the present and future supply–demand relationship. A crop calendar (CC), which defines the date or month when farmers sow and harvest crops, is an essential input for the numerical estimations. This study aims to present a new global data set, the SAtellite-derived CRop calendar for Agricultural simulations (SACRA), and to discuss advantages and disadvantages compared to existing census-based and model-derived products. We estimate global CC at a spatial resolution of 5 arcmin using satellite-sensed normalized difference vegetation index (NDVI) data, which corresponds to vegetation vitality and senescence on the land surface. Using the time series of the NDVI averaged from three consecutive years (2004–2006), sowing/harvesting dates are estimated for six crops (temperate-wheat, snow-wheat, maize, rice, soybean and cotton). We assume time series of the NDVI represent the phenology of one dominant crop and estimate CCs of the dominant crop in each grid. The dominant crops are determined using harvested areas based on census-based data. The cultivation period of SACRA is identified from the time series of the NDVI; therefore, SACRA considers current effects of human decisions and natural disasters. The difference between the estimated sowing dates and other existing products is less than 2 months (< 62 days) in most of the areas. A major disadvantage of our method is that the mixture of several crops in a grid is not considered in SACRA. The assumption of one dominant crop in each grid is a major source of discrepancy in crop calendars between SACRA and other products. The disadvantages of our approach may be reduced with future improvements based on finer satellite sensors and crop-type classification studies to consider several dominant crops in each grid. The comparison of the CC also demonstrates that identification of wheat type (sowing in spring or fall) is a major source of error in global CC estimations.

Citation: Kotsuki, S. and Tanaka, K.: SACRA – a method for the estimation of global high-resolution crop calendars from a satellite-sensed NDVI, Hydrol. Earth Syst. Sci., 19, 4441-4461, doi:10.5194/hess-19-4441-2015, 2015.

Background

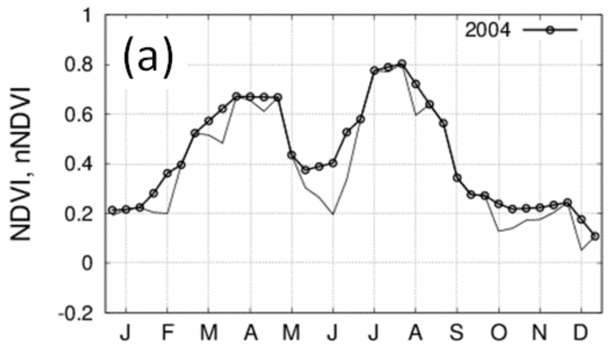
	Census-based	Model-based	Satellite-based (this study)
Main inputs	Census Data	Atmos. Forcing	Satellite Obs.
Resolution	Country/State scale	Equal to inputs	5 arc-min
Detection of cultivation	Hard	Hard	Easy
Mixture of crops (phenology)	Possible	Possible	Impossible
Future projection	Impossible	Possible	Impossible

Method

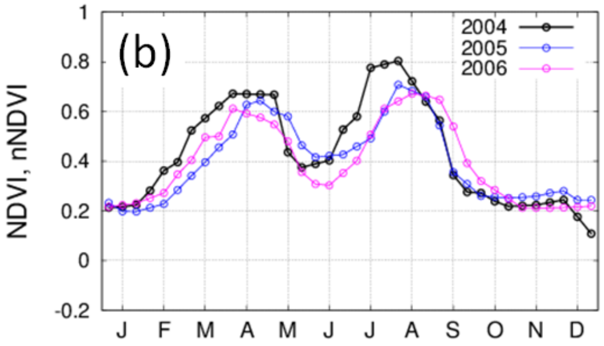
EX) Double cropping grid in India

— :2004 — :2005 — :2006 — :Average (2004-2006)

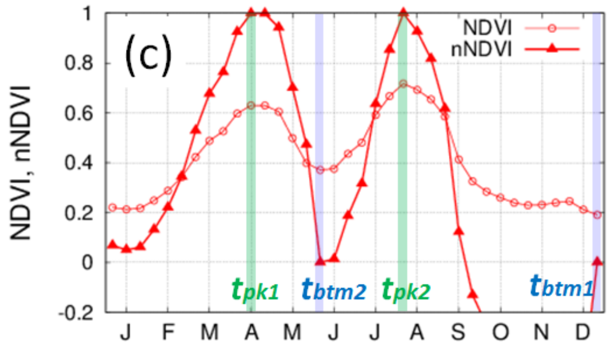
— :NDVI —○— :NDVI with BISE —▲— :Normalized NDVI



1. Remove cloud effect



2. Aggregation (time & space)



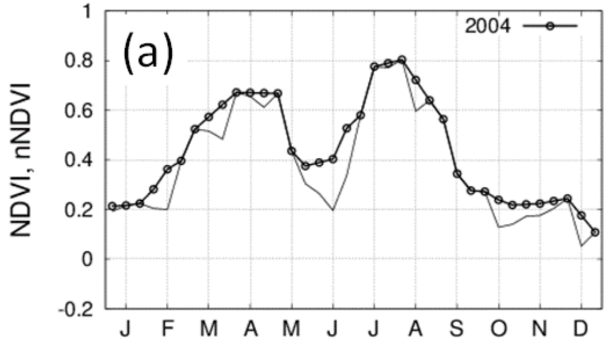
3. Normalization

Method

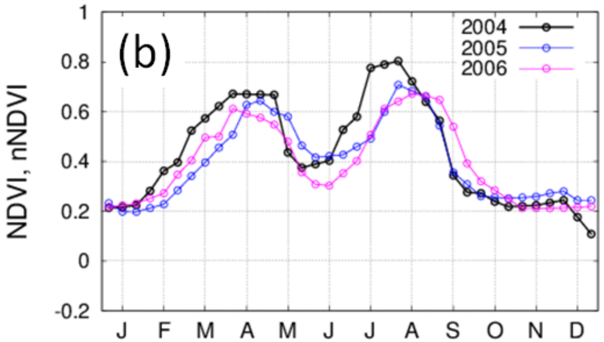
EX) Double cropping grid in India

— :2004 — :2005 — :2006 — :Average (2004-2006)

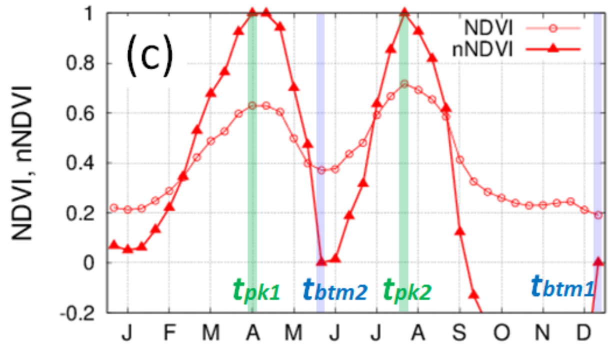
— :NDVI —o— :NDVI with BISE —▲— :Normalized NDVI



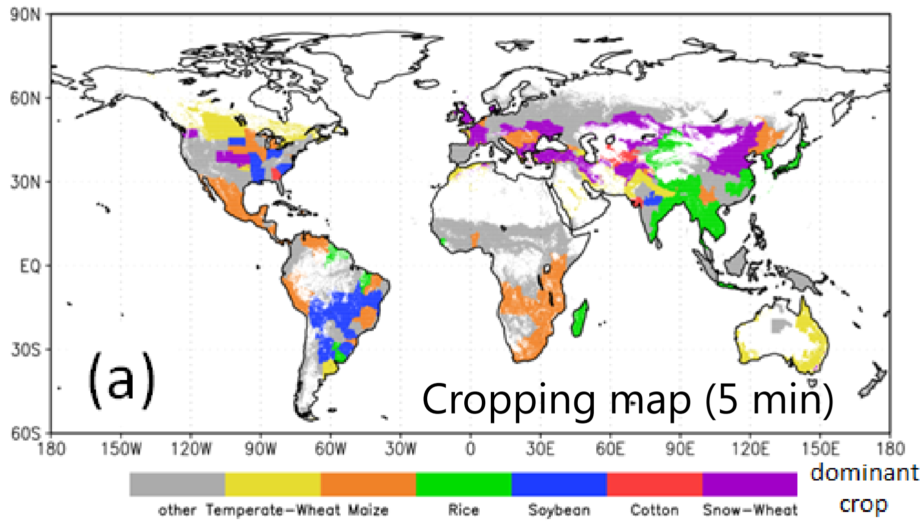
1. Remove cloud effect

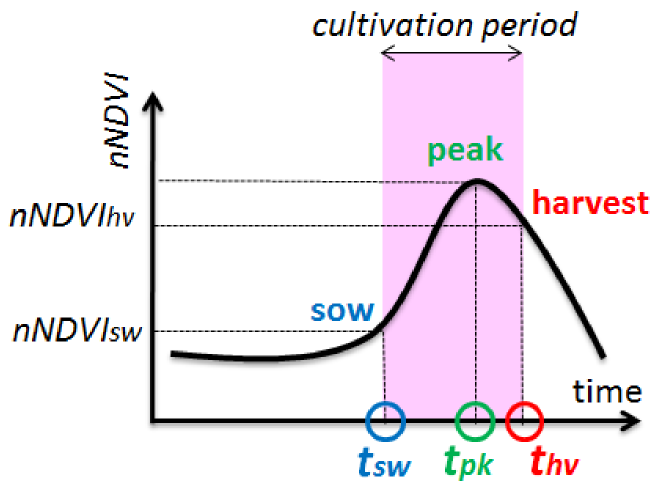


2. Aggregation (time & space)



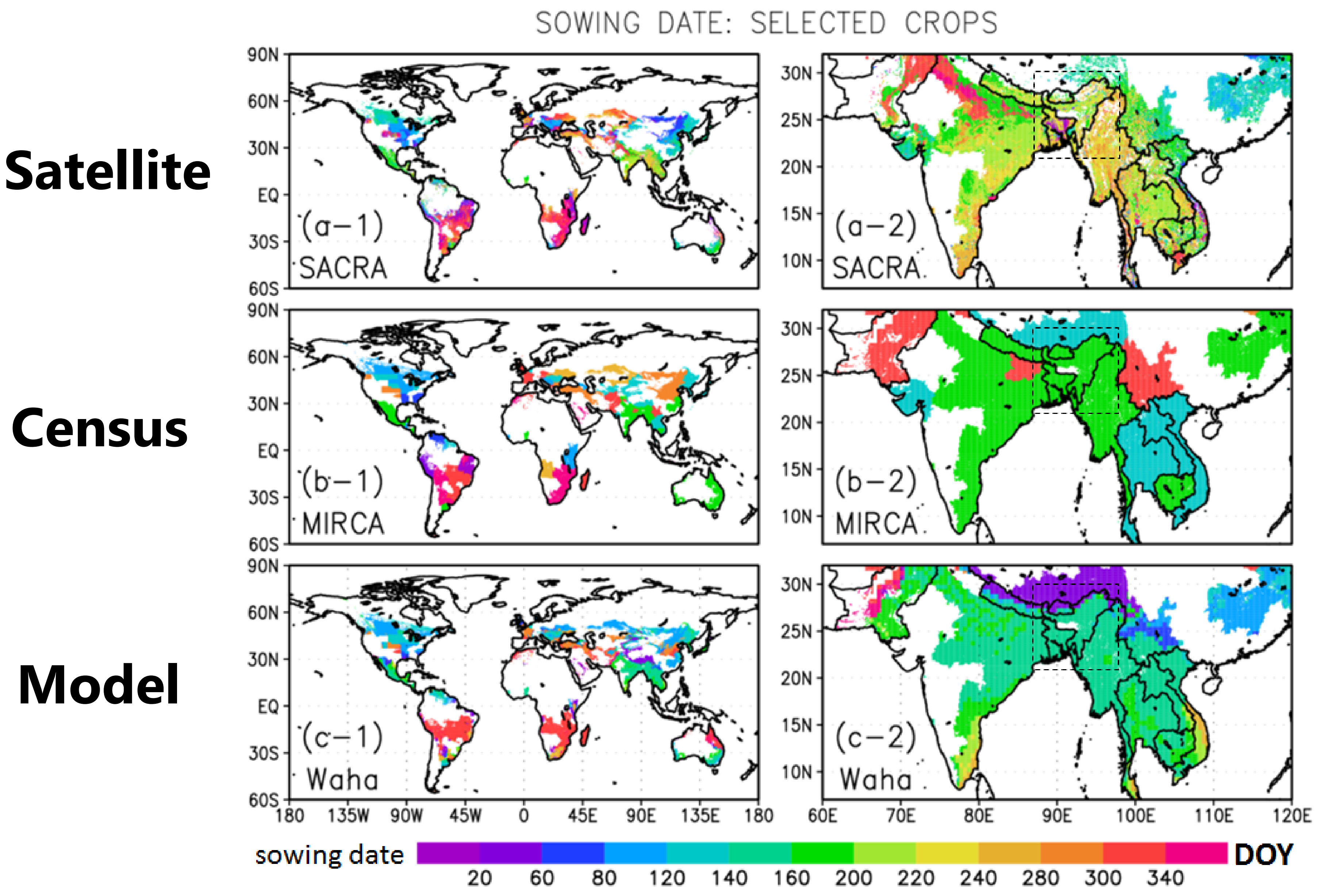
3. Normalization



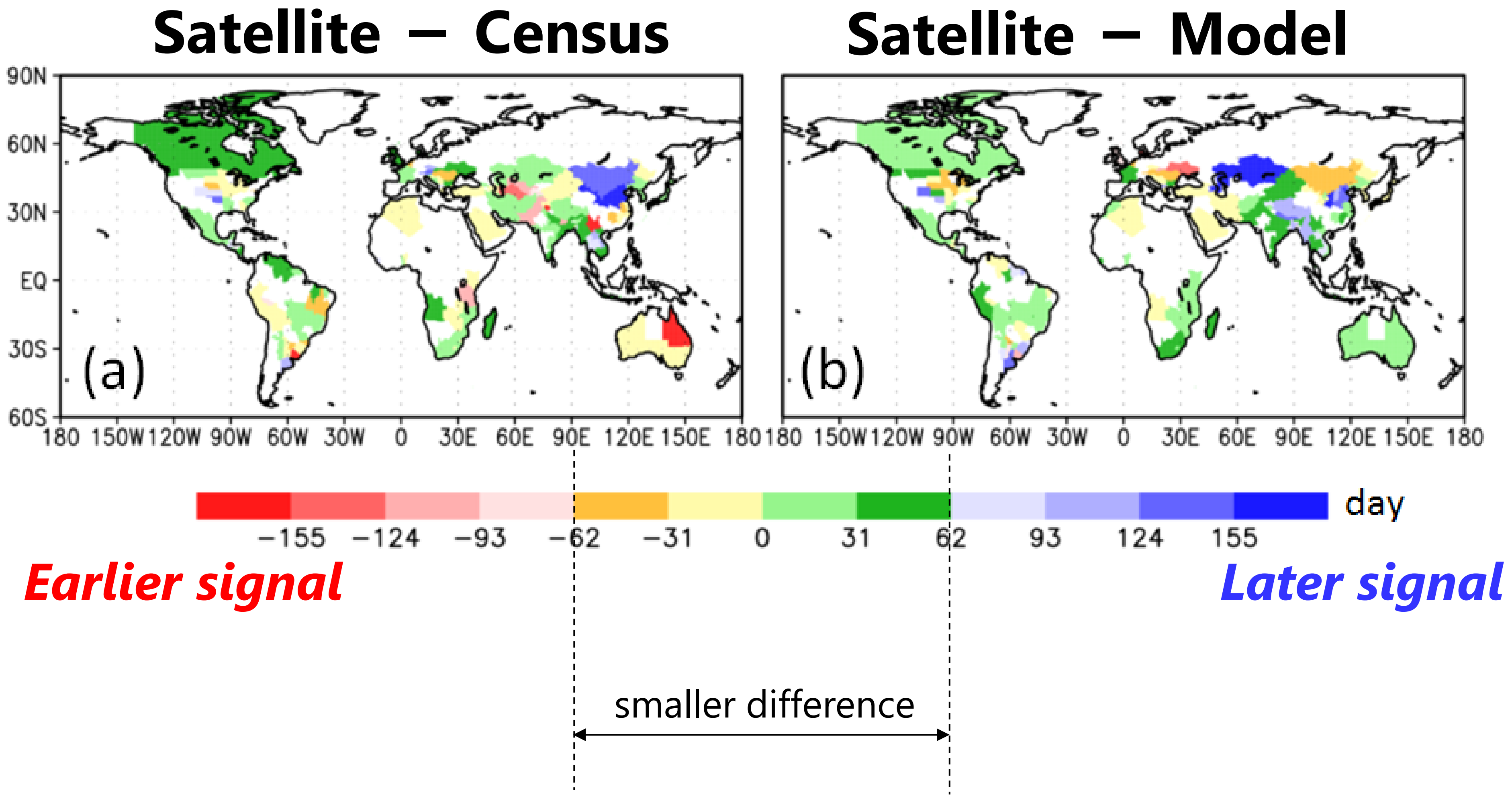


4. Detect sowing/harvesting date

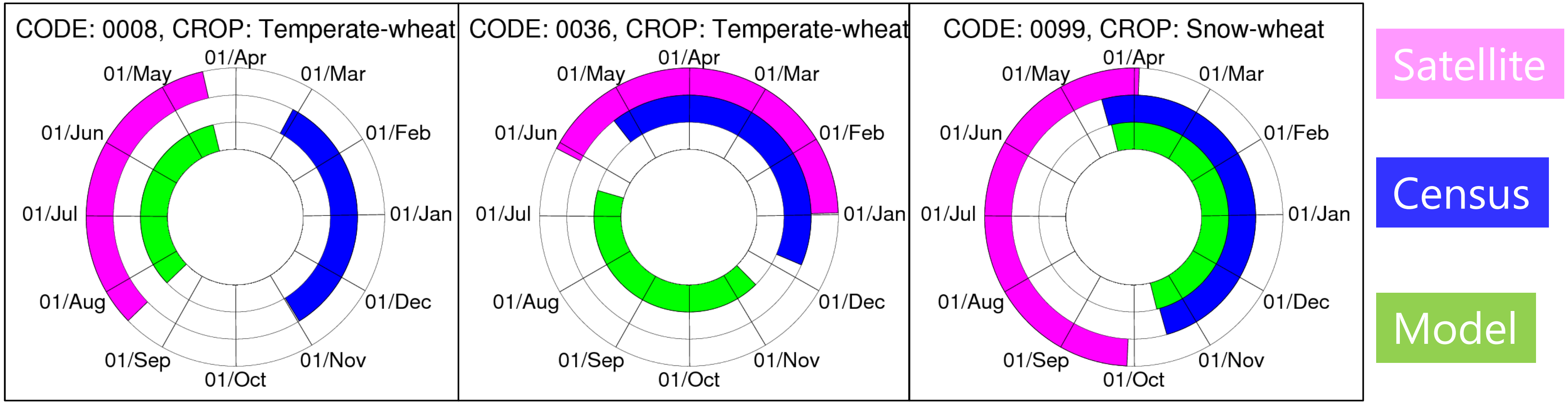
Estimated crop calendar (major crop)



Difference btw products



Summary and Challenges



Azerbaijan　　Australia (Queensland)　　China (Beijing)

- Major sources of uncertainty
  - Spring or winter wheat
  - Census-based: no data region (U.N.'s survey)
  - Model-based: sowing date (human's decision)
  - Satellite-based : land cover (grass or cropland)

Thank you for your attention