July 18, 2024, IPWG-11, Tokyo

Advances and applications of satellite data assimilation of clouds, precipitation, and the ocean

Data Assimilation Team

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History of LETKF implementation

- 2005 SPEEDY-LETKF *(Miyoshi, Ph.D. thesis)*
- 2006 NHM-LETKF *(Miyoshi and Aranami, SOLA)*
- 2007 AFES-LETKF *(Miyoshi and Yamane, MWR)*
- 2007 GSM-LETKF *(Miyoshi and Sato, SOLA)*
- 2010 MarsGCM-LETKF *(Hoffman et al., Icarus)*
- 2010 MASINGAR-LETKF *(Sekiyama et al., ACP)*
- 2010 SPRINTARS-LETKF *(Schutgens et al., ACP)*
- 2012 WRF-LETKF *(Miyoshi and Kunii, Pure and Appl. Geophys.)*
- 2012 ROMS-LETKF *(Hoffman et al., J. Atmos. Oceanic Tech.)*
- 2014 IsoGCM-LETKF *(Yoshimura et al., JGR)*
- **2015 NICAM-LETKF *(Terasaki, Sawada, Miyoshi, SOLA)***
- 2017 SCALE-LETKF *(Lien et al., SOLA)*
- **2022 sbPOM-LETKF *(Ohishi et al., GMD)***
- More… (e.g., AFES-Venus-LETKF, …)

Project Overview (FY2013-21)

GPM

NICAM

(JAXA)

Local Ensemble Transform Kalman Filter
(Hunt et al. 2007)

Goal: Look for most effective use of GPM precipitation measurements.

Project Overview (FY2022-)

GPM

AMSR3&GCOM-W

GCOM-C, EarthCARE

NICAM

sbPOM

(JAXA)

Local Ensemble Transform Kalman Filter

(Hunt et al. 2007)

Goal: Look for most effective use of satellite observations for clouds, precipitation, and the ocean

Research plans

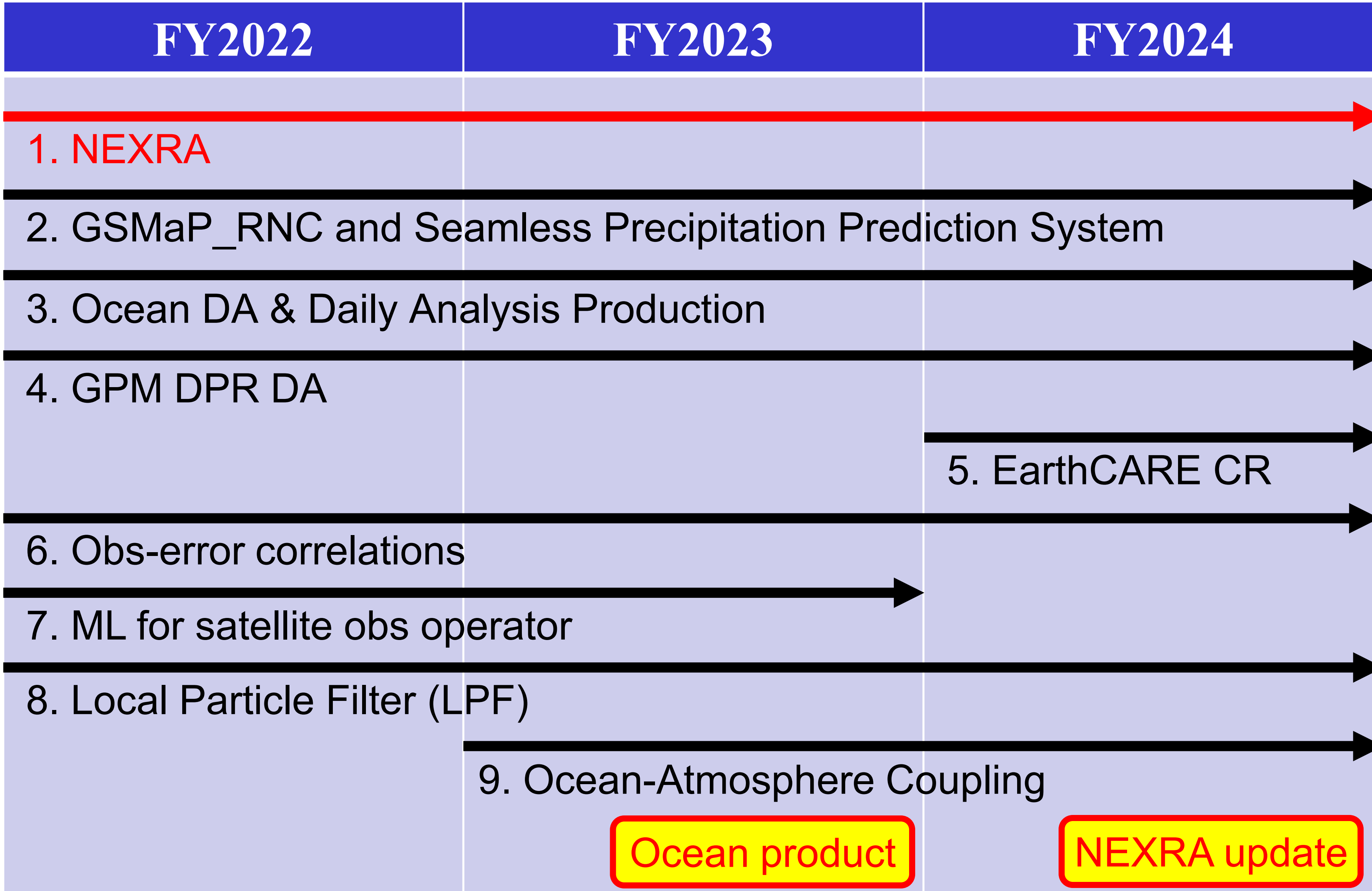
FY2022	FY2023	FY2024

1. NEXRA
2. GSMaP_RNC and Seamless Precipitation Prediction System
3. Ocean DA & Daily Analysis Production
4. GPM DPR DA
5. EarthCARE CR
6. Obs-error correlations
7. ML for satellite obs operator
8. Local Particle Filter (LPF)
9. Ocean-Atmosphere Coupling

Ocean product

NEXRA update

Research plans

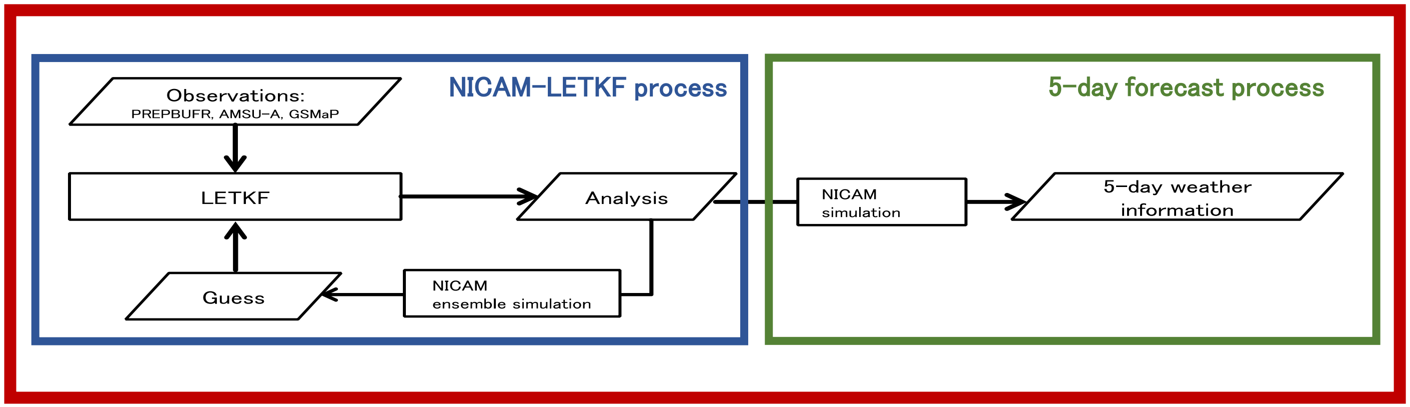


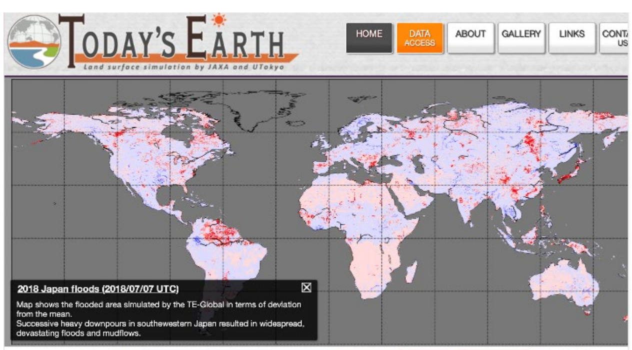
NEXRA: overview

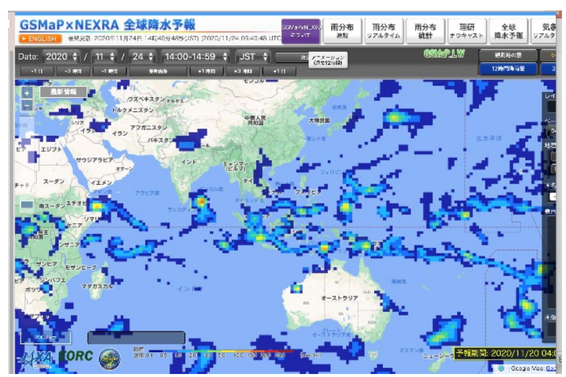
NICAM-LETKF JAXA Research Analysis

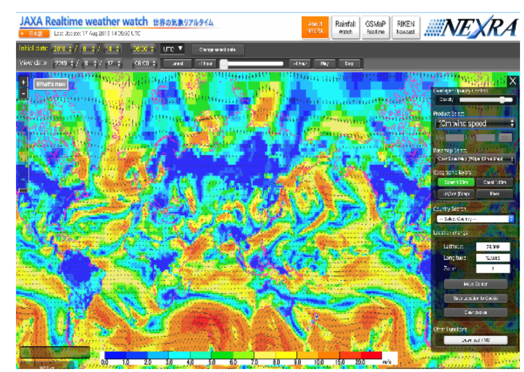
- A 5-day semi-realtime weather prediction system
- Co-developed by AORI, RIKEN, and JAXA.
- https://www.eorc.jaxa.jp/theme/NEXRA/index_e.htm

DA cycle: 6 hourly (00, 06, 12, 18 UTC)
Resolution: Glevel-6（**112 km**）
Ensemble size: **128**
Assimilated Observations: PREPBUFR, AMSU-A, and GSMaP



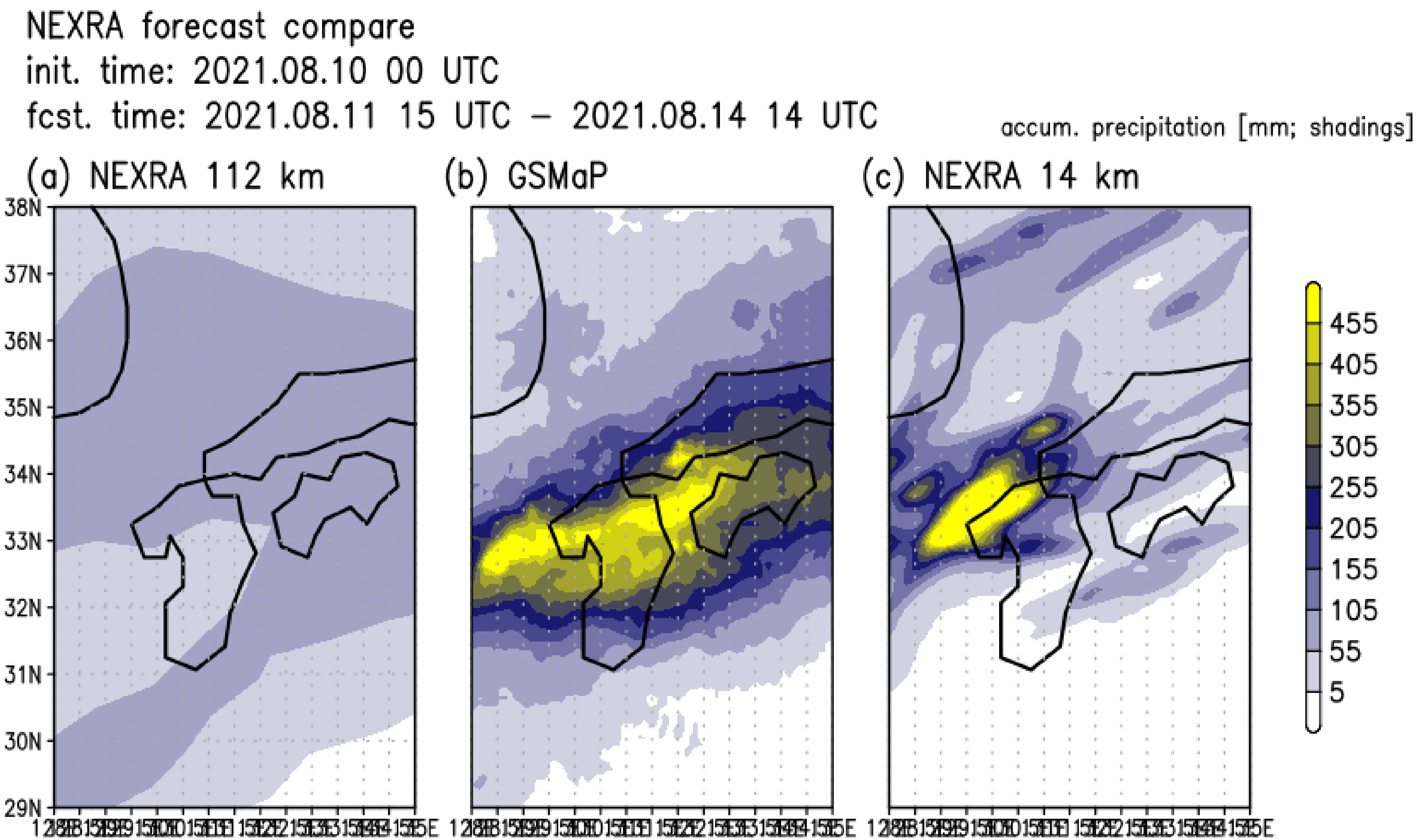






NEXRA_2.0 14 km ensemble forecast test

- Accumulated precipitation
- Initial time：**8/10 09JST (00UTC)**
- Duration：08/12 00JST–08/14 23JST



DA cycle and Forecast of NEXRA 2.0/3.0

DA cycle (LETKF)	NEXRA 2.0	NEXRA 3.0
NICAM version	16.2 (bug on land surface precipitation)	21.1 (bug fix, Optimized A64fx)
Horizontal res.	112km (GL06)	56 km (GL07)
Vertical layer	38	78
Cloud microphysics	LSC	NSW6-Roh
Cumulus parameterization	PAS	None
Member	128	128
Analysis(Forecast)	U, V, W, T, Qv, (Qc)	U, V, W, T, Qv, (Qc, Qr, Qi, Qs, Qg)
Observation	Prepbufr, Amsu-A, GSMaP, mhs, atms	Same as the left column

Deterministic Forecast	NEXRA 2.0	NEXRA 3.0
NICAM version	16.2 (bug on land surface precipitation)	21.3 (bug fix, Optimized A64fx)
Horizontal res.	14 km (GL09)	14 km (GL09)
Vertical resolution	38	78
Cloud process	NSW6	NSW6-Roh +(Cumulus Parameterization?)
ATM initial condition	Pressure level NEXRA ens-mean(26 layer) P, U, V, W, T, Qv, Qc,	Model level NEXRA ens-mean(78 layer) P, U, V, W, T, Qv, Qc, Qr, Qi, Qs, Qg
LND initial condition	Climatology	A forecast ensemble member

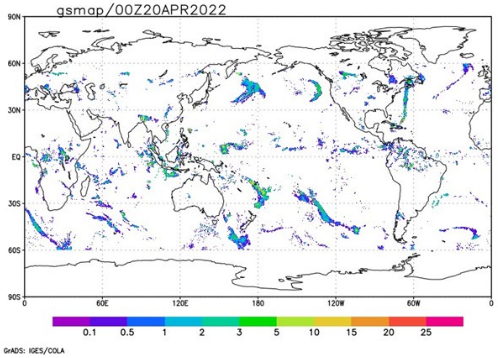
Impact of Cumulus Parameterization (CP) using NICAM

Hourly rain[mm/hr]

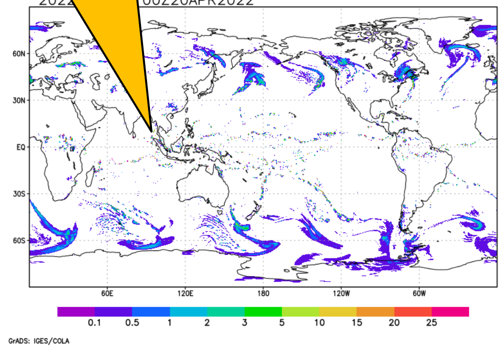
Little rainfall

NICAM GL09 (dx=14km) <u>**1-day forecast**</u>

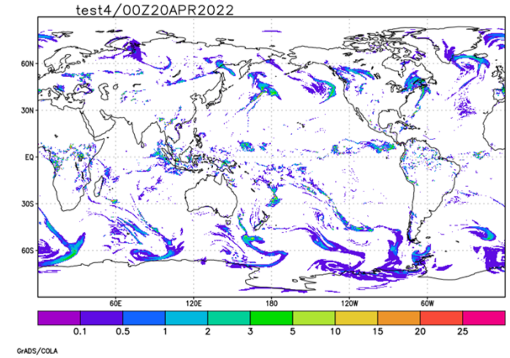
GSMaP (dx=0.1°)



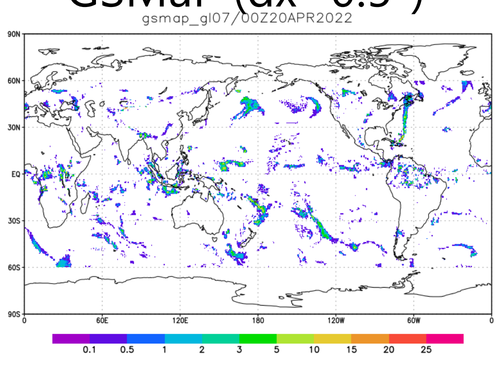
w/o CP



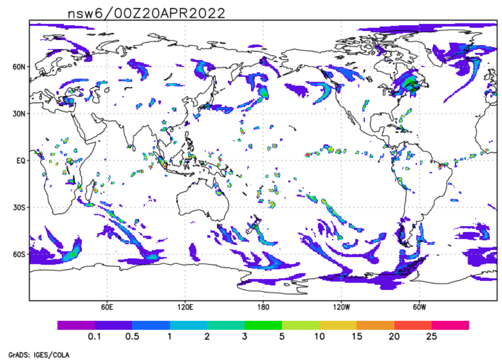
with CP

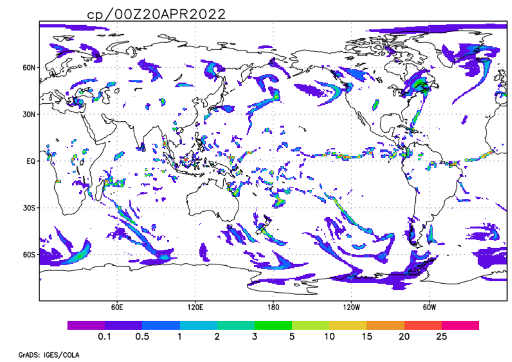


GSMaP (dx=0.5°)



GL07 (dx=56 km)





Cumulus Parameterization (CP) would be required for NEXRA (GL09).

Sensitivity experiments using NEXRA

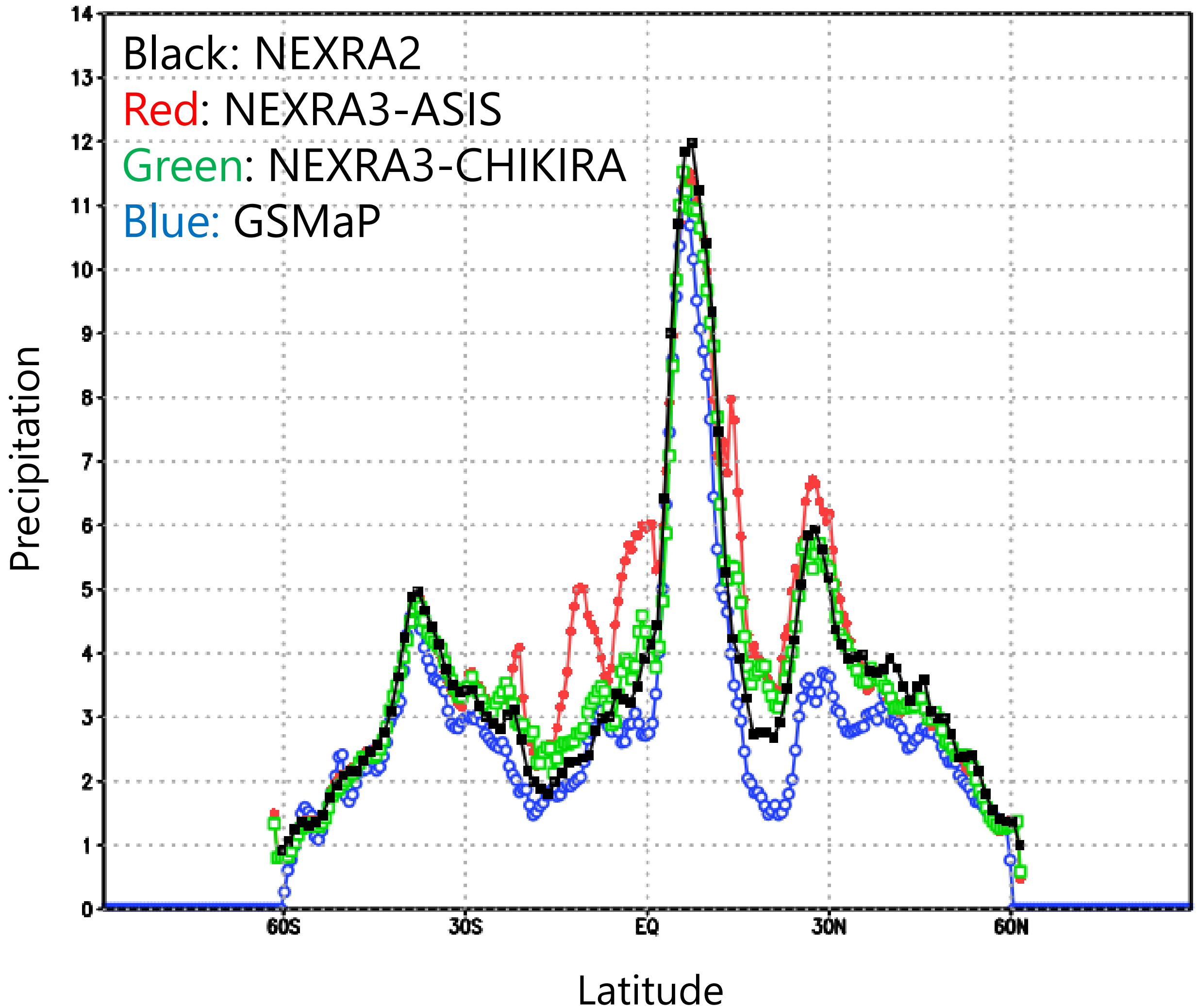
	Resolution	Cloud	Convection
NEXRA2.0	GL06 (dx=112km)	LSC	PAS
NEXRA3.0 -ASIS	GL07 (dx=56 km)	NSW6-Roh	None
NEXRA3.0 -CHIKIRA	GL07	NSW6-Roh	CHIKIRA

Data Assimilation period: 2022/04/16 0600UTC-2022/05/31 1800UTC

Analysis period: 2022/05/16 0600UTC-2022/05/31 1800UTC (half month)

Ensemble size: 32

Zonal-mean Precipitation



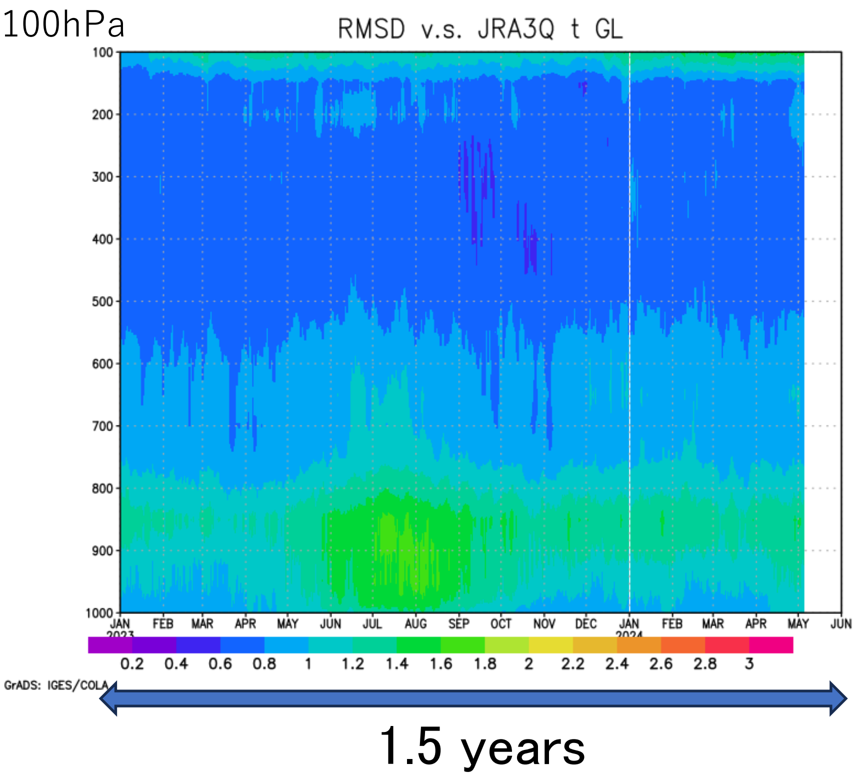
NEXRA3-ASIS overestimated precipitation compared with GSMaP.

→ **NEXRA3-CHIKIRA would be the most accurate.**

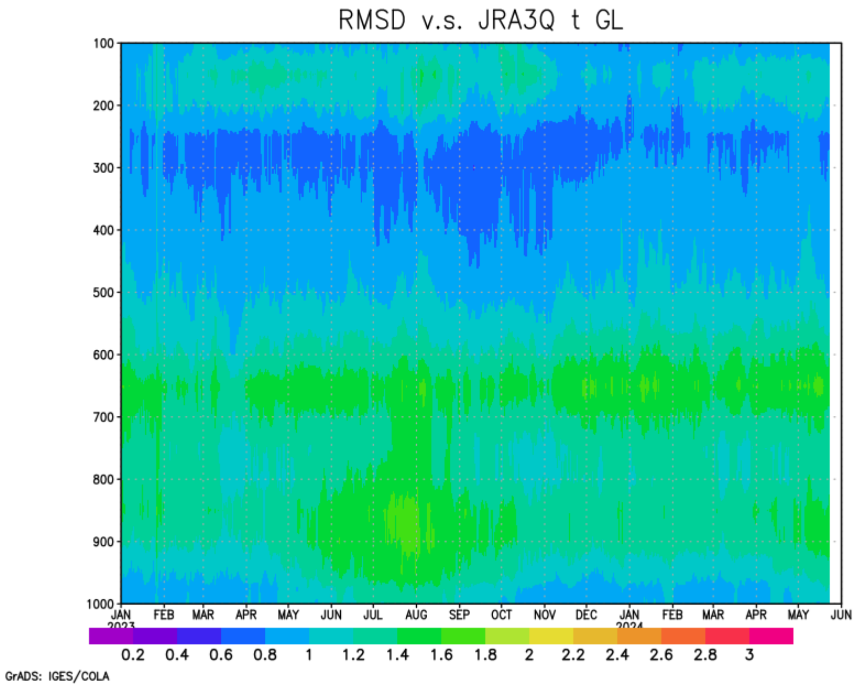
Compare between NEXRA2 and NEXRA 3 (LETKF, analysis mean)

- RMSD time series of temperature vs. JRA3Q : NEXRA 3 is better

NEXRA3.0



NEXRA2.0

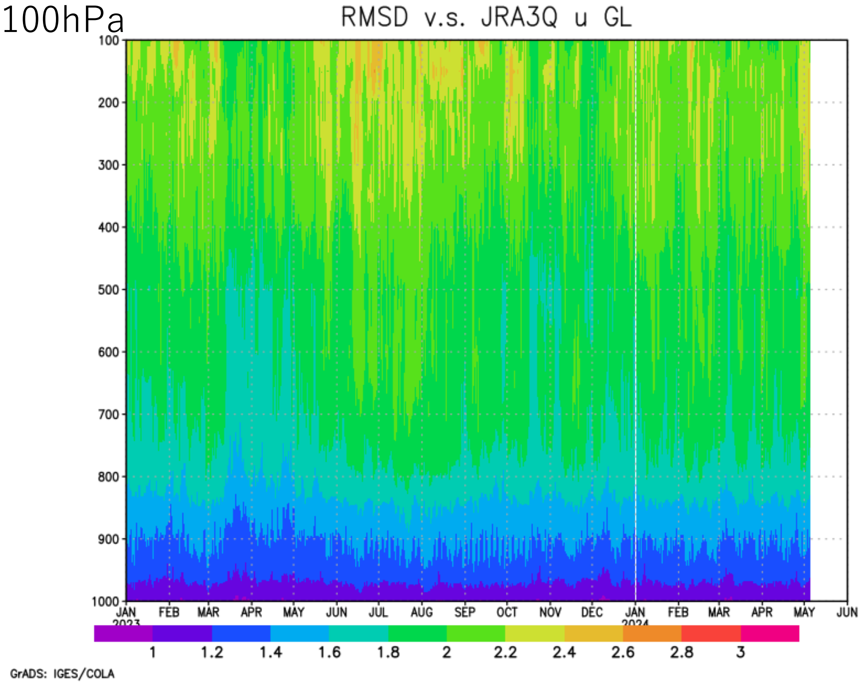


Compare between NEXRA2 and NEXRA 3 (LETKF, analysis mean)

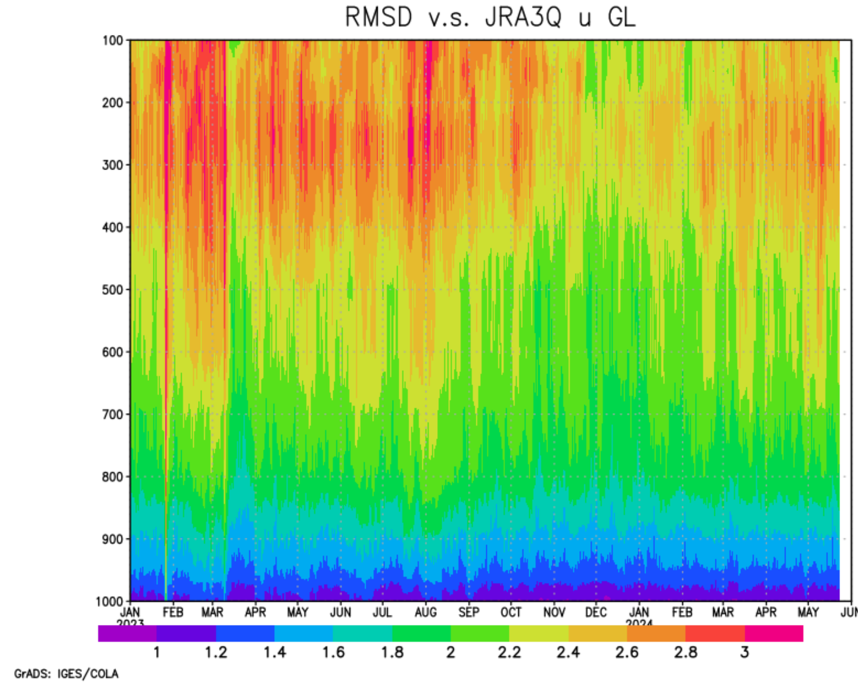
- RMSD time series of zonal winds vs. JRA3Q : NEXRA 3 is better

NEXRA3.0

100hPa



NEXRA2.0

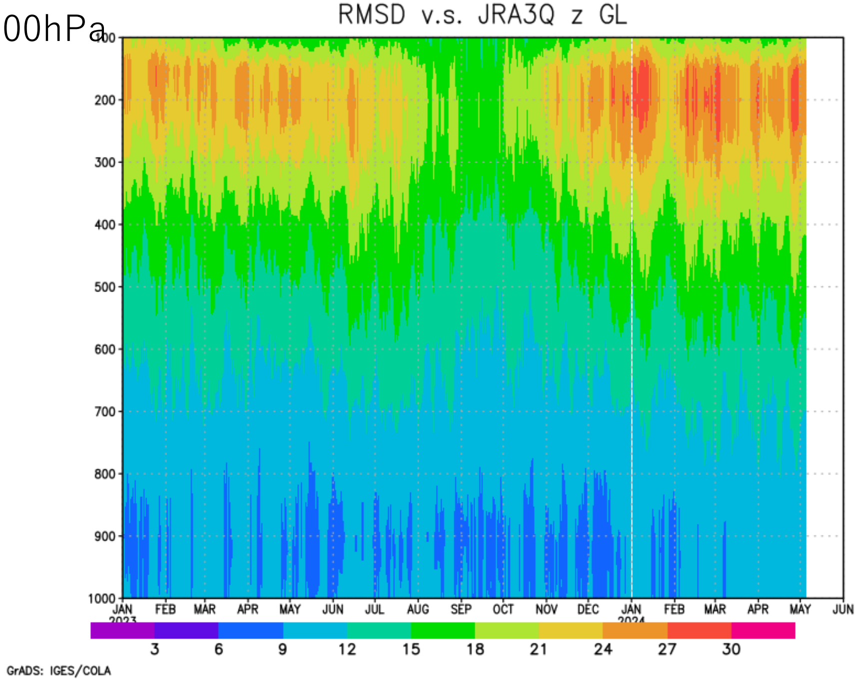


Compare between NEXRA2 and NEXRA 3 (LETKF, analysis mean)

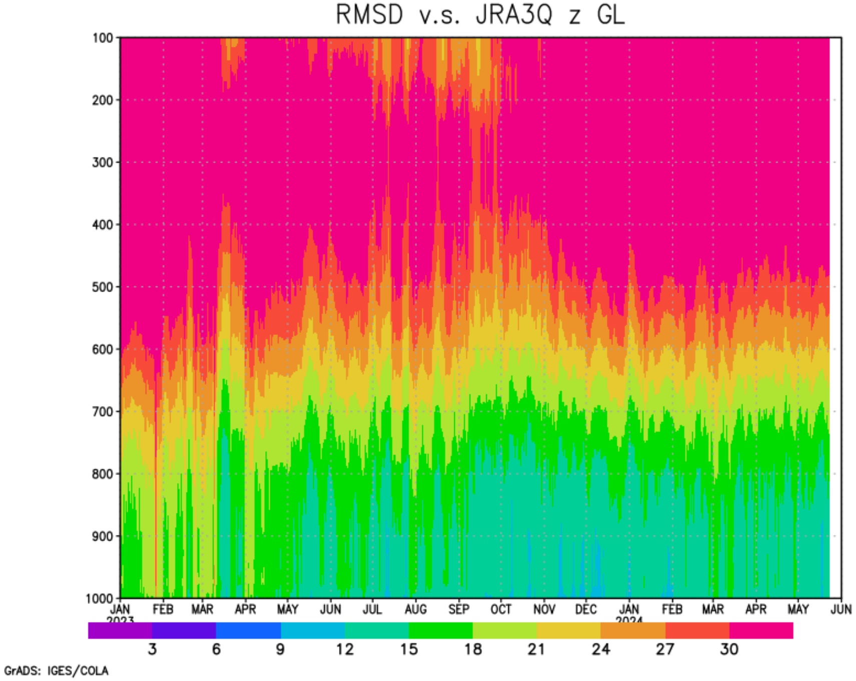
- RMSD time series of geopotential height vs. JRA3Q : NEXRA 3 is better

NEXRA3.0

100hPa

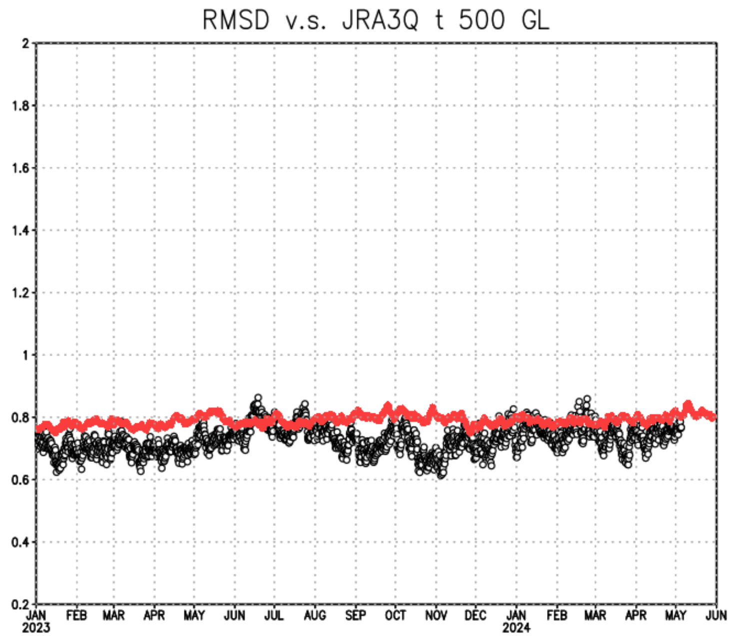


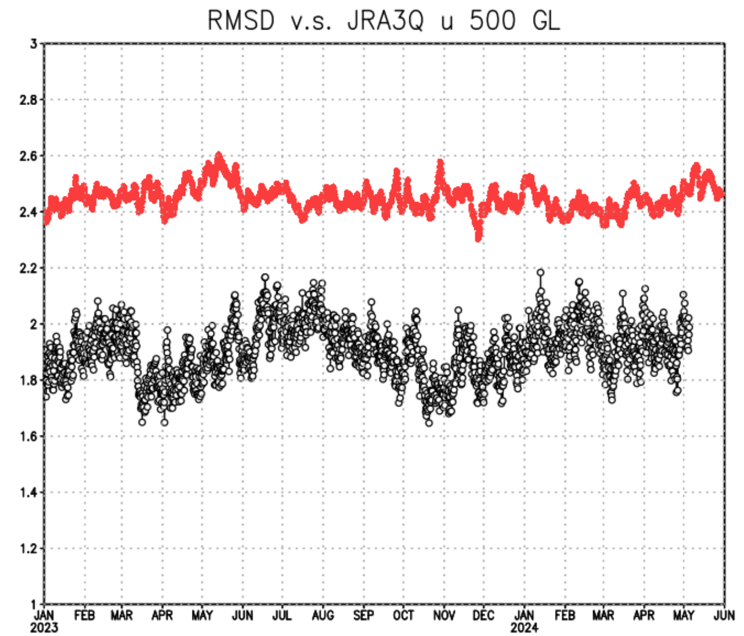
NEXRA2.0



NEXRA3.0 analysis

- Time series of RMSD(Black)、Spread(red) 500hPa 60N-60S



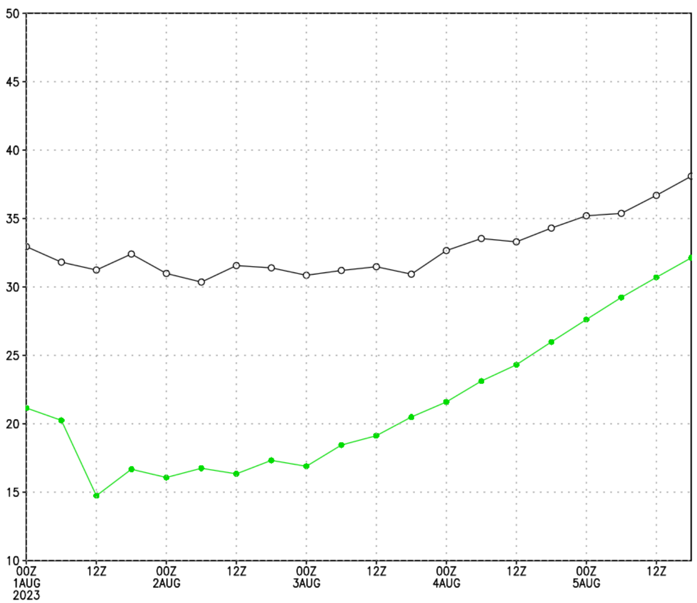


NEXRA 3.0 5 day forecast

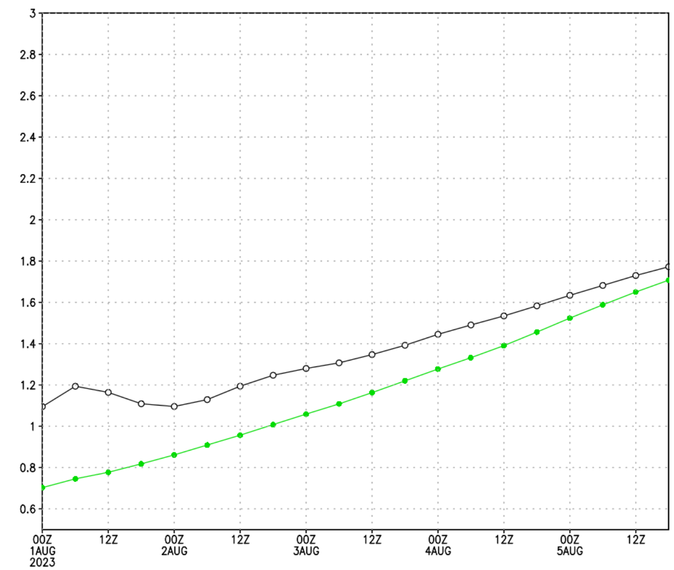
- 2023/08/01-31 (120+ forecasts are used)
- RMSD time series vs. JRA3Q : NEXRA 3 is better

Black : NEXRA2
Green : NEXRA3

z500@NH



T500@NH

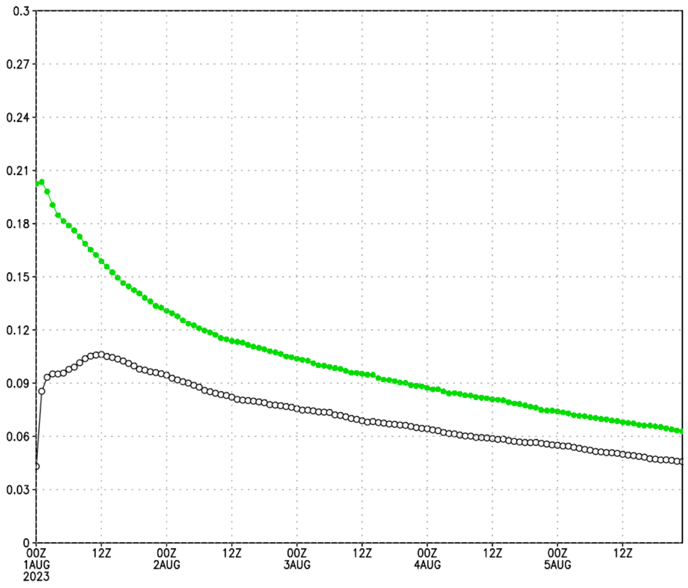


NEXRA 3.0 forecast

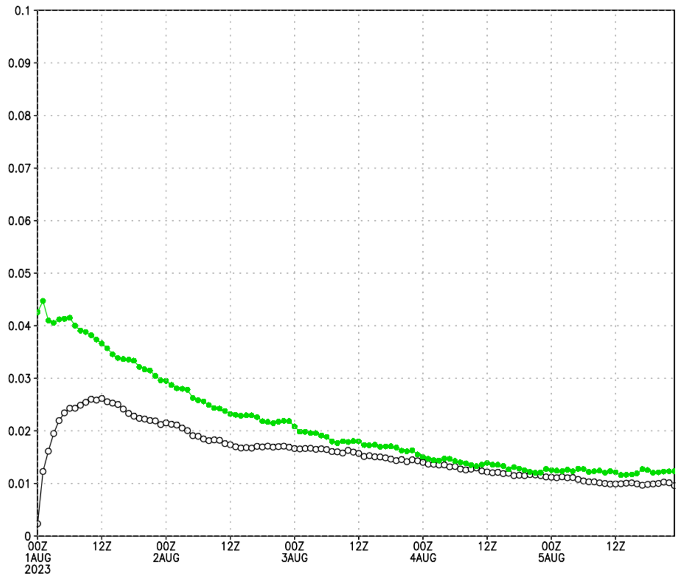
- Thread score vs. GsMAPv8

Black：NEXRA2
Green：NEXRA3

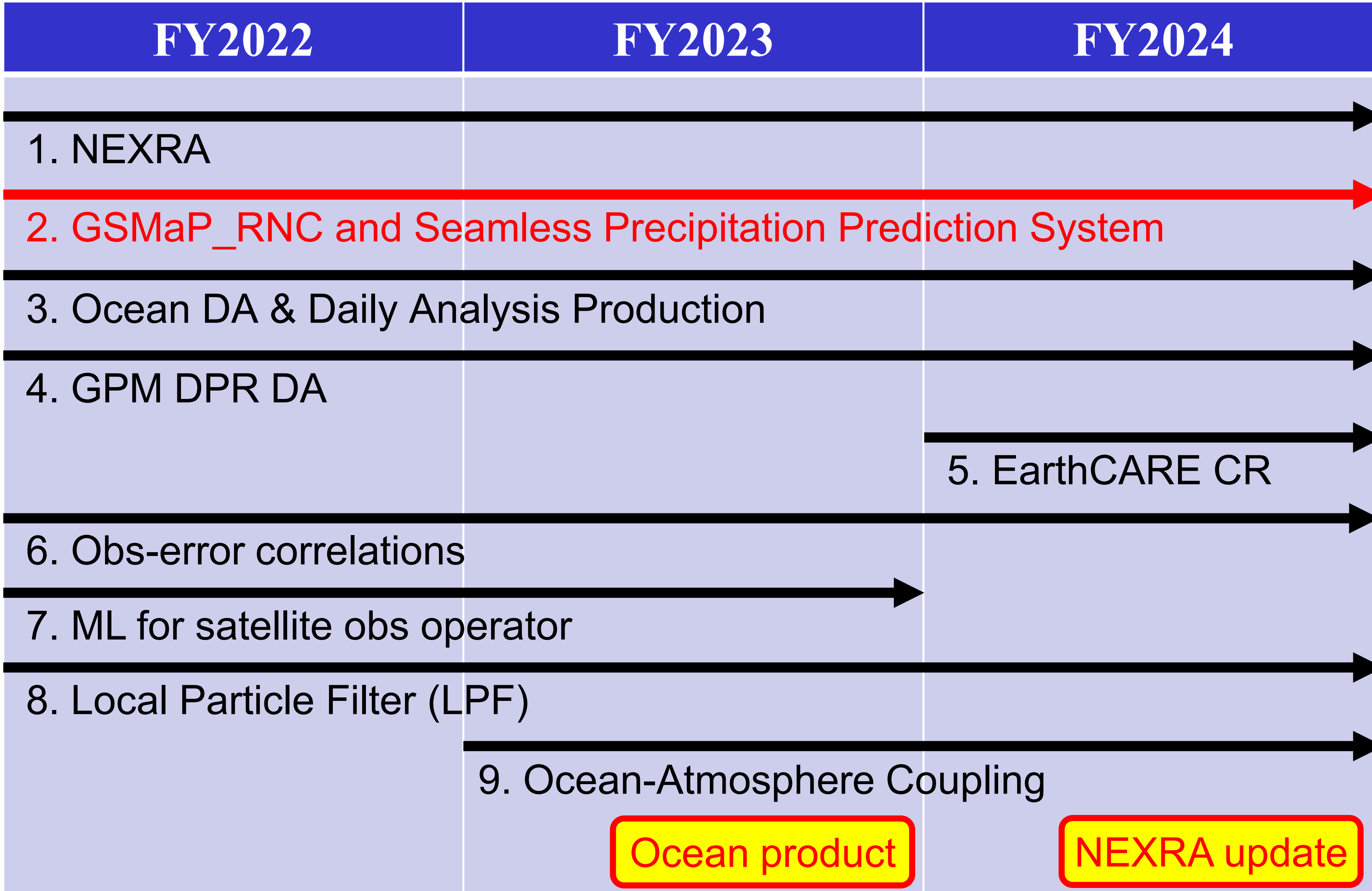
Over 0.5 mm/hr, 60N-60S



Over 5 mm/hr , 60N-60S

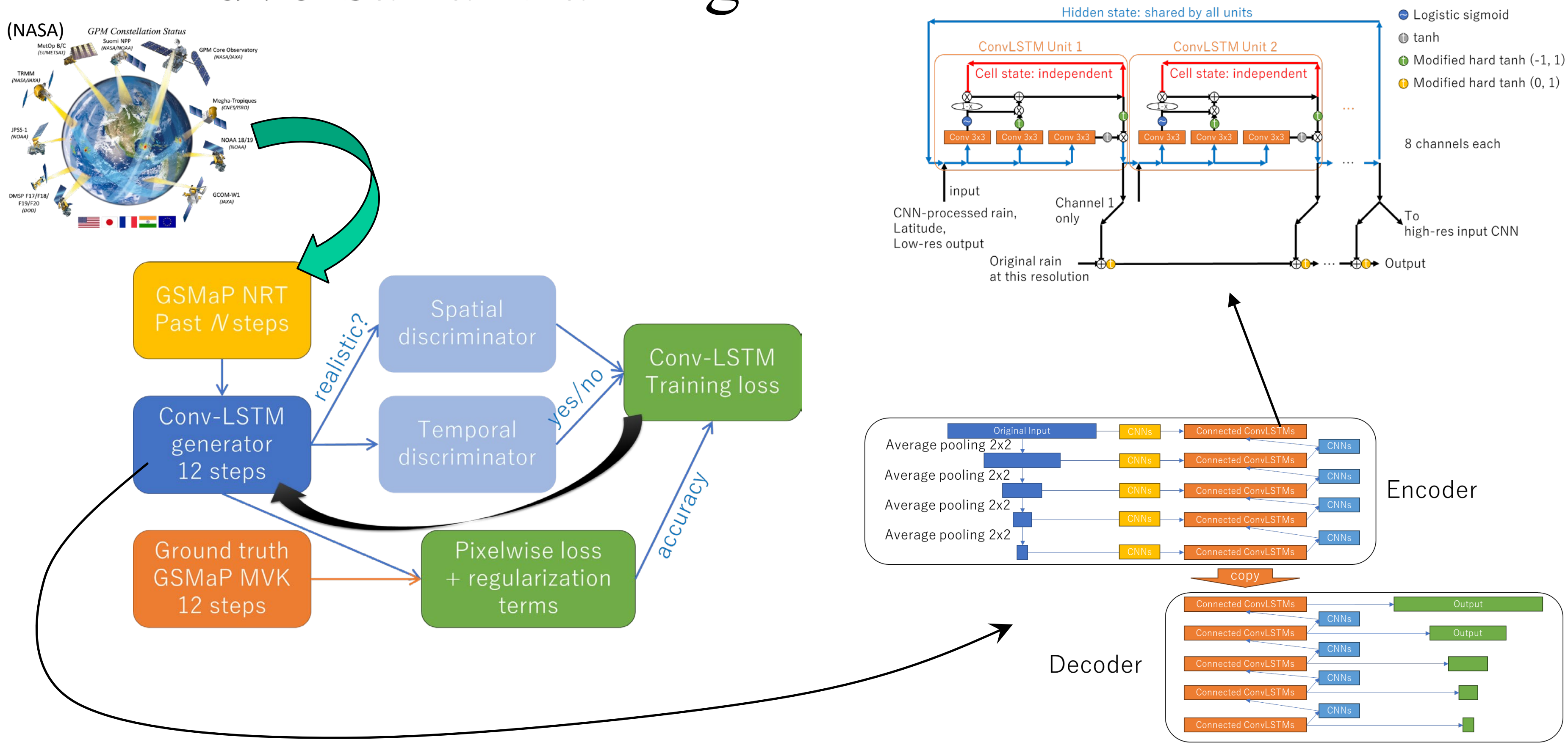


Research plans



Machine Leaning approach for nowcasting

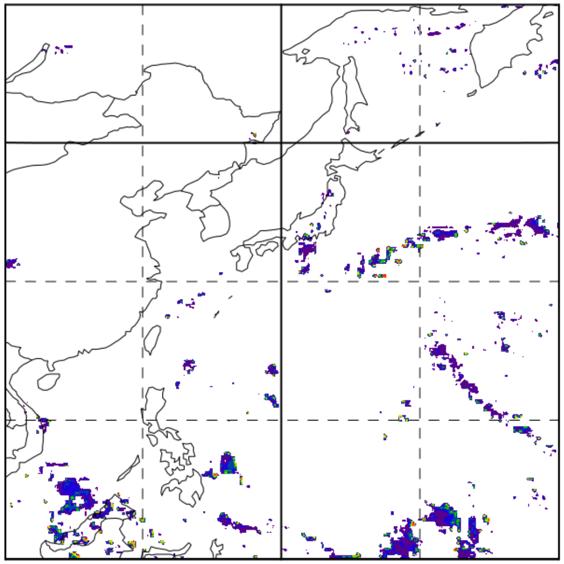
- GSMaP-based AI forecast
- ConvLSTM-based encoder-decoder
- Adversarial training



Machine Leaning approach for nowcasting

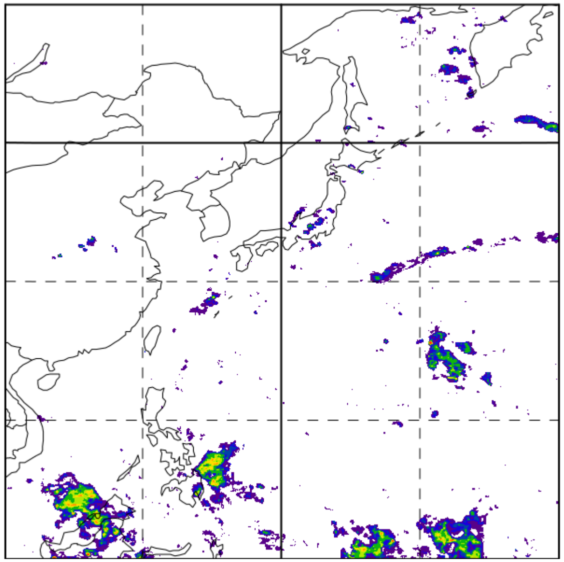
Previous version

forecast 12 h

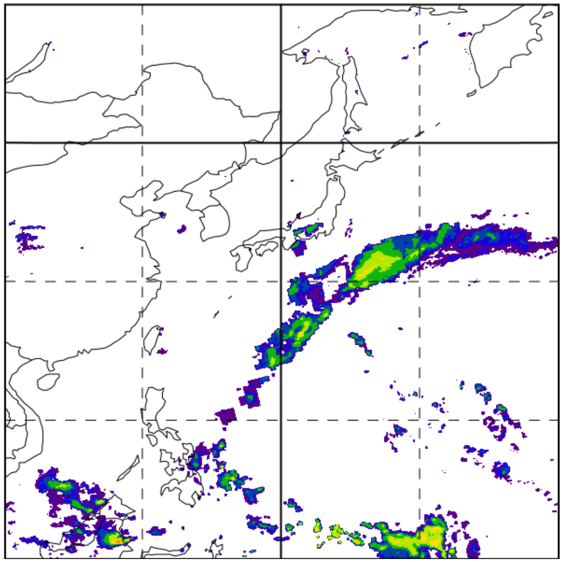


New version

forecast 12 h

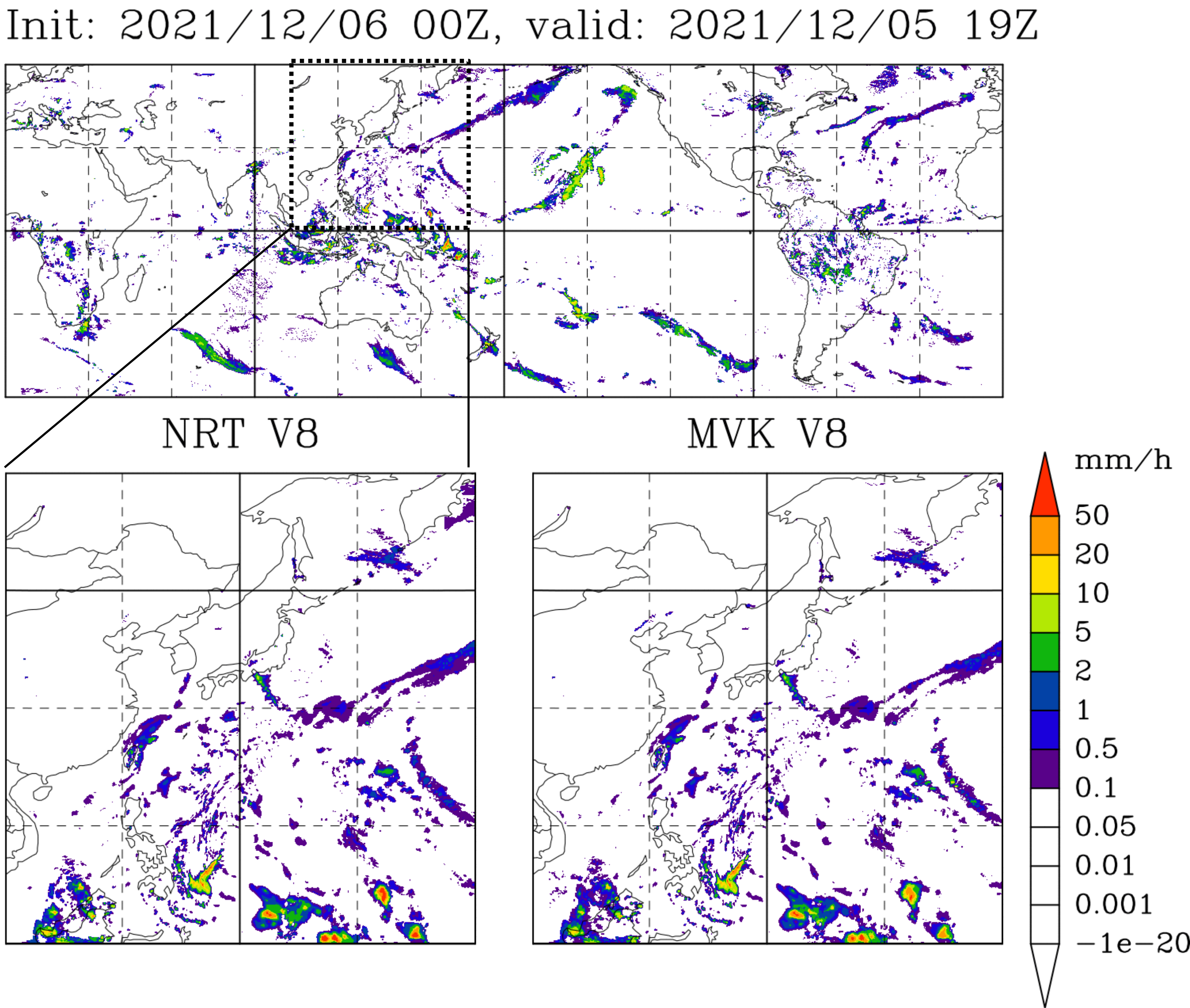


MVK V8

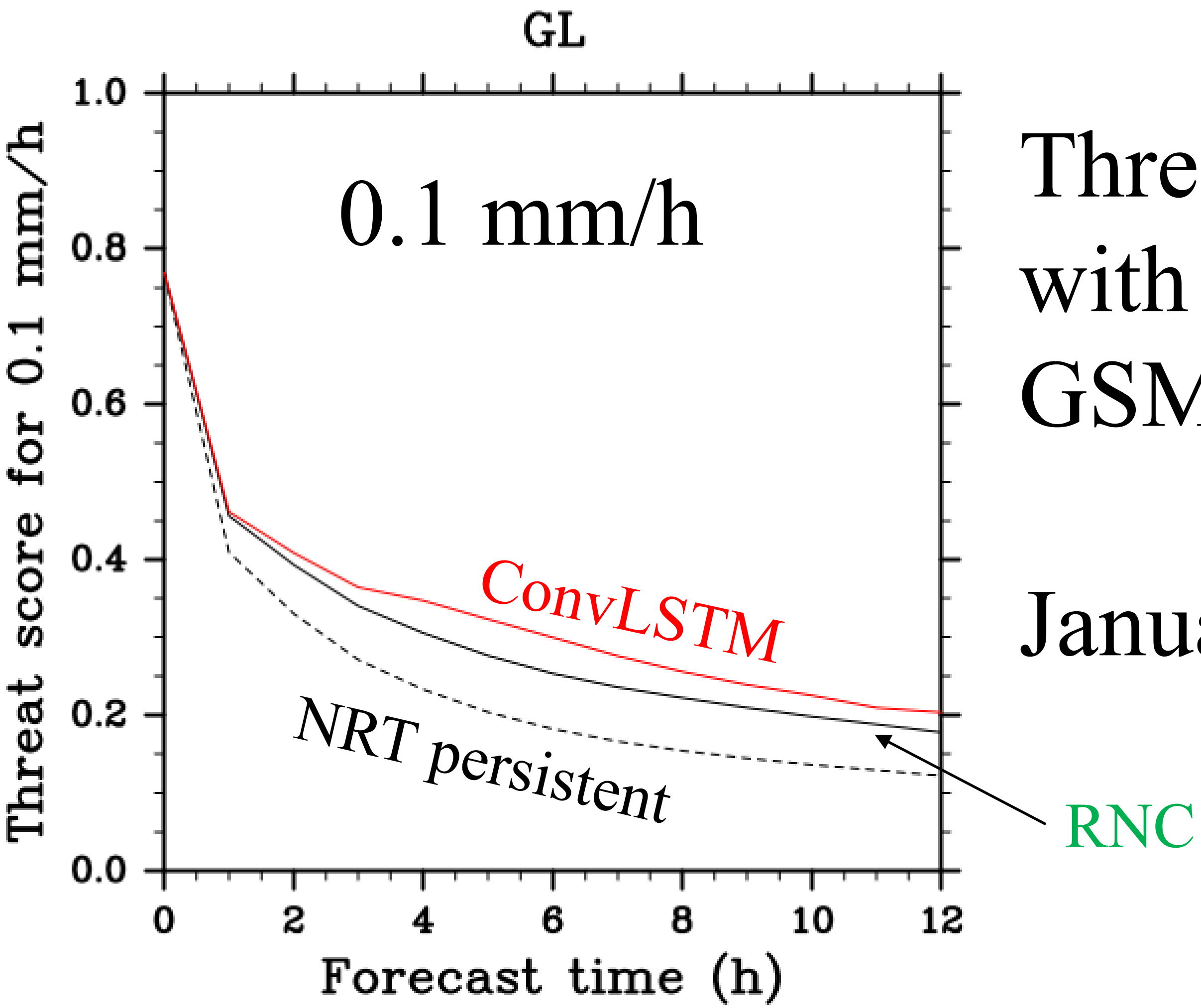


Machine Leaning approach for nowcasting

New version



Machine Leaning approach for nowcasting



Threat scores with respect to GSMaP MVK

January 2024

MVK/NRT v8-based

Research plans

FY2022	FY2023	FY2024

1. NEXRA
2. GSMaP_RNC and Seamless Precipitation Prediction System
3. Ocean DA & Daily Analysis Production
4. GPM DPR DA
5. EarthCARE CR
6. Obs-error correlations
7. ML for satellite obs operator
8. Local Particle Filter (LPF)
9. Ocean-Atmosphere Coupling

Ocean product

NEXRA update

Machine Learning for satellite obs. operator

$$\boldsymbol{x}^a = \boldsymbol{x}^f + \mathbf{K}\boxed{\left[\boldsymbol{y} - H\left(\boldsymbol{x}^f\right)\right]}$$

Nonlinear obs. operator

(1) Physically-based Observation Operator (P-OO)

$\boldsymbol{y}$: Observation (e.g., Satellite radiance) **−** $H\left(\boldsymbol{x}^f\right)$: Forecast in obs. space (e.g., Radiance) ← ***H*: Physical Model (RTTOV)** ← $\boldsymbol{x}^f$: Forecast in model space (e.g., Temperature)

Issue: Large effort to develop observation operator *H*

(2) Machine Learning (ML) Observation Operator (ML-OO)

$\boldsymbol{y}$: Observation (e.g., Satellite radiance) **−** $H\left(\boldsymbol{x}^f\right)$: Forecast in obs. space (e.g., Radiance) ← ***H*: Machine Learning (DNN)** ← $\boldsymbol{x}^f$: Forecast in model space (e.g., Temperature)

↑ Training

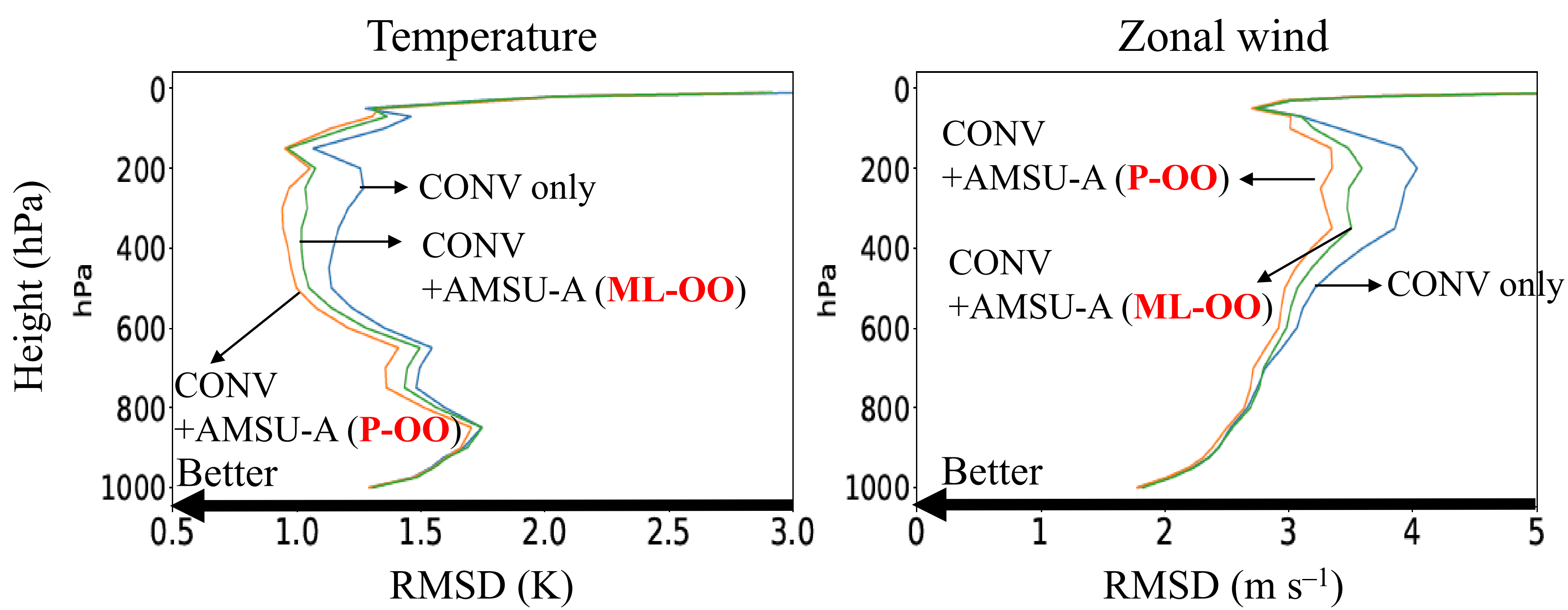
$\boldsymbol{y}$: Observation (AMSU-A)
$\boldsymbol{x}^a$: Analysis (Temperature)

Goal: Build ML-OO without physical-based model

Validation relative to ERA Interim

- Sensitivity experiment
  - CONV+AMSU-A（with bias correction) (P-OO)
  - CONV+AMSU-A (ML-OO)
  - CONV only

- Spatiotemporally averaged RMSD over the global and 1 month



ML-OO is slightly worse than P-OO,
but it is better than assimilating only CONV observations.

Liang et al. (2023; JMSJ)

Journal of the Meteorological Society of Japan, **101**(1), 79−95, 2023. doi:10.2151/jmsj.2023-005 **79**

A Machine Learning Approach to the Observation Operator for Satellite Radiance Data Assimilation

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(Manuscript received 1 September 2021, in final form 13 October 2022)

Abstract

The observation operator (OO) is essential in data assimilation (DA) to derive the model equivalent of observations from the model variables. In the satellite DA, the OO for satellite microwave brightness temperature (BT) is usually based on the radiative transfer model (RTM) with a bias correction procedure. To explore the possi-

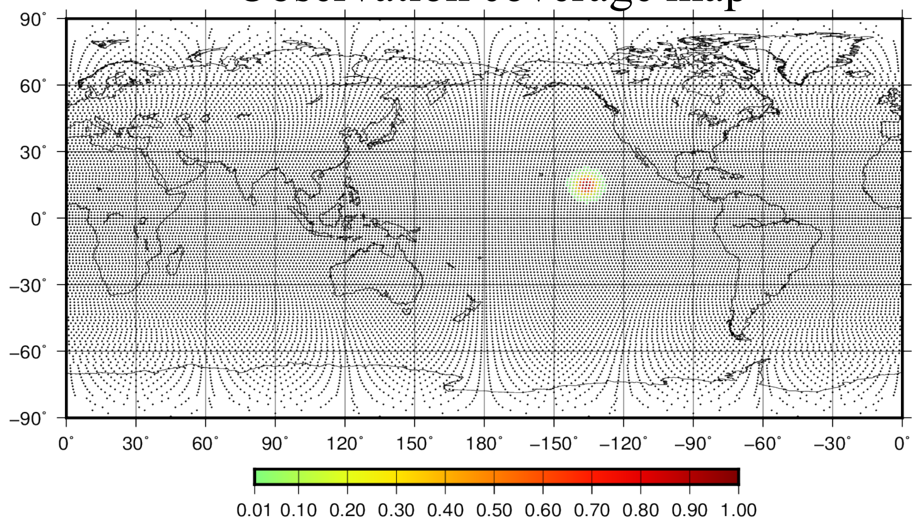
Research plans

FY2022	FY2023	FY2024
1. NEXRA	→	→
2. GSMaP_RNC and Seamless Precipitation Prediction System	→	→
3. Ocean DA & Daily Analysis Production	→	→
4. GPM DPR DA	→	→
		5. EarthCARE CR
6. Obs-error correlations	→	→
7. ML for satellite obs operator	→	
8. Local Particle Filter (LPF)	→	→
	9. Ocean-Atmosphere Coupling	→
	Ocean product	NEXRA update

Idealized Experiment with NICAM-LETKF

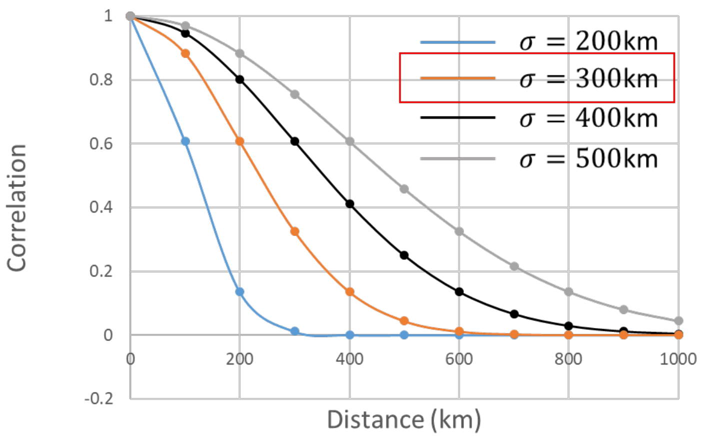
- Simulated observations with Δx = 150 km
  - <u>Error standard deviations</u>
    - T = 2 (K),   U & V = 4 (m/s)
  - <u>Error correlations</u>
    - 15 pressure levels
    - No correlation in different levels
    - **Condition number > 10^{10}**

Observation coverage map



Error correlations:
Use Gaussian Function

$$(R_{i,j}) = e^{\left[\frac{1}{2}\left(\frac{d(i,j)}{\sigma}\right)^2\right]}$$

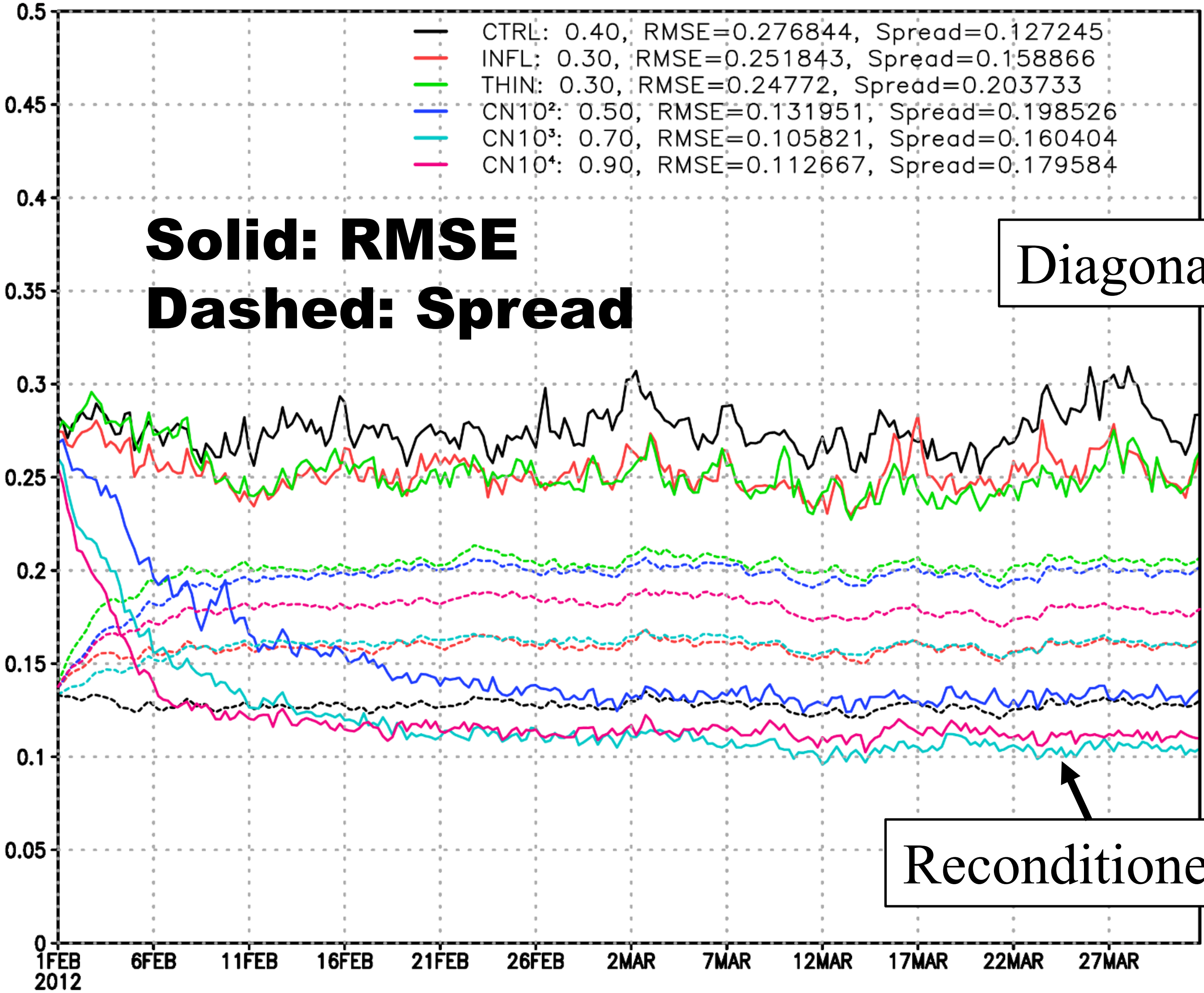


Error correlation for the observation located at 136.047°W and 14.887°N

Reconditioning the **R** Matrix

- The purpose of reconditioning is to stabilize the LETKF by reducing the condition number of the R matrix (cf. *Weston et al. 2014* for 4D-VAR)
  - $\lambda_{inc} = \frac{\lambda_{max} - \lambda_{min}\kappa_{req}}{\kappa_{req} - 1} \approx \frac{\boldsymbol{\lambda_{max}}}{\boldsymbol{\kappa_{req}}}$
    - *Friedman et al. (1981)* estimate the largest eigenvalue of correlation matrix
      - $\lambda_{max} \geq 1 + (n-1)\bar{r}$, where $\bar{r}$ is the average of the non-diagonal components

(K) Analysis RMSE of temperature at 500 hPa



Diagonal R is not optimal

Reconditioned to 10^3 is the best

Summary of Idealized Experiments (1/2)

- Monthly-mean analysis RMSE (T at 500 hPa)
  - Experiments with diagonal **R** (Monthly mean of March)

	RTPS parameter				
	0.2	0.3	0.4	0.5	0.6
CTRL	0.3095	0.2772	0.2768	0.2798	0.2914
INFL	0.2591	0.2518	0.2522	0.2577	0.2705
THIN	0.2541	0.2477	0.2496	0.2598	0.2710

  - Experiments with non-diagonal **R** (Gray: No experiment)

	RTPS parameter							
	0.4	0.5	0.6	0.7	0.8	0.9	0.95	1.0
Full R							F/D	F/D
CN10^2	0.1362	0.1320	0.1386	0.1547				
CN10^3		F/D	0.1108	0.1058	0.1173	0.1595		
CN10^4			F/D	F/D	F/D	0.1127	0.1591	

Summary of Idealized Experiments (2/2)

- Monthly-mean analysis spread (T at 500 hPa)
  - Experiments with diagonal **R** (Monthly mean of March)

	RTPS parameter				
	0.2	0.3	0.4	0.5	0.6
CTRL	0.1086	0.1169	0.1272	0.1403	0.1557
INFL	0.1472	0.1589	0.1731	0.1921	0.2158
THIN	0.1889	0.2037	0.2225	0.2470	0.2767

  - Experiments with non-diagonal **R** (Gray: No experiment)

	RTPS parameter							
	0.4	0.5	0.6	0.7	0.8	0.9	0.95	1.0
Full R							F/D	F/D
CN10^2	0.1717	0.1985	0.2351	0.2854				
CN10^3		0.1118	0.1284	0.1604	0.2101	0.3110		
CN10^4			0.067	0.087	0.1183	0.1796	0.2802	

Terasaki and Miyoshi (2024, MWR)

Including the Horizontal Observation Error Correlation in the Ensemble Kalman Filter: Idealized Experiments with NICAM-LETKF

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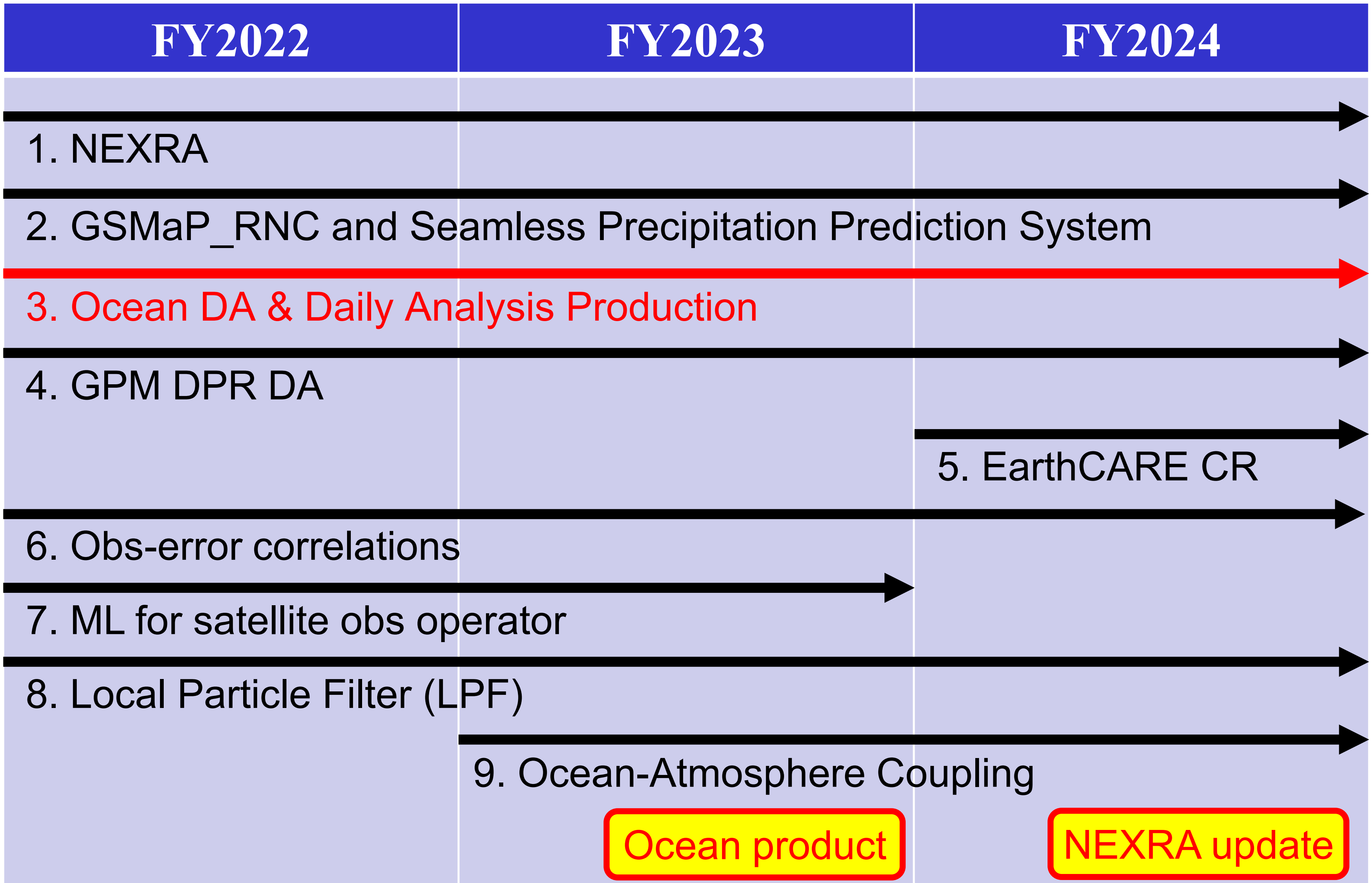
ABSTRACT: Densely observed remote sensing data such as radars and satellites generally contain significant spatial error correlations. In data assimilation, the observation error covariance matrix is usually assumed to be diagonal, and the dense data are thinned or spatially averaged to compensate for neglecting the spatial observation error correlation. However, in theory, including the spatial observation error correlation in data assimilation can make better use of the dense data. This study performs perfect model observing system simulation experiments (OSSEs) using the nonhydrostatic icosahedral atmospheric model (NICAM) and the local ensemble transform Kalman filter (LETKF) to assess the impact of assimilating horizontally dense and error-correlated observations. The condition number of the observation error covariance matrix, defined as the ratio of the largest to smallest eigenvalues, is important for the numerical stability of the LETKF computation. A large condition number makes it difficult to compute the ensemble transform matrix correctly. Reducing the condition number by reconditioning is found effective for stable computation. The results show that including the horizontal observation error correlation with reconditioning makes the analysis more accurate but requires 6 times more computations than the case with the diagonal observation error covariance matrix.

SIGNIFICANCE STATEMENT: It is important to effectively utilize observations in data assimilation for more accurate weather prediction. Spatially dense observations are known to have an error correlation that is ignored in the data assimilation. This study explores assimilating dense observations by explicitly including observation error correlations with an idealized experiment. The results shows that the analysis is improved by including the observation error correlations. Also, the condition number of the observation error covariance matrix is essential for stable computations.

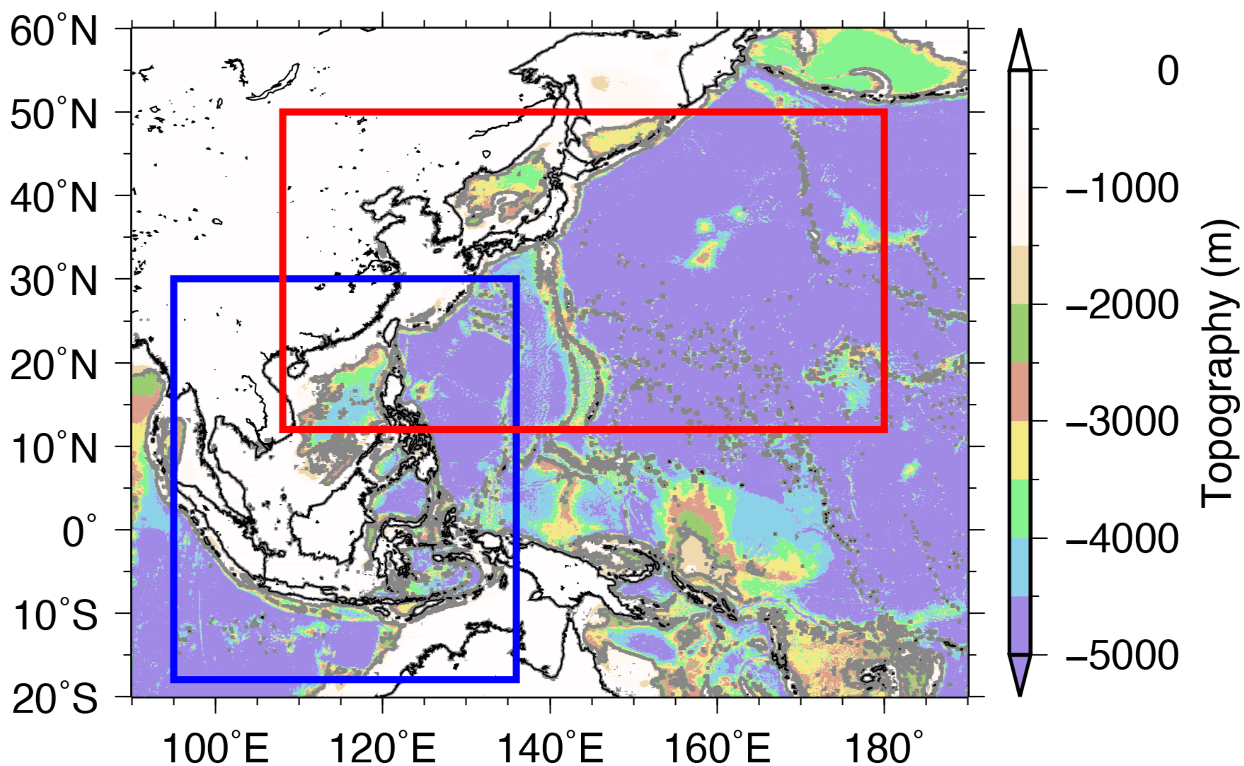
KEYWORDS: Atmosphere; Numerical weather prediction/forecasting; Data assimilation

Research plans



LORA: LETKF-based Ocean Research Analysis ver. 1.0

- Daily 3D-analysis ensemble mean and spread
- Daily 128 ensemble analyses at the sea surface
- Daily each term of MLT and MLS budget equations



Western North Pacific (WNP)
- dx = 0.1°, 50 σ-layers
- 2015.07–2024.01

Maritime Continent (MC)
- dx = 0.1°, 50 σ-layers
- 2015.07–2024.01

*LETKF: Local Ensemble Transform Kalman Filter (Hunt et al. 2007)

What's new in LORA ?

Currently not available

■ Global reanalysis datasets

3D-VAR	4D-VAR	KF	EnKF
5 datasets	2	2	**PEODAS**

■ High-resolution regional reanalysis datasets (dx < 1/10°) in **the Pacific region**

3D-VAR	4D-VAR	KF	EnKF
JCOPE2M (JAMSTEC) FRA-ROMS (FRA)	FORA-WNP30 (MRI & JAMSTEC)	DREAMS (Kyushu Univ.)	**LORA**

(c.f. Balmaseda et al. 2015; Martin et al. 2015)

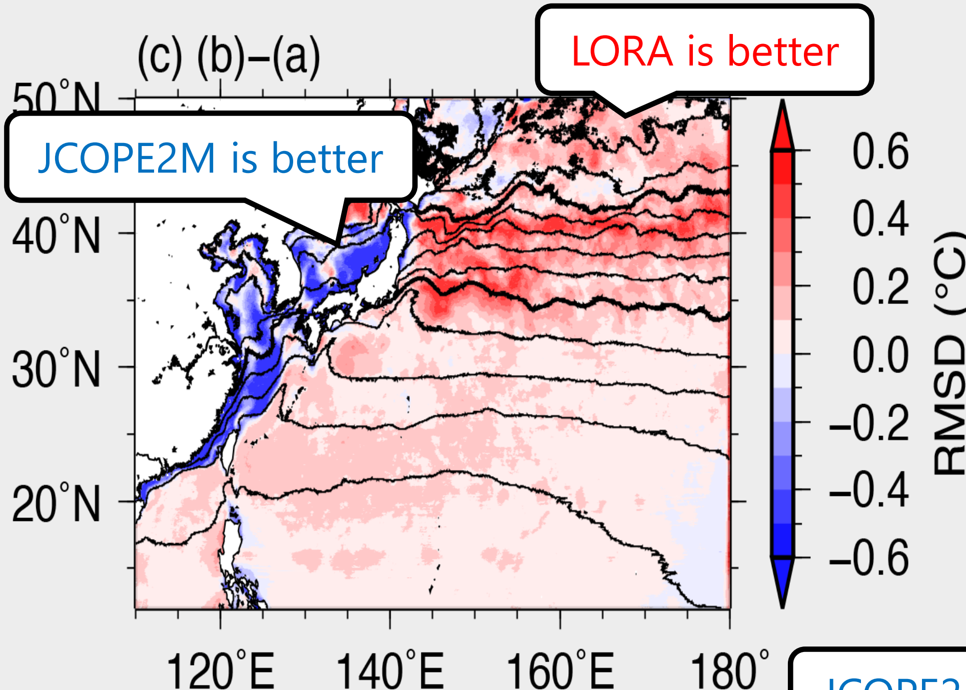
***3 (4)D-VAR:** 3 (4) Dimensional VARiational data assimilation

*__KF:__ Kalman Filter *__EnKF:__ Ensemble Kalman Filter

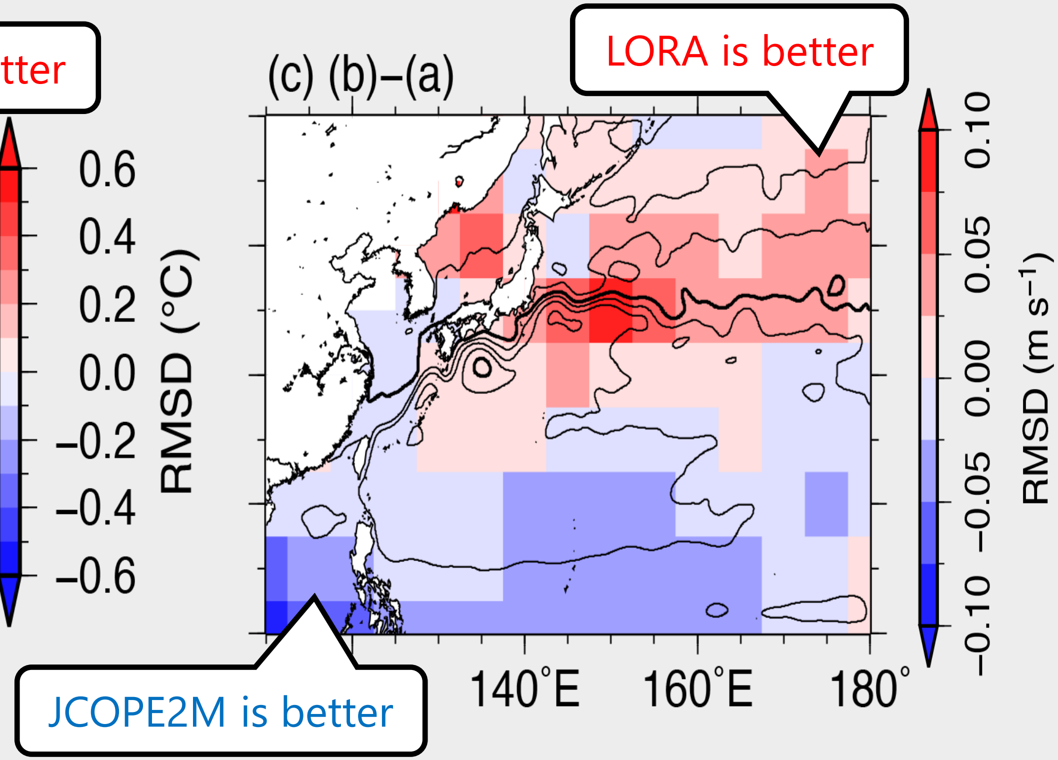
New high-resolution ensemble analysis product in the Pacific region

■ RMSD differences between JCOPE2M (3D-VAR product) and LORA

Sea surface temperature

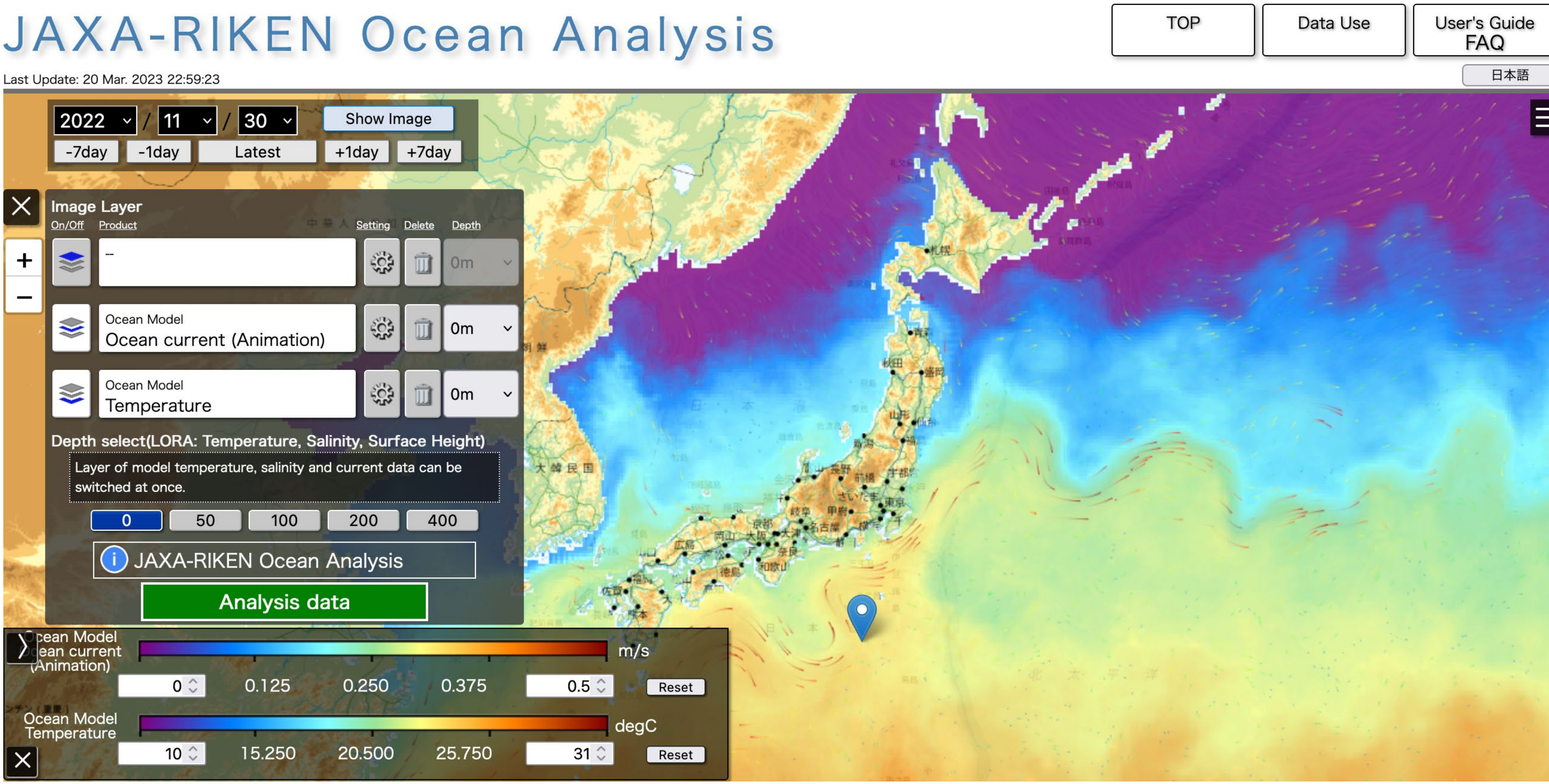


Surface zonal velocity



LORA has sufficient accuracy for geoscience researches etc.

Release LORA v1.0 website



Release on 31st March 2023

Ohishi et al. (2022a, b, GMD; 2023, OD; 2024, OM)

Geosci. Model Dev., 15, 8395–8410, 2022
https://doi.org/10.5194/gmd-15-8395-2022

Geoscientific Model Development
Open Access
EGU

Development and technical paper

An ensemble Kalman filter system with the Stony Brook Parallel Ocean Model v1.0

Shun Ohishi[1,2,3,7], Tsutomu Hihara[4], Hidenori Aiki[3,5], Joji Ishizaka[3], Yasumasa Miyazawa[5], Misako Kachi[6], and Takemasa Miyoshi[1,2,7]

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https://doi.org/10.1007/s10236-023-01541-3

Check for updates

LORA: a local ensemble transform Kalman filter-based ocean research analysis

Shun Ohishi[1,2,3,4] · Takemasa Miyoshi[1,2,3] · Misako Kachi[5]

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Abstract

We have produced an eddy-resolving local ensemble transform Kalman filter (LETKF)-based ocean research analysis (LORA) for the western North Pacific (WNP) and Maritime Continent (MC) regions (LORA-WNP and LORA-MC, respectively). This paper describes the system configuration and validation comparisons with Japan Coastal Ocean Predictability Experiment 2M (JCOPE2M) reanalysis and Archiving, Validation, and Interpretation of Satellite Oceanographic Data (AVISO) observational datasets. The results show that the surface horizontal velocity in the LORA-WNP is closer to independent drifter buoy observations in the mid-latitude region, especially along the Kuroshio Extension (KE), and is less close in the subtropical region than the JCOPE2M, although the AVISO is the closest over the whole domain. The sea surface temperatures (SSTs) in the LORA-WNP correspond better to assimilated satellite observations than the JCOPE2M over most of the domain except for coastal regions. The results using an independent buoy south of the KE indicate that better fit of temperature in the LORA-WNP may be limited to the upper 300 m depth, probably because of the prescribed vertical localization cutoff length of 370 m. In the MC region, the surface velocity in the LORA-MC is closer to the independent drifter buoys in the equatorial coastal region and is less close in the offshore region than the AVISO. The SSTs in the LORA-MC correspond better to the assimilated satellite observations in the offshore region than the nearshore region. Therefore, the LORA-WNP and LORA-MC have sufficient accuracy for geoscience research applications as well as for fisheries, marine transport, and environment consultants.

Keywords Regional ocean data assimilation · Research analysis product · Ensemble Kalman filter · Validation comparison · Western North Pacific · Maritime Continent

Geosci. Model Dev., 15, 9057–9073, 2022
https://doi.org/10.5194/gmd-15-9057-2022

Geoscientific Model Development
Open Access
EGU

Development and technical paper

An ensemble Kalman filter-based ocean data assimilation system improved by adaptive observation error inflation (AOEI)

Shun Ohishi[1,2,3,4], Takemasa Miyoshi[1,2,3], and Misako Kachi[5]

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Impact of atmospheric forcing on SST biases in the LETKF-based ocean research analysis (LORA)

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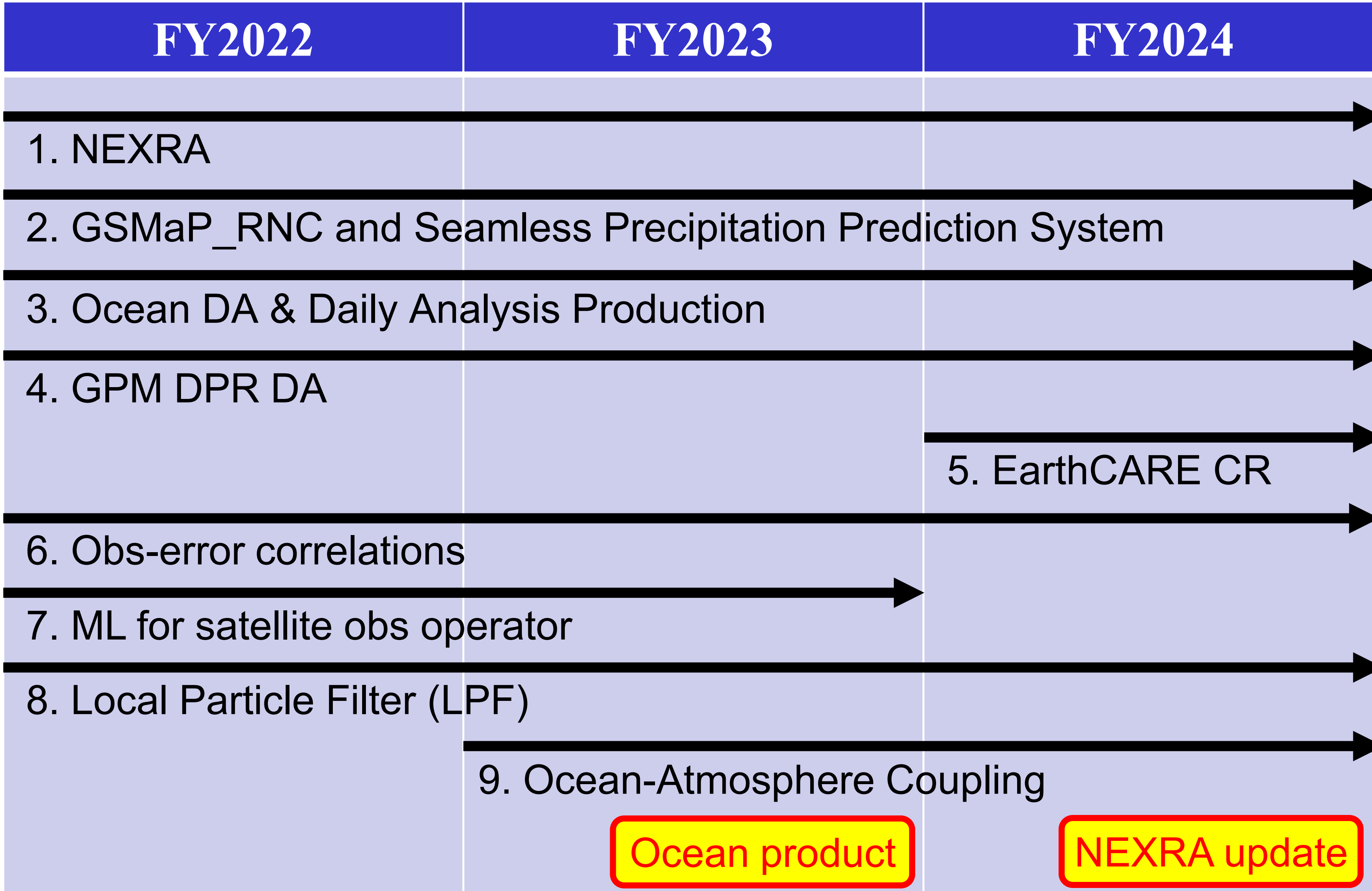
A R T I C L E I N F O

Keywords:
Ensemble Kalman filter
LORA
Atmospheric reanalysis
Ocean forcing dataset
SST bias
Mixed-layer temperature budget

A B S T R A C T

In the previous study, the authors have produced an eddy-resolving ocean ensemble analysis product called the local ensemble transform Kalman filter (LETKF)-based ocean research analysis (LORA) over the western North Pacific and Maritime Continent regions using an ocean data assimilation system driven by the Japanese operational atmospheric reanalysis dataset known as the JRA-55. However, the LORA includes warm biases in sea surface temperatures (SSTs) in coastal regions during the boreal winter. In this study, we perform sensitivity experiments with atmospheric forcing using an ocean forcing dataset known as the JRA55-do, which adjusts the JRA-55 to high-quality reference datasets to reduce biases and uncertainties. The results show that the nearshore

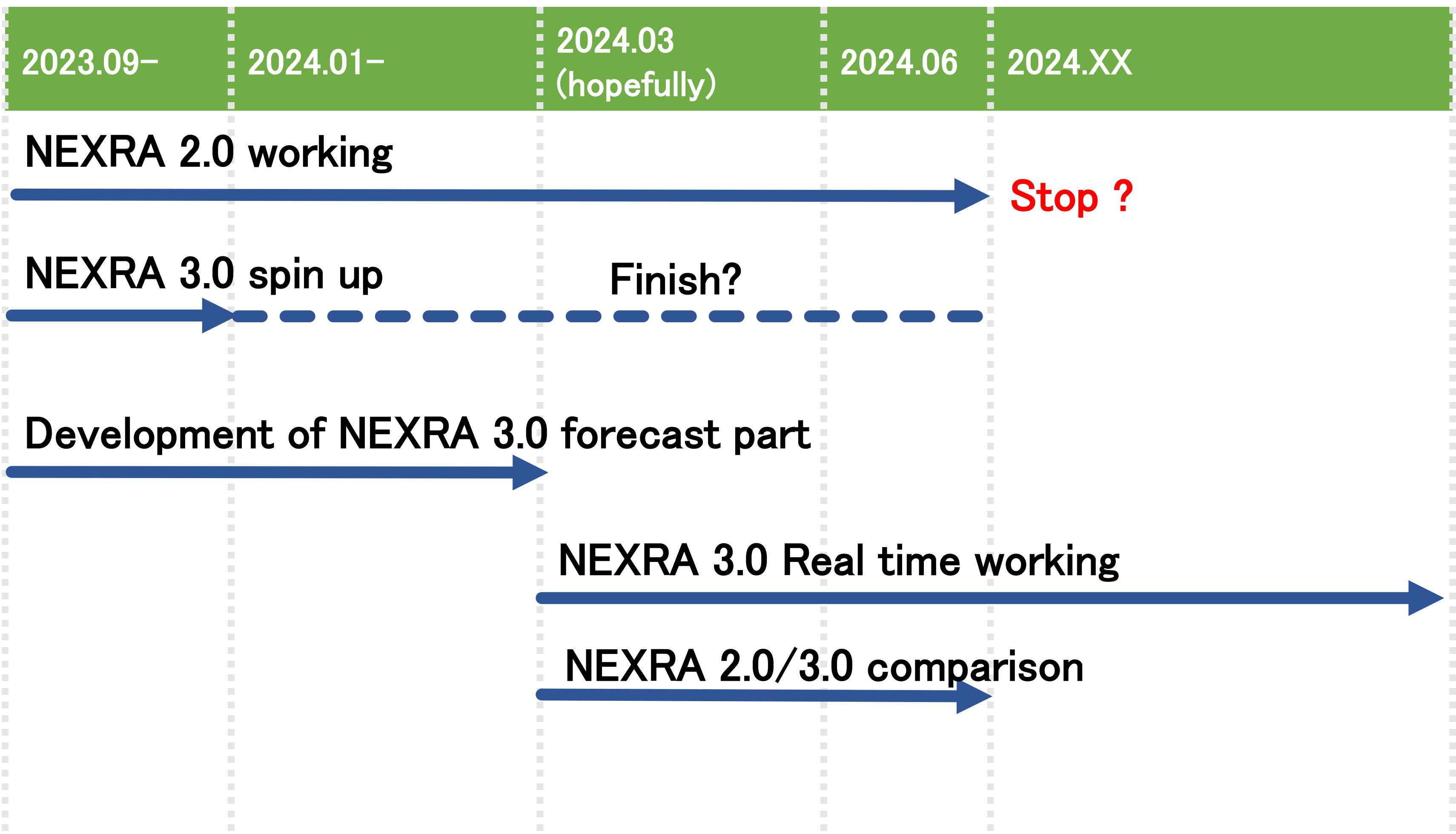
Research plans



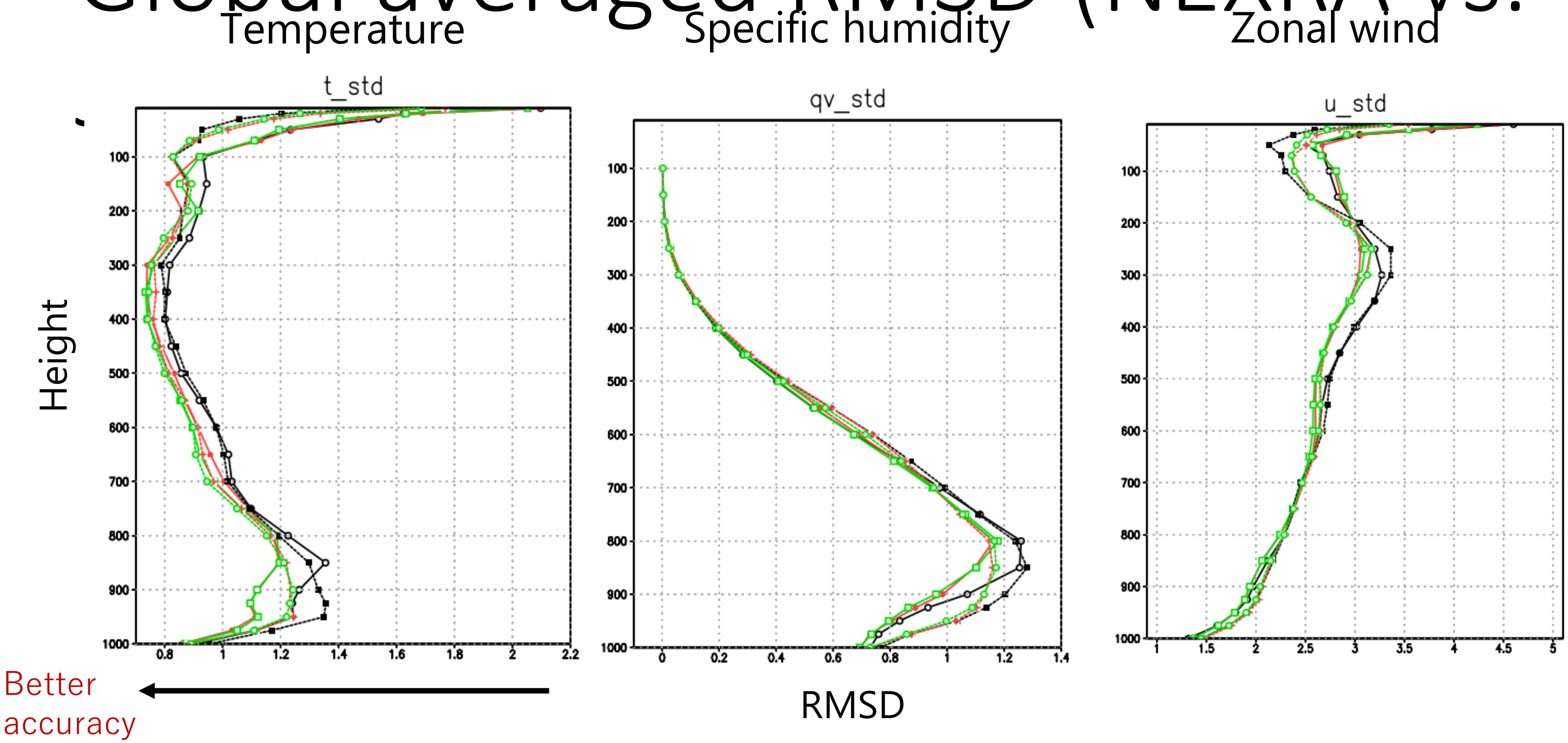
Appendix

NEXRA Development schedule

Current version; as 2023.09



Global averaged RMSD (NEXRA vs.



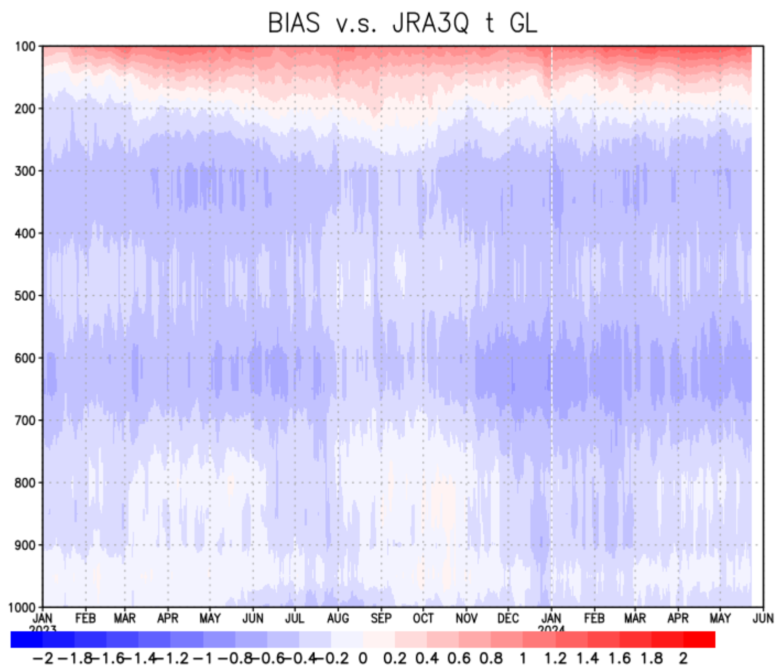
Black: NEXRA2, Red: NEXRA3-ASIS, Green: NEXRA3-CHIKIRA
Solid: RMSD, Dash: Spread

NEXRA3-ASIS and -CHIKIRA are more accurate than NEXRA2.

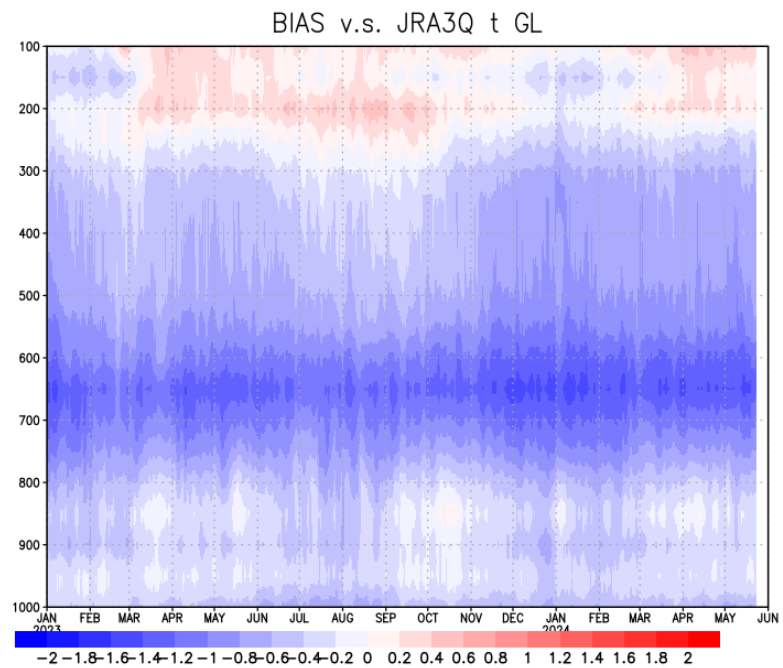
NEXRA3.0 analysis

- Bias time series of temperature vs. JRA3Q

NEXRA3.0



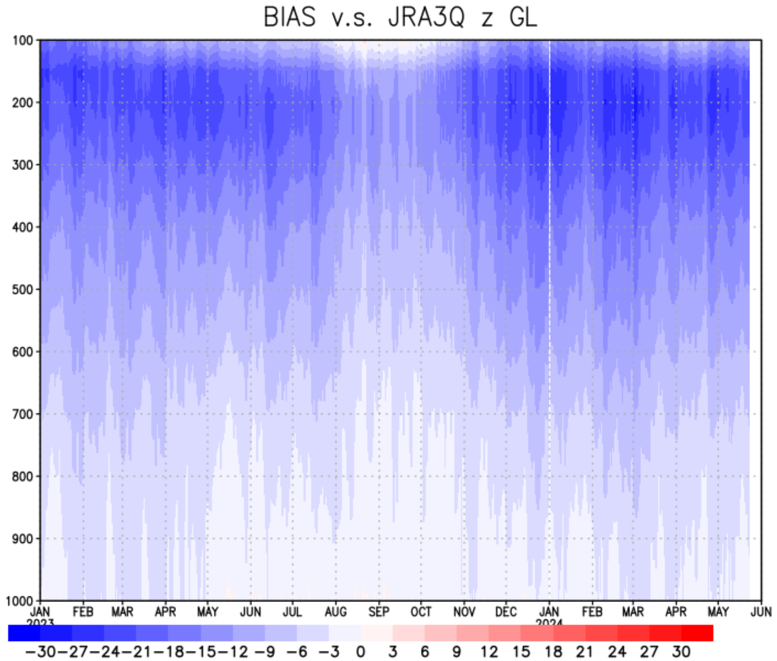
NEXRA2.0



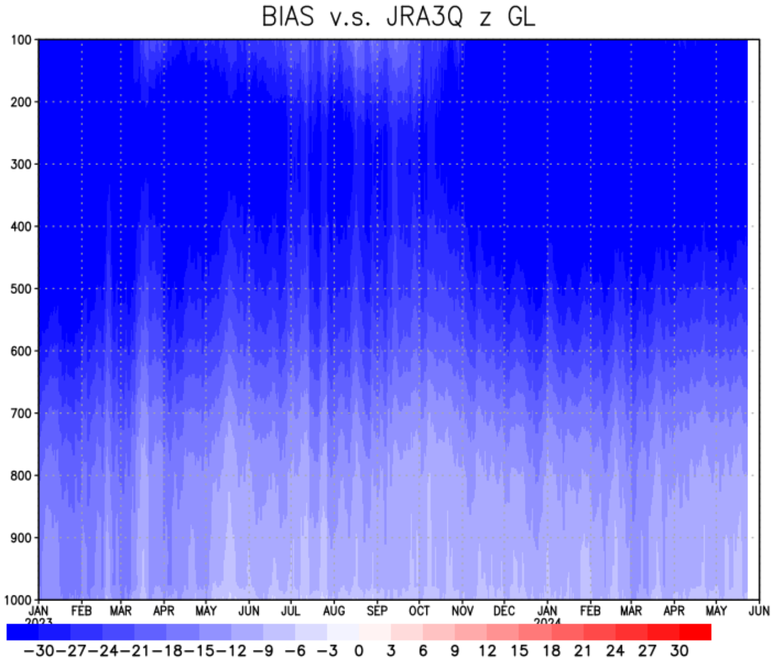
NEXRA3.0 analysis

- Bias time series of geopotential height vs. JRA3Q

NEXRA3.0



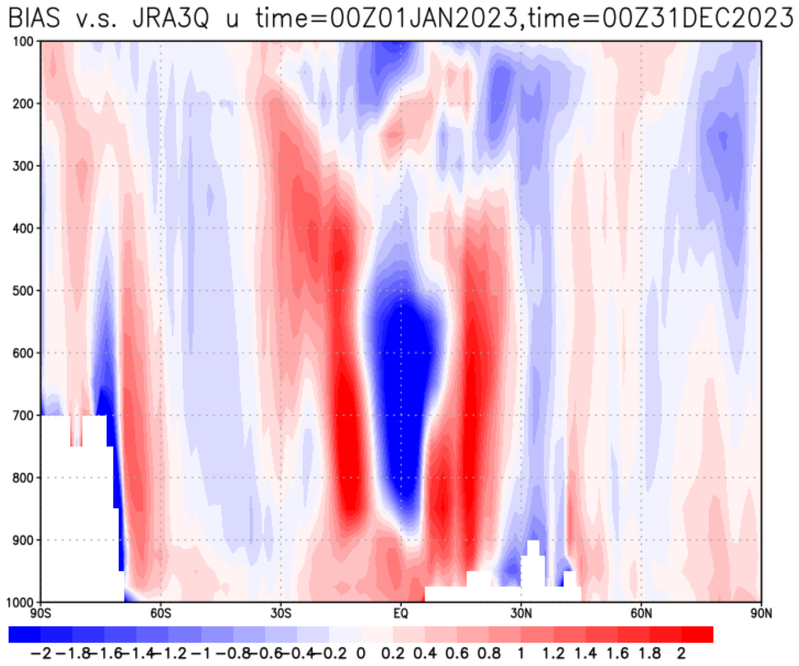
NEXRA2.0



NEXRA3.0 analysis

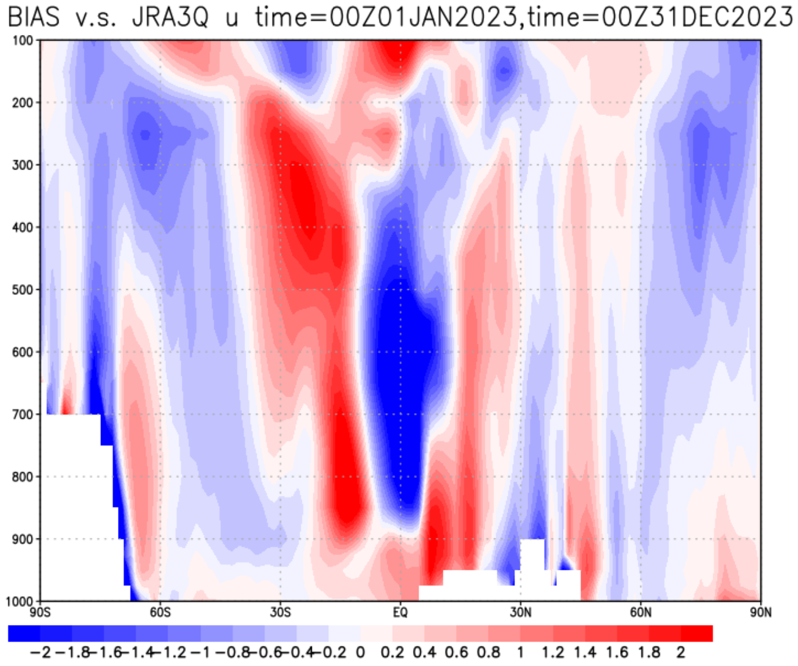
- Bias zonal mean u vs. JRA3Q

NEXRA3.0



latitude

NEXRA2.0

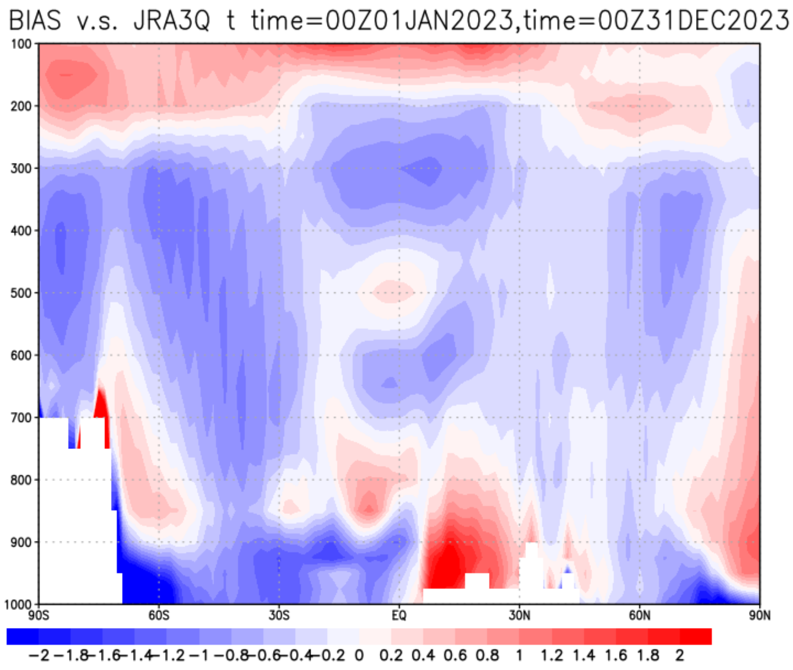


latitude

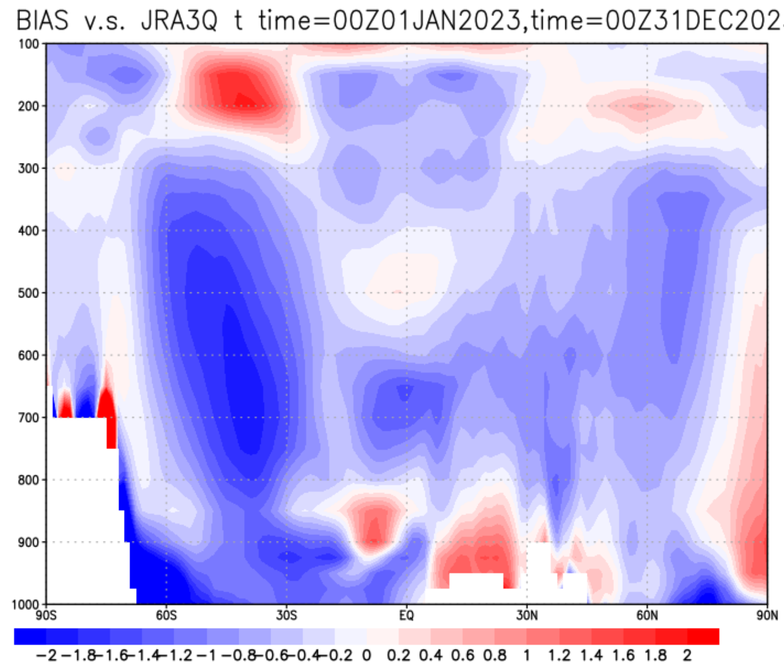
NEXRA3.0 analysis

- Bias zonal mean t vs. JRA3Q

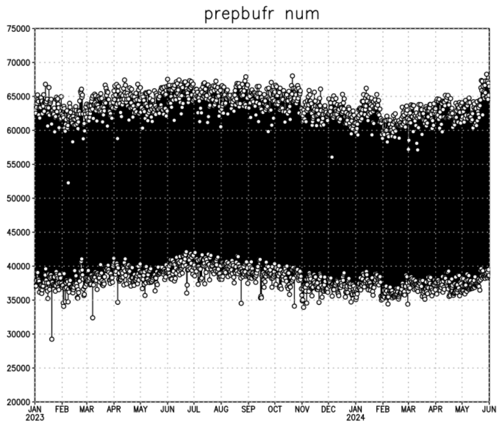
NEXRA3.0

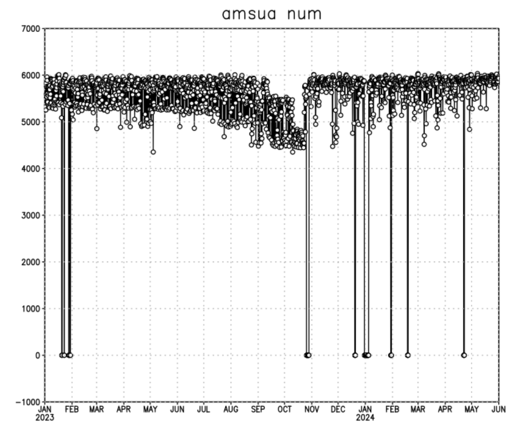


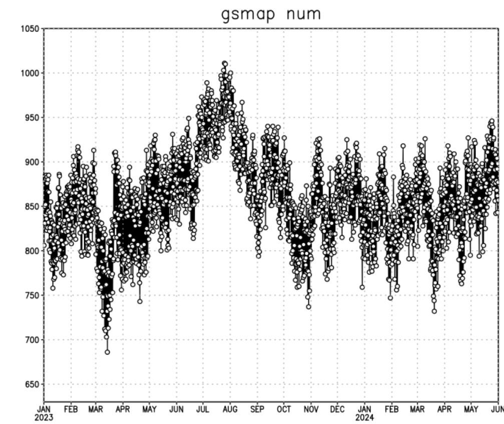
NEXRA2.0

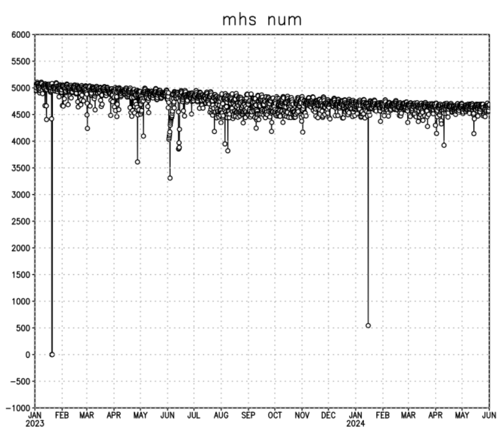


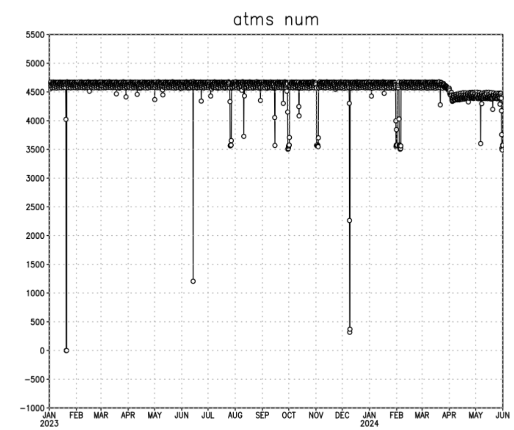
NEXRA3.0 LETKF observation number



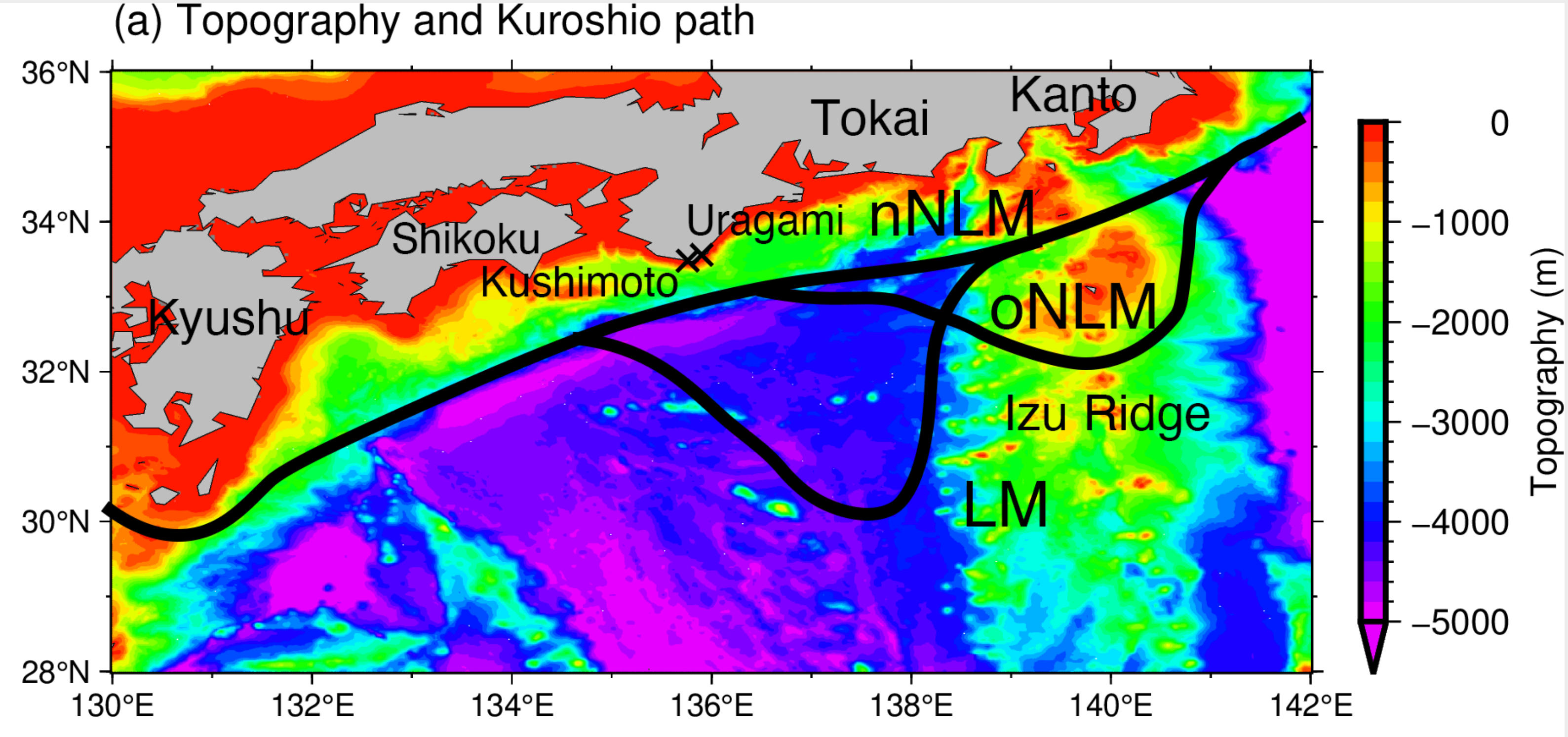






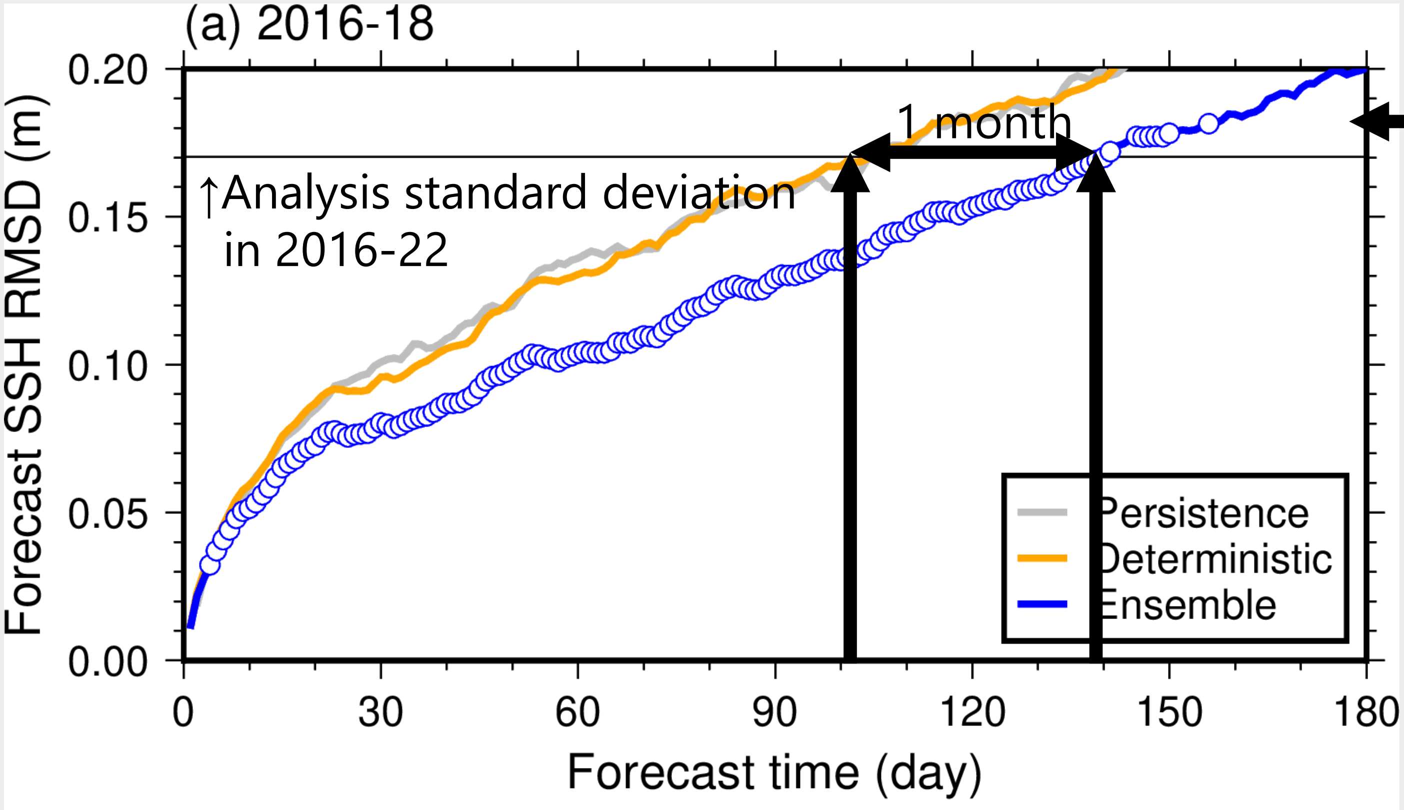


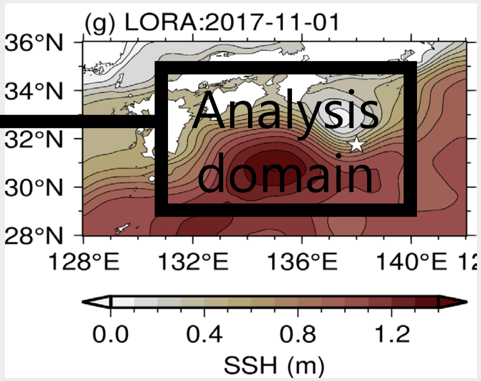
– Kuroshio path south of Japan –



- Three typical paths in Kuroshio (Kawabe 1995)
  - nNLM (**n**earshore **N**onLarge **M**eander)
  - **<u>oNLM (offshore NonLarge Meander)</u>**
  - **<u>LM</u>** <u>(Large Meander)</u>

– Predictability –

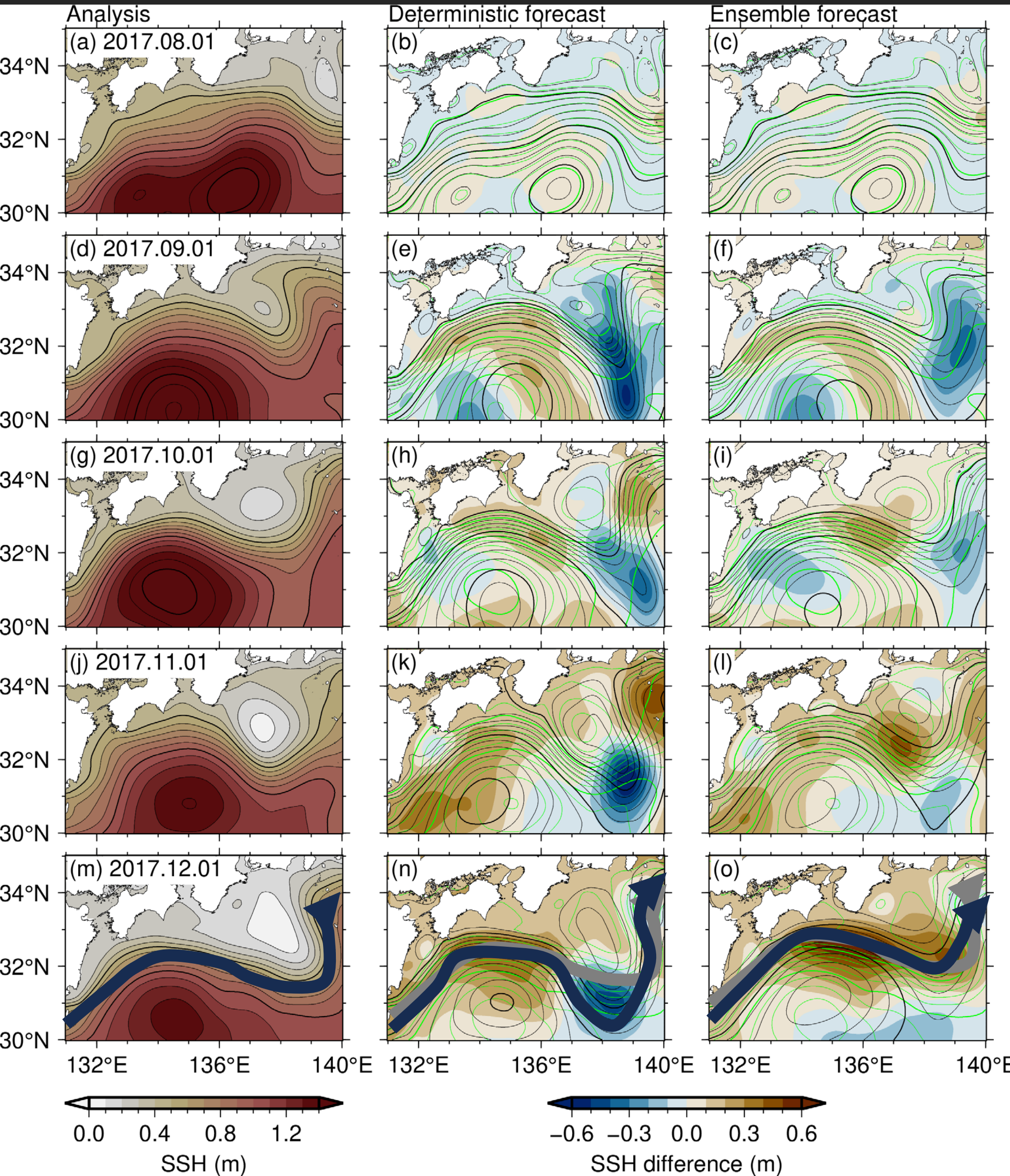




*Persistence: RMSD of the initial analysis condition
*Ensemble: RMSD of the forecast ensemble mean
*○: Significant difference relative to the persistence

Deterministic: 100-110 days < Ensemble: 130-140 days

– Initial: 2017.08 (Straight to Meander) –



Larger southward meandering

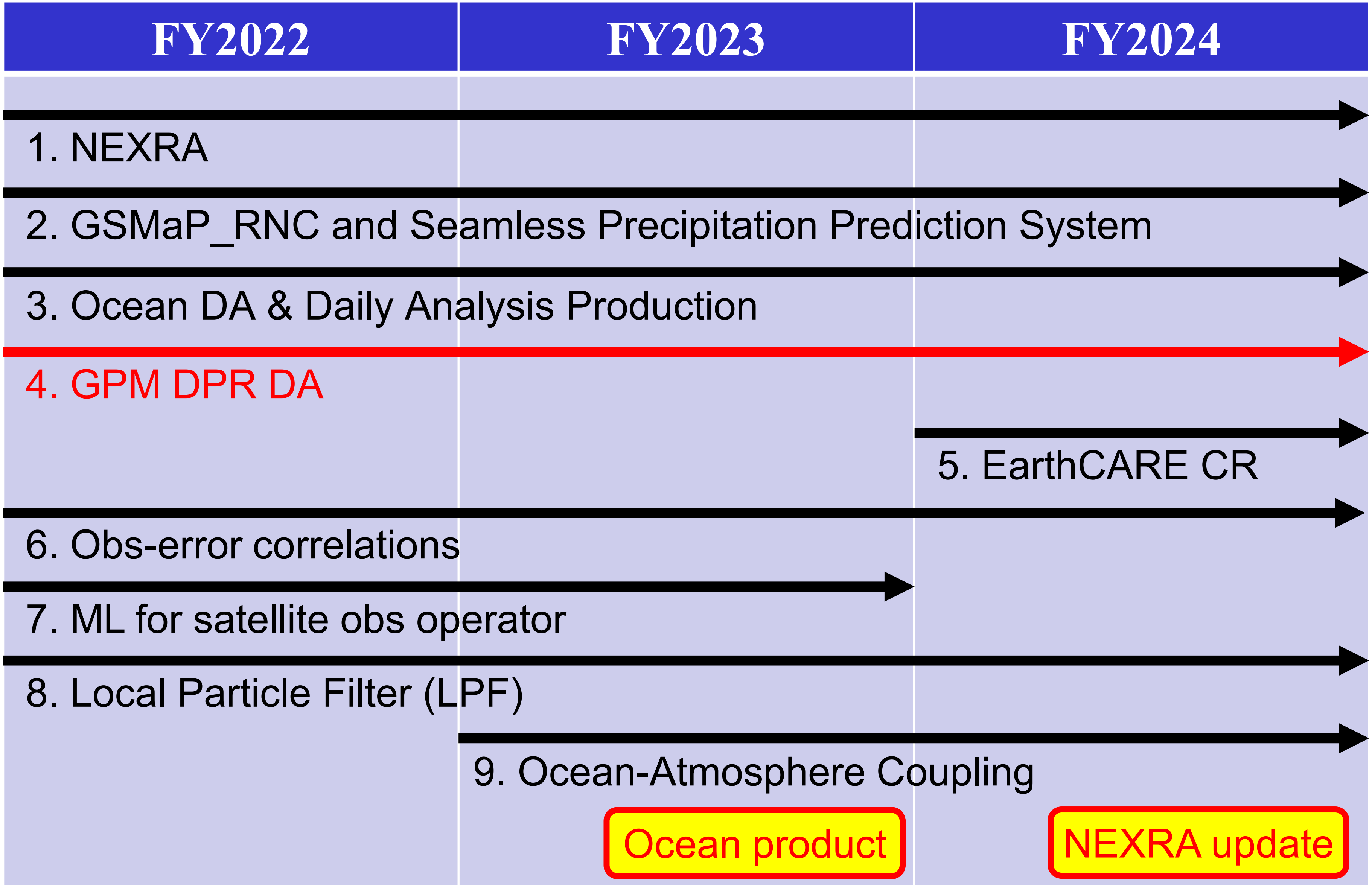
in deterministic forecast

Black contour: (left) analysis

(middle and right) forecast

Green contour: (middle and right) analysis

Research plans



Estimating parameters for cloud microphysics

- NSW6 (vapor, cloud, ice, **rain, snow, graupel**)
  - Parameters : terminal velocity coefficients

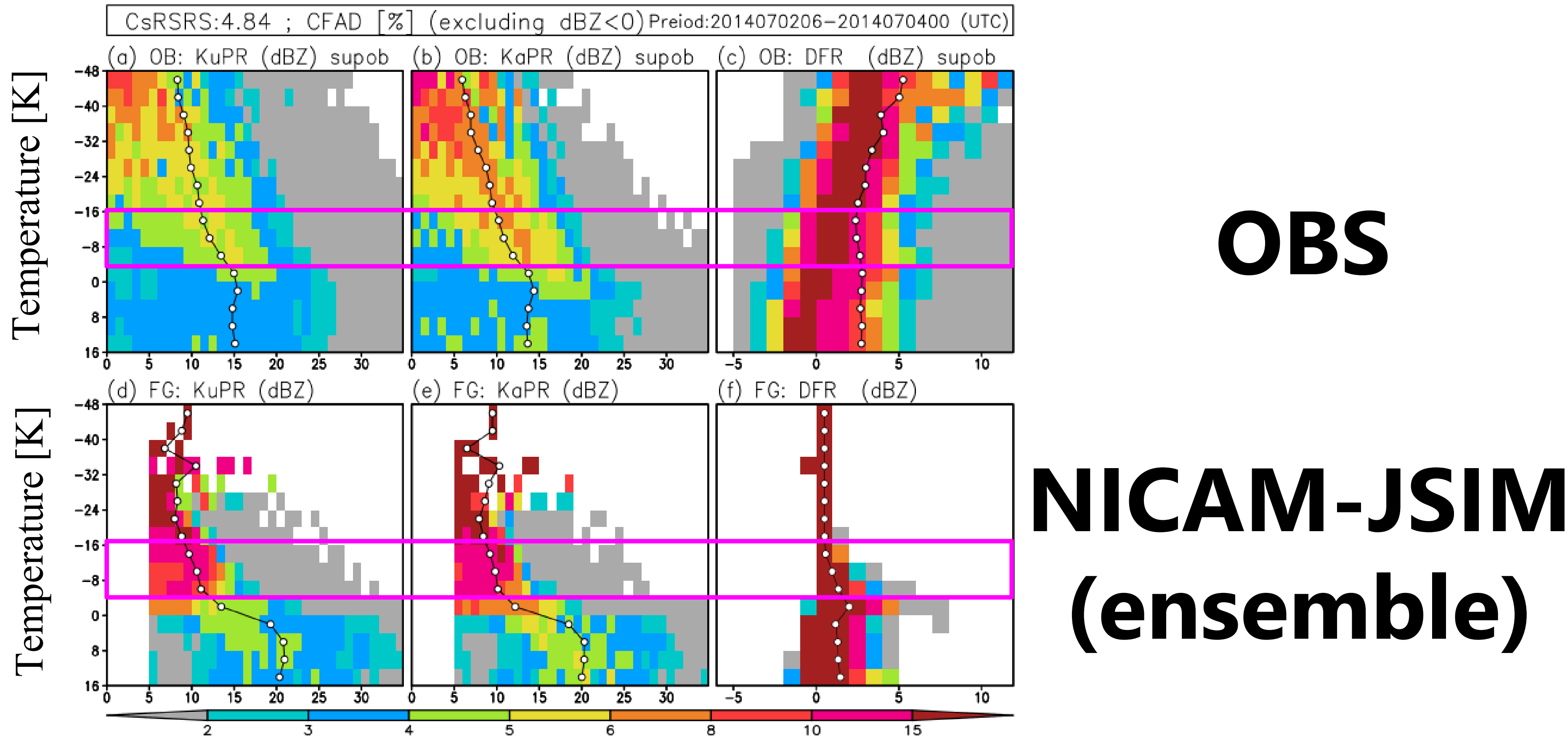
$$v_{t[r,s,g]}(D) = \boxed{c_{[r,s,g]}} D^{d[r,s,g]} \left(\rho_0 / \rho\right)^{1/2}$$

$$c_g = \left(\frac{4 g \rho_g}{3 \boxed{C_D} \rho_0} \right)^{1/2}$$

	NICAM default	NICAM for MJO
Cr	130.0	58.0
Cs	4.84	0.90
C_D	0.60	2.50

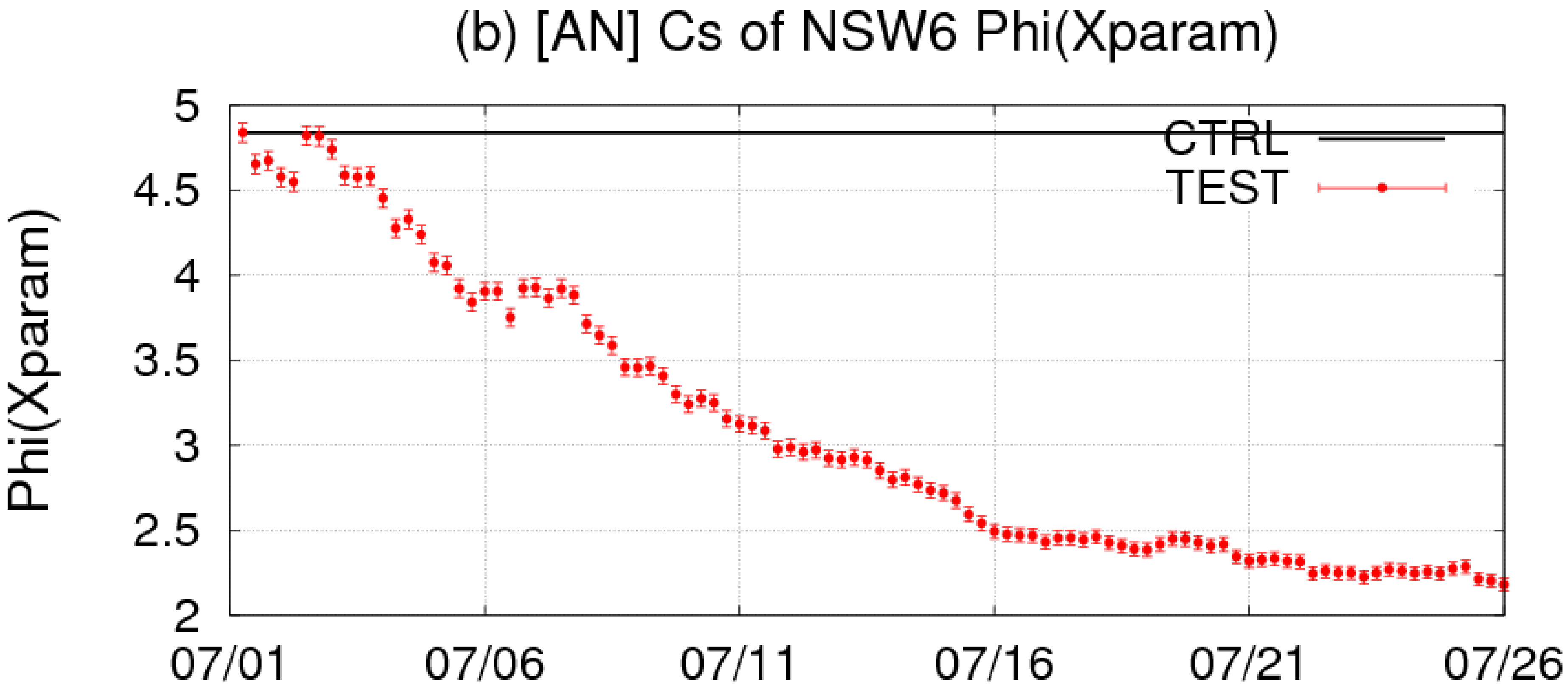
To estimate model parameters of cloud microphysics w/ GPM/DPR

Parameter Estimation based on CFAD

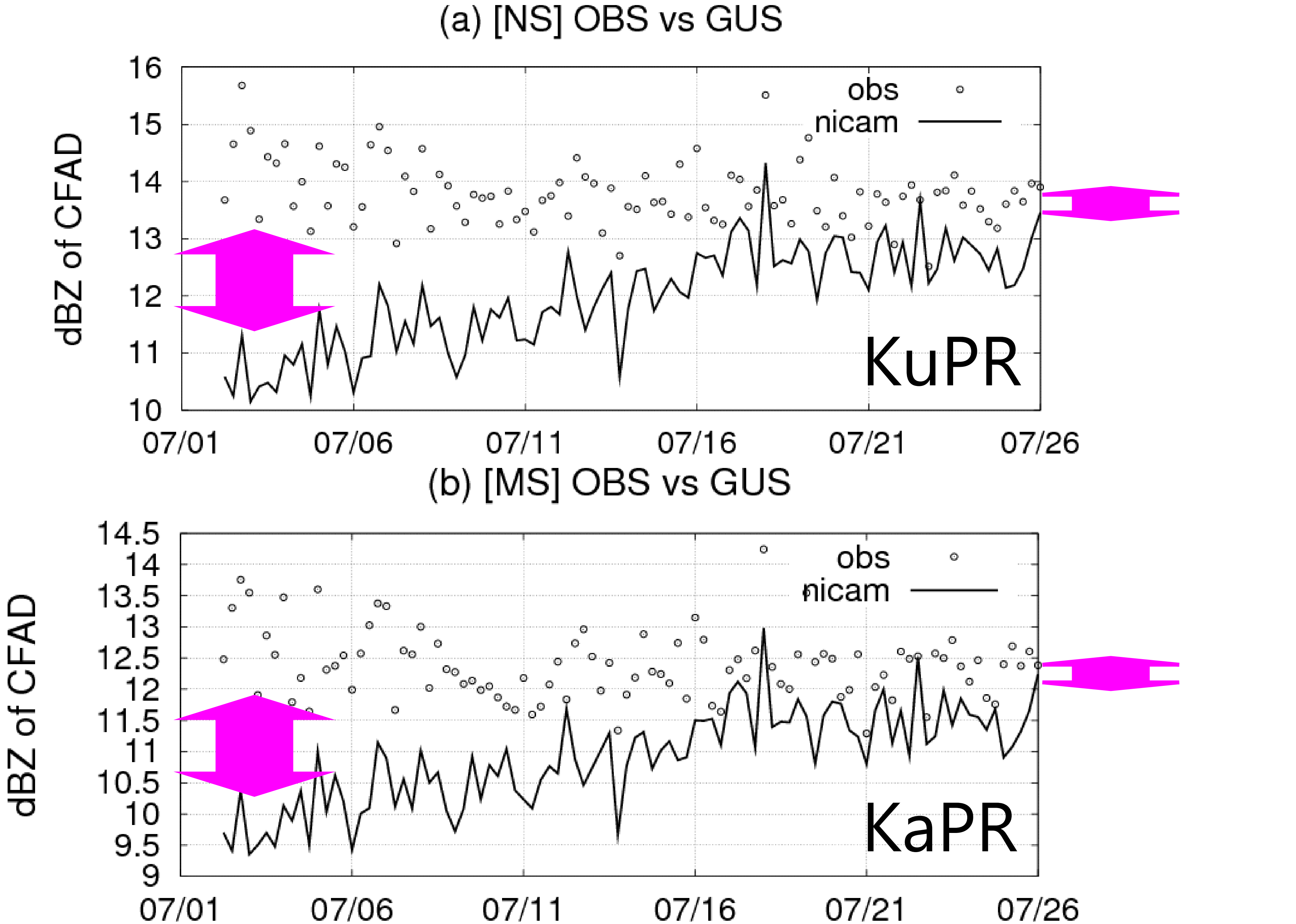


- **Data used for parameter estimation**
  - weighted average of reflectivity (-16→-4 deg.)
  - KuPR, KaPR & DFR are used

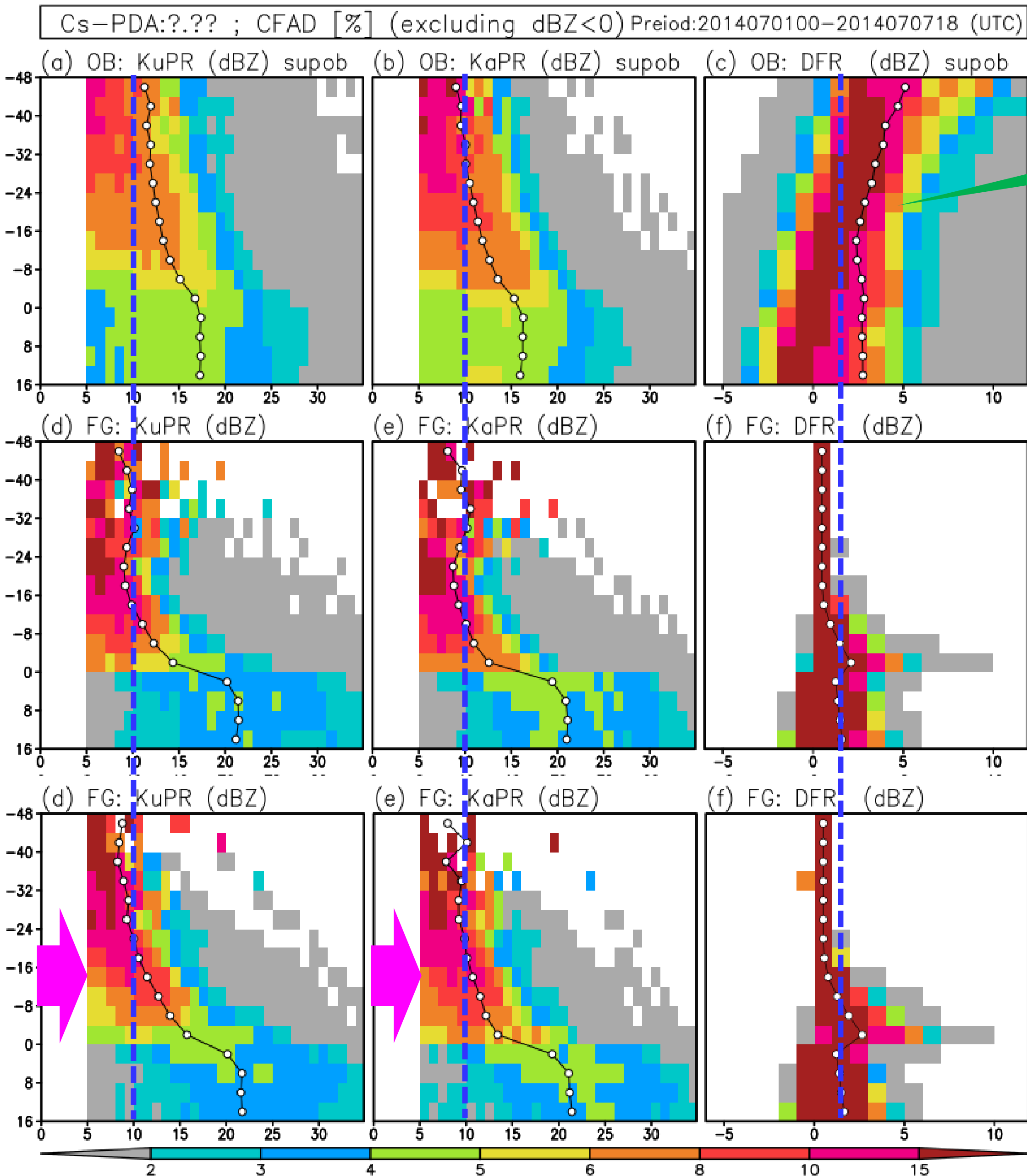
Estimated Parameter



Misfit to Observation (averaged over three height)



Change in CFAD (Parameter DA Experiment)



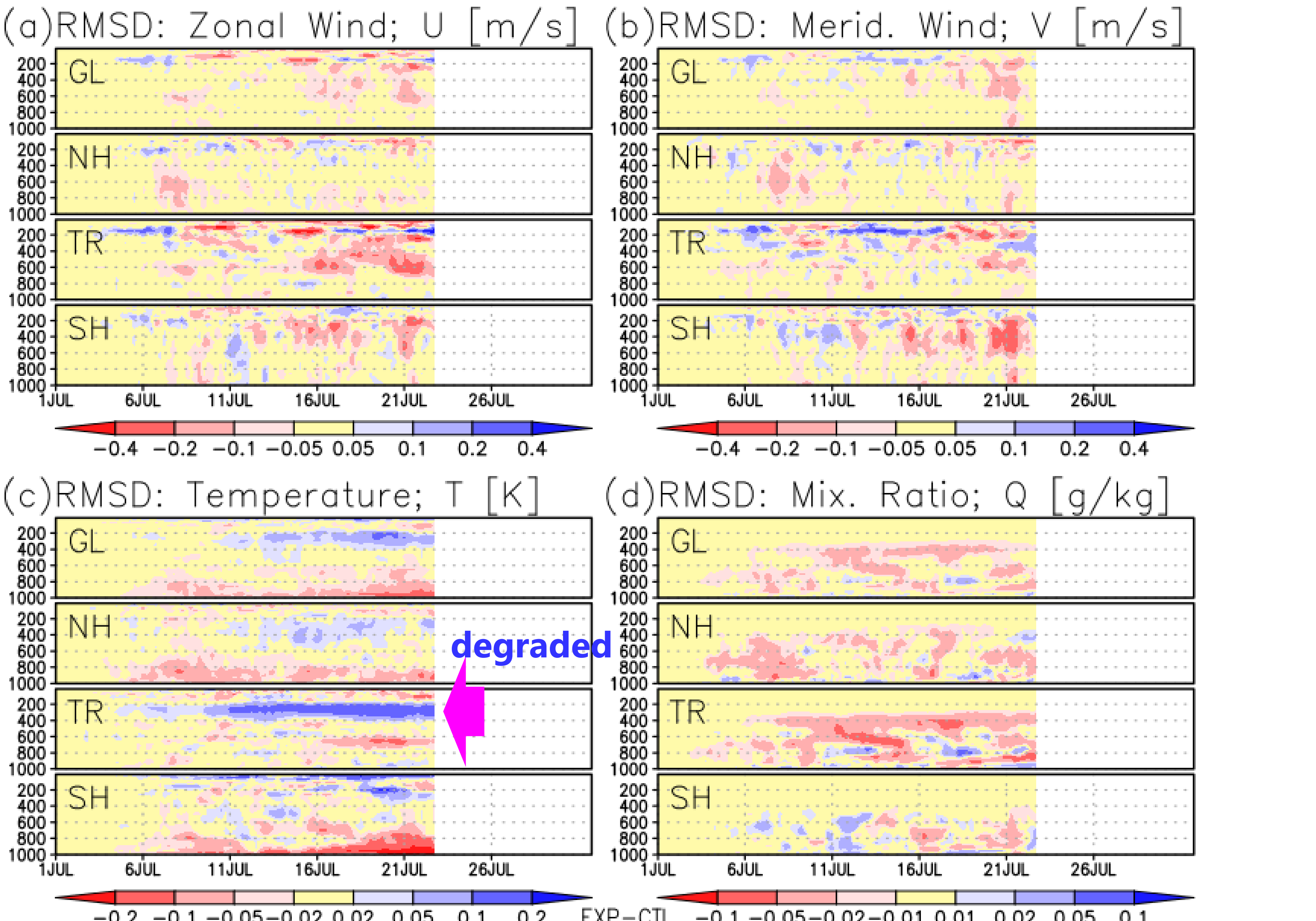
Heil or Graupel?

OBS (GPM/DPR)

NICAM (7/1-7/7)

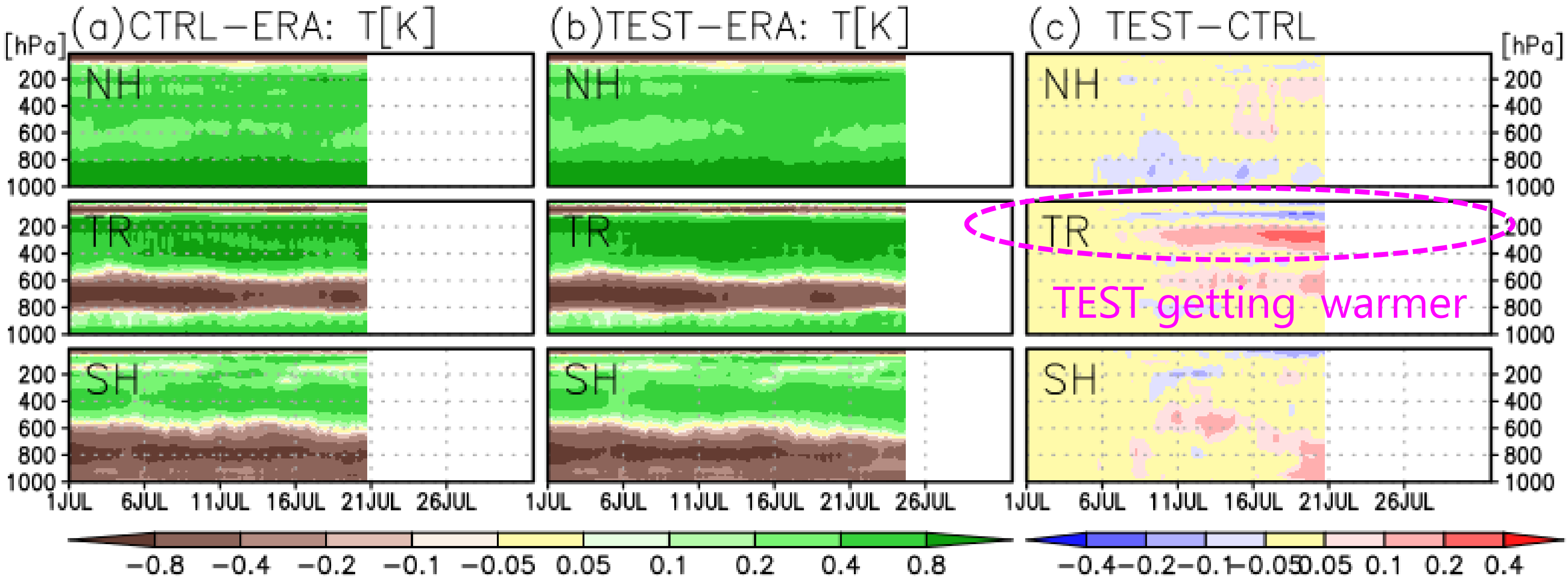
NICAM (7/19-7/25)

RMSD vs. ERA Interim



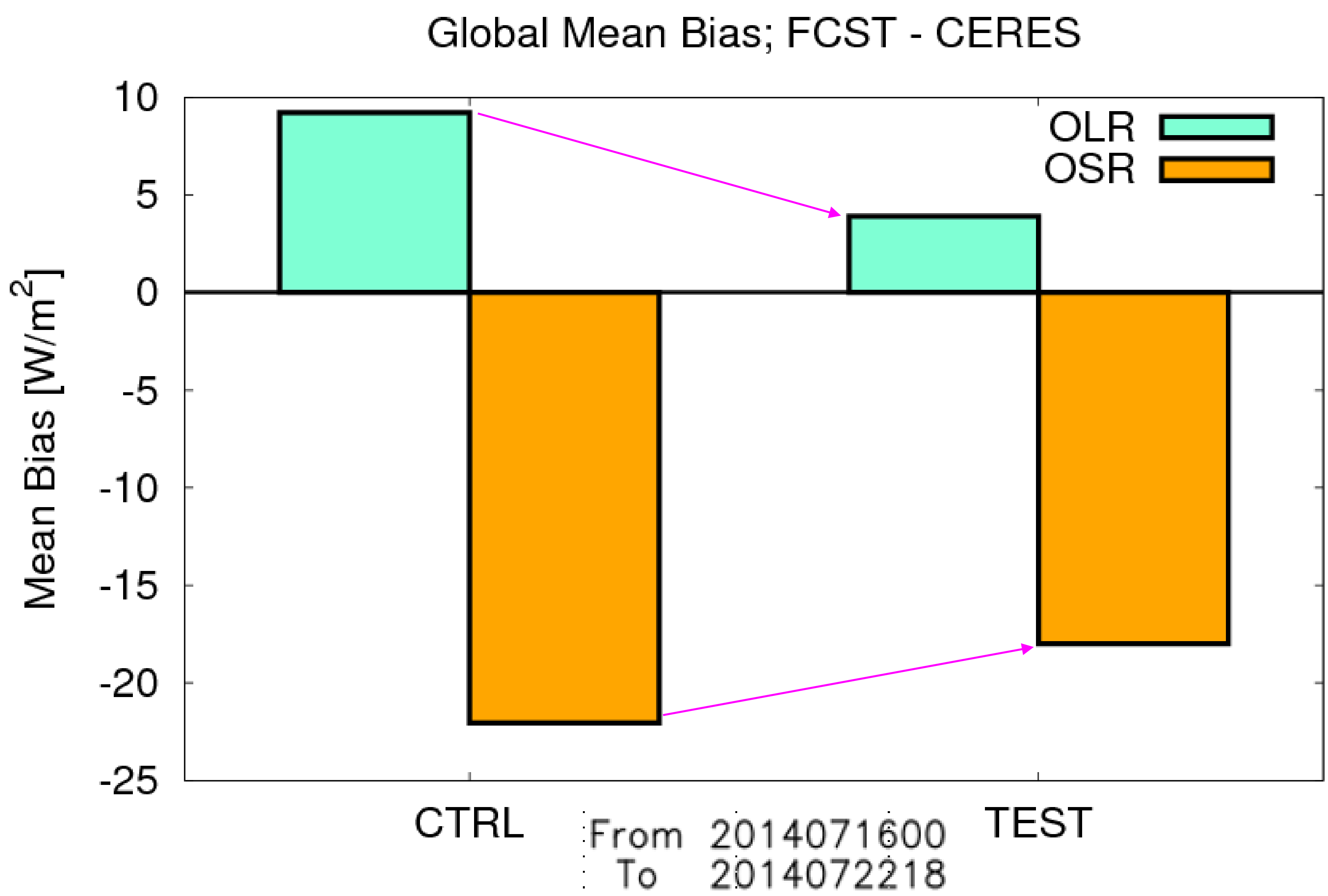
← Parameter DA is better　　Parameter DA is worse →

BIAS vs. ERA: CTRL (Cs=4.84) & TEST (Cs DA'ed)

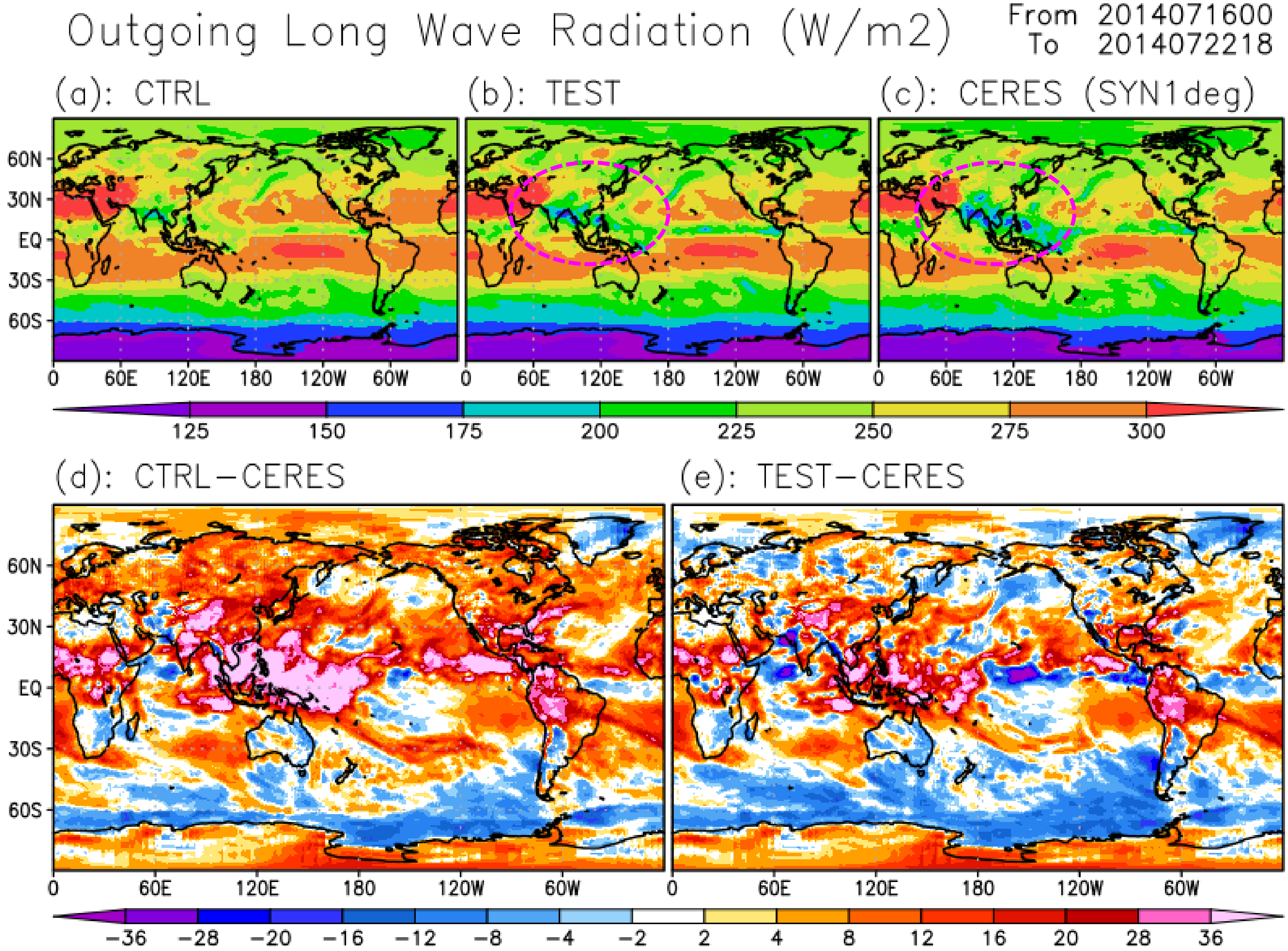


- **Warmer bias in higher troposphere** **test is warmer ➔**
  - (1) smaller Cs (i.e., slower snowfall) increased snow
  - (2) snow absorb long wave radiation ➔ warmer
- **How can we solve?**
  - Dr. Seiki proposed using optical parameters of NICAM high-resolution-MIP that reduces the absorption of long wave radiation
    - e.g. crystal shape,
    - http://jmsj.metsoc.jp/EOR/2021-018.pdf
  - Do we need to tune other model parameters?
    - e.g. radiation-related parameters
  - To estimate latitude-dependent Cs estimation
    - should be universally constant, but practically different

OLR & OSR Bias w.r.t. CERES



OLR :: CTRL (Cs=4.84) vs. TEST (Cs Estimated)



Kotsuki et al. (2023, JGR-A)

ADVANCING EARTH AND SPACE SCIENCE

JGR Atmospheres

RESEARCH ARTICLE
10.1029/2022JD037447

Ensemble-Based Data Assimilation of GPM DPR Reflectivity: Cloud Microphysics Parameter Estimation With the Nonhydrostatic Icosahedral Atmospheric Model (NICAM)

Shunji Kotsuki[1,2,3,4,5,6], Koji Terasaki[1], Masaki Satoh[7], and Takemasa Miyoshi[1,5,6,8]

[1]RIKEN Center for Computational Science, Kobe, Japan, [2]Center for Environmental Remote Sensing, Chiba University, Chiba, Japan, [3]Institute for Advanced Academic Research, Chiba University, Chiba, Japan, [4]PRESTO, Japan Science and Technology Agency, Chiba, Japan, [5]RIKEN Interdisciplinary Theoretical and Mathematical Sciences Program, Kobe, Japan, [6]RIKEN Cluster for Pioneering Research, Kobe, Japan, [7]Atmosphere and Ocean Research Institute, The University of Tokyo, Tokyo, Japan, [8]Department of Atmospheric and Oceanic Science, University of Maryland, College Park, MD, USA

Key Points:

- Direct assimilation of GPM DPR reflectivity is challenging due to its long revisiting intervals relative to the time scale of precipitation
- A new model parameter estimation approach based on a reflectivity-temperature histogram is used to improve global precipitation forecasts
- Parameter estimation of snow terminal velocity mitigated the gap between simulated and observed reflectivity, resulting in improved forecasts

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S. Kotsuki,
shunji.kotsuki@chiba-u.jp

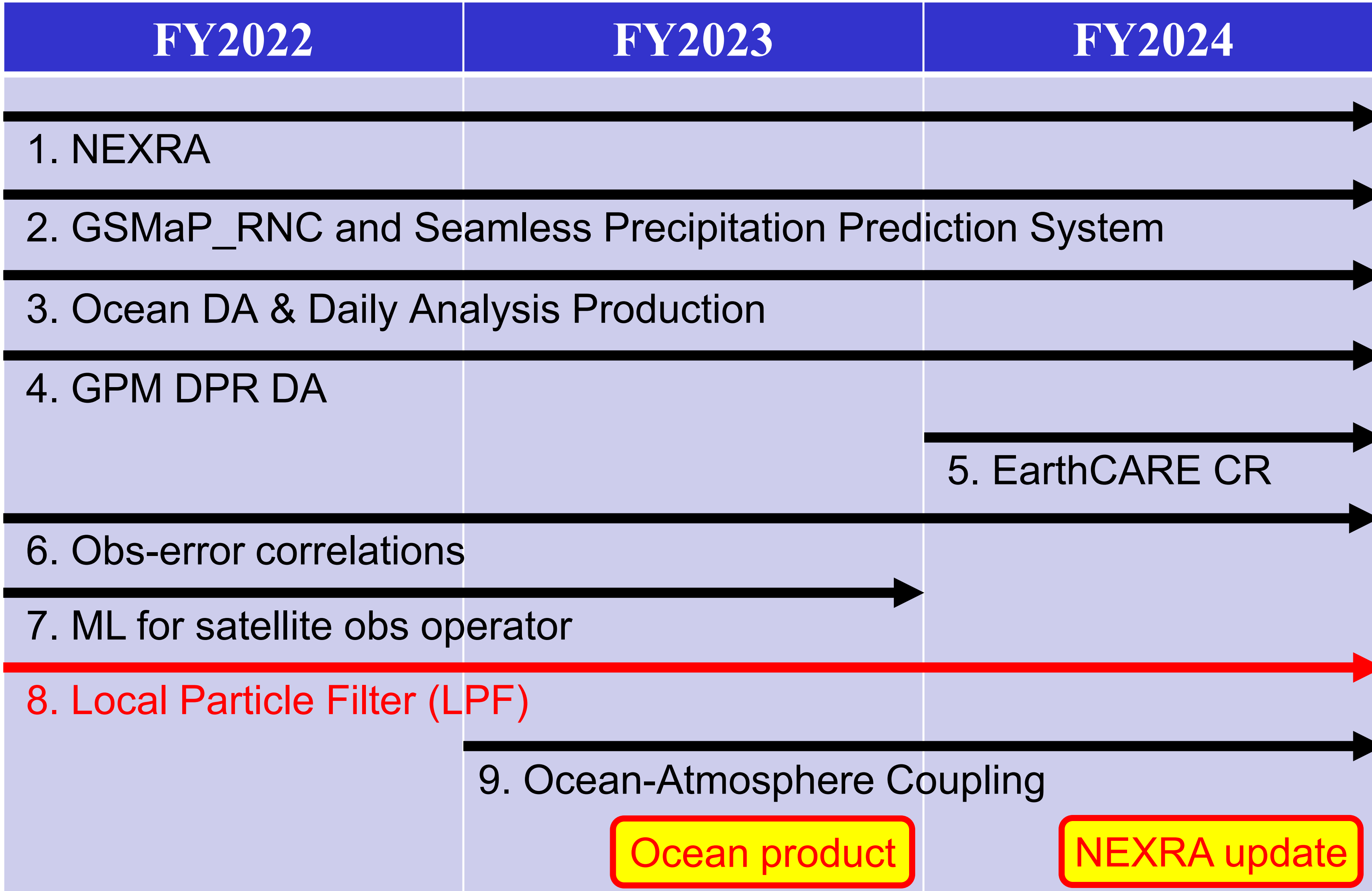
Citation:

Kotsuki, S., Terasaki, K., Satoh, M., & Miyoshi, T. (2023). Ensemble-based data assimilation of GPM DPR reflectivity: Cloud microphysics parameter estimation with the Nonhydrostatic Icosahedral Atmospheric Model (NICAM). *Journal of Geophysical Research: Atmospheres, 128*, e2022JD037447. https://doi.org/10.1029/2022JD037447

Abstract Direct assimilation of Dual-frequency Precipitation Radar (DPR) data of the Global Precipitation Measurement (GPM) core satellite is challenging mainly due to its long revisiting intervals relative to the time scale of precipitation, and precipitation location errors. This study explores a method for improving precipitation forecasts using GPM DPR through model parameter estimation. We developed a 28 km mesh global atmospheric data assimilation system that integrates the Nonhydrostatic ICosahedral Atmospheric Model (NICAM) and Local Ensemble Transform Kalman Filter (LETKF) coupled with a satellite radar simulator. Using the NICAM-LETKF and GPM DPR observations, this study estimates a model cloud physics parameter corresponding to snowfall terminal velocity. To overcome the difficulties of long revisiting intervals and precipitation location errors, we propose a parameter estimation method based on a two-dimensional histogram known as the contoured frequency by temperature diagram (CFTD). Parameter estimation effectively mitigated the gap between simulated and observed CFTD, resulting in improved 6 hr precipitation forecasts.

Plain Language Summary Direct assimilation of satellite-borne radar data into weather forecasting models is challenging mainly due to its long revisiting intervals and precipitation location errors. This study explores a method for improving precipitation forecasts using the satellite radar data for optimizing an uncertain

Research plans



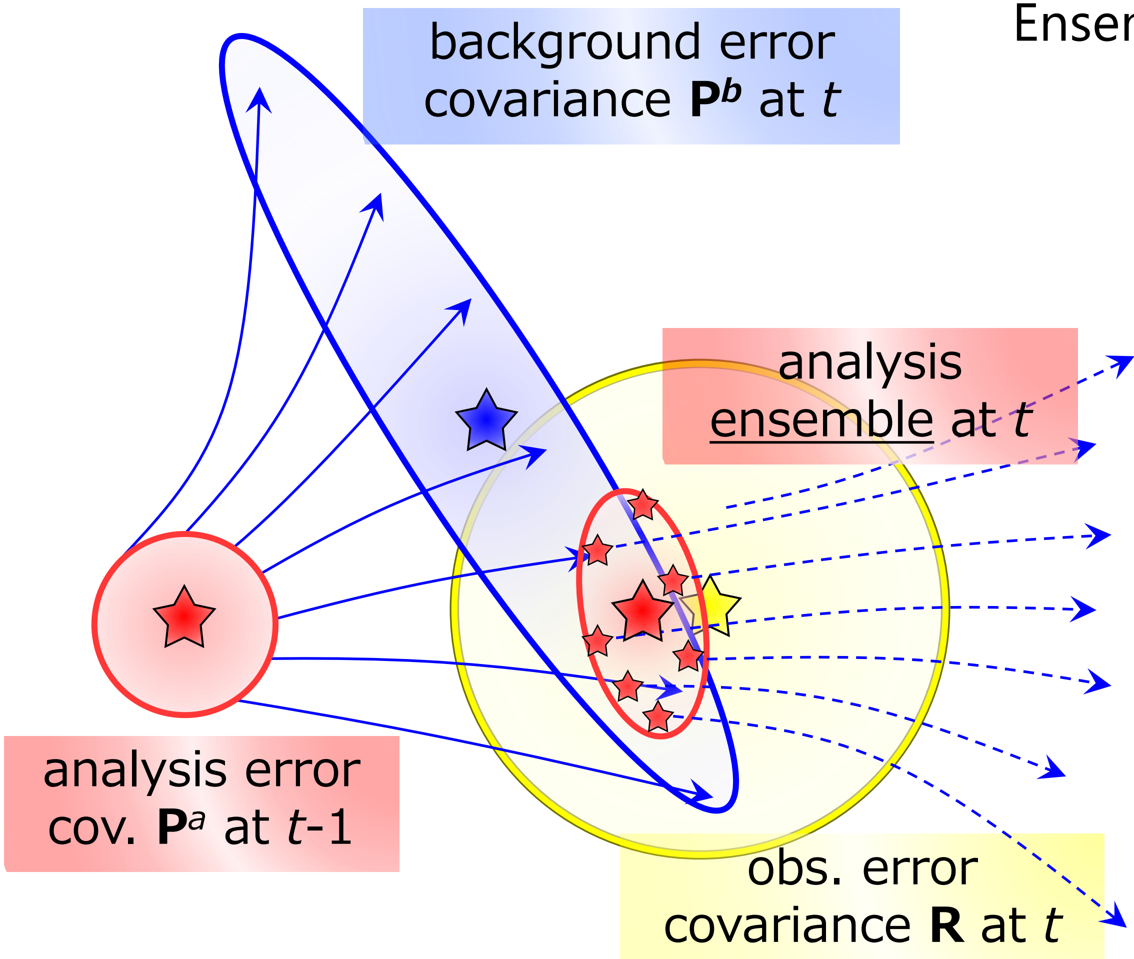
Ensemble Transform Matrix

Ensemble matrix:

$$\mathbf{X}_t = \underbrace{\left(\mathbf{x}_1, \cdots, \mathbf{x}_m\right)}_{\text{ens. members}}$$

Ensemble perturbation matrix:

$$\delta\mathbf{X}_t = \underbrace{\left(\mathbf{x}_1 - \overline{\mathbf{x}}, \cdots, \mathbf{x}_m - \overline{\mathbf{x}}\right)}_{\text{ens. members}}$$



Ensemble approximation of error cov.

$$\mathbf{P} \approx \frac{1}{m-1}\delta\mathbf{X}\left(\delta\mathbf{X}\right)^{\mathrm{T}}$$

analysis is given by a linear combination of forecast ensemble

$$\mathbf{X}_t^a = \overline{\mathbf{x}}_t^b \cdot \mathbf{1} + \delta\mathbf{X}_t^b \mathbf{T}_t$$

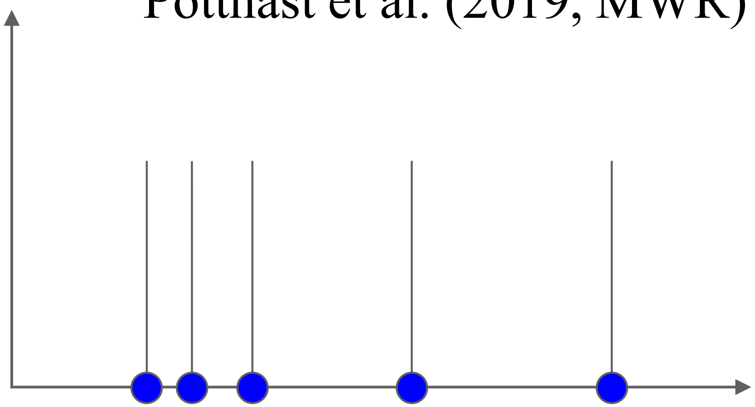
ensemble transform matrix

LPF and GM extension

LPF

Penny and Miyoshi (2016, NPG)
Potthast et al. (2019, MWR)

Pr



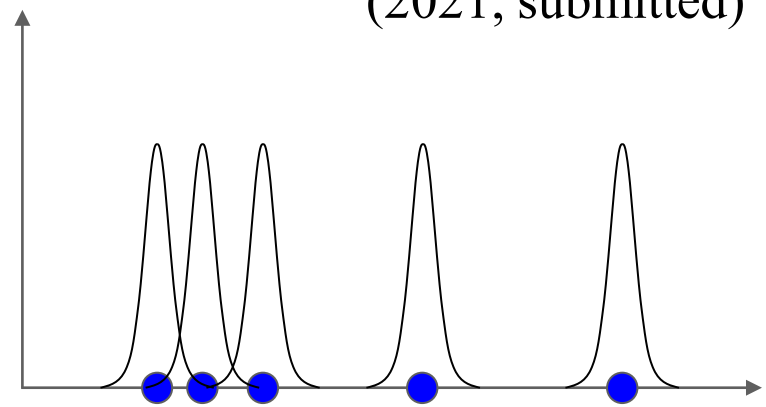
$$\Pr(x) = \frac{1}{m}\sum_{k} \delta(x - x_k)$$

the delta function

GM extention (LPFGM)

Walter and Potthast
(2021, submitted)

Pr



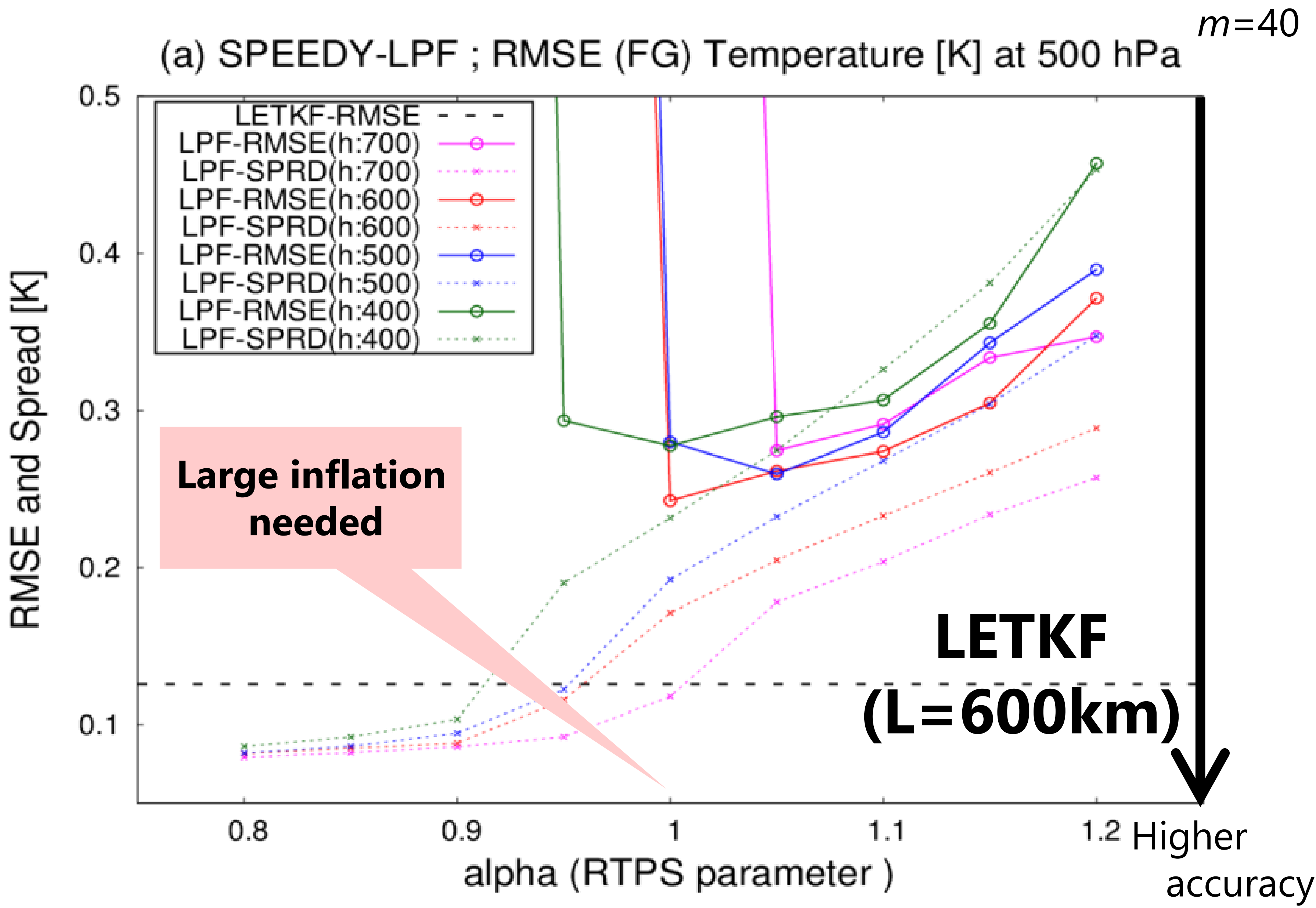
$$\Pr(x) = \frac{1}{m}\sum_{k} N(x_k, \mathbf{B}_k)$$

Gaussian kernel

$$\mathbf{B}_k = \gamma \mathbf{P}_t^b \approx \frac{\gamma}{m-1}\delta\mathbf{X}_t^b\left(\delta\mathbf{X}_t^b\right)^{\mathbf{T}}$$

γ is a tuning parameter to determine width of Gaussian kernel.
(tuned to be 1.5 in this study)

SPEEDY, REG2, LETKF vs LPF



Kotsuki et al. (2022, GMD)

https://doi.org/10.5194/gmd-2022-69
Preprint. Discussion started: 7 June 2022

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A Local Particle Filter and Its Gaussian Mixture Extension Implemented with Minor Modifications to the LETKF

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Abstract. A particle filter (PF) is an ensemble data assimilation method that does not assume Gaussian error distributions. Recent studies proposed local PFs (LPFs), which use localization as in the ensemble Kalman filter, to apply the PF for high-dimensional dynamics efficiently. Among others, Penny and Miyoshi developed an LPF in the form of the ensemble transform matrix of the Local Ensemble Transform Kalman Filter (LETKF). The LETKF has been widely accepted for various geophysical systems including numerical weather prediction (NWP) models. Therefore, implementing consistently with an existing LETKF code is useful.

Transform Matrix in LPF

LPF

$$\mathbf{X}^a_{LPF} = \overline{\mathbf{x}}^b \cdot \mathbf{1} + \delta \mathbf{X}^b \mathbf{T}_{LPF}$$

*j*th particle is given by weighted average of *m* prior particles

Ideal transform matrix satisfies

(1) $$\sum_{i=1}^{m} \mathbf{T}_{i,j} = 1 \quad (j = 1, \ldots, m)$$

(necessary condition)

(2) $$\frac{1}{m} \sum_{j=1}^{m} \mathbf{T}_{i,j} = w_i \quad (i = 1, \ldots, m)$$

(ideal condition)

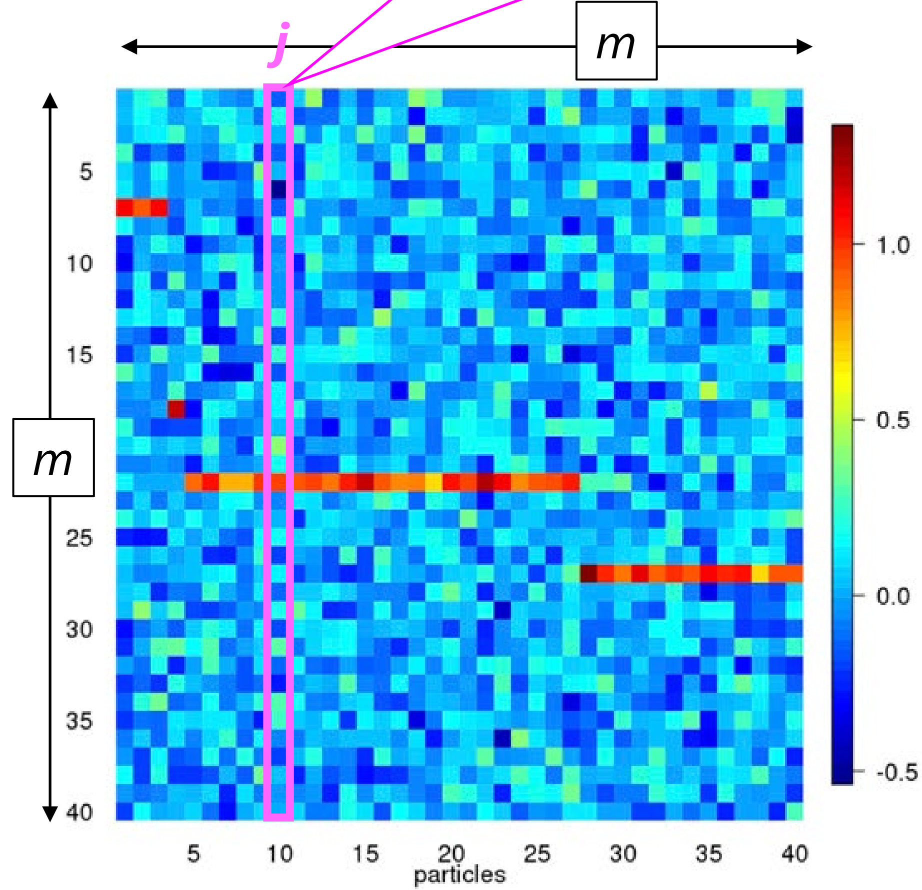
➔ **infinite solutions**

(3) $$minimize \sum_{j=1}^{m} \sum_{i=1}^{n} \left| T_{i,j} C_{i,j} \right|$$

$C_{i,j}$: transport cost from i ➔ j

➔ **a unique solution (a.k.a. optimal transport; OT)**

Used for LPF by Reich (2013) and Farchi and Bocquet (2018)



a resampling matrix
Potthast et al (2019; MWR)

Comparison

Used in our paper to GMD

		SU	MR	Stochastic MR	OT	Sinkhorn
	Computational order	m	$m\log m$	$m\log m \times N$	m^2	m^2
(1)	$\sum_{i=1}^{m} \mathbf{T}_{i,j} = 1 \quad (j = 1,\ldots,m)$ must be satisfied	◎	◎	◎	◎	◎
(2)	$\frac{1}{m}\sum_{j=1}^{m} \mathbf{T}_{i,j} = w_i \quad (i = 1,\ldots,m)$ ➔ analysis accuracy	△	△	○	◎	○
(3)	$minimize \sum_{j=1}^{m}\sum_{i=1}^{n} \left\| T_{i,j} C_{i,j} \right\|$	×	×	×	◎	○

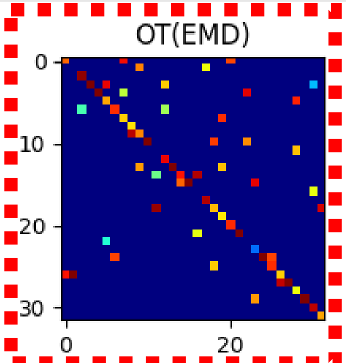
= to minimize increment of each ensemble ➔ Physically balanced AN ensemble

m: ensemble size

◎: exactly satisfied
○: approximately satisfied
△: roughly satisfied
×: not considered

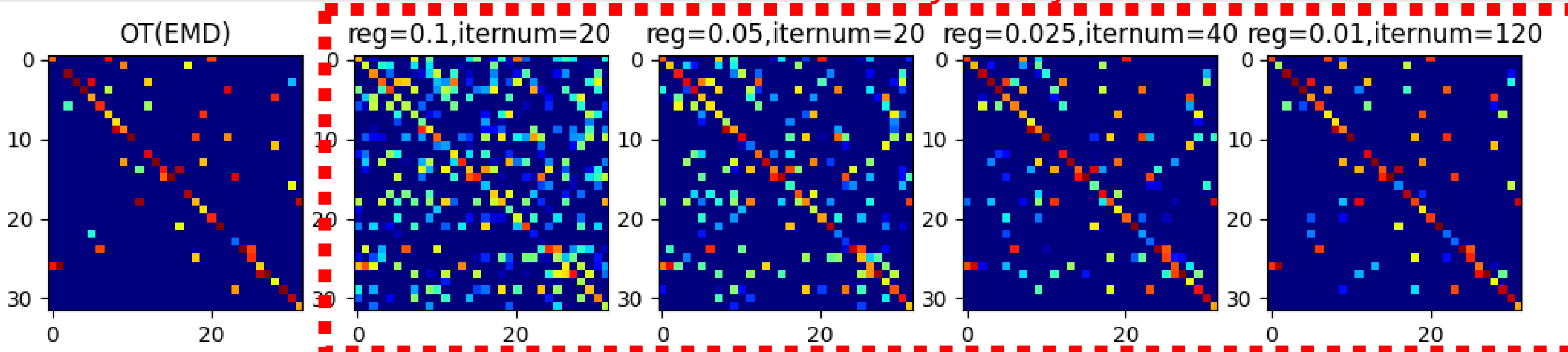
	SU	MR	Stochastic MR	OT	Sinkhorn
Computational order	*m*	*mlogm*	*mlogm* x *N*	m^2	m^2
(1) $\sum_{i=1}^{m} \mathbf{T}_{i,j} = 1 \quad (j = 1, \ldots, m)$ must be satisfied	◎	◎	◎	◎	◎
(2) $\frac{1}{m}\sum_{j=1}^{m} \mathbf{T}_{i,j} = w_i \quad (i = 1, \ldots, m)$ ➔ analysis accuracy	△	△	○	◎	○
(3) $minimize \sum_{j=1}^{m}\sum_{i=1}^{n} \left\| T_{i,j} C_{i,j} \right\|$	×	×	×	◎	○

= to minimize increment of each ensemble➔ Physically balanced AN ensemble

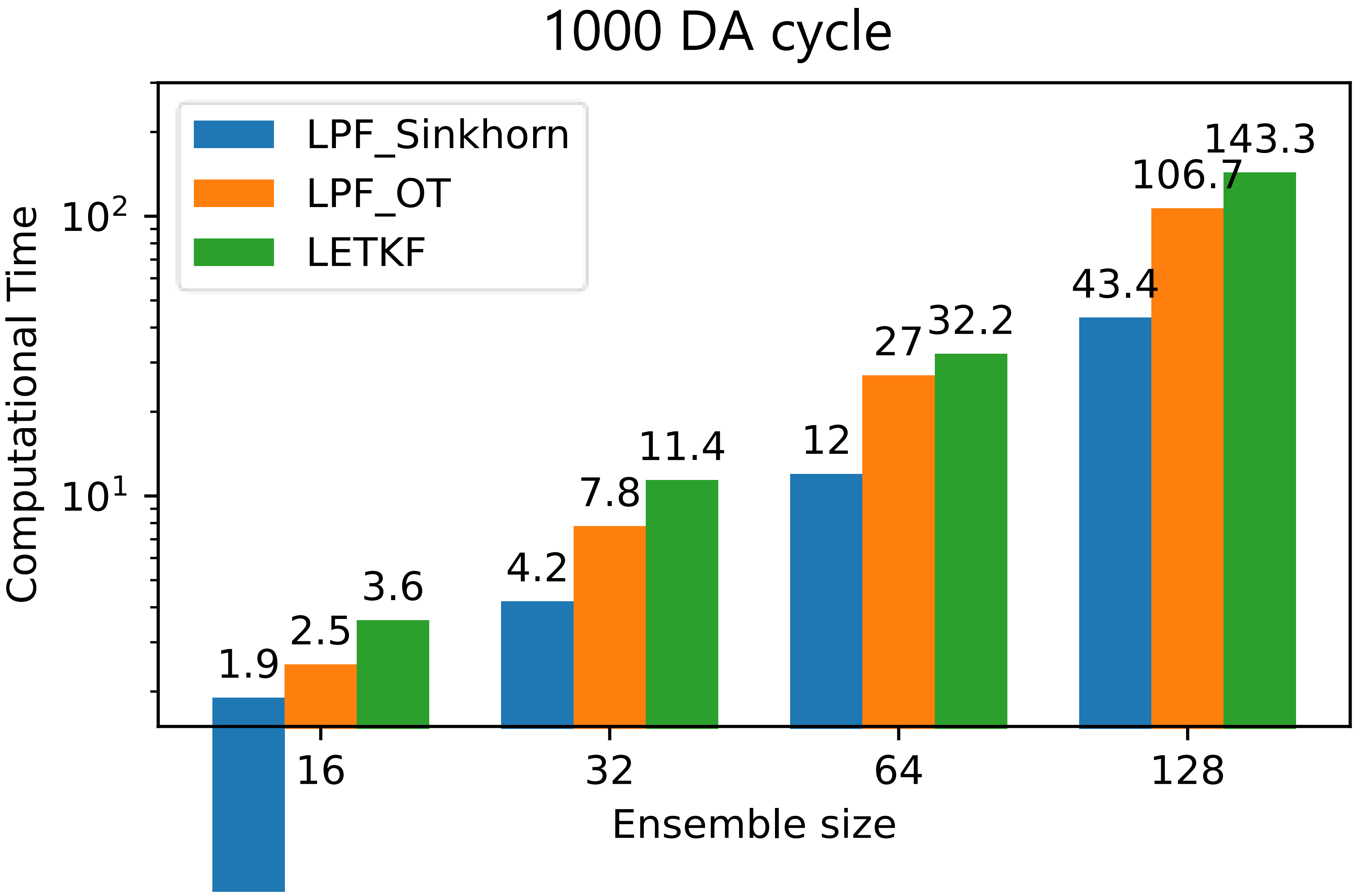


		SU	MR	Stochastic MR	OT	Sinkhorn
	Computational order	m	$m\log m$	$m\log m$ x N	m^2	m^2
(1)	$$\sum_{i=1}^{m}\mathbf{T}_{i,j}=1 \quad (j=1,\ldots,m)$$ must be satisfied	◎	◎	◎	◎	◎
(2)	$$\frac{1}{m}\sum_{j=1}^{m}\mathbf{T}_{i,j}=w_i \quad (i=1,\ldots,m)$$ ➔ analysis accuracy	△	△	○	◎	○
(3)	$$minimize\sum_{j=1}^{m}\sum_{i=1}^{n}\left\|T_{i,j}C_{i,j}\right\|$$	×	×	×	◎	○

= to minimize increment of each ensemble➔ Physically balanced AN ensemble



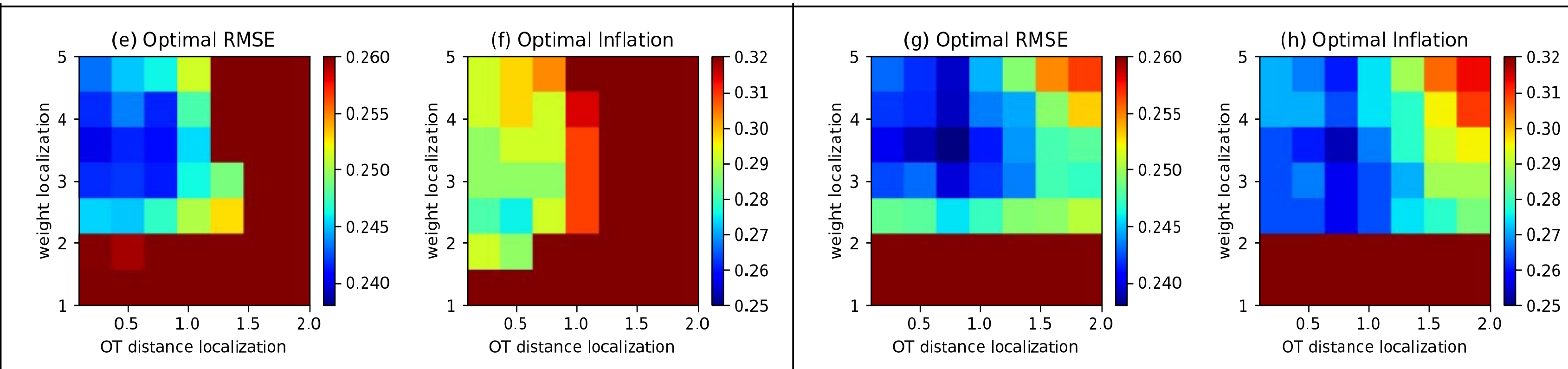
Computational Time (LPF-L96)



Impacts on RMSE and inflations

Sinkhorn   Optimal Transport

Member: 64



	SU	OT	Sinkhorn
Computational time	Best	△	○
Analysis accuracy	△	◎	○

OT and Sinkhorn were implemented into SPEEDY-LPF and LPFGM

➔ will be compared

Oishi and Kotsuki (2023, SOLA)

SOLA, 2023, *Vol.* 19, 185−193, doi:10.2151/sola.2023-024

Applying the Sinkhorn Algorithm for Resampling of Local Particle Filter

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Abstract The particle filter attracts interest from the data assimilation research community since it does not assume a Gaussian prior error distribution. Several local particle filters (LPFs) have been proposed to avoid weight collapse due to assimilation of observations in high dimensional systems. This study focuses on an LPF that uses the ensemble transform matrix as used in the local ensemble transform Kalman filter. Resampling of the transform-matrix-based LPF has been employed using Optimal Transport (OT) that minimizes analysis increments of particles. However, computations of OT increase by order of square, which limits its application for large-ensemble LPF problems.

This study proposes using the fast Sinkhorn algorithm, an approximated solver of the OT method, for the resampling of LPFs. A series of perfect model experiments with a 40-variable toy model show that the Sinkhorn algorithm produces accurate analyses equivalent to that obtained with the OT method. In addition, the Sinkhorn algorithm accelerates total computational time more than two times compared to the OT-based LPF when the ensemble size is 64 or more. The Sinkhorn-based resampling would be a promising tool for applying the LPFs to account for non-Gaussian prior error distribution with many ensemble members.

Citation: Oishi, K. and S. Kotsuki, 2023: Applying the Sinkhorn algorithm for resampling of local particle filter. *SOLA*, **19**, 185−193, doi:10.2151/sola.2023-024.