From Real-Time Big Data Assimilation on Fugaku to Synergistic Development of DA and AI: Osaka Expo 2025 and Beyond

Takemasa Miyoshi*

S. Otsuka, J. Taylor, J. Liang, M. Goodliff, Y. Tarumi (RIKEN)

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RIKEN Center for Computational Science

Data Assimilation Team

iTHEMS

RIKEN R-CCS, Kobe, Japan

Pushing the limits

Big Data × *Big Simulations*

Big ensemble (10240 ensemble members)

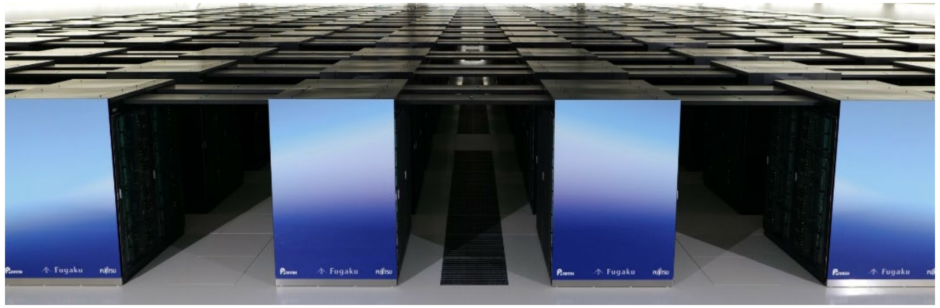
Rapid update (30-second update)

High resolution (100-m mesh)

➔ Future Numerical Weather Prediction

September 2012

~100x



March 2021

https://awards.acm.org/bell-climate

SC23 in Denver, CO (November 2023)

Specific Types of Contributions

ACM Gordon Bell Prize for Climate Modelling

Innovations in applying high-performance computing to climate modelling applications

Award Recipients **Nominations** **Committee Members**

FINALIST 3

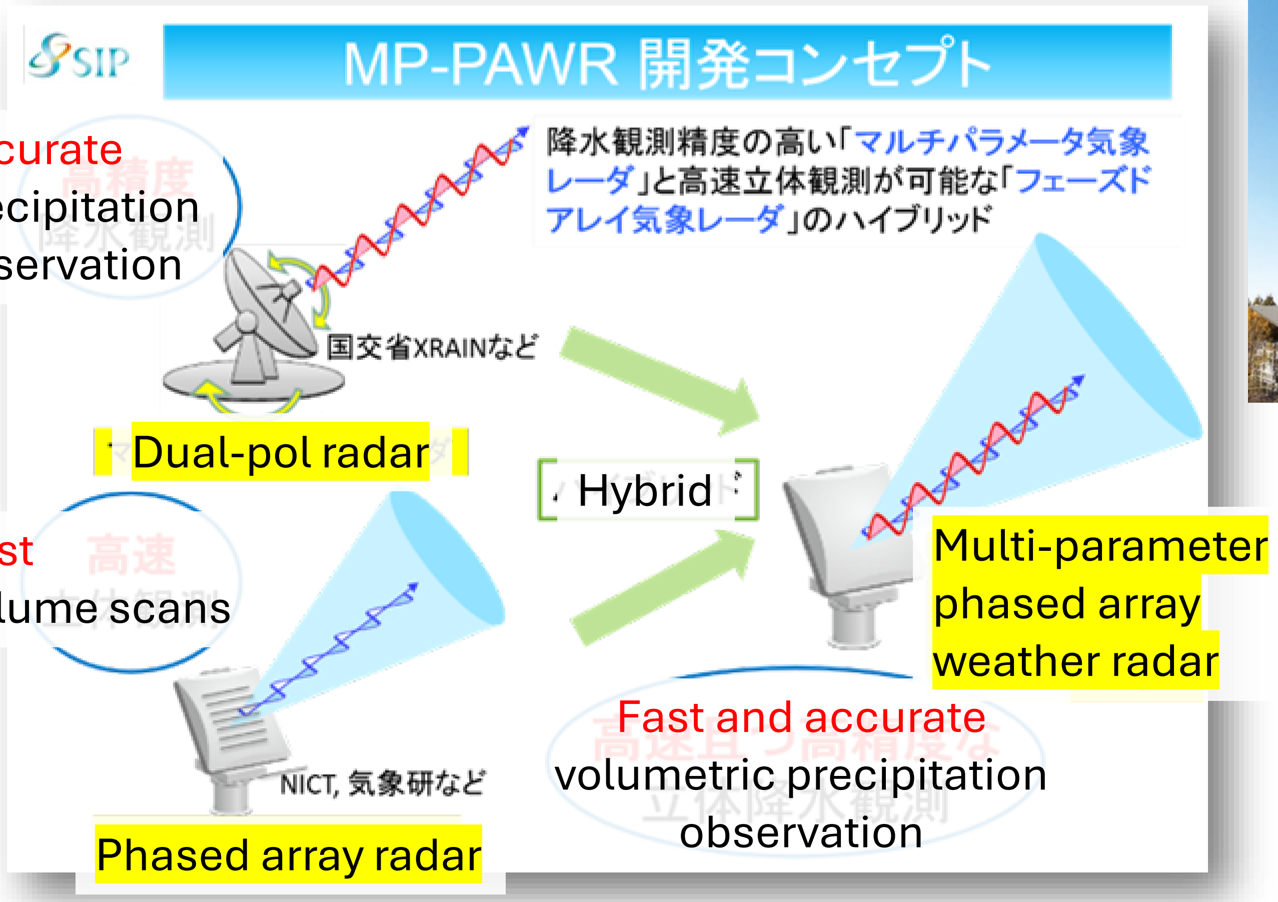
Big Data Assimilation: Real-time 30-second-refresh Heavy Rain Forecast Using Fugaku During Tokyo Olympics and Paralympics

Authors: Takemasa Miyoshi, Arata Amemiya, Shigenori Otsuka, Yasumitsu Maejima, James Taylor, Takumi Honda, Hirofumi Tomita, Seiya Nishizawa, Kenta Sueki, Tsuyoshi Yamaura, Yutaka Ishikawa, Shinsuke Satoh, Tomoo Ushio, Kana Koike, and Atsuya Uno

https://sc23.supercomputing.org/2023/09/eyes-beyond-the-prize/

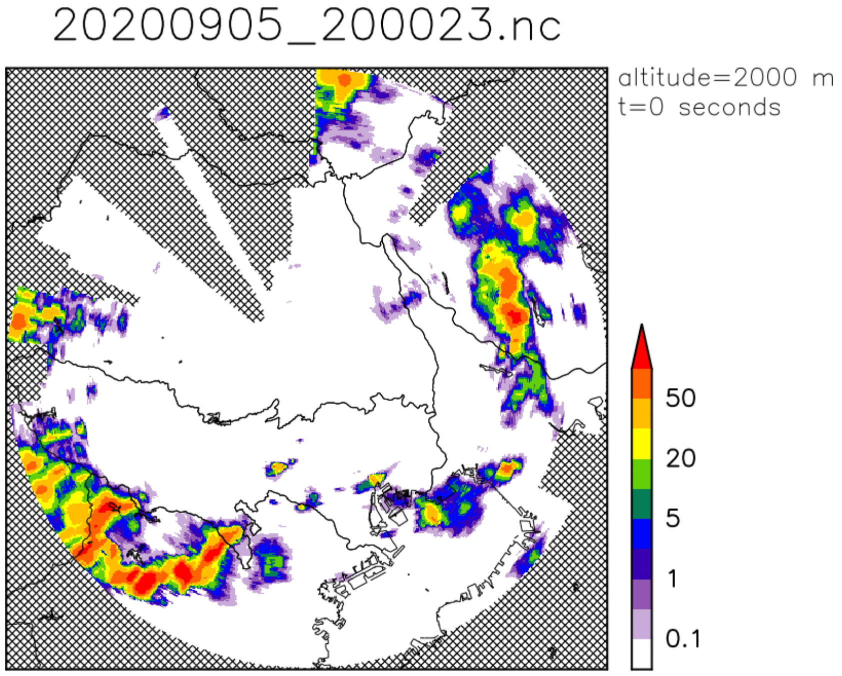

スーパーコンピュータ「富岳」
Japanese
English
運用状況
通常運用中
「富岳」運用ステータス
運用スケジュール
利用者支援
利用者ポータル
成果発表
申請
利用に関して
お問い合わせ
[運用情報]Resource for ordinary users is reduced (available resource: 91%, due to real-time execution)
この期間、一般向けの提供資源が縮小されます。
実時間型ジョブ実行のため、提供される資源規模は、全体の約91%ま となります。
この期間、一般向けにはログインノード１は利用できません。
2021-06-02
スケジュール終了日時
2021-08-09 00:00
スケジュール開始日時
2021-07-19 15:00
Exclusive use of
~7% of Fugaku
(~0.5M cores)
Fugaku
FUJITSU

Multi-Parameter Phased Array Weather Radar (MP-PAWR)



https://www.nict.go.jp/press/2017/11/29-1.html
(partially translated by S. Otsuka)

(Takahashi et al. 2019)

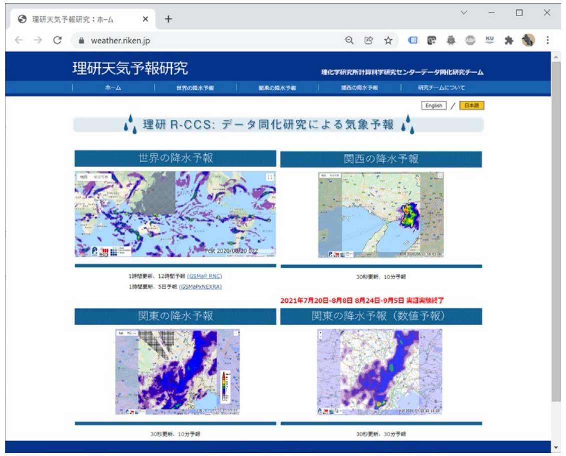


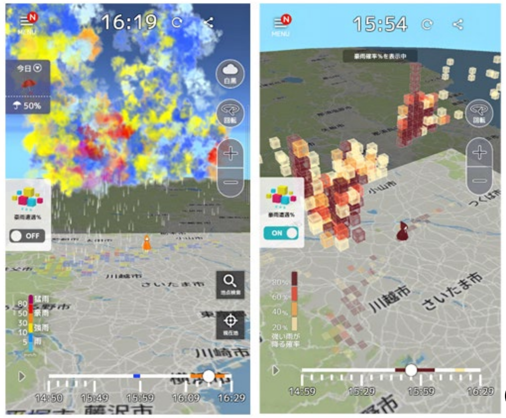
- X-Band Frequency Radar
- 75m range resolution
- ~100 elevation angles
- Full-sky scan every 30 seconds

30-s refresh real-time workflow with "Fugaku"

Multi-Parameter Phased Array Weather Radar
(at Saitama Univ.)

(Takahashi et al. 2019)





(MTI Ltd.)

NICT
Saitama Univ.
TOSHIBA

Saitama Univ. MP-PAWR → NICT ds01

JIT-DT
106 MB per obs.
in 3 seconds

→ Fugaku login1 → SCALE-LETKF

SCALE-LETKF → weather.riken.jp (webpage)

SCALE-LETKF → MTI Amazon AWS (smartphone)

RIKEN R-CCS

理研天気予報研究

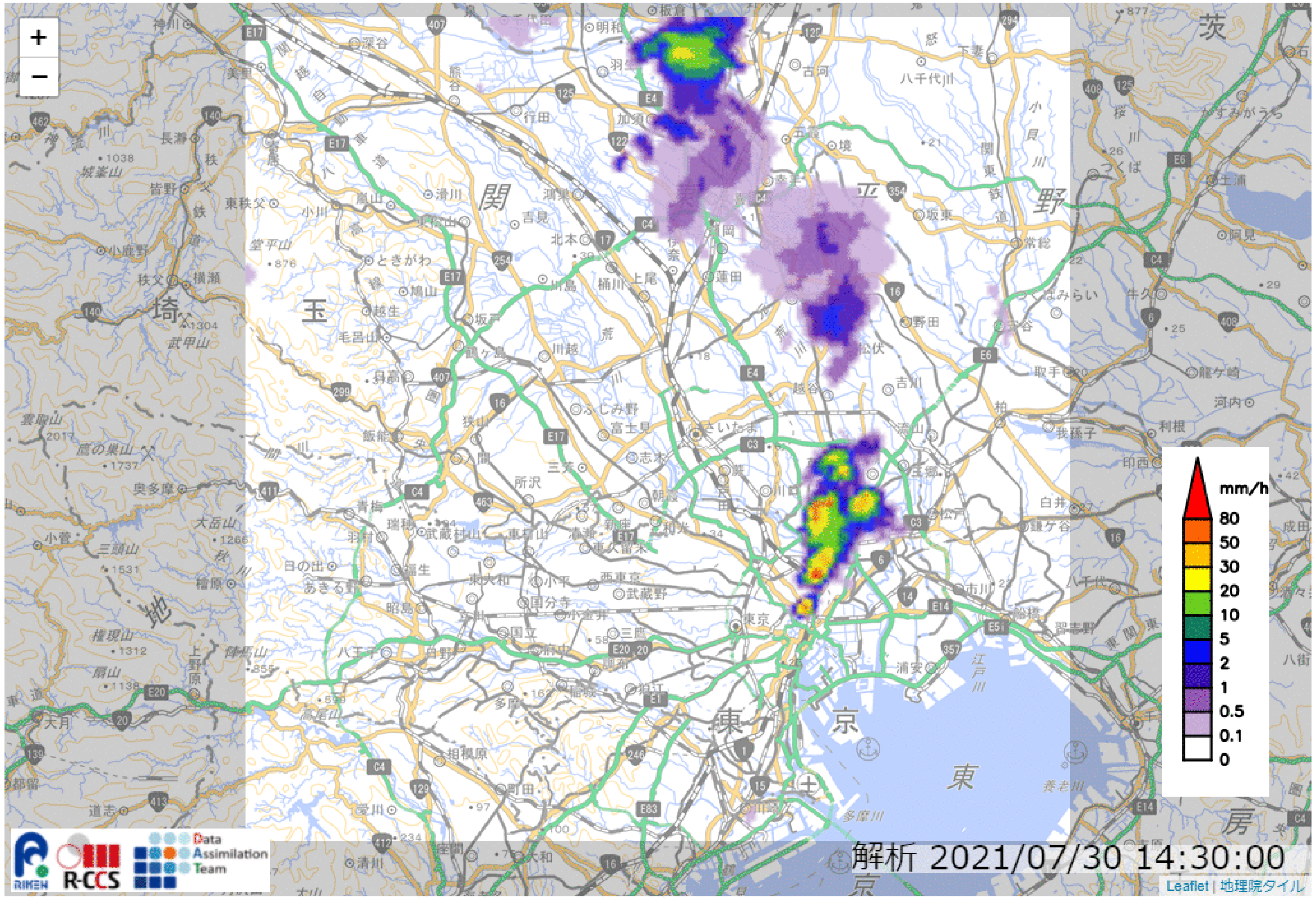
理化学研究所計算科学研究センターデータ同化研究チーム

ホーム | 世界の降水予報 | 関東の降水予報 | 関西の降水予報 | データ同化研究チームについて

https://weather.riken.jp/

予報開始時刻: 2021/07/30 14:30:00 ?

<< 解析 2021/07/30 14:30:00 >> 予測 確率予測 観測 解析 気象庁レーダー ? アニメーション



Bird’s-eye view

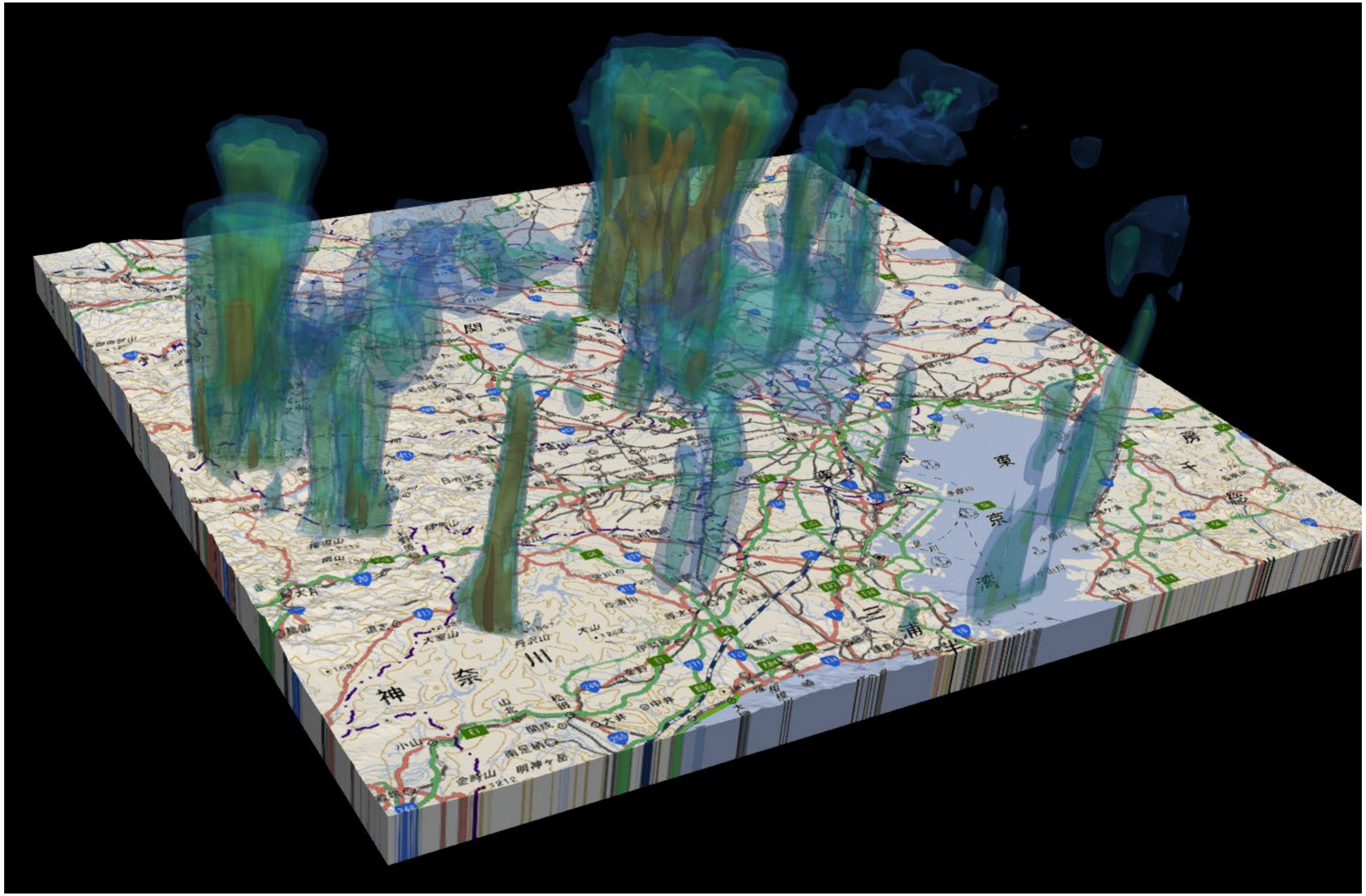


Figure 8: 3-D bird’s-eye view of 30-minute forecast rains at 04:48:00 UTC, July 30, 2021. Colors represent simulated radar reflectivity every 10 dBZ for 10-50 dBZ. Vertical scale is stretched by three times. Map data is from the web page of the Geospatial Information Authority of Japan (Courtesy of H. Sakamoto of RIKEN).

120x faster, big ensemble, precision

(as of early 2023)

NWP system	Center	Data assimilation method	Forecast grid spacing / # grid points	Frequency for initialization / free forecast	Use of radar data	Ensemble forecast grid spacing / # members
LFM [6,7,8,9]	JMA, Japan	Hybrid 3DVar, 5-km grid spacing	2 km / 1581 x 1301 x 76	1 h / 1 h	Assimilation of RH from radar and radial wind	None (MEPS: 5 km / 21 members)
HRRR v4 [10,11,12]	NCEP, US	Hybrid 3D EnVar, 36 members	3 km / 1799 x 1059 x 51	1 h / 1 h	Latent heating	None
HRDPS 6.0.0 [13,14,15]	ECCC, Canada	4DEnVar perturbations from global ensemble	2.5 km / 2576 x 1456 x 62	6 h / 6 h	Latent heat nudging	None
UKV [16,17]	Met Office, UK	4DVar	1.5 km / 622 x 810 x 70	1 h / 1 h	Latent heat nudging	2.2 km / 3 members
AROME France [18,19,20]	Météo-France	3DVar	1.25 km / 2801 x 1791 x 90	1 h / 3 h	Assimilation of pseudo-RH from radar	2.5 km / 12 members
ICON-D2 [21,22,23]	DWD, Germany	LETKF 40 members	2.2 km / 542040 cells x 65 levels	1 h / 3 h	Latent heat nudging	2.2 km / 20 members
BDA2021 This paper	RIKEN, Japan	LETKF **1000 members**	**500 m** / 256 x 256 x 60	**30 s / 30 s**	**Reflectivity, Doppler velocity**	**500 m** / 11 members

Future?

SC25
ST. LOUIS NOV 16–21

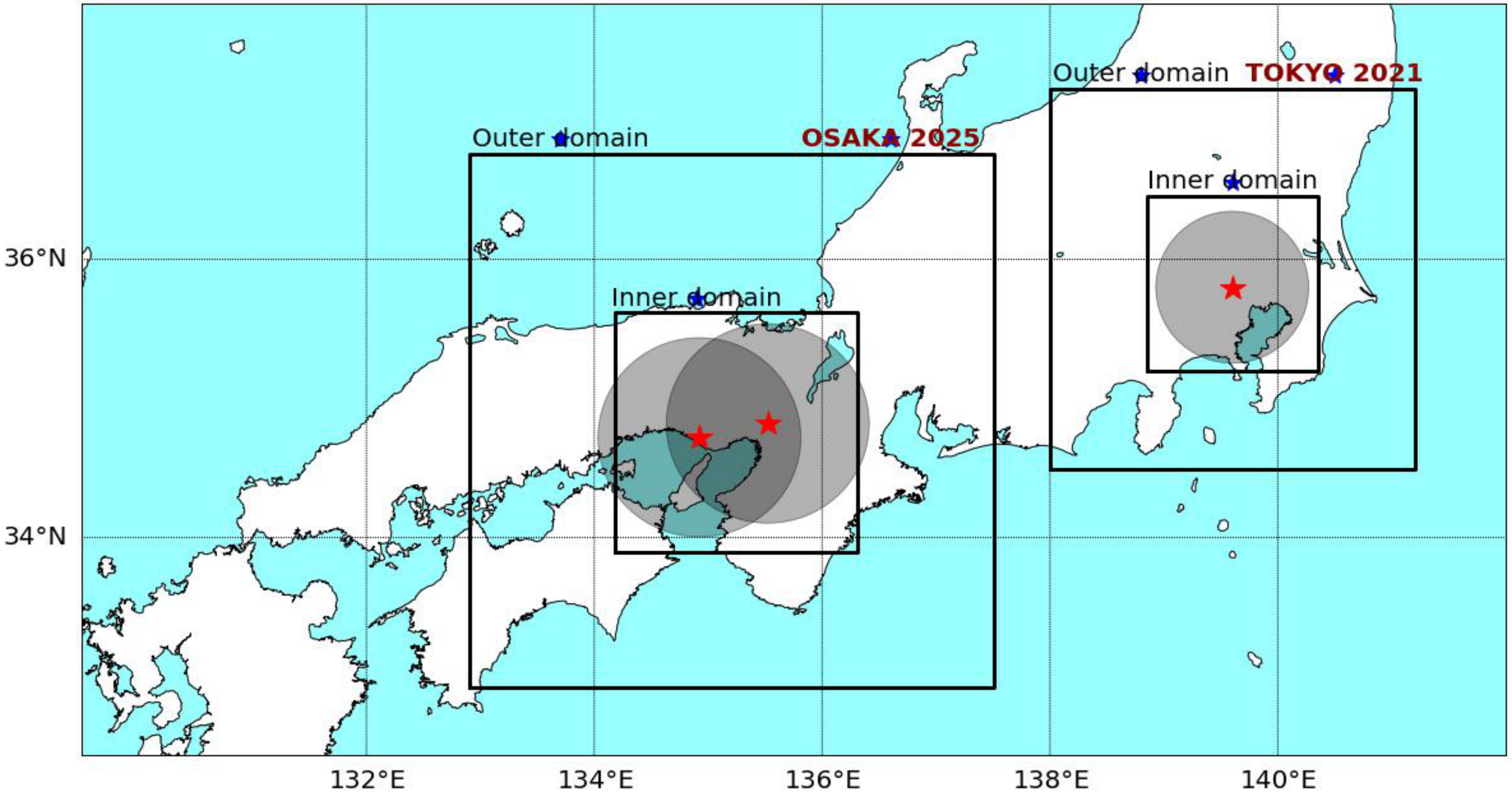
Home › Program › Invited Talks

BIG DATA

10:30–11:15 am CST

From Gordon Bell Finalist to the Osaka Expo: The Evolution of Real-Time Forecasting on Fugaku

Takemasa Miyoshi
RIKEN Center for Computational Science (R-CCS)



	Osaka 2025 Real-Time Experiment	Tokyo 2021 Real-Time Experiment
Experiment Duration	1 month	1 month
Number of forecasts	>75,000	75,248
Ensemble size (LETKF)	1000	1000
Number of MP-PAWRs	2 (Kobe and Osaka MP-PAWR) 2 x Doppler wind and Reflectivity	1 (Saitama MP-PAWR) 1 x Doppler wind and Reflectivity
Inner Domain Size	192 x 192 km	128 x 128 km
Number of computational nodes	26,648 (16% of total nodes on Fugaku)	11,580 (7%)

Experimental real-time NWP system to assimilate MP-PAWR every 30s

Obtain latest JMA MSM and MP-PAWR observations

JMA Atmospheric Data

JMBSC Latest JMA Mesoscale Model (MSM) Analysis/Forecasts (atmosphere)

NCEP Land Data

Latest NCEP GFS (land)

Every 3-hours

3 hours

Fast data transfer

Radar Observations (MP-PAWR)

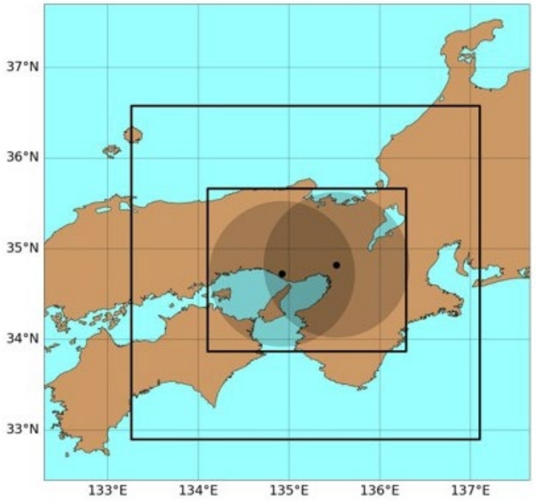
NICT National Institute of Information and Communications Technology

JIT-DT (Just-In-Time-DT)

30 sec

Every 30-seconds

Run the SCALE-LETKF on Fugaku



Outer Domain

(1000-members generating 9hr forecasts every

00 03 06 09 12 15 18 21

Init/boundary conditions

Inner Domain

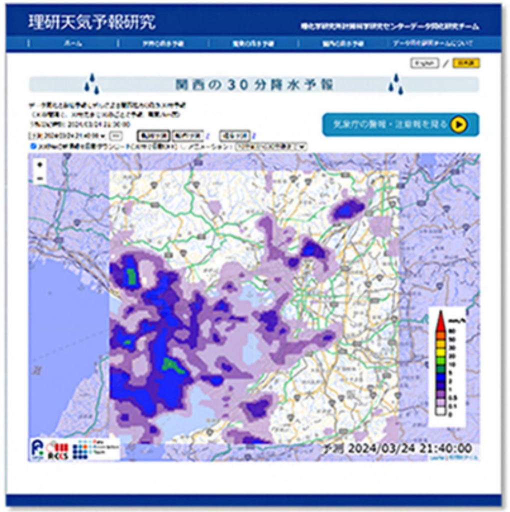
(1000-member ensemble cycled every 30-seconds)

00:00 00:30 01:00 01:30 02:00 02:30 03:00 03:30

10-members generate a 30-minute extended rain forecast after each 30-second update

Forecasts to Public

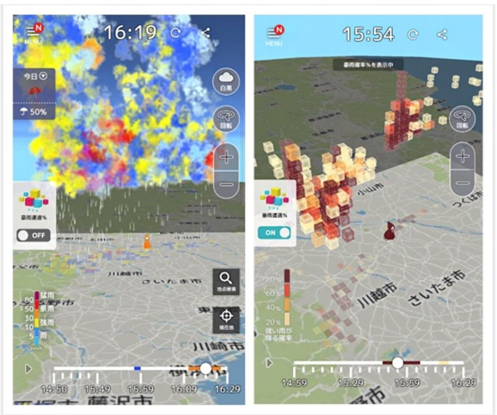
weather.riken.jp



30 sec Every 30-seconds

Forecasts to RIKEN website

MTI Ltd smartphone app



30 sec Every 30-seconds

Forecasts 3D Rain Watch Smartphone App

Osaka Expo Experiment Summary – August 2025

MON	TUE	WED	THUR	FRI	SAT	SUN
				1	2	3
4	5 – Experiment Start 12:00 **500 mems**	6	7	8	9	10
11	12	13	14	15	16	17
18	19	20	21	22	23	24
25 **1000 mem** Switch at 12:00	26	27	28	29	30	31 – Experiment End 00:00

Osaka Expo Experiment Summary – August 2025

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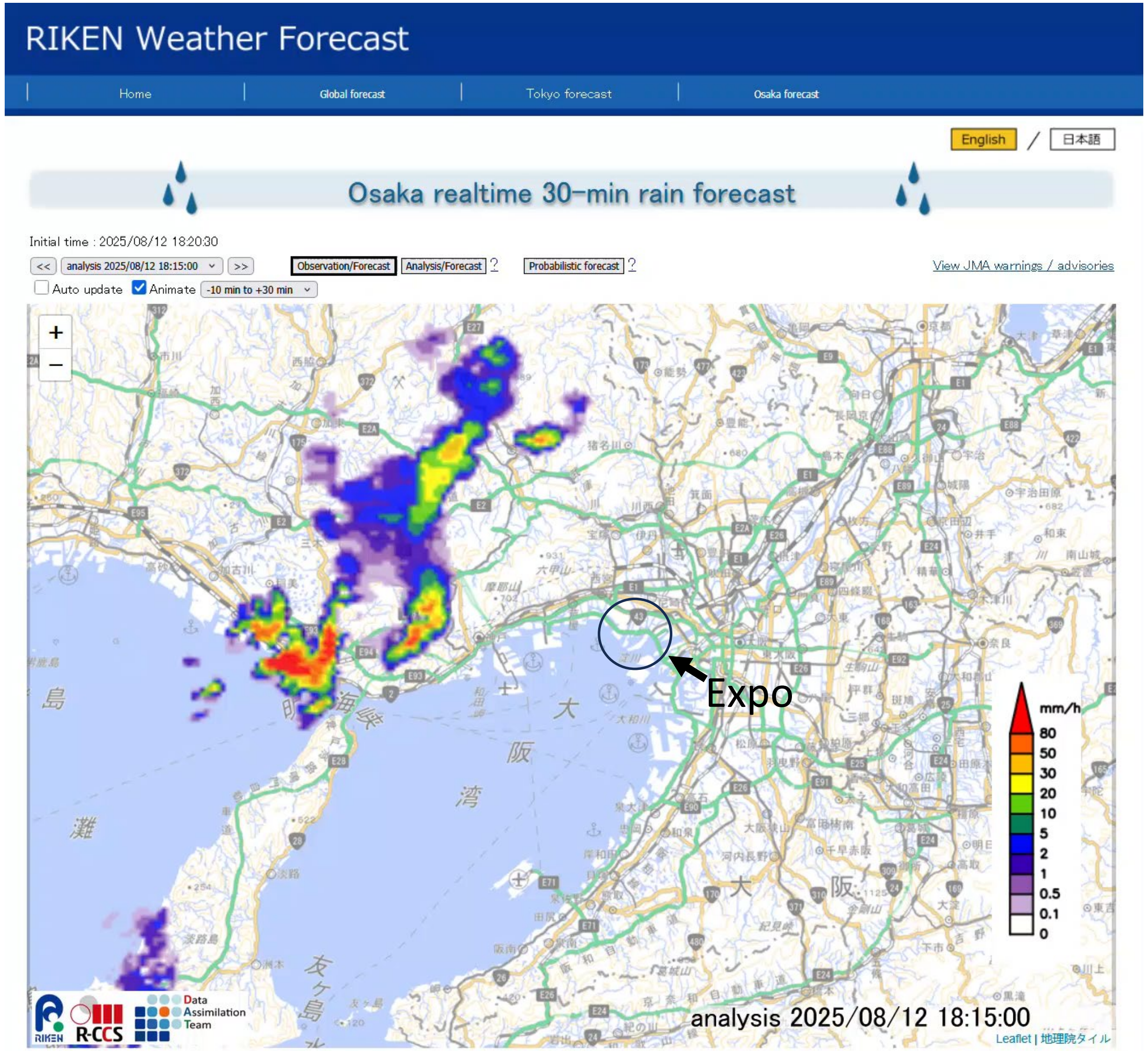
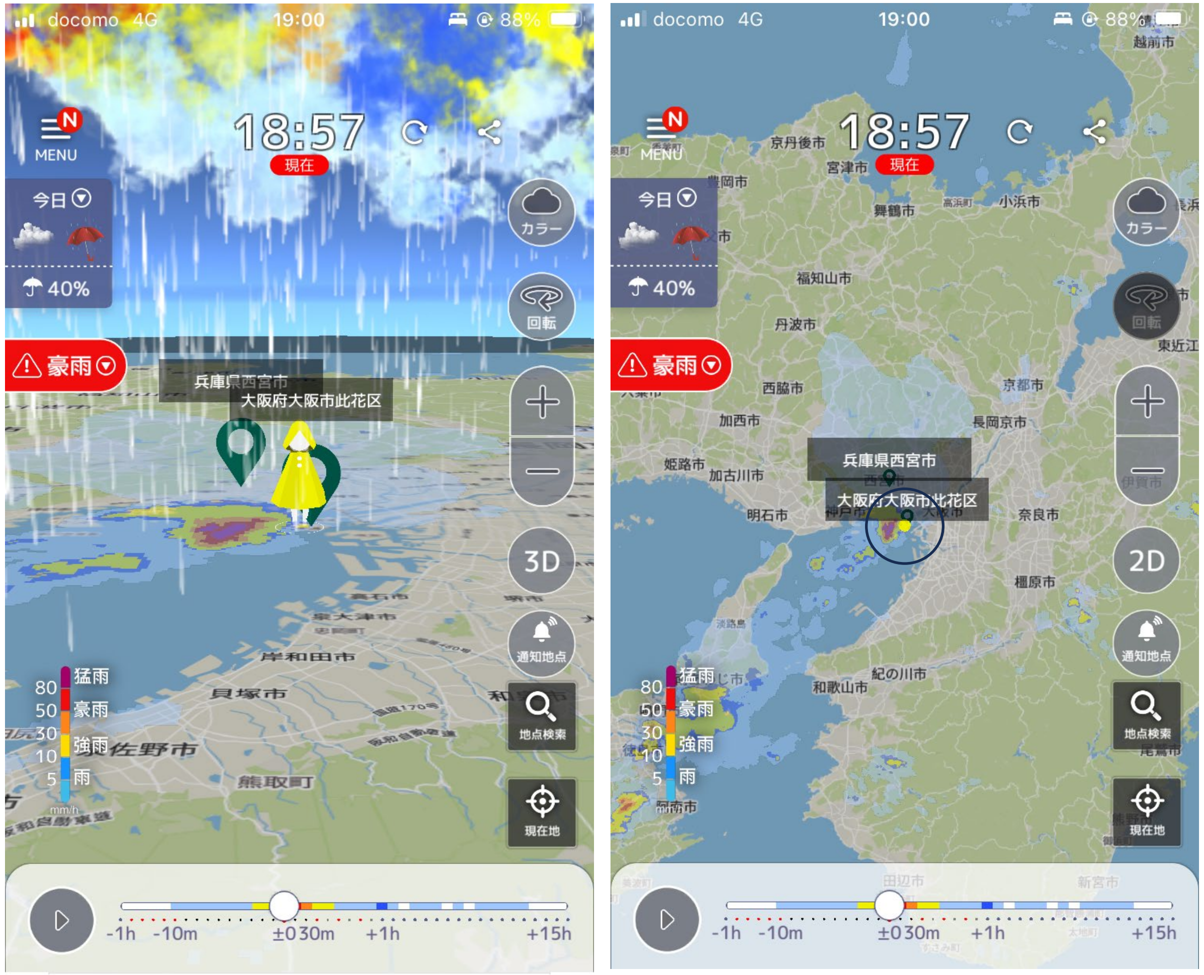
11	12	13	14	15	16	17
18	19	20	21	22	23	24
25 **1000 mem** Switch at 12:00	26	27	28	29	30	31 – Experiment End 00:00

Osaka Expo 2025 30-minute Rain Forecast: 18:20 12th Aug 2025

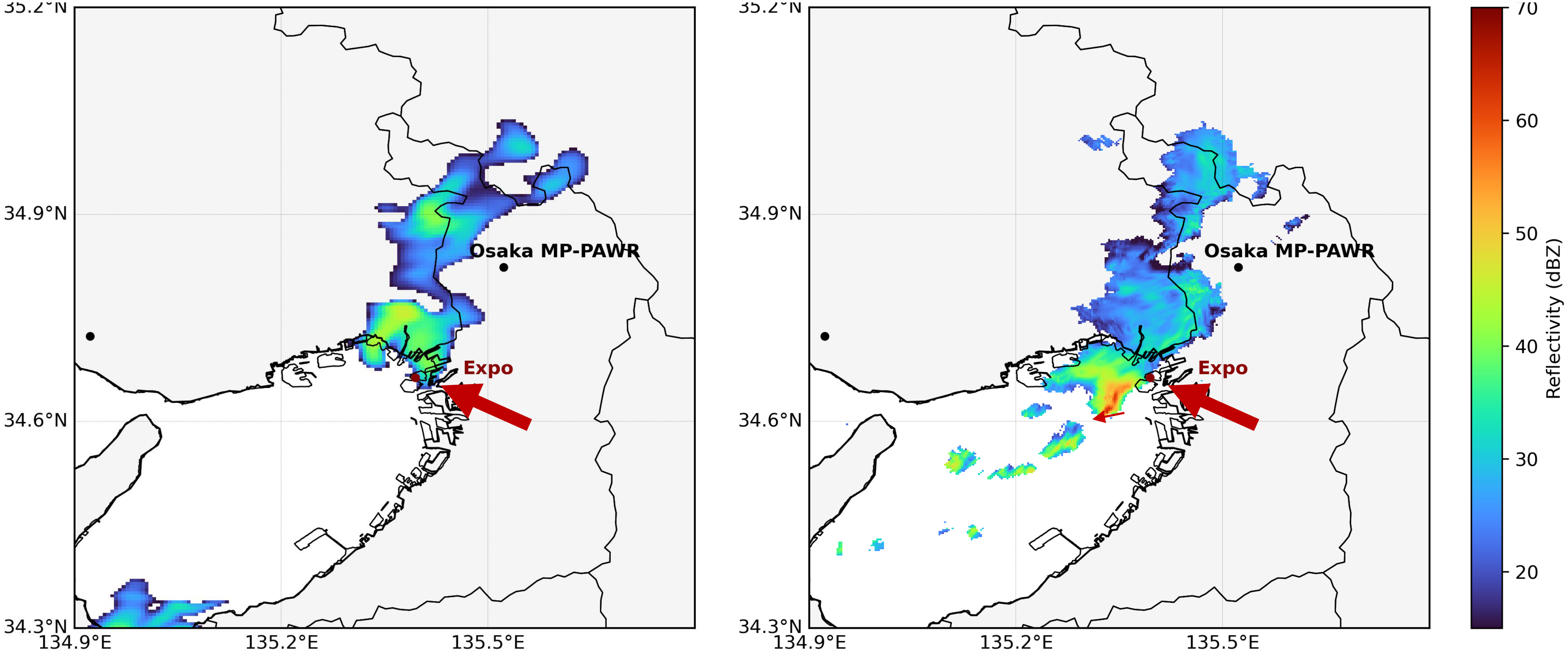


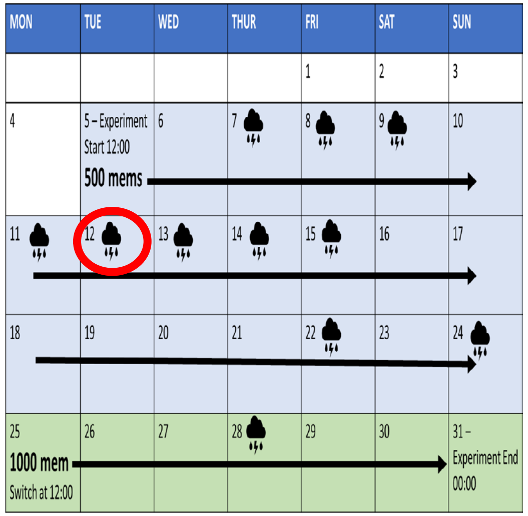
Smartphone screen shot of 3D rain cloud watch app showing rain at Osaka Expo site (circled)



- Fast moving line of convection from west with >80 mm/hr rainfall
- Advanced warning given to visitors via smartphone app

30-min.-lead forecast   Verification truth (observations)





A case of forecasting rain clouds using "Fugaku" during Expo 2025 Osaka, Kansai.

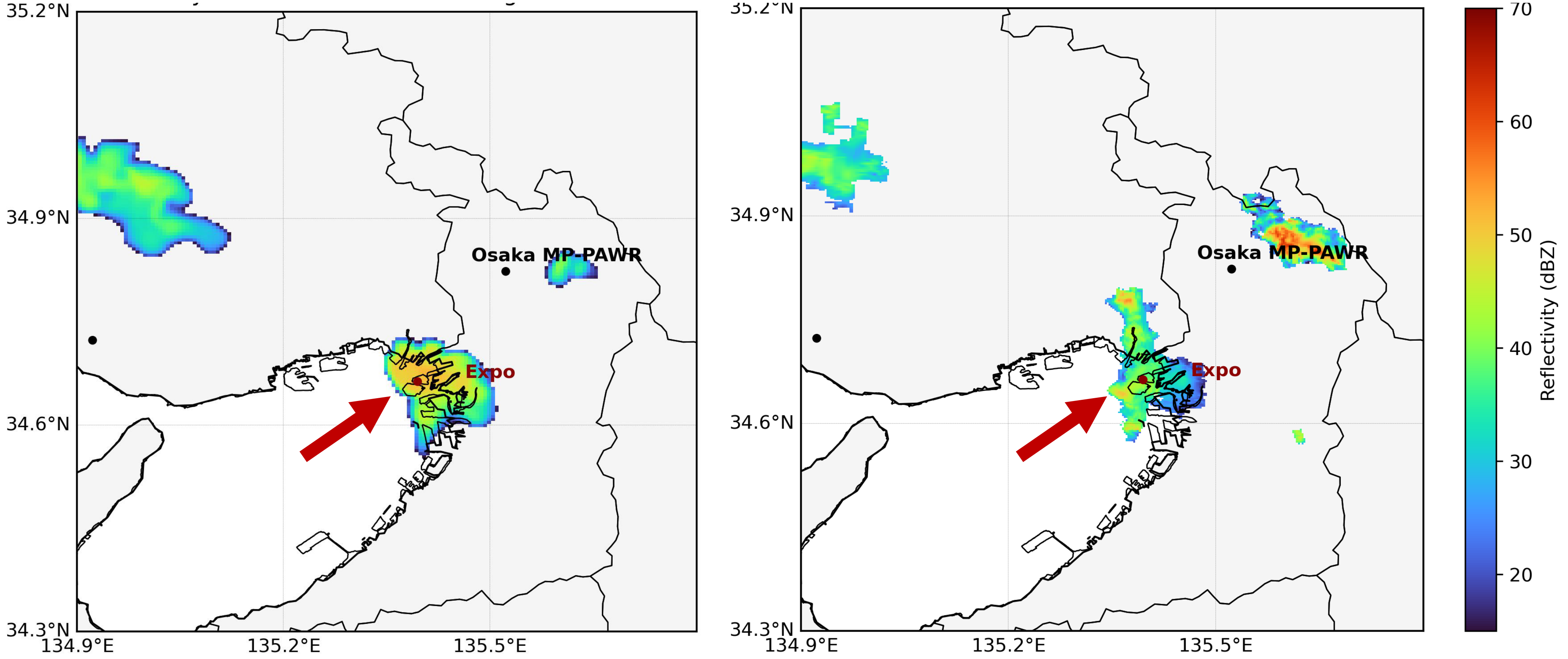
Reflectivity intensity (red is stronger) at 18:53 JST 12 August 2025.
Push notification via smartphone app was made successfully based on this forecast.

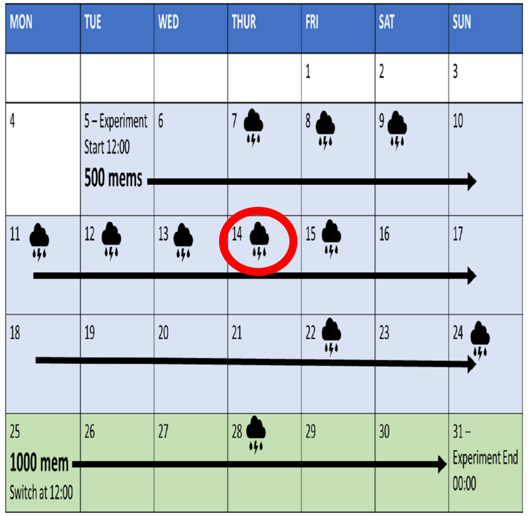
Osaka Expo Experiment Summary – August 2025

MON	TUE	WED	THUR	FRI	SAT	SUN
				1	2	3
4	5 – Experiment Start 12:00 **500 mems**	6	7	8	9	10
11	12	13	14	15	16	17
18	19	20	21	22	23	24
25 **1000 mem** Switch at 12:00	26	27	28	29	30	31 – Experiment End 00:00

Model 30 min Forecast

Radar Observations
18:30 JST





A case of forecasting rain clouds using "Fugaku" during Expo 2025 Osaka, Kansai.

Reflectivity intensity (red is stronger) at 18:30 JST 14 August 2025.
Push notification via smartphone app was made successfully based on this forecast.

Osaka Expo Experiment Summary – August 2025

MON	TUE	WED	THUR	FRI	SAT	SUN
				1	2	3
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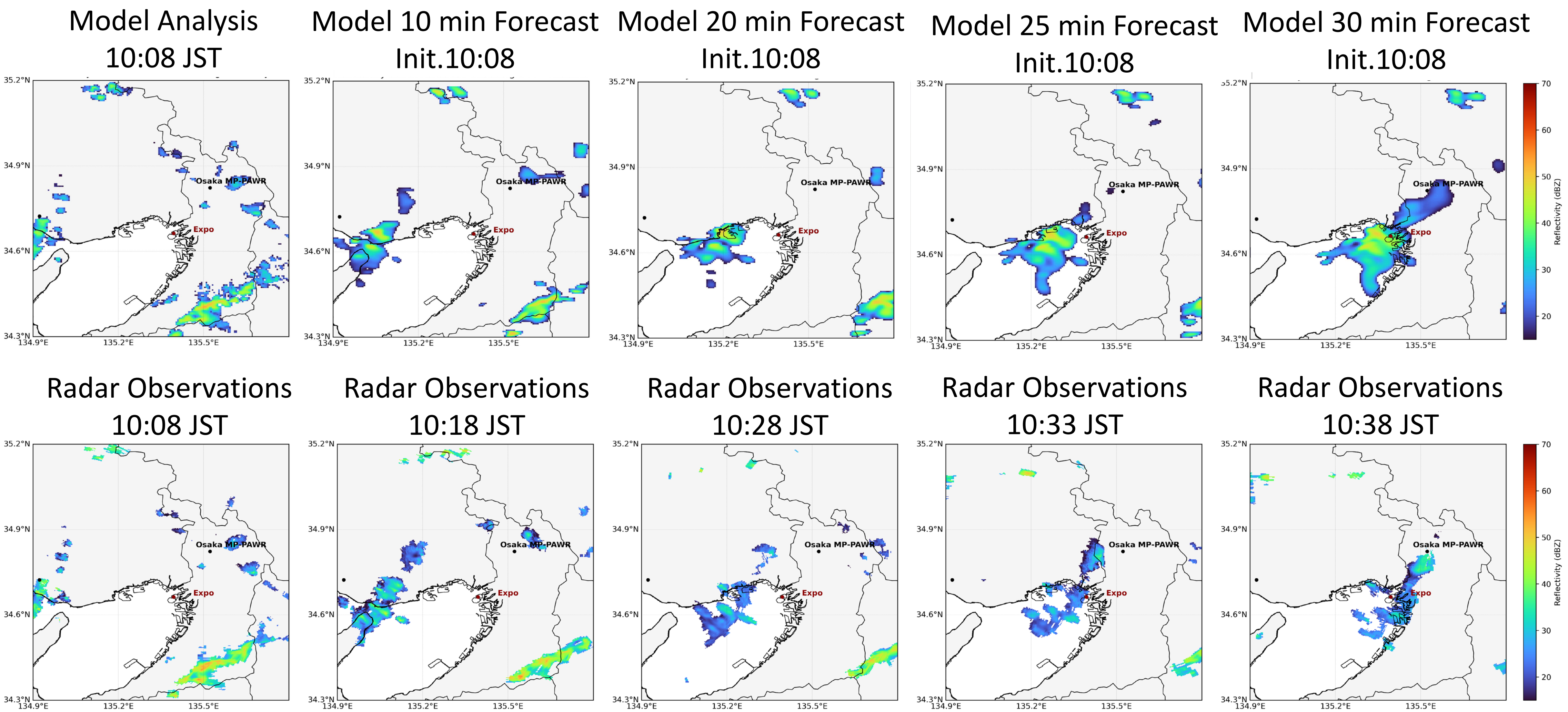
11	12	13	14	15	16	17
18	19	20	21	22	23	24
25 **1000 mem** Switch at 12:00	26	27	28	29	30	31 – Experiment End 00:00

SCALE-LETKF predicted rainfall over Expo: Initialized at 10:08 JST on 7th August 2025



Osaka Expo Experiment Summary – August 2025

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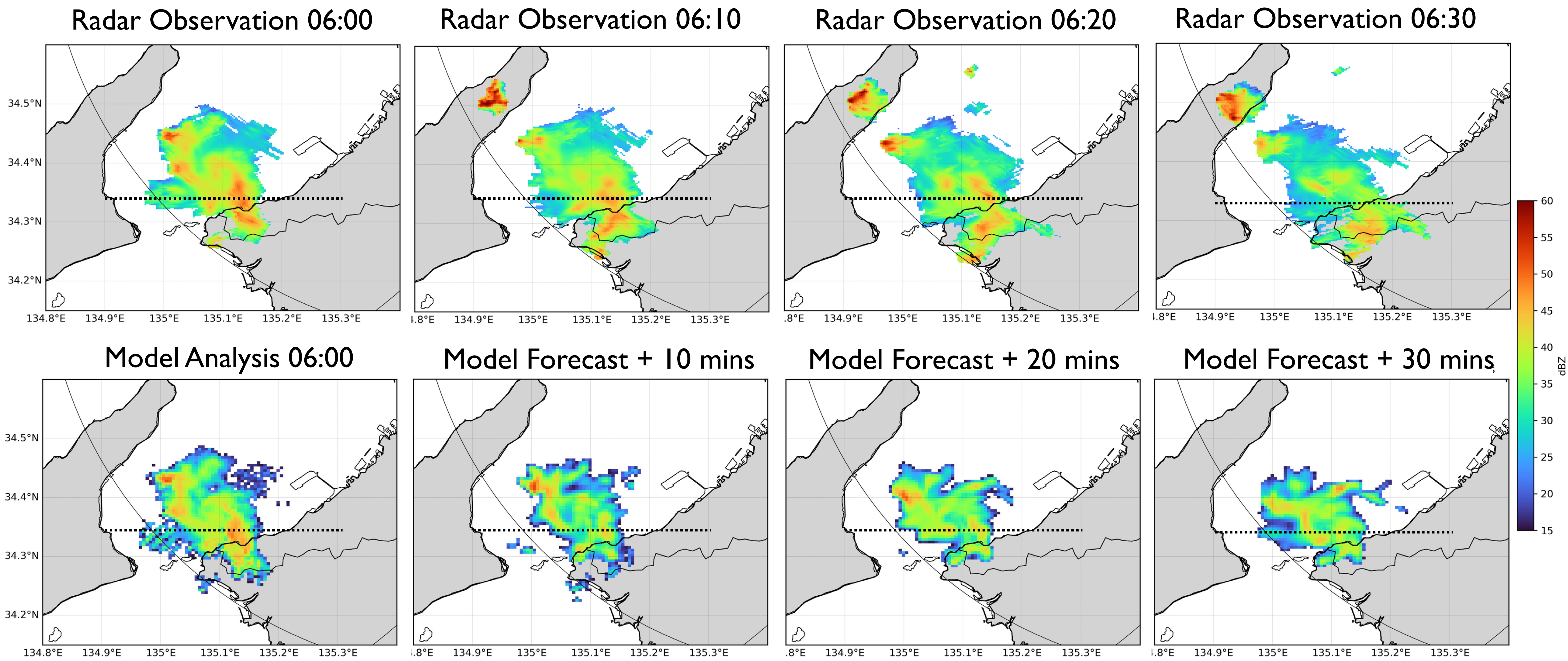
11	12	13	14	15	16	17
18	19	20	21	22	23	24
25 **1000 mem** Switch at 12:00	26	27	28	29	30	31 – Experiment End 00:00

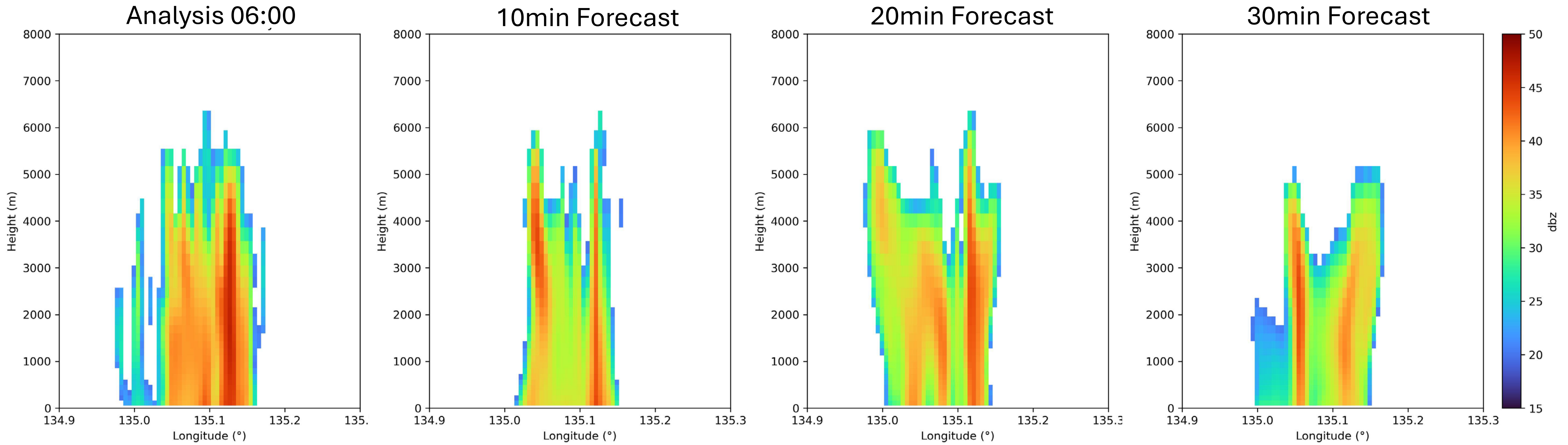
Case study 3: Localized heavy rain forecast for 30 minutes ahead at 06:00 on August 24, 2025



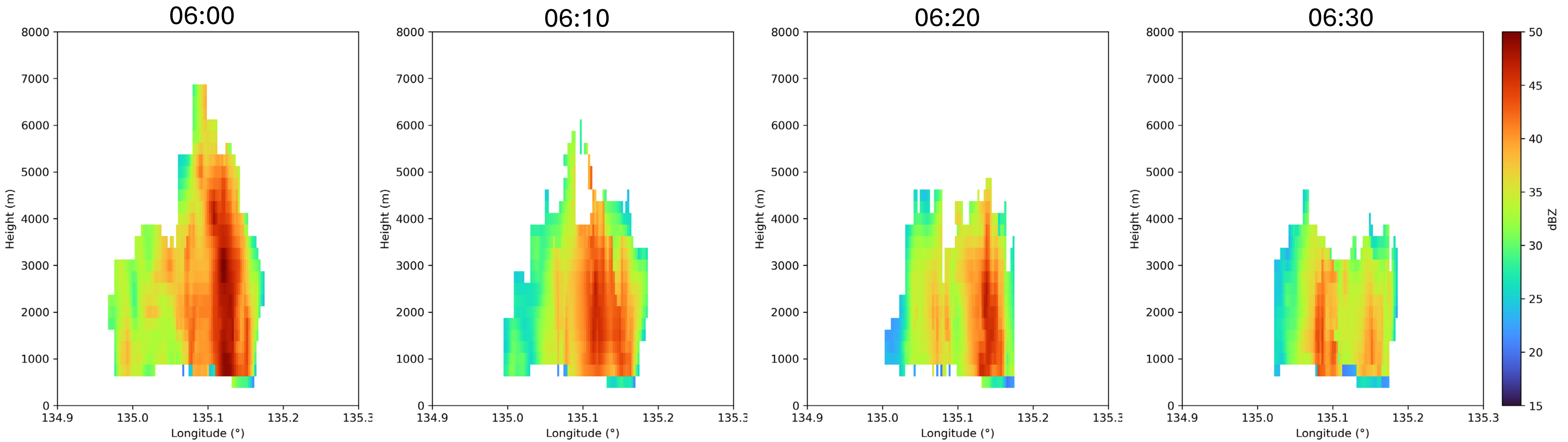
- General structure and intensity of main convection is predicted by the model
- Rapid development of convective activity over Awaji Island (further west) missed by forecast

Case study 3: Localized heavy rain forecast for 30 minutes ahead at 06:00 on August 24, 2025

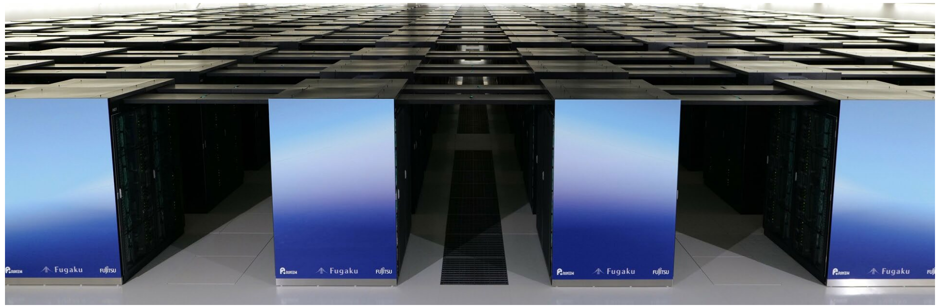
Model Analysis and Forecast (Initialized 6:00 24th August)



Radar Observations



September 2012

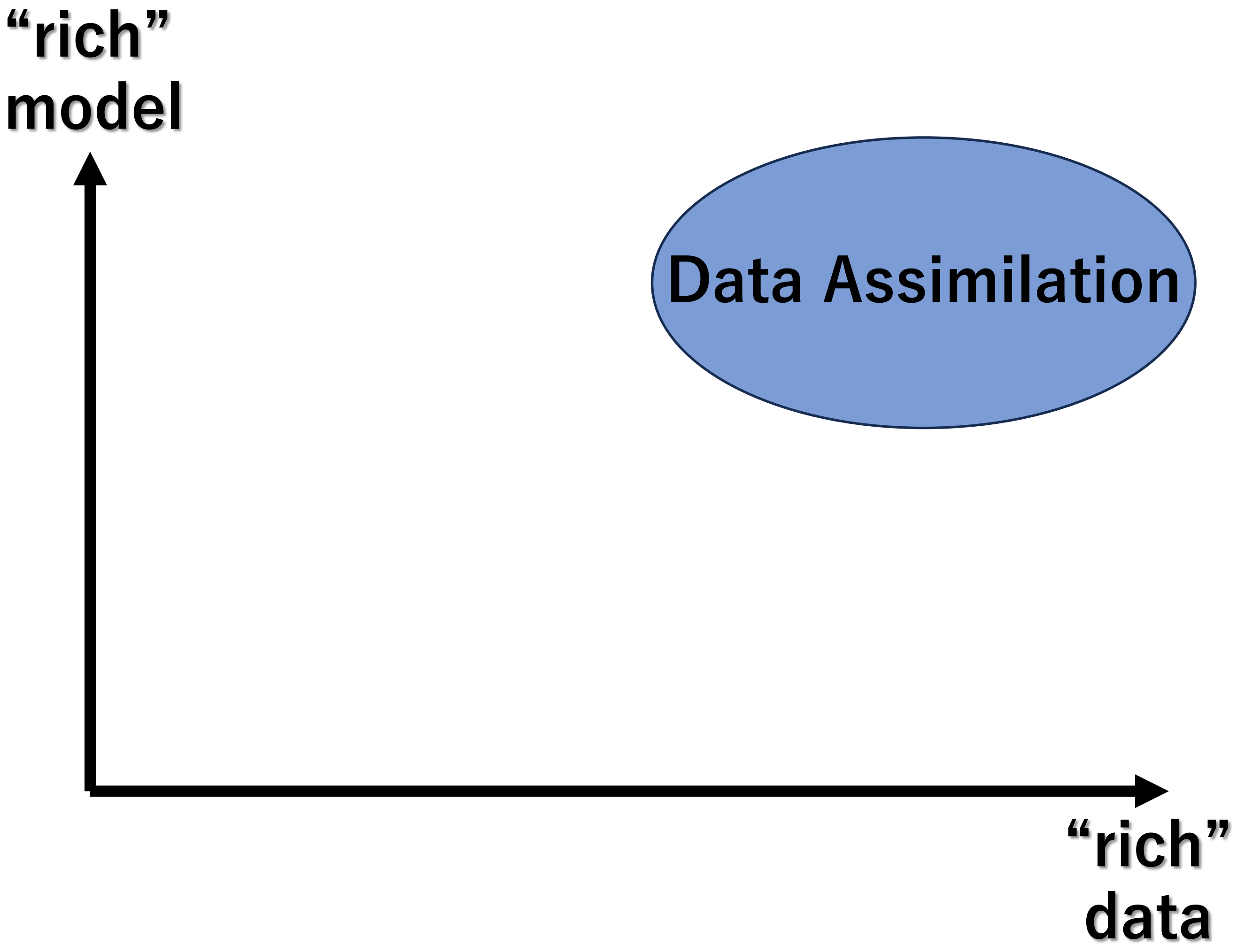


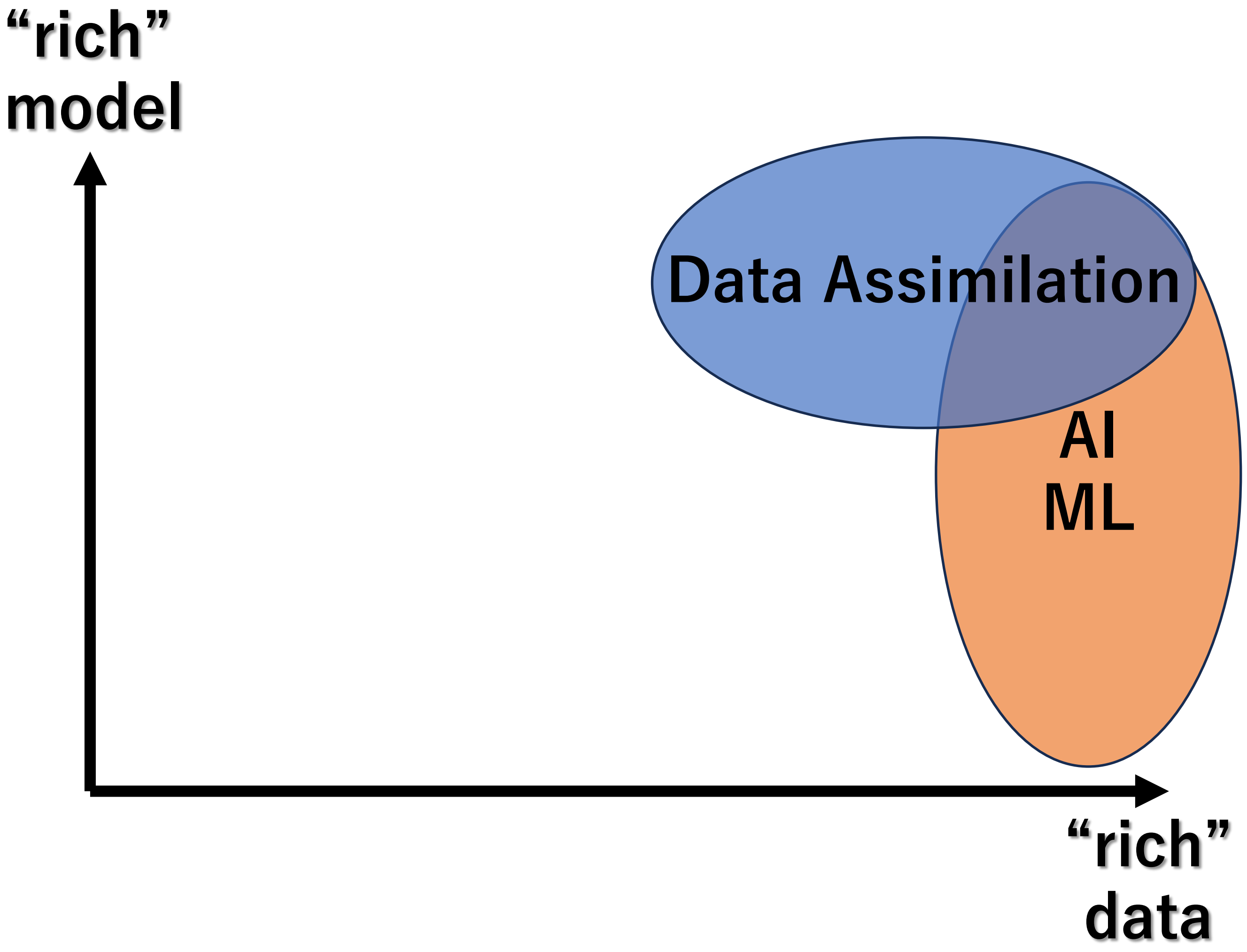
March 2021

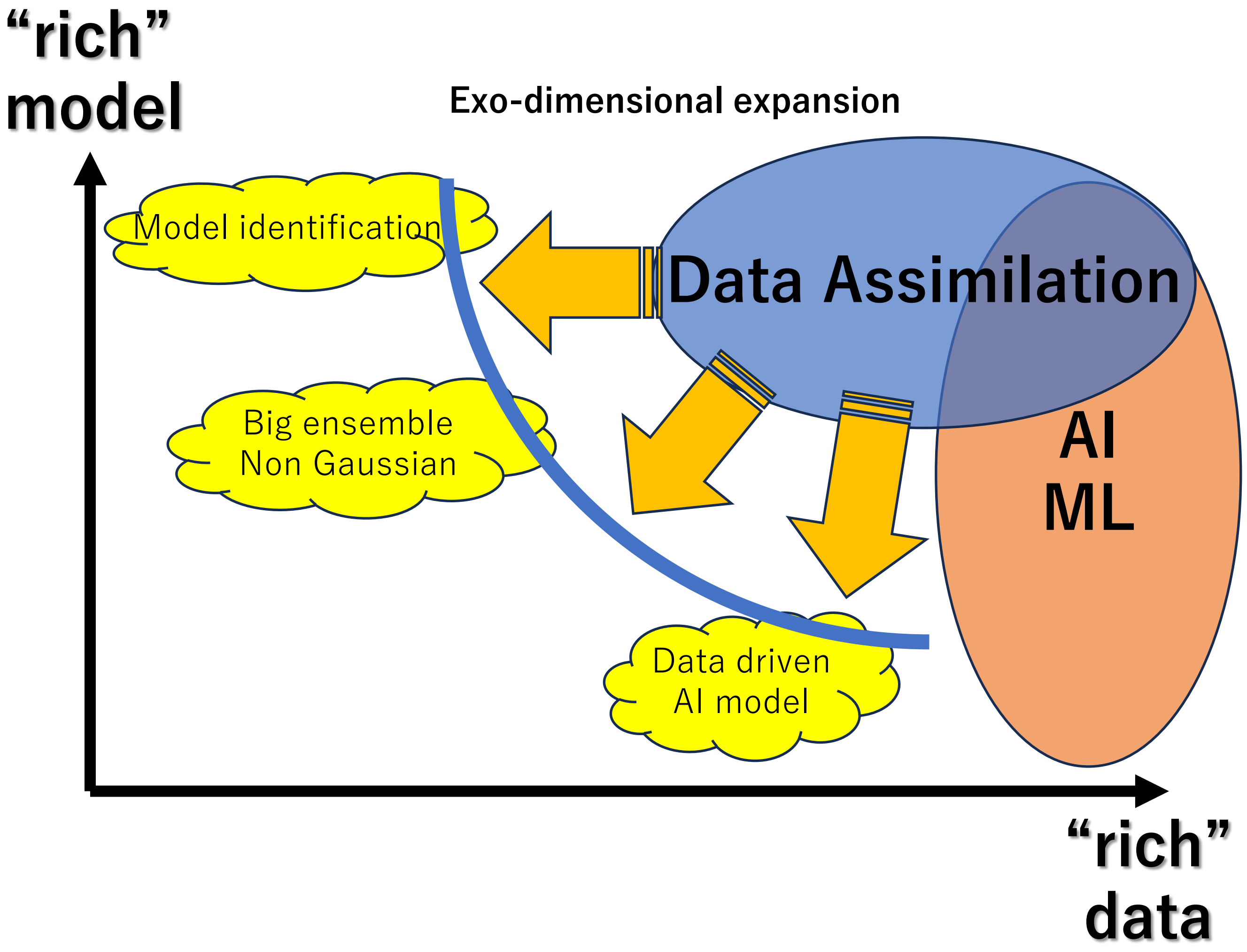
Good for Big DA
Not suitable for ML

Good for both Big DA
and ML

"Fugaku Next"
(2030-?)
AI focused


"rich"
model
Data Assimilation
"rich"
data


"rich"
model
Data Assimilation
AI
ML
"rich"
data



“rich” model
Exo-dimensional expansion
Model identification
Data Assimilation
Big ensemble
Non Gaussian
AI
ML
Data driven
AI model
“rich” data

Precipitation nowcasting with deep learning

S. Otsuka and T. Miyoshi (RIKEN)

Acknowledgment

Y. Maejima, P. Tandeo, M. Ohhigashi, V. P. Huynh, S. Satoh, T. Ushio, P. Baron

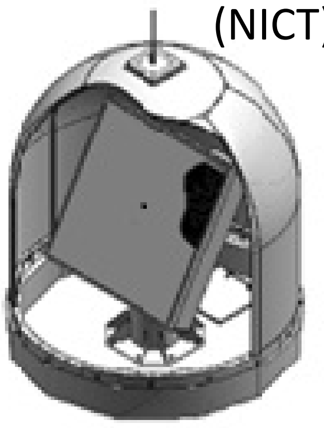
RIKEN Center for Computational Science

Data Assimilation Team

BIG DATA ASSIMILATION

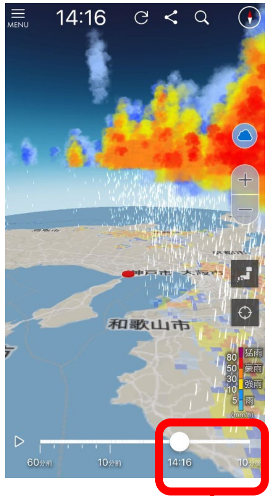
Phased-Array Weather Radar
3D nowcast (https://weather.riken.jp/)

(NICT)



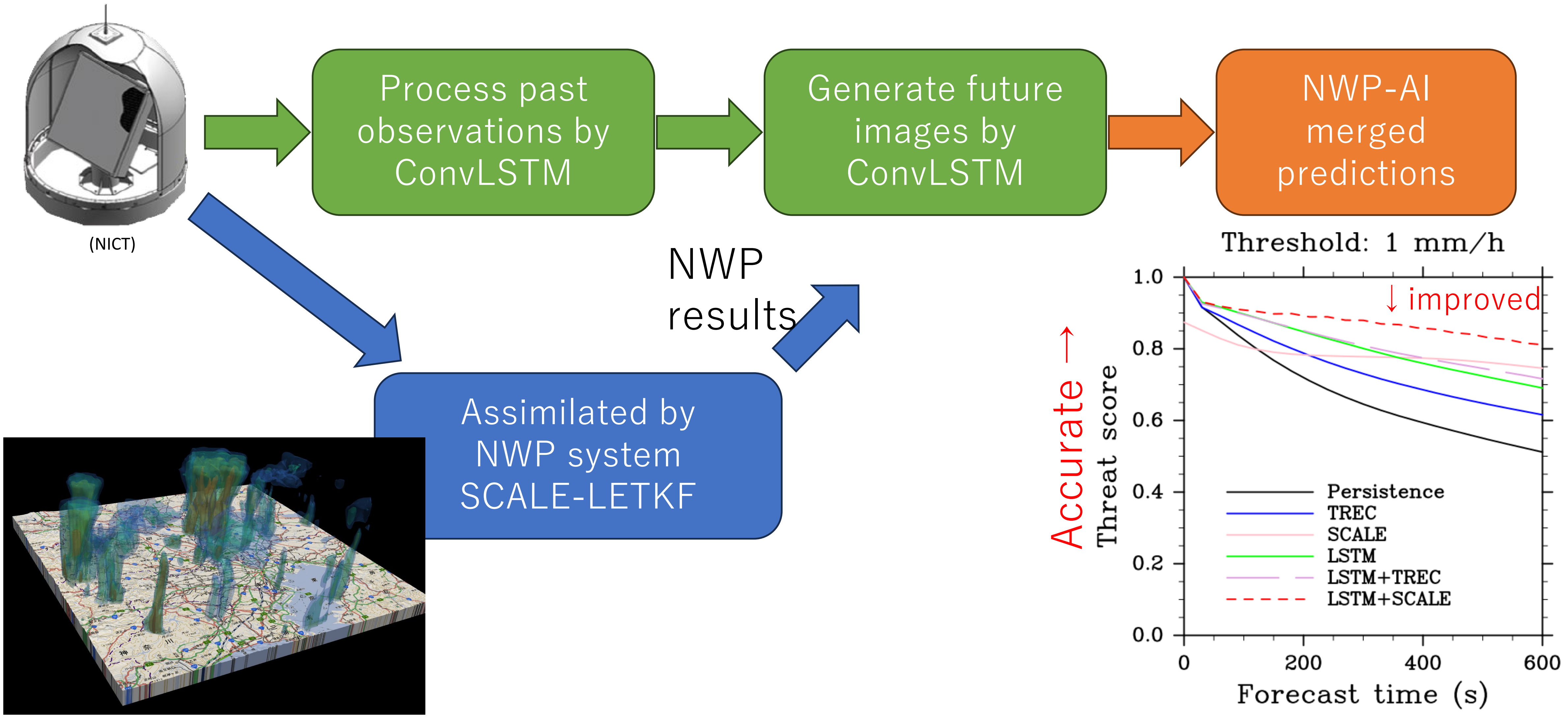
Open to the public since July 2017 (Licensed by JMA)

Updated every 30



App by MTI Ltd.

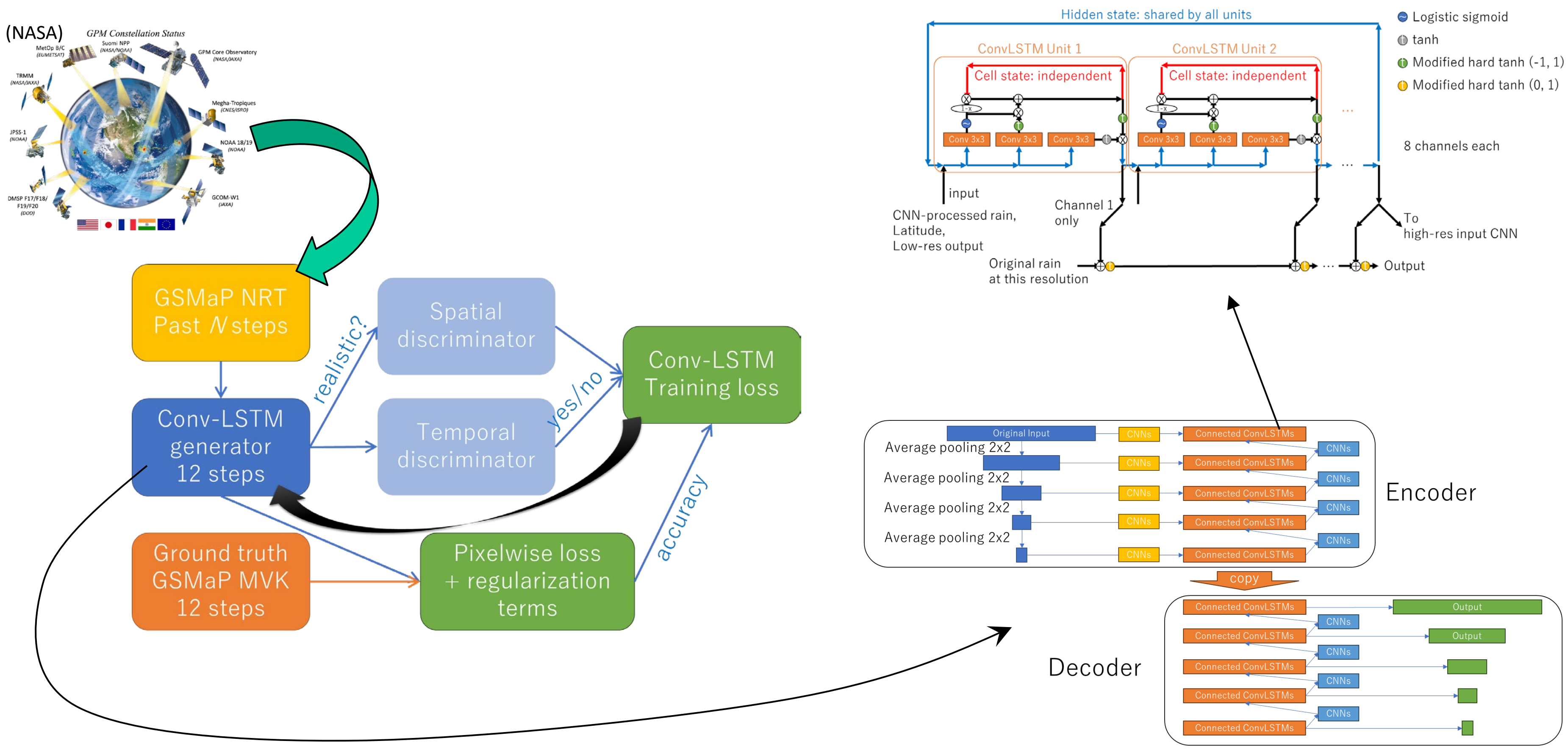
247,000+ downloaded



Integrating big data assimilation and deep learning for precipitation nowcasting

Machine Learning approach to nowcasting

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

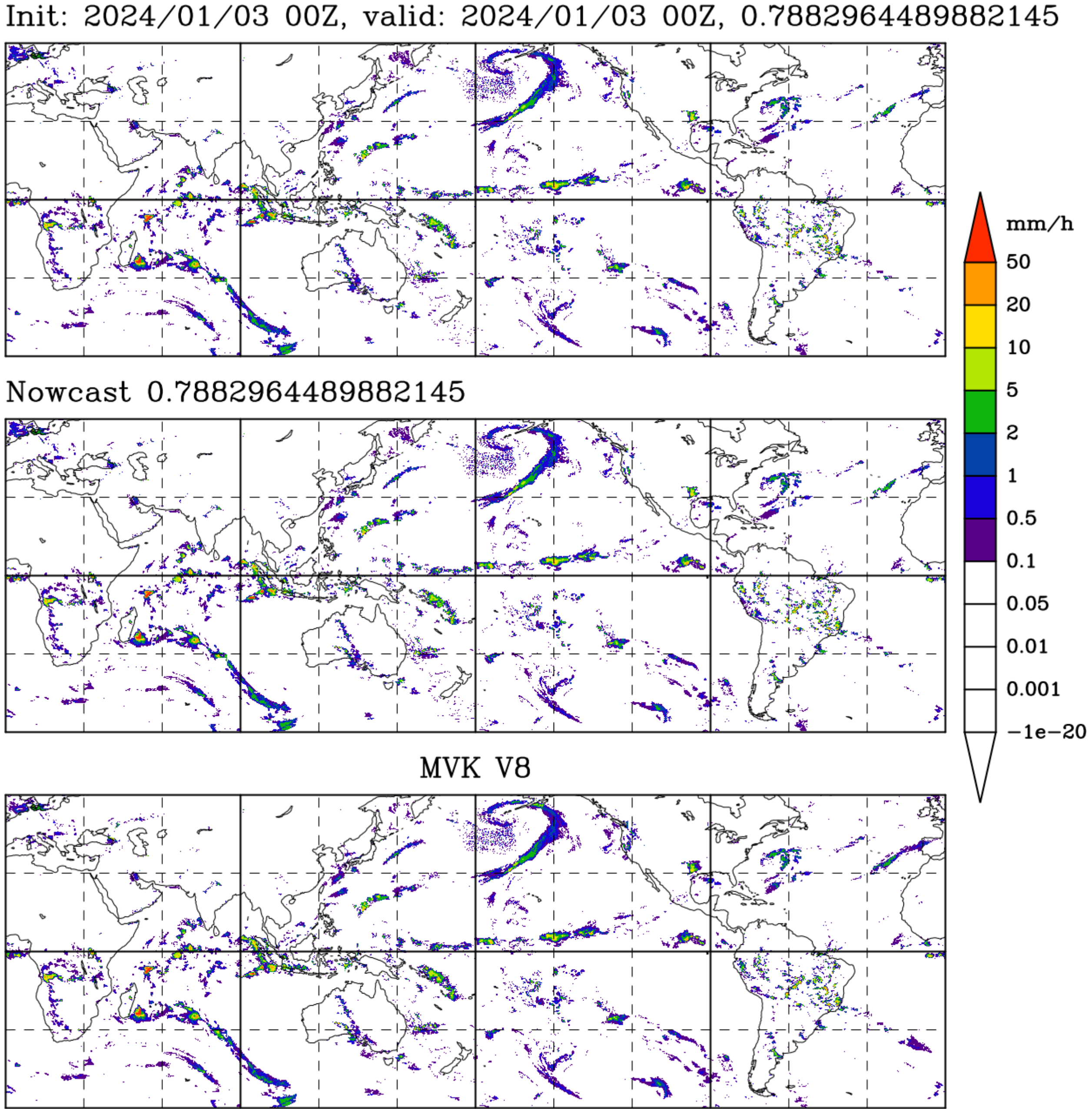


Comparison with a conventional algorithm

Proposed

Conventional tracking algorithm

Observations

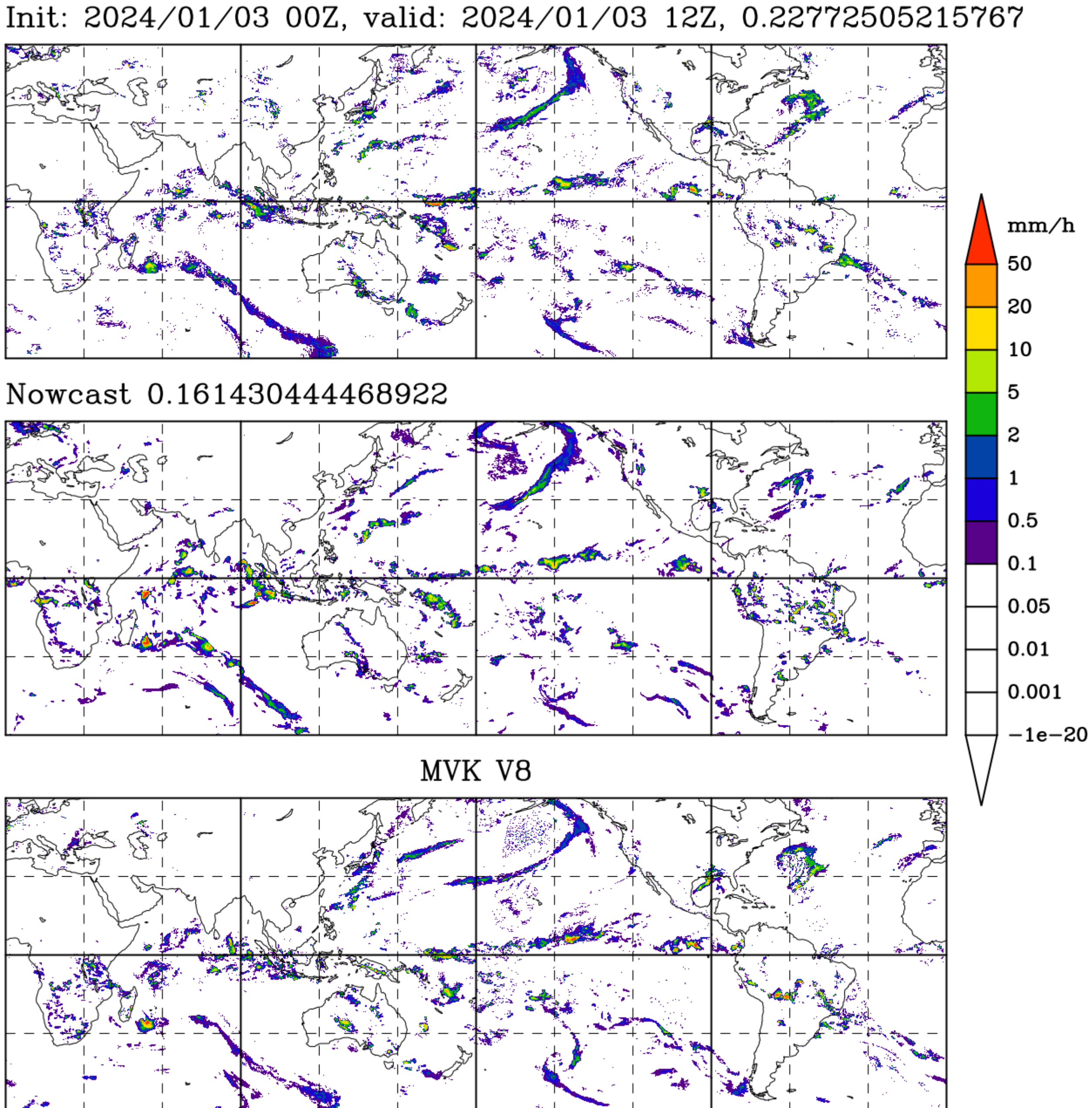


Comparison with a conventional algorithm

Proposed

Conventional tracking algorithm

Observations



Comparison with a conventional algorithm

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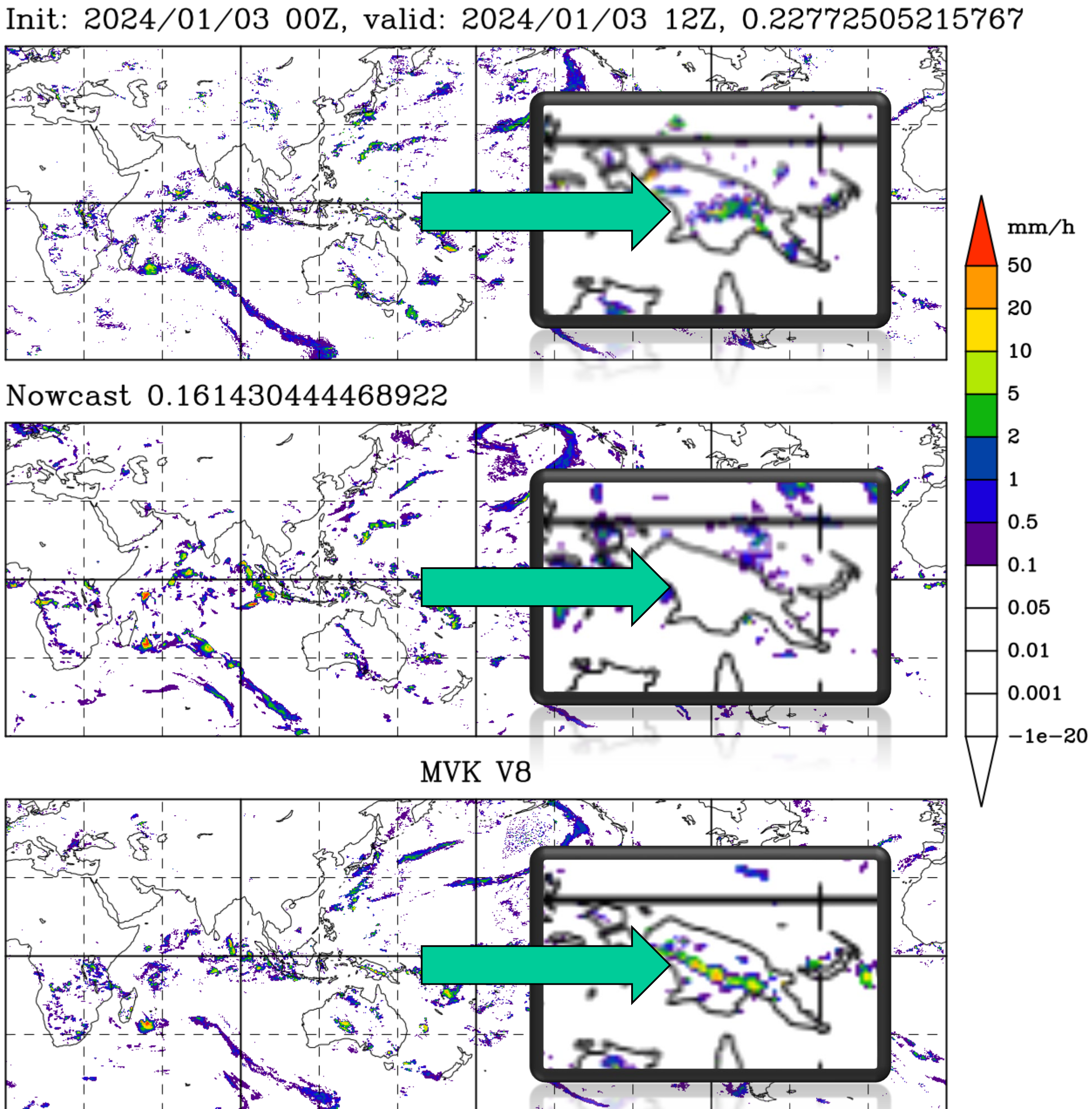
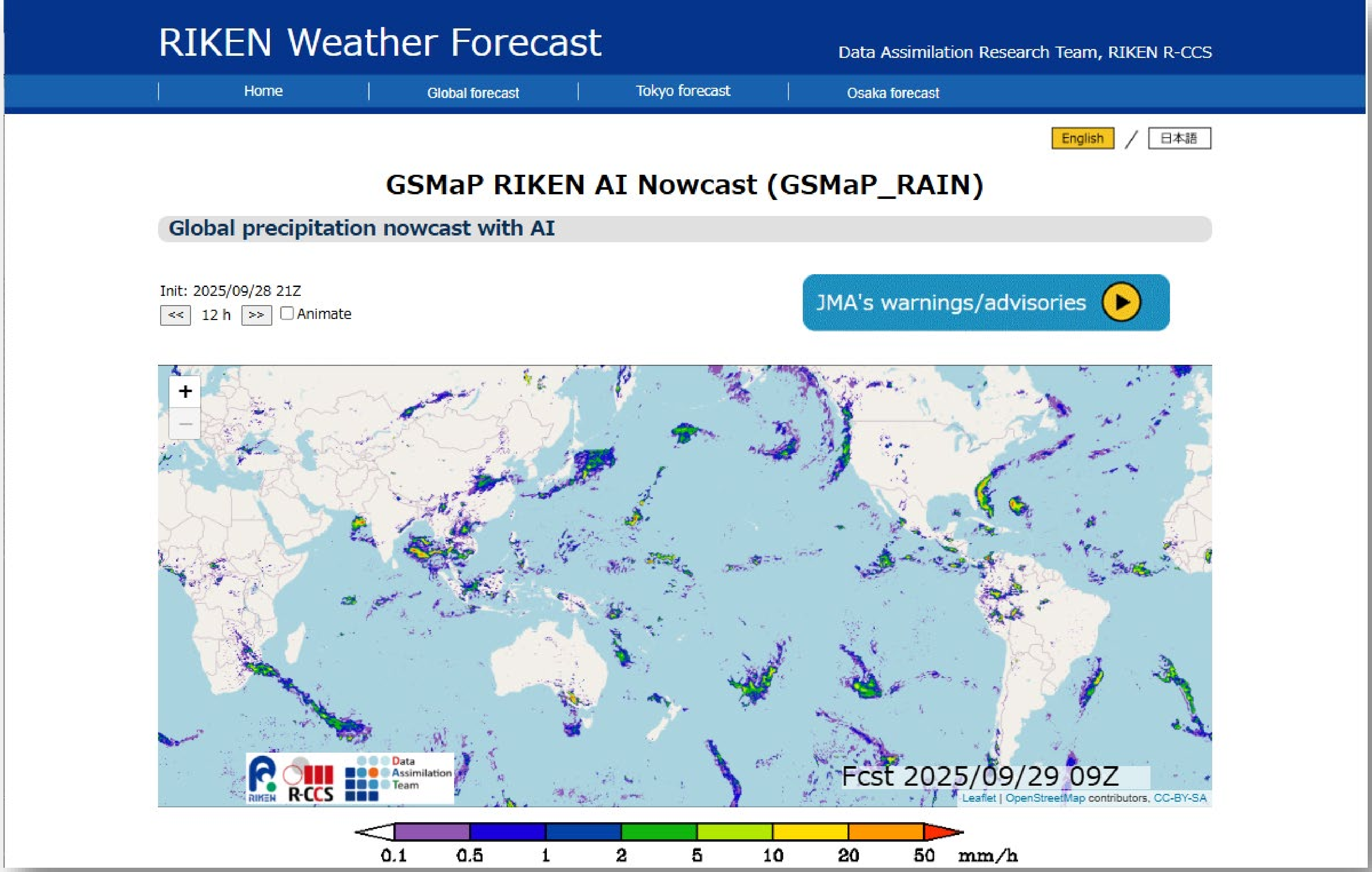
Conventional tracking algorithm

Observations



Verification scores for Jan-Dec 2024



https://weather.riken.jp/en/gsmap_rain/gsmap_rain.html

A machine learning approach to the observation operator for satellite radiance data assimilation

J. Liang and T. Miyoshi

Machine Learning for satellite obs. operator

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

(1) **Physically-based**
Radiative Transfer
Model (RTM)

$\boldsymbol{x}^f$: Forecast
in model space
(e.g., Temperature)

H: RTM-LinebyLine

$H(\boldsymbol{x}^f)$: Forecast
in obs. space
(e.g., Radiance)

Machine Learning for satellite obs. operator

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

(1) **Physically-based** Radiative Transfer Model (RTM)

$\boldsymbol{x}^f$: Forecast in model space (e.g., Temperature)

H: RTM-LinebyLine

$H(\boldsymbol{x}^f)$: Forecast in obs. space (e.g., Radiance)

Slow

Training

(2) Linear regression model

Fast

H: RTTOV

Machine Learning for satellite obs. operator

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

(1) **Physically-based** Radiative Transfer Model (RTM)

$\boldsymbol{x}^f$: Forecast in model space (e.g., Temperature)

H: RTM-LinebyLine

$H(\boldsymbol{x}^f)$: Forecast in obs. space (e.g., Radiance)

Slow

Training

(2) Linear regression model

Fast

$\boldsymbol{x}^f$ $\xrightarrow{H:\ \text{RTTOV}}$ $\boldsymbol{y}$

Training

(3) Machine learning model

Fast

H: ML

$$\boldsymbol{y} = H(\boldsymbol{x}^{true}) + \boldsymbol{\varepsilon}^o$$

$\boldsymbol{y}$: Real observations (e.g., AMSU-A)

$\boldsymbol{x}^{true}$: Approximated by $\boldsymbol{x}^f$ and $\boldsymbol{x}^a$ from the NICAM-LETKF system

Machine Learning for satellite obs. operator

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

(1) **Physically-based** Radiative Transfer Model (RTM)

$\boldsymbol{x}^f$: Forecast in model space (e.g., Temperature) → H: RTM-LinebyLine → $H(\boldsymbol{x}^f)$: Forecast in obs. space (e.g., Radiance)

Slow

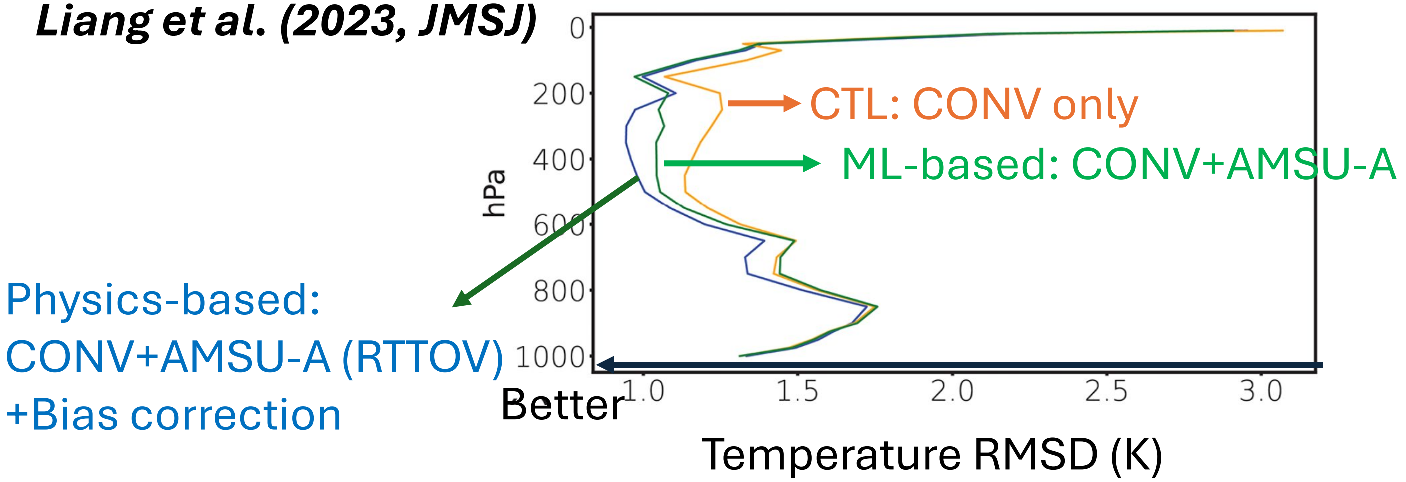
Training

(2) Linear regression model — Fast — $\boldsymbol{x}^f$ → H: RTTOV → $\boldsymbol{y}$

Training

(3) Machine learning model — Fast — H: ML

Liang et al. (2023, JMSJ)



Machine Learning for satellite obs. operator

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

(1) **<u>Physically-based</u>** Radiative Transfer Model (RTM)

$\boldsymbol{x}^f$: Forecast in model space (e.g., Temperature)

H: RTM-LinebyLine

$H(\boldsymbol{x}^f)$: Forecast in obs. space (e.g., Radiance)

Slow

Training

(2) Linear regression model

Fast

H: RTTOV

DA w/o satellite data

$\boldsymbol{x}^a$ → $\boldsymbol{y}$

Training

<u>(4) Machine learning model (this study)</u>

H: ML

<u>Purely data-driven approach</u>: Utilize obs. promptly without the physically-based models

$$\boldsymbol{y} = H(\boldsymbol{x}^{true}) + \boldsymbol{\varepsilon}^o$$

$\boldsymbol{y}$: Real observations (e.g., AMSU-A)

$\boldsymbol{x}^{true}$: Approximated by $\boldsymbol{x}^f$ and $\boldsymbol{x}^a$ from the NICAM-LETKF system

Design of the machine learning models

$$y = h_{ml}(x_b, \theta, \emptyset, p) + e_{ml}$$

output input

input

3D variables:

pressure (78 levels)

temperature (78 levels)

specific humidity (40 levels)

2D variables:

surface pressure

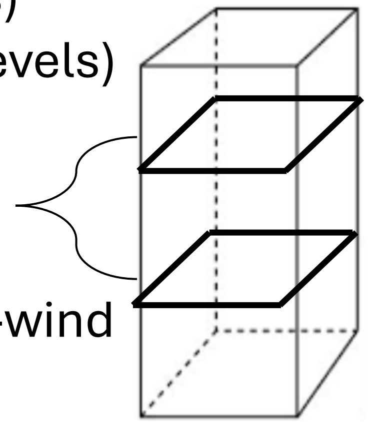
surface temperature

10-meter u-wind and v-wind

2-meter temperature

2-m specific humidity

other bias predictor: Satellite zenith angle, Scan angle, latitude

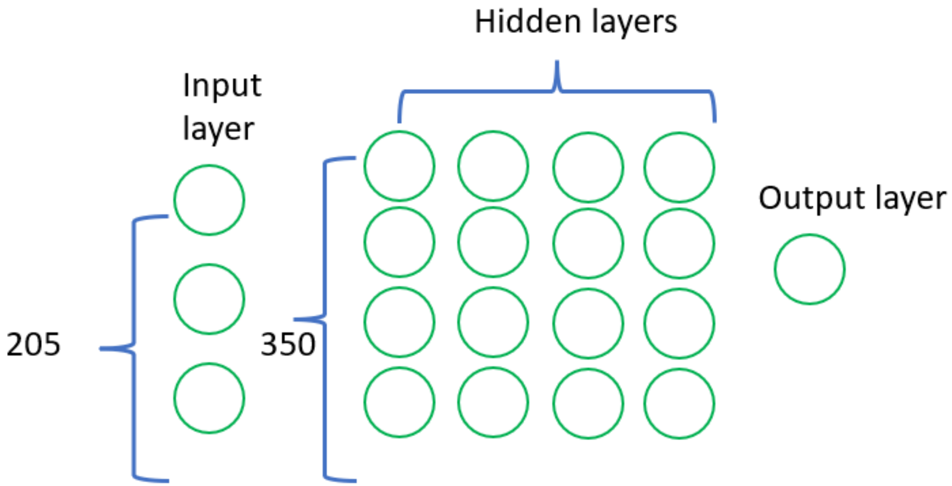


Output: y

satellite brightness temperature from channel 6, 7, 8

Deep neural networks (DNNs) for each channel and satellite

205 features, includes different vertical levels

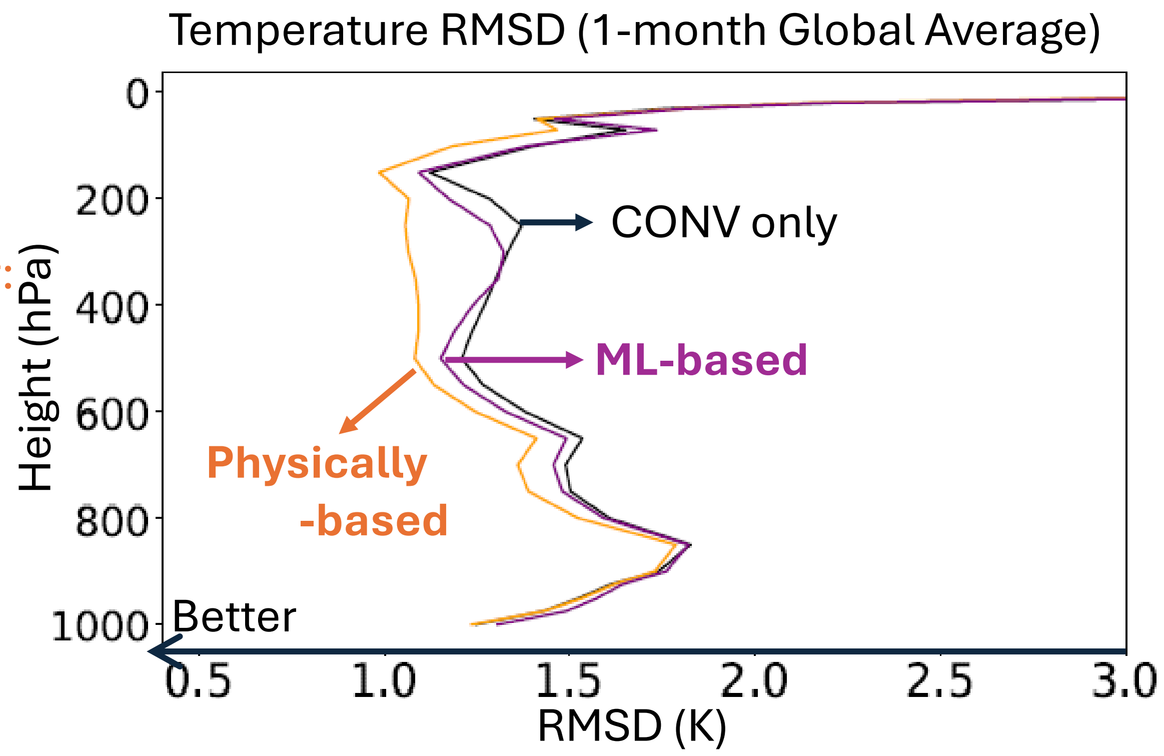


Hyperparameters searching:

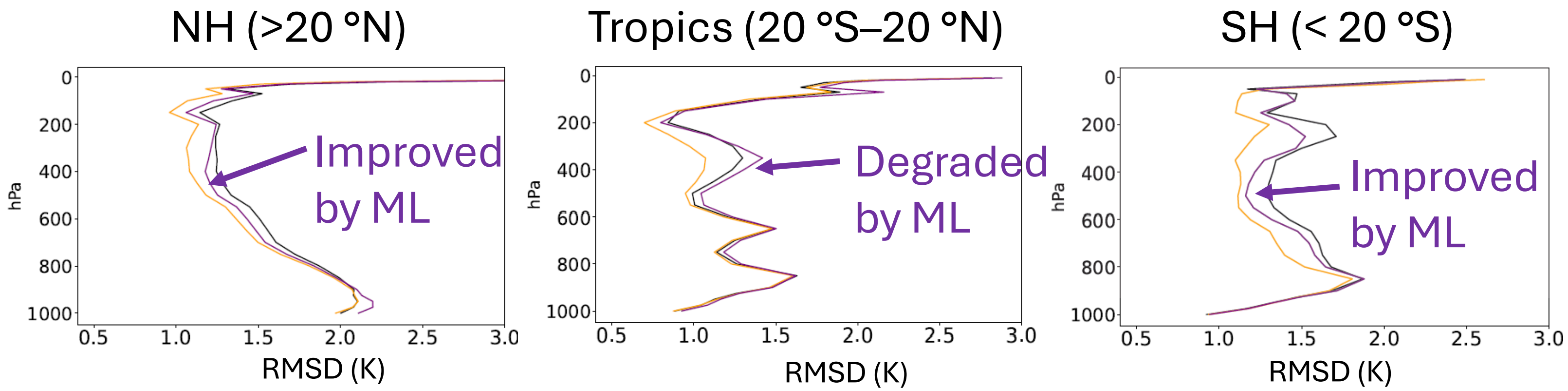
activation function	ReLu
learning rate	1e-6
Units	300
Layers	4

Validation relative to ERA Interim

- ■ Sensitivity experiments
- - CONV only
- - **Physically-based** obs. operator:
  CONV+AMSU-A (RTTOV)
  +Bias correction
- - **ML-based** obs. operator:
  CONV+AMSU-A

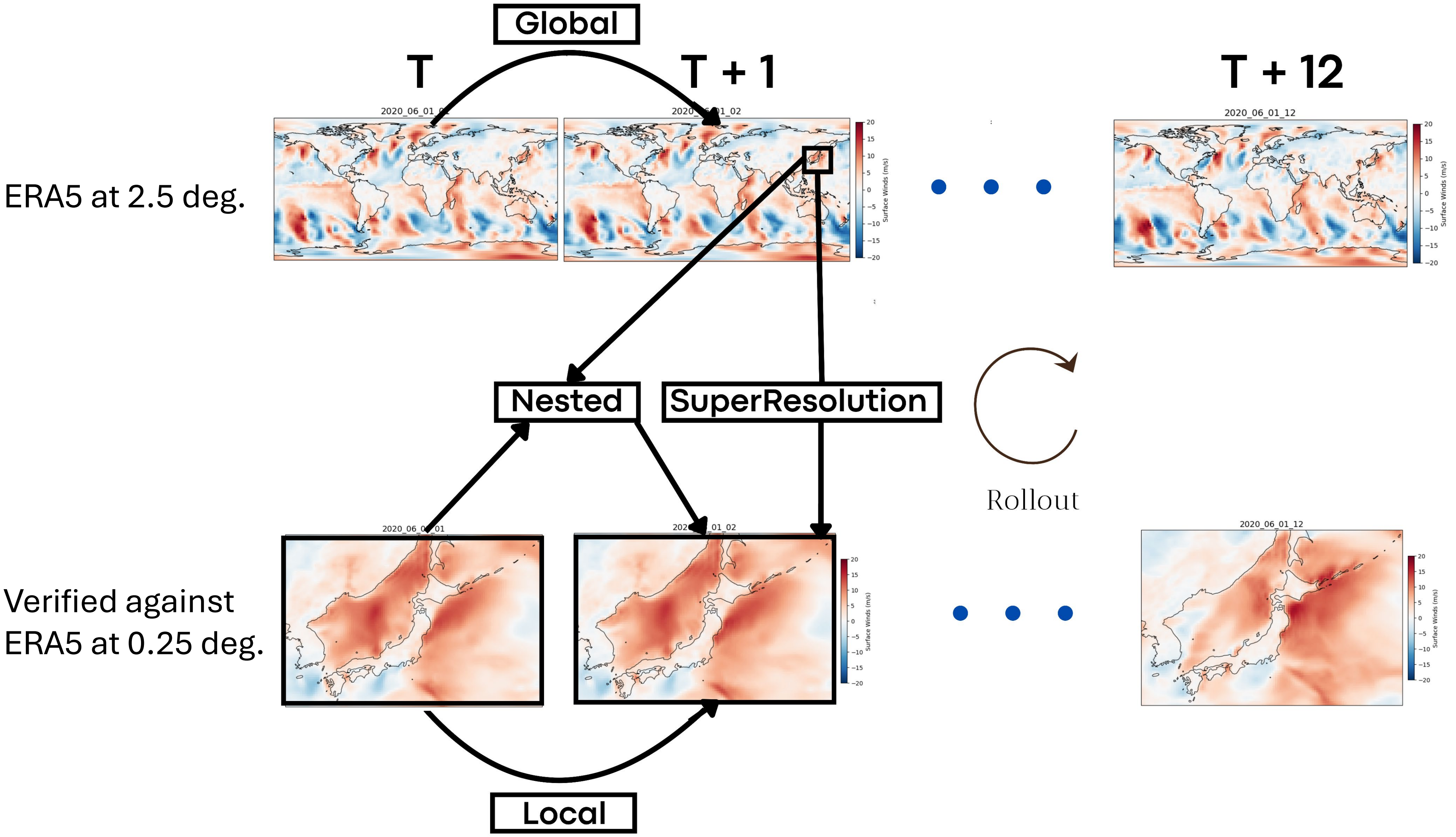


Accuracy: **Physically-based** > **ML-based** > CONV only



Machine Learning-Based Regional Weather Prediction

G. Saliou, S. Ouala, P. Tandeo,
M. Goodliff, T. Miyoshi



MSLP

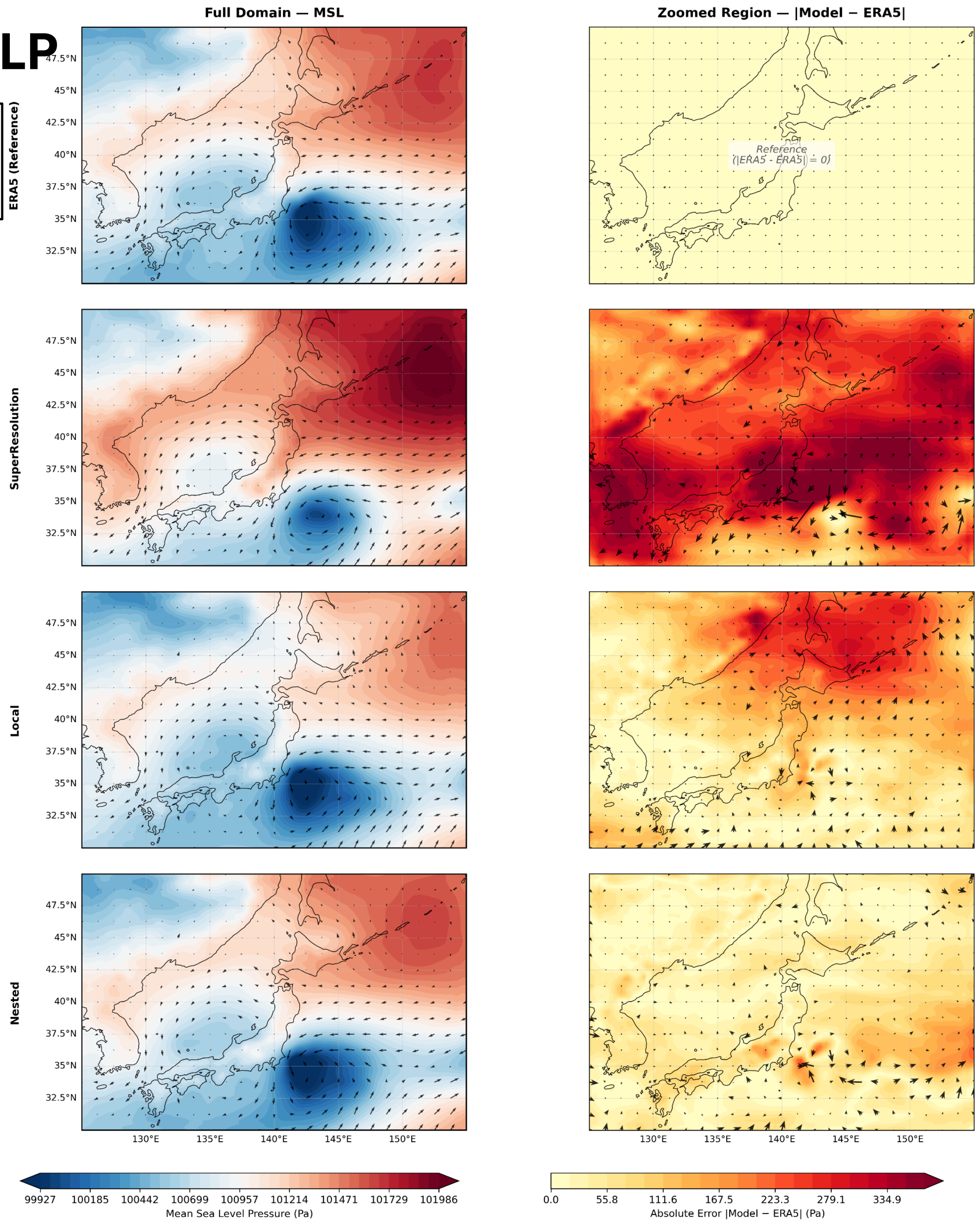
Difference from ERA5

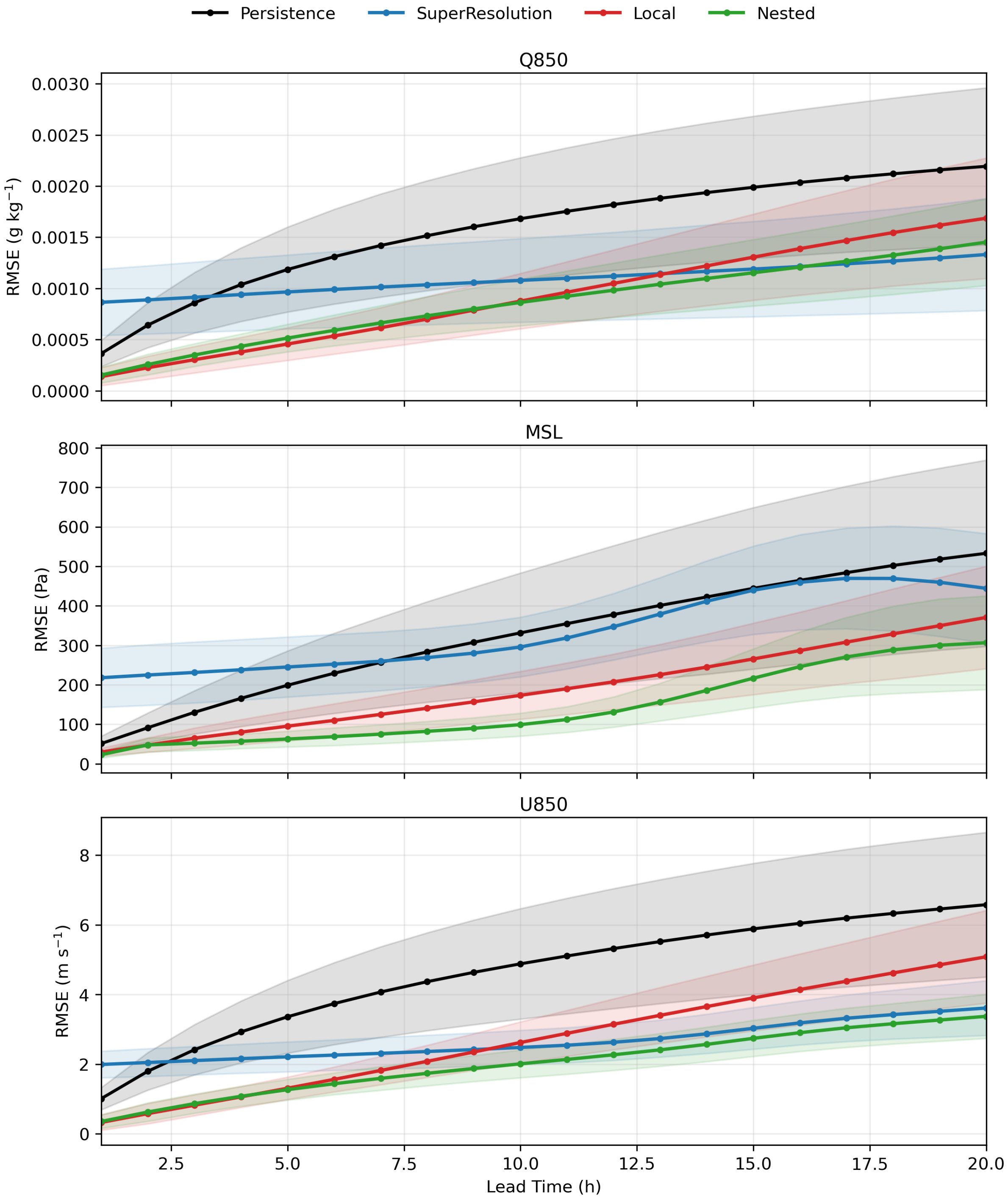
ERA5
(Verification truth)

Super-resolution

Local

Nested





Persistence
SuperResolution
Local
Nested
Q850
RMSE (g kg^{-1})
MSL
RMSE (Pa)
U850
RMSE (m s^{-1})
Lead Time (h)

Using Data Assimilation to Improve Data-Driven Surrogate Models

Michael Goodliff and Takemasa Miyoshi

NPG preprint available:
DOI:10.5194/egusphere-2025-933

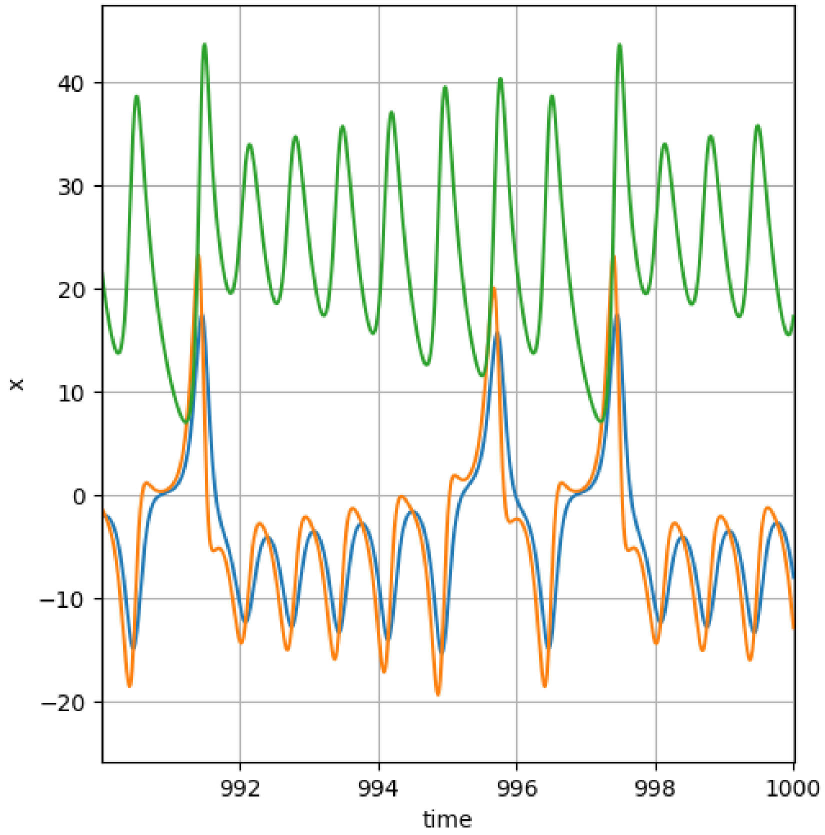
The Systems: Lorenz 63 (3 and 5 variables)

Using the 3 variable Lorenz 63 Numerical Model, can we use machine learning and data assimilation to create a surrogate model of the 5 variables Lorenz 63 model, for the same 3 variables?

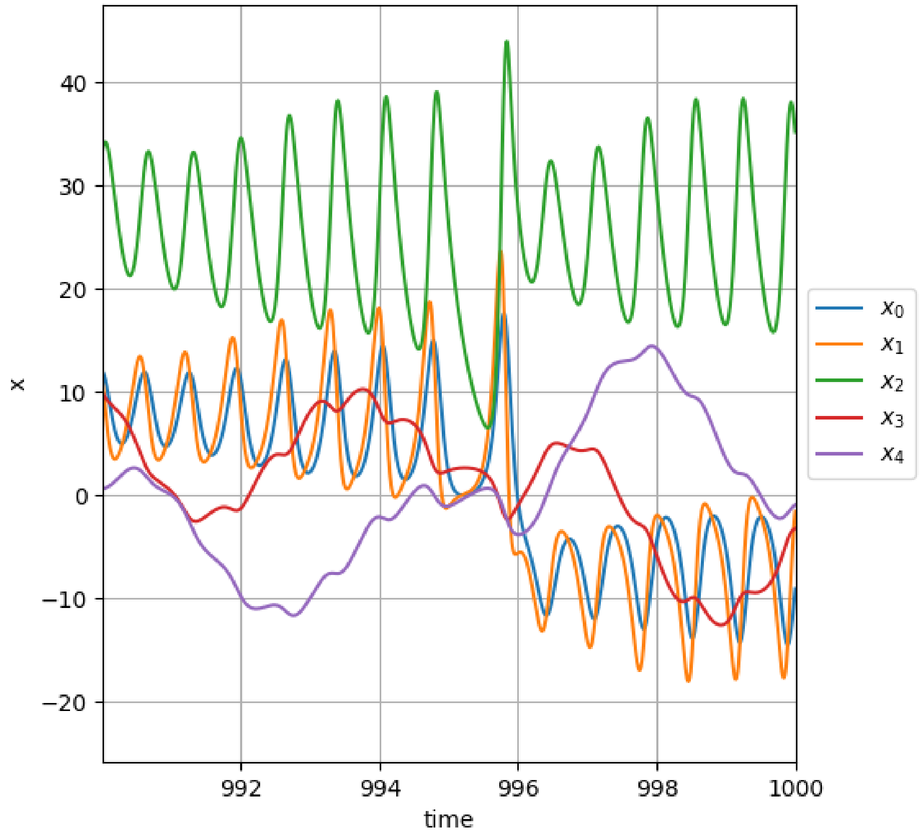
Lorenz 63 Models

$$\frac{dx_0}{dt} = -\sigma(x_0 - x_1) + x_4$$
$$\frac{dx_1}{dt} = -\rho x_0 - x_1 - x_2 x_0 + x_3$$
$$\frac{dx_2}{dt} = x_0 x_1 - \beta x_2$$
$$\frac{dx_3}{dt} = -\omega x_4 - k(x_3 - x_3^*) - x_1$$
$$\frac{dx_4}{dt} = \omega(x_3 - x_3^*) - k x_4 - x_0$$

Numerical Model (Imperfect Model)



Goal (Perfect Model)



Experiment Setup

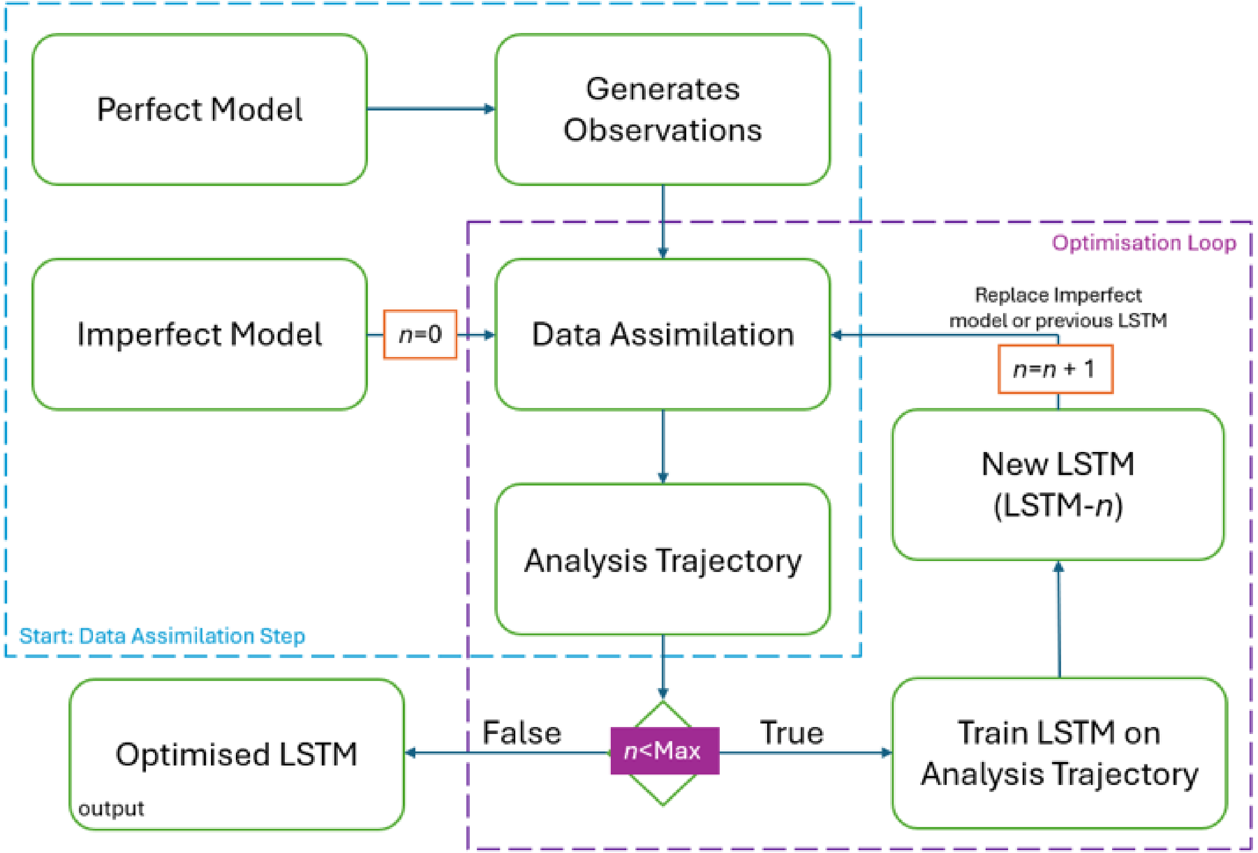
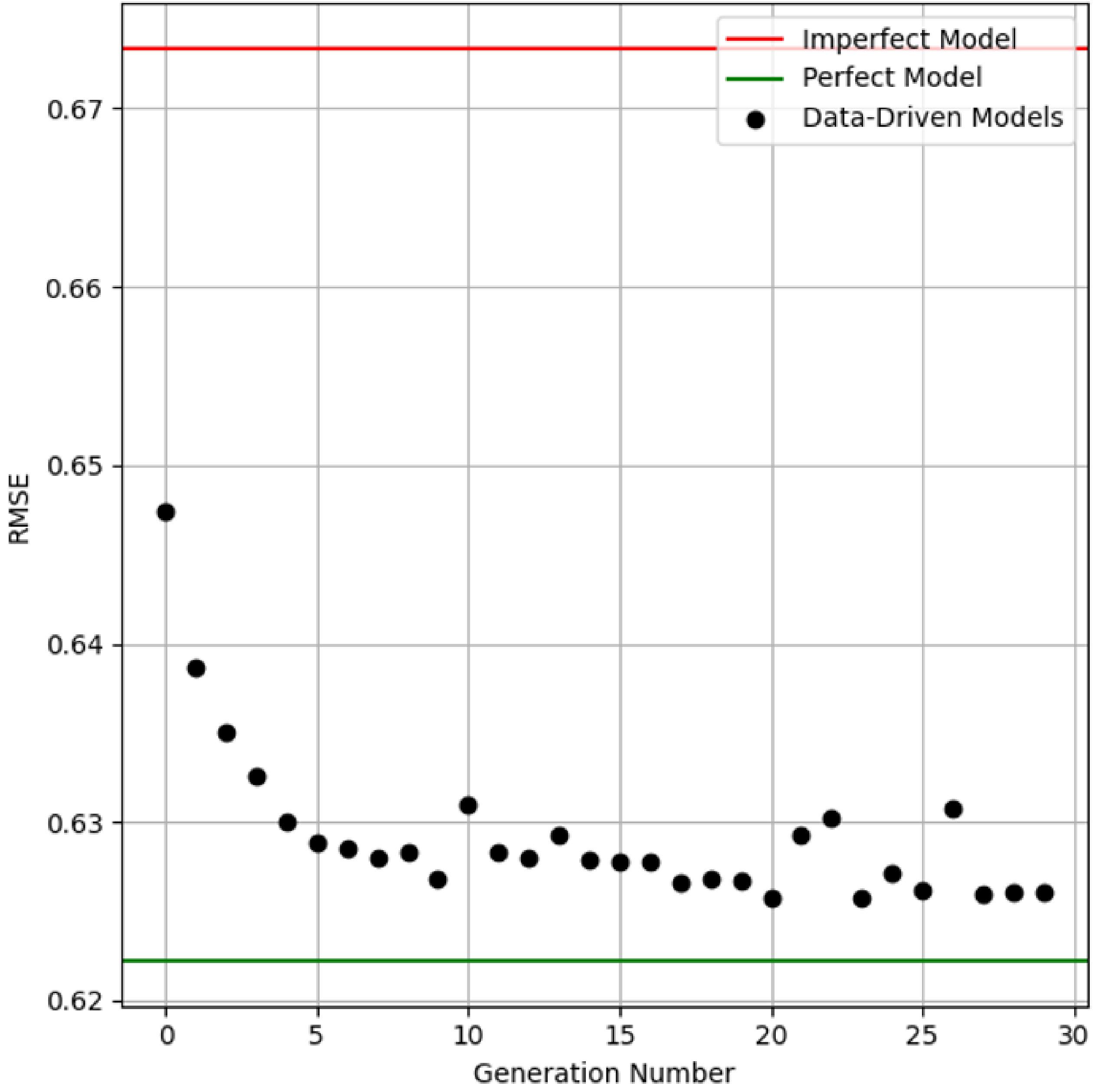


Figure 1. This figure shows the cycling algorithm implemented in this paper. The blue dashed box is the traditional DA cycle, the purple dashed box is our additional loop until the max iteration number is reached, giving an optimised LSTM. When *n*=0 indicates the iteration number, LSTM-0 would be the initial LSTM trained on the imperfect model analysis trajectory after its correction using DA.

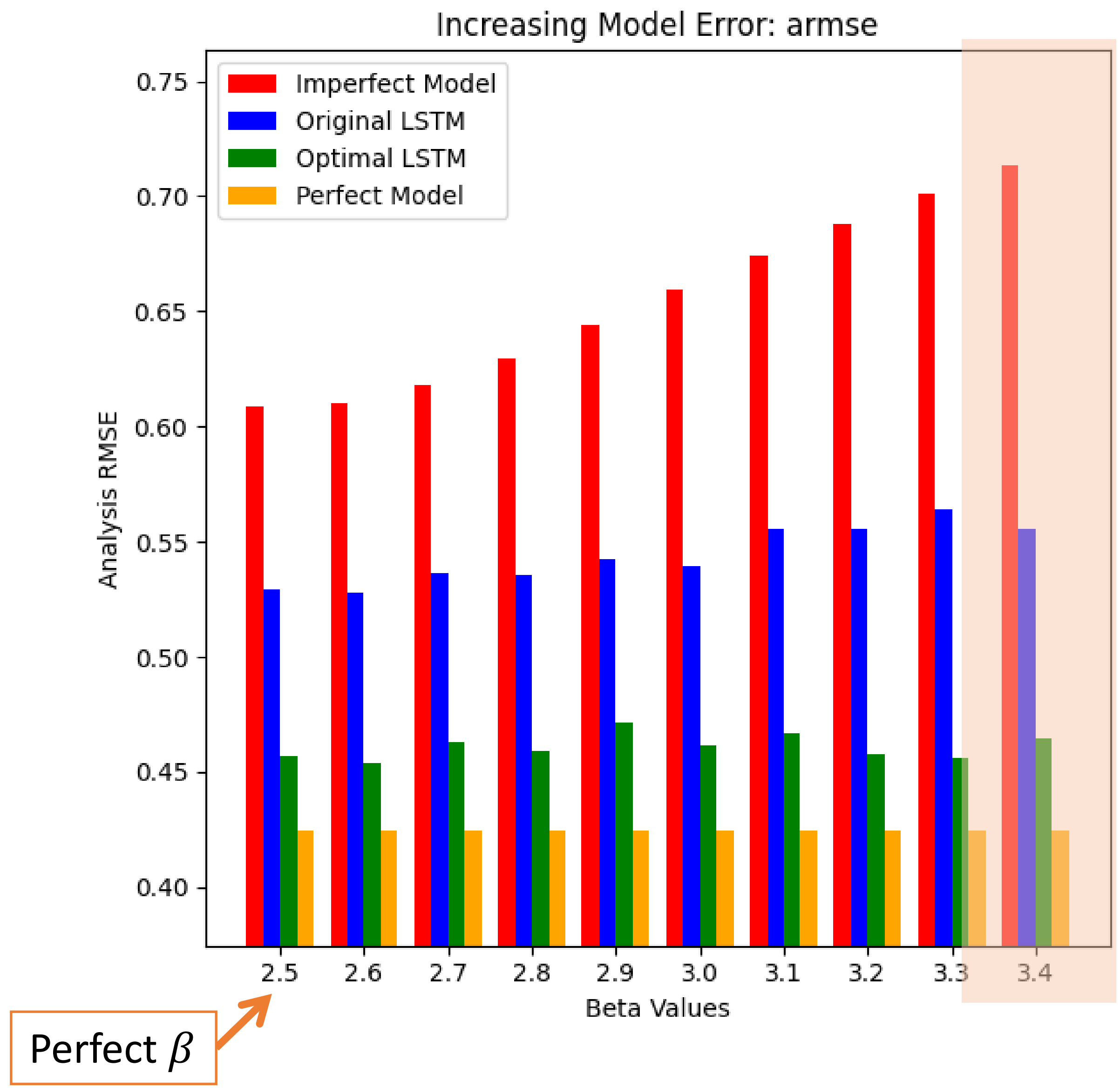
(Goodliff and Miyoshi, 2025, submitted, DOI:10.5194/egusphere-2025-933)

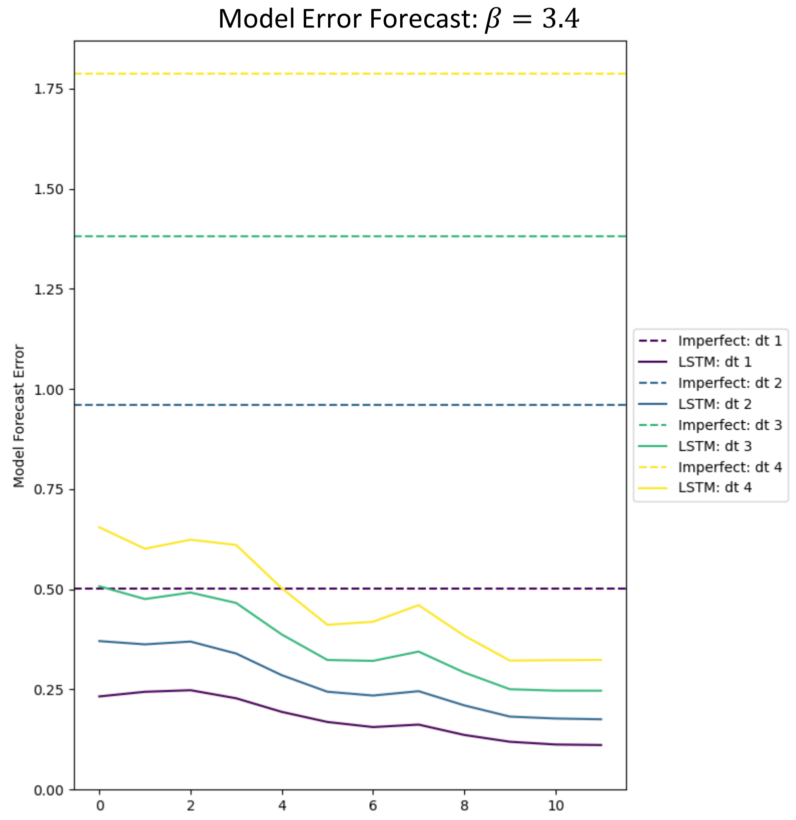
1. Run our numerical model
2. Update trajectories using data assimilation on observations from the 5-variable system.
   $\sigma \in \{x_0^{5v}, x_1^{5v}, x_2^{5v}\}$
3. Create an LSTM using the analysis trajectory.
4. Use this LSTM to run a new trajectory
5. Repeat 2-4 until convergence



(Goodliff and Miyoshi, 2025, submitted, DOI:10.5194/egusphere-2025-933)

Figure 2. This figure shows the analysis RMSE of our cycling algorithm on the Lorenz 63 model. As we cycle through the algorithm, we see the analysis/forecasts getting closer to the perfect system.



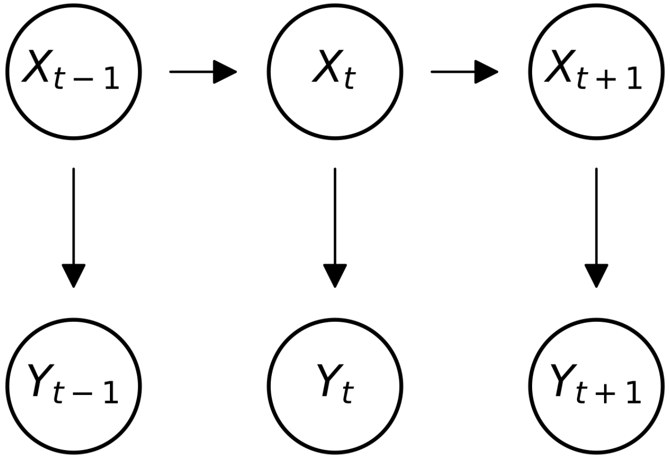


- Here, we show what happens over a range of model error values (2.5 to 3.4).
  - (perfect model is 2.5).
- As the model error increase, the imperfect model moves away from the perfect model (as expected).
- The Original LSTM also slowly increases in ARMSE with increased model error.
- The Optimal LSTM ARMSE stays at similar levels (approx.).

Deep Bayesian Filter (DBF) with SPEEDY

Yuta Tarumi

Data Assimilation
(Regular formulation)

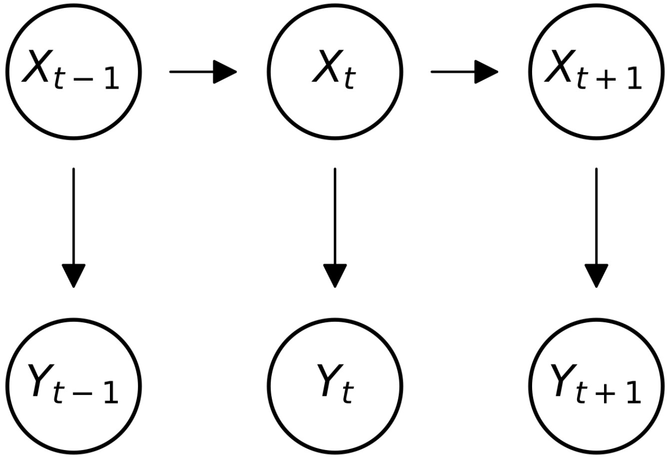


Deep Bayesian Filter (DBF) with SPEEDY

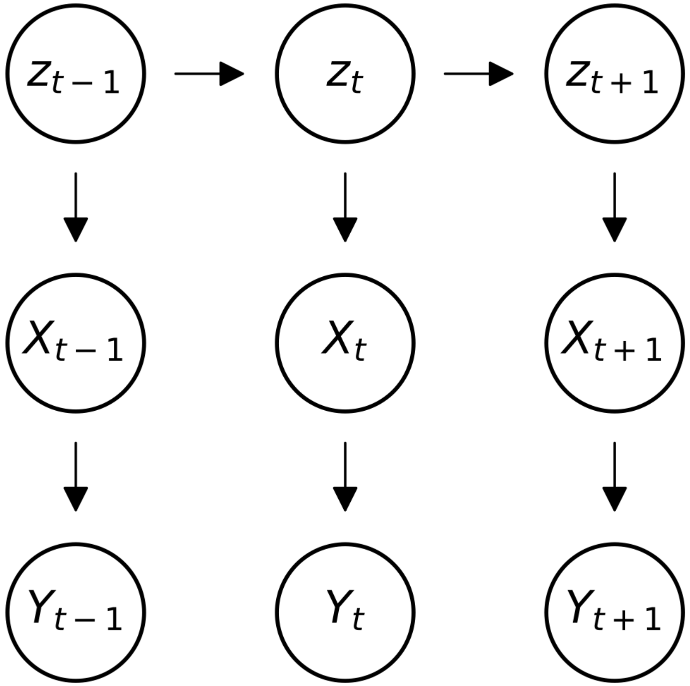
Yuta Tarumi

https://arxiv.org/pdf/2405.18674

Data Assimilation
(Regular formulation)



DBF
(z: latent variables)



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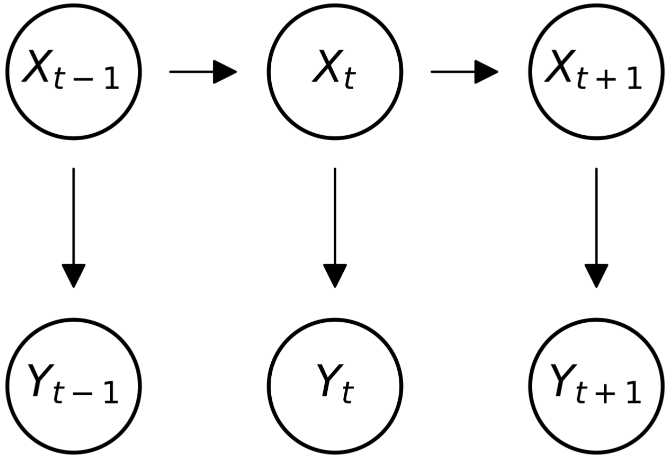

DBF
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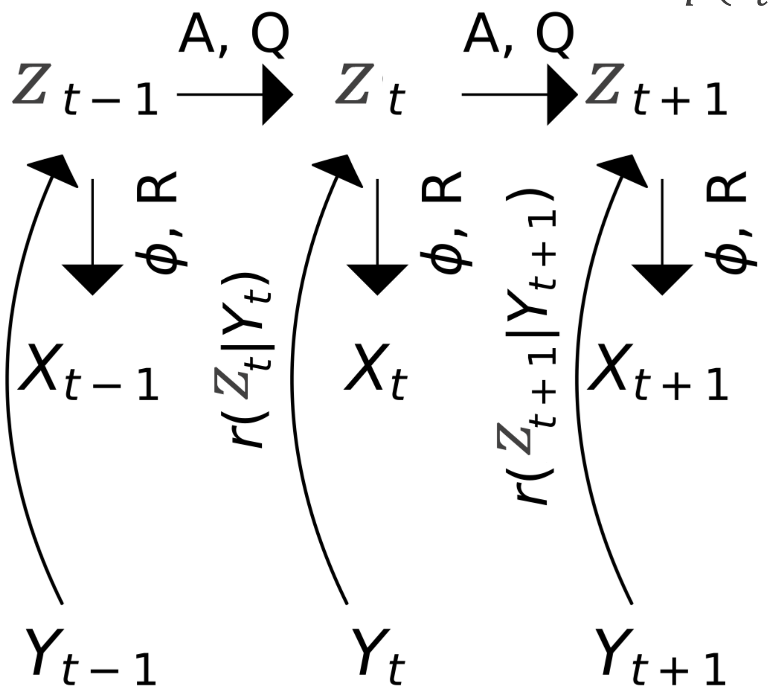
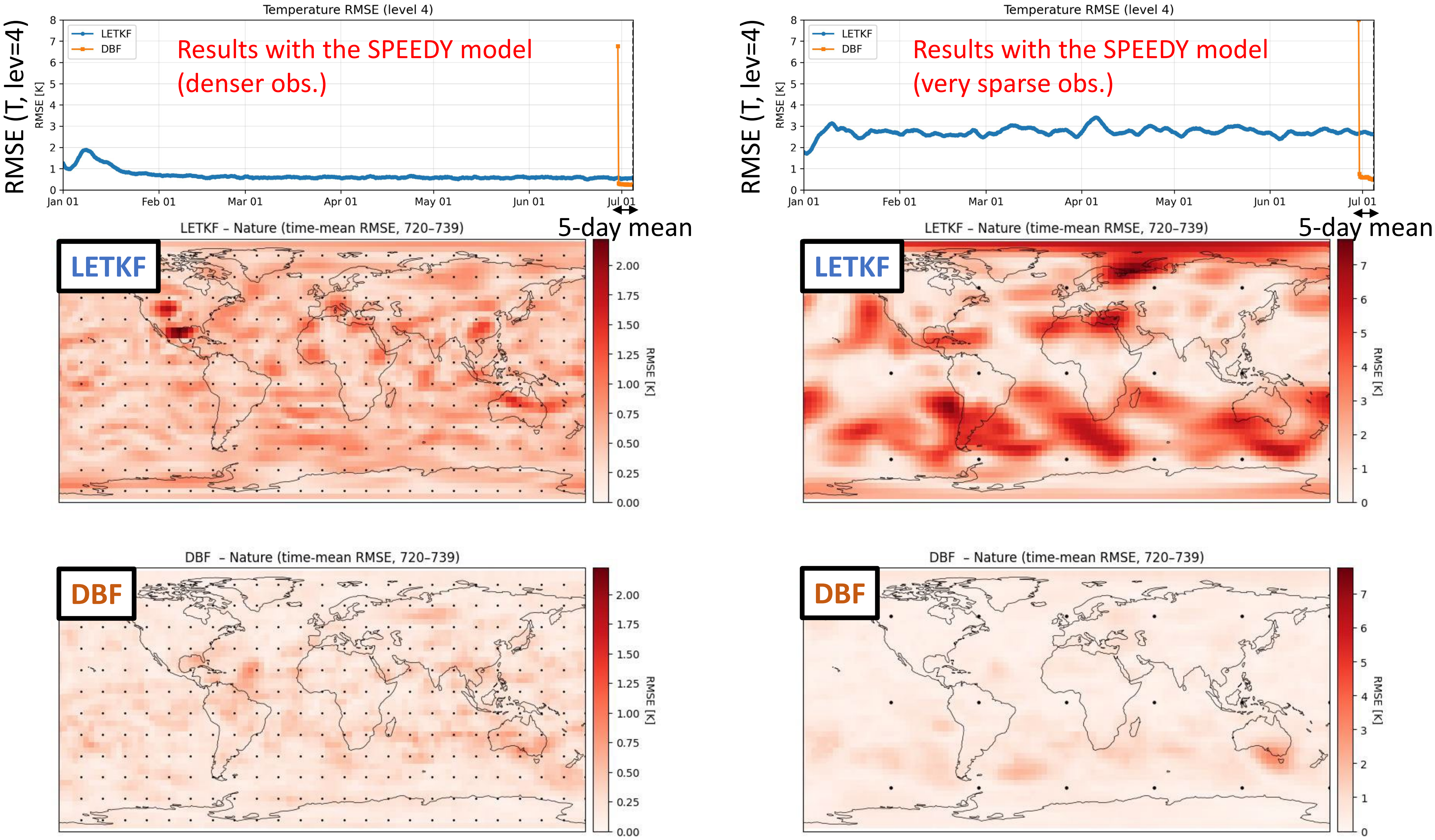


$p(z_{t+1}|z_t) = \mathcal{N}[z_{t+1}; Az_t, Q]$

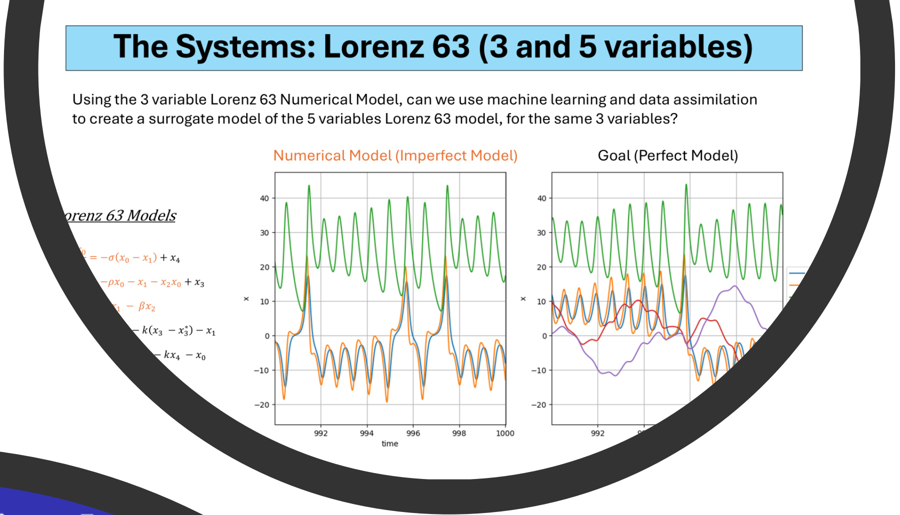
$p(X_t|z_t) = \mathcal{N}[X_t; \phi(z_t), R]$

Train r, ϕ, A

- Compute Gaussian-constrained “test posteriors” $p(z_t|Y_{1:t})$ on the latent space
- Limiting the latent dynamics to linear and assume Gaussianity of $r(z_t|Y_t)$, KF-like recursive formula applies



Temperature RMSE (level 4)
RMSE (T, lev=4)
RMSE [K]
LETKF
DBF
Results with the SPEEDY model
(denser obs.)
Jan 01
Feb 01
Mar 01
Apr 01
May 01
Jun 01
Jul 01
5-day mean
LETKF – Nature (time-mean RMSE, 720–739)
LETKF
DBF – Nature (time-mean RMSE, 720–739)
DBF
Temperature RMSE (level 4)
RMSE (T, lev=4)
Results with the SPEEDY model
(very sparse obs.)
5-day mean
LETKF – Nature (time-mean RMSE, 720–739)
LETKF
DBF – Nature (time-mean RMSE, 720–739)
DBF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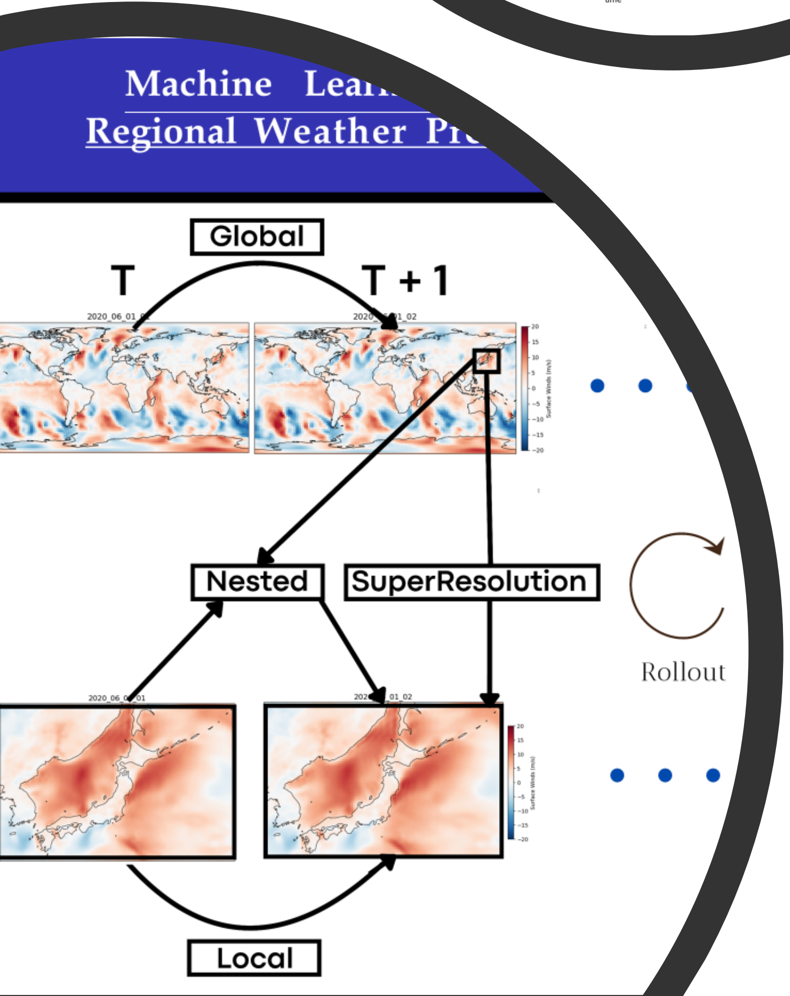
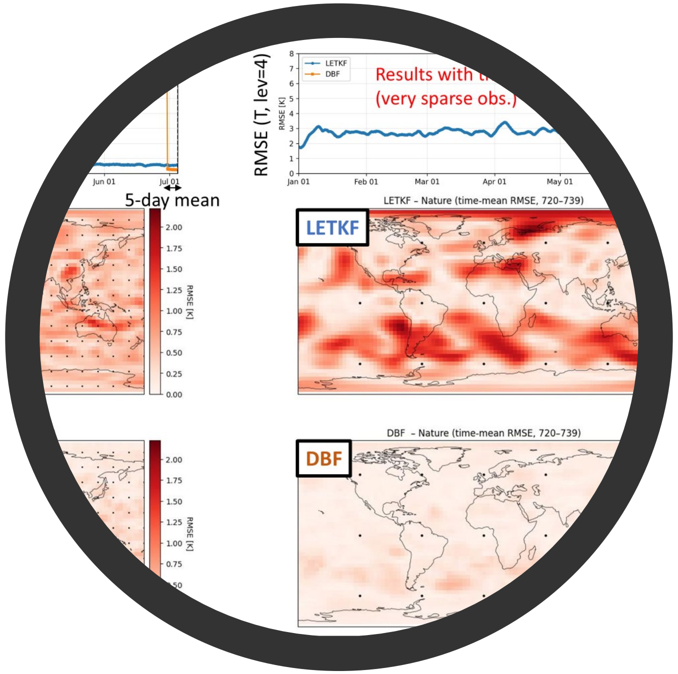
Numerical Model (Imperfect Model)
Goal (Perfect Model)
orenz 63 Models
time


Machine Lea
Regional Weather Pr
Global
T
T + 1
Nested
SuperResolution
Rollout
Local


RMSE (T, lev=4)
LETKF
DBF
Results with
(very sparse obs.)
5-day mean
LETKF - Nature (time-mean RMSE, 720–739)
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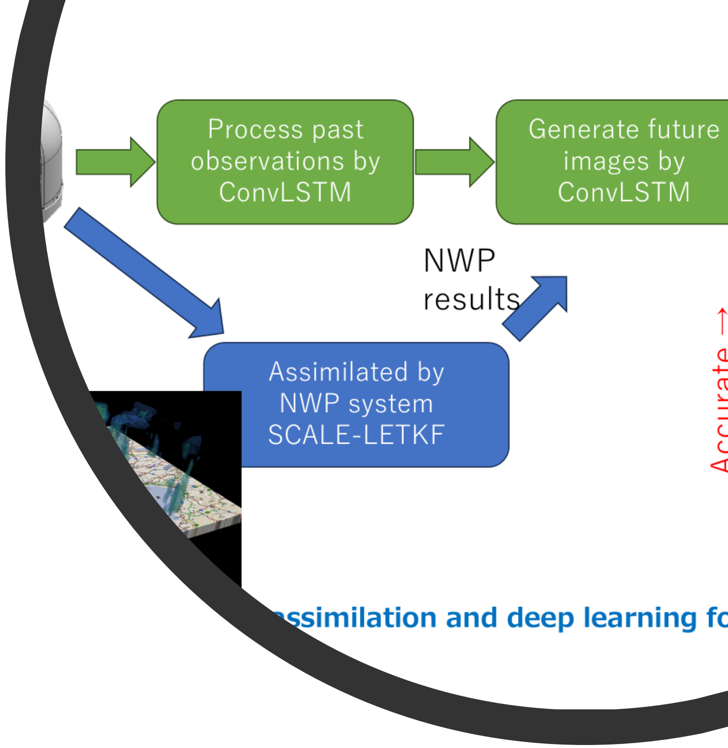
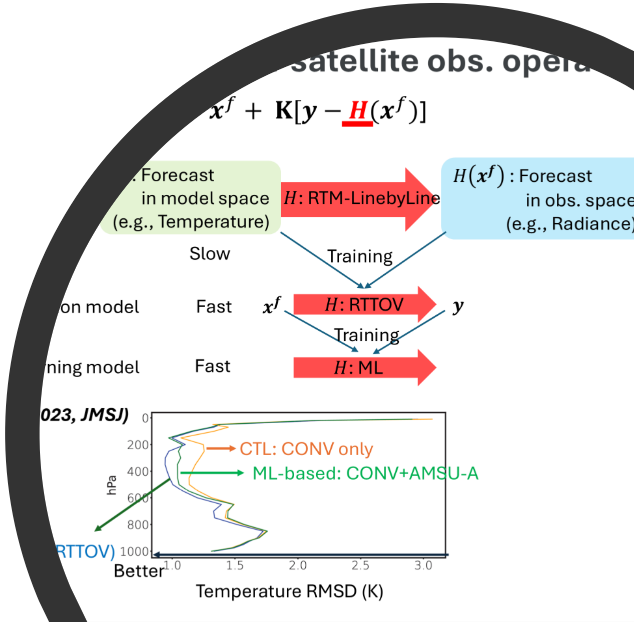
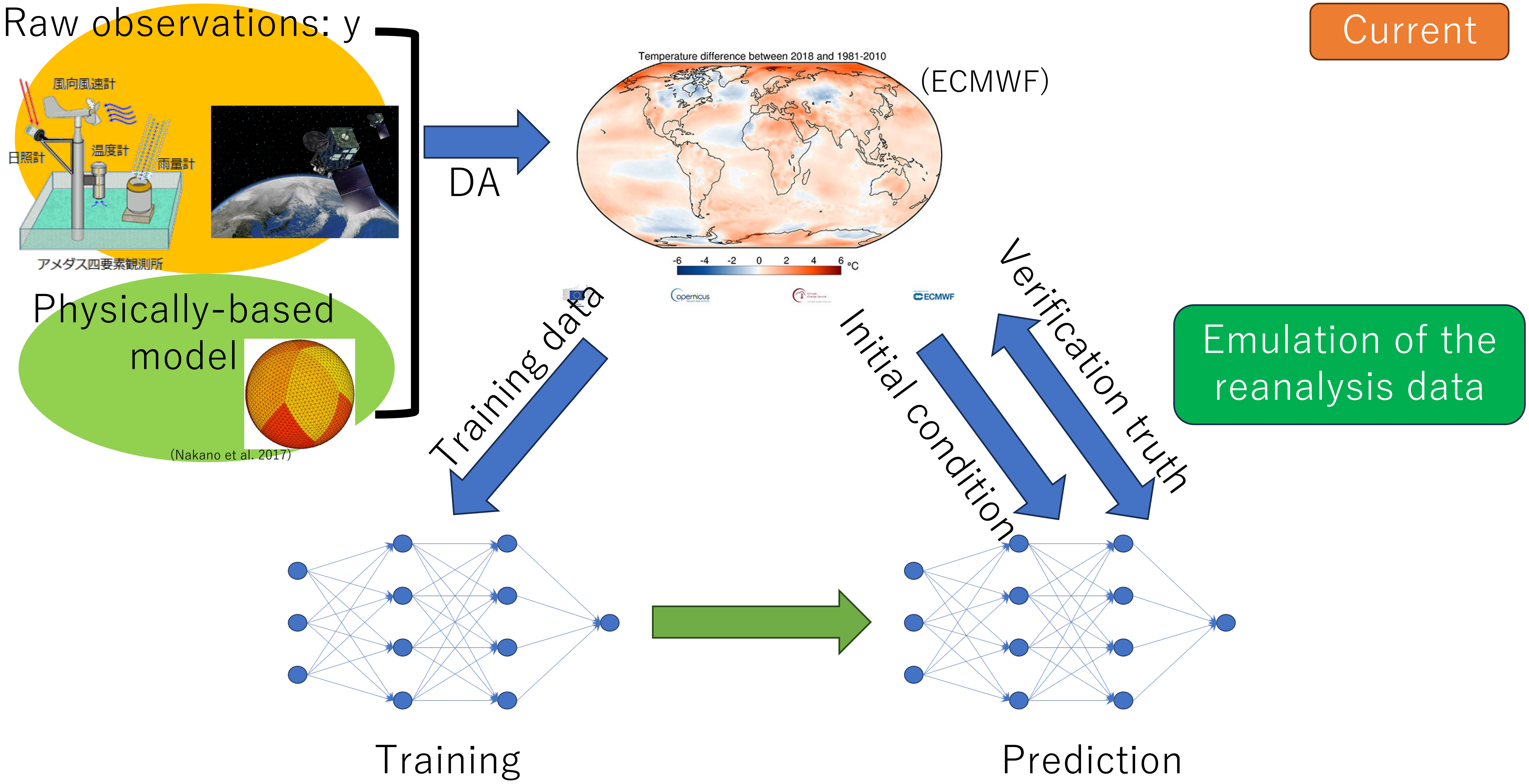
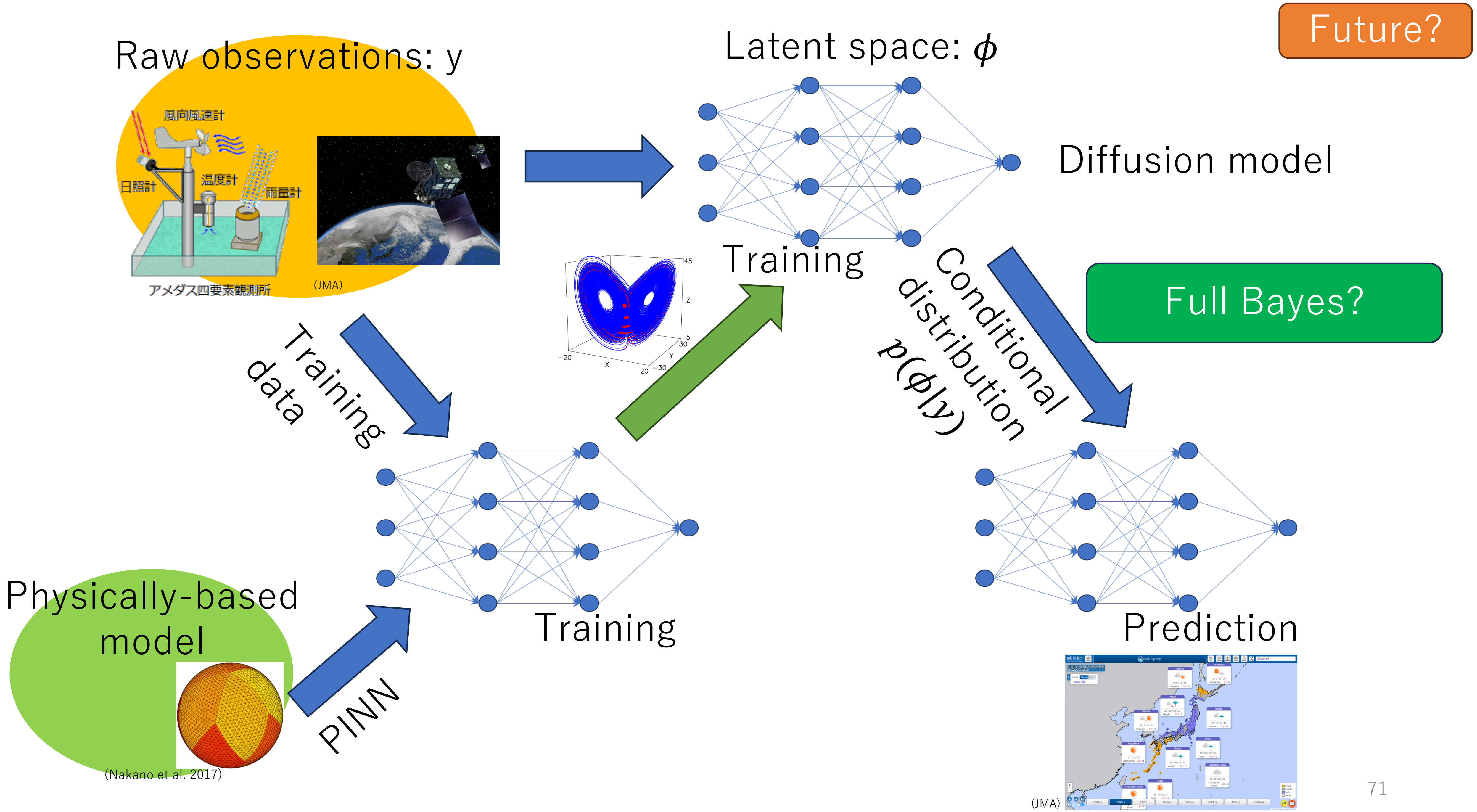

Process past observations by ConvLSTM
Generate future images by ConvLSTM
NWP results
Assimilated by NWP system SCALE-LETKF
Accurate
ssimilation and deep learning fo

Summary


satellite obs. opera
$x^f + \mathbf{K}[y - H(x^f)]$
: Forecast in model space (e.g., Temperature)
H: RTM-LinebyLine
$H(x^f)$: Forecast in obs. space (e.g., Radiance)
Slow
Training
on model
Fast
H: RTTOV
ning model
Fast
H: ML
023, JMSJ)
CTL: CONV only
ML-based: CONV+AMSU-A
hPa
RTTOV)
Better
Temperature RMSD (K)


Raw observations: y
風向風速計
日照計
温度計
雨量計
アメダス四要素観測所
Physically-based model
(Nakano et al. 2017)
DA
Temperature difference between 2018 and 1981-2010
(ECMWF)
-6 -4 -2 0 2 4 6 °C
Current
Training data
Initial condition
Verification truth
Emulation of the reanalysis data
Training
Prediction


Raw observations: y
風向風速計
日照計
温度計
雨量計
アメダス四要素観測所
(JMA)
Latent space: ϕ
Future?
Diffusion model
Training
Conditional distribution $p(\phi|y)$
Full Bayes?
Training data
Training
Physically-based model
PINN
(Nakano et al. 2017)
Prediction
(JMA)