RIKEN's activities to integrate DA and AI/ML

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RIKEN Center for Computational Science

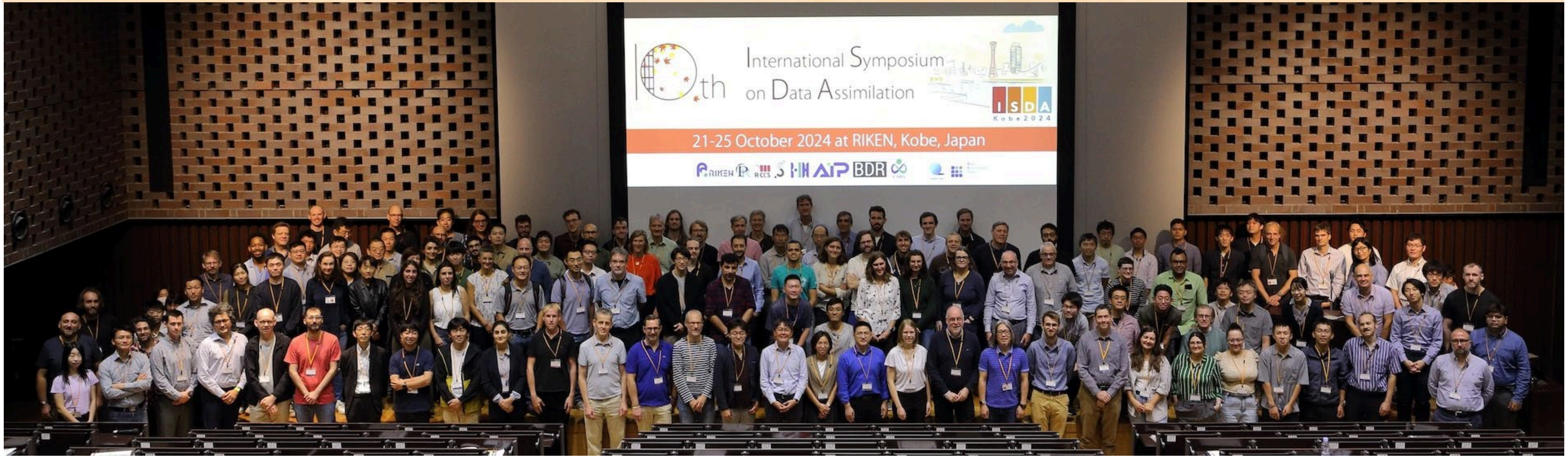
Data Assimilation Team

iTHEMS

RIKEN R-CCS, Kobe, Japan

Thank you!!!

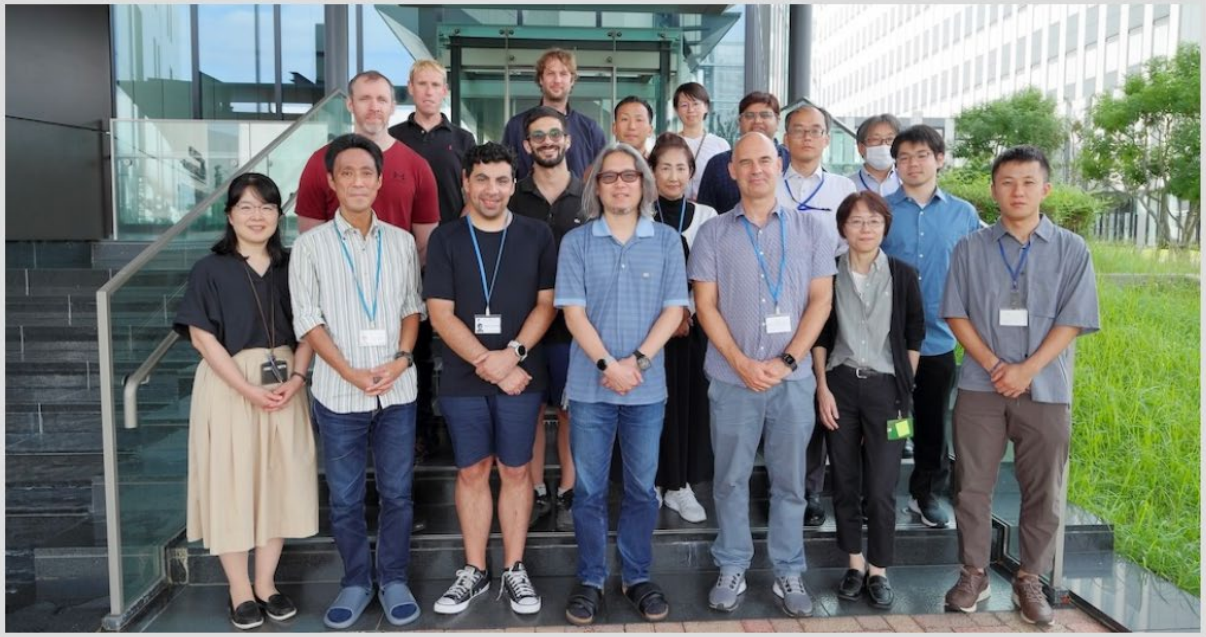
https://www.data-assimilation.riken.jp/isda2024/



Data Assimilation Research Team

Weather prediction is a great achievement of human intelligence by integrating advanced sensing, supercomputing, and information and communications technologies. Here, data assimilation plays a pivotal role. Connecting the most advanced radar sensing technology and supercomputers "K" and "Fugaku", data assimilation made it possible to predict sudden downpours. Data assimilation brings links to the future and expands synergistic opportunities.

- RIKEN Weather Forecast
- COVID-19 Realtime Forecast
- Youtube: AGU-TV RIKEN Digest(1 minute) / Full(5 minutes)
- RIKEN Data Assimilation Channel



October 15, 2024 at R-CCS

Pushing the limits

Big Data × *Big Simulations*

Big ensemble (10240 ensemble members)

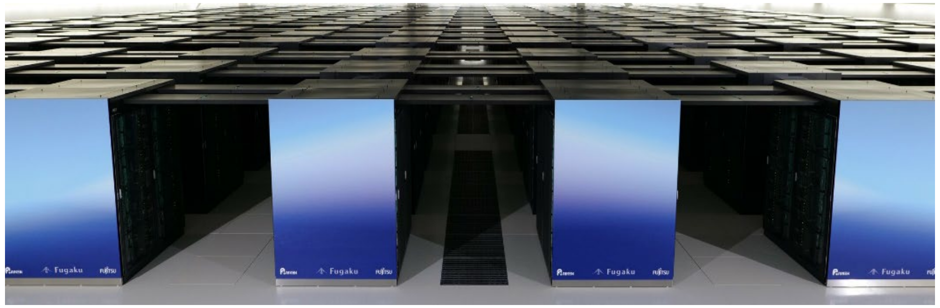
Rapid update (30-second update)

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)

2021-06-02

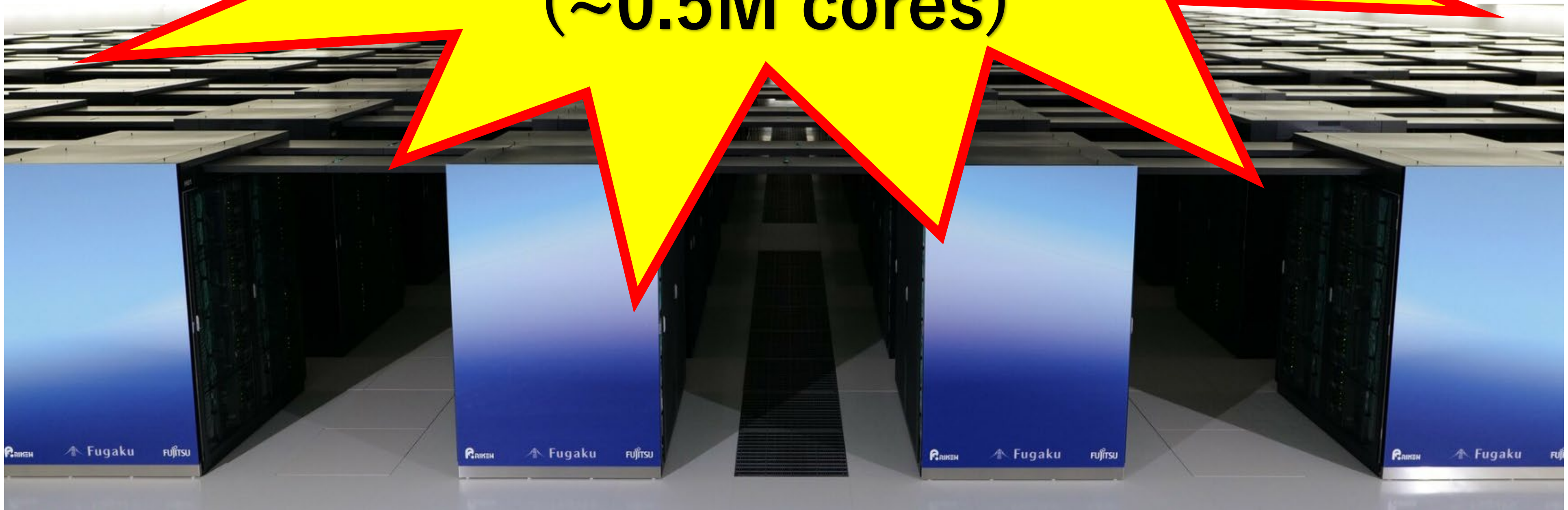
この期間、一般向けの提供資源が縮小されます。
実時間型ジョブ実行のため、提供される資源規模は、全体の約91%ま　となります。
この期間、一般向けにはログインノード１は利用できません。

During this period, the resources provided to the public will b
Due to real-time job e　　　, the resource size provide　　　bout 91% of the total.
During this period, L　　　is not available fo

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

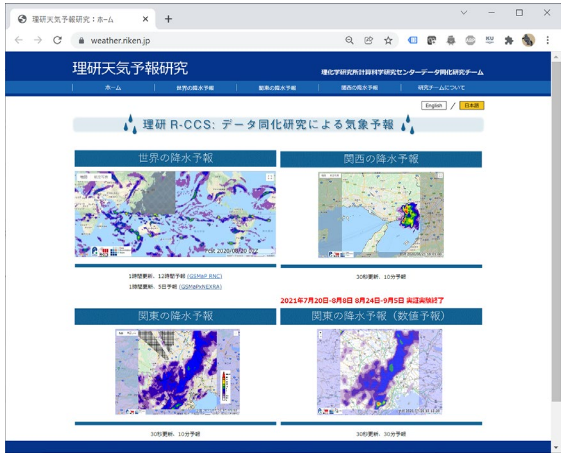
Exclusive use of
~7% of Fugaku
(~0.5M cores)

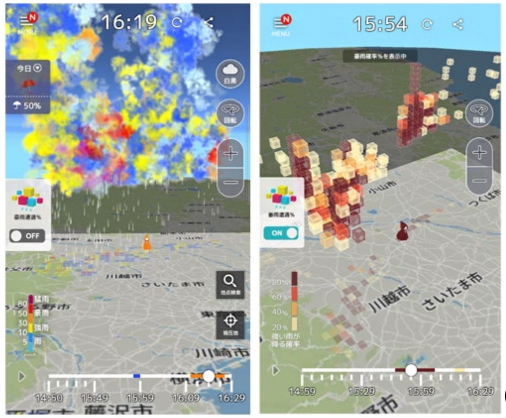


30-s refresh real-time workflow with “Fugaku”

Dual-polarimetric Phased Array Weather Radar
(installed 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

RIKEN R-CCS

SCALE-LETKF → weather.riken.jp — webpage

SCALE-LETKF → MTI Amazon AWS — smartphone

理研天気予報研究

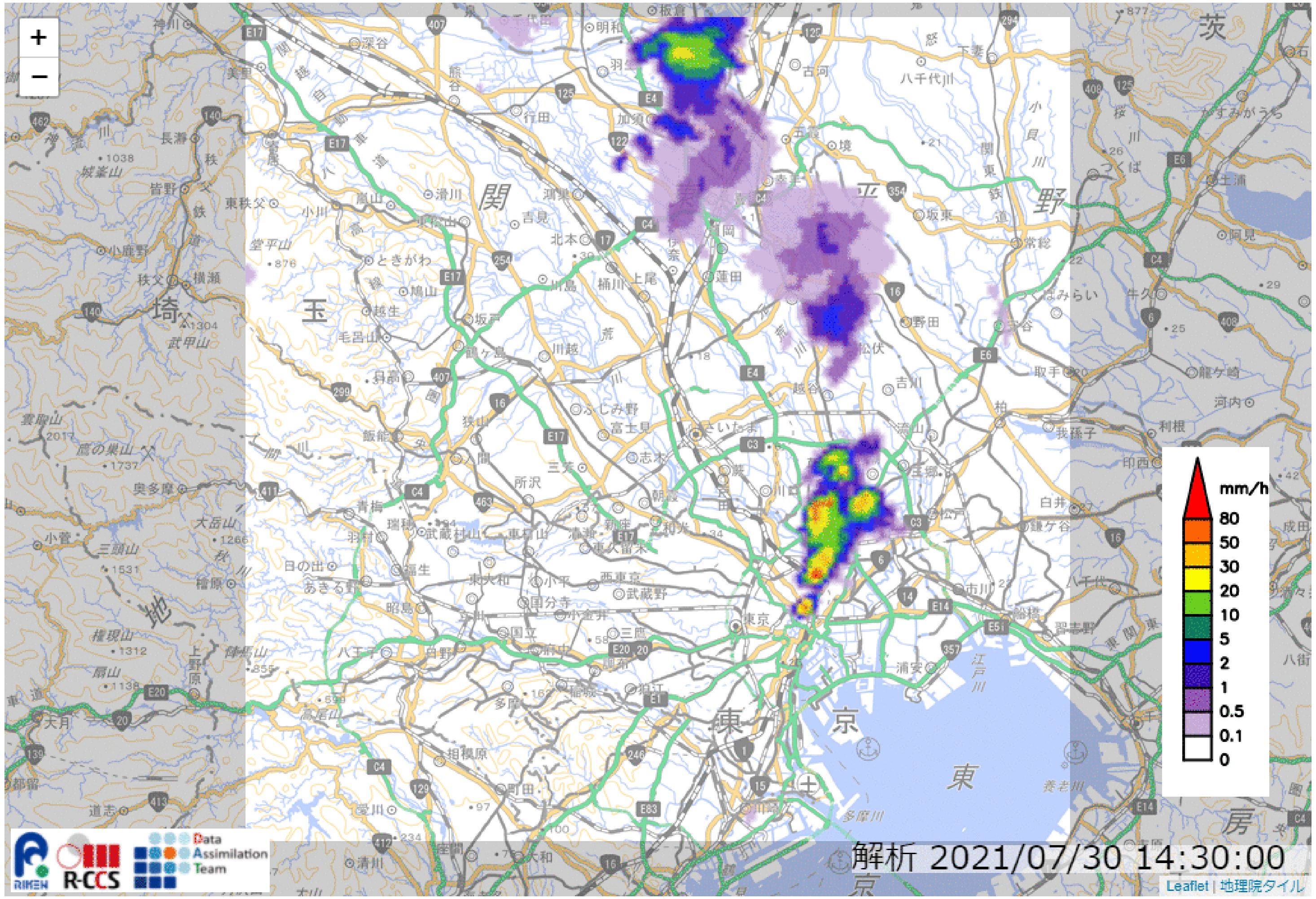
理化学研究所計算科学研究センターデータ同化研究チーム

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

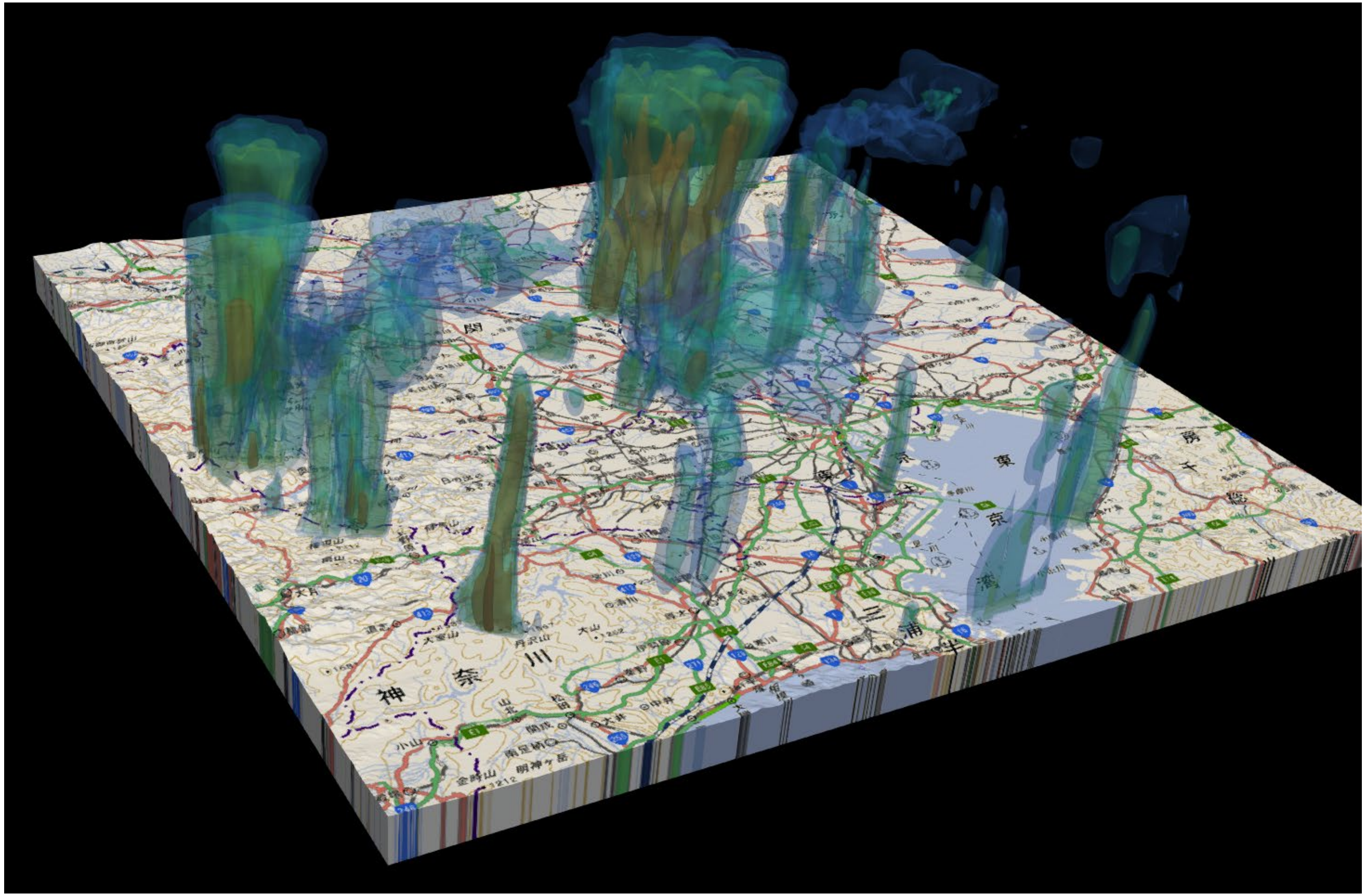


Figure 8: 3-D bird’s-eye view of 30-minute forecast rains at 04:48:00 UTC, July 30, 2021. Colors represent simulated radar reflectivity every 10 dBZ for 10-50 dBZ. Vertical scale is stretched by three times. Map data is from the web page of the Geospatial Information Authority of Japan (Courtesy of H.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

Skillful forecast achieved

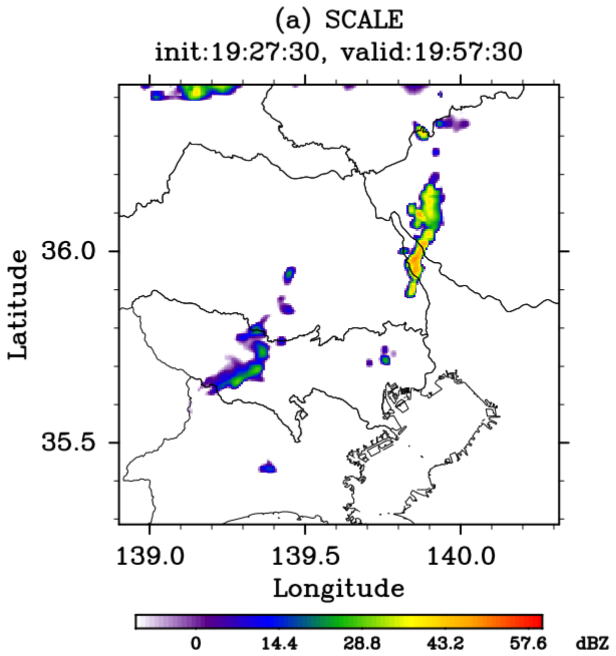


Figure 6: (a) 30-minute forecast rains at 19:57:30 UTC, July 29, 2021. Colors represent radar reflectivity (dBZ) at the 2-km height. (b) Similar to (a), but for the actual MP-PAWR observation at the closest time. Hatched areas indicate no data due to out of the 60-km range, radar beam blockage, or other reasons.

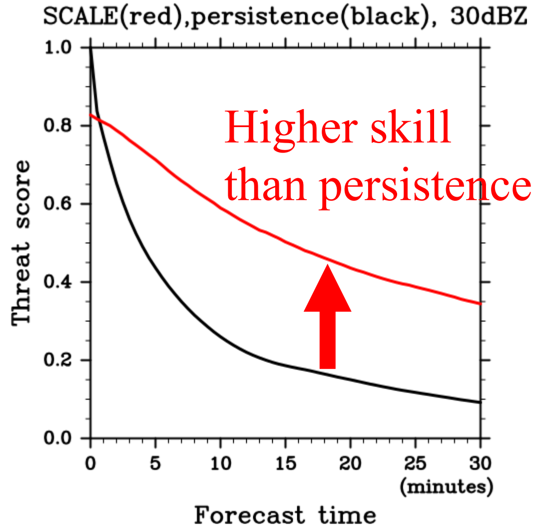


Figure 7: Heavy rain forecast skill as shown by threat scores (the higher, the more skillful) for radar reflectivity at the 30dBZ threshold for 120 forecast cases between 19:00:00 UTC and 20:00:00 UTC, July 29, 2021. Red and black lines indicate the BDA system and persistence, respectively.

Possible deep learning applications

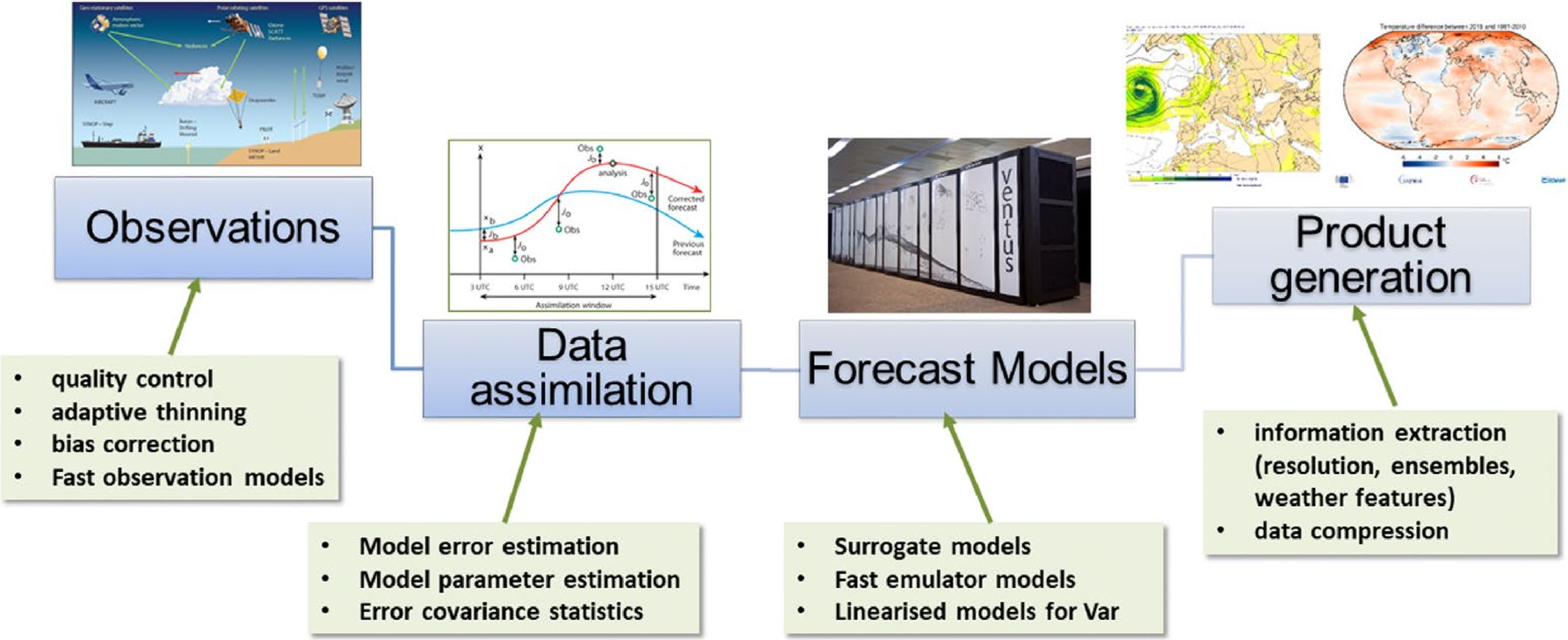
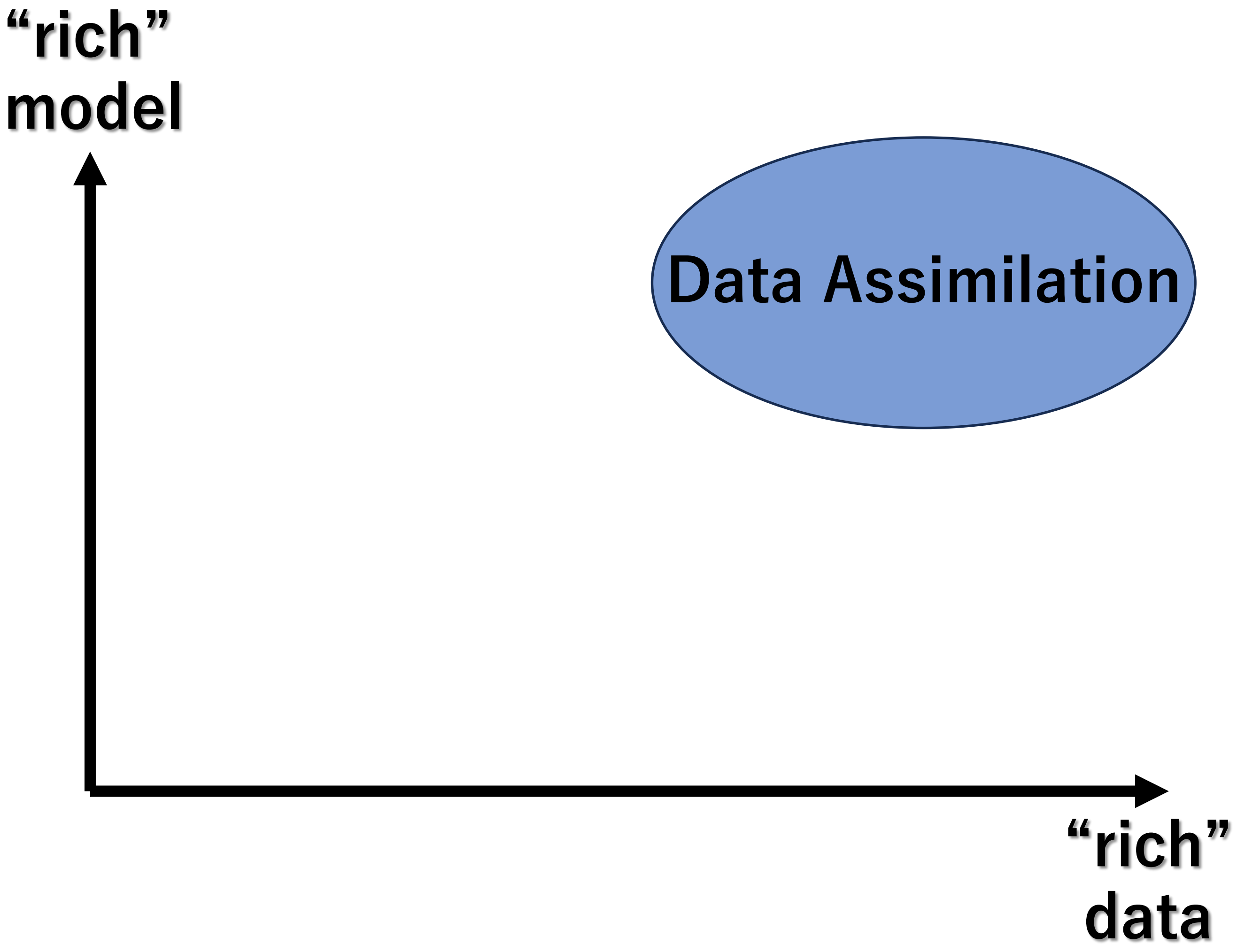
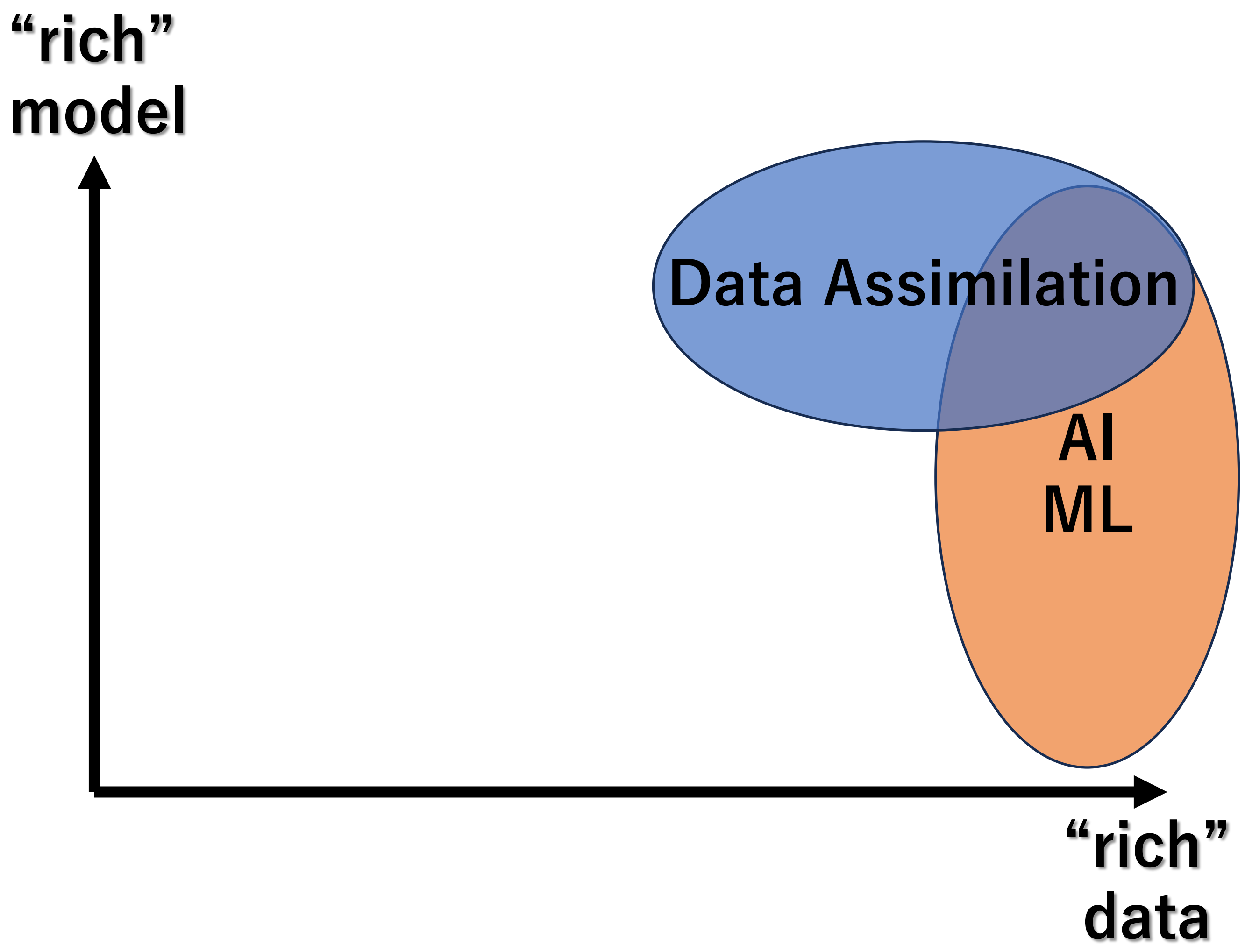


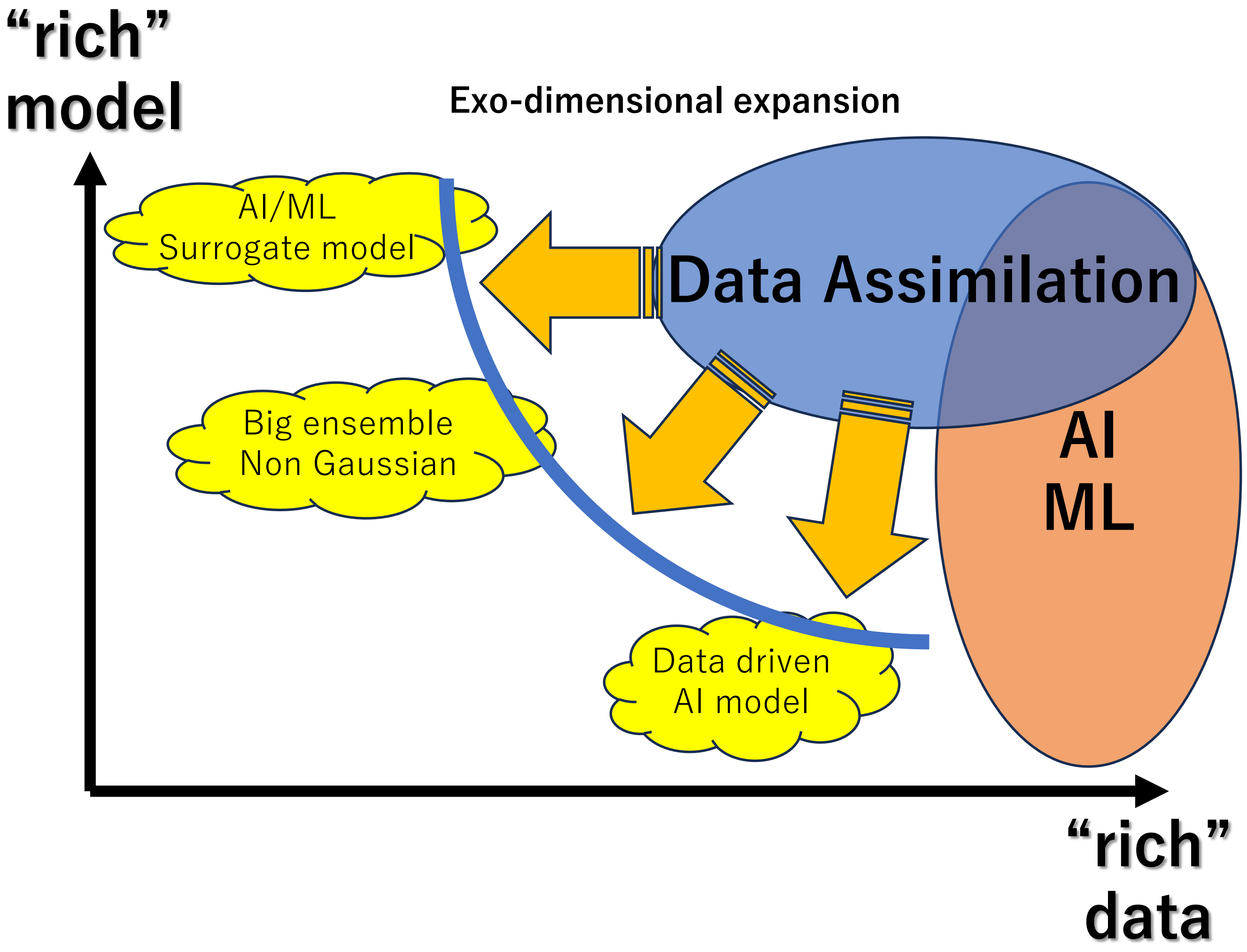
Fig. 1. Examples of possible machine learning applications in the various components of a standard NWP workflow.

Bonavita et al. (2020, *BAMS*)


"rich"
model
Data Assimilation
"rich"
data



“rich”
model
Data Assimilation
AI
ML
“rich”
data


"rich" model
Exo-dimensional expansion
AI/ML
Surrogate model
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)

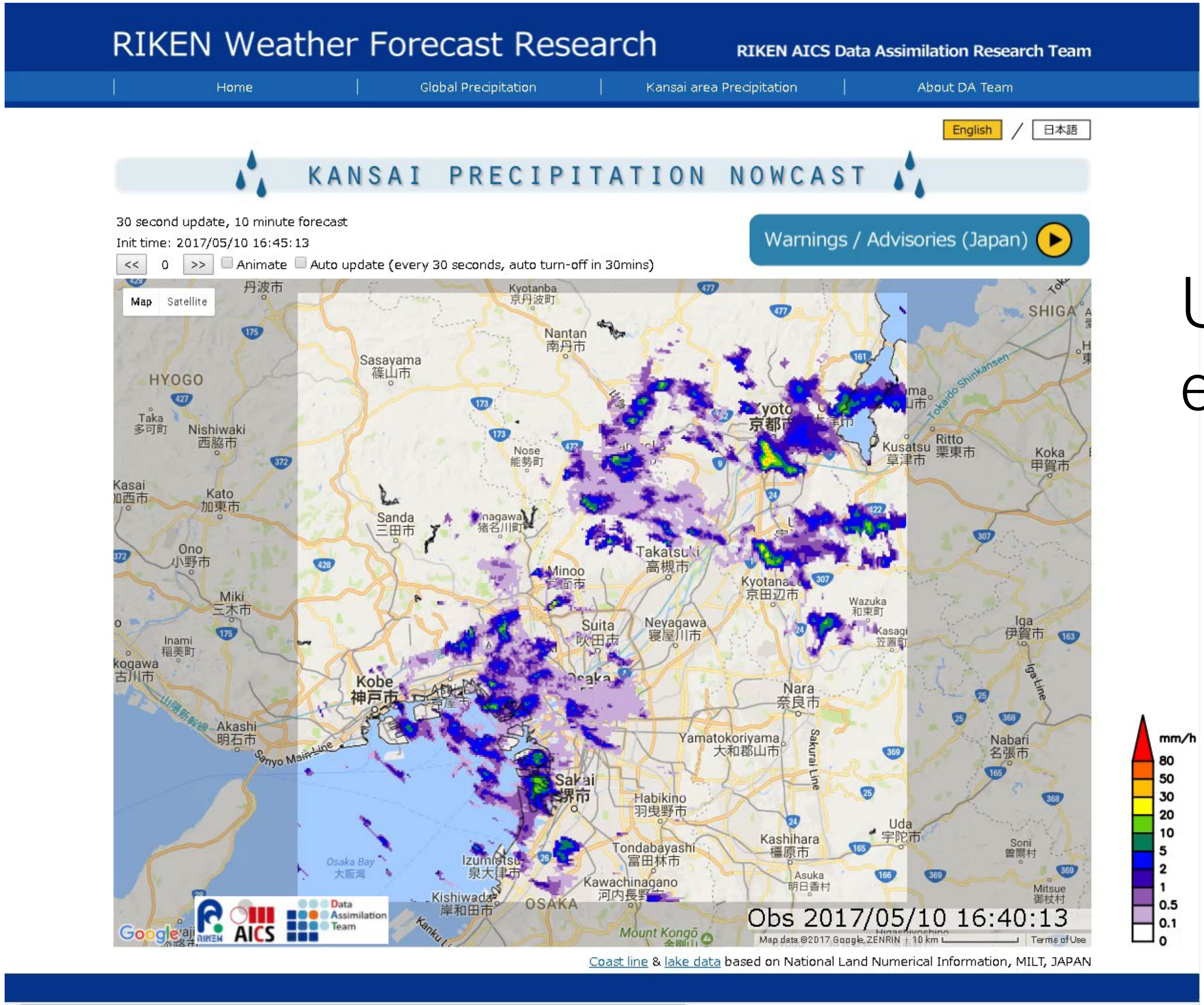
Acknowledgment

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

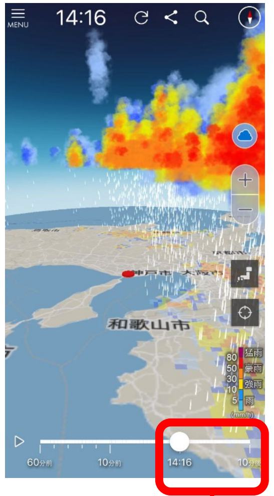
Phased-Array Weather Radar 3D nowcast (https://weather.riken.jp/)

(NICT)

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

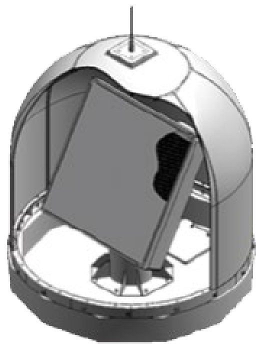


Updated every 30



App by MTI Ltd.

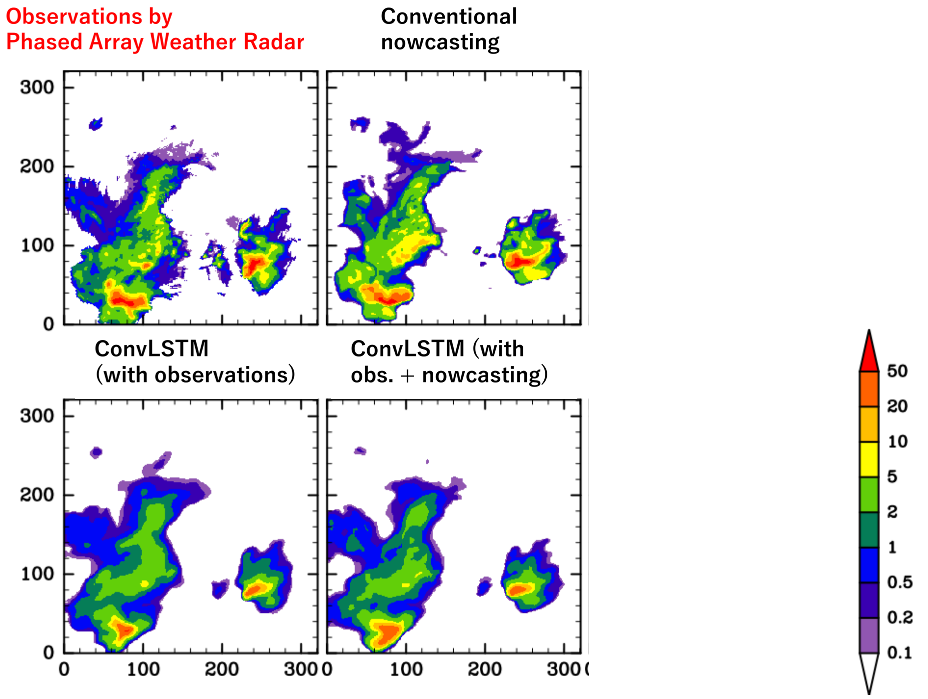
247,000+ downloaded

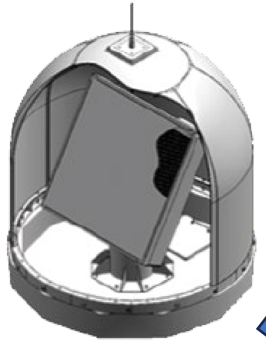


(NICT)

Process past observations by ConvLSTM

→ Generate future images by ConvLSTM



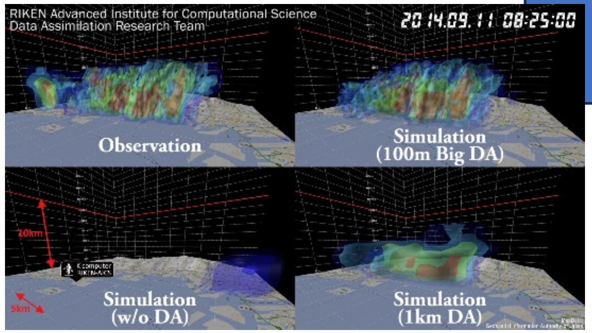


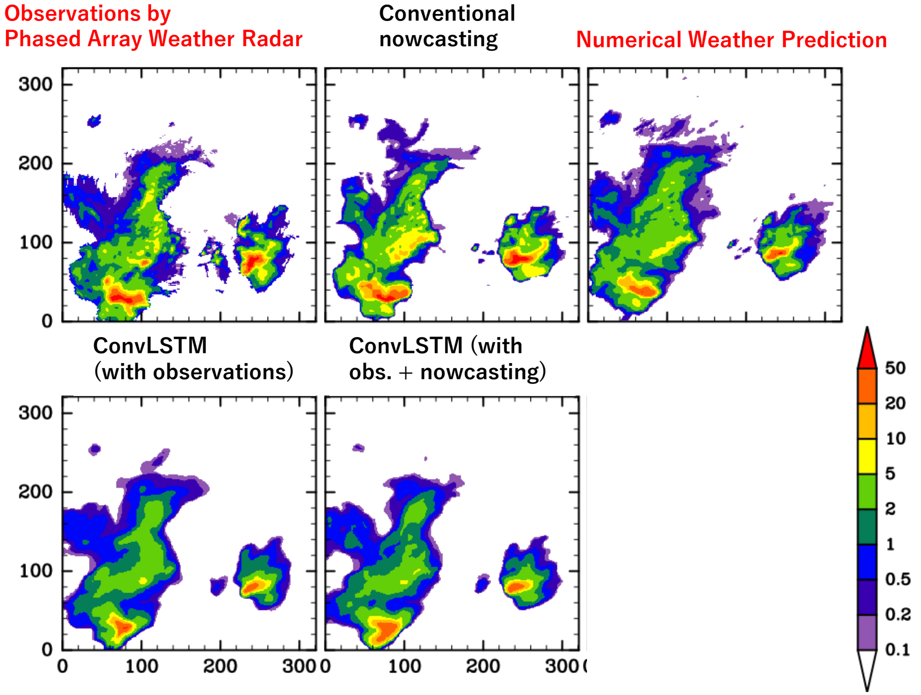
(NICT)

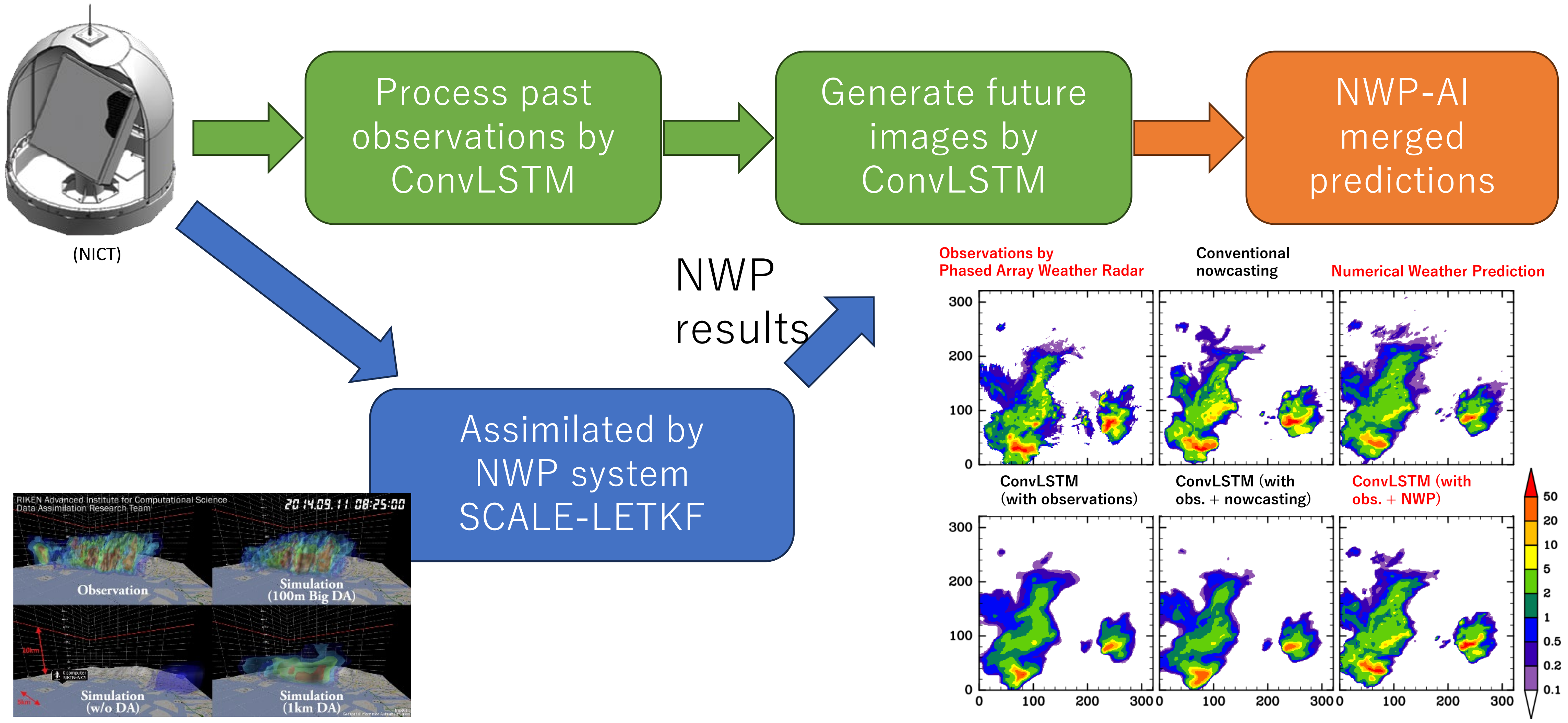
Process past observations by ConvLSTM

Generate future images by ConvLSTM

Assimilated by NWP system SCALE-LETKF

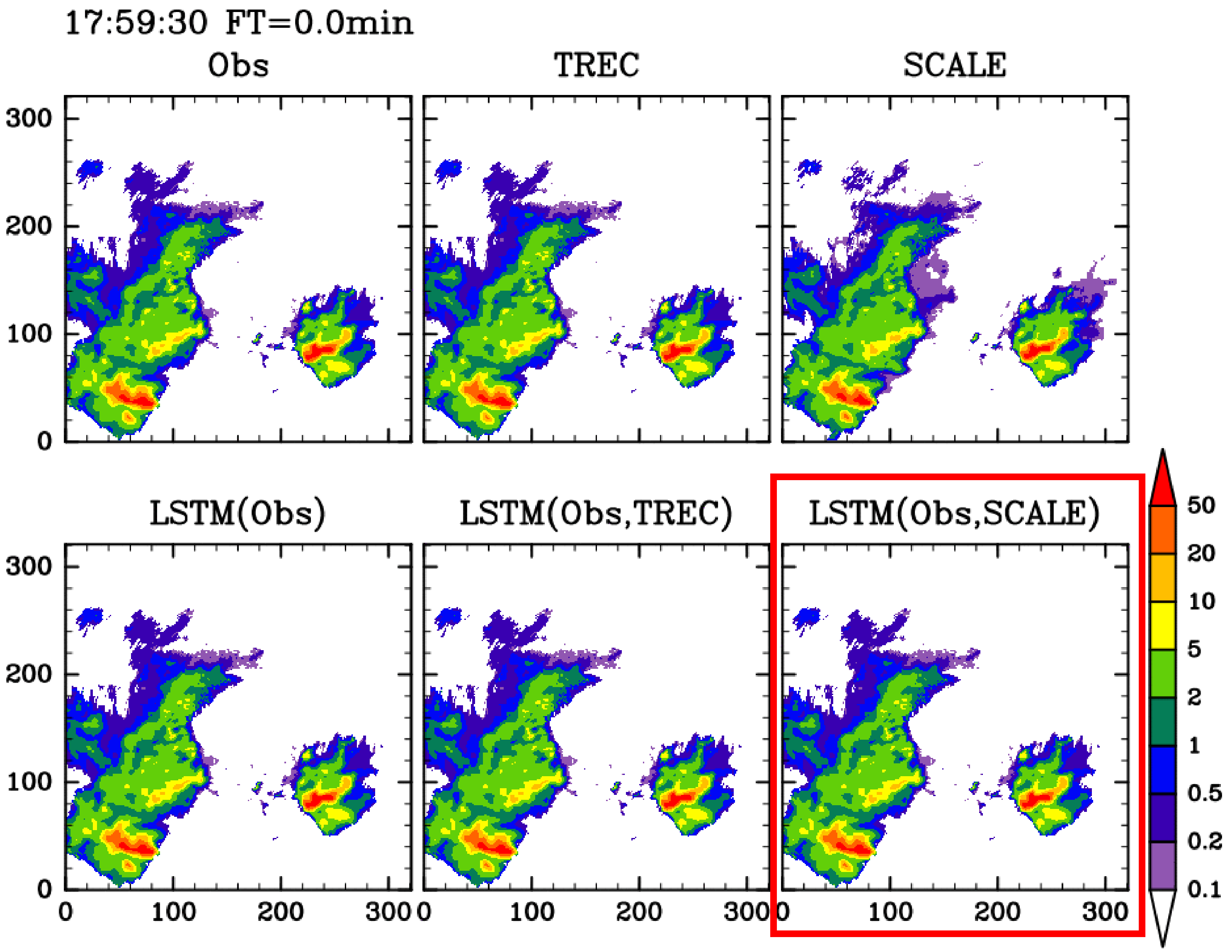


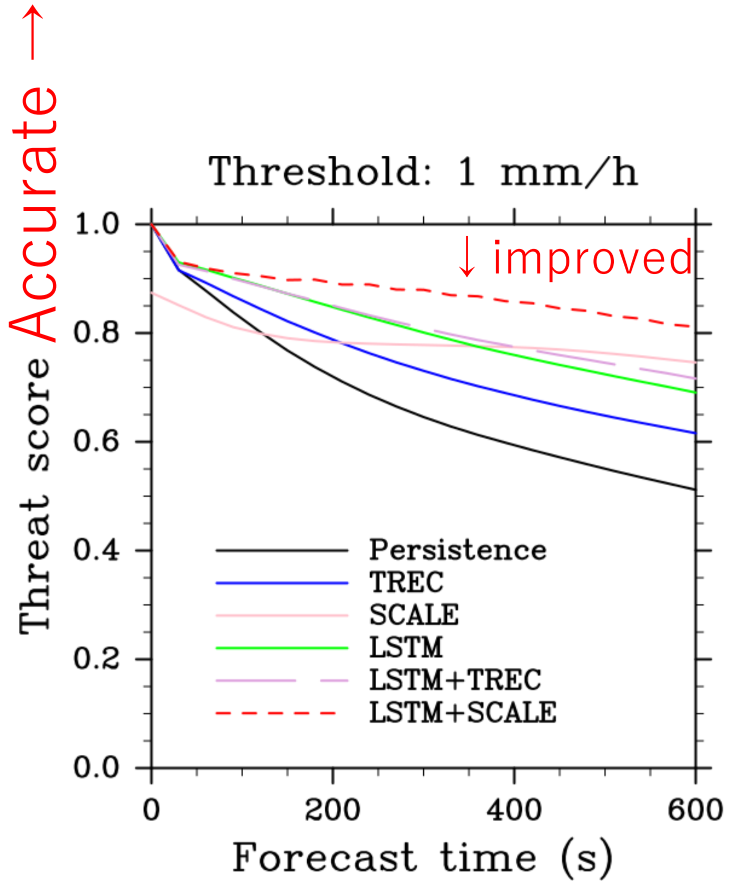




Integrating big data assimilation and deep learning for precipitation nowcasting

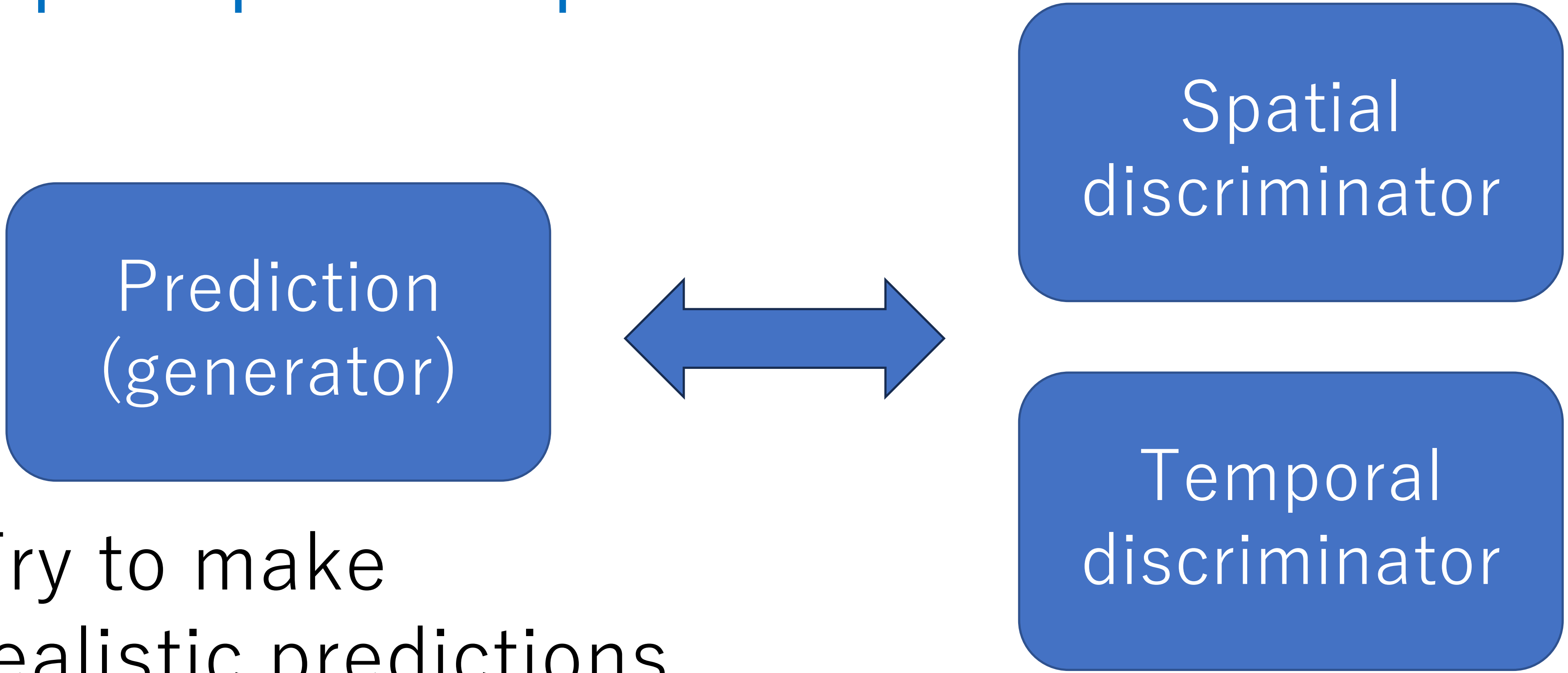
Preliminary results (rain rate @ 2km)





Adversarial training for precipitation predictions

- e.g., Ravuri et al. (2021), Baron et al. (2023)

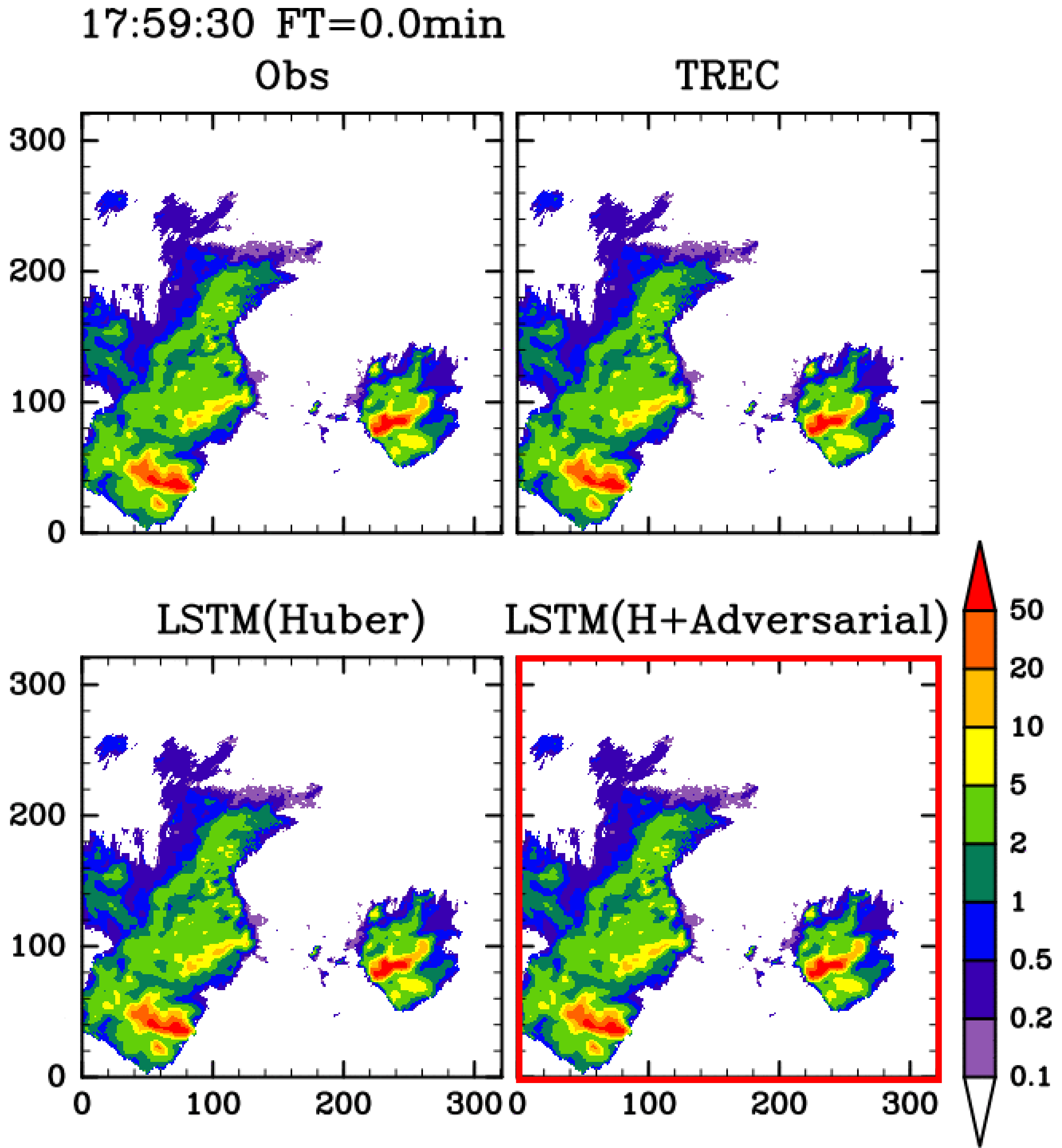


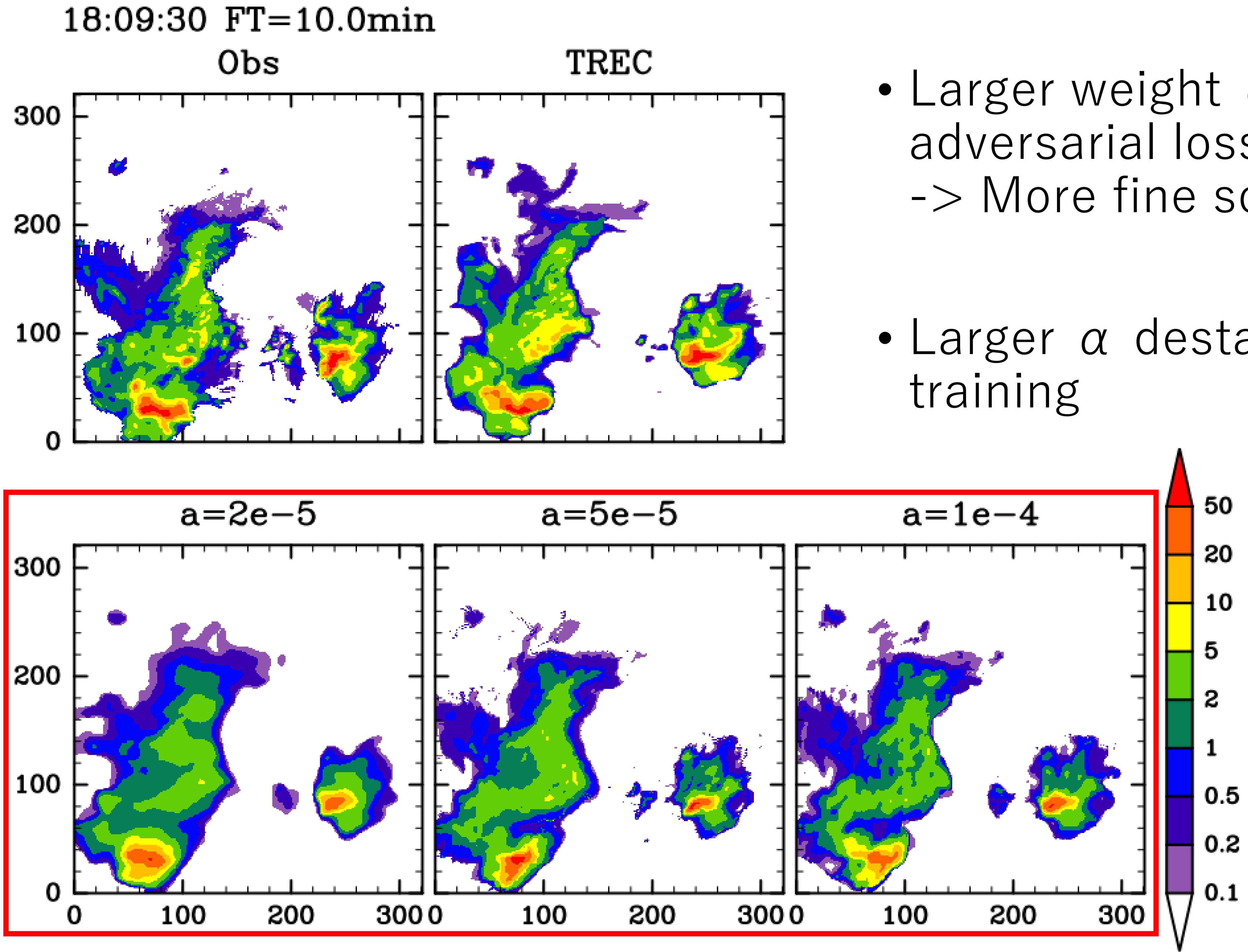
Try to make realistic predictions

Try to discriminate predictions from observations

Preliminary results

- LSTM with adversarial training produces small-scale signals



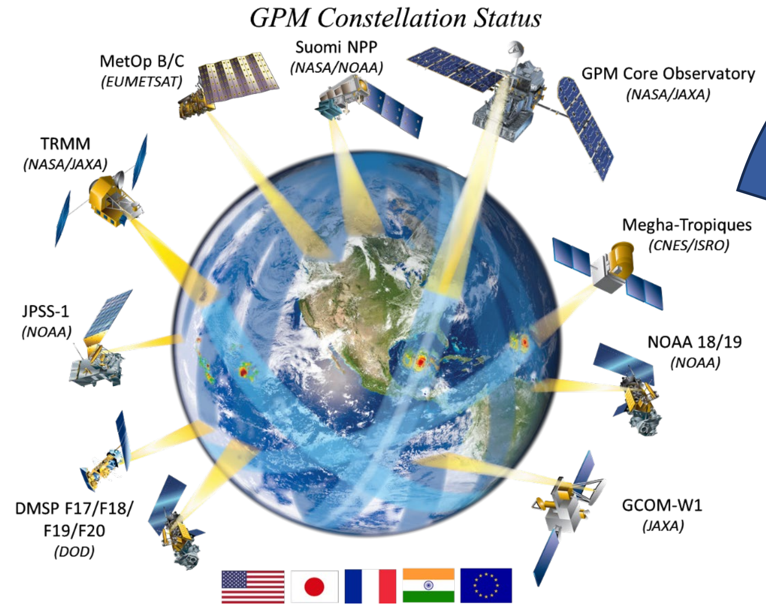


- Larger weight α for the adversarial loss
  -> More fine scale features

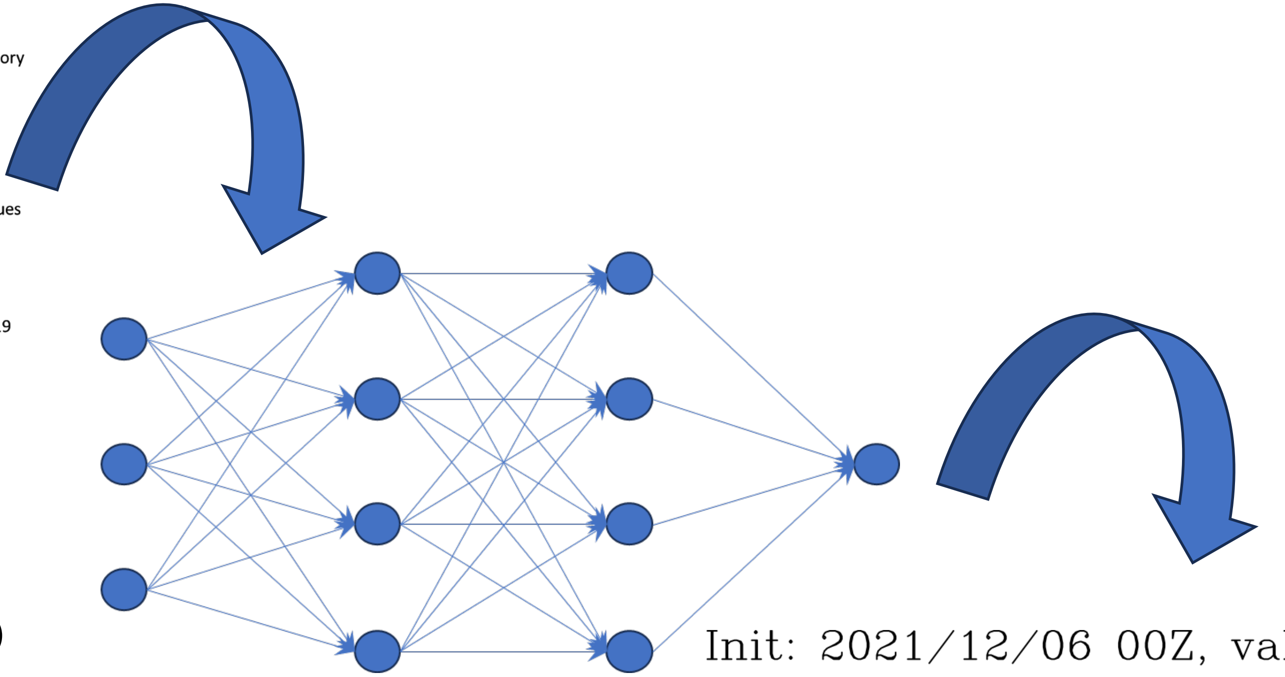
- Larger α destabilizes training

ML-based global precipitation nowcasting

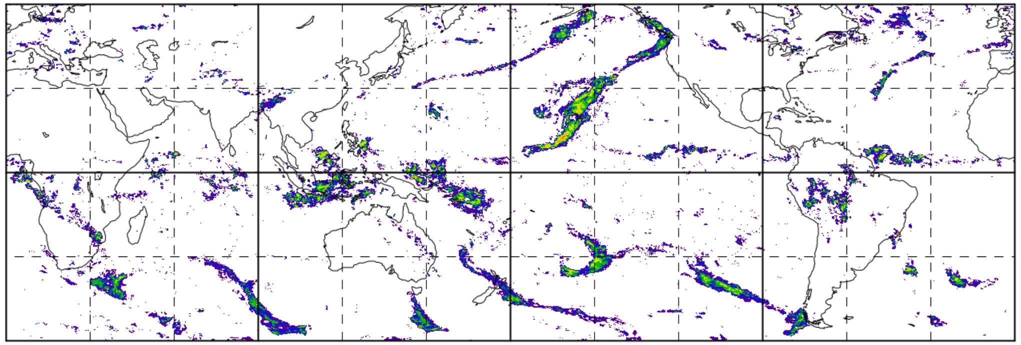
- GSMaP-based AI forecast



(NASA)



Init: 2021/12/06 00Z, valid: 2021/12/06 12Z



Difficulties when applying ML to global precipitation nowcasting

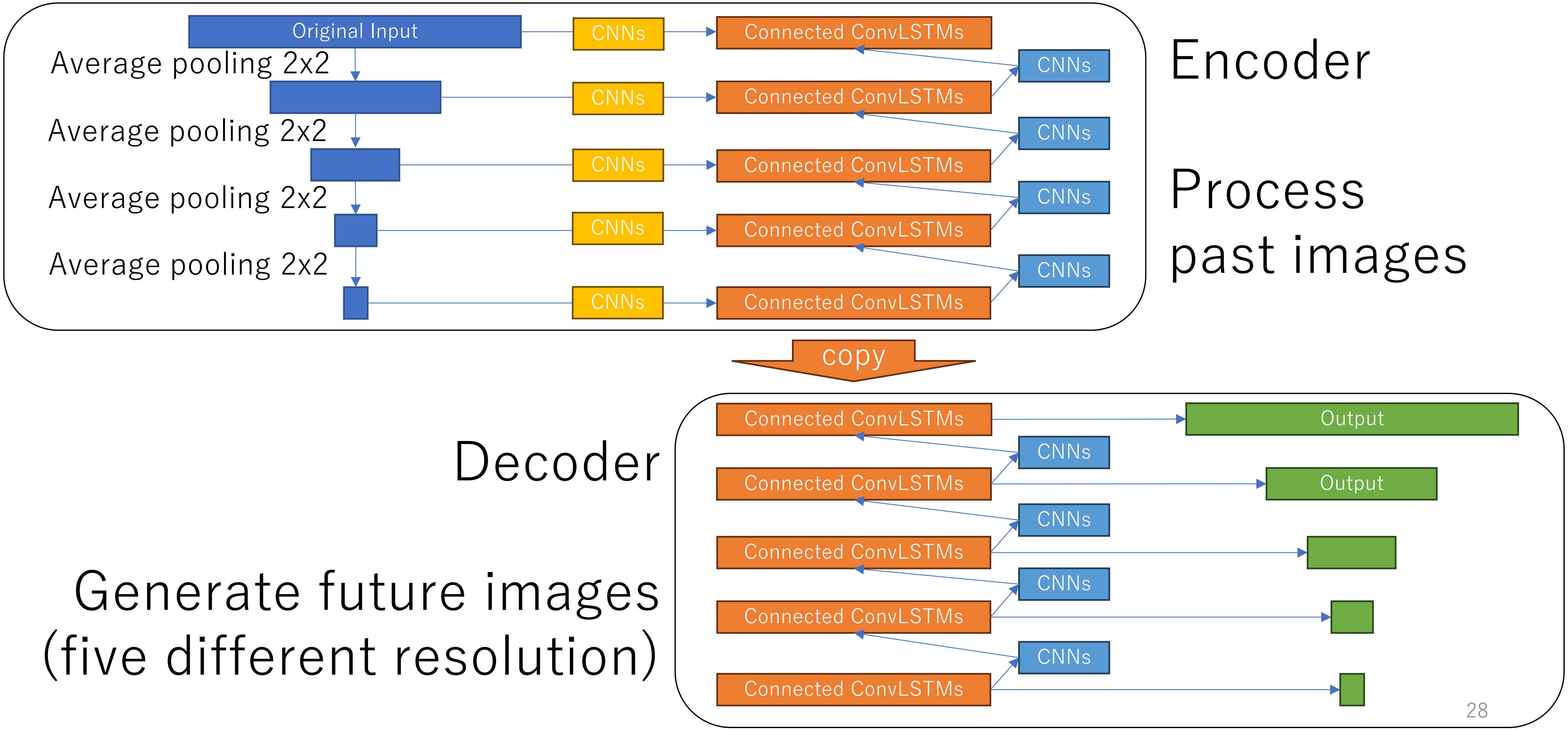
- Inhomogeneity due to multi-satellite observations

  → Use of quality index by the data provider
- Scale mismatch
  - Spatial resolution: 0.1° vs. temporal resolution: 1 h

  → Hierarchical network structure
- Blurry prediction

  → Adversarial training, non-local loss

ConvLSTM-based generator for adversarial training



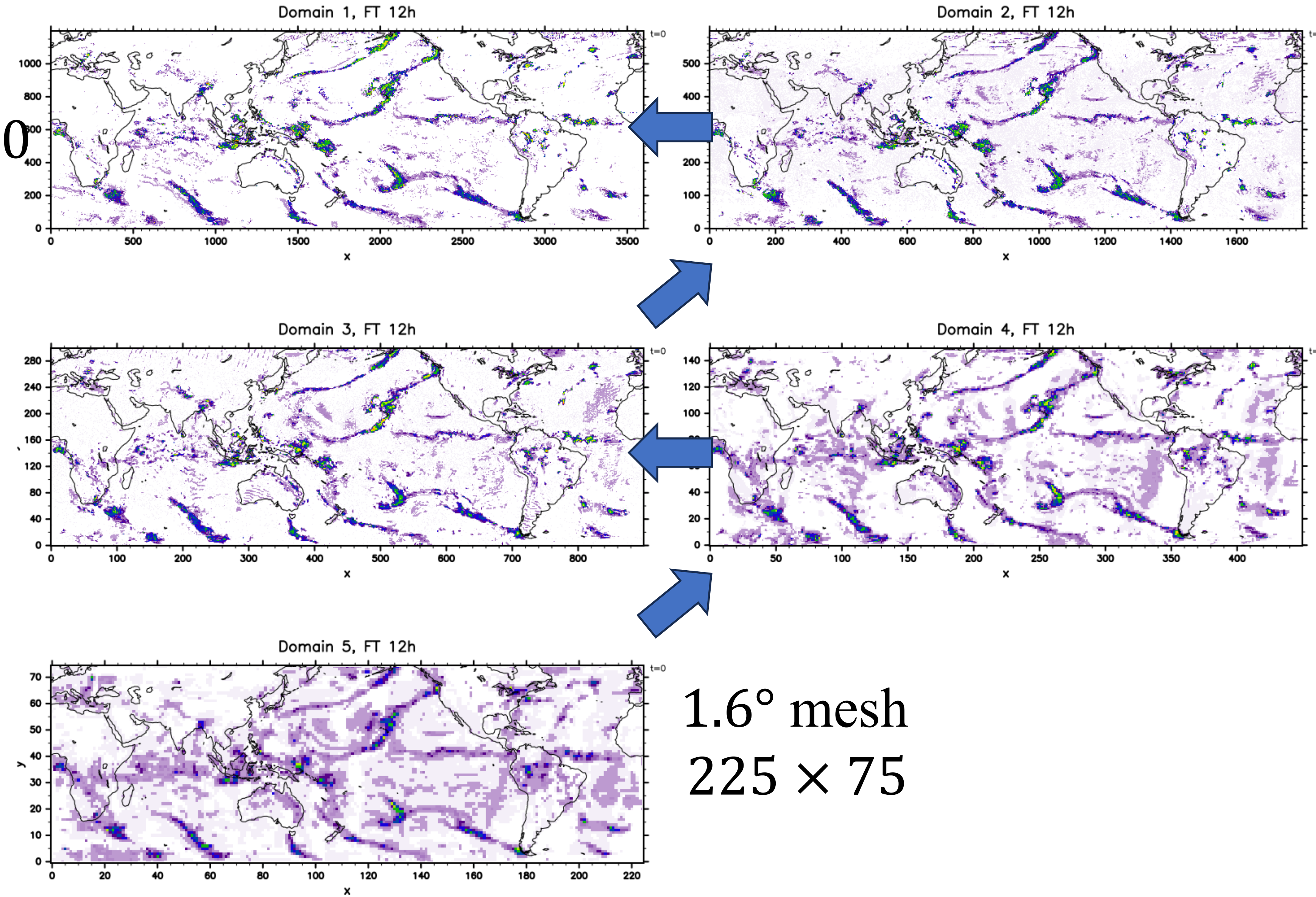
Progressive training from low- to high-res

0.1° mesh
3600 × 1200

0.2° mesh
1800 × 600

0.4° mesh
900 × 300

0.8° mesh
450 × 150



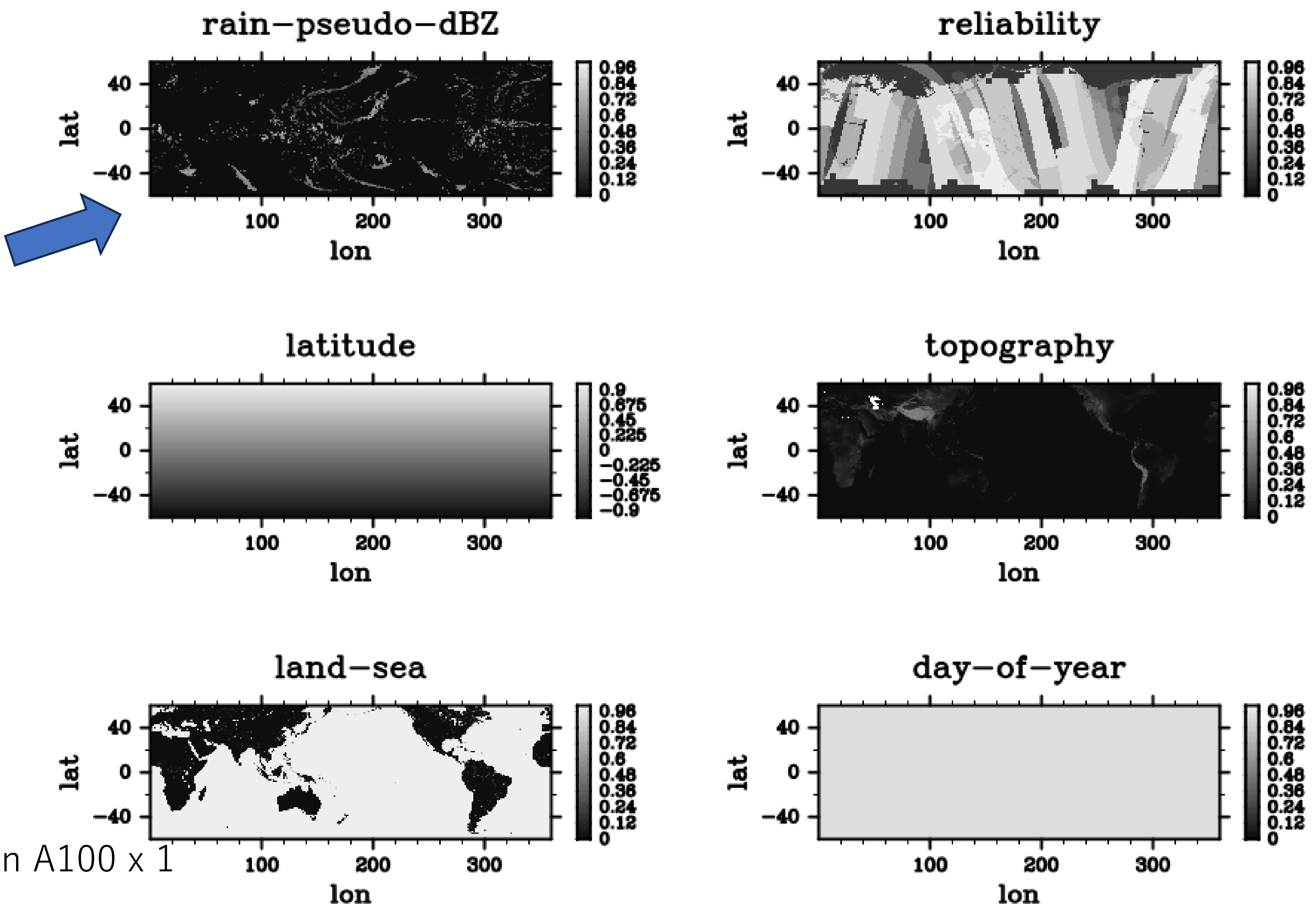
1.6° mesh
225 × 75

Training loss

- Loss_pixelwise = Σ i(Huber(xi, yi) * wi)
- Loss_adversarial = BinaryCrossEntropy(D_spatial(x, 0.8))
  + BinaryCrossEntropy(D_temporal(x, 0.8))
- Loss_non_local:
  - parameters:
    - Mean and higher-order moments: For each time step, $(\overline{x^p})^{\frac{1}{p}}, p = 1,2,4,6,8,10$
    - Sharpness: For each time step, $\left(\overline{(\nabla^q x - \overline{\nabla^q x})^p}\right)^{\frac{1}{p}}, p = 2,4, q = 2,4,6,8$
    - To avoid unrealistic pattern: For time-averaged value, $\left(\overline{(\nabla^q x - \overline{\nabla^q x})^p}\right)^{\frac{1}{p}}, p = 2,4, q = 2,4,6,8$
    - To avoid unrealistic pattern: For each time step, $\left(\overline{(x\nabla^q x - \overline{x\nabla^q x})^p}\right)^{\frac{1}{p}}, p = 2,4, q = 2,4,6,8$
  - Loss for each resolution, each parameter X: $\left(\frac{X_{Prediction} - X_{Truth}}{X_{Time-averaged\ truth}}\right)^2$

Data

- Input: hourly, past 24 h
  - GSMaP
    Near-Real-Time (NRT) v8
- Truth: hourly, 12-h lead
  - GSMaP Standard (MVK) v8
- Training:
  2022/01/01 - 2023/12/31
  - ~2 weeks on A100 x 1
- Validation:
  2021/12/06
- Test:
  2024/01/01 - 2024/01/31
  - ~5 seconds/12-h-prediction on A100 x 1
    - ~10 seconds for I/O

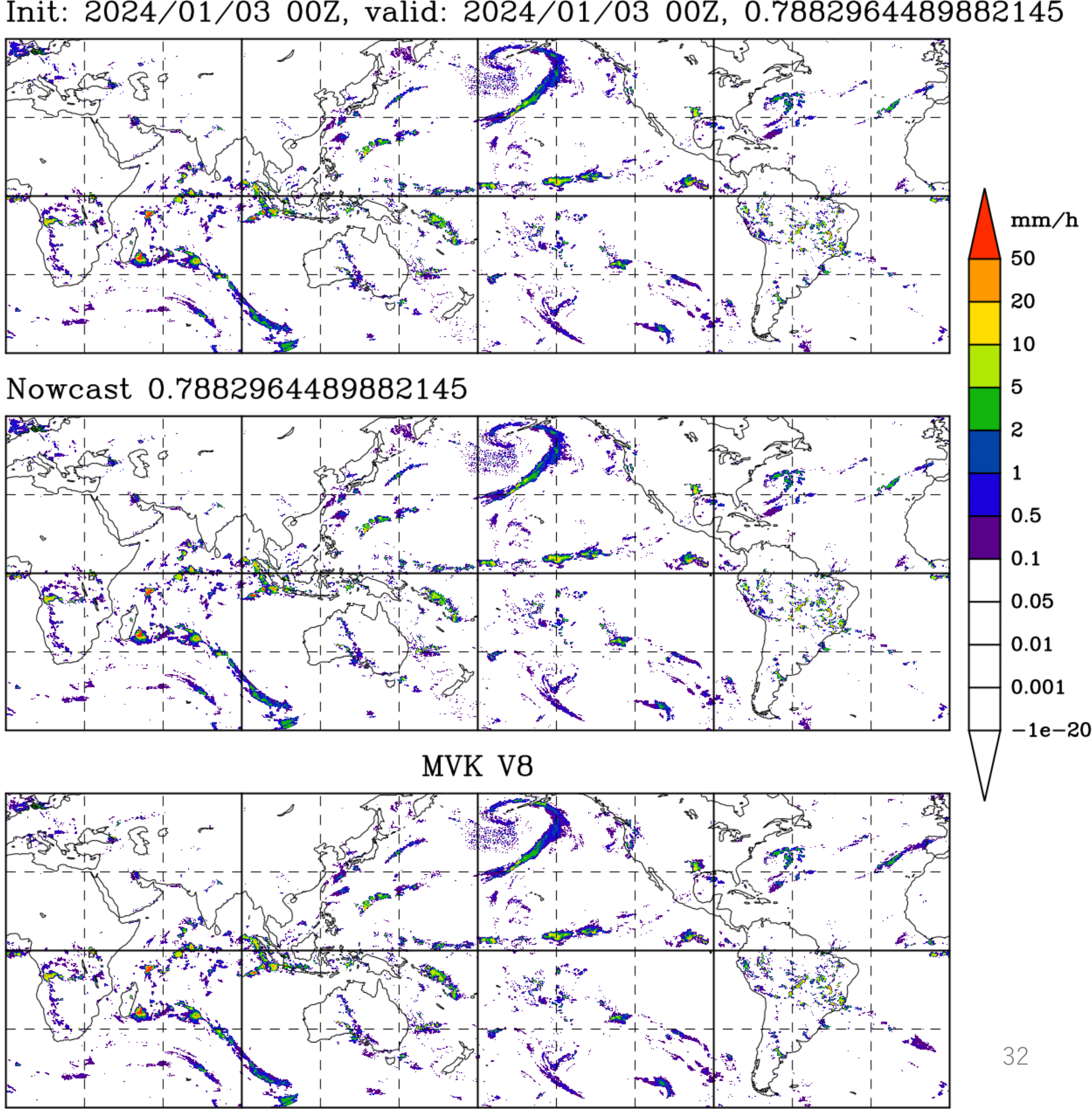


Comparison with a conventional algorithm

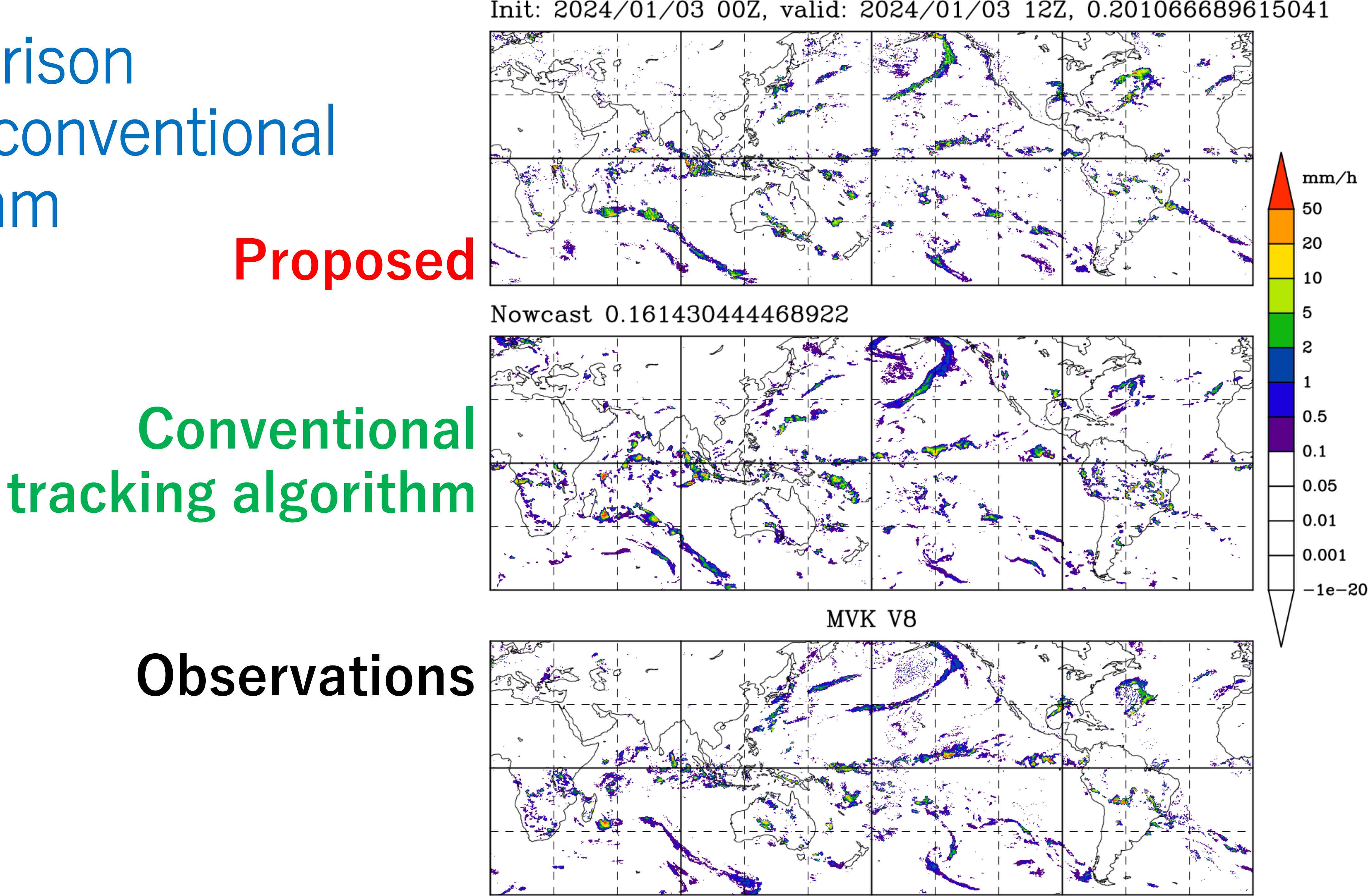
Proposed

Conventional tracking algorithm

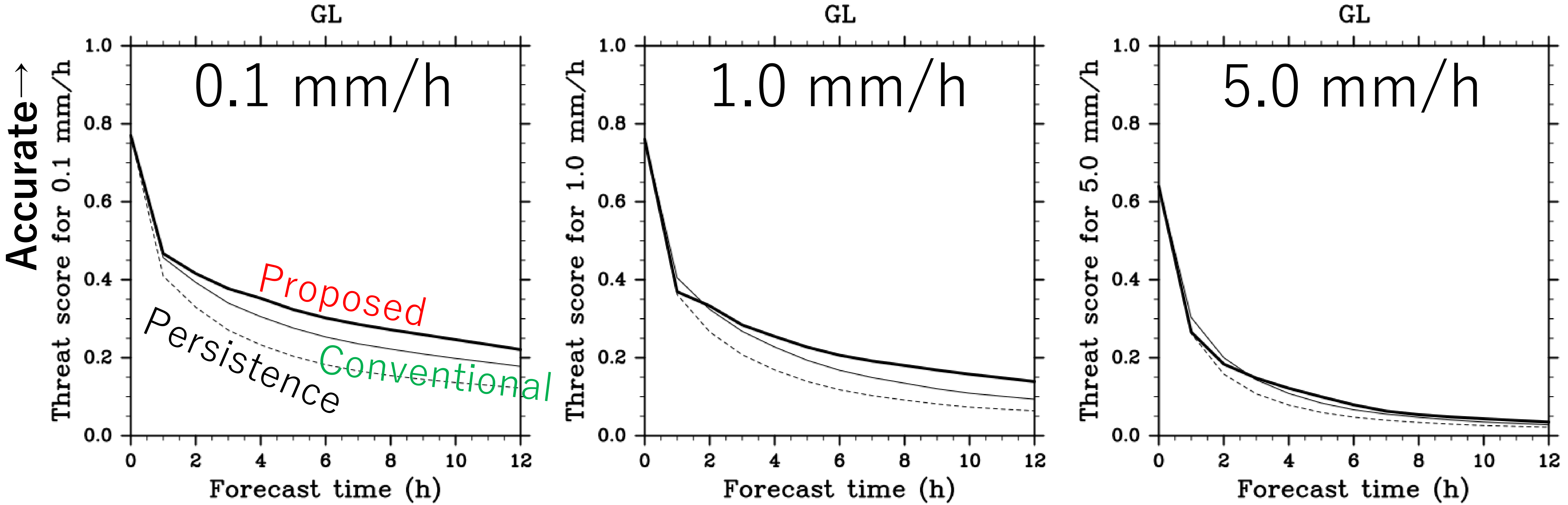
Observations



Comparison with a conventional algorithm



Verification scores for January 2024



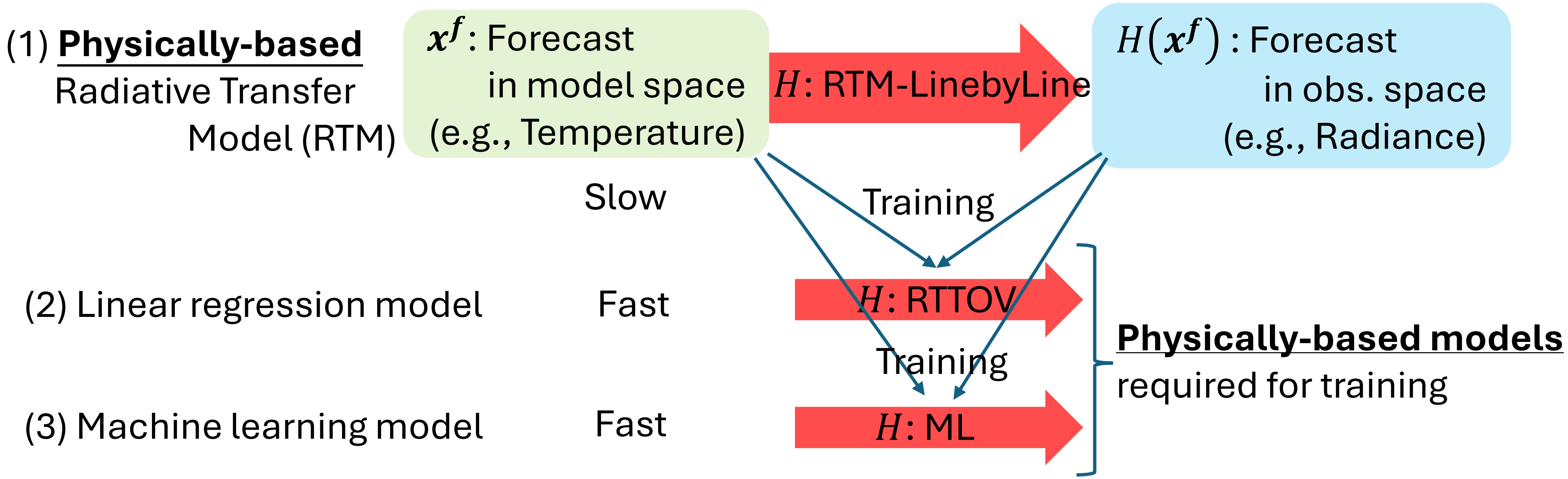
Threat scores with respect to GSMaP MVKv8

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

J. Liang and T. Miyoshi

Machine Learning for satellite obs. operator

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



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

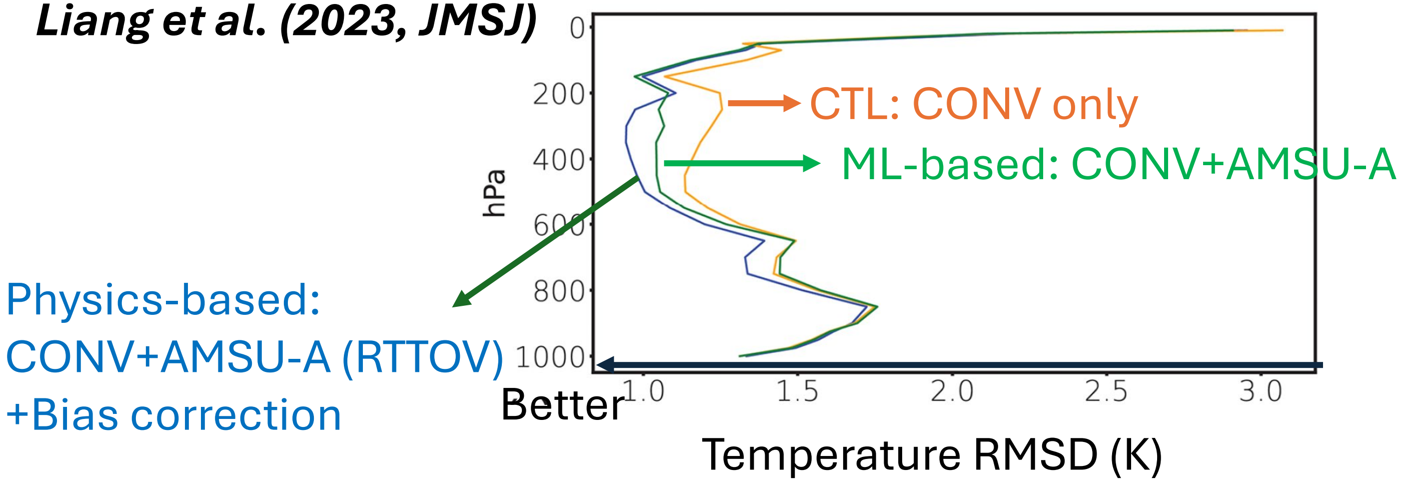
(2) Linear regression model — Fast — H: RTTOV

Training

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

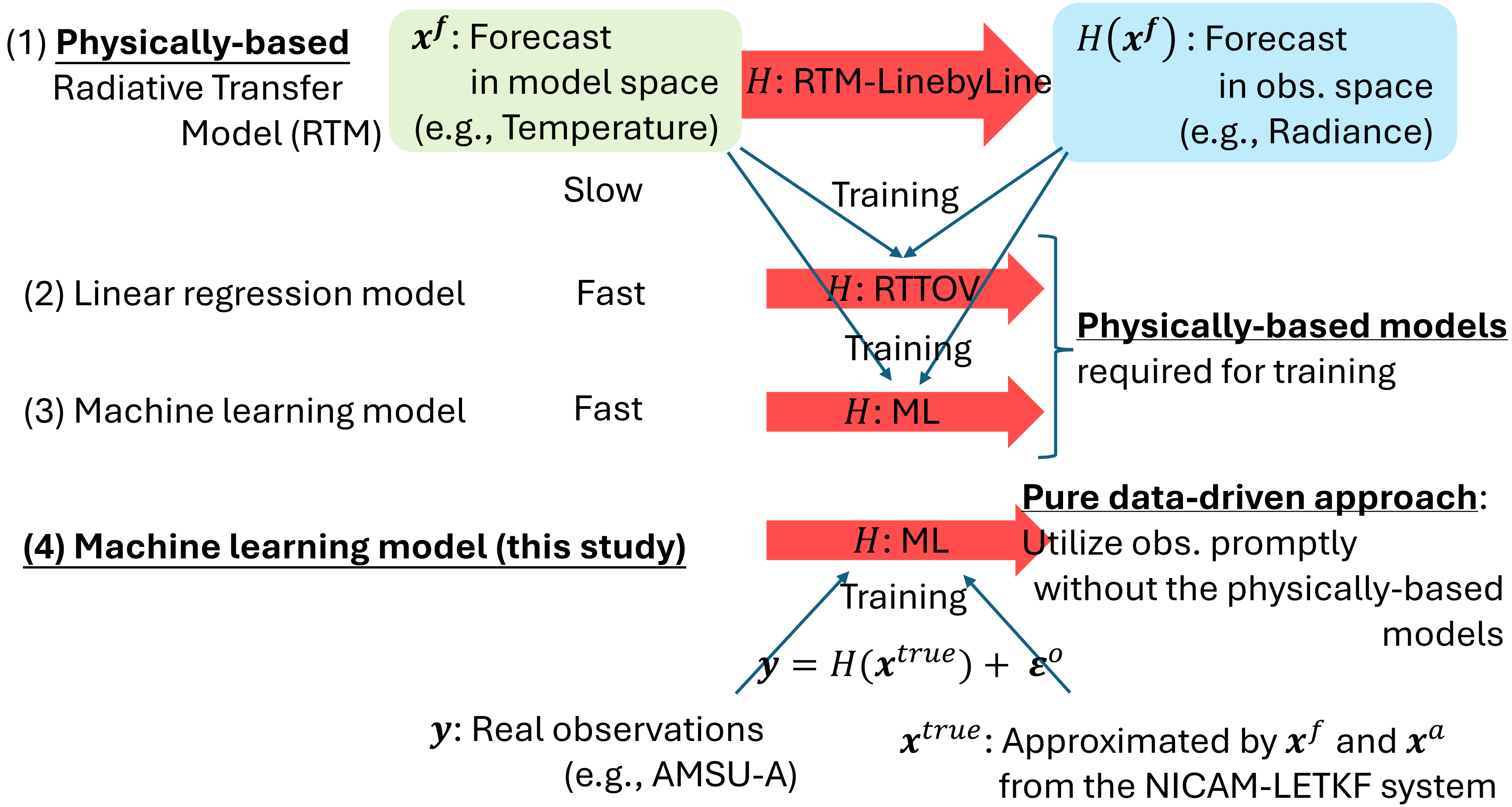
Physically-based models required for training

Liang et al. (2023, JMSJ)



Machine Learning for satellite obs. operator

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



Design of the machine learning models

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

output input

input

3D variables:

pressure (78 levels)

temperature (78 levels)

specific humidity (40 levels)

2D variables:

surface pressure

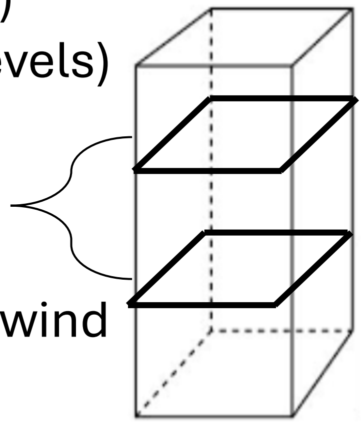
surface temperature

10-meter u-wind and v-wind

2-meter temperature

2-m specific humidity

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

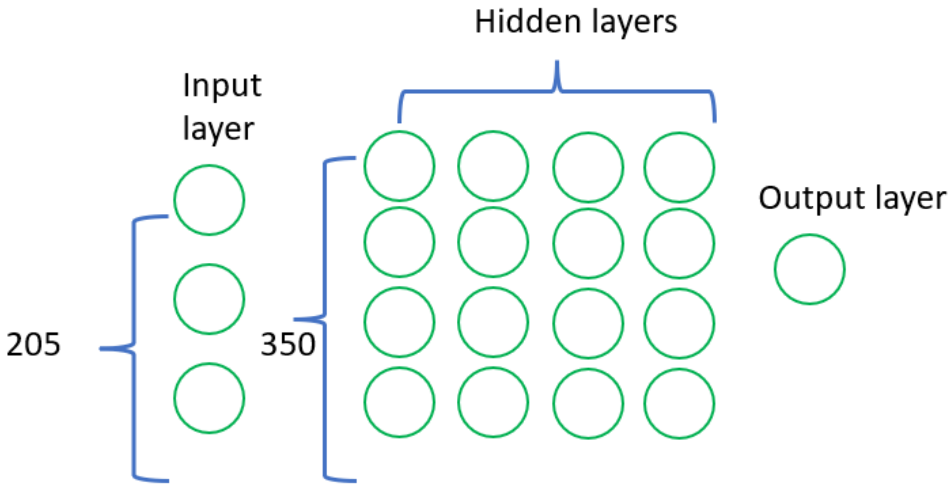


Output: y

satellite brightness temperature from channel 6, 7, 8

Deep neural networks (DNNs) for each channel and satellite

205 features, includes different vertical levels



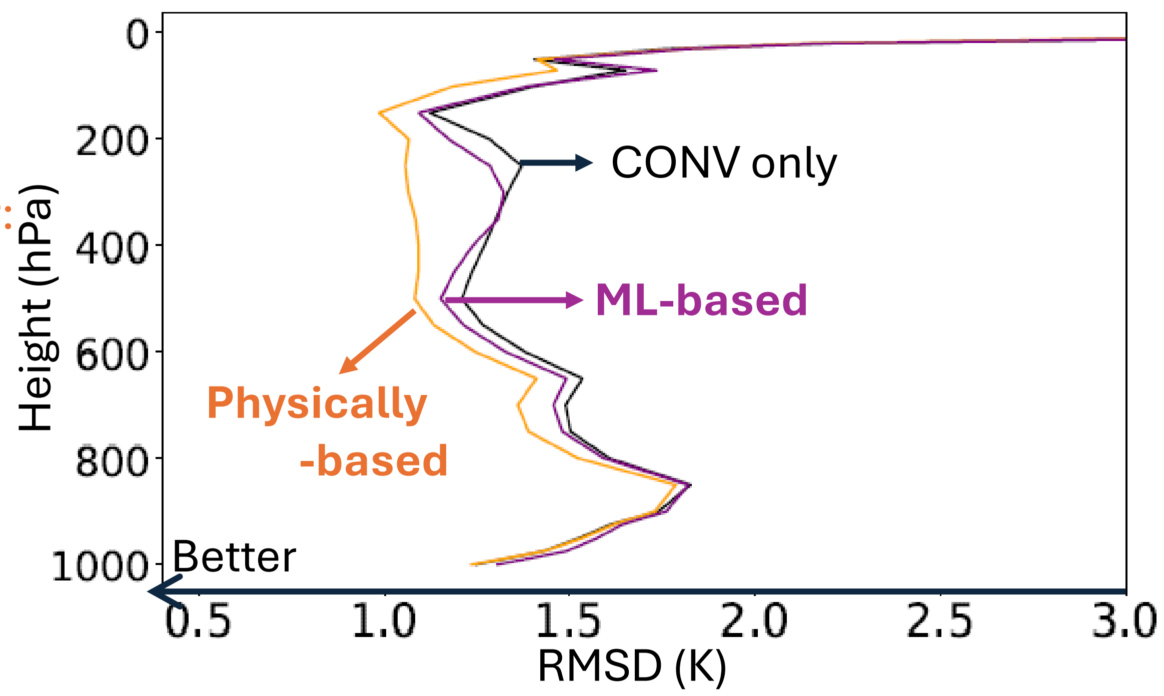
Hyperparameters searching:

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

Validation relative to ERA Interim

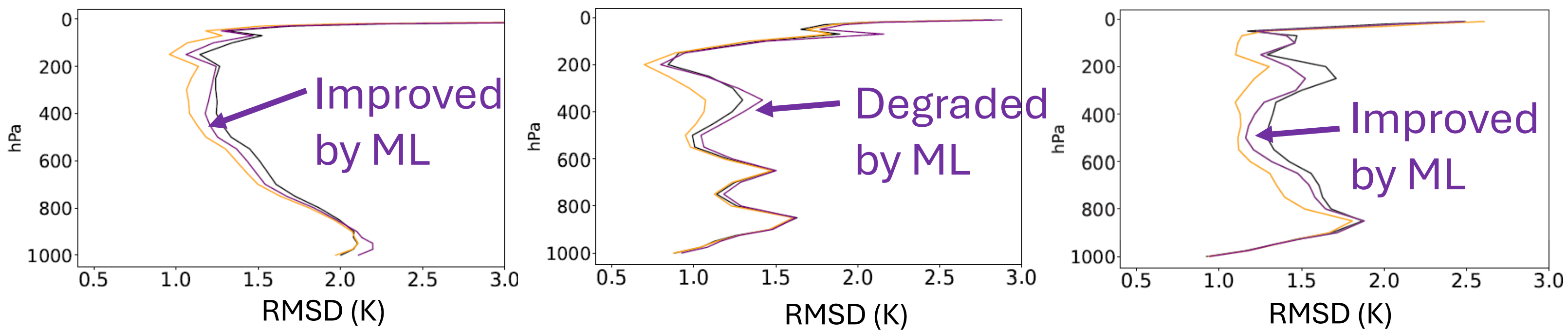
- ■ Sensitivity experiments
- CONV only
- **Physically-based** obs. operator:
  CONV+AMSU-A (RTTOV)
  +Bias correction
- **ML-based** obs. operator:
  CONV+AMSU-A

Temperature RMSD (1-month Global Average)



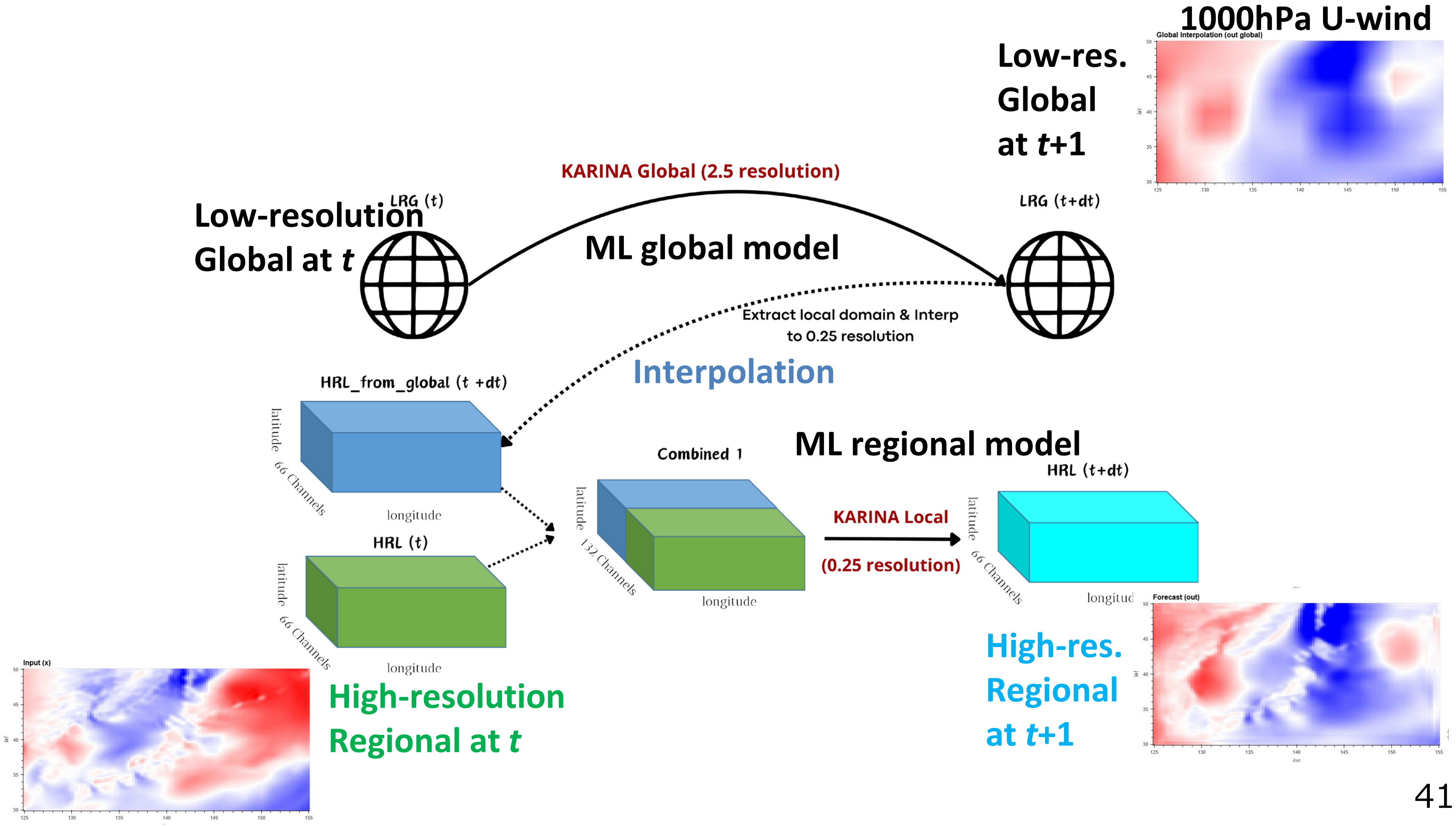
Accuracy: **Physically-based** > **ML-based** > CONV only

NH (>20 °N) Tropics (20 °S–20 °N) SH (< 20 °S)



Machine Learning-Based Regional Weather Prediction

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



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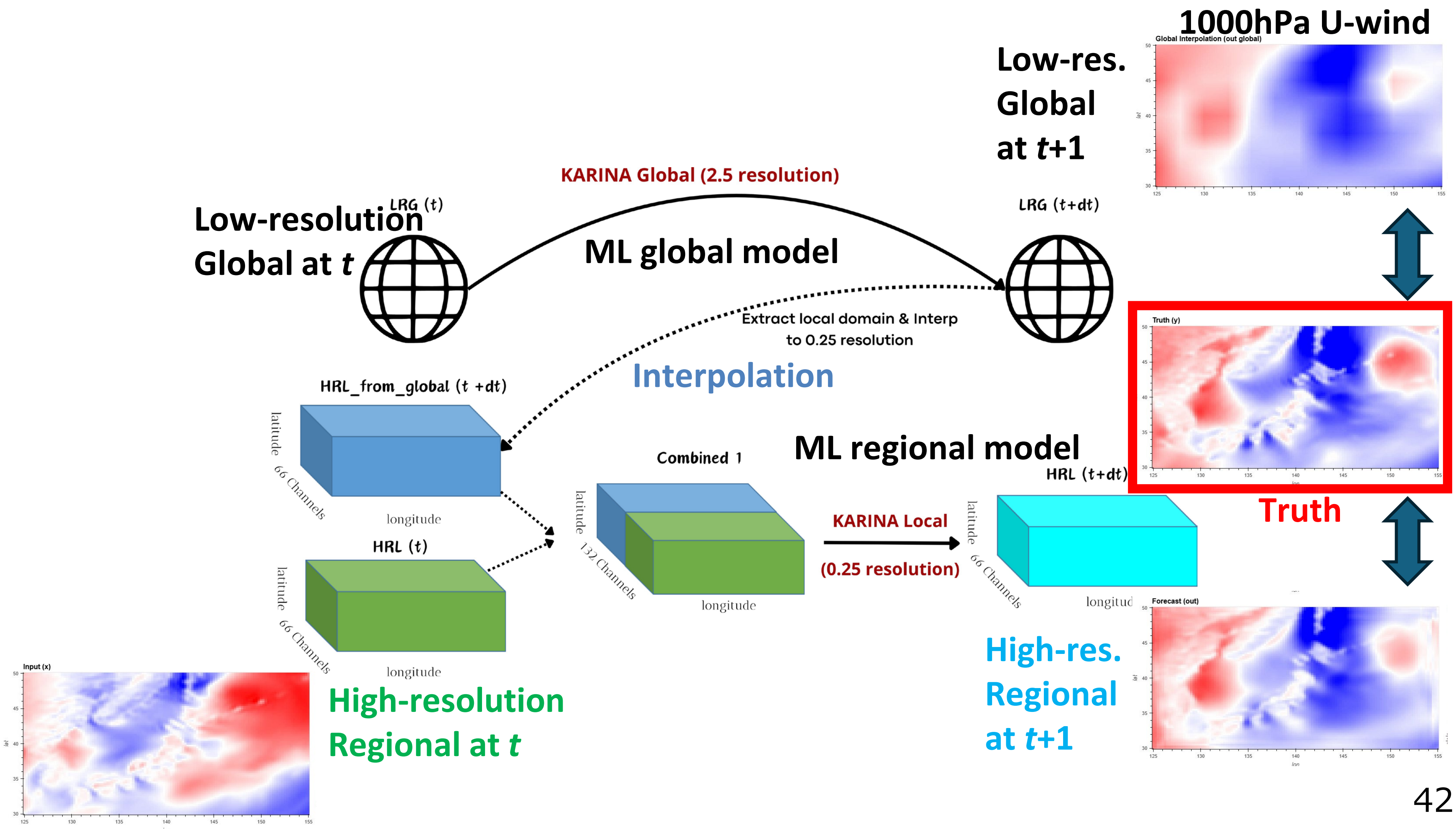


Using Data Assimilation to Improve Data-Driven Surrogate Models

Michael Goodliff and Takemasa Miyoshi

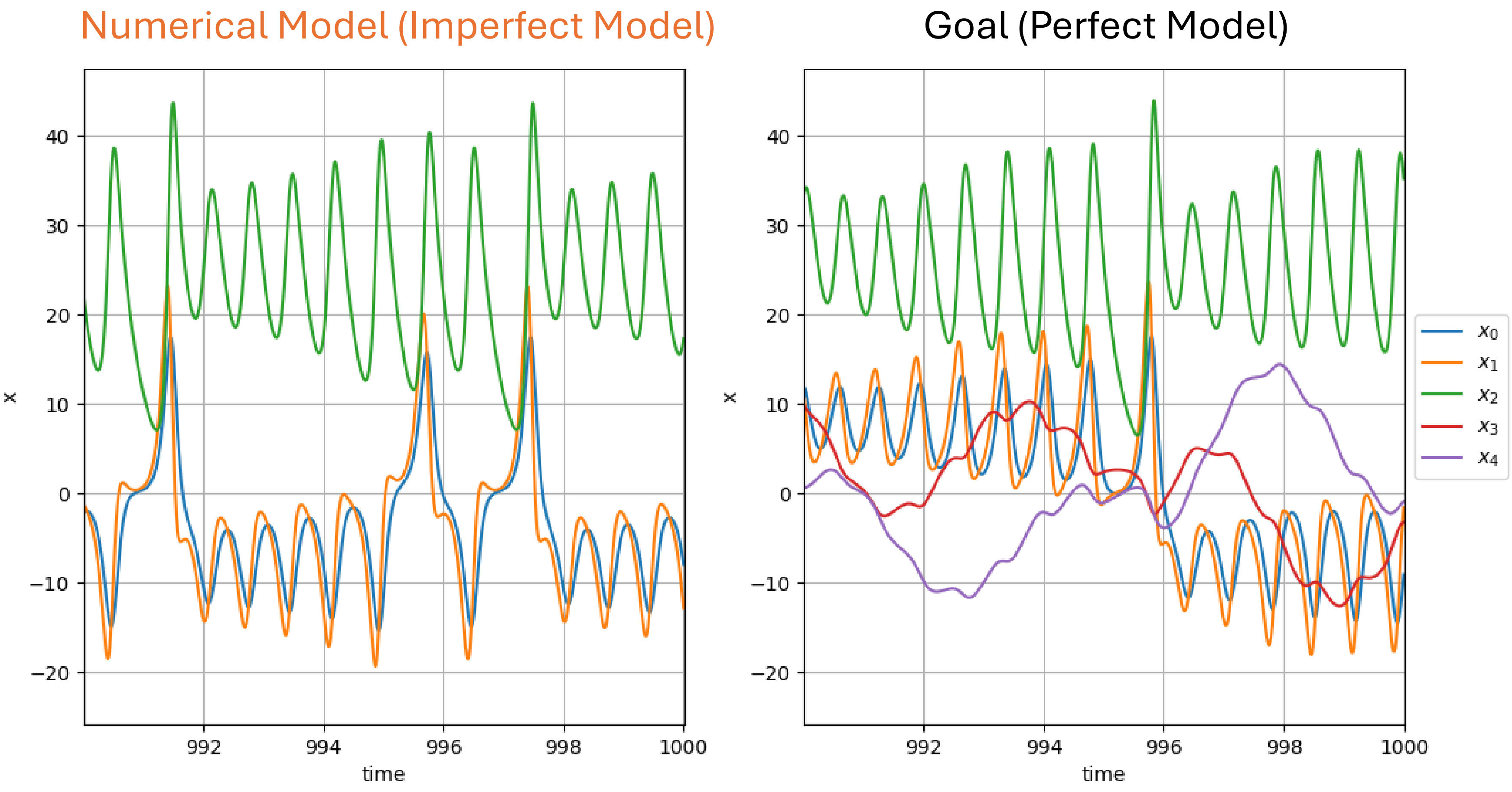
NPG preprint available:
DOI:10.5194/egusphere-2025-933

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

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



Experiment Setup

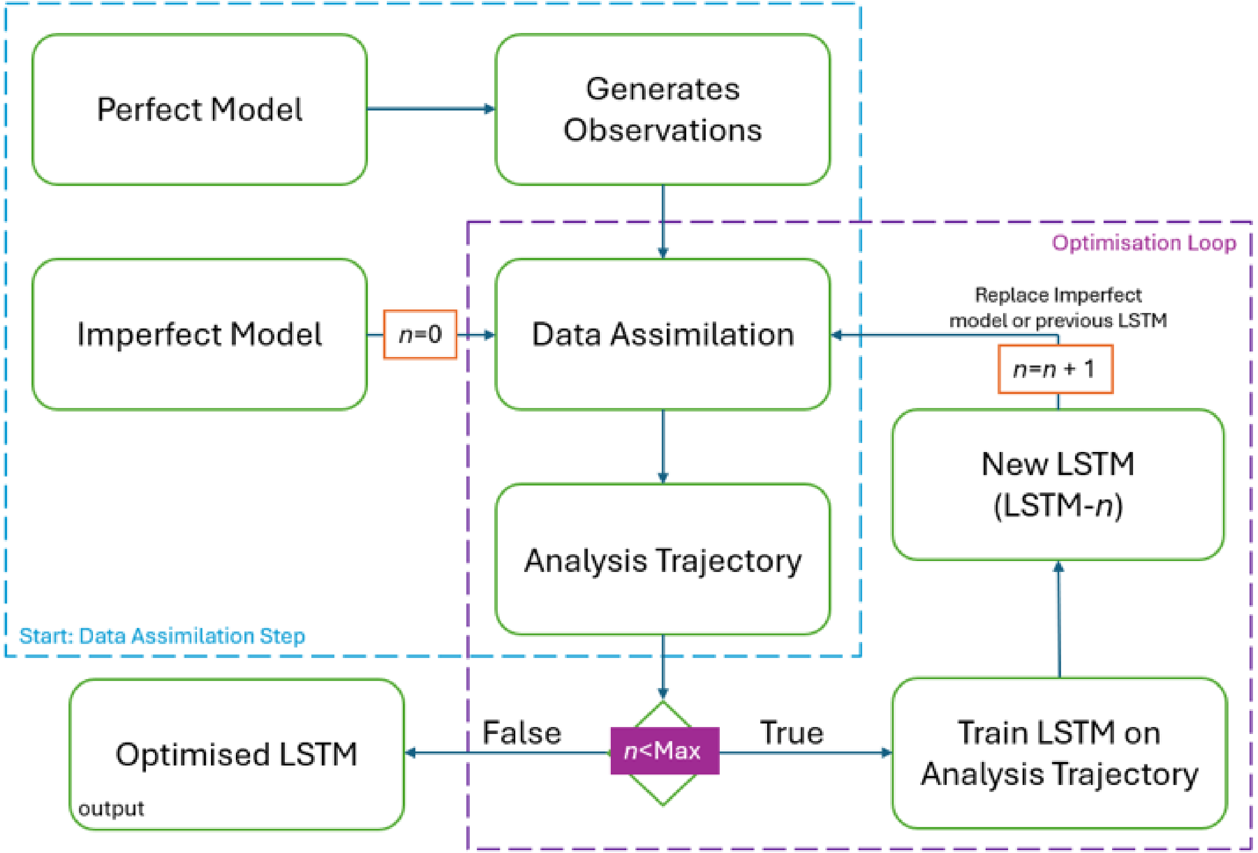
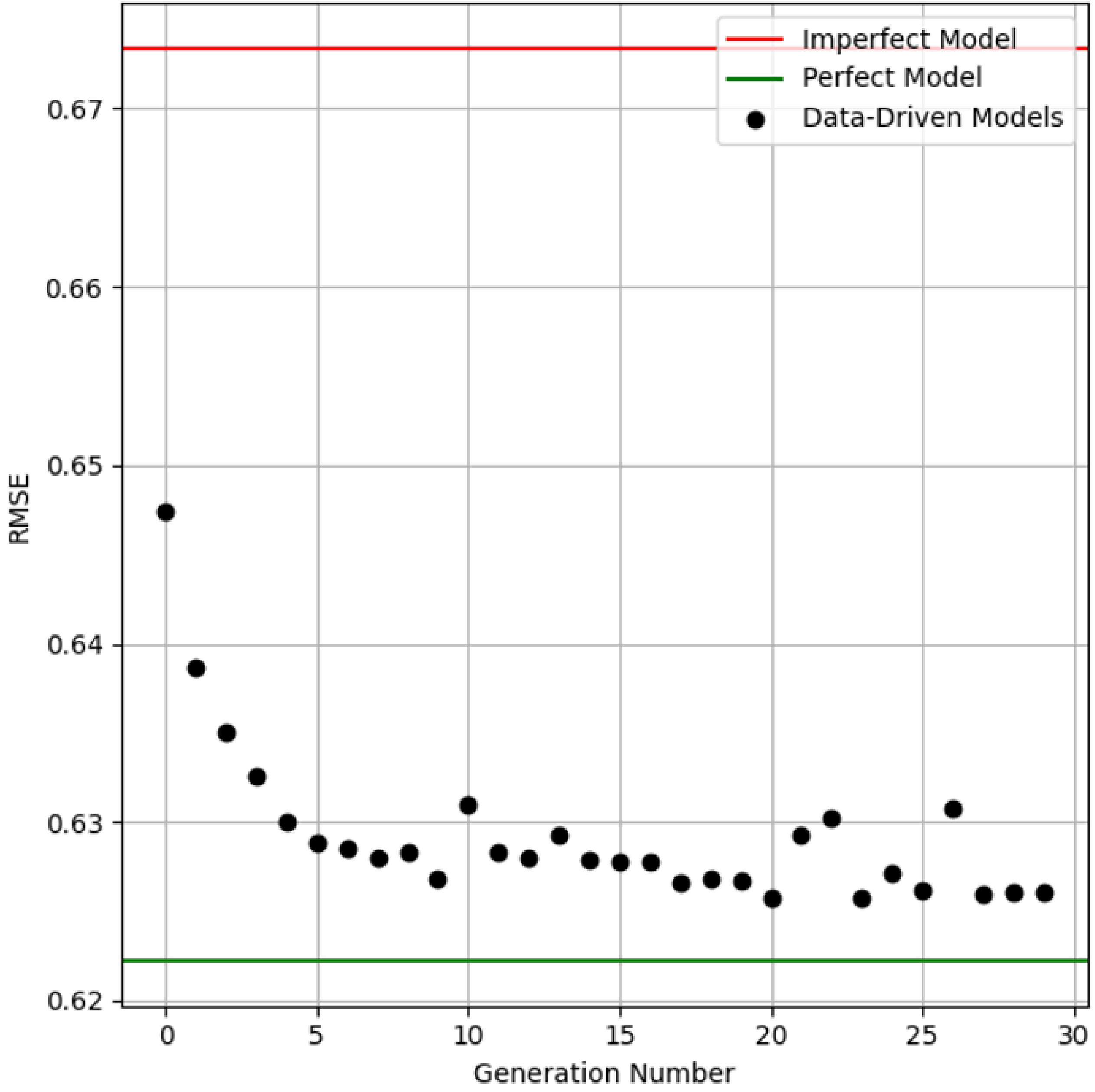


Figure 1. This figure shows the cycling algorithm implemented in this paper. The blue dashed box is the traditional DA cycle, the purple dashed box is our additional loop until the max iteration number is reached, giving an optimised LSTM. When n=0 indicates the iteration number, LSTM-0 would be the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

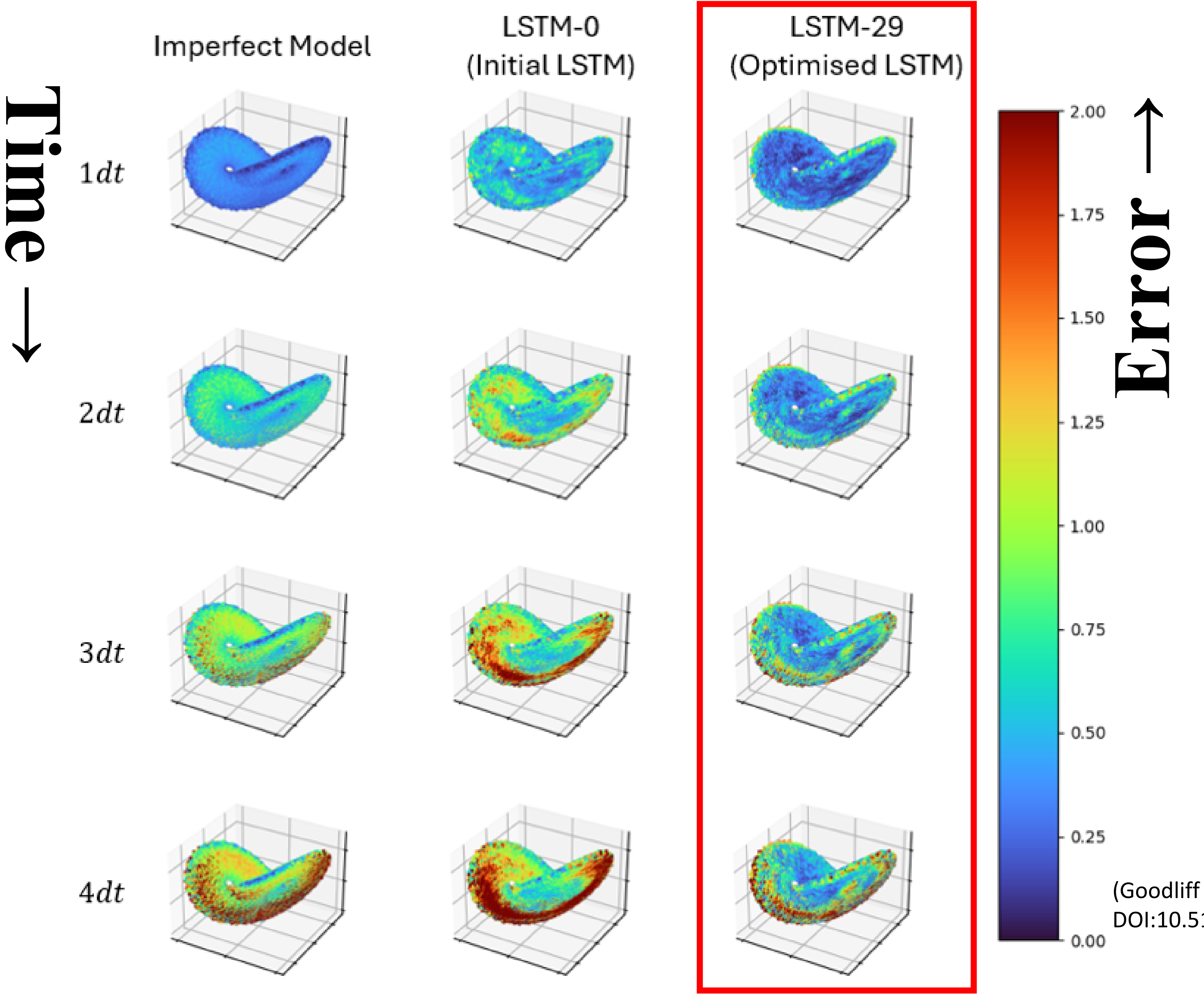
(Goodliff and Miyoshi, 2025, submitted, DOI:10.5194/egusphere-2025-933)

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.

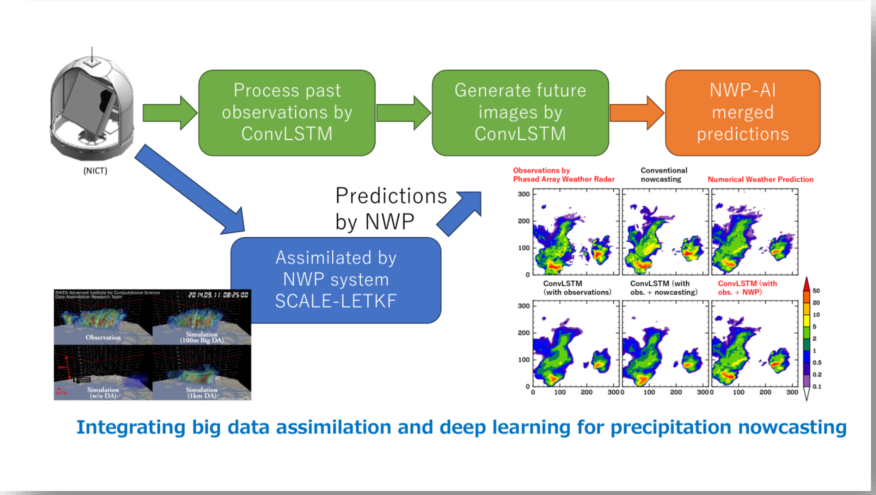


(Goodliff and Miyoshi, 2025, submitted, DOI:10.5194/egusphere-2025-933)

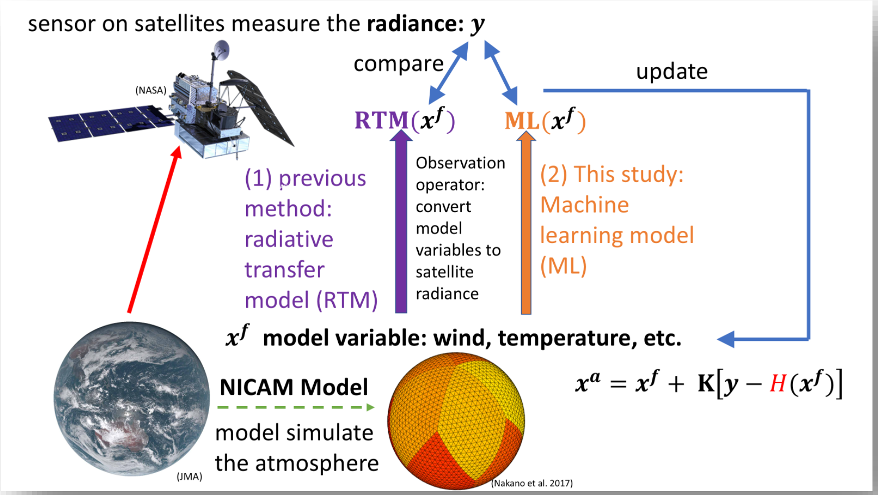
Figure 4. This plot illustrates the spatial distribution of forecast errors for 1–4*dt* forecasts. The colours represent the model forecast error for three cases: (1) the imperfect model, (2) the initial LSTM (LSTM-0), and (3) the Optimised LSTM (LSTM-29).

Summary

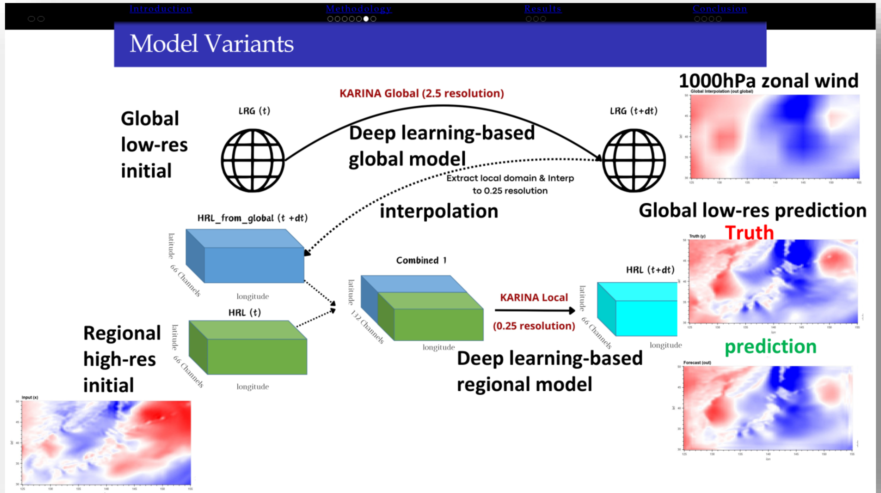
Precipitation prediction with ML/DA/NWP



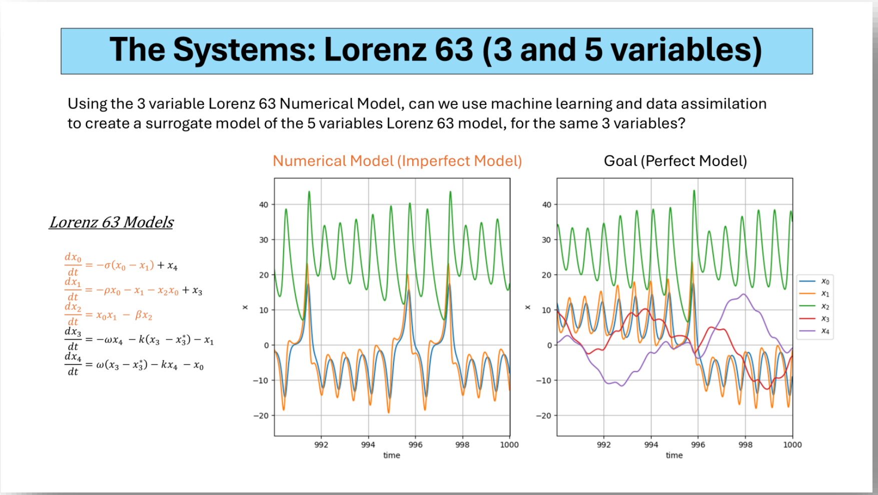
ML observation operator in DA



ML regional weather prediction

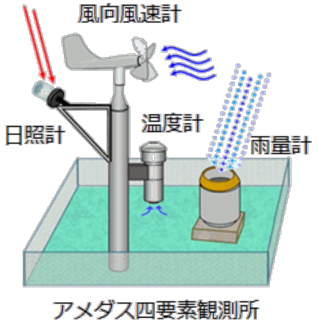


Model improvement through DA

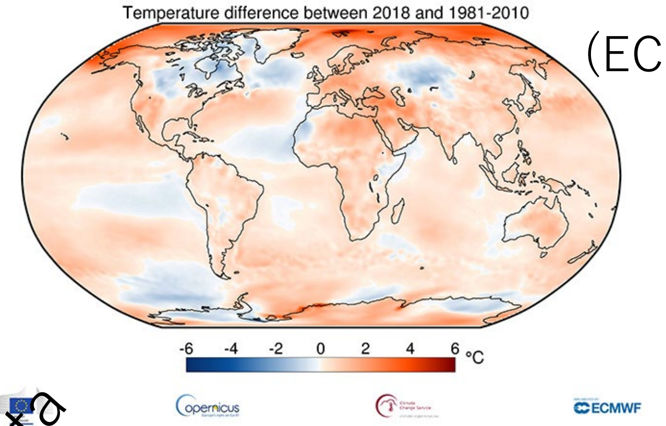


Current

Raw observations: y

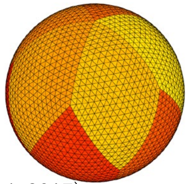


DA



(ECMWF)

Physically-based model

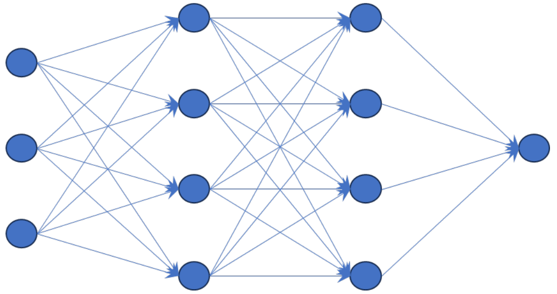


(Nakano et al. 2017)

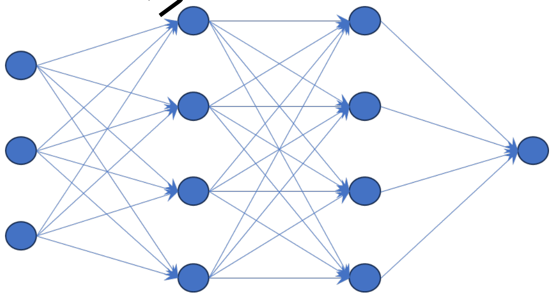
Training data

Initial condition

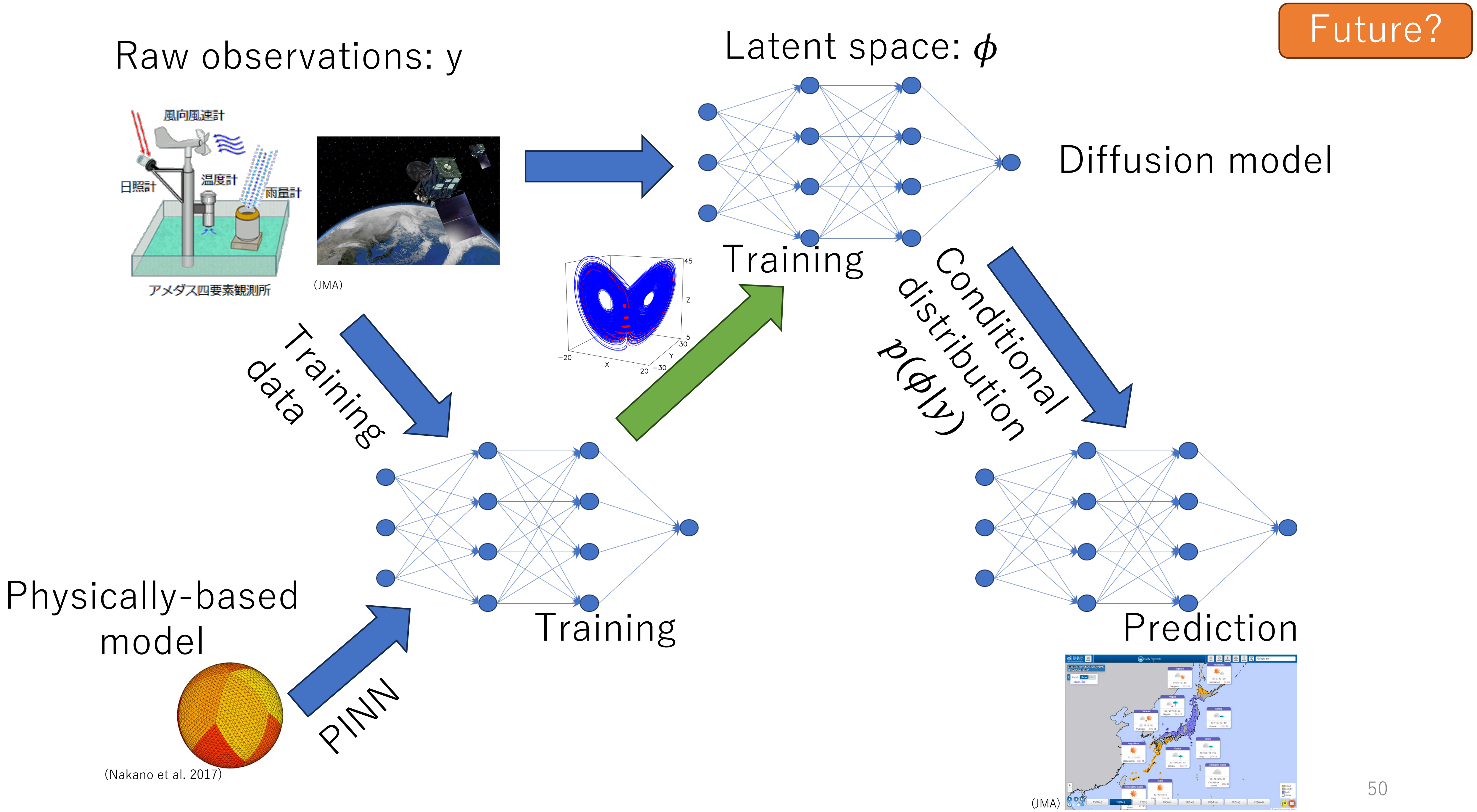
Verification truth



Training



Prediction


Future?
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
Diffusion model
Training
Conditional distribution $p(\phi|y)$
Training data
Physically-based model
PINN
(Nakano et al. 2017)
Training
Prediction
(JMA)