Exploring weather control technology to steer the atmosphere towards favorable directions based on ensemble DA

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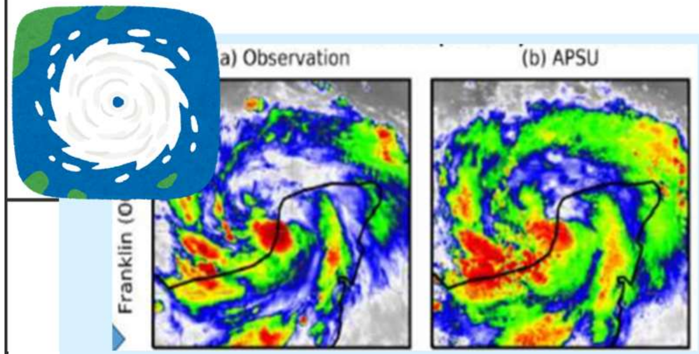
2024/10/23 ISDA at Kobe

Contents of my talk

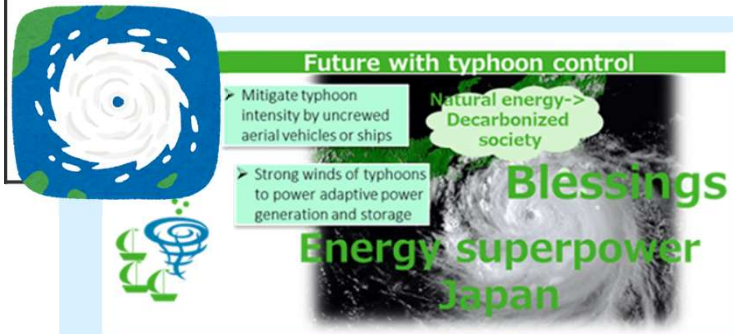
- (1) Our R & D Strategy for mitigating heavy-rain-induced disasters
- (2) Coupling AI-based weather prediction model w/ ensemble DA
- (3) Identifying disastrous/preferable trajectories from ensemble FCSTs
- (4) Quantum data assimilation for accelerating optimizations
- (5) Take Home Message

Japan's Moonshot Goal 8 Program & Core Projects

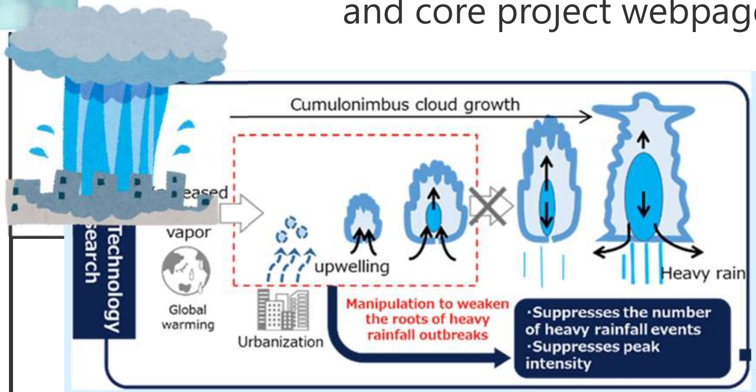
from
https://www.jst.go.jp/moonshot/en/program/goal8/
and core project webpages



Prof. Sawada (U. Tokyo)

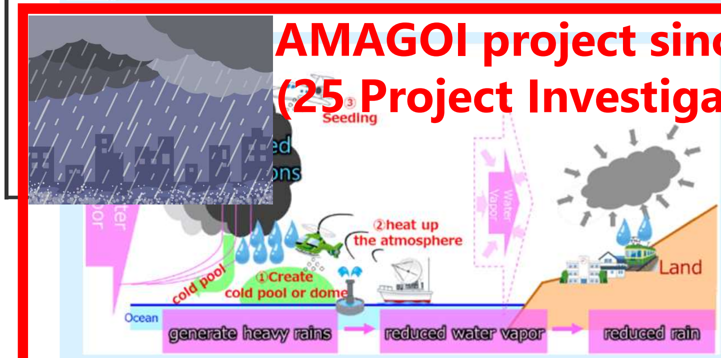


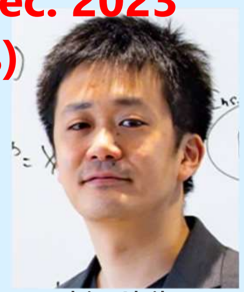
Prof. Fudeyasu (NTU)



Prof. Yamaguchi (Kyoto U.)

AMAGOI project since Dec. 2023 (25 Project Investigators)



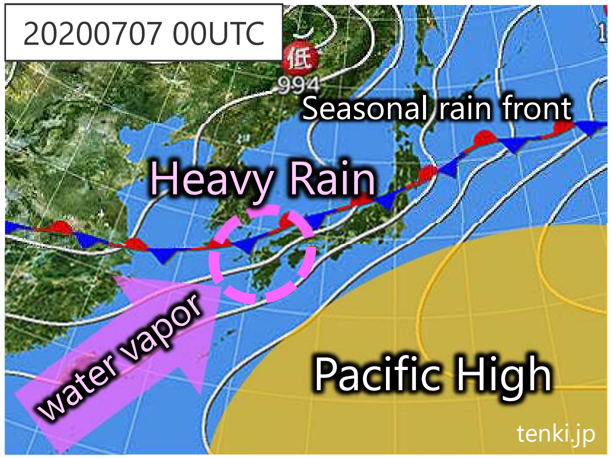


S. Kotsuki (Chiba U.)

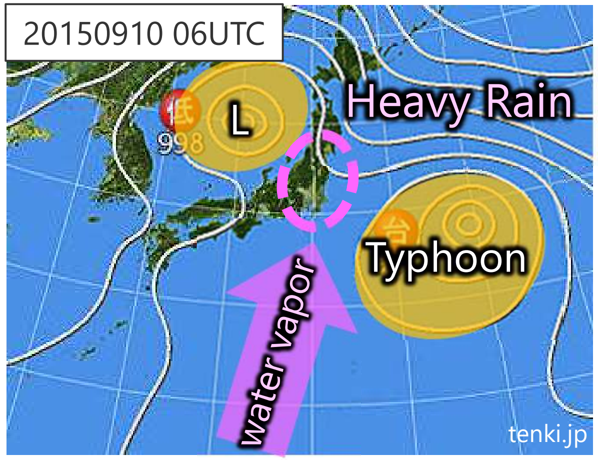
Heavy Rains and Our R & D Strategy

Examples for heavy-rain-induced disasters

July 2020 in Kyushu
(Damage: 4.1billion USD)



Sept 2015 in Kanto/Tohoku
(Damage: 2.1billion USD)



Jan 2023 in California, US
(Damage: 31 billion USD)

Possible strategies to mitigate such disasters

- to limit evaporation from the ocean ☹
- to change large-scale circulations ☹
- to reduce water vapor before arrival on land

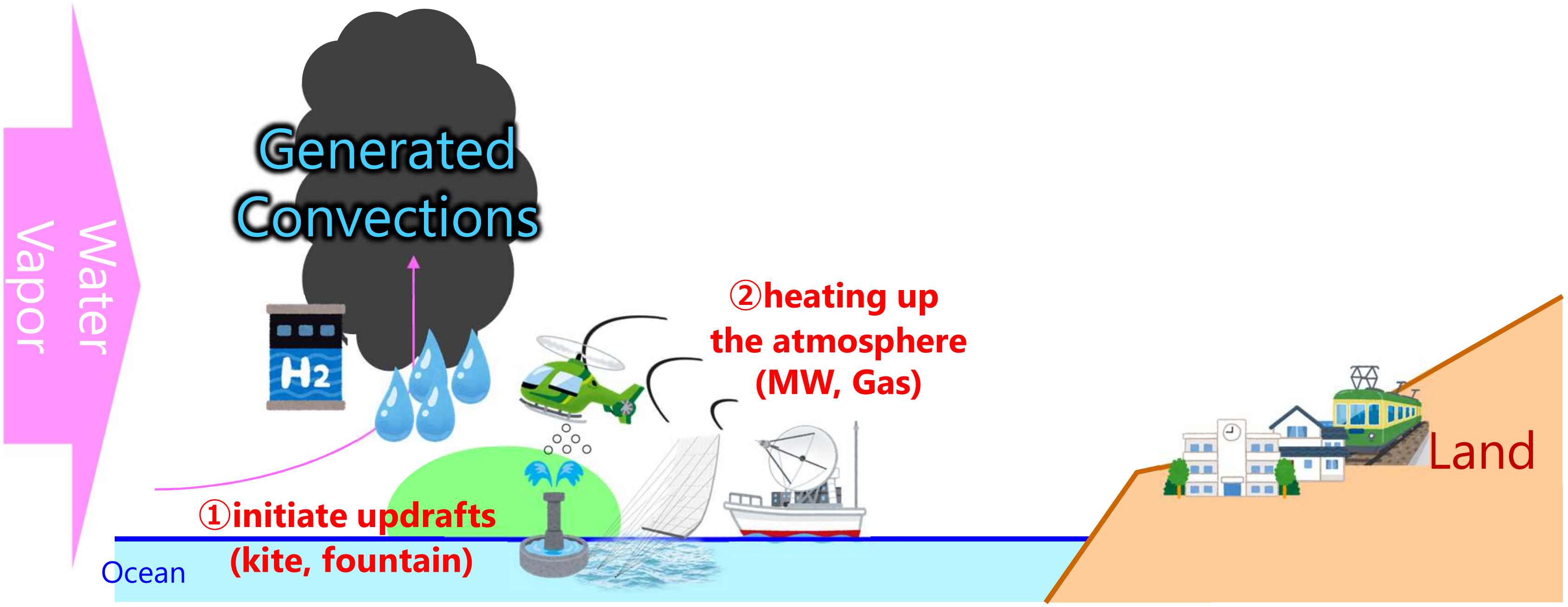
➔ generating heavy rain artificially over upstream ocean

Generation of Heavy Rains

To generate heavy rains artificially, we need to

(1) generate convections

by lifting up dynamically (~LFC), or heating thermodynamically (~CIN)



Generation of Heavy Rains

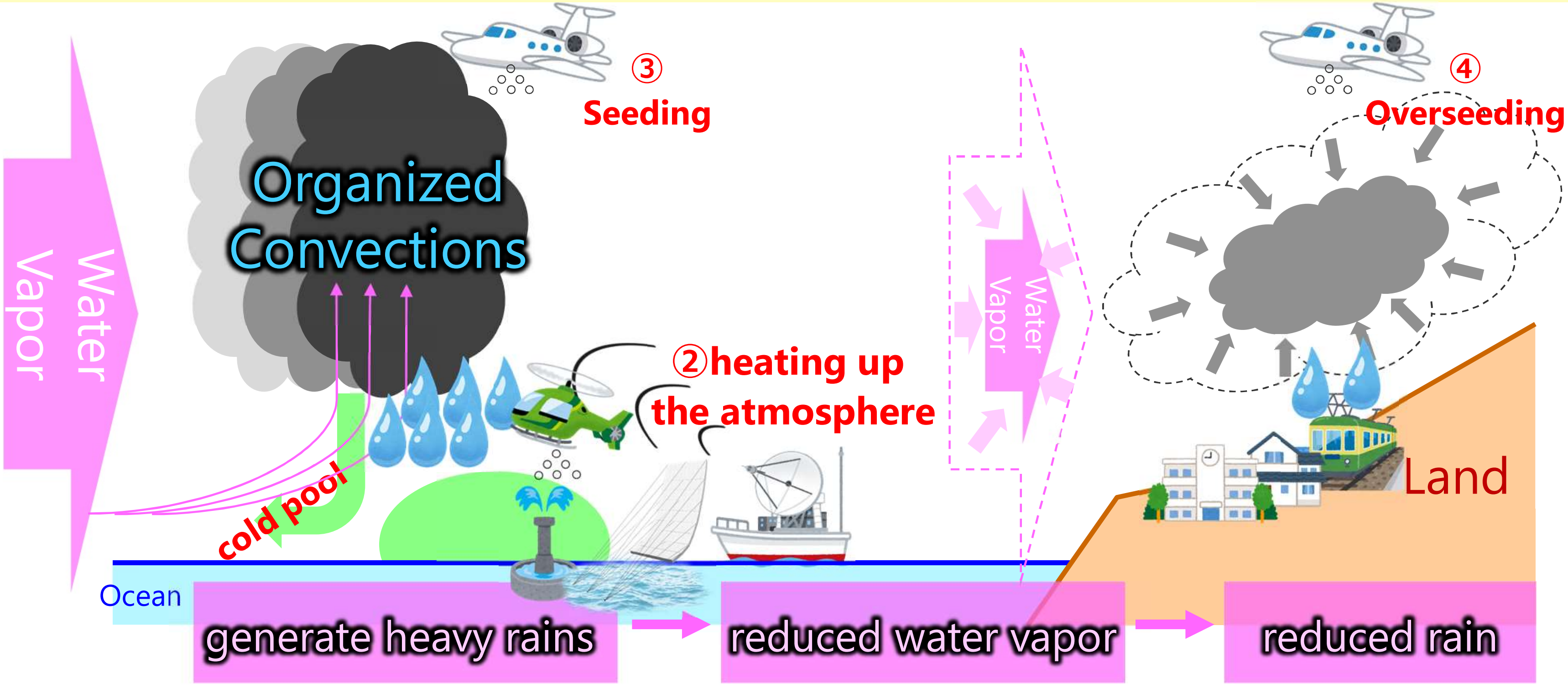
To generate heavy rains artificially, we need to

(1) <u>generate convections</u>

by lifting up dynamically (~LFC), or heating thermodynamically (~CIN)

(2) <u>organize subsequent convections</u>

by leading back-building-type successive rains using cold pool



Orders of LFC and CIN

To generate heavy rains artificially, we need to
(1) generate convections
by lifting up dynamically (~LFC), or heat thermodynamically (~CIN)

just before the heavy rain (20210810 00UTC)	during a heavy rain (20210811 00UTC)

LFC : **770 m**
CIN Energy : **1.31 (J/kg)**

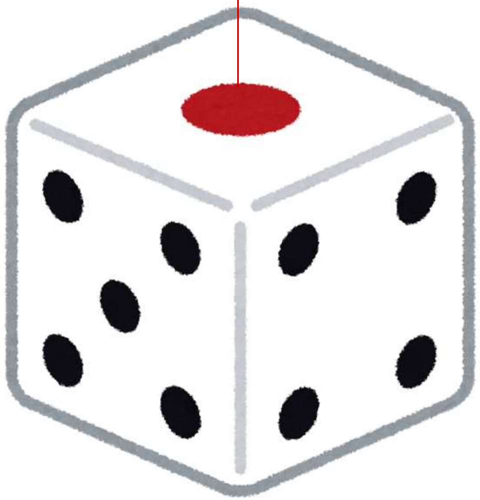
LFC : 3,200 m
CIN Energy : 47.0 (J/kg)

(Data: Kagoshima sonde of University of Wyoming, USA)

Problems to be solved toward weather control

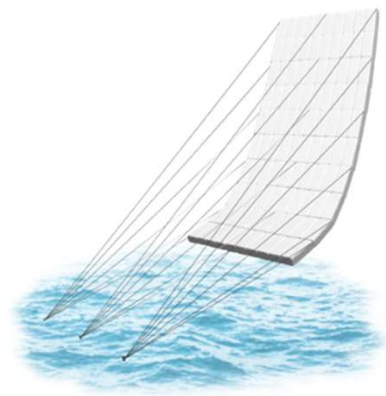
Meteorology

how to generate heavy rains?



Overseeding

Kites

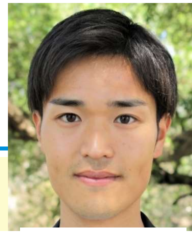


Question: Can artificial interventions mitigate heavy rains?

➔ <u>Numerical experiments with NWP models</u> before field experiments.

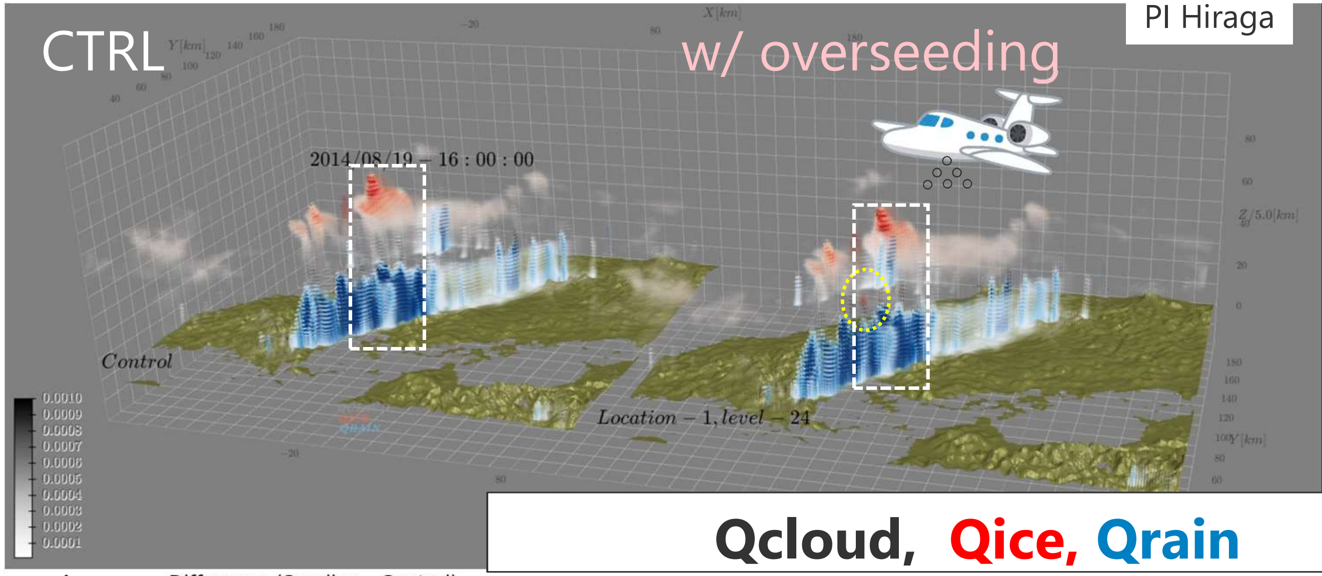
An over-seeding experiment using an NWP model (WRF)

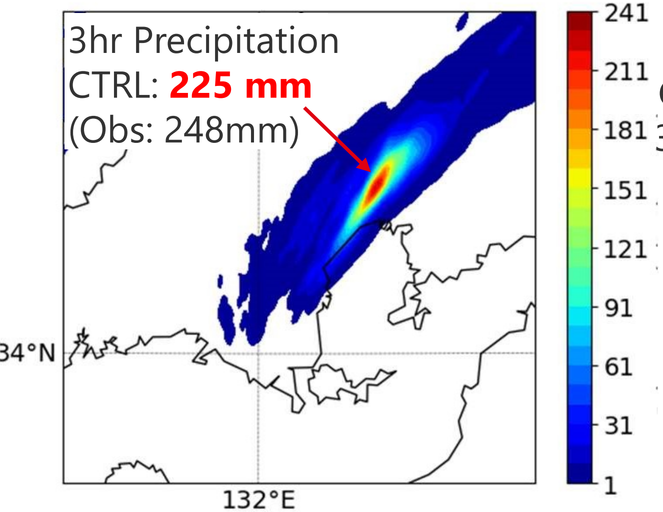
Overseeding successfully reduces heavy rain by suppressing deep convections.


PI Hiraga

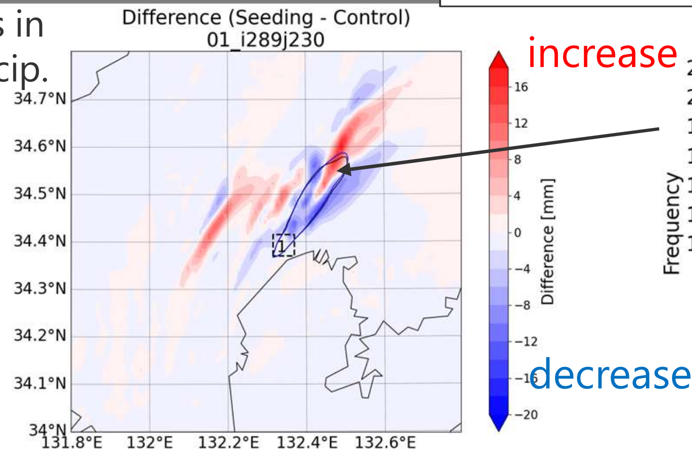

PI Kazama

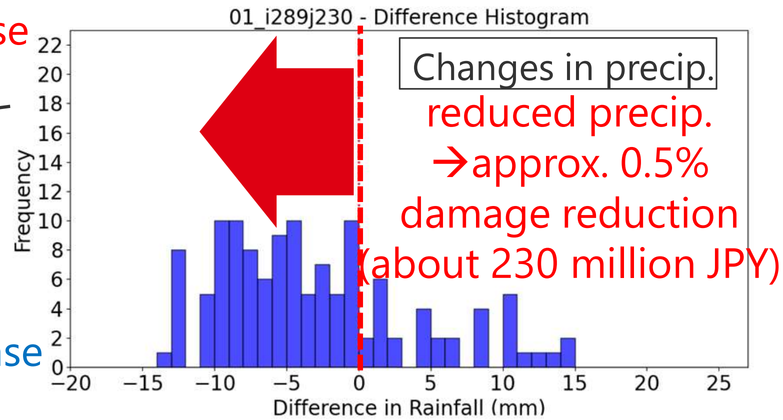
Heavy rain in Hiroshima (2014)





Changes in 3-hr precip.

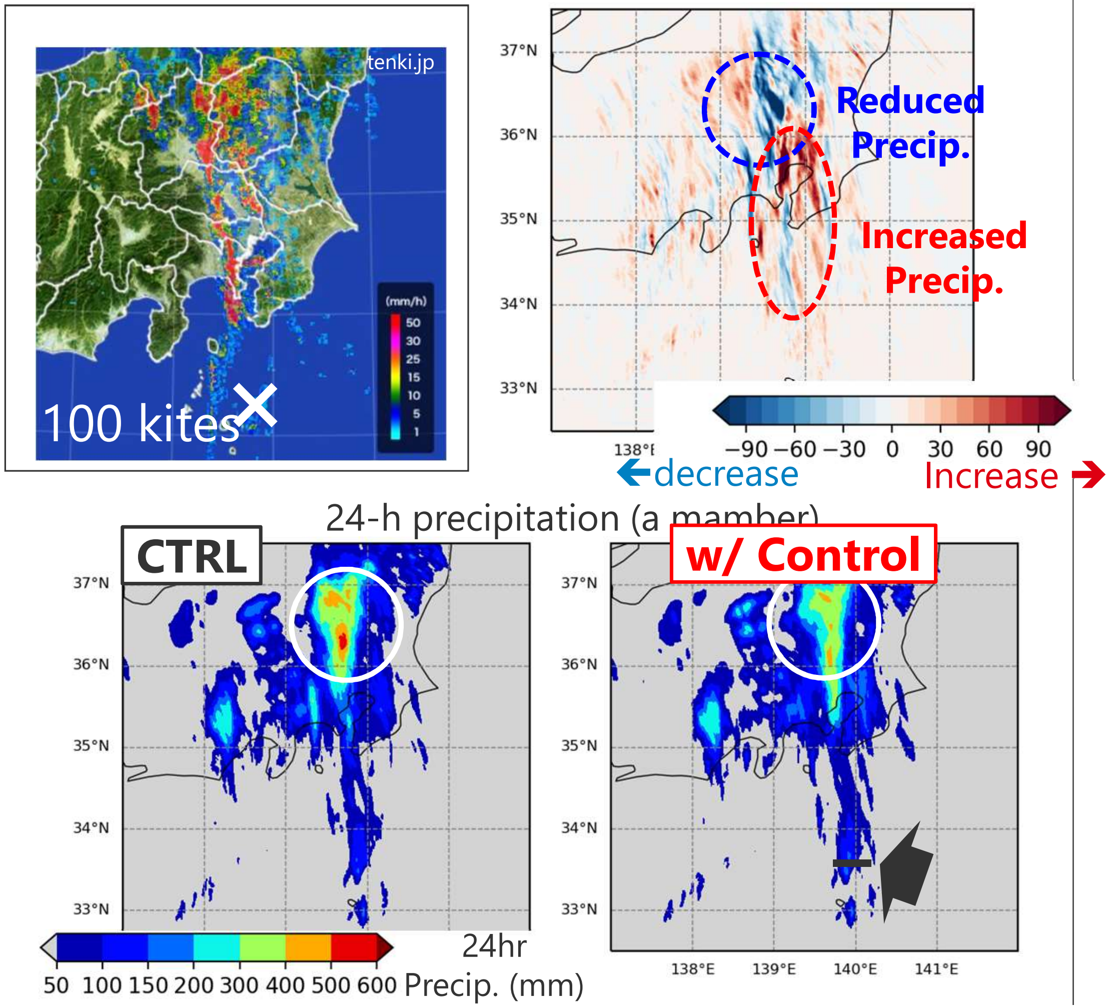


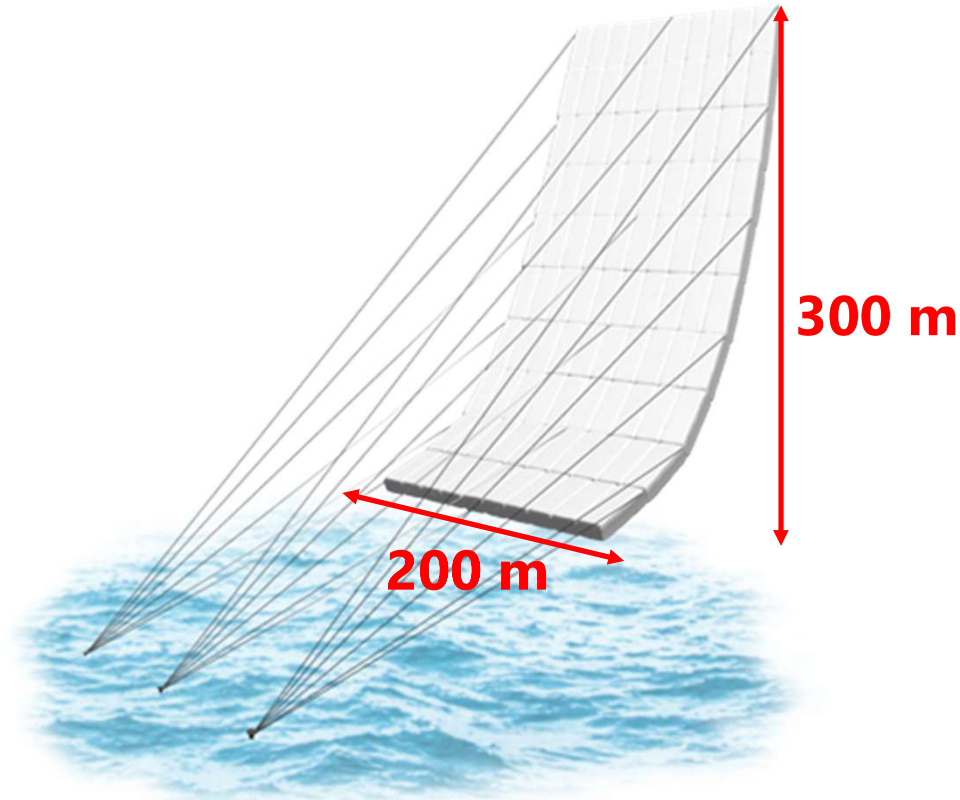


Kite experiments using an NWP model (SCALE)

Kites increase precip. over upstream ocean, leading to reduced precip. in downstream regions.

PI Yasunaga (Toyama U.)   PI Okazaki (Chiba U.)



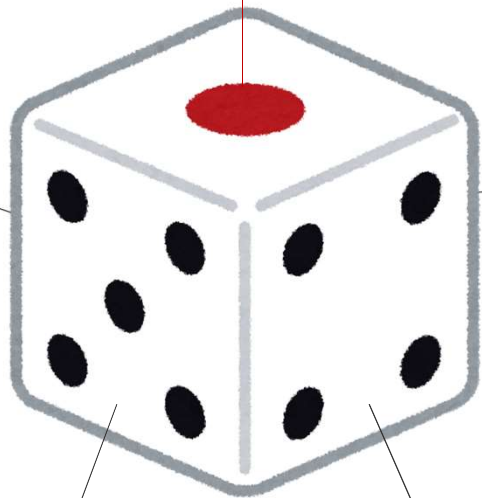


a kite (or atmospheric embankment) over ocean.

Problems to be solved toward weather control

Meteorology
how to generate heavy rains?

Mathematics
how to optimize manipulations?



RRI
how to realize in society?

RRI: Responsible Research and Innovation

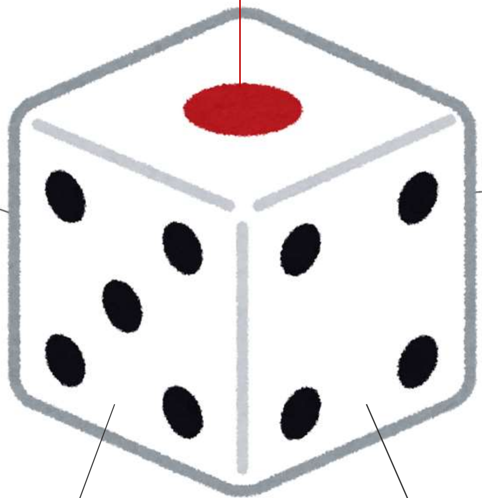
Manipulations
how to realize interventions?

Legal Problems
how to design society?

Problems to be solved toward weather control

Meteorology
how to generate heavy rains?

Mathematics
how to optimize manipulations?



RRI
how to realize in society?

Manipulations
how to realize interventions?

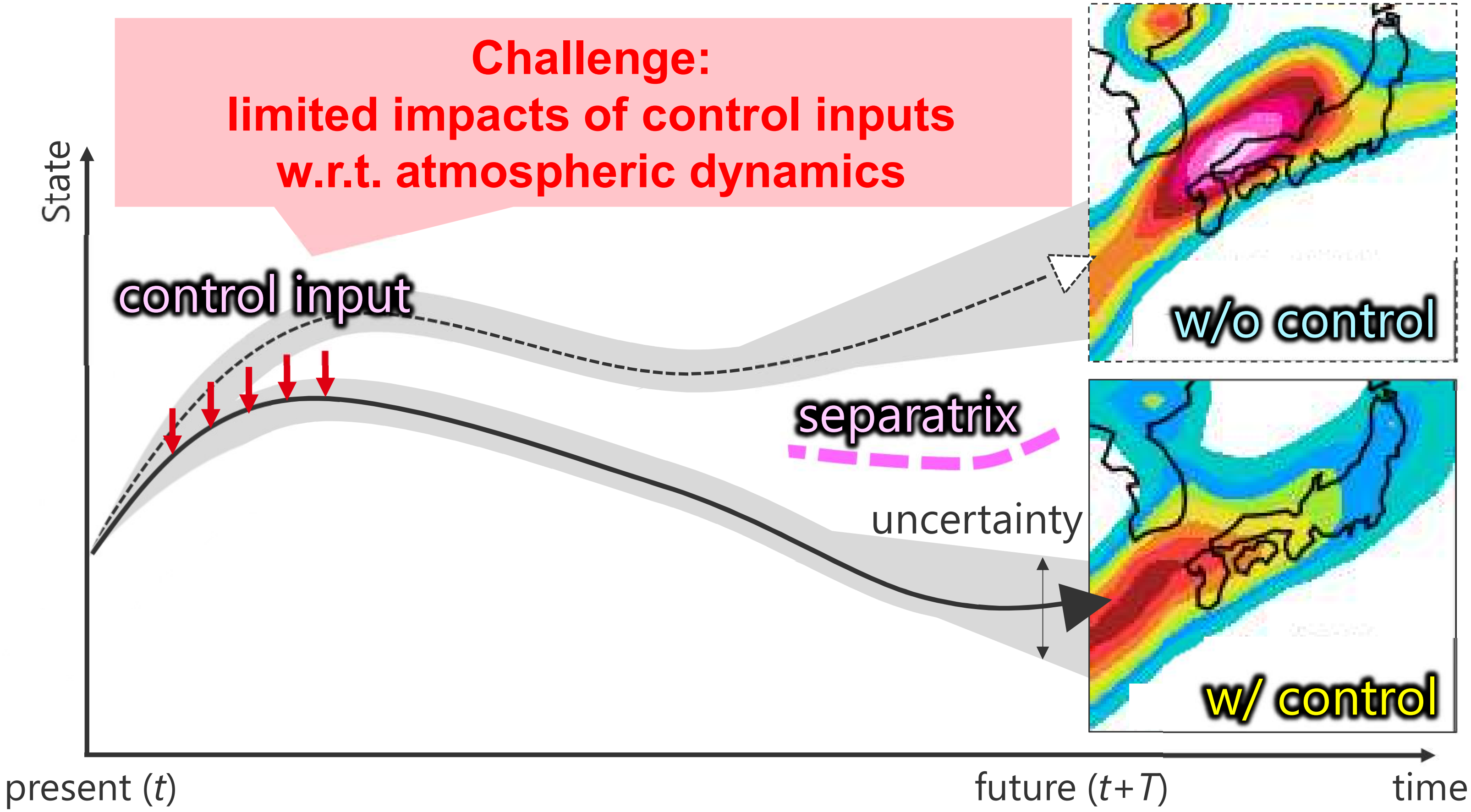
Legal Problems
how to design society?

DA Research for Weather Control

MOONSHOT
RESEARCH & DEVELOPMENT PROGRAM

Objective of Data Assimilation Research

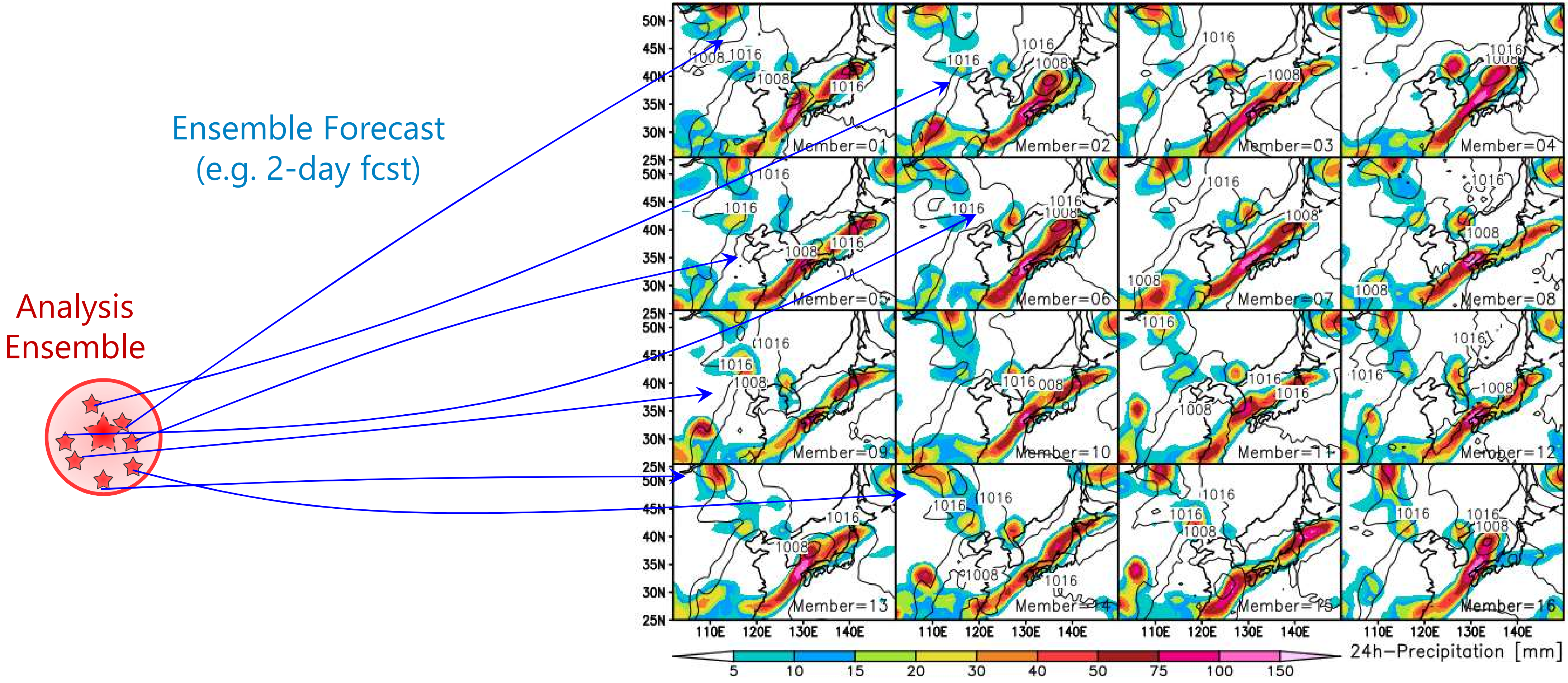
Mathematical weather control methods are necessary to optimize interventions.
➔ to introduce the model predictive control (MPC) into data assimilation



Model Predictive Control for Weather Control

Suppose we would like to lead the atmosphere toward a desirable future

From NICAM-LETKF 100 member forecasts



Model Predictive Control for Weather Control

Suppose we would like to lead the atmosphere toward a desirable future

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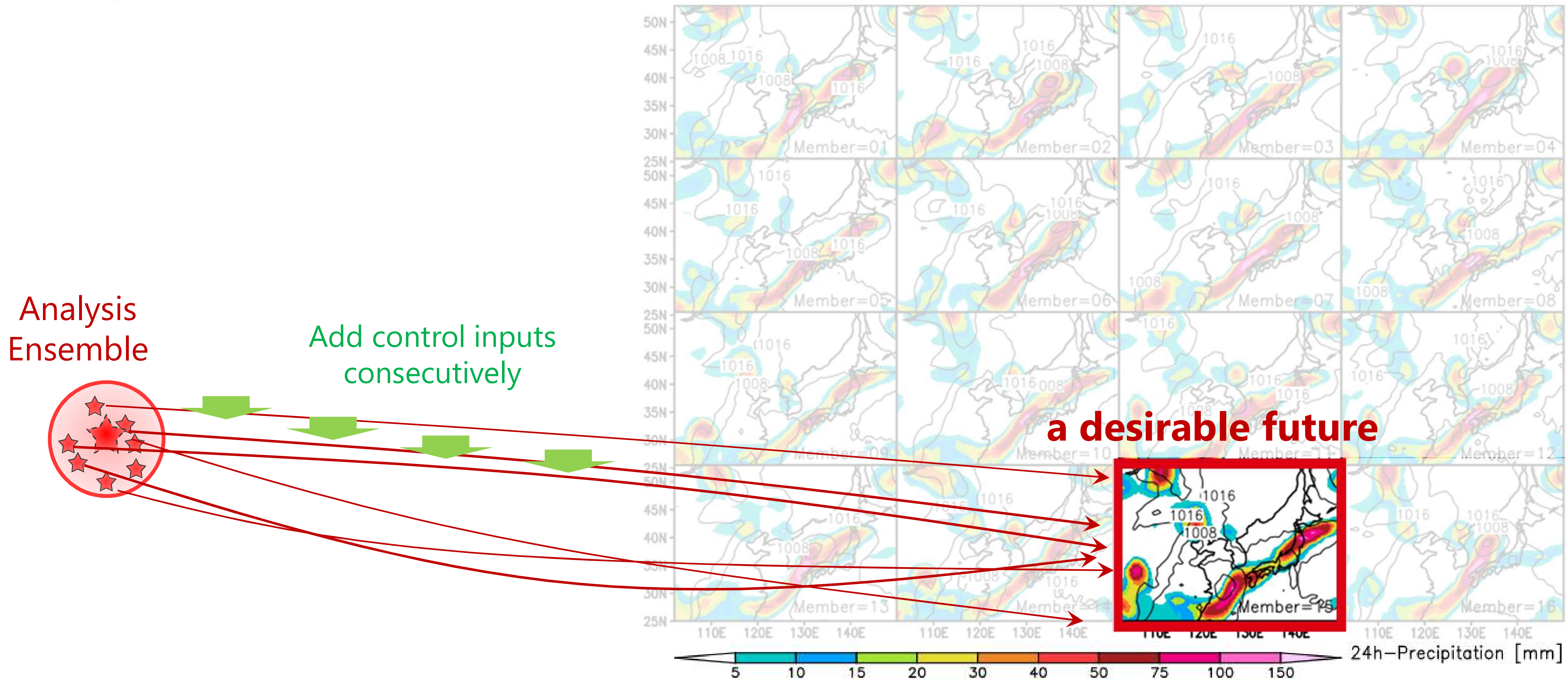


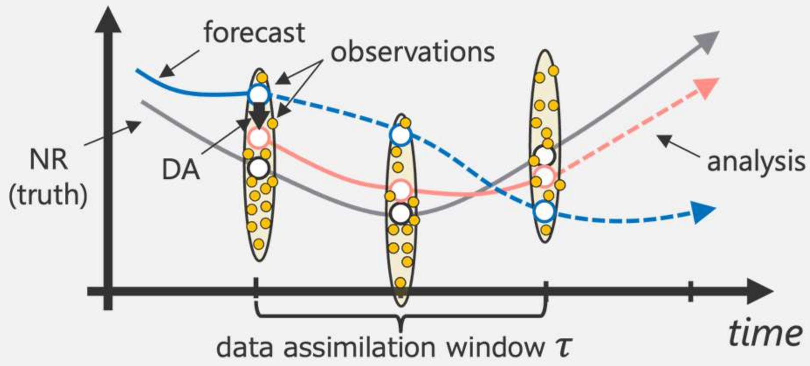
Trajectory-tracking MPC as DA

Oral (Day 3)
by K. Kurosawa

Dr. Kurosawa

Kurosawa et al. (in prep.)

Data Assimilation

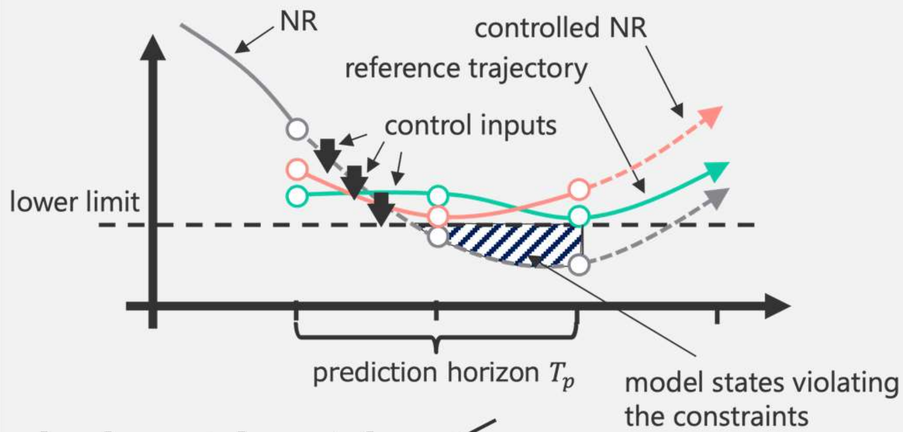


$$J(\mathbf{x}_0) = (\mathbf{x}_0 - \mathbf{x}_0^f)^{\mathrm{T}} \mathbf{B}^{-1} (\mathbf{x}_0 - \mathbf{x}_0^f) + \sum_{t=1}^{\tau} (H_t(\mathbf{x}_t) - \boldsymbol{y}_t)^{\mathrm{T}} \mathbf{R}^{-1} (H_t(\mathbf{x}_t) - \boldsymbol{y}_t)$$

$$= \underbrace{\|\delta \mathbf{x}_0\|_{\mathbf{B}}^2}_{J_{background}} + \underbrace{\sum_{t=1}^{\tau} \|H_t(\mathbf{x}_t) - \boldsymbol{y}_t\|_{\mathbf{R}}^2}_{J_{observation}}$$

H: observation operator
$\mathbf{B}$: background error covariance matrix
$\mathbf{R}$: observation error covariance matrix

MPC



$$J = J_{input} + J_{state} + \cancel{J_{terminal}}$$

J_{input} J_{state}

1. penalty term approach: $J = \|\mathbf{u}_0\|_{\mathbf{S_u}}^2 + \sum_{t=1}^{T_p} \|H_t^p(\mathbf{x}_t) - y_t^p\|_{\mathbf{S_p}}^2$

2. trajectory tracking approach: $J = \|\mathbf{u}_0\|_{\mathbf{S_u}}^2 + \sum_{t=1}^{T_p} \|H_t^r(\mathbf{x}_t) - y_t^r\|_{\mathbf{S_r}}^2$

y^r, y^p : pseudo-observations
H^r, H^p : pseudo-observation operators
$\mathbf{S}_r, \mathbf{S}_p$: pseudo-observation error covariance matrix

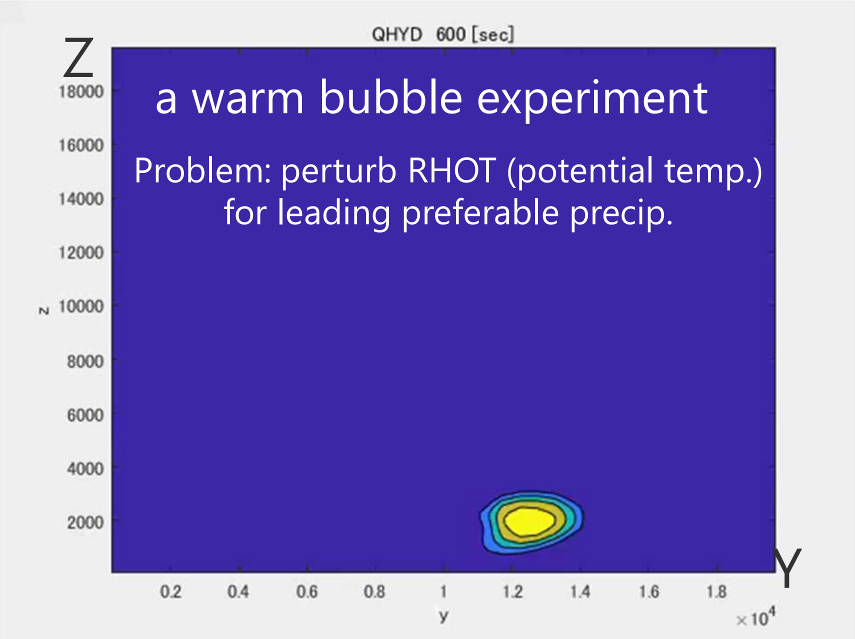
MPC can be represented by data assimilation: Henderson et al. (2005), Sawada et al. (arXiv)

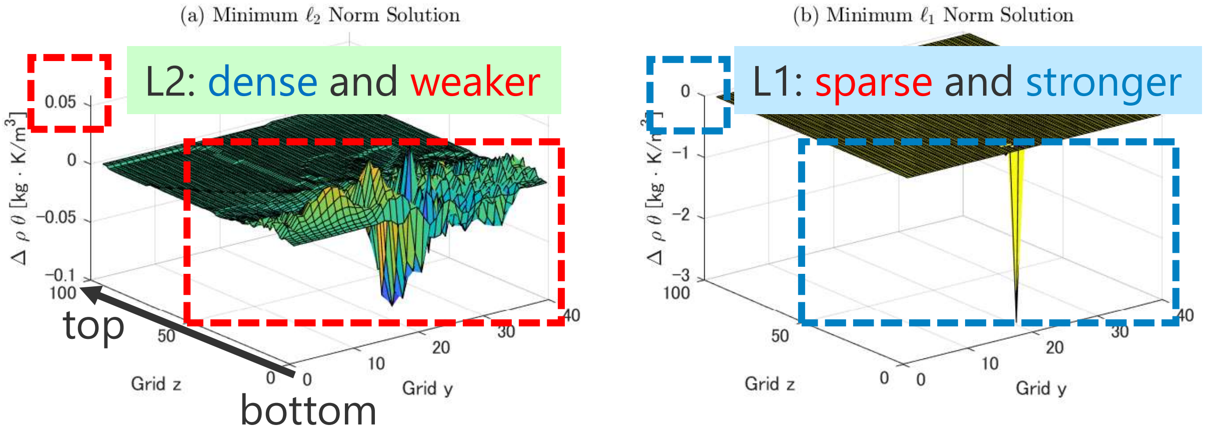
Optimizing Interventions using SCALE-MPC

We started coupling model predictive control (MPC) with NWP model, in which initial perturbations are optimized by solving convex optimization problem.

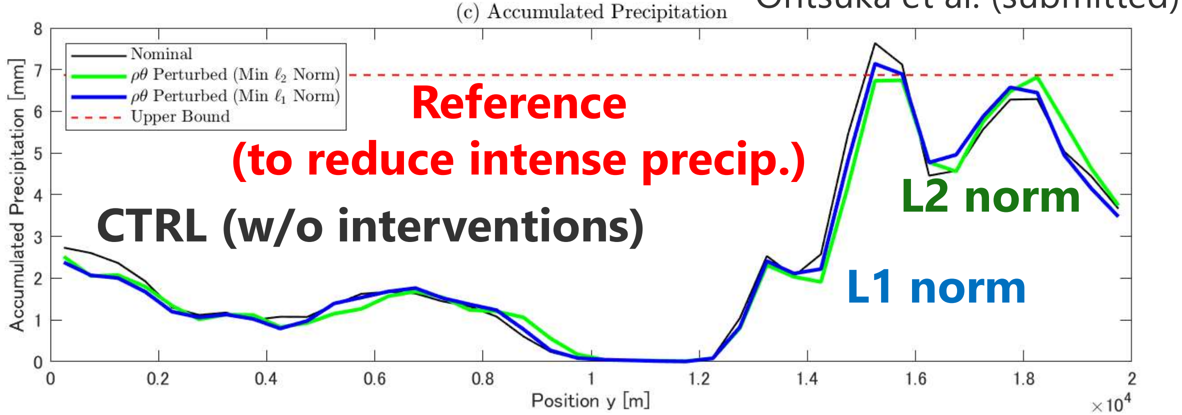
Convex optimization using SCALE

$$\min_{\Delta \mathbf{x}^{init}} \|\Delta \mathbf{x}^{init}\| \text{ s.t. } \mathbf{S}(\mathbf{x}^{init})\Delta \mathbf{x}^{init} = \Delta Y^{ref}$$





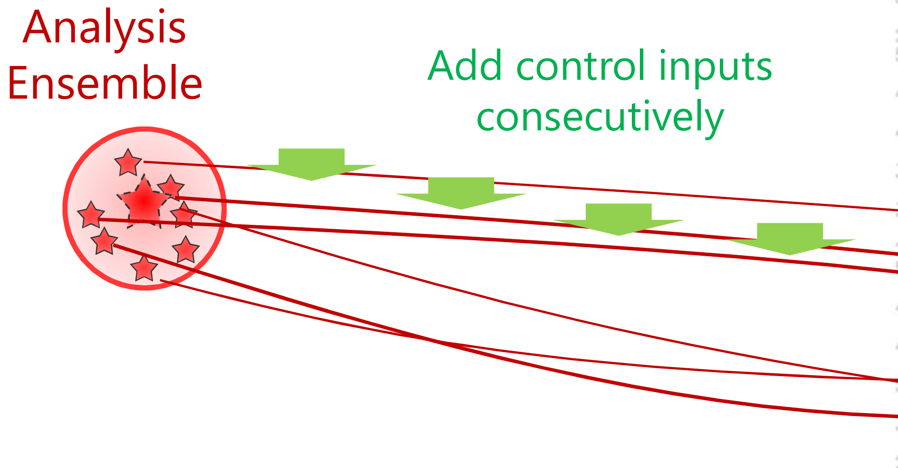
Ohtsuka et al. (submitted)



Remaining Issues

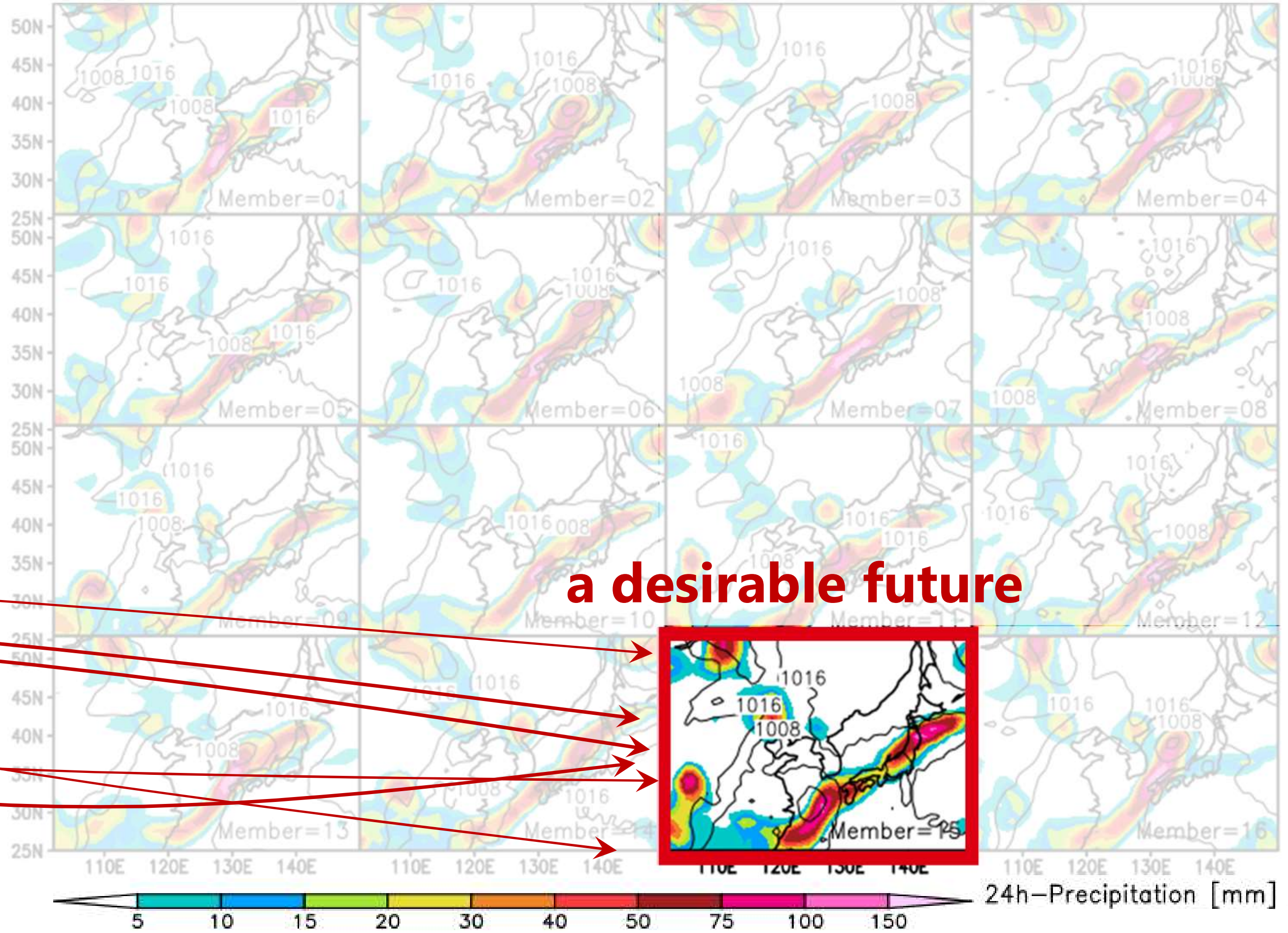
Suppose we would like to lead the atmosphere toward a desirable future

Step 1. to boost ensemble forecasts
Step 2. to find a desirable trajectory
from ensemble forecasts
Step 3. to accelerate MPC optimization

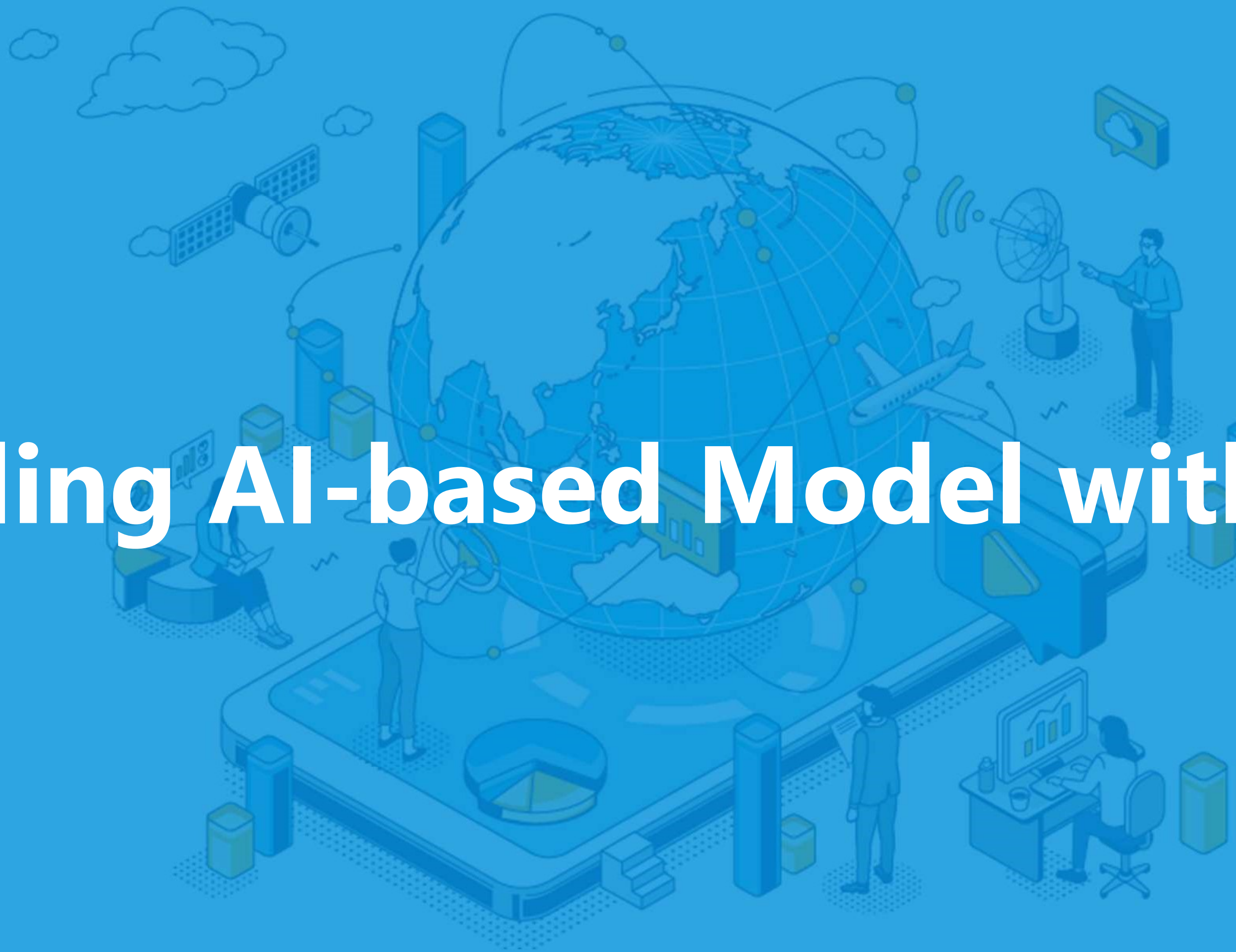


a case of heavy rain in 2018

From NICAM-LETKF 100 member forecasts



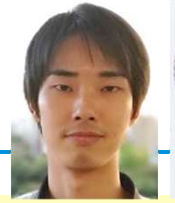
Coupling AI-based Model with DA



Kotsuki et al. (arXiv, and submitted)

Boosting ensemble predictions using AIs


PI Matsuoka


PI Kera


PI Kotsuki

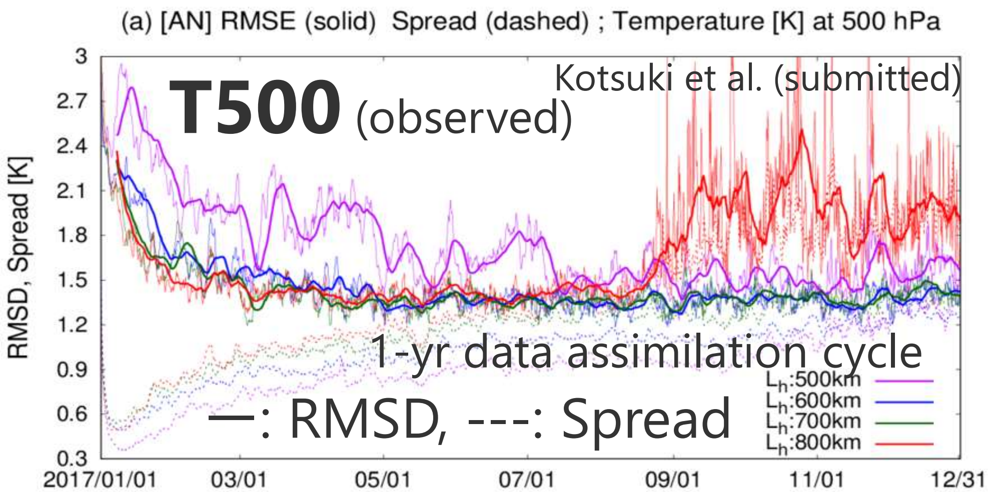
We are advancing <u>downscaling AI</u> to predict heavy rainfall as well as medium-range forecasts enabled by <u>AI weather model coupled with data assimilation</u>.

Medium-range ensemble forecasts (~5days)

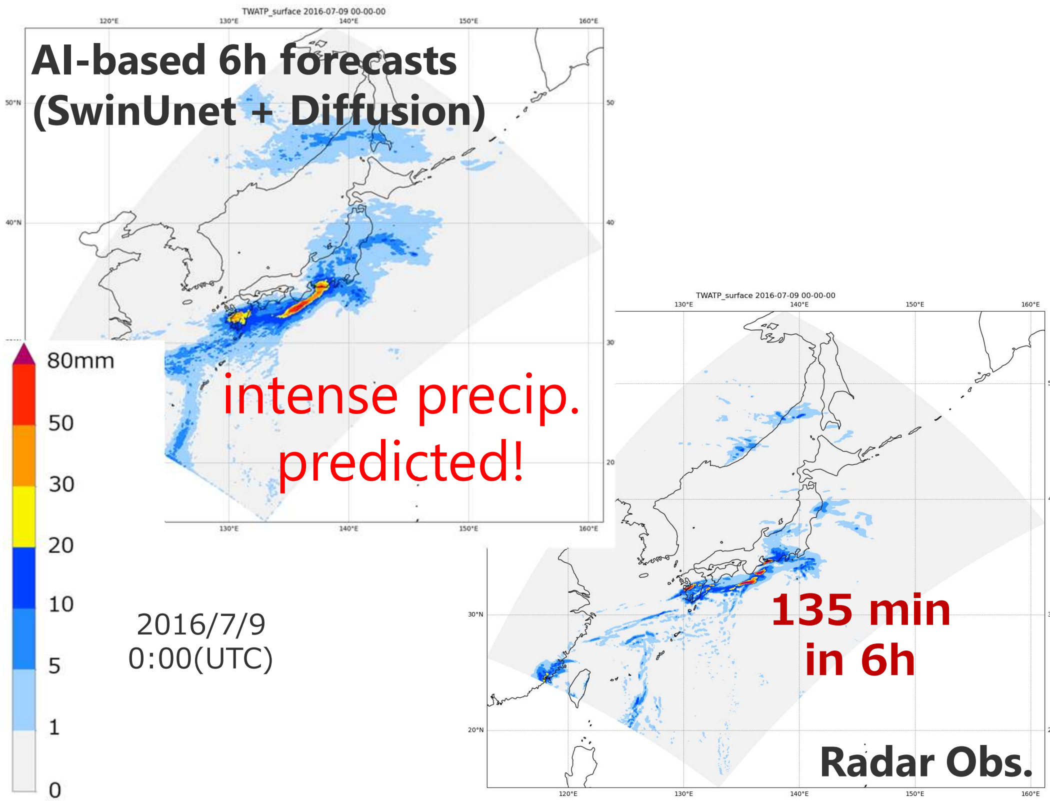
AI model (ViT)
(Cyber Space)

Obs
(Real Word)

AI model ClimaX coupled with LETKF



Downscaling & ensemble generation (~1day)



Training of ClimaX

- **This study: low-resolution version of ClimaX (x:64, y:32, z:7)**
  - about 12 hours for training using an NVIDIA/A6000ada

- **Reference Information: GraphCast (0.25 resolution)**

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RESEARCH ARTICLE | WEATHER FORECASTING

Learning skillful medium-range global weather forecasting

REMI LAM, ALVARO SANCHEZ-GONZALEZ, MATTHEW WILLSON, PETER WIRNSBERGER, MEIRE FORTUNATO, FERRAN ALET, SUMAN RAVURI, TIMO EWALDS, ZACH EATON-ROSEN, [...], AND PETER BATTAGLIA +8 authors Authors Info & Affiliations

SCIENCE · 14 Nov 2023 · Vol 382, Issue 6677 · pp. 1416-1421 · DOI: 10.1126/science.adi2336

was computed by backpropagation through time (22). GraphCast was trained to minimize the training objective using gradient descent, which took roughly 4 weeks on 32 Cloud TPU v4 devices using batch parallelism. See supplementary materials section 4 for further training details. Consistent with real deployment scenarios, ...

With 36.7 million parameters, GraphCast is a relatively small model by modern ML standards, chosen to keep the memory footprint tractable. And while HRES is released on 0.1° resolution, 137 levels, and up to 1-hour time steps, GraphCast operates on 0.25° latitude and longitude resolution, 37 vertical levels, and 6-hour time steps, because of the ERA5 training data's native 0.25° resolution and engineering challenges in fitting higher-resolution data on hardware. Generally, GraphCast should be viewed as a

Cloud TPU バージョン（チップ時間あたり）	リージョン	ロケーション	オンデマンド（米ドル）	1 年間のコミットメント（米ドル）	3 年間のコミットメント（米ドル）
TPU v4 Pod	us-central2	オクラホマ	$3.2200	$2.0286	$1.4490

3.22 (/hr/TPU) * 32 (TPU) * 24 (hr) * 28 (days) ≃ 69,242 USD ≃ 10,386,150 JPY
(only for the final training)

SPEEDY/ClimaX – LETKF System (as of Oct. 2024)

Using two docker containers for ClimaX-LETKF
approx. 20 hrs for 1yr cycle with 20-core CPU

Simulation Models

- SPEEDY (96x48x7; Global)
- ClimaX (64x32x7; Global)
- *NWP model(s)?*

Fortran or Python

forecast

Obs Operator

Fortran

obs

Obs Data

- OSSE for SPEEDY
- OSE for ClimaX (based on WB)

→ Prepbufr (WIP)

obs-fcst

analysis

Data Assimilation Core

- LETKF, Stochastic EnKF (i.e., PO)
  LPF, LPFGM and their hybrid
  (transform mtx-based implementations)
- Inflations: multiplicative, RTPP/RTPS, additive

Fortran

Verification Metrics

- RMSD vs. Spread
- CRPS

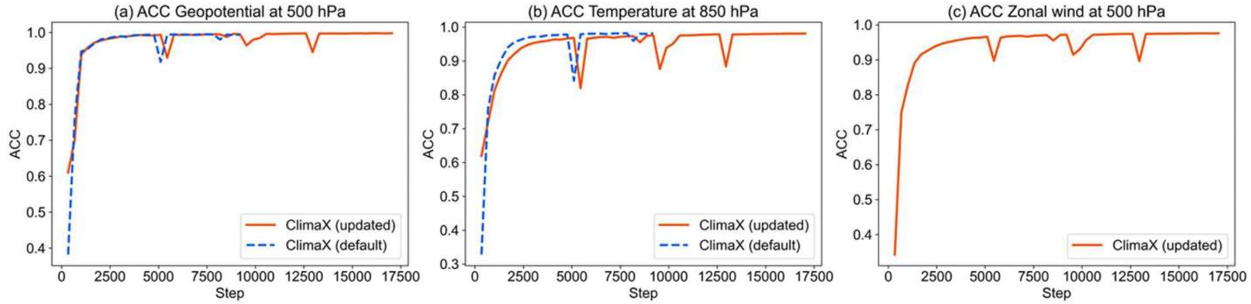
ClimaX (Training, Observation)

Supplementary Table A1. Variables of the ClimaX–local ensemble transform Kalman filter (LETKF) model used in this study. ClimaX requires input variables to predict output variables, and the LETKF assimilates observation (Obs) variables with associated error standard deviation (Error SD).

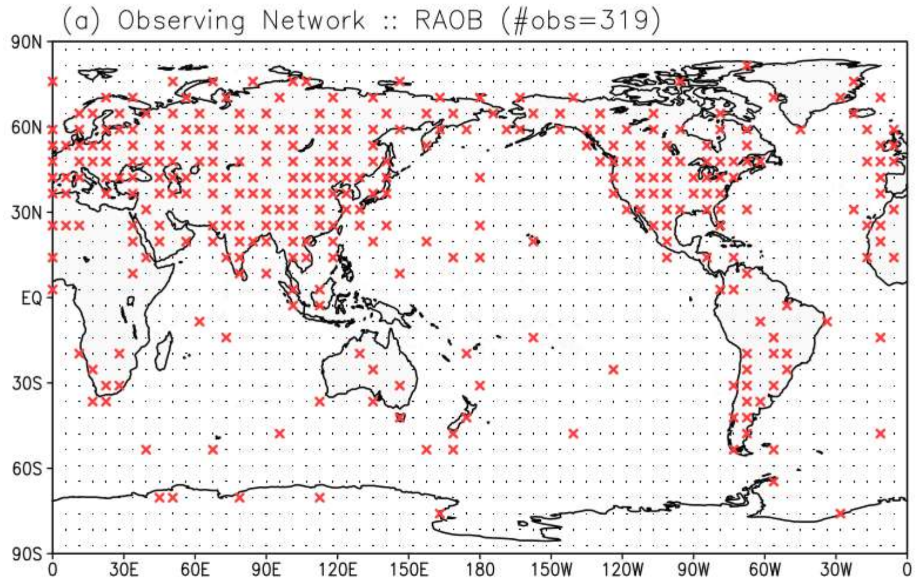
Symbol	Variable	Unit	Input	Output	Obs	Error SD	Height
U	Zonal wind	m/s	X	X	X	1.0	925, 850, 700, 600, 500, 250, 50 (hPa)
V	Meridional wind	m/s	X	X	X	1.0	
T	Temperature	K	X	X	X	1.0	
Q	Specific humidity	kg/kg	X	X	X (※)	0.1	
Geo	Geopotential	m^2/s^2	X	X			
U10m	10-m zonal wind	m/s	X	X			10 m
V10m	10-m meridional wind	m/s	X	X			10 m
T2m	2-m temperature	m/s	X	X			2 m
Ps	Surface pressure	hPa			X	1.0	Surface
Elev	Surface elevation	m	X				Surface
Lon	Longitude	degree	X				–
Lat	Latitude	degree	X				–
Mask	Land–sea mask	1 or 0	X				–

※ Specific humidity was observed up to 4th model level (i.e., 925, 850, 700 and 600 hPa).

(1) Training Curve (ACC)



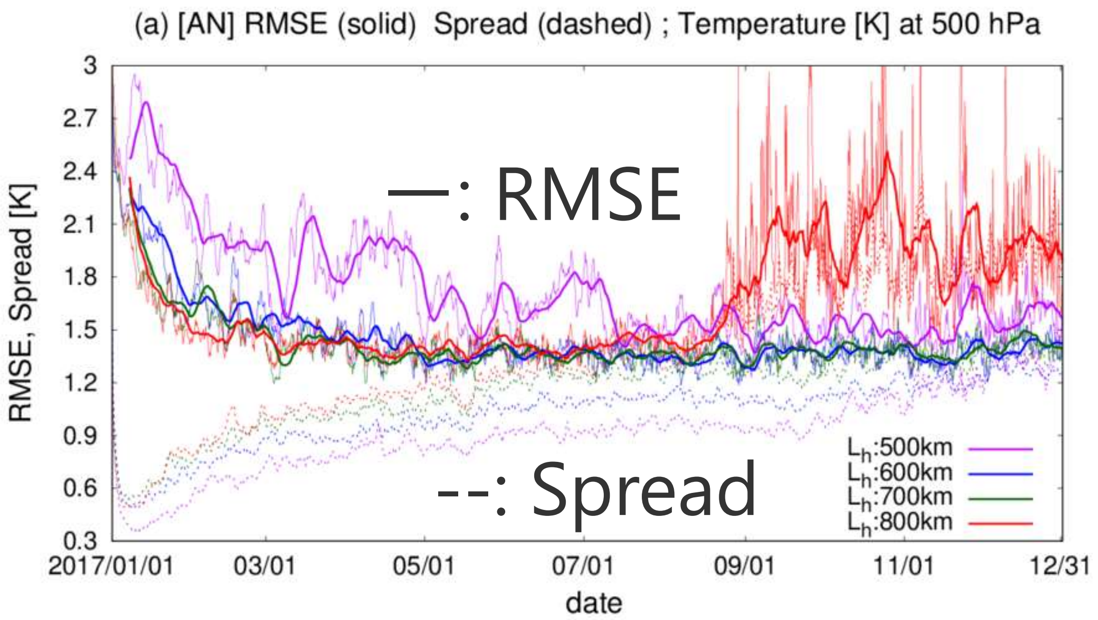
(2) Observing Network (Simulated obs)



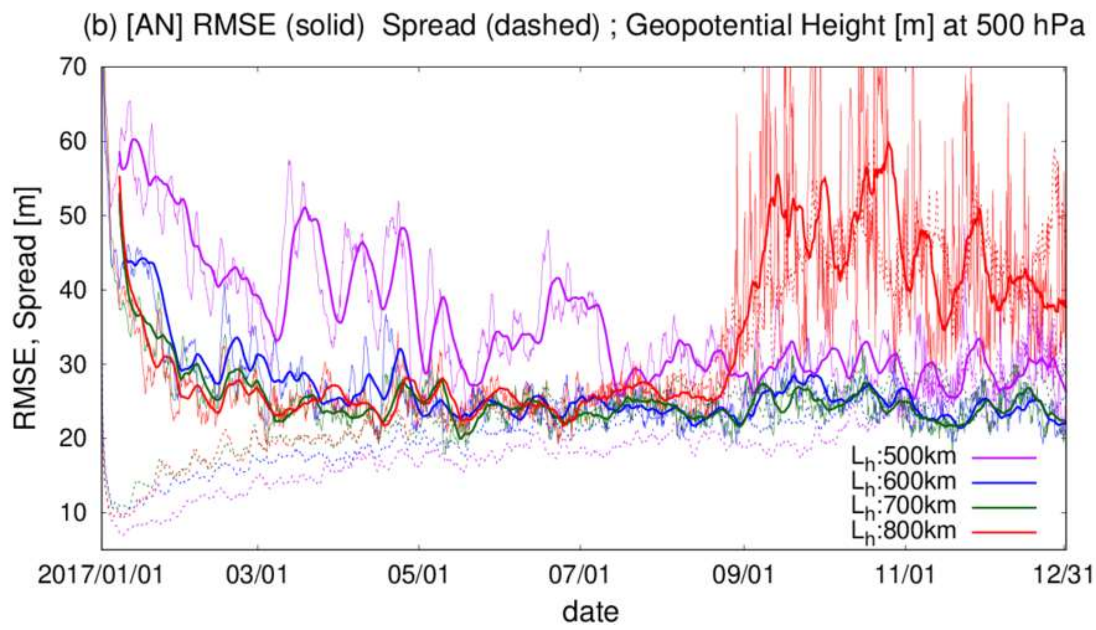
Data Assimilation Experiments (20-member)

Data assimilation cycled stably for ClimaX over one year with EnKF.

Temperature at 500 hPa (observed)



GPH at 500 hPa (unobserved)



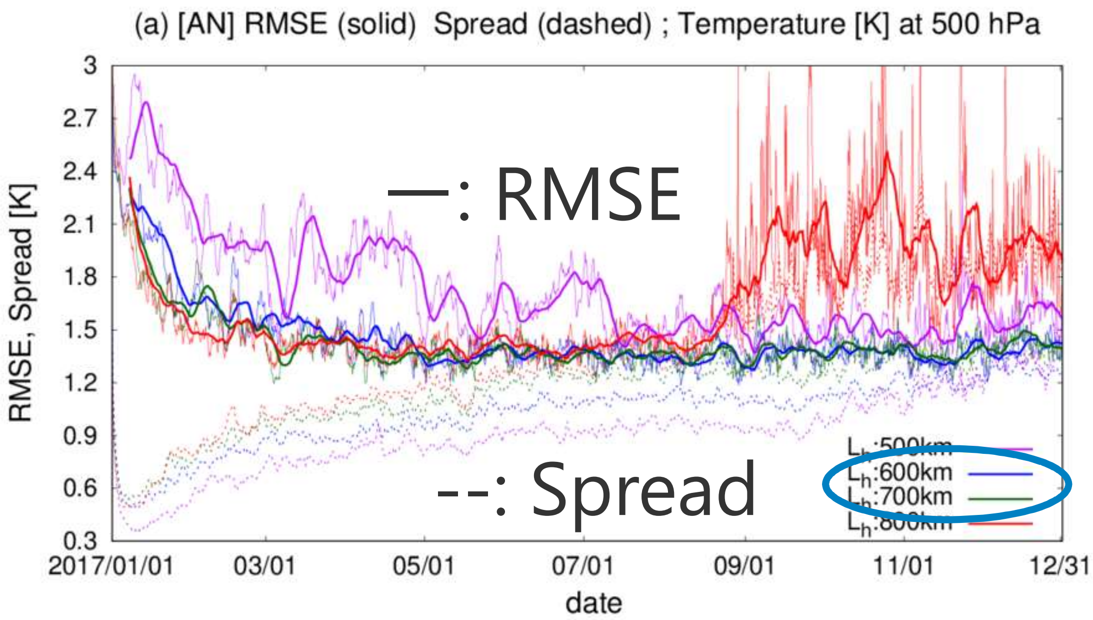
Improvements due to direct and indirect impacts

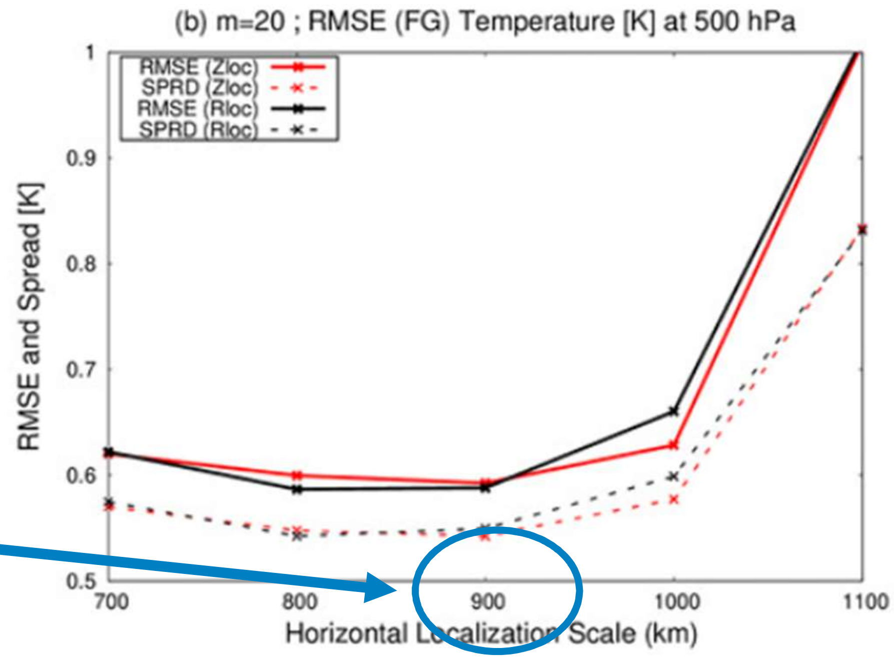
RMSE: verified against WeatherBench

Data Assimilation Experiments

Optimal localization scale for ClimaX was much shorter than NWP model.
This implies the AI model is less efficient to capture dynamically-balanced error cov.

Temperature at 500 hPa (observed)





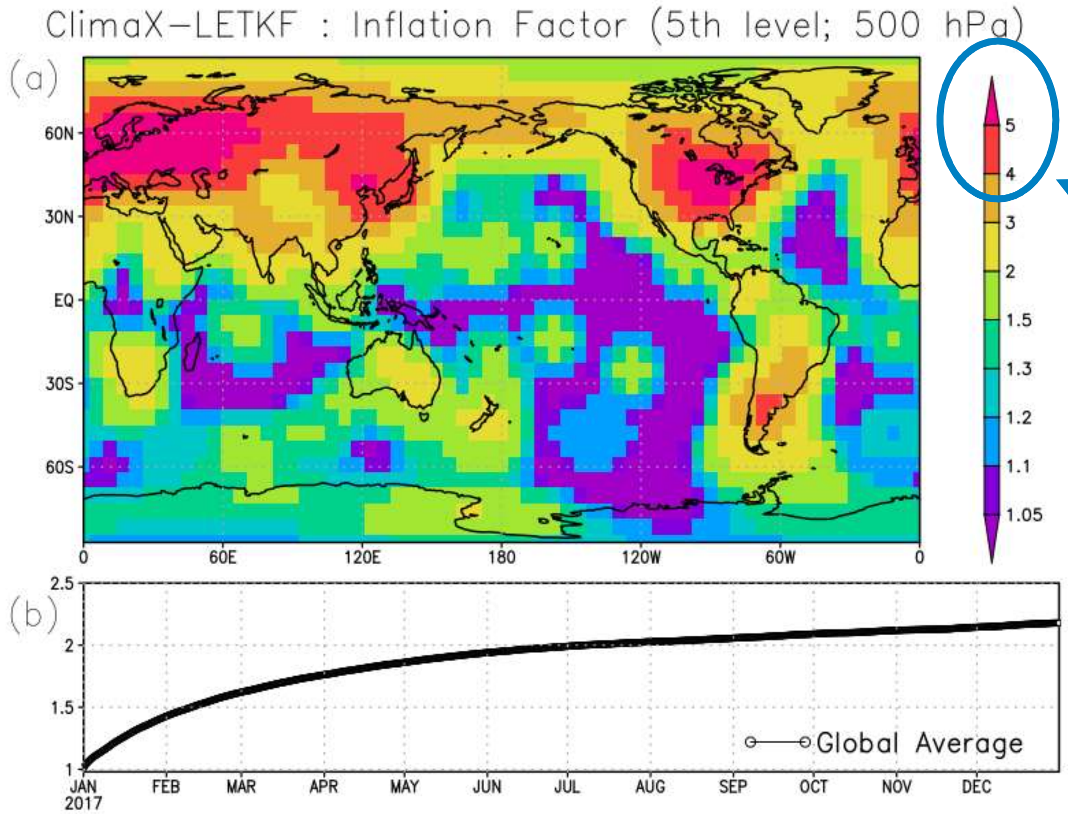
20-member ClimaX-LETKF
(AI model ~ 500 km resolution)

20-member SPEEDY-LETKF
(an NWP model ~ 400 km resolution)

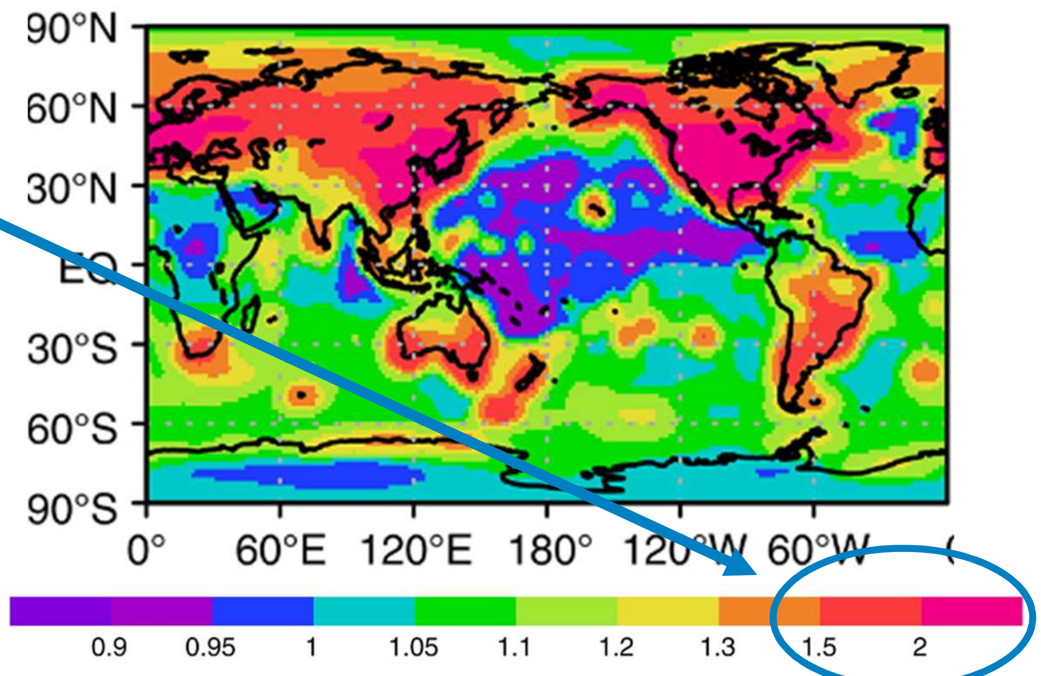
Covariance Inflation (L=600 km)

ClimaX required much more inflation than NWP model.
This implies the AI model is much less chaotic, maybe due to training w.r.t. reanalysis

ClimaX-LETKF (AI model)



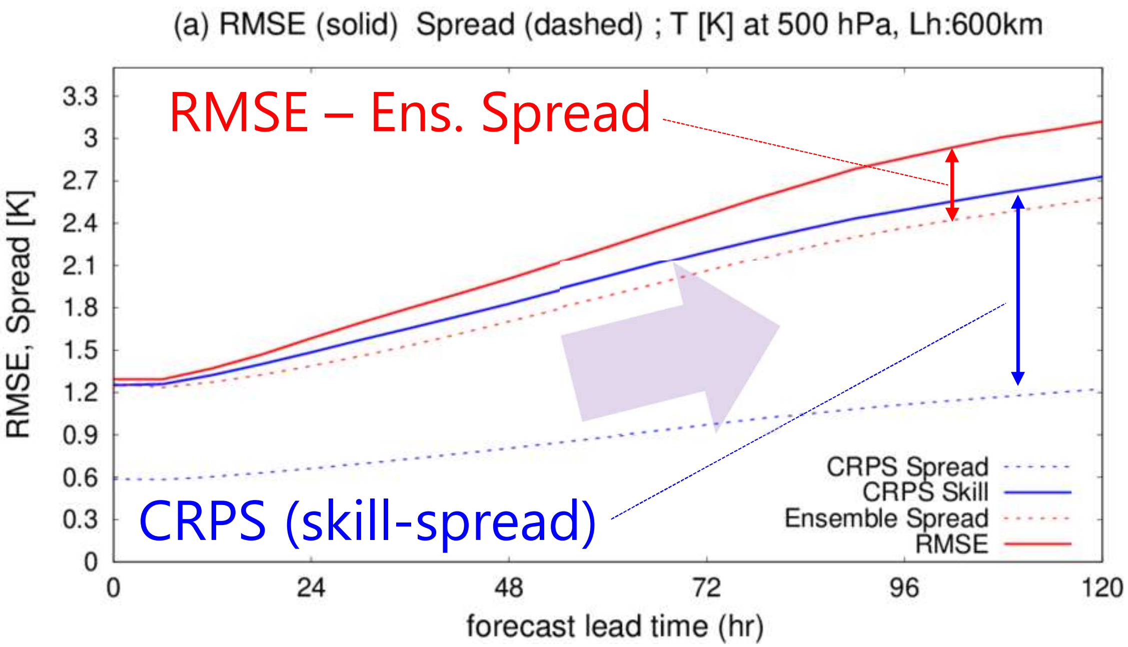
NICAM-LETKF (NWP model)



Kotsuki+17, QJRMS

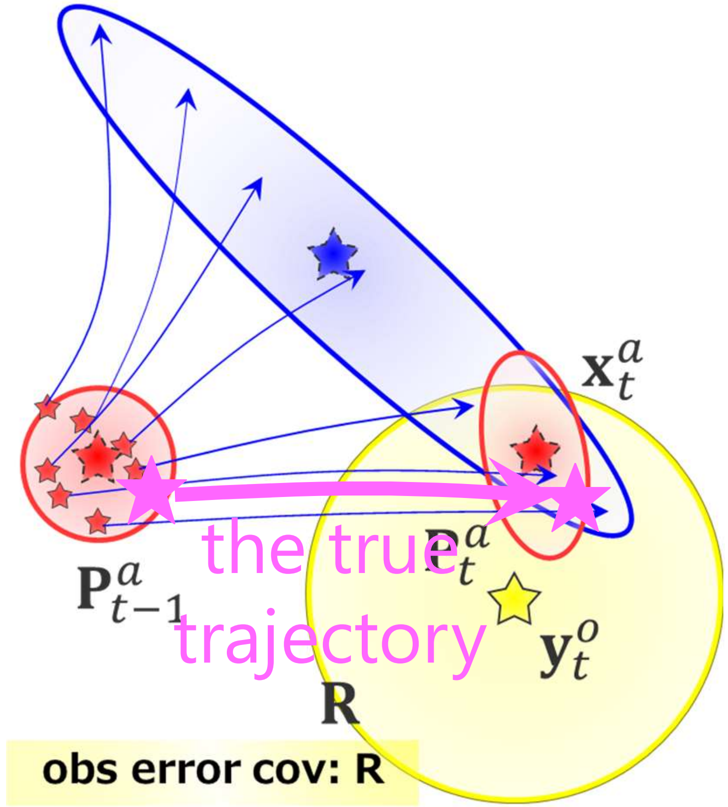
A naïve wonder: Can AI acquire “Chaos”?

DNNs use “edge of chaos” to realize various predictions from slightly different inputs.
Whether or not such AIs can acquire “chaos”?
Or, the less chaoticness came from the training w.r.t. analysis w/ MSE?



averaged over December 01, 2017

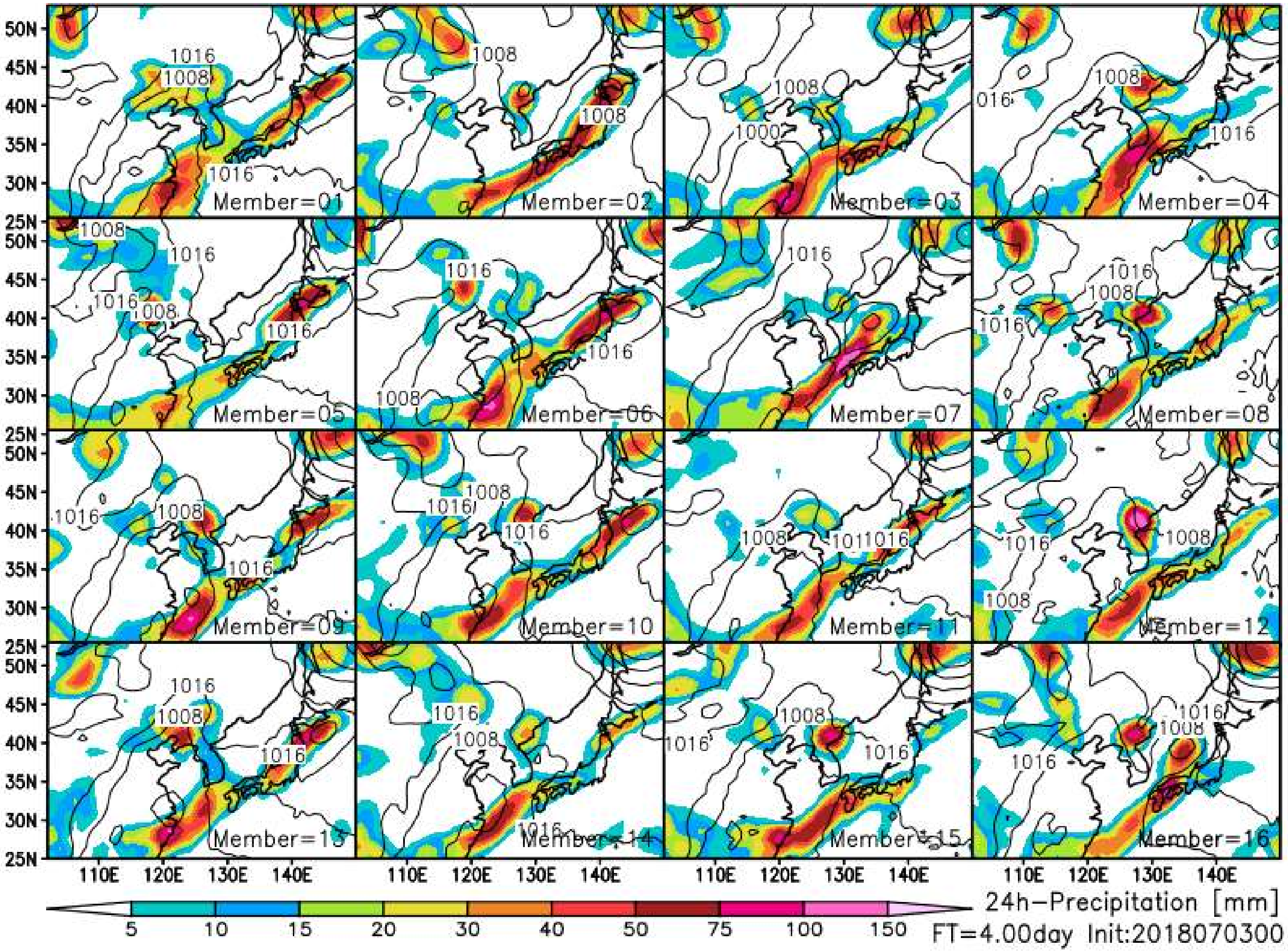
RMSE and Skill verified against Weather Bench



Capturing Preferable Trajectory

Oettli and Kotsuki (2024; JGR-A)
Oettli et al. (in prep.)

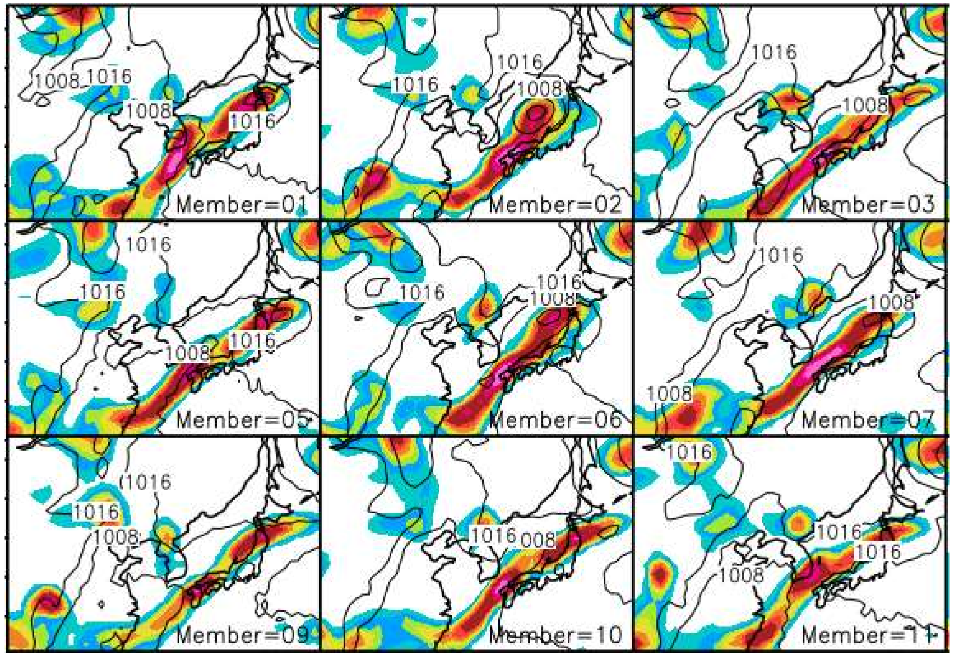
Question: Which trajectory should we track?



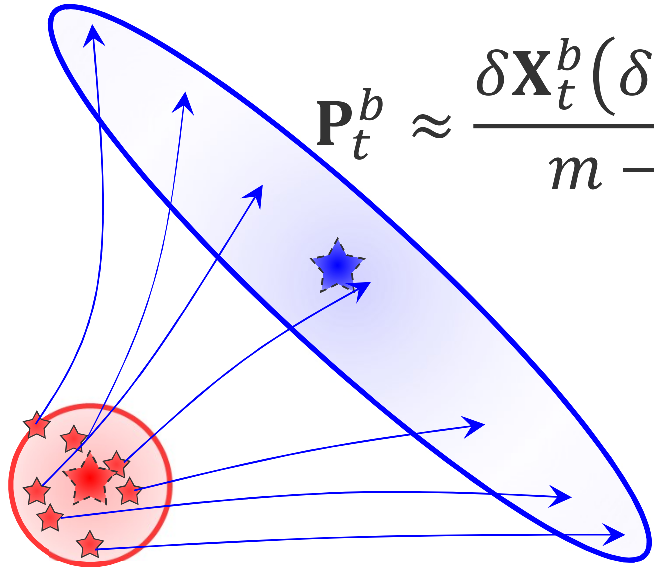
a case for 16-member forecast

How to interpret ensemble forecasts (conventional)

State-space Ensemble Prediction



Schematic Image of Ensemble Prediction



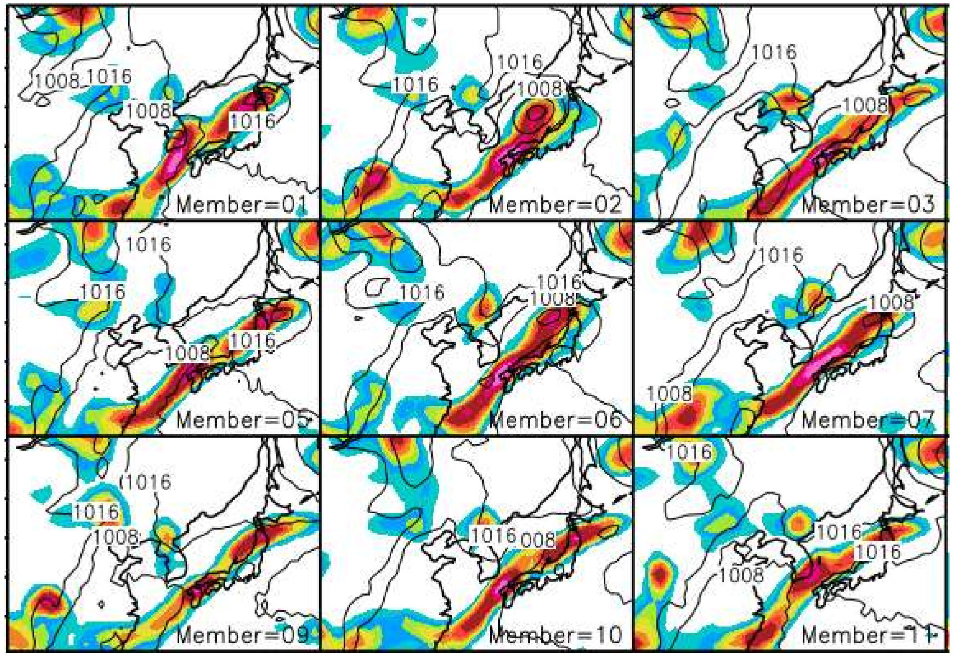
$$\mathbf{P}_t^b \approx \frac{\delta\mathbf{X}_t^b\left(\delta\mathbf{X}_t^b\right)^T}{m-1}$$

$\mathbf{P}_{t-1}^a$

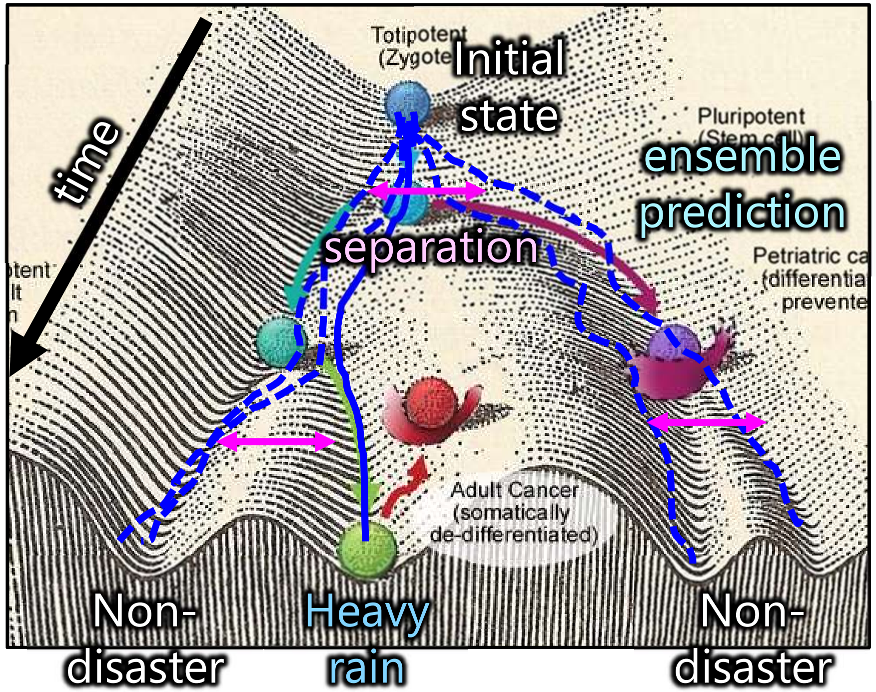
<u>homogeneously-spreading</u> forecasts

How to interpret ensemble forecasts (proposed)

State-space Ensemble Prediction



Latent-space Landscape

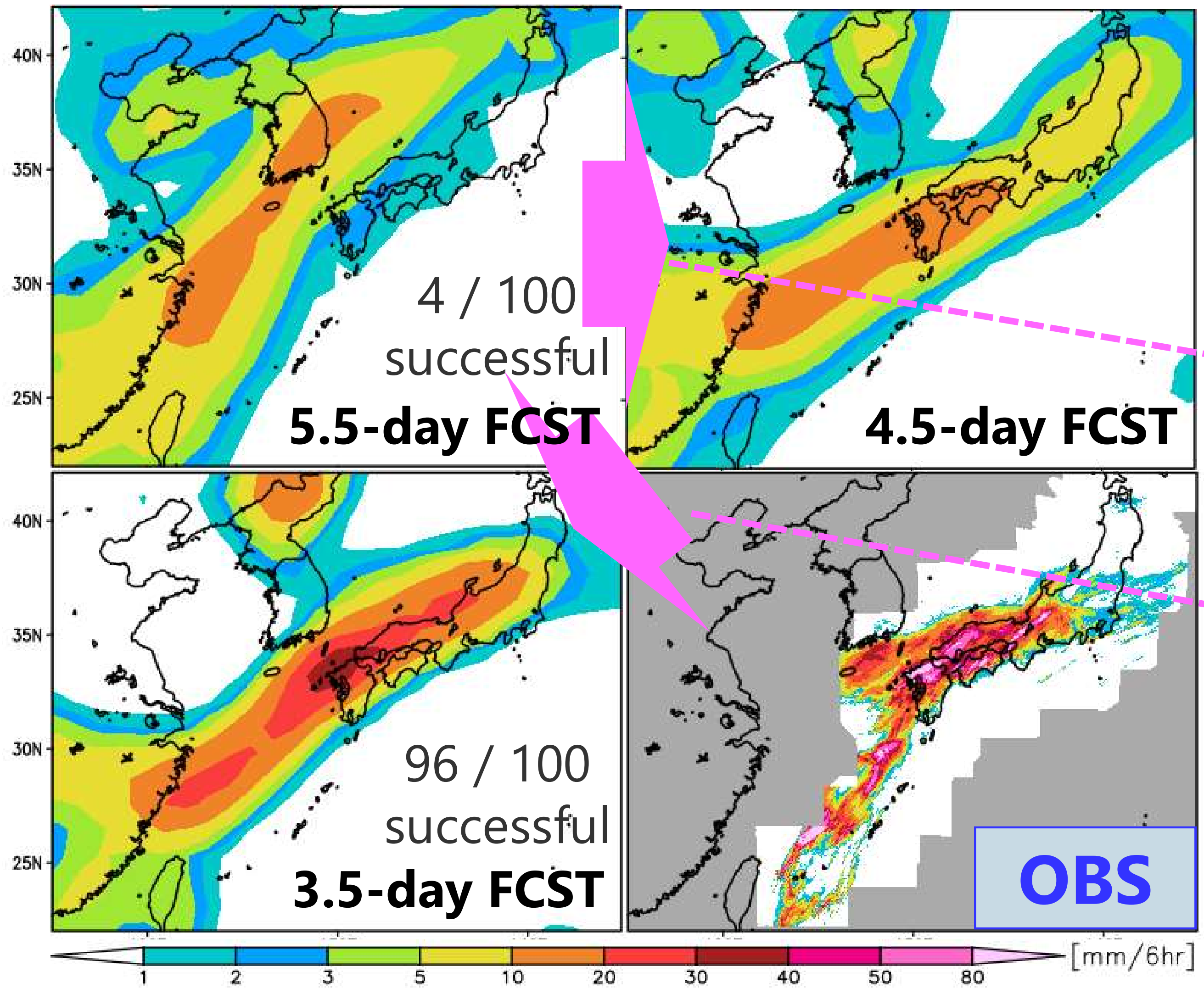


Forecasts <u>clustered by attractor</u>

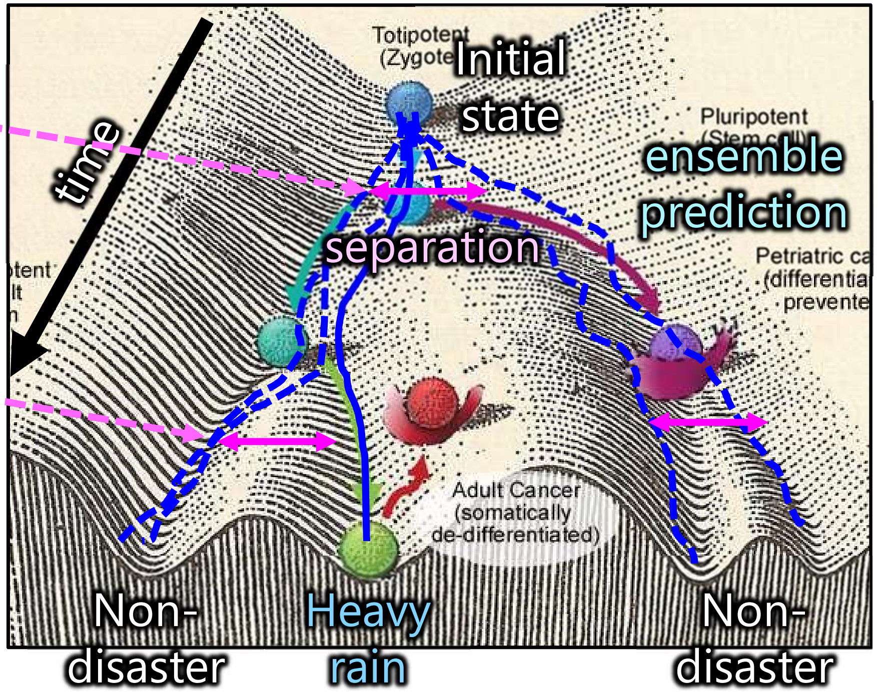
Idea comes from Waddington's epigenetic landscape

100-member Prediction of Heavy Rain in 2018

w/ NICAM-LETKF
(Kotsuki et al. 2019)



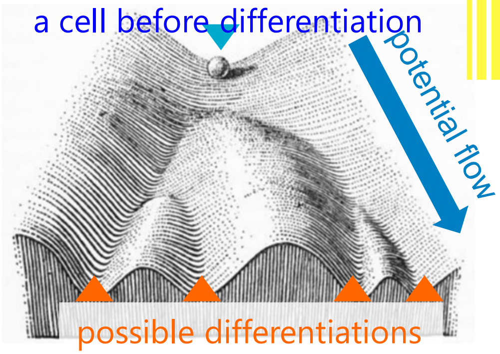
We have been encountering regime changes of forecasts for disastrous events

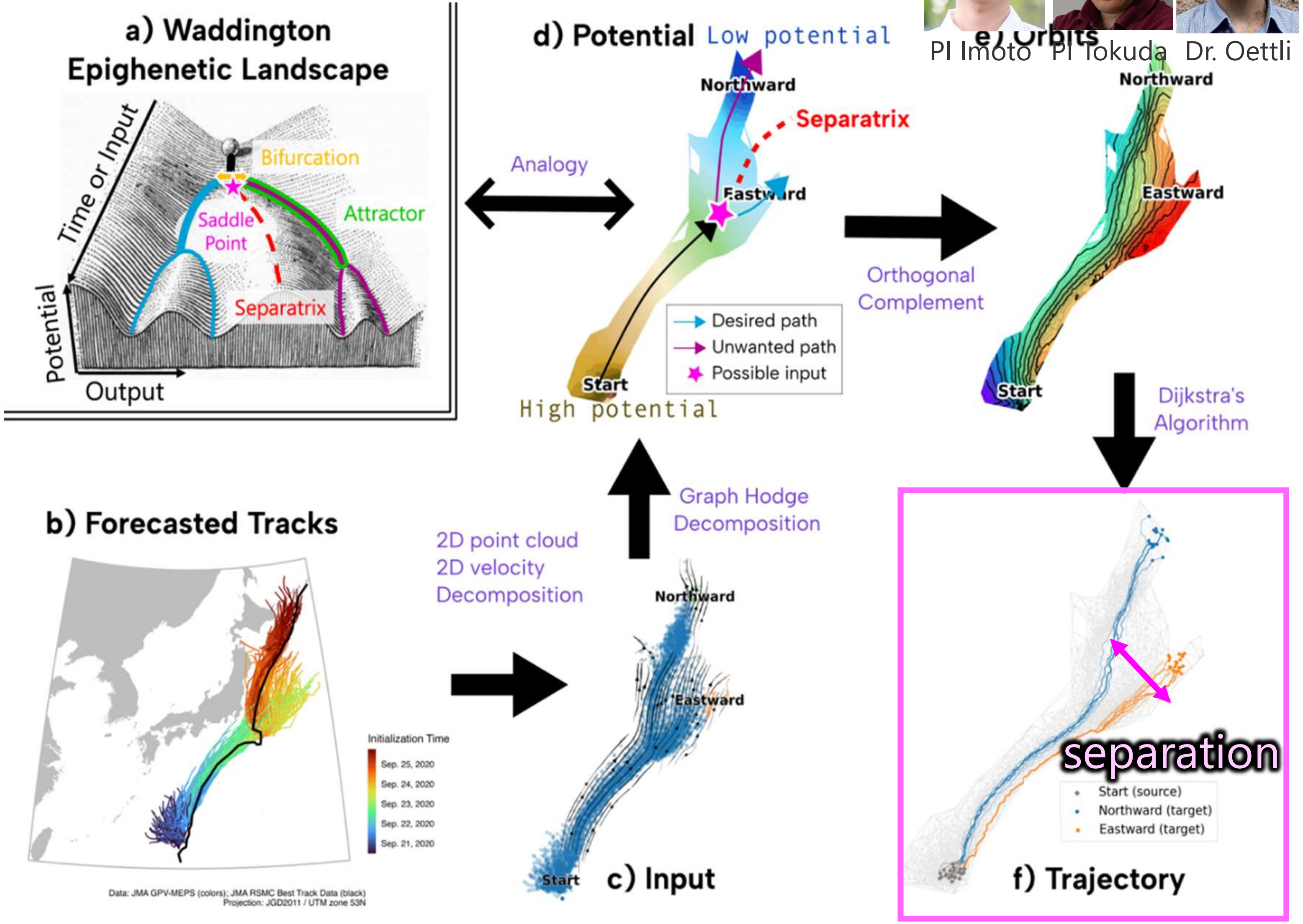


A trial to capture “meteorological” landscape

PI Imoto PI Tokuda Dr. Oettli

Waddington’s
Epigenetic Landscape (1957)





Oettli et al. (in prep.)

Quantum Data Assimilation

Kotsuki et al. (2024; NPG Letters)
Tsuyuki et al. (in prep.)

MOONSHOT RESEARCH & DEVELOPMENT PROGRAM

Challenges for Weather MPC (DA)

- Implications from L63, L96 & SCALE MPC experiments
  - (1) MPC should be accelerated
  - (2) sometimes optimizations drop into local minima

🤔

👀

OPEN

Model Predictive Control for Finite Input Systems using the D-Wave Quantum Annealer

Daisuke Inoue* & Hiroaki Yoshida

The D-Wave quantum annealer has emerged as a novel computational architecture that is attracting significant interest, but there have been only a few practical algorithms exploiting the power of quantum annealers. Here we present a model predictive control (MPC) algorithm using a quantum annealer for a system allowing a finite number of input values. Such an MPC problem is classified as a non-deterministic polynomial-time-hard combinatorial problem, and thus real-time sequential optimization is difficult to obtain with conventional computational systems. We circumvent this difficulty by converting the original MPC problem into a quadratic unconstrained binary optimization problem, which is then solved by the D-Wave quantum annealer. Two practical applications, namely stabilization of a spring-mass-damper system and dynamic audio quantization, are demonstrated. For both, the D-Wave method exhibits better performance than the classical simulated annealing method. Our results suggest new applications of quantum annealers in the direction of dynamic control problems.

Quantum Annealers (QA) may solve the issues above.

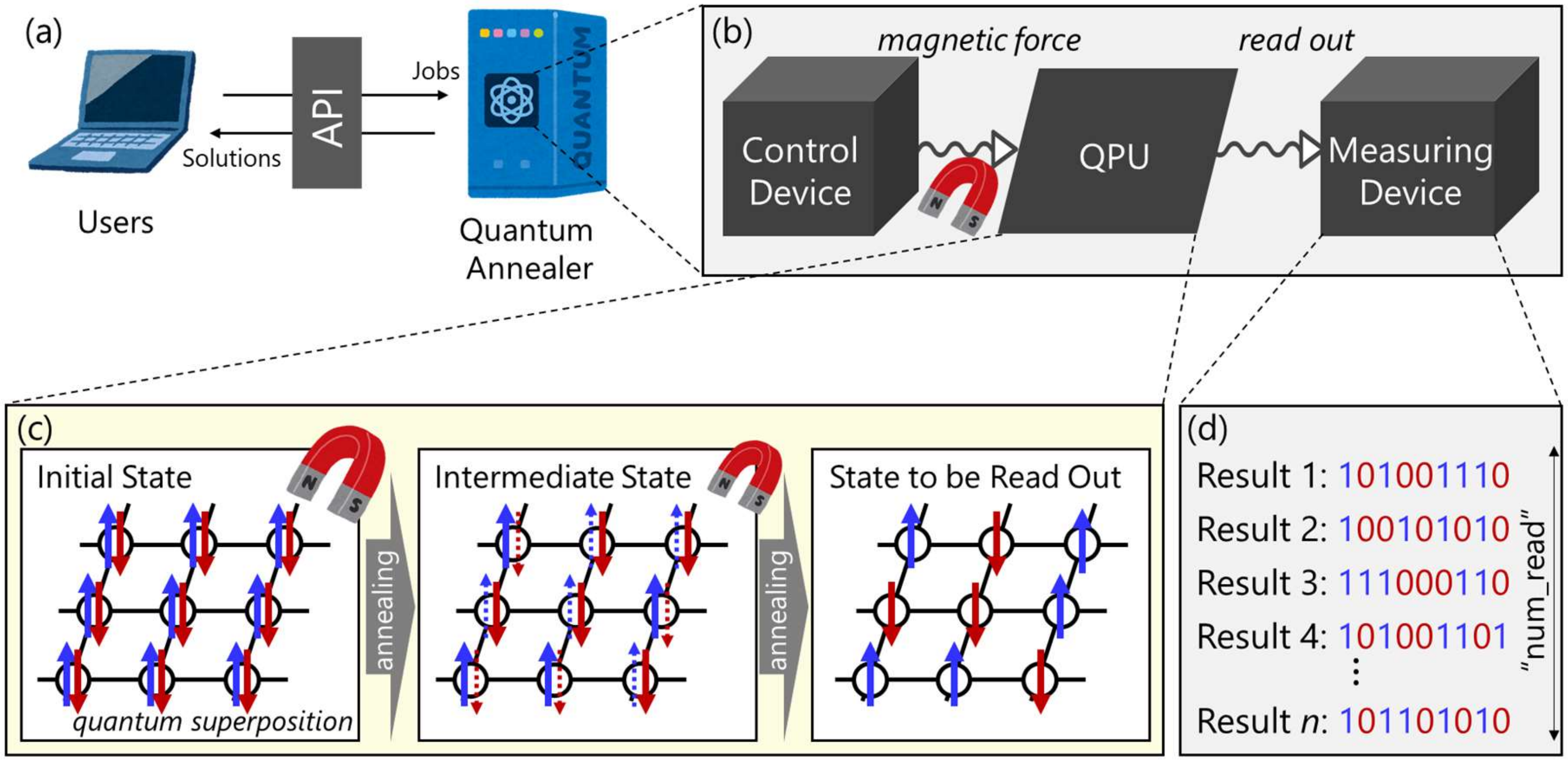
➔ Start investigating QAs for 4DVAR, a well-known DA problem

Quantum Annealer

Quadratic Unconstrained Binary Optimization (QUBO; a.k.a. Ising model)

$$\underline{H} = \sum_{i<j} J_{ij} q_i q_j + \sum_i h_i q_i \qquad \underline{q_i} \in \{0, +1\}$$

Hamiltonian *input* **Qubits (to be read out from QPU)**



To reformulate 4DVAR to QUBO

① *4DVAR w/ inner and outer loops*

$$J(\delta\mathbf{x}_0) = \delta\mathbf{x}_0^T\mathbf{B}^{-1}\delta\mathbf{x}_0 + \left[\mathbf{d}_{1:L}^o - \mathbf{H}_{1:L}\mathbf{M}_{1:L|0}\delta\mathbf{x}_0\right]^T\mathbf{R}_{1:L}^{-1}\left[\mathbf{d}_{1:L}^o - \mathbf{H}_{1:L}\mathbf{M}_{1:L|0}\delta\mathbf{x}_0\right]$$

TLM around the FG trajectory

② *4DVAR w/ only inner loop*

$$\approx \tilde{J}(\delta\mathbf{x}_0) = \delta\mathbf{x}_0^T\mathbf{B}^{-1}\delta\mathbf{x}_0 + \left[\mathbf{d}_{1:L}^o - \mathbf{H}_{1:L}\widetilde{\mathbf{M}}_{1:L|0}\delta\mathbf{x}_0\right]^T\mathbf{R}_{1:L}^{-1}\left[\mathbf{d}_{1:L}^o - \mathbf{H}_{1:L}\widetilde{\mathbf{M}}_{1:L|0}\delta\mathbf{x}_0\right]$$

$$= \delta\mathbf{x}_0^T\left[\mathbf{B}^{-1} + \widetilde{\mathbf{M}}_{1:L|0}^T\mathbf{H}_{1:L}^T\mathbf{R}_{1:L}^{-1}\mathbf{H}_{1:L}\widetilde{\mathbf{M}}_{1:L|0}\right]\delta\mathbf{x}_0 - 2(\mathbf{d}_{1:L}^o)^T\mathbf{R}_{1:L}^{-1}\mathbf{H}_{1:L}\widetilde{\mathbf{M}}_{1:L|0}\delta\mathbf{x}_0 + C$$

Binarized

③ *QUBO*

$$\approx \mathcal{H}(\mathbf{b}) = \left(\frac{1}{\alpha}\mathbf{G}\mathbf{b}\right)^T\left[\mathbf{B}^{-1} + \widetilde{\mathbf{M}}_{1:L|0}^T\mathbf{H}_{1:L}^T\mathbf{R}_{1:L}^{-1}\mathbf{H}_{1:L}\widetilde{\mathbf{M}}_{1:L|0}\right]\left(\frac{1}{\alpha}\mathbf{G}\mathbf{b}\right)$$
$$-2(\mathbf{d}_{1:L}^o)^T\mathbf{R}_{1:L}^{-1}\mathbf{H}_{1:L}\widetilde{\mathbf{M}}_{1:L|0}\left(\frac{1}{\alpha}\mathbf{G}\mathbf{b}\right) + C$$

$$= \mathbf{b}^\mathbf{T}\mathbf{A}\mathbf{b} + \mathbf{u}^\mathbf{T}\mathbf{b} + C \qquad \left(\mathbf{b}^\mathbf{T} = [q_0, q_1, \cdots, q_n]\right)$$

Binarization for L96 model

$$\delta x_{0,i} = \frac{1}{\alpha}\underbrace{(-2^3q_1 + 2^2q_2 + 2^1q_3 + 2^0q_4)}_{\text{Can handle 16 integers (-8, -7, ….., +7)}} \quad q_i \in \{0, +1\} \quad \alpha = 50$$

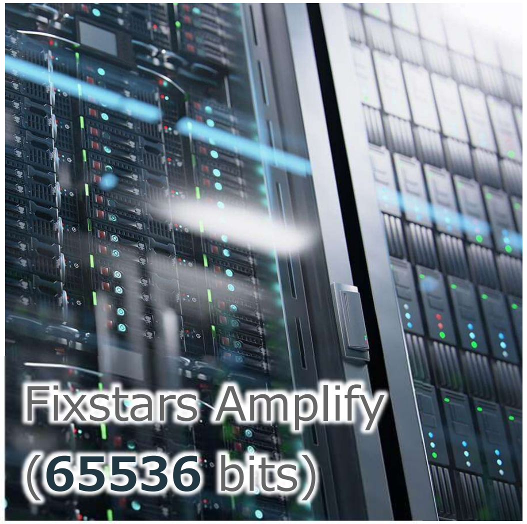
$$\mathbf{g}^T = [-2^{Z-1}, 2^{Z-2}, \cdots, 2^1, 2^0]$$

$$\mathbf{G} = \begin{bmatrix} \mathbf{g}^T & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & \mathbf{g}^T \end{bmatrix}$$

Experiments

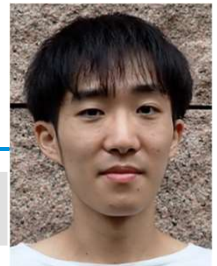
- **Model** : Lorenz-96
- **DA** : 2-day window 4DVAR , every 6-hourly 40 obs
- **Experimental period** : 100 day (off-line DA)

	Cost Function	Method
QUO-NL	① $J = \delta\mathbf{x}_0^T\mathbf{B}^{-1}\delta\mathbf{x}_0 + \sum\left(\mathbf{d}_i^o - \mathbf{H}_i\mathbf{M}_{i\vert 0}\delta\mathbf{x}_0\right)^T\mathbf{R}_i^{-1}\left(\mathbf{d}_i^o - \mathbf{H}_i\mathbf{M}_{i\vert 0}\delta\mathbf{x}_0\right)$	Quasi-Newton Method
QUO-L	② $J = \delta\mathbf{x}_0^T\mathbf{B}^{-1}\delta\mathbf{x}_0 + \sum\left(\mathbf{d}_i^o - \mathbf{H}_i\widetilde{\mathbf{M}}_{i\vert 0}\delta\mathbf{x}_0\right)^T\mathbf{R}_i^{-1}\left(\mathbf{d}_i^o - \mathbf{H}_i\widetilde{\mathbf{M}}_{i\vert 0}\delta\mathbf{x}_0\right)$	Quasi-Newton Method
QUBO-Sim	③ $\mathcal{H}(\mathbf{b}) = \mathbf{b}^T\mathbf{A}\mathbf{b} + \mathbf{u}^T\mathbf{b} + C$	Simulated QA
QUBO-Phy	③ $\mathcal{H}(\mathbf{b}) = \mathbf{b}^T\mathbf{A}\mathbf{b} + \mathbf{u}^T\mathbf{b} + C$	QA



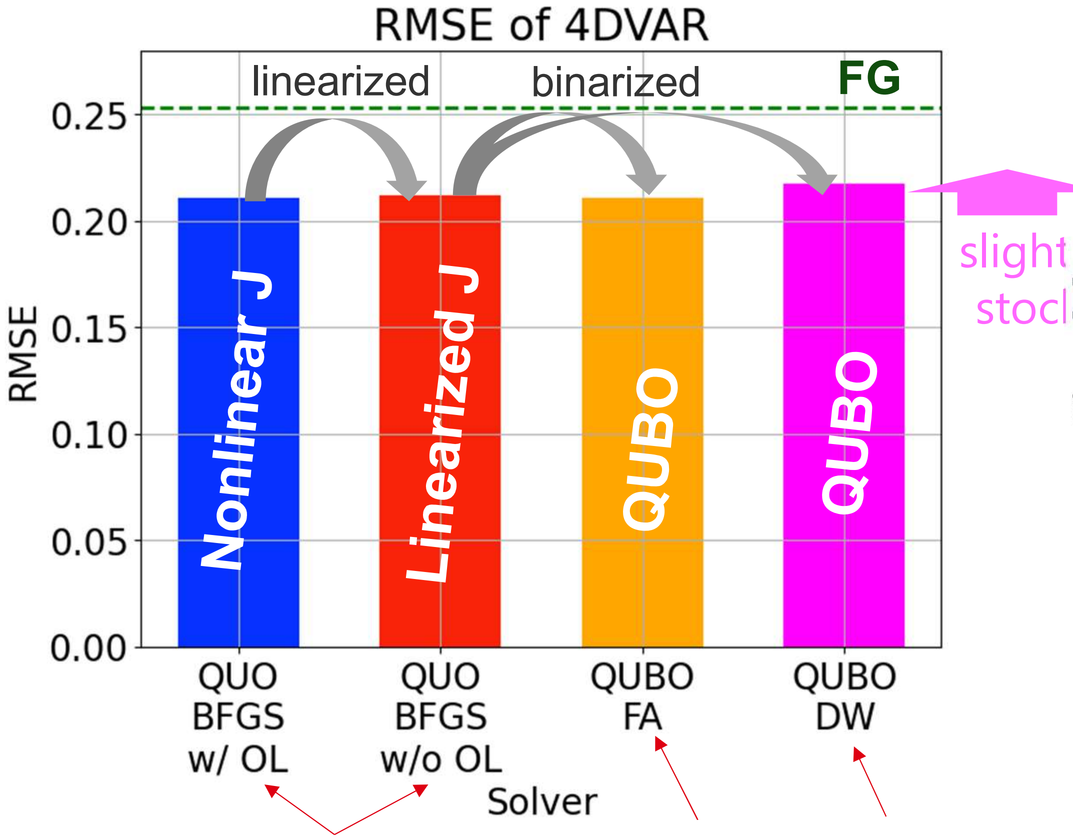
Quantum Data Assimilation for 4DVAR w/ L96

Poster Session 4



F. Kawasaki

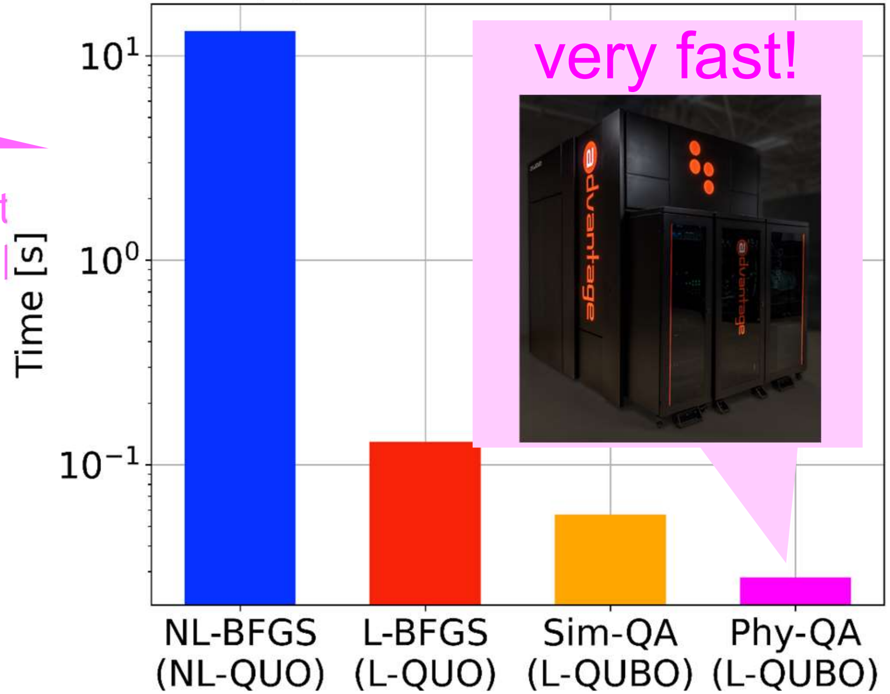
Average of 50 data assimilations (window: 2 days, 40 obs, **B** is manually tuned)



Scipy BFGS
w/wo outer loop
(w/wo TLM/ADJ updates)

Simulated
QA
(GPU-based)

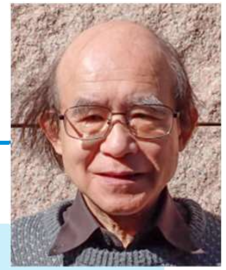
Physical
QA
(D-Wave)



QAs used 4 quantum bits (QBs)
for a real number
due to the limitation of total QB. (170 QBs)

Kotsuki et al. (2024; NPG Letters)

Considering "quartic" cost function

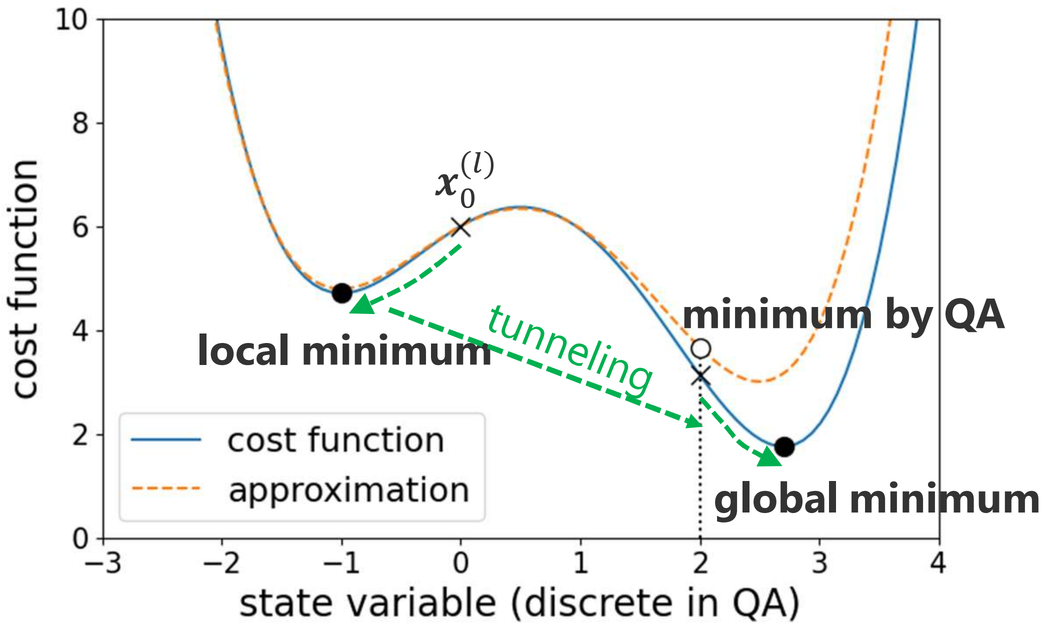


Prof. Tsuyuki

- Cost function for the *l* th outer loop

$$J\left(\delta x_0^{(l)}\right) = \frac{1}{2}\left(\delta x_0^{(l)} + \Delta x_0^{(l)}\right)^{\mathrm{T}} \boldsymbol{B}^{-1}\left(\delta x_0^{(l)} + \Delta x_0^{(l)}\right) + \frac{1}{2}\sum_{k=1}^{K}\left(\boldsymbol{H}_k \delta \boldsymbol{x}_k^{(l)} - \boldsymbol{d}_k^{(l)}\right)^{\mathrm{T}} \boldsymbol{R}_k^{-1}\left(\boldsymbol{H}_k \delta \boldsymbol{x}_k^{(l)} - \boldsymbol{d}_k^{(l)}\right)$$

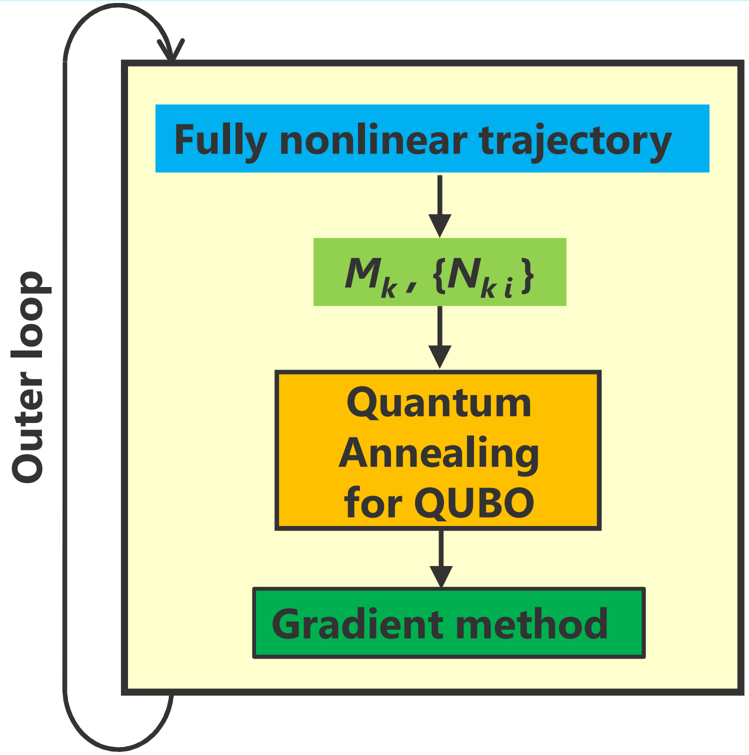
$$\delta \boldsymbol{x}_0^{(l)} \coloneqq \boldsymbol{x}_0 - \boldsymbol{x}_0^{(l)} = \boldsymbol{L}\boldsymbol{u}, \qquad \Delta \boldsymbol{x}_0^{(l)} \coloneqq \boldsymbol{x}_0^{(l)} - \boldsymbol{x}_0^{b}, \qquad \boldsymbol{B} = \boldsymbol{L}\boldsymbol{L}^{\mathrm{T}}$$



- 2nd-order approximation

$$\delta \boldsymbol{x}_k^{(l)} \coloneqq \boldsymbol{x}_k - \boldsymbol{x}_k^{(l)}$$

$$\approx \boldsymbol{M}_k^{(l)} \delta \boldsymbol{x}_0^{(l)} + \frac{1}{2}\left(\delta \boldsymbol{x}_0^{(l)}\right)^{\mathrm{T}} \begin{pmatrix} \boldsymbol{N}_{k\,1}^{(l)} \\ \vdots \\ \boldsymbol{N}_{k\,n}^{(l)} \end{pmatrix} \delta \boldsymbol{x}_0^{(l)}$$



How can we treat quartic function by QA?

- QDA can solve polynomial equations
  - i.e., beyond quadratic unconstrained problems like 4DVars

a simple example with three binaries: $q_1 q_2 q_3 \in \{0,1\}$ $\tilde{q} \in \{0,1\}$

a dummy variable

$$\mathcal{H} = q_1 q_2 q_3$$ *a cubic function*

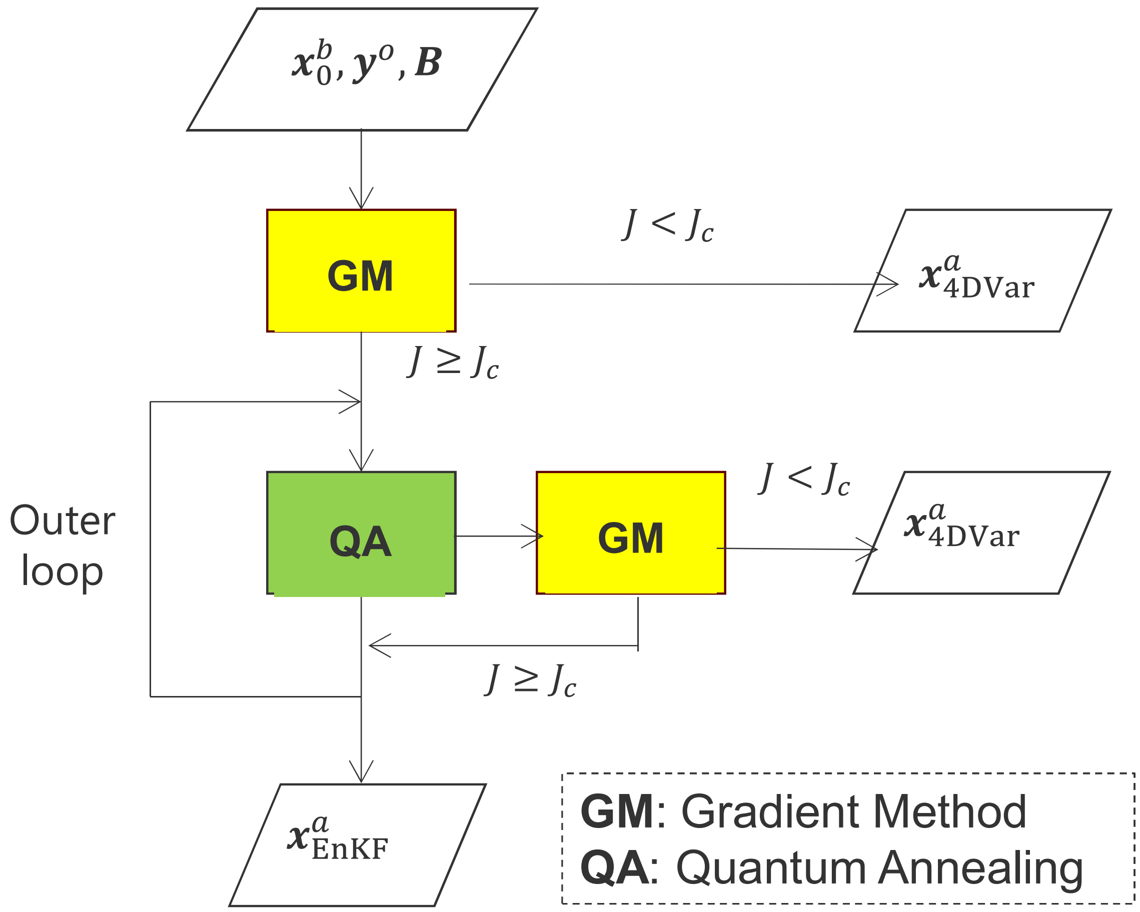
$$\rightarrow \tilde{q} q_3 + \underbrace{\gamma}_{\text{a scalar}} \overbrace{\boxed{(3\tilde{q} + q_1 q_2 - 2q_1\tilde{q} - 2q_2\tilde{q})}}^{E}$$ *a quadratic function*

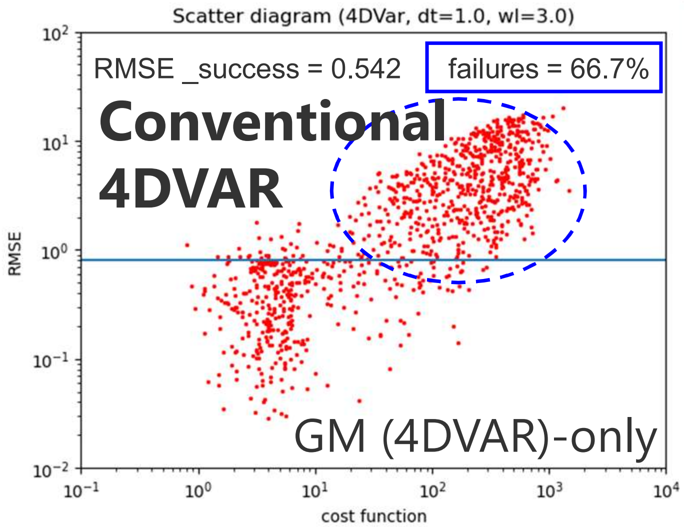
q_1	q_2	$\tilde{q}$	E
0	0	0	0
0	1	0	0
1	0	0	0
1	1	0	1
0	0	1	3
0	1	1	1
1	0	1	1
1	1	1	0

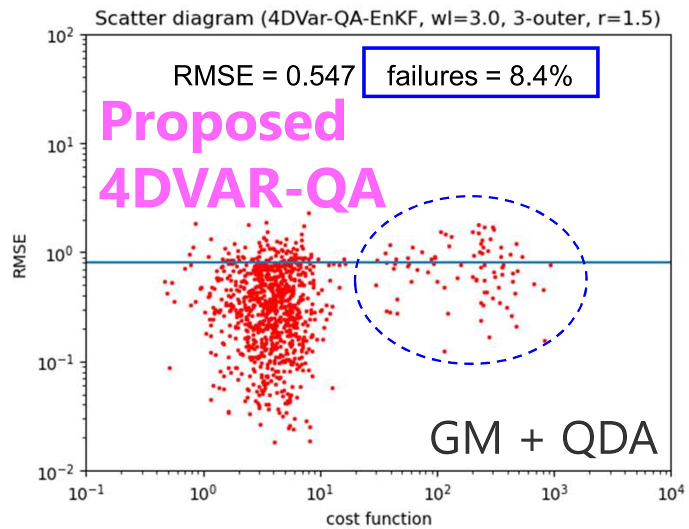
E becomes 0 only when $\tilde{q} = q_1 q_2$
➔ adding this term
imposes $\tilde{q} = q_1 q_2$

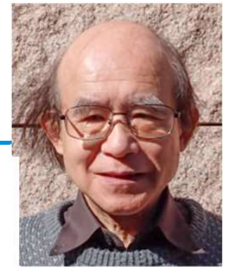
Point:
Any polynomial equations can be converted into QUBO.

4DVAR-QA Experiments w/ Lorenz63 (w/ long window)








Prof. Tsuyuki

DA window length = 3.0

Tsuyuki et al. (in prep.)

Summary

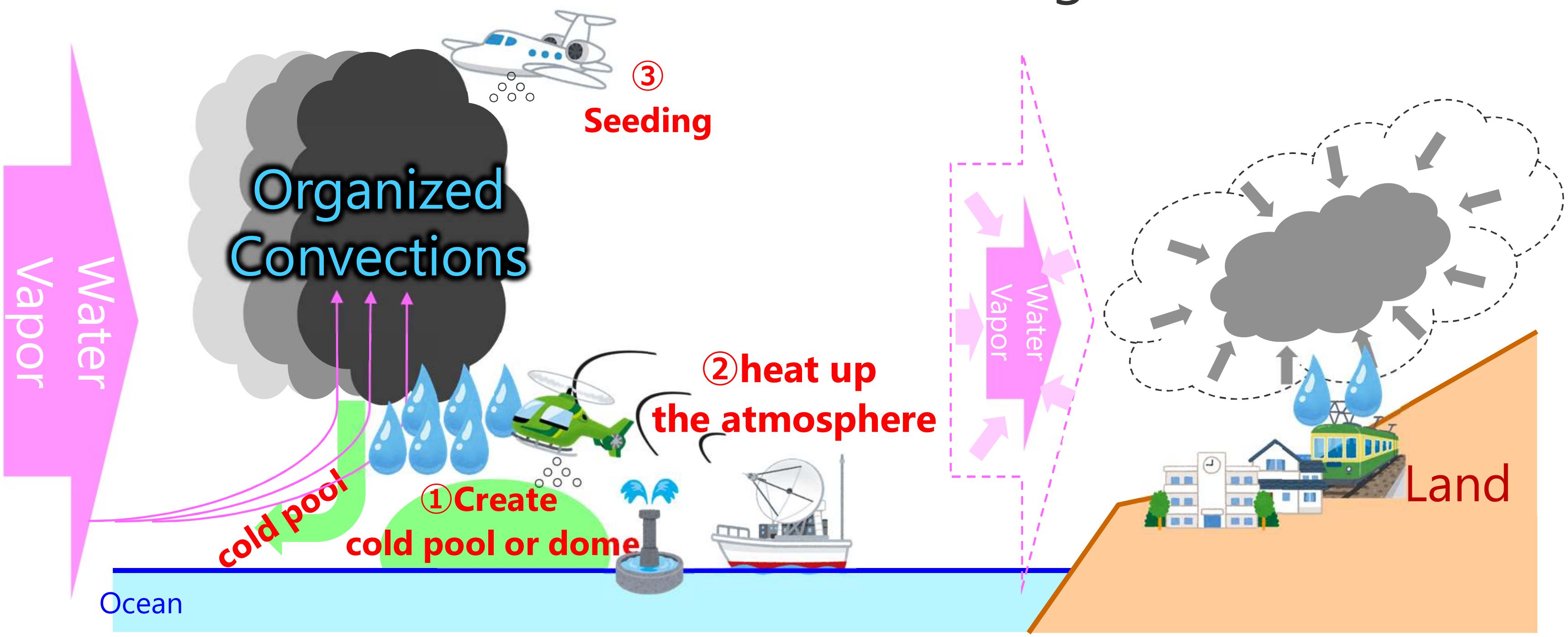
Contents of my talk

- (1) Our R & D Strategy for mitigating heavy-rain-induced disasters
- (2) Coupling AI-based weather prediction model w/ ensemble DA
- (3) Identifying disastrous/preferable trajectories from ensemble FCSTs
- (4) Quantum data assimilation for accelerating optimizations
- (5) Take Home Message

Summary and Future Plans

- We started the new weather control project for heavy rains.
- Our project needs to be enhanced for
  - engineering studies for interventions
  - international collaborations for accelerating R & D

We are happy to take any suggestions!



Take Home Message

The DA community has realized generalized synchronization via data assimilation.
Weather control tries to realize another synchronization for the atmosphere as physical reservoir.
Weather control is a data assimilation problem, and can deepen DA research too.

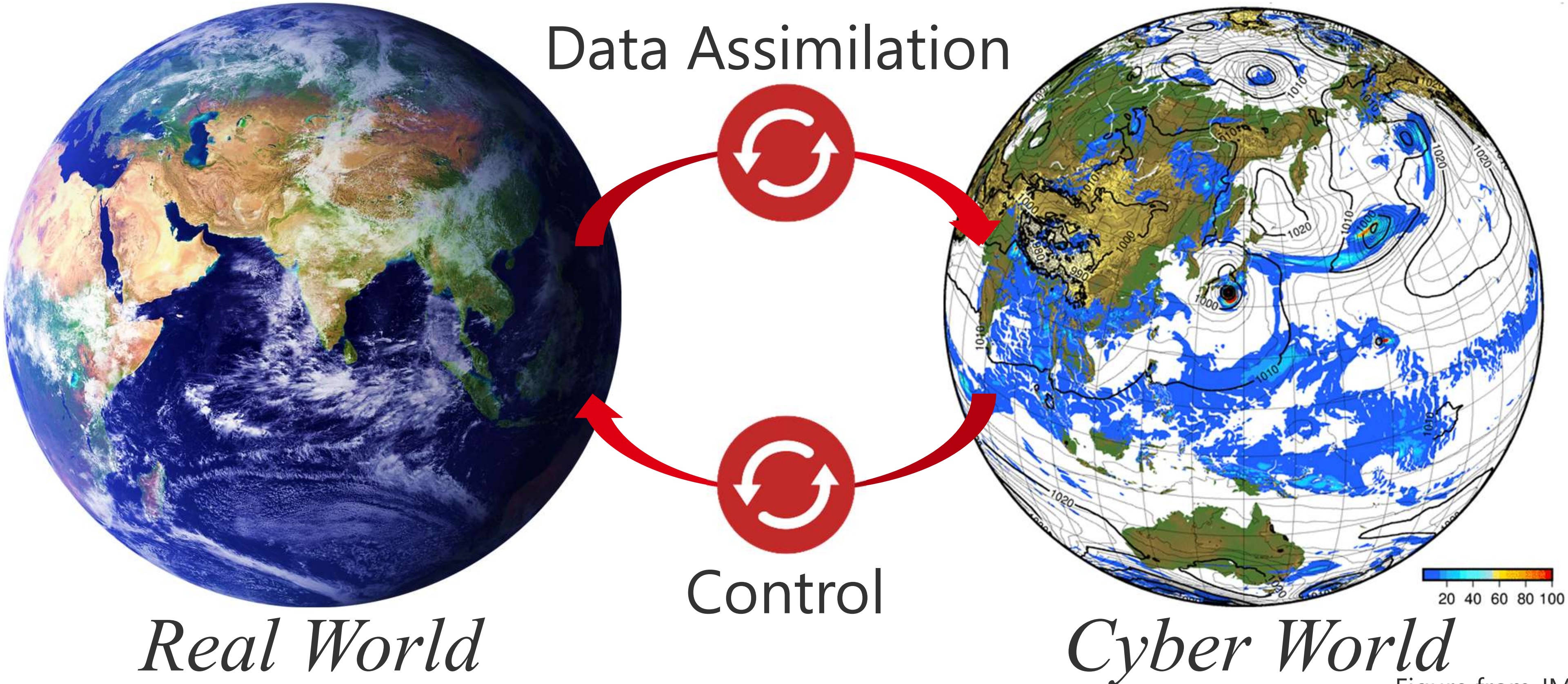


Figure from JMA website