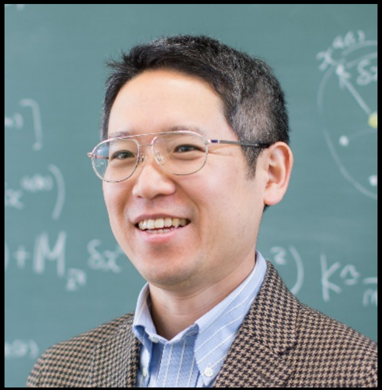
Big Data Assimilation

A New Science for Weather Prediction and Beyond



Takemasa Miyoshi

Ph.D. (Meteorology)
Data Assimilation Scientist

Data Assimilation Research Team

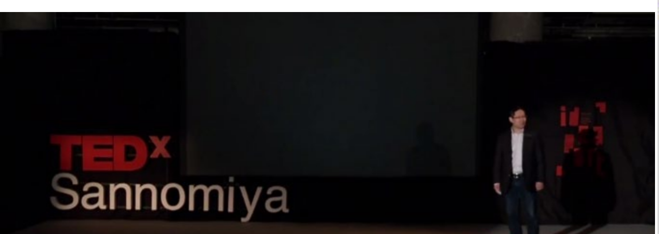
RIKEN

Data Assimilation Team

Who am I?

http://data-assimilation.riken.jp/~miyoshi/

B.S. from Kyoto U
↓
JMA administration (2y)
↓
JMA NWP (1.25y)
↓
UMD (2y, M.S. and Ph.D.)
↓
JMA NWP (3.5y)
↓
UMD (4y)
↓
RIKEN (6y+)



http://tedxsannomiya.com/en/speakers/takemasa-miyoshi/

Takemasa Miyoshi, Ph.D.

Team Leader
Data Assimilation Research Team
RIKEN Center for Computational Science

Deputy Director
RIKEN interdisciplinary Theoretical and Mathematical Sciences (iTHEMS) Program

Chief Scientist
Prediction Science Laboratory
RIKEN Cluster for Pioneering Research

Visiting Professor
University of Maryland, College Park

Affiliate Professor
Graduate School of Science, Kyoto University

Visiting Principal Scientist
Application Laboratory, JAMSTEC

Research Counselor
Servicio Meteorológico Nacional (National Meteorological Service), Argentina

Education

- **2005** Ph.D. in Meteorology, University of Maryland, College Park, Maryland, USA (Dissertation PDF)
- **2004** M.S. in Meteorology, University of Maryland, College Park, Maryland, USA (Scholarly Paper PDF)
- **2000** B.S. in Physics, Faculty of Science, Kyoto University, Kyoto, Japan

RIKEN Center for Computational Science (R-CCS)

Japan's flagship institute for computational science

Missions:

1) Development & operation of the Japanese flagship supercomputer

2) Center of Excellence for research on computational science

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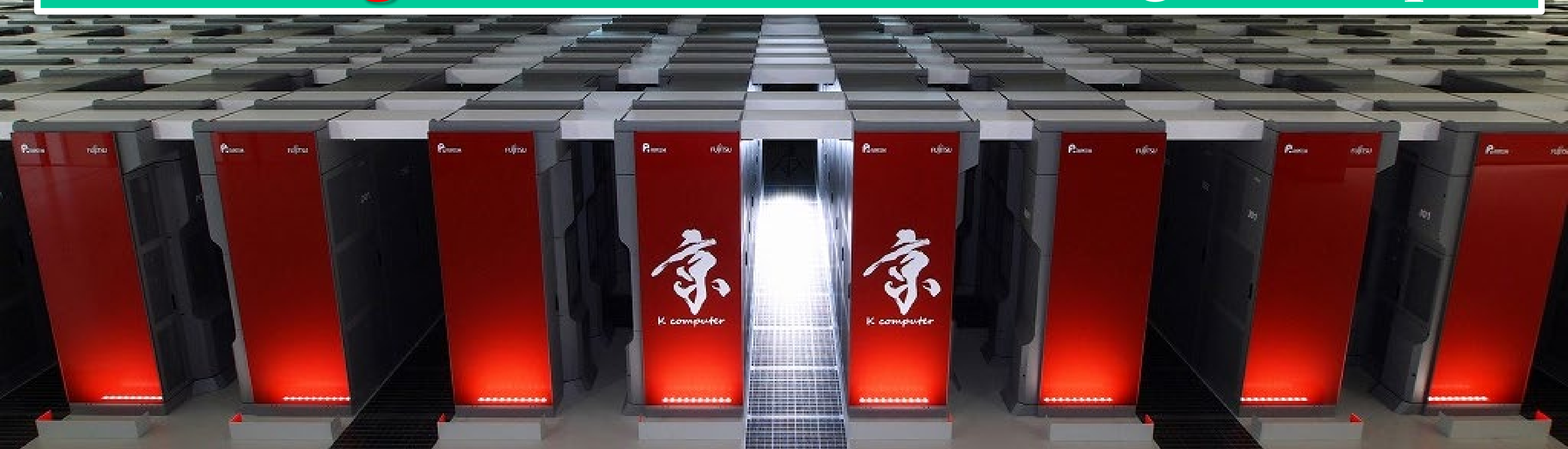
New **"Fugaku" or "富岳"** is being developed



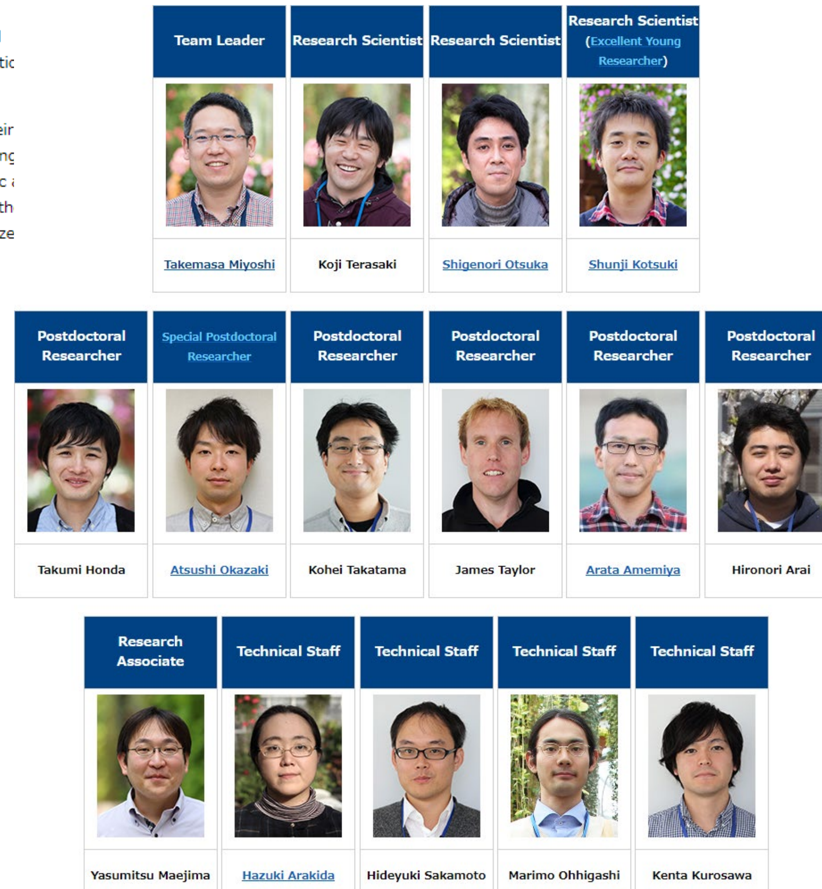
http://www.data-assimilation.riken.jp/

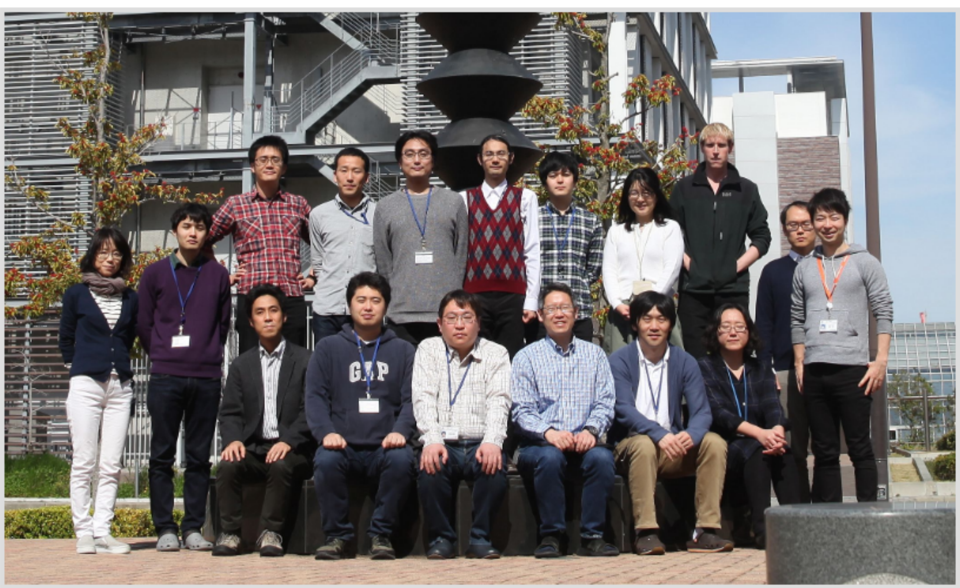
Data Assimilation Research Team

Data Assimilation Research Team was launched in October, 2012, in RIKEN Advanced Institute for Computational Science (AICS), conveniently located in the beautiful and historic city of Kobe. RIKEN is known as the flagship research institution in Japan. On April 1, 2018, RIKEN AICS was renamed RIKEN Center for Computational Science (R-CCS). R-CCS is operating the world's leading K computer, and also has a strong Research Division. R-CCS takes the lead in advancing the computational science and aims to be an international center of excellence for computational science in collaboration with a wide range of research organizations. R-CCS integrates the computer science and computational science to conduct most advanced resear and development of a wide range of applied scientific computation, as well as of high performance computing technologies.

Data assimilation is a cross-disciplinary science to synergize numerical simulations and observational data, using statistical methods and applied mathematics. As computers become more powerful and enable more precise simulations, it will become more important to compare the simulatic with actual observations.

Data Assimilation Research Team ("DA team") performs cutting-edge research and development on advanced data assimilation methodsand their applications, aiming at integrating computer simulations and observational data in the wisest way. Particularly, the DA team will tackle challenginc problems of developing efficient and accurate data assimilation systems for high-dimensional simulations with large amount of data. The specific include 1) research on parallel-efficient algorithms for data assimilation with the super-parallel K computer, 2) research on data assimilation meth and applications by taking advantage of the world-leading K computer, and 3) development of most advanced data assimilation software optimize the K computer.





April 5, 2019 at R-CCS


京
K computer
京
K computer
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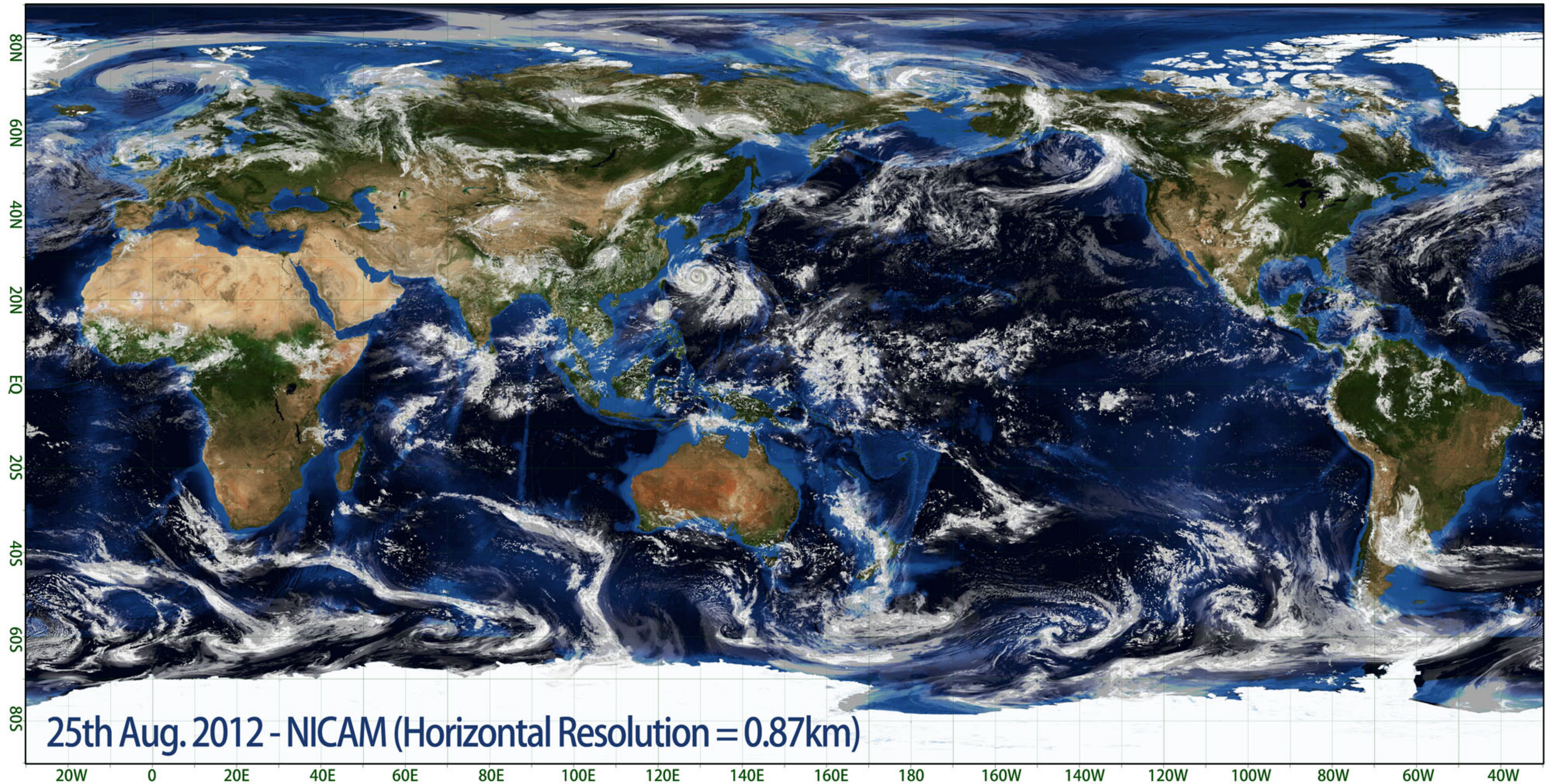
TimeStep: 7

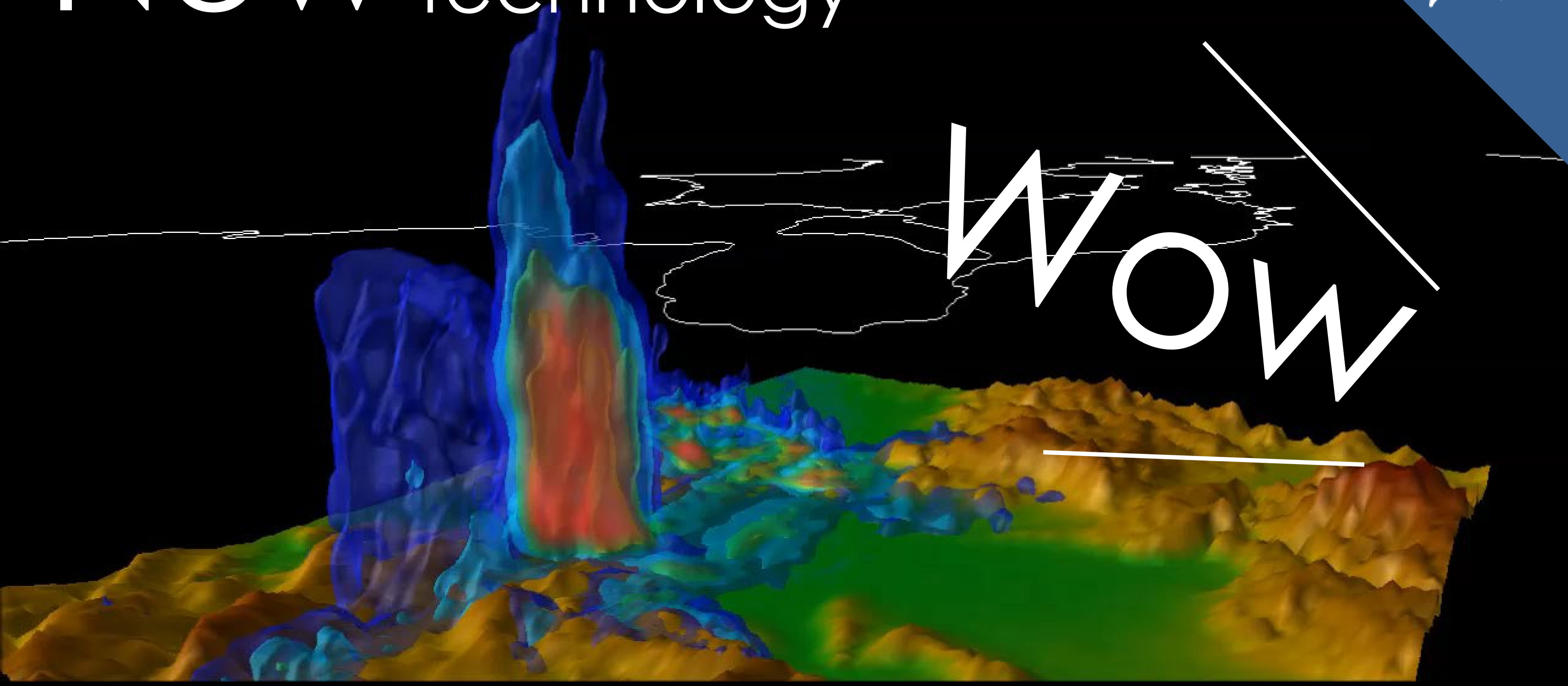
cf. TEDxSannomiya
http://tedxsannomiya.com/speakers/takemasa-miyoshi/

Global 870-m simulation (*Miyamoto et al. 2013*)

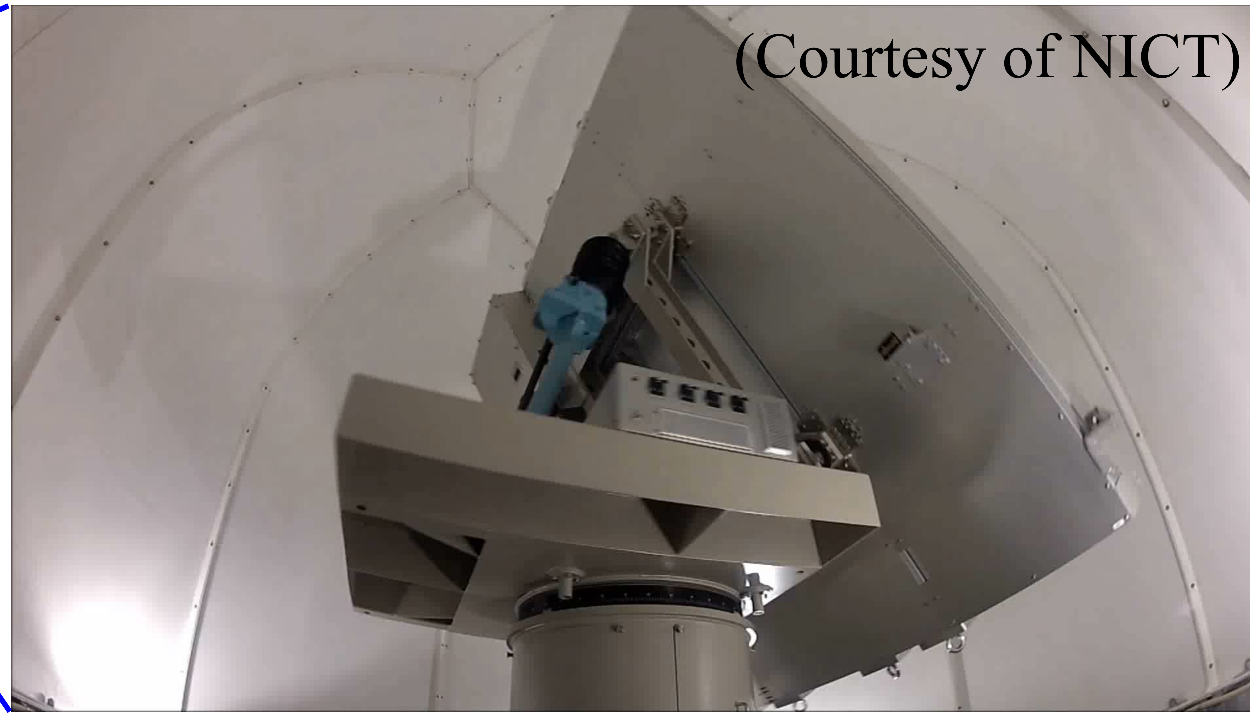


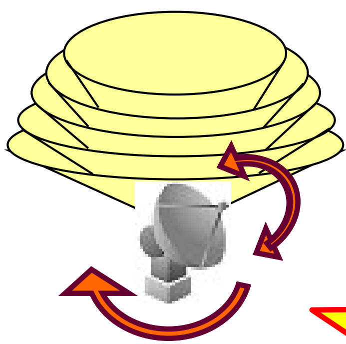
Visualized by Ryuji Yoshida

New radar technology



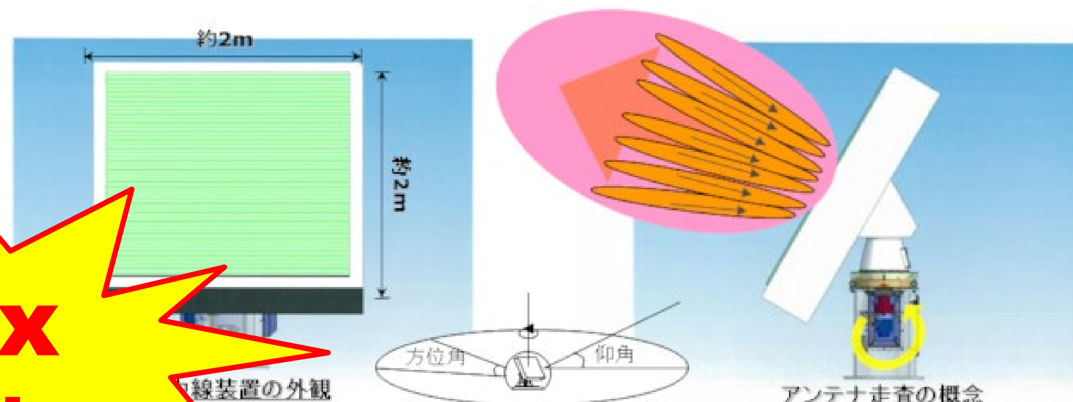
Phased Array Weather Radar (PAWR)



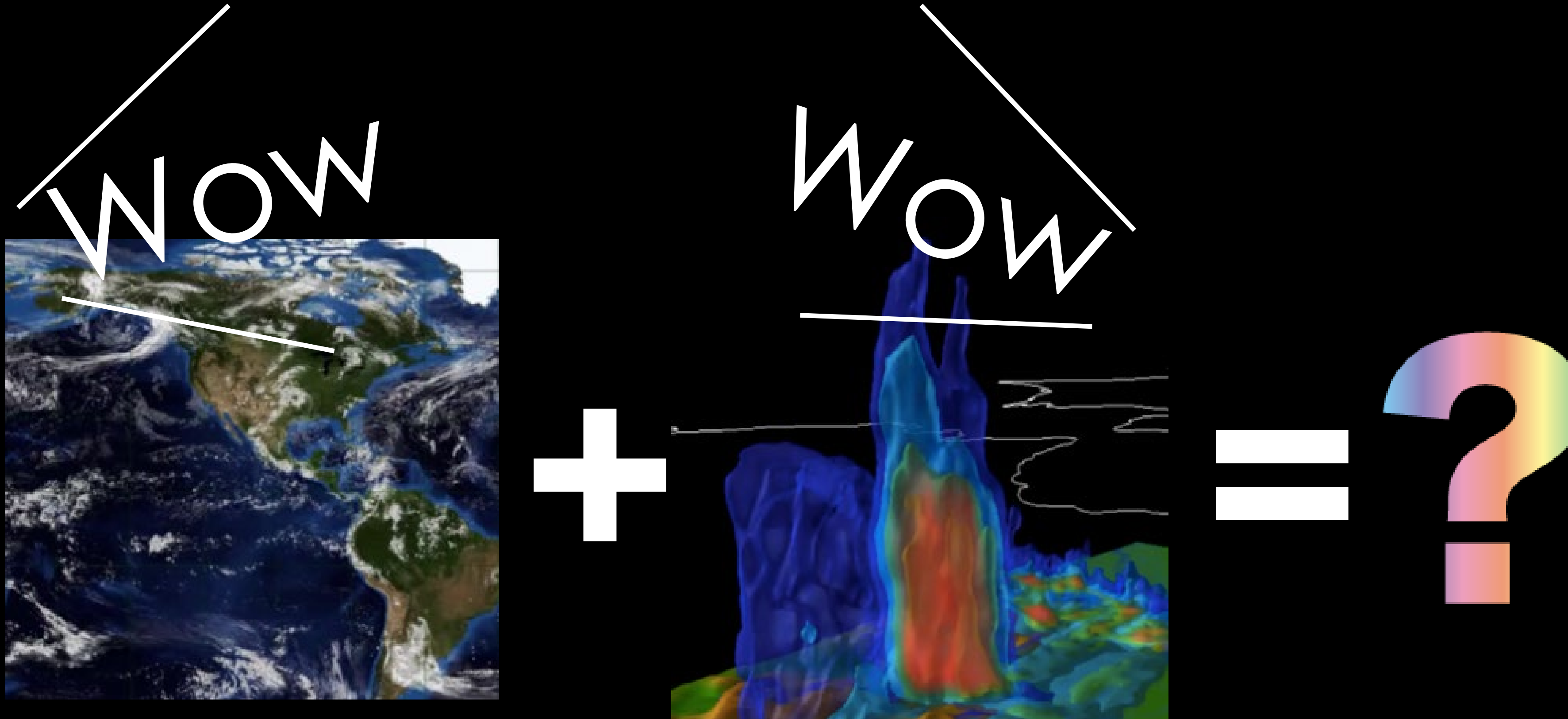


3-dim measurement using a parabolic antenna (150 m, 15 EL angles in 5 min)

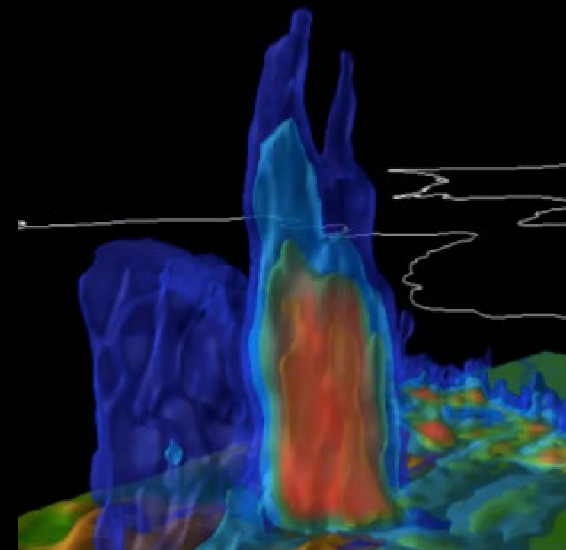
100x data size



3-dim measurement using a phased array antenna (100 m, 100 EL angles in 30 sec)

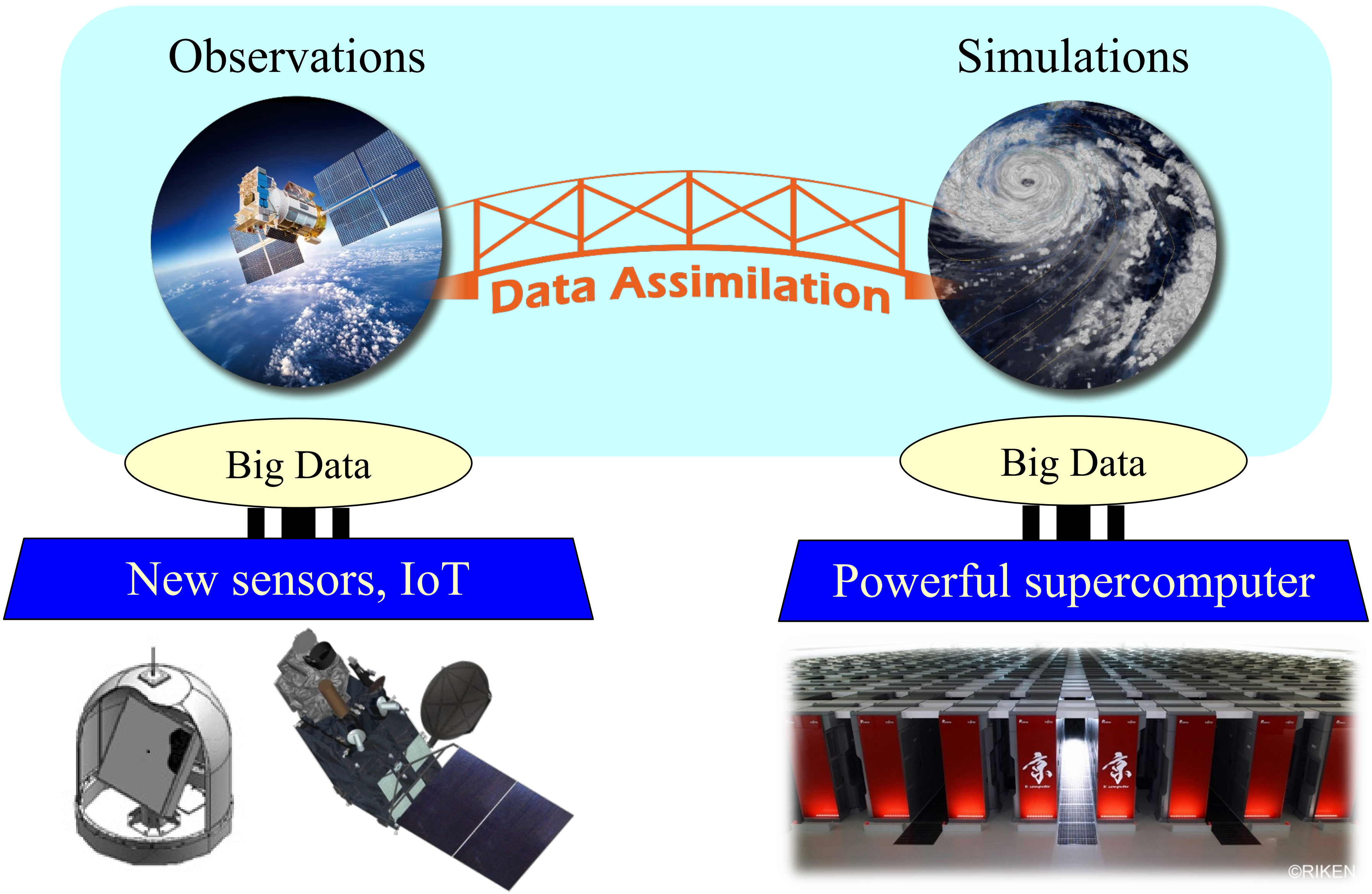

Wow
Wow

Data Assimilation



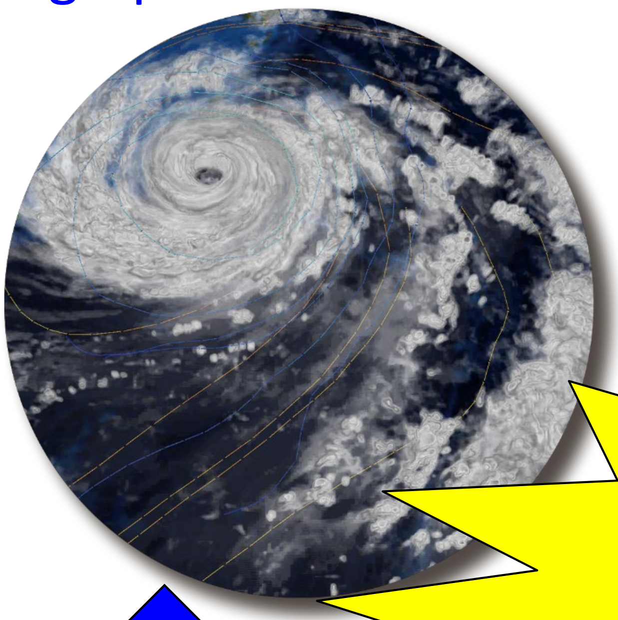
= ~~Sudden~~ heavy rain

Big Data Assimilation



Pioneering "Big Data Assimilation" Era

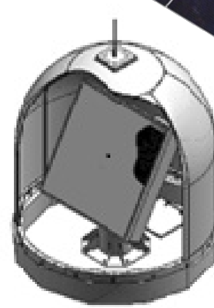
High-precision Simulations

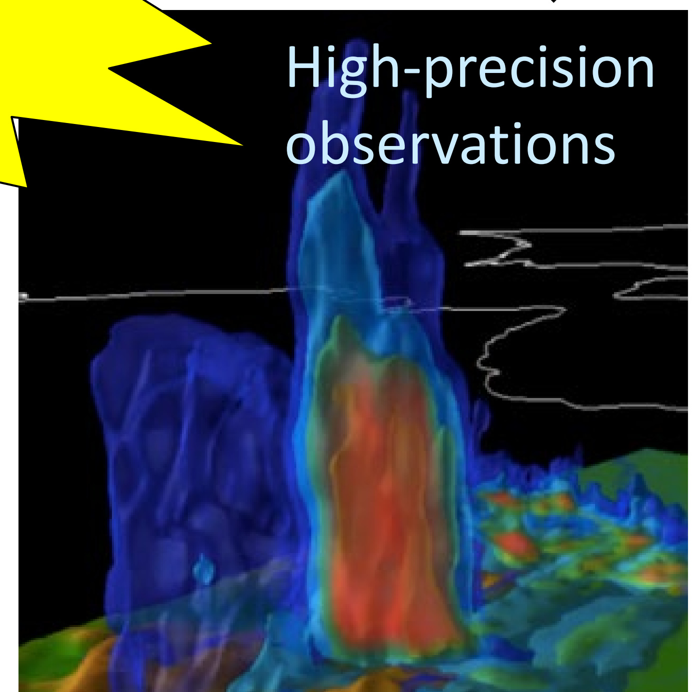


国立研究開発法人
科学技術振興機構
Japan Science and Technology Agency
CREST

Future-generation technologies available 10 years in advance

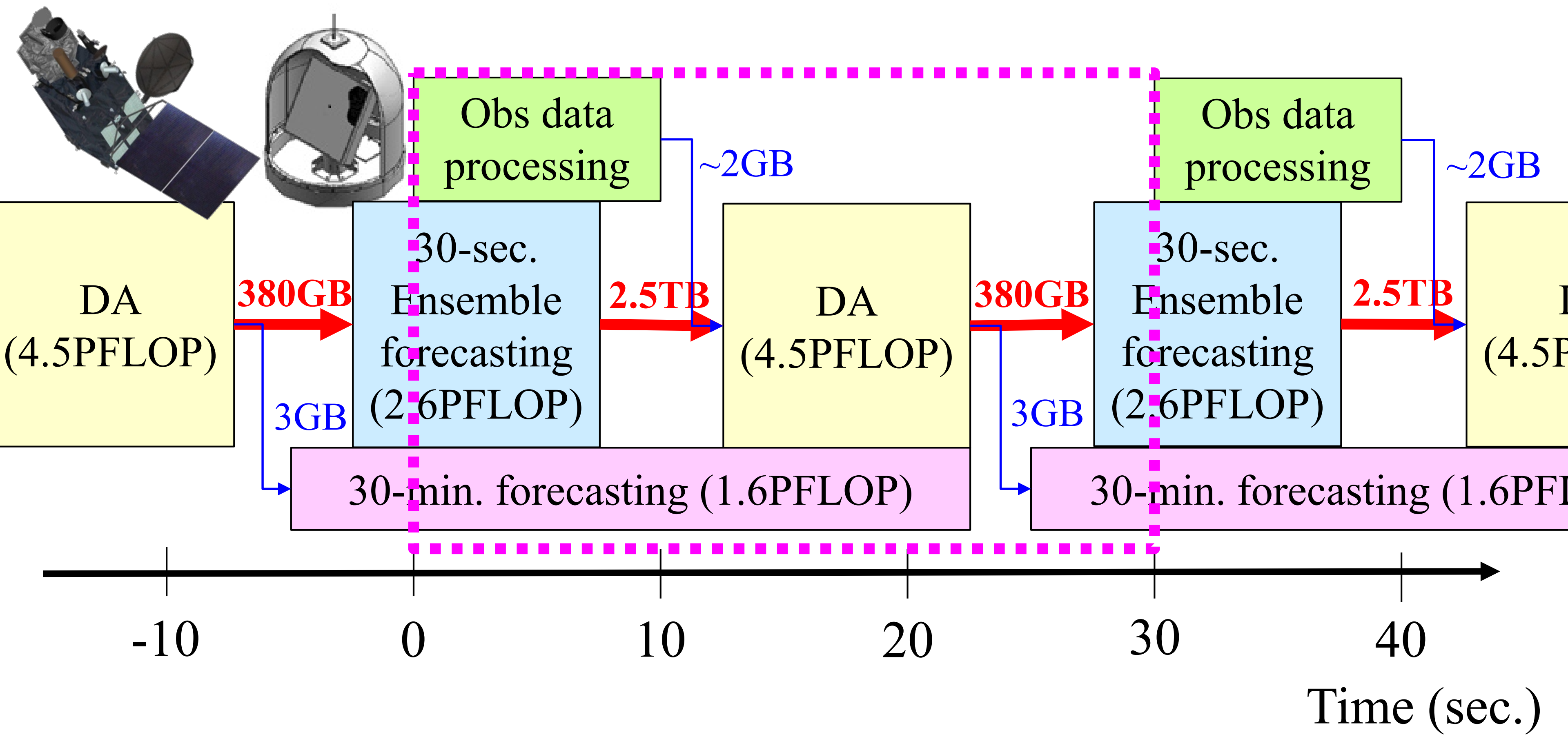
BDA
BIG DATA ASSIMILATION





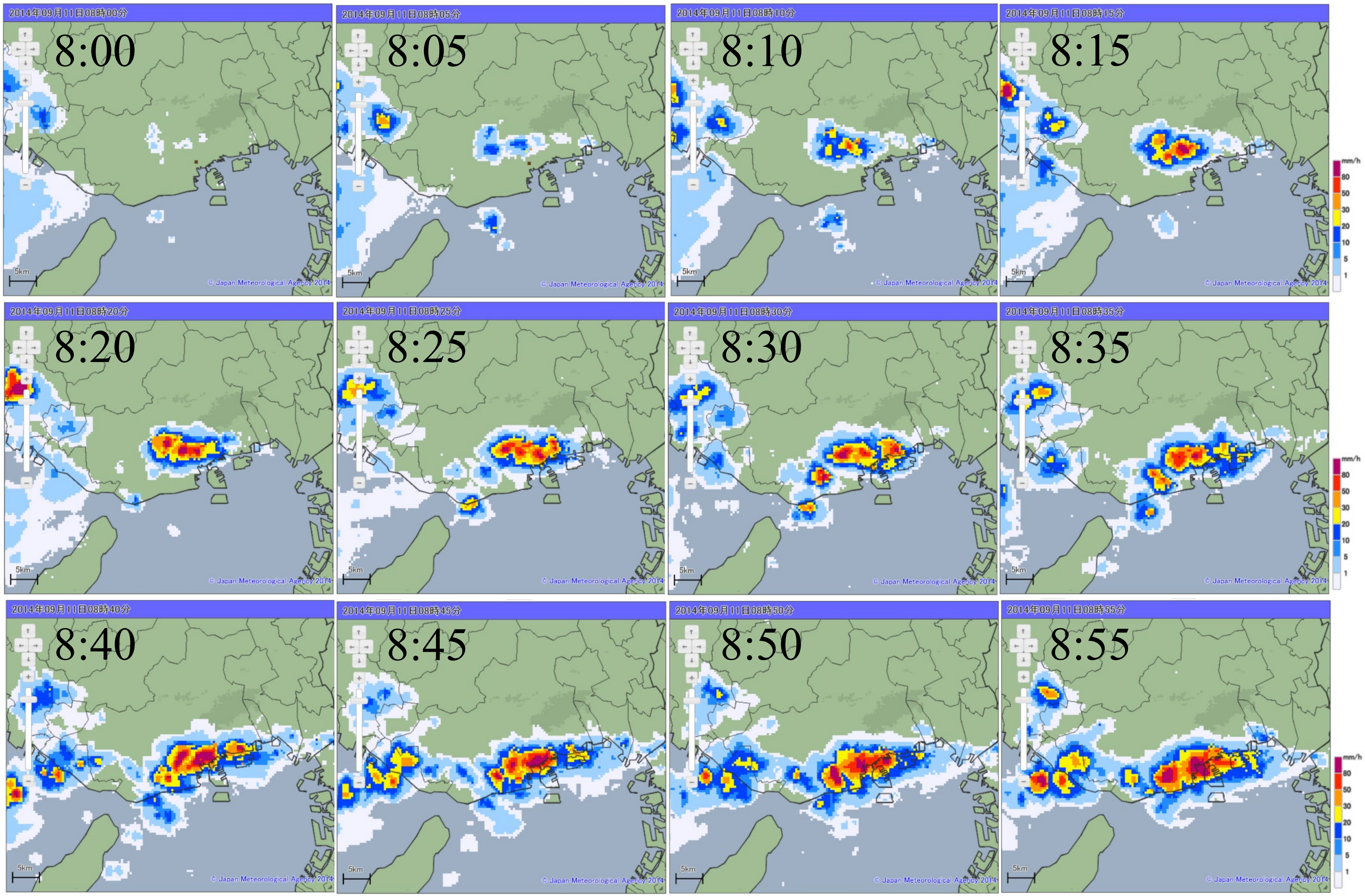
Mutual feedback

Revolutionary super-rapid 30-sec. cycle

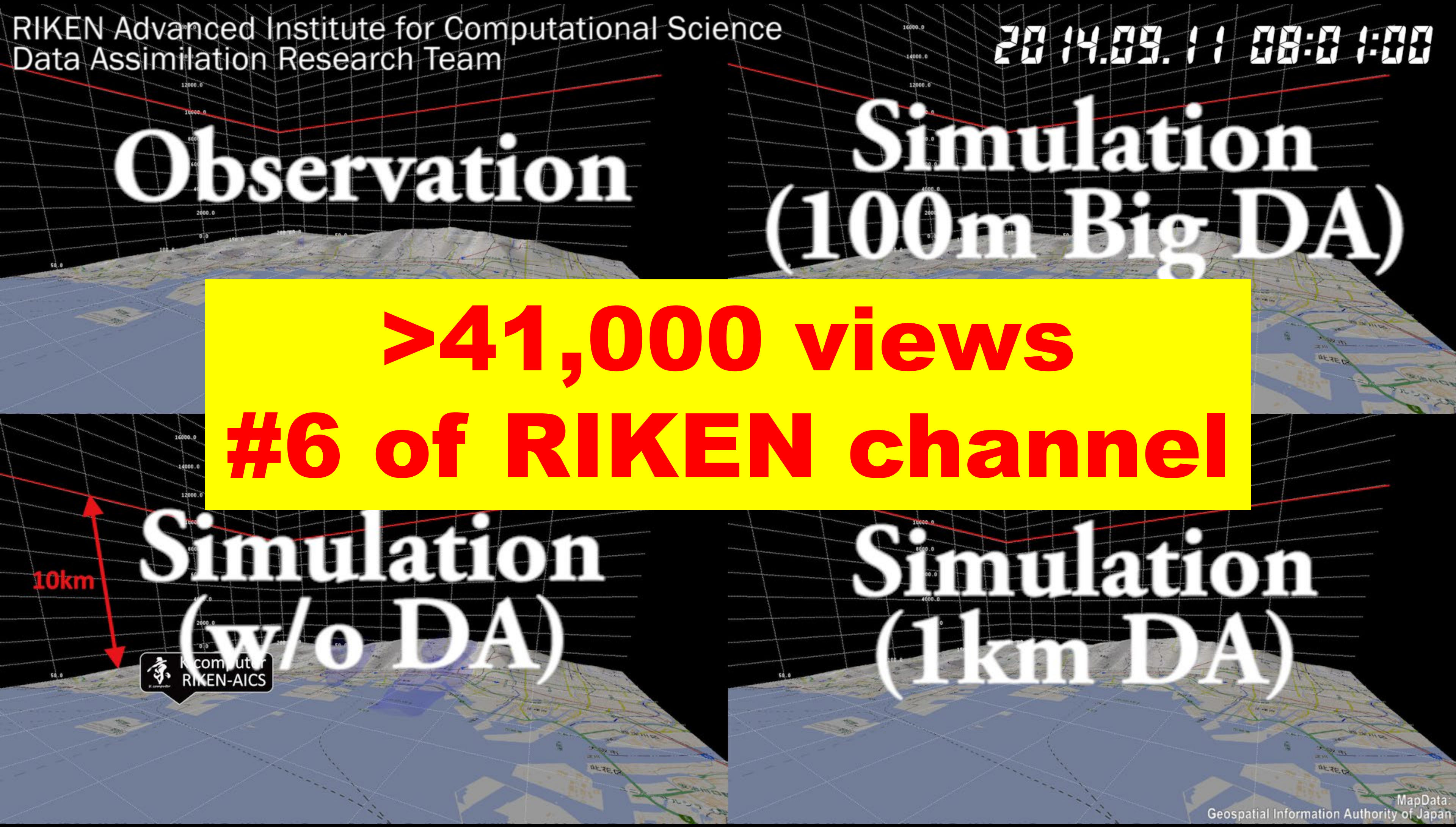


120 times more rapid than hourly update cycles

9/11/2014 morning, sudden rain

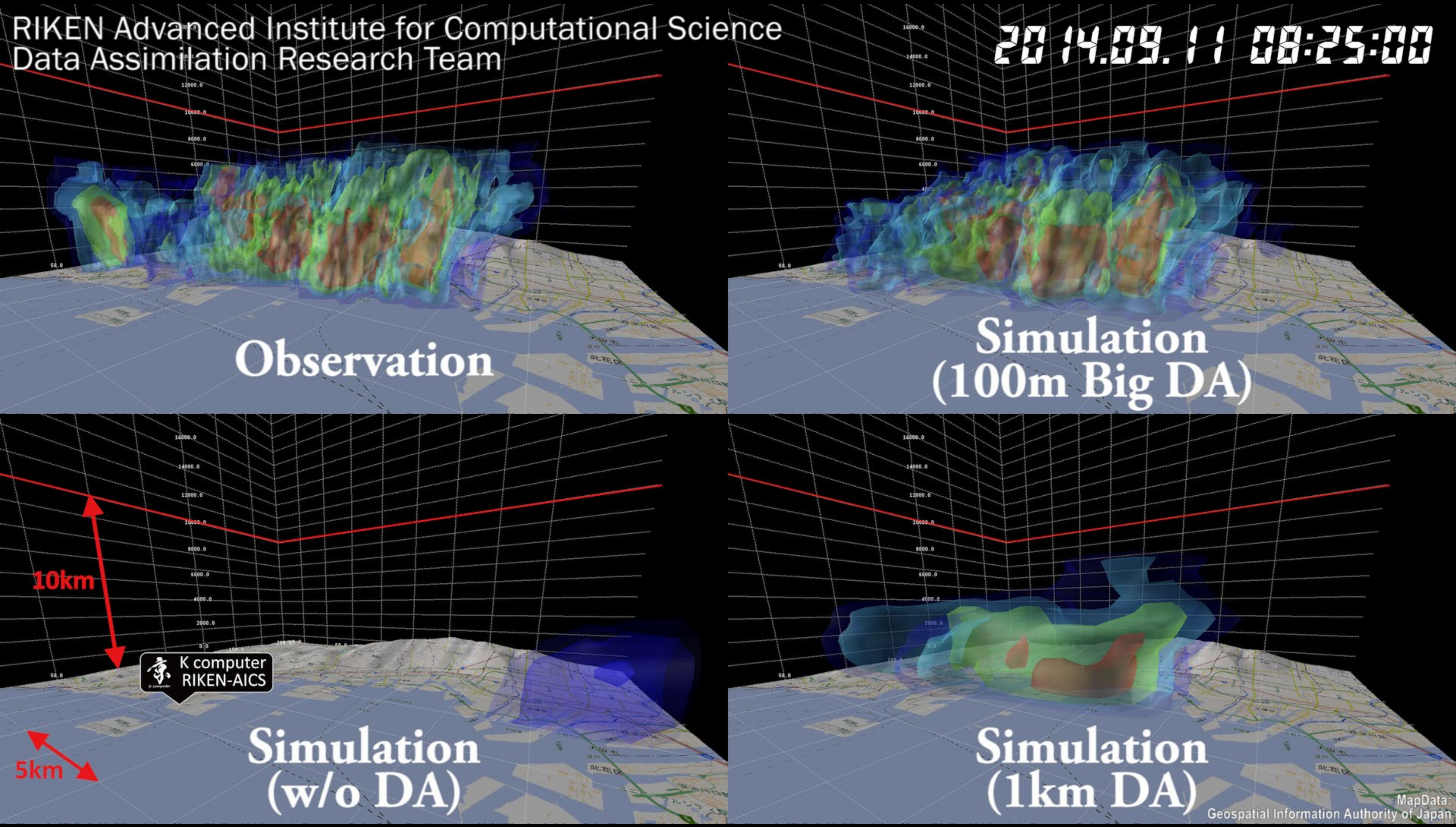


9/11/2014, sudden local rain



>41,000 views
#6 of RIKEN channel

9/11/2014, sudden local rain



January 18, 2018

Himawari-8 data assimilated simulation enables 10-minute updates of rain and flood predictions

Using the power of Japan's K computer, scientists from the RIKEN Advanced Institute for Computational Science and collaborators have shown that incorporating satellite data at frequent intervals—ten minutes in the case of this study—into weather prediction models can significantly improve the rainfall predictions of the models and allow more precise predictions of the rapid development of a typhoon.

Weather prediction models attempt to predict future weather by running simulations based on current conditions taken from various sources of data. However, the inherently complex nature of the systems, coupled with the lack of precision and timeliness of the data, makes it difficult to conduct accurate predictions, especially with weather systems such as sudden precipitation.

As a means to improve models, scientists are using powerful supercomputers to run simulations based on more frequently updated and accurate data. The team led by Takemasa Miyoshi of AICS decided to work with data from Himawari-8, a geostationary satellite that began operating in 2015. Its instruments can scan the entire area it covers every ten minutes in both visible and infrared light, at a resolution of up to 500 meters, and the data is provided to meteorological agencies. Infrared measurements are useful for indirectly gauging rainfall, as they make it possible to see where clouds are located and at what altitude.

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January 18, 2018

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Himawari-8 data assimilated simulation enables 10-minute updates of rain and flood predictions

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Himawari-8: a new generation geostationary meteorological satellite

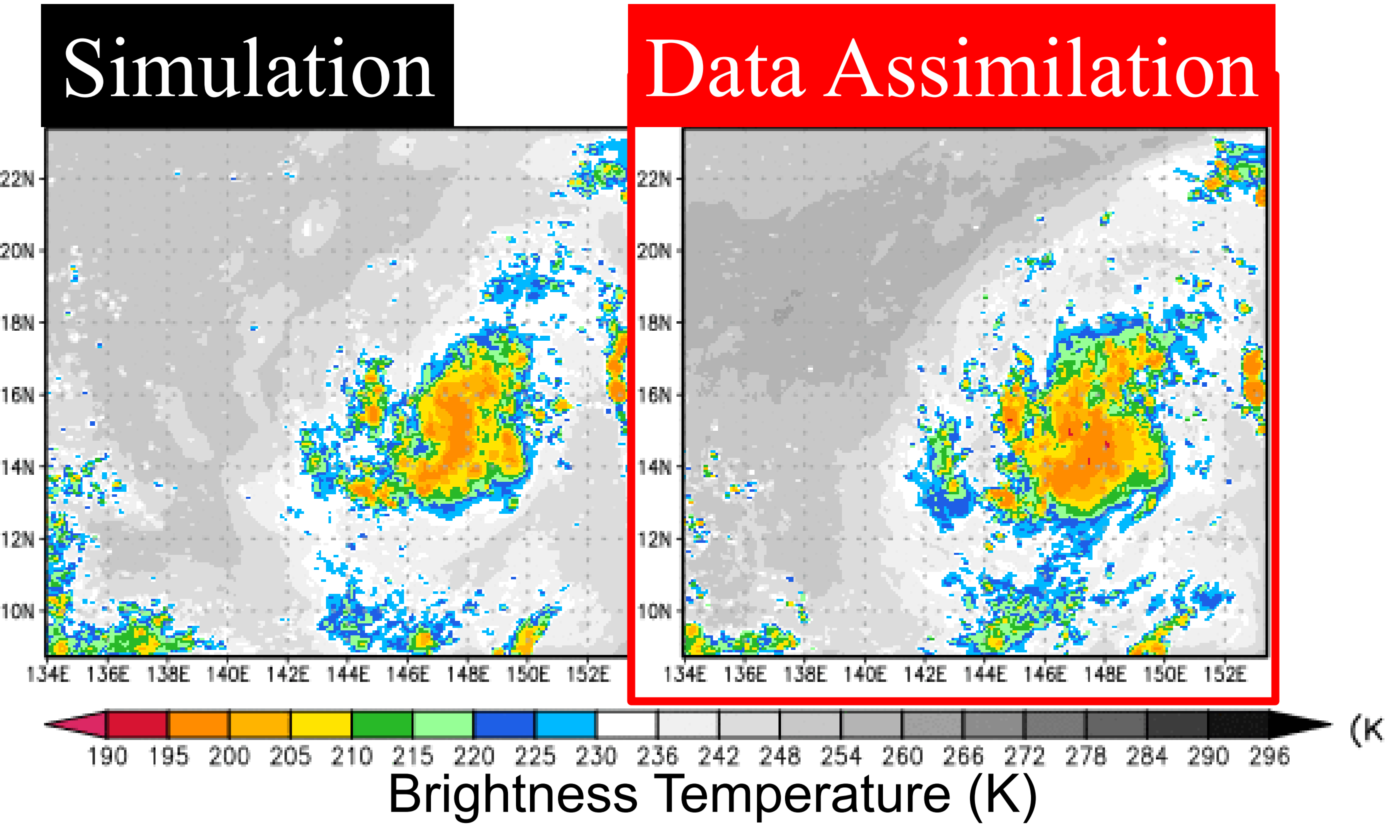
16UTC 2 to 13UTC 3 April 2015
MTSAT-2 (VIS)
Every 1 hour

16UTC 2 to 13UTC 3 April 2015
Himawari-8 (True Color)
Every 10 minutes

(Courtesy of JMA)

Himawari-8 ***"Big Data Assimilation"***

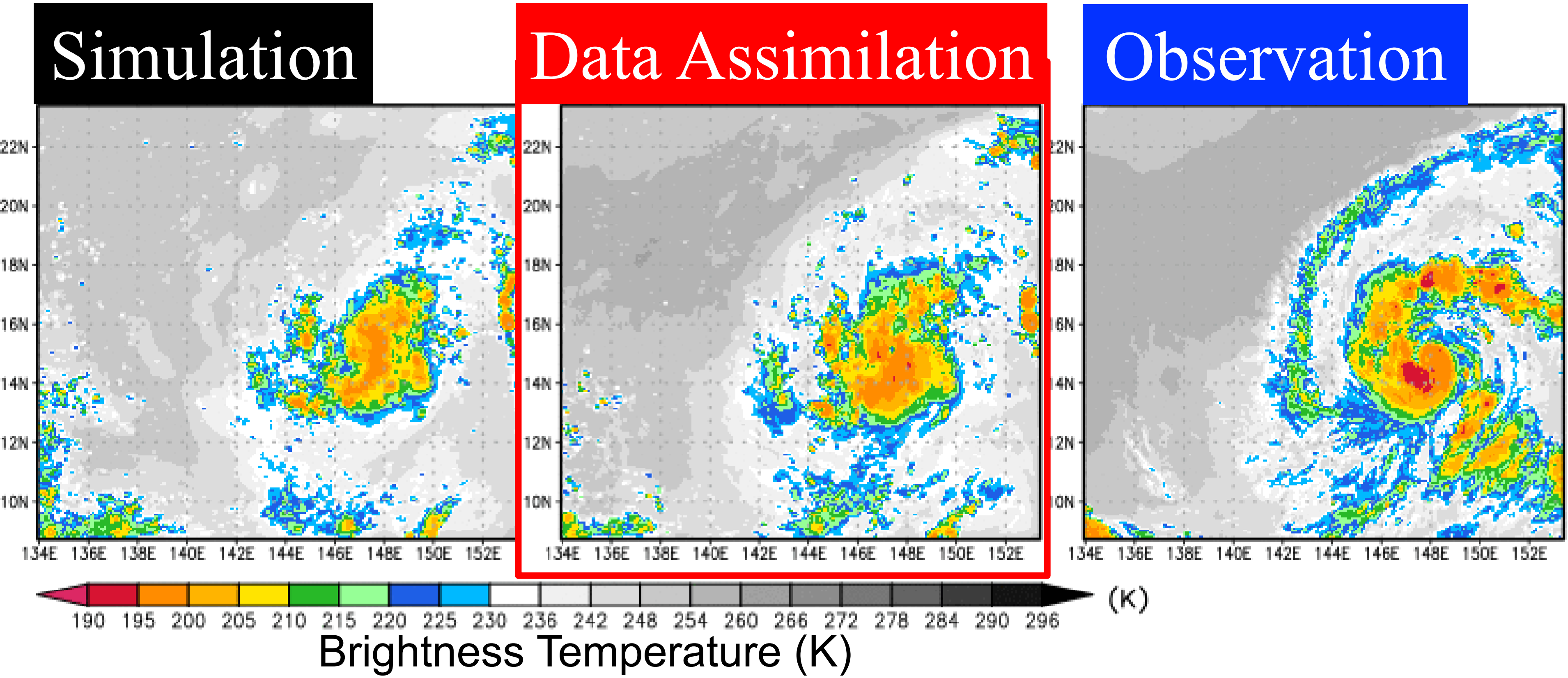
Typhoon Soudelor (2015)



Honda, Miyoshi, et al. (2018)

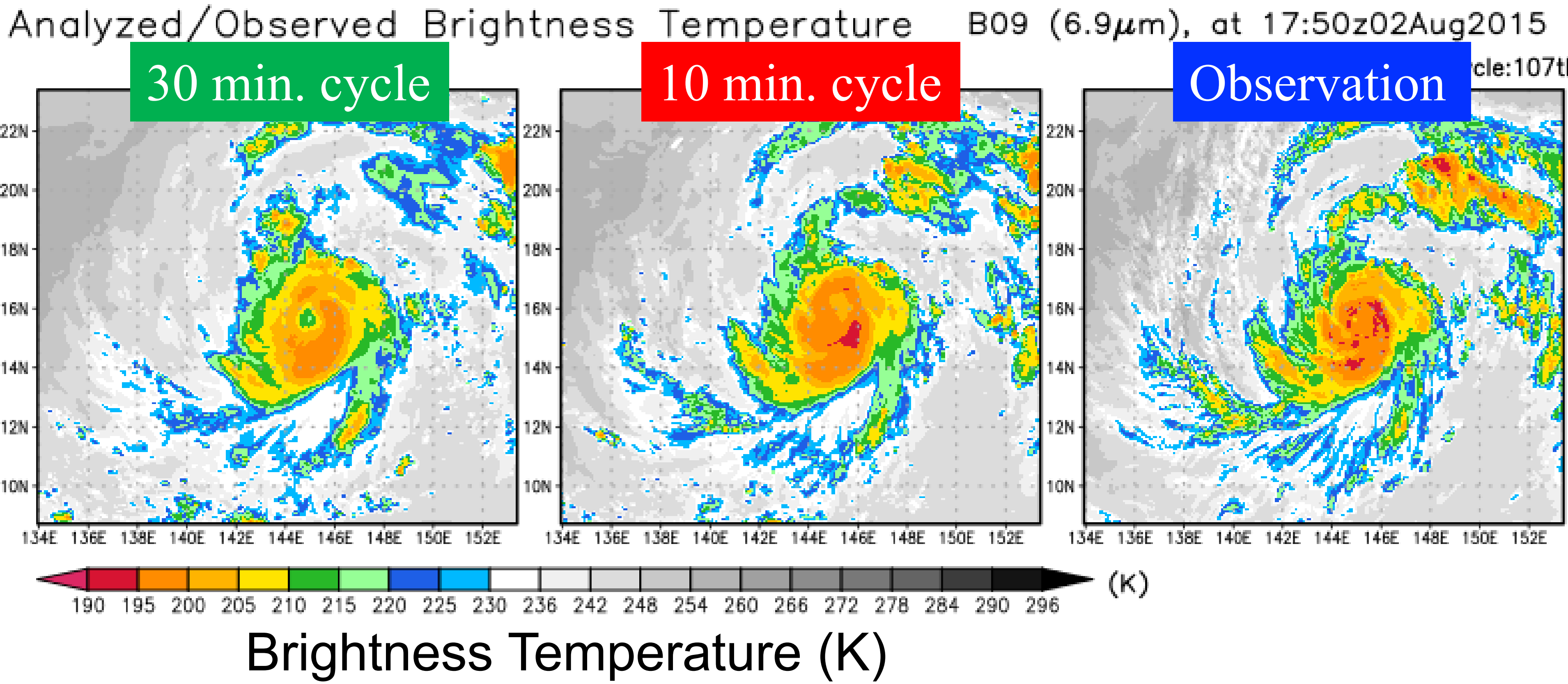
Himawari-8 ***"Big Data Assimilation"***

Typhoon Soudelor (2015)

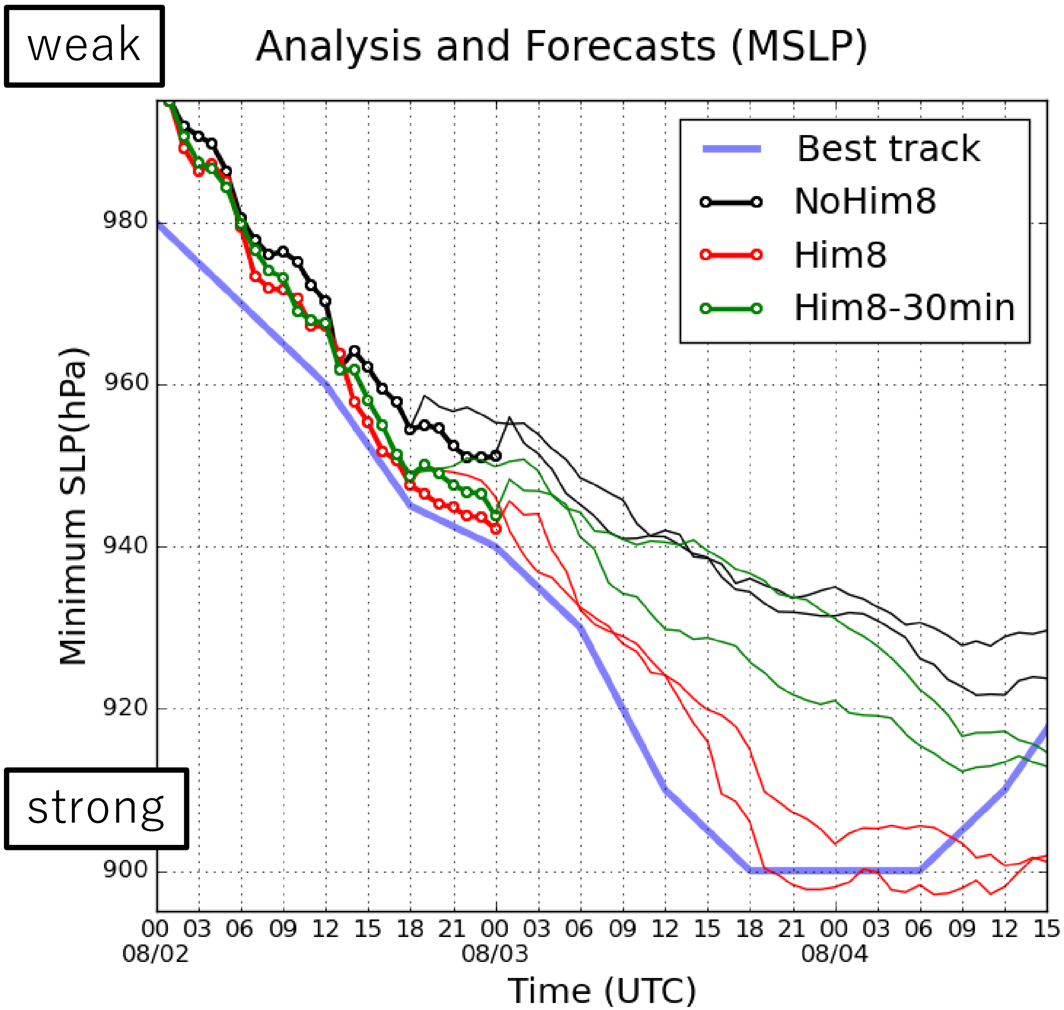


Honda, Miyoshi, et al. (2018)

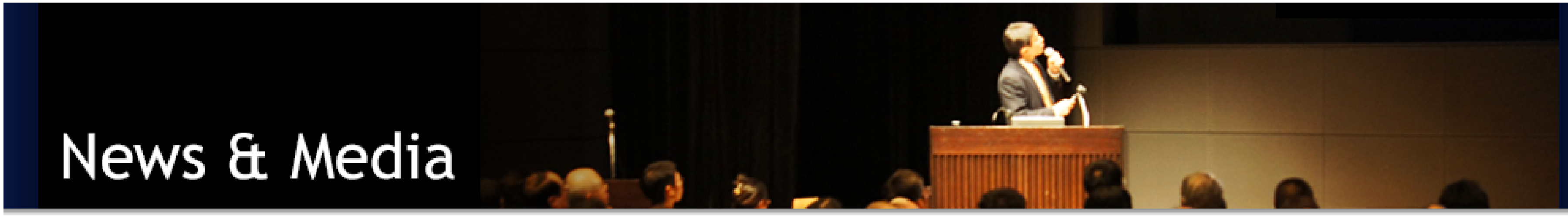
Every 10 min. vs. 30 min. DA



Intensity forecast (30 min. vs. 10 min.)



Assimilating every 10-min. is essential.



Press Release

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July 23, 2014

Like 59 Tweet 21

K computer runs largest ever ensemble simulation of global weather

Ensemble forecasting is a key part of weather forecasting today. Computers typically run multiple simulations, called ensembles, using slightly different initial conditions or assumptions, and then analyze them together to try to improve forecasts. Now, in research published in *Geophysical Research Letters*, using Japan's flagship 10-petaFLOPS K computer, researchers from the RIKEN Advanced Institute for Computational Science (AICS) have succeeded in running 10,240 parallel simulations of global weather, the largest number ever performed, using data assimilation to reduce the range of uncertainties.

The assimilation of the 10,240 ensemble data sets was made possible by a cross-disciplinary collaboration of data assimilation experts and eigenvalue solver scientists at RIKEN AICS. The "Local Ensemble Transform Kalman Filter" (LETKF), an already efficient system, was further improved by a factor of eight using the "EigenExa" high-performance eigenvalue solver software, making possible a three-week computation of data from the 10,240 ensembles for simulated global weather. By analyzing the 10,240 equally probable estimates of atmospheric states, the team discovered that faraway observations, even going beyond 10,000 kilometers in distance, may have an immediate impact on eventual state of the estimation. This finding suggests the need for further research on advanced methods that can make better use of faraway observations, as this could potentially lead to an improvement of weather forecasts.

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Press Release

July 23, 2014

Like 59 Tweet 21

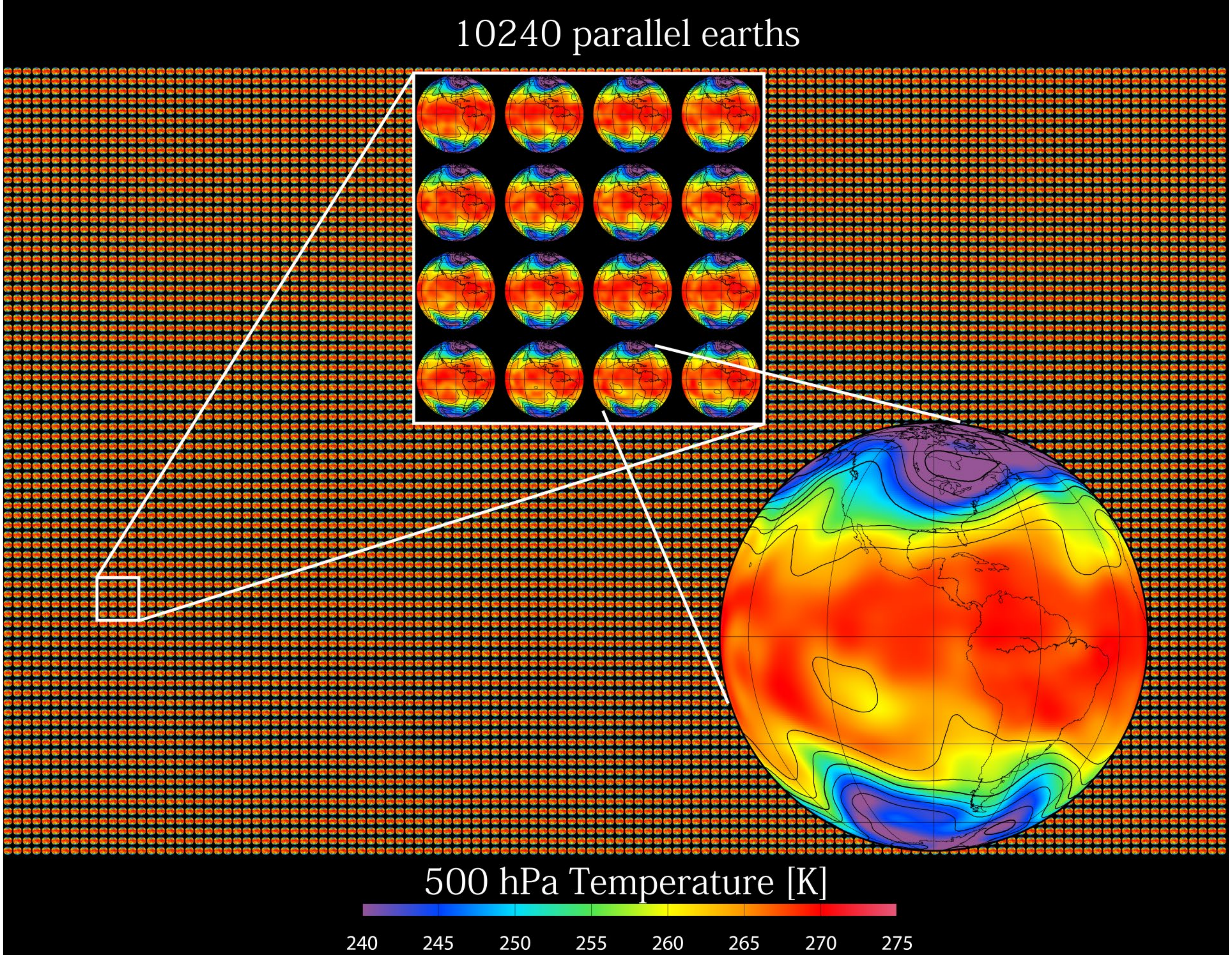
K computer runs largest ever ensemble simulation of global weather

A simulated study using the T30/L7 SPEEDY AGCM

(Miyoshi, Kondo, Imamura 2014)

Ensemble forecasti
called ensembles,
try to improve fore
10-petaFLOPS K co
have succeeded in
using data assimila

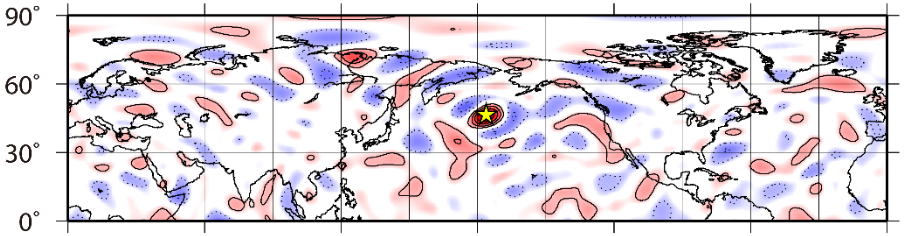
The assimilation of the 10,240 ensemble data sets was made possible by a cross-disciplinary collaboration of data assimilation experts and eigenvalue solver scientists at RIKEN AICS. The "Local Ensemble Transform Kalman Filter" (LETKF), an already efficient system, was further improved by a factor of eight using the "EigenExa" high-performance eigenvalue solver software, making possible a three-week computation of data from the 10,240 ensembles for simulated global weather. By analyzing the 10,240 equally probable estimates of atmospheric states, the team discovered that faraway observations, even going beyond 10,000 kilometers in distance, may have an immediate impact on eventual state of the estimation. This finding suggests the need for further research on advanced methods that can make better use of faraway observations, as this could potentially lead to an improvement of weather forecasts.

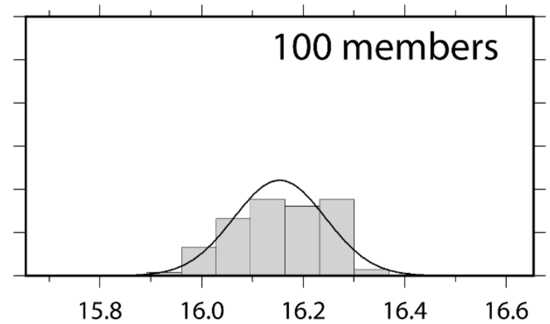

10240 parallel earths
500 hPa Temperature [K]
240
245
250
255
260
265
270
275

Advantage of large ensemble

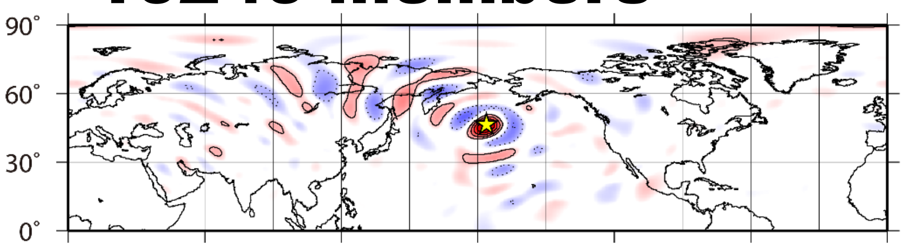
(Miyoshi, Kondo, Imamura 2014)

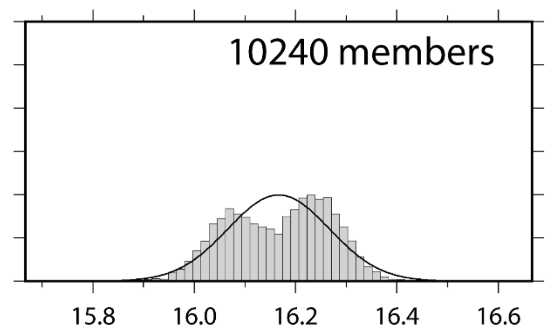
100 members





10240 members

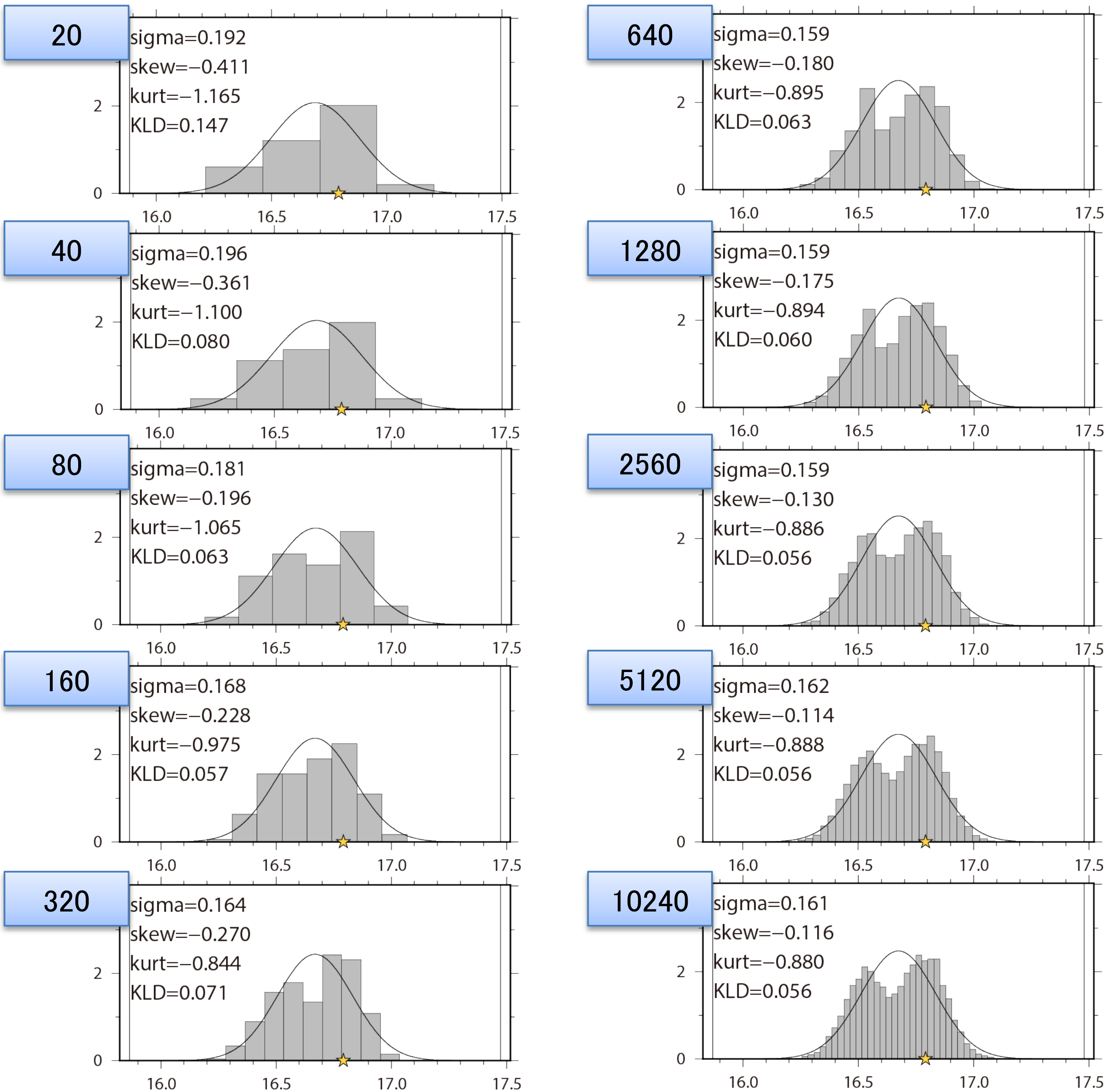




Sampling noise reduced

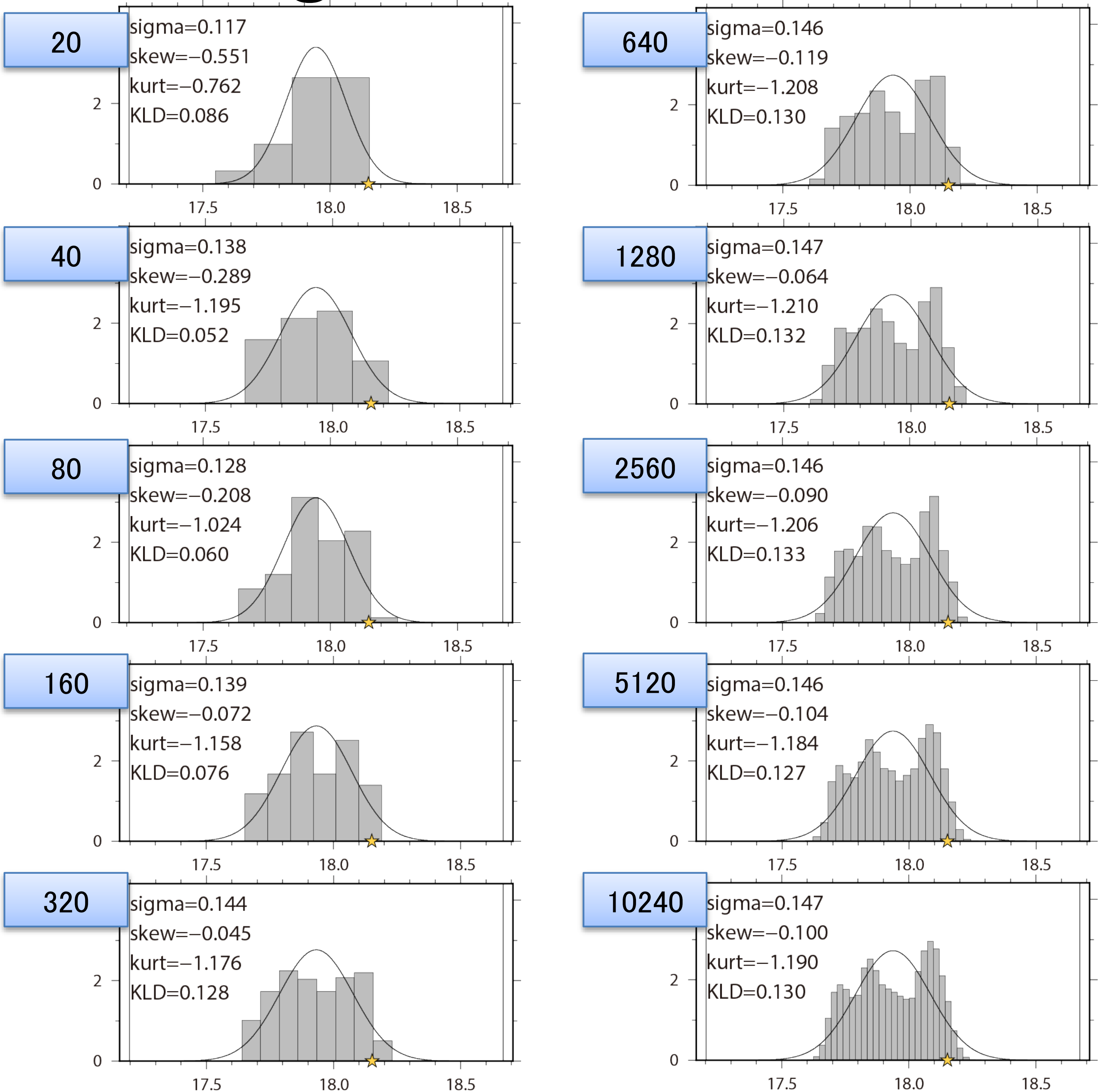
High-precision probabilistic representation

Histogram, Q, lev=1, 1982/02/01 06Z



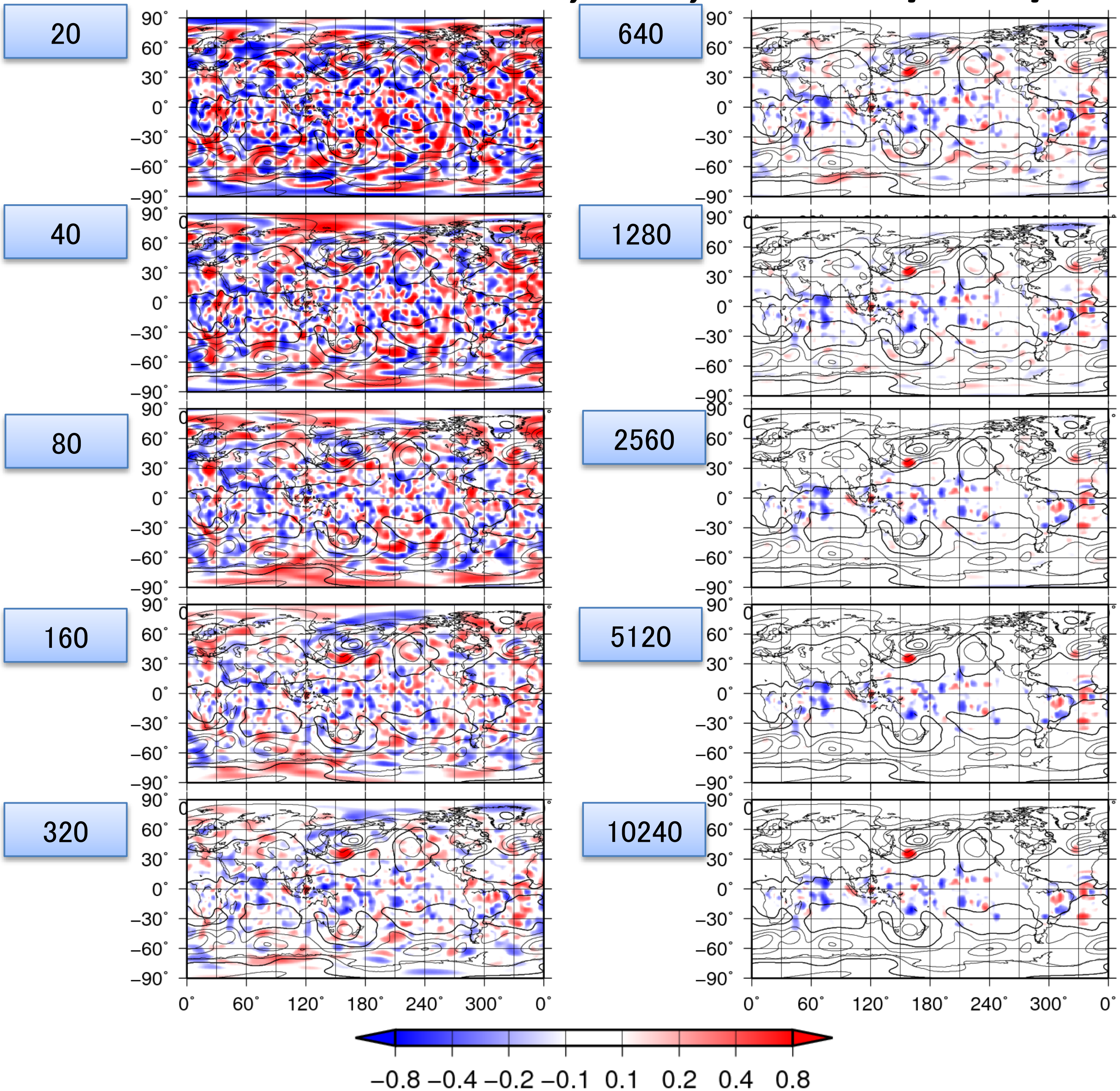
1.856N, 120.000E

Histogram, Q, lev=1, 1982/02/01 06Z

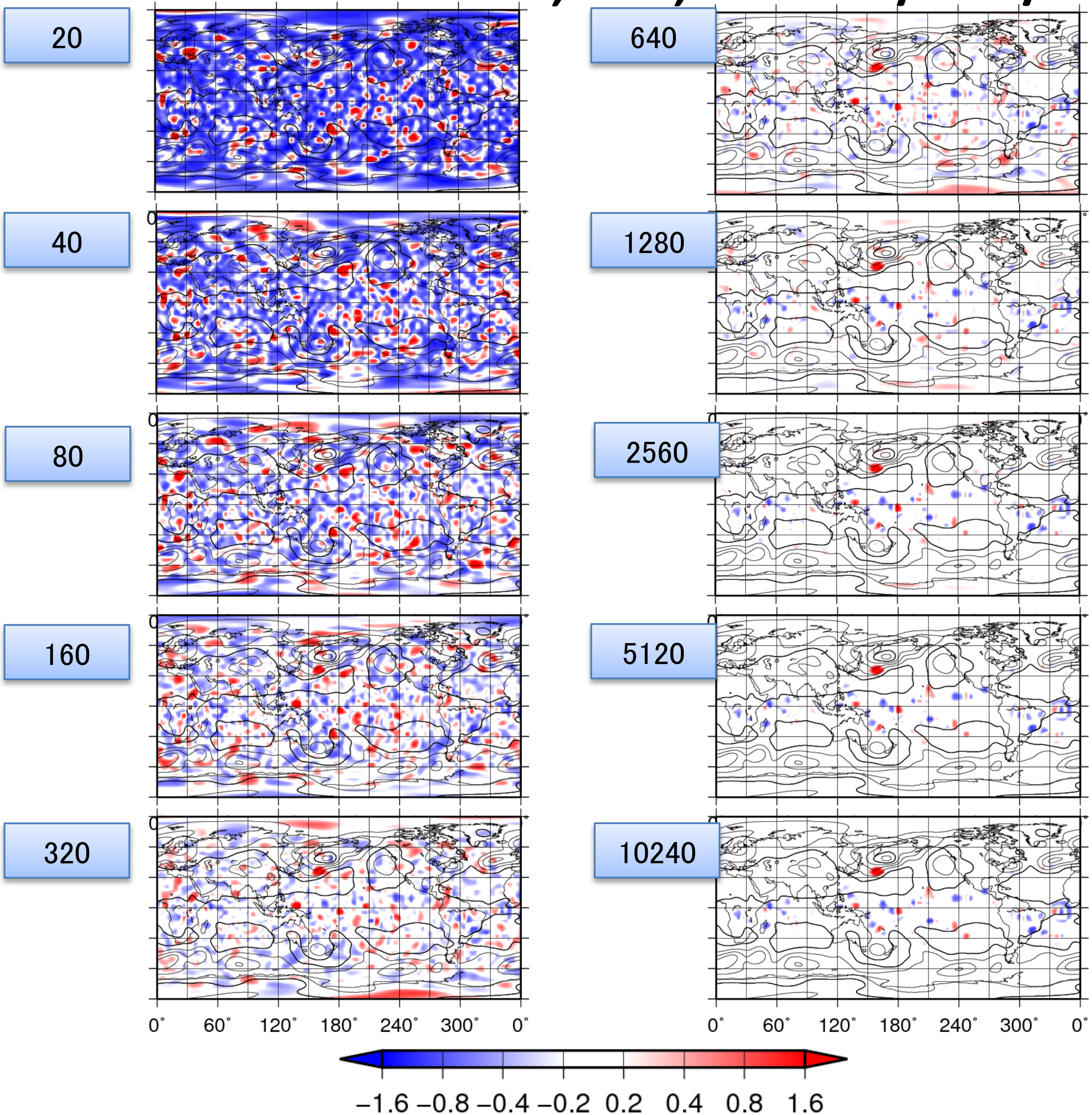


1.856N, 176.25E

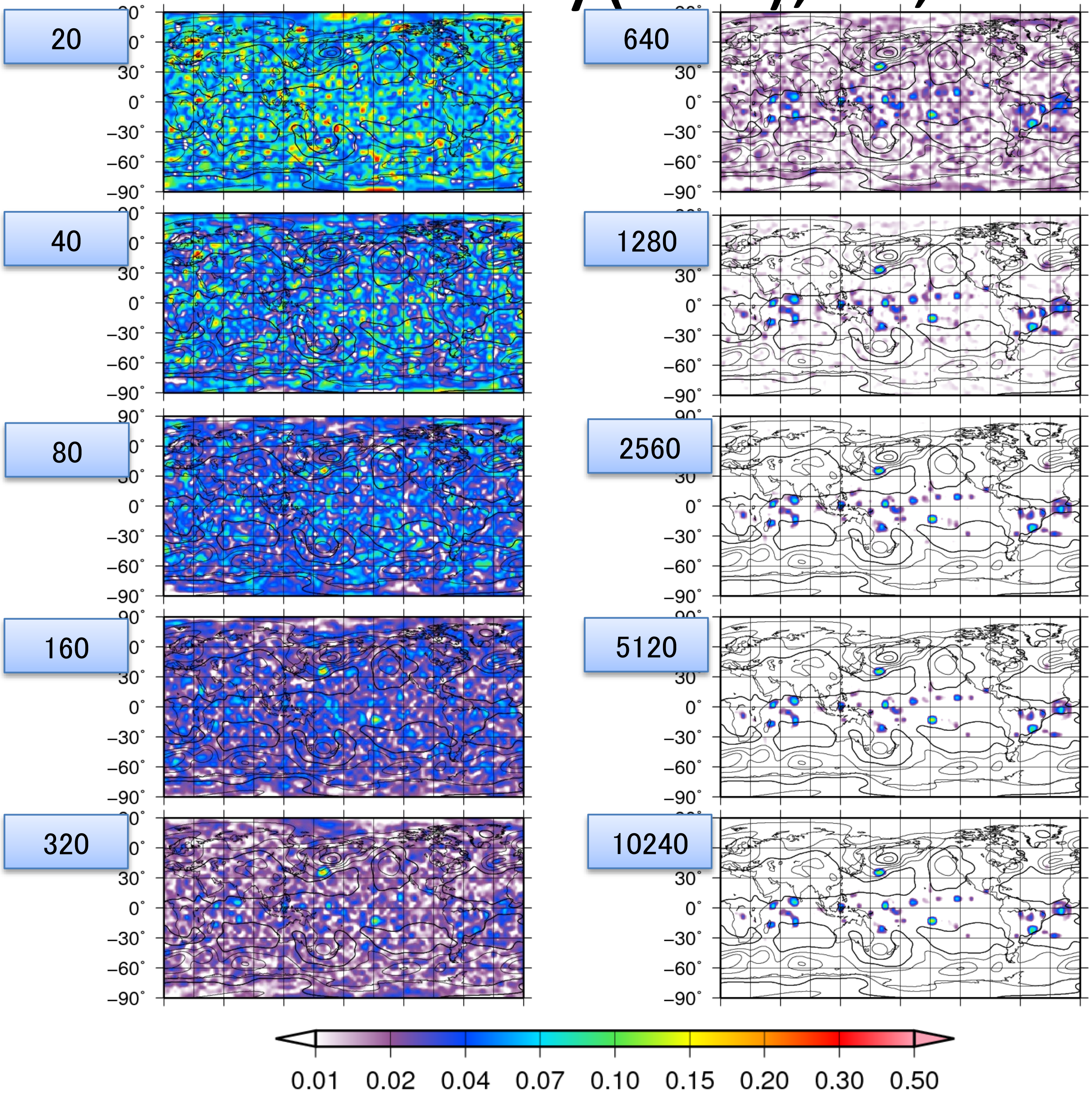
Skewness, Ps, 1982/02/01 06Z



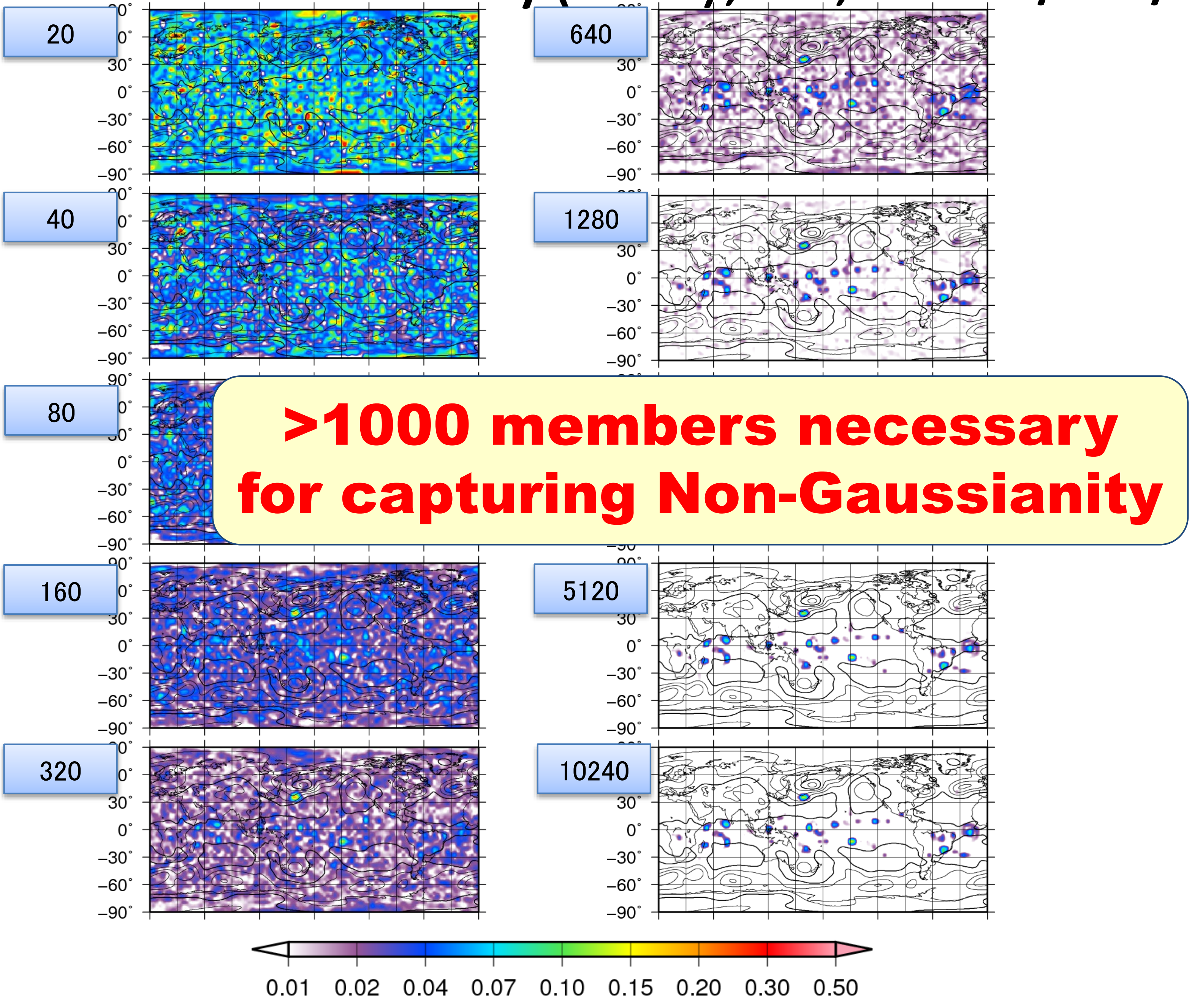
Kurtosis, Ps, 1982/02/01 06Z



Non-Gaussianity(KLD), Ps, 1982/02/01 06Z

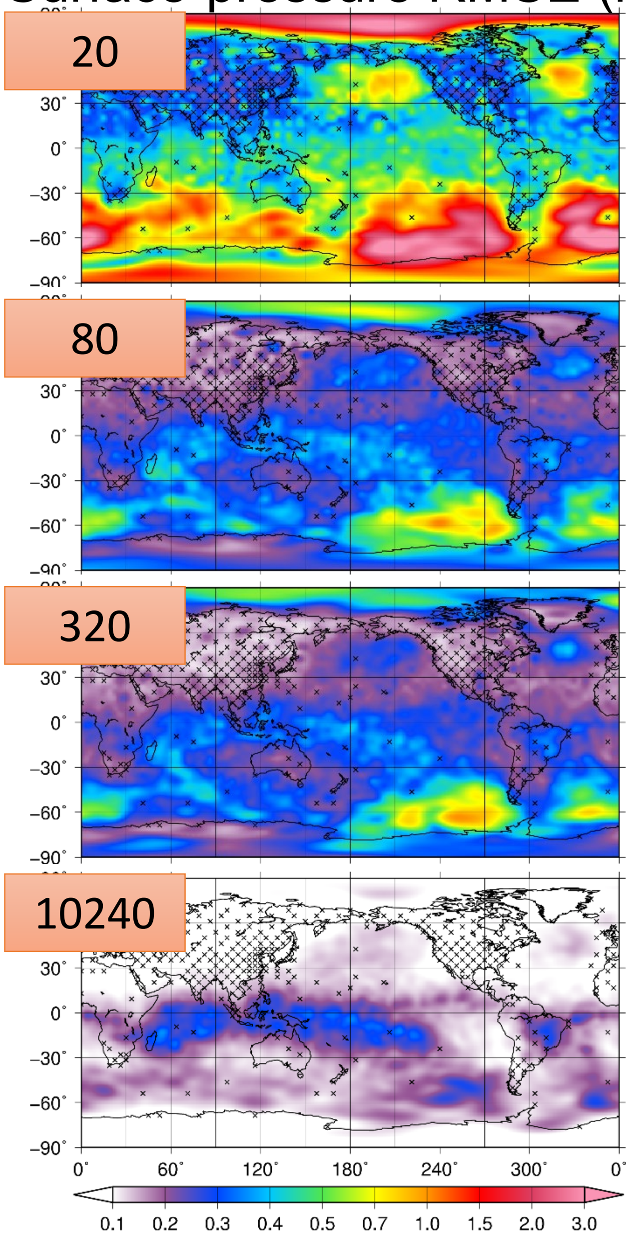


Non-Gaussianity(KLD), Ps, 1982/02/01 06Z

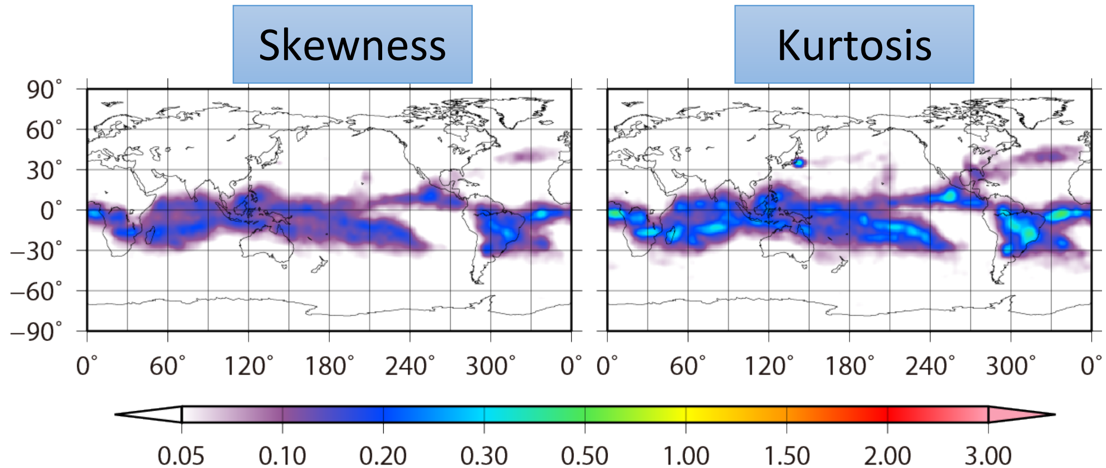


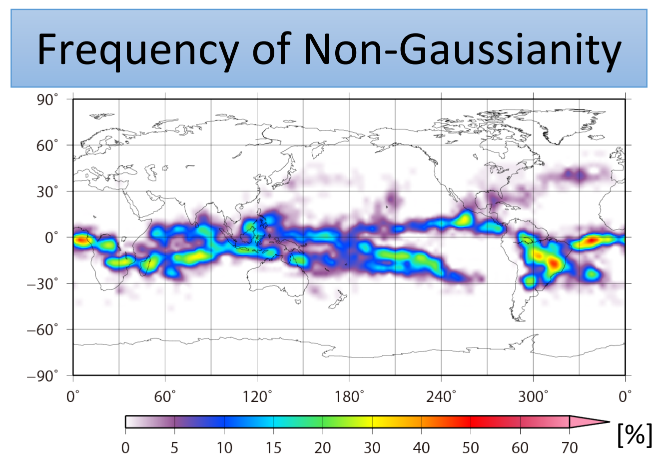
RMSE ⇔ Non-Gaussianity *(Kondo, Miyoshi 2016)*

Surface-pressure RMSE (hPa)



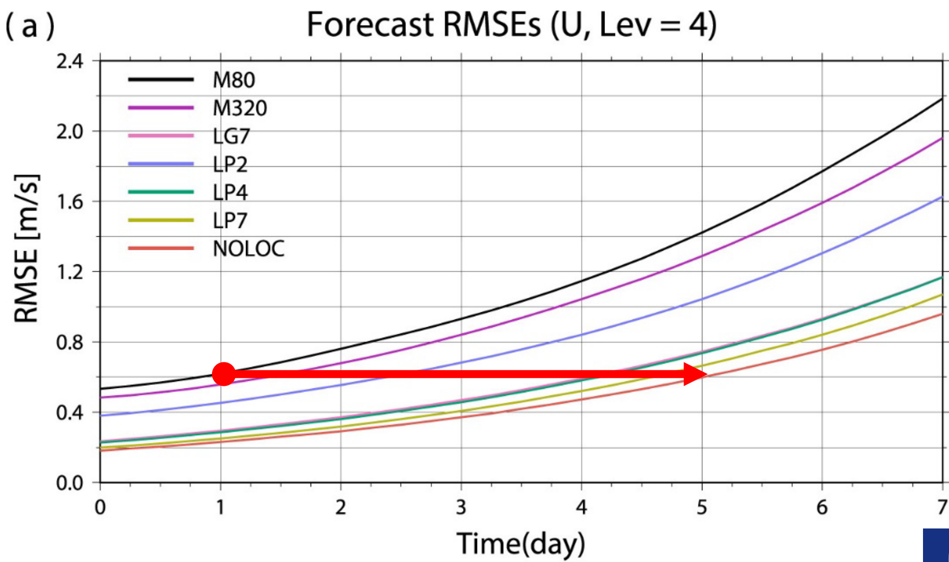
Non-Gaussianity based on 10240 members





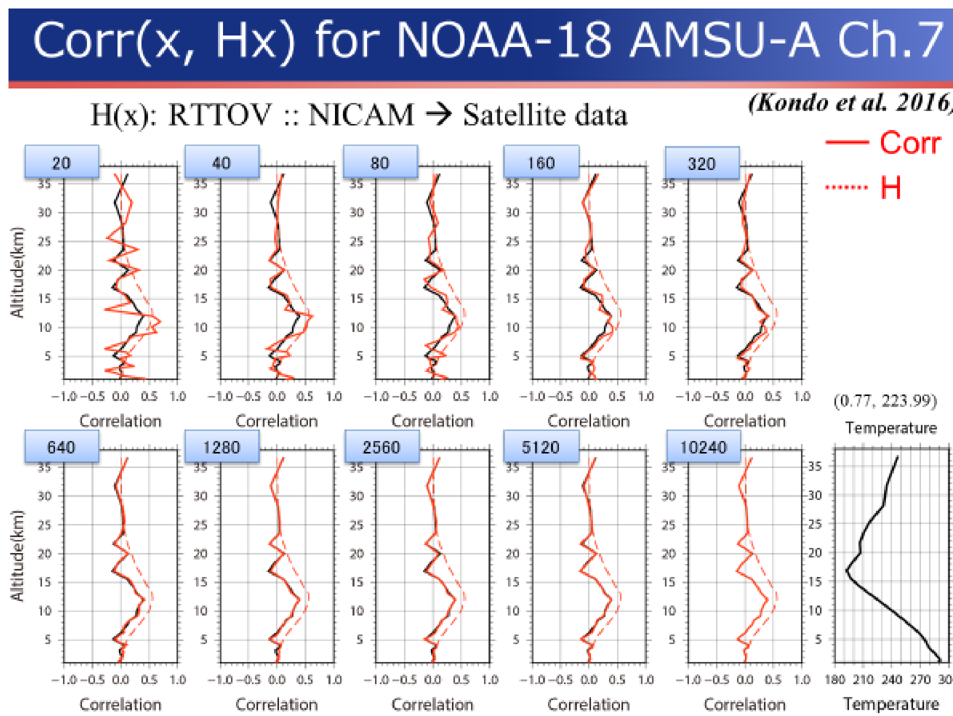
Larger errors ⇔ Non-Gaussian regions

To improve data assimilation



1-day fcst error = 5-day fcst error

80 members 10240 members w/o localization



Implications to vertical localization for satellite data

MULTIMEDIA

NOVEMBER 2015
FEATURES

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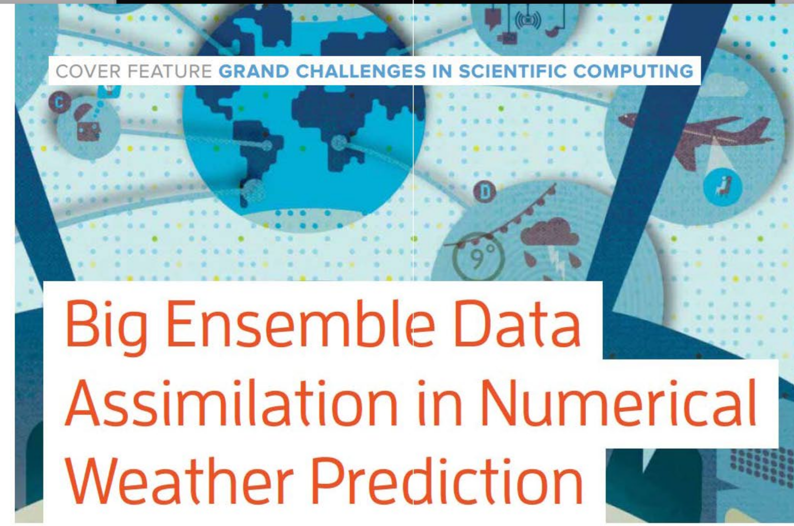
COVER FEATURE **GRAND CHALLENGES IN SCIENTIFIC COMPUTING**

VIDEO



Big Ensemble Data Assimilation in Numerical Weather Prediction

Takemasa Miyoshi, RIKEN Advanced Institute for Computational Science, University of Maryland, and Japan Agency for Marine-Earth Science and Technology

Keiichi Kondo and Koji Terasaki, RIKEN Advanced Institute for Computational Science

Powerful computers and advanced sensors enable precise simulations of the atmospheric state, requiring data assimilation to connect simulations to real-world sensor data using statistical mathematics and dynamical systems theory. Numerical weather prediction (NWP) thus enables simulations that more closely represent the real world. The authors explore the NWP-associated challenges in managing big data through supercomputing.

High-performance computing (HPC) is essential for *numerical weather prediction* (NWP), the method by which computer models of the atmosphere are used to predict the weather. Advances in computing power enable higher resolution and more complex physical representations of the atmosphere. Although these more advanced representations have led to more accurate weather forecasts from supercomputers than the first models from 1950, the technology is still far from ideal.[1]

In NWP, synchronizing the computer simulation with the real world is essential to accurately determine the atmosphere's current state and likely evolution. Although more precise simulations and more powerful computing are helpful in improving accuracy, data assimilation (DA) plays a key role in improving integration between the computer simulation and real-world observation data.[2,3] DA also employs HPC; in fact, global NWP systems devote equivalent computational resources to DA and 10-day forecast simulation.

To accurately represent the probability density function (PDF) in the ensemble Kalman filter (EnKF)—an advanced DA approach widely used in NWP—within the global atmosphere, we used a large sample size and the

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Pushing the limits

Big Data × *Big Simulations*

Big ensemble (10240 ensemble members)

Rapid update (30-second update)

High resolution (100-m mesh)

➔ Future NWP

Pushing the limits

Big Data* × *Big Simulations

Big ensemble (10240 ensemble members)

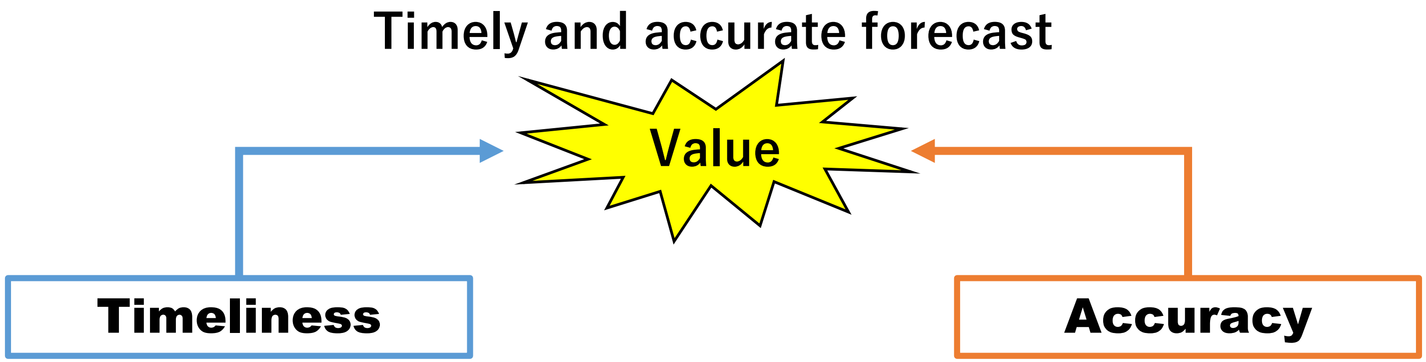
Rapid update (30-second update)

High resolution (100-m mesh)

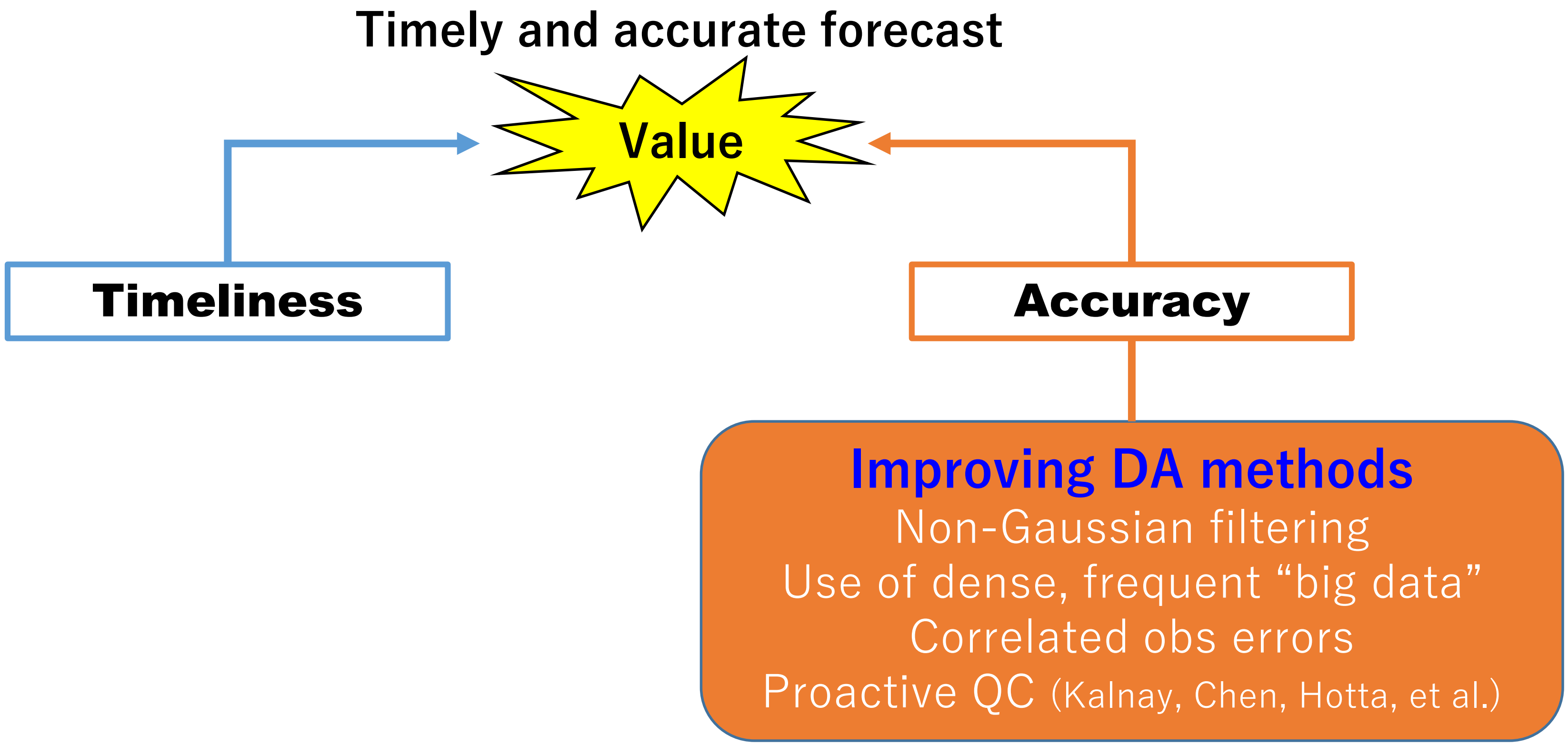
➔ Future NWP

With new **"Fugaku"**, we will run a
3.5-km-mesh global LETKF w/ 1000 members.

Research directions

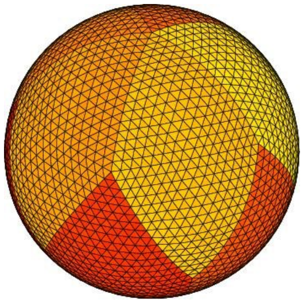


Research directions

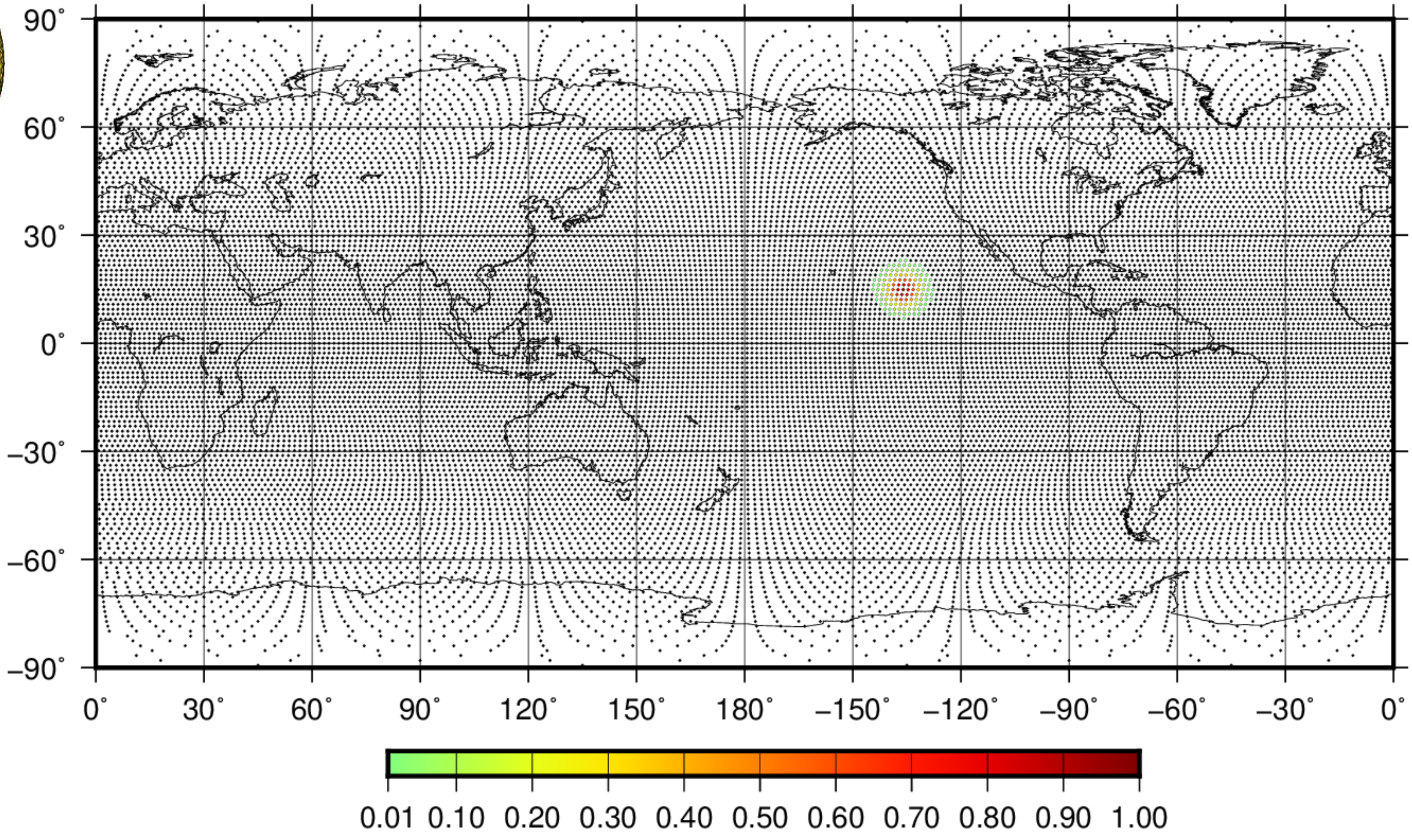


OSSE with Full-R

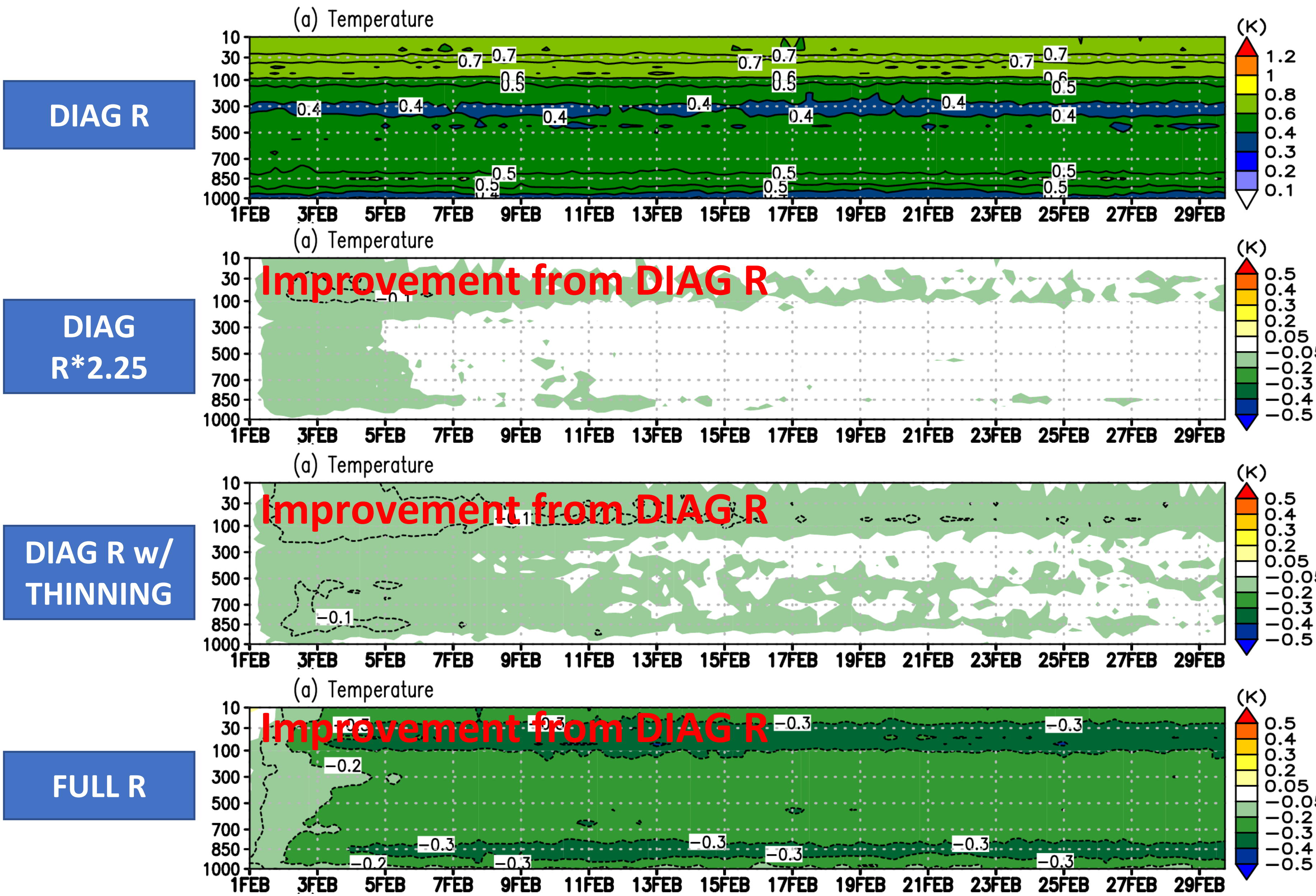
NICAM-LETKF
system



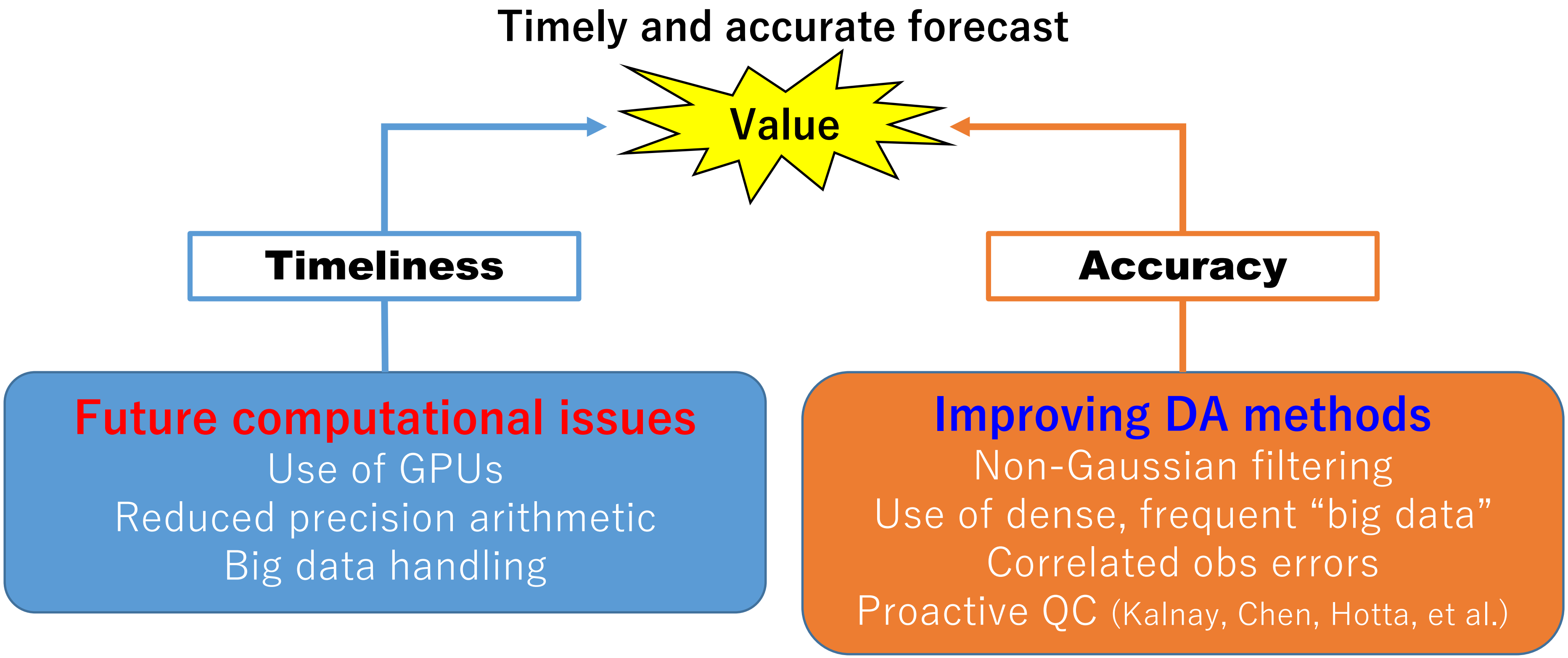
Observation coverage (Δx=150km) &
observation error correlation for an observation



Results: Temperature RMSE (K)



Research directions



Use of AI, Machine Learning methods

Use of reduced precision arithmetic

Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE

10.1029/2018MS001341

Choosing the Optimal Numerical Precision for Data Assimilation in the Presence of Model Error

Sam Hatfield[1], Peter Düben[2], Matthew Chantry[1], Keiichi Kondo[3], Takemasa Miyoshi[4], and Tim Palmer[1]

[1] Atmospheric, Oceanic and Planetary Physics, University of Oxford, Oxford, UK, [2] European Centre for Medium Range Weather Forecasts, Reading, UK, [3] Japan Meteorological Agency, Meteorological Research Institute, Tsukuba, Japan, [4] RIKEN Center for Computational Science, Kobe, Japan

Key Points:

- Lowering precision could accelerate an ensemble Kalman filter
- The level of precision used should fit the level of model error
- We perform tests with a spectral dynamical core

Correspondence to:
S. Hatfield,
samuel.hatfield@physics.ox.ac.uk

Citation:
Hatfield, S. E., Düben, P. D., Chantry, M., Kondo, K., Miyoshi, T., & Palmer, T. N. (2018). Choosing the optimal numerical precision for data assimilation in the presence of model error. *Journal of Advances in Modeling Earth Systems*, *10*, 2177–2191. https://doi.org/10.1029/2018MS001341

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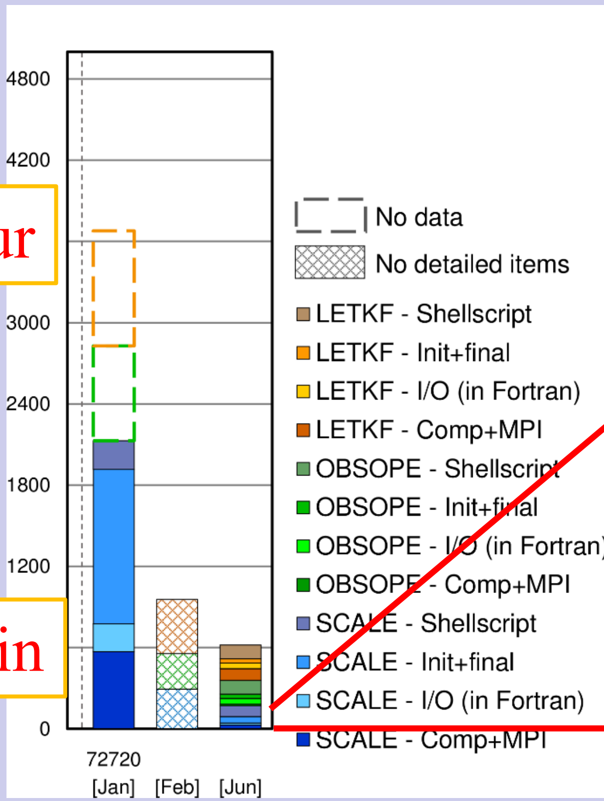
Abstract The use of reduced numerical precision within an atmospheric data assimilation system is investigated. An atmospheric model with a spectral dynamical core is used to generate synthetic observations, which are then assimilated back into the same model using an ensemble Kalman filter. The effect on the analysis error of reducing precision from 64 bits to only 22 bits is measured and found to depend strongly on the degree of model uncertainty within the system. When the model used to generate the observations is identical to the model used to assimilate observations, the reduced-precision results suffer substantially. However, when model error is introduced by changing the diffusion scheme in the assimilation model or by using a higher-resolution model to generate observations, the difference in analysis quality between the two levels of precision is almost eliminated. Lower-precision arithmetic has a lower computational cost, so lowering precision could free up computational resources in operational data assimilation and allow an increase in ensemble size or grid resolution.

Plain Language Summary In order to produce a weather forecast, we must have a good estimate of the current state of the atmosphere. We can observe the atmosphere using satellites and other

Compute time (73440 nodes of K computer)

ensemble forecasts + data assimilation

2016 results reported in mid-term evaluation

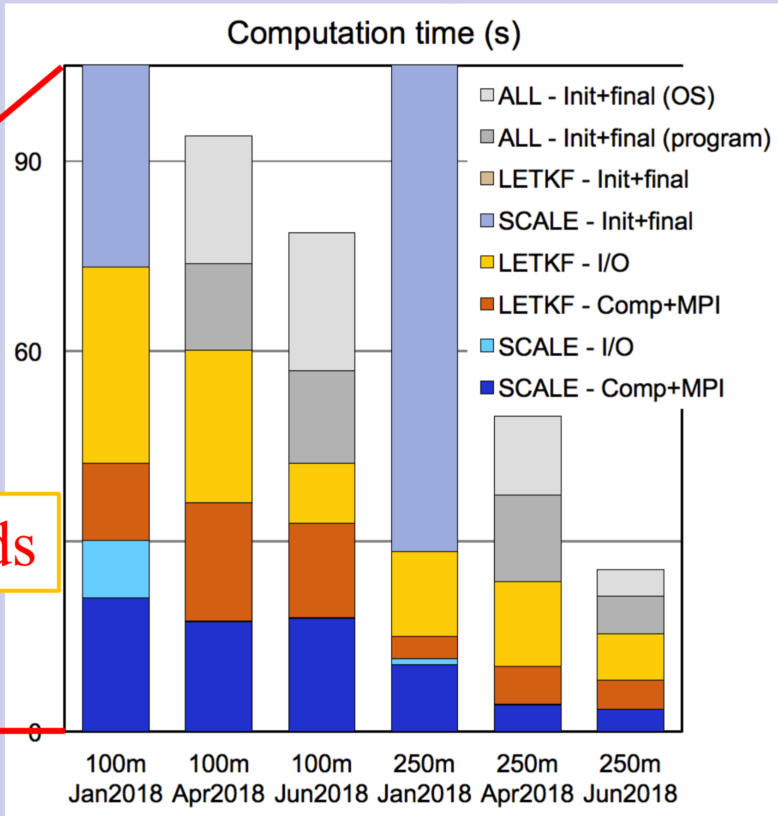


1 hour

10 min

100 m

2018 results



30 seconds

100 m / 250 m

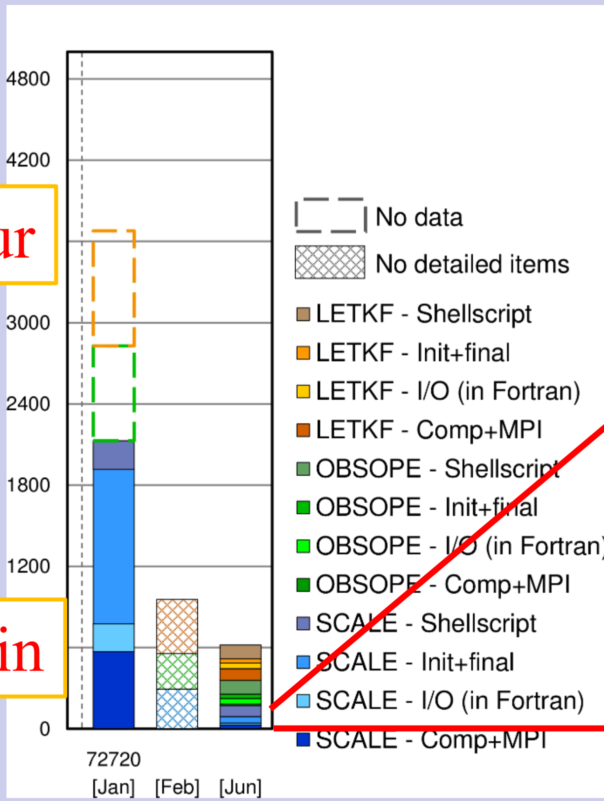
Compute time (73440 nodes of K computer)

ensemble forecasts + data assimilation

2016 results reported in mid-term evaluation

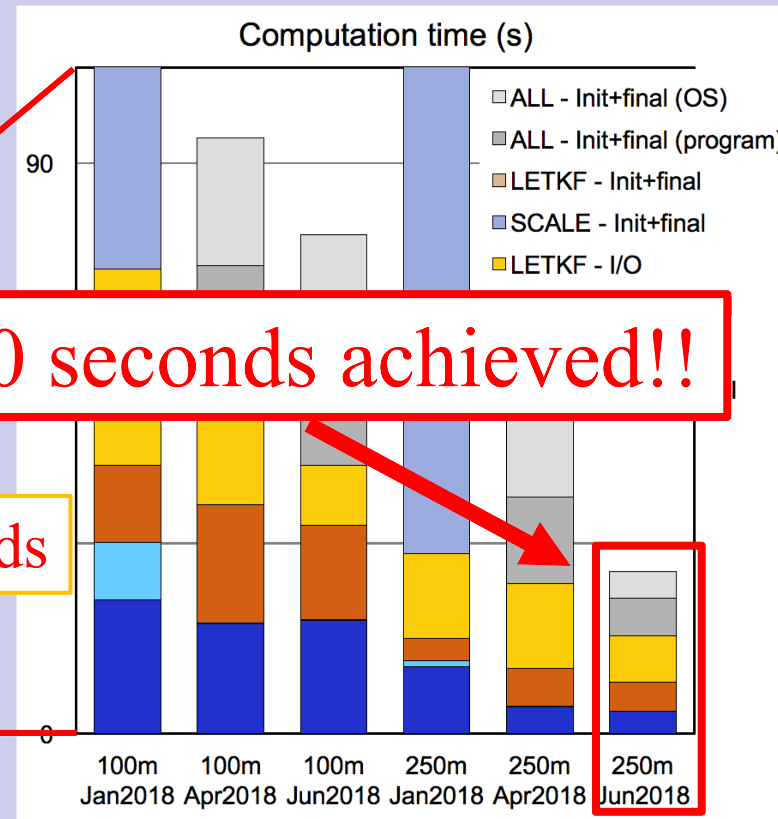
1 hour

10 min



100 m

2018 results



<30 seconds achieved!!

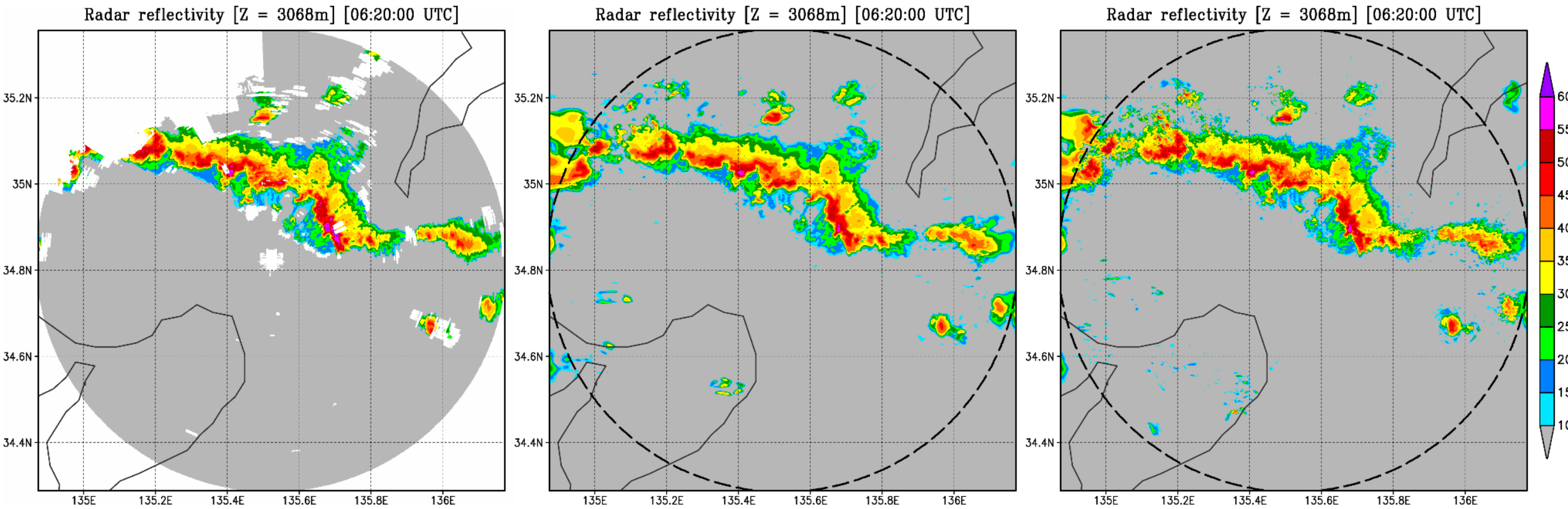
30 seconds

100 m / 250 m

250-m mesh vs. 100-m mesh forecasts

Analysis - 06:20 UTC 13 July, 2013

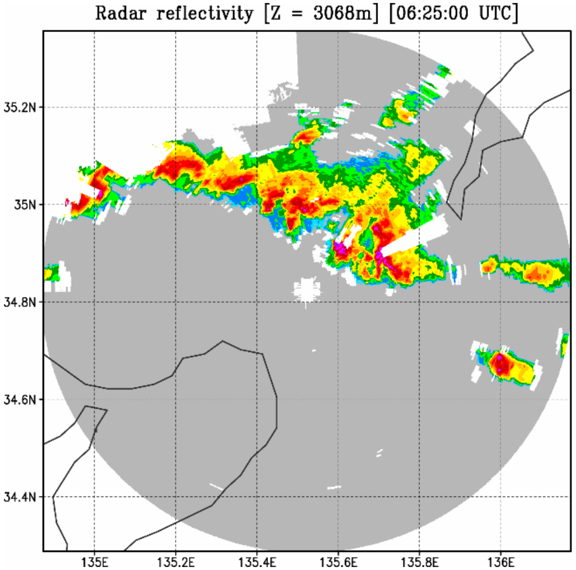
Observation **250 M** **100 M**



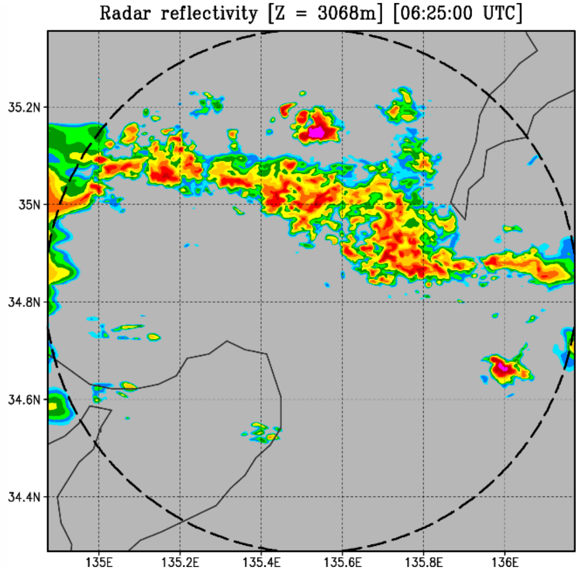
250-m mesh vs. 100-m mesh forecasts

5-min forecast - 06:25 UTC 13 July, 2013

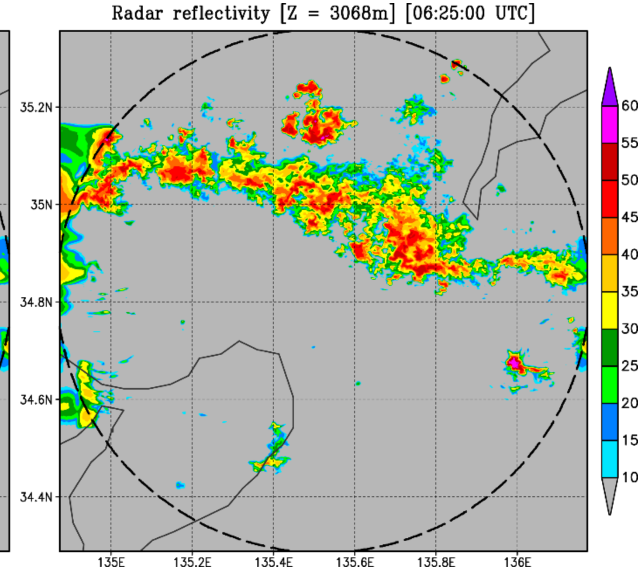
Observation



250 M



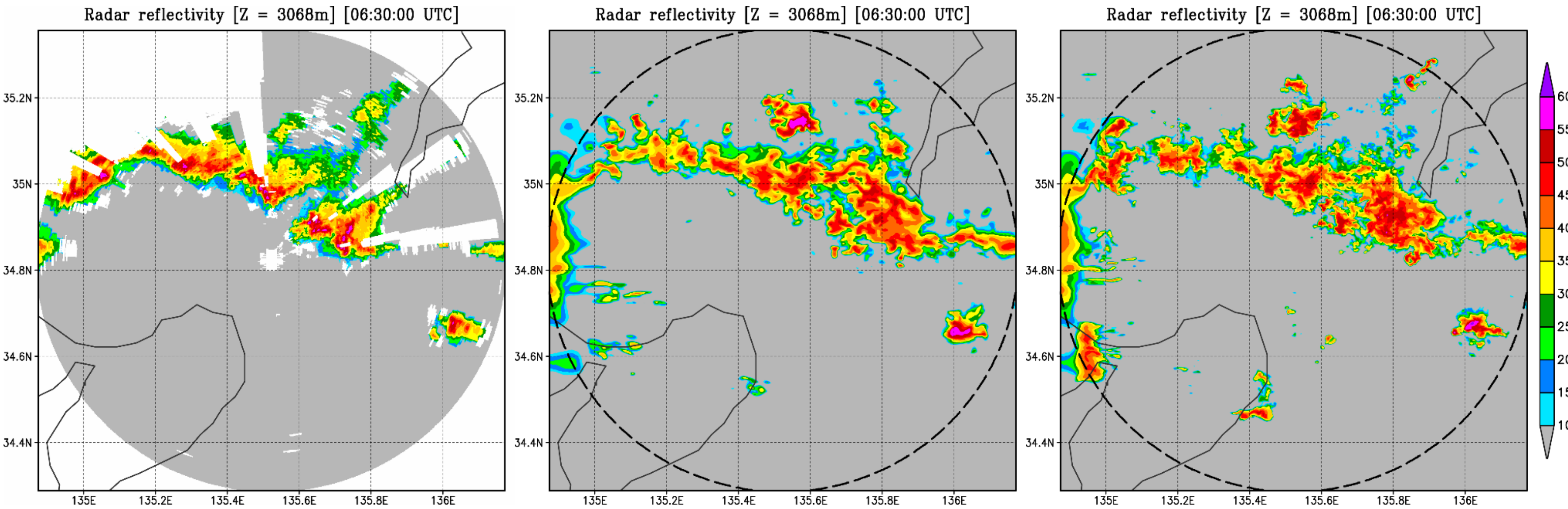
100 M



250-m mesh vs. 100-m mesh forecasts

10-min forecast - 06:30 UTC 13 July, 2013

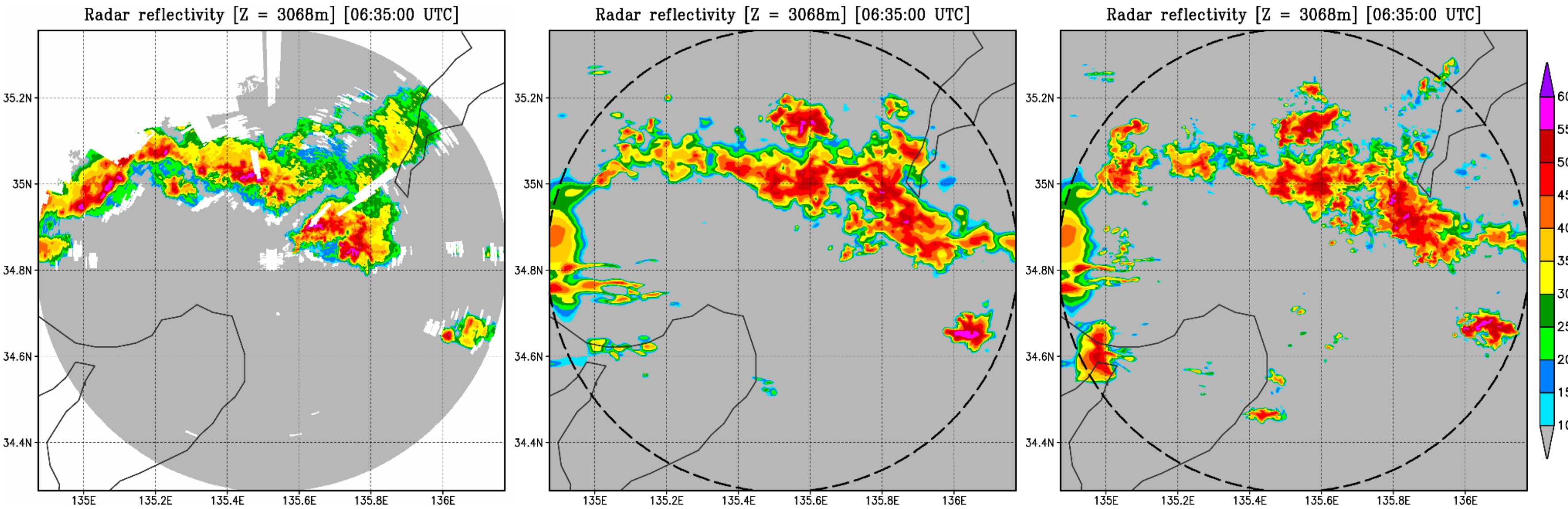
Observation | 250 M | 100 M



250-m mesh vs. 100-m mesh forecasts

15-min forecast - 06:35 UTC 13 July, 2013

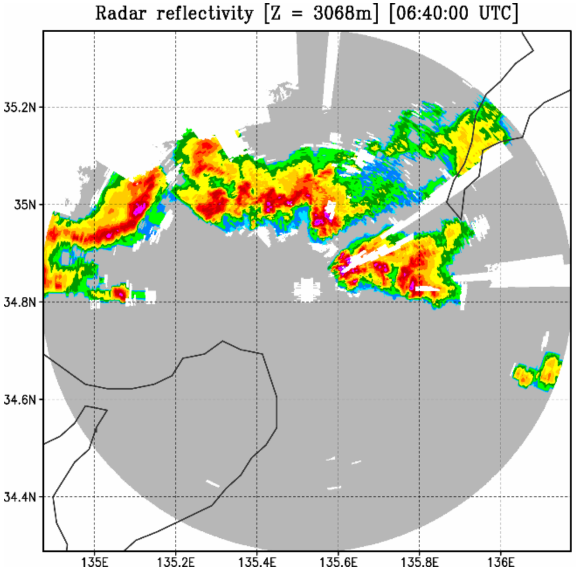
Observation **250 M** **100 M**



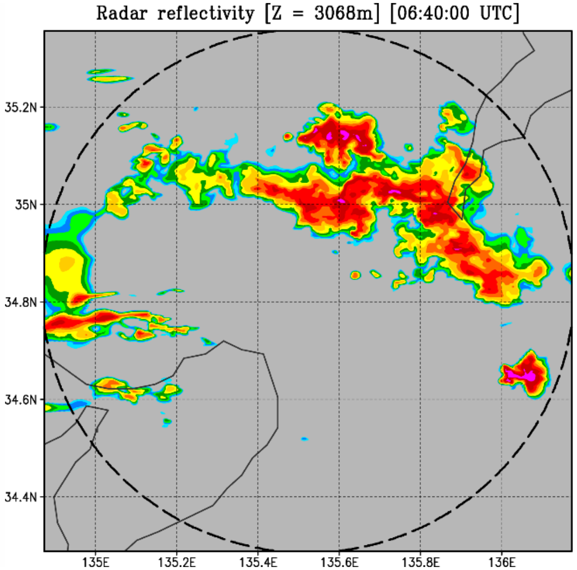
250-m mesh vs. 100-m mesh forecasts

20-min forecast - 06:40 UTC 13 July, 2013

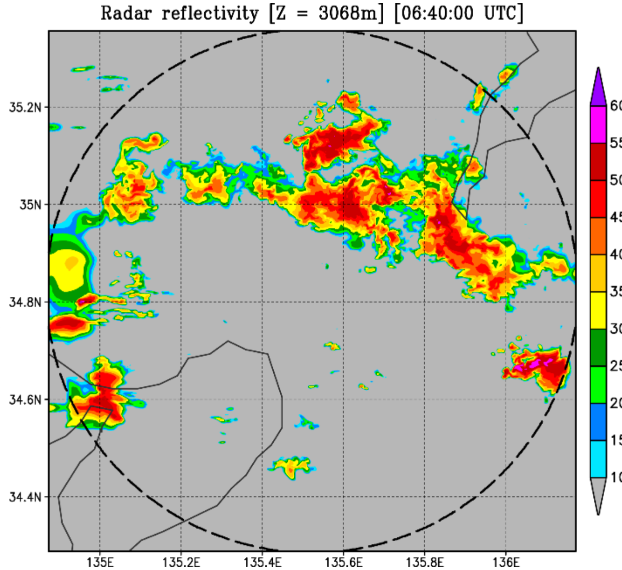
Observation



250 M



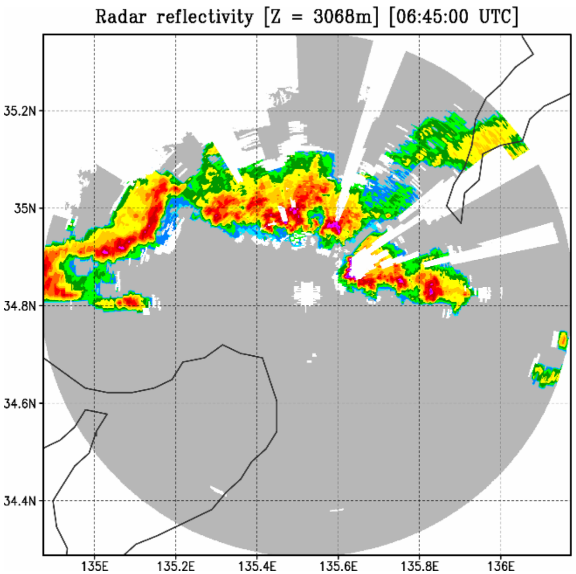
100 M



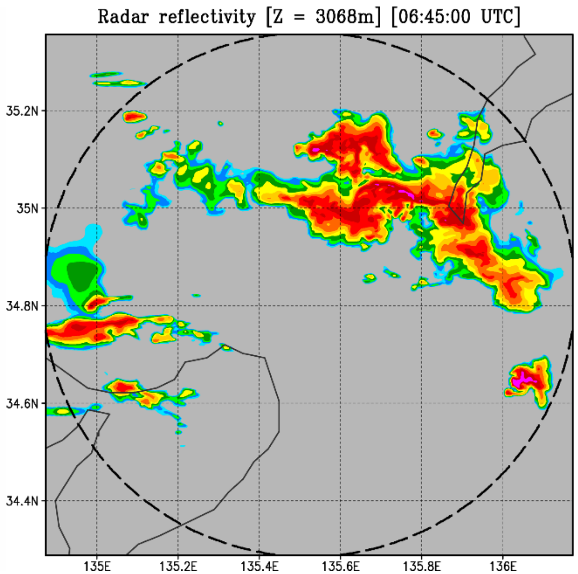
250-m mesh vs. 100-m mesh forecasts

25-min forecast - 06:45 UTC 13 July, 2013

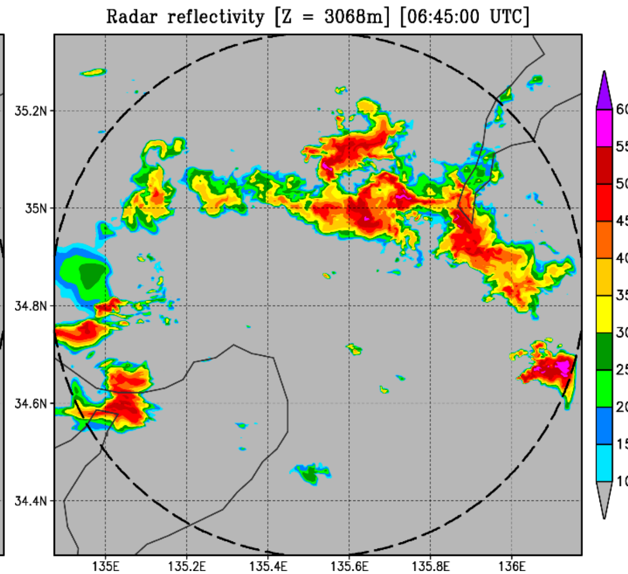
Observation



250 M



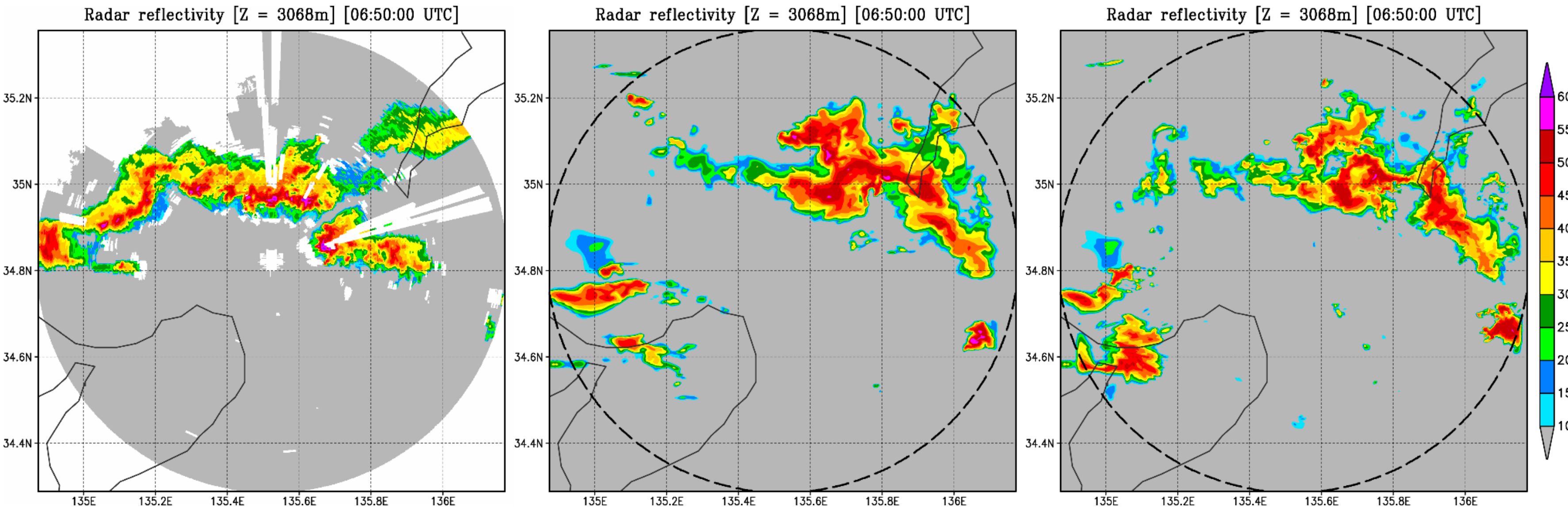
100 M



250-m mesh vs. 100-m mesh forecasts

30-min forecast - 06:50 UTC 13 July, 2013

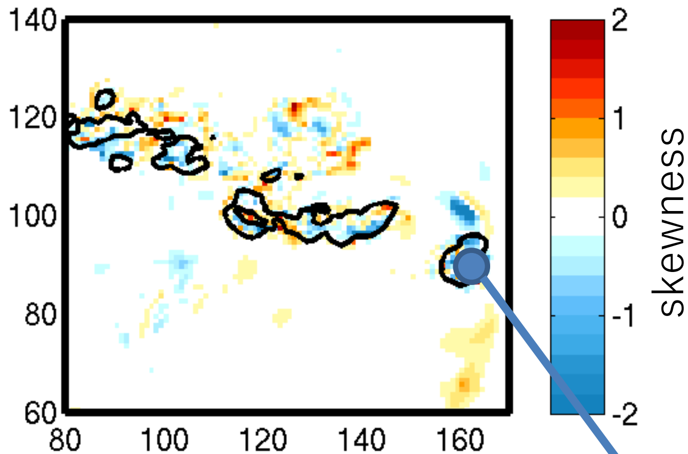
Observation | **250 M** | **100 M**



1-km-mesh, 1000-member LETKF

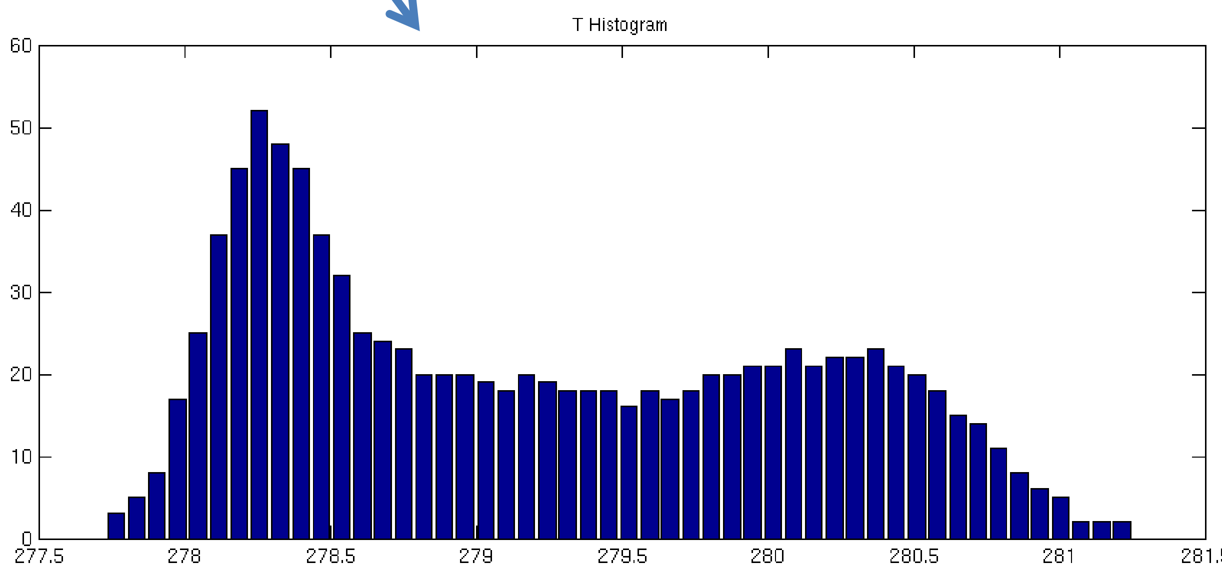
T skewness at z=3845 m

(Ruiz et al. in prep.)



contours: 30 dBZ reflectivity

Even 30-second update shows strong non-Gaussianity with 1000 members.



1-km-mesh, 1000-member LETKF

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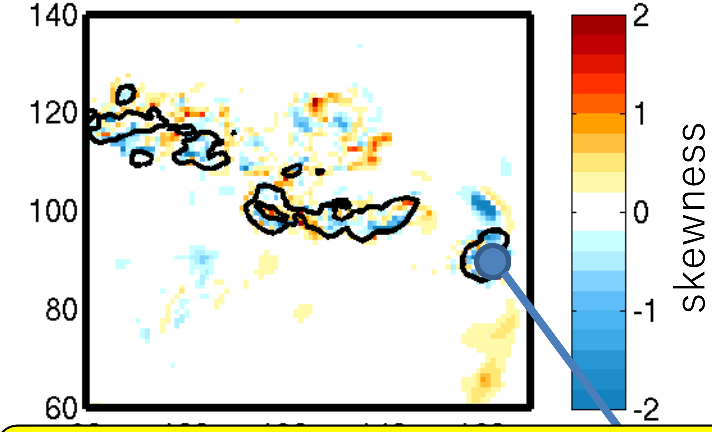
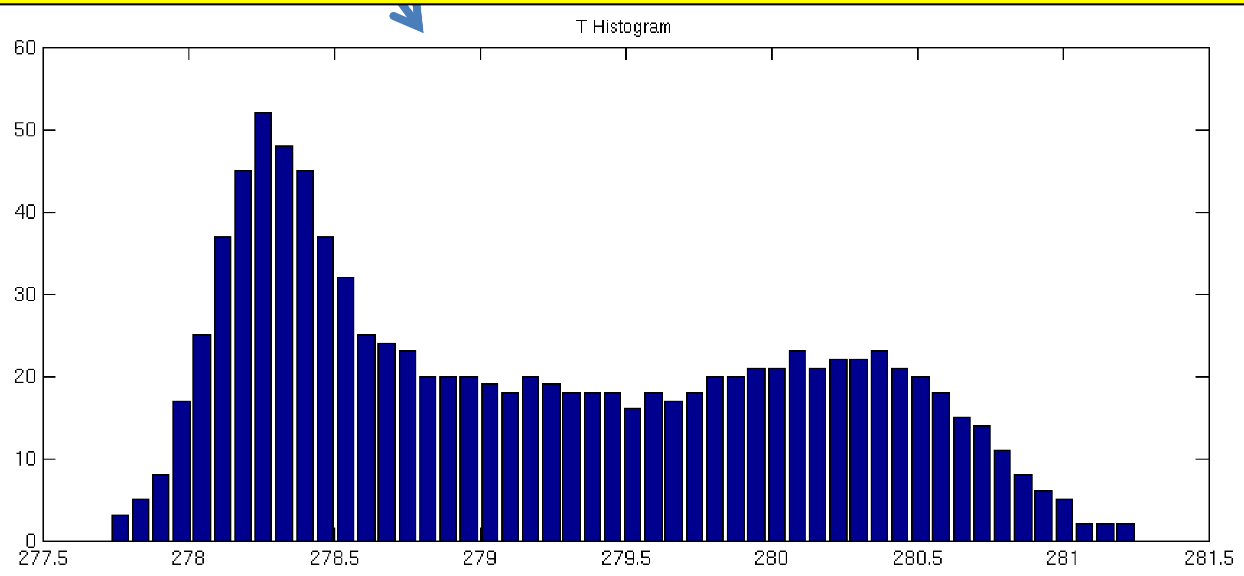


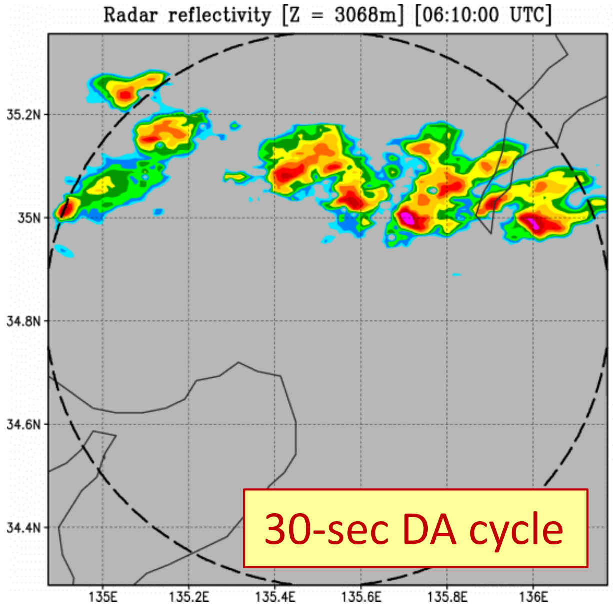
Even 30-second update shows strong non-Gaussianity with 1000 members.

30-sec. update may not be fast enough!

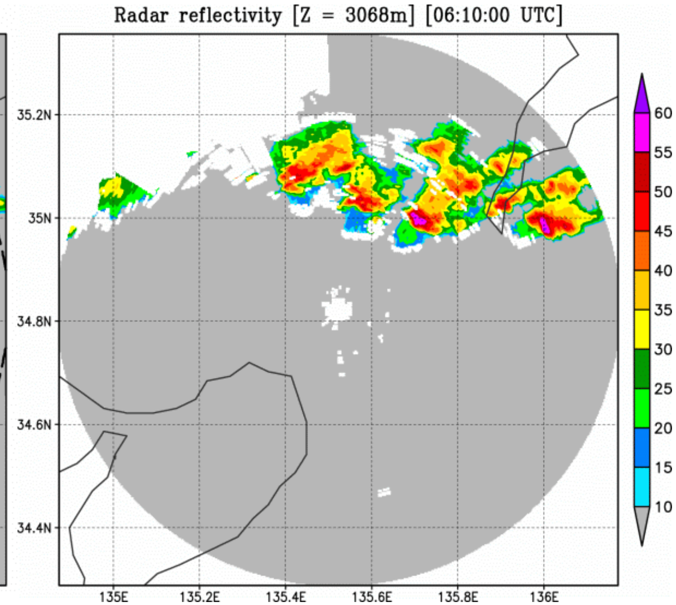


30-min **forecast**: 15:10L – 15:40L

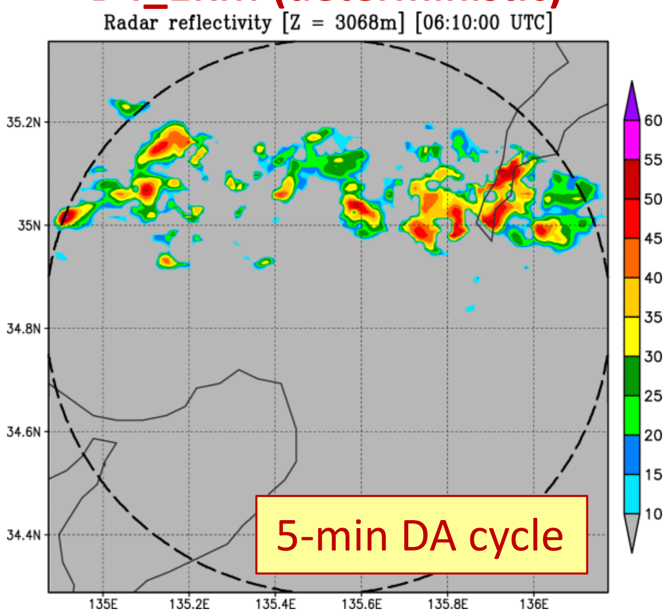
D4_1KM (deterministic)



OBS after QC



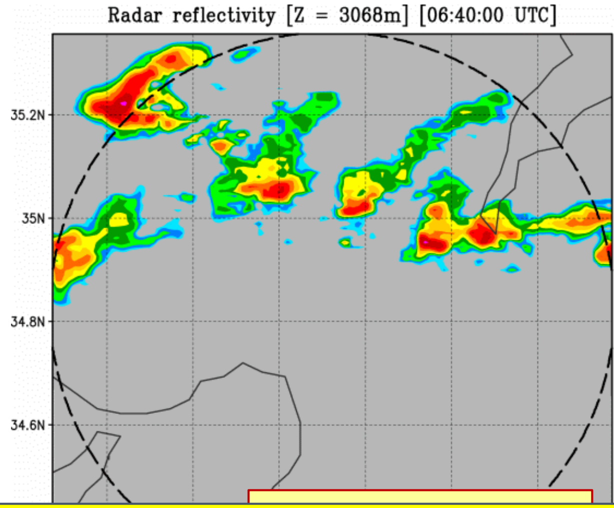
D4_1KM (deterministic)



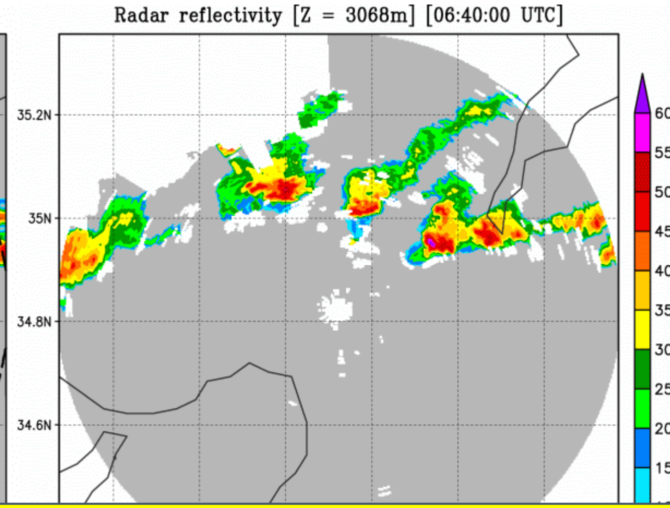
Lien et al. (in prep.)

30-min **forecast**: 15:40L – 16:10L

D4_1KM (deterministic)

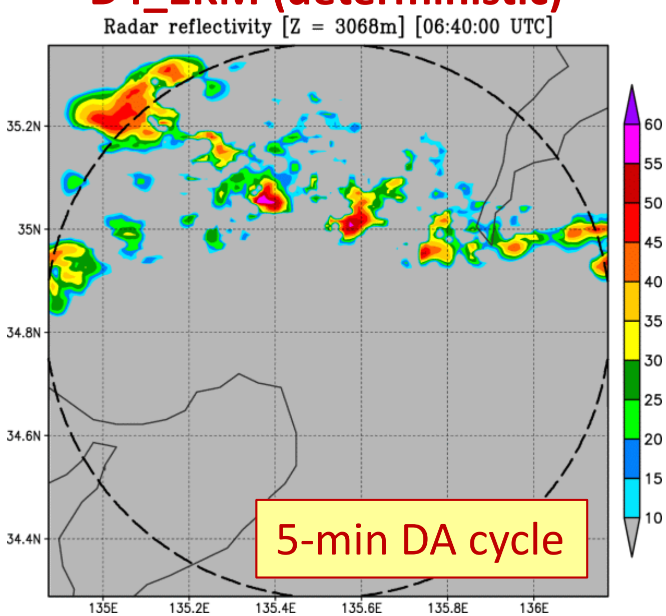


OBS after QC



30-sec. update certainly helps.

D4_1KM (deterministic)

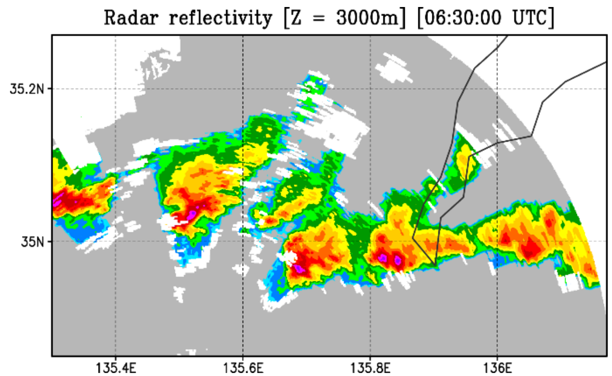


Lien et al. (in prep.)

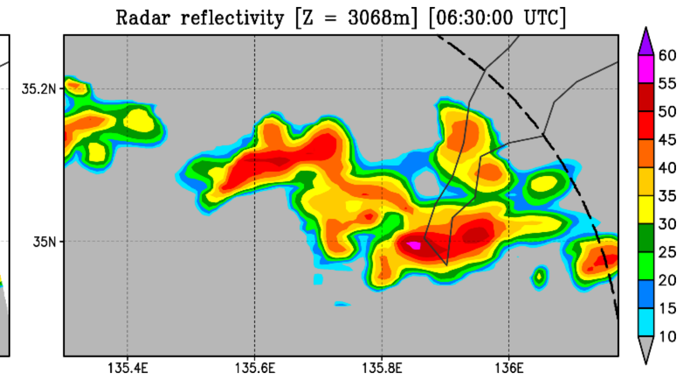
20-min forecast: 15:30L

Lien et al. (in prep.)

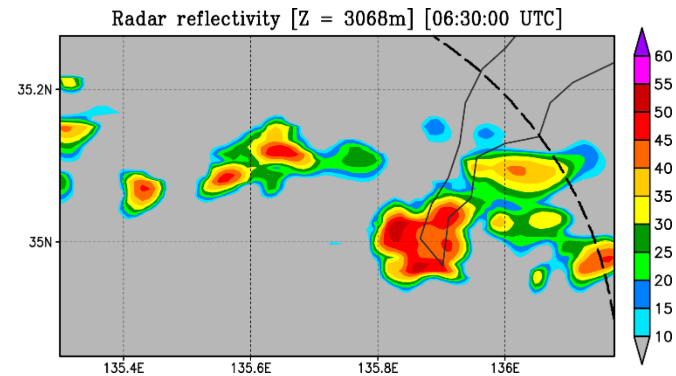
OBS after QC



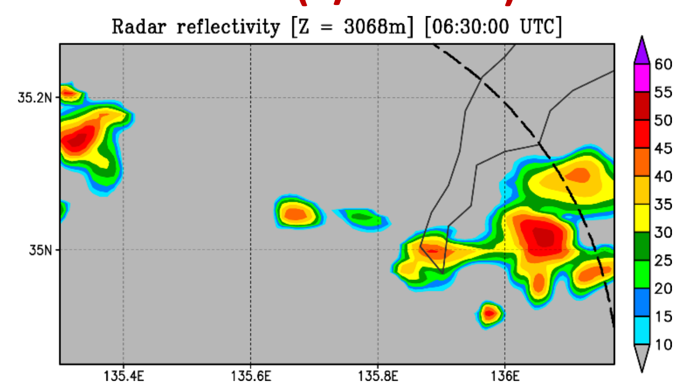
30 sec



5 min (4D)

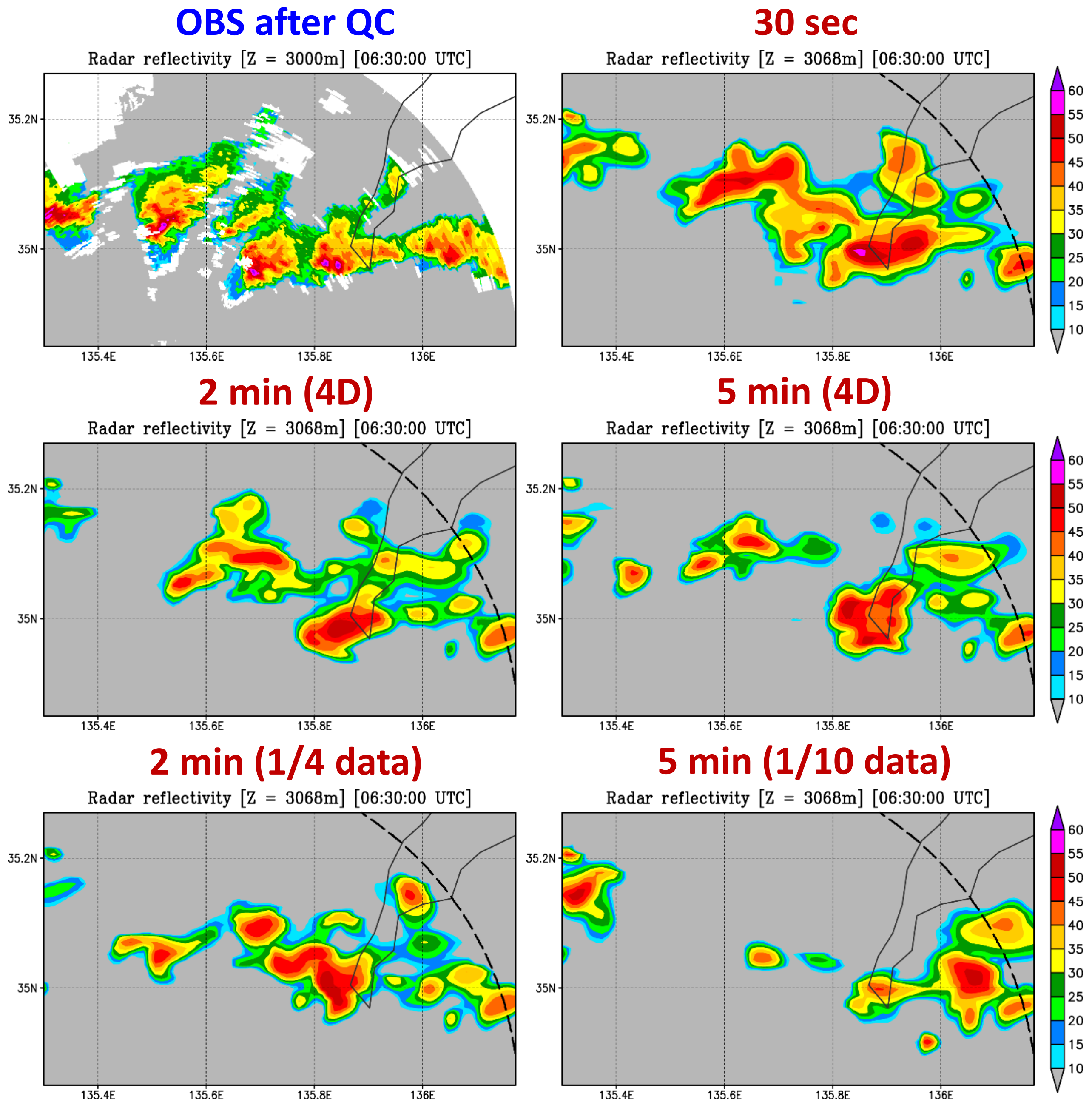


5 min (1/10 data)



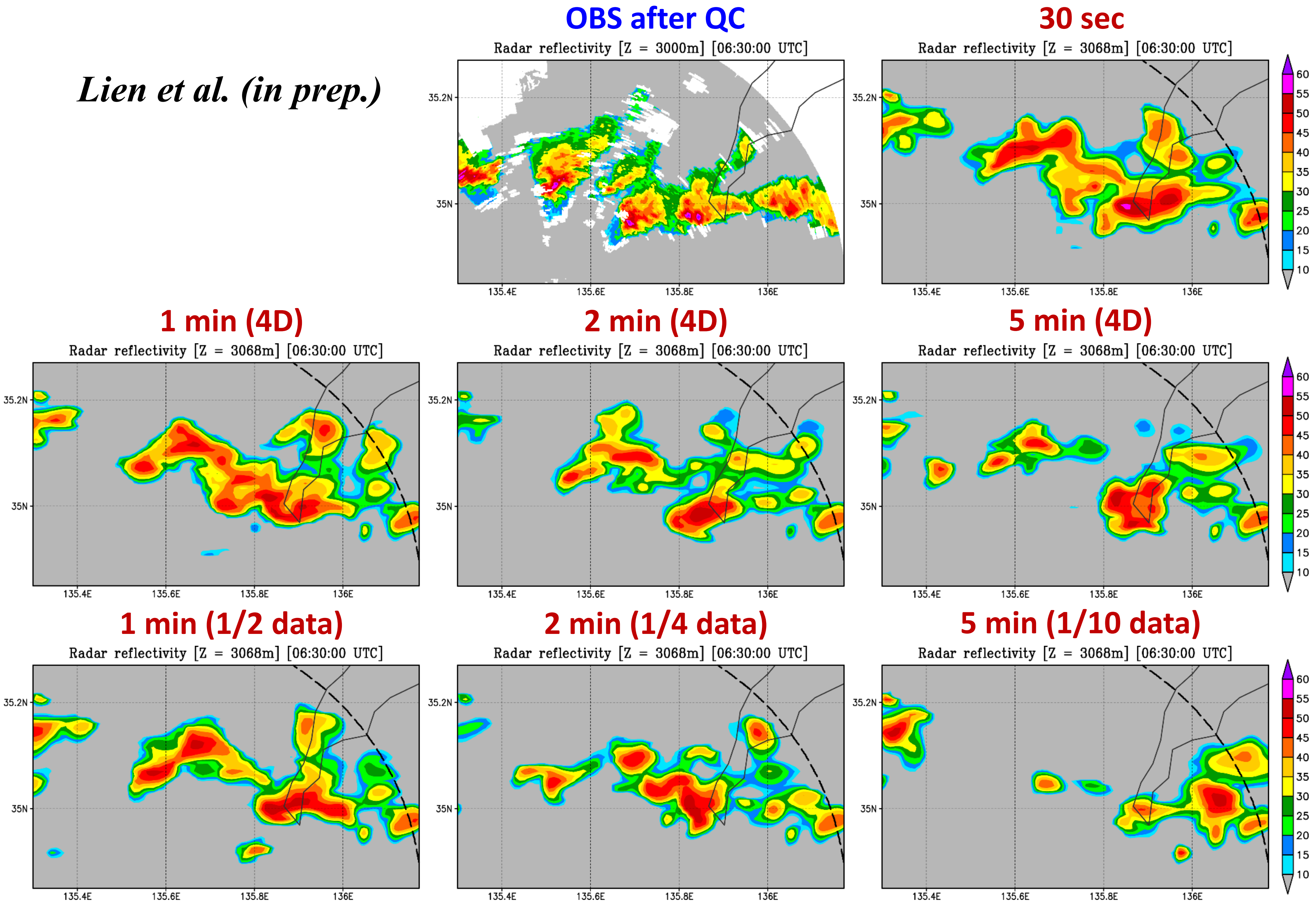
20-min forecast: 15:30L

Lien et al. (in prep.)

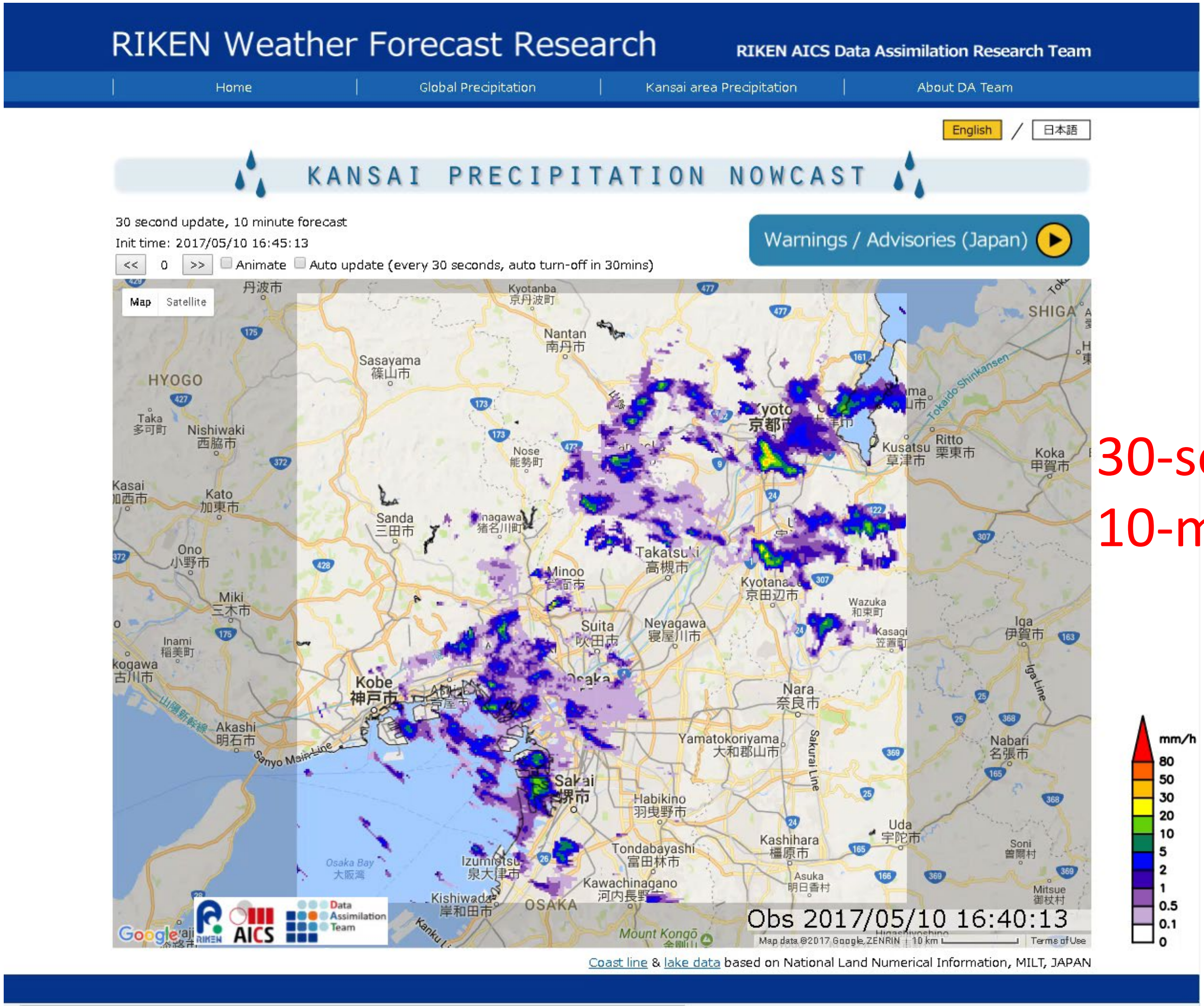


20-min forecast: 15:30L

Lien et al. (in prep.)

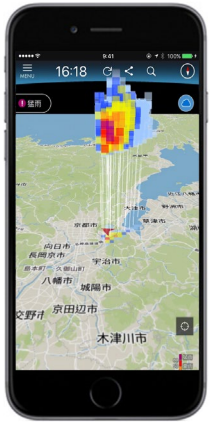


Phased-Array Weather Radar
3D precipitation nowcasting



(NICT)

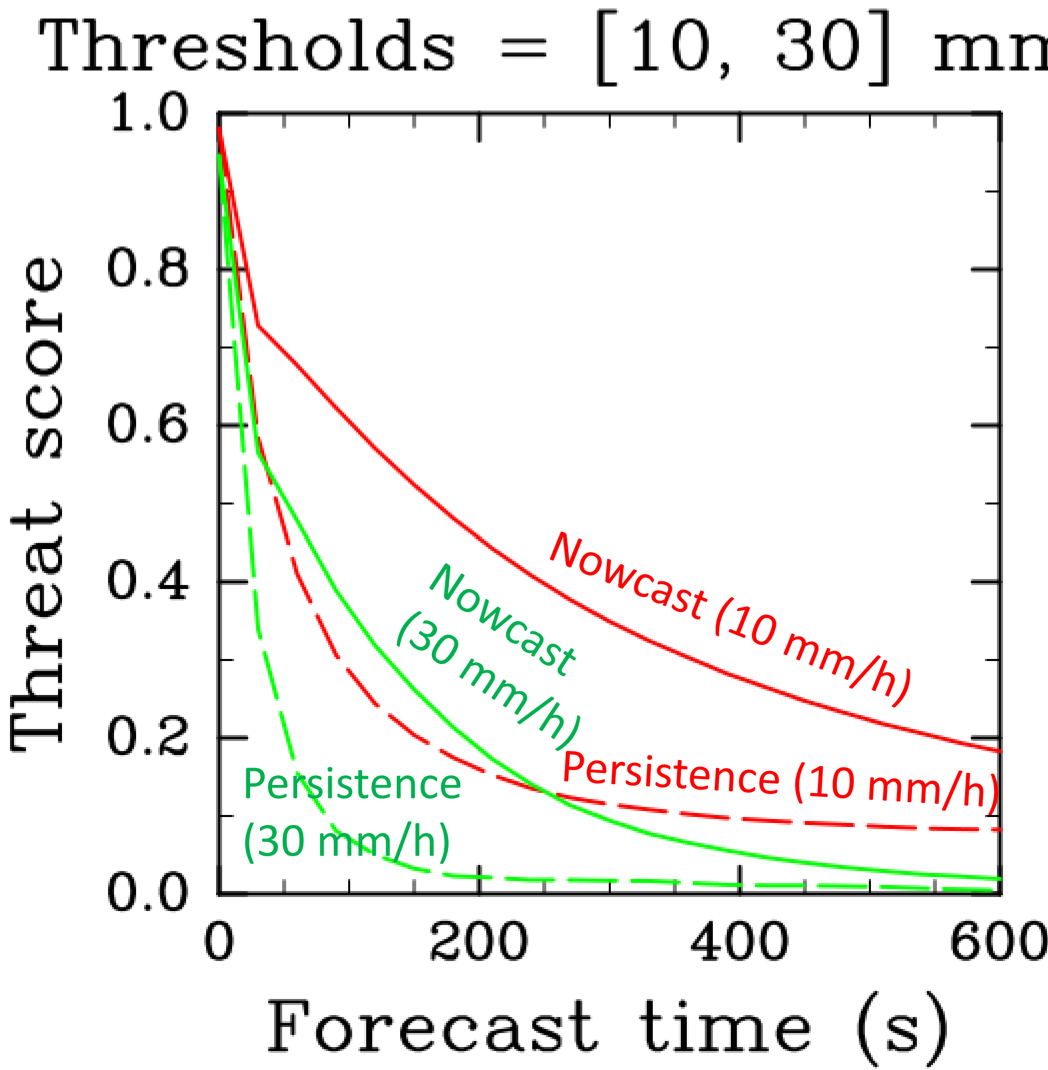
30-second-update
10-min forecast



App by MTI

Real-time dissemination started on 7/27/2017 in collaboration with MTI Ltd.

2018/7/6 10-15 JST, Average of 388 forecasts



Threat scores of rain rate at the 2-km altitude against PAWR

Convective features were well predicted

Convolutional LSTM

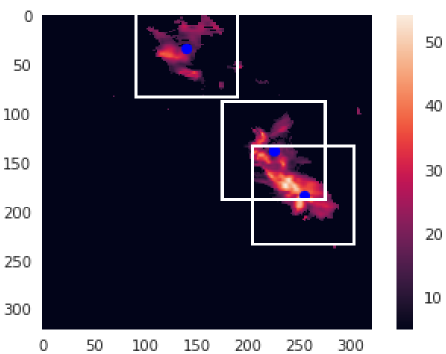
(Work with Mr. Viet Phi Huynh and Prof. Pierre Tandeo)

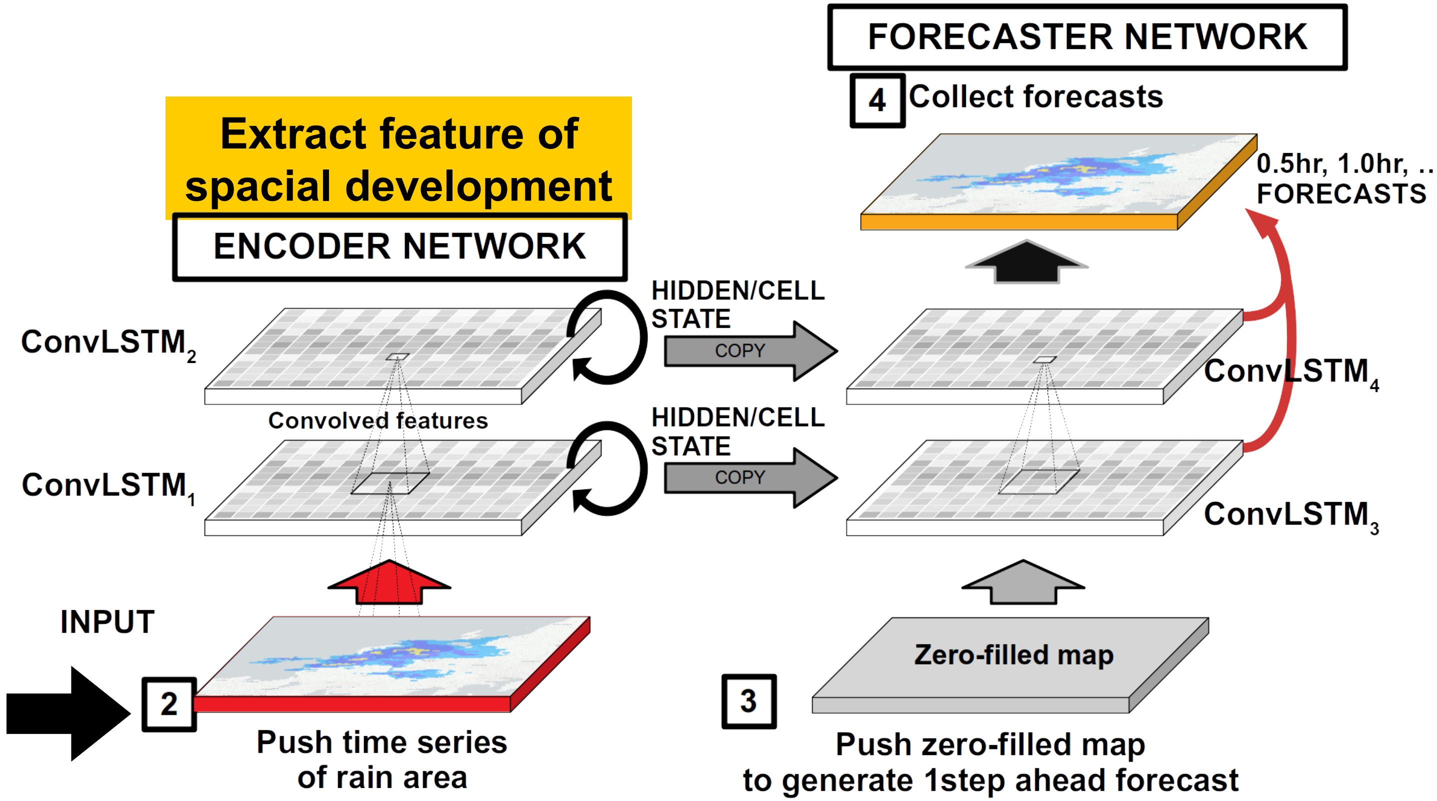
Shi et.al (2015)

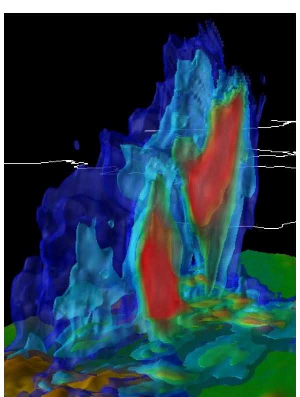
OUTPUT 5 time steps (2.5min)
Future 3D forecast

Structure of Machine1

1. Extract rain area
2. Run encoder net
3. Run forecaster net
4. Collect forecasts
5. Rearrange map







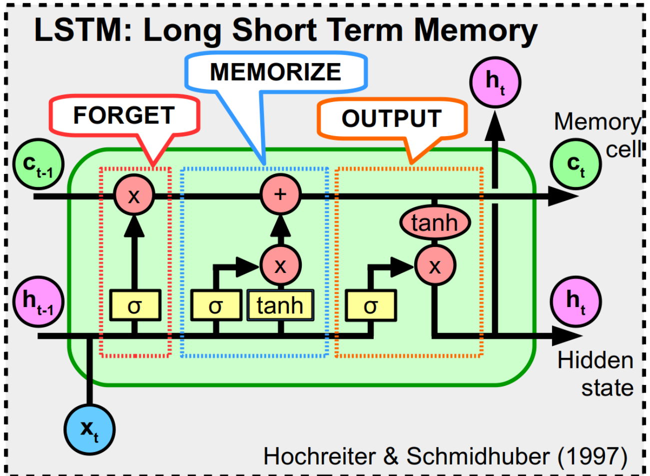
INPUT 6 time steps (3min)
Past 3D observation

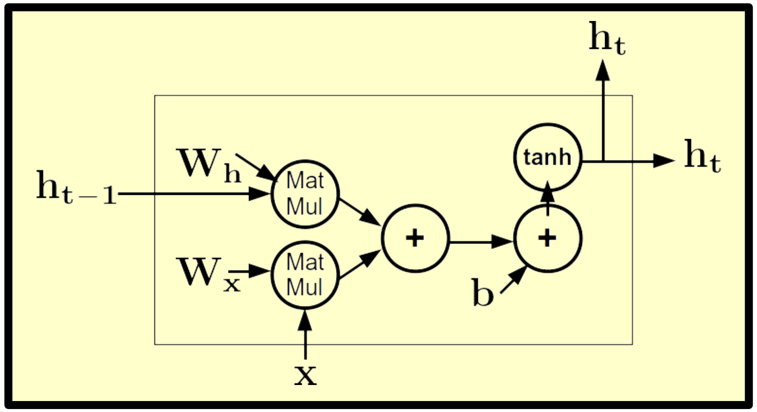
Forecast rain-map based on extracted features

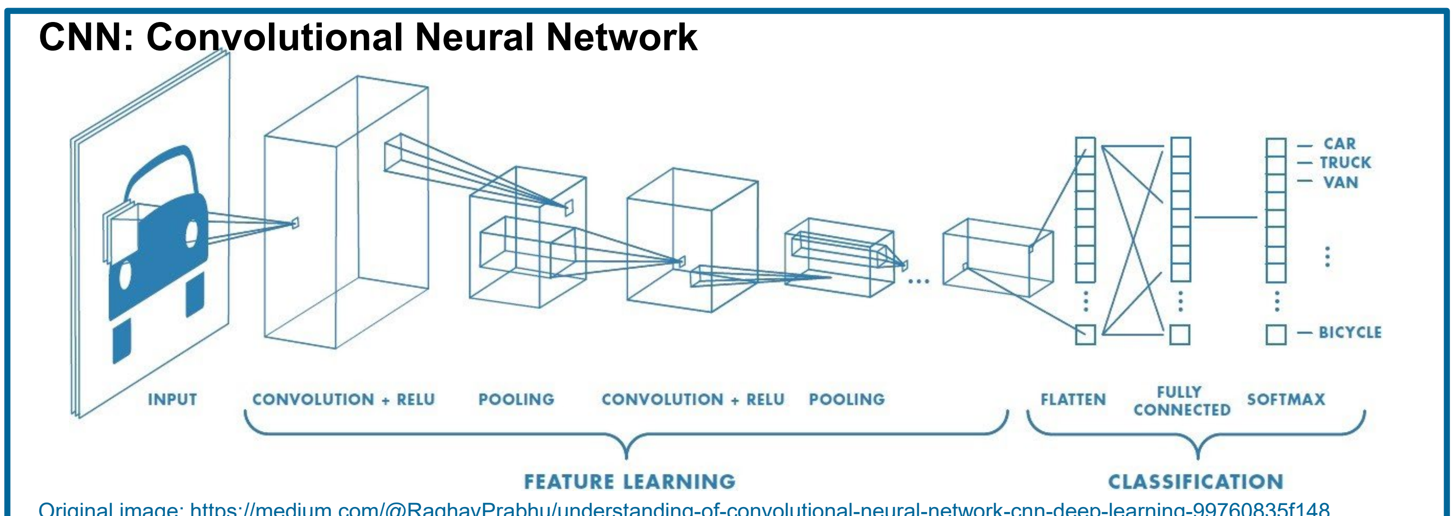
Strategy

- **Combine 2 well known neural network structure**

LSTM & CNN → Convolutional LSTM







Settings

(Work with Mr. Viet Phi Huynh and Prof. Pierre Tandeo)

DATASET

NICT
Phased Array Radar
- 250m
- Every 30 second radar echo
- Min-max normalization
- Input past 3 mins
  - Forecast 2.5 mins

Training period:
31 May & 26-27 July, 2018

Training settings

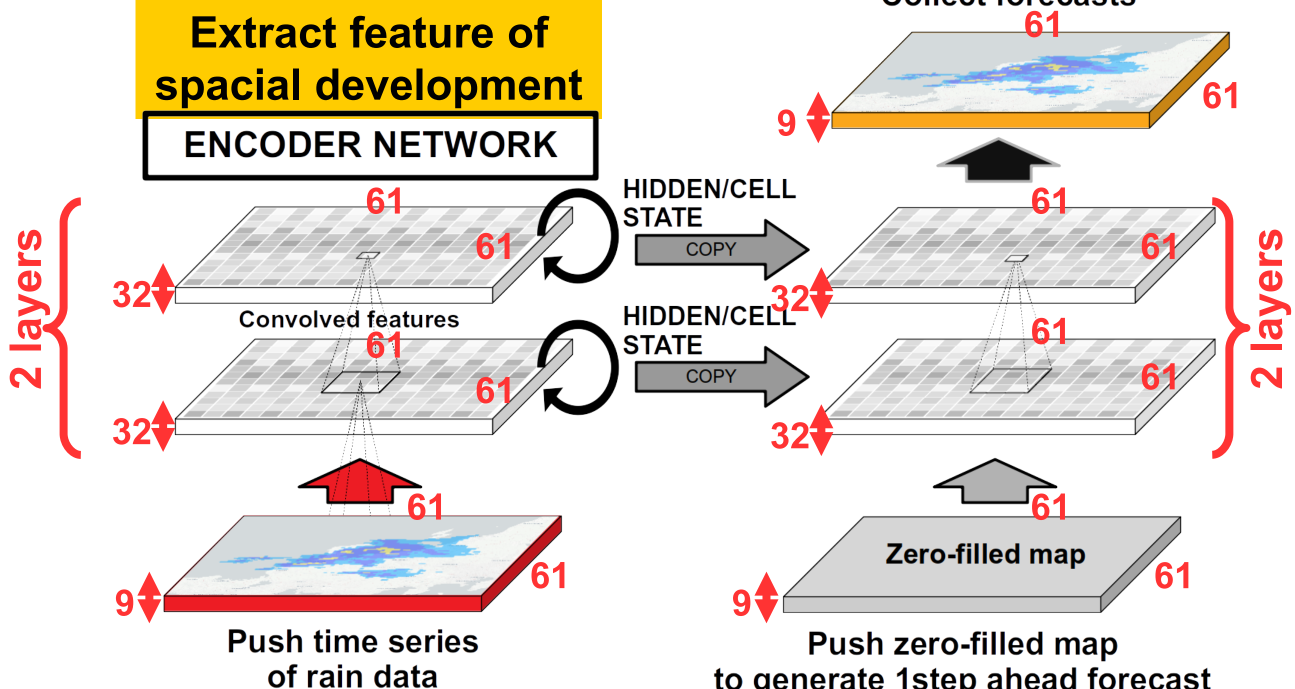
Library: Theano
Loss function:
 Balanced MSE
Optimizer:
 AdaDelta (lr=1e-4)
Mini batch: 10

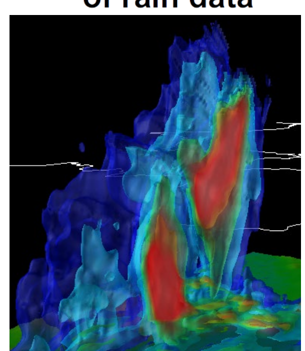
“Convolutional LSTM”

Shi et.al (2015)

Extract feature of spacial development

FORECASTER NETWORK

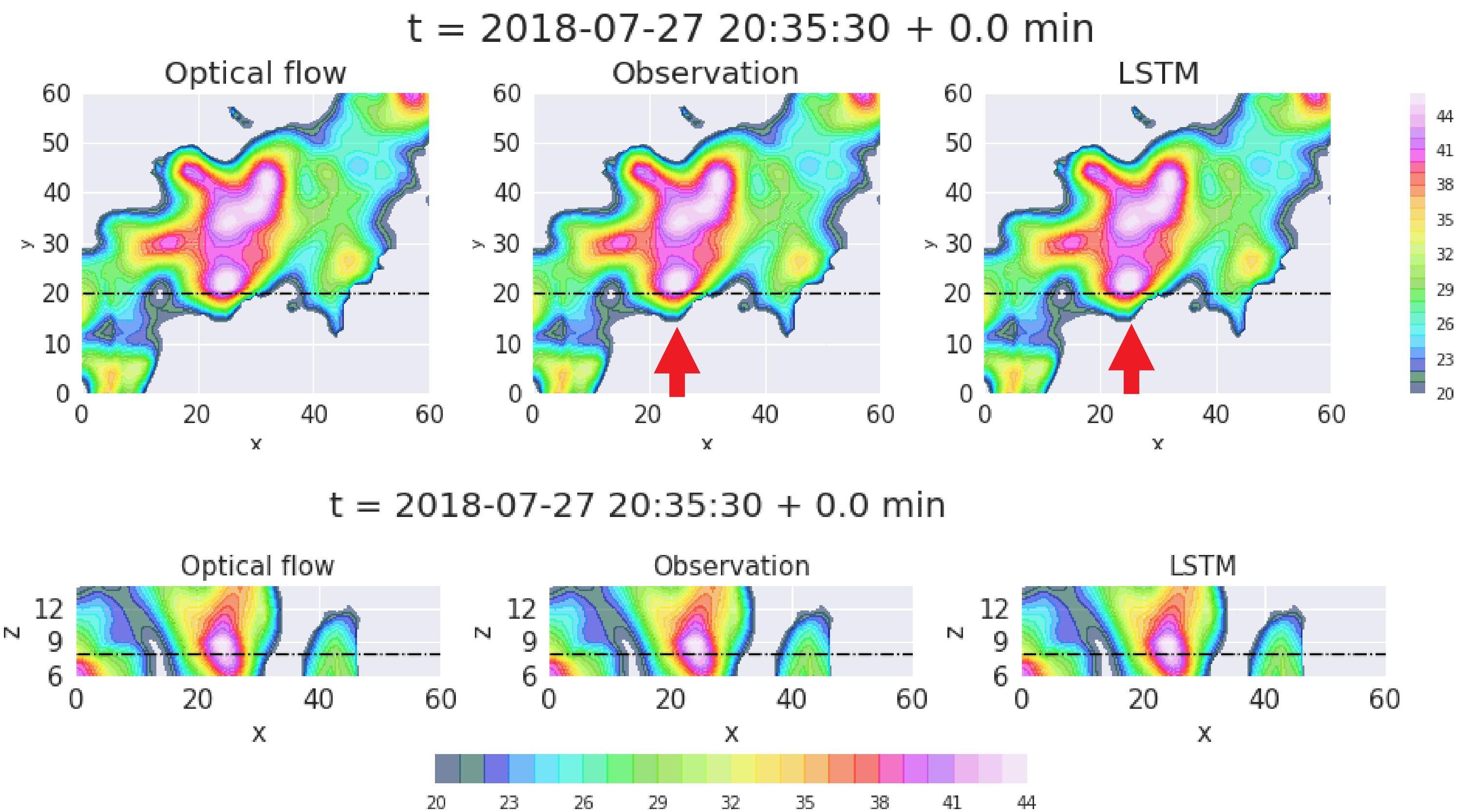




Forecast rain-map based on extracted features

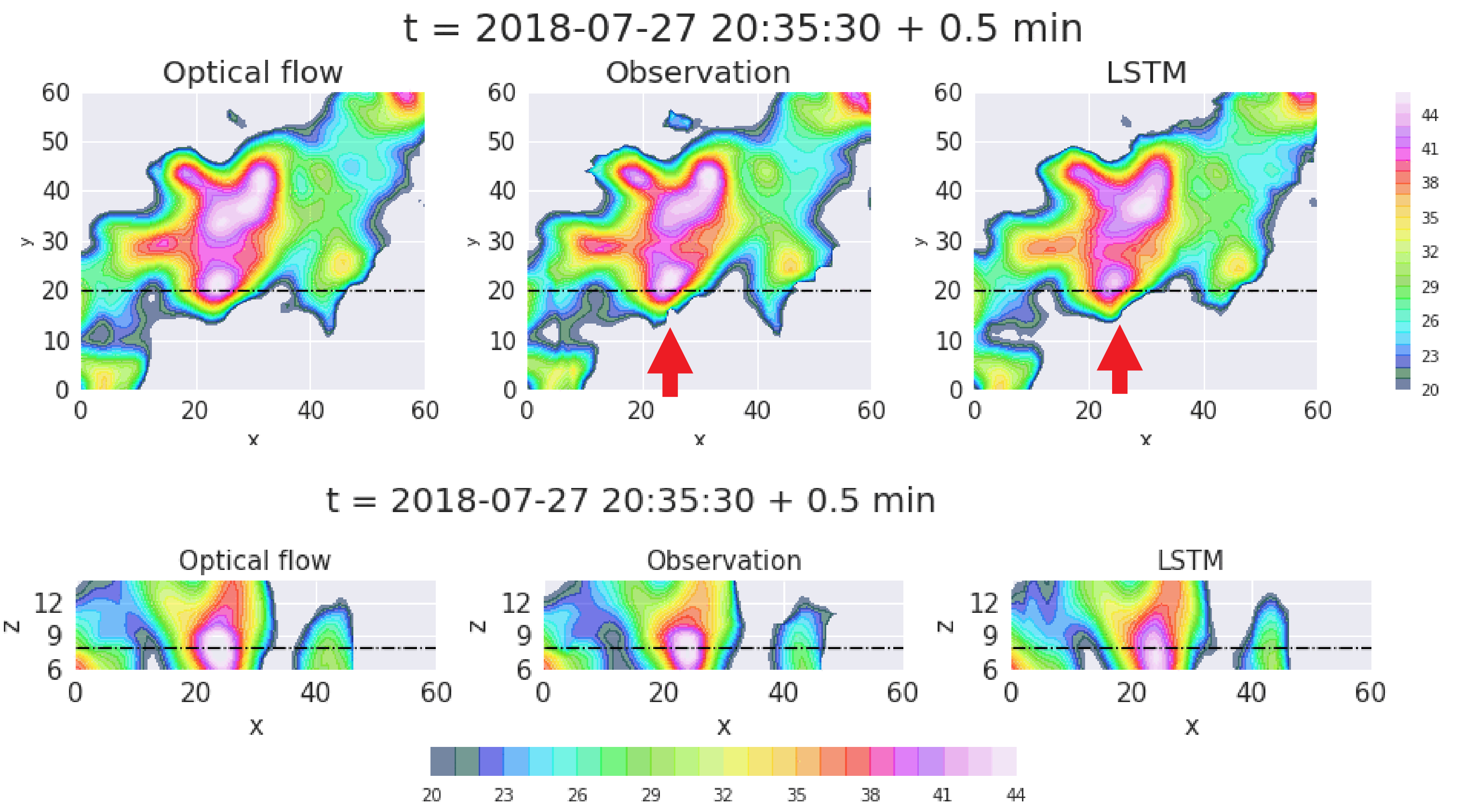
3D Nowcast by Conv-LSTM

(Work with Mr. Viet Phi Huynh and Prof. Pierre Tandeo)



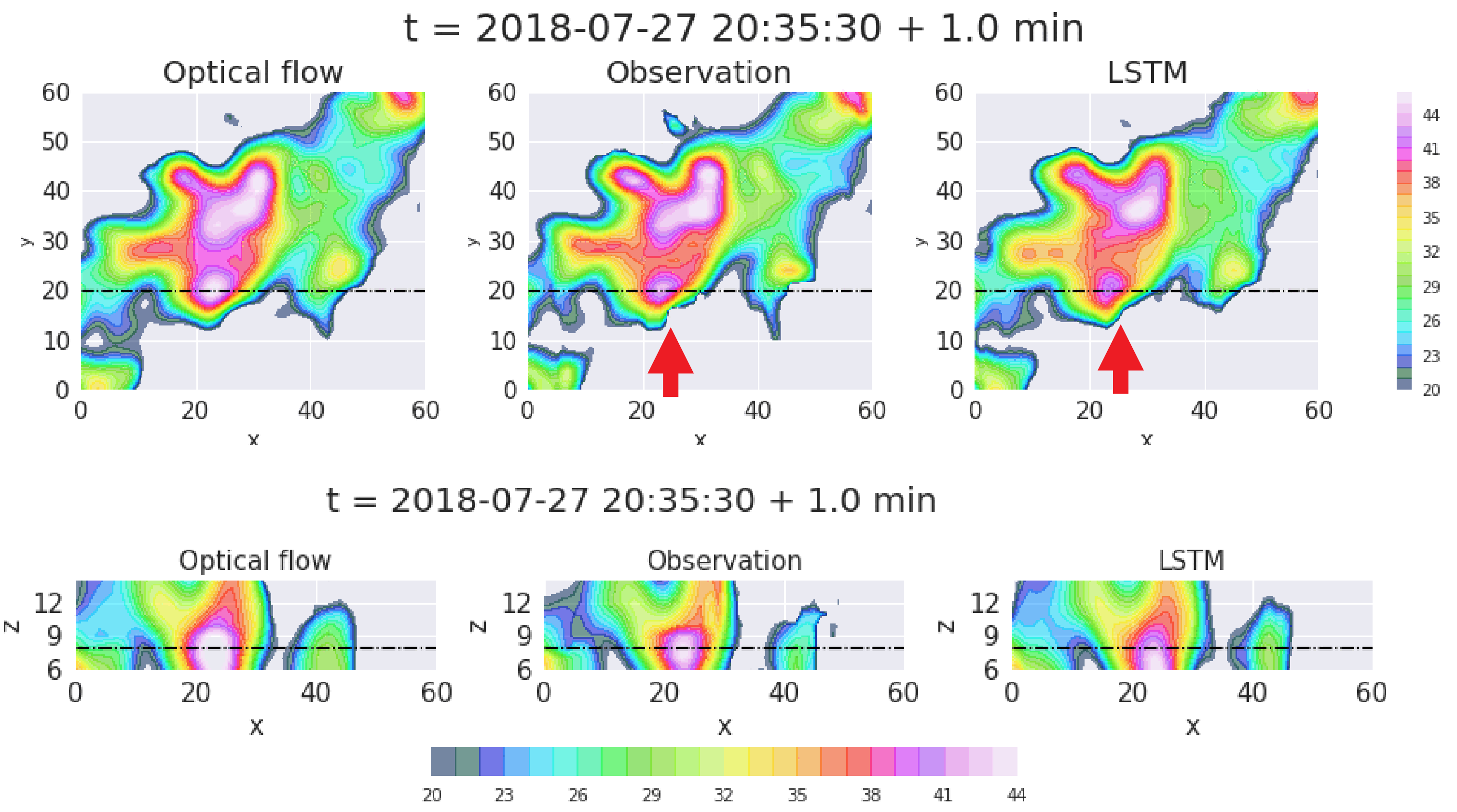
3D Nowcast by Conv-LSTM

(Work with Mr. Viet Phi Huynh and Prof. Pierre Tandeo)



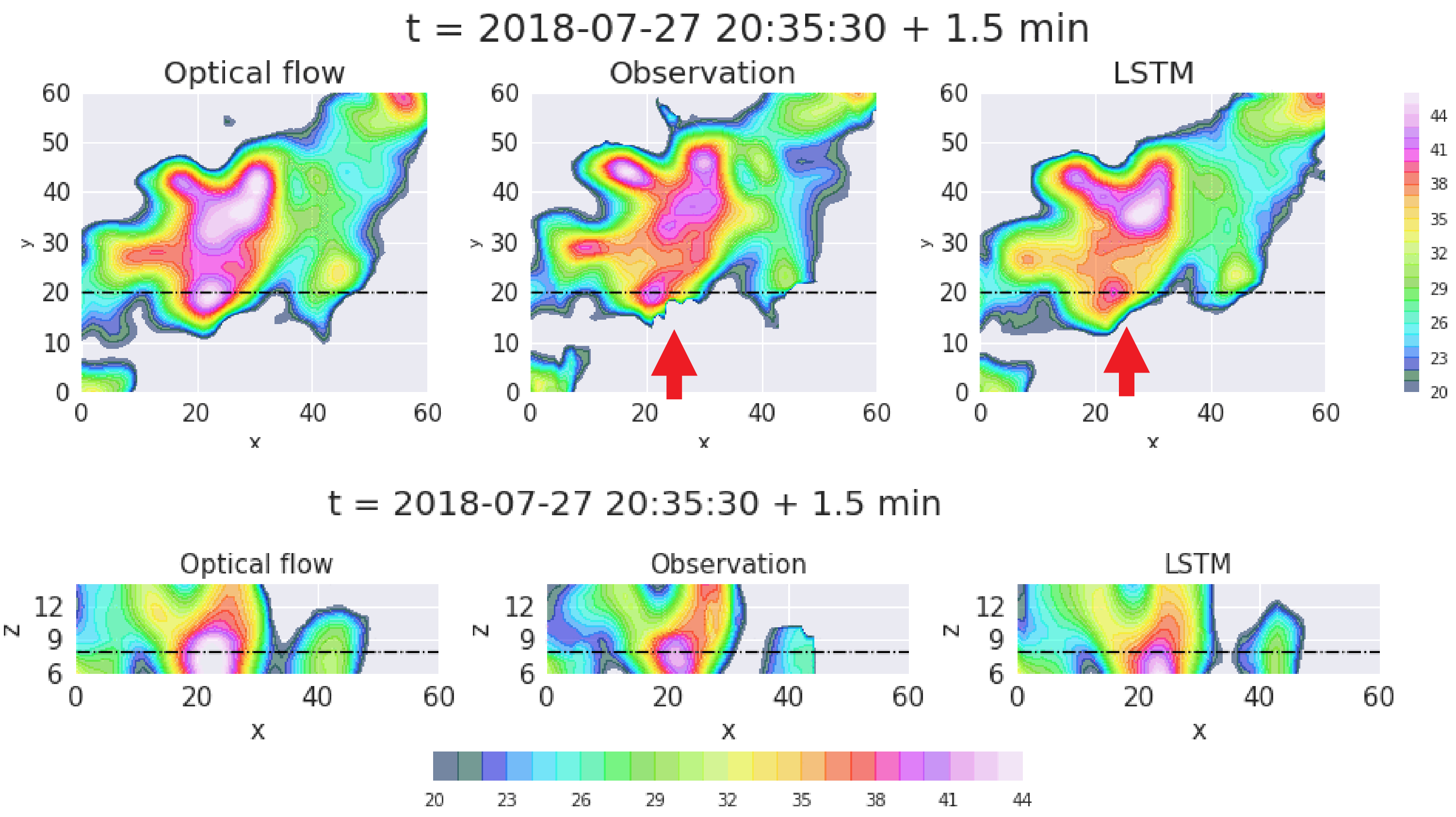
3D Nowcast by Conv-LSTM

(Work with Mr. Viet Phi Huynh and Prof. Pierre Tandeo)



3D Nowcast by Conv-LSTM

(Work with Mr. Viet Phi Huynh and Prof. Pierre Tandeo)



3D Nowcast by Conv-LSTM

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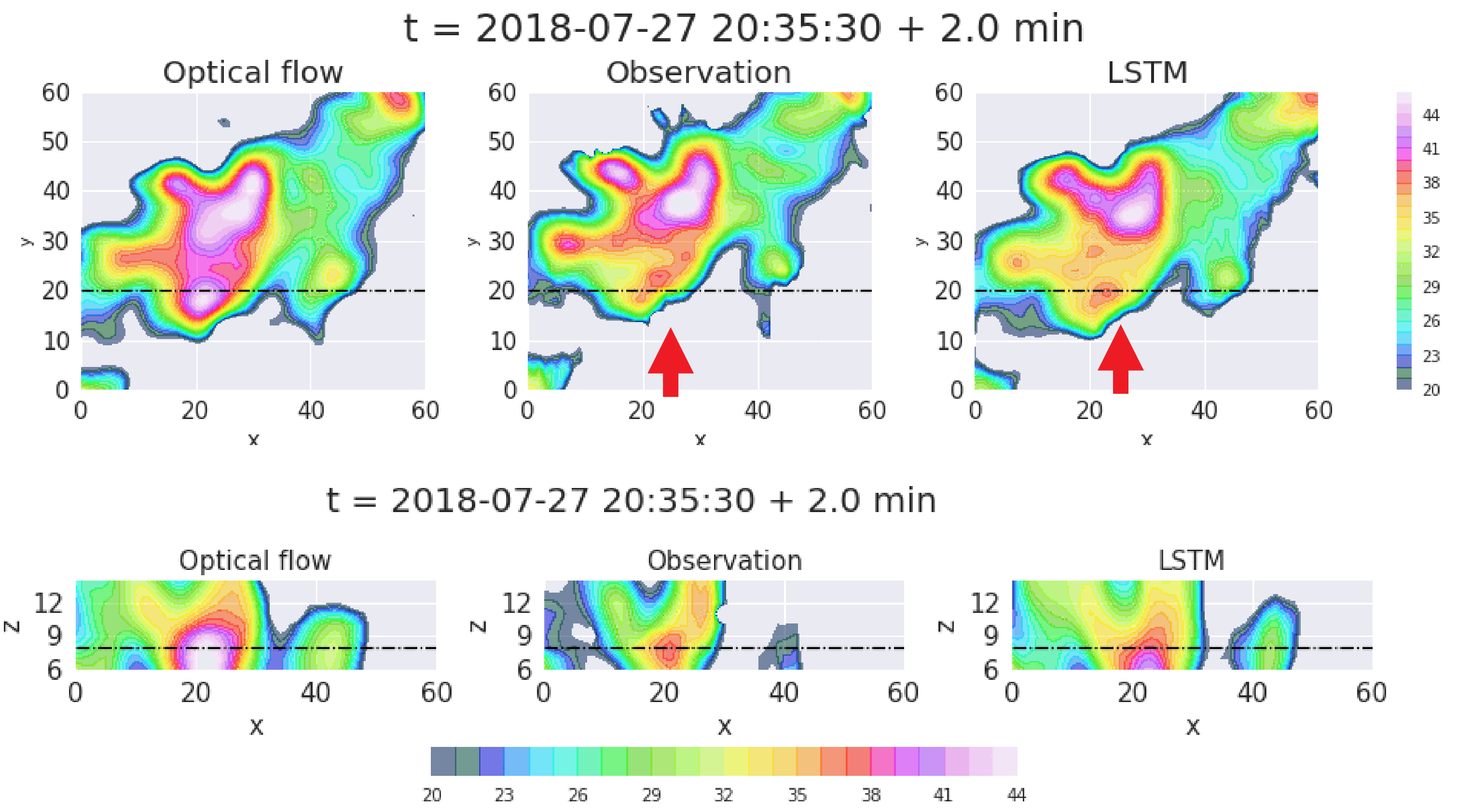
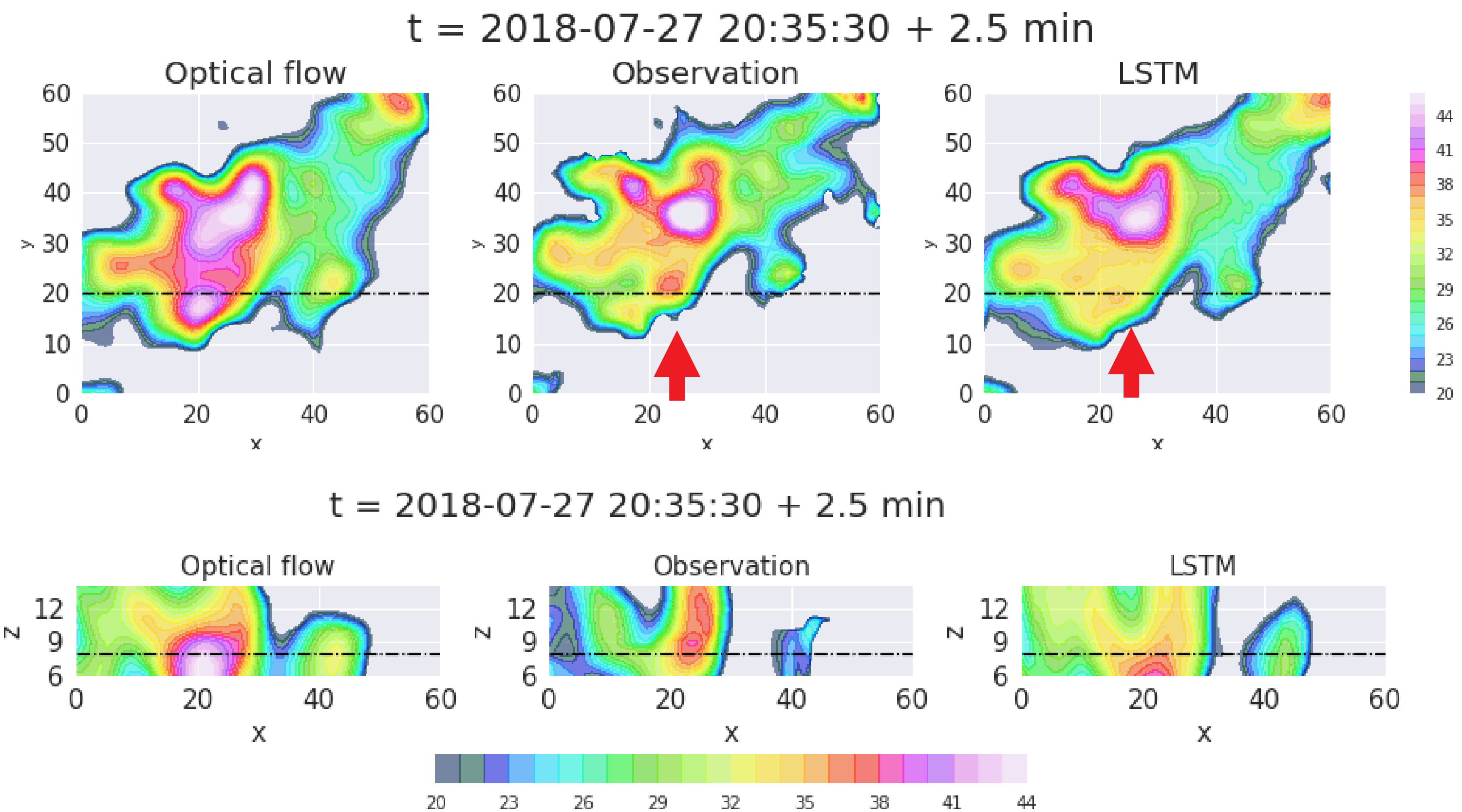
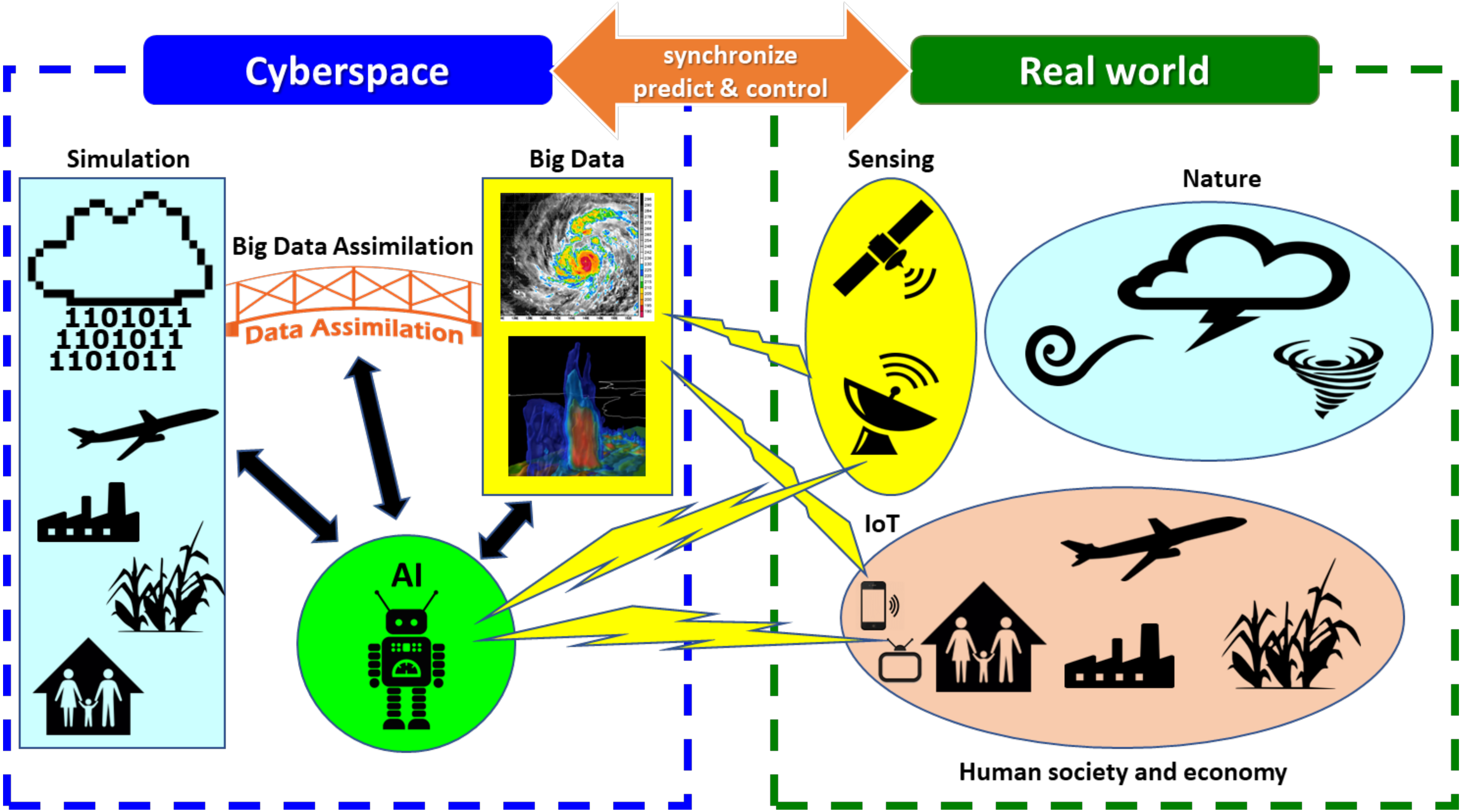


3D Nowcast by Conv-LSTM

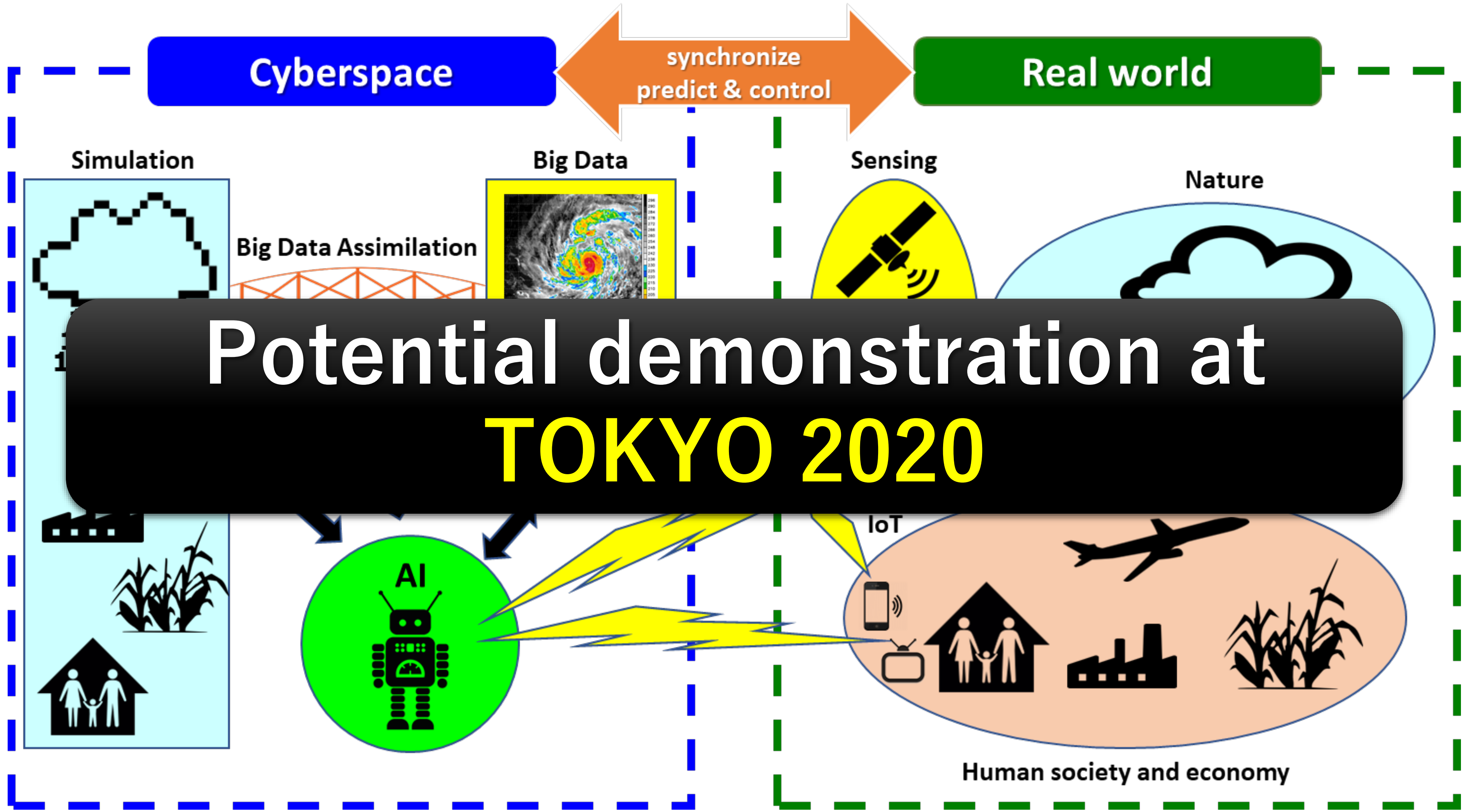
(Work with Mr. Viet Phi Huynh and Prof. Pierre Tandeo)



Toward Weather-Ready Society5.0 with BDA

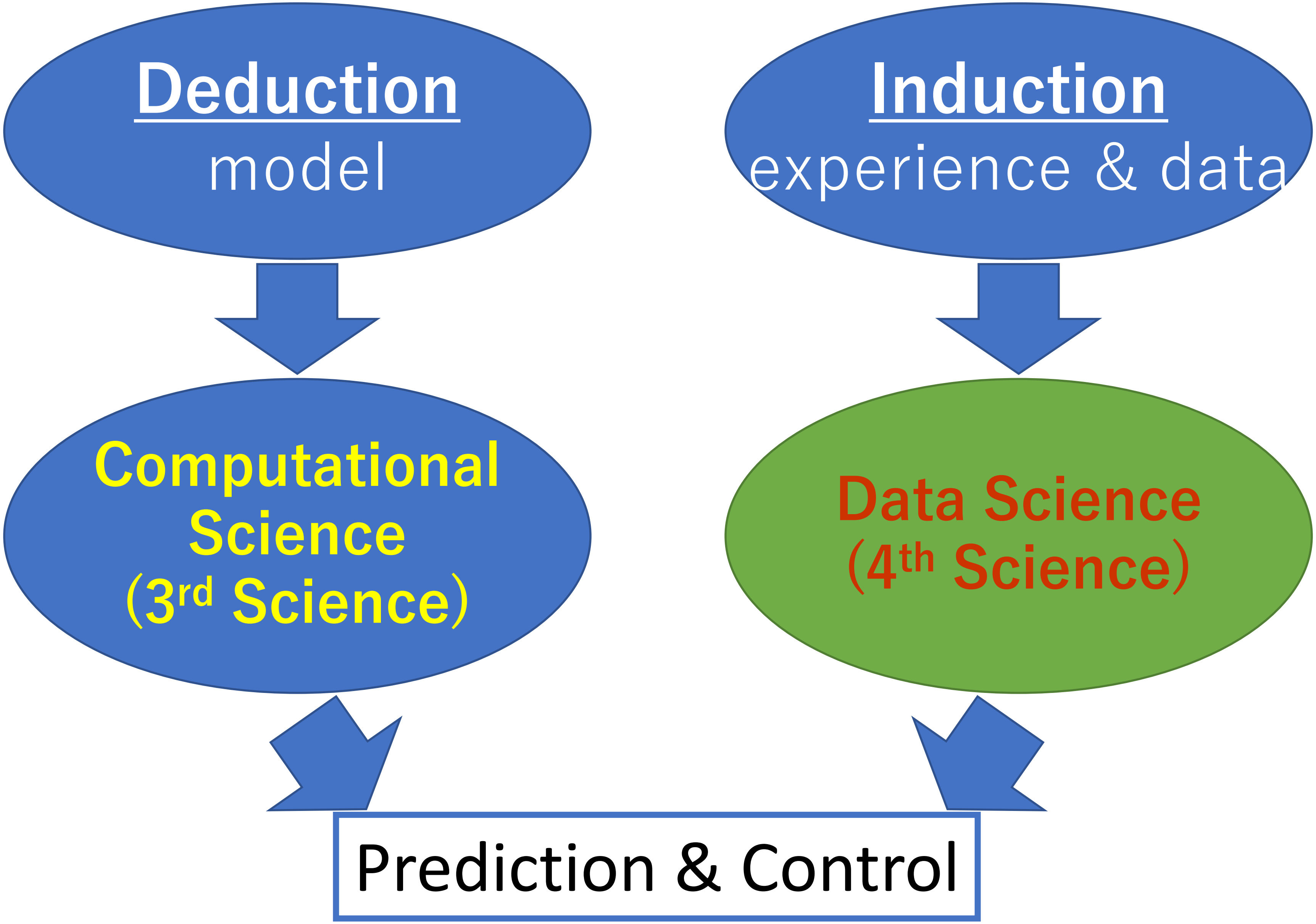


Toward Weather-Ready Society5.0 with BDA

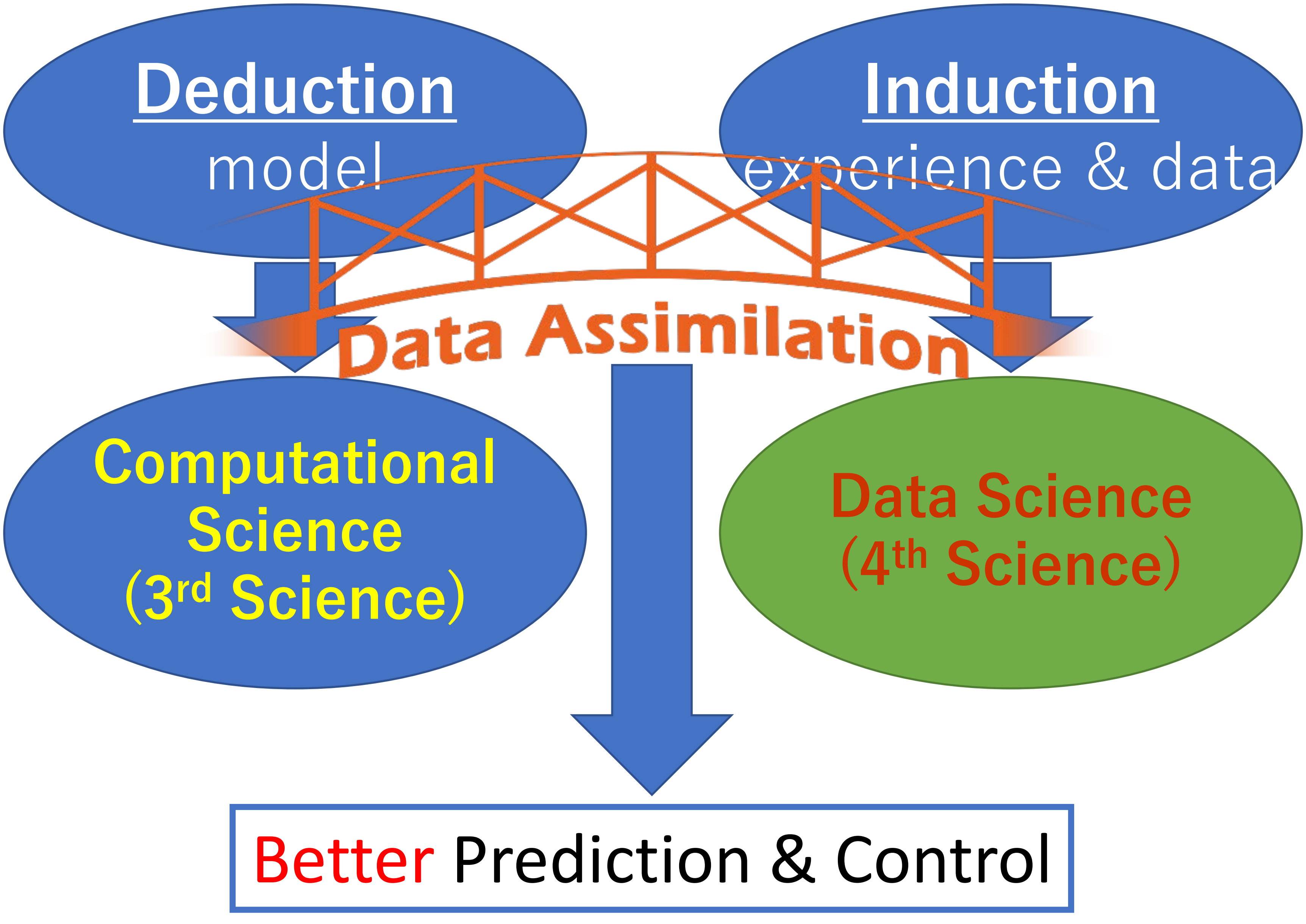


Potential demonstration at TOKYO 2020

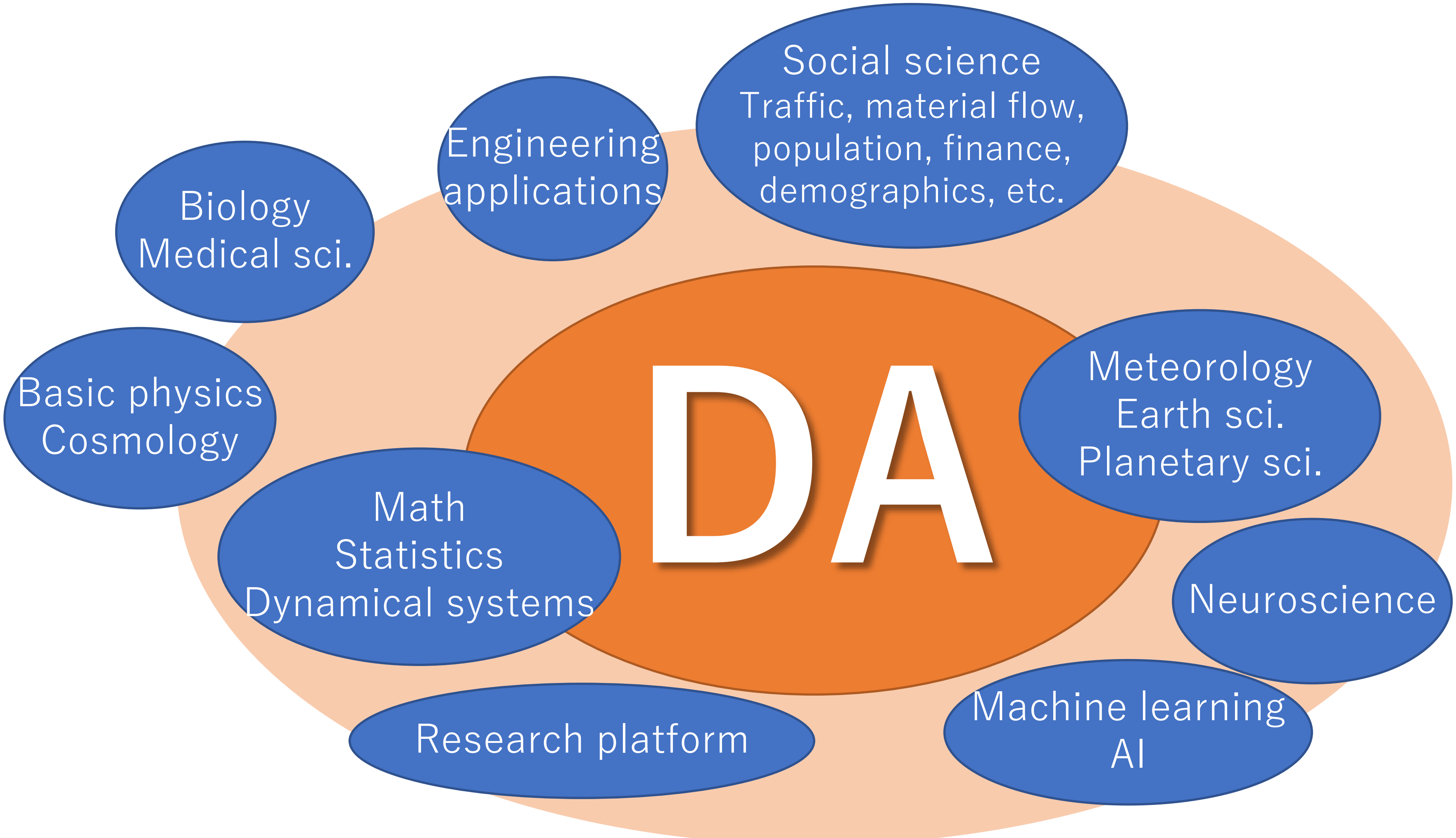
Methods for prediction & control

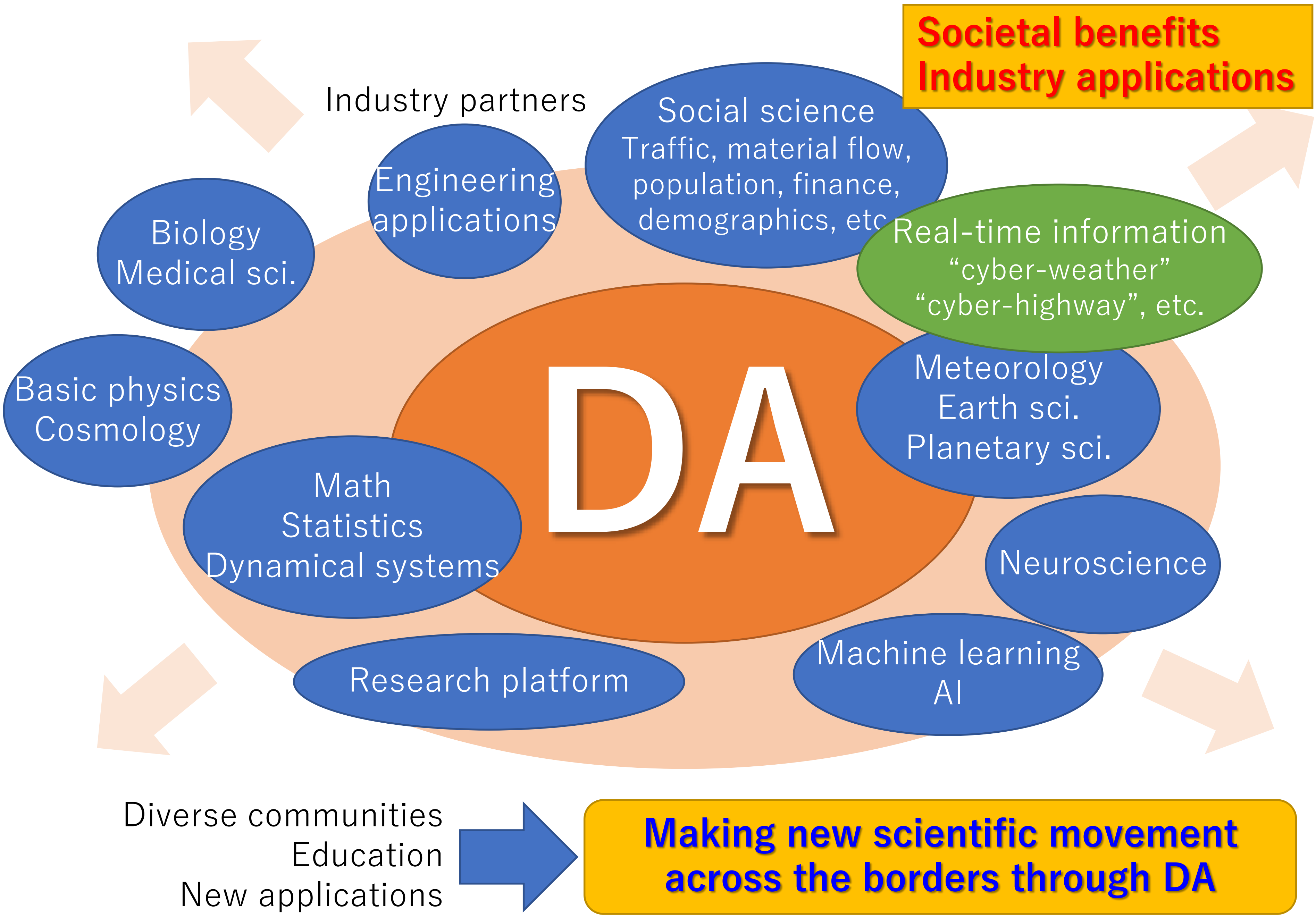


Methods for prediction & control

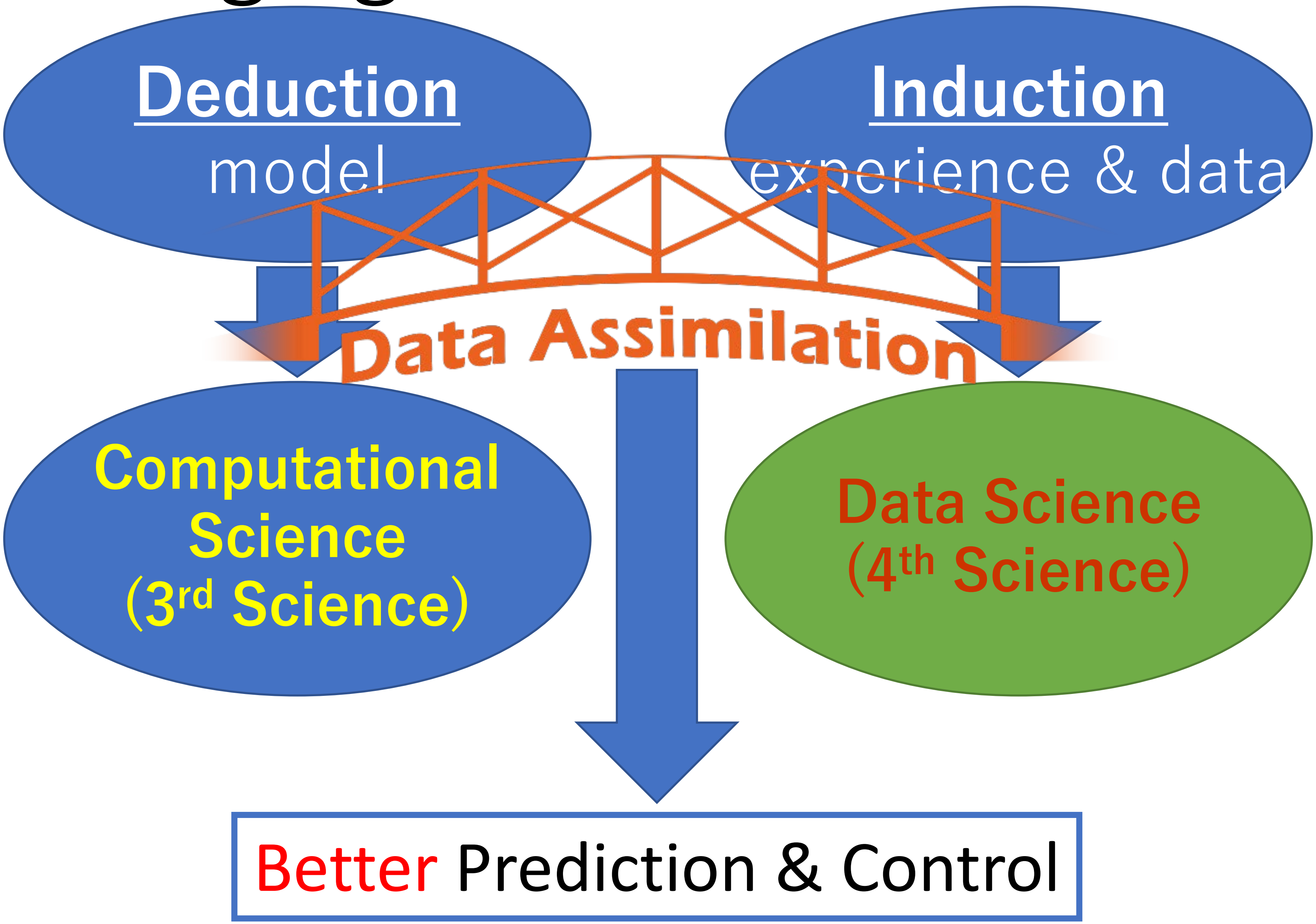



DA
Math
Statistics
Dynamical systems
Meteorology
Earth sci.
Planetary sci.


DA
Social science
Traffic, material flow,
population, finance,
demographics, etc.
Engineering
applications
Biology
Medical sci.
Basic physics
Cosmology
Math
Statistics
Dynamical systems
Meteorology
Earth sci.
Planetary sci.
Neuroscience
Machine learning
AI
Research platform

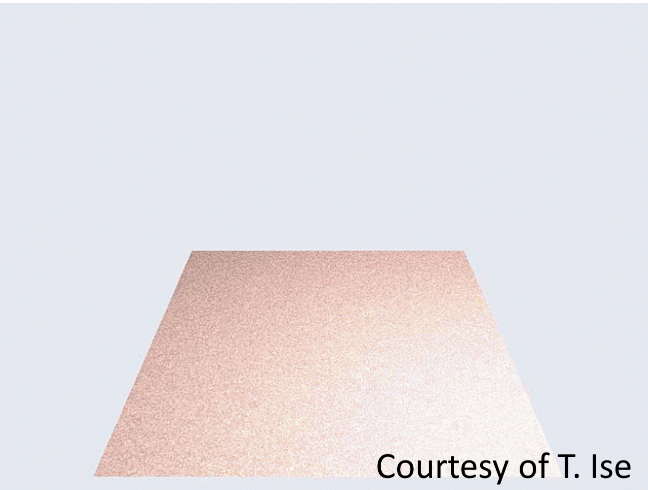

Societal benefits
Industry applications
Industry partners
Social science
Traffic, material flow, population, finance, demographics, etc
Engineering applications
Biology
Medical sci.
Real-time information
"cyber-weather"
"cyber-highway", etc.
Basic physics
Cosmology
DA
Meteorology
Earth sci.
Planetary sci.
Math
Statistics
Dynamical systems
Neuroscience
Research platform
Machine learning
AI
Diverse communities
Education
New applications
Making new scientific movement across the borders through DA

Bringing DA into new areas



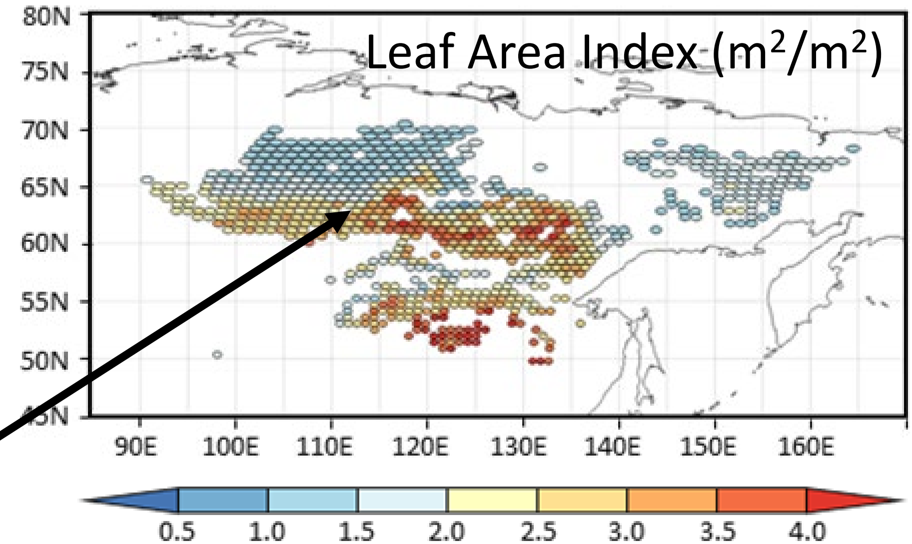
Ecosystem control with DA

Forest simulation



for 100 years at
a single location

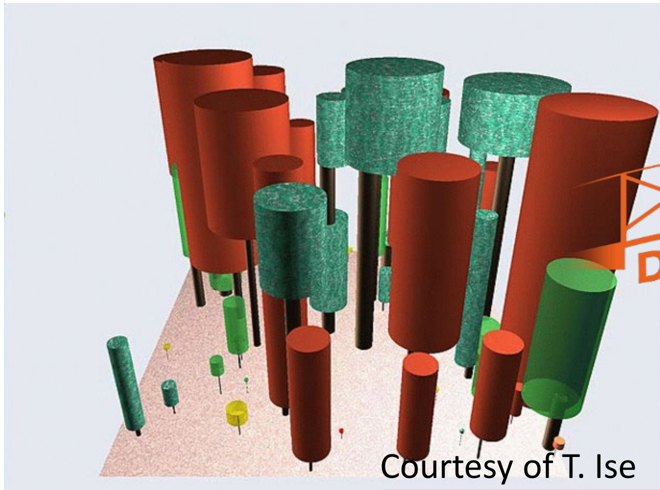
Satellite observation

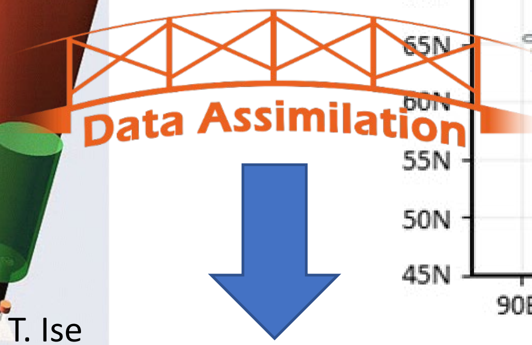


every 4 days

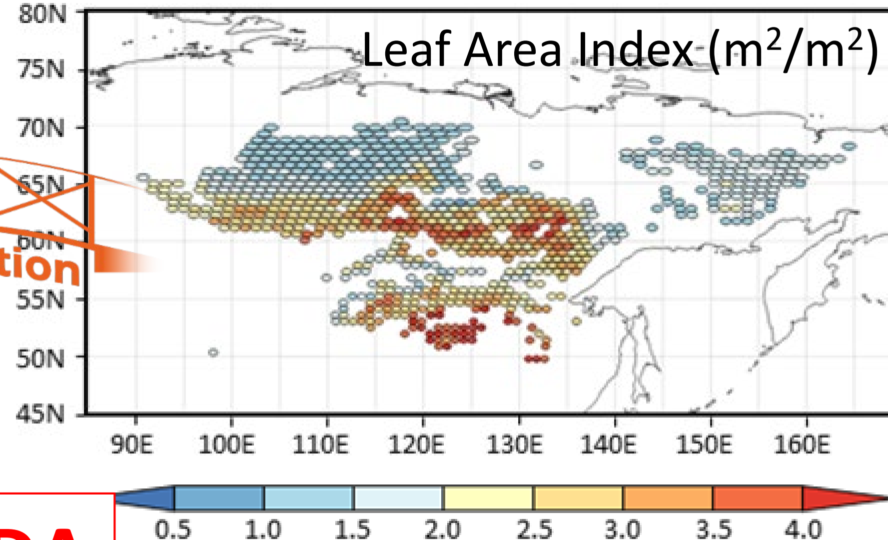
Ecosystem control with DA

Forest simulation

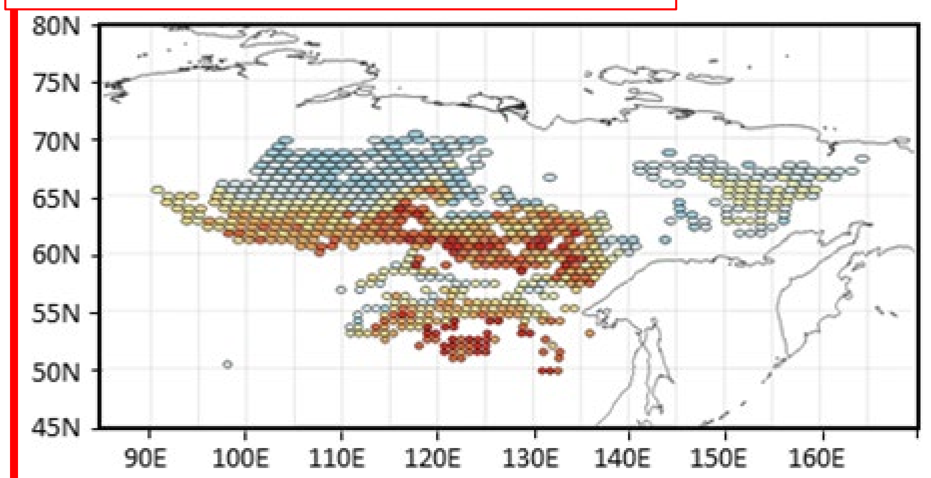




Satellite observation

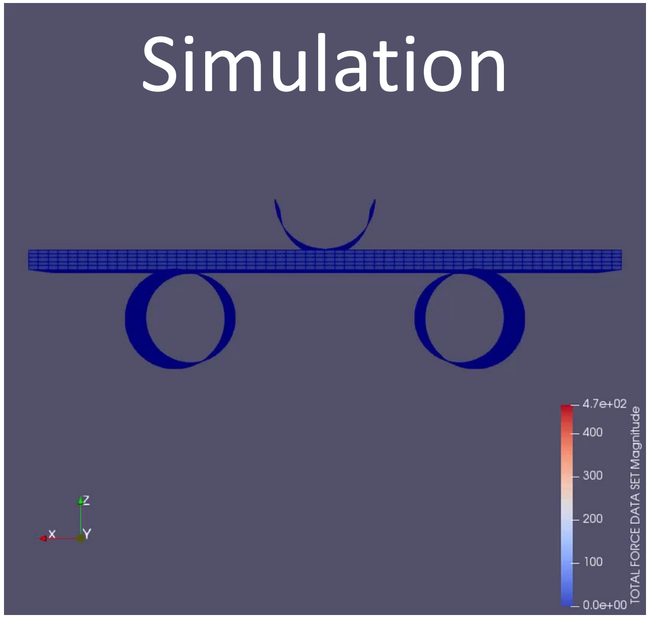


Simulation w/ DA



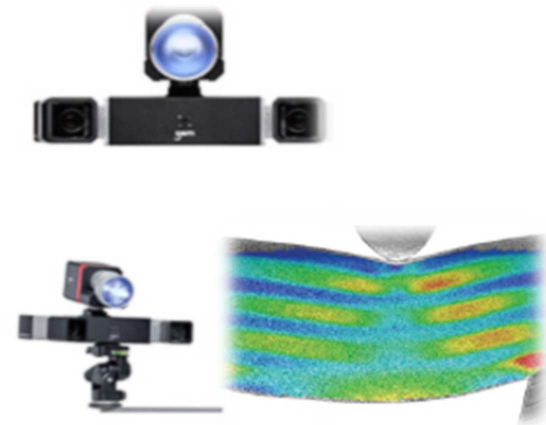
Arakida, Miyoshi, et al. (2018)

DA for press-forming simulation



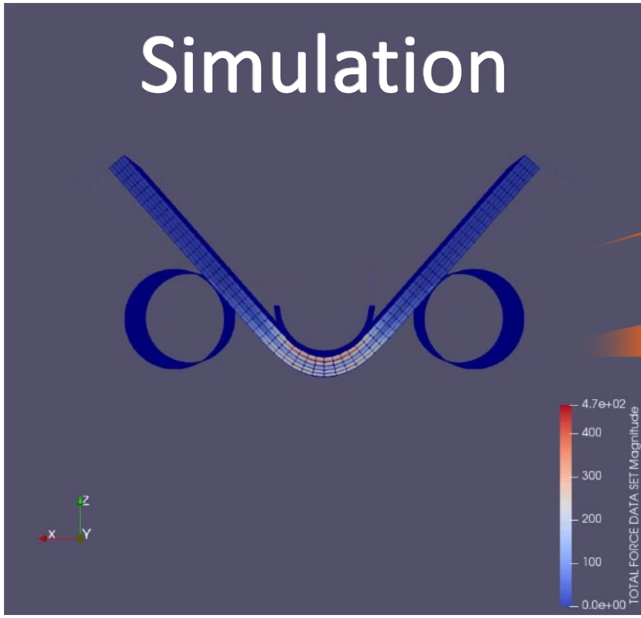
(Sakamoto, Takamura)

Sensor data



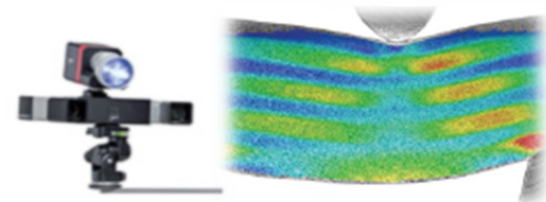
Surface strain measured by ARAMIS

DA for press-forming simulation



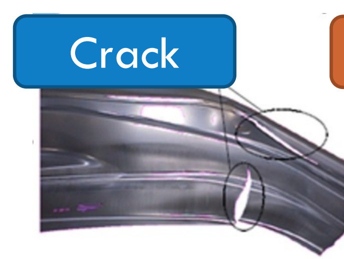
(Sakamoto, Takamura)

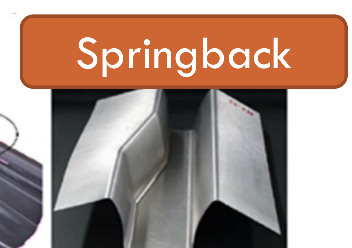
Sensor data



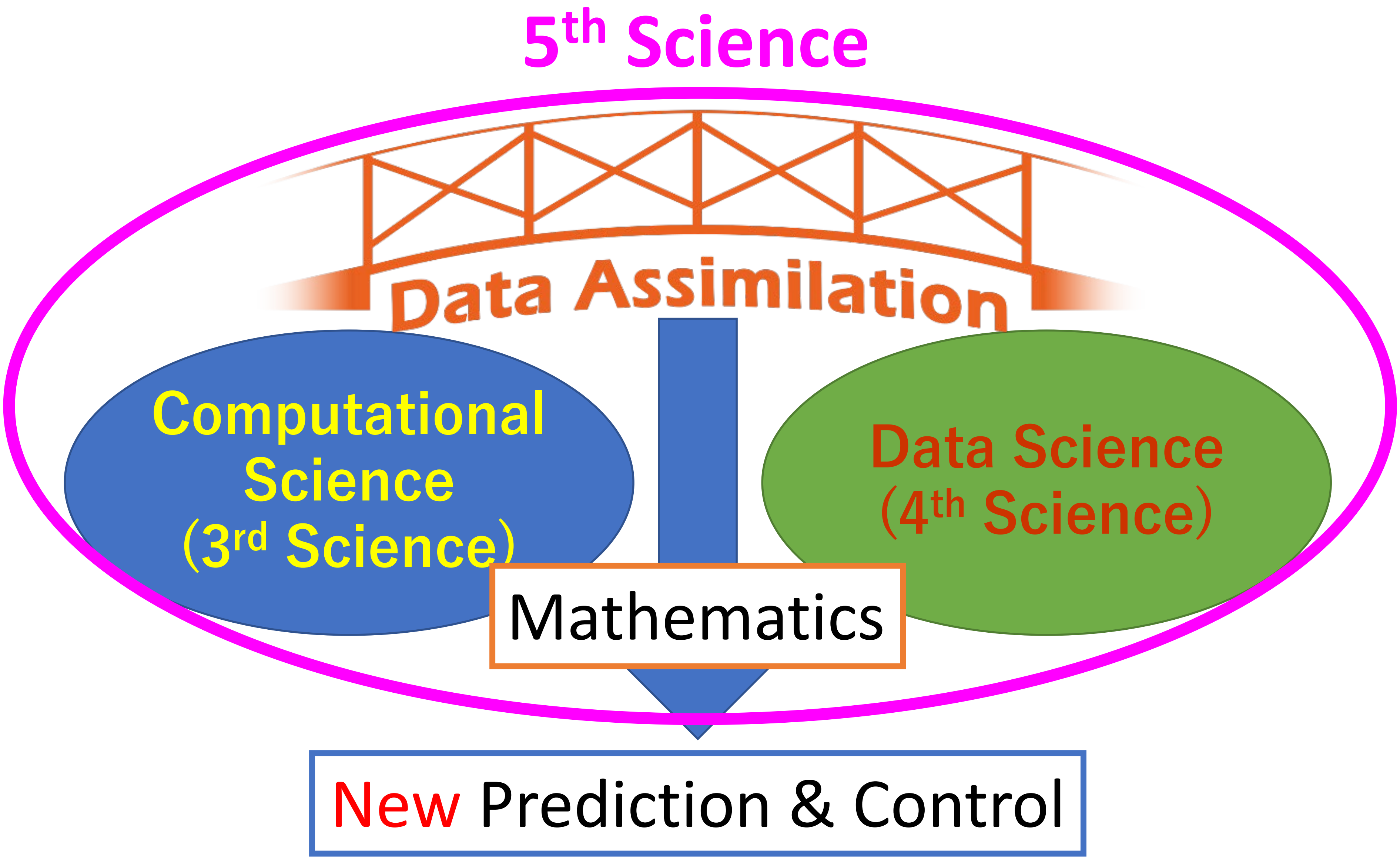
Surface strain measured by ARAMIS

Optimize press-forming parameters



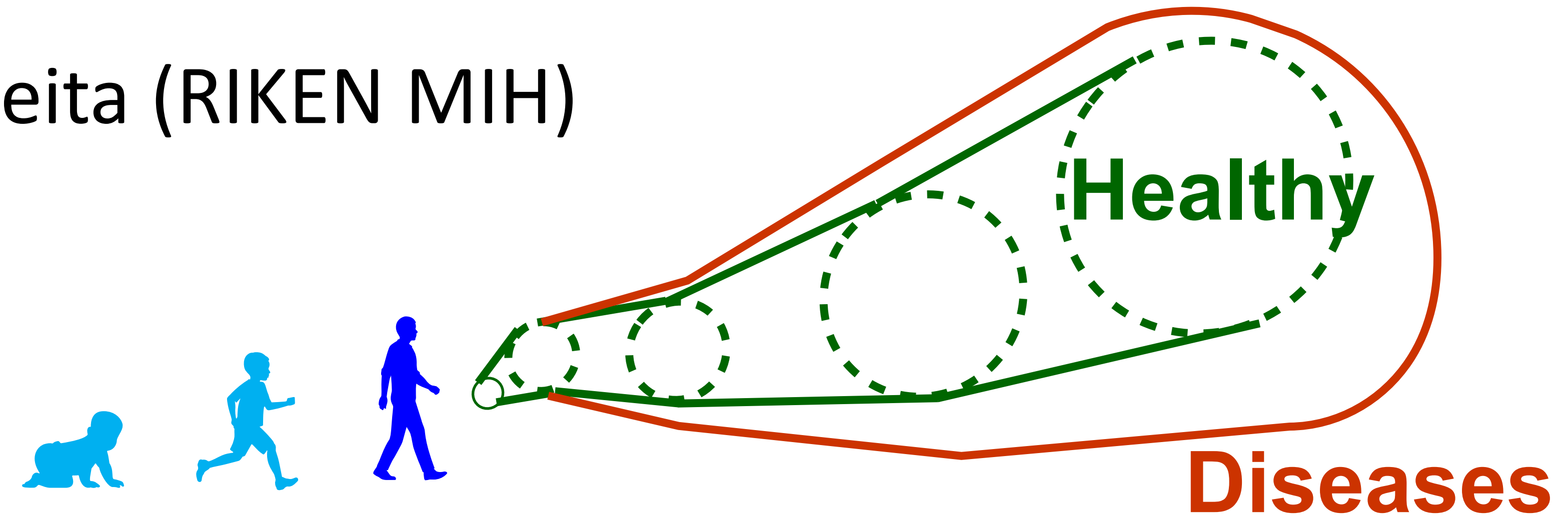


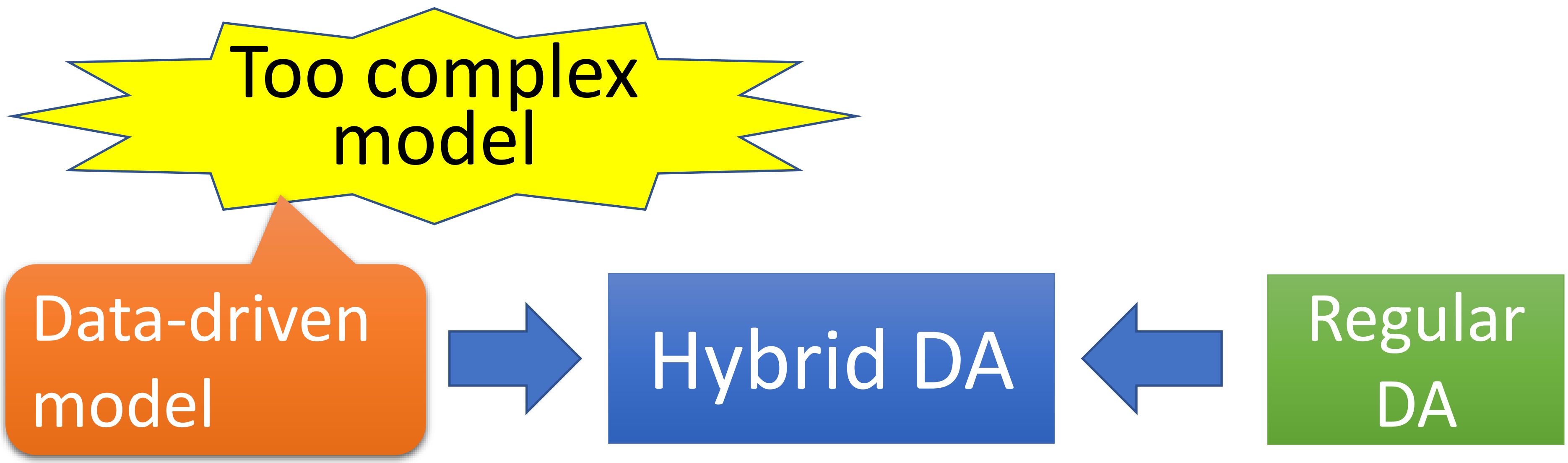
The 5th Paradigm

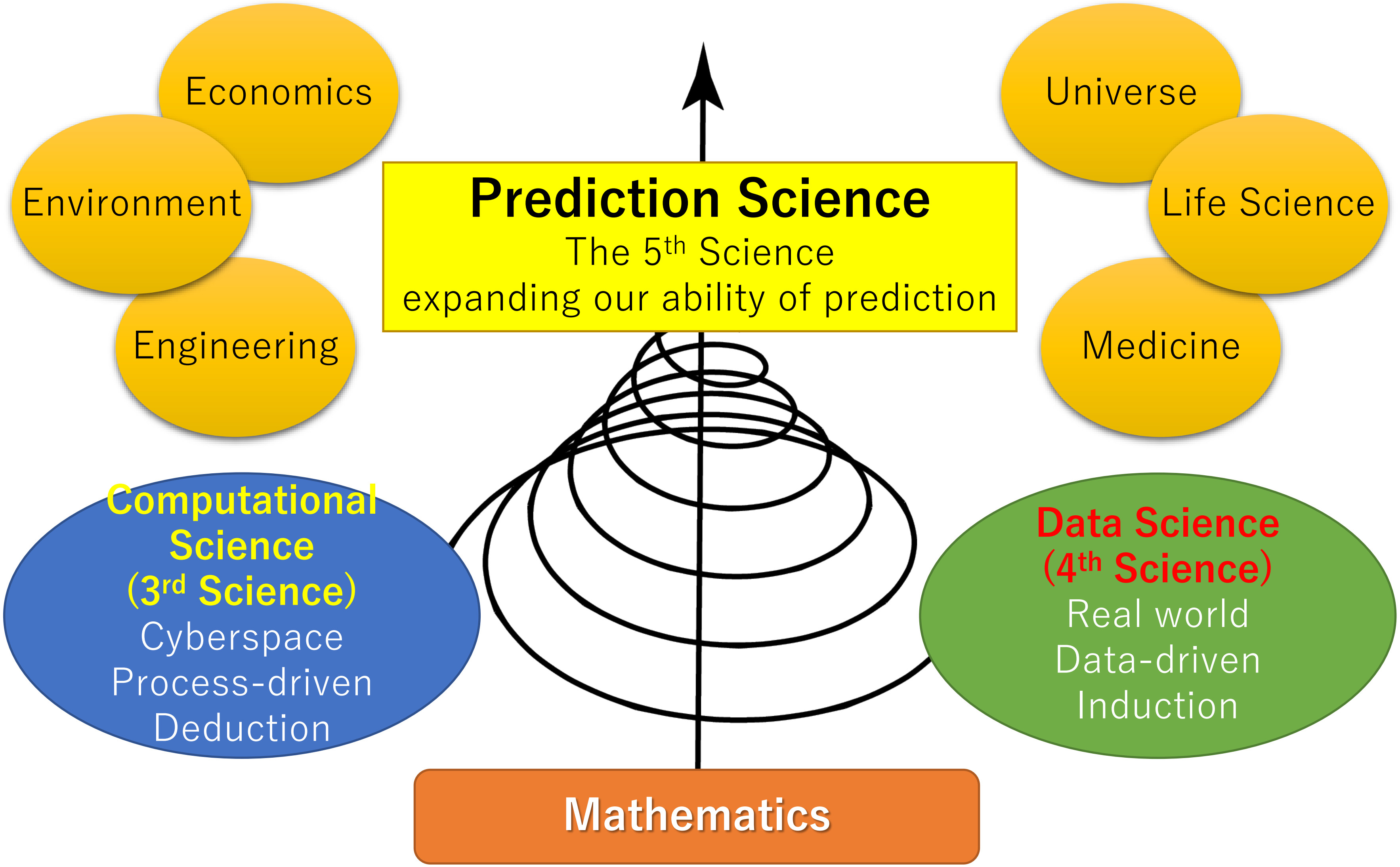


Hybrid DA for human life

J. Seita (RIKEN MIH)






Economics
Environment
Engineering
Universe
Life Science
Medicine
Prediction Science
The 5th Science
expanding our ability of prediction
Computational Science
(3rd Science)
Cyberspace
Process-driven
Deduction
Data Science
(4th Science)
Real world
Data-driven
Induction
Mathematics